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Recommendation System Based on Singular Value Decomposition and Multi-Objective Immune Optimization

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ABSTRACT Recommendation system plays a significant role in helping people to get effective information from mass data. Traditional recommendation systems focus on the recommendation accuracy, which is not sufficient. In this paper, we also consider the various needs of users to achieve more diverse recommendation. However, accuracy and diversity are two conflicting goals for recommendation system. Hence, we model the recommendation system as a multi-objective optimization problem, and aim to find tradeoff solutions between the two goals. Because the rating matrix is rather sparser in recommendation, we first use singular value decomposition to get the recommendation list, then multi-objective immune algorithm is used to optimize it. The experimental results illustrate that the proposed algorithm can get more diverse and accurate recommendation results.

INDEX TERMS Accuracy, diversity, multi-objective immune optimization, recommendation system, singular value decomposition.

I. INTRODUCTION

The amount of information is increasing so rapidly that the consumers are overwhelmed by the choices presented to them. Lots of products are offered by the electronic retailers and content providers to meet user's special tastes and needs. How can we get what we like? This emphasizes the importance of recommendation system, which provides personalized products that suit a user's preferences [1], [2]. Recommendation system has been widely used in many websites, such as Amazon.com, TiVo.com, and Netflix.com [3].

Over the years, many scholars paid their attentions to the research of recommendation system and developed a series of methods [4]–[6]. In general, according to Fang and Guo [7], the existing methods mainly include content-based filtering, collaborative filtering (CF) and hybrid recommendation. The content-based methods focus on information analysis of users and items [8]. According to the user's age, gender, educational background and other personal information, the algorithm predicts the user's interest. Similarly, content-based filtering is based on the item's color, type, price and other information to find the appropriate user. Collaborative filtering focuses on mining the user's preferences from the user's behavior information, i.e., mainly the relationship between the user and the item [9]. Hybrid recommendation is the fusion of multiple recommendation technologies. Collaborative filtering is one of the most fundamental and widely used recommendation systems because of its simplicity and promising results in Amazon and other mobile applications [10]–[12]. In this work, we restrict our attention to the method based on CF.

In collaborative filtering, these recommendation algorithms can be divided into two general categories [9]: memory-based and model-based. The memory-based recommendation is based on the assumption that similar users have similar ratings for the same item, and the user rates the similar items with the same ratings. Its basic principle is to predict ratings for the target users through the similar users or items. In contrast, the model-based recommendation aims to use the training data to construct model for the scoring rules. In general, the memory-based recommendation is simple, but the calculations of the similarity between users and items are particularly critical, so the memory-based recommendation is suitable for the dense scoring matrix. When the score matrix is sparse, it works very poorly. On the contrary, the model-based recommendation is relatively complex, but it can combat data sparse problem based on feature extraction of users and items. One of the most notable model-based recommendations relies on matrix factorization (MF), where SVD (singular value decomposition) can be used to make recommendation. Based on this, we prefer the SVD approach in this research because the rating matrix is rather sparser in recommendation.

In recent years, lots of various recommendation algorithms have been proposed [12]–[15]. However, traditional recommendation systems focus on the recommended accuracy. As discussed in [16]–[20], it is necessary for the recommendation system, but it is not sufficient. We should also consider recommendation diversity.

Why we need diverse recommendation? Accuracy-based recommendation always suggests items with exceptional similarity, which may lead to some meaningless recommendation for the users. For example, if a recommendation system of academic literature only recommends the same author's publications to the reader, even if the accuracy is high, the reader may also think it is a poor recommendation. It should also recommend some same topic literatures written by different authors, which may be amazing to the reader. Another example, if a user bought several pots for his new kitchen in the past several weeks, an accuracy-based recommendation system will still recommend some pots to him. Obviously, it is not a good recommendation because the user may no longer need it. A recommendation considering diversity may recommend some different but relevant items such as spoons and bowls to the user, which are perhaps just what the user needs. Recommendation system should benefit both information providers and users. On the one hand, popular and similar items can be found without recommendation system, recommendation system should help users to mine a number of diverse items. On the other hand, diverse items will increase the providers' revenue.

