Analysis of Emotional Evolution of Emergent Events Network Based on Spatial Measurement

Qingyue Luo1*, Yinghua Song2 and Shanyao Liu3

1China research center for emergency management, Wuhan University of Technology, Wuhan Hubei 430070; liudan8575@whut.edu.cn  *Corresponding author’s e-mail: 2389728887@qq.com

Abstract: I study the temporal and spatial evolution of network emotions in emergencies, and provide decision support for public opinion guidance. This paper uses python to compile a crawler to obtain the comment information of Weibo, calculates its network sentiment value based on the naive Bayes classifier, uses spatial analysis methods and the SAAR spatial measurement model system, and analyzes the temporal and spatial pattern evolution and spatial agglomeration of network sentiment Characteristics, and further reveals its influencing factors and complex spatial correlation. At the same time, there is a spatial spillover effect of online emotions, and the intensity of comments and public opinion has a promoting effect on it, while geographical distance has an obvious inhibitory effect on it. Online emotions have regional differences. Disaster management departments can use this difference to more efficiently identify emotionally hot areas from social media data, so as to take timely response measures.

1. Introduction
In recent years, frequent emergencies spread rapidly through social network platforms such as Weibo and WeChat, attracting the intervention of a large number of netizens. During the dissemination of emergencies, the expression of user emotion not only affects the breadth and depth of information dissemination, but also quickly infects the emotions of other users to promote the outbreak of online public opinion[1]. The Internet sentiment of emergencies refers to the use of Internet platforms to express opinions and opinions on emergencies[2]. Network emotion is a collection of emotions of network users in a specific time and space, which has spatial attributes. According to the first law of geography, all affairs are related to other affairs, but closer affairs are more related than distant affairs[3]. Therefore, there is a spatial distribution law of network emotion under the restriction of geographic space[4].

In recent years, scholars at home and abroad have successively launched the sentiment analysis research of Internet public opinion. The emotional research of emergencies that considers spatial factors mainly revolves around the distribution of network emotions in geographic space. For example, Venkata K et al[5] conducted sentiment analysis on the tweets posted on Twitter during the catastrophic hurricane Sandy, and visualized the emotions of Internet users on a map surrounding the hurricane. Mandel[6] trained an sentiment classifier to classify messages according to the degree of attention, and perform statistical analysis on the online sentiment of the public in different regions when natural disasters are about to occur.

In the current research on network emotions in emergencies, we should not only consider the geographical distribution of network emotions, but also fully consider the complex temporal and spatial relationships between network emotions and their influencing factors. The SARAR model[7,8] can not only reflect the spatial correlation of network emotions in neighboring areas, but also take into account
the spatial correlation of other explanatory variables that affect network emotions in the disturbance term. Therefore, based on the SAAR model, this article uses 31 provinces (cities, autonomous regions) in China as the research unit to analyze the spatial agglomeration characteristics of online emotion distribution, study the influencing factors and complex spatial effects of online emotions, and explore the temporal and spatial laws of the evolution of online emotions, provide decision support for online public opinion warning and public opinion guidance.

2. Build model
The network emotions of emergencies are distributed in a wide area. The network emotions in the region are affected by the popularity of comments, and the network emotions between regions are affected by geographic distance, and the spatial effect is obvious. In order to effectively measure the spatial effects of network emotions, a network emotion space evolution model is constructed based on the SAAR model, as shown in equation (1).

\[ A = \lambda W A + \beta_0 + \beta_1 \ln(P) + \beta_2 \ln(G) + \mu \]  
\[ \mu = \rho Mu + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2) \]  

According to formula (1), the spatial autoregressive coefficient \( \lambda \), which represents the influence of network emotions in neighboring areas on the network emotions in the region, can be obtained, as shown in formula (3).

\[ \lambda = (A - \beta_0 - \beta_1 \ln(P) - \beta_2 \ln(G) - \mu)(WA)^{-1} \]  

In formula (3), \( A \): the network emotion vector represents the network emotion of each area, \( A = [a_1, a_2, \ldots, a_n]^T \) (n is the number of regions), \( a_i \) represents the network sentiment value of area \( i \). \( P \): the geographic distance vector represents the linear distance between each area and the origin of the epidemic, \( P = [p_1, p_2, \ldots, p_n]^T \). \( G \): The comment heat vector indicates the popularity of netizens' comments in each region, \( G = [g_1, g_2, \ldots, g_n]^T \). \( \varepsilon \): Random disturbance term, \( \varepsilon \sim N(0, \sigma^2) \). \( \beta_0 \) is a constant term, \( \beta_1 \) and \( \beta_2 \) are the estimated coefficients of geographic distance and comment popularity. \( W \): adjacent space weight matrix, using the extended rook adjacent calculation method[9] indicates the weight of the spatial distance between regions, \( w_{ij} = \begin{cases} 1, & \text{Adjacent between regions} \\ 0, & \text{Not adjacent to each other} \end{cases} \).

Usually, Maximum Likelihood Estimate (MLE) is used to estimate the parameters of the SAAR model consistently and effectively.

