Twitter Sentiment Analysis

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1 Introduction:

In this research project, our purpose is to build a machine learning model to classify political orientation of a Twitter user. We will be discussing two methods of accomplishing this task: using an already fine-tuned language model to classify text into political categories and manually fine-tuning a language model to do this task. We will then aggregate results from the model to calculate a score for the Twitter user on a scale of -10 to +10, where -10 indicates a revolutionary and +10 indicates a reactionary.

2 Literature Review:

In this section, we will take a look at an overview of the area of twitter sentiment analysis. We will first go over some basic definitions of relevant concepts, then we will see briefly what other researchers have done in this area.

A tweet is a post made by users on Twitter to share their thoughts on something to other users on the platform. As of the time of this writing, a tweet has a limit of 280 characters and can contain other forms of content such as links, videos, images, hashtags, user tags, comments, etc., all of which are relevant to the sentiment of the tweet. When we look at the page of the user, we can gather other information that can help to classify the user such as follower/following lists, other tweets that they liked/shared, and their biography description.

There are certain challenges that we can expect to face when working with twitter data. We should expect that most content in a tweet is not geared towards politics specifically unless the user is involved in politics in some way or has a history of tweeting about politics. This would mean that even if we collect data from politicians, we also need to keep in mind that some tweets may be neutral and do not contain political sentiment. We also need to be aware of typos, stop words, and word families that can affect how text can be used as features. Lastly, if possible, we should also be aware that non-text elements of a tweet can have a huge impact on the meaning of the tweet. For example, some tweets may contain a small amount of text with neutral/trivial meaning but can also come with an image or video that provides much more context into the political orientation of that tweet.

In general, the most common method of classification is supervised learning: use a labeled dataset of tweets (democrat, neutral, republican or left-leaning, neutral, right-leaning) and train a classification model (such as SVM, Naive Bayes, KNN, etc.) on this dataset. The features will be tokens created from the contents of the tweets (Giachanou et al., 2016).

It is becoming more popular, however, to also employ the use of complex deep learning / neural network models that can help with recognizing keywords. These come in the form of transformer models (i.e. BERT or DistilBERT) which are large language models trained on a giant corpus of text data and can be fine-tuned to complete tasks in natural language understanding or natural language generation.

3 Data and Analysis:

For the dataset, we can use a dataset already available online (Giachanou et al., 2016) or crawl our own data using the Twitter API and the Tweepy library (https://docs.tweepy.org/en/stable/). The goal is to have a dataset with all the features that we will be using (for this project, we will only use the text portion of a tweet, but this can also extend to other elements as mentioned in the previous section) as well as the label for the tweet (1 for democrat or 0 for republican).

The Tweepy library has good documentation that can show a user how to pull data from Twitter with certain specifications. We will go through shortly how Tweepy was used in this project. The first step is to sign up for the Twitter API to get access tokens which are necessary for authentication. After we're able to authenticate, we can use Tweepy methods to retrieve tweets from the API filtered by user, keywords, number of tweets, etc. In this project, we are pulling 200 tweets from the target user timeline, which is also the max number of tweets allowed by Tweepy. We can then get the necessary information from the tweet (i.e. the text) and process that tweet to remove links, videos, and user tags to create our dataframe. Here is an example of the dataframe from an example Twitter user:

```
Give me a Twitter user handle: @forsberg370
                                            tweets  len                date
0  Learn with me on Duolingo! I’m moving up the l...  180 2023-01-16 15:18:17
1  Learn a language with me for free! Duolingo is...  142 2023-01-11 16:42:29
2  Look how much I learned on Duolingo in 2022! H...   97 2022-12-07 03:16:26
3  Look how much I learned on Duolingo in 2022! H...   97 2022-12-07 03:16:15
4  Learn with me on Duolingo! I’m moving up the l...  180 2022-12-05 03:00:53
```

4 Method:

The model we will be using for this project is a DistilBERT-based model that was already fine-tuned and available as open-source on HuggingFace (https://huggingface.co/m-newhauser/distilbert-political-tweets). This model was trained using a dataset of U.S. senators evenly spread among the two political parties. It contains their tweets as well as labels for the tweets. In order to use this model, we will import the model as well as its tokenizer from HuggingFace. The tokenizer will take the text from our tweet as input and create tokens which will be input for the model. The final output will be a score of either 1 for republican or -1 for democrat. We will repeat this process for all the tweets from our dataframe, then aggregate all the scores to and standardize it to get a final score in a range from -10 (revolutionary) to 10 (reactionary).

If we were to fine-tune the model ourselves, we would prepare a dataset of politicians, their tweets, and a label for the political orientation of the tweet. Then we would need to clean and tokenize the text using some sort of vectorizer (i.e. TF-IDF) or tokenizer (i.e. BERT or DistilBERT) and train a supervised learning model (i.e. SVM, Naive Bayes, etc) to classify tweets. This method has two big advantages in that we would have autonomy on the model and we also have a clear way to evaluate the model using a train and test dataset to measure accuracy.

5 Results:

```
Give me a Twitter user handle:
@forsberg370
                                            tweets  len                date  likes  retweets
0  Learn with me on Duolingo! I’m moving up the l...  180 2023-01-16 15:18:17      0         0
1  Learn a language with me for free! Duolingo is...  142 2023-01-11 16:42:29      0         0
2  Look how much I learned on Duolingo in 2022! H...   97 2022-12-07 03:16:26      0         0
3  Look how much I learned on Duolingo in 2022! H...   97 2022-12-07 03:16:15      0         0
4  Learn with me on Duolingo! I’m moving up the l...  180 2022-12-05 03:00:53      1         0

I predict this user to have a score of 1.33 on the political orientation scale.
```

Here is an example of the final output. The user can run the notebook and give the program a twitter handle as input. Then the program will go through the process of retrieving tweets, building the data frame, training the model, and giving the final score in one go.

6 Conclusion:

We were able to find an effective way to determine where a Twitter user falls on the political spectrum without using much memory or time. There are certain weaknesses that come along with this "convenient" method. We didn't train the main model ourselves, which makes it harder to attest to the validity and performance of the model. For future endeavors, we would ideally work on the entire process ourselves, as well as adding other components to improve the result of the model by analyzing the sentiment of non-text elements such as images, videos, emojis, etc. since they contain much content of a tweet.

References

Anastasia Giachanou and Fabio Crestani. 2016. Like it or not: A survey of twitter sentiment analysis methods. *ACM Computing Surveys (CSUR)*, 49(2):1–41.

https://huggingface.co/m-newhauser/distilbert-political-tweets

https://docs.tweepy.org/en/stable/