THE UNIVERSITY OF HONG KONG

FACULTY OF EDUCATION

BSDS4999_FA_2021

Project

COVID-19 news on Twitter, a statistical analysis

Final Report

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Abstract

Recent statistics have shown that about 6.26 million people have died and about 520 million people have been affected by moderate or serious health issues caused by the COVID-19 pandemic. Concerns raised about the spread of fake news and misleading information about COVID-19 from social media platforms have worsened the problem. Social media platforms like Facebook and Twitter facilitate connection and communication on a large scale. Because of the massive amount of news transmitted through social media, manual verification is impossible, prompting the development and implementation of automated methods for fake news identification. This article tries to identify the Users are not only the news consumers but also the news creator and distributors. Fake news creators employ a variety of aesthetic tactics to ensure the success of their works, one of which is to excite the sentiment of the recipients. Therefore, to analyze whether sentiment words and emotional words in social media could explain the situations between the spread of true and fake news by sentiment analysis. It could be observed that fake news may become a serious virus to the general public when they convey a higher proportion of terms associated with a positive sentiment. In view of that, the government could take action to help the general public to identify fake news and curb the fake news at its source. It offers insights to the public on the importance and impacts of sentiment words in social media content.

Work Allocation

Lu Yuk Ho	**Introduction, Methods, Discussions, Conclusion**
Chiu Chin Fung	**Literature Review, Methods, Discussions, Limitations**

Table of Contents

List of figures

List of tables

1. Introduction

People in this day and age receive information through a wide variety of means. Particularly, young people rely on social media instead of traditional media to get to know what is happening around the World. Traditional media usually have governmental authority to monitor their content and it is delivered by professional journalists to ensure the news meets their professional standards. Therefore, the traditional media serve as gatekeepers to provide accurate information to the public (McElroy 2013; Skovsgaard & Van Dalen, 2013). Nevertheless, traditional media is no longer the primary source of information. Today, we spend most of our time on the Internet, ranging from working, and socializing to entertaining. As a result, we are largely exposed to online information rather than physical ones. Social networking sites dominate the role of information providers as it is a major platform for working, socializing, and entertaining. Despite its popularity, the accuracy of information is not guaranteed. They do not have a review prior to surface them and require the social networking sites themselves to formulate policy on monitoring inappropriate information, including fake news and hateful speech. They often rely on the report of users after the posting of that suspected content and do an investigation to delete the content and restrict the user who had posted that content. As a consequence, it may be too late to stop that inappropriate information from spreading. Therefore, it is important for the public to identify the characteristics of fake news and do fake-checking.

Fake news is "the deliberate presentation of false or misleading claims as news, where the claims are misleading by design" (Gelfert, 2018, p. 108). In this paper, 'misinformation' and 'fake news' will be used interchangeably. Fake news aims to make a social, political, and economic bias in the minds of people for individual benefits. It aims at affecting and exploiting people by making misleading information that sounds authorized (Shu et al.,2017) On the extreme end, fake news may lead to a public health crisis or even a riot. The sudden rise of COVID-19 has been assisted by an outburst of misinformation about the disease. Social media platforms have become an important means for receiving, sharing, and posting information regarding the pandemic(Naaem et al., 2020).

Regarding the topics and words about fake news, misinformation includes healthcare issues like fake cures of gargling with salt water and injecting with bleach, and also 5G cellular network can cause the pandemic(Van Bavel et al.,2020). Political issues like Wuhan are the origin of the disease and US President Donald Trump embraced hydroxychloroquine, which is an anti-malaria drug against the new COVID-19 with unproven medical evidence on Twitter(Paz,2020). Besides, special words in headlines like “Die”, “Death”, “Disaster”, and “End of the world” may arouse the spreading of news as those words are life-related and induce fear in the readers (Paz,2020). Those topics and the use of words may lead to fake news spreading in a wider scope with no boundaries.

