Research Article

Research on the Propagation Characteristics of Negative News Information Based on Personalized Recommendation Algorithm

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This article will focus on how to reduce the negative information in the main theme report. Negative information contains subjectivity, deviation, interference, and cancellation characteristics, which will influence the primary theme report’s communication effect, interfere with the audience’s interpretation of the report, and cancel out the report’s positive energy. The original intention of the theme report is to promote social harmony and safeguard social justice, but the appearance of negative information makes the reported effect fail to reach the expected purpose. The concept of theme reports and negative information is defined in this work. This study examines the primary topic report’s qualities, such as The Times’ mainstream, good content, and strong report. In addition, the form and characteristics of negative information are also described. In this paper, a collaborative filtering recommendation method based on non-neighbor user contributions is suggested, which uses a linear fitting formula to apply the responsibilities of both neighbor and non-neighbor users to the recommendation system. The results show that the accuracy and diversity of our algorithm are better than those of traditional collaborative filtering algorithms. The diversity of several common recommendation algorithms is studied. The findings reveal that the diversity of recommendation algorithms is linked to the sparsity of data as well as the algorithm’s suggestion mechanism. In general, the more scarce the data, the higher the recommendation algorithm’s variety. At the same time, we also study the diversity of recommendation systems, and the results show that although the overall diversity of the system is gradually decreasing, user behavior is becoming more and more diverse.

1. Introduction

Our country is now in a critical period of social development. While singing the main melody, we should also realize that the emergence of some negative information does not come from criticism, reports from neighbors, not from news from the road but from sources of special reports, such as TV news reports. Leading cadres go to the countryside to guide work and so on. Another example is the meeting news report, not from the perspective of work to report the requirements of “why to do,” and “how to do,” but according to the position of high and low ranked order of the “elite meeting,” or in the flowers, there are wearing ribbons, graceful beauty pouring water, handing the “happiness meeting,” and so on.

Firstly, this negative information, which mostly appeared in the theme of the report, great harm, offset the positive energy in the theme of the report. Secondly, in some thematic reports, the phenomenon of violating the authenticity of news appears from time to time. For example, there is a phenomenon of “reporting good news but not bad news” in the reports of some major events, and some use the method of commendation to report some disastrous events, causing psychological antipathy to the audience. For example, in some legal reports, excessive disclosure of details of the case and excessive rendering of criminal methods may be imitated by some ignorant people and used by lawbreakers, affecting social stability.

Facing these problems, people have sought many solutions, such as calculating the collaborative filtering method based on content and hot news weighted hybrid real-time Top N recommendations, through certain weighted processing of the hottest news, and users browse similar mixed news from the suggestion list to
recommend, but this approach does not have to distinguish between user preferences; the user interest model is established and recorded by user’s basic information and preferences into the formation of the user model, in the process of recommendation based on the user’s interest model recommended, respectively, but there are some problems with samples, such as user preferences are not the same, as time goes on, as preferences change, this led to a decline in recommended effect; The user tag model refers to setting user dynamic preference tags through news classification, user browsing time, forwarding comments, browsing similar news, etc.; this recommendation algorithm is relatively popular at present and has relatively good effect. However, with the change of lifestyle and the acceleration of the pace of life, people spend more time on buses and subways to obtain information through mobile electronic devices, rather than traditional newspapers, TV, and other means. In this case, the acquisition of information is more to kill the boring time, which makes people browse the news with less purpose but a way to broaden their horizons. According to psychological knowledge and surveys, when people browse news, they are not affected by the news they have previously viewed, and the next news they browse is just a random choice. For example, the current user who is reading news has fully displayed the news content, while making a comprehensive analysis of the news; there are also many people who give different comments and views. The user is less interested in the next similar story, so he chooses to read another story. This can also be seen in the amount of time spent for browsing news, with similar stories being viewed for less and less time. Therefore, how to provide personalized recommendation services for each user in the mass news is the main research direction of the major mainstream platforms. This is also the main research content of this paper, through the personalized news recommendation algorithm, to achieve personalized services for each user so as to reduce the probability of users browsing the same news information, expand the scope of users’ news coverage, and improve users’ reading experience. In this paper, the advantages of the traditional recommendation algorithm are mixed, and the news recommendation is carried out with the help of the Markov model. The problems such as cold start, narrow range of recommended news, low recommendation efficiency, and poor user experience are sought to be solved in the current recommendation system so as to improve the effect of news push.

