Analyzing Cornhole Success:

Toss Ability and

Board Management

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1. INTRODUCTION

Our group analyzed the sport cornhole, specifically, games from the 2021 American Cornhole League World Championship. Cornhole is a traditional American lawn game where players (or teams) take turns tossing bean bags into an angled wooden board with a hole placed in the center, nine inches from the top of the board. Players receive four throws per round and alternate in their tosses. Three points are rewarded if the bag goes through the hole; one point is rewarded if the bag finishes on the board; zero points are awarded if the bag ends entirely off the board. Our purpose in analyzing the 2021 American Cornhole League World Championship is to determine the strategies used by successful cornhole players. We hypothesized that a player's performance in an individual match should be separated into two somewhat independent spheres: raw throwing ability and strategy used to navigate the board. Navigating the board implies the action of blocking the hole or evading blocked holes in general. We hoped to discover the best combination of throwing ability and board management to determine which plays a greater role in winning a cornhole match. To investigate this, we recorded 21 different numerical and categorical variables.

Table 1 (Data Snapshot)

Player 1	Player 2	Thrower	Match	Round	Bag #	Throw #	Player 1 Round Score	Player 2 Round Score	Player 1 Match Score	Player 2 Match Score	On Board
Erick Davis	Ryan Windsor	Ryan Windsor	6	8	1	1	0	3	5	4	0
Erick Davis	Ryan Windsor	Erick Davis	6	8	1	2	1	3	5	4	1
Erick Davis	Ryan Windsor	Ryan Windsor	6	8	2	3	1	4	5	4	1
Erick Davis	Ryan Windsor	Erick Davis	6	8	2	4	2	4	5	4	1
Erick Davis	Ryan Windsor	Ryan Windsor	6	8	3	5	2	5	5	4	1

Player 1	Player 2	Thrower	In Hole	Missed Board	Own Bag Dragged In	Opponent Bag Dragged In	Own Bag Knocked Off	Opponent Bag Knocked Off	Hole Blocked	Hole Blocked Before Shot	Block Created
Erick Davis	Ryan Windsor	Ryan Windsor	1	0	0	0	0	0	0	0	0
Erick Davis	Ryan Windsor	Erick Davis	0	0	0	0	0	0	0	0	0
Erick Davis	Ryan Windsor	Ryan Windsor	0	0	0	0	0	0	1	0	1
Erick Davis	Ryan Windsor	Erick Davis	0	0	0	0	0	0	1	1	0
Erick Davis	Ryan Windsor	Ryan Windsor	0	0	0	0	0	0	1	1	0

We gathered data during the early weeks of February 2023, retrieving it from a YouTube live stream uploaded by DraftKings broadcasting the 2021 American Cornhole League World Championship. As a group, we watched the first match together to create a foundation of standardization and understanding of how to assign values to each variable when watching our own. Afterwards, each member was assigned a match (or matches) to watch and record data from. We recorded our data in a shared Google Sheets file. Each observation represents a single throw of a round. In total, nine matches were watched, with 14 rounds being the shortest game, and 26 rounds being the longest game. Altogether, we collected 1,432 unique observations. Our variables are *Player 1 Round Score, Player 2 Round Score, Player 1 Game Score, Player 2 Game Score, On Board, In Hole, Missed Board, Own Bags Dragged In, Opponent Bags Dragged In, Own Bags Knocked Off, Opponent Bags Knocked Off, Hole Blocked After Throw, Hole Blocked Before Throw, and Block Created*. The two variables, *Player 1 Round Score* and *Player 2 Round Score*, were used to track the cumulative score for the round of each player as a result of each individual toss. The next two variables, *Player 1 Game Score* and *Player 2 Game Score*, were used to track the cumulative game score as it stood when that particular round started. *On Board*, *In Hole*, and *Missed Board* were binary variables that served as the result of the individual bag that was thrown. Therefore, each observation received a "0" for the two results it did not exhibit, but a "1" for the result that occurred. The two variables, *Own Bags Dragged In* and *Opponent Bags Dragged In*, represented how many of the thrower's existing bags finished in the hole as a result of the bag they threw and how many of the non-thrower's existing bags finished in the hole as a result of the bag that the thrower tossed. Similarly, the next two variables, *Own Bags Knocked Off* and *Opponent Bags Knocked Off*, measure how many existing bags were knocked off as a result of the throw, and who these bags belonged to. Next, *Hole Blocked After Throw* signifies whether the hole became blocked (or continued to be blocked) after the toss, and *Hole Blocked Before Throw* represents whether the hole was already blocked prior to the toss, both being binary, “0” for no, “1” for yes. Lastly, the variable *Block Created* was used to characterize a scenario where the hole was not blocked prior to the toss but became blocked as a result of the toss.

