Team Performance Evaluation Model based on Network Feature Extraction

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ABSTRACT
Teamwork is increasingly important in today’s society. This paper aims at the problem of team performance evaluation. Through complex network feature extraction, we establishes the passing network and team performance evaluation model. Finally, this paper proposes strategy for Huskies team and extend the model to the general team.

KEYWORDS
Network feature, Network pattern, Motifs, Evaluation model

1 INTRODUCTION
As societies become more interconnected, the set of challenges they face have become increasingly complex. Our conceptual understanding of team success has advanced significantly over the past 50+ years allowing for better scientific, creative, or physical teams to address these complex issues. Researchers promote teams to perform complex tasks by proposing strategy for the team. One of the most informative settings to explore team processes is in athletic. Team success is not only the sum of the abilities of single players, but also based on many other factors that involve how well the teammates play together[6].

The Huskie coach hopes that your group can improve their performance for the next season by analyzing that in last season. Your team should use the provided data to address the following:

- Create a network for the ball passing between players to identify network patterns.
- Create a model that captures structural, configurational, and dynamical aspects of teamwork.
- Use the insights gained from your teamwork model to inform the coach about the useful strategies.
- How to design more effective teams? What other aspects of teamwork should be pay attention to.

1.1 Previous Work
In soccer, the pass motifs that the team often uses indicates the opponent’s game format[7][9]. But they did not consider the problem of community clustering in the network, and the motifs obtained were relatively single. Paolo[8] extract a set of pass-based performance indicators and summarize them in the H indicator but not included information about defensive events. Buldu[5] focuses on the temporal nature of soccer passing networks and identifies those network metrics that enhance the probability of scoring/receiving a goal. A network approach was proposed provides a powerful quantification of the contributions of individual players and of overall team performance[2]. However, these methods only consider the player or team level, and it is difficult to design strategies for different opponents. In this paper, a team-department-team three-layer model is designed to comprehensively study the teamwork of soccer players. They propose complex networks model to analyze the relevant indicators of the team and extend it to general teams.

1.2 Problem Analysis
To solve tasks stated in ICM 2020 Problem D, we need to construct passing network to identify network patterns which can capture structural, configurational, and dynamical aspects of teamwork. We provide strategic advice to Huskies soccer teams through the established evaluation model and design more successful teams by improving existing models.

For task 1, we need to establish a passing network to identify network patterns. The problem are divided into macro and micro levels. At the level of the season, 30 players âĂŹpassing are represented by a network. In order to simplify the network, our team performs community clustering. At each game level, motifs are used to represent network patterns.

For task 2, we need to build a model to evaluate the performance of a team. The indicators are divided into three levels: player, department, and team levels. For the player level, the indicators are divided into 8 aspects. For the department level, we quantitatively analyze the cooperation between departments through the connectivity between nodes in the community. For the team level, a dynamic chain of soccer to reflect the team’s flexibility, tempo and other indicators.

For task 3, we need to provide strategic advice for Huskies soccer team. Strategies are divided into universal strategies and strategies against opponents. For the universal strategy, we use the model in task1 to improve the assessment score of Huskies soccer team by changing the indicators of people, departments and teams. For the strategy against the opponent, we adjust the personnel and formation according to the actual situation of the opponent.

For task 4, we need to improve the existing model to design a more successful team. For the network model, we promote the passing to communication and collaboration in the team. The community model is used to study cooperation between departments. The motifs model extracts the network pattern from the network. For the team evaluation model, we promote each layer, and introduce some new indicators in it to establish a scoring model for evaluation.

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To identify network patterns in passing network. We build a community model and clustered 30 players into 3 communities through the community clustering algorithm. In each match, we build the motifs model to identify the network patterns of Huskies and opponents. The motifs show that Huskies team mostly adopts a kind of three-man passing pattern.

The passing network is extracted into three main features: the number of degrees, motifs, and clustering community. We combine these three characteristics to build a three-tier (player, department, team) team performance evaluation model. For the player level, we constructed 8 indicators based on self-ability and coordination. For the department level, we divided the clustered communities into three types: Offensive-Corporation type, Defensive-Corporation type, and Offensive-Defensive type. For the team level, we innovatively use the concept of dynamic chain to show the Huskies' Adaptability, Flexibility, Tempo, and Flow. Finally, we integrate the evaluation indicators after normalizing the data, and get the team’s total score.

Through sensitivity analysis of the team performance evaluation model, we obtain several indicators that have the greatest impact on performance scores. We combine these metrics with a team performance evaluation model to propose recommendations to Huskies coaches. We propose universal strategies and strategies against opponents. In the universal strategy, we adjust the players and formation to improve the score by 12.09%. In the strategy against the opponent, the final score is in the range of [47.28, 92.71].

For general teams, we promote the community model, motifs model and team performance evaluation model. We use member as a node and business, technical and interpersonal relationship as edges to construct a complex network model. Similar to the soccer team performance evaluation model, we constructed the member, department and team level, and established a general team performance evaluation model. Based on email communication data from a university, we build the communication network, which average clustering coefficient is 0.0671.