3. Empirical result analysis
3.1. Data Sources
Weibo is one of the important social platforms where the emotions of online users appear, and it is also the main position of current online sentiment analysis research. This article uses the Weibo public opinion caused by the "Shanxi Pingyao Coal Mine Gas Explosion Accident" on November 18, 2019 as the data source, and uses web crawlers to capture 24,237 Weibo data. The Weibo release time span is from November 18, 2019 to December 9, 2019. First, delete invalid and severely missing data from the data crawled by Weibo, and then filter out data with user addresses in 31 provinces (cities, autonomous regions) in China. This article takes selected original Weibo (21,755 in total) for research, including Weibo text, release time, geographic tags, user information and other metadata.

3.2. Naive Bayes classifier training
Select 5000 positive and negative sentiment samples from these Weibo comments, manually calibrate the positive and negative sentiment tendencies, and construct a new corpus. Use Snow NLP to segment the comment content in the corpus, then download the stop word dictionary, remove the stop words, and perform Bayesian classifier for emotional training. The trained classifier has an accuracy verification result of 0.927, which shows that its classification effect is good, and it can be used to predict the sentiment value of Weibo comments.
3.3. Agglomeration characteristics of network emotion space

Using Stata 16.0 to calculate the spatial agglomeration characteristics of network emotions in 31 provinces (municipalities, autonomous regions) of China in the coal mine gas explosion accident in Pingyao, Shanxi, the results are shown in Table 1. The global Moran’s I[10] is a positive value, passing the 5% significance test (P<0.05), and the z value is 2.288, which indicates that the network emotion distribution has a positive spatial correlation and presents a spatial aggregation distribution.

| Explained variable | Moran’s I | S.d | z    | P    |
|--------------------|-----------|-----|------|------|
| Network emotion    | 0.091     | 0.054 | 2.288 | 0.011 |

Calculate the local Moran’s I of online emotions, and further explore the spatial heterogeneity of online emotion distribution. According to the local Moran’s I formula, the software is used to draw the spatial aggregation map of network emotions, and the regions are divided into four types: high-low (HL), low-low (LL), low-high (LH), and insignificant. As shown in Figure 1, the high-low type province is Beijing, which indicates that Beijing has a high degree of emotional enthusiasm on the Internet, a high degree of participation by netizens, and a high degree of public opinion. Jilin, Heilongjiang, Jiangxi, Hainan, Qinghai, and Xinjiang belong to the low-low type, indicating that the local network sentiment is low-concentration, and the surrounding provinces are also low-concentration, showing a vicious spillover effect. Low-low types such as Heilongjiang and Qinghai are generally far away from Shanxi. Due to geographical location and other reasons, the online participation in the gas explosion accident in Pingyao, Shanxi is not high, and the online sentiment is low.

3.4. Estimated result

This paper adopts the maximum likelihood estimation method and uses Stata16.0 to calculate. The results are shown in Table 2. Among them, the Wald statistic passes the test with a confidence level of 1%. In the regression results of the spatial measurement model, the spatial lag coefficient λ and the spatial error coefficient ρ have passed the significance test at 5% and 1% confidence levels respectively, which fully demonstrates that there is a clear spatial correlation between the network sentiment of each province. The λ coefficient is positive, which reflects the positive spatial correlation of network emotions in neighboring areas on local network emotions, that is, there is a spatial spillover effect. For example, in the coal mine gas explosion accident in Pingyao, Shanxi, Jiangsu’s internet sentiment value was very high, so for every 1% increase in internet sentiment in the neighboring areas of Jiangsu, the local internet sentiment in Jiangsu will increase by 0.452%.
From Table 2, the P value of geographic distance and comment intensity is 0, and both pass the 1% significance test. On the whole, there are significant differences in the influence of each explanatory variable on network sentiment. The coefficient of geographic distance is significantly negative, which means that as the distance to the disaster site decreases, the network sentiment increases. The coefficient of influence of geographic distance on online emotion is -9.232, that is, for every 1% increase in geographic distance, online emotion decreases by 9.232%. The intensity of public opinion will significantly promote the improvement of online sentiment. In the process of network dissemination of emergencies, the intensity of public opinion of comments reflects the enthusiasm of user comments. The more Internet users discuss the emergencies, the greater the emotional stage, and the increase in online sentiment.

4 Conclusion and discussion

Based on the spatial measurement model, this paper analyzes the changing trend of the spatial pattern of online emotions according to different development stages of public opinion, explores the spatial agglomeration characteristics of online emotions, and draws the following conclusions:

(1) The distribution of online emotions has a positive spatial correlation, and presents a spatial aggregation distribution.

(2) There is a spatial spillover effect of online emotion, that is, there is a positive spatial correlation between the online emotion of neighboring areas and the local online emotion. At the same time, geographic distance has a significant inhibitory effect on online emotions, while the intensity of public opinion comments is an obvious promotion.

In response to the above research conclusions, the following countermeasures are proposed: First, grasp the critical period. The government focuses on grasping one week after the disaster, promptly adopting guiding measures and releasing information in a timely manner to achieve better public opinion guidance effects. The second is to focus on controlling emotional hot spots on the Internet. The government needs to pay close attention to emotional hot spots on the Internet, and conduct public opinion monitoring and early warning scientifically and effectively. In addition, in the future, we can further explore how informational comments on Weibo affect emotional disagreements and how geographic mapping emotional analysis can play a role in various disasters.

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