In addition to recording these various statistics, we also included several organizational variables: *Match,* stating which match of the tournament it was, *Round,* signifying which round of the match the observation occurred, *Bag Number*, explaining which number bag out of four the player was on, *Throw Number*, stating which number throw out of the eight total the round was on, *Player 1*, signifying who we chose as Player 1, *Player 2*, explaining who we chose as Player 2, and finally *Thrower*, the player that tossed the bag. These last seven variables served as a solid reference point, allowing us to attribute all of the previous statistical variables to a particular game, round, or player, granting us greater analytical ability.

2. SUMMARY

The following variables were omitted from the tables below, as they were collected for organizational purposes: *Match*, *Round*, *Bag Number*, *Throw Number*, *Player 1*, *Player 2*, *Thrower*, *Player 1 Round Score*, *Player 2 Round Score*, *Player 1 Game Score*, and *Player 2 Game Score*. All non-whole numbers are rounded to the nearest thousandth.

Table 2 (Numerical Variables)

Statistic	Min	Median	Max	Mean	SD	Total Count
Own Other Bags Dragged In	0	0	2	0.087	0.301	124
Opponent Bags Dragged In	0	0	2	0.103	0.327	156
Own Other Bags Knocked Off	0	0	1	0.002	0.046	3
Opponent Other Bags Knocked Off	0	0	1	0.003	0.053	4

Table 2 visualizes the statistics of the four numerical variables involving bags that existed on the board prior to a toss. The minimum, median, maximum, mean, standard deviation, and total count were determined for each variable to provide further insight. From the table, it can be determined by the mean and count that it was more likely that a thrower would knock their opponent's bag in rather than their own. The measures of spread conclude that through these 1,432 observations, it is more likely that a bag will be dragged in rather than knocked off but even more likely that a toss results in neither of these outcomes.

Table 3 (Categorical Variables)

Statistic	Count	Relative Frequency
On Board	572	0.399
In Hole	803	0.561
Missed Board	55	0.038
Hole Blocked	604	0.422
Hole Blocked Before Shot	549	0.383
Block Created	169	0.188

Table 3 displays the relative frequencies of the six categorical variables that signify the direct result of the bag thrown itself. The total count and the percentage at which they occurred were calculated to better understand the throws themselves. The relative frequency was calculated by dividing the counts of each statistic divided by the total number of throws (1,432).

