Topic mining and sentiment analysis based on microblog data related to the new crown epidemic

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Abstract

In this paper, we studied the microblogs related to the Xin Guan epidemic posted on Sina Weibo from January 1, 2020 to February 18, 2020. Word frequencies were calculated and word clouds were drawn through jieba word splitting and deactivation. A sentiment classifier was trained based on the topic of the new epidemic using a plain Bayesian approach, and all texts were rated on a 0-1 sentiment scale. Clustering analysis and kernel density estimation were performed on the sentiment tendency data, and the fluctuation of community sentiment over time was investigated. It was found that Internet users reacted promptly and sensitively to the news of the epidemic, while they were widely affected by negative sentiment at the early stage of the epidemic. The sentiment analysis classifier was used to explore the microblog topics and uncovered a strong correlation between topic sentiment polarity and user attention. In addition, the LDA topic generation model was used to identify six potential topics in the microblog content. Using the root words provided in the topics, a domain sentiment dictionary closely related to the Xin Guan epidemic data was developed with the help of Dr. Huanyong Liu's research to support others' research in this domain.

Keywords: topic extraction, sentiment analysis, opinion analysis

I. Background of the study

Before and after the outbreak of pneumonia caused by the novel coronavirus, a large number of texts related to the reality of the outbreak, personal emotions, and knowledge were generated on various social networking platforms. Apart from Sina Weibo's tag (content enclosed in ##), is there a strong thematic connection between the texts? What kind of personal emotions are expressed behind users' text expressions? How did the collective psychology and emotions of the public change over time, as information about the epidemic was released, and as the development of the epidemic changed? How does the polarity of emotions affect the attention of Weibo users? Can a domain-specific sentiment dictionary be generated for Chinese expressions related to the epidemic? This study evaluates these questions with the help of machine learning methods in natural language processing and supports other research in this area.

II. Data pre-processing and descriptive analysis

1. Data source

The data for this question was obtained from the public data provided by https://www.kaggle.com/liangqingyuan/chinese-text-multi- classification, and excerpted from the Technology Warfare Epidemic - Big Data Public Welfare, jointly sponsored by the Beijing Municipal Bureau of Economy and Information Technology and the Big Data Expert Committee of the Chinese Computer Society. Challenge. This question is also the question of the 26th China Conference on Information Retrieval (CCIR 2020) evaluation contest. The data was collected from the period of January 1, 2020 to February 18, 2020 by extracting the text and information of microblogs collected from Weibo through keywords related to the epidemic. The data include Weibo id, Weibo posting time, publisher account, Weibo Chinese content, Weibo picture (address) and Weibo video (address) Among them, 100k pieces of data provide a priori sentiment tags of the Chinese content of Weibo to -1 for negative sentiment, 1 for positive sentiment, and 0 for no significant sentiment are used as training data for supervised learning. Also, 10k data without sentiment labels are provided for model testing.

In addition the dataset provided by www.kaggle.com was used in this question, including the textual content of Weibo hot topics and their views during the epidemic. This study investigates the potential connection between extreme emotions and user attention by analyzing the relationship between the sentiment tendency and the number of views on these topics.

2. Data pre-processing

The .csv file is read in UTF-8 encoding, and the text is finely patterned and deactivated with the help of the Chinese word separation tool provided by jieba library, based on the deactivation word list of Harvard University, the deactivation word list of Baidu and the common Chinese deactivation word collation provided by CSDN forum. The obtained [vocabulary: word frequency] matrix is observed, the missing deactivated words are manually added to the deactivated word list, and the above splitting operation is repeated until there are no more obvious deactivated words in the high frequency words.

3. Descriptive analysis

The [vocabulary:word frequency] matrix was obtained, and bar charts, kernel density curves and word cloud plots were drawn to describe the frequency of occurrence of different words in the text and the relationship between them in comparison.

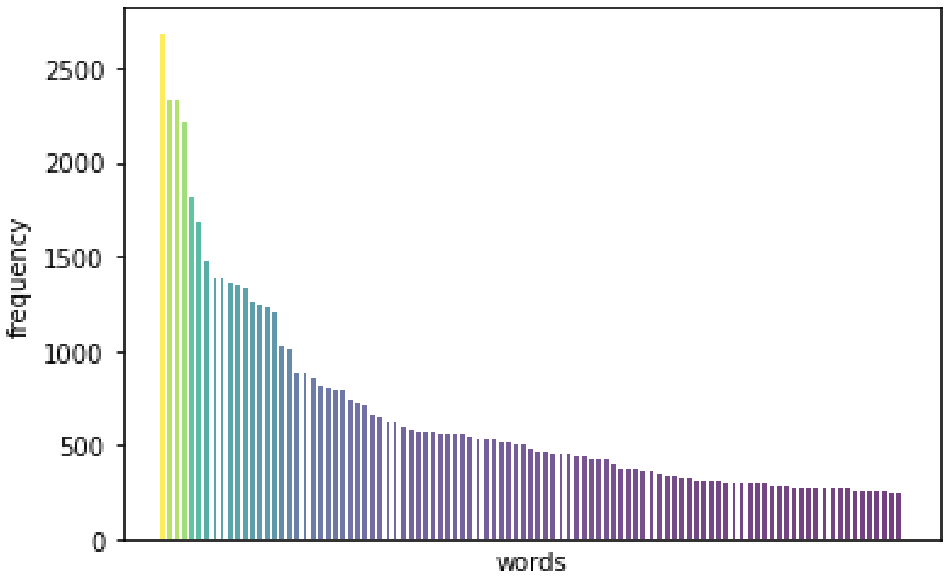

Fig. 1 Frequency distribution of words in the top 100 words

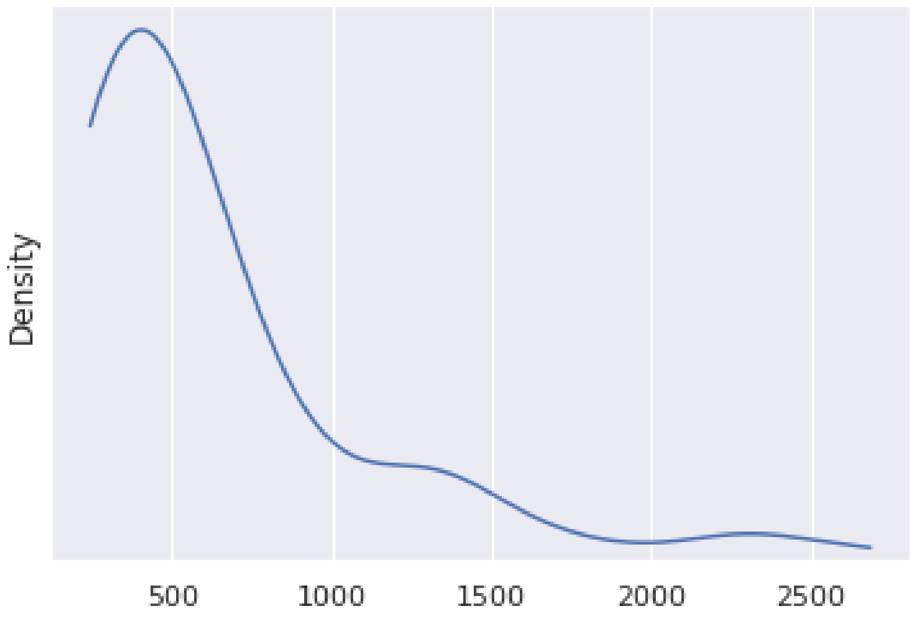

Figure 2 Kernel Density Estimation (KDE) of word frequency for the top 100 words

Figure 3 Word cloud map of epidemic-related words

The results of the word cloud map show that "Wuhan" became the most popular topic of discussion among Weibo users, which is in line with the reality that netizens nationwide focused on Wuhan in the early stage of the outbreak in terms of epidemic prevention and control, patient treatment, and supply of materials. In addition, words such as "China" and "cheer" reflected the optimism of netizens in the fight against the epidemic. The occasional figures were collected from the daily epidemic release data, reflecting netizens' concern for the daily epidemic data.