Regarding the sentiment to the real and fake news in social media, it usually stresses the polarity of the content of the news, whether it is positive, negative, or neutral. Realizing the categories of the sentiment from the news, could influence human judgment and decision-making, and strongly affect how the news could grab people's attention. Moreover, sentiment, as well as emotion could trigger cognitive processing, to affect online behavior like sharing and commenting, which would drive the online diffusion of some fake news (Alonso et al., 2021). It then promotes the public to believe in misleading information. As a result, we can investigate the differences in the spreading of real and fake news through the analysis of sentiment.

It is important to realize the spread of false information. For the government, identifying the spread of fake news could make policymakers target the negative effects of fake news and educate the public through propaganda. It is crucial as repeated exposure to fake news may lead more users to believe that it is a piece of trustable information. For social media platforms, when investigating the most common topics of fake news in social media platforms, the developers could design an early warning system that could automatically detect the emergence and spread of misleading information and stop it at the source. In light of this, this paper is going to explore the characteristics of fake news to help the public to identify the possible misinformation as it is undoubtedly time-consuming and requires a great deal of effort to do fact-checking on every news we read. More importantly, this paper will lay emphasis on the words and sentiment. We will adopt machine learning techniques to scientifically identify the contribution words and major sentiments.

2. Literature review

Many recent studies have provided insights into how social media platforms have changed the ways and forms we consume and receive news under the outbreak of COVID-19, which induces the spread of fake news and misinformation. Besides, previous studies have touched upon the state-of-the-art detection of fake news. However, regarding the research on the news of COVID-19, there have been few studies on digging out the most common type of fake news and the spreading dynamics between real and fake news, which are related to sentiment analysis as the main focus.

2.1 The emergence of fake news

Social media users consume and send news through social media platforms like Facebook, Twitter, and Instagram. The general public is no longer the news receivers, but also the news distributors and creators. Accessible to a wider range of users and audiences, social media tools provide a simple and straightforward way for people in the public to participate in the discussions of social issues and express themselves freely with a large group of people(Picard,2009). Moreover, the cost of entry to posting and delivering news online is much lower than that of traditional print media like newspapers, regardless of its trueness and monitoring by the government authority(Lazer et al.,2018). Therefore, this trend has favored many small publishers to publish their news content on the internet. With attracting more online readers and viewers, they may frame some fake news in order to draw the public's attention. Social media has provided chances and loopholes for them to spread fake news to massive groups of people through the internet. In sum, existing literature lays emphasis on the phenomenon of fake news rather than taking its characteristics into account in the field of machine learning.

2.2 Believing in fake news

An interesting finding from past studies has shown that fake news and misinformation usually tend to spread faster than some hot topics released by the mainstream. Moreover, most people love to read and tend to believe fake news. The reason for that could be explained by Elgerly and Vraga's (2020) works, they have stated the importance of the content and reporting style of the news, which will largely affect the public to decide whether it is news or not, and hence on their corresponding all-round behaviors. They have outlined four factors that shape the assessments of news: what is communicated, how is it communicated, who communicates it, and where it is communicated. It reveals that the content of the fake news acts as an important role for the reader to determine whether to believe it or not, which is also an important identifier for the categories of sentiment analysis. Moreover, the “continued influence effect” would make people believe fake news continuously even if the fake news has been disconfirmed (Ecker et al.,2010).