Figure 1

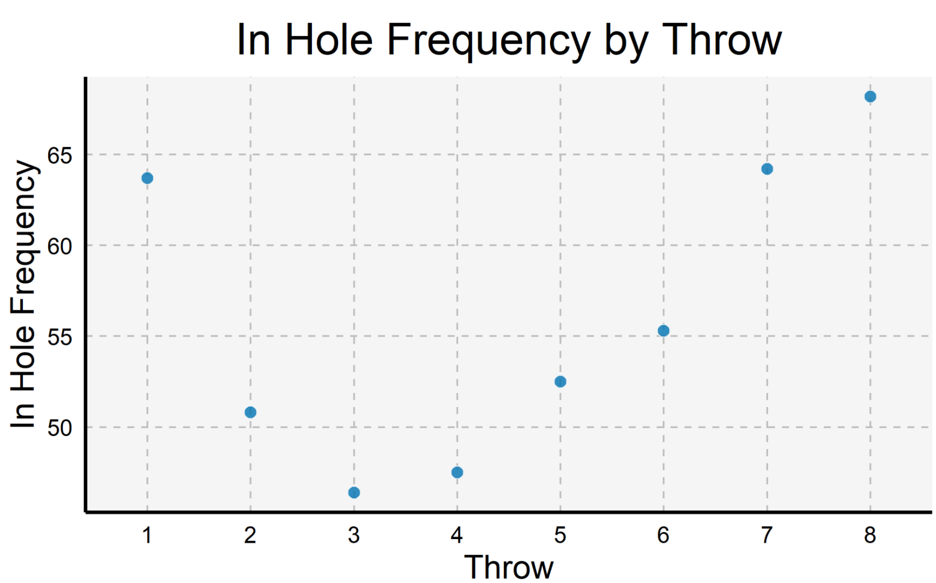
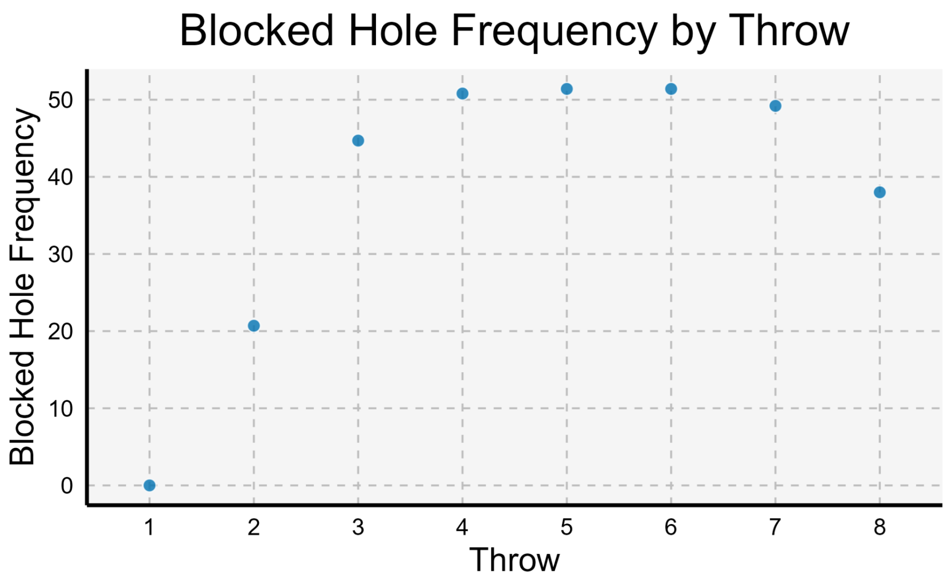


Figure 2



Figures 1 and 2 represent the frequency of throws *In Hole* and *Hole Blocked Before Shot* (*HBBS*), respectively, for each of the eight throws within a round of cornhole. It is worth noting that the first throw shows zero chance of throwing to a blocked hole because the board is clear at the start of a round.

3. INSIGHTS

3.1 Creating Metrics for Analysis

Through our observations, we determined that a match of cornhole can be split into two main aspects: toss ability and board management. To measure these two aspects, we created a set of metrics that capture the key elements of each one. For toss ability, we defined a metric called *Average Toss Score*. For board management, we split it into two parts: impact on the board and blocking ability. Impact on board is defined as how a player plays when there are already blocks on the board, while their blocking ability is defined as how a player uses or does not use blocks to their advantage. Impact on board has two metrics: *Net Board Score* and *Board Impact*. A player's blocking ability also has two metrics: *Blocks Created* and *Net Score After Block*. We then combined these metrics to determine an overall *Board Management Score*, which would then be plotted against the *Average Toss Score*. This would provide us with a comprehensive view of the players' performance and allow us to identify patterns and trends in the winners' play styles.

3.1.1 Tossing Ability

To measure a player's toss ability, we calculated a metric *Average Toss Score* (*ATS*), which uses the number of points a player gained only on their tosses and divides that value by the total number of throws the player had during the game. *Total Bags on Board* and *Total Bags in Hole* are scaled by one and three because those are the associated point values from those cornhole tosses. This metric can be calculated on a round or match level for each player.

$$Total\ Bags\ on\ Board \ = \ Own\ Bags\ on\ Board \ + \ Opponent\ Bags\ on\ Board$$
$$Total\ Bags\ in\ Hole \ = \ Own\ Bags\ in\ Hole \ + \ Opponent\ Bags\ in\ Hole$$
$$Total\ Throws \ = \ 4 \ \times \ \#\ of\ Rounds$$
$$Average\ Toss\ Score\ (ATS) \ = \ \frac{Total\ Bags\ on\ Board + (3 \times Total\ Bags\ in\ Hole)}{Total\ Throws}$$

Average Toss Score provides us insight into how well a player performed solely off their throws. Our players had an *ATS* ranging from 1.42 to 2.50. Since this metric is normalized by the player's total throws, these values can be interpreted as the average number of points a player gained per throw only on the bag that they tossed.

3.1.2 Board Management

To assess a player's board management ability, we first split this broad idea into two subcategories: the player's impact on the board and a player's blocking ability. These are important aspects of a game that determine a player's play style because of the way that bags that land on the board without going in the hole are positioned.

