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Pulling Punches: A Non-parameteric Approach to Punch Force Estimation and the Development of Novel Boxing Metrics

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Pulling Punches: A Non-parameteric Approach to Punch Force Estimation and the Development of Novel Boxing Metrics

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Statistics

by

Nathan James Langholz

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Abstract of the Dissertation

Pulling Punches: A Non-parameteric Approach to Punch Force Estimation and the Development of Novel Boxing Metrics

by

Nathan James Langholz

Doctor of Philosophy in Statistics

University of California, Los Angeles, 2013

Professor Mark Hansen, Chair

Boxing has seen limited advancements in way of quantification of the sport during live professional fights. The PunchR system is an automated measurement system to collect information about a fight in realtime with fine-grained temporal resolution. The system employs nonintrusive accelerometers placed on the insides of boxers' wrists beneath their gloves to wirelessly relay acceleration data to a ringside laptop. Statistical models process the data for realtime estimates of fight metrics to quantify the action taking place in the ring including punch count, punch speed, punch force, and punch type. There are no new risks provided to the boxers during the fight nor do these accelerometers affect either of the boxers physical performances.

The statistical methods used to construct these statistical models are non-parametric in a sense that the data is really driving the modeling procedure without any notion of a structure prior to model construction. Data for the models is collected in a controlled experimental boxing setting or through video review of live fights. Model features are derived from the acceleration profiles of punches combined with boxer physical measurements to create a complete feature set to train the models.

Primarily, the boxing metrics are largely tangible quantities that already are commonplace in boxing discussions (count, speed, force, and type) but have no prior method of measure. Methods are also developed to measure number of counterpunches and flurries using the timing of certain punches. Newly proposed metrics not in typical boxing terminology are either combinations of the common punch metrics or other measures taken from the acceleration data. These metrics attempt to measure a boxers aggression and different measures of overall punch quality. The groundwork for these new contributions to boxing metrics and resulting visualizations for these metrics arise through the study of 65 professional boxing matches. Two complete fight summaries illustrate how a fight narrative can be told through use of the new metrics and visualizations. The PunchR system has been developed to begin the higher level quantification of boxing.

The dissertation of Nathan James Langholz is approved.

Mani Srivastiva

Ying Nian Wu

Jan de Leeuw

Mark Hansen, Committee Chair

University of California, Los Angeles

2013

To my parents...

Table of Contents

List of Figures

List of Tables

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Vita

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CHAPTER 1

Introduction

Much is made of boxing's declining popularity in the United States with the rise of a direct competitor in mixed martial arts (MMA), along with the ever increasing popularity of team sports especially American football and basketball. The non-existent broadcasting of large fights on national network television, dwindling media coverage, and controversial judging decisions have dismayed existing fans while failing to attract new fans. A Gallup poll conducted at the end of 2008 has boxing as the seventh most popular viewer sport with only 2% of respondents favoring it while American football leads the way at 41%, followed by baseball at 10%[Jones, Dec 2008]. Nonetheless, a Forbes list ranking the top money-making athletes in 2012 has the top two athletes being boxers Floyd "Money" Mayweather and Manny Pacquiao making $85 million and $62 million respectively [Badenhausen, June 2012]. Pay-per-view events broadcast by Home Box Office (HBO) and Showtime consistently reach one million buys providing huge profits for each event [Jay, Dec 2012, Rafael, May 2013]. So despite some of boxing's popular decline it continues to have every reason to be included in the popular sports discussion.

One issue that cannot be contended is that boxing is definitely falling behind in numerical analysis of the sport during live events. Recently, sports have seen an explosion of sorts in quantification and statistics, much of it realtime, but boxing, so far, has been left behind. Leading the way in these statistical innovations in sports is baseball. The publication of the book *Moneyball* (and subsequent major motion picture) put baseball Sabermetrics with Bill James' work into the public conscience. This strengthened the case for high level analysis that Sabermetricians had been promoting for years. As a result many baseball teams have hired statisticians to improve player drafting strategies and roster construction, to reduce contracts while improving performance on the field.

For example, the importance of commonly held measures like batting average (BA) and earned run average (ERA) have been supplanted with on-base plus slugging (OPS) and walks plus hits per inning pitched (WHIP) when trying to quantify the value of an individual player to a team's success. Available since 2006, the *PITCHF/X* system is employed in all Major League Baseball stadiums, which uses two cameras to record information about pitch location, type, rotation, and speed adding a vast array of measurements to evaluate pitching performance [Sportvision.com, 2013]. There are countless other example in baseball that could serve as examples of how measures are being developed to increase analytical thinking about the sport.

Other sports have followed baseball's lead often searching for value in overlooked non-traditional locations with systems like *SportsVu* for basketball and soccer. *SportsVU* considers spatial locations and relationships of players during games to assess team dynamics and how players perform with different combinations of teammates or against varying opponent defensive techniques [STATS.com, 2013]. In football, ESPN has introduced the Quarterback Rating (QBR), an advanced metric to quantify a quarterback's performance throughout a game [Oliver, Aug 2011]. In an attempt to improve fan enjoyment of the 2012 NBA Slam Dunk Contest, the NBA employed the *Slam Net Force* to record force of all the slam dunks as developed by the MIT Media Lab [Novy et al., 2012] . Further, the annual MIT Sloan Sports Analytic Conference has boomed in popularity with teams' owners, general managers, sports analysts, and quantitative analysts all in attendance to discuss topics relating to the advancement of quantitative analytics in sport [Sloan, 2013, Arnovitz, Mar 2013].

Many new measurement systems have been devised through the use of video cameras. Another inexpensive, widely deployed sensor is the accelerometer. In recent decades, these devices have become commodity sensors, finding their way en masse to consumer products like mobile phones. In sports, Major League Soccer has introduced accelerometers to record measures [Squatriglia, April 2012, Duffy, July 2012] about players during matches while the National Football League (NFL) has begun testing accelerometer placement in helmets, mouthpieces, and earpieces to record the severity of blows to the head as a result of tackles [Maske, Jan 2007]. Some NFL prospects wore accelerometer equipped compression shirts while participating in workouts prior to the NFL draft [Stack, Feb 2011]. Similarly rugby in New Zealand has equipped mouthpieces and patches behind players ears with accelerometers to record all impacts that occur throughout a match [Stoney, April 2013, Knouse et al., 2003].

Not only are accelerometers being frequently used at the professional level of sports, non-professionals are taking advantage of accelerometers for fitness monitoring in devices such as the Nike+ *Fuelband* and smart phone applications. The data collected from these devices are pushed to online servers where it is viewable via website or online device. These measurement devices become valuable training tools even at the amateur level. This widespread use of accelerometers advances the development of higher functioning hardware and associated research methods to take advantage the ever increasing amount of data.

With this push for more data in all sports and the available technology to record this information professional boxing has made few advances. CompuBox, the main provider of live fight statistics claims it "produces live stats in 16 categories," but has measured these same metrics since 1985 [CompuBox, 2013]. CompuBox employs professional human operators ringside to record punches landed and punches missed. PunchZone, launched in 2009, is an extension to the numbers recorded by CompuBox providing five rough spatial locations to these measurements [HBOSports, 2010]. Amateur boxing has seen the use of accelerometers in headgear to record head acceleration as a result of punch impact [Stojsih, 2010] and flexible wrist bands to record punch impacts for an automated scoring system [Hahn et al., 2010]. These did not lead to further advancements in professional boxing as headgear is not used and in amateur fights to score points only a "reasonably forceful punch" is necessary [Mack et al., 2010]. An article on `thesweetscience.com` from February 14, 2011 penned "*A Numbers Game? Assessing Boxing's Place in the Statistical Revolution*" discusses the limitations boxing has in recording statistics being dissimilar to other sports. The article states, "Ultimately, there's only so much you can do with statistical data in boxing. The sport just doesn't lend itself conveniently to numbers or acronyms [Raskin, February 2011]."

With so little activity taking place in the boxing community comparisons must be made to another one-on-one combat sport, MMA. MMA is a relatively new sport but has already made comparable headway to boxing in the realm of numerical analysis [Meltzer, Sep 2010]. CompuStrike, developed in 2007, is a natural extension by CompuBox employing operators to record various live statistics, outnumbering those used in boxing with a total of 26 metrics [CompuStrike, 2007]. Another independent company, FightMetric, also started providing MMA fight statistics in 2007. FightMetric reviews fights post event using video recordings to derive metrics frame-by-frame. They have numerous categories dealing with volume, accuracy, and location of strikes in addition to wrestling movements. An overall fight performance metric has been created to provide one score to summarize each fighters performance in a fight [FightMetric, 2011]. There are more movements and attacks in MMA to quantify where boxing is solely restricted to punching, but more thought has gone into developing new ideas more recently.

In both boxing and MMA the problem with data collection during live professional fights so far has been the reliance on human operators making judgement calls based on previously defined definitions of fighter actions. The pitfall of this collection method is different operators having different interpretations of these definitions, having to make split second decisions often with compromised viewing angles and loud fan bases, and possibly having preconceived notions about fight participants. It is inevitable that under these conditions there is bias introduced based on the operators in charge of scoring the different fights in addition to the human error that will occur. It is impossible to remove all subjectivity when collecting data in this manner.

This dissertation discusses the development as well as the implementation of the automated measurement system called PunchR to make advances in boxing quantification in live professional boxing matches. The PunchR system employs nonintrusive accelerometers placed on the wrists of the boxers inside their gloves. The accelerometers wirelessly relay acceleration data to a ringside laptop providing high grain temporal data that can be used instantaneously at ringside. Statistical models process the data for realtime estimates of fight metrics to quantify the action taking place in the ring. There are no new risks provided to the boxers during the fight nor do these accelerometers affect either of the boxers' physical performances. As there is no human involvement of data collection during each fight measurements are recorded identically from fight to fight provided the accelerometers are properly calibrated and the ring conditions provided sufficient sample rates. This is not to say there is no error involved in this system, so while humans as obvious sources subjectivity and bias are removed, error still remains through choice of technology to record measurements, along with modeling assumptions and techniques.

The new boxing metrics metrics are largely tangible quantities that already are commonplace in boxing discussions but had no prior method of measure including punch counts, speed, force, and punch type. Additionally, methods to measure number of counterpunches and flurries using the timing of certain punches are constructed. There are also new proposed metrics that are not in typical boxing terminology, which are either combinations of the common punch metrics or other measures taken from the acceleration data. These metrics attempt to measure a boxer's aggression and different measures of overall punch quality.

The statistical methods used to model punch detection, speed, force, and punch classification are non-parametric in a sense that the data is really driving the modeling procedure without any notion of a structure prior to model construction. Data for the models is collected in an experimental setting to construct models to be translated to live fights. Features are derived from the acceleration profiles of punches combined with physical measurements to create a complete feature set to train the models.

This dissertation outlines many new statistical ideas relating to the sport of boxing while laying the groundwork for many new contributions to the quantitative analysis of the sport. The remaining format is as follows: Chapter 2 provides a review of previous boxing methods of quantifying boxing during live fights as well as in controlled experimental settings. These include punch counts, punch speed, punch force, and punch type classification. Chapter 3 provides a system overview of the hardware, statistical modeling, and model instantiation for use during fights. Chapter 4 looks at complete fight results with the construction of novel boxing metrics and visualizations. Finally, chapter 5 discusses remaining possibilities for future work with the system, other possibilities in the development of the quantification of boxing, and a small section about fight outcome predictions.

CHAPTER 2

Boxing Quantification

As discussed in the introduction, there has been previous work to quantify boxing in the ring as well as in experimental settings. This chapter will survey the ways in which boxing has been quantified prior to this dissertation. This includes private companies' measurement systems along with academic studies interested in the biomechanics of boxers' punches, health implications, and training techniques. Largely, boxing measurements outside of punch counts have come in controlled environments with few studies taking live measurements during fights. At times weaknesses in each measurement system will be discussed not to discredit these in favor of PunchR, but to point out possibilities where PunchR provides a different approach.

In addition to exploring the measurements available in boxing, the speed and force measurements are used as guides during data collection for the respective statistical models. Using these measurements as a guide is necessary to verify that the data that has been collected is representative of a larger population of boxers in order to extrapolate the speed and force estimations to boxers that did not participate in this data collection process.

2.1 Live Fight Measurements

Currently, live boxing statistics in professional fights are limited to CompuBox and HBO PunchZone. There have been other attempts to bring live numerical analysis to fights, but little headway has been made to leave a lasting impression on the sport. The *bestshot* System attempted to bring an automated quantification method to live professional matches but ultimately was only used in a total of six fights [Pierce et al., 2006]. Some work has been done with amateur fights, incorporating new technology to measure boxing, but these do not often translate well to the professional level because of the rule implementations at the different levels of the sport.

2.1.1 CompuBox

The most well-known, longest standing provider of live fight statistics is CompuBox, started in 1985. CompuBox has two professional operators sitting ringside with a laptop counting boxers' punches looking for jabs missed, jabs landed, power punches missed, and power punches landed. Power punches are any punch that is not a straight lead hand jab. This system does not differentiate between punching hand so a lead hook is counted the same as a rear uppercut, both as power punches. The punch counts are aggregated by round and fight for use in fight broadcasts along with post fight analysis. [CompuBox, 2013, Perry, Feb 2007]

CompuBox is the starting pointing for all conversations involving fight statistics, but remains very contentious in terms of its accuracy and effectiveness in describing a fight [Magno, January 2011, InterAksyon.com, June 2012]. With human operators inevitably there system some amount of human error in each fight. In addition, prior knowledge about boxer's record, opponents, and CompuBox results may bias an operator to record more punches as landed or missed in comparison to a different operator. The operators sit ringside providing only one angle of the fight where the view of one fighter can easily be blocked by the opposing fighter or the referee making missing punches very conceivable. Not to mention a raucous crowd during a title-fight in favor of one fighter over another may lend an operator to count more landed punches over misses or vice versa. One of the founders, Bob Canobbio, pointed out the system flaws best when mentioning the possibility of evolving the system in an interview,

> "From my standpoint, I could probably add more categories, but I don't want to sacrifice accuracy. We could do left hand and right hand if we wanted. But too many keys leads to too much thinking, and we dont want to be thinking while we're working. I don't want to sacrifice accuracy [Raskin, February 2011]."

He does stress the desire for accuracy, but the idea of having to mitigate thinking is a concession of the possibility of outside influence on the human operators.

Even with these weaknesses in the system CompuBox remains the standard for boxing metrics in professional boxing providing rich information about the story of the fight. These statistics are used in on-air broadcasts by HBO and Showtime to provide live round-by-round analysis. Also, they provide measures to preview a fight to highlight match-ups and to summarize a fight following completion to compare fighter's performances. Figure 2.1 is a fight report taken from CompuBox [2013] summarizing the Mike Alvarado versus Brandon Rios fight that took place in Carson, CA. Overall, Rios lands more total punches, jabs, and power punches with the fight ending in the seventh round of a ten round fight. Unlike other sports, for instance baseball, there is no community that uses this data to take a high-level quantitative view of boxing.

2.1.2 PunchZone

HBO PunchZone, launched in 2009 by HBO, is really a supplement to CompuBox numbers making use of a nice visualization to provide spatial location of landed punches. Like CompuBox, HBO employs operators to watch live fights, done remotely, again counting boxers' punches with CompuBox numbers acting as cross

» Rios vs. Alvarado - CompuBox

CompuBox PunchStat Report

Brandon Rios KO 7 Mike Alvarado
10/12/2012 Carson , CA

This one may have exceeded the hype. They avg'd nearly 80 punches thrown per round coming into the fight. Tonight Alvarado avg'd 111 per round, Rios 77 per round. 82% of their combined landed punches (276 of 336) were power shots.

Total Punches Landed / Thrown

Round	1	2	3	4	5	6	7	8	9	10
Rios	28/90	26/95	29/85	17/73	18/84	29/78	14/36			
	31%	27%	34%	23%	21%	37%	39%			
Alvarado	17/100	26/113	24/117	30/117	41/147	25/124	12/61			
	17%	23%	21%	26%	28%	20%	20%			

Jabs Landed / Thrown

Round	1	2	3	4	5	6	7	8	9	10
Rios	3/17	2/11	3/21	1/13	1/11	6/16	1/12			
	18%	18%	14%	8%	9%	38%	8%			
Alvarado	7/54	3/44	8/60	9/52	7/53	4/51	5/42			
	13%	7%	13%	17%	13%	8%	12%			

Power Punches Landed / Thrown

Round	1	2	3	4	5	6	7	8	9	10
Rios	25/73	24/84	26/64	16/60	17/73	23/62	13/24			
	34%	29%	41%	27%	23%	37%	54%			
Alvarado	10/46	23/69	16/57	21/65	34/94	21/73	7/19			
	22%	33%	28%	32%	36%	29%	37%			

Final PunchStat Report

	Total Punches	Jabs	Power Punches
Rios	161 / 541	17 / 101	144 / 440
	30%	17%	33%
Alvarado	175 / 779	43 / 356	132 / 423
	22%	12%	31%

Figure 2.1: CompuBox from the Mike Alvarado versus Brandon Rios fight. Taken from CompuBox [2013].

reference for accuracy. The types of punches recorded are still jab miss, jab landed, power punch miss, power punch landed. The added dimension by PunchZone is the grouping of the landed punches to five body locations including two sides of the head, the chin, and two sides of the body. This provides visual reference to where punches are landing on each boxer on top of just the raw counts with a heat match darkening where more punches are landing. [HBOSports, 2010]

The main use of PunchZone is as an online website for boxing fans without the HBO television broadcast to follow a live fight online round-by-round. Again only round summaries are available as in CompuBox, but this does provide the first way to follow a fight live online. The visualization is also used during live broadcasts on HBO to provide an additional level of depth to the announcer's commentary [Braff, Mar 2010]. This has many of the same downfalls as CompuBox with the possibility of human error and bias. Also, in both systems the temporal resolution is aggregated by round. There is no second-by-second breakdown of each round which leaves something to be desired. Lastly, there is no distinction between lead hand punches and rear hand punches, a lead hook is counted the same as a rear jab, which for different fighters may vary wildly in effectiveness.

Figure 2.2: PunchZone from the Rocky Martinez versus Juan Carlos Burgos fight. Heatmap shows Burgos landing a high volume of body shots on Martinez.

2.1.3 Live Fight Force Measurements

Pierce et al. [2006] is the first attempt to record measurements of punch force in any boxing match. This is also the one prior attempt to provide automated measurements to live professional fights. In this study, the company SensorPad Systems, Inc. developed the proprietary *bestshot* System that uses a lightweight force sensor placed on the glove to directly measure contact force of punches. This study included twelve boxers in six professional boxing matches across five different weight classes. Contrary to every other lab study which have used responsive sensors or accelerometers in the object being hit, this study had instrumentation in the boxers' gloves to directly measure the force. A lower limit of 500 Newtons (122.4 lbs) is set so as not to record incidental contact or "pity-pats," which are not considered punches. Two of the fights ended in the first round as a result of injury leaving only four complete fights for comparison [Pierce et al., 2006].

During these fights a total of 1,675 punches were recorded, with 500 of them coming in a single fight. The maximal punch force across all of these fights was thrown by a cruiserweight with a value of 1204.5 lbs. Of the 1,675 punches more than half the force measurements are below 245 lbs. Additionally only three punches were recorded over 900 lbs [Pierce et al., 2006]. Five of the twelve boxers averaged below 245 lbs for the entire fight. The authors attribute these small force measurements (in comparison to previous experimental studies) to boxers having to be cautious in the ring so not to get hit, which becomes more clear when presented with the lab force measurements in the following section. All force measurements have been translated to pounds for consistency across this dissertation.

The main drawback to this system is that the force sensors alter the punching surface of the glove. As a result, this system causes concern for boxers who have trepidation towards any foreign object being placed in or on their opponents' gloves that could result in further harm being caused during a violent fight. Further boxers' also have concern for their own hands when punching with an additional device on their own gloves. Similarly, boxing commissions who have responsibility for boxers safety have difficulty allowing equipment to be used in fights that will come in direct contact with a fighter's body and face that has the possibility of increasing the amount of punishment that these fighters already endure.

2.1.4 Amateur Fights

At the amateur level the motivations vary for the different attempts to quantify boxing ranging from a desire to improve scoring, to learn about health risks, and to improve training methods. The study Hahn et al. [2010] used a combination of sensor-outfitted body vests, head protection, and accelerometers in the gloves to record when body punches were landed during fights. The information is uploaded wirelessly to a ringside computer where it is processed to record valid scoring punches. This system is called *BoxTag* [Bruch et al., 2010]. In amateur fights a point is awarded by judges for a punch that lands with the knuckle surface of the glove to an opponents head or body. This system has been employed in eight fights providing an objective scoring method in response to many controversial decisions seen at the amateur level. The use of accelerometers in the boxing gloves to aid the punch count and impacts mirrors the PunchR study using an automated method to make the desired measurements.

Both Beckwith et al. [2007] and Stojsih et al. [2008] are concerned with the Head Injury Criterion (HIC) and the Gadd Severity Index (GSI), which study the possibility of concussions based on the estimated severity of head impacts. These studies use accelerometer equipped head gear to be used to record HIC and GSI during amateur fights. Beckwith et al. [2007] investigated the properties of the head gear when blows were applied to a manikin head in a controlled experimental environment. Stojsih et al. [2008] adapted the technology taking to sparring rounds amongst a number of men and women amateur fighters preparing it for use in a live event. Neither have taken the head gear to live amateur bouts yet.

Unfortunately, using sensor-equipped body vests in combination with accelerometers in the gloves nor sensor-equipped head gear cannot be translated to the professional level because of the tightened restrictions on boxer's equipment including no body wear or headgear.

2.2 Boxing Lab Measurements

The boxing lab measurements are a complete look at all academic published papers pertaining to punch speed followed by punch force. A majority of the published speed measurements are recorded using some high speed camera with scaling markers as points of reference. There have been no studies that have measured punch speeds during live fights. Most of the force measurements have also been collected in the lab or gym setting using a variety of techniques involving known mass targets with accelerometers. The majority of these studies have been to assess the effects of punch force in relation to boxer injuries or boxer biomechanics [Stojsih, 2010].

2.2.1 Speed

To begin we consider seven studies that recorded speed for boxer punches along with two more studies that assessed karate strikes for further velocity reference. Essentially there are two methods to record punch speed: using high speed video to record boxers' punches while placing reference points on the boxers glove to measure the gloves' movement over time or using accelerometers within the boxers' gloves with the acceleration measurements being integrated up to punch impact. The second measurement technique falls in line with the measurement technique to be used by PunchR. All studies' measurements have been converted to miles per hour (mph).

Five studies used high speed video with reference points on the boxers' gloves to measure speed including the earliest study, the oft cited, Atha et al. [1985] measured a single punch from professional heavyweight Frank Bruno. This single punch recorded a speed of his fist at impact of 19.9 mph [Atha et al., 1985].

Another older study with high speed video recordings, Whiting et al. [1988], had speeds recorded on 83 punches. The peak speeds for hooks were 28.0 $\pm$ 5.1 mph noticeably faster than for jabs with peak speeds of 14.8 $\pm$ 2.5 mph.

During the next study of four punches by welterweight Ricky Hatton,"...his fastest effort was clocked at 32 mph- a blistering left hook..." with the three other punches being recorded at speeds of 22, 24, and 24 mph respectively [Manchester, June 2007].

Mack et al. [2010] had no specific speeds listed, but the published figures show a maximum punch speed for hooks of just under 47.0 mph ranging all the way down to 15 mph. There are fifteen punches with velocities above 35.8 mph, which are some of the fastest speed measurements recorded in any of the studies. The speeds for straight punches are slower ranging from just above 22.4 mph down to 13.4 mph. [Mack et al., 2010]

Piorkowski et al. [2011], recorded individual punches as well as punches in combinations. Again, hooks were noticeably faster than straight punches, and rear hand punches were faster than lead hand punches. The fastest punches were rear hand hooks at 24.6 $\pm$ 4.9 mph, while the lower end were at 16.2 $\pm$ 1.6 mph. All the combination punches were slower than the single punches with the left combination punches going as slow as 12.6 $\pm$ 2.1 mph. [Piorkowski et al., 2011]

The remaining two boxing studies we consider used accelerometers to measure speed. In Walilko et al. [Jan 2005] speed was measured using both an accelerometer placed in the hands of each boxer along with video analysis. The accelerations were integrated up to face contact while the glove motion was tracked to verify the accuracy of the integration. "The results showed good correlation between the two speed measurements," so the integrated hand accelerations were reported as speed. The mean speed was 20.5 ± 4.6 mph for 18 total punches from four boxers with a maximum of 30.0 mph for the middleweight boxer. The minimum punch speed was 13.6 mph.

