Ideological and Political Education of Minority Students Based on Network Information Security Model

Xiaojun Fu and Qihua Li(✉)

Dianchi College of Yunnan University, Kunming 650000, China
liqihua202109@163.com

Abstract. Education is the basis of promoting the process of national unity and development. The educational model of colleges and universities is constantly changing. But it also faces many challenges. How to effectively implement the work of national unity education, innovate educational methods, cultivate national consciousness and identity consciousness is a problem that should be considered in the current national unity education. This paper studies the intergroup effect of network cluster emotion based on negative emotional leaders in information security. Based on minority students' information security behavior data, the paper applies the integrated empirical mode decomposition method and VAR model to explore the impact of information security network cluster emotion on the formation of network cluster behavior, which reveals the dynamic process of information security network cluster behavior formation. The research content of this paper plays an auxiliary role in the ideological and political education in colleges and universities, which provides theoretical support for the study of negative public opinion and emotion.

Keywords: College Education · The Ideological and Political · Ethnic Minorities · Network Information Security · EEMD

1 Introduction

With the development of information security, network public opinion, information asymmetry, and other conditions, minority students show an unprecedented cluster intention. For the relationship between cluster intentions, some studies have confirmed the important role of cluster emotion in the formation of non-information security network cluster behavior [6]. At the same time, due to the close relationship between information security and people's production and life, information security is closely related to the network cluster behavior of minority students under the purpose of information security protection. Therefore, it has become an important task to explore the relationship between network cluster emotion and network cluster behavior under the background of information security.

Rogers et al. [5] further pointed out the important role of opinion leaders in innovation communication in the study of innovation diffusion, which laid the foundation

C. F. Peng et al. (Eds.): EIMT 2022, AHSSEH 3, pp. 189–197, 2023.
https://doi.org/10.2991/978-94-6463-012-1_21

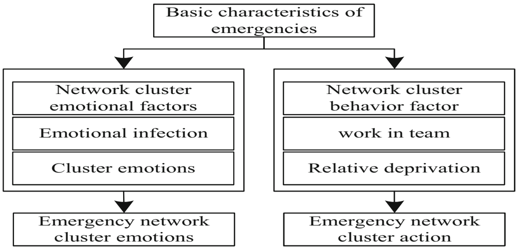

Fig. 1. Definition of network cluster emotion and cluster behavior in information security emergencies

for the study of opinion leaders in the field of public opinion communication. Hollar [2] points out that opinion leaders can influence the behavior and attitudes of others. The network community environment is another way of existence of opinion leaders in the traditional media environment. With the emergence and development of Web2.0 technology, academic research on traditional opinion leaders has gradually extended to social networks. Many scholars have begun to study opinion leaders and their influence on social networks [1].

Combined with the related concepts and theoretical basis of network cluster emotion and network cluster behavior, this paper defines the basic concepts and characteristics of network cluster emotion and network cluster behavior in information security emergencies, and discusses the influence principle of network group emotion on network group behavior. The concept definition of network cluster emotion and network cluster behavior in information security emergencies is shown in Fig. 1.

In the development of information security, minority students' emotions and behavior are full of uncertainty. Thus, to explore the impact of information security network cluster emotion on network cluster behavior, this paper will introduce EEMD (Ensemble Empirical Mode Decomposition) method based on a multi-scale perspective. This paper analyzes the fluctuation law of information security network cluster emotion and network cluster behavior in short-term, medium-term, and long-term scales. The paper reveals the influence effect of information security network cluster emotion on the network cluster behavior. The paper also provides a reference for information security emergency management departments to reasonably guide information security network group emotion and then grasps the law of network group behavior under the background of information security.

The main innovations of this paper are:

(1) Based on the concept of opinion leader, the concept of an emotional leader is put forward;
(2) Combine the information security network cluster emotion with the network cluster behavior research.