3.1.2.1 Impact on the Board

We needed a way to measure the impact of a player's ability to strategically impact the bags on the board. This led to the creation of *Net Board Score* (*NBS*), using a linear weights system and assigning a value of two when a bag was knocked in and one if a bag was pushed off. A negative weight was attached to events that hurt the thrower, and a positive weight was attached to events that helped the thrower. *NBS* is most useful when calculated at the match level but can still be used at a round level.

$$\begin{gathered} Net\ Board\ Score\ (NBS) \ = \\ (2 \ \times \ Own\ bags\ dragged\ in) \ - \ Own\ bags\ knocked\ off \ - \\ (2 \ \times \ Opponent\ bags\ dragged\ in) \ + \ Opponent\ bags\ knocked\ off \end{gathered}$$

Net Board Score allows us to analyze how well a player was able to manage their bags that were left on the board. However, it should be noted that the score does not fully represent a player's board management ability because if they make all their bags in the hole, their *NBS* would be zero or possibly less if they dragged in an opponent's bag with their own.

We also wanted to evaluate players' ability to move bags around the board, so we created a *Board Impact Percentage* (*BI%*) metric. This metric does not use linear weights and instead sums up the total amount of bags a player dragged in the hole and knocked off the board and then divides that sum by the total number of bags on the board. Like *NBS*, *BI%* is best understood at a match level because of the larger sample size compared to the round level.

$$Total\ Bags\ Dragged\ In\ =\ Own\ Bags\ Dragged\ In\ +\ Opponent\ Bags\ Dragged\ In$$

$$Total\ Bags\ Knocked\ Off\ =\ Own\ Bags\ Knocked\ Off\ +\ Opponent\ Bags\ Knocked\ Off$$

$$Total\ Bags\ on\ Board\ =\ sum(On\ Board)$$

$$Board\ Impact\ (BI\%)\ =\ \frac{Total\ Bags\ Dragged\ In + Total\ Bags\ Knocked\ Off}{Total\ Bags\ on\ the\ Board}$$

Board Impact Percentage allows us to study how aggressive a player plays with how many bags they affect. It can also be used in conjunction with *NBS* to give an idea of how a player received a high *NBS*. Not all equivalent *NBS* values represent the same situation. Did a player reach an *NBS* of +4 by dragging in one of their opponent's bags and three of their own bags, or did they reach the same *NBS* by affecting over a dozen bags in a way that eventually evens out to +4? With *BI,* we add context to *NBS.* We can see that the latter example would have a higher *BI* because they would have affected more bags to reach their +4 *NBS*.

3.1.2.2 Blocking Ability

To determine the impact of blocks, we created a *Net Score After Block* (NSAB) metric, which calculates a player's score after a *Block Created* occurred in the round. Every time a *Block Created* was recorded, we would record the scores for the two players, and then at the end of the round, we would re-record the score and calculate the difference. Therefore, this metric can be positive or negative depending on if they scored after a block or if their opponent did. For our conclusions, we used this metric at the match level derived from the cumulative sum of each round's *NSAB*.

$$Net\ Score\ After\ Block\ (NSAB)\ =\ sum(Score\ After\ a\ Block\ Created\ -\ Score\ Before\ a\ Block\ Created)$$

Net Score After Block allows us to view how well a player can navigate the board once a block is implemented. We can determine what players can perform well with unideal board conditions; Appendix A.1 shows that most winners had a higher *NSAB* than their opponents.

3.1.2.3 Overall Board Management Score

The board impact and blocking represent two aspects of cornhole board management. To combine these aspects, we determined a board management score metric that takes a player's *NSAB* per block they created and added that to their *NBS* per throw.

$$Board\ Management\ Score\ (BMS)\ =\ \frac{NSAB}{BC} + \frac{NBS}{Total\ Throws}$$

Board Management Score (*BMS*) is an important metric for us to determine how well players play with adverse board conditions. Players had a *BMS* ranging from -1.76 to +1.79. Additionally, the *NSAB* and *NBS* are measured in a player's net score, and both are normalized by their respective attempts. The final score can be interpreted as how many points a player gained or lost per throw based on how the board was set up. However, it is not a determining factor in whether a player will win their match because by creating the block, they are losing points for the bag not going in the hole. Therefore, we need to compare this metric against a player's toss ability to help determine a player's performance.

3.2 Results

In Appendix A.1, we can see how the metrics we created manifested across each of our tournament games.

