A Team Decisionmaking Model Based on Optimization and Network Analysis

Abstract

With the rapid development of big data technology in the past 50 years, it has become common and practical to use data analysis to solve problems, especially using data to build networks in computers. It is a fabulous way to solve the problem of teams by using network. This year we were invited by the coach of the Huskies to build a network based on team data to help understand the team 's dynamics, especially exploring how the complex interactions among the players on the field impacts their success. Based on the data set provided by the team, we propose the following solutions to the requirements of the coach:

For the require I: We construct an *unidirectional weighted passing network* and redesign some parameters of the network to make it more realistic to the football. For the accuracy of the analysis, we establish a series of networks to analyze teams and games on various scales. We also set up a network to analyze the specific game according to set the average position of players in the contest as the coordinates of nodes. At the same time, we used the *Fruchterman-Reingold algorithm* and the *K-nearest Neighbor Analysis* to group players in the team from the global optimal perspective, so as to facilitate subsequent selection of the tactics and the more detailed exploration of the impact between players and players on the team.

For the require II: We firstly dig deep into the data and define some different performance indicators to reflect successful teamwork. Then via the *reward mechanism* of the *reinforcement learning* we establish a team decision model and use this model to analyze the deployment of specific team work for a simple competition process. Here we use the *kmeans* unsupervised learning method to classify team types. Because the data is less, we use the *SOR algorithm* to make full use of the data to determine the style that each team may play in the first half and the second half, and use the predicted style to carry out the dynamic deployment of the team.

For the require III: We aim to increase the robustness of the network, and analyze the indicators of the network such as *network density* and *clustering coefficients* to improve the strength of the network and find ways to improve the competitiveness of the team. At the same time, some suggestions for improving the team are made from the team's performance this season and the analysis of other teams' data.

For the require IV: Based on the indicators of question three, we found that some of them can well describe how to make a group better. Some of these indicators are also meaningful for building effective social teams. Such as: subset, centrality, etc., while continuously adjusting the composition of the team, continuous optimization can make the team grow better and better.

Keyword: passing network, network identification, network analysis, reinforcement learning, reward mechanism

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Abstract

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1. Introduction

As social ties are getting closer, scientists are gradually realizing the importance of teamwork. Therefore, in the past 50 years, research on factors that can make teamwork successful has emerged. The results of studies to date have shown that the leadership style, interactions among team members, and the degree of dependence on individual team members all relate to the success.

One of the best ways to explore teamwork is to use competitive teams as research objects. Our goal is to use social networks and mathematical theories to process team statistics in competitions and analyze team performance and team characteristics to identify possible Factors that contribute to team success. Among them, compared with other sports, football has become a research object favored by researchers due to its unique game characteristics. However, most of the academic researches on the performance of passing in football matches are based on the analysis of individual participants, ignoring the relationship between individuals. And the statistical indicators are not representative enough to reflect the characteristics of the team. Therefore, it is necessary to develop new research methods to explore the index system of football performance research, so that the research results are richer and more specific.

In a paper published by Gould and Gatrell in the late 1970s, the concept of a passing network related to football matches was first proposed^[1]But it didn't catch people's attention at the time. About 30 years later, Duch and his collaborators proved the role of social network analysis in understanding complex social phenomena, and thought that this method could be extended to teamwork^[2]. Since then, the use of the passing network method to study football matches has gradually become mainstream. Researchers have found that using the passing network can show repeated passing sequences and can summarize the team's playing style from it^[3]. With the deepening of research, in 2014, Narizuka introduced a network model considering player positions in the paper, so that the distribution of players and team characteristics can be seen more intuitively. But for the convenience of observation, he did not compare the target team with his opponent^[4].Despite these achievements, there are still some shortcomings in the analysis method. For example, a single-analyzed network cannot provide powerful quantitative analysis, and the use of network analysis does not determine the level of heterogeneity of the team or the cluster within the team. Therefore, in 2015, Clemente's article introduced a set of network indicators that can help obtain quantitative information about the team, and use some methods in other scientific fields (such as social science) to propose a set of metrics for macro Analysis to characterize the overall distribution of the team^[5].

