Survivor Social Network Analysis

Abstract:

This paper examines the Survivor social networks in order to gain insight into how contestants can strategically position themselves to improve their chances of success. By examining centrality measures and conducting network analyses, this paper identifies which measures of centrality encourage and discourage increased success. Through this analysis, we also attempted to see how these strategies might change as each season progresses. This analysis was run on the social network that shows relationships between contestants for each time they both voted out the same other contestant. This analysis was run on a social network which documents the relationships between contestants who both voted out the same player.

Key Words: Network Analysis, Measures of Centrality, Survivor

Introduction:

Survivor is a reality competition television show which places a number of contestants on an isolated island where they must compete to survive by finding food, water, and shelter for themselves. The show was based on the Swedish show of a similar premise, Expedition Robinson. The American version premiered on CBS in 2000, and many other versions of the show have emerged around the world.

The basic format is that 16 or more contestants are taken to a remote island to live off the land for 39 days. At the beginning of the show, each of the contestants are split into two or three “tribes”, which compete against each other in physical and mental challenges throughout the beginning of each season. Winning tribes are granted rewards in the form of flint (for fire), rice (for sustenance), or some other prize to make surviving on the island easier. On the other hand, the losing losing tribe must vote off one of their own members off the island. Around halfway through the show, the tribes are small enough that they are merged, and they work on surviving together, still voting one member off each week. Throughout the season, members can find or win immunity as well as other advantages. Once there are only three remaining contestants, the eliminated players will vote for a winner.

Contestants will frequently make and break alliances to attempt to further their position. One way that these alliances are known is through two or more players voting off the same contestant. For our network analysis, any two contestants who have cast the same vote are considered to have a tie. In our analysis, we will use various measures of social network centrality to predict success in Survivor to determine strategies to improve finding standings. In a more broad sense, we will also analyze measures of coreness to attempt to determine the most ideal initial position to be successful in Survivor.

Related Work:

Data:

We obtained our data from https://en.wikipedia.org/wiki/Survivor_(American_TV_series). The data contains voting information for each season. For each of these seasons, there is a chart displaying who was voted out for each episode. A visual of what this raw data looked like is shown below.

Figure 1: Raw Voting Data - Survivor Season 11

	Original tribes			Switched tribes					Merged tribe							
Episode #	1	2	3	4	5	6		7	8	9	10	11	12	13	14	
Day #	3	6	8	11	14	15		18	21	24	27	30	33	36	37	38
Eliminated	Jim	Morgan	Brianna	Brooke	Blake	Margaret	Brian	Amy	Brandon	Bobby Jon	Jamie	Gary	Judd	Cindy	Lydia	Rafe
Votes	8–1	8–1	7–1	5–3	5–2	6–1	5–1	4–1	6–4	6–2–1	6–2	6–1	4–2	4–1	3–1	1–0
Voter	**Vote**															
Danni	Jim				Blake		Brian	Amy	Jamie	Stephenie	Jamie	Gary	Judd	Cindy	Lydia	Rafe
Stephenie		Morgan	Brianna	Brooke		Margaret			Brandon	Bobby Jon	Jamie	Gary	Judd	Cindy	Lydia	None[a]
Rafe		Morgan	Brianna	Brooke		Margaret			Brandon	Bobby Jon	Jamie	Gary	Judd	Cindy	Lydia	None[a]
Lydia		Morgan	Brianna	Brooke		Margaret			Brandon	Bobby Jon	Jamie	Gary	Judd	Cindy	Danni	
Cindy	Jim			Lydia		Margaret			Brandon	Bobby Jon	Jamie	Gary	Lydia	Rafe		
Judd	Jim			Brooke		Margaret			Brandon	Bobby Jon	Gary	Gary	Lydia			
Gary		Morgan	Brianna		Blake		Brian	Amy	Jamie	Cindy	Jamie	Cindy				
Jamie		Morgan	Brianna	Brooke		Margaret			Brandon	Bobby Jon	Gary					
Bobby Jon	Jim				Blake		Brian	Amy	Jamie	Stephenie						
Brandon	Jim				Brian		Brian	Amy	Jamie							
Amy		Morgan	Brianna		Blake		Brian	Bobby Jon								
Brian		Morgan	Brianna		Blake		Bobby Jon									
Margaret	Jim			Lydia		Judd										
Blake	Jim				Brian											
Brooke	Jim			Lydia												
Brianna		Morgan	Lydia													
Morgan		Lydia														
Jim	Margaret															

Process:

In our raw data, the order of the listed contestants represents their final rankings. The yellow and turquoise colors represent the different tribe allegiances, and the red shows the merging of the ties at episode 8.

