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RECOMMENDATION ALGORITHM BASED ON TIME CONTEXT AND TAG OPTIMIZATION

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ABSTRACT

At present, some progress has been made in the research of context-based recommendation algorithm and label-based recommendation algorithm. However, there are some problems such as sparse scoring data for items by users and low precision of recommendation results. In response to the above problems, this paper proposes a recommendation algorithm that integrates time context and tag optimization. The recommendation algorithm is improved by integrating user behavior time interval and user attribute label information. Firstly, Long Short-Term Memory (LSTM) is introduced to study the effect of time interval on tags. Then, each output layer is combined with Latent Dirichlet Allocation (LDA) to weigh the tags with high importance. Finally, the prediction value is obtained by fusing the scoring information. Experiments show that the new algorithm has effectively alleviated the problem of sparse scoring data and improves the precision of recommendation results.

Keywords: *recommender system; time context; tags; Long Short-Term Memory; topic model；Scoring Matrix*

1. INTRODUCTION

With the advancement of the Internet and the development of the sharing economy, various services provided by the Internet technology have not only become more and more abundant, but their costs have also gradually decreased, bringing many convenient experiences to users' lives [1] [2]. At the same time, this makes users also troubled by how to find information that meets their needs in a mass of information, that is, the "information overload" problem. Therefore, how to alleviate this kind of "information overload" problem, assist users to find items that meet their needs, and help merchants recommend suitable items to target users, has become very important [3].

The history tag record can reflect the user's preferences, and combined with the time context information can better capture the preference rules. Through the analysis of human time behavior characteristics, it can be found that as the span of the time interval increases, the influence of its user's corresponding tag information will gradually decrease. In other words, when the time interval of the tag information is too large, it will result in low or no relevance to the upcoming event of the user. Moreover, the degree of relevance of each label to the user is different, and the importance of different labels to the user is different. Considering the impact of time interval and label importance, this paper proposes a recommendation algorithm based on time context and tag optimization to improve the accuracy of recommendation.

2. RELATED WORK

At present, some research results show that the behavior interval distribution of human behavior does not obey the Poisson distribution, but presents power-rate characteristics [4]. This means that after a relatively long period of inactivity, users will suddenly have high-frequency events in a short period of time. From this characteristic of human behavior, it can be known that certain periods of time have a great impact on users, and certain periods of time have little impact on users themselves. With the popularity of the Internet, a large amount of data including user activity time provides great convenience for better characterizing user interests and inferring user activity rules. Zhang et al. Combined the time-series correlation analysis of check-in locations and found that the time interval between similar users visiting the same place is concentrated within one hour [5]; Zhao et al. research found that the main factors affecting users to start new activities are Historical interest, inertia, and the degree of interest in new activities [6]; research by Yang et al. Shows that in addition to the current project itself, current user ratings are also affected by a recent score. Li et al. Have studied the increase in the time interval, and the weight of its impact on current activities has gradually decreased [7]. The above analysis further illustrates the importance of time information and fully explains the reason for the proposed new algorithm in this paper.

With the further development of the recommendation system, the label-based recommendation system has also been continuously improved. Regarding the degree of relevance of the tags, the term "co-occurrence" needs to be introduced here, that is, the mode of co-occurrence between tags. For example, the tags "Apple", "mobile phone", and "iPhone" often appear together, and the tags "data mining" and "machine learning" appear together. The co-occurrence of tags can reflect the association between tags. At present, the algorithm research that uses tag co-occurrence to improve the recommendation algorithm has been developed. [8] uses the item set method to calculate the correlation between tags. In [9-10], the number of co-occurrences of tags is directly used as a value for calculating the close relationship between tags. In [11], in the co-occurrence mode of tags, the tags are further subdivided into tags by using the tag probability relationship diagram Further research on importance and correlation between tags. Among them, the degrees of the vertices in the importance correspondence graph are various. When the vertices correspond to a larger degree, it indicates that the directionality of the label is more blurred; at the same time, the correlation between the labels is also found to be asymmetric.

The user's interest preference usually does not maintain a very stable state and has frequent interactive behaviors, so the time series dynamic factor is particularly important. For dynamic interest modeling, recurrent neural networks have the advantage of better processing serialized data, and can dynamically display the temporal sequence behavior of users [12] [13]. Combining related technologies of deep learning with label recommendation can Better learn users' long-term and short-term interest preferences [14]. With the deepening of research, scholars have discovered that the gradient neural network disappears when it processes important information with long delay. In order to solve this problem, some researchers have improved the neural network through embedded methods [15] [16], derived from Long Short-Term Memory (LSTM) [17] and Gated Recurrent Unit (GRU), these methods can effectively process the user's time series data information.

