Title

Managing Astronomy Research Data: Data Practices in the Sloan Digital Sky Survey and Large Synoptic Survey Telescope Projects

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Publication Date

2017

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Managing Astronomy Research Data:
Data Practices in the Sloan Digital Sky Survey and Large Synoptic Survey Telescope Projects

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Information Studies

by

Ashley Elizabeth Sands

2017

ABSTRACT OF THE DISSERTATION

Managing Astronomy Research Data:

Data Practices in the Sloan Digital Sky Survey and

Large Synoptic Survey Telescope Projects

by

Ashley Elizabeth Sands

Doctor of Philosophy in Information Studies

University of California, Los Angeles, 2017

Professor Christine L. Borgman, Chair

Ground-based astronomy sky surveys are massive, decades-long investments in scientific data collection. Stakeholders expect these datasets to retain scientific value well beyond the lifetime of the sky survey. However, the necessary investments in knowledge infrastructures for managing sky survey data are not yet in place to ensure the long-term management and exploitation of these scientific data. How are sky survey data perceived and managed, by whom, and what are the implications for the infrastructures necessary to sustain the long-term value of data? This dissertation used semi-structured interviews, document analysis, and ethnographic fieldwork to explain how perspectives on data management differ among the stakeholder populations of two major sky surveys: the Sloan Digital Sky Survey (SDSS) and the Large Synoptic Survey Telescope (LSST). Perspectives on sky survey data cluster into two categories:

"data as a process" is where data are perceived in terms of the practices and contexts surrounding data production; and "data as a product" is where data are perceived as objective representations of reality, divorced from their production context. Analysis reveals these different perspectives result from stakeholders' differing data management responsibilities throughout the research life cycle, as reflected through their professional role, career stage, and level of astronomy education. These results were used to construct a data management life cycle model for ground-based astronomy sky surveys. Stakeholders involved in day-to-day construction, operations, and processing activities perceive data as a process because they are intimately familiar with how the data are produced. In contrast, sky survey leaders perceive data as a product due to their roles as liaisons to external stakeholders. During the proposal stage, leaders must present the data as objective and accurate to secure financial support; during data release, leaders must attract researchers to trust the data for scientific use. The tendency of sky survey leaders to regard data as a product leads them, and other stakeholders, to undervalue workforces, funding, and the other knowledge infrastructures necessary to sustain the value of scientific data. Planning for long-term data management must include stakeholders who view data as a process as well as those who view data as a product.

The dissertation of Ashley Elizabeth Sands is approved.

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Beverly P. Lynch

Sharon Traweek

Christine L. Borgman, Committee Chair

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2017

For Mom and Father

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Acknowledgements

I was able to write this dissertation and earn my PhD due to the support of my family, friends, teachers, and colleagues. Thank you to my advisor, Christine Borgman, who has provided the motivation and incentive to ensure I become the best possible version of myself. Thank you to Sharon Traweek, for your sincerity in mentoring. Thank you to Jonathan Furner for supporting my work since I arrived at UCLA in 2009. Finally, thank you to Beverly Lynch for your guidance on my committee and devotion to the importance of libraries and librarians for decades.

Thank you to my parents, Tom and Patty, who have never failed to support my passions. To my sister, Lindsey Smith-Sands, who helped me laugh through all the ups and downs. To Lynn Swartz Dodd, for pointing me toward Information Studies, and Bruce Zuckerman for providing me opportunities when I needed them most. Thank you to my friends for staying by my side even while I disappeared to complete my degree. Thank you to Katie, Sarah, Michelle, Alex, Joel, Rachel, Melissa, Hilary, Kat, Carole, Joanie, Terry, and particularly to Dimi, who never doubted my ability to succeed.

Thank you to all the members of the UCLA Center for Knowledge Infrastructures during my tenure; you have been my colleagues and friends. These collaborators include Rebekah Cummings, Milena Golshan, Rachel Mandell, Jaklyn Nunga, Irene Pasquetto, Bernie Randles, Lizzy Rolando, and Jillian Wallis. Particular appreciation goes to Peter T. Darch who has gone above and beyond as my friend, collaborator, and mentor.

I appreciate the time and commitment of our team advisory board. The thoughtful considerations of these successful astronomers have catalyzed our analysis over the years:

George Djorgovski, Alyssa Goodman, and Alexander Szalay. This research was conducted under approval of the UCLA Institutional Review Board, Study Protocol ID# 10-000909.

Thank you to the Alfred P. Sloan Foundation and the National Science Foundation for supporting the full tenure of this research. The generous support included (A) the National Science Foundation ("Data Conservancy" OCI0830976, S. Choudhury, PI, Johns Hopkins University) and (2) ("Knowledge & Data Transfer: the Formation of a New Workforce" # 1145888. C.L. Borgman, PI; S. Traweek, Co-PI) and (B) the Alfred P. Sloan Foundation (3) ("The Transformation of Knowledge, Culture, and Practice in Data-Driven Science: A Knowledge Infrastructures Perspective" # 20113194. C.L. Borgman, PI; S. Traweek, Co-PI) and (4) "If Data Sharing is the Answer, What is the Question?" # 201514001 C.L. Borgman, PI). Thank you particularly to Joshua Greenberg who generously supported our UCLA team research, and who believed in me as a team member and as an individual.

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1 Introduction

> *Interviewer: "You're an astronomer by training, right?"*
> *Interviewee: "Yeah, but I don't really do any astronomy, I haven't done for years now, I'm basically just doing data-intensive science and providing access to astronomical data" (Staff Scientist, 2014).*

Innovative data collection methods, tools, and technologies are enabling qualitative changes to scientific research, including the ability to ask new kinds of research questions (W. L. Anderson, 2004; Borgman, 2015; Borne, 2013; Goble & De Roure, 2009; Goodman & Wong, 2009; Kitchin, 2014; McCray, 2014; National Science Board (U.S.), 2005). The changes in modern science have been interpreted in various ways. Some argue the large quantities of data have enabled a "Fourth Paradigm" (Borne, 2013, p. 407; Hey, Tansley, & Tolle, 2009b). Others assert we have entered an era of "e-science" (Bell, Hey, & Szalay, 2009, p. 1298), or "big data" (Galison & Hevly, 1992a; Gitelman & Jackson, 2013; Price, 1963; R. W. Smith, 1992; Weinberg, 1961), in which scientists can ask new scientific questions that can only be investigated by, "analyzing hundreds of billions of data points" (Mayer-Schonberger & Cukier, 2013, p. 11).

1.1 Scientific Data Revolution

Scientists in each generation have declared "the dawning of a new age" (Bowker, 2005, p. 12), and academics have often referenced information overload (Blair, 2010; Kitchin, 2014). The size of electronic datasets continue to increase since the "start of modern science" (Kitchin, 2014, p. 67), the early nineteenth century (Bowker, 2005, p. 6), the 1960s (Mayer-Schonberger & Cukier, 2013, p. 9), the 1990s (Ray, 2014a), and the new millennium (Gitelman & Jackson, 2013). Technological advances have contributed to concerns over data management; however,

the current period is uniquely transformational for scientific data management and sharing because of both technological and cultural changes in research data.

Ann Blair (2010) explains that eras of information overload—such as the modern "data deluge"—come about only when technological and societal factors occur simultaneously. Describing the heightened respect for the printed word during the Renaissance, she cites not only the technological innovation of "printing and the availability of paper," but also the change in social perspective to "a newly invigorated info-lust that sought to gather and manage as much information as possible" (Blair, 2010, p. 6). A combination of shifts in societal thinking and modern technology, has similarly culminated in the current attention to data management and sharing in the sciences (CODATA-ICSTI Task Group on Data Citation Standards Practices, 2013; Joint Information Systems Committee (JISC) & Coalition for Networked Information (CNI), 2015; Michener et al., 2011; Miller, 2012; Treloar, 2014). One modern shift is the growing interest in research data (Ray, 2014a) and our society's fascination with "big data." boyd and Crawford confirm the newly emphasized importance of data-intensive research, asserting that "Big Data not only refers to very large data sets and the tools and procedures used to manipulate and analyze them, but also to a *computational turn* in thought and research" (2011, p. 3).

Another modern shift in information priorities is parallels the information overload experienced during the Renaissance. One impetus for that shift was recognizing that current practices ultimately lost ancient information, producing a subsequent desire to prevent further loss (Blair, 2010, p. 12,64). Technology development within data-intensive sciences is only one factor for the surge of attention paid to data management, sharing, and preservation. Given the modern speed of digital technology development, both scholars and citizens alike are losing

information that was not migrated forward through successive generations of hardware and software. Most individuals in 2017 have experienced the inability to access data, photos, or other kinds of important information because they were saved to outdated disks or hard drives. Some even evangelize that our future will result in a "Digital Dark Age" (Bollacker, 2010; Neuman, 2015). To combat the potential for loss, and to ensure data are available for data-intensive scientific reuse, a worldwide movement of funding bodies and governments are pushing for data management planning and publicly available scientific journal articles.

Respect for and concerted retention of information during the Renaissance was not an inevitable result of the invention of the printing press; it only occurred due to the simultaneous social agreements about the importance of the information (Blair, 2010). Similarly, the recent turn towards the importance of sharing and preserving scientific research data was not an inevitable consequence of the emergence of large datasets and data-intensive sciences. Only through the current and continued cultural focus on data will scientific data continue to be actively shared and preserved.

1.1.1 Data-intensive sciences

*Data-intensive science*s are those in which the collected data are of a scale beyond the other resources available to researchers (Burns, Vogelstein, & Szalay, 2014; Schroeder & Meyer, 2012). Technological advances have enabled data-intensive sciences. Throughout recent decades, leading to the modern era of data-driven science, "a number of transformative effects took place: computational power grew exponentially; devices were networked together; …data became ever more indexical and machine-readable; and data storage expanded and became distributed" (Kitchin, 2014, p. 81).

The scale of collected data in data-intensive sciences may be enormous in terms of volume, variety, velocity, value, and veracity (Critchlow & Van Dam, 2013; Ekbia et al., 2015; Hey, 2015; Kitchin, 2014; Laney, 2001). These large-scale datasets may be combined from multiple sources, enabling investigation of complex research questions The combination of discrete datasets may be a complex exercise, but it is essential to actualizing powerful big data networks (boyd & Crawford, 2012; Gitelman & Jackson, 2013; Kitchin, 2014; Kitching et al., 2013; Van de Sompel, 2013). While all observational sciences rely on data, data-intensive sciences notably investigate questions that can only be answered through the use and combination of large quantities of data.

In the data-intensive sciences, disciplinary boundaries are often crossed as research questions and necessary tools require a sizeable number of collaborators and kinds of expertise: "It is no longer the case that knowledge held in a particular discipline is enough to carry out scientific work" (Bowker, 2005, p. 123). This kind of cross-disciplinary scientific research is described as a "synthesis of information technology and science that enables challenges on previously unimaginable scales to be tackled" in which science is "collaborative, networked, and data-driven" (Bell et al., 2009, p. 1298).

The drastic increase in data volume and scale has become standard in many scientific research communities, generating a qualitatively different kind of scientific investigation (Mayer-Schonberger & Cukier, 2013). In these research communities, data are more likely to be generated directly from instruments rather than gathered by hand. For example, in the environmental sciences, data collection has accelerated due to embedded sensor networks (Borgman, Wallis, & Enyedy, 2007; Estrin, Michener, & Bonito, 2003; McNally, Mackenzie, Hui, & Tomomitsu, 2012). High Energy Physics (HEP) is widely considered the academic field

generating the highest data volume, and HEP experiments are among the most financially expensive and labor-intensive scientific experiments. Construction of the Large Hadron Collider in Geneva for instance cost over 2.5 billion euros ("Large Hadron Collider (LHC)," 2015). In astronomy, international collaborations collect hundreds of terabytes of data and are now planning petabyte-scale data collection projects ("Large Synoptic Survey Telescope: Home," 2016; "Sloan Digital Sky Survey: Home," 2016).

One consequence of modern scientific data collection is that quick and easy data accumulation requires greater processing and analysis (Borne, 2013; Hey, Tansley, & Tolle, 2009a; Szalay, 2011). The preparation, cleaning, and reduction components of research can be considered aspects of the broader concept of data management, and "only now is the range of problems in dealing with data becoming apparent" (Borgman, 2015, p. 32).

The relationship between data and journal articles has also evolved (Borgman, 2007; Levine, 2014). Databases and other scientific datasets are now often considered valuable beyond their initial research use and viewed as an academic deliverable in their own right (Bowker, 2005; Mayer-Schonberger & Cukier, 2013). The Human Genome Project and astronomy sky surveys are examples of scientific investigations in which the creation of a database can be an end product of a scientific endeavor. Accelerated data collection in data-intensive sciences now outpaces the evolution of data management practices and the workforce necessary to maintain these voluminous datasets.

1.1.2 Data-intensive astronomy

Astronomy is one field transformed by big science and data-intensive research methods. Formerly a discipline of individual investigators using private telescopes, (Bowker, 2005; Mayer-Schonberger & Cukier, 2013) modern "big science" astronomy (Borne, 2013; N. Gray,

Carozzi, & Woan, 2012; R. W. Smith, 1992) requires collaborative efforts to design, build, and maintain innovative telescope facilities (Bicarregui et al., 2013; Flannery et al., 2009). One of the oldest disciplines in the world, data-intensive astronomy is an example of a discipline changing from data-poverty to data-wealth (Sawyer, 2008). This wave of data-intensive science in astronomy broadens data use beyond those initially involved in data collection: "Astronomical research now goes beyond the paradigm of the original scientific team consuming only the observational data for which they proposed" (Thomas et al., 2014, p. 352). The current "revolution in data availability" (Kitching et al., 2013, pp. 381–382) increases the number of people with access to data.

While sky surveys are not new and observational star catalogs have been generated for millennia, modern sky surveys are a qualitatively different kind of data collection. The Hubble Space Telescope (Zimmerman, 2008), and the Sloan Digital Sky Survey (SDSS) became gold standards for data sharing and reuse in astronomy. These collaborations released their survey data in annual intervals, using a short proprietary period to clean the data prior to release. SDSS collaboration members confidently released the data, because the project collected more information than could possibly be analyzed by the team members alone (Borgman, 2015). SDSS thus serves as an example of the changing nature of data collection, which has revolutionized data sharing by making data catalogs and databases available to and useable by those not initially involved in data collection.

Astronomy is an excellent venue in which to study data-intensive science. Astronomers have arguably made the furthest strides toward an integrated, online sharing of research publications and data (refer to Chapter 2 Literature Review). Collectively astronomy is a computationally advanced field in regards to data management, sharing, and reuse best practices;

however, long-term data access necessitates further development. The technical and workforce data management infrastructures available to large telescopes and missions are currently unavailable to smaller telescopes, satellites, and other instruments. While many astronomers are moving toward computational analysis of shared datasets, some professionals closely analyzing smaller scale phenomena push back on resource investments into data sharing.

1.2 Motivation for this Study

How are astronomy data managed, for what purposes, and who does the work to sustain scientific astronomy data usability and meet data-intensive science objectives? The current approach to these questions will influence future scientific discovery (boyd & Crawford, 2012).

Multiple factors, however, complicate managing the scientific usefulness of data. Different stakeholders hold diverging understandings of key terms and components of the scientific process (Gall, 1976; Mol, 2002), and the boundaries and definitions of data exist within locally construed contexts (Latour, 1987, 1993; Latour & Woolgar, 1986; Rijcke & Beaulieu, 2014). Most policy makers and funding agencies now agree that research data should be made publicly available (Directorate of Mathematical and Physical Sciences Division of Astronomical Sciences (AST), 2010; Holdren, 2013; National Institute of Health, 2003; National Science Foundation, 2010b). Data management, access, and archiving are challenging and expensive undertakings however (Kitchin, 2014), especially given the dearth of highly skilled and well-trained workforces vital for building and maintaining data management infrastructures (Hedstrom et al., 2015, p. 73). No one-size-fits-all policy exists, nor would one enable effective data management across disciplines, projects, or even between individuals in a single team (Darch et al., 2015).

Empirical studies that investigate data-intensive knowledge infrastructures are necessary to understand how, when, and by whom data can be managed (Bowker, 2005; Kitchin, 2014). The UCLA Center for Knowledge Infrastructures (CKI) investigates the human and physical infrastructures in scientific data management ("UCLA Center for Knowledge Infrastructures: Home," 2016). The CKI team currently conducts research funded by the Alfred P. Sloan Foundation, and this dissertation research is one component of the grant-funded research. This dissertation presents an empirical examination of astronomer data practices to investigate how various stakeholders understand what data are, how they are managed, and who does the work.

An astronomy dataset is "incomprehensible and hence useless unless there is a detailed and clear description of how and when it was gathered, and how the derived data was produced" (J. Gray, Szalay, Thakar, Stoughton, & vandenBerg, 2002, p. 5). This dissertation analysis reveals the data infrastructures necessary to support data management for reuse, because while "it is easy enough to develop a potentially revolutionary technology; it is extremely hard to implement it—and even harder to maintain it" (Bowker, 2005, p. 115). Similar to Blair's analysis of the Renaissance however, data-intensive sciences will not flourish solely upon technological advances. In addition, sustainable infrastructures and workforces must be socially prioritized to enable a truly scientific data revolution.

2 Literature Review

For decades, scholars have observed and analyzed how scientists shape their scientific data practices (Galison, 1997; Latour & Woolgar, 1979; Merton, 1973; Shapin & Shaffer, 1985; Traweek, 1988). The information science field has tackled the meanings of data, information, documents, knowledge, and similar concepts (Borgman, 1999; Buckland, 1991, 1997; Carlson & Anderson, 2007). The library community has standardized the management of journals, articles, and books to improve search and retrieval for patrons. Despite these efforts, the meaning of the term "data" does not have a universally agreed upon or standardized definition (Borgman, 2015; Parsons & Fox, 2013), nor has the scientific research process been found to be neatly bound with a finite beginning or end (Latour & Woolgar, 1979). Considering the scientific research process outspans a single researcher in breadth and longevity, competing notions emerge concerning what data are, what is needed to manage data, and who is best equipped to take on the challenge. These considerations allow a potentially broad array of stakeholders to define needs and assign roles.

Multiple types of stakeholders in research data and research data management activities engage at differing degrees. Data management stakeholders include scientists, researchers, research staff, institutions, funders, policy makers, future data re-users, and more (Hahn, Lowry, Lynch, & Shulenberger, 2009; Research Information Network, 2008; Swan & Brown, 2008). The faculty, staff, and students conducting investigations as individuals or teams are closest to the research data. The centers, departments, libraries, and universities supporting the work are also stakeholders of effective research. Funding bodies at any scale are stakeholders in the success of the research they support. Policy makers both influence and are influenced by large research agendas, as well as individual research projects. Finally, the government, education

systems, and private individuals are stakeholders in research that may be funded from their tax dollars and could influence their lives. These varied local and global stakeholders in academic research may prioritize data management goals differently (Borgman, 2013; Edwards, 2010; Leonelli, 2013; Sands, Borgman, Traweek, & Wynholds, 2014; Treloar, 2014). The myriad of stakeholder interests in data-intensive academic research necessitates further analysis to unpack diverse motivations and perspectives.

2.1 Scientific Research Data

Modern science is built upon a model of inquiry in which conclusions require supporting evidence; data collection and analysis are integral to this model. Despite widely accepted scientific methods, a universally recognized definition of data remains elusive (Borgman, 2012a; Consultative Committee for Space Data Systems, 2002, 2012; Renear, Sacchi, & Wickett, 2010; Rosenberg, 2013). Indeed, "data is a complex notion, and one that is not well understood even by the parties creating and using them" (Borgman, Wallis, & Mayernik, 2012, p. 517).

One commonly cited definition of data comes from the Open Archival Information System (OAIS) Reference Model. The OAIS defines data as:

> "A reinterpretable representation of information in a formalized manner suitable for communication, interpretation, or processing. Examples of data include a sequence of bits, a table of numbers, the characters on a page, the recording of sounds made by a person speaking, or a moon rock specimen" (Consultative Committee for Space Data Systems, 2012, pp. 1–10).

In the OAIS definition, data are representations of information, independent of the media in which the data are embedded. The OAIS definition is purposefully broad and includes digital files, electronic files, written records, and scientific specimens. However, each scientific community may have further boundaries for what counts as data within their field. Borgman defines data as "representations of observation, objects, or other entities used as evidence of

phenomena for the purposes of research or scholarship" (2015, p. 28). These overarching definitions of scientific data offer each community a broad context they can amend to provide a more specific definition. For the purposes of this dissertation, *data* are defined by the OAIS Reference Model as "…reinterpretable representation[s] of information in a formalized manner…" (Consultative Committee for Space Data Systems, 2012, pp. 1–10).

Data require additional contextual information to enable future scientific use (Borgman, 2015). Karasti and Baker (2008) distinguish between the management of data and scholarly publications, because a large amount of contextual information must be retained and management activities must take place for data to remain usable beyond the timeframe of the initial project. Often this contextual information is recorded in the form of documentation or metadata. While colloquially referred to as 'data about data,' metadata can be as difficult to define as data itself. Mayernik defines metadata by referring to, "documentation, descriptions, and annotations created and used to manage, discover, access, use, share, and preserve informational resources" (2011, p. 28). Some refer to the metadata as just as essential as the data (Levine, 2014). It can prove difficult to define metadata and data because these concepts are fluid; the same piece of information could be data to a user in one context and metadata to another user (Borgman et al., 2012).

The National Information Standards Organization (NISO) definition of metadata is used for the purposes of this dissertation. NISO defines *metadata* as, "structured information that describes, explains, locates, or otherwise makes it easier to retrieve, use, or manage an information resource" (National Information Standards Organization, 2004, p. 1). The NISO definition of metadata applies to this dissertation research, because it stresses the importance of metadata for facilitating data reuse. In terms of scientific research data, the importance of

metadata is that it provides the context to enable data discoverability and usability into the future; the more metadata that is available, the larger the potential user community (Bowker, 2005).

2.1.1 Knowledge infrastructures

Research indicates that what counts as data varies by discipline and even by individual researcher (Borgman, 2012a; Borgman et al., 2007; Renear et al., 2010). As Latour and other scholars discuss, scientific research is a complex social and technical practice; "the construction of facts and machines is a collective process" (1987, p. 29). Even "factual" information is only useful within its context, and therefore even facts are constructs and not inherent truths. Borgman explains, "even the most concrete metrics, such as temperature, height, and geo-spatial location, are human inventions" (Borgman, 2015, p. 26). However, scientists may build external user trust in established resources by presenting those resources as a black box. Latour explains that a *black box* was termed by cyberneticians and is used, "whenever a piece of machinery or a set of commands is too complex… they draw a little box about which they need to know nothing but its input and output" (1987, pp. 2–3).

Research contexts can be referred to as knowledge infrastructures. *Knowledge infrastructures* are defined as "robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds" (Edwards, 2010, p. 17). According to Bowker, no data can emerge free of infrastructure: "Acts of committing to record (such as writing a scientific paper) do not occur in isolation; they are embedded within a range of practices (technical, formal, social)…" (Bowker, 2005, p. 7). Data are generated within knowledge infrastructures, including "people, places, documents, and technologies," and

continue to require infrastructures to retain meaning throughout the lifetime of the data (Ribes & Jackson, 2013, p. 147).

Infrastructures may exist at a variety of scales. For example, while the World Wide Web is an international phenomenon that many researchers rely upon for collaboration, others may instead use local intranets to collaborate. While some scientific investigations require decades of planning and execution, others are conceived of and completed within months. Ribes and Finholt (2009) address potential existing tensions between infrastructures at different scales and timelines through the premise of The Long Now Foundation (The Long Now Foundation, est. 01996). They refer to "The Long Now" as a way "to understand that participants seek to simultaneously address" infrastructures with goals in the short-, medium-, and long-term (Ribes & Finholt, 2009, p. 375).

The complexities, local variation, and temporal qualities of knowledge infrastructures complicate what and how infrastructures should be built, particularly in dynamic contexts of ever-changing scientific technologies (Bell et al., 2009; Borgman, 2007, 2015; Darch & Sands, 2017; Edwards et al., 2013; Van de Sompel, 2013). Infrastructures, data, and their contexts are all dynamic and interdependent (Borgman, 2015; Gitelman & Jackson, 2013; Ribes & Jackson, 2013; Star & Ruhleder, 1996); this interrelatedness further complicates policy-setting initiatives (Borgman, 2015).

While policy reports provide summary information for the evolving field, they are professional recommendations as opposed to empirical findings. These landmark reports are useful in terms of general professional advice (Association of Research Libraries, 2009, 2009; Atkins et al., 2011; Hahn et al., 2009; Joint Leadership Group of the National Digital Stewardship Alliance, 2013; Lyon, 2007; National Science Board (U.S.), 2005; Swan & Brown,

2008). However, the reports are limited by their generalities and necessitate complementary empirical studies focused on the intricacies of scientific data practices. This dissertation contributes empirical analysis of scientific data practices, while augmenting "policy level reports on e-Science, cyberinfrastructure and data curation…" (Karasti, Baker, & Halkola, 2006, p. 323). Only through understanding specific knowledge infrastructures can data management policies be determined and deployed (National Science Board (U.S.), 2005).

2.1.2 Astronomy sky survey data

Astronomy is a millennia-old discipline in which data were initially gathered by hand, then data collection advanced through photography, and now data are amassed digitally (Munns, 2012). In the late twentieth century, astronomy made the evolution from photographic to electronic data collection and then transitioned to born-digital (McCray, 2014, p. 4). This dissertation research is focused on data management practices for data that are born digital, the scope of which does not include the digitization of photographic plates.

Astronomy *sky surveys* are a "systematic, controlled, and repeatable" method to study the sky (Borne, 2013, p. 413). They are often referred to as a data-intensive inquiries because these surveys often gather enough uniform data that astronomers can ask statistical questions of the data, creating tremendous potential for new discoveries (Borne, 2013, p. 413). Sky surveys include, "uniform calibrations and well-engineered pipelines for the production of a comprehensive set of quality-controlled data products" (Borne, 2013, p. 413). The specific surveys studied in this dissertation research are detailed in section 2.4 Astronomy Sky Survey Knowledge Infrastructures.

Until the 1930s, astronomers collected data limited to the visible wavelengths of the electromagnetic spectrum. The visible band is the narrow section of light humans can see. Since

the mid 20th century, astronomers began studying the sky using additional wavelengths (National Aeronautics and Space Administration, Science Mission Directorate, 2010). Astronomers now can collect data of the gamma ray, X-ray, ultraviolet, microwave, infrared, and radio wavelengths (R. C. Smith, 1995). While data are collected differently based on wavelength, properly managed data can be integrated and analyzed across the electromagnetic spectrum.

Astronomy research is often roughly divided between observational and theoretical work. Telescopes and other devices gather observational data. Conversely, theoretical data are generally computer simulations. This study primarily focuses on self-identified observational astronomers, as opposed to theorists. Additionally, this dissertation focuses on astronomers, whose work is largely contained within the portion of the electromagnetic spectrum from ultraviolet through near infrared, including the visible wavelengths.

Some astronomy data have been reused for hundreds of years (N. Gray et al., 2012, p. 9). Astronomy has a long tradition of "dependence on data collected by others as well as data collected in the past. They have a well-developed culture of sharing" (W. L. Anderson, 2004, p. 194; McCray, 2000). Modern astronomy data are more standardized than data in many other disciplines, though require contextual information for reuse (Accomazzi, Derriere, Biemesderfer, & Gray, 2012). Particularly in astronomy, "data are inseparable from the software code used to clean, reduce, and analyze them" (Borgman, 2015, p. 106).

This dissertation examines the data practices of a limited number of astronomy research projects within one subfield; it does not cover data practices of the entire discipline. Here the focus is on observational astronomy data collected in digital form through optical, ground-based sky surveys. Space historian Robert Zimmerman notes astronomy data has always captured the public's imagination,

> "Though the optical wavelengths form only a small part of the tapestry astronomers use to try to understand what is going on in the heavens, to all humans the optical wavelengths give us a direct window into those phenomena" (2008, p. 179).

2.2 Scientific Research Data Management

Data management is also far from a unified concept (Wallis, 2012). Many attempts to define data management involve non-exhaustive lists of its possible components. For example, a National Academy of Sciences (NAS) study clustered together terms related to data management practices: "Information management, data management, data stewardship, data governance, and digital archiving are related terms used to describe processes and activities that overlap with curation" (Hedstrom et al., 2015, p. 13). The NAS study employs the Data Management International definition of data management: "the development and execution of architectures, policies, and practices and procedures that properly manage the full data lifecycle needs of an enterprise…" ("About Us | DAMA," 2015; Hedstrom et al., 2015, p. 13).

A similarly broad definition of data management is used for the purposes of this dissertation: *data management* is an umbrella term encompassing actions taken on data aimed at enabling scientific progress. The enumerations of data management actions may vary based on institutional and individual motivations. In the short- and medium-term, data are managed for scientific research; in the long-term, reasons for data management include permitting future scientific reuse or ensuring replicable studies.

As an overarching term used in this study, data management includes activities involving the collection, organization, analysis, release, storage, archiving, preservation, and curation of research data. Each of these additional terms also have different meanings between communities (Abrams, Cruse, & Kunze, 2009; Choudhury, Palmer, Baker, & DiLauro, 2013; Digital Curation

Centre, 2005; Walters & Skinner, 2011). While converging on similar issues, many stakeholders hold different meanings for each of these terms, sometimes employing discrete definitions, and other times muddling the concepts.

Data remain challenging to manage, curate, preserve, and reuse (Parsons & Berman, 2013). The current physical size of data overextends existing infrastructures, which prevents scientists from properly creating, accessing, storing, curating, and preserving data for the long-term. As the role of scientific research data has expanded in recent years to include the data-intensive sciences, the motivation for focused data curation and preservation has also broadened. Indeed, "…the development of digital technologies has radically changed our ability to manage, structure, process, analyse, share and reuse data, especially those born digital" (Kitchin, 2014, p. 46). Data management throughout the full research process may require dedicated funding to support the necessary technical and human infrastructures.

2.2.1 Life cycles

One reason a universal definition of data and data management are difficult to achieve is because the conceptions cover many incremental steps within the research life cycle. Data and metadata are active, fluid parts of scientific research, often as much process as product (Edwards, Mayernik, Batcheller, Bowker, & Borgman, 2011). Data are mutable depending on context, "over time and space as they flow through interconnected but different socio-cultural contexts each with their own conceptual frameworks and value systems" (Bates, Goodale, & Lin, 2015, p. 14).

The path of data through the scientific process is often discussed in terms of a data life cycle. The process of scientific research can also be discussed as a research life cycle. *Research data life cycles*, as used in the literature of archives, libraries, digital libraries, and records

management, are models for illustrating form and character changes to data over time, usually from their origin to their ultimate disposition, which may be preservation or destruction (Borgman et al., 1996; Brunsmann, Wilkes, Schlageter, & Hemmje, 2012; Greenberg, 2009; Higgins, 2008, 2012; Humphrey, 2006; Pepe, Mayernik, Borgman, & Van de Sompel, 2010; Wallis, Borgman, Mayernik, & Pepe, 2008). *Data management life cycle* models demonstrate the presence of data management activities throughout the research life cycle. Activities may take place in the short, medium, and long-term timescales of the full research life cycle.

Various life cycle models exist and depict different levels of specificity to the relevant domain. For the purposes of illustration, Wallis et al.'s (2008, p. 119) research data life cycle model is depicted in Figure 1. This model analyzed the Center for Embedded Network Sensing (CENS), a National Science Foundation (NSF) Science and Technology Center. This data life cycle shows how data are essential throughout the research process. The arrow following preservation illustrates that data can be reused for other research projects, thus continuing the life cycle indefinitely. The life cycle is intended to illustrate that data are continuing resources beyond the project for which they were initially captured. The CENS research data life cycle model can be extrapolated to astronomy sky survey research data, because both sciences rely heavily on the collection of data through calibrated sensors that collect data that must then be cleaned before use.

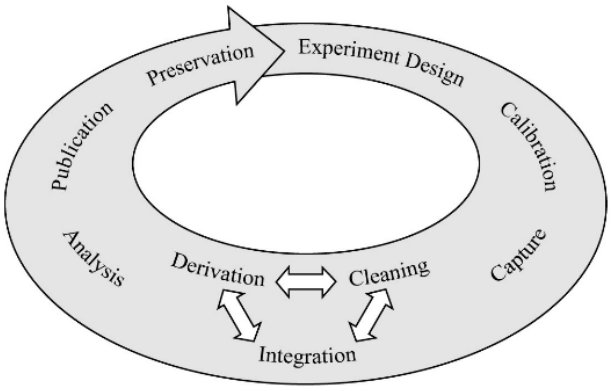


Figure 1 Research data life cycle model developed by (Wallis et al., 2008) to analyze a NSF Science and Technology Center

However, life cycle models are not universally accepted and are certainly not the only way to understand the temporal nature of scientific research. Often, life cycle models reduce the complicated nature of scientific research into seemingly simple, linear paths of knowledge gain (Baker & Millerand, 2010). While a starting point to analyze scientific workflow, life cycle models are not without limitations. Life cycle models should be analyzed within the setting they were created and only carefully reused in new fields or situations. Because those who generate life cycle models are doing so for a specific intent, that situated perspective should be considered any time life cycle models are re-deployed.

The time period during which research is conducted has also been framed in terms of "collaborative rhythms" (Jackson, Ribes, & Buyuktur, 2010; Jackson, Ribes, Buyuktur, & Bowker, 2011; Steinhardt & Jackson, 2014). Instead of a single life cycle, the rhythms perspective illustrates how research collaborations and multiple concurrent timelines shape one another (Jackson et al., 2011, p. 247). Technological and research rhythms often do not align. For example, the pace at which team research laptops become obsolete likely does not align with funding cycles, making it difficult to buy technology when it is needed. This leads to a "paradoxical" environment in which long-term planning must be conducted alongside a rapidly

changing information technology environment (Ribes & Finholt, 2009, p. 376). Another simultaneous rhythm are workforce career paths: "The ritual has been repeated thousands of times, but no single practical or material element endures the years: students graduate to faculty, instruments become outdated or imprecise, even buckets wear out" (Ribes & Jackson, 2013, p. 156). Given the many changes that occur through the full life of a dataset, life cycle models and rhythms analysis can help understand the many temporal factors influencing the research life cycle.

Effective data management aimed at enabling future data reuse is complex, locally contingent, and requires reliable workforces and funding. Data management stakeholders often use research life cycle models to plan long-term projects, starting as early as possible in the research process (Atkins et al., 2011; Carlson & Anderson, 2007; Corrall, 2012; Lee, 2009). Ball explains the use of data management life cycle models in that they "provide a structure for considering the many operations that will need to be performed on a data record throughout its life. Many curatorial actions can be made considerably easier if they have been prepared for in advance…" (Ball, 2012, p. 3). Beyond immediate scientific use, if data are to remain scientifically valuable to unknown users in the future, they must be managed effectively through the full course of the research life cycle (Abrams et al., 2009; Sands et al., 2014). Earlier planning in the research life cycle for long-term data management increases the likelihood that the efforts will be successful (Research Information Network, 2008, p. 9).

Astronomy data management nominally refers to all actions taken on data over the course of the broadly construed research process. Data management, given this inclusive definition of the research life cycle, begins in the research planning stages and may never have a definite conclusion (Rots, Winkelman, Paltani, & DeLuca, 2002, p. 172). The ultimate goal of astronomy

data management is to further the scientific goals of the discipline; however, each stage and each stakeholder may have other pressing goals in the near, medium, and long-term.

2.2.2 Sustainability

The life cycle model shows that data may require long-term management beyond data collection, processing, analysis, and publication. Long-term data management is often referred to as data stewardship. Baker and Yarmey (2009) refer to data stewardship as a collection of data curation activities taking place within an infrastructure with the goal of research data care. Conversely, the OAIS reference model fails to mention the word steward or stewardship anywhere in the 135-page document (Consultative Committee for Space Data Systems, 2012). In other sources, stewardship is used as another umbrella term for data management (Borgman, 2015; Data and Visualization Task Force, 2011; Joint Leadership Group of the National Digital Stewardship Alliance, 2013; Parsons & Fox, 2013; Research Information Network, 2008). For the purposes of this dissertation, *data stewardship* is the facet of data management work undertaken to enable the potential future reuse of data, beyond that of immediate scientific returns.

Data stewardship is one component of ensuring the sustainability of scientific research data. Scientific research data sustainability is also a complex notion lacking a unified definition. Eschenfelder and Shankar (2016) identify and compare multiple sustainability frameworks developed for institutions required to continue the access and preservation of research data. Indices are available for institutions to analyze their available knowledge infrastructures to determine their data sustainability "grade" throughout multiple categories (Australian National Data Service (ANDS), 2017; Crowston & Qin, 2011; Sallans & Lake, 2014). For the purposes of this dissertation, *data sustainability* refers to notions of reliability in the knowledge

infrastructures supporting access to, and preservation of, scientific research data. While not all data will require sustainable infrastructures, the data deemed worthy of long-term management do necessitate ongoing support.

Scientific communities, funding bodies, and the general public expect research endeavors to have broad success given the large financial investments and human labor. The High Energy Physics (HEP) community participated in a global self-study examining, "long-term data analysis as a way to maximise the scientific return for investment in large-scale accelerator facilities" (Study Group for Data Preservation and Long Term Analysis in High Energy Physics, 2012, p. 6). The report indicates data preservation in HEP requires "urgent action" (Study Group for Data Preservation and Long Term Analysis in High Energy Physics, 2012, p. 6). Similarly, the International Astronomical Union (IAU) adopted a resolution in 2003 stating:

> "data obtained at major astronomical facilities should…be placed in an archive where they may be accessed via the internet by all research astronomers. As far as possible, the data should be accompanied by appropriate metadata and other information to tools [sic] to make them scientifically valuable" (XXVth General Assembly of the International Astronomical Union, 2003).

Policymakers and funders have begun to implement data management requirements, often intended to promote data sharing. Beginning in 2011, the NSF-mandated data management plans as a component of all new grant proposals. In February 2013, the United States Executive Office of the President, Office of Science and Technology Policy, released a memorandum requiring large federal agencies to ensure federally funded scientific research data are made available to the "public, industry, and the scientific community" (Holdren, 2013, p. 1). In addition to data, many universities and academic researchers are shifting toward open access publication of scientific results (Office of Scholarly Communication, University of California, 2013a, 2013b; Provost & EVP - Academic Affairs, 2015). Some university libraries are

developing data management departments, and some universities are establishing data management and data science education tracks within existing departments or as new programs (Thompson, Mayernik, Palmer, Allard, & Tenopir, 2015; Varvel Jr., Bammerlin, & Palmer, 2012; Weber, Palmer, & Chao, 2012).

Arguments for data sharing as a collective good indicate that data release can reduce replication of effort while enabling scientific verification and reproducibility. Data sharing is especially heralded as important when data are collected using public funds; "Right now, taxpayer-funded research is probably generating data that is not being fully utilized… we may waste money on the same research or miss opportunities to reuse existing data for new inquiries" (Levine, 2014, p. 134). Data sharing also enables scientific advancement in the form of data "amplification," in which the combination of discrete datasets results in information larger than the sum of the parts (Kitchin, 2014). Funding agencies, universities, and researchers alike largely agree that data management, sharing, and preservation benefit both individual scientific outputs and global scientific progress. However, questions remain: what kind of data management must take place, when, and by whom, to enable future scientists to make use of preserved data?

Sustainable infrastructures can be expensive and require consistent funding over time. There remains an "Availability-Usability Gap" between the aspirations of funding agencies and the reality of how research data can and are managed under current infrastructures (Levine, 2014, p. 129). Funding agencies may expect long-term data management to take place by individuals and teams who lack sustainable infrastructures. Not only can the technological and workforce costs be high for long-term data management, but also the costs for data management are often placed on those who will not reap the benefits. The unclear nature of who pays and who benefits from long-term scientific data management raise questions of which stakeholders should be

responsible for the time spent and costs incurred. Data managers may find themselves wondering what level of effort should be given to data of uncertain long-term value (N. Gray et al., 2012).

Economies of scale, like "Moore's Law" help, but they do not negate the expense of long-term data management (Blair, 2010; Kitchin, 2014). Long-term data management activities can be time consuming, and do not always result in immediate scientific returns. Making data available requires technological and human infrastructure, which are both "precondition[s] to meaningful access and reuse…" (Berman & Cerf, 2013, p. 341; Edwards et al., 2013; Hine, 2006). Other research communities could serve as examples. For instance, "…it may be informative to consider NSF processes for managing large facilities as a way of better understanding the issues involved in developing policy to manage long-lived digital data collections" (National Science Board (U.S.), 2005, p. 40). The Inter-university Consortium for Political and Social Research is a consortium that has worked together since the 1960s to sustain social science research data (Regents of the University of Michigan, 2016). The ICPSR seeks to ensure, "leadership and training in data access, curation, and methods of analysis for the social science research community" (Regents of the University of Michigan, 2016).

In the era of data-driven science, increased importance is placed on data with long-term value since it can be combined with multiple sources (National Science Board (U.S.), 2005, p. 13). Data management throughout the full research life cycle is necessary to ensure future data can be reused, however the specific tasks entailed in data management may differ by setting. In all contexts, however, data management requires human and technical resources (Levine, 2014, p. 136). Despite mounting pressure from funding agencies and policy makers, little consensus exists regarding what, when, how, and how long data should be managed (Borgman, 2015). Policies and procedures are necessary to determine whether or not data will retain long-term

value and therefore necessitate long-term management (Blair, 2010; Bowker, 2005; National Science Board (U.S.), 2005; Research Information Network, 2008).

Data context is required for datasets to retain their scientific usability (Research Information Network, 2008, p. 10). Data sharing is not a simple endeavor, as data are inherently removed from their surrounding contexts when shared and reused (Borgman, 2015; Bowker, 2005; Edwards, 2010; Edwards et al., 2013). For example, data sharing and subsequent reuse are challenging in that reusers must trust choices made by others during data collection. Software and other kinds of information may need to accompany datasets to enable reuse (Bowker, 2005; Edwards, 2010; Edwards et al., 2013), which may present additional management challenges (N. Gray et al., 2012, p. 7). Metadata and other documentation may be created to mitigate the contextual shift, but these activities also require investment in resources. Given these complexities, long-term data management to enable future discovery and reuse can be considered a "grand challenge" (Ray, 2014a, p. 2).

A number of valid reasons exist why researchers may choose to not share data. While some scientific collaborations choose to release their data, resulting in scientific advances, data sharing is not inherently "good" (Kitchin, 2014, p. 62). Scholars may still be actively using a dataset and fear that other researchers could "scoop" their research findings by publishing first (Borgman, 2015). Researchers often lack the time and expertise necessary to make data useful to others, and the creator may not even envision the future uses of their data since the data may not have been created with the intent of reuse (Borgman, 2012a, 2015; Fecher, Friesike, & Hebing, 2015; Kratz & Strasser, 2015; Mayernik, 2011; Wallis, 2012; Wallis, Rolando, & Borgman, 2013). Today, like in fourth-century Athens, there remains the "fear that written words, in

circulating beyond the author's control, were more readily misunderstood and misused than words spoken to an interlocutor" (Blair, 2010, p. 14).

2.3 Scientific Research Data Management Workforces

Sustainable data infrastructures require investments in technology and workforces. As data-driven sciences continue to emerge, it concurrently necessitates "an accompanying surge in the advancement of digital curation, and therefore in the digital curation workforce" (Hedstrom et al., 2015, p. 9). Data management expertise is important; "Without such support, there is the danger that data will be created in unusable forms, managed inappropriately, or stored ineffectively" (Research Information Network, 2008, p. 13). Workforces are an essential component of the management of research data, since a solely technological solution does not exist to ensure research data management (Baker & Millerand, 2010; Borgman, 2015; Ray, 2014a).

However, identifying relevant workforces for data management and sustainability is also complex. Regardless of the precise definition, research data management workforces are critical to the support of data-intensive science and yet policy makers and many researchers decry a gap in the quality and quantity of data management professionals available for modern science (Kitchin, 2014; Ray, 2014a). For the purposes of this dissertation, the *scientific research data workforce* encompasses those that are tasked with managing, stewarding, sustaining, serving, storing, archiving, curating, or preserving scientific research data; and the *expertise and experience* are the existing knowledgebase the workforces bring to these tasks (Sands et al., 2014).

It is unclear whether new workforces will bring these data management skills to research collaborations, or whether existing stakeholders will be trained in data-intensive science data

management (National Science Board (U.S.), 2005). Whether data curation is conducted by data specialists, or by domain experts, expertise must be shared:

> "Digital curation specialists will need some knowledge of the disciplines and domains in which the digital information they curate will be used. Without some familiarity with the problems to be addressed, the goals to be pursued, as well as the customary methods, nomenclature, and practices of the fields in which the digital information assets are used, curators will not be able to make good decisions as they manage and enhance those assets for current and future use. Similarly, those who conduct curatorial activities as only a small part of their work, will need some study and command of the knowledge and skills of digital curation, regardless of how well they are educated in their own domains" (Hedstrom et al., 2015, p. 63).

For collaborations as large and complex as astronomy sky surveys, it is impossible for one person to be an expert on the details of the full data life cycle (Borgman, 2015). Data must be managed well across the life cycle, which requires overlapping expertise as data move through a distributed workforce and across time. Action or inaction at any point in the life cycle could reduce the ability for data to be reused in the future. For example, the work done by content creators, early in the life cycle may impact the future usability of a dataset as much as the actions of a data manager at the end of the life cycle (National Digital Stewardship Alliance of the Library of Congress, 2013).

A sustainable workforce is necessary at multiple scales, both within individual projects as well as across the larger field of data-intensive sciences (National Science Board (U.S.), 2005, p. 38). The Research Information Network report explicitly states that to ensure "…arrangements for their stewardship are sustainable—not least [by] the training and supply of a cadre of specialist curation personal. Otherwise there is the danger of loss or damage to valuable data" (2008, p. 14). Depending on the context, a sustainable workforce may require the same staff working on a project over the long-term. Alternatively, continuity may mean clearly defined

handoff and coordination procedures are in place. Regardless, a sustainable workforce is necessary to ensure data remain supported over time.

2.3.1 Professional data practices

Management of scientific data involves a large number of data practices. Just as data management, sustainability, and other terms have multiple meanings between stakeholders, so do terms describing the data management workforce. The data management workforce in the information science (IS) community have been referred to as research technologists (Lyon, 2007), data scientists (National Science Board (U.S.), 2005; van der Graaf & Waaijers, 2011), e-science professionals (Stanton et al., 2011), and data curators (Higgins, 2008). Some of these examples reflect generic roles in scientific data curation and others are specific to university-based academic settings. Data science programs appear with greater frequency in colleges and universities. In 2015, nearly 100 universities offered programs in "data science" including bachelors, masters, graduate certificates, and PhDs (Borgman, Darch, Sands, Pasquetto, & Golshan, 2015; Sands et al., 2014). However, not all of these roles refer to data management practice for science as described in this dissertation. Most of these programs are geared to business, many of the scientific programs were focused in the biological sciences, and only three IS departments included data science programs. While a number of IS departments offered individual courses in data management, these curricula generally focused on professional practices for work at the end of the life cycle, including data curation, preservation, and stewardship (Lyon, 2007; Mayernik et al., 2013; Ray, 2014b). Rarely is data management taught explicitly within graduate programs in the sciences (Mossink, Bijsterbosch, & Nortier, 2013; National Health and Medical Research Council, 2007). While most educators concur with an increased need for data managers in all fields, agreed upon definitions of these workforces and

established career paths are lacking (Manyika et al., 2013; Mayer-Schonberger & Cukier, 2013; M. A. Nielsen, 2012).

Some argue that research library staff in particular should have a role in scientific data management, because libraries have already established infrastructures for the management of research publications (Choudhury, 2010; Levine, 2014; H. J. Nielsen & Hjørland, 2014; Tenopir, Birch, & Allard, 2012). However, exactly how libraries can manage data-intensive scientific data without a re-skilling of the workforce is undetermined (Borgman, 2015; Sands et al., 2014; Sands, Darch, Borgman, Golshan, & Traweek, In Progress). Due to the long-lived nature of university libraries, it is reasonable to consider them as sustainable institutions for research data management (Corrall, 2012; Data and Visualization Task Force, 2011; Heidorn, 2011; Hey & Hey, 2006). Unfortunately, the expertise necessary to manage literary resources does not necessarily translate to the management of research data (Borgman, 2015; Heidorn, 2011; Sands et al., 2014).