A good match for understanding our metric is the 2nd match in which Jordan Power beat Trey Burchfield by a score of 21 to 10 (Table A.2). Without using sophisticated metrics, we can hazard a good guess at how Power was able win this game: he shot 73.8% of his bags in the hole, the second highest of any player across all of the matches. He did not block as often as Burchfield, and in the rounds where he did block, he lost points (shown by his *NSAB*). This poor block management and poor overall management of the bags on the board (shown by his low *NBS*) led to a fairly low *BMS* of -0.452.

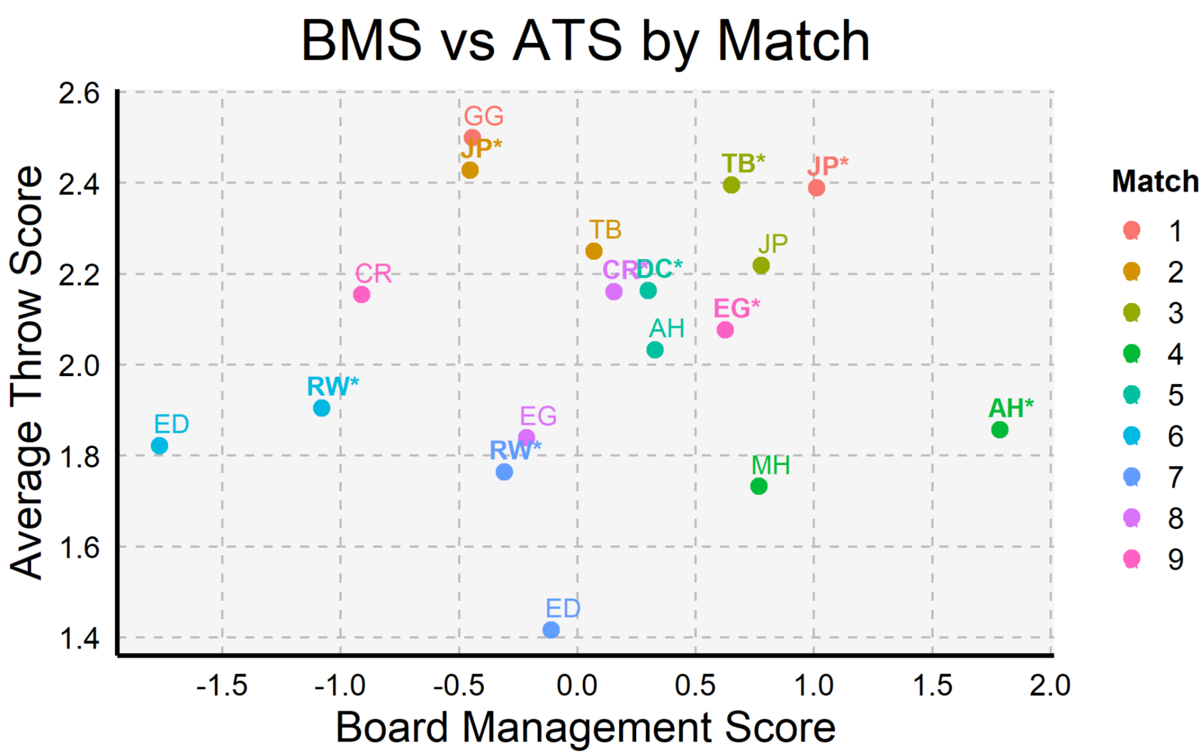
Now let's compare this match to Power's first match against Greg Geary. Power also threw the bag well, but his 2.389 *ATS* would not be enough to win this time as Geary shot an *In Hole Percentage* of 76.5%, leading to an *ATS* of 2.5, 0.011 more than Power's in this game and the highest of the day. Power created seven more blocks than Geary in this match, but it is critical to remember that each of those blocks is a bag on the board and not in the hole. Power essentially put himself down two points every time he blocked. This is why we looked at Power's *Net Score After Block* and saw that in the ten times, he blocked the hole, he beat Geary's score after that block by an average of 0.9 points. This shows that Power recovered about a point back from every time he lost two points by throwing the bag just short of the hole. Power recovered well with his blocks, but did he do enough for the bags he affected in general to overcome Geary's throw accuracy? To answer this, we can look at Power's *Net Board Score* to see how his throws affected the bags placed on the board in terms of salvaging his score or punishing his opponent for leaving a bag on the board. Power beat Geary's *NBS* by +16 in this match, meaning that Geary was often dragging Power's bags into the hole while Power was sweeping in his own bags but leaving Geary's on the board and pushing them off. Combined, Power's high *NBS* and *NSAB* make for a high overall *Board Management Score*, and it's safe to credit Power's eventual win to the resulting net +1.455 *BMS* in favor of Jordan Power.

