Ultimate Analytics: A study of elite teams' offenses

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Abstract

Many traditional, powerhouse sports are currently undergoing an analytics revolution. While ultimate is a relatively young sport, it is certainly not immune to this revolution. Most ultimate data presently track basic summary statistics, but some more advanced work in the field on spatial analytics has been done. We stand on the brink of an explosion in advanced ultimate analytics. This paper attempts to progress that field, analyzing data from elite men's club teams, namely Denver Johnny Bravo, Boston Ironside, and San Francisco Revolver. We analyze how variables beyond just spatial location affect the probability of scoring. Our results demonstrate that elite teams should attack downfield to gain yards while prioritizing the creation of "entropy"—throwing more passes rather than fewer and holding the disc as briefly as possible; once in the red zone, teams should modify their offense to maximize space while changing their points of attack by swinging the disc laterally. We propose two new end zone sets for offenses to run. Our method, when combined with conventional ultimate wisdom, provides a strong attempt at streamlining offenses to be more efficient at scoring.

Dedication

This thesis is dedicated to Jules Dickson Mappus, Jr., a dear friend who helped me find my love for ultimate. Jules, I miss throwing an orange disc with you, talking about how you were going to make it big with the stock market, joking with you about both of us being O-line only players, so much more, and—most of all—you. Love, always.

Acknowledgements

These things always seem so hard to write and yet knowing who to thank is so obvious. Here we go. First and foremost, thank you to my adviser and first reader, Professor Luke Bornn, for providing motivation in the form of your own research and for providing guidance on ideas for me to pursue. Thanks to Kevin Rader for graciously agreeing to be my second reader and for the abundance of statistics classes in which you've taught me. Thank you, thank you, thank you to Margo Levine for everything in the last four years and beyond; you're an unbelievable mentor and friend. Thank you to my parents for always being there, now and forever. Thanks to Brian Cronin for discussing the potential of and entertaining the idea of "sauermetrics" with me back in the fall of 2013, for late thesis nights together—at least until yours was completed, and for sharing so much about sports with me—both the X's and O's as well as a love for them. Thanks to my brother William for everything, always, and also for teaching me everything I know about LaTeX. Of course, thank you to all of my friends who have been there in the past few months and have had to endure listening to me talk endlessly about my thesis. And finally, three big thank yous to 1) everyone associated with Harvard Ultimate for cultivating the greatest community and for teaching me so much about ultimate, 2) BRed Line for being my favorite group of guys year in and year out, and 3) anyone that has ever thrown a disc or chased 175 grams of plastic—with me or otherwise—this one's for you.

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Chapter 1

Introduction

ESPN announcer Evan Lepler commenting on Denver Johnny Bravo player Jimmy Mickle after the latter threw a break side throw from 25 yards out that led to two immediate continuation break throws for the score: "Jimmy Mickle's not in the stat sheet in terms of goals and assists, but Bravo scored because he got that first break. We need to have better statistics to account for the most important throw that led to the score." - 2014 U.S. Open Final

1.1 Motivation

Ultimate frisbee, or just "ultimate," [1] is a sport that was founded in 1968 by Columbia High School students in New Jersey. Though the invention of the sport is relatively recent, ultimate is a fast-growing sport, and over 100,000 people play the sport in 50 countries (Parinella & Zaslow, 2004). The sport has grown tremendously over the past decades, but the sport is still evolving, and with that, there are still strategies to be invented and analytics to be formulated.

We wish to study the sport of ultimate and its current offensive and defensive strategies by assigning values to certain actions. Does the location of the disc on the field matter? If one player is catching the disc, where should the other players on the team be

[1] Throughout this paper, we will refer to the sport as ultimate, as the company Wham-O trademarks the term Frisbee®. Furthermore, the actual "frisbee" itself will always be referred to as a "disc."

located in order to optimize the probability of scoring? Do these questions reveal enough insight to innovate new, efficient offenses and defenses? We attack these questions with spatial methods and beyond to be presented later in this paper. But first, an introduction to the sport and work already done in the field.

1.2 Definitions

In ultimate, there are seven players on either of the two teams. [2] The offense starts with the disc [3] and tries to advance it to the other end zone, where the player scores and the team is awarded one point. A regulation field is 110 yards by 40 yards, with two end zones of 20 yards deep and a field proper of 70 yards long. Players may advance the disc by passing only and may not run with it. Players with the disc are allowed to pivot on one foot. [4] If the pass is incomplete, a catch out of bounds, or a pass intercepted, the result is a turnover, and the other team gains possession from the location of the turnover. Alternatively, if a defensive player known as the "mark," a defensive player within 10 feet of the offensive player with the disc, counts to ten (known as the "stall") before the disc is thrown, the offense has stalled and turns the disc over. [5]

Before each point, one team throws the disc the length of the field to the other team: This is known as the pull. [6] After a point is scored, the scoring team pulls to the other team from the end zone on which they just scored. Per USAU rules, the game is usually played to a certain score such as 15. Halftime occurs after either team first reaches

[2] This paper will assume the 11th Edition Rules of USA Ultimate (USAU), the governing body for ultimate in the United States. Though other leagues (such as Major League Ultimate and American Ultimate Disc League) exist with slight variations on these rules, we will approach ultimate with USAU's rules, as the majority of ultimate played in this country is played under those rules.

[3] The standard disc allowed for play is currently Discraft's 175 gram UltraStar disc.

[4] Similar to pivoting in basketball.

[5] This stall count is similar to a shot clock in basketball, but can instead be thought of as a "pass clock."

[6] Analogous to the kickoff in football. One difference is that a drop on the pull (any contact with the disc without securing possession of the disc before it hits the ground) results in an automatic turnover.

half of the sum of the score limit and one: In most cases, that is 8 points.

1.3 Style of play

Though the sport of ultimate is played on a field similarly sized to that of football, the style of play—on a macroscopic level—tends to resemble more closely that of basketball (and, to some extent, soccer as well). While the objective on offense is to score points, the basic principle on offense to help achieve that goal is to create space. Hence, the basic principle on defense is to take away space. There are two large categories of positions on offense: handlers and cutters. Though the play of ultimate is fluid and though neither position is as specialized as positions in other sports may be (for example, those of football), handlers are designated throwers while cutters are designated receivers.

Similar to basketball, most defenses can play either man-to-man (or just "man") defense or zone defense. In a man defense, each defensive player is assigned one offensive player to guard. In a zone defense, each defensive player covers players within a certain area, rather than any specific player.

A fundamental concept of defense is the mark, as defined above. The mark establishes a "force," allowing the player with the disc to throw into only one lateral half of the field. Given the nature of the disc, the two basic throws are a forehand and a backhand. [7] A right-handed thrower will throw a forehand, also known as a "flick," to his right side and a backhand to his left side. The mark forces the throw to one of these sides (so allowing the forehand to be thrown is called a "flick force") while the downfield defenders take away the opposite half the field. In the example of a force forehand, the mark takes away the left half of the field (from the perspective of the player with the disc) while the downfield defenders position themselves on the right side of their offensive players to take away the right half of the field. The right side of the field, in this case, is designated the "force side," also known as the "open side." The left half of the field is termed the "break side" because the thrower has to "break" the mark in order to throw

[7] Analogous to tennis.

to that side. See the figure below for a pictorial depiction of these ideas. (In any figures in this paper containing a field, the offense will be assumed to be advancing from the bottom of the field to the top.)

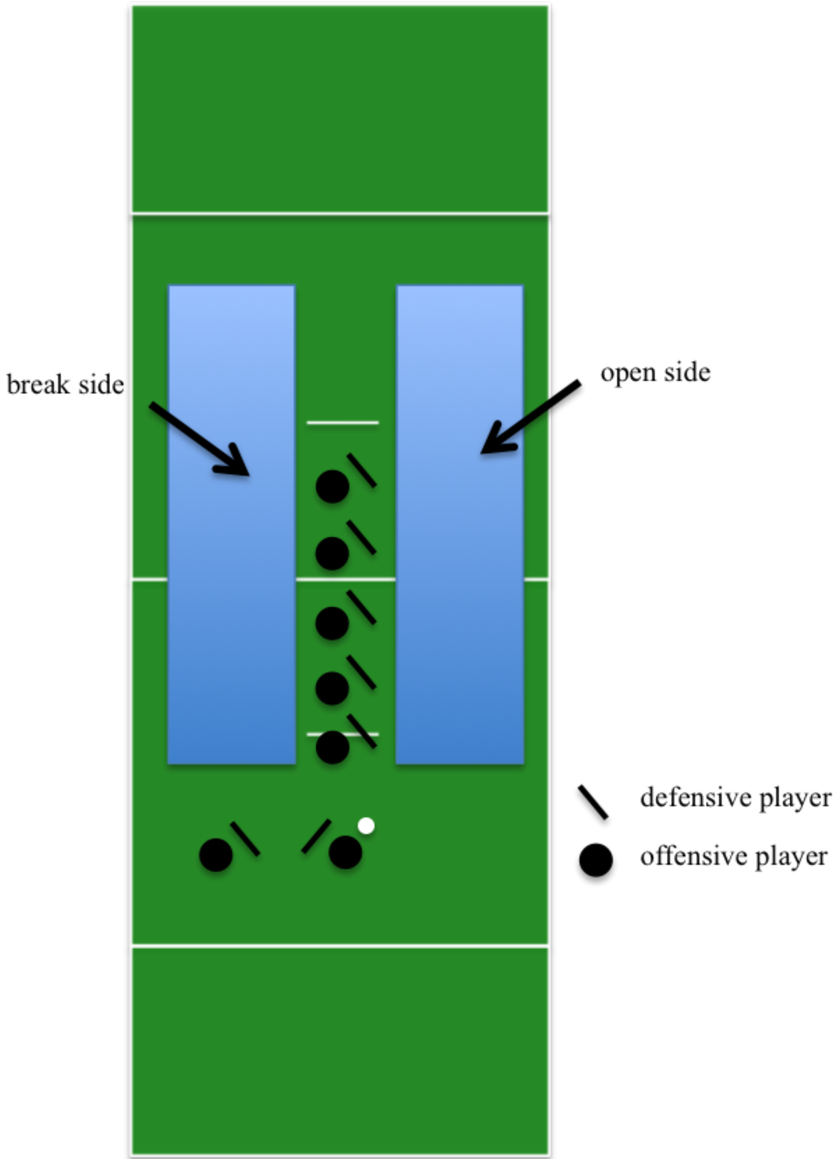

Figure 1.1: Flick force, open side, break side, and vertical stack.