Combining the histogram results with the kernel density estimation, except for a small number of ultra-high frequency words mentioned above, the remaining words appear less frequently and show a more uniform distribution. This realistically indicates that the similarity of word dimensions among the text data is low and has good research value.

III. Microblog Topic Extraction Based on LDA Topic Generation Model

The LDA (Latent Dirichlet Allocation) topic generation model, with the help of Bayes' theorem and twice probability extraction for similarity assessment of texts, and extracts topic words with greater co-occurrence possibility according to the similarity between texts, so as to achieve the extraction of topic words of texts and discover potential common topics in texts.

A lexicon of words is created from the word separation results and each individual word is given an index. With the help of indexes, the corpus is transformed into a matrix labeled with index values, and the LDA model is trained on this matrix. Because of the large size of the corpus data, only 5 iterations of the corpus were chosen.

1. Number of themes selection

The number of topics included in the text needs to be artificially set in the model parameters, which is usually based on the distribution of the data and the personal experience of the researcher. Perplexity and Coherence are introduced in this study to evaluate the validity of LDA models trained with different number of topics.

$$\text{Perpexity}(\mathcal{W}|\mathcal{M}) = \prod_{m=1}^{M} p(\vec{\tilde{w}}_{\bar{m}}|\mathcal{M})^{-\frac{1}{N}} = \exp\left(-\frac{\sum_{m=1}^{M} \log p(\vec{\tilde{w}}_{\bar{m}}|\mathcal{M})}{\sum_{m=1}^{M} N_m}\right)$$

Calculation of Perplexity

$$\text{Coherence}(z; S^z) = \sum_{n=2}^{N}\sum_{l=1}^{n-1} \log \frac{D(w_n^z, w_l^z) + 1}{D_1(w_l^z)}$$

Calculation of model consistency Coherence

Generally, the lower the Perplexity and the higher the Coherence, the better the fit of the LDA model for that number of topics is implied.

This study measures the perplexity and consistency of different LDA models with parameter settings ranging from 1 to 20 in the number of topics.

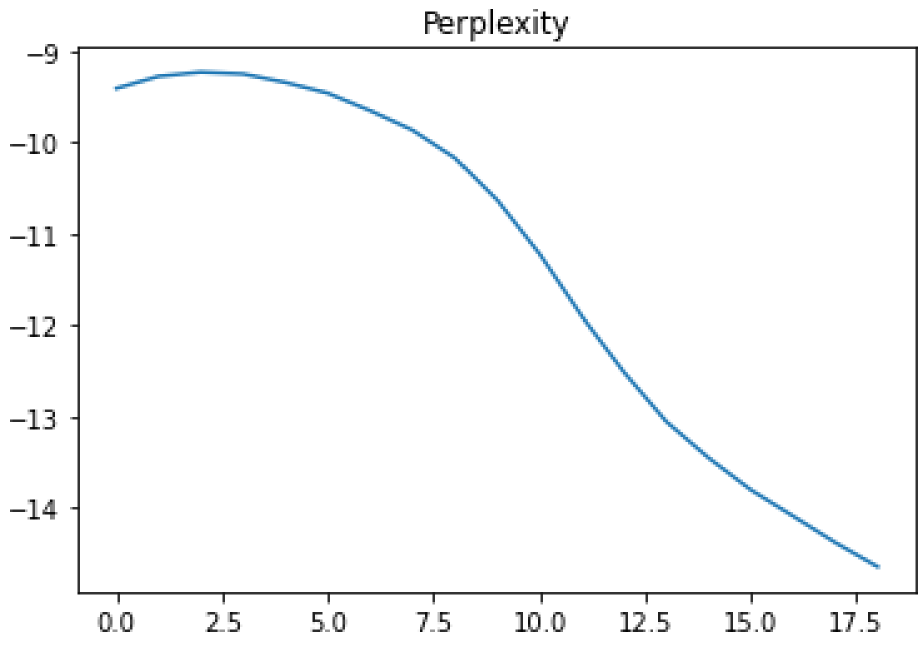

Figure 4: Perplexity of models with different number of topics Horizontal coordinate: number of topics Vertical coordinate: perplexity

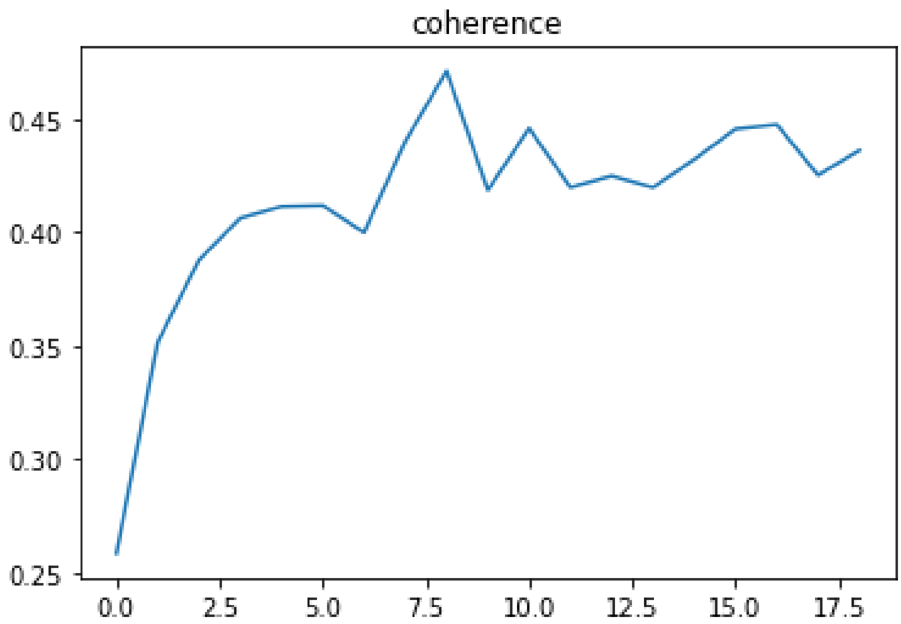

Figure 5 Consistency of models with different number of topics Horizontal coordinate: number of topics Vertical coordinate: consistency

The results show a continuous and significant downward trend in perplexity when the number of topics exceeds 7, implying that overfitting The consistency situation will become more and more severe. The consistency metric shows that the best consistency is achieved when the number of topics is chosen to be 7.
The consistency is fair when 5 is chosen. Finally, the LDA models with topic number 5 and 7 were evaluated and analyzed separately.

2. Theme Evaluation and Analysis

2.1 Assessment of the distribution of themes

Figure 6 Distribution of models under 5 topics (left) and 7 topics (right)

The above figure shows the distribution of different topics under 5 topics and 7 topics. The size of the circles indicates the overall frequency of occurrence of the topic, and the relative position relationship between the circles indicates the connection between the topics, the closer the distance, the more obvious the connection. There may be duplication between some topics. The evaluation results show that with 5 topics and 7 topics, the topics show a good degree of independence, although there is a certain degree of overlap. Among them, 7 topics allow certain smaller topics that are more similar to be explored, enabling further refinement of the data.