In our research, we use the team's passing distribution in the game to build a weighted and directional network, where the nodes correspond to a single player, the weighted arrows indicate the relationship between successful passing between players, and the width of the weighted arrows indicates successful passing The number of balls. By analyzing the network graph, we can get information about team style and game characteristics. For example, it can be used to determine players with a high number of passes, teams that tend to use short or long distance passes, and whether the players are adequately involved in the game. Teams can also use the

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network to detect under-performing players, fix weaknesses, detect potential problems between teammates who fail to pass frequently based on location, and detect competitors' weaknesses. We used Huskies and its 19 opponents in 38 games and 23,429 successful passing data as a sample to construct a passing network. Through the analysis of the network and team intimacy, we found out the complex characteristics that affect its success, and then extended it Look for factors that influence the success of social groups.

2. Assumptions and Justifications

- Points system: We assume 2 points for winning and 1 point for tying
- We assume the substitutions of a competition are unlimited, all the teammates can play on the pitch.
- We do not consider the impact of player injuries on the network. In addition, due to the complexity of the factors that may cause fouls, they are not considered in these requirements either.
- We assume that there is no effect of home and away factors on the team network.

3. Notation

Table 1. Notation

Symbols	Meaning	Symbols	Meaning
\overline{D}	All the nodes in the network	$W_{i,j}$	The weight of the link from node i to node j
d_{i}	The degree of the node <i>i</i>	$C_{i,j}$	The node-closeness between node i and j
O_{ji}	The total number of actions of the j team in the opponent's half in the i game	S_{ji}	The number of shots of the j team in the i game
n_j	Total number of games for j team	t_{j}	The number of shots needs to organize for j team
$\overline{a_{l}}$	The average style of this team	a_2	The average style of the same type 's teams
a_3	The average style of all the teams	ω	Weights in style determination
b	The possibility vector	β	Weights in the possibility vector determination

P.s.Other symbols instructions will be given in the text.

4. Passing Networks

4.1 The Definition of Passing Networks

Based on the analysis of require I, we preprocess the passingevents.csv data set and build the *passing network* model based on this data set to quantify and formalize the structural and dynamical features of the Huskies.We set players as nodes, connect these nodes with passes as unidirectional links(from player A to play B), weight links according to the number of passes between different players and build a series of passing networks on a variety of scales to analyze teams and games.We redefine the concept of degree of the node in networks to better characterize networks as follow:

$$d_i = \sum_{i \in \mathcal{N}} (w_{i,j} + w_{j,i})$$

By calculating the degree of the corresponding node in the network, it can reflect the importance of the node corresponding to the player in the network and the importance of the player in the team as the following **Table 2:**

Table 2 The degree of all 30 players in

Name of Players	Degree	Name of Players	Degree
Huskies_M1	2258	Huskies_F6	518
Huskies_F2	1776	Huskies_F4	408
Huskies_M3	1604	Huskies_F5	379
Huskies_D1	1525	Huskies_M12	345
Huskies_D3	1299	Huskies_M8	310
Huskies_D5	1194	Huskies_M9	270
Huskies_D4	1180	Huskies_M2	141
Huskies_D2	1043	Huskies_M13	129
Huskies_M6	1039	Huskies_F3	129
Huskies_M4	1002	Huskies_M11	115
Huskies_G1	965	Huskies_D9	98
Huskies_D7	855	Huskies_M5	81
Huskies_F1	709	Huskies_M10	76
Huskies_D6	645	Huskies_D10	69
Huskies_D8	548	Huskies_M7	40

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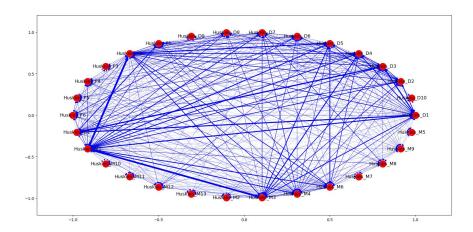


Fig.1 The network of 30 players in the whole season

Fig.1 shows the network about 30 players of the Huskies during the whole season, in total 38 games.

