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Precision Recommendation Algorithm for E-commerce Service：Taking Online Tutoring as an Example

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ABSTRACT. *With continuous improvement of individualized demand for consumers, traditional e-commerce has been unable to meet the growing demand for a better life. E-commerce service presents the intelligent development tendency in order to provide accurate and personalized service. Recommendation system for e-commerce provides customers with the most suitable product or service based on precise recommendation for customer's demand and preference. This paper first establishes user portrait and service portrait to achieve precision matching for both parties supply and demand in e-commerce, and further analyzes the precise recommendation service by taking tutoring service as an example to accurately meet the demand of students for tutoring service.*

KEYWORDS: *precision matching, recommendation service, algorithm, tutoring service*

1. Research background

With the wide application of information technology such as Big data and cloud computing, precision matching for supply and demand has been improved and further promotes the consumption efficiency and service level for e-commerce[1]. As an transaction medium, various recommendation technologies play an active role in promoting e-commerce transaction. GroupLens, Amazon recommendation appliance and Google recommendation appliance are typical recommendation systems [2-3].

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Algorithms for traditional recommendation system include collaborative filtering recommendation algorithm, demographics recommendation, knowledge-based recommendation, content-based recommendation and hybrid filtering recommendation. However, whether these algorithms are based on content, knowledge, behavior and so on, traditional recommendation systems encounter challenge to achieve the precision matching for both parties of supply and demand in e-commerce, because the recommendation results from the unilateral analysis by the perspective of e-commerce service providers and is only considering existing consumption behavior data of users that is not able to entirely infer consumer preference[4-5].

This paper focuses on the matching demands for supplier and consumer in e-commerce service and provides more precision matching for e-commerce transaction through figuring the attribute portrait of both supplier and consumer, and accurately meeting the demand of final customer. This study can achieve precision and effective matching for e-commerce services by providing more accurate and better portrait analysis for consumers and appropriately quantitative description for goods or services.

2. Analysis of precision recommendation for e-commerce service

With personalized demand in e-commerce consumption becoming more and more prominent, accurate description for e-commerce service seem to very crucial. To achieve the precision matching for user, supplier, payment platform and logistics, this study first analyzes the relevant data of user, supplier, payment and logistics, and then scientifically develops portraits of user and supplier to improve the final customer with consumption experience and consumption stickiness.

User portrait is the detailed description and labeling for user image [6]. By analysing consumer personal information and financial and relational data, user portrait can form a map for demand visualization and reflect real demands of the consumer.

User portrait is widely adopted in various e-commerce recommendation systems. User portrait mainly reflects user's natural attributes, interest attributes, value attributes and social attributes. Figure 1 is a typical user portrait diagram, which can depict the overall image such as gender, age, income level, education background, occupation, geographical distribution, hobbies, consumption preferences and income conditions of the user. Different from the traditional statistical methods, each user label represents a category and has a detailed description about the user. It is better to entirely perfect details of the user portrait as there are enough labels of the user.

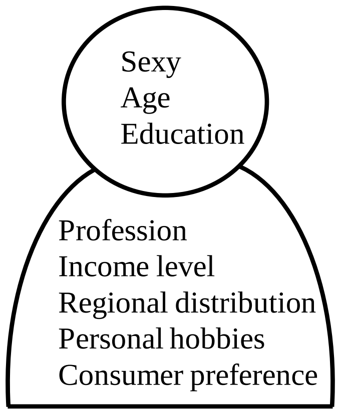

Figure. 1 Sample diagram of a user portrait

User portrait can be used to analyze not only for a single target user, but also for user community. User labels are the basic feature of user, and user portrait embodies variou relationship of the user. As thus, in order to develop target user with authenticity, user community portrait is derived to abstract comprehensive features for the user community. User community portrait analysis is first to classify a group of users with similar characteristics into a set by clustering, and then divides thes groups into different core large-scale user community. Therefore, the more precision recommendation system can be designed.

