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In this paper, we study community structures in the United States Congress by analyzing a bipartite graph of senators and their political donors. We form a bipartite graph where one group of nodes represents senators from the 117th Congress, and the other group of nodes represents organizations (e.g., corporations, unions, school districts, etc.) who have made contributions to a politician's election campaign as recent as 2020 (as reported on www.opensecrets.org). Our project aims to infer relationships between Congress members through shared political donors. We use centrality measures, clustering, and community detection methods to investigate evidence of party polarization. We find (SUMMARIZE RESULTS HERE)

Keyword 1 | Keyword 2 | Keyword 3 | ...

Significance Statement

Campaign donations play a critical role in shaping political outcomes, yet the structure of donors influence across elected groups remains poorly understood. In this study, we construct and analyze a network of US senators based on their shared campaign donors. We use network analysis and community detection to reveal patterns of donor connectivity that cut across party lines, suggesting that donors may influence policy stances beyond what is captured by political affiliation.

With party polarization on the rise, the United States Congress has become a topic of interest for network science researchers. The tools of network science provide ways of quantifying and characterizing polarization (through metrics like modularity as in Reference (1)). In network studies of Congress, the chief object of study is a weighted network where nodes represent Congress members, edges represent political affinity, and weights represent the intensity of affinity. A common approach in the construction of such models is to take a one-mode projection of a bipartite graph. In such bipartite graphs, one collection of nodes represents Congress members, and the other collection of nodes represents some indicator of similarity between Congress members. For example, these nodes may represent legislative bills (Zhang et al. (1)), political committees (Porter et al. (2)), or press conferences (Desmarais et al. (3)). In turn, edges in the bipartite network may then indicate a vote for a particular bill, membership in a committee, or attendance at a conference. Then, the projection of this bipartite graph is a network of Congress members with edges whose weights are determined by the number of groups that two Congress members share (e.g., the number of bills cosponsored by the two politicians).

Our project takes a slightly different approach. Rather than consider cosponsorship of bills or co-attendance at press events, our model instead infers relations between politicians by considering their political donors. This modeling choice presents some advantages. Intuitively, one might expect that a politician's donors are a much stronger indicator of a politician's beliefs than membership in political committees or attendance at press conferences. Previous papers have looked at bipartite graphs of politicians and political donors (Rockey (4)), but our model considers a wider data set obtained through opensecrets.org.

Building on this tradition of bipartite modeling in political networks, we draw particular inspiration from recent work that highlights the structural implications of donor influence in Congress. Rockey et al. developed a bipartite network linking corporate-elite donors to congressional candidates, and then demonstrates how projecting the bipartite graph onto each mode can reveal hidden structure. It reveals that degree distributions of candidates have become more concave over time, indicating an increasing dominance of mega-donors as well as a handful of pivotal politicians. It also uses betweenness and eigenvector centralities to calculate the power of donors and legislators. Our project builds on this research that was performed on only corporate elite donors, while our project will be using all itemized individual contributions, allowing us to compare the network structure of elite-only versus mass-donors.

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Please declare any competing interests here.

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To study patterns of political influence, we will construct a bipartite network in which one set of nodes represents all 100 U.S. Senators from the 117th Congress (2021-2023), and the other set represents their top political donors, as listed on opensecrets.org. An edge between a senator and a donor represents a recorded financial contribution, with edges weighted by the total amount donated. Once the bipartite graph is built, we will analyze projections onto each node type, ultimately creating a senator-senator network where two senators are connected if they share common donors, and a donor-donor network where two donors are connected if they support the same senator(s). To extract meaningful insights, we will apply centrality measures such as degree, betweenness, and eigenvector centralities, along with community detection algorithms.

Why donor-politician relationships matter

This subject is extremely important in today's day and age where money is much more than just material. Money's role in politics is influence, and it is the citizens' responsibility to hold politicians accountable. Otherwise, it is easy for politicians to act in accordance with the interests of their major donors rather than the broader public. While these dynamics already play out in uneven ways, research projects like this help increase public understanding. Recognizing structural imbalances and staying informed on these issues is a key part of being an active constituent. Studying the role of political donations can help us understand why certain policies are enacted, and whose interests are most represented. Following the money can uncover hidden drivers of legislative behavior, which is why this project seeks to make those patterns more visible.(5)

Understanding the relationships between donors and elected officials is essential for making sense of political behavior in the United States. While party affiliation and public rhetoric often dominate headlines, campaign contributions offer a less visible, yet deeply influential, channel through which priorities are shaped and decisions are made. Donors—whether individuals, corporations, unions, or PACs—often carry specific interests, and their financial support can create powerful incentives that extend beyond party lines.