Many experts and scholars consider how to improve the reported negative information from the practical level and do not make a special and systematic analysis of the negative information in the main theme of the report, which lacks pertinence. The research emphasis of this paper is to combine negative information in a theme report in recent years, put them on the whole induction, analysis, and impact of negative information in the thematic coverage performance, analyze the cause of the negative information appear, try to make the theme reports play the best communication effect, and reduce the occurrence of negative information, hoping to provide more targeted guidance for the practice of news media.

For a long time, many media have had a certain misunderstanding of the spread of negative news on the Internet, believing that it will have a negative impact on the social atmosphere and will bring negative and destructive effects to the audience. However, through the analysis of the concept of negative news on the Internet, we can find that this is not the case. Therefore, it is necessary to deal with the relationship between positive news and negative news, carry on moderate dissemination, and make it produce a positive effect.

The use of the concept of negative press is widespread and wide ranging, not just in journalism and academia. However, there are many different solutions, and there are two main concepts of representing opinions, one is the ability to report news, and the other is events that violate social ethics and moral standards, such as crimes, scandals, and sex. The second point of view is that the impact of news reports on the audience is negative and destructive. The material of these news reports is not necessarily negative events, but the effect achieved in the dissemination process is negative. The two viewpoints illustrate the concept of negative news from different angles. The first point of view is from the perspective of the content of news reports; the second point of view is from the impact and effect of news reports. In fact, whether it is the content of the news or its effect, there are positive and negative points. Generally, positive news produces positive social effects, and negative news produces negative social effects, and there are a few other cases. However, for the second view mentioned above, there are certain problems in determining whether the news is negative or not according to the standard of the social impact of the news. Some news produces good results, but some reported data may be exaggerated. Although such news produces certain effects, it does not belong to positive news. Therefore, since the second view is prone to ambiguity, we generally define the concept of negative news from the first view.

On this basis, the definition of negative news on the Internet is clear. It refers to the news report on negative social events published on the Internet, which is different from traditional newspapers, radio, television, and other media.

A personalized recommendation system is based on online users’ past behavior information (such as clicking, viewing, and purchasing) and uses certain recommendation algorithms to recommend products that users may be interested in. There is so much information, not to mention finding the part you are interested in. Even going through them all is impossible. Personalized recommendations, including personalized search, are considered to be one of the most effective tools to solve the problem of information overload. Personalized recommendation research was not put forward as an independent concept until the 1990s. The recent surge in growth stems from the maturation of Web2.0 technologies. With this technology, users are no longer
passive web browsers but active participants. In an actual recommendation system, there may be thousands or even millions of products to be recommended, and the number of users will be very large. An accurate and efficient recommendation system can provide personalized service for numerous users by mining the potential consumption tendency of users [1, 2]. More generally, information recommendation can also be regarded as a reconstruction problem on an incomplete sparse matrix [3], while matrix reconstruction problem is the common basis of most scientific and engineering problems.

Users are more likely to stay on online news portals if they can get personalized news. A key factor in news domain suggestion is the prediction of the user’s future news read. Personalizing the material on the homepage is one technique to persuade users. In web-based service environments such as online stores, movie rentals, news, and e-learning, the provider provides individualized service to the customer, builds trust, and uses recommender systems to convince and market products.

Information recommendation technology is a typical interdisciplinary research field, involving information science, physics, management science, operations research, and other disciplines. It was put forward in the 1990s and has been developed and applied in almost all fields of information technology [4]. So far, many recommendation algorithms have been proposed, for example, cofiltering algorithm [3], content analysis-based [5], spectral analysis-based [6], network diffusion-based algorithm [7], heat conduction [8], label-based [9], random walk algorithm [10], implicit semantic analysis [11], and matrix-based singular value decomposition algorithm [12, 13]. So, the nearest neighbor of the target user can calculate the predicted score between him and all unselected goods. The basic idea of project-based collaborative filtering is that users have similar preferences for similar products.