Here we use python's package, networkx, as the visualization tool and visually display the weights with the width of the line. Despite of the large number of players, we can still find <code>Huskies_M1</code> is more important in the network according to the <code>Fig.1</code>, which is also consistent with our <code>Table 2</code>. It is obvious that this network is too complex and not conducive to our analysis of the network, at the same time can also be observed a number of players on the edge of the network effect relatively small for the team and games and even cause interference on the analysis of the network. Because of this we eliminate some edges whose weights under 45 to simplify the network. Via this way, we build a network with 16 nodes(players) which is used for the grouping, because we don't consider the effect of injuries to players and combine with the actual survey data about football, 16 people list is reasonable.

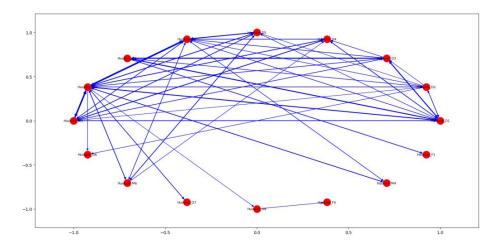


Fig.2 The network of 16 players in the whole season

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4.2 The Network Pattern Identification

Both teams and games are closely linked networks. Therefore it is not accurate to study the network from an individual node in the network. We use the whole networks analysis to analyze the network we built. But when talking about the cooperation or style of players and addressing the question II, the tactics of different opponents, it is too complex and inaccurate to analyse our team from the whole network. Here we split the team into triadic configurations: normally each configuration has three players. It is well known that triangles are the most stable in geometric shapes, as well as in networks and football competition. When two players are cut off from passing the ball by the rivals, they can hit the mark successfully by another player. In order to realize the grouping of players and construct a small network of several players, firstly, we defined a new parameter: node-closeness, which reflects the closeness of the corresponding players of the pair of nodes as following:

$$C_{i,j} = C_{j,i} = w_{i,j} + w_{j,i}$$

Then it is normalized:

$$C_{i,j}' = C_{j,i}' = \frac{C_{i,j}}{\max C_{i,j}}$$

It is important to point out that our players grouping mode does not simply put the three players with the highest node-closeness together, because the result of this method is only locally optimal. Perhaps <code>Huskies_M1</code> player is close to <code>Huskies_M4</code> because <code>Huskies_M1</code> is close to all of the rest players. Here, we adopt the FR algorithm (<code>Fruchterman-Reingold algorithm</code>). The FR algorithm propose the concept of "force guidance", which simulates the relationship between two nodes with a spring. After receiving the effect of the spring force, the overclose nodes will be bounced off and the nodes passing through will be pulled closer. Through multiple iterations, the overall layout is balanced and stable.

The equilibrium separation k:

$$k = \frac{area}{num}$$

area is the area of the layout and num is the number of the nodes in the network. The geometric distance dist between nodes i and j:

$$dist(i, j) = \sqrt{(i.pos_x - j.pos_x)^2 + (i.pos_y - i.pos_y)^2}$$

The attraction function between nodes i and j:

$$f_{\alpha}(i,j) = \frac{(dist(i,j))^2}{k}$$

The repulsion function between nodes i and j:

$$f_{\gamma}(i,j) = \frac{k^2}{dist(i,j)}$$

The implementation of this algorithm has good symmetry and local convergence, which is convenient to find a global optimal solution for our grouping problem. First the weight on the links will be replaced by the node-closeness and then lay out the network by using the FR algorithm.

