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Exploring the Innovation Path of Cultural Communication News Forms Combined with the BERT Model

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Abstract In the era of big data, the news form of cultural communication is closely related to its dissemination depth and coverage. This paper takes news information as the research object and explores its morphological innovation path based on neural network algorithm. The characterization method of complex network is briefly analyzed as the theoretical basis for the research. Two commonly used key node description indexes, namely, compact centrality and median centrality, are successively described, and the PageBank algorithm is adopted to identify the important nodes in the process of network news dissemination. Considering the multimodal information in the process of news dissemination, a variant of BERT model (HFBM) based on the Transormer model is introduced, and a convolutional neural network is used to extract the modal eigenvectors of tagged words of news information. The model performs classification and prediction of news information sentiment by fusing modalities and their corresponding feature vectors. Combining the above, the model method design of news feature mining and prediction based on BERT model is completed. At the same time, it elaborates the characteristics of news dissemination in the era of fusion media, and combines the proposed news feature mining and extraction algorithm to realize the innovation of the news form path of cultural dissemination. In the news forwarding volume prediction module constructed based on the proposed algorithm, the algorithmic model of this paper always maintains better prediction results during the whole information dissemination process (within 15h). It shows that the designed news feature mining and extraction algorithm is able to accurately model and predict news dissemination trends.

Index Terms BERT model, news feature mining, PageBank algorithm, news dissemination

I. Introduction

In today's world, with the deep development of information globalization and the intense collision of multiple cultures, traditional culture is facing unprecedented opportunities and challenges [1]. As a key channel of information dissemination, news media has a strong social influence, which can make traditional culture blossom in the new era across the limitations of time and space [2], [3]. At the same time, news media have had a significant impact on spreading socialist core values, creating social and cultural atmosphere, promoting cultural innovation and development, and promoting social and cultural heritage and development [4], [5]. News media bear the important responsibility of guiding public opinion, shaping social values, and inheriting cultural essence, and play an irreplaceable role in social and cultural dissemination by guiding the public to think and discuss deeply about the hot issues in society through timely information transmission, in-depth reports and professional comments [6]-[9].

Studying the value of the news media in the process of traditional cultural communication is not only conducive to the in-depth excavation of the social and cultural influence of the news media, but also can further provide new ideas for the innovative development of traditional culture in the new era, which is an important initiative to guard the roots of the national culture, strengthen the cultural self-confidence, and establish cultural identity [10]-[12]. Therefore, actively playing the role of news media to promote social and cultural communication, which is not only the requirements of the times, but also the inevitable trend of social development [13], [14].

In this paper, we firstly explain the complex network characterization method among news information, and use the key node mining algorithm to identify the important nodes in the process of news dissemination. It also discusses in detail the two kinds of descriptive indexes of key nodes, and the definition and operation method of PageBank algorithm. Subsequently, to address the shortcomings of the existing multimodal sentiment analysis methods, based on the BERT model, a multimodal sentiment analysis model (HFBM) is proposed. And analyze how to use the HFBM model to extract the modal features of tag words in network news. Combined with the characteristics of news dissemination in the era of integrated media again, it explores the innovative direction of the news form path of cultural communication. Finally, the sentiment classification performance, news feature mining effect and prediction ability test of HFBM model are unfolded respectively.

II. News Feature Mining and Prediction Based on BERT Modeling

II. A. Complex network characterization methods

The primary difficulty in applying complex network theory to practical scenarios is how to characterize the objective world in terms of complex networks. Multiple sets of time series are transformed into complex networks, and then the structural characteristics of the networks are studied. The most common method is time series characterization. Among them, they are mainly categorized into correlation coefficient method and phase space reconstruction method.

Taking mobile source pollution emissions as an example, the monitoring data of each pollutant emission is a time series that varies with time, meteorology and other factors. Let the time series of pollutant X be $\{X\}=[X(1),\cdots,X(L)]$, and the time series of pollutant Y be $\{Y\}=[Y(1),\cdots,Y(L)]$, and L is the sequence length. The correlation between two time series is calculated by equation (1). If two pollutants have the same trend, it is more likely that there is a propagation path between them. Calculate the correlation coefficients between all pollutant time series of all pollution monitoring points, and use the correlation coefficients as the weights of the edges of the complex network to construct a complex network representation of the pollutant propagation process.

$$\rho_{X,Y}=\frac{\sum_{i=1}^{L}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{L}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{L}(Y_i-\bar{Y})^2}} \tag{1}$$