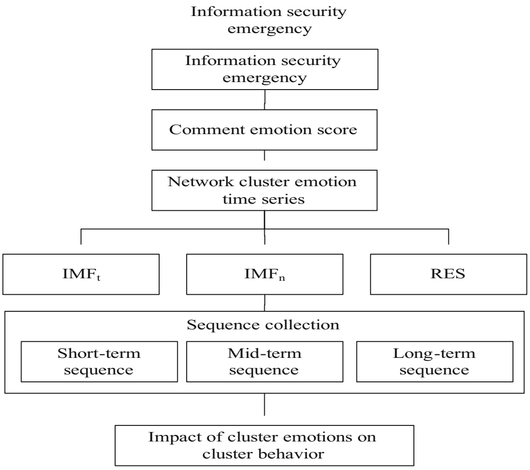

Fig. 2. The effect model of network cluster emotion on cluster behavior

2 Empirical Mode Decomposition Model for Network Cluster Time Series Integration

This paper will apply the EEMD method to explore the effect of cluster emotion on cluster behavior in information security network. The research ideas are shown in Fig. 2.

Construct the affective time series of information security network clusters. Based on the Sentiment score of Micro-blog comments, the Sentiment tendency of the network cluster emotion cycle is further considered. Finally, the effective time series of information security network cluster is constructed [4].

The specific steps are as follows:

The calculation periodic network cluster emotional tendency refers to the overall positive or negative network cluster effective tendency of users in a given period. The number of comments with Sentiment greater than 0 in the observation period t is recorded as N_t^{pos}, and the number of comments with Sentiment less than 0 is recorded as N_t^{neg}, then the sentiment tendency of the periodic network cluster is shown in formula (1):

$$sentiment_t = \ln \frac{\sqrt{1 - N_t^{pos}}}{\sqrt{1 + N_t^{neg}}} \tag{1}$$

In formula (1), the periodic network cluster sentiment tendency Sentiment can be interpreted as: in the period t, if the network cluster sentiment tendency of the comment is greater than 0, it indicates that the network cluster sentiment of the observation period is positive; if the comment is less than 0, it indicates that the user cluster sentiment is negative in the observation period.

In this paper, the information security network cluster emotion takes the day as a cycle. There are multiple emotional catharsis processes every day, and the intensity of each emotional catharsis is different. Therefore, the construction of the network cluster emotion time series in this paper should consider each emotional score in the cycle on the basis of the emotional tendency of the periodic network cluster, and the network cluster emotion time series is shown in formula 2:

$$sum_1^N = \sin t_1^N \times 1n[\frac{1+\sqrt{n}}{1+n^k t}]/N \tag{2}$$

In formula (2), Sentindex is the network cluster emotion time series considering each emotion score in the cycle. N represents the number of emotional catharsis in the cycle, and Sentiment represents the emotion score of the ith catharsis in the cycle.

3 Empirical Modal Decomposition for Cluster Time Series Integration

The Ensemble Empirical Mode Decomposition (EEMD) is based on the Empirical Mode Decomposition (EMD). The process is shown in Fig. 3.

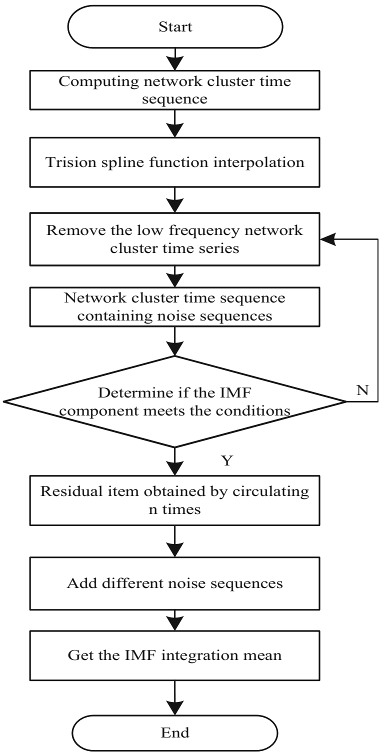

Fig. 3. Modal Decomposition Process

(1) Add a noise sequence $e(t)$ with a given standard deviation to an original network cluster time sequence $X(t)$ to obtain a network cluster time sequence $x(t)$ containing noise, as shown in formula (3):

$$x(t) = X(t) + e(t) \tag{3}$$

(2) Identify a local maximum value and a local minimum value of the network cluster time series x(t) containing noise. Perform the cubic spline function interpolation on the local maximum value and the local minimum value to form an upper envelope line $X_{\max}(t)$ and a lower envelope line $X_{\min}(t)$.

