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A Similarity Scenario-Based Recommendation Model With Small Disturbances for Unknown Items in Social Networks

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ABSTRACT In existing recommendation systems, there exist the issues of ''cold start'' and ''excessively mature recommendation,'' which cause the recommendation systems to have weak effectiveness; thus, a trust-based recommendation model with a small recommendation probability for unknown items (RM-UI) is proposed for social networks. In the RM-UI scheme, the recommendation values of items are primarily derived from the probabilities calculated by a similar mature recommendation system during the initiation stage of the recommendation system. Thus, the ''cold start'' phenomenon can be overcome. When the recommendation system enters the period of maturation, the recommendation probabilities mainly adopt the recommendation values computed by the self-system. However, in the existing recommendation systems, there remains the problem of ''excessively mature recommendation,'' which causes the system to lose the opportunity to recommend more optimized items. Thus, in the RM-UI scheme, except for recommending items with higher recommendation probabilities, we recommend items with lower recommendation probabilities with a small probability to enable those items that can bring greater welfare to recommendation systems to be recommended. This breaks the weakness of a confined recommendation that exists in previous recommendation systems, and it enlarges the welfare of the system. After theoretical analysis, it has been proven that the RM-UI scheme can achieve greater welfare than the previous recommendation scheme and gain more vitality. Experiments based on real social network data are conducted to show the effectiveness and efficiency of the RM-UI scheme: in the initiation stage, the performance criteria of precision ratio, recall ratio, and F1-measure are improved by approximately 21.08%, 21.57%, and 21.32%, respectively, over the previous schemes, and in the mature stage, although the three indications are similar to those of the previous schemes, the improvement in the overall revenue of the system is 17.6%.

INDEX TERMS Recommendation system, small recommendation probability, trust, social networks.

I. INTRODUCTION

Pervasive social networking (PSN) ensures social communication at any time and in any place in a universal manner. PSN supports on-line and instant (i.e., pervasive) social activities [1]–[5]. There are various applications for PSN. Recommending systems and their application are one important example [2], [3], [5], [8], [9]. Recently, pervasive social networking has become increasingly important in daily social life, and people purchase items more frequently on each domestic shopping platform and online social shopping website, such as Amazon and eBay [3]. The question of how to establish an effective recommendation model is attracting increasing attention [3], [10]. The recommendation system is an important technology for information filtering and can recommend items to members of a group according to the preferences of the group. It has been proven to play an important role in social networks by providing users with more personalized and intelligent information services, and it has been successfully deployed in a variety of online social websites [6]–[8], [11]–[13].

Researchers have proposed a variety of recommendation systems. The main recommendation systems include [1], [3], [4], [9], [10] (1) content-based recommendation systems, which predict and recommend the items that users will purchase according to the contents of historical purchases [3]; (2) a collaborative filtering recommendation systems, which use the similarity between users' purchase behaviors to recommend products and can better reflect the recommendation process in social networks [3]; (3) user-product biography network structure-based recommendation systems; and (4) hybrid recommendation systems. To the shop owner, the effectiveness of a recommendation system depends on how accurately items are recommended to users. Although there are various methods recommended in previous studies, there still exist two significant issues that need to be further investigated.

(1) The first issue is the problem of "cold start," which is common in recommendation systems. The "cold start" issue is a type of problem that exists in recommendation systems and is difficult to effectively solve. A recommendation system needs to predict the purchase preferences of users on the basis of their purchase histories to make effective item recommendations. However, for newly opened shops or users with nonexistent or sparse transaction records, it is difficult for the recommendation system to make an effective recommendation. This phenomenon is called "cold start" and results from the lack of basic corresponding data in the recommendation system.

(2) The other common issue in recommendation systems is called "maturation recommendation." This type of issue occurs frequently in systems that have been running for some time. Consider the example of store systems: for high-probability items in existing recommendation systems, the recommendation system will further enhance the recommended probability of items that have been recommended. This tendency leads to the phenomenon that those items that have been recommended will be further recommended, and non-recommended items will suffer further reductions in their recommendation probabilities. Therefore, the recommendation system will become stuck in a closed state of over-maturation, and this state does not conform to the interests of the store. The regular users of shops are more loyal, and those loyal users are aware of those items that they need after a period of interaction. Therefore, the items that over-matured systems regularly recommend have less significance to this type of user, which means that the recommendation of those items to users will not affect their purchase results. Thus, over-matured information recommendation systems will not yield benefits for either the shop or the users. Therefore, for an over-matured system, it is necessary to break the phenomenon of excessive and closed-loop recommendation. The system should calculate and recommend a number of low-probability items. Those items are fairly likely to prompt new purchase behaviors among the loyal users and thus expand the purchase lists of users, yielding more interest in the shop and the users in practice. In addition, the recommendation system recommends items with lower probabilities, which means that the cost of spending is much less but generates a large profile. Additionally, reducing the recommendation of mature items has little influence on the original users, and therefore this method will be more meaningful.

Based on the analysis above, a similarity scenario-based Recommendation Model with small disturbances for Unknown Items (RM-UI) in social networks is proposed. The main contributions of the RM-UI scheme are as follows:

(1). To overcome the problem of "mature recommendation" when the recommendation system enters a period of over-maturation, apart from mainly recommending items to users according to the calculation results of the recommendation system, the RM-UI scheme will also recommend other items with small probabilities to users, which is referred to as the "small disturbance for unknown items" in our paper. Therefore, the RM-UI scheme can break the weakness of the over-matured phenomenon in existing recommendation systems, thus obtaining increased benefits and dynamics. To improve the precision of the recommendation model, the recommendation attributes can be combined with the inherent correlation relationships among items to comprehensively derive the recommendation matrixes of probabilities for items. The trust factor is considered to be an important part of the recommendation system, and it is composed of purchase frequency, sales rank and reputation.

(2). To solve the "cold start" recommendation problem, the RM-UI scheme combines the historical purchase records of a mature shop and those of a new shop together to form a union recommendation probability matrix for the target user.

(3). In the experiment, we adopt the Amazon product co-purchasing metadata and reviews of a certain category to verify the effectiveness of the RM-UI scheme through comprehensive experiments. In addition, the precision, recall and F1-measure of the RM-UI scheme are compared with those of the trust-based scheme in different time cycles under a certain transition probability influence factor, and the impact of the transition probability influence factor x for the RM-UI scheme is analyzed through experiments. Finally, the performance results of various detailed attributes are compared in the experiments. Experiments based on real social network data are conducted to show the effectiveness and efficiency of the RM-UI scheme; for the initiation stage, the performance criteria of the precision ratio, recall ratio and F1-measure are improved by approximately 21.08%, 21.57% and 21.32%, respectively, over the previous schemes, and for the maturity stage, although the three indications are similar to those of the previous schemes, the improvement in the overall revenue of the system is 17.6%.

II. RELATED WORK

Recommendation systems in social networks were first proposed in the 90s [14] and received substantial attention and research from all over the world [15].

Generally, recommendation systems can be divided into three categories according to the different recommendation algorithms, which have been introduced before.

The employment of a recommendation system in social networks was first defined by Resnick and Varian [21] and was used to provide advice to users regarding what items can be bought in online social networks. Then, different methods of recommendation systems arose and formed different categories. In general, a recommendation system should consist of the following elements: recommended items, users and recommendation algorithms. Because of uncertainty factors in the activities of online networks, the recommendation system might recommend unexpected items to users. This section presents related works on recommendation models and illustrates the three classic recommendation systems according to the categories to which they belong.

A. CONTENT-BASED RECOMMENDATION SYSTEMS

Content-based recommendation systems are the earliest recommendation schemes used to recommend items to users [22]. According to the items that users have liked, a content-based system can recommend similar items to users. Such systems were developed based on information retrieval and filtering, using the historical purchase records of target users or analysis of the characteristics from purchase information via statistics and machine learning. Generally, a content-based method consists of three steps: item representation, profile learning and recommendation generation. There are many classic content-based methods, such as the model-based recommendation system [23]. There are many advantages of content-based methods, such as their independence of users, transparency, the new item problem, etc. At the same time, there still exist some disadvantages, such as the limited content analysis and the new user problem [24].

B. COLLABORATIVE FILTERING RECOMMENDATION SYSTEMS

Collaborative filtering recommendation systems are the most widely used method in social networks out of the three recommendation schemes, and their applications include Amazon [13], Last.fm and Digg [25]. These types of schemes recommend items based on other users that have relationships that are similar to those of the target user. They take personalized service into consideration. The classic methods in collaborative filtering recommendation are: model-based, user-based and item-based. Pálovics and Benczúr [26] and Breese *et al.* [27] divided the collaborative filtering scheme into two categories: memory-based and model-based. A combination of memory-based and model-based schemes was applied to Google News by Das *et al.* [13]. As a typical recommendation method, collaborative filtering recommendation systems still have some problems that need to be addressed, such as the sparse database problem and cold start.

C. HYBRID RECOMMENDATION SYSTEMS

Because each recommendation algorithm has its advantages and disadvantages, hybrid recommendation systems are frequently adopted in practical applications [27]. Combinations of content-based and collaborative filtering recommendation systems are widely used in social networks and have gained much attention [28]. Although there are theoretically many combinations of recommendation schemes, not all combination methods are effective in concrete circumstances. The main principle of a hybrid recommendation system is to avoid the weaknesses of each single recommendation scheme. Generally, there are seven combination methods: weight, switch, mixed, feature combination [29], cascade, feature augmentation and meta-level [30]. According to these combination methods, hybrid recommendation systems can be divided into three categories: independent systems with recommendation models, collaborative filtering schemes combined with content-based schemes, and other hybrid systems used in concrete circumstances [31].

In addition to the recommendation systems discussed above, there are still other recommendation schemes that have been proposed recently, such as a recommendation algorithm based on the trust factor [32], a personalized system based on user information [33] and a recommendation scheme regarding user cold start based on trust and distrust [34]. These methods have further improved the performance of recommendation systems in social networks, but there still exist various problems that need to be solved:

1. When computing the probabilities of the recommendation model for each item, most of the recommendation models fail to consider the problem of cold start for a certain shop, and thus it is difficult to appropriately recommend items to users appropriate.

2. When computing similarities of users' behaviors, most recommendation models fail to consider the inherent correlation relationships among items.

3. Most recommendation schemes do not consider the trust factor of each item, which may cause the recommendation system to provide distrusted items to target users.

III. THE RESEARCH MOTIVATION

The problem studied in this paper targets a particular store and regards how to effectively recommend items to users to maximize the benefits of the store and how to improve the performance indexes of the recommended strategy, such as the precision ratio, recall ratio and F1-measure.

To recommend items to users more accurately, it is necessary to consider the problem of how a shop, from its opening to the stage of mature business, can appropriately recommend products to target customers appropriate. Because users' behaviors can be seen as probabilistic events and the factor of trust for each product is very important in recommendation models, the recommendation model studied in [3] is based on the probabilistic and trust method, called the trust-based model. However, a model based on trust cannot solve the cold start problem of a newly opened shop.

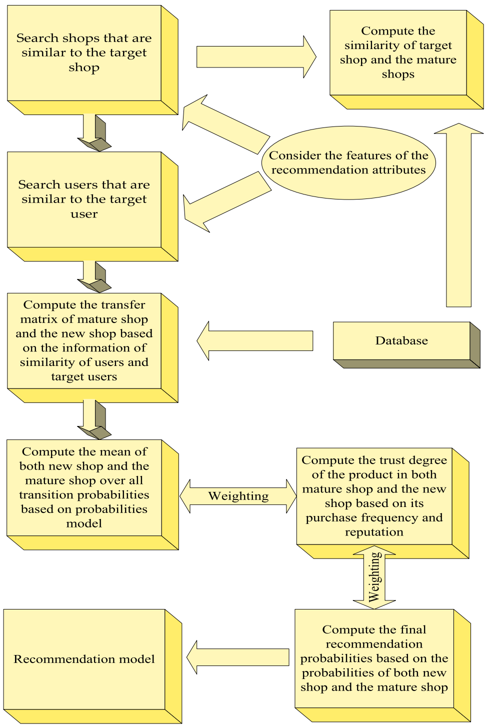

FIGURE 1. The overall idea for cold start.

Therefore, in this paper, a similarity scenario-based recommendation model with small disturbances for unknown items (the RM-UI scheme) in social networks is proposed. First, the RM-UI scheme searches shops that are similar to the target shop to determine which shop can be referred to for recommendations. Then, users that are similar to the target user are found according to the purchase records in the mature reference shop. To improve the accuracy of the results in the recommendation strategy, we consider the recommendation attributes in social networks. The RM-UI scheme takes the similarity among customers into account to search for similar users. Then, the recommendation matrix of the target user based on the historical purchase records of similar users in both the mature reference shop and the newly opened shop can be derived. Combined with the inherent correlation relationship among products, the mean recommendation probability matrix of the target user in the mature shop and the newly opened shop can then be determined based on the transfer matrix. In addition, the work derives the trust of products based on their reputations given by users, sales rank and purchase frequencies. Then, the RM-UI scheme solves the problem of user cold start based on the users' latent factor and handles the problem of a newly opened shop's cold start by referring to the selected similar mature shop. The problem of "over-maturation" is discussed and addressed in this paper. The RM-UI recommendation model is finally established according to the above factors. The overall idea for cold start is shown in Figure 1.

The main challenge of our scheme is how to make it effective and efficient in a newly opened shop.

TABLE 1. Main notations.

