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Full Length Article

Public opinion analysis of novel coronavirus from online data

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1. Introduction

The outbreak of novel coronavirus [1] with pneumonia-like symptoms has spread widely throughout the world, with millions of cases reported in hundreds of countries. Public around the world are accessing novel coronavirus information, expressing opinions and sharing ideas freely through online media. The amount of the netizens’ active comments about novel coronavirus has reached unprecedented levels. One reason why this event attracted so much attention is that no specific treatment is available for the novel coronavirus. In addition, it belongs to the subfamily Coronavirinae in the family Coronaviridae [2] as the well-known coronavirus SARS-CoV in 2002. As of July 23, the COVID-19 epidemic has infected 15,429,889 and caused more than 600,000 deaths all over the world, whose situation is more severe than SARS.

Generally, public opinion refers to the social and political attitudes held by the public towards the emergence, spread, and change of social events in a certain social space. Public opinion is expressed through three basic components: entities, behaviors and emotional words. The entities of public opinion include public, the media, administrative departments and service departments involved in the COVID-19 event. The news about COVID-19 proves an important part of the public opinion evolution by affecting the behaviors of objects. Public opinion greatly affects epidemic prevention and control in many aspects. Motivated by the positive public opinion, public behaves under the guidance of experts, reduces trips actively as well as begins to wear masks, which partially benefit the positive effects of COVID-19 epidemic prevention and control. However, during the epidemic, public opinion leads to a negative impact on epidemic prevention and control for public’s passive attitude on this epidemic. For instance, countries such as Italy and Japan take no measure to the spread of virus, resulting in a rapid infection growth. The behaviors like ignoring the experts’ suggestions, fleeing the severely affected area of the epidemic, going out without masks, also impact the prevention and control of the epidemic negatively.

The potential reasons for the changes of public opinion are the evolution of public knowledge for the spread and development of social event. The information contained in social events enhances the public’s knowledge. The knowledge acquired by the public will cause their emotional changes, further resulting in behavior adjustment, which will impact on entities. In the standard model prediction in social psychology, behavior is a product of a series of cognitive and affective events [3]. As a proverb goes, "Once bitten, twice shy of ten years ". After being bitten (the process of harvesting knowledge), people develop a fear for snakes, preventing themselves from being bitten again to some extent. Therefore, the public’s mood will become negative following public’s knowledge from negative public opinion, and subsequently leading to a series of negative behaviors. In summary, the implicit knowledge evolution and public opinion during the epidemic is closely related to the emotions, behaviors, and entities.

Quantitative survey with structured questionnaires is a kind of prominent methodology in public opinion evaluation. Nevertheless, our approach takes advantage over the questionnaires by applying continuous and time-sensitive news as research data and improving the objectivity and reliability of the changes of public opinion on various stages.

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Our contributions are as follows. First, we build a knowledge set including public opinion, behaviors and entities as well as part of speech according to their characteristic of distribution in corpus. Second, a deep neural network model, Key-Information-oriented Convolutional Neural Network, is proposed to mine the public opinion hidden in the texts. The consequence shows that public opinion changes rapidly since the emergence of the COVID-19, especially when explosive news occurs. News information results in people’s knowledge evolution, further leading to changes in behaviors and public opinion. The rest of the paper is organized as follows. We start by reviewing related work. In Section 3, the details of the models are introduced. Finally, the experimental results are drawn in Section 4.

2. Related work

Scientific research is of great significance in solving epidemics. There have been many studies on novel coronavirus pathology, transmission as well as treatment guides people to use the right methods to fight against novel coronavirus.

Pathological research All these viruses (SARS-CoV in 2002, MERS-CoV, and the 2019 novel coronavirus) belong to the subfamily Coronavirinae in the family Coronaviridae [2]. Studies of pathology suggested the 2019 novel coronavirus probably transmitted from bats after mutation conferring ability to infect humans [4-6], which is currently thought to be milder than SARS and MERS, and takes longer to develop symptoms. In terms of laboratory tests, the absolute values of lymphocytes in most patients were reduced [7]. Scientists suggested that 2019 novel coronavirus might use ACE2 as the receptor, despite the presence of amino acid mutations in the 2019 novel coronavirus receptor-binding domain [8].

