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Mapping Individual Variations in Learning Capacity

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Individual differences in learning capacity are evident in humans and most other animals. Traditionally, such differences are described in terms of variations along a relatively small number of psychological dimensions corresponding to behavioral traits. Here, an alternative approach is considered in which individual differences in learning capacity are characterized by spatially sorting behavioral patterns. To illustrate this approach, a two-dimensional self-organizing feature map was used to analyze patterns in the performances of intact and cortically-lesioned rats engaged in multiple learning tasks. After training, the spatial structure of the map revealed systematic variations in learning across rats that were related to the degree of brain damage. Individual nodes within the map described prototypical performance profiles that corresponded closely to patterns of learning seen in individual rats, including individuals with idiosyncratic profiles. Techniques that automatically identify modal patterns of performance during learning may provide new insights into the processes that determine what an individual organism can learn.

What do intelligence, strength, dexterity, charisma, constitution, and wisdom have in common? They are all descriptors of characteristics that an organism may possess that are predictive of the feats that the organism can achieve. A strong animal can move objects a weaker animal cannot. A wise human can understand complex situations in ways that a clueless person would never grasp. These descriptors also all share the property of varying along a quantifiable continuum. An individual's strength can be measured in terms of the number of kilograms they can lift; her charisma can be estimated based on the number of friends she has. This intuitive framework for describing individual differences is aptly captured by the role-playing game Dungeons & Dragons. In this game, a player's capacities are defined in terms of specific numbers associated with each of the six descriptors noted above; a player's "trait scores" shape the outcome of almost every important event in the game. Similarly, in the real world quantitative assessments of aptitude or personality can determine who gets to attend the top universities and which individuals are identified as a perfect match by a dating website. But, do such descriptors really correspond to properties of individuals? Or, are they just a useful way of summarizing a set of salient behavioral observations? Might there be ways to precisely describe individual variations that do not rely so heavily on intuitive notions about the qualities that define an individual, and that more closely relate to the mechanisms underlying those variations?

The goal of the current paper is to develop an approach for characterizing individual differences that depends less on rating an individual's abilities (or

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proclivities) relative to conspecifics, and that avoids using existing verbal descriptors to classify and evaluate such differences. This approach is applied to the analysis of individual variations in learning capacity, a property that varies within and across individuals of many different species. The following sections review: (1) current hypotheses about the mechanisms underlying variations in learning capacity within and across humans and other animals; (2) methods for characterizing individual differences in learning capacity and intellectual ability in terms of behavioral traits; and (3) methods that characterize these variations in terms of behavioral patterns. An alternative strategy for analyzing individual variations in learning capacity is then presented; this strategy avoids some limitations of past approaches. The tentative conclusion reached is that traditional trait-based approaches are not well suited for quantifying variations in learning capacity. The complex and dynamic nature of learning warrants the development of more flexible tools for exploring why some individuals are more successful learners than others.

The Nature and Origins of Learning Capacity

The terms *learning capacity* and *learning potential* are used here to mean the ability to change one's abilities or knowledge through experience. It is simply meant to convey that organisms are able to learn, something enables them to do so, and this something (which is actually a multitude of things) varies across individuals. Estes (1970) used the terms to refer to, "any source of individual differences, determined either genetically or by some combination of genetic factors and developmental processes which are independent of previous learning" (p. 30). He also noted, however, that "except perhaps in infancy, a great part of the variance in rates of learning between individuals must be attributable to differences in the results of past learning" (p. 31). In fact, many experiences may impact an individual's learning capacity, including prenatal experiences (e.g., Lemaire, Koehl, Le Moal, & Abrous, 2000). Estes's requirement that sources of individual differences in learning capacity must be "experience-independent" might easily exclude many basic mechanisms thought to contribute to variations in learning abilities (e.g., sensory abilities and neural plasticity). Here, the term learning capacity is used to refer to sources of individual differences in learning mechanisms determined by some combination of genes, developmental processes, and experience.

Learning capacity has received less scientific attention than psychological dimensions such as intelligence, personality, interests, and cognitive abilities. Some psychometricians have suggested that variations in learning ability are intimately linked to individual differences in intelligence (Duncanson, 1964; Jensen, 1989). The relationship between intelligence and learning capacity has been notoriously difficult to pin down, however (Gagne, 1967, 1989; Hundal & Horn, 1977; Lohman, 1999; Woodrow, 1946). Mercado (2008, 2009) suggested that variations in intellectual capacity partly reflect how well individuals distinguish events, which is known to be learning-dependent. From this

perspective, measures of intelligence are indicative of an individual's capacity to learn cognitive skills, and variations in learning capacity contribute to (but are not equivalent to) variations in intellectual abilities. Because so few studies directly examine individual variations in learning capacity, much of the discussion below focuses on variations in measures of intelligence. It is important to keep in mind, however, that intelligence tests usually measure performance rather than learning capacity.

A talent for learning

Current evolutionary models of individual variation heavily emphasize the genetic origins of abilities, assigning only a minor role to learning or other experiences (Bolnick et al., 2003; Hayes & Jenkins, 1997). Researchers have debated the relative contributions of genes (or heredity) and experience to individual differences in mental abilities for well over a hundred years (Chabris, 2007; Fuller & Thompson, 1978; Galton, 1883; Gray & Thompson, 2004; Plomin, 2001; Plomin & Spinath, 2002). As illustrated by the quote from Estes (1970) above, learning capacity has often been portrayed as a genetic endowment analogous to growth potential (see also Hull, 1945). Galton (1883) was one of the first to seriously explore the idea that intellectual abilities were traits that could be inherited. He tested this hypothesis and found correlational evidence consistent with this idea. Later experimental studies confirmed that learning capacity could be manipulated using artificial selection techniques (reviewed by Dukas, 2004; Wahlsten, 1978). The earliest work of this kind showed that rats could be bred so that subpopulations were faster or slower at learning particular kinds of mazes (Heron, 1935; Tolman, 1924; Tryon, 1929, 1942). More recent work with genetically engineered flies and mice also shows that it is possible to create individuals that learn certain tasks faster or slower than the norm (Dubnau, Chiang, & Tully, 2003; Skoulakis & Grammenoudi, 2006; Tang et al., 1999; Waddell & Quinn, 2001).

Within comparative psychology, adaptive specializations for learning have been discussed in relation to the evolution of niche-dependent strategies or abilities (e.g., song learning) in a particular species (Bolhuis & Macphail, 2001; Dwyer & Clayton, 2002; Macphail & Bolhuis, 2001; Shettleworth, 1998; Timberlake, 2001). It is not immediately obvious how individual variations in learning capacity might relate to such specializations (see Bolnick, et al., 2003, for some possibilities). However, biologists and educational psychologists increasingly are emphasizing that "trait-like" differences between individuals can strongly affect how those individuals learn (Chen, Gully, Whiteman, & Kilcullen, 2000; Chiappe & MacDonald, 2005; Dugatkin & Alfieri, 2003; Sih & Bell, 2008; Sih, Bell, Johnson, & Ziemba, 2004).

