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A Content-Based Approach to Recommend TV Programs Enhanced with Delayering Tagging

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Abstract

In response to explore how to extract the recommended items' features, a method is put forward called a Content-based TV Program Recommendation Approach Enhanced with Delayering Tagging. The Content-based approach is optimized to recommend TV programs and improved the way to extract the recommended items' features. Besides, the existing way of using supervised method to build user modeling is replaced with an unsupervised method using delayering tagging to show recommended TV program's content features and set up user preference model. After compared with Latent Factor Model and Collaborative Filtering recommendation algorithm with the same experimental data, the proposed algorithm in this paper increased the accuracy of 2.67\%, coverage rate of 3.02\% and 3.2\% of the Feature 1 value and achieved good recommendation results compared to the Latent Factor Model which revealed the best effect of recommendation.

Keywords*: program tagging; interestingness; TV program recommendation; data mining*

1. Introduction

Due to the hit of tri-networks integration to broadcasting and television industry, various television stations begin to enrich their program range and improve program quantity in order to save the loss of TV viewers. However, a large number of program resource make television viewers dazzling. More and more researchers and program suppliers begin to pay close attention to how to help the audience to find their favorite television programs. Many cable operators provides viewers with electronic service guide (EPG), to assist the audience find programs they are interested in quickly [1-2]. However this kind of electronic playbill just shows all the program provided with the present of forms, and does not help the audience to find their favorite program type. What the audience really need is a personalized program guide, which is able to recommend certain TV program type to whoever is interested in.

Recommendation system is capable of predicting the user's interests, and offer users an adaptive system meeting the content of the user preferences. The purpose of recommendation system is to overcome difficulties in choosing useful information in the vast content and enables users to efficiently browse the content of their interest. Content-based recommendation and collaborative filtering recommendation are two of the most important recommendation technologies [3].Their common limitation lies in the cold-start [4] and new user problem. Other deficiencies rest in Content-based recommendation systems tending to excessive specialization; meanwhile, the collaborative filtering recommendation may expose gray sheep problem and sparsity problems [5-6]. In [7], a kind of memory-based coordination filtering algorithm is put forward and the user rating's differences in distribution are used to calculate the new similarity in order to overcome the cold-start problem. [8] and [9] respectively put forward recommendation system based

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on cloud computing environment and MapReduce big data environment and improve recommendation system scalability to large amount of data through the parallel computing. In addition, there exist the knowledge-based recommendation and hybrid recommendation technology [10] .Although collaborative filtering recommendation technology has a prominent advantage in the application based on the Internet, but individual TV program recommendation can be more effectively when applied to TV viewers. Therefore, content-based recommendation is applied to TV program recommendation system by some scholars. In [11], every TV program is described as a type vector and user preferences are represented by the degree of user interests towards some certain type. The degree of user interest in a TV show is presented by the dot product of the program vectors and the user vectors. Vector Space Model is also applied to [12] at the same time. In that literature, cosine similarity is used to calculate the users' interestingness in TV programs, and program features are extracted from metadata and program description vector is determined by each user. AVATAR [13] is a kind of system providing recommendation for broadband TV users; [14] describes a personalized hybrid TV show recommended web applications. [15] puts forward a kind of TV program recommendation menu system based on community. And it can be divided into different communities according to different users' viewing habits. [16] puts forward a kind of embedded system, the system which using the classification-based and keyword-based combination model to rank the content of the program in order to recommend the limited programs in relevant programs to the users .These system described above are only for individual TV users, while a set of TV is usually shared by the family, so [17-19] propose television recommendation systems aiming at home users, In [17] ,the characteristics of home users is made up by each individual user. [18] defines the homogeneous and heterogeneous group, recommending programs to groups according to the group internal viewing preferences' level of similarity. [19] combines Bayesian network with analytic hierarchy process, short as AHP, to predict the viewing preferences in both individual user and group users. This TV show tag system in this paper comes from [20]. The TV shows tag system mentioned in this research overcomes the defects that television content generalization is too general, then proposes a relatively more comprehensive system of TV program tag and solves the problem of presenting the content of the programs flexibly from multi dimensions. A Content-based Approach to Recommend TV Programs Enhanced With Delayering Tagging (CART) is proposed in this paper which uses the tag to represent the recommended Content characteristics of the items and overcome the large amount of calculation in the collaborative filtering based on neighborhood problems; the method improved the Content-based recommendation method, using unsupervised way to build user preferences model, breaking the original supervised manner of user modeling method.

