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Application od Markov Chain and Eigenvector Centrality in Football Passing Among Players

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Abstract
Football and algebra may seem to have nothing in common to the untrained eye. Few would attempt to explain the outcome of the game by pulling out their old math's or statistics books. This graph theory report analyses football player relationships. Using a passing graph, the intricate network of passing trades between players in the 2022-23 UEFA Champions League between FC Bayern München and Manchester City FC. Analyzing a match's passes by player type can reveal the team's structure. This study proposes to investigate the application of graph theory in football teams, investigate the application of graph theory in football teams, and determine whether football matches can be analyzed using eigenvector centrality. This study starts with studying the concept of Markov Chain, Eigenvector Centrality and Centrality Measure. Next, the calculation to find the most important player. In addition, the passing graphs will be shown after generalizing of the tactical football position. By using eigenvectors, the value of each individual can be found and the player who has the higher value is the most central player. Markov Chains calculate eigenvector centrality, which quantifies node impact. Football eigenvector centrality demonstrates how important each player is to their team.
Keywords: Graph Theory; Passing Graph; Eigenvector Centrality; Markov Chain; Centrality Measure.

Introduction

To the untrained eye, football and algebra may appear to have nothing incommon. Few would get out their old math or statistics books to try to explain the result of the game, whether it was a dull draw with few highlights or a thrilling 7-1 victory in a world cup semi-final [1]. There are several mathematical applications in football, including yardage, angles, and field. Every football play involves a positive or negative numerical computation, depending on whether the play resulted in a gain or loss. There are so many things to count and calculate. From the basic number of goals in a game to creating graphs by using the passing pattern of a team. When these graphs have been made, there is no stopping mathematicians trying to analyze a game of football.

Sport competition analysis seeks to provide precise performance measures that may help coaches better comprehending the behavior of the team and players. Coach can then correctly modify game-play methods or develop more effective training approaches [2]. Due to the vast amount of information presently accessible to coaches, it is essential to understand how to identify important information and then correctly use that information. This is a difficult, if not impossible, job if the proper technique is not used or if no appropriate instrument is available.

However, it is possible that football, like everything else in the world, may be better understood via the analytical lens of mathematics [1]. Many people are unaware that when they evaluate recent games and make predictions about prospective games, they are very likely to use mathematics to back up their claims. Unfortunately, not everyone understands this. Betting companies utilize statistics to evaluate the market and set prices that are competitive with the market average. When deciding which players to acquire, sell, or keep for the upcoming season, teams analyst a few data before making their final decisions. Mathematics is used in the process of ranking players, teams, and leagues.

2. Literature Review

2.1 Markov Chains

In Markov chains [5], each iteration's state vector is a probability vector indicating the likelihood of a certain event occurring after a given number of iterations. The equation that relates state vectors across time is

$$x(k+1) = Px(k)$$

where P = [p_ij] is a stochastic matrix, a matrix in which each column is a probability vector indicating the likelihood that a system in state j at time t = 1 would be in state i at time t = k+1. The matrix P denotes the changeover. In many situations, the state vector does not change after a certain number of repeats. It is this vector that is referred to as the steady-state vector [5]. According to Javier Galeano [6], a novel method for assessing the performance of badminton players is provided by analyzing their striking patterns. Using the location of players during three consecutive strokes, by developing length-3 patterns that correspond to each player's playing style. In addition, extract from the videomatches the data on the initiative obtained by a player during a stroke, as well as the player who won the point at the conclusion of each rally. Next, by compare the chance that a 3-order pattern is executed by a player to the average of the top twenty players. Compute the odds of transitioning between patterns and then construct the appropriate Markov Chains, which include two interesting states: winning and losing the rally. The Markov matrix enables us to calculate the likelihood of scoring apoint after a specific pattern has appeared in a rally, which they refer to as the Expected Pattern Value (EPV). Finally, they examine the connection between the EPV and the gain of initiative a player achieves when completing each pattern. With this information, we can determine which patterns a player executes more effectivelyand correlate the pattern values with the player's real chance of winning a rally.

