Sociological analysis of emotions based on epidemic rumors

- Quantitative Sentiment Analysis of Weibo Rumors

Abstract

The report is based on the Sina Weibo social media platform, starting from the basic elements of information dissemination, and conducts a quantitative analysis of rumors related to the new coronavirus pneumonia epidemic, including the emotions carried by rumors, and the quantification of the spread of rumors of different emotional categories. We also attempt to analyze how the spread of false rumors changes and the sentiment of comments changes as the epidemic develops.

The spread of rumors reveals the public's demand for various epidemic information. After the outbreak, local governments implemented isolation policies to reduce the movement of people. People were isolated from others in the real environment, and the Internet and media became the only channels for obtaining information. Insufficient understanding of the new coronavirus has led to the spread of panic among the public, and the spread of information has become the biggest motivation for people to remind others to pay attention, seek help, and seek peace of mind. At the same time, the failure to disclose information in a timely manner gives rumors space to survive, and negative rumors related to livelihood security and life safety have also intensified social conflicts.

The amount of data in this experiment was of a small scope, and a lot of information was lost due to blocking or deletion. Since the raw data is not labeled with emotions and polarity, we modeled the comments on Weibo during the epidemic and used this model to judge the emotional classification of rumors. This approach itself will bring certain biases. In-depth and accurate qualitative or quantitative research requires the support of larger-scale data and better modeling.

1 Introduction

We use the nCoV_100k[1] for training models to classify a rumor to negative/positive/neutral sentiment as a baseline, since the CSDC-Rumor[2] data is not labeled. All the analyses are based on this model's output. The analysis of epidemic-related social media rumors carried out in this article is based on the false information data reported and verified in the Sina Weibo Community Management Center, which inevitably suffers from incomplete coverage and errors in manual judgment. At the same time, the judgment of rumors is uncertain and may change as more information is introduced and affected due to the quality of the neural network.

Besides using a Bert-BiLSTM classifier, we also introduced a sentiment-subwords dictionary to get more detailed classification on sentiments, such as happy, anger, and so on.

A Bert-BiLSTM model is used for sentiment classifying. After tuning hyperparameters to achieve a comparatively good performance on the labeled data set, we then feed in the CSDC-Rumor data for sentiment classification. Based on this classification, we introduced a sentiment-subwords dictionary to get a more detailed classification on sentiments, such as happy, anger and fear.

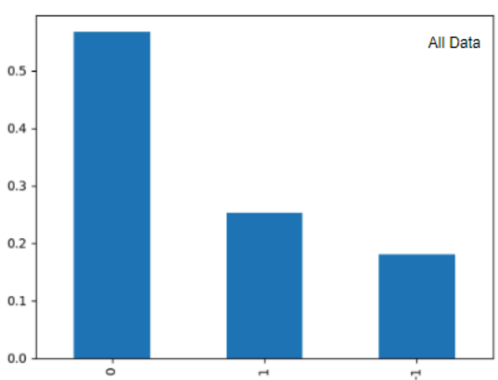
2 Data Preprocess

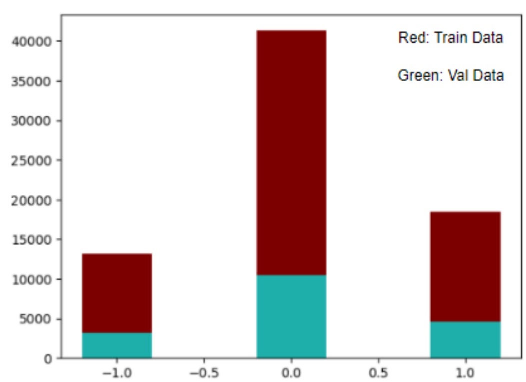
2.1 nCov_100K

For easier information extraction, we converted the raw data from GB2312 format to csv. Since the main information for adapting the research direction of the project in CSDC-Rumor is only the textual content of Weibo rumors, during preprocessing, we therefore only retained the text information and sentiment annotation in nCoV_100k. Below are examples of the preprocessed data from nCoV_100k. In addition, we clean up Nan and abnormal samples from the dataset. For example, the sentiment annotation should fall in -1, 0, or 1, whilst few samples are annotated as 10. After cleaning up, there are in total 91060 out of 100000 samples left.

	Unnamed: 0	微博中文内容	情感倾向
0	0	写在年末冬初孩子流感的第五天，我们仍然没有忘记热情拥抱这2020年的第一天。带着一丝迷信，早...	0
1	1	开年大模型...累到以为自己发烧了腰疼膝盖疼腿疼胳膊疼脖子疼#Luna的Krystallife#?	-1
2	2	邱晨这就是我爹，爹，发烧快好，毕竟美好的假期拿来养病不太好，假期还是要好好享受快乐，爹，新年...	1
3	3	新年的第一天感冒又发烧的也太衰了但是我要想着明天一定会好的?	1
4	4	问：我们意念里有坏的想法了，天神就会给记下来，那如果有好的想法也会被记下来吗？答：那当然了。...	1
5	5	发高烧反反复复，眼睛都快睁不开了。今天室友带我去看，还在发烧中建议我输液，我拒绝了。给我打针...	-1
6	6	明天考试今天发烧跨年给我跨坏了？？2兰州·兰州交通大学?	-1
7	7	#元旦快乐##枇杷手法小结#每个娃都是有故事的娃。每个大人也是有故事的大人。小枇杷有茶有手法...	0
8	8	我真的服了xkh昨天vv去和她说自己不舒服，描述了症状她说啊你这不是感冒没有发烧没事的晚上一...	-1
9	9	新年第一天，为自己鼓掌??????发烧了也要来看线下演出！因为热爱，所以才会克服困难线上演出...	1

The train set and the validation set are splitted from these 91060 samples with a proportion 8:2. Bar plots are drawn to ensure that the ratio of the amount of samples of each sentiment type in the two data sets is similar.





