Title
Social Network Analysis of the 2022-2023 Spurs

Author
De La Cueva, Pedro Eduardo

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Social Network Analysis of the 2022-2023 Spurs

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Master of Science in Statistics

by

Pedro De La Cueva

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ABSTRACT OF THE THESIS

Social Network Analysis
of the 2022-2023 Spurs

by

Pedro De La Cueva
Master of Science in Statistics
University of California, Los Angeles, 2023
Professor Mark S. Handcock, Chair

In this thesis, we aimed to obtain a better understanding of the public and private Twitter/X personas of a professional basketball team (the 2022-2023 NBA Spurs). We used the data to form a social network and utilized statistical network analysis methodology to study our data. We studied this network to understand how an average NBA team's players represent themselves to the public as opposed to studying the top teams/players in the NBA. We found that stochastic block models group the players correctly into two groups but mishandles the classification of some players due to their network structure. Analysis with Exponential-family random graph models (ERGMs) reinforce the idea that players often tend to keep their social media presence professional. Players also rated higher on an ESPN metric of performance tended to be more involved with social media.

The thesis of Pedro De La Cueva is approved.

Frederic (Rick) Paik Schoenberg

George Michailidis

Mark S. Handcock, Committee Chair

University of California, Los Angeles

2023

To my mentors . . .

who—among so many other things—

encouraged me to complete my study's

and helped me find my way in life.

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CHAPTER 1

Introduction

1.1 Introduction & Motivation

The NBA is a popular sporting organization that has instantly recognizable teams such as the Los Angeles Lakers, Maimi Heat, and the Golden State Warriors. However there are also lesser known teams in the NBA that do not have as much notoriety. These teams are considered average amongst the NBA in terms of sporting performance but they are still notable participants in the NBA sphere. We decided to take a look at one of these ”average” teams because they are notable participants and were curious to see if performance affected how they presented themselves to the public. We constructed a list of teams that may fit our conditions and settled on a team that we had heard about when visiting Texas, the San Antonio Spurs.

The San Antonio Spurs (SAS) is a NBA team based out of San Antonio, Texas that has recently had a consistently average career, although they have been one of the more successful franchises over a longer period. SAS is known in the NBA but people outside of this sphere may have only heard about this team in passing.

We choose to represent the data gathered from SAS players as a network because network analysis has been used to model friendship and acquaintance networks[3]. It also has been a key technique in modern sociology and has a variety of visualization tool we thought would lend itself nicely to our data. It allows us to add covariates to our data which we feel would be invaluable when explaining the structure of our network.

The motivation for using Twitter data to create a network is based on the prominence of social media in our daily lives. Government, celebrities, and sports teams all use social media as a way to connect to the public.

In our network we look at player to player ties but we also choose to add the ties from player to other Twitter accounts, termed non-player accounts. The reasoning behind this decision is that players do not exist in a vacuum. Behind every player there exist their own individual background and support system. Taking a quick glance at player Blake Wesley we see ties to the organizations that helped foster his development of basketball and cursory glances at other players reflect similar ties. These non-player nodes are also composed of the NBA, ESPN, Spurs and other organizations Twitter account. Seeing as these nodes would give us more insight into the players and ultimately into the network structure we added them in. These non-player nodes we will consider sports affiliates, because of their varied nature. We will be filtering to eliminate nodes that are not integral to the network structure but were tweeted at players. We do this because we assume players make some tweets for publicity.

1.2 Background

Statistical network analysis has been used to analyze friendship networks e.g., the relationships between monks using Sampson's monastery data and the so called 'karate club network' of Zachary[5]. These networks set up the foundation to study more complex networks that take on other dimension such as with what we see with social network of public sports teams. Networks of sports teams are based around public figures which can add nationality, friendships, publicity outreach, ect. Our goal is to explore a public figure social network and try to see if we can find rhyme or reason to why we the network has the structure we observed as opposed to any other structure.

The network that we will be taking a look at is composed of Twitter data from the Spurs players during 2022-2023 NBA regular season. The motivation for using Twitter data to create a network is based on the prominence of social media in our daily lives. Government, celebrities, and sports teams all use social media as a way to connect to the public.

