Application of User-level Personalized Recommendation Algorithm in Sports Websites

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Abstract
The network shopping has become one of the main forms of the present shopping, the sales of sports products are also developing to the network direction. Due to the differences between different customer preferences of sports products, and many kinds of sports products, sports website according to the needs and preferences of customers of sports products make a personalized recommend the reasonable is very difficult. In view of the problems encountered by the sports website in the movement of products in the process of recommendation, take user level personalized recommendation algorithm, using different optimal recommendation algorithm for different customers, and strive to make recommendation has targeted. This paper by Li Ning Sports sites, for example, user level of personalized recommendation algorithm application analysis, pointed out that different users and recommend the best algorithm matching relationship through other recommendation algorithm and compared. The results showed that the user personalized recommendation algorithm's superiority. The results shows that there is no association of user characteristics and recommend the best algorithm is obtained, promoting user level personalized recommendation algorithms improve.
Key words: USER LEVEL PERSONALIZED RECOMMENDATION ALGORITHM; SPORTS WEBSITE; MATCHING

Introduction

Network recommendation demand has increased with social development. The increase of recommendation demand makes the research on recommendation algorithms constantly deep and makes their connotations constantly wider [1]. Recommendation algorithms have completed the transition from impersonality to humanization. There are many effective personalized recommendation algorithms currently, including recommendation algorithm based on product popularity (Popular), collaborative filtering recommendation algorithm based on product (ICF), collaborative filtering recommendation algorithm based on user (UCF), recommendation algorithm based on heat conduction (HeatS) and recommendation algorithm based on substance diffusion (Diffuse) [2]. These personalized recommendation algorithms have their unique advantages and many deficiencies. To give full play to advantages of these personalized recommendation algorithms, user-level personalized recommendation algorithm has emerged [3]. User-level personalized recommendation algorithm is composed of various basic recommendation algorithms above and different optimal recommendation algorithms are provided for different customers so as to guarantee that products recommended satisfy the needs of different customers. User-level personalized recommendation algorithm integrates advantages of various recommendation algorithms and match different customers and different recommendation algorithms optimally. Therefore, they are widely applied in current website recommendation products.

With the popularization of network, online shopping has become a fashion and many shopping websites have emerged and gained great success. Sports products comply with the development trend of online shopping. Many domestic and foreign sports brands have established their own sales websites so as to expand the market and seize market shares [4]. However, problems faced by other shopping websites are also encountered in the process of sports product website operation, i.e. various forms and types of products; how to help different customers find desirable products on their websites rapidly and conveniently; how to recommend reasonable and optimal products to different customers [5]. Sports websites have taken certain recommendation measures, such as search keywords, product categorization and recommendation of featured products on the main page. However, these recommendation methods cannot satisfy the needs of customers. It is required to seek for better recommendation methods to improve their service level. Therefore, sports websites have used various recommendation algorithms. However, the result is not satisfactory because some recommendation algorithms are only effective for some people and their recommendation reliability cannot be guaranteed [6]. Due to the limitation of people using different recommendation algorithms, this paper studies user-level personalized recommendation algorithm of sports products so as to match recommendation algorithms and customer demands and improve the reliability of products recommended. Currently, many experts and scholars have studied user-level personalized recommendation algorithm, e.g. hybrid recommendation algorithm (HHP) formed by the combination of recommendation algorithm based on substance diffusion and recommendation algorithm based on heat conduction [4]. It is found that HHP can improve the recommendation effect significantly and respond to user diversification trend better. Various recommendation algorithms contained by user-level personalized recommendation algorithm can adapt to diversified user demands better.

User-level personalized recommendation algorithm is the product of high combination between internet and e-commerce. Multiple personalized recommendation algorithms are the core content of user-level personalized recommendation algorithm and the match of optimal core algorithm is the emphasis of user-level personalized recommendation algorithm [7]. This paper takes the application of user-level personalized recommendation algorithm in sports websites for example, which is representative and has great realistic and theoretical significance. In terms of realistic significance, we have entered internet shopping era and there are a wide variety of commodities on the internet. How to guarantee that customers can find products they are interested in in the shortest time is the key to keep customers. Therefore, user-level personalized recommendation algorithm influences the survival and development of enterprises because they can greatly improve recommendation efficiency and match user demands better. In terms of theoretical significance, network recommendation system has become one of the focus issues in domestic and foreign researches since 1990s. The research on user-level personalized recommendation system with Li-Ning sports products as example will impel the improvement of recommendation system and allow recommendation system to bring greater convenience to shopping.

