A method for evaluating player decision-making in the Australian Football League

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Abstract

Expected possession value metrics have been a recurring motif in the team sports analytics literature. They provide a means of identifying changes in the expected outcome (EO) as a result of a decision being made and executed by a player. Whilst existing methods identify whether a decision improved the EO, we wish to measure the value of a decision relative to alternative options. Hence, in the presence of multiple positive options, improving the EO is not the only measure of success. In our work on Australian Rules football, the EO of kicking to a teammate is quantified *via* both the probability and value of retaining possession. We measure the former by identifying the theoretical between-player contest that could occur. We model this based on players' velocity, orientation, and the effects of these constraints on re-positioning, as measured from player-tracking data. Unlike traditional metrics such as Voronoi tessellations that limit spatial ownership to a single player, we express the partial (or, contested) dominance of players. We treat players as dynamic objects, capable of repositioning during the ball's trajectory, and consider variation in kicking accuracy. Hence, the optimal receiving location of targets are identified, by searching for local maximums in their vicinity. Analysis of Australian Football League (AFL) matches played at Etihad Stadium in 2017 reveals a trend towards short-range kicks with minor improvements in EO, rather than higher value decisions which are typically to long-range targets. The difference between the theoretical contest of successful and unsuccessful kicks is found to be statistically significant. We present a framework for analysing the decision-making of individuals by quantifying the value of a decision and identifying more valuable alternatives. This metric has applications in player selection and recruitment, performance analysis and predictive analytics.

Keywords: performance analysis, player tracking, spatiotemporal, team sports

1. Introduction

Quantifying the expected outcome of a possession has been a commonly researched topic in team sports, such as in basketball [1], soccer [2], and Australian Rules football [3, 4]. Results of these studies reveal the importance of space, effects of congestion and pressure, and provide novel insights into player decisions by quantifying the net increase in the expected outcome (EO). While these studies have evaluated the decision-making abilities of players by identifying positive increases in the EO (such as in [1]), we wish to measure the value of a decision relative to alternative options. Hence, in the presence of multiple positive outcomes, improving the EO is not the only measure of a good decision.

In this study we demonstrate a method for quantifying the value of decisions that players make in Australian Rules football. We calculate the EO of a kick by measuring the probability that it will be successful and the value of retaining possession. The probability of retaining possession is calculated by modelling the theoretical contest that could occur based on player positions, orientation and velocity. In doing so, we measure spatial occupancy as a contest that could develop in the time between a kick is made and its arrival (i.e., the travel time of the ball). While Voronoi tessellations have traditionally been used to measure spatial dominance in team sports [5], we believe a contested occupancy model is more appropriate if we consider players as moving objects, capable of repositioning. The model is built upon player-tracking data collected in the Australian Football League (AFL).

2. Methods

Data

Player tracking data was collected for all matches played in the 2017 AFL regular season. Matches were limited to those played at Etihad Stadium, ensuring consistent field dimensions and data quality. Tracking data, recorded at 10 Hz, were collected via Catapult's Clearsky local position system (LPS). Matches in which tracking of one or more players was missing for any period were omitted. Detailed match events (e.g. marks, kicks, goals and associated constraints such as pressure type and location), referred to as *transactions*, were manually recorded to the nearest second by Champion Data. In total, seven matches were used in this study, each consisting of approximately 1.5 million rows of time-stamped coordinates and 3285 rows of transactions. Field equity values were provided by Champion Data. Ball location was extracted from consolidated transaction and tracking datasets by identifying the gain and loss of possession. For model formation and analysis, only possession beginning in a mark and resulting in a kick were included, as these conditions provide the player with adequate opportunity to make an informed decision. Player velocity and orientation were derived from raw positional data. We assume a player's orientation is equal to the deviation of the vector of two consecutive tracking samples.

DECISION MAKING MODEL

While methods exist for measuring the net contribution a decision has made to the expected outcome of a possession chain [1], including transaction-based models in AFL [3], our objective is to identify the value of a decision, relative to available options. If a kick results in an equity improvement of x, while an alternative option existed that would have resulted in an equity gain of y (where $y > x$), the decision behind the decision is sub-optimal despite a positive equity gain. The value of a decision is quantified as the EO of the decision that was made, divided by the EO of the optimal decision. We refer to this metric as the Decision Value (DV).

$$DV = EO_{decision}/EO_{max} \tag{1}$$

The EO of deciding to kick to a spatial location, x, is quantified by measuring the risk and reward components of that decision (2). The reward is equal to the probability of retaining possession when kicking to x (p_x), multiplied by the equity (e) of the attacking team at x, while the risk is the probability of losing possession ($1 - p_x$), multiplied by the opponent's equity.

