Analyzing The Network of Congress
CS224W Project Milestone

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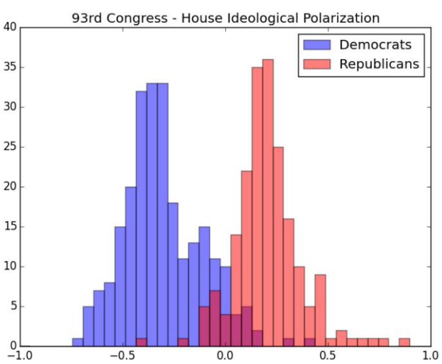
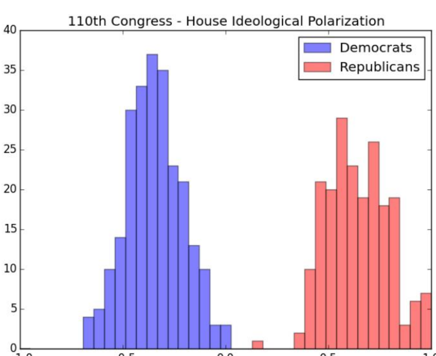
1 Abstract

Growing partisan polarization has dominated the conversation about Congress in recent years. While there have always been issue differences between the major parties, these differences have grown and calcified along multiple dimensions [9]. Quantitative metrics based on roll-call votes that label legislators as points in multi-dimensional ideological space have borne out the story of major polarization [8].





At the same time, the United States Congress is a rich social network where each legislator interacts with their peers through committees, house leadership positions, and bill co-sponsorships and amendments. The extent to which these relationships have changed in recent years is not as well understood as the changes in ideology. If ideologically distinct groups are still able to work together on crafting bills, and it turns out that those working relationships are important in legislative outcomes beyond the ideological content of bills, then partisan polarization in roll-call voting might be less worrying than it appears.

We build out a network using bill sponsorship-cosponsorship relationships to track the state of working relationships over time and the nature of legislative deal-making. Legislators may vote together relatively infrequently but still find some areas of common ground and work together on bills in those areas. They may also form communities of multiple legislators and influence which bills get taken up by committee and ultimately succeed. These and many more features of the working relationship network can give more fine-grained insight into Congressional activity, and how it has changed over time, than just the final votes.

In particular, we build a cosponsorship network of the 93^{rd} through 109^{th} Congress and supplement the network with information about each Congressman (node attributes). From this we are able to track broad patterns of how Congress has changed over time such as how many and and what kind of working relationships exist in Congress.

Next, we build stable clusters in the network that represent real-life communities of legislators based on their bill-writing activity. To do this, we implement the Community Detection in Networks with Node Attributes (CESNA) algorithm on the network and track communities and community attributes over time, noting how important partisianship was in defining each community.

Finally, we investigate to what extent the sponsor and early cosponsors of a bill can provide insight on the chances of a bill succeeding. Here, we draw upon not just various features of the working relationship network but also data from multiple sources characterizing the demographics and prominence of different legislators. We are interested not just in how predictable bill outcomes are but on what factors matter over time.

2 Related Work

2.1 Fowler

Fowler [6] presents a graph model for the 93^{rd} through 108^{th} Congress of the United States. He sought to infer the connectedness between legislators primarily through a network of bill cosponsorships. He claims that legislators cosponsoring each others bills is a signal for a relationship between legislators. Specifically, he organized his graph by partitioning by both Congress and house (Senate versus The House of Representatives), which created 32 $((108 - 93 + 1) \times 2)$ distinct partitions. He primarily considered how connected legislators are by representing each legislator as a node with a directional edge between legislator A to legislator B if legislator A cosponsored a bill for legislator B.

Fowler's main analysis is tracking different centrality measurements over time. He also constructs a network using his own metrics and tries to predict bill passage. We wish to use the data he devised to develop our own network representing the collaboration of Congress and track how collaboration has changed through time as Congress has become more partisan.

We believe that Fowler is correct in using the cosponsorships network as a measure of collaboration between legislators. We, however, think that designating a working relationship (i.e. an edge) as whether two legislators cosponsored each other's bills at least once is too noisy of an indicator. We develop a less noisy indicator as thresholding on legislators sponsoring at least a number of each other's bills, trying to target an average edge density in our networks (see our data and methods section for more details).

2.2 DW-NOMINATE

Poole and Rosenthal [8] made a major contribution to the quantitative study of political science with their procedure for computing ideological scores of members of Congress. Under the assumption that legislators and bills can be represented as points in two-dimensional ideological space, they solve for an equilibrium which determines these scores in which each legislator probabilistically votes for the bills closer to her.

The resulting DW-NOMINATE scores are useful because ideology is an incredibly important factor in how legislators behave. The polarization between parties is reflected in the widening gap between the DW-NOMINATE scores of Democrats and the scores of Republicans.

