Spread Mechanism and Influence Measurement of Online Rumors during COVID-19 Epidemic in China

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ABSTRACT In early 2020, the Corona Virus Disease 2019 (COVID-19) epidemic swept the world. In China, COVID-19 has caused severe consequences. Moreover, online rumors during COVID-19 epidemic increased people’s panic about public health and social stability. Understanding and curbing the spread of online rumor is an urgent task at present. Therefore, we analyzed the rumor spread mechanism and proposed a method to quantify the rumor influence by the speed of new insiders. We use the search frequency of rumor as an observation variable of new insiders. We calculated the peak coefficient and attenuation coefficient for the search frequency, which conform to the exponential distribution. Then we designed several rumor features and used the above two coefficients as predictable labels. The 5-fold cross-validation experiment using MSE as the loss function shows that the decision tree is suitable for predicting the peak coefficient, and the linear regression model is ideal for predicting the attenuation coefficient. Our feature analysis shows that precursor features are the most important for the outbreak coefficient, while location information and rumor entity information are the most important for the attenuation coefficient. Meanwhile, features which are conducive to the outbreak are usually harmful to the continued spread of rumors. At the same time, anxiety is a crucial rumor-causing factor. Finally, we discussed how to use deep learning technology to reduce forecast loss by use BERT model.

INDEX TERMS COVID-19, rumor spread mechanism, new media, peak coefficient, attenuation coefficient, machine learning.

I. INTRODUCTION
Since December 2019, some hospitals in Wuhan City, China have discovered multiple cases of unexplained pneumonia with a history of exposure to the South China Seafood Market[1]. The cases have now been confirmed as acute respiratory infectious diseases named COVID-19. At the time of writing (December 3, 2020), the global number of COVID-19 infections exceeded 64.7 million, and the deaths exceeded 1.49 million. The COVID-19 crisis has caused economic, social, and mental crises in a brief period and spread internationally and affected all aspects of human life[2]. When Lockdown and social distancing measures to prevent the spread of COVID-19 started, Wei et al. pointed out that the prevalence of mental and psychological problems was as follows: sleep problems was 49.8%, anxiety symptoms was 44.5%. Among them, stress-induced excitatory symptoms accounted for 21.6%, and depression symptoms was 18. 9% [3]. Meanwhile, the present COVID-19 pandemic appears to be leading to higher suicidality. Griffiths et al. presented six cases in chronological order of couple suicides and attempted suicides relating to COVID-19[4]. Research on rumors has a long tradition; for decades, one of the most popular ideas in rumor research is the idea that rumors are always accompanied by crises[5]. According to a cross-sectional survey, for all the respondents, 30.9% reported believing in some unverified COVID-19 crisis related-rumors from internet media[6]. Now we are in an Internet era of information explosion. Recent theoretical developments have revealed that the role of the Internet and the media during the present epidemic crisis should not be underestimated [7]. Due to the lack of moderation and guarantee, as a platform for freedom of speech, online social media and networks are highly susceptible to the spread of rumors [8]. For example, after the Fukushima Nuclear Disaster in 2011, there was a rumor that the nuclear leak would cause salt being in short supply. This rumor led to panic buying and hoarding salt. Similarly, misinformation about COVID-19 medication regimen or unreliable protection measures...
has a severe impact on public health even affected social stability[9]. For example, on January 31, it was reported that the “Shuanghuanglian” Oral Liquid (a Chinese patent medicine) had an inhibitory effect on the COVID-19. After the news was released, “Shuanghuanglian” products were snapped up and stocked, causing market chaos. Thus it has theoretical significance to quantitatively describe the rumor spread and measure the influence of rumors during COVID-19 epidemic. In the past several decades, common strategies used to study rumor mechanism are simulation experiments and statistical learning. With the rise of deep learning, natural language processing (NLP) has been widely used in interdisciplinary fields[10]. This research of rumor mechanism constitutes a relatively new area which has emerged from NLP and deep learning technology.

This study is based on a quantitative analysis of data extracted from Sogou (China’s second-largest search engine company) search index. We believed that Internet surveillance is a convenient and cost-effective way to assess public responses, and can provide evidence for government decision-making. The main contributions of this paper are summarized as follows:

1. We propose an epidemic-like model to quantitatively describe the law of rumors spreading during the COVID epidemic. The model includes four-node states: susceptible state, infected state, refuted state, and removal state. Calculation by simulation, ideally, we found that the density of infected state conforms to a power-law distribution.