Latent Dirichlet Allocation (LDA) topic regression model, the popular point interpretation is the conditional probability of words in a word list [18]. In the new algorithm proposed in this paper, all the user's existing tag information is used as the full semantic information of a topic, and LDA is used to learn the interaction between each tag and the topic, or it can be understood that under the current topic, the tag the importance of labeling and topic interaction as the attention mechanism, integrating weight values.

3. FTTO-RA ALGORITHM

This algorithm fuses the user's label information with the time interval, studies the impact of the time interval on the user's label information, and uses the LDA topic model to further improve the highly relevant label weight. According to the principle and structure of the LSTM method of the long-term and short-term memory network model, it is known that it uses the mark symbols on the conveyor belt to indicate the importance of the current information. When the information is considered important, the state is represented as 1, that is, the current information is transmitted to the next time for information fusion, otherwise throw away. Therefore, the new algorithm uses the two models of LDA and LSTM to conduct in-depth research, and proposes a Fusion Time-context and Tag Optimization Recommendation Algorithm (FTTO-RA).

3.1 Algorithm Core Structure

In order to distinguish and better integrate into the LSTM, we define a global object-tag record matrix, where matrix parameter is denoted as U^u, $U^u = \{(At^u{}_1, t^u{}_1), (At^u{}_2, t^u{}_2), \cdots, (At^u{}_m, t^u{}_m)\}$, $\left(At_i^u . t_i^u\right)$ represents the preference label that user u has at time t_i^u, and At_i^u represents the label. Then, the global object label record matrix is integrated into the LDA topic model to mine the specific topic probability distribution corresponding to the global object-tag. We use the project attribute matrix to represent the personalized feature label matrix information of the project itself, that is, to build the project attribute label matrix based on the project's own feature label. Corresponding to the reconstructed user tag matrix information and item tag matrix information, it is divided into two sub-

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algorithms, namely user tag-based preference user set recommendation algorithm and item tag related item set recommendation algorithm. Secondly, this article introduces the LSTM model for further research, introduces the session segment into the LSTM model, and studies the impact of time interval information on user labels. (For the convenience of algorithm description, a certain time interval is referred to as a session segment in this section.). Finally, the constructed topic probability distribution is fused with the output of each session in the LSTM to further capture the more relevant labels. As shown in Figure 1.

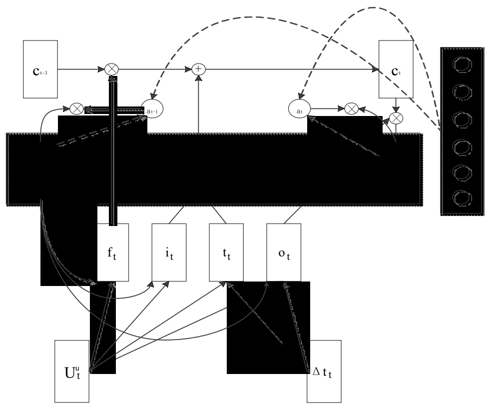

Figure 1. Schematic diagram of FTTO-RA fusion

3.2 FTTO-RA algorithm description

According to the algorithm description of the above algorithm, we integrate a certain session segment into the long-term and short-term memory network model. Here we add a specific time conversion matrix $t_{\Delta t_t}$ to store the information of session segment Δt_t and study the impact of session segment on labels. Then at time t, the new candidate set is updated as:

$$\tilde{C}_t = \tanh(W_{ch} h_{t-1} + W_{c*}[U^u{}_t, t_{\Delta t_t}] + b_C)$$

where W_{ch} and W_{c*} are model parameters, U_t^u is the embedded representation of user tag information on the session segment at t, h_{t-1} is the embedded representation of the output of the previous session segment, and b_c is the offset vector, and Δt_t is the session segment information at time t. At the same time, in order to fully consider the impact of the session segment, we borrow time-LSTM [19] and add a time information gate t to further control the impact of the session segment on the input user tag information of the current session segment at a certain time, and finally update the status. We define the objective function as follows:

$$C_t = f_t * C_{t-1} + i_t * t_t * \tilde{C}_t \quad (1)$$

$$t_t = \sigma(W_{tu} U^u{}_t + \sigma(W_{tt} t_{\Delta t_t}) + b_t) \quad (2)$$

where W_{tu} and W_{tt} are model parameters, $U^u{}_t$ is the embedded representation of user tag information on the session segment at t, and b_t is the offset vector, and Δt_t is the session segment information at time t. In summary, we define the objective function of LSTM as follows:

$$f_t = \sigma(W_f * [h_{t-1}, U^u{}_t] + b_f) \quad (3)$$

$$i_t = \sigma(W_i * [h_{t-1}, U^u{}_t] + b_i) \quad (4)$$

$$\tilde{C}_t = \tanh(W_c * [h_{t-1}, U^u{}_t, t_{\Delta t_t}] + b_C) \quad (5)$$

$$C_t = f_t * C_{t-1} + i_t * t_t * \tilde{C}_t \quad (6)$$

$$o_t = \sigma(W_o * [h_{t-1}, U^u{}_t, t_{\Delta t_t}] + b_o) \quad (7)$$

$$h_t = o_t * \tanh(C_t) \quad (8)$$

Where W_* are model parameters, $U^u{}_t$ is the embedded representation of user tag information on the session segment at t, h_{t-1} is the embedded representation of the output of the previous session segment, and b_* is the offset vector.

Then we use the LDA topic model to construct the label's topic probability distribution corresponding to the label distribution. According to the prior parameters W and E, LDA's joint probability distribution formula is as follows:

$$p(\theta,\beta,\mathbf{z},\mathbf{w}|\alpha,\eta) = p(\beta|\eta)\prod_{m=1}^{M\text{-}l} p(w_m|\beta_{z_m})p(z_m|\theta)p(\theta|\alpha) \quad (9)$$

We use the following formula to compute the whole label document Ω:

$$p(\mathbf{\Omega}|\alpha,\eta) = \prod_{u=1}^{N\text{-}u}\int\int p(\beta|\eta)\left(\prod_{m=1}^{M\text{-}l}\sum_{z_{u,m}} p(w_{u,m}|\beta_{z_{u,m}})p(z_{u,m}|\theta_u)p(\theta_u|\alpha)\right)d\theta_u \quad (10)$$

Where $N\text{-}u$ is the number of users and $M\text{-}l$ is the number of tags per user. Then use the posterior probability to estimate θ and β:

$$p(\mathbf{z},\theta,\beta|\mathbf{w},\alpha,\eta) = \frac{p(\theta,\beta,\mathbf{z},\mathbf{w}|\alpha,\eta)}{p(\mathbf{\Omega}|\alpha,\eta)} \quad (11)$$

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Next, we will get all $\left[h_1, h_2, h_3, \cdots, h_m\right]$ and the calculated label topic probability distribution $\theta_u \in R^{k\times 1}$ to embed each layer. The embedding method is as follows:

$$h_t^{\ u} = a_t h_t \tag{12}$$

Where a_t is calculated obtain the following formula:

$$a_t = \frac{\exp(e_t)}{\sum_{t=1}^{m} \exp(e_t)} \tag{13}$$

$$e_t = v_a \tanh(W_e \theta_u + U_h h_t) \tag{14}$$

Where $v_a \in R^{1\times m}$, $W_e \in R^{m\times k}$, $U_h \in R^{m\times m}$ are the model parameters, and e_t represents the current relationship score between θ_u and h_t. When the score is large, this indicates that the correlation is relatively high.

Finally, the user's label information $U^u{}_h = \sum_{t=1}^{M} h_t^{\ u}$ is obtained through two embeddings of the time session segment and the topic distribution. Then it is further fully connected and integrated into collaborative filtering for recommendation. We then use $w_{uv} = sim(U^u{}_h, U^v{}_h) + sim(R_u, R_v)$ to improve formula (15) to get the final predicted score r' for the project.

$$r' = \overline{r_u} + \frac{\sum_{v\in S(u,K)\cap N(i)} w_{uv}(r_{vi} - \overline{r_v})}{\sum_{v\in S(u,K)\cap N(i)} |w_{uv}|} \tag{15}$$

Where $S(u,K)$ represents the set of users who are most similar to user U's interests, $N(i)$ is the number of users interested in item i, r_{ui} and r_{vi} are the ratings of user u and v for item i, $\overline{r_u}$ and $\overline{r_v}$ are the average scores of user u and v on all their evaluated projects.