Also using accelerometers the thesis Stojsih [2010] determined speed by integrating the resultant hand acceleration up to punch impact. The mean speed is reported as 22.4 ± 6. mph for 113 punches from male fighters ranging from a minimum of 20.13 ± 6.7 mph to 26.9 ± 9.0 mph. The mean speed for 30 punches from eight female fighters is 17.9 ± 4.5 mph, ranging from a minimum of 13.4 ± 0.7 mph to a maximum of 24.6 ± 2.2 mph. This study does not list a single minimum punch value or maximum punch value. [Stojsih, 2010]

Further, to gain an even better understanding of athletes hand speed when striking their opponents we also report on two studies done on karate strikes that are similar to those performed for boxing. Both karate studies used high speed cameras to measure the speed of the athletes' strikes. Cesari and Bertucco [2008] recorded a mean of 18.4 ± 3.6 mph for six single punches from expert karate participants, and a mean of 10.9 ± 1.6 mph for six single punches from novice karate participants. Not surprisingly the maximum recorded for the cohort of expert fighters was 21.8 mph much faster than the maximum for the novice fighters of only 13.3 mph [Cesari and Bertucco, 2008]. In the far older study Vos and Binkhorst [1966], five total karate strikes were recorded with velocities of 31.1, 30.5, 28.6, 24.9, and 24.2 mph. The measurements for the karate studies are comparable to those from the boxing studies.

Table 2.1 is a comprehensive summary of all the speed studies. This table combines all groups seen in each of these papers including males and females, elite and novice fighters, as well as different punch types. All values are listed in mph.

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[1] No specific values listed. The approximated (∼) from the published plots.

Study	Punches	Mean	Max	Min
Atha et al. [1985]	1	-	19.9	-
Whiting et al. [1988]	83	20.4 ± 4.1	28.0 ± 5.1	13.2 ± 2.5
Walilko et al. [Jan 2005]	18	20.5 ± 4.6	30.0	13.6
Manchester [June 2007]	4	25.5 ± 4.4	32.0	22.0
Stojsih [2010]	143	21.4 ± 6.3	26.9 ± 9.0	13.4 ± 0.7
Mack et al. [2010][1]	39	-	$\sim$47.0	$\sim$13.5
Piorkowski et al. [2011]	160	18.3 ± 3.3	24.6 ± 4.9	12.6 ± 2.1
Vos and Binkhorst [1966]	5	27.8 ± 3.2	31.1	24.2
Cesari and Bertucco [2008]	12	14.6 ± 4.7	21.8	8.7

Table 2.1: Speed studies comparison.

Table 2.1 is visualized in Figure 2.3 with the mean plotted as a black dot, with standard deviation as the dotted line, the maximum value as the red asterisk and minimum value as the blue asterisk. The studies are listed across the x-axis with the publication year.

To summarize all the studies, the majority of the speeds fall between 10 and 35 mph. One study measured extremely fast punches of over 35 mph all the way up to roughly 47 mph. Rear punches are typically faster than lead punches, hook punches are typically faster than straight punches, more advanced fighters typically faster than newer fighters, and men typically faster than women. The only study with a large variety of weight classes, Stojsih [2010], did not show a trend of smaller being faster than larger fighters. No speed measurements have been made on uppercut punches nor have any measurements been made during live fights. These points are all important to keep in consideration when addressing the speed modeling.

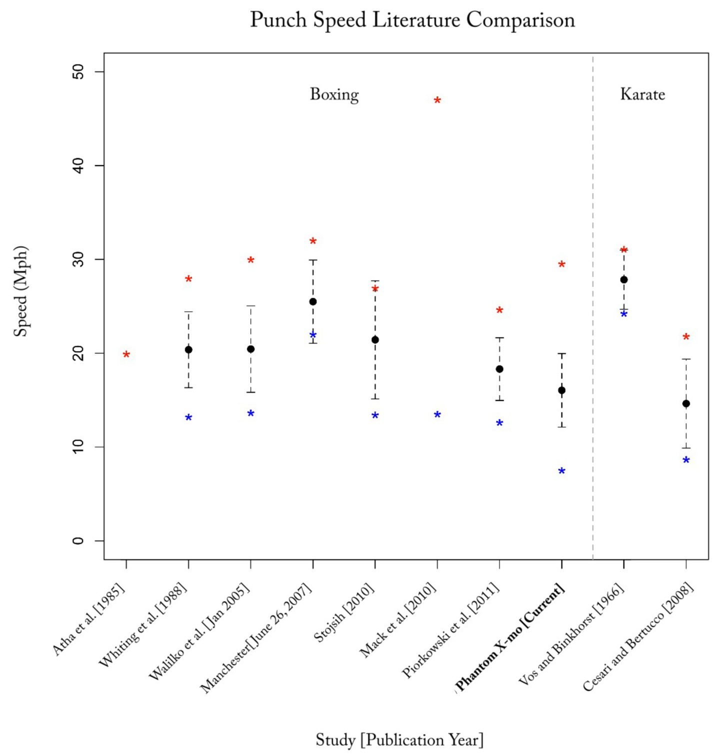

Figure 2.3: Punch speed literature comparison.

2.2.2 Straight Punch Force

With force we first discuss straight punches as initial boxing studies only took measurements on straights. Very few papers have studied hooks or uppercuts. Revisiting the Atha et al. [1985] study, Bruno punched an instrumented, padded target mass suspended as a ballistic pendulum. The one punch analyzed in detail had a peak force on impact of 920 lbs This punch was extrapolated to the equivalent maximal force delivered to a human's head of 1,421 lbs.

Two older studies reported maximal punch forces of 776 lbs for 24 elite boxers, 680 lbs for 23 national boxers and 659 lbs for 23 intermediate boxers [Joch et al., 1981], along with 606 lbs for a heavyweight amateur boxer [Karpilowski et al., 1994].

In the study, Manchester [June 2007], where Hatton threw four punches the researchers attached a force sensor to a 30 kg punching bag with the sensor attached to a laptop. At first glance the researchers thought he had landed a blow with 3,307 lbs of instantaneous force. During further analysis it was revealed that the power of the punch caused the sensor to malfunction, giving a false reading. So the researchers used (undocumented) alternative data and examined (unspecified) previous studies to conclude he had thrown a punch with 882 lbs of force. [Manchester, June 2007]

The more recent method to record force is boxing dynamometer, which is a combination of a triaxial accelerometer force measurement system and a boxing manikin built specifically to record punch force. This was first outlined in the study Smith et al. [2000], which measured forces for elite, intermediate, and novice boxers. The maximal punches forces in this study for each group were 1079 $\pm$ 51 lbs, 837 $\pm$ 30 lbs, and 535 $\pm$ 26 lbs for rear hand punches. The lead hand punches were significantly lower for each group at 640 $\pm$ 51 lbs, 513 $\pm$ 28 lbs and 361 $\pm$ 22 lbs, respectively.

Six other studies also used the boxing dynamometer to record force on straight punches. Sherman et al. [2004] had eleven olympic boxers record a mean value of 513 $\pm$ 214 lbs. This is also the first study to consider other types of punches, such as hooks, which we will cover in the next section, and the only study to consider uppercuts which had a mean of 347 $\pm$ 192 lbs [Sherman et al., 2004].

In Walilko et al. [Jan 2005] boxers weighing between 112 pounds and 240 pounds recorded eighteen direct hits to be used in analysis. Peak punch force ranged from 447 to 1,066 lbs, with a mean of 770 $\pm$182 [Walilko et al., Jan 2005].

The next study, Dyson et al. [2005], had six amateur boxers throw punches during a 30 second period from which their maximal punch force was analyzed. Typically between 19-20 punches were recorded for each hand during the 30 second time period. The goal of this study was to compare forces of punches that were either thrown for maximal speed or maximal force [Dyson et al., 2005]. The mean maximal punch force for the lead hand was 468 ± 14 lbs and 592 ± 22 lbs for the rear hand.

Smith [2006] analyzed 29 senior English amateur boxers maximum punch forces for straight punches to head and body again using the boxing dynamometer. Here, they recorded the rear hand mean maximal force to the head at 594 ± 286 lbs and lead hand force at 387 ± 157 lbs. The recorded forces were lower for punches thrown to at the body at 595 ± 243 lbs and 378 ± 143 lbs, for rear and lead hands respectively. These are very similar to the force values recorded in Dyson et al. [2005] for the punches thrown for maximal speed to the body and the head.

The Stojsih [2010] study had 18 boxers, both male and female, throw a varying number of punches as was discussed in the speed section. In all there were 99 straight punches thrown during testing. For all boxers the mean force was 450 ± 308 lbs. In the comparison of males and females, the 10 males threw 113 punches with a mean punch force of 547 ± 335 lbs while the 8 females threw 30 punches with a mean of 335 ± 189 lbs.

Lastly, Mack et al. [2010] had 42 amateur boxers to record force resulting in only 39 reliable straight punches to be analyzed. Again no specific values were listed but force values were estimated from the published scatterplots. From these 39 punches the peak force was roughly 1,034 lbs with a minimum value of roughly 270 lbs.

2.2.3 Hook Punch Force

There have been considerably fewer studies that have recorded force measurements from hook punches resulting in a less extensive section as the straight punch section. As in the speed studies, overall the hooks have higher measurements than the straight punches. The maximum force across all punch categories was a hook.

First, we return to Sherman et al. [2004], which was the first study to consider hooks separately from straight punches. The measured hooks had a mean force of 980 ± 524 lbs with a maximum of 2,234 lbs. This maximum of 2,234 lbs is the highest recorded force in any of the studies. Additionally, the smallest force seen in this study was only 103 lbs, one of the lowest of any of the studies.

Smith [2006] is the only study that had mean rear hooks that were lower than the straight punches by the rear hand. This study recorded the rear hand hooks to the head at 582 ± 234 and rear hooks to the body at 574 ± 208 lbs. The lead hooks to the head and to the body are 542 ± 161 lbs and 543 ± 161 lbs, respectively.

The Stojsih [2010] study had male boxers throw a total 34 hooks and females throw at total of ten hooks. Separately, the means for the males was 771 ± 285 lbs and for the females was 399 ± 126 lbs. The mean hook force was well above the mean straight punch force.

By again examining the published plots in Mack et al. [2010], the hook force for the 39 amateur boxers the maximal punch force is just above 1,800 lbs for a hook. Additionally, there is a punch with a force slightly under 1,575 lbs and five punches between 1,125 and 1350 lbs. On the lower end there is a hook that is slightly below 450 lbs. Outside of the Sherman et al. [2004] study, this study had some of the highest individual force punches of any that are being compared.

A similar table (2.2) as seen in the speed section summarizes the available force data. All groups seen in each of these papers including males and females as well as elite and novice are combined for one mean, max, and min value per study. Also included are the force measurements from the live fight system Pierce et al. [2006] as it is the only study to have previously record force during live fights.

[2] No specific values listed. The approximated (∼) from the published plots.

Type	Study	Punches	Mean	Max	Min
Straight	Joch et al. [1981]	70	-	776	-
	Atha et al. [1985]	1	-	921	-
	Karpilowski et al. [1994]	1	-	606	-
	Smith et al. [2000]	46	652±252	1,297	277
	Sherman et al. [2004]	-	513±214	-	-
	Walilko et al. [Jan 2005]	18	770±182	1,066	447
	Dyson et al. [2005]	36	-	952±41	420±9
	Smith [2006]	29	-	592±286	378±143
	Manchester [June 2007]	4	-	882	-
	Stojsih [2010]	79	450±308	-	97
	Mack et al. [2010][2]	39	-	∼1,034	∼270
Hook	Sherman et al. [2004]	-	980±524	2,234	103
	Smith [2006]	29	-	582±294	543±161
	Stojsih [2010]	34	771±285	-	-
	Mack et al. [2010][2]	39	-	∼1,798	∼405
Fight	Pierce et al. [2006]	1,675	234±123	1,205	195±71

Table 2.2: Force studies comparison.

Table 2.2 is visualized in Figure 2.4 with the mean plotted as a black dot, with standard deviation as the dotted line, the maximum value as the red asterisk and minimum value as the blue asterisk. The studies are listed across the x-axis with the publication year.

To summarize, the majority of the force measurements in the experimental setting fall between 250 to 1,100 lbs of force with a mean near 700 lbs. The highest maximal punch force is all the way at 2,234 lbs with a minimum of only 97 lbs. Hooks are more generally more forceful than straight punches, experienced fighters throw harder punches, and males punch harder than females. There is also a large discrepancy between the force measured in the experimental setting in comparison to in the live fight with the live fight having far less forceful punches overall. Unfortunately, the difference between experimental punches and live fight punches is confounded by the measurement process. The live fight study is the only system to have used a force sensor on the glove rather than having to measured force in the response to a punch. Only one study measured force for uppercuts, which had lower force values than the straight punches in that same study.

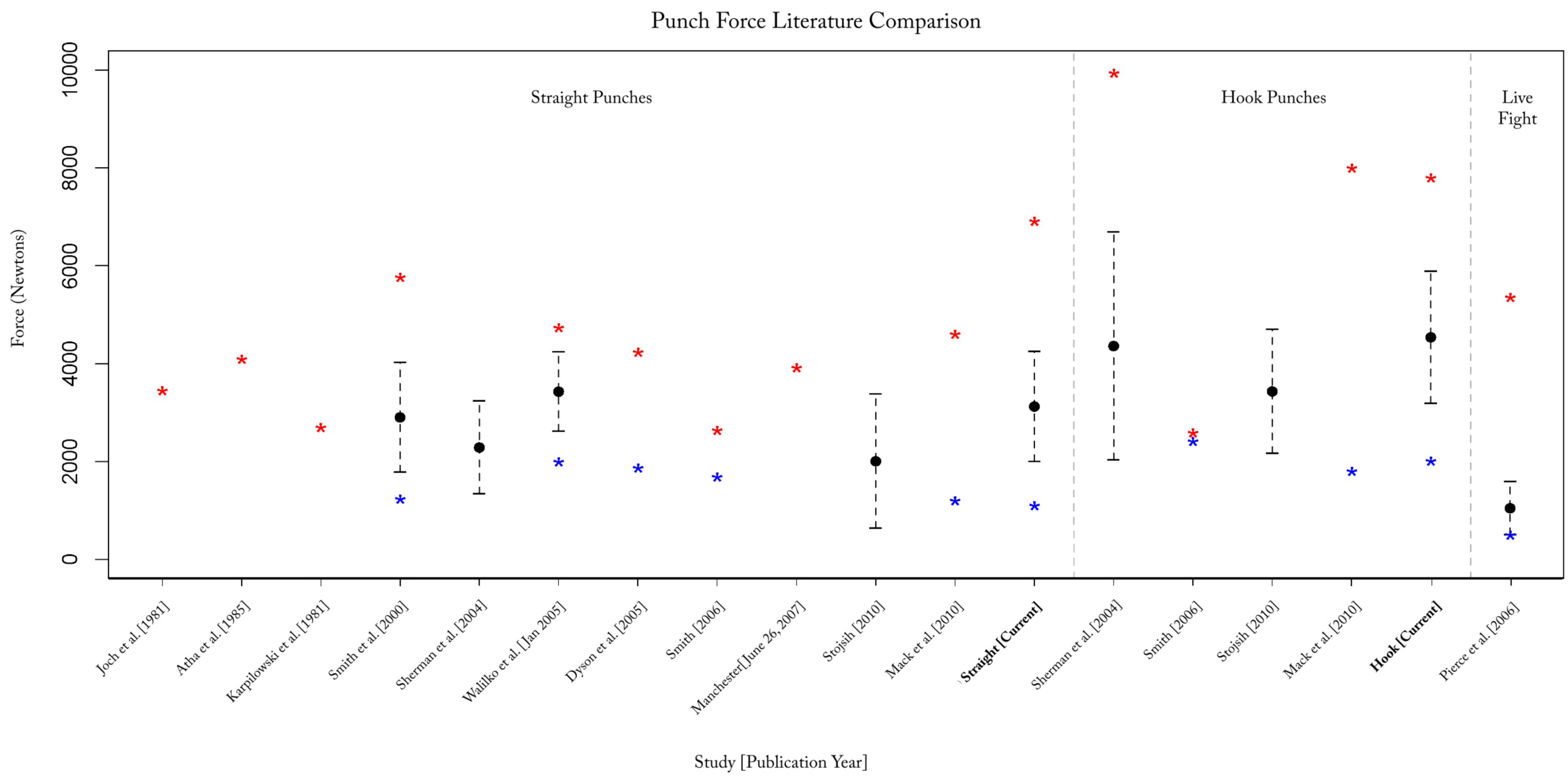

Figure 2.4: Punch force literature comparison.

CHAPTER 3

PunchR System Overview

Having seen all the prior methods of quantifying boxing we turn to outlining the PunchR system for taking real-time measurements during live boxing matches. The PunchR system is comprised of many different hardware and software components. This chapter first discusses the hardware necessary for use of the system during a live fight in addition to considerations about system quality and consistency needed to provide appropriately reliable output for on-air broadcast. Following the hardware description, we present an overview of our data collection for the PunchR system, statistical methods used for modeling, and results for punch detection, speed, force and type. Lastly, is the model instantiation in concordance with the hardware pieces for use during live fights.

3.1 Hardware Development

A custom dual-axis accelerometer has been designed in previous phases (prior to any of this work) of the PunchR project to record hand accelerations during boxers' punches [Eveland, 2011]. Prior to use in live fights these accelerometers had to be finalized from the previous versions, making minor calibration changes for each of the units and monitoring the sampling rates. The final glove units measure 1.7 inches by 0.9 inches by 0.38 inches weighing 7.9 grams, small enough and lightweight enough to be placed underneath a boxing glove, but taped above a hand wrapping on the inside of the wrist. The one base unit that handles communication between the glove units and the PunchR system computer is only

2.6 inches by 2.6 inches by 1.2 inches weighing 66 grams. As designed, the system measures and wirelessly communicates the accelerations of a boxer's hands during live boxing matches.

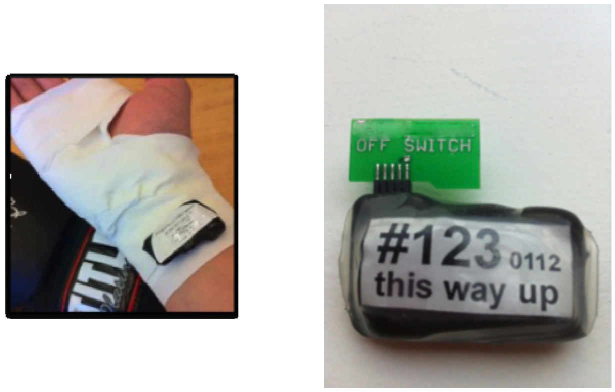

Figure 3.1: PunchR unit attached to wrist (left) and in standby mode (right).

3.1.1 Hardware Technical Specification

The PunchR system consists of a number of primary hardware elements and associated primary software elements. Taken from the Eveland [2011], the typical physical setup uses:

- Four glove units - wireless sensor units inserted, one per hand, in the gloves of the fighters to be monitored.
- One base unit - USB-attached wireless transceiver which handles communication between the glove units and the system computer.
- One host computer - d laptop which receives and analyzes glove data, preparing it for further production use.
- One or more glove unit chargers - battery chargers used to charge and condition glove unit batteries in advance of a fight.
- Assorted antennas, cables, and mounting hardware.

PunchR glove units are compact, battery-powered, wireless sensor devices used to measure and transmit the acceleration experienced by a boxer's fist over the course of a punch.

System radio operation is in the 2.4 GHz ISM band and makes use of *Nordic* brand low-power embedded transceiver system-on-chip (SoC) modules with 0 dBm output power. Radio firmware implements frequency-agility, with support for 20 channels spanning 2.4-2.5 GHz. The operator can selectively change the system's operating frequency to avoid interference with other devices operating in same band.

The glove units feature an onboard ceramic chip antenna while the base unit operates with a variety of high-gain uni- and omni-directional antennas. Available antenna configurations include a highly-directional *Luxul* brand circularly-polarized *Yagi* antenna with 10 dBi gain and a 50-degree beamwidth, an omni-directional *WiFi+* brand multi-polarized antenna with 7.5 dBi gain, and a number of other directional and omni-directional models.

The antenna and base unit are typically mounted together near the ring. Optimal performance requires line-of-sight to the ring, a mounting position several feet above the level of the ring and, when a directional antenna is used, enough "throw" distance to take in the entire ring.

The PunchR system operates with a minimum range of 50 feet from glove units to base unit. Data transfer over the air is at the rate of 2 Mbps or approximately 600 sensor data packets per second.

Inertial sensing is provided by a single-package two-axis MEMS accelerometer with +/- 35 g range. The accelerometer provides a highly linear, high-fidelity indication of instantaneous acceleration for analysis. A passive filter network on board further reduces noise and scales the signal to the range of the system-on-chip's integrated DAC. The sensor input is over-sampled with a resolution of

10-bits and further filtered before being packed and transmitted.

3.1.2 Unit Calibration

These final versions of the PunchR glove units had to be calibrated so that in each use the units would have the same saturation value in g's. Three punch tests were completed in the fall of 2009, on October 30, November 12, and December 1, all at Gleason's Gym in New York, NY to record data for force modeling. In a large portion of punches during these tests the acceleration measurements reached a saturation value in the x-axis. The saturation values varied greatly from test to test so it was deemed that the results from these three were incomparable to one another. As a result a number of in house tests were completed at the start of 2010 to make certain that the units were calibrated so the saturation value became the same from test to test. This was completed before any of the testing done for the speed or force modeling.

The glove units are calibrated prior to being attached to a boxer's wrist during each fight event. Units that have a maximal acceleration of 30 ± 1 g's in addition to a stationary mean of 0 ± 1 g are deemed acceptable for use during a live fight. Sufficient extra units are available at each fight that if initial units do not meet the standards replacements are readily available. The mean calibration of the units are monitored during live fights so that if a deviation away from 0 ± 1 g's is noted on-air reference to PunchR is cautious for the remainder of that fight. Following the fight the defective unit is assessed for damage or re-calibrated for later use.

3.1.3 Unit Sample Rates

An important part of the testing during 2010 was to assess the sample rates. There was no specific goal in mind of sample rate, but the higher the better. During the sample rate tests the optimal sample rate while four units were running simultaneously fell between 6 and 7 ms/sample.

Similarly to calibration, the units are tested for sample rates prior to use during a fight event. Again, all four units to be used in the fight should maintain a sample rate as close as possible to the optimal sample rate. The sample rates are also monitored during live use. If the units sample rates slows to more than 10 ms/sample the data becomes largely insufficient for proper estimations by any of the statistical models. Another issue that is also monitored is the loss of packets or length of gaps seen between observations. During a fight, loss of packets occur as a result of loss of unit connectivity to the base station whether it be as a result of referee interference, venue setup or any other unforeseen issue. Gaps between data collection of over 200 ms are monitored during a fight with a filter in place to deal with punches that may include gaps of this nature (discussed further in Punch Detection).

3.2 Punch Detection

Throughout the development of the PunchR system a necessary goal has been to reliably detect a punch "event" from acceleration values from the glove units in real time. To do this it is necessary to take the rough acceleration values recorded by each accelerometer unit splitting them into a regularized format of a single punch. A number of criterion will be used to assess whether or not a punch is in fact thrown, which will all be validated using video recordings of the actual punches. This is an important step along with a primary step in both speed estimations, force estimations, and any other future work resulting from the PunchR system.

3.2.1 Data Collection

There have been two phases of data collection to train a punch detection model. Initially, fitness boxers simulated multiple rounds of sparring to replicate live boxing match conditions. The boxers were equipped with two units, one on each hand, to record a number of punches and flurries of punches. The PunchR system was run as it is during a live fight with the acceleration time series recorded. A punch detection model trained on these "rounds" of sparring was deemed satisfactory, but improvable through the use of data from live professional boxing matches.

As the PunchR system continued to see use in live boxing matches the simulated sparring "rounds" were replaced by actual fight data. The raw data recorded by the PunchR system was matched frame-by-frame with fight videos that had associated timestamps. First, a professional CompuBox operator tagged all acceleration peaks of over 5 g's as landed punch, missed punch, block, and other (any other strange hand motions) from rounds of a fight between Kentrell Claiborne and Seanie Monaghan that took place in Atlantic City, NJ on October 1, 2011.

When considering the profiles of landed punches and missed punches as tagged by the CompuBox operator there is little, to no difference in many of the profiles because the fundamental punching motion is the same. In many cases a "miss" occurs when a boxer actually hits the opposition's gloves who is in a blocking stance. There is effectively minimal difference when comparing these acceleration values to the acceleration values when a boxer actually hits the opposition in the body, which is considered a landed punch. As a result, we categorized landed punches and missed punch, which both have punching motions, as punch, and all other movements as non-punch. Using similar criterion as the CompuBox operator to differentiate punch motions and any other movement, videos from nine other fights were reviewed tagging acceleration peaks using the punch/non-punch tags for at least one round per fighter. These tagged fights totaled 17 different boxers for use in the punch detection algorithm training process.