2 ASSUMPTIONS AND JUSTIFICATION
1. Huskies players will not change significantly next season.
2. The technical level and physical fitness of the players will basically not change in a short period of time.
3. We assume that the player types are only divided into forward, defense, midfield and goalkeeper.

3 NOTATIONS

| Symbols | Meanings |
|---------|----------|
| $< V, E >$ | Graph vertices and graph edges |
| $Q$ | The modularity of the community detection |
| $Pla_i$ | Rating of player $i$ |
| $Dep$ | Department level rating |
| $Tea$ | Team level rating |
| $Sco$ | Team total score |

4 PASSING NETWORK

4.1 Community Model

From a macro perspective of time, we solve Huskies’ team performance last season and extract the network pattern from it.

Data Processing and Analysis. Each player is a node, and each pass on the soccer field is regarded as a connection between the nodes which forms a passing network between players. The expression of the passing network is\[4\]:

$$G = < V, E >$$

where, $G$ denotes the passing network graph, $V$ denotes the edges set, $E$ denotes the edges set. Since we first study the overview model, the direction of the pass was not important. We first establish an undirected graph to describe the passing network between players.

Figure 1: Passing network of 30 players

As shown in Figure 1, we draw the pass of each player in the 38 matches of Huskies team last season according to the passingevents data set (e.g., passingevents.csv) in the attachment. The node in the figure represents a player. The node size presents the number of passes the player has made. The edge represents a pass between two players. The edge container represents the number of passes. Considering the performance of Huskies team throughout the season, there are 30 nodes in the figure.

Community Model

In real soccer game, each team has 11 soccer players which have their own positions on the field (e.g., forward, defense and midfield). We gather several players into a large node according to the closeness of the pass shown in Figure 2. Each small node represents a player. Large node is composed of multiple small nodes. It can be considered that the passing is only performed in large nodes, and the passing network in large nodes is the network pattern.

In order to gather small nodes into large nodes, we aggregate small nodes in following rules:

- Only small nodes that are closely related can gather into a large node.
- The connections between large nodes are relatively sparse compared to the connections between small nodes.
Figure 2: Small nodes gathering

The large node in the network model presents a community structure. The nodes in the community are closely connected, while the links between the communities are relatively weak. The edges between communities represent key passes (e.g. clearance, consecutive passes). Therefore, the edges between communities are the network pattern. The community quality evaluation formula is:

\[
Q(c) = \frac{I_c}{m} - \left( \frac{D_c}{2m} \right)^2
\]

where, \(m\) represents the total number of edges in the graph. \(I_c\) denotes the number of all internal edges in community \(c\). \(D_c\) represents the sum of the degrees of all vertices in the community \(c\). \(D_c\) can also be written as:

\[
D_c = 2l_c + O_c
\]

where, \(O_c\) represents the edge between community \(c\) and other communities.

\(Q\) of the community presents dense of the community-to-community connection. It shows that these passes are more critical, and these edges can better reflect the team’s network pattern. Therefore, our model is finally transformed into an optimization model that finds the largest \(Q\) by changing the number of different communities:

\[
\max_{c} Q(c) \quad s.t. \; c = 1, 2, \ldots, 30
\]

where, \(c\) denotes the index of community. With a total of 30 players, the community has a maximum of 30.

4.2 Motifs Model

From the micro perspective of time, we get the performance of each game of Huskies last season and identify the network pattern.

Graph and Subgraphs. In soccer match, the soccer ball is passed from one’s foot to the other, so the passing is directional. Players represent nodes, and the passing process is connected with directional edges.

As shown in Figure 3, the number of nodes in passing network presents times the player has passed / received the ball. This graph shows all nodes and all directed edges.

In soccer matches, the cooperation of players is two people, three people or even four people. Such a combination allows one player to pass the ball to the player when they encounter the threat of the opponent. In Figure 4, the blue jersey stands for Huskies players and the red jersey stands for opponents. After being threatened by the opponent, the player with the ball can pass the ball to his teammates who are traveling together to resolve the threat. This three-person pattern can be transformed into a network.

Constructing Motifs. Generally, the scheme of passing in a soccer game is variable, unpredictable and context-specific. But there is a pass scheme that appears most often in a game, either offensively or defensively. We propose this most frequent pass scheme as the network pattern for this game.

There are many subgraphs in a graph (e.g., 2-nodes, 3-nodes subgraphs). In order to select the appropriate subgraph as the network pattern, we count the number of directed graphs. As shown in Table 1, the number of 2-nodes isomorphic graphs is only 3, which cannot represent the pass scheme well and cannot be used as an indicator of the network pattern. The 4-nodes and 5-nodes have too isomorphic graphs. Due to the limited number of passes in a match, the network pattern of each match cannot be displayed.