These ideas will become important later on, as the open side is theoretically where throws are anticipated while throws to the break side are theoretically much more dangerous, as successive defenders are not in good defensive position. Zone defense will not be discussed because most elite teams do not play zone defense often, as offenses attack these with ease. [8]

The basic two formations for any offense are the vertical stack and the horizontal stack. Any other offense is a variation of one of these two formations or a hybrid of the two. The vertical offense employs two handlers in the backfield and five cutters spread vertically downfield, creating a perpendicular L shape. Usually, the vertical stack lines up centered with the disc so that there are two lanes to throw into: both the open side and break side (see figure above). The horizontal stack uses three handlers in the backfield with four cutters spread horizontally downfield of the handlers, creating a parallel set of two lines. The same principles in a vertical stack hold true in a horizontal stack. In either stack formation, the cutters have one of two options to cut: either "deep" (away from the handler) or "under" (toward the handler). [9] The horizontal stack is the most popular form of offense right now at most levels of ultimate. However, most elite teams default into a vertical stack in the "red zone." Generally, the exact type of offense is less important than the overall idea of maintaining space on offense and throwing to favorable matchups.

One concept fundamental to ultimate is the idea of the "dump-swing." The "dump" is the handler that is laterally aligned with the disc but not holding the disc; to "dump" the disc means to reset the disc to the person playing as the dump handler. The "dump-swing" in ultimate is the idea that the handler with the disc dumps (connotes reseting the stall count and/or passing the disc backwards) the disc or swings (connotes moving the disc laterally) the disc to the break side. Now, when the player previously playing as the dump handler possesses the disc, the mark has shifted to maintain the flick force, thereby opening up the lane that was previously the break side. Suddenly, the downfield defenders are all positioned on the wrong side and trail the cutters who have an open lane to cut into (see figure below). Thus, the dump-swing is used by ultimate teams to change the point of attack, referred to as "flipping the field." Though a fundamental idea ingrained

[8]Not unlike in the NBA.

[9]There is no consensus on the terms "downfield" and "upfield," though they usually mean the same thing. Downfield denotes the space away from the disc. Backfield refers to the space closer to the disc.

in conventional ultimate wisdom, the dump-swing has not yet been rigorously shown to create more effective and dangerous offenses. We explore this idea further in this paper.

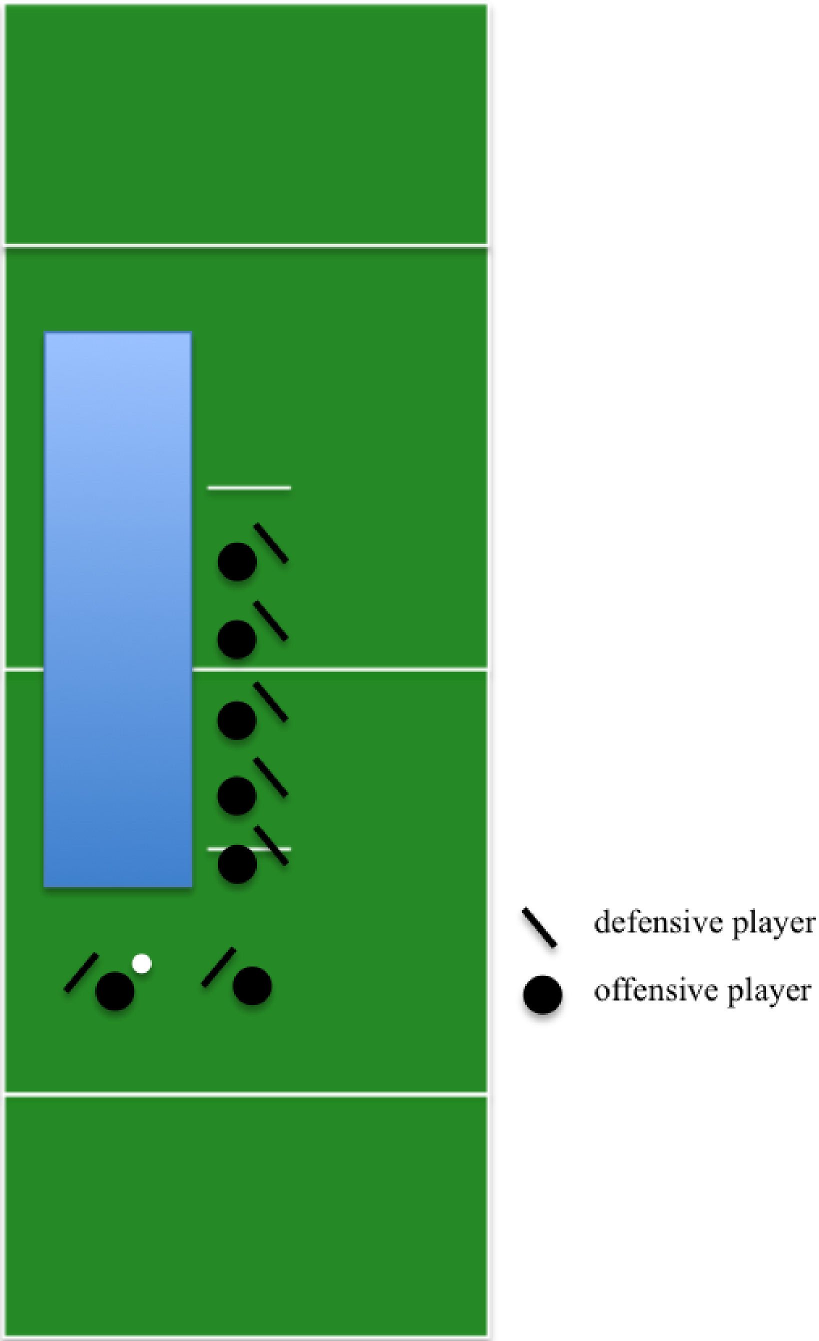

Figure 1.2: Dump-swing: Open lane for cutters with trailing defenders.

Chapter 2

Literature Review

2.1 Current state of statistics in ultimate

Most of the major sports in this country—baseball, basketball, football, and hockey—have had statistics around for a long time. Some, such as baseball, have even delved into advanced statistics such as sabermetrics. Theses advanced metrics attempt to explain a lot of intuition that experts suspect about the sport as well as to quantify value of players in ways that basic metrics cannot.

With ultimate being a relatively young sport, the same depth of analytics does not yet exist. However, the population of those who play ultimate or are interested in the sport tend to be a more number-centric group, similar to that of baseball. As a result, and perhaps in conjunction with the explosion of more advanced statistics in other sports, the statistical side of ultimate has advanced more quickly than the relatively young age of the sport would perhaps reveal.

Basic statistics in ultimate on offense include goals and assists: the former going to the player who caught the disc in the end zone and the latter going to the player who threw the goal. On defense, there is only one large type of statistic, and that is blocks. [1] Sometimes, blocks are categorized more specifically, with "normal" interceptions being termed blocks while blocks as the mark on the thrower are either hand blocks or foot

[1] Often colloquially referred to as "Ds."

blocks (though both are categorized as "point blocks"). Further statistics measure the completion percentage of throws and catches, with turnovers either being characterized as a throwaway (blame on the thrower) or drop (blame on the receiver). Finally, one thing to highlight is that most players at the elite level specialize as either an offensive player or defensive player. [2]

2.2 Classifying players by summary statistics

Given this, Sprong (2014) attempted to use Major League Ultimate (MLU) [3] data to cluster ultimate players into distinct groups. Using recorded statistics, Sprong (2014) formed four metrics: "the percentage of the player's total points played that were offensive points, the percentage of the player's total points played that ended in them scoring a goal, the percentage of the player's total points played that ended in them throwing an assist, and a combined retention rate factoring in drops and throwaways (the percentage of time that targeting the player doesn't end in a turnover)." Clustering using k-means into five groups yielded the following: "26 offensive players who catch scores (they throw some, too), 32 offensive players who primarily throw scores, 42 offensive role-players, 35 defensive players who throw scores, and 96 pure defenders" (Sprong, 2014). [4] The results he obtained are quite accurate when compared to the roles the players actually play.

[2] Given the fluid nature of the sport in that a turnover makes the offense become the defense and vice versa, it may perhaps seem strange that ultimate players specialize in either offense or defense. However, among other reasons, a few reasons for doing so are to preserve the chemistry of the "line" of seven players and to avoid player fatigue.

[3] The MLU was founded in 2012 as a spinoff of the American Ultimate Disc League (AUDL), both being a first-of-its-kind semi-professional league. The MLU held its inaugural season beginning in April 2013 and currently has eight teams in the league at the time of writing.

[4] Sprong only publishes players' names for two of his five groups, the offensive cutters and offensive handlers. Some highlights are listed here. Offensive goal scorers: Brendan Wong, Jeff Graham, Cody Bjorklund, Peter Prial, Donnie Clark, Jeff Wodatch, and Danny Clark. Offensive goal throwers: Alan Kolick, Brandon Malecek, Daniel Trytiak, Josh Markette, Markham Shofner, Eli Friedman, and Christopher Mazur.

This is not the first time that someone has attempted to classify the position of players based on statistics. In fact, Ultiworld, the "premier news media site dedicated to ultimate," has produced a number of statistical pieces, among them one in 2012 on using statistics to define positions. Childers (2012) analyzed the data of the 2012 NexGen team, a college all-star team that traveled across the country throughout the summer to play the most elite "club" teams. [5] As the author says, "position is a much more nebulously defined concept" because "[e]very competitive player is expected to be able to throw, catch, cut, and defend, at least to some degree" (Childers, 2012). He uses three metrics: percentage of yards obtained from throwing, total number of receptions (across about a dozen games), and number of receptions per offensive possession (the previous metric, but as a rate). The theme across all three of these metrics is that handlers are more prone to having higher numbers as they throw the disc more and touch the disc more than players in other positions. Combining these three metrics and looking at all fifteen players on NexGen produced a rough idea of the cutters, the handlers, and the "hybrids." Childers poses some interesting questions in trying to interpret the data from this accurate, albeit quite simplistic, measurement of the 15 players. He asks if the hybrid players are classified as such because they play a position that is somewhat a mix of both positions or if they just alternate between playing both positions.