Analyzing these networks allows us to trace how influence moves within Congress, revealing patterns that are not immediately obvious through votes or public statements alone. For instance, if certain donors consistently fund senators across party lines, this may point to shared policy interests or coordinated lobbying efforts. Conversely, tightly clustered donor networks that align with party boundaries may reflect deeper polarization and ideological divides. These patterns are crucial to understand, particularly in an era where political accountability and transparency are pressing public concerns.

By examining donor-senator connections through the lens of network theory, this project seeks to move beyond surface-level affiliations and explore the structural relationships that underpin political power. Mapping these ties helps illuminate which voices have the most access to legislators—and which may be underrepresented. In doing so, we aim to contribute a data-driven perspective to broader conversations about equity, influence, and representation in American politics.

Background

(Extra math details that can't doesn't fit in Intro or Methods and Models sections)

Methods and Models

Data Acquisition and Pre-processing. To construct the model, we began by gathering the data from OpenSecrets. For each senator in the 117'th Congress, we visit the senator's page on the OpenSecrets website, navigate to the "Contributors" tab, and download the csv file containing info on their top 100 donors across their campaign committee and leadership PAC combined for the 2020 election cycle. Note that OpenSecrets blocks web-scraping, so this was done manually. We discuss this more on the Limitations section, but this is one reason why we narrowed the scope of our project to studying only a single Congressional term. Each csv file contains the names of the top 100 organizations (which we refer to as donors) that contributed to a given senator, as well as the dollar amount donated through individual donations, through PACs, and the total dollar amount (i.e. the sum of individual and PAC contributions). For simplicity, we care only about the total dollar amount each donor has contributed. Once all one-hundred csv files have been obtained, we merge the data into a dataframe (i.e. an array) with columns indicating the senator, their political party, their corresponding donors, and the dollar amount contributed by each donor. The result is a dataframe of the form:

Senator	Party	Organization	Contribution
Senator 1	(D/I/R)	Org (1,1)	$
⋮	⋮	⋮	⋮
Senator 1	(D/I/R)	Org (1,100)	$
⋮	⋮	⋮	⋮
Senator 100	(D/I/R)	Org (100,1)	$
⋮	⋮	⋮	⋮
Senator 100	(D/I/R)	Org (100, 100)	$

Table 1. General form of dataset after pre-processing

Model Construction. To construct the bipartite network, we create a node for each senator and each donor. To assign weights, we perform a series of computations. Naively, we may want to construct the bipartite graph by simply letting the edge between senator i and donor j have weight given by the total dollar amount contributed by j to i. However, different senators may receive different amounts of funds from their top 100 donors. For example, according to the data acquired from OpenSecrets, senator James Lankford received only $\$2,005,719$ from his top 100 donors, while senator Jon Ossoff received $\$12,195,623$. So, roughly speaking, one might expect that a donor seeking to buy influence might need to contribute more to Jon Ossoff's campaign funds in comparison to what they might need to contribute to James Lankford's funds. To account for this discrepancy, we normalize each donor's contributions by dividing their contribution by the total sum of funds received by a senator across their top 100 donors. Thus, the incidence matrix B of the bipartite graph (with rows representing senators and columns representing donors) is given by

$$B_{ij} = \frac{\substack{\text{Dollar amount donated} \\ \text{by donor } j \text{ to senator } i}}{\substack{\text{Total amount received by senator } i \\ \text{from all of } i\text{'s donors}}} \qquad [1]$$

For example, if donor j donated \$20 to senator i and Senator i received \$200 in total from their top donors, then $B_{ij} = 0.1$. As a result of this normalization, all senators have weighted degree 1. Loosely speaking, B_{ij} represents the amount of influence donor j has over senator i.

To obtain the projections onto the senator nodes and donor nodes respectively, we simply multiply B by its transpose, with the order depending on which projection is desired. That is, the weighted adjacency matrices for the projections are given by

$$A_{\text{senators}} = BB^T \qquad [2]$$

$$A_{\text{donors}} = B^T B \qquad [3]$$

Recall that B_{ij} represents the amount of influence donor j has over senator i. Then, $(A_{\text{senators}})_{ij}$ represents the extent to which the influences of two senators' influences align. Similarly, $(A_{\text{donors}})_{ij}$ represents the extent to which two donors donate to the same collection of senators.