Several professional practice frameworks elucidate the knowledge and expertise necessary for the data management workforce (Choudhury, 2013; Engelhardt, Strathmann, & McCadden, 2012; Hedstrom, 2012; Hedstrom et al., 2015; Y. Kim, Addom, & Stanton, 2011; Swan & Brown, 2008). These frameworks, while varied by goals and structure, each attempt to illustrate the array of traits required for scientific data managers. The frameworks categorize into lists of knowledge and expertise, without ordering their individual value. For example, Swan and Brown differentiate data management personnel expertise between three categories: subject knowledge, technical skills, and people skills (2008); Engelhardt, et al. differentiate these lists of skills between technical expertise, information science, and subject knowledge (2012, p. 4). While these examples are helpful to recognize the broad range of knowledge and expertise

exhibited in data management, they often blur the specific skills and individuals involved in the data workforce. These data management personnel frameworks cluster together an array of careers, education, experience, expertise, and life cycle stages. The amount of domain knowledge required for data management at different life cycle stages appears to vary by context.

Initial studies of astronomy data practices indicated that those managing data require domain knowledge to ensure data are useable (W. L. Anderson, 2004; Sands et al., 2014). Astronomy communities tend to embrace information technology knowledge; however, astronomers are rarely formally trained in computer science and software engineering (N. Gray et al., 2012). Data management experience without formal training can lead to technologically successful short-term collaborations that require further education for managing data in the long-term (N. Gray et al., 2012). Information Studies (IS) analyses of the knowledge and expertise required for data management are often based on evidence gathered from interviews with professionals in the field, evaluation of job descriptions, and internship experiences (J. Kim, Warga, & Moen, 2013; Y. Kim et al., 2011; Pryor & Donnelly, 2009). However, these frameworks tend to ignore the data management practices of the scientists themselves, focusing on an IS-based workforce. Further domain-based case studies are necessary to delineate specifically the specializations and roles professionals play in data management (Renear et al., 2010, p. 4).The Data Conservancy employs the data-driven Stack Model for Data management (Figure 2) to distinguish data management practices (*Sayeed Choudhury on Data Stack Model*, 2012). The Data Conservancy is an university-based collaboration addressing research data management ("Data Conservancy," 2014). The model is an example of a professional practice framework that provides definitions for components of data management (Choudhury, 2013;

Choudhury et al., 2013). The figure uses data as the focal point; it refers to four kinds of data management actions that take place on data. Library staff generated the model to facilitate clearer communication among themselves and with scientists about the data.

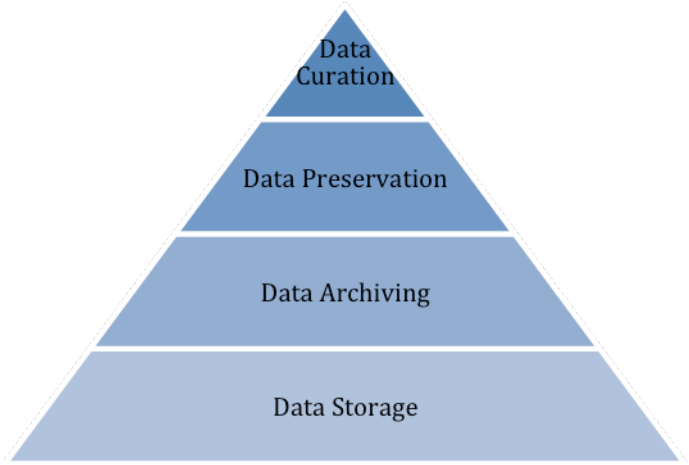


Figure 2 Data Conservancy Stack Model for Data Management. Adapted from (Choudhury, 2013); published in (Sands et al., 2014).

Figure 2 is one useful example of how to conceptualize the tasks associated with long-term data management. The four-part model does not intend to be exhaustive of data management practices throughout the full research life cycle. Developed by library staff, the model details only the long-term data management component of the broader research life cycle, namely the points after a scientist has delivered the data to library staff. The model explicates four levels of data management needed once the initial scientific use of the data concludes in order to ensure subsequent reuse of the data is possible.

Each of the four components illustrated in the figure represent different types of actions necessary for long-term data management. The Data Conservancy model's relationships between, and definitions of, data storage, archiving, preservation, and curation are used for the purposes of this dissertation. Data storage represents the underpinning of long-term data management, with successive layers building upon this foundation. *Data storage* refers to

ensuring the security, back up, and potential restoration of digital data bits (Choudhury et al., 2013). Data storage can be a critical component to data management both during and after the initial scientific use of the data.

The term *archive* is often used in its noun form, referring to archives as institutions or archivists as information managers. The oft-cited OAIS reference model consistently uses the term archive in the noun form. An archive is: "an organization that intends to preserve information for access and use by a Designated Community" (Consultative Committee for Space Data Systems, 2012). In this dissertation, however, the verb form "to archive" is used to describe the act of archiving information. Data managers are *archiving* data when they act in ways enabling data to be searched for and retrieved in the future. Given the Data Conservancy model, once data are stored properly, archiving can include adding unique and persistent identifiers to data, enabling reliable data findability for indeterminate future retrieval (Choudhury et al., 2013).*Data preservation* practices are those that ensure data are maintained in the long-term. In the Data Conservancy model, preservation activities ensure archived data are physically conserved into the future. Preservation activities may include, "maintaining information, independently understandable by a designated community, and with evidence supporting its authenticity, over the long term" (Consultative Committee for Space Data Systems, 2012, pp. 1–13). Data preservation includes the actions needed to secure information over the course of time, which often includes preemptive hardware and software migration and other technical updates.

Data curation is the highest-level long-term data management activity in the Data Conservancy model. Once data are stored, archived, and preserved, data curation activities are performed in accordance with given institutional capacities and priorities. *Data curation* is an aspect of data management which includes adding value to extant data "through documentation,

standardization, migration to new formats" and is critical to effective data reuse (Borgman et al., 2012, p. 486). While some employ data curation as an umbrella term for data management (Abrams et al., 2009; Henry, 2012, p. 1), data curation can be distinguished from other data management activities by noting that, "what distinguishes curation from these other fields is its emphasis on enhancing the value of information assets for current and future use and its attention to the repurposing and reuse of information, both within and beyond the context in which it was first created or collected" (Hedstrom et al., 2015, p. 13).

2.3.2 Data management expertise

The kinds of experience and expertise necessary to support research data management, much like the definition of research data management, are not agreed upon. As the scale of data swells, the qualitative nature of data education must also adapt; "today's graduate students need formal training in areas beyond their central discipline: they need to know some data management, computational concepts and statistical techniques" (Szalay & Gray, 2006, p. 413). Rita Colwell (former Director of the NSF) describes the needed domain experts as "T-shaped" individuals whose knowledge is both "broad and deep" (Benderly, 2008; Colwell, 2009; Committee on Enhancing the Master's Degree in the Natural Sciences, Board on Higher Education and Workforce, Policy and Global Affairs, & National Research Council, 2008).

Others in business and academia describe more specifically the need for expertise strength in two fields, namely domain knowledge and technical skills. Scientific *domain knowledge*, which for this dissertation is astronomy, is the knowledge obtained through higher education in a specific field of study. Technical expertise, or computational skills, alternatively can be acquired in multiple ways and various levels. *Computer science knowledge* is that obtained through a higher education degree in computer science. Other times, *computational*

skills are acquired through one or more components of higher education coursework, experience, or self-education. Often, scientists acquired computational expertise out of necessity while pursuing their scientific work. The combination of domain knowledge and computational skills has been used to refer to "pi-shaped workforces" (Braniff, 2009; Feldman, 2006; Hartman, 2005). Pi-shaped workforces are those where:

> "You can imagine that each person has some combination of horizontal breadth of knowledge as in 'I know a little bit about a lot of things.' and vertical slices of expertise as in 'I know how every layer of this technology works from concept to low-level coding and performance tuning'" (Hartman, 2005).

Figure 3 provides a summary of the concepts of a T- and Pi-shaped person, including the breadth and depth illustrated by the vertical and horizontal lines in the shapes of the letters.

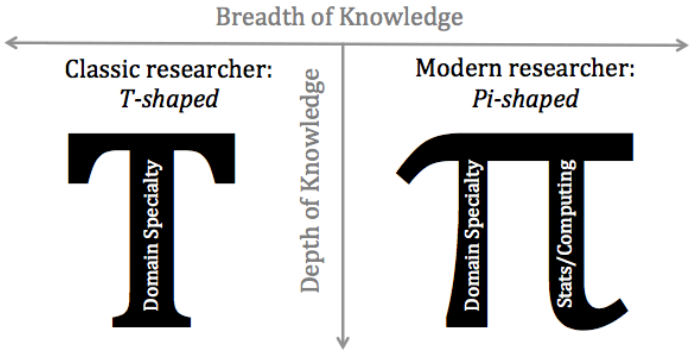


Figure 3 Workforce knowledge breadth and depth illustrated with the letters T and Pi. Figure by Jake VanderPlas, reprinted with author's permission (2014a, 2014b).

The kinds of expertise necessary for scientific data management, as expressed by the term "pi-shaped," cross at least two disciplines, highlighting the onset of a multidisciplinary age in which sole-discipline studies are no longer adequate (Szalay, 2012). Existing professional education paths and job titles do not yet exist to support careers in digital curation (Hedstrom et al., 2015; National Science Board (U.S.), 2005; Ribes & Finholt, 2009). Clear career paths are

needed to increase professional opportunities for individuals with "pi-shaped" expertise (Bowker, 2005; Hedstrom et al., 2015).

While deep knowledge in two domains is said to be increasingly necessary for data-driven science, these experts may or may not be compensated accordingly for their dual expertise. For example, modern scientific collaborations require experts from different disciplines, yet universities remain organized to reward individuals publishing within single, established disciplines (Bowker, 2005, p. 125; Hedstrom et al., 2015). While the expertise is necessary for sky surveys, there remains a paradox between the disparate reward structures for instrument builders, software developers, and data managers, compared to those who perform scientific research with the resulting data (Ribes & Finholt, 2009).

Sky surveys in astronomy are an example of big science (Galison & Hevly, 1992b), in which more than half of the project funding and person-time may be devoted to data collection, cleaning, and management. Those who perform this data management work often require expertise in astronomy as well as computational skills. Sky survey data managers may have the expertise and desire to publish scientific journal articles, without the time to pursue those tasks. While writing and publishing scientific journal articles is generally the most important measure by which academic tenure and promotion decisions are determined, data management work often detracts from writing time (Levine, 2014; Ribes & Finholt, 2009; Star & Ruhleder, 1996). Given that infrastructure work detracts from the writing and publication of journal articles, data managers may find it difficult to be competitive for tenure-track academic careers.

Formal education and career paths for data management are still emerging; currently scientific collaborations manage data through a variety of methods. Data management work is often a part of infrastructure building and maintenance (Borgman, 2000, 2015) and may become

"invisible" (Paisley, 1980; Shapin, 1989). Invisible work most closely related to knowledge infrastructures and data management is that in which, "Work may become expected, part of the background, and invisible by virtue of routine (and social status). If one looked, one could literally see the work being done – but the taken for granted status means that it is functionally invisible" (Star & Strauss, 1999, p. 20). System administrators, long-term data managers, software engineers, and others involved in the daily maintenance of existing infrastructures, whose continued availability is taken for granted, may be performing invisible work (Borgman, 2015; Bowker & Star, 1999; Ribes & Finholt, 2009; Ribes & Jackson, 2013; Star & Strauss, 1999). Despite perceptions, "infrastructural development and maintenance requires work, a relatively stable technology, and communication" (Bowker, 2005, p. 114).

2.4 Astronomy Sky Survey Knowledge Infrastructures

As defined in 2.1.1 Knowledge infrastructures, knowledge infrastructures are "robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds" (Edwards, 2010, p. 17). Astronomy has some of the most established human and technical infrastructures of any scientific field. International tools are generally built within the discipline by domain experts (Kurtz et al., 2005). In addition to tools, human infrastructures are important to the functioning of astronomy. Accomazzi and Dave (2011) explain the interactions of large, existing infrastructure projects (See Figure 4). In their assessment, future astronomy goals include the interoperability of astronomical objects (celestial objects), observations (the data), and publications (scholarly communication). Figure 4 begins to elucidate an emerging web of astronomy resources. The Virtual Astronomical Observatory (VAO) is central to multiple resources and tools (Accomazzi & Dave, 2011; Budavari, 2010; Djorgovski & Williams, 2005; Hanisch, 2013). NED and SIMBAD, as well as

the astronomy journals, libraries, missions, and archives are all examples of services that enable astronomy objects, observations, and publications to interact with one another. Curation, inference cross-matching, extraction, and annotation search describe the kinds of data management services provided by the available tools.

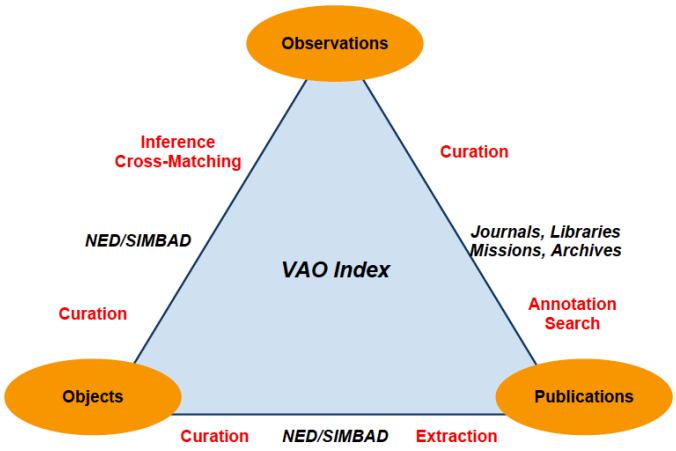


Figure 4 Adaptation of "Relationships between Publications, Objects, Observations and the corresponding major actors in the curating process and their activities" (Accomazzi & Dave, 2011, p. 3).

Some tools and services have been accepted as standards across the larger astronomy domain. Several larger projects have combined datasets to enable data search and discovery. Examples include the World Wide Telescope (WWT) (Goodman et al., 2012; Szalay & Gray, 2001; "WorldWide Telescope," 2013), multiple endeavors by the International Virtual Observatory Alliance (IVOA) ("International Virtual Observatory Alliance," 2015), and various instantiations of virtual observatory efforts within the United States (Ackerman, Hofer, & Hanisch, 2008; Hanisch, 2012; Moore, 2004; NVO Interim Steering Committee, 2001; US Virtual Astronomical Observatory, 2012; *Virtual Astronomical Observatory (VAO) Project Execution Plan*, 2010). The NASA/IPAC Extragalactic Database (NED) ("NASA/IPAC Extragalactic Database (NED)," 2016) and the Set of Identifications, Measurements, and Bibliography for *Astronomical* Data (SIMBAD) (CDS, 2016; Wenger et al., 2000) are examples

of federated databases enabling simplified search and retrieval of information about astronomical objects.

In terms of scholarly communication, astronomers extensively and consistently rely on the Astrophysics Data System (ADS) for bibliographic records and document access (Accomazzi et al., 2015; Accomazzi, Grant, Eichhorn, Kurtz, & Murray, 1996; Henneken et al., 2010; Henneken, Kurtz, & Accomazzi, 2011; Kurtz et al., 1999; McKiernan, 2001). The ADS "provides easy on-line access to journal abstracts and articles, maintains a digital library and data catalogs, and provides access to archival data" (Accomazzi, 2011; Hasan, Hanisch, & Bredekamp, 2000, p. 136). ADS has served the astronomy community with a bibliographic database for over 20 years, and in 2010 began including the service of linking data to publications (Henneken & Thompson, 2013). Similarly, the community broadly uses the pre-print document archive service "arXiv" (Cornell University, 2016; Ginsparg, 2011). arXiv is used by thousands of astronomers internationally (Henneken et al., 2007; Kurtz et al., 2007). Additional projects are still considering tools for data in addition to existing tools for publications (Norris et al., 2006, p. 5).

From the outside, astronomy infrastructure appears solidly in place in the form of the many projects, tools, and services described above. However, astronomers continue pursuing better scholarly infrastructure dimensions and attempting to resolve problems that remain unaddressed by existing tools and services, including the automating some existing processes. Some infrastructures are more fragile than others (Borgman, Darch, Sands, & Golshan, 2016). Accordingly, much infrastructure work remains necessary to create a truly seamless astronomy environment (Accomazzi, Henneken, Erdmann, & Rots, 2012; Crosas, 2013; Goodman, 2009; Goodman & Wong, 2009; Norris et al., 2006).

The scientific community works together to, "coordinate conventions, types of data (images, time series, spectra etc.), and a basic lexicon…" (Hasan et al., 2000, p. 133). Most notably, astronomy data standardization includes international use of the Flexible Image Transport System (FITS) file format (Hanisch et al., 2001). FITS has been the agreed upon file format for over forty years and proved itself as a powerful standard within the discipline, enabling data interoperability and reuse. However, some argue the format is now showing its age, and the community should seek to adapt or replace the standard to face the "new challenges for the 21st century" (Thomas et al., 2014, p. 354). The SDSS and LSST projects emerged from within this environment where standardization enabled huge interoperability gains, but in which the community continues to push boundaries.

Long a grievance of instrument builders and laboratory technicians (Blair, 2010; Shapin, 1989), a reward-structure hierarchy persists in scientific research, even when one component is agreed to be critical to the success of the other. Ribes and Finholt state, "The implicit hierarchy places scientific research first, followed by deployment of new analytic tools and resources, and trailed by maintenance work" (2009, p. 388). In many scientific fields, team members are rewarded for time spent building shared infrastructures by being allowed access to resulting data during the proprietary period. Proprietary periods, also referred to in some communities as embargos, are time periods with which investigators are able "to control their data before releasing [the data]" (Borgman, 2015, p. 12). Proprietary periods enable team members the chance to publish findings first, before the data are released to outside investigators who have not invested time into the project.

While some data management and infrastructure building may be rewarded through journal article citations, the data citation model is also not agreed upon (Altman, Borgman,

Crosas, & Martone, 2015; Altman & Crosas, 2013; Borgman, 2012b; CODATA-ICSTI Task Group on Data Citation Standards Practices, 2013; Crosas, Carpenter, Shotton, & Borgman, 2013; National Academies of Science. US CODATA and the Board on Research Data and Information, in collaboration with CODATA-ICSTI Task Group on Data Citation Standards and Practices, 2012; Uhlir, 2012). Multiple genres of journal articles can also complicate data citation.

The astronomy community uses these three different kinds of journal articles to alert colleagues to new information, contribute details for data and instrument reuse, and provide a way to reference instruments or data within the confines of traditional bibliographic references. Common among scientific communities are "science papers." Science papers are journal articles that describe the methods and analysis that enabled scientific discoveries. Astronomers in particular may also publish "instrument papers." Instrument papers provide detailed information about instruments such as telescopes, detectors, cameras, and other data collection materials. End-user scientists may need the information provided in these papers to guide their use of the resultant data. The third kind of astronomy journal article is a "data paper" or "data release" article. Data papers describe in detail a set of data, often as it is released for public use. The SDSS provides data release articles for each official public release. The data paper provides context and processing information to assist users in understanding the benefits and limitations of the data. Authorship and citation in each kind of paper are important ways stakeholders derive credit for their work on scientific and infrastructure-building collaborations.

Scientists, engineers, instrument builders, and other infrastructure engineers earn credit for their work through authorship and citations to each of these three kinds of journal articles. Most scientific communities are familiar with the citation of science papers. However, the

astronomy community will also cite the instrument papers and data papers to reference useful resources. These citations benefit the careers of the authors and provide feedback to funding agencies regarding how much use are coming from the projects, instruments, and datasets they fund. Individual collaborations define their own criteria for authorship for each type of journal article.

2.4.1 US space- and ground-based astronomy

The United States' National Aeronautics and Space Administration (NASA) funds astronomy missions in which the telescope and instruments are physically located in space, while other agencies fund missions where the telescope is located on earth. Therefore, data practices of astronomers are differentiated between space-based (generally NASA-operated) missions, and ground-based (generally NSF, multi-university, and donor-funded) operations. NASA missions have well-formed data management practices and human resource infrastructures. NASA data are collected, processed, and archived at specific locations among a dedicated workforce (Committee on NASA Astronomy Science Centers, & National Research Council, 2007). For example, Hubble Space Telescope data are processed and archived at the Mikulski Archive for Space Telescopes (MAST) in Baltimore, Maryland (R. L. White et al., 2009). A dedicated, full-time staff of dozens of astronomers and computer scientists manage the Hubble data from collection, analysis, archiving, and preservation. The dedicated staff manages the Hubble data to ensure their scientific usability. Astronomy data are complex and differ between telescopes and even among instruments on a single telescope. The long-term MAST archive is important for Hubble data because of the dedicated, long-term archive staff who can perform consistent management over time, leading to a stable dataset (Zimmerman, 2008, pp. 166–167).

MAST is one example of the multiple NASA supported field and science centers. The science centers "serve as the interfaces between astronomy missions and the community of scientists who utilize the data;" a large part of the science center work is that of data management (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 1). Science center staff enable the usability of the collected data during and "for years" after the end of a mission (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 1). These science centers embody well the technical and domain knowledge necessary to sustain astronomy data into the future. To continue enabling the scientific usability of astronomy data, these data centers must be able to consistently, "attract, retain, and effectively deploy individuals with the mix of research and engineering skills necessary to maintain continuity of service" (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 3).

NASA created a model to distinguish distinct levels of data processing. The model moves from Level 0 to Level 4. Level 0 are raw data directly off the telescope or other instrument, while Level 4 are final data products. Table 1 gives a brief definition for each of the five NASA levels of astronomy data. The scope of this dissertation research includes data management at any and all of these possible levels.

Level 0 (raw measurements)
Level 1A & 1B (calibrated scientific data)
Level 2 (data with coordinates, other information)
Level 3 (data products)
Level 4 (final data products typically include object catalogs, spectra, and images)

Figure 5 Adaptation of the NASA data processing levels. Table modified from NASA (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 12; "Data Processing Levels for EOSDIS Data Products - NASA Science," 2010).

The data collected by ground-based telescopes and other instruments do not generally have dedicated staff to perform consistent data management through the full data life cycle like

is available at the NASA science centers. Many ground-based telescopes follow a sole-researcher model for data management. Many telescopes designed for individual and small groups of scientists may have a different, single astronomer collecting data each night and require these individuals to manage the data they collect. These astronomers are managing their data for their own use and are expected to manage the data through the entirety of the data life cycle.

Other ground-based data are collected through sky survey teams, not individuals. Unlike individual investigator-driven research, sky surveys result in uniformly captured data. The same team collects the data over the course of the survey instead of data being collected by a different scientist each night. The data management activities are generally split between team members with different kinds of expertise. In projects involving a sole astronomer, that researcher manages data through the whole life cycle; in contrast, sky survey data are managed by different sets of team members at different stages in the life cycle. A more specialized workforce develops in sky surveys, as team members manage data at different junctures in the life cycle, aiming to support data use by a whole community beyond their own scientific needs.

This dissertation research investigates astronomy data practices among the population of team members and data end-users of modern astronomy sky survey data. More specifically, the three study populations are those involved in The Sloan Digital Sky Survey (SDSS) project collaboration, the Large Synoptic Survey Telescope (LSST) project collaboration, and individual astronomers who make use of SDSS data. The SDSS and the LSST projects are both ground-based, optical sky surveys, and are each at different stages in their research life cycles. Individual astronomers in this study may work alone or in small groups using SDSS data. The next three subsections provide background on each of the three study populations. Chapter

3 Research Methods describes how the study populations were operationalized and the study sampling methods.

2.4.2 The Sloan Digital Sky Survey

The Sloan Digital Sky Survey (SDSS) ("Sloan Digital Sky Survey: Home," 2016) produces a significant astronomy dataset in terms of its scope, quality, public access, and extent of uses and users. The survey covered over a quarter of the night sky with high quality photometric and spectroscopic imaging. The first phase of the SDSS project (SDSS I) ran from 2000 to 2005, the second (SDSS II) from 2005 to 2008, and subsequent SDSS projects continue today; SDSS IV began taking data during Summer 2014. The final data release of the SDSS I and II project collaboration occurred in June 2009 (Abazajian et al., 2009). A timeline of the SDSS project is included in Appendix I. This dissertation examines the SDSS I and II phases of data management. SDSS was the first astronomy ground-based survey to ensure prompt public release of data, and many current collaborative telescope projects now emulate SDSS data practices. Indeed, "By altering the traditional interactions between a telescope, its data and communities of astronomers, Sloan … is indeed a legacy to be celebrated" (Kennicutt Jr, 2007, p. 489).

SDSS data are consulted millions of times each month; in April 2014, the SDSS SkyServer (the online public SDSS database) was visited more than four million times (SDSS Collaboration, 2014). SDSS data are some of the most used astronomy data, arguably second only to the Hubble Space Telescope (Borne et al., 2009; Hand, 2009; Kennicutt Jr, 2007; Reichhardt, 2006; Singh et al., 2006). Because the SDSS data are publicly available, project collaborators, external individuals, international scientists, and the general public alike can use SDSS data for educational purposes and scientific research.

While often referred to as 'the data,' the SDSS I and II dataset is a complex aggregation of materials representing multiple elements of the international project. Generally speaking, the SDSS includes four kinds of data 1) a photometric catalog, 2) spectroscopic catalog, 3) images, and 4) spectra (Szalay, Kunszt, Thakar, & Gray, 1999, p. 3). Specifically, the SDSS I and II Long-Term Scientific Data Archive (the SDSS Archive) is comprised of four related datasets: (1) the Data Archive Server (DAS) contains the processed flat image files; (2) the Catalog Archive Server (CAS) contains multiple releases of the image and spectroscopy SQL [Structured Query Language] database; (3) the Software includes the code generated for the data collection, data processing, database creation, user interfaces, and the SDSS website; and (4) the Raw Data are the unprocessed data as received from the scientific instruments. In total, the SDSS I and II archive forms a collection between 100 and 200 terabytes (Astrophysical Research Consortium, 2008).

The SDSS collaboration manages SDSS data for use by the team and countless others. This process can prove difficult, because one cannot predict all potential future users and uses of a dataset (Huang et al., 1995). SDSS astronomers and computer scientists spent more than a decade planning for data collection to ensure standardized, consistent data products over time (Huang et al., 1995; Szalay et al., 1999; Szalay, Kunszt, Thakar, Gray, & Slutz, 2000). Data management for the sky survey involves a number of steps beginning with the collection of raw data by the instruments. The SDSS data were then processed through the software pipeline. Astronomy processing *pipelines* are specific collections of algorithms and software designed to calibrate, process, and derive information from raw digital data produced by scientific instruments, which result in intelligible images, spectra, and catalogs.

Construction of the processing pipeline was a critical aspect of the entire SDSS project.

The pipeline software accounted for approximately 25% of the entire survey's total "cost and effort" (J. Gray, Slutz, et al., 2002, p. 2). Following pipeline processing, the SDSS data were then made publicly available as flat files (DAS) and a Structured Query Language (SQL) database (CAS). The construction and maintenance of the SQL database was a large software project of its own due to the vast size, amount, and complexity of the SDSS dataset (J. Gray, Slutz, et al., 2002; Szalay et al., 1999, p. 5). Now that the SDSS I and II collaboration no longer collects new data, the data management considerations focus on the continued ability to serve and preserve the data as a valuable resource to astronomers around the world.

2.4.3 The Large Synoptic Survey Telescope

The Large Synoptic Survey Telescope (LSST) is an international astronomy project currently under construction. Planning for the LSST began in the late 1990s (Tyson, 1998), enabling project recognition in time for the 2000 Astronomy Decadal Survey (Astronomy and Astrophysics Survey Committee, 2001). The LSST collaboration now plans for data collection to begin approximately 2020 ("LSST project schedule," 2015). By the time of the 2010 Decadal Survey, the LSST was chosen as the single most important astronomy project in terms of funding and time investment for the current decade (Committee for a Decadal Survey of Astronomy and Astrophysics; National Research Council, 2010). A timeline of the LSST project is included as Appendix 2. Astronomers estimate that the LSST will have an even larger impact on the astronomy community than the SDSS, in part because of the larger scale of research data expected to be collected (Ivezić et al., 2007).

The LSST survey plans to cover more of the night sky and provide better imaging than the SDSS project achieved due to continued advances in technology (See Table 1). Additionally, the LSST project will acquire more data, which will address a larger number of scientific

questions than the SDSS (Lupton, 2010). The LSST plans to make a map of the sky every three to four days, resulting in an estimated 15 terabytes of data collected each evening over the course of ten years of observation (Becla et al., 2006; Borne et al., 2009; Borne, 2013, p. 414; Kantor et al., 2007; Plante et al., 2010; "Technology Innovation | LSST public website," 2015). The SDSS I and II dataset was on the order of hundreds of terabytes at the conclusion of the project; LSST is expected to amass research data on the order of many petabytes. As evidenced in the scale difference between the SDSS and the LSST, astronomy sky survey data, "have grown from gigabytes into terabytes during the past decade, and will grow from terabytes into Petabytes (even hundreds of Petabytes) in the next decade" (Borne et al., 2009, p. 1).

	SDSS I and II Project Collaboration	**LSST Project Collaboration**
Project Timeline	Survey data collection 2000-2008	Survey data collection (predicted) 2022-2032
Type of Project	Photometric and spectroscopic Sky Survey	Photometric Sky Survey
Primary Scientific Objectives	Galaxies, quasars, and stars	Dark energy and dark matter, solar system, transient optical sky, milky way.
Scale	930,000 unique galaxies	10 billion unique galaxies (prediction)

Table 1 Comparison of the scale and goals of the SDSS and LSST Projects

While the immense growth in the scale of data promises new scientific discoveries, it also influences data management practices. As the size of data continue to grow, it raises the expectations of users and the need for an "increasingly skilled workforce in the areas of computational and data sciences" (Borne et al., 2009, p. 2). The LSST collaboration members are aware of the demands of managing large amounts of scientific data and have devoted time and resources to preparing for the data (Connolly, 2014). An active data management team

collaborates across six institutions to build the software necessary to manage the impending LSST data deluge ("Data management | LSST public website," 2015; "LSST Data Management Wiki," 2015).

2.4.4 Individual and small-group astronomy projects

Large sky surveys have significantly shaped research practices in astronomy. However, meaningful astronomy research is still conducted individually or by small groups. In addition to those directly involved in the SDSS and LSST collaborations, many independent astronomers make use of publicly available survey data.

Despite the large size of the SDSS and LSST collaborations, individuals or small teams of faculty accomplish most astronomy research. The individuals and small teams considered in this dissertation obtained astronomy research datasets in part or whole from sky surveys, particularly the SDSS. Depending on the research question, these teams may use only SDSS data, SDSS data alongside data from other sky surveys, or may collect their own data from new photometric or spectroscopic observations. Subsequently, data from across the electromagnetic spectrum are combined and analyzed to generate derived data. In this dissertation, *derived data* in astronomy are defined as copies of an original dataset that have been re-processed by one or more end-users.

The growing number of astronomy tools and infrastructures, as well as the presence of large sky surveys, suggests that astronomy data and therefore data management practices are largely homogenous. However, the management practices of individual and small groups differ from large project data management, and are mainly heterogeneous among one another (Darch & Sands, 2015; Sands, Borgman, Wynholds, & Traweek, 2012). These highly processed derived data are rarely provided long-term archiving, whereas the SDSS and LSST projects planned for

data sharing from the beginning of project development (Norris et al., 2006, p. 7).

3 Research Methods

This dissertation emerged from the author's five-year collaboration in the UCLA Center for Knowledge Infrastructures (CKI), funded by the National Science Foundation and the Alfred P. Sloan Foundation. This dissertation addresses integral questions to the CKI's grant-funded research, as well as key outcomes. Within the scope of the CKI work, this dissertation research pursues four specific research questions (RQs) among three study populations. The study benefits from the coordination of three complementary research methods. The primary source of data for this dissertation is semi-structured interviews. Over five years (2011-2015), the author conducted more than 100 interviews with astronomy community members. All of those interviews were transcribed and are part of the UCLA CKI dataset. Given the specific operationalization of the three study populations, 80 interviews were used to represent the three study populations for this dissertation. Ethnographic methods and document analysis were used to prepare for, support, and explain the interview findings. Further details on the analytical relationships between the methods are now presented.

3.1 Research Questions

This dissertation examines stakeholder perspectives of the data practices employed by sky survey team members and data end-users. The study focuses on scientific research data; data management tasks; the knowledge, expertise, and experience required; the workforce responsible; and how data management activities differ between astronomy populations.

The fourth research question in this study is: How does data management differ between populations? To address this question, the first three successive research questions had to be examined. The expertise involved in astronomy data management was examined prior to

investigating how astronomy data management differs between populations. To analyze the required expertise for data management, data management had to be understood first. Finally, to analyze what data management is, data itself had to be scoped. The four research questions for this dissertation successively build on one another and cumulate to the fourth question.

1. What are astronomy research data?
2. What is data management in astronomy?
3. What expertise is applied to the management of data?
4. How does data management differ between populations?

These research questions focus on revealing how data management differs between populations. While stakeholder understandings of data, data management, and expertise openly differ, the reasons for these differences are unclear.

3.1.1 What are astronomy research data?

Data can mean different things to different people (Borgman et al., 2012) and therefore a single definition is impossible (Parsons & Fox, 2013). This study sought to understand how these differences surface among the SDSS and LSST study populations, and what the implications are for scientific research and data management infrastructures. Astronomy research data were nominally defined in section 2.1 Scientific Research Data as "…reinterpretable representation[s] of information in a formalized manner…" (Consultative Committee for Space Data Systems, 2012, pp. 1–10). *Astronomy research data* were operationalized for this dissertation to include digital information developed for, or exploited by, the SDSS, the LSST, and SDSS data end-users. The term *data* was intentionally operationalized broadly, to ensure information considered data to some but not all stakeholders remained within the scope of the investigation.

3.1.2 What is data management in astronomy?

To reveal how stakeholders discussed data management, data interpretations were analyzed. Data management was defined nominally as an umbrella term referring to actions taken on data aimed at enabling scientific progress (refer back to 2.2 Scientific Research Data Management). *Data management* was operationalized to include all activities related to planning, collecting, processing, documenting, analyzing, sharing, and maintaining SDSS and LSST data as defined in the previous subsection. Data management included tasks throughout the full data life cycle, including storage, archiving, preservation, curation, and other undertakings for data analysis in the short- and medium-term and data stewardship in the long-term. The broad definition was critical to ensure potential outlying perspectives were included during analysis.

3.1.3 What expertise is applied to the management of data?

Necessary data management expertise was interpreted by analyzing how interviewees expressed data management tasks. The scientific research data workforce was defined nominally as to encompass all individuals tasked with managing, stewarding, sustaining, serving, storing, archiving, curating, or preserving scientific research data, whereas expertise and experience are the existing knowledge the workforce bring to these tasks (Sands et al., 2014). These terms were operationalized broadly to avoid unduly restricting study participant interpretations. The data management *workforce* was operationalized to include all individuals who either self-identify, or are identified by others, as affiliated with the management of the SDSS and LSST data (see operationalized definitions of data and data management in previous sub-sections). *Experience and expertise* were operationalized as any formal or informal education, skill, and knowledge that informed or managed the SDSS and LSST data.

3.1.4 How does data management differ between populations?

Finally, the ways interviewees described data, and therefore data management, and the expertise needed to manage data was analyzed based on seven demographic variables gathered for each interviewee. The perspectives revealed in the first three cumulative research questions informed analysis of the fourth question. Findings operationally were grouped according to the seven demographic characteristics of interviewees recorded for this study, discussed in detail in section 3.2.2 Semi-structured interviews.

3.2 Data Collection

This study was conducted using three qualitative research methods: semi-structured interviews, ethnographic fieldwork, and document analysis. Table 2 shows the relationship between the research questions (described and operationalized 3.1 Research Questions), the three study populations and interviewee demographics, and the three research methods, which are detailed in the following section. The table also provides a visual of the Results chapter.

Research Question (RQ): Method:	RQ1: What are astronomy research data?	RQ2: What is data management in astronomy?	RQ3: What expertise is applied to the management of data?	RQ4: How does data management differ between populations?
Document Analysis	SDSS Team LSST Team	SDSS Team LSST Team	SDSS Team LSST Team	Primary Institutional Affiliation; Year of Interview; Career Stage; Level of Astronomy Education; Current Workforce; Role in SDSS and LSST; Theorist
Semi-Structured Interviews	SDSS Team LSST Team SDSS End-Users	SDSS Team LSST Team SDSS End-Users	SDSS Team LSST Team SDSS End-Users	
Ethnographic Participant Observation	SDSS Team LSST Team	SDSS Team LSST Team	SDSS Team LSST Team	

Table 2 Relationship between research questions, study populations, and research methods

Interviews and fieldwork were conducted from Fall 2011 through Summer 2015. Interviews were conducted with individuals affiliated at 26 different institutions, and were conducted in-person at 23 of those institutions. Half of the interviews were conducted in 2015, following approval of the dissertation proposal. Periods of ethnographic fieldwork occurred at 10 institutions central to the SDSS and LSST data management teams. SDSS and LSST documents were read throughout the study, though most of the critical analysis took place in 2015.

In the next section, the three study populations are operationalized. Then the three research methods are each detailed and their relationship to one another is described. Finally, analytical approaches and ethical implications are addressed.

3.2.1 Study populations

This dissertation includes document analysis, interviews, and fieldwork with astronomy faculty, students, and staff from three study populations: SDSS collaboration team members, LSST collaboration team members, and SDSS data end-users. Fieldwork sites were chosen based on their centrality to data management activities for the SDSS, LSST, or both. Interviewees were chosen due to their affiliation with one of the three study populations.

Study participants directly involved with the planning and construction of the SDSS and LSST are referred to in this study as *team members*. Those not involved directly in a team, but who took advantage of the released SDSS data, are referred to in this study as *SDSS end-users*. LSST remains in the construction stage, so LSST data end-users do not exist yet. More explicit information about how these populations were operationalized is presented in the next three subsections.

The three study populations overlap; individuals may be members of one, two, or all three populations. For example, some SDSS team members are also part of the LSST team. Others may be an LSST team member and also use SDSS data. For the purposes of ethnographic fieldwork and document analysis, the entirety of an individual's affiliations was considered. However, each interviewee was only questioned using a single interview protocol, which was chosen based on their primary affiliation. Interviewees were questioned based on their experience as an SDSS team member, an LSST team member, or as an SDSS data user. A nearly even array of interviews were conducted among the three study populations: 28 interviews were conducted using the SDSS team protocols, 26 were conducted with the LSST team protocol, and 26 were conducted with the SDSS data end-user interview protocol (see Table 3).

Interviews	Total In Sample
SDSS team member	28
LSST team member	26
SDSS data end-user	26

Table 3 Number of interviewees in each of the three study populations

A comprehensive cross-section of each interviewee's affiliations is illustrated in Table 4 and replicated in Table 11. As shown in the tables, 22 interviewees were members of the SDSS team, 25 interviewees were members of the LSST team, 17 interviewees were members of both teams, and 16 interviewees were not members of either team and instead were interviewed based on their use of SDSS data. The primary affiliation of each interviewee was determined through analysis of their existing journal article publications, web presence, and based on feedback from other interviewees and information gathered through ethnographic fieldwork. Preliminary determinations were made as to potential interviewee's affiliations in each of the three populations to determine whether they should be contacted. Individuals were then asked for an interview focusing on only one of the three affiliations. To determine interview type, the focus of the interviewee's recent work was weighed as well as the need to distribute the demographic categories across study populations (see 3.2.2 Semi-structured interviews). Through email exchanges and during each interview, an interviewee was able to self-report their affiliation in each population, allowing the author to update the interviewee records and ensure the interview fit the specific study populations for this dissertation.

SDSS or LSST team affiliation	Total In Sample
SDSS team member only	22
LSST team member only	25
Member of both SDSS and LSST teams	17
SDSS end-users, member of neither team	16
Total	**80**

Table 4 Interviewees organized by role in SDSS and LSST (See also Table 11)

Seven interviewee attributes were recorded for each interviewee. These demographic variables meant interviewees could be recognized by multiple demographic attributes, beyond their study population affiliations. The seven demographic variables are detailed in 3.2.2 Semi-structured interviews.

3.2.1.1 Sloan Digital Sky Survey team

Participating members of the SDSS collaboration during the first or second phase of the SDSS project were operationalized as part of the SDSS team member study population. Team participation was determined through journal article authorship. If an individual was one of the authors of a SDSS I and II data release journal article (Early Data Release through Data Release 7), they were considered a member of the SDSS team population for this study. The data release articles abide by the SDSS authorship policies and therefore encompass the individuals working on the project. The authorship for each data release was dictated by the SDSS Scientific and Technical Publication policy which stated, "Those who have contributed to the writing of the data release paper, or who have contributed in a substantive way to the creation or validation of the data described in the paper, are eligible to be authors" ("SDSS scientific and technical publication policy," 2014, sec. 7.3 Data-release publications). Therefore, data release authorship effectively operationalized SDSS team membership for this study.

Prior to visiting an institution for this dissertation work, the author emailed every person at the institution who qualified as a study participant to request an interview. This recruitment method was effective and not overwhelming due to the level of interviewee willingness to participate in the study. Many potential interviewees did not respond to two e-mail attempts to schedule an interview, while others were unable to find a mutually agreeable time to meet. Participation in interviews was solely at the discretion of the interviewee.

Two protocols were used for the SDSS team interviews. Most interviews were conducted using the UCLA CKI "Phase1" interview protocol. In December 2013, eight SDSS team interviews were conducted using a modified version of the "Phase1" protocol, which included greater focus on the later stages of the SDSS I and II data life cycle. As the interviews were semi-structured, the protocols were modified to pertain specifically to each individual's role in the collaboration(s). Questions were related to data management, curation, and preservation of the SDSS data as a resource for the astronomy community.

3.2.1.2 Large Synoptic Survey Telescope team

LSST team interviews for this dissertation parallel research conducted by other UCLA CKI team members. Peter T. Darch, also of the UCLA CKI, similarly interviewed other LSST team members regarding their data practices. There are six primary LSST data management (DM) construction sites, Darch and the author each focused on fieldwork and interviews at three of the six sites. Therefore, the LSST team interviews for this dissertation were conducted with interviewees from half of the primary LSST DM institutions in the United States.

Potential research subjects were considered members of the LSST team if they were an author on *LSST: from Science Drivers to Reference Design and Anticipated Data Products (Version 4.0)* (Ivezić et al., 2014) or *LSST Science Book (Version 2.0)* (LSST Science

Collaboration et al., 2009). LSST team members consistently described these two documents as essential blueprints to the project.

Authorship for the "Science Drivers" paper included individuals who had contributed to LSST design and development and are largely paid members of the team. However, there were many other individuals who were not paid members of the LSST team, but instead contributed their time and expertise to LSST as a member of an LSST Science Collaboration ("Science collaborations | LSST Corporation," 2015). These individuals collaborated in the writing of the LSST "Science Book" and continue to plan for future scientific cases made possible by the LSST. Science Collaboration members are not directly paid through LSST funding; they are paid through their primary institutions and volunteer their time to LSST to help shape the anticipated scientific work. Therefore, both paid team members and scientific collaboration members were included broadly in the LSST team study population, operationalized by authorship on either or both of the aforementioned documents. As with the SDSS, while every potential interviewee at all visited sites were contacted, each individual had the choice to participate in the study.

Interviewees who joined the LSST team too recently to be included as authors on either the Science Drivers or Science Book documents were not considered eligible as interviewees for this dissertation. However, the author may have interviewed these new team members for the broader UCLA CKI investigations. While these interviews were not included in the operationalized dataset for this dissertation, the interviews have been transcribed and made available to the UCLA CKI team for further examination.

LSST interviews were conducted using the UCLA CKI "LSST1" interview protocol. While having emerged from existing UCLA CKI team protocols, modifications were required to reflect LSST's early life cycle stage. Questions were related to the design and construction of

data management infrastructures for LSST, the workforces involved in these activities, the nature of the expected data, and the influence of the collaboration and the larger astronomy field.

3.2.1.3 Sloan Digital Sky Survey data end-users

SDSS data end-users are the third study population, which includes astronomers at all career stages who (co-)authored a journal article using SDSS data. Specifically, the interviewee must have authored a journal article available on arXiv.org that referenced SDSS in the article title or abstract. arXiv is a widely used pre-print archiving service for the physics and astronomy community (Cornell University, 2016). Prior to visiting each institution, the author investigated potential interviewees by searching arXiv for articles with "SDSS" or "Sloan Digital Sky Survey" in either the title or the abstract, published in the preceding couple of years, and having at least one author affiliated with the institution. Only articles published recently were chosen, because authors tend to change institutions and forget details of the research process over time. Prior to each trip, relevant authors were emailed requesting an interview, which included mention of the pre-identified journal article.

This sampling method had two limitations. First, the sample was limited to institutions in Southern California, or the institutions (or nearby institutions) already scheduled for SDSS or LSST team research. However, strong project funding (see Acknowledgements) enabled considerable travel, which permitted interviews at 23 institutions. Second, as stated with the other study populations, the method was limited due to interviewee willingness to participate. Many interviewees did not respond to two e-mail attempts to schedule an interview, while others were unable to find a mutually available time to meet.

The SDSS end-user interviews were conducted using the UCLA CKI "Follow the Data" interview protocol. Follow the Data interview questions inquired about data management

practices used by the interviewee as an individual or among their small research group. The interview protocol is effective in identifying specific data sources, types, and uses (Sands et al., 2012). The protocol allows the interviewer to use the publication (co-) authored by the interviewee as a lens to identify data uses leading into and out of the journal article. The article was chosen prior to the interview session, and the interviewer performed a close reading of the text to identify authors, data sources, links to data, and other relevant characteristics. This background research enabled rich interviews that addressed questions pre-identified during the close reading of the text. These interviews facilitated exploration of how small-scale research projects employing SDSS data compare and contrast to the data management activities involved in the large-scale SDSS and LSST collaborations.

3.2.2 Semi-structured interviews

Interviews included questions adapted from existing UCLA CKI protocols to engage researchers on their data practices, perspectives on data management, curation, and preservation activities, and perceptions of data management knowledge and expertise needs. Semi-structured interviews balance the rigidity of structured interviews, while enabling more focus than unstructured interviews like oral histories. Interviews were conducted with a protocol, including mostly open-ended, but also strategically pointed, questions. The specific protocol used for each interview was addressed in 3.2.1 Study populations.

Often, interviewees addressed themes before the protocol question about that theme were asked. In these cases, the interviewer adjusted the protocol question sequence accordingly. When themes were addressed already, the interview question was often omitted. Alternatively, some interviewees addressed themes that were not in the protocol. In these cases, the interviewer could choose to encourage the line of thinking by asking more specific questions if relevant, or return

to the predetermined questions. Semi-structured interviews therefore allowed the interviewer to focus on data management topics, while enabling interviewees to focus on the aspects of the topic they found most important. The semi-structured interviews enabled analytical comparisons between all interviewees, and across multiple sites and kinds of expertise.

Interviewees were chosen through a nonprobability sampling method referred to as Quota Sampling (Babbie, 2007, pp. 185–187), with a reliance on subject availability and voluntary participation. Quota sampling was used in this study to ensure a broad mix of demographic participation. As a field research project, quota sampling is an excellent method to compare and contrast informant perspectives across multiple parameters (Babbie, 2007, pp. 185–186). A matrix was created to ensure study participants held a breadth of the following parameters: institutional affiliation, career stage, level of astronomy education, current workforce, association with theoretical astronomy, and most importantly affiliation with the SDSS team, LSST team, and SDSS data use. The interviews also occurred over five years. These seven parameters were chosen because they were hypothesized to be factors relevant to the primary research question: How does data management differ between populations? From preliminary interviews, these demographics were chosen as sources of distinction between individuals and their data management practices. Demographics largely were determined through institutional website searches before each interview and confirmed during each interview.