2. Architecture of Content-Based TV Program Recommendation Approach Enhanced with Delayering Tagging

2.1. Architecture

This paper, on the basis of the Content-based recommendation technology, shows the program content with the specified tag for each TV program, meanwhile it makes certain improvement to the method of building user preference model and changes the existing status that only supervised classification method are used to learn characteristics of the user's preferences. Also the user preferences analysis for time dimension are added, adopting the unsupervised method for user groups' division, thus accomplishing building user group preference model. The framework of Content-based TV Program Recommendation Approach Enhanced with Delayering Tagging is displayed in Figure 1.

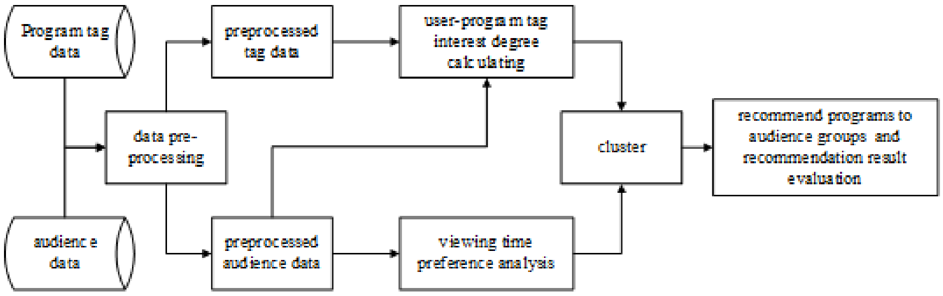

Figure 1. The Framework of Content-Based TV Program Recommendation Approach Enhanced with Delayering Tagging

The detailed algorithm process is as followed:

(1) Data Preprocess. The audience data used in this paper comes from a Chinese province in a month of 2013.

(2) Divide the training set and the testing set.

(3) Set up user-program tag interest degree models.

(4) Mine user viewing preferences for time.

(5) Cluster based on user preferences for time.

(6) Produce recommendation.

2.2. Related Researches

2.2.1. The Portraits Depicting TV Users

The essence of user portraits depicting is the process of user behavior modeling. In this paper the concept of portraits depicting is applied to radio and television sector. A challenge of TV user portrait-depicting is that as the user's interaction pattern is relatively single, it is unable to obtain as large number of information as from the Internet. For traditional TV users, it is only audience records that can be get, therefore, the research explores effective ways from limited data resources to show the user's interest degree, mining the maximal value of information. This paper adopts the TV program tag mentioned in [20], sets up TV user preferences model combining with the method of the below, calculates the user interest degree towards TV program tag, and then portraits every TV user. This method breaks the traditional statistical analysis indicators, accurately portraits every user based on television viewing behavior, eventually showing the viewing characteristics of group. It has the guiding significance on the judgment of the viewing preferences of the user, at the same time, lays a solid foundation of TV program personalization recommendation for users.