$$EO_x = p_x e_{team} - (1 - p_x)e_{opp} \tag{2}$$

We measure the probability of successfully retaining possession by modelling the theoretical contest that could occur at x based on the current position, velocity, and orientation of all players. We refer to the time it would taken an object (i.e., a player or the ball) to reach a spatial location as its *time-to-point*. Ball velocity was considered as fixed at 18.5 m/s as approximated from measuring the travel time of kicks from a match of AFL data. Hence, the players who could contest a kick to x are those with a time-to-point less than the ball's. The probability of retaining possession is equal to the number of teammates with a time-to-point less than the ball's for a location, x, divided by the total number of players who meet the same criteria.

Determining if a player could reach a location, x, in less time than the ball's time-to-point requires measuring the effects of orientation and velocity on repositioning. We record every movement (distance, metres, and angle, degrees) for whole-second integers (≤ 5 s) across four matches of tracking data. These movements are normalised for orientation, grouped into integers, and individual ellipses are fitted in the positive and negative y-axis (equivalent to moving forwards or backwards, relative to current orientation) such that the y- displacements are equal to the maximum and minimum recorded y- values respectively, and the x- displacement for both ellipses is equal to the maximum x- value recorded. The ellipses are joined around the y- axis origin, producing egg-shaped boundaries that represent the maximum distance a player could reach in specified time intervals. We refer to these as *Reachable Regions* (RR). The concept of RR in team sports were introduced in [6] and further explored in [7] where they were fit via a number of methods including convex hulls and motion models. In [7], RR were used in the formation of dominant regions, a variation of Voronoi tessellations that consider player orientation and velocity. Our use of ellipses reduces computation time and produces a smoother bound, at the cost of precision. That is, our method fits ellipses based on the maximum movements, then extrapolates limits between these points, while convex hulls produce unsmoothed bounds that consider all available data. This method represents a novel way of quantifying special dominance.

To calculate the probability of retaining possession at x, RR are produced for all players for the ball's time-to-point. As RR are fit on whole second increments, extrapolation is needed for partial seconds. Any player whose RR contains x is said to be able to contest the kick. We employ the standard ellipse function to check for this (3), which determines that a player could reach the given location (x, y) based on the ellipse width and height (a, b), if the function is satisfied. The dominance, or probability of retaining possession, is equal to the number of teammates divided by the total number of players who could contest. This approach assumes the worst case – that any player who could reach x, based on physical constraints, will do so.

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} \leq 1 \tag{3}$$

As we consider players as able to reposition, rather than as stationary objects, the optimal location to receive a kick need not be the player's current location. We employ a local maximum search to determine the optimal receiving location, based on EO, for a kicking player's 17 teammates.

KICKING VARIATION

Given that players lack perfect kicking accuracy, we introduce variability in the form of a 2D Gaussian distribution. Player accuracy is difficult to quantify with existing data as we require perfect information on intended targets. For the purpose of this study, we assume variability can be quantified by a Gaussian with covariance equal to 5% of the total kicking distance, suggesting that long-range kicks are more difficult to execute than short-range. With the addition of variation, the modified EO of a kick is equal to the summed product of the Gaussian's probability density function (PDF) and the raw EO values.

STATISTICAL ANALYSIS

The EO, DV and dominance were calculated for approximately 560 kicks in the 2017 AFL season. The explanatory power of our theoretical contest measure was examined by comparing the contest of successful and unsuccessful kicks. Decisions were extracted from the analysed matches and their characteristics summarised, providing insights into the types of decisions that are made in the AFL. We further explore decision making habits of players by summarising the characteristics of decisions that were identified as better options. These include the DV, the Euclidean distance between the kicker and target, and the dominance. Decisions, grouped by team, are compared across quarters to measure the correlation between decisions and score margins, calculated via the Spearman correlation coefficient (ρ).

3. RESULTS

An example of a decision-making output is displayed in Figure 1. In this example, the player, highlighted in red, made a short kick resulting in a DV of 0.48. Local max searches identified two decisions that would achieve a DV of at least 0.55. Note that DV calculations consider variability, hence identified decisions are unlikely to have a DV of 1.0.

