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Evaluating Player Interaction and Performance using Network Analysis

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Abstract— In professional sports, a team's biggest concern is winning a game every time they step on the pitch. All teams aspire to give their best effort during a game, and doing so necessitates taking into account players interaction with their teammates during playing time. Therefore, determining each players interaction and evaluating their performance plays an important role in basketball. The study reviewed and evaluated players interaction for the 2017/2018 NBA season. Though there are known techniques for analysis and player performance evaluation which have been developed overtime, several other techniques have been proposed. However, in order to better manage the game and positioning of players, network analysis a better way to understand players preference in passing the ball to other players. The study used Network analysis to assess and analyze basketball players interaction and general performance. Statistics for every player for 2017/2018 season were gathered by scraping data from Basketball-Reference and used custom R scripts to gather box score data from basketball reference. Precisely there were 30 teams and had initially 23 variables related to their performance with attributes such as fields goals made, field goals made, points scored with field goals, points scored and so on. Network nodes for each players assist performance was highlighted. Network diagram were then generated for different teams such as Milwaukee Bucks, Cleveland which shown the consistency of passes for each player and interaction.

Keywords — evaluate, network, analysis, performance.

I. INTRODUCTION

Numerous activities in living applications benefit from network analysis. We can use it to analyze biological systems of organisms or to gain a deeper knowledge of the structure of a relationship in social networks, a natural phenomenon's structure or process of change and so on. Network analysis provides the capacity to estimate complex patterns of relationships and the network structure can be analyzed to reveal core features of the network [1]. This can be extended to sport where it can be used to measure, evaluate and study performances of players on the field of play weekly. It can also be used to study player interaction during and

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after a match. One of the biggest difficulties in team sports is the coordination between teammates [2]. The dynamic aspects of the game, the interaction between collaboration and opposition, and the external circumstances limit how well the team members cooperate [3]. Due to these factors, team members' relationship inclinations and patterns are not always consistent or predictable [4].

Basketball's conventional statistics assess players apart from their teammates or opponents, and traditional player positions are decided by personal qualities. These network-based statistics, in contrast, are created by building player networks at the team or league level, where each player is a node connected to other players through the movement of the ball or by some other similarity metric. The metrics are then calculated by adding up network attributes including degree, density, centrality, clustering, and distance, among others. This strategy adds new individual and team level statistics to basketball analysis and provides a fresh method for designating a player's position [5]. Researchers from Arizona State University under the direction of Jennifer H. Fewell made the largest contribution to the team level metrics. They built networks for each team utilizing players as nodes and ball movement between them as links using 2010 NBA first round playoff data. They made a distinction between the trade-off between the team's unpredictable nature, as assessed by Team entropy, and the division of labor, which need not necessarily be mutually exclusive [5]. We incorporated several parameters to measure in the study to evaluate players performance which was explained in details in the methodology section.

The rest of the paper is organized as follows. We describe related works in section 2 and methods in Section 3, which includes network analyses. In Section 4, the results of the measures are empirically demonstrated. Section 5 is the conclusion.

II. RELATED WORKS

[7] attempted to evaluate basketball players' worth by looking at their conduct. However, conventional approaches always rely on isolated statistical data, which results in inefficient and incorrect assessments. The outcomes of such evaluations can be much improved by using dynamic network theory-based models, but these models are still not precise because they only evaluate the values of individual players without taking their present teams into account. They suggested a network-based, hidden Markov model-based analysis and assessment model to address this issue. The strategy was used using SportVU. Data gathered from the National Basketball Association demonstrates that this analysis and evaluation methodology can efficiently examine each player's performance in a game and offers team managers with a helpful tool. [8] worked on Network Analysis of NBA playoffs via flow dynamics by analyzing performance and strategy through how NBA players move the ball in a game.