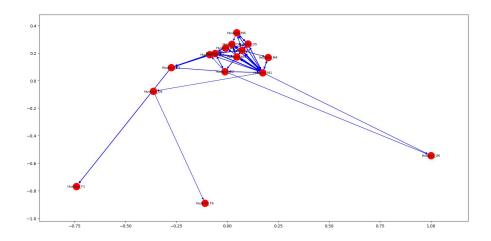


Fig.3 The layout of the network by FR algorithm

As shown in the **Fig.3**. Then we use the KNN(K-nearest Neighbor Analysis). We choose k = 2 and select the two closest nodes to the largest degree node in the network to form a triadic congratulation. After removing those three nodes from the network, FR algorithm is used again to construct the layout to find the point with the largest degree in the current network, and the KNN is applied again to find the grouping until all the players are finished. At the same time, we observe that there is only one goalkeeper, $Huskies_GI$, in the team, so $Huskies_GI$ is not considered in the grouping, and the simplified network is divided into five groups of players as shown in the **Table 3** below:

Serial Number	Name of Players
A	Huskies_M1&Huskies_M4&Huskies_F2
В	Huskies_D1&Huskies_D3&Huskies_D7
С	Huskies_M3&Huskies_D5&Huskies_D4
D	Huskies_D2&Huskies_M6&Huskies_D8
Е	Huskies_F1&Huskies_F6&Huskies_D6

Table 3. The group of players

4.3 The Passing Network of a Single Game

Furthermore, we also want to know how the team's performance in a single game maps to the network. We transform the y coordinate of the original data set.

$$y' = 100 - y$$

When taking the average position of players in this game as the coordinate and the left bottom of the pitch as the origin to establish a coordinate system, we construct and drew the *passing network* on the football field as **Fig.4**:

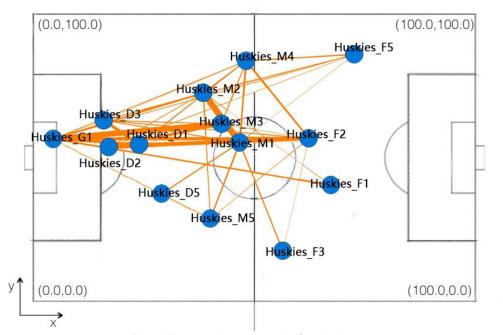


Fig.4 The passing network of a single game

Through such a network, we can more intuitively see some of the characteristics of the team's game, such as the focusing area, the offensive direction and the players' passing area.

5. Team Decision Model

5.1 Identify performance indicators for successful teamwork

In addition to wins, losses, and goals. We performed high-level data processing, and defined the number of shots that each team needs to organize and the continuous ball control rate. These two performance indicators can reflect the success of teamwork.

The number of shots each team needs to organize:

We record o_{ji} as the total number of actions of the j team in the opponent's half in the i game. s_{ji} as the number of shots of the j team in the i game. n_j is the total number of games for j team. Then, we can get the number of shots needs to organize for j team by this way:

$$t_{j} = \frac{\sum_{i} o_{ji}}{\sum_{i} s_{ji}}$$

Plotting with the number of shots needs to organize:

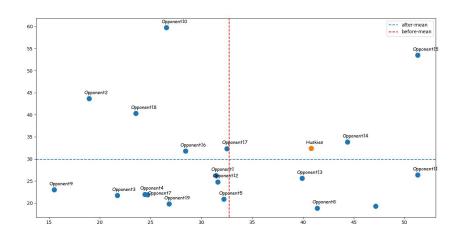


Fig.5 The number of shots needs to organize of each teams

It can be seen from **Fig.5** that for teams with fewer shots to organize, their offensive efficiency can be higher, so reducing the number of shots required to organize can better strengthen the team's offensiveness.

