Time series analysis of COVID-19 related emotion detection using natural language processing

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Abstract

The COVID-19 outbreak which started in early 2020 not only influences human's physical health, causes a rapid number of confirmed cases and death globally but also directly affects mental health issues worldwide. Social media like Twitter has been a valuable resource to gather public opinion with the help of natural language processing techniques and tools. This project aims to analyze the association between the global COVID-19 confirmed case number and the emotional response of English Twitter users over time.To answer the question, we first compare the f1-score of SVM, LSTM and pre-trained BERT classification model on a labeled tweet datasets, then apply the best-performing model to a public twitter dataset which captured COVID-19 related tweets posted from March 2020 to November 2020 in order to annotate tweets with four emotion, anger, fear, joy and sadness. Finally, we investigate the trend of emotions across time. Our result shows a correlation between XX and XX. Results also revealed that XXXXXX. We believe that the result of this paper generates some valuable information on people's emotional reaction toward COVID-19 related issues and will aid in public health questions and provide practical strategies for supporting the public and navigating the pandemic.

1 Approach

1.1 Data Processing

Prior to training, the original corpus was cleaned from various symbols like @, , URLs and punctuation marks using the "re" python module. Emojis and unicode emoticons were handled and transformed into textual ASCII representations. All texts were converted to lowercase, tokenized, lemmatized and stemmed to obtain the original forms, and stop-words were removed.

1.2 Models

We used the Support Vector Machine (SVM) classifier as our baseline model. Cleaned unigrams were vectorized with CountVectorizer in scikit-learn library and served as the input.

1.2.1 SVM Model

We first used fastText, a pre-trained word embedding library, to generate word embedding features. Then we employed SVM as the classifier to predict the emotion category of each tweet.

1.2.2 LSTM Model

The Long Short-Term Memory (LSTM) deep neural network we used contained five layers: a fastText embedding layer, three LSTM layers, and an output layer. For word embedding features, we used fastText to generate 100-dimensional word vectors as the input for downstream classification tasks. To be able to train the sequential neural network in batches, we normalized each tweet length by zero padding. We applied XX dropout rate on the LSTM layers to prevent overfitting and used Sigmoid neurons for the output layer. The models used binary cross-entropy loss and ADAM optimization, the best model was trained for XX epochs with learning rate XX.

1.2.3 BERT Model

Bidirectional Encoder Representations from Transformers (BERT) is a new method of pre-training language representations which obtains state-of-the-art results of Natural Language Processing tasks including sentiment analysis or text classification. In our project, we used BERT Tokenizer along with BERT Embeddings as the input, then fine-tuned a English-only BERT-Small model on our classification task. We then added a single-layer classifier with the Sigmoid activation function, which receives BERT output and predicted the emotion category of the targeted tweet. The models used binary cross-entropy loss and the best model was trained for XX epochs with learning rate XX.

2 Experiments

2.1 Model Selection

2.1.1 Data

To assess the performance of different models on emotion classification tasks, we chose an annotated English twitter dataset as our train and dev set, which was released from Semeval-2018 Task 1: Affect in Tweets. The EI-oc datasets we used included 7102 training data and 1464 development data, labeled with one emotion category from anger, fear, joy and sadness.

	Train set	Dev set
anger	1701	388
fear	2252	289
joy	1616	290
sadness	1533	397

2.1.2 Evaluation Method

To evaluate the models, we used the macro-averaged F1 score, which computes the metric independently for each class and then takes the average.

2.1.3 Experimental Details

For each of the model types, we trained models with different combinations of hyper-parameters. Still work-in-progress

2.1.4 Results and Quantitative Analysis

Still work-in-progress

Model	Baseline	SVM	LSTM	BERT
F1score	0.23	0.31		

2.2 Time Series Tweets Analysis

2.2.1 Data

We used the coronavirus (COVID-19) geo-tagged tweets dataset as our corpus, which is an open dataset which captured a collection of tweets ID using 90+ different keywords and hashtags that are commonly used while referencing the COVID-19 pandemic. The dataset collected tweets posted from March 20, 2020 and updated daily. We hydrated the tweets ID dated from March 20 to November 20, 2020, and a total of 266,670 tweets were collected.

2.2.2 Evaluation Method

Since the data was unlabeled, we were not able to conduct quantitative evaluations.

2.2.3 Experimental Details

We plotted the proportion of tweets in each emotion category for every 10 days with a line chart and compared it with the number of global COVID-19 confirmed cases.

2.2.4 Results and Qualitative Analysis

Still work-in-progress

3 Future Work

We are currently classifying the tweets into four emotions and investigating the trend of emotions in relation to the infected case number. Since the original training dataset also annotated the valence and emotion intensity, we could train different models, identify the tweets with low to high emotion intensity class and gain more insight of the emotion response in scale. We could also apply our model on a larger corpus for a more accurate and meaningful result. Besides the time analysis, the geographical differences could also be investigated to see the influence of pandemic for people located in different countries or states. The project could also be extended to apply topic modeling on top of current results for better understanding of public concerns.

4 Reference

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