Virus transmission Studies showed that person-to-person transmission exists [9]. It often happens when someone comes into contact with an infected person’s secretions, such as droplets in a cough. Experts also confirmed that asymptomatic carriers can also spread virus to others [10]. For individuals, good personal hygiene, fitted mask, ventilation, and avoiding crowded places will help to prevent CoVs infection [11]. Both N95 respirators and medical masks can effectively prevent influenza and other viral respiratory infections [12]. Scientists estimated the mean incubation period of 2019-nCoV was 5.2 days and a R0 of approximately 2.2, meaning that on average each patient has been spreading infection to 2.2 other people [13]. In addition, results derived from evolutionary analysis suggest that a homologous recombination may occur within the viral receptor-binding spike glycoprotein, which may determine cross-species transmission [14].

Public Opinion Public Opinion is defined as the aggregated preferences of the populace, or some subset thereof, on a matter of social interest [15], which is closely related to social psychology. Public opinion research has been used in many disciplines since the 1930s, including political science, psychology, media/communications and history. Quantitative surveys with structured questionnaires are the most prominent methodology [16]. Studies in recent years have shown that network public opinion reflects people’s social and political attitudes, so it is of great significance to study the trend prediction and evaluation of network public opinion, which can provide decision basis for managers [17]. Some WeChat Official Accounts using collected questionnaires as research data stated that the public’s mentality has changed significantly during the epidemic. However, collecting questionnaires as research data has certain limitations. First, the limited number of options may not contain the one people wanna choose. Moreover, the collection and collation of questionnaires is cumbersome. In addition, evaluating individual’s emotion is an inherently subjective task. Using questionnaires does not adequately account for the diversity of reply, for example, some individuals may tend to avoid the extremes of the scale while others may not. Continuous and highly time-sensitive news helps improving the objectivity and reliability of the changes of public opinion across several stages as opposed to questionnaires.

3. Model

Public opinion data and model are the two factors which influence the performance of public opinion calculation and analysis. The quality of data impacts on the result of the public opinion calculation model. The model’s result furthermore impacts on analysis of public opinion trend. This section introduces the data cleaning method, public opinion calculation model and public opinion trend analysis methods.

3.1. Words similarity model

The news posted online by the media or netizens expresses public opinion truthfully. However, data preprocessing is inevitable since the data always containing much noise.

Obtaining a large number of trigger words, a set of synonyms, is essential to the process of selecting related sentences from corpus. The skip-gram model of word to vector [18] is applied to train word vectors. The skip-gram model converts words to vectors to predict the probability of each word appears in texts context window based on the current word in a sentence. The vector representation of the word contains more semantic information of the context window, which is helpful for calculating the similarity of two words. The learned vectors explicitly encode many linguistic regularities and patterns. For example, the result of a vector calculation vec(“Germany”) + vec(“capital”) is closer to vec(“Berlin”) than to any other word vector [18]. The similarity between two words obtained by calculating the cosine value between the two vectors.

We define some trigger words manually as the seed words for similarity calculation. After finishing word vectors training by word to vector model, it outputs the similar words with the seed trigger words defined. Give a sequence words \( \{w_1, w_2, w_3, \ldots , w_N\} \) with size \( N \), whose vectors are represented as \( \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \ldots , \mathbf{v}_N\} \). The similarity between word \( w_i \) and \( w_j \) is:

\[
sim_{ij} = \cos(\mathbf{v}_i, \mathbf{v}_j)
\]

However, trigger words calculated by word to vector model is not always accurate. For example, top 10 words similar with ‘病毒 (virus)’ calculated by word to vector model are ‘nCov’, ‘病原体 (pathogen)’, ‘肺炎 (pneumonia)’, ’支原体 (mycoplasma)’, ‘潜伏期 (incubation period)’, ‘病毒性 (virulence)’, ‘特性 (character)’, ‘SARS-CoV’, ‘宿主 (host)’. There are two words ‘潜伏期 (incubation period)’ and ‘特性 (character)’ appear frequently with ‘病毒 (virus)’ at the same sentence. But it’s not related closely with ‘病毒 (virus)’ in this particular research. Manual screening is further launched to ensure trigger words calculated as accurate as possible. After that, sentences contain trigger words are selected as dataset of this research.

