Predicting the Success of NFL Teams using Complex Network Analysis

Matheus de Oliveira Salim and Wladmir Cardoso Brandão
Department of Computer Science, Pontifical Catholic University of Minas Gerais (PUC Minas), Belo Horizonte, Brazil

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Abstract: The NFL (National Football League) is the most popular sports league in the United States and has the highest average attendance of any professional sports league in the world, moving billions of dollars annually through licensing agreements, sponsorships, television deals, ticket and product sales. In addition, it moves a billionaire betting market, which heavily consumes statistical data on games to produce forecasts. Moreover, game statistics are also used to characterize players performance, dictating their salaries. Thus, the discovery of implicit knowledge in the NFL statistics becomes a challenging problem. In this article, we model the behavior of NFL players and teams using complex network analysis. In particular, we represent quarterbacks and teams as nodes in a graph and labor relationships among them as edges to compute metrics from the graph, using them to discover implicit properties of the NFL social network and predict team success. Experimental results show that this social network is a scale-free and small-world network. Furthermore, node degree and clustering coefficient can be effectively used to predict team success, outperforming the usual passer rating statistic.

1 INTRODUCTION

The NFL (National Football League) was formed in 1920 and today is the most popular sports league in the United States, having the highest average attendance of any professional sports league in the world. The NFL is also a successful franchise business, with its 32 teams ranked among the top 50 most valuable sports teams in the world, moving billions of dollars annually through licensing agreements, sponsorships, television deals, ticket and product sales (Ejiochi, 2014). After each NFL game, a large amount of statistics are generated to describe the performance of the players. These statistics are used to move a betting market estimated in $93 billion dollars of legal and illegal gambling annually (Heitner, 2015). For instance, Internet sites use NFL game statistics to aid gamblers, giving them more reliable predictions on the outcome of upcoming games.

NFL salary structures are notoriously complex, with base pay, bonuses, and guarantees, and game statistics are also regularly used to characterize the performance of each player over time, dictating their salaries and the duration of their contracts. For instance, Elvis Dumervil, the outside linebacker of the Baltimore Ravens in the 2014 season, triggered $3 million in base salary escalators and earned $1 million in incentives during Week 12's contest against the New Orleans Saints by reaching the 12-sack mark. His 2015, 2016 and 2017 base salaries of $4 million, $4 million and $5 million each increased by $1 million. However, hiring players based exclusively on their game statistics and paying them the highest salaries is not a guarantee of team success.

In fact, a recent study has provided clues that large wage distortions is not a good strategy for team success (Burke, 2012). Analyzing the offensive line salary and performance, the author shows that the more teams pay their linemen, the more sacks and tackles for losses they tend to give up. By the contrary, a higher median salary indicates better performance. This results suggests that game statistics alone are not enough to effectively predict team success. The adoption of models and metrics that capture collective behavior of players appear promising to increase prediction effectiveness. Therefore, the theory of complex networks can be used to investigate the collective behavior of social agents, including teams and players in a sporting context. Particularly, a network is a set of nodes and connections between them, called edges. Complex networks are networks with a large number of nodes and edges following relevant patterns, such as hubs, i.e., clusters with highly connected nodes. While the analysis of simple networks can be done through visual inspection, the discovery of relevant patterns in complex networks de-

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mands statistical methods.

In this article, we investigate the properties of the NFL social network, a network with players and teams as nodes and labor relationships among them as edges. Additionally, we propose to predict the success of teams by modeling the behavior of players and teams in the NFL social network. Experiments show that the number of quarterbacks with significant impact in the NFL history and in their teams is negligible if we exclusively rely on game statistics, such as passer rating. In addition, we show that the NFL social network is scale-free, i.e., a very small number of quarterbacks present extraordinary performance, while a large number of quarterbacks perform poorly. Moreover, we show that the NFL social network follows a small-world behavior, where the distance between any two nodes are very small. Particularly, the key contributions of this article are:

- We investigate the properties on the NFL social network, showing that it can be characterized as a scale-free and small-world network.
- We propose a method to predict the success of NFL teams based on the network properties and metrics.
- We thoroughly evaluate the network metrics used by our method by contrasting them with usual passer rating statistic. We show that our metrics outperform this quarterback performance statistic to predict the success of NFL teams.