Recent work on the evolution of neural mechanisms of learning has revealed subtle cross-species differences, as well as many similarities, in the processes that give rise to synaptic changes (Dubnau, et al., 2003; Dukas, 2004; Matzel & Gandhi, 2000; Ryan & Grant, 2009; Wright, Kirschman, Rozen, &

Maynard, 1996). Variations in synaptic plasticity mechanisms across individuals within a species are also known to impact learning capacity (Rankin, 2004). These differences undoubtedly impact how organisms learn. Evolutionary psychologists (Kanazawa, 2004), and comparative neuroanatomists (Rakic, 2009), have argued for special adaptations in human brains that confer enhanced learning abilities. But, the evidence for unique enhancements in the neural substrates of human learning remains questionable (Borsboom & Dolan, 2006). Both natural and artificial genetic variation can contribute to individual differences in learning capacity, but this does not preclude modulation or control of these mechanisms by environmental variables, including learning experiences and neural activity (Dukas, 2004).

Constructing learning mechanisms

As an organism's brain develops, certain chains of events are experienced that trigger predictable outcomes in neural circuits. For example, when an infant is born, novel excitation associated with respiration and the reception of light will begin to change the way that neural circuits respond to such events. Since these events are typical of birth, the kinds of changes that will occur are relatively stereotyped across individuals. This basic process, called experience-expectant plasticity (Fahrbach, Moore, Capaldi, Farris, & Robinson, 1998; Greenough, Black, & Wallace, 1987), provides a loose account of why one might see developmental progression in capacity occurring in a predictable sequence, and why a neglected infant might show reduced abilities compared to an infant that is engaged by its parents. Experience-expectant plasticity is associated with the whittling down of neural connections to assimilate environmental information common to all members of a particular species; atypical experiences can lead to abnormal neural circuits. This process generates neural changes that can dramatically impact learning processes, and that become increasingly difficult to reverse over time (Greenough et al., 1987).

Some developmental theorists have discussed growth-related changes in learning capacity in terms of the experience-dependent restructuring of perceptual and cognitive processes (Hebb, 1949; Quartz & Sejnowski, 1997; Vygotsky, 1978). For example, the neural constructivist perspective on cognitive development suggests that an individual's brain acquires the ability to represent events through exposure to the environment (Hebb, 1949; Quartz, 1999; Quartz & Sejnowski, 1997, 2000). In this framework, what the individual is able to learn depends on which constructed representations are available (Mercado, 2008). Consequently, variations in an individual's learning capacity are not simply a consequence of genetically-specified differences in computational power, but are also a function of experience-dependent neural growth. Furthermore, changes in the learning mechanisms of an individual follow idiosyncratic trajectories throughout the lifespan (Baltes, Reuter-Lorenz, & Rosler, 2006). Variations in these trajectories are likely a major contributor to individual differences in learning capacity and intelligence (Shaw et al., 2006; Thelen, 1990).

Expert learners

Learning capacity is a peculiar characteristic to consider in terms of genetic origins because learning could be viewed as a process that picks up where evolution left off, serving to refine and customize an individual's behavior to accommodate its particular circumstances. Some researchers hold that no amount of experience can overcome the boundaries on intellect set by genetic predispositions (Jensen, 1998), whereas others suggest that individuals who achieve the highest levels of performance in a particular intellectual domain are those that have the greatest quantity and quality of training and practice (Ericsson & Lehmann, 1996). Hebb's (1949) report that rats raised by his children as pets showed greater learning capacity than laboratory-reared rats, provided some indication that experience was a critical component of learning capacity. This observation sparked a series of studies on the effects of enriched environments on the learning abilities of rodents, many of which showed that non-specific learning opportunities could amplify individual differences in learning capacity (Cooper & Zubek, 1958; Dukas, 2004; Nithianantharajah & Hannan, 2006). Directed practice and more active learning experiences lead to similar changes. These kinds of environmentally-driven changes in ability are described as experience-dependent plasticity. Experience-dependent plasticity is associated with the formation of new or stronger neural connections. Genetic codes determine only rough patterns of neural connectivity (Udin & Grant, 1999); differential use of networks determines how these circuits are refined.

Environmental (including cultural) contributions to variability in intellectual abilities have received increasing attention (Baltes et al., 2006; Ceci & Bruck, 1994; Flynn, 2007). For instance, recent work on lifespan development emphasizes reciprocal interactions between the social environment and brain development (termed biocultural co-constructivism), and proposes that multiple experience-driven neural plasticity mechanisms operate on multiple time scales (evolutionary, developmental, and situational) to determine an individual's abilities (Li, 2003). Many of these proposed plasticity mechanisms likely also contribute to learning capacity (Mercado, 2008).

State-dependent variations in learning capacity

The genetic, developmental, and environmental factors described above directly impact an individual's learning capacity. There are also other more indirect sources of variation in learning, however, such as individual differences in personality or temperament (Bell, Hankison, & Laskowski, 2009; Gosling, 2001; Reale, Reader, Sol, McDougall, & Dingemanse, 2007). Much of the research examining links between temperament or personality and learning capacity has been conducted with non-humans (Coleman, Tully, & McMillan, 2005; Moreira, Pulman, & Pottinger, 2004; Range, Bugnyar, Schloegl, & Kotrschal, 2006; Toxopeus, Sterck, van Hooff, Spruijt, & Heeren, 2005). Pavlov (1927) was one of the first to note the impact of temperament on animal learning. He reported

dramatic differences in conditioning between what he described as sanguine versus melancholic dogs. More recent work has noted similar differences in learning between bold versus cautious animals and between females and males (Agar, Drummond, Tiegs, & Gunson, 1954; Guillette, Reddon, Hurd, & Sturdy, 2009; Sneddon, 2003). Coping style theory suggests that more proactive individuals have advantages learning simple discrimination tasks, and disadvantages when learning other more complex tasks (Koolhaas et al., 1999; Ruiz-Gomez et al., 2008). As with maze learning, temperament differences within subpopulations can be increased through selective breeding (Groothuis & Carere, 2005). Animals that have been bred to be more or less bold differ in learning capacity (Dugatkin & Alfieri, 2003).

Individual differences in temperament can be viewed as variations in the likelihood that certain motivational or emotional states will occur. Dynamic changes in such states within each individual also occur daily. These intra-individual variations are known to impact learning capacity. For example, certain oscillatory states in the brain facilitate classical conditioning in rabbits (Griffin, Asaka, Darling, & Berry, 2004; Hoffmann & Berry, 2009; Seager, Johnson, Chabot, Asaka, & Berry, 2002). Similarly, gamma oscillations in the human brain are associated with better encoding and recall of word lists (Sederberg et al., 2004). Diurnal cycles of neural states also predict cognitive performance (Mackenberg, Broverman, Vogel, & Klaiber, 1974) and modulate learning (Lyons, Green, & Eskin, 2008). Collectively, these findings suggest that learning capacity can vary substantially within and across individuals as a function of global variations in brain state occurring over multiple time scales.

