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## Abstract

**Purpose** – Collaborative recommender systems play a crucial role in providing personalized services to online consumers. Most online shopping sites and many other applications now use the collaborative recommender systems. The measurement of the similarity plays a fundamental role in collaborative recommender systems. Some of the most well-known similarity measures are: Pearson's correlation coefficient, cosine similarity and mean squared differences. However, due to data sparsity, accuracy of the above similarity measures decreases, which makes the formation of inaccurate neighborhood, thereby resulting in poor recommendations. The purpose of this paper is to propose a novel similarity measure based on potential field.

**Design/methodology/approach** – The proposed approach constructs a dense matrix: user-user potential matrix, and uses this matrix to compute potential similarities between users. Then the potential similarities are modified based on users' preliminary neighborhoods, and $k$ users with the highest modified similarity values are selected as the active user's nearest neighbors. Compared to the rating matrix, the potential matrix is much denser. Thus, the sparsity problem can be efficiently alleviated. The similarity modification scheme considers the number of common neighbors of two users, which can further improve the accuracy of similarity computation.

**Findings** – Experimental results show that the proposed approach is superior to the traditional similarity measures.

**Originality/value** – The research highlights of this paper are as follows: the authors construct a dense matrix: user-user potential matrix, and use this matrix to compute potential similarities between users; the potential similarities are modified based on users' preliminary neighborhoods, and $k$ users with the highest modified similarity values are selected as the active user's nearest neighbors; and the proposed approach performs better than the traditional similarity measures. The manuscript will be of particular interests to the scientists interested in recommender systems research as well as to readers interested in solution of related complex practical engineering problems.

**Keywords** Algorithms, Systems theory

**Paper type** Research paper

## 1. Introduction

As the amount of information on the Web grows explosively, people often feel puzzled and helpless in finding and getting the intended information they really need. For overcoming this problem, recommender systems appeared and became a focus of researchers and practitioners. Recommender systems help users finding relevant information, products or services by providing personalized recommendations based on their profiles (Lee *et al.*, 2009). Recommender systems are especially useful in an e-commerce environment, they enhance e-commerce sales in three ways (Schafer *et al.*, 2001): converting browsers into buyers; improving cross-sell by suggesting additional

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products for the customer to purchase; improving loyalty by creating a value-added relationship between the site and the customer.

One of the most successful techniques among recommender systems is collaborative filtering. Collaborative filtering identifies users whose tastes are similar to those of the active user and recommends items that those users have liked. Collaborative filtering provides personalized recommendations based on users' tastes rather than objective properties of items, which allows it to be able to filter any type of items, such as text, music, videos and photos (Kim *et al.*, 2011). Many online companies such as Amazon.com, Yahoo.com and Netflix.com apply collaborative filtering to provide recommendations to their customers. The measurement of the similarity plays a fundamental role in collaborative filtering (Resnick *et al.*, 1994; Wang *et al.*, 2006; Luo *et al.*, 2008). Some of the most well-known similarity measures are (Ahn, 2008; Bobadilla *et al.*, 2012b): Pearson's correlation coefficient (Pearson), cosine similarity (cosine) and mean squared differences (MSD). However, due to data sparsity, accuracy of the above similarity measures decreases, which makes the formation of inaccurate neighborhood, thereby resulting in poor recommendations (Adomavicius and Tuzhilin, 2005; Albadvi and Shahbazi, 2009).

To address the above issue, in this paper, we propose a novel similarity measure based on potential field. Our approach first computes potential values between users, and subsequently constructs a user-user potential matrix. Then the potential similarities between users are computed, and each user's preliminary neighborhood is formed. Finally, based on the preliminary neighborhoods, the potential similarities between users are modified. Our approach possesses the following advantages:

(1) It uses potential matrix to compute similarities between users. Compared to the rating matrix, the potential matrix is much denser. Thus, the sparsity problem can be efficiently alleviated.