The remainder of this article is organized as follows: Section 2 reviews the related literature on complex networks. Section 3 presents related work. Section 4 show that the usual passer rating statistic plays a significant role in only a small fraction of the NFL players. Section 5 presents the properties of the NFL social network, including the method we propose to predict team success. Section 6 shows experimental results, attesting the effectiveness of our method and metrics to predict team success, when compared with passer rating. Finally, Section 7 provides a summary of the contributions and the conclusions made throughout the other sections, presenting directions for future research.

2 BACKGROUND

Complex networks are huge sets of interconnected items with a structure that do not follow a regular pattern. For instance, the Internet is a complex network composed by millions of interconnected routers, following a pattern in which a small number of items are extremely highly-connected, and the great majority of items have very few connections (Faloutsos et al., 1999). They usually are represented as graphs, with items as nodes (or vertices), and the connections between the nodes as edges (or links).

Particularly, a complex network models a real-world problem with nodes and edges storing information on the problem (Wasserman and Faust, 1994). In multi-modal networks, the information are in the nodes, while in multidimensional or multi-relational networks, the information are in the edges. We can also classify complex networks by their application in real-world problems (Newman, 2010). Biological networks represent biological systems, e.g., neural, protein, vascular and metabolic pathways networks. Information networks represent information and knowledge systems where nodes are information items, such as research articles, documents, and Web pages. Citation networks and the Web are examples of information networks. Social networks represent relationships between people or groups, such as friendships, family and professional relationships. Usually, social networks present a small-world behavior, where no one is far from anyone (Watts and Strogatz, 1998). Technological networks represent man-made systems, usually built for efficiently distribution of resources, e.g., electrical grid, telephony, water distribution and the Internet (Newman, 2003).

Figures 1, 2, and 3, present three different kind of complex networks. Particularly, they differ according to how the connections between nodes are built (Costa et al., 2007): randomly or non-randomly. Random networks are built from a graph with n nodes, where e edges are randomly drawn between the nodes (Erdös and Rényi, 1959), so that all nodes have the same probability of receiving new connections. In random networks, the more connections one add to the graph, the greater the chance of a cluster to occur.

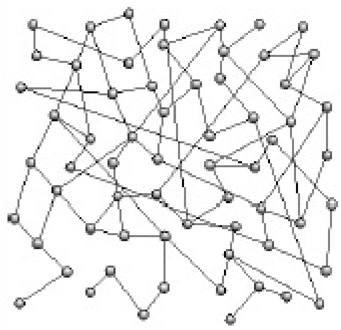

Figure 1: Example of a random network.

Scale-free networks are built from a graph with n nodes, where e edges are not randomly drawn between the nodes (Albert and Barabási, 2002), so that the more connections a node has, the greater the chance of it receives new connections. In scale-free networks, the more connections one add to the graph, the greater the chance of a few nodes getting more connected. As result, scale-free networks have a very low degree of connectivity and present a behavior known as *the rich get richer*.

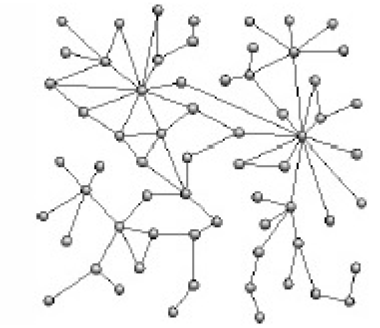

Figure 2: Example of a scale-free network.

Small-world networks are built from a graph with n nodes, where e edges are not randomly drawn between the nodes (Watts and Strogatz, 1998), so that the closer a node is to another, the greater the chance of they are connected. In small-world networks, the average distance between two nodes do not exceed a small number of nodes, as long as some random edges between clusters are established. Thus, a few edges between clusters are necessary to create a small-world effect, transforming the hole network into a set of huge clusters.

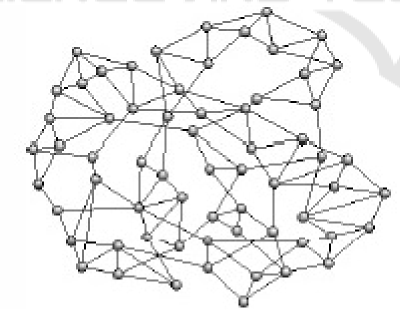

Figure 3: Example of a small-world network.

3 RELATED WORK

Recently, the theory of complex networks has been used to address problems in the context of sports. The interactions between NFL teams and coaches were modeled as a complex network (Fast and Jensen, 2006). The authors investigate the relationships between coaches and mentors, characterizing the influence of champion coaches on their protegés. They also exploit the network to understand how coaches contribute to team's success, proposing a model to predict the success of teams in the NFL playoffs based on the network topology.

