Using Machine Learning to Track Emotional Responses to COVID-19 through Social Media Data

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Introduction

- COVID-19 has shifted the Twitter emotional landscape.
- Machine Learning (ML), can be used to find the emotional responses of individuals regarding COVID-19 through public tweets.
- Community responses and emotions regarding major events can be influential when forming public policies and disaster relief plans.
    - This project provides information that would be beneficial to community leaders in times of crisis.
    - It can be used for other major events aside from the Coronavirus pandemic.

Methods

- Obtained public tweets with the hashtags #Coronavirus, #Coronaoutbreak, and #COVID19 between March and December 2020
- Clean the data:
    - Create labels for emojis
    - Remove special characters and @usernames
    - Retain only English tweets from the US
- Hand label randomly selected set of tweets (7500 tweets) with one of the chosen emotions or as neutral
    - Happy(h), anger(h), sad(s), surprise(u), or worry(w)
- Use hand labeled tweets to train multiple models
- Use the best model to analyze unlabeled tweets and find aggregate emotional responses per day
- Deep Neural Network (DNN) with 512 nodes and 5 layers was used as an additional model.

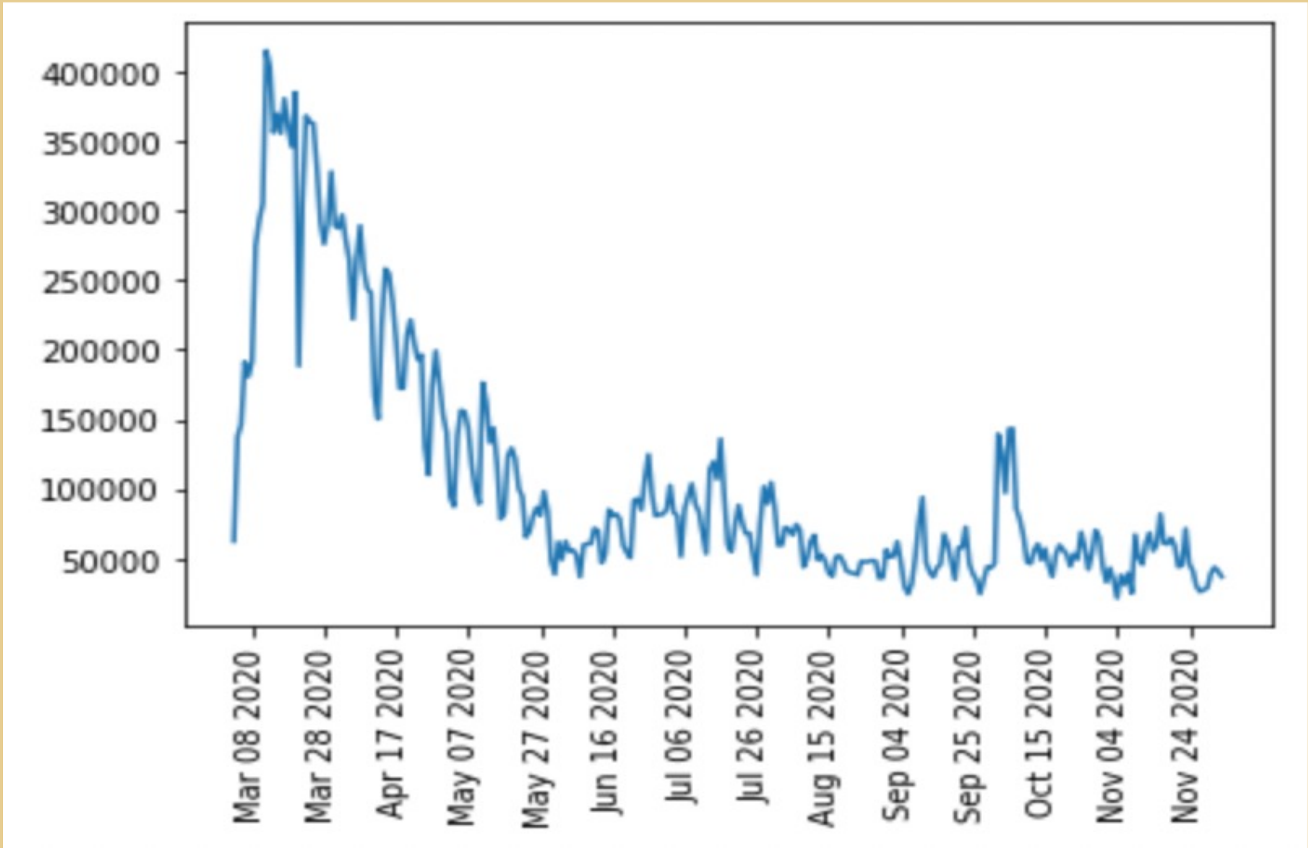

Fig. 2 No. of COVID-19 tweets per week (Mar – Dec 2020)