Symbol	Description
$Sim_{u_{[i]}}$	The set of similar users to the target user
$SMX_{l_{[i]}}$	The purchase matrixes of similar users
h	The proportion of M
$\gimel^{S}_{i,j}$	The relationship among item i and item j
$\mathcal{W}_i(p)$	The system welfare
x	The proportion of the mean recommendation probability
n	The number of final purchases in the new shop
sum	The number of purchases in each round
$List_i$	The number of recommended products in each round
m	The length of the time window
y	The proportion of the influence factor of trust
z	The proportion of the influence factor of the latent factor
$M[i][j]$	The recommendation matrix of the target user based on the similarity of users
$S[i][j]$	The recommendation matrix of the target user based on the correlation relationship among products
$A[i][j]$	The recommendation probability matrix of the target user based on $M[i][j]$ and $S[i][j]$
trust[i]	The value of trust for product i
$rep[i]$	The reputation of product i
$fre[i]$	The purchase frequency of product i
Fre	A constant number in the experiments
μ	The proportion of the recommendation probability for the new shop
$R[i][j]$	The relationship between product i and product j
$\mathbb{I}$	The symbol of a product
p[i]	The reputation of product i
$recall$	The probability that users purchase what they like in the recommendation list
$F_{1-measure}$	The standard measurement for the classification accuracy of a recommendation algorithm
B_i	The number of products that user i likes
N_i	The number of products that user i has purchased in the recommendation list

The RM-UI scheme handles this problem by combining the historical purchase records from both the mature and new shops together to determine the recommendation probability matrix of the target customer. Finally, the recommendation model is obtained.

The main notations used in our experiments are shown in the Table I.

IV. RM-UI ALGORITHM

A. SEARCH FOR MATURE AND SIMILAR REFERENCE USERS IN THE MATURE SHOP FOR THE TARGET USER

1) THE CALCULATION METHOD FOR SIMILAR SHOPS

First, the RM-UI scheme defines $U = (u_1, u_2, \ldots\ldots, u_m)$ as the set of users, $shop_i = (I_1, I_2, \ldots\ldots, I_n)$ as the set of shops, $I = (\mathbb{I}_1, \mathbb{I}_2, \ldots\ldots, \mathbb{I}_n)$ as the set of products in the new target shop, $I_1 = (\mathbb{I}_{11}, \mathbb{I}_{12}, \ldots\ldots, \mathbb{I}_{1n})$ as the set of items in mature shop I_1, $I_2 = (\mathbb{I}_{21}, \mathbb{I}_{22}, \ldots\ldots, \mathbb{I}_{2n})$ as the set of items in mature shop I_2 and as so on. At the beginning, the RM-UI scheme needs to find the shop that is most similar to the target shop, which means finding the maximum number of items that the target shop and mature shop both have in common. The reference mature shop can be obtained according to equation (1) below:

$$Ps_{[i]} = \frac{count(I) \cap count(I_i)}{count(I) \cup count(I_i)} \tag{1}$$

where count$[I_i]$ represents the products that mature shop I_i has and count$[I]$ represents the products that the new target shop has. In the experiment, we select the most similar shop I_i to be the reference, which means choosing the maximum result of $Ps_{[i]}$ according to (1).

Then, the most similar mature shop can be set as the reference for the newly opened shop.

2) THE CALCULATION METHOD FOR SIMILAR USERS

According to the historical information of purchase records, the relationships in the recommendation model between similar users and the target user are as shown in Figure 2 below:

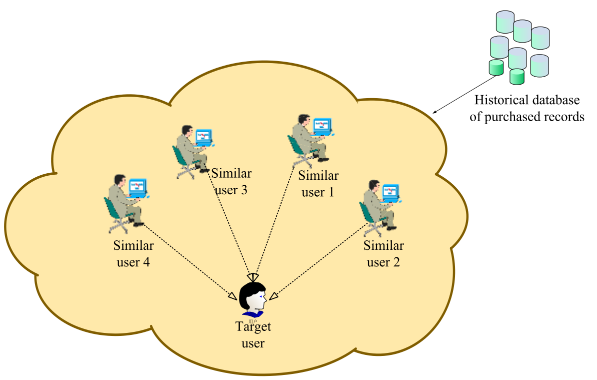

FIGURE 2. The relationships among similar users and the target user.

According to the flow of information in the online network, the target user is randomly selected by the algorithm, and then we need to find users that are similar to the target user. In this step, the RM-UI scheme chooses the Pearson correlation coefficient scheme to compute similar users of target users. To solve the problem of the various recommendation attributes, which may be ignored by most recommendation methods when considering similarity relationships among user behaviors, the attributes of reputation, sales rank and purchase frequency for products should be taken into account (defined as *fre* and *rep* and illustrated in Table I). To obtain the similarity between user u_j and target user u_i, equation (2) can be derived as follows:

$$W_{i,j} = \frac{\sum_{k \in S_{i,j}} \sqrt{\lambda \frac{1}{rep_k^2} + (1-\lambda)\frac{1}{fre_k^2}} (r_{i,k} - \bar{r_i})(r_{j,k} - \bar{r_j})}{\sigma_j \sigma} \tag{2}$$

where $W_{i,j}$ represents the correlation similarity relationship degree among user u_j and user u_i (the higher, the better) and rep_k and fre_k respectively represent the reputation and frequency of item $\mathbb{I}_k$. $S_{i,j}$ represents the set of items that both user u_j and user u_i have ever purchased. $\bar{r_i}$ and $\bar{r_j}$ are the mean ratings of user u_j and user u_i, respectively. $r_{j,k}$ and $r_{i,k}$ respectively represent the ratings of user u_j and user u_i for item $\mathbb{I}_k$. σ_j and σ_i respectively represent the standard deviations for user u_j and u_i, and the calculation method is shown by equation (3) as follows:

$$\sigma_j = \sqrt{\sum\nolimits_{k \in S_{i,j}} (r_{j,k} - \bar{r_j})^2}$$
$$\sigma_i = \sqrt{\sum\nolimits_{k \in S_{i,j}} (r_{i,k} - \bar{r_i})^2} \tag{3}$$

According to (3), the similarity degree among user u_j and user u_i can be obtained, and the selection of the set of similar users is sorted by $W_{i,j}$ in descending order. The set of similar users for the target user u_i is defined as $Sim_{u_{[i]}}$, and the threshold number of similar users is defined as p in the experiment. Therefore, the dataset of similar users for the target user u_i can be defined as $Sim_{u_{[i]}} = (u_1, u_2, \ldots, u_p)$.

B. ESTABLISHMENT OF THE RECOMMENDATION MODEL

1) THE RECOMMENDATION PROBABILITY FOR EACH ITEM BASED ON THE HISTORICAL PURCHASE RECORDS

To recommend more accurate items to users, we need to compute the recommendation probability of each item according to the historical purchase records of users. The main calculation methods are illustrated as follows:

Suppose that the past states are $X_0 = i_0, X_1 = i_1, X_2 = i_2, \ldots, X_{t-1} = i_{t-1}$ and that the present state is $X_t = i_t$, where $X_t = i_t$ represents the state being i_t at time t; the value of i_j is 0 or 1. In that case, the probability of the state at the next time step i_{t+1} is shown by equation (4) below:

$$p\left(X_{t+1} = i_{t+1} | X_t = i, X_{t-1} = i_{t-1}, \ldots, X_{t-m+1} = i_{t-m+1}\right) \tag{4}$$

where p represents the probability. Therefore, the probability recommendation matrix of both the selected mature shop and the new shop for the target user can be obtained. For instance, to obtain the transfer matrix of the mature shop for target user u_i, supposing that the current time is t, the recommendation probability matrix of the next time instant $t+1$ can be expressed as the following equation (12):

$$M_{u_i}^l = \begin{bmatrix} a_{1,1}^l & a_{1,2}^l & \ldots & a_{1,n}^l \\ a_{2,1}^l & a_{2,2}^l & \ldots & a_{2,n}^l \\ & & \ldots & \\ & & \ldots & \\ a_{n,1}^l & a_{n,2}^l & \ldots & a_{n,n}^l \end{bmatrix} \tag{5}$$

where $M_{u_i}^l$ represents the probability recommendation matrix of each item for the target user and l represents the historical purchase records in the selected mature shop for similar users and the target user. $a_{i,j}^l$ represents the probability that the target user will purchase item $\mathbb{I}_j$ at the next time instant t + 1 in the condition that the historical purchase records are l and the target user has purchased item $\mathbb{I}_i$ at the current time t. The equation for calculation of $a^l_{i,j}$ is as follows:

$$a^l_{i,j} = \mathrm{p}\left(i_{t+1} \in B^{u_i}_{t+1} | \mathrm{i} \in B^{u_i}_t\right) = \frac{\mathrm{p}(i_{t+1} \in B^{u_i}_{t+1} \bigwedge i \in B^{u_i}_t)}{p(i \in B^{u_i}_t)} = \frac{count(u(i \to i+1))}{count(u(i))} \tag{6}$$

where $B^{u_i}_{t+1}$ indicates the set of items that user u_i will purchase at time t+1 and $B^{u_i}_t$ represents the set of items that user u_i has purchased at the current time t. Moreover, count(u(i)) represents the number of users that ever purchased product $\mathbb{I}_i$, and count(u($i \to i+1$)) represents the number of users that ever purchased product $\mathbb{I}_j$ at time t+1 under the circumstance that they purchased product $\mathbb{I}_i$ at time t. In addition, the set of users contains both the target user and the similar users. Therefore, the transfer probability matrix of the target user can be determined according to the historical records of similar users and the target user in the reference mature shop. At the beginning of the experiment, the purchase records of the new shop almost approach zero, so it is difficult to find similar users for the target user u_i. Along with the experimental training, the purchase records of the new shop start to grow, and thus we can gradually find similar users for the target user, and the procedures are the same as above.

For example, suppose that there is a target user u_i and that similar users can first be determined according to the historical purchase records in the reference mature shop; the recommendation probability matrix of the target user u_i can then be determined. Let the threshold number of similar users be p = 4, the time window be m = 3 and the number of selected items be five. According to the experiments, the time window is shorter, the purchase information will be more valuable because of time sensitivity. However, if the length of time window is too short, then the purchase information will be incomplete. Therefore, the set of similar users can be expressed as $Sim_{u[i]} = (u_1, u_2, u_3, u_4)$, and the set of purchase matrixes of $Sim_{u[i]}$ is defined as follows: $SMX_{l[i]} = (\ell_1, \ell_2, \ell_3, \ell_4)$. The set of products can be expressed as $I = (\mathbb{I}_1, \mathbb{I}_2, \mathbb{I}_3, \mathbb{I}_4, \mathbb{I}_5)$, and the matrix of purchase records for the target user is defined as ℓ. The historical purchase records of similar users in the selected mature shop when the time window m <= 3 are as follows:

$$\ell_1 : \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \ell_2 : \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\ell_3 : \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \quad \ell_4 : \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

where the row from the first line to the last of matrix ℓ_i represents the serial number of items from $\mathbb{I}_1$ to $\mathbb{I}_5$ and the column of matrix ℓ_i represents the historical state X_j. If a user has purchased item $\mathbb{I}_k$ at time X_j, the result of row k and column j is 1. Otherwise, the result is 0.

The historical purchase records of the target user are shown as follows:

$$\ell : \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

According to (6), the recommendation matrix of u_i at B_{t+1} can be calculated as follows:

$$M^l_{u_i} = \begin{bmatrix} 0 & 0 & 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 & 0 & 0 \\ 0.2 & 0.2 & 0 & 0.2 & 0.6 \\ 0.4 & 0 & 0.4 & 0 & 0 \\ 0.2 & 0 & 0.2 & 0.2 & 0 \end{bmatrix}$$

To explain the results shown above, calculate the result of $a_{3,1}$ as an example. It can be seen that when the product is $\mathbb{I}_3$, the number of users among both the similar users and the target user that have ever purchased it is 5 at time t. Therefore, the denominator is five. Under the circumstance that users have bought product $\mathbb{I}_3$, the number of users that bought product $\mathbb{I}_1$ is one at time t+1 (ℓ_4). Therefore, the numerator in the equation is one. Thus, the result for $a_{3,1}$ is 0.2.

From the historical purchase matrix ℓ, when the column is three (the time state is three), the target user only purchased item $\mathbb{I}_4$, and therefore the probabilities of purchasing the items from $\mathbb{I}_1$ to $\mathbb{I}_5$ in the next time instant are as shown in row 4.