Table 1: Number of networks

| Network types | 2-nodes | 3-nodes | 4-nodes | 5-nodes |
|---------------|---------|---------|---------|---------|
| Number of networks | 3       | 13      | 199     | 9364    |
well. Therefore, we choose the 3-nodes subgraph as an indicator for evaluating the network pattern. The 13 isomorphic graphs of the 3-nodes subgraph are shown in Figure 5.

![Figure 5: 3-nodes subgraph](image)

We use the codes of # 1 to # 13 to represent these subgraphs. The subgraph that appears most often in the graph is called motifs. The motifs represent the network pattern for a match, which can be expressed as:

$$M = \max(g_{si}), \ i = 1, 2, 3$$  \hspace{1cm} (5)

where, $M$ denotes the network pattern, $g_{si}$ denotes the number of subgraphs $i$ appearing in the overall graph. Therefore, the solution $M$ is the network pattern for this game.

### 4.3 Model Solution and Analysis

**Community Model.** We clustered all 30 players from the previous season and solved the community model using Fast Greedy Algorithm[3]. The clustering results are as follows.

![Figure 6: Community clustering results](image)

As shown in Figure 6, 30 players are clustered into 3 communities. In Figure (a), the nodes of different colors represent different clustered communities. The larger the node, the more times the node passes. Figure (b) shows the network pattern we identified after clustering. Different colors represent different communities. The small nodes in the three communities are shown in the Table 2.

**Table 2: Nodes in communities**

| Communities | Nodes                  |
|-------------|------------------------|
| 1           | D1, M1, G1, D2, D4, F3, F1, M5, D6, M7, M8, M10 |
| 2           | M2, D3, M3, F2, D5, M4, M6, F4, D7, M12, D9 |
| 3           | M9, M11, M13, F5, F6, D8, D10 |

F, D, M, and G in the Table 2 represent ‘F’: forward, ‘D’: defense, ‘M’: midfield, or ‘G’: goalkeeper. The order of the nodes in the Table 2 is arranged according to the number of passes. D1 is the player with the most passes in Community 1, M2 is the player with the most passes in Community 2, and M9 is the player with the most passes in Community 3.

**Motifs Model.** We use the data from the previous season to get the motifs of Huskies and the opponents. The motifs formula is:

$$Z = \frac{N_{\text{real}} - N_{\text{rand}}}{\sigma_{\text{rand}}}$$  \hspace{1cm} (6)

where, $N_{\text{real}}$ denotes the number of subgraphs in the real graph, $N_{\text{rand}}$ denotes the number of subgraphs in the rand graph, $\sigma_{\text{rand}}$ denotes the standard deviation of rand graph. The result is as follows.

**Table 3: Huskies motifs**

| H1 | H2 | H3 | H4 | H5 | H6 | H7 | H8 | H9 | H10 |
|----|----|----|----|----|----|----|----|----|-----|
| #12 | #12 | #12 | #12 | #8 | #13 | #12 | #12 | #12 | #13 |
| H11 | H12 | H13 | H14 | H15 | H16 | H17 | H18 | H19 |
| #12 | #3 | #12 | #12 | #2 | #13 | #12 | #12 |

The Huskies team’s motifs are shown in the Table 3. The main motifs of Huskies team is #12 and #13 two subgraph networks. The Huskies team’s passing scheme is more inclined to cooperate with the three players to pass.

The Table 4 shows the motifs of each match of the opponent.

**Table 4: Opponents motifs**

| O1 | O2 | O3 | O4 | O5 | O6 | O7 | O8 | O9 | O10 |
|----|----|----|----|----|----|----|----|----|-----|
| #12 | #12 | #13 | #12 | #13 | #12 | #12 | #12 | #13 | #12 |
| O11 | O12 | O13 | O14 | O15 | O16 | O17 | O18 | O19 |
| #3 | #12 | #13 | #12 | #8 | #13 | #12 | #3 | #3 |

### 4.4 Analysis of Community Model Results

We evaluated the community model to show that the clustering effect is the best when the number of community clusters is 3. As mentioned in the community model, the evaluation uses the modularity formula[3]:

$$Q = \sum_{c \in C} \left( \frac{k_c}{m} - \left( \frac{D_c}{2m} \right)^2 \right)$$

The $Q$ value in this formula presents clustering effect. Figure 7 shows that the clustering effect is the best when the number of communities is 3. This verifies the correctness of our model.
5 TEAM PERFORMANCE EVALUATION MODEL

In this section, we propose Team Performance Evaluation Model to address the problem of identifying performance indicators that reflect successful teamwork.

We first analyze data structure feature of the soccer data set. The dimensions of indicators are not unified. (e.g., variance indicators in soccer data set have values in range 0.1 to 5, while statistical probabilities have values in range 0 to 1.) Therefore, we normalize the indicators in the soccer data set. The data normalization method is showed as following:

\[ V_{\text{normal}} = \frac{V_{\text{origin}} - \text{min}}{\text{max} - \text{min}} \]  \hspace{1cm} (7)

where \( V_{\text{origin}} \) denotes the indicator of the current data element, \( \text{min} \) denotes the minimum indicator of the soccer data set, \( \text{max} \) denotes the maximum indicator of the soccer data set. In order to unify the dimensions, all the indicators in this solution paper are in normalization before it is used.