2.3 Responses and discussion of Fake news

Regarding the content of the news, research from Naaem et al. (2020) also stated the common types of misinformation regarding COVID-19, which included false claims, conspiracy theories, and pseudoscientific health therapies, on how these three types of misinformation determine the responses and actions towards fake news. On the other hand, sharing acts as a formal function on social media platforms and has made fake news and information become more widespread and reliable. Some key opinion leaders(KOL) on Twitter love to re-tweet news from mainstream news channels and add their personal opinion, as well as emotion to it. Because of their popularity, users often share those postings to their connection, which may result in a more positive sentiment regarding the news. From the sharing, those opinion leaders are in the information flow(Katz & Lazarsfeld, 1995). Those people could easily gain social status and be presented as reliable sources of news information. As a result, public opinion could be easily driven by those leaders, especially during the pandemic when the information flow is messy on social media platforms. People start to use social networking functions to filter, access, and react to the news. For example, about 40% of internet users love the function that they can customize their favorite news from the site. However, this influencing trend may lead to the self-selective nature of online news and accelerate audience fragmentation among the users (Willnat,2006). The custom function in social networking sites may result in one-sided information and discussion on the page. The above situation could be explained by the theory of confirmation bias that was raised by Nickerson (1998), stating that people tend to believe what is consistent with their beliefs and ignore other things that are inconsistent with their beliefs. As the pandemic continues, people will only continue suffering from the fake COVID-19 news, which could induce a big public health crisis.

2.4 The detection of fake news

In the work of Bondielli and Marcelloni (2019), they have presented the qualities that have been evaluated in false news and rumor detection approaches, offered an overview of the many methodologies used to conduct these tasks, and highlighted how gathering appropriate data to complete them is troublesome. They hypothesized that sentiment analysis techniques may be utilized to extract one of the most important semantic aspects of fake news pieces. Besides, Meel and Vishwakarma (2020) have investigated how the content of fake news destroys web dynamics. They investigated the false information ecosystem, from the classification of false information to the incentives for spreading it, as well as the social impact and user perception. They also talked about the level of fact-checking today, including source detection, propagation dynamics, detection approaches, and containment and intervention strategies. They saw sentiment analysis as one of the most important sources of data for detecting misleading information. In Zhang and Ghorbani works(2020), they evaluated the negative impact of fake news on the internet and investigated strategies for detecting this type of information. They claim that accurate false news identification is difficult owing to the dynamic nature of social media as well as the complexity and diversity of online communication data, and that the scarcity of high-quality training data is a major problem when it comes to training supervised learning models. After investigating news including the content, format, emotion, attitudes and opinion, they believe sentiment analysis is a good tool for illustrating the emotions, attitudes, and ideas expressed on online social media, and that sentiment-related elements are crucial qualities for identifying suspect accounts. Lastly, Sharma et al.(2019) also revealed the importance of sentiment analysis for the detection of fake news. They addressed false news detection and mitigation approaches that rely on computational methods, produced a list of accessible data sets for fake news identification, and offered a list of obstacles and unresolved issues. They discovered that sentiment analysis was a good signal for detecting fake news, as positive sentiment terms in favorable false reviews tended to be exaggerated relative to their actual counterparts, whereas responses to fake news on social media tended to be negative. Furthermore, Perdana & Pinandito (2018) found that non-textual characteristics, namely count of likes and count of retweets, and textual characteristics were both statistically significant to sentiment analysis.

2.5 Research questions

Today, there is a myriad of active users on different social networking sites. For instance, in the last quarter, Twitter reported an average of 217 million daily active users (Statista, 2021). In view of the popularity and the research gap, two research questions are established in the following.

1: What are the most common topics and types of words for identifying fake news about COVID-19 on Twitter?

2: What is the major sentiment in the real and fake news about COVID-19 on Twitter?

3. Methods

3.1 Data preprocessing

Before fitting into machine learning algorithms, the data needs to be preprocessed.

3.1.1 Data source and cleansing

This research would apply the dataset from the paper "Comprehensive Fake News Diffusion Dataset during COVID-19 Period" which collected data to solve challenges in Fake News detection during the COVID-19 period (Kim et al.,2021) (link in Appendix). All the data were labeled as follows : 0 as COVID True claims and 1 as COVID Fake claims. The news claims were collected from two fact-checking sites Politifact and Snopes, from January 2020 to December 2020. After that, claim-related tweets and retweets were extracted from Twitter. During data cleansing, we omitted the missing values, stemmed the words, removed the stopwords, converted them to lowercase, and removed all digits and punctuations. We created two new variables, first called ‘nchar’ to count the number of characters in the clean tweets, second called ‘sentiment’ to record the sentiment of tweets predicted by deep learning.