The core of phase space reconstruction is to map a low-dimensional time series to a high-dimensional phase space, and the dynamics of the transformed time series remain unchanged. For the monitoring data time series $\{X\}=[X(1),\cdots,X(L)]$ of pollutant X, its fluctuation index sequence $v(t)$ is obtained by Eq. (2).

$$v(t)=\frac{X(t+\Delta t)-X(t)}{\Delta t} \tag{2}$$

where Δt is the selected time interval, which can be selected according to the actual significance of the time series, and in the case of pollutant monitoring data, the selected time interval is 1 hour. Then the fluctuation index sequence is transformed into the corresponding symbolic sequence $s(t)$, the symbolic sequence is generally defined as three levels as in equation (3):

$$s(t)=\begin{cases} R & v(t)>0 \\ S & v(t)=0 \\ D & v(t)<0 \end{cases} \tag{3}$$

where R denotes rising, S denotes stabilizing, and D denotes falling.

The time series X is transformed into the symbolic sequence $s(t)$. Based on the coarse-graining method and the phase space reconstruction theory, the dynamic properties of the symbolic sequence can well reflect the properties of the time series. If the symbol sequence $s(t)=[R,S,D,D,D,S]$, from which two combinations of symbols RSD and DDS can be extracted, each combination is regarded as a fluctuation mode. Each unique fluctuation mode represents a node in the network, and the frequency of transformation from one node to another node represents the weights of the directed edges between the two nodes, thus establishing a directed weighted complex network.

II. B. Key Node Mining Algorithm

Key node mining is an important research direction in network analysis. With the development of complex networks such as social networks, transportation networks, logistics networks and so on, key node mining algorithms in complex networks have received wide attention. Key node mining algorithms can be categorized into sorting algorithms and iterative updating algorithms.

II. B. 1) Close centrality

The compact centrality (CC) of a node is defined as equation (4):

$$c_i=\frac{1}{\sum_{j}^{n}d_{ij}} \tag{4}$$

where d_{ij} denotes the shortest distance between nodes i and j and n denotes the total number of nodes.

The tight centrality of a node calculates the reciprocal of the sum of the shortest distances from the node to other nodes. The closer a node is to the center of the network, the greater the tight centrality. This ranking method considers nodes at the center of the network to be of higher importance because the other nodes in the network can be reached the fastest through the sub-nodes.

II. B. 2) Cartesian Centrality

The median centrality (BC) is also concerned with the position of nodes in the network. But unlike tight centrality, median centrality considers nodes with a higher percentage on the propagation path as more critical and is defined as equation (5).

$$b_i = \sum_{j,k\neq i} \frac{g_{jk}(i)}{g_{jk}} \tag{5}$$

where g_{jk} is the number of shortest paths from node j to k, and $g_{jk}(i)$ is the number of shortest paths passing through node i. Mediator centrality takes into account the effect of nodes' location on network connectivity, and pays more attention to nodes at “bridge” positions in the network.

II. B. 3) PageBank Algorithm

PageRank is an iterative updating algorithm for search ranking of websites, and the core idea is to calculate the score value of a web page using the hopping relationship between pages, expressed as equation (6):

$$PageRank(p_i) = \frac{1-q}{N} + q \sum_{p_j \in M(p_i)} \frac{PageRank(p_j)}{L(p_j)} \tag{6}$$

where p_i is the page to be evaluated, q is the jump probability between nodes, $M(p_i)$ is the set of pages linking to p_i, and $L(p_j)$ denotes the set of pages linking from page p_j to other pages.

The PageRank algorithm assumes that the priority of a page depends not only on the number of pages linking to it, but also on the quality of the pages linking to it. This idea focuses on both types of information and fuses both perspectives by means of iterative updating. In complex networks, this is reflected in the fact that the importance of a node is not only related to the number of neighboring nodes, but also to the importance of the neighboring nodes.The disadvantage of PageRank is that it assumes that the probability of jumping between pages is the same, and does not take into account the issue of weights.

II. C.Multimodal Sentiment Analysis Neural Network Model HFBM

While existing multimodal sentiment analysis methods are able to predict, to some extent, the sentiment embedded in the messages posted by users, these models generally have two drawbacks.

The first drawback of existing models is that the models cannot adequately extract the feature information embedded in each modality, i.e., they do not understand the multimodal information deeply enough. With the development of natural language processing in recent years, the Bert model can better extract the feature information embedded in the textual modal information. The Bert model can better extract the feature vectors embedded in the textual modal information and has stronger characterization ability, and through pre-training and fine-tuning, the Bert model can also be well embedded into the multimodal sentiment analysis network model.