2.2 Eigenvector Centrality

Based on Laishui Lv, [7] over the last several years, many centralities have been introduced to help pinpoint pivotal nodes in both static and dynamic networks. Eigenvector-based centralities are among the most effective ranking algorithms among these centrality measurements. Some complex systems in the actual world have a multilayer structure and edges are dynamic, i.e. they form and vanish over time, and are hence called multilayer temporal networks. In addition, several centralities based on eigenvectors have been refined for use in ranking nodes in multilayer temporal networks. These current eigenvector-based centralities, however, may provide inaccurate ranking results of nodes since they do not account for the inter-layer interactions between distinct time stamps. He builds a sixth-order tensor to characterize multilayer temporal networks, which allows us to more accurately define their multilayer and temporal properties. In particular, inter-layer connections are represented by the cosine similarity metric. After that, he offers MTEIGBC and MTPRBC centralities, which rank nodes, layers, and timestamps in networks using the sixth-order tensor and cosine similarity, respectively. Furthermore, given relatively reasonable circumstances, he can ensure the existence and uniqueness of our centrality measurements. Finally, he conducts numerical tests on three networks to show that our suggested ranking algorithms are better and effective.

The eigenvector of an A, an ($n \times n$) matrix, is a vector x, if Ax is a scalar multiple of x for some scalar λ. The scalar is the eigenvalue of the vector. Therefore,

$$Ax = \lambda x \cdot$$

Connections with a node that is more central in a system contribute a greater score to a node than edges to and from nodes that are less central.

The centrality of node i is represented by x_i and determined with the following equation:

$$x_i = \frac{1}{\lambda}\sum_{j=i}^{n} A_{ij} x_j \cdot$$

The vector of centralities can be written X = (x_1, x_2,...) and the equation can be rewritten in matrix form as

$$x_{t+1} = P_{x_t} \cdot$$

The eigenvalue corresponding to the eigenvector x, where x is an eigenvector and λ is the eigenvalue for ***A*** [8].

2.3 Centrality Measure

From the Onur Ugurlu, [9] identification of key nodes, the removal of which would cause severe disruption of network connection, is a vital job in complex networks. Topological properties of the network, such as its susceptibility and resilience, may be analyzed with the assistance of the identification of essential nodes. He compare different centrality measures for identifying critical nodes and think about a well-known critical node detection problem variant called the Maximize the Number of Connected

Components Problem. This problem seeks to identify a set of nodes whose removal maximizes the number of connected components. He investigates the popular topology-based centrality metrics across a variety of synthetic and real-world networks, while the prior research primarily looked at tiny datasets. As he have shown, degree-like centralities are more useful than path-like centralities for partitioning networks into smaller, more manageable pieces. They findings, however, also show that conventional centrality methods fail to identify the most crucial nodes. To address this shortcoming, he introduce Isolating Centrality, a novel centrality metric that focuses on pinpointing the nodes that have the most influence on the network's degree of connectivity. A thorough computer research shows that the suggested metric is superior to baseline methods for identifying vulnerable nodes.

This centrality metric seeks to identify the diversity of a data collection. It indicates the value's deviation from the set's mean. The centrality metric is computed according to the formula.

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_1 - \bar{x})^2} \cdot$$

Where x_i represents each value in eigenvector x.

3 Methodology

3.1 Determine the Number of Games and Players

The number of games from which to draw data is an essential decision since it affects the validity of this report. This analysis is based on quarter final UCL 2022-23 statistics for the two team which is Manchester City FC and FC Bayern München. A larger number of teams studied, on the other hand, would provide a more reliable outcome. It is critical to collect a significant quantity of data to form conclusions. Choosing teams that ended far apart on the standings might result in vastly disparate results. The findings may indicate that teams benefit from differing arrangements. However, it may have the opposite effect and demonstrate that, regardless of the team's level, playing a specific method is always effective.

When deciding how many players to put in the matrix, it is vital to examine how a football game really appears. Initially, the matrix size ranges from 11×11 to 16×16, depending on how many replacements are employed in the game. Reducing it to simply the first eleven results in the 11×11 matrix regardless of the number of replacements. Two more players will be removed next in order to get more accurate statistics. These are the two nodes with the lowest degree among the starting eleven, i.e., the players with the fewest made and received passes. This increases the reliability of the data by excluding participants that make little contributions to the game. For example, the goalkeeper in a game when the team outnumbers their opponents, or a player who is sent out with a red card before completing many passes.

3.2 Finding Most Central Player

Markov chains were employed in this research to establish the steady-state vector for the team's passing matrices. Starting with a graph of all players passes, the numbers of passes are placed into a matrix. The matrix is then reduced to 9×9 dimensions. The Markov chain is applied to the transition matrix, P, which corresponds to the passing matrix. The eigenvector, x, is discovered to be connected to P by $x_{t+1} = Px_t$. The values in the vector x represent the eigenvector centrality for each network actor. It determines the most important player in each game by measuring how influential each participant is. Whereas degree centrality merely counts the number of passes to and from a node in a network, eigenvector centrality recognizes that not all connections are equal and assigns a greater score to passes to and from more significant actors. A player with a greater number in the steady state vector is more important to his or her squad than a player with a lower value.

