TweetCaster: Predicting Pandemic Trend from Tweets

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ABSTRACT

In this paper we research the correlation between COVID-19 related tweets and number of new COVID-19 cases. We propose a machine learning model using natural language processing techniques to analyze keywords and sentiments of COVID-19 related tweets to predict future COVID-19 spikes. We utilized a dataset of COVID-19 related tweets and a data repository of COVID-19 time series data from the United States.

KEYWORDS

machine learning, neural networks, epidemiology, COVID-19, pandemic spread

1 INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The disease has spread worldwide since its first discovery in Wuhan, China, in December 2019, leading to an ongoing pandemic [18]. The first confirmed case in the United States was discovered on January 20, 2020 [9]. Recently, the death toll of COVID-19 has passed 700,000, with over 43,000,000 total cases in the United States [7].

In such a pandemic, it is important for health professionals to be able to predict upcoming spikes and have rough estimates of the new cases so that they can prepare and distribute necessary medical resources accordingly and make policy adjustment to reflect more strict public health rules. Social media chatters may serve as a good data source for this task because there is a strong correlation between COVID-related talks and actual COVID case spikes, and there is usually a lag between people experiencing the COVID-19 symptoms and being officially diagnosed with COVID-19. Therefore, we can use the trend of COVID-related keywords discovered in social media chatters along with other extrapolated information (for example, sentiment attached) and metadata (for example, time of posting the tweet) to effectively analyze prior COVID case trends and use learned knowledge to predict future new COVID cases.

This project aims to analyze posts from Twitter (tweets) with COVID-19-related content to capture the connection between the trend of discussion in Tweets and the actual trend of COVID-19 cases, which will make it able to predict future COVID-19 trends.

2 RESPONSE TO MILESTONE COMMENT

From our milestone report, we received three main comments.

The first comment was in regards to one of the references we used. We omitted this reference and any discussion we had using this reference as a source. Instead, we replaced it with a more reputable source about the applications of sentiment analysis in fighting COVID-19.

The second comment we received was redundancy in one of our paragraphs in our approach section and related work section. We fixed this by removing this paragraph since it related to the source from the first comment. We also gave the entire report another pass to remove any redundant parts.

The third comment sought more results. We had only visual results on data processing and sentiment analysis of the dataset. We addressed this comment by running a series of experiments aimed at finding some correlation between data we could extract from the tweets and the new COVID-19 cases. These experiments include, running our dataset through a linear regression model with Sentiment Analysis, some time series models, an ensemble model combining our linear regression and time series models, and a TF-IDF and BERT encoding of tweets passed into a neural network to predict COVID-19 cases.

3 PROBLEM FORMULATION

Given $\mathcal{D} = \{X_i\}_{i=1}^{N}$ micro-blogs (tweets) from real-world users related to the target pandemic (where $X_i = \{a_i, b_i\}$ is the i-th tweet and N is the total number of tweets, with a_i being the vector representation of the i-th tweet and b_i being the timestamp at which the tweet was posted), and $C = \{z_j\}_{i=1,j=1}^{M}$ data about the number of cases per day (where z_j is the number of cases on the j-th day from when the data started getting recorded for the United States and M is the index of the last day on which the data got recorded), we are interested in finding $\hat{y}$, the expected number of new cases in the United States for the seventh day from the present day. In other words, given the tweets from the United States about the pandemic of interest (POI) and the data about the number of cases for the POI, we are interested in predicting the number of new cases that might show up in seven days.

4 DATA PREPARATION

For this project, we are using the "Covid-19 Twitter chatter dataset for scientific use" maintained by the Panacea Lab at Georgia State University [4]. This dataset consists of tweets retrieved from the Twitter Stream related to COVID-19 chatter on a daily basis, from January 04, 2020 to October 12, 2021 (ongoing). The data collected from the Twitter stream captures all languages with English as the most prevalent, Spanish as the second most prevalent, and French as the third most prevalent.

We first downloaded the whole dataset that Panacea Lab had provided [5], which was roughly 15 Gigabytes in size and largely exceeded our computing power. To facilitate our research, we filtered the raw dataset using two criteria: 1) only take data from the year of 2021 (specifically from March 01, 2021 to August 22, 2021 because this period captures the second spike and valley of COVID-19 cases in the U.S.), and 2) only take data with United States being the country information attached. This gave us 361661 total records

to work with. We believe this amount of data is sufficient to provide valuable information about the trend because it is able to capture the second spike and valley of COVID-19 cases in the United States.

