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Perspective

A survey on football network analysis

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Abstract – Being the world's most popular sport, football research has traditionally concentrated on empirical summaries or statistics, with only limited data available in the past. In recent years, social network analysis has been applied to a variety of fields, which also brings new perspectives to the study of football sports. In this paper, we survey the literature related to football networks and discuss the use of network measures to analyze the performance of footballers and teams in different types of football networks. We aim to find out how to construct appropriate football networks based on different perspectives on football research. Various studies on football network analysis, including team performance, player interactions, and club behavior, are reviewed. The findings provide insights into team performance, player roles, and social dynamics within football teams and clubs.

Introduction. – Football (also called soccer) is one of the most popular sports in the world. Its history can be traced back to the Chinese Cuju game thousands of years ago. The modern game of football is generally considered to have originated in England. Today, according to FIFA reports, nearly half of the world's population participates in football games. The quadrennial World Cup, the most influential sporting event in the world, also brings economic development to each host country. According to a report released by the Qatar Chamber of Commerce and Industry, the 2022 Qatar World Cup is expected to bring Qatar direct economic revenue of approximately \$2.2 billions and long-term economic revenue of up to \$2.7 billions from 2023 to 2035. Such a large audience and economic benefits have brought more attention to the development of football.

In the past, the study of football activities was mostly based on historical experience. With the development of science and technology, various kinds of data in football can be collected and organized artificially. Relying on objective data, more people began to analyze football activities based on mathematical statistics and other methods, such as the FIFA website. However, these studies tend to be phenomenological analyses of data and lack precise definitions to explain activities in football.

In recent decades, the concept of social networks and the methods of social network analysis have aroused great interest and curiosity in the social and behavioral sciences. Many researchers have realized that a precise definition of aspects of the political, economic, or social structural environment from a network perspective provides new tools to answer questions in social and behavioral science [1]. In football, a large number of scholars are using social networks to investigate football activities due to the enormous number of interrelationships between different individuals in football, such as passing behaviors between footballers, footballers' transfer behaviors between clubs, etc. From the perspective of social networks, football activities can be expressed as patterns or relationships among different individuals. The characteristics of individual behaviors in football can be explained from a new perspective. In this paper, we will focus on the distinct types of football networks that consist of different individuals, such as players and clubs.

Football networks of players. – In football games, each attack is not made by the shooter alone but with the cooperation of several players. When evaluating the performance of a football team, one cannot only focus on

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the shooting of a shooter but also on the cooperation of the whole team. Lots of studies have investigated the performance of the whole team by identifying the core players in the team through different methods.

Passing network of footballers. Passing is one of the most important interactions in a football game. Improving the success rate of passing will increase the team's possession rate, which will lead to a better chance of winning the game. In addition, different paths of passing also reflect the different attacking styles of the team. Usually, people use passing activities to quantify the performance of footballers in a football game [2,3]. Cho *et al.* presented a football win-lose prediction system based on passing activities [4]. It provided the information, such as the "problem of a specific player" or "the need to change passes between specific players". Buldú *et al.* found strong relations between network metrics and match outcomes by comparing Barcelona's and its opponents' passing network measures [5]. Praça *et al.* used a passing network to characterize the performance of footballers and found that the drops in individual tactical performance were not age-dependent [6].

To characterize the performance of a team through network analysis, Passos *et al.* defined a "unit of attack", which started when a team gained the ball and ended when they lost the ball [7]. Figure 1 is a sample pass sequence of an attack that started from footballer 1 and ended at footballer 10. In each unit of attack, the players of a team are directly connected as the ball passes. Naturally, a passing network for a unit of attack, $G(V, E)$, is formed, where V is the set of nodes and $E = \{(i, j)|i, j \in V\}$ is the set of links. Each passing network is composed of 11 nodes, corresponding to the 11 footballers of a team. A link connecting a node i to a node j refers to a pass that occurred between the corresponding passer and receiver:

$$a_{ij} = \begin{cases} 1, & \text{if } i \text{ passes to } j, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Each network corresponds to an adjacency matrix $\{a_{ij}\}$. Taking into account the number of passes, one obtains a weighted football passing network, $\{w_{ij}\}$. For example, w_{ij} can be the number of passes from i to j. If considering the difference in playing time of footballers, Medina *et al.* weighted the number of passes of each footballer by the fraction of time a footballer played [8].