3.3 Measuring Team's Centralisation

The centrality measure of all nine players in the steady state vector may be used to calculate a team's centralisation. The data set consists of all nine values, and the centrality metric depicts the deviation from the mean. A low centrality number suggests a decentralised passing system, while a high centrality value represents a centralised organisation. By examining the probable relationship between centrality value and game outcomes, various teams' advantages and drawbacks with centralised and decentralised passing arrangements may be identified.

4 Results and discussion

4.1 Passing Graph

The structure of Bayern München's and Manchester City's passing respectively in their away and home games in the Quarter-finals Champions League (2023) for the 1st leg and 2nd leg. Edges are produced between players only if they have been completed between them. Each player is placed in the spot where they often stand when passing and receiving passes.

Each symbol represents each player. The Tables 4.1 & 4.2 below show the name of each player and the symbol used.

Figure 1 & 2 shows a graph that has been produced based on the number of ball passes to team members by each individual of the Manchester City & Bayern München team. The arrow shows the passes made for each individual player and the value on the arrow shows the number of passes made by the player. For example, the player representing symbol A makes 2 passes to the player representing symbol B in that one match.

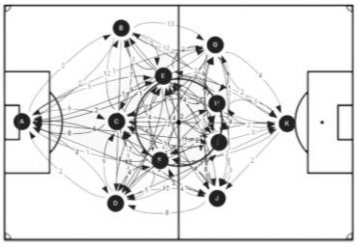

Figure 1 Graph showing Manchester City's in the game against Bayern München.

Name Player's	Symbol player's
Ederson (GK)	A
Rúben Dias	C
John Stones	F
Nathan Aké	B
İlkay Gündoğan	H
Erling Haaland	K
Jack Grealish	G
Rodri	E
Kevin De Bruyne	I
Bernardo Silva	J
Manuel Akanji	D

Table 1 The sign of Manchester City FC players for the first leg

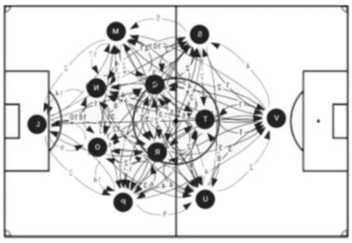

Figure 2 Graph showing Bayern München's passing in the game against Manchester City.

Name Player's	Symbol player's
Yann Sommer (GK)	L
Dayot Upamecano	N
Matthijs de Ligt	O
Benjamin Pavard	M
Joshua Kimmich	R
Serge Gnabry	V
Leon Goretzka	Q
Leroy Sané	U
Kingsley Coman	S
Alphonso Davies	P
Jamal Musiala	T

Table 2 The sign of FC Bayern München players for the first leg

Although the graphs present a good overview of (Figure 1and.2), they do not give detailed information and cannot be used to support or disprove any theory. For that, the corresponding matrices, MC_1 for Manchester City and BM_1 for Bayern München, consisting of all involved players are created.

The following matrix shows the matrix that has been produced based on the number of ball passes produced by each player to members of the same team who played in that one match. The diagonal of the matrix shows all 0 values because each player will not pass the ball to himself. Each team will have a different matrix size because it depends on the number of players used in that one match. For example, Manchester City's matrix size is (12 x 12) because the team uses 12 players for the first leg match. The team made only one substitution in the match. While the Bayern München team, the size of the matrix is (14 x 14) because the team uses as many as 14 players for the first leg match. The Bayern München team made 3 substitutions for the match.

$$MC_1 = \begin{pmatrix} 0 & 9 & 1 & 2 & 0 & 0 & 1 & 3 & 0 & 1 & 4 & 0 \\ 8 & 0 & 4 & 12 & 4 & 1 & 2 & 9 & 3 & 2 & 12 & 0 \\ 1 & 7 & 0 & 1 & 1 & 1 & 0 & 4 & 1 & 4 & 4 & 0 \\ 2 & 7 & 0 & 0 & 3 & 1 & 13 & 5 & 3 & 0 & 2 & 1 \\ 0 & 2 & 2 & 4 & 0 & 3 & 6 & 4 & 4 & 1 & 1 & 2 \\ 0 & 0 & 2 & 0 & 2 & 0 & 2 & 4 & 0 & 2 & 0 & 1 \\ 1 & 3 & 0 & 12 & 6 & 4 & 0 & 2 & 2 & 1 & 1 & 1 \\ 2 & 12 & 4 & 3 & 7 & 1 & 3 & 0 & 8 & 3 & 5 & 1 \\ 1 & 1 & 1 & 0 & 3 & 3 & 7 & 2 & 0 & 3 & 2 & 0 \\ 0 & 2 & 4 & 0 & 1 & 0 & 1 & 2 & 8 & 0 & 8 & 3 \\ 4 & 9 & 4 & 0 & 0 & 1 & 0 & 6 & 3 & 12 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 2 & 1 & 1 & 0 & 1 & 0 & 0 \end{pmatrix}.$$