2) THE CALCULATION METHOD FOR THE CORRELATION RELATIONSHIPS AMONG ITEMS

Then, the inherent correlations among items are taken into consideration to improve the accuracy of the recommendation model. According to the survey, people are more likely to purchase or browse items related to the items that they have already purchased before. Therefore, it is necessary to consider the correlation relationships among products. According to the characteristics of products and the categories they belong to, the relationships among products are taken into consideration on the basis of the information flow in the Internet, which means that if the flow of information is larger, the correlation relationship among the items is closer. In the example given above, the correlation relationships of products are as shown in Figure 3 below:

According to the information flow of items, $S = (s_{i,j})$ is defined to be the correlation relationship among products in the experiment, where $s_{i,j}$ represents the probability of the correlation relationship of product $\mathbb{I}_i$ and product $\mathbb{I}_j$. From the definition of $\boldsymbol{s_{i,j}}$, it is clear that the value of $\boldsymbol{s_{i,j}}$ is in the interval (0, 1). If there is no relationship among $\mathbb{I}_i$ and $\mathbb{I}_j$, the

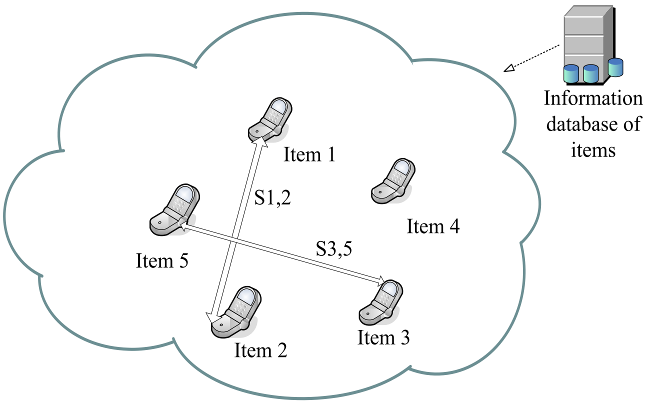

FIGURE 3. **The correlation of products.**

value of $s_{i,j}$ is 0. The equation for the correlation relationship of products is shown below:

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,n} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,n} \\ & & \cdots & \\ & & \cdots & \\ s_{n,1} & s_{n,2} & \cdots & s_{n,n} \end{bmatrix} \tag{7}$$

Then, we start to compute the value of each correlation relationship $s_{i,j}$. Let $B_{i,j}$ represent the number of users that have purchased both product $\mathbb{I}_i$ and product $\mathbb{I}_j$. The calculation method of $s_{i,j}$ is shown as the following equation:

$$S_{i,j} = \lambda_{i,j}^{S} \times g(B_{i,j}) = \lambda_{i,j}^{S} \times \frac{1}{1+e^{-B_{i,j}}} \tag{8}$$

where $\lambda_{i,j}^{S}$ indicates whether there is a relationship between product $\mathbb{I}_i$ and product $\mathbb{I}_j$, which is shown by equation (9) below:

$$\lambda_{i,j}^{S} = \begin{cases} 1, & \textit{there is a relationship between } \mathbb{I}_i \textit{ and } \mathbb{I}_j \\ 0, & \textit{there is no relationship among } \mathbb{I}_j \textit{ and } \mathbb{I}_i \end{cases} \tag{9}$$

$g(B_{i,j})$ is a logic equation that ensures that the results are in the interval [0, 1]:

$$g\left(B_{i,j}\right) = \frac{1}{1+e^{-B_{i,j}}} \tag{10}$$

It is clear that the correlation relationship among products is symmetric, which means that $s_{i,j}$ is equal to $s_{j,i}$ in the correlation relationship matrix of items.

On the basis of the example shown above, suppose that there is a correlation relationship between $\mathbb{I}_1$ and $\mathbb{I}_2$ and between $\mathbb{I}_3$ and $\mathbb{I}_5$. If $B_{1,2} = 4$ and $B_{3,5} = 2$, then we can get the results that $s_{1,2} = s_{2,1}, = 0.892$, $s_{3,5} = s_{5,3} = 0.889$, and others in the recommendation probability matrix S are zero because there are no correlation relationships between them. The results for the recommendation matrix of the relationship correlations among items in S are shown below:

$$S = \begin{bmatrix} 0 & 0.892 & 0 & 0 & 0 \\ 0.892 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.889 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.889 & 0 & 0 \end{bmatrix}$$

3) THE MEAN RECOMMENDATION PROBABILITY MATRIX OF ITEMS

Then, the combination recommendation probability matrix can be obtained in the selected mature shop on the basis of $M_{u_i}^{l}$ and S, which have been computed above, and the calculation method is as follows:

$$A_{u_i}^{l} = h * M_{u_i}^{l} + (1-h) * S \tag{11}$$

where $A_{u_i}^{l}$ represents the recommendation probability matrix and h is the influence factor. The presentation is as shown below:

$$A_{u_i}^{l} = \begin{bmatrix} b_{1,1}^{l} & b_{1,2}^{l} & b_{1,3}^{l} & b_{1,4}^{l} & b_{1,5}^{l} \\ b_{2,1}^{l} & b_{2,2}^{l} & b_{2,3}^{l} & b_{2,4}^{l} & b_{2,5}^{l} \\ b_{3,1}^{l} & b_{3,2}^{l} & b_{3,3}^{l} & b_{3,4}^{l} & b_{3,5}^{l} \\ b_{4,1}^{l} & b_{4,2}^{l} & b_{4,3}^{l} & b_{4,4}^{l} & b_{4,5}^{l} \\ b_{5,1}^{l} & b_{5,2}^{l} & b_{5,3}^{l} & b_{5,4}^{l} & b_{5,5}^{l} \end{bmatrix} \tag{12}$$

where $b_{i,j}^{l}$ indicates the recommendation probability of each item after adding the factor of the correlation relationship among items into $M_{u_i}^{l}$.

As (11) illustrated, let $h = 0.6$, based on the results of $M_{u_i}^{l}$ and S; the results of the mean probability recommendation matrix $A_{u_i}^{l}$ based on the purchase records of similar users and the correlation relationships among items can be obtained in the experiment, as shown below:

$$A_{u_i}^{l} = \begin{bmatrix} 0 & 0.36 & 0.2 & 0.15 & 0.15 \\ 0.66 & 0 & 0.3 & 0 & 0 \\ 0.12 & 0.12 & 0 & 0.12 & 0.72 \\ 0.24 & 0 & 0.24 & 0 & 0 \\ 0.12 & 0 & 0.48 & 0.12 & 0 \end{bmatrix}$$

Therefore, according to the matrix of analysis above, the mean transition probability of each item in the reference mature shop can be computed by the following equation:

$$p(i_{t+1} \in B_{t+1}^{u_i}) = \frac{1}{|B_t^{u_i}|} \cdot \sum_{i \in B_t^{u_i}} p\left(i_{t+1} \in B_{t+1}^{u_i} | B_t^{u_i}\right) \tag{13}$$

where $|B_t^{u_i}|$ indicates the number of items that the target user has purchased at time t.

According to the above example and (13), the mean transition probability of each item in the mature shop is as shown below:

$$p\left(\mathbb{I}_1 \in B_{t+1}^{u_i} | \mathbb{I}_4\right) = \frac{1}{1} \cdot 0.24 = 0.24$$
$$p\left(\mathbb{I}_2 \in B_{t+1}^{u_i} | \mathbb{I}_4\right) = \frac{1}{1} \cdot 0 = 0$$
$$p\left(\mathbb{I}_3 \in B_{t+1}^{u_i} | \mathbb{I}_4\right) = \frac{1}{1} \cdot 0.24 = 0.24$$
$$p\left(\mathbb{I}_4 \in B_{t+1}^{u_i} | \mathbb{I}_4\right) = \frac{1}{1} \cdot 0 = 0$$
$$p\left(\mathbb{I}_5 \in B_{t+1}^{u_i} | \mathbb{I}_4\right) = \frac{1}{1} \cdot 0 = 0$$

When a new shop opens, although it does not have purchase records, the relationships among products is certain by referring to those of the selected mature shop. The mean recommendation probability $\mathrm{p}\left(i_{t+1} \in B_{t+1}^{u_i} | \mathrm{i} \in B_t^{u_i}\right)$ in the new shop can be computed by the same method as illustrated above.

4) THE TRUST FACTOR OF ITEMS IN THE RM-UI SCHEME

In traditional recommendation schemes, there exists dependency among customers. Because of numerous reasons that exist in social networks, it is significant to consider the trust factor of items to avoid recommending malicious items to users. Thus, the accuracy of recommendation results can be improved by adding the trust factor into the RM-UI scheme. In the RM-UI scheme proposed, the trust factor of each item is based on its reputation as given by purchasing users, sales rank and purchase frequency in a stage.

In the RM-UI scheme, the trust degree of an item is based on the reputation, sales rank and frequency and is shown in the equation below:

$$trust_i = \tau \cdot rep_i + \theta \cdot \frac{1}{e^{rank_i}} + (1 - \tau - \theta) \cdot fre_i / Fre \quad (14)$$

where $trust_i$ is the trust degree of item i, rep_i represents the reputation of item i, and fre_i represents the purchased frequency of item i. Fre is a logic number in the experiment that can make sure that fre_i/Fre is in the interval [0, 1], τ is the scale factor of reputation for item $\mathbb{I}_i$ in the equation, and θ is the influence factor of sales rank for item $\mathbb{I}_i$. $rank_i$ is the sales rank of item $\mathbb{I}_i$ according to the metadata information of items, and the higher, the better.

In the reference mature shop, because the historical purchase records are rich, supposed that the reputation, sales rank and purchase frequency of a certain item have constant values. Therefore, the value of trust for item i in the mature shop is certain. With the running of the RM-UI scheme, rep_i, $rank_i$ and fre_i in the new shop are changing at different time cycles. The calculation method of the trust degree for each item in the new shop is the same as that in the reference mature shop.

5) THE LATENT FACTOR OF USERS IN THE RM-UI SCHEME

In the mature shop, it is easy to determine the target user's transition matrix of probability by browsing the histories and trust degrees of items if the target user is not new. However, it is difficult to calculate those attributes for a new user, which is called "cold start." Therefore, we choose according to the latent factors of users to solve the problem illustrated above (Xu et al., 2014). The definition of the attribute set of the latent factor is shown as follows:

$$L_i = (age, gender, location, browse)$$

If the target user is new, which means that the historical purchase records are empty, it is difficult to recommend appropriate items. However, according to the attribute set shown above, the set of latent similar users can be determined to calculate the latent items that the target user may like. To determine the set of similar users for the target user u_i, the definition is given as $\mathrm{si}(\mathrm{lat}\,(u_i)\,, \mathrm{lat}(u_j))$, which can be obtained by calculating the four factors shown in the equation.

$$\begin{aligned} &\mathrm{si}\left(\mathrm{lat}\,(u_i)\,, \mathrm{lat}\left(u_j\right)\right) \\ &= \delta_1 \cdot \mathrm{si}\left(\mathrm{A}\,(u_i)\,, \mathrm{A}\left(u_j\right)\right) + \delta_2 \cdot \mathrm{si}\left(\mathrm{G}\,(u_i)\,, \mathrm{G}\left(u_j\right)\right) \\ &\quad + \delta_3 \cdot \mathrm{si}\left(\mathrm{L}\,(u_i)\,, \mathrm{L}\left(u_j\right)\right) + \delta_4 \cdot \mathrm{si}\left(\mathrm{B}\,(u_i)\,, \mathrm{B}\left(u_j\right)\right) \quad (15) \end{aligned}$$

where φ represents the weight of attribute similarity, $\delta_1 + \delta_2 + \delta_3 + \delta_4 = 1$, $\mathrm{si}\left(\mathrm{A}\,(u_i)\,, \mathrm{A}\left(u_j\right)\right)$ represents the latent similarity relationship of age between u_i and u_j, $\mathrm{si}\left(\mathrm{G}\,(u_i)\,, \mathrm{G}\left(u_j\right)\right)$ represents the latent similarity of gender between u_i and u_j, $\mathrm{si}\left(\mathrm{L}\,(u_i)\,, \mathrm{L}\left(u_j\right)\right)$ represents the latent similarity of location between u_i and u_j, and $\mathrm{si}\left(\mathrm{B}\,(u_i)\,, \mathrm{B}\left(u_j\right)\right)$ represents the latent similarity of browsing between u_i and u_j.

Regardless of the type of shop, if the target user is new, this method is suitable.

6) THE ESTABLISHMENT OF COMBINATION CALCULATION

According to the methods illustrated above, the RM-UI scheme combines the mean recommendation matrix of items for target users, trust degree of selected items and latent factor of target users, if they are new, to establish the calculation equation shown as follows:

$$\begin{aligned} R_{u_i}^{\mathbb{I}_j} &= x \cdot \mathrm{p}\left(i_{t+1} \in B_{t+1}^{u_i}\right) + y \cdot trust_i + z \cdot latent_{u_i}^{\mathbb{I}_j}, \\ x + y + z &= 1 \end{aligned} \quad (16)$$

where $R_{u_i}^{\mathbb{I}_j}$ indicates the recommendation probability in the mature selected shop to recommend item $\mathbb{I}_j$ to target user u_i. x is the influence factor of the mean probability matrix of recommended items for user u_i, y is the influence factor of the trust degree for product $\mathbb{I}_j$, and z is the influence factor when the target user u_i is new. If the target user selected is new, then there are no historical purchase records, and thus $x + y = 0$ and $z = 1$. In our experiment, the users selected are not new, and therefore in (16), $x + y = 1$ and $z = 0$, which means that the recommendation probability of product $\mathbb{I}_j$ for user u_i is determined by the mean probability matrix of items and the influence factor of the trust degree for item $\mathbb{I}_j$.

In the RM-UI scheme, we need to calculate $R_{u_i}^{\mathbb{I}_j}$ in both the mature shop and the newly opened shop and then combine them together to recommend items to some degree. Suppose the recommendation probabilities of products in the new shop are $R_{1_{u_i}}^{\mathbb{I}_j}$; the calculation method of $R_{1_{u_i}}^{\mathbb{I}_j}$ is the same as that in $R_{u_i}^{\mathbb{I}_j}$. The equation for the combination of $R_{u_i}^{\mathbb{I}_j}$ and $R_{1_{u_i}}^{\mathbb{I}_j}$ can be derived by the following equation:

$$R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j} = \mu \cdot R_{1_{u_i}}^{\mathbb{I}_j} + (1-\mu) \cdot R_{u_i}^{\mathbb{I}_j} \tag{17}$$

where $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j}$ represents the recommendation probability of providing product $\mathbb{I}_j$ to user u_i after combining $R_{u_i}^{\mathbb{I}_j}$ and $R_{1_{u_i}}^{\mathbb{I}_j}$ together, and μ is the influence factor of historical purchase records in the new shop. When the shop is new, the historical purchase records are sparse, and thus the result of $R_{1_{u_i}}^{\mathbb{I}_j}$ for the new shop is nearly zero. Therefore, at the beginning of our experiment, the value of the influence factor μ is zero; as time passes, the influence of purchase records in the new shop will grow larger, and the value of μ will become greater. The value of the influence factor μ can be derived by the following equation:

$$\mu = \frac{\sum_{i=1}^{n} fre_i}{Fre} \tag{18}$$

where $\sum_{i=1}^{n} fre_i$ is the sum of the purchase frequencies of items $\mathbb{I}_1$ to $\mathbb{I}_n$ in a time cycle and Fre is a constant number defined in the experiment before. With the running of the new shop, the purchase record will grow; thus, according to (18), the influence factor μ will grow. When $\sum_{i=1}^{n} fre_i$ is greater than the threshold total purchase number n, which means that the new shop is mature, the shop can recommend items according to its own historical purchase records without referring to those of the mature shop.