A more discreet way of preprocessing should also be involved in clearing stopwords and punctuations. However, we did not run such a step since the stopword and punctuations also can bring sentiment related information. Such as a sequence with continuous question marks could suggest shock, irony or confused feelings. We are hoping that the network could learn such hard historical meanings with a large database.

2.2 CSDC-RUMOR with BERT+BiLSTM

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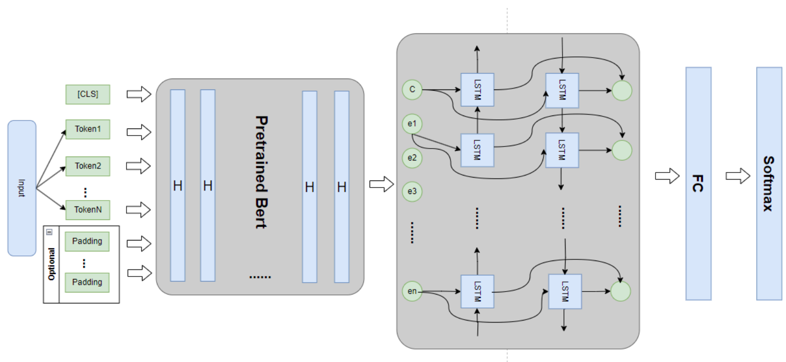
3 Classifier Network

3.1 Network Architecture

A Bert-BiLSTM network is chosen for our project, inspired by “A Study on the Emotional Tendency of Aquatic Product Quality and Safety Texts Based on Emotional Dictionaries and Deep Learning”[3]. If time applies, we will try an improved version known as Bert-BiLSTM-Attention inspired by “BERT-BiLSTM-Attention model for sentiment analysis on Chinese stock reviews”[4].




```
class SentimentClassifier(nn.Module):
    def __init__(self, bert_model_name, hidden_size, device, n_layers=2, dropout=0.5, num_classes=3):
        super(SentimentClassifier, self).__init__()

        self.device = device

        self.bert = BertModel.from_pretrained(bert_model_name)
        embedding_size = self.bert.config.to_dict()["hidden_size"]

        self.lstm = nn.LSTM(
            input_size=embedding_size,
            hidden_size=hidden_size,
            num_layers=n_layers,
            dropout=dropout,
            bidirectional=True,
            batch_first=True
        )

        self.fc = nn.Linear(hidden_size*2, num_classes)
        self.softmax = nn.Softmax(dim=1)

    def forward(self, batch):
        doc_ids, doc_mask = batch['context_idxs'], batch['context_mask']
        with torch.no_grad():
            # embedded: [batch size, sequence length, embed_dim]
            embedded = self.bert(input_ids=doc_ids, attention_mask=doc_mask)[0]  # last hidden state

        # h, c: [2(bidirectional)*num_layers, batch size, hidden size]
        _, (h, c) = self.lstm(embedded)

        # through linear layer
        # concatenate the two hidden states from bidirectional LSTM
        logits = self.fc(torch.cat( tensors: (h[0], h[1]), dim=1))
        logits = self.softmax(logits)

        return logits
```

The above is a diagram describing the architecture of the network. Dropout is also used for regularization to significantly reduce overfitting. The left image is the code snippet for the network, inspired by [5].

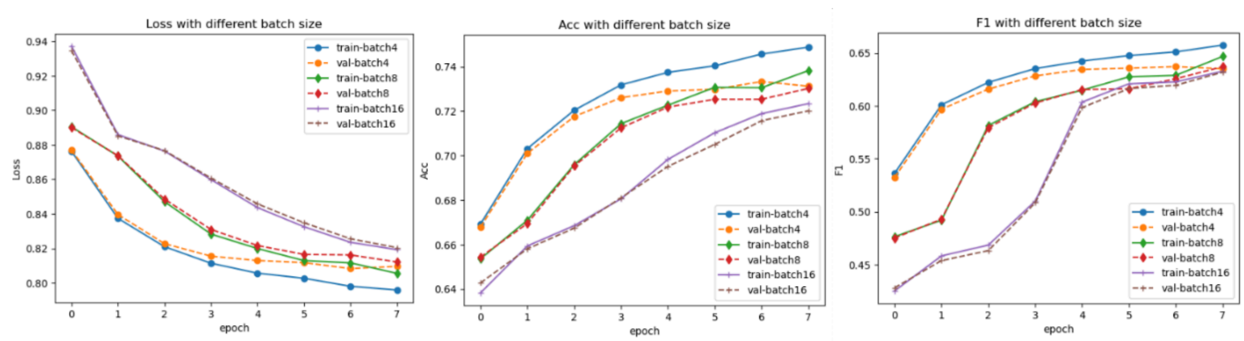
We encode the rumor contents by BERT to enhance the semantic feature representation of the text, BiLSTM is then utilized to enhance the contextual information of the overall context of the review as well as the model’s comprehension of the text sequences[4]. Most of the pretrained BERT models for Chinese only support byte-base encoding and do not consider context information according to different context backgrounds. Therefore, the BiLSTM is used on top of the

BERT since BiLSTM are known for solving the problem of insufficient dependence on long text and enhancing the model's ability to capture context information.