Figure 3 Showing transformed form passing graph of Manchester City FC to matrix form.

$$BM_1 = \begin{pmatrix} 0 & 10 & 9 & 4 & 4 & 2 & 1 & 0 & 1 & 2 & 0 & 0 & 3 & 0 \\ 14 & 0 & 18 & 14 & 12 & 5 & 3 & 1 & 3 & 6 & 0 & 1 & 1 & 2 \\ 9 & 31 & 0 & 1 & 2 & 0 & 5 & 3 & 2 & 14 & 2 & 0 & 2 & 0 \\ 2 & 17 & 0 & 0 & 4 & 4 & 2 & 3 & 10 & 0 & 1 & 0 & 0 & 1 \\ 2 & 7 & 7 & 9 & 0 & 3 & 7 & 4 & 2 & 13 & 2 & 0 & 2 & 0 \\ 0 & 4 & 0 & 3 & 4 & 0 & 2 & 3 & 4 & 1 & 1 & 1 & 0 & 0 \\ 0 & 4 & 8 & 4 & 7 & 3 & 0 & 4 & 2 & 3 & 5 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 8 & 2 & 3 & 0 & 4 & 4 & 8 & 0 & 0 & 0 \\ 0 & 1 & 0 & 5 & 4 & 1 & 2 & 6 & 0 & 1 & 2 & 0 & 0 & 0 \\ 3 & 0 & 17 & 0 & 6 & 4 & 3 & 9 & 3 & 0 & 7 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 3 & 1 & 4 & 5 & 0 & 6 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 6 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}.$$

Figure 4 Showing transformed form passing graph of FC Bayern München to matrix form.

The Markov chain models for the passes in the games show the probability of the ball travelling to a certain player in transition matrices MC_2 and BM_2.

$$MC_2 = \begin{pmatrix} 0 & \frac{9}{21} & \frac{1}{21} & \frac{2}{21} & 0 & 0 & \frac{1}{21} & \frac{3}{21} & 0 & \frac{1}{21} & \frac{4}{21} & 0 \\ \frac{8}{57} & 0 & \frac{4}{57} & \frac{12}{57} & \frac{4}{57} & \frac{1}{57} & \frac{2}{57} & \frac{9}{57} & \frac{3}{57} & \frac{2}{57} & \frac{12}{57} & 0 \\ \frac{1}{24} & \frac{7}{24} & 0 & \frac{1}{24} & \frac{1}{24} & \frac{1}{24} & 0 & \frac{4}{24} & \frac{1}{24} & \frac{4}{24} & \frac{4}{24} & 0 \\ \frac{2}{37} & \frac{7}{37} & 0 & 0 & \frac{3}{37} & \frac{1}{37} & \frac{13}{37} & \frac{5}{37} & \frac{3}{37} & 0 & \frac{2}{37} & \frac{1}{37} \\ 0 & \frac{2}{29} & \frac{2}{29} & \frac{4}{29} & 0 & \frac{3}{29} & \frac{6}{29} & \frac{4}{29} & \frac{4}{29} & \frac{1}{29} & \frac{1}{29} & \frac{2}{29} \\ 0 & 0 & \frac{2}{13} & 0 & \frac{2}{13} & 0 & \frac{2}{13} & \frac{4}{13} & 0 & \frac{2}{13} & 0 & \frac{1}{13} \\ \frac{1}{33} & \frac{3}{33} & 0 & \frac{12}{33} & \frac{6}{33} & \frac{4}{33} & 0 & \frac{2}{33} & \frac{2}{33} & \frac{1}{33} & \frac{1}{33} & \frac{1}{33} \\ \frac{2}{49} & \frac{12}{49} & \frac{4}{49} & \frac{3}{49} & \frac{7}{49} & \frac{1}{49} & \frac{3}{49} & 0 & \frac{8}{49} & \frac{3}{49} & \frac{5}{49} & \frac{1}{49} \\ \frac{1}{23} & \frac{1}{23} & \frac{1}{23} & 0 & \frac{3}{23} & \frac{3}{23} & \frac{7}{23} & \frac{2}{23} & 0 & \frac{3}{23} & \frac{2}{23} & 0 \\ 0 & \frac{2}{29} & \frac{4}{29} & 0 & \frac{1}{29} & 0 & \frac{1}{29} & \frac{2}{29} & \frac{8}{29} & 0 & \frac{8}{29} & \frac{3}{29} \\ \frac{4}{40} & \frac{9}{40} & \frac{4}{40} & 0 & 0 & \frac{1}{40} & 0 & \frac{6}{40} & \frac{3}{40} & \frac{12}{40} & 0 & \frac{1}{40} \\ 0 & 0 & \frac{1}{6} & 0 & 0 & \frac{2}{6} & \frac{1}{6} & \frac{1}{6} & 0 & \frac{1}{6} & 0 & 0 \end{pmatrix}.$$