Community Detection and Clustering. We perform community detection on each of the one-mode projections using modularity optimization. In the context of unweighted networks, modularity represents the extent to which nodes of like-community are connected in comparison to a random graph model (namely the configuration model Cite Newman textbook). More precisely, given an unweighted network with adjacency matrix $A \in \mathbb{R}^{n\times n}$ and a community assignment vector $g \in \mathbb{R}^n$, the modularity of this network is

$$Q(G, g) = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta_{g_i, g_j} \qquad [4]$$

Here, the $A_{ij}\delta_{g_i,g_j}$ term represents the number of edges whose endpoints are nodes which share a community, while the $\frac{k_i k_J}{2m}\delta_{g_i,g_j}$ term represents the expected number of edges between nodes of the same community for a graph generated using the configuration model. So, the larger Q is, the more likely the network contains connections between nodes of the like communities. Thus, one can identify community structure in a network by choosing community assignments which maximize the modularity.

By Newman, this definition of modularity, as well as the interpretation of the terms, generalizes well to weighted networks with integer weights (Cite Newman "Analysis of Weighted Networks" here)(**?**). This reasoning can be further extended to weighted networks with weights in say $[0, 1]$ (which is the case for the one-mode projections that we study). To see this, first note that the modularity Q is independent of the scale of the weights of the network (because if all the edge weights are scaled uniformly by some $\alpha > 0$, then the weighted adjacency matrix A, the weighted degrees k_i, and the weighted edge sum m are all also scaled by α). So, given a weighted network with weights in $[0, 1]$, one scale the edge weights by some sufficiently large $\alpha > 0$, round the weights to the nearest integer, and apply Newman's definition of modularity for integer-weighted networks. Since modularity is independent of the scale of the weights, optimizing the modularity for this new integer-weighted network is equivalent to optimizing the modularity for the original $[0, 1]$-weighted network (up to some errors arising from rounding the edge weights).

Results

This section discusses our findings. The first subsection discusses observations made on the full bipartite graph, while the second and third subsections discuss observations made on the projections onto the senator nodes and donor nodes respectively.

The Bipartite Graph. Recall that the dataset was assembled by gathering the top 100 donors of each of the 100 senators. So, a crude upper bound for the number of unique donors is $10,000$. In truth, we found $3,150$ unique donors in the dataset (0.315% of the upper bound), which suggests that a majority of the donors are contributing to multiple senators. This is seen in the following visualization of the bipartite graph:

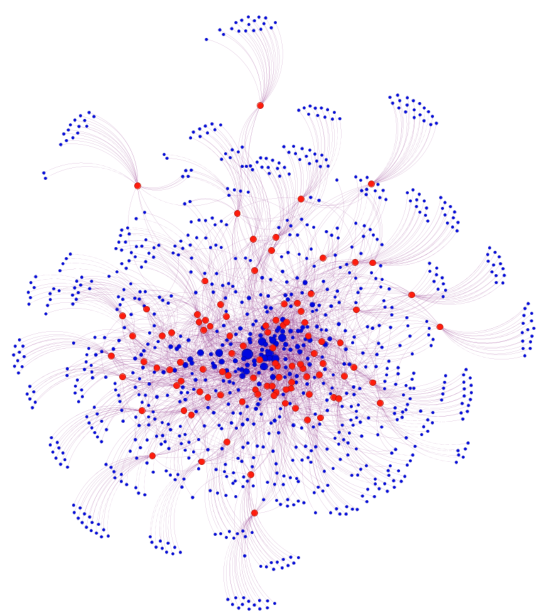

Fig. 1. Visualizing the Senator-Donor Bipartite Network

Here, red nodes represent donors, and blue nodes represent senators. Edges indicate financial contributions from donors to senators, with node sizes reflecting weighted degree—larger nodes have more or larger connections. The clustering and overlap of red nodes in the center suggest that certain senators receive funding from a shared pool of major donors, which might indicate influence or shared community interest, and can be explored further. Donors that appear on the periphery, connected to only one or two senators, indicate more targeted or limited engagement. One hypothesis we had from this graph was that the degree distribution of donors (blue nodes) seems to be more varied than the degree distribution of senators (red nodes). We could further explore this by making degree distribution plots for senators and donors separately.