To create an incidence matrix from this data, we say there is a tie between any two players who vote out the same contestant during a given voting period. For example, in episode 1, Danni, Cindy, Judd, Bobby Jon, Brandon, Maragaret, Blake, and Brooke all vote to eliminate Jim, so each combination of those players shares a tie. With this, we make the assumption that voting off the same contestant represents a sort of alliance for that week. With more shared votes, those alliances grow stronger. The incidence matrices for each new vote for each new season are created in R.

Before we begin to create igraphs of the data and run regressions to predict rank, the question of leakage must be raised. If we use sets of data from complete season, it would mean that we could only predict the winner of a season after that season has ended. Though interesting, that would not be a particularly useful task. Predicting the winners after the first episode, however, is not preferable due to a lack of data. In order to resolve this issue, we decided to create multiple igraph objects as the season goes on. From here, we can compile data from every season at certain time intervals. That compilation can be split into training and test data to find the MSE for each time interval. This way, we can weigh the value of our prediction against the ability of our prediction to find the ideal time interval at which to create a season's final predictions.

While we originally wanted to choose those time intervals as each episode, there are some nuances to data that have not yet been discussed. As we can see in Figure 1, during Episode 6 there are two contestants voted off. Though not pictured here, some seasons also have votes that end in a tie, where revotes are necessary. In both of these cases, there are two votes for each episode. To resolve this, we decided to create cumulative igraph objects after each vote instead of after each episode, as each vote holds important information. This will later allow us to find the ideal number of voting rounds after which to make predictions. So, for figure 1, there are 14 episodes but 16 sets of votes. Therefore, we will create 16 incidence matrices and igraphs for this season.

Once we have each of these graphs, we are able to calculate measures of centrality. For the final graph from Season 11 as shown above, we get the following centrality measures.

Figure 2: Final Centrality Measures - Survivor Season 11

	name	perc	closeness	betweenness	degree	eigencentrality	pagerank
Danni	Danni	0.94444444	0.018867925	20.7252915	40	6.002514e-01	0.088354589
Stephenie	Stephenie	0.88888889	0.017857143	5.4074638	51	1.000000e+00	0.101960433
Rafe	Rafe	0.83333333	0.017857143	5.4074638	51	1.000000e+00	0.101960433
Lydia	Lydia	0.77777778	0.017857143	5.1454425	48	9.452327e-01	0.096575680
Cindy	Cindy	0.72222222	0.018518519	16.1995030	35	6.294892e-01	0.077143352
Judd	Judd	0.66666667	0.018181818	12.1166922	33	6.317613e-01	0.071540217
Gary	Gary	0.61111111	0.018181818	9.7409031	32	4.664170e-01	0.071707100
Jamie	Jamie	0.55555556	0.017543860	3.1808584	33	6.663252e-01	0.069360888
Bobby Jon	Bobby Jon	0.50000000	0.017857143	8.1637530	22	2.290749e-01	0.055439375
Brandon	Brandon	0.44444444	0.017543860	3.6204526	18	1.761441e-01	0.048055412
Amy	Amy	0.38888889	0.017857143	3.3447232	21	3.172805e-01	0.049822069
Brian	Brian	0.33333333	0.017543860	0.9474528	17	2.809181e-01	0.041459459
Margaret	Margaret	0.27777778	0.016666667	0.0000000	9	8.359645e-02	0.029534240
Blake	Blake	0.22222222	0.016666667	0.0000000	8	6.964202e-02	0.027055405
Brooke	Brooke	0.16666667	0.016666667	0.0000000	9	8.359645e-02	0.029534240
Brianna	Brianna	0.11111111	0.016129032	0.0000000	7	1.247705e-01	0.022092198
Morgan	Morgan	0.05555556	0.003267974	0.0000000	0	1.864143e-18	0.009202454
Jim	Jim	0.00000000	0.003267974	0.0000000	0	1.864143e-18	0.009202454