Figure 5 Showing transition matrix MC_1 to Markov Chain matrix.

$$BM_2 = \begin{pmatrix}
0 & \frac{10}{36} & \frac{9}{36} & \frac{4}{36} & \frac{4}{36} & \frac{2}{36} & \frac{1}{36} & 0 & \frac{1}{36} & \frac{2}{36} & 0 & 0 & \frac{3}{36} & 0 \\
\frac{14}{80} & 0 & \frac{18}{80} & \frac{14}{80} & \frac{12}{80} & \frac{5}{80} & \frac{3}{80} & \frac{1}{80} & \frac{3}{80} & \frac{6}{80} & 0 & \frac{1}{80} & \frac{1}{80} & \frac{2}{80} \\
\frac{9}{71} & \frac{31}{71} & 0 & \frac{1}{71} & \frac{2}{71} & 0 & \frac{5}{71} & \frac{3}{71} & \frac{2}{71} & \frac{14}{71} & \frac{2}{71} & 0 & \frac{2}{71} & 0 \\
\frac{2}{44} & \frac{17}{44} & 0 & 0 & \frac{4}{44} & \frac{4}{44} & \frac{2}{44} & \frac{3}{44} & \frac{10}{44} & 0 & \frac{1}{44} & 0 & 0 & \frac{1}{44} \\
\frac{2}{58} & \frac{7}{58} & \frac{7}{58} & \frac{9}{58} & 0 & \frac{3}{58} & \frac{7}{58} & \frac{4}{58} & \frac{2}{58} & \frac{13}{58} & \frac{2}{58} & 0 & \frac{2}{58} & 0 \\
0 & \frac{4}{23} & 0 & \frac{3}{23} & \frac{4}{23} & 0 & \frac{2}{23} & \frac{3}{23} & \frac{4}{23} & \frac{1}{23} & \frac{1}{23} & \frac{1}{23} & 0 & 0 \\
0 & \frac{4}{41} & \frac{8}{41} & \frac{4}{41} & \frac{7}{41} & \frac{3}{41} & 0 & \frac{4}{41} & \frac{2}{41} & \frac{3}{41} & \frac{5}{41} & \frac{1}{41} & 0 & 0 \\
0 & \frac{1}{31} & \frac{1}{31} & 0 & \frac{8}{31} & \frac{2}{31} & \frac{3}{31} & 0 & \frac{4}{31} & \frac{4}{31} & \frac{8}{31} & 0 & 0 & 0 \\
0 & \frac{1}{22} & 0 & \frac{5}{22} & \frac{4}{22} & \frac{1}{22} & \frac{2}{22} & \frac{6}{22} & 0 & \frac{1}{22} & \frac{2}{22} & 0 & 0 & 0 \\
\frac{3}{52} & 0 & \frac{17}{52} & 0 & \frac{6}{52} & \frac{4}{52} & \frac{3}{52} & \frac{9}{52} & \frac{3}{52} & 0 & \frac{7}{52} & 0 & 0 & 0 \\
0 & \frac{1}{22} & \frac{1}{22} & \frac{1}{22} & \frac{3}{22} & \frac{1}{22} & \frac{4}{22} & \frac{5}{22} & 0 & \frac{6}{22} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{1}{4} & 0 & 0 & \frac{1}{4} & 0 & \frac{1}{4} & 0 & 0 & 0 & 0 & \frac{1}{4} \\
0 & \frac{1}{8} & \frac{6}{8} & 0 & \frac{1}{8} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{2}{3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0
\end{pmatrix}.$$

Figure 6 Showing transition matrix BM_1 to Markov Chain matrix.

