District Demographic Impact on Partisan Activity in U.S. Congressional Voting Patterns

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I. INTRODUCTION

Most democratic governments rely on some level of cooperation between political parties to achieve success in passing major legislation. America's two-party system creates an environment that allows for success without requiring cooperation with the other party. As compared to other democracies that require the formation of coalitions across party lines, one party can succeed in passing legislation by winning elections and maintaining solidarity. This environment can incentivize a system that prioritizes partisanship both in supporting bills important to one's own party and minimizing support of the other party when solidarity is possible. Enforcing this, previous research has shown a growth in partisanship over the past 25+ years of congressional voting patterns. [1]

This creates ongoing problems where congresses at close thresholds in the house or the senate can cause devastating gridlock as either party's only major successes are at halting the action of the other. Recent stalemates has led to government shutdowns, ongoing inaction to major issues (e.g. healthcare and immigration) and political whiplash as either parties first steps on taking office are to reverse as much as possible that was completed by the party before it.

Causes for partisanship over recent years have been attributed to changes in political identity within the American southeast [2] the actions – success and failures – of presidential agendas [3] changes to political agendas that highlight partisanship at higher rates [4] and increased wealth inequalities. [5] [6]

The intent of this paper is to outline the ways that network science has been applied to the idea of partisanship in the Congressional Bodies of the United States. After reviewing work completed in clustering and modularity, a new domain in district level analysis will be applied to find where there are areas of heightened or diminished partisanship in the 116th house of representatives. Congressional districts will be categorized by single and multi-dimensional techniques to compare partisanship metrics to the entire body.

Before continuing, it is important to define partisanship and polarization because these two words are often interchanged where in this paper, I will maintain a valuable distinction. Polarization refers to dividing political beliefs between both parties. When one or more political parties become more extreme in their views, polarization is increasing. Multiple studies have shown the rise in polarization among the public [7] and political parties. [8] Partisanship on the other hand refers to political activity becoming more defined along party lines. A highly partisan congress is one where participants in competing parties do not work together to pass legislative action. It's reasonable to expect that an increase in political polarization leads to an increase in partisanship but they are two distinct phenomena. Their research is tightly intertwined as both correlate in political bodies. However, this paper will largely be focused on party cooperation, aka partisanship, instead of changes in political beliefs.

II. RELATED WORK

Quantifying levels of American political partisanship has been predominantly done through role call voting often because of its accessibility and it's direct relation to political activity. The data often consists of a series of columns and rows indicating which politician voted for each bill. Other designations such as paired, announced, or abstained votes may also be included. Some studies discriminate data based on the type of vote being taken - proposed actions, new laws, or procedural agenda votes – by choosing to exclude any votes of a particular type if the researchers feel that category does not pertain to what is in question. This voting data for individual bills is available through a variety of sources with databases stretching back to the eightieth century and are consistently updated as new votes are made, often within the same day the votes were cast. [9]

Using roll call history, graphs can then be created connecting individual politicians through similar voting patterns. These graphs can then be analyzed for group cohesion, associativity, modularity, and other methods to quantify the interconnection between the nodes. The challenge is then deciding at what point an edge should be created between two politicians. In any congress, there are legislative actions where every member votes in the same way so surely a fully connected graph is not a helpful object to study. Some resolve this by not creating an all or nothing binary edge, but instead a weighted edge based on the count of co-voting instances. [1] [10]

Once the graph is created, network and political scientists have investigated congressional political action through a variety of actions. These include community detection methods [11] to estimate party affiliation using a newly proposed GLaSS method. They also concluded that this problem has become far easier to solve in recent years as voting patter distributions have become increasingly stratified, further supporting previous work with similar goals. [1] [8]

A. Modularity

Waugh et al. [10] uses modularity as their central focus to quantitatively describe changes in polarization from the 91st to 112th congresses. Modularity, first proposed by Newman & Girvan [12] is a method to greedily optimize partitions to maximize the strength of ties within a group as compared to the total tie strength between nodes of other groups.

$$mod(\mathscr{E}) = \sum_{k=1}^{K} [f_{kk}(\mathscr{E}) - f^*_{kk}]^2 \quad (1)$$

Given $\mathscr{E} = \{C_1, .., C_K\}$ is list of graph partitions and $f_{ij}\mathscr{E}$ is the proportion of edges that connect C_i to C_j. The resulting equation 1 provides the modularity of that partition where f^*_{kk} is the expected value of f_{kk} under a random model. Often this is defined to be $f_{k+}f_{+k}$ where each are the k-th row and column sums of f. This represents a model with the same degree distribution as G but with random rather than observed edges. The resulting summation, if large, leads to an expectation that $\mathscr{E}$ comprises of a significant group since its interconnection of edges occur at higher rates than what is expected in a random model.