5.1 3 Layer Model

We build 3 layer team performance evaluation models from player, department and team levels.

Player. Individual performance evaluations play important roles in team performance evaluations. In this subsection, we demonstrate series of indicators to evaluate player’s performance.

Event analysis

As event attributes of the soccer data set, EventType and EventSubType present players in various aspects (e.g., ‘High pass’ is more skillful than ‘Simple pass’ even if they are in the same Event (‘Pass’)). In the passing events data set, the ball was passed to the opposing player occasionally. According to the rules of soccer games, there is a low probability that players give the ball to the opponent continuously. Therefore we define this pass event as a steal event. The total number of steal events in soccer match is as following:

\[ E_{\text{steal}} = \sum_{i=2}^{N} f(S, i) \]  \hspace{1cm} (8)

where \( N \) denotes the number of data elements, \( f(S, i) \) denotes whether an steal event occurs. The judgment expression of event is defined as:

\[ f(S, i) = [S_{\text{TeamID}_{i-1}} \neq S_{\text{TeamID}_i}] \]

where \( S_{\text{TeamID}_{i-1}} \) denotes TeamID of the \( t-1 \) moment, \( S_{\text{TeamID}_i} \) denotes TeamID of the \( t \) moment (i.e., current moment). The TeamIDs at these two moments are different, indicating that a steal event has occurred.

Quantification of Indicators

In order for each player to show his or her own strengths (e.g., some players are good at offense, some players are good at defense), we considered the following individual indicators and quantified them.

We use Event to represent the EventType attribute in the data set, and SubEvent to represent the EventSubType.

• Trust

Trust indicator measures the probability that a player is passing destination in the team. The higher the Trust indicator, the more the player is trusted by his/her teammates. It presents the player’s ability to receive the ball. The formula is defined as following:

\[ Tru = \frac{E_{\text{pass}}}{E_{\text{all}}} \]  \hspace{1cm} (9)

where \( E_{\text{pass}} \) denotes number of passes to a player, \( E_{\text{all}} \) denotes total number of pass events.

• Defence

Defence indicator measures a player’s defensive capabilities. The higher the Defence indicator, the stronger the player’s defensive ability. The formula is defined as following:

\[ Def = \frac{E_{\text{steal}} + E_{\text{defence}}}{E_{\text{all}}} \]  \hspace{1cm} (10)

where \( E_{\text{all}} \) denotes the total number of occurrences of all events, \( E_{\text{steal}} \) denotes the total number of steal events, \( E_{\text{defence}} \) denotes the total number of ”Save attempt” and ”Others on the ball” in the events of a player.

• Active

Active indicator measures the enthusiasm of a player for an event. The more active a player is, the more likely he/she is to start an event (e.g., initiating a pass, stealing a ball, shooting). The enthusiasm shows that a player can quickly participate in an event to better cooperate with his teammates. The formula is defined as following:

\[ Act = \frac{E_{\text{Origin}}}{E_{\text{all}}} \]  \hspace{1cm} (11)

where \( E_{\text{Origin}} \) denotes total number of events started by a player.

• Stability

Stability indicator measures the performance of a player in the second half. The higher the Stability, the better performance the player has in the second half, indicating that the player’s physical
strength is good enough. The formula is defined as following:

\[ \text{Sta} = \frac{E_{2H}}{E_{2H} + E_{1H}} \quad (12) \]

where \( E_{2H} \) denotes total number of events for a player in the second half, \( E_{1H} \) denotes the total number of events that a player have in the first half.

• **Strength**

Strength indicator measures how far a player passes. The higher the strength, the longer the passing distance, indicating the better the player’s passing ability. The formula is defined as following:

\[ \text{Str} = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(x_{ori,i} - x_{des,i})^2 + (y_{ori,i} - y_{des,i})^2} \quad (13) \]

where \((x_{ori,i}, y_{ori,i})\) denotes the ith origin coordinates of the pass, \((x_{des,i}, y_{des,i})\) denotes the ith destination coordinates of the pass.

• **Rules**

Rules indicator measures the extent of a player’s fouls. The higher the rules, the less likely a player is to foul, and the more the player will bring to the team. The formula is defined as following:

\[ \text{Rul} = 1 - \frac{E_{against}}{E_{all}} \quad (14) \]

where \( E_{against} \) denotes total number of "Foul", "Offside", "Goal-keeper leaving line" in the event of one player.

• **Offence**

Offence measures a player’s offensive ability. The higher the Offence indicator, the stronger the offensive ability of the player. The formula is defined as following:

\[ \text{Off} = \frac{E_{offence}}{E_{all}} \quad (15) \]

where \( E_{offence} \) denotes total number of "Free Kick", "Shot", "Duel" in the event of a player.