The second drawback of the existing models is that they do not do a good enough job of fusing multimodal information; they splice feature vectors from multiple modalities into one long feature vector. This increases the training cost of the network and can result in the fusion-generated feature vector being too long.

The network structure of HFBM, a novel neural network model for sentiment classification prediction for multimodal data proposed in this paper, is shown in Fig. 1. The direct and simple use of pictures cannot well correspond the information of picture modals to the information of text modals, and the existing research results have demonstrated that the experimental results can be better improved by adding its high abstraction level of picture content representation, i.e., picture-extracted tag-word modals, to the information of picture modals. So the multimodal information input to the HFBM contains three modalities in total: picture modality, tag word modality extracted from the picture, and text modality, the convolutional neural network is used for feature extraction of the picture modality information, and the pre-trained Bert model is used for feature extraction of the tag word modality and the text modality, and finally, the feature fusion of the feature vector from the multimodality is carried out by using the attentional mechanism, instead of Finally, the attention mechanism is used to fuse the multimodal feature vectors instead of directly splicing the feature vectors from multiple modalities, and finally the fused feature vectors are classified by SoftMax to obtain the sentiment classification results.

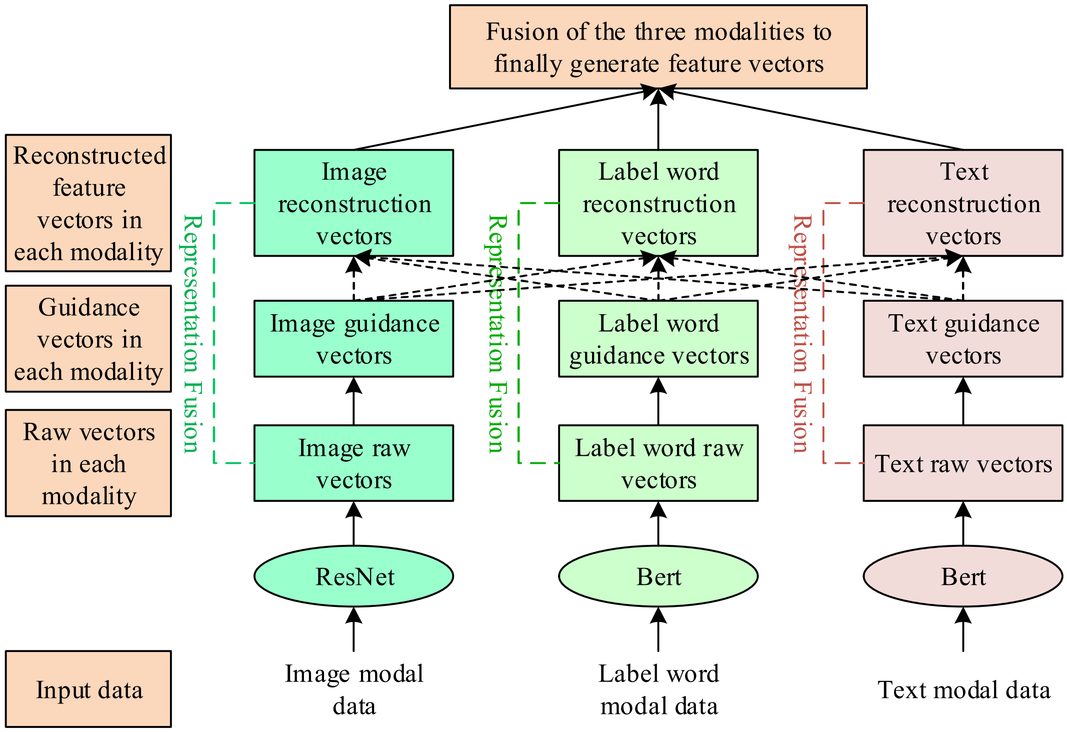


Figure 1: HFBM network structure

II. D.Tag word modal feature extraction

Unlike existing HFM methods that use bidirectional LSTM processing for tag word modals, HFBM uses the Bert model to process tag word modal information, and since the core of the Bert model lies in pre-training and fine-tuning, the Bert model needs to be pre-trained and fine-tuned to work for the sentiment analysis task before training HFBM.