Using this framework, they partitioned roll call voting networks using hierarchical clustering to maximize modularity scores compared to the standard Newman-Girvan null model with the same degree distributions. [13] [14] With these partitions, each nodes political party were then revealed to reviewing the intermixing across party lines.

They then also found the modularity of each individual politician. More specifically, it is their history of voting within or outside of their assigned group. This allowed them to explore the connection between voting behavior and the result of subsequent reelection expectations.

$$|x_i|^2 = \sum_{j=1}^{p} (\sqrt{\lambda_j} U_{ij})^2 \quad (2)$$

Defined in equation 2, the divisiveness of a node i first introduced by Newman [13] where p is the number of positive eigenvalues defined as lambda. U then represents the corresponding eigenvector. The resulting value represents the potential impact on aggregate modularity for each member. These values will range from 1, indicating strong cohesion, to 0.

The results of this study found strong evidence of increasing modularity through the scope period showing a change in group dynamics between either political party. Further they found that congresses with strong parity between polarization levels, deemed ‘partially-polarized’ congress often preceded major changes in party dynamics in subsequent years.

B. Assortativity

Another way of testing partisanship is through assortativity coefficients. Instead of clustering nodes to maximize disconnection and then reviewing party status, assortativity looks directly at the latent qualities of each node to quantify their interconnection, or lack there of.

Given f_{ij} as the proportion of edges that connect nodes i to j, $f_{+i} and f_{i+}$ represent the i-th marginal row and column sums. The resulting equation 3 provides r_a, the assortativity coefficient of the graph.

$$r_a = \frac{\sum_i f_{ii} - \sum_i f_{i+} f_{+i}}{1 - \sum_i f_{i+} f_{+i}} \quad (3)$$

This value provides a regularized score of interconnectivity between nodes with different latent variables. Those variables can even be categorical, ordinal, or continuous.

Using these techniques, the rest of this paper will focus on a different avenue to investigate these topics of partisanship. Specifically to evaluate the impact of district diversity on a representative’s voting patterns. The diversity of the American population across racial, financial, educational, and lifestyle spectrums lead to wide differences in thought for the challenges facing political leadership. These populations elect politicians to represent their views at the federal level. As such this diversity of thought is going to lead to natural partisan behavior. Studies have found that parties have been increasingly successful in identifying the populations that they choose to represent leading to more district populations consisting of homogeneous voters. [15] [16] By taking a graph of roll call votes and inducing subgraphs by identifying similar district populations, I expect to see areas of varying levels of partisan behaviors. By restricting the graph to all those that, for example, represent higher income areas we may see increased party cooperation than the country as a whole. Further, by including a variety of demographic information districts can be grouped by similar constituencies through an unsupervised machine learning method, possibly OPTICS. By doing so, changes to levels of modularity imply either inter-party cooperation or highlighting areas of party solidarity overriding constituent needs.

III. Data

This study will focus on the 116th US house of representatives, first by investigating modularity and assortativity of either party through the entire congressional network. These totals will provide a bench mark to then compare to district level investigations. The 116th congress was chosen as this is the most recent congressional body with up to date demographics. The conclusion of the 117th congress will pair well for further research as the 2020 census is fully investigated and settled.

Roll call voting is provided through VoteView. [9] Their database contains a row for each member and their vote to a particular bill. Abstinence “votes” are seen has unsupportive and are then counted as a “nay”. This data provides an

ICPSR ID which is then connected to that representative's congressional district. District demographics are provided from exports from the US Governmental Census website. Major distribution fields are age, racial makeup, ancestry, occupation, industry, home ownership rates, income levels, poverty levels, and educational levels. These are provided as varying buckets, e.g. count of households making $10,000-14{,}999$, $15,000-24{,}000$, etc. These distinct volumes were then aggregated and then converted into z-scores so that singular values can be compared across districts and overall deviations can be compared.

IV. Methodology

The combination of these data sources creates a graph with nodes of congressional members connected by edge weights representing their co-voting patterns. That means each co-voting instance of "yay" or "nay" between two members represents one unit of edge weight.