Some scholars have taken recommendation diversity into account [20]–[25]. In recommendation system, the diversity includes three aspects, which are individual diversity, aggregate diversity and timing diversity. It is proved that accuracy and diversity are conflicting aspects in recommendation system. In recent years, some researches have been proposed to solve the accuracy–diversity dilemma, such as information physics method [26], heuristic optimization [27], social network method [28] and time perception method [29]. It is pointed out that heuristic optimization is more effective because it further optimizes the candidate list. Hurley *et al.* [29] considered the matching quality and diversity as an optimization problem. Zhou *et al.* [30] proposed a hybrid algorithm which focused on accuracy, diversity and novelty. Then SPEA-2 was used to find a sequence of weights for each item. Geng *et al.* [31] proposed an NNIA-based recommendation system, which was to improve the diversity of recommendation list. Zuo *et al.* [32] presented a MOEA-based recommendation system by optimizing the accuracy and diversity at the same time and got a better result. Cui *et al.* [33] also proposed a novel multi-objective evolutionary algorithm for recommendation system, he used a new topic diversity metric in the paper.

In this paper, our motivation is to deal with the accuracy-diversity dilemma of recommendation system. It is relatively easy if we simply improve diversity by loss of accuracy. But the challenge is to improve recommendation diversity as possible without loss of accuracy. To deal with it, we model the recommendation system as a multi-objective problem due to the conflict between accuracy and diversity, and aim to find tradeoff solutions between the two goals. We propose a new algorithm called SVD-MOIA to solve it. We get the recommendation matrix with singular value decomposition (SVD), then use a multi-objective immune algorithm (MOIA) to optimize the two goals.

Why we use SVD? It is a kind of model-based recommendations and is effective in data sparse problem while the rating matrix is rather spare in recommendation system. Meanwhile, it is well known that multi-objective immune optimization is ideal for such optimization problem and has been widely and successful used in engineering-oriented fields in recent years [33], [34]. Compared with genetic algorithm, immune optimization has the unique clonal operator, in which both local search and global search are taken into account, and thus it has better population diversity. So, we choose them for the recommendation system.

Different from traditional recommendation techniques, the main innovations of this paper are as follows:

1) We propose a framework for recommendation based on SVD and multi-objective immune optimization to find trade-off solutions of accuracy and diversity.

2) Without reducing the accuracy of recommendation, the proposed algorithm increases the diversity of recommendation list.

3) For a target user, the proposed algorithm can provide recommendation list with different weights of accuracy and diversity in only one run to meet user's demand.

II. MULTI-OBJECTIVE RECOMMENDATION SYSTEM FORMULATION

Suppose that the recommendation problem mainly consists of three parts: the user set, denoted as U, the item set, denoted as I, the rating matrix $R_{\mathrm{U}\times\mathrm{I}}$. For $u \in U$, $i \in I$, each $r_{u,i} \in R_{\mathrm{U}\times\mathrm{I}}$ represents the rating score of user u on item i. If $r_{u,i} = 0$, it means user u doesn't rate item i. The recommendation system is to recommend those unrated items for target users. Usually, top-n recommendation technique will choose n items to the target user, which are the user most preferred.

Accuracy is used for the only target in traditional recommendation system [12]. Recommendation system should also consider the users' multiple requirements and provide a various recommendation. In this paper, we take diversity into account to achieve more personalized recommendation.

The recommendation system is primarily concerned with the accuracy of the recommended result. For the target user, R is the list of items recommended for user u. Just like other methods [31], [32], we use function f_1 to define the accuracy of the recommendation list as follows.

$$f_1 = \frac{\sum_{i \in R} S(u, i)}{|R|}$$

$S(u, i)$ denotes the similarity between the user u and item i. $|R|$ is the length of R. The accuracy is better if the function value is higher.