3.2. Key-Information-oriented convolutional neural network (KIN–CNN)

Public opinion is described by emotions, behaviors and entities. For the problems of entity diversity and the semantic variability in the dataset, a Key-Information-oriented Convolutional Neural Network (KIN–CNN) is proposed to mine the public opinion hidden in the texts. In this section, the details about this model are introduced. The input of this model is sentences processed according to the method of Section 3.1. The output is emotions, behaviors and entities.

The proposed information mining model is based on Convolutional Neural Network (CNN) [19]. To improve its performance, we integrate prior knowledge from knowledge set. The key information in this model includes two information channels, each as a kind of convolutional kernel. One is data-oriented channel, which consists of the main features effectively extracted from the texts. Another channel is based on priori knowledge, called PK-based channel (Fig. 1).

3.2.1. Data-oriented channel

Data-oriented channel is one of the important component of this model. It consists of emotions, behaviors and entities in the knowl-
edge set. The collection of different kinds of words is called word filters. All of the information is extracted from our dataset automatically by word similarity calculation. Six-dimensional emotions are used in this research for analyzing the public opinion, which named ‘love’, ‘joy’, ‘angry’, ‘fear’, ‘sad’ and ‘surprise’. Five kinds of entities and four kinds of behaviors are constructed respectively. The entities are ‘media’, ‘specialist’, ‘virus’, ‘patient’ and ‘government’. The behaviors contain ‘media reports’, ‘increase in infections’, ‘adopt policies’ and ‘not cooperate’. Then, we generate the similar words by Eq. (1) for each category of emotions, entities and behaviors.

In the data-oriented channel part, word filter is selected by data category, which means that when searching the entities about category A, the word filters used in this stage are the synonym set of category A.

To capture the significant information of public opinion in the sentence. The word filters established are convolved with the n-grams in the sentence to calculate the similarity scores. The approach based on convolution is able to capture semantically similar public opinion words other than the words in the word filters.

In particular, the word filter \( f = [f_1, f_2, \ldots, f_d]^T \) is convolved with input matrix \([v_1, v_2, v_3, \ldots, v_N]\). The convolutional window size is \( k \). Traditional convolution operation is modified by us to enable each word filter to generate a feature map \( f_m \), which represents the similarity between word filters and k-gram word vectors \([v_i, \ldots, v_{i+k-1}]^T\) in the sentence. The feature map \( f_m \) can be precisely expressed by the following equation:

\[
f_m = \frac{1}{k} \sum_{j=1}^{k} f_j^T v_{i+j-1} + b
\]

where \( b \) is a bias term. In Eq. (2), the result \( f_m \) represents cosine similarity between word filters \( f_j^T \) and input vector \( v_{i+j-1} \).

The purpose of this model is to extract significant feature from the feature map. Therefore, max-pooling is chosen to further aggregate the convolution results for each filter. The process of max-pooling for each feature map is described in Eq. (3).

\[
pol = \max \{ f_m \} = \max \{ f_{m_1}, f_{m_2}, \ldots, f_{m_{n-k+1}} \}
\]

3.2.2. Priori-Knowledge-Based channel

We integrate part-of-speech into convolutional kernel calculation for most involved words can be characterized by this essential feature. Commonly, what we need is noun, verb, adjective and adverb words. Therefore, the representation of part-of-speech feature is part of the knowledge set, included as another convolutional kernel for the calculation process.

In the KIN-CNN model proposed in this research, another feature map is based on the part-of-speech. It is calculated by the Eq. (2). Where \( f = [f_1, \ldots, f_d]^T \) represents the vectors of different part-of-speech selected from the knowledge set and \( k = 1, [v_i, \ldots, v_{i+k-1}]^T \) is the part-of-speech vector of k-gram. It means that all feature maps of nouns, verbs, adjectives, and adverbs are found by convolving part-of-speech set with the input matrix. Max-pooling is operated to aggregate the convolution results by Eq. (3).

The feature map for words is obtained by two convolutional processes described above. After that, the final features are gotten by intersection or union process.

