W23 BTMA 431 Final Project Report: MoneyPuck

Isaac Lutzko
Nolan Ruzicki
Karl Specht
Doug Strueby

Instructor: Duy Dao

Introduction

The final project topic we decided to conduct a study on and investigate is NHL player and team data for the hockey seasons from 2005-2006 to 2022-2023. The motivation for this study is to learn about what makes NHL teams successful during the regular season and/or during the playoffs, by diving much deeper into NHL player and team data rather than just analyzing basic statistics like goals, points, or wins. It is easy to look at players that are leading the league in a specific statistic (e.g., goals for skaters, save percentage for goalies, etc.) or teams that are at the top of the standings and see who have been successful, but just because a player lead the league in goals doesn't always mean their team is successful and just because a team finishes the regular season at the top of the standings doesn't always mean they'll win the Stanley Cup. With that in mind, as a group, we wanted to use data analytics to look beyond the more basic player and team statistics to see if there are other factors that may come into play and this idea was partly inspired by the movie *Moneyball* (Miller, 2011). We first wanted to figure out what NHL statistics are most relevant to making the playoffs, and from there we wondered what teams should make the playoffs and then who will win the Stanley Cup this year. Next, we wanted to know which NHL team has the most depth in the league in the current season (2022-2023), and then how this measure of depth compares to the league standings of the current season. Finally, we were curious about what previous Stanley Cup-winning teams did that made them successful. Although our questions here are mostly related to the success of a team, it is important to note that it's essential we look at both player statistics (aggregated for each team and for each season) and team statistics to answer these questions. There are multiple different groups of people that may be interested in this study, specifically hockey teams (specifically the general managers of their teams), inquisitive hockey fans, and those looking for information that could be useful for NHL betting odds (it is important to note that we do not condone or recommend any kind of gambling of any kind). However, the main target audience for this study is hockey teams and their management group so that they can learn about what kind of statistics to focus on so that they can put together a successful team.

Methodology

Data Source & Data Collection Process

To decide on a data source and our data collection process we first looked to see if there were any viable APIs or if our best option would be web scraping. Generally using an API can be somewhat easier and simpler than web scraping to collect the data you need, but unfortunately for the NHL player and team data we needed we couldn't find a trustworthy, free API to use, so we decided to use web scraping to ensure we get the data we need. After looking through multiple different websites that could be used for web scraping, we landed on using https://www.hockey-reference.com/ (Sports Reference LLC, 2023). This site works well because it has extensive team and player data for every regular season and playoffs and each web page contains full-page HTML tables that make scraping them easier. Another benefit of this site as well is that once the data has been web scraped and converted into an R data frame format, there is minimal cleaning of the data that is needed.

Now to complete this web scraping we created an R script (titled "BTMA431_FinalGroupProject_DataCollection.R") that made use of the R packages rvest, XML, httr, and dplyr (Dao, 2023). Although there was some difficulty with collecting the data via web scraping with R, for the most part, it was fairly simple due to the packages that R offers. Before beginning web scraping https://www.hockey-reference.com/, we first had to decide on what specific data we wanted so that we could answer our questions for this study because we obviously did not need all the player and team data that could be gathered from this website. The first thing we realized was that for the questions we want to answer, getting data from every season in NHL history would not be appropriate seeing that comparing data from the 1950-1951 hockey season to the current 2022-2023 season for example, would not be relevant and would most likely cause many false positive outcomes from our data analysis. This is because the way that the game was played, the technology of the equipment that was used, the number of teams in the league, and the data that was available in the majority of the 20th century is very different than it is now (note: the first season of the NHL was in 1917). Therefore we decided it would be best to choose more current data that can give us more accurate insights, so we chose data from the seasons from 2005-2006 to 2022-2023. Although we could have chosen the 2003-2004 season for example and that could be considered to be current enough to give us accurate data analysis outcomes, we chose to start from the 2005-2006 season because this is when the NHL salary cap was implemented ("NHL salary cap", 2023). Prior to this 2005-2006 season, each team in the NHL was able to choose how much they wanted to spend on their player's salaries, in other words, one team could spend $50M on their teams' players' salaries and another team could spend $25M on their teams' players salaries, so one team could have a lot better players on it than another team. By starting from the 2005-2006 season, we're looking to avoid introducing any outliers into the data so that the players that play for each team are more fair. Now once we decided what seasons we want to focus on, we then needed to collect both player data (for skaters and for goalies) and team data as previously mentioned. Because there is a large amount of unnecessary skater data that is available in our https://www.hockey-reference.com/ data source (Sports Reference LLC, 2023) (seeing that it won't be useful for answering the questions for this study), we ensured we only gathered the player data that was essential. Thus, to gather the appropriate data we need, we selected 4 data categories to collect for each regular season and playoffs: basic skater statistics, advanced skater statistics, goalie statistics, and general team statistics. To get all the necessary data for the 2017-2018 season, for example, we needed to get the data for each of these 4 categories for both the regular season and the playoffs, which means 8 different web pages to web scrape the HTML tables from (e.g., 2017-2018 regular season basic skater statistics, 2017-2018 playoffs basic skater statistics, 2017-2018 regular season advanced skater statistics, 2017-2018 playoffs advanced skater statistics, 2017-2018 regular season goalie statistics, 2017-2018 playoffs goalie statistics, 2017-2018 regular season general team statistics, and 2017-2018 playoffs general team statistics).