2.3 Advanced player analytics

All of these statistics are interesting in their employment of classifying players, but even more useful would be using statistics to characterize the value of a player. Childers, Weiss, and Carneige (2013) do exactly that with their work on "expected contribution." They begin by stating that the sum of goals, assists, and blocks—a commonly used

[5] The "club" level is the highest level of competition for USAU. Players usually compete at this level after college, though some (read: the best players) certainly compete in both simultaneously, with the most talented sometimes competing at the club level before they even enroll in college. At the time of writing, the top club teams of USAU are perceived to be more talented than the semi-professional teams of either the MLU or AUDL.

metric in ultimate to measure the value of a player—is too simple and not robust enough. They create a metric called expected contribution (EC) that is similar in motivation to "baseball's Wins Above Replacement Player (WARP) or basketball's Player Efficiency Rating (PER)" (Childers, Weiss, & Carneige, 2013). The authors state the intuitive definition of EC to be a number that "measures any change in the probability that your team would win the point from the moment 'before' you arrived on the scene compared to the moment after your involvement" (Childers, Weiss, & Carneige, 2013). This metric does more than just value the simple statistics of goals, assists, and blocks though. It instead encompasses things like yardage gained and field position to achieve a better understanding of a player's worth.

2.4 Spatial analytics

Weiss and Childers (2014) in a different paper extend the work with EC into spatial statistics. They state that current statistical work with ultimate involves summary statistics like the ones discussed previously but caution that there is a certain limit in using them to understand the player's ability to contribute to scoring a point. Using EC, they created spatial heat maps to determine the probability of scoring as a function of location on the field. They used data from 2013 club teams (both men's and women's) to gather "location-based data. . .[to] produce team-specific and aggregate scoring probability graphs using logistic regression, LOESS, and k-nearest neighbors models" (Weiss & Childers, 2014). One result is the ability to summarize the probability of scoring on a given possession or point, given a certain yardage away from the end zone, for both home and away teams. [6] The authors extend this by two-dimensionally plotting the probability of scoring. One interesting find negates common ultimate theory. Players intuit that centering the disc laterally is valuable, as it gives more space to throw into; instead, the authors find that the lateral location of the disc is less significant than previously thought

[6] It is not entirely clear how home and away teams were designated, as ultimate games are usually played over the course of a tournament at a central location, so only one team out of all of those at the tournament should really be the "home" team.

(Weiss & Childers, 2014).

Weiss and Childers (2014) continue by discussing the use of probability models to determine the most successful strategy for the offense and defense on the men's side. They find that the offense's safest throw is a backward throw toward the middle of the field. On the opposite side of the disc, for defenses, the authors studied two basic types of defense: the prevent defense and the pressure defense, where the former gives up shorter, under passes and the latter gives up deep throws. The conclusion is that the defense should employ the prevent defense and the obvious counter by the offense should be a short pass forward (Weiss & Childers, 2014). An interesting note from analyzing women's data is that their best offensive strategy is to "huck" (similar to punting in football) and to play defense in the hope that the other team will turn the disc over and generate a more optimal field position. Weiss and Childers (2014) concede that there are a few limitations to their work: 1) that both the player throwing the disc and the player receiving the disc are credited in their EC, somewhat double counting, and 2) that they examine the spatial movement of only the disc: only one player at any given time is being tracked while the other thirteen are not. However, limitations aside, this work has been crucial in advancing the sport of ultimate, and we see similar work in other sports.

2.5 Current state of statistics in basketball

As stated before, the macroscopic play of ultimate is similar to that of basketball, and somewhat to that of soccer, in the sense of continuous flow. Strategies and mindsets also overlap in playing under similar conditions such as against zone defenses. Much work has been done with the sport of basketball thus far, but a pioneering paper by Cervone, D'Amour, Bornn, and Goldsberry (2014) shows the value of looking at basketball from an entirely new perspective. Instead of examining "terminal states of possessions like points, rebounds, and turnovers," the authors investigated what happens in between these terminal states such as "the value of a dribble penetration or…the option of taking a contested shot to the option of passing to an open teammate" (Cervone, D'Amour, Bornn,

& Goldsberry, 2014). The challenge, of course, is in obtaining data relevant to player movement and then analyzing it.

The authors used player-tracking data from the NBA to "develop a coherent, quantitative representation of a whole possession that summarizes each moment of the possession in terms of the number of points the offense is expected to score," an expected value of sorts (Cervone, D'Amour, Bornn, & Goldsberry, 2014). Indeed, Cervone, D'Amour, Bornn, and Goldsberry (2014) term such a metric "expected possession value," or EPV. The basic definition of EPV is a "conditional expectation – the expected number of points the offense will score, given the spatial configuration of the players and ball at time t during the possession" (Cervone, D'Amour, Bornn, & Goldsberry, 2014). The authors use what they call a possession model and a Markovian assumption to analyze macrotransactions (passing or shooting) and microtransactions (movements with the ball) to continuously model the EPV over time. By doing so, they create a possession stock ticker of sorts, where the EPV rises and falls based on the movement of the player with the ball and the location of the nine other players at that time.

The authors go on to examine a player's worth in a single EPV metric—termed EPV-added over replacement (EPVA)—comparing that player's EPV to the league-average player in the same situation (Cervone, D'Amour, Bornn, & Goldsberry, 2014). The authors also calculate a metric of shot satisfaction in order to determine if the player making a shot adds more value to his team than if he had passed the ball instead. Cervone, D'Amour, Bornn, and Goldsberry (2014) add that there are more areas to explore with the idea of EPV and concede that there are limitations to the work done here. However, the work presented in this paper should allow offenses to adjust their strategy based on what the defense takes and gives, raising the EPV of the offense. Certainly, both the research of Weiss and Childers (2014) and Cervone, D'Amour, Bornn, and Goldsberry (2014) chart a completely new direction for sports analytics to head.

Chapter 3

Methodology

3.1 Introduction

Cervone, D'Amour, Bornn, and Goldsberry (2014) do one crucial thing more than Weiss and Childers (2014): They track the location of the off-ball players. This is important to note as it is a fundamental difference between the nature of the two sports: In basketball, the player with the ball can move while, in ultimate, the player with the disc cannot. In this regard, much of the offense in ultimate must come from the decisions of the other six offensive players: That is, the on-ball player initiates the offense in basketball while the off-disc players initiate the offense in ultimate. While the work of Weiss and Childers (2014) is certainly revolutionary for the sport, it is only the first step in the right direction.

3.2 Current limitations

There are considerations that simply cannot be measured by the spatial statistics of Weiss and Childers (2014), which considered just the x and y location of the players. For example, what is the value of a throw to the break side? (This was a point raised by the quote that opened Chapter 1.) This has long been commonly thought to place defensive players at a disadvantage, allowing the offense to score much more easily.

Another question to consider is what is the value of the stall count or number of passes in a given possession? There is a tension between these two variables, as holding the disc for less time will increase the number of passes, assuming a constant possession time. Conventional ultimate wisdom dictates that the disc should move quickly—thus keeping the stall count low while increasing the number of passes—in order to keep the defenses on their heels. We can think of such an idea as a measure of "entropy." Teams that hold the disc longer tend to have more stagnant offenses and less entropy while teams that hold the disc for shorter tend to have more fluid offenses and more entropy.

However, one downside to moving the disc constantly is increasing the probability of a turnover. No throw in ultimate is going to be 100%: In fact, most throws at the elite level have a 90-95% of being completed (Sprong, 2014). (Indeed, the author's own analysis later shows the completion rate of the collected data to be 91.4%.) Using simple probability and a conservative estimate of 95% completion rate, we see that at 14 throws, there is already a $1 - 0.95^{14} = 0.51$ chance of a turnover. Obviously, teams must strike a balance between moving the disc quickly and not overpassing and forcing turnovers.

3.3 Data collection

Keeping these questions in mind, we analyze elite men's club ultimate teams by watching game videos filmed by the NexGen (NGN) Network [1] and ESPN3. Each pass is recorded and coded with several variables, namely: offensive team, defensive team, offensive player, defensive player, type of throw (pull, beginning of possession after dead disc situation, completion, turnover, or score), [2] direction of force, stall count, x (lateral) location, and y (vertical) location.

The x and y locations present a unique challenge, as most ultimate fields do not contain yardage lines such as football fields. In order to overcome this obstacle and eliminate any bias in an eye test, we use MATLAB and a special command of *ginput* with

[1] The "new online television network for ultimate frisbee that's putting traditional broadcasting to the test" that has shut down operations as of December 2014.

[2] As an aside, the pull will be coded as a -1, beginning of possession as 2, completion as 1, turnover as 0, and score as 7 (because of football).

the image below to determine the pixel coordinates of the disc and then convert those to the real location.

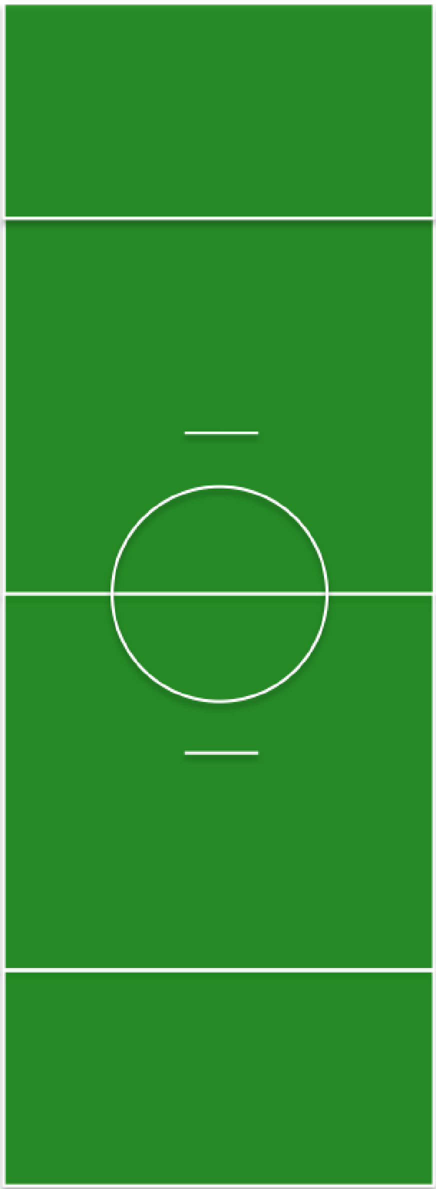

Figure 3.1: Image of field used in conjunction with MATLAB command *ginput* to determine location of disc.