(2) The potential similarities between users are modified based on the preliminary neighborhoods, which can further improve the accuracy of similarity computation.

The remainder of this paper is organized as follows. Section 2 summarizes previous studies related to collaborative filtering and potential model. In Section 3, we present the details of the proposed approach. In Section 4, we present the performance of our approach through experimental evaluations. Finally, the conclusions are given in Section 5.

## 2. Related work

### 2.1 Collaborative filtering

The task of recommender systems is to maximize an active user's satisfaction by suggesting him/her a set of items from many. Based on how recommendations are made, recommender systems are usually classified into three categories (Adomavicius and Tuzhilin, 2005): content-based recommendations, collaborative recommendations and hybrid approaches. Collaborative recommender systems recommend items to an active user based on the opinions of other users. Collaborative recommender systems do not take into account content information, and are easier to implement. Therefore, they are more popular than the other two types of recommender systems (Leung *et al.*, 2006). Sarwar *et al.* (2002) divided the entire process of collaborative filtering into three sub-tasks, namely, representation, neighborhood formation and recommendation generation. In a typical collaborative filtering scenario, there is a $m \times n$ user-item rating matrix $R$ (Table I). Each entry $R_{g,h}$ in $R$ represents the rating that the $g$th user gives to the $h$th item, where the possible values of $R_{g,h}$ are defined through the set $V = \{v_{min}, \ldots, v_{max}, \bullet\}$, where $v_{min}$ is the lowest possible value, $v_{max}$ is the highest possible value and $\bullet$ represents the absence of a rating (Bobadilla *et al.*, 2012a). Collaborative filtering computes similarities between an active user and other users, and selects the $k$ most similar users as the nearest neighbors of the active user. Some of the most well-known similarity measures are: Pearson, cosine and MSD. Once the neighborhood is identified, the most frequent item recommendation (MFIR) method (Sarwar *et al.*, 2000; Liu and Liou, 2011) can be used to provide recommendations to the active user. MFIR counts the purchase frequency of each product by scanning the products purchased by the users in the neighborhood. Next, all the products are sorted by the purchase frequency in descending order. Finally, MFIR recommends the top-$N$ products that have not been purchased by the active user.

In practice, most e-commerce sites have a huge number of products. In these sites, even active users may have rated well under 1 percent of the products. Accordingly, the user-item rating matrix is very sparse. Due to data sparsity, accuracy of the traditional similarity measures (i.e. Pearson, cosine and MSD) decreases, which makes the formation of inaccurate neighborhood, thereby resulting in poor recommendations. It is often the case that there is no intersection at all between two users and hence the similarity is not computable at all. Even when the computation of similarity is possible, it may not be very reliable, because of insufficient information processed (Papagelis *et al.*, 2005; Kim *et al.*, 2010).

### 2.2 Potential model

The potential model is derived from gravitational force model (GFM). Over the last decades, there has been a growing interest in algorithms based on the law of gravity. Rashedi *et al.* (2009) proposed a new optimization algorithm called Gravitational Search Algorithm (GSA). GSA uses the theory of Newtonian physics and its searcher agents are the collection of masses. Using the gravitational force, every mass in the system can see the situation of other masses. The gravitational force is therefore a way of transferring information between different masses. To reduce the computation complexity of the GSA, Shams *et al.* (2015) proposed a novel version of GSA, named Clustered-GSA. Clustered-GSA is originated from calculating central mass of a system in nature and improves the ability of GSA by reducing the number of objective function evaluations. Hatamlou *et al.* (2012) used GSA to improve $k$-means algorithm. They presented a hybrid data clustering algorithm based on GSA and $k$-means (GSA-KM). GSA-KM tries to exploit the merits of two algorithms simultaneously, where the $k$-means is used in generating the initial solution and the GSA is employed as an improvement algorithm. Sanchez *et al.* (2014) designed a gravitational clustering algorithm for finding fuzzy information granules from multivariate data. Their algorithm incorporates the theory of granular computing, which adapts the cluster size with respect to the context of the given data. Via an inspiration in Newton's law of