To provide more context on the Spurs performance we explore a bit of their history. The Spurs in the last 5 years have struggled to top their division or move on in conference but won the NBA finals back in 2014. The Spurs as a team consistently has a younger demographic of player as opposed to other teams. The team also has a higher wins then losses ratio over their career as a team.

There is challenges that arise from studying a NBA team throughout the season. It is not uncommon for players during a regular seasons to be added, traded or let go and the Spurs is no exception. We will be only adding players to the network who stayed on the roster[1] for most of the season to combat this issue (active play from February 2022 and on). Players are also sometimes not as active on social media so we may struggle to get certain players social network information.

1.3 Data Description

We convert our Twitter data into a network structure in order to study it better. The network is bipartite and contains two sets of nodes players p, and non-players np, though we do allow player to player ties which the traditional bipartite networks do not. Table 1.2 holds a list of the np nodes. As mentioned before we do need to address the issue with how we choose the players in our data. We began with about 16 players in our data set and narrowed down the list. Players are sometimes traded, retire or otherwise during a season so we choose to only look at players who were on the team for a majority of the season. Some players also deleted their social media accounts or were too inactive on Twitter to pull any meaningful data. After the cleaning there are 14 players total in the data set.

Tweets are introduced into our network as edges. Not all tweets however, are needed for

Table 1.1: Player list.

Player	**Twitter handle**	**Player**	**Twitter handle**
Blake Wesley	blakewesley0	Dominick Barlow	Dominickbarlow_
Josh Richardson	J_Rich1	Jeremy Sochan	JeremySochan
Keita Bates-Diop	KBD_33	Tre Jones	Tre3Jones
Devin Vassell	Yvngdevo	Romeo Langford	yeahyeah22
Zach Collins	zcollins_33	Charles Bassey	CB_ONES23
Devonte' Graham	Devonte4Graham	Julian Champagnie	JulianChampagn2
Sandro Mamukelashvili	Mamukelashvili5	Doug McDermott	dougmcdermott

our network. We discard tweets made by a player without a specific mention of an account. This means any tweets without an @ symbol are discarded, for example players just updating their daily mood. This would not add an edge to our network because we are focused on the ties formed between accounts. Some tweets have multiple mentions, such as when an article talks about the team as a whole. When a player retweets these type of articles they create multiple ties between the player that posted and those accounts mentioned in the article.

All ties will be sent out from players. Our non-player accounts do not have any out ties by design. This means that any terms in our model for non-players ties will not exist but that also means these accounts potential edges will not affect the results.

Our data set contains three networks. We will describe all networks in further detail later but the main network we will be looking at is the Player/Non-Player network and the Player only network.

Every player node comes with a variety of supplemental information which we call covariates. The covariates included are a position on the team, nationality, age, height, weight, ect. We also include statistics for a players performance. We have things like PTS, game

Table 1.2: Significant Non-Players list.

Non-player	**Non-player**
austin_spurs	Ballislife
BallySportsSA	spurs
Arsenal	NBA
SpursGive	BleacherReport
espn	DejounteMurray
lonniewalker_4	SportsCenter

time, rebounds but we will be using an aggregate of these measures to rate a players overall performance.

ESPN[2] is our main metric for a players performance. While we have a node called espn any mention of ESPN in our models refers to the metric. The espn node is a major sporting agency for a variety of sports including basketball. They released a player rating for the 2022-2023 season. As shown in Figure 1.1 ESPN is a rating created as an aggregate of metrics such as PTS points, REB rebounds ect.. The higher a players ESPN rating the better a player they are considered. For reference the highest score is a 55.6 for Nikola Jokic and a -0.8 is the lowest. The better a player is the higher their ESPN rating will be. The range ESPN score for the players in our network is 0-30 with mean being around 17. These covarites when added to our model help explain the network structure and why ties are formed.