Similarly, the interactions between NBA (National Basketball Association) teams and players were modeled as a complex network (Vaz de Melo et al., 2008). The authors model the labor relationships between NBA players and teams as a complex network to investigate team's behavior, proposing different approaches to predict team success using network metrics. The authors also contrast their proposed approaches with box score statistics usually adopted by teams to measure players performance, and show that network metrics are more effective than box score statistics for team success prediction.

Additionally, the labor relationships between NBA players and teams were also modeled as a complex network but, differently from previous work, no box score statistics are used to predict outcomes and the network evolves over time (Vaz de Melo et al., 2012). The knowledge acquired from the evolving network is applied to build a prediction model, which estimates how well a team will perform in seasons. The use of temporal information to predict team success was effective and the authors argued that the proposed model could be applied to other sports.

4 MOTIVATION

Currently, the NFL has 32 teams equally divided between the AFC (American Football Conference) and the NFC (National Football Conference). In the field, the players are organized in offensive and defensive lines, which perform different functions. The quarterback is the man in charge, calling signals in the primary passer, performing passes, and occasionally running the ball. Quarterbacks are the team's greatest decision-makers with outstanding skills, and their performance usually determines the success of the team in a game.

The NFL teams characterize players performance over time by using several game statistics, which regularly dictate player's salaries and the duration of their contracts. In addition, game statistics are also used to move a billionaire betting market. For instance, pass attempts (ATT), passes completed (COMP), passes intercepted (INT), passing touchdowns (TD), and passing yards (YARDS) are important game statistics used by teams to evaluate the quarterbacks, and by gamblers to place bets on games. Particularly, the NFL officially suggests the passer rating (*PR*) metric, to estimate the quarterback performance. The metric is a combination of four factors computed based on the previous reported game statistics:

$$a = \left(\frac{COMP}{ATT} - 0.3\right) \times 5$$

$$b = \left(\frac{YARDS}{ATT} - 3\right) \times 0.25$$

$$c = \left(\frac{TD}{ATT}\right) \times 20$$

$$d = 2.375 - \left(\frac{INT}{ATT} \times 25\right)$$

$$PR = \frac{mm(a) + mm(b) + mm(c) + mm(d)}{6} \times 100 \quad (1)$$

Equation 1 presents the formula for the passer rating metric, where $mm(x) = max(0, min(x, 2.375))$. According to Equation 1, the minimum value of PR is 0, when the quarterback complete up to 30% of the passes, wins less than 3 yards per attempt, fails to touchdowns and is intercepted at least 9.5% of the rolls. Inversely, the maximum value is 158.3, when a quarterback completes at least 77.5% of the passes, wins at least 12.5 yards per attempt, pass a touchdown on at least 11.875% of the attempts and is not intercepted. Figure 4 presents the ATT metric of the NFL quarterbacks.

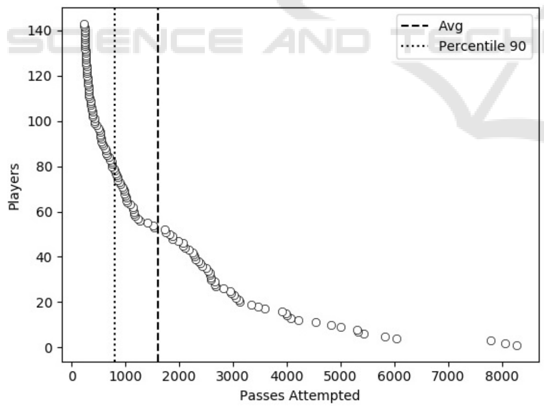

Figure 4: ATT metric of the quarterbacks.

From Figure 4, we observe that the distribution of ATT follows a power law, i.e., a very small number of quarterbacks present extraordinary performance, while a large number of quarterbacks perform poorly. This behavior suggests that the NFL can be represented as a scale-free network. Therefore, we believe that it is possible to build effective models to predict team success through the investigation of the network topology and properties. Additionally, Figure 5 presents the PR metric of the NFL quarterbacks.

