NFL In-Game Player Interaction Network Analysis

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Abstract

This paper explores the use of Social Network Analysis to analyze in game player interactions in the NFL. Focusing on the first 9 weeks of the 2022 NFL Season. NFL teams operate as a highly structured organization, with individual players fulfilling specific roles that contribute to a combined goal. Player interactions within individual plays perform a complex web that influences team performance. By modeling these interactions as a network, we can provide a quantitative method for analyzing the relationship between these players. This study aims to uncover patterns of player interactions across multiple games and identify key players who maintain central roles in facilitating team coordination. Through this analysis, we will deepen our understanding of NFL team behavior and the individual contributions players make to their team's success.

1 Introduction

NFL football teams are a highly structured organization where players interact with each other in a multitude of complex ways to achieve a common goal, winning games. Through the structure of games, each player has a specific role to fulfill, and their actions on the field are interdependent. This in turn forms a web of interactions that influence the overall performance of the team. Understanding these interactions is crucial to gaining insights into team strategy, individual player contributions and factors that help to drive success. While traditional analyses often focus on individual player stats or team performance a deeper understanding of how players interact during plays can bring light to the nuances of team dynamics.

Social Network Analysis (SNA) offers a powerful method for examining relationships between players by modeling their interactions based on the events that occur during a game. Using players as nodes and their interactions with each other as edges, SNA can provide a way to measure the connections between players and their roles in team strategy. Considering the context of a football game, interactions such as passes, rush attempts, tackles, or interceptions are key moments that define player roles and team performance. Using SNA allows for not only the analysis of these interactions through multiple games, but can help reveal patterns or key players who facilitate team coordination.

In this paper we will explore the application of SNA to analyze player interactions during NFL games across the first 9 weeks of the 2022 NFL season. By focusing on these in-game dynamics between players, we aim to find out how player relationships evolve throughout different games. As well as determine what these interactions reveal about the contributions of individual players to their team's success. Through this analysis we seek to continue growing the understanding of the behavior of NFL teams and the individual roles players have within this complex game.

2 Background

2.1 Benefits of SNA in Team Sports

Before we jump into our research, it is important to review relevant literature to understand the context for applying SNA to team sports. The article "The Application of Social Network Analysis to Team Sports" provides a foundation for examining the limitations of traditional methods and the advantages of network analysis in studying team dynamics [Lusher et al., 2010].

The author starts the paper by arguing that traditional tools are insufficient for understanding the complex social dynamics of team sports. For example, the Team Norm Questionnaire (TNQ) has been used in previous publications, but validating its results has proven difficult, causing researchers to abandon it. The TNQ requires large sample sizes to be able to achieve adequate statistical power, but team rosters have limited sizes, constraining the number of possible responses. This in turn reduces the quality of results provided by the TNQ. As well, teams often have a hierarchical structure to them, where senior players or players considered 'best' have more influence. This creates further challenges in separating individual responses from team-wide patterns. These limitations highlight the need for alternative approaches such as SNA to analyze team sports effectively.

The author's thesis states that SNA is a powerful tool that can aid in examining the social interactions in teams. Rather than replacing traditional methods, SNA can improve them by enabling the study of social hierarchies and power dynamics in teams. This applies to sports teams particularly well, due to them being "bounded, well-defined groups (full networks) with interdependent members." Teams also have clear performance outcomes, and the quality of player relationships has a direct correlation to team performance. All of these characteristics make sports teams an ideal candidate for applying network analysis.

The paper then moves into outlining several ways SNA can be used in team sports. Firstly, SNA can identify popular and influential members within a team, using social hierarchies rather than assuming equality among team members. This provides insights into how leadership and influence impact team cohesion and performance. Second, SNA can explore trust dynamics within teams. Helping to examine the relationship between interpersonal trust and individual attributes such as experience and/or ability. In addition, the author proposes SNA can assess team climate by analyzing specific social structures, such as sub-group clusters, or reciprocated relationships, and how they impact team success. These applications demonstrate the versatility and utility of SNA in studying team sports.

Finally, the author presents how the network would be structured, having individual players represent nodes. And edges between them would be specific to an individual's research thesis. Beyond creating the network certain tools can be used to analyze node (player) importance. Examining different centrality measures such as betweenness can help to identify the most influential nodes.

In summary, the article emphasizes that SNA provides tools to analyze complex social processes in sports teams that traditional methods often overlook. By identifying influential players, exploring trust and relationships, and assessing team climate, SNA can significantly enhance our understanding of how social networks influence team performance and dynamics. This insight forms a critical foundation for our research and supports the adoption of network analysis as a valuable addition to existing methods.

2.2 Analysis of SNA in Team Sports

Moving past the benefits and uses of using SNA on team sports, we can dive deeper into ways in which it has been applied. The paper "Play-by-Play Network Analysis in Football" examines how SNA can be applied to study player interactions in European football [Korte et al., 2019]. This specific paper focuses on aggregated match-level data, examining play-by-play passing interactions. The author does so by introducing two metrics. Firstly flow centrality which measures player involvement across all plays. Secondly flow betweenness which identifies players who are intermediaries in passing sequences. These are used to help identify dominant and intermediary players in successful or unsuccessful plays.