The raw data only records "tweet_id", which is the unique identifier used by Twitter to identify tweets. Therefore, we attached the content to the "tweet_id" (hydration) in order to do any text-related analysis. To accomplish this, we utilized the Tweepy[17] library, which serves as a wrapper around Twitter's API to provide a smoother experience when working with the API. After some experiment, we found that using the batch GET endpoint was much more efficient than using the single GET endpoint because Twitter temporarily blocks access when a user hits 900 requests in a 15-minute interval. Fortunately, Tweepy provides an internal sleeper to help us monitor this threshold, so the hydrating process was fully automatic. Twitter returns an empty response for tweet that has been deleted. We account for this case by further filtering out such entries. The final hydrated dataset was 69.4 MB in size, which was reasonably easy to process and analyze. We originally planned to also retrieve the geo information about a tweet to do some further analyses. However, this turned out to be infeasible because there was rarely specific geolocation information (coordinates) attached to a tweet and we could only get the "place_id" of a tweet. This is problematic because Twitter hosts their geolocation data on the Standard V1.1 API that allows up to 75 requests every 15 minutes.

For sentiment analysis, in order to analyze the sentiment of these tweets, we first had to clean up the format of the tweets using regular expressions. We cleaned up the tweets by omitting any mentions in a tweet (signified with an @), hashtags, rt or RT which signify a user retweeted the tweet, and we removed any tweets that include a URL to process better with text blob.

5 PROPOSED METHODS

5.1 Intuition

We propose a five-step process for forecasting the number of new COVID-19 cases from tweets.

First, we perform sentiment analysis on all tweets available to us in the given date range. Prior work has shown some correlation between social media posts from users and new pandemic or epidemic case numbers [3]. Next, we aggregate these numbers by day and retrieve the number of tweets linked with positive, negative and neutral sentiments.

Second, we retrieve some metadata that might be useful in predicting number of new COVID-19 cases. The first input point we use is the day of the week a tweet is posted. We had a hypothesis that the day of the week when a tweet is posted might directly impact the number of cases reported in exactly seven days from when the tweet is published. As we mention in the experiments section later, this metric is pretty handy for keeping track of the weekends. Since certain states do not report new case numbers over the weekend, our model learned to use this input point to mimic the actual data. The second input point we use is the hour of the day when a tweet is posted. We had a hypothesis that more COVID-19 related tweets might be posted at odd hours in the day if people are not feeling well or if they want to express concerns about people getting sick in areas surrounding them. As we discuss later, our model uses this metric to give better predictions. Also, since we aggregate tweets by day, we get the number of tweets posted at every hour of the day (for example, 12:00 AM - 01:00 AM, 01:00 AM - 02:00 AM, and so on) and present it as a data point.

Third, we vectorize the tweets using a suitable embedding (we use BERTweet for our work) for making the predictions. Due to the limitation of computational resources, finding the BERTweet encoding of each tweet and storing it in memory is not possible. Because of this, we aggregate all the tweets from the same day in one line (multiple sentence paragraph, each tweet separated by a comma) and then encode it. This would allow us to take into account what people might be talking about and not rely on just the sentiment or tweet's metadata, and it would thus allow our model to be able to make even better predictions.

Fourth, we merge the above-mentioned data together to get vectors for each day.

Finally, we use this vector to pass to our neural network that then predicts the number of new COVID-19 cases to expect in seven days from the current day. Here, we use a rolling window of training data, meaning that only a certain window of training data is available to the model to train itself on and then make a prediction based on the tweets from the day immediately following the window. The prediction is compared with the actual number of new cases and we then move the window forward by one day. The general intuition behind this is that the trend of people talking about the disease continuously changes and what was trending two months back might not be trending anymore. The rolling window helps the model make sure that it does not learn from outdated information.

On a sidenote, we also attempted to vectorize the tweets using a range of embeddings to use for making predictions, but we could not get the best performance from any of them. We hypothesize that BERTweet [13] might be able to provide us better results, but we could not use it due to the limitation of computation resources available to us. Instead, we aggregated all the tweets from the same day into one big paragraph, but this is unable to achieve the best results. We discuss this further in the Experiments section.

5.2 Sentiment Analysis

Sentiment analysis refers to taking a piece of text and outputting the sentiment of the text with labels such as positive, neutral, or negative. In this project, we analyze tweets and label each tweet with its respective sentiment. as a sentiment. Using this sentiment analysis label for each tweet,we wanted to see if analysis would have an impact on predicting To a rise in the number of COVID-19 cases day by day. Thus, to see if sentiment of tweets for a day is correlated to the number of new cases we add three new features to our dataset representing the number of positive,negative, neutral tweets for each day.