Glossary

GP: Games Played
MPG: Minutes Per Game
FG%: Field Goal Percentage
FT%: Free Throws Percentage
3PM: 3-Point Field Goals Made Per Game
RPG: Rebounds Per Game

APG: Assists Per Game
STPG: Steals Per Game
BLKPG: Blocks Per Game
TOPG: Turnovers Per Game
PTS: Points Per Game

ESPN: ESPN rating = PTS + REB + 1.4*AST + STL + 1.4*BLK -.7*TO + FGM + .5*TGM -.8*(FGA-FGM) + .25*FTM - .8*(FTA-FTM)

Figure 1.1: Basketball metrics

CHAPTER 2

Methods

2.1 Introduction to Social Network

Networks are composed of both nodes and vertices. Nodes represents individuals and in the context of our work they represent the players and other Twitter entities, non-players. Vertices are what we call edges and they describe the ties or tweets between individuals.

Edges or ties are also known as relations. These relations can be characterized as directed or undirected. Undireced ties are considered to be ties out from both nodes. Lets say node A and B have a conversation, the conversation would be the tie which is being had between node A and B. We will be working with directed ties which have a value one way from a given node. The reason for this is the nature of a tweet. If node A tweets node B, node A has taken an action towards node B. If node B tweets back at node A we add a tie going from B to A. The reason this matters in Twitter is because accounts are not required to reciprocate ties. Directed ties therefore give us a better understanding of our network. Relations can be characterized as binary or valued. A binary relations takes only two values (0,1) while a valued relation can have more then two values (0,1,2,...). Though our data only used binary values.

Individual heterogeneity in the propensity refers to the formation of or receiving of ties, standing for the popularity or attractiveness of nodes. Homophily by actor attributes means there might be higher propensity to form ties between actors with similar attributes. Mutual ties refers to the propensity for entities to reciprocate a tie.

2.1.1 Density, Degree and other measures

When working with a n node directed graph, the density of the graph will be

$$\bar{Y} = \frac{1}{n(n-1)} \sum_{j:j \neq i} y_{ij} \tag{2.1}$$

Density is a global measure of the sociability of the graph. Similarly if we focus on node level summarising, the density of a node is the mean of the tie values, which also measures how social a node is. We would expect to see that each node has a different levels of sociability (in our context some players being more communicative on Twitter than others).
The density for a node i in a directed graph is

$$\bar{Y}^o = \frac{1}{n(n-1)} \sum_{j:j \neq i} y_{ij} \tag{2.2}$$

$$\bar{Y}^i = \frac{1}{n(n-1)} \sum_{j:j \neq i} y_{ij} \tag{2.3}$$

For binary relations, nodal heterogeneity can be described by nodal degrees. High degree positions are influential, but also may be subject to a great deal of influence or stress from others. For directed relations, the in degree of a node is the nodes number of incoming ties while the out degree of a node is the nodes number of outgoing ties.

ERGM has model terms that we introduce to explain the network structure. The `Nodeofactor` term adds network statistics to the model which gives the number of times a node with that attribute or those attributes appears as the node of origin of a directed tie. For `Nodematch`, this term adds one network statistic to the model, which counts the number of edges (i, j) for which attr(i)==attr(j) when diff = FALSE. When diff = TRUE, p network statistics are added to the model, where p is the number of unique values of the attr attribute. The k-th such statistic counts the number of edges (i, j) for which attr(i) == attr(j) == value(k), where value(k) is the kth smallest unique value of the attr attribute. Each group is allowed to have a unique propensity for within-group ties and is also known as the "differential homophily". ERGM allows us to add dyad and triad terms, which adds a statistic for smaller groupings of 2 and 3 nodes. If we were to add a dyad or triad term to the model it causes issues with our model because of how sparse our network is.

2.2 Analysis with Stochastic block models

To start we will fit a Stochastic block model[4] or SBM to our network to see if we can see any under laying structures. Stochastic block model is a network model that clusters nodes into "blocks" or groups of nodes. Nodes are grouped by similarity in their edges. The equation for a SBM is as follows,

$$P(A|g, w) = \Pi_{i<j}(W_{g_i g_j})^{A_{ij}}(A_{ij}!)^{-1}exp(-w_{g_i g_j}) \tag{2.4}$$

where g represents which of the K groups each node belongs to, A_{ij} is the edge value between node i and node j, and w is a K by K matrix of expected edge counts between the groups.

The strength of these models allow us to a strong jumping off point. They provide an explicit model for data variability, direct model for relational ties and parameters are summarized as structural features. There are newer models of SBM that allow for covariates but we will instead be using the ERGM as our main model.