3.2 Hyperparameter Tuning

In this section, we will mainly tune the batch size and the layer amount in the BiLSTM architecture. Since all the quantifications of the rumors are based on the classification output from the classifier network, it is essential to ensure the model has a good learning quality and accurate predictions. The metrics used for evaluating the model are accuracy score and F1 score. Accuracy score is the measure of all the correctly identified cases. It is most used when all the classes are equally important. F1, on the other hand, gives a better measure of the incorrectly classified cases[7].

3.2.1 Batch Size



We started from learning rate 1e-6 and the layer amount 8 in the BiLSTM network. We iterate each model for 8 epochs.

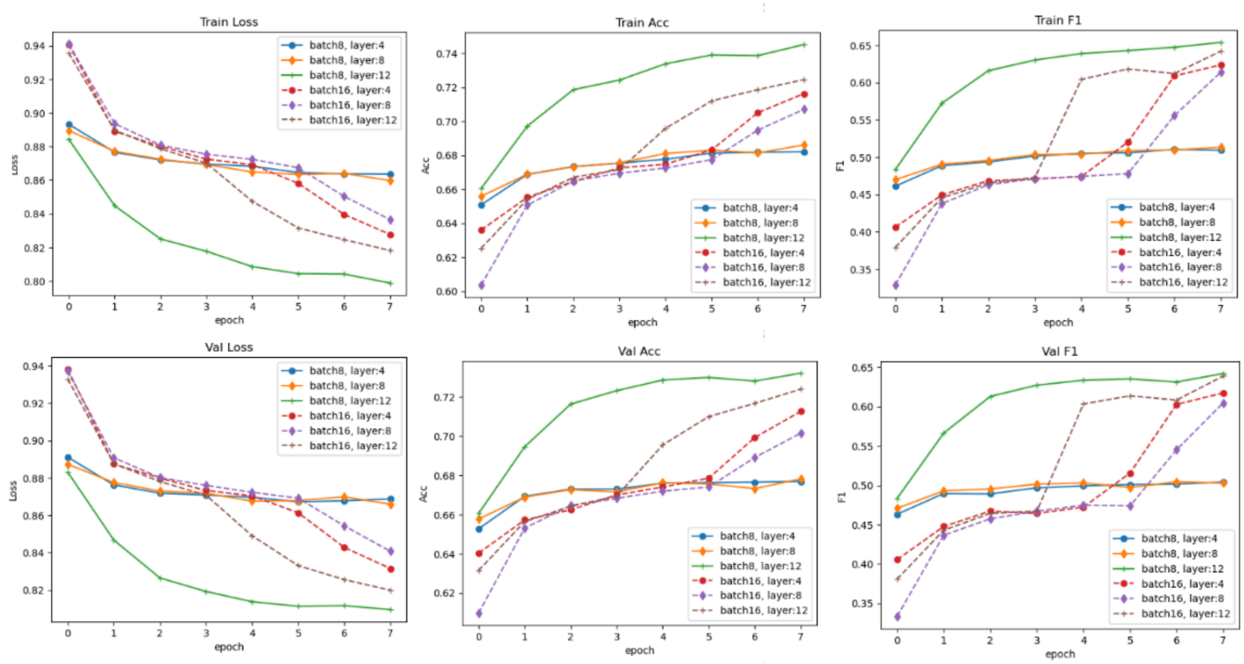
The smaller the batch size, the faster the model converges. The reason being we allow the model to start updating and learning before seeing large amounts of data. The downside of using a smaller batch size is that the model is not guaranteed to converge to the global optima[6]. Also, with too small batch sizes, the model can overfit since the model updates too frequently. As we can see, when the batch size is set to 4, the model overfits after 7 epochs.

Models with batch size 8 and 16 haven't finished convergence at the end of training. Yet their accuracy scores on the validation set are close to the model with batch size 4, and even exceed. Therefore, we will use batch size 8 and 16 for later experiments.

3.2.2 Layer Amount in BiLSTM

Increasing the number of hidden layers allows the model to capture more complex and hierarchical features in the data. Deeper architectures can learn intricate patterns and relationships, potentially leading to better performance on complex tasks[8].

We still run the models for 8 epochs. From Section 3.2.1, we could notice that 1e-6 is not too small as a learning rate, thus we will keep the learning rate too.



Observations:

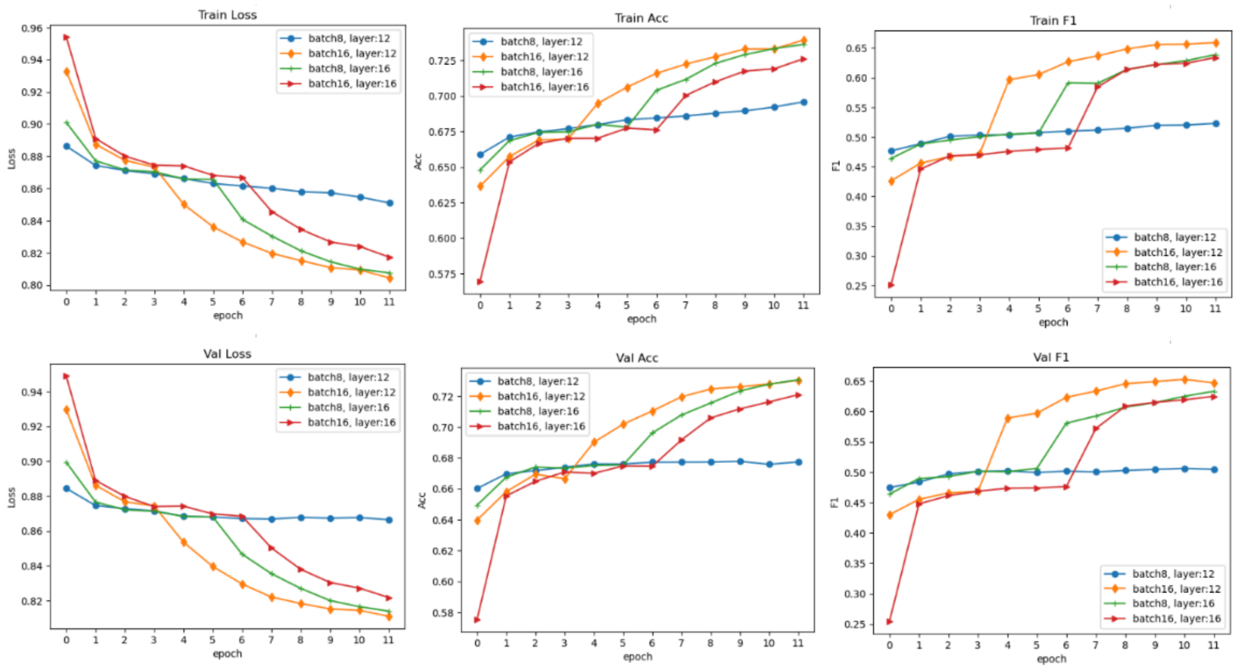
1. With batch size 8 and layer amount 12, the classifier reaches the highest accuracy and F1 on the validation set. The network also converges the fastest.
2. The second best model performance is with batch size 16 and layer amount 12. Metrics with this model start to get close to the best performance model after 5 epochs of iteration.
3. The model's predictions get significantly improved with deeper networks.
4. Small batch sizes have comparatively weaker performances with shallow network architectures.
5. The more layers the BiLSTM has, the faster the model converges and the better the prediction results will be.
6. We will choose the first and second best models' parameters to find the final model.

3.2.3 More Epochs to Choose the Final Model

Except for the two hyperparameter combinations we choose from above, we will also increase the layer amount to 16. Each model will iterate for 12 epochs for us to better understand its strengths and limitations.

The four models compared in this section are: {'batch': 8, 'n_layer': 12}, {'batch': 16, 'n_layer': 12}, {'batch': 8, 'n_layer': 16}, {'batch': 16, 'n_layer': 16}.

The best prediction results are generated by the models with {'batch': 16, 'n_layer': 12} and {'batch': 8, 'n_layer': 16}. The model with {'batch': 16, 'n_layer': 12} is slightly better. Therefore, we will choose batch size 8 and layer amount 12 for training our model.



3.2.4 Final Model

Except for the two hyperparameter combinations we choose from above, we will also increase the layer amount to 16. Each model will iterate for 12 epochs for us to better understand its strengths and limitations.

An early stopping strategy was applied during training. We count the number of continuous epochs which had not improved from the best metrics the model had once achieved. If the count was greater than a given threshold, we stopped the training and saved the best model out.

The model reached its best at the 14th epoch. We will use it for quantification analysis on the CSDC-RUMOR dataset.

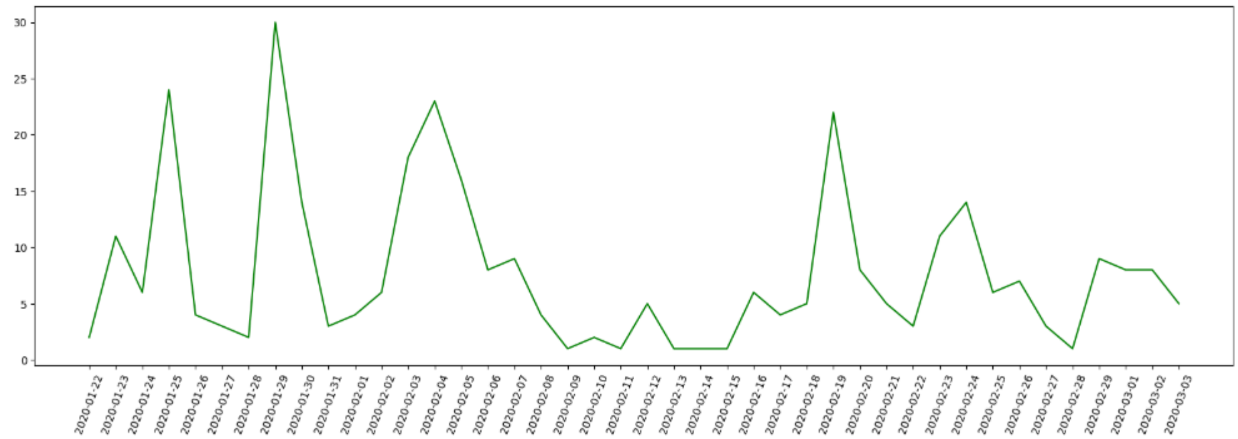
```
100%|██████████████████████████████████████████████████| 4553/4553 [10:15<00:00,  7.39it/s]
Current Epoch: 14 -- Val Loss: 0.8052904220188366, Val Acc:0.7374890254609298, Val F1:0.668399794737435
Epochs after best: 0
```

4 Sociological analysis of emotions based on epidemic rumors

The epidemic broke out in Wuhan and the city lockdown was from January 23, 2020, and the city was closed until the end of April. The data we collected covers false rumor contents on Weibo from January 22 to March 3. The coincidence of time periods encompasses the most panicked stages of people's emotions. In this section, we will analyze people's emotional changes during this period based on information from neural networks and machine learning.