Examining how the author created the network, it is noteworthy that the data came from 70 Bundesliga matches, totaling 24,990 passes across 5409 plays. The study focuses on sequences from the data that involve at least two completed passes. Using flow centrality we can capture the involvement of players in plays. Meanwhile flow betweenness identifies players who are bridges helping to connect different parts of the team during passing. This approach provides a deeper understanding of players roles than overarching match level statistics.

Looking at the results of this research we gain insight into significant differences in player roles based on position. We learn that central defenders are more involved in unsuccessful plays. This reflects their role in maintaining ball possession but not transitioning to successful attacks. As well, we learn central offensive midfielders are the most involved in successful plays. Considering central defensive midfielders we learn they act as intermediaries, helping to transition between defense and offense. Lastly, forwards play a special role in finishing offensive plays rather than distributing passes.

Looking beyond player positions this article examines the influence of player involvement based on field position. Plays that start on a team's own half were more likely to involve wing players. Meanwhile, plays starting on the other team's side involved offensive players. This helps to understand the nature of player roles depending on the play's origin and position of the pitch.

Overall this paper helps to demonstrate the potential of SNA to provide deeper insights into player dynamics in football (soccer). By using flow based metrics clubs can gain a better understanding of player contributions during differing play contexts

3 Methods & Materials

3.1 Data

With a firm foundation now in the advantages of using social networks to examine social hierarchies and how they can be applied to team sports, we can begin to examine methods used to analyze our data. The data was collected during the 2022 NFL season by Pro Football Focus. It contains detailed information about advanced player statistics within offensive and defensive plays. The data was collected to analyze the tendencies of plays in the NFL and was made available by Kaggle and the NFL for the annual Big Data Bowl competition [Lopez et al., 2023].

We specifically will be using two CSV files from the data set. The first, "player_plays", contains 354,727 observations with 50 columns of attributes that are specialized player statistics during plays. The second file, "players" contains 1,697 observations with seven attribute columns, such as player names and positions. These data sets are then able to be connected using player specific "NFLId", a unique identifier for each player.

3.2 Creating Our Network

We created our network to analyze NFL players in game interactions with eachother. We define each node in the network as an individual player in our data set that has a edge to another player. The way in which we determined edges in our network was by examining the recorded statistics for players and connecting two players if they would interact during a play. The way this works is we have data on all 22 players on the field for each play. For each specific play we have statistics or conditions that we consider as an edge in our network, as two players are interacting during the play. For example if player A has a rush attempt, and player B tackles player A, we determine rush attempt and solo tackle are an edge worthy condition pair and create an undirected edge between player A and B. We can examine Table 1 to visualize every statistic pair that we determined as an edge worthy interaction during a play. As well we denote no direction for edges as we felt player interaction was constrained due to the way in which NFL games are structured and felt that this would cause disproportions in player importance.

It is important to note that offensive lineman only have one pair of conditions that allow for them to receive an edge. The condition being "pressureAllowedAsBlocker". This was done intently to reduce high edge repetition between offensive and defensive lineman. Through this analysis we wish to determine the relations of player interaction following the ball. Tracking every offensive lineman's blocking assignment each play would greatly skew the relations and importance of nodes in the network.

To create our network, we look through every play in our games from our data and connect nodes accordingly. A noteworthy piece of this method is a lack of interaction between an individual teams offense and defense. This results in the output of two separate networks when analyzing one specific game. We can visualize this in Figure 1. Here we can easily understand how Texan's offensive players only connect with each others and Bear's defensive players, while the second is Bear's offensive players connected to each other and Texans defensive players.

Condition 1	**Condition 2**
hadDropback	hadPassReception
hadDropback	wasTargettedReceiver
hadPassReception	soloTackle
hadPassReception	tackleAssist
hadRushAttempt	soloTackle
hadRushAttempt	tackleAssist
hadDropback	hadInterception
fumbleLost	fumbleRecoveries
fumbleLost	forcedFumbleAsDefense
forcedFumbleAsDefense	hadPassReception
forcedFumbleAsDefense	hadRushAttempt
hadDropback	causedPressure
pressureAllowedAsBlocker	causedPressure
hadDropback	passDefensed
wasTargettedReceiver	passDefensed
hadDropback	quarterbackHit
hadDropback	sackYardsAsDefense
hadDropback	tackleAssist
hadDropback	soloTackle
tackleAssist	tackleAssist
forcedFumbleAsDefense	fumbleRecoveries