• **Skills**

Skills indicator measures a player’s ability to perform difficult moves. The higher the Skills, the easier it is for players to complete difficult movements, thus cooperating with teammates’ movements and interrupting the opponent’s movements. The expression is:

\[ \text{Ski} = \frac{E_{trick}}{E_{all}} \quad (16) \]

where \( E_{trick} \) denotes total number of "Head pass", "High pass", "Ground attacking duel", "Smart pass", "Corner", "Cross" in a SubEvent that a player has made.

**Department Level.** Athletics are completed by the participation of multiple people. The quality of teamwork between teammates determines the quality of the whole team. Therefore, we primarily consider the cooperation among teammates and evaluate different cooperation in this section.

Each player has a different position in a soccer match, such as forward, midfielder, defender, etc. Their responsibilities are also different (e.g., forwards focus on offense, defenders focus on defense, midfielder focus on the cooperation of forwards and defenders.) These concepts are similar to departments in a team. We use forward, midfielder, and defender to indicate the department in which a player is located.

In Task 1, we propose Community Model to cluster 30 players into 3 different communities. Table 2 shows the members of the community. The order of the vertexes in the table is arranged according to the number of passes, so the players with the most passes in each community are concentrated on the front. We summarize each community and conclude as follows:

- Since the number of D and M players in community 1 are large, community 1 is the guard and midfielder department.
- Since the number of M, D, and F players in community 2 are large, community 2 is the Offense-Defense department.
- Since the number of M and F players pass more in community 3, community 3 is the midfielder and forward department.

According to the different departments in the community, we divide the community into 3 parts: Offensive-Cooperation (community 3), Defensive-Cooperation (community 1), and Offensive-Defensive (community 2). These three communities respectively presents the coordination ability of the forward department and the midfield department, the coordination ability of the defender department and the midfield department, and the common coordination ability of the three.

The coordination ability of different departments is presented by the connectivity within different communities, as shown in Figure 8. Figure 8 shows connection edges of internal vertexes in a certain community. As can be seen from the figure, this community contains forward and midfield department and belongs to an Offensive-Cooperation community. The better the cooperation, the higher the number of passes between the departments and the greater the degree of each vertex in the graph. We use the degree of all nodes in the community, which is defined as following:

\[ \text{Com} = \sum_{i=1}^{n} d[v_i] \quad (17) \]

where \( n \) denotes number of vertexes in a community, \( d[v_i] \) denotes degree of the ith vertex. The formula of \( d[v_i] \) is defined as following:

\[ d[v_i] = \sum_{j=1}^{N} \delta_{ij} \quad (18) \]

where \( \delta_{ij} \) denotes a directional edge from vertex \( i \) to vertex \( j \).

**Team Level.** A team’s grasp of the overall situation may determine the outcome of a match. In this section, we primarily consider the impact of team flexibility, flow, tempo and adaptability on the team.

**Soccer Dynamic Chain Model**

During the match, soccer ball passes on the pitch until an out-of-bounds event occurs. During the passing of soccer ball, there may be multiple passes between players and they may be intercepted by opponents. Therefore, we treat the passing process of soccer ball in the field as a chain. When the soccer ball goes out of bounds, the
We use teams in the chain length $L$ denotes the percentage in the

where $C$ denotes soccer dynamic chain coding, $H$ denotes soccer at

the feet of Huskies players, $O$ denotes soccer at the feet of Opponent

players, $S$ denotes goal event, $F$ denotes foul event, $T$ denotes an

out-of-bounds event caused by other conditions.

It can be seen from the chain that every time the chain comes
to end, an out-of-bounds occurs. We use $L$ denotes chain length.
We use teams in the chain length $L$ denotes the percentage in the

team’s Ball Possession in the chain. $P_H$ denotes Ball Possession

of Huskies. $P_O$ denotes the Ball Possession of the Opponent. The

formula is defined as following:

$$P = \frac{N}{L} \quad (19)$$

where $P$ denotes Team’s Ball Possession, $N$ denotes number of

teams in the chain, $L$ denotes chain length.

According to the data structure of the soccer data set, We stipu-
late: $S$ means shot and free kick, $F$ means foul or offside, $T$ means

out of bounds caused by other conditions. We use this model for

quantitative analysis of flexibility, flow, tempo, and adaptability.

**Quantitative analysis of indicators**

- **Flexibility**

  The flexibility of the team is presented in the ability of the team
to quickly switch between offense and defense. In general, the team
will make multiple long-distance passes when defending, and the
chain length is long. When the team is offending, the team will
shoot or foul, and the chain length is short. Therefore, the difference
of the chain length represents the flexibility of the team. We use the
variance of the chain length of a match to indicate the flexibility of
the team. The formula is defined as following:

$$Fle = \frac{\sum (L_i - \bar{L})^2}{n} \quad (20)$$

where $n$ denotes number of dynamic chains in a match, $L_i$
denotes ith dynamic chain length, $\bar{L}$ denotes dynamic chain mean.
The formula is defined as following:

$$\bar{L} = \frac{\sum L_i}{n} \quad (21)$$

- **Flow**

  Flow of the team is presented in the number of successful passes
of the team in the chain. If a team successfully passes more times,
the team has more consecutive nodes in a chain, then the team flow
is better. If the number of successful passes is less, the team has
fewer consecutive nodes in a chain, which means the team flow
worse. We take the longest chain in each chain as the evaluation
index of flow after summing and averaging. The formula is defined
as following:

$$Flo = \frac{\sum l_i}{n} \quad (22)$$

where $n$ denotes the number of dynamic chains in a match. $l_i$
denotes the longest length of a team in a chain.