3.1.2 Sampling

The clean dataset has 157,882 news claims, including 26,831 true and 131,051 false claims. The dataset is highly imbalanced and such an utterly uneven distribution will deteriorate the prediction performance of the Naive Bayes classifier. In light of this, we need to extract the same number of both claims to let the machine learning model learn the characteristics of both types. We extracted 5000 true and 5000 fake news claims randomly from the clean dataset (hereinafter Sample 1). Moreover, for investigating the major sentiment of real and fake news about COVID-19, we extracted 30000 random samples from the clean dataset (hereinafter Sample 2).

3.1.2 Variables of Interest

We are interested in the following variables in the sample.

Table 3.1.2.1 List of variables of interest

	Name of variables	Explanation
Dependent variable	Group	The label of news claim, either 0 or 1 0 : True claim 1: Fake claim
Independent variables	Like_count	The number of likes of a tweet
	Retweet_count	The number of retweets of a tweet
	nchar	The count of characters of a tweet
	post_text	The text of a tweet

3.1.3 TF-IDF

Besides, a method of Tf-idf vectorizer would also be used. TF-IDF stands for "Term Frequency, Inverse Document Frequency." It's a way to score the importance of words (or "terms") in a document based on how frequently they appear across multiple documents. It combines with two concepts: Term Frequency (TF) and Document Frequency(DF) (Abdeen et al. ,2021)

In Term Frequency (TF), this measures how frequently a word occurs in a document. This highly depends on the length of the document and the generality of a word, so to normalize the value, we divide the frequency by the total number of words in the document. The final value of the normalized TF value will be in the range of [0 to 1], while 0 means that the term doesn't exist in the dataset and 1 means all the words in the document are the same. Term frequency is calculated as:

tf(t,d) = frequency that term t appears in document d

tf(t,d)=log(1+raw counts that term t appears in document d)

In Document Frequency (DF), this is similar to TF in that it gauges the relevance of a document in the context of the entire corpus. The only difference is that TF is the frequency counter for a term t in document d, whereas DF is the count of occurrences of term t in the document set D. We count a term as one occurrence if it appears in the document at least once; we don't need to know how many times it appears.

In Inverse Document Frequency(IDF), IDF is the inverse of document frequency, which indicates how informative the term t is. When we compute IDF, the most often occurring words, such as stop words, will have a very low value. This provides us with what we're looking for: relative weighting. There are a few other issues with the IDF; for example, if the corpus is large enough, say 10,000, the IDF value explodes. To counteract the effect, we use IDF logs. In the worst-case scenario, there may be no documents with zero occurrences, and we will be unable to divide by 0. As a result, we usually add 1 to the denominator to smooth out the effect(Abdeen et al.,2021) Finally, by taking a multiplicative value of TF and IDF, we get the TF-IDF score.

3.1.4 ANOVA Feature selection

ANOVA (Analysis of Variance) is a statistical test that is used to examine the differences between the means of many groups. When you have data on one categorical independent variable and one quantitative dependent variable, use a one-way ANOVA. At least three levels should be present in the independent variable. ANOVA informs you if the dependent variable changes when the independent variable changes. ANOVA's null hypothesis (H0) states that no differences in group mean exist. The alternative hypothesis (Ha) states that at least one group differs significantly from the dependent variable's overall mean.

By determining whether the means of the treatment levels differ from the overall mean of the dependent variable, ANOVA establishes if the groups formed by the levels of the independent variable are statistically different. The null hypothesis is rejected if any of the group means deviate considerably from the overall mean.

The F-test is used as an ANOVA to determine statistical significance. Because the error is calculated for the entire set of comparisons rather than for each two-way comparison, this enables simultaneous comparison of multiple means. The F-test compares the variation in each group's mean to the variance in the entire group. The F-test will reveal a higher F-value if the variance within groups is smaller than the variance between groups, indicating that the difference seen is real and not due to chance.