Results

- We analyzed over 30 million COVID-19 related tweets originating from the U.S.
    - We wanted to understand how the average emotions in tweets changed from March to November 2020.
- We tested SVC, MLP, and RoBERTa based models to find the most efficient model and found Deep Neural Network (DNN) to be most effective.
- The trained model was used to find how the emotional responses changed daily/weekly toward the pandemic (Fig. 3).
- The most common emotion was surprise (~45%), and anger was second (~35%).
    - Tweets portraying worry, happiness, and sadness had low percentages and remained constant over time. Sadness was the least common emotion.
- Anger and surprise were the emotions with the highest detection accuracy
    - Worry was the hardest emotion for the model to detect and was least accurate.
- As a simple experiment, we had four different people manually label the emotions of 400 tweets regarding random topics to look for comparisons.
    - They all agreed on the emotion of the tweet only 35% of the time.
    - At least three people agreed on the emotion 68% of the time.
    - This helps to justify the accuracy of our models as the emotional value of a tweet seems to be ambiguous in some cases.

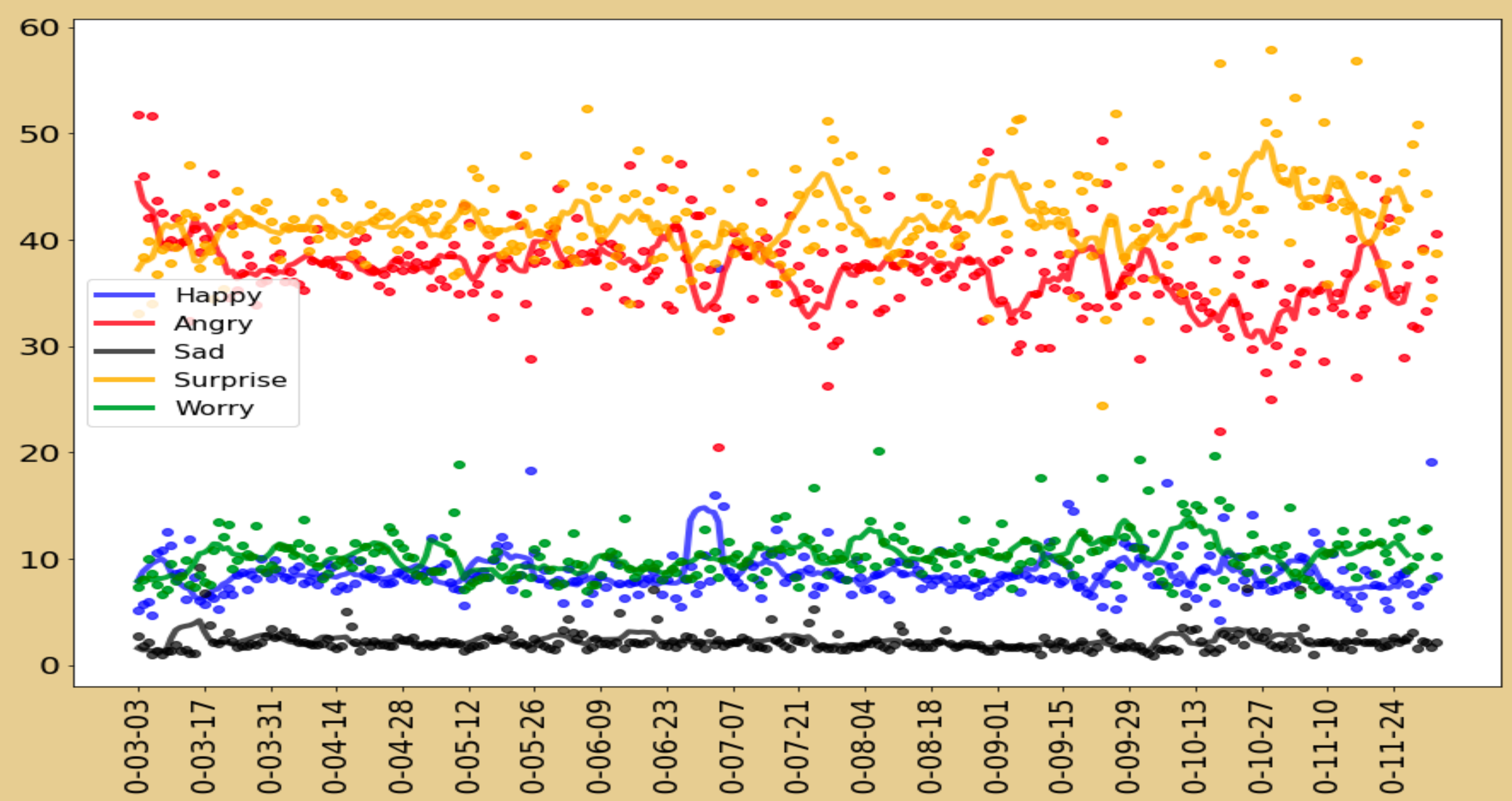

Fig. 3 Daily and weekly average percentages of emotions present in COVID-19 tweets