The eigenvectors corresponding to the transition matrix gives the centrality of each of all players in the matrix. These are presented below in order from least central player to most central player for each team respectively.

4.2 The Eigenvector each player

In Table 3, this stage of the Markov chain, the value that is shown is the one that occurs as a consequence of each player passing the ball along to the next player in the chain. It may be deduced from the fact that the table has a value of 0 that the player in question did not complete any passes to the other player. To get the reading value, a total of 12 football players are chosen, just as in the graph shown. It is well knowledge that a football game may include up to 11 players from each side competing on the same field at the same time. Despite this, the Manchester City squad was given the opportunity to participate in as many as 12 games. This is due to the fact that during the contest, the team made a substitution with one of its players. As a result, each and every ball pass that any of the 12 players have completed has been accounted for.

	A	B	C	D	E	F	G	H	I	J	K	L
A	0.0000	0.4286	0.0476	0.0952	0.0000	0.0000	0.0476	0.1429	0.0000	0.0476	0.1905	0.0000
B	0.1404	0.0000	0.0702	0.2105	0.0702	0.0175	0.0351	0.1579	0.0526	0.0351	0.2105	0.0000
C	0.0417	0.2917	0.0000	0.0417	0.0417	0.0417	0.0000	0.1667	0.0417	0.1667	0.1667	0.0000
D	0.0541	0.1892	0.0000	0.0000	0.0811	0.0270	0.3514	0.1351	0.0811	0.0000	0.0541	0.0270
E	0.0000	0.0690	0.0690	0.1379	0.0000	0.1034	0.2069	0.1379	0.1379	0.0345	0.0345	0.0690
F	0.0000	0.0000	0.1538	0.0000	0.1538	0.0000	0.1538	0.3077	0.0000	0.1538	0.0000	0.0769
G	0.0303	0.0909	0.0000	0.3636	0.1818	0.1212	0.0000	0.0606	0.0606	0.0303	0.0303	0.0303
H	0.0408	0.2449	0.0816	0.0612	0.1429	0.0204	0.0612	0.0000	0.1633	0.0612	0.1020	0.0204
I	0.0435	0.0435	0.0435	0.0000	0.0345	0.0000	0.0345	0.0690	0.2759	0.0000	0.2759	0.1034
J	0.0000	0.0690	0.1379	0.0000	0.0345	0.0000	0.0345	0.0690	0.2759	0.0000	0.2759	0.1034
K	0.1000	0.2250	0.1000	0.0000	0.0000	0.0250	0.0000	0.1500	0.0750	0.3000	0.0000	0.0250
L	0.0000	0.0000	0.1667	0.0000	0.0000	0.3333	0.1667	0.1667	0.0000	0.1667	0.0000	0.0000

Table 3 Matrix table in Markov Chain for Manchester City

In Table 4, the transposed results of the matrix table in the Markov chain are shown for Manchester City team. The outcome of performing this transposition is what is utilised to determine the value of each player's eigenvector.

	A	B	C	D	E	F	G	H	I	J	K	L
A	0.0000	0.1404	0.0417	0.0541	0.0000	0.0000	0.0303	0.0408	0.0435	0.0000	0.1000	0.0000
B	0.4286	0.0000	0.2917	0.1892	0.0690	0.0000	0.0909	0.2449	0.0435	0.0690	0.2250	0.0000
C	0.0476	0.0702	0.0000	0.0000	0.0690	0.1538	0.0000	0.0816	0.0435	0.1379	0.1000	0.1667
D	0.0952	0.2105	0.0417	0.0000	0.1379	0.0000	0.3636	0.0612	0.0000	0.0000	0.0000	0.0000
E	0.0000	0.0702	0.0417	0.0811	0.0000	0.1538	0.1818	0.1429	0.0345	0.0345	0.0000	0.0000
F	0.0000	0.0175	0.0417	0.0270	0.1034	0.0000	0.1212	0.0204	0.0000	0.0000	0.0250	0.3333
G	0.0476	0.0351	0.0000	0.3514	0.2069	0.1538	0.0000	0.0612	0.0345	0.0345	0.0000	0.1667
H	0.1429	0.1579	0.1667	0.1351	0.1379	0.3077	0.0606	0.0000	0.0690	0.0690	0.1500	0.1667
I	0.0000	0.0526	0.0417	0.0811	0.1379	0.0000	0.0606	0.1633	0.2759	0.2759	0.0750	0.0000
J	0.0476	0.0351	0.1667	0.0000	0.0345	0.1538	0.0303	0.0612	0.0000	0.0000	0.3000	0.1667
K	0.1905	0.2105	0.1667	0.0541	0.0345	0.0000	0.0303	0.1020	0.2759	0.2759	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0270	0.0690	0.0769	0.0303	0.0204	0.1034	0.1034	0.0250	0.0000

Table 4 Transpose of matrix table Markov Chain for Manchester City

Due to the fact that each match consists of a total of 12 players, the identity matrix (12x12) has been chosen to represent the board.