Ultimately, individual differences in learning capacity reflect differences in neural states and dynamics that are strongly determined by the structure and function of circuits constructed through accumulated experiences. The progressive, experience-dependent nature of brain circuit construction suggests that learning capacity may change considerably across the lifespan, and that changes may progress differently depending on an individual's specific environmental and physical conditions. In contrast, many past and current approaches to describing individual differences presume that the psychological dimensions being measured correspond to relatively stable, innate features of individuals.

Methods for Characterizing Variations in Learning Capacity

> *Despite clear and evident data proving that genetic factors and adjustments to stimulating situations are extremely numerous and complex in determining behavior variations, we psychologists, like people generally, find it difficult to face these realities.* (Tryon, 1958, p. 478)

Current strategies for characterizing individual differences generally do not attempt to relate scales or metrics to the underlying mechanisms that give rise to these variations. The foundation for these approaches is instead human language

and intuitions about how well labels capture the essence of the phenomena being labeled. The hundreds of words present in each language that describe people represent a synthetic, communicable understanding of how individuals vary. Although the existing lexicon provides a reasonable starting point for developing simpler schemes for describing individual variation (Ashton & Lee, 2005), this intuitive approach leaves several critical questions unanswered. Do lexically-based psychometric approaches characterize how individuals actually vary? Or, do they simply reflect how humans communicate their conceptualizations of individuals? Does the quantification of psychological attributes reflect systematic, continuous variation in some property of individuals? Or, do such scales correspond to the likelihood that a particular label will be used to describe a particular behavior? Can words adequately describe variations in the qualities of individuals, and if not, what are the alternatives? The following subsections discuss past attempts at characterizing individual differences in learning capacity and intelligence, distinguishing efforts to identify variations in behavioral traits from those seeking to identify systematic patterns of individual differences in performance.

Locating individuals in trait space

The development of various assessment tests and scales by psychometricians can be viewed as an attempt to objectively identify individuals' positions along one or more psychological dimensions corresponding to behavioral traits (Anastasi, 1948; Carroll & Maxwell, 1979; Horn & Masunaga, 2006; Lubinski, 2000). The value of a particular quantifying test or metric depends on its reliability and validity, which correspond roughly to consistency across repetitions and interpretability/utility respectively. An implicit assumption of these criteria is that an individual's position along a particular dimension is relatively stable over time. Otherwise, the measures would not be consistent across repetitions (i.e., unreliable), and thus of little use. The psychological dimensions that have been studied most extensively are bounded by familiar endpoints (e.g, dullard to genius; aloof to amiable), suggesting that the validity of the metrics developed to measure variations along these dimensions depend on the pre-existing lexicon. Relative to simple labeling, however, the quantification of psychological dimensions represents a major advance in the measurement of individual differences.

Standard approaches to quantifying individual differences in intellectual capacity depend heavily on factor analysis and related techniques such as principal components analysis. Factor analysis uses correlations between performance measures to identify simpler ways of accounting for the relationships between those measures. The factors correspond to axes of an *n*-dimensional subspace of the space defined by the data (Wickens, 1995). The basic premise underlying factor analytic approaches to describing individual variation is that there are semi-independent, latent sources of variance across measures of ability, and that these sources can be effectively described in a lower dimensional space than the one defined by the original measures. Decreasing the dimensionality of a data set simplifies the quantification of individual differences and focuses attention on the

largest systematic variations across individuals. Dimensions identified through factor analysis that correspond to verbalizable qualities (e.g., mathematical or spatial abilities) are pragmatically the most useful. The main criterion for successful descriptors derived through factor analysis is that they explain the most variation with the least dimensions. Dimensions that meet this criterion are considered to be the most relevant for understanding the nature of individual differences. Although the psychological dimensions identified via factor analyses do not necessarily correspond to behavioral traits, it is often assumed that something like traits map onto these dimensions (Ackerman & Heggestad, 1997; Horn & Masunaga, 2006).

Factor analysis provides a descriptive framework that in principle allows for the parameterization of the intellectual capacity of any human in terms of a small number of dimensions. This framework matches well with intuitive ideas about individual differences in intellectual talents (e.g., the whiz kids in the class will be better at most academic tasks, but some will have a gift for words, whereas others will be endowed with superior mathematical abilities). Opinions differ, however, as to the relative importance and nature of different factors, which has resulted in different camps of researchers endorsing different sets of dimensions as being important for understanding intelligence (Neisser et al., 1996). When factor analyses are applied to multiple measures of human intellectual performance, one factor called the *g* factor is often found that links performance across multiple test measures. The *g* factor is associated with general intelligence metrics (e.g., IQ), has relatively high heritability (Gray & Thompson, 2004; Plomin, 2001), and is viewed by some as indicative of a unitary capacity underlying variations in intellect (Jensen, 1998). Other researchers suggest, however, that there are multiple dimensions of intellect that must be considered separately to gain a complete picture of individual variation in intelligence (Brown & Thomson, 1925; Gardner, 1999; Sternberg, 1977; Thorndike, 1926).

General intelligence in rodents. The factor analytic frameworks developed to describe individual differences in human intelligence have also been used to measure variation in the learning abilities of non-humans (Anastasi, Fuller, Scott, & Schmitt, 1955; Banerjee et al., 2009; Dunlap, 1933; Harrington, 1968, 1988; Herrmann, Hernandez-Lloreda, Call, Hare, & Tomasello, 2010; McCullock, 1935; Tomlin & Stone, 1934; Van Steenberg, 1939). Early studies with rats found little evidence of general intelligence comparable to that seen in human intelligence tests (Campbell, 1935; Commins, McNemar, & Stone, 1932; Livesey, 1970; Loevinger, 1938; Searle, 1949; Tomlin & Stone, 1934; Tryon, 1942; Wahlsten, 1978; Warren, 1961). For example, it was impossible to predict which rats would learn a discrimination task the fastest based on their performance in a maze task (Rajalakshi & Jeeves, 1968; Tolman & Ritchie, 1943; Tryon, 1942). There are, however, consistent reports of individual differences in learning capacity within a particular domain (Anderson, 1992; Commins, et al., 1932; Davids & Tolman, 1924; Liggett, 1925; Tryon, 1931). When the range of performance was increased, for example by including animals with brain lesions (Crinella, 1993; Crinella & Yu, 1995; Locurto, 1997; Thompson, Crinella, & Yu,

1990; Yu, Thompson, Huestis, Bjelajac, & Crinella, 1989), or of different strains (Harrington, 1988; Locurto & Scanlon, 1998), statistical factors associated with general intelligence were found. Efforts to measure individual differences in rodent intelligence recently have resurged due in part to the availability of genetically modified individuals (mice) and new methods for identifying the neural and genetic sources of variability in behavior (Anderson, 1993, 1995, 2000; Brooks, Pask, Jones, & Dunnett, 2005; Galsworthy, et al., 2005; Galsworthy, Paya-Cano, Monleon, & Plomin, 2002; Grossman, et al., 2007; Kolata, Light, Grossman, Hale, & Matzel, 2007; Kolata, Light, & Matzel, 2008; Kolata et al., 2004; Light, Kolata, Hale, Grossman, & Matzel, 2008; Locurto, Benoit, Crowley, & Miele, 2006; Locurto, Fortin, & Sullivan, 2003; Matzel, Grossman, Light, Townsend, & Kolata, 2008; Matzel, et al., 2003). Although none of this work directly measures learning capacity, differences in performance are often correlated with individual differences in learning capacity (Lashley, 1929; Orduña, Mercado, Gluck, & Merzenich, 2005).