According to (17), the probability recommendation matrix of the RM-UI scheme can be obtained. Then, in the experiment, let the recommendation threshold be α. If the result of $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j}$ is greater than the threshold α, the system will recommend item $\mathbb{I}_j$ to target user u_i and observe whether the target user purchases it or not in the next time cycle. Otherwise, the recommendation system will not recommend item $\mathbb{I}_j$ to target user u_i.

The algorithm of the RM-UI scheme proposed in this paper can be illustrated as below:

Below is the pseudo-code of the RM-UI algorithm:

Algorithm 1 The Main RM-UI Algorithm

Input: n, sum, a$[i][j][k]$, $a_1[i][j][k]$, $I[i][j]$, $I_1[i][j]$, $rep[i]$, $rep_1[i]$, $fre[i]$, $fre_1[i]$, Fre, x, y, z, μ
(Tips: The calculation method of probabilities for products in the new shop is the same as that in the reference shop)

Output: $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j}$

read the file, search for the reference mature shop
$Ps_{[i]} = \frac{count(I) \cap count(I_i)}{count(I) \cup count(I_i)}$, refer $= \max(Ps_{[i]})$
while sum < n
  judge();
    read the file
    Compute similar users $\sigma_j = \sqrt{\sum_{k \in S_{i,j}} (r_{j,k} - \bar{r}_j)^2}$
    $\sigma_i = \sqrt{\sum_{k \in S_{i,j}} (r_{i,k} - \bar{r}_i)^2}$
    $W_{i,j} = \frac{\sum_{k \in S_{i,j}} \sqrt{\lambda \frac{1}{rep_k^2} + (1-\lambda) \frac{1}{fre_k^2}} (r_{i,k} - \bar{r}_i)(r_{j,k} - \bar{r}_j)}{\sigma_j \sigma_i}$
    Compute the transfer matrix based on the users above:
    $a_{i,j}^{l} = \frac{count(u(i \to j))}{count(u(i))}$, transfer matrix $M_{u_i}^{l}$
    Compute the transfer matrix based on the relationship
    $\boldsymbol{s_{i,j}} = \lambda_{i,j}^{S} \times \frac{1}{1+e^{-\boldsymbol{B_{i,j}}}}$, transfer matrix S
    Compute the final transfer matrix based on $M_{u_i}^{l}$ and S
    $A_{u_i}^{l} = h * M_{u_i}^{l} + (1-h) * S$, final matrix $A_{u_i}^{l}$
    Compute the recommendation probability at the next time instance
    $p(i_{t+1} \in B_{t+1}^{u_i}) = \frac{1}{|B_t^{u_i}|} \sum_{i \in B_t^{u_i}} p\left(j \in B_{t+1}^{u_i} | B_t^{u_i}\right)$
    Compute the trust degree of each item
    $trust_i = \tau \cdot rep_i + \theta \cdot \frac{1}{e^{rank_i}} + (1-\tau-\theta) \cdot fre_i / Fre$
    Compute the latent factor if the target user is new
    Comprehensively compute the probability
    $R_{u_i}^{\mathbb{I}_j} = x \cdot \mathrm{p}(i_{t+1} \in B_{t+1}^{u_i}) + y \cdot trust_i + z \cdot latent_{u_i}^{\mathbb{I}_j}$
    Combine the recommendation probabilities of the reference shop and new shop
      $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j} = \mu \cdot R_{1_{u_i}}^{\mathbb{I}_j} + (1-\mu) \cdot R_{u_i}^{\mathbb{I}_j}$, $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j}$ is results
      End
End
Return $R_{\mathrm{f}_{u_i}}^{\mathbb{I}_j}$

C. SMALL DISTURBANCES FOR UNKNOWN ITEMS

In previous recommendation systems, the effectiveness of a recommendation scheme is primarily evaluated by the precision and recall of the recommendation. However, there is no consideration of whether the scheme can bring new benefits to the system or not. The essence of the recommendation system is to, through recommendations, bring more revenue to the shop, which is the real concern of the store owners. For the precision rate and recall rate, they are considered from the technical level. Specifically, there will exist a so-called "over-matured" problem for a mature recommendation system. In an over-matured system, the system almost always recommends the same items to regular users, and the recommended success probability of these items is very high. However, this is not the main goal of the store owner. In such a mature recommendation system, loyal users are aware of the items that they need and purchase them. Therefore, even if the recommendation probabilities of the recommendation system are accurate, the profiles that it brings to the shop are quite limited. Thus, in such situations, the items recommended by systems will have little influence on the purchase results of users. These users will exhibit the same purchase behaviors without any recommendation. Therefore, what the shop owners expect is to provide those loyal users with various new items that they may purchase. If successful, those users will add some new purchased items and bring new income to the shop owners instead of being stuck in the phenomenon of an ''over-matured'' closed system. According to the analysis illustrated above, the second innovation of the RM-UI scheme is the addition of various disturbances to the recommendation system, which means adding some lower recommendation probability items into the recommendation system, and those items have successful probabilities of recommendation to a certain extent. Therefore, after recommending in this manner, the overall welfare of the system can be further improved. In this paper, we recommend small disturbance probabilities for items to increase the probability of the system welfare in general, which is called DP (disturbance probability) in this paper.

The following mainly analyzes how to select the probability of disturbance to increase the welfare of the system. The main goal for the selection of disturbance probabilities is to increase the welfare of the system. In the existing recommendation systems, there generally exists a positive correlation between the probability of recommendation and the success rate of the recommendation, which means that if the recommendation probabilities of items are higher, the success rate of user purchase is higher. The better the performance of the recommendation system, the stronger the positive correlation will be, which is shown in Figure 4.

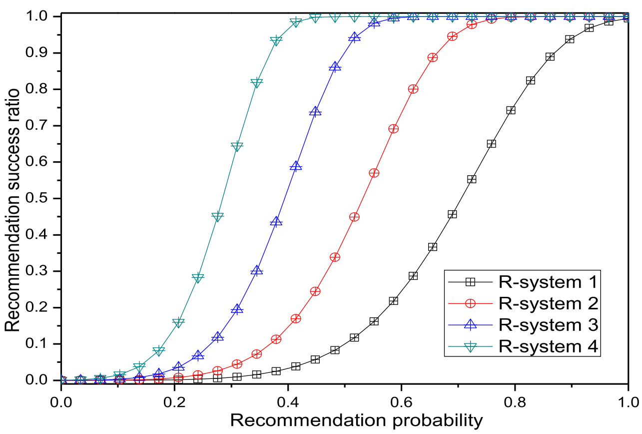

FIGURE 4. The correlation of recommendation probabilities and successful recommendation rates.

Figure 4 represents four correlations of recommendation probabilities and success rates of recommendation for four recommendation systems. From Figure 4, it can be concluded that the recommendation precision of recommendation system 4 is highest. However, high recommendation probability of items is not necessarily able to bring new welfare to the system, which is shown in Figure 5. Figure 5 represents how different recommendation probabilities of items, if successful, will bring new welfare to the system. According to Figure 5, it can be seen that even if the recommendation is successful, because of the high recommendation probability, those items are often the consensus of users and systems. In that case, it will bring less new welfare to the systems (see Figure 5). In the recommendation systems of mature situations, if we only recommend those items that have higher recommendation probabilities, the system will not undergo new welfare growth. In other words, even if those recommendations are decreased, the welfare of the system will have only minimally changed. However, under the situation that decreases the high recommendation probability of items, recommend some items that may bring the system newly increasing welfare at a certain disturbance probability. This type of recommendation system will be more effective.

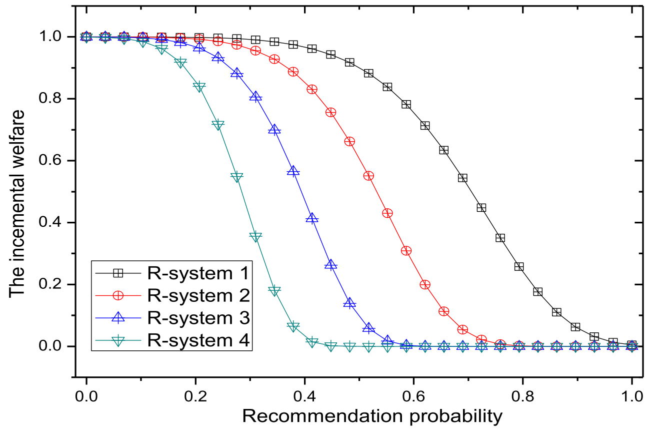

FIGURE 5. The correlation of recommendation probabilities and new welfare.

As shown in Figure 5, consider a certain recommendation system; if recommending the recommendation probability p of certain items successfully, and bring the system welfare, which is defined as $\mathcal{W}_i(p)$. From the analysis illustrated above, the value of p is higher, and the result of $\mathcal{W}_i(p)$ is lower. The probability of successfully recommending items that have a recommendation probability p is defined as $\mathcal{V}_i(p)$ (see Figure 4). Therefore, the calculation of weighted welfare can be derived as follows:

$$\mathcal{U}_i(p) = \mathcal{W}_i(p) \times \mathcal{V}_i(p) \tag{19}$$

For the weighted welfare $\mathcal{U}_i(p)$ in the recommendation system i, which is shown in Figure 5, although the welfare of recommending the items with small recommendation probabilities is very high if successful, because the probability of successful recommendation is very small, the welfare is small by recommending those items with lower recommendation probabilities to the system. In contrast, the welfare is also relatively small by recommending those items that have higher recommendation probabilities. Therefore, to add the systems with new welfare, a recommendation scheme should recommend the items that can make the results of $\mathcal{U}_i(p)$ maximum.

Suppose the general recommendation probability of a recommendation system as $\mathcal{P}$ and the disturbance probability as $\mathcal{E}$. Then, the main idea of the disturbance recommendation algorithm proposed in our paper is illustrated as follows:

The main idea of the disturbance recommendation algorithm is to recommend items that have lower recommendation

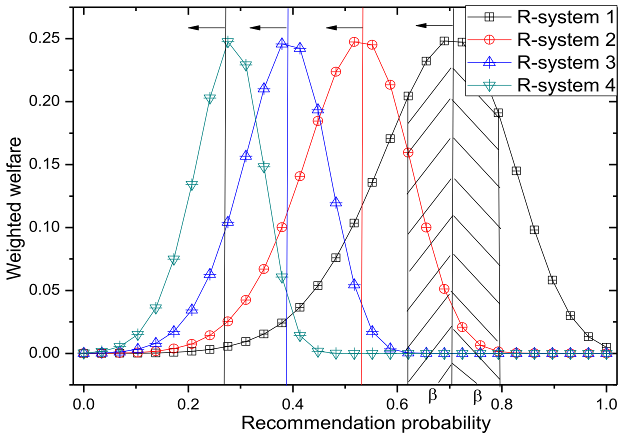

FIGURE 6. The weighted welfare.

probabilities with a small probability $\mathcal{E}$, to make the system obtain the maximum welfare. Thus, the system can eliminate the inherent over rate of the mature recommendation dilemma. Because the value of the disturbance probability is $\mathcal{E}$, the general number of items is n, and therefore the number of items that are recommended by the disturbance scheme can be shown by the following: $n_d = n\mathcal{E}$. Clearly, as for the welfare brought into the systems, we should choose the items of $\mathcal{U}_i(p)$. However, in practice, the functions $\mathcal{W}_i(p)$ and $\mathcal{V}_i(p)$ are not accurate. Therefore, in our paper, the recommended number n_d of items are randomly selected in a region of items that can bring the largest welfare to the system. As shown in Figure 6, suppose p_{max} is the probability p that can yield the maximum $\mathcal{U}_i(p)$. Afterwards, choose the items with recommendation probabilities in the range of $p_{max} \pm \beta$ to recommend. Therefore, the scheme not only meets the requirements of higher-welfare items but also increases the flexibility of the recommendation system. In aggregate, the disturbance recommendation algorithm proposed in this section is part of the RM-UI scheme, which means, on the basis of the original recommendation algorithm, reduce a portion of the original recommendation items. The disturbance recommendation algorithm proposed in this section can recommend items that can bring more welfare to the recommendation system. At the beginning of the recommendation system, the items with higher recommendation probabilities can bring the system high welfare, and therefore the items from adopting the traditional recommendation algorithm are the same as those from adopting the disturbance recommendation algorithm. However, with the maturity of the system, the welfare brought by the high-recommendation-probability items is reduced, and those items with lower recommendation probability may bring the system greater welfare. Therefore, the original recommendation system differs from the disturbance recommendation system at this moment and can overcome the deficiency of "over-maturation" in the recommendation system. In conclusion, the disturbance recommendation algorithm in our paper is shown in Algorithm 2:

Algorithm 2 Disturbance Recommendation Algorithm

Input: general recommendation probability $\mathcal{P}$, disturbance probability $\mathcal{E}$, function $\mathcal{W}_i(p)$ and function $\mathrm{V}_i(p)$

Output: recommend the items that can bring more welfare

1: Compute $\mathcal{U}_i(p)$ using $\mathcal{U}_i(p) = \mathcal{W}_i(p) \times \mathcal{V}_i(p)$;

2: Let p_{max} be the probability p that can make $\mathcal{U}_i(p)$ maximum;

3: Let $k = 1$;

4: **While** $k < n_d$ **Do** //$n_d = nE$

//choose n_d number of items

//that can make the welfare greater

5: Randomly pick one item to recommend from the recommendation probability interval $[p_{max} - \beta, p_{max} + \beta]$ recommendation;

6: $k = k + 1$;

7: **End Do**

8: **End**

Next, we prove the welfare of the RM-UI scheme using a disturbance recommendation algorithm that is better than that of the original recommendation algorithm in theory. The items recommended by the RM-UI scheme can be divided into two sections: (1) the items recommended by algorithm 1, with the set of recommended items denoted as $\mathfrak{R}_1$; and (2) the items recommended by algorithm 2, with the set of recommended items denoted as $\mathfrak{R}_2$. The strategy of the previous recommendation algorithm is to choose the highest-recommendation-probability items to recommend, with the set of recommended items denoted as $\mathfrak{R}_r$. Algorithm 1 of the RM-UI scheme proposed in our paper also recommends the items that have the highest recommendation probabilities, and therefore $\mathfrak{R}_1 \in \mathfrak{R}_r$. Let $\mathfrak{R}_3 = \mathfrak{R}_r - \mathfrak{R}_1$ and $\mathcal{W}_i(p)$ represents the welfare bought by the recommendation-probability-p items in the system. Let $\mathcal{W}(\mathfrak{R}_1)$, $\mathcal{W}(\mathfrak{R}_2)$, and $\mathcal{W}(\mathfrak{R}_3)$ represent the welfare obtained by recommending the corresponding set of items.