From these variables, we can extract a number of other variables which will prove useful in our analysis: the horizontal distance between passes, the vertical distance between passes, the total distance between passes, the swing distance between passes (defined as the absolute value of the horizontal distance between passes), an indicator variable for which side the disc gets passed to (depending on the mark, this can be the open side, break side, or neither), [3] an indicator variable for whether the disc is a dump throw (defined as a vertically backwards throw), [4] an indicator variable for whether each throw is part of a possession that scores or not, and a pass counter for the number of passes per possession.

For games, we analyze videos from the top elite men's club teams playing in the 2014 season. We decide which teams those are. Some of the most dominant teams in the past decade include Seattle Sockeye, [5] San Francisco Revolver, [6] and Boston Ironside. [7] Quite recently, Denver Johnny Bravo has become a powerhouse, though only after sporadically placing at nationals in the past decade with one second place finish and a few semifinal appearances. Especially interesting to the 2014 club season was the news that Johnny Bravo acquired some of the best individual talent from across the country—forming a team of all-stars. [8] (The ultimate community immediately speculated whether this all-star team could find the chemistry to compete at a championship level given the limited number of touches for so much talent. [9] Short answer: Yes. Longer answer: They went on to win the 2014 Club National Championship.)

These four teams form the current elite tier of men's club ultimate. We will analyze data from the 2014 club season. We examine only Revolver, Ironside, and Johnny Bravo (colloquially referred to as "Bravo") because Sockeye performed below expectations at

[3] Coded as 1, -1, and 0, respectively.

[4] It is usually useful to reset the stall count while retaining position.

[5] Seattle Sockeye finished second place in 1995, 1996, 1997, 2005, and 2013 and won the national championship in 2004, 2006, and 2007. They have also placed as a semifinalist twice in that time period. Overall, their success has been sustained the most in the past two decades though with fewer top results more recently.

[6] San Francisco Revolver's success has been more recent, finishing second in both 2009 and 2012 and winning it all in 2010, 2011, and 2013.

[7] Though Boston Ironside has never won the national championship, they have never finished worse than semifinalists since their inception in 2008, coming up just short with second place three out of the past seven years.

[8] Not unlike the NBA's 2011-2014 Miami Heat.

[9] http://ultiworld.com/livewire/2014-denver-johnny-bravo-roster/

Club Nationals (whether due to a bad weekend or overall just an underwhelming season is unclear) while the other three contended. In particular, we look at the 2014 U.S. Open [10] semifinals game between Revolver and Ironside, the 2014 U.S. Open championship game between Revolver and Johnny Bravo, and the 2014 Club Nationals pool play game [11] between Ironside and Johnny Bravo.

After we collect this data, 1219 passes total, we can extract the useful variables described above and analyze the data with IPython and Stata. To summarize, our variables and their corresponding domains of theoretical values are as follows:

Table 3.1: List of variables collected and extracted and their respective domains of theoretical values.

Variables	Theoretical Values
$force$	(0, 1, 2, . . ., 5)
$seconds$	(0, 1, 2, . . ., 5)
x	[-20, 20]
y	[-20, 90]
$horizontal\_distance$	[-40, 40]
$vertical\_distance$	[-110, 110]
$total\_distance$	[0, 117]
$swing\_distance$	[0, 40]
$side$	(-1, 0, 1)
is_dump	(0, 1)
$is\_scoring$	(0, 1)
$pass\_count$	$\mathbb{Z}^+$

We analyze data for each team as well as for the aggregate data. From there, we draw conclusions about each team as well as elite-level ultimate more generally.

[10] One of the three major tournaments in the club division.

[11] Ultimate tournaments are played in a similar format to that of the FIFA World Cup: Pool play games are similar to the group stage and bracket play to the knockout stage.

Chapter 4

Results

4.1 Pass charts

In a style motivated by Kirk Goldsberry's NBA shot charts (see figure below), we create pass charts for the three teams: Johnny Bravo, Ironside, and Revolver.

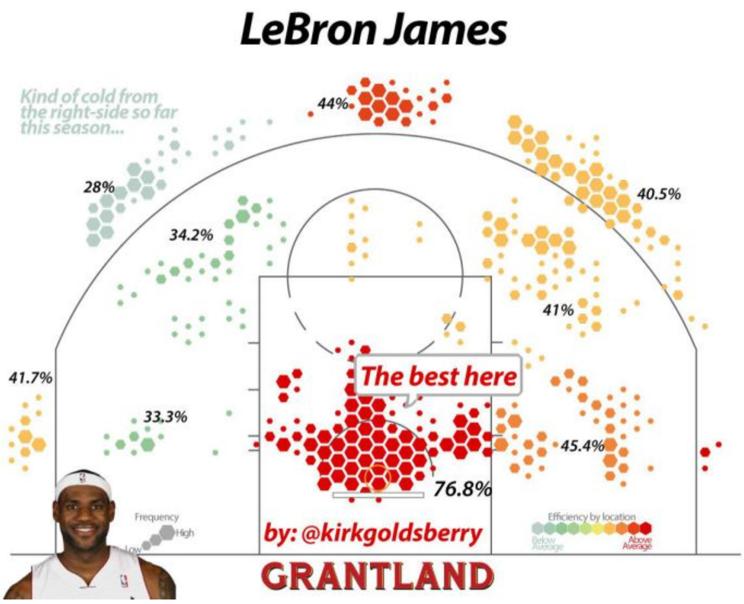

Figure 4.1: LeBron James' 2014 shot chart.

These pass charts plot each pass as a dot: Red is a pass that's part of a scoring possession, and blue is a pass that's part of a turnover possession; the larger the dot, the higher the stall count. As a reminder, in each of these charts, possessions go from the bottom of the field to the top.

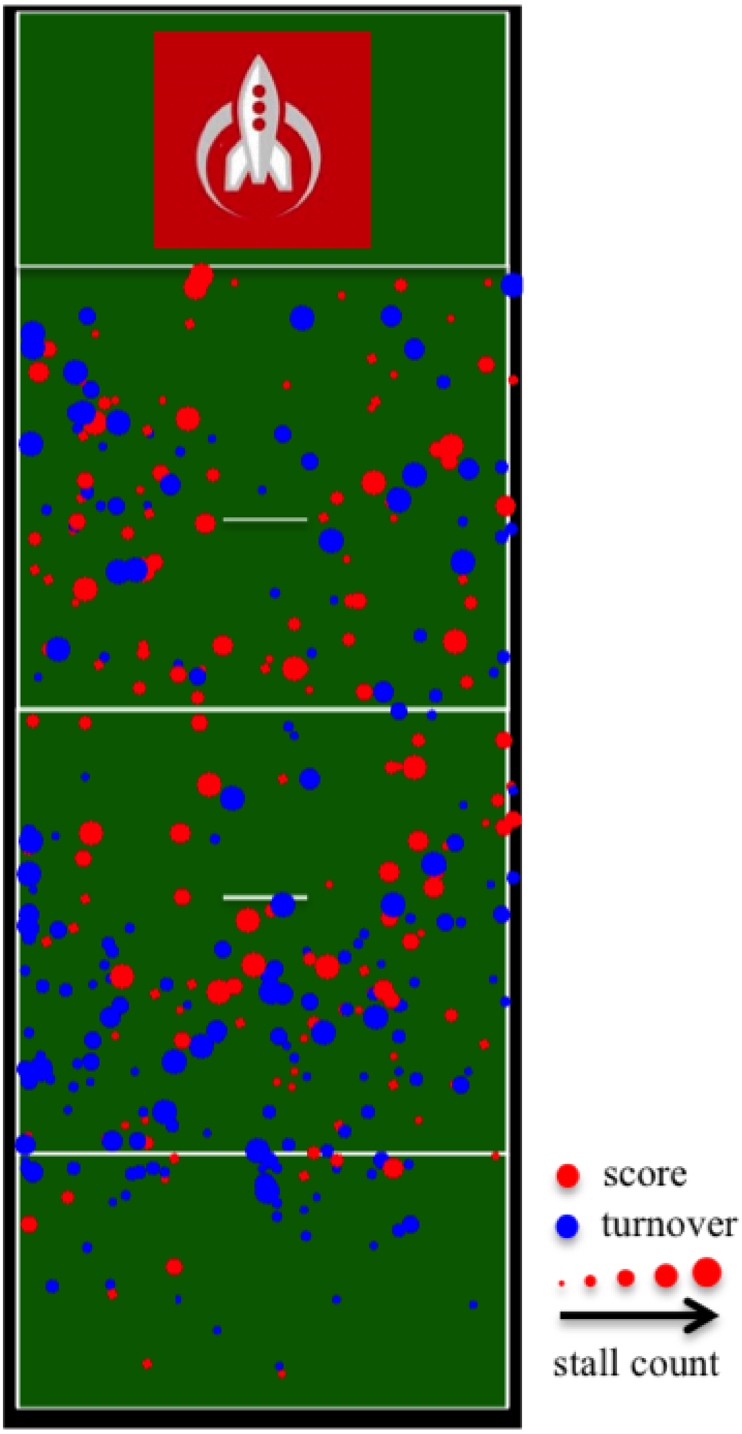

Figure 4.2: Denver Johnny Bravo's pass chart for various stall counts that lead to scores or turnovers.