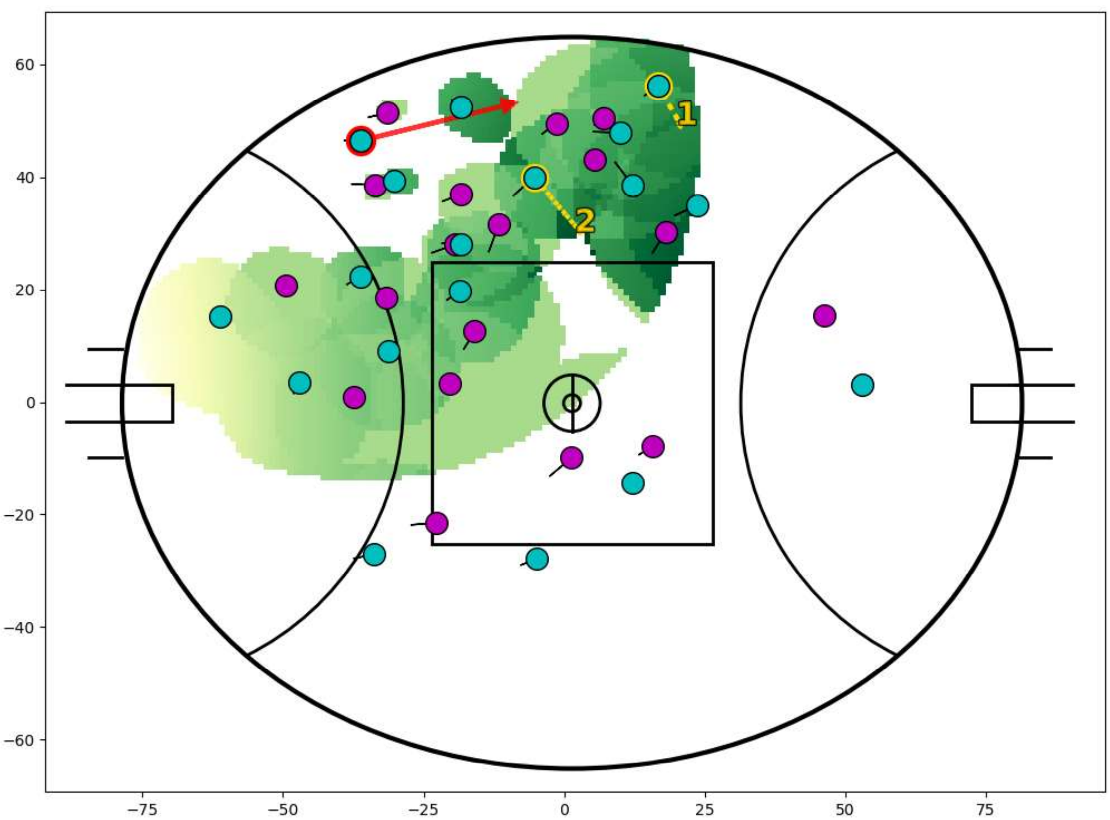

Figure 1. An example output of the decision-making model. The decision that was made by the player in possession is indicated by a red arrow pointing to the final position of the ball. Options identified as having higher EO are highlighted in yellow, with dotted lines representing the optimal receiving location of the identified

players. EO values within 60m of the kicker are visualised, with higher values represented by darker shades of green.

Fitting ellipses to movement data resulted in the RR presented in Figure 2. Due to sampling, data volume, and inaccuracies in wearable technology, some inconsistencies are present in the bands (e.g., subsequent whole-second movements can increase the ellipse boundary by smaller increments than previous bands).

The mean and standard deviation of calculated contests for successful and unsuccessful kicks across all matches was 0.60 ± 0.37 and 0.40 ± 0.25 respectively. There was found to be a significant difference between these two groups ($p < 0.001$).