- **Tempo**

  Team’s Ball Possession presents the tempo of the team. The
higher the Ball Possession, the better the team’s tempo. The formula
is defined as following:

$$Tem = \frac{\sum N_i}{\sum L_i} \quad (23)$$

where $N_i$ denotes number of teams in the ith chain, $L_i$ denotes the
chain length of the ith chain.

- **Adaptability**

  The home goal difference generally represents the team’s real
strength, and the away team’s strength will decline. Therefore, the
team’s adaptability is related to the team’s performance between
home and away. We use the difference between the away goal dif-
fERENCE and the home goal difference to represent the team’s ability
to adapt to the away match. The formula is defined as following:

$$Ada = W_a - W_h \quad (24)$$

where $W_a$ denotes away goal difference, $W_h$ denotes home goal
difference.

### 5.2 Team Performance Evaluation Model

In the previous section, We quantified the indicators for three dif-
fERENT levels. The various quantified indicators are shown as Fig 9.

**Figure 9: Evaluation pyramid**

However, these indicators can only be used in the same level.
They cannot be used directly in the evaluation of the team level.
Therefore, these indicators need to be integrated into the overall
indicators.

Since all indicators have been normalized, the indicators of each
level can be obtained by direct addition.

**Player Level.** The indicator expression of the Player Level is defined
as following:

$$Pla_i = True_i + Def_i + Act_i + Sta_i + Str_i + Rule_i + Off_i + Ski_i \quad (25)$$

where $Pla_i$ denotes the ith indicator of the members in a team.
However, the indicators inside the player level actually express
the characteristics of a player. Huskies team has a total of 30 players.
Therefore, the player level’s score should indicate that 30 players
are composed of them. The formula is:

$$Pla' = \frac{1}{30} \sum_{i=1}^{30} Pla_i \quad (26)$$

where $Pla'$ denotes the player level’s score.
We take the soccer data set into the formulas (9)-(16), and solve the
where $Com_i$ denotes degree in the ith community.

**Team Level.** The indicator expression of the Team Level is:

$$Tea = Fle + Flo + Tem + Ada$$

At this point we get our three levels of normalized scores, which
can be directly added to obtain the total score. The final team
performance evaluation model is:

$$Sco = Pla' + Dep + Tea$$

### 5.3 Model Solution and Analysis

We take the soccer data set into the formulas (9)-(16), and solve the
various indicator scores of each player. Figure 10 is an 8-dimensional
radar chart showing the scores of different Huskies players at the
player level. We take the soccer data set into the formula (17). The
degree of all the vertices inside each community are showed in
Table 5. We take the soccer data set into the formulas (20) to (24).
Figure 11 is a 4-dimensional radar chart showing the indicator score
of each team through 38 matches. The black line in the picture
indicates Huskies team.

#### Table 5: Degree of all the internal vertexes

| Community 1 | Community 2 | Community 3 |
|-------------|-------------|-------------|
| 23821       | 19472       | 5233        |

As shown in Table 5, Huskies team has the most degree of
Defensive-Coordination community. The Defense-Coordination community of it has the least degree. It shows that the cooperation between the three departments of the team is not very good.

We obtain a total Huskies team score of 70.15 by summing them together.

### 5.4 Sensitivity Analysis

The problem requires us to adjust our strategy so that Huskies
team can deal with different enemies. We first perform a sensitivity
analysis to determine which indicators have a greater impact on
the results of the model. We propose the strategy of Huskies team.

We choose the following indicators for sensitivity analysis. Player
level indicators are “StabilityÃĂ“AI, “Average”, “Skills”, “Trust”. Team-
level indicators are “Flow”, “Flexibility”, “Adaptability”, “Tempo”. The reasons for choosing these indicators are as follows: 1) Among the
Player-level indicators, the Trust, Stability, Active, and Skills indicators represent the member’s ability to cooperate and have a greater impact on the team. 2) Team-level indicators have a large impact on the team. We choose all of them. The result of the sensitivity analysis is shown in Figure 12. The slope of Flow is 9.2%, which is
the most sensitive and has the most effect on the performance.

As shown in Figure 12, the four team-level indicators have a
greater impact on system sensitivity. It indicates that team-level
indicators have a great impact on the teamwork.

### 6 STRATEGY ADVICE

In this section, we propose universal strategies and strategies for
opponent. Based on the team performance evaluate model, we
propose the strategy on player level, department level and team
level.