While the model is not posed as a network problem, there is a network-related interpretation: legislators who vote together frequently (e.g. have highly weighted edges between each other) end up with very similar ideology scores. Similarly, those who vote together least would be most ideologically distinct. We can therefore think of DW-NOMINATE as encapsulating the information contained in roll call voting similarity. The task of this paper, then, is to see what additional information can be learned from the information contained in bill cosponsorships.

3 Data and Methodology

3.1 Data Overview

Our primary source of data was aggregated by James Fowler [6]. Fowler developed several datasets of House and Senate social networks for the 93^{rd} through the 110^{th} Congress. His data contains the names and Interuniversity Consortium for Political and Social Research (ICPSR) ids for all legislators for each Congress, as well as the list of all bills, amendments, and resolutions introduced and whether they passed. Importantly, he also has an indicator matrix of which legislator was a sponsor of a bill and which legislators were cosponsors of a bill. With this, we know who sponsored and cosponsored each bill, and thus, which legislators each individual Congressman has cosponsored a bill with.

We supplement this data with additional information for each legislator. We get party, region, and most significantly ideology scores from DW Nominate [3]. We get other demographic variables like age and sex from GovTrack, another major database of Congressional information [4]. Finally, we get information on committee membership and seniority gathered from the Congressional Record and CQ Press by Garrison Nelson, Charles Stewart, and Jonathan Woon [10, 7]. To our knowledge, we are the first to combine this many sources of information about Congresspeople and their working relationships.

The data from GovTrack had many missing identifiers for the 110^{th} Congress, which made joining data for this Congress impossible. Because of this, we omitted analysis for this congress.

3.2 Constructing the Network

The questions we are primarily concerned about answering in this paper relate to how can we model working and collaborative relationships among legislators. We want to achieve this by creating a network between legislators where a connection represents a collaborative working relationship. We have a number of options to construct the network. We ultimately chose to define a working relationship between Congressman A and B if they meet the following conditions:

- For the House, there exists at least 4 cosponsorships between A and B on which either A or B was the primary sponsor. For the Senate, there needs to be at least 12.
- A needs to cosponsor at least one of B's bills and vice versa.

We discuss our choice of this network over others in the following sections.

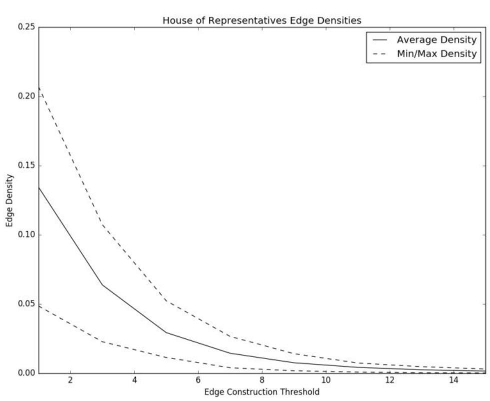
Why Not Mutual Cosponsorship

Instead of considering only cosponsorships of one-another's bills, one might consider instead building a network that accounted for mutual cosponsorships of a third legislators' bills. It's certainly true that at times, cosponsoring a bill together might mean working together on shepherding the bill through Congress. However, there are many other times when a simple mutual cosponsorship might be more of a shared ideological expression than anything else and not imply any sort of actual working relationship between the mutual cosponsors. Since we are already capturing ideological affinity with DW-NOMINATE scores, we don't want our collaborative network to cover the same ground. Cosponsoring someone else's bill and having them cosponsor yours, on the other hand, requires direct interaction and a public signal of a willingness to work together.

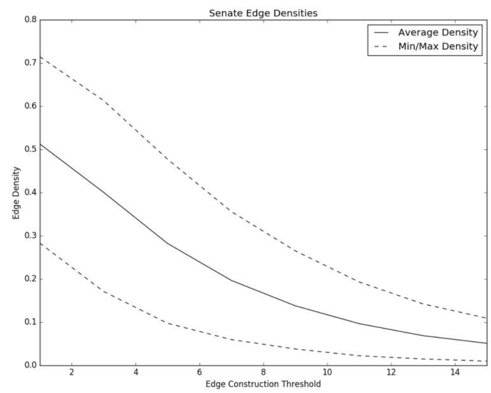
Determining the Cosponsorship Threshold

Not all bills, resolutions, or amendments are serious affairs that require a great deal of collaboration. Some cover trivial matters like commemorations that are cheap opportunities to signal support for a popular cause via a cosponsorship. As a result, absent a cosponsorship threshold, we will get too noisy of a signal for working relationships. Requiring consistent cosponsorship support between legislators is the best way to smooth the noise out and detect bona fide working relationships. We also add in the requirement that both legislators must cosponsor each other's bills. This is because we want to model mutual working relationships. One-way cosponsorships could include any number of situations that are not working relationships such as party pressure to cosponsor the bills of leadership or the aforementioned cheap cosponsrships of popular resolutions in which you are one of a hundred cosponsors.