In the passing network, nodes are the specific footballers. Network measures can quantify the participation of players in a team's offensive process. Clemente *et al.* believed that prominent levels of goals scored were associated with prominent levels of the number of total links, network density, and clustering coefficient [9]. The number of links is the number of passing paths among footballers. The more links in a passing network, the more passes occur among the footballers. To compare the number of links in

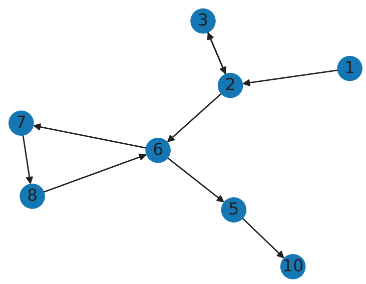

Fig. 1: Sample of a unit of attack.

different networks, one can use network density:

$$\rho = \frac{\sum_{i \neq j} a_{ij}}{n_N(n_N - 1)}, \tag{2}$$

which is the ratio of the empirical number of links in the network to the maximum possible number of links. The clustering coefficient of a network, also called transitivity T, is the ratio of the number of triangles to the number of connected triads:

$$T = \frac{\sum\limits_{i \neq j, j \neq k, k \neq i} a_{ij} a_{jk} a_{ki}}{\sum\limits_{i \neq j, j \neq k, k \neq i} a_{ij} a_{ik}}. \tag{3}$$

The higher clustering coefficient of a passing network indicates a higher passing rate between footballers. Usually, network density and clustering coefficient are used to measure footballers' interactions [10]. Aquino *et al.* found that the clustering coefficient affected the outcome of a football game because the winning teams commonly had a higher level of interconnectivity between close teammates [11].

Network centrality measures are highly related to the footballers' positions [12,13]. Node degree is the simplest centrality measure. It is denoted by the number of links connected to a node in the network:

$$k_i = \sum_{i \neq j} a_{ij}. \tag{4}$$

When it comes to a directed passing network, node degrees can be changed into outdegree or indegree, also called degree centrality and degree prestige. The outdegree and indegree of a node are the numbers of football players one passed to and received from:

$$k_i^{\text{out}} = \sum_{i \neq j} a_{ij}, \quad k_i^{\text{in}} = \sum_{i \neq j} a_{ji}. \tag{5}$$

Players with large outdegrees are important contributors to the team's passing, and players with large indegrees are popular with teammates. McLean *et al.* used the outdegree and indegree metrics to determine the connectivity of the playing positions, which provides valuable information on team functioning [14]. Like many real-world networks, the degree distribution followed a power law in a passing network [15] in which nodes are players from both competing teams. It indicated that a passing network might share a scale-free property.

Many studies showed that a footballer with lower betweenness and higher closeness was related to better outcomes [16]. The key player can be identified by closeness centrality, which responds to the proximity of a node to other nodes [17,18]:

$$C_i = 1/\langle d_{ij} \rangle, \tag{6}$$

where d_{ij} is the shortest path length and $\langle d_{ij} \rangle$ is the average value of d_{ij} over j. A higher closeness in a passing network indicates that a footballer is close to connecting with other footballers. Unlike closeness, which describes the distance of passes from a footballer, betweenness describes the importance of the transition point in all passes. It is defined as the fraction of the number of shortest paths that pass through that node:

$$B_j = \sum_{i<j<k} \frac{n_{ik}(j)}{n_{ik}}, \tag{7}$$

where n_{ik} is the number of shortest paths from node i to node j and $n_{ik}(j)$ is the number of shortest paths that start from node i, pass through node j, and end at node k. It can help us identify the intermediary footballers in a team [18].