With the initial graph constructed, district demographics were then joined in as individual attributes quantifying a variety of census sourced data. I then removed any members that were not part of either the Democratic or Republican districts. The exclusion of these limited members was done to focus the scope of the work as the goal was to investigate inter-party cooperation between either major party. Independents aren't able to be studied as a monolith as there are a plethora of reasons that one may wish to not identify with either party. Those varied reason significantly influence their voting patterns. Further, members that did not vote on at least 75% of the votes were excluded as their output was not representative of other similar members.

Once that was completed, the districts were categorized across a variety of a clustering methods including KMeans, spectral clustering, affinity propagation, optics, DBscan, and birch. Most were later dropped as poorly fitting the data. Specifically, the high dimensional landscape caused far too many districts to not be categorized using density based methods. Others such as spectral and affinity led to massive clusters with >80% of the districts in one group with outliers populating the rest. Ultimately, KMeans and Birch proved to be the best options as they provided both valuable and interesting clusters to work with.

For both methods the models were trained to find three clusters. This was because two did not provide enough definition while more then three lead to clusters of small groups of outliers. Despite the similarities, both algorithms found noteworthy differences in how to differentiate the districts.

These groups were then be measured in a similar manner to the full congressional graph to determine modularity and assortativity between parties. In this final output we expect to find clusters where partisanship activity presents itself at different levels showing us where it is more of a problem as well as where both parties are working together.

V. Results

A. Basic Analysis and Benchmarks

The final constructed graph consisted of 426 nodes, aka congressional members, with over 90,525 shared voting patterns. Drawing this graph provided incomprehensible results as it is fully connected with an average weight between 500 and 600 shared votes. The distribution of votes can be viewed in figure 1 showing histograms of edges within and between either party. The left chart shows the volume of binned edge weights from republican nodes to either other republicans or democrats. The right chart shows the same except coming from democratic nodes to either in or out of party connections. These distributions do line up with the work of Glonek [11] showing distinct intra-party centers with few overlaps between. It should be noted that the imbalance between either parity's charts do not indicate differences in cohesion. For this congress the democratic majority leads to more of their members voting with each other leading to higher overall histogram totals.

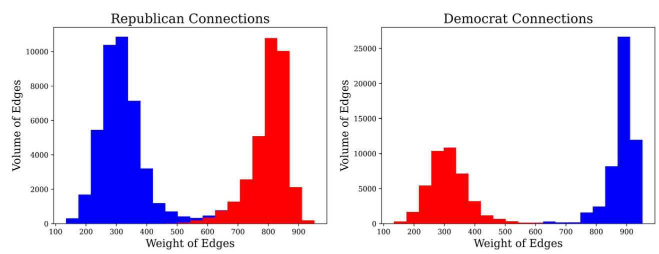

Fig. 1. Edge Weights by Party

To benchmark inter-party cohesion, using party affiliation as community distinction I found an overall modularity value of .2182. Reversing this premise, this is also the maximum modularity of the graph as greedy modularity partitioning also fell along party lines. In addition, assortative mixing values are provided in table I. This does show higher levels of democrats voting amongst themselves, then democrats voting with republicans and lastly republicans voting with themselves.

TABLE I
OVERALL ASSORTIVITY BENCHMARK

	Democrats	Republicans
Democrats	.3061	.2471
Republicans	.2471	.1992

B. Single Attribute Filters and Clustering

Before diving into clustering, I wanted to look at district demographics as a singular lens. For example, do representatives of predominantly white districts vote in similar ways to representatives of non-white communities. Do representatives of poor communities vote in similar ways to rich ones. Figure 2 shows a series of modality scores over varying splits in attribute z-scores. Each line shows the modularity values

TABLE II
CLUSTER ATTRIBUTES FROM KMEANS AND BIRCH ALGORITHMS

		Cluster 1		**Cluster 2**		**Cluster 3**	
KMeans	Party Count	Dem: 61	Rep: 160	Dem: 96	Rep: 19	Dem: 71	Rep: 8
	Attributes Z-Score	% Minority % Veteran % Car Commuting	-0.5579 0.5784 0.3920	% Bachelors Median Income Poverty Rate	1.2237 1.1757 -0.8019	Poverty Rate % Unemployed % Minority	1.3001 1.2599 1.208
	Assortivity	.0753 .2007	.2007 .5232	.6957 .1391	.1391 .0261	.8066 .0922	.0922 .0091
	Modularity	.1254		.0374		.0152	
Birch	Party Count	Dem: 78	Rep: 21	Dem: 111	Rep: 36	Dem: 39	Rep: 130
	Attributes	Poverty Rate Unemployment % Minority	1.1721 1.1078 0.9120	% Bachelors Median Income Poverty Rate	0.9030 0.8915 -0.7758	% Veteran % Minority % Blue-collar	0.7190 -0.4877 0.4634
	Assortivity	.6190 .1688	.1688 .0433	.5689 .1862	.1862 .0587	.0522 .1786	.1785 .5907
	Modularity	.0707		.0860		.0898	