User-level personalized recommendation algorithm

User-level personalized recommendation algorithm is composed of the following basic personalized recommendation algorithms, including ICF, UCF, Popular, HeatS and Diffuse. User-level personalized recommendation algorithm matches the optimal recommendation algorithm according to features of different users so as to provide the optimal recommendation mode for users.

ICF

ICF is a recommendation algorithm under the principle of regarding products selected by users as their favorite products and recommending similar products to customers. ICF needs to calculate and grade the similarity of products and recommend products with the grade over a certain limit to customers.

UCF

UCF is a recommendation algorithm under the design principle that similar users like similar products. It calculates and grades the similarity of users, sorts them according to similarity and recommends products liked by users with similarity grade over a certain limit to customers so as to achieve the purpose of personalized recommendation. UCF is a popular personalized recommendation algorithm.

Popular

Popular is a typical non-personalized recommendation algorithm based on product popularity. It sorts products according to the times of selection by users in the current system and recommends the most popular commodities to customers. However, Popular has a defect, i.e. huge number of products and relatively smaller amount of selection by customers. Therefore, the same products are recommended to customers with different demands.

HeatS

Similar to ICF, HeatS also needs to calculate the similarity of products. However, there are significant differences. HeatS needs to introduce resource allocation matrix $W_{\alpha\beta}$ to characterize the transmission probability of possessing resource product α to target product β. The computational formula of product similarity is:

$$S(a,b)^H = \frac{1}{K_a}\sum_{j\text{-}1}^{M}\frac{a_{aj}a_{bj}}{k_j} \quad (1)$$

HeatS use bipartite graph network as the basis for preference information modeling and uses bipartite graph as recommended product transfer mechanism to obtain the preference of users to products. The prediction rating of preference of users to products is:

$$P_{i,\ a} = f_{i,\ a} = \sum_{b\text{-}1}^{M} S(a,b)a_{ib} \quad (2)$$

Diffuse

Similar to HeatS recommendation algorithm, Diffuse, i.e. substance diffusion algorithm, also needs to introduce resource allocation matrix $W_{\alpha\beta}$ when predicting the preference of users to products. However, different from HeatS with the introduction of $W_{\alpha\beta}$, Diffuse also needs to calculate product similarity. Finally, Diffuse recommends products to users through the score of product α.

Experimental designs

User-level personalized recommendation algorithm is analyzed with data on Li-Ning sports product website and three analysis indicators are used for evaluation.

Experimental data

This experiment uses data on Li-Ning sports product website to test the performance of user-level personalized recommendation algorithm and find the matching relation between users and optimal recommendation algorithm. Data set is Lining100k, which includes evaluation and scoring records of 1230 users for 1590 kinds of Li-Ning sports products. Scoring criteria are as below: 1 means that users do not like this sports product at all; 5 means that users like this product very much; integers between 1 and 5 follow the ascending order of likeability. As the research aims at finding preferred products of users and recommending products to them, data with the score less than 3 are neglected. Therefore, effective data $|E|$=95600, number of users M=$|U|$=1230 and number of products N=$|O|$=1590. The statistical result of data set Lining100k of Li-Ning website sports products is as below:

Table 1. Data set statistical information table

Data set	$\lvert U\rvert$	$\lvert O\rvert$	$\lvert E\rvert$	Sparseness
Lining100k	1230	1590	95600	4.89×10^{-2}

Evaluation indicators

In this experimental study, AUS, average ranking score (RS) and precision are used to evaluate the effect of user-level personalized recommendation algorithm. These three evaluation indicators are very common and representative in bipartite graph network recommendation.

(1) ACU indicator. ACU indicator can characterize the degree of distinguishing products liked and disliked by users in some recommendation algorithm. ACU indicator can be estimated with the following method: first, choose a product randomly among products liked by users; second, choose a product not contained in test set and training set randomly; third, add 1 when the forecast score of relevant product is higher than that of irrelevant product and add 0.5 when the forecast score of relevant product is equal to that of irrelevant product; finally, repeat steps above for n times.

According to statistics, if the times when the forecast score of relevant product is higher than that of irrelevant product is n' and the times when the forecast score of relevant product is equal to that of irrelevant product is n'' after n experiments, ACU can be estimated with the following formula:

$$ACU = \frac{n' + 0.5n''}{n} \quad (3)$$

(2) Average ranking score – RS. RS can evaluate the ability of a recommendation algorithm in predicting products liked by users according to statistics of the position of products liked by users in the recommendation table. RS can be calculated with the following formula:

$$RS_{i,\alpha} = \frac{r_{i,\alpha}}{L_i} \quad (4)$$

Where, $r_{i,\alpha}$ - position of side (I, α) in test set in the recommendation table.