To find the specific threshold, we constructed networks with varying levels of mutual cosponship thresholds and examined their edge densities. We had two goals when searching for a threshold. We wanted to hone in on a reasonable average number of working relationships proportional to the size of the network (5-10%, probably with the Senate on the higher end of that range to avoid having too few working relationships in absolute terms), and we wanted the resulting edge density to be similar for each Congress's network.



From the plots of density, we see that the average density of the House dips much more sharply (and gets smaller gaps between Congresses) than that of the Senate as a function of the threshold. Choosing a threshold of 4 for the House and 12 for the Senate works well in balancing our goals: about 5% density for the House (or



20 working relationships on average) and 10% density in the Senate (or 10 working relationships on average), both of which are reasonable, while seeing relatively low variation between Congresses. The higher density on the Senate side is further justified by the high threshold needed just to reach that limit: 12 cases of working together is certainly significant.

3.3 Data Manipulations

We manually massage the legislator IDs in Fowler, DW- Nominate, Stewart, and GovTrack in order to get them to agree with one another and give legislators unique IDs. Most of these changes occured when a Legislator changes party. For a detailed list of changes, please refer to our github repository.

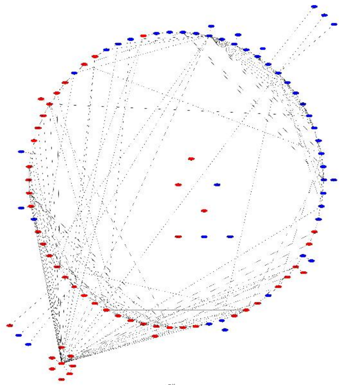
3.4 Change In Law

Starting with the 96^{th} Congress, a law passed which allowed a bill to have more than 25 legislators cosponsor it at a time. As a result, legislators started to cosponsor more bills than usual. We can see this behavior manifest itself in the uptick in average network degrees in Congresses after the 96^{th}. As such, the behavior and the number of communities we receive from before the 96^{th} Congress appear to be fundamentally different.

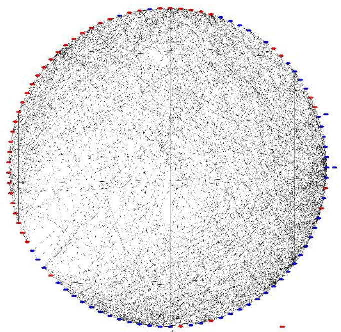
4 Graph Summary Stats

We start by visualizing some of the working relationship graphs. The two examples we choose are from the Senate (which has fewer nodes) and depict a high-density Congressional session (101st) and a low-density session (104th).

One thing that is immediately noticeable is the party clustering. There is a core of party loyalists in each graph who are densely connected to one another. Nestled among the party loyalists are a couple members from the other party. Then there are members who work closely with members from both parties who have less dense subnetworks but many edges to disparate parts of the graph.



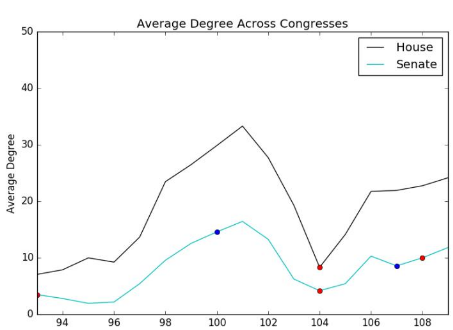
104 Congress - Senate Network



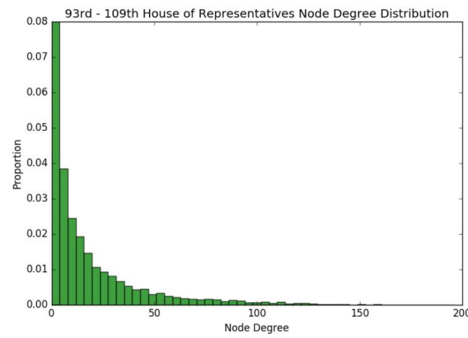
101 Congress - Senate Network

There are also noticeable authority figures in both parties who have strong working relationships with numerous others. On the other end of the spectrum are a handful of Senators with no strong working relationships at all; these members appear to be cashing their paycheck and not doing much legislating.

The two graphs side-by-side also illustrate just how much things can change between Congressional sessions. The definition of an edge is the same in both graphs but the number of edges created is starkly different between the two Congressional sessions depicted. The brutal and combative 104th Congress, culminating in a government shutdown, saw substantially less legislative work done and working relationships developed then the 101st just a handful of years earlier.

