Emotion Analysis of Elon Musk Tweets to Predict Audience Interaction

Skylar Kolisko, 2022 | Dr. Eni Mustafaraj, Advisor

Research Question

Twitter is a social media platform that, for over a decade, has been a place for people to make their opinions known, within a certain set of boundaries. As of October 28, 2022, Twitter is owned by Elon Musk. As a self proclaimed "free-speech absolutist" (1), much of Musk's motivation in acquiring the company comes from his desire to see the platform permit complete free speech. The goal of this project is to see if, using an NLP model which has been fine tuned to function as a Multiple Choice Question and Answer NLP Model, can the past tweets of Elon Musk be analysed to see what type of tweets his audience is most likely to positively receive, or react to? How can this be useful for understanding what could be in store for the future of Twitter as an online community?

Technical Background

In order to understand the project, following definitions are useful:

Natural Language Processing (NLP) - a type of machine learning that makes it so a machine can carry out tasks related to human language as opposed to machine language.

Sentiment Analysis Task- an NLP task that takes in a piece of natural language (ex: a sentence) and outputs a vector of three weights which sum to one, where each weight represents the model's confidence that the input's emotion is either positive, negative, or neutral.

Emotion Analysis Task- Similar to sentiment analysis, but looking at specific emotions instead of positive, negative, or neutral.

Question and Answer Models - NLP models fine-tuned for the task of outputting a most likely answer to an input question.

Multiple Choice Question and Answer Task - entails a model taking as input a piece of context as natural language, a natural language question, and a series of possible answers. Given these three inputs, it must output a vector containing weights which sum to one, where each weight represents the model's confidence in that answer. We will utilize the RoBERTa fine-tuned RACE model available on Huggingface by the Logics, Artificial Intelligence and Formal Methods Lab at University of São Paulo (2).

It is also helpful to understand the pliability of Question and Answer models. Models trained for Q&A tasks have been shown to be useful for many NLP tasks, including text generation, document classification, and emotion analysis. For this project, we will utilize a Multiple Choice Q&A model for the task of emotion analysis.

Original Data

The original data for this project comes from a Kaggle dataset that has since been removed from the site. The data set includes 635 of Musk's tweets from early July, 2022 to late September, 2022. It was collected via the Twitter API, meaning that the data comes directly from Elon Musk's Twitter account. The original data included the tweet, the tweet id, the time and date of the posting, the tweet's number of retweets, it's number of favorites, the number of followers Musk had at the time of posting, the device he used, and his account information.

Data Preprocessing

Each tweet must be preprocessed before it is run through the "emotion analysis" (Q and A) model. The function preprocess will strip each tweet of identifying information, i.e. usernames, not exactly for the sake of privacy, but instead so that the emotion is based strictly on Elon's words and is not swayed by the usernames of others, since some usernames contain words with strong associations. It will also strip out any urls for the same purpose.

Another important preprocessing step is to get the non-truncated version, as in the original version, of each tweet. This is necessary because the original data only recorded a certain number of characters from each tweet, where that certain number was far fewer than the 140 characters allowed per tweet. There were many tweets that were not fully recorded in the original data, which means that, if these truncated tweets were fed to the Q&A model, it would not be observing the full tweet. This would cause the emotion scores to not be accurate against the favorite score of each tweet. So, it was clear that it would be critical to collect the full version of each tweet before being able to feed the tweet to the Q&A model. This entailed using the twitter API to get non truncated tweets. Twitter's lowest API access, ie the free version, only allows a user to query up to 500 tweets at a time. Because my original data set had more than 500 tweets, I had to run this step twice because I had to query more tweets than allowed at one time. There are some files in the repo that are named starting with "only_after_500", and these files are a result of needing to requery for those remaining tweets.

Emotion Collection

Each tweet is input to the Q&A model as the context for the multiple choice question. The question for each tweet follows the same format: "How can this statement be described?" There are then two multiple choice answers given to the model to place weights onto, and those are an adjective and the word "not" followed directly by the same adjective. There are forty different adjectives the model has to give scores to for each tweet.