The operationalization of the SDSS team, LSST team, and SDSS end-users was largely detailed in the previous section on study populations. Potential interviewees were determined by geographic location, authorship in designated journal articles, and willingness to participate in the study. Toward the end of data collection in 2015, interviewees were targeted more strictly to ensure the demographic variables were covered evenly. For example, to ensure they were well

represented in the sample, graduate students were sought out specifically to participate in the study in 2015. All but one of the study interviews were conducted in-person; one was conducted via Skype.

Data collection took place from 2011 to 2015 and later interviews and coding responded to the themes that emerged from earlier work. For example, the research questions used in this dissertation were developed by the author in 2013 and formalized in 2014. The third research question seeks to understand the expertise necessary for data management. However, questions addressing experience and expertise were not explicit in earlier interview protocols because the author developed the line of questioning from ongoing complementary UCLA CKI research. The author added questions aimed toward eliciting the interviewee's educational and experiential backgrounds, as well as how they are training the next generation to work with sky surveys. While experience and expertise were one of many lines of inquiry for the UCLA CKI, their prominence in this dissertation led to an increased focus on related interview questions as the years passed.

This dissertation research amassed 80 semi-structured interviews. The corpus is composed of 28 interviews with SDSS team members, 26 with LSST team members, and 26 with SDSS data end-users. Interviews ranged from 20 minutes to three hours, with most lasting about one hour and thirty minutes. Thirty-one of the 80 interviews were conducted prior to the dissertation proposal (24 by the author), under the auspices of the UCLA CKI grant-funded research (see Table 5). Two UCLA CKI team members conducted seven of the interviews included in the study: David S. Fearon, Jr. (four) and Christine L. Borgman (three). The company *Scribie* confidentially transcribed the interviews. The transcripts were audio-verified by the UCLA CKI team, usually the author. Milena S. Golshan of the UCLA CKI also assisted with

some audio-verification, ingesting the transcripts into the NVivo qualitative data analysis software, and some preliminary coding. More detailed information on the analytical process is presented in the following section.

Table 5 indicates the three subject populations and compares the number of interviews for each population. Each column addresses: The total number of interviews, the number collected prior to the June 2014 dissertation proposal oral defense, the number collected following the proposal, the total number of interviews collected by the author, and the number of interviews not collected by her.

Study Population:	SDSS TEAM	LSST TEAM	SDSS USER	TOTAL
Interviews Total	28	26	26	80
Interviews conducted prior to proposal	18	0	13	31
Interviews conducted after proposal	10	26	13	49
Interviews conducted by Sands	26	26	21	73
Interviews conducted by others	2	0	5	7

Table 5 Number of interviewees in each of the three study populations

Interview sampling was designed to guarantee a broad array of demographics among the interviewees beyond membership in one of the three study populations. Interviewee parameters included type of institutional affiliation, career stage, career type, level of education, whether or not they were a member of the SDSS or LSST team, whether they are theorists, and the year of the interview. These categories were chosen to enable analysis for RQ4: How does data management differ between populations? The breakdown of these statistics is visualized in Appendix III; the demographic categories are described below.

3.2.2.1 Primary institutional affiliation

All eighty interviewees were associated with an institution, and eight of those interviewees had two institutional affiliations. The majority of interviewees were affiliated with a university. However, approximately one-third of interviewees were affiliated with (either primarily or secondarily) another institution including data centers, national laboratories, research institutes, and planetariums. Eight interviewees were affiliated primarily with a university, but had secondary affiliation with another institution (one data center, one national laboratory, one planetarium, and five research institutes). For example, some faculty whose primary appointment is at a university also have an appointment at a nearby research institute. For the purposes of this analysis, interviewees are indicated by their primary affiliation, which was initially predicted through their web presence, and then confirmed through self-identification during the interview. Distinctions were expected to arise between how data are managed at different institutions.

Primary Affiliation	Total In Sample
University	62
Research Institute	4
Data Center	6
National Laboratory	8
Total	**80**

Table 6 Interviewees organized by primary affiliation

3.2.2.2 Year of interview

Interviewees are grouped by the year the interview was conducted. Exactly half of the interviews were conducted in 2015. The other half were conducted nearly evenly between 2011 and 2014. It was hypothesized that there would be a gradual, but evident, aggregate change in

how data management practices were discussed over the years, as individuals grew more accustomed to data-intensive techniques and ways of thinking.

Year of Interview	Total In Sample
2011	11
2012	9
2013	10
2014	10
2015	40
Total	**80**

Table 7 Interviewees organized by year of interview

3.2.2.3 Career stage

Interviewees were clustered by their career stage at the time of the interview. Interviewees span career stages from graduate school students through emeriti faculty. Based on primary affiliation, approximately 40% of interviewees were faculty, approximately 40% were staff, and the remaining nearly 20% were graduate students or post-doctoral researchers. It was hypothesized that data management practices would vary between early and late career researchers, as well as between staff and tenure-track individuals.

Similar career stages were grouped together in the following ways: non-tenure-track faculty researchers were grouped with staff scientists. Non-scientific staff include two administrators and one mechanical engineer. Staff programmers were distinguished from staff scientists in that they described their roles as only requiring computer science expertise and not astronomy domain knowledge. Staff scientists are non-faculty astronomers whose work was largely based on computationally driven astronomy. The career stages were split between junior and senior career levels, as well as between careers along faculty-lines (the first four rows in Table 8) and staff career paths (the final three rows in Table 8).

Career Stage	Career Stage	Career Path	Total In Sample
Graduate Student	"Junior"	Faculty-line	6
Post-Doc	"Junior"	Faculty-line	8
Faculty Professor	"Senior"	Faculty-line	30
Faculty Emeritus/Retired	"Senior"	Faculty-line	3
Staff Programmer	"Senior"	Staff-line	6
Staff Scientist	"Senior"	Staff-line	24
Non-scientific staff	"Senior"	Staff-line	3
		Total	**80**

Table 8 Interviewees organized by career stage

3.2.2.4 Level of astronomy education

Interviewees are grouped by level of astronomy education. The astronomy education category consists of those who hold a PhD in an astronomy-related domain: astronomy, astrophysics, or physics. While nearly 40% of the interviewees hold staff positions, more than 80% of the interviewees have PhD degrees. 10% of interviewees were either current graduate students or had completed some graduate education in astronomy. The "some astronomy graduate work" category includes current students, one interviewee with a master's degree in physics, and another interviewee who began but did not complete a PhD in astronomy. The "other graduate degree" category includes one interviewee with an MBA, one with a master's degree in computer science, and one interviewee with both an MBA and a master's degree in computer science. One interviewee does not have any higher education degrees. It was hypothesized that individuals with PhDs in astronomy or a related discipline would approach data management differently than those with non-domain specific educations.

Level of Astronomy Education	Total In Sample
No Higher Education	1
Some Astronomy Graduate Work	8
Astronomy PhD	65
Other Graduate Degree	6
Total	**80**

Table 9 Interviewees organized by level of astronomy education

3.2.2.5 Current workforce

Interviewees were also clustered by the kind of career they held at the time of the interview. The astronomer label encompasses all interviewees who self-identified as astronomers and whose work includes performing scientific analysis in astronomy, employing the skillsets gained through higher education in the field. The computer scientist designation is used to describe those who have obtained a higher education degree in computer science; it includes interviewees who identified as system programmer and database administrator. The computational astronomer label is used for those whose work is focused on the computer-science aspects of astronomy projects. The computational astronomers hold PhDs in astronomy, but their jobs are computationally driven. The "other" identification row includes those who are not on a faculty or computer-science career path and includes two administrators, a mechanical engineer, and a non-research lecturer. More than 70% of the interviewees were practicing, or student, astronomers. More than 10% of interviewees were astronomers now working on the computational aspects of science, and another 10% were computer scientists. It was hypothesized that individuals in research roles would manage data differently than those whose careers did not rely on journal article publication.

Current Workforce	Total In Sample
Astronomer	58
Computational Astronomer	9
Computer Scientist	9
Other (non-research)	4
Total	**80**

Table 10 Interviewees organized by workforce

3.2.2.6 Role in SDSS and LSST

Interviewees are grouped by whether they were a member of the SDSS team, the LSST team, both teams, or neither team. The way in which team membership was determined was described earlier in this chapter. It was hypothesized that team membership would shape the way an individual managed their data.

SDSS or LSST team affiliation	Total In Sample
SDSS team	22
LSST team	25
Both	17
Neither	16
Total	**80**

Table 11 Interviewees organized by role in SDSS and LSST (See also Table 4)

3.2.2.7 Theorists

Here, interviewees are clustered according to whether or not they had been involved in theoretical astronomy research. Theoretical astronomy is a large component of astronomical research, often described in contrast to observational astronomy. An interviewee was considered to have been involved in theoretical astronomy if they 1) identified as a theorist in the interview, or 2) their research webpage described their work as involving simulations, Monte Carlo methods, or theoretical astronomy. Since the interview sample for this dissertation was targeted at those who built or used sky survey data, it was less likely these interviewees would also identify as theorists. Only about 10% of the interviewees are considered theorists for the

purposes of this study. It was hypothesized that those who identify as theorists may manage data differently than those who work solely in observational astronomy.

Theorist?	Total In Sample
Yes	9
No	71
Total	**80**

Table 12 Interviewees organized by participation in theoretical work

3.2.3 Ethnography

Ethnographic work was an important part of the study's methods. The SDSS and LSST teams are distributed across the United States (and internationally). The focus of this study was to seek ongoing engagement with SDSS and LSST team members focused on data management. Since 2011, the author has spent time in the company of various members of the study populations and the larger astronomy community, building relationships with the study participants and in particular with key informants. The primary ethnographic fieldwork method employed for this study is defined as sustained interactions with key informants.

Beginning in 2011, the author visited and began observing SDSS and LSST members at their institutions. As with the interviewee locations, these institutions included universities, data centers, research institutes, and national laboratories. She recorded in-depth field notes describing and analyzing observations of the study populations. Most importantly, she cultivated and sustained personal relationships with individuals, and some developed into friendships.

The author spent time in the company of the study population in three capacities. Two of the ways were in-person, in environments structured by the study populations. Most commonly, she spent time with the study populations at their institutions (places of work). She also attended their special events, their meetings and conferences, held in other locations. The third way was through digitally-mediated interactions using various software for virtual meetings, for example

the software GoToMeeting. Most commonly, this enabled the author to join virtual meetings, or perform virtual interviews. While not in-person, her presence at virtual meetings was an important way to sustain interactions with the study populations. The continued presence at meetings served to build community and trust because "extended presence signals commitment and sincere interest, opening dialogue with a variety of informants…" (Boellstorff, 2012, p. 66).

Over the course of the project, the author had sustained interactions with key informants at their institutions for more than 17 workweeks, joined in conferences and meetings with the community for more than three workweeks, and participated in virtual meetings more than 30 times. These interactions resulted in spending 21 workweeks in the physical company of study populations as well as additional virtual interactions of 30 minutes to 2 hours each on 30 different days. The summary of sustained interactions with the study populations is presented in Table 13.

Type of Interaction	**Amount of Interaction**
In-person at study population institutions	17.5 workweeks
In-person at study population conferences and meetings	3.5 workweeks
Virtually attending study population meetings and conducting interviews	30 occasions

Table 13 Author's sustained interactions with study populations

Over the course of the time spent with study populations, the author identified a number of key informants. Individual study participants are considered "key informants" when they become "important guides to insider understandings" of the study population (Lofland & Lofland, 1995, p. 61). Key informant relationships can develop into friendships, enabling the researcher to understand study populations. These relationships are a strength of this type of study. Murchison explains in Ethnography Essentials (2010),

> "While they aim to interact with and rely on a number of different informants, certain individuals turn out to be more skilled as guides and teachers. In many instances, ethnographers and their key informants become close friends. Working with one or a few key informants can by very productive because the close relationship allows you to glean deeper levels of information" (Murchison, 2010, p. 91).

The author developed relationships with key informants both through UCLA CKI team membership and also as an individual researcher. In total, she identified 15 key informants for the study of astronomy data practices. Five of the relationships were developed through participation in the UCLA CKI. These five informants have guided continued investigations into astronomy data practices since 2009, prior to the author joining the team. As an individual, she began developing relationships with key informants in 2011. She established ten relationships with key informants outside the UCLA CKI team; six are members of the astronomy community and four are members of the library community working closely with astronomers and astronomy data. Seven of the key informants were also interviewees in the 80-interview sample for this dissertation; the other 8 key informants were important to the overall research but did not fit the operationalized requirements for the dissertation populations. While the identities of the key informants are confidential, Table 14 presents some collocated information on the informants. Informant names were replaced with unique identification numbers, and institutions were replaced with unique identification letters. Most of the key informants primarily were affiliated with a university, one was affiliated with a data center, and one was affiliated with a research institute. The workforce, career stage, and year the author began a relationship with the key informant are indicated in Table 14.

Informant ID	Institution ID	Workforce	Career Stage (in 2015)	Year Relationship Began
01	A	Astronomer	Faculty Professor	2012
02	A	Astronomer	Staff Scientist	2012
03	B	Library Staff	Library Staff	2012
04	B	Library Staff	Library Staff	2012
05	B	Library Staff	Library Staff	2012
06	C	Astronomer	Faculty Professor	2012
07	D	Computer Scientist	Staff Programmer	2014
08	E	Astronomer	Staff Scientist	2012
09	F	Astronomer	Staff Scientist	2013
10	F	Library Staff	Library Staff	2013
11	F	Astronomer	Faculty Professor	2012
12	G	Astronomer	Faculty Professor	2011
13	G	Astronomer	Graduate Student	2014
14	G	Astronomer	Graduate Student	2011
15	H	Astronomer	Staff Scientist	2012

Table 14 Detailed parameter information on the 15 key informants

3.2.4 Document analysis

The author began participating in the UCLA CKI's larger study of astronomy data practices in 2011. Over the years, many SDSS and LSST documents were read or cursorily examined. Through the course of her investigations into both sky surveys, a smaller set of documents gained significance as the most prominent information necessary to understand data practices in the two teams. These documents were chosen for deep analysis based on the number of citations, mentions by interviewees, and use during observed activities. Each of the documents used in the sample had been referred to more than once during an interview or ethnographic observations. Document selection is one example of how the three research methods informed one another. This smaller set of documents was scrutinized more systematically and thoroughly than the full corpus of information. The deeply analyzed texts from the SDSS project range in

time from 1993 to 2011; documents from the LSST collaboration range from 2005 to 2015. These timelines each cover the majority time period of the project's existence.

Analysis of team documentation was one important avenue of investigation. As Latour explains in *Science in Action*, scientific literature is a form of rhetoric, or argument building, as opposed to a mere presentation of facts (1987, Chapter 1). While documents released on behalf of a project may imply agreement by all project members, individuals with dissimilar purposes wrote these documents to specific audiences. The documents were analyzed with the author and audience in mind. Team documents may be attempts to standardize meaning among disparate geographic locations and kinds of expertise, however all documents are interpreted at the local level. The meanings of the documents are inseparable from the authors and readers (Ribes & Finholt, 2009). This extensive document analysis for this dissertation was critical because, "Texts are understood to be mediators of both explicit and implicit messages, and through a forensic examination of a text its deeper meanings can be revealed and understood…" (Kitchin, 2014, p. 190).

Four types of writing styles emerged from careful document analysis. By comparing the kinds of documents and intended audiences, three distinct writing style patterns emerged from the documents: Promotional and Aspirational, Operational, and Reporting. Promotional and Aspirational documents are those that are used to plan or solicit support for the project. Operational documents are used as guidelines to set policies or explain procedures. Reporting documents describe the status of the project. Each of these writing styles employs a distinct combination of document genres and intended audience (see Table 15).

Writing Styles	Document Genres	Intended Audiences
Promotional, Aspirational	Grant proposals, Planning reports and other documents, presentations and articles, Memoranda of Understanding	Potential funders, existing funding agencies, the larger astronomy discipline including potential future collaboration members, current collaboration members
Operational	Technical journal articles, internal documents, presentations and articles, Memoranda of Understanding	Current collaboration members, potential data end-users
Reporting	Funding final reports, Data release journal articles, Project websites, presentations and articles	Funding agencies, all potential data end-users, general scientific community, general public

Table 15 The kinds of SDSS and LSST documents and writing styles

The document corpus enabled analysis of SDSS and LSST across time and type of document. For example, grant proposals provided a glimpse into some of the earlier iterations of the project, while final reports (also prepared for funders) provided hindsight interpretations. Alternatively, grant proposals and final reports are often promotional while other genres utilize different writing tones. Publicly released journal articles and planning documents set forth data policies and report information for future data end-users. For the SDSS, data release articles demonstrated how the collaboration defined data to the end-user. The LSST has yet to release data, and therefore no data release articles were available. The closely analyzed document corpus also included both project websites, which revealed how the project presents itself to the public. Interviewees and observed ethnographic participants recommended additional presentations and papers for analysis. The examined document collection included various writing genres spanning each project's inception through 2015. The corpus covers the breadth of the project over time and across different levels of formality, as well as covering the depth provided by journal articles and reports.

3.3 Validity and Reliability

Interviews encompassed the largest amount of time devoted to data collection and analysis. However, document analysis and ethnographic methods were complementary, often used to support and frame the interview findings over the course of this multi-year study. For example, sustained interactions with key informants were critical to identifying important team documents for deeper analysis, as described above. Often, interviews were used to understand the context surrounding the documents and unearth their underlying meaning. The three methods were used to validate each other, often providing more nuance or context to the information obtained by the other methods.

As described earlier, the interview protocols used in this study were modified from those used by the UCLA CKI longitudinal work. The consistency of interview protocols over time is a strength of the UCLA CKI team research. This dissertation is included in the CKI's longitudinal, cross-disciplinary study of knowledge infrastructures and scientific data practices. The strength of the longitudinal team research means that many interview questions and protocol themes were generated before the team began specifically researching the astronomy community in 2009. Ethnography and document analysis were important methods to support the interviews and to ensure the details specific to astronomy research were revealed. These additional methods also helped create context and dimension to assist in performing and analyzing the interviews. In turn, the interviews provided entrée to relationships with study populations, some who evolved into key informants. The three methods informed one another, over time, in the study planning, execution, and analysis.

The qualitative nature of this three-method study provides a high level of validity to its findings. The research methods were chosen to "follow the best of all guides, scientists

themselves" (Latour, 1987, p. 21). The ability for the author to visit 23 different institutions, while participating in sustained conversations with key informants over years strengthens the validity of the work. Indeed, "'Being there' is a powerful technique for gaining insights into the nature of human affairs in all their rich complexity," showing the high level of validity obtained through fieldwork in this study (Babbie, 2007, pp. 313–314).

The use of three methods to qualify the findings of each other method increased the level of validity in the study. The time spent "on the ground" performing in-person interviews and ethnography also increased the quality of the study. However, the research was weaker in reliability due to the personal nature of these methods (Babbie, 2007, p. 314). For example, interviewee and informant opinions may change over the course of time and due to experience, as cultures are in flux and not stagnant (Babbie, 2007, p. 230; Murchison, 2010, p. 11). This study combatted threats to reliability by conducting complementary document analysis, interviews, and sustained interactions with key informants. These three methods were specifically used over the course of years to prevent drawing conclusions from only a "snapshot" in the timeline of the projects or from interactions with one individual. The interviewee demographic matrix was developed to ensure a single perspective was not prioritized over other voices. The use of ethnography further broadened the number of perspectives examined for the study. The document analysis was also conducted with a critical perspective, ensuring the motivations of the authors were considered. Each of the three research methods were used to certify a broad array of perspectives were included in this study, over a period of years, and with careful consideration of the potential biases and motivations of the participants.

3.4 Analysis

The collected transcripts, interview notes, ethnographic field notes, and the document

corpus were analyzed based on this dissertation's research questions. These materials were coded using the "UCLA Data Conservancy Data Practices Interview Code Book." The UCLA CKI created the codebook through an iterative process beginning in 2006. The codebook was adapted as needed based on emerging themes, under the principles of grounded theory (Clarke, 2005; Glaser & Strauss, 1967; Star, 1999). The continued use of the codebook, beyond that of this dissertation, will benefit the UCLA CKI's longitudinal analysis of scientific data practices across disciplines.

NVivo 10 qualitative analysis software was used for all collected materials, which were coded using the full codebook. Passages ranged from requiring no relevant codes, one code, and sometimes a handful of codes were relevant for the same passage. The resulting NVivo coding file remains available and in use by the UCLA CKI team to support future research.

For the analysis of each research question, findings were drawn based on identified themes in the NVivo software, according to the codebook. The author's coding process informed the shape of the results of this dissertation, whether or not a specific passage was captured specifically for each research question. The analysis of each of the research questions was focused on a single code from the codebook. The three codes used in this study (one for each of the cumulative research questions, see Table 16), were from the UCLA CKI codebook and best reflected each research question. Each code provided more than 200 pages of relevant interview passages, observational and interview field notes, as well as passages from documentation. The author printed the pages of relevant materials for each code. Through iterative reading and analysis of the passages, subcodes were identified within each research question. The iterative coding of interviews, field notes, and documents resulted in the "interpretive template" (Parmiggiani, Monteiro, & Hepsø, 2015) detailed in Table 16. The table presents each research

question, the existing UCLA CKI code used to pull relevant passages for each research question, and the emergent subcodes used to further analyze the passages. The use of three existing codes enables future comparisons between the UCLA CKI's multiple disciplinary case studies. While the existing codes will enable that continuity at the CKI, the emergent subcodes enabled the details of the SDSS and LSST case studies to surface for this dissertation. These subcodes arose as the themes most commonly discussed in the interviews. Each population or code was analyzed in a disorganized manner to ensure the subcodes were identified iteratively and by moving between populations, interviews, codes, and research questions. This technique enabled emergent themes within each code to guide the way themes emerged in the other codes. The Results chapter of this dissertation provides the full evidence for each emergent code and how those codes were analyzed.

Research Question	**Existing Codes**	**Emergent Subcodes**
What are astronomy research data?	Data Definition	See Table 21 Emergent "Data Characteristics"
What is data management in astronomy?	Data Organization and Archival Storage	Data Collection
		Data Storage, Processing, Transfer
		Long-term Serving & Archiving
What expertise is applied to the management of data?	Important Skills, Abilities	Domain Knowledge
		Computational Knowledge

Table 16 Research questions and associated codes

3.5 Ethical Standards

This dissertation was conducted with the highest ethical regard. The author completed the CITI training and is a member of the UCLA CKI Institutional Review Board (IRB) approved protocol #10-000909. Dissertation interviews were conducted with the full consent of participating interviewees who were provided with consent information documents and asked to sign IRB-approved consent forms [See APPENDIX IV]. Consent materials informed each interviewee of the research scope and enabled the interviewee to make an educated decision as to

whether or not to opt-in to the study. In addition to the consent materials, an IRB-approved Deed of Gift form [See APPENDIX IV] was used for all recorded interviews. The Deed of Gift document was signed by the interviewee and ensures the audio recording and transcription can be used and retained by the interviewer and the UCLA CKI research team into the future.

Interviewees had the right to complete each form as they felt comfortable, and the right to end participation in the study at any time. The privileges of the individual continue to be respected. Interviewees were asked always and never coerced to participate. Many potential interviewees never responded to two email requests for an interview. For example, for a long research trip in late winter 2015, the author contacted 59 potential interviewees before arriving at the destination institutions. These 59 contacts resulted in 29 interviews, revealing a 49% success rate. For this period in 2015, less than half of contacted individuals agreed and were able to find the time to be interviewed for this study. Choices to ignore a second e-mail interview request and requests not to be interviewed were always honored.

Interviewees were not quoted by name in this document nor in subsequent publications. While full anonymity is impossible due to the nature of in-person interviews (Babbie, 2007, pp. 64–65; Lofland & Lofland, 1995, pp. 43–44), all efforts continue to be made to maintain the confidentiality of interviewees under approval of the UCLA CKI IRB-approved study (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1978; UCLA Office of Research Administration, 2015).

Study participants are ensured confidentiality. When gender-based pronouns are used to reference interviewees in this document, the genders have been randomly assigned to each interviewee. For the purposes of confidentiality, all interviewees have been assigned surname pseudonyms within this dissertation. The surname pseudonyms were randomly assigned to each

interviewee from the United States' most common surnames according to the US Census (US Census Bureau, 2014). When an interview is quoted, a citation is included. The citation references the interviewee's pseudonym, the career stage of the interviewee at the time of the interview (see 3.2.2.3 Career stage), and the year of the interview (see 3.2.2.2 Year of interview). For example, the following citation: (Reyes, Graduate Student, 2014) would reference an interview with participant Reyes who was a graduate student at the time of the interview in 2014.

4 Results

The Sloan Digital Sky Survey (SDSS) and Large Synoptic Survey Telescope (LSST) collaborations are large, modern sky surveys. The SDSS was conceived in the late 1980s, and SDSS I and II operations ran from 2005-2008. At the time of this writing, the SDSS I and II data have been collected, the SDSS III has completed operations, and the SDSS IV is collecting data. The first presentation about what is now called the Large Synoptic Survey Telescope (LSST) was given in 1998, ten years after the organization known today as SDSS was established. LSST commenced construction in 2014, and the team anticipates beginning data collection in 2022. Often referred to as the next generation of SDSS, considerable personnel and institutional overlap exist between the two projects. Some scientists whose careers grew with the SDSS now occupy LSST leadership roles. However, LSST will be conducted at a scale beyond the original SDSS in terms of survey years, project cost, data volume, and scientific aims.

The objective of this dissertation research is to garner further knowledge about how data management differs between these sky survey populations through accumulating research questions. Research Question 1 (RQ1) examines how *data* are understood by SDSS and LSST team members and end-users. The successive research questions then build on this foundation. Given how study participants understand data, RQ2 examines how these participants comprehend what it means to *manage* those data. Given how data management is interpreted, RQ3 next examines what kinds of *expertise* are viewed as necessary for data management. The findings for RQ1 to RQ3 are presented here in the Results chapter based on three factors: research question, research method, and study population. In terms of research method, document analysis results are presented first, semi-structured interview results second, ethnography findings third. Study populations are described first by SDSS team members, then

LSST team members, and finally by SDSS data end-users. RQ4 clearly examines the different understandings of data between study participants given the seven individual demographic variables in the study (refer back to 3.2.2 Semi-structured interviews for an explanation of each demographic variable). RQ4 builds on the combination of the first three questions and is presented by the seven demographic variables in the study population matrix. The results are now presented sequentially by research question.

4.1 RQ1 Results: What are Scientific Astronomy Data?

The first research question asks: "What are scientific astronomy data?" These results explore the three study populations (SDSS team members, LSST team members, and SDSS data end-users) and how individuals within each population define astronomy data. After fully coding the documents, interview transcripts, and field notes, the passages coded with "Data Definition" were extracted from the NVivo qualitative coding software for further scrutiny. The "Data Definition" code is intended to capture notions of how astronomy data, broadly construed, are interpreted and defined.

After close examination of the extracted passages from all three methods, patterns of how data were discussed emerged. These patterns were indicated with descriptive "subcodes." Table 17 presents the subcodes and indicates the method from which each subcode emerged. An "x" in the table indicates the perspective emerged from evidence using that research method. Statements made specifically about the SDSS or LSST are indicated as such.

Method: Emergent subcode, Data are ___:	Document Analysis	Interview Transcripts	Ethnographic Field notes
Information cleaned and processed to a certain degree	SDSS LSST	x	
Images, Spectra, and Catalogs	SDSS LSST	x	
Information that has value through its relationship to other information	SDSS		
Information that is made available to scientific end-users, the general public, or both	SDSS LSST		
Digital Information; Bits		x	
Information from or used by a specific set of people		x	LSST
Evidence of natural phenomena		x	
Information that has been used to conduct scientific research		x	
Information from a specific source		x	LSST
Photons that are processed		x	
Information from a specific source that are processed		x	
Images, Spectra, and Catalogs at various levels of processing		x	
Pixels that are processed into Images, Spectra, and Catalogs		x	
Information from a specific source that are processed into Images, Spectra, and Catalogs		x	
The Data Archive Server (DAS)	SDSS		SDSS
The Catalog Archive Server (CAS)	SDSS		SDSS
Software	SDSS		SDSS
Raw Data	SDSS		SDSS
The Help Desk			SDSS
The Administrative Archive			SDSS
The Operational Database	SDSS		
The Scientific Database	SDSS		
LSST Level 1	LSST		
LSST Level 2	LSST		
LSST Level 3	LSST		
The work necessary to prepare for data collection	LSST		

Table 17 Emergent "Data Characteristics" subcodes

Table 17 provides a glimpse of the 26 ways data were described between each of the three research methods used in this study. Next, the specific results that revealed these 26 subcodes are presented: first from the documents, then the interviews, and finally from the ethnographic observations. Analysis and refinement of these emergent subcodes is presented at the conclusion of the RQ1 findings (see 4.1.4 RQ1 results summary).

4.1.1 RQ1 documentation results

The following results reveal how data were described within SDSS and LSST project documentation. Documents closely examined for the SDSS project range in time from 1993-2011; documents from the LSST collaboration range from 2005-2015. These intervals cover the majority of each project's duration (see APPENDIX I and APPENDIX II for succinct timelines of each project). The Methods chapter provides a more detailed description of the document corpus.

4.1.1.1 SDSS data in documents

SDSS documentation analysis reveals how the boundaries and definitions of the SDSS data changed over time. While presentations and conference proceedings are the most common documents to explicitly define SDSS data, a number of genres also discuss the boundaries of the data. "The SDSS data" are referred to in a number of ways: "database" (Abazajian et al., 2003; Gunn & Knapp, 1993), "data bank" (Margon, 1998), "data products" (Astrophysical Research Consortium, 2008; Boroski, 2007; Kent, 1994; York et al., 2000), "data sets" (Szalay et al., 1999), "data archive" (Astrophysical Research Consortium, 2008; Stoughton et al., 2002; Yanny, 2011), "the data" (Kron, Gunn, Weinberg, Boroski, & Evans, 2008; Xiang, 2008), "the SDSS Archive" (Szalay et al., 2000), and "science archive" (Astrophysical Research Consortium, 2000,

2005; Brunner et al., 1996; Kunszt, Szalay, Csabai, & Thakar, 2000). The terms data base (sic) and data bank (sic) are only used through the first couple of data releases; the term data archive continues to be used often over the course of the project. While SDSS data are repeatedly referenced in different documents, the described boundaries of the data archive differ. Individual documents referred to the SDSS data as though there were an agreed-upon definition, but close analysis reveals the boundaries differed through time and by author. Overall, the most common way SDSS data were described in project documents was based on their content, which includes: images (photometric data), spectra (spectroscopic data), and catalogs (object attributes derived from the images and spectra).

By the time SDSS I and II data collection neared completion, plans were already underway to ensure the data could be archived and served into the near future. Multiple institutions were chosen to manage the SDSS data following data collection. Planning meetings between the SDSS leadership, represented by the Astrophysical Research Consortium, and the chosen astronomy departments and university libraries resulted in Memoranda of Understanding (MOUs). Each MOU included the Appendix "SDSS Long-Term Scientific Data Archive." The Appendix "summarizes the SDSS data products that will be maintained in the long-term scientific data archive" (Astrophysical Research Consortium, 2008). After multiple years of planning, the documents were signed near the end of 2008, and the participating institutions archived and served the SDSS data from January 2009-December 2013. By the end of SDSS data collection in 2008, "the SDSS data" were defined in the MOUs as consisting of the: Data Archive Server (DAS), Catalog Archive Server (CAS), Survey Software, and Raw Data. While the MOUs and Appendix appear to indicate a shared understanding of the boundaries of the SDSS dataset, analysis of the implementation of these agreements revealed divergent

understandings. See 4.1.3.1 SDSS data in ethnography for observational findings explaining how these MOU documents were interpreted and implemented in practice.

In addition to describing data as images, spectra, and catalogs, or based on the contents of the "SDSS Long-Term Scientific Data Archive," three additional ways of describing the data emerged from the document corpus: the level of data processing, the relationships between data products, and the internal and external divisions of data.

- Levels of data processing

The phrase "levels of data processing" is used here to refer to the ways and extent by which astronomy data are processed. A number of software pipelines processed SDSS data to ensure the raw data from the detectors were calibrated and smoothed, and the artifacts from the detector, also referred to as systematics, were cleaned. Documents often refer to data in terms of the level of data processing, most commonly in policy papers and presentations. The processed, cleaned data were circulated through formal data releases, and some data were processed further by end-users into other derived data products (Kron, Gunn, Strauss, Boroski, & Evans, 2005). For many, the data release was the point at which data were considered "processed" as opposed to "raw." These documents refer to data in terms of multiple levels of data processing. SDSS documents describe the importance of retaining copies of the data at each point along the continuum of data processing: "The data should be retained as a full data set of all pixels on the sky as well as in reduced data sets for later analysis and distribution" (Astrophysical Research Consortium, 2000).

- Relationships between data products

SDSS database builders authored documents regarding the importance of retaining relationships between datasets. SDSS data releases include both flat files and a relational database. Builders explained the importance of capturing both types of files: "The success of the archive depends on capturing the spatial nature of this large-scale scientific data" (Szalay et al., 1999, p. 4). The SDSS science archive is described not as a stand-alone data product, but in relation to other aspects of the project. Data here are described by their relationships to other information, including other data and the tools and services that enable community access and retrieval. The relationships between images, spectra, and catalogs are related inextricably to other data, information sources, and tools that enable the scientific usefulness of the data.

- Public availability of SDSS data

Prior to data collection, collaboration documents used the terms SDSS Archive or data to encompass all information throughout the lifetime of the project, from the internal data necessary to build and run the survey, through the final data products as delivered to external end-users. For example, Huang et al. (1995) described the importance of the data archive for internal collaborators in terms of the "development and testing of software algorithms; quality analysis on both the raw and processed data; selection of spectroscopic targets from the photometric catalogs; and scientific analysis…" (1995, sec. Abstract). Documents written early in the collaboration clarified the difference between, but noted the importance of both the data used to run the survey, and the data released for scientific end-use. After data collection was completed, the term "science archive" referred only to the data available to end-users, and stopped including the data used in survey operations. After the first few data releases, the operational database, the

information necessary for survey operations, was no longer referred to as a part of the science archive.

The Principles of Operation policy documents (released in 2000 for SDSS I and 2005 for SDSS II) purport to present a formalized and mutual definition of the science archive. According to these documents, the science archive encompasses all SDSS data and information necessary for scientific results, which was acknowledged as the main product of the survey (Astrophysical Research Consortium, 2005, sec. 1.3). Data base (sic) or data bank (sic) may refer to information for survey operations or end-user data; however, data products, data archive, and science archive are consistently used only to describe information intended for scientific end-use. In these later documents, data are described as information used in scientific research, and not the data used to operate the survey itself.

Some SDSS information was designated for internal project use, while other information was intended for external end-users. Documents authored by upper SDSS administrators characterize SDSS data by distinguishing information used within the team from data released to the end-user community. The public release of SDSS data was an important milestone in project development, as it ensured continued funding support and support from the end-user community. Richard Kron, et al. (2008) describes the SDSS data as consisting of "object catalogs, imaging data, and spectra," but goes on to note these data are, "all available through the SDSS web site http://www.sdss.org, along with detailed documentation and powerful search tools" (Kron et al., 2008, p. 2). Thus, these authors describe the SDSS dataset as information available to a broad range of scientists. Data use was contingent on the SDSS team's ability to make the data public, accessible, and retrievable: "The data are publicly available in searchable databases and flat

files…" (Kron et al., 2005, p. 1). Here, only the information destined for end-users are considered data, while internal, operational information are not considered data.

4.1.1.2 LSST data in documents

LSST documents and presentations note that the project will have produced the most data-voluminous optical survey in history when the ten-year operations are completed (now expected to commence in 2022). According to a presentation by the LSST Project Scientist for Data Management, the data will be the most important outcome of the project: "the ultimate deliverable of LSST is not the telescope, nor the instruments; it is the fully reduced data. All science will be [sic] come from survey catalogs and images" (Juric, 2014, sec. 2). LSST staff refer to "fully reduced" data as data that has completed its processing by the LSST team and is ready for end-users. Juric's statement references the most common way data were described in documents, as scientific products: images, spectra, and catalogs. Through different authors and document genres, the project employs grandiose language to describe the size and quality of the expected data, software tools, and infrastructures to support data collection, processing, and analysis.

LSST document analysis reveals documents representing different genres define the boundaries of "the LSST data" differently. LSST data have been referred to as a "data set" (National Science Foundation, 2005; Pike, Stein, Szalay, & Tyson, 2001), "data" (Becla et al., 2005; Ivezić et al., 2011), and a "database" (Kantor et al., 2007; National Science Foundation, 2012); however, LSST data are most commonly referred to as "data products" (Becla et al., 2006; Freemon & Kantor, 2013; Juric et al., 2013; LSST Science Collaboration et al., 2009; National Science Foundation, 2010a). In addition to referring to data as images, spectra, and catalogs, three themes emerged summarizing the ways LSST documents reference LSST data.

First, similar to the SDSS documents, the data are referred to by the level of data processing. Next, documents, and in particular the LSST website, refer to data, according to the work required to prepare the data for scientific end-use. Finally, documents written to interact with funding agencies often refer to data in terms of the level of public availability.

- Levels of data processing

The LSST Data Processing Plan references three distinct levels of LSST data; Figure 6 presents the 2015 website description of these three levels ("Data products | LSST public website," 2015; Juric, 2014, sec. 4). Level 1 data products are often called alerts, and provide recent event notifications. The current intention is to distribute these alerts world-wide within 60 seconds of each event (Juric, 2014, sec. 4). Level 2 data will be disseminated online in data releases, similar to the way SDSS data were collected and made available. These data will be released to LSST membership countries and institutions on an approximate annual basis. While not referencing data per se, LSST's Level 3 tier designates an infrastructure available for end-users to engage in scientific investigations using LSST data. For example, software, APIs, and computing time will be made available to assist LSST data end-users in processing and analyzing LSST data. These three levels are distinct from the NASA data levels (as detailed earlier in 2.4.1 US space- and ground-based astronomy), and detail instead the manner in which LSST specifically will make its data and resources available.

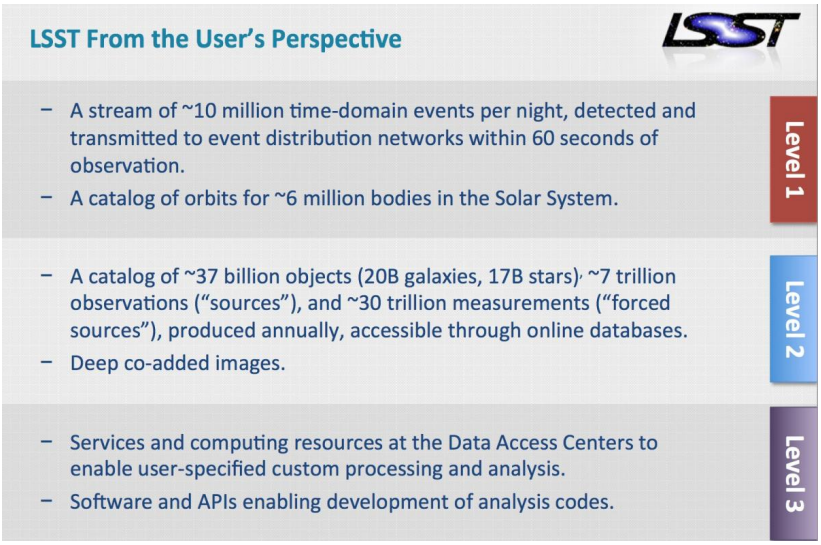


Figure 6 The three LSST data levels ("Data products | LSST public website," 2015; Juric, 2014, sec. 4)

- Relationship between data products and data management tasks

Often, LSST data are described in relationship to the amount and kind of work remaining to prepare for the collection, processing, and usability of the LSST data. For example, Juric reported on data management "roles" however these data management roles were established without a project-wide definition of data (2014, sec. 10). Instead, the boundaries of LSST data were assumed, and the data or database was compared to the work necessary to construct the science pipelines, middleware, and user interfaces (Juric, 2014, sec. 17).

The summer 2015 LSST website revision also described LSST data relative to the remaining data management tasks necessary to prepare for the survey. The website audience includes team members, data end-users, and the general public. However, the website depicted the LSST data differently on each page. The data management page expressly described the LSST data in terms of the work necessary for project completion. The page stated the following as the challenges: "processing such a large volume of data, converting the raw images into a faithful representation of the universe, implementing automated data quality assessment and

automated discovery of moving or transient sources, and archiving the results in useful form for a broad community of users…" ("Data management | LSST public website," 2015). The website goes into extensive detail on the data itself in five separate pages, describing the same data products using slightly different language on each page ("Data management system requirements | LSST public website," 2015; "Data products | LSST public website," 2015; "Petascale R&D challenges | LSST public website," 2015; "Pipelines | LSST public website," 2015; "Technology Innovation | LSST public website," 2015). Consistently, the LSST presentations and website refer to the data in terms of the work still required to collect, manage, and use the data.

- Public availability of LSST data

LSST NSF grant proposals describe the importance of LSST data in terms of the international benefit to science (National Science Foundation, 2005, 2010a, 2012, 2014a). In these documents, data are construed by their accessibility to astronomers and the public. In 2005, LSST acquired an 11-million-dollar planning grant from the NSF. In the application, the collaboration promised to "produce the largest non-proprietary data set in the world" (National Science Foundation, 2005). The grant proposal refers to data in terms of its accessibility and potential for broad scientific impact.

The tools created by the LSST collaboration aim to benefit astronomical work well beyond that of project members. The 2010 proposal explains, "In addition, the [larger astronomy] community will see significant technical overlap between the LSST and the needs of other imaging systems and software under development in the national security arena" (National Science Foundation, 2010a). In addition to pedagogical training of the next generation of scientists and public education resources, the proposals indicate the development of tools to ensure the scientific and public accessibility of LSST data (National Science Foundation, 2005).

These NSF proposals stress the importance of data access by stating **"**the broader impacts of the LSST will be profound, as scientists, the public, and schoolchildren around the world will have ready access to the data" (National Science Foundation, 2005, 2010a). The 2012 NSF proposal pinpoints LSST's mission to broadly benefit astronomy by explaining that the data management system is being developed open source (National Science Foundation, 2012). The writing focused strategically on LSST's public, broader impacts to enable the LSST to attract and retain funders from the United States and around the world.

4.1.2 RQ1 interview results

Analysis of eighty semi-structured interviews generated the following results for the first research question. As a component of each interview, interviewees specified their definition of astronomy data. Interview results for RQ1 - What are astronomy research data? - are presented from each study population.

4.1.2.2 How responses were elicited

All interviewees discussed how they understood astronomy data. However, their descriptions were evoked in one of three ways. Twenty-five interviewees defined data indirectly over the course of the interview, doing so without a specific prompt or question from the interviewer. These freely expressed definitions are important because they emerged organically, thus reducing the potential bias of the interviewer through the wording of the question. When interviewees did not define data to the satisfaction of the interviewer, interviewees were explicitly asked for a definition. Thirty-three interviewees were directly asked to define astronomy data. Twenty-three end-user interviewees were interviewed using the "Follow the Data" protocol, and their understanding of data emerged from direct questioning about the

information they used to write a particular journal article. While an interview protocol was used for each semi-structured interview, interviewees naturally answered questions to varying degrees of depth.

- SDSS and LSST team members

Of the SDSS and LSST team interviews, 24 interviewees expressed their definition of data spontaneously. When interviewees did not volunteer a sufficient explanation of how they understood data, they were asked. Thirty-three interviewees were asked in this explicit manner. Table 18 provides a list of the ways interviewees were asked about their understanding of data.

Manner in which data definition responses were elicited	Interviewee Population	Number of Respondents who were asked this question
Within your work, what is typically considered to be "data?"	SDSS Team	11
What do you consider to be the LSST data?	LSST Team	22
Response provided spontaneously	SDSS and LSST Team	24

Table 18 Manner in which SDSS and LSST team interviewee data definition responses were elicited

- SDSS data end-users

SDSS data end-users were interviewed using the "Follow the Data" interview protocol, which included asking about data through a practical exercise. The exercise asked SDSS data end-users to discuss how they understood their data use in light of one article. Interviewees were selected for this task when they co-authored a recent article that used SDSS data (according to the title or abstract). Further details about the operationalization of the "end-user" participants and the interview protocol are available in the Methods chapter.

The interviewer read the relevant journal article prior to each interview and generated a list of data sources that she understood were used in the article. The interviewees then were asked to verify the list during the interview. An example list, which is an amalgam of many

interviews to ensure article and author confidentiality, is provided in Table 19. Specifically relevant for RQ1, the 23 end-user interviewees were asked, "From your article, we identified [#] sources of data. Could you verify this list is correct? Are these all the sources you used?" The interviewees' responses to this question constitute the RQ1 SDSS end-user findings.

SOURCE TYPE	EXAMPLE
Public Archival Survey Data	SDSS Data Release 7, Catalina Real-Time Transient Survey
Proprietary Survey Data	Pan-STARRS
PI-Collected data	Hubble Space Telescope images; Keck spectra
Value-Added Catalog	NYU Value-Added Galaxy Catalog (Blanton et al., 2005)
Code/Software	Supersmoother (Reimann, 1994)
Mathematical Technique/Algorithm	Linear Regression
Resources/ Processing Center/ Archive	MAST; SIMBAD

Table 19 Example source-list for SDSS end-user article-based interviews

Journal article topics represented a range of observational astronomical inquiry. Some articles reported results from combining data from multiple sources. For example, one of the articles describes the creation of a new SDSS value-added catalog. The authors took an existing value-added catalog and added radio and spectroscopic data to create a new, more precise catalog. Another astronomer utilizing this technique expounded, "So the short answer… is we combined two existing models, each with their own strengths and weaknesses to get a third model" (Garcia, Staff Scientist, 2011). Other studies created new rare object catalogs from a certain region of the sky by combining multiple datasets. Still others provided detailed reports on individual astronomical objects, created new dust maps of the sky, located and studied gravitational lenses, or reported on the effectiveness of automated data collection and statistical techniques. These various journal article findings relied, in part or in full, on SDSS data.

The interviewer took a very broad potential definition of "data" and "use" to construct the data list (refer back to Table 19 as an example). Some of the lists consisted of a dozen or more

potential sources. While the interviewer brought a very broadly construed source-list to the interview, only three interviewees chose to make changes. Wilson clarified that the Monte Carlo (simulation) listed on the source list should be identified as a "technique" instead of data. He explained, "It's not a data source, but instead it's actually just a mathematical technique that was used…" (Wilson, Graduate Student, 2015). Rodriguez wanted to clarify that the Supersmoother was software and not data, and another listed source was an analysis method instead of data (Rodriguez, Professor, 2011). Lee referred to SDSS data as different from the other kinds of data used in his journal article. He stated, "Yeah, so we used Sloan to select objects, but we couldn't do the science we wanted to with the Sloan data. So, for us, Sloan is a finder" (Lee, Post-Doc, 2013). The other 20 interviewees confirmed the data source lists as identified by the interviewer.

4.1.2.3 SDSS team

The following findings present the different ways SDSS team interviewees defined data during the interviews. As described in the introduction to the RQ1 Results, the following results summarize the findings culled from the code "Data Definition," and are organized by emergent subcode. Within each subsection, the number of interviewees who described data in that way are noted, and a representative set of quotes illustrate the meaning of the emergent subcode.

- Content

Six interviewees, questioned using SDSS interview protocols, discussed astronomy data in terms of the content of the data. These individuals discussed astronomy data as encompassing images, spectra, and catalogs. For example, James described the data she uses in her research: "So, definitely, for me it is essential to have the spectra. Surveys… they are great, because they will have the images and everything. But for me without spectra it's tough" (James, Professor,

2015). Flores explained data similarly as involving, "…all photographic and spectra. Spectra is photographic, but it's photographs of spectrum" (Flores, Staff Engineer, 2015). Lopez described collecting data from various sources and then generating catalogs from those images and spectra (Lopez, Professor 2013). Each of these six interviewees described astronomy data as images, spectra, and catalogs.

