Quantifying the Last Shot: Introducing DAWG

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Description of Contribution:

Fall 2022 Semester-Long Independent Study. Worked, researched, and wrote independently, consulting mentor for advice and assistance when needed, will be presented in front of the entire student body.

Abstract

The last shot has long mystified basketball fans. From who was shooting it to where on the court it was, images of famous last shots have remained burned in the minds of basketball fans all across the world. Through this research work, we look to evaluate the personnel aspect of the last-second, game-changing shot by proposing a metric that looks to quantify the ability of NBA players to make last-second shots. This metric, DAWG(Daggers Adequately Winning Games), combines two aspects of the shot, the difficulty of the shot and the importance of the shot. Through a Sentiment Analysis Algorithm, we managed to quantify the NBA general fanbase's opinion on the importance of a shot. Additionally, using previous shot data, we create a Random Forest Model which will predict a given shot's chance of going in given certain variables to measure the difficulty of the shot.

1. Introduction

With a new technological revolution within the sports analytics field, there has been a newfound interest in using machine learning techniques to tackle problems in the sports world. Such common machine learning techniques include the Random Forest Algorithm, which has been used to predict NBA game attendance(King, 2017), and a natural language processing technique called Sentiment Analysis, described in section 2.2, which has been used to determine substantial differences in how men and women write about the sport of soccer(Babac et. al, 2016).

Using these machine learning techniques, we look to tackle the problem of the last shot in basketball. Though an NBA game may have thousands of shots, the last shot is perhaps the most important shot in the entire game. It is not uncommon for this shot to decide the outcome of the entire match, so it would be of great importance to the teams to maximize the odds of making the final shot of the game.

These last shots have become immortalized and made legendary by NBA fans all across the globe. From "The Shot" by Michael Jordan to eliminate the Cleveland Cavaliers in 1989 to Damian Lillard's game-winner from 37 feet out against the Oklahoma City Thunder in 2017, NBA audiences have been enthralled by the last shot which beats the buzzer and changes the game. Buzzer-beating game-winners have become one of the most famous and memorable moments in basketball history, with those shots becoming the most-watched NBA moments of every decade since the 1980s(Googletrends, 2017).

With this interest and the importance of these shots, one of the most important factors which can be controlled is the person who takes the shot. There is an age-old debate, from informal discussions in bars to debates on national television on sports networks like ESPN, over who should take the final shot, with coaches and players coming under intense scrutiny for failing to give the ball to the “right” person.

Involving public NBA shot data and tweets on the social networking site Twitter, this research work aims to answer this question of the last shot by creating a quantifiable metric called DAWG(Daggers Adequately Winning Games) based on previous final shot attempts which describes a given player's ability to make the last-second shot.

The development of DAWG is two-fold, as we look to analyze the difficulty of a last-second shot through an "Expected Points" metric which is created by using the Random Forest Algorithm to predict the probability of a given shot scoring based on previous shots, similar to the "Expected Goals" metric in soccer which looks to describe the odds of scoring for a given shot as well as the importance of the shot by measuring the fan reaction through analyzing tweets with the usage of Sentiment Analysis.

Using this metric we look to investigate who is the most likely to score when the game is on the line both in the entire NBA and for each franchise. This metric can also be used by NBA executives and coaching staff for decision-making in trading and acquiring new players as well as deciding who should receive the last shot.

2. Background

2.1 Data

For the expected points metric, we used the official NBA statistics website(stats.nba.com) as well as an API client package called nba_api to find the distance and type (dunk, jump-shot, etc.) of shot and the position, height, and weight of the shooter for every shot from the 2015-2016 NBA Season to the 2021-2022 NBA Season, numbering to just over 1.5 million unique shots. Since shots from many years ago may not be an accurate representation of a players current ability, we decided to limit the data collection to the last 5 seasons. Additionally, 1.5 million unique shots were more than appropriate for the training of a Random Forest Model. We also found the date and time of each shot for use for the importance metric. Unfortunately, useful variables like the distance as well as any biometric data of the closest defender are proprietary by the NBA and not accessible.

For the importance metric, we found every single tweet involving the first and last name of the shooter exactly 24 hours after a game-winning shot attempt using the snscrape module. The full name was used because some players are commonly referred to by their first name, like “Lebron” for “Lebron James” and some other players are commonly referred to by their last name, like “Westbrook” for “Russell Westbrook.” Because of this difference in nomenclature, it is best to search by a player’s full name to ensure an equal possibility of tweets. We used 24 hours after as our guideline so that we can account for people who may have not been watching the shot live but may react to it later. In essence, we want to see how large of a buzz the shot has created in a relatively short timeframe. In total, we scrapped 1095624 tweets over 977 shots.