Therefore, for the original system, the obtained welfare $\mathbb{W}_r$ is:

$$\mathbb{W}_r = \mathcal{W}(\mathfrak{R}_r) = \mathcal{W}(\mathfrak{R}_1) + \mathcal{W}(\mathfrak{R}_3) \tag{20}$$

For the RM-UI scheme in this paper, the obtained welfare is:

$$\mathbb{W}_R = \mathcal{W}(\mathfrak{R}_1) + \mathcal{W}(\mathfrak{R}_2) \tag{21}$$

Therefore, if $\mathcal{W}(\mathfrak{R}_2) \geq \mathcal{W}(\mathfrak{R}_3)$, then the RM-UI scheme is superior to the existing strategies.

Clearly, the items that are recommended by $\mathfrak{R}_2$ can make the system welfare maximal. $\mathfrak{R}_3$ recommends the maximum recommendation probability items. It is clear that $\mathcal{W}(\mathfrak{R}_2) \geq \mathcal{W}(\mathfrak{R}_3)$, from which the following equation can be derived:

$$\mathbb{W}_R \geq \mathbb{W}_r \tag{22}$$

According to Figure 4 and Figure 6, it can be shown that the original recommendation systems always choose the items that have higher recommendation probabilities to recommend, but higher recommendation probability items and items that can bring greater welfare to the system are not always the same. In a mature recommendation system, as shown in Figure 6, the recommendation probabilities of items that can bring the system greater welfare are frequently not the highest. Only if the type of items recommended by the previous recommendation system is equal to the items recommended by the scheme in this paper is the welfare the same. Therefore, the RM-UI scheme proposed in our paper is better than the previous strategy.

V. EXPERIMENTAL EVALUATIONS AND RESULTS

A. EXPERIMENTAL SETTINGS

To evaluate the performance of the RM-UI scheme, the Amazon product purchasing network metadata and review information are adopted for experiments. First, the effectiveness of the RM-UI scheme is evaluated under a certain influence factor of transition probability x in different time cycles by closely comparing the RM-UI scheme with the classic trust-based scheme. Then, we verify the influence factor of transition probability x in the RM-UI scheme. Moreover, the trust degree of each selected item is compared under different time cycles. Finally, various detailed results, such as sales numbers, are compared during the experiment.

The dataset is obtained by enquiring into the dataset of co-purchasing on the Amazon website, and we choose the metadata and reviews of the video game category, which contains approximately 50,953 different products, to be the experimental dataset. For each product, the following information is available: the ID of the item (asin), description, sales rank, categories, and list of similar products. For each user, the following information can be obtained: the review id, ID of the item bought (asin), comment on the product and review time. From the video game catalogue, in the experiment, the most purchased items are selected to be the training set according to the sales rank. The results of the experiment are shown in Section 5. In our experiments, we use three-quarter of the selected purchase records to be the training set and the rest to be the test set.

Then, to verify the effectiveness of the RM-UI scheme, the *precision*, *recall* and $F_{1-measure}$ of the results of the RM-UI scheme are compared for evaluation. The three symbols stated above are three standard measurements of the classification accuracy of a recommendation algorithm. They can verify the accuracy degree of a recommendation algorithm: the higher, the better. The calculation method of precision in the RM-UI scheme is shown by the following equation:

$$precision = \frac{1}{H} \cdot \sum\nolimits_{i=1}^{H} \frac{N_i}{List_i} \tag{23}$$

where H is the total number of both the target user and similar users, N_i represents the number of items that user u_i purchased at time t+1 in the recommendation list, and $List_i$ represents the number of items recommended in the recommendation list.

The calculation method of *recall* can be derived by the following equation:

$$recall = \frac{1}{H} \cdot \sum\nolimits_{i=1}^{H} \frac{N_i}{B_i} \tag{24}$$

where B_i represents the number of items that user u_i likes according to the comments given by user u_i and *recall* represents the probability of the recommendation of items that will be liked by user u_i (the bigger, the better).

After computing the *precision* and *recall* by (23) and (24), the metric $F_{1-measure}$ is computed as a combination of both *precision* and *recall*, as illustrated above. Therefore, the $F_{1-measure}$ can comprehensively evaluate the effectiveness of the RM-UI scheme proposed in this paper. The calculation method of $F_{1-measure}$ can be derived by the following equation:

$$F_{1-measure} = \frac{2 \cdot recall \cdot precision}{recall + precision} \tag{25}$$

If the $F_{1-measure}$ of the recommendation scheme is higher, the performance of the recommendation scheme is better.

B. EXPERIMENTAL RESULTS

1) THE PERFORMANCE OF TIME, PRECISION, RECALL AND $F_{1\text{-measure}}$

In this section, the performance of the RM-UI scheme is compared with that of the trust-based scheme proposed in [3]. The main idea of the trust-based scheme is a recommendation model that is based on the factor of trust to recommend appropriate products to target users. Then, observe which recommended product the target user will buy to obtain the precision and recall. In the proposed RM-UI scheme, it is first required to select the shop most similar to the target shop, which is shown in Figure 7. According to this comparison, the video game shop is selected as the reference of the newly opened shop. The computation of similarity is the number of items in the new shop divided by that in the mature shop. This is because the most similar shop shares the maximum numbers of items with the target shop, so we can recommend products to target customers by referring to those in the mature shop.

As illustrated above, to evaluate the effectiveness of the proposed recommendation model for a newly opened shop, the method is compared with the trust-based probabilistic recommendation model [3]. The users selected in our experiments are not new, therefore the latent factor of users is not considered in the simulation. In other words, $x + y = 1$ and $z = 0$. Figure 8 shows that, as time passes, the simulation precision of our proposed method is higher than that of the trust-based recommendation model on average. When a new shop opens, the purchase matrix is more likely to be sparse or empty (cold start), and therefore the recommendation precision is definitely low. RM-UI performs better than the trust-based model, especially when T is in the interval [0, 5]. When time is 8, the precision of recommendation of the new shop is higher than that of the mature shop, so it can recommend

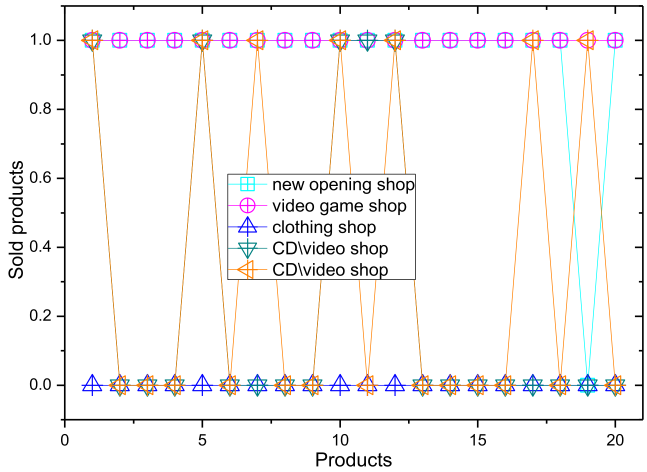

FIGURE 7. Shop comparison (video games).

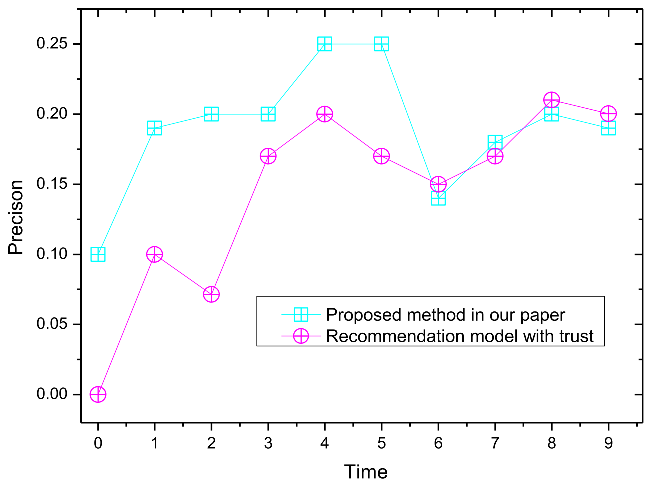

FIGURE 8. The precision results over time in a video game shop.

products to target users by itself. All in all, the RM-UI scheme has better performance than the trust-based model.

From the experimental results of precision, it can be seen that the RE-UI scheme has a higher recommendation precision when a new shop opens; however, the precision of the trust-based scheme is low. This is because similar shops have similarity, and the correlation of products of the mature shop is effective for the newly opened shop at the same time. Therefore, the RE-UI scheme mines these data from the mature store at first and then guides the new shop to recommend products. Therefore, when a new shop opens, though it has few purchase records, it can still have better effective recommendation results than other methods. When a new store opens, the data is sparse, so it is difficult to effectively recommend, i.e., the "cold start" phenomenon. Therefore, it can be seen that the RM-UI scheme can overcome the "cold start" phenomenon that has existed in social recommendation systems in the past.

With the operation of the new store, there are more and more purchase records in the new shop, so compared with datasets of other shops, it is more effective to use its own data, which means that, as time passes, when the precision of the RM-UI scheme reaches a certain degree, it will remain at an ideal level. This is similar to other methods that only use their purchase records to recommend products to target customers. Therefore, the precision of recommendation is similar as well.

A comparison of percent improvements of precision when time <6 is shown in Figure 9. It is clear that, at the beginning, the percent improvements are very high. This is because when a new store opens, it has few purchase records, so it cannot recommend products to target users appropriately. However, our proposed model can combine both the RM-UI scheme and the trust-based method together to recommend products to target users; when the purchase records of the new shop are sparse, its weighting u is nearly 0, which means that the RM-UI scheme only uses the purchase records of the mature shop to recommend products. Therefore, the percentage of improved precision is high.

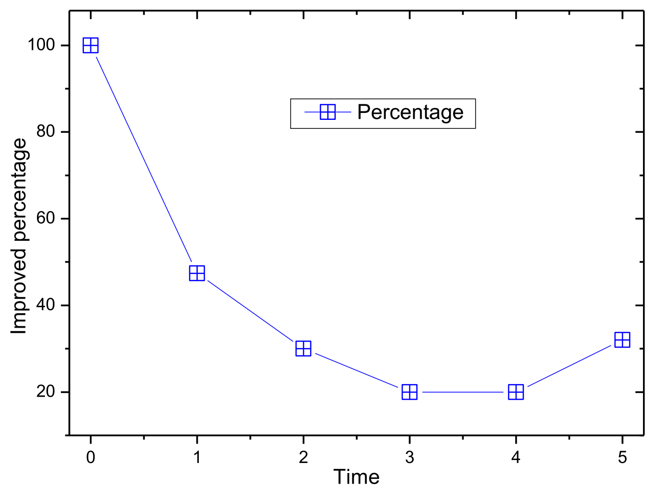

FIGURE 9. The percent improvements of precision when time<6.

Then, the results of recall of the two recommendation models are closely compared, which is shown in Figure 10. From the experimental results of recall, we can obtain the conclusion that the RM-UI scheme has better performance at its beginning. When the shop is newly opened, there are almost no purchase records in the store, so according to the records of customers in the new shop, it cannot easily recommend products to target users appropriately, which means that the problem of cold start has occurred. However, the mature shop, which has been selected as a reference shop, has enough purchase records to recommend products to target users. Thus, the results of recall that only use the purchase records of a new shop to recommend are definitely lower than those of the recall that is the combination of both the mature shop and the newly opened shop. However, it can be seen that there is a fluctuation during the experiment. This is because uncertainty is a significant feature in online social networks, and therefore the recall of recommendation may

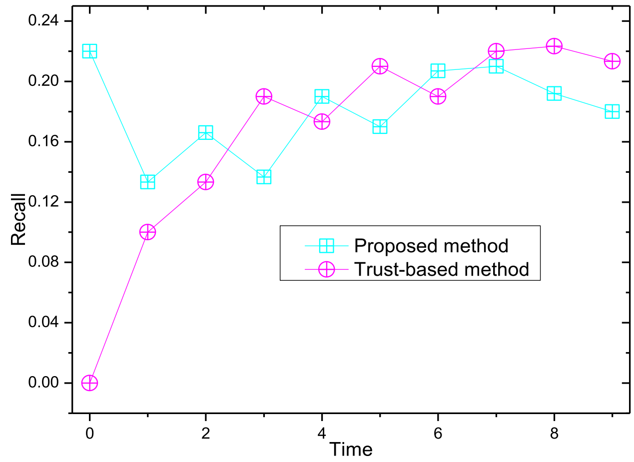

FIGURE 10. The recall result of time in a video game shop.

have fluctuations. With the new shop running, it brings more purchase records to the new shop, so the appropriately of recommendation for each product in the new shop grows higher in the trust-based scheme. As a result, the new shop begins to recommend products to customers by itself more effectively than the RM-UI scheme proposed in our paper, and the results of recall in the RM-UI scheme reach a stable degree. At this time, it is similar to other methods that only use their purchase records to recommend products to target customers. The tendency of recall is similar, as well.