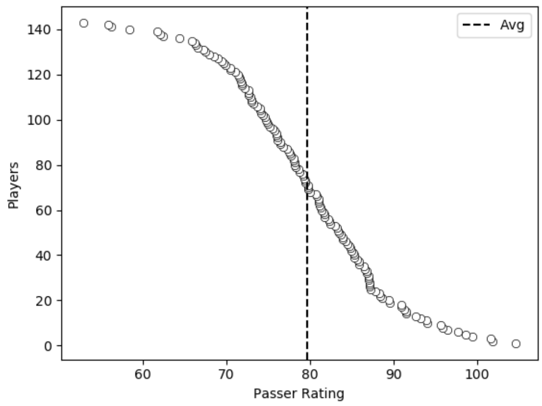

Figure 5: PR metric of the quarterbacks.

From Figure 5, we observe that PR values concentrate near the mean, increasing or decreasing significantly when PR lies more than a few standard deviations away from the mean, which characterizes a Gaussian distribution. Therefore, a very small number of quarterbacks present extraordinary (or mediocre) performance, while a large number of quarterbacks perform similarly to each other. We perform the previous analysis on Figures 4 and 5 by collecting teams, scores, and quarterbacks game statistics from the official NFL site[1]. Table 1 summarizes the records we collected.

Table 1: NFL dataset records.

Conferences	2 (AFC-NFC)
Seasons	16 (2000-2015)
Teams	32
Games	512
Quarterbacks	143

From Table 1, we observe that our dataset comprises 2 NFL conferences, 16 seasons, 32 teams equally divided in the conferences in each season, with each team playing 16 games per season.

5 THE NFL NETWORK

In this article, we model the labor relationship between teams and players as a social network. Particularly, each team and quarterback is represented as a node, and a labor relation between a team and a quarterback is represented as an edge. In addition, two quarterbacks have an edge connecting them if they ever played on the same team. We collect labor relationships from the official NFL site from 2000 to

[1] http://www.nfl.com

2015 between 32 teams and 143 quarterbacks. Figure 6 show the degrees of the quarterbacks and teams.

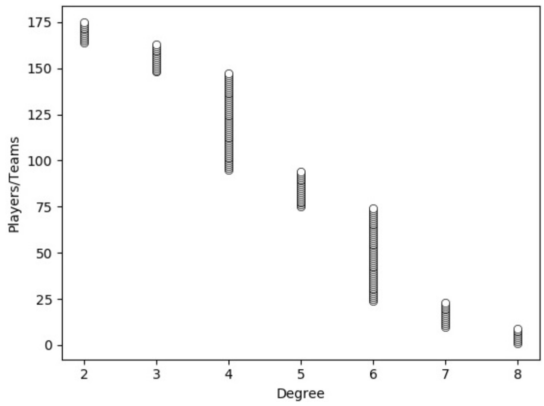

Figure 6: Degree of quarterbacks and teams.

From Figure 6 we observe that most players and teams have the degree between 4 and 6, i.e., the majority of players and teams are connected with up to 6 other players and teams. In addition, Figure 7 shows the annually average degree of quarterbacks and teams.

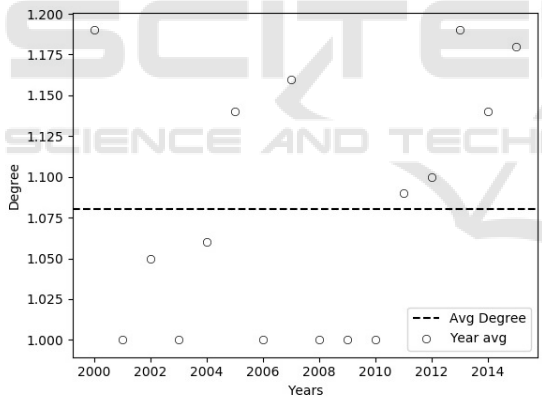

Figure 7: Average degree of quarterbacks and teams by year.

From Figure 7 we observe that the number of connections between quarterbacks and teams have increased in the last years, which shows a potential growth in NFL quarterback turnover, i.e., the rate of quarterbacks replacement. Moreover, Figure 8 show the distribution of the clustering coefficients of NFL players and teams.

Clustering coefficient measures the density of connections closest to the nodes, and is commonly used to estimate the connection likelihood between nodes. From Figure 8 we observe that the values of the NFL clustering coefficients significantly differs from the Erdos-Rényi (ER) network, showing that the

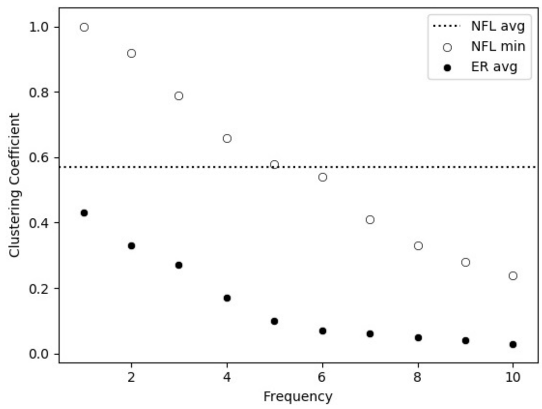

Figure 8: Clustering coefficient of quarterbacks and teams.