User portrait clustering aims to classify user portraits according to their own characteristics, because there is as few as possible different within a set of user portrait while the difference between sets is big enough.

3. Precision recommendation algorithm

K-means algorithm is adopted which has been widely used in clustering practices, and its calculation process with intuitive flow is shown in Figure 2.

Meanwhile, k represents a user selecting k other users with similar interests, and then K items of goods or services are recommended to the user which would have been consumed or be interested. The value of k would be set in advance, and its value has great influence for clustering results.

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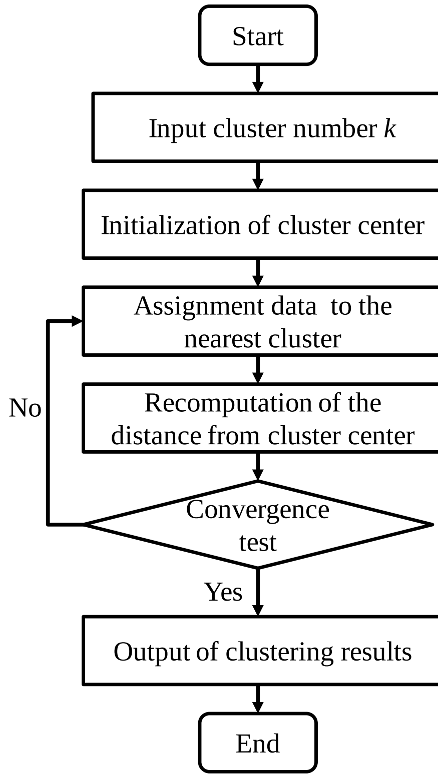

Figure. 2 Calculation process of clustering

The difference within a cluster is few based on user portraits. A target user is then selected and its set is found where the user is listed. In order to provide the user with precision recommendation service, these goods or services are filter out for the target user, which would be interested or consumed with relatively high satisfaction but the target user has never consumed.

Based on the user requirement analysis by clustering, it is significant that the interest similarity of the target user to the remaining users within the same set is higher than its interest similarity to users in other sets. The interest similarity analysis model can be expressed as follows for user *u* and user *v*.

$$\mathrm{w}_{uv} = \frac{\left|N(u) \bigcap N(v)\right|}{\left|N(u) \bigcup N(v)\right|}$$

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Through analyzing the similarity of users, goods or service with high interest similarity or high satisfaction after consumption are recommended to the target user. The measure model of interest similarity for user *u* and item *i* is as follows,

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

where *w* refers to the similarity between user *u* and user *v*, *r* represents the interest for user *v* for the good or service *i*, and *r* is defined as 1 since all the feedback data used are implicit.

S (*u, k*) contains *k* users who have most similar interests to user *u*, and *N*(*i*) is a set of users who have consumed some goods or services.

4. Example analysis

While more and more training and tutoring institutions, such as New Oriental School and TAL Education Group, have carried out online services, the traditional teaching and studying methods have continuously been reformed for innovation and new breakthrough, and tutoring methods are also developing to intelligent tendency.

On account of tutoring practices, user portrait analysis mainly focuses on the natural and behavioral attributes of users. The basic attributes include students' age, gender, location, subject of online course, school ranking in the city, personal academic achievement ranking in the grade, etc. Main behavioral attributes include students' consumption of online tutoring, expenditure of home education funds (Yuan/Month), and frequency of tutoring visits (Times/Year). In order to effectively evaluate home tutoring services, only age of student, expenditure of family education and tutoring frequency are considered in the paper. The specific data from a tutoring institution in Chengdu of China are shown in Table 1.