Table 1: Relationships that would occur between nodes that would create an edge

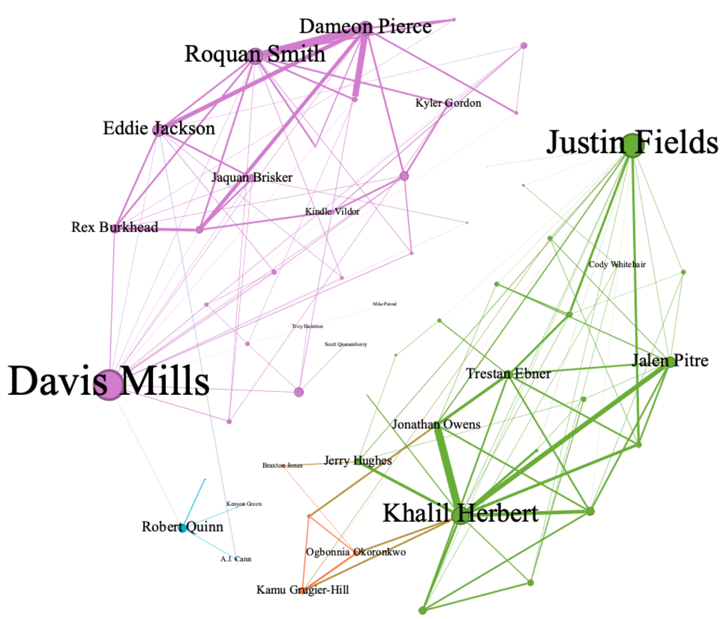


Figure 1: Network of Week 2, Bears vs Texans game, nodes sized by PageRank

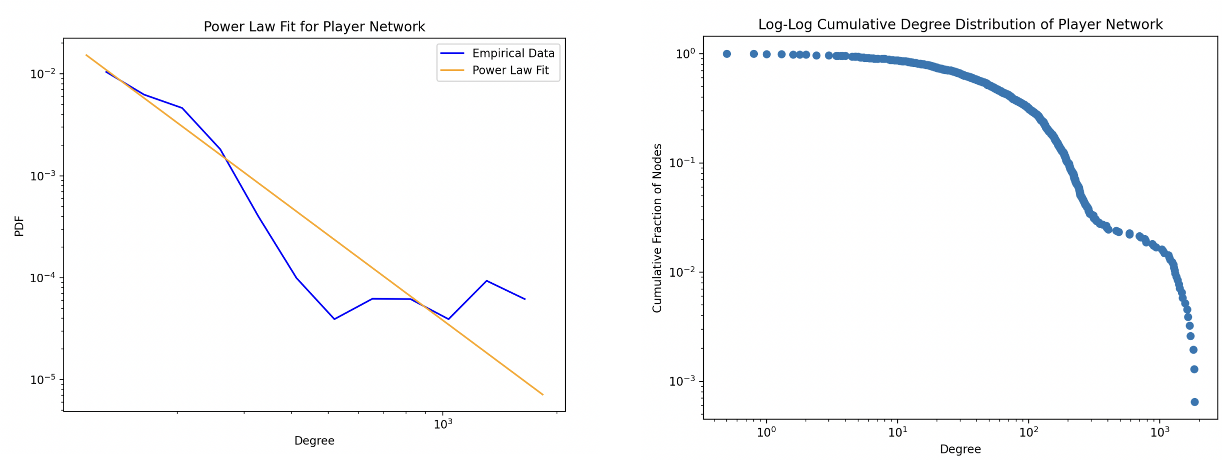
3.3 Initial Analysis

With the understanding of how our network is created we can begin to analyze nodes and edges within. To do so we find it important to weight edges within our network to equalize the occurrence of events. In NFL games certain players naturally will have events occurring more often due to how the game is played. For example QB's and RB's are offenses primary ways of moving the ball and have a high frequency of usage. In comparison a defensive player making an interception is often a game changing play and may only happen once a game, if that often. Below we can examine the way in which we determined edge weights.

Frequency of Events	**Weight**
High Frequency	1
Medium Frequency	2
Low Frequency	3
Defensive Ball Disruption	4
Turnover Worthy Play	7

Table 2: Event Frequencies and Associated Weights

We add these weights and analyzed our network on a base of its fit to a power law to determine the validation of these weights. In a sense these weights provided a sufficient power law fit, giving a power law value of $\alpha = 2.77$. Although this sounded promising we used Python and its powerlaw package to make an ideal power law fit for our data as well as construct a log log degree distribution plot. In Figure 2 we can analyze the two results we received.



(a) (b)

Figure 2: (a) Ideal power law fit determined by Python (Orange), vs the actual fit made by out weighted data (Blue) and (b) Log Log degree distribution of nodes in our player interaction network.

Here we can visualize that although we have an ideal power law value, the way in which our degree's are distributed are not ideally done. Taking a step back we determined that the way in which we assigned weights was overall too broad. Very different relationships would receive the same weight which we believe caused for the large dip in our middle degree counts. On top of this offensive players would receive very large weights for having a turn over worth play, which we believe inflexed the larger tick in higher degree nodes. Understanding all of this we began to rethink the ways in which we will weight our edges.