Researchers occasionally have interpreted results from factor analyses of non-human intelligence as evidence that the dimensions underlying non-human intellect differ qualitatively from those of non-humans (e.g., Herrmann et al., 2010). It has even been suggested that there are few common psychological dimensions across species, because each species has developed abilities that are specialized to meet the needs of a specific ecological niche (Shettleworth, 1998, 2009). Following this reasoning, one might predict that different sets of factors would be needed to adequately describe individual variation in the learning abilities of each species. Consistent with this idea, different species of *Aplysia* show different learning abilities, as well as variations in neural circuits that are correlated with these differences in learning (Marinesco, Duran, & Wright, 2003; Wright et al., 1996). At the other extreme, Macphail (1990) argues that there is no clear evidence of any individual or species differences in the intellectual abilities of non-humans. Differences in testing conditions make it difficult to assess whether variation in the abilities of rodents or any other non-human species is comparable to what has been observed in humans. For example, the tasks used to measure rodent intelligence have been limited to those that naïve rats or mice can learn in a few sessions (Hebb & Williams, 1946; Locurto, et al., 2006). This situation differs greatly from standardized testing of humans, which depends upon numerous pre-existing cognitive skills (e.g., language, problem solving, writing, mathematical training, etc.). Additionally, tests of humans have been extensively developed specifically to reveal individual differences in intellectual performance, whereas those used to tests rodents were developed to minimize individual differences. Recent factor analytic work comparing individual differences in the cognitive capacities of chimpanzees and children has attempted to address this issue by testing both species with similar tasks and in similar conditions (Herrmann, et al., 2010). Interestingly, this study failed to find evidence of an overarching *g* factor in either species, consistent with the idea that the presence or absence of particular factors may depend on the testing conditions (Banerjee et al., 2009; Locurto et al., 2006).

Dynamic testing. Although studies of individual differences in intellectual performance are much more common, there have been some studies that directly measured individual differences in learning potential. This approach, called dynamic testing, involves repeated measures of ability, often with feedback and practice between testing sessions (Feuerstein, Rand, Jensen, Kaniel, & Tzuriel, 1987; Grigorenko & Sternberg, 1998; Lidz, 1987; Sternberg & Grigorenko, 2002). The basic goal of these measures is to identify an individual's rate of improvement, and to use this as a measure of underlying capacity (Feuerstein et al., 1987), or of an individual's zone of proximal development (Vygotsky, 1978). In some cases, results from tests of learning potential appear to be uncoupled from standard IQ measures (Hundal & Horn, 1977), but in others a strong correlation between learning and intellectual performance is evident (Embretson, 1992). Dynamic tests are more cumbersome than standard intelligence tests, and they are not significantly better at predicting future performance, which may explain why they are less popular. If the goal is simply to differentiate individuals and predict what they can do, then factors extracted from a standard intelligence test are as useful as those extracted from a dynamic test.

Despite their limitations, dynamic tests illustrate one way in which factor analyses can be used to quantitatively measure differences in learning capacity. The dynamic testing approach rejects the assumption that individual differences in performance reflect stable differences in innate mental abilities. Instead, it assumes that abilities are malleable and that changes in performance are indicators of developing expertise resulting from practice (Ericsson & Lehmann, 1996; Sternberg & Grigorenko, 2002). Dynamic tests reveal individual differences in learning trajectories during the acquisition of skills in multiple domains, link intelligence to expertise, and focus on the potential for improvement rather than on an individual's intellectual talents.

Criticisms of the factor analytic approach. In developmental research, the factor analytic approach to characterizing individual differences is sometimes referred to as the "variable approach" because it focuses on single variables or combinations of variables and their interrelations (Bergman, Cairns, Nilsson, & Nystedt, 2000; Cairns, Bergman, & Kagan, 1998). The adequacy of factor analytic models for describing individual variations in learning capacity rests on several basic assumptions: (1) individuals differ quantitatively along psychological dimensions; (2) individuals can be compared quantitatively using such dimensions; (3) relationships between dimensions are equivalent across individuals and situations; (4) these relationships can be used to understand how the variables relate to an individual's performance; and (5) the psychological meaning of dimensions is independent of the individual's age (Borsboom, Mellenbergh, & van Heerden, 2003; Magnusson, 1998). A major critique of the factor analytic approach is that the dynamic, complex features of experience-dependent development make it difficult to understand or predict the impacts of any single psychological dimension independent of the context, individual's age, and other dimensions (Mischel, 1973; Tryon, 1958). This critique seems particularly applicable in the case of characterizing learning capacity, which undoubtedly

varies across the life span in complex ways (Hultsch, Nesselroade, & Plemons, 1976). Factor analyses are ill-suited for describing individual variations in ability that are dynamic, experience-dependent, or idiosyncratic. More generally, any metrics that presume a fixed, unidimensional learning potential throughout the lifespan can only provide a limited view of individual variation, and one that necessarily does not reflect the complexity of the mechanisms that give rise to these variations.

Identifying components of abilities

A few comparative and developmental researchers have questioned the usefulness of characterizing individual differences in terms of their "least common factors," instead arguing that descriptions of individual variation should reflect the psychological complexity of the individual's performance (Bergman, 1998, 2000; Magnusson, 1998; Tryon, 1940, 1958). They have argued that there is not a strict divide between intellectual, emotional, motivational, and physical contributors to individual differences (see also Ackerman, 1996). Rather, these psychological factors all impact an individual's abilities in a situation-dependent manner (Ceci & Bruck, 1994; Davison, Kuang, & Kim, 1999).