After getting the preprocessed tweets, the data had to be put into a format useable by the Q&A "emotional analysis" model. This was done using the file make_input_to_qa_model.py and then using its output to run tweet_qa.py. Thanks to Professor Carolyn Anderson for letting me use her server to query the Q&A model. (Otherwise would have been days worth of collection on my laptop). The emotional analysis scores of all 635 tweets are stored in ALL_COMBINED_FINAL.csv.

This data is then loaded into yes-keys_analysis.R for analysis. Note: the "yes" keys are the weights the model put on the answer to the question, as in, the amount it believed the tweet to be best aligned with some adjective.

Multiple Linear Regression Model

From the original forty adjectives, two multiple linear regression models were made.

The first predicts what can be referred to as "favorite score", which simply is the natural log of the amount of times Twitter users favorited a tweet divided by the number of followers Elon had at the time the tweet was posted. This mode uses 26 adjectives' predictions. In this model, the most influential adjectives for the model's predictions include "diplomatic", "rude", and "compassionate". The model has a multiple R^2 of 0.1915 and Adjusted R^2 of 0.1497, suggesting that the model overfits slightly to the training data. It makes predictions of the test set's "favorite score" with a Mean Squared Error of 1.57.

The second model predicts the "retweet score", which is the natural log of the amount of times Twitter users retweeted a tweet divided by the number of followers Elon had at the time the tweet was posted. The model has a multiple R^2 of 0.235 and Adjusted R^2 of 0.1939.

Neither model is particularly good at predicting either of their respective scores. This is likely because there are very few patterns in the data when it comes to what emotions correlate to higher retweet scores and higher favorite scores. For example, we can see in Fig. 2 that even the rating assigned to a tweet for rudeness, which is one of the first model's largest regression coefficients, shows basically no pattern between favorite score and rudeness rating.

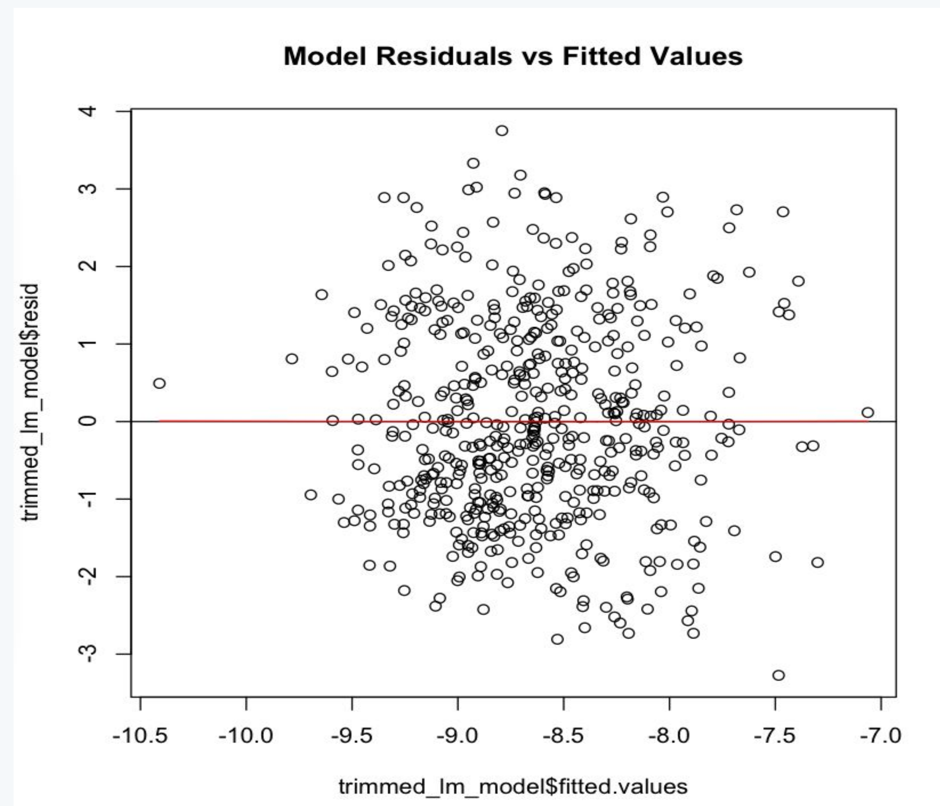

Fig 1. The plot of the residuals vs. fitted values for the favorite score model.