[9] worked on basketball lineup performance prediction using network analysis. The authors built a directed, weighted, and signed network of every lineup used by teams in National Basketball Association (NBA) games from the 2007 to 2016 seasons in order to examine and forecast lineup performance. By employing graph theory and Inverse Squared Metric, the suggested methodology employs machine learning and network analysis techniques to forecast how a lineup will perform in a specific scenario. A number of baseline models are built, and the results are compared, in order to assess the performance of the suggested strategy. The final results over a ten-year period demonstrate that the suggested strategy in this research increases the accuracy of the baseline values by 10%. The average of the best baseline results has an accuracy of 58% in lineup outcome prediction; however, the new method yields accuracy of 68%.

[10] reviewed network analysis in basketball. [11] analyzed the team-members cooperation in basketball by using centrality metrics of network. Different ages were compared in the study. Forty players (10 players of under-14; 10 players of under-16; 10 players of under-18 and 10

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players in amateurs with more than 20 years) participated in the study. A total of 326 units of attack were generated based on the team-members interactions and then converted in final graphs. The one-way ANOVA for the factor tactical position found statistical differences in the dependent variables of %DCentrality ($F(4,15) = 13.622$; p-value = 0.001; $\eta^2 = 0.784$; Large Effect Size) and %DPrestige ($F(4,15) = 20.590$; p-value = 0.001; $\eta^2 = 0.846$; Large Effect Size). The study showed that point guard was the prominent position during the attacking organization and that social network analysis is a useful approach to identify the patterns of interactions in the game of basketball. [12] constructed a signed, directed, and weighted network from the results of all matchups and lineups of the teams in NBA from 2007 to 2019. The approach used machine learning and graph theory to develop a new metric called Inverse Square Metric and edge-centric multi-view networks to predict the performance of a lineup in a given situation. The edge-centric approach provided a deep analysis of any condition between two teams from 16 different perspectives. The average accuracy achieved by ISM and edge-centric multi-view is 68% and 80%, respectively.

III. METHODOLOGY

Statistics for every player for 2017/2018 season were gathered by scraping data from Basketball-Reference. Using custom R [14] scripts to gather box score data from basketball reference. Precisely there are 30 teams and had initially 23 variables related to their performance. Acronyms used in the assist.net framework and its meaning are;

i. Assist: character, indicating the name of the variable with players who made the assists, if any.
ii. Player: character, indicating the name of the variable with players who made the shot.
iii. Points: character, indicating the name of the variable with points.
iv. FGM - fields goals made
v. FGM_AST - field goals made thanks to a teammate's assist
vi. FGM_ASTP - percentage of FGM_AST over FGM
vii. FGPTS - points scored with field goals
viii. FGPTS_AST - points scored thanks to a teammate's assist
ix. FGPTS_ASTP - percentage of FGPTS_AST over FGPTS
x. AST - assists made
xi. ASTPTS - point scored by assist's teammates

A. Network Analysis

A network refers to a structure representing a group of objects/people and relationships between them [13]. A network structure is made up of nodes and edges. The nodes represent objects to be analyzed while edges represent the relationships between those objects.

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IV. RESULTS AND DISCUSSION

Figure 1 shows how many data points are available for each team during the 2017/2018 season with the Atlanta having 422 play-by-play data, 459 for Boston and the highest is 17,096 for Golden State Warriors because this data is mainly GSW (Golden State Warriors) versus others.

	ATL	BKN	BOS	CHA	CHI	CLE	DAL	DEN	DET	GSW	HOU	IND
3075	422	451	459	421	428	439	816	837	401	17096	640	397
LAC	LAL	MEM	MIA	MIL	MIN	NOP	NYK	OKC	ORL	PHI	PHX	POR
879	869	638	382	365	619	857	396	919	395	437	828	630
SAC	SAS	TOR	UTA	WAS								
778	837	427	859	433								

Fig 1 – data points for teams during the 2017/2018 season

Considering Boston Celtics, figure 2 shows the statistics of see each player from Boston Celtics and how many times each player assisted other players. It was observed that Kyrie Irving had more assist to Al Horford than he had to Marcus Morris.