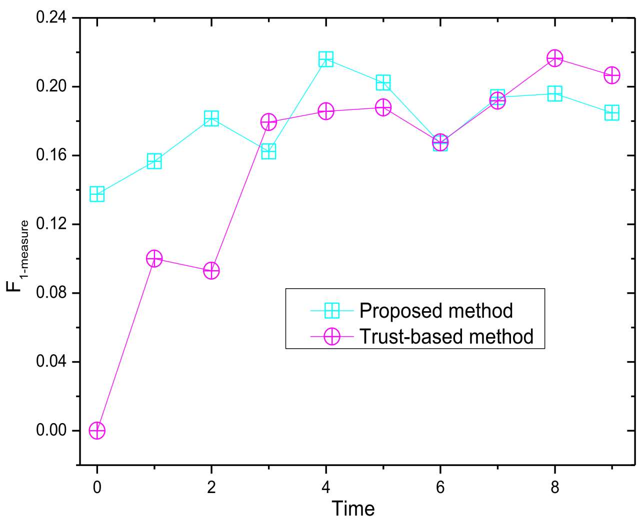

FIGURE 11. The $F_{1\text{-measure}}$ results over time in a video game shop.

Then, we closely compare the F1-measure result for the two recommendation models with time passing to comprehensively measure the effectiveness of the proposed recommendation model. The comparison of results for the F1-measure of the two recommendation models is shown in Figure 11. From the experimental results of the F1-measure, it is obvious that, when the shop is new, the F1-measure of the trust-based model is lower than that of our proposed model, which means that RM-UI can comprehensively improve the percentage of recommendation probabilities. This is because the F1-measure refers to its precision and recall. When a shop is newly opened, the precisions and recalls are lower than those of the proposed method because of the sparse purchase records, as illustrated above. Thus, the F1-measure of the other model is lower than that of the proposed model at the same time. With the passage of time, the purchase matrixes of the new shop grow gradually denser. Therefore, it is more effective to use its own records. The results for the F1-measure of the proposed model remain at a preferable level. It is similar with the trust-based model, which only use its own purchased records to recommend products to target users. Therefore, the F1-measures of the recommendation models are similar, as well.

To further verify the effectiveness and performance of the RM-UI scheme proposed in the paper, after the experiment of the video game category is complete, we closely carry on the experiment of a new clothing shop by utilizing the RM-UI scheme and trust-based scheme. In the category of clothing, there exists about 1,503,384 different kinds of products. We select several kinds of items with higher purchased ranking in our experiments. The comparisons of experimental results are shown as follows:

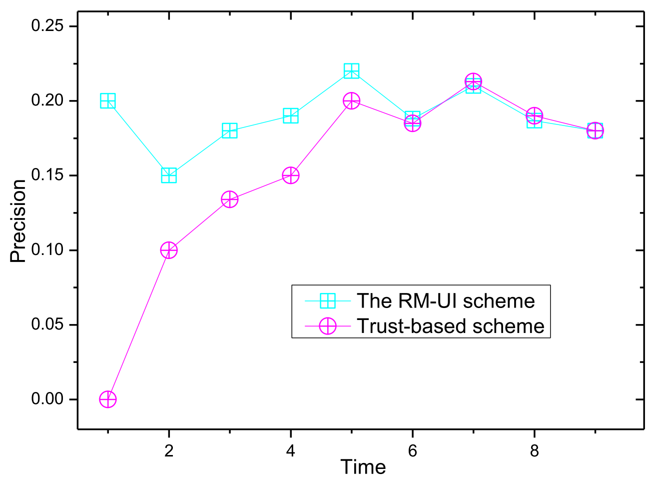

FIGURE 12. The precision results over time in the clothing shop.

Figure 12 shows the comparison results for the precision of the RM-UI scheme and that of the trust-based method applied to a new clothing shop, and Figure 13 shows the percent improvements of precision by employing the RM-UI scheme. Figure 14 shows that when running the experiment, the comparison results of recall in the RM-UI scheme and that in the trust-based scheme and Figure 15 show the percent improvements by utilizing the RM-UI scheme. Based on the category of clothing, according to the value of precious and recall, Figure 16 comprehensively compares the effectiveness of the RM-UI scheme and that of the trust-based scheme when considering the new clothing shop, the tendency shows the superiority of the proposed RM-UI scheme. Figure 17 is the percent improvements of the $F_{1-\text{measure}}$ in the RM-UI scheme shown as below.

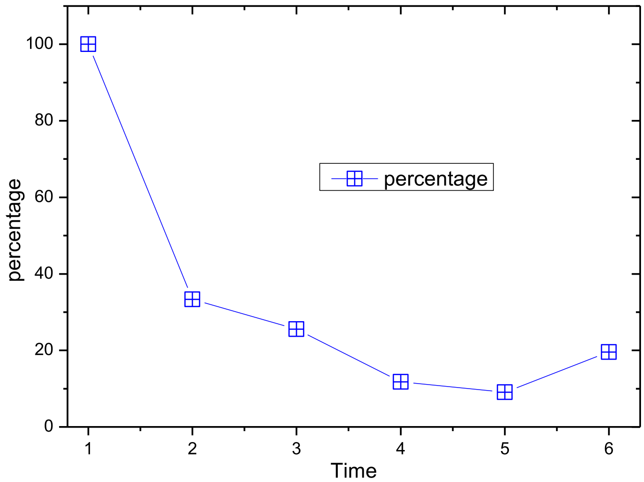

FIGURE 13. **The percent improvement of precision in the clothing shop.**

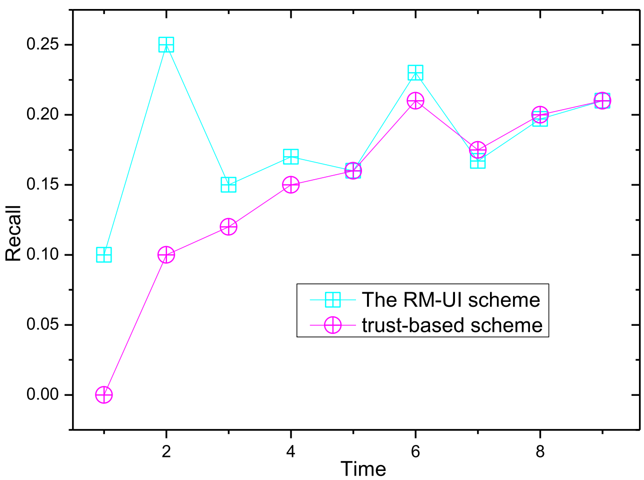

FIGURE 14. **The recall results over time in the clothing shop.**

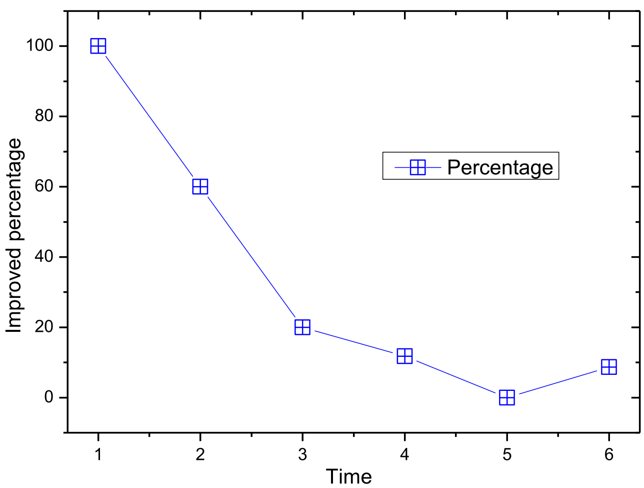

FIGURE 15. **The percent improvement of recall in the clothing shop.**

The precisions of the two recommendation models under different recommendation thresholds are shown in Figure 18. In Figure 18, it can be seen that the performance

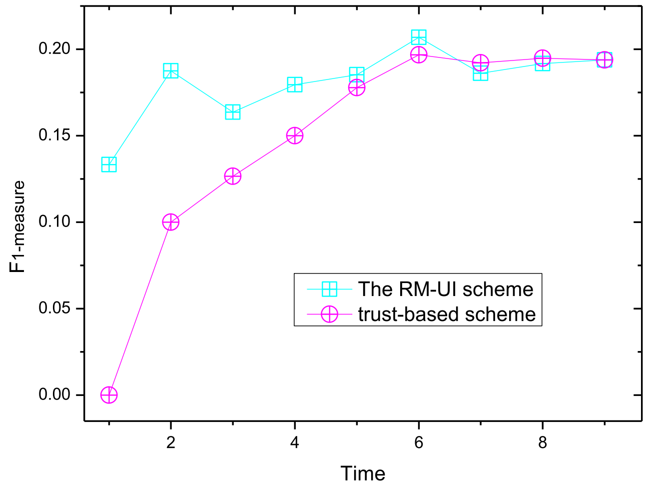

FIGURE 16. **The F1-measure results over time in the clothing shop.**

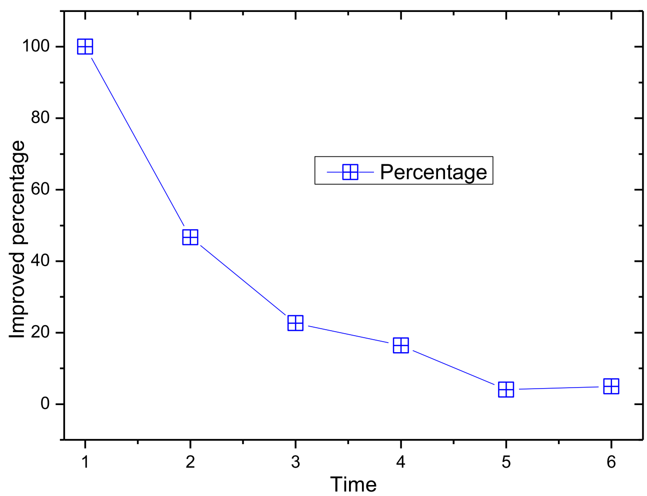

FIGURE 17. **The percent improvement of F1-measure in the clothing shop.**

of the proposed recommendation model is better than that in other methods under different recommendation thresholds α. As illustrated above, this is because the other shops choose using purchase matrixes of their own, and at the beginning, the purchase matrixes are sparse. Thus, recommendation probabilities cannot be computed accurately to recommend products to target users. However, the RM-UI scheme proposed in our paper chooses to recommend products according to the purchase matrixes of both the selected mature shop and the target shop. Thus, the recommendation probabilities are more accurate for recommending products. Therefore, the results of precision in our proposed method are better than those in other methods under different recommendation thresholds, as shown in Figure 18. When the recommendation threshold is greater than 0.5, the results for precision in the RM-UI scheme decrease as time passes, and they stay at 0 when the threshold $=0.9$.

The percent improvements of precision for the proposed method in our paper under different recommendation thresholds are shown in Figure 19. From the picture below, it is

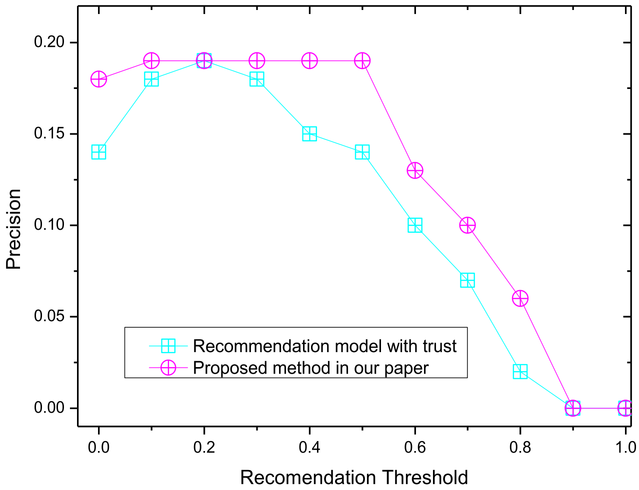

FIGURE 18. The results of precisio.

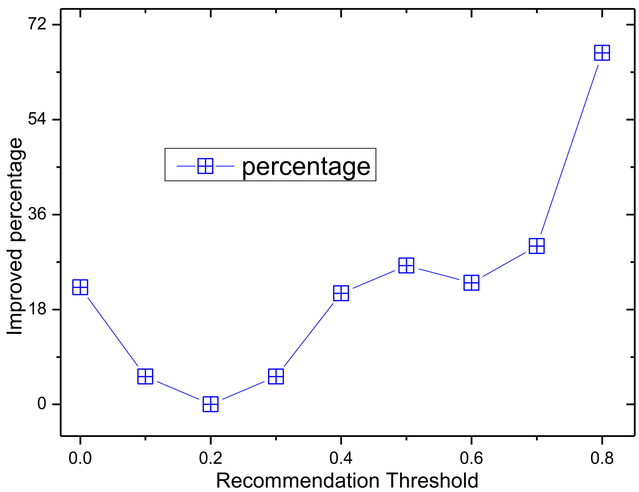

FIGURE 19. The percent improvement of precision.

clear that the percentage of precision is further improved in the RM-UI scheme.