In addition to the recommended accuracy, we also hope there are diverse recommended items in the list, which may bring a surprise to the user. Diversity of the recommended list can be formulated with function f_2 as follows [32].

$$f_2 = \frac{\sum_{i \in R} \sum_{j \in R, i \neq j} S(i, j)}{|R| \times (|R| - 1)}$$

The function f_2 is a measure of the similarity between the recommendation items. The smaller the similarity, the better the diversity.

However, accuracy-based recommendation can be easily achieved by recommending popular items, it will certainly lose recommendation diversity. Likewise, recommending diverse items may lead to a decrease in recommendation accuracy. For the target user u, if the function f_1 value increases, the accuracy is also higher. Meanwhile the value function f_2 corresponding increases, resulting in the decrease of item diversity. Obviously, accuracy and diversity are conflicting goals in recommendation. We hope to get the recommendation result with high accuracy and more diversity, which means a larger f_1 and the smaller f_2.

Then, the recommendation problem is converted into a multi-objective optimization problem as follows.

$$\min \{-f_1, f_2\}$$

III. THE PROPOSED ALGORITHM

In this section, we first generalize the proposed algorithm, which is short for SVD-MOIA. Then we describe in detail the proposed algorithm based on SVD and multi-object immune optimization.

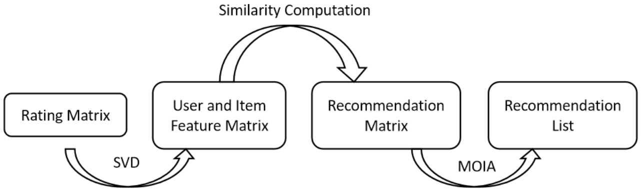

FIGURE 1. Framework of SVD-MOIA.

A. FRAMEWORK OF THE PROPOSED ALGORITHM

The framework of SVD-MOIA is shown in Fig.1. It is composed by two procedures. In procedure 1, by inputting a $m \times n$ rating matrix, we make SVD decomposition of the matrix and get the feature matrixes of user $m \times k$ and item $n \times k$, respectively. By the similarity calculation, we obtain the $m \times r$ recommendation matrix. The rows of recommendation matrix are candidate recommendation lists with the length of r. In procedure 2, the MOIA is used for each user to select the L items form recommendation matrix.

In summary, the original input is *train_matrix* (rating matrix composed of training dataset) and *Useri* (target user ID), the final output is *R_list* set (final recommendation list set). In Procedure 1, we input the *train_matrix* and get the *R_matrix*(recommendation matrix). Then *R_matrix* is the input of procedure2, then we get the *R_list* set (final recommendation list set).

We described the procedures in detail as follows.

B. SVD BASED RECOMMENDATION (PROCEDURE 1)

1) DESCRIPTION OF THE ALGORITHM

The proposed algorithm is as follows.

Procedure 1 SVD Based Recommendation

Input: *train_matrix* (rating matrix composed of training dataset)
Output: *R_matrix* (recommendation matrix)

Step1: Using SVD to decompose the train_matrix into $X, \sum, Y$, as described in section III-B-2.
Step2: To reduce the dimension of the matrix $X, \sum, Y$, then get $X_k, \sum_k, Y_k$.
Step3: Computing user feature matrix $M = X_k \sum_k^{1/2}$ and item feature matrix $N = Y_k \sum_k^{1/2}$
Step4: According to section III-B-3, calculating the similarity between the features of users and items. Then we get *R_matrix*, in which the i$^{\text{th}}$ row represents the most similar r items list with user i feature vector in descending order.

Some key techniques are described as follows.

2) SVD

SVD (singular value decomposition) is one of the methods of matrix factorization. The recommendation algorithm based on SVD can be formalized as follows.

$$R_{U \times I} = X \sum Y^T = X \sum^{1/2} (Y \sum^{1/2})^T$$

Where X, Y is orthogonal matrix, Σ is Diagonal matrix. Then we can get a $m \times k$ user feature matrix $M = X \sum^{1/2}$ and a $n \times k$ item feature matrix $N = Y \sum^{1/2}$. k is the dimension of feature space. The rows of matrix M and N are the user and item feature vectors respectively.