L_i - the length of user product recommendation table, products not selected by users;

(3) Precision. Precision indicator can be used to evaluate the ability of a recommendation algorithm in predicting whether users like or dislike a product correctly. Precision only pays attention to the former L statistical results in the recommendation table. Precision can be estimated with the following formula:

$$P_i(L) = \frac{H_i(L)}{L} \quad (5)$$

Where, $H_i(L)$ - the number of products liked by users in the former L recommended products of user i.

Experimental method and process

User-level personalized recommendation algorithm includes 5 basic algorithms. To verify the applicability of each algorithm, the ratio of training set to data set is 9:1. Data set Lining100k is divided for 5 times. The mean value is used as the experimental result.

To determine the optimal recommendation algorithm of each user and actually reflect the significance of user-level personalized recommendation algorithm, this experiment analyzes the recommendation result of different recommendation algorithms and compares the recommendation effect of user-level personalized recommendation algorithm with that of single recommendation algorithm so as to verify the superiority of user-level personalized recommendation algorithm.

This experiment forms five data sets, namely ICF, UCF, Popular, HeatS and Diffuse according to statistics of optimal recommendation algorithm of different users, illustrates the necessity of user-level personalized recommendation algorithm through comparison and obtains the proportional allocation of optimal recommendation algorithms of users.

This experiment evaluates characteristics of users according to three indicators, i.e. the average degree d_i of product selection of users, degree k_i of product use of users and average similarity s_i of product selection of users. These three indicators are used to describe characteristics of users so as to determine different optimal recommendation algorithms of each user.

This experiment analyzes optimal recommendation algorithm of sensitive users. Optimal recommendation algorithm has greater influence on sensitive users than common users. When these users are matched with optimal recommendation algorithm, the recommendation effect is greatly improved. This experiment analyzes features of optimal recommendation algorithm of sensitive users through the comparison of optimal recommendation algorithm and suboptimal recommendation algorithm of users.

This experiment conducts correlation analysis on the selection basis of optimal recommendation algorithm and considers experiments respectively with RS and precision as the basis of optimal recommendation algorithm. In the experiment, values of L are respectively 1, 2, 5, 8, 10, 20, 50, 80 and 100.

Analysis on experimental result

Improvement magnitude of optimal algorithm

This experiment analyzes and compares the effect of five different candidate recommendation algorithms and obtains optimal recommendation algorithm of different users. Analysis on indicators of each recommendation algorithm is shown in the table below:

Table 2. Manifestation of each recommendation algorithm in data set Lining100k

Algorithm	Indicator		
	AUC	RS	Precision
ICF	0.9012	0.1192	0.1892
UCF	0.8872	0.1203	0.1604

Popular	0.8618	0.1502	0.1068
HeatS	0.8698	0.1498	0.0024
Diffuse	0.9123	0.1022	0.1905

Table 3. Improvement of effect of optimal algorithm in data set Lining100k compared to single algorithm

Algorithm	Indicator		
	AUC	RS	Precision
Optimal algorithm	0.9233	0.0905	0.1702
ICF	0.0257	0.2055	-0.0671
UCF	0.0347	0.2704	0.0605
Popular	0.0723	0.4033	0.6142
HeatS	0.0668	0.3929	69.83
Diffuse	0.0139	0.1235	-0.0871

According to tables 2 and 3, AUS, RS and Precision values of user-level personalized recommendation algorithm are higher than those of single recommendation algorithm, indicating the superiority and applicability of user-level personalized recommendation algorithm. According to table 3, if products are recommended to customers through optimal algorithm in user-level personalized recommendation algorithm, the recommendation effect is greatly improved compared to single recommendation algorithm. This also proves the superiority of user-level personalized recommendation algorithm.

Differences of optimal recommendation algorithm for users

Table 4 shows the proportion of optimal recommendation algorithm suitable for different users. According to table 4 and fig.1, the selection of optimal recommendation algorithm for different users has great differences. Proportions of Diffuse and ICF as optimal recommendation algorithm are highest, respectively 42% and 37%. The proportion of HeatS as optimal recommendation algorithm is 11% and other optimal recommendation algorithms are UCF or Popular. This obviously reflects differences of selection of optimal recommendation algorithm for users.