Question 1: Which Statistics Are Most Significant to Making The Playoffs? When we first came up with this question we knew that we didn't want to just look at the more obvious statistics that would show which teams should make the playoffs such as the wins, losses, and point percentage because stats like these make things too easy since higher placed teams would have won more games and had a better point percentage. We wanted to find the outliers that most people might not have thought of before our model. So in the beginning we had decided that regression analysis was the best way to find which stats ended up being the most significant. To build this model for this question we had to do some data cleaning, this began by removing the wins, losses, and point percentage columns. Then there were some stats that would have to be changed since there were the columns that had percentages in them, such as shot percentage, save percentage, power play percentage, and penalty kill percentage, which needed to be converted into decimal representation. Once we had all the columns filtered that we wanted and the percentages changed to decimals we also had to convert the stats into per-game-based averages in order to ensure the best possible model, and since the season we were using for validation wasn't over, meaning that each team hasn't played the same amount of games, in order to compare them we would have to use a per game based average.

We then had to make the regression model; this was simple since R has a built-in linear model function. Using this model we trained the data on the stats from the year 2006-2022 - this amount of data should give our model a sufficient amount of information to accurately predict a teams' points at the end of the season. Once this was done we were able to answer the question of which stats were the most significant, by seeing which stats had the lowest p-values from our regression model. Next, we had to find out which teams would make the playoffs. Now in the NHL, they run a playoff system that is called the "Wild Card " system which can be complicated so for the purpose of this model we just determine the top sixteen teams in the league will make the playoffs. Using our regression model we were able to determine what each team's points would be after the season was finished and then by sorting them in decreasing order we were able to find which teams should make the playoffs this year.

Once we had the team playoff matchups we had to find out who would win. The best way we thought of for this was a simulation. In order for this to work for us we had set it up the same way the NHL playoffs are, that means we have to test for a best of 7 series, with four rounds, and whoever loses four games is eliminated from the playoffs. To calculate the probability that a team will win a game against their opponent by taking their points divided by the sum of their out and their opponent's points, we then are able to use this as a threshold to determine if they will win. The way that we decided to determine if a team would move on to the next was to generate seven random numbers between 0 and 1000 and compare each of these numbers to the threshold we had determined before multiplying by 1000. This would tell us which team would end up winning and moving on to the next round then we ran this for the subsequent 3 rounds and were able to determine who the Stanley Cup winner should be.

Question 2: Which Team has the Best Depth in the League?

We were interested in measuring depth because it is an often used term, but with no single measure to define it. This gave us the idea to attempt to determine a 'depth rating' for each team in the league, allowing us to compare teams with a sense of how large the difference in depth is, using the numerical difference between the ratings.

The concept of depth in hockey is related to the quality of players on a team. A team with a high amount of depth will have the average player be of high quality. Additionally, having depth means to have a low amount of variation between players. In other words, a team aiming to have a high amount of depth would focus on having many above-average players, as opposed to focusing on having one or two league-leading players to the detriment of the rest of the roster.

For our measure of depth, we chose to use six factors: Goals, Assists, Shots on Goal, Average Time on Ice, Hits, and Blocks. Goals were chosen as classic measures of a player's value; a team without significant numbers of goals and assists is a losing team. Assists were also included to better balance the model to include defencemen and pass-first forwards. Shots on Goal were chosen for similar reasons as

Assists, a shot on net can be a useful contribution to a play without showing up anywhere on the scoresheet. Average Time on Ice was chosen as the best representative of depth in the score sheet. A team with many players getting significant time on ice is more likely to have depth than a team with a few players getting the majority of the ice time. Finally, Hits and Blocks were added to the model to help account for some of the defensive contributions a player can make.

An important note is that no goalie statistics were used when calculating the depth of a team. We decided to exclude this position from our model because the depth of a team's skaters and goalies are considered to be separate. Additionally, goalies have unique statistical categories that would need to be chosen and accounted for, increasing the complexity of the model when considering that a team only has two goalies compared to twenty or more skaters.

To begin the process of calculating depth, we had to decide on a minimum number of games played for a player to be included in our model. We chose forty games as the requirement for the minimum number of games played. This number was chosen because it represents just under half the number of possible games a player could play for one team in a season, meaning that a player who met this threshold contributed to his team for at least half the season. This excludes any players who were called up for short stints to cover for injuries, gathering low totals for statistics and skewing the results down.

Once this data was filtered to include only players that met the minimum games played requirement, we calculated the value of each factor for each team and the league according to the method chosen. The four methods we used were mean, median, mean minus standard deviation, and mean divided by standard deviation. We decided on these methods because they provided us with multiple angles to look at the teams. The Mean method is the simplest and easiest to explain but it does not take into account variance, an important part of depth. This led us to the Median method, which does not directly take into account the variance but by focusing on the midpoints it excludes any outliers at the top or bottom of the data sets.