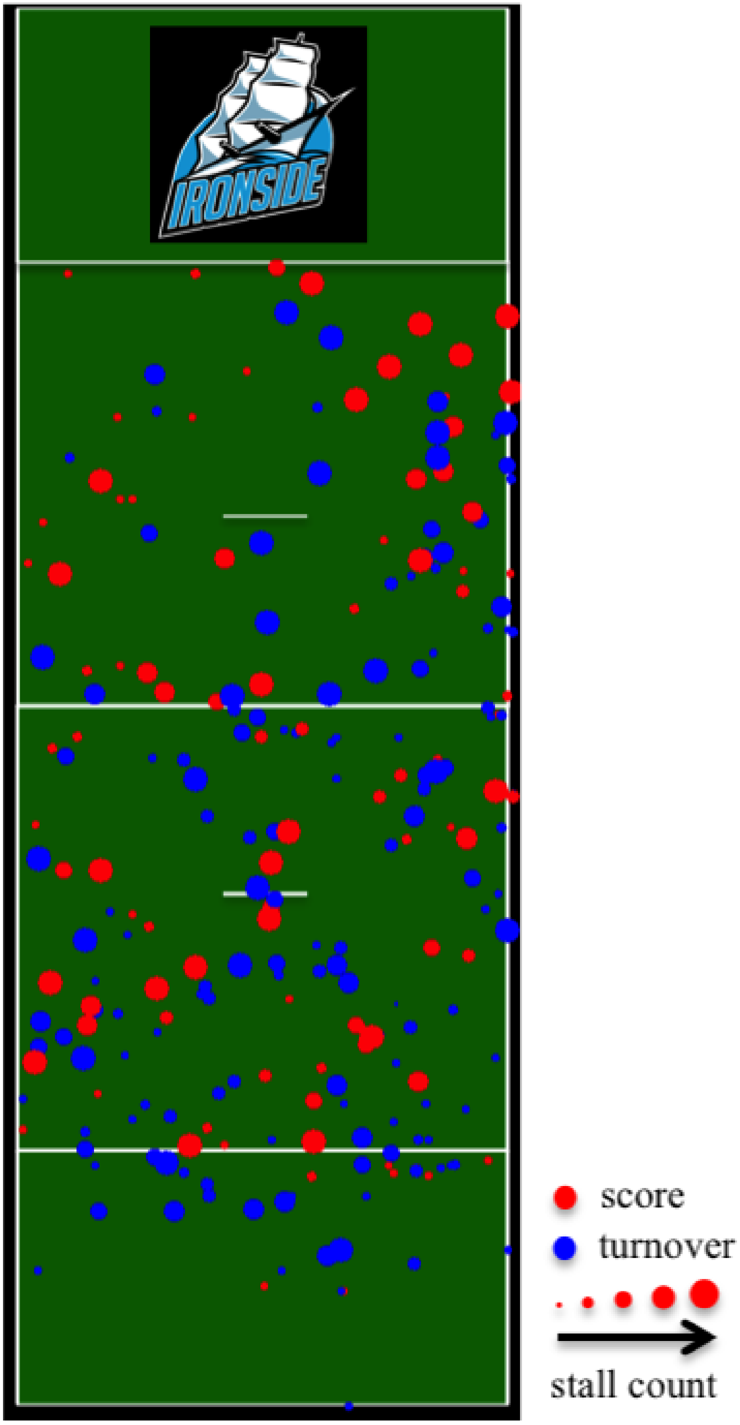

Figure 4.3: Boston Ironside's pass chart for various stall counts that lead to scores or turnovers.

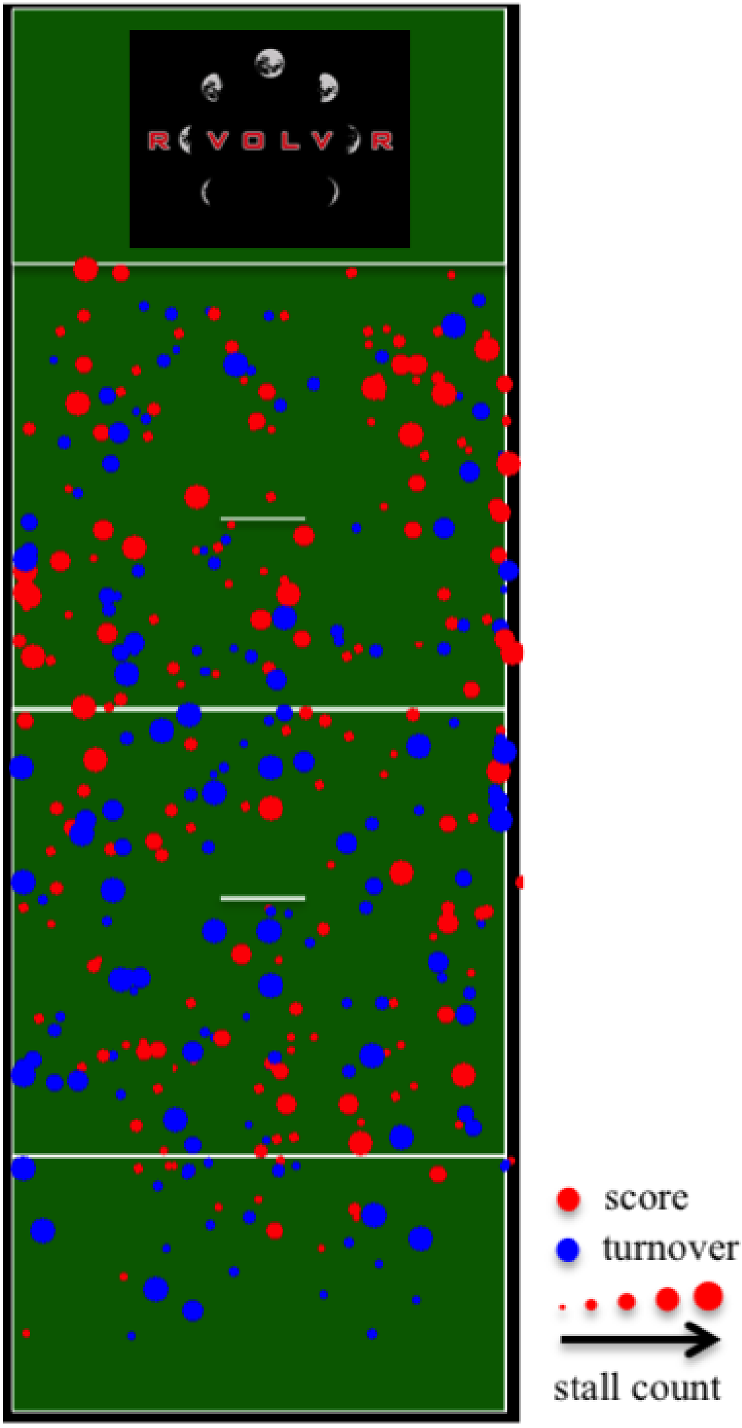

Figure 4.4: San Francisco Revolver's pass chart for various stall counts that lead to scores or turnovers.

From these pass charts, we can make some inferences about the tendencies of each team as well as ultimate more generally. For all three of these teams, we see that there tends to be more red dots in the last 35 yards rather than the first 35 yards. This makes sense that a team would be more likely to score closer to the end zone. On the other hand, it's not immediately obvious—but looks likely—that lateral position tends to make no difference for either scoring or turnover possessions.

Denver Johnny Bravo tends to have larger dots from 20-25 yards out. We suspect that this is because they tend to hold the disc longer to look for the best possible throw. One difference between the last 35 yards and the first 35 yards is the lack of throws in the middle of the field in the last 35 yards. Perhaps, Johnny Bravo dump-swings the disc from side to side looking for a score.

Boston Ironside similarly has larger dots, both red and blue, from about 35 yards out, but also throughout the field. They generally hold the disc for higher stall counts before throwing the disc. Of particular interest to note, there is an asymmetry in Ironside's offense 25 yards from scoring: The majority of the passes are on the right side of the field, showing that they have a tendency to "jam" the disc up the flick sideline. Whether because their offensive system values such gameplay or because defenses are allowing receivers to get open on the flick sideline is unclear. Lastly, Ironside has fewer passes in the last 35 yards compared to the first 35 yards. This is due to perhaps turning the disc over more in the "red zone" as well as being able to score with longer throws.

Most interesting of all may be San Francisco Revolver's pass chart. The sheer quantity of passes is immediately apparent when compared to the other teams. In addition, many of the dots appear on the smaller side. We hypothesize that Revolver employs a quick-attack strategy that emphasizes "entropy" and de-emphasizes yardage. Furthermore, their offense appears to be a similarly bimodal offense as Johnny Bravo's in the red zone, with few passes coming from the middle.

Looking at the numbers to confirm some of these findings, we see that Ironside gains the most yards per throw at 12.1 yards per throw on possessions which score and 11.0 yards per throw on possessions which don't. Johnny Bravo gains 8.5 yards per throw on scoring possessions and 6.9 yards per throw on turnover possessions. Finally, Revolver gains 8.5 yards per throw when scoring and 6.8 yards otherwise. Overall, we see that teams gain fewer yards per throw when they don't score, and Ironside tends to have the offense with the most yards per throw.

4.2 Neyman method of confidence intervals

We run regressions to pinpoint some of the ideas developed from looking at the pass charts. In particular, we first use the idea of causal inference. Causal inference is the study of proving causation instead of just correlation, a common warning in statistics classes. However, with the study of causal inference, we can draw more profound implications than we could otherwise. For causal inference, we set up an experiment where one group receives treatment and the other does not. Looking at the difference in their results allows us to conclude whether treatment is effective.

If we let Y represent the response variable that we're measuring, s be the standard deviation, n be the sample size, subscript t representing the treatment group and subscript c representing the control group, and τ representing the treatment effect (difference in response variable between treatment and control groups) within the population. Using the Neyman method, we know that $\hat{\tau} = \bar{Y}_t - \bar{Y}_c$. We can find the variance of $\hat{\tau}$: $\hat{\mathbb{V}}(\hat{\tau}) = \frac{s_t^2}{n_t} + \frac{s_c^2}{n_c}$ Therefore, a 95% confidence interval for the estimate of τ is

$$\left(\hat{\tau} - 1.96\sqrt{\hat{\mathbb{V}}(\hat{\tau})}, \hat{\tau} + 1.96\sqrt{\hat{\mathbb{V}}(\hat{\tau})}\right)$$

We apply Neyman's method to multiple variables across the three teams as well as to all of the data. Though not this study doesn't constitute an experiment, we take treatment as whether the possession scores (treatment group) or not (control group) and proceed cautiously interpreting the results. In particular, we look at the variables *vertical_distance*, *swing_distance*, *seconds*, *pass_count*, *is_dump*, and *side*.