	player				
assist	Al Horford	Aron Baynes	Daniel Theis	Kyrie Irving	Marcus Morris
Al Horford	0	0	0	1	0
Aron Baynes	0	0	0	0	0
Daniel Theis	0	0	0	2	1
Kyrie Irving	6	0	0	0	3
Marcus Morris	1	0	0	1	0
Marcus Smart	0	1	0	1	0
Shane Larkin	0	0	1	0	0
Terry Rozier	1	0	0	0	0
Jaylen Brown	0	0	0	0	0
Jayson Tatum	0	0	0	0	0

Fig 2 – Player Assist Statistics

The nodes statistics in the network analysis is shown in figure 3. It shows the various metrics for each player from Boston Celtics such as FGM, AST and so on.

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	player	FGM	FGM_AST	FGM_ASTp	FGPTS	FGPTS_AST	FGPTS_ASTp	AST	ASTPTS
1	Al Horford	13	8	61.53846	28	18	0.6428571	5	11
2	Aron Baynes	1	1	100.00000	2	2	1.0000000	1	2
3	Daniel Theis	1	1	100.00000	3	3	1.0000000	3	7
4	Jaylen Brown	13	9	69.23077	32	23	0.7187500	NA	NA
5	Jayson Tatum	4	3	75.00000	8	6	0.7500000	NA	NA
6	Kyrie Irving	17	5	29.41176	40	12	0.3000000	10	26
7	Marcus Morris	9	4	44.44444	21	11	0.5238095	3	8
8	Marcus Smart	NA	NA	NA	NA	NA	NA	3	7
9	Shane Larkin	2	0	0.00000	4	0	0.0000000	2	5
10	Terry Rozier	3	1	33.33333	9	3	0.3333333	5	12

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Fig 3 – Network Node Statistics

Table 1 basically stores network information which was useful for network analysis. It showed the network analysis of all the plays made by Boston Celtics when they were playing Golden State Warriors in other to get network diagram.

Table 1 – Network information

Network Attributes	Value
Vertices	10
Directed	TRUE
Hyper	FALSE
Loops	FALSE
Multiple	FALSE
Bipartite	FALSE
total edges	19
missing edges	0
Non-missing edges	19

Figure 5 showed a plot that gave a network analysis of all the plays made by Boston Celtics when they were playing Golden State Warriors to produce the network diagram. The network diagram has nodes and these nodes are represented as circles which represent the players. The edges are the lines that connect two players and each one of these edges have arrow pointing towards one of the players which gave us the direction of the assist. For example, Kyrie Irving was one of the key players and made a lot of assists represented by color red and had highest number of assists. Also, it was observed most of the assist were made for Horford and quite a few went to Marcus Morris. Similarly, Terry Rozier had made lot of assists to Jaylen Brown and Horford also has made lot of assist Brown during the 2017 2018 season. It was observed Jason Tatum who was a rookie player in 2017/2018 and was not yet a key player in Boston Celtics at that time. The network diagram also showed who were the key players during that season.

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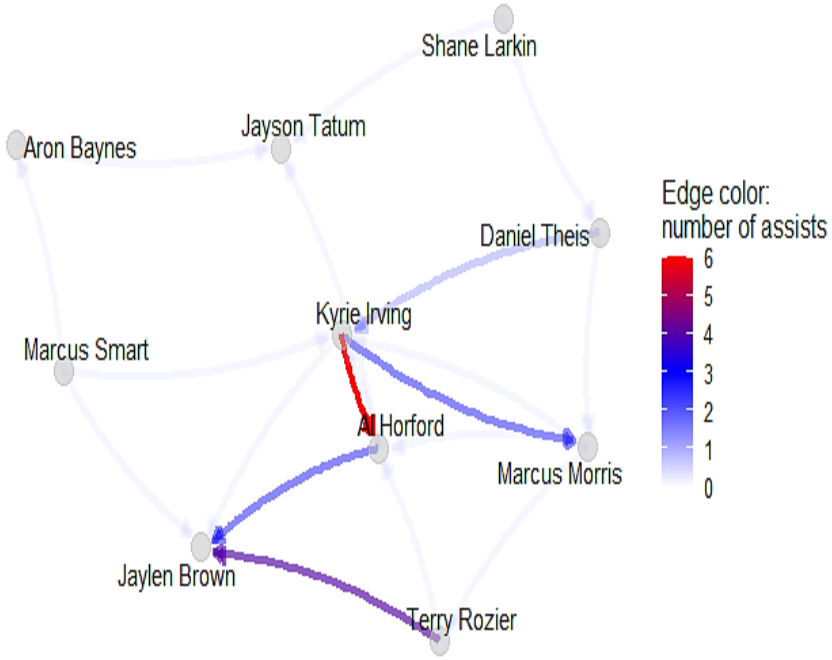