However, we wanted to try some methods that directly accounted for variance, leading us to the Mean Minus Standard Deviation and Mean Divided by Standard Deviation methods. Mean Minus Standard Deviation heavily accounts for variance by subtracting the standard deviation of a factor from the mean of that factor but has the potential to be overly rewarding or punishing to a team. Mean Divided by Standard Deviation also accounts for variance, but by making a ratio of Mean to Standard Deviation it is less harsh than Mean Minus Standard Deviation. This ratio allows a team with a high mean and high standard deviation for a factor to be valued similarly to a team with a low mean and low standard deviation, which is what we desire.

Once we had these values output by the chosen method, we made them relative scores by taking the value of each factor for each team and dividing them by the value of that factor for the league. For example, to get the relative score for the Goals of the Anaheim Ducks using the mean method, we took the average of the goals for each Anaheim player and divided it by the league average of goals. Once the relative score was calculated for all factors and all teams, the depth rating was calculated using those relative scores and manually assigned weights for each factor. These weights represent what percentage of the depth rating each factor should have. For our final model, we assigned weights of 20% to Goals, Assists, Shots on Goal, and Average time on Ice and weights of 10% to Blocks and Hits. Taking the relative score for each factor for a team, multiplying by the weight for that factor, summing the results, and multiplying by 100 gave us our depth rating for each team.

In our model, the league always has a depth rating of 100, so the depth rating can be read as the percentage compared to the league. For example, a team with a depth rating of 125 would have 25% more depth than the league average.

Question 3: What Did Champions Excel At?

In our process for determining what champions excelled at, we first chose to go for a range of 2008 –

2022 rather than 2006 as we found that the columns didn't match up for the years 2006 and 2007 to the rest of our data, so to get a better result we chose to exclude these years for this particular question. We then split our data into four separate data frames, these being skaters from teams who won the Stanley Cup, and we took these team's data from both the regular season (data.NHL.2008 – 2022) and the playoffs (ploffs.data.NHL.2008-2022). Our other two data frames were the regular season stats and the playoff stats for the skaters on all teams except for the championship team in that season. We then stored the averages for each of these four newly created datasets. In terms of the regular season, we took the averages for the entirety of the season as each team will end up playing 82 games in total so the comparison between championship teams and the rest of the league would be accurate and unbiased. However, for the playoffs data frames, due to the structure of the playoffs, a championship team will end up playing a minimum of 16 games while the remainder of the teams will play a minimum of 4 games. Due to this structure, we made the playoff averages except for age, in terms of a per-game basis, therefore we divided the mean of each player's stats by the number of games that they played allowing us to get a less biased result. Before we implemented the per-game averages the champions had far better stats in all categories which we found to be inaccurate. At this point, we were able to simply subtract the championship teams' averages from the rest of the league averages for both the playoffs and the regular season, and based on these differences we were able to determine what champions excel at, which we will take a further look at in the results.

Results

Question 1: Which Statistics Are Most Significant to Making The Playoffs? After building our linear model we had to determine which variables were the most significant to making the playoffs. We did this by seeing which variables had the lowest p-values in our model, we ended up with only two variables that were significant. These were goal differential with a p-value of 0.00625 and a coefficient of

44.75.46, and an average age with a p-value of 0.01029 and a coefficient of 1.1976.

Follow-up to Question 1: Who Should Make the Playoffs?

To answer the question of who should make the playoffs, we would use our linear model to predict all 32 of the team's points and then sort them in decreasing order and the top 16 teams make the playoffs. Our playoff team are as such the Boston Bruins finished first with 106 points, then the New York Islanders, the Minnesota Wild, Seattle Kraken, Colorado Avalanche, Dallas Stars, Vegas Golden Knights, Winnipeg Jets, New York Rangers, Toronto Maple Leafs, Tampa Bay Lightning, New Jersey Devils, Florida Panthers, Carolina Hurricanes, Los Angeles Kings, Edmonton Oilers all making the playoffs. These teams will battle it out to see who will become victorious and win the hardest trophy in sports.

Follow-up to Question 1's Follow-up: Who Should Win the Stanley Cup? Finally, to determine who will win the Stanley Cup using our simulation model we were able to predict each round of the playoff for each match up and we determined that the Winnipeg Jets will win the Stanley Cup.

Question 2: Which Team has the Best Depth in the League?

With our use of multiple methods to calculate depth ranking, there is not one definitive answer to which team has the most depth. However, the Florida Panthers had the highest depth rating in the league for Mean, Mean Minus Standard Deviation, and Median methods. Also, they were the fourth-ranked team by the Mean Divided by Standard Deviation method. This gives us the confidence to say that the Florida Panthers are the deepest team in the National Hockey League. Looking at Appendix 3, the Calgary Flames, Carolina Hurricanes, and Seattle Kraken are also strong contenders for this title, each finishing top five in at least three of the four methods.

Follow-up to Question 2: How does our depth rating compare to current league standings?

