

Analysis of Parliamentary Debate Transcripts Using Community-Based Graphical Approaches (Student Abstract)

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Abstract

Gauging political sentiments and analyzing stances of elected representatives pose an important challenge today, and one with wide-ranging ramifications. Community-based analysis of parliamentary debate sentiments could pave a way for better insights into the political happenings of a nation and help in keeping the voters informed. Such analysis could be given another dimension by studying the underlying connections and networks in such data. We present a sentiment classification method for UK Parliament debate transcripts, which is a combination of a graphical method based on DeepWalk embeddings and text-based analytical methods. We also present proof for our hypothesis that parliamentarians with similar voting patterns tend to deliver similar speeches. We also provide some further avenues and future work towards the end.

Introduction

With a rise in political and social turbulence across the world, there is a greater need than ever to gain more awareness about what elected representatives at all levels of governance have to say about matters of importance. Public knowledge of political affiliations helps in aiding the democratic process and enables transparent, healthy governance.

In this case, analyzing the sentiments presented by parliamentarians and other representatives can be of immense help. A good source for this is speeches and debates delivered in parliament sessions. However, since both politicians and speeches are numerous in quantity, it is more practicable to analyze them using mathematical models and sentiment analytical techniques.

In recent times, graph-based solutions for problem areas like sentiment analysis, fraud detection, *etc.* have demonstrated considerable performance, and are gaining in ubiquity across several other fields of study. Analyzing the communities inherent in various datasets could help provide better insights, further enhancements and new conclusions as well. Constructing graphs to map such communities and study them leads to a concise, mathematical representation

of properties like homophily, which could further describe patterns in the community itself.

We construct two graphs for the underlying communities in the Hansard parliamentary debates dataset (Abercrombie and Batista-Navarro 2018) to codify party affiliations, motion polarities and debate sentiments. We use DeepWalk (Perozzi, Al-Rfou, and Skiena 2014) to generate embeddings for both, combine them using a deep learning-based approach, and then use these embeddings with two text-based features (TF-IDF scores and Harvard General Inquirer lexicon's subjectivity scores) for speech polarity classification. We then construct a new graph to test our hypothesis that politicians who vote similarly on motions tend to speak similarly as well. Finally, some further directions for the problem that could be explored as presented.

Related Work

Sentiment analysis of political content has recently attracted the attention of several researchers. (Bakliwal et al. 2013) presented a sentiment classification system based on tweets centered around the Irish general elections.

Sentiment Classification

The Hansard debates dataset consists of speeches of 607 politicians on various issues regarding governance, health-care, security, *etc.* Motions along with their polarities are presented, along with speeches, speaker party affiliations and speech polarities. There are two types of motion polarity labels: a manually-annotated label which assigns motions as positive or negative, and a government/opposition-based labelling: if the motion is presented by someone of the ruling party, then the polarity is positive, else negative.

A two-step classification approach is followed. Firstly, motion classification is performed using a multi-layer perceptron, which enables us to separate the dataset out into those with positive motions and those with negative.

In the second step, to construct a feature set for analysis we use a combination of graph embeddings and text-based features. The text-based features, derived from each speech, are given below.

- TF-IDF scores: TF-IDF features were extracted from n-grams in the transcription. Upto 3 (tri-grams) were used.

** Indicates equal contribution

Feature set	Precision	Recall	F1 Score
HI + TF-IDF + DeepWalk	0.932	0.927	0.93
HI+DeepWalk	0.911	0.908	0.907
TF-IDF + DeepWalk	0.902	0.906	0.903

Table 1: Results using DeepWalk and text-based features

- Harvard General Inquirer lexicon: It is a lexicon of English words with categorical labels which could be used for performing sentiment analysis. We used this lexicon to calculate subjectivity scores for each speech.

For the graph-based features, we constructed two graphs namely SimGraph and OppGraph. These graphs are based on those presented in (Bhavan et al. 2019).

- *simGraph*: In order to model the similarity on stances among members, $G_{sim}(v, e)$ is an undirected graph constructed on the dataset with vertices v corresponding to the members m of political parties, where an edge e between two vertices v and u is defined as $weight(e) = |f(v) \cap f(u)|$ where $f(v)$ is the set of stances taken by the member that is represented by node v .
- *oppGraph*: Similarly, to model the differences among the members in terms of affiliations and voting patterns, $G_{opp}(v, e)$ is induced on the dataset such that an edge e between two vertices v and u is defined as $weight(e) = |(f(v) \setminus f(u)) \cap (f(u) \setminus f(v))|$.

After constructing these graph, embeddings for each were generated using DeepWalk, with walk length 70, embedding dimensions 128 and the number of walks 10. The two embedding sets were then combined using a deep learning approach. The neural network consisted of two layers to take input as the two embeddings, which were then combined and passed through two dense layers with ReLU activation.

Once the final set of combined embeddings was generated, it was concatenated with the textual features. This feature set was then used to train a multi-layer perceptron using ten-fold cross validation. The results and observations are presented in Table 1.

Compared to the results presented in (Bhavan et al. 2019), classification performance was enhanced by using DeepWalk instead of node2vec and lesser number of textual features (2, compared to 3 used in the baseline paper). The dimensionality of the feature vector is thus reduced to a great extent. The difference, however, is not very big, raising the need for further investigations using community detection-based methods. The best results were obtained by combining both TF-IDF features and lexicon subjectivity with DeepWalk embeddings, rather than the two being used individually.

Hypothesis and Testing

Hypothesis: Politicians who exhibit similar voting patterns have speeches of high similarity.

In order to study this hypothesis, we construct a new graph based on speech similarity. Each politician is con-

nected to the other, and edge weight is computed as the sum of the cosine similarities of the Word2Vec embeddings of the speeches delivered by the politicians on the motions they have both presented their views on. Further, this sum is weighted, we take the speech polarity confidence scores and based on the similarity of predicted speech polarity, we take a weighted sum of the cosine Word2Vec similarities, weighted by the raw log probabilities (positive for match and negative for mismatch)

Once this graph is constructed, we calculate the Pearson correlation coefficient between the edge weights and the sums of the respective polarities of both speech sets. The coefficient score came out to be 0.697, which indicates a positive correlation between the two quantities. This leads to the conclusion that politicians with similar voting habits on various issues tend to deliver speeches of similar natures, a fact that could help in discerning blocs among parliamentarians which cut across party lines in various issues. Such affiliations could help one study ‘rebel’ politicians, or those that vote against the party stand on matters of considerable importance.

Future Work

Some further avenues that we are investigating in this subject area are given below.

- Most of the misclassified data points were of those politicians who have gone against the party voting habits on one or more motions. We have explored some clustering and community detection approaches to single out the rebel politicians from the rest of the speakers to enhance classification performance. The idea is to devise some clustering metrics based on the dataset, which can help in clearly demarcating rebellious and non-rebellious politicians.
- What kind of motions tend to elicit more rebellion from the politicians? Some issues of ethical and moral principles (abortion, national security, immigration *etc.*) could be an indication of voting habits.
- How can multimodal information be leveraged for more enhanced political sentiment analysis? (Shah and Zimmermann 2017)

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