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AIUCD 2021

DH per la società: e-guaglianza, partecipazione, diritti e valori nell'era digitale

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Capturing Political Polarization of Reddit Submissions in the Trump Era

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ABSTRACT

The American political situation of the last years, combined with the incredible growth of Social Networks, led to the spreading of political polarization phenomenon online. Our work presents a model that attempts to measure Reddit political polarization of submissions during the first half of Donald Trump's presidency. For such a purpose, we design a text classification task in which the political polarization of submissions is assessed by quantifying their degree of alignment with pro-Trump ideologies and vice versa. First, we build our ground truth by picking submissions from subreddits known to be strongly polarized. Then, we perform a model selection by testing different hyper-parameters of a Neural Network with word embeddings and a Long Short-Term Memory layer. Finally, we assess model performances on both the test set and three less polarized corpora.

KEYWORDS

Political Polarization, Classification, Text Analysis.

1. INTRODUCTION

During the last decade, the rise of social networks has drastically changed how people interact and communicate. The number of opinions shared publicly among users is increasing, and particular attention turned on the diffusion of political discourse online and its implications. The sharing of political beliefs, combined with the contemporary political situation, leads to political polarization. This phenomenon refers to the increasing gap between two different political ideologies. During Donald Trump's presidency, online polarization found its fertile ground in the debate between Trump supporters and anti-Trump citizens [1].

This paper proposes a model to quantify Reddit submissions political polarization in the Trump Era. We model the issue as a text classification task. Given new submissions, we assess their political polarization by quantifying their degree of alignment with pro-Trump or anti-Trump ideologies. To assess the existence of a strongly polarized environment, we build a model to measure its components polarization. As a case study, we choose Reddit because of its internal structure which is composed of thousands of subreddits. This makes it easier to identify homogenous communities concerning a specific topic. Additionally, since users can write anonymously and posts are not limited in length, this platform is particularly active in political discussions [11].

The rest of the paper is organized as follows. Section 2 discusses the literature on text classification in general and with respect to the political domain. Section 3 describes the data collection and preparation to build the dataset. Section 4 proposes the model selection, while Section 5 concludes the paper and sets future research directions.

2. RELATED WORKS

With the growth of Social Networks, researchers focused on studying methods to extract information from a large quantity of unstructured data. For such a purpose, text preprocessing plays a key role in data cleaning, allowing to remarkably improve text classifier performances [4,16]. Furthermore, with classification tasks, we also need to take into account the suitable type of word representation. Since traditional ones, i.e., bag-of-words, encode words as discrete symbols not directly comparable to others [8], they are not fully able to model semantic relations between words. Word embedding (e.g., Word2vec [10] and Glove [12]), instead, map words to a continuously-valued low dimensional space, capturing their semantic and syntactic features. Also, their structure makes them suitable to be deployed with Deep Learning models, fruitfully used to address NLP-related classification tasks. Specifically, as shown in this survey [9], Recurrent Neural Networks (RNNs) have been proven to be extremely successful for sequence learning. Among them, Long Short-Term Memory (LSTM) network can maintain long-term dependencies through an elaborate gates mechanism, overcoming the vanishing gradient problem of standard RNNs [15]. Finally, concerning political leaning

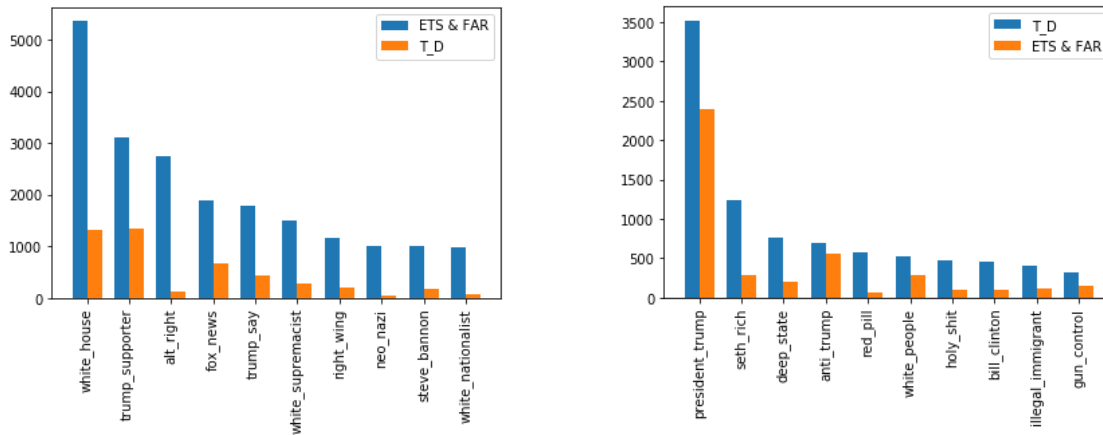


Figure 1. Top 10 most frequent bigrams of subreddits and their frequencies in opposite political ideology.

classification on Social Network textual data, in the last few years have been presented several encouraging works. For example, Chang et al. [5] propose a model to predict the political affiliation of Facebook posts in Taiwan. They build two models, one using the K-NN algorithm and the other one using AdaBoost combined with Naive Bayes classifier. Instead, Rao et al. [14] use word embeddings and LSTM to predict if a Twitter post deals with Republican or Democratic beliefs. To the best of our knowledge, research about political classification on Reddit is sparse or nonexistent.