Table 1: Algorithm Describes the Details.

Algorithm： FTTO-RA algorithm
Input: User label matrix information U^u and Scoring matrix information ***R***
Output: predicted ratings of item r'
For each $u \in U$ **do** // for a certain user
For each Δt_t **do** // time window length
$t_{\Delta t_t} = \Delta t_t$ // specific time interval transition, that is, the time interval value between the user's previous and next behavior
End For
$\tilde{C}_t = \tanh(W_c * [h_{t-1}, U^u{}_t, t_{\Delta t_t}] + b_C)$ //candidate state vector at time t
$C_t = f_t * C_{t-1} + i_t * t_t * \tilde{C}_t$ // new state
$o_t = \sigma(W_o * [h_{t-1}, U^u{}_t, t_{\Delta t_t}] + b_o)$
$h_t = o_t * \tanh(C_t)$ //output at time t
$h_t^u = a_t h_t$ // new output after merging topic distributions
$U^u{}_h = \sum_{t=1}^{M} h_t^{\ u}$ // get the current user output tag information
$r' \leftarrow CF(U^u{}_h, R)$
End For

4. EXPERIMENT

4.1 Dataset

In the experiment the data set used in this article is movielens-1, which obtained the updated data set in October 2016. In order to better study the effect of the fusion of tag information and time interval, we remove the users with less movie interaction events in this data, and obtain the records of interactions between 2652 users and 4,127 movies. The tag information has a corresponding time stamp. Then, data records are uniformly divided into 80% as training data and 20% as test data. In order to prove the accuracy of the experimental results, this experiment is mainly divided into two modules, which are introduced in the experimental comparison.

4.2 Experimental comparison algorithm

In order to verify the effectiveness of the new recommendation algorithm proposed in this section, we have selected the following related recommendation algorithms as comparison algorithms to compare with the new algorithm proposed in this section.

User-CF : User-based collaborative filtering algorithm. The algorithm calculates user similarity based on user rating data, and then uses traditional collaborative filtering algorithms for recommendation.

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LDA-userCF：A collaborative filtering recommendation algorithm for computing neighbors by combining LDA topic models. The algorithm directly converts the user-item rating information into a global object-item document, uses the LDA topic model to obtain the "hidden vector", and then uses the "hidden vector" matrix to obtain the user similarity, and then predicts the rating information.

UTLR-CF ： Collaborative filtering recommendation algorithm combining label-scoring and LDA topic models. The algorithm considers three factors: label information, latent topic information hidden in the label, and scoring information, and then recommends based on the collaborative filtering algorithm. Algorithm referred to as UTLR-CF [20].

Table 2 shows the comparison of different data information used between the FTTO-RA algorithm and each algorithm.

Table 2 Data Information Utilization

<table>
<tr><th rowspan="2">Algorithm</th><th>Rating</th><th colspan="2">Tag</th><th rowspan="2">Time</th></tr>
<tr><th></th><th>User</th><th>Item</th></tr>
<tr><td>User-CF</td><td>✓</td><td></td><td></td><td></td></tr>
<tr><td>LDA-userCF</td><td>✓</td><td></td><td></td><td></td></tr>
<tr><td>UTLR-CF</td><td>✓</td><td>✓</td><td></td><td></td></tr>
<tr><td>FTTO-RA</td><td>✓</td><td colspan="2">✓</td><td>✓</td></tr>
</table>

4.3 Metrics

The Mean Absolute Error refers to the average value of the absolute value of the deviation between the predicted score value of each individual item and the user's real score. Its main function is to reflect the accuracy of the recommendation, which is expressed as MAE. If the value of *MAE* is smaller, the recommended accuracy is higher. The calculation formula is as follows:

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|R_{ui}-R'_{ui}\right| \qquad (16)$$

The Root Mean Square Error is the square of the deviation between the predicted score and the user's actual score, and the ratio to the number of ratings. It mainly reflects the accuracy of prediction, expressed as RMSE. The calculation formula is as follows:

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_{ui}-R'_{ui})^{2}} \qquad (17)$$

4.4 Experiment analysis

In this section, MAE and RMSE are used as evaluation indicators. User-CF, UTLR-CF, and LDA-userCF are compared with the FTTO-RA algorithm proposed in this paper. It is divided into two parts: one is to determine the FTTO-RA algorithm the number of user topics. The second is to compare the effectiveness of different algorithms.