2.2.2. Viewing Preferences Model

The method of user preference modeling is directly related to the quality of the user portraits depicting. User modeling is different from user segmentation, which analyzes the user according to the demographic characteristics and the behavior psychology; however, user modeling pays more attention to the interaction between the user and the system, which is a continuous process. Explicit behavior is a kind of feedback behavior which can directly reflect the user's interests, and the behavior of users expressing their willingness actively. This behavior is especially likely to occur along with a strong feeling, so, normally, explicit behavior can clearly reflect the extent to which the user is interested in the program. Implicit behavior indirectly reflects user interests, mainly including clicking the browser, watching the play, and so on. It cannot accurately reflect the user interest degree in video, however, the number of implicit behavior and the duration can, to a certain extent, reflect the user's interest degree, and the frequency of implicit behavior is much higher than explicit behavior and implicit behavior reflects users' interests better. Compared with Explicit behavior, the number of types of implicit behavior is much greater, and implicit behavior occurs usually along with the every part in the process of using the system, as a result the data volume is various. If the relationship between implicit behavior and user interest is quantified objectively and effectively, it would greatly help the preference modeling. So for personalized recommendation model of user preference information collection, the Explicit and implicit dual behaviors of users will be collected at the same time.

3. Content-Based TV Program Recommendation Technology Improved by Delayering Tagging Improvement

3.1. Traditional Recommendation Methods

In the process of the development of the recommendation system, there are many recommendation algorithms mainly divided into two categories: one is content-based recommendation algorithm; the other is collaborative filtering recommendation algorithm. And collaborative filtering algorithm can be divided into the memory-based recommendation algorithm and model-based recommendation algorithm.

3.1.1 Content-Based Recommendation Algorithm

Content-based recommendation algorithm, is generated from general information retrieval methods [21]. This algorithm is based on evaluation characteristics of the user, learns the user interest, and therefore matches the user with the object to forecast.

User data model, the Content-based Profile, on the other hand, depends on the machine learning methods used, such as decision tree, Bayesian algorithm, neural network model and so on. Combined with the feature of object content and user data model, the utility function can be calculated through the object content characteristics combined with user data model. That the cosine distance calculation method is commonly used: User data model, the Content-based Profile, on the other hand, depends on the machine learning methods used, such as decision tree, Bayesian algorithm, neural network model and so on. Combined with the feature of object content and user data model, the utility function can be calculated through the object content characteristics combined with user data model. That the cosine distance calculation method is commonly used:

$$\cos(u,i) = \frac{\sum(U_f I_f)}{\sqrt{(\sum(U_f^2))}\sqrt{(\sum(I_f^2))}} \tag{1}$$

The symbol U_f represents the preference value of users towards to the feature *f*. I_f represents the intensity of items and the feature *f*.

3.1.2 Collaborative Filtering Recommendation Algorithm: Memory-Based Recommendation Algorithm

The memory-based recommendation algorithm contains user-based collaborative filtering algorithm and item-based collaborative filtering algorithm. In the running period, this algorithm needs to call the entire database into the memory, as a result producing the latest recommendation information.

User-based collaborative filtering algorithm

$$p(u,i) = \sum_{v \in S(u,K) \cap N(i)} w_{uv} r_{vi} \tag{2}$$

$S(u,K)$ represents the K-users set closest to user u 's interest; $N(i)$ represents the user set having had positive feedbacks on the items I; $w(u,v)$ represents the interest similarities between user u and user v; $r(v,i)$ represents user v's interest in the goods I. The default value of $r(v,i)$ is 1 or 0.

Item-based collaborative filtering algorithm

$$p(u,j) = \sum_{i \in N(u) \cap S(j,K)} w_{ij} r_{ui} \tag{3}$$

$S(i,K)$ represents the K-users set closest to item I; $N(u)$ represents the item set that user likes; $w(i,j)$ represents the similarities between item I and item j; $r(u,i)$ represents how user u is interested in item I. The default value of $r(u,i)$ is 1 or 0.

3.1.3. Model-Based Recommendation Method

Model-based recommendation algorithm firstly models according to user data. Online module will call the model into the memory, and recommend. The recommendation algorithm includes the Bayes network recommendation algorithm, association rules recommendation algorithm, clustering recommendation algorithm and so on.

In general, memory-based recommendation algorithm, though, is more suitable for the recommendation system which requires rapidly updating the recommendation result, but when the database is too large to fit in the memory, the algorithm is stretched; And model-based recommendation algorithm is more suitable for the electronic commerce system containing large data, but difficult to meet the real-time recommendation system.