The research is organized as follows: The related work is presented in Section 2. Section 3 analyzes the personalized recommendation system, the entitled network-based recommendation algorithm, the mark-based network recommendation algorithm, and the information recommendation algorithm based on network structure. Section 4 discusses the experiment and result in analysis. Finally, in Section 5, the research work is concluded.

2. Related Work

Negative news on the Internet has the characteristics of both network news and negative news, so we should understand the characteristics of the dissemination of the concept of its genus, respectively.

2.1. Characteristics of Network News Dissemination. First, timeliness is strong. At present, the speed of network transmission is very fast. Moreover, the transmission of the network avoids the limitation of traditional media printing, transportation, and distribution [14, 15]. The information is released quickly, the transmission speed is also fast, and the timeliness is strong. The second is multimedia. Online news brings together the advantages of traditional media and organically combines pictures, sounds, texts, and images, making new news and reports more vivid and vivid, and further enhancing their influence and appeal. The third is hypertext. Network news designers design news information into a text, users click some images or keywords and can open another text so that the comprehensive news report is enhanced, and readers can choose their own interesting content more initiative. Fourth, it can be stored. Network news can be stored on the computer for a long time, which is more conducive to the subsequent dissemination of news. Fifth is interactivity. The interaction between the network news and the audience is enhanced, and the audience can express their own comments on the news on the network platform such as chat room, e-mail, and thematic forum. Sixth is global. The Internet has broken down the barriers of space and made the whole world closely connected. Real distances no longer exist, and there are no national boundaries.

2.2. Dissemination Characteristics of Negative News. First is fast and sensational. People pay more attention to the negative news. In order to create a more sensational effect, the abnormal aspects of the event should be deliberately highlighted in the report. In this way, the attention of the news increases rapidly. Second is impact. Because negative news events do not conform to people’s cognitive laws and traditional concepts, and the media exaggerate these contents, the impact of negative news is greatly enhanced. Third is to follow suit and false facts. After the occurrence of a certain news event, some media follow the trend of mining the same type of news event in order to meet the needs of the audience so that this type of news presents a copycat report. In the reporting process, it is inevitable to add some personal subjective assumptions, resulting in the distortion of the content.

The communication characteristics of network negative news are the interaction between network news and negative news. It can be said that the communication characteristics of network negative news are mainly the reinforcement of the communication characteristics of network news to negative news. Firstly, the timeliness and globality of network news lead to the faster spread of negative news on the Internet. Secondly, the multimedia characteristics of network news further enhance the sensational effect of negative news on the network. For example, the big head baby incident, spread through the Internet, intensified the rendering of the harm of inferior milk powder; thirdly, the multimedia and interactive nature of network news exert a stronger impact on the negative news on the network. Negative news originally has a great impact, and then the Internet such a rendering naturally will have a strong shock to the audience’s senses and hearts; fourthly, the characteristics of network news determine the wide range of copycat negative news on the Internet. Fifthly, the instan- taneity, hypertext, and interactivity of network news make the untruthfulness of network negative news more severe.
The spread of negative news through the Internet will have a larger scope and more participants, which is easy to cause the “square effect,” resulting in too many versions of the report. Moreover, some network sailors deliberately release some false information for the sake of economic interests, making the authenticity of negative news on the Internet worse. In addition, user behavior characteristics and personalized domain knowledge are also used in personalized recommendation systems.

In recent years, ubiquitous large-scale complex networks have recently aroused great interest of scientists and engineering scientists in computer science, physics, management science, mathematics, sociology, systems science, and other directions, and have gradually formed a discipline field of network science [13–15]. As the dataset processed by the recommendation system can be well represented as a two-part user-object graph [16–18] (even a multigrade recommendation system can also be represented as a two-part graph), the two research directions of information recommendation technology and complex network have a common basis [9, 10]. Recently, some scholars have applied some concepts and methods of the complex network to the design and analysis of recommendation algorithms and put forward information recommendation methods based on the network structure. The algorithm regards users and products as abstract nodes, and users’ choice relation to products as edges so as to establish a two-part graph network for a recommendation. Studies show that the recommendation quality of the network-based recommendation algorithm may be superior to the currently widely used Pearson coefficient method in the case of sparse data [19].