By using the network measures, one can quantitatively portray the footballers' performance in the game from different perspectives. Clemente *et al.* investigated the tactical prominence variables by using the centrality measures [19]. Pina *et al.* found that network density, but not clustering coefficient or centralization, was a significant predictor of the success of offensive plays [20]. Arriaza-Ardiles *et al.* used the clustering coefficient, and centrality metrics to analyze the performance of a professional Spanish team [21]. Castellano and Echeazarra found a correlation between network centrality measures and physical demands [22]. Pereira *et al.* composed the Golden Index formula to describe the performance of footballers by collecting several network measures [23]. However, it was also found that network measures were not sensitive to the outcomes of games [24] but were related to the style of the team [25]. de Jong *et al.* investigated professional women's football [26] and showed that footballers in successful teams are highly connected and the distribution of ball possession is centralized. Zhou *et al.* weighted the links of the passing network by the physical distance between two players [27]. The ratio of the average clustering coefficient to the average intermediate centrality could be used to measure the coordination of the football team's performance.

Football is an overly complex sport. It has a large field with many football players. This makes the position of each footballer on the field quite different. Each footballer plays separate roles, and the responsibilities of the footballers in various positions are different, such as defender, midfielder, forward, and so on. By classifying a footballer according to the position he/she plays, one can find that footballers in different positions have different characteristics in the passing network. Praça *et al.* investigated a passing network in small-sized and conditioned football games [28]. They found midfielders had higher outdegrees than defenders and forwards. Midfielders and forwards had higher indegrees than defenders. Clemente *et al.* found that wingers and forwards with large wins have a higher central position [29]. By investigating the passing network among the Brazilian professional footballers, Aquino *et al.* found that central/external midfielders had greater node centralities compared with central/external defenders and forwards [30]. Large decreases in indegree were found in winger positions compared to external defenders. It was also found in central forwards in comparison to external defenders, central defenders, defensive midfielders, and midfielders [31]. Yu *et al.* found foreign midfielders had higher values in outdegree, indegree, betweenness, and closeness centralities than domestic footballers in the Chinese Football Super League [32].

Spatial-dependent passing network. Cotta *et al.* [33] found that if a passing network of specific footballers developed slowly with a small number of passes, the prediction of the performance of footballers by using network measures was not good. To avoid confusion with the meaning of the position of a footballer, we call the passing network that added the spatial information the spatial-dependent passing network, $G_s(V_s, E_s)$. In the spatial-dependent passing network, node $V_s = \{(p, z)\}$ is a virtual footballer, where p is one of the actual footballers and z is the location of the footballer.

To simply mark the spatial information of the players, Cotta *et al.* split the football field into nine zones (see fig. 2). As the game progresses, players may appear in different zones. The same player in different zones corresponds to different nodes in the spatial-dependent passing network. The number of nodes in the spatial-dependent passing network will be greater than the number of real footballers (which is 11). The links, $E_s = \{(i, j)|i, j \in V_s\}$, correspond to the passes that occurred among the virtual footballers. They found that the clustering coefficient of a spatial-dependent passing network revealed the nature of the "tiki-taka" style, indicating that the network had a small-world property. Gama *et al.* used average positioning to characterize the field location of footballers and found the weighted network degree to be helpful in identifying the key players [34]. Narizuka *et al.* found that the networks had the small-world property, and their degree distributions were well fitted by a truncated gamma distribution [35]. They also proposed a simple stochastic model describing the spatial-dependent passing network [36]. Mclean *et al.* used four equal-sized zones to describe the spatial information of footballers. They found most passes were played within zones or progressed through the zones towards the goal [37].

