Shared Structures in Campaign Donation Networks & Congressional Voting Patterns on Union-Related Bills

Nina-Marie Cielo* Cameron Eller† Jake Pellett‡ Tommy Schupp§

2024-01-12

Abstract

We explore the potential variations in congressional AFL-CIO union scorescards among communities created by donor networks. The Null Hypothesis posits that these communities exhibit the same mean union score, while the Alternative Hypothesis suggests differences in mean union scores. To investigate these hypotheses, we conduct a comprehensive analysis of various donor network communities, employing Analysis of Variance methods to assess and compare their union scores. We find that communities created by donor networks meaningfully represent different mean AFL-CIO union scores.

1 Introduction

In the ever-evolving landscape of political campaigns, understanding the intricate web of connections between individual donors, political action committees (PACs), and candidates is paramount. In this paper we argue that there exists a connection between donation networks and congressional voting behavior as related to favoribility towards unions.

This paper presents a comprehensive analysis utilizing graph theory methods as well as the igraph package in R to unravel the dynamics of political contributions and community structures. Our analysis utilizes donor information available on Open Secrets to create a bipartite graph connecting like donation recipients (members of Congress), which we then projected onto a one-mode graph. The donor information we collected is of donations over $1000 made by both individuals and PACs in the year 2022.

After projecting onto a one-mode graph, we utilize the walktrap algorithim to create like groups of congresspeople. With these groups, we performed an Analysis of Variance test (ANOVA) to investigate a connection between donor network groups and union scores, (as calculated by the AFL-CIO union scorecard for 2022). The union score is a measure representing the favorability a congressperson has in their voting behavior towards union related legislation and nominations. Were there no connection between donor network groups and congressional union scores, we expect that the result of the ANOVA test will conclude the different network groups have the same mean union score. Our results indicate that the mean union scores amongst groups are in fact different,

*American University
†American University
‡American University
§American University

and therefore we reject that there is no connection between union scores and donation network groups.

These results offer insight into the ways in which money donated to campaigns, on both an individual and PAC level, influence the voting behaviors of members of Congress. Utilizing the different groups formed in our network analysis we classify such groups by identifying common attributes within each group. We hope that by identifying and classifying these groups, as well as associating their union score information, we can inspire future research to utilize graph theory to answer questions about the relationship between congressional voting patterns, influential donators, donation networks, and investigation of dark money.

2 Political Donations and Network Analysis

The last year has been marked by a growing number of coordinated labor movements and union action across several industries in the United States. Our research explores the nature of connections between labor union legislative scorecards from members of congress and the networks that prolific and wide reaching large campaign contributors create.

When a donation is made to a campaign there are a number of political implications involed, including but not limited to ideological transparency and the degree of a representative agenda. The actions that a congressperson takes to attract donations to further their own interests is also a deep topic of study. La Raja, Raymond J., and Brian Schaffner (2015) theorize that candidates who receive very large funding from individuals are very likely to be ideologically centrist, while candidates who seek funding from large amounts of small donations are more likely to be ideologically extreme. Additionally, the theory extends to corporations and business groups to claim that they will tend to favor moderate and conservative officeholders who will bargain over specifics rather than overarching ideological change. Ultimately, large donations from corporations are likely to skew toward conservative networks in congress, while large donations from individuals are likely to flow to centrist networks.

The academic literary body surrounding lobbying and political donations is dense, but there is a distinct reduction in the post Citizens United v Federal Election Commission (2010) world. Hansen and Rocca (2019) draw a clear line in analysis of individual campaign contributors in the pre and post Citizens landscape to argue that a flood of extremely large donations to super PACs have contributed to a reduction in academic research surrounding political donations. A disproportionately large influence of massive donations and dark money came into elections after the Citizens United decision, making money harder to track as it flows through super PACs instead of traditional systems. We are drawing connections from known data points and contributors so that the picture can become clearer and more nodes on the network can be explained.

Graph theory is a powerful tool for analyzing complex systems of interacting agents in the political context. Porter et al. (2005) set the precedent to project bipartite networks onto one-mode networks, where the strength of connections can be quantified using the normalized interlock, as an effective method of congressional network analysis. Our chosen method of clustering is the walktrap algorithm, discussed in greater detail in the following sections.

3 Data and Methods

For this study, we utilize two primary datasets. The first dataset is donation information to congresspeople from both individuals and PACs throughout 2022, collected from Open Secrets. The second dataset is the 2022 union scorecards of both House and Senate members as calculated by the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO).

To clean the Open Secrets data we isolate the donors who contributed over \$1000, identifying these as 'large donors' for the purposes of our analysis. Typically, a large donation is classified as anything over \$200, but including all donations greater than \$200 is not within the scope of our current analysis. Therefore our networks are constructed of particularly large donors.