We noted that some senators appear to be closely huddled in the center with the high-degree donor nodes, while other senators drift on the periphery. This could suggest that some senators receive a majority of their funds from a small, select group of donors, while others receive their funds from a wide, diverse collection of donors. This can be investigated further by inspecting the distribution of edge weights for each senator node. That is, for each fixed senator node, how much weight is assigned to each of the 100 edges incident to the senator? This can be visualized as in Figure 2.

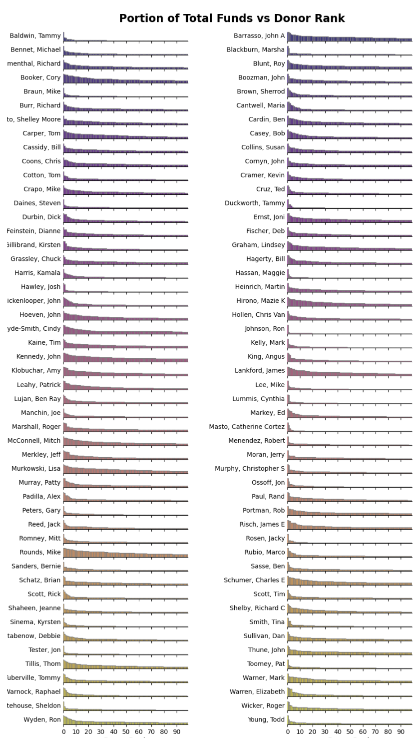

Fig. 2. Portion of total funds contributed by donors for each senator. Note that each subplot has the same total mass, but within each fixed subplot, the bar heights have be normalized so that the tallest bar has height 1.

In Figure 2, we've plotted the distribution of edge weights for each fixed senator within the bipartite graph. Each individual plot in this figure demonstrates how evenly spread or concentrated a fixed senator's campaign funds are across their top donors. For example, senators like Tammy Baldwin and Ron Johnson receive most of their funds from their top 5 or so donors. On the other hand, senators like Cory Booker and John Barrasso have their funds more evenly distributed across their donors.

Centrality in the Bipartite Network. To contextualize the network structure, we examined degree distributions for both types of nodes in the bipartite graph. As expected, most organizations donate to only one or two senators, while a smaller group of donors contribute broadly across many. This right-skewed distribution suggests the presence of a few powerful or well-resourced organizations.

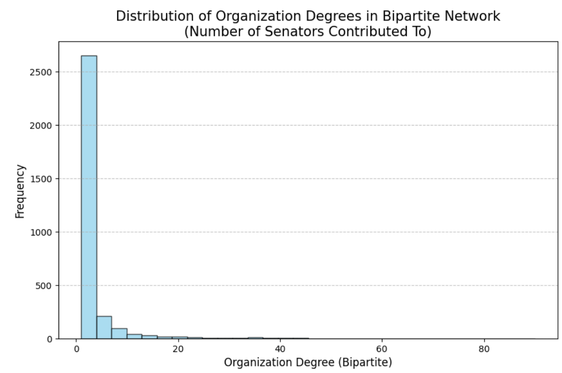

Fig. 3. Distribution of Organization Degrees in the Bipartite Network

By design, each senator in our dataset has exactly 100 contributing organizations, resulting in a uniform degree distribution for senators in the bipartite network:

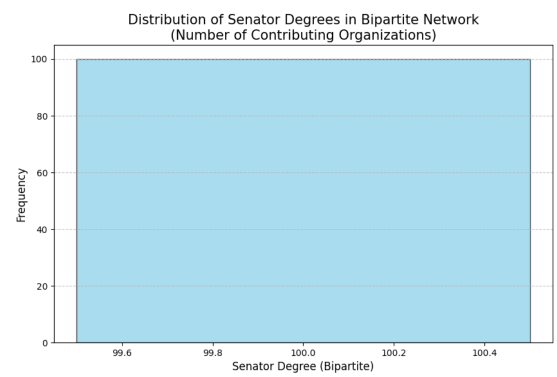

Fig. 4. Distribution of Senator Degrees in the Bipartite Network

The Senator Projection Network. To analyze patterns in shared campaign donors among U.S. senators, we first constructed a one-mode projection of our original bipartite graph, which consisted of edges between senators and donors. In the senator projection network, each node represents a senator. An edge is drawn between two senators if they have at least one donor in common, and edge weights reflect the number of shared donors. This network allows us to explore the underlying structure of sentor relationships based on campaign funding, independent of their actual political affiliations.

