Personalized recommendation algorithm based on online comment sentiment analysis

Qing Lian
School of Business, Central South University, Changsha, Hunan, 410000, China
email: lianqing1007@csu.edu.cn (revision)

Abstract. Artificial intelligence is one of the many branches of computer science. With the continuous development of information technology and computer networks, artificial intelligence technology has also received tremendous support and rapid development. In the computer field, recommendation systems can be said to be the most extensive and successful application of artificial intelligence technology. This paper focuses on the problems of cold start and low recommendation accuracy caused by sparse rating data in traditional recommendation systems, proposes a personalized recommendation algorithm based on online comment sentiment analysis. The algorithm uses feature-level sentiment analysis to mine user preference information implicit in comments, and finally implements recommendations based on user ratings and preference information. Experiments show that the algorithm proposed in this paper can effectively make up for the shortcomings of traditional collaborative filtering recommendation algorithms, and is of great help in improving user cold start and the quality of recommendation results.

1. Introduction
With the rapid development of information technology, computer networks are becoming larger and larger, and hundreds of millions of information and data are generated on the network every day. The era of big data has come, and information overload has become one of the headaches. As the data on the Internet becomes more and more complex, it is difficult for us to accurately find the information we need or are interested in in such a large amount of data, the time cost of information search and screening has greatly increased. In the context of big data, a personalized recommendation system based on information technology came into being.

Personalized recommendation system is one of the most extensive applications of artificial intelligence technology in the computer field. Artificial intelligence refers to a technology in which computers simulate human thinking and behavior through complex algorithms and calculations. Its main applications in recommendation systems are reflected in: According to the historical behavior of users in the system, algorithms are used to automatically mine and update user preference information, improve user models, and provide personalized recommendations for different users. The personalized recommendation algorithm is the key to the recommendation system. Traditional personalized recommendation algorithms can be divided into content-based recommendation and collaborative filtering recommendation. Among them, collaborative filtering recommendation is very popular because of its simple calculation and good recommendation effect. It is widely used in many fields such as books\cite{1}, movies\cite{2}, music\cite{3}, product recommendations\cite{4} and smart cities\cite{5}. However, as the amount of user and item data in the system continues to increase, there is less and less common scoring data between two users, and the recommendation quality of collaborative filtering recommendation...
algorithm that rely on common scoring data is greatly reduced, so the algorithm needs to be improved.

Usually, when users rate an item, they will also post comments. These comments contain rich information and are of great value. Therefore, this paper proposes a recommendation algorithm that combines user ratings and comments, uses sentiment analysis to process user comment data, and then predicts ratings from two aspects of rating similarity and sentiment similarity to implement personalized recommendations.

2. Related work
With the continuous development and maturity of natural language processing technology, many scholars have begun to think about how to introduce text information into the recommendation model. Dong et al. used a topic model to represent user comments in several topics, set topic weights according to audience preferences, and finally made movie recommendations based on user preferences[6]. Chen et al. used the Apriori association rule algorithm to extract attributes from book reviews for recommendation[7]. In addition, sentiment analysis can also mine useful information in online reviews. Lei et al. mine the features of movie reviews and calculate the emotional value of the reviews, establish a more accurate user preference model, and improve the accuracy of the recommendation algorithm[8]. Shan et al. used sentiment analysis on online reviews as a supplement to users’ orientations toward products[9]. Qian et al. considered the uncertain information in the comment language, designed a sentiment analysis model based on fuzzy theory, and experiments on real data sets showed that the proposed algorithm is effective[10].

3. Algorithm proposed
3.1 Feature-level sentiment analysis
Sentiment analysis is one of the commonly used methods in the field of natural language processing. According to different research objects, sentiment analysis can be divided into three levels: text level, sentence level and feature level[11]. Feature-level sentiment analysis can dig out more specific and useful information from review text. The analysis process generally includes mining features, building domain lexicons, and calculating sentiment orientations.

3.1.1 Mining features
Feature refers to the specific evaluation object in online reviews. For example, in the sentence "The plot is really great" in film reviews, "Plot" is a characteristic word, "great" is an emotion word used to modify the characteristic word, and "really" is a degree word used to modify emotion word. In order to obtain the user's sentiment for the item features, the feature words of the field of the review must be established. Generally speaking, domain feature words are nouns, after using text processing tools to preprocess comments, such as word segmentation and part-of-speech tagging, nouns with higher word frequencies can be extracted as candidate feature words. Common text processing tools have NLTK, StanfordCoreNLP, Jieba, etc. and then filter the candidate feature words. In order to improve the accuracy of feature selection, this paper performs feature selection based on word vectors. The steps are as follows:

(1) Extract a group of highly discriminating domain seed words \( F = \{ f_1, f_2, \ldots, f_k \} \) from reviews based on artificial prior knowledge.
(2) Use Word2vec tool to train the comment corpus, and obtain the optimal word vector representation by continuously adjusting the context window distance and dimensional parameters.
(3) Use the trained word vector model to calculate the cosine distance between the seed words and the candidate feature words, and select words with higher similarity to retain as the feature words.