2.2 Subject content analysis

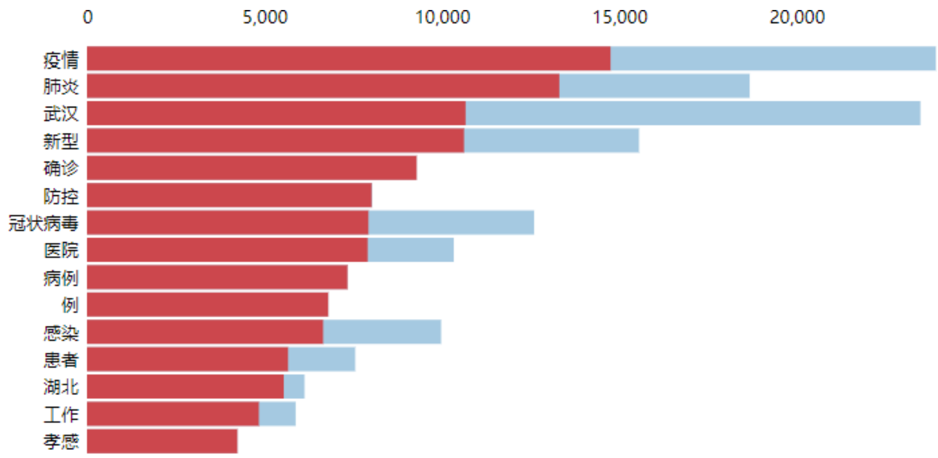

Figure 7 Topic 1: Key terms included in the release of epidemic data and their frequency

Topic 1: Epidemic data release. In Figure 7, the combination of words in the topic implies that the text contains a large number of uniform and rigorous forms of terms related to New Coronary Pneumonia, which is more likely to be the official release of the outbreak data. This topic points to the widespread interest during the epidemic regarding changes in the development of the epidemic, the number of confirmed infections, and geographic developments.

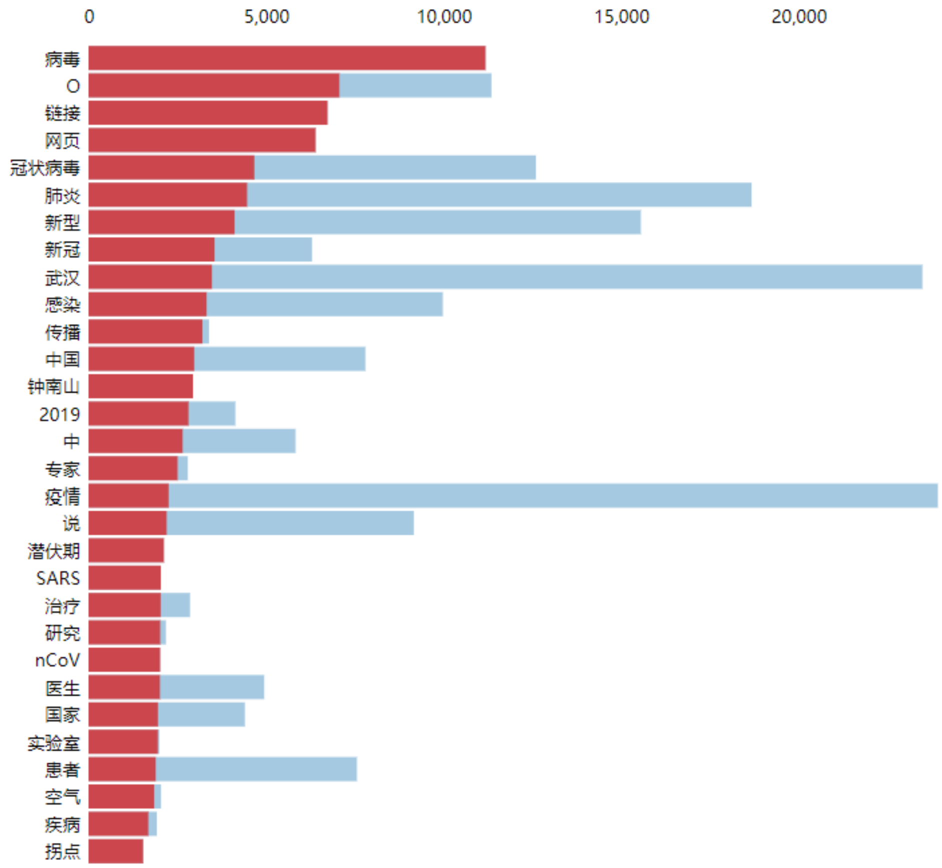

Figure 8 Topic 2: Key vocabulary and frequency included in the scientific problem study

Topic 2: Scientific Issues Seminar. Compared with Topic 1, the appearance of words such as "SARS", "experts", "incubation period" and "laboratory" in Topic 2 implies that the topic involves public discussions about the type of pneumonia, the transmission route of pneumonia, the pathogenesis of pneumonia and the origin of pneumonia virus. The appearance of words such as "SARS", "experts", "incubation period" and "laboratory" implies that the topic involves public discussion on the type of pneumonia, the transmission route of pneumonia, the pathogenesis of pneumonia and the traceability of pneumonia virus. It is noteworthy that Academician Zhong Nanshan appears among the topics with high frequency, which is related to his active public interaction and extensive social trust during the New Crown epidemic.

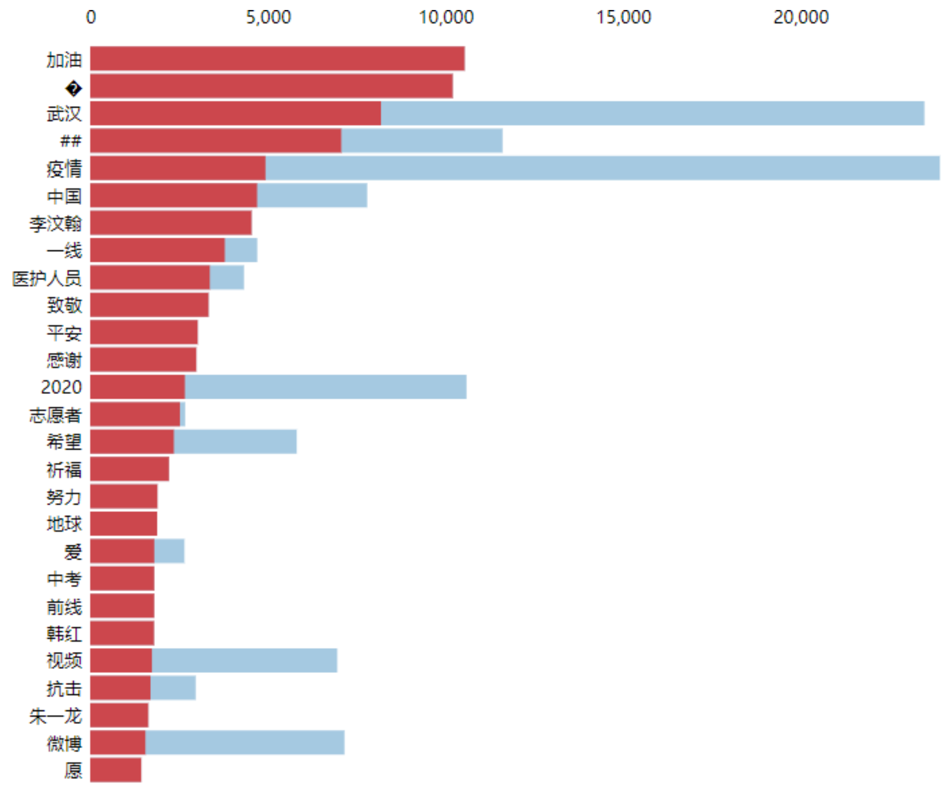

Figure 9 Topic 3: Public welfare and social-emotional engagement include key terms and frequency

Topic 3: Public Welfare and Social Emotional Engagement. There are a lot of positive emotional words in Topic 3, such as "cheer", "tribute", "peace", "hope", "pray", etc., expressing the public's good wishes for the epidemic to be controlled and the patients to be treated. ", "pray", etc., expressing the public's good wishes for the epidemic to be controlled and the patients to be treated. The words "Han Hong", "Zhu Yilong" and "Li Wenhan" imply that celebrity figures' social responsibility and participation in social public undertakings during the epidemic have reaped extensive social Discussion.

