Analyzing Defense Networks to Predict Play Outcomes in Basketball

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1 INTRODUCTION

Team contact sports like basketball, soccer, and hockey rely on passing an object (a ball or puck) around to move it into the goal. This requires coordination amongst the players of the team while facing opposition from players of the opponent team. As a result, the quality of a team is not simply the sum of its players; instead, success (a goal) emerges from dynamic interactions within the group [5]. This makes network analysis a natural tool to analyze player interactions. The network structure also comes naturally. It makes sense that players can be encoded as nodes and interactions amongst them, the passes, as edges. This leads to the creation of passing networks that model a network of passes in the game. Indeed, the community has recognized this natural fit, and network analysis has become a standard method for analyzing players and teams in soccer, basketball, and hockey.

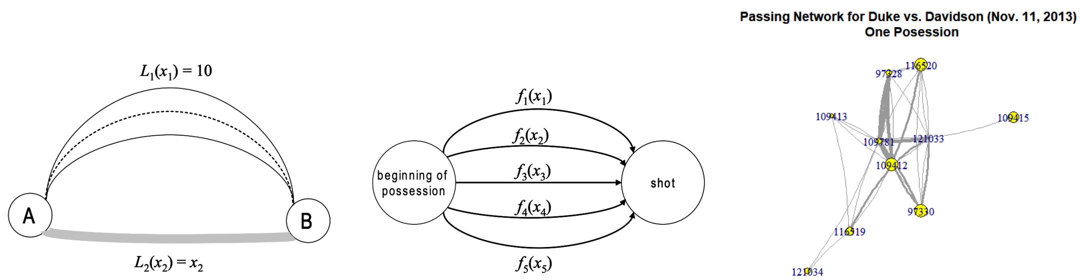
In this work, we focus on basketball, building upon past work that has modeled basketball using networks. Skinner [13] simplified each basketball play[1] to a two-node network (see Figure 1b) where different paths in the network correspond to different 'pathways' to the goal. They showed that greedy decision-making in basketball may lead to sub-optimal results. Xu [14] built upon this play-level analysis. They predicted the outcome of each play (e.g., shot, turnover, etc.) using network features of the passing network.

Both these works break down a basketball game into a series of plays — a series of passes from an inbound pass to the goal. While game-wide networks have been used to analyze player importance (e.g., betweenness centrality) and team strategy [3], they are large, noisy, and hence complex to analyze. Breaking down games into a series of plays reduces the complexity of analysis. Despite a rich body of work using these network analysis techniques, most work in this area needs to account for the defense. Here, the lack of defensive modeling can be construed in two ways. First, modeling techniques that rate players and teams only rate their offensive capabilities, whereas, in real life, the same five players must also perform defensive duties. Second, even when modeling just the offense, more is needed to model the passes, as well as how the team interacts with the opposition's defense; a successful offense involves breaching the opposition's defense.

Admittedly, defense is hard to model. There are three main problems. First, during offensive plays, ball passes are natural connectors between nodes. On the other hand, defensive pressure is built up by mere presence, without any physical interactions. This makes it hard to model it as a network. Secondly, even if we have the theoretical model to model the defense, doing so in practice requires *off-ball* movement data. However, even sophisticated data providers track pass-by-pass data, obscuring players' positions who were not involved in the pass. Finally, even after building a 'defensive network' with a theoretical model and data for empirical analysis, there is another problem: Since the offensive team does not interact physically with the defensive team, how do we model the *interaction* between the offense and defense? The defensive formation changes in response to every pass during a play. Hence, a single offensive network interacts with not one but a series of defensive networks. We aim to define a model that solves these difficulties.

In the context of CS 6850, the complexity here lies in the modeling itself. While Skinner [13] poses basketball as a 'path-finding' problem from an inbound pass to the goal, we are not currently focusing on that problem. Instead of

[1] A play (or possession) is the movement of the ball from an inbound pass to the point that the team loses possession of the ball (e.g., shot, turnover, etc.).