Sentiment analysis is important to study in regards to predictions of new COVID-19 cases, because various research have indicated that outbreaks and pandemics could have been predicted and controlled if experts studied social media data [2]. These authors hypothesize that by studying the role of social media we can understand symptoms being exhibited, visits to hospitals, and sentiments to predict trends in COVID-19 cases.

5.2.1 Algorithms and Libraries. We use two libraries in python to analyze the sentiment of the tweets that we pass into our regression and neural network models. **TextBlob**[16] is a NLP library that is able to analyze text and analyze whether a certain text is positive, neutral, or negative. The reason of why we chose to use TextBlob for sentiment analysis is because of it has a very similarly accuracy score compared to VADER, and higher accuracy score than Flair [15]. The way that it can label text is through three metrics of polarity, subjectivity, intensity. Polarity means how "negative" or "positive" a word is. Subjectivity means whether the text is more opinion based or factual based. Intensity refers to how many modifiers were used in the phrase which could "intensify" the sentiment, such as "very great" would be considered as high intensity and of greater subjectivity. The way TextBlob works for text phrases is that the library has a set dictionary or "lexicon" of words. Each word in the lexicon has a polarity, subjectivity, and intensity score. However, it should also be noted that each unique word in the lexicon can have multiple scores for the metrics as one word can have different levels of sentiment based on the context of the word being used. Thus, if TextBlob wanted to find the sentiment of a single word it would average all the metrics of the single word values from the lexicon and output a sentiment and subjectivity score. For text phrases, TextBlob applies the same logic for each word in the phrase and combines polarity score. The phrase is labeled negative if the polarity score is < 0, neutral if the polarity score is = 0, and positive if the polarity score is > 0. It should also be noted that polarity values are between -1 to 1, and subjectivity values are between 0 to 1. The subjectivity score for each tweet helps us understand whether it is more of an opinion or fact. This plays a role into its sentiment classification as subjectivity and intensity are used to help make the sentiment classification for each tweet.

We use the **WordCloud**[12] library in our project to analyze the cluster of words and frequency of these words in these COVID-19 related tweets. This helps us understand how sentiments were being assigned to their respective tweets and the most common words in tweets during this time period.

5.3 Tweet Vectorization

In order for computers to understand text information, we have to convert text into a machine-understandable form - vector, this step is typically called vectorization, or encoding.

The first step is to divide tweets into separate words, or "tokens". This step is typically called tokenization. It can be as simple as splitting the text by space, tab, or new line character. Or can be specific to the domain of the text data. For example, Python's Natural Language Toolkit (NLTK) provides a special TweetTokenizer[14] that handles tweet text. It has information about tweet-specific syntax such as that "@" means mention, and that "#" means topic. More recently since the state-of-the-art BERT model was introduced, Huggingface added a BERTweet[10] model, which was pretrained on a large-scale English tweet dataset, and it also includes a BertweetTokenizer. In this project, we plan to experiment with all three tokenizers to see which one can help us achieve the best performance.

The second step would be to convert the tokens into vectors, which is usually called vectorization or featurization. There are a number of established methods in this area, including bag-of-words, TF-IDF, Word2Vec, BERT, etc. Here's a brief introduction on each of the above:

- Bag of Words (BoW) is very popular because of its simplicity. BoW consists of a dictionary of known words, and a measure (usually count) of known words. This method is concerned with whether a certain word is in a document and its frequency. We are not using BoW in this project.
- Term Frequency-Inverse Document Frequency (TF-IDF) tends to capture more information than BoW. It also consists of two parts: TF accounts for how frequently a word appears in a document, and IDF measures how infrequently the same word appears in the whole dataset (containing the document). This gives more weight to words which appear in fewer documents and less weight to words which appear in many documents because the word that appears in many documents is unlikely to be important, e.g., stop words.
- Word2Vec is based on a neural network and learns word associations from a large corpus of text, while generating a low dimensionality vector representation of the word, which can be compared with each other to determine semantic similarity by applying cosine similarity. We are not using Word2Vec in this project because it only provides word embeddings, while we need sentence embeddings. It's worth mentioning that there is a method called Doc2Vec, which can be thought of as a sentence version of Word2Vec.
- Bidirectional Encoder Representations from Transformers (BERT) is a state-of-the-art NLP model developed by Google. BERT was pre-trained on language modeling and next sentence prediction, so it captures contextual embeddings for words. For this project, we will be using the BERTweet [13] model which has the same architecture as the base BERT and was pre-trained on a large dataset with 850M English tweets.