The illustration of this algorithm is depicted in Fig. 2.

3) SIMILARITY COMPUTATION

If we want to find out the correlation between the user and the item, similarity computation is a very important step. There are many methods that can be used to calculate the similarity, such as cosine similarity, Pearson correlation, and so on [22]. Here, we use the cosine similarity because of its effectiveness. Each row of user feature matrix M represents a user feature

Procedure 2 Multi-Objective Immune Algorithm for Recommendation (MOIA)

Input: *Useri* (target user ID)
R_matrix (recommendation matrix)
g_{max} (maximum number of iteration)
n_d (maximum size of dominant population)
n_a(maximum size of active population)
c_s(the size of clone population)
Output: *R_list* set (final recommendation list set)

Step1: Initialization: generate the *Useri*'s initial antibody population $\mathbf{B}_0$ with size n_d. Each solution (antibody) is a recommendation list $X = \{x_1, x_2, \ldots, x_L\}$. The encoding of solution is described in the following section. Set $t = 0$, $\mathbf{D}_0 = \emptyset$, $\mathbf{A}_0 = \emptyset$, $\mathbf{C}_0 = \emptyset$.
Step2: Affinity evaluation and Update Dominant Population:
The Affinity values of the objective functions f_1, f_2 are calculated for each antibody in $\mathbf{B}_t$.
In accordance with Pareto dominant [20]–[23], the antibodies in $\mathbf{B}_t$ are divided into non-dominated individuals and dominated individuals. Copy all the dominating individual in $\mathbf{B}_t$ to form $\mathbf{DT}_{t+1}$. If $|\boldsymbol{DT}_{t+1}| \le n_d$, let $\boldsymbol{D}_{t+1} = \boldsymbol{DT}_{t+1}$. Otherwise, sort the individuals according to the crowding distance, select the first n_d individuals form $\mathbf{D}_{t+1}$. The calculation of crowding distance is in agreement with the Qi *et al.* [36].
Step3: Termination: if $t \ge g_{\max}$, stop the algorithm and export $\mathbf{D}_{t+1}$ as *R_list* set. Otherwise, $t = t + 1$.
Step4: Non-dominated Neighbor-Based Selection. Select and Update Active Population:
If $|\boldsymbol{D}_{t+1}| \le n_a$, let $\mathbf{A}_t = \mathbf{D}_t$, Otherwise, sort the individuals according to the crowding distance, select the first n_a individual for $\mathbf{A}_t$.
Setp5: Adaptive Ranks Clone: Get clone population $\mathbf{C}_t$ by applying adaptive ranks clone [35] to $\mathbf{A}_t$, the population size is c_s.
Step6: Crossover: Applying crossover to $\mathbf{C}_t$ with probability P_c as described in 3.3.4 and get $\mathbf{C}_t^{'}$.
Setp7: Mutation: Applying mutation to $\mathbf{C}_t^{'}$ with probability P_m as described in 3.3.4 and get $\mathbf{C}_t^{''}$.
Step8: combining $\mathbf{D}_t$ and $\mathbf{C}_t^{''}$ to form B_t, go back Step2.

vector and each row of item feature matrix N represents an item feature vector. The cosine similarity between user u and item i is given by

$$S(u, i) = \cos(\overrightarrow{M_u}, \overrightarrow{N_i}) = \frac{\overrightarrow{M_u} \cdot \overrightarrow{N_i}}{\left\|\overrightarrow{M_u}\right\| \times \left\|\overrightarrow{N_i}\right\|}$$

Likewise, the similarity of two items is:

$$S(i, j) = \cos(\overrightarrow{N_i}, \overrightarrow{N_j}) = \frac{\overrightarrow{N_i} \cdot \overrightarrow{N_j}}{\left\|\overrightarrow{N_i}\right\| \times \left\|\overrightarrow{N_j}\right\|}$$

Where $\cdot$ denotes the dot-product of the two vectors.