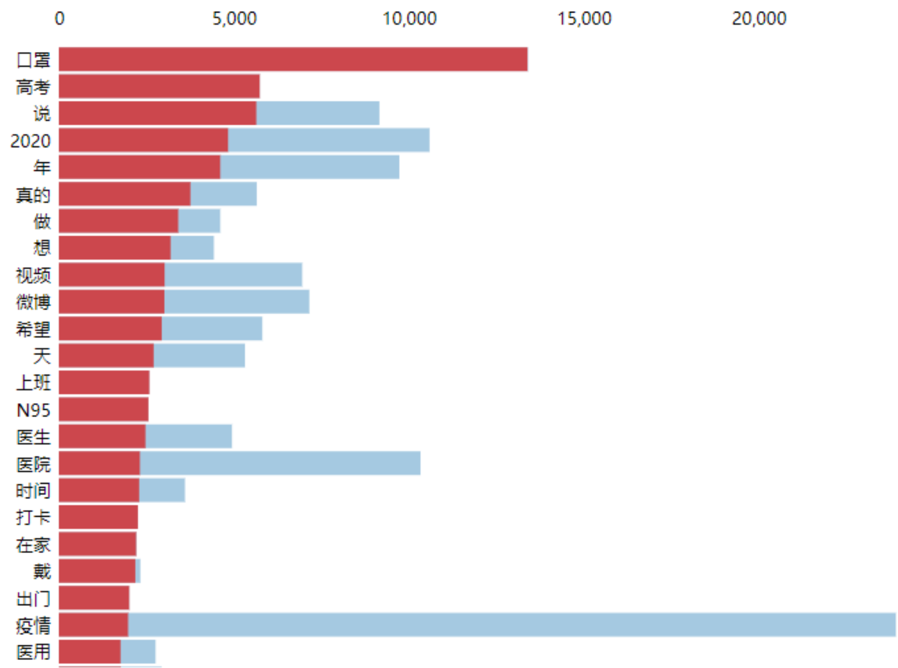

Figure 10 Topic 4: Key terms included in personal virus protection and frequency

Topic 4: Personal protection against viruses. In Topic 4, "mask" is in the first place, in addition to the words "at home", "N95" and "wear". The words "at home", "N95", and "wear" imply the personal record of isolation and self-protection during the epidemic, and also include the popularization and discussion of home protection measures.

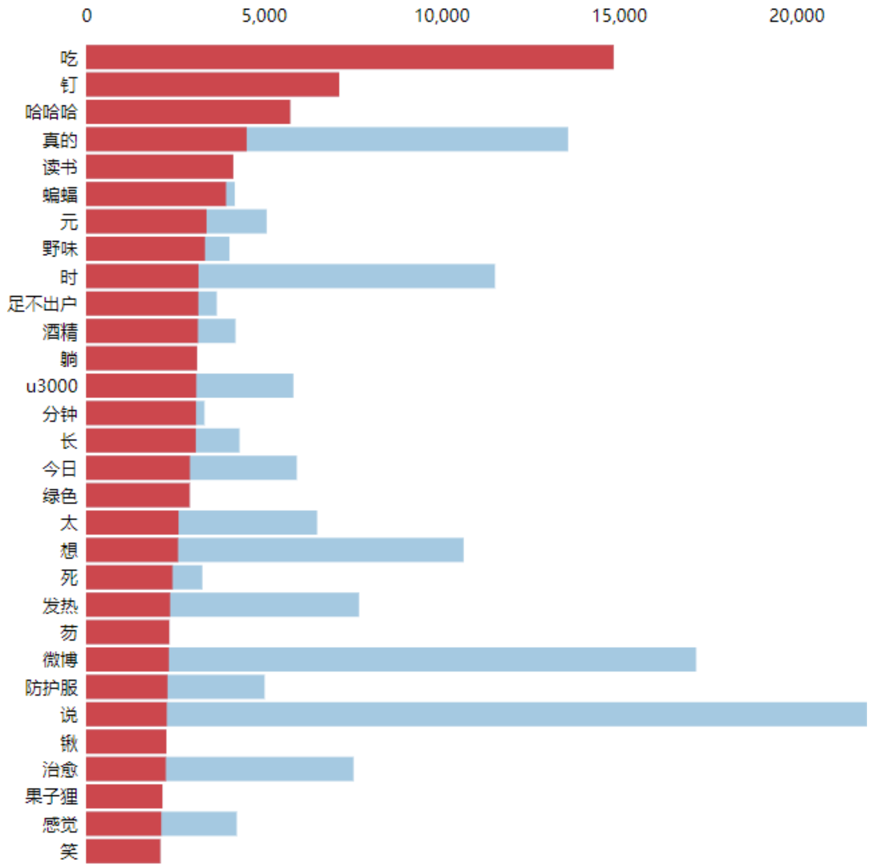

Figure 11 Topic 5: Key words and frequency of words included in daily life at home

Topic 5: Daily life at home. The word "eat" tops the list, while "nail" suggests the widespread use of the "nail" platform for online office and online learning. The word "nail" hints at the widespread use of the "nail" platform for online office and online learning. In addition, words such as "hahaha", "reading" and "not leaving home" also reflect the life of people who are trying to enrich their lives, relieve boredom and make fun out of their misery during the epidemic.

The seven-topic model unearthed two new topics of smaller scale and finer classification in addition to the above five topics, of which topic six and topic five are similar in essence and are combined. The vocabulary distribution of topic six is as follows.