2. We collected a COVID-19 related rumor data crawled from search engine results, based on which we propose a method to determine the peak coefficient and attenuation coefficient of rumor outbreak. As far as we know, no previous research has investigated.

3. Using NLP technique and machine learning methods, we analyze the relationship between rumor features and rumor indexes, including peak coefficient and attenuation coefficient. Analyzing the experimental results, we reveal several exciting conclusions. We also run deep learning techniques and show how semantic features help improve peak coefficient prediction.

The remainder of this paper is organized as follows. In the next section, we firstly introduce the literature on rumor propagation and NLP techniques used in this article. In the third section, we build the epidemic-like rumor model and conducted simulation experiments. Then we develop our hypotheses and the ideas for verification these hypotheses, and calculate the peak coefficient and attenuation coefficient in the fourth section. After that, we perform three models to predicate these two coefficients, discuss results and analysis features. In closing, our conclusions and future research possibilities are suggested.

II. RELATED WORKS
We reviewed several research papers and mentioned a few indicative works about rumor theory and propagation. Rumor refers to a cooperative transaction in which community members offer, evaluate, and interpret information to reach a common understanding of uncertain situations, alleviate social tension, and solve collective crisis problems[11–13]. From its birth, as rumor involves communication dynamics surrounding shared issues in a community, the generation and transmission are inseparable in practice[8]. Rumor propagation is often modeled as a process of social contagion[14]. Therefore, epidemiological models are highly relevant to the literature on rumor propagation[15]. Kermack and McKendrick studied the mathematical theory of epidemics and proposed the Susceptible-Infected-Removed (SIR) model, which is the most widely used model in the research of rumor spreading[16]. Currently, many studies have proposed more rumor spreading models through the addition and modification of node state types and state transformation mechanisms[17–18]. Motivated by the above work, we proposed a rumor spread mechanism. In addition to the above simulation research, the empirical research of rumors has attracted people’s attention. The spread of rumors on social networks (such as Twitter and Weibo) is especially valued[5–19]. However, rumor forwarding in social networks as the rumor spread metric has two main disadvantages: 1. The users of social networks are limited, mainly young people. 2. The dissemination data will become unreliable when rumor information is gradually deleted. In response to this situation, the search index of web search engines have become a common choice. The search index data has been applied to many aspects, such as forecasting tourist arrivals[20–21], hotel registrations[22], economic indicators[23] and monitoring influenza epidemics[24]. Search index is also helpful for epidemic prevention and control. An extensive search trends-based analysis of public attention proved that Internet monitoring could be particularly incredibly and economical in the prevention and control of epidemic and rumors[25]. Meanwhile, social media is also helping in predicting the number of COVID-2019 cases[26], mapping of health literacy and social panic[27], and predicting the peak of the COVID-19 pandemic with Internet search[28]. Although the search index has been widely used, the application combined with the field of rumor analysis has not yet been proposed. Therefore, this article attempts to unearth the inner connection between user searches and online rumors.

From a modeling perspective, we need to quantify user searches and online rumors separately. The user’s search behavior will leave a search record and form a search index. So the real difficulty lies in how to express online rumors. Online rumors can be regarded as a kind of short text, and the short text representation method is very mature[29–30]. We employed content-based features as well as semantic features. The technologies we used in this article include part of speech (POS)[31], named entity recognition (NER)[32] and Bidirectional Encoder Representations from Transformers (BERT)[33].

The internal connection between two variables is a mathematical mapping relationship, which can be described by a machine learning model. Combining machine learning and
the representation of rumors, Raveena et al. investigated in retrospect a dataset on which tweets spreading rumor detection was done by performing machine learning algorithms including the k-nearest neighbor and Naive Bayes classifier [8]. Onook Oh et al. studied citizen-driven information processing and first proposed the application of rumor theory to social media and community intelligence [8]. The work of Li et al. analyzed the association between user features and rumor forwarding behavior in five main rumor categories: economics, society, disaster, politics, and military [19]. The work of Li et al. failed to take into account the influence of rumor features on forwarding behavior. Therefore, because of the shortcomings of the above work, we proposed our method to quantify the rumor spread influence based on the search frequency and rumor representation.