In comparative psychology, one of the strongest early proponents of this viewpoint was Tryon (1940, 1958). He argued that the psychological components that contribute to individual differences in learning of a particular task can only be safely inferred from analyzing how animals perform in that task. Tryon illustrated this by analyzing the performance of ~1,000 rats as they learned to make their way through a specific kind of maze (Tryon, 1940). Using a combination of statistical analyses and his own behavioral observations, he inferred ten components that contributed to a rat's performance in the maze. These components correspond more closely to frequent strategies, hypotheses, or inclinations than to the sorts of dimensions or behavioral traits identified through factor analysis. Tryon expanded this approach into a general theory of individual variation in which performance reflects the engagement of a dynamic set of psychological components[1]. In this theory, the set of psychological components that determine performance is not fixed, but varies with experience; not all components act at all times and some may even compete for control. Furthermore, this theory assumes that the content, form, and utility of these psychological components change with experience. In this framework, individual differences reflect constellations of interacting components rather than different levels of a universal factor (or set of factors) that acts in all individuals to determine capacity.

Data from maze learning experiments can readily be characterized using factor analysis to create a smaller set of three fixed orthogonal dimensions that predicts errors as well as Tryon's ten components (Wherry, 1941). The issue,

[1]Thorndike (1926) and Brown and Thomson (1925) proposed similar frameworks for assessing intellectual abilities in human

however, is not how efficiently the data set can be described, but whether these factors actually map onto sources of variation in individual rats. Tryon's (1940) claim was that despite their predictive power, these fixed factors poorly captured what a researcher would likely observe after putting a naïve rat into a maze. He argued that the components involved were not fixed over time, and that consequently using fixed dimensions obscured the processes underlying performance. This claim was actually supported by factor analyses, which showed that the identified factors were not stable during learning (Wherry, 1941).

Subsequent attempts to characterize individual differences in learning capacity have largely discounted or ignored Tryon's (1940, 1958) proposals. This is probably because one implication of his theory is that different components would need to be identified for every task and across stages of learning. Even performance in different classes of maze would require separate analyses. Additionally, the subjective elements of Tryon's approach make the implementation of this approach impractical. Tryon was aware of these limitations, but felt that the complexity of the phenomena should not be ignored simply because of methodological inconveniences. Despite its disadvantages, a key strength of the componential approach is its ability to identify sources of individual variation that directly reflect the behavior of individuals and to account for changes in these sources over time.

Methods for characterizing individual differences that capture situational, learning-dependent changes in performance have greatly impacted recent studies of personality and social psychology (e.g., Mischel, 2009; Mischel & Shoda, 1995). For example, the Cognitive-Affective System theory of personality proposes that individuals differ in (1) the ease with which they can engage psychological processes (components) in a given situation, and (2) how these processes interact with each other given the circumstances (Mischel & Shoda, 1995). In this framework, the goal is to identify prevalent behavioral patterns, as well as the dynamics of the interactions between components that underlie these patterns. The role of situation in this personality theory is equivalent to the role of task in Tryon's (1940) theory. Similarly, the interactions between mediating psychological processes are comparable to the interactions between components that Tryon hypothesized were determining the actions of rats in mazes. Mischel and Shoda (1995) went a step further, however, by computationally instantiating their theory as a neural network. Within this network, individual differences in interactions between components were represented as differences between connection weights. The neural network made it possible to simulate the effects of individual variations on both situation-dependent and overall performance trends, and to show how interactions of psychological components can give rise to both behavioral traits and idiosyncratic, situation-dependent, behavioral profiles. This framework also provided a way to conceptualize how environment-gene interactions might impact individual differences (e.g., connection weights may be differentially adjusted by experience depending on their initial values). Although Mischel and Shoda's theory was developed to account for variations in social behavior rather than variations in learning capacity, it illustrates how the

limitations of earlier components-based approaches might be overcome through the use of computational models.

Identifying Prototypical Individual Differences in Learning

All of the approaches described above attempt to succinctly characterize individual variations, but with different emphases. Factor analysis captures key differences between individuals with as few dimensions as possible. These dimensions have been related to latent behavioral traits that are analogous to physical traits. Component analyses instead emphasize context-dependent descriptions of behavioral dynamics. This approach assumes that the processes underlying individual variation are extremely numerous and complex in their relation to observed behavior, and that numerous scenarios could lead to correlations that do not depend on behavioral traits.

Given the hundreds of thousands of genes that exist in the animal kingdom, the complex effects that the difference of even a single gene can have on an individual, and the fact that most variations in neural connections are not directly controlled by genes, the sources of individual differences in learning capacity are likely to be numerous. On the other hand, similarities in neural organization and synaptic mechanisms across subgroups of organisms, such as mammals, provide some hope that systematic patterns of variation in the sources of learning capacity exist. Similarly, the generality of many conditioning phenomena across species suggests that certain constraints on learning are shared across species.

Mapping recurrent patterns

Rather than arguing that one descriptive framework is better or worse than another for characterizing individual differences in learning capacity, the goal of this section is to further explore ways of overcoming past limitations of the components approach to characterizing individual differences in learning capacity. Although this approach lacks the mathematical rigor, simplicity, and elegance of factor analysis, it has the advantage that it does not assume that psychological dimensions are fixed, universal, or few in number. Components-based analyses are thus better able to accommodate processes like experience-expectant and experience-dependent plasticity that can change the nature of how learning proceeds.

As noted above, Tryon's (1940) approach to identifying components was to combine statistical regularities in position-dependent maze errors with his personal experiences watching rats perform in mazes. Both sources of information reflect the regularity of behavior: statistics reveal repetitions across rats, and personal observations reveal repetitions of salient actions exhibited by many rats. Tryon's approach suggests a more general way of isolating regularities in behavior across individuals that emphasizes frequency of occurrence rather than correlations between variables. The goal of such a descriptive framework would not be to

isolate “common causes” of correlated measures, but to organize the full range of observed outcomes in such a way that recurrent patterns of behavior and behavioral change can be related to one another.

A classic example of this approach is the development of the periodic table of elements, which maps recurrent patterns in the properties of matter onto a two dimensional grid. Early versions of the periodic table did not identify unifying principles or overarching dimensions that linked all matter, but simply summarized the fundamental forms of matter that were known and spatially organized them based on similarities in qualities. The “elemental” components of learning capacity remain unknown, and how variations in these components might engender individual differences in learning capacity is similarly unclear (however, see Hull, 1945; Mercado, 2008). Nevertheless, assuming that there are such elemental components, one would expect that their variation should lead to predictable, systematic patterns of individual differences in learning capacity.

The approach proposed here for identifying patterns of individual variation in learning capacity discards the assumption that components or factors underlying individual variation are independent, as well as the assumption that their interacting effects can be adequately conceptualized in terms of linear summations. It seeks to identify regularities in quantitative measures of learning capacity and examine relationships between these regularities. This approach of course has its own limitations, including the lack of any theoretical criteria for selecting the behavioral tasks and measures used to search for such regularities.