Table 4 (Winner Statistics)

Result	Tossing Ability				Board Management				
Result	Average Toss Score	In Hole %	On Board %	Missed Board %	Blocks per Throw	NBS per Throw	Board Impact	NSAB per Block	Board Management Score
Loser	1.996	52.8%	41.2%	6.0%	0.125	-0.063	26.5%	-0.104	-0.167
Winner	2.127	57.5%	40.2%	2.1%	0.113	-0.031	25.1%	0.330	0.298

Using the winner's table above, we can see how our metrics differed on average between the winning and losing performances. At least for our sample, the winners tossed it in the hole more than the losers and missed the board about a third as often. As expected, the winners tossed more accurately and accrued more points per toss (*ATS*). In terms of board management, both winners and losers impacted a similar percentage of the bags that sat on the board (as shown by the close Board Impact %), but the winners threw fewer blocks on average, and when they did block, they recovered points much better (shown by the difference in their *NSAB*). All these factors lead to a fairly large gap in the overall *BMS* in favor of the winners. Since both *ATS* and *BMS* are noticeably higher for the winners, it helps to validate our created metrics' ability to evaluate cornhole players and their gameplay.

Figure 3



To better understand the relationship between *ATS* and *BMS*, we plotted them against each other for each of our players' games. In Figure 3, each point represents one player in one of their matches. The winning player has an asterisk next to their initials, and data points are color-coded by matchup. We can see from the plot that many of the players are close to their opponents. In literal terms, the ordinal distance between a player's and their opponent's points is much smaller than the average distance between that player and all the other points. We assert that this pair-wise clumping trend is because one player's throws in a game depend on their opponent's throws. For example, in Match 7, Erick Davis consistently missed the hole. We also know that Davis had a relatively high *Blocks per Throw* in this game from Table A.1. These are very correlated observations, Davis missed his shots, and with those misses, his bags blocked the hole. If Jordan Power had matched up against Davis in this game, it is unlikely that he would have achieved such a high *ATS* or even *BMS* because the cluttered board would lead to fewer points per round. Thus, pairs are clumped together as their different game flows lead to different stat clusterings, and a player's performance depends very directly on their opponent’s performance.

In general, the more successful match performances will be closer to the top right corner of the graph in Figure 3. We see many losing player performances closer to this “ideal” region of the graph than many of the winning performances. For example, Jordan Power from Match 3 is much closer to the top right corner than Ryan Windsor’s winning performances from Match 6 and 7. This may point out a flaw in our metrics' ability to separate winning performances from losing ones. Instead, we would contend that there is no problem that a loser from one game outshines a winner from another in the stats because the only thing that separates a winner from a loser is their performance with respect to their opponent. The only meaningful comparisons to be made with this ordinal map of our data are pairwise comparisons between a player and their opponent. We can see that each pair of points can tell a good story about the game. Every winning player is either considerably higher than their opponent on the BMS axis (like Eddie Grinderslev from Match 9) or the ATS axis (like Ryan Windsor in Match 7) or both (like Cheyenne Renner in Match 8, the largest blowout in the tournament with a final score of 21-1).

3.3 Conclusions

We can draw a few conclusions to answer the questions that fueled this report. First and foremost, a player can win a game with great toss accuracy, and many of our winners outscored their opponents on their *ATS*. That being said, human error exists, and bags will miss the hole and land on the board. So perhaps just as important as a player’s toss accuracy with respect to the points from just that throw is a player’s ability to clean up the bags left near the hole. Examples like the first match between Jordan Power and Greg Geary show that *BMS* can save a player’s game. The pairwise comparison results visualized in Figure 3 validate our invented metrics and help us visualize the statistical framework of a cornhole match. Through our data, we assert that winning at least one of these aspects of a match is necessary to win at cornhole.

3.3.1 Blocking

In addition to our main question of analyzing the two main aspects of a cornhole match, an interesting side question arose regarding the nature of blocking bags. Is it helpful to block the hole? Intuitively, a blocking bag could provide some value in slowing down an opponent who, whether by general ability or in-game form, cannot seem to miss the hole. Once a bag blocks the hole, a round becomes more about strategy and maneuverability than when the board has a clear path to the hole.

Figures 1 and 2 show that blocking is important in affecting the flow of a match.