Fig. 4 Confusion Matrix

True \ Predicted	h	a	s	u	w
h	56.93	2.34	7.20	4.65	8.93
a	2.52	72.40	5.05	0.00	4.93
s	7.66	8.85	61.87	0.00	15.81
u	5.08	4.95	2.80	86.05	5.50
w	11.59	9.64	16.92	6.98	45.59

Discussion

- The number of COVID-19 related tweets was the highest in March 2020 and decreased through November 2020 (Fig. 2).
- During our preliminary analysis, we identified the most common two-word phrases (bigrams) in the tweets as shown in the word cloud (Fig. 1).
    - Bigrams show how the main concerns change over time.
- It was found that most COVID-19 tweets portrayed surprise and anger.
- A confusion matrix was created to illustrate the accuracy of the model.
    - The accuracy of individual emotions was lowest for 'worry' (45%) and highest for surprise (86%) (Fig. 4).
- This emotional analysis ML model can be used for other projects as it is applicable to any topic and any sample size of tweets.
- A random sample of tweets prior to 2020 showed happy was the predominant emotion (33%) among tweets with 12% anger and 5% surprise
- Multiple emotions in one tweet, sarcasm, and slang words have a major role in decreasing the overall accuracy of this Machine Learning model.

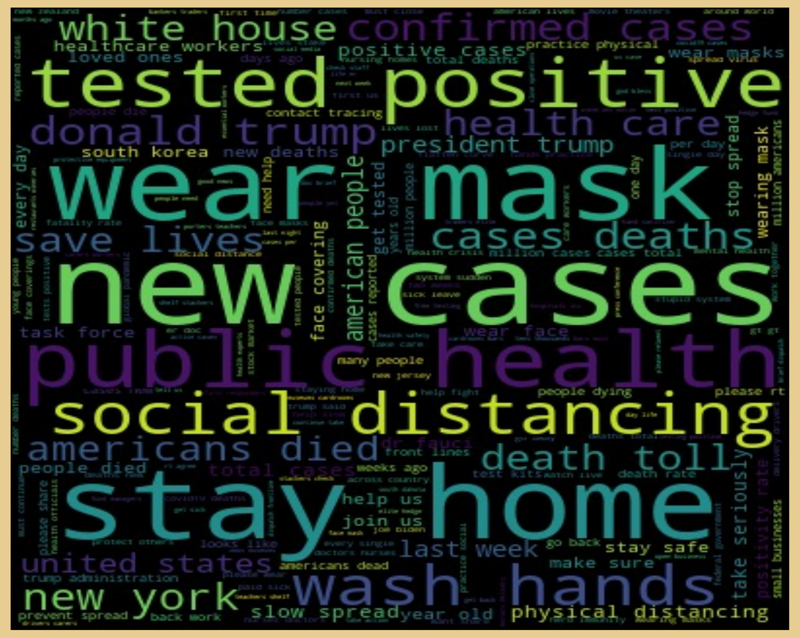

Fig. 1 Most used bigrams in tweets regarding COVID-19, enlarged based on frequency (Mar – Dec 2020)

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