Traffic Network [13] Basketball Network [13] Play Network [14]

Fig. 1. Networks used in our reference papers.

focusing on a specific network process (e.g., path-finding, cascading, etc.), we are in a domain where there currently does not exist a network to run these processes in the first place. Hence, our paper focuses on the step before analysis: modeling a real-world phenomenon as a network. This is interesting (and hard) for the reasons mentioned above. Below, we summarize the two papers we chose. With that setup, we will then propose our specific model.

2 RELATED WORK

Starting around 2010, researchers began to use social networks as a tool to analyze sports [7, 10]. Since then, there has been a diverse body of work using network analysis in sports, including play networks of soccer [4, 8], batsmen and bowler networks in cricket [9], and so on. In our work, we focus on modeling basketball using networks.

In 2011, Skinner [13], drew inspiration from traffic networks to model basketball gameplay. The author defined the term “price of anarchy” to be the difference between taking the greedy and short-sighted route and the globally optimum route. Just like cars need to travel from their origin to their destination through a choice of roads (Figure 1a), each basketball play (like each car) needs to go from point A (the inbound pass) to point B (the basket) as shown in Figure 1b. The paper modeled each player to have a scoring efficiency based on their shot-taking frequency and showed that just like in traffic networks, the most optimal route to the basket may not be the most obvious. The modeling effort of this work influenced a series of network analyses of basketball gameplay, such as comparing statistics across games [5], analyzing how game state affects players [15], and improving game strategies [6, 12].

Subsequent works have tried to refine the network modeling and the selection of network features. Piette et al. [11] focused on finding the series of plays that generate the most points to quantify player performances and used the frequency of visits in a random walk on the network as a proxy. Xu [14] worked on determining the most salient network features in a passing network that can predict the outcome of a play. They investigated features including betweenness centrality, reciprocity, and number of triangles. More formally, they represented each play as a network, with players as nodes and passes between them as edges. An example of one such play is shown in Figure 1c. Then, for play i, Xu [14] trained the following model to predict the outcome of the play y_i:

$$y_i = \beta_{tri} x_{tri,i} + \beta_{recip} x_{recip,i} + \beta_{between} x_{between,i} + \epsilon_i \tag{1}$$

Xu found that these features were not significant predictors of the outcome of a play; however, it was found that betweenness centrality and number of triangles (indicators of collaboration) had a direct relationship with positive outcomes such as scoring a basket.

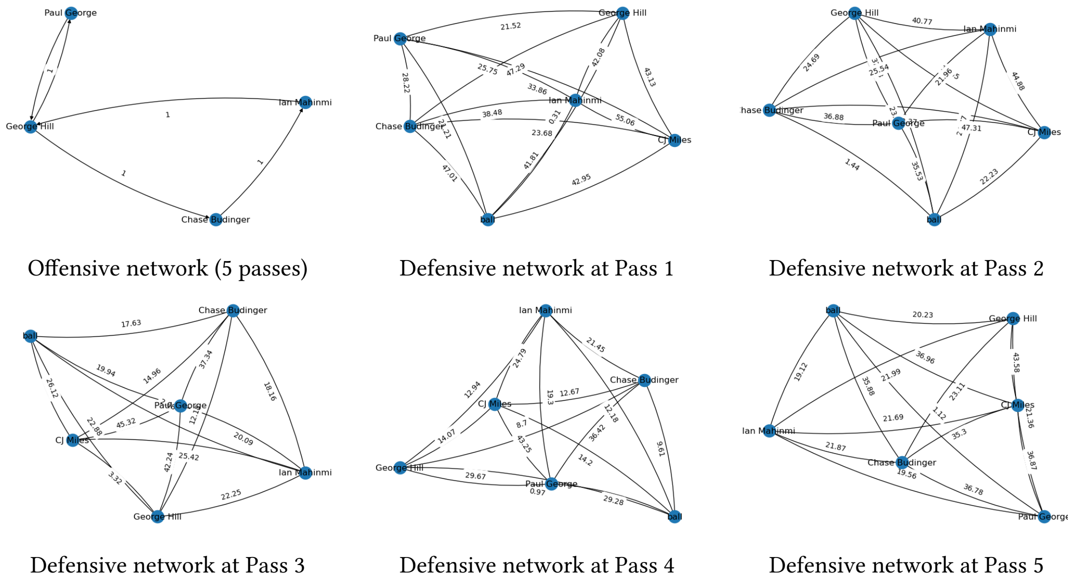


Fig. 2. The first image shows the offensive network for a particular play involving five passes from a Spurs vs Wizards game. The other five images show the defensive network when at each of those five passes.