The senator projection network seems to be a densely connected graph, where most senators share donors with one

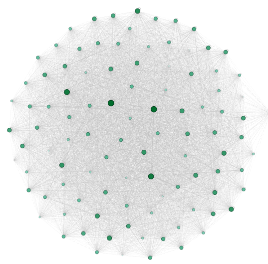

Fig. 5. Senator projection network, where nodes represent senators and edge weights reflect number of shared donors. Node colors represent party affiliation.

another. Node sizes are determined by weighted degree, so larger central nodes represent senators with widespread donor reach.

Given that we already have known party affiliations for each senator (Democrat, Republican, or Independent), we wanted to compare data-driven communities formed purely from shared donors against these political groups. This allows us to examine whether campaign donor networks reinforce or cut across party lines.

To perform community detection through modularity optimization, we used the Louvain algorithm. As with any optimization algorithm, the final result is dependent on the random initialization. But, in general, the Louvain algorithm yields 4 distinct communities as pictured in Figure 6.

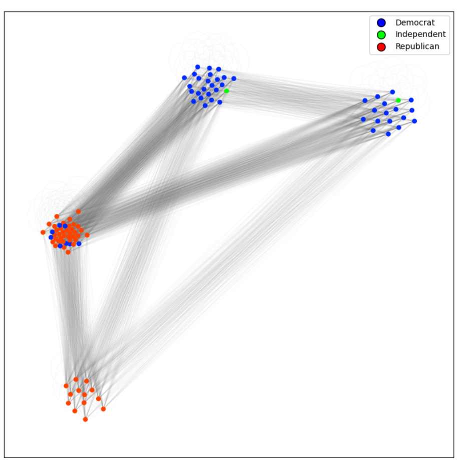

Fig. 6. Community Structure of U.S. Senators Based on Shared Donors (Louvain Clustering).

In Figure 6, we observe four distinct communities arising. As expected, we observe communities which are, for the most part, homogeneous with respect to party. Interestingly, the two major parties (Democrats and Republicans) both appear to have splintered off into two sub-communities. Additionally, intra-party connections appear to be common, but we also observe a surprisingly large amount of inter-party connections. In particular, the left-most community pictured in Figure 6 appears to have strong connections to each of the other three communities. This is surprising for two reasons. Firstly, this community contains a majority of the Republican party (in most runs of the algorithm, it contained 36 Republicans) and only a few (usually 8) Democrats. So, one would expect that this community is highly connected to the strictly Republican community and sparsely connected to the two Democrat communities. In truth, we observe the exact opposite. This suggests that a majority of Republicans share donors a considerable number of Democrats, while a small contingent of Republicans appear to have very few donors in common with both Democrats and the majority of other Republicans.

To better understand the fine-grained structure of donor-sharing, we created a heatmap where each cell represents the number of shared donors between a pair of senators.

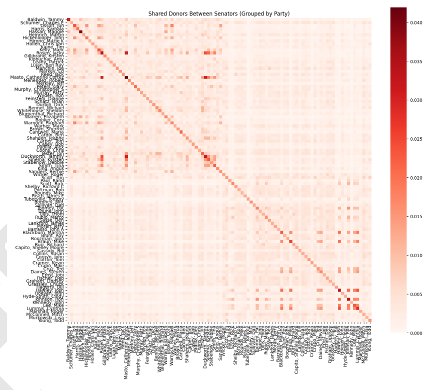

Fig. 7. Heatmap of number of shared donors between each pair of senators.

This heatmap visualizes the shared donors between each pair of senators. Darker cells indicate a higher fraction of shared donors. The donors are grouped by political party, with Democrats in the upper left section of the graph and Republicans in the lower right section. This results in visible denser blocks along the diagonal for both Democrats (upper-left) and Republicans (lower-right), which would reflect strong intra-party overlap between donors. However, there are also some off-diagonal entries that highlight cross-party donor sharing.

Aggregating this data by party, we computed the average number of shared donors between groups: Democrats, Republicans, and Independents.