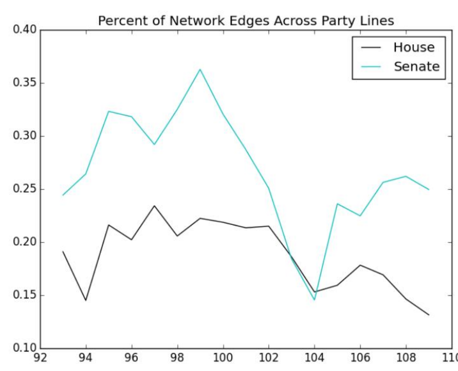


Going along with this last observation, we can visualize the average degree of the working relationship graph across time. Changes in party control are labeled as dots on the chart. After the first few Congresses, which as explained had different rules for cosponsorships, we see a burst of legislative activity and relationships between the 98th and 102nd Congress under Ronald Reagan and George H.W. Bush before a decline and recovery late in the Bill Clinton years and under George W. Bush.



Building on the point about party authorities, meanwhile, we see a degree distribution that like most networks has heavy tails; the Senate's plot looks quite similar to that of those House. Most members have only a handful of close working relationships but there is a long tail of legislators who work extensively with a substantial fraction of the entire body. Understanding the work of these high-degree legislators is important to understanding the work of Congress as a whole.

Consistent Bipartisanship



We can also look at the percent of edges over time that cross party lines. Interestingly, this plot is roughly stable over time, with a possible slight decline in general from beginning to end keyed by the famous 104th Congress. This is nothing like the dramatic growth in party polarization demonstrated by the DW-NOMINATE scores; Congresspeople are forming working relationships across the aisle in similar proportions to when ideological disparities between parties were much greater. As a methodological note, we found that the same pattern held even when controlling for the change in possible bipartisan edges due to differently sized majority and minority caucuses.

5 CESNA

5.1 CESNA Clustering Description

We are interested in analyzing clusters of legislators based on their network of working relationships. Crucially, we are particularly interested in how these clusters relate to the attributes of the legislators. We have seen that there remain a significant number of individual bipartisan working relationships but do we see diverse working groups that frequently collaborate together?

A promising approach is laid out in Yang et al. [13], who describe an algorithm for finding Communities from Edge Structure and Node Attributes, which they call CESNA. CESNA incorporates node features and edge structure to find communities instead of just relying on one or the other. It explicitly computes the importance of different node features in forming each cluster. Additionally, it allows for overlapping and nested communities, which is one of the key features of our dataset. Legislators are likely to have distinct communities of working relationships with their regional peers, ideological peers, committee peers, and of course party peers.

In particular, we make use of the authors' C++ implementation and feed in details of our own network. As is necessary for the models, we binarize all of our variables. This means that categorical variables like region are split into distinct dummy variables and continuous variables like ideology are split into buckets. We choose to split each ideological dimension into five groups: left, center-left, moderate, center-right, and right, each of which roughly contain a fifth of the members. The motivation behind selecting an odd number of groups is to allow for a moderate group that straddles the DW-NOMINATE center point of 0. The final list of variables, appropriately binarized, are party, ideology, region, committee, gender, and age.

5.2 Community Sensitivity and Stability

It is important that the clusters we generate be meaningful and stable given the degrees of freedom present in constructing clusters, edges, and features [12]. In particular, we have direct control over the number of clusters we wish to generate using the CESNA algorithm and implicit control over the edges and features due to the decision rules we used: edges are formed only if the number of reciprocal sponsorship-cosponsorship pairs meets a specific threshold in a given term and some features are converted from continuous variables to discrete variables using cutoffs. There are also a large number of features and so there is some opportunity for 'overfitting' the clusters to noise.

To combat all of these problems, we employ the following strategy to validate our clusters on each Congress:

- Run CESNA to create 20 communities, the maximum of its default search space.
- Repeatedly perturb the edges and features of the network (described below) and recompute 20 CESNA communities for each perturbation.
- Use the Hungarian matching algorithm (described below) to pair up the communities in the original and each perturbed graph according to the Jaccard similarity score associated with each pair.
- Prune the original clusters that changed too much (i.e. dipped below a similarity score of 2/3 more than 20% of the time).

The remaining clusters have proven stable to numerous minor alterations in the graph and so are more likely to represent robust communities of working relationships.

Feature Perturbations

Our CESNA variables are all discrete despite the underlying variables being continuous (e.g. age is bucketed into 10 year discrete time intervals). We decided to directly perturb the CESNA variables directly rather than the underlying variables. This is because we wanted more control over when a CESNA feature would change, rather than tweaking noise variables when perturbing continuous features.