3. DATA DESCRIPTION AND PREPARATION

We collect submissions belonging to known pro-Trump and anti-Trump subreddits in the first two years and a half of Donald Trump's presidency (Jan. 2017 - May 2019) by using the Pushshift API [2]. We choose `r/TheDonald` (151,395 posts) as pro-Trump, and `r/Fuckthealtright` (78,200 posts) and `r/EnoughTrumpSpam` (73,168 posts) for anti-Trump, to obtain a balanced dataset. For each submission, we collect the fields *id*, *selftext*, and *title*, respectively, the identifier, the content, and the title of the submission. We merge the last two fields in a unique one, because the *selftext* of a post may be empty or just a reference to the title itself. Then, we label submissions with 1 if pro-Trump, 0 otherwise. Furthermore, we remove noise due to free form writing by applying a standard preprocessing pipeline to give clean data to LSTM. Specifically, we convert text to lowercase, then remove punctuation and number, as well as stop words. Lastly, to check the validity of our initial choice of polarized subreddits, we identify some of the most frequent bigrams of each subreddit to analyze their frequencies in the opposite one. As shown in Figure 1, these words are discriminant and semantically related to their belonging subreddit.

4. MEASURING THE POLITICAL POLARIZATION

To assess the best model, we preprocess input text sequences, we perform model selection, and we test it on new instances.

Neural Network Preprocessing. We vectorized submissions into sequences of integers to pass them as model inputs. Thus, we build a lexicon index based on word frequency (0 is for padding), and we replace submissions words with their index in the lexicon (e.g., "president trump says" becomes [5,1,39]). Also, we pad sequences to the same length l to optimize the batch matrix operations, based on the mean length of all submissions.

Neural Network Architecture. Since our training data consists of sequences, standard Neural Networks (NNs) are not suitable for our task. Thus, we choose the LSTM network [6] for its ability to model a sentence meaning by considering its paradigmatic structure. Figure 2 shows the high-level architecture of our model, composed of three layers:

1. The *Embedding layer* takes as input the sequences of integers w_1, \dots, w_t and turns them into 100-dimensional dense vectors x_t , where t is the length of the sequence. Specifically, we experience both pre-trained and learned word embeddings (i.e., embeddings learned directly from our corpora).
2. The *LSTM layer* consists of multiple LSTM units, each maintaining a memory cell. Cells encode the information of the inputs observed up to that step through the gates mechanism. The *input gate* controls whether the memory cell is updated. The *forget gate* controls if the cell is zero; lastly, the *output gate* controls whether the cell state information is visible. To avoid over-fitting, we add a dropout regularization of 0.3.

Emb. type	LSTM units	Training Acc.	Validation Acc.
Learned	32	0.832	0.816
	64	0.837	0.816
	128	0.828	0.816
Glove	32	0.831	0.814
	64	0.839	0.819
	128	0.846	0.829

Table 1. Hyper-parameters tuning for models with learned and Glove embeddings.

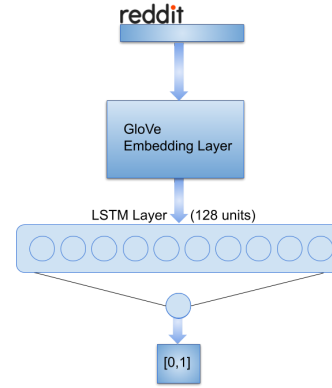


Figure 2. High-level architecture of our LSTM model.

- The *Output layer* is a fully connected layer which outputs a single neuron to perform binary predictions. We use the Sigmoid activation function to have a probability output between 0 and 1. Consequently, we label submissions with a probability score of ≥ 0.5 as pro-Trump and as anti-Trump otherwise. As a loss function, we use Binary cross-entropy and as optimizer Adam.

Model Selection. We use a training set of 242,763 instances, balanced among the two political ideologies. We perform a 3-fold Cross-Validation trying different values of LSTM units (32,64,128) and embeddings (learned and pre-trained), with a fixed 100 embedding dimension. As detailed in Table 1, the model with Glove pre-trained embeddings and 128 LSTM units achieves the best accuracy in training and validation sets (84,6% and 83%, respectively).

Model Evaluation. On the test set, the best model reaches an encouraging accuracy of 84,3% (Table 2). We further assess model performances on three less polarized sociopolitical topics (Jan. 2017 - Dec. 2019), i.e., gun control, minority discrimination, political discussion. Given the absence of ground truth, we validate our model through polarized users. We compute users' polarization scores, and we select the most polarized ones, i.e., ≤ 0.2 , and ≥ 0.8 , to label submissions. Finally, we assess model performances on the three sets to evaluate its ability to generalize. Despite differences in size, the model always reaches an accuracy of over 72%.

5. CONCLUSION AND FUTURE WORKS

This study proposes an approach to measure the degree of political polarization of Reddit submissions in the Trump Era. We design a NN with word embeddings and LSTM layer to quantify submissions political alignment. The model with Glove embeddings achieves 83% and 84,3% accuracy, respectively on validation and test set. Such results are in line with previous works on different Social Networks, i.e., 86,3% on Facebook [5] and 85% on Twitter [14]. Also, we assess model performances on other three less polarized topics to evaluate its ability to generalize. We achieve quite good results with accuracy ranging from 72% to 82%. As a future research direction, it would be interesting to extend our case study, including data related to other polarizing public figures, in such a way to give a broader contribution to the literature.

Dataset	#post	Accuracy
Test set	60,000	0.843
Gun control	2,411	0.712
Minority discrimination	4,839	0.732
Political discussion	46,339	0.721

Table 2. Model performances on the test set and the less polarized topics.

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