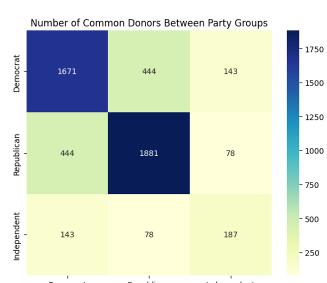

Fig. 8. Average number of shared donors between and within political party groups.

This heatmap shows the total number of shared donors between senators, grouped by political party. As expected, senators tend to share donors mostly within their own parties, with Republican-Republican and Democrat-Democrat pairs having the highest donor overlap. However, there are also a substantial number of shared donors between Democrats and Republicans (444) which represents the presence of donors whose contributions span across party lines. Independents share fewer donors with both major parties, reflecting their smaller representation.

Finally, we reordered the heatmap from Figure 7 to group senators by the communities detected via the Louvain algorithm.

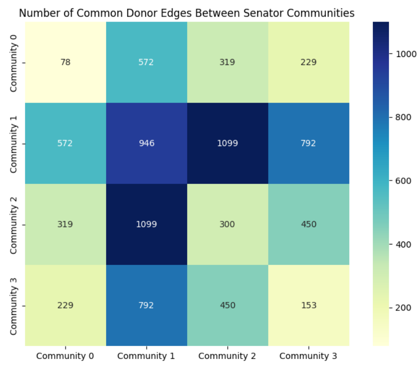

Fig. 9. Heatmap of shared donors, re-ordered by community clustering rather than party.

The heatmap, borrowing from the Louvain communities plot from Figure 6 shows 4 communities. Darker blocks represent a larger proportion of common donors between senator communities. While we would expect that the diagonal blocks would have the highest number of common donors, we see that there is a significant number of cross-community overlap. Most notably, there is a significant overlap in donors between Communities 0 and 1, Communities 1 and 2 and Communities 1 and 3.

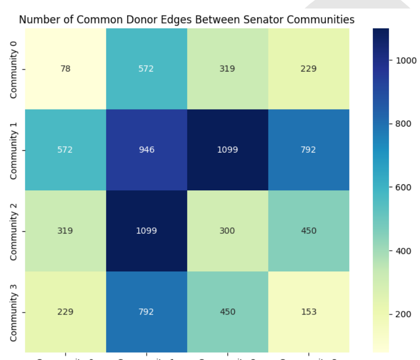

Fig. 10. Heatmap of shared donors, re-ordered by community clustering rather than party.

Fig. 11

Centrality in the Senator Projection Network. To deepen our understanding of influence within the senator projection network, we computed three centrality metrics: degree, betweenness, and eigenvector centrality. These help identify not just highly connected senators, but those that act as structural intermediaries or occupy key positions in the donor-sharing landscape.

Degree Centrality. This reflects how many other senators a given senator shares donors with. Most senators are connected to nearly all others, indicating a highly dense donor overlap network.

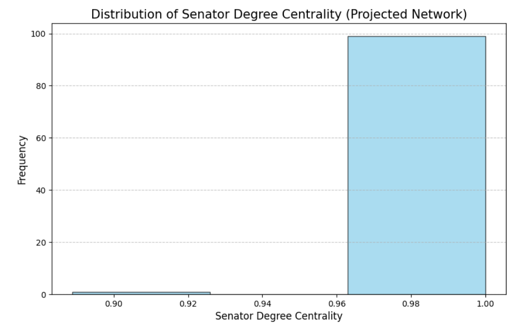

Fig. 12. Distribution of Senator Degree Centrality (Projected Network)

Betweenness Centrality. This highlights senators who bridge otherwise separate communities. These senators may represent ideological moderates or those with broad donor appeal.

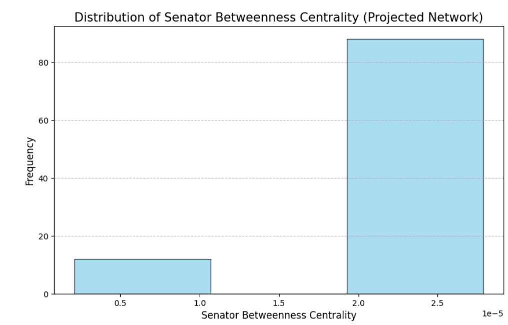

Fig. 13. Distribution of Senator Betweenness Centrality (Projected Network)

Eigenvector Centrality. This identifies senators connected to other influential figures. A few stand out, likely reflecting strong positioning within donor-dense communities.