To calculate the final DAWG metric for every player, we found every last-second shot with game-changing potential from the 2015-2016 NBA season to the 2021-2022 NBA season. We first found the last shot attempt for every game, ending in a margin equal to or less than 3. With those shots, we eliminated all two-point attempts in games with a margin of 3(since a two-point attempt would not have any effect on the outcome of the game) as well as any converted shot where the shooter's team still lost(e.g. a player scoring a basket to make the score 105-108 from 102-108). After these changes, we generated a set of 977 shots with game-changing potential where we could generate the DAWG for a player.

2.2 Sentiment Analysis

Sentiment Analysis is a natural-language-processing classifier that looks to classify the nature of a block of text as either positive, negative, or neutral. In this paper, we elected to use VADER(Valence Aware Directory for sEntiment Reasoning), a sentiment analysis algorithm designed specifically for social media, because VADER also calculates sentiment intensity, which quantifies to what extent a block of text would be positive or negative(with +1 being most positive and -1 being most negative). By calculating the sentiment intensity of tweets in direct reaction to an event, we can determine numerically how polarizing an event was. By determining this polarization, we can quantify the shot's importance, since it follows that if an event generated a more polarizing reaction, it was viewed as more important in the eyes of the general public.

VADER generates sentiment intensity by going word-by-word through a block of text, relying on a dictionary of words and their corresponding sentiment scores(how positive or negative a word is). VADER then sums these sentiment scores to generate a sentiment intensity for the block of text.

Additionally, VADER also uses five heuristics to analyze a block of text: punctuation, capitalization, degree modifiers(describing intensity), a shift in polarity due to the conjunction “but,” and polarity negation. Those five heuristics along with the individual sentiment scores of each word are used by VADER to generate the sentiment intensity of a block of text.

For example, if we took the sentence “That was awesome!” VADER would analyze the words “That” and “was,” with a neutral sentiment score of 1 and a positive sentiment score of 0, and “awesome!” with a neutral sentiment score of 0 and a positive sentiment score of 1, and combine those scores to get a neutral sentiment score of 0.313 and a positive sentiment score of 0.6588. Through this process, we can find to what extent a statement was positive or negative.

A more comprehensive explanation can be found in the work by Hutto et. al(2015) which first introduces VADER.

2.3 Contribution and Existing Work

This research works aim to quantify a player’s ability to score game-changing shots through a two-folded process involving the combination of the impact of the shot, using Sentiment Analysis, and the difficulty of the shot, using a Random Forest Algorithm.

Using Sentiment Analysis on tweets to measure an event’s impact is not a novel invention. For instance, Jabalameli et.al used a sentiment analysis algorithm to note the extent to which tweets in reaction to the Covid-19 Pandemic were either positive or negative in order to measure the impact of the pandemic on citizens of the states of Ohio and Michigan. In the sports world, Sentiment Analysis has been used to gauge public opinion of a new soccer video-assisted referee system(Knopp, 2020) and perceptions of players of NBA teams(Li et. al, 2022).

Through our expected points metric, we also are building on already existing sports frameworks for predicting whether a score will happen or not. In soccer, the “Expected Goals” Metric, which predicts the odds of a shot in soccer scoring, is already a commonplace statistic, with extensive research and optimization on the metric(Anzer et. al, 2021 and Rathke, 2017). Our expected points metric is an extension of soccer’s expected goals statistic, where we look to predict the odds of a score occurring and then multiply those odds by the point value of the shot to evaluate how many points that shot is expected to make.