2.3 ERGM

In order to analyse our player network we will be taking advantage of the Exponential-family Random Graph models (ERGM) methodology. ERGMS are a family of statistical models that allow us to study social networks. They have been used to study the monastery monk network as well as others.

ERGMS attempt to uncover the underlying social processes that lead to the ties we are observing, such as friendships, and different groups within the network. This helps us see if the network was a result of a stochastic process or a result of these underlying ties.

Network ties are going to be considered variables and the nodes fixed. We will estimate parameters and see if they are significant.

We will also perform a goodness of fit using classical diagnostic measures including Akaike information criterion (AIC), and Bayesian information criterion (BIC).

$$P(Y = y) = \frac{\exp\{\sum_{k=1}^{K} \theta_k g_k(y)\}}{c(\theta)} \tag{2.5}$$

where $\theta_{1,2,\ldots k}$ are parameters, $g_{1,2,\ldots k}(y)$ are statistics, and $c(\theta)$ is a normalizing constant.

$$c(\theta) = \sum_{y \in Y} \exp\{\sum_{k=1}^{K} \theta_k g_k(y)\} \tag{2.6}$$

$$\log \frac{P(Y_{ij} = 1|y_{ij}^c)}{P(Y_{ij} = o|y_{ij}^c)} = \sum_{k=1}^{K} \theta_k [g_k(y_{ij}^+) - g_k(y_{ij}^-)] \tag{2.7}$$

where y_{ij}^c is the rest of a graph excluding y_{ij}, y_{ij}^+ is the graph with Y_{ij}= 1 and y^{ij} is the graph with Y_{ij}= 0.

Then we can get some useful implications. Each unit change in g_k for tie (i, j) present increases the conditional log-odds of (i, j) by θ_k. The statistics g_k used here can be some summary measurement of networks, e.g., triad census, and node attributes.

CHAPTER 3

Analysis and results

3.1 Network Description

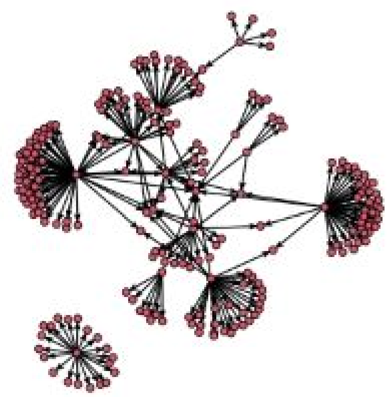

Figure 3.1: 2022-2023 complete Spurs network.

The network we begin with is a directed network with 44 vertices and 1900 edge, which we will be referring to as the complete network. Our network is a bipartite network with a set of nodes being the players p and a set of nodes being non-players np. We will however allow player to player ties but do not have any outgoing ties from our non-player nodes as they are not what we are interested in. Looking at Figure 3.1, we notice that the network has a cauliflower structure which indicate the network should be broken down a bit. We break down the network because some ties are superfluous. Players will sometimes tweet out to a random account to promote themselves. These tweets create edges and add unnecessary random noise. Some nodes will also be removed after removing edges because they will also become unnecessary. We break down the network to look at the ties between players and non-players where there is regular or semi regular contact.

Our broken down network is very different then what we initially plot. We see our original 44 vertices become 26 vertices and the number of edges drop down to 49 meaning most ties where publicity ties. This network is very sparse with a density of 0.075. We plot ESPN as our node size in Figure 3.2 and see that the higher the ESPN score, the more it looks to be central to the network. The blue nodes are players nodes and we can see some players are not connected. We will be referring to this network as the Player/Non-player network.

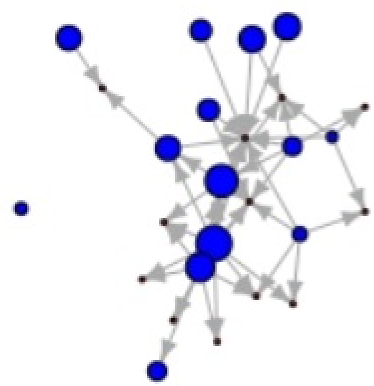

Figure 3.2: Non-Player/Player network model: Nodes are sized by ESPN rating and colorized Blue player, Red non-player

When we look at the network of only players our network is looking empty. We have 14 vertices but only 8 edges. As a result of the lack of ties or player connection we will not be looking too much into the network but it does provide good information about player connection.