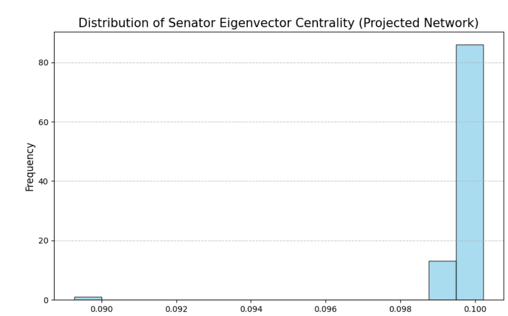

Fig. 14. Distribution of Senator Eigenvector Centrality (Projected Network)

Dendrogram of Senator Projection Network. Displays the hierarchical clustering of U.S. Senators based on their weighted projection similarities, derived from edge weights of donors using Ward's method. Each branch represents a senator, and the horizontal distance indicates dissimilarity between clusters. The linkage method (Ward's Method) highlights donor-based similarities.

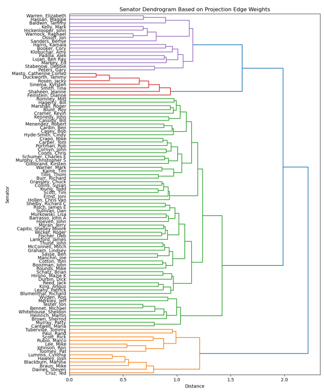

Fig. 15. Senator Dendrogram Based on Projection Edge Weights

The Donor Projection Network. We also applied the Louvain community detection algorithm to the donor projection network. We obtained the following communities:

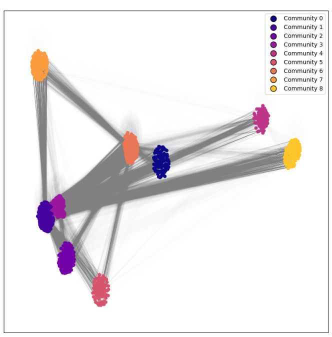

Fig. 16. Community structure of donor network obtained using Louvain algorithm.

Unlike the senator network, this clustering is less interpretable as there is no ground-truth to serve as a point of comparison. But, to get an idea of what each of the communities may represent, we can, for each community, determine what percentage of their donations go to each political party:

From Table 2, we see that the Louvain algorithm appears to have grouped the donors into communities which have discernible party preferences. For example, a majority of the funds from Communities 3 and 8 go towards Republican senators while a majority of funds from Communities 0 and 6 go towards Democratic senators.

Centrality in the Donor Projection Network. While we applied community detection to the senator projection network, we did not compute centrality metrics for this network, as our primary focus was on the structural roles of senators within the network and the interpretability of donor communities through partisan contribution patterns.

		Percent Contributed To		
Community	Size	Democrats	Independents	Republicans
0	94	**0.809**	0	0.191
1	814	0.387	0.005	**0.608**
2	131	0.387	0.003	**0.610**
3	645	0.061	0.002	**0.937**
4	110	0.143	0.003	**0.854**
5	70	0.263	0	**0.737**
6	1017	**0.923**	0.012	0.065
7	120	**0.797**	0.081	0.122
8	149	0.036	0	**0.964**

Table 2. Contribution breakdown of each donor community to each political party

Discussion and Conclusion

Our study applied network analysis to campaign finance data from the 117th U.S. Senate, using a bipartite graph structure to explore how senators are connected through shared donors. Projecting this network onto the set of senators allowed us to examine patterns of donor overlap and assess whether financial networks mirror or transcend partisan divisions.

The Louvain community detection results revealed that most senators are clustered according to political party, which suggests that campaign financing largely reinforces existing ideological boundaries. The communities detected in the senator-senator projection exhibited high modularity, with few connections bridging Democratic and Republican senators. This pattern was further supported by our heatmaps, which showed that donor overlap is denser within parties than across them. While a small number of cross-party donor connections exist, they tend to occur between ideologically adjacent senators, such as moderates or swing-state representatives, rather than representing systematic bipartisanship.