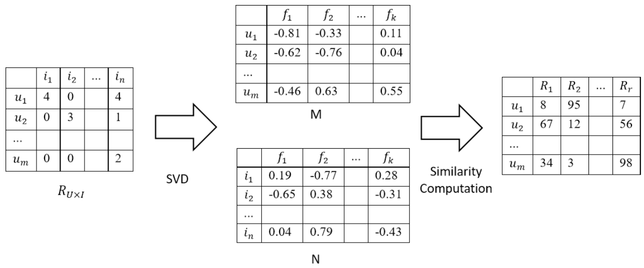

FIGURE 2. Illustration of the SVD and Similarity Computation.

C. MULTI-OBJECTIVE IMMUNE ALGORITHM FOR RECOMMENDATION (PROCEDURE 2)

We get *R_matrix* after Procedure 1, then multi-objective immune algorithm is used to optimize it according to recommendation accuracy and diversity.

Some related technologies are described as follows.

1) MULTI-OBJECTIVE OPTIMIZATION

Multi-objective problem (MOP) can be formalized as follows [35]

$$\min F(x) = \{f_1(x), f_2(x), \ldots f_l(x)\}$$

where x is the decision vector, $f_I\ (x)$ is the $\mathrm{I^{TH}}$ objective. different objectives are often contradictory.

In MOP, if we say decision vector x_i dominates x_j, it means $\forall k = 1, 2, \ldots l, f_k(x_i) \le f_k(x_j)$ and $\exists k = 1, 2, \ldots l, f_k(x_i) < f_k(x_j)$.

If no x^* dominate x, then x is called a Pareto-optimal solution. The set of Pareto-optimal solutions is called Pareto Set (PS). When PS is mapped into the objective function space, it is called the Pareto front (PF). Multi-objective optimization aims to find the set of Pareto-optimal solutions (PS).

In this paper, there are two objectives f_1, f_2 to be optimized at the same time so that we can get accuracy and diversity recommendation. Multi-objective optimization aims to find the set of Pareto-optimal solutions approximating the true Pareto-optimal front.

2) MULTI-OBJECTIVE IMMUNE OPTIMIZATION ALGORITHM (MOIA)

Immune optimization simulates immune recognition and immune response of the biological immune system, in which the optimization problem and its constraints are regarded as antigens, and the candidate solution of the target problem is regarded as antibody. MOIA is done by iteration of the clone operation, mutation operation and selection operation so that antibody population obtains the optimal solution [35]. AN increasing number of studies show that the immune optimization algorithm has a good effect on solving multi-objective optimization problems.

Some related terms in this paper are described briefly as follows.

1. Antigen: An antigen represents one sample in the problem space. in this paper, antigen refers to the recommendation problem to be solved.

2. Antibody: An antibody represents a candidate solution to the problem in this paper.

3. Antibody Population: The entire antibodies consist of antibody population.

4. Affinity: Affinity is the fitness measurement for an antibody, which exhibits the extent that antibody satisfies the problem requirements.

5. Clone. In immunology, clone means asexual propagation so that a group of identical cells can be descended from a single common ancestor. It is used to enlarge search space.

6. Mutation. In immunology, mutation means the immune system recognizes external pattern by antibody gene mutation in order to gain higher affinity. Mutations take the search procedure out of a locally optimal region, and enable it to possibly enter into a better region of the search space.

7. Selection. An immune algorithm takes antibody from a population using an operation called selection. The selection operation serves the purpose of eliminating the relatively bad candidates and focusing the search operation on a relatively good region of the solution space.

8. Dominant population. In this paper, we store non-dominated individuals found so far in an external population, called the dominant population.

9. active antibodies. Only partial less-crowded non-dominated individuals, called active antibodies, are selected to do clone, crossover, and mutation.