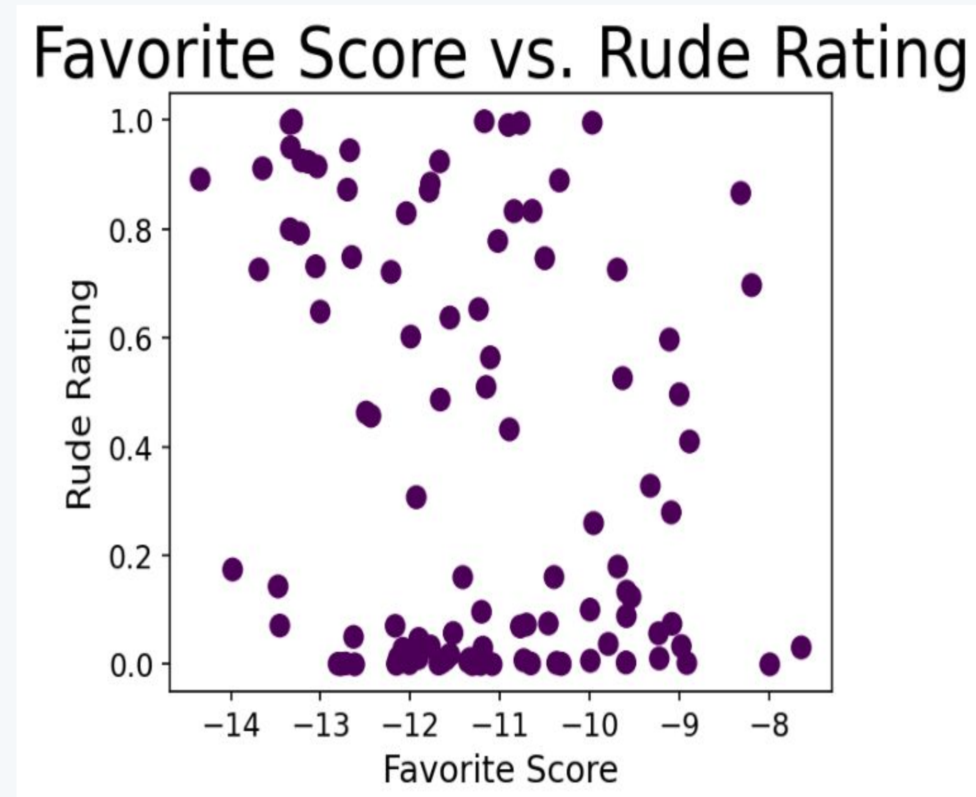

Fig 2 shows the relationship between favorite score and a tweet's "rude rating".

Privacy Implications

After the initial learning curve of the how to collect the tweets and the collection emotion scores, the collection of the data necessary to make a full profile of a user's tweets' emotions is accessible to anyone who wants to put in the effort to do so. This opens the door to very specific ad targeting without a user needing to give their explicit permission to advertisers. The fact that there are no safeguards in place for users to opt out of having their tweets available for query via the API means that users do not have the option for their words to not be potentially monetized.

Another privacy implication could also be tracking of citizen's emotions by the government. This could lead to the squashing of rebellion before they can be better organized simply by observing an uptick of tweets with rebellious emotions.

References

1. https://www.npr.org/2022/10/08/1127689351/elon-musk-calls-himself-a-free-speech-absolutist-what-could-twitter-look-like-un
2. https://huggingface.co/LIAMF-USP/roberta-large-finetuned-race