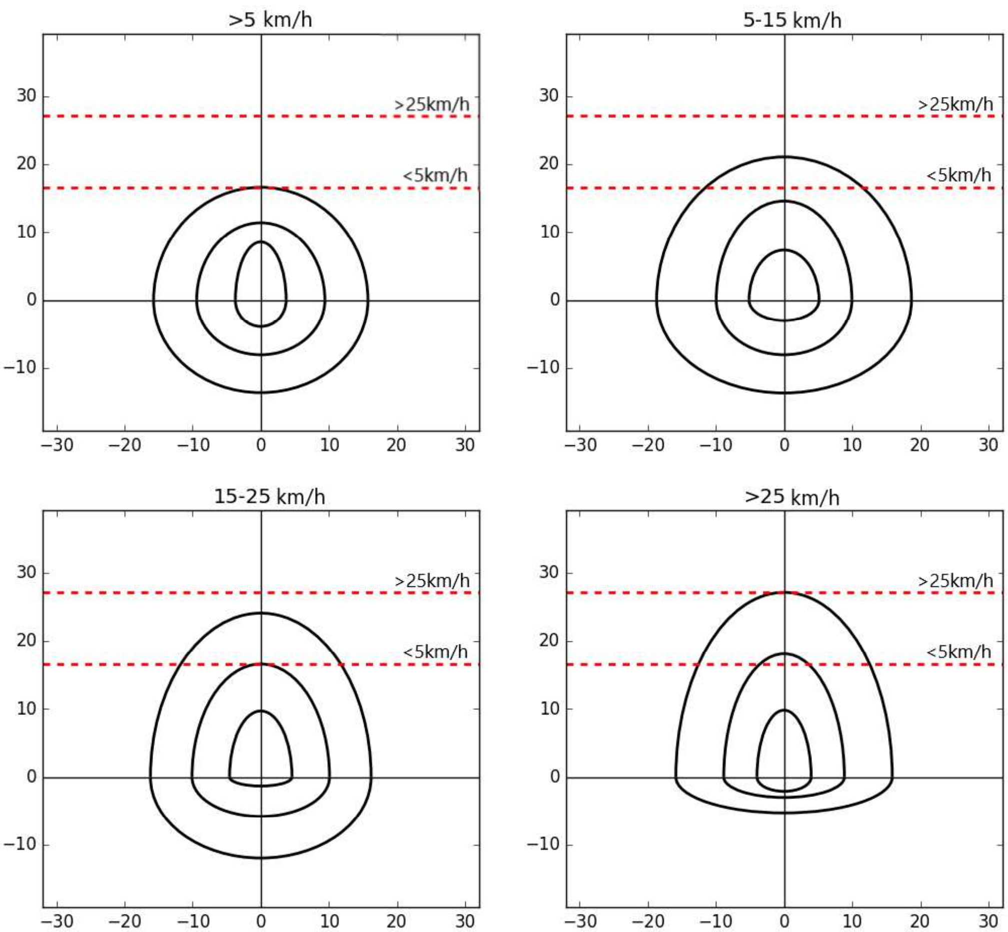

Figure 2. The RR of different speed bands for 1, 2, and 3-second integers. The red dotted lines refer to the 3-second maximum distance for the minimum and maximum speed bands.

Characteristics of kicking options are presented in Table 1. Options are grouped into the decisions that were made and the alternative options that were identified as having higher DV by the decision-making model. There was found to be significant differences between the characteristics of decisions that were made and the alternative options that were identified ($p < 0.001$). On average, kicks that were made are shorter (25.8 m) with lower average dominance but higher variance.

A weak, negative correlation was identified between decision making and score margin (ρ = -0.14). Further, there was not a statistically significant difference between the DV of winning and losing teams ($p = 0.85$).

	Distance (m)		Dominance		Decision Value	
	Mean	St.D.	Mean	S.D.	Mean	S.D.
Decisions	25.8	11.1	0.58	0.30	0.24	0.24
Alternatives	36.0	10.0	0.85	0.18	0.55	0.15

Table 1. Summarised decision data.

4. DISCUSSION

Our objective of this research was to develop a method for measuring player decision making in the AFL. To achieve this, we the theoretical spatial dominance of teams derived from player tracking data. Our methods consider the velocity and orientation of individuals. While prior studies have quantified if a decision resulted in an improved possession outcome, the methods detailed in this study value a decision relative to alternatives.

Decision-making results revealed a tendency towards short kicks, while statistical modelling identified long-range targets as having higher EO due to their much higher equity and generally lower theoretical contest. This trend towards shorter kicks is logical due to the lower variability and execution time. Perhaps more importantly, close options are more likely to be identified by players in a shorter period of time due to less visible obstruction. These decisions having a lower theoretical contest may suggest limitations in its calculations. Notably, we assume equal contest ability from players (hence, a player who excels at contesting the ball would be undervalued). Further, we do not consider the effects of interference (e.g., a player standing in front of another). Developing a predictive model to quantify the probability that an individual will commit to a contest, based on spatial features, may address these concerns.

Analysis of player movements revealed minimal differences between speed-bands, particularly in the walking and running categories. At higher velocities, players are not able to cover as much negative space. Inaccuracies in player tracking devices resulted in noisier bands than would be expected in optimal conditions. As we collect more data, it will be possible to produce RR for individuals, allowing for consideration of their maximum velocity and varying ability to accelerate and reorient.

