CSE 6242 Project Progress Report

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1 INTRODUCTION

Twitter, as a leading social platform, generates over 800 million Tweets in a single day. A majority of discussions focus on COVID-19, which is way too overwhelming for us to extract the useful information. Meanwhile, current COVID-related websites only provide visualizations on daily cases. The relationship between COVID-19 and twitter topics has not been fully explored yet. Therefore, in this project, our goal is to evaluate the relationship between the COVID-19 cases and number of tweets in each country, and provide data visualization to assist users make decisions and provide guidelines for work and school during the pandemic. To be specific, we would like to demonstrate how COVID-19 spread across the world and manifest the correlation between trend in tweets and the actual trend in COVID-19. Besides, a word cloud of most frequently occurring tokenized words is presented to give users a brief overview of the most popular topics regarding COVID-19 on Twitter.

2 LITERATURE SURVEY

Trajkova et al. [18] presented a study of Twitter retweet frequencies during the period the COVID-19 epidemic. Their findings can be considered to facilitate our understanding of Twitter information spread. However, the study does not discuss methods for altering Twitter information flows. Al-Rakhami et al. [1] conducted an analysis on information credibility of Twitter posts during the COVID-19 pandemic. These models can be used for COVID-19 information refinement in our project. This study can be improved by considering complex tweets with news and emotional contents. Rufai et al. [12] demonstrated the increasing of Twitter usages by the majority of G7 world leaders on the subject of COVID-19. Such information from the G7 leaders can be analyzed in our project. But, the safety and accuracy of the tweets should be paid attention. Samant et al. [13] developed a flexible interactive dashboard for COVID-19 data visualization with their demographics based on multi-layer network. The event-based and parameter-based aggregate analysis and visualization can be used for comparisons of features and consequences in the COVID-19 data and as an improvement for their study. Amin et al. [2] proposed an intelligent model for COVID-19 pandemic detection from Twitter messages based multiple machine models. This dataset can be incorporated into our project. However, more categories can provide fine-grained datasets. Torres et al. [17] analyzed the URL sources being posted by influential Twitter accounts, which can help us comprehend the information dissemination of the COVID-19 tweets. Their Twitter data can be extended to contain epidemiology and vaccinations questions.

Xue J. et al. [20] proposed a machine learning algorithm that uses a Twitter dataset to understand discussions related to the pandemic. It provides us some ideas of techniques when analyzing our own dataset. However, we plan to generate an interactive interface to present our analyzing results. Clement et al. [6] built an interactive dashboard to display real-time global trends of COVID-19, from which our team could learn the packages and tools for data visualization. But our team would elaborate on that by interpreting our dataset to extract more information before displaying it to the users. Kwan et al. [14] discussed a framework constructed to analyze general public's emotions and sentiments in response to COVID-19 based on their tweets. Its topic has some overlaps with our project as we both use tweets as the data source. However, we would build an interactive interface to visualize our analysis results. Signorini et al. [15] proposed that Twitter could be a reliable data source for both tracking disease level and analyzing public's reactions to a pandemic. Although it talked about H1N1 instead of the COVID-19, our team could learn what hidden information we might obtain from our dataset. Rufai et al. [12] analyzed word frequency pattern and conducted sentiment analysis on tweets posted by the public and WHO. Although not decided yet, our group may include word frequency pattern as part of our analysis. But besides that, we would

also focus on visualizing the data and the result of analysis. Thomas et al. [16] built a neural network to predict users' location based on the Twitter data. It might not be helpful to our project as our dataset should already include the geological information. Also, besides location, we will include more features like time and frequency.

Burton et al. [5] evaluated the location information provided by Twitter's Global Positioning System for infoveillance and infodemiology to prevent overrepresenting or underrepresenting. As Karami et al. [8] stated, the number is less than 1% now while the number of users has increased by 90 million required an update. Nekliudov et al. [11] studied the impact of COVID-19 pandemic on mental health. This paper expounded a potential function of our project, monitoring COVID-related social anxiety. One drawback is the generalizability of this paper, since they only sampled from Russian. Li et al. [10] conducted a survey on social media use in China during the COVID-19 pandemic. This study is geographically complementary to our research. They also stated that the aggregated social media had more influence than public media in China as a potential improvement. Skunkan et al. [4] analyzed public recognition to COVID-19 pandemic by data mining. This research may provide validation to our analysis results. However, they only collected data from English language twitters not representing the general situation. Xu et al. [19] used the same database, the geotagged tweets to measure how many people had travelled since the pandemic of COVID-19. This article inspires us the correlation between data statistics and corresponding state laws. Kim et al. [9] studied the influence of media on people's information obtaining and decision making. They pointed out that keywords and filters may biased people's understanding of truth, such as facts about COVID-19. Our project may improve this phenomenon by explicitly showing the discussion popularity.