The last step for this model is an intersection or union calculation. Intersection and union process are employed under different circumstance. Specifically, we choose union set when calculating emotional word because public express their opinion by vocabularies with different part-of-speech. On the contrary, intersection is chosen when calculating behavior word to improve the accuracy of the features.
3.3. Public opinion analysis

In terms of the content, public opinion data can be divided into two categories, objective texts and subjective texts. Objective texts are the content expressed in words. Subjective texts represent one view of the public, which are shown as the adjectives and adverbs. The subjective view is represented by the objective content. And analysis of subjective texts is helpful to mine the correlation between subjective information and public opinion. The details for public opinion calculation process are shown in Fig. 2.

To analyze the opinion trend, the KIN–CNN model outputs the key words that can describe various public opinion categories within each period, whose frequency and probability are analyzed to get the leading opinion of each period as the event develops.

\[
P_{op}^t = \frac{N_{op}^t}{N_{all}^t}
\]

(4)

where \( P_{op}^t \) refers the probability of public opinion of \( t \)-th category in the \( i \)-th period, \( op \) belong to one of the six opinion categories, \( N_{op}^t \) represents the number of the words about public opinion of \( t \)-th category in the \( i \)-th period. If \( P_{any>op}^t \) is higher than the probability of other categories in \( i \)-th stage, it means that public feel angry about this issue in this stage.

The variation of public opinion is driven by the development of social events. Formula (5) is to find the behavior leading to the dominant public opinion of \( i \)-th stage, \( S(V_i^{OP_{main}}) \) is the score of each kind of behavior.

\[
S(V_i^{OP_{main}}) = \frac{f_{re}(V_i^{OP_{main}})}{f_{re}(V_i)}
\]

(5)

where \( f_{re}(V_i^{OP_{main}}) \) indicates the number of sentences including behaviors of category \( j \) and the dominant public opinion words of \( i \)-th stage at the same time, \( f_{re}(V_i^t) \) is the number of sentences containing behaviors of category \( j \). The behavior with the highest score is the main reason leading to dominant public opinion of \( i \)-th stage.

In the chain of events, public opinion will influence the decision-making of the object entities, leading to new behaviors.

\[
S(OP_i^t) = \frac{f_{re}(V_i^{OP_{main}})}{f_{re}(OP_i^{main})}
\]

(6)

where \( S(OP_i^t) \) means the score of dominant public opinion of \( i \)-th stage leading to the new behavior \( V_i \), \( f_{re}(OP_i^{main}) \) represents the number of sentences that contain the dominant opinion words at this stage.

The subject of public opinion are entities. If the specific public with dominant opinion is found, many kinds of measures can be made to keep things under control. In this research, all of the entities are mined from the dataset.

\[
S\left( E_i^{OP_{main}} \right) = \frac{f_{re}(E_i^{OP_{main}})}{f_{re}(E_i^t)}
\]

(7)

The result of function (7) implies the correlations of entities in objective texts and the public opinion. Where \( S(E_i^{OP_{main}}) \) is the score of entities of each category with dominant public opinion \( OP_{main} \), \( f_{re}(E_i^{OP_{main}}) \) refers the number of sentences contain entities of category \( j \) and dominant public opinion words of \( i \)-th stage, \( f_{re}(E_i) \) is the number of sentences with entities of category \( j \).

4. Experiment

Experiments are launched by the model proposed in Section 3 to study the trend of public opinion. First, the useful dataset is collected from baidu search engine1 and processed according to the process of Section 3.1. Then we mine the trend of potential public opinion in the texts. As a conclusion, the experimental results are analyzed in Section 4.2.

4.1. Datasets

The dataset used in this research is crawled from a popular news websites. The key words used to claw news about the new coronavirus epidemic are ‘病毒 (virus)’, ‘冠状病毒 (coronavirus)’, ‘19-nCov’, ‘COVID-19’, ‘肺炎 (pneumonia)’, ‘感染 (infection)’ and so on. The news data is mined from Internet, whose release date is ranging from January 1, 2020 to July 7, 2020. We filter and sort the data to obtain 80,183 sentences in chronological order. The sentence filtering method is discussed in Section 3.1.

The words involved in the calculation of the sentences include emotions, behaviors, and entities. Six-dimensional emotions are used to classify emotional words, they are ‘love’, ‘joy’, ‘angry’, ‘sad’, ‘fear’ and ‘surprise’. The five entity categories are ‘media’, ‘specialist’, ‘virus’, ‘patient’ and ‘government’. The behavior categories are ‘media reports’, ‘increase in infections’, ‘adopt policies’ and ‘not cooperate’. Part of the emotional words calculated are shown in Table 1 which will be used in subsequent public opinion calculation.