III. SPREAD MECHANISM

After rumors appear in real social networks, the government or relevant authoritative organizations dispel the rumors through mainstream media or the Internet. However, existing researches on rumor dissemination mostly involve the modeling of single rumor without refuting information [45, 50], or only analyzed the key factors affecting mass communication behavior from the information dissemination level [37]. In order to more reasonably describe the interactive propagation process and to understand the interactive propagation mechanism of different rumors, this paper uses the mean-field theory commonly used in complex network propagation dynamics to establish equations to characterize dynamics propagation model of the interactive process. We discussed the impact of rumor rejection nodes and analyze the key factors affecting the spread of rumors based on the simulation results.

Drawing lessons from the spreading characteristics of viruses in the network, this article combines the attitudes of users on rumors and other information in social networks to classify the status of users in the network.

In the process of rumor spreading, there are four node states: susceptible state, infected state, refuted state, and removal state. Users who are infected by refuted node are the disseminators of positive information, including those who publish positive information and users who believe in authoritative information and disseminate. Removal nodes say that such users will neither be infected by rumors nor by positive information. All users in the network are regarded as nodes, and the relationship between friends is regarded as edges. There is the following transition relationship between node states as shown in Fig. 1.

In Fig. 1, Susceptible means ignorant, Infected means disseminator, Removed means who lost interest in the rumor, and Refuted means who sees through the rumor and disseminate positive information. The status change is based on the following four rules.

1) If a susceptible node contacts a rumor-infected node, it will change to rumor-infected state with a probability of $\beta$, change to removed state with a probability of $\alpha$, change to a refuted node with a probability of $1 - \beta - \alpha$ respectively.

2) If a susceptible node contacts a refuted node, it will change to removed state with a probability of $\sigma$ or change to another refuted node with a probability of $1 - \sigma$.

3) If an infected node contacts a refuted node, it will change to removed state with a probability of $\theta$ or remain unchanged.

4) In each iteration, an infected node or a refuted node has a probability of $\epsilon$ of being forgotten, and changes to be a removed node.

In a homogeneous network, $S(t)$, $I(t)$, $R_1(t)$ and $R_2(t)$ denote the density of susceptible node, infected node, removed node (who know about the rumor but do not care about it), and refuted node (who do not accept the rumor and try to stop it) through the rumors at time t, respectively. They reach the normalization condition: $S(t) + I(t) + R_1(t) + R_2(t) = 1$. And combine the above dissemination rules to establish the average spread of rumors, the mean-field equations can be described as follows

\[
\frac{dS(t)}{dt} = -\alpha\langle k \rangle(I(t) + R_2(t))S(t) - \beta\langle k \rangle I(t)S(t) - \langle k \rangle S(t)((1 - \alpha - \beta)I(t) + (1 - \alpha)R_2(t))
\]

\[
\frac{dI(t)}{dt} = \beta\langle k \rangle S(t) - (\delta + \theta)(k)R_2(t) - \epsilon I(t)
\]

\[
\frac{dR_1(t)}{dt} = \alpha\langle k \rangle(I(t) + R_2(t))S(t) + \delta\langle k \rangle I(t)R_2(t)
\]

\[
\frac{dR_2(t)}{dt} = \langle k \rangle S(t)((1 - \alpha - \beta)I(t) + (1 - \alpha)R_2(t)) + \theta\langle k \rangle I(t)R_2(t) - \epsilon R_2(t)
\]

Where $\langle k \rangle$ is the average degree of the network, which is usually set to 1 in the simulation experiment. At the beginning of the rumor spreading, there are few spreaders, so it is usually assumed that there is only a very small number of infected nodes in the initial state network, and the rest are marked as susceptible nodes. Afterwards, the number of the
infected nodes firstly increases to the peak, then decreases until it goes down to zero, at which point the rumor dies out, and the system reaches a stable state. The various node densities $S(t), I(t), R_1(t)$ and $R_2(t)$ under these four states evolve with time $t$ (see Fig.2). The parameters used in the numerical simulation are $N = 10000, \alpha = 0.6, \beta = 0.3, \delta = 0.1, \epsilon = 0.2, \theta = 0.3, I(0) = 0.01$.

From Fig.2 the spread of rumors caused about 80% of the population to be infected by rumors finally. Because of the forgetting rate $\epsilon$, people lose interest in rumors or their factors cease to spread and eventually become removed. At this time, record the density of new insiders who knew but did not spread the rumors at the end as $R$, then we know that $R = \text{final} \{R(t)\} = \lim_{t \to +\infty} R(t) = R(\infty) = R_2(\infty) = 1 - S(\infty) \approx -\int_0^{+\infty} S'(t)dt$.