We perturbed all features simultaneously. We designed our perturbation analysis for features such that each individual would have approximately 5% total chance of changing at least one of their CESNA features. This corresponds to changing each individual's feature with approximately 0.5% probability. We deemed this perturbation strategy appropriate because clusters that are robust to this tolerance of change are likely to be stable. After perturbation, we will rerun CESNA and develop perturbed communities.

Given two sets of clusters, the original and the perturbed, we wish to find a 1-to-1 matching such that the most similar clusters are paired up. The way we do this is with the Hungarian Matching algorithm [5], which can be used to find a maximum weight perfect matching on a complete bipartite graph. Here, the nodes in the graph are the two sets of clusters and the weight on the edge between original cluster i and perturbed cluster j is the Jaccard similarity (intersection over union) between i and j. Upon finding the perfect matching, we assign each original cluster the weight of its edge in the perfect matching; that is, the Jaccard overlap with its similar cluster in the perturbed results.

Edge Perturbations

CESNA community creation also relies on the edges of the underlying graph. We will check community robustness by adding and deleting edges in the graph for each Congress. That is, for each edge and potential edge within a Congress, we will randomly delete or add an edge between legislators. We want the probability of perturbation to be on the same order as our feature perturbation. As such, we computed that approximately using a probability of 0.025% to add or delete an edge will give us approximately a 5% chance of affecting any given legislator.

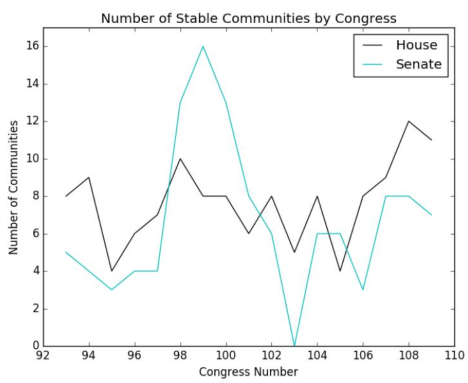
After rerunning CESNA on the perturbed graph, we develop a similarity score in the same manner as we did under feature perturbation.

Cluster Similarity and Pruning

Our goal is to fit a large number of communities to our graphs and prune off communities that are not robust to perturbation. We fit 20 communities, which is the default CESNA maximal range of communities.

A single perturbation simulation is a high variance measure of cluster stability. [12] In order to lower variance, we employ a repeated perturbation strategy. We perturbed CESNA features and graph edges for 50 separate instances for each Congress. For each of the 100 perturbations, we computed the community similarity to the unperturbed communities. We counted the number of times each community stayed about 2/3 similarity across each perturbation. If a community stayed above the 2/3 similarity threshold over at least 80 of the perturbations, we kept the community for analysis. Otherwise, we pruned the community.

Resulting Clusters

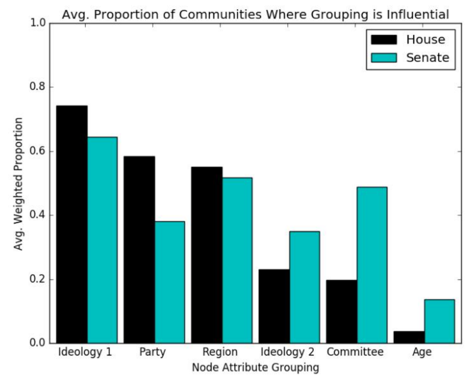


From our original 20 communities, we end up obtaining 5-10 stable communities in the House fairly consistently. The Senate is much more variable, seeing a high of 16 stable communities in the 99th Congress and a low of 0 in the 103rd. This last result is worrying but came amidst a term of low legislative activity and is an isolated occurrence. More generally, it makes sense to expect more variance in Senate clustering due to the lower number of individuals.

The resulting communities are quite healthy in terms of size as well. For both the House and the Senate, clusters have on average about 5% of the body, which corresponds to around 20-25 members in the House and 5 members in the Senate. The largest communities have greater than 50 representatives and 20 Senators while the smallest have around 10 Representatives and 4 Senators. As a result, it's clear that we are picking up genuine working groups rather than having a rogue cluster with half of the body or a bunch of tiny 2-3 person clusters.