From the live fights, each acceleration trace for each boxer was scanned using the buffer of 100 observations marking a total of 2,411 acceleration peaks rising above the noise threshold of 5 g's as possible punches. Of these acceleration peaks there were a total of 1,172 tagged punches all matched to video. These tagged possible punches were broken into a training set (for model fitting), validation set (for model selection), and testing set (for final model assessment). The following table 3.1 list boxer name, number of possible punches, number of actual punches, and which data set (training, validation, or testing).

3.2.2 Methods

The initial step in detecting a punch event is identifying when a punch has taken place. This is trivial in an experimental data collection setup (force and speed data collection) with a wired punching bag where the punch events occur on a nearly regular basis making them easily identifiable by a large deviation from the majority of the acceleration values. In these rounds of data collection boxers are prompted to hit the bag with equal time intervals. A punch "event" is simply identified when the acceleration values cross a fixed noise threshold until they drop back below that same noise threshold. The maximum acceleration of those acceleration above the noise threshold is the peak acceleration and is when punch impact occurs.

In the live fighting environment a more sophisticated algorithm becomes necessary as punches are thrown consecutively or in rapid succession with opponents hitting the PunchR equipped gloves. Deciphering when one punch ends and another begins is difficult because often the acceleration values will not drop back below the noise threshold before the next punch begins or there are large acceleration peaks as a result of a boxer blocking an opponent's punches.

[1]Kentrell Claiborne punches were tagged by a CompuBox operator

Boxer	Tagged Punches	Possible Punches	Dataset
Thomas Dulorme	30	47	training
Harrison Cuello	18	107	training
Kentrell Claiborne[1]	132	222	training
Isaac Chilemba	119	208	training
Jameson Bostic	54	193	training
Magomed Abdusalamov	19	51	training
Kevin Burnett	7	24	training
Danny Garcia	105	183	training
Dwanye July	128	292	training
Ivan Najera	156	215	validation
David Castillo	81	219	validation
Juan Colon de Jesus	19	32	validation
Alex Saucedo	24	38	validation
Deontay Wilder	66	122	testing
Marlon Hayes	23	110	testing
Eddie Gomez	121	180	testing
David Lopez	75	168	testing
Total	1,172	2,411	

Table 3.1: Punches tagged during video review.

Punch detection operates on a buffer of the acceleration measurements. Again when an acceleration value crosses a fixed noise threshold the following measurements are surveyed for the peak acceleration, which is just marked as a possible punch. The threshold here is set intentionally low compared to the training rounds mentioned above. The buffer of acceleration values is then scanned to extract a complete profile of the event, which fills in data both before and after the possible punch. Finally, logistic regression is used to determine the probability that an identified punch profile comes from a punch.

To fit the logistic regression, the collected data is split into three parts, training, validation, and testing. The training and validation sets are used to fit the logistic regression while the testing set is used in final assessment. Unique features about the possible punch acceleration profiles are considered to identify whether each specific profile is a punch or not a punch. The features include the height of the maximum acceleration (both x- and y-axis), the width of the maximum acceleration, minimum acceleration, slope from the minimum acceleration to the maximum, indicator whether the max occurred prior to the peak or post, and some quadratic and interaction terms. These feature are paired down using stepwise logistic regression with the Akaike Information Criterion (AIC) or with the Bayesian Information Criterion (BIC), as the criterion for model selection. Recursive feature elimination (`rfe`)[2] and classification and regression trees (CART)[3] [Breiman et al., 1984] are implemented for comparison. The different models and combinations of acceleration features are fit on the training data and compared using the validation set to ultimately decide on the best features to identify actual punches. All modeling takes place in the open source statistical software package `R` [R Core Team, 2013].

The final step in determining whether to keep an acceleration peak as a punch is to set a probability estimated by the logistic regression at which we accept a possible punch as a being an actual punch for estimation. In selecting the model, we assume that if the probability of a possible punch is greater than 0.5 based on the logistic regression we consider the profile to be a punch. It is preferable that no punches are missed in detection for future estimations so we would like to set the probability at which we accept a possible punch as a punch at a low threshold for liberal inclusion of punches. In the results above the model does well to reduce

[2] `rfe` implements the `caret` package in `R` [from Jed Wing et al., 2013]
[3] CART implements the `rpart` package in `R` [Therneau et al., 2012]

false positives, but the next step is to increase the number of punches correctly detect without drastically increasing the false positive rate. To do this we used receiver operating characteristic (ROC) curves [Peterson et al., 1954, Egan, 1975] by varying the threshold at which we will accept a punch from 0.5 down to 0.001. Finally, the logistic regression and probability threshold are used to assess the model using the testing data.

In assessment of the models there are both false positives and false negatives. A false positive is when a punch is detected by the model, but is not actually a punch as determined through video analysis. A false negative occurs when a punch should be detected by the model, but is missed. Assessment considered three rates described below:

- Detected Punches - percent of correctly identified punches out of punches identified from video analysis.
- False Positives - percent of incorrectly identified punches out of all identified punches from video analysis
- Overall Accuracy Rate - percent of correctly identified punches and non-punches out of all peak accelerations over 5 g's

In model assessment we want to find a balance between correctly detecting punches and minimizing false positives. When it comes to deciding the between the two, correctly detecting punches is more important to make sure we do not miss any estimations of force or speed. Overall accuracy rate is the least useful in this problem because it is directly related to the threshold that we have set. If we lower the threshold from all acceleration peaks over 5 g's down to 3 g's, for example, we would increase the number of possible punches, which would easily be identified as non-punches thus increasing the overall accuracy rate percentage. If we want to artificially inflate this we could simply lower the threshold. It is included in assessment as the traditional measure of accuracy in classification problems.

Next, the detected punch events that are deemed punches by the logistic regression are registered to a regular grid of time values. The detected punches each have a varying number of samples that are collected within the 500 millisecond buffer on either side of the punch profile acceleration peak. So that each punch profile is consistent with another, each profile is set to a grid size of 1,001 points. This ensures that each punch profile is the same number of observations as well as that each observation is equivalent to 1 millisecond. The grid is formed in a way so that none of the original acceleration peak values are changed.

Finally, we "smooth" the acceleration values. There is some amount of noise recorded by the accelerometers even when a boxer is holding a hand still. To reduce the noise in the acceleration measurements each punch profile is passed through a local linear smoother. The smoothing will allow for more robust calculations of features that will be used in both speed along with force calculations.

3.2.3 Results

Using the training data, nineteen different features were considered from the punch profiles. Different models fit using stepwise regression with AIC or BIC and CART were assessed on 280 punches in the validation set until ultimately a model fit using stepwise regression with BIC was selected. With the features selected we included the validation set in addition to the training set to fit the model to determine if there was a drastic change in the coefficients of the model. As this model will be used to extrapolate punches for many other fighters we wanted to have as many fighters used in fitting the model as possible. There was not a significant change in the coefficients so the final coefficients use the punches from all the fighters from the training and validation set. The final logistic regression fit to determine the chance that an identified punch profile is actually a punch is as follows:

$$\begin{aligned}\text{prob} = exp(&0.452 \cdot \text{value\_acc\_peak} - 0.049 \cdot \text{fwqmax} + 0.038 \cdot \text{y\_acc\_peak} \\ &+ 0.035 \cdot \text{y\_acc\_min} - 0.107 \cdot \text{min\_acc\_peak} - 0.607 \cdot \text{avg\_slope} - 2.323 \cdot \text{ind} \\ &+ 0.006 \cdot \text{fwqmax} \cdot \text{value\_acc\_peak} - 0.008 \cdot \text{value\_acc\_peak}^2 - 6.432) \end{aligned} \quad (3.1)$$

$$\text{probability of punch} = \frac{\text{prob}}{(1 + \text{prob})} \quad (3.2)$$

The features are listed in the following table (3.2) with a description of how each feature is constructed.

Feature Name	Description
value_acc_peak	max acceleration value in the x-axis
min_acc_peak	min acceleration value in the x-axis
fwqmax	the width of the acceleration profile at 1/4 the height of the max acceleration
y_acc_peak	max acceleration value in the y-axis
y_acc_min	min acceleration value in the y-axis
avg_slope	average slope of the acceleration from the min acceleration to the max acceleration
ind	indicator if the min acceleration is prior to the max acceleration and if its absolute value is larger than the max

Table 3.2: Punch detection features.

Overall, for the training and validation sets combined the percent of correctly identified punch was 88.7% and the false positive rate was only 14.6%. The next step was to consider ROC curves varying the probability of determining whether a peak should be considered a punch. The ROC curves in Figure 3.2 indicate that between 0.4 and 0.3 is where we begin to lose in the trade-off between increasing number of correctly identified punches and false positives.

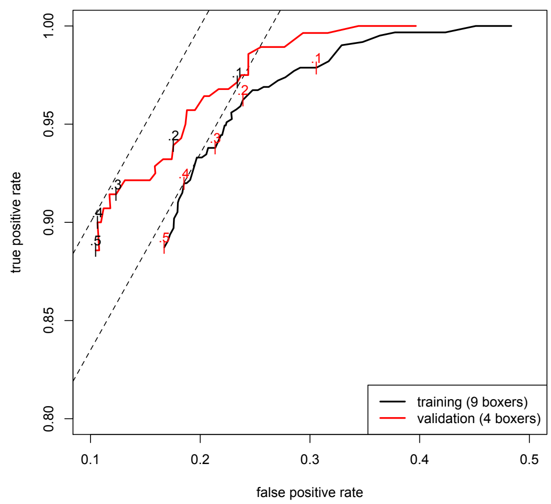

Figure 3.2: ROC curves.

Ultimately, the threshold of 0.4 was selected in combination with another threshold of any acceleration peak greater than 20 g's being deemed a punch. The 20 g's hard threshold has been included as a failsafe to make sure all large punches are surely tagged. Table 3.3 summarizes the model performance on the training and validation punches.

Finally, with the logistic regression model and the selected thresholds we assessed the entire punch detection algorithm on the testing set as show in Table 3.4 below. For the four boxers included in the testing set the percent of correctly identified punches was just over 90% with a false positive rate of 14.6%. The two fighters that had the higher false positive rates (Hayes and Lopez) were the losers in their respective fights.

Overall, for all 17 boxers in training, validation, and testing sets the percent of correctly identified punches is 91.1% with a false positive rate of 15.9%. The majority of punches that are not being identified are insignificant punches or punches that look different than a typical punch. The boxers that see high false positive rates are generally the boxers who are being significantly out-boxed by

Boxer	Detected Punches	False Positive	Overall Accuracy Rate
Dulorme	30/30 = 100%	0/30 = 0.00%	47/47 = 100%
Cuello	15/18 = 83.3%	25/40 = 62.5%	79/107 = 73.8%
Claiborne	120/132 = 90.9%	17/137 = 12.4%	193/222 = 86.9%
Chilemba	110/119 = 92.4%	12/122 = 9.8%	187/208 = 89.9%
Bostic	47/54 = 87.0%	28/75 = 37.3%	158/193 = 81.9%
Abdusalamov	19/19 = 100%	1/20 = 0.05%	50/51 = 98.0%
Burnett	7/7 = 100%	2/9 = 22.2%	22/24 = 91.7%
Garcia	102/105 = 97.1%	11/113 = 9.73%	169/183 = 92.4%
July	113/128 = 88.3%	32/145 = 22.1%	245/292 = 83.9%
Najera	141/156 = 90.4 %	14/155 = 9.0%	186/215 = 86.5%
Castillo	72/81 = 88.9%	12/84 = 14.3%	198/219 = 90.4%
Colon de Jesus	16/19 = 84.2%	3/19 = 15.8%	26/32 = 81.3%
Saucedo	23/24 = 95.8%	1/26 = 4.17%	36/38 = 94.7%
Total	815/892 = 91.4%	158/973 = 16.2%	1596/1831 = 87.2%

Table 3.3: Training and validation boxers' punch detection model assessment.

Boxer	Detected Punches	False Positive	Overall Accuracy Rate
Wilder	64/66 = 97.0 %	9/73 = 12.3%	111/122 = 91.0%
Hayes	21/23 = 91.3%	15/36 = 41.7%	93/110 = 84.5%
Gomez	109/121 = 90.1%	6/115 = 5.22%	162/180 = 90.0%
Lopez	63/75 = 84.0%	14/77 = 18.2%	142/168 = 84.5%
Total	257/285 = 90.2%	44/301 = 14.6%	508/580 = 87.6%

Table 3.4: Testing boxers' model assessment.

their opponents so their gloves are in the block position being struck by their opponents more frequently.

With the algorithm complete to identify punches from the acceleration traces we now provide an example of a single round of the fight between Thomas Dulorme and Harrison Cuello from Thomas Dulorme's right hand only. To begin, we show acceleration values in the x-axis prior to punch detection (Figure 3.3) and then following punch detection with the detected punches overlain in red (Figure 3.4). Looking at the running acceleration values, the punch "events" are easily identifiable as the major spikes in acceleration where the logistic regression is used to determine if they are punches for estimation. About half way through the round the peaks disappear as Dulorme knocked out Cuello to end the fight.

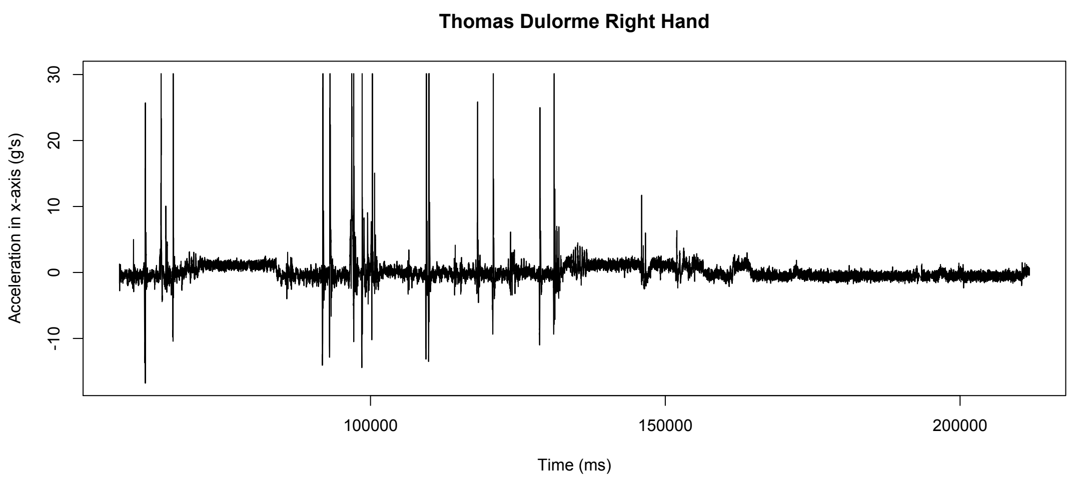

Figure 3.3: Thomas Dulorme right hand acceleration values (x-axis only).

The punch detection algorithm recorded 17 punches from this single round of Thomas Dulorme's fight. From the previous table (3.3), we can see that this is one of the cleaner rounds in terms of punch detection where 100% of punches were identified correctly. The smaller spikes were when punches occurred in the opposite (left) hand, which resulted in a small hand movement or when Cuello punched his glove.

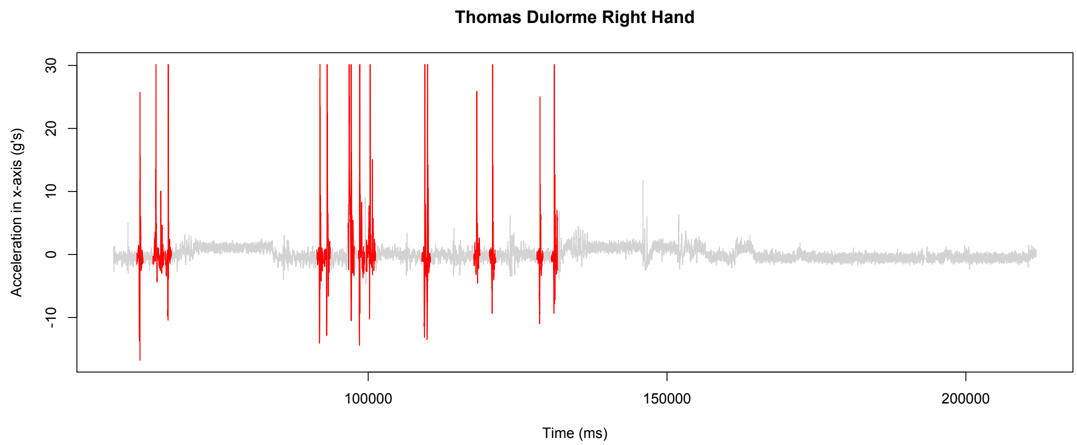

Figure 3.4: Detected punch profiles (red) over Dulorme acceleration values.

From the preceding string of punches, we consider the first detected punch to be placed on the grid of 1,001 points in Figure 3.5. Prior to regularization this specific punch had 543 values, which is one observation every 3 milliseconds.

Once the punch has been placed on a regular time grid we turn to the smoothing of the punch. The main characteristics of the punch profile are maintained during this process, including peak acceleration, minimum acceleration, other local maxima/minima, other unique features, and the general shape. In this example, the most notable smoothing occurs in the observations before the peak acceleration, which will help provide more stable calculations of feature estimation. The following Figure 3.5 is the punch profile before and after the smoothing.

We have completed the example of the punch detection on a single punch from the Dulorme fight. This process of punch detection is the first step in all modeling and real-time fight estimations. With each resulting punch profile, it is possible to extract the necessary features to input into both the speed and the force models.

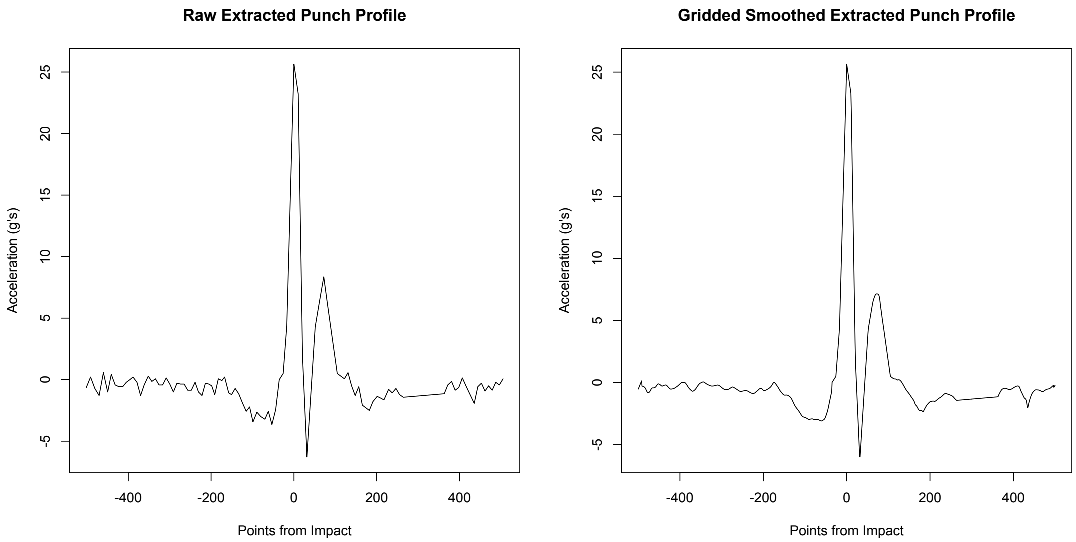

Figure 3.5: Comparison of raw and smoothed punch profile.

3.3 Punch Speed

One of the main goals of the PunchR project is to provide a reliable speed measurement during live boxing matches. As the PunchR project is based on the accelerations of punches, these accelerations can be used to provided a measurement of punch speed. This can be done with more accuracy using high speed cameras outside of the ring, but the goal in section is to provide live speed measurements quickly and for all punches during each match.

3.3.1 Data Collection

September 20, 2010 saw a data collection trial of the PunchR hardware setup coinciding with Inertia Unlimited's Phantom High Speed X-mo camera [InertiaUnlimited, 2010] with the goal of validating speed measurements from the PunchR system. Six boxers threw between fourteen and twenty-four punches that each had a punch acceleration trace along with the calculated speed from the high speed X-mo video. The calculated speed from the high speed X-mo video was considered actual punch speed. The only types of punches thrown during this trial were lead hand jabs and rear hand crosses, with the first punch always being a jab followed by a cross.

To ascertain accurate recordings using the Phantom High Speed X-mo camera, boxers punched a heavy punching bag with both lead and rear hands. The high speed X-mo camera was placed perpendicular to each boxer who was facing the bag so the full extent of the punch could be recorded. A 1-inch marker was placed on each glove facing the camera to serve as the necessary reference point in all the recorded video. While each punch was recorded with the camera the PunchR system was also run to record the punch acceleration time series. Once all the punches had been video recorded each punch was analyzed with the Phantom Software to get actual punch speed.

A second round of data collection with Inertia Unlimited took place on May 26 and 27, 2011 completing another trial of the PunchR system in alignment with the Phantom Speed X-mo camera. During this trial there was a larger variety of boxers along with types of punches recorded. Some boxers were instructed to only throw hooks, while the other boxers were instructed to throw alternating left and right straight punches followed by left and right uppercuts.

For the second speed collection trial the same setup as the first trial was used for the straight and uppercut punches. A new setup was employed for the hook punches as a result of the movement in both the x-axis plane (straight ahead) and y-plane (side-to-side). Here the camera was placed beneath the boxer to catch the entire range of the motion of the punch. The 1-inch scaling markers were placed on the bottom the glove facing the camera as reference points for speed measurements. As this was the first time this method has ever been used there was difficulty with some boxers in the placement of the camera not always catching enough of the punch on video to make the speed calculations.

From the original 109 punches thrown by the six different boxers form the first speed trial, we were able to pair 100 total punches that had readable scaling marks on the high speed X-mo camera to the PunchR acceleration punch profiles. From the second trial we were able to match another 248 punches from fifteen different boxers from the readable scaling markers on the high speed video to the PunchR acceleration punch profiles. There was a large amount of difficulty in making the readings from the high speed camera especially in the new camera setup for the hook punches. The following table (Table 3.5) is a numerical summary of the speed of the 348 punches thrown as recorded by the high speed X-mo camera. All the punch speeds are recorded in miles per hour.

Boxer	Minimum	25^{th}	Median	Mean	75^{th}	Maximum	Punch Count
Total	7.0	13.3	15.9	16.3	18.2	31.4	348 (143 lead)

Table 3.5: Phantom X-mo speed measurements (mph).

Finally, there was a third trial of data collection done by a group from BASE Productions [BASEProductions, 1992], a production company with trademark motion-capture technology, that used similar methods as the Inertia Unlimited trials to record straight punches for five different boxers. This testing also used a high speed camera perpendicular to a boxer punching a dummy with scaling markers as reference points. The measurements recorded from this trial were not used in any of the model fitting, but solely in validation of the model fit once completed.

3.3.2 Methods

In this high speed X-mo camera testing each punch acceleration time series is recorded as a single event in separate files, rather than one long time series with multiple punches. Nonetheless, each punch file is treated as an acceleration time series run through the real-time system, first extracting a punch event with a 500 millisecond buffer around the peak force, second placing the punch event on a regular grid 1,001 points, and finally the smoothing the punch event. The resulting punch profiles are then paired with the corresponding calculated speed from the high speed X-mo video.

The first step in the modeling is to use simple physics to compare velocity measurements. Velocity is the rate of distance moved over time with an associated direction. To derive velocity from acceleration we take the integral of acceleration over a specified period of time. As each punch profile is an acceleration trace, velocity at impact should just be the integral from the start of the punch (if we assume hand velocity is 0 at punch start) event acceleration until impact.

$$v(t) = \int_{\text{start}}^{\text{impact}} \text{acc}(t)dt$$

This is calculated with the trapezoidal rule using the accelerations from the start of the punch until the time of impact, as each acceleration occurs at 1 ms resolution. Velocity is speed with a direction so we will simply use speed throughout. In theory this speed should be similar to speed from the high speed X-mo camera.

The integral is the obvious, preferable path for speed measurement, but ultimately prove unreliable. The characteristics of these small accelerometer systems as well as missing data packets as a result of the wireless data upload make just using the integral not robust enough to make reasonable speed predictions in all cases. Searching for any improvement in the speed predictions we use the acceleration punch profiles to extract features (i.e predictors) which is also done in the force modeling. These features are entirely composed of the acceleration curve both preceding impact as well as following impact. Features from the punch profiles are sums of acceleration values over different periods during the punch.

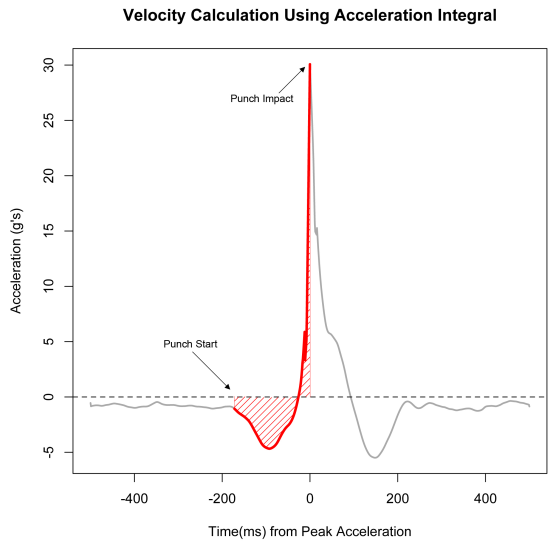

Figure 3.6: Example of the integral of a single punch from the punch start to punch impact.