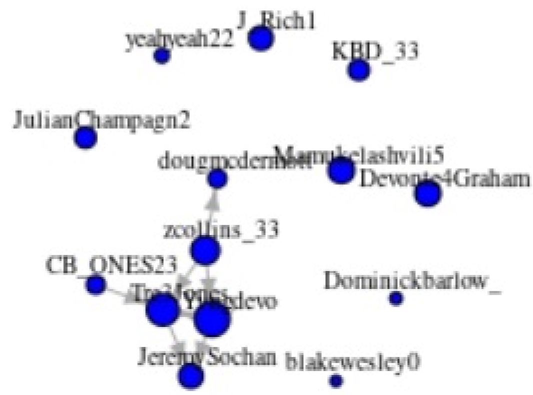

Figure 3.3: Players only network

3.2 Degree analysis

First we will take a look at the degrees for our completed graph. In the figure below, we see that most of the nodes are without any outwards ties. This is by design and demonstrate the need to break down the network a bit. We see that there are some nodes with 30, 60 or 15 ties. The nodes with a high amount of out-ties are responsible for the cauliflower structure we see in the complete network. A group of nodes (players) messages many nodes (Twitter accounts) for friendships and publicity. Taking a look at the top 2 out degrees nodes we find they belong to Yvngdevo, Devin Vassel, and blakewesley0, Blake Wesley. Devin's tweets consists of engagement, his contract deal and comments on networks who post about him. Blake Wesley has also similar posts on his Twitter. Tre Jones is the player with the lease amount of ties but the content of Twitter is slightly different. He post more updates about his life while still posting sometimes about his career.

Next we will be looking at the out ties to specific accounts that are 2 or more. This is done in order to eliminate any account/node that is not being consistently contacted by the players. As we see from the histogram of significant out-degree ties, most players do not

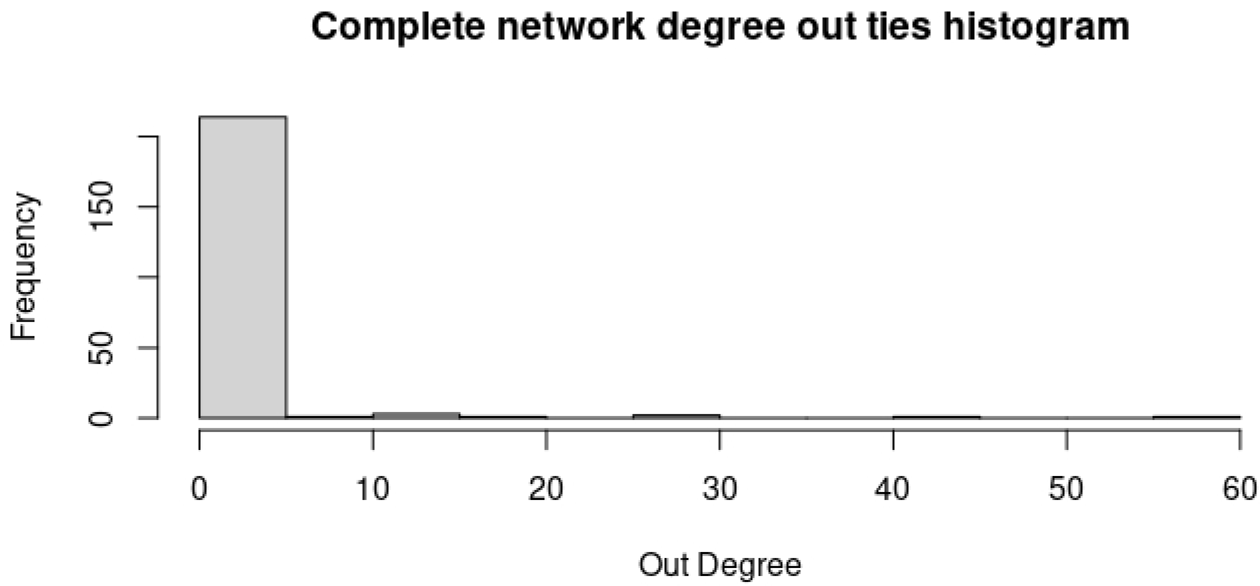

Figure 3.4: Complete network out ties.

have any consistent contact to any given account. Most players do not message any account consistently. 5 players do not message any account consistently but we have some players who do. This looks good for out player/non-player network but we may experience some trouble in our player to player network if those ties are more towards Twitter accounts than other players.