The ANOVA test is based on the same general assumptions as any other parametric test:

Observation independence: data were acquired using statistically acceptable methods, and there are no hidden correlations between observations. Use an ANOVA with blocking variables if your data do not match this assumption because you have a confounding variable that you need to statistically adjust for.

Response variable with a normal distribution: The values of the dependent variable follow a normal distribution. Homogeneity of variance refers to how much variation there is within each group being compared. If the variances change between groups, ANOVA is probably not the best fit for the data.

3.2 Analytical procedure

3.2.1 Classification techniques

A total of 2 machine learning algorithms have been used to identify the real and fake news from the datasets. TF-IDF vectorizer is used to convert data into vectors. After feature selection, it will pass into the Multinomial Naive Bayes model to evaluate the feature importance and apply the random forest as a benchmark of accuracy to support the evaluation. With these techniques, the important textual characteristics of identifying real fake news can be analyzed.

3.2.2.1 Splitting training and testing dataset

It requires two sets of data to run in machine learning models. The data is then separated into two sections for training and testing purposes. The first 80% of the data is utilized for training the models to optimize the parameters, while the remaining 20% is used to predict the labels and test their accuracy. Therefore, the performance of models can be evaluated.

3.2.2.2 Naive Bayes

Naive Bayes methods are a set of supervised learning algorithms. The basis of these methods is Bayes' Theorem, the probability of an event based on past knowledge of factors that may be associated with the event (Puga et al., 2015). A prior for the probability of each class by counting the relative frequency of class labels in the dataset. This research adopted one of the Naive Bayes methods which are the Multinomial Naive Bayes. It is a multinomial distributed data implementation of the naive Bayes algorithm. It is commonly used in text classification, where the data is typically represented as word vector counts and tf-idf vectors. The distribution is parametrized by vectors $\theta_y = (\theta_{y1}, \cdots, \theta_{yn})$ for each class y , where n is the number of features (in text classification, the size of the vocabulary) and θ_{yi} and is the probability $P(x_i|y)$ of feature i appearing in a sample belonging to class y.

A smoothed variant of maximum likelihood, i.e. relative frequency counting, is used to estimate the parameters θ_y :

$$\widehat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n}$$

where N_{yi} is the number of times feature i appears in a sample of class y in the training set , and N_y is the total count of all features for class . Smoothing priors α accommodate for features that aren't present in the learning samples and prevent zero probabilities in subsequent calculations.

The log probability of features can be utilized to evaluate the informative features, which is the feature importance.

3.2.2.3 Random Forest

Our data is in the context of high-dimensional and thus the random forest model can serve as a benchmark and a standard model for classification(Couronné et al.,2018). Firstly, for the model fitting part, Random Forest would first do a resampling, the method is called bootstrapping (Hastie et al, n.d.). It refers to the process of taking a random sample of the training data but the sample size is the same as that of the training set but allows duplication. For the number of trees, the Random Forest will have more than one decision tree. The number of trees is defined by users. When we consider each split, we select the square root of the total number of features after bootstrapping. For finding the best split first, calculate the Gina impurity scores of all of the variables. If the node itself has the lowest score it becomes a leaf node. If separating the data results is an improvement, pick the separation with the lowest impurity value.

For the prediction, the observation will follow the split till reaching the terminal node to know which label it belongs to. Random Forest method allows the observation to pass through each tree and get a series of labels. In the series, which label is the majority will be the label of that observation.

3.2.2 Sentiment

3.2.2.1 Sentiment analysis

Sentiment Analysis (SA) is a branch of Natural Language Processing (NLP) that is responsible for the development and implementation of models, methods, and techniques for determining whether a text contains objective or subjective information, and, in the latter case, whether that information is expressed in a positive, neutral, or negative manner, as well as whether it is expressed in a strong or weak manner(Iwendi et al., 2022)

Deep learning is about learning the knowledge chunk in a form of multiple levels of representations and abstraction to make up higher-level information from lower-level information, for example, sound and image (Donghyuk Shin et al.,2020). The variable is generated by the Transformers package which employs a deep learning approach to predict the sentiment of a text (Vaswani, 2017). The sentiment variable is generated by the above process.