3.4 Retuning and Revamping

Moving away from this approach we now recognize each individual condition as its own event. Each condition has a varying occurrence due to the nature of NFL games. The way in which we determine to assign weights was we went through our data and found the 75th percentile of each condition. We chose this value as we deemed players who have a condition occurring more often are deemed better. Looking back at this logic it does not necessarily hold true to every position in the NFL. There are a lot of advanced statistics on efficiency and certain players will naturally have less stats occurring due to their position. Nonetheless we can examine Table 3, which now holds values for each condition individually. From here we would match values according to condition pairs, and the inverse of newly added value would be the weight of the condition pair. This helps to even the playing field when it comes to determining condition pair weights as we now individualistically examine each condition. As well we add a new value which we call adjusted, or adj for short. This value is added to conditions previously classified as defensive ball disruption or turn over worthy plays. This value is added to help decrease the weights of these conditions and the impacts they have on offensive players. As mentioned above we believe these high weighted conditions were causing a large influx in our high degree nodes. To try and deter this we add an extra 10 percent of weight from each primary ball movement condition. We identify these as RushAttempt, hadDropback, hasPassReception.

Condition	**Value**
Rush Attempt	87
hadDropback	184
wasTargettedReceiver	37
hadPassReception	27
soloTackle	23
tackleAssist	14
hadInterception	2 + adj
fumbleLost	2 + adj
fumbleRecoveries	1 + adj
forcedFumbleAsDefense	1 + adj
causedPressure	10 + adj
pressureAllowedAsBlocker	16
passDefensed	3 + adj
quarterbackHit	4 + adj
sackYardsAsDefense	18 + adj
adj	18.4 + 8.7 + 2.7

Table 3: Conditions and their 75th percentile values of occurrence. adj is a an equalizing value taking 10 percent of the primary ball movement plays into account. Weights are applied inversly to conditions when creating an edge.

4 Results

4.1 Important Nodes

With the weights of our networks finalized, we can now begin to analyze the results of which our network produces. In Figure 3 we can examine the most important nodes of our network ranked on betweenness.

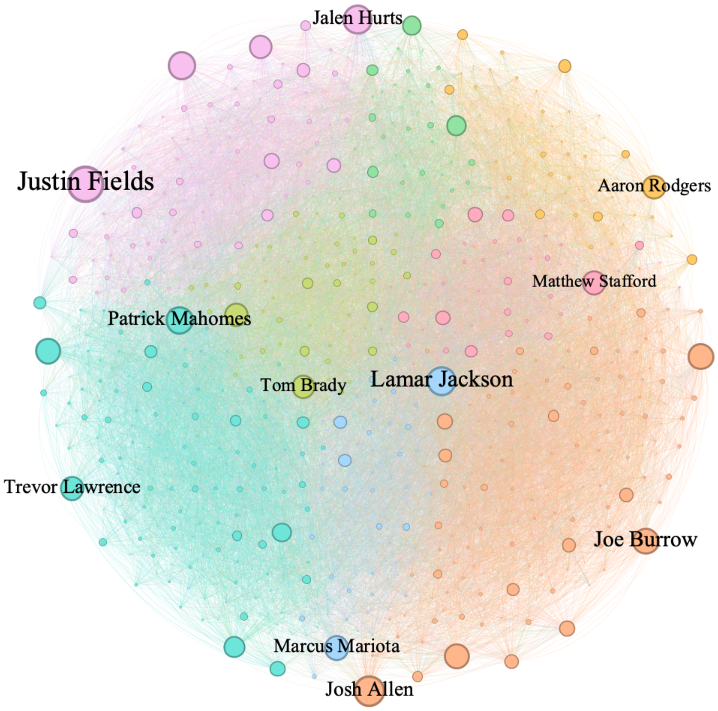


Figure 3: Network Visualization of most important nodes sized on Betweenness

Here we observe a quarterback dominated network when ranked on betweenness. Specifically we see two distinct forms of quarterbacks, the two groups being dual threats, and gun slingers. Dual threat quarterbacks are players who are good at throwing the ball, but also are very talented at rushing it as well. Players such as Justin Fields, Josh Allen, or Jalen Hurts are all examples. These individuals have high betweenness due to their ability to connect to many different players from multiple facets of the game may it be passing to receivers or rushing and being tackled by defenders. Gun slinger quarterbacks are individuals who pass the ball a lot more than average during games. Players such as Joe Burrow, Arron Rodgers, or Matthew Stafford are good examples. These players we find to have high betweenness due to their high pass attempts to many receivers as well as being able to connect to defenders more often on plays like interceptions or sacks due to their high dropback rate. Let's move on from betweenness and see how this compares to other important network measures.