Unlike the force modeling, no boxer specific or physical features are used because the definition of velocity only considers distances and times, but nothing pertaining to mass. The specific features initially considered are combinations of the following three plots in Figure 3.7 where the light grey is the acceleration trace with the red being the acceleration features.

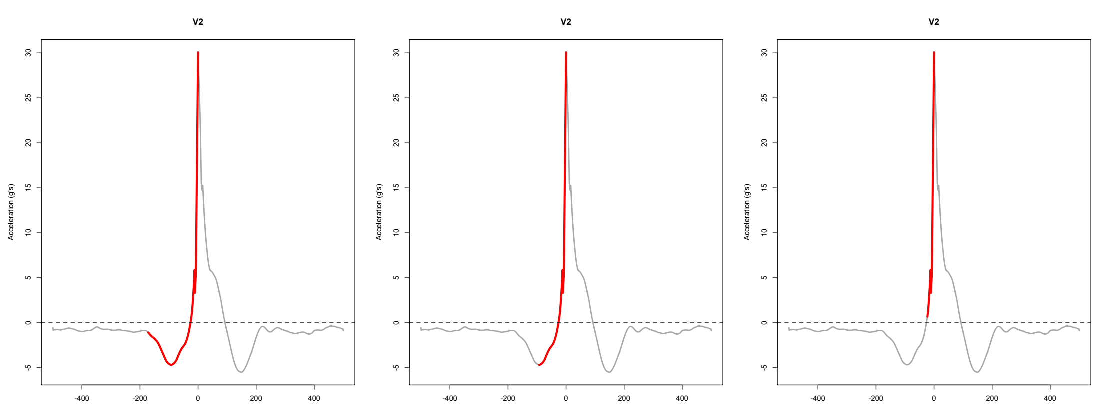

Figure 3.7: Sample features for speed modeling.

The first plot is an example of the punch start to punch impact. The punch start is determined by moving backwards from the impact point looking at each point one by one summing the previous value to the impact. Once ten accelerations have been added to the total and the total has not changed by more than 10% the last value added is considered the punch start. The third plot is the first time the acceleration rises above a 1.5 g's noise threshold until the punch impact. This will be referred to as "noise" when describing the features. The second plot is the minimum acceleration to the punch impact. This is determined as the minimum value between the punch start and the "noise". Again, the speed features are sums from one of these points to another, time between one of these and another, or means over these time periods.

The modeling techniques in the speed modeling differ only slightly to that of the force modeling. Polynomial multivariate adaptive regression splines (`polymars`) [Friedman, 1991, Kooperberg et al., 1997, Stone et al., 1997][4] is considered, along with variable selection again using `rfe` and a regression subsets method that uses exhaustive variable selection (`leaps`)[5] as well as linear models using LASSO regression[Tibshirani, 1996, Efron et al., 2004][6]. Starting with all the features, the ten best model to predict speed for each model size (from 1 predictor to 35 predictors) are selected using `leaps`. Additionally, `rfe` is used to indicate the most important features in modeling. Comparing the most important features selected in the `leaps` models as well as the most important features from `rfe` we can reduce the total number of features. This reduced the total number of features from 35 to a more manageable, parsimonious number of the nine best features.

With the reduced number of important features different models are fit with previously mentioned modeling techniques assessing uncertainty and fit through bootstrap methods. In bootstrapping we select random punches along with the corresponding speed value, with replacement, from the original punch set, in a

[4] `polymars` models fit using `polspline` package in `R` [Kooperberg, 2013]
[5] `leaps` implements the `leaps` package in `R` [using Fortran code by Alan Miller, 2009]
[6] LASSO models fit using `lars` package in `R` [Hastie and Efron, 2012]

bootstrapped sample. The bootstrap sample is the same size as the original data set. Each model estimates speed based on the bootstrapped sample features with which we then calculate residual sum of squares (RSS) as well as relative error. The smaller the RSS the more closely the model fits the data. Specifically, RSS is calculated by:

$$\sum (\text{observed speed - predicted speed})^2$$

The RSS is recorded for the bootstrapped sample. Relative error is a statement about the accuracy of the speed predictions. The definition of relative error is:

$$\text{relative error} = \frac{\mid \text{error} \mid}{\text{observed speed}}$$

Thus, relative error is difference of the prediction from the observed value relative to the observed value. This is a value we would like to minimize in the predictions. Mean relative error is also calculated on each bootstrapped sample. Lastly, accuracy of the punch predictions will be defined as: accuracy = 1 - relative error. Once RSS and relative error have been recorded a new bootstrap sample is selected. This process is repeated a large number of times ($> 20,000$) recording the RSS and relative error for each bootstrap sample.

The final item considered in choosing the speed model is robustness to predicting many different punches from many different boxers. There are two groups of punches used together in assessing the robustness of the final model. The 1,631 punches collected in experimental settings for the force modeling as well as from the heavyweight boxer for force calibration. Additionally, another 3,309 punches from 11 different fights from five different dates. This brings us to a total of 4,940 punches with which we are able to predict speed to make sure a large volume of punches are being predicted at physically reasonable levels on par with speed seen in previous boxing studies.

In previous speed modeling attempts some model fits were resulting in these extrapolated speed predictions at physically unattainable levels especially during live fights as a result of the much more varied conditions than the gym testing days. Also, punches may come in with atrophied acceleration profiles as a result of the wireless communication (or lack thereof) between units within a glove and the laptop. Slower sampling rates for small periods of time is a problem. All of these possible shortcomings must be addressed with a robust model. Finally, as with any statistical modeling model diagnostics are performed to address glaring problems with the model; mostly to address any major outliers.

Once a final model has been selected, the model estimates speed on the BASE testing measurements to further assess how well the model. The BASE speed measurements are compared to the model estimations.

3.3.3 Results

The first task once the actual speed from the high X-mo camera was paired with the PunchR acceleration traces was to calculate the velocity simply based on the acceleration integral. The integral of each punch acceleration profile resulted in an RSS of 8,165 and a relative error of 0.24. A relative error of 0.24 is equivalent to deeming that the punch speed predictions are 76% accurate. More importantly, predicting on the 4,940 punches from the force modeling resulted in a number of punches being predicted at levels not physically reasonable. There was improvement to be made from just using the straight integral that would both increase accuracy as well as reduce the number of physically impossible predictions.

Following the consideration of the simple integral we began exploring a number of other feature combinations to improve the accuracy. The best models as chosen by `leaps` are the models of size 15 using Mallow's Cp as the selection method, while using adjusted-R^2 this jumps all the way up to models of size 20. These large models of up to size 20 are much too big its just a lot of cancelation of one feature by another and over-fitting. Also, these larger models continue to predict punches at extremely high speeds (over 100 mph) or negative speeds. From here we started considering the features that are consistently picked by `leaps` as more important features. These are crossed referenced with the most important features from the `rfe` process to come up with the nine most important features as seen in Table 3.6. These are the features that contribute the most in predicting speed while resulting in fewer high speed or negative speed predictions.

Feature	Description
X1	sum punch noise to impact in x-axis
X5	sum of forty points around minimum acceleration in x-axis
X6	sum from point 470 to impact in x-axis
X14	sum from impact to point 520 in x-axis
X16	sum from point 550 to point 600 in x-axis
X22	sum from point 470 to impact in y-axis
X24	sum from punch start to noise in y-axis
X29	sum from impact to point 520 in y-axis
X32	magnitude of x- and y-axis from minimum acceleration to impact

Table 3.6: Features used in speed modeling.

There were 6 models considered that each had 20,000 bootstrapped samples on which both RSS and relative error were calculated. There were four `polymars` models and two `lars` models. None of these models used more than five of the nine important features. Following the bootstrapping the two `lars` models were dropped because the mean relative errors for 20,000 bootstrapped samples was above 0.20 (accuracy less than 80%). In the end the decision for the final model was between two models that had similar mean relative errors and RSS. The final model chosen had predictors included that followed more what a physical model would include. The mean relative error for this final speed model was 0.182 from the 20,000 bootstrapped samples. Hence, the accuracy was 81.8%. The RSS for this model is 4,666. The final speed model `polymars` regression output is reported in Table 3.7.

Feature	Knot	Coefs	SE
Intercept		8.6148	2.0771
X32		0.0070	0.0009
X14		-0.0128	0.0070
X14	286.1078	0.0342	0.0082
X16		0.0097	0.0023
X32	994.3653	0.3172	0.0567
X32	1067.5225	-0.1274	0.0245
X32	963.2239	-0.1946	0.0390
X5		-0.0157	0.0030
X5	-175.4262	0.0292	0.0062

Table 3.7: Polymars regression coefficients and standard errors.

The model included only 10 total terms with only four features included in the model with the remaining six terms being all knots with no interactions. If we refer back to Table 3.6 we see that X32 is the magnitude of acceleration from the minimum acceleration value to the maximum, X14 is the sum 20 accelerations after impact in the x-axis, X16 is the sum of 50 more accelerations further after impact, and X5 is the sum of 40 accelerations around the minimum acceleration. The first three seem to make sense even in a physical model standpoint. Basically, it is just what happens in the punch up until impact and then how fast is the arm being pulled straight back. The fourth feature is maybe some type of scaling feature, but is less identifiable as to what it may be doing. The associated RSS for the model is 3008 with an R^2 equal to 0.576. Then the correlation between observed and predicted is 0.75.

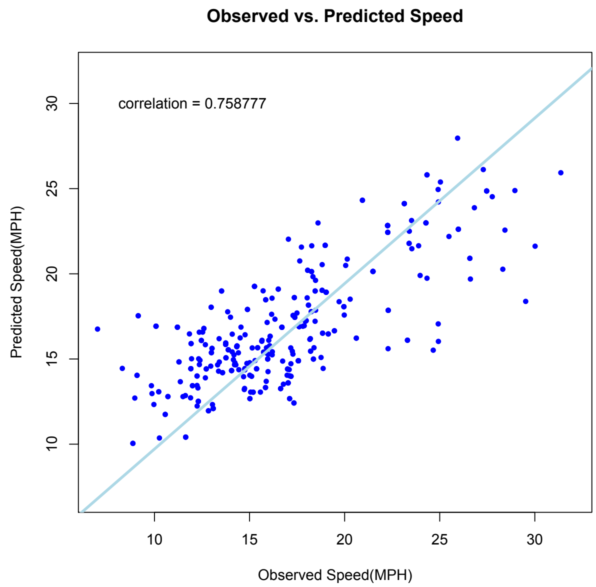

Figure 3.8: Observed and predicted punch speed values.

An additional step in fitting this speed model was to make sure it is robust over a large number of punches. This model predicts no negative punches nor any punches above 40 mph for the 4,940 punches from both the force modeling combined with 11 different fights. From the Phantom X-mo High Speed Camera measurements we saw speeds ranging from 7 mph to 32 mph, while most previous other studies were in the range of 10 mph to 35 mph, with one study having speeds up almost 47 mph.

Following the selection of the speed model it was tested in concordance with the BASE measurements. From the BASE testing we were able to match 42 punches from five different boxers that had an associated PunchR acceleration punch profile with a measured BASE speed.

The relative error for the BASE measurements is 0.13 giving us an accuracy of 1 - 0.13 = 0.87 or 87%. The correlation between the PunchR predictions and BASE measurements is 0.69, while the slope of the simple linear relationship

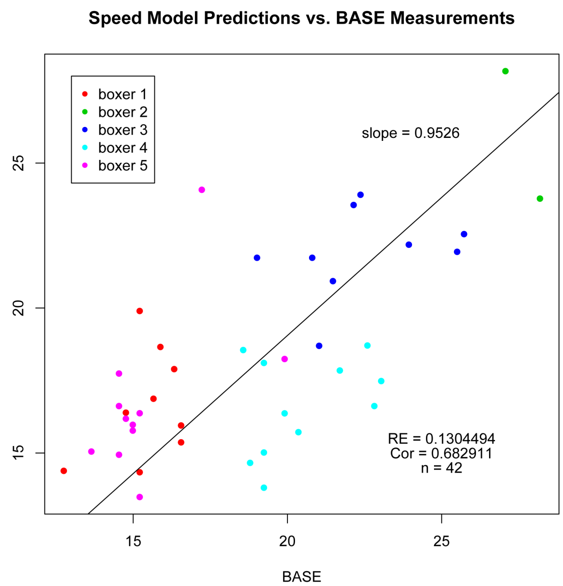

Figure 3.9: Punch speed predictions for 42 punches from the BASE testing.

without an intercept between the two is 0.96 which indicates no necessary linear calibration between the two measurements. This shows despite two groups making independent measurements and the method of processing the images may vary slightly, the underlying measurements are similar. The plot in Figure 3.9 provides a graphical representation of these relationships.

3.4 Punch Force

Another main goal of the PunchR system is to determine punch force in real-time during live boxing matches. Acceleration measurements, boxer physical attributes, and corresponding punch force measurements from experiments are used to develop a robust statistical model to estimate punch force. In estimating force, we have the acceleration necessary, but the difficulty lies in finding some combination of boxer physical attributes that becomes a stand-in for effective mass behind the punch. Recording force in the experimental setting has been done previously on numerous occasions so this has other reliable measures for comparison. Once a statistical model has been fit from the experimental data it can be translated to live fight punch force estimations.

3.4.1 Data Collection

To record punch force there were fours days of testing over a period of two months. These tests all occurred at Gleason's Gym in New York, NY. The same setup to record force was employed for each of the four days of testing. Each of the four tests were also video recorded for validation at a later date or item analysis on each punch.

The setup to record the punch force measurements prior to being used in the current force experiments had been adapted from three different studies Broker and Crawley [2010], Manchester [June 2007], Baagrev and Trachimovitch [1981]. A heavy punching bag was hung from an overhead bar allowing it to swing freely. During testing the movement was restricted for minimal movement in the y (side-to-side) acceleration plane. The bag was equipped with a wired sensor attached to a computer. The mass of the bag was known, so by measuring the acceleration of the bag as it was punched we could then determine the actual force received by the bag. In this edition of the setup, the bag sensor was now wired to the computer to provide higher resolution of acceleration measurements throughout the testing. This was done to make sure to attain the most accurate acceleration profiles possible. Each boxer then had the wireless units placed on both their right and left hand as is done during all live fights.

Boxer specific measurements were collected prior to each test including: gender, commitment level, hours training before test, glove weight, height, wingspan, arm length, bicep circumference, elbow circumference, forearm circumference, wrist circumference. Measurements were taken on both arms for all boxers to take into account any differences between arms. Level is the commitment level at which each boxer classified themselves either professional, amateur or fitness level. All the boxers tested were volunteers working out at the gym each day and where chosen to cover a full range of boxer sizes, fighting level, stances, and even gender. Table 3.8 lists all the recorded measurements, along with measurement units.

Measurement	Units
Stance	Orthodox or Southpaw
Gender	Male or Female
Level	Pro, Amateur, or Fitness
Hours Training	Minutes
Glove Weight	Pounds
Weight	Pounds
Height	Inches
Wingspan	Inches
Arm Length	Inches
Bicep Circumference	Inches
Elbow Circumference	Inches
Forearm Circumference	Inches
Wrist Circumference	Inches

Table 3.8: Boxer measurements.

On March 19, 2010, eight boxers at Gleason's Gym each threw forty punches. The boxers were instructed to first throw twenty punches alternating lead hand jabs with rear hand crosses followed by ten lead hand hooks and finally ten more rear hand hooks. Occasionally an extra punch was thrown during any one of these sequences resulting in more than forty total punches. Each boxer is identified by the 24 hour time when the system was run.

On both April 5, 2010 and April 20, 2010, ten boxers at Gleason's Gym again each threw forty punches. The boxers were instructed to first throw twenty punches alternating lead hand jabs with rear hand crosses except this time followed by alternating twenty lead hand and rear hand hooks.

May 20, 2010, six boxers at Gleason's Gym again each threw up to fifty-five total punches. Like the three previous tests the boxers first threw twenty punches alternating lead hand jabs with rear hand crosses. These were followed by ten left hooks. Lastly they were instructed to throw a combination of either jabs, crosses or hooks where the bag was not stopped between combinations. These punches were unused in the force modeling because a bag acceleration profile from these combinations would not give an accurate measurement of force for a single punch.

Table 3.9 counts the number of boxers by commitment level and boxer stance. Most the boxers in this training data come as amateur fighters with only seven being professionals. The number of orthodox fighters greatly outnumber the southpaw fighters, but this holds true overall in the boxing world.

	Commitment Level			
	Fitness	Amateur	Pro	Total
Orthodox	9	11	7	27
Southpaw	0	5	0	5
Total	9	16	7	32

Table 3.9: Boxer stance and commitment level

Now we look at the boxers by weight class. The two dots colored in green are the female boxers. There are lots of boxers between 140 and 200 lbs, but not as many below 140 lbs for the lower weight classes or above 200 lbs for heavyweights.

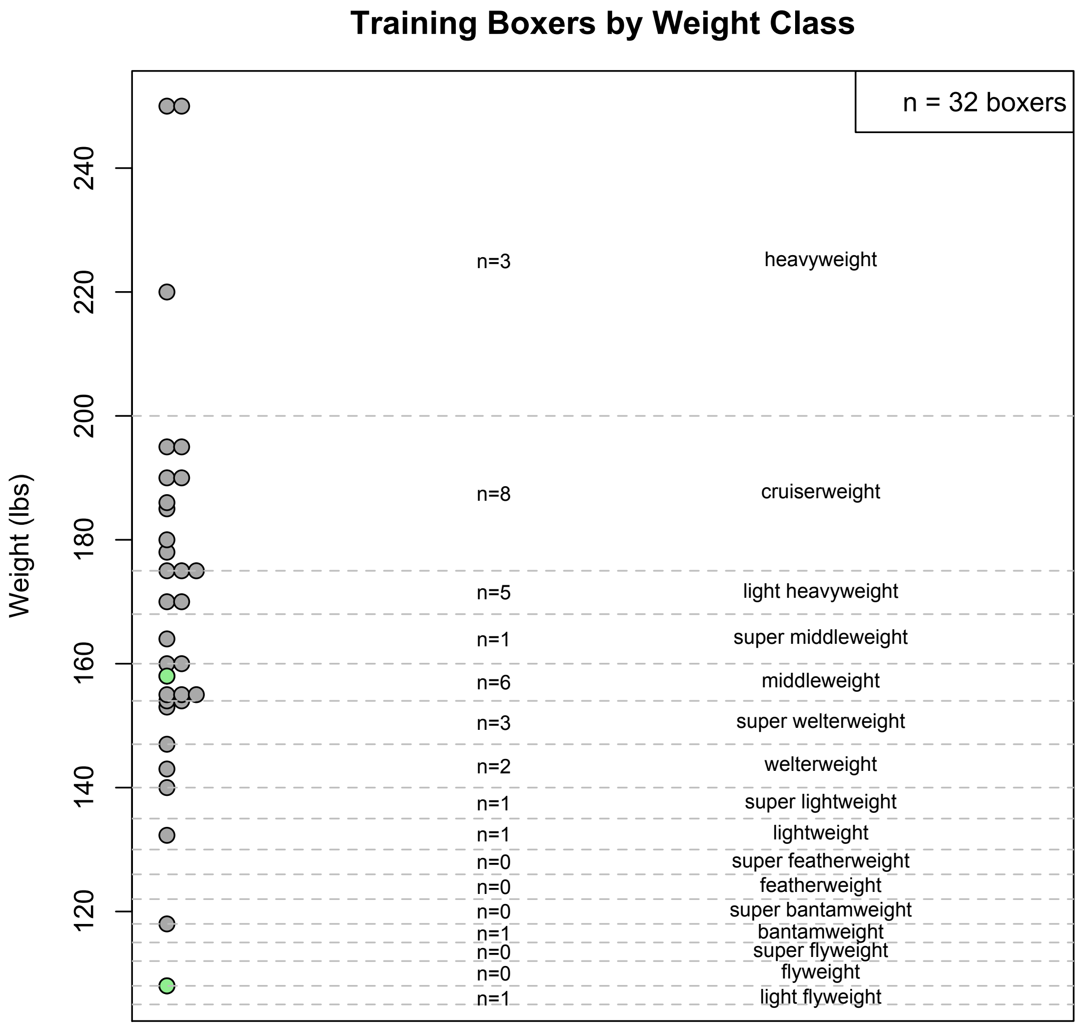

Figure 3.10: Training boxers by weight class.

Finally, a correlation matrix of some of the major boxer physical features (figure 3.11). The arm circumferences are highly correlated as are the measures corresponding to arm lengths.

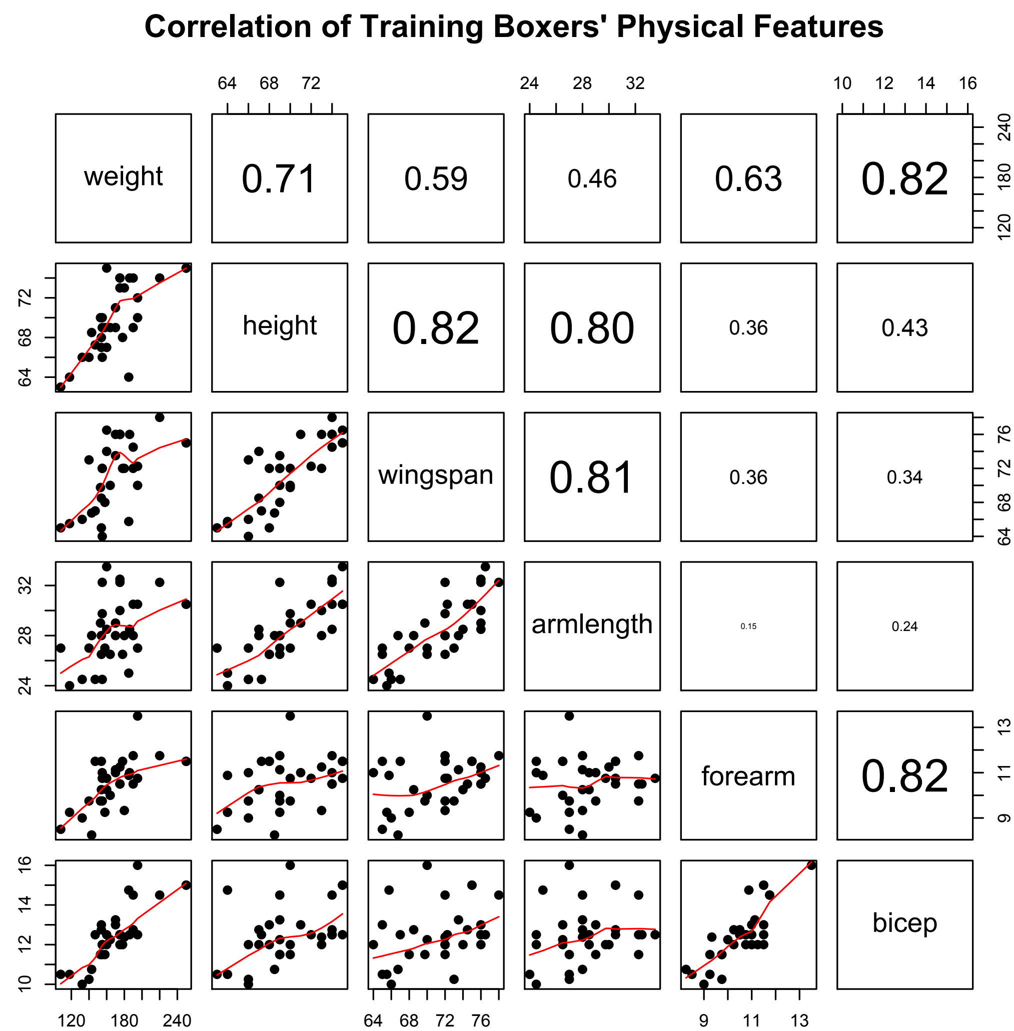

Figure 3.11: Correlation matrix of boxers' physical features.

There was one final day of data collection on July 7, 2011 done by a group from BASE Productions [BASEProductions, 1992] that used entirely different methods to record straight punches for five different boxers. This testing used a boxing dynamometer instrumented with three accelerometers as discussed in the straight punch force measurement section of the Boxing Quantification chapter. The measurements recorded from this trial were not used in any of the model fitting, but solely to assess whether the two measurement approaches would agree.

3.4.2 Methods

Each boxer's acceleration time series is treated like it will be during a live fight being passed through the punch extraction algorithm, extracting the punch, placing the punch on a regularized grid of 1,001 points and finally smoothing the acceleration values. Similarly, the corresponding bag acceleration time series is passed through a bag extraction algorithm that is a simple adaptation of the punch extraction algorithm. Each punch acceleration profile is paired with the corresponding bag acceleration profile to create a complete set of punches.