In this project, we utilize TF-IDF and BERT to generate embeddings that we then use to predict baseline predictions. We use TF-IDF to generate two variations of tweet embeddings using 200 features and 500 features. We also use BERTweet to generate embeddings by running a mean pooling procedure on the "last_hidden_state" returned by the model, which gives us a vector of length 768 for every set of aggregated tweets - this is defined by BERT's internal architecture. The features generated by BERTweet on the original dataset were too large to fit in the RAM of the Google Colab notebook that we used. As a result, we aggregate the tweets for each day into a single line of text, which is simply achieved by grouping the original data by date. This leaves us with a final vector of shape (253, 768), which we are able to fit in the RAM.

5.4 Metadata Extraction

To get more information that might be helpful for predicting the number of new COVID-19 cases, we use the available metadata from Twitter's API. This metadata includes,

- Day of the week the tweet was created, and
- Hour of the day the tweet was created

We think this information may be helpful because there are more reported cases on weekdays than weekends, and more cases during day hours than night hours based on our observation. We share further intuition behind this decision in the Intuition section. While more metadata might have been useful, it was not feasible to access it due to Twitter's API restrictions of not serving more than 75 requests in a window of 15 minutes. To aggregate the data by day, we calculate the number of tweets posted at every hour of the day and present it as 24 different data points. We make no modifications to day of the week because it remains the same for each tweet.

5.5 Vector Creation

After classifying each tweet's sentiment and extracting the relevant metadata, we merge all the data into one vector where each row represents a day from March 1, 2021 until August 22,202, and contains the following features: number of positive tweets, number of negative tweets,number of neutral tweets, and the number of tweets for each hour of the day. We maintain a separate vector that contains the number of new cases per day.

5.6 Neural Network Architecture

The neural network attempts to find a mapping from the data points that we extract from the tweets to the number of new COVID-19 cases. For this, we use a two-layer network, both of the layers being linear layers. We avoid usage of any activation function because it led to poor performance. For our work, we found 20 to be the ideal number for the number of hidden dimensions.

$$H = A \times X + b$$
$$\hat{y} = C \times H + d$$

Here, A and C are the weight matrices and b and d are the bias vectors. H represents the hidden layer.

As discussed earlier, we use a rolling window to predict the number of new COVID-19 cases for the seventh day from the present day. Let us refer to the rolling window size by r. We also determine the number of days in future for which we want the prediction. Let us refer to this number by f.

To give an example of how this method works, let's say we start at day t. Here, we can assume that we know everything about days before the day t. Since we are at day t, we are looking for the number of cases that might be reported on day $t+f$. While we train our model, we cannot have it go past day t because we never have future data available. As a result, the last prediction that the model can make must be of day $t-1$. Since the model predicts f days in the future, we limit one end of the rolling window to be at $t-1-f$. As a result, the other end of the rolling window would need to be at $t-1-f-r$ because the size of the rolling window is set to be r. Hence, we would have the rolling window (or otherwise referred to as the x matrix) would have data about tweets from day $t-1-f-r$ until day $t-1-f$. The ideal values that we attempt to match for such a rolling window would be the number of COVID-19 cases for day $t-1$ after seeing the data about tweets from day $t-1-f$. This is further illustrated in figure 1. Once the model has been trained, we use the data about tweets from day t to predict the number of the new COVID-19 cases on day $t+f$.

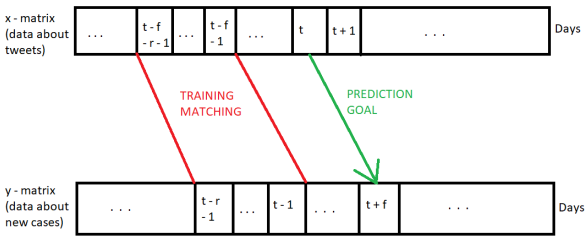

Figure 1: Figure illustrating how rolling window works

For training our model, we use the Adam optimizer [11] with a learning rate of 0.1 and number of epochs for each training session (for each rolling window) to be 10. We set the rolling window size to be 7 days (we discuss why we chose the size to be 7 days in the experiments section) and the number of days for which to make the prediction to also be 7 days.

6 EXPERIMENTS, RESULTS & EVALUATION

6.1 Evaluation

For our work, we use root mean squared error (RMSE) to get a measure of how far our model is from the goal. This is often also referred to as our loss function.

6.2 Analysis of Tweet Sentiments

We analyze the sentiment of 361661 tweets the dataset of March 1, 2021 to August, 22, 2021. After cleaning up the text of the tweets for sentiment analysis, we apply TextBlob's subjectivity and polarity functions on each row of text and assign a sentiment score of negative if the polarity score is less than 0, neutral if the score is equal to 0, and positive if the score is greater than 0.