4.2 Comparing Network Measures

We begin by comparing how Betweenness Centrality relates to PageRank and Weighted Degree in our network. Table 4 presents the top 10 results for each metric. From this table, we observe that Betweenness and PageRank produce relatively similar rankings. This similarity arises from the dense connectivity of our network and the structural roles within NFL teams. Specifically, PageRank, which depends on the overall connectivity of nodes, and Betweenness, which depends on an individual node's ability to connect different parts of the network, yield comparable results in this context.

The structure of NFL games, which heavily emphasizes the quarterback as the primary coordinator of ball movement, further explains why only quarterbacks rank in the top 10 for these metrics. Interestingly, the top 5 players in Betweenness Centrality are quarterbacks classified as 'dual-threat,' emphasizing their ability to connect with defensive players more directly through their rushing abilities.

In contrast, Weighted Degree highlights a different set of players. All top 10 players are running backs, a direct result of the edge weighting system we applied during network construction, which assigns higher influence to players involved in rushing plays. This can be seen in Figure 1 as there are very thick edges between RB Dameon Pierce and Bear's defenders such as Roquan Smith.

Rank	Weighted Degree	PageRank	Betweenness Centrality
1	Joe Mixon	Derrick Henry	Justin Fields
2	Derrick Henry	Joe Mixon	Josh Allen
3	Dameon Pierce	Dameon Pierce	Jalen Hurts
4	Christian McCaffrey	Christian Mccaffrey	Lamar Jackson
5	Saquon Barkley	Saquon Barkley	Kyler Murray
6	Jamaal Williams	Jamaal Williams	Patrick Mahomes
7	Jonathan Taylor	Josh Jacobs	Jacoby Brissett
8	Nick Chubb	Jonathan Taylor	Joe Burrow
9	Josh Jacobs	Nick Chubb	Davis Mills
10	Dalvin Cook	Rhamondre Stevenson	Daniel Jones

Table 4: Top 10 Players in Weighted Degree, PageRank, and Betweenness Centrality

Beyond the top 10, we examine correlations between these metrics across the entire network. Figure 4 illustrates the relationship between Betweenness Centrality and PageRank. The strong correlation of 92.55% confirms our hypothesis that the dense structure of the network contributes to the similarity between these metrics.

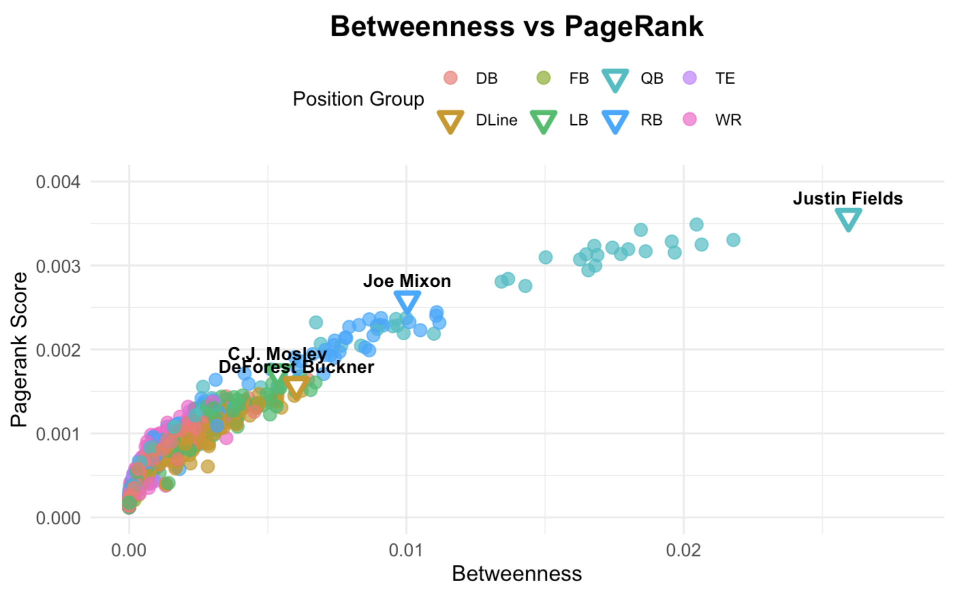


Figure 4: Scatter plot of Betweenness Centrality and PageRank scores. Key players in QB, RB, DLine, and LB positions are highlighted.

In comparison, the correlation between PageRank and Weighted Degree is lower, at 85.78%. This reflects the influence of our edge weighting scheme, which prioritizes running backs and amplifies their importance in Weighted Degree rankings.