6 CESNA Analysis

6.1 Overall Important Features

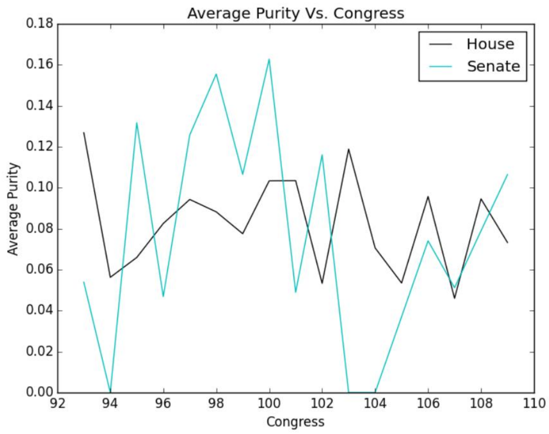


As expected, party and ideology are among the most important features when deciding working group clusters. But there are a fair number of interesting insights here as well. First, ideology is more likely to be an important contributor to a working group than party. That suggests that legislators often gather with like-minded colleagues who may not be homogenous from a party-standpoint. Second, region proves to be an extremely strong contributor to working groups even beyond party in the Senate. It's natural for legislators to gather with others who confront similar regional issues even when that involves working across the aisle. Third, committee proves to be very important in the Senate, again trumping partisanship. This reflects the traditional wisdom that Senate committees are deliberative bodies working through complex legislation while legislative activity in the House may be more governed by partisanship and ideology. Fourth, there is little evidence of legislators forming working groups based on the social issues (2nd) dimension of ideology; economic issues (1st dimension) predominate.

6.2 Party Impurity

One powerful application of CESNA clusters is to analyze how bipartisan working group clusters have been over time. To track this, we use the metric of party impurity. The party impurity of a cluster is defined as $p \times (1 - p)$, where p is the proportion of the cluster belonging to the Democratic Party (or equivalently, the Republican Party). Note that p ranges from 0 to 1. A value of $p = 1$ or $p = 0$ corresponds to a community comprised of only one party, and results in an impurity of 0. We note that the largest the impurity criterion can be is when $p = 0.5$; then, impurity equals 0.25.

We proceed with this analysis by first computing the impurity of of each stable community in each congress. We then compute the average cluter impurity within each congress. We then examine the trend of average community impurity as it differs from congress to congress.



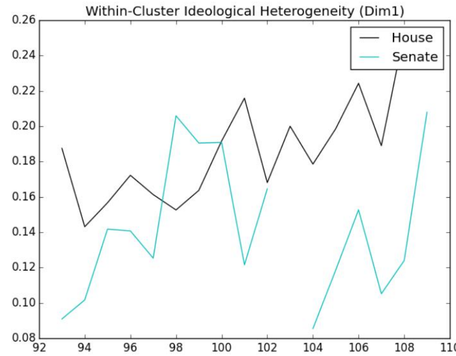
The results conclusively show that collaborative communities have not become more partisan over time. The Senate in particular saw dips in bipartisanship during the 103rd and 104th Congress but that is within a context of higher variance in general. In the House, things are more stable; working group clusters have had an impurity of around 0.08 for the past 40 years.

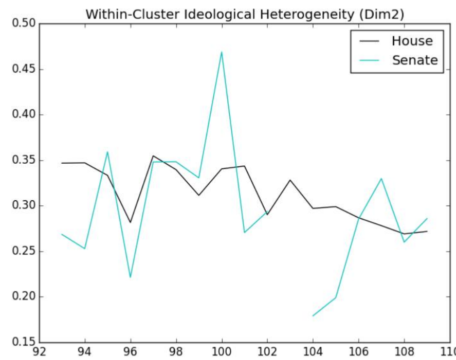
6.3 Ideological Heterogeneity

An interesting question is how ideologically diverse the clusters of working relationships are and how this has changed over time. Is it true that there used to be more diverse clusters in the past but that in an era of high polarization we now find only like-minded clusters? The metric we use to answer this question is the average of the within-cluster ideological variances in each Congress.

The evidence does not support the view of increasing homogeneity. If anything, it is fairly clear that along the primary ideological dimension (economic issues), working-group clusters in the House have become more diverse, while on the second dimension heterogeneity has remained stable. The Senate sees higher variance from year-to-year (punctuated by the 103rd Senate which is missing stable clusters altogether) but broadly follows the patterns of the House.

It is again striking how different this is from the sharp ideological clustering demonstrated in roll-call voting. When it comes to groups of legislators working together on bills, there is as much ideological diversity today, if not more, as there has been in the last 40 years.





7 Bill Passage

The web of working relationships in Congress is also interesting because of the effect it may have on legislative outcomes. A basic model of legislation, along the lines of the Median Voter Theorem [2], would say that legislation is most likely to pass if its ideological content matches most closely the median ideology of legislators. A more sophisticated take would include the effects of party such as the level of support by the majority party and party leaders, who can exert control on which amendments or bills will come up for a vote. Under this view of legislative activity, partisan polarization is a serious and potentially fatal roadblock to legislative compromise and productivity.

But there are several reasons to believe that there are factors beyond just party and ideology that would determine the success of a piece of legislation. For one, relatively few bills are passed relative the the amount introduced, so there is the question of which bills will be prioritized. Additionally, bills are often technical in nature without a major ideological component or are compromises between various factions. Finally, bills themselves might be subjects of larger compromises, in which legislators vote for each others' bills in what is known as 'logrolling' [11].