However, this work, and indeed most work in the area, simplistically assumes that a play's outcome depends only on the attacking team. This ignores the impact of the opposing team's defense, for example, the same player may be a less successful shooter against a stronger defensive team. While there has been work on modeling defense play using generative models[1, 2], their focus on player trajectory generation is orthogonal to ours. The challenge of modeling defensive team play lies in quantifying this defensive pressure and incorporating team defense strategies into the network model. A play's success depends not just on the effectiveness of the team's offense, but also on how it interacts with—and potentially breaks through—the other team's defense. Specifically, we hypothesize that it is possible to improve the model shown in equation 1 by adding more features that incorporate the team's interaction with the opposing team. In other words, the red term below is missing.

$$y_i = \beta_{tri} x_{tri,i} + \beta_{recip} x_{recip,i} + \beta_{between} x_{between,i} + \color{red}{\beta_{interaction} x_{interaction,i}} + \epsilon_i$$

However, the complexity lies in calculating this term. As explained briefly in the introduction, this requires first modeling the defense as a network, and then quantifying the interaction between a team's offensive network and its opposing team's defensive network at each time step (since the defensive formation changes at every time step). In the next section, we propose our model.

3 PROPOSED MODEL

As explained in the previous sections, we aim to model the defense as a network and then quantify the interactions between the offensive and defensive networks. Each network in our model models a *play*: a series of passes from an in-bound ball to a loss of possession by the team. Let V be the subset of offensive team players who touched the ball in a particular play. Note that $|V| \leq 5$ since each team has five players on the court[2].

Each play is represented by an offensive network (a passing network), designed similarly to Xu [14]. It is a directed graph $G = (V, E)$ where the players are modeled as nodes. A directed edge $(v, w) \in E$ represents that the ball was passed from player v to player w in this play. The weight of this edge $w(v, w)$ represents the number of passes from v to w in this play. We now define the defensive network (our contribution).

In our model, the defensive network is defined as an offensive network. This follows the intuition that the defensive is reactive and changes its formation in response to the attacking team's offensive maneuvers. As defined above, the current play is a graph G. The number of passes P in this play is the sum of all edge weights, *i.e.*, $P = \Sigma_{(v,w) \in E} w(v, w)$. Since the defensive formation changes in response to every pass in the offensive network, we have a defensive network $\hat{G}_i$ for each $i = 1, \ldots, P$. $\hat{G}_i$ represents the defensive formation when the ith pass was made. Each $\hat{G}_i$ is an undirected complete graph over $\hat{V}_i$, the set of all the players in defensive formation i and the ball. Hence, $\hat{G}_i = (\hat{V}_i, \hat{E}_i)$ where $|\hat{V}_i| = 5 + 1 = 6$. An edge $(a, b) \in \hat{E}_i$ represents the proximity between defenders a and b (or the ball) in the ith formation, and the weight of this edge $\hat{w}_i(a, b)$ is the distance between them at that point. Hence, the complete graph $\hat{G}_i$ encompasses the defending team's defensive formation, such as their relative positions and distance from each other and the ball.

Figure 2 visualizes our proposed model for a single play involving five passes (and, therefore, five defensive networks). The sequence of passes in this offensive graph was: Paul George → George Hill → Chase Budinger → Ian Mahinmi → George Hill → Paul George.

Analyzing Model Size

It is essential to consider the size of our model to ensure that analyses on it remain tractable. The offensive graph G has $|V| \leq 5$ nodes. In the worst case, every player may pass to every other player, leading to a directed complete graph with $|E| = \frac{|V| \times (|V|-1)}{2} \times 2 = 20$ edges. Hence, while the number of passes in each play P (as defined earlier) may be unbounded, the size of the graph is bounded by a constant. However, a considerable P is undesirable because that would blow up the number of defensive networks. Fortunately, we see empirically that an average offensive play is 2.67 passes long. Finally, each defensive model $\hat{G}_i$ is also bounded since the number of nodes $|\hat{V}_i| = 5$ and it is an undirected complete graph, bounding $|\hat{E}_i|$ to 10.