Calculate the mean value $m(t)$ of the upper and lower envelopes, as shown in Formula (4):

$$m(t) = (x_{\sin}(t) + x_{\sin}a(t))/2 \tag{4}$$

(3) A network cluster time series $x(t)$ with low frequency removed is obtained by subtracting the sequence formed by the mean values $m(t)$ of the upper and lower envelopes from the network cluster time series $h(t)$ containing the noise sequence, as shown in formula (5):

$$h(t) = x(t) - m(t) \tag{5}$$

(4) Replace the network cluster time series $x(t)$ containing the noise sequence with h(t). Repeat the above process for k times to obtain the first-order IMF component of the network cluster time series $x(t)$ containing the noise sequence as IMF_1(t), as shown in formula (6):

$$MAF_1(t) = h_k(t) = h_{k-1} - m_k(t) \tag{6}$$

Judge whether the obtained IMF component meets the two conditions of IMF. If so, $IMF_1(t) = h_k(t)$. Subtract the network cluster time series $x(t)$ containing the noise sequence with low frequency, which is removed from the network cluster time series containing the noise sequence to obtain a network cluster time sequence $h(t)$, which contains noise sequence with high frequency removed [3]. The residual term $r(t)$ is shown in Eq. (7):

$$r(t) = x(t) - h(t) \tag{7}$$

If the condition is not met, $h(t)$ is used to express $x(t)$.

(5) Time series $r(t)$ or $h(t)$ are as a new network cluster time series. Repeat the above process until the residual term obtained by n cycles is a monotone function or constant, so the original network cluster time series can be decomposed into:

$$X(t) = \sum_{n}^{i=1} h_k(t) + r_n(t) \tag{8}$$

In Eq. (8), n is the final number of IMFs, $r_n(t)$ is the final residual term, which represents the trend or mean part of $h_k(t)$.

(6) $h_k(t)$ is the IMF component of each layer, including the local variation characteristics of the time series.

(7) Add different noise sequences to that original network clust time sequence respectively, and repeat the step 2.

(8) Take the obtained IMF integrated mean value as the final decomposition result.

4 Experimental Analysis

4.1 Data Sampling

This paper uses data to capture all microblogs containing at least one of the above keywords from 2018-10-20 to 2021-11-30 with the keywords of "ethnic minorities" and "national unity". Then screen out the microblogs with more than two comments. Finally, a total of 1968 micro-blog topics, comments and follow-up texts were obtained, with 91, 623 and 1254 texts respectively.

4.2 Analysis of Experimental Results

The network crawler software is used to construct the emotion time series of information security network cluster. The descriptive statistics of the emotion and network cluster behavior time series of information security network cluster are shown in Table 1 respectively.

It can be seen from Table 1 that the average emotional score of minority students is negative. There is a big gap between the maximum and minimum emotional scores. Most of the students' emotions tend to be negative during the event period. According to the maximum, minimum and standard deviation, the students' emotions fluctuate sharply during the event period. Similarly, according to the average, maximum, minimum and standard deviation of the number of daily active users of security protection software, the activity of information security behavior of minority students is relatively high and basically stable during the period of the incident.

The NLPIR semantic analysis platform of the Chinese Academy of Sciences and the BosonNLP Chinese semantic open platform are used to perform the coarse-grained sentiment analysis on the collected text, as shown in Fig. 4 and Table 2.

After considering the user's emotional score, it is found that the emotional intensity expressed by nodes is higher, which is in line with the characteristics of emotional leaders because their influence makes their information widely spread. In the whole network structure, there are still many nodes that have more structural holes but have low centrality or lack of strong emotional expression, which do not conform to the characteristics of network emotional leaders.

Model accuracy evaluation:

In order to verify the effectiveness of the sentiment analysis method in this paper, 30% of the total data set was randomly selected as the test data, and the test data were manually labeled with the corpus. The above corpus was applied to the sentiment vocabulary

Table 1. Descriptive statistics of network cluster emotion time series

Average value	The median	Maximum value	Minimum value	standard deviation	Partial degrees	Kurtosis	Degree of confidence (95%)
Emotional score-0.096	−0.087	0.053	−0.291	0.089	0.449	0.448	0.024