Each of these factors can be influenced by considering the network of working relationships. Congresspeople with more numerous, important, and strategic relationships may be more likely to get the bills they write or cosponsor passed, even holding fixed party and ideology variables. If working relationships remain important to the success of a bill, beyond its ideological content and even as the parties have moved further apart, that suggests that there is still a role for compromise and negotiation.

In many ways, the question of what makes bill passage more likely is similar to the question of community growth in the network literature. The success of a bill is analagous to the spreading of the early community formed by the early cosponsors to cover a majority of Congress. Backstrom et al. [1] identify several features of early networks that they see as important for growth. In particular, they find a lot of significance in the number of nodes that have edges to someone in the early network, which they call the 'fringe'. Additionally, they look at features related to clustering in the early network, such as the ratio of closed to open triads which is negatively correlated with growth. Finally, they look at the 'activity' of the initial group, which in our context might include the legislative productivity of the early cosponsor networks.

7.1 Features

We split our feature set into *demographic* features, *visibility* features, and *network* features over the early cosponsorship network. In the case where a bill does not have any cosponsors, the features are computed for the sponsor alone. To focus on the main backers and supporters of a bill and to avoid including cosponsors who join onto a bill when it looks like it will pass, we limit the pool of considered cosponsors to only those who sign on in the first 30 days after the bill was introduced.

The demographic features most prominently include party and ideology, and include age, gender, and region as well. These features are meant to capture the palatability of the bill to various factions. If a bill's chance of success really does depend primarily on its content, we would expect these demographic variables to be the important ones. In particular, we consider

- whether sponsor is from majority party
- party impurity of early cosponsors
- ideology of sponsor
- mean ideology of early cosponsors
- variance of ideology of early cosponsors

The visibility features are meant to capture how prominent or well-known a legislator is in Congress. In some ways, these can be thought of as a poor man's version of the network features, which explicitly capture how embedded a legislator is in the Congressional network. The idea is that more visible legislators will have greater success in attracting support for their initiatives. All variables that are computed in 'real time' are measured as of the first of the month after the bill was sponsored to reflect the state of the world after the initial cosponsorship network was formed. Our specific considered features are

- number of terms served by sponsor
- whether the sponsor is a chairman or ranking member of a standing committee
- number of bills written by sponsor so far
- number of bills cosponsored by sponsor so far
- number of consponsorships received by sponsor so far

Finally, we introduce our network features gleaned directly from the constructed web of working relationships. We construct the network in 'real time' for each bill, seeding it with the network from the prior Congress and keeping it up to date as of the bill's date so as to capture recent relationships and the situation for new Congressmembers. We view these relationships as the operationalization of the theory mentioned above that more visible legislators will succeed more often with their bills. Legislators with more useful working relationships with their peers may be more likely to get their bills taken seriously as good-faith legislative efforts, prioritized, and passed. It is useful to have more working relationships but it is also useful if those working relationships are with other influential members of Congress. Furthermore, it may be better if the early cosponsorship network has a diverse set of working relationships and don't cluster too tightly among themselves. These intuitions lead us to the following set of features

- degree of sponsor
- eigenvector centrality of sponsor
- cut size of set of early cosponsors
- clustering of early cosponsors
- presence of early cosponsors in stable CESNA clusters

7.2 Variable Importance and Significance

Joint Variable Significance

To demonstrate that certain sets of variables were significant, we first developed a logistic regression model using all of our data across all congressional years, separately for the house and senate. We then used an F-test for each regime of variables outlined in our feature section (ie. visibility features, network features, demographic features) to see if in conjunction they are all significant predictors or not. The results of the F-tests are as follows:

As we can see, each regime of features is highly significant in our models. This is evidence that each regime is providing joint importance in our model.

Variable Importance

We note from the prior subsection that many of the network features are among the most important features

Chamber	Vars	F-Statistic	p-value
House	Demographic	37.27	0.0
House	Visibility	150.93	0.0
House	Network	158.84	0.0
Senate	Demographic	54.93	0.0
Senate	Visibility	281.04	0.0
Senate	Network	35.89	0.0

Table 1: F-Tests of variable significance on different subsets of data

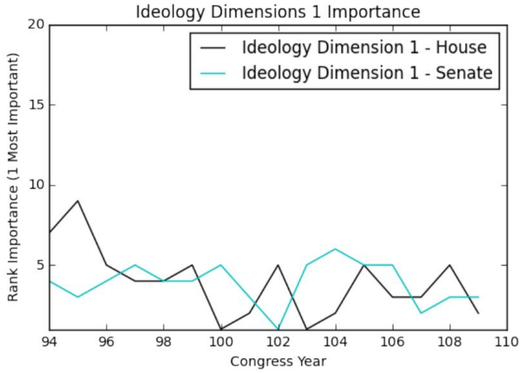
Chamber	Vars	F1 Score	Log Loss
House	Demographic	0.062	0.487
House	D + Visibility	0.063	0.480
House	D + V + Network	0.090	0.470
Senate	Demographic	0.585	0.524
Senate	D + Visibility	0.573	0.523
Senate	D + V + Network	0.627	0.512