Of course, we are trying to estimate force. In our experimental setup we stated we know the mass (m) of the bag, so using the acceleration (a) of the bag as it is punched we can then determine the actual force (F) received by the bag, with the simple relationship $\mathrm{F} = m \cdot a$. The maximum acceleration in each bag profile is multiplied by the bag weight to get a resultant force. This is used as the response variable in the modeling throughout.

At this point, features are extracted from the punch acceleration profile. Features from the punch profiles are sums of acceleration values over different periods during the punch. These features included sums of values in both the x and y acceleration planes as well as acceleration before and after impact. These sums become necessary instead of just the maximum acceleration or largest change in acceleration because the accelerometer units reach a saturation point upon impact. There is no telling if the actual maximum is close to what is recorded because of saturation. In the speed modeling, we have some idea of what features would be important so we were able to list them all out. In the force modeling nearly 50 different features are included in the modeling step at some point so all of these will not be listed. As these features are all based on acceleration they represent the acceleration (a) in our $\mathrm{F} = m \cdot a$ equation.

The features extracted from each punch profile are then paired with the boxers physical features to complete a full set of features for all the punches that will be used to estimate force. For specific arm measurements only the punching arm measurements are included as physical features for each punch. For instance, if the boxer is throwing a right hand punch then only the right arm weight, arm length, forearm circumference, bicep circumference, elbow circumference, and wrist circumference are included. The left hand measurements are not included for this punch. The combination of the physical features are basically the effective mass behind each punch or the m in $\mathrm{F} = m \cdot a$.

It should be noted that one last additional feature must be added. Although stance is recorded as a feature it can not be used as a predictor. Fundamentally, a boxer who has the exact same physical attributes that throws a punch with a specific acceleration profile should have the same punch force whether the boxer is has an orthodox stance or a southpaw stance. Additionally, denoting which hand (right vs. left) is throwing the punch is trivial by which unit has indicated a punch. Combining stance and hand throwing the punch we have the final feature of punching hand, which is either rear or lead. An orthodox boxer throwing a right hand punch is indicated as rear while a left hand punch is lead. The converse is true for a southpaw boxer.

With a full set of features we can now begin the force modeling. The force modeling will use `polymars` regression as is used in the speed modeling. Other methods of modeling are considered, again including LASSO and CART, but the implementation of the `polymars` into a functional real-time model for estimations in addition to the possibility of non-linearity in the data make it ideal in this scenario as a modeling technique.

The first step in modeling is to ascertain whether or not a boxer could be modeled individually. Basically, can we show evidence that each boxers' punches have consistency in their forces based solely on their acceleration profiles. If each boxer can not be modeled accurately there is no way we can construct a model to estimate multiple boxers punch forces. A model for each boxer is fit to try to show this generalizability in punches for a single boxer. Comparing the RSS gives us some idea if all the boxers will be able to be modeled individually. Any deviation from by one or multiple boxers from the rest may give reason for that specific boxer to be dealt with in a slightly different manner than the rest. If it looks as all the boxers are agreeably close we can continue with the modeling.

To include as much information as possible from all the different types of boxers as well as to improve the relative error, traditional regression bootstrapping is again employed for the modeling. The bootstrapping is used both to choose the complexity parameter in the model fitting process along with estimating uncertainty when the final model is selected. As in the speed modeling the bootstrapping calls for a random sample with replacement of all the punches and corresponding forces with which a model is fit. The model size, predictors, and model itself are recorded. Next the model estimates force on the true dataset recording RSS, along with recording relative error. This sequence is repeated for a large number of random samples ($> 20,000$).

The function to fit `polymars` has an input that constrains the number of terms allowable by the model fit. This constraint is changed to create models of different sizes to compare and the bootstrap procedure repeated. Fewer predictors in the model as well as fewer interactions between predictors reduces any over-fitting that might occur when training the models. A parsimonious model that maintains the estimations levels is a preferred model of choice.

A simple function is created to test the sensitivity of the model to varying boxer sizes. The physical features included in the models are varied singularly and in combinations making sure that there are no drastically unrealistic force estimations. The final model is selected based on a combination of relative error, parsimony, and robustness to varying boxer sizes as well as hitting styles.

Once a final model has been selected, the model is with the BASE testing physical measurements to further assess how well the measurements used to train the PunchR algorithm parallel measurements taken from the BASE boxing dynamometer.

3.4.3 Results

To begin there were 1,239 punches that had matching punch acceleration traces with corresponding bag acceleration traces. Modeling each boxer individually resulted in one boxer being noticeably worse than the rest. A fitness boxer from April 20, 2010 had a within model RSS (13,415) that was six times that of the mean within boxer RSS (2221) of the other 32 boxers. Additionally, his RSS was almost double the next highest RSS (7,775). As the goal is to make an algorithm to estimate for all boxers and most specifically during professional bouts leaving this boxer out seems ideal. This left us with 1,199 punches from 32 boxers for the modeling.

The following table (3.10) is a summary of all the remaining boxers' recorded force by the wired unit bag setup. Overall, the forces all fall within a similar range to those seen in the Boxing Quantification chapter. Here, the mean force is 681 lbs, with 75% of punches having force below 815 lbs with a max of 1,754 lbs. As summarized in previous studies the majority of the force measurements in the experimental setting fall between 250 to 1,100 lbs of force with a mean near 700 lbs. The highest maximal punch force is all the way at 2,234 lbs.

Additionally, Figure 3.12 plots force by boxer weight followed by force by punch type and hand. The force by weight plot has a localized regression (LOESS)

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Force	197	466	619	681	815	1,754

Table 3.10: Punch force for 1,199 experimental punches.

line plotted over the top to outline the general trend of an increase in force as weight increases. One fighter, near 160 lbs, had some of the highest punch forces recorded. In the force by punch type boxplot, jabs have the lowest overall median force with crosses having the highest median force. Hooks are only slightly above jabs although the overall hardest punches came as hooks. In both cases the lead hand punches are lower than rear hand punches staying a little closer for hooks.

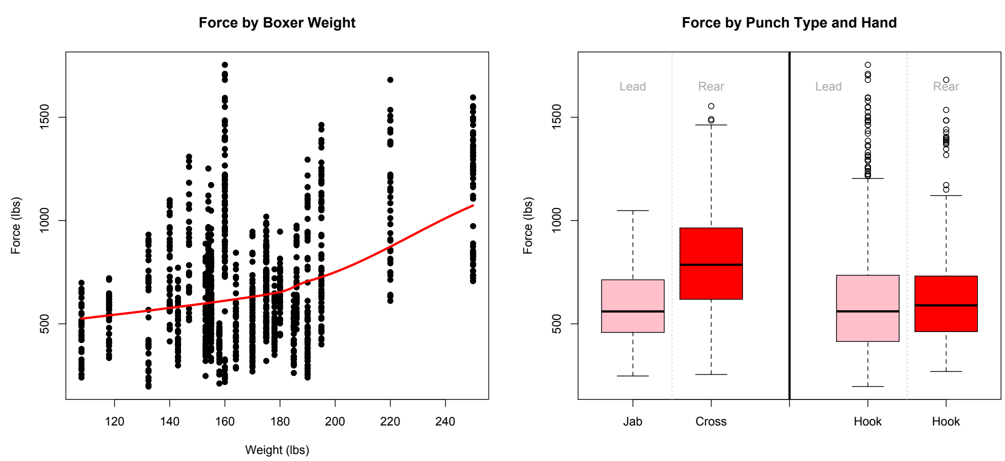

Figure 3.12: Force by boxer weight (left) and force by punch type and hand (right)

Although the remaining boxers had relatively similar RSS when constructing models within each boxer this in no way shows that the boxers' models are similar. The next step is to create generalizable model for all boxers. All the models were fit on 20,000 bootstrap samples. In the generalized cross validation (GCV) setting the lambda was changed by increments of one from 0.1 to 10 to construct different `polymars` models with different sizes and different feature sets. For lambdas up to seven we have a mean relative error below 0.20. The higher the lambda is set results in fewer predictors and interactions allowed in the model. We would like to choose a model that has fewer terms without drastically lowering the relative error so models where the lambda was equal to five, six, and seven were compared.

Following sensitivity testing while varying the different physical features a final model was selected where the lambda was set to seven for the 20,000 bootstrapped samples. In the bootstrapping procedure the models fit with lambda of seven had a mean relative error of 0.198 (0.195 median) or an accuracy of 80.2% (median of 80.5 %). Table 3.11 has the features included in the force model.

Feature	Description
forearm.hit	circumference of forearm doing the punching
weight	weight in pounds
wingspan	wingspan in inches
hand	rear or lead punching hand
X6	sum of x acceleration from profile time 470 to 501
X14	sum of x acceleration from profile time 501 to 520
X15	sum of x acceleration from profile time 501 to 550
X32	magnitude of x- and y-axis from minimum acceleration to impact

Table 3.11: Features included in force model.

Next we have the regression output. Previously we stated that the sums of the acceleration model were the a in our $\mathrm{F} = m \cdot a$ equation while the combination of the physical features would be the m. There are 17 total terms made up of 8 different features. As there are many interactions between terms there is no benefit to interpret the coefficients on any of the estimations in terms of acceleration or effective mass. All we remain interested in is the force estimations.

The correlation between observed and estimated force is 0.77. There is a slight trend of higher variability in estimation as force increases partially as a result of

Feature1	Knot1	Feature2	Knot2	Coefs	SE
intercept				-1353.89	1839.64
X14				4.96	4.80
weight				-8.92	1.80
X6				-25.96	5.94
forearm.hit				-58.87	168.65
weight	190.00			33.90	2.91
wingspan				79.06	7.58
X32				0.68	0.12
forearm.hit		X14		-0.19	0.45
hand				293.63	49.45
forearm		X6		1.97	0.55
X14	411.02			-38.10	9.02
forearm.hit		X14	411.02	3.95	0.84
X15				-1.44	0.31
X6	107.34			17.94	7.36
forearm	11.38			365.37	89.62
forearm		X6	107.34	-1.37	0.68

Table 3.12: Force model feature coefficients and interactions.

fewer overall punches at the higher force value. This model is also robust on 30,695 punches from available fight data keeping most of the fight estimations at a level comparable to the values recorded in this study as well as the force values seen in all other previous studies. All the fight results will be discussed further in the following chapter.

As in the speed modeling the force model was also compared to the BASE measurements. The relationship between the two was not as similar as in the speed model. In Figure 3.14 we see a low correlation of 0.171 between the 42

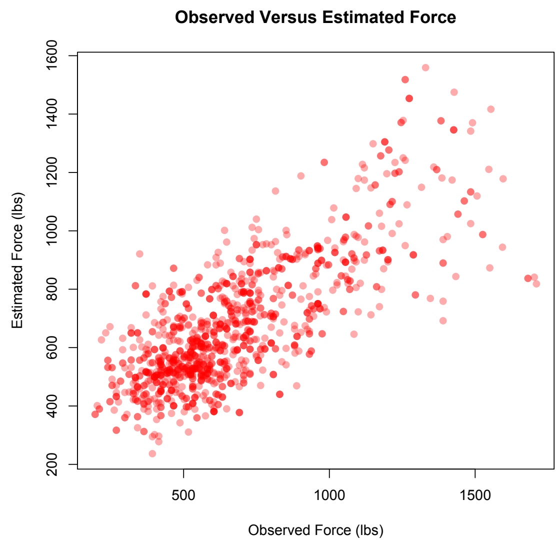

Figure 3.13: Observed versus estimated force.

BASE measurements and their corresponding force model estimations. There are two punches from boxer 2 that are influencing this relationship greatly. When removing boxer 2 punches from this comparison the correlation jumps all the way to a more reasonable 0.452. With only 42 punches from the different measurement system it is difficult to make general conclusions about about the relationship between the two measurement systems, but there is some case to be made for a boxer specific model as we see that one boxer larger deviated from the rest of the group (albeit with only 2 punches).

3.5 Punch Type Classification

In addition to punch detection, speed, and force, PunchR lends itself to many other possibilities to quantify boxing. The acceleration profiles can be used to classify punches into four main punches: jabs, crosses, hooks, and uppercuts. Currently, during live fights the only attempt to classify punch type has been by CompuBox differentiating between jab and non-jab punches. The *Nintendo Wii*

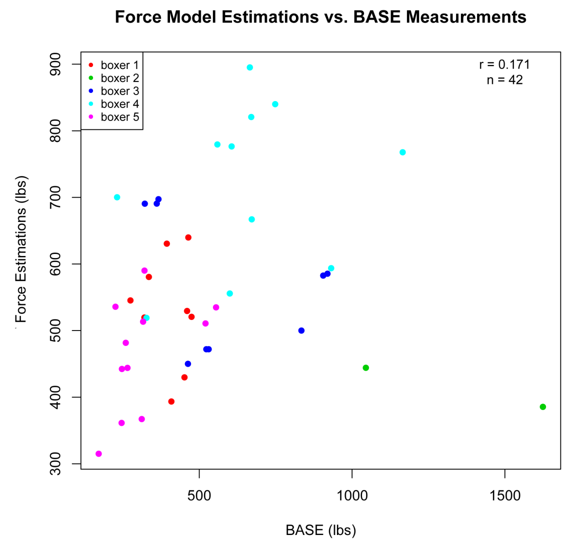

Figure 3.14: BASE measurements versus force model estimations.

has made use of their hand-held accelerometer to further classify jabs, hooks, and uppercuts in their popular *WiiSports Boxing* [Nintendo, 2011]. Adding this new dimension to live fights will provide added depth to story that is able to be told about a single fight.

3.5.1 Data Collection

Data collection for punch type came as a result of data collection for force modeling and punch detection. Unlike the other PunchR experiments there was no data collection directed only towards the goal of classifying punch type. First, during each of the force collection dates boxers were given a string of punches to complete in combinations of jabs, crosses, and hooks so each punch with a recorded force also has an associated punch type. Second, during the video review of the live fights where acceleration peaks were tagged as punch/non-punch for punch detection, all punches were additionally tagged with punch type. The punch types include only four main types of punches: jab, crosses, hooks, and uppercuts. With a data collection experiment directed solely at punch type this could be further expanded to other types such as overhands.

As there was no data collection experiment solely for punch classification some of the punches were not fundamentally sound in their technique. Further the classification from live fights required some judgment calls about punches based on some limited camera angles and punches straddling the line between two possible punch types. These punches were included in modeling and assessment with caution.

From the list of punches used in force modeling along with punches from the heavyweight used to assess the force model there was a total of 1,143 punches from these gym experiments. Following video review of a number of the boxers' punching technique a number of the original punches were omitted from this modeling. Specifically, the heavyweight's uppercuts had very similar trajectories to his hooks making classification between the two incredibly difficult. Additionally, there were 3 amateur fighters and 3 fitness fighters whose straight punches and hooks were not visually different in the video so they have no reason to be different in their acceleration data either. Further, there were 992 punches tagged from from live fights.

In the end we have a total of 2,135 punches that are tagged with punch type. Table 3.13 lists the punches by type used to train the punch type classification model. Right away it is clear there are more lead punches and very, very few uppercuts. The small number of uppercuts will make it difficult to classify these with so many of the other types of punches if there is not a large difference in acceleration profiles.

3.5.2 Methods

Similar to the modeling in other chapters we use the smoothed punch profiles to extract features as first considered in the speed modeling. All punches are split

Lead			Rear		
Jab	Hook	Upper	Cross	Hook	Upper
818	409	35	490	335	48

Table 3.13: Classified punch types.

into lead and rear punches as they will be classified separately. Southpaw fighters have their y-acceleration inverted to match the side-to-side direction of orthodox fighters so that a lead hook is always looping out the left and a rear hook out to the right. The only difference between the names of punches between lead and rear is for straight punches where leads are jabs and rears are crosses.

The below diagram in Figure 3.15 has two dimensional vector graphics of acceleration traces for the three punch types given the best case scenario. For both the straight punches and the hooks the graphs are from a bird's eye view as if looking down on a boxer from above. The third panel for the uppercut is looking from the side of the boxer with the two dimensions being x-axis (forward-and-back) and z-axis (up-and-down). As has been discussed in the punch detection chapter, the accelerometers are only two-dimensional in the x-axis and y-axis (side-to-side) so right away there is inherent difficulty in classifying uppercuts with no z-axis.

Modeling first separates the classification into two slightly easier problems of classifying hooks versus other punches and then jabs versus uppercuts. Breaking it down into these two problems serves two purposes: to identify how easy it will be to differentiate punches without having the third vertical dimension in the accelerometers and to identify any punches that may have been misclassified. This serves as a screening process to some of the problems that will be encountered when trying to do all the classification at once along with exploring some of the more important acceleration features that separate the punches.

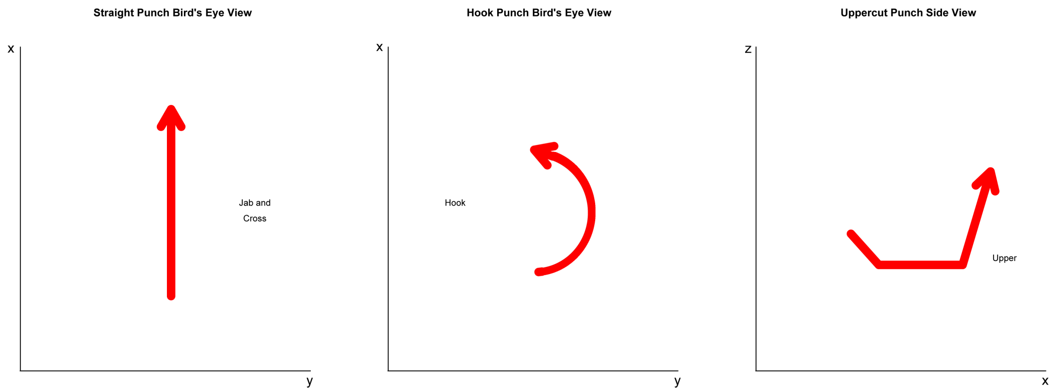

Figure 3.15: Example of bird's eye of straight punches (far left) and hooks (middle) with side view of uppercut (far right).

Classification methods for all three types of punches at once compares multinomial logistic regression[7], polyclass MARS[8], regular and sparse linear discriminant analysis. The different model fits are assessed on percent of correctly classified punches out of all available punches. Extra importance is given to higher accuracy of uppercuts because there are so few of them in the training data.

Also, since there are so few uppercuts in both the lead and rear punches an additional step is considered where all the lead and rear punches are combined to fit a single model. Basically, we want to increase the available number uppercuts used in the model to determine if there is any improvement in modeling. Again, similar modeling techniques are used in separate lead and rear modeling.

Following the initial modeling with the different techniques, models with higher levels of classification accuracy are compared using bootstrapping. For each model 20,000 bootstrapped samples are selected from the list of punches and accuracy is computed for all punch types. The final punch type classification model is selected based on the bootstrapped results.

[7]Multinomial models and linear discriminant models fit using `MASS` package in `R` [Venables and Ripley, 2002]

[8]polyclass MARS models fit using `polspline` package in `R` [Kooperberg, 2013]

3.5.3 Results

The initial modeling showed a difference in hooks and other punches as well as a difference in jabs and uppercuts. Mostly, these separate modeling procedures were used to reduce the original 33 features down to a smaller set of 23 more stable features. In addition this was used to note individual punches that were having a difficult time being classified.

With the final data set of punch types and features in place modeling started using the multiple class methods. The four different methods compared accuracy of punch type classification accuracy; overall as well as by punch type. The two linear discriminant analysis methods were inferior in modeling (accuracies $< 90\%$) in comparison to the polyclass MARS and multinomial models which both have accuracies over 90%. This was true for both lead and rear punches.

The combining of the lead and rear punches into one group for modeling did not improve the overall classification accuracies. In fact, all three punch types: hooks, straights, and uppers had more difficulty being classified. Keeping the lead and rear punches separate with two different hand specific models is ideal.

The last step in modeling was comparing the bootstrapped samples of 20,000 samples for the two best models from the initial four: the polyclass MARS and the multinomial models for both lead and rear punches. In both cases the polyclass MARS model outperformed the multinomial models in overall accuracy as well as by individual types of punches. In the Tables 3.14 and 3.15 below it is clear that the straight punches are easiest to classify, followed by hooks, and lastly uppercuts, which in the lead models are only being classified correctly around 20% of the time. There does not seem to be much difference between hooks and uppercuts for lead punches available. The polyclass MARS model does perform slightly better than the multinomial model.

Tables 3.16 and 3.17 making the same comparison for the rear hand classifi-

Type	Min.	Med.	Mean	Max.
Jab	0.940	0.965	0.965	0.985
Hook	0.790	0.882	0.881	0.943
Upper	0.000	0.140	0.157	0.632
Total	0.879	0.915	0.915	0.950

Table 3.14: Lead multinomial 20,000 bootstrapped accuracies.

Type	Min.	Med.	Mean	Max.
Jab	0.878	0.966	0.965	0.996
Hook	0.726	0.901	0.909	1.000
Upper	0.000	0.212	0.257	1.000
Total	0.812	0.923	0.923	0.991

Table 3.15: Lead polyclass MARS 10,000 bootstrapped accuracies.

cation models. Again, the polyclass MARS model outperformed the multinomial model. Here though there is a large amount of accuracy in classifying the uppercuts in contrast to the lead modeling. This is very encouraging to be able to classify all three types of punches using only two dimensions.

Type	Min.	Med.	Mean	Max.
Cross	0.905	0.948	0.947	0.984
Hook	0.809	0.891	0.890	0.950
Upper	0.355	0.744	0.738	1.000
Total	0.859	0.914	0.914	0.959

Table 3.16: Rear multinomial 10,000 bootstrapped accuracies.

Type	Min.	Med.	Mean	Max.
Cross	0.897	0.953	0.957	1.000
Hook	0.749	0.892	0.889	0.970
Upper	0.000	0.800	0.760	1.000
Total	0.814	0.918	0.916	0.979

Table 3.17: Rear polyclass MARS 10,000 bootstrapped accuracies.

After comparing the different models, the model selected for both lead and rear punches is the polyclass MARS model. From the training data we have Table 3.18 and 3.19 of classified punches. So from the bootstrapping we have an accuracy of 92.3% and of 91.9% on lead punches using the polyclass model with the accuracy on all of the training data is 91.6% and 90.6% on rear punches. See Tables

The overall accuracy for these models at almost 92% is quite good, but in both cases the uppercut accuracies are far below the hooks and straights. The overall

	Actual Punch Type				
		Jab	Hook	Upper	Total
Predicted Punch Type	Jab	788	40	8	836
	Hook	29	365	24	418
	Upper	1	4	3	8
	total	818	409	35	1262

Table 3.18: Lead punch type.

	Actual Punch Type				
		Cross	Hook	Upper	Total
Predicted Punch Type	Cross	462	34	4	500
	Hook	23	295	10	328
	Upper	5	6	34	45
	Total	490	335	48	873

Table 3.19: Rear punch type.

accuracy for straight punches is $1250/1308 = 95.6\%$, hook punches is $660/744 = 88.7\%$, and uppercuts is $37/83 = 44.5\%$ using these two models. There is definitely a signal in the rear uppercuts and with more punches the accuracy is expected to increase. In any case, this is a model where accuracy may be misleading because the straights and hooks were so easily classified having so many of them. In short, the overall accuracy is not significantly affected by the small number of uppercuts we do have.

Knowing that there is a difference in straights, hooks, and uppers (as evidenced by the rear modeling) we could have any number of technically sound boxers throw an equal number of each punch with their very best form, make sure the variance between features in these punches is minimal, fit a model to this data set, and whatever this model estimates during a fight is the punch type. We have seen similarities in the modeling between uppercuts and hooks so whichever a specific punch seems to emulate more is what it would be classified. The error no longer would come in the way of what a human decides the punch type to be, but the boxer not having a technically correct punching motion.

3.6 Model Instantiation

All data from the PunchR accelerometers is recorded to static CSV files for post processing and analysis. The data cleaning, modeling, and analysis was done in the open source statistical package `R` [R Core Team, 2013]. These models are integrated for use with the real-time accelerations from the accelerometers for on-air broadcasts. `R` works well for the static statistical modeling, but when it comes to integration with the live system it is not practical.

3.6.1 Punch Extraction Algorithm

The punch detection algorithm evolved over the period of the project based on needs. It was first outlined in `R` to be run on all of the static data from the different trials to fit the necessary models. In order to be integrated with the entire PunchR system the `R` algorithm code is translated into JAVA.

3.6.2 Model XML Specifications

Each of the speed and force linear models fit in `R` are translated into an XML file. Additionally, there is a feature construction file for each of these models. This makes a total of four XML files; one for the speed model, one for the speed features, one for the force model, and one for the force features. The models then are instantiated at system startup. As the models are self contained allowing for model updates with their corresponding feature file without requiring any other system programming. Punch type classification has yet to be integrated into the system, but similar XML files are appropriated to have similar functionality as speed and force.