4 METHODOLOGY

Implementing our model is challenging because it requires off-ball tracking data to know the positions of the defensive players. However, even sophisticated data providers track only on-ball actions (e.g., who passed and to whom, starting and ending positions of the pass, etc.). Off-ball movement data is provided by only one provider, SportVU. We used their free dataset for the 2015-2016 NBA season. We sliced the games in this dataset into specific plays. We then created an offensive network for each play and a defensive network for each pass in the play. Figure 2 visualizes our proposed model for a single play involving five passes (and therefore five defensive networks).

[2]Sometimes there may be substitutions mid-way, increasing the count beyond five. We ignore such plays.

4.1 Data Description

As mentioned, we use SportVU's dataset on NBA Play-by-Play Data for the 2015-2016 season to implement our model and analyze basketball game dynamics. The data is available freely for public use[3]. This is a rich dataset that provides the positions of all players of both teams and the ball's position (including its altitude) at a 25 Hz frequency.

This dataset provides a holistic view of the entire game. However, it is very *raw*; it captures a snapshot of the court (the positions of all players and the ball) at a frequency of 25 Hz throughout each game quarter. Hence, we used heuristics to process this data into plays. Following a method similar to that used in Xu [14], we identified passes by determining the last player to control the ball. To be considered in possession, a player must be the closest to the ball for consecutive snapshots, and the ball must be moving at a low speed and height. A pass is recorded whenever there is a change in the last player in possession of the ball, encompassing all snapshots from the start of possession by the first player to the point where a new player is identified as having control of the ball. In this way, we computed passes. Next, we needed to compute "plays", the basic unit of analysis in our proposed model.

4.2 Computing Plays

Our work defines a "play" as a series of passes within the same team. We developed a script to parse and categorize plays from raw play-by-play text data, aligning it with game timestamps from freely available data from ESPN[4]. A play illustrates the team's possession, so we identify the offensive team as the team more involved in ball passing during a play. Since it is unlikely for a defensive team player to possess the ball, we exclude defending players from the pass count to minimize false identifications of ball possessors. This is achieved by merging passes involving defense players until they are both from and to an offense team player.

By doing this, each play was transformed from raw text data into a structured format. However, one detail still needed to be included in this dataset: the outcome or result of each play. Our dataset did not have any structured way of defining whether a play resulted in a positive (e.g., shot) or negative (e.g., turnover) outcome. Hence, we had to use data from ESPN to correlate our plays with outcomes. The ESPN dataset provides information about game state changes such as score changes, overturns, fouls, etc. By aligning the game clock in the two datasets, we augmented our play data with positive (e.g., made shot), damaging (e.g., missed shot), or neutral (e.g., inbound ball) outcomes from the ESPN data. These outcomes are described below.

4.3 Assigning Outcome Weights

Since we wanted to predict the outcome of each play, we assigned weights (or labels) to each outcome. To account for the varying impact of different outcomes in basketball, we assigned weights ranging from -2 to +3 (instead of just 0 and 1). The weight assignment is described below:

- **Three Points (+3):** Awarded to successful three-point field goals. This reflects the higher scoring value of three-pointers in a basketball game.
- **Two Points (+2):** Given to successful two-point field goals and free throws. This represents the direct scoring contribution of these plays.
- **One Point (+1):** Assigned to plays that indirectly contribute to scoring or defensive efforts, such as offensive rebounds (creating additional scoring opportunities) or assists (facilitating successful scoring plays).

[3]https://github.com/linouk23/NBA-Player-Movements
[4]https://www.kaggle.com/datasets/schmadam97/nba-playbyplay-data-20182019

- **Zero Points (0):** For plays with a neutral or unclear impact on the team's performance, such as a play stoppage or non-scoring actions. This is not used in modeling and testing.
- **Negative One Point (-1):** Deducted for defensive rebounds, indicating a successful defense but a missed opportunity for scoring.
- **Negative Two Points (-2):** Assigned to plays with a detrimental effect, such as turnovers (loss of ball possession) or fouls (potential for the opposing team to score). This is not used in modeling and testing.

