Identifying Factors in Congressional Bill Success

CS224w Project Proposal

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Introduction

During an era of government where Congress has been criticized repeatedly as being the most polarized and unproductive (in terms of bills passed) in American history [5, 6], understanding group decision making and the power dynamics behind it has peaked our interest. We would like to investigate what factors are involved in the success of Congressional bills, and use this data to develop a model for predicting the success of a bill.

Unlike previous groups' projects which attempted to predict an individual Congress member's voting behavior based on the voting behavior of other party members on the same bill, our goal is to predict whether a bill will be successfully passed by Congress with only information that is available prior to a bill being voted upon. Additionally, we are interested in the network structure introduced by collaboration between Congress members and by campaign contributions to Congress members and investigating how the structure of this network might impact bill success. Previous projects used network structure derived from Congress members' social media accounts; we're unsure whether this adds much value, as these accounts are likely maintained by staff members and probably don't accurately represent connections between Congress members that would strongly influence voting behavior. (The previous project mentioned is *Utilizing Network Analysis to Model Congressional Voting Behavior* by Janice Lan, Mengke Li, and Suril Shah).

As such, we have chosen papers that discuss collaboration, propagation of ideas as well as recommender systems in order to better understand the methods for predicting group and individual decision making within the context of a robust network of interaction.

Governance in Social Media: A Case Study of the Wikipedia Promotion Process

by Leskovec, Huttenlocher, Kleinberg

This paper studies the Wikipedia promotion process as a model for group decision making through online social media. Leskovec et al. analyze forms of relative assessment to understand how individual users will vote on a candidate and how those votes will aggregate to form a final election decision. They use several "figures of merit," most notably the user's number of edits and number of *barnstars* in order to describe a merit based relationship between voter and candidate. They show that there are non-monotonic effects of relative merit and a clear difference in voting patterns when a voter has less merit versus more merit than the candidate.

They also analyze how voters respond to the behavior of other voters. Since all votes are public and sequential, they explore whether time is correlated to the vote outcome. Although the aggregate behavior tends to follow what seems to be a "herding" model, this behavior is "not typical of any particular individual, but instead represent averages over populations that are highly heterogeneous." Thus, the propensity to vote positive after a certain threshold of previously seen positive votes is highly dependant on the individual, but as a group average, closely matches the baseline. This baseline is calculated by randomizing each vote and then biasing it proportionally to the current fraction of positive votes. Last, they discuss patterns among the first few votes and map them to the probability of a positive election outcome.

Critique

By focusing almost entirely on the individual's voting behavior, we do not learn much about the groups deliberation habits and how this plays a role in the election process. The Wikipedia promotion process is heavily weighted in the positive direction. There are, in total almost 4 time as many positive votes as negative and 49.6% of elections result in a positive outcome. We would like to know if this is because of who decides to go up for election and who decides to show up to vote. These two factors are presumably affected by the deliberation process prior to the actual voting period, and it would be interesting to understand its contribution to the election outcome.

The analysis of the first few votes and how those can predict end outcomes does not seem very robust. Given that relatively few opposing votes are actually given across all elections, 23,118 out of 114,040 of total votes and 3.1 out of 56.8 votes in positive outcome elections, having even one opposing vote in the first few votes dramatically changes the probability of a positive election. We believe more analysis could be done to understand the best indicators of a certain election outcome, i.e. who are those first few votes coming from, what is their position in the network, and how do they relate to the candidate. It seems that their insights from studying relative merit between voter and candidate could have been extended beyond just individual voting habits but also predictors of entire election outcomes.

Brainstorming

It will be useful to understand the objective measures of each congressman, how the congressmen relate to each other using these measures, and how that relationship influences an individual congressman’s vote, but we would like to extend this to include how those congressmen relate to each other within the network’s structure. By developing networks of collaboration and outside contributions, as well as triad analysis, we can understand more about the context of a congressman’s decision, and hopefully find strong correlations.

While Leskovec et. al’s paper sites Burke and Kraut in their study on the Wikipedia promotion decisions as focusing on the candidate and their objective characteristics to predict election outcomes and voting behavior, we feel more can be done to understand the candidate, or in our case the bill, and its context within a network. By developing a network of bills, where edges between bills correspond to shared sponsorship, and analyzing the clustering of this network, we hope to better understand the relationships between bills that get passed and those that don’t.

We also believe that congressional voting data may be a better platform for understanding and modeling the deliberation process and how it relates to a particular group decision outcome. Since only 5% of bills are actually passed, even within likeminded groups of people, it is difficult to get a positive outcome on a bill. The Wikipedia article is only able to discuss a binary, positive or negative, outcome, however we can use data from Govtrack to create a success score for each bill. The farther into the process a bill makes it the more successful it is.

Propagation of Trust and Distrust

by Guha, Kumar, Raghavan, Tomkins

Guha et al. investigate the flow of trust (and distrust) through a network, taking the web of trust as an example. Trust plays an important role in both physical and online networks, for example setting the price range of an item on eBay.