**Table I.** User-item rating matrix

| | $i_1$ | … | $i_h$ | … | $i_n$ |
|---|---|---|---|---|---|
| $u_1$ | $R_{1,1}$ | … | $R_{1,h}$ | … | $R_{1,n}$ |
| … | … | … | … | … | … |
| $u_g$ | $R_{g,1}$ | … | $R_{g,h}$ | … | $R_{g,n}$ |
| … | … | … | … | … | … |
| $u_m$ | $R_{m,1}$ | … | $R_{m,h}$ | … | $R_{m,n}$ |

gravitation, both conditions of clustering similar data and adapting to the size of each granule are achieved. Yamachi *et al.* (2009) proposed a partitional clustering method based on a potential field similar to gravity. They derive clusters by moving data points along the gradient of the potential field. Then the clusters are formed by the data points moving close to each other. Shi *et al.* (2002) used potentials to compute similarity metrics for hierarchical clustering. They defined two potential-based similarity metrics: APES and AMAPES. APES and AMAPES use the average potential energy similarity and the average maximal potential energy similarity between two clusters, respectively. Lu and Wan (2012) proposed a potential-based clustering approach called Clustering by Sorting Potential Values (CSPV). CSPV first computes potential values at the locations of all the data points, and then it seeks to find cluster centers directly from the points having relatively lower potential values than their neighbors while simultaneously classifying all the other points to these centers in an efficient tree-growing fashion. Lu and Wan (2013) extended the potential field idea to hierarchical clustering and proposed a potential-based hierarchical agglomerative clustering method (PHA). In the PHA method, both the potential field produced by all the data points and the distance matrix are used to define a new similarity metric, which leads to a fast agglomerative clustering algorithm with time complexity.

## 3. The proposed approach

Inspired by Lu and Wan (2012), we use potential model to enhance traditional collaborative filtering. We construct a dense matrix: user-user potential matrix, and use this matrix to compute potential similarities between users. Then the potential similarities are modified based on users' preliminary neighborhoods, which can further improve the accuracy of similarity computation.

The potential model is derived from a GFM. The mechanism of GFM is based on the interaction of masses in the universe via Newton's law of gravitation. The gravitation is the tendency of masses to accelerate toward each other. It is defined by Newton as, "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of the masses of the particles and inversely proportional to the square of the distance between them" (Holliday *et al.*, 1993):

$$F = G\frac{M_1 M_2}{R^2} \tag{1}$$

where $F$ is the gravitational force, $G$ is the gravitational constant, $M_1$ and $M_2$ are the mass of the first and second particles, respectively, and $R$ is the distance between the two particles.

GFM needs the explicit coordinates of all the data points in order to compute new data point locations after movements. However, explicit data coordinates may not be available in some cases. The potential model does not require the explicit data coordinates, which makes it be used in more general settings (Lu and Wan, 2012). Therefore, we apply the potential model to compute similarities between users. In the potential model, all the data points are considered to have unit mass $m = 1$ and interact with each other following the Newton's law of gravitation. For two users $u$ and $v$ located at positions $\vec{r}_u$ and $\vec{r}_v$, $\vec{r}_{uv} = \vec{r}_v - \vec{r}_u$ is the vector from $u$ to $v$, $r_{uv} = ||\vec{r}_{uv}|| = \sqrt{\sum_{i \in I_{uv}} (R_{u,i} - R_{v,i})^2 / |I_{uv}|}$ ($I_{uv}$ is the set of items rated by both users $u$ and $v$) is the distance between them, $\hat{r}_{uv} = \vec{r}_{uv} / r_{uv}$ is the unit vector from $u$ to $v$, and the attractive force on $u$ from $v$ is $\overrightarrow{F}_{uv}(\overrightarrow{r}_{uv}) = G(\hat{r}_{uv}/r_{uv}^2)$. When $r_{uv}$ is zero, in order to avoid the problem of singularity, we set $r_{uv}$ to 1 which is the lowest distance value in our approach. So the modified force is computed as:

$$\overrightarrow{F}_{uv}\left(\overrightarrow{r}_{uv}\right) = \begin{cases} G\left(\hat{r}_{uv}/r_{uv}^2\right), & \text{if } r_{uv} \neq 0; \\ G\hat{r}_{uv}, & \text{otherwise.} \end{cases} \tag{2}$$