Table 4. Proportions of users with each algorithm as optimal recommendation algorithm

Algorithm	ICF	UCF	Popular	HeatS	Diffuse
Number of users	455	86	37	135	517
Proportion (%)	37	7	3	11	42

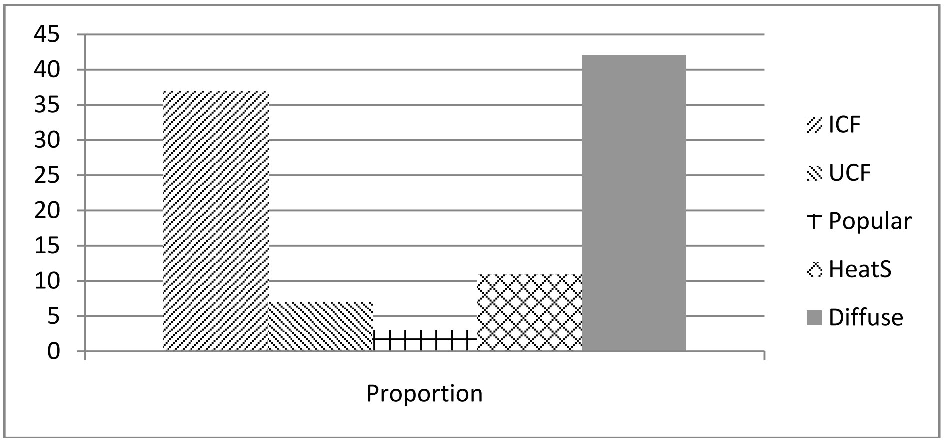

Figure1. proportions of users with each algorithm as optimal recommendation algorithm

Relevance between characteristics of users and optimal recommendation algorithm

Figures 2, 3 and 4 respectively show the distribution of indicators for user characteristics in different recommendation algorithms.

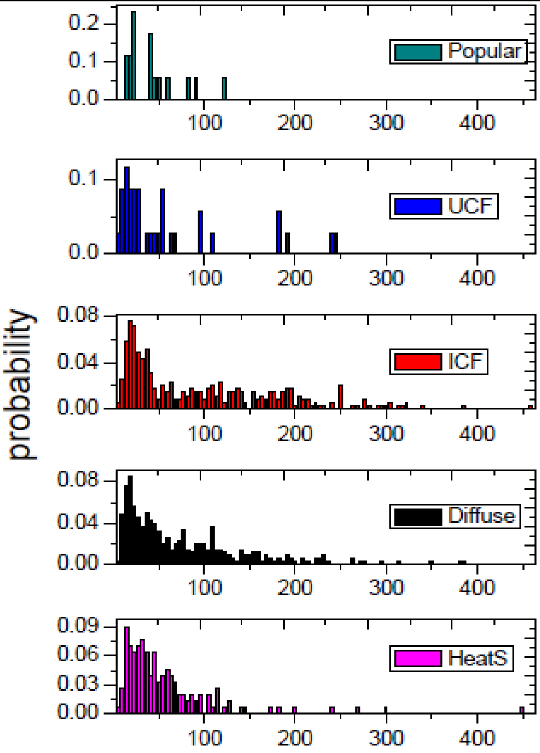

Figure 2. Distribution diagram of degree k_i of product use of users

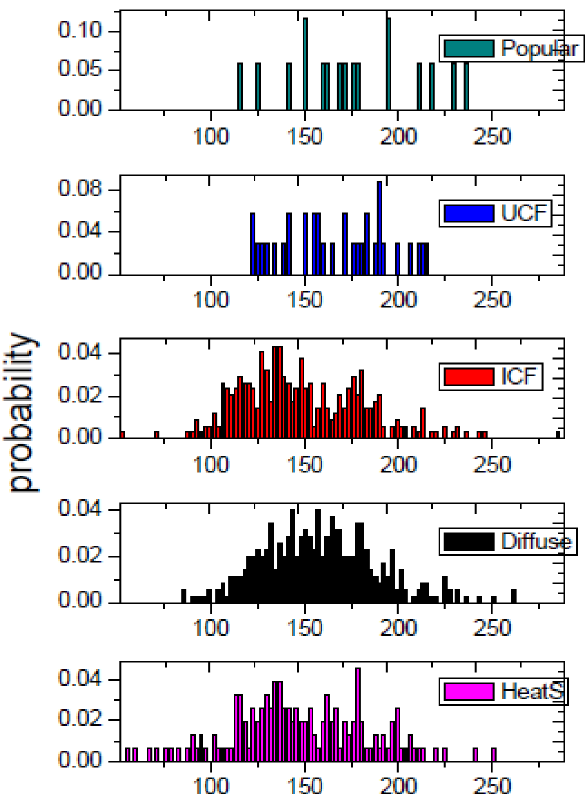

Figure 3. Distribution diagram of average degree d_i of product selection of users