We see that, of the 18 team-based confidence intervals, 4 are significant. Of the 6 confidence intervals from all of the data, 2 are significant. Interestingly, those two variables

Table 4.1: 95% confidence intervals for τ of *vertical_distance*, *swing_distance*, and *seconds*.

Team	*vertical_distance*	*swing_distance*	*seconds*
Johnny Bravo	(-1.416, 4.529)	(-1.793, 0.690)	(-0.625, 0.127)
Ironside	(-3.214, 4.763)	(-2.313, 0.961)	(-0.324, 0.831)
Revolver	(-1.636, 4.717)	(-1.985, 0.368)	(-0.924, -0.147)*
All data	(-0.832, 2.948)	(-1.413, 0.091)	(-0.495, -0.005)*

Table 4.2: 95% confidence intervals for τ of *pass_count*, *is_dump*, and *side*.

Team	*pass_count*	*is_dump*	*side*
Johnny Bravo	(-0.420, 1.507)	(-0.194, -0.013)*	(-0.062, 0.258)
Ironside	(0.888, 2.272)*	(-0.077, 0.106)	(-0.286, 0.111)
Revolver	(0.660, 2.032)*	(-0.092, 0.084)	(-0.127, 0.190)
All data	(0.656, 1.634)*	(-0.085, 0.020)	(-0.062, 0.133)

are *seconds* and *pass_count*. Because the confidence interval of *seconds* is on the negative side, we know that teams score on possessions when they hold the disc shorter than the possessions when they don't score. We suspect that moving the disc more quickly creates more "entropy" and leads to a better chance of scoring. For *pass_count*, the confidence interval is on the positive side, meaning that teams throw more passes on possessions that score than possessions that don't score. This result agrees with that of *seconds*. There is likely a positive correlation between holding the disc less and throwing more passes. Taking these two results together, we hypothesize that an offense is most effective when moving the disc as quickly as possible.

Finally, the only other variable that yielded a significant confidence interval was Johnny Bravo's *is_dump*. Because this is negative, we conclude that Bravo does not dump and reset the disc as often on possessions that score versus those that don't. This is an interesting conclusion, as it clashes with conventional ultimate wisdom. Perhaps, with the athletic talent that Bravo had in the 2014 club season, they simply didn't need to play a "safe" offense: When they attacked downfield, they were more likely to score; when they became complement at cutting downfield and instead dumped and swung the disc more, they were less likely to score.

4.3 Logistic regressions

We run logistic regressions on several data subsets: all data, individual teams, and several different definitions of what constitutes the "red zone." [1] The formula below provides our relevant regression; we test the variables already discussed as well as some new interaction variables. Table 3 depicts the logistic regression results for all data, Tables 4-6 for individual teams, and Tables 7-9 for different definitions of the red zone.

$$\begin{aligned}\log\left(\frac{p}{1-p}\right) = {} & \beta_1 \cdot seconds + \beta_2 \cdot x + \beta_3 \cdot y + \beta_4 \cdot vertical\_distance + \beta_5 \cdot swing\_distance \\ & + \beta_6 \cdot is\_dump + \beta_7 \cdot pass\_count + \beta_8 \cdot side * vertical\_distance \\ & + \beta_9 \cdot is\_dump * swing\_distance + \beta_{10} \cdot is\_dump * pass\_count + \beta_0\end{aligned}$$

Table 4.3: Logistic regression results on scoring probability for all data

Variable	**Coefficient**	**(Std. Err.)**
seconds	-0.096**	(0.036)
x	0.005	(0.006)
y	0.019***	(0.004)
vertical_distance	0.005	(0.005)
swing_distance	-0.003	(0.013)
side	0.010	(0.105)
0b.is_dump	0.000	(0.000)
1.is_dump	0.498	(0.362)
pass_count	0.056*	(0.023)
c.side#c.vertical_distance	0.006	(0.006)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.041	(0.028)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.077	(0.042)
Intercept	-0.480*	(0.210)

*p<0.05; **p<0.01; ***p<0.001

[1] Unlike football which defines the red zone offense as 20 yards out from the end zone, there is no clearly defined red zone for ultimate. Here, we look at three different definitions: 25 yards out, 20 yards out, and 15 yards out.

Table 4.4: Logistic regression results on scoring probability for Denver Johnny Bravo

Variable	Coefficient	(Std. Err.)
seconds	-0.088	(0.065)
x	0.015	(0.010)
y	0.031***	(0.006)
vertical_distance	0.007	(0.010)
swing_distance	0.001	(0.022)
side	0.042	(0.171)
0b.is_dump	0.000	(0.000)
1.is_dump	0.415	(0.581)
pass_count	-0.003	(0.031)
c.side#c.vertical_distance	0.021	(0.012)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.056	(0.045)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.100	(0.057)
Intercept	-0.598	(0.346)

*p<0.05; **p<0.01; ***p<0.001

Table 4.5: Logistic regression results on scoring probability for Boston Ironside

Variable	Coefficient	(Std. Err.)
seconds	-0.039	(0.070)
x	-0.014	(0.013)
y	0.011	(0.008)
vertical_distance	0.008	(0.010)
swing_distance	-0.012	(0.024)
side	-0.166	(0.243)
0b.is_dump	0.000	(0.000)
1.is_dump	-0.572	(0.998)
pass_count	0.203**	(0.073)
c.side#c.vertical_distance	0.007	(0.013)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.052	(0.077)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	0.306	(0.245)
Intercept	-1.003*	(0.414)

*p<0.05; **p<0.01; ***p<0.001

Table 4.6: Logistic regression results on scoring probability for San Francisco Revolver

Variable	Coefficient	(Std. Err.)
seconds	-0.197**	(0.066)
x	0.010	(0.010)
y	0.006	(0.006)
vertical_distance	0.002	(0.009)
swing_distance	-0.020	(0.023)
side	0.139	(0.180)
0b.is_dump	0.000	(0.000)
1.is_dump	0.324	(0.649)
pass_count	0.089*	(0.045)
c.side#c.vertical_distance	-0.007	(0.009)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.040	(0.048)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	0.061	(0.097)
Intercept	0.403	(0.388)

*p<0.05; **p<0.01; ***p<0.001

Table 4.7: Logistic regression results on scoring probability for red zone 25 yards out

Variable	Coefficient	(Std. Err.)
seconds	-0.134*	(0.067)
x	0.014	(0.011)
y	0.024	(0.020)
vertical_distance	0.013	(0.022)
swing_distance	-0.019	(0.028)
side	-0.203	(0.200)
0b.is_dump	0.000	(0.000)
1.is_dump	0.461	(0.757)
pass_count	0.076*	(0.038)
c.side#c.vertical_distance	0.050*	(0.020)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.054	(0.053)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.076	(0.066)
Intercept	-0.689	(1.297)

*p<0.05; **p<0.01; ***p<0.001

Table 4.8: Logistic regression results on scoring probability for red zone 20 yards out

Variable	Coefficient	(Std. Err.)
seconds	-0.143	(0.080)
x	0.030*	(0.014)
y	0.037	(0.031)
vertical_distance	-0.005	(0.031)
swing_distance	-0.018	(0.034)
side	-0.074	(0.224)
0b.is_dump	0.000	(0.000)
1.is_dump	0.625	(0.934)
pass_count	0.083	(0.044)
c.side#c.vertical_distance	0.063**	(0.025)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.066	(0.066)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.116	(0.077)
Intercept	-1.379	(2.048)

*p<0.05; **p<0.01; ***p<0.001

Table 4.9: Logistic regression results on scoring probability for red zone 15 yards out

Variable	Coefficient	(Std. Err.)
seconds	-0.137	(0.095)
x	0.042*	(0.018)
y	0.095	(0.054)
vertical_distance	-0.016	(0.038)
swing_distance	0.006	(0.059)
side	0.030	(0.269)
0b.is_dump	0.000	(0.000)
1.is_dump	0.092	(1.154)
pass_count	0.102	(0.054)
c.side#c.vertical_distance	0.071*	(0.030)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	-0.122	(0.106)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.075	(0.094)
Intercept	-5.061	(3.606)

*p<0.05; **p<0.01; ***p<0.001

We run a few more regressions, this time a linear model, on y for all data and the three teams and their first 50 yards—the non-red zone.

$$
\begin{aligned}
y = {} & \beta_1 \cdot seconds + \beta_2 \cdot x + \beta_3 \cdot swing\_distance + \beta_4 \cdot side \\
& + \beta_5 \cdot is\_dump + \beta_6 \cdot pass\_count + \beta_7 \cdot is\_dump * swing\_distance \\
& + \beta_8 \cdot is\_dump * pass\_count + \beta_0
\end{aligned}
$$

Table 4.10: Linear regression results on y for all data and first 50 yards

Variable	**Coefficient**	**(Std. Err.)**
seconds	0.886**	(0.292)
x	0.123**	(0.048)
swing_distance	-0.073	(0.101)
side	-0.746	(0.709)
0b.is_dump	0.000	(0.000)
1.is_dump	2.353	(2.855)
pass_count	2.167***	(0.189)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	0.361	(0.221)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.525	(0.405)
Intercept	10.091***	(1.452)

*p<0.05; **p<0.01; ***p<0.001

Table 4.11: Linear regression results on y for Denver Johnny Bravo and first 50 yards

Variable	**Coefficient**	**(Std. Err.)**
seconds	1.103*	(0.495)
x	0.143	(0.075)
swing_distance	0.151	(0.160)
side	-1.110	(1.102)
0b.is_dump	0.000	(0.000)
1.is_dump	3.046	(4.118)
pass_count	1.475***	(0.244)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	0.282	(0.324)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	-0.392	(0.490)
Intercept	6.620**	(2.260)

*p<0.05; **p<0.01; ***p<0.001

Table 4.12: Linear regression results on y for Boston Ironside and first 50 yards

Variable	Coefficient	(Std. Err.)
seconds	0.338	(0.492)
x	0.361***	(0.090)
swing_distance	-0.112	(0.171)
side	-1.616	(1.294)
0b.is_dump	0.000	(0.000)
1.is_dump	2.148	(6.175)
pass_count	4.168***	(0.504)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	0.222	(0.481)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	0.208	(1.433)
Intercept	8.869***	(2.517)