Lashley’s learning profiles

Human metrics for assessing individual differences in intellectual capacity or learning potential usually require responses to verbalizable test items. This is true for both static and dynamic testing methods and for both intelligence and personality metrics. Because these sorts of measures are useless for comparative purposes, the focus here is on measures of learning collected from non-humans, specifically rats. The main data Tryon (1940) used for identifying components of maze learning ability were specific types of errors that rats made within a complex maze at different stages of learning. Simpler performance measures will be used here to illustrate an alternative implementation of the components-based approach, but almost any measure of learning or behavior during a task could in principle be used. The basic goals of the current analysis were to determine whether there were regularities in individual rats’ patterns of performance, and if so, what those patterns were like.

In this analysis, learning capacity was operationalized as the performance of rats in several tasks, as reported by Lashley (1929) in his classic studies examining the neural mechanisms of learning. Lashley collected measures from 59 rats (including 37 with cortical damage) performing ten tasks; these measures included the time each rat required to reach a performance criterion, the number of trials to reach criterion, and the number of errors. Five of these tasks involved training (in a maze or in a visual discrimination task); the other five were memory,

generalization, or motor control tasks. I restricted my data analyses to rats that completed at least four of the five training tasks (fourteen of Lashley's rats died before completing all tasks). Measures of speed and accuracy for learning in each task were computed by dividing trial and error counts by total time tested, yielding thirteen performance measures for 43 rats; missing data points were replaced by mean values. In this way, a 13-element vector was constructed corresponding to each rats' performance across several tasks. The measures used in the current analysis do not capture variations in learning trajectories over time. It is straightforward, however, to expand the space of descriptors used to describe each individual so that they include such measures when they are available, or to treat individuals measured at different times as separate points in the input space.

Rats' performance profiles were used to train a self-organizing feature map created with the data mining program Orange (Demsar, Zupan, Leban, & Curk, 2004). The self-organizing map is a type of unsupervised neural network that adjusts its response properties so that nodes within the map have connection weight vectors similar to the most frequent input vectors (Kohonen, 2001). With training, the map becomes spatially organized such that nodes that are closest together respond to similar inputs. The map provides a graphical representation of inputs that characterizes both the prevalence of different input vectors, and systematic relationships between inputs. Maps are unsupervised in that no predefined classes constrain the spatial organization of the map or connection weight values. Instead, map nodes acquire their selectivity to certain inputs by competing to match an input, and then adjusting the weights of the winner node and its neighbors to increase their similarity to "matching" inputs (by minimizing the Euclidean distance between the input and weight vectors). In this way, map nodes effectively generate prototypes of inputs. Although self-organizing maps are unsupervised, many parameters impact the final structure of the map. Unlike classical statistical approaches, the details of map structure and weight values may vary each time a simulation is performed. Despite this variability, consistent prototypes and spatial organizations typically emerge.

Figure 1 shows a map that was trained with the 43 performance profiles from Lashley's rats. Each hexagon corresponds to a node in the map, and the size of the circle within each hexagon indicates the number of inputs that best matched a particular node (the smallest circle corresponds to one rat, and the largest to seven rats). To reveal the structure of the map, circles were color-coded corresponding to whether the matching rats were intact (blue), or had lesions to more (red) or less (green) than 25% of their cortices. The pie charts show the proportion of rats from each of these three groups associated with each map node. Note that without any explicit information about brain damage being provided to the self-organizing map, the map has become spatially organized such that intact rats are associated with the upper right corner of the map, rats with major damage are associated with the bottom of the map, and rats with intermediate damage are in the middle. The map has "discovered" a systematic difference in learning capacity between individual rats that corresponds roughly to the amount of intact cortex. This is the same relationship that Lashley (1929) found through

correlational analyses, and subsequently used as the basis for his theory of cortical equipotentiality.

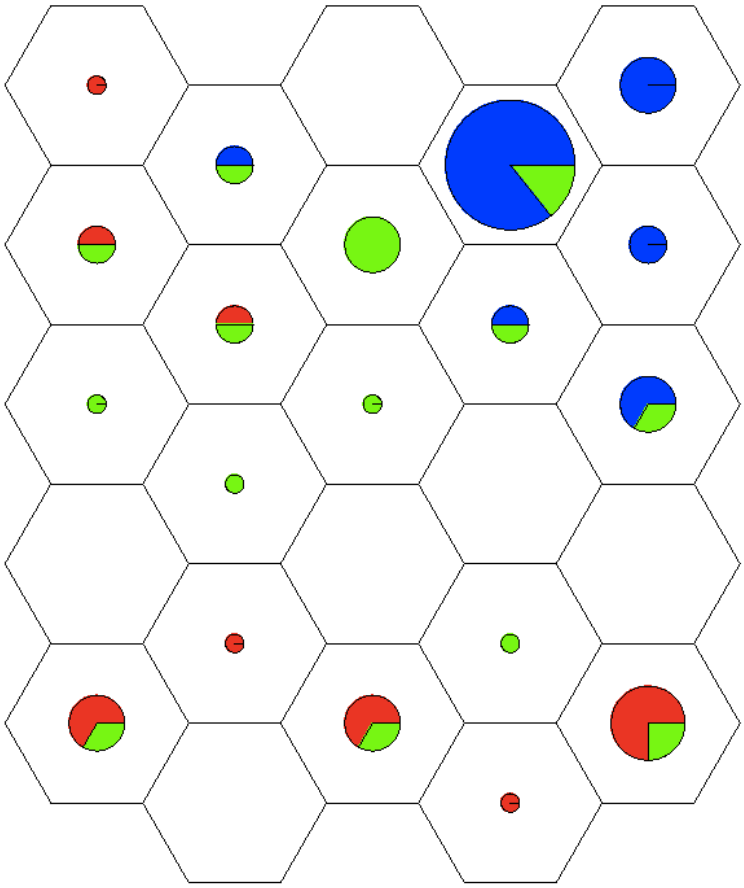

Figure 1. Best matching nodes of a 5x5 self-organizing map after training with performance profiles from 43 rats. Each hexagon corresponds to a node in the map. The size of the circle within each node indicates the number of rats that best matched that node (the smallest circles correspond to a single rat). The pie chart within each circle shows the proportion of best matching rats that had brain damage: blue = intact; green = minor damage; red = major damage.

Analyses of spatially contiguous nodes within the map provide a profile of the prototypical rat from each of the three levels of brain damage (Fig. 2). These performance profiles once again reveal the classic effect of cortical damage on maze accuracy and the time required to reach criterion. But, the profiles also suggest a surprising contrast between maze learning and visual discrimination learning that was *not* noted by Lashley (1929). Specifically, as accuracy in maze learning decreases with damage, accuracy in learning a visual discrimination task appears to increase. In other words, the more cortical damage a rat had, the better it learned to perform the visual discrimination task. Although the nature of these

analyses precludes tests of the statistical significance of this effect, it qualitatively appears comparable in magnitude to the deleterious effects of brain damage on maze learning, and is much more counterintuitive. Although a similar negative relationship between complex and simple learning tasks has previously been observed in intact humans (Broverman & Klaiber, 1969), reports of brain damage increasing learning capacity in humans or other animals are relatively rare. This result fortuitously illustrates one way in which self-organized, spatial sorting of learning-related behavioral profiles can potentially generate new insights into the mechanisms underlying variations in learning. There is no *prima facie* reason to expect that the mechanisms that enable rats to learn mazes might interfere with their ability to learn visual discriminations, or that weakening rats' "spatial abilities" through structural damage might simultaneously increase their "visual abilities." The behavioral patterns revealed by the self-organizing map analysis, however, suggest that this may have happened in Lashley's rats. It can, of course, be argued that appropriately designed factor analyses would also have revealed this pattern. This begs the question of how one determines an appropriate design without knowing in advance what the psychologically relevant patterns are.