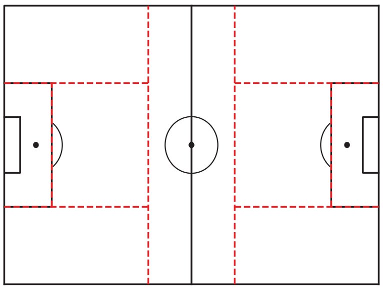

Fig. 2: A football field split into nine zones. There are four defensive zones (own box, wingback lanes, own midfield), four offensive zones (opponent's box, wingers' lanes, opponent's midfield), and one central zone.

Sarmento *et al.* split the field into 12 zones and identified the main players in the attacking process by using network measures [38]. Ichinose *et al.* investigated the robustness of a spatial-dependent passing network using two strategies: node removal and link removal [39]. Compared to the random removal, the robustness of the passing network was weaker for targeted attacks, for example, removing key footballers making passes. They also found that the robustness of the passing network positively correlated with team performance (total point).

Pitch-passing network. Besides the spatial-dependent passing network above, there is also another way of constructing a passing network including spatial information, called a pitch-passing network. In this network, nodes are not players but the different zones of football fields. Links between two nodes correspond to passes from one zone to another:

$$a_{ij} = \begin{cases} 1, & \text{if passes occur from } i \text{ to } j, \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

where i, j are different zones of a field. If $i = j$, a_{ii} stands for the pass from zone i to itself, called a self-loop. The weight of each link w_{ij} is usually characterized by the number of passes from zone i to zone j. The number of nodes in a pitch-passing network depends on the number of split zones. The higher the number of nodes, the fewer the self-loops and the higher the spatial resolution.

To find out the characteristics of the effective attack path, Clemente *et al.* built pitch-passing networks consisting of 18 zones on a field [40]. They discovered that a majority of the offensive maneuvers that led to successful goals were instigated by both the lateral defenders and midfield players, culminating with the forward players in the forward zones. Herrera-Diestra *et al.* found that the characteristics of the pitch-passing network are quite different between FC Barcelona and the rest of the teams in the Spanish leagues [41]. By comparing the pitch-passing networks, Gong *et al.* quantified the consistency and identifiability of the performances of different teams [42]. They found that the majority of high-performing teams possessed a greater identifiability value, while the lower-ranking teams had a notably lower identifiability value in the context of the Chinese Football Super League.

Relationship network. From the passing network, one can identify the key footballers in the attack process of a football game by network measures. However, footballers who get more passes are not necessarily the core of the entire team but may be affected by their relationship.

In human society, there are many types of relationships, such as friendship, leadership, acquaintances, and so on. Fransen *et al.* constructed a network of leadership by investigating each footballer's evaluation of other players [43–45]. Four types of leadership roles (task, motivational, social, and external leadership) had been considered. After each footballer scored the leadership quality of all other teammates, a fully connected leadership network was built. Each directed link (i, j) is weighted by the leadership quality of footballer j perceived by footballer i, where the weight w_{ij} is 0 for very poor leader, 1 for poor leader, 2 for normal leader, 3 for good leader, and 4 for very good leader.

The weighted indegree represented one's leadership quality among all other footballers. A node with a high weighted indegree was a footballer seen as a good leader by his teammates. Mertens *et al.* also investigated a leadership network consisting of 20 semi-professional football teams [46]. Duguay *et al.* studied athlete leadership on competitive female youth football teams [47].

Onody and de Castro constructed a bipartite network between 13411 footballers and 127 clubs in the Brazilian football championship [48]. The probability that a Brazilian footballer has worked at N clubs or played M games shows an exponential decay, while the probability that he has scored G goals is power-law distributed.

By converting the bipartite graph into a non-bipartite graph, we can obtain a membership (or friendship) network of social relationships between players. If two players are in the same club C at the same time t, a link is connected between the two nodes.

$$a_{ij} = \begin{cases} 1, & \text{if } i, j \in C(t), \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

where $C(t)$ stands for the members in club C at the time t. $a_{ij} = 1$ stands for footballer i and j may represent acquaintances. The node degree in this network is the number of possible acquaintances. The higher the degree, the more other footballers the corresponding footballer knows.