OpenSecrets' bulk data is freely available for educational purposes, but it is available "warts and all". The data is available only as .txt files that are delimited using a non-standardized coding. Campaign finance data from OpenSecrets is compiled, cleaned, and standardized using data from the Federal Election Commission (FEC). The data guidebook emphasizes that users should avoid double counting individual contributions to PACs, so we did not include individual donations to PACs in our analysis.

Data provided by
OpenSecrets.org
Center for Responsive Politics

We standardize the names of the Congress members to simplify key-matching across our data sets, and simplify the recorded party information of the members. We also encode each observation with a ('p') or an ('i') to represent whether that donation was from a PAC or individual respectively.

This data set has many features making it difficult to navigate and clean. First, the files are extraordinarily large. Before cleaning, the original individual donations file is 15GB. We also use joins and merges to connect disparate data sets containing different information so that we can consolidate the information we want. For example, the individual donors data set does not have candidate names, only their ID numbers. So, we have to cross-reference with a key set that corresponds ID numbers to candidate names. Additionally, our analysis does not depend on the date the donation was made, as long as it was within the year 2022.

Many PACs made multiple donations to the same candidate. To reduce our required processing power and the time it takes to run our network analysis, we total the amount donated by one PAC to a specific candidate, and list it as one observation, removing duplicates.

Our finalized data set includes the donor name, the amount donated, whether the donor was an individual or PAC, the member of Congress who recieved the donation, the party of the congressperson, and the lifetime union score of the congressperson. We have a total of over 14 million observations.

The AFL-CIO Union Score is a number created by the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO), which represents a congressperson's favorability towards unions through their voting patterns. The AFL-CIO separates their score calculations based on the chamber the congressperson is in as the House and Senate hold different votes. Additionally, while the union score for House members is calculated using bills and resolutions, the union score for Senate members also takes into account nominations. The score itself is calculated by taking a percentage of how often a congressperson voted in favor of union interests out of how often that member actively voted. The score is also calculated for each year, and averaged into a lifetime score. For example, as Representative Mary Peltola of Alaska did not take office until September 13 2022, her score calculation in the 2022 dataset for the House does not take into account the eight bills the score card tracked before September 13. The first bill tracked by the score card that she was eligible to vote on was the Presidential Election Reform Act (H.R. 8873), which held its roll call vote on September 20, 2022. After she took office the score card tracked five bills, four of which she voted yes on and one that she abstained, making her score for 2022 100%.

For our paper, we use the lifetime scores of congresspeople as calculated in the 2022 data sets. In the House data set, the score card tracked twelve bills and one resolution. In the Senate data set, the score card tracked five nominations, six bills, and one resolution.

Notably, the union scores are not weighted by popularity of the legislation or nomination up for vote or any other factors. For example, a congressperson voting in favor of a bill despite many of their peers not voting for it does not influence their score other than the fact that they voted affirmatively. In future analysis, weighting the union score by different legislation's popularity, as well as taking into account type (for example appropriations, resolutions, or even levels of nomination such as Supreme Court nominations), could help to identify the 'extremeness' and 'strength of convictions' of a candidate.

We leverage the igraph package in R to construct network graphs, visualizing connections between Congress members based on donor contributions. We start with a bipartite graph: directed connections from donors to Congresspeople. The method we use to project this is that two Congresspeople are connected if they have a mutual donor. The weight of the connection is the sum of the contributions of the mutual donor to both candidates. Nodes, representing Congress members, are sized proportionally to the total amount donated.

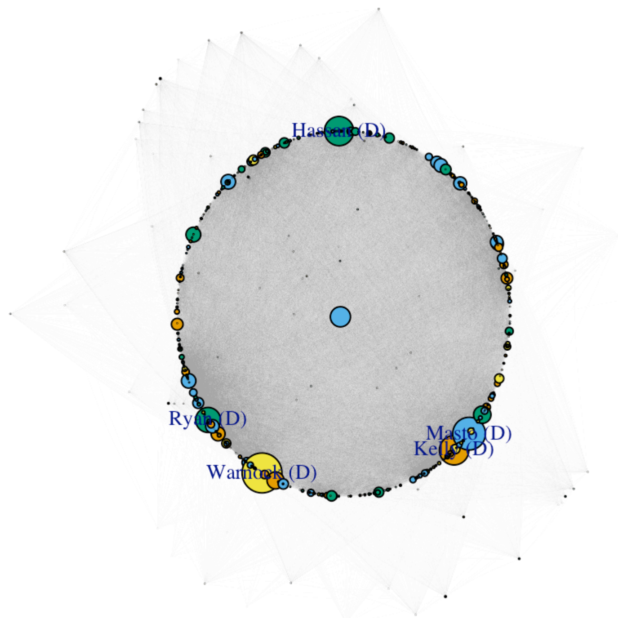
This took an extraordinarily long time to learn, but the results are fascinating. The graphs that we create are extremely complex and with more time, we would learn more methods of representing the information. This is our first time using graph theory, as we were deeply inspired by Dr. Hans Noel, and we used the notes provided to us by him. Moreover, we were originally not aware of the LGL (large graph layout), which sped up our processing time by orders of magnitude. When we first ran the code to draw these graphs, it took 15 hours to draw a single graph. With LGL, the process is sped up into minutes. We also achieve increased performance speed by vectorizing the operations we use, which is demonstrated in the code we have in our GitHub.