4.4 Data Compilation

After processing the SportVU and ESPN data, each play was parsed and assigned a weight. This resulted in a dataset that included, for each play, the offensive graph for the play, the set of defensive graphs for each pass in the play, and the outcome/weight for the play. Due to the limited availability of free data and compute restrictions, we prepared the dataset for 30 randomly chosen games in the 2015-16 NBA season. However, our analysis can be easily extended to the entire or multiple seasons. Finally, we had 697 basketball plays[5] from 30 games, each with an outcome as defined previously.

5 EXPERIMENTS AND RESULTS

We performed two sets of analyses. First, we analyzed the defensive graphs. Since this is the first work to model defensive network features, we conducted these experiments to establish the legitimacy of our model. Second, we built a predictive model to quantify the offensive-defensive interactions in predicting a play's outcome. We present these results below.

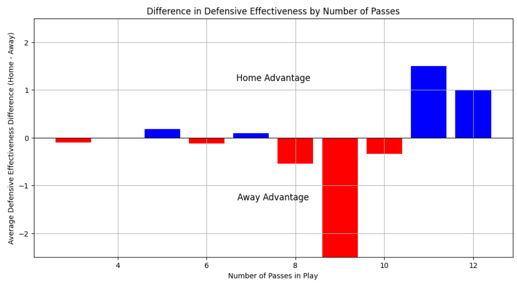
5.1 Analyzing Defensive Networks

The results of our analysis of the defensive networks are visually represented through a series of figures that illustrate various aspects of defensive performance about passing dynamics. We used the networks and the supplementary game data to make interesting graphs.

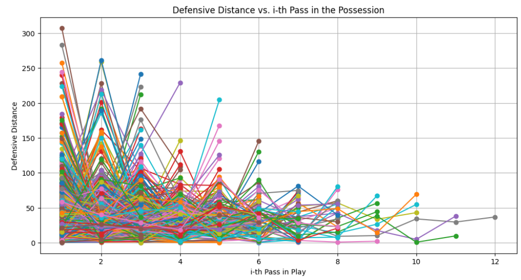
5.1.1 Difference in Defensive Effectiveness by Number of Passes (Figure a). Figure (a) shows the difference in defensive performance by the number of passes. Defensive effectiveness is measured by the weight of the outcome for each play, where the more negative, the better the defense. The bar graph indicates that home teams display a significant defensive advantage with an increasing number of passes, peaking notably at 11 passes per play. Conversely, away teams demonstrate a superior defensive performance with fewer passes, with the most substantial advantage occurring at plays of 9 passes. This finding suggests that home teams utilize more complex passing strategies that are effective defensively, whereas away teams tend to optimize their defense in shorter passing sequences.

5.1.2 Defensive Distance vs. i-th Pass in Each Play (Figure b). Figure (b) presents a scatter plot that relates the i-th pass in a play to the defensive distance covered. Defensive distance is how far apart the defense is from each other in the network. There is a wide dispersion in defensive movements for initial passes. However, as the number of passes increases, a trend emerges where defensive distance converges, potentially indicating defensive adaptation throughout a play.

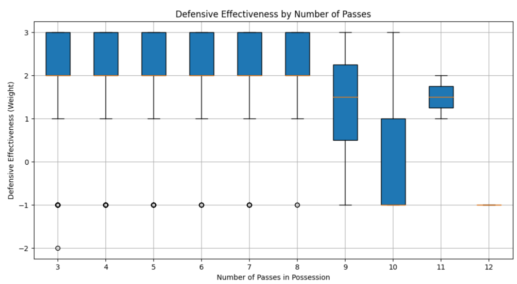
[5]This number is smaller than expected for 30 games because we removed plays with data cleanliness issues, for example, when a play's game clock did not align in the two datasets.