Using the graph in Appendix 4, we showed that while the Mean Minus Standard Deviation Method is quite inaccurate when taken independently, the other three methods may be useful. Indeed, when looking at Appendix 5, which excludes the Mean Minus Standard Deviation Method, the correlation between Actual Ranking and Depth Rating is clear. While there are some outliers, the general trend follows the expectation that the deeper a team is, the better the ranking.

Question 3: What Did Champions Excel At?

In terms of our results for what championship teams excelled at, we found that the biggest differences in the playoffs were the average plus-minus being 0.25 higher per game which makes sense as teams who win games are going to be outscoring their opponents. We also found that the average age for these championship teams was on average 0.32 years older which ties back into our important statistics for making the playoffs as a more experienced team appears to excel both in the regular season and playoffs. We found this to be an odd correlation, but we found that typically a team won't surpass 32 years in average age so based on that information, going from a team age of around 27 – 32 typically the older team on that ladder does better. Lastly, we found that the average penalty minutes were 0.01 lower per game once again in the playoffs which goes to show that a well-disciplined team who doesn’t give the opponent a chance to capitalize on a man advantage is key to winning a championship. For the regular season, the largest discrepancies were once again plus-minus as in the season the championship team ended up having roughly 6.25 higher plus-minus. They also had 0.16 more power play which goes to show that these championship teams can capitalize on opportunities beyond the ability of the average team. We also found that the average number of shots was 6.7 shots higher in the regular season, which once again makes sense as these teams will likely be in the offensive zone and outscoring their opponents in the average regular season game, therefore they will need to take more shots. We wanted to take a deeper look at the shot distribution between championship teams and the rest of the league, and we found that based on the plot charts in Appendix 6 & 7 that the championship teams appear to have more players that they can call up/trade for who can still produce at a significant level. As for the rest of the league, we can see a major drop off below the trend line in the range of 40-60 games played while in terms of the championship teams, they were much closer to the trend line. For average penalty minutes as mentioned earlier, the rest of the league had more penalties than the championship teams, and we wanted to test these results for the regular season by the position which is shown in Appendix 8. We can see that the rest of the league had more penalty minutes than the champions in all positions but for the left wing which we found very intriguing. This resulted in us making a filter for this visualization to determine what teams/players created this disparity in penalty minutes. We were able to determine that the team most responsible for this disparity was the Boston Bruins as on the left wing they had an average of 75 penalty minutes in the regular season while the rest of the league averaged around 25. The particular player we found to be in the lead from our drill-down table in Appendix 9 was Milan Lucic who was third in the league for average penalty minutes and first for the left wing at 121 penalty minutes.

Discussion

Now looking at the findings we've derived based on the questions of our study, all taken together, there are a couple of main takeaways and recommendations we have for our target audience - hockey teams and their management groups.

The first takeaway we have from our question regarding what statistics are most relevant towards making the playoffs for teams is that it is important to have a team with solid defense as well as offense. This was shown by the fact that goal differential is a statistically significant predictor of a team's success. There might be a team for example that has a lot of goals and this is an important aspect of the game, but if you're not also taking care of your own end and playing good defense, you are going to have issues and as a result have a negative goal differential. Putting together a team with skilled defensemen, defensively-minded forwards, and solid goaltending is important for achieving a positive goal differential.

On top of that, it's beneficial if the coaches of a team spends time emphasizing the importance of solid defense. On the other side of things, if you have relatively good defense but your team is not scoring many goals, this is also a problem and could also mean having a negative goal differential. We recommend either acquiring players that are proficient at scoring goals or spending more time on goal-scoring in practices or both, as this will help accomplish a positive goal differential. All in all, it's hard to always have great both defense and offense, but it is important to still have a relative level of both. It is also important to note that this is related to the importance of the depth of a team and the takeaways and recommendations for this will be discussed shortly.

The second takeaway we have from this same study question and its related follow-up questions is that you need to have a team with players that are younger with more skill, strength, and speed, as well as older, more experienced players. Although it was surprising for us as data analysts to see that the average age of a team being a statistically significant predictor of making the playoffs, it does make some logical sense. This is because you want players that have youth on their side and have a lot of speed, skill, and strength, but you still want some players on your team that are a little bit older and have some experience so that they can help lead and teach their younger players on how to be successful and effective in the NHL. We recommend not having too much of either of these (i.e., a relatively low team average age or relatively high team average age), so finding a team with a team average age of roughly 27 would be most advantageous.

Now the next takeaway we have is that although there is a general trend that shows that the more depth a team has, the higher it will be in the standings, there are still many instances where teams with a high level of depth are still not very high in the standings (based on our findings from our study question regarding what teams have the most depth in the NHL). For teams that are having this issue, we recommend looking at making coaching, management, and/or other personnel changes within the team. If a team has a lot of depth and skill but is still not overly successful, it could be the case that making management/personnel changes could bring about a new team strategy and/or team attitude that could help the team turn things around on the ice and in the dressing room.