- State

Six interviewees from the SDSS team interviews described data in relation to the current state of the data, specifically in terms of the levels of data processing. Martin explained that in order to prepare data for scientific analysis, data must first undergo numerous processing stages (Martin, Staff Scientist, 2012). Clark mentioned multiple levels of data, including an early stage when the instruments are run without "expecting to get science out," raw data, and transformed data (Clark, Research Programmer, 2013). Brooks described how NASA science centers ideally archive data at each of the multiple levels of processing. He explained, "So, yes, [NASA science centers] they're doing a great job. … So they preserve the raw data from the space craft and then these high level data products" (Brooks, Professor, 2015). These interviewees all spoke about data by focusing on the extent of processing.

- Use

Four SDSS team members described data in terms of its scientific usability. These interviewees described data in terms of its potential usefulness for specific inquiries. For example, one interviewee described data in the context of its use in publications. When asked about the data from a recent publication, he explained, "The actual data are online. … The paper doesn't have any data actually. It has a bunch of words and a few pictures and a table of numbers

or two, but the data is far too large" (Thomas, Professor, 2012). Gray described data in terms of precision, which he based on his current project. He explained, "I want to write the papers for those two things before we have any data. I want to take the simulations, treat them as if the real data, and I want to publish a paper based on that" (Gray, Professor, 2015). Gray defines data as information that is useful to his scientific work, whether the data are simulated or observations. These interviewees distinguish their data based on the scientific objective for which the data are being used.

- Format

Two SDSS interviewees referred to data in terms of its digital nature. For example, Harris used the term data "loosely," when he explained, "Data to me is anything with numbers…" (Harris, Staff Scientist, 2013). Gonzalez also described data as any information obtained from scientific instruments. He elaborated, **"**The analog of the digital converter that brings us a file, so that we call data. And so, it could be pixels, it could be quantities that derive from the pixels, that would be data too" (Gonzalez, Professor, 2013). These interviewees referenced data by describing aspects of data as digital information.

- Source

One SDSS team interviewee described data as anything from a specific project's instruments. Walker described the SDSS data as information involved in the SDSS "project history," or as the information generated by the SDSS project (Walker, Project Manager, 2013). This interviewee referred to data as information from a specific source or group of people.

- Evidence

Two SDSS team members described data as evidence of phenomena. Cooper characterized data as, "any inferred quantity from the sky or from a simulation" (Cooper, Professor, 2015). Anderson differentiated between data and understanding, in which data are information collected about the universe (Anderson, Emeritus Professor, 2012). These interviewees labeled data as evidence of the natural world.

- Content and state

Two interviewees described data based on both its content and its state. In other words, these interviewees discussed images, spectra, and catalogs based on their level of data processing. Wilson described raw data as images or spectra processed into usable data, which are then reduced into data products (for example, catalogs) (Wilson, Graduate Student, 2011). Carter agreed, stating that within her work data are, "photometric measurements or catalogs and spectral files" (Carter, Professor, 2015). She then immediately proceeded to discuss the differences between what he defines as data compared to raw and unreduced data and "machine readable tables of published, inferred values in papers" (Carter, Professor, 2015). Both of these interviewees discussed data in terms of images, spectra, and catalogs processed to a certain extent.

- Format, content, and state

Robinson began discussing data as digital information processed into images, spectra, and catalogs. Robinson distinguished between images and spectra: **"**So for the images, it's like a digital picture of the sky… for the spectroscopy, it's sort of like a one dimensional digital picture. You have to actually do some processing to get it there… But it all ends up in digital form…"

(Robinson, Staff Scientist, 2013). Robinson thus provides a complex explanation of data by referencing it as digital information processed into images, spectra, and catalogs.

- Content, state, and source

Moore described SDSS data as information that comes from the SDSS instruments, requires a lot of processing, and then turns into images, spectra, and catalogs that could be processed even further. She described SDSS data as anything from the SDSS camera: "[We] very much designed the Sloan codes to do no harm to the data, to extract almost everything that came off the cameras" (Moore, Staff Scientist, 2012). Moore goes into great detail about the data processing pipelines and concludes the information from the SDSS cameras and spectrographs ultimately results in images, spectra, and catalogs.

- State and format

No SDSS interviewees described data based on State or Format.

- State and source

One SDSS interviewee described data based on the source of the information and its level of processing. She described SDSS data as information "obtained by observers in the New Mexico Observatory" that was then "sent to [the SDSS data center] in a FITS file" (Lewis, Research Programmer, 2013). She then discussed in detail the processing that takes place once the SDSS information arrived at the data center. Lewis described SDSS data as information collected by the SDSS instruments and processed by the SDSS team.

4.1.2.4 LSST team

The following are the different ways LSST team members defined data. As described in the RQ1 Results introduction, the following results summarize the findings from the code "Data Definition," and are organized by emergent subcode. Within each subsection, the number of LSST team interviewees who described data in each way are noted, and a representative set of quotes illustrate the meaning of the emergent subcode.

- Content

Six LSST team member interviewees described data in terms of its content, specifically as images, spectra, and catalogs. When asked about data within his work, Thomas explained the nature of astronomy data succinctly: "…We have the images of the sky, we have the catalogs derived from those images, we have spectra, and then we have all the metadata that come with that…" (Thomas, Professor, 2015). When asked what he considers to be the LSST data, another interviewee answered, "…I don't know, were you looking for catalogs, images I can just say that. [chuckle] I was going to just describe everything in the catalogs" (Baker, Graduate Student, 2014). Each of these interviewees discussed data in terms of its content, by describing data as images, spectra, and catalogs.

- State

Four interviewees from the LSST team described data in terms of data processing levels. Three of these interviewees were directly involved in the technical development of the LSST data management system over multiple years. Kelly, a computer scientist and long-time member of LSST described the future project data by mentioning the alerts and data releases, two of the three LSST data levels. He described the first two LSST levels by saying, "I mean because

there's two different types of processing. …one's the alert production stuff, which is nightly. And then the data release processing stuff… and since we do that every year, there's gonna be some time to improve everything" (Kelly, Research Programmer, 2015). Rivera explained data are processed information by revealing, "So for me, data, usually it's sort of a processed version" (Rivera, Professor, 2015). These interviewees each described astronomy data by referencing the different levels of data processing.

- Use

One interviewee described data in terms of its uses for scientific research. Sanchez described data in terms of its use as a pedagogical tool. She explained, "So we came up and did a lot of work with her students and all the research there and using all of the Sloan data for that" (Sanchez, Lecturer, 2014). Sanchez described data in relationship to its use teaching future scientists.

- Format

Three LSST team member interviewees described data in terms of its digital materiality. For example, Nelson described data in terms of its digital "binary" nature (Nelson, Staff Scientist, 2014). When asked if what is considered LSST data has changed over time, an LSST team leader answered, "We never defined it. That's a very interesting question. We talked many, many times about LSST data, but we never defined the term. I think most people would think of pixel values in LSST images, plus everything you derive from those pixel values…" (Martinez, Professor, 2011). Phillips agreed, noting, "At a more fundamental level of course is the LSST pixels" (Phillips, Staff Scientist, 2015). These interviewees each discussed the digital nature of data, whether stored in binary or as pixels.

❖ Source

Four LSST team members described data in terms of the data's origin. Two interviewees described the data source in terms of the distinction between simulated data and observational data. Diaz described how the LSST uses simulated data as input for the data management team processing. He believes that the simulated data are "real data" even though they are not "from the sky" because the LSST team is using them (Diaz, Research Programmer, 2015). He also explained the LSST is using data from previous surveys in addition to simulated data, including the SDSS Data Release Seven "Stripe 82" data. King described LSST data as simulations, while in the future the LSST data will be information from the LSST camera (King, Research Programmer, 2014). These interviewees describe LSST data by referring to the project that created or uses the data, whether simulated or observational.

❖ Evidence

One LSST team member described data as evidence of a phenomenon. Bailey illustrated this in her broad response by saying the LSST data are, "Basically, any information they derive about the external world. … All of that is the data" (Bailey, Staff Scientist, 2015).

❖ Content and state

Three interviewees described data as extensively processed images, spectra, and catalogs. For example, Adams explained astronomy data are catalogs and images, but the kind of research question determines the necessary processing level for the scientist to work with the data (Adams, Staff Scientist, 2014). Scott was asked, "From your perspective, what are the LSST data?" He explained that while he generally uses processed data, he is eager to begin using the LSST Level 1 data: "So for most applications other than that I would be looking at [a] more

processed version. I think this is the only one where I foresee myself actually want[ing] to look at the raw images or doing something with that" (Scott, Post-Doc, 2014). Lee explained that the LSST data for him is "the calibrated images and DM-produced object and source catalogs," but acknowledged other researchers may want to analyze the data at different levels of processing (Lee, Post Doc, 2013). These interviewees each described data as images, spectra, and catalogs available at different levels of processing.

- Format, content, and state

Two interviewees described data based on its digital nature, content, and state of processing. When asked how he understood astronomy data, Murphy was surprised by the question and responded, **"**That's a very metaphysical question - a bunch of ones and zeros" (Murphy, Professor, 2015). Murphy goes on to explain that LSST data are information from the telescope, processed into images, spectra, and catalogs. Stewart similarly described data as pixels processed through a few stages and result in catalogs. These interviewees discussed data in terms of its digital nature, its extent of processing, and its content as images, spectra, and catalogs.

- Content, state, and source

No LSST team member interviewees described data based on content, state, and source.

- State and format

One LSST team member described data based on the state of processing and format as digital information. When asked what she considered to be data, she explained, "…the primary data would be the photons that come in. ...Because there'll be so much of it, like with all of these things, I would hope that the pipeline data would do the trick. But the raw data, or the 1.5 data, or how you do, all that stuff..." (Reed, Staff Scientist, 2015).

- State and source

No LSST team member described data based on the state of processing and its source.

4.1.2.5 SDSS data end-users

The SDSS end-user interviews corroborated how data were described in the SDSS and LSST team interviews by discussing the data they used in a particular journal article. The number of SDSS end-user interviewees who described data in each way is presented below.

- Content

Nine interviewees described data by referencing its content: astronomical images, spectra, and catalogs. Morris explained, "What kind of data I use? Imaging data. So, anything that is measured from astronomy images. And then spectroscopic data. So, things that are measured from spectroscopic measurements. Those are the two main data sets" (Morris, Professor, 2015). Johnson agreed by noting, "So in [the] case of say, digital sky surveys, data would be tables in the database and images…" (Johnson, Professor, 2011). More specifically, Smith described how she begins using SDSS catalog data and then adds spectral information to create the dataset for a journal article. She explained, "Now I have that catalog then I go to Sloan database… and I compiled the radio properties as a subset of the columns in this catalog. And also the database, the individual spectrum…" (Smith, Post-Doc, 2011). These interviewees described the data they used in their journal article by referencing the information as images, spectra, and catalogs.

- State

While SDSS and LSST team members frequently discussed data in terms of the level of data processing, only three SDSS data end-user interviewees discussed data by state or level of

processing. These three interviewees disagreed as to whether the level of processing creates a distinction between "data" and "data products." Collins considered data products, which have been highly processed, as distinct from other kinds of data (Collins, Professor, 2015). Edwards did not distinguish between data and data products, and instead described data as information along a path of processing. He explained, "Anything from the raw image on a detector, up through something derived, like a sensitivity limit, is usually considered data. Brightnesses, spectra, all these things are considered data" (Edwards, Post-Doc, 2015).

- Use

Five SDSS data end-user interviewees described data in terms of scientific use. End-user interviewees often discussed data in terms of primary or parent datasets in comparison to secondary or follow-up datasets. These data end-user interviewees described data in relationship to other research information. The interviewees referred to the dataset that they used to begin an investigation as the parent or primary dataset; secondary datasets were those they added to the primary dataset for analysis. For example, White explained a quasar catalog was the parent sample in his study: "Okay. The first of three, so the SDSS quasar catalog DR8, all of those were things that existed. That's the parent sample" (White, Staff Scientist, 2012). He went on to explain that he calls other data added to the catalog ancillary data. Similarly, Ward began his study with an interesting discovery from one particular dataset. He then referred to all other data he used as follow-up data, including SDSS data he was able to download (Ward, Professor, 2015). Jackson referred to his data as primary and secondary (Jackson, Staff Scientist, 2012). These interviewees all described data by referencing the priority of the data in a specific analysis.

- Format

Three SDSS data end-users described data in terms of its digital medium. One computer science researcher explained that she did not cite the data source in his publication because the particulars of the astronomy data he used in his study were not important. She explained the decision: “This is a lame excuse, but from the computer science point of view... Yeah, it's bits; it's zeros and ones that you have there…. In hindsight, that's true, that's where they got the images was Sloan” (Hill, Professor, 2015). Williams described astronomy data as photons, “But the data will be the number of photons that are associated with physical source. That would be the primary thing” (Williams, Staff Scientist, 2011). These three interviewees described data by referring to characteristics of its digital form.

- Source

Three SDSS data end-users described data in terms of where, or by whom, the data had originated. For example, one interviewee working in a technical capacity for the SDSS project referred to data as “whatever [the SDSS leaders] tell me that needs to be saved” (Bennett, Staff Scientist, 2015). Mitchell referred to datasets by the name of the survey that initially collected the data (Mitchell, Graduate Student, 2015). These interviewees referenced data in terms of the project or instrument that collected the data.

- Evidence

Only one SDSS data end-user described data in terms of its evidentiary value for scientific research. When asked, “So, in your work, what do you consider to be data?” Nguyen responded, “Effectively, everything that has relation to reality” (Nguyen, Professor, 2015). This category may have only been referred to once in the end-user interviews because these

interviews were focused on data from a specific journal article. Since concrete options for data were discussed, end-user interviewees may have been less inclined to describe data generically, as evidence of phenomena.

- Content and state

No SDSS data end-user interviewees described data based on its content as images, spectra, and catalogs alongside its nature as processed information.

- Format, content, and state

No SDSS data end-users described data based on its format as digital information, its content as images, spectra, and catalogs, and its state as processed information.

- Content, state, and source

Two SDSS data end-user interviewees discussed data based on its content, state, and source. For example, Lee went into detail about the different levels of data processing he uses for his research, "…what I actually mean by data is the higher, reduced, processed, end science product," also noting the content are images, spectra, and catalogs coming from specific project sources (Lee, Staff Scientist, 2015). Similarly, Wood, described data in terms of images, spectra, and catalogs from specific sources, "anything I get from the telescope…[which]…go through several steps to what we call data reduction, where you go from this raw off-the-telescope kind of information down to something that you want to analyze" (Wood, Professor, 2015).

- State and format

One SDSS data end-user described data based on its state of processing and its format as digital information. Rogers explained, "Datasets, we preserve the core bits of information, all the

telemetry data that comes off of the telescopes… Those are just like save the bits… For that initial data off the telescope" (Rogers, Professor, 2015). Rogers described data as digital bits directly from an instrument or digital bits processed to different degrees.

- State and source

No SDSS data end-users described data based on its level of processing and its origin from a specific set of instruments or collaboration.

4.1.3 RQ1 ethnography results

Ethnographic observations revealed nuance to stakeholder understandings of data in both the SDSS and the LSST. Fieldwork following the SDSS I and II data collection and release revealed the different ways stakeholders interpret the boundaries of the dataset. Fieldwork with LSST team members revealed different interpretations as to whether or not LSST data existed during the construction phase of the project.

4.1.3.1 SDSS data in ethnography

In 2008, the SDSS I and II completed data collection and distributed the final data release for those phases. As those initial phases of the project ended, the SDSS collaborators knew the SDSS data retained great value to the astronomy community. SDSS leaders determined plans were necessary to ensure the data were archived and served following the fiscal close of the SDSS I and II. On behalf of the SDSS collaboration, the Astrophysical Research Consortium (ARC), signed Memoranda of Understanding (MOUs) with four different institutions to continue managing the SDSS I and II data for five years from January 1, 2009-December 31, 2013. Two of the MOUs were signed with institutions already involved in the collaboration; the other two

MOUs were signed with two university libraries. For the purposes of confidentiality, the two libraries are here referred to as "Red" University Library and "Blue" University Library.

The following section details the observed differences in how each institution interpreted the boundaries of the SDSS I and II dataset. The MOUs are employed here to organize the presentation of the ethnographic findings. While the MOU documents listed the information retained by each library, multiple weeks of ethnographic observations at the two libraries and two astronomy departments revealed why and how the information was transferred, archived, and served.

Both libraries have completed the "serving" component of the MOU agreements, but continue SDSS data archiving activities, funded by their own institutions. The two libraries each signed a MOU subtitled "Archiving and Serving Data from the SDSS." At the time of the MOU signings, astronomers and library staff had already been through two years of discussions and believed they were in agreement as to the meaning of the MOU key terms and intentions. During MOU negotiations, ARC leaders, SDSS astronomers, and staff from both libraries together settled on the phrase *SDSS Long-Term Data Archive* (SDSS Archive) to reference the SDSS information that required serving and archiving. Despite extensive planning, ethnography revealed that each stakeholder group interpreted the boundaries of the dataset involved in these tasks differently, as well as what it meant to archive and serve the data. Despite the common language used in the formal agreements, each library ultimately prioritized the management of different components of the overall dataset. The information components that each library chose to include in the SDSS Archive are summarized in Table 20.

SDSS Long-Term Scientific Data Archive Components	"Blue" University Library	"Red" University Library
Data Archive Server (DAS)	X	X
Catalog Archive Server (CAS)	X	X
Administrative archive	X	--
Help desk	X	--
Raw data	--	X
Software	--	X

Table 20 SDSS long-term scientific data archive: Library task distribution

Both libraries managed the two publicly accessible datasets, which are defined in the MOUs: "The *Data Archive Server* (DAS) is a complete set of all the processed data, in a flat file format. The *Catalog Archive Server* (CAS) refers to a collection of each version of the searchable database released to the public during SDSS I and II" (Astrophysical Research Consortium, 2008). Both libraries also served one CAS data release mirror. Thus, both libraries considered the DAS and CAS as part of the SDSS Archive.

Each library also chose to manage additional components of the SDSS Archive beyond the DAS and CAS. The Blue University Library took responsibility for the help desk and administrative archive. This library had managed the help desk question-and-answer referral program since 2007 and agreed to continue the service through the MOU period. The Blue University Library also elected to preserve the administrative records indefinitely (both physical and digital). In contrast, the Red University Library chose to archive the raw data and software alongside the DAS and CAS. The raw data are the bits delivered by the scientific instruments, prior to processing. The software includes a variety of code developed and used at multiple institutions throughout the life of the project. The two libraries agreed the DAS and CAS were included in the boundary of the SDSS Archive, but the institutions diverged in what other information was included.

Two years of discussions by stakeholders resulted in the MOU agreements. However, as time passed, differing expectations about the scope of the SDSS Archive grew apparent. The boundaries of the SDSS data therefore are not inherent to the dataset. The boundaries of the SDSS Archive are instead emergent based on the perspectives of different stakeholders. These differing perspectives, and thus the divergent understandings of the boundaries of the SDSS Archive, resulted from the differences in the existing infrastructures of each institution, including institutional interests, affordances, and constraints.

4.1.3.2 LSST data in ethnography

LSST community members disagree as to whether LSST data exists during the construction phase of the project. Five study participants believed LSST does not have data as of the time of discussion because the LSST instruments have not begun collecting data. For example, when asked about LSST data, some participants noted that they do not consider simulated data to be "real" data and thus LSST data do not exist yet. However, eight participants noted the simulations the LSST team generates and uses for data management planning should be considered LSST data. For example, Diaz described how the LSST uses simulated data as input for the data management team processing. He explained that he believes simulated data are "real data" even though they are not "from the sky" (Diaz, Research Programmer, 2015). He also explained the LSST uses data from other previous surveys in addition to simulated data.

Thirteen LSST team members discussed whether or not simulated data are included as LSST data. Eight team members interpreted data generated or used by LSST team members (whether simulated or from a previous survey), to be part of LSST's data. Alternatively, five individuals noted LSST data do not yet exist, and only the information collected by the LSST instruments should be considered LSST data.

During observations at one of the primary LSST data management institutions, the author observed a presentation by LSST server managers. The presentation included a list of the folders on the LSST servers, each folder containing materials for use in LSST construction. The folders were:

-Data Challenge data
-Image Simulation (Imsim) Data
-Data from other surveys:
    -Pan-STARRS 6.2 TB
    -Calypso
    -SDSS 3.5 TB
    -Stripe82, 11 TB
-All Sky Camera Data
-Other

The folders' location on the LSST server in 2015 implies that the LSST team employs these sets of information. The information within these server folders is information created by the LSST collaboration (Data Challenge Data, and ImSim Data), as well as data collected by other surveys but applied to LSST development. Notably, there are two sets of SDSS data stored and used for LSST: 3.5 TB of "SDSS" data and 11 TB of a specific subset of SDSS data from the "Stripe82" segment of the sky. While there are arguably no LSST data, because the instruments especially engineered for the project have not begun collecting data, there are multiple datasets (both created especially for the project, or borrowed from other projects) already being used for LSST.

4.1.4 RQ1 results summary

Each of the three research methods demonstrated SDSS and LSST data could be interpreted in multiple ways, by different people, and over time. Table 17 indicates the 26 ways data are described by the document authors, interviewees, and observed participants. The evidence for each of the 26 ways data were described was just presented by research method.

Document authors described data in 14 ways, interviewees in 12 ways, and observations revealed eight ways data were described.

While there is some consistency between research methods, there are also a number of ways data were described that are reflected in only one or two of the three research methods. This fact highlights the strength of this dissertation study and its ability to capture many perspectives by employing all three methods. If only one method, for example interviews, was used in this study, the official perspectives represented in SDSS and LSST team documents would have been missed. If only document analysis had occurred, then the less-formal perspectives of interviewees would not have emerged. Each method validates the findings of the other methods, while also increasing the reliability of the findings in that the quantity of methods ensured a broad array of perspectives were included in the study.

As already noted, Table 17 demonstrates the full array of subcodes that emerged from the ways data were defined in the documents, interview transcripts, and ethnographic field-notes. Once this full list was generated, the contents were analyzed, and thematic patterns between subcodes became apparent. Perspectives from any of the three research methods were then combined into broader emergent themes.

Table 21 visualizes the result of analyzing and grouping like-items from the list of 26 ways data were described (refer back to Table 17). Some interviews and observations revealed data described as information collected by a certain instrument or employed by a certain group of people. These notions of data are related to the process, the where and when, of data collection. Alternatively, others described data as the product of that data collection, as the bits or raw data. Similarly, a number of interviewees described data as a specific kind of information that must be processed through some or many stages of handling. Others went into greater detail and

described the processing stages and the information more precisely: They described data as photons, from a specific source, as images, spectra, and catalogs, or as pixels. These study participants each highlighted the nature of the information being processed. Since each of these interpretations highlighted the processed nature of the information, over the type of information, they were grouped together under a refined subcode of processing. In opposition to the way data were described as an active state of processing, others described data as the result of an action, or as a product. For example, data were frequently described in the documents and interviews as images, spectra, and catalogs. In this way, data were described as the resulting products of processing actions. Some interviewees and documents described data as information used in the process of scientific research. Others identified data as the results of that scientific research, as scientific evidence from a specific journal article, or as the derived data resulting from said research.

Method: Emergent subcode, Data are ___:	Type of Description: Process; Product	Temporal Stage: Collection; Processing; Analysis
Information cleaned and processed to a certain degree	Process	Processing
Images, Spectra, and Catalogs	Product	Processing
Information that has value through its relationship to other information	Process	Processing
Information that is made available to scientific end-users, the general public, or both	Process	Analysis
Digital Information; Bits	Product	Collection
Information from or used by a specific set of people	Process	Collection
Evidence of natural phenomena	Process	Analysis
Information that has been used to conduct scientific research	Product	Analysis
Information from a specific source	Process	Collection
Photons that are processed	Process	Processing
Information from a specific source that are processed	Process	Processing
Images, Spectra, and Catalogs at various levels of processing	Process	Processing
Pixels that are processed into Images, Spectra, and Catalogs	Process	Processing
Information from a specific source that are processed into Images, Spectra, and Catalogs	Process	Processing
The Data Archive Server (DAS)	Product	Processing
The Catalog Archive Server (CAS)	Product	Processing
Software	Process	Processing
Raw Data	Product	Collection
The Help Desk	Process	Analysis
The Administrative Archive	Process	Analysis
The Operational Database	Product	Collection
The Scientific Database	Product	Processing
LSST Level 1	Product	Collection
LSST Level 2	Product	Processing
LSST Level 3	Process	Analysis
The work necessary to prepare for data collection	Process	Processing

Table 21 Emergent "Data Characteristics" subcodes

Through extensive, iterative analysis of the documents, interview transcripts, and ethnographic field-notes, two variables emerged and provide an exhaustive and mutually exclusive demonstration of the different ways data were described. For example, during the iterative data analysis, a potential scale emerged relative to whether information was identified as data based on the extent of information processing. However, while increased processing aligns with increased potential for scientific use for many study participants, others find non-processed information the most scientifically usable, as they prefer to process data themselves. Therefore, the scale logic did not hold. In addition, while the scale was exhaustive, the categories within did not prove mutually exclusive.

Thus, the long list of ways data were described in Table 17 can be collapsed into definitions of data that describe a process and those that describe a product (presented in Table 21). Three temporal data stages were used for the purposes of presenting the results, data collection, data processing, and data analysis. However the stages are not intended to be discrete, and in reality, are overlapping and indistinct. Table 22 provides an alternate illustration of the information presented in Table 21, by aligning the initial emergent subcodes with the emergent dimensions of process versus product, across time. Note that each of the definitions encompasses either process or product. When each of the 26 ways data were described in all three research methods are clustered with like kinds, it results in the exhaustive and mutually exclusive categorization presented in Table 22.

Temporal Stage: Way Described:	**Collection**	**Processing**	**Analysis**
Process	Information from or used by a specific set of people Information from a specific source	Information cleaned and processed to a certain degree Information that has value through its relationship to other information Photons that are processed Information from a specific source that are processed Images, Spectra, and Catalogs at various levels of processing Pixels that are processed into Images, Spectra, and Catalogs Information from a specific source that are processed into Images, Spectra, and Catalogs The work necessary to prepare for data collection	Evidence of natural phenomena Information that is made available to scientific end-users, the general public, or both The Help Desk The Administrative Archive LSST Level 3

Product	Digital Information; Bits Raw Data The Operational Database LSST Level 1	Images, Spectra, and Catalogs The Data Archive Server (DAS) The Catalog Archive Server (CAS) Software The Scientific Database LSST Level 2	Information that has been used to conduct scientific research

Table 22 Emergent categorization from analysis of the "Data Characteristics" code from all three research methods

The emergent categories in Table 22 can be reduced to a nominal classification of the two major ways data were described: data as process and data as product. For example, developers charged with writing data collection software may describe data as a process (information being collected), while sky survey leadership may publicly tout the importance of the survey in terms of data as the end product, as collected information. Software developers working on LSST's processing pipeline most often describe LSST data as information being processed through the pipeline (process), while SDSS data end-users describe SDSS data as the resultant dataset released online by the collaboration (product). SDSS data end-users often describe any information they are analyzing (process) for a specific journal article to be data, whereas library staff may consider the discrete set of analyzed information deposited with a journal article to be data (product). These examples of the distinction between data as process, and data as product, exist throughout the sky survey research data life cycle.

4.2 RQ2 Results: What is Data Management in Astronomy?

The following are the results for the second research question (RQ2): What is data management in astronomy? As presented in the RQ1 results, data were interpreted different ways, at different times, by different stakeholders. The boundaries of the SDSS and the LSST data were described in multiple ways over the course of the projects. Data were described as either a process or a product, and were described differently across the life cycle (refer back to Table 22).

As described in the Methods chapter, the documents, interview transcripts, and field notes were all coded as part of the analysis for this study. For RQ2, data were extracted for analysis from the code "Data Organization and Archival Storage." The code encompasses passages related to questions of what it means to manage data in astronomy. Passages were coded and analyzed from the three research methods and three study populations.

4.2.1 RQ2 documentation results

The SDSS and the LSST projects each generated multiple document genres. Particularly relevant to RQ2 are the policy documents, which often refer to data management tasks. The following subsections describe data management interpretations based on SDSS documents and then LSST documents.

4.2.1.1 SDSS data management in documents

SDSS data management is a complex endeavor that permeates the decades-long project. Many formal and informal documents list the tasks involved in SDSS data management. While the specific data management priorities differed across project stages, the temporal way data

management was described in the SDSS team documents was divided into three rough periods: data collection; data storage, processing, and transfer; and long-term serving and archiving.

- Data collection

The SDSS data acquisition software collects and provides initial data testing. First, data are analyzed for continuing operations and then for end-user science. Early documents describe both an "operational archive" and a "science archive," reflecting these two different data uses. The operational archive "is the central collection of scientific and bookkeeping data used to run the survey" (York et al., 2000, p. 1585). As described in the RQ1 findings, the operational archive is referred to as part of the SDSS data through the first few data releases, and then is no longer referenced in relationship to SDSS data.

As both a photometric and spectroscopic survey, the SDSS first identifies objects through photometry and then collects spectra of objects. The photometric data are collected, processed, and analyzed to determine which spectroscopic data should be collected (Margon, 1998, p. 6; Szalay et al., 2000, p. 5). Photometric data must be processed quickly to ensure that the best spectra data collection choices are made. Data are processed through a complicated set of software pipelines to prepare for scientific use. The pipelines perform operations such as "astrometric calibration… and detect and measure the brightnesses, positions, and shapes of objects" (Abazajian et al., 2009, p. 545). Margon described the time-sensitive nature of the work as placing, "severe demands on the complex software pipeline that acquires the data, performs image recognition, classification, astrometry, and precision, calibrated photometry, followed by target selection for a myriad of different scientific project" (Margon, 1998, p. 3). Spectra are then collected and processed through the pipeline for further calibration and to extract measurements

(York et al., 2000, p. 1585). Once ready, the operational database is migrated into the science database for end-user retrieval and use (Lupton, 2002; York et al., 2000).

- Data storage, processing and transfer

SDSS data maintenance required faculty and staff efforts at multiple institutions across the country. For example, the SDSS data management tasks at just one of the institutions included, "Operating system upgrades, Security patches, Corrupt file detection/recovery, Disk or controller replacements, System performance monitoring, Machine replacements" (Boroski, 2007, p. 12). This task list reveals that in addition to working with the processing pipeline specific to SDSS data, team members also needed to perform general digital maintenance activities necessary for the continued processing, management, and serving of any kind of digital information.

The SDSS II Project Execution Plan (PEP) provides the most detailed information for SDSS data management tasks (Kron, 2008). The purpose of the PEP document is "the cost, schedule, product goals, management structure, education and public outreach, metrics, and other aspects of the project" (Kron, 2008, sec. Preface). While prepared for the NSF, the document reflects on the project as a whole. The Principles of Operation documents also contain relevant information describing data management, but they only provide simple lists of SDSS team positions alongside short descriptions (1989, 2000, 2005). Instead, the NSF PEP goes into significant detail on the team positions and tasks; the information relevant to data management is organized into two sections: "Data Processing" and "Data Distribution." The Work Breakdown Structure is also further organized into six subsections: "Survey Management, Survey Operations, New Development, ARC Corporate Support, Education and Public Outreach, and Management Reserve" (Kron, 2008, p. 15). The PEP document reflects the extensive amount and

kinds of work considered aspects of processing, managing, and serving the SDSS data.

Once collected and ready for processing, data were sent from Apache Point Observatory to the data center, which conducted the SDSS I and II data processing. In the early days of SDSS data collection, the data were too large to be transferred online. Instead, magnetic tapes were mailed to the data center for processing by an express courier service (Margon, 1998, p. 6). Technology improved over the first few years of the survey, enabling data delivery directly from the observatory to the data center, first through a microwave Internet link and then through a high-speed Internet connection.

- Long-term serving and archiving

As they planned the survey, the SDSS collaboration knew that the resulting data would be important to the astronomy community in the long-term. In 2000, SDSS team members described their data management work as needing to be useful "for the next several decades" (Szalay et al., 2000, p. 3). The data necessitated being recorded, organized, and distributed in a sufficient and sustainable manner for long-term use. They went on to explain, "This long-lifetime presents design and legacy problems. The design of the SDSS archival system must allow the archive to grow beyond the actual completion of the survey" (Szalay et al., 2000, p. 3). Therefore, once collected and processed, the data required "a carefully defined schema and metadata" to ensure scientific usability into the future (Szalay et al., 2000, p. 3).

SDSS team members realized that timely serving was not enough to enable the SDSS data to remain relevant and scientifically usable into the future. The team did begin to consider long-term data management prior to the end of data collection; however, no long-term plans were mentioned in the earlier texts that alluded to the expectation that the data would be valuable for decades. For example, in 2007 the project manager presented only "preliminary thoughts" on

the long-term data management needs of the SDSS: recognizing the importance of both "required (format conversion; platform migration) and 'value-added' (errata, bug fixes, annotations)" data management activities (Boroski, 2007, p. 17). By 2011, SDSS data serving and archiving had already begun and the descriptions were more concrete. A presentation by Brian Yanny regarding care of the SDSS Archive explained the SDSS data must be "preserved in a readable, understandable format for long periods of time…" which includes, "long term store copies" and "active working copies" of the data (Yanny, 2011). He went on to explain the uniquely long-lived value of SDSS data is precisely one of the difficulties of managing the data because of the changes that can occur to the timeline of the project. He said, "The life expectancy of data can be decades or centuries, making the technical aspects of data preservation and dissemination an interesting challenge. Methods and practices are evolving continuously…" (Yanny, 2011).

4.2.1.2 LSST data management in documents

The LSST collaboration provides a corpus of documentation outlining data management requirements. In particular, internal policy documents describe data management activities and responsibilities. The hierarchy of these internal policy documents is important because despite careful change control, there can be inconsistencies between documents and distributed authors. An LSST team leader described the LSST System Science Requirements Document (2011) as "like our constitution. That's the highest-level document from which we derive all other documents. That describes what we want to accomplish with LSST" (Martinez, Professor, 2011).

In 2014, the LSST project completed the design and development phase of funding and began construction. While the SDSS data management practices were presented in previous

subsections in terms of each of the data management stages, LSST results presented here are arranged by type of document because LSST is early in the research life cycle.

- Data management in funding proposals

The LSST NSF funding proposal abstracts briefly describe the work necessary to complete LSST project goals. The 2012 proposal abstract lists task priorities. Two of the main priorities are directly related to data management, and include creating the complicated simulations and software pipelines. Specifically, the proposal abstract notes the priorities as: "Developing improved algorithms for data… hardware and software prototyping and system simulations… innovative, large-scale database techniques… [and a] general-purpose data and algorithm-parallel framework…" (National Science Foundation, 2012). LSST expects to collect a huge volume of data, which requires the construction of new facilities, dedicated hardware, highly expert staff, and newly created software. Two years later, the 2014 NSF grant proposal abstract emphasized how the project plans to push the boundaries of computational capabilities. A massive effort is required due to the expected data volume, most important, the creation of a new, "sophisticated" data management software system (National Science Foundation, 2014a).

- Data management in presentations

Two internal 2014 presentations detailed data management requirements, summarizing the extensive software systems and algorithms into bullet points. For example, the LSST Data Management "Principal Responsibilities" (Kantor, 2014, p. 2) or "Roles" (Juric, 2014, p. 10) were listed as:

> "1) Archive Raw Data: Receive the incoming stream of images that the Camera system generates to archive the raw images
>
> 2) Process to Data Products: Detect and alert on transient events within one

> minute of visit acquisition. Approximately once per year create and archive a Data Release, a static self-consistent collection of data products generated from all survey data taken from the date of survey initiation to the cutoff date for the Data Release.
>
> 3) Publish: Make all LSST data available through an interface that uses community-accepted standards, and facilitate user data analysis and production of user-defined data products at Data Access Centers (DACs) and external sites."

LSST data management work was also described in terms of necessary LSST software features. The data management team is working on creating the LSST Software Stack. The stack is described as including "(science pipelines, middleware, database, user interfaces)" (Juric, 2014, p. 17). Data management team leaders viewed the team's ultimate tasks as creating tools to archive, process, and publish the data.

The LSST project is sometimes considered so similar to the SDSS project, that the only difference will be data volume (Ivezić et al., 2011, p. 20; LSST Science Collaboration et al., 2009, p. 15). The expected data volume creates hurdles for the data management team to overcome. While serving the LSST data, the collaboration expects the high volume to influence their ability to serve the data. While the SDSS collaboration kept all data releases actively available to the public, the LSST only plans to retain the two most recent releases on "fast storage and with catalogs loaded into the database…Older releases will be archived to mass storage (tape)" (Juric et al., 2013, p. 52). Each consecutive data release will include the entirety of the preceding LSST data, however the datasets are reprocessed with each new release, resulting in non-identical data between releases.

In addition to the volume of data, LSST data management tasks are also difficult because of the speed by which the data will need to be released (Becla et al., 2005). For example, the Level 1 alerts need to be made available within 60 seconds of data capture. The Level 2 data also needs to be made available to international partners as quickly as it can be collected and

processed. Despite challenges presented by data volume and speed, as of 2014, the most pressing problem was considered to be that of "insufficient documentation" for the work already accomplished (Juric, 2014, p. 22).

The System Capabilities section of the Systems Requirements Document itself includes five main subcategories. Three of the five categories are related to data management. These include Data Collection, Data Products & Processing, and Data Archiving and Services (Claver & LSST Systems Engineering Integrated Product Team, 2015, p. 14). The document indicates the need for data curation planning, though it does not provide details and instead merely indicates "The LSST Observatory shall develop a data curation plan" (Claver & LSST Systems Engineering Integrated Product Team, 2015, p. 29).

- Data management in the public website

According to the LSST Data Management Website, the data management team is tasked with the challenge of, "Processing such a large volume of data, converting the raw images into a faithful representation of the universe, implementing automated data quality assessment and automated discovery… and archiving the results in useful form for a broad community of users" ("Data management | LSST public website," 2015). The webpage details how the system is broken into three architectural layers: the infrastructure layer, middleware layer, and an applications layer ("Data management | LSST public website," 2015). Importantly, a number of pipelines (nightly, data release, calibration, and more) require development to process collected information into usable data for scientific investigation.

The Data Products website ("Data products | LSST public website," 2015) detailed the tasks required of the LSST data management team in terms of managing the immediate, Level 1 data as well as the fully processed Level 2 data:

"1) Process the incoming stream of images generated by the camera system during observing to generate and archive the nightly data products:

- Raw science images
- Catalog of variable sources
- Transient alerts.

2) Periodically process accumulated nightly data products to:

- Generate co-added images of several types
- Optimally measure the properties of fainter objects
- Perform astrometric and photometric calibration of the full survey object catalog
- Classify objects based on both their static properties and time-dependent behavior" ("Data products | LSST public website," 2015).

❖ Data management in policy documents

Internal LSST policy documents describe the goals and requirements of the LSST data management system in great detail. These documents provide the most extensive data management explanations and appear to have no limitation on document length like most other document genres. The Science Book (2009) explains the LSST data management component of the project by detailing the Level 1 and Level 2 data production, where "production" means, "a group of pipelines that together carry out a large-scale DMS function" (LSST Science Collaboration et al., 2009, p. 39).

The Science Book also describes the planned transit of the data after collection. Data will be captured at the Summit and quickly moved to the base facility in Chile. Next, dedicated fibers will transfer the data from Chile to the archive center in the United States. The archive center is described as, "a super-computing-class data center with high reliability and availability. This is where the data will undergo complete processing and re-processing and permanent storage. It is also the main repository feeding the distribution of LSST data to the community…" and will provide a help desk and other end-user support (LSST Science Collaboration et al., 2009, p. 37).

The Science Book also describes the potential plans for long-term data because the data are expected to be scientifically important for decades. Similar to the SDSS documents at the

same point in the project, LSST documents also note that the collaboration recognizes the data will be long-lived, but do not yet specify plans for long-term data management. The Science Book explains, "The LSST will archive all observatory-generated data products during its entire 10-year survey…. The longer-term curation plan for the LSST data beyond the survey period is not determined, but it is recognized as a serious concern" (LSST Science Collaboration et al., 2009, p. 45).

4.2.2 RQ2 interview results

All 80 interviews in this study were coded using the full codebook as discussed in the Methods chapter. Following completion of coding for all interviews, passages coded with "Data organization and archival storage" were collocated and retrieved. The results from this code fell into three major categories. Interviewees spoke about data collection; data storage, processing, and transfer; and long-term serving and archiving. Within each study population, results are provided at the three data management stages. First, results from the SDSS team are presented, then the LSST team, and finally SDSS data end-users.

Responses coded with "Data organization and archival storage" arose from questions on the official interview protocols and also from information voluntarily offered by interviewees. Often, the specifics regarding the data management work conducted by SDSS and LSST team members was revealed through narratives describing the path of data through the project life cycle. More specifically, some interview questions proved particularly helpful in enabling interviewees to discuss data management. For example, the protocols included questions for interviewees about their data management and analysis tools. SDSS team member interviewees were asked to tell a data narrative, "Could you walk us through some of the steps from collecting datasets from a database to analysis?" SDSS team members were also asked, "What happened to

your data at the end of your last project?" LSST arguably does not have data yet, so interviewees were instead asked to describe the planned data management policies for the project. LSST team members were also asked to explain their personal data and information storage and management strategies. One particularly useful question for the LSST team members was: "What is your process – from data collection and analysis design, to archiving?" SDSS data end-users were walked through a practical exercise regarding the data they recently used in one of their published journal articles. SDSS data end-user interviewees were asked, "Where does the data used for this paper reside? Where is it stored and accessed?" Interviewees were then asked to locate a specific dataset used in that journal article. End-users were asked to explain aloud their short- and long-term data management techniques as they located the data during the interview. Interviewees from all three populations were asked how they keep track of multiple versions or states of their research data.

4.2.2.1 SDSS team

The SDSS collaboration began collecting scientific data in 1997. Data are collected from the telescope and instrumentation at Apache Point in New Mexico. Once collected, data are processed through complicated pipelines, which include data cleaning and calibration, prior to being released to the public. The SDSS I and II data were released through eight official data releases, each documented with a data release journal article. The three SDSS team member data management phases are presented below.

- SDSS team data collection

Most SDSS team member interviewees described the SDSS data path as beginning after data had already been collected. Only two interviewees in this study population discussed data

collection directly. Moore recalled having written some of the data collection and immediate processing software. However, she is not sure where that information is today and regrets that the code is currently unavailable (Moore, Staff Scientist, 2012). Taylor discussed how team members wrote software at the mountain to help determine, in near real-time, whether the data were being successfully collected. She noted that once the software was activated, it improved data collection efficiency (Taylor, Emeritus Professor, 2012).

Two SDSS team members explained the data path from the mountaintop to the data processing center. When the data arrived at the data processing center, a team of computer scientists and astronomers then managed the information. Robinson explained there was a small team at the data center who were, "… trained in computer science, who would do the nightly data processing... And if there was… something they didn't know how to deal with, something that required a scientist intervention, then they would come to me (Robinson, Staff Scientist, 2013). Another interviewee described the path of the data more specifically after it arrived at the data center. She described how data arrived as standardized FITS files, and then the DAS experts would process the data into flat files using Linux. The data were then given to the SQL Server database experts for processing to prepare for data release (Lewis, Research Programmer, 2013). These interviewees described how the SDSS data were collected by one team on the mountaintop, and then transferred to the data center facility where two teams of computer scientists processed the data while relying on astronomer support.

- SDSS team data storage, processing, and transfer

After SDSS data were collected and initially processed for operations, they were processed further, stored, and made available to external data end-users. Clark explained that data management was a tough job that included the work of multiple departments at the data

center. She explained, “So, this issue of maintenance, support, operations…one of the reasons for having a software infrastructure group involved--that was not just the scientists--was to provide that kind of sustainability and long-term provision of software and support” (Clark, Research Programmer, 2013). The data management work at the data center included computer science experts as well as astronomy domain experts.

During this dissertation study, five local, unofficial copies of the SDSS I and II data were discovered at various institutions in the United States. Ethnographic work also revealed unofficial copies in the United Kingdom and Brazil. The author predicts there are more unofficial copies of the SDSS dataset, including several other copies worldwide. These copies are used for both project-level and personal-level work. Some copies were used to test and refine tools that were later re-integrated into the project itself. For example, at one SDSS-affiliated university astronomy department, long-term work on the data processing and data management algorithms required testing with the data itself. Taylor agreed that the SDSS project team members required access to copies of the SDSS data to test the tools that they were constructing for the project. She explained, “…we made a deal with them that we would keep a copy of the reduced data here and use it to tweak up the pipeline and fix the problems” (Taylor, Emeritus Professor, 2012). In addition to using local data copies to test project-level processes, astronomers often also tested tools for their own personal scientific inquiries on these local datasets, “So, we had a copy of it here and we did, actually, a fair amount of our science on the copy here” (Taylor, Emeritus Professor, 2012).

Many interviewees applaud the SDSS data distribution system. While other systems were initially tested, the resultant tool, SkyServer, is considered one of the major SDSS accomplishments. An administrator on the SDSS team praised the SkyServer system as a fast

and impressive data collection process for end-users (Walker, Project Manager, 2013). Lewis noted that end-users could access data through multiple systems including CasJobs and SkyServer. Since there was a lot of demand, and multiple ways to access the data, the data center needed to maintain and serve multiple copies at any given time.

In hindsight, SDSS collaboration members indicated that they did not budget enough money for data storage. However, they explained that as the project timeline stretched, storage costs continued to decrease, and the budget resolved itself. Despite some concerns with data storage, all data releases were retained and serviced as individual datasets even when newer versions were released.

- SDSS team long-term serving and archiving

Following initial data release, SDSS data were maintained and continually served to the public over the course of the eight-year survey and beyond. Clark explained the data processing center retains the datasets at multiple data processing stages on tape even though phases I and II of the project were completed. She said, "We keep copies of the transformed data and then we keep copies of the raw data for significant data sets…. So we archive... Keep everything basically on tape... (Clark, Research Programmer, 2013).

The SDSS I and II data were archived and served by four institutions for the five years following the end of SDSS I and II data collection (see also 4.1.3.1 SDSS data in ethnography). Each institution signed a MOU, dictating the data serving and archiving work they would complete over the course of the five-year agreement period (2009-2013). After 2013, the four institutions that signed MOUs have retained a version of the dataset.

4.2.2.2 LSST team

The LSST team plans to begin collecting data in 2020. As of this writing, the team members are actively working on the construction phase of the project. Data management staff, primarily at universities, are currently focused on writing components of the processing pipeline software. Data center technical staff are preparing the hardware and software for massive data volumes.

- LSST team data collection

LSST data will be collected on the mountain at Cerro Pachón, Chile and then travel through fiber networks to the data processing center in the United States. King described the beginning of the path, "They get fiber off the mountain to the bottom of the mountain, and then I think there's some fiber networks across the ocean. There'll be multiple data repositories…where they serve the data to the world" (King, Research Programmer, 2014). King is not concerned about the data volume and its impact on the ability for the data to transfer from Chile to the United States. She explained, "You basically throw more hardware at it …It's not gonna be easy, but we know how to do it. There's things we don't know how to do, that worry me" (King, Research Programmer, 2014). King explained that while the task of transferring large amounts of LSST data across continents may appear daunting, it is a task that basically requires funding instead of new, creative solutions.

Howard explained that data will leave the mountain as a data stream, "We don't do catalogues. We just send out a stream of data. And it's up to them to organize it…" (Howard, Professor, 2015). Data will arrive at the processing center, and the data center staff will store, process, and reduce the data (Cox, Project Manager, 2015). Diaz explained that once the data arrive at the processing center the difficult data management tasks begin. A major investment is

necessary to keep an environment that's stable and reliable for the LSST data over time.

- LSST team data storage, processing, and transfer

As of this writing, the LSST data management team is developing the software and infrastructures necessary to process, manage, and release LSST data. Given the long-term nature of the project, Martinez explained that the systems are now being designed to enable changes over time. He detailed that the LSST team is making sure they continue "designing a system to be flexible enough that you can just switch from one storage to the other….agnostic" (Martinez, Professor, 2011). Indeed, the project team members likely will not begin collecting data until 2020, and therefore expect major changes in computing technology before data collection ends, or even before it begins.