3.2.3 Expected outcomes

In this part, we will have several expected outcomes from the analytical procedure. First, Naive Bayes's accuracy should be similar to a random forest. Second, we expect the precision score will be about 80%. Thirdly, the Naive Bayes score will be 80%. Lastly, the false news claims are mainly negative in sentiment while the positive news claims are mainly positive.

3.2.4 Evaluation Criteria

The performance of machine learning models will be evaluated using the following criteria.

3.2.4.1 Classification

Datasets are originally classified into groups. Machine learning algorithms would learn the parameter of features to predict the group. In the prediction, the four classification results of true positive, true negative, false positive, and false negative. The equation is used to compute the precision measure.

Precision = TruePositive/ (TruePositives + FalsePositives)

The precision score will be computed on the prediction result. The result is a value between 0.0 for no precision and 1.0 for perfect precision.

3.2.4.2 Sentiment

Despite the rigorous approach of deep learning, the sentiment of tweets is just a prediction and thus the performance requires to be evaluated. According to the aforementioned literature, like_count and retweet_count are statistically significant for fake news classification. Therefore, we will use the p-value and logistic regression to prove the significance. If non-textual characteristics are statistically significant to analyze sentiments, the sentiment should be accurate.

For logistic regression, Inputs are $X \in R^{N \times D}$ with N observations and D covariates(Stoltzfuz,2011). Targets are $y \in \{0, 1\}^{N}$. The regression parameters are $\beta \in R^{D}$ and the link function between the linear model $X\beta$ and the target is the logistic function $\sigma(X\beta) = \frac{1}{1+exp\{-X\beta\}}$. Assume that the observations are independent and identically distributed that follows a Bernoulli likelihood. In logistic regression, the likelihood is maximizing the likelihood.

For p-value, it refers to the probability of a null hypothesis in which two variables are not statistically significant(Vickers, 2010). If the p-value is smaller than 0.5, it rejects the null hypothesis. It indicates the two variables are statistically significant to each other. On the other hand, if the p-value is over 0.5, it fails to reject the null hypothesis, indicating that the two variables are statistically insignificant to each other.

4. Results and discussion

4.1 Descriptive Statistics

The descriptive statistics are shown below in the tabular form.

4.1.1 Sample 1

Table 4.1.1.1 Descriptive Statistics for all dependent variables expect post_text in Sample

Variables	n	Minimum	Maximum	Mean	Standard deviation
Like_count	10,000	0	293,731	302.261	5474.752
Retweet_count	10,000	0	54,472	73.99	1226.822
nchar	10,000	5	280	74.459	53.570

4.1.2 Sample 2

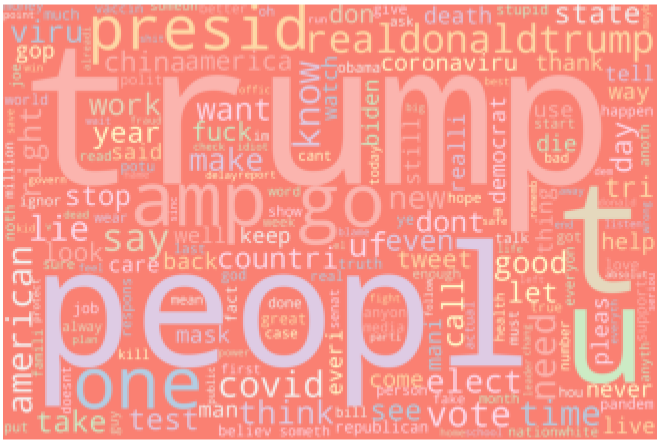
Table 4.1.2 Descriptive Statistics for all dependent variables expect post_text in Sample 2

Variables	n	Minimum	Maximum	Mean	Standard deviation
Like_count	30,000	0	993,167	412.730	9168.278
Retweet_count	30,000	0	234,387	101.735	2202.435

4.2 Common topic and words of fake news

The following figure is a word cloud as a visual representation of the prominence of words, the greater prominence of words, the greater their size is shown in the word cloud. We extracted the fake news from our sample (see Fig 4.1.1).