As seen in figure 3, after labeling each of the COVID-19 related tweets from the dataset we found that,

- 36% of the tweets were classified as Positive,
- 45% of the tweets were classified as Neutral, and
- 19% of the tweets were classified as Negative.

This shows that almost half of the tweets are considered to be neutral or have conflicting sentiment of words.

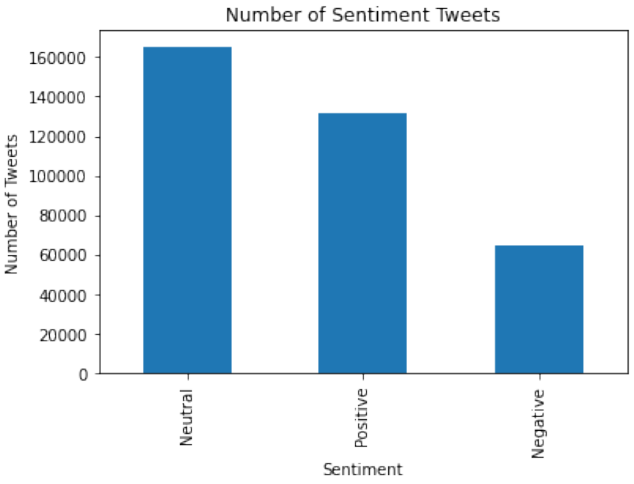

Figure 2: Frequency of Sentiment of the Tweets

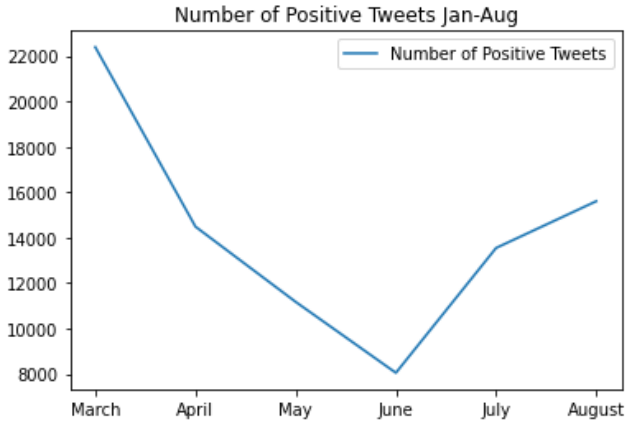

Figure 3: Number of Positive Tweets by month

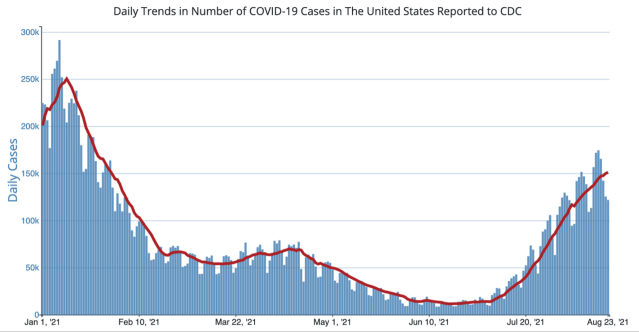

Figure 4: Number of COVID Cases by month [1]

We analyze the trend of positive, negative and neutral tweets over months and compare them with number of new COVID-19 cases and found some pattern between the new COVID-19 cases and positive tweets. Figure 3 shows the trend of the number of positive, negative and neutral tweets from March to August of 2021, and Figure 4 shows the trend of COVID-19 cases from March to August of 2021. From comparing these two graphs, we can see that both graphs follow a similar trend where the number of positive tweets and cases decrease from March to early June, and then start increasing again from June to August 23, 2021.

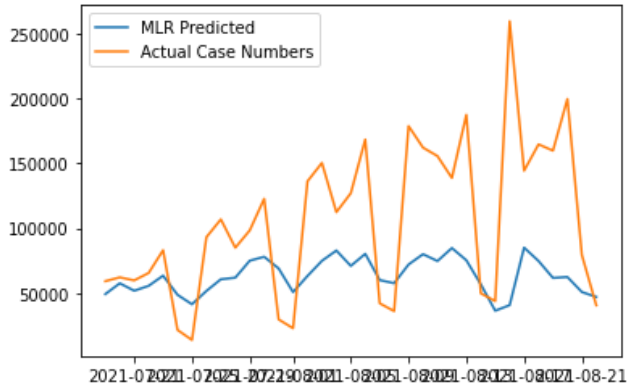

Figure 5: Predicted Number of Cases with Multi-variable Linear Regression with Sentiment Analysis Data

The above-mentioned observation encouraged us to try to regress the number of new COVID-19 cases from just the sentiment information. The overall goal of this experiment was to see if we can find a direct correlation between the tweets' sentiments and the number of new COVID-19 cases.