When asked to describe the LSST data management team's responsibilities, Wright responded by listing many assigned tasks. In summary, all of these activities can be considered part of the data processing pipeline: "…what the data management team is all about, is working on making the pipeline for telescope to internet release" (Wright, Graduate Student, 2014). As Wright described, the LSST data management team as in charge of the tasks that will process and prepare LSST data for scientific usability.

- LSST team long-term serving and archiving

Three interviewees tried to predict the LSST data long-term plans. Hernandez is unclear of the official long-term plans for the LSST data, however she does believe SDSS lessons learned are going to shape LSST. She explained the relationship, "A lot of the people who were involved in LSST were SDSS people, a lot of the institutions for example are similar and so I would imagine that lessons learned from SDSS are moving on in the course of LSST…"

(Hernandez, Post-Doc, 2012). In addition to noting the similarity in individuals and institutions between the two projects, Hernandez also noted an ideal way to manage the data. She noted that the best archive environment would be the Mikulski Archive for Space Telescopes (MAST), however she knows that MAST itself is only available for space-based (NASA) data and not LSST data, which is ground-based.

Cox is an administrator at the data center and thus is concerned with providing the hardware and computing power necessary for LSST. However, she acknowledges that the specific needs will change over time. Cox discussed factors, including the long period of time and finite resources, which can impact how to make data available to LSST end-users. From the perspective of the LSST team, it is unclear how many of the intermediate processing levels will be stored, for how long, and in what medium. She explained that data processing levels might each need to be stored differently based on the amount and kind of user demand. She explained, "... How much you keep? Storing data is expensive. …'It takes me this much to process it. So that's fast. It's inexpensive.' …And then you have to do like, 'How many times do I access the data?' This cost comparison" (Cox, Project Manager, 2015). Some materials may be stored on fast disc, some on slow disc, and some on tape. In the long-term, LSST storage and serving conditions are unclear. While data center staff have chosen to assume that Moore's Law will work in their favor over time, it is unclear to what extent exactly the "law" will continue to benefit the project.

4.2.2.3 SDSS data end-users

The following subsections present data management descriptions by the SDSS data end-user interviewees. The following includes results from individual, small, and medium-sized collaborative projects undertaken by interviewees.

- SDSS end-users data collection

Interviewees described collecting data in multiple ways; even data from the same source could be collected in different manners. The kind and amount of data particularly influenced data collection methods. For example, data volume determined whether an interviewee would hand collect individual data, download some data, or query a database to download large amounts of information.

Many interviewees described downloading large amounts of SDSS data from SkyServer or CasJobs, and then relying on that local copy of the data for further analysis or queries. For example, Jones explained that he created datasets linking SDSS and other datasets together (value-added catalogs). Since generating those catalogs, he has not gone back to the original SDSS dataset, "…having produced these value-added catalogs, we're more extracting stuff from those catalogs rather than going back to the actual raw data themselves" (Jones, Professor, 2011).

While some interviewees now rely on writing Structured Query Language (SQL) to query databases, Carter managed to collect data without using SQL. Instead, she uses the survey databases in a different way, picking specific objects one at a time, instead of querying a large dataset. She explained how he collects sky survey data: "So I'm still operating in this weird, bizarro land where I just focus on a subset of the Sloan dataset as if it were a classical telescope" (Carter, Professor, 2015).

Sky survey data end-users collect data using multiple methods. End-users query the sky survey resource using multiple tools, and then may download the data for future reuse. Some data end-users rely on their knowledge of SQL to obtain data, while others rely on the sky survey to have created non-SQL based data retrieval tools.

- SDSS end-users data storage, processing, and transfer

Five interviewees mentioned using Dropbox, or a similar kind of storage software, as a helpful data management tool for both individual and collaborative projects. Some enjoyed the feature that Dropbox essentially generates backups across computers, others appreciated that they can work on the same documents from different machines, and still others relied on it for version control among collaborators.

Three interviewees discussed data management based on data processing stages. Garcia explained that each stage in a processing pipeline creates new copies of data. A large amount of storage space is required if copies are retained at each processing stage. White explained that it is simply not possible to retain all his data at each level of data processing. He explained that he decides to retain an intermediate level of data only if the next processing step cannot be reversed. As data are processed through various stages, interviewees must determine whether and how to manage divergent copies.

Interviewees discussed managing data for their research projects in one of four ways. Seven SDSS data end-users described their data management as involving folder structure organization on their personal computer. For example, when asked to explain how he organized his data, Nguyen responded, "Organize? Well, just try to keep them in different directories, I guess" (Nguyen, Professor, 2015). Next, four interviewees described how they use the Interactive Data Language (IDL) database structure to organize data on their personal computers. For example, Rodriguez uses IDL to organize and analyze FITS files (Rodriguez, Professor, 2011). Three interviewees explained they are unable to manage their research data on a personal computer, and instead require local workstations to provide the storage space and memory necessary for scientific data storage and analysis. One interviewee's office was full of monitor-

less computers and he used these computers as nodes for his data work (White, Staff Scientist, 2012). Five interviewees described relying on a shared server to manage and analyze their scientific data. Garcia used the university computer cluster to process data for his work. Evans explained that it is only during the final stage of journal article data analysis and writing that she is able to work with data on her local computer. The rest of her data analysis requires infrastructure on the scale of server farms (Evans, Post-Doc, 2015). SDSS data end-user interviewees indeed described four different ways they store data used for scientific analysis: through folder structures, IDL, local workstations, or shared servers.

- SDSS end-users long-term serving and archiving

This section presents how interviewees managed their project data at the end of a project. As described in the methods, each end-user interviewee was questioned using the "Follow the Data" interview protocol, which asked about their data management practices through the full research process of a single journal article. The interviewees in this study generally defined the end of a project as coinciding with journal article publication.

Twenty-five interviewees were asked to locate the data behind a specific figure in their recent journal article. Specifically, the interview protocol asked, "Could you locate the data for this [table/graphic/image]?" Of the 25 interviewees, there were seven kinds of responses to the question, organized into four categories (Table 23). The four categories of responses were 1) I have the data (n=12), 2) someone else has the data, but I do not (n=16), 3) the data are available, but in an earlier level of processing, (n=3) and 4) the data are not available (n=1). Six interviewees responded by using more than one of the categories. Five of those interviewees responded with more than one category because the reason that they did not have a copy of the data was that the data were not important enough to retain. The sixth interviewee offered two

responses because he noted his data are available publicly on his website, while his code is maintained locally. The response categories are detailed below.

Response categorization to the question "Could you locate the data for this [table/graphic/image]?"	**Number of responses**	**Response categorization**
I have a local copy and can show you the data now	9	I have the data
The data are publicly available on my website	3	
The first author has the data	8	Someone else has the data, but I do not
The student or post-doc has the data	5	
The data were included with the published journal article	3	
It was not necessary to keep the data because the data I obtained are publicly available and it is easy to replicate the data processing	3	The data are available in an earlier level of processing
The data are not available because new, better data should be collected instead of relying on my data	1	The data are not available

Table 23 SDSS end-user responses to "Could you locate the data for this [table/graphic/image]?"

Nearly half of the end-user interviewees (12/25) had the data they were asked to locate. These interviewees either had the data available on local disk (9), or had publicly posted the data on their website (3). Davis said he believes in lots of backups of his data, even after publication. White had many copies of his data and continues to migrate old and new data forward so that they are always on his current computer (White, Staff Scientist, 2012). However, Morgan was not confident in his ability to retrieve the relevant data. Instead, this interviewee relies on the original data archive to gain access to his dissertation data now and into the future. However, Morgan clarified that he does have local possession of the code he used for data analysis and thus the data could be reproduced if necessary, as long as the project continues to serve the data. Three interviewees noted their data are available on their website. Martinez posted data to his

website when his journal article was published. In fact, he posts data on his website not only for other users, but also for himself. He explained, “when I do additional analysis, I want to be dead certain that I’m using the same thing we’ve made available to other people” (Martinez, Professor, 2014). These interviewees each have possession of the data they used in the journal article discussed in their interview.

Roughly half (12/25) of the interviewees noted that they do not have the data, but that a co-author of the study has the data used in the journal article. When interviewees noted someone else had the data, they referred to one of two people: the first author of the article (8), or the graduate student or post doc who collaborated on the project (5). One of the interviewees noted the person with the data was both their student and the first author of the paper. Some interviewees felt it was the first author’s responsibility to have the data and did not think about data disposition beyond that assumption. Johnson said, “Well, there is probably a folder [student/first author name] has somewhere… Well no, they actually have to go ask [student/first author name]” (Johnson, Professor, 2011). Williams indicated that during some collaborative research projects, co-authors with different interests might manage the datasets most relevant to their specialty. Wilson, a graduate student, was directly asked who generally managed research data. He responded that students usually were designated as data managers, “Well, these around here, that's fallen to the students...” (Wilson, Graduate Student, 2011). However, he explained that student data management was not an official policy and instead an ad hoc tendency. Morgan laughed during the interview when he realized he did not have access to the data that contributed to a journal article and that it could affect the reproducibility of his study (Morgan, Post-Doc, 2015).

Three interviewees noted that they do not have the final data products that led to journal article publication. However, they noted the original data remains available publicly and it would not take very much time to transform the available data into the data product they used for journal article analysis. For example, Bennett mentioned that not all code needs to be kept, because some is easy to replicate (Bennett, Staff Scientist, 2015). These three interviewees did not have access to the data used for their journal article. However, they believed that they could re-create their processing steps by using the original data, which remains publicly available.

Finally, one interviewee stated that he did not retain his data because he believed that the particular dataset was unimportant. Wood explained, "… if you talk to somebody who works on galaxies or something… they would never use data from two decades ago. They would be like, 'Why would I do that? I'll just go to the telescope and get another spectrum…'" (Wood, Professor, 2015). This interviewee admitted to no longer having the data, however he argued that a potential data reuser should instead collect their own data using newer, and thus more sophisticated, instruments.

4.2.3 RQ2 ethnography results

In both the SDSS and LSST observational findings, academics from different disciplines worked together, and in both projects culture clashes were found. The SDSS I and II project has completed data collection when the author of this dissertation began observing the collaboration. SDSS ethnography results reveal how the term "archive" was understood and used multiple ways by members of the SDSS collaboration. LSST observations for this dissertation were conducted at the close of the research and development and start of the construction stage of the project. LSST ethnography results reveal the joining of divergent cultures influenced how data management was interpreted.

4.2.3.1 SDSS data management in ethnography

When the author began observing SDSS in Spring 2012, the project had already transferred operations from SDSS II to SDSS III. However, the SDSS I and II data continued to be managed and served to the public. From the author's perspective, the time following data collection could be referred to as the archival period. However, the term "archive" held various meanings for members of the SDSS collaboration.

In Summer 2012, four years after SDSS I and II data collection was completed, the author had a confusing conversation with Taylor, an SDSS team member and leader. When asked about the long-term plans and data archiving for the SDSS, Taylor referred to the SDSS I and II dataset as the "science archive" (see also 4.2.1.1 SDSS data management in documents). When pushed to describe the long-term management plans and practices for the data, Taylor noted that multiple universities "have copies." While referring to the SDSS science archive, Taylor had no conception of the meaning of the term "archive" as defined in this dissertation and related to data management, preservation, and curation. The same ambiguity of the term occurred with another important SDSS team member at the same institution. Once the author and Anderson reached consensus on the subject, Anderson stated that there was no need for preservation or archiving. He explained, "We put it up on the web, so it's good, it's done" (Anderson, Emeritus Professor, 2012). Even though these SDSS team members and leaders committed more than a decade of their lives to the SDSS project, they were unclear of the meaning of "archive" beyond that of the SDSS "science archive," and once pressed found little need for long-term data management.

Alternatively, there remains much pressure on the SDSS collaboration to ensure the data are served and preserved in the long-term. As presented in RQ2 section SDSS end-users long-

term serving and archiving, the most conscientious data end-users explained that while they save and backup their SDSS data retrieval queries, as well as the intermediate and final data products from their analysis, they do not feel a need to save the data initially retrieved from the SDSS server. End-users are not managing copies of the SDSS data used for their science because they assume the data will remain consistently available from the SDSS collaboration. SDSS team members need to serve and preserve the SDSS data because end-users rely on that data to remain available for the reproducibility of their science.

Luckily, many other SDSS team members have considered and prioritized long-term management of SDSS data and understand the importance of data preservation. While SDSS leaders admit they considered long-term management later than they should have, steps were taken to archive and serve the SDSS data prior to the end of project funding (refer back to 4.1.3.1 SDSS data in ethnography).

4.2.3.2 LSST data management in ethnography

LSST data management systems are currently under development: the project is under construction, having completed the research and development phase of the work. The LSST project as a whole, including telescope, camera, data management system, and operations, is a more than one billion dollar enterprise. Given the complexity and expense of the project, funding bodies require data management software construction to occur on time and within budget. The NSF in particular requires extensive planning and reporting to ensure progress.

Most university-based astronomers have never participated in a project the size of LSST, which has led to a clash of cultures. On one side are PhD astronomers who generally work in small or medium collaborations, and have never worked on a project at LSST's scale. The majority of those employed by LSST for data management have PhDs in astronomy and are

located at a university, and as such are more accustomed to the university-based research environment, which is in sharp contrast to NSF requirements for strong reporting to ensure the continued success of the software development project.

Many informants described their struggle between moving from an university environment to a highly regulated NSF culture when they began working on LSST. One individual was a team member of SDSS and then an early member of LSST. He described working with LSST leadership to determine, "how do we design the code in a pseudo-professional way?" (Campbell, Professor, 2015). He explained that much early data management work during research and development involved attending classes on professional programming. He explained how important, and yet frustrating, it was to be forced to learn a whole new way to write software. As astronomers, he and his colleagues generally wrote code well enough to accomplish a certain task, and then moved on. However, he understood that with a large collaboration and thousands of potential end-users, the software would have to be created in a more deliberate way. He described more specifically that this LSST project period was spent learning how to build data management software as programmers instead of as astronomers: "Yeah, that involved training us on a lot of new tools, stuff that we had certainly never thought about having to do in academia" (Campbell, Professor, 2015).

The astronomer described above was frustrated by having to learn all new tools and techniques for writing code. At another LSST institution, during construction, different software writing cultures frustrated other LSST team members. Many of the LSST team members have degrees in computer science and the team as a whole was happy to follow professional software writing guidelines. They agreed with the importance of professional software techniques, even

though the detailed manner in which the Agile software method was deployed by LSST was difficult to implement across institutions.

Multiple institutions had difficulty reconciling what they saw as two competing cultures: that of professional software writing and that of the NSF reporting system. “Earned value” is a term often heard at the LSST data management (DM) leadership meetings. The NSF requires that software engineering work time is carefully recorded and short- and long-term goals are well managed. While seemingly simple at first, the devil is in the details of the extensive spreadsheet system LSST DM leadership uses to track team performance for the NSF. An informant explained the earned value language from the NSF could sometimes even be in direct contrast to the Agile professional software engineering system. He explained that Agile enables a software engineering team to learn how productive their unit is over time, and then to measure and predict production accordingly. They went on to explain the Agile method is the “antithesis” of the earned value model that the NSF requires.

The LSST DM leadership specifically tries to shield software writers from the NSF and earned value language, instead leaving those worries to the leadership team. Despite these attempts, the discrete cultures of the NSF earned value and the Agile software engineering system do influence the way software writers go about their work. Each of the institutions studied for this dissertation found that adapting to working within these two divergent cultures remained difficult. When specifically asked, one informant noted that the reasons a person may want to work on an academic project do not align with the way LSST needs to be managed for the NSF. He explained, “People don't come into academia for the money right? Typically it's for other perks, …the opportunity to be involved with something kind of grand... [But] at this point feels like we’re trying to check off boxes for bureaucrats” (ethnographic fieldnotes, 2015). Over

the course of the observations, each institution began to more successfully grapple with these competing cultures.

4.2.4 RQ2 results summary

A number of perspectives emerged for what it means to manage astronomy data. The SDSS team documents parsed data management into three stages: Data Collection; Data Storage, Processing, and Transfer; and Long-Term Serving and Archiving. LSST documents did not describe data management in this kind of temporal fashion because the project is early in the full project life cycle. Since a temporal pattern across LSST documents did not emerge, these results were presented by document genre. Different LSST document authors described data management in terms of the remaining work to prepare for data collection, lists of tasks and responsibilities, or difficulties associated with the volume of the data and the speed with which it will need to be made available. The interviewees in all three populations described data across three rough temporal periods: Data Collection; Data Storage, Processing, and Transfer; and Long-Term Serving and Archiving. These three stages were the same across the large SDSS and LSST team projects, as well as the small- and medium-sized projects described by SDSS data end-user interviewees. The RQ2 ethnography findings illustrated nuance to these larger categorizations. SDSS ethnography findings showed the term "archive" held many meanings across the SDSS collaboration, and therefore there were different understandings of what long-term data management entailed. LSST ethnography revealed different data management working traditions, which split along professional programming and university settings. While many university employees had never worked in large, dictated collaborations, the NSF requires precise recordkeeping to ensure LSST remains a good steward of federal funds. Each of the three

research methods elicited complementary understandings of the temporal and nuanced nature of astronomy data management in the study populations.

Through close analysis and the combination of the three research methods, a descriptive model emerged showing the stages of sky survey data management over the course of a project. The RQ2 findings demonstrate that astronomy sky survey data management takes place over the course of a set of stages. As outlined in the presentation of the results, six data management stages emerged from the document and interview results from both the SDSS and LSST team members and the SDSS data end-users. Figure 7 illustrates the Sky Survey Data Stages that emerged from combining the temporal and nuanced ethnography findings with the document and interview results. Sky survey data are shown to originate with the sky survey team after project proposal, construction, and data collection. Data are then processed, documented, and released to potential end-users. The team members manage the data in the long-term, however "long-term" is defined locally. Once data are released, end-users can employ the data in their planned research. This end-user work often requires further data cleaning and processing, analysis, writing, and publication of findings. The derived data are sometimes then documented and released to other potential end-users, which begins the cycle anew. More often however, end-users do not provide long-term data management for derived data, as detailed in 4.2.2.3 SDSS end-users long-term serving and archiving.

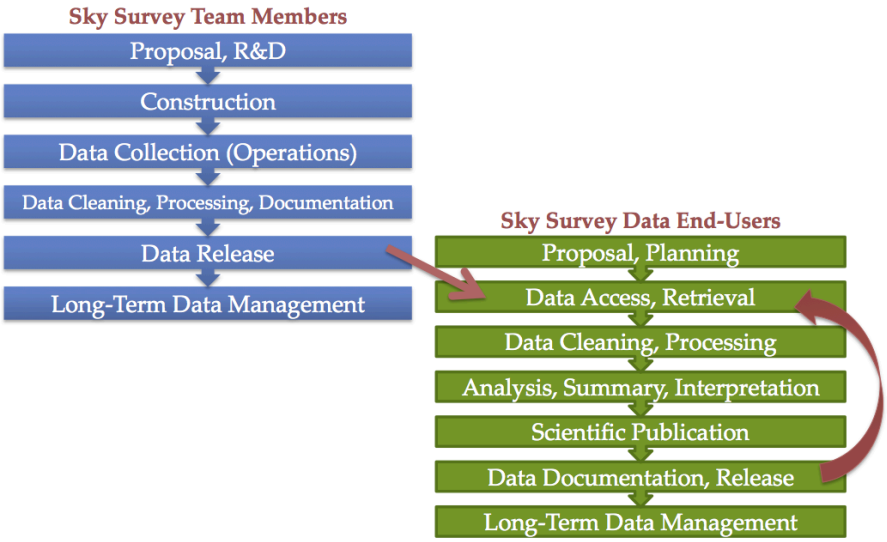


Figure 7 Sky Survey Data Stages

Each data management life cycle stage depends on the successful implementation of the previous stage. For example, data cannot be released until they have been processed, nor can they be available for scientific reuse. While SDSS and LSST team members usually specialize in their data management tasks, end-users often must manage data from planning to disposition.

4.3 RQ3 Results: What Expertise is Applied to the Management of Data?

The following results address the third research question (RQ3): What expertise is applied to the management of data? Documents, transcripts, and ethnography field notes were fully coded and all materials coded with "Important Skills, Abilities" were pulled from the NVivo software for closer analysis. The "Important Skills, Abilities" code captures all information related to workforce experience and expertise. Results are first presented based on findings from document analysis, then interviews, and finally findings from ethnography.

4.3.1 RQ3 documentation results

The following are the findings from documents coded "Important Skills, Abilities." SDSS documentation results are presented first followed by LSST documentation results.

4.3.1.1 SDSS data management expertise in documents

SDSS is often described as a pioneering project because lessons learned have influenced subsequent astronomy sky surveys. Team members describe a range of expertise they developed from working on the SDSS that they now apply to new projects, including the Dark Energy Survey (Yanny, 2011, p. 20). However at the time of SDSS I and II, a number of lessons were yet to be learned and a number of new kinds of expertise were not yet developed in the astronomy sky survey community.

- Continual expertise and learning

The formal SDSS hierarchy reflects the breadth of expertise necessary for the collaboration to succeed. The following kinds of positions are within the SDSS leadership hierarchy: Astrophysical Research Consortium Board, Advisory Council, Advisory Council Executive Committee, Advisory Council, Chair, Director, Project Scientist, Project Manager, Spokesperson, Collaboration Council, Project Teams, Management Committee (Astrophysical Research Consortium, 1989, 2000, 2005). The NSF Project Execution Plan (PEP) reveals further kinds of expertise embodied throughout discrete components of the larger SDSS project. Of particular relevance to data management are Survey Operations, Data Processing, and Data Distribution. In the PEP, each of these components is broken down into a long list of required tasks and kinds of expertise. For example, the plan disambiguates "Survey Operations" into four

different components: Observing Systems, Observatory Operations, Data Processing, and Data Distribution (Kron, 2008, p. 4).

By the early days of operations, the SDSS collaboration was aware that a breadth of astronomy, physics, and computer science expertise was necessary to collect and analyze the SDSS data successfully (Szalay et al., 2000, p. 2). A SDSS team member explained that an important lesson learned from the SDSS was to ensure depth of expertise by not allowing one individual to be the only expert along a critical path. He clearly explained,

> "Avoid single points of failure. OK, so this is totally obvious, but there are subtler aspects. If one person is allowed to become essential it implies that it's proved impossible to find someone else who could fill their role. In consequence, if they are on the critical path, and problems arise, it's hard to add resources to solve the problem" (Lupton, 2002, p. 9).

However, despite the large number of team members and implemented hierarchy, SDSS team members acknowledged there was no way all potentially necessary expertise could be present at once within the collaboration. The SDSS made provisions to enable the team membership, and therefore range of expertise on hand, to grow over time. In particular, when an individual possesses a scientific expertise the collaboration currently lacks, there are ways to add that individual to the relevant parts of the project (Astrophysical Research Consortium, 2005, p. 11).

- Data-intensive expertise

SDSS data were collected and made available at such a relatively high volume and scale that it was beyond most astronomers' expertise to manage (Margon, 1998, p. 6). At the time, the SDSS collaboration was aware that working with these data volumes was primarily limited by their data management learning curve. Margon explained, "All SDSS data will be entirely public,

on a schedule limited only by our (chiefly human) resources needed to process and calibrate this very large volume of information" (1998, p. 6).

The SDSS collaboration soon discovered it would not just be the SDSS team members, but also the data end-users, who would require new expertise to work with these volumes of data. Some SDSS team member leaders explained, "In this era, astronomers will have to be just as familiar with mining data as with observing on telescopes" (Szalay et al., 2000, p. 2). Early in the SDSS data collection, team members recognized that many potential end-user scientists held little expertise working with big data (Szalay et al., 2000, p. 9). Given the level of expertise generally necessary to analyze large volumes of data, the SDSS team members who developed the data access mechanisms were highly successful at creating a way for end-users to search, retrieve, and use SDSS data.

- Help desk

Despite the SDSS collaboration's extensive data management tools and quality documentation, a help desk remains necessary to assist end-users. End-users ask a variety of scientific questions about SDSS data. Some of these questions require the end-user to understand the methodological details of how the SDSS team collected and processed the SDSS data. Indeed, "In many cases… Users often require support from SDSS personnel with expertise in the relevant parts of the pipeline to properly interpret the files provided; a helpdesk supported by the experts is essential" (Neilsen Jr. & Stoughton, 2006, p. 3). The importance of the help desk illustrates that the SDSS team members who built the infrastructure possess expertise beyond what can be recorded. For some science questions, team member expertise may prove essential. However, an individual, even one highly involved in the collection and processing of SDSS data, cannot answer all help desk questions. Full knowledge of the data requires a team.

4.3.1.2 LSST data management expertise in documents

LSST data management documents and funding proposals acknowledge the need for many kinds of expertise available only through the engagement of faculty and staff from distributed locations (National Science Foundation, 2005). During a period of hiring in 2014, two presentations aimed at the larger LSST collaboration highlighted the dispersed expertise necessary for the LSST data management team. Figure 8 is an LSST presentation slide titled "Going Where the Talent is: Distributed Team" (Juric, 2014, p. 16; Kantor, 2014, p. 12). The figure demonstrates that expertise is required from seven different institutions to build the data management software stack. The stack involves six different kinds of modules, some components themselves requiring expertise from multiple locations. The LSST data management system is constructed through the expertise of a wide array of individuals geographically distributed across the U.S.

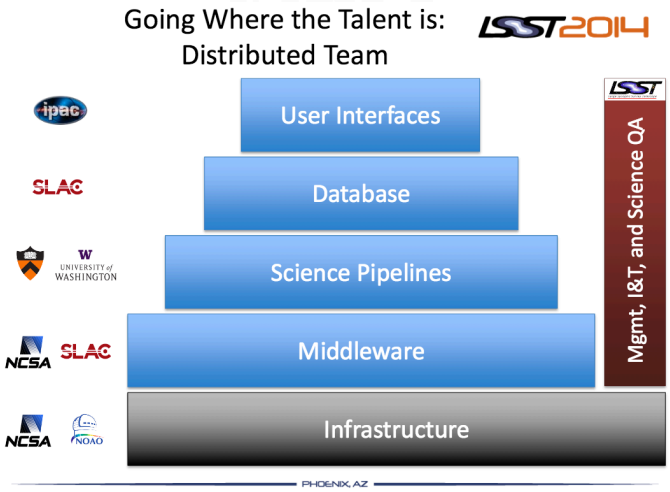


Figure 8 The Distributed Nature of the Expertise Necessary to Develop the LSST Data Management Software Stack (Juric, 2014, p. 16; Kantor, 2014, p. 12).

- Software engineering knowledge

Mario Juric, LSST Data Management Project Scientist, explained why the project requires building a new software stack, as opposed to amending existing software to LSST specifications. He included six reasons for new code, including the need for "running efficiently at scale," and the need for the code to be agnostic and flexible over its predicted 25 years of use (Juric, 2014, p. 19).

LSST team members refer to the project as one that requires collaborators to push the limits of computational capabilities. The Technology Innovation page on the LSST website explains, "The role of the experimental scientist increasingly is as inventor of ambitious new searches and new algorithms. Novel theories of nature are tested through searching for predicted statistical relationships across big databases" ("Technology Innovation | LSST public website," 2015). The expertise necessary to build software from scratch is more extensive than that of modifying existing software. LSST thus requires software engineers who write ambitiously, and not just make adaptations to existing software.

- Big data expertise

LSST data will be used for a broad range of scientific inquiries. Many of these investigations will not require experience working with big data; however, many will need the expertise necessary to analyze large datasets. Similar to SDSS, LSST is expected to enable breakthroughs in scientific research beyond known fields of inquiry (Ivezić et al., 2011, p. 28). To ensure LSST data will be used to their full potential, data management team members and data end-users will need to become familiar with big data analytical techniques and the data management necessities involved in utilizing big data. The LSST collaboration must face "Data Mining Challenges" (Ivezić et al., 2011, p. 20), and the collaboration has begun working with

experts outside astronomy including machine learning and statistics. Partnering with experts in data mining, statistics, and machine learning will likely enable more and different scientific uses of the LSST data.

- Breadth in astronomy expertise

LSST is expected to contribute to the scientific goals of a broad range of astronomy inquiry. Due to the expansiveness of the field, it is not possible for the LSST team to possess high levels of expertise for every relevant avenue of astronomical investigation. Therefore, in addition to those paid through LSST funding to build LSST infrastructure, a cadre of scientists are preparing for LSST data by providing feedback to the systems under construction. Referred to as members of the "science collaborations," many scientists donate their time to specify their scientific needs to the LSST community. The Science Book (2009) required significant analytical efforts from many members of the science collaborations. As of 2011, "eleven science collaborations have been established by the project in core science areas. As of the time of this contribution, there are over 250 participants in these collaborations, mostly from LSST member institutions" (Ivezić et al., 2011, p. 30). The role of the science collaborations and their members is vital to LSST because the project requires such a vast breadth of expertise.

4.3.2 RQ3 interview results

The following results address the expertise necessary to manage astronomy data that emerged from the interviews. Results are presented first from the SDSS team, next from the LSST team, and finally from the SDSS data end-uses. Together, the SDSS team, LSST team, and SDSS end-users proceed through the three broad sky survey data stages as revealed in the RQ2

results: data collection; data storage, processing and transfer; and long-term serving and archiving (refer back to 4.2.2 RQ2 interview results).

As already noted, the following interview findings are those that resulted from analysis of the interview transcript passages coded as "Important Skills, Abilities." A few interview questions led to particularly illustrative responses. The LSST team member interview protocol, in particular, emphasized questions about experience and expertise. For example, two questions asked interviewees to consider the experience and expertise that has particularly benefitted their success in the field: "What experience/education/expertise do you think you in particular bring to LSST?" and "Are there skills or knowledge you gained from a different project that are particularly useful for LSST work?" While experience and expertise were not brought up as explicitly in other protocols, the experience and expertise necessary for data management work emerged from all interviews. For example, follow-up questions were often used to ask interviewees to delve further into how they were able to accomplish data management tasks. These follow-up questions often revealed the kinds of experience and expertise the interviewee identified as important to their data management work. The expertise necessary for data management at each of the temporal stages that emerged from RQ2 findings are now presented, beginning with the SDSS team interviews.

4.3.2.1 SDSS team expertise

At the time of writing, the SDSS I and II had already reached the long-term serving and archiving project life cycle stage. Each of the results below thus addresses stages in the life of the SDSS data that have already occurred or begun.

- Data collection

The expertise specifically necessary for SDSS team data collection was rarely discussed in the interviews, most likely because interviews were conducted years after the SDSS I and II had completed data collection. This also speaks to the kind of expertise necessary for data collection, in that it was largely outside the scope of the expertise generally germane to this study's populations. Interviewees were chosen for this study based on their relationship to SDSS data management efforts. Generally speaking, the individuals collecting data on the mountain are not the same individuals as those processing information at the data center or preparing the data for release. Once SDSS construction and commissioning were completed, an operations crew distinct from the data management individuals interviewed for this study, managed the data at the point of data collection.

However, there can be crossover between the individuals and teams writing the data processing software and those writing the "mountain-top software" (Moore, Staff Scientist, 2012). While interviewed long after data collection was stabilized, Moore explained that sometimes the hardware and software on the mountain required management. For example, she wrote some of the mountaintop software, and sometimes returned when problems arose or updates were required (Moore, Staff Scientist, 2012). Largely outside of the scope of the study populations, data management software was, and continues to be, modified for data collection.

- Data storage, processing, and transfer

Three interviewees noted the importance of choosing an appropriate institution for the SDSS data center. They agreed the final SDSS choice was appropriate because it is a large institution with complementary and redundant expertise across staff. Hall explained the data center's extensive previous experience with large volumes of physics data made it an excellent

institution to manage SDSS data. A team member at the data center explained that their staff have, "…expertise in dealing with large datasets. So that's one of the connections between particle physics and astronomy, was the so-called data processing, taking…large amounts of data…and turning it into something useful [for] scientists…" (Hall, Staff Scientist, 2013). Despite the data center's experience primarily being in physics, and not specifically in astronomy, the institution had experience managing large datasets, which was the greater SDSS need.

Two interviewees spoke about the expertise surrounding the hardware needed to serve the SDSS data. Both interviewees referenced how SDSS required an external group to perform bulk data distribution. Brown explained they sent SDSS data releases to a team with the expertise to run large volumes of available hardware, "…then everybody else used to download from there, because they had... a lot of space to have, to hold our data, and also they had fast pipes to hook major centers in the world" (Brown, Staff Scientist, 2014). In addition to the hardware and bandwidth available for bulk data movement, SDSS team members relied on the external team because that team held expertise, which the SDSS team members did not necessarily possess. One SDSS team member explained that stable technical experience and expertise are not available just anywhere, "Like we have a just a superb sys admin and a really nice machine room, but it's not the sort of thing you would take a $50 million survey and say, 'We're relying on this infrastructure'" (Watson, Professor, 2015).

Two SDSS team members spoke to the importance of the SDSS software writers' ability to self-teach and learn quickly. They explained that data-intensive astronomy was an actively changing environment, and required individuals who could adapt accordingly. Martin explained what he looks for in job candidates: "Because it's changing so fast and our environment is

cutting edge in many ways… that nobody has the full spectrum [of expertise], but we try to find people who can learn fast and have some background" (Martin, Staff Scientist, 2012). SDSS team members needed to be able to learn quickly and remain up-to-date with ever-adapting technologies.

- Long-term serving and archiving

SDSS did not plan for the long-term serving and archiving of the data in the early days of the project. One reason that they did not plan early on is the team members did not initially possess the long-term archival expertise needed for long-lived data management. Brooks explained, "…whenever we talk about data archives, it always comes up that to properly archive data, you need expertise… Astronomers, like physicists, we tend to believe we can just figure it all out ourselves…. I don't think it crossed our mind that there's people we could just call…" (Brooks, Professor, 2015). The SDSS did work with two university libraries to add long-term data management expertise to the project (Refer back to 4.1.3.1 SDSS data in ethnography). One SDSS team member in a leadership position discussed how collaborating with two university libraries during the SDSS archival phase brought important expertise to the team. He explained that the libraries taught the SDSS team to focus on the "long-term mindset," adding metadata and documentation, migrating to new formats, gathering documents, and the libraries "probably pushed us to more than we would've ourselves" (Robinson, Staff Scientist, 2013). While library expertise on the collaboration benefitted SDSS according to this interviewee, three different SDSS team members noted SDSS continued to lack archival expertise present in the NASA science centers. An SDSS leader noted a NASA science center could have easily archived the SDSS data because of their existing expertise. Another SDSS leader noted the NASA science centers are reliable because the data archiving expertise is located in one place, which

encourages experts to remain in careers that build and exploit their expertise over time. Bell explained that one particular NASA science center is a great example of the confluence of expertise,

> "'Cause they have staff who know how to do all these things…. Yeah, it can even be hard to hire that expertise, because someone who's good at that, what are we gonna do? Tell them to move to Hawaii for three years so you can do this, and then you'll have no job at the end? Whereas, [NASA science center], you know it will still be there in 20 years" (Bell, Professor, 2015).

In addition to noting the expertise available at the NASA science centers, two SDSS team members described how the SDSS team lacked the archival expertise necessary to accommodate long-term data serving and archiving.

4.3.2.2 LSST team expertise

LSST is currently in the construction phase of the project. Operations will likely not begin for another five years after this writing, with the end of data collection ten years further off. While data collection has not begun on the mountaintop, the LSST project data management team has team members at six primary institutions employing various skills to prepare for data collection.

- Data collection

Similar to SDSS, most of the interviewees for this study do not describe their expertise as residing in the data collection stage. No LSST interviewees spoke about data management on the mountain or at the point of data collection. Therefore, no evidence was provided from these study populations for the kinds of expertise needed for LSST data collection.

- Data storage, processing, and transfer

Four interviewees spoke about the expertise necessary to develop LSST data processing and management software. While data collection will not likely begin until 2020 (as of the time of this dissertation writing), the data management teams are heavily invested in developing the infrastructures necessary to support data processing. One SDSS leader explained that it will be important to maintain the expertise of those team members who are currently building the software pipelines. Martinez explained that while specifics cannot be predicted, the team knows LSST software will require updates and maintenance throughout operations, and so it is important to retain the expertise of those who initially built the software. He explained,

> "And the way to understand such a complex system is often related to doing complex simulations. So we cannot let our simulations team go after first light, we'll have to keep them…. And then with data management, too, once you learn how your data actually look like as opposed to what you thought they would look like. You need at least [a] few years to recode your pipelines and to make them good again and then you need to maintain them for a few years" (Martinez, Professor, 2014).

While some kinds of expertise must be retained over the course of the LSST project, some are necessary only at specific points in the project. Martinez continued to explain that the kinds of personnel needed for data management can differ between stages, "… you want slightly more science-y people to define what the project is supposed to deliver. …in construction then you need people who are better at, for example, coding, who are better at programming…the profile changed over the time…" (Martinez, Professor, 2014). While different kinds of expertise prove more important at each LSST stage, past experience on the project remains important in each stage to retain continuity.

Nelson explained that expertise is important for writing LSST software, but so is working in a supportive environment of colleagues. He explained, "I'm not, ya know, formally trained in

software engineering. Everything that I have learned has been through experience…. And so having a community... Having an interaction around the solution I think just produces a better solution, in general" (Nelson, Staff Scientist, 2014). While Nelson was not formally trained in software engineering, he finds that working alongside his teammates allows them all to succeed in their work.

Four interviewees discussed the kinds of technical expertise necessary for LSST data center staff. Staff expertise at the data center is often different than the expertise needed at the universities developing the software pipelines. The data center is where the data will be stored, processed, and made available to end-users. One interviewee at the data center listed off the kinds of experience needed for data management work there: Storage systems, workflow managing, processing of the data, storage and retrieving data to some extent, networking, administration of systems, security of systems (Diaz, Research Programmer, 2015). Given the breadth of expertise and experience needed in the data center, that team requires staff with expertise in computing, software, and networking, as opposed to experts in astronomy domain knowledge. Another data center interviewee explained the data center team members are intended to be more technical experts so the astronomers do not have to gain computer science expertise on top of their domain knowledge. The LSST team members working at the data center seek to provide the technical expertise to enable the LSST team to successfully manage their astronomy data.

- Long-term serving and archiving

As noted in the RQ2 results, interviewees provided very few perspectives for the long-term serving and archiving of LSST data. Three individuals predicted what kind of management might prove necessary in the long-term (refer back to the section on LSST team long-term

serving and archiving). However, no one noted the expertise necessary for long-term data management. Future social science research into LSST should investigate how long-term serving and archiving of the data is being planned, what the expectations are for data management, and what kinds of expertise are predicted to be necessary.

4.3.2.3 SDSS end-users expertise

SDSS data end-users are able to obtain sky survey data once team members make the data available to the public. At a different scale, data end-users also manage their data first through data collection, then data storage, processing and transfer, and finally through the extent to which they offer long-term serving or archiving (refer back to 4.2.2.3 SDSS data end-users). The expertise necessary for these three stages, within the context of data end-users, is expressed below. Jackson outlined a distinction between large sky surveys, and end-user research projects. He explained that in terms of expertise, when he works on an end-user project he requires the data management expertise for all stages of the research project. He explained,

> "But it tends to be that I'm a one-man factory and I do from start to finish. At least for this work, because I made the data...There's too much data and there aren't enough of us to... specialize on particular areas. So, you need to be able to do a bit of everything. So, it tends to be you... So, therefore, it becomes slightly more efficient to be vertical" (Jackson, Staff Scientist, 2012).

Given that individuals or small teams need to possess all of the data management expertise necessary for their work (while the SDSS and LSST team members can rely on specific deep dives in expertise spread over a larger team), it is reasonable that sometimes end-user scientists may require outsourcing for portions of their work.

- Data collection

Five SDSS data end-users discussed the expertise necessary to obtain SDSS data from the collaboration. Three interviewees discussed the importance of knowing SQL as a necessary skillset for easy data retrieval. One interviewee noted that while SQL may not have been an expertise necessary for astronomers in the past, it has now become a critical skill. He explained that learning coding languages and how to use databases are important for asking new research questions, "You're not restricted by the options someone gave you on a pull-down menu, but you can just do anything that you can express in Python" (Bell, Professor, 2015). Another interviewee explained that, given the volume of data he works with, he often must employ his system administrator knowledge, which "was one of the engineering skills, that I learned as a grad student [in astronomy]. Was how to be sys[tem] admin[istrator] for my own machine" (Campbell, Professor, 2015). These interviewees explained that successfully accessing and retrieving data from the SDSS interface could require technical knowledge in managing hardware and software.

- Data storage, processing, and transfer

Three interviewees discussed the importance of having experience writing software to manage SDSS data during analysis. These interviewees mentioned specific programming languages, while also noting the preferred language may change over time. Not only does it take time to learn a new language, but also it may require rewriting existing code an end-user may rely on for multiple projects. A young faculty member explained why he continues to write in the script he first learned in graduate school instead of learning Python or another modern language: "And while in principle I should switch, it's so much work for me that I doubt I will ever do that…. Well, I mean I lose everything. So. You have to really start again" (Rogers, Professor,

2015). These interviewees noted they need software writing expertise to process and analyze their data, and that it can be difficult to find the time to continue learning and adopting new languages as they change in popularity over the course of their careers.

- Long-term serving and archiving

No interviewees discussed the expertise necessary to manage personal research data in the long-term. RQ2 results presented the range of ways data are maintained following the publication of a journal article. Data may be organized on personal computers or institutional servers, and the media may be migrated forward over time, the data may be posted to a website, or simply forgotten. None of the ways end-users discussed data management after publication reflected on skills or expertise. Aside from recognizing the importance of media migration, no activities or kinds of expertise were noted in the long-term management of end-user data.

4.3.3 RQ3 ethnography results

As of this writing, SDSS I and II operations are complete, while the LSST construction phase is ongoing. As the two projects are both sky surveys, and have overlapping leadership, many team members expect the LSST to benefit from lessons learned during SDSS. One important lesson learned by SDSS team members is that software engineering for a sky survey project is an intensive exercise that requires extensive dedicated resources. While the time and labor of many individuals has shown necessary to successfully generate sky survey software infrastructure, astronomy is a typical academic discipline in which rewards and promotions are determined largely by scientific journal article authorship, and not teamwork that results in infrastructure. The SDSS, and now the LSST, must grapple with how to reward staff members who have astronomy PhDs, but cannot spend time writing personal scientific papers while they

build sky survey infrastructures that benefit the discipline as a whole. As LSST seeks a full environment of team members with astronomy domain knowledge and computational skills, the leadership must consider how to reward this workforce in a way to retain the experience and expertise needed for LSST to succeed into the next decade.

4.3.3.1 SDSS expertise in ethnography

SDSS team members learned a number of lessons that individuals have applied to subsequent astronomy surveys. Despite having to learn through trial and error, SDSS is today considered a great success.

Visionary leaders are often cited as critical components of the SDSS data management end-user services (Finkbeiner, 2010). While it is not advised to expect faculty to build software systems in their spare time, a handful of such visionary SDSS team members did just that and enabled the project's success. However, ethnographic work illustrates it was not just these individual visionaries, but a team-wide shared desire for project success that enabled SDSS to persevere through multiple waves of potential budget failures over the years. LSST staff now emphasize that new team members must have a sense of teamwork and a shared drive for the successful work of LSST as a whole.

While they may or may not have realized it at the time, the visionaries and others who dedicated time to building the SDSS data management infrastructure sacrificed much for the good of the project and the domain as a whole. The PhD astronomers who dedicated their time and expertise to infrastructure building were unable to spend that time researching and writing scientific journal articles. For established faculty, the time spent on infrastructure was likely not problematic. However, junior astronomers' careers may have suffered due to spending time on infrastructure instead of publishable scientific research. Since the academic tenure track is

designed to reward journal articles, and that is at odds with the SDSS' need to produce infrastructure, individual careers have suffered for the good of the project.

Study participants brought up the "scientist's dilemma" regularly across the five years of fieldwork for this dissertation. Not new to SDSS or LSST, "the scientist dilemma occurs whenever highly-skilled, scientifically motivated people are needed for support work" (Kleinman et al., 2008, sec. 5). Much technical support work is necessary for sky surveys, however this infrastructure work can derail an individual's chances at a tenure-track faculty position. A limited number of faculty were noted as having "beat" the system; they achieved faculty positions even after spending extensive time on infrastructure projects. However, most individuals who spent time building infrastructure now have staff-level, rather than faculty-level careers. Since their interviews, the two study participants most vocally unhappy with their staff-level positions have since left academia for industry. Luckily, the majority of these staff informants explained that they were happy with staff-level, infrastructure building positions because they enjoyed working with software as much as, or more, than doing basic astronomy research.

While many astronomers may have first realized the reward structure problem with SDSS, the scientist's dilemma still shapes astronomy collaboration involvement. Some will speak to whoever will listen about the improperly placed incentives in infrastructure-building projects like SDSS and LSST (Finkbeiner, 2001). These large collaborations require individuals with domain and software-writing expertise, but career disincentives can prevent projects from finding excellent astronomy software engineers who are also interested in pursuing tenure-track careers.

4.3.3.2 LSST expertise in ethnography

As of 2016, the LSST Data Management team remained in the process of hiring to full capacity. The leaders work strategically, trying to hire well for the large amount of work still necessary and spanning multiple US institutions. The leader at one primary LSST data management institution seeks to create an "environment" of expertise for LSST work, beyond that of merely a group of individuals who can perform data management tasks. The team leader explained a rich environment is necessary to keep operations proceeding smoothly. He continued to explain that even though the LSST project spent the past few years in research and development, they are now in construction and soon astronomers and the general public will expect a system that provides data in a technically mature way. Instead of hiring a set of individuals, his focus is on hiring a sustainable team with large amounts of overlapping experience, to ensure a high-level end-user product.

At another primary LSST data management institution, the team leader also described intentionally hiring a team of experts who overlap and complement one another's expertise, as opposed to hiring individuals. He explained that while he wants to hire the extraordinary kind of person that cannot be duplicated, that would leave the group open to a single point of failure. From his experience working on SDSS, he learned that instead of relying on a small number of extraordinary individuals, the collaboration's knowledge should be spread among team members. The knowledge of products and processes, big and small, should be distributed across many team members as it reduces the potential for failure in the case of team member loss. While continuing to hire extremely bright and experienced team members, multiple branches of the LSST data management team have noted that it is the team, as a whole, that will ensure success of the project, and not extraordinarily intelligent and devoted individuals. While SDSS may have relied

on visionary individuals, LSST has learned from that experience, and instead is trying to generate a workforce that includes a meshwork of teamwork, skills, and expertise.

4.3.4 RQ3 results summary

The RQ3 findings from the documents, interviews, and ethnography in this study complement one another. Each of the three methods revealed the importance of both astronomy domain knowledge and data-intensive, technical experience for successful astronomy sky survey data management. SDSS documents revealed astronomy and data-intensive experience as team traits that can always be improved upon by adding more team members, as well as something that requires the long-term commitment of individuals to retain institutional memory and survey-specific knowledge through the life of the project. LSST documentation discussed the necessity of a distributed team to ensure the range of experience and expertise necessary for project success. LSST documents also discussed the importance of team members encompassing both a depth of software engineering knowledge as well as a breadth in astronomy domain knowledge.

RQ3 interview results confirmed the temporal phases that emerged from the RQ2 document and interview results. Not only do interviewees in this study discuss data management in terms of three distinct temporal stages, the interviewees also discuss data management expertise in terms of these three stages. However, each study population focused on only one or two of the three stages (see Table 24). SDSS team members did not discuss data collection, instead focusing on data storage, processing, and transfer as well as long-term serving and archiving. In comparison, LSST team members only focused on the second of those three stages, while the SDSS data end-users failed to focus on the third stage. While all three populations discussed the experience and expertise necessary for data storage, processing, and transfer, only

the end-users discussed data collection, and only the SDSS team discussed the long-term serving and archiving of data.

	SDSS Team	LSST Team	SDSS Data End-User
Stage 1) Data Collection	-	-	YES
Stage 2) Data Storage, Processing, and Transfer	YES	YES	YES
Stage 3) Long-Term Serving and Archiving	YES	-	-

Table 24 Temporal stages in which experience and expertise were discussed

In terms of the temporal understanding of the experience and expertise necessary to develop and use sky survey data, the initial responsibility is that of the sky survey team. The SDSS and LSST both have diversified workforces. On both projects, the data collection staff on the mountain is distinct from the multiple software processing teams located at universities, who are also distinct from the data storage and transfer teams located at national laboratories. The distinction between workforces "on the mountain" and those working at universities processing data is likely a reason why the SDSS and LSST team interviewees did not discuss data collection; the two team study populations focused on experts in the life cycle after data collection. Alternatively, end-user data collection was discussed because it is a necessary early step in the small- and medium-sized projects that employ SDSS data.