3 PROPOSED METHOD

3.1 Dataset

In this project, we will be using two datasets: COVID-19 daily cases [7] and COVID-19 Twitter chatter dataset [3]. COVID-19 Data is provided by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, which has detailed COVID-19 cases each day, month and year. Twitter chatter dataset is a public
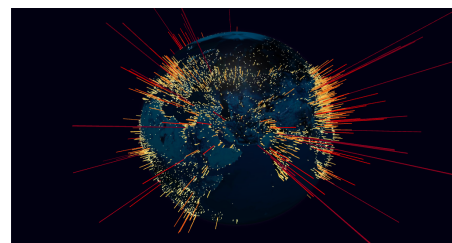

Figure 1: Google WebGL Globe

dataset maintained by the Panacea Lab at GSU. It consists of tweets acquired from the Twitter Stream related to COVID-19 chatter and provides top 1000 frequent terms, bigrams, and trigrams for Natural Language Processing (NLP) tasks.

The frequent terms from the Tweet dataset are shown in the Figure 2a with their counts. We can find the most frequent terms includes "covid", "19", "covid19", "coronavirus", and "vaccine". Most frequent terms are related to COVID-19 pandemic and vaccines, which present people's concern about this world-wide health crisis. A bigram is a sequence of two adjacent elements. The frequent bigrams from the Tweet dataset are shown in the Figure 2b. Similar to the comment terms, these bigrams are close to the COVID-19 pandemic and vaccines. For distributions of tweets over countries and languages, the countries with the largest numbers of the tweets are shown in the Figure 2c. The most tweets are from the United States, India, Brazil, United Kingdom, and Canada. These countries have large populations of Tweet users. Also, the languages with the largest numbers of the tweets are shown in the Figure 2d. The most tweets use English, Spanish, Portuguese, Hindi, and French.

3.2 Global COVID-19 Visualization

In this section, we mainly discuss steps to visualize the COVID-19 data in 3D format.

The first step is collecting COVID-19 data including daily cases, deaths and recovered. The CSSE raw data introduced in the previous section has the following schema: Province/State, Country/Region, Longitude, Latitude and the daily COVID-19 cases. We can directly join the data with the global geo dataset, which has the 3D coordinates of each country in the world.

The second step is plotting all the countries on a sphere. Inspired by the Google WebGL Globe as shown

(a) Counts of Terms (b) Counts of Bigrams (c) Countries with Tweets (d) Languages with Tweets
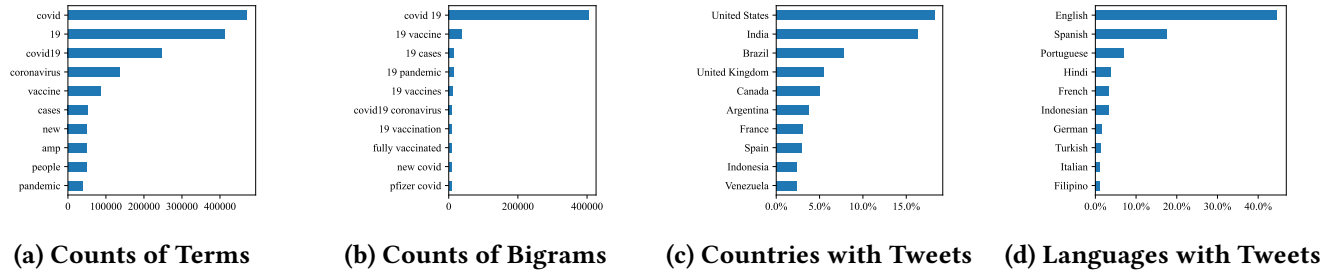
Figure 2: COVID-19 Related Tweets

in Fig. 1, we will modify the code to display the Choropleth on the sphere. WebGL is a web component to represent data visualization layers on a 3D globe in a spherical projection. To obtain the coordinates of all the countries on the globe, we will adopt GeoJSON, which is a format for encoding a variety of geographic data structures. All the corresponding COVID-19 data will be displayed with a window when hovering on it.

Finally, we provide the dynamic visualization function. The user can easily visualize how the COVID-19 has grown starting from the pandemic breakout to the latest date. The animation is implemented by the slide bar and get value function. A slide bar displaying all the dates will be placed on the bottom. When the date proceeds, the get value function will use the current date on the slide bar as an input and fetch the corresponding COVID-19 case data on that day and attach it to the sphere with the correct color scheme. The larger the infected numbers, the darker the color selected.

3.3 COVID-19 Tweet Visualization

In this section, we visualize the Twitter chatter dataset on a similar globe described in 3.2. We will be displaying the number of tweets, the most popular terms, along with some other useful information in a country over a time period.

To accomplish this, we first retrieve the full Twitter chatter dataset from [3], filter out records without geo location, then partition the data into small blocks indexed by date and country. This arrangement provides major advantages when it comes to visualizing time-related data.