They use a data set from the Epinions website, where users write reviews on products, services and entertainment, with helpfulness of reviews indicating trust. Starting from an initial matrix of beliefs of trust and distrust on the world, they model the spreading of trust during a single time period by applying a matrix operation. These steps are repeated k times to a final matrix. There are various factors in their model including:

1. The manner in which trust is propagated: by transitivity (direct propagation), by symmetry (transpose), by implication of shared beliefs (co-citation), etc.
2. Whether distrust is propagated and, if it so, fully or partially: trust-only, one-step distrust, distrust propagation.

They discovered that using a combination of all propagation techniques and one-step distrust, the model was most accurate in predicting the direction and magnitude of trust .

Critique

The authors are thorough in their investigation, choosing to run experiments with 3^4 dimensions of factors. However, we believe that they ignore some factors which, albeit not as relevant to the online world where everyone is a stranger, have more importance in the physical one as when applied to the political domain. For example, the magnitude of trust between two people will decrease with distance (distance measured as the shortest length of a chain of mutual connections connecting two people). If two people are connected via a series of mutual neighbours, then it is unlikely that they trust each other as much as their immediate neighbour, even if all the people in the chain trust each other highly.

The paper does not capture the effect when outcomes of decisions are influenced by other external potentially emotional factors. Members of rival parties may have opposing voting patterns but may have a mutual trust (or respect) of each other. It would be interesting to analyse how this could be measured and whether it would reveal any insights to improve predictions.

In the paper, trust is determined solely using review ratings, whereas it is quite believable that trust is affected by any homophily in age, gender, ethnic, etc. The authors of this paper do not investigate the structure of the resulting network and so can provide no insight towards this.

Brainstorming

In the political domain, people belong to parties and are, sometimes, forced to vote in blocks. People disregard their personal views, and by implication trust network, for their party's. It would be interesting to see how this could be modeled. It may create noise when looking at trust from the perspective of individuals. Alternatively, taking the perspective of parties, individual behaviour may also create noise. One goal is to be able to predict the association of political parties to individuals based on their voting patterns, by analysing clustering.

It would be useful to analyse whether there are any clusters of high trust or distrust in the final network, and attempt to infer what this means. By looking at the quantity of unstable triads, and how this value changes over time, it may be possible to predict when bills with very small winning margins arise.

The model could be extended by including additional attributes of homophily into the trust measure and making it a decreasing function of distance. The voting patterns could be an output of these measures. If circumstances where there is no prior relationship with the sponsors of a bill, their background will play a part. This may only impact newly elected members or those from obscure locations. We could explore whether adding these attributes into the trust measure produces a better prediction.

Improving regularized singular value decomposition for collaborative filtering.

by Paterek, Arkadiusz

This paper describes and improves upon several techniques used in the Netflix Prize competition. The goal of the competition was to use historic rating data to provide better content recommendations to Netflix viewers, improving upon the performance offered by Netflix's algorithm.

The paper presents several basic models, and improvements upon these: regularized singular value decomposition (also referred to as matrix factorization in other works) of a user-rating matrix, K-means using vectors of user ratings, and using K-nearest neighbors with the results of matrix factorization. The most successful techniques built upon matrix factorization. The basic idea is to model a user's rating as the dot product between two vectors of k parameters, representing some quality about the user and the movie. The vectors are trained using a gradient descent algorithm. The paper found that the basic method and enhancements to it were successful in providing improvements upon Netflix's algorithm.

One of the most interesting alternative methods applied is using the resulting movie vectors in combination with a K-nearest neighbors algorithm to predict user ratings, using cosine similarity as a distance metric.

Critique

As the author notes, cross-validation was not used to evaluate the methods; instead a test set was used. Cross-validation might give more accurate performance measures. However, the main weakness in these methods is that they use limited information about the user or movies. This is because the data provided for the Netflix competition consisted only of ratings, but in practice Netflix and other recommender systems have additional information about the user, such as demographic information and information about the users' connections to other users. Information about individual movies, such as genre, age, length, etc. is also not incorporated into any of the models.

Brainstorming

The ideas used to predict a user's rating of movies based on the rating graph of other users can be applied to the task of predicting how congress members will vote on bills. A useful aspect of the matrix factorization methods is that they can be used in scenarios with sparse ratings. For example, we could find values for user vectors corresponding to each congress member using historical data. For newly introduced bills, we could approximate the vector representing the bill using the user vectors of only the bills' sponsors; this would be useful in building a model that allows prediction of a member's vote without needing to take into account the votes of all members of Congress, which would be unknown at the time of the bill's presentation.

A way in which these techniques could be improved upon is to incorporate explicit information on network structure into the system. (4) presents some techniques for using matrix factorization in combination with additional information known about the users and items. An example of information that could be included would be network centrality metrics measuring centrality of the congress member whose vote is being predicted, and the network centrality of the sponsors of the bill.