We do this by performing an 80:20 train-test split and graphing the predictions along with nothing the RMSE value for the method. We use Adam optimizer with a learning rate of 0.1 and 1000 epochs. Figure 5 shows our observation. The RMSE recorded for the test set was 68441.

Interpretation: Such high RMSE value is probably a result of lack of information. While the model is able to get a sense of rise and fall in number of cases over the week and weekend (probably through change in number of tweets over the weekend), it is still unable to predict what might happen on the next day with just the aggregated sentiment analysis data.

6.3 Time Series Models

Since the number of new COVID-19 cases is a time series dataset, we also attempted to fit time series models, like ARIMA, OLS and their ensembles, to predict the new cases. The purpose of this experiment was to check if we can directly use time series models to predict the number of new COVID-19 cases. However, we found that neither of the three approaches could get us close enough to the actual number of new cases. ARIMA got us close to the true number, but it always had a delay in its predictions.

As mentioned earlier, we again use an 80:20 train-test split for the data. We use ARIMA model with hyperparameters being $p = 2, d = 0, q = 2$ because we found them to work the best with COVID-19 dataset. For the ensemble of the two methods, we use the inverse

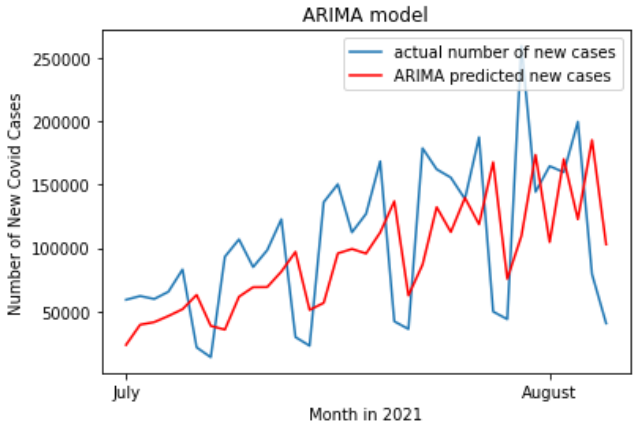

Figure 6: ARIMA Model

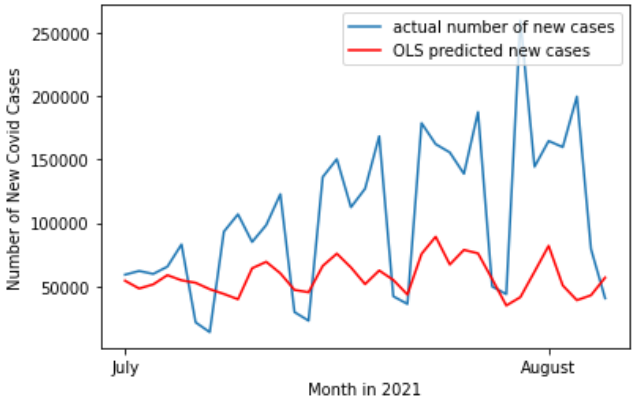

Figure 7: OLS Model

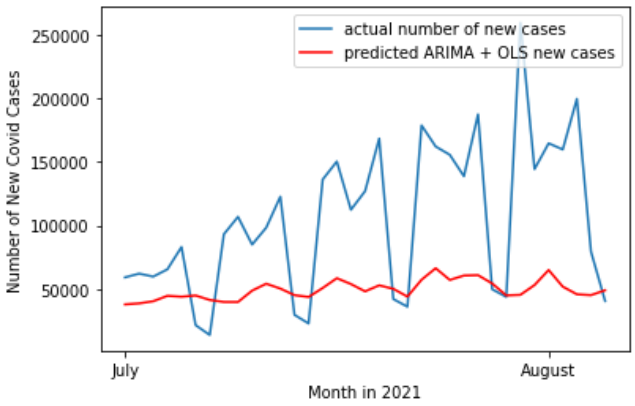

Figure 8: ARIMA + OLS Model

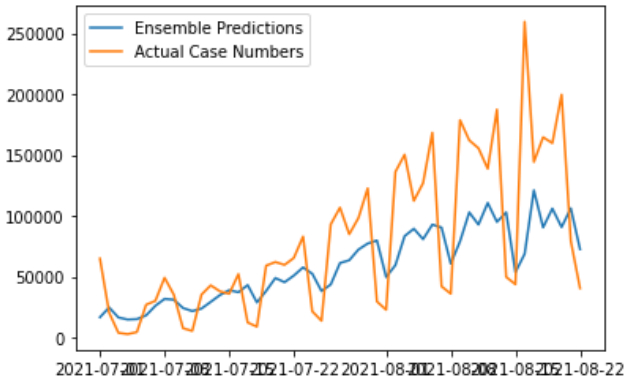

Figure 9: Linear Regression + ARIMA + OLS Model

of the RMSE produced by both methods as their weights and then normalize the sum of product of the weight and the prediction of each method.