For each contestant in the series, we see their name, various centrality measures, and the variable “perc”. Since the various seasons have differing numbers of contestants, to run regressions predicting performance we must create a measure consistent across seasons. To do this, we found the final percentile of performance, which is our y variable. For each season, this variable will stay consistent across votes, as it represents their final percentile. Our x variables will be the measures of centrality: closeness, betweenness, degree, eigen-centrality, and pagerank. By figuring out what effect these measures have on final percentile, we can help develop strategies for Survivor success.

To reiterate, these voting intervals are cumulative. While “Vote_1” holds incidence matrices for only the first round of voting, the incidence matrices held in “Vote_4” hold the cumulative voting ties from rounds 1 through 4.

At this point in our process, we have 16 lists, representing the 16 voting time intervals needed for the seasons. Each of these lists contains data frames for each season with 7 columns as shown in figure 2, and a row for each contestant in that season. Figure 2 is one entry in our 16th list, denoted “stat16”.

Now, we are finally able to create our 16 regressions. For each, we split our data into a test set and a training set. After using the model trained on our training set to predict results on our test set, we are able to calculate the MSE after each vote.

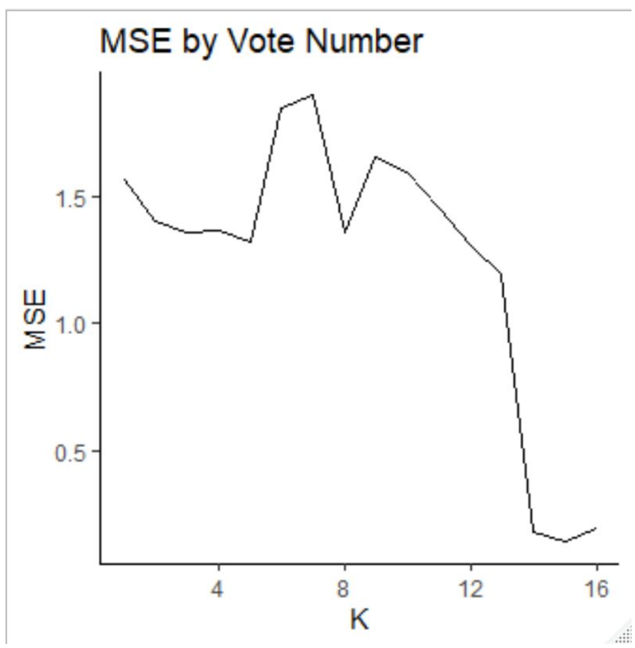
As mentioned earlier, we also want to determine which initial position, core or periphery, is ideal for success in Survivor. In order to observe ideal coreness trends over time, we first must calculate the coreness statistics for each player for each vote. We did this in the same way that we calculated centrality statistics. Next, since we only want to observe top players, we needed to define what it means to be a top player. As stated earlier, since each season has a different number of total players, we decided on percentiles. We define top players as the top 80% of players. Our subset of “elite” player wound up as about 3 or 4 players per season. Once we filtered for top players, we had 16 lists, of coreness values for each elite player as the season progresses. After taking the average of all elite players coreness statistics over the course of their seasons, we’re able to observe how the most successful players coreness changes over time.

Results:

Ideal Amount of Data

As stated in our process, we found the MSE for the predictions using regressions after each episode. The graphed MSE is below.