The recalls of the two recommendation models under different recommendation thresholds are shown in Figure 20. From Figure 20, we can obtain the conclusion that the results of recall for the proposed model are greater than that in other models under different recommendation thresholds. This is because when a new shop opens, the purchase records are nearly to 0%; therefore, it cannot recommend products to target customers appropriately. As a result, the recall of other methods is low. With running of the new shop, the purchase records of the new shop are dense, so it can recommend products to target users more appropriately than it used to be. Therefore, the average of recall under different recommendation thresholds in the trust-based method are shown as below. However, the datasets of the proposed model in our paper are a combination of mature shop data and target shop data. Therefore, the recalls of the RM-UI scheme are high at the beginning, and with time going, the recalls are

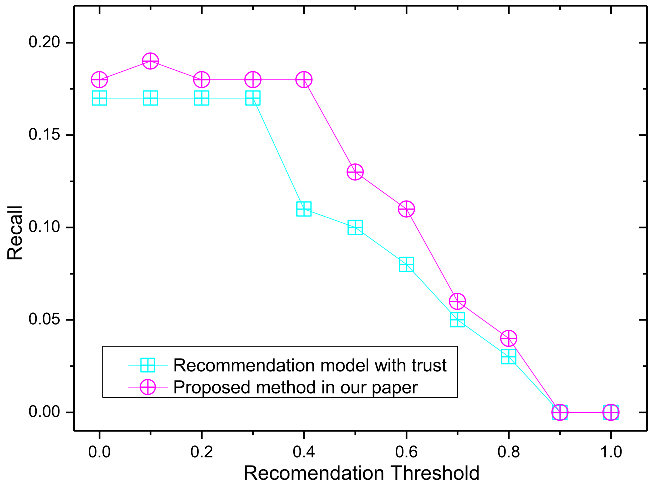

FIGURE 20. The results of recall.

stay at a more stable stage. The average recall under different recommendation thresholds in the RM-UI scheme are shown as below. The results of recall in the RM-UI scheme get smaller when the recommendation threshold $\alpha > 0.4$. When the recommendation threshold is 0.9, the recalls of the two recommendation models stay at 0.

The percent improvements of recall in the RM-UI scheme under different recommendation thresholds are shown in Figure 21. From the picture below, it is clear that the percentages are further improved in the RM-UI scheme under different thresholds.

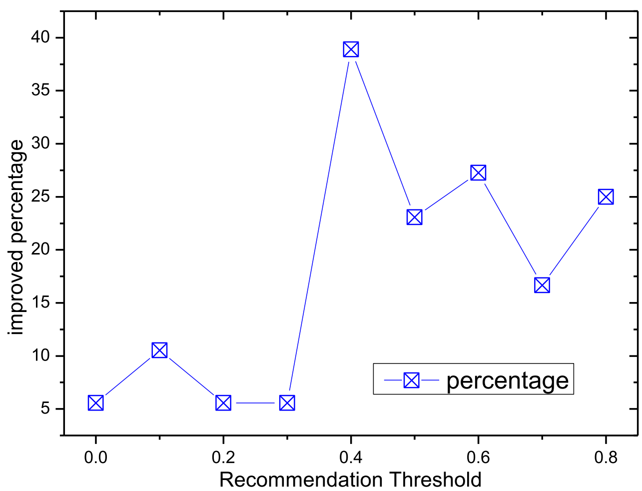

FIGURE 21. The percent improvement of recall.

The F1-measure of the two recommendation models under different recommendation thresholds is shown in Figure 22. To comprehensively measure the effectiveness of the proposed model, the F1-measure results are compared in the two recommendation models under different recommendation thresholds, which are shown in Figure 22. It can be seen that the performance of the F1-measure in the RM-UI scheme is higher than that of the trust-based model. This is

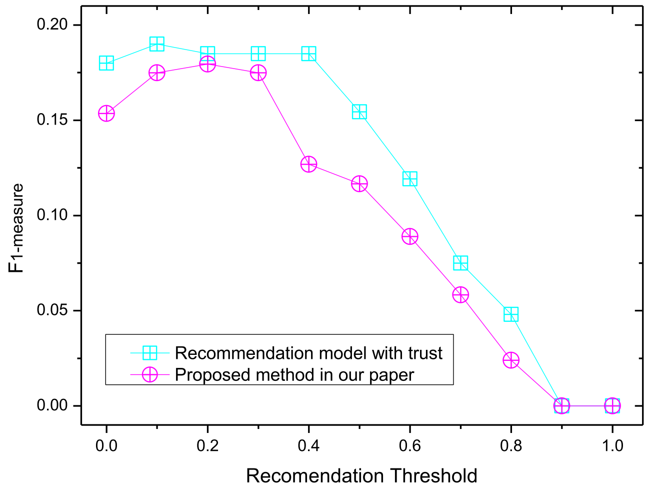

FIGURE 22. **The results of F1-measure.**

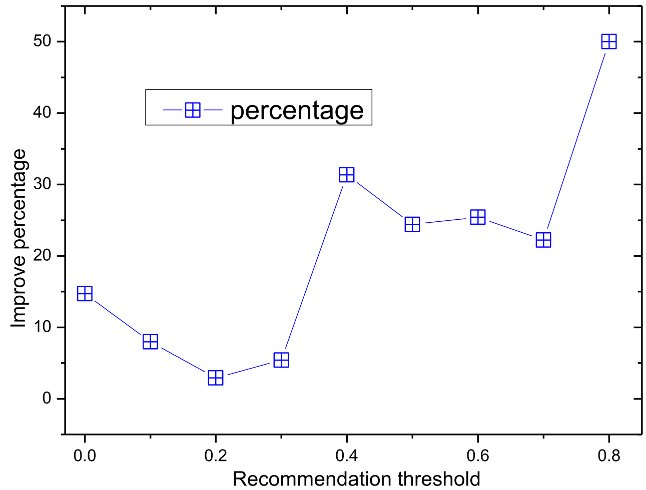

FIGURE 23. **The percent improvement of F1-measure.**

because the purchase records of the new shop are sparse, so according to its own purchase records, the new shop cannot recommend appropriate products to target users. However, the RM-UI scheme proposed in our paper combines both the purchase records of mature shops and new shops together. Therefore, at the beginning, it can recommend products to users more appropriately. Therefore, the recall and precision of the trusted-based shop are both lower than that of in the RM-UI scheme. The results of the F1-measure for the new shop are markedly lower than that in the RM-UI scheme under different recommendation thresholds. When the recommendation threshold = 0.9, the recall and precision in both a trust-based model and RM-UI scheme are 0, so their F1-measures are both 0. In addition, as can be seen from the results below, the RM-UI scheme proposed in our paper is more stable than other recommendation schemes.

The percent improvements of the F1-measure for the RM-UI scheme under different recommendation thresholds are shown in Figure 23. From the results shown below, it is clear that the percentages of the F1-measure are further improved in the RM-UI scheme under different thresholds. When the threshold >0.8, the recall and precision of both the RM-UI scheme and the other scheme are 0, so the F1-measure reaches 0 in the experiment.

2) THE PERFORMANCE RESULTS FOR INFLUENCE FACTORS

Next, we adopt different values of the transition probability influence factor x for the precision, recall and F1-measure of the two recommendation models to evaluate the influence of different factors on the recommendation results. It is well known that a different influence factor can result in different experimental results. Figure 24 shows the results for precision under different values of x. It can be seen in Figure 24 that there is a fluctuation when $x = 0.5$ and the recommendation threshold $\alpha = 0.4$, and the precision is highest. However, after that, the precision is lower than that of $x = 0.3$ and $x = 0.4$. This is because of uncertainty factors in social networks, so the results may show fluctuations. On average, when $x = 0.3$, the precision of the recommendation probabilities is highest. When $x = 0.6$, the value of precision is lowest. Generally, for different values of x, the changing trends of the precision results are similar. In the interval [0, 0.2] and the interval [0.9, 1.0], the precision results are the same for different values of x. From Figure 21, we can conclude that when the transition probability influence factor x is smaller, the precision of the recommendation probability is higher. Therefore, the transition probability influence factor has a great influence on the performance of RM-UI.

While the values of the transition probability influence factor x increase, the proportions of trust decrease, which means that in the RM-UI scheme, the recommendation system will likely recommend more trustless products to target customers based on the purchase records of both the mature shop and newly opened shop. Because the products recommended may be more distrustful, it is therefore more likely that the target users will not purchase those distrustful products at time t+1 that were recommended at time t. As a result, the precision of the RM-UI scheme decreases as the values of the transition probability influence factor x increase. Thus, the results for the precision of recommendation will not have a better performance as the influence factor x increases, as shown in Figure 24.

Next, we closely measure recall under different values of x, and the results are shown in Figure 25. From the picture below, we can conclude that when the transition probability influence factor x is 0.3, 0.4 or 0.5, the tendency of recall is similar. When $x = 0.3$, the recall of the recommendation model is highest, and when $x = 0.6$, the recall of recommendation model is lowest. When the recommendation threshold T is within the interval [0, 0.2] or the interval [0.9, 1.0], the recall results are the same despite the different values of x. Generally, for the interval [0.2, 0.8] and $x = 0.3$, the RM-UI scheme can obtain higher recalls. Therefore, the trust influence factor has a greater influence on the recall of the proposed recommendation model.

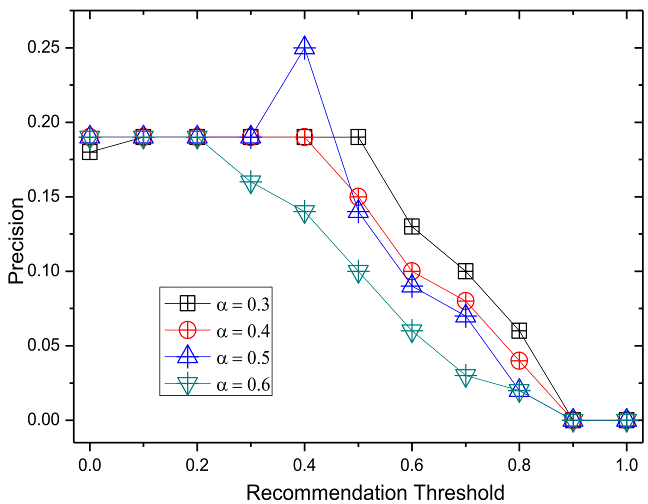

FIGURE 24. The results of precision for different values of x.

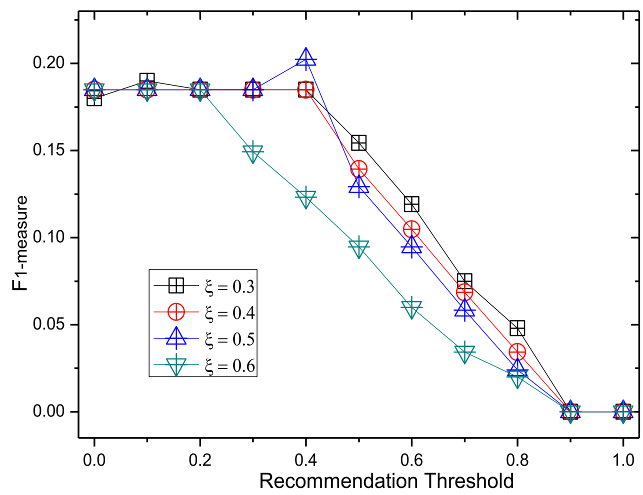

FIGURE 26. The result of F1-measure for different values of x.

This is because, according to equation (16), as the value of the transition probability influence factor x increasing, the value of influence factor y decreases, causing the result that the factor of trust among different products becomes lower, and the system may recommend malicious items to target users at time t. Recall represents whether the target customers like the products or not. If the products are trustless, it is more likely that target users will not like or purchase them. Therefore, without considering the factor of trust, we may recommend the distrusted products to target users at time t, and they may not purchase them at the next time instant. As a result, the recall for a higher transition probability influence factor x in the RM-UI scheme is lower than that under the same recommendation threshold, as shown in Figure 25. Generally, when the transition probability influence factor is smaller, the recall of recommendation probability is higher under the same thresholds.

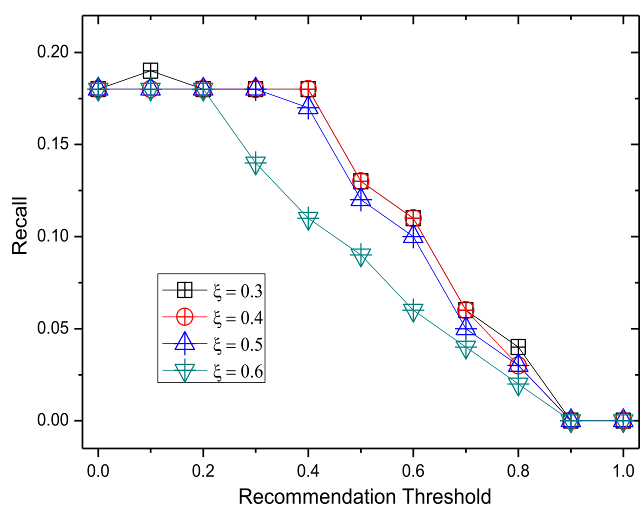

FIGURE 25. The result of recall for different values of x.