Existing research results have demonstrated that the experimental results can be better improved by adding its high abstraction level of picture content representation, i.e., picture-extracted labeled word modality, to the information of picture modality. In existing research results, these tag words are generally used as labels to train the convolutional neural network, and in the HFBM, the picture-extracted tag word modality is used as an additional modality input to the network model, and the picture-extracted tag word modality is used as a bridge connecting the picture modality and the text modality.

Using the ResNet model that has been pre-trained and fine-tuned for ImageNet, and using Microsoft's publicly available COCO dataset as the training set, five tag words are generated for the images of the dataset used in this experiment, and after this step, all the metadata information needed for the whole model is obtained: i.e., image modality, tag word modality extracted from the images, and text modality.

The Bert model further improves the machine's understanding of natural language based on the Transformer model. The core of the Bert model is pre-training and fine-tuning, which generates in-depth bi-directional language features. The internal structure of Bert is based on the encoder part of the Transformer, which treats each Transformer's encoder as an element, and connecting multiple such elements in sequence constitutes the Bert model.

The five tag words a_f extracted from each image are input into the Bert module in HFBM, and the rawvector of tag word modality is obtained after the training of Bert model: $e(a_f)$, as in Equation (7), where $f=1,2,\cdots$ and N_a denotes the number of tagged words, which is 5 in this experiment.

$$e(a_f)=Bert(a_f) \tag{7}$$

After obtaining the raw vector of each labeled word, it is necessary to obtain the vector representation of the modality of the labeled word corresponding to the whole picture. The raw vector of each tag word is inputted into a two-layer neural network to get the weight value α_f of each word for the attention mechanism, as shown in Eq.

(8), and the attention mechanism and weight value α_f are used to generate the guidance vector of the tag word modality corresponding to each picture: v_{attr}, as shown in Eqs. (9) and (10), where N_a denotes the number of labeled words, which is 5 in this experiment, W_1 and W_2 are the weight vectors of the two-layer neural network, and b_1 and b_2 are the bias vectors of the two-layer neural network, respectively.

$$\alpha_f = W_2 \cdot \tanh\left(W_1 \cdot e\left(a_f\right) + b_1\right) + b_2 \tag{8}$$

$$\alpha = soft\max\left(\alpha\right) \tag{9}$$

$$v_{attr} = \sum_{f=1}^{N_a} \alpha_f e\left(a_f\right) \tag{10}$$

III. Form path innovation based on the characteristics of news dissemination

III. A. Content Diversification and Personalized Services

In the context of the era of integrated media, the diversified characteristics of news dissemination content have become increasingly prominent, and this trend has greatly expanded the forms and media scope of information dissemination. In addition to the traditional textual reports that continue to play a key role, diversified forms of content continue to emerge, and news content distribution has cross-platform characteristics, including social media, websites, mobile applications, television and radio, etc., all of which can be synchronized or differentiated distribution. The core objective is to expand news coverage, reach a wider audience, and make full use of the characteristics of each platform to enhance the attractiveness and influence of news content.

The key to multi-platform distribution is to understand the audience characteristics and content preferences of each platform. For example, the use of big data technology can provide news dissemination platforms with powerful user profiling capabilities. Through in-depth mining and multi-dimensional analysis of users' news browsing behavior, news dissemination platforms are able to accurately capture users' interests and preferences, reading habits and information demand characteristics. This insight into user needs enables news distribution platforms to provide personalized information services, such as customized content delivery and accurate news recommendations. This kind of service not only fully meets the increasingly diversified information needs of the audience, but also promotes the in-depth transformation and innovative development of the news dissemination industry.

III. B. Diversified and interactive communication channels

In the era of integrated media, news dissemination channels show significant diversification characteristics, and this change has profoundly broken the limitations of the traditional media pattern and comprehensively expanded and upgraded the communication channels. In the past, news dissemination mainly relied on traditional media platforms such as TV, radio, newspapers, etc., which was limited by time and space factors, and its dissemination coverage and interactivity had obvious limitations. Therefore, the mobile Internet has become an important emerging channel for news dissemination by virtue of its convenient, instantaneous and extensive advantages. Smart phones, tablet computers and other mobile devices also enable users to access news information anytime and anywhere, completely breaking the geographical location and time constraints.

At the same time, news dissemination has changed from a one-way transmission mode to a two-way interactive mode. The audience has not only been the passive receiver of news, but also become the creator and disseminator of news. After seeing the news, the public can participate in discussions and express their views through online comments and social sharing, and interact with news organizations and other audiences. This approach not only enhances the interactivity of news dissemination, but also helps news organizations to better understand the needs of their audiences.