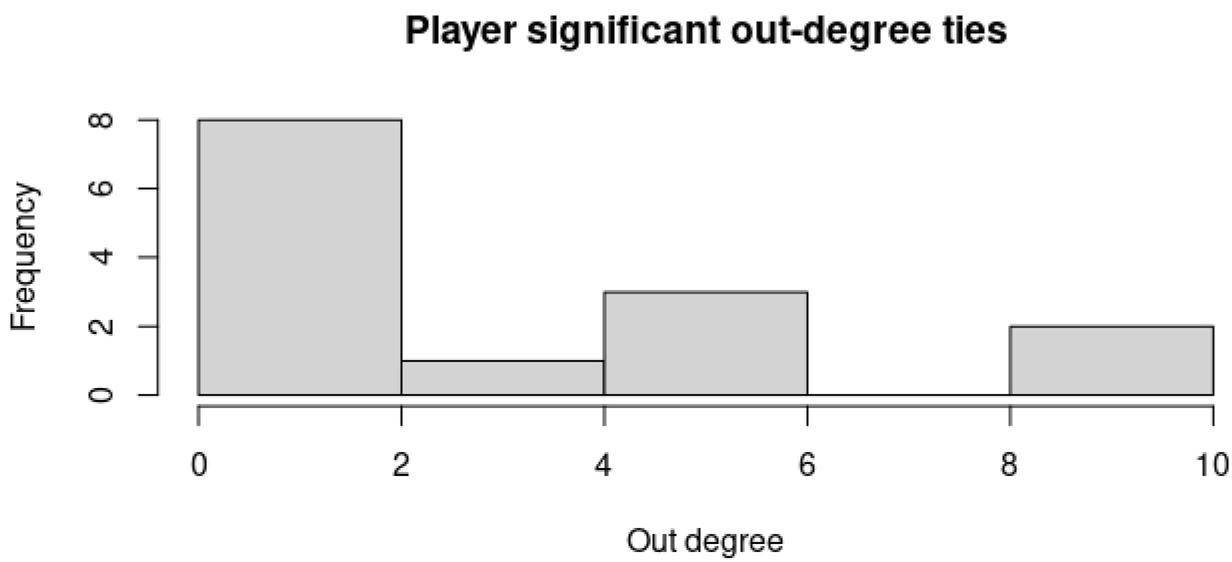

Figure 3.5: Player consistent out degree ties

CHAPTER 4

Models

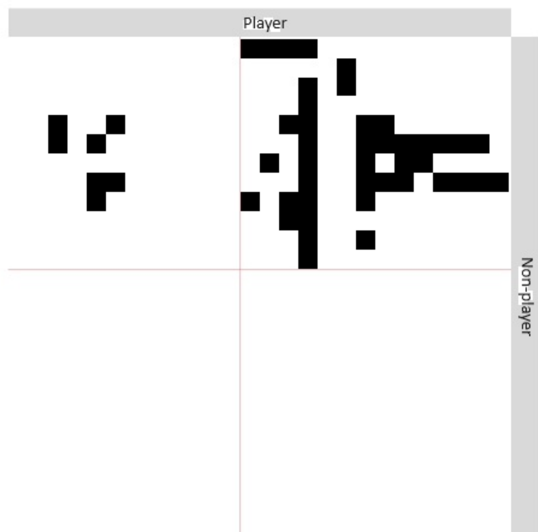

Figure 4.1: Stochastic Block model for Non-Player/Player network

We will be using statistical modeling techniques on our network in order to study the edge structure. The two modeling techniques we will be using are the SBM & ERGMs modeling techniques.