3.6.3 Ringside Laptop Application

On fight night the models are called with the PunchR application, but before the models are used in real-time application there are prior steps that take place. First, an event is defined in the user interface including the name, date, and location. As the force model is trained using a number of boxer physical attributes (weight, wingspan, and forearm circumference) these must be recorded in each locker room to be entered into the application. At this step one boxer is assigned to be the red boxer while the other is to be the blue boxer. Once the boxer has had their hands wrapped the glove units themselves must be attached inside the boxer's wrists with athletic tape. The sensors are checked with the sensor monitor to assure they are "awake", have enough battery power, and providing measurements. The boxer puts on gloves to head to the ring for the fight.

Once inside the ring, the In-Fight Dashboard is used to start, stop, or reset the recording of the acceleration measurements by the units. This is when the JAVA coded punch extraction algorithm comes into play. As the accelerometers record the data, the algorithm extracts the punch in real-time. With the extracted punch, the system then calls the XML feature extraction files followed by the model predictions, in a similar fashion as is outlined by the model fitting sections.

The In-Fight Dashboard displays the resulting punch speed and force predictions in a couple of ways. The first is a visualization of punch force as a bar chart with each punch graphed to the height of the force predicted. Each new punch is graphed to the right of the previous punch with the blue boxers punches showing up as blue bars and the red boxers as red bars. There are fixed views showing the max force per boxer across all rounds as well as the current round. It is also possible to toggle between each round. Punch speed is located in a similar chart beneath the force chart. The second display in the In-Fight Dashboard is simply a table that records round, boxer that throws the punch, speed, force, and time the punch is thrown.

Simultaneously, while the punches are being displayed on the In-Fight dashboard the acceleration traces are being recorded to be used in static modeling, along with trouble shooting, at a later time.

CHAPTER 4

Fight Results

The PunchR system has been used in hundreds of fights to test the technology, the different environments provided by professional boxing matches, and the process of incorporating the accelerometers into a fighter's pre-fight routine. As with any new technology there have been some setbacks and challenges in implementation so not every fight has a complete record as a result of things like transmission interference, sensor damage, and even refusal by boxers to use the sensors. Lots of the fights have partial data recorded from a few rounds which is informative about the process as well as providing some information about fighters' tendencies. More importantly there have been 65 fights complete fights where 130 boxers have been equipped with the PunchR sensors, totaling 359 rounds for an average of 5.5 rounds per fight.

The following chapter will begin with two fight reports that include a highly controversial decision that was reviewed by the World Boxing Organization (WBO) and the Sports Illustrated Fight of the Year for 2012. These are the first looks at a higher level numerical review of a professional boxing matches. Following these individual fight summaries will be results from all 65 of the complete fights occasionally referring to results from partial fights when necessary. All of these results include numerical summaries, visualizations, the introduction of new metrics.

The new metrics and visualizations included in this section come as a response to the Sabermetric movement in baseball and other high level analysis of other sports. These are all creative, novel ideas in boxing to bring a higher level numerical understanding of the sport. Having seen the limited ways boxing currently is quantified, these are attempts to advance the way boxing can be analyzed, viewed, and critiqued. Ultimately, not every idea presented here will prove useful, but are provided as introductory ideas into boxing quantification.

4.1 Fight Summaries

The fight summaries come from two major fights where PunchR was employed. These summaries provide a different understanding about the entirety of the fight outside of the outcome and the information provided by CompuBox or PunchZone.

4.1.1 Rocky Martinez - Juan Carlos Burgos

The Rocky Martinez versus Juan Carlos Burgos WBO super featherweight title fight ended in a twelve round draw taking place on January 19, 2013 at Madison Square Garden in New York City. The three judges scored the fight 117-111 Burgos, 116-112 Martinez, 114-114 shedding light on the wide discrepancy that can arise in judging a fight. This draw allowed Rocky Martinez to retain his title to the dismay of many observers. This was a significantly controversial decision with a HBO poll having 84% of respondents considered Burgos the winner of the fight in addition to various other media sources also scoring the fight for Burgos. There was enough public outcry that the WBO officially reviewed the decision of the fight. Ultimately, the WBO decided there was not enough evidence to require an immediate rematch by the two fighters. [Reports, Jan 2013, Donovan, Feb 2013, Christ, Jan 2013]

As in any fight the precursor is the "Tale of the Tape" providing information about the fighters sizes. In Table 4.1 there is not a big advantage either way in height or weight with Burgos being the younger fighter. This table also combines additional information about the fighters' records prior to the fight that was taken from BoxRec.com [2011]. As it was a title fight the two fighters should have similarly excellent resumes warranting Martinez to already hold the WBO title and Burgos deserving to be the contender in title fight. They have boxed almost the exact same number of rounds although Burgos did so in 3 more fights. Neither fighter had been knocked out prior to this fight so it is no surprise that in this fight they went the full twelve rounds.

	Rocky Martinez	Juan Carlos Burgos
Color	red	blue
Stance	orthodox	orthodox
Weight	130	129
Height	68	70
Wingspan	68	69
Age	29	25
Wins	26	30
Losses	1	1
Draws	1	0
KOs	16	20
% KOs	57.1	64.5
KOed	0	0
% KOed	0	0
Decisions	12	11
% Decisions	42.9	35.5
Rounds Boxed	180	183

Table 4.1: Tale of the tape and fighter's previous record per BoxRec.com [2011].

Now that the pre-fight fighter comparison has been outlined we follow with the fight analysis. This numerical analysis provides a round-by-round look into the fight to consider if PunchR presented a difference between the two fighters in contrast to the judges' scores.

First is punches by round in Table 4.2. This fight had the most punches thrown in any fight recorded by PunchR with both fighters having thrown over 850 punches. Burgos averaged 81.9 punches per round (PPR) while Martinez averaged 71.2 PPR. In the early rounds Burgos threw quite a few more punches than Martinez until rounds 7-9 where Martinez looked to even things up. Rounds 10 and 11 Burgos again picked up the pace until a fairly even, but most active final round. In all of the tables that follow, Burgos will be listed above Martinez.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	88	73	83	81	86	92	61	76	71	86	88	98	983
Martinez	64	59	57	64	73	73	63	77	82	68	71	103	854

Table 4.2: Total punches thrown in each round.

Table 4.3 compares speed by round for the two fighters. Burgos was faster in ten rounds with a median speed 1.1 mph faster than his opponent. This was a metric where Burgos really outclassed Martinez. Although Martinez's fastest punch of 34.1 mph nearly equalled Burgos' fastest punch of 34.9 mph. Burgos' round 4 with a median of 19.2 mph was the fastest round by a full mph.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	18.1	17.7	17.8	19.2	17.1	18.0	17.0	15.8	16.4	18.2	17.0	18.2	17.4
Martinez	16.7	17.4	17.9	15.9	16.3	16.2	15.9	16.5	15.9	15.8	16.2	16.3	16.3

Table 4.3: Median speed by round in mph.

Burgos also had the higher overall median force with a higher median force in a majority of the rounds. In rounds 1 and 8 Martinez did throw harder punches than Burgos. They both averaged just under 500 lbs of force for the entire fight as seen in Table 4.4. Burgos' hardest punch was 1,184 lbs while Martinez's slightly lower at 1,051 lbs Martinez's first round is the only round to have his median force over 500 lbs Burgos had three rounds with a median force of over 500 lbs.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	474	485	490	500	467	503	487	446	477	516	489	513	490
Martinez	506	472	483	478	463	481	470	485	474	484	460	456	474

Table 4.4: Median force by round in lbs.

Both Burgos and Martinez averaged about 1.5 lead punches for every rear punch (LTRP) over the entire fight. In the first round they both averaged over 2 leads to rears being a bit tentative trying to read each other. In round 8 Burgos had over 2.5 lead to rear punches which was one of Martinez's more effective rounds. Similarly, Martinez had 2.2 lead to rear in the tenth round which was one of Burgos' more effective rounds. Both fighters had nearly equal speed in their lead and rear hands (LTRS), while Burgos' lead had was slightly more comparable to his rear hand in regards to force (LTRF).

	1	2	3	4	5	6	7	8	9	10	11	12	Total
LTRP	2.03	1.81	1.77	1.13	1.61	1.36	1.90	2.62	1.96	1.21	1.67	1.45	1.64
LTRS	0.97	0.93	1.08	0.99	0.90	1.21	0.96	1.02	1.11	1.09	0.97	1.04	1.02
LTRF	0.81	0.81	0.85	0.81	0.87	0.94	0.85	0.89	0.94	0.94	0.88	0.90	0.87

Table 4.5: Lead to rear ratios by round for Burgos.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
LTRP	2.56	1.57	1.59	1.91	1.61	1.03	1.33	1.75	1.41	1.00	2.23	1.51	1.55
LTRS	1.06	1.13	1.14	1.06	1.01	1.02	1.04	1.05	0.98	1.05	1.10	1.04	1.05
LTRF	0.81	0.79	0.76	0.81	0.84	0.80	0.77	0.77	0.80	0.79	0.87	0.84	0.81

Table 4.6: Lead to rear ratios by round for Martinez.

Next is the flurry analysis between the two fighters. The idea of flurry analysis is to determine whether a fighter throws consistently individual punches, quick bursts, or longer successions of punches throughout the fight. This can help provide an idea about how the punches are occurring in relation to one another. A flurry is defined here as at least 3 consecutive punches or more with each punch being thrown less than 750 ms after the previous punch.

Flurries is something that Martinez was more active with than Burgos. Burgos had more overall flurries (seen in the top half of table 4.7) and they had a similar percentage of his punches come during flurries (seen in the bottom half of table 4.7) . Martinez's average flurry length was almost a full punch longer than Burgos. Martinez's max flurry length of 15 was also five punches longer than Burgos' max flurry length of 10. Something future opponents can take from this is if Martinez throws a punch expect to have 3 to 4 more following that while Burgos will throw more controlled bursts of punches throughout the round.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	10	8	10	9	8	8	4	5	6	10	12	11	91
Martinez	8	6	6	4	6	5	5	8	8	4	6	12	78
Burgos	0.38	0.30	0.51	0.35	0.34	0.33	0.15	0.18	0.27	0.38	0.59	0.34	0.35
Martinez	0.44	0.42	0.42	0.17	0.32	0.18	0.33	0.45	0.39	0.31	0.31	0.46	0.35

Table 4.7: Total flurries per round (top) and Percent of punches in flurries (bottom).

Following the definition of a flurry it is possible to consider information about the number of flurries in each round (TF), the rate of flurries per round (FPR), and the percent of punches (POPIF) that were parts of flurries. In addition we can take a look at some of the information about each of the flurries. The punches per flurry (PPF) and the maximum flurry length (MFL). Because the minimum length of a flurry is 3 punches and flurries of lots of punches are difficult to maintain because the energy expended by throwing so many punches in a row, flurries have a very right skewed distribution. Tables 4.8 and 4.9 show punches per flurry, max flurry length, and percent of counterpunch flurries. Almost a third of Martinez's flurry started as a result of a counterpunch while only a quarter of Burgos' flurries started as a counter.

This leads us to counterpunches where Martinez threw almost twice as many counterpunches as Burgos. So far we have seen that Burgos threw more punches,

	1	2	3	4	5	6	7	8	9	10	11	12	Total
PPF	3.67	3.14	4.67	3.50	4.14	4.29	3.00	3.50	3.80	3.67	4.73	3.30	3.87
MF	6	4	9	5	8	8	3	4	6	7	10	4	10
PCPF	0.30	0.25	0.00	0.22	0.25	0.12	0.25	0.20	0.33	0.30	0.25	0.27	0.26

Table 4.8: Punches per flurry, max flurry length and percent of counter punch flurries for Burgos.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
PPF	4.00	5.00	4.80	3.67	4.60	3.25	5.25	5.00	4.57	7.00	4.40	4.27	4.65
MF	6	11	8	4	7	4	7	14	7	15	7	7	15
PCPF	0.12	0.33	0.17	0.25	0.17	0.20	0.20	0.50	0.25	0.25	0.50	0.42	0.35

Table 4.9: Punches per flurry, max flurry length and percent of counter punch flurries for Martinez.

but now we also see that Burgos is also initiating the exchanges. In all Martinez averaged 19.9 counterpunches per round while Burgos averaged 11.4. A counterpunch occurs when a boxer immediately punches an opponent following an attack initiated by the opponent. A counterpunch is often a tactical punch used to take an advantage of an opponent's mistake when throwing a punch leaving them exposed. Using PunchR we can identify when punches are considered counterpunches by each boxer to identify who is the more defensive fighter or trying to take advantage of an opponents mistake. Unlike the other metrics outlined so far, computing a counterpunch will take into account information from two opponents using the timecodes from the acceleration peak of each punch recorded during the fight.

Here, a counterpunch is defined as a punch that occurs within 750 ms of an opponent throwing a punch. There can not be two counterpunches in a row and any flurry of punches can only have one counterpunch, which is the first punch of that flurry indicating a counter-flurry. A fighter who engages his opponent, who in turn throws a counterpunch, does not get credit for a counterpunch following his opponent's counterpunch. In other words, it is not possible to throw a counterpunch to a counterpunch.

In defining counterpunches the inherent problem arises that they will often be tied to a losing fighter. If facing an overwhelming opponent it is likely that many punches a boxer throws in defense will be classified as counterpunches. A fighter who can win while throwing a high number of counterpunches can be considered a good defensive fighter trying to take advantage of their opponent's mistakes.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	9	5	8	10	13	12	7	12	19	13	12	17	137
Martinez	16	17	17	20	18	22	18	20	18	23	24	26	239
Burgos	0.10	0.07	0.10	0.12	0.15	0.13	0.11	0.16	0.27	0.15	0.14	0.17	0.10
Martinez	0.25	0.29	0.30	0.31	0.25	0.30	0.29	0.26	0.22	0.34	0.34	0.25	0.30

Table 4.10: Counterpunches by round (top) and percent of all punches that are counterpunches (bottom).

Punch sharpness (PSHARP) metric is based on the punch detection algorithm equation. Basically, taking the probability that a profile is a punch is an indication of how "clean" or "sharp" a profile looks. Profiles that are unimpeded by the opponent that closely represent the training data have higher probabilities based on the logistic regression of being a punch. It is not quite the equivalent of landing a punch, but a fighter whose punches have profiles that consistently match the training profiles are more likely to be landing these punches. As discussed in the punch detection section there is a threshold of 20 g's of any acceleration to be included as a punch which occasionally includes a block or a blocked punch. These have low probabilities of being punches so the recorded PSHARP will be closer to 0. Like just about every other metric so far Burgos dominated the punch sharpness as well. He had sharper punches in 10 of 12 rounds with one round being equal.

Punch time (PTIME) is the time in milliseconds from the estimated punch

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	0.88	0.88	0.85	0.83	0.83	0.85	0.87	0.85	0.84	0.89	0.86	0.87	0.86
Martinez	0.84	0.87	0.78	0.84	0.83	0.78	0.79	0.79	0.83	0.79	0.82	0.72	0.80

Table 4.11: PSHARP by round.

start to impact. This is one of the features used in force and speed modeling having some relation to the speed of the punch. In terms of PTIME Martinez average punch times were 10 ms shorter than Burgos' punch times.

Punch quality is something that will assess each individual punch with the idea being faster, stronger punches qualify as a "better" punch than a slower, weaker punch. It is not always the case that the hardest punches are the fastest or the fastest punches are the hardest. The punch quality metrics will be a combination of force and speed that will provide a single measure to indicate the "quality" of each punch. These metrics will also help compare individual punches across weight classes. Speed is something that is easily compared, but it is unfair to compare a heavyweight boxer's force to a lightweight's force.

The first punch quality metric compares each punch to the average of all other punches from boxers of similar size. The punch quality index (PQI) is the average of the two standardized scores of force and speed in comparison to boxers that are within 5 pounds larger and 5 pounds smaller than the boxer doing the punching. So PQI is defined as:

$$\mathrm{P}unch\ Quality\ Index = \frac{\frac{\mathrm{p}f - \mu_{force}}{\sigma_{force}} + \frac{\mathrm{p}s - \mu_{speed}}{\sigma_{speed}}}{2} \tag{4.1}$$

where pf is the individual punch force, μ_{force} is the mean of all punch force for boxers within 5 pounds of the boxer weight, and σ_{force} is the standard deviation of force for boxers within 5 pounds. Similarly, ps is individual punch speed, μ_{speed} is the mean of all punch speed for boxers within 5 pounds of the boxer weight, and σ_{speed} is the standard deviation of speed for boxers within 5 pounds. Anything below zero would be considered a less than average quality punch and anything above zero is quality.

The second punch quality metric has no relationship to any other boxer and is just a combination of speed and force, but that will still be able to be compared across different weight classes. The punch quality aggregate (PQA) is force per pound of the boxer, squared, added to speed. PQA is defined as:

$$\mathrm{P}unch\ Quality\ Aggregate = (\frac{\mathrm{p}f}{\mathrm{b}oxer\ weight})^2 + \mathrm{p}s \tag{4.2}$$

again, where pf is the punch force and ps is the punch speed. The punch force over boxer weight is squared so they are roughly on the same scale as punch speed so the importance of one term does not outweigh the other.

The punch quality metrics both went Burgos' way in all rounds except for round 8. Martinez threw most of his punches at a level that were a combined slower and less forceful than other fighters his size that have used PunchR as realized by having a mean PQI of less than zero. Only in two of the first three rounds did he have a mean PQI above zero with his quality falling off as the fight went on. Burgos, on the other hand, averaged only slightly above those of similar size, but only had 3 total rounds where he was below the average PQI.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	35.2	36.0	35.3	36.8	34.5	35.2	33.2	31.1	33.6	36.5	35.2	36.7	35.1
Martinez	34.5	33.1	34.4	31.5	29.9	32.7	31.1	32.6	31.6	30.9	30.1	30.2	31.8
Burgos	0.11	0.21	0.14	0.34	0.01	0.15	−0.10	−0.41	−0.05	0.33	0.07	0.37	0.11
Martinez	0.09	−0.11	0.05	−0.28	−0.5	−0.13	−0.35	−0.2	−0.29	−0.35	−0.5	−0.45	−0.27

Table 4.12: Mean Punch Quality Aggregate (top) and mean Punch Quality Index (bottom) by round.

Boxer aggression will indicate how aggressive each boxer is during the round and the entire fight. The boxer aggression metrics combines flurries initiated and non-counter punches. The higher the aggression metric the more aggressive the fighter, but this does not necessarily mean the fighter is winning the fight. An example that comes to mind is the Miguel Cotto versus Floyd Mayweather fight on May 5, 2012. The conjecture is that Cotto would have the higher aggression metric, but Mayweather (a notorious defender and counterpuncher) controlled the fight for a victory.

Here are two boxer aggression metrics that take into account flurries initiated (non-counter punch flurries) and non-counter punches. First, is Boxer Aggression Rate (BAR) which is defined as:

$$Boxer\ Aggression\ Rate = \frac{\frac{flurries\ initiated}{total\ flurries} + \frac{non-counterpunches}{total\ punches}}{2} \tag{4.3}$$

Basically, BAR is the average of two percents so the closer the value is to 1 indicates the more aggressive boxer. The glaring issue with this metric is it does not take into account volume of punches so if a boxer only threw three punches in a flurry that he initiated in a round he would have have a BAR of 1 despite having thrown very few punches.

The second boxer aggression metric is the Boxer Aggression Aggregate (BAA), which does take into account volume of flurries and non-counterpunches. The BAA is the total number of flurries plus the rate of non-counter punches per round. BAA can be simply defined as:

$$Boxer\ Aggression\ Aggregate = flurries\ initiated + \frac{non - counterpunches}{rounds} \tag{4.4}$$

Comparing the two boxer aggression metrics Burgos again came out on top. Martinez had a higher BAR in round 1 and round 9 and when volume came in play with BAA he only came out ahead in round 9. When considering all the previous metrics in the fight these are results we expected to see as Burgos has outperformed Martinez in just about every previous metric so far. In Table 4.13 BAR is the top half with values between 0 and 1 while BAA is on the bottom for each fighter.

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Burgos	0.78	0.82	0.95	0.81	0.78	0.86	0.78	0.80	0.67	0.76	0.80	0.76	0.80
Martinez	0.80	0.66	0.75	0.68	0.78	0.72	0.73	0.58	0.75	0.66	0.53	0.65	0.68
Burgos	85	73	84	77	78	86	56	67	55	79	84	88	76
Martinez	54	45	44	46	59	54	48	60	69	47	49	83	54.8

Table 4.13: Boxer Aggression Rate (top) and Boxer Aggression Aggregate (bottom) by round.

Having assessed this fight using all these new metrics we will provide a score for this fight based on the round-by-round 10 point system that boxing currently employs. The scoring includes median force and speed, punch count (PPR), PSHARP, total flurries (TF), punches per flurry (PPF) , counter punches per round (CPPR), both punch quality measures (mean PQI and PQA), and both boxer aggression measures (BAR and BAA). By having so many metrics to score on the 10 point system does not have to be absolute. Another method of scoring this fight is to give a 10 to the boxer with the higher round for each metric that was considered in scoring the fight and a 9 for the boxer with the lower metric value. Then average the 12 metrics to get a score that tells us how close each round was. The following visualization (figure 4.1) provides a row for each of the twelve metrics and a column for each of the twelve rounds. The grid cell is colored by the boxer who had the higher value for each metric during the round with white cells being a tie.

Averaging each column in Figure 4.1 results in the scoring in Table 4.14. Still Burgos won 10 rounds, but this provides an idea bout which rounds were closely contested. Rounds 1, 7, 8, 9, and 12 looked to be close possibly going either way. The final fight score summing these round scores is 117.2 - 110.8 which is very

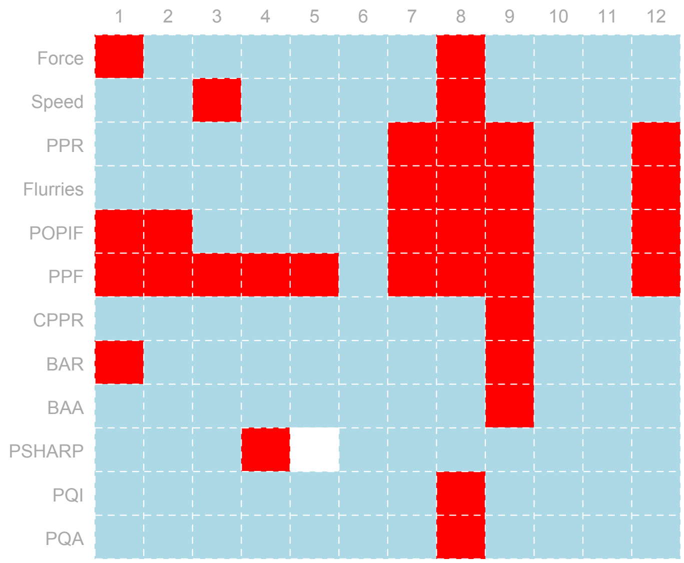

Figure 4.1: Metrics by round colored for the fighter with the higher metric value. Burgos is blue, Martinez is red, and white is a tie.

close to what one of the three judges scored the fight for Burgos at 117 - 111.

	1	2	3	4	5	6	7	8	9	10	11	12	Score
Burgos	9.67	9.83	9.83	9.83	9.92	10	9.67	9.33	9.42	10	10	9.67	117.2
Martinez	9.33	9.17	9.17	9.17	9.17	9	9.33	9.67	9.58	9	9	9.33	110.8

Table 4.14: Round by round fight score based on averaged PunchR metrics for Burgos versus Martinez.

The official review of this fight by the WBO had Burgos winning rounds 2, 10, and 12 by 100%, 6 and 11 by 87.5%, and round 3 by 75%. They had Martinez winning round 5 by 100%, round 9 by 87.5%, round 8 by 75%, and round 1 by 62.5%. Rounds 4 and 7 were scored as draws. [Reports, Jan 2013, Donovan, Feb 2013, Christ, Jan 2013] So the major difference between this analysis was round 4 and 5 which these metrics had strongly for Burgos in contrast to the WBO review.

These new PunchR metrics are not in any way intended to replace judges, but are presented as an additional tool to further think about how the fight played out. The analysis presented here does provide good evidence towards Burgos being the victor. As all of these metrics are new it is hard to tell if they are representative of what is happening in the fight. All of these metrics will be continued to be studied to determine whether they do help provide information about the outcome of the fight.

4.1.2 Brandon Rios - Mike Alvarado

The fight between Brandon Rios and Mike Alvarado, was named Sports Illustrated Fight of the Year in 2012, and runner-up in numerous other media outlets. [Fischer, Dec 2012, Illustrated, Dec 2012] This was a slugfest with the two fighters standing toe-to-toe punching each other round after round. Rios came away the victor with a referee stoppage in the 7th round after barrage of punches on October 13, 2012 at the Home Depot Center in Carson, CA. As this was a decisive fight we take a different approach, presenting the fight largely through visualizations for many of the metrics discussed. Throughout this summary Rios will be presented as the red fighter and Alvarado as the blue fighter.