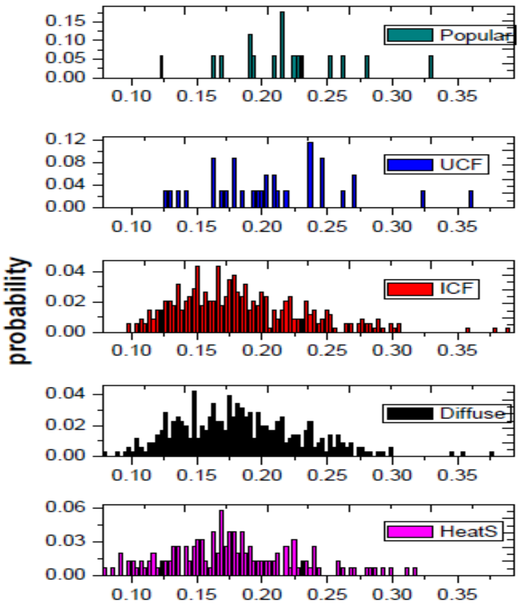

Figure 4. Distribution diagram of average similarity s_i of product selection of users

X-coordinates in figures above refer to the value of three user indicators and Y-coordinates refer to the proportion of corresponding users using each recommendation algorithm as optimal recommendation algorithm. For the convenience of comparative analysis, limit proportions on X-coordinates are the same. It is used to represent the relevance between user characteristics and optimal recommendation algorithm.

According to fig.2, k_i have significant differences as optimal recommendation algorithm is different. We cannot distinguish and infer the optimal recommendation algorithm of different users according to differences of k_i.

According to fig.3, d_i does not differ a lot due to different optimal algorithms. This shows that we cannot infer personalized recommendation algorithm of different users according to differences of d_i.

Fig.4 shows a result similar to fig.3. S_i does not have significant differences due to different optimal recommendation algorithms. This also shows that we cannot infer optimal recommendation algorithm of users according to differences of S_i.

According to the analysis above, these three indicators of user characteristics cannot infer optimal recommendation algorithm of users accurately. The influence of user characteristics on optimal recommendation algorithm is unclear.

Optimal recommendation algorithm of sensitive users

Table 5 shows the improvement magnitude of effect of optimal recommendation algorithm of each user compared to suboptimal recommendation algorithm. According to table 5, the number of users with effect fluctuation amplitude less than 1% accounts for about 48% of the total number of users. For these users of Li-Ning sports website, the change of recommendation algorithm does not have great influence on users. If users with 10% effect improvement are considered as sensitive users, we find 45 sensitive users among 1230 users. The proportion of new sensitive users is lower compared to the total number of users. Further research shows that optimal recommendation algorithm of these sensitive users is HeatS.

Table 5. Improvement magnitude of recommendation effect

Improvement magnitude	0	1	2	3	4	5	10	15	20
User proportion	0.48	0.22	0.15	0.09	0.08	0.03	0.02	0.01	0.01

4.5 AUC and RS as selection basis of optimal recommendation algorithm

The figure below shows ACU and RS distribution. According to the figure, ACU+RS fluctuates around 1.

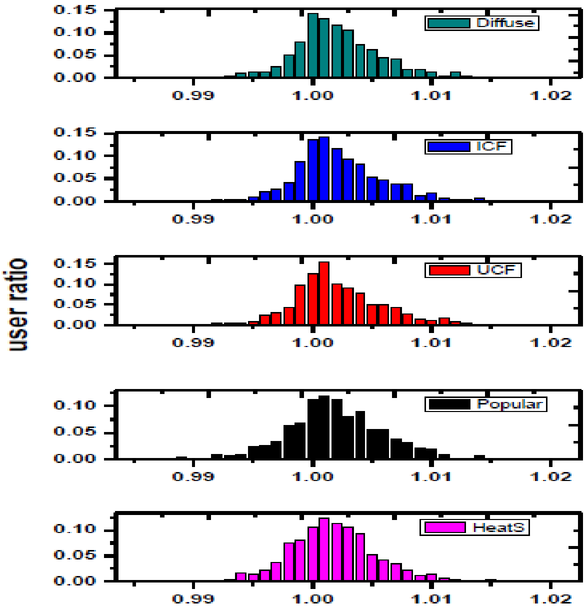

Figure 5. Distribution diagram of AUC+RS

Fig.6 shows the distribution of the number of users when RS and AUC are used as the selection basis of optimal recommendation algorithm.