Aggarwal first studied graph (network structure)-based collaborative recommendation algorithm in KDD’99, and the results show that the graph-based collaborative filtering method is superior to the traditional collaborative recommendation algorithm in computing speed, recommendation accuracy, scalability, learning time, and other aspects [20]. Huang et al. will use the two-layer graph model to depict the customer-product recommendation system and discuss the influence of the small-world effect and aggregation nature of the two-part graph on different recommendation algorithms [17]. Since 2007, the research center of information recommendation based on the network structure has shifted to the University of Fribourg in Switzerland. Zhang Yicheng, Zhou Tao et al. conducted a systematic study on the information recommendation algorithm based on the network and proposed that personalized recommendation is equivalent to the weighted projection problem of the two-part graph to a part graph to a certain extent. Based on this, a recommendation algorithm based on complex network resource allocation is proposed [18]. Based on the principles of material diffusion and heat transfer, a recommendation algorithm based on a bipartite graph network was proposed [21, 22]. Liu Jianguo et al. systematically studied the influence of bipartite graph network features on the recommendation algorithm. Lu et al. calculated the similarity between users based on the network structure and applied it to the collaborative recommendation algorithm [19]. Chinese Journal of Software, Journal of Computers, and JCST have also published many papers on the recommendation system. For example, Han Shuang et al. studied the two-layer hybrid graph model for a personalized recommendation.

3. Personalized Recommendation System

The recommendation system includes user sets $\{U_1, U_2, \ldots, U_m\}$ and commodity sets $\{O_1, O_2, \ldots, O_n\}$, and can be represented by a two-part graph. If there is an edging relationship between user $U$ and product $O$, it means that $U$ has selected, purchased, or collected $O$. For a powerless two-part network, all edges have the same weight, and each edge represents the same meaning. The positive side represents the product that the user likes to choose, while the negative side represents the product that the user does not like to choose. However, the negative edge is essentially different from the nonexistent edge because the former contains abundant information. For example, in Figure 1, the graph on the left represents different users, while the graph on the right represents different movies, with the red edge representing “likes” and the blue edge representing “dislikes.”

The goal of the recommendation system is to recommend the movies that the user is most likely to be interested in. Therefore, for the target user interface (UI), the recommendation system firstly calculates the predicted score between UI and the product that he has not selected and then selects the first $L$ product with the highest predicted score to recommend to UI. The data in the test set are considered unknown and not visible during the recommendation process. The precision of the UI recommendation list is defined as the ratio between the number of positive edge hits $H_i(L)$ and the length of the recommendation list $L$ in the first $L$ items recommended, namely:

$$P_i(L) = \frac{H_i(L)}{L}. \tag{1}$$

The precision value of the whole system is the average value of $P(L)$ of all users, namely:

$$P(L) = \frac{1}{m} \sum_{i=1}^{m} P_i(L). \tag{2}$$

3.1. Entitled Network-Based Recommendation Algorithm

Literature [18] provides a diffusion recommendation algorithm based on unauthorized networks, and this paper introduces a material diffusion recommendation algorithm based on an authorized network. Assuming access to network $W = \{w_{ia}\}$, $w_{ia} > 0$ if there is a link between node $i$ and $a$, otherwise $w_{ia} = 0$, if each good is assigned a unit of resources, and each good allocates its resources equally to the users who select it, and each user allocates the resources he/she receives to the goods he/she chooses. Then, the resources received by the commodity $a$ from the commodity $\beta$ are
A scoring system can be represented by a two-part network $G (U, O, E)$, where $U$, $O$, and $E$ represent users, goods, and edges (marked as scoring values), respectively. Using the collaborative filtering algorithm, the predicted value of user $U$ and commodity $\alpha$ is

$$r_{ua} = \bar{r}_u + k \sum_{v \in U} s_{uv} (r_{va} - \bar{r}_v),$$

where $s_{uv}$ is the similarity of $u$ and $v$, and $k / (\sum_{v \in U} s_{uv})$ is the normalization coefficient. One measure of similarity using score information is the Pearson coefficient.

$$s_{uv} = \frac{\sum_{a} (r_{uva} - \bar{r}_u)(r_{ava} - \bar{r}_v)}{\sqrt{\sum_{a} (r_{uva} - \bar{r}_u)^2 \sum_{a} (r_{ava} - \bar{r}_v)^2}}$$

There are roughly two reasons why users score low:

1. Users really do not like the product they choose
2. The user is very strict with the commodities he likes and does not score high easily

Either way, a score (high or low) indicates that the user has paid attention to the selected product. In this chapter, we apply the NBI algorithm to the labeled network, where high scores are represented by a “positive” edge and low scores by a “negative” edge.