Figure 3: MSE by Vote Number



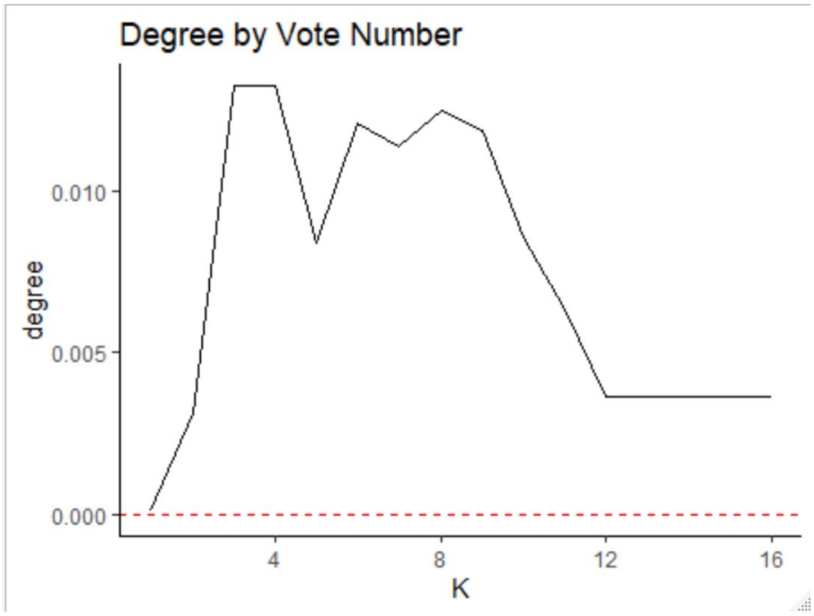
As we can see, the data has two notable local minimums at k=5 and k=8. After episode 9, the MSE consistently decreases, with a global maximum at vote 15. As stated earlier, although accurate, these predictions may not be valuable as votes earlier on, since many of the contestants have already been eliminated at this point. We would label vote 5 as the ideal number of votes to make a final prediction. At this point, there are enough contestants still in the show to make educated guessing unreliable, but we are still confident that we can make good predictions.

Importance of Centrality Measures

While the results of the first few regressions are less reliable due to a lack of data, as we move forward in the time interval the variables that are consistently statistically significant are degree, eigen-centrality, and pagerank.

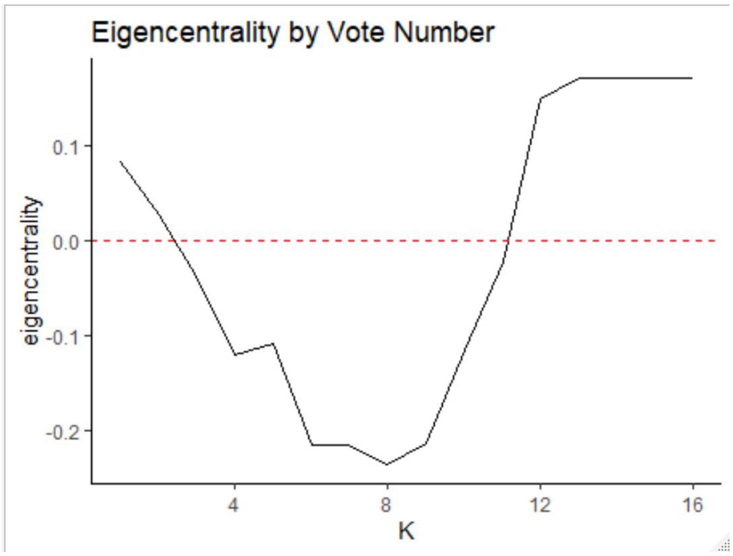
The degree centrality is enormously important to success. The more times a player can vote similarly to the people around them, the better. Averaging over all the voting periods, each additional tie will raise a player's final percentile by about 1%. This indicates that a player should always vote with the majority, as it will give them the most social ties, and therefore, the greatest chance at success. Figure 4 indicates how the coefficient of degree changes over the voting periods. As we can see, it is consistently positive, showing more social ties will always help a player's chances of winning.

Figure 4: Degree Coefficient Over Time



Eigen-centrality, or the importance of a player's strong social ties, is also significant in determining final percentile. However, its coefficient varies quite a bit over time. In general, for the middle of the season, a higher eigen-centrality will indicate a lower final percentile, while later in a season a higher eigen-centrality will result in more success. This is displayed in the figure below.