Interestingly, although many senators share donors with colleagues from the opposite party, our data showed no single donor appearing in the top 100 lists for both Democratic and Republican senators. This absence of bipartisan donors reinforces the notion that campaign finance operates within largely polarized ecosystems, even at the highest levels of financial influence. It suggests that donor preferences are sharply aligned with party identity, and that even major contributors rarely split support across party lines.

Our centrality analysis added another layer of insight, identifying senators with high degree and betweenness centrality in the projection graph. These senators occupy structurally important positions, either as bridges between donor clusters or as central figures with widespread donor connections. Their placement within the network may correlate with strategic fundraising capacity, policy influence, or visibility within national politics.

Although we considered incorporating weighted stochastic block modeling, we ultimately shifted focus toward more interpretable tools—community detection and centrality analysis—that better aligned with the nature of our data and project goals. The insights derived from our current methods provided a meaningful picture of how donor relationships shape the Senate's financial landscape.

Overall, our findings point to a donor network that both reflects and reinforces political polarization. While a few structural exceptions exist, the general trend is one of party-driven clustering and minimal bipartisan overlap in campaign support. Network analysis enabled us to uncover these patterns systematically, going beyond donor totals to reveal how influence is distributed across the legislative body.

Future Directions. Future research could incorporate additional donor-level metadata, such as industry classification, type (e.g., PAC vs. individual), or geographic origin, to investigate how specific sectors contribute to partisan clustering. Expanding the analysis to include multiple congressional sessions could also reveal how donor networks evolve over time, especially in response to political realignments or shifts in campaign finance laws. Linking donor-sharing patterns with roll-call voting records or policy co-sponsorships could further help quantify the potential downstream impact of shared financial backers on legislative behavior.

Limitations

While our analysis reveals meaningful patterns in donor influence and community structure within the 117th U.S. Senate, there are several limitations that should be acknowledged.

As noted in the Data Acquisition and Pre-processing subsection, the manner in which we obtained the data proved to be a bottleneck. In that section, we noted that OpenSecrets blocked all attempts at web-scraping, requiring all the data to be downloaded manually. This significantly narrowed our scope. Our project studies only one Congressional term of the Senate, but our initial plan was to study both houses of Congress. Further, we had hoped to form networks for multiple Congressional terms to study changes and trends in community structure. The House of Representatives and Senate together contain 535 Congress members, so downloading all the data manually was simply infeasible. OpenSecrets does not provide an easy way to obtain all the desired data all at once, and they also block all attempts at web-scraping. OpenSecrets used to have an online API, but this was discontinued as recently as April 15, 2025 (just three weeks into the Spring quarter). We explored other alternatives, namely www.followthemoney.org, but the data retrieval limits on this website were too restrictive for our what we wanted to accomplish.

In addition to scale, data completeness posed a challenge. The dataset includes only the top 100 donors per senator, omitting small-dollar or grassroots contributions that may significantly impact candidate support. Consequently, our analysis reflects high-level patterns in elite donor behavior but cannot account for the full range of financial influence in the electoral process.

Another limitation we faced was the lack of metadata about donors. Without information such as industry affiliation, geographic location, or donor type (e.g., PAC, individual, corporation), we were unable to interpret the meaning of connections beyond structural patterns. This became particularly evident when analyzing the donor-donor projection, as without ground truth labels such as donor industry or dominant political alignment, interpreting the results of community detection was inherently speculative. Adding such labels in future work could provide clearer insight into which sectors or interests dominate specific communities of influence.

Our use of the senator-senator projection also involved information loss. By converting the bipartite network to a one-mode projection, we risked flattening the nuances of donor-senator relationships. Two senators may appear similarly connected even if their overlap is limited to a few high-weight donors. A richer analysis might examine donor profile similarity directly or incorporate edge weights more systematically.

While we initially planned to explore weighted stochastic block modeling for community detection, we ultimately focused on Louvain modularity due to interpretability and implementation feasibility. While effective at revealing large-scale community structure, Louvain is sensitive to resolution parameters and may miss more subtle or hierarchical patterns that other methods could detect.

Altogether, our analysis represents a single, static snapshot of donor behavior during one election cycle. Without longitudinal data, we cannot assess how financial networks change over time or respond to political events, policy shifts, or campaign finance reforms.

These limitations highlight important directions for future research. Expanding the dataset to include additional metadata, multiple congressional sessions, and a broader range of contributors would enhance the robustness and interpretability of the analysis.

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