As a secondary note, another interesting use of the techniques presented is to use the user vectors to measure similarity between congress members, in a similar method to how the author of the paper proposed examining cosine similarity between movie vectors. K-means or another clustering algorithm could be used to find groups within the members; it would be interesting to see if these correspond to party lines.

Summary

The main pieces that we felt were missing from the literature discussed above were

- The use of more substantial networks and topology to understand the context of decisions.
- An analysis of robust indicators that can predict a final outcome, i.e. group decision.
- Full use of the data points and inputs at hand, e.g. attributes of homophily, network centrality, network clustering, etc…

These papers relate to each other in that they discuss indicators for preferences, decision making and influence within social networks. In Leskovec et. al's paper, they explain that group decision making and governance heavily involve both deliberation and enforcement, and they chose the Wikipedia promotion data set because it is a "deliberative process carried out by core, committed members of a social-media community." While these paper certainly expose interesting correlations between the actor (voter/user/rater) to object (candidate/movie/products) relationship and the individual actor's behavior, it doesn't factor in the entire network structure and context. Rather they use mostly discrete measures to and linear relationships in order to suggest causality for a positive vote/recommendation/review.

We want to more thoroughly explore how these discrete measures compare to more contextual measures found using a variety of graph topologies that relate object to object and actor to actor as well as actor to object. Using these kinds of networks as well as modeling success as a score rather than a binary outcome, we hope to shed more light on deliberation and decision making, and how they play a role in the final outcome of a congressional vote

THE PROPOSAL

The Problem

We propose investigating what factors are involved in the success of Congressional bills, and whether these factors can be used to predict the success of a bill. If we are able to identify indicative characteristics, we would like to investigate how these characteristics might be manipulated to increase likelihood that a bill will succeed.

The Data

The questions and techniques posed will require information on congress members' voting behavior, connections with other congress members, and campaign finance information. All of this data is readily available from several sources.

GovTrack.us hosts detailed information about Congress members and bills. The most useful data provided is likely the voting record of each member. In addition, information about Congress members' involvement and position in different committees is present and can be used to construct a graph modeling members' collaboration in such committees. Sponsorship information about each bill introduced is also provided and could be used to create a collaboration network between members, draw connections between separate bills, or infer information about the bill.

The Federal Election Commission provides data on campaign contributions to public officials from action committees and individual contributors. This information can be used to construct a graph modeling connections between Congress members and their sources of campaign contributions.

The Algorithms, Techniques, and Models

In modeling bill success, we will use several techniques. We are particularly interested in the connection between campaign finance sources and bill success. We plan to use collaboration networks between Congress members to find network centrality of the members, using an algorithm such as PageRank, to better inform our models. We are also interested in using a tripartite graph linking campaign finance sources to the candidates they supported, and the bills supported or sponsored by those candidates to see if this sponsorship affects bill success. A third network structure we would like to examine is the network of bills linked by common sponsors to see if any community structure is present that may provide information about bill success.

Another component in predicting bill success is modeling individual voting behavior of congress members. We are interested in investigating how Congress members relate to a particular bill across several dimensions. A starting point for this investigation could be the matrix factorization methods presented by Paterek. Vectors modeling Congress members' preferences can be derived from historic voting data. When attempting to predict behavior on a new bill, a vector describing representing the bills' characteristics can be derived from the vectors modeling the bills' sponsors. These vectors could be used to predict the voting behavior of each Congress member individually.

In addition, as illustrated by Koren et al., additional information known about the bills and Congress members can be used to enrich these vector representations. Network centrality, measured by PageRank or a similar algorithm, of each Congress member over the collaboration network formed by bill co-sponsorship or committee membership could be included as a characteristic of the member whose vote is being predicted. Similarly, information known about bill sponsors, such as the sponsors' network centrality, committee involvement, and time of year could be included as known characteristics of the bill.

Types of Networks and Relationships
Congressman ---[co-sponsorship]--- Congressman
Congressman ---[co-membership of committee]--- Congressman
Bill ----[shared sponsor]--- Bill
Interest group ----[contribution]----> Congressman
Congressman ---[vote (+ | -)]---> Bill
Congressman ---[vote (+ | -)]---> Bill Sponsor
Interest group ---[contribution]---> Congressman ---[vote (+ | -)]---> Bill

Depending on which of these techniques provide information about bill success, we could potentially use results of several methods as features to be used in a machine learned model that may increase our success at predicting bill success.

Evaluation
Our model will be created and trained based on historical voting records from the data available at GovTrack.us. A subset of this data will be set aside as a test set for evaluating how well the model is able to predict a bill's success through congress. If appropriate and the time needed to train the model multiple times is feasible, cross-validation on the training set could also be performed.

Goal/Deliverables
We would like to identify what characteristics lead to a bill's success. If such characteristics can be identified, we would like to propose methods of maximizing these characteristics and thus likelihood of bill success.

RESOURCES

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