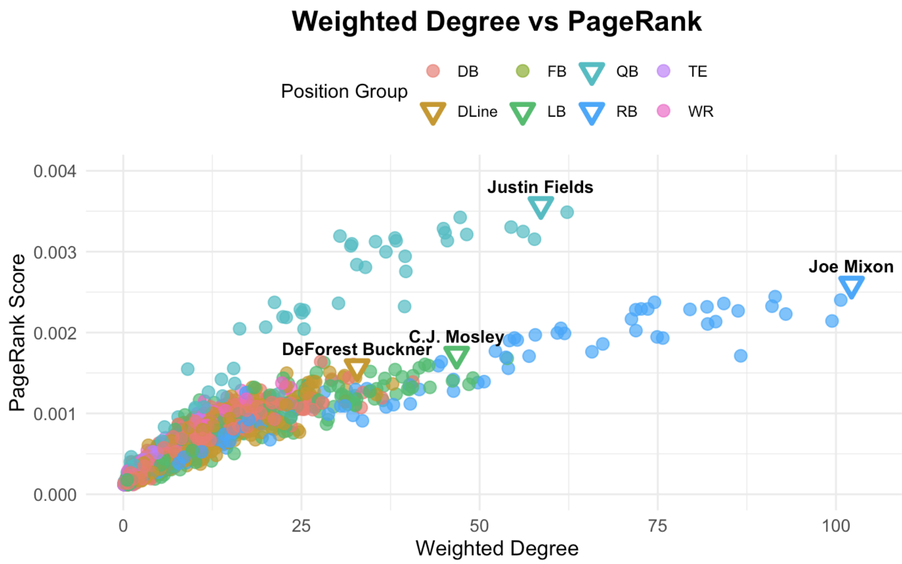
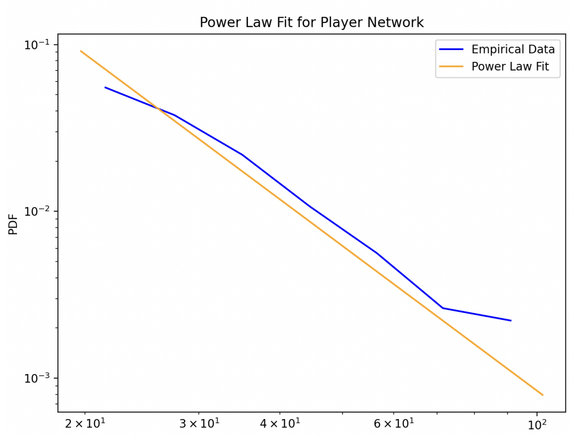


Figure 5: Scatter plot of betweenness and page rank score of the nodes in the network. The highest scoring Pagerank players in QB, RB, DLine, and LB are emphasized.

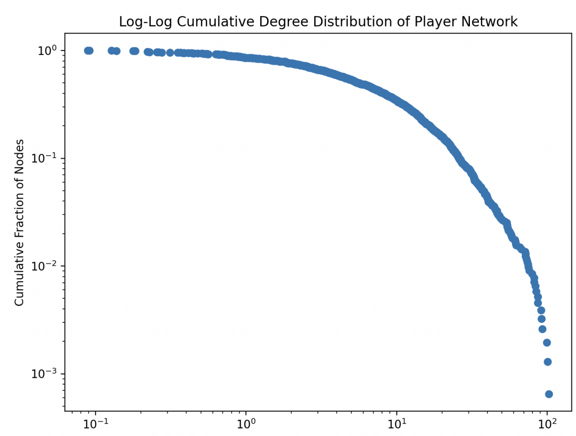
4.3 Power Law Fit

Examining our finalized network weight distributions, we observe that the degree distribution aligns well with a power-law, as illustrated in Figure 6 (a). Using Python's power-law fitting function, we calculated a scaling exponent of $\alpha = 2.917$, indicating that our network exhibits the characteristics of a scale-free network. This implies that while most nodes have a relatively low degree , a small number of nodes have a significantly higher degree, following the expected long-tail distribution.

However, we note an uptick in the distribution at the higher-degree range, deviating from a strict power-law fit. This uptick can be attributed to the structural characteristics of NFL teams and gameplay dynamics. In NFL networks, specific player positions are consistently central to the game, leading to a clustering of high-degree nodes. Specifically, QBs and RBs stand out as key contributors to this phenomenon.



(a)



(b)

Figure 6: Comparison of Pagerank vs Betweenness Centrality (a) and Pagerank vs Weighted Degree (b).

4.4 Modularity

Understanding modularity in this network in a complex and difficult process due to the relationships that occur when evaluating an individual game. Figure 1 helps to visualize this, as a team does not have connections between its offense and defense. In turn we evaluate the modularity groups looking at a teams offense and defense separately. Below we can analyze a table of all teams present within each modularity group.