IV. 4 News feature mining and testing of prediction models

In this chapter, corresponding experiments and application scenarios are designed to test the effectiveness of the news feature mining and prediction model based on the BERT model proposed above from three perspectives, namely, sentiment classification ability, news feature mining and analysis ability, and news dissemination prediction ability, respectively.

IV. A. Sentiment classification and analysis

IV. A. 1) Estimating the emotional impact of users

Based on the model designed in this paper, the connection function estimation results of the user's emotional influence are obtained as shown in Fig. 2.

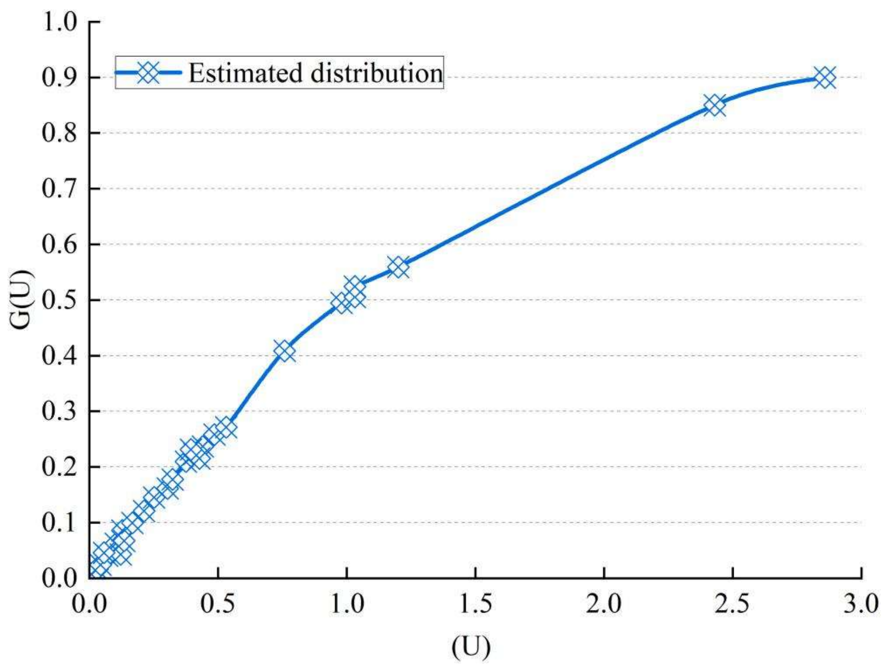


Figure 2: The estimation result of the connection function

From Figure 2, it can be clearly seen that the connection function has an increasing trend, from the overall point of view, the estimated connection function values are all greater than 0, this result shows that there is a positive correlation between the role of influence between the users, at the same time, it can be found that the connection function of the influence of the value of the large point is relatively sparse, in line with the concept that opinion leaders are a very small part of the group of users.

IV. A. 2) Critical Incident Opinion Leader Identification

Table 1 shows the information of the top 10 opinion leaders in the S new media platform for the “7·20 Zhengzhou heavy rainstorm event”, with the following information: (a) number of followers, (b) number of updates, (c) number of retweets, (d) number of comments, and (e) value of emotional influence. The official media number is OM, the individual accounts with some influence are numbered IA, and the individual accounts with less overall influence but which gained more attention in this event are numbered PM.

Table 1: Information on the top 10 opinion leaders

Ranking	Number	(a)	(b)	(c)	(d)	(e)
1	OM1	133546203	159150	11767	3854	0.8931
2	OM2	151132115	148785	4633	5167	0.8584
3	PM1	136	1347	5987	21261	0.5024
4	OM3	15151306	96495	14346	21404	0.4762
5	OM4	19847325	166473	11463	1460	0.4551
6	OM5	15448133	69981	7406	11533	0.4445
7	OM6	2434523	28591	15669	5279	0.3674
8	IA1	12131654	2158	5243	2319	0.3648
9	OM7	4034166	34450	12224	13389	0.3098
10	IA2	885043	29175	7802	1562	0.2499

In order to further verify the rationality and scientificity of the empirical results, the ranking methods of “Hall of Fame” and “Popular Grassroots” on S new media platform are used as a comparison to analyze the results of opinion leader identification given by this paper's model, which are shown in Table 2. The ranking methods of “Hall of Fame” and “Popular Grassroots” on S new media platform are mainly ranked according to the number of fans, which is also the most primitive sorting method.