For better analysis, we referenced an epidemic timeline[9] put up on github.

4.1 Number of Rumors on Weibo



Although our rumor data is of a small scope, by combining the epidemic news timeline and the rumor quantity line chart above, we can roughly analyze the relationship between the number of rumors and events at the corresponding time

The number of rumors was much higher from January 22 to early February than at other subsequent times, and continued to decline in mid-February. After which the amount of rumors increased rapidly at the end of February, and entered the second peak period of rumor publishing.

Since the Hubei Provincial Government launched the Level II public health emergency response and issued a provincial announcement on January 22, people were eager to know the truth and details of the epidemic, which led to the spread of rumors; as of January 23, the Wuhan city was officially locked down, public's anxiety, panic and other emotions have risen sharply, causing more rumors and pseudoscience to be published and spread.

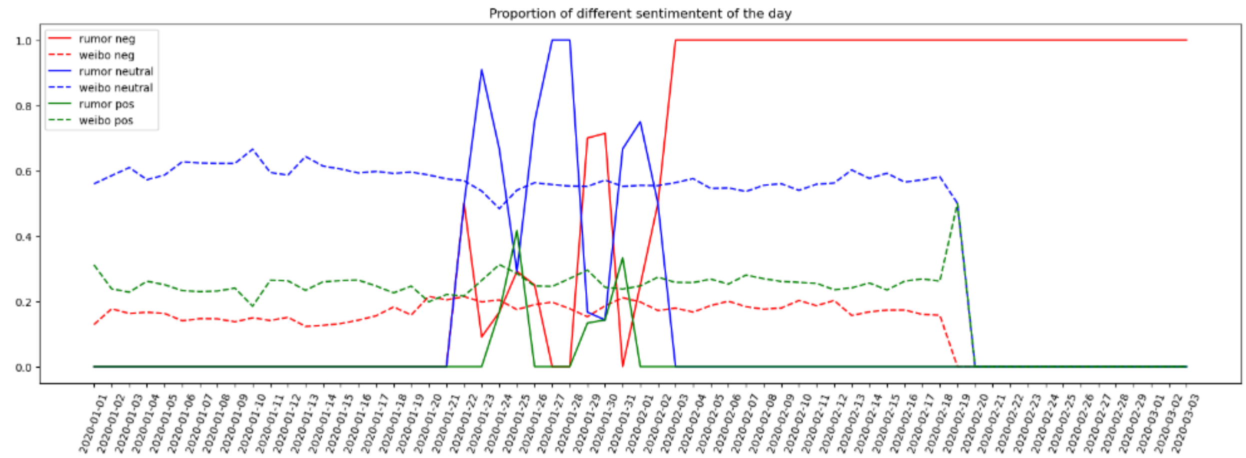
Starting from February 6, the number of rumors related to the epidemic gradually dropped to underestimation. At this time, Wuhan Leishenshan Hospital began to gradually hand over, and the work of fighting the epidemic began to advance steadily. At the same time, a large number of Weibo topics of "Pneumonia Help Super Chat" were cleared, and This resulted in a reduction in the number of rumors.

Combined with the news event line, the time period corresponding to the second rumor peak coincides with the relaxation of control and responses on social media (such as Douban's diary function).

4.2 Number of Rumors on Weibo with Different Polarity

In this section, we will only focus on negative/positive/neutral sentiment mining.

By observing the missing values from the raw data, we could notice that the missing samples all have high visit times. This is probably the reason why the values are missing, since they have too negative social impact. Therefore, we will acknowledge them as pure negative sentiment for statistics. We will in addition combine the nCoV_100k data for co-analysis the connection between the public's emotional tendencies and rumors.



The horizontal axis of the table is from January 1, 2020 to March 3, 2020. The data on epidemic rumors starts from January 22, and the Weibo epidemic-related information data starts from January 1 and ends on February 17. The main intersection time of the two data is from January 21 to February 17.