Continuous ball control rate: The pass table for each match is first reduced to a vector such as (0,1.05,1.05,0,1.05), where 0 means the pass was initiated by the opponent and 1.05 means the pass was initiated by the opponent. Then exponentially calculate all consecutive 1.05s to show

the continuity of the pass, such as (0,1.05, 1.05²,0,1.05). Quoting the initial vector sum value and the transformation vector sum value, call this number as Continuous Ball Control.

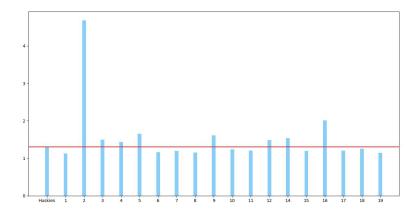


Fig6. The continuous ball control rate of each team

This **Fig.6** from above shows that properly increasing the continuous ball control rate can improve the cooperation between members of the team, but increasing the continuous ball control rate too high may indicate that the team only controls the ball in the game, and the offensive organization efficiency is too low.

5.2 Model establishment and simple process analysis application

For team selection and decision-making in a team confrontation project to achieve a certain purpose, you can use the idea of reinforcement learning to build a model.

What is reinforcement learning? Reinforcement learning is more like trial and error. An event is divided into n steps to complete. There are m ways to solve these n steps. Reward factors for each step can be obtained through machine learning. Iteratively select the method with the highest reward factor to solve the problem. In the establishment of the team cooperation model, we have learned more from the reward mechanism in reinforcement learning.

The process of the game is more like a process of confrontation. In order to achieve our goal, we need to make a list of 11 starters based on the type of opponent. However, the game is a dynamic process. After determining the starting 11 people, we need to change our team strategy according to the team strategy that the opponent may implement.

Below we will make a team configuration with the goal of a higher continuous ball control rate in this game:

First we need to assign the starting players according to the characteristics of the opponent.

Originally we wanted to judge the type of team only by a simple comparison of the data. As shown in Fig.7 and Fig.8:

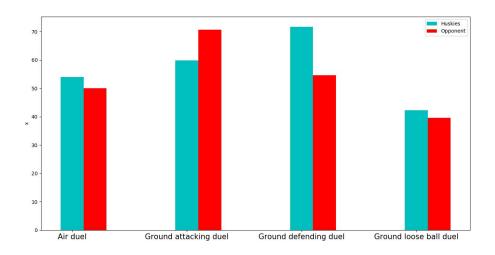


Fig7. Specific comparison of duel

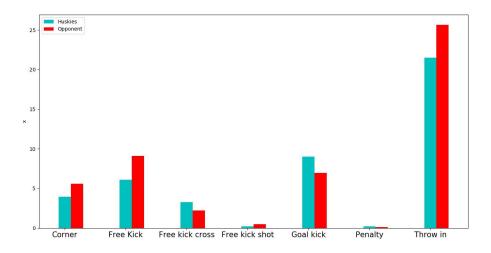


Fig8. Specific comparison of free kick

But this may lack the correlation between the factors, and cannot comprehensively measure the team type. Then we use the k-means method. The step is to randomly select K objects as the initial cluster center, then calculate the distance between each object and each seed cluster center, and assign each object to the cluster center closest to it. The cluster centers and the objects assigned to them represent a cluster. Each time a sample is assigned, the clustering center of the cluster is updated according to the average position of the existing objects in the cluster. Until the cluster center no longer changes. We take as input each team's 22 attributes such as the average number of passes and the number of shots per game. Then output the approximate type of each team. The types are shown in the **Table 4**:

Table4. Type of each team

Team_Name	Туре	Team_Name	Type
Huskies	Defensive	Opponent1	Defensive
Opponent2	Equilibrium	Opponent3	Equilibrium
Opponent4	Offensive	Opponent5	Offensive
Opponent6	Defensive	Opponent7	Defensive
Opponent8	Defensive	Opponent9	Offensive
Opponent10	Defensive	Opponent11	Defensive
Opponent12	Defensive	Opponent13	Offensive
Opponent14	Offensive	Opponent15	Defensive
Opponent16	Equilibrium	Opponent17	Defensive
Opponent18	Defensive	Opponent19	Defensive