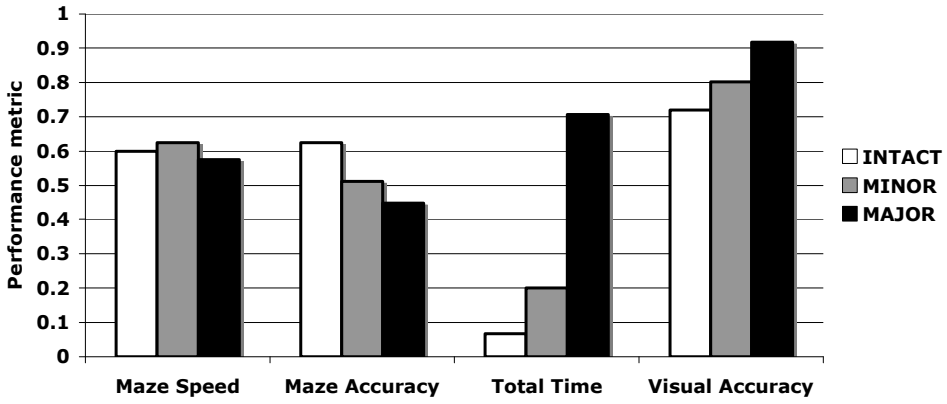

Figure 2. Mean values from self-organizing map nodes (across nodes and tasks) after training for those nodes that responded selectively to performance measures from rats with either no cortical damage (intact - white), less than 25% of cortex removed (minor damage - gray), or greater than 25% of cortex removed (major damage - black). More damage was associated with lower accuracy and longer training times in maze tasks, but greater accuracy in a visual discrimination task.

The focus on prototypical performance profiles made possible by the self-organizing map effectively emphasizes systematic differences between profiles, and minimizes overlapping features, in much the same way as analyses of extremes in statistical distributions (Broverman & Klaiber, 1969; Kagan, Snidman, & Arcus, 1998). This approach thus can reveal patterns that might be obscured by more global correlational approaches (Broverman & Klaiber, 1969). Furthermore, the map preserves the heterogeneity of behavioral profiles from individual rats. For example, although most rats with large lesions match the prototypical profile, three rats (associated with the upper left corner of the map) appear to diverge

systematically from this profile. These three rats may represent a distinct subgroup in which either the specific location of cortical damage made a difference, or they might be rats whose compensatory mechanisms were atypical. Regardless, the map avoids the oddity of describing individuals with large lesions in terms of summary statistics (or latent variables) that might not be representative of any individual in the sample (see Magnusson, 1998, for further discussion of this issue). Behavioral profile maps can potentially aid in identifying especially interesting individuals or groups with extraordinary potential for clarifying mechanisms of learning. For example, the amnesic patient H.M. was unique among individuals that received surgical brain lesions as a treatment for epilepsy, and it was his unique behavioral profile that made him invaluable to memory research (Squire, 2009).

As noted earlier, the purpose of this simulation was not to demonstrate that components-based, neural network analyses of individual differences are superior to factor analytic approaches, but to explore whether neural networks might facilitate the quantitative analysis of complex behavioral patterns. The example simulation shows that much of the information that can be obtained through traditional correlational analyses is also revealed through frequency-based sorting of behavioral profile patterns. It also illustrates how self-organized "clustering" of behavioral profiles can reveal potentially important patterns of individual variation that would be difficult to discern using factor analytic approaches. Finally, the simulation shows that individual variations in learning capacity can be systematically and objectively characterized in ways that do not require any correspondence between existing psychological terms and statistically-derived dimensions in trait space.

Investigating Differences in Learning: Expanding the Scope

Describing a person as intelligent is as reasonable as describing them as strong or tall. All of these descriptors can provide useful information about what a person is like relative to others. Such terms can also be usefully applied to animals other than humans, but unlike strength or height, the relative intelligence of different animals is open to interpretation. Similarly, when detailed comparisons of peoples' intellectual abilities are attempted, controversies often arise. Why is this? In everyday usage, the word intelligence often refers to one's impression of an individual's actions (similar to "niceness" or "weirdness"). The likelihood that someone is described as intelligent depends on what they achieve. It is thus natural to infer that the likelihood that someone will be described as intelligent depends on how intelligent they actually are. However, this leap from label to quality is precarious. For instance, the likelihood that someone will be described as blessed also varies, but few scientists would infer from this that some quality or trait of blessedness within individuals accounts for this variation.

Current psychometric frameworks for describing individual differences in intelligence parallel pre-existing intuitive notions about the mental abilities of humans, as evidenced by the lexicon. Whether such naturalistic conceptions of intelligence are an adequate foundation for understanding individual variation in

mental abilities remains unclear. These intuitions potentially could obscure understanding of individual differences in the same way that visual perception in daily life distorted understanding of the solar system's structure and misled people about the nature of matter. For example, Aristotle described variations in matter as resulting from different combinations of the elements of fire, earth, air, and water. This dimensionalization of physical properties provides a convenient system for classifying matter, but is inadequate for describing differences in atomic structure. Factor analyses of intelligence measures have proven useful in describing and ranking individuals along various psychological dimensions, as well as for predicting future performance in certain circumstances. Nevertheless, the fact that quantitative scales can be developed that assign aptitude scores to individuals provides no evidence that intelligence refers to one or more traits possessed by individuals. Techniques that search for structure in behavioral patterns without the need to conform to existing trait labels may provide new insights into the qualities and processes that underlie individual differences in intellectual abilities (Lee & Webb, 2005; Mercado, 2008).

Beyond trait space

There is increasing awareness among researchers studying human individual differences that statistical dimensionalization of one-shot performance measures collected from groups of individuals provides an incomplete view of how individual's abilities vary (Borsboom et al., 2003; Hofmann, Jacobs, & Gerras, 1992; Hultsch et al., 1976; Nesselroade, Gerstorf, Hardy, & Ram, 2007; Sternberg & Grigorenko, 2002; Thelen, 1990). For example, the person-centered approach to understanding individual differences during development focuses on analyzing patterns across multiple descriptors of an individual (Bergman, 1998, 2000), and emphasizes that the context of the measures is key to interpreting their relevance (Hinde, 1998; Lau & Roeser, 2008; Magnusson, 1998). Similarly, Shoda and Mischel (2000) suggest that dynamic, situation-dependent patterns of responding that are stable within an individual (called "behavioral signatures") provide a more comprehensive way of characterizing individual variations in personality than the more traditional five-dimensional space of personality traits derived through factor analyses. These approaches, which closely parallel those advocated by Tryon (1940) in animal studies and Brown and Thomson (1925) in human intelligence research, suggest that more flexible methods for characterizing individual differences in intellectual abilities are feasible.