We use the search frequency of rumor as an observation variable of new insiders. Search frequency was first used to track the public event such as influenza-like illness by Google in 2009[38]. The experiments have proved that the frequency of specific queries was positively correlated with relative events. The size of $S'(t)$ represents the rate of increase of people who are new to the rumor, and those who are new to the rumors will use the Internet to query the rumors with a fixed probability and leave a query record. It can be found that $S'(t)$ conforms to the power-law distribution as shown in Fig.3. The same conclusion and case studies can be found in rumor spreading among micro-blog followers based on user browsing behavior[39]. Ideally, assuming that susceptible persons will query the rumors with the same probability after being exposed to it, then the query index of the rumors should have a similar distribution. Like a roller coaster track, the rate of spread of rumors will first accelerate and increase, then decelerate and decrease. The rate of new contacts of rumors rises to the apex first, then falls, and the rate of decline gradually slows down. Furthermore, the rate has an apparent long-tail distribution.

IV. RUMOUR MODELING

A. MODEL SIMULATION

Compared with the rate of spread of rumors based on the spread mechanism, we found that the actual result is slightly different. As an example, the search index of the rumor, "Louis Koo donated 10 million yuan to Wuhan", is shown in Fig.4 provided by Sogou indicates. We can see that Louis Koo received unusual attention when rumor occurred (January 26, 2020), and reached the highest heat within 24 hours. Compared with Fig.3 We guess the reasons for the above phenomenon are as follows: In an era when traffic is king, in order to attract attention, news media and self-media always forward rumors as soon as possible. The right to speak in public opinion is in the hands of news media and self-media. Use push technology and hot searches, they push rumors directly to interested users. We can also find that the rumor has caused Louis Koo’s related searches to increase. After nearly two months, the search value of Louis Koo’s search index returned to the historical average. Since rumors usually peak on the first day, they fit the exponential decline distribution more than the power-law distribution.

$$y_t = e^{at+b} + c$$ (5)

Mark the search frequency motivated by rumor as $\tilde{y}_t = y_t - c$ and $Y = [\ln(y_0 - c), \ln(y_1 - c), \ldots, \ln(y_n - c)]^T$ where $t$ is the time, $n$ represents the total number of days $a$ and $b$ are rumor-related variables, $c$ is the bias which is unrelated to rumor (initialized with the minimum search frequency multiply by 0.9 in seven days) and $y$ is the search frequency.

$$J_{LS}(\theta) = \frac{1}{2}||X\theta - Y||^2.$$ \hspace{1cm} (6) s.t. $X = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 0 & 1 & \cdots & n \end{pmatrix}$ and $\theta = (a, b)$, thus let the gradient of $J_{LS}(\theta)$ be $0$, we can get

$$\nabla_\theta J_{LS} = \begin{pmatrix} \frac{\partial J_{LS}}{\partial \theta_1} \\ \frac{\partial J_{LS}}{\partial \theta_2} \end{pmatrix} = X^T\theta - X^TY = 0$$ \hspace{1cm} (7)

$$\theta = (a, b) = (X^TX)^{-1}X^TY$$ \hspace{1cm} (8)
Iterative calculation equations (6)-(9) several times until parameter $c$ convergence. Use the least square method, Fig. 5 shows the variation of parameter $c$ with the number of iterations under different initial conditions. From what we observed, usually, the intensity of rumor will not exceed seven days and can be calculated by rumor-related variables $a$ and $b$. For each rumor, parameter $a$ is the attenuation coefficient and, $b$ is the peak coefficient of each rumor. Since $\tilde{y}_t$ is a geometric series, the sum of $\tilde{y}_t$ could be calculated as follows

$$\sum_0^n \tilde{y}_t = \tilde{y}_0 \cdot \left(1 - e^{a(n+1)}\right) / (1 - e^a) \quad (10)$$

For the rumor, "Louis Koo donated 10 million yuan to Wuhan", the solution $a$, $b$ and $c$ finally equal to -0.605, 10.69 and 22653 respectively. After experiments, the range of $a$ is determined at [-0.26, -1.45], then we can get inequation as follows

$$1.31\tilde{y}_0 \leq \sum_0^\infty \tilde{y}_t = \tilde{y}_0 / (1 - e^a) \leq 4.37\tilde{y}_0 \quad (11)$$

From what has been discussed above, usually, the intensity of rumor will not exceed five times the search frequency of the first outbreak day and can be expressed by the sum of the search frequency.