Fig 5 – Network Analysis

In a more complex form showing the AST points which is points scored by assists teammates in figure 6. To vary the size of the node, bigger the size that means more points code and lower the size means less points code. It was observed that the Kyrie Irving has the biggest circle which means that he made maximum assists and made lot of assists to Horford and Marcus Morris.

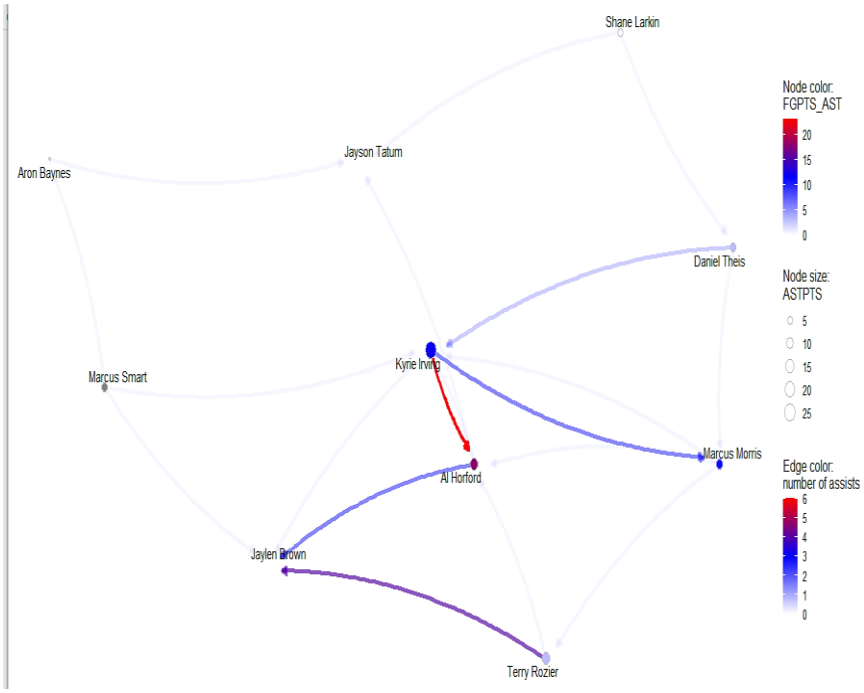

Fig 6 – Network analysis with AST

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Another key team during 2017/2018 season was Cleveland which had LeBron James in the team. Figure 6 showed the statistics of see each player from Cleveland and how many times each player assisted other players. It was observed that Lebron James had more assist to Jae Crowder than he had to Isaiah Thomas.

player

assist	Dwyane Wade	Isaiah Thomas	Jae Crowder	Jose Calderon	JR Smith
Dwyane Wade	0	1	1	0	0
Isaiah Thomas	0	0	0	0	1
Jae Crowder	0	0	0	0	0
Jose Calderon	0	0	1	0	0
JR Smith	1	1	1	0	0
Kevin Love	0	0	0	0	0
Kyle Korver	0	0	0	0	0
LeBron James	0	2	3	0	1
Channing Frye	0	0	0	0	0
Jeff Green	0	0	0	0	0
Tristan Thompson	0	0	0	0	0

player

Fig 6 – Player Assist Statistics

The nodes statistics in the network analysis is shown in figure 7. It showed the various metrics for each player from Cleveland such as FGM, AST and so on.