Figure 5: Eigen-Centrality Coefficient Over Time



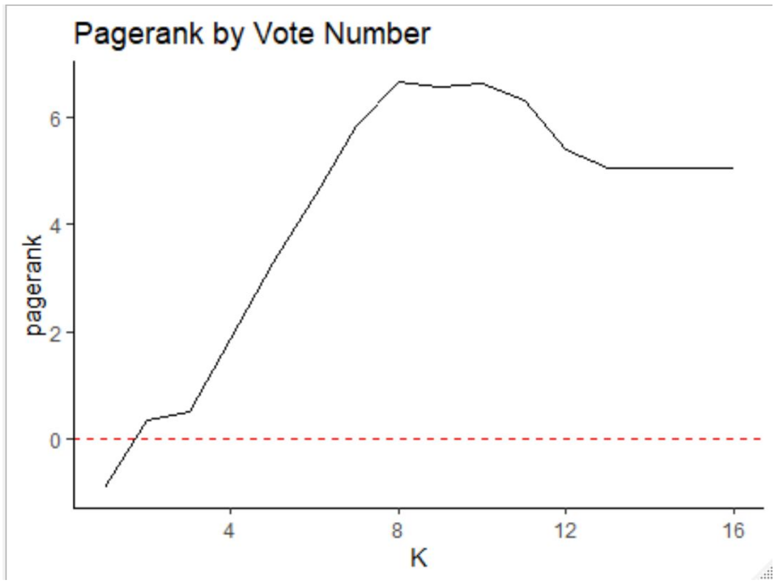
It seems like it steadily decreases until Episode 8 and then steadily increases until 11 or 12 where it levels off. Interpreted in the context of the show, it seems that before the merge, it is better to be connected to weaker players that will be voted off for simple things (like being bad at challenges or having a personality that people don't want to live with). These little things contribute to eliminations in Survivor's "early-game". By the merge, when many of these smaller players have been voted out, it is ideal for an individual to surround themselves with power players, rather than associating with weak players, in order to avoid being voted out. Players who surround themselves with weaker players will, themselves, be seen as weak. Ideally, a player should be in the middle of the pack: they aren't a weakling (bad strategist, not a lot of connections, bad at challenges, etc.) but they also are not the top player, which would make them a clear target. In terms of the show, an ideal strategy is for a player to fly under the radar and be the most average person they can be, so they don't draw a lot of attention to themselves but still have the "in" with the stronger players (i.e. a high eigen-centrality).

By the end of the game, a player's eigen-centrality can be high because there are so few people left that it is hard for a huge group to turn against them at this point. Here, a player's connections are crucial to their success.

Another possible explanation for the steady increase towards the end of the season, which may pose as a limitation, is that there are fewer people left in the game so most people left are more powerful on average than those in the beginning of the competition.

Pagerank is also significant when it comes to determining success. As shown in figure 6, pagerank consistently has a positive effect on success. On average, a 0.01 increase in pagerank will result in about a 4% increase in success.

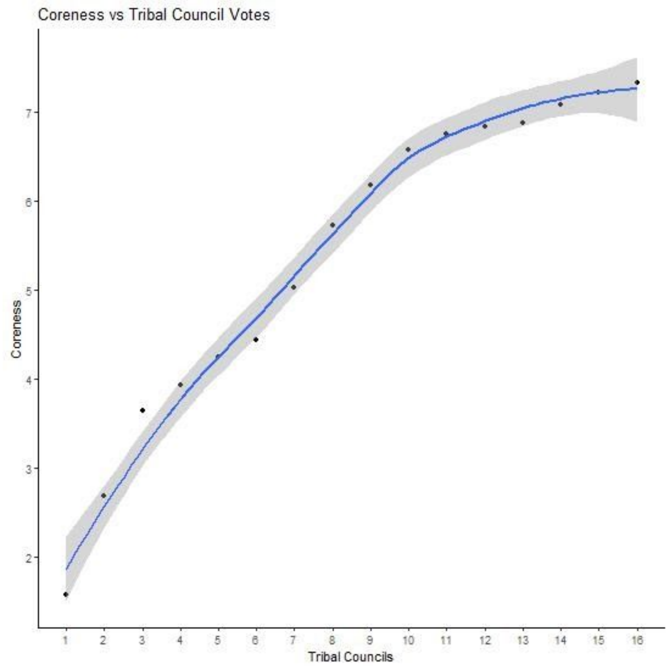
Figure 6: Pagerank Coefficient Over Time