if communities were created by splitting along that attribute z-score. All attributes roughly saw maximum modularity centered at zero. Showing the most distinct communities are created along the mean. Car commuting and percent veteran show the highest values topping .06 with .045 from % minority. However, all of these values are very close to zero indicating that singular demographic community splits do not meaningfully explain total congress partisan behaviours.

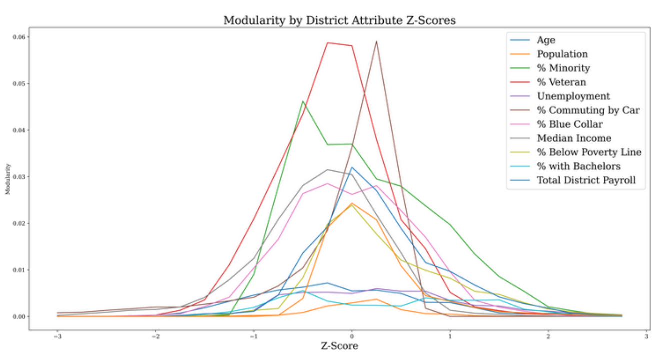

Fig. 2. Modularity Across Attribute Z-Scores

Contrary to our earlier results, we do begin to see partisan behavior rise within the clustered groups. Table II presents a variety of information about each of the six clusters. Particularly notable are how distinct some of the cluster's party counts are. KMeans and Birch are not classification algorithms, yet just by looking at district attributes, both found groups that captured high party imbalances. KMeans cluster three, consists of 90% democratic districts. Cluster one, while being more diverse, has picked up 86% of all republican seats.

Within all three KMeans clusters, assortativity values rise higher than our full congress benchmark. This shows an increased tendency for working within parties. However, this tendency is exaggerated by the significant imbalance in these clusters. More interesting are the minority party members which show much lower levels of partisan behaviors when compared to districts of similar demographics.

Across every cluster, modularity values from party communities are lower than the congressional bench mark of .2182. In almost every case, these values are also the maximum modularity partitions of the graph. There are a handful of cases where members from the dominant party break to the minority but they have insignificant impacts on the final value. These results show that by breaking the congressional body into similar constituent blocks, overall partisanship behaviors reduce.

VI. CONCLUSION

In this paper, I extended the work completed by Waugh et al. [10] to investigate partisan activity through the network science principles of assortativity and modularity. These techniques which quantify the propensity for communities and their nodes to interact with each other, allowed us to look into how the U.S. House of Representatives worked together through the 116th congress. Extending this work to account for district demographics, we looked for areas of different partisan activity levels. Among single attribute lenses, (e.g. high to low income districts) the greatest levels of community distinction consistently centered around the average of the attribute's values. However, none of these splits resulted in any significant modularity values.

Next the districts were categorized through a variety of clustering methods, landing on KMeans and Birch to partition the districts into three individual clusters each. I expected some clusters to be have party imbalances. However, the extent to which democratic and republican districts tend to collate was surprising. Within these imbalanced clusters, the minority members consistently showed increased levels of cross party cooperation suggesting that constituent needs do still counter party solidarity in meaningful ways.

These results show that by accounting for the diversity of constituencies, hyper partisan activity falls. If trends of districting continue, it would not be surprising to find overall partisan activities to continue to increase as members increasingly rely on a homogenized base which supports more extreme choices. The results of this would be continued and stronger gridlock than what already bogs this political system.

A. Further Research

Further research to support this argument would be to reverse the premise. If we compare districts with the largest demographic differences, do we see increased rates of partisan activity. I did compare voting patterns between parties of different clusters and in every case modularity was higher than what was found within their own clusters. However only the combination of Republicans in KMeans cluster three compared to Democrats of clusters 1 and 2 produced a value larger than our benchmark with .2309. Continued study focused on maximizing modularity may find success comparing a subgrah of districts picked for maximum distance.

Further, a longitudinal study comparing congressional votes to changes in historical district demographics would be another opportunity to extend this study. As demographics and districting strategies have changed over the nation's history, I'd expect their connection to voting pattern would change as well.

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