3.2. CADT Recommendation Methods

3.2.1 User Preferences Model Based on Program Tags

This paper is based on space vector model combining ontology model to show the automatic modeling of user, and puts forward user preference model based on the program tags. Every user's program tag vector, namely user-tag interest degree, uses as an n-dimensional feature vector $\{(t_1,w_1),(t_2,w_2),\cdots,(t_n,w_n)\}$, among which t represents program tag, represents the value of interest degree. User-tag vector is used to represent the user interest degree. The calculation method of the interest degree w is as followed:

Define $U=\{u_1,\cdots,u_i,\cdots,u_n\}$ as viewing user set, and n as the total number of users. $S=\{s_1,\cdots,s_i,\cdots,s_n\}$ is defined as program set, and *m* as the total number of programs. The users viewing time matrix is defined as $L=\{l_{u_i,s_j} \mid u_i \in U, s_j \in S\}$. The symbol l_{u_i,s_j} represents the total time for user u_i to watch show s_j in a certain time.

TV Shows Interest Degree

Time proportion. Viewing time proportion of users for a certain program, represents how the total length of viewing time in a certain time accounts for the total length of programs in this time period. Calculation formula of time proportion is as shown in (4).

$$R_{u_i,s_j} = \frac{l_{u_i,s_j}}{\sum d_{s_j}} \tag{4}$$

The symbol R_{u_i,s_j} represents the time proportion of user u_i watching program s_j , $\sum d_{s_i}$ represents the total length of program s_j .

On the basis of the time proportion, the user interest for a program is defined as how the user's viewing time of this program accounts for the total viewing time of all the programs. Calculation formula of program interest degree is as shown in (5).

$$F_{u_i,s_j} = \frac{R_{u_i,s_j}}{\sum_{s_j} R_{u_i,s_j}} \tag{5}$$

F_{u_i,s_j} represents user u_i 's interest in the program s_j , R_{u_i,s_j} represents the time proportion of user u_i watching program s_j , $\sum_{s_j} R_{u_i,s_j}$ represents the sum of time proportion.

Program tag interest. TV program tag interest is the basis of calculating program tag interest. Here, $T = \{t_1, \cdots, t_k \cdots, t_q\}$ is defined as a program tag set, and q as the total number of tags. User interest in a particular tag represents as a product of the user interest in the tagged program and the weight of the program tag. Program tag interest can be expressed by (6).

$$P_{u_i,t_k} = \sum_{s_j \in \{s_n | t_k \in s_n\}} w_{s_j,t_k} \times F_{u_i,s_j} \tag{6}$$

The symbol P_{u_i,t_k} represents the user u_i 's interest in the program tag t_k , w_{s_j,t_k} represents the weight of the tag.

Using the formula (4), (5), (6), we can calculate the different program tag interest for every user.

3.2.2. User Viewing Time Preference Analysis

In the TV viewing market, the user's preference viewing time period is the important factor which should be included in the TV program recommendation. Taking the factor of the viewing time into consideration, the TV program begins to pursue the accuracy of the broadcast time, and for the user, under the influence of the working time and the life habits, the viewing time has a certain regularity. Searching for these specific rules can be able to get more comprehensive of user's viewing preferences, so that we can recommend television programs more accurately. Therefore, it is very important to explore the preference of the user's viewing time.

User-program tag interest based on viewing time preference measures the user-tag preference based on period of time (UTPT). The user’s interest in a particular tag in the viewing period may be expressed as a sum of interest for the user to have the tag in the period of time. The user interest degree based on the viewing time preference can be expressed by (7).

$$P_{u_i,t_k,T_j} = \sum_{T_j} P_{u_i t_k} \tag{7}$$

P_{u_i,t_k,T_j} represents the interest degree of user u_i towards program tag t_k in a period T_j , P_{u_i,t_k} represents the interest degree of user u_i towards program tag t_k , T_j represents a certain viewing time period.