Coreness:

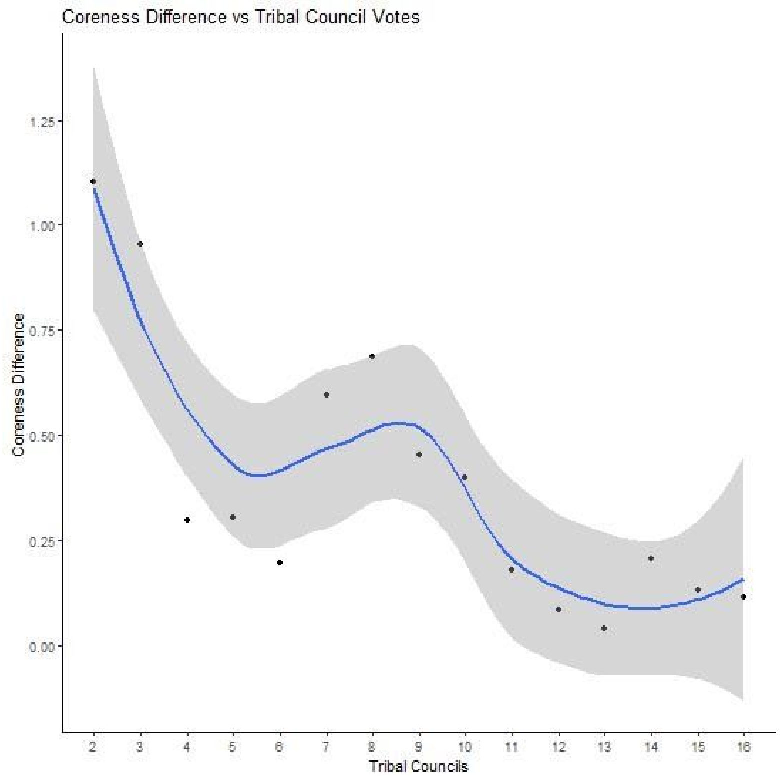
Once we had the measures of elite player coreness over time, we are able to graph their averages in figure 7 below for each of the 16 possible voting rounds. Viewing it, we see a clear and consistent upward trend of coreness.

Figure 7: Elite Player Coreness Over Time



This is what we expected, as top players have coreness values that should steadily increase throughout a season given that they will have more ties as the season goes on. We understand, however, that this is clearly biassing our results, as coreness will naturally increase for all players who are in the game for a longer period of time. To find a more meaningful interpretation, we looked at the rate of change of coreness for elite players over time, as shown in Figure 8.

Figure 8: Change in Coreness Over Time



We see that the rate of change in coreness starts fairly high. In the beginning of the game, it's better to be in the core because many of the players haven't formed strong ties yet, and the periphery could be seen as an easy target. But then, relative coreness should be a bit lower, as a player doesn't want to be seen as an early threat to tribemates, which could lead to their tribemates voting them out early. Around Episode 8 or 9, coreness rate of change spikes up again. We believe that the coreness increases here for a similar reason to why it starts out very high - Episode 8 or 9 is right after the remaining players from each tribe merge into one group. At this second critical juncture, players from both tribes come together and begin forming new ties. Here, it is essential for players to form ties with members of the other tribe. At the end of the show, remember, the players who have already been eliminated will vote for the winner, so it's important to form relationships with as many new people as possible to branch out into the other tribe. But in the few votes before the final vote, as we stated earlier, if a player is in the periphery, it could help prevent competitors from seeing them as too much competition and voting for their early elimination. Overall, it's best for a player to strategically form ties to players from both tribes while also not seeming so powerful that they are targeted. This is consistent with our earlier evaluation of eigen-centrality.

Following link has visuals for season 15 to see how the top 3 players have taken place in core-periphery structure over time

GIF Legend: GIF of Survivor China; Season 15

Still Playing	First Place
Just Voted Out That Episode	Second Place
Already Eliminated	Third Place

Strategies Over Time:

We also looked into whether or not we could evaluate social whether there were any trends present in changes in game strategies. For example, we hypothesized that in the first five-ten seasons or so, the show would be so new that advanced strategies would not be formed. Theoretically then, in the next ten-twenty seasons, players would come into the game with more awareness of the show and strategies that worked over time.