We plan to offer a heatmap-like visualization over the globe to help users easily understand the tweet distribution and its correlation with COVID cases. By dragging the slide bar that controls time and clicking on each

country, the users will be able to see the most popular terms discussed on a specific day in that country.
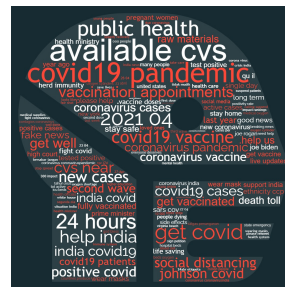
3.4 COVID-19 Twitter Word Clouds

The relationship between COVID-19 related tweets focus and the severity of COVID-19 is studied. From the world daily new confirmed COVID-19 cases collected by Our world in Data, we collect and combine the data date_top1000bigrams.csv from three time periods within the COVID-19 second wave(from 2021-03 to 2021-07): [2021-03-02,2021-03-06], [2021-04-23,2021-04,27], and [2021-06-19,2021-06,23] illustrate the lowest daily case before the second wave, the highest daily cases in the second wave, and the lowest daily cases after the second wave, respectively. The reason why we only use the bigram data is that the terms data contains redundant information, such as "covid", "COVID", "covid-19", and "19", and the triterms data contains lots of foreign language such as French, Arabic, and Hindi.

The Word Clouds are introduced to evaluate frequently discussed topics during the second wave (2021-03 to 2021-06).The topics are chosen based on the discussed frequencies in five-day periods centered at the peak and valleys of COVID-19 confirms in English-based contexts. The data is cleaned by filtering out non-English vocabularies and deleting words with repetitive meanings. All topics on the cloud were mentioned more than 1000 times. The font size are determined by the frequency of words appear in tweets. We choose red and white as the displayed word color to give a sense of urgency, and black as the background color to add solemnity. Three fonts are applied to words randomly to add visual variation to the graph. We also design the overall shape of the clouds to be a human head wearing a mask, which is a combination of the symbol of COVID-19 and an analogy of "what people are thinking."

(a) 2021 03-First Valley   (b) 2021 04-Second Peak   (c) 2021 06-Second Valley

Figure 3: Three simple graphs

4 EXPERIMENTS AND EVALUATIONS

To evaluate if our interactive COVID-19 global distribution map is user-friendly and informational, we will examine it in the following aspects:

- Hovering on a country allows users to see Country, Longitude, Latitude and daily COVID-19 cases.
- Pressing the globe rotates the 3D sphere.
- Moving the mouse along the slide bar displays COVID-19 case data on each day and the globe changes to corresponding color scheme.
- Data displayed matches "Coronavirus World Map" published on New York Times.

We will also invite individuals to thoroughly interact with our map and share with us their feedback. The purpose for such testing is to check if our interactive map is enjoyable to use, so we could fine tune our visualization based on the feedback we collect.

For the COVID-19 related tweets, we will compare the number of tweets from one country with its number of COVID-19 cases. We will also compare the number of tweets using one language with its number of Tweeter users. A ratio of the tweet count per day from a country with the case count will be computed. A circle with a dynamic size will be used to present to the number of tweets from each country for each day. The area of the circle will be proportional to the number of tweets. The following functions will be inspected:

- Displaying dynamic circles to show the number of tweets for all countries.
- Showing the most common terms, bigrams, and trigrams.
- Listing the most common used languages for tweets of each day.

We can find patterns from the word clouds. The first finding is that the public attention was positively correlated to the confirm numbers. The peak cloud is more densely filled with topics than the valley clouds. In addition, people got sensitive during the peak and used words like "people dying" and "life saving", while at valleys the topics are more likely to be specific terms like "public health" and "Joe Biden". Another finding is the change of ways people fighting against covid. At the beginning, besides vaccines, people believed in hear immunity and wearing masks, but as the confirmed number rapidly grows, people dived into vaccination and talked about specific brands, doses, and appointments of vaccines.

5 CONCLUSION

(Under Construction)

6 PLAN OF ACTIVITIES

All team members have contributed similar amount of effort. To be more specific, S.H. Peng and G.C. Meng are working on the global visualization part. Here is our timeline: Finish basic 3D mesh by Nov. 7th, Display the corresponding countries through global-geo data by Nov. 15th, and Visualize the daily cases when hovering on the country and add the slide bar function by Nov. 30th. J.Y. Mao and Z.F. Liu will work on tweet visualization and plan to finish data preparation by Nov. 7th, globe visualization by Nov. 15th, and finally data connection and interaction by Nov. 30th. H.L. Huang and Y.X. Wang are working on Twitter word clouds. The plan is finish data preparation by Nov. 7th, finish basic Twitter word clouds by Nov. 15th, and finish the combination with the tweet visualization section.

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