While LSST is still early in the project and leaders have not yet considered the workforce responsible for long-term serving and archiving, SDSS has employed multiple workforces in that role. As of this writing, the SDSS workforce choice for long-term data management is a university astronomy department. LSST arguably has time to determine the appropriate workforce, and will likely use lessons learned by SDSS to make the determination. SDSS data end-users were shown to be less concerned with the management of their end-user data products

in the RQ2 results. This lack of concern explains why the end-users did not focus on expressing long-term serving and archiving experience and expertise.

The RQ3 ethnography findings add further dimension to the documentation and interview findings. The ethnography findings revealed the SDSS team initially relied on visionary leaders for success, but learned that teamwork among a diverse collaboration proved more sustainable. LSST collaboration members learned this lesson in expertise sustainability from the SDSS project and described wanting to build a full "environment" of experts for the project. However, both projects are faced with problems ensuring successful career paths in academia for staff who focus time and effort on building infrastructure for the sky surveys.

4.4 RQ4 Results: How Does Data Management Differ Between Populations?

As described in the Methods chapter, the interview population sample was developed to enable cross-comparisons between population demographics. Understanding participant perspectives across demographic dimensions reveals how data management differs between populations. Seven demographic dimensions were chosen because they were hypothesized to influence data management. Variety was ensured through interviewee institutional affiliation, career stage, level of astronomy education, current workforce, role in SDSS and LSST, and participation in theoretical research. Interviews were conducted over a five-year period. The seven demographic parameters are recapped in Table 25; refer back to the Methods chapter for operationalization of the demographic variables.

Demographic Parameter	Variables
Primary Institutional Affiliation	University Research Institute Data Center National Laboratory
Year of Interview	2011 2012 2013 2014 2015
Career Stage	Graduate Student Post-Doc Faculty Professor Faculty Emeritus/Retired Staff Programmer Staff Scientist Non-scientific staff
Level of Astronomy Education	No Higher Education Some Astronomy Graduate Work Astronomy PhD Other Graduate Degree
Current Workforce	Astronomer Computational Astronomer Computer Scientist Other (non-research)
Role in SDSS and LSST	SDSS Team LSST Team Both Neither
Theorist?	Yes No

Table 25 Demographic parameters used in study population sampling design

Generally speaking, data management was described in more ways, but with fewer demographic patterns, than had been hypothesized. The most prominent finding for how data management differs between populations is that overall, astronomy research data management does *not* divide decisively along most demographic parameters. However, the following subsections describe the patterns that did emerge within each demographic parameter in the sampling design.

4.4.1 Primary institutional affiliation

Interviewee responses are grouped by the primary institutional affiliation of the interviewee. The majority of interviewees (nearly 80%) were affiliated with a university. More than 20% of interviewees were affiliated primarily with a research institute, data center, or national laboratory (refer back to Table 6).

Institutional affiliation is a factor in determining how interviewees discussed data. Refer back to Table 22 for a breakdown of the ways data were described. University employees and research institute staff were highly likely to discuss data in terms of content, the product of data processing. Alternatively, no one from a data center or national laboratory described data based on its content as images, spectra, and catalogs. Instead, national laboratory staff were most likely to describe data in terms of level of processing. These findings confirm that those who are most likely to be working on scientific research are more likely to think of data as scientific content, whereas those who are most likely to be working on building data infrastructures for others to use are more focused on data as information that is processed through those infrastructures. Individuals who use data for research thus consider data in terms of its resultant scientific nature and less its nature as developing information; indeed, only individuals at a university described data in terms of its evidentiary value. Individuals who are not using data for immediate scientific research instead focus on the process of preparing data. These findings align with types of careers, and therefore the way data are used and managed, in each institution.

These results demonstrate the amount and kind of interaction individuals had with data influenced the way that they spoke about data. Individuals working at Data Centers and National Laboratories were more likely to work with data on a daily basis, often for building sky survey infrastructures, and thus were more likely to describe data in terms of its state or level of data

processing. These interviewees outside universities were not faculty members and were less likely to be concerned, for example, with the content (images, spectra, and catalogs), or the analytical uses of the data for publishing journal articles. Instead, those working infrastructures were most likely to refer to data in a manner resonating with the interactions they had with data, generally through pipeline development and data processing. Furthermore, LSST interviewees at data centers *only* described data in terms of the level of processing. Thus, primary institutional affiliation proved a distinguishing factor between data management perspectives. However, the explanation relates more to the types of careers interviewees at each kind of institution held, rather than to the type of institution per se. The institutions point more to the distinctions between interviewees affiliated with tenure-track research careers, than those who build infrastructures and do not rely on research publications for career advancement.

4.4.2 Year of interview

Interviewees are grouped by the year the interview was conducted. Exactly half (n=40) of the interviews were conducted in 2015. The other forty interviews were conducted at a rate of about ten interviews each year from 2011-2014 (refer back to Table 7). No patterns emerged to differentiate the ways interviewees described data based on the year of the interview. Instead, data and data management were described differently based on an individuals' type of data work, and not the year they were asked to describe their data work. A strong pattern may not have emerged because there were three different interview protocols, and they were not evenly used over the five years of the study. For example, more SDSS team members were interviewed early in the study, while LSST team members were only interviewed in 2014 and 2015. SDSS data end-users were largely interviewed in sets either early or later in the study duration. More LSST team members were interviewed in 2015 (during LSST construction) than at any other time. This

may be a reason why data as processing was discussed considerably more in 2015 than in any other year. The year of the interview was not a factor in how data were interpreted, but instead served as a tool to recognize the extent to which active LSST team members understood data in terms of processing.

4.4.3 Career stage

Interviewees are organized by their career stage at the time of the interview. Approximately 40% of interviewees were faculty, approximately 40% were staff, and the remaining nearly 20% of interviewees were graduate students or post-doctoral researchers (refer back to Table 8). Interviewees and ethnographic participants across career stages explained that students and post-docs are most likely to spend time manipulating, analyzing, and managing data. Faculty generally have less time to interact regularly with data, and instead coordinate research projects with younger scholars who work with the data to produce initial results. According to interviews and ethnography, students were much more likely to perform data calibration, management, and analysis regularly. Accordingly, faculty members were most likely to note that they were "behind" in learning the latest scientific software languages. Aside from a few who have made concerted efforts to learn new languages, most later career astronomers described using the programming language they learned in graduate school over their entire careers. Only later career staff scientists and emeritus faculty described data in terms of its evidentiary value. Younger scholars tended to work directly with data, while later scholars tended to coordinate research, which may explain why only late career interviewees discussed data theoretically, in terms of evidentiary value.

Faculty had the broadest number of ways of describing data management. More specifically, those interviewees whose careers do not rely on writing scientific papers were more

likely to describe data as a process. Indeed, staff scientists were most likely to describe data in terms of its state than any other way. Interviewees actively engaged in academic research leading to journal articles were more likely to describe data as astronomical products: images, spectra, and catalogs. Thus, the extent to which an interviewee regularly interacts with data, and whether that is in a context of "doing science" or in managing data for others, influenced the way data management was discussed.

Only later career professors and staff described data based on format, as digital information. This may be because these individuals began their careers using analog data, and thus make the distinction when discussing astronomy data. Additionally, there was a clear split between those who described data in terms of source or origin. Faculty never described data based on its source (i.e., the SDSS telescope or the MAST archive). Instead, this language was used by early career individuals (students and post docs) or staff working on sky survey teams. These differences show that early and late career individuals consider data differently in terms of format and origin.

4.4.4 Level of astronomy education

Interviewees are grouped according to their level of astronomy education. Astronomy education here refers to a PhD in an astronomy-related field, which includes astronomy, astrophysics, or physics. While nearly 40% of the interviewees held staff positions, more than 80% of the interviewees held astronomy-related PhDs (Refer back to Table 9). Interviewees with astronomy PhD degrees described data in many ways, though more than half described data in one of only two ways: either by its state (level of data processing) or by the content of the data (images, spectra, and catalogs). These two manners were also the most common ways data were described over all.

Those with computer science or other higher degrees never described data in terms of astronomy content (images, spectra, and catalogs) and never described data in terms of its scientific research use (for example, in relationship to a journal article). Indeed, only two interviewees of the 15 who lacked a PhD in an astronomy-related field discussed data in terms of its astronomical content.

4.4.5 Current workforce

Interviewee responses are clustered by the kind of career the interviewee held at the time of the interview (refer back to Table 10). There are no evident patterns in the way interviewees described data when organized by current workforce. Similar to the other demographic dimensions, the two most common ways to describe data management were consistently the most common across all four workforces. The state of the data (level of data processing) and the content of the data (images, spectra, and catalogs) remain the most common ways to describe data management, regardless of current workforce. The type of institution for which the interviewee worked, described earlier, provides a clearer distinction between perspectives than does the current workforce.

4.4.6 Role in SDSS and LSST

The ways interviewees described astronomy data are grouped by whether the interviewee was a member of the SDSS team, the LSST team, both teams, or neither team (refer back to Table 11). Team membership (astronomer, computational astronomer, computer scientist, and other) is operationalized in the Methods chapter. Surprisingly, few patterns emerged in terms of how data management was described by team membership. Computational astronomers were more likely to describe data in terms of processing than any other way. Computer scientists never

described data in terms of its use for science or its evidentiary value. These two patterns were predictable based on the kinds of data work performed in each role.

As across the other demographic variables, state (level of data processing) and content (images, spectra, and catalogs) were the most common ways data were described across all team affiliation categories. SDSS-only team members were slightly more likely to refer to data in terms of the source of the data (generally by referring to data as any information from the SDSS telescope and instruments). SDSS end-users were most likely to discuss data based on content rather than state.

4.4.7 Theorists

The interviewee responses regarding the definition of data are clustered according to whether or not an interviewee has been involved in theoretical research. Since the interview sample included individuals who built or used sky survey data, it was less likely that they would identify as theorists. Only about 10% of the interviewees are considered theorists for the purpose of this study (refer back to Table 12). Interviewees affiliated with theoretical research were very likely to describe data in terms of the state (level of data processing) of the data, which is consistent with non-theorists and across the other demographics already described. However, a larger percentage of theorists described data in terms of its digital medium than other demographic categories. Surprisingly, only one of the nine theorists described data in terms of its evidentiary value.

4.4.8 Summary

The interview sample includes an array of interviewees across seven different demographic dimensions. Surprisingly, most of these dimensions did not produce strongly

discernable distinctions in the ways interviewees described data management. The primary institutional affiliation of the interviewee proved to be the most useful way to distinguish interviewee perspectives, largely because it drew out the distinction between faculty and staff. However, examination of career stage unearthed the biggest distinctions between the amount and type of an individual's direct interaction with data. Finally, while interviewees with computer sciences degrees and astronomy degrees often described data in terms of its state (level of processing), astronomy PhDs were more likely to describe data in terms of its content (images, spectra, and catalogs), while computer science degree holders described data in terms of its origin (specific astronomical instrument) or digital nature.

Document analysis and ethnography confirmed the strong interview findings of these distinctions between interviewee demographic perspectives. For example, documents confirmed the types of tasks that experts with different educational backgrounds, and at different institutions, undertook. Ethnography confirmed the extent to which students and post-docs directly managed research data, as opposed to faculty who often worked on managerial tasks. Taken together, the demographic distinctions clearly expressed through the interviewee responses are confirmed and explained in each section above through contextual information provided by document analysis and ethnography.

5 Discussion

The Sloan Digital Sky Survey (SDSS) and the Large Synoptic Survey Telescope (LSST) are two large, innovative astronomy sky surveys. The SDSS I and II completed operations in 2008, while LSST is predicted to begin data collection in 2020. The two projects were conceived more than a decade apart and LSST endeavors to proceed with an even greater scale of data collection, data volume, and necessary expertise. The ultimate goal of each collaboration is to advance scientific understanding by generating and making available astronomy data. The data are then retrieved by end-users for scientific analysis, ultimately benefitting the field as a whole.

The Discussion ultimately reveals that SDSS and LSST stakeholders define data through local, limited perspectives. Stakeholder perspectives on what it means to manage data, and the kind of expertise needed for data management are each colored by these diverging perspectives of what data are. Data management best practices for ground-based, astronomy sky surveys have not fully developed because individual stakeholders necessarily have these limited perspectives on what is involved in managing data.

The Conclusion accepts that astronomy stakeholders have local, limited perspectives on data, data management, and data management expertise. Accepting those diverse perspectives, the Conclusion chapter looks to the future, addressing what can be done to develop and strengthen the ground-based astronomy sky survey workforces and other infrastructures necessary to manage data for the full research data life cycle.

5.1 Summary of Results

This dissertation is the result of a five-year qualitative study of the data practices of sky survey astronomers. The central question is: How does data management differ between

stakeholders, and to what end? To address how data management differs, the study first examined how the populations understand what astronomy research data are, then what astronomy data management entails, and finally what experience and expertise are applied to the management of astronomy data. Progressing through these successive research questions, the study sheds light on how and why data management differs between populations.

A corpus of project documents, a diverse interview set, and weeks of ethnographic field notes were collected and iteratively analyzed. Specifically, 80 semi-structured interviews, 21 workweeks of ethnography, and extensive document analysis were conducted. Data were assembled through qualitative coding software and analyzed to address each research question. The interviewee dataset matrix was developed to ensure participant breadth across seven characteristics (refer back to 3.2.2 Semi-structured interviews). These characteristics were Primary Affiliation, Year of Interview, Career Stage, Level of Astronomy Education, Current Workforce, Role in SDSS and LSST, and whether the stakeholder was a Theorist.

Astronomy data stakeholder perspectives were found to differ regarding what data are, which influenced stakeholder understandings of data management. The remainder of this subsection advances through the four progressive research questions, ultimately revealing that data management differs based on stakeholder professional role, career stage, and level of astronomy education.

5.1.1 What are astronomy research data?

Stakeholders in this dissertation study describe SDSS and LSST data as either a process or a product. Data descriptions were tied to the ways individuals interacted with data. The distinction between process and product emerged through cross-analysis of the three study populations and the three research methods. Data were described across a temporal spectrum, for

example as information being collected, collected information, information being processed, processed information, information being analyzed, or analyzed information. This empirical confirmation that different SDSS and LSST stakeholders hold differing interpretations of what SDSS and LSST data are can serve as a critical communication tool in facilitating cross-stakeholder discussions by acknowledging the differing perspectives of what data management entails.

5.1.2 What is data management in astronomy?

As reflected in Figure 7, sky survey data management was described chronologically, beginning with data management work conducted by the sky survey team, leading up to and data release, and beyond. Data management work is then conducted by scientific data end-users. Sky survey teams are responsible for the way the sky survey data are managed in the long-term, and sky survey data end-users are responsible for any long-term management of their resultant data products.

5.1.3 What expertise is applied to the management of data?

Documents, interviews, and ethnographic observations revealed stakeholder perspectives on the expertise necessary for data management, which also were expressed by study participants with the same temporal stages that emerged in descriptions of data management (Figure 7). The expertise necessary to manage SDSS and LSST data was described as a mix of astronomy domain knowledge and computational skillsets. The necessary experiences and expertise were described in relation to the temporal research life cycle period that the skills and knowledge were deployed. Beyond individuals possessing experience and expertise, the SDSS and LSST team members highlighted the importance of developing collaborative teams with overlapping and

complementary knowledgebases and skillsets. The importance of in-project experience and expertise retention throughout the full research life cycle was stressed also. SDSS data end-users usually lacked the resources to compile a stratified team and instead must rely on individual skillsets for success in their research projects, albeit at a smaller scale.

5.1.4 How does data management differ between populations?

Stakeholder perspectives on data management differ between populations based on professional role, career stage, and level of astronomy education. The primary institutional affiliation of the interviewee was the most distinguishing demographic, which revealed differing interviewee perspectives based on professional role. Individuals working at a university or research center were more likely to discuss data in terms of its content, which is a product of data processing that can be used for scientific research. They were more likely to be reliant on publishing scientific research papers for career advancement, and they described data management based on their relationships to data as information deployed for scientific research. Alternatively, data center and national laboratory staff were much less likely to describe data in terms of content, and were also less likely to have tenure-track-seeking career paths. Instead, these individuals at national laboratories were much more likely to discuss data as information that requires processing. The description of data as information requiring processing aligns with SDSS and LSST communities, because many SDSS and LSST processing pipelines staff are employed at national laboratories. Data management also varies between populations based on career-stage. Young tenure-track academics rarely participated in long-term infrastructure building. Young scholars instead focused on collecting and publishing short-term research results to further their careers. Very senior academics also rarely participated in these long-term projects early on, because they could fail to see new data by their career ends. As a consequence, much

infrastructure work was conducted by mid-career, tenure-track academics and staff members of all professional stages whose careers are not dependent on the "publish or perish" mantra. Finally, data management differs based on the level of astronomy education the stakeholder has earned. The extent to which a stakeholder has computer science expertise and astronomy domain knowledge determined the stratified role they played in the sky survey.

5.2 Discussion of Findings

This dissertation focused on examining SDSS and LSST data management infrastructures. These knowledge infrastructures were analyzed through the study's research questions in terms of the data, data management practices, and workforces associated with SDSS and LSST. This study developed as a unique piece of inquiry from the UCLA Center for Knowledge Infrastructures (CKI). The author developed the specific research aims and questions, and the findings presented here are a distinct component of the larger UCLA CKI investigations. This dissertation is the result of the author's iterative analysis, firmly planted in the tradition of Grounded Theory (Glaser & Strauss, 1967). To reduce the potential for biased interpretations, the themes discussed in this dissertation emerged through iterative reading and coding of the documents, interview transcripts, and ethnographic field notes. Interviews, field notes, and documents were coded iteratively using the UCLA CKI codebook, throughout the course of data collection, culminating in dedicated, immersive coding in Fall 2015. By repetitive reading, analyzing, and coding, trends emerged from the data. For research questions one, two, and three (RQ1-RQ3), one code was selected and closely analyzed. RQ4 was analyzed based on the accumulated findings from the first three research questions and according to the seven participant demographic variables used in this study. The research questions for this study are as follows:

1. What are astronomy research data?
2. What is data management in astronomy?
3. What expertise is applied to the management of data?
4. How does data management differ between populations?

This study was designed ultimately to understand RQ4: How does data management differ between populations? To ask this question, the first three RQs were employed to deconstruct the variables and to reveal the underlying assumptions present in the research question. The three questions built on one another to answer ultimately how data management diverges between populations.

The SDSS and LSST projects both exhibit complex knowledge infrastructures that emerged from decades of project development and hundreds of collaborators. The term knowledge infrastructures is used in this study to refer to "robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds" (Edwards, 2010, p. 17). The SDSS and LSST each arose from within existing infrastructures while shaping simultaneously these existing and new infrastructures. Each project has, or is, constructing a mirror, telescope, and data collection site. The mountaintop facilities can be considered ecologies of infrastructures in their own right (Star & Ruhleder, 1996). At the same time, these two projects fit within the existing larger social, political, and technical infrastructures at hand for scientific investigation as a whole. These infrastructures are found at multiple overlapping scales or collaborative rhythms (Jackson et al., 2011, p. 247). Study participants are affiliated with universities, data centers, research institutes, and national laboratories; each institution both exists within and is its own knowledge infrastructure.

While distinct projects, each at different temporal stages, the SDSS and LSST infrastructures are interconnected in multiple ways. The first connection is through the workforce. More than 20% of this study's interviewee population has been team members of both the SDSS and LSST (see Table 4). Many SDSS leaders, especially those who were students and post-docs during the period of SDSS data collection, now hold leadership positions within LSST: "A lot of the people who were involved in LSST were SDSS people, a lot of the institutions for example are similar…" (Hernandez, Post-Doc, 2012). The workforce carry-over and the international trust placed on SDSS data are reasons many of the same policies and practices were transferred from the successful SDSS project to LSST.

The SDSS and LSST projects also overlap through data. As noted in section 4.2.3.2 LSST data management in ethnography, SDSS data are used in LSST development. The LSST data center has copies of some subsets of the SDSS data. The center holds 3.5 terabytes of "SDSS" data and 11 terabytes of "Stripe82" data (the SDSS data from a specific portion of the night sky). LSST team members use the SDSS datasets, alongside simulated data developed by the LSST team, to test new calibrations and pipeline processes during LSST data management software construction. The SDSS and LSST projects are intricately connected to one another as both individuals and datasets pass from one project to another. The LSST has chosen largely to follow the path of SDSS in terms of the data collection and release plans, varying in scale but not quality.

While infrastructures and scientific technologies are constantly evolving (Bell et al., 2009; Borgman, 2007, 2015; Edwards et al., 2013; Van de Sompel, 2013), infrastructures emerge from within an existing context (Bowker, 2005; Ribes & Jackson, 2013). LSST would not be the project it is today without the existence and success of the SDSS. The value of the SDSS data

evolves beyond the SDSS itself, through its use in the next generation of sky survey development. SDSS data are used in LSST development generating a use case beyond that of the traditional end-user.

5.2.1 Astronomy research data

To understand how data management differs between stakeholders, this study first investigated how stakeholders understand data. This study is an empirical examination of narrowly defined communities to understand their perceptions of data; it does not attempt to provide a definition of data that can be all things to all people. Instead, this dissertation confirms that similar to 'beauty being in the eye of the beholder,' stakeholders perceive data differently based on their institutional affiliation, career stage, and level of astronomy-related education. Given the different stakeholder perspectives in this study, SDSS and LSST data can be understood as multiple sides of a faceted diamond.

SDSS and LSST stakeholders described and defined data as a process or product, contingent upon the point at which the stakeholder works along the research data life cycle. Depending on how a study stakeholder interacts with relevant infrastructure, collaboration, and dataset, their perspective on the importance and priorities of the SDSS and LSST data differ. The way data are understood in these sky surveys is locally contingent (boyd & Crawford, 2012; Gitelman & Jackson, 2013).

SDSS and LSST stakeholders' differing backgrounds and experiences shaped their perspectives on data, data management, and data management expertise. Computer science experts more often discussed data in terms of bits, because that meaning is consonant with their experiences. Interpreting data as bits also reflects a computer scientist's career, as discussing images, spectra, and catalogs would not support career advancement in the field of computer

science. This understanding of data is very different from how SDSS end-users described data as images, spectra, and catalogs, or as information used for scientific research. These discrete meanings of data resonate with the prior experiences, current work, and future uses of data for each stakeholder.

SDSS and LSST stakeholders also often differed according to their role in the research data life cycle (refer back to 4.1.4 RQ1 results summary). The categorization emerged because of the distributed nature of the teams and the diverse necessary expertise applicable in these large sky surveys. As noted in the Results (refer back to 4.2.1.2 LSST data management in documents), the LSST documentation often referred to data based on the amount and kind of data management activities necessary to produce and prepare the data for use. For example, whether or not stakeholders believe LSST data exist (refer back to 4.1.3.2 LSST data in ethnography) is reflected by data management roles in the project. Interviewees who engaged in simulation activities for the data management team believe LSST data exist within the simulations. Diaz believes simulated data are "real data" even though they are not "from the sky" (Diaz, Research Programmer, 2015). Alternatively, a future LSST end-user who is not involved with building of the LSST simulations and data management system had the opposite perspective. She does not believe LSST data exist yet and said, "There isn't data yet, it's all simulation…. I don't believe in the fake universe" (Evans, Post-Doc, 2015). Diaz is a programmer developing the simulations via hands-on work for the LSST data management team; Evans is a researcher who hopes to one-day use LSST data. For the potential future end-user, LSST data do not exist yet, because there is no data for her to conduct her scientific research. For the LSST employed researcher on the data management team, simulation data are real LSST data, because he is currently using that data for the LSST project. This example illustrates the

dissertation's finding that stakeholder perceptions of data are determined by their roles and interactions with data in the project. SDSS and LSST stakeholders include distributed and specialized workforces who hold diverging perspectives on data.

Data definitions are locally contingent and should only be re-deployed in other contexts carefully. This dissertation's results confirm that even highly regarded, broad data definitions are far from universal (Borgman, 2015; Consultative Committee for Space Data Systems, 2012; Fox & Harris, 2013; National Research Council, 1999; Renear et al., 2010). These findings reaffirm that data exist within a contextual setting (Latour, 1987, 1993; Latour & Woolgar, 1986; Rijcke & Beaulieu, 2014). This dissertation's demonstration of stakeholder perspectives varying across process and product can serve as a starting point for cross-disciplinary conversations when a shared understanding of astronomy data remains illusory (Borgman, 2012a; Consultative Committee for Space Data Systems, 2002, 2012; Renear et al., 2010; Rosenberg, 2013).

5.2.2 Astronomy data management

Data management is a major undertaking in data-intensive sciences, including the SDSS and LSST projects. SDSS pipeline development and implementation was estimated at 25% of project personnel time and resource expenses (J. Gray, Slutz, et al., 2002, p. 2). Years later, the LSST budget dictates more than half of operations costs will go toward data management (National Science Foundation, 2014b). Previous research has also found that data-intensive projects like sky surveys usually devote a huge percentage of project time and resources to data management (Borne, 2013; Hey et al., 2009a; Szalay, 2011). The popular media often repeats the idea that 50%-80% of a data scientist's work is spent cleaning data (Lohr, 2014). Given the massive financial and labor costs devoted to the processing and management of data in data-driven sciences, it is unsurprising that many SDSS and LSST stakeholders discuss data based on

degree of processing. The SDSS and LSST documents and interviews confirm that data processing and management is a large percentage of the time and funding spent on the sky survey projects, even increasing over time.

The results for each research question revealed temporal stages to research data, data management, and research data management expertise. However, the emergent stages regarding data are different than the temporal stages relative to data *management* and data *management expertise*. A comparison of the temporal stages that emerged from each RQ in this dissertation is presented in Table 26, and detailed throughout the Results.

	RQ1) Astronomy Research Data	RQ2) Data Management in Astronomy	RQ3) Expertise Applied to Data Management in Astronomy
SDSS/LSST Stage 1	Data Collection	Proposal, R&D; Construction; Data Collection (Operations)	Data Collection
SDSS/LSST Stage 2	Data Processing	Data Cleaning, Processing; Data Documentation, Release	Data Storage, Processing, and Transfer
SDSS/LSST Stage 3	Data Analysis	Long-Term Data Management	Long-Term Serving and Archiving
SDSS Data End-User Stage 1	Data Collection	Proposal, Planning; Data Access, Retrieval	Data Collection
SDSS Data End-User Stage 2	Data Processing	Data Cleaning, Processing; Analysis, Summary, Interpretation; Scientific Publication	Data Storage, Processing, and Transfer
SDSS Data End-User Stage 3	Data Analysis	Data Documentation, Release; Long-Term Data Management	Long-Term Serving and Archiving

Table 26 Comparison of temporal stages between research questions

While not conveyed verbatim by study participants as a "life cycle," the documents, interviews, and ethnographic observations each revealed temporal ways stakeholders understood data, data management, and expertise. The distinction between the RQ1 and RQ2 columns in

Table 26 demonstrates stakeholders in this study understand the astronomy research data life cycle and the astronomy research data *management* life cycles as occurring in different temporal stages. While the data life cycle was considered complete after analysis, stakeholders articulated the importance of data management beyond an initial analytical need.

Stakeholders also expressed a distinction between the temporal nature of data and the temporal nature of data management. Data are discussed as a completed product or as an ongoing process. When stakeholders thought of data, data were considered information for an immediate concern. When asked to consider data management, stakeholders expressed data as information for immediate and also potential future concerns. These findings demonstrate that the language used for discussing research data has temporal implications for data management. For stakeholders to consider data use beyond the immediate need, appropriate language must indicate the importance and potential future uses of data. The way stakeholders defined data directly shaped their perceptions for what could or should be involved in data management.

The distinction is essential, because many still conflate research data and research data *management* life cycles. A number of life cycle models have been published; some provide a complicated, universal scientific research data life cycle (Higgins, 2008), while others try to reflect only a small research community (Wallis et al., 2008). Each of these models reflect a starting point when research ideas are conceived, and most point to an "indefinite end" in which data may be reused for perpetual analysis, re-starting the life cycle (Rots et al., 2002, p. 172). Ultimately, each data management life cycle reflects the concerns the authors found important.

The DCC Curation Lifecycle Model describes itself as a "high-level overview of the stages required for successful curation and preservation of data…" (Higgins, 2008, p. 137). According to the original publication, the model is intended as only a data management life

cycle. However, the DCC Lifecycle is often re-deployed for many other aims, including as a full research life cycle, a data life cycle, and the original data management life cycle. Wallis et al.'s "Life cycle of CENS data" model from the same year is also only intended to reflect the *data* life cycle of a specific community (Wallis et al., 2008). Subsequent uses of these specific models, however, often fail to recognize the difference between a data life cycle and a data management life cycle (Pepe, Mayernik, Borgman, & Van de Sompel, 2009). The conflation of information existence and the tasks necessary to manage that information can derail collaborative efforts. The Swiss University Conference (SUC) presents "Data Life-Cycle steps and corresponding roles," which allows the reader to recognize that a data life cycle is not the same as a data management life cycle (Blumer & Burgi, 2015). The Interagency Working Group on Digital Data (IWGDD) also clearly understood the distinction between a data (product) life cycle and a data management (process) life cycle (2009). In the IWGDD life cycle (Figure 9), different kinds of temporal stages are indicated through the use of multiple rings. One ring (Document, Organize, Protect, Access) indicates the stage of "Data Management Functions" (2009). The other ring indicates the data life cycle (Plan, Create, Keep, Disposition). While officially titled as a data life cycle model, the model incorporates both "Life Cycle Functions for Digital Data" and "Data Management Functions for Scientific and Technical Data" (2009, pp. B3-5). The stakeholders in this dissertation study understood data and data management with distinct temporal stages, just as the IWGDD discovered.

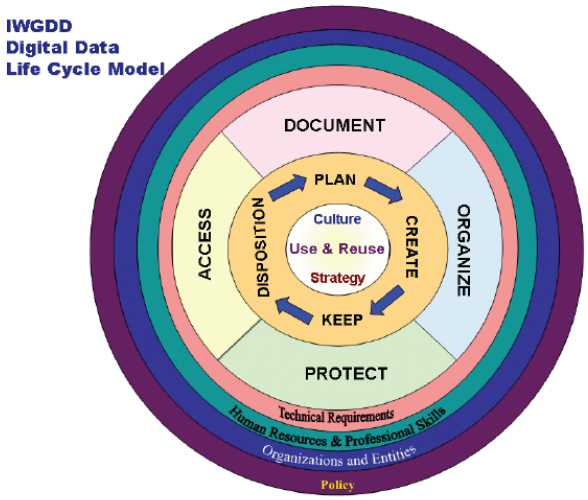


Figure 9 IWGDD Digital Data Life Cycle Model (2009, p. B3)

The term life cycle implies that the accompanying model covers the full "life" of the data in question. The distinction between data and data *management* life cycles is important because each life cycle is necessarily generated by stakeholder(s) who focus the model on the components they find most important – often forsaking other parts of the "full" life cycle. Given divergent perspectives, data management for potential future reuse could be forgotten or identified as unimportant in models built for a different purpose. Choudhury et al. (2013; 2013) define data management as encompassing discrete tasks including storage, archiving, preservation, and curation. This model developed for and by library staff is necessarily limited. Compared to the temporal stages in this dissertation, the Choudhury, et al. model does not include earlier components of data management, such as data collection and processing. Figure 2 only focuses on the role of library staff, as understood within a context at Johns Hopkins University. The four components of data management in that model serve as a "close-up" of only the "Stage 3" components of the temporal stages illustrated in this dissertation (Table 26). The

stakeholders' perspectives strongly shape the development of the life cycle models. This dissertation examined the perspectives of the sky survey stakeholders, primarily focusing on the domain scientists. The Choudhury, et al. model instead focuses on the tasks of the libraries. Still others instead focus on the astronomy curation work performed by data center staff, splitting discussion and acknowledgement of these tasks by workforce (Norris et al., 2006, p. 4). Helpful for their immediate audiences, these segmented models are reminders that multiple kinds of workforces may be charged with discrete components of scientific data management, so a single individual may not be aware of the full life cycle. As data management work and expertise increasingly becomes stratified in data-intensive "big data" projects, more work is necessary to reconcile disparate perspectives. Generating a definition of data management that encompasses the full longevity of scientific work remains tedious, because data management practices differ between disciplines, stakeholders, and across the life of the data.

At the time of writing, the data collected by the SDSS Phase I and II collaboration remain highly valuable for scientific research, and the LSST data are predicted to be at least as highly valued. Taken together, SDSS data generated by all four project phases have been used in over 6500 peer-reviewed journal articles, which have been cited more than 300,000 times (ADS, 2016; SDSS Collaboration, 2016). In 2015, including only the English language portions, the SDSS website had more than 63 million hits (SDSS Collaboration, 2014). One interviewee clearly explained the importance of the SDSS data: "So I use Sloan as a finding chart. … So I use it every day" (Wilson, Graduate Student, 2011). New journal articles continue to be published utilizing the multiple SDSS data releases. The "overwhelming majority" of science papers employing SDSS data have been written by end-users unaffiliated with the formal project (SDSS Collaboration, 2016).

Despite the extensive, daily use of SDSS data by astronomers worldwide, the SDSS collaboration is no different than most scientific projects. It is funded through a series of successive short-term grants, with specific beginning and end dates. SDSS collaborators believe that the SDSS data will remain important for decades, or possibly hundreds of years (Margon, 1998; Yanny, 2011). The close of funding for LSST is more than a decade away, although the LSST collaboration expects the data will be scientifically useful for far longer (2014, NSF Proposal). SDSS data end-users' long-term management of data products range from neglect to long-term storage and serving services. The heterogeneous extent to which individual end-users maintain their data confirms the indefinite and often unpredictable "end" to scientific research data (Rots et al., 2002).

At each stage of the research life cycle, collaborations must prioritize different parts of the larger project to realize short and medium-term goals. To ensure future access however, the long-term view also warrants consideration, even at the early stages of the research life cycle. Ribes and Finholt (2009) employ "The Long Now" metaphor to reflect on how projects must manage competing priorities for the short-, medium-, and long-term benefit of the project. The SDSS and LSST are sky surveys with multi-decade histories, including expectations for the data to remain valuable for one or more decades into the future (N. Gray et al., 2012); "The Long Now" is a considerable period for these astronomy sky surveys. A particular difficulty for long-term projects is that while funding is provided for shorter timespans, the data are expected to be scientifically relevant for decades. The SDSS and LSST are among scientific data projects that are "…intended to persist for decades, but whose financial support comes in increments of years" (Ribes & Finholt, 2009, p. 383). Funding is necessary to continue serving the SDSS and LSST data because data accessibility requires technological and human infrastructure, which are

both “precondition[s] to meaningful access and reuse…” (Berman & Cerf, 2013, p. 341; Edwards et al., 2013; Hine, 2006). The temporal misalignment of funding structures and funding needs is an example of differences in collaborative rhythms (Jackson et al., 2010, 2011; Steinhardt & Jackson, 2014).

In 2016, an SDSS team member and leader explained that the current SDSS I and II data management objective is to provide sufficient data management continuity to ensure SDSS data usability for an additional 15 years. Instead of promising naively to maintain the data forever, the team believes this finite timeline will permit other astronomy infrastructures to grow and additional telescopes to begin operations. By the end of that 15-year period, SDSS team members expect the SDSS dataset could then be integrated into a newer, larger astronomy project. For example, by 2030 or 2032, LSST infrastructures will likely be so strong that ingesting the full final SDSS Data Release would be a trivial exercise. However, continuous care for the SDSS data over the intervening 15 years requires committed resources and is not a trivial exercise (Borgman, 2015; Bowker, 2005; N. Gray et al., 2012; Parsons & Berman, 2013; Ray, 2014a). The data will require a commitment of sustained funding, workforce expertise, and physical infrastructures; in fact, this long-term data management to enable future use can be considered a “grand challenge” (Ray, 2014a, p. 2). In effect, the data will require knowledge infrastructures be developed with the short, medium, and long-term management needs of the data in mind. While enabling scientific use of the SDSS data consistently over the long-term is a data management goal, the project struggles to retain that kind of continuity amid funding models providing only short- and medium-term options. While these stakeholders would prefer to be able to generate long-term infrastructures, funding patterns and the regular lifetimes of

physical and human infrastructures prevent long-lived knowledge infrastructures for scientific data.

Some stakeholders believe that long-term data management is an integral component to the data life cycle; others are indifferent to managing data beyond its primary use. The data distinction that emerged from this study centers on data as process versus data as product. Stakeholders viewing data as a product, and the research life cycle as a data life cycle, may not focus on potential future uses. In contrast, stakeholders who view data as a process, and the research life cycle in terms of data management, may prioritize long-term efforts. Both perspectives are accurate and have meaning for the stakeholder; however only one prioritizes the long-term data management of information for potential future secondary uses.

5.2.3 Data management expertise

The workforces involved in astronomy sky surveys may be the most important component of knowledge infrastructures: human infrastructure. Skilled workforces are essential to the success of the SDSS and LSST, because each project is an extremely complicated endeavor requiring geographically distributed individuals and teams to collaborate over years and even decades.

Study stakeholders described expertise for the SDSS and LSST similarly to the way they spoke about data and data management. Just like data and data management, analytical expertise was revealed according to stages in the data management life cycle. Data management expertise was discussed based on the necessary data management work across points in the data life cycle.

The data management activities and the expertise required to perform those activities are interrelated. Martinez, a leader in both SDSS and LSST, described two types of data management work in the LSST project: one with a known solution and one without a known

solution. The known solution may be difficult to manage, but a solution exists and the task can be accomplished with rigorous work. Alternatively, because LSST plans include pushing data-intensive boundaries, a number of tasks need to be accomplished that have no known solution. Martinez explained, "So the actual data transfer is not a big deal. Even storing the data is not big deal… The big deal is to actually touch each bit of that data, to process the data and then to do something intelligent with it" (Martinez, Professor, 2014). Given that there remain unknown challenges in these sky surveys, the SDSS and LSST leadership realize that their teams can always use additional and complementary kinds of expertise. Questions remain unsolved, such as how to process and analyze the 15 terabytes of data that will be collected each day once the LSST survey begins.

The LSST and SDSS workforces must be adaptive. It is not always clear what will prove to be the best mixture of experience and expertise, and expertise composition will depend on the individual roles played in the larger survey. In both the SDSS and LSST, data centers require individuals and teams of computer science experts. However, Martinez explained that personnel needs change over the course of the project, "… you want slightly more science-y people to define what the project is supposed to deliver. But once you go into construction then you need people who are better at, for example, coding…" (Martinez, Professor, 2014). The ratio of computer science experts to astronomy domain researchers on the sky survey teams remains fluid as the projects cycle through stages including planning, construction, operations, and archiving and serving data.

Debate continues as how best to educate and develop a career path for the kinds of expertise necessary for SDSS and LSST data management team members, who require both domain expertise and computational knowledge. These specialists are essential to the success of

modern sky surveys, and yet their job titles remain unclear and educational and career paths are unstandardized. Attempts to identify the critical data management workforce competencies needed result in lists of kinds of expertise (Choudhury, 2013; Engelhardt et al., 2012; Hedstrom, 2012; Hedstrom et al., 2015; Y. Kim et al., 2011; Swan & Brown, 2008). This dissertation does not endeavor to compile yet another list of the expertise needed for SDSS and LSST participation, as it would likely be outdated by the time of publication. These lists of typical examples of data, data management, or expertise are often unhelpful (Borgman, 2015, p. 28) as highly technical jobs and careers are in flux and adapt quickly. As Martin explained, sky survey team members need the ability to adapt to change, without knowing what that change will entail,

> "…Yeah, I mean the tools keep changing. Projects, long term projects have the disadvantage that they have to sort of come up with design plans or other standards like what languages to use and things like that and what's the effect if we're going to stick with them… So, because the context will change in the next 10 years significantly... We really have to essentially keep that in mind and prepare for this transition. It's not clear what's going to be the main solution, but it's clear that it's going to change" (Martin, Staff Scientist, 2012).

The lack of an existing educational or career path for astronomy data management experts is a symptom of the quickly changing and adapting skillsets projects like the SDSS and LSST require.

The documents, interviews, and ethnography observations analyzed for this dissertation provide two expansive areas that stakeholders revealed as critical for SDSS and LSST data management work. Astronomy domain knowledge and computational literacy were consistently described as essential kinds of expertise for SDSS and LSST data management workforces. However, instead of providing long lists of skillsets, stakeholders noted that it was more important that data managers are able to learn new skills than that they necessarily already possess a particular set of expertise at a given time. Martin went on to explain, "Because it's

changing so fast and our environment is cutting edge in many ways… nobody has the full spectrum, but we try to find people who can learn fast…" (Martin, Staff Scientist, 2012). The ability to continue learning domain and computational skills, as well as the ability to work as a team with other experts, were seen as the strongest kinds of workforce expertise for SDSS and LSST data managers.

The kind of data management expertise revealed in this dissertation resonates with the concept of "pi-shaped" expertise. Pi-shaped experts are members of a workforce who have a shallow breadth of general knowledge and extensive knowledge of two domains (Braniff, 2009; Feldman, 2006; Hartman, 2005; Szalay, 2012). In terms of SDSS and LSST data management, the two deep domains are astronomy knowledge and computational knowledge. The inclusion of astronomy and computational sciences into the required expertise, such as with pi-shaped experts, is one way of indicating astronomy sky surveys are data-intensive sciences.

The scale and distribution of work in these data-driven projects is more extensive than many fields. A single individual cannot be an expert in all aspects of the full SDSS or LSST research life cycle (Borgman, 2015). Instead collaboration members must develop trust between institutions and individuals (Committee on NASA Astronomy Science Centers, & National Research Council, 2007; Kitching et al., 2013; Research Information Network, 2008). Without respected connections between each institution in the project, neither SDSS nor LSST could operate at scale. Systemic trust, which requires leadership traits and the ability to contribute respectfully, is essential to these data-intensive collaborations.

Interviewees for this dissertation bemoaned a dearth of long-term data management workforce expertise. This finding aligns with Hedstrom et al.'s (2015) detection that highly skilled and well-trained workforces necessary to build and maintain data management

infrastructures are lacking. Noting the dearth of highly skilled workforce members, participants instead sought a full "environment" of expertise. In the three study populations, stakeholders minimized project reliance on individuals and instead focused on developing teams with overlapping skillsets. Ribes and Finholt noted concerns over holes in expertise when explaining that, "…in the face of short-term funding, CI [cyberinfrastructure] projects will attempt to transition to facilities by forming alliances with the persistent institutions of science in their domain fields" (2009, p. 394). In astronomy, facilities more persistent than the SDSS or LSST collaborations are the NASA science centers (Committee on NASA Astronomy Science Centers, & National Research Council, 2007).

The NASA science centers possess the centralized expertise for management through the full life cycle of astronomy data. In 2015, Professor Bell explained that another astronomy collaboration he participates in had secured a long-term solution for access and preservation of their dataset. He explained the difficulties in securing that kind of long-term data expertise, "Yeah, it can even be hard to hire that expertise, because someone who's good at that, what are we gonna do? Tell them to move to Hawaii for three years so you can do this, and then you'll have no job at the end?" (Bell, Professor, 2015). Data collected under the auspices of Bell's project will be managed at one of the NASA science centers, which provides continuity of knowledge infrastructures and workforces to support long-term data management. Dr. Bell explained his relief that a NASA science center accepted their project data. He understands that finding stable data management expertise is challenging and especially difficult to secure for smaller projects where data were collected outside the context of a larger mission.

The NASA science centers themselves were built for NASA-funded investigations, which are primarily space-based endeavors. The SDSS and LSST are largely funded from the

NSF and private funders, and are ground-based projects, therefore outside of the mission of the NASA science centers. SDSS team members did once propose that their data be included in a NASA science center, however the proposal was denied due to the science center's space-based mission (Gonzalez, Professor, 2013).

Study participants from the three study populations consistently referred to the NASA science centers as the prime example of a stable environment of expertise. MAST, for example, employs dedicated, full-time staff to manage the Hubble telescope data through the full life of the data (Zimmerman, 2008, pp. 166–167). The physical and human infrastructures exist within a single geographic location and provide data management for large, long-term NASA missions (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 3). MAST and other NASA science centers specifically work to "serve as the interfaces between astronomy missions and the community of scientists who utilize the data" (Committee on NASA Astronomy Science Centers, & National Research Council, 2007, p. 1). As noted in this dissertation, sky survey team members and data end-users often have different understandings of data and data management. Also confirmed in this dissertation, expertise generally is divided based on the stage of the project, so few people have a full understanding of how data are processed through the full life cycle (Borgman, 2015). Similar to MAST, a persistent team able to liaise between these two communities and experts throughout the project could be a strong asset to the SDSS and LSST projects.

The long-term, overlapping expertise at NASA science center institutions is the envy of many participants in this study. While devoted individuals may have ensured the SDSS project survived tumultuous times (Finkbeiner, 2010), it was the widespread commitment of team members that ensured SDSS project success overall. SDSS survived potential terminations of

funding, often thanks to the efforts of individuals who went above and beyond their assigned duties (Finkbeiner, 2010).

In hindsight, SDSS leaders confirmed that the project worked more smoothly when expertise and information were spread across team members. LSST team members noted that they value this SDSS lesson and are instead building a set of staff with complementary strengths and overlapping skillsets. While SDSS may have relied on visionary individuals, the LSST is relying on a web of teamwork, skills, and expertise. Compelling leadership forged SDSS success, and LSST leadership agrees that relying on individuals would leave their project open to points of failure (Moore, Staff Scientist, 2015).

SDSS and LSST are data-intensive scientific projects that require infrastructures beyond the scale of individual researchers (Burns et al., 2014; National Science Board (U.S.), 2005; Schroeder & Meyer, 2012). These human investments are essential to the success of data-intensive science. Data management and data recombination is fundamental to seeing through the potential power of the relational, or networked, nature of big data (boyd & Crawford, 2012; Gitelman & Jackson, 2013, p. 8; Kitchin, 2014, p. 1; Kitching et al., 2013, p. 382; Van de Sompel, 2013).

This dissertation confirms that data management aimed at enabling future data reuse is complex, depends on local circumstances, and requires consistent workforces and funding. These requirements suggest that ideally SDSS and LSST data management occur within an environment similar to a NASA science center. However, the NASA science centers themselves have missions to manage only space-based, NASA-funded projects. Most study participants recognize that the high level of data security supplied through NASA science center infrastructures is prohibitively expensive and unlikely for ground-based projects like the SDSS

or LSST. Ground-based projects have different funders, different funding models, and exist within different scientific cultures than that of space-based missions.

The NSF is a major funding agency for ground-based astronomers. While many projects are funded through short-term grants, the NSF also has longer-term funding, including that for facilities. Perhaps the facilities funding model, combined with the NASA science center workforce model, could be used to sustain NSF-funded data, that like the SDSS and LSST are determined to be "long-lived digital data collections" (National Science Board (U.S.), 2005, p. 40). Despite the cost differences, diverging missions, and cultural dissimilarities, the NASA science centers currently remain the best practice for long-term astronomy data management, whether ground- or space-based.

The preceding sections described how the three cumulating research questions for this dissertation built on one another and analyzed how the findings compare to existing literature. First, the study sought to understand how participants understood sky survey data. The data were understood as differing along temporal stages and as either a process or product. This data model directly revealed how study participants understood data management. Data management was described in temporal stages that reflect the work necessary to collect, process, and release the data. In turn, the expertise needed to participate in the sky survey projects was described based on the data management activities needed for each of these data management temporal stages. SDSS and LSST stakeholders described data, data management, and data management expertise based on the activities performed during the course of the project, all influenced by individuals' perspectives on data. These findings provide the foundation to answer the fourth research question: How does data management differ between populations?