4.2. Public opinion calculation result

Public opinion changes rapidly from the beginning of the COVID-19 event as is shown in Fig. 3. The subgraph left describes the trend of dominant public opinion of each period from January 1, 2020 to July 7, 2020. At the same time, the subgraph right expresses the probability of each emotion category.

The histogram describes that the dominant public opinion at the first period is fear. However, in a long period from January 1, 2020 to July 7, 2020, the dominant public opinion is love and joy. In the early morning

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1 https://www.baidu.com/?tn=news
of January 21, 2020, the world health organization gave a respond to the outbreak of pneumonia caused by the COVID-19 infection. “There is currently evidence of limited human-to-human transmission but no clear evidence of sustained human-to-human transmission”, according to a report in the Beijing news. The next day, the infection further expanded. At the same time, the Hubei government decided to initiate a secondary emergency response to public health emergencies. Public still keep a positive attitude to the break and spread of COVID-19. It’s surprise that the COVID-19 spread wildly around the world when the epidemic in China is under control. At around April 20, 2020, the emo-
tion of surprise reached the peak. After that, angry become the dominant emotion, mainly because public in many countries is against to government’s effort of controlling the epidemic by restricting civil liberties.

The histogram of Fig. 4 shows the behaviors which lead to dominant opinion variation within each period. The curve in the right block is the probability of each behavior category of the total. At the beginning, the infections keep growing, leading to the fear emotion of public. It’s hard for public to foresee the seriousness of the situation at that period. Most people keep optimistic about this event. As the infection number grows, the government begins to adopt policies to limit activities available for the public. The yellow line of right subgraph keeps growing shaky among January and February. It causes widespread concern and a wave of panic. An obvious inflection point in the above two charts appears in late February. The event of refusal to cooperate has increased significantly for most people has been stayed at home for a long time. Workers can’t return to work, students can’t go back to school, and it is hard to go out for entertainment. Both elders and youngsters are very anxious. As the epidemic develops, more people refuse to cooperate and protest government to control the epidemic by restricting civil liberties in many countries. In addition, many officers execute the affair violently to cause the dissatisfaction.

As is shown in Fig. 5, the participants of the event mainly include the media, health-care experts, viral pneumonia, patients and government or organization. The histogram of Fig. 5 shows the influential entity leads dominant opinion of each period. The curve describes the probability of entities belonged to different categories of the total. At the beginning of the time line, the virus outbreaks and keeps increasing steeply. It has dwindled after late February while rapidly risen with the global outbreak. The left subgraph shows dominant emotion is determined by the experts, since their words proved more authoritative and easier to be convinced. After April, the voice of the government came to dominate gradually. The policy adopted by government has played a decisive role in the development of the epidemic and has largely influenced the public’s opinion. The curve of Fig. 5 shows more and more citizens pay attention to the voices of patients as the event developed. Some patients were cured and discharged to be a vocal individual.

Fighting the epidemic is a long process against all expectations. In the process, the whole society experienced panic, anger and hope. Thankfully, people have basically been confident in the measures taken by the government as is shown of Fig. 6. It shows that though this is an once-in-a-century event, the government’s behaviors have largely maintained social stability. Although there have been actions such as violent law enforcement, privately setting up checkpoints and roadblocks, preventing medical personnel from entering the community, they are only an episode in the anti-epidemic process to ensure the overall trend remains good.

The frequency of words appearing in texts can express public’s attitude to an event. We construct a three-level relationship among emotions, behaviors and entities by counting the frequency. For example, we calculate the frequency of all emotion words in corpus of stage 1, and the top four words with the highest frequency are positive, severe, worry and panic. Then we calculate the frequency of words about behaviors that appear in the same sentence with the four high-frequency emotional words respectively, and then count the highest frequency entities related to these behaviors using the same method to establish the relationship of emotions, behaviors as well as entities. Marked by boxes are the different high frequency emotional words that appear at each stage compared to the previous one. The first stage is compared with stage 2. The original vocabularies are Chinese, which are translated into English as Fig. 7 shown.