Lastly, we have a couple of different takeaways and recommendations we've drawn based on our findings from our study question regarding what previous Stanley Cup winners excelled at. First, special teams (i.e., power play and penalty kill) are a huge factor in both the regular season and the playoffs. We noticed that championship teams are more disciplined and take fewer penalties than the other playoff contenders, so we recommend drilling down on making sure that your team is disciplined during the playoffs. This should be maintained throughout the team by coaches by the player's leadership group. Building on top of this, we noticed that Stanley Cup winners had strong power play statistics in the regular season. We recommend that teams work towards having a strong power play throughout the regular season and to carry that through into the playoffs.

Next, we noticed that there happens to be more shots made per game in the regular season compared to the playoffs. This means that defense is an important factor because teams are doing whatever they can to prevent their opponent's scoring opportunities more so in the playoffs than they are in the regular season. Therefore because defense becomes a more important factor during the playoffs, we recommend that teams work on their overall defensive strategy as a team and possibly acquire more defensively-minded players (if needed) throughout the regular season so that when the playoffs begin the team is able to react appropriately to the increased importance of defense at that time.

Lastly, we already touched on the average age of a team and how it's important to the success of a team, but we'd also like to add that this is especially important throughout the playoffs. The level of intensity and speed of the game in the playoffs goes up compared to the regular season, so we recommend that teams ensure they have players on their team that have playoff experience. These players are then able to lead by example and show less-experienced players how to compete during the playoffs.

References

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Appendices

Appendix 1

Regression Output for Question 1

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	547.8290	495.9348	1.105	0.26981	
AvAge	1.1976	0.4651	2.575	0.01029	*
PIM.G	0.3576	0.5392	0.663	0.50751	
oPIM.G	0.5280	0.5617	0.940	0.34758	
SV.	-460.6209	495.0773	-0.930	0.35258	
GD.G	44.7546	16.3032	2.745	0.00625	**
SD.G	-1.7357	1.5374	-1.129	0.25941	
S.	-672.7012	498.1979	-1.350	0.17750	
PK.	-31.0659	20.4732	-1.517	0.12976	
PP.	7.7861	20.2788	0.384	0.70117	

Appendix 2

Predicted Standings Using the Regression for Question

Boston Bruins*	128
Edmonton Oilers*	105
Dallas Stars*	103
New Jersey Devils*	102
New York Rangers*	102
Colorado Avalanche*	102
Carolina Hurricanes*	101
Toronto Maple Leafs*	101
Tampa Bay Lightning*	99
Vegas Golden Knights*	98
Minnesota Wild*	97
Seattle Kraken	96
Florida Panthers	95
New York Islanders	93
Los Angeles Kings*	92
Winnipeg Jets	91
Calgary Flames	89
Pittsburgh Penguins	88
Washington Capitals	85
Nashville Predators	83
Ottawa Senators	82
Buffalo Sabres	80
Detroit Red Wings	75
Vancouver Canucks	75
St. Louis Blues	72
Philadelphia Flyers	68
Montreal Canadiens	61
Arizona Coyotes	60
San Jose Sharks	59
Chicago Blackhawks	54
Anaheim Ducks	45
Columbus Blue Jackets	44