Modularity	**Offensive Teams**	**Defensive Teams**	**Other**
0	SF, LAC, TB	ATL, KC, DEN	TEN, ARI, BUF, HOU
1	LA, CAR, DAL	LA, SF, NYG	ARI, ATL, DET, BAL, BUF, CHI, DEN, TB, TEN, SF
2	SEA, MN	ARI, NO	BAL, LV, PHI, ATL, LAC, NYG, TB
3	ATL, PIT, BAL	TB, CIN, CLE	BUF, NO, LA, MIA
4	GB	NE, BUF, CHI	DET, MIA, BAL, NYJ, DAL, IND, NYG, SF
5	NYJ, MIA, CLE, CIN, NE, BUF	NYJ, MIA, BAL, CLE, CAR, PIT, GB	None
6	DET, WAS, ARI, NO, CHI	DET, PHI, DAL, SEA, MIN	GB
7	HOU, LV, TEN, IND, JAX, KC, DEN	HOU, LV, TEN, IND, JAX, WAS, LAC	PHI

Table 5: Teams present within each modularity score. A team is assigned to offensive/defensive column if 10 or more players from that teams offense or defense are present within the modlarity group. Teams in the other category are present in the modularity group but have less than 10 players from either side of the ball present.

We note that, for a team to be classified as an offense or defensive team within our table 10 or more players must be present in the community on that side of the ball. Teams listed in the other category are present in the community but less than 10 players are there for either offense or defense. Overall, looking at this table does not lead to any quick and easy conclusions. So we move on to looking at statistics for prominent teams. Understanding how our network is aligned understand the importance of QB's and RB's in determining these modularity groupings. Both individuals rank very highly when using network measurement metrics and are likely to have high influence in creating communities. This proved true, as there were some connections between QB's top performing games and the defensive teams they were connected with. For example, when analyzing modularity group 0, we note that SF had 2 of its highest 3 passing performances against KC and ATL. The same is true for TB, and we see that LAC had its 3rd highest passing game against KC. Beyond just QB stats, interconnectedness is important as well. We see that TB and SF played 2 of the 3 defensive teams listed, and that LAC played all 3. We also note that DEN played HOU, and KC played ARI, TEN, and BUF to understand how some teams in other are connected.