The emotional words with high-frequency in the first stage are positive, severe, worry and panic. At this stage, the epidemic situation has emerged more than one month whose influence is growing. Even though the highest frequency emotional word is positive, another three emotions, severe, worry and panic, express the negative emotion of the public. The high-frequency behaviors at this stage are mainly infection, cold, prevention and control, cooperation and so on, which describes the prevention and control proceeded in an orderly manner. The high-frequency entities involve countries, viruses, patients, and hospitals.
Optimistic and love appears in the high-frequency emotional words in the second stage, because the epidemic of China has been under control. In the third stage, the epidemic outbreaks globally. The public’s emotion become negative again during that period. Optimistic and love change to severe and panic. The high-frequency entities at this time still fall in words related to the virus and pneumonia. However, positive still is the high-frequency emotional word at this stage. Vigilant and anxiety become the high-frequency emotional words in the fourth stage. The number of confirmed cases continues to rise around the world to affect the national economy.
However, positive is the high-frequency emotional words on the whole, indicating that despite the serious developments, the whole society still maintains a positive attitude.

5. Conclusion

This paper proposes a public opinion trend analysis method on Novel Coronavirus. The research helps to raise constructive guidance for epidemic prevention and control by monitoring public emotions. To support the research, a Key-Information-oriented Convolutional Neural Network (KIN-CNN) is proposed to output the key words possessing potential public opinion from the texts. Caused by objective information, public opinion prevents prediction from drawbacks of subjectivity and complexity like questionnaire survey. We construct relationship between the dominant public opinion in every stage and entities as well as behaviors by analyzing the frequency and probability of key words in each category. We come to a conclusion that public opinion keeps changing in the epidemic development. But on the whole, the circumstance is optimistic, and public is positive towards future development.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Michelle Holshue, Chas DeBolt, Scott Lindquist, Kathy Lofy, John Wiesman, Hollieanne Bruce, Christopher Spitters, Keith Ericson, Sara Willkerson, Ahmet Tural, George Diuk, Amanda Cohn, LeAnne Fox, Anita Patel, Susan Gerber, Lindsay Kim, Suxiang Tong, Xiaoyan Lu, Steve Lindstrom, Satish Pillai, First case of 2019 novel coronavirus in the United States, N. Engl. J. Med. (2020), doi:10.1056/NEJMo2001191.

[2] Geng Li, Yaoshuo Fan, Yanzi Lai, Tianian Han, Zonghui Li, Peiwen Zhou, Pan Pan, Wenhao Wang, Dingwen Hu, Xiaohong Liu, Qiwei Zhang, Jianguo Wu, Coronavirus infections and immune responses, J. Med. Virol. 92 (2020), doi:10.1002/jmv.25685.

[3] Wendy Wood, J.M. Quinn, D.A Kashy, Habits in everyday life: thought, emotion, and action, J. Pers. Soc. Psychol. 83 (2002) 1281–1297, doi:10.1037/0022-3514.83.6.1281.

[4] Na Zhu, Dingyu Zhang, Wenling Wang, Xinwang Li, Bo Yang, Jingdong Song, Xiang Zhao, Baiying Huang, Weifeng Shi, Roujian Lu, Peihua Niu, Faxian Zhan, Xuejun Ma, Dayan Wang, Wenbo Xu, Guihen Wu, George Gao, A novel coronavirus from patients with pneumonia in China, 2019, N. Engl. J. Med. 382 (2020), doi:10.1056/NEJMo2001017.

[5] Fan Wu, Su Zhao, Bin Yu, Yanmei Chen, Wen Wang, Zhi-Gang Song, Yi Hu, Zhao-Wu Tao, Jun-Hua Tian, Yuan-Yuan Pei, Ming-Li Yuan, Yu-Ling Zhang, Fa-Hui Dai, Yi Liu, Qi-Min Wang, Jiao-Jiao Zheng, Lin Xu, Edward Holmes, Yong-Zhen Zhang, A new coronavirus associated with human respiratory disease in China, Nature (2020) 1–8, doi:10.1038/s41586-020-2008-3.

[6] Domenico Benvenuto, Marta Giovannetti, Alessandra Ciccozzi, Silvia Spoto, Silvia Angeletti, Massimo Ciccozzi, The 2019-new coronavirus epidemic: evidence for virus evolution, J. Med. Virol. 92 (2020), doi:10.1002/jmv.25688.