3.2.2. User Viewing Time Preference Analysis

Clustering algorithm is an unsupervised classification learning algorithm[22], people clustering divides users into several multiple groups of similar users according to users interest in the program tag data set, making the degree of similarity from users in the same group to maximize, the degree of similarity in users from different groups to minimize.

Grouping the user based on viewing time preference can directly obtain the viewing characteristic of every group. This paper adopts the clustering way to group users of every viewing time. According to the result of clustering, we can reversely position programs that this kind of user is interested in from several program tags which are highest in interest degree.

K-means clustering algorithm is used to cluster users. The user's program tag interest degree data set D is composed of N users tag vector. User tag vector is an n-dimensional vector $\{p_1, p_2, \cdots p_k, \cdots p_n\}$. Among them, p_k can take from the interest degree $P_{u_i t_k}$ of user u_i to the program tag t_k or the interest degree $P_{u_i t_k T_j}$ of user u_i to the programs tag t_k during the time T_j.

1. choose k users as the initial cluster centers from user's program interest degree data set D
2. Repeat
3. For every user p in the data set D do:
4. Calculate the user p's distance to the center of the k clusters.
5. Assign the user p to the cluster which has shortest distance from it
6. end for
7. Calculate the average of users in each cluster, as a new cluster center
8. Until the centers of k clusters converge

4. Experiment and Result Analysis

Combining the data characteristics in this paper, we select the accuracy rate, recall rate and F1 index of classification accuracy index to evaluate the recommendation technology. What the classification accuracy index measures is if the recommended system can correctly reckon whether the user likes or does not like the project. The index is often used in Top-N recommendation system. Currently the most commonly used classification indicators are accuracy rate (Precision) and recall rate (Recall) [23].

Accuracy rate represents the probability of the user interest in the project system recommended. Detailed calculation is as followed in (8):

$$\mathrm{Pr}ecision = \frac{N_{t,p}}{N_p} \tag{8}$$

The symbol $N_{t,p}$ represents the project that the recommendation system has recommended and tests have intensely contained, N_p represents the number of projects that the recommendation system has recommended.

Recall rate represents the probability of a user's favorite project being recommended, defined as the proportion of the project from the recommendation list that user likes and the total project from the system that user likes. Detail calculation is as followed (9):

$$\mathrm{Re}call = \frac{N_{t,p}}{N_t} \tag{9}$$

The symbol $N_{t,p}$ represents the subject that the recommended system has recommended and tests have intensively contained, N_t represents the number of projects that tests intensively user has evaluated.

Combined with the accuracy and recall rate, F1 index is also one of the important indices for evaluating the recommender system. Detailed calculation is as followed in (10):

$$F1 = \frac{2}{\dfrac{1}{Precision} + \dfrac{1}{Recall}} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

This paper chooses the recommendation algorithm based on lingo righteousness model and as a comparison with the recommendation algorithm based on the neighborhood, evaluating the algorithm respectively using the same experimental data.

4.1. Experiment 1: Recommend Model Based on Lingo Righteousness

With recommendation model based on lingo righteousness, this paper uses the viewing data from a Chinese province in a month of 2013, realizes the TV program recommendation, and calculates the accuracy rate, recall rate and F1 index of this method.

The selecting parameters process during lingo righteousness experiment is as followed. In the experiments we find that for the collaborative filtering recommendation algorithm based on lingo righteousness model (LFM), the value of ratio has the biggest influence on the result of the experiment. Figure 2 shows how the accuracy rate, recall rate and F1 index change along with the different values of radio. The experimental results indicates that when the value of ratio is 10, we can obtain the best recommendation result, in which the accuracy rate is 12.65%, the recall rate is 32.78%, and F1 index is 18.26%. From Figure 2, with the increase of the value of ratio, the accuracy rate and the recall rate of the recommendation method based on lingo righteousness increased. And when ratio is more than 10, the index levels off or even becomes less than the value of ratio when it is equal to 10. From all the indicators in the table, we conclude that when the value of ratio is 10, the recommendation result is the best.