For the graphs, some of the most influential individual large donors are the physician Karla Jurvetson, investor Seth Klarman, philanthropist Ari Nessel, philanthropist Cherna Moskowitz, and investor Steve Mandel. The most influential PAC donors are the Congressional Leadership Fund, the Senate Leadership Fund, the Senate Majority PAC, the National Republican Congressional Committee, and the Club for Growth Action.

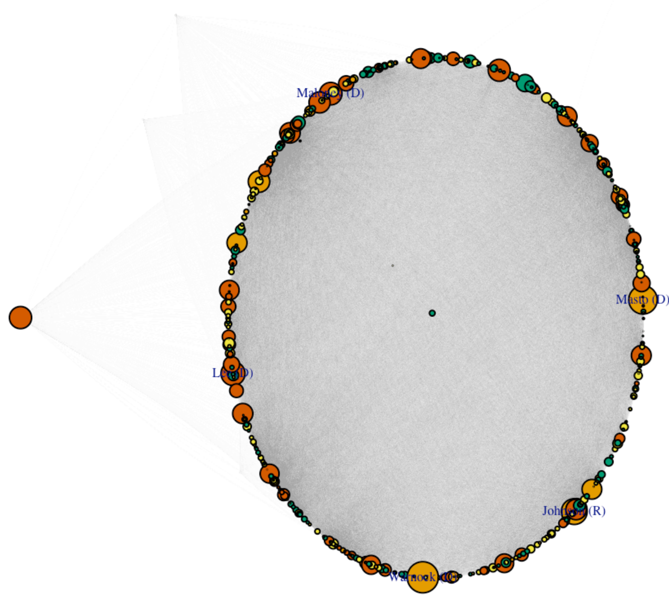
We also employ a walktrap function to identify groups within the network. We choose a number of steps that provide us with a number of groups that align with our expectations (more than 2, but not too many). Many configurations of the steps parameter lead to either far too many groups or simply two (Democrats and Republicans). We then transform the final communities we land on into a data frame, enabling us to associate the union scores and group ids to speicific Congress members.

This graphical representation facilitates a comprehensive exploration of relationships within and between these donor groups. The graphs could be a lot cleaner and more thoughtful.

The size of the vertex in the graph is a function of how well connected they are: it is a sum of their total edge weights to all other Congresspeople.

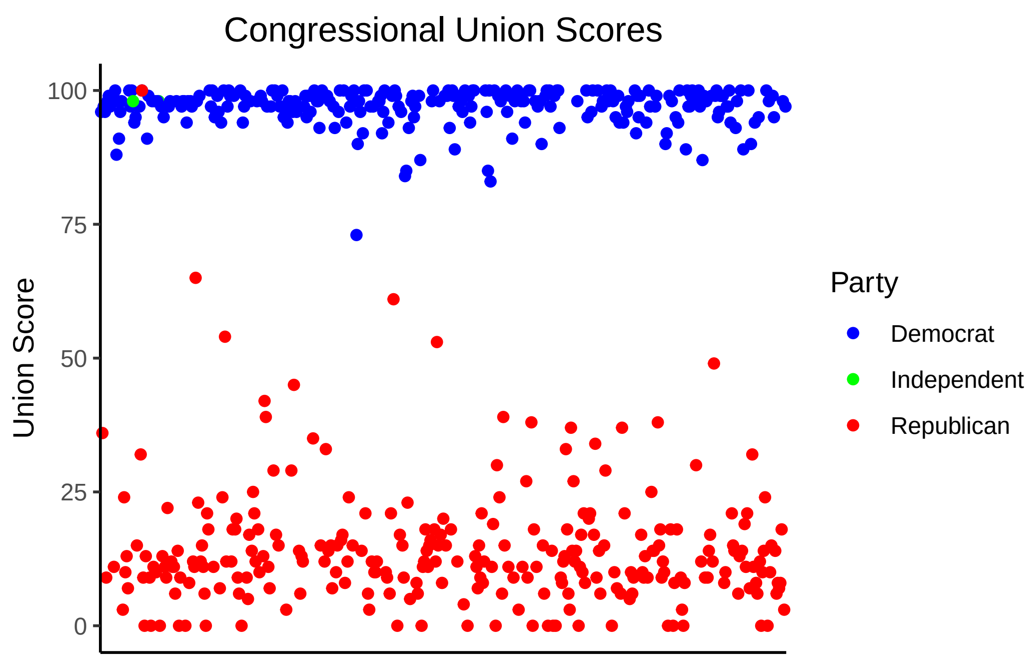


Above is the graph of the individual donation network. The candidates with the most prolific donor connections are highlighted by showing their names. Communities are distinguished by colors. The most connected Congresspeople are Raphael Warnock, Catherine Cortez Masto, Mark Kelly, Maggie Hassan, and Tim Ryan.