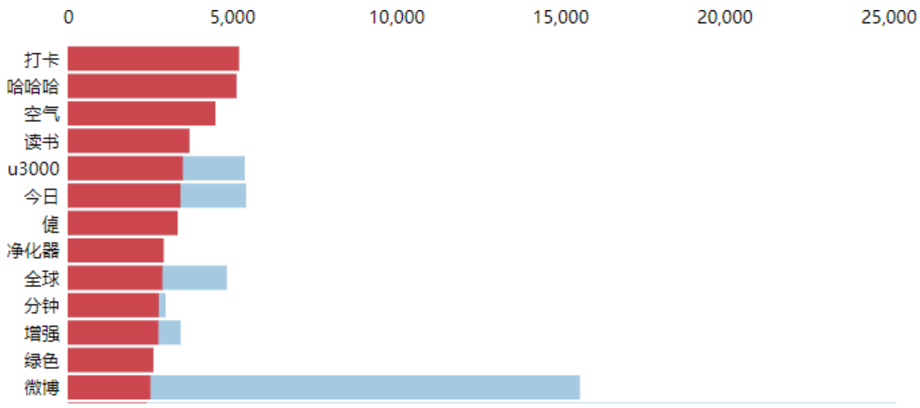

Figure 12: Key words and frequency of Topic 6

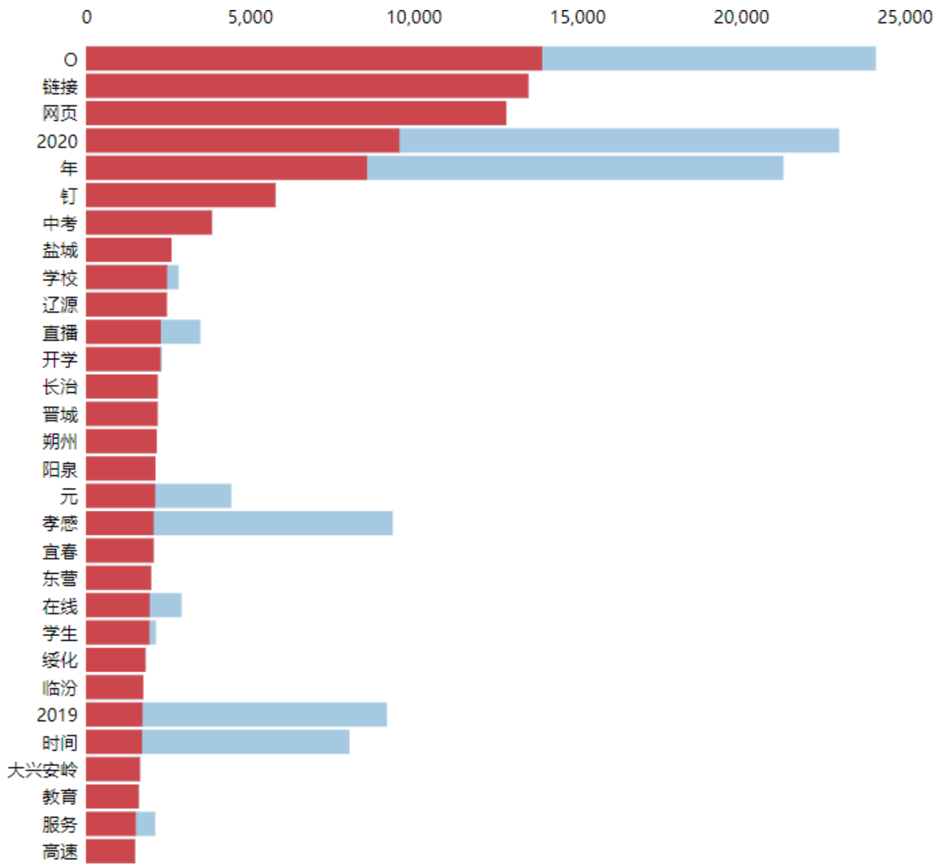

Figure 13 Topic 7: Key terms included in online teaching policies around the world and their frequency

Topic 7: Online teaching policies around the world. "nail," "midterm," "school," "live," and "start of school The words "nail," "midterm," "school," "live," and "school start" imply that the topic is highly relevant to education issues, while the presence of local names suggests that the issue of school start times in various places was a key concern for student groups during the early stages of the outbreak.

The results of topic extraction show that from January 1, 2020 to February 18, 2020, six different topics were discussed by the public in the early stages of the epidemic, including epidemic data release, scientific issue discussion, public welfare and social-emotional engagement, personal virus protection, daily life at home, and online teaching policies in various locations, and other epidemic-related topics.

It covers all aspects of the epidemic data, scientific research on the virus, personal protection, home life, public welfare donations and social participation, online teaching and office work, etc. The high level of discussion of scientific information on social media at the beginning of the outbreak, the widespread participation in public service, and the high level of consciousness in home quarantine and self-protection all bode well for the critical role that scientific attitudes, humanitarianism, and sacrifice will play in China's fight against the epidemic.

IV. Sentiment analysis of microblog text based on plain Bayesian model

1. Model Training

In the original data training set, 100k text data with sentiment labels are provided, where '-1' indicates negative sentiment tendency, '0' indicates no significant sentiment tendency, and '1 ' indicates positive affective tendency. The SnowNLP library uses a plain Bayesian model to classify new texts by measuring the frequency of displaying different words in positive and negative texts. In this study, the corpus samples in the SnowNLP library were replaced with the positive and negative corpus related to the new crown epidemic, and the text classifier was retrained for the new crown epidemic data to produce a numerical evaluation from 0 to 1. The closer the value is to 1, the more likely the text expresses positive sentiment; the closer the value is to 0, the more likely the text expresses negative sentiment.

2. Evaluation of results

The sentiment classifier is applied to the labeled sentiment data and compared with the original labels. Under the assumption that the original labels are all correct, there are 4374 misclassified samples out of 30k total samples, and the average classification error is 0.5053.

A perusal of the data revealed that the misclassified samples were concentrated on samples that were labeled as having no significant affect in the original data. In fact, many samples labeled as no tendency still have some degree of sentiment tendency. At the same time, large classification errors can hardly be avoided because the original labeling is taken to be highly discrete. Taken together, the results provided by this classifier are acceptable.

3. Analysis of results and clustering

3.1 Histogram and kernel density estimation

Histograms were plotted and kernel density estimates were obtained for the results of the above sentiment analysis.

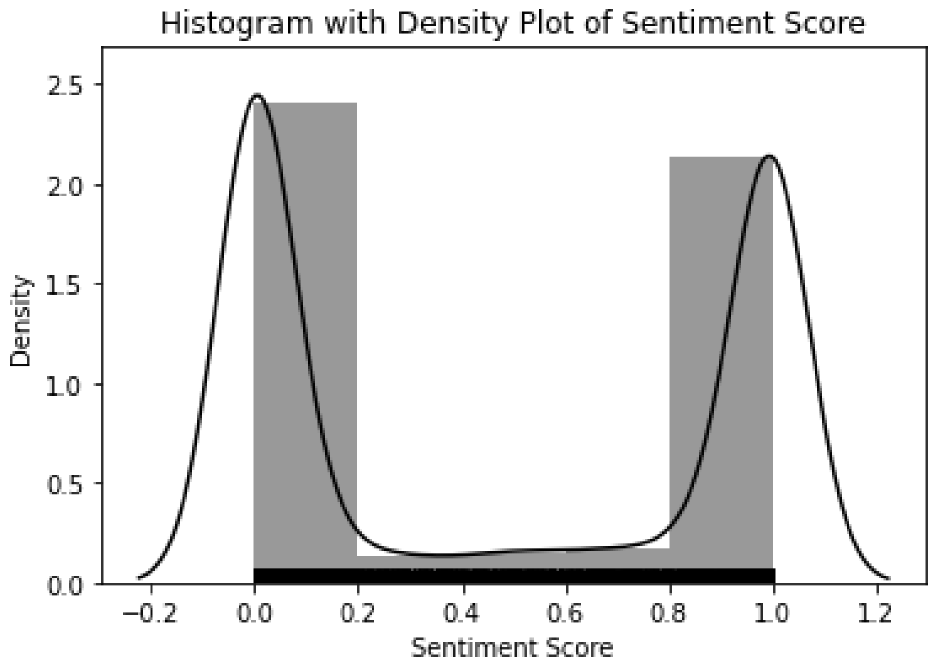

Figure 14 Histogram of emotion scores and kernel density estimates

Both histograms and kernel density estimates for the full data exhibit significant bimodality, with a large amount of data concentrated near the two extreme sentiments and a sparse and flat distribution of moderate sentiments. This reflects the fact that people are more willing to express emotionally intense views or retweet with a clear tendency to do so during the duration of the epidemic. Fear of the spread of the epidemic and the bitterness of home isolation contribute to this dynamic.