To analyze the role of low scores in the recommendation system, we assign each “positive” edge to $\lambda_1$ and each “negative” edge to $\lambda_2$, and then use the NBI algorithm based on the markup network. Figure 2 shows the specific process of the algorithm, in which both $\lambda_1$ and $\lambda_2$ are adjustable parameters.

3.3. Information Recommendation Algorithm Based on Network Structure. A scoring system can be represented by a two-part network $G (U, O, E)$, where $U$, $O$, and $E$ represent users, goods, and edges (marked as scoring values), respectively. Using the collaborative filtering algorithm, the predicted value of user $U$ and commodity $\alpha$ is

$$r_{ua} = \bar{r}_u + k \sum_{v \in U} s_{uv} (r_{va} - \bar{r}_v),$$

where $s_{uv}$ is the similarity of $u$ and $v$, and $k / (\sum_{v \in U} s_{uv})$ is the normalization coefficient. One measure of similarity using score information is the Pearson coefficient.

$$s_{uv} = \frac{\sum_{a} (r_{uva} - \bar{r}_u)(r_{ava} - \bar{r}_v)}{\sqrt{\sum_{a} (r_{uva} - \bar{r}_u)^2 \sum_{a} (r_{ava} - \bar{r}_v)^2}}$$

Assuming that $G_I$ represents the probability of stopping in the steady state $j$, then

$$\bar{\gamma}^j_i = c P^T \bar{\gamma}^j + (1 - c) \bar{\gamma}^j_i.$$

We transpose (6) to obtain

$$\bar{\gamma}^j_i = (1 - c)(I - c P^T)^{-1}.$$

4. Experiment and Result Analysis

Three datasets were used to test the accuracy and diversity of the algorithm:

1. Movie Lens is a movie recommendation system that predicts that movie users may be interested in the future based on their past rating behavior.
2. Netflix is an online digital video disc (DVD) rental e-commerce site. The data used in this experiment is a sample of Netflix prize, which includes 3,000 users and 2,779 items.
3. Amazon is a multinational e-commerce website. The original data are from July 28, 2005, to September 27, 2005. The data used in this experiment is also sample data, including 3,604 users, and 4,000 books.

Some statistical characteristics of these three data are shown in Table 1. It can be seen from the table that users are more inclined to give high marks to products.
Figure 2: NBI algorithm based on tag network.

Table 1: Some statistical characteristics of the dataset.

| Dataset      | #Users | #Objects | #Edges  | Sparsity \(|(+)/(-)\) |
|--------------|--------|----------|---------|-------------------|
| Movie Lens   | 9243   | 1626     | 102300  | 5.3 \(\times\) 10^{-2} | 4.69 |
| Amazon       | 3674   | 4011     | 163780  | 2.4 \(\times\) 10^{-3} | 8.51 |
| Netflix      | 3210   | 2718     | 199228  | 9.3 \(\times\) 10^{-2} | 5.66 |

(a) Figure 3: Continued.
Figure 3: Relationship between $F_1$ and $P$. The length of the recommendation list is 10 and 20, respectively. (a) Amazon. (b) Movie Lens. (c) Netflix.
In the training set, the weights of positive and negative sides are 1 and \( A \), respectively. By adjusting the value, the contribution weight of negative edge in the recommendation system can be changed. The experimental results are shown in Figure 3. For Movie Lens and Netflix datasets, when the datasets become sparse from dense, the optimal value also changes from negative to positive. This contradicts the conventional view that a low score should play a negative role in a recommendation system. As mentioned above, a low score actually hides two kinds of information in the recommendation system. On the one hand, it indicates that users do not like the selected products, but on the other hand, it indicates that users pay attention to the selected products. However, when the data are sparse, the importance of the “concern” information gradually increases, resulting in the positive value of the optimal. The above results imply that in the process of recommending products, it is taken for granted to remove the low users’ risk of losing a lot of valuable information, thus leading to inaccurate recommendation results. The relationship between \( F_1 \) and \( P \) is shown in Figure 3.