If the potential at infinity is zero, the corresponding potential at $u$ from $v$ is computed as:

$$\Phi_{uv}(r_{uv}) = \int_{r_{uv}}^{\infty} \overrightarrow{F}_{uv}\left(\overrightarrow{r}\right)\hat{r}dr = \begin{cases} G\left(1/r_{uv}\right), & \text{if } r_{uv} \neq 0; \\ G, & \text{otherwise.} \end{cases} \tag{3}$$

Using Equation (3), the potential between any two users can be computed. Based on potential values between users, we construct a user-user potential matrix $P$ (Table II). There are $m$ users in $P$, each entry $P_{g,h}$ in $P$ represents the potential at the $g$th user from the $h$th user. Then the potential similarity between users is measured by using cosine similarity:

$$sim_p(u,v) = \frac{\sum_{g=1}^{m} P_{u,u_g} \times P_{v,u_g}}{\sqrt{\sum_{g=1}^{m} {P_{u,u_g}}^2}\sqrt{\sum_{g=1}^{m} {P_{v,u_g}}^2}} \tag{4}$$

where $sim_P(u, v)$ denotes the potential similarity between users $u$ and $v$, and $P_{u,u_g}$ is the potential at $u$ from $u_g$.

For any user $v$, $f$ users with the highest potential similarity values are selected as $v$'s preliminary neighborhood $U_v^p$. Based on the preliminary neighborhoods, we calculate the common neighbor similarity (Qin and Gao, 2010) between users:

$$sim_C(u,v) = \frac{\left|U_u^p \cap U_v^p\right|}{\left|U_u^p \cup U_v^p\right|} \tag{5}$$

where $sim_C(u, v)$ denotes the common neighbor similarity between users $u$ and $v$, and $U_u^p$ is the preliminary neighborhood of user $u$. The basic idea of Equation (5) is that two users are considered similar if they share many of the same neighbors. It seems reasonable that two individuals in a social network have something in common if they share many of the same friends.

Then, we modify the potential similarity between users by using the common neighbor similarity, and the final similarity between users is computed as:

$$sim_F(u,v) = sim_P(u,v) \times sim_C(u,v) \tag{6}$$

where $sim_F(u, v)$ denotes the final similarity between users $u$ and $v$.

**Table II.**
User-user potential matrix

| | $u_1$ | … | $u_h$ | … | $u_m$ |
|---|---|---|---|---|---|
| $u_1$ | $P_{1,1}$ | … | $P_{1,h}$ | … | $P_{1,m}$ |
| … | … | … | … | … | … |
| $u_g$ | $P_{g,1}$ | … | $P_{g,h}$ | … | $P_{g,m}$ |
| … | … | … | … | … | … |
| $u_m$ | $P_{m,1}$ | … | $P_{m,h}$ | … | $P_{m,m}$ |

Finally, we apply our similarity measure to collaborative filtering, and propose a novel collaborative filtering method called PSSM-CF. PSSM-CF is summarized as follows:

(1) calculate the potential value between any two users by using the user-item rating matrix;

(2) construct the user-user potential matrix based on the potential values;

(3) calculate the potential similarities between users and determine the preliminary neighborhood for each user;

(4) calculate the common neighbor similarities between the active user and other users;

(5) combine the above two types of similarities and obtain the final similarities between the active user and other users;

(6) sort the final similarities and select the $k$ most similar users as the active user's nearest neighbors; and

(7) apply MFIR to provide top-$N$ recommendations to the active user.