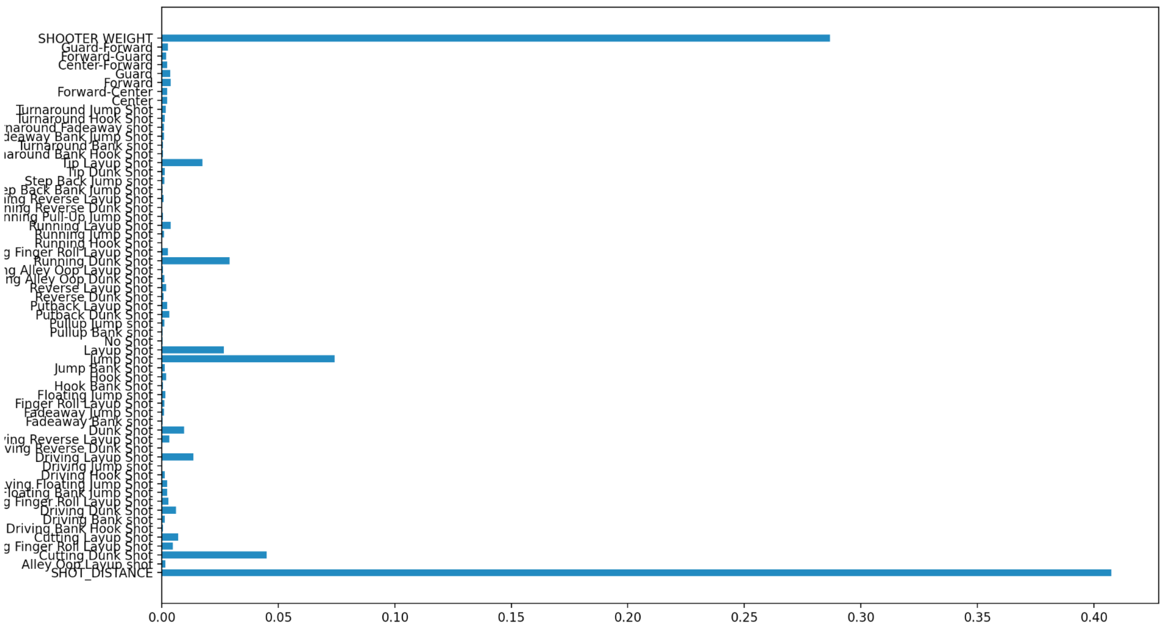
However, the study of the “last shot” in research is a relatively new idea. Solomov, et. al(2015) investigate the existence of “clutch,” in basketball which measures how much a player elevates his game when it matters the most, with extensive debate over the existence of clutch in the game of baseball(Otten, et. al, 2013, and Ruane, 2015). It should be noted that the study of the last shot differs from the notion of clutch as clutch measures the change of a player’s ability during the most meaningful moments while our work looks to quantify which player has the highest chance of scoring the last score of the game, not evaluating any changes in a player’s ability.

3 Methodology

3.1.1 The Expected Points Metric

To generate the expected points metric, we use the scikit-learn python library to create a random forest algorithm that looks to generate the probability of a given shot scoring. Using the total shot dataset as training data, the random forest algorithm generated 40 decision trees and took the average result of each decision tree to generate a prediction.

Furthermore, within the random forest, the model trained on 8 explanatory variables. Those variables and their feature importance can be found here:



We then run the random forest algorithm on the last-second shots dataset to generate the probabilities of all 977 shots. We then multiply those probabilities by the point value of the shot(2 or 3) if the shot were to go score to generate an expected points metric, or how many points we expect that shot to be worth. The difference between the expected points and the actual points for each shot would then reward players for making difficult shots and punish players for missing easy shots.

3.1.2 Model Validation

Since we are looking to evaluate the strength of probabilities of scoring and not the binary classifications(score or no score), we use the AUC-ROC score of 0.67, which measures the area under the curve(the integral) of the graph between the true positive and false positive rate. This AUC-ROC score, although not perfect, shows that the model performs relatively well considering the event it models. The actual probability for most shots taken in the NBA is very close to 50%, as out of all the shots taken in the total shots dataset, the field goal percentage(percent of shots that actually go in) is 45.917%. Therefore, there would be many situations where a shot's actual probability of scoring is slightly above 50%(e.g. 52%) but the model may estimate that the shot's probability is slightly below 50%(e.g. 48%), or vice-versa. The model's guess is very good, but an AUC-ROC score would still punish the model's estimate. We also know that the model performs relatively well since the average of the predictions used for evaluation(.45879) is extremely close to the field goal percentage of the entire total dataset(.45917). Because of the large amounts of elements in each average(462,178 and 1.5 million, respectively), we can infer that the model is predicting values relatively close to the actual probabilities of each shot.

However, we feel that the model can easily be improved by adding variables like the distance and biometric data of the closest defender, which are unfortunately proprietary by the NBA and therefore unable to be used.