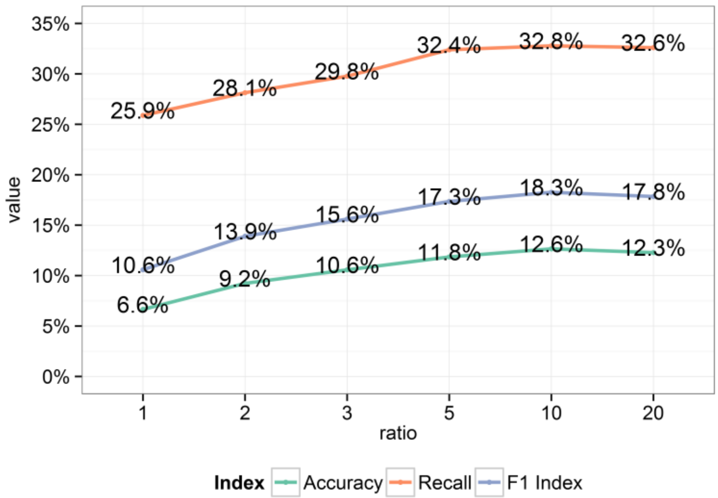

Figure 2. Evaluation Results of the LFM Recommendation Method

4.2. Experiment 2: Collaborative Filtering Recommendation Based on Neighborhood

The collaborative filtering recommendation based on neighborhood includes user-based collaborative filtering (User-CF) and item-based collaborative filtering (Item-CF). For the collaborative filtering recommendation technology based on neighborhood, closest neighbors threshold K represents taking K users who rank the top K in the similarity with targeted users (program) as closest neighbors. When recommended, the recommendation result is generated by closest neighbors.

The paper respectively uses the user-based collaborative filtering recommendation and item-based collaborative filtering recommendation model, with the data from a Chinese province in a month 2013, realizes the TV program recommendation, and calculates the accuracy rate, the recall rate and F1 index of the method.

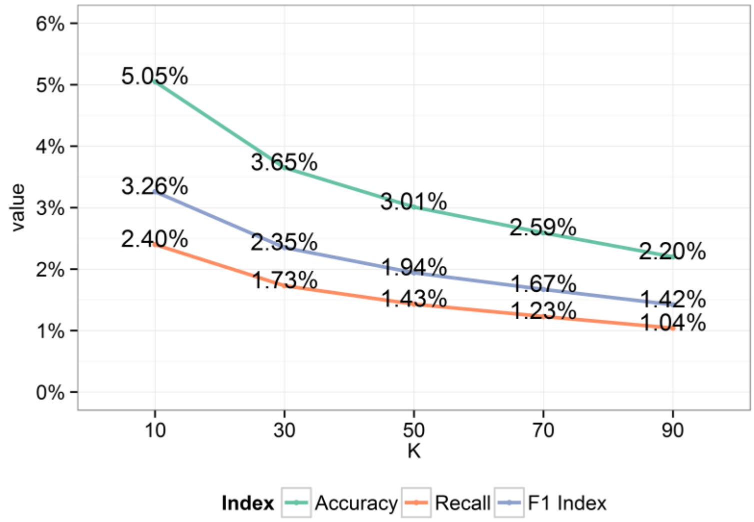

Figure 3. Evaluation Result of User-Based Collaborative Filtering Recommendation Method

The value of K affects the result of the collaborative filtering recommendation. The following is a recommendation performance comparison when the value of K is different. Figure 3 shows the evaluation result of user-based collaborative filtering recommendation method. In case of taking different values in the parameter K and a gradual increase, various recommendation evaluation indicators fall. When the value of K is 10, the recommend result is the best, in which the accuracy is 5.05%, the recall rate is 2.40% and the F1 index is 3.26%.