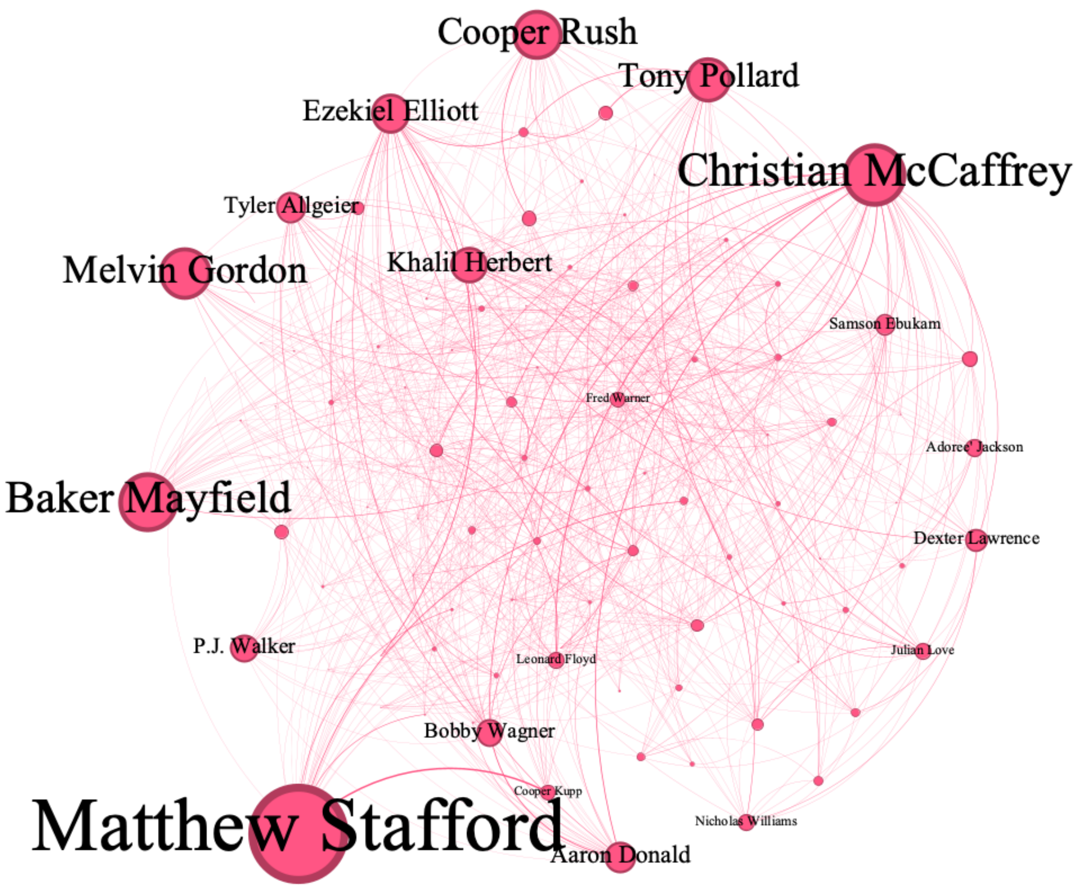


Figure 7: Prominent Nodes in Modularity group 1, sized on betweenness

Understanding the category listed as other was a little more complex. These were players who were separated from their teams and listed semi individually or in small clusters. We visualize modularity group 1 above to gain insight into why these teams may be included. One key takeaway right away is that from the other category we see prominent running backs that are present. Melvin Gordon DEN, Khalil Herbert CHI, Tyler Algeier ATL, Christian McCaffrey SF. Understanding the prominent position RB's play in the network makes sense as to why they may be separated from the rest of the team. From the way we defined our network, RB's only connect with their QB when they get a reception. Therefore, RB's who have dominant games against certain defenses are more likely to end up in that defenses modularity group. Considering some other players that may end up in modularity groups, we refer back to Figure 1, where we see offensive lineman being put in a different modularity group than their offense. This again is a result of our network having minimal connections for offensive lineman to the rest of the offense, and therefore they connect more to defensive players. Not labeled, but some players present are Taylor Lewan TEN, Rodger Saffold BUF, and Ronnie Stanley BAL.

4.5 Position Dominance

To compare the value of different position groups within the network, we analyze the distribution of players by position in Table 6. Despite being the second smallest position group, QBs hold the largest influence as central nodes in the network.

Position	n	Color
DB	309	Yellow
DLine	270	Orange
OLine	251	Green
LB	229	Pink
WR	198	Purple
RB	122	Blue
TE	110	Light Green
QB	57	Brown
FB	13	Red

Table 6: Player Counts by Position in Network Data

Figure 8 visualizes the networks colored by position groups. In Figure 8 (a), the nodes are sized based on betweenness centrality. Most nodes are small, reflecting lower influence, while QB nodes are significantly larger, highlighting their central role. RBs form the next largest group, but QBs have higher betweenness due to their unique ability to interact with defensive players, similar to RBs, while also distributing edges to WRs and TEs.

In Figure 8 (b), the nodes are sized based on PageRank, showing a network with more medium-sized nodes. This structure emphasizes the importance of all players, as the increased density results in many edges connecting various positions. PageRank distributes importance more evenly, reflecting the influence of all nodes based on this metric.

(a) (b)

Figure 8: (a) Network with nodes sized by betweenness centrality; (b) Network with nodes sized by PageRank. Both networks have nodes colored by position.

5 Conclusion

To conclude, this paper presents the construction of a network based on player interaction in NFL games. This network focused on in game events and their roles in offensive and defensive structures. By defining edges based on player interactions around the ball and assigning weights reflecting the frequency and importance of interactions, the resulting network provides a unique lens in analyzing structural elements of NFL games.

The results gave insights into the distinct roles of key positions in the NFL. QBs and RBs both emerged as central nodes in the network. With QBs dominating metrics such as Betweenness Centrality and PageRank due to their as ball distributors and roles as offensive commanders. RBs rank highly in Weighted Degree, which helps to explain their key roles in offensive rushing strategies. The analysis also highlights the scale-free nature of the network, with a power-law distribution that captures the hierarchies with NFL teams. As well as deviations in high degree nodes suggest structural dependencies connected to position dominance around the ball in game dynamics.

This paper contributes to the strong growing body of literature on sports network analysis. Helping to demonstrate how network science can be applied to understanding player interactions, and identify critical contributors in NFL games. By providing both theoretical insights and practical tools for analyzing these networks, this work opens the door for further studies and applications in sport analytics.

6 Limitations

Reflecting back on the work and creation of this paper it is important to state there has been several limitations. First the edge creation of the network emphasizes only players having influence on the ball. We note this is not entirely representative of the player interaction of the NFL, as it is common that players interact on every play even without the influence of the ball. As well we had limited data that only allowed for us to create edges within the constraints of the recorded statistics.

Additionally, the scope of the dataset is another limiting factor. It was a restricted subset of NFL games with uneven amounts of games for specific teams due to bye weeks. This could result in bias related to teams that played all 9 weeks, or possibly played teams more than once. Expanding the dataset is necessary to enhance the findings in this research. Furthermore, by only evaluating offensive and defensive plays of NFL games, we ignore the complex interactions of special teams where players on both sides of the ball on the same team interact. Evaluating this third phase of NFL games would give a more complete understanding of NFL player interactions.

7 Future Work

With the conclusion of this paper, there are several directions for future research. One interesting avenue would be the development of advanced edge weighting algorithms. Implementing methods to weight based on down and distance scenarios would be something that could offer a richer context and help to put greater emphasis on more influential players that make big plays on important downs.

The expansion of edge conditions would also be an item that would prove fruitful. The edge conditions right now are based on player ball interaction. The data given was advanced and held information on a large amount of other complex statistics that could be used to create more advanced edge conditions that may prove to create a more complex network with new insights.

Examining positional or team subnetworks could also provide deeper insights into the positional dependencies of NFL teams. Especially examining positions like WR or LB that ranked as slightly less important, and we did not do a lot of research on would provide new important insights into NFL games. Using a team specific network could also help to learn trends and strategies used between players and how they develop through different games.

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