(1) Impact of the number of user topics in FTTO-RA

Topic number Topic-K is mainly used to indicate the number of topics for which the global object-tag is obtained, which affects the quality of capturing user tag information and then affects the recommendation result. Therefore, the value of Topic-K affects the effectiveness of the algorithm.

We give the average absolute error MAE and the root mean square error RMSE corresponding to the number of topics Topic-K, so as to determine the Topic-K value, so that the recommendation result of the FTTO-RA algorithm is optimal. The following experiments were performed on the above real dataset. The experimental results based on the MovieLen-1 dataset are shown in Figures 2 and Figures 3. The horizontal axis is the value of Topic-K in FTTO-RA, and the vertical axis is the average absolute error and the root mean square error, respectively. It can be seen from the trend that with the increase of the topic number of Topic-K, the value of MAE and the calculation result of RMSE both show a decline, and the trend is relatively stable in the later period. According to the evaluation index rules, it can be judged that the recommendation effect tends to increase first. After that, a stable condition appears. When the topic number of Topic-K is about 6, it is the value that M performs better. In the experimental results of R, when the topic number of Topic-K is 6, the better state appears. Therefore, in this paper, we combine the experimental results of M and R and set the topic number Topic-K to 6 to make the algorithm reach the optimal state (where User-K takes the value of 30).

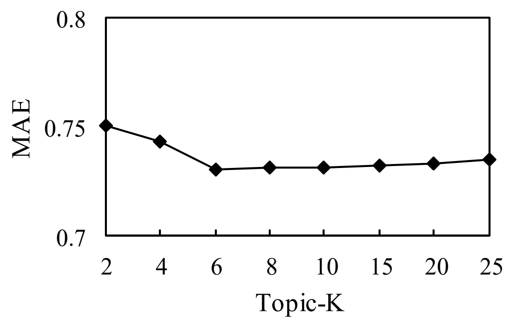

Figure 2. MAE values for different Topic-K on the MovieLen-1 dataset

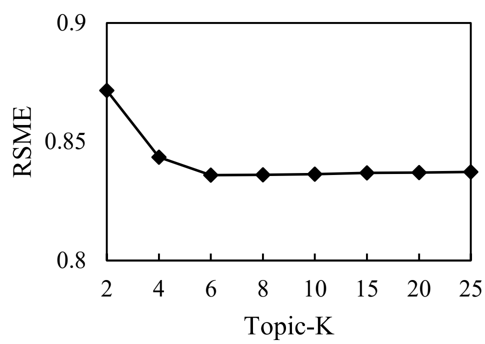

Figure 3. RSME values for different Topic-K on the MovieLen-1 dataset

(2) Comparison results

The first set of comparative experiments is as follows:

The FTTO-RA algorithm proposed in this paper is compared with User-CF and LDA-userCF, and it is verified that the improved recommendation algorithm through tagging information and labeling potential subject information can further improve the accuracy of recommendation. Considering that the recommendation result will be affected by the value of the neighbor User-K, the values of the neighbor User-K are 5, 10, 20, and 30 as the abscissas respectively, and Topic-K is set to 6. The experimental results are shown in Figures 4 and 5.