5.2.4 How data management differs between populations

This dissertation investigated what are data, data management, and data management expertise to whom, when, and why these differences matter. A wide variety of SDSS and LSST team members and end-users reflections were presented in the findings. Study participants were chosen to reflect a matrix of kinds of expertise and experience. These characteristics were Primary Affiliation, Year of Interview, Career Stage, Level of Astronomy Education, Current Workforce, Role in SDSS and LSST, and whether the stakeholder was a Theorist. These seven variables were chosen to generate a demographically varied set of interviewees. Workforce demographics of the study population are listed in Table 10 and roles in SDSS and LSST are listed in Table 4. The study was designed specifically with this population variety to enable critical analysis of the factors that influence stakeholder perceptions.

As described in the previous subsections, SDSS and LSST stakeholders hold differing perspectives of what data are, and therefore what data management is and what data management expertise are necessary. These findings resonate with earlier work that describes how discrete perspectives across individuals can make up a coherent, larger workforce. Annemarie Mol shows how stakeholders in a Dutch university hospital define atherosclerosis differently based on their day-to-day work and their specific role in combating the disease (Mol, 2002). The results are also reminiscent of John Gall's metaphor for ship-building:

> "Now if you go down to Hampton Roads or any other shipyard and look around for a shipbuilder, you will be disappointed. You will find—in abundance—welders, carpenters, foremen, engineers and many other specialists, but no shipbuilders. True, the company executives may call themselves shipbuilders, but if you observe them at their work, you will see that it really consists of writing contracts, planning budgets and other administrative activities. Clearly, they are not in any concrete sense building ships" (Gall, 1976).

Just as shipyard employees describe their day-to-day tasks, so too do the SDSS and LSST stakeholders describe data management from their day-to-day perspectives. Software developers working on SDSS and LSST describe their work as writing software to build pipelines, not as building a sky survey. Similar to Gall's company executives, the SDSS and LSST leaders are the most likely to describe their work in terms of developing sky surveys. However, each stakeholder's perspective on data and data management is most closely influenced by the daily work they do for the project. Despite differing descriptions among team members, atherosclerosis is treated and ships are built. The SDSS was and the LSST likely will be highly successful sky surveys. The remainder of this section first describes specifically how stakeholder perspectives varied in this dissertation study. Next, these findings are coalesced into a ground-based sky survey model of data management. Further elucidation of the model and its implications close the Discussion.

5.2.4.1 Professional Role

Analyses of the professional roles stakeholders play in the sky survey data management life cycle revealed distinctions between the perspectives on data and data management. The following sub-sections discuss distinctions between team members and data end-users, SDSS and LSST team leaders, and SDSS library workforces.

- Team members and data end-users

A sharp contrast in how data, data management, and expertise were described emerged between individuals building infrastructure and those using resultant data for scientific research. Three study populations were chosen for this study: SDSS team members, LSST team members, and SDSS data end-users. Differences were predicted between these three populations. However,

it was surprising how similar members of the two teams were to one another and how sharply they differed from the SDSS end-users.

The clearest example of the data management differences between team members and data end-users is the way they share and manage data in the long-term. Sky survey team members manage the SDSS and LSST data as part of the official project. The team then releases the project data and end-users retrieve said data. Often, end-users manipulate their copy of the project data by then combining it with other datasets or running it through additional processing pipelines. Additional processing by the end-user results in derived datasets. However, these derived datasets are rarely released or managed as consistently as the originally collected sky survey data.

Long-term data management includes ensuring data integrity, preventing cyber attacks, updating software, and performing hardware migrations over time. Most sky survey team members agree that data management activities are important for the team to perform, and the SDSS and LSST both promised their funding agencies that the data would remain available to end-users. In 2011, Brian Yanny spoke about the long-term care of the SDSS data by saying the data must be "preserved in a readable, understandable format for long periods of time…" which includes, "long term store copies" and "active working copies" of the data (Yanny, 2011). However, most end-users do not carefully perform these long-term data management activities on their derived datasets. This result parallels previous studies that demonstrate highly processed, derived datasets of individual and small group research projects are rarely provided long-term management (Norris et al., 2006, p. 7).

There are a number of reasons why astronomy data end-users treat their collected data differently than the collaboration treats its data. Many of these motivations resonate with other

studies of why scientists do or do not share or archive their data. First, astronomy data, like all scientific data, are "incomprehensible and hence useless unless there is a detailed and clear description" of the provenance of the data (J. Gray, Szalay, et al., 2002, p. 5). Data sharing and long-term management are challenging and expensive undertakings, and can impact decisions throughout the project timeline (Abrams et al., 2009; Kitchin, 2014; Sands et al., 2014). Therefore, a project or individual must actively decide to provide a set of resources and expertise to ensure data are productively shared and managed in the long-term.

Data management to enable future reuse by a team or as an individual can also prove daunting, because all potential future users and uses of a dataset cannot be predicted (Borgman, 2012a, 2015; Fecher et al., 2015; Kratz & Strasser, 2015; Mayernik, 2011; Wallis, 2012; Wallis et al., 2013). Many end-user astronomers may not have the expertise or capacity to manage derived data as effectively as a large team could maintain sky survey data. While an individual manages data through the whole life cycle in the scope of end-user data projects, a more specialized workforce develops in sky surveys.

End-users may not consider their derived data as valuable enough to warrant data management efforts in the medium and long-term. Instead of managing their derived data, many blindly rely on sky survey projects to ensure the originally collected data are preserved and remain accessible over time. Others believe their data that is at least partially derived from SDSS data does not have value and therefore do not consider long-term data management activities. These astronomers do not perceive future data reuse value, because the derived data used for a research project could be easily or quickly re-derived from the original project dataset. Or, the end-user considers their derived data to only be of fleeting value, expecting the data or findings to be quickly supplanted by the next wave of technology. These findings resonate with earlier

studies that show researchers often lack the resources necessary to make data useful for sharing, data may not have been created with the intent of reuse, and they may not be able to imagine future uses of their data (Borgman, 2012a, 2015; Fecher et al., 2015; Kratz & Strasser, 2015; Mayernik, 2011; Wallis, 2012; Wallis et al., 2013).

The preceding were the reasons provided by data end-users explaining why they do not provide long-term management for their *derived* datasets. However, those reasons rely on the sky survey team itself ensuring the durability and accessibility of the originally collected data in the long-term. The reasons also assume that the data they use is exactly the same as the original sky survey data. While most of the data management labor takes place before data are released to end-users, the infrastructure work continues after data have been released. A large amount of "invisible work" takes place to ensure data remain available to users. Therefore, data end-users rely on a misnomer: the sky survey team will perpetually manage the original datasets.

- SDSS and LSST leadership

The voices expressed by SDSS and LSST leadership in documentation are distinct from the broader set of voices that emerged from team member interviews. SDSS documentation describes the SDSS data, or science archive, several ways over time: as images, spectra and catalogs, by level of data processing, as related to other information, as related to the public availability of information, or specifically based on the component parts. LSST data, data products, or the scientific database, were described in terms of images, spectra, and catalogs, the level of data processing, according to the work still required to prepare the data for use, the extent to which the data are public, and as one of the three levels of project data. A comparison of these differences is below in Table 27, and the documentation results are further contextualized with the three research methods in Table 17.

SDSS Documentation	LSST Documentation
Level of Data Processing	Level of Data Processing
Public Availability	Public Availability
As Related to Other Information	
	Work Remaining
DAS, CAS, Raw, Software	
	Level 1, Level 2, Level 3
Images, Spectra, & Catalogs	Images, Spectra, & Catalogs

Table 27 Comparison of the ways data were described in SDSS and LSST documentation

Level of data processing was one of the most common ways interviewees and sky survey documentation described data. Team members from both sky surveys especially emphasized pipeline processing, confirming the important role of infrastructure building for both projects. This strong commitment to processing and calibration work results in uniform data. The resultant homogeneous dataset is an integral reason why sky survey data can be used for many kinds of research questions by disparate end-users (Borne, 2013). Data processing levels are integral to the way stakeholders understand and discuss data. According to a presentation by the LSST Project Scientist for Data Management, "The ultimate deliverable of LSST is not the telescope, nor the instruments; it is the fully reduced data. All science will be [sic] come from survey catalogs and images" (Juric, 2014, sec. 2). The underlining in this quotation is original, indicating the author intends to speak to the importance of processing.

Beyond processing, SDSS and LSST documentation also often referenced data based on its public availability. Documentation for both projects often lauded plans for data release. However, interviewees rarely discussed the extent to which data were available beyond team members. For the SDSS, the Alfred P. Sloan Foundation was the largest funder, and the Foundation required the data be released beyond the project team (Finkbeiner, 2010). Similarly, as of the time of writing, LSST continues security resources to fund fully the project. To maintain enthusiasm from the NSF, LSST needs to reiterate that the resulting data will be made

available to all United States taxpayers. LSST leadership can use documents to convince funding agencies that the project is worth fully funding. While leadership focused on data availability in documentation, most sky survey team members minimized data release importance, because their interviews for this dissertation were not part of a larger agenda to securing funding. Instead, interviewees more often spoke about their work cleaning data, and therefore data were often discussed based on that level of processing.

- SDSS library workforces

The results also revealed important distinctions between the ways SDSS data were discussed by the astronomers and the library staff involved in archiving and serving the SDSS data from 2009-2013. As presented in the Results section 4.1.3.1 SDSS data in ethnography, two university libraries agreed to archive and serve the SDSS data for a five-year period. From 2007-2009, the stakeholders met with one another to draft and sign Memoranda of Understanding (MOU). While MOUs generally help interdisciplinary communities define roles and responsibilities (Research Information Network, 2008; Shankar, 2010), disparate perspectives remained during the archiving and serving of the SDSS data. The libraries executed the task differently from one another based on the infrastructures at their disposal, including each existing workforce (Borgman et al., 2012). Earlier studies (Carusi et al., 2010; Edwards et al., 2011; Olson & Olson, 2000) note it is essential for collaborators to develop shared understandings. The SDSS long-term data management experiences from 2009-2013 reveal the communication difficulties that can occur when shared understandings are not generated and re-established over time.

During ethnographic observations and interviews from 2012-2015, staff at both libraries described their participation in the SDSS project as successful. The libraries each felt positive

about the collaborative project because each gained experience managing scientific data, as well as providing a service to the SDSS astronomy community. A number of astronomers involved with the SDSS however, did not see the library collaborations as productive uses of funds.

Astronomers and library staff held misaligned goals and expectations, despite years of planning, because the libraries and the SDSS leadership perceived the data and the data management tasks differently. It is foreseeable that the meaning of data, and what it meant to manage data, would be multiple and local (Hedstrom et al., 2015; Lynch, 2013; Star & Ruhleder, 1996; Walters & Skinner, 2011). For example, Ribes and Jackson (2013) also discovered that the boundaries change depending on the lens by which a research subject considers data. In the context of their study, the boundaries of the "stream data archive" were malleable based on how far an interviewee was prodded to think about their data. They explained,

> "When asked, 'Where is the stream data archive?," a researcher will first insistently direct us to a public online page with an embedded web service. But thereafter, with only a little further prodding from the interviewer, the database becomes multimedia: it is digital; it is paper and pen; it is water…. The archive's borders stretch to a receding horizon that include the pen and paper field sheets backfilled for years, a cold room of samples, and the uncaptured experience of scientists and technicians entrusted with the production of the archive" (Ribes & Jackson, 2013, pp. 164–165).

While the variety of perspectives on data could have been predicted because of particular workforces involved, the astronomers and library staff believed they had developed shared understandings from the years spent collaborating in the development of the MOU documents prior to the data management work beginning. Despite faithful attempts to generate shared meanings of SDSS data, each library and the SDSS astronomers held divergent understandings of what were the SDSS data and what it meant to archive and serve the data.

For example, one of the libraries focused on carefully transferring and preserving the SDSS bits. In hindsight, the astronomers can now explain that they had been more concerned

with the *serving* portion of "archiving and serving." The library staff were interpreting the SDSS data in terms of the bits that had been generated. The astronomers, as domain experts, interpreted the SDSS data in terms of its potential usefulness and scientific value. While the library staff successfully managed the bits, the astronomers actually wanted the data managed to ensure scientific use. This dissertation reveals the SDSS astronomers and participating library staff held misaligned data management expectations. This finding validates earlier studies where the definition of data is only seemingly shared among stakeholders (Borgman, 2012a, 2015; Borgman et al., 2012; Consultative Committee for Space Data Systems, 2002, 2012; Cronin, 2013).

5.2.4.2 Career stage

Interviewee relationships to the SDSS and LSST sky surveys differed by career stage (Career stage demographics for this study are listed in Table 8).

- Sky survey participation stages by career stage

Career stage was often referenced as a reason to join, or not join, an infrastructure-building project. The SDSS and LSST projects were both envisaged by academic scientists. These academic scientists set in motion the sky survey projects, which were conducted largely by team members, and which were then used by a wide range of end-users. A basic timeline of when team members joined the SDSS and LSST projects is presented in Figure 10.

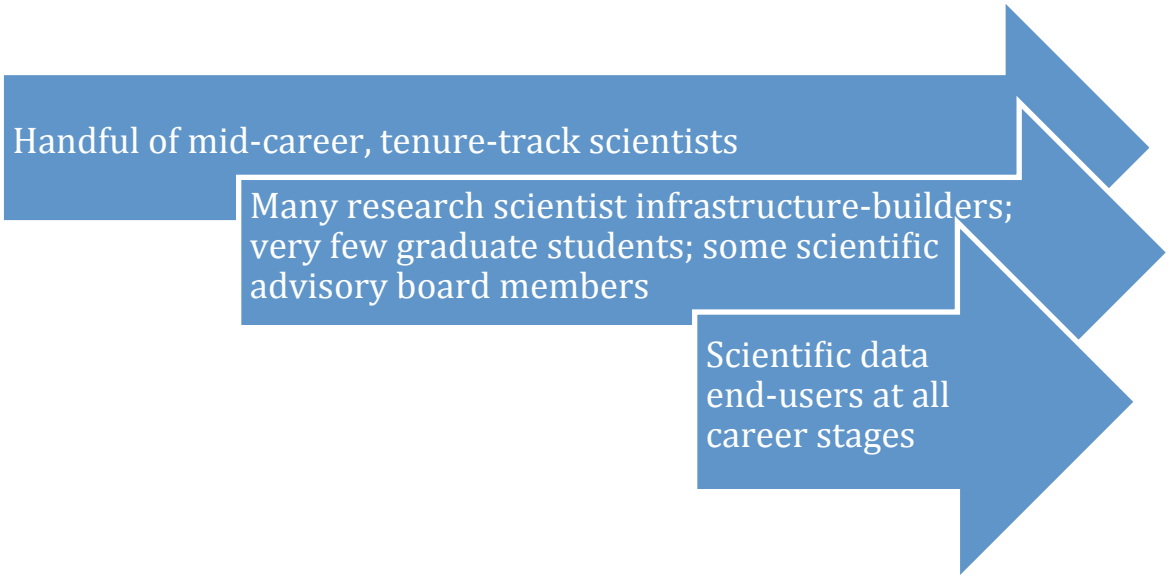


Figure 10 Sky survey participant career stages over time

A small core of scientists in both the SDSS and LSST planned and guided each of these projects from the beginning. These scientists were generally mid- to late-career scientists. Young scientists were not involved in this very early stage for two reasons. First, they would not have the clout to propose a decades-long project. Second, early career scientists focus on attaining tenure, which is earned largely through timely publication of high quality scientific journal articles. The SDSS and LSST projects each require at least a decade of infrastructure-building work before survey data are collected. Early career scientists could not devote multiple years to building infrastructure, as it would hinder their ability to publish enough scientific analysis to attain tenure. However, very late career scientists also generally did not plan the SDSS or LSST because their careers could end before data collection. Due to the long timelines of these sky surveys, early and late career scientists rarely worked on the initial stages of these sky survey projects.

Large teams are involved in the project as a whole during the research and development, construction, and operations stages of the SDSS and LSST projects. This workforce is larger for LSST than SDSS, because the scale of the project is much larger. The team members involved are generally employed in research scientist career tracks independent of scholarly journal article publications requirements. Years passed before SDSS data were collected, and more than a decade will pass before LSST data are collected. Without new data, team members have been unable to use their expertise in the projects to analyze new data and publish scientific journal articles. Similarly, graduate students are highly unlikely to be involved with infrastructure-building, particularly in the early stages of a sky survey project, because they need to ensure data are collected and usable within a timeframe that allows for analysis and writing of theses and dissertations.

Alternatively, LSST has motivated a large number of scientists to participate in project planning and construction, even before data are collected. Scientists participate in working groups that can influence how the survey will be conducted. In 2016, team members in the nine active Science Collaboration working groups each provide scientific case studies related to their ongoing research interests to influence the survey cadence. Survey cadence describes how data will be collected; discrete data collection patterns better support different kinds of science. These scientists contribute time and effort to working groups before the LSST data are collected, because they may be able to influence the project to prioritize their astronomy specialization. Collaboration members may also gain a better understanding of the data prior to its public release, speeding up their ability to use collected data once they are made available.

Finally, the majority SDSS or LSST associates are data end-users. These data end-users include the scientists and team members. Joining these team and working group members are

hundreds to thousands of individuals who deploy the data for scientific research as end-users. Given the long period over which sky surveys are conducted, persons at different career stages participate in sky surveys in numerous ways and at distinct times.

- Sky survey participation incentives by career stage

There are incentives for future data end-users to join the SDSS or LSST collaboration years or decades before data become available. First, these academics can help drive how the project is planned and built, they can advocate for the project to enable better data collection for their research questions. However, while scientists involved in a sky survey early can influence o how the project is made, the investment may not pay off for possibly decades. While it may require a long-term time investment, these scientists have intimate knowledge of the data and metadata before they are made public. The intricacies of born-digital sky survey data are vast; after it has been released, new end-users will have a steep learning curve before they can use the data for scientific analysis effectively. Interviewee Gray, an LSST Science Collaboration member, explained why it is worth committing time to the LSST prior to data collection, "… you could say, '…here's what we expect the measurement to be' …when you get the real data, and you find it's something else, then you have to explain why. So you've already done the machinery, right?" (Gray, Professor, 2015). The SDSS had only a short proprietary period, and the LSST plans to effectively have no proprietary period. Those who have dedicated time to infrastructure building will benefit from having deep knowledge of the data before public release. While there may not be a specific proprietary period, those familiar with the project can begin using the data immediately, whereas newcomers must first become acquainted with the dataset. For many scientists in mid-career, the benefits of helping form the research directives

and developing pre-release familiarity with the dataset, provide great incentive for dedicating time to building sky surveys like SDSS and LSST.

Younger scientists generally cannot devote time to a project that is not yet collecting data, and instead benefit from the rich trove of sky survey data that are publicly released. However, while they benefit from data availability, they must wait until after release to learn the intricacies of the data, how data collection decisions were made, and the other factors that influenced how the data were collected and processed.

Scientists involved in sky survey development must invest resources for many years prior to collection and use of the data, although they have the opportunity to optimize the data for their interests and are ready to analyze the data immediately upon its availability. Young scientists may not have the time to devote resources into the building of the project, but eventually benefit from an abundant cache of data. Sky survey projects may require decades of planning and construction before scientific data are generated and released, and therefore the career stages of survey participants follow very clear patterns in SDSS and LSST.

5.2.4.3 Level of astronomy education

While distinctions between sky survey team members and data end-users were predicted by the research design, the strength of the distinction was stronger than expected. The differences are particularly surprising because the majority of interviewees (73/80) hold, or are pursuing, a PhD in astronomy (refer back to Table 9). While astronomy expertise is indispensable, the SDSS and LSST also require team members outside the traditional astronomy curriculum expertise. For example, some LSST team members have computer science degrees, not astronomy degrees. Broad expertise is important at each stage of the project. For example, the LSST data center requires more computer science experts and fewer astronomy domain experts during project

construction. Martinez explained, “But once you go into construction then you need people who are better at, for example, coding, who are better at programming…” (Martinez, Professor, 2014). This LSST expertise pattern is expected to change once data are collected and more domain experts are needed to ensure the project moves forward scientifically.

More than half of this dissertation study’s astronomy PhD degree-holders described data in only two ways: by the state (level of data processing), or by the content of the data (images, spectra, and catalogs). Alternatively, study participants with computer science degrees never described data in terms of the content of images, spectra, and catalogs. While astronomy PhD-holders often described data based on its scientific use, computer science degree holders never referenced data based on its scientific use. More specifically, interviewees employed at universities were most likely to describe data based on its content.

University employed study participants share with astronomy-related PhDs a likelihood to be in jobs requiring they work with data for their own scientific research (as opposed to working with data to build infrastructure for others to use). Interviewees focused on writing scientific journal articles (largely those with astronomy-related PhDs and working in university settings), data were understood in terms of their content as astronomical images, spectra, and catalogs.

Alternatively, those with computer science degrees were most likely to describe data in terms of the digital medium or project source. When data were described in terms of its digital nature, they were describing data based on its medium. For example, they referred to data as bits, or zeros and ones. These computer scientists considered astronomy data as computational information to be managed. Similarly, examples of data described by source would include when individuals referenced data by describing its project or instrument of origin. For example, data

were described as anything resulting from the SDSS detectors. This way of understanding data attributes the data definition to its source, anything created by a certain instrument or from a certain site. These notions of data reflect computer scientists' relationship to the data. This finding aligns with Borgman et al.'s (2012) research from the Center for Embedded Network Sensing (CENS). CENS research showed that domain scientists viewed data as central to their projects, whereas computer scientists and technicians viewed data as a means to test their instrumentation. These dissertation findings demonstrate that as sky survey workforces bring together team members with different educational backgrounds, their perspectives may remain distinct even while working on the same project.

5.2.5 Model of Sky Survey Data Management

The preceding discussion of the dissertation results was used to construct a model of data management in ground-based astronomy sky surveys. The model brings together the results from each research question, method, and study population and presents a holistic illustration of the sky survey data management life cycle. The model is presented in Figure 11.

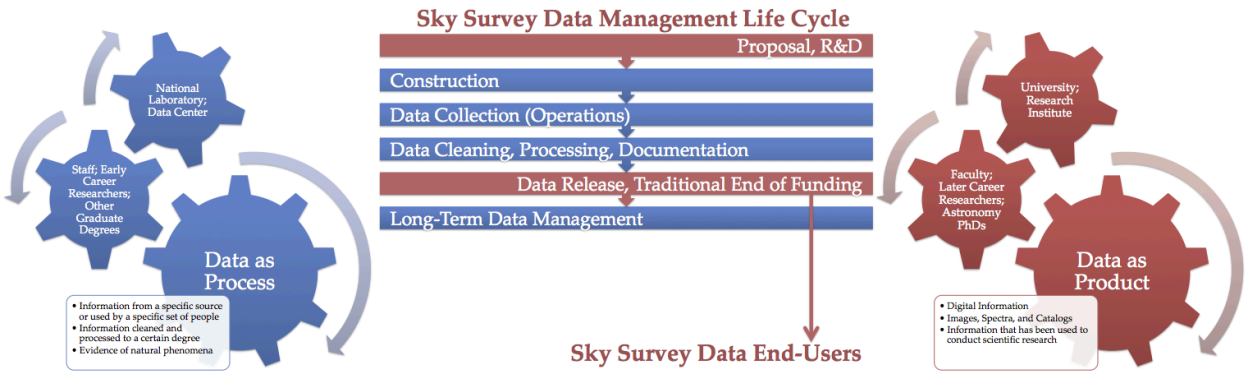


Figure 11 Sky Survey Data Management Life Cycle model

As detailed in the Results chapter and in the preceding sections of the Discussion chapter, perspectives on sky survey data, data management, and data management expertise differed based on a stakeholder's professional role in the sky survey, their career stage, and their level of astronomy education. These differences in stakeholder perceptions are illustrated in the cogs on the left and right of the figure, and the sky survey data management life cycle is presented at the center of the model.

5.2.5.1 Data as a Process

The left side of the model represents stakeholders who view data as a process. Data perspectives were clustered into this classification when data were identified as information undergoing a process or when data were perceived in terms of the practices and contexts surrounding data production. The 15 ways data as a process emerged from documents, interviewees, and ethnographic participants was presented in Table 22. These perspectives include references to data as information cleaned and processed to a certain degree and information that has value through its relationship to other information.

Staff working at national laboratories or data centers usually described data as a process. These stakeholders likely described data as a process because their day-to-day interactions with the sky survey project involved hands-on SDSS data processing (or for LSST stakeholders, hands-on development of the procedures by which the data will be processed). These stakeholders, including graduate students, post-docs, and team members without astronomy-related PhD degrees, are often referred to as pi-shaped experts (refer back to section 2.3.2 Data management expertise). These individuals' careers do not rely on the 'publish or perish' mantra of scientific research because they are in staff positions, are early career, or their expertise is in business or computer science instead of within astronomy.

5.2.5.2 Data as a Product

The right side of the model reflects the perspectives of stakeholders who view data as a product. There are 11 ways data as a product emerged from documents, interviewees, and ethnographic participants, which was presented in Table 22. These perspectives include references to data as digital information or bits, or data as images, spectra, and catalogs. These perspectives on data were more likely to reference the nature of the data specifically as astronomical information. In these examples, data were perceived as objective representations of reality, divorced from their context of production.

Stakeholders who perceived data as a product were more likely to have tenure-track careers and work in a university or a research center. These stakeholders were usually faculty, had completed their PhD degrees, and those degrees were in astronomy or a related field. These stakeholders were more likely to describe data as a product because of the nature of their interactions with data. As revealed in section 4.2.2.3 SDSS data end-users, students and post-docs are more likely to work in the data collection and cleaning phases of research, while faculty are more likely to focus their time on the research management, analysis, and writing phases of the research process. Faculty view data as a product, because their daily tasks center on the analysis of information, as opposed to the activities involved in collecting and preparing data for analysis. Faculty participation in the processing of data has waned, and they instead employ data for scientific analysis once it is already processed. These distinctions between data as a process and data as a product are further summarized in section 4.1.4 RQ1 results summary and will be discussed in more depth in section 5.2.6 Sky Survey Data Management Model Explanation and Significance.

5.2.5.1 Data Management Life Cycle

The center of the model illustrates the research data management life cycle for sky surveys. The model begins with proposal writing and R&D work, which are generally completed by tenure-track, mid-career faculty stakeholders who view data as a product (sky survey participation by career stage is further detailed in 5.2.4.2 Career stage). These stakeholders develop the project vision and begin the sky survey life cycle. Essential to this stage is convincing funders and future team members of the importance of the project and the value of the eventually collected data.

After faculty leaders have sustained funder buy-in and recruited a starting staff, the bulk of the data management life cycle is then carried out by those staff who view data as a process. These steps in the sky survey life cycle include construction, data collection or operations, and data cleaning, processing, and documentation. Non-tenure-track staff who see data as a process are the bulk of those who participate in the sky survey at this point in the life cycle.

At distinct points in the sky survey life cycle, data are prepared and released for end-users. Sky survey leaders, who describe data as the product being released, are those who publicize the formal data releases. These sky survey leaders must convince external astronomers that the data are valuable for scientific use. Similar to their work securing funding, sky survey leaders must recruit data end-users for the project to be successful.

The final data release marks the end of data collection and is traditionally the end of sky survey funding. Following the close of operations, any steps toward long-term data management take place. These long-term data management actions take place by staff who view data as a process. However, the extent to which long-term data management occurs depends on initial planning by sky survey leadership, who view data as a product. The model thus compares

stakeholder perspectives on data within the data management life cycle. The following sub-section explains the model and why it is important.

5.2.6 Sky Survey Data Management Model Explanation and Significance

The Sky Survey Data Management Life Cycle model presented in Figure 11 illustrates the ways disparate sky survey stakeholder data perceptions intersect with points in the data management life cycle. These different perspectives can be explained through multiple stakeholder demographic variables, including the stakeholder's relationship to the data at different points in the life cycle, their role in building infrastructure or writing scientific journal articles, and their engagement with stakeholders external to the sky survey (including funders and potential data end-users). The reason some stakeholders viewed data as a process, while others viewed it as a product, is thus explained by the life cycle.

5.2.6.1 Data as a Process

One explanation for why perspectives on data diverged across stakeholders is the extent to which a stakeholder is involved directly with managing sky survey data, as identified in previous studies (Gall, 1976, 2002; Mol, 2002; Orphanides, 2017). As revealed in section 4.4.3 Career stage, early career tenure-track stakeholders, including students and post-docs, as well as sky survey staff, are more likely to work with data closely. Alternatively, astronomy faculty are more likely to manage or oversee data collection and processing. This proximity to the daily, hands-on, work involved in data management influences perspectives on data and data management.

Early career stakeholders and staff viewed data as a process, within context, because of their close relationship to the many practices involved in preparing data before release. These

stakeholders are intimately familiar with the labor, infrastructures, relationships, and decisions that went into collecting and preparing the data for release. Having participated in these processes, staff members know of any weaknesses in the data and understand the decisions that went into developing the data management workflows. As Latour explained, these staff see data as "science in the making" (1987). Far from each datum being an objective truth, these staff engaged in meetings where specific decision-making developed the processing software, which cleans and calibrates collected data, in one way versus another. They directly witnessed how the individuals making up the sky survey team influenced how the data are processed. For example, their work removing instrument artifacts from images demonstrates the imperfect nature of scientific data collection and processing. To these staff team members, sky survey data are not a perfectly clean Latourian black box (1987), they instead have viewed deep into the work processes that collected and processed the data. Staff hold essential roles and perspectives in sky surveys because they embody how data are processed through the life cycle.

5.2.6.2 Data as a Product

Stakeholders who expressed a perception of data as a product also developed their perspectives because of their roles in the sky survey life cycle. Mid-career, tenure-track faculty are generally the instigators of complex sky surveys, as revealed in section 5.2.4.2 Career stage and Figure 10. Tenure-track positions within universities and data centers enable faculty to manage the larger scientific goals while students and staff directly collect and process data. These faculty generally control decisive points in the sky survey: they have constructed the funding proposals as well as the framing of each data release. Faculty sky-survey leaders hold essential roles in the sky survey because their visions and the manner in which they explain the project to external stakeholders are essential factors in the success of the project overall.

❖ Proposal; R&D

Tenure-track faculty, including sky survey leaders, often describe data as a product, because it is in the project's best interest to do so. This dissertation model reveals that two points in particular when faculty are intimately involved in the sky survey process (Proposal, R&D and Data Release), necessitate that these faculty perceive and express data as a product.

The mid-career, tenure-track faculty who begin sky surveys express data as a product through funding proposals, journal articles, and presentations, because the ability to gain project funding and community buy-in likely require that perspective. Limited funds are available for the astronomy community; the process of obtaining funding from public or private sources is intensely competitive. Developing the trust of funders is an essential component of securing funding for a sky survey. In proposals, sky survey leaders present the data they plan to collect as objective information that will be useful for scientific advancement.

These faculty demonstrate certainty to funders, because highlighting the contingent nature of data could undermine their message and instead demonstrate that the project team does not have the capacity or expertise to generate an excellent dataset. SDSS was able to secure multiple grants from the Alfred P. Sloan Foundation, as well as other funders, in part due to their ability to persuade funders of the efficacy of the dataset they were to produce. LSST leaders have been generating funds planning to total more than one billion dollars; the NSF and other funders would be less likely to invest these large sums of money in stakeholders who describe their future data as locally contingent. LSST was rated first in the 2010 Decadal Survey (Committee for a Decadal Survey of Astronomy and Astrophysics; National Research Council, 2010) partially because of the ability of the leaders to describe the future dataset as objectively valuable scientific data products. Indeed, LSST proposals to the NSF declare that the resulting data will

benefit not only astronomers, but that, **"**the broader impacts of the LSST will be profound, as scientists, the public, and schoolchildren around the world will have ready access to the data" (National Science Foundation, 2005, 2010a).

While all astronomers and funders are aware that science takes place within a context, bringing that information to the forefront of an application would likely instill concern of inadequate planning. Instead, SDSS and LSST leaders described the project and future data as objective, scientifically-sound images, spectra, and catalogs.

- Data Release

The other period in the sky survey life cycle in which faculty play a pivotal role is the point of data release. The collected and processed data are presented as a formal release, in which a single data release journal article can purportedly provide all the information necessary for successful use of the dataset. These staff thus understand data as "ready-made science" (Latour, 1987). This black box view of the data at the time of release may be essential to gaining the trust of the broader astronomy community. As described in section 2.2.2 Sustainability, end-users must trust sky survey team members for the choices made during data collection and processing.

SDSS is considered a success in many ways, including because the broader astronomy community highly trusts and frequently uses the data. As noted in section 4.1.1.1 SDSS data in documents, the public release of SDSS data was an important milestone in project development as it ensured continued support from funders and the end-user community. Trust in the data product by external end-users is essential; sky survey leaders have incentives to present data as spotless, objective sources of scientific truth. If these leaders were to present sky survey data as a contingent process, astronomers could be less likely to trust the end product. While all

astronomers are aware to some extent that data are made in a context, bringing that subjective, contingent information to the forefront of a data release could cause doubt in the scientific community. To be accepted, the data must be recognized as objective information with truth-value and thereby useful for scientific research. If the broader community does not trust the data for use, then the sky survey will ultimately be a failed project.

5.2.6.3 Astronomy Knowledge Infrastructures

The perspectives of data as a process or a product, as illustrated throughout the life cycle in the data management model, reflect the larger knowledge infrastructures within which these sky surveys are embedded (Edwards, 2010; Jackson et al., 2011; Star & Ruhleder, 1996). These findings indicate sky survey leaders likely *must* perceive and relate data as a product in order for the sky survey to be successful.

Sky surveys are embedded within larger infrastructures, including the highly competitive funding apparatus that leaves no room for a nuanced view of information as a process. Faculty must persuade themselves, funders, and the larger astronomy field of the objective nature of their projects' data releases. This need for sky survey leaders to convince external stakeholders of the value of the data means that leaders often directly influence external stakeholders to perceive the data as a product. This dissertation model thus reveals that funding agencies and the broader astronomy community are taught to understand sky survey data results as a product.

The necessity of presenting astronomy data as a black box to further project success has implications for long-term data management. As data are always presented as a product to funders and to the broader astronomy field, the processes necessary to prepare and manage data in the short-, medium-, and long-term are often invisible to anyone outside of the project. Indeed, the metaphorical black box conceals the intricacies involved in the work. This invisibility can

contribute to funders and the external astronomy community not being aware of the challenges and highly specialized expertise necessary for data collection, processing, and long-term management because these details are always hidden under the black box.

Funders may not appreciate the infrastructures and workforce necessary to truly manage the value of data in the long-term, because they are not involved in the day-to-day processes and are only ever presented data as a product. SDSS collaborators believe SDSS data will remain important for decades, or possibly hundreds of years (Margon, 1998; Yanny, 2011). However, presenting data as a product whenever communicating with external stakeholders, such as funders, may dissuade these agencies from devoting sufficient resources to ensuring data are available beyond data collection and the traditional end of funding.

The broader knowledge infrastructures at play in astronomy today, including the methods to acquire funding, the manner in which to recruit and sustain a workforce, and the ways to garner the trust of fellow astronomers have caused sky survey leaders to present sky survey data as a product. While internal staff understand the process and expertise involved in sky survey data management, these details are not made explicit to the external community because of the way these funding infrastructures and community practices have evolved. It is because of these infrastructures that leaders present data as a product, which can prevent funders and the broader community from fully understanding the process and expertise necessary to sustain data into the long-term. The Conclusion chapter provides a more nuanced examination of the implications of this black-boxing of scientific data for long-term infrastructures and the workforces involved in data management.

6 Conclusion

> *"I define getting, understanding, and characterizing the astrophysical objects in data as a scientific task… [But,] if you ask the average member of the AAS, the American Astronomical Society, they'll say, '…He hasn't done any science in years,' because I haven't done any science, in that sense, in years…."*
> (Staff Scientist, 2012).

A new era of scientific data collection and analysis is underway. The wave of data-intensive research promises to propel scientific knowledge gains by enabling the collection and combination of data at a scale and complexity never before possible. However, strong data management knowledge infrastructures must be in place to enable the discoveries promised by data-intensive science. Digital data must be managed properly throughout the research data life cycle to retain the efficacy of the information bytes as well as the contextual metadata, documentation, and relationships to other information. Astronomy sky survey data, like other scientific data, are "incomprehensible and hence useless" without accompanying contextual information about how data were collected, processed, and curated (J. Gray, Szalay, et al., 2002, p. 5).

While the sky survey data management model revealed in this dissertation (Figure 11) demonstrates the importance of framing data as a product to gain the trust of the community, data are also understood as a process by the stakeholders intimately involved in collection and processing. A single gap in the life cycle can prevent data from being retained and reused into the future (Borgman, 2015), and therefore data must be considered as a process when planning for long-term data management. Only through sustainable workforces and digital infrastructures can research data appropriately be used, recombined, and reanalyzed in the age of data-intensive science.

The following subsections conclude this dissertation. The first subsection discusses the factors that prevent sustainable workforces and expertise in the SDSS and LSST. Many study participants expressed the workforce conundrum as a point of angst in their career development. Many SDSS and LSST sky survey team members felt under-rewarded for their essential contributions to these sky survey projects. Astronomy sky survey leaders are encouraged to consider the career path desires of current and future team members. In particular, sky survey leaders are encouraged to respect and find non-financial ways to reward team members, even when their work may initially seem "invisible." This section is intended to increase awareness of the disparate reward structures available to highly educated staff involved in SDSS and LSST infrastructure work. Sky survey staff are not rewarded based on the essential nature of their skillsets for project success, and these misaligned rewards structures reveal a point of weakness for the sustainability of long-term sky survey projects.

Second, factors that inhibit long-term sky survey infrastructures are examined. Funding bodies and other policy makers are encouraged to consider the importance of providing funding for data management beyond the end of data collection. As revealed in this dissertation's sky survey data management model (Figure 11), funders and policy makers inherently are provided only the data as a product perspective. Funders are thus not given all perspectives of what data are. The presentation of data as a product, which can black box the infrastructures necessary to sustain the value of data, may partially explain why sky survey funding ends before long-term data management begins. Perspectives on data will always vary to some extent; stakeholders should focus on what can be done to translate between when stakeholders see data as a process, and when data is seen as a product, to construct collaboratively long-term infrastructures. The

dissertation concludes with a discussion of the limitations of this study and a glimpse at future work.

6.1 Difficulties Sustaining Sky Survey Expertise

This dissertation highlighted the workforces and activities required for effective sky survey data management across the research life cycle. Recent astronomy sky surveys, including the SDSS and LSST, are examples of data-intensive scientific investigations. The term data-intensive science refers to the data collection, processing, and analysis in which scientific questions are investigated by, "analyzing hundreds of billions of data points" (Mayer-Schonberger & Cukier, 2013, p. 11). Often referred to as a new era of science, the implications for data management based on these quantitative differences in the scale of data collection must be addressed. Data-intensive sciences may require new data practices, including more resources for data cleaning and analysis rather than data collection (Borne, 2013; Hey et al., 2009a; Szalay, 2011). These changes may require a highly adaptable workforce. As this dissertation revealed, an essential factor in the success of these projects is that of securing qualified, sustainable workforces.

The data management workforces essential to the success of the SDSS and LSST projects require expertise in both astronomy and in computational techniques. These "pi-shaped" experts have proven essential to the functioning of the SDSS and LSST (refer back to Figure 3). While demand remains for pi-shaped experts to work on the LSST data management team, these experts are in short supply (Kitchin, 2014; Ray, 2014a). Reasons for the dearth in trained experts are the poor incentives that dissuade astronomy students from pursuing pi-shaped careers. Tenure-track careers are at odds with infrastructure-building activities. One senior scientist often

explains to her students that decisions to work on scientific software will damage their potential tenure-track career opportunities,

> "The real problem though is that I can't take a good graduate student honestly and tell them they ought to work on this stuff [scientific software] because they're not going to have a career. If they want to end up at a major university then they should not become… software… they shouldn't specialize in that. So that's why I think it needs... That's I think the real change that if it were a respected part of the community…" (Moore, Staff Scientist, 2012).

The conundrum remains and shapes the future of astronomy sky surveys and many other data-intensive research fields: The expertise needed for data management is that of pi-shaped staff who are experts in astronomy and the computational sciences. However, individuals pursuing computational work are unable to publish scientific articles concurrently, which remains essential for acquiring competitive tenure-track career opportunities. In the data management model revealed in this dissertation study, tenure-track stakeholders and staff stakeholders are shown to have distinct responsibilities in the data management life cycle, as well as distinct perspectives on data (Figure 11). The following subsections discuss this conundrum, its implications for the future of astronomy sky surveys, and how sky survey leaders can reflect on these findings.

6.1.1 Data management expertise reward structures

One reason it is difficult for astronomy sky surveys to maintain data in the long-term, is because existing workforce reward structures encourage discontinuity. Multiple factors may prevent a single data team from continuously managing SDSS or LSST data in the short, medium, and long-term. One obvious notion is that the workforce of a multi-decade project will include retirements, but there are other nuanced reasons why individuals are dissuaded from managing data in the long-term. For example, data managers usually desire job security beyond

that of the 3-5 year funding cycle. The rhythms of collaborative funding (Jackson et al., 2010) are often shorter than the length of long-term projects, which creates uncertainty, and are much shorter than the full career of an individual. The finitely funded SDSS and LSST projects must also attempt to hire strong data management workforces. However, the inherently short-term nature of individual projects can be detrimental to the career and work-life balance of a data manager. Professor Bell confirmed that NASA science centers fulfill the requirements for data management continuity because, "… you know it will still be there in 20 years, and someone can go get a job there and have the confidence they have a future at the institution" (Bell, Professor, 2015). However, as discussed in section 5.2.3 Data management expertise, the strong data management career options at NASA science centers are not available for ground-based astronomy investigators.

As with most disciplines, staff technologist positions in astronomy are less lucrative than faculty research positions and are often funded on short-term grants that lack long-term stability. These staff are not provided as many resources (such as post-docs or students) and are generally not as well respected in the discipline, despite often having the same education and experience as their faculty peers. Due to this hierarchy, time spent performing tasks such as documentation and software programming is often viewed as distractions from performing the "science" necessary for faculty advancement.

While a sustainable data management workforce is essential for the success of data-intensive sciences (National Science Board (U.S.), 2005; Research Information Network, 2008), many interviewees for this dissertation felt their expertise was under-appreciated. Many interviewees in non-tenure track jobs wanted to share their frustration at their difficulty obtaining tenure-track careers. Despite holding PhDs in astronomy or computer science and contributing

essential expertise to the sky survey, they felt their work and compensation were relegated to that of untrained support staff. One reason for this discrepancy is that most university and academic systems are built to prioritize rewarding scientific analysis, as quantified through journal article publications. Time spent generating infrastructures—including building tools and performing data management tasks—has been considered a detriment to time spent "doing science" and writing journal articles (Levine, 2014; Ribes & Finholt, 2009; Star & Ruhleder, 1996). While many SDSS and LSST infrastructure building staff members enjoy their work, some feel participating in the sky survey team has stunted their careers. While SDSS and LSST could not collect or release data without the tireless efforts of these team members, the data management work is not rewarded as highly as those who perform scientific investigations from that resulting data (Ribes & Finholt, 2009).

The SDSS team interviewees in this dissertation were usually heavily invested members of the collaboration. Some had committed years to writing data management software and performing other team duties for SDSS. Following the conclusion of SDSS I and II, many of these team members went on to contribute their distinctive expertise to newer projects like the Dark Energy Survey (DES), the Hyper Suprime-Cam on the Subaru Telescope, and the LSST. While some SDSS team members have participated in both infrastructure building and scientific research projects using the SDSS data, many have not found the resources to actually use the SDSS data for their own research. One senior team member acknowledged that SDSS relied on individuals who were willing to forgo their science, and therefore their career goals, for the good of the project (Perez, Emeritus Scientist, 2013).

Data management careers, in astronomy as well as other disciplines, lack an established and accepted educational path and workforce structure (Hedstrom et al., 2015; National Science

Board (U.S.), 2005; Ribes & Finholt, 2009). The development of clear career trajectories could increase professional opportunities for highly skilled, pi-shaped academics (Bowker, 2005; Hedstrom et al., 2015). Robert Lupton, a leader in both SDSS and LSST, explained that current reward structures in universities and astronomy do not properly support essential infrastructure-building work – whether that work is with hardware or software. Lupton also exposed that current workforce incentives are unsustainable. Specifically, Lupton suggested that new projects should learn from SDSS:

> "Find some way to reward people working on the project. In SDSS we did this by promising them early access to the data via a proprietary period. Not only is this impossible for publically funded projects, but it doesn't really work very well. One problem is that the promise of data in the distant future doesn't help a post-doc much; another is that the community (at least in the US) doesn't value work on the technical aspects of a large project. …My personal belief is that the only long term way out of this is to integrate instrumentation (hardware and software) into the astronomy career path, much the way that the high-energy physicists appear to have done (at least from the outside)" (Lupton, 2002, p. 10).

While modern scientific collaborations require experts from complementary disciplines, universities remain structured to support best those whose expertise fits within a single discipline (Bowker, 2005, p. 125; Hedstrom et al., 2015).

A reward structure hierarchy is not a novel scientific investigation phenomenon (Blair, 2010; Shapin, 1989). However, the highly educated, pi-shaped team members from this study seem to expect a stronger set of rewards from the university environment. It has never been expected that all, or even most, astronomy PhD-holders will gain employment in a university faculty position. According to statistics from the American Institute of Physics, only approximately 10% of those who receive a PhD in Astronomy or Astrophysics in the US will go on to hold full-time, tenure-track faculty jobs (Ivie, Ephraim, & White, 2009; Mulvey & Nicholson, 2014; Nicholson & Mulvey, 2011; S. White, Ivie, Ephraim, & Anderson, 2010). The

PhD-holding pay scale is even lower at universities than in private industry or in government work (G. Anderson & Mulvey, 2012; Mulvey & Pold, 2014). Despite the fact that only a small percentage of US-based astronomy PhD-recipients are known to go on to tenure-track faculty careers, many interviewees in this dissertation study expected a better-rewarded career for themselves because of their in-demand, pi-shaped expertise.

6.1.2 Data management as invisible work

As revealed in this dissertation, sky survey data management work is often hidden under the metaphorical black box when data are presented to external stakeholders. Further black boxing of long-term data management needs occurs through interviewees noting their reliance on Moore's Law for the success of SDSS, LSST, or their personal research. By referencing Moore's Law, these interviewees are saying that as time passes, data management costs become smaller. However, while data *storage* costs have continued to decrease over time, storage is only one component of data management. According to the Data Conservancy (Figure 2), data storage is a basic long-term data management activity, but it may be the least expensive component of the four activities (Choudhury, 2013; Choudhury et al., 2013).

Human labor and other resources are required to ensure data are managed over time. Long-lived data must be migrated through successive software and hardware iterations. Beyond migration, data must also be continuously checked for bit rot and other technical errors. To maintain the value of scientific data, documentation and other curatorial services must also be performed. While essential, data maintenance work can become invisible; as an infrastructure becomes more ubiquitous, it also becomes less apparent (Borgman, 2000). The long-term sky survey data management work may be considered invisible work as it becomes routine (Borgman, 2015; Bowker, 2005; Daniels, 1987; Ribes & Finholt, 2009; Ribes & Jackson, 2013;

Star & Strauss, 1999). The work becomes invisible when performed well, and often is only brought to the forefront of attention when problems arise. As revealed in this dissertation's data management model (Figure 11), long-term data management activities partially are invisible, because data are presented to external stakeholders as a product instead of a process. With data always appearing as a black box, the practices and workforces necessary for long-term data management have become invisible. Professor Bell complained that many stakeholders fail to realize the costs associated with enabling astronomy data access and preservation. He sarcastically exclaimed, "Kind of tragic, things do cost money. People are like, "Why didn't you do it?" "Well, it costs money." This isn't a gigabyte dataset that you put on your home page" (Bell, 2015).

Some interviewees in this dissertation study were oblivious to the technical and human resource expenses associated with ensuring availability and usability of SDSS data over time. One astronomy professor and former member of the SDSS Board of Governors believed long-term data management was not something the SDSS collaboration ever needed to consider. When asked about the plans for the longer-term care of the SDSS data that facilitate data-intensive discoveries, he responded, "Well, I think we made an agreement with NSF that all data would become public after blank length of time and that basically took care of it" (Anderson, Emeritus Professor, 2012). While acknowledging the need for a "permanent archive," Anderson did not have a sense of data preservation costs or the need for an accessible, actively served copy of the data. He continued,

> "I mean, what we did is we made it all public. And that was our obligation and it was to our interest to do so. … Once we made it public, it's public. So you know, Lincoln wrote the Gettysburg Address, he didn't have to archive that for all time. But people liked it; they could collect it and put it in their drawer. [laughter] Because it's just bits. In other words, if this is public, then anybody can collect all

> those bits and do with them what they want" (Anderson, Emeritus Professor, 2012).