Table 2: Comparison of the results of two opinion leader ranking methods

Sort	The sorting of the textual model		Sorting of the S media platform	
	Number	Opinion leader value	Number	The number of fans
1	OM1	0.8931	OM2	151132115
2	OM2	0.8584	OM1	133546203
3	PM1	0.5024	OM8	60340488
4	OM3	0.4762	OM9	37669951
5	OM4	0.4551	OM10	22880521
6	OM5	0.4445	OM4	19847325
7	OM6	0.3674	OM6	15448133
8	IA1	0.3648	OM3	15151306
9	OM7	0.3098	OM11	14044574
10	IA2	0.2499	IA3	12131654

The opinion leaders identified in this paper's model and the overall results of the sorting based on the number of followers are closer, reflecting the scientific nature of this paper's model in this breaking news. Among them, in the list sorted according to the number of followers, although the number of followers of the official media such as OM8, OM9, OM10, OM11 is large, the blog posts they publish contain fewer values of the indicators such as comments and retweets so they do not have a strong influence in the breaking news. In the list sorted according to the model of this paper, although the number of fans of PM1, OM6, OM7, and IA2 is not very large, they play a key role in the online emergencies, and the blog posts they publish play an important role in the trend of the whole event, and receive a wide range of retweets and comments.

In general, there exists a part of the result of sorting by the number of followers in the breaking news that is not the real opinion leader, while sorting according to the model of this paper can better reflect the real opinion leaders and their high or low level of emotional influence in the breaking news.

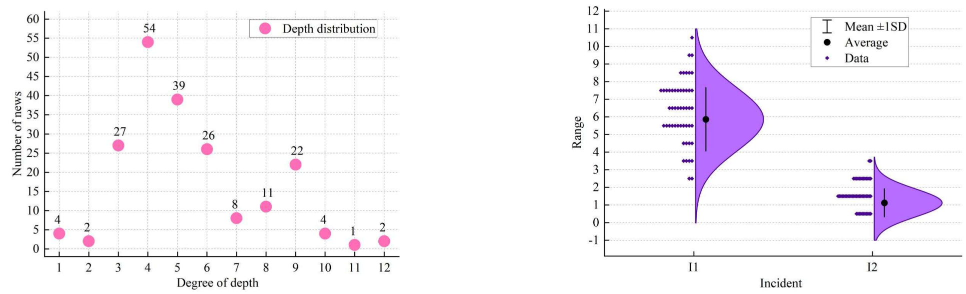
IV. B. Feature mining analysis of different news

This section is based on the data of news related to neocoronavirus pneumonia with the popularity of the top 200 news items in S new media platforms during the period of December 1, 2019-March 1, 2020, aiming to analyze the dissemination characteristics of (I1) neocoronavirus pneumonia-related news in social network platforms. Among these characteristics, they include the dissemination period of news in terms of temporal order, the length of the active period of news, the dissemination range in terms of space, and the number of people involved in the dissemination. Meanwhile, these characteristics are compared and analyzed with those of (I2) the news of the 7·20 China Zhengzhou Extraordinarily Heavy Rainstorm event to further explore the social concern situation of (I1) the new coronary pneumonia public opinion event.

IV. B. 1) Dissemination depth analysis

The results of the spatial dissemination tree analysis of the new crown epidemic news are shown in Fig. 3, in which Fig. 3(a) shows the depth distribution of the news dissemination tree of the new crown epidemic, and Fig. 3(b) shows the comparison of the depth distribution of the news dissemination tree of the (I1) news of the new crown epidemic and the (I2) news dissemination tree of the 7·20 Zhengzhou, China, extraordinarily heavy rainstorm event.

In terms of depth of dissemination, (I1) the distribution of news related to the New Crown outbreak was approximately normally distributed, with the depth of dissemination of the majority of news developments being in the middle of the range. The majority (73%) of the news on the new crown outbreak had a depth of transmission between 3 and 6, which represents a maximum of 2-5 people between the majority of the news re-tweeters and the original news publisher. Larger values of depth of transmission indicate that the relationship between the retweeter and the original tweeter in the social network is weaker and the likelihood that they know each other is lower. Compared to (I2) the news about the 7·20 China Zhengzhou mega-rainstorm event, the depth of dissemination of the news related to this Xinguan outbreak is deeper, which makes it easier for the news to spread to a larger spatial extent.