In friendship networks, it is common to see that one's friends may also be friends with each other, which can be characterized by the clustering coefficient. Onody and de Castro found that the Brazilian football membership network is highly clustered [48]. It was likely that acquaintances of a Brazilian footballer knew each other as well. In addition, they also found a short average shortest path length between all Brazilian footballers, $\langle d_{ij} \rangle = 3.29$. It says that there are no more than 3.29 people between one footballer and any other footballer, which is smaller than a well-known result in social networks, the "Six Degrees of Separation".

Networks of football clubs. – A football club is a symbol of the professionalization and specialization of football, and is an organization by which footballers are employed when they earn a living from football. A professional football club is an entrepreneurial organization that provides competitive football performance services and related products to the public. A professional football club is mainly engaged in competitive football games with the main purpose of maximizing profit. To maximize the value of the club, it will continuously improve the quality of its product (football games) to attract most consumers (fans), which greatly contributes to the improvement of the level of competitive football.

Network-based ranking of clubs. For most people, rankings are the most attractive thing about competitive sports. The top-ranked teams are usually high-performing teams, and these teams tend to get more resources and attention. There are many types of rankings in football games, such as the FIFA World Ranking, Premier League Standings, UEFA Club Ranking, and so on. The results of different games among teams usually affect their ranking. Therefore, many scholars constructed different social networks based on the win-loss relationship between teams to analyze the changes in football rankings:

$$a_{ij} = \begin{cases} 1, & \text{if team } i \text{ beat team } j, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

Node degree in this network reflects the level of a team. The higher the degree, the stronger the corresponding team. After the network is built, a PageRank-based ranking method could be used to determine the rankings of each team, which is well known for reflecting the relevance and importance of Google pages. Since the performance of the team closely relates to the ability of the coach, Hu and Erkol *et al.* built win-loss networks of coaches [49,50]. By using PageRank centrality, they ranked the performances of all the coaches and identified the top coaches in different football leagues.

Usually, the level of a team does not change dramatically in a brief period of time but stays within a certain range. Therefore, Jessop ranked teams by grouping them according to their game performance [51]. An undirected network was constructed based on the difference in performance between two teams. In this network, the adjacency matrix was defined as follows:

$$a_{ij} = \begin{cases} 1, & \text{if } |g_{ij}| \leq \alpha; \alpha \geq 0, \\ 0, & \text{otherwise,} \end{cases} \tag{11}$$

where g_{ij} is the goal difference between two teams, i and j. If $|g_{ij}| \leq \alpha$, two teams had similar performances in football games. In this network, teams with the same level were often closely connected, while teams with large differences in performance had sparse connections. Therefore, the football network could help us know the competitiveness of teams in the league by finding the blocks of the network, which is a new way to rank the performance of different football teams.

There are also various methods for ranking teams. Each ranking has its own evaluation criteria and calculation method. There are still many questions about whether a ranking reflects the actual strength of a team. Criado *et al.* constructed a competing network based on the changes in football teams' ranking orders over time to study the competitiveness of the rankings [52]. If the relative ranking positions of two teams were changed, an undirected link was connected between the two teams in the competing network. Its adjacency matrix was defined as follows:

$$a_{ij} = \begin{cases} 1, & \text{if } \dfrac{p_i(t+1) - p_j(t+1)}{p_i(t) - p_j(t)} < 0, \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where $p_i(t)$ is the relative position of team i in the t-th ranking. The weight of each link is defined as the number of changes in ranking order. In the competing network, some network measures (average degree, average weighted degree, and clustering coefficient) are able to measure the competitive balance of a sport's ranking. Garcia-Zorita *et al.* also investigated the dynamics of the competing network, including ranking with ties, entrants, and leavers [53].