The self-organizing neural network analysis described above is just one example of how automated, nonlinear, numerical classification techniques can be used to characterize individual differences in learning capacity (Clifford & Stephenson, 1975; Dunn & Everitt, 1982; Thelen, 1990). This approach can be viewed as an extension of more traditional clustering analyses (Green, 1990; Tryon, 1958). A major advantage of this kind of analysis is that it reveals patterns and trajectories of patterns without relying on preconceptions about how the patterns should look, how stable they should be, or how different aspects of the

patterns should interact. Self-organizing maps, in particular, are not constrained to grouping patterns based on a small number of recognizable features or to creating hierarchical clusters or taxonomies of patterns. Technological advances comparable to those made in sequencing and comparing DNA across species may increase the ease and precision with which individual variations in learning can be analyzed. With suitable analytical frameworks for characterizing individual differences in learning capacity, neural or psychological components contributing to individual differences might be mapped out in a fashion analogous to the human genome or the periodic table of elements. Of course, one disadvantage of the periodic table relative to Aristotle's dimensional description of matter is that it is less intuitive, and therefore more unwieldy. Everyone has some experience with fire and water, but few people have any intuition about what Indium, Cerium, or Scandium are like. Techniques for sorting behavioral profiles may similarly reveal patterns that bear little relation to existing taxonomies of mental dimensions. The extent to which such patterns can provide novel insights into the origins and nature of individual variations in learning capacity is an empirical question that can only be answered by expanding beyond traditional trait-based psychometric frameworks.

From intelligence to learning capacity

Learning capacity may vary systematically within and across species in ways that directly relate to the neural substrates of learning (Mercado, 2008), and may also vary as a function of the complexity of the task to be learned. For example, the learning mechanisms subserving perceptual-motor learning capacity may vary more (or less) across individuals than those involved in cognitive skill learning. Recent work on intelligence measures has revealed that the ubiquitous *g* factor may be the outcome of multiple component processes interacting during development rather than some unitary trait across which individuals vary (van der Maas et al., 2006). These component processes differ from the semi-independent faculties presumed to underlie "multiple intelligences," which correspond more directly to intuitive notions about what people can do intellectually (Gardner, 1999). These processes have been conceptualized as cognitive abilities like working memory, or decision and reasoning processes (Sternberg, 1977; van der Maas et al., 2006), but could just as easily correspond to learning mechanisms (Mercado, 2008). For example, Hebb (1949) theorized that perceptual and cognitive abilities acquired through learning experiences can increase learning potential, which can in turn facilitate the acquisition of new intellectual competencies. From this perspective, intellectual abilities are a consequence of learning capacity, and intelligence tests measure a product rather than a trait.

Intelligence tests are useful tools for ranking individuals and making educational decisions, but their potential for clarifying the processes that give rise to variations in intellectual abilities is limited. In particular, they currently preclude comparisons across species and limit developmental comparisons, both of which are critical to understanding the origins of mental abilities. New techniques for

characterizing individual differences in the learning abilities of non-humans could provide a way to break away from the intuitive dimensionalization of latent traits, and would make it possible to experimentally explore the mechanisms underlying that variation in ways that will never be feasible with humans (Harrington, 1988). For example, researchers could examine precisely how different genetic, neural, and environmental treatments impact learning capacity and cognitive abilities during adulthood. Such studies can provide new insights not only into the mechanisms driving variation, but also into the nature of the processes that give rise to various intellectual abilities (Mercado, 2008, 2009).

Future Directions in Comparative Assessments of Learning Capacity

Anyone who has ever trained animals is well aware that individuals often vary in the speed with which they improve and in their ultimate performance levels. Kohler (1927) noted the superior abilities of Sultan relative to other chimpanzees he studied, and Premack reported large differences between the competencies of different chimpanzees (Premack, 1976; Premack & Premack, 1983). Similar intra-species variations in cognitive skill learning capacity have also been reported in monkeys (Smith, Beran, Redford, & Washburn, 2006; Smith, Shields, Schull, & Washburn, 1997), dolphins (Mercado, Murray, Uyeyama, Pack, & Herman, 1998), and dogs (Coren, 1994). These differences in learning capacity correspond closely to what a layperson would describe as variations in intelligence - pets that can learn tricks quickly are described as clever, whereas those that cannot are "slow."

The prevalence and relevance of individual variations in learning capacity were recognized early on in the development of comparative psychology (Maier & Schneirla, 1935; Mills, 1898; Washburn, 1913). In the classic text, *Principles of Animal Psychology*, Maier and Schneirla (1935) proposed that studying individual variations was one of five necessary steps required to understand animal behavior. Nevertheless, there are few detailed scientific reports of how learning capacity or intellectual ability varies within any non-human species. Why have scientists given so little attention to analyzing individual variations in the learning capacity or intelligence of animals other than humans? In part, this neglect may reflect the Cartesian perspective that human intellectual abilities arise from reasoning minds, whereas other animals' abilities reflect mindless learning or genetic algorithms (Jensen, 1985; Macphail, 1990). However, it may also be a consequence of the emphasis early experimental psychologists placed on identifying universal laws of behavior. For example, Thorndike (1898) suggested that even cross-species differences in learning capacity, though clearly present, were of minimal theoretical importance. He and many other prominent learning theorists believed that the core scientific problem was to identify learning laws that applied to all organisms in all contexts. Ecologically-minded comparative psychologists eventually rejected the assumption that species-differences were irrelevant to understanding how animals learn (Healy, Bacon, Haggis, Harris, & Kelley, 2009; Shettleworth, 1998, 2009; Timberlake, 1994, 2001). Nevertheless, most

comparative research continues to emphasize patterns of abilities prevalent across groups of subjects, treating individual differences in learning capacity within species like variations in the shape of gold – an incidental feature that reveals little of importance.

Future development of objective methods for experimentally differentiating animal geniuses from dullards would facilitate more direct comparisons between learning mechanisms, learning capacity, and intellectual variability in humans and other animals. While these methods may include traditional factor analytic approaches, the complexity of learning mechanisms suggests that techniques for sorting behavioral patterns may be better suited for identifying and understanding the processes that give rise to variations. Even more important to future progress, however, is the development of new experimental designs that focus on revealing and understanding individual differences rather than on minimizing them. Just as studying a broader range of species can provide new insights into the behavior of all species (including humans), so too can studying a broader range of individuals within each species.

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