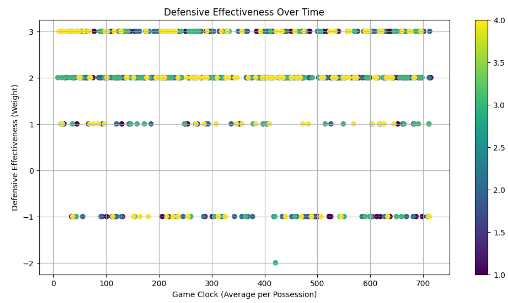
(a) Difference in Defensive Effectiveness



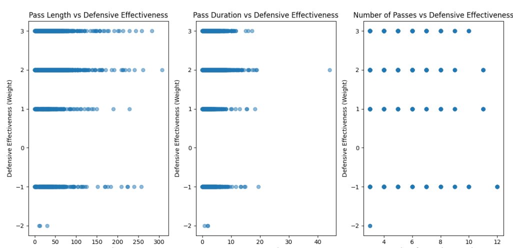
(b) Defensive Distance vs. i-th Pass



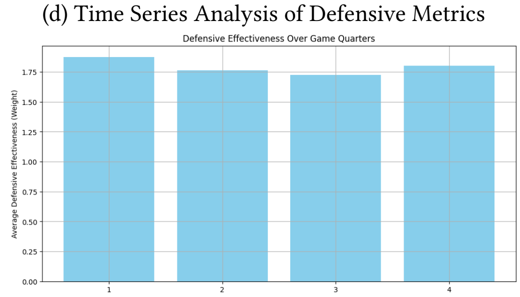
(c) Defensive Effectiveness



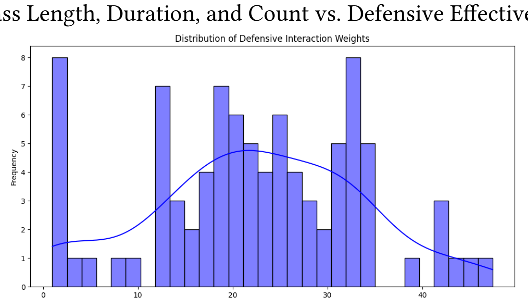
(d) Time Series Analysis of Defensive Metrics



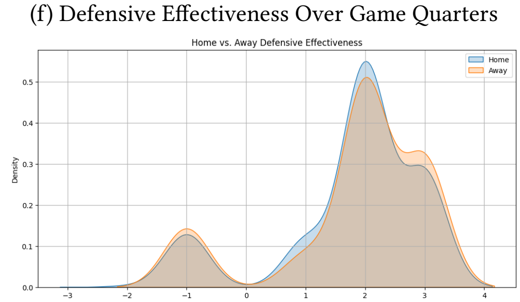
(e) Pass Length, Duration, and Count vs. Defensive Effectiveness



(f) Defensive Effectiveness Over Game Quarters



(g) Distribution of Defensive Interaction Weights



(h) Home vs. Away Defensive Performance

Fig. 3. The figures show an array of defensive analyses in a logical sequence. Figure (a) introduces the difference in defensive performance by the number of passes, leading into Figure (b) which expands on this by relating defensive distance to the i-th pass. Figure (c) examines the spread of defensive effectiveness in relation to the number of passes, followed by Figure (d) which correlates pass characteristics with defensive effectiveness. Figure (e) presents a time series analysis of defensive metrics, and Figure (f) shows how defensive effectiveness varies over the game quarters. Figure (g) presents the distribution of defensive interactions, and Figure (h) contrasts home versus away team performances, emphasizing the influence of the venue on defensive strategy.

5.1.3 Defensive Effectiveness by Number of Passes (Figure c). Figure (c) provides a box-and-whisker plot detailing the defensive effectiveness related to the number of passes in a play. Higher passes (10 and 12) show greater variability in defensive effectiveness, with a few significant outliers suggesting that longer passing sequences can lead to high and low extremes in defensive outcomes.

5.1.4 Time Series Analysis of Defensive Metrics (Figure d). Figure (d) delivers a time series analysis of defensive metrics. The scatter plots demonstrate a correlation between pass length, duration, and count against defensive effectiveness, with distinct clusters indicating specific pass lengths and durations corresponding to varying levels of defensive success.

5.1.5 Pass Length, Duration, and Count vs. Defensive Effectiveness (Figure e). Figure (e) provides a composite analysis of three scatter plots that compare pass length, pass duration, and the number of passes against defensive effectiveness. Each plot reveals patterns of defensive performance relative to different aspects of passing. The concentration of data points suggests there are optimal pass lengths and durations for maintaining defensive effectiveness. In contrast, the number of passes shows a more dispersed correlation, indicating that the relationship between pass count and defensive success is significantly complex.