4.1 Stochastic Block model

The Stochastic Block model that we fit assigns the nodes groupings based on similar edges. In applications to real data for SBM's, neither the group memberships nor the block matrix is observed or given. Therefore, the goal of fitting an SBM to a graph is to infer these two components simultaneously. There have been advancements in SBM modeling that allow covariates in the model but we will not be looking at those models

As described earlier our network contains two sets of nodes. We have the Players and Non-players nodes so we would expect our SBM to group these two nodes separately. Our SBM does determine that we split our nodes into two major groups with group 1 having 12 nodes and group 2 having 14 nodes. Group 1's 12 nodes are composed of only players. Groups 2 nodes consists of mostly the non-players but has 2 player in this grouping. The players that are incorrectly labeled are Dominick Barlow and Doug Mcdermott. If we take a look at the out degrees for these two nodes we see that both these two players have no significant ties. These players ESPN scores are also 10.2 ad 15.2 respectively, with ages 20 and 31. Both players also have under 2 years with the team which may explain the reason for the lack of ties.

Figure 4.1 also points out that the SBM model recognizes the two groups. The non-players have no ties to any player or non-player and that is why the bottom half of the figure is blank. The half that is populated is based on the players out ties. The SBM fails to show difference between player to player ties and non-players to player ties. We move to the ERGMs to provide us with more insight into our network.

4.2 Exponential Family Random Graph Models

We start by fitting Exponential Family Random Graph models (ERGMs) on the network by just fitting simplest model. For this model the ties do not depend on any other tie and we simply fit the density. The ERGM model would solve the logistic regression instead of resorting to MCMC because it only contains the edges measure. It is important to note that the edges term represents exactly the density of the network (in log-odds). The edge term is significant but we do not gain much from this model so we will explore further by adding a mutual term. We notice that the mutual term is not significant. While this term is insignificant, we also see it is a negative term showing players are unlikely to tweet anything back. This makes sense when we also take into account the the largest component we could find in the complete model was between two players (Tre Jones and Devin Vassell). Publicly, as far as our network is concerned, there does not seem to strong ties between players on the team and they tend to exist more solitary, that is to themselves. The lack of strong ties or ties in general from player to player ties shows the public that the team is not united or at least has a weak team unity. Though this could also just mean that the team, as a whole, is more private with communication. It would be interesting to compare this with a team like the Celtics or Lakers and check how good team unity is. This also brings up the question, do players have a more significant ties to non-players (np) than to players(p).

```
Call:
ergm(formula = net2 ~ edges + mutual)

Monte Carlo Maximum Likelihood Results:

       Estimate Std. Error MCMC % z value Pr(>|z|)
edges   -2.4718     0.1483      0 -16.665   <1e-04 ***
mutual  -0.7775     1.0858      0  -0.716    0.474
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 901.1  on 650  degrees of freedom
 Residual Deviance: 347.0  on 648  degrees of freedom

AIC: 351  BIC: 359.9  (Smaller is better. MC Std. Err. = 0.04543)
```

Figure 4.2: ERGM with mutual term

In this next model, Figure 4.2, we see that players are more likely to form ties than to not form ties. The `Nodematch` terms reinforce that np cannot form ties hence the -Inf and the second `Nodematch` term tells us that players do not tend to form ties with other players on Twitter. When comparing the ties count from player to player vs player to non-player we found that there are not enough ties to compare the two. The ESPN term after considering the player out ties and the the `Nodematch` terms we see that players with higher ESPN ratings are less likely to form ties than to form ties with a probability of 0.47. This does not mean that players with a higher ESPN score tend to form less ties, because we have the Nodeofactor in our model. This term already took into account the networks density which causes ESPN to have a negative coefficient. ESPN is positive when in the model alone meaning that our small network cannot handle too many covariates.

```
Call:
ergm(formula = net2 ~ nodeofactor("playerindict") + nodematch("playerindict",
    diff = T) + nodecov("ESPN"))

Maximum Likelihood Results:

                           Estimate Std. Error MCMC % z value Pr(>|z|)
nodeofactor.playerindict.p  0.84730    0.28274      0   2.997  0.00273 **
nodematch.playerindict.np      -Inf    0.00000      0    -Inf  < 1e-04 ***
nodematch.playerindict.p   -0.09464    0.45231      0  -0.209  0.83426
nodecov.ESPN               -0.11184    0.01265      0  -8.844  < 1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 718.1  on 650  degrees of freedom
 Residual Deviance: 356.8  on 646  degrees of freedom

AIC: 362.8  BIC: 375.5  (Smaller is better. MC Std. Err. = 0)

 Warning: The following terms have infinite coefficient estimates:
  nodematch.playerindict.np
```