Footballer transfer network between clubs. Besides the ranking of football teams, another thing that deserves attention is the transfer of footballers between different clubs. Football transfers are usually done through negotiations and deals between clubs, while player transfer fees are determined by agreements between clubs. Football transfers can be beneficial for both clubs and players. For the club, they can improve their team by acquiring a player they want from another club. For the players, they can get better pay and greater challenges through transfers to achieve higher personal goals. Football transfers not only improve the strength of a club but also raise its popularity. When big-name players leave a club in a transfer, they attract more attention, which helps the club promote itself. In addition, football transfers also help to improve the club's revenue because player transfer fees can generate significant income for the club.

Football transfers take place between different clubs. A node in a football transfer network represents a football club. A direct link is established between the clubs where the transfer takes place,

$$a_{ij} = \begin{cases} 1, & \text{if a player transfers from club } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

The direction of a link is consistent with the direction of players' transfers. The weight of each edge can be the number or fee of transfers, etc. Liu *et al.* constructed a transfer network among 410 clubs in 24 top-class professional football leagues from 2011 to 2015. They aimed to relate a club's success to its activities in the player transfer market from a network perspective [54]. Based on 470792 transfer records among 23605 football clubs in 206 countries and regions, Li *et al.* constructed both directed and mutual footballer transfer networks and investigated their basic topological characteristics [55,56]. They found the mutual transfer network exhibits assortative mixing for most nodes or clubs but disassortative mixing for clubs with large degrees. Bond *et al.* showed that some elite football clubs were taking profits from other clubs by calculating the European loan network measures, such as average degree, density, and various centrality measures [57]. Lombardi *et al.* built a network of professional footballers' transfers among five leagues [58]. By analyzing the global transfer network, Velema found that most transfers occurred domestically [59]. Seiberth and Thiel studied the transfer network for young top football players with migrant backgrounds [60]. Wand considered a transfer network with only non-zero fee transfers [61]. They explored the network properties and found the transfer network had a power-law degree distribution but not a small-world characteristic. Clemente and Cornaro grouped different football clubs at country level by using the transfer network [62]. They discovered that leagues with comparable economic values belonged to the same cluster.

Discussion. – In recent years, social networks and social network analysis methods have attracted great attention. Social networks, as a tool for analyzing the relationships between individuals, can provide precise formal definitions for answering social behavior science problems. By using social network analysis, football behaviors can be explained as regular patterns in relationships between different footballers or football clubs. By analyzing these patterns, it is possible to reveal the characteristics of individual and group behavior in football.

In this paper, various football networks were mentioned based on different research objects. When using passing sequences of attacks among footballers, a passing network was built to determine the performance of a football team or to identify key players in an attack. It can help coaches analyze the performance of a team and adjust appropriate coping strategies. Building a network of social relationships between football players can identify core players (leaders) in the team. Considering the results of football games, a win-loss network was built between clubs. By using the PageRank centrality measures, one could establish a new ranking system. Besides that, a competing network was built to measure the stability of different ranking systems. Based on the transfer activities of footballers between different clubs, a transfer network was built to characterize the football transfer market and identify footballers' preferential transfer paths. All these networks provide a new perspective for football professionals to analyze football.

When analyzing football networks, most studies focused on clustering coefficients and average path length to characterize the whole network and node centralities to characterize the network nodes. All these measures are common variables to quantify topological properties in social networks. While there are still different views in social network analysis, such as community detection [63], network dynamics [64], and network controllability [65], which can also be used for further analysis in football.

Studying football networks enhances our understanding of players' performance and the real-time game situation, which is helpful to estimate the outcome of the game. In recent years, deep learning methods such as convolutional neural networks have been used to predict the outcomes of different sports games [66–68]. Their models outperformed traditional approaches like Bayesian Networks and SVMs. In football networks, one can also use the network measures as inputs and the outcomes of games as outputs to train the model, which presents a new possible direction for football network studies. In this vein, a detailed analysis of the factors that contribute to the success of models can be performed. In addition, such future studies will benefit if more data sets are included.

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