Above is the graph of the PAC donation network. The candidates with the most prolific donor connections are highlighted by showing their names. Communities are distinguished by colors. The most connected Congresspeople are Raphael Warnock, Catherine Cortez Masto, Ron Johnson, Susie Lee, and Sean Patrick Maloney.

For statistical insights, we implement code to perform ANOVA on the identified communities, assessing differences in mean Union Scores. We also conduct additional analyses, such as graphical representations of score and donation distributions.



For ease, we rename the communities we create based on the political characteristics of their members. The full communities are not included, but are available on our GitHub.

3.0.1 For Individual Contributions:

3.0.1.1 Community 1: Major Fundraisers

Major names: Bernie Sanders, Kyrsten Sinema, Alexandria Ocasio-Cortez, Joe Manchin, Chuck Schumer, Jon Ossoff, Tammy Duckworth

This group is comprised of both Senators and Representatives, primarily Democrats and some Independents, but mainly 'very nameable' players who are successful at fundraising.

3.0.1.2 Community 2: Extreme Ideological Statements

Major names: Elizabeth Warren, Ed Markey, Nancy Pelosi, Matt Gaetz, Lauren Boebert Marjorie Taylor Green

Individual donors generally donate to congresspeople with more extreme ideological positions, but they also cast their financial support to institutional players or congresspeople that they are making a clear statement to by donating. This is a more extreme group of donors, placing a focus on contemporary and new shifts in the political landscape.

3.0.1.3 Community 3: The Fringe

Major names: Adam Schiff, Scott Perry, Connie Conway

A majority of the members in this group are congresspeople on the political fringe or are developing and shifting their niche. They are not engrossed in the current political machine, but they do have developments that are upcoming.

3.0.1.4 Community 4: The Battleground

Major names: Raphael Warnock, Hakeem Jeffries, Rand Paul, Rick Scott

A majority of these are either currently elected or are elected into competitive districts. The major connections in this community will be found in donors who are spending on current competitive elections.

3.0.2 For PAC Contributions:

3.0.2.1 Community 1: Battleground Senators

Major names: Bill Foster, Tim Ryan, Raphael Warnock, Jon Ossoff, Elizabeth Warren

A majority of the members in this grouping are Senators, and many are also either recently elected or have been elected in battleground states.

3.0.2.2 Community 2: New Era Conservatives

Major names: Ted Cruz, Lindsey Graham, Marjorie Taylor Greene, Lauren Boebert

This group was not used for analysis due to the relatively small group size, but it is comprised of the major players in the new era conservative movement.

3.0.2.3 Community 3: Range Senators

Major names: Tammy Baldwin, Rick Scott, Joe Manchin, Kyrsten Sinema.

This group holds both the most ideologically extreme senators and the most centrist senators who generally act as swing votes in key legislative moments, it is likely that 'far' left PACs and 'far' right PACs donate with the interest to sway them.

3.0.2.4 Community 4: Catch All

Major names: Nancy Pelosi, Jared Huffman, Sheila Lee, Al Green, Adam Schiff, Ayanna Pressley, Yvette Clarke, Ed Markey

The largest community features pillars of the Democratic party and the generally left leaning house of representative members. It seems that these PACs donate to candidates with the intention of having a majority of house members to pass democrat-agenda legislation.

3.0.2.5 Community 6: Centrist House Members

Major names: Chris Pappas, Tom Malinowksi, Susie Lee, Haley Stevens

This group is very similar to group 4, but featuring some pillars of the modern Republican strategy with a slight weight towards the ideological center. This group is also smaller than group 4, placing a bigger emphasis on members with generally strong positions on a single main issue.