Figure 4.3: Ergm Fit on Non-Player/Player network model

The last network we will run a Ergm model on is the Player to player network. Because the number of player to player edges is so few we cannot fit more than a couple covariates. Our main covariate of interest is the ESPN rank due to it being an aggregate of the player statistics created during the game. Players who are higher rated by the ESPN score tend to create more ties. Though we need to take into consideration how sparse our network is and how low the estimate for the ESPN term is. The model with ESPN also fits our player-player network the best using the AIC.

While ESPN is an aggregate score we still want to look at player statistics. First we check MPG or minutes per game. We get a significant positive effect. This makes sense as the more time on the court the more of a connection/camaraderie you can build with your fellow players. These players with more edges also have a higher points per game score, assists and steals per game. Rebounds, and free throw percentages were found to be insignificant in the model. Surprisingly there is no one basketball role that was found to have more ties than any other role on the team.

```
Call:
ergm(formula = g3net ~ edges + nodecov("ESPN"))

Maximum Likelihood Results:

              Estimate Std. Error MCMC % z value Pr(>|z|)
edges        -16.34312    4.10877      0  -3.978  < 1e-04 ***
nodecov.ESPN   0.30269    0.08526      0   3.550 0.000385 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

     Null Deviance: 252.31  on 182  degrees of freedom
 Residual Deviance:  42.08  on 180  degrees of freedom

AIC: 46.08  BIC: 52.49  (Smaller is better. MC Std. Err. = 0)
```

Figure 4.4: Ergm Player to Player

CHAPTER 5

Conclusion

In this thesis we analyzed the social network relationship of the 2022-2023 Spurs team. When initially building our network we saw a cauliflower like structure that told us we needed to trim the network. We eliminated nodes that were unimportant to the over-all structure. This dropped our number of ties and nodes significantly. Our SBM showed clear groupings of nodes in the network but incorrectly qualified a couple of players. These players did not have much tenure with the team but it was ultimately their lack of connection to their fellow players that led them to be grouped with the non-players.

Our Ergms gave more significant results as we were able to add covariates to the model. Players were unlikely to reciprocate any bonds and had no clear preference whether they associated with players or non-players. This showed us that as far as Twitter goes we do not see the team as being particularly close. We also found that a generally better performing player connects more to other players than they do to non-players. Other covariates such as age, or years of service that we would think would be important were found insignificant in our model.

The biggest issue we faced with our network is how sparse it was. Players tended to only tweet for publicity and kept their close ties off of social media. We would had liked to add some dyad or triad terms to see how well the models fits the data using mcmc methods. Some thoughts and ideas we had in order to add more ties was to look at our players nodes across multiple years but the very nature of how players are handled in the NBA make this difficult if not impossible. Players are traded between teams, move, or retire mid seasons, and in between seasons. This of course means we will not have any core player nodes as our Spurs team roster would be perpetually changing. We could also extend the network to add more players and add their respective NBA team as a covariates but this would bring us out of our scope. We would also like to compare and contrast this networks results with those of a popular team or even a team ranked lower than the Spurs.

References

[1] Basketball-reference.com. 2022-23 San Antonio spurs roster and stats, team roster and movements. Accessed August 3, 2023. https://www.basketball-reference.com/teams/SAS/2023.html.

[2] ESPN-Internet-Ventures. Nba rank 2022: Ranking the best players for 2022-23. Accessed Sep 3, 2023.

[3] Goodreau, S.M., K. J. . M. M. (2009). Birds of a feather, or friend of a friend? using exponential random graph models to investigate adolescent social networks. *Demography 46*(1), 103–125.

[4] Holland, P. W., K. B. Laskey, and S. Leinhardt (1983). Stochastic blockmodels: First steps. *Social Networks 5*(2), 109–137.

[5] Zachary, W. W. (1977). An information flow model for conflict and fission in small groups. *Journal of Anthropological Research 33*(4), 452–473.