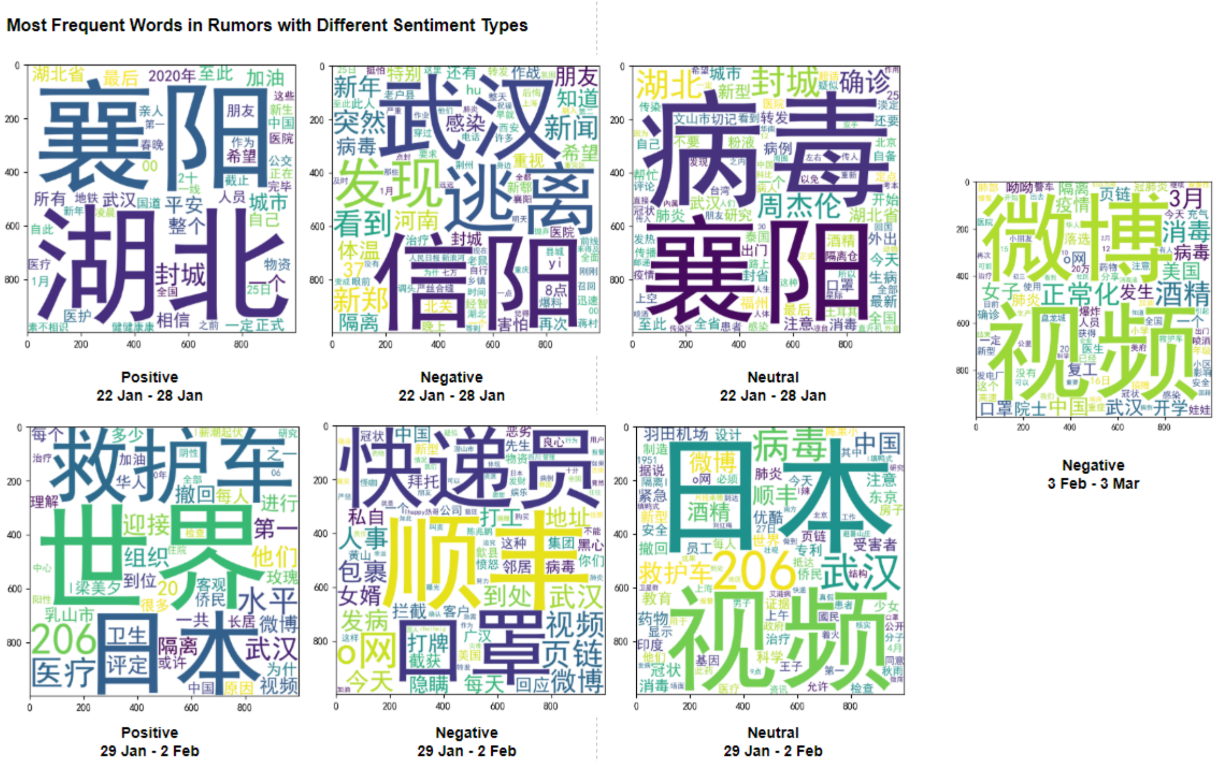
The proportion of Weibo information in each emotion category to all information collected on the day has been relatively stable. Neutral emotions have always occupied the largest proportion. As the lockdown period progressed, neutral Weibo contents decreased slightly and negative comments began to increase. At the same time, by reading the data set, we can find that the proportion of positive comments increases with the in-depth research on the epidemic and the disclosure of relevant information.

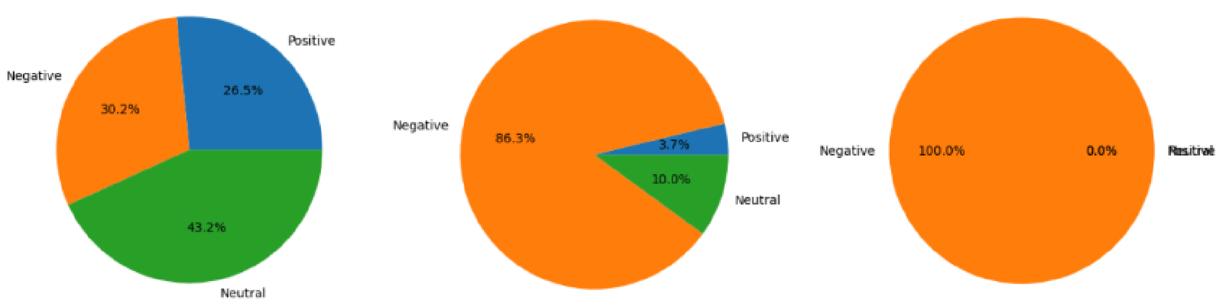
Neutral and negative emotions have always occupied the main part of rumors, and show a negative correlation with the number of positive emotion rumors. Reading the data, we can find that most of the neutral rumors belong to pseudoscience or fake social news, such as: the date to release from lockdown, etc. Rumors with positive emotions are mainly based on expectations and confidence in the country's control of the epidemic. Especially on January 29 and 30, the number of positive rumors climbed to the peak, mainly corresponding to rumor information related to Japan's evacuation of overseas Chinese. The evacuation showed China's strength and cohesion have given the people confidence after days of control.

After entering February, rumors about the epidemic with negative emotions surged. It can be inferred from the diagram that the vast majority of rumors at that time were basically negative emotions. Comparing the original data, it was found that the rumors with negative emotions mainly involve: 1. Uneasiness and anxiety caused by the epidemic situation and control policies; 2. Anger about the interception of relief materials by express delivery; 3. Conspiracies about the new coronavirus inhibitor remdesivir and counter-conspiracy theories; 4. Accidents caused by the indiscriminate use of alcohol for disinfection; 5. Information related to resumption of work and school. The public's uneasiness was growing day by day, and there is a stronger negative reaction to the instability and unknown of epidemic treatment, disease prevention, and life security.

4.3 Spread of Epidemic Rumors

Based on the analysis above, we will clip the rumor data to three stages: 22 January to 28 January, 29 January to 2 February, and time afterwards.





Rumor Visit Times
22 Jan - 28 Jan

Rumor Visit Times
29 Jan - 2 Feb

Rumor Visit Times
3 Feb - 3 Mar

We tried to quantitatively analyze the spread of epidemic rumors through the number of views, retweets, and comments; however, among the total 324 pieces of data, there are more than 300 with unknown retweet counts, so we only focus on the average number of views on different sentiment types.

In addition, we extracted and visualized the most frequent subwords based on the sentiment type and the stage of time, which helped us to better understand the public's focus.

It can be seen from the pie chart that in the first week of Wuhan's lockdown, rumors with positive and negative emotions had similar views; neutral rumors, that is, pseudoscience-based rumors, had the most views. Since Wuhan just started to lock down the city (in the early stages of the epidemic), the public did not know much about the actual situation of the epidemic. This unknown about the symptoms also led to people's desire to understand the full picture of the epidemic, prevention and treatment measures, which contributed to the spread of pseudoscience with broad audiences.

From January 29 to February 2, although the number of rumors with positive emotions increased, the number of views of rumors with positive and neutral emotions dropped significantly. Rumors of negative emotions were widely viewed, and as time went on and the epidemic was still not under control, the public felt more panic. At the same time, as the demand for anti-epidemic supplies and other guarantees increased, more anxiety, even anger or hate, has also arisen.