## 4. Experimental evaluation

### *4.1 Data set*

We used MovieLens 100K (ML100K) data set (Sarwar *et al.*, 2002) to evaluate the proposed approach. The ML100K data set was collected by the GroupLens Research Project at the University of Minnesota. It contains 100,000 ratings (on a 1-5 scale) from 943 users and 1,682 movies. Table III briefly describes the data set used in the experiments.

### *4.2 Evaluation metric*

We adopted *precision* (Symeonidis *et al.*, 2008; Liu *et al.*, 2009) as the evaluation metric. For an active user that receives a top-$N$ recommendation list, let $A$ denote the number of relevant recommended items (the items of the top-$N$ list that are in the test set and rated higher than the positive rating-threshold $P_r$ by the active user)[1]. The *precision* is defined in the following way:

$$precision = \frac{A}{N} \tag{7}$$

### *4.3 Experimental results*

We started our experiments by dividing the data set into a training and a test portion. The training set was used to generate recommendation lists, and the test set was used to verify the quality of the recommendations made by the methods. We conducted a fivefold cross-validation of our experiments by randomly choosing different training

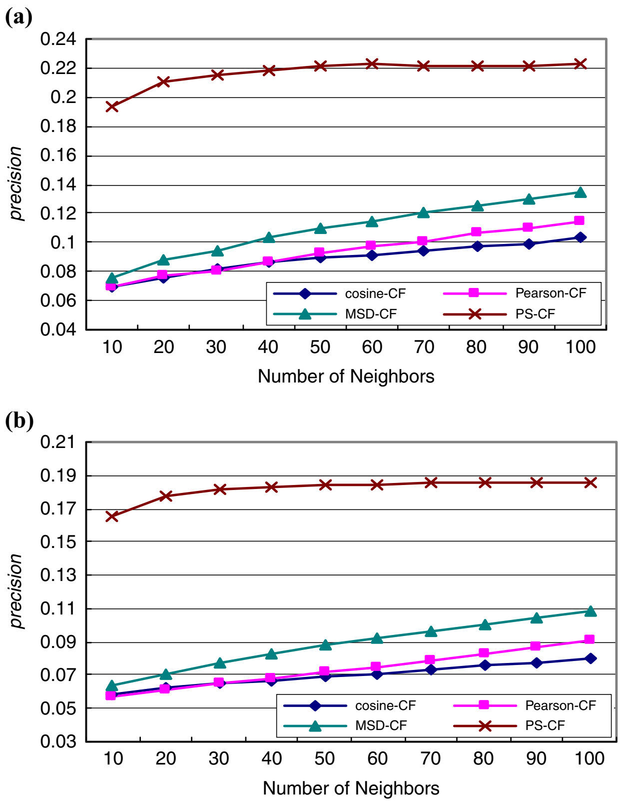
| | Number of users | Number of items | Number of ratings | Sparsity level[a] |
|---|---|---|---|---|
| ML100K | 943 | 1,682 | 100,000 | 0.9370 |

**Note:** [a]Sparsity level = 1 − nonzero entries/total entries

**Table III.** Summary of the data set used in the experiments and test sets each time and taking the average of the MAE values. We first investigated the effectiveness of potential similarity and determined the optimal value of the number of preliminary neighbors. Then, based on the optimal value, we compared our method PSSM-CF with other collaborative filtering methods. All our experiments were implemented using Java. We ran all experiments on a Windows XP based PC with Intel Pentium 4 processor having a speed of 2.66 GHz and 1 GB of RAM.

*4.3.1 Effectiveness of potential similarity*. In this section, we investigate the effectiveness of potential similarity and identify the optimal value of the number of preliminary neighbors *f*. We compared the potential similarity method with traditional similarity measures. To this end, we implemented the potential similarity-based collaborative filtering method (PS-CF), the cosine-based collaborative filtering method (cosine-CF), the Pearson-based collaborative filtering method (Pearson-CF) and the MSD-based collaborative filtering method (MSD-CF).