5.1.6 Defensive Effectiveness Over Game Quarters (Figure f). Figure (f) illustrates the defensive effectiveness over game quarters. This bar chart shows the average defensive effectiveness weight by quarter, providing insights into how defensive strategies and effectiveness evolve throughout the game. The consistency across the quarters suggests that teams maintain a steady defensive approach, with slight variations indicating fatigue, strategic adjustments, or the changing dynamics of the opponent's offense as the game progresses. The effectiveness falls slights over the game for these reasons but recuperates in the last quarter, perhaps due to heightened pressure closer to the end of the game.

5.1.7 Distribution of Defensive Interaction Weights (Figure g). In Figure (g), the histogram with an overlaying density curve shows the distribution of defensive interaction weights. The distribution is usually distributed with a slight rightward skew, highlighting that most defensive interactions occur within a moderate range of weight values, suggesting a commonality in the impact of typical defensive actions.

5.1.8 Home vs. Away Defensive Effectiveness (Figure h). Lastly, using a density plot, Figure (h) contrasts the defensive effectiveness between home and away teams. It reveals distinct peaks for home and away teams, with home teams typically demonstrating higher defensive effectiveness, reaffirming the notion of a home-court advantage in basketball.

5.1.9 General Discussion. The analysis presented in Figures (a) through (h) offers an exploration of defensive strategies in basketball, with a particular emphasis on the role of network analysis. This methodological approach allowed for an examination of player interactions and defensive formations. By mapping out defensive networks, we analyzed various metrics, including pass counts, defensive distances, and the dynamic changes in defense throughout a game. These figures highlight the complex interplay between offensive plays and defensive responses, demonstrating how various factors, such as the number of passes and positional adjustments, impact overall defensive performance. The network analysis also shows the adaptability required in defensive strategies, particularly in game context and progression. The insights gained from this approach provide an understanding of the interplay between offensive and defensive tactics in basketball, offering clear strategic implications for teams, especially in different settings like home and away games.

5.2 Predictive Model

After analyzing the defensive networks, we wanted to model the interaction between a team's offensive tactics and their opponent's defensive strategy.

5.2.1 Experimental Setup. To model the offensive-defensive interaction, we built a logistic regression model to predict the outcome of a play. However instead of using features only from the offensive graph (as done by Xu [14]), we also added features from the play's defensive graphs. By doing this, the model would also encompass information about the opposing team's defense in predicting the outcome of the play. We also ensured that we did not use any features that would make this prediction trivial, for example, the absolute coordinates of players or the ball.

Since the number of passes in a play is variable, we used the defensive graphs from the play's first, middle, and last pass. To ensure these three graphs are distinct, we used plays with at least three passes for this experiment. For each of these three defensive graphs, we computed the following features:

- Max Pagerank across all nodes. This feature computes the most important node in the defensive graph and helps us quantify the importance of players in the defensive formation.
- Sum of distance of players from the ball. This feature quantifies the defensive formation of players around the ball.
- Sum of all edge weights. This feature quantifies the "overall" defensive spread of the team, for example, how far apart or close together the defending team is as a whole.

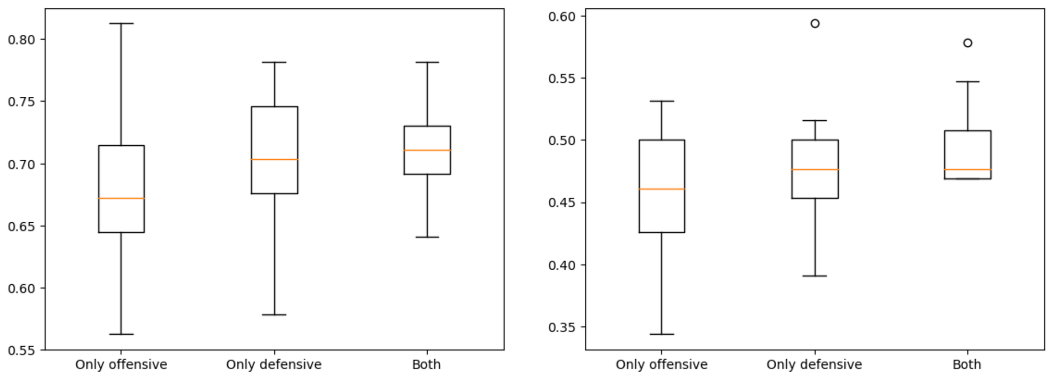
In addition, there were four features from the offensive graph: max. betweenness centrality, reciprocity, number of triangles, and number of passes (sum of edge weights). These are the same features chosen by Xu [14] in their work. The overall feature set is shown in Table 1.