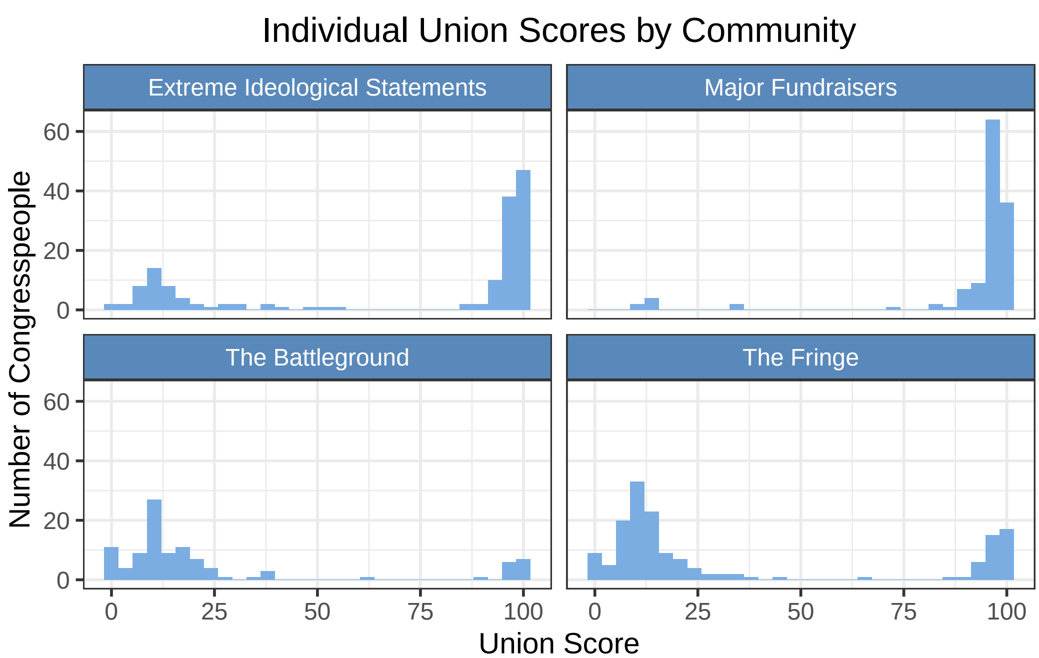
4 Results

After organizing communities by donor networks for both large individual donors and large PAC donors, we test the mean union scores of the communities using an Analysis of Variance (ANOVA) Test. Using an ANOVA depends on certain assumptions being fulfilled.

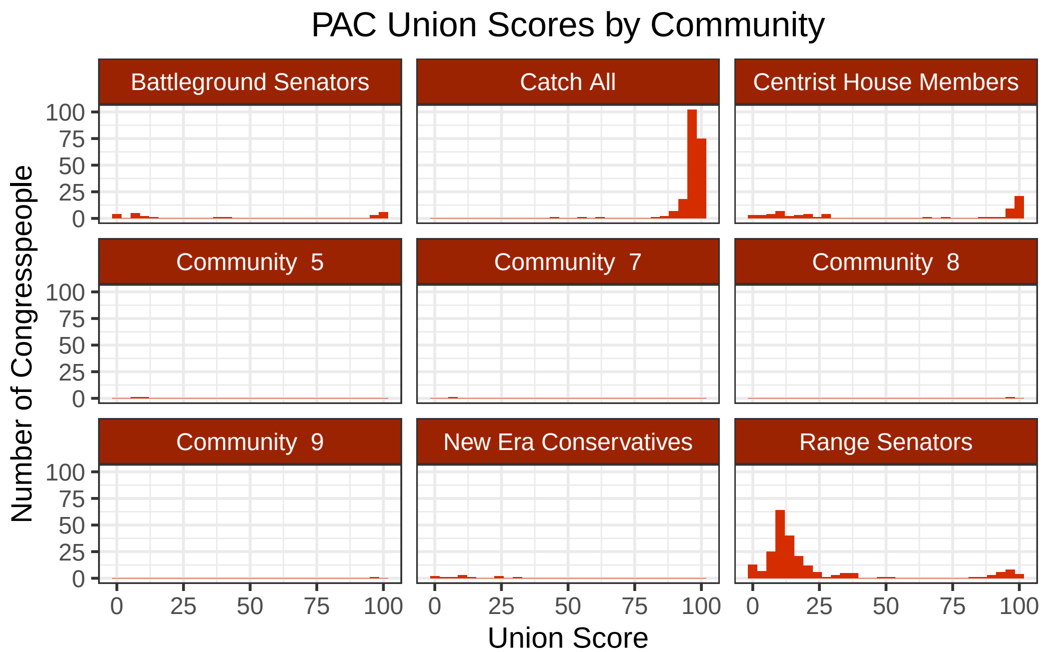
The ANOVA Assumptions are that 1. Each community has a normal population distribution of union score, 2. The union scores of congresspeople are independent, 3. The union scores between communities have an equal variance.

We begin by addressing these assumptions.

First, we examine the union score histograms of the large individual donor communities. Community 1 and Community 4 both seem to be unimodal and normally distributed, however, both communities have some skew. Community 2 and Community 3 are both bimodal with peaks on both ends of the union score spectrum. They do not seem to fit the normality assumption very well.