3) DESCRIPTION OF THE ALGORITHM

In this paper, we employ a novel multi-objective optimization algorithm for recommendation. The proposed algorithm is described as follows.

Some key techniques are described as follows.

4) KEY TECHNIQUES OF MOIA BASED RECOMMENDATION

a: ENCODING OF SOLUTION

Encoding is a key technique to immune algorithm. different from Geng *et al.* [31], we use real encoding. in our algorithm, each solution represents one recommendation list. the l is the length of recommendation list. the encoding of each solution can be expressed as

$$X = \{x_1, x_2, \ldots, x_l\}$$

where x_1, x_2, $\ldots$, x_l is selected randomly from candidate lists, which x_i stands for an item. in the solution X, every x_i, $i = \{1, 2, \ldots, L\}$ is different from each other. an example is illustrated in fig.3.

b: AFFINITY FUNCTION

Affinity function is the measurement of the solution. the optimization object is to min $\{-f_1, f_2\}$. so, it is directly used for Affinity function. that is, calculating the values of -f_1 and f_2.

1	2	3	4	5	6	7	8	9	10
31	23	21	36	28	51	3	2	5	12

FIGURE 3. An example of encoding with length of ten.

X_1	6	1	5	66	8	3	28	16	12	62
X_2	31	23	21	36	28	51	3	2	5	12

Y_1	6	1	5	66	8	3	3	2	5	12
Y_2	31	23	21	36	28	51	28	16	12	62

new Y_1	6	1	5	66	8	3	36	2	31	12
new Y_2	31	23	21	36	28	51	8	16	12	62

FIGURE 4. Crossover Process.

c: CROSSOVER OPERATOR

Crossover is used to produce new antibody (it is also can be called individual). in this process, the single point crossover operation is adopted. but traditional method may cause duplicate elements in the recommendation list [21]. in this paper, we do a simple improvement. for example, in fig. 4, X_1, X_2 use the single point (6^{th}) crossover to generate two new solution Y_1, Y_2. in the solution Y_1, the 3^{th} and 9^{th} element is same, the 6^{th} and 7^{th} is also same. in the solution y_2, the 5^{th} and 7^{th} element is same. then, we randomly select elements from the other solution, which is to get different elements.

d: MUTATION OPERATOR

We use single point mutation. from the target solution X, we randomly select an element. then we use other element that not belong to solution X to replace selected element. an example of mutation for 4^{th} element can be shown in fig.5.

8	54	31	6	70	18	40	37	3	4

8	54	31	28	70	18	40	37	3	4

FIGURE 5. Mutation Process.

5) ADVANTAGES OF THE PROPOSED ALGORITHM

1. Improvement single point mutation is easy to realized and eliminate duplicate elements in the recommendation list.

2. Adaptive ranks clone ensures that the antibody with better affinity has more opportunity to evolve to the next generation.

3. Non-dominated neighbor based selection technique only selects minority non-dominated individuals in the population, which pays more attention to the less crowded regions of the current trade-off front.

4. By selecting individuals with greater crowding-distance values as active antibodies, it realized that the active antibodies are the less-crowded individuals in objective space.

D. COMPLEXITY ANALYSIS

Recall m and n are the numbers of users and items. The computational complexity of SVD is O (m^*n^2). Then, we analyze the complexity of MIOA recommendation. Assume that the maximum size of dominant population is n_d, the size of clone population is c_s, the time complexity of one generation for the algorithm can be calculated as follows:

The time complexity for identifying non-dominated individuals in the population is $O((n_d+c_s)^2)$; the worst time complexity for updating the dominant population is $O((n_d + c_s) \log(n_d + c_s))$; the worst time complexity for non-dominated neighbor-based selection is $O(n_d \log(n_d))$; the time complexity for cloning is $O(c_s)$; and the time complexity for crossover and mutation is O (c_s). So the worst total time complexity is $O((n_d + c_s)^2) + O((n_d + c_s) \log(n_d + c_s)) + O(n_d \log(n_d)) + 2\,O\,(c_s)$.