B. MODEL HYPOTHESES

In the following chapters, our goal is to study the elements which can be used to estimate rumor-related variables $a$ and $b$. For this goal, we introduce empirically testable hypotheses:

1. The fundamental entity which owns the least search frequency can represent the rumor search index.
2. Public anxiety helped spread the rumor.
3. The outbreak intensity is associated with historical awareness on named entities of each rumor.
4. The daily search frequency sequence before rumor can be used to predict the burst strength of rumor.
5. Under the background of the epidemic, the feedback of network media is associated with the rumor spread.

In this work, the first hypothesis is the premise of our research. As shown in Fig. 6, other common entities usually have far more searches than the fundamental entity, which means they are not representative. Public sentiment is calculated by daily average sentiment of Weibo text, as shown in Fig. 8. The historical awareness of named entities is measured by natural logarithms of average daily search frequency in the last two months in 2019. The feedback of the network media is presented by the results returned by the search engine, as shown in Fig. 9.

V. EXPERIMENT AND RESULT ANALYSIS

A. DATA SET AND FEATURE EXTRACTION

We use crawler frame selection to collect a public rumor corpus include 1029 rumors from Dingxiangyuan (a medical
knowledge-sharing website) and Tencent (an Internet-based platform company). For each rumor, we extract two keywords and draw the word cloud graph in Fig.7. We can figure out that Rumors abound with some elements such as viruses, drugs, celebrities, protections, locations. Since search frequency of common named entities (such as “Wuhan” and “donate”) are easily influenced by other rumors or facts, but the fundamental entity (“Louis Koo”) which owns the least search frequency has obvious guiding significance as shown in Fig.4 and Fig.6, we empirically accept hypotheses one, and manually filtered 120 rumor based on the hypothesis one, of which variable $a$ and $b$ could be accurately estimated and parameterized. To find the key features that can accurately predict the variable $a$ and $b$ of each type of situational information, we extract the Boolean features of six NER tags. The historical awareness of Top-2 most common named entities and the fundamental entity before the outbreak of the epidemic are selected. Meanwhile, we get a rumor portrait through the search engine. As an example, shown in Fig.9, we offer the search results about the rumor “Louis Koo donated 10 million yuan to Wuhan”. Three elements are deserved to pay attention, including resulting amount (224,000), start date (January 26, 2020) and rumor flag (fake news). The resulting amount is used as statistical feature feedback by network media.

For hypotheses two, Allport and Postman[40] proposed a point that rumor is motivated by intellectual pressure along with the emotional. Also, Anthony[41] introduced anxiety as a proxy variable for rumor-mongering conditions. We use a public COVID-19 related microblog corpus[1] As shown in Fig.8, the index of public sentiment reached its lowest point before Wuhan was closed due to the epidemic, the public sentiment index reached its lowest point. After that, the index rose quickly and fluctuated violently. Using the start data extracted from the search results of rumor, as shown in Fig.8, we can locate current public emotion density value. Meanwhile, to verify hypotheses three, the search frequency sequence of the fundamental named entity in a week before the rumor breakout is extracted.

In summary, a rumor like “Louis Koo donated 10 million yuan to Wuhan”, can be extracted into [(top2: “donated”, ln(800)), (top1: “Wuhan”, ln(2,200,000)), (key: “Louis Koo”, ln(11,000)), (PER, 1), (ORG, 0), (LAC, 1), (NZ, 0), (N,

1https://www.datafountain.cn/competitions/423
FIGURE 9: Results returned by search engines that use rumors as the queries.

0), (V, 1), (“resulting amount”, ln(224,000)), (“public emotion”, 0.0032), (“search frequency sequence before the rumor broke”, (ln(13850), ln(10584), ln(10278), ln(12281), ln(10105), ln(8738), ln(10548))). At last, all features will be transformed into the range [0, 1] using Min-Max Normalization.

B. REGRESSION MODELS

Machine learning methods, such as linear regression model and decision tree model, have been applied in the field of rumor analysis [8, 42]. The linear regression model is the most basic type of statistical techniques and widely used predictive analysis. It shows a relationship between two variables with a linear algorithm and equation. Decision tree model is a decision support tool that uses a tree-like model of decisions and their possible consequences. The main advantage of the decision tree classifier is its ability to using different feature subsets, and the model is readable. After using min-max normalization to covert features into the same scale, a linear regression model can measures the significance of features by weights directly, while tree model can handle with the nonlinear situation. We use the mean-square error (MSE) as a loss function and use formula (6)-(8) to calculate linear weights. The decision tree learning includes three steps: feature selection, decision tree generation and decision tree pruning. In order to build a tree, we use the CART algorithm to train a regression tree. Compared to the linear model using 5-folds cross-validation, experiments show that the decision tree model reduced the MSE of variable $b$ from 3.77 to 1.79, but increase the MSE of variable $a$ from 0.14 to 0.21. We extract the essential features for each model and list them as Table 1.