3.1.2 Building domain lexicons
Lexicons are the basis of sentiment analysis. In order to ensure the accuracy of sentiment analysis, it is necessary to establish lexicons of positive and negative emotion words, degree words and negative
words. Commonly used emotion word lexicons include SentiWordNet, HowNet, NTUSD, etc. In addition, it is also necessary to establish field emotion word lexicons according to different research fields. This article uses the SO-PMI algorithm to build it, which is mainly used to determine the emotional polarity of the words to be evaluated. In the field of text processing, PMI is usually used to calculate the similarity between two words. The higher the value, the greater the correlation between the two words. The calculation formula of the PMI is shown in formula (1):

$$PMI(w_1, w_2) = \log_2 \frac{P(w_1, w_2)}{P(w_1)P(w_2)}$$ (1)

In formula (1), $P(w_1, w_2)$ represents the number of times that the words $w_1$ and $w_2$ appear together in the sentence, and $P(w_1)$ and $P(w_2)$ represent the number of times that the words $w_1$ and $w_2$ appear respectively.

Therefore, the emotional polarity of a word $w$ to be evaluated can be expressed by the SO-PMI algorithm as:

$$SO - PMI(w) = \sum_{pword}P(w, pword) - \sum_{nword}P(w, nword)$$ (2)

In formula (2), $pwords$ and $nwords$ respectively represent as positive and negative seed word sets. Finally, in view of the three possible situations in the $SO - PMI(w)$ calculation result, the following provisions are made:

$$SO - PMI(w) \begin{cases} > 0, & \text{w is positive emotion word} \\ = 0, & \text{w is neutral emotion word} \\ < 0, & \text{w is negative emotion word} \end{cases}$$ (3)

3.1.3 calculating sentiment orientations

The user's sentiment orientation includes two aspects: emotional polarity and emotional intensity. The calculation of user's emotional orientation is the key to feature-level sentiment analysis. In the review text, users' evaluations of item features are usually described using three types of words: emotion words, degree words, and negative words. Therefore, in order to quantify the user's emotional orientation towards item features, the three types of words must be assigned values. For emotion words, positive emotion words have positive emotions and are assigned a value of 1. On the contrary, negative emotion words are assigned a value of -1; different levels of degree words show different strengths, such as “very good” shows stronger likes than “generally good”, so it is necessary to assign different weights to different grades of degree words; negative words usually express opposite emotional polarity, for example, "good" and "bad" are a pair of antonyms, so the weight of negative words is set to -1. Finally, use formula (4) to calculate the user’s emotional orientation score for item features:

$$S(f) = P(SW) \times W(adv) \times (W(neg))^n$$ (4)

In formula (4), $P(SW)$ represents the score of emotion words, $W(adv)$ represents the weight of degree words, $W(neg)$ represents the weight of negative words, and $n$ represents the number of negative words. Finally, each comment is expressed in the form of $(u, i, f, s)$, where $u$ is the user, $i$ is the item, $f$ is the feature, and $s$ is the emotional orientation score.

3.2 Score prediction and recommendation

Similarity calculation is the core of collaborative filtering recommendation, and the quality of the calculation result directly affects the quality of the final recommendation result. The traditional collaborative filtering recommendation algorithm only calculates the similarity between users based on the user's overall rating data of the item, ignoring the user's emotional orientation toward the specific features of the item, resulting in recommending items with features that the target user does not like to the user, affecting the recommendation quality and user’s satisfaction. Therefore, in order to obtain a better recommendation effect, this article combines sentiment similarity and score similarity to make score prediction and implement recommendation.
3.2.1 User similarity

(1) Sentiment similarity

In Section 3, the user comment data is processed by the sentiment analysis algorithm to obtain the user's sentiment score for the item features, and then the cosine similarity calculation algorithm is used to calculate the sentiment similarity \( \text{sim}(u, v)^{emo} \) between user \( u \) and user \( v \):

\[
\text{sim}(u, v)^{emo} = \frac{\sum_{i \in I_{uxv}} \sum_{j \in F_{uxvi}} S_{ui} \times S_{uj}}{\sqrt{\sum_{i \in I_{uxv}} \sum_{j \in F_{uxvi}} S_{ui}^2} \sqrt{\sum_{i \in I_{uxv}} \sum_{j \in F_{uxvi}} S_{uj}^2}}
\]

\( I_{uxv} \) represents the set of items that user \( u \) and \( v \) have commented together, and \( F_{uxvi} \) represents the intersection of features that appear in the comments of user \( u \) and \( v \) on item \( i \).