*p<0.05; **p<0.01; ***p<0.001

Table 4.13: Linear regression results on y for San Francisco Revolver and first 50 yards

Variable	Coefficient	(Std. Err.)
seconds	0.791	(0.503)
x	-0.064	(0.079)
swing_distance	-0.042	(0.181)
side	0.404	(1.194)
0b.is_dump	0.000	(0.000)
1.is_dump	1.419	(5.080)
pass_count	3.147***	(0.355)
0b.is_dump#co.swing_distance	0.000	(0.000)
1.is_dump#c.swing_distance	0.089	(0.372)
0b.is_dump#co.pass_count	0.000	(0.000)
1.is_dump#c.pass_count	0.328	(0.837)
Intercept	9.043***	(2.760)

*p<0.05; **p<0.01; ***p<0.001

Chapter 5

Conclusions

5.1 Regression interpretations

For the aggregate data, we saw that the variables *seconds*, y, and *pass_count* have statistically significant coefficients: The first has a negative coefficient and the latter two a positive coefficient. These results make sense with conventional ultimate wisdom. Holding the disc longer results in a likelier chance of a turnover, usually indicative of either 1) weak downfield cutting that's tightly defended or 2) a rising stall count that forces a bad decision. From the three pass charts, we saw more red dots downfield, and this is confirmed by the positive coefficient of y. The positive coefficient of *pass_count* can be explained by a similar idea to the negative coefficient of *seconds*: Increasing the pass count keeps the defense on its heels and increases entropy. Finally, each team has its own significant variables. Johnny Bravo relies on its vertical position to score, likely indicative of their strong athletic talent. Ironside's only variable that significantly correlates with probability of scoring is its pass count. Perhaps, this is why their offense cannot get over the hump to win a national championship. [1] Revolver uses a combination of quick movement and many throws to increase its probability of scoring.

We also looked at red zone offense. For a red zone defined as 25 yards out, the

[1] http://ultiworld.com/2015/01/07/expanding-ironside-offense-video-breakdown-powered-agility-five-ultimate/

significant variables include *seconds*, *pass_count*, and the interaction variable $side * vertical\_distance$. Perhaps 25 yards is too large of a red zone, as it still includes the variables *seconds* and *pass_count*. When we look at a red zone defined as 20 yards out and 15 yards out, we have significant variables x and the interaction variable $side * vertical\_distance$. No longer does quick movement matter: Now, we prioritize the point of attack, as evidenced by the variables x and $side * vertical\_distance$. In fact, both variables have positive coefficients for both 20 yards and 15 yards out. Because of the possible values these variables can take on, this means that the probability of scoring is expected to increase with throws from the right half of the field and open side throws.

We now know that increasing vertical position y leads to an increase in scoring probability. But how do we increase y? It makes sense to examine the relationship between y and the other variables. We regress on data within the first 50 yards, the non-red zone. The variables that were significant were *seconds*, x, and *pass_count*. The positive coefficient on *pass_count* agrees with our results from the logistic regressions. Also, x has a positive coefficient, corroborating the idea that the flick side tends to be used more. Though it is important to note that this is mostly due to Ironside, as seen in their regression on y and also previously in their pass charts. Finally, *seconds* has a positive coefficient, which is not entirely in line with the results from the logistic regressions. The logistic regressions showed that, holding all other variables constant, holding the disc for fewer seconds leads to a higher probability of scoring as well as, holding all other variables constant, increasing vertical position y. However, the linear regressions on y seem to demonstrate a contradiction: Holding the disc for longer leads to an increase in y. It is not entirely clear what mechanism exists to explain why *seconds* has a negative relationship with probability of scoring and y has a positive relationship with probability of scoring while *seconds* has a positive relationship with y. Important to note is that the significance of the *seconds* coefficient is seemingly largely due to Johnny Bravo's data, which may be more skewed from "normal" team offenses because of their sheer collection of talent.

5.2 Implications

Overall, the implications from these results are that teams should prioritize attacking downfield quickly and with multiple throws to gain yards until they are in the red zone—about 20 yards out— in order to maximize their chances at scoring. Teams can use any effective offense to move downfield. Sockeye famously employs a "small ball" tactic which relies heavily on quick throws and smart handlers. [2] Revolver spaces well in order to create isolation cuts for their best players. [3] Ironside famously uses a no-dump vertical stack most of the time [4] and also strongly emphasizes possession and grinding for under cuts rather than throwing hucks. [5] (One of Ironside's main handler's commented on this when he joined the team a few years ago. [6]) Finally, Johnny Bravo may have simply just had too much talent to employ an offensive system that does anything other than one that moves downfield quickly because their athletes are faster and stronger.

When teams are in the red zone, they should prioritize swinging the disc back and forth until the right throw opens up. Here, teams' offenses should adjust to a different system other than the ones mentioned above.

5.3 Proposal of new end zone offensive sets

We propose an unconventional offense that teams should employ in order to score in the red zone. Most of these elite teams default to a vertical stack in the end zone; we think that this forces too many players in too little of a space, counter to the main principle of offense. In the figures below, we observe two potential new offense sets in the red zone–think of these as miniature horizontal stacks.

[2] http://skydmagazine.com/2012/09/tuesday-morning-standler-small-ball-sockeye/

[3] http://ultiworld.com/2014/07/23/new-fundamental-revolvers-isolation-cutting-presented-agility-five-ultimate/

[4] http://ultiworld.com/2014/08/12/breaking-dump-vertical-stack-powered-agility-five-ultimate/

[5] http://skydmagazine.com/2012/10/down-with-the-ship/

[6] http://dopacetic.blogspot.com/2012/02/diva-dilemma.html

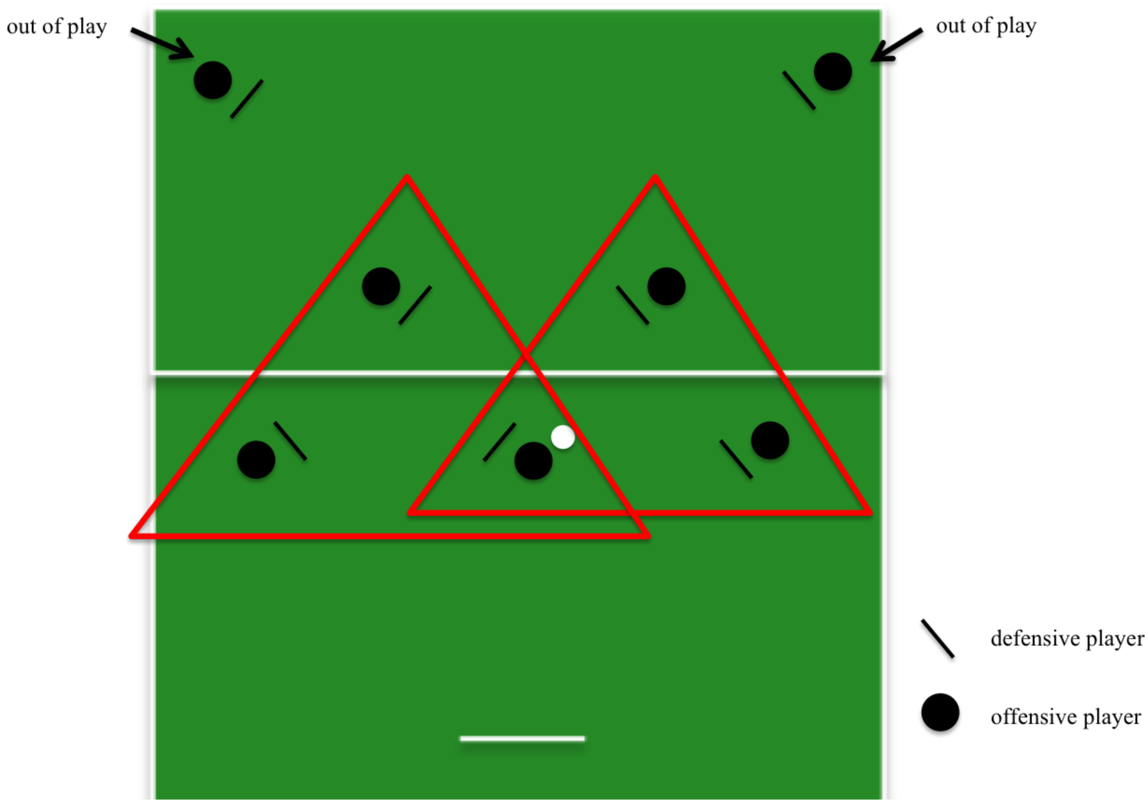

Figure 5.1: New end zone offense: Two handlers, one cutter.