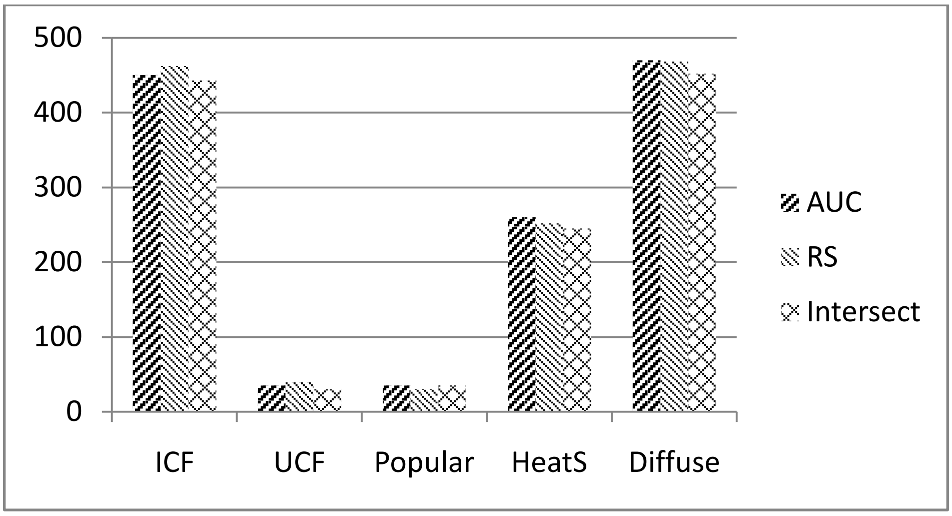

Figure 6. Comparison of each algorithm when RS and AUC are used as the selection basis of optimal recommendation algorithm

According to fig.6, user classification of each recommendation algorithm does not have significant differences when Rs+AUC is used as the selection basis of optimal recommendation algorithm. The relevance between user characteristics and optimal recommendation algorithm cannot be found when Rs and AUC are used as the selection basis of optimal recommendation algorithm. Therefore, the opinion of using RS+AUC as the selection basis of optimal recommendation algorithm is infeasible.

Precision as selection basis of optimal recommendation algorithm

Table 6 shows the improvement magnitude of optimal accuracy rate compared to suboptimal accuracy rate when users use different recommendation algorithms. As shown in the figure below, proportion in the figure refers to the proportion of users when optimal accuracy rate is equal to suboptimal accuracy rate. Values with improvement magnitude 0 are higher and always more than 50%. Separate extraction is also shown in the figure. This shows that over half users cannot obtain single optimal recommendation algorithm when precision is used as the selection basis of optimal recommendation algorithm. It characterizes that precision cannot be used as the selection basis of optimal recommendation algorithm.

Table 6. Improvement magnitude of use different recommendation algorithms

List length	0	1	2	3	4	5	20	40	60	80	100
Proportion	0.95	0.75	0.64	0.58	0.55	0.5	0.23	0.54	0.43	0.42	0.68

According to table 6, as values of precision are centralized, irregardless of recommendation list length, the possibility of occurrence of multiple values is very high; it is very easy to have the situation that several recommendation algorithms cannot be compared for superiority and inferiority. Moreover, optimal recommendation algorithm has a high fluctuation. Therefore, it is not appropriate to use precision as the selection basis of optimal recommendation algorithm.

Conclusion

With data set on Li-Ning sports website as the analysis object, this paper analyzes the superiority of user-level personalized algorithm based on five recommendation algorithms. According to the comparison, user-level personalized recommendation algorithm is superior to single recommendation algorithm and its recommendation effect is improved significantly. In addition, it can be obtained that the selection of optimal recommendation algorithm of different users has great differences. This paper analyzes the relevance between user characteristics and optimal recommendation algorithm according to three user indicators and makes the conclusion that user characteristics and optimal recommendation algorithm do not have clear relevance. Finally, it studies the selection basis of optimal recommendation algorithm. However, the result is that RS, AUC and precision cannot be used as the selection basis of optimal recommendation algorithm. This paper takes website data of Li-Ning sports products for example and studies user-level personalized recommendation algorithm. These data are accurate and representative and have certain significance for promoting the development of user-level personalized recommendation algorithm.

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