From February 3 to March 3, all rumors appearing in the dataset are negative rumors. This is obviously counterintuitive, mainly because we have so little data available. However, we can still speculate on the distribution trend of pageviews based on the above two sections. That is, people want to have their negative feelings heard more, and the public are also more attentive to how others feel during difficult times (empathy).

More accurate emotional changes in rumors require the support of more data, and the differences in people's attention to information containing different emotions also require a deeper sociological or psychological background.

4.4 Fine-grained Emotion Analysis Based on Emotion Lexicon

We used an emotional lexicon to get a more detailed sentiment classification based on eight emotion types: happiness, fear, surprise, sadness, evil, anger, good and the unknown. The lexicon we used is from [10].

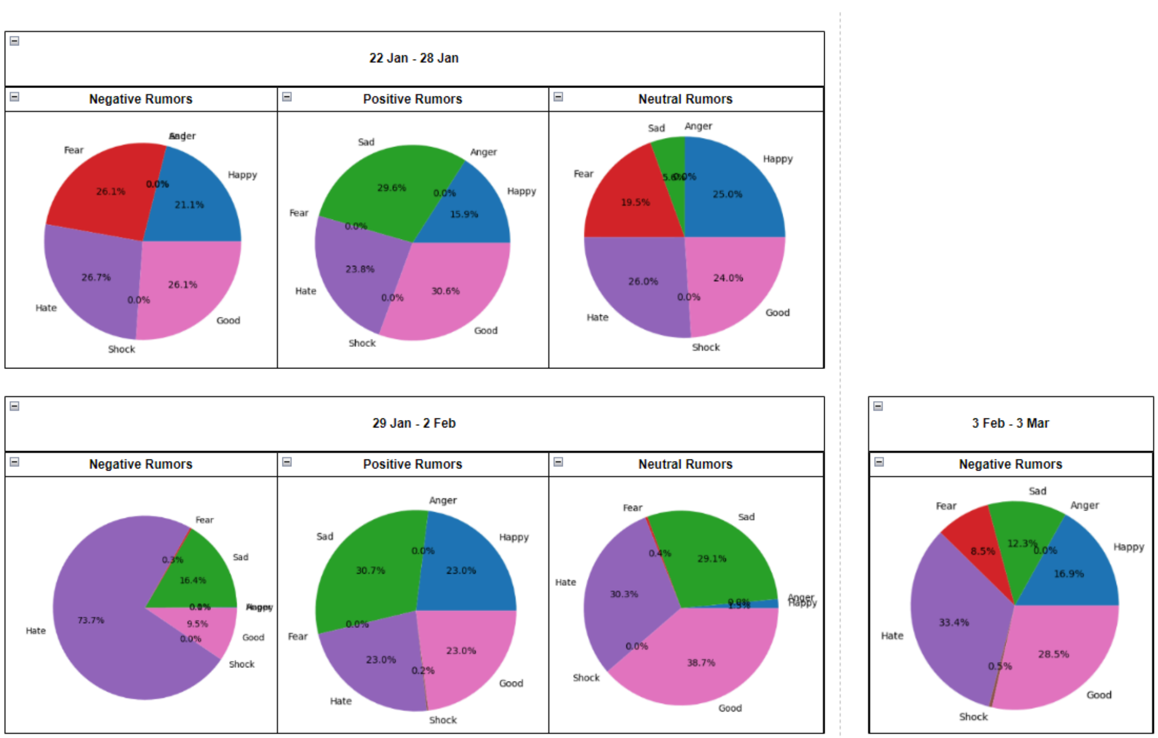
The diagram below shows a fine-grained division of rumors of different polarities during different time periods. The content of many negative-polarity rumors is unknown, and only the rumors that can be obtained are observed here, so the proportion of fine-grained emotion divisions in the chart may not be accurate. It should be noted that "good" in emotion classification is more inclined to emotions such as wishes and belief, and is not entirely tied to information polarity.

In the initial stages of the epidemic (within the first week of Wuhan’s lockdown), negative rumors were dominated by hatred and fear. A quarter of them are emotions of happiness. By looking up corresponding examples, we can find that this happy emotion mainly comes from: 1. The lockdown coincides with the Chinese Spring Festival; 2. People are cheering for the control of the epidemic. Most of the hatred and fear come from annoyance about not closing the city earlier, panic about the lockdown and the disease. The positive emotion rumors at this stage are mainly blessings and prayers, while the fine-grained emotions in neutral rumors are relatively evenly distributed, because most of the neutral rumors at this stage are pseudoscientific remarks related to the epidemic and epidemic prevention.

From January 29 to February 2, the main Weibo rumors were: 1. Evacuated overseas Chinese from Japan; 2. SF Express misappropriated epidemic prevention supplies; 3. The United States developed a specific drug to suppress the coronavirus. Rumors about evacuation of overseas Chinese (positive polarity) demonstrate the power of the country and bring pride and peace of mind to the people. This is also the reason why the proportion of good emotions in positive and neutral rumors increases. Rumors that SF Express had misappropriated anti-epidemic supplies also caused people’s shock and disgust. As the epidemic worsens and rumors about related research emerge, people are becoming more panicked.

From February 3 to March 3, since our data set only has rumors of negative polarity, we will only conduct analysis based on existing data. It can be seen that sad emotions began to appear, people were more affected by the tragedy caused by the epidemic, and the emotions related to prayer began to decrease greatly. At the same time, rumors spread widely during this period, such as "A Chinese woman received a green card from the United States, by generously donating 200,000 masks to the United States, and said, "I am not Chinese." This unpatriotic behavior also filled the public with derogatory comments.