As a fan, it's easy to see how common player strategies have changed over time, so we wanted to see if that in any way affected the data and our regressions.

Figure 9: Regression Using Bin Variables

```
> vote_5_regression=lm(perc~degree+closeness+betweenness+eigencentrality+pagerank+seasons ,data=vot
e_5_train)
> summary(vote_5_regression)

Call:
lm(formula = perc ~ degree + closeness + betweenness + eigencentrality +
    pagerank + seasons, data = vote_5_train)

Residuals:
     Min       1Q   Median       3Q      Max
-0.64636 -0.23052  0.02555  0.24104  0.61505

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.7477454  0.0344646  21.696  < 2e-16 ***
degree              -0.0087376  0.0037568  -2.326  0.02032 *
closeness           -1.4040415  2.1949448  -0.640  0.52260
betweenness          0.0004724  0.0007383   0.640  0.52249
eigencentrality      0.1165148  0.0418301   2.785  0.00549 **
pagerank            -3.3860191  0.5705578  -5.935 4.69e-09 ***
seasonsseason1to9    0.0158076  0.0310370   0.509  0.61070
seasonsseason20to28 -0.0118223  0.0297446  -0.397  0.69115
seasonsseason29to38 -0.0267730  0.0293435  -0.912  0.36188
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2741 on 682 degrees of freedom
Multiple R-squared:  0.1078,    Adjusted R-squared:  0.09734
F-statistic:  10.3 on 8 and 682 DF,  p-value: 1.159e-13
```

From our data, we were not able to find any significance in these "meta-changes". As we can see, the t value for season bins are all < 1 and the Pr(>|t|) are all > 0.05, so the results are insignificant. However, this does not mean strategies haven't changed since Survivor's conception - in fact they most certainly have, it is just that our data is not able to measure them. Our ties are formed when two players vote the same person out at a tribal council. Thus, it doesn't really account for lots of different strategies take place forming prior to the vote itself. Rather, our data just gives us the end result. In this way, we don't get to see the process behind *why* a person is voting for another out. Thus, there are limitations to our data.

Current Season Predictions:

As of the day of submission, December 9, 2019, there have been 14 rounds of voting and 11 episodes in the current season, 39. The season began with 20 contestants and only 7 remain. We used our model to predict the final ranking, using the model from vote 5, our ideal choice, inputting only the players that remain. The results are as follows.

Figure 10: Season 39 Predictions Using Model 5

	players	predict_5	rank
1	Dan	0.5244337	3
2	Dean	0.5318854	1
3	Elaine	0.4532687	6
4	Janet	0.4421472	7
5	Lauren	0.5244337	5
6	Noura	0.5244337	2
7	Tommy	0.5244337	4

We will have to continue watching to see how accurate our predictions are.

Conclusion:

In conclusion, our findings are consistent with our understanding of the show. We can see in our figures how strategies tend to change during the critical moment of the tribal merge, and as the season comes to a close. We find that at the key moments of the beginning of the show and the time of the tribal merge, it is important to be a central player, making as many ties as possible. However, in the interim, it can be helpful to blend in with the crowd and be a well liked member of the middle of the pack.

In terms of our ability to predict the ranks, although our results will be more accurate towards the very end of the season, our ability to predict is still quite good throughout the show. Therefore, we can use our models from each voting period to continuously update our predicted ranks as new seasons progress.

Future Work:

In terms of future work, it might benefit our results to come up with a more creative concept behind a social tie. It could be something as simple as how many seconds two contestants interact in a given episode. Or perhaps, we could have tried to gather the script from each episode and use that to measure how many lines come in between two players speaking on the show. While the data collection behind more subjective measures like this may be incredibly time consuming, it may provide a more nuanced idea of what kinds of social interaction is important.

We also would like to look into different measures of connectivity between the tribes and how those ties can play out in the end-game. This could mean looking closer into the length of time two people have had a tie - the earlier the tie was formed, likely the stronger the tie is. In this way, we could establish another method to measure the strength of a tie.