	A	B	C	D	E	F	G	H	I	J	K	L
A	1	0	0	0	0	0	0	0	0	0	0	0
B	0	1	0	0	0	0	0	0	0	0	0	0
C	0	0	1	0	0	0	0	0	0	0	0	0
D	0	0	0	1	0	0	0	0	0	0	0	0
E	0	0	0	0	1	0	0	0	0	0	0	0
F	0	0	0	0	0	1	0	0	0	0	0	0
G	0	0	0	0	0	0	1	0	0	0	0	0
H	0	0	0	0	0	0	0	1	0	0	0	0
I	0	0	0	0	0	0	0	0	1	0	0	0
J	0	0	0	0	0	0	0	0	0	1	0	0
K	0	0	0	0	0	0	0	0	0	0	1	0
L	0	0	0	0	0	0	0	0	0	0	0	1

Table 5 Identity Matrix (12x12)

The eigenvector values of each player who has ever been a member of the Manchester City squad are shown in the Table 6. This number may be acquired by taking the result of Table 3's transpose matrix and subtracting it with identity matrix (Table 5). Table 6 shows the outcome of the subtraction that was performed. The reading value in the yellow table displays the eigenvector value that corresponds to each player who is representing the Manchester City team in the diagram. A data solver that is compatible with Microsoft Excel was used in obtain to get the value in problem. The eigenvector value indicates that player B has the greatest reading value, which is 0.1391; player L has the lowest eigenvector value, which is 0.0392; nonetheless, player B has the highest reading value. Player B has the highest reading of this because he is the player who distributes the ball to the most other players, and this number also indicates that Player B plays the ball in the most central part of the field. In addition, player L had the worst reading since he was a substitute who came into the game in the last minutes and did not have enough time to complete a pass before the game ended.

	A	B	C	D	E	F	G	H	I	J	K	L			
A	-1.0000	0.1404	0.0417	0.0541	0.0000	0.0000	0.0303	0.0408	0.0435	0.0000	0.1000	0.0000	-0.0016	=	0
B	0.4286	-1.0000	0.2917	0.1892	0.0690	0.0000	0.0909	0.2449	0.0435	0.0690	0.2250	0.0000	-0.0022	=	0
C	0.0476	0.0702	-1.0000	0.0000	0.0690	0.1538	0.0000	0.0816	0.0435	0.1379	0.1000	0.1667	-0.0001	=	0
D	0.0952	0.2105	0.0417	-1.0000	0.1379	0.0000	0.3636	0.0612	0.0000	0.0000	0.0000	0.0000	0.0000	=	0
E	0.0000	0.0702	0.0417	0.0811	-1.0000	0.1538	0.1818	0.1429	0.0345	0.0345	0.0000	0.0000	-0.0003	=	0
F	0.0000	0.0175	0.0417	0.0270	0.1034	-1.0000	0.1212	0.0204	0.0000	0.0000	0.0250	0.3333	-0.0005	=	0
G	0.0476	0.0351	0.0000	0.3514	0.2069	0.1538	-1.0000	0.0612	0.0345	0.0345	0.0000	0.1667	0.0000	=	0
H	0.1429	0.1579	0.1667	0.1351	0.1379	0.3077	0.0606	-1.0000	0.0690	0.0690	0.1500	0.1667	-0.0016	=	0
I	0.0000	0.0526	0.0417	0.0811	0.1379	0.0000	0.0606	0.1633	-0.7241	0.2759	0.0750	0.0000	-0.0001	=	0
J	0.0476	0.0351	0.1667	0.0000	0.0345	0.1538	0.0303	0.0612	0.0000	-1.0000	0.3000	0.1667	0.0000	=	0
K	0.1905	0.2105	0.1667	0.0541	0.0345	0.0000	0.0303	0.1020	0.2759	0.2759	-1.0000	0.0000	-0.0006	=	0
L	0.0000	0.0000	0.0000	0.0270	0.0690	0.0769	0.0303	0.0204	0.1034	0.1034	0.0250	-1.0000	-0.0015	=	0
	0.052888	0.139111	0.068151	0.080842	0.06345	0.042378	0.075973	0.118565	0.112414	0.081279	0.1257	0.039249	1.0000	=	1

Table 6 The Eigenvector for each player for Manchester City.