In the next section, we discuss the different significance in the use of features by regression models including the linear regression model and decision tree model.

C. FEATURE ANALYSIS

Through the experiment, we find that only three kinds of named entities were useful in the prediction of the attenuation coefficient (parameter $a$), including PER, ORG and LOC, but only LOC makes sense for the peak coefficient (parameter $b$). This suggests that rumors involving institutions were more quickly quelled because the authorities will deny it in time while rumors involving specific celebrities and locations are more likely to be believed by people. We can draw two other conclusions. One is that Top-1, SFR-1 and PE are not conducive to the persistence of rumors, while ANE and RA are the opposites. Second, all five of these features are essential to predict parameter $b$ and SFR-1 is the most important.

Since most rumors die down within seven days, one possible inference is that the feature which makes rumors more intense is not conducive to their sustainable renewal. The correlation analysis of features and parameters is shown below using the Pearson correlation coefficient. From Table 2, we can find that this inference is not entirely correct because ANE and RA are positively correlated with all three parameters $a$, $b$, $c$. As for hypotheses two, PE and parameter $a$ are negatively correlated, that is to say, when the public mood is negative, the rumor search frequency drops more slowly, and the rumor is to spread more continuously. At the same time, the outbreak of rumors is also related to PE. In detail, for the tree model, the importance of PE for parameter $b$ is $1.2 \times 10^{-1}$, and the linear correlation of $b$ is only 0.02, indicating that the outbreak degree of rumor and PE is not a simple linear relationship. Hypotheses three is also correct, but only ANE and TOP-1 play a significant role in entity search records. Hypotheses four can be refined as that the outbreak of rumors could be predicted by precursors. The experiments show that only the precursor which happened the day before rumor happens makes sense due to the suddenness of rumor’s explosive eruption. Compared with other features, SFR-1 (the intensity of precursors) has the strongest positive correlation with the intensity of rumor outbreak. In terms of Hypotheses five, we only used RA as the feedback of the search engine in the statistical characteristics, and the results showed that rumors with a more massive RA tend to break out violently and spread for a longer time.

D. D&W MODEL

In the field of natural language processing, BERT has apparent advantages in small sample learning and transfer learning. We used the rumor data and the result text on the first page of the search engine as both the training corpus. We propose a hybrid model that applies the common deep and wide framework of the recommendation system to solve our task. As the Deep part is directly implemented using the
At the same time, it timely authoritative refutation of rumor sources play a perfect role in hindering the spread of a rumor. Thus, the key differentials are the rumor itself, the release time and the publishers. Experiments show that this operation implies that the outbreak of rumor is strong enough to attract the attention of those involved in refuting the rumor. By using D&W model, MSE of parameter $a$ is reduced from 0.14 to 0.10. Meanwhile, the output of the three semantic hidden layer neurons extracted by D&W model was added to the tree model, and the experiment shows that MSE of parameter $b$ increased from 1.79 to 1.83. This means that information on the front page hardly works on predicting outbreak intensity. Through Table 3 we can find that the first two semantic features make sense in promoting the prediction result of parameter $a$. We assume that semantic features don’t work for parameter $b$ because it duplicates the function of RA.

### VI. CONCLUSION AND FUTURE WORK

In this paper, we construct a corpus of rumor in China during the epidemic. We propose a method to determine the peak coefficient and attenuation coefficient of rumor outbreak based on the change of fundamental entity search index. Based on this method, we calculate the corresponding indexes of rumor and analyze the relationship between the characteristics and the indexes. In the future, we will continue to study the differences and connections between rumor and ordinary hot events’ propagation behaviors on the Internet, and study the use of unified models to describe parameters. We will use more data and train a unified model methods to identify the peak coefficient and attenuation coefficient of rumor outbreak. This research still needs filter the training set to manually and is highly dependent on feature engineering. In future, we plan to apply automatic labeling methods and the language model to avoid this limitation.

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