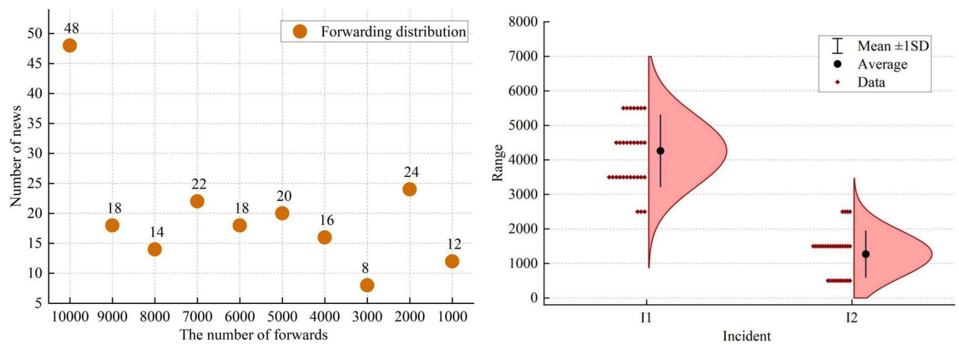
(a) Depth distribution of the news dissemination tree

(b) Comparison of the depth distribution of event propagation trees in I1 and I2

Figure 3: Analysis of the news space dissemination tree of the COVID-19 epidemic

IV. B. 2) Analysis of forwarding users

The results of the analysis of the number of users who forwarded news about the new crown outbreak are shown in Figure 4.



(a) Distribution of news forwarding users

(b) Comparison of the number of event forwarding users between I1 and I2

Figure 4: Analysis of the number of News Forwarding Users

The distribution of the number of retweeting users shows that a significant portion (24%) (I1) of the new crown outbreaks kept the number of retweeting users in the 9,000-10,000 range. Among them, 49% of the news retweets had less than 6000 users. Compared to the (I2) 7·20 China Zhengzhou mega-rainstorm event, overall, the number of users involved in the forwarding of news related to the new (I1) New Crown outbreak did not significantly increase, but there existed a number of news with up to 3,000 forwarding users, which exceeded the number of people who spread the news of the (I2) 7·20 China Zhengzhou mega-rainstorm event.

IV. C. Module for predicting the degree of information dissemination

The system's information dissemination popularity prediction model provides a popularity prediction function, which consists of two sub-modules that predict the amount of forwarding in the future period and the amount of current information coverage, respectively.

IV. C. 1) Forwarding forecasting module

Figure 5 shows the prediction results of the retweet volume of a news message. In this case, the retweet data within one hour after the release of this piece of information is used as observation data for model training, and the retweets per hour after one hour are the prediction results. Comparing the prediction results of this paper's algorithmic model with (M1)RPP model and (M2)mixRPP model, it is found that (M1)RPP model achieves better prediction results in the first 6 hours of information dissemination, but worse prediction results after 6 hours, (M2)mixRPP model has worse prediction results in the 6-hour period, and achieves better prediction results after the 6-hour period, while this paper's algorithmic model achieves good prediction results throughout the information dissemination process.

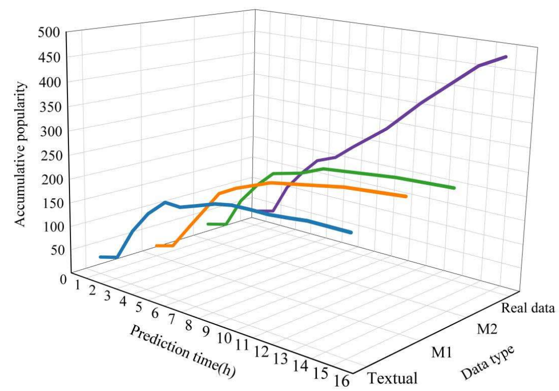


Figure 5: The prediction result of the forwarding volume prediction module

IV. C. 2) Information coverage prediction module

The information coverage prediction module is based on the mining algorithm, which converts the forwarding list information into time series information data and spatial forwarding tree structure respectively to generate spatio-temporal feature data. The spatio-temporal feature data at the current moment is used as the input for prediction, which contains the life cycle feature, active period feature, fluctuation frequency feature, forwarding volume feature, propagation depth feature, propagation breadth feature and propagation scale feature of the news information. Comparison of the information coverage prediction based on this paper's algorithm with the real value of the news is shown in Fig. 6.The prediction trend of this paper's algorithm for news coverage on different spatio-temporal features is consistent with the real value at all times, which demonstrates the reliability in popularity prediction.