NFL social network is not a random network. In addition, we observe that the values of the NFL clustering coefficients are greater than the clustering coefficients of the ER network. Small-world networks are characterized by having a clustering coefficient significantly higher than its equivalent ER network (Watts and Strogatz, 1998). Thus, we observe that the NFL social network follows a small-world behavior. Consequently, information exchanged between players and teams, such as game tactics and team attractiveness, are quickly propagated between players, impacting the teams' turnover and performance. Figure 9 presents the NFL small-world network.

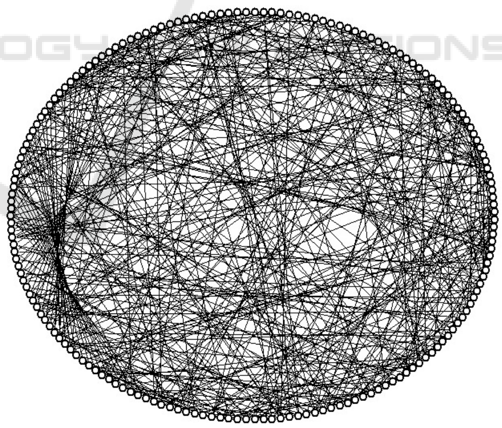

Figure 9: The NFL small-world network.

6 PREDICTION MODELS

In this section we present two models to predict NFL team success: i) the EM (efficiency model), based on the passer rating statistic; ii) the DM (degree model), based on the node degree metric. As described in Section 1, the first model is used as baseline to evaluate the other model based on network metrics. To evaluate the models, we use the Pearson coefficient to measure the correlation r between the performance metric used by the model and the real team success, i.e., the team's final rank position in the regular season.

$$r = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i)}{\sqrt{(n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2)(n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2)}}$$

Considering the equation above, The Pearson coefficient measure the correlation r between the performance metric used by the model (x_i) and the real team success (y_i), where r is a real value between -1 and 1, expressing the strength of the correlation between the two variables, with 1 expressing the most positive correlation, -1 expressing the most negative correlation, and 0 expressing no correlation. The samples were collected only by the top-6 teams in the AFC and NFC regular seasons, which are the teams that advanced to the next phase of the NFL championship.

6.1 Efficiency Model

The first prediction model is EM (Efficiency Model), which is based on game statistics, as described in Section 4. Particularly, the quarterback *PR* metric described in Equation 1 is used to measure team success. We use the *PR* metric of one year as predictor for the next year. For instance, we rank quarterbacks by their performance in 2000 season, and we predict the rank position of the teams in 2001 season using their quarterbacks performance in the previous year. Figure 10 presents the Pearson's coefficient for the correlation between *PR* and team success.

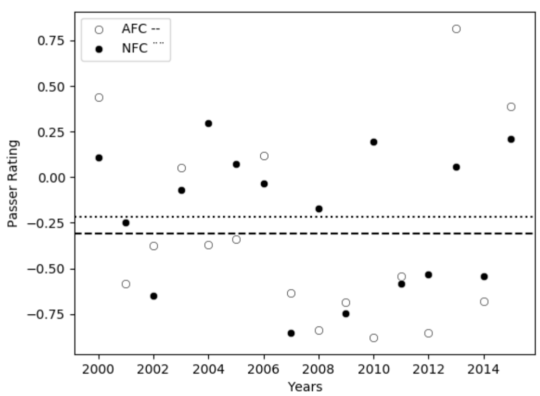

Figure 10: Pearson's coefficient for the correlation between *PR* and team success.

From Figure 10 we observe that there is no clear pattern of correlation between passer rating and team success. While in a season we observe a strong correlation, in other seasons we observe a weak or no correlation at all. For instance, in AFC 2009 season we observe a strong positive correlation, while in AFC 2001 and 2014 seasons we observe a strong negative correlation, and in AFC 2007 season we observe a negligible value of correlation. We observe the same for the NFC, a strong positive correlation in 2003, 2008 and 2010 seasons, a negative correlation in 2005 season and a negligible value of correlation in 2004, 2006 and 2007 seasons.