The results are shown in Figure 1. As shown, the number of neighbors varies from 10 to 100 in an increment of ten. Each of the four methods demonstrates similar types of charts for $N = 10$ and 20 ($N$ is the number of recommended items). The *precision* of each method is higher for $N = 10$. PS-CF outperforms the other three methods at all values of neighborhood size. PS-CF improves as we increase neighborhood size from 10 to 40,



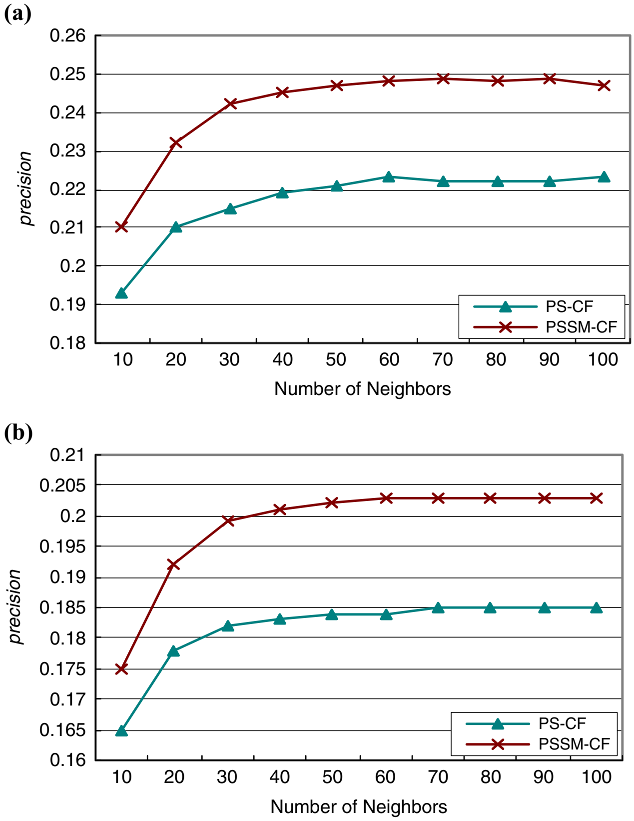

**Notes:** (a) $N$=10 and (b) $N$=20

**Figure 1.**
Effectiveness of potential similarity

after that the rate of increase diminishes and the curve tends to be flat. The best value of the number of preliminary neighbors $f$ is 40 for PS-CF. Therefore, we set $f = 40$ in the subsequent experiments.

*4.3.2 Effect of similarity modification.* Next, we investigate the effect of similarity modification. Figure 2 shows the experimental results. The green curve denotes PS-CF, and the red curve denotes the collaborative filtering method which applies Equation (6) to modify the potential similarity between users (i.e. PSSM-CF presented in the above list). We observe that each of the two methods demonstrates similar types of charts for $N = 10$ and 20. The recommendation accuracy of the two methods increases as we increase the number of neighbors $k$. PSSM-CF performs better than PS-CF at all values of $k$.

The average *precision* of each similarity measure is summarized in Table IV. Bold font indicates the best performance among all methods. We observe that both PS-CF