1

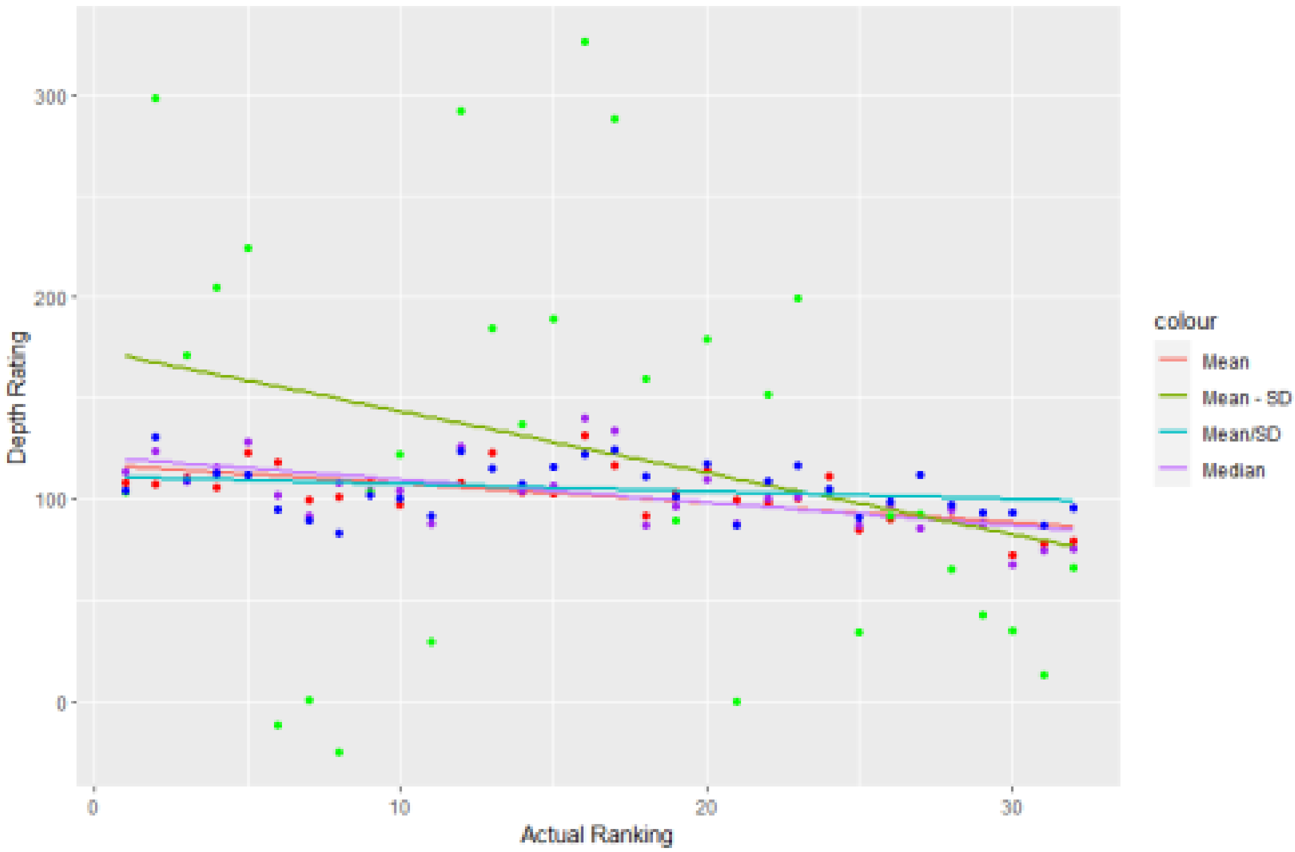
Appendix 3

Actual & Depth Rankings for each team and each method

	Team	Actual Ranking	Mean Ranking	Median Ranking	Mean Minus SD Ranking	Mean Divided by SD Ranking
13	FLA	16	1	1	1	4
7	CGY	17	5	2	4	2
20	NYR	5	3	3	5	11
24	SEA	12	11	4	3	3
5	CAR	2	12	5	2	1
30	VEG	4	13	6	6	9
27	TBL	13	2	7	9	8
3	BOS	1	10	8	16	17
4	BUF	20	6	9	10	5
17	NJD	3	8	10	11	13
9	COL	8	17	11	32	32
19	NYI	15	16	12	8	7
29	VAN	24	7	13	18	16
31	WPG	14	14	14	14	15
10	DAL	9	9	15	17	18
14	LAK	10	22	16	15	20
12	EDM	6	4	17	31	24
11	DET	23	18	18	7	6
26	STL	22	21	19	13	14
22	PHI	26	25	20	20	21
23	PIT	19	15	21	21	19
2	ARI	28	26	22	23	22
28	TOR	7	19	23	29	29
21	OTT	21	20	24	30	30
25	SJS	29	27	25	24	25
15	MIN	11	23	26	27	27
32	WSH	25	29	27	26	28
18	NSH	18	24	28	12	12
16	MTL	27	28	29	19	10
1	ANA	32	30	30	22	23
6	CBJ	31	31	31	28	31
8	CHI	30	32	32	25	26