Table 7 displays the eigenvalues that were calculated as a consequence of the Markov chain matrix that was used to track the ball's progression through the hands of all of the players who had competed for the Bayern Munich squad. Because the squad made three substitutions during that single game, the diagram that is shown above is in the form of a matrix that has 14 rows and 14 columns. As a consequence of the fact that the team was successful in obtaining an eigenvector value, player B has the highest reading, which is 0.1449; hence, this player is the one who contributes the most to the team. Despite this, player C had the second most effective game out of everyone on the squad. Due to the fact that players B and C both play defense for the club, the defensive zone is the area of the pitch that is considered to be the most central by the Bayern München squad.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N			
A	-1.0000	0.1750	0.1268	0.0455	0.0345	0.0000	0.0000	0.0000	0.0000	0.0577	0.0000	0.0000	0.0000	0.0000	0.0000	=	0
B	0.2778	-1.0000	0.4366	0.3864	0.1207	0.1739	0.0976	0.0323	0.0455	0.0000	0.0455	0.0000	0.1250	0.0000	0.0000	=	0
C	0.2500	0.2250	-1.0000	0.0000	0.1207	0.0000	0.1951	0.0323	0.0000	0.3269	0.0455	0.0000	0.7500	0.0000	0.0000	=	0
D	0.1111	0.1750	0.0141	-1.0000	0.1552	0.1304	0.0976	0.0000	0.2273	0.0000	0.0455	0.2500	0.0000	0.6667	0.0000	=	0
E	0.1111	0.1500	0.0282	0.0909	-1.0000	0.1739	0.1707	0.2581	0.1818	0.1154	0.1364	0.0000	0.1250	0.0000	0.0000	=	0
F	0.0769	0.0625	0.0000	0.0909	0.0517	-1.0000	0.0732	0.0645	0.0455	0.0769	0.0455	0.0000	0.0000	0.0000	0.0000	=	0
G	0.0278	0.0375	0.0704	0.0455	0.1207	0.0870	-1.0000	0.0968	0.0909	0.0577	0.1818	0.2500	0.0000	0.0000	-0.0001	=	0
H	0.0000	0.0125	0.0423	0.0682	0.0690	0.1304	0.0976	-1.0000	0.2727	0.1731	0.2273	0.0000	0.0000	0.0000	0.0000	=	0
I	0.0278	0.0375	0.0282	0.2273	0.0345	0.1739	0.0488	0.1290	-1.0000	0.0577	0.0000	0.2500	0.0000	0.0000	0.0000	=	0
J	0.0556	0.0750	0.1972	0.0000	0.2241	0.0435	0.0732	0.1290	0.0455	-1.0000	0.2727	0.0000	0.0000	0.0000	-0.0037	=	0
K	0.0000	0.0000	0.0282	0.0227	0.0345	0.0435	0.1220	0.1951	0.0909	0.1346	-1.0000	0.0000	0.0000	0.0000	-0.0003	=	0
L	0.0000	0.0125	0.0000	0.0000	0.0000	0.0435	0.0244	0.0000	0.0000	0.0000	0.0000	-1.0000	0.0000	0.3333	0.0000	=	0
M	0.0833	0.0125	0.0282	0.0000	0.0345	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-1.0000	0.0000	0.0000	=	0
N	0.0000	0.0250	0.0000	0.0227	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2500	0.0000	-1.0000	0.0000	=	0
	0.0554	0.1449	0.1248	0.0902	0.1166	0.0520	0.0714	0.0846	0.0666	0.1056	0.0576	0.0084	0.0140	0.0078	1.0000	=	1

Table 7 The Eigenvector for each player for Bayern München.

Conclusion

In conclusion, the outcomes of the structure that was produced by each team may be constructed using graph theory. It is possible to determine the value of each player's eigenvector by first computing the number of times they passed the ball to one another and then forming that information into a matrix. This allows the value of the player's eigenvector to be determined. Because of the value of the eigenvector, player is the most effective and which zone is the zone with the highest centrality can be determined. According to the data collected during the quarterfinal encounter of the UEFA Champions League on the amount of time each side spent passing the ball. It has been determined where the transmission structure and the center will go. The central level of each squad was evaluated in connection to the outcomes of their respective games, and the findings were analyzed. The eigenvector centrality approach is a helpful tool for using while analyzing of football games. There is a wide range of potential applications for both the importance of the team as a whole and the specific contributions of each player.

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