There is a similar parabola trend in both plots as they show an inverted and somewhat dependent relationship. Throws that miss the hole from the first plot often end up blocking it for the later rounds. Due to these trends, one can view a round of cornhole in two distinct phases, one for the first few throws as most of the blocks are created, and the board is cluttered, and the next in the last half of the round as the board is cleaned, and players scramble to drag their on board bags into the hole. The last throw of the round has the highest In Hole Frequency as players no longer have any incentive to block the hole; their objective is simple: get the most points with this throw.

One important conclusion we drew from these two figures is that players block on purpose. Otherwise, the *In Hole Frequency* would likely be highest in the first round, assuming that it is easiest to get the bag in the hole on a clear board. Even though the hole is blocked at a rate of about 40% on the 8th throw, the *In Hole Frequency* is higher than on the first throw. So with a messy board, players are still getting the bag in the hole at a higher rate. This fact implies a purposeful effort by some players to miss the hole in favor of blocking in the first round.

Since people are blocking on purpose, the question still stands: is it worth it? Based on our data, the most basic answer to this question would be that blocking is a bad strategy because players who created more blocks in our sample often lost their games. In an analysis at the round level, we also saw that players who block the hole end with fewer points than their opponent on average. Simply put, creating a block in a round lowers your chances of winning that round. Yet, using this fact to conclude that blocking is useless would be shortsighted. The observed reduction in win likelihood is not the only way to analyze the strength of a block. As mentioned earlier, a bag blocked is worth fewer points than a bag put in the hole, but a good block, a more obstructive block, will likely end up in the hole eventually. A "good block" could make an opponent with bad board management or maneuverability miss a chance at what would have been three points on a clear board for a pile-up of their own bags in front of the hole. This leaves a good chance for the original blocker to come in and incisively clean up their original block, dragging it into the hole with one of their later throws, creating a six-point swing, and leaving a board spotted with their opponent’s obstructed bags.

To differentiate a "good" block from a bad one, we used *NSAB* to get a sense of the strategic value of the individual block by its impact on the round. We can see from the *NSAB* that the players who win games manage their blocks better after they occur. In essence, a block is often bad because, at its core, it is always a loss of thrown points from three to one. However, when a bag is going to miss the hole and create a block, it is very important that a player recovers that immediate loss of points with clever maneuvering and board management. So our answer to our blocking on purpose question is: no. In an ideal world, you would never intentionally block the hole because, unsurprisingly, the perfect cornhole strategy is to put every bag in the hole. But when that fails, it's all about board management and making a block created work in your favor.

3.4 Limitations

Due to inconsistent camera angles and the difficulty of creating and maintaining a system for bag location, that statistic was omitted from our collection for ease and efficiency. The location statistic we used was *Hole Blocked*, but it was a subjective observation as each group member independently concluded whether or not a hole was blocked. This statistic may have created inconsistencies based on the opinions of each group member.

We almost always made comparisons against the result of the match: win or loss. For a more robust analysis of our metrics, we could have incorporated more win margins and final score differences to highlight the strength of the victory. For example, an interesting additional figure may have been a plot of the ordinal distance between two players' ATS and BMS against the actual difference in the players' final scores for that match.

Cornhole professionals commonly use techniques such as airmails and skipping bags to avoid blocks, and we initially didn't consider them necessary due to our *In Hole* tracking. In hindsight, however, incorporating these strategies would have helped us analyze blocks more comprehensively, enabling us to apply our findings to the specific players' abilities and strategies.

Although we gathered 1,432 individual observations, our sample size of players was limited. There are very few live cornhole tournament streams with reliable camera work that would have allowed us to collect data accurately and efficiently. Given this, the three-hour livestream we observed only had ten professionals compete. With a larger sample size of professionals, perhaps our data would have more accurately represented the landscape of professional cornhole.

3.5 Further Research

Initially, we wanted to create a model to predict win probability. Our model that predicted round results had variables with low p-values and high statistical significance of correlation, but the R-Squared values were below 0.4 after many adjustments. Thus, these models were not enough for us to make accurate conclusions from the modeling round results and were disregarded. Due to the insubstantial dimensions of cornhole itself as a game, it was difficult to develop enough additional variables that would allow us to create better models to predict the probability of winning a particular round.