3.2 The Importance Metric

As stated above, to generate an importance metric for each shot, we ran a sentiment analysis on every tweet exactly 24 hours after a last-second shot involving the full name of the player which generated a sentiment intensity for each tweet. The sentiment intensity is described with three digits: the positive, neutral, and negative scores. To find the polarity of the shot, we add the positive and negative sentiment intensity scores for each tweet. If a reaction to a shot has a higher polarity, it follows that the event was more important in the eyes of fans, since if people were to have a reaction on the ends of the spectrum(either very positive or very negative), they have put more emotional investment in the event and therefore value the event higher. This polarity then becomes the importance metric.

The importance metric also accounts for the added pressure star players or large market franchises may have. A player like Lebron James or a large team like the Los Angeles Lakers would have to face more criticism and pressure for a shot compared to a bench player or a smaller-market team. There are simply more people and more emotional investment in a player like Lebron shooting a game-winner than a relatively unknown bench player, even if they are in the exact same situation.

To account for the growth of NBA Twitter over the last six years, we multiply each importance score by the number of Twitter followers of the official NBA account today divided by the number of Twitter followers of the official NBA account during the month and year of the shot. Since the growth of the NBA Twitter-sphere is directly correlated to the size of the official NBA account, we can use this multiplication to account for the growth of the NBA Twitter space throughout the last few years.

Additionally, we then weigh more recent events by using exponential weights. We multiply each sentiment score by $.95^{n}$, where n is the number of months from June 2022, the last month of the 2021-2022 NBA season.

The importance metrics make sense since shots scoring high either involve high-stakes playoff games with plenty of media buzz, like the Kawhi Leonard Game 7 Winner against Philadelphia, or regular season games with some sort of sentimental value, like Dwayne Wade's buzzer-beater to beat the Golden State Warriors in one of the very last shots of his 16-year career.

3.3 Combining Expected Points and the Importance Metric

The individual DAWG for a player can be determined using this formula:

$$\sum_{i=0}^{j} ((Sentiment\ Score_i)(Expected\ Points_i - Actual\ Points_i))$$

Where j is the number of last-second, game-deciding shots a player has taken and i describes each last-second shot.

We use this methodology so that the only factor determining whether a player will gain or lose DAWG after a shot attempt is whether the shot went in or not. This change in DAWG is then amplified by the importance metric, so that scoring difficult higher pressure shots and missing easy lower pressure shots see the highest change in DAWG.

4. Results

4.1 Who Should Be Taking the Last Shot for Every NBA Franchise?

Below are the players who ranked the highest for all 32 NBA Franchises:

Eastern Conference

Team	Player	DAWG
Boston Celtics	Payton Pritchard	226.183
Brooklyn Nets	Ben Simmons	0
New York Knicks	RJ Barrett	1948.583
Philadelphia 76ers	Furkan Korkmaz	206.380
Toronto Raptors	OG Anunoby	706.033
Chicago Bulls	DeMar DeRozan	4216.131
Cleveland Cavaliers	Rajon Rondo	281.419
Detroit Pistons	Bojan Bogdanovic	32.011
Indiana Pacers	Jeremy Lamb	320.256
Milwaukee Bucks	Rodney Hood	22.167
Atlanta Hawks	Trae Young	4089.179
Charlotte Hornets	Terry Rozier	226.183
Miami Heat	Bam Adebayo	76.278
Orlando Magic	Cole Anthony	1270.743
Washington Wizards	Kyle Kuzma	33.347

Western Conference

Team	**Player**	**DAWG**
Denver Nuggets	Monte Morris	376.211
Minnesota Timberwolves	D’Angelo Russell	171.879
Oklahoma City Thunder	Shai Gilgeous-Alexander	71.378
Portland Trail Blazers	Damian Lillard	3811.417
Utah Jazz	Rudy Gay	58.447
Golden State Warriors	Stephen Curry	2087.999
Los Angeles Clippers	Kawhi Leonard	1516.832
Los Angeles Lakers	Anthony Davis	4901.256
Phoenix Suns	Cameron Johnson	266.776
Sacramento Kings	Harrison Barnes	667.518
Dallas Mavericks	Luka Doncic	1896.680
Houston Rockets	Eric Gordon	21.900
Memphis Grizzlies	Ja Morant	244.470
New Orleans Pelicans	Tony Snell	607.448
San Antonio Spurs	Keita Bates-Diop	-0.046

4.2 Who is the Best?

The NBA players which had the highest DAWG rank can be found below:

Player	**Number of Shots**	**DAWG**
Anthony Davis	8	4901.256
Demar DeRozan	18	4216.131
Trae Young	6	4089.179
Damian Lillard	23	3811.417