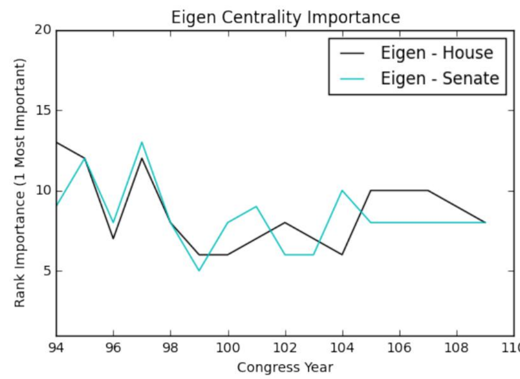
Table 2: Model performance on different subsets of data

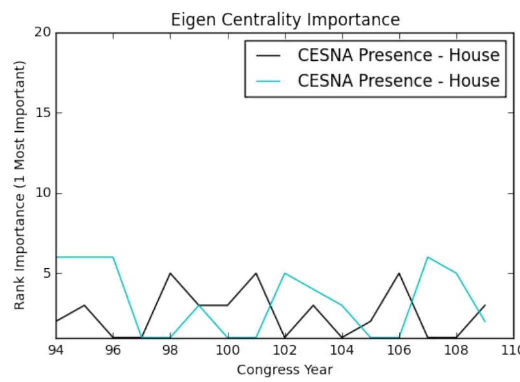
in the each logistic regression model, followed by ideology. However, we are unsure if we can trust these results due to the liklihood of strong colinearity between our features (for example, our network features are likely colinear since they approximately measure similar network features) and strong interaction effects. As such, we investigated a model that is robust to colinearity and can model interaction effects. We chose to use a boosted tree model.

We fit a boosted tree model separately for each chamber and year of Congress. We examined the variable importance for each model and plotted the rank of each feature's importance as it changes over time. We wished to see if certain features became more or less important over time.

By far the most consistently important features were our ideology features, followed by network centrality measures and presence in CESNA communities. We show plots for ideology dimension 1 and eigen centrality, omitting other ideology and network measures. These other measures behave similarly to these two.







Notice that these features are more or less stable in terms of importance over the years. This implies that the features that were important during the 94^{th} Congress remain important even to the 109^{th} Congress. This story appears to be the same for most features. Most features rarely change importance significantly.

7.3 Predictive Performance

Predictive models in both the House and the Senate bore out the finding above that network features are important to predicting bill success. Interestingly, crude approximations of working relationships like the number of cosponsorships given out and the number of cosponsorships received (contained in the 'visibility' section) did not meaningfully add predictive power. It was only when considering variables related to our network of actual working relationships that a boost was received above and beyond ideology and demographic variables alone.

The F1 score, a weighted average of precision and recall, depends on the actual 0-1 predictions. As a result, it is more jumpy. Adding visibility variables makes essentially no impact as few predictions flipped, even if predicted probabilities changed. Meanwhile, adding the network moved enough predicted probabilities across the 50% threshold, leading to sharply improved F1. On the other hand, log loss, which steadily rewards more accurate probabilistic predictions, shows smaller but still substantial gains to adding network features.

8 Conclusion

Party and ideology dominate every discussion about Congressional activity and rightly so. Yet even as partisanship has grown to record levels, a look at the network of working relationships reveals that things are not quite as polarized as a simple look at roll call votes would reveal. Bipartisan working relationships are as plentiful as ever and nonpartisan variables like region and committee remain instrumental in characterizing the clusters of working groups that form in the House and Senate. Within the clusters that form, ideological heterogeneity has if anything been increasing which is the opposite of what one would expect.

When it comes to bill passage, ideology is still the most important factor in determining legislative outcomes. But ideology alone, as represented by the ideology of the sponsor and early cosponsors, does not tell the whole story of a bill. Congressmembers with more numerous and important working relationships are significantly more successful in getting their bills passed. Strong relationships to multiple factions within one's party and across the aisle, and the flexibility and compromise that having those relationships signifies, are critical to achieving legislative success.

Going forward, it is important that we monitor not just the ideological gap between the parties but also the state of collaboration in general. If the web of working relationships, which has thus far been managing to stay healthy, starts to deteriorate, the level of Congressional dysfunction will only continue to grow.

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