Next, we need to find a suitable strategy based on the performance of the opponent on the field. The following is a simple analysis of the competition process:

In the game, the two teams may play different styles in the first and second half. The interaction between different styles is crucial. So how do you make style predictions? Below we will take *opponent_1* as an example to explain how to make predictions and give a team configuration plan:

What is style? Take the first game as an example:

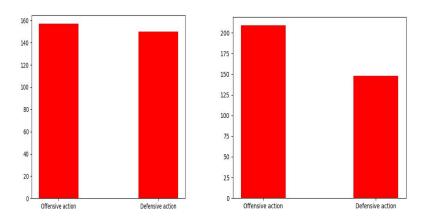


Fig.9 Comparison of offensive and defensive actions(The left picture shows the first half and the right picture shows the second half)

It can be judged that the opponent is more balanced in the first half, and offensive in the second half

Put all the games on the style label as above and standardize the labels. After standardization:

 a_1 represents the average style of this team. a_2 represents the average style of the same type's teams. a_3 represents the average style of all the teams. Calculate:

$$\omega_1 \cdot a_1 + \omega_2 \cdot a_2 + \omega_3 \cdot a_3 (\omega_1 = 0.6, \omega_2 = 0.3, \omega_3 = 0.1)$$

to get the style that the team is most likely to play.

For example: The value calculated by opponent_1 in the first half is 2.235, which is closer to 2, can be predicted as:Moderate.The second half is: 2.825 closer to 3 can be predicted as:Attack.

After predicting patterns, we use the ideas of reinforcement learning to develop strategies. First, give rewards. For different types of teams, calculate the average continuous ball control rate for all matches against that type of team. The distribution of rewards is based on the extent to which the starting 11 players exceed or fall below the average continuous ball control rate. The higher the average continuous ball control rate, the higher the reward. The more below the average continuous ball control rate, the more penalties. According to the previous grouping, we can roughly get 7 starting ways.

The specific reward factors after traversing the data are as follows:

GroupingABC:2 GroupingABD:1 GroupingABE:0 GroupingACD:3;

GroupingACE:-3 GroupingBDE:-2 GroupingCDE:-1

After determining 11 players to play, you need to count all the styles that the 11 players can play. Here we will connect the styles that can be played with the previous team group, determine that the 11 people have the best fit with that group, calculate the proportion of game styles in this group, and obtain the possibility vector b_1 of the style that the 11 people can play.

$$b_{I} = (b_{I}^{(1)}, b_{I}^{(2)}, b_{I}^{(3)})$$
 $b_{1}^{(i)} = \frac{m_{i}}{m} (i = 1, 2, 3)$

Among them m_1, m_2, m_3 respectively represent the number of Attack.

Moderate, Defense, m represents the total number of matches. Similarly, calculate the probability vector b_2 of all matches. Get a more accurate vector based on the first and second vectors:

$$b = \beta_1 \cdot b_1 + \beta_2 \cdot b_2 (\beta_1 = 0.7, \beta_2 = 0.3)$$

When our team chooses a style higher than the average ball possession rate to give a reward, otherwise it is punished. The reward and punishment mechanism is the same as above. After traversing the data, multiplying the reward factor by the probability vector \boldsymbol{b} , the result is as follows:

Attack: 0 Moderate: 0.8 Defense: -0.1

Continue this step until the opponent implements the last strategy, this example is the second half strategy where the factors are rewarded as follows:

Attack: -0.1 Moderate: 0 Defense: 0.7

Then we can start team deployment. Obviously, we only need to choose the strategy set with the highest reward amount. For the defensive type, it is expected that the style will be balanced in the first half, and the opponents on the offensive side in the second half. To achieve a higher continuous ball control rate, we choose:

GroupingACD as Starting First Half: Moderate Second Half: Defense

It will be more meaningful if we further refine the process of the game, for example, to deploy a node for strategy deployment in 10 minutes. However, due to the lack of data sets, more detailed analysis cannot be performed because there may be abnormal conditions that affect the final result. But after the process is simplified, the model can have relatively good results.