According to the operational rules of the symbol O, the worst time complexity of one generation can be simplified as $O((n_d + c_s)^2)$. The whole complexity of Pareto based evaluation is $O((n_d + c_s)^2)$.

The computational complexity of MOIA is O ($g_{max} \times n_u \times (n_d + c_s)^2$), where g_{max} is the number of generations, n_u is the number of objective functions. Thus, for given g_{max}, n_u, $(n_d + c_s)^2$, the gradual computational complexity of the proposed algorithm is $O(m^*n^2)$ in accordance with the properties of symbolic O.

Hence, the whole computational complexity is $O(m^*n^2)$. It doesn't increase the complexity compared with the available algorithms.

TABLE 1. Description of two datasets.

	Users	Items	Ratings	Sparsity
MovieLens	6,040	3,952	1,000,209	0.9581
Donation Dashboard	490	70	22101	0.3557

IV. EXPERIMENTS AND RESULTS

A. EXPERIMENTAL DATASETS

In order to verify the effectiveness of the SVD-MOIA, we perform experiments on datasets of MovieLens and Donation Dashboard. We adopt the Movielens dataset which contains 1,000,209 ratings from 6,040 users on 3,952 movies. And all ratings are integers belonging to [1, 5]. For Donation Dashboard dataset, we extract the user whose rating records more than 20 times, and normalize original [−10, 10] score to integer [1, 5]. Then we get a dataset which consists of 22101 ratings of 70 items from 490 users. The two Datasets are shown in table 1. In our Experiments, we randomly divide the data into two parts, the training set and test set. The training set accounts for 80% of all data and the test set contains the remaining 20% of the data.

Besides, for different dataset, the feature matrix dimensions of user and item are also different. For MovieLens dataset after SVD, we obtain a 3900-dimensional feature matrix and 70 for Donation Dashboard dataset. But not each dimension is very useful. Fig.6 shows the weight change of all dimensions. Obviously, only a few feature dimensions play an important role. Therefore, we set a threshold value σ as shown below:

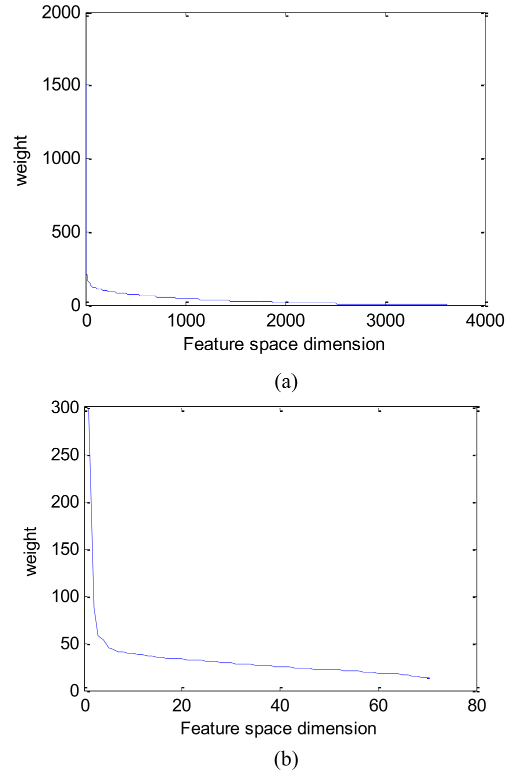

FIGURE 6. The Weight Change of all Feature Dimensions. (a) MovieLens. (b) Donation Dashboard.

$$\sigma = \frac{P_k}{P}$$

where P_k is the sum of the squares of the first k feature vector weights, P is the sum of squares of all feature vectors. In experiments, we set $\sigma \geq \frac{1}{3}$ for MovieLens and $\sigma \geq \frac{2}{3}$ for Donation Dashboard due to the differences of the two datasets. Thus, we obtain the feature matrix of the user and the item after the dimension reduction.