4.3. Experiment 3: Recommendation Method Contrast Experiment

According to the formula (5), (6), (7), calculate the accuracy rate, the recall rate and F1 index of this experiment. The accuracy rate is 15.32%, the recall rate is 35.8%, and F1 index is 21.46%. Select the different parameters from all the experiment. Obtain the indicators of the best recommendation result and compare it with the experiment results, as shown in Table 1.

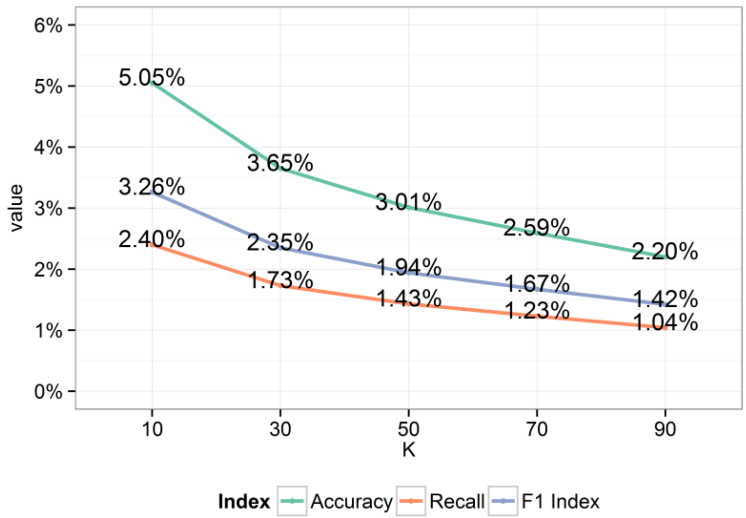

Figure 3. Evaluation Result of User-Based Collaborative Filtering Recommendation Method

Table 1. The Evaluation Result Comparison of the Recommendation Algorithm

	accuracy rate	recall rate	index of F1
CADT	**15.32%**	**35.8%**	**21.46%**
User-CF	5.05%	2.40%	3.26%
Item-CF	2.69%	1.28%	1.73%
LMF	12.65%	32.78%	18.26%

Each indicator in the table is generated, in addition that different recommendation algorithms are used, the data set used is exactly same, which is the viewing data of a province in a month. From the table we can conclude that the algorithm indicators proposed in this paper excel the other algorithm, in the meanwhile the accuracy rate, the recall rate, and F1 index are higher than other algorithms'.

In the traditional TV program recommendation algorithm, most directly calculate user interest in TV programs, not only resulting in large amount of calculation and the unideal recommendation result. Yet the algorithm proposed in this paper puts forward the user-program tag interest degree, a new method to measure the user interest degree in TV programs. Using the introduction of tags overcomes the problem of large amount of calculation in the collaborative filtering based on neighborhood and avoids to recommend programs by calculating the similarity of users. The algorithm absorbs the advantages of content-based recommendation technology, presents the content of the recommendation project in a way of program-tagging, and in the meanwhile, makes improvement to the user modeling method, replacing the supervised classification method with the unsupervised classification method. The system can automatically categorize users and mine the viewing preference characteristics. Therefore we can obtain each type of the program tag that users are interested in, recommending users the corresponding programs with tags. As a result, the algorithm of this paper is superior to the traditional recommendation algorithm, which is confirmed by the result in Table 1.

5. Conclusion

In this paper, the content-based TV program recommendation method is optimized and an effective TV program recommendation method, A Content-based approach to recommend TV programs enhanced with delayering tagging, is put forward. The algorithm proposed optimizes content-based TV program recommendation, improves the method to extract the feature of the recommendation projects, uses program tags to indicate the content of the recommendation project characteristics, adopts the unsupervised method for user preference modeling and breaks the original supervised method. Compared with lingo righteousness recommendation algorithm and the collaborative filtering recommendation algorithm, the algorithm proposed is superior to the two algorithms above, and achieves good recommendation results.

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