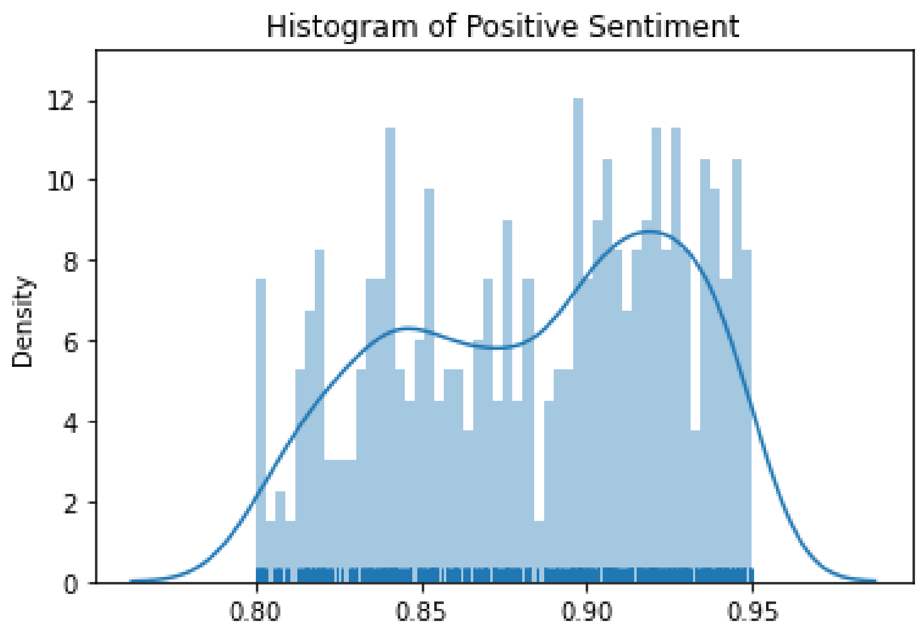

Figure 15 Histogram of positive emotion scores and kernel density estimates

The figure above shows the sentiment distribution of positive sentiment texts (sentiment scores between 0.8 and 0.95). The data show that among the positive texts, a significant portion shows strong positive sentiment, but it cannot be ignored that a small peak still appears around 0.83. This suggests that in the context of an epidemic, positive messages may also be partly counterbalanced by negative emotions and lose their positivity.

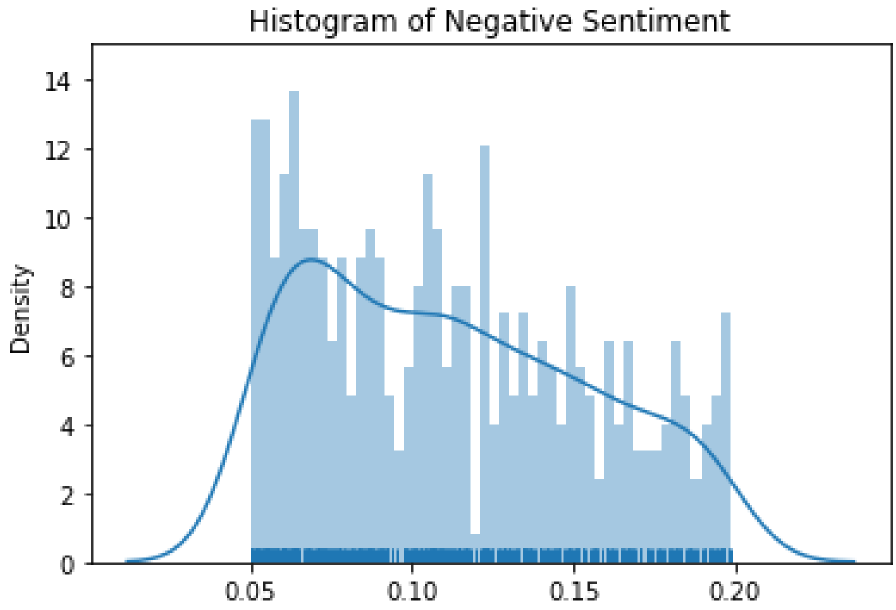

Figure 16 Histogram of negative affect scores and kernel density estimates

The performance of negative sentiment is more different. Except for the clustering around extreme values, the distribution of negative emotions was relatively balanced and without peaks, but the shift toward mild emotions was extremely insignificant. This indicates that the ability of social network participants to regulate their own emotions was relatively weak at the beginning of the outbreak, and people were immersed in fear and suspicion and were more susceptible to extreme negative emotions.

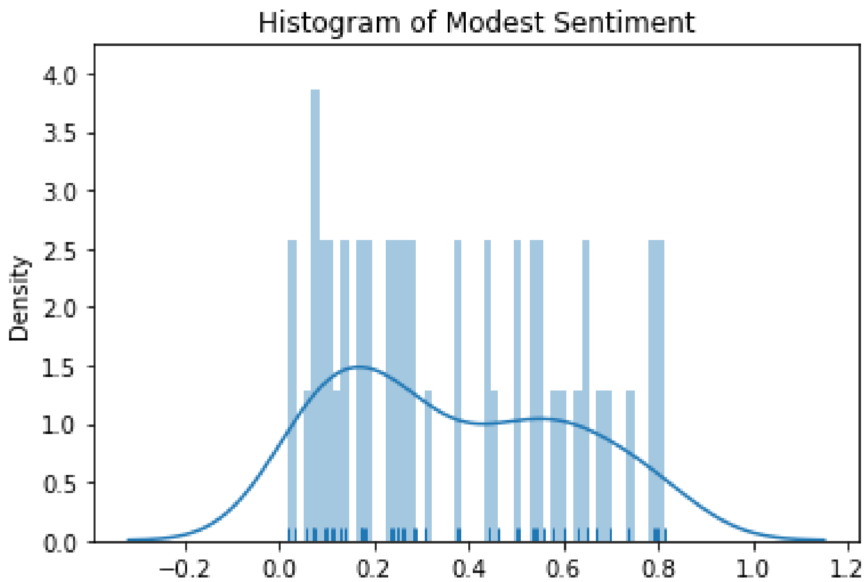

Figure 17 Histogram and kernel density estimation of moderate mood score

The above graph depicts the distribution of moderate sentiment. The distribution of moderate sentiment shows a stronger balance, but still shows peaks in the lower (pessimistic) part of the values. This indicates that moderate sentiment internet users generally hold a cautiously pessimistic attitude at the beginning of the epidemic.

In summary, the sentiment of Internet users at the early stage of the outbreak was severely polarized, with the majority of the sample showing strong extreme emotions. Internet users' attitudes are generally pessimistic, and positive emotions and moderate attitudes are also affected by the epidemic background of

Influence, and there is a tilt toward negative emotions.

3.2 Clustering and classification number selection

As mentioned above, the disparity in the number of extreme and non-extreme samples makes the overall-based studies over-amplify the extreme samples and ignore the moderate samples. To ameliorate this problem, this study uses a k-means-based clustering approach to classify the sentiment samples.

In order to find the optimal number of clusters, two evaluation metrics are introduced to assess the effectiveness of different clustering models.

3.2.1 **Silhouette Coefficient** (**Silhouette Coefficient**)

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

$$s(i) = \begin{cases} 1 - \frac{a(i)}{b(i)}, & a(i) < b(i) \\ 0, & a(i) = b(i) \\ \frac{a(i)}{b(i)} - 1, & a(i) > b(i) \end{cases}$$

$$S = \frac{1}{n} \sum_{i=1}^{n} s(i)$$

$S(i)$ is close to 1, then the sample i is reasonably clustered.

$S(i)$ is close to -1, it means that sample i is more deserving to be classified to another cluster; if $S(i)$ is close to 0, it means that sample i is on the boundary of two clusters.

The profile coefficient S is the mean of all samples $S(i)$

The values of the contour coefficients of the clustering results are taken between [-1,1], and the larger the value, the closer the similar samples are to each other, and the farther the different samples are from each other, the better the clustering effect.

3.2.2 Overall sum of squares (Inertia)

$$\text{Cluster Sum of Square(CSS)} = \sum_{j=0}^{m} \sum_{i=1}^{n} (x_i - \mu_i)^2$$

$$\text{Total Cluster Sum of Square} = \sum_{l=1}^{k} CSS_l$$

Total Cluster Sum of Square is the sum of the sum of squares within a cluster, also called total

The smaller the Total Inertia, the more similar the samples are within each cluster, and the better the clustering.