Although there is no clearly pattern of correlation between passer rating and team success, in 68.75% of AFC seasons we observe a positive correlation, with Pearson's coefficient varying from 0.31 to 0.94, and in 56.25% of NFC seasons we also observe a positive correlation, with Pearson's coefficient varying from 0.08 to 0.94. Particularly, a strong positive correlation pattern is more frequent in the AFC, where in 37.5% of the seasons the Pearson's coefficient was greater than 0.71. For NFC, only in 18.75% of the seasons the Pearson's coefficient was greater than 0.71.

In addition, in seasons 2001, 2005, 2006, and 2011 we observe a difference in the polarity of the correlation in the AFC and NFC Conferences, i.e., when in one Conference we observe a positive correlation in the other we observe a negative correlation. Moreover, only in season 2010 we observe a strong and positive correlation in both AFC and NFC Conferences, with Pearson's coefficient of 0.77 and 0.82 respectively. In 2002, 2003, 2008, 2009, 2012, 2013, and 2015 we also observe a positive correlation in both AFC and NFC Conferences, but with a wide range of values between them.

The AFC 2015 season is a good example on how unfeasible can be passer rating metric to predict team success. The Denver Broncos, took the first place in the regular season, being the Superbowl champion. However, their quarterback Peyton Manning, the best quarterback in the NFL history, made one of his worst performance throughout the championship, standing only one position ahead of the worst quarterback with a $PR = 67.9$ in that season.

6.2 Degree Model

The second prediction model is DM (Degree Model), which is based on the degree distribution of the quarterbacks and teams, considering the NFL social network described in Section 5. Particularly, in the model a team with a high degree is probably a team that often traded quarterbacks or had quarterbacks who retired. The intuition behind the model is that a team that recently switches their quarterbacks is a team that performs badly in the next seasons.

We use a window of three years to build the social network and extract the node degrees. For instance, we rank teams by their degrees extracted from the NFL social network of 2000, 2001 and 2002 seasons, and we predict the ranking position of the teams in 2003 season using these degrees. Figure 11 presents the Pearson's coefficient for the correlation between node degree and team success.

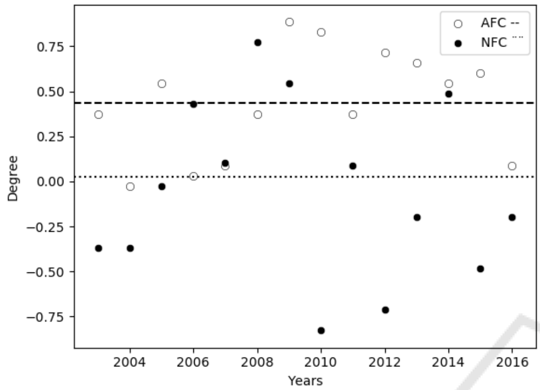

Figure 11: Pearson's coefficient for the correlation between node degree and team success.

From Figure 11 we observe that there is a clear pattern of correlation between node degree and team success in AFC. However, we do not observe the same for NFC. In 92.85% of AFC seasons we observe a positive correlation, with Pearson's coefficient of up to 0.88, and in a half of AFC seasons the Pearson's coefficient was greater than 0.54. But in 28.57% of AFC seasons the value of the Pearson's coefficient is almost zero, pointing to a negligible correlation. For NFC, while in a season we observe a strong correlation, in other seasons we observe a weak or no correlation at all. For instance, in NFC 2008 season we observe a strong positive correlation, while in NFC 2010 and 2012 seasons we observe a strong negative correlation, and in NFC 2005 season we observe no correlation at all.

7 CONCLUSIONS

In this article, we proposed a method that exploits NFL social network properties and metrics to predict the success of NFL teams. Particularly, we modeled the labor relationships between NFL teams and players (quarterbacks) by representing them as nodes and their relations as edges in a graph, and we used network metrics extracted from the graph as a predictor of team success. We thoroughly evaluated the network metrics by contrasting them with usual game statistics from NFL and the results of this evaluation showed that node degree is a more effective predictor than passer rating statistic. In addition, complex network analysis showed that the NFL social network is a scale-free and small-world network, where a large number of quarterbacks perform poorly, while a very small number of quarterbacks perform extraordinarily, and the distance between any two quarterbacks in the network is very small.

For future work, we plan to investigate how the NFL social network evolves over time to propose and evaluate new network metrics as team success predictors. We also plan to combine network metrics with usual game statistics to improve the prediction effectiveness.

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