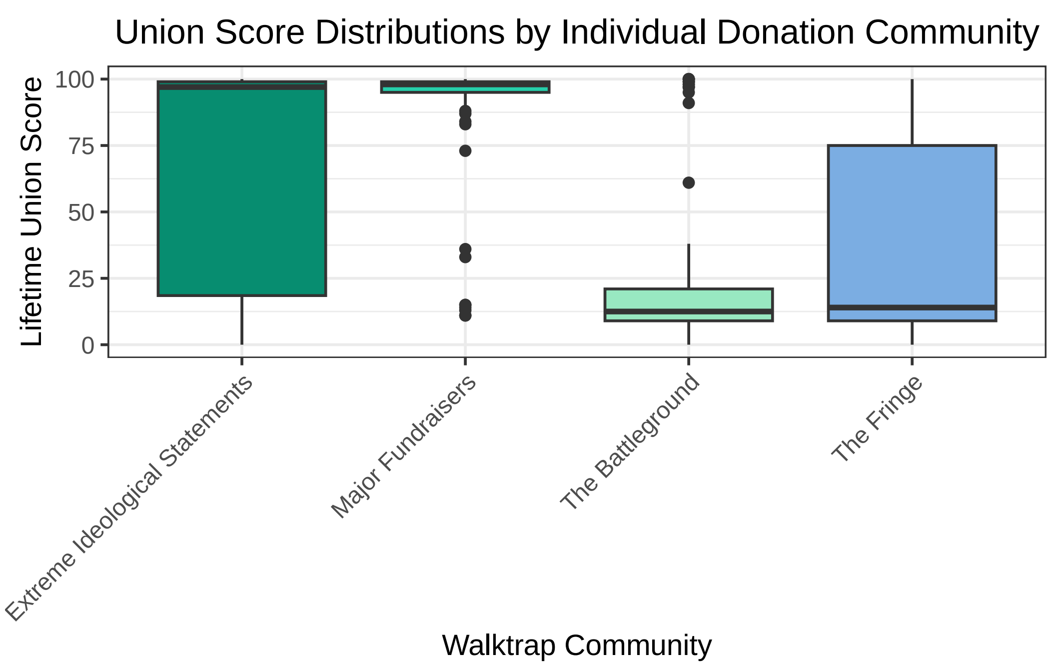
Now, we examine the union score histograms of the large PAC donor communities. First, note that Community 2, Community 5, Community 7, Community 8, and Community 9 are all extremely small, between 1 and 10 members each. For that reason, we drop those communities from the analysis, as they are too small to gain meaningful insight. Community 3 and Community 4 are both unimodal and have some light skew. Meanwhile, Community 6 and Community 1 are more evenly distributed. Like the individual section, these do not seem to fit the normality assumptions very well.



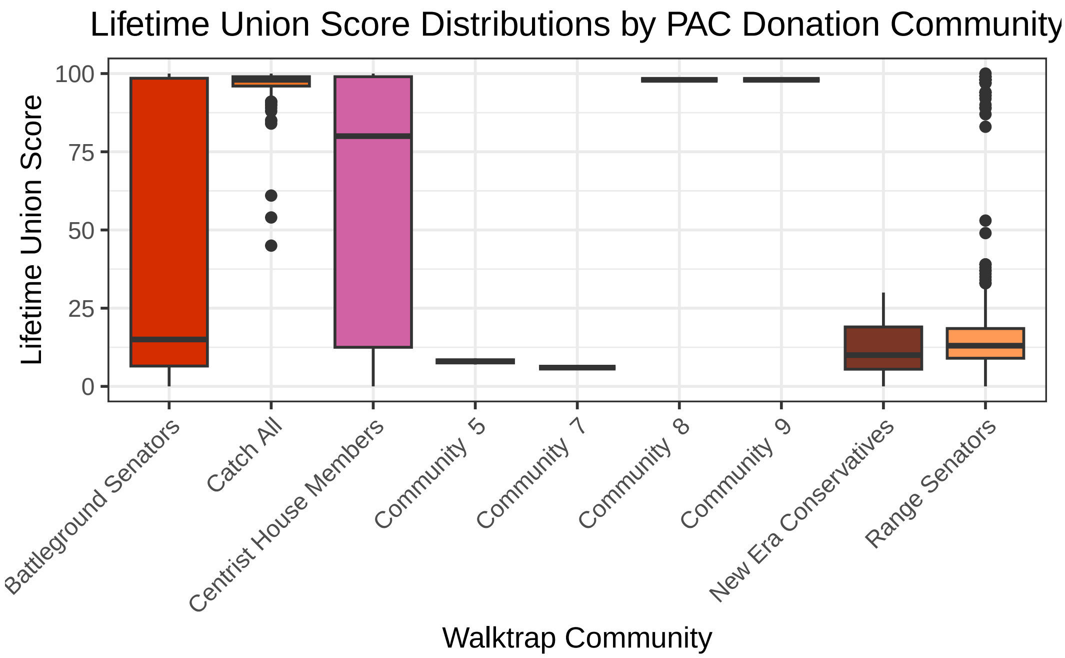
Even though the communities have skewed distributions, we treat them as normally distributed.