	player	FGM	FGM_AST	FGM_ASTp	FGPTS	FGPTS_AST	FGPTS_ASTp	AST	ASTPTS
1	Al Horford	13	8	61.53846	28	18	0.6428571	5	11
2	Aron Baynes	1	1	100.00000	2	2	1.0000000	1	2
3	Daniel Theis	1	1	100.00000	3	3	1.0000000	3	7
4	Jaylen Brown	13	9	69.23077	32	23	0.7187500	NA	NA
5	Jayson Tatum	4	3	75.00000	8	6	0.7500000	NA	NA
6	Kyrie Irving	17	5	29.41176	40	12	0.3000000	10	26
7	Marcus Morris	9	4	44.44444	21	11	0.5238095	3	8
8	Marcus Smart	NA	NA	NA	NA	NA	NA	3	7
9	Shane Larkin	2	0	0.00000	4	0	0.0000000	2	5
10	Terry Rozier	3	1	33.33333	9	3	0.3333333	5	12

>

Fig 7 – Network Node Statistics

Again, for Cleveland, it was observed in figure 8 the key players during that season with LeBron James having the biggest circle meaning he made maximum assists for the team when they played the Golden State Warriors. He also made maximum assist to Kevin Love because of the deep colored red in the network diagram. Evaluation also showed that Kevin Love was able to convert most of the assists into points.

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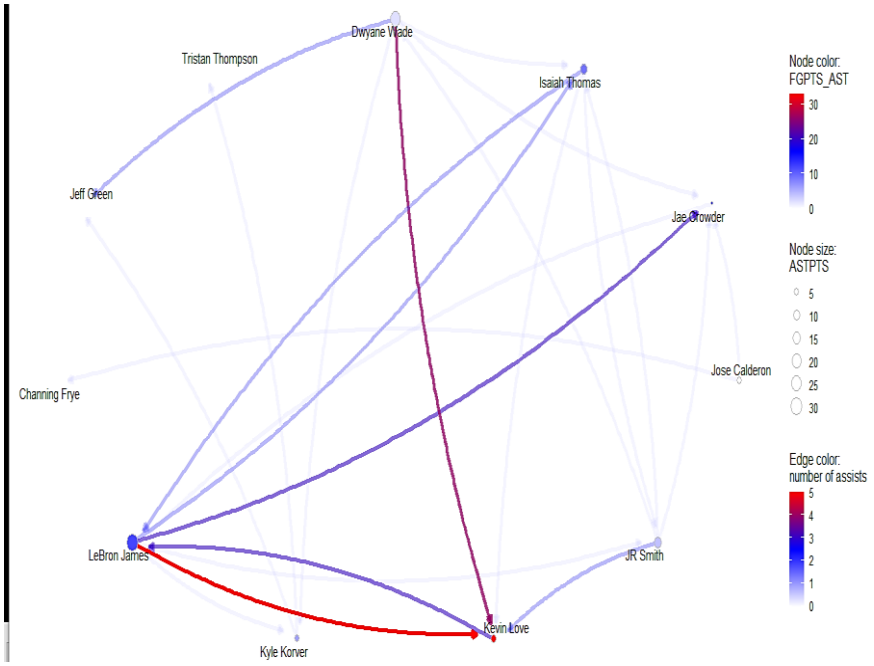

Fig 8 – Network diagram for Cleveland

Other teams like Milwaukee Bucks who had Jonas as one of the key players showed he gave most key assists during the season as shown in figure 9. It showed that Milwaukee Bucks revolved around Yanis. His node or the circle was quite big as well as he had converted meaning he had converted most of the assists into points.