6. Result and Analysis

6.1 Evaluation of the Huskies

Observing the entire 38 games, we chose the 23rd game as the main research object. In this game, the Huskies lost to the opponent 0-4. We hope to find out the problems existing in the team and propose corresponding solutions.

Network density refers to the ratio of the number of actual connections between nodes to the maximum number of connections that may exist between nodes. It is an important variable to measure the tightness of the network structure or the strength of the connection between nodes.

$$C$$
 AD $i = d(i) = \sum_{i} X_{ij}$

According to the analysis of the network diagram of Huskies and its opponent 4, the Huskies's passing network density is 1.2418, which is much lower than its opponents, indicating that the Huskies teammates are relatively inadequately connected and have fewer passes. Generally speaking, the higher the network density, the closer the relationship between the teams, the better the team members' cooperation and the better the team's performance; In the contrast, the network density is low, and the teams that are not tacitly cooperating with each other often have poor information, less communication, and Low job satisfaction among members.

Therefore, the Huskies team should pay attention to the closeness of the team, build a tight passing network, increase the ball control rate on the court, improve the passing accuracy, and avoid leaving opportunities for opponents, we can see directly in **Fig.10**:

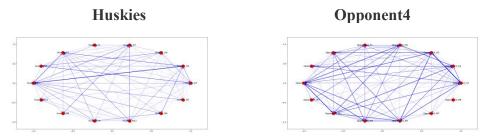


Fig.10 Passing networks of two teams

6.1.2 Betweeness

which measures the extent to which a node lies on paths between other nodes This quantity is defined as the percentage of shortest paths that go through players^[6]. Betweeness is an indicator to measure the importance of individuals in a team, and is divided into degree betweeness and intermediate betweeness.

Degree betweenness is mainly used to measure and determine the core people who are generally the most influential in the team, and also one of the important people that determines the success of the entire team.

$$C_{AB} = \sum_{j \le k} b_{jk}(i) = \frac{\sum g_{jk}(i)}{g_{jk}}$$

Intermediary betweeness is mainly used to measure a person's ability to act as an intermediary in the network, these people connect the teamates who are not directly connected to the network.

$$C_{AP_i}^{-1} = \sum_{j} dij$$

The core degree of Huskies and opponent 4's core players are basically the same, but the intermediary betweeness of Huskies is low, indicating that the two teams rely on the same degree of core members, but the core members of opponent 4 have stronger personal abilities and can better connect other members, and his passing range is also wider, we can see the results in **Table 5**.

Therefore, the football team should focus on improving the player's personal ability, especially the key players' own qualities, so that he can give full play to the ability of the hub in the game, mobilize the team enthusiasm, and lead the entire team to success. At the same time, we should pay attention to the coordinated development of the entire team, not to rely too much on a certain player, guarantee that every players can play a role.