In regards to the independence of union scores, it is very unlikely that they are independent. Because of the nature of Congress, voting tends to occur in coalitions and by party line. However, to perform this analysis, we can assume that the observations are independent.

Now, we examine the variances of the communities using boxplots.

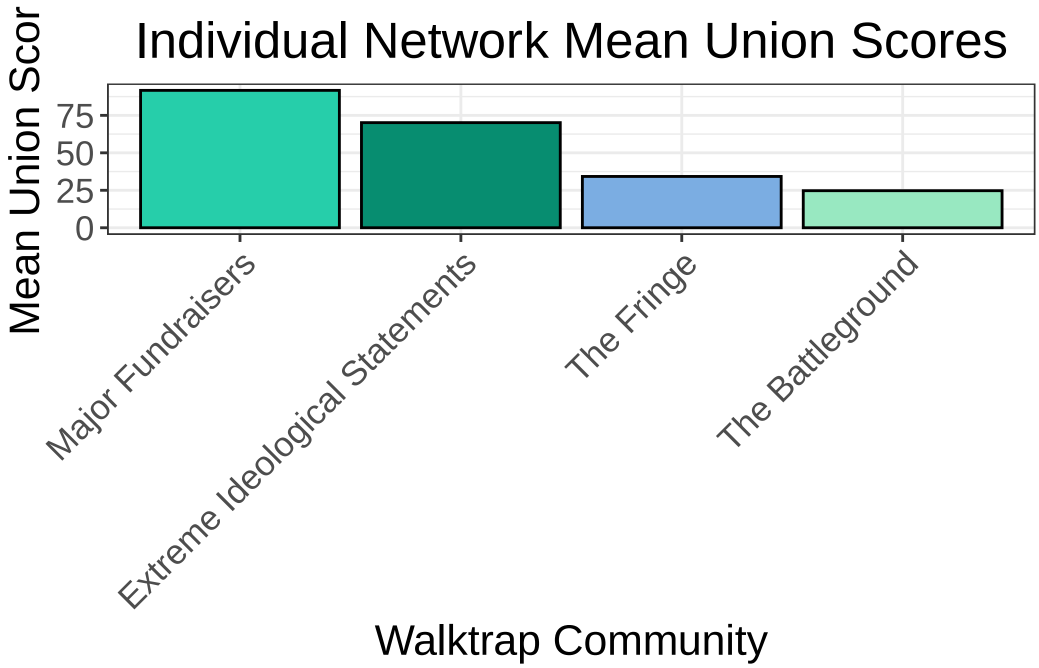


In the boxplots of large individual donation communities, we can see that the variances of Community 1 and Community 4 seem to be approximately equal. The variances of Community 2 and Community 3 also seem to be approximately equal. However, the variances of Community 1 and Community 4 are not equal to Community 2 and Community 3.



In the boxplots of large PAC donations communities, we find that Community 2, Community 3, and Community 4 have similar variances. We also find that Community 1 and Community 6 have similar variances. Also, Community 5, Community 7, Community 8, and Community 9 have similar variances. Again, the variances between these groupings of communities are quite different.

Though the ANOVA assumptions are violated, we still think that the test is appropriate to test the means of these communities. Future research could apply more complex non-parametric tests.