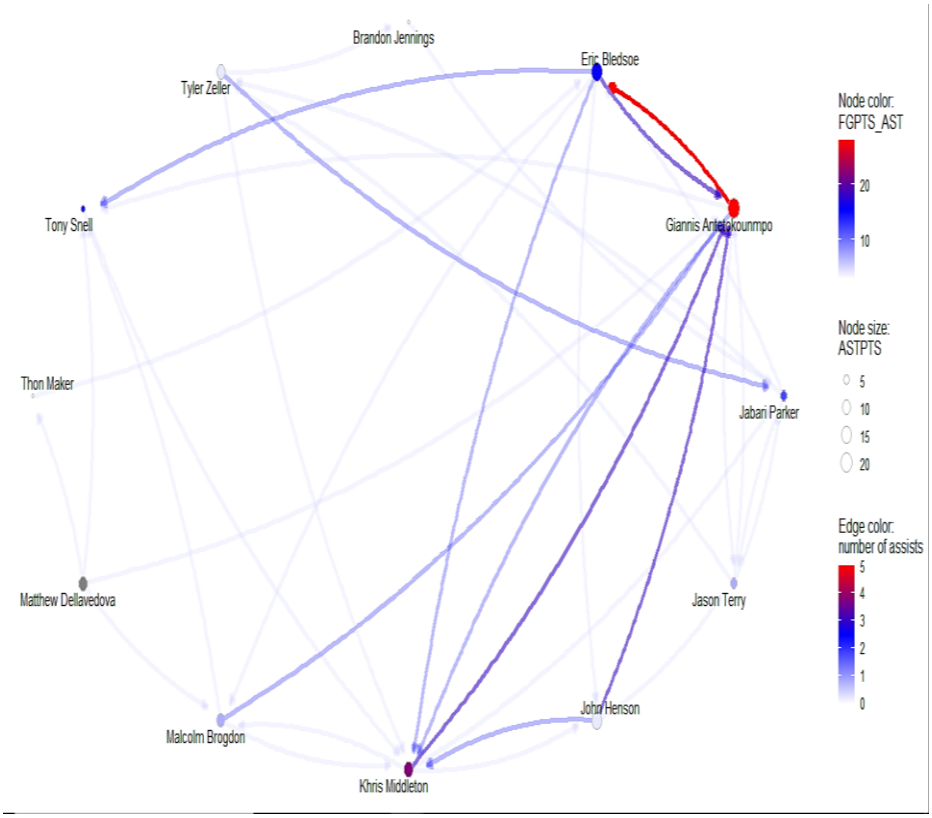

Fig 9 – Network diagram for Milwaukee Bucks

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Evaluating Golden State Warriors team generated more than 17,000 observations. It was observed that generating the network diagram was very busy. So key players, like, Kevin Durant, Steph Curry, Draymond, Green, Klay Thompson and so on were identified in the network diagram. To remove the clutter, a threshold of 20 was used which translated to anybody who made less than 20 assists during the 17,000 plus games were not included in the diagram. Figure 9 showed network diagram with clutter and figure 10 showed network diagram without clutter.