#### 6.1 Universal Strategy

**Player Level.** According to the formula (25), We get the score of
each player and rank them, as shown in Table 6:

From Table 6, we get the strongest players in each department, so
that we can form a team with the strongest players. The formation is:
$G1-F1-F2-M1-M3-M4-D1-D3-D4-D5$ (4-3-3 formation). Since these
players have the highest scores, this team is universal.

According to Table 2 and Table 6, M1, M3, F2, and D1 play a vital role in the passing network (relative degrees are 125, 88, 85,
84). M1, F2, D1, and D5 have the highest scores at the player level.
All things considered, M1, F2, and D1 are the starting players in
midfield, forward, and defender.

**Department Level.** According to the scoring results in Table 6, Huskies
performs best in Defensive-Cooperation and performs good in
Offensive-Cooperation and performs bad in Offensive Defensive.
Therefore, the team needs players who are good at passing to im-
prove Offensive Defensive, such as M1, D1, F2.

**Team Level.**  • Try to use # 12 and # 13 network patterns. These two
modes have high connectivity, and it is difficult to take countermea-
sures. But avoid the # 2, # 3, # 8 network patterns that are used in
teams 6, 12, 16, 17. These modes are easily targeted by opponents.
• It can be seen from Figure 23 that Huskies’ tempo is in the middle
level (10th) among 20 teams. Flexibility (8th), adaptability (8th),
and flow (7th) are at the middle-to-high level in 20 teams. Therefore, the
team needs to improve continuous passing and adaptability to the
away. And the team needs to improve the transition between fast
break and combination passed, and improve the soccer possession
to improve Tempo.
• It can be seen from the sensitive analysis that team level indica-
tors have a great impact on team scores. Therefore, the team can
improve the strength of the team by improving the scores of the
Flow, Flexibility, Adaptability, and Tempo indicators.

By adopting the universal strategy, Huskies’ score is 78.63,
which is 12.09% higher than the previous score.

#### 6.2 Strategy Against Opponents

**Player Level.** Based on the scores of the players in Table 6, we
recommend different starting formations based on opponent char-
acteristics.

• For offensive opponents, we recommend Huskies to uses the 4-4-2
formation. The starting players are $G1-M1-M3-M4-M6-D1-D3-D4-D5$.
• For field-controlled opponents, we recommend Huskies to uses the
3-5-2 formation. The starting players are $G1-M1-M3-M4-D1-D3-D4-D5$.
• For defensive opponents, we recommend Huskies to uses the
4-3-3 formation. The starting players are $G1-M1-M3-M4-M6-D1-D3-D4-F1-F2-F6$. 
Team Performance Evaluation Model based on Network Feature Extraction

**Figure 10: Player Level Radar chart**

**Figure 11: Team Level Radar chart**

**Table 6: Player ranking**

|   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| M1| D2  | D3  | M6  | D1  | M3  | D5  | M1  | F1  | D4  | D7  | M4  | D2  | G1  | D6  | M8  |
| 16| 17  | 18  | 19  | 20  | 21  | 22  | 23  | 24  | 25  | 26  | 27  | 28  | 29  | 30  |
| F6| F4  | M12 | M9  | M8  | F5  | M10 | M11 | D10 | M2  | F3  | M5  | M13 | D9  | M7  | D11 |

**Department Level.** It is difficult for Huskies to find breakthrough in the face of the defensive team, because Huskies performs bad in Offensive Defensive. Therefore, Huskies can consider replacing players with skills to make space for the team. (e.g., M2, M11, D9 are good at High pass, M10 is good at Ground attacking duel, F3 is good at Cross, F2 is good at Smart pass.)

**Team Level.**

**Network pattern analysis**
- Most teams use #12 and #13 network patterns. These two modes have high connectivity, and it is difficult to take effective countermeasures.
- Opponents 11, 18, and 19 use the #3 network pattern. Huskies needs to break the two-player pass in the three-player mode.
- Opponent 15 use the #8 network pattern. Huskies needs to use the “man-for-man marking” strategy to offence the core player in the three-player mode to break the opponent’s passing strategy.

**Indicator analysis**
- For opponents 2, 16, and 17 with high Adaptability score, Huskies needs to be careful at home, because the opponents play little difference at home and away.
- For opponents 3, 14, and 17 with high Flexibility score, Huskies needs to prevent the opponents from switching between fast break and combination passed, because the opponent is very adaptable to different offensive strategies.
- For opponents 3, 9 and 16 with high Flow score, Huskies needs to play with high Defense players to reduce the opponents’ passes.
- For opponents 1, 7 and 10 with high Tempo score, Huskies needs to find loopholes in the opponent’s passing mode, improve the possession rate, and grasp the Tempo.

**Figure 12: Sensitive Analysis Result**
The mathematical expression of the network formed by these relationships is:
\[ G = \langle v_{member}, E_{team} \rangle \]  
where, \( E_{team} \) is the set of three relationships:
\[ E_{team} \in \{ E_{busi}, E_{people}, E_{tech} \} \]  

Since the network is similar to a passing network, the network pattern can be identified according to the community model and the motifs model.