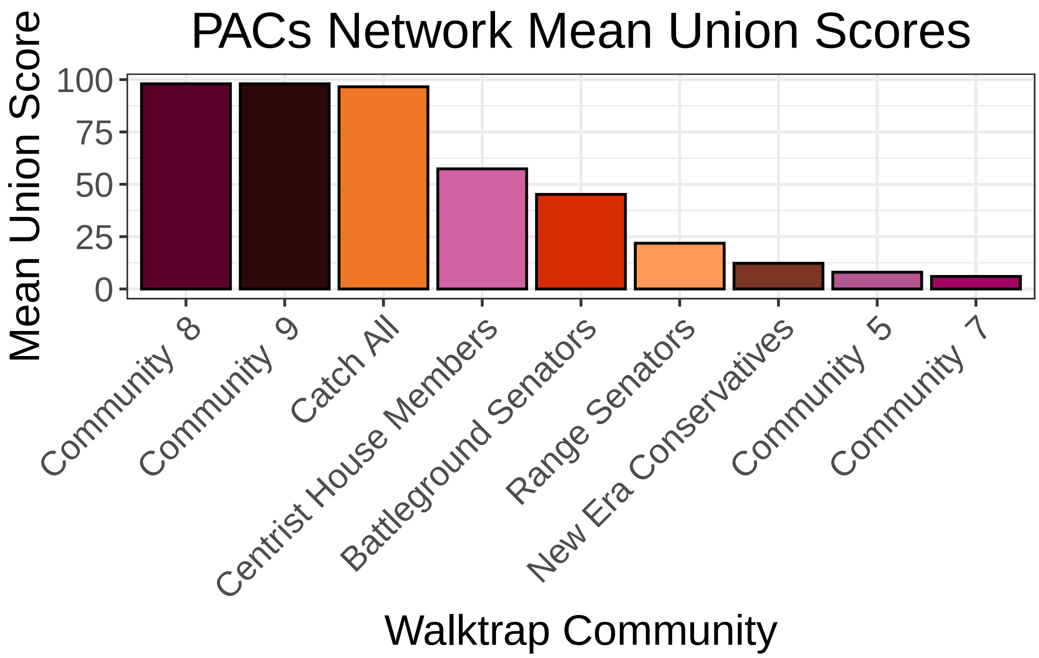


Examining the means of the large individual donor communities, we see that the mean union score of Community 1 and Community 2 is favorable towards unions. Conversely, Community 3 and Community 4 are less favorable towards unions.

```
individual_anova = aov(lifetime_score ~ community, data = individuals)
summary(individual_anova)
```

```
             Df Sum Sq Mean Sq F value Pr(>F)
community     3 367608  122536   110.3 <2e-16 ***
Residuals   535 594267    1111
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We find that, with F-Value 110.3 and level of significance $p<0.001$, we reject that the means of these communities are the same. This means that for the distinct communities of congresspeople generated by mutual large individual donors, voting patterns on bills related to unions are distinct. In particular, this shows that structure in relational campaign donation behavior encodes information about the voting patterns of congresspeople towards unions.




```
pacs_anova = aov(lifetime_score ~ community, data = pacs)
summary(pacs_anova)
```

```
             Df Sum Sq Mean Sq F value Pr(>F)
community     8 641578   80197   132.2 <2e-16 ***
Residuals   531 322078     607
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We find that, with F-Value 329 and level of significance $p<0.001$, we reject that means of the communities created by PAC donation networks are the same. This means that for the distinct communities of congresspeople generated by mutual large PAC donors, voting patterns on bills related to unions are distinct. In particular, this shows that structure in relational campaign donation behavior encodes information about the voting patterns of congresspeople towards unions.

Between the two groups of donors, these results show that union scores are legitimate ways of distinguishing communities created by large PAC donations and large individual donations networks. This is a meaningful result because it shows that donation patterns are important in finding out information about congressional voting behavior.

5 Discussion

In this study, we delve into the intricate voting behavior of congresspeople, particularly concerning favorability toward unions. The mystery surrounding how members act on legislation, especially in relation to unions, has long intrigued political researchers. Our findings underscore the significance of understanding donor networks to decipher this complex behavior. Essentially, our research illuminates that comprehending donor networks is a more accessible route to understanding voting behavior on unions. This crucial insight serves as a cornerstone for understanding the complexities of congressional decision-making.

However, our study is not without limitations. Time constraints posed challenges, restricting the depth of our analysis. Additionally, computing power limitations influenced the complexity of our methods. A notable limitation stems from missing data due to the Citizens United decision and changes in campaign donations research. Despite these constraints, we propose that graph theory could offer valuable insights into the connections among donors, mitigating the impact of missing data.

Looking ahead, our research lays a foundation for future investigations. Incorporating small donations into the analysis could further enrich our understanding of donor networks. Time series analysis, exploring the directionality of voting behavior, is a logical next step for a more dynamic perspective. Investigating dark money and tracking donations through Super PACs would provide a more comprehensive view of the financial landscape influencing congressional decisions Furthermore, engaging with other scorecards or metrics could offer additional dimensions for analysis.

6 References

Hansen, W. L., & Rocca, M. S. (2019). The Impact of “Citizens United” on Large Corporations and Their Employees. Political Research Quarterly, 72(2), 403–419. https://doi.org/10.1177/1065912918793230

La Raja, R. J., & Schaffner, B. F. (2015). The Hydraulics of Campaign Money. In Campaign Finance and Political Polarization: When Purists Prevail (pp. 108–133). University of Michigan Press. http://www.jstor.org/stable/j.ctvdtpj2w.9

Porter, M. A., Mucha, P. J., Newman, M. E. J., Warmbrand, C. M., & Levin, S. A. (2005). A Network Analysis of Committees in the U.S. House of Representatives. Proceedings of the National Academy of Sciences - PNAS, 102(20), 7057–7062. https://doi.org/10.1073/pnas.0500191102

OpenSecrets (2022). Campaign Finance Data. Center for Responsible Politics. https://www.opensecrets.org/bulk-data/downloads

American Federation of Labor and Congress of Industrial Organizations (2023). Legislative Voting Records. https://aflcio.org/scorecard/legislators