**Notes**: (a) $N$=10 and (b) $N$=20

**Figure 2.** Effect of similarity modification

**Table IV.** Precision comparison with traditional similarity measures

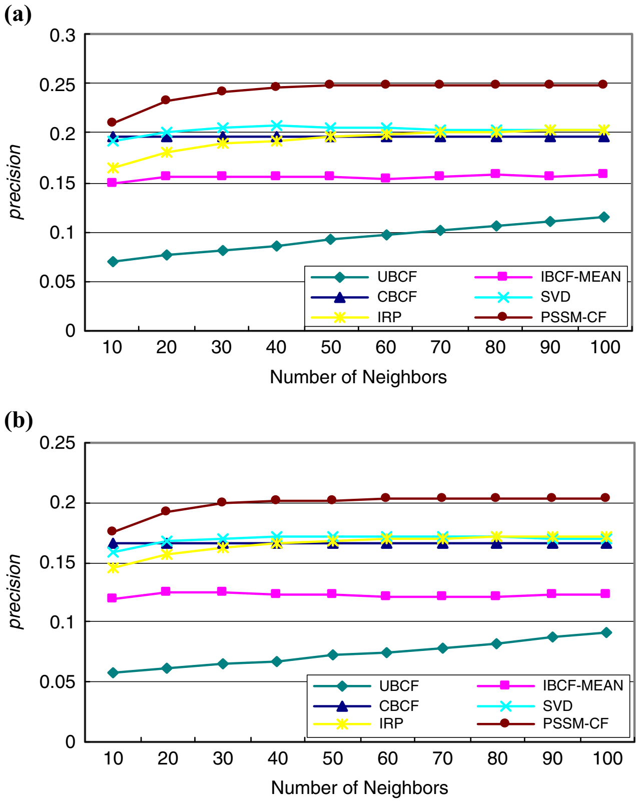
| | Cosine-CF | Pearson-CF | MSD-CF | PS-CF | PSSM-CF |
|---|---|---|---|---|---|
| Top-10 | 0.089 | 0.094 | 0.110 | 0.217 | *0.242* |
| Top-20 | 0.070 | 0.074 | 0.089 | 0.182 | *0.198* |

and PSSM-CF perform better than the traditional collaborative filtering methods, and PSSM-CF has the best performance among the five methods. Thus, it proves that the proposed similarity measure is superior to the traditional ones.

*4.3.3 Comparison with other collaborative filtering methods*. Finally, we compared our method PSSM-CF with some popular collaborative filtering methods. To this end, we implemented the user-based collaborative filtering method (UBCF) (Resnick *et al.*, 1994), the imputation-boosted collaborative filtering method (IBCF-MEAN) (Su *et al.*, 2008), the cluster-based collaborative filtering method (CBCF) (Sarwar *et al.*, 2002), the SVD-based collaborative filtering method (SVD-CF) (Sarwar *et al.*, 2000) and the item rating prediction method (IRP-CF) (Deng *et al.*, 2003). The results are shown in Figure 3. As shown, the number of neighbors varies from 10 to 100 in an increment of ten. Each of the six methods demonstrates similar types of charts for $N=10$ and 20. The *precision* of each method is higher for $N=10$. PSSM-CF outperforms the other five methods at all values of *k*. It proves again that the proposed method is effectiveness.

## 5. Conclusions

Collaborative recommender systems play a crucial role in providing personalized services to online users. Most online shopping sites and many other applications now




**Notes:** (a) $N$=10 and (b) $N$=20

**Figure 3.**
Precision comparison with popular methods

use the collaborative recommender systems. The measurement of the similarity plays a fundamental role in collaborative filtering methods. Some of the most well-known similarity measures are: Pearson, cosine and MSD. However, due to data sparsity, accuracy of the above similarity measures decreases, which makes the formation of inaccurate neighborhood, thereby resulting in poor recommendations. In this paper, we propose a novel similarity measure based on potential field. Our approach constructs a dense matrix: user-user potential matrix, and uses this matrix to compute potential similarities between users. Then the potential similarities are modified based on users' preliminary neighborhoods, and $k$ users with the highest modified similarity values are selected as the active user's nearest neighbors. Compared to the rating matrix, the potential matrix is much denser. Thus, the sparsity problem is efficiently alleviated. The similarity modification scheme considers the number of common neighbors of two users, which further improves the accuracy of similarity computation. Experimental results based on MovieLens data set show that the proposed similarity measure performs better than the traditional ones. In the future, we will apply our approach to more real-world data sets and design more effective similarity measures.

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## Note

1. In our experiments, we set the positive rating-threshold $P_r$ to 2.

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