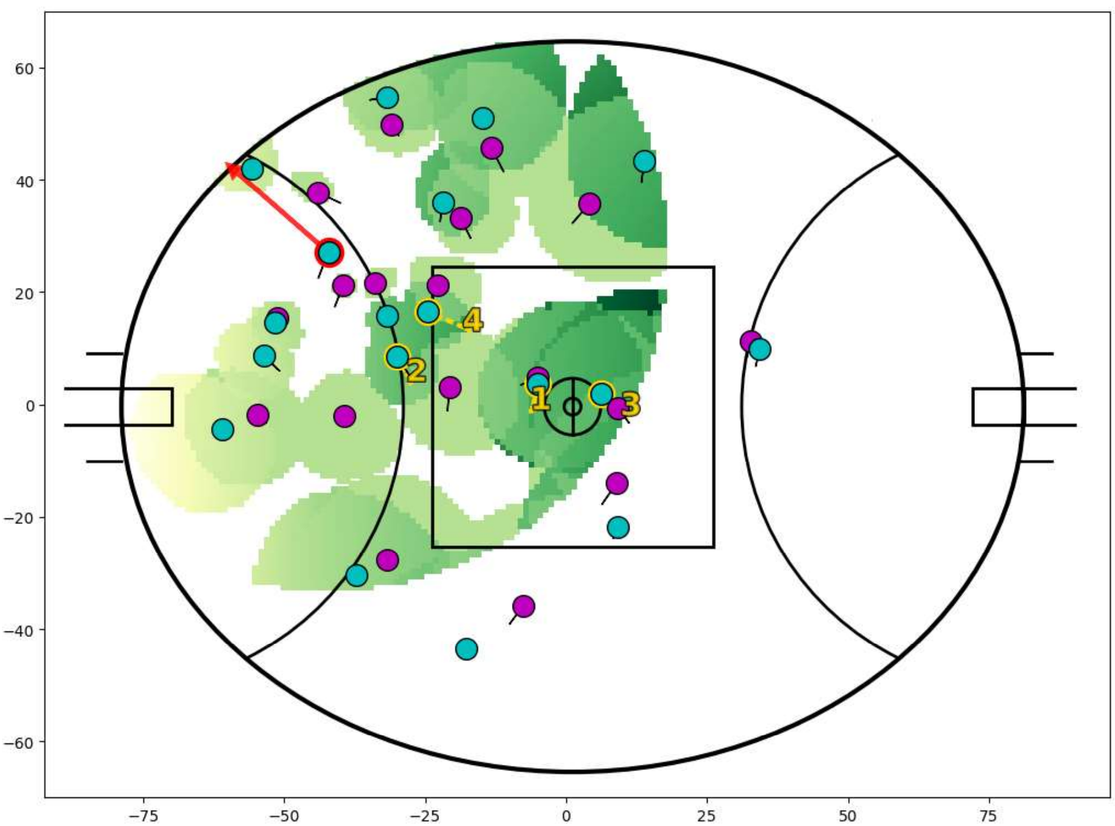

Figure 3. An example output that identifies optimal decisions requiring the ball to be kicked along a path that contains opponents.

While insightful, our decision-making model has limitations due to assumptions that must be made in the absence of additional data. Ball tracking technology does not exist in AFL, hence a reliance on play-by-play possession data to infer its position. If a kick results in a contest, isn't collected cleanly, or goes out-of-bounds, this must be omitted from the analysis as the target location cannot be determined with reasonable accuracy. Without precise locations, it is difficult to record information on kicks that were unsuccessful, as these are less frequently marked by opponents than they are recovered after a contest. Hence, without enough samples to model their relationship, we assume a linear relationship between a team's dominance and retaining possession. Despite that limitation, it was observed that successful kicks had a much higher calculated dominance than those that were unsuccessful. Finally, we assume balls can be kicked to any teammate, which may be unrealistic depending on the trajectory required to pass by opponents. Figure 3 demonstrates optimal decisions that would require the ball to be kicked above opponents. Physics-based modelling of kicks could be added to the calculations to omit unrealistic receiving locations such as in [8].

Should continued work address these limitations, a more robust decision-making metric could be developed. Applications of such a metric would include the ability to measure a player's decision-making capabilities, akin to how we conventionally measure other aspects of performance. This would allow for more informed recruitment, tactics, and match preparation. This need not be limited to the decision-making of players with the ball. For example, movements of players who don't possess the ball may lead to the creation of areas of space, measured by EO, and methods to quantify this could be the subject of future research.

5. Conclusion

The primary aim of this research was to develop a method for quantifying decisions made by players in Australian Rules football. Our focus has been on the expression of space as a continuous contest comprising of individuals who are capable of repositioning during the time between possessions. We express the value of a decision as the expected outcome of the kick that was made, divided by the maximum value identified *via* statistical analysis of field equity and possession retention. These methods were exemplified on kicks resulting from marks. Analysis of decisions found a trend towards kicking to close teammates with lower calculated EO than long-range targets. The decoupling of player decision-making from current performance metrics has applications in player selection, recruitment, and performance analysis.

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