[7] Nanshan Chen, Min Zhou, Xuan Dong, Jiemin Qu, Fengyun Gong, Yang Han, Yang Qiu, Jingli Wang, Ying Liu, Yuan Wei, Jia’an Xia, Ting Yu, Xinzin Zhang, Li Zhang, Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study, Lancet 395 (2020), doi:10.1016/S0140-6736(20)30211-7.

[8] Roujian Lu, Xiang Zhao, Juan Li, Peihua Niu, Bo Yang, Honglong Wu, Wenling Wang, Hao Song, Baiying Huang, Na Zhu, Yuehai Bi, Xuejun Ma, Faxian Zhan, Liang Wang, Tao Hu, Hong Zhou, Zhenhong Hu, Weimin Zhou, Li Zhao, Genomic characterisation and epidemiology of 2019 novel coronavirus: implications for virus origins and receptor binding, Lancet 395 (2020), doi:10.1016/S0140-6736(20)30251-8.

[9] Jasper Chan, Shuofeng Yuan, Kin-Hang Kok, Kelvin To, Hin Chu, Jin Yang, Fan-fan Xing, Jieling Liu, Cyril Yip, Rosanna Poon, Hoi-Wah Tsio, Simon Lo, Kowk-Hung Chan, Vincent Poon, Wan-Mui Chan, Jonathan Ip, Cai Juice, Vincent Cheng, Honglin Chen, Kwok-Yung Yuen, A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster, Lancet 395 (2020), doi:10.1016/S0140-6736(20)30154-9.

[10] Camilla Rothe, Mirjam Schunk, Peter Sothmann, Gisela Bretzel, Guenter Froschel, Claudia Wallrauch, Thorbjörn Zimmer, Verena Thiel, Christian Janke, Wolfgang Goggemos, Michael Seilmair, Christian Drosen, Patrick Vollam, Karin Zwirglmaier, Sabine Zange, Roman Wölfe, Michael Hoelscher, Transmission of 2019-nCoV infection from an asymptomatic contact in Germany, N Engl J Med (2020), doi:10.1056/NEJMc2001468.

[11] Yu Chen, Qianyun Liu, Deyin Guo, Emerging coronaviruses: genome structure, replication, and pathogenesis, J. Med. Virol. 92 (4) (2020) 399–459.

[12] Ming, Wai-Kit, Huang, Jian, Zhang, Casper. (2020). Breaking down of the healthcare system: mathematical modelling for controlling the novel coronavirus (2019-nCoV) outbreak in Wuhan, China. 10.1101/2020.01.27.922443.

[13] Qin Li, Xuhua Guan, Peng Wu, Xiaoye Wang, Lei Zhou, Yeqing Tong, Ruixi Ren, Kathy Leung, Eric Lau, Jessica Y Wong, Xuesen Xing, Nijuan Xiang, Yang Wu, Chao Li, Qi Chen, Dan Li, Tian Liu, Jing Zhao, Man Li, Zijian Feng. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia, N Engl J Med (2020), doi:10.1056/NEJMc2001316.

[14] W. Ji, W. Wang, X. Zhao, J. Zai, X. Li, Cross-species transmission of the newly identified coronavirus 2019-nCoV, J. Med. Virol. 92 (4) (2020) 399–459.

[15] E. Lamp, H.M. Keplinger, Public opinion, media effects on, The International Encyclopedia of Communication, 2008, doi:10.1002/9781405186407.ebicelp125.

[16] Roger Mortimore, in: Public Opinion Research, The Blackwell Encyclopedia of Sociology, 2018, pp. 1–8.

[17] G. Chen, S. Duan, L. Wang, Research on trend prediction and evaluation of network public opinion, Concurr. Comput.: Pract. Expp. 29 (24) (2017).

[18] T. Mikolv, I. Sutskever, K. Chen, et al., Distributed representations of words and phrases and their compositionality[J], Adv. Neural Inf. Process. Syst. 26 (2013) 3111–3119.

[19] R. Collobert, J. Weston, L. Bottou, Bottou Le, M. Karlen, K. Kavukcuoglu, P Kukka, Natural language processing (almost) from scratch, J. Mach. Learn. Res. 12 (Aug) (2011) 2493–2537.