We define the extracted features in team network as follows:

- **Degree**
  In the R & D team network, the degree of the vertex can be regarded as a quantification of the cooperative relationship between members. The number of vertexes in the team network presents the frequency they interact with others. These vertexes master various technical skills, communication methods and business points, which are the core of the team. The mathematical expression of degree is:
  \[ \text{Degree}(i) = \text{Degree}(i, \text{busi}) + \text{Degree}(i, \text{people}) + \text{Degree}(i, \text{tech}) \]  
where, \( \text{Degree}(i, \text{busi}) \) denotes the degree of business relationship of vertex \( i \), \( \text{Degree}(i, \text{people}) \) denotes the degree of relationship of vertex \( i \), \( \text{Degree}(i, \text{tech}) \) denotes the technical relationship degree of vertex \( i \).

- **Motifs**
  Network motifs analyzes teamwork patterns at member level. Network motifs represents small local connection patterns. They are assumed to act as functional meaningful building blocks of a team network(e.g., three-person cooperation, four-person cooperation). The results are presented in the form of directed graph.

- **Community clustering**
  Community clustering analyzes team cooperation at department level. It clusters members of different departments through the connectivity of the graph and indicates the degree of cooperation between different departments.

### 7.2 Team Performance Evaluation Model

We build evaluation models based on three levels of indicators.

**Member.** The characteristics of players include multiple attributes. Corresponding to the eight characteristics in soccer, we define the following indicators[1]: **Research ability:** Corresponds to Skills and Offence indicators. **Communication ability:** Corresponds to Trust and Strength indicators. **Risk aversion ability:** Corresponds to the Defense indicator.

In order to make the model universal, these indicators are not carefully divided. The member evaluation formula is:
\[ Mem = \text{study} + \text{com} + \text{risk} \]  
where, \( \text{study} \) denotes the research ability, \( \text{com} \) denotes the communication ability, \( \text{risk} \) denotes the risk aversion ability. The member level evaluation formula is:
\[ Mem' = \frac{1}{N} \sum_{i=1}^{N} Mem_i \]  
where, \( Mem_i \) denotes the score of member \( i \), \( N \) denotes the number of total members.
Department. Similar to forward, defense, midfield in soccer field, the general department types are: promotion department (e.g., sales, marketing and research and development), prevention department (e.g., human, legal and procurement). The degree of cooperation between different departments is represented in community clustering. The degree of vertexes within a community can indicate the cooperation ability of the department. The formula is:

\[ \text{Dep} = \sum_{i=1}^{n} \text{Com}_i \]

where, \( \text{Com}_i \) denotes community \( i \), \( n \) denotes the total number of the communities.

Team. We establish a chain similar to that in soccer. Cooperation represents the connection of the chain. The completion or failure represents the termination of the chain. Team level processes are also divided into Adaptability, Flexibility, Tempo, and Flow. The formula of team level is:

\[ \text{Tea} = \text{Flo} + \text{Flo} + \text{Tem} + \text{Ada} \]

The Extensive team evaluation model expression is:

\[ \text{Sco} = \text{Mem} + \text{De} + \text{Tea} \]

7.3 Model Solution

We collected email correspondence data of an institute. However, there is no enough indicators in the data set. So we only solve the network of mail exchanges. We selected the team data of 87 members and performed community clustering. The clustering results are shown in Figure 14:

![Figure 14: Clustering results](image.png)

Different colored vertexes set in Figure 14 represent different communities. Single vertex represents a team member. The average clustering coefficient of the data set is 0.0671 there are huge connections within the same community, but there are fewer connections between the communities. The community cluster was successfully performed.

We make several suggestions to improve team performance based on indicators in the model:

- Strengthen the core nodes of the team, promote the communication and exchange of new vertexes, and avoid the loss of key vertexes.
- Improve the interaction between nodes through training, guidance, management, etc., and strengthen team building based on dynamic characteristics.
- Increase cooperation between departments to achieve the effectiveness of community clustering.
- Improve the formulation of team goals and the specification of task processes to provide guidance for improving the team’s Adaptability, Flexibility, Tempo, and Flow.

8 CONCLUSIONS

8.1 Strengths

- The passing model takes the idea of clustering which facilitates the simplification of complex networks and shows the cooperation of different departments.
- The team performance model uses a three-layer model of team members, departments, and teams to select indicators. Not only conducive to the comprehensive display of teamwork capabilities, but also conducive to strategic suggestions at different levels.
- At the team level, we innovatively use the concept of dynamic chain to show the team’s adaptability, flexibility, tempo, and flow. It is helpful to show the game between teams and provide coaches with strategies against opponents.

8.2 Weaknesses

- Since there is no match data for opponent team, it is difficult for us to accurately evaluate the team cooperation of other teams.
- Due to the data constraints, the model fails to consider the differences of each coach.

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