More dynamic insights could have come from using more non-binary variables to better describe throws and states of the board as causes and effects of one another. To combat this, further research can be done to create a variable based on the location of the board where the bag ended. Then perhaps, enough information will be recorded to create a reliable model that predicts win probability or to better assess *Blocks Created*, *NSAB*, and *BMS*. In addition, bag placement would allow for a deeper analysis of throwing strategies.

Appendix A:

Table A.1 (Final Results)

Match Details		Tossing Ability					Board Management									Result
Match	Player	Total Throws	In Hole %	On Board %	Missed Board %	Average Toss Score	Blocks	Blocks per Throw	Bags Affected	Board Impact	Net Board Score	NBS per Throw	Net Score After Block	NSAB per Block	Board Management Score	Result
1	Greg Geary	72	76.4%	20.8%	2.8%	2.500	3	0.042	8	23.5%	-8	-0.111	-1	-0.333	-0.444	Loser
1	Jordan Power	72	70.8%	26.4%	2.8%	2.389	10	0.139	12	35.3%	8	0.111	9	0.900	1.011	Winner
2	Jordan Power	84	73.8%	21.4%	4.8%	2.429	6	0.071	15	33.3%	-10	-0.119	-2	-0.333	-0.452	Winner
2	Trey Burchfield	84	64.3%	32.1%	3.6%	2.250	14	0.167	11	24.4%	-6	-0.071	2	0.143	0.071	Loser
3	Jordan Power	96	63.5%	31.2%	5.2%	2.219	9	0.094	10	16.9%	0	0.000	7	0.778	0.778	Loser
3	Trey Burchfield	96	69.8%	30.2%	0.0%	2.396	7	0.073	13	22.0%	-6	-0.062	5	0.714	0.652	Winner
4	Adam Hissner	56	42.9%	57.1%	0.0%	1.857	8	0.143	13	22.8%	2	0.036	14	1.750	1.786	Winner
4	Mike Harvey	56	42.9%	44.6%	12.5%	1.732	7	0.125	16	28.1%	-5	-0.089	6	0.857	0.768	Loser
5	Adam Hissner	92	54.3%	40.2%	5.4%	2.033	14	0.152	28	39.4%	4	0.043	4	0.286	0.329	Loser
5	Duncan Clemmer	92	59.8%	37.0%	3.3%	2.163	9	0.098	14	19.7%	7	0.076	2	0.222	0.298	Winner
6	Erick Davis	84	41.7%	57.1%	1.2%	1.821	10	0.119	19	20.9%	3	0.036	-18	-1.800	-1.764	Loser
6	Ryan Windsor	84	46.4%	51.2%	2.4%	1.905	10	0.119	19	20.9%	10	0.119	-12	-1.200	-1.081	Winner
7	Erick Davis	72	27.8%	58.3%	13.9%	1.417	12	0.167	20	24.4%	4	0.056	-2	-0.167	-0.111	Loser
7	Ryan Windsor	72	40.3%	55.6%	4.2%	1.764	7	0.097	14	17.1%	-12	-0.167	-1	-0.143	-0.310	Winner
8	Cheyenne Renner	56	58.9%	39.3%	1.8%	2.161	6	0.107	17	34.0%	-10	-0.179	2	0.333	0.155	Winner
8	Eddie Grinderslev	56	44.6%	50.0%	5.4%	1.839	9	0.161	14	28.0%	-12	-0.214	0	0.000	-0.214	Loser
9	Cheyenne Renner	104	59.6%	36.5%	3.8%	2.154	10	0.096	27	32.5%	-22	-0.212	-7	-0.700	-0.912	Loser
9	Eddie Grinderslev	104	54.8%	43.3%	0.0%	2.077	18	0.173	17	20.5%	-10	-0.096	13	0.722	0.626	Winner

Table A.2 (Game Scores)

Match	Player 1	Player 2	Player 1 Score	Player 2 Score	Winner
1	Greg Geary	Jordan Power	9	21	Jordan Power
2	Trey Burchfield	Jordan Power	10	21	Jordan Power
3	Jordan Power	Trey Burchfield	10	21	Trey Burchfield
4	Adam Hissner	Mike Harvey	25	11	Adam Hissner
5	Duncan Clemmer	Adam Hissner	26	11	Duncan Clemmer
6	Erick Davis	Ryan Windsor	9	21	Ryan Windsor
7	Ryan Windsor	Erick Davis	21	12	Ryan Windsor
8	Eddie Grinderslev	Cheyenne Renner	1	21	Cheyenne Renner
9	Cheyenne Renner	Eddie Grinderslev	14	22	Eddie Grinderslev