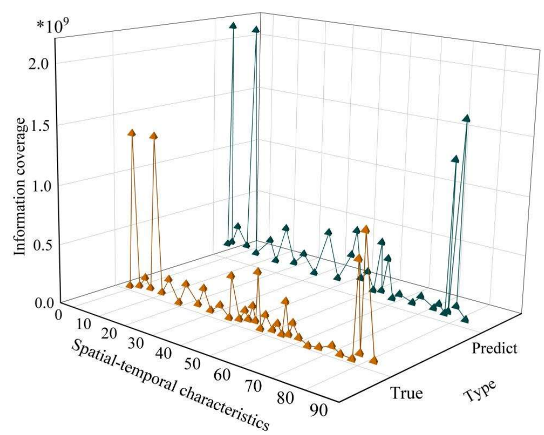


Figure 6: The prediction result of the information coverage volume prediction module

V. Conclusion

This paper uses the key node mining algorithm to obtain the important nodes in the cultural communication news, and then adopts the BERT model (HFBM), a variant of the Transormer model, to mine and extract the modal characteristics of the tagged words of the news information, and analyze the emotional characteristics and influence of the news information, so as to predict the amount of forwarding and coverage of the news information in the network. Based on the model's prediction of news dissemination, combined with the current content of news dissemination and the characteristics of interactivity, it gives three suggestions for the innovation path of the current cultural communication news: (1) constructing an integrated media dissemination system; (2) innovating dissemination modes in terms of content, form and technology; and (3) integrating data resources to improve dissemination capabilities.

The news feature mining and prediction model based on the BERT model can not only more accurately analyze and reflect the emotional impact of different spokespersons in mega-news, but also effectively mine and analyze the depth of dissemination of different news events and the distribution of forwarding users. The news dissemination prediction module supported by the model algorithm is able to predict the amount of news retweets for up to 15h, and at the same time, achieve the prediction effect consistent with the real coverage.

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References

[1] Tombleson, B., & Wolf, K. (2017). Rethinking the circuit of culture: How participatory culture has transformed cross-cultural communication. Public Relations Review, 43(1), 14-25.
[2] Bengtsson, S., & Johansson, S. (2021). A phenomenology of news: Understanding news in digital culture. Journalism, 22(11), 2873-2889.
[3] Holt, K., Ustad Figenschou, T., & Frischlich, L. (2019). Key dimensions of alternative news media. Digital Journalism, 7(7), 860-869.
[4] Nelson, J. L. (2020). The enduring popularity of legacy journalism: An analysis of online audience data. Media and Communication, 8(2), 40-50.
[5] Peeters, H., Van Damme, K., & Truyens, P. (2024). News use within media repertoires: prominent and diverse or absent and narrow?. In ECREA Journalism Studies Conference.
[6] Mihailidis, P., & Viotty, S. (2017). Spreadable spectacle in digital culture: Civic expression, fake news, and the role of media literacies in “post-fact” society. American behavioral scientist, 61(4), 441-454.
[7] Dwyer, T., & Martin, F. (2017). Sharing news online: Social media news analytics and their implications for media pluralism policies. Digital journalism, 5(8), 1080-1100.
[8] Hendrickx, J., & Opgenhaffen, M. (2024). Introduction: Understanding social media journalism. Journalism Studies, 25(9), 919-930.
[9] Wang, L. (2022). Factors influencing public opinion in mass media news coverage. BCP Business & Management, 34, 1109-1114.
[10] Kavoura, A., & Sylaiou, S. (2019). Effective cultural communication via information and communication technologies and social media use. In Advanced methodologies and Technologies in Media and Communications (pp. 377-390). IGI global.
[11] Huang, M. (2024). Cross-cultural communication in the digital era: Insights from social media interactions. Lecture Notes in Education Psychology and Public Media, 54, 23-29.
[12] Alsaleh, D. A., Elliott, M. T., Fu, F. Q., & Thakur, R. (2019). Cross-cultural differences in the adoption of social media. Journal of Research in Interactive Marketing, 13(1), 119-140.
[13] Maniou, T. A. (2021). Semantic analysis of cultural heritage news propagation in social media: Assessing the role of media and journalists in the era of big data. Sustainability, 13(1), 341.
[14] Lewis, S. C., & Molyneux, L. (2018). A decade of research on social media and journalism: Assumptions, blind spots, and a way forward. Media and communication, 6(4), 11-23.