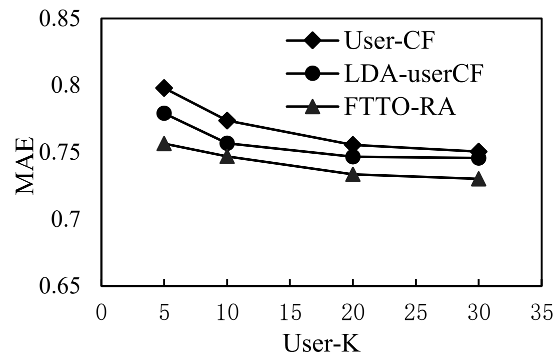

Figure 4. MAE values for different User-K in the first group

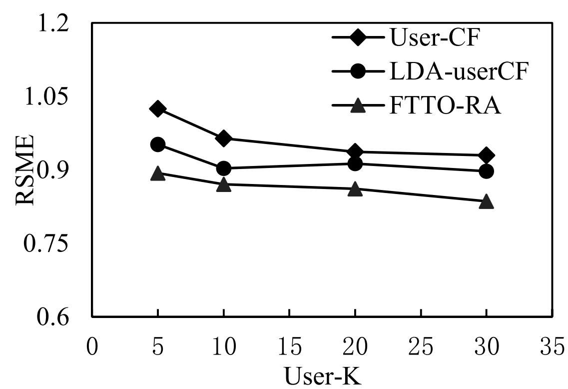

Figure 5. RSME values for different User-K in the first group

From Figures 4 and 5, we can see that both the LDA-userCF algorithm and the FTTO-RA algorithm are below the data values of the two evaluation indicators corresponding to the User-CF algorithm. Therefore, incorporating label information into the recommendation algorithm can improve the accuracy of the recommendation.

The second set of comparative experiments is as follows:

The FTTO-RA algorithm proposed in this paper fully considers the impact of time intervals on user tags. Tags with too long-time intervals will have less value. Therefore, we have performed a comparative experiment of the FTTO-RA algorithm and the UTLR-CF algorithm to prove that after merging the session segments, the recommendation results obtained by mixing multi-source information are more accurate. As shown in Figure 6 and Figure 7.

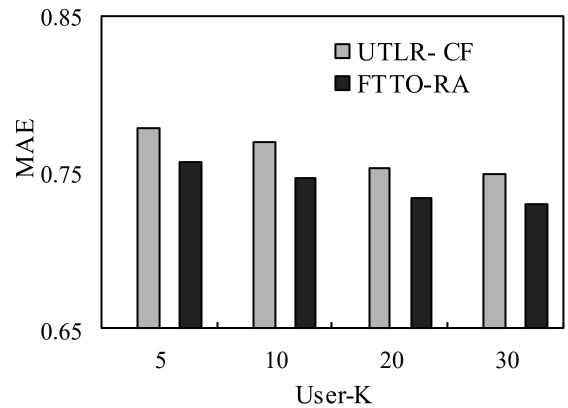

Figure 6. MAE values for different User-K in the second group

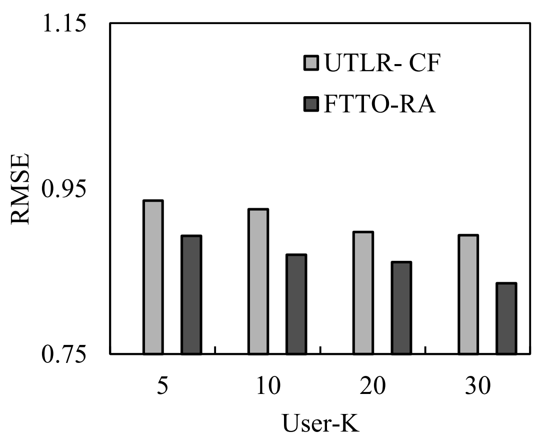

Figure 7. RMSE values for different User-K in the second group

From Figures 6 and 7, we can see that, as the value of User-K in the neighborhood increases, the MAE and RMSE values of the two algorithms decrease. In the two figures, the data values of the two evaluation indexes corresponding to the FTTO-RA algorithm are below, and it is obvious that the proposed algorithm has better recommendation effect than the UTLR-CF algorithm. When the neighbor User-K is set to 5, the FTTO-RA algorithm proposed in this paper is 2.16% lower in value and 4.26% lower than the UTLR-CF algorithm. When the nearest user-K value is 30, the lowest value is obtained. The average absolute error of the FTTO-RA algorithm is 1.87% lower than the average absolute error of the UTLR-CF algorithm. At the same time, the result ratio of the root means square error the UTLR-CF algorithm is reduced by 5.78%. The second set of experiments verified the new algorithm of merging conversational segments into tag (attribute) information, and indeed further improved the accuracy of recommendations. The comparison of the two experimental results also shows that the full fusion of conversational segments, tag information, and scoring information is indeed conducive to improving the effectiveness of the recommendation results.

This paper comprehensively compares the experimental results. The accuracy of FTTO-RA algorithm, UTLR-CF algorithm, and LDA-userCF algorithm is better than User-CF algorithm. It can be proved that embedding tag information can improve the accuracy of recommendation. At the same time, it was found that the FTTO-RA algorithm achieved better recommendation results than the UTLR-CF algorithm, indicating that the fusion of session segment and tag information in the FTTO-RA algorithm was more helpful to improve the accuracy of the recommendation.