3.2.3 Number of clusters selected

For the Kmeans method provided in sci-kit learn, the number of clusters was used to traverse from 1 to 20, and the contour coefficients and overall sum of squares were calculated for each clustering model, and the number of clusters selected based on the elbow criterion.

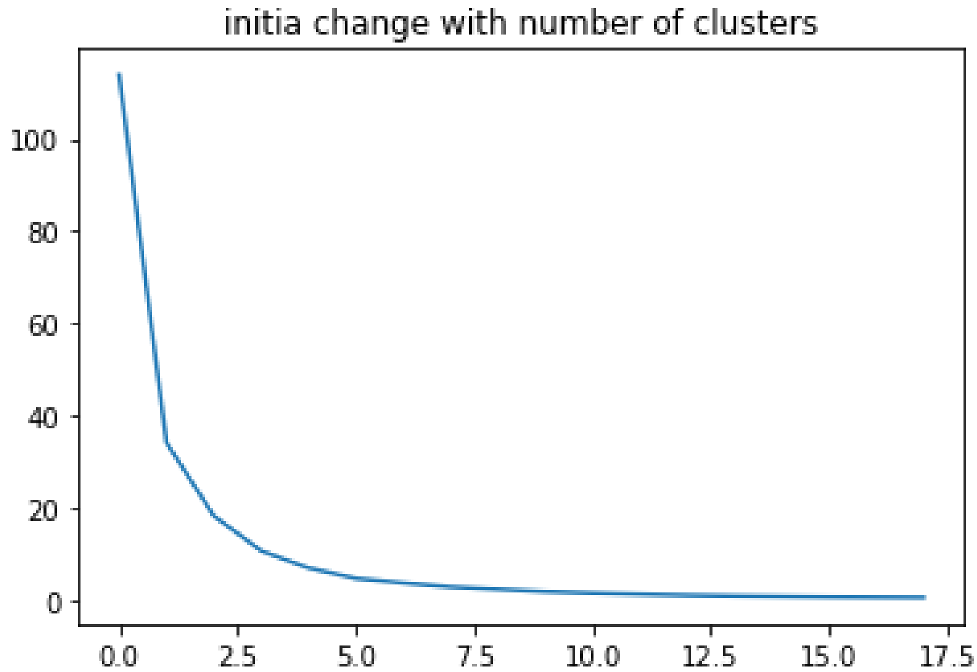

Figure 18 Variation of overall sum of squares with the number of clusters

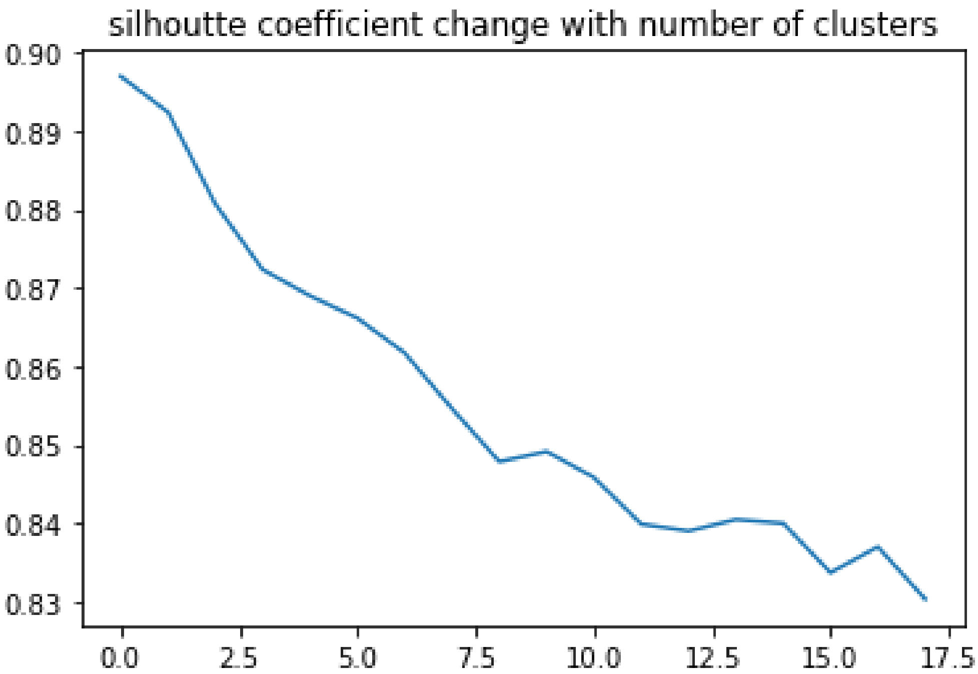

Figure 19 Variation of profile coefficient with the number of clusters

It is observed that when the number of clusters is greater than 5, the overall sum of squares no longer decreases significantly, and the effect of increasing the number of clusters on improving the classification is limited at this time, while the contour coefficient remains high at this time. Therefore, it is reasonable to choose the number of clusters as 5.

3.2.4 Clustering Conclusion

The number of clusters judged by the relevant evaluation criteria is 5, that is, based on the positive and negative emotion judgment, the epidemic expression emotion of Internet users should be classified into 5 categories. According to the social psychology research, there is a wide range of theories on the classification methods and number of human emotions, among which the one that is closer to the present clustering results and can be widely populated is the emotion classification method of American researchers Ekman and Friesen. They believe that humans have six basic emotions, namely happiness, sadness, fear, surprise, anger, and jealousy. Considering the context of this study, the jealousy category was removed. Thus, it was concluded that at the beginning of the outbreak of the new crown epidemic, Internet users mainly showed five emotions such as happiness, sadness, fear, surprise, and anger in their microblog content, and the polarity of emotions was stronger and the negative emotions were more infectious.

4. Descriptive analysis based on time series

After obtaining the sentiment tendency of each text, this study focused on exploring the fluctuation of public sentiment at the beginning of the epidemic, i.e., whether the generation of specific epidemic news would have a more significant impact on the overall public sentiment. The texts were reaggregated on a daily basis to find the mean value of daily sentiment in the sample, and a line graph was plotted against the timeline of the new crown epidemic news.

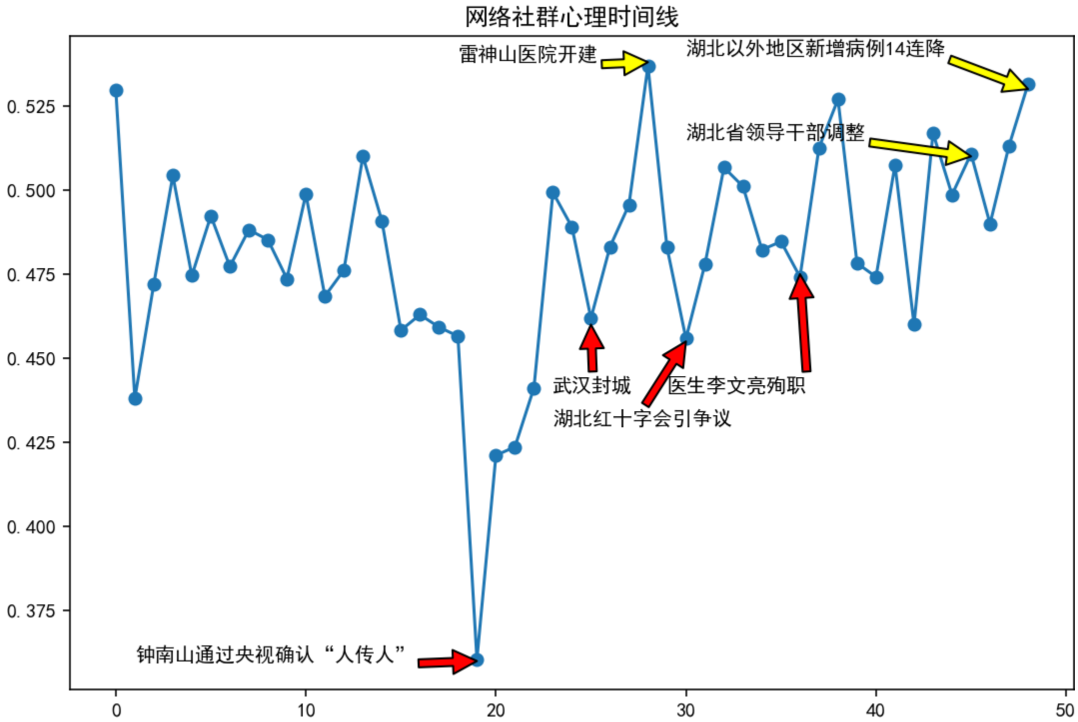

Figure 20 Psychological timeline of online communities
Horizontal coordinate: time (January 1 to
February 18, 2020) Vertical coordinate:
average sentiment score for the day