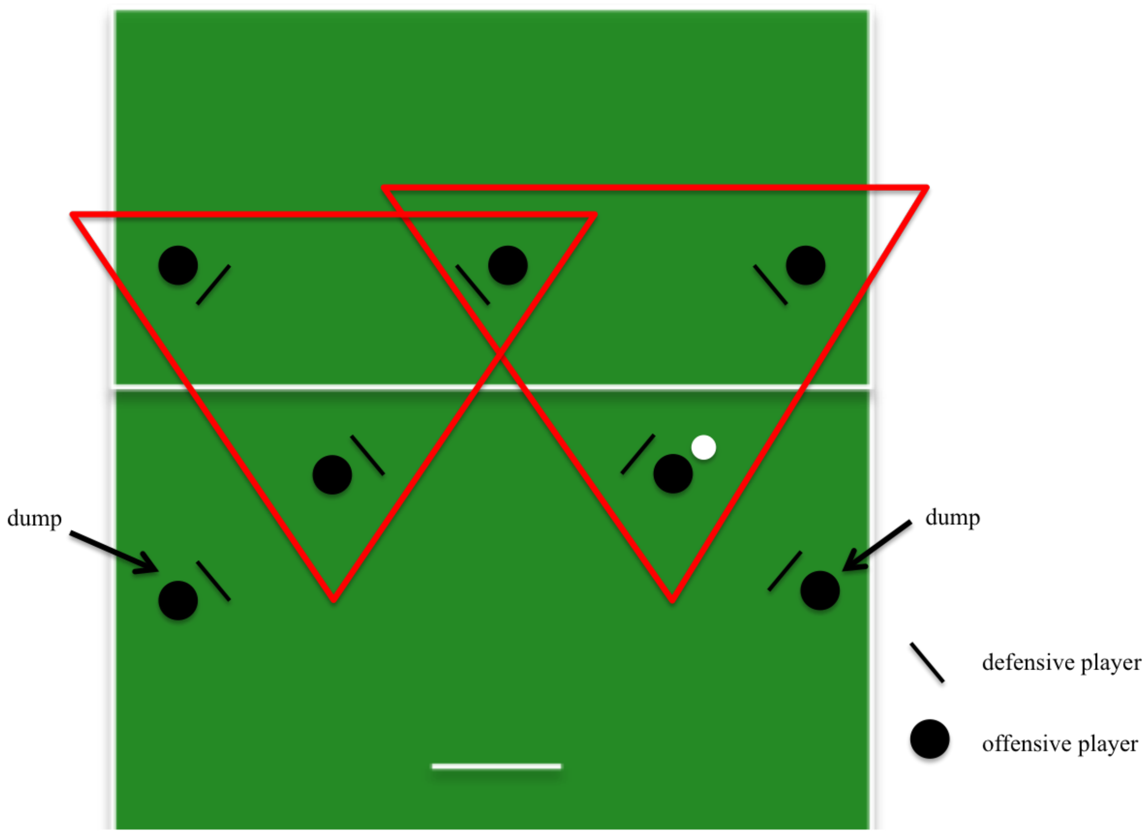

Figure 5.2: New end zone offense: One handler, two cutters.

Both end zone offenses are motivated by two principles: maximizing space while maintaining the ability to change the point of attack (allowing the disc to swing laterally). These offenses are created by taking two of the seven offensive players out of play and allowing five players to run the offense. (Fewer players gives an advantage to the offense. Imagine the opposite, extreme scenario where teams play 100 players on offense and 100 players on defense. The disc would never be able to advance downfield.)

In the first end zone set, the two players stand in the back of the end zone, where they are threats to score, albeit, minimally. In the second end zone set, the two players sit wide behind the handlers on "rails" acting as dumps. These two placements—the back of the end zone and the rail dumps—are not distinct to either end zone set; we could have easily switched them around. The five other offensive players are the intriguing part of the end zone offense: Both sets rest on the principle of three players working the disc. The first end zone set sees two handlers and one cutter, and the second set sees one handler and two cutters. Depending on the strengths of the offensive team and the individual match ups on defense, teams should adapt one of these two end zone sets in order to maximize their chance of scoring.

An interesting lack of a finding is that the break side is not as valuable as previously thought in attacking downfield. It may be that athletes at this elite level are fast enough that "being on the wrong side" of their offensive player isn't as much a disadvantage as it is at lower levels of play.

A related point to this is handlers throwing to the break side. One thing to note is that the entirety of this paper assumes a man defense. (As mentioned before, this is because elite ultimate offenses attack zones with ease.) Given the concept of a mark, one would think that throwing to the break side is more difficult than throwing to the open side. However, a quick look at the data demonstrates that the number of throws to the open side to be roughly equivalent to the number of throws to the break side. The implications of this are that perhaps the mark is not as valuable as theoretically thought. Teams on defense could consider moving the defensive player on the mark downfield to defend the cutters 7-on-6, a defense perhaps even stronger than strict man defense.

5.4 Limitations

The limitations of this study mostly exist because of the data collected. The limited number of games may provide a biased view of these analytics. There may be specific team trends in these games that are less indicative of their normal offensive systems.

Furthermore, ultimate is an outdoor sport, and among many of the environmental conditions imposed on the gameplay, wind is by far the most significant factor. The data didn't account for the direction nor strength of the wind, as this is not readily apparent from game film. Further work would account for the important variable of wind.

5.5 Future work

The work presented here focused on three elite club men's teams: Denver Johnny Bravo, Boston Ironside, and San Francisco Revolver. Future work could examine other teams and perhaps expand into the women's and mixed divisions.

Furthermore, the analytics here addressed team on-disc offense and spacing. We could use the data to improve individual player statistics, furthering the work of Childers, Weiss, and Carneige (2013). Additionally, while on-disc offense is important, off-disc offense may be even more important. The videos used could not capture all 14 players on the field, and thus off-disc offense data could not be collected. However, future work could hopefully account for all of the players on offense, in the spirit of Cervone, D'Amour, Bornn, and Goldsberry (2014).

One other possibility would be to test the proposed end zone sets presented in this paper. Ideally, teams could adopt the red zone offenses suggested above, leading to similar work presented in this paper in order to analyze the efficacy of such systems.

Finally, another direction for later work could spotlight defensive analytics, which "continue to remain almost entirely overlooked" (Franks, Miller, Bornn, & Goldsberry, 2015).

Overall, the work in this paper attempts to push the sport of ultimate in a different direction and hopefully illuminates a new perspective for elite teams on running a successful offense. These results are just a small piece of the larger picture that is the exciting analytics revolution. Though more work certainly remains to be done, we are confident that our method, when combined with conventional ultimate wisdom, provides a strong attempt at streamlining offenses to be more efficient at scoring.

Appendix A

MATLAB Code

See below for the MATLAB script that helped record the (x, y) coordinates of passes.

```
%% cordinates.m
% convert mouse clicking to (x, y) coordinates
clear all
close all
clc
%% import image
imshow('field_with_circle.png')
%% track coordinates
[x, y] = ginput
```

See below for the MATLAB programs that created pass charts.

```
function [x1,y1] = importfile(filename, startRow, endRow)
%IMPORTFILE Import numeric data from a text file as column vectors.
%   [X1,Y1] = IMPORTFILE(FILENAME) Reads data from text file FILENAME for
%   the default selection.
%
%   [X1,Y1] = IMPORTFILE(FILENAME, STARTROW, ENDROW) Reads data from rows
%   STARTROW through ENDROW of text file FILENAME.
%
% Example:
```

```
%   [x1,y1] = importfile('no_sevens.csv',2, 20);
%
%    See also TEXTSCAN.

% Auto-generated by MATLAB on 2015/03/29 21:57:01

%% Initialize variables.
delimiter = ',';
if nargin<=2
    startRow = 2;
    endRow = 20;
end

%% Format string for each line of text:
%   column10: double (%f)
%   column11: double (%f)
% For more information, see the TEXTSCAN documentation.
formatSpec = '%*s%*s%*s%*s%*s%*s%*s%*s%*s%f%f%*s%*s%*s%*s%*s%*s%*s%*s%*s%*s%[^\n\r]';

%% Open the text file.
fileID = fopen(filename,'r');

%% Read columns of data according to format string.
% This call is based on the structure of the file used to generate this
% code. If an error occurs for a different file, try regenerating the code
% from the Import Tool.
dataArray = textscan(fileID, formatSpec, endRow(1)-startRow(1)+1, 'Delimiter',...
    delimiter, 'HeaderLines', startRow(1)-1, 'ReturnOnError', false);
for block=2:length(startRow)
    frewind(fileID);
    dataArrayBlock = textscan(fileID, formatSpec, endRow(block)-startRow(block)+1,...
        'Delimiter', delimiter, 'HeaderLines', startRow(block)-1,...
        'ReturnOnError', false);
    for col=1:length(dataArray)
        dataArray{col} = [dataArray{col};dataArrayBlock{col}];
```

```
    end
end

%% Close the text file.
fclose(fileID);

%% Post processing for unimportable data.
% No unimportable data rules were applied during the import, so no post
% processing code is included. To generate code which works for
% unimportable data, select unimportable cells in a file and regenerate the
% script.

%% Allocate imported array to column variable names
x1 = dataArray{:, 1};
y1 = dataArray{:, 2};



%% fields.m
% create pass charts
close all
clear all
clc
%% Plot
% replace with an image of your choice
img = imread('field.png');

% set the range of the axes
% The image will be stretched to this.
min_x = -20;
max_x = 20;
min_y = -20;
max_y = 90;

% Flip the image upside down before showing it
imagesc([min_x max_x], [min_y max_y], flipud(img));
```

```
[x0yes,y0yes] = importfile('score_0.csv', 2, 999);
[x0no,y0no] = importfile('no_score_0.csv', 2, 999);

[x1yes,y1yes] = importfile('score_1.csv', 2, 999);
[x1no,y1no] = importfile('no_score_1.csv', 2, 999);

[x2yes,y2yes] = importfile('score_2.csv', 2, 999);
[x2no,y2no] = importfile('no_score_2.csv', 2, 999);

[x3yes,y3yes] = importfile('score_3.csv', 2, 999);
[x3no,y3no] = importfile('no_score_3.csv', 2, 999);

[x4yes,y4yes] = importfile('score_4.csv', 2, 999);
[x4no,y4no] = importfile('no_score_4.csv', 2, 999);

[x5yes,y5yes] = importfile('score_5.csv', 2, 999);
[x5no,y5no] = importfile('no_score_5.csv', 2, 999);

[x6yes,y6yes] = importfile('score_6.csv', 2, 999);
[x6no,y6no] = importfile('no_score_6.csv', 2, 999);

hold on;
axis off
plot(x0yes, y0yes, 'r.', 'markersize', 3);
plot(x0no, y0no, 'b.', 'markersize', 3);

plot(x1yes, y1yes, 'r.', 'markersize', 6);
plot(x1no, y1no, 'b.', 'markersize', 6);

plot(x2yes, y2yes, 'r.', 'markersize', 9);
plot(x2no, y2no, 'b.', 'markersize', 9);

plot(x3yes, y3yes, 'r.', 'markersize', 12);
plot(x3no, y3no, 'b.', 'markersize', 12);
```

```
plot(x4yes, y4yes, 'r.', 'markersize', 15);
plot(x4no, y4no, 'b.', 'markersize', 15);

plot(x5yes, y5yes, 'r.', 'markersize', 18);
plot(x5no, y5no, 'b.', 'markersize', 18);

plot(x6yes, y6yes, 'r.', 'markersize', 21);
plot(x6no, y6no, 'b.', 'markersize', 21);

% set the y-axis back to normal.
set(gca, 'ydir', 'normal');

axis equal tight

saveas(gcf,'pass_chart_revolver.png')
```

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