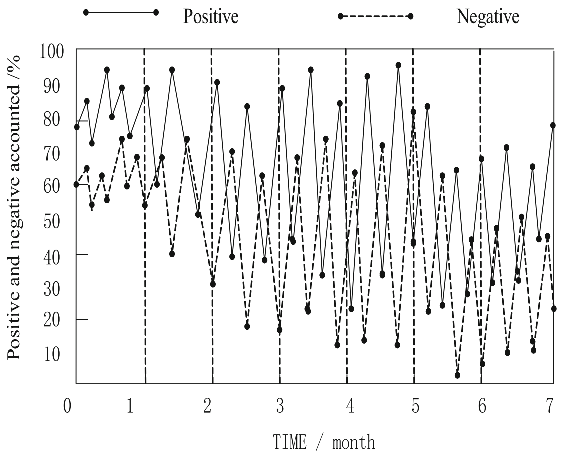

Fig. 4. NLPIR analysis result

Table 2. Emotional leader identification results

Number	Point degree center degree	Network effective scale	Network constraint coefficient	Emotional score	Emotion classification	Total
1	8	8	0.125	9	sad	33
2	7	7	0.143	7	sad	28
3	3	3	0.333	7	sad	16
4	13	13	0.077	3	sad	42
5	19	19	0.053	5	hate	62
6	27	27	0.037	9	angry	90
7	40	40	0.025	7	hate	127

ontology and the sentiment dictionary constructed in this paper, respectively, using the weighted method of sentiment word meaning to conduct a comparative test. Precision, Recall and the comprehensive evaluation index F-value are used as the evaluation indexes of the cluster affective computing model in this study, and the definitions of each index are as follows:

$$\text{Precision} = \frac{\text{Judgment total}}{\text{Identification}} \tag{9}$$

$$\text{Recall} = \frac{\text{Identification}}{\text{Suspected amount}} \tag{10}$$

$$F = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{11}$$

The calculation results are shown in Table 3.

Table 3. Comparison between the results of this method and the traditional method

Model	Method of this paper			Traditional method		
Emotional classification	A1	B1	C1	A2	B2	C2
Precision	82%	80%	78%	72%	70%	69%
Recall	85%	80%	87%	75%	77%	71%
F	83%	81%	80%	74%	71%	73%

As shown in Table 3, the sentiment classification effect of the proposed method is better than that of the original method. Recall and F-score are also the highest.

5 Conclusions

In this paper, the EEMD method is used to analyze the effect of information security network cluster emotion on the network cluster behavior from a multi-scale perspective. The VAR model of the effect of network cluster emotion on network cluster behavior at various scales is established. The experiment proves that the network cluster emotion promotes the formation of network cluster behavior. The network cluster behavior itself in the lag period will also promote its formation, but the network cluster emotion has a stronger role in promoting the formation of network cluster behavior. Based on this, this paper provides a reference for the effectiveness of national unity education for minority college students in the new era.

Acknowledgements. The study was supported by "China Association of Private Education, Improving the development financial aid system for economically (Number: CANFZG21141)" and "Yunnan Provincial Department of Education, Research on the current situation, effectiveness and mode of funded education from the perspective of innovation and Entrepreneurship Education – Taking Dianchi College of Yunnan University as an example (Number: XSZZ1917)".

References

1. Babac, M.B., and V. Podopnik. 2018. What social media activities reveal about election results? The use of Facebook during the 2015 general election campaign in Croatia. *Information Technology & People* 31 (2): 327–347.
2. Bogaret, M., M. Ballings, and D.V.D. Poel. 2018. Evaluating the importance of different communication types in romantic tie prediction on social media. *Annals of Operations Research* 263 (2): 1–27.
3. Darcy, J., and P.L. Teh. 2019. Predicting employee information security policy compliance on a daily basis: The interplay of security-related stress, emotions, and neutralization. *Information & Management* 56 (7): 103–151.
4. Liang, H., Y. Xue, A. Pinsonneault, et al. 2019. What users do besides problem-focused coping when facing IT security threats: An emotion-focused coping perspective. *MIS Quarterly* 43 (2): 1–22.

5. Mamonov, S., and F.R. Benbunan. 2018. The impact of information security threat awareness on privacy-protective behaviors. *Computers in Human Behavior* 83: 32–44.
6. Xiong, X., Y.Y. Li, S.J. Qiao, et al. 2018. An emotional contagion model for heterogeneous social media with multiple behaviors. *Physical A Statistical Mechanics & Its Applications* 490: 185–202.