5. CONCLUSION

Multi-source tag information into collaborative filtering algorithm can alleviate the "sparse data" problem, and improve the recommendation accuracy. However, simply embedding it into existing recommendation algorithms cannot fully utilize the validity of the label information. Therefore, this paper uses the long-term and short-term memory network model LSTM to study the impact of time intervals on label information, combines session segments, label correlations, and scoring information, and then combines the potential topic probability distribution with the label output information of each layer. That is, the attention mechanism is introduced to capture more valuable tag information, and then it is embedded in the score information for collaborative filtering to obtain the final recommendation. Finally, we conducted experiments on MovieLens-1 data sets, and indeed proved that the new algorithm is proposed to improve the recommendation accuracy.

REFRENCES:

[1] Yadav R, Sharma S K, Tarhini A. A multi-analytical approach to understand and predict the mobile commerce adoption[J]. Journal of Enterprise Information Management, 2016, 29(2): 222-237.

[2] Schor J. Debating the sharing economy[J]. Journal of Self-Governance & Management Economics, 2016, 4(3): 7-22.

[3] Yong H Y. Research on recommendation algorithms via incorporating side information[D]. Nanjing University,2017.

[4] Zhao Z D. Research on analysis, modeling and dynamics of spatial-temporal characteristics of human behaviors[D]. School of Computer Science and Engineering,2014.

[5] Zhang J D, Chow C Y. TICRec: A probabilistic framework to utilize temporal influence correlations for time-aware location recommendations[J]. IEEE Transactions on Services Computing, 2016, 9(4): 633-646.

[6] Zhao Z D, Yang Z, Zhang Z, et al. Emergence of scaling in human-interest dynamics[J]. Scientific Reports, 2013, 3: 3472.

[7] Li W J. Research on time-aware recommendation algorithms[D]. School of Computer Science and Engineering,2017.

[8] Hung C C, Huang Y C, Hsu J Y, et al. Tag-based user profiling for social media recommendation[C]// Workshop on Intelligent Techniques for Web Personalization & Recommender Systems. AAAI, 2008: 49-55.

[9] Wartena C, Brussee R. Instanced-based mapping between thesauri and folksonomies[C]// International Semantic Web Conference. Springer, Berlin, Heidelberg, 2008: 356-370.

[10] Cattuto C, Benz D, Hotho A, et al. Semantic grounding of tag relatedness in social bookmarking systems[C]// International Semantic Web Conference. Springer, Berlin, Heidelberg, 2008: 615-631.

[11] Ai P Q. Research of personalized news recommendation system based on time-ordered behaviors and tad relation[D]. Tianjin University Of Technology,2016.

[12] Huang L W, Jiang B T, Lv S Y et al. Survey on deep learning based recommender systems[J]. Chinese Journal of Computers, 2018 41(7)：1619-1647.

[13] Wu C Y, Ahmed A, Beutel A, et al. Recurrent recommender networks[C]// ACM International Conference on Web Search and Data Mining. ACM, 2017: 495-503.

[14] Quadrana M, Karatzoglou A, Hidasi B, et al. Personalizing session-based recommendations with hierarchical recurrent neural networks[C]// ACM Conference on Recommender Systems. ACM, 2017: 130-137.

[15] Feng Y, Zhang B, Qiang B H, et al. MN-HDRM: A novel hybrid dynamic recommendation model based on Long-Short-Term interests multiple Neural networks[J]. Chinese Journal of Computers,2019,42(1):16-28.

[16] Zhang Q, Gong Y, Sun X, et al. Time-aware personalized hashtag recommendation on social media[C]// International Conference on Computational Linguistics: Technical Papers. 2014: 203-212.

[17] Greff K, Srivastava R K, Koutník J, et al. LSTM: A search space odyssey[J]. IEEE transactions on neural networks and learning systems, 2017, 28(10): 2222-2232.

[18] Hua S W. Research on patient analysis based on LSTM and LDA model[D]. Zhejiang Sci-Tech University,2019.

[19] Zhu Y, Li H, Liao Y, et al. What to Do Next: Modeling User Behaviors by Time- LSTM[C]// International Joint Conference on Artificial Intelligence. Morgan Kaufmann, 2017: 3602-3608.

[20] Gao Na. Research on collaborative filtering recommendation algorithm based on joint learning of tags and ratings[D]. Nanjing Normal University,2015.