Finally, we would also like to take a deeper dive into strong triadic closure on the show. Perhaps, it would be interesting to see if it is significant, but since we felt we would need more subjective data to determine a strong vs. weak tie, we were unable to properly measure STC in Survivor.

Citations:

"Survivor (American TV Series)." Wikipedia, Wikimedia Foundation, 9 Dec. 2019, https://en.wikipedia.org/wiki/Survivor_(American_TV_series).

Appendix:

We came up with two methods in training the model, which is as follows.

Model5, Method 1:

Train the model using data from the first 5 episodes in all 37 seasons, then predict episode 5 of the 38th season. This model uses the 38th season as a validation set, in order to see how it would fare on new unseen data from new seasons in the future.

```
> #run regression
> vote_5_regression=lm(perc~degree+eigencentrality+pagerank ,data=vote_5_train)
> summary(vote_5_regression)

Call:
lm(formula = perc ~ degree + eigencentrality + pagerank, data = vote_5_train)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.64488 -0.22423  0.02351  0.24399  0.60155 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)      0.727547   0.025090  28.997  < 2e-16 ***
degree          -0.008928   0.003460  -2.580  0.01008 *  
eigencentrality  0.111261   0.041078   2.709  0.00693 ** 
pagerank        -3.244870   0.548827  -5.912 5.31e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2735 on 687 degrees of freedom
Multiple R-squared:  0.1048,    Adjusted R-squared:  0.1009 
F-statistic:  26.8 on 3 and 687 DF,  p-value: < 2.2e-16
```

Model 5, Method 2:

This model combines players from all seasons. The model trains by randomly sampling 70% of the data into a train dataset, and then predict 30%, the test dataset.

```
> #run regression
> vote_5_regression=lm(perc~degree+closeness+betweenness+eigencentrality+pagerank+seasons ,data=vote_5_train)
> summary(vote_5_regression)

Call:
lm(formula = perc ~ degree + closeness + betweenness + eigencentrality +
    pagerank + seasons, data = vote_5_train)

Residuals:
     Min       1Q   Median       3Q      Max
-0.64636 -0.23052  0.02555  0.24104  0.61505

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.7477454  0.0344646  21.696  < 2e-16 ***
degree              -0.0087376  0.0037568  -2.326  0.02032 *
closeness           -1.4040415  2.1949448  -0.640  0.52260
betweenness          0.0004724  0.0007383   0.640  0.52249
eigencentrality      0.1165148  0.0418301   2.785  0.00549 **
pagerank            -3.3860191  0.5705578  -5.935 4.69e-09 ***
seasonsseason1to9    0.0158076  0.0310370   0.509  0.61070
seasonsseason20to28 -0.0118223  0.0297446  -0.397  0.69115
seasonsseason29to38 -0.0267730  0.0293435  -0.912  0.36188
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2741 on 682 degrees of freedom
Multiple R-squared:  0.1078,    Adjusted R-squared:  0.09734
F-statistic:  10.3 on 8 and 682 DF,  p-value: 1.159e-13
```

With only significant coefficients:

```
> #run regression
> epi_5_regression_70_30 =lm(perc~degree+eigencentrality+pagerank ,data=train_df5)
> summary(epi_5_regression_70_30)

Call:
lm(formula = perc ~ degree + eigencentrality + pagerank, data = train_df5)

Residuals:
     Min       1Q   Median       3Q      Max
-0.66733 -0.21004  0.02245  0.23777  0.49273

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.770523   0.030262  25.461  < 2e-16 ***
degree          -0.006839   0.004112  -1.663   0.0969 .
eigencentrality  0.104878   0.048139   2.179   0.0298 *
pagerank        -4.096986   0.681936  -6.008 3.66e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2672 on 493 degrees of freedom
Multiple R-squared:  0.1291,    Adjusted R-squared:  0.1238
F-statistic: 24.36 on 3 and 493 DF,  p-value: 1.025e-14
```

Based on the two methods, we choose method 1 for Model5. This is because, RMSE for method 1 is 1.33, while RMSE for method 2 is 1.71