EECS 4414 Project Proposal: Analyzing the Extent of Polarization around COVID-19 Policies using Social Media

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1 INTRODUCTION

1.1 Motivation

Over the past decades, the phenomena of polarization and echo chambers in social networks has gained a great deal of attention. Despite the availability of vast amounts of information, users are more likely to seek and interact with information that reinforces their existing beliefs. Having said that, it is interesting to explore the relationship between ideologically opposing communities and to understand the spread of information within each community. In a social network like Twitter, one can analyze a profile's beliefs by looking at its engagement such as "mentions" and "retweets." There are many ways that users can interact on Twitter. Mentions are posts that include the username of another account. Sharing a tweet is referred to as a retweet.

Interestingly, similar polarization seems to exist with respect to the recent global response to COVID-19—the rollout of vaccines and associated policies. Hence, for our project, we wish to explore the extent of this polarization. Our goal is to identify ideological communities corresponding to the pro-vs-anti movements, the nature of their interactions, to provide us with an approximate score of the extent of polarization, and to determine whether each of these communities share a common set of interests.

1.2 Related Work

There has been extensive work done in detecting belief communities in social networks and understanding polarization. In the work of Adamic et al [1], they used pre-identified liberal and conservative online blogs and built out a citation network using an algorithm similar to PageRank to analyze important interactions within and between the dataset. Then they implement a pruning algorithm until there are no links between blogs of opposite beliefs—a technique which we will also utilize.

Conover et al [4] used Twitter data to classify political ideological communities by constructing networks of Twitter users. The two networks constructed were mention and retweet networks: each node was a Twitter account and each weighted edge denoted the number of interactions. A community detection algorithm was applied to each network. The authors were able to conclude that while both networks exhibited an echo chamber phenomenon—where users are primarily consuming information which aligns with their beliefs—the mention network was much more heterogeneous. We will be using network constructions and community detection in our approach.

Finally, our approach is heavily inspired by Aguilar et al's project [2]. In their project, they investigated interactions between and within liberal and conservative classified communities. For our adaptation, we wish to investigate communities not of political leanings but rather concerning COVID-19 vaccine and related policies. In addition to performing community detection using networks of Twitter users, the authors analyzed cross-community edges.

1.3 Problem Definition

Inspired by the polarization regarding COVID-19 policy, we aim to expand on these previous studies, using similar analysis techniques to investigate the extent to which this polarization exists. We will use a social media platform, like Twitter, to construct a network in which we can analyze how common engagements relating to favouring or opposing these policies can form communities, and how information tends to propagate across and within these communities. To do this, we will identify key individuals or influencers which we will build the initial core of each side, where each core consists of a group of individuals who mutually interact with each other.

Using these networks, we will test some community detection algorithms with aims to distinguish the communities that represent a bifurcation of COVID-19 policy approval. The points of contact between these two communities will be noted, especially to determine where their engagements are aimed at in the opposing community. We are also interested in identifying some of the underlying interests among each of the groups, and so we will also search for interests in common within these two communities. Ultimately, this analysis should enable us to have a better understanding of both the nature of polarization and the evolution of the communities over time, as well as provide us with visual representations of these communities.

2 METHODOLOGY

2.1 Network Construction

Using our dataset(s), we define a set of nodes N and a set of directed edges E, where N contains Twitter users and E denotes a type of interaction (either Retweet or mention) between them. Edge e points from user A to user B if user A has Retweeted or mentioned user B in a Tweet. Each edge has a weight corresponding to the number of interactions. For each time period of our interest, we will create two networks—a Retweet network and a mention network. Moreover, we will also create an undirected version of these networks for the purposes of community detection methods.

2.2 Connected Components Construction

We will build our research on the biggest strongly connected component in both networks. We will then count the pre-identified pro and anti-vaccine users in those components to understand what each component represents.

To better understand the essence of the network and remove non-significant interactions, we will remove edges with low weight. If a node becomes disconnected from the graph, it is removed.

2.3 Community Detection

As stated, we will apply community detection algorithms on the constructed networks. We chose the same algorithms used in Aguilar's paper [2], namely Louvain Modularity Optimization and Label Propagation Algorithm (LPA). The Louvain method is a greedy algorithm that maximizes modularity, where modularity is a measure of relative edge density inside a community compared to outside. On the other hand, LPA works in a similar manner to the popular K-nearest neighbor; the label it assigns to a node is one which appears most frequently amongst its neighbors. If time permits, we would like to explore other community detection algorithms. We will compare the output of these community detection algorithms to better understand modularity in the network.

Additionally, we are interested in detecting and understanding any underlying interests that may exist in each of the communities—particularly the anti-community.

2.4 Bridge Nodes

To best understand the significance of the interactions between communities, we analyze bridge nodes, which are defined to be nodes which connect to a node of the opposite community. The bridge nodes will be selected only if the edge which connects them to a node of the opposite community has sufficient weight.

3 EVALUATION

3.1 Dataset

To construct our network, we will make use of an existing data set developed in the study by Banda J. M. et al [3]. It is a collection of tab separated value (.tsv) files representing 152,920,832 Tweets which can either be classified as Tweets (with or without mentions) and Retweets. The Tweets themselves consist of 280 characters with some notable keywords related to COVID-19. Some examples of these keywords include neutral phrases to COVID-19 policies such as "coronavirus," to phrases against it like "scamdemic," to phrases in favour of it like "stayhome" . These were collected from Twitter's streaming API for several languages, primarily English, Spanish and French.

3.2 Analysis and visualization

For visualizations, we will create a graph of interactions between users. The interactions we will focus on is Retweet data. The Tweets themselves will contain keywords (e.g., hashtags) which will be used to identify users as members of certain communities. We will also be looking at direct interactions between users (e.g., mentions). Additionally, we will analyze the networks' modularity using the scores outputted by the algorithm.

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