Figures 6, 7 and 8 display the performance we see with the test dataset. Table 1 shows the RMSE values we found for each method.

Interpretation: While ARIMA and OLS are generally good for fitting time series datasets, they do not account for unknown variables that can cause deviation from the usual trend for such datasets. For example, for COVID-19, such deviations can be a result of introduction of a new COVID-19 variant, some mass gathering or even state or country wide lockdowns. As a result, although ARIMA and OLS predict the drops of cases decently well, they are not able to predict the spikes in cases with high accuracy. ARIMA seems to perform better than OLS probably because ARIMA takes into account the previous time steps and how the target variable is changing over time steps. OLS, on the other hand, is another way to do linear regression which relies on the fact that XX^{-1} is invertible (where X is the input matrix). This might not always be the case which may result in poor performance of OLS. Since both the models seem to underestimate the new COVID-19 case numbers, their ensemble seems to do the same.

To check if adding some sentiment value might help at all, we also try ensembling ARIMA and OLS with the linear regression described in the previous section. Running this experiment while keeping rest of the parameters the same, we get a series of predictions that look like they are getting closer to the actual number of new cases, but they still seem to lack the ability to recognize upcoming spikes. Results of this experiment have been shown in Figure 9 and Table 1.

Interpretation: This might probably be a result of the data available to us because the number of new COVID-19 cases every day start to increase only towards the end of July, while the models are trained on data from March 2021 until the beginning of July 2021, where no such trend is observed.

Table 2: RMSE Values - Neural Network with Tweet Encodings

Encoding Type	Rolling Window Size	RMSE
TF-IDF - 200 features	7	25974
TF-IDF - 200 features	14	28504
TF-IDF - 200 features	21	30352
TF-IDF - 200 features	28	30370
TF-IDF - 500 features	7	26025
TF-IDF - 500 features	14	28340
TF-IDF - 500 features	21	29919
TF-IDF - 500 features	28	29893
BERTweet	7	25729
BERTweet	14	27266
BERTweet	21	29243
BERTweet	28	31007

Table 1: RMSE Values

Model Type	RMSE
ARIMA	58886
OLS	72963
ARIMA + OLS	78597
Linear Regression + ARIMA + OLS	71349

6.4 Neural Network with Tweet Encodings and Metadata

We have been ignoring the contents of the tweets and their metadata thus far. We shall now run an experiment to check if we can get better results if we include the encoded tweets and the metadata discussed earlier. We are also not sure about what encoding method might be the best one to use. As a result, we shall now run experiments with TF-IDF with 200 and 500 features (to see how does increasing the number of features affect the results) and BERTweet to test one of the state-of-the-art ways to encode tweets. For this section, we shall be using the neural network architecture proposed in our work. However, we are not sure about the size of the rolling window yet. Thus, we shall also test it as well with sizes of 7, 14, 21 and 28 days to see what gives the best results. Please note that we take multiples of 7 because they might help our model notice any trends between weeks.

Table 2 shows the results of running the proposed models with the given rolling window sizes.

Interpretation: TF-IDF and BERTweet are able to produce almost equally good results. TF-IDF is probably able to produce similar results with different number of features because the most important 200 features might be able to cover everything that we need to predict the number of new COVID-19 cases because of which adding in more less-important features does not make too much of a difference. As for BERTweet, it is probably not able to do better because we mix the tweets together due to computation limitations. It might be able to do better if we have more computational resources. As far as the size of the rolling window goes, it probably makes sense to limit to a smaller window so that we do not capture outdated trends. This is something that we see from our experiment as well where the smaller size rolling window is able to produce better results.