Table.5 The Betweeness

Huskies		Opponent4			
	Betweeness1	Betweeness2		Betweeness1	Betweeness2
Huskies_D6	20.001	12.821	Opponent4_D 2	20.417	13.088
Huskies_D3	11.039	7.076	Opponent4_D 2	8.249	5.288
Huskies_D5	9.142	5.860	Opponent4_D 2	6.153	3.944
Huskies_M13	8.856	5.677	Opponent4_D 2	4.864	3.118
Huskies_F2	7.919	5.076	Opponent4_D 2	4.467	2.864
Huskies_M1	7.533	4.829	Opponent4_D 2	4.329	2.775
Huskies_G1	7.452	4.777	Opponent4_D 2	4.119	2.640
Huskies_F5	6.537	4.190	Opponent4_D 2	4.098	2.627
Huskies_M6	5.485	3.516	Opponent4_D 2	3.541	2.270
Huskies_M8	4.543	2.912	Opponent4_D 2	1.406	0.902
Huskies_D7	3.995	2.561	Opponent4_D 2	0.893	0.572
Huskies_M3	2.037	1.306	Opponent4_D 2	0.740	0.474
Huskies_F1	1.376	0.882	Opponent4_D 2	0.722	0.463
Huskies_M12	1.085	0.695	Opponent4_D 2	0.000	0.000

Calculated by Ucinet, based on the data of two teams

6.1.3 Clustering coefficient

The clustering coefficient is a coefficient used to describe the degree of clustering between vertices in a graph. Specifically, it is the degree to which adjacent points of a point are connected to each other.

In the network diagram of the football team we studied, the clustering coefficient describes the success rate of passing between triangular players. As can be seen from the foregoing, the triangle player mix is stable, so the stability of each subset constitutes the entire Stability of the

passing network. Analyzing the match data of Husky and his opponent, we can see that the cluster coefficient of Husky is 1.304, and the cluster coefficient of opponent is 2.781, which shows that the opponent's network is more stable and teammates cooperate tacitly. Therefore, in a football team, we should pay attention to the cooperation between teammates to maintain the stability of the network.

6.2 Construction of other social groups

We found that the results obtained from the analysis of the network parameters of the Huskies and their opponents are also useful in the construction of other social groups.

Subsets: When designing a team, we should conceive of the division of labor, clarify the functions of each subset, and strengthen the internal connections within the subset. Therefore, the characteristics of each member of the team should be fully considered, and the performance of the entire subset should be considered, and the complementary people should be formed into a group to fully communicate within the subset. Only when microcosmic stability is achieved can the entire team network be guaranteed. stability.

Betweeness: It can be seen from the general data that the victory of each team is inseparable from the existence of core members. From this, it can be seen that the individual is also the foundation of the team, playing an important role. An excellent core member is the key to the success of a team. He should not only have strong own ability, but also have good communication skills with others. Only under the correct leadership can the effectiveness of the entire team be maximized. Therefore, when designing a team, you should also consider the centrality of the team network and find a suitable leader.

Intimacy: The unity of a team is important to maintain the relationship within the team and resolve conflicts. Therefore, when setting up a team, you should carefully understand the background of the members, strengthen the internal construction of the team, make the team members closer, and the social network of the team more stable.

The designing of a team must not be solid and unbreakable once the design is completed, but it should be updated at any time. As in football matches, it is necessary to make adjustments to personnel within the group in a timely manner, and to adjust the assignment of tasks suitable for them in a timely manner according to the characteristics of the team members to ensure the efficiency and quality of the entire team.

7. Strengths and Weakness

7.1 Strengths

- In the *passing network*, we introduce some new parameters of the network to make it more realistic to the team and games. We also construct a series of networks from various scales to accurately analyze the team and games, especially we establish a single network with the coordinates of nodes.
- When identify the network patterns, we use a method which is a combination of FR algorithm and the KNN to find a global optimal solution.
- *The team decision model* adds more dynamic changes than the ordinary evaluation model, which can better reduce the impact of opponents' counter-strategy on the target.
- We use an efficient way of using the data set to make the model more accurate.

7.2 Weakness

- The standard of the simplification of the *passing network* is just from the actual cognitive lacking of enough statistic evidence.
- The data of the opponent is not enough to ensure the accuracy of the model.
- The team decision model is too idealistic, for example, when selecting the best starting lineup, one player should be selected by one player or one small group and one small group to select instead of directly selecting 11 people.
- The environment variables can be more but because of the limit of the time, we only select several typical variables.

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