Then, the F1-measure is utilized to comprehensively combine recall and precision together for different values of the transition probability influence factor to evaluate the performance of the proposed recommendation model with different values of x. The results for the F1-measure with different values of x are shown in Figure 26. From the picture below, we can conclude that when $x = 0.3$, the value of the F1-measure is the highest, and when $x = 0.6$, the F1-measure is the lowest. Therefore, the trust influence factor x has a greater influence on the proposed recommendation model.

The reason for this result is that the F1-measure is a standard that combines both recall and precision. Therefore, when the results of recall and precision in the RM-UI scheme under the same recommendation threshold are higher, the F1-measure is also higher. When the results of recall and precision under the same threshold are lower, the F1-measure is lower, as well. The F1-measure shown in Figure 26 presents the overall performance of the RM-UI scheme proposed in our paper.

Then, we closely compare more experimental details of the RM-UI scheme and other schemes during our experiments. Figure 27 shows the purchase product number of both the RM-UI scheme and trust-based scheme as time passes. It is clear that at the beginning, the number of purchased products in the RM-UI scheme is higher than that in the trust-based scheme. As time passes, there are more purchased products in the trust-based scheme.

When a shop is new, there are almost no purchase records, and the products that the target customers would like and would purchase the next time are not known. As the result, the purchase product number in other methods is zero (cold start) at the beginning. However, the RM-UI scheme proposed in our paper refers to the purchase records of both the selected mature shop and new shop. When the purchase records of the new shop are sparse, the RM-UI scheme chooses to recommend products to target users that rely more on the purchase records of the mature shop. Therefore, the RM-UI scheme can recommend more preferable products to target customers when the shop is new, and as a result, target

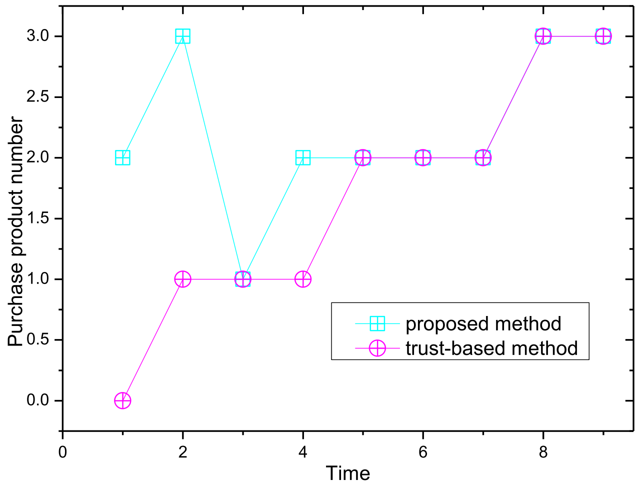

FIGURE 27. The result of purchased product numbers.

customers are more likely to purchase products at time t+1 that were recommended at time t. Therefore, the number of purchased products in the RM-UI scheme is higher than that in the trust-based scheme at the beginning. As time passes, the new shop has its own purchase records, so it can recommend products by itself more accurately, and the target customers would prefer to purchase the products recommended in the trust-based scheme, as shown in the graph below.

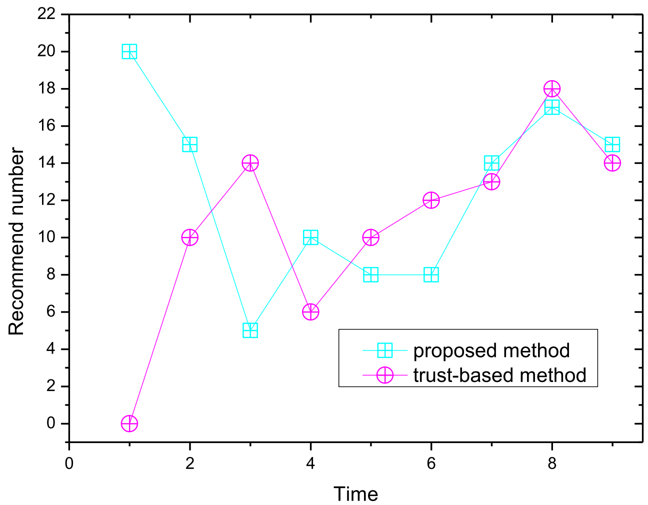

FIGURE 28. Total recommended products.

Then, we closely compare the total recommended numbers of products for each time round in both the RM-UI scheme and trust-based scheme in Figure 28. In Figure 28, it can be concluded that the number of recommended products in the trust-based scheme is zero at the beginning. This is because the purchase matrix of the trust-based scheme is sparse, which causes the recommendation system to be unable to recommend products to target users at the beginning. As time passes, the purchase matrix of the trust-based method becomes dense.

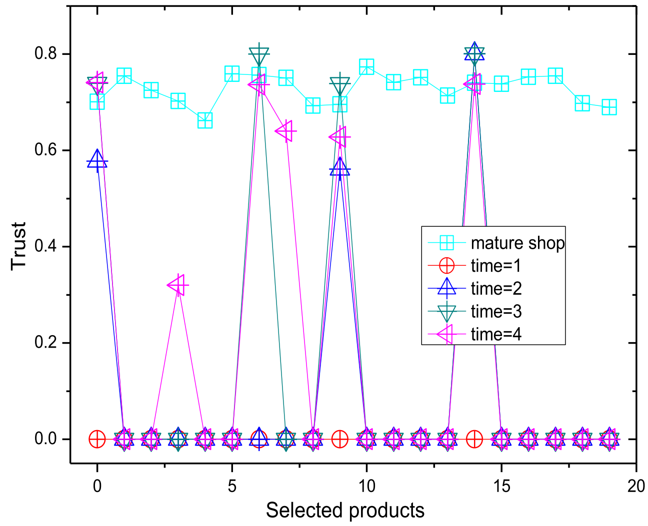

FIGURE 29. The value of trust when time=1/2/3/4.

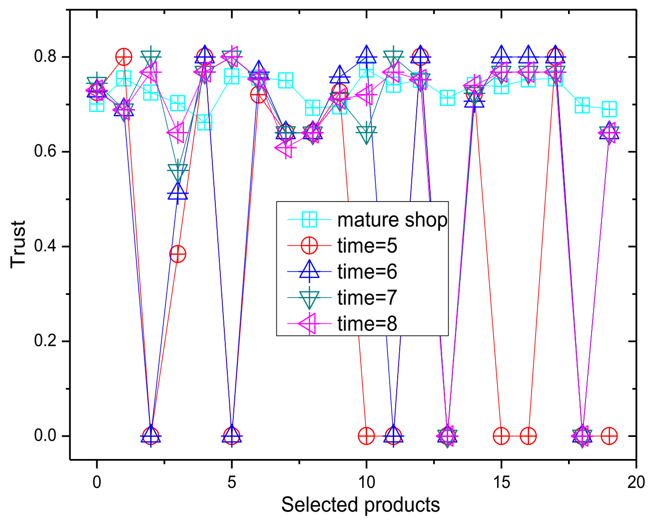

FIGURE 30. The value of trust when time=5/6/7/8.

Thus, the trust-based system can recommend products to users by itself, as shown in the picture below. However, it can be seen that in the RM-UI scheme that is proposed in our paper, the number of recommended products is high at the beginning because we choose both the purchase records of the selected mature shop and the new shop to formulate the purchase matrixes, which means that it can recommend more appropriate products to target users at the beginning, and as a result, it has solved the cold start problem. As the new shop matures, the purchase matrixes become dense, and it can recommend products more appropriately; therefore, the number of recommended products becomes similar to that of the selected mature shop, as shown below.

The values of trust for each selected product in each time round when the value of the transition probability influence factor x is 0.3 are shown in Figure 29, Figure 30 and Figure 31. It can be seen from the three pictures below that the tendency of selected products' trusts become more similar

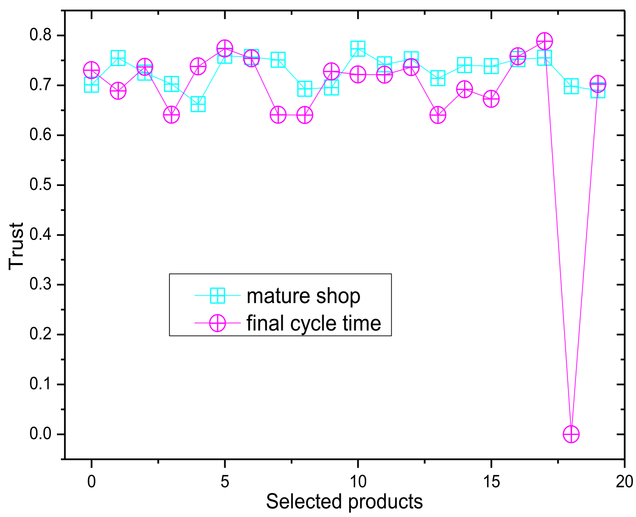

FIGURE 31. The final value of trust.

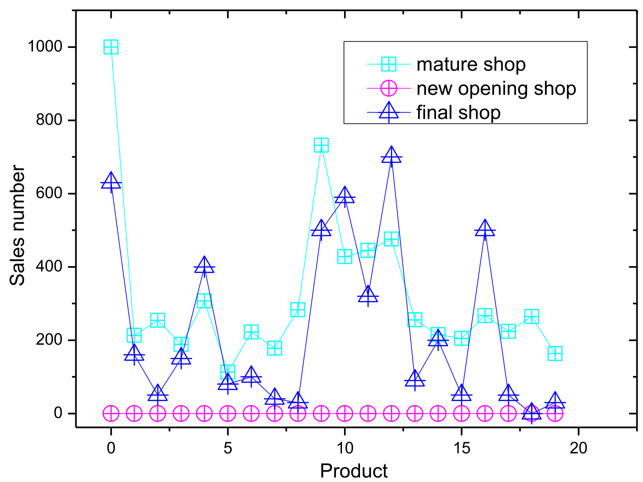

FIGURE 32. Final sales numbers.

to those of the mature shop we selected above and have the fluctuations themselves. At the beginning, the trust values of products in the new shop are almost zero because there are no purchase records for them, and the reviews of customers for products are zero overall.

With the passage of time, the purchase records of the new shop grow, and by the last time round, the purchase matrix of the new shop is dense, which means that it is a mature shop and can recommend products using the RM-UI scheme or the trust-based model. It can be seen that in Figure 31, there is a fluctuation when the selected products is 19, which is because the new shop does not sell the product, so it does not have purchase records regardless of the time round. Therefore, the trust value of product 19 is zero under all circumstances. Because the shop selected is mature, the trust value of each product selected is stable in our experiment, as shown in the three figures below.

The final sales numbers of each product are shown in Figure 32, where the final shop represents the sale number of the new shop when it becomes a mature shop. It can be seen that the tendency of the sale number of products in new shop is similar to that in the mature shop but with some differences. As shown in Figure 32 below, the RM-UI scheme is effective in our experiment.

Table II shows a summary of the experimental results. TB indicates the trust-based algorithm. The others represent the proposed recommendation model RM-UI scheme with trust in the case of $x = 0.3$, $x = 0.4$, $x = 0.5$ and $x = 0.6$.

TABLE 2. The experimental results of precision, recall and F1-measure.

Evaluation	TB	$x = 0.3$	$x = 0.4$	$x = 0.5$	$x = 0.6$
Pre	0.117	0.142	0.132	0.133	0.108
Rec	0.105	0.138	0.136	0.132	0.1
F_1	0.1107	0.13997	0.13397	0.13249	0.10385

The bold values indicate the best measurement results compared with other experimental results. From Table II, it can be summarized that the proposed recommendation model, the RM-UI scheme, has the best measurement results. In addition, in the proposed recommendation model, the best measurement results can be obtained when the influence factor of transition probability $x = 0.3$.

At the initiation stage, the performance criteria of precision ratio, recall ratio and F1-measure are improved by approximately 21.08%, 21.57% and 21.32%, respectively, over the previous schemes.

Generally, the precision of the RM-UI scheme proposed in this paper has been improved by approximately 17.6%, and the recall of this scheme has been improved by approximately 16%. Comprehensively speaking, the value of the F1-measure metric has been improved by 16.9% in the RM-UI scheme over that in the trust-based scheme. The accuracy of recommendation results is further improved by utilizing the RM-UI scheme.

VI. CONCLUSIONS

In this paper, based on the trust-based recommendation model, the RM-UI recommendation model is proposed for social networks to solve the "cold start" and "over-matured recommendation" problems of recommendation systems. First, the recommendation attributes of items are considered to determine similarities among users and stores. Then, the most similar shop is chosen as the reference mature shop in the experiment. The inherent similarity among items is considered to derive the transition probability of a target customer. Then, the recommendation probability matrix of both the mature shop and the newly opened shop is computed based on the information flow of similarity among users and target users, who are randomly selected. In addition, the trust factors of items are derived based on their reputations, sales ranks and purchase frequencies. The reputations of products are given by historical purchases of customers. The RM-UI scheme can refer to the combination of purchased records in the mature shop and the newly opened shop to some degree to solve the problem of the store's cold start. To overcome the deficiency of ''over-matured recommendation,'' in this paper, we propose a disturbance recommendation algorithm in which some items with lower recommendation probabilities can be recommended to bring the system higher welfare. Therefore, the recommendation system can be more optimistic and open, bringing more welfare. Finally, the Amazon product co-purchasing network metadata and review information are adopted to verify the effectiveness and performance of the proposed recommendation model through comprehensive experiments. Furthermore, our experiment simulates the precision, recall and F1-measure in both the RM-UI scheme and the trust-based scheme when $x = 0.3$ and analyzes the impact of the transition probability influence factors in the RM-UI scheme through experiments. Finally, we compare detailed information in the RM-UI scheme with that in the trust-based scheme through experiments.

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