(2) Rating similarity

Taking into account the different scoring habits of different users, this article uses the Pearson similarity calculation algorithm to calculate the scoring similarity \( \text{sim}(u, v)^{sco} \) between user \( u \) and \( v \):

\[
\text{sim}(u, v)^{sco} = \frac{\sum_{i \in I_{uxv}} (r_{ui} - \bar{r}_u) (r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{uxv}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in I_{uxv}} (r_{vi} - \bar{r}_v)^2}}
\]

(3) Comprehensive similarity

The two similarities are summed through the parameter \( \alpha \) to obtain the comprehensive similarity \( \text{sim}(u, v) \):

\[
\text{sim}(u, v) = \alpha \text{sim}(u, v)^{emo} + (1 - \alpha) \text{sim}(u, v)^{sco}
\]

3.2.2 Recommendation

After obtaining the comprehensive similarity between user \( u \) and \( v \), the predicted score of user \( u \) for unrated item \( i \) can be calculated:

\[
\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{v \in N_k(u)} \text{sim}(u, v)(r_{vi} - \bar{r}_v)}{\sum_{v \in N_k(u)} \text{sim}(u, v)}
\]

\( N_k(u) \) represents the set of neighbors of user \( u \). Finally, by sorting the predicted scores of each unrated item in descending order, the final \( TOP - N \) recommendation list is obtained.

4. Results & Discussion

4.1 Experimental data set and evaluation indicators

This paper selects 253,524 movie reviews of 990 movies from 4301 users on Douban Movies website (https://movie.douban.com/) as the experimental data set, and the sparsity of the data set is 94.05%. And use the average absolute error MAE as the evaluation indicator:

\[
\text{MAE} = \frac{1}{|T|} \sum_{(u,i)} |\hat{r}_{ui} - r_{ui}|
\]

\( |T| \) represents the total number of review data in the test set, \( \hat{r}_{ui} \) represents user’s predicted rating for movie \( i \), and \( r_{ui} \) represents user’s actual rating for movie \( i \).

4.2 Experimental results and analysis

(1) The influence of parameter \( \alpha \) on the accuracy of recommended algorithm (MAE)

In order to determine the appropriate value of \( \alpha \), the value of \( \alpha \) is set from 0 to 1 in this experiment, and the step size is 0.1. Pre-set the number of user’s nearest neighbors \( L = 80 \), observe the change of MAE value under different \( \alpha \), and get the experimental results as shown in the figure 1.
It can be seen from Figure 1. that when the value of $\alpha$ is 0.4, the MAE value takes the minimum value, which is 0.7701. The results show that the user emotional similarity can better correct the user similarity, make up for the shortcomings of only using the original user score data to calculate the user similarity, and improve the prediction accuracy.

(2) Comparative experiment
In order to verify the effectiveness of the personalized recommendation algorithm based on online comment sentiment analysis proposed in this article, the following comparison algorithms are selected in this article:

1. UBCF, User-based collaborative filtering algorithm;
2. IBCF, Item-based collaborative filtering algorithm;
3. PSCF, a collaborative filtering recommendation algorithm based on user sentiment similarity;
4. UPSCF, the algorithm proposed in this paper.

In this experiment, $\alpha = 0.4$, $L$ is set to 10-100, and the step size is 10. The experimental results are shown in Table 1. and Figure 2.

Table 1. MAE values of different recommended algorithms

| L   | 10   | 20   | 30   | 40   | 50   | 60   | 70   | 80   | 90   | 100  |
|-----|------|------|------|------|------|------|------|------|------|------|
| UBCF| 0.9126 | 0.8830 | 0.8673 | 0.8504 | 0.8358 | 0.8223 | 0.8116 | 0.8023 | 0.7945 | 0.7883 |
| IBCF| 1.0398 | 0.9464 | 0.9121 | 0.8908 | 0.8756 | 0.8654 | 0.8571 | 0.8520 | 0.8426 | 0.8366 |
| PSCF| 0.8960 | 0.8782 | 0.8464 | 0.8239 | 0.8135 | 0.8052 | 0.7936 | 0.7860 | 0.7824 | 0.7807 |
| UPSCF| 0.8842 | 0.8636 | 0.8328 | 0.8187 | 0.8069 | 0.7923 | 0.7797 | 0.7701 | 0.7614 | 0.7588 |
As shown in Table 1. and Figure 2., as the number of neighbors $L$ increases, the MAE values of the four recommended algorithms are constantly decreasing, and finally tend to be stable. The algorithm proposed in this paper to comprehensively consider rating similarity and sentiment similarity is better than the other three comparison algorithms. It shows that using feature-level sentiment analysis to process comments and combine them with user ratings can be more accurate Measure the similarity between users, make up for the lack of similarity calculations using single rating data or single review data, and improve recommendation accuracy.

5. Conclusions
This paper proposes a personalized recommendation algorithm based on online comment sentiment analysis. The algorithm uses natural language processing technology to introduce online comments into the recommendation model, improves the traditional model, and finally verifies the effectiveness of the algorithm on a real data set. The author believes that with the continuous development and maturity of artificial intelligence technology, the recommendation system will also become more intelligent and humanized, providing users with better services.

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