Fig 4.1.1 Word cloud of fake news text after cleansing



The precision score of the Naive Bayes classifier is 76.905% (correct to 3 decimal places). It is higher than that of random forest, the standard classification model, with 72.152 %. It indicates that the trained parameters of the Naive Bayes classifier are convincing to discuss the feature importance. Likewise, Agarwal et al. (2019) conducted a study on the accuracy of machine learning classifiers in detecting fake news, it is found that the precision score of the Naive Bayes classifier and random forest classifier was approximately 64% and 60% respectively. Nevertheless, a more recent study found a much higher precision score of approximately 87% with regard to the Naive Bayes classifier in fake news detection(Pandey, 2022). Therefore, a significant difference in regard to the precision score can be observed between the existent literature and our research. One possible explanation is that the length of tweets is likely to have a negative correlation with the accuracy of fake news detection. This is consistent with the findings of a study on detecting COVID-19 fake news that when the length of tweets was over 70, the accuracy would be significantly reduced from approximately 91.43% to 57.14% (Samuel et al., 2020). Similarly, the average length of tweets in our sample is 74.459, indicating our dataset contains relatively longer tweets (See table 4.1.1). As a consequence, the discount of the accuracy of the Naive Bayes classifier on COVID-19 tweets is probably reasonable and necessary. Therefore, we can apply the trained parameters of the Naive Bayes classifier to evaluate the feature importance to discuss the textual characteristics of identifying fake news.

As mentioned in the Methods section, the log probability can show the features' importance. We observed that words with disapproving tone are informative in identifying fake news such as "imposter" and "hypocrisies". The log probabilities of these two words are at the top among other features. It indicates that the words with disapproving tone are likely to be the common type of words in fake news. One possible explanation is that the authors of fake news hope to arouse people's awareness with their tweets. Our findings resemble studies about the textual characteristics of fake news, in which fake news mainly contains negative valence in order to attract more reply and attention (Brummette et al.,2018, Tandoc et a1., 2018). It implies that the fake news probably spread the negative sentiment on social media amid the COVID-19 pandemic.

From the Naive Bayes classifier, we observe words like " Trump", " President", " donald trump", "COVID" and "virus" are often presented in the headlines or content of the fake news. One possible explanation of the above result is that people tend to believe the news that comes from representative figures like presidents Donald Trump as his words contain authority. Democratic governments usually gain high confidence as the president is representing the whole government authority, most people would not fact-check the news content but believe and spread the news. This is consistent with a study on finding the reason why people may believe the news that is published by the government. It states that citizens can be persuaded by the authorities labeling a piece as real news and increase their belief in the news(Wang and Huang, 2021). Also, the work of Muramaya et al. (2021), states that some influencers on social media (i.e. politicians, government officials) in turn, inspire others to use the term "fake news" to question the opposition and support thoughts and viewpoints that are similar to their own ideology. Moreover, citizens may decrease their belief in the government once they found the news is fake, it also decreases their belief in a similar government news claim in the future. As a result, people's overall contentment with the government in the relevant subject area will be badly affected by such an encounter with the government's lack of legitimacy. In other words, The public's awareness of the government's lack of credibility not only will have an immediate effect on the general public and continue to impact people's attitudes toward the government in the future (Wang and Huang, 2021).