4.5 Emotional Analysis on Rumor Comments Based on Emotional Lexicon



We will conduct a fine-grained sentiment analysis on the comments of the rumors. It is worth mentioning that many comments are missing from the original data. It is speculated that it may be because the rumors are spread too widely and cause too many negative emotions, which leads to the blocking or deleting of relevant information.

In the early days of the epidemic, since the impact of the epidemic had not yet spread across the country, good and happy accounted for nearly half of the proportion of comments. Negative rumors mainly focus on information about the lockdown and about people escaping from the lockdown. Disgust and fear accounted for more than half of the comments, mainly "refuting rumors" and fear of closing the city; the other half were good and happy emotions to cheer up the fight against the epidemic. There are also many positive rumors that are mainly about closing the city, they are classified as positive due to expressions similar to "Sealing a province to protect a country's people". In the comments of such rumors, blessings dominate the comments. There are still a lot of sad or hate comments, mainly condemning the untimely closure of the city and worrying about the people affected by the epidemic. There are also schadenfreude comments that are similar to "hahahaha". However, the model we built did not do a good job of integrating this, such emotions are distinguished directly under the happy category.

The analysis from January 29 to February 2 requires reference to the fine-grained sentiment analysis of the rumor itself in the previous section. During this period, negative rumors were mainly about SF Express secretly intercepting materials to fight against the epidemic. From the comments, we can feel that people have strong disgust and pessimism about this bad incident that affects personal safety and nation unity. A small part of the positive segmentation comes from "Good morning" and other comments unrelated to the incident. The positive rumors are about "Japan evacuating overseas Japanese from China", in which the four emotions of sadness, happiness, good, and disgust are relatively evenly distributed. The comments are mainly: 1. Envy of Japan's display of national power (good); 2. Complaining about China's policies (sad, hate); 3. Dislike (disgust) about spreading rumors that harm national unity. Neutral rumors are mainly social news and some popular science. Comparing charts and raw data, we can see that people have a strong ability to identify rumors, and they also have strong aversion to the spread of false news (shock, sadness) . As for the news that the United States has found a way to suppress the coronavirus, the sentiments in the comments are mostly based on prayers, conspiracy theories, and anti-conspiracy theories. This is also the reason for the high proportion of good, sad, and hate.

After February 3, many rumors were related to the news that the United States had found ways to suppress the coronavirus. This news gave many people hope that the epidemic could be quickly controlled, and the sentiment breakdown of the comments also showed this. Similar to this situation, there are rumors about the unblocking and elimination of the epidemic. The main aversion still comes from people's disgust with the spread of false news. The proportion of fear has also begun to increase, mainly due to the increasingly serious situation of the epidemic and the panic caused by many "suspected science popularization" rumors.

5 Summary

In this assignment, we conducted quantitative analysis and sociological analysis based on Weibo rumors collected from January 22 to March 3, trying to examine the influencing factors of rumor spread and predict the development trend of rumors. At the same time, we mainly analyzed the emotions contained in the rumors. These emotions help the government understand the information that the people need during the epidemic, so as to better unite the people and fight the epidemic together; this study can also prepare for the corresponding future responses by providing some guidance during negative events.

The spread of rumors reveals the public's demand for various epidemic information. After the outbreak, local governments implemented isolation policies to reduce the movement of people. People were isolated from others in the real environment, and the Internet and media became the only channels for obtaining information. Insufficient understanding of the coronavirus has led to the spread of panic among the public, and the spread of information has become the biggest motivation for people to remind others to pay attention, seek help, and seek peace of mind. At the same time, disclosing information in a timely manner gives rumors space to survive, and negative rumors related to livelihood security and life safety have also intensified social conflicts.

The "unknown" about the epidemic has provided a wide range of attention and space for pseudoscience or rumors about epidemic research and drugs. Fortunately, most people have the ability to distinguish the truth from falsehoods of such rumors, and are disgusted by the spread of such false news, which to a certain extent, speeds up the official screening and blocking of false news in a "self-purification" manner.

The control of rumor spread is inseparable from the government's participation, and the control of rumor spread in public health emergencies is an important part of the government's emergency management. The government must be oriented to expand governance space, integrate governance tools, and mobilize governance subjects in order to comprehensively respond to public opinion caused by the spread of rumors. Strengthening communication between the government and the public and satisfying the people's right to know are considered to be the most effective means of controlling the spread of rumors.

The generation and dissemination of rumors are ultimately achieved by word of mouth or reprinting on the Internet. Many researchers also realize that the uneven quality of citizens contributes to the spread of rumors. "Old rumors are spread new" is partly due to malicious spreading by netizens, and partly because the public lacks basic discernment capabilities. We can find from research data that the same rumor event will be spread repeatedly in different ways of expression. This kind of out-of-context, or The expression method of synonym substitution also makes it more difficult to identify rumors. Only by improving the scientific literacy of the public, providing psychological counseling to the public, and quantifying positive social psychology can the public become immune to rumors.

The amount of data in this experiment was small, and a lot of information was lost due to blocking or deletion. Since the raw data is not labeled with emotions and polarity, we modeled the comments on Weibo during the epidemic and used this model to judge the emotional classification of rumors. This approach itself will bring certain biases. In-depth and accurate qualitative or quantitative research requires the support of larger-scale data and better modeling.

References

[1] nCoV_100k https://aistudio.baidu.com/datasetdetail/24278

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