Table 1 Characteristics for user attribute

User	Age（Years）	Expenditure of Family Education (Yuan/Month)	Frequency of Tutoring Visits (Times/Year)
P1	8	2000	2
P2	10	8000	3
P3	9	3000	1
P4	18	6000	3
P5	12	7000	8

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P6	11	10000	4
P7	16	5000	5
P8	15	9000	2

In order to normalize the data in [0, 1], the normalization transformation model can be expressed as follows with the linear function transformation method:

$y=(x\text{-}MinValue)/(MaxValue\text{-}MinValue)$,

where x and y represent the normalization value before and after transformation, respectively, *MaxValue* and *MinValue* represent the maximum and minimum values of the sample, and characteristics data standardized are shown in Table 2.

Table 2 Characteristics for user attribute by normalization

User	Age	Expenditure of Family Education	Frequency of Tutoring Visits
P1	0	0	0.143
P2	0.2	0.75	0.286
P3	0.1	0.125	0
P4	1	0.5	0.286
P5	0.4	0.625	1
P6	0.3	1	0.429
P7	0.8	0.375	0.571
P8	0.7	0.875	0.143

In clustering analysis for the example, k is set as 3 which means user portrait is classified as three classes. The initial centers of the three clusters are randomly selected, namely user P1, user P5 and user P8, and values of user portrait are expressed as follows.

A: {0，0，0.143}, B: {0.4，0.625，1}, and C: {0.7，0.875，0.143}

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As thus, the similarity of all user portraits to the center point of clusters is calculated using *Euclidean Distance Measure*, respectively. The first clustering results are as follows:

Cluster A：{P1,P3}, Cluster B:{P5,P7}, Cluster C:{P8,P2,P4,P6}.

Following the first clustering analysis, the new center point of clusters is recalculated, and the new center point of cluster A can be worked out, namely

{0.05，0.0625，0.0715}.

In a similar way, the new central point of cluster B and the new central point of cluster C can be worked out, respectively

{0.6，0.5，0.7855} and {0.55，0.781，0.286}.

The rest can be done in the same manner by adjusting the center point for clustering analysis until the final result has not changed, that is, the classification has converged, and so the final clustering result can be obtained, namely

Cluster A：{P1,P3}, Cluster B:{P5,P7}, and Cluster C:{P8,P2,P4,P6}.

User community portrait represents a group of users, and it is a comprehensive figuring and description for all users rather than for some given users in the community. Clustering analysis makes it more convenient to calculate interest similarity of individual users, and also helpful to implement the recommendation algorithm.

Referring online tutoring service providers, basic attributes can include the age, gender, subject of tutoring, education background, tutoring experience, the satisfaction evaluation, and service regions, etc. Behavioral attributes just refer to charge standard and tutor employment status in the past year.

The related performance for online tutoring service is evaluated on *MovieLens* dataset, as shown in Table 3.

Table 3 Parameter and performance for the example

k	Accuracy Rate	Recall Rate	Coverage Rate	Popularity Rate
5	16.99%	8.21%	51.33%	6.813293
10	20.59%	9.95%	41.49%	6.978854
20	22.99%	11.11%	33.17%	7.10162
40	24.50%	11.83%	25.87%	7.203149
80	25.20%	12.17%	20.29%	7.289817
160	24.90%	12.03%	15.21%	7.369063

Following the example analysis, it is illustrated that the accuracy rate and recall rate of recommendation system are not linear with *k*, but the coverage rate of recommendation system decreases with *k*, while the popularity rate of recommendation system increases with *k*, and when *k* = 80, the accuracy and recall rate of the recommendation system reach the maximum. Therefore, it is crucial for precision recommend system to select an appropriate value for *k* [7-8].

5. Conclusion

Nowadays, personalized demand of e-commerce is becoming its development tendency. In order to achieve the precision matching for both parties of the supply and demand in e-commerce, this paper focuses the construction of portraits of users and services, and further develops clustering analysis to acquire the interest similarity measurement for the target user with others in the user set. Moreover, this paper takes an online tutoring service as an example to analyze the precision recommendation service by figuring the portrait for both user and tutoring service provided, and further discusses the variation regulation of recommendation algorithm and the influence upon the accuracy, recall rate, coverage rate, popularity rate, and number of customer similar to the target user.

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