Besides, the result from the Naive Bayes classifier also predicts that the fake news is shared and spread quickly on popular Twitter accounts like the former U.S. President Donald Trump with some arousing topics, for example, topics about lies, death figures, and Americans, which induce an intense discussion, likes, and retweets. As a result, the tweets from Donald Trump about the news of COVID-19 has spread through the whole Twitter and people easily believe in fake news. This is also consistent with a study on the fake news on Twitter by Brummette et al., (2018). They stated that fake news discussions take place in big clusters (i.e., online communities) dominated by members of the general public (as opposed to the media, nongovernmental organizations [NGOs], or politicians). Indeed, when you join a community on Twitter, you can tweet directly to the community rather than to all of your followers. People love to join different big communities to view and retweet posts they like and believe. As a result, people would believe the fake news that is retweeted largely from online communities.

4.3 Major sentiment in the real and fake news

From logistic regression, we observe the p-values of like_count (4.698292e-07) and retweet_count (1.023639e-07) smaller than 0.05. Therefore, it rejected the null hypothesis. In view of this, the count of likes and the count of retweets are statistically significant to the sentiment. It implies that the sentiment predicted by the deep learning model is likely to resemble the analysis done by humans. Therefore, it should be largely accurate, sample 2 is the a a random sample of the clean dataset and thus the major news is also fake. One possible explanation is that negative sentiment is more likely to draw attention and increase the number of counts and retweets. Our findings are similar to a study on predicting sentiment by the number of counts and retweets and textual characteristics, concluding that non-textual characteristics should occupy a significant portion in predicting sentiment (Perdana & Pinandito, 2018).

From the result, the sentiment score of both real and fake news is negative. One of the possible explanations is that the negative atmosphere is still arousing from the start of COVID-19. Because of the rising seriousness of the pandemic, it is normal to observe that both real and fake news reveal the negative sentiment. The claim can be supported by the literature by Verity et al.,(2020), which stated that the COVID-19 was a worldwide pandemic and that the confirmed cases and death toll are a rising trend, and predicted the trend will continue in the next three years. This has shown the seriousness of the pandemic, which leads to a generally negative attitude in both real and fake news.

Besides, the ratio of negative sentiment in fake news is slightly higher than that of real news while the ratio of positive sentiment in real news is slightly higher than that of fake news. One of the possible explanations is that fake news sustains more negative and emotional words that exaggerate the seriousness of the news, and aims to attract more people to discuss and share false information on big social media platforms i.e. Twitter. The above result can be explained by Ding et al.(2020) study on the sentiment analysis of real and fake news. The analysis revealed that negative sentiment is higher in fake news than that in real news. The authors concluded the reason for the finding was that fake news tweets were expected to include more emotive content, that to attract the reader's attention to read through the whole fake article i.e. more negative content. In contrast to fake news, the real news was mostly reporting the facts and actual situations about the pandemic, in which the use of words and topics will be slightly milder than that in fake news.

5. Conclusion

Today, we typically spend a great of time on social networking sites and we rely on them to receive information. Therefore, a post can be very influential and crucial to affecting our decision-making. COVID-19 is a public health issue, misinformation ought to be effectively solved and people should be aware of its characteristics of them. From the above, we analyzed that negative valence, some controversial figures probably the common topic, and words of fake news. Furthermore, negative sentiment is prominent in both true and fake news and they should be aware of it. The public should be more careful when they observe the above characteristics on social networking sites and do fact-checking. As a consequence, they can decide with accurate information to eventually combat the COV1D-19 pandemic.

There are two possible limitations in our research. Firstly, the precision score is relatively low when compared to other existing literature. To improve the precision score, further research can combine textual and non-textual features into the training dataset. Secondly, sentiment analysis may contain inaccurate results with the use of the machine learning methods which may contain misclassification of the sentiments compared to the analysis done by humans. The label is generated by artificial intelligence. In this research, only two features and one machine learning algorithm is applied. Therefore, further research can be done on the use of predicted sentiment in other machine learning algorithms.

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7. Appendix

The dataset is available on Github https://github.com/merry555/FibVID . The link of the dataset is https://raw.githubusercontent.com/merry555/FibVID/main/claim_propagation/claim_propagation.csv.