In this study, a total of seven key event nodes at the beginning of the outbreak were selected, with red arrows indicating negative news and yellow arrows indicating positive news. These events and trends in group psychological fluctuations yielded good of the fit. This also verifies the reliability of the sentiment analysis model from the side.

From the line graph, it should be clearly seen that at the beginning of the outbreak, Academician Zhong Nanshan's confirmation of the "human-to-human" phenomenon in the CCTV broadcast triggered a high degree of concern and panic among netizens about the unknown infectious disease. Subsequently, the news of Wuhan's closure further increased netizens' concerns about the contagiousness of the virus and the status of the epidemic. The news that the Hubei Red Cross was accused of unfavorable distribution of supplies and hoarding of large quantities of supplies caused public outrage over its backward logistics distribution system and emergency management capabilities, while the death of Dr. Li Wenliang aroused public concern about public information disclosure and freedom of expression, and sparked heated discussions about "whistle blowers.

In addition, the opening of Mount Thor and Mount Vulcan hospitals, the reshuffling of Hubei's leading cadres in response to the epidemic's prevention and control requirements, and the news of the initial results of the epidemic's prevention and control have improved the sluggish community sentiment outside the outbreak and boosted public confidence in the epidemic's prevention and control efforts.

5. Potential connection between emotional polarity and user attention

The sentiment analysis model was used to process the text of trending topics on Weibo during the epidemic, and the histograms of text sentiment and views were plotted. The horizontal coordinate is the topic sentiment score, the closer to 1 the more likely to indicate positive sentiment and the more
The closer to 0, the more likely it is to indicate negative sentiment. The vertical coordinate indicates the number of views of the topic.

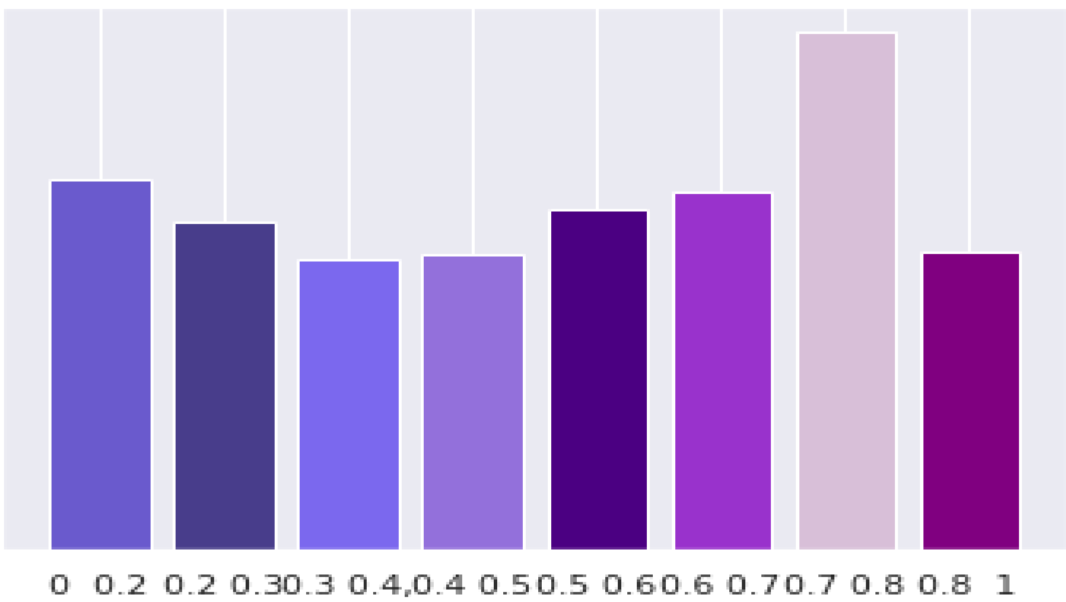

Figure 21 Statistics of Weibo hot topics views for different emotions Horizontal coordinate: emotion score
Vertical coordinate: number of views

The histogram shows that topics with extreme values close to 0 and 1 have a higher number of views, and the number of views decreases to a certain extent as the polarity of emotions decreases (values close to 0.5). This indicates that during the epidemic, extreme optimism and pessimism are more likely to attract the attention of Internet users than mild emotions, while topics with ambiguous emotional expressions appear to be less popular. Among the extreme emotions, positive news is more attractive, which also reflects people's expectation of good news about the epidemic and their confidence that the fight against the epidemic will eventually be successful.

V. Building a domain sentiment dictionary using root words

Sentiment analysis is an important topic in the field of natural language processing, and traditional approaches to sentiment analysis include methods for measuring the sentiment of texts with the help of sentiment dictionaries. The literature shows that building sentiment dictionaries is the most difficult and costly part of this approach. When checking the github open source code, we found that Dr. Huan-Yong Liu developed a method to develop a domain sentiment dictionary using a small number of root words and text corpus, thus providing an important sentence for sentiment analysis methods. In this study, the 44 words obtained from topic extraction were manually classified into positive and negative sentiment, and the wordexpansion library developed by Dr. Huanyong Liu was used to create a sentiment dictionary specifically for the study of the New Coronary Pneumonia epidemic, which can be used as a help and reference for others' research. For the root word lexicon and sentiment dictionary, see the Appendix and the separate files pos_candi.txt and neg_candi.txt.

VI. Summary of results

The results of this study include four main aspects. One is the cleaning, slicing and word frequency statistics, and word cloud display of the microblog text data. Second, we used LDA (implicit Dirichlet distribution) topic generation model method to extract topics from the microblog text and obtained six hot topics at the beginning of the epidemic. Third, a text sentiment classifier for the discussions related to the new crown epidemic was trained using a plain Bayesian model, and good results were obtained. Using this sentiment analysis model, the extremity expression pattern of Internet users was analyzed. Through the sentiment analysis of Weibo hot text, the measure of the degree of attraction of extreme emotions and social topics to Internet users was obtained. Meanwhile, the sentiment of Internet users was classified into five categories by cluster analysis, and the day-to-day sentiment changes of social media at the beginning of the New Crown epidemic were analyzed by combining with the epidemic timeline. Fourth, a domain sentiment lexicon with significant effect in social seminars of the New Coronation pneumonia epidemic was trained to help others' research.

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Appendix.

Root word

Frontline pos Defend pos Han Hong pos Medical team pos Resistance pos War on

the epidemic pos Healing pos Prayer pos Zhong Nanshan pos Inflection

point pos Academician pos Clove pos Strength pos Donation pos Hope pos

Medical staff pos Peace pos Anti-epidemic pos Go pos Thank pos Love pos Nail pos Volunteer pos

tribute pos may pos wear pos blockade pos support pos game neg bat

neg game neg beaver neg outbreak neg confirmed neg pneumonia neg

virus neg infection neg coronavirus neg