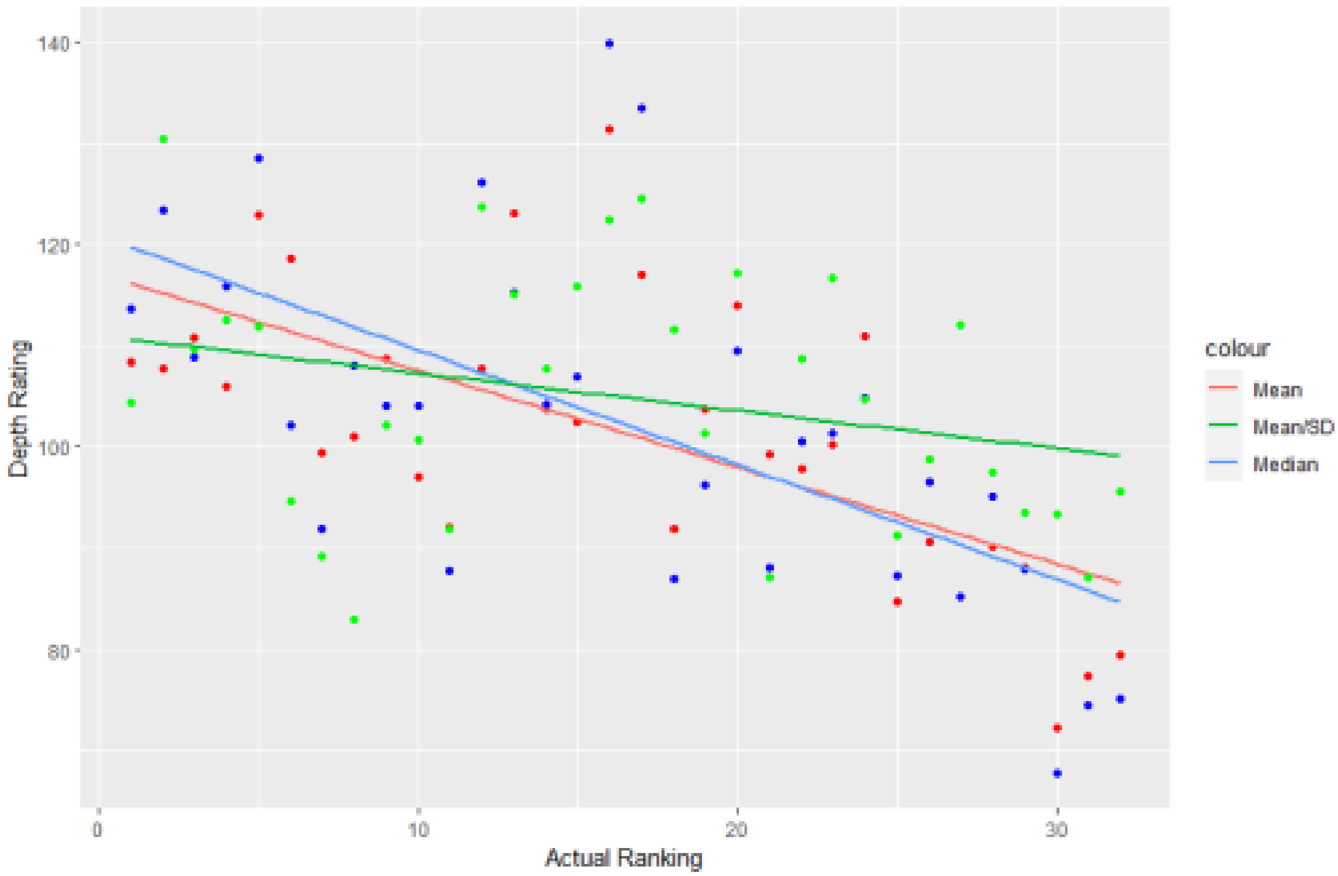
Appendix 4

Depth Rating vs. Actual Rating Across All Methods



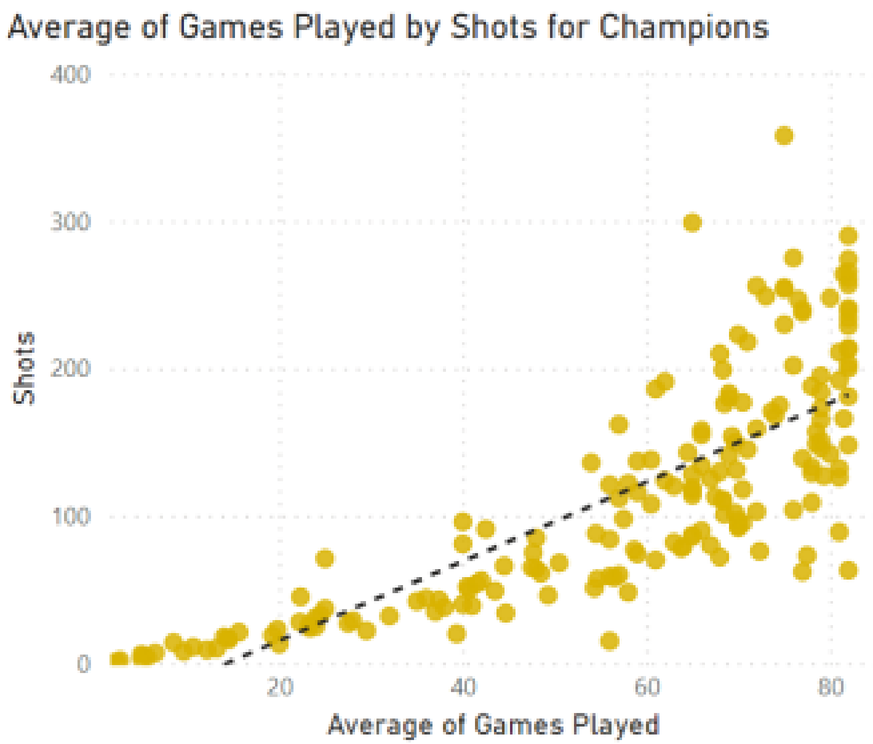
Appendix 5

Depth Rating vs. Actual Rating Across the Top 3 Methods



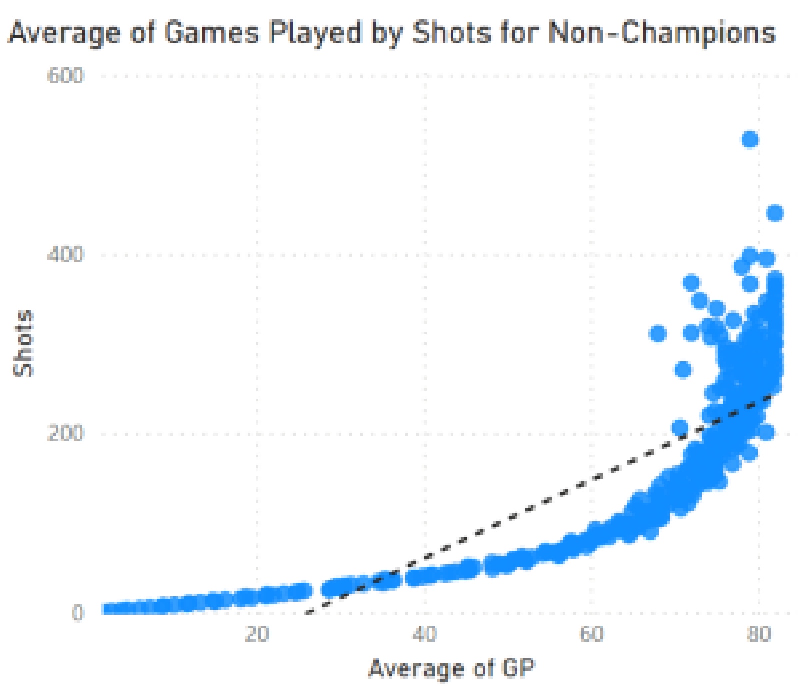
Appendix 6

Average of Games Played by Shots for Champions



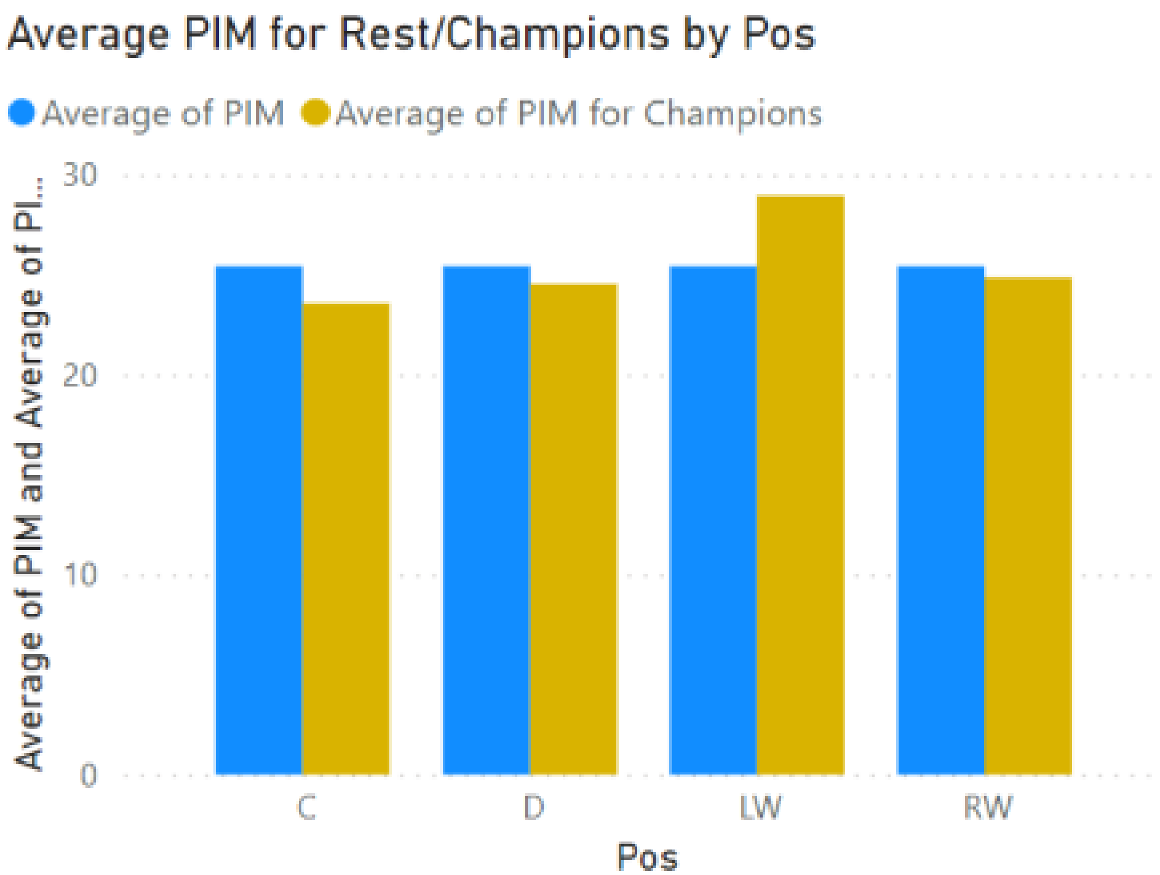
Appendix 7

Shots for Champions and Non-Champions



Appendix 8

Average Penalties in Minutes by Position



Appendix 9

Average PIM for left wingers on championship teams

Player	Average of PIM
Milan Lucic	121.00
Ben Eager	120.00
Kyle Clifford	102.00
Matt Cooke	101.00
Gabriel Landeskog	78.00
Andrew Ladd	67.00
Pat Maroon	65.00
Brandon Bollig	51.00
Ruslan Fedotenko	44.00
Daniel Carcillo	40.67
David Perron	37.00
Kris Versteeg	35.00
Henrik Zetterberg	34.00
Tom Sestito	33.50
Patrick Sharp	33.00
Kirk Maltby	32.00
Chris Kunitz	31.00
Pascal Dupuis	30.00
Daniel Paille	28.00
J.T. Compher	25.00
Viktor Stålberg	25.00
Ondřej Palát	24.00
Total	**28.94**