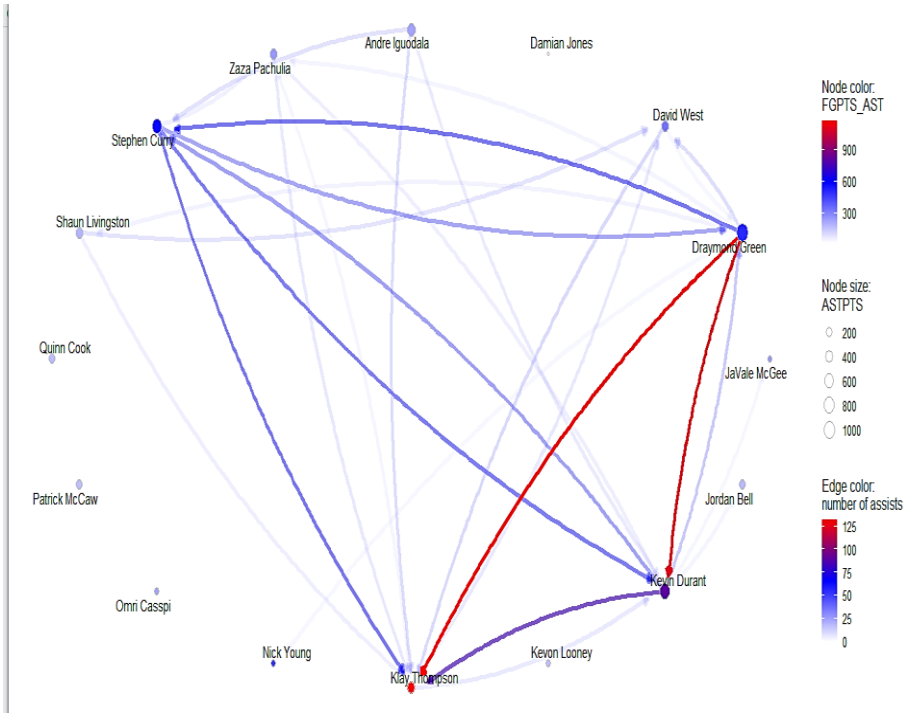

Fig 9 – Network diagram for Golden State Warriors without clutter

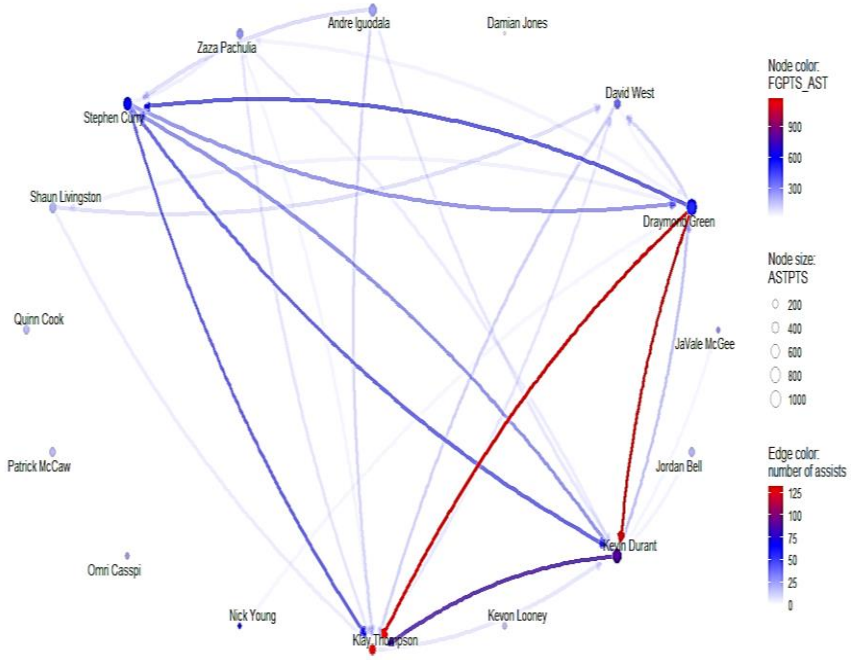

Fig 10 – Network diagram for Golden State Warriors with clutter

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V. CONCLUSION

Based on the network analysis different team performance and players, teams like Milwaukee Bucks who had Jonas as one of the key players showed he gave most key assists during the season as shown in figure 8. It also showed that Milwaukee Bucks revolved around Yanis. His node or the circle was quite big as well as he had converted meaning he had converted most of the assists into points. Golden State Warriors team generated more than 17,000 observations. So key players, like, Kevin Durant, Steph Curry, Draymond, Green, Klay Thompson and so on were identified in the network diagram. To remove the clutter, a threshold of 20 was used which translated to anybody who made less than 20 assists during the 17,000 plus games were not included in the network diagram. This analysis could be used to further study players in succeeding seasons.

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