Figure 4.2 is running average speed by round with the white gaps in the colored lines being the round intermissions. The first ten punches were omitted in the plot until the average speed estimate stabilized. The first two rounds were close, averaging just under 17.5 mph for both fighters, until the third round when Rios started getting faster while Alvarado got slower. The fourth round saw both fighters maintain until they both saw some decline until the final round as they tired with so many punches. In the end Rios averaged 17.4 mph while Alvarado was just over 17.0 mph. Alvarado did have the faster maximum punch speed at 35.6 mph while Rios only reached 31.4 mph.

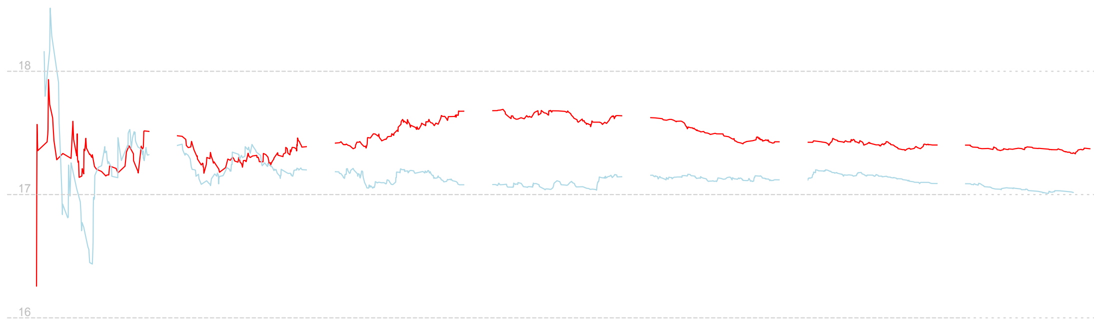

Figure 4.2: Running average speed in mph.

Figure 4.3 is associated with force. The plot on the top is the distribution of force for each fighter overlaid with their density. It is easy to see that Alvarado threw harder punches for the entire fight with his median force at just over 500 lbs while Rios was slightly lower at 470 lbs The distributions for each fighter are similar making the histograms in the background largely indistinguishable. Rios had the maximum force punch of 1,036 lbs The plots on the bottom are cumulative force by round making these a combination of punches thrown in addition to force. Rounds 1-4 are the four top panels with rounds 5-7 on the bottom. Rounds 1 and 2 were the two closest rounds. In both cases Rios started off ahead in both rounds until finally falling only slightly behind at the end of the rounds. Round 3 and 5 Alvarado threw punches that combined for over a total of 60,000 lbs of estimated cumulative force. Round 7 saw the least as Rios won the fight about two minutes into the round.

The following figure (4.4) is from round 1 of the fight. It is a timeline of each punch thrown by Rios and by Alvarado with the symbol indicating punch type with darker colors indicating rear punches. Triangles indicate straight punches, circles indicate hooks, X indicate uppercuts. The colored mound along the timeline is aggregate punch count. Rios started out strong throwing quite a few more

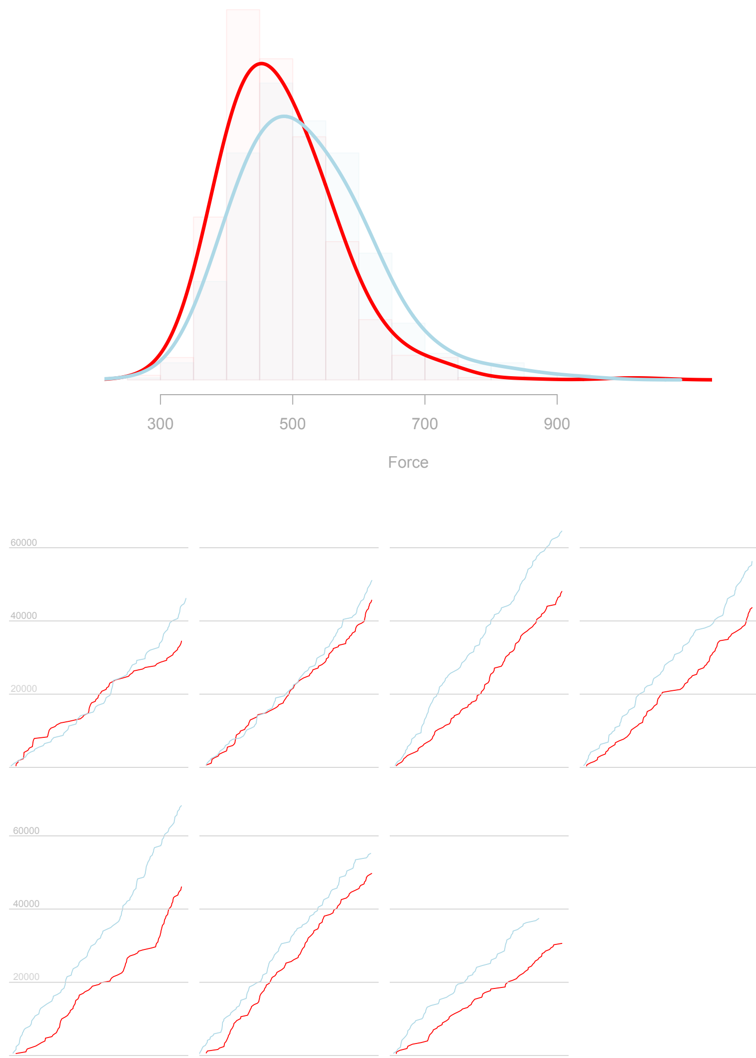

Figure 4.3: Distribution of force of punches from entire fight (top). Cumulative force by round (bottom).

punches than Alvarado in the first minute. Alvarado only threw one rear hand cross in the first minute sticking almost entirely to his lead hand. By the end of the round Alvarado was more active most notably in the final minute.

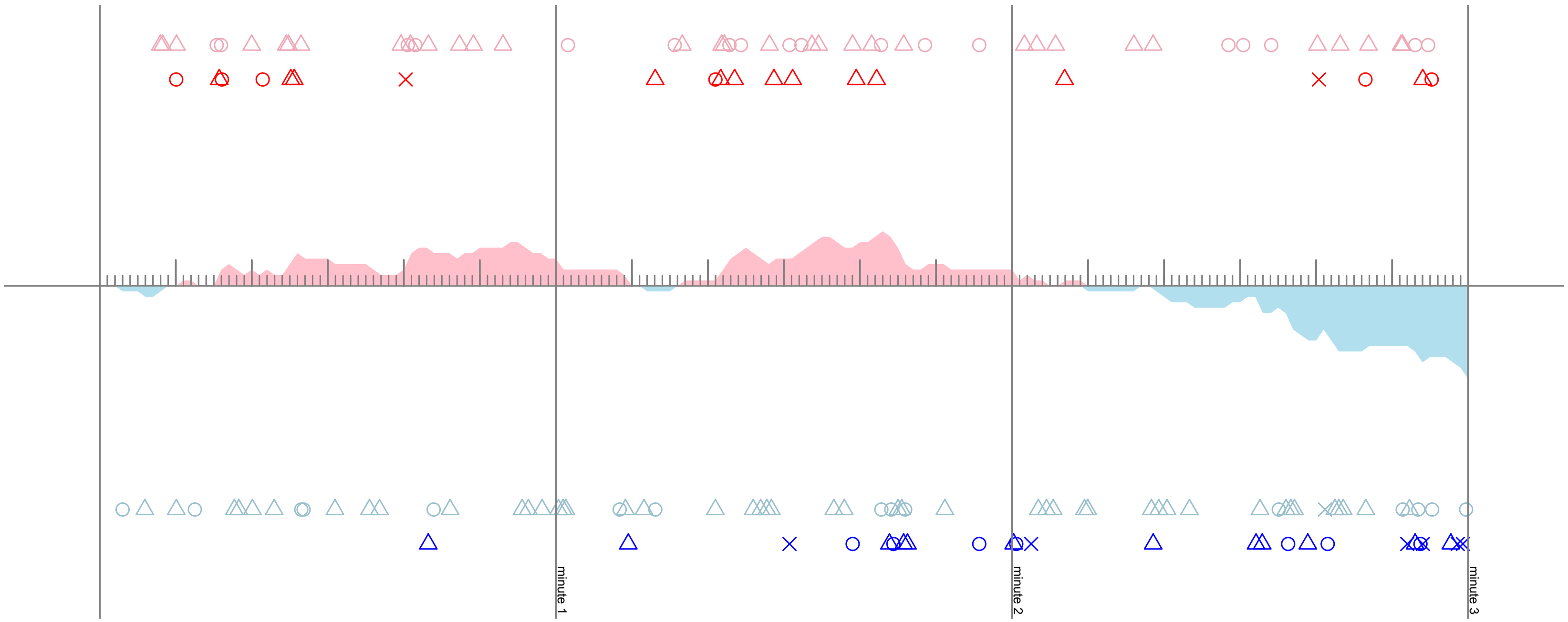

Figure 4.4: Round 1 punches by type throughout the round. Triangle indicates straight punches, circles indicates hooks, X indicates uppercuts. Darker color represents rear hand punches. Lighter color represents lead hand punches. The colored mound along the timeline in the middle is aggregate punch count.

The treemap in Figure 4.5 shows punch type by fighter as area of each rectangle. Overall, Alvarado threw more punches as evidenced by his slightly overall larger area. Both fighters threw mostly jabs. Relatively, Rios looped his lead hand having proportionally more lead hooks to jabs than Alvarado. Conversely, Alvarado looped his rear hand a little more with proportionally more rear hooks to crosses than Rios. The number of uppercuts are roughly the same. These are rear uppercuts with there only being 2 lead uppercuts for Alvarado and 1 for Rios, so few, that the boxes are almost non-existent in the plot.

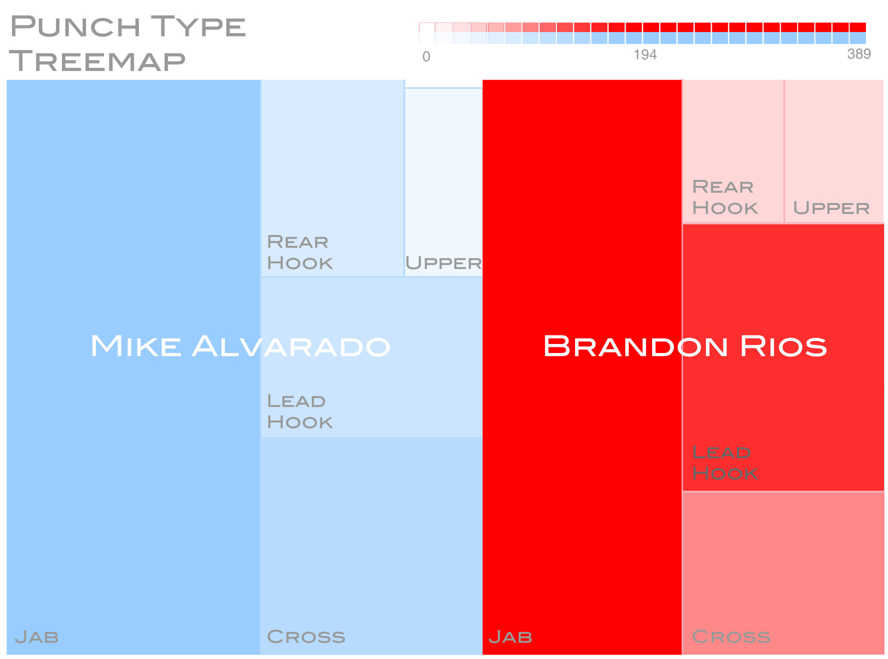

Figure 4.5: Treemap of punch type by fighter. Box size and color darkness indicate more punches of each type. There are very few lead upper cuts that the boxes are almost non-existent in the plot.

Figure 4.6 helps visualize the flurry activity by round. Each line in the plot is a round making the x-axis time in each round. The larger the bubble the more punches included in the flurry. The largest flurry occurred in the fifth round by Rios, while there are more larger blue bubbles indicating Alvarado had more flurries overall. The most flurry action came in round five especially towards the end with round six and the start of round seven seeing quite a few flurries as well. The middle parts of rounds tended to see fewer flurries, especially in rounds two and five.

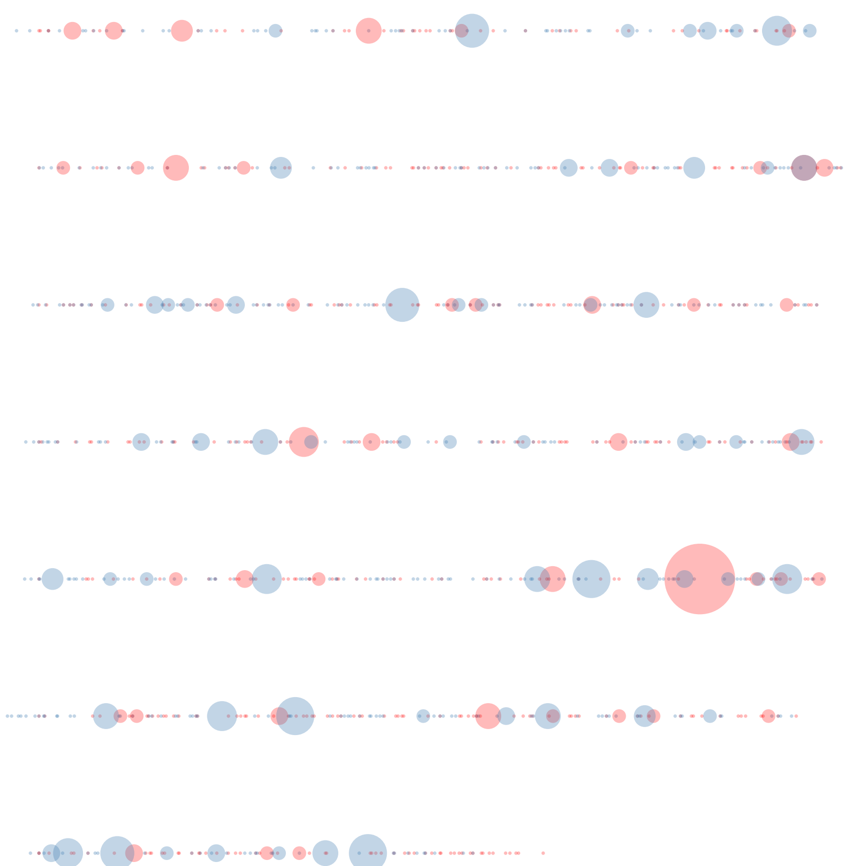

Figure 4.6: Flurries by round. Each row of bubbles is one round plotted over time. The larger the bubble indicates more punches included in the flurry.

A spider (radar) chart is seen in Figure 4.7 that summarizes twelve metrics about each fighter from the entire fight. Spider charts have become popular in basketball analysis in comparing match and see a natural use in boxing as the fighters are going head-to-head so we can directly compare different measurements [Pimentel, 2009, Moghadam, 2013]. These are plotted as distance away from the center relative to all other fighters that have used the PunchR system. Included metrics are media force, median speed, punches per round (PPR), percent of punches if flurries (POPIF), punches per flurry (PPF), counterpunches per round (CPPR), counterpunch percent (CPP), Boxer Aggression Rate (BAR), mean Punch Quality Aggregate (PQA), punch sharpness (PSHARP), hook to straight punch ratio (HTS) and lead to rear punch ratio (LTRP). It is easy to see that both fighters were throwing large amounts of punches with more of Alvarado's coming in way of flurries. Alvarado had very high values for PSHARP throughout the fight. Rios was counterpunching more frequently, throwing more hooks relative to straight punches, and lead punches relative to rear punches. This is a quick way to summarize how the fight played out in many metrics over all the rounds combined.

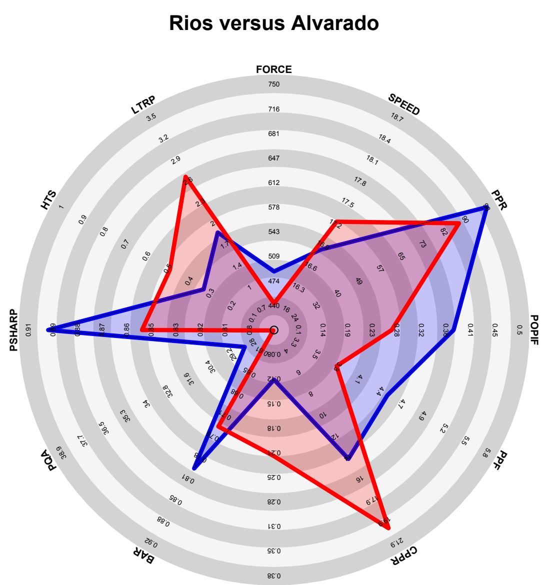

Figure 4.7: Spider chart for the entire fight. Each metric is plotted relative to all other fighters that have used the PunchR system.

Finally, we again have the grid of boxer metrics colored by the boxer with the higher value (figure 4.8). This is largely dominated by Alvarado with speed being Rios' best metric. Round 3 and 5 were also his two best rounds when comparing at all metrics. With Rios winning by TKO in the seventh round this brings up the limitations of predicting the victor with these measures. Many of these measures point to Alvarado being in control of the fight, but Rios was able to hurt Alvarado and end the fight prematurely. The judges had even scorecards at the end of six rounds although some media outlets did have Alvarado firmly ahead in the fight similiar to what we have seen here. CompuBox numbers had Rios out landing Alvarado in the power punch category 144 to 132. So despite providing a compelling story in many accounts there is still some information not being provided by this system. Chapter 5 further addresses the usefulness of these new metrics in relation to predicting fight outcomes.

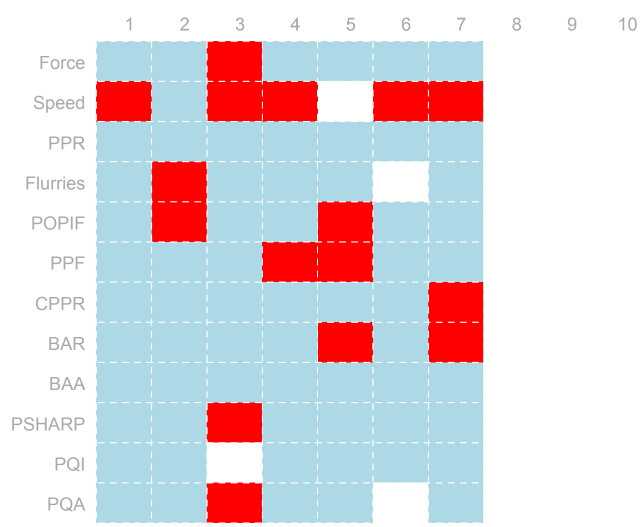

Figure 4.8: Round-by-round fight score based on averaged PunchR metrics for Rios versus Alvarado.

4.2 Punch Counts

Having taken a comprehensive view of two fights we now outline each of the metrics for all PunchR fight results. The easiest thing to summarize are metrics related to punch volume and rate based on the punch detection algorithm. This is really the only metric that boxing already records during fights, measured by CompuBox and PunchZone. Metrics relating to punch counts provide the most basic look at the activity that is occurring in the ring.

4.2.1 Total Punches

To begin we look at the most punches recorded in any of the fights. The total punches (TP) is testament to both a very active fighter and a fighter who fights a lot of rounds. Table 4.15 is the top 15 total punches thrown by a fighter in a fight. The two fighters with the most total punches thrown in a single fight came in the draw between Burgos and Martinez. They are the only two fighters to have thrown over 800 punches in a single fight coming against one another. Two other fights contributed four fighters to this list including the Alvarado versus Rios fight as well as the Dashon Johnson versus Jermell Charlo fight. These were high action fights by both fighters that lasted into the later rounds of the fight.

4.2.2 Punches Per Round

Punches per round (PPR) is a rate that can be compared across fights for fighters who have fought different fight lengths. Rigoberto Casillas leads the way with 120 punches per round being one of five fighters to break the 100 punches per round level. Three fighters (Rios, Alvarado, Kavanagh) that fought at least 7 rounds at these high punching rates made both the total punch list and this PPR list. Jamie Kavanagh made this list for three separate fights indicating he always throws a high rate of punches. For all fighters in all weight classes the average is 56.4 PPR.

Boxer	TP	RDs	Weight	Victor
Juan Carlos Burgos	983	12	129	draw
Rocky Martinez	854	12	130	draw
Sakio Bika	792	12	172	winner
Isaac Chilemba	784	8	179	winner
Luis Orlando Del Valle	772	10	122	loser
Jamie Kavanagh	754	8	136	winner
Mike Alvarado	723	7	140	loser
Dashon Johnson	696	10	153	loser
Jose Medina	692	10	162	loser
Jermell Charlo	672	10	154	winner
Javier Fortuna	669	12	126	winner
Victor Terrazas	665	8	136	winner
Lanard Lane	630	8	144	winner
Brandon Rios	622	7	140	winner
Marvin Quintero	613	12	135	loser

Table 4.15: Top 15 Boxers for total punches (TP) thrown during a fight using PunchR.

Figure 4.9 illustrates PPR by weight. There is a definite trend of decreasing PPR as weight increases.

4.2.3 Compubox Comparison

There have been 9 partial fights with PunchR data where Compubox has also published a fight report. These fights are a good opportunity to compare the two systems. CompuBox records punches on a round-by-round basis so this will be the level at which we compare punch totals by fighter. We do not expect the two counts to be exactly the same as both systems have some error involved in

Boxer	PPR	RDs	Weight	Victor
Rigoberto Casillas	120.0	3	118	loser
Jamie Kavanagh	110.5	5	136	winner
Mike Alvarado	103.3	7	140	loser
Saul Rodriguez	103.0	2	130	draw
Randy Caballero	102.0	3	119	winner
Jamie Kavanagh	98.8	6	136	winner
Keith Thurman	98.0	1	147	winner
Isaac Chilemba	98.0	8	179	winner
Hector Orozco	96.3	6	148	loser
Jamie Kavanagh	94.3	8	136	winner
Sean Monaghan	93.0	6	175	winner
Phil Lo Greco	93.0	6	148	winner
Brandon Rios	88.9	7	140	winner
Cesar Garcia	88.5	2	130	draw
Edner Cherry	85.2	6	130	winner

Table 4.16: Top 15 boxers for total punches (TP) thrown during a fight using PunchR.

recording the punches, but there should be a high correlation between the two.

The correlation between PunchR and CompuBox is 0.847. As seen in Figure 4.10 the diagonal line is the 1-1 line, with more of the points falling below the line showing PunchR more often records more punches than the CompuBox operators. On average it records 5.5 more punches than CompuBox per round. This higher punch count by PunchR can be attributed to the threshold set in the punch detection algorithm to allow a possible peak to be consider a punch. This was set to allow for the liberal inclusion of more punches in order to not miss a punch during a live broadcast.

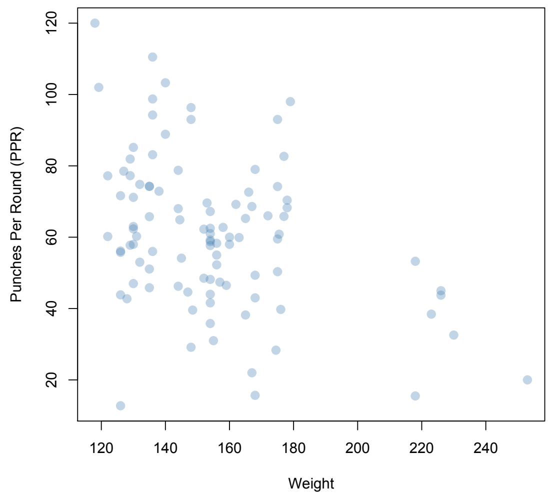

Figure 4.9: Punches per round by weight.

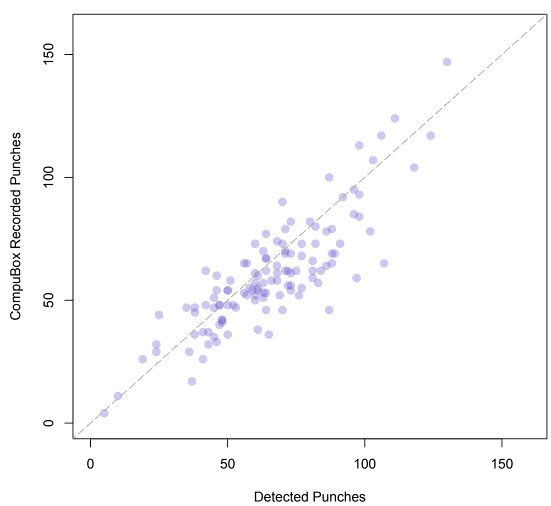

Figure 4.10: CompuBox versus PunchR punches recorded by round.

4.3 Speed

The speed measurements are the first measurements of speed of punches during live professional fights. The comparisons will be made looking at median speeds because the distribution of speeds of all punches is slightly right skewed so the medians will provide a better measure of center.