Professor Anderson assumed that releasing the SDSS data inherently meant that valuable data would be saved. However, this assumption has proven false, and instead digital data require continuous, intentional management by experts to remain preserved and usable over time (Borgman, 2000; Hedstrom et al., 2015). As a senior scholar with a naïve understanding of data management efforts, Professor Anderson's perspective provides a clear example of how work becomes invisible. Despite some SDSS leadership misperceptions, these short, medium, and long-term data management tasks require sustainable physical and human infrastructures (Bowker, 2005, p. 114).

Ignorance of the invisible work necessary to ensure long-term maintenance may be one reason for the under-valuing of data management work and the common lack of planning and budgeting foresight for long-term data management. As demonstrated in Figure 10 Sky survey participant career stage, sky survey leadership is largely separated by career stage. Results also confirmed that as astronomers become more senior, they are increasingly involved in the management of students and post-docs, who are then the ones directly analyzing datasets, which resonates with Wallis' findings of the roles of students and post-docs at the Center for Embedded Networked Sensing. A temporal expertise gap results: those most familiar with current data management practices are too early in their careers to be sky survey leaders; at the same time, current sky survey leaders may have dated understandings of the effort required to manage sky survey data.

However, ignorance of the labor required for long-term data management can be combatted. As shown in this dissertation's data management model, acknowledgement of the labor involved in data management is a result of the broader infrastructures surrounding sky

surveys. Sky survey leaders, funders, and the other workforces surrounding these sky surveys (including Dean and Provost-level leaders at universities) must acknowledge the divide in perspectives between staff who work directly with data and later career faculty who manage data collection and analysis. Ongoing acknowledgement of the differences between data as a process and data as a product, coupled with efforts by leaders to understand the resources needed to properly manage data, are necessary steps to making data management work visible. Long-term data management requires funding, hardware and software, and an expert workforce. The SDSS and LSST are large-scale projects and require high levels of what may currently be invisible infrastructure work in design and development, maintenance, infrastructure construction, and system administration.

6.1.3 Astronomy sky survey leadership

Many essential SDSS and LSST team members are "pi-shaped" experts. Pi-shaped experts in terms of the SDSS and LSST possess a high degree of expertise in both astronomy and computational science. Data-intensive sciences often require expertise that crosses these disciplinary boundaries (Bell et al., 2009; Bowker, 2005; Szalay, 2012). The specific nature of asking new research questions, which can only be answered by the combination of multiple datasets, is the hallmark of data-intensive sciences and what necessitates inter-disciplinary expertise. Pi-shaped sky survey team members are recruited and hired because of their extensive expertise that generally includes a PhD in astronomy or a related discipline. However, LSST has not been able to easily attract and retain the needed pi-shaped team members for open data management positions.

While many potential recruits may desire to be part of the fast-moving and forward-thinking LSST team, the downsides to joining an infrastructure-building team member persist.

As just described, working as a SDSS or LSST infrastructure-building team member will likely hinder future career opportunities. However, the repercussions of this conundrum can be reduced. First, SDSS and LSST leadership must inform potential team members honestly of the ways participation in the SDSS or LSST could hurt their chances at obtaining tenure-track faculty positions. Second, existing sky survey students, post-docs, and staff should be treated respectfully, regardless of their hierarchical position on the sky survey team. While some team members made a concerted choice to join an infrastructure team, because they enjoy the work, others described unintentionally landing in an unwanted position. Given the university hiring and promotion climate, individuals who want to pursue tenure-track faculty careers should not be encouraged to join infrastructure-building projects. As described earlier, interviewee Moore is forthright with her students about the ways infrastructure work detracts from time that could be spent writing scientific papers.

Most interviewees drew a sharp line between infrastructure building, and "doing science." In this dissertation's data management model, this distinction is that all work taking place on behalf of the sky survey is infrastructure work, while analysis of its resulting datasets is scientific work. Some SDSS team members have remained so busy with SDSS and other emerging infrastructure projects that they never found time to use SDSS data for their own personal scientific research projects. Current LSST team members are generally granted 20% of their work schedule for "science time." However, many have not actually used the allotted time for personal science because of the extensive time demands of the LSST infrastructure building team. For example, staff scientist Stewart explained that while he is granted science time as part of his LSST job, the time is taken up by LSST priorities, and he has yet to use that time to further his own scientific interests (Stewart, Staff Scientist, 2015). The practical nature of developing

sky survey infrastructures often prevents PhD astronomers from continuing their scientific research projects and nearly always prevents them from attaining tenure-track faculty careers. In the long-term, sky survey team leaders could use their academic influence to help shape reward structures to support better the pi-shaped expertise they need for sky survey collaboration success. In the meantime, sky survey leaders should be honest with current and future students, post-docs, and staff about the career repercussions that result from choosing paths in astronomy infrastructure building and data management.

Despite the hierarchical organizational structures in SDSS and LSST, all sky survey team members should be treated with respect, and their contributions should be acknowledged. Some SDSS and LSST team members noted they felt their service to their sky survey project was not treated with due respect. For example, Campbell explained how different sky survey projects demonstrate different levels of career support for their staff. He explained how in one sky survey, he felt supported by the faculty involved but in another he felt, "that the people kind of in the trenches doing the work were not getting that kind of credit or that kind of exposure" (Campbell, Professor, 2015). He went on to explain that existing reward structures do not encourage staff to join and remain in sky survey projects and suggested, "the trick is to keep these people on, you've got to reward them somehow. Not just monetarily, but their career. …you need to support the people working for you, and it's tough to do on these big projects" (Campbell, Professor, 2015). Campbell and others feel they require more support from SDSS or LSST leaders to support their careers while they spend years supplying their expertise to working on essential infrastructures. One reason team members may feel their work is disregarded is because they are performing invisible work. SDSS and LSST leaders will benefit their projects

by appreciating all team members, preventing essential work from becoming invisible and particularly under-rewarded.

Respecting the contributions of all team members is important for the individuals involved, as well as the overall team confidence. Morale is important for SDSS and LSST, because the projects can span a decade or more and require geographically disparate teams to coordinate with and trust one another. High staff turnover can hinder project timelines and ultimate project success. When team members leave, they take with them the institutional knowledge and relationships necessary for project continuity. Two interviewees for this dissertation have since left the SDSS and LSST collaborations and moved to industry careers. They chose to leave academia, because they not only were unable to obtain faculty tenure-track careers, and they felt SDSS or LSST leadership undervalued their infrastructure contributions to the project.

Team members are essential to the SDSS and LSST collaborations. Sky survey team members must work for up to a decade before end-users can employ the resulting data for scientific articles. While some team members will also use the resultant data for scientific analysis, many will find themselves too busy with infrastructure to pursue that end goal. While SDSS and LSST datasets cannot be collected, processed, and released without the work of many infrastructure team members, these contributions are often overlooked. However, team members must feel appreciated and supported in their sky survey work for the project to retain continuous expertise. Disrespect in each project hierarchy will reduce the supply of willing highly qualified, pi-shaped available to sky survey teams even further.

This dissertation has opened the black box of long-term data management, demonstrating the essential roles and perspectives of the staff who manage data across the research life cycle. A

dearth in the number of pi-shaped experts in data-intensive science remains at least partially because the academic reward-structure is at odds with supporting these new, essential experts (Kitchin, 2014; Ray, 2014a). Sky survey stakeholders should work together to determine and establish career paths and best practices that can reward and support sky survey staff in ways comparable to the essential skills they bring to the team. For example, this study has shown that even when LSST staff are presented with 20% time for their own scientific work, staff tend to find themselves too busy to use the time for anything other than their regular infrastructure-building duties. Different models could incentivize these essential pi-shaped staff to remain in sky surveys and academia instead of losing these talented individuals to industry. Perhaps teams could be constructed in a way that scientific sabbaticals can be offered without stalling infrastructure development. Perhaps sky survey projects at different stages of development could share proprietary data access among one another. In this way, the astronomy community could work together to support the retention of crucial staff. Specific models could be built into funding requests to support the intellectual and scientific pursuits of the staff that are crucial for infrastructure building, but who are not currently appropriately rewarded to the extent that their expertise is necessary. Perhaps business or industry leaders who specialize in incentives and workforce development should be consulted to intentionally develop a stronger astronomy workforce ecosystem that supports sky survey staff.

6.2 Difficulties Sustaining Digital Infrastructures

As shown in this dissertation, sky survey data management stakeholders are diverse and distributed, each with their own set of understandings for what data management entails. This dissertation has served to collect, analyze, and provide suggestions for data management best practices based on the holistic perspective obtained by conducting this study and presented in

Figure 11. Data management in the short, medium, and long-term requires monetary resources, sustainable workforces, and sustained infrastructural commitments.

The SDSS and LSST projects represent incredible feats of cross-disciplinary collaboration. As shown in the Results chapter, the SDSS compiled a dataset considered by the worldwide astronomy community as a gold standard to calibrate other datasets. Some end-user study participants went further to note that their research relies daily on SDSS data. The thousands of published scholarly articles employing SDSS data further confirm the authority and quality of SDSS data, which influences research well beyond that of the members of the initial collaboration. LSST is well on its way to becoming just as critical. Jointly, these two ground-based, astronomy projects have a successful history of data collection, processing, and release. However, despite these undeniably successful undertakings, a major impediment prevents these datasets from being sources of information into the future.

The "Availability-Usability Gap" has emerged from the SDSS and LSST communities, illustrating the differences between funder mandated data management plans and the actual accessibility of data given current infrastructures (Levine, 2014, p. 129). Funding agencies and policy makers should hold community forums in consideration of long-term data funding for prominent datasets. SDSS and LSST have operated on multiple grants of two to ten years in length (refer back to 4.1.1 RQ1 documentation results). Each individual award provided funds to support a distinct portion of the research life cycle. However, there remains a vulnerability to the sustainability of these quality datasets. Appropriately funded during data planning, collection, processing, and release, budgeted financial support for long-term data management remains rare. This dissertation revealed the research life cycle for SDSS and LSST (refer back to Figure 7).

Figure 12 focuses in on the data management life cycle model to highlight the point at which funding traditionally ends for sky surveys and many other scientific investigations.

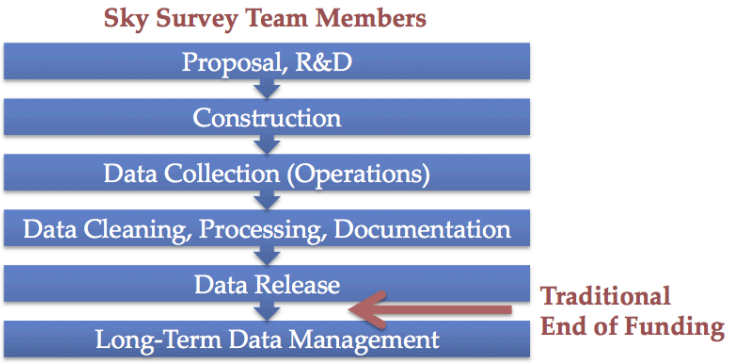


Figure 12 Traditional end of funding for sky survey projects

Long-term data management, beyond data collection and release, was not factored into initial SDSS I and II funding proposals and budgets. As just presented, one reason for this is because data are presented to funders as a product, which makes invisible the practices and workforces necessary for long-term data management.

Despite the end of project funding, the SDSS data retain enormous value through continued use by end-users. SDSS I and II data have remained available to end-users after 2008 through a series of cobbled-together efforts. First, a sum of funds were unused at the end of funding for operations, and the Astrophysical Research Consortium chose to deploy those funds to support data management for five years (see sections 4.1.3.1 SDSS data in ethnography and SDSS library workforces). Second, additional teams of astronomers sought funding to continue use of the SDSS facilities. These projects ultimately were funded, and the data collected through the SDSS III and IV collaborations have been added to the initial SDSS I and II dataset. While SDSS IV remains funded, the growing database of SDSS I-IV materials continue to be managed and served. Finally, a few individuals within the SDSS project team have devoted their personal

resources to ensure the SDSS I and II data are preserved into the near future. However, each of the three ways SDSS data have remained archived and served from 2009 to now have been serendipitous, were not strategically planned for, and could have crumbled at any point. Indeed, these three interim solutions are fragile, temporary infrastructures (Borgman et al., 2016). Instead, durable infrastructures are necessary to support SDSS data management. Data management for LSST data has also not been considered beyond the end of operations. LSST staff even noted that they are unable to plan for long-term data management, citing how funders have scoped their current project funding to focus solely on construction. SDSS data are highly used, years after the end of their operations. LSST data are expected to be the same, and LSST documents have asserted the extensive lifetime expected of the data (refer back to 4.1.1.2 LSST data in documents). However, there is a stark gap in data management infrastructure planning and action for the long-term.

As illustrated in Figure 12, traditional agency funding ends prior to activities focused on the long-term archiving and serving of data. Table 26 shows that SDSS and LSST stakeholders life cycle stages interpretation depend on whether the discussion is focused on data, data management, or data management expertise. Interviewees discussed a longer, more nuanced life cycle when discussing *data management*, while long-term data management was largely ignored when discussing *data*. This dissertation has demonstrated that stakeholder conversations must explicitly focus on data management beyond initial use, referencing data as a process and not as a product. Without explicit redirection of planning toward future reuse, astronomy project planning is destined to end with "data analysis" and initial journal article publication as found in this dissertation study's RQ1 conversations (refer back to Table 26). Funding agencies and sky

survey leadership must continue to re-focus project planning discussions toward future data reuse for data-intensive advances to occur.

Sustainable funding is essential because archiving and serving require knowledge infrastructures. Data management before, during, and beyond data collection are active processes. Data require hardware and software upgrades and migrations and bit rot analysis, to name a few of the actions necessary for digital information bit management. However, this dissertation demonstrates that data are more than only bits of information to be digitally stored; data must also be retained as scientific evidence that can be used for research (refer back to 4.1.4 RQ1 results summary). Active data curation is necessary to develop and maintain relationships between data at distinct processing levels, and between data and other kinds of information including documentation and metadata. Finally, for data to remain usable, the information must be served actively, which includes a host of other system administration and help desk tasks. While a dark archive may prove cheaper and ensure preservation, that decision limits access.

This dissertation study data management model specifically has shown that SDSS and LSST data are not just bits, but also evidence for scientific use, and require serving as well as archiving. Continuous acts of data management require funding, and without them digital data can become unreadable quickly (Borgman, 2015). Sustainable archiving and serving of scientific data requires ongoing investments in the knowledge infrastructures and workforces surrounding these collaborations. These ongoing investments currently do not exist however for ground-based astronomy projects, which are funded through individual grants a few years at a time and cease when data collection is complete.

Federal and private funding may have prioritized the SDSS and LSST projects, because their proposals indicated the enormous future potential in future decades of data-intensive

scientific uses and reuses of their data. Traditional funding models effectively support astronomy when the field is scoped by individual investigators using private telescopes (Bowker, 2005; Mayer-Schonberger & Cukier, 2013). However, collaborative efforts like SDSS and LSST require shared telescope facilities, which may also impact the funding models and infrastructures appropriate for that work. Traditional funding models do not support the invisible labor required to enable data availability beyond operations, while the promises of future data-intensive achievement require that data remain available beyond the period of a single project (Burns et al., 2014; Schroeder & Meyer, 2012). When funding ceases upon data collection completion, or even shortly thereafter, the research community is unable to realize the full potential of these multi-million and billion dollar scientific investments.

End-users will be unable to continue using SDSS or LSST data if the data are not continuously archived and served. As described in 4.2.2.3 SDSS data end-users, SDSS data end-users rely on continued access to SDSS data, and do not retain copies of the data because they expect always easily to re-attain the data through the collaboration website. While some pervasive infrastructures were effectively adapted to modern "big science" approaches to astronomy research, the prompt end of funding following data collection remains a problem for the community, inhibiting advances from data-intensive science.

While many funding agencies encourage the development of data management plans and enabling data access (Directorate of Mathematical and Physical Sciences Division of Astronomical Sciences (AST), 2010; Holdren, 2013; National Institute of Health, 2003; National Science Foundation, 2010b), the infrastructures to support these expectations do not exist yet in ground-based astronomy community. Despite funding proposal promises to facilitate scientific findings beyond data collection, SDSS, LSST, and other similar projects are unable to fulfill

those promises because long-term astronomy and funding infrastructures do not exist to support such work. As noted in Figure 12, financial support decisively falls off after data collection is complete, and community infrastructures like NASA science centers do not exist in ground-based astronomy.

LSST data undeniably will be used highly beyond the end of the ten-year survey. However, the haphazard ways SDSS data were maintained after survey close cannot serve as data management solutions for LSST. Instead, funding and personnel must be dedicated early to ensure the archiving and serving of LSST data until the point at which the community itself decides the data no longer require maintenance. Judging by the impact of the SDSS data on the astronomy community, LSST data are expected to remain an important part of astronomy research for a decade or more beyond data collection. The scientific community, rather than the common three-to-five year funding model, should determine when datasets are no longer archived and served.

Some disciplines have largely resolved the funding gap problem for data management beyond the close of data collection grants. For example, the Inter-University Consortium for Political and Social Research (ICPSR) established shared infrastructures to support social science research data. While the NSF largely funds projects through short-term grants, like those supporting LSST, NSF also has longer-term, large "facilities" funding models (National Science Board (U.S.), 2005). Even space-based, NASA-funded astronomy research data are distributed to NASA science centers following the end of a mission (Committee on NASA Astronomy Science Centers, & National Research Council, 2007). Those communities have established infrastructures to archive and serve important data following the end of funding for the individual created projects. Each of those solutions is discipline specific. ICPSR uses a paid

membership model to manage shared data. NASA science centers rely on continued favorable performance reporting and congressional appropriations. However, in ground-based astronomy, there is no established infrastructure by which a project can hand-off its data for expert archiving and serving beyond individual project funding.

Ground-based projects like the SDSS and LSST are prioritized for funding in part because the data be collected and used in the short-term, and then the data are expected to be reused and combined in many ways into the future to serve important components of data-driven research. However, SDSS and LSST leaders and funding agencies are failing to recognize the chasm disconnecting data collected through project funding and reuse after project close. Anderson was a senior SDSS leader, and yet his understanding of archiving and serving SDSS data falls far short of the necessary steps to enable data-intensive science: "We put it up on the web, so it's good, it's done" (Anderson, Emeritus Professor, 2012).

Systemic change in ground-based astronomy funding rhythms is necessary to ensure data remain usable following data collection, enabling the promises of data-driven research. However, this change requires the development of knowledge infrastructures available at the end of the project life cycle to support data management. Thus, the current sky survey data management model revealed in this dissertation study must be amended by stakeholders to include the funding, infrastructures, and workforces necessary for long-term data management for data-intensive reuse. As the social sciences and NASA-funded projects have established these bridges for their communities, a center(s) may be required to house the knowledge infrastructures necessary to support ground-based astronomy data beyond the end of project funding.

The sustainability model that will work best for ground-based astronomy is not yet clear. Funding agencies should work alongside scientists to determine the best path forward to bridge

the gap in support for ground-based astronomy research data. Stakeholders will need to determine the kinds of workforces and technical infrastructures necessary to sustain data, which data are determined to have long-term value, what length of time datasets require management, and other pressing details. These determinations must arise from within the community, and be aided by funders who invested in the long-term impact of their investments. This necessary field-wide work is urgent; as time passes, data become increasingly vulnerable to bit rot and other forms of mismanagement.

6.3 Limitations

This dissertation does not attempt to discuss data management expertise across all of science, or even the full discipline of astronomy. The intended population was that of modern, ground-based optical sky survey team members and end-users. In practice, the study populations were the SDSS and LSST data management team members, as well as end-users of SDSS data. SDSS and LSST are not the only sky surveys in astronomy, but are arguably some of the best funded and most respected. The same workforce stratification within these two teams may not be reasonably expected in other surveys.

This dissertation is also limited by the length and intensity of the study. While a five-year study involving interviews and observations provides a strong set of data, increasing the longitudinal nature of the study, as well as increasing the depth of investigation, could vastly improve the study of these projects. Ideally, the number of study years would be increased to ensure observations of the full life of a sky survey. Long-term, fully immersive ethnographic participant observation fieldwork, as identified by the anthropology community, would provide a stronger set of evidence for the ways workforces interact with one another across time and place. Alternatively, the internal validity of this dissertation may be influenced by the years-long nature

of the study. Maturation of study participants can have an effect on findings as "people are continually growing and changing" (Babbie, 2007, p. 230). To lessen the impact of maturation on this study, all documents, transcripts, and observations include indications of the year they took place. Year of interview was also a demographic factor in interview analysis.

Finally, this study was limited by study population self-selection. Observations and interviews were not conducted with individuals who were disinterested in study participation for any reason. Some potential for study bias is present, however, the right for a study participant to opt-in is critical to the ethical nature of the study and cannot, and will not, be rescinded.

6.4 Future Work

Given the abundance of interviews conducted for this dissertation, and the fact that only a portion of the vast materials were exposed within this document, further analyses should be conducted with the 80 interview transcripts. The transcripts remain protected under the UCLA IRB, and the UCLA CKI team members should continue to investigate these findings.

First, data collection for the current case studies should continue to increase the longitudinal nature of the study and the potential for more thorough analysis. The UCLA CKI has investigated SDSS since 2009; LSST has only been studied since 2014. The CKI should at minimum continue to study LSST to obtain comparable depths of understanding for both astronomy sky survey projects. Ideally, LSST will continue to be studied through the transition from construction to commissioning and further as funding allows.

The interviews conducted for this study were distributed and diverse. Interviewees were affiliated with 26 institutions, and clustered based on seven demographic variables. However, while the coverage was broad, study analysis could have improved by also including specific stakeholder institutions as an interviewee variable. For example, preliminary analysis indicates

collaborative differences between team members at each LSST data management institution. Future work includes coordinating with fellow team members at the UCLA CKI to analyze the consistencies and differences between SDSS and LSST stakeholders at different institutions.

Astronomy data are not the only kinds of information integral to astronomy research. Important contextual information may include the software that has processed, or is necessary to analyze, the data (Borgman, 2015; N. Gray et al., 2012; Howison & Bullard, 2016). Software revealed itself during analysis as an important information type for astronomy research. However, it quickly became difficult to discover the boundaries between data and software. Further research is needed to understand the role that data, software, and other kinds of information play in astronomy sky surveys.

Finally, further research is necessary to understand the way sky survey team members are rewarded and how their educations and careers progress. Pi-shaped stakeholders, who are experts at astronomy as well as software engineering and infrastructure building, hold an essential knowledgebase for sky survey growth. However, study participants expressed displeasure that infrastructure work is often "invisible" and rarely results in tenure-track faculty careers. At the same time, sky survey participants noted difficulty finding the data management experts needed for their projects. Highly skilled individuals are poorly rewarded, even though they are in high demand. Further research should be conducted to gather more evidence about the current reward structures and their implications for successful research data management now and into the future.

6.5 Closing Remarks

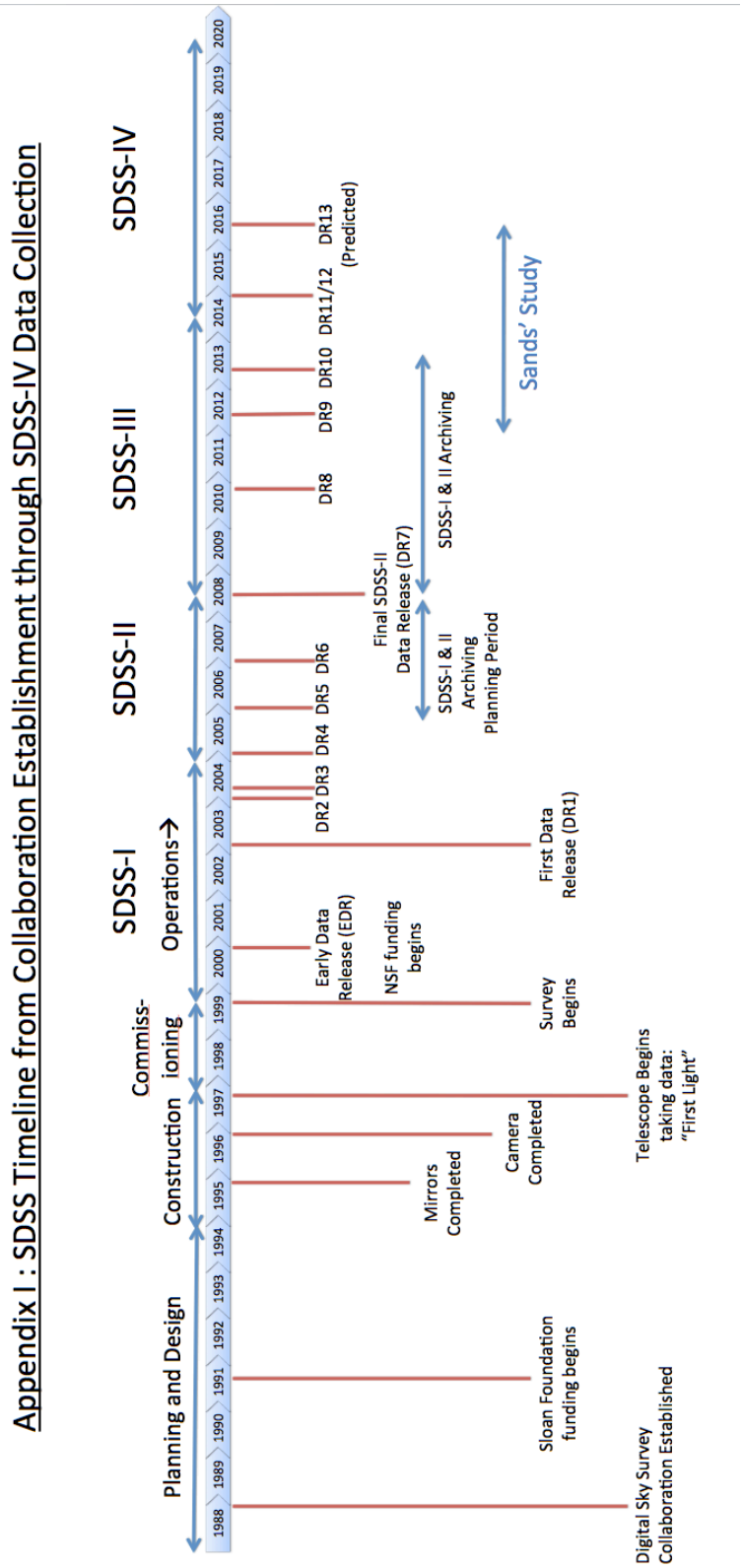
As discussed in the Introduction chapter, information preservation during the Renaissance was not an inherent result of the printing press and only occurred because society

also specifically acted to respect and preserve information (Blair, 2010, p. 61). Sky survey leaders, funders, and other policy makers can no longer remain naïve to the notion that data management requires sustainable resources; while these workforces and infrastructures may currently be absent, black boxed, or "invisible," they remain essential to reap the promised benefits of data-intensive science. Society must once again make a conscious effort to archive and serve information. While many funders have begun requiring data management plans, a further social change is also necessary. Funders must also acknowledge the human and physical infrastructures necessary to accomplish the effective data management they champion for in these plans. In the era of data-intensive science, data must be managed beyond that of initial use, because combining and re-combining various datasets in data-intensive research promises to enhance scientific understanding. These promised insights can only be made if data are managed beyond data collection; however, data project funding currently ceases at data collection close. Just as was the case with the printing press in the Renaissance, advances in data-intensive scientific collection techniques do not inherently beget archived and served datasets of value. It is only through active decision-making and long-term planning that SDSS and LSST data will remain available beyond initial use.

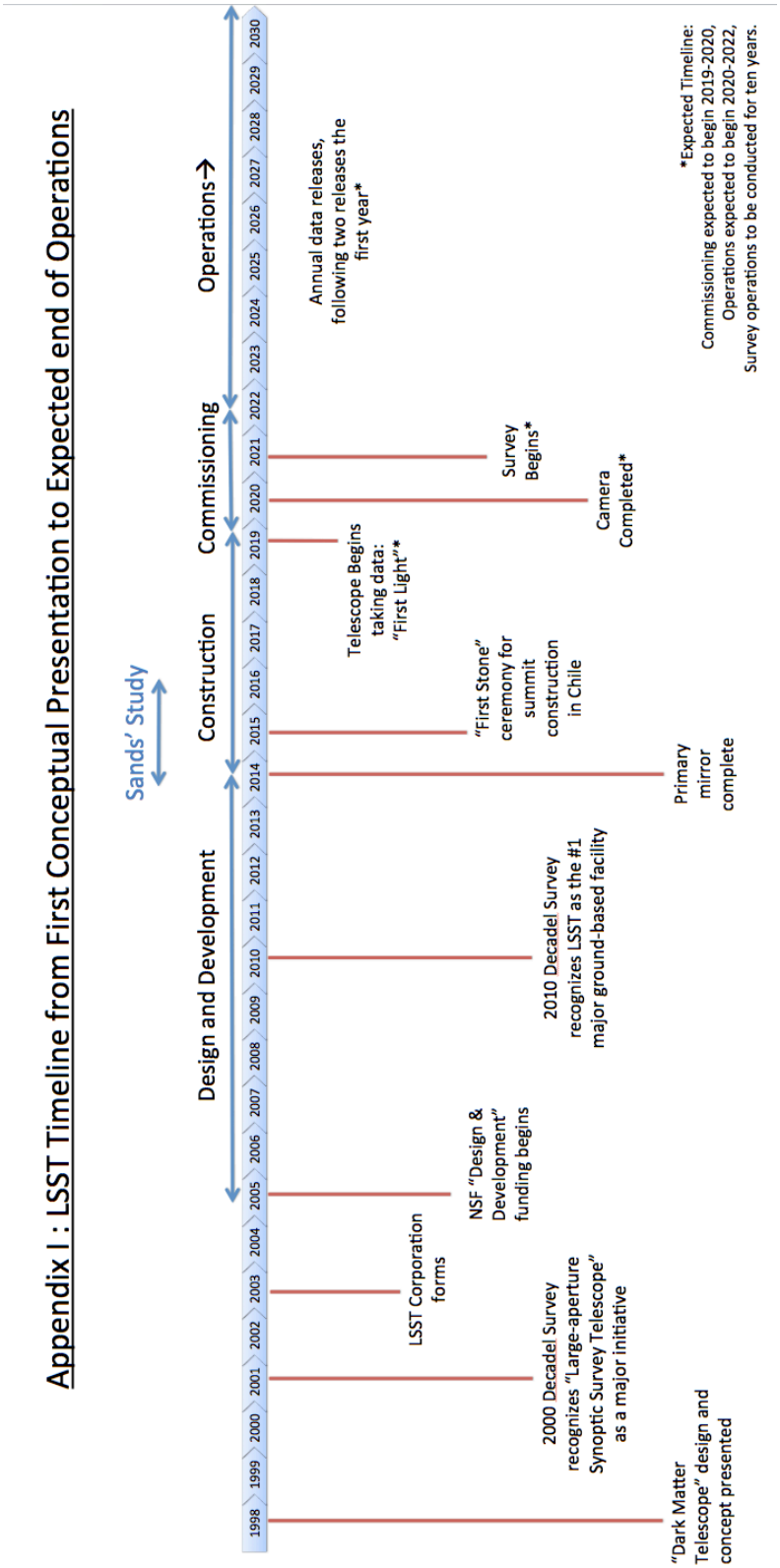
The first step in the process of planning for SDSS and LSST long-term legacies is to accept that stakeholders, including astronomers, computer scientists, librarians, and funders, have differing perspectives. The next step is to move forward inclusive of these diverse perspectives, instead of despite them. By recognizing these data management perspectives, including those of process and product across the full research data life cycle, the strongest sustainability plans and research infrastructures can be developed and deployed.

A consistent, expert workforce with a reliable salary is necessary to ensure the appropriate long-term management and utility of scientific data (Committee on NASA Astronomy Science Centers, & National Research Council, 2007; Research Information Network, 2008). Funding, or a lack thereof, impacts the stability of all knowledge infrastructures, including the human expertise critical to ensuring data usefulness for years to come (Berman & Cerf, 2013; Edwards et al., 2013; Hine, 2006). While funding for data collection and scientific investigation are important, additional funding beyond the point of initial scientific return is necessary to retain the research efficacy of data over time. For SDSS and LSST data to remain usable over the long-term, a new funding model and a full environment of sustainable expertise that bridges the current chasm in the research life cycle are required. These changes may resemble NSF facilities, NASA science centers, social science consortia like ICPSR, or perhaps a solution not yet envisioned. It is only once stakeholders acknowledge the true costs of data management beyond collection (instead of remaining naïve to "invisible" workforces and currently absent infrastructures) that the SDSS and LSST can contribute fully to the data-intensive science revolution already underway.

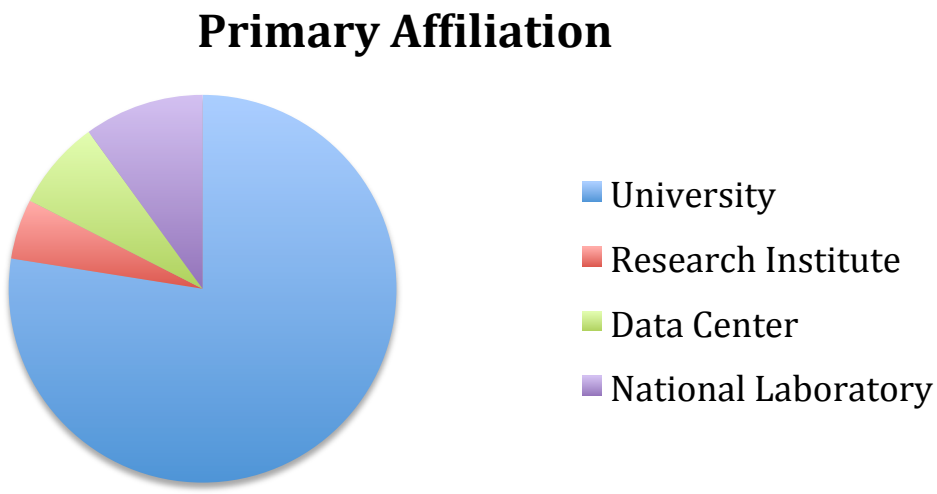
Appendix I: Sloan Digital Sky Survey Timeline

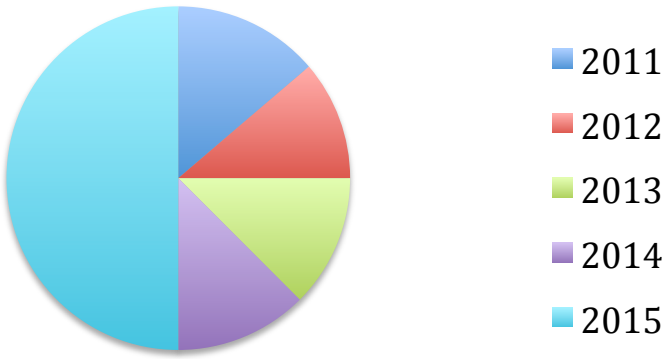


Appendix II: Large Synoptic Survey Telescope Timeline

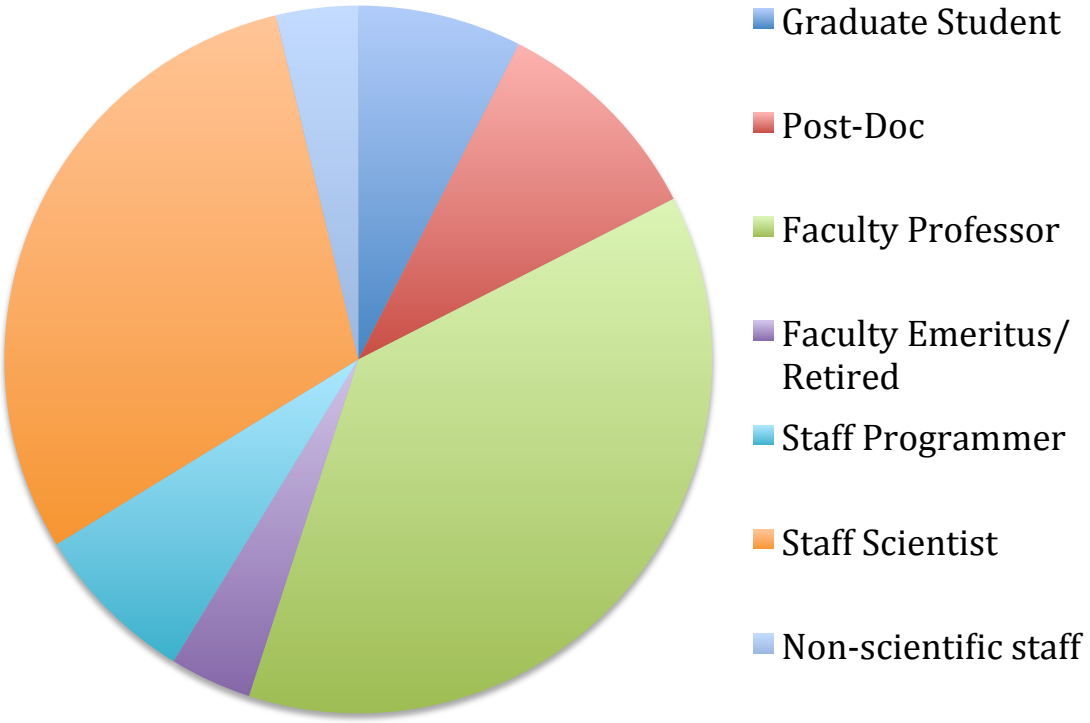


Appendix III: Interviewee Demographics

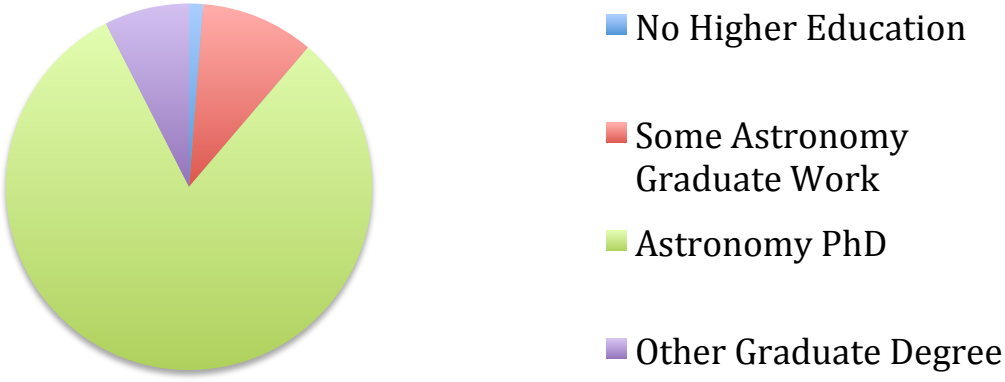




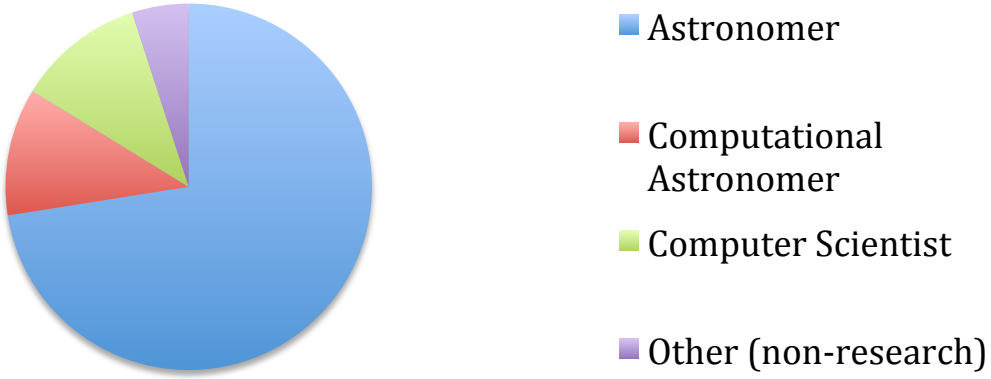
Career Stage



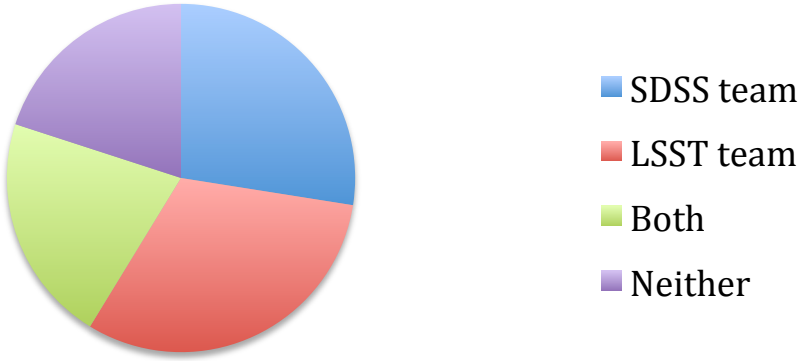
Level of Astronomy Education



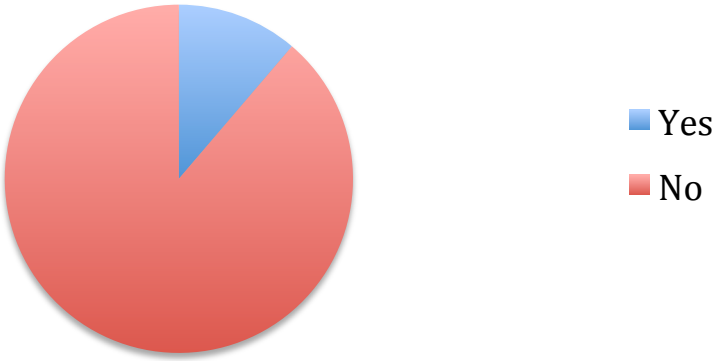
Current Workforce



SDSS or LSST Team Affiliation



Theorist?



Appendix IV: Interview Consent Form

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SANTA BARBARA • SANTA CRUZ

GRADUATE SCHOOL OF EDUCATION & INFORMATION STUDIES
BOX 951520
LOS ANGELES, CALIFORNIA 90095-1520

CONSENT TO PARTICIPATE IN INTERVIEW

The Transformation of Knowledge, Culture, and Practice in Data-Driven Science:
Research study conducted by PI Prof. Christine L. Borgman of Information Studies, and Co-PI Prof. Sharon Traweek of Gender Studies and History at the University of California, Los Angeles. This project is funded for by the Alfred P. Sloan Foundation and the NSF. [Full proposal descriptions available on request.]

Please read this form carefully and feel free to ask any questions you may have about this study and the information given below. You will be given an opportunity to ask questions and your questions will be answered. You will be given a copy of this consent form. This consent form applies to adults (18 years or older).

Name _____

Affiliation _____

City _____ State _____ Country _____

Date _____

1. I hereby agree to participate in at least one individual and/or cohort interview and/or to be observed in connection with the research project named above. I understand that I will be asked about my participation in data-intensive science projects, my research data practices, and collaborations with colleagues involved in these projects.

2. The interview may be audio or video recorded. In the interview I may be identified by name, subject to my consent. I may also be identified by name in any transcript (whether verbatim or edited) of such interview, subject to my consent. If I choose to remain anonymous, I know that my name will not appear in the transcript or reference to any material contained in the interview. I know that, in the case of choosing to remain anonymous, my interview will only be identified by a tracking number.

3. I understand that each interview will take approximately one to two hours and that I can withdraw from the project without prejudice prior to the execution and delivery of a deed of gift, a form of which is attached hereto. In the event that I withdraw from the interview, any recording made of the interview will be either given to me or destroyed, and no transcript will be made of the interview.

4. Subject to the provisions of paragraph five below, I understand that, upon completion of the interview, the recording and content of the interview belong to PI's Christine L. Borgman and Sharon Traweek, and that the information in the interview can be used by them in any manner they will determine, including, but not limited to, use by researchers in presentations and publications.

5. (i) No one will use or exercise any rights to the information in the interview prior to the signing of the deed of gift; (ii) the deed of gift will be submitted to me for my signature at completion of the interview; and (iii) restrictions on the use of the interview can be placed in the deed of gift and will be accepted as amending the researchers' rights to the content of the interview. I understand that I have the right to review, edit, or erase the recordings of the interview before I sign the deed of gift.

6. Any restrictions as to use of portions of the interview indicated by me will be edited from the final copy of the transcript.

7. I understand that at the conclusion of this particular study and upon signing the deed of gift, the recordings and one copy of the transcript will be kept by the principal investigator of this project, Prof. Christine Borgman, Graduate School of Education & Information Sciences at UCLA.

8. If I have questions about the research project or procedures, I know I can contact the principal investigators of this project:

Prof. Christine Borgman
University of California at Los Angeles
Graduate School of Education & Information Studies
borgman@gseis.ucla.edu
(310) 825-6164

Prof. Sharon Traweek
Department of Gender Studies
University of California at Los Angeles
traweek@history.ucla.edu
(310) 825-4601

If you wish to ask questions about your rights as a research participant or if you wish to voice any problems or concerns you may have about the study to someone other than the researchers, please call the Office of the Human Research Protection Program at (310) 825-7122 or write to Office for Protection of Research Subjects, UCLA, 11000 Kinross Avenue, Suite 211, Box 951694, Los Angeles, CA 90095-1694.

The content of this informed consent document is drawn from:

Center for the History of Physics, American Institute of Physics:
http://www.aip.org/history
http://www.aip.org/history/oral_history/conducting.html

Indiana University Center for the Study of History and Memory [CSHM]:
http://www.indiana.edu/~cshm/
http://www.indiana.edu/~cshm/informed_consent.pdf

CONSENT TO PARTICIPATE IN INTERVIEW

Step 1: Check one of the following

___ I agree to be identified by name in any transcript or reference to any information contained in this interview.	____ I wish to remain anonymous in any transcript or reference to any information contained in this interview, and I wish to have my transcript only identified by an internal tracking number.

Step 2: Optional Restrictions

___ I wish to restrict access to recordings and transcripts of this interview to the following kinds of researchers:

- ___ initial research team conducting the interviews [led by PI's Borgman & Traweek]
- ___ university-based researchers _____
- ___ others_____

These restrictions to recordings and transcripts of this interview are for the following number of years_____

___ I wish to add the following restrictions _____

_____

_____

- **Interviewee signature** _____

Address _____

_____

_____

Phone number _____

Consent date ____/____/____

Interviewer signature _____

Appendix V: Interview Deed of Gift Form

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BOX 951520
LOS ANGELES, CALIFORNIA 90095-1520

ORAL HISTORY DEED OF GIFT

The Transformation of Knowledge, Culture, and Practice in Data-Driven Science:
Research study conducted by PI Prof. Christine L. Borgman of Information Studies, and Co-PI Prof. Sharon Traweek of Gender Studies and History at the University of California, Los Angeles. This project is funded for by the Alfred P. Sloan Foundation and the NSF. [Full proposal descriptions available on request.]

I, _____ hereby give to Prof. Christine Borgman and Prof. Sharon Traweek for scholarly and educational use the audio or video recordings of individual and cohort interview(s) conducted with me
by _____ on _____ [date]

I understand that I can authorize others to make any use of the content of these recordings, and that Prof. Borgman and Prof. Traweek will, at my request, make available a copy of those recordings for such use.

Step 1: Please check one of the following

_____ *I agree to have my oral history interview stored for future use by the Principal Investigator and/or research team*

_____ *I do not want my oral history interview stored for future use by the Principal Investigator and/or research team.*

Step 2: Restrictions (optional)

If I wish to remain anonymous in any interview transcript or reference to any information contained in this interview, I will specify that restriction here:

_____

The foregoing gift and grant of rights is subject to the following restrictions:

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Step 3: Signatures

This agreement may be revised or amended by mutual consent of the parties undersigned:

_____ Interviewee signature, date	_____ Interviewer name, signature, and date

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