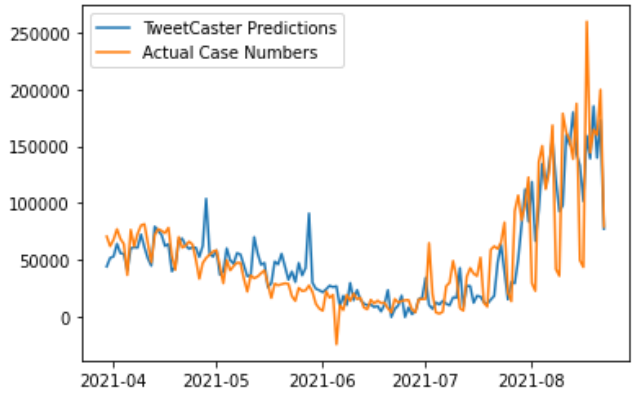

Figure 10: Performance of BERTweet with rolling window of 7 days

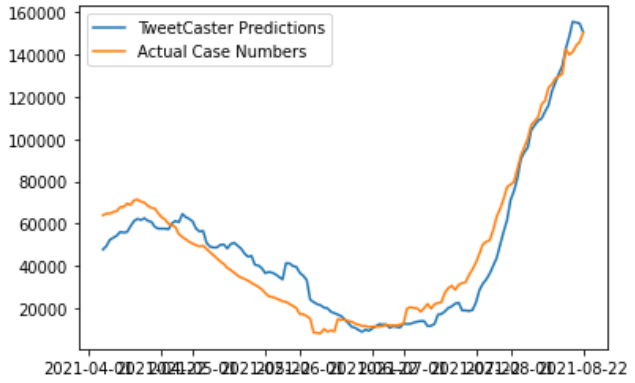

Figure 11: Smoothed graph of performance of BERTweet with rolling window of 7 days

Figures 10 and 11 show how the BERTweet encoding performs with the rolling window of 7 days.

7 SURVEY OF RELATED WORK

There have been multiple researches that are focused on alternative approaches to evaluate an emerging health crisis like COVID-19, given that nationwide mass testing is not feasible in the majority of countries. This phenomenon of social media's ability to provide insights into pandemic activity has been referred to as "wisdom of the crowds", where the collective knowledge and experience of individual users are used to predict trend of a pandemic in the absence of a large-scale virus tracking system [6].

Some of the papers we read had different approaches, but a common objective of using COVID-19 symptom related tweets or searches in predicting COVID-19 spikes. Researchers from the University of Guleph [19] and researchers from the University College London (UCL) [6] both had similar approaches of analyzing features within Twitter datasets and identifying anomalies within the number of tweets related to COVID-19 symptoms to predict

when the wave or spike of COVID would happen. We can use insights and results made from both of these papers in helping us detect anomalies and correlations between keywords in the twitter dataset and COVID-19 cases to predict a future spike in COVID-19. A weakness from the paper by the researchers from the University of Guleph [19] was that they used twitter data when testing was not as prevalent because it was the beginning of the pandemic, and also regions had travel-based policies that were not identified, which could explain some of the delayed lag between their prediction of a COVID-19 spike and the actual COVID-19 spikes. Another limitation we found between both of these papers in the twitter data they used was that there may be a bias in the tweet data of the age of the people who are tweeting, as well as a bias of the socioeconomic class of people tweeting as both papers do not take into consideration of people who did not have access to tweet or search these highly correlated symptoms (e.g. cough and fever) of COVID-19[6, 19].

Some limitations we found that were common between papers was that during period in which they conducted their research or built their prediction models, they did not have much data due to being in the early stages of COVID-19.

Besides social media, recent researches also focused on utilizing human mobility data to detect COVID-19 outbreaks in the early stage [8]. Contact mixing is critical in the spread of COVID-19, therefore mobility restrictions of various degrees have been implemented in over 200 countries in the attempt to slow down the spread of the disease. In the paper, the researches found that, using macro-level human mobility data (cell phone mobility data from Israel) along with health improves predictions of when and where COVID-19 outbreaks are likely to occur. The main concern over this type of work is about its privacy, which is addressed by using anonymized data.

8 CONCLUSION

In today's world, we have realized the impact of data science in regards to detecting epidemic outbreaks and case spikes to better help us take actions to minimize them. With the development of new variants of COVID-19, our project can help regional and national officials know when a rise in the number of new COVID-19 cases will happen, and help them promptly develop an action plan and steps to control the rise in cases. In our project, we were able to use Regression and a Neural Network with sentiment analysis and tweet encoding to predict new COVID-19 cases.

9 FUTURE WORK

We plan to make a few improvements to our work in the future:

(1) We were able to run experiments on a date range that would allow us to test with rise and decrease in the number of new COVID-19 cases. We would like to add more training data (a wider date range, more tweets, etc.) to our models and see if we can better observe the trend in COVID-19.
(2) We would also want to extend our model to predict new cases for more countries. As of now, we are predicting new cases for the United States, but the project can be easily extended to another country by switching the language model.
(3) Within the same country, regional prediction is possible given specific location data. This is an important application to research into because it provides more insightful and accurate predictions than the current country-level prediction.
(4) Given more RAM, we can vectorize all the tweets for each day with BERTweet instead of aggregating them together, and see if it produces a better result.

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