4.3.1 Speed by Weight Class

Summarizing speed by weight class is a natural comparison. Table 4.17 splits all the punches from all fights with partial data into 8 large, general weight classes. Overall, there was data from 154 different fighters with almost 50,000 punches. Boxing has 18 different weight classes, depending on the sanctioning body, so at the lower weight classes the weight differences are very minimal which in this comparison would separate out to too many groups of boxers. The middle weight classes have seen the most fighters. Typically, the rear hand is faster than the lead hand and there is a slight decrease in speed as weight class increases. Fighters weighing below 147 pounds had median punch speed above the median punch speed of 16.85 mph.

Weight Class	Fighters	TP	Lead	Rear	Med	Max
Below 118 lbs	2	175	17.5	18.2	18.1	31.2
118 - 126 lbs	15	2714	17.5	16.9	17.2	36.7
126 - 135 lbs	25	9419	16.8	17.5	17.1	38.8
135 - 147 lbs	30	12491	16.8	17.3	17.0	38.3
147 - 160 lbs	42	11560	16.8	16.9	16.8	41.8
160 - 175 lbs	19	5869	16.4	17.0	16.7	36.5
175 - 200 lbs	11	5359	15.9	17.5	16.3	38.3
Above 200 lbs	10	1595	16.2	17.5	16.9	37.6
Total	154	49192	16.6	17.2	16.9	41.8

Table 4.17: Median speed by weight class including number of fighters, total punches, lead, rear, and max speed in miles per hour.

The following figure (4.11) has plotted speed of all the punches with a LOESS smooth fitted line over the top to point out the slight downward trend of the line as weight increases.

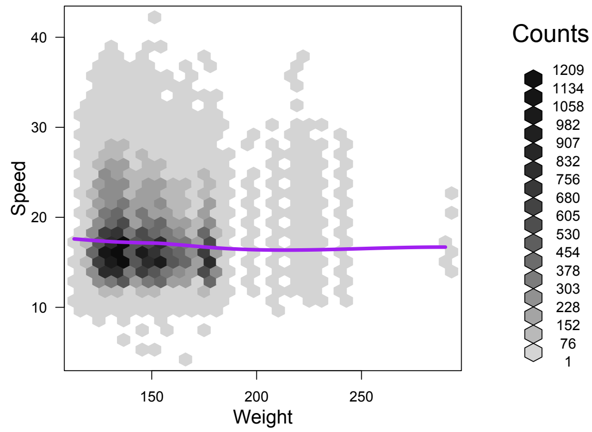

Figure 4.11: Speed by weight with LOESS smooth fitted line.

4.3.2 Top Median Speed

Table 4.18 lists the 15 fastest fighters by median speed for fighters with over 100 punches in a fight. Lots of the fights had fewer than 100 punches but with such a small sample of punches we see quite a bit of variation in punch speed. Having to throw at least 100 punches settles the median speeds to a more representative estimate of each fighters speed. DeVonte Allen averaged just around 2 mph faster than the average punch. Surprisingly the top two fastest punchers were losers of their respective fights but of the top 15, twelve (12/15 = 80%) of the fighters were winners. Out of the 65 fights, 42 (42/65 =65%) winners had a higher median speed than their opponent. Further, for those that had a median speed more than a half a mph faster than their opponent 32/45 = 71% were winners.

Boxer	Median Speed	Weight	TP	Victor
DeVonte Allen	18.8	128	171	loser
Jay Krupp	18.6	154	296	loser
Jermell Charlo	18.5	154	132	winner
Abraham Han	18.5	160	232	winner
Rigoberto Casillas	18.4	118	360	loser
DeAndre Latimore	18.4	154	150	winner
Saul Rodriguez	18.3	129	309	winner
Deontay Wilder	18.3	218	213	winner
Brandon Bennett	18.2	135	144	winner
Rau'shee Warren	18.2	116	107	winner
Bryant Jennings	18.2	223	269	winner
Wale Omotoso	18.1	148	360	winner
Demetrius Hopkins	18.1	154	179	winner
Cedric Agnew	18.1	175	365	winner
Luis Carlos Abregu	18.1	147	106	winner

Table 4.18: Top 15 boxers for median speed of punches thrown during a fight using PunchR with a minimum of 100 punches.

4.4 Force

4.4.1 Force by Weight Class

In Table 4.19 we have the rear median force always larger than the lead median force. The highest maximal force punch came in the heavyweight division with the maximal punch force being 1,925 lbs There is a large positive trend showing an increase in force as weight increases.

The force by weight plot with LOESS curve in Table 4.12 shows the positive trend of an increase in force as weight increases.

Weight Class	Fighters	TP	Lead	Rear	Med	Max
Below 118 lbs	2	175	395	379	386	1083
118 - 126 lbs	15	2714	451	499	468	1076
126 - 135 lbs	25	9419	467	517	486	1574
135 - 147 lbs	30	12491	472	527	492	1613
147 - 160 lbs	42	11560	516	555	531	1304
160 - 175 lbs	19	5869	587	639	604	1536
175 - 200 lbs	11	5359	549	652	580	1379
Above 200 lbs	10	1595	859	1012	929	1925

Table 4.19: Median force by weight class including number of fighters, total punches, lead, rear, and max speed in lbs of force.

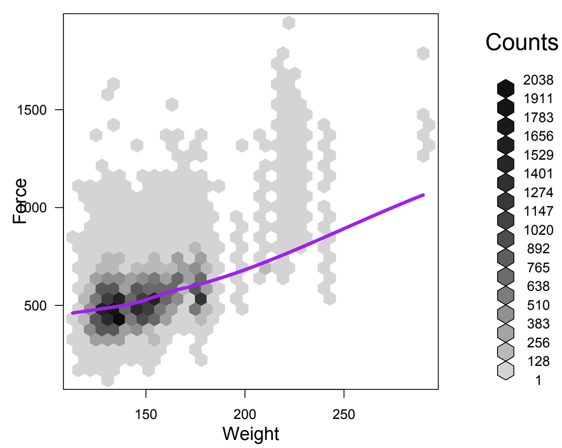

Figure 4.12: Force by weight with LOESS smooth fitted line.

4.4.2 Top Median Force

The top 15 median force by fighter is not quite as interesting to compare because the heavier fighters dominate the top of the list. It is harder to make comparisons across weight classes because of the strong increase in force as weight increases.

The top fighters come from the heavyweight division. In $41/65 = 63.1\%$ of fights the fighter with the higher median force was the victor. In 30 fights were there was a difference in median force of larger than 50 lbs, 21 fights had the boxer with the higher force being the winner ($21/30 = 70\%$).

Boxer	Median Force	Weight	TP	Victor
Bryant Jennings	1077	223	269	winner
Deontay Wilder	1071	218	213	winner
Theron Johnson	1051	230	228	loser
Isa Akberbayev	748	210	411	loser
Ronald Ellis	716	168	316	winner
Cedric Agnew	708	175.5	365	winner
Ryan McKenzie	674	175	302	winner
Nikola Sjekloca	670	168	592	loser
Sakio Bika	649	172	792	winner
Anthony Ferrante	643	196	226	winner
Chris Chatman	635	154	173	loser
Jason Escalera	631	166	581	loser
Edwin Rodriguez	621	165	522	winner
J'Leon Love	619	158	502	winner
Josiah Judah	614	165	191	winner

Table 4.20: Top 15 boxers for median force of punches thrown during a fight using PunchR with a minimum of 100 punches.

4.5 New Metrics

The following new metrics are proposed as additions to punch counts, speed, force, and punch types many of which were outlined in the Burgos and Martinez fight summary. Metrics relating to counterpunches and flurries are based on common boxing terminology and techniques, but have had no previous method of quantification while other metrics are entirely novel conceptually. Most of these new metrics are an attempt to quantify something tangible in the boxing ring while some are a bit more abstract.

4.5.1 Punch Time

The average PTIME is 152 ms with a standard deviation of 57 ms for all fighters. There is no intuition as to whether shorter or longer punches are of any benefit so no list will be included, but it does tell us something stylistically about the fighters.

4.5.2 Punch Sharpness

For the remaining new metrics there is really no sense of the levels that each will be recorded at so only top 5 fighters for each will be presented. Table 4.21 has the top 5 fighters for PSHARP. The mean fighter PSHARP is 0.835. There were 14 boxers who surpassed an average PSHARP of 0.9, eleven (11/14 = 78.6%) of whom were victors.

Boxer	PSHARP	Weight	Victor
Thomas Dulorme	0.915	145	winner
Adam Lopez	0.911	118	winner
Rau'shee Warren	0.908	116.8	winner
Jay Krupp	0.906	154	loser
Keith Thurman	0.905	147.5	winner

Table 4.21: Top 5 boxers for mean PSHARP of punches thrown during a fight.

4.5.3 Punch Quality

Comparing punch quality across weight classes is a possibility as well. In the top 5 for mean PQI and PQA we have fighters from various weight classes. In the mean PQA top 5 the first two are heavyweights, while the next three come from fighters nearly 100 lbs smaller. Bryant Jennings manages to make the top 5 for both lists.

Boxer	PQI	Weight	Victor	Boxer	PQA	Weight	Victor
Theron Johnson	3.0	230	loser	Deontay Wilder	46.3	218	winner
Bryant Jennings	2.7	223	winner	Bryant Jennings	43.8	223	winner
Cedric Agnew	1.4	175	winner	Patrick Hyland	39.9	126	loser
Chris Chatman	1.0	154	loser	Miguel Garcia	39.0	126	winner
J'Leon Love	0.9	158	winner	Dodie Penalosa Jr	38.8	123	winner

Table 4.22: Top 5 boxers for punch quality index and punch quality aggregate.

4.5.4 Flurries

The median number of flurries per round is three with the median number of punches per flurry being 4.1. Below we have the top 5 flurries per round and punches per flurry. Jamie Kavanagh leads the way with 11.5 flurries per round while Rau'shee Warren throws the most punches in his flurries averaging 6.5 PPF.

Boxer	FPR	Weight	Victor	Boxer	PPF	Weight	Victor
Jamie Kavanagh	11.5	136	winner	Rau'shee Warren	6.5	116	winner
Rigoberto Casillas	11.0	118	loser	Isaac Chilemba	6.2	185	winner
Saul Rodriguez	9.5	130	draw	Eddie Cordova	6.2	152	loser
Mike Alvarado	8.9	140	loser	Keith Thurman	6.0	147	winner
Cesar Garcia	8.5	130	draw	Saul Rodriguez	5.8	130	draw

Table 4.23: Top 5 boxers for flurries per round and punches per flurry.

4.5.5 Counterpunches

In Table 4.24 we see Randy Caballero averaging the highest number of counterpunches per round and winning in addition to Miguel Garcia having the highest percentage of his punches being counterpunches also winning. These two could be considered good counterpunches in their fights. The remaining fighters on these lists are losers (one draw) of their fights making it impossible to differentiate if this is their style or if they were severely outclassed by their opponents.

Boxer	CPPR	Weight	Victor	Boxer	CPP	Weight	Victor
Randy Caballero	24.3	119	winner	Miguel Garcia	0.6	126	winner
Marcos Herrera	24.2	135	loser	Rayco Saunders	0.5	176	loser
Cesar Cisneros	23.8	135	loser	Katrell Straus	0.4	168	loser
Cesar Garcia	23.5	130	draw	Ayi Bruce	0.4	154	loser
Hector Orozco	22.5	148	loser	Paul Velarde	0.4	136	loser

Table 4.24: Top 5 boxers for counterpunches per round and counterpunch percent.

4.5.6 Boxer Aggression

The top 5 boxer aggression measures are listed in Table 4.25. This measure we can easily compare across weight classes like many of the measures we have presented so far outside of force. Both Orlando Salido and Deontay Wilder had perfect BAR during their fights indicating they were the aggressor throughout the entirety of their fights. Surprisingly, Salido lost. Isaac Chilemba made both top 5 lists meaning he was a high volume, high percentage aggressor.

Boxer	BAR	Weight	Victor	Boxer	BAA	Weight	Victor
Orlando Salido	1.0	126.0	loser	Rigoberto Casillas	38.6	118.0	loser
Deontay Wilder	1.0	218.0	winner	Jamie Kavanagh	35.4	136.0	winner
Isaac Chilemba	0.9	179.0	winner	Isaac Chilemba	33.2	179.0	winner
Raeese Aleem	0.9	127.0	winner	Keith Thurman	32.3	147.5	winner
Eddie Cordova	0.9	152.0	loser	Saul Rodriguez	32.3	130.0	draw

Table 4.25: Top 5 boxers for boxer aggression rate and boxer aggression aggregate.

CHAPTER 5

Conclusions and Future Work

5.1 Conclusions

This dissertation accomplished a number of different things in bringing more quantitative thought to the sport of boxing. Without even mentioning any of the fight results with PunchR a lot of new territory has been covered. Chapter 2 brought about the largest assessment of boxing quantification in one place looking at both in-fight measures in addition to studies in controlled experimental settings. In Chapter 3, the PunchR system overview outlined the construction of an objective system to vastly increase the available measurements that can be recorded in live professional boxing matches. The data collection exercises alone for both speed and force modeling recorded more punches with known speed and force than all other experimental studies combined.

Including the fight results into the discussion the amount of new information that can generated with each new fight is staggering in comparison to what has been previously available. When considering prior to PunchR only one study with a total of six fights had attempted to make estimates about force of punches during live professional boxing matches it is evident boxing was in its infancy in relation to the available data. Further no fights had had any measures of speed and very little had been done in way of uppercut punches. Now 65 complete fights have estimates of speed, force, punch type and a variety of other metrics. Not only were new metrics presented, but so were a number of new visualizations to help create a narrative about each fight.

5.2 Future Work

As the PunchR system sees continued use further possibilities begin to present themselves. These possibilities can be separated into improving upon the PunchR system, improvements in quantifying the sport of boxing, or making more knowledgable fight predictions.

5.2.1 Model Improvements

First, when talking about improving upon the system the difficulty of extrapolation is a main issue. For boxers that may have different fighting styles or physical sizes than those used to train the force model, the estimations become difficult. The cohort of 30 boxers used to train the force model only consisted of seven professional fighters. As the fights using PunchR are all professional fighters this training data may not be entirely representative of the fighters we are trying to encapsulate. The first step would to be further data collection for the force model with more professional fighters making sure to get boxers from many of the weight classes with as many replicates from each weight class as possible. Refitting the force model on additional punches from a more representative group of professional boxers would improve the force estimates.

With force being such a difficult problem to provide accurate estimates the desired solution would be to dynamically update the force model. Boxer specific punches prior to a fight would provide a solution to this difficulty. This would entail each boxer to punch a portable boxing dynamometer while using the PunchR units in the weeks or days prior to using the system in an upcoming fight. The resulting punches could be included into a boxer specific force model prior to fight to provide more accurate estimations for each boxer.

Outside of force, as accelerometer technology improves incorporating new, better quality sensors with higher sampling rates will only improve data collection. Adding a third dimension (z-axis) to the accelerometer will further improve data integrity for modeling most specifically in the punch type classification when comparing hooks to uppercuts. Further the use of a combination accelerometer, gyrometer could prove beneficial.

5.2.2 Further Quantification of Boxing

Of course, the implications of a comprehensive, automated quantitative system in boxing are far reaching. Fighters, historians, and fans alike can make conjectures like, "Roy Jones, Jr. or Sugar Ray Leonard are the fastest punching fighters of all-time" or "Mike Tyson is undoubtedly the hardest puncher who ever fought," but outside of video of a blur of punches or a devastating knockout these comparisons can only be made following an "eye-test" without any concrete evidence. Historical comparisons about speed and force will never be able to be resolved, but as PunchR sees continued use comparisons will be able to be made across weight classes and across different fighter eras.

For fighters and boxing promoters any number of quantitative measures could be used when considering future opponents. Fighting styles can begin to be summarized numerically used in training up to a fight to scout an upcoming opponent to come up with a fight plan for success. Training can be tailored to improve fighters deficiencies. The promoters can use similar information to provide fights to viewers that have more action or stylistically provide an intriguing fight.

Further, the possibility of medical information becomes a possibility. Ringside doctors could this information to stop fights earlier if these new metrics start to indicate a fight is getting more out of hand than it may look. Or possible metrics can be developed to help educate fighters about long term health risks if they continue to fight.

5.2.3 Fighter Styles

One fighter, Jamie Kavanagh, has participated in three bouts using the PunchR system. He was victorious in all three fights recording two unanimous decisions and one technical knockout (TKO). Visualizing all three fights by way of the spider chart we see that he had similar performances across all three fights especially in fights 1 and 2. He is a high volume puncher, with average PSHARP, and a low counterpunch percent. In fight 2, where he recorded his TKO is where his speed was the fastest of all three fights. With the similar shapes of these spider charts we can see how a fighter style begins to shape up over multiple fights. This would likely when he is faced with a more difficult opponent, but it does give a good representation about the type of fighter Kavanagh looks to be.

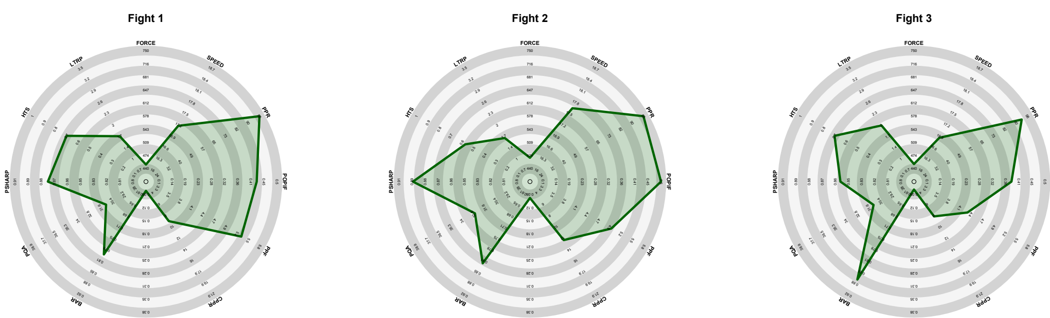

Figure 5.1: Spider chart for three different Jamie Kavanagh fights using the PunchR system.

5.2.4 Fight Predictions

There have been minimal studies trying to predict fight outcomes using statistical analysis. The only study available is Warnick and Warnick [2007] and its extension, Warnick and Warnick [2009]. These studies compiled results of 739 male professional boxers from the website BoxRec.com [2011]. In Warnick and Warnick [2007] they indicated age, career wins and losses, and the outcome of the preceding fight are predictive of a fight's outcome. Warnick and Warnick [2009] again cited prior performance in a preceding fight, prior performance against the same opponent, and prior performance at a particular location were all good indicators of fight outcomes. These studies only consider measures pertaining to fight outcomes, opponents, and boxer characteristics. No studies have considered using in-fight measures like CompuBox. There is plenty of room for research in fight predictions even prior to PunchR.

With the PunchR system fight predictions become even more interesting. The fight summary of the Rocky Martinez versus Juan Carlos Burgos fight took a look at using some of the new PunchR metrics to help frame the story of the fight to come to a decision about the victor. This begs the question which of these new metrics are more important in predicting a winner. With only 65 complete fights (62 of which ended in a victor; 3 draws) there is not an extensive amount of outcomes to make a strong case for certain new metrics over the others, but an exploratory analysis is presented here. A small CART using the difference in metrics between two opponents indicates a few metrics possibly more important than others. The CART (seen in figure 5.2) fit on the 62 fights with outcomes has only three splits from the new metrics including the difference in PSHARP, PQA, and median punch speed. Using these only these three metrics the correct victor is selected $54/62 = 87.1\%$ of the fights.

This was just a quick into look at the possibility of fight prediction, but the opportunities to improve on this become very clear with more and more PunchR data being recorded. Despite all this new information it is not to say all boxers, boxing fans, or boxing historians will readily adopt PunchR numbers. Boxing has a way of remaining true to it's traditional roots. Nonetheless publication of data recorded from the PunchR system could go a long way in making boxing a sport

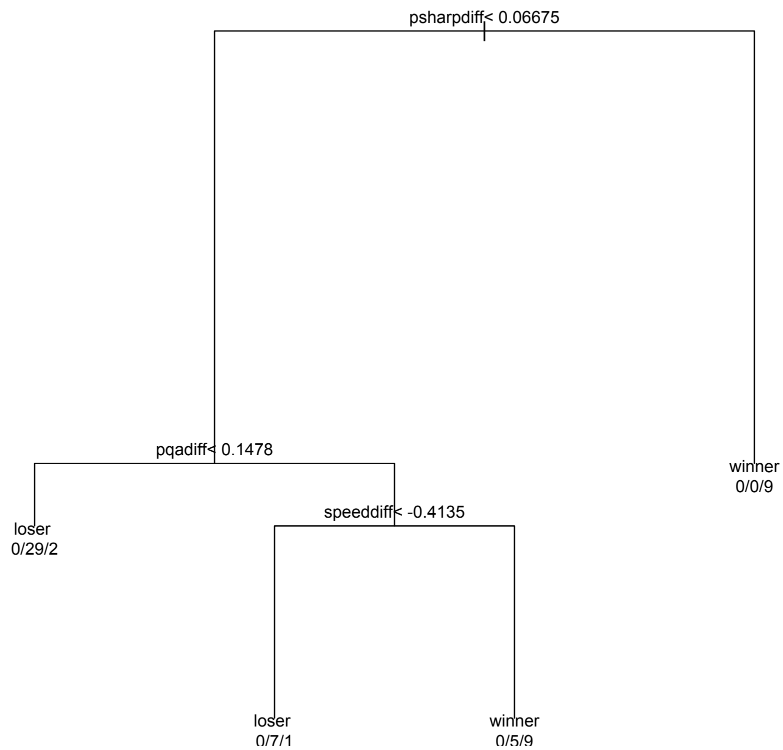

Figure 5.2: CART fit on the 62 fights with outcomes using the new PunchR metrics.

no longer starving for data and numerical analysis, but one that can be compared to baseball with the analysis being done in the Sabermetric movement and other sports who are heading in the same direction. The trove of data will beg for fan usage, interaction, and development, in addition to building a more educated fan base. It will be hard to deny the rich experience that this new data will add to boxing and the evidence that it provides that boxing does need to move towards higher numerical analysis of the sport. PunchR is a much needed step in the right direction to quantify the sport of boxing.

APPENDIX A

Appendix

A.1 List of Single Punch Metrics

New individual punch measurements with abbreviations and descriptions.

Metric	Abbreviation	Description
Punch Force	pf	Estimated punch force in pounds
Punch Speed	ps	Estimated punch speed in mph
Punch Type	pt	Punch type classified as straight (jab or cross), hook, or upper
Punch Sharpness	PSHARP	Estimated probability a profile is a punch in detection
Punch Time	PTIME	Time of punch from estimated start to impact
Counterpunch	cp	Indicator if a punch is a counterpunch
Flurry Punch	fp	Indicator if a punch is included in a flurry
Punch Quality Aggregate	PQA	force per pound squared plus speed
Punch Quality Index	PQI	Average of standardized speed and standardized force
		in relation to all boxers within 5 lbs of the boxer weight

A.2 List of Fight Metrics

List of overall fight metrics with abbreviations and descriptions.

Metric	Abbreviation	Description
Total Punches	TP	Punches thrown in a fight
Punches Per Round	PPR	Mean number of punches per round
Max Force		Max force value of all punches in pounds
Median Force		Median force value of all punches in pounds
Cumulative Force	CF	Sum of all punch force values in pounds
Force Per Pound	FPP	Force of punch divided by boxer weight
Max Speed		Max speed value of all punches in mph
Median Speed		Median speed value of all punches in mph
Cumulative Speed	CS	Sum of all punch speed values in mph
Lead to Rear Punches	LTRP	Number of lead punches for every rear punch
Lead to Rear Force	LTRF	Ratio of force lead punches to rear punches
Lead to Rear Speed	LTRS	Ratio of speed lead punches to rear punches
Hook to Straight	HTS	Ratio of hook to straight punches
Total Flurries	TF	Total number of flurries of 3 or more punches
Flurries Per Round	FPR	Mean number of flurries of 3 or more punches per round
Percent of Punches in Flurries	POPIF	Percent of punches in flurries of 3 or more punches
Punches Per Flurry	PPF	Mean number of punches in flurries of 3 or more punches
Max Flurry Length	MFL	Max number of punches in flurries of 3 or more punches
Percent Counter Punch Flurries	PCPF	Percent of flurries started with a counterpunch
Total Counter Punches	TCP	Counterpunches thrown in a fight
Counter Punches Per Round	CPPR	Mean number of counterpunches thrown per round
Counter Punch Percentage	CPP	Percent of all punches that are counterpunches
Mean Punch Quality Aggregate	mPQA	Mean PQA value of all punches
Mean Punch Quality Index	mPQI	Mean PQI value of all punches (0 is average)
Boxer Agression Aggregate	BAA	Flurries initiated plus non-counterpunches over rounds
Boxer Agression Rate	BAR	Average of the percent of flurries initiated and percent of non-counterpunches

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