Stephen Curry	7	2087.999
RJ Barrett	4	1948.583
Luka Doncic	11	1896.680
Kawhi Leonard	10	1516.832
Cole Anthony	4	1270.743
Spencer Dinwiddie	12	1159.490

4.3 Who is the Worst?

The NBA players which had the lowest DAWG rank can be found below:

Player	**Number of Shots**	**DAWG**
Kyle Lowry	6	-2397.270
Royce O’Neal	1	-2006.255
Russell Westbrook	26	-1618.276
Kevin Durant	6	-962.537
Paul George	14	-732.623
Jimmy Butler	12	-642.241
Julius Randle	6	-566.770
Joel Embiid	8	-555.050
Khris Middleton	9	-480.554
Mike Conley	5	-390.199

4.4 Discussion

Conventional basketball knowledge states that the last shot should go to your star player, but in our case, the DAWG rankings have proven this to be true only sometimes. The players who ranked highest in DAWG were mostly star players, although there were a notable number of bench and non-star starters who also scored highly. However, the players who ranked lowest in DAWG were consistently considered conventionally star players which alludes to the idea that the star player should not be receiving every single last shot. Although it should be noted that bench players usually are not given as many opportunities to gain or lose DAWG score, since they do not receive the last shot as much as star players do.

Additionally, there are a few surprises on the upper echelon of the DAWG rankings. Players like RJ Barrett, Cole Anthony, and Harrison Barnes, who are rarely considered for the last shot or as the number one player on any of the teams that they have played for rank highly in DAWG because the one or two shots that they have hit were massive, important moments generating a substantial amount of fan buzz, while the shots that they have missed were not seen as important.

4.4.1 The "Damian Lillard" Test

In soccer analytics, there is a general idea of the "Lionel Messi Test," where if a metric describing some sort of attacking ability does not rate Lionel Messi highly, there is something inherently wrong with the metric, given Messi's obvious ability, but the metric does not have to describe Messi as the best, since there is room for new discovery. This same principle can be applied to Damian Lillard for last-second shooting. Lillard has created an entire reputation of being able to nail last-second, game-changing shots, even garnering a name for these moments, "Dame Time," so if a metric describing last-second shots does not highly rank Damian Lillard, something is inherently wrong. Fortunately, DAWG passes the Damian Lillard test, ranking Lillard as the 4th best to receive the last shot in the entire league.

4.4 Further Research

Because DAWG only uses past last-second shots, we cannot fully judge a player's last-second shot-scoring ability because they have not been given very many opportunities to attempt those last-second shots. However, considering nearly all of these players were the star, number-one players for their teams before arriving in the NBA(either playing in foreign leagues or for an NCAA college basketball team), further research can be done by implementing the DAWG metric on shots a player took before arriving in the NBA, so we could gain a more complete understanding of a player's ability to score last-second shots, even if they are not given many opportunities in the NBA. This same implementation of DAWG can also be used by teams for draft evaluation, as they could see a player's ability to score last-second shots before they are drafted.

Additionally, the expected points portion of DAWG can easily be improved by adding proprietary variables like the distance of the closest defender, so that a better-expected points metric can be developed.

5. Conclusion

In this work, we were able to develop a new metric, DAWG, which quantified an NBA player's ability to score last-second, high-pressure shots. The development of DAWG was two-fold, with a combination of expected points and importance metric.

Through this combination, we were able to use this metric and determine which players were the best and worst both in the entire NBA and for each NBA franchise to receive the last shot of an NBA game. This metric can then be used by NBA coaching staff and executives to evaluate players as well as determine in-game decisions.

Possible improvement and work in the future may involve adding other variables such as defender data to improve the accuracy of the expected points metric as well as applying DAWG to shots taken before a player's career in the NBA(e.g. shots taken while a player was playing in college or in a foreign league) so that we can evaluate a player's ability to score last-second shots, even if they are not given many opportunities for last-second shots in the NBA.

6. Acknowledgements

This research work would not have been possible without Mr. Darin Clifft, whose guidance and expertise was indispensable in the creation of this work.

The author would also like to thank Memphis University School, in particular Mr. Flip Eikner, Mr. Pete Sanders, Dr. Steve Gadbois, and the entire Memphis University School academic council for providing the opportunity and resources to undertake this project.

Finally, the author would like to extend his thanks to Mr. Alex Gonzalez and Mr. Joseph Keeler, whose expertise and viewpoints as a fan of the NBA proved invaluable in aiding in the creation of this work.

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