4.2. Local Effects of Low Score. We mainly analyze the role of low score in the recommendation system from the micro-level. In the same way, we divide the above three datasets. The difference is that the ratio of the total number of edges in the training set to the total number of edges in the total number of datasets is fixed at 0.2, and only the score of not less than 3 in the test set is used to test the accuracy of the algorithm. Similarly, \( F_1 \) is used to evaluate the accuracy of the algorithm.

Figure 4 and Table 2 show the microscopic results of the role of low scores in the recommendation system. In Figure 4, the dotted line represents the \( F_1 \) value corresponding to the algorithm when only high time-sharing is considered, and the solid line represents the optimal \( F_1 \) value corresponding to the algorithm when only low time-sharing in subset \( L_R_i \) is considered. Table 2 gives the optimal \( A \) values of different subsets \( L_R_i \). From Figure 4 and Table 2, we can draw two important conclusions as follows:

1. In the recommendation system, it is not enough for the recommendation algorithm to only consider users’ high scores

| Table 2: Optimal \( A \) values of several cases. |
|-----------------|-----|-----|-----|-----|-----|
|                | \( R \) | \( R \) | \( R \) | \( R \) | \( R \) |
| Movie lens      | \( X = 100 \) | \(-2.14\) | \(-2.25\) | \(-2.12\) | \(-0.45\) | \(1.22\) |
|                 | \( X = 200 \) | \(-2.21\) | \(-2.11\) | \(-2.11\) | \(0.00\)  | \(1.10\) |
| Netflix         | \( X = 100 \) | \(-2.22\) | \(-2.24\) | \(0.00\)  | \(0.00\)  | \(2.12\) |
|                 | \( X = 200 \) | \(-2.24\) | \(-2.17\) | \(-1.14\) | \(0.00\)  | \(1.45\) |
| Amazon          | \( X = 100 \) | \(-2.20\) | \(-1.55\) | \(0.40\)  | \(0.55\)  | \(1.05\) |
|                 | \( X = 200 \) | \(-2.20\) | \(-1.4\)  | \(0.52\)  | \(1.11\)  | \(0.11\) |
(2) As shown in Table 2, the low score between active users and popular products always plays a negative role in the recommendation system, while the low score between inactive users and popular products always plays a positive role in the recommendation system. The results further support our previous analysis that “follows” information represented by a low score is more important in the promotion process, especially for inactive users and nonpopular products.

4.3. Impact of a Low Score on Diversity. In accordance with the same method, we assign 1 to all the high scores in the training set, and A to all the low scores. Figure 5 shows the experimental results. As can be seen from Figure 5, the larger the weight of low score is, the more diversified the recommendation results are.

5. Conclusion

In recent decades, driven by the performance requirements of recommender systems, many machine learning methods have been applied to recommender systems. Some learning-based approaches may involve thousands of parameters or complex learning processes. In addition to the accuracy of the recommendation system, this chapter pays more attention to the understanding of the recommendation system itself, namely, the understanding of the user’s behavior. For the traditional recommendation algorithm, especially the collaborative filtering recommendation algorithm based on Pearson coefficient, low score plays a negative role in the process of product recommendation. In other words, the more low scores a product receives, the harder it will be to recommend it. By adjusting the sparsity of the training set, the experimental results show that in dense datasets, the low score of users plays a negative role in the recommendation process, while in sparse data, the low score of users plays a positive role in the recommendation process. This result implies that low user scores play two roles: on the one hand, they dislike the product, and on the other hand, they care about the product. In the case of sparse data, the “attention” information contained in low scores is particularly important. Therefore, when the data is particularly sparse, the weight of these low scores should be given positive values. Further analysis showed that low scores between inactive users and nonpopular items had a positive effect on recommendations, while low scores between active users and popular items had a negative effect on recommendations. This result further confirms that low scores play a dual role in product recommendation, as low scores for an unpopular product by inactive users actually reflect more of the user’s attention to the product.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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