Betweenness centrality	Features from the offensive graph
Reciprocity	
Number of triangles	
Number of passes	
Pagerank ×3	Features from the three defensive graphs
Distance from ball ×3	
Sum of edge weights ×3	

Table 1. Feature set for the predictive model

5.2.2 Results. First, we built a binomial logistic regression model for binary classification (where weights ≥ 3 are a "successful" outcome and everything else is "unsuccessful"). We trained three kinds of models: with only `offensive` features, with only `defensive` features, and with `both` attacking and defensive features. For each model, we trained 10 independent instances with random train-test splits and computed the prediction accuracy. We find that the `offensive` model has a mean accuracy of 68.28%, followed by the `defensive` model with 70.16%, and `both` model with 71.1% accuracy. The spread of the accuracy for each model is shown in Figure 4a.

Then, we trained a multinomial logistic regression model with the original weights. We used the same setup as described above. Due to multiple classes, the overall accuracy dropped, but the trend remained the same: the `offensive` model performed the worst (45.63%), followed by the `defensive` model (47.97%), and the `both` model performed the best (49.53%).



(a) Binomial logistic regression

(b) Multinomial logistic regression

Fig. 4. Model accuracies for the three models with offensive, defensive, and both offensive and defensive features. Figure (a) shows these accuracies for a binomial logistic regression and (b) for a multinomial logistic regression.

Further, we found that out of the 13 features in the binomial `both` model, most were not significant predictors of the outcome. Interestingly, the only significant predictors were the three features from the last defensive graph before the play ended. This provides statistically significant evidence that the opponent's defense (or the lack thereof) plays a vital role in determining the outcome of a play.

6 CONCLUSION

Our research has shown insights into the dynamics between defensive strategies and play outcomes in basketball. Our modeling and analysis of defensive network features, a first in this field, shed light on the crucial aspects of defensive performance about passing dynamics. Our key findings include the variation in defensive effectiveness in correlation to the number of passes. Home teams demonstrated a distinct defensive advantage with an increasing number of passes, particularly at 11 passes per play. In contrast, away teams showed better defensive performance with fewer passes, notably at nine passes. Additionally, the analysis revealed a convergence in defensive distances as the number of passes increased, suggesting an adaptation in defensive strategies during a play. Our other observations included the variability in defensive effectiveness with longer passing sequences, pointing to the potential for both high and low extremes in outcomes.

By integrating features from both offensive and defensive graphs into our predictive models, we demonstrated an improvement in prediction accuracy. The combined offensive and defensive model outperformed those with only single-sided features, reaching an accuracy of 71.1% in binomial logistic regression and 49.53% in multinomial logistic regression. This underscores the critical role of defense in determining play outcomes. The research highlighted the importance of modeling defensive strategies in basketball analysis.

Future Work

With the following steps, there is room to explore the impact of individual players' roles within the defensive network. One can quantify the strategic importance of player positioning and movements by identifying key players and their influence on the team's defensive effectiveness. Work can also be done to extend our analysis across different teams to uncover unique defensive styles or effectiveness linked to specific coaching strategies or player compositions.

The results of this project show an analysis of the previous defensive strategy and its effectiveness. We do some work to predict what outcomes defensive strategy can produce, but further analysis can be done to inform coaching decisions on a play-by-play basis. This work would directly benefit the coaching staff by allowing them to quantify a defensive approach and implement it live into the game. This paper sets up a solid foundation for this work, leading to more direct suggestions for defensive strategy in basketball.

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