B. SENSITIVITY IN RELATION TO THE IMMUNE ALGORITHM PARAMETERS

Serval parameters are to be set at the initialization phase: the number of candidate list r, maximum size of active population n_a, maximum size of dominant population n_d, the clone population size c_s, the mutation probability p_m, the crossover probability p_c and the maximum number of generations g_{max}. The sequential experimental design method of employing a series of smaller experiments each with a specific objective is a common method in experimental design, because the experimenter can quickly learn crucial information from a small group of runs that can be used to plan the next experiment. n_d, n_a and c_s directly influence the computational complexity of the algorithm [35], [36]. Given n_d, n_a and c_s large enough, the diversity of the population can be enhanced and the prematurity can be avoided in some extent, but the computational complexity will also be very high. $g_{\max}$ depends on search space of problem obviously. The more complex the search space is, the larger the number of generation should be. p_{m} is very important for local search in algorithm. A larger p_{m} has the ability to produce more new antibodies, but it also has the probability to destroy some good antibodies. When p_{m} is too small, the convergence speed is not quick enough to find the best solution in specific generation. p_{C} works just like p_{m}. The parameter L and r, we use the same value as the relevant algorithms [31].

Since the optimal choice is hard to determine by theoretical analysis, it is important to analyze the performance influence by experiments in different cases. After trial and error, the parameters employed in the proposed algorithm are displayed in Table 2.

TABLE 2. Settings of the parameters.

Parameters	Meaning	Value
r	The number of candidate List	50
L	The length of final recommendation list	10
g_{max}	the number of iterations	200
n_a	maximum size of active population	10
c_s	the size of clone population	50
n_d	maximum size of dominant population	20
p_c	The probability of crossover	0.8
p_m	The probability of mutation	0.1

C. EVALUATION METRICS

In this section, we evaluate recommendation algorithm from three aspects, precision, novelty and diversity.

1) PRECISION

Precision is a measure of the accuracy of recommendation list [31]. It calculates percentage of items that are relevant to the target user in the recommendation list. In this paper, we regard these items with a score >= 3 in test set as user relevant ones. Precision can be defined as follows [32]:

$$P(R) = \frac{|R \cap T|}{|R|}$$

Where R is the recommendation list, and T is the item set which is relevant with target user in test set. || is the length of set. The greater the value $P(R)$ is, the better the accuracy of the results is.

2) NOVELTY

In recommendation system, high accuracy recommendation can be easily achieved by safely recommending popular items. However, there are only a few items of high popularity, which is so-called long tail theory. Thus, the other goal is to recommend items which are in the long tail. Novelty is the measure of recommendation for unpopular items. Novelty metric is shown as follows:

$$N(R) = \frac{1}{|R|} \sum_{i=1,2,\ldots,|R|} d_i$$

Where d_{i} is the degree of the i^{th} item in recommendation list, that is, the number of users that rated the item i [27]. A smaller value means higher novelty.

3) DIVERSITY

In our paper, we use the intra-user diversity as the evaluation metric [31]. For a recommendation list, we want to get all kinds of items. Thus, the value of diversity is expected to be as low as possible. Diversity can be formulated as follows [32]:

$$D(R) = \frac{1}{|R| \times (|R| - 1)} \sum_{i \neq j} S(i,j)$$

Where $S(i,j)$ is the similarity of item i and j in recommendation list R.

D. EXPERIMENTAL RESULTS

As we describe above, the outputs of proposed SVD-MOIA are a number of non-dominated solutions, that is, a series of recommendation list for a target user. For different target user, the algorithm gives different recommendation list. We give the Pareto-optimal solutions on a specific user of each dataset, for example, user 3411 in the MovieLens and user 111 in the Donation Dashboard. The outputs are shown in fig7.

Each point in the figure represents a set of recommendation list for the user, which is a trade-off between accuracy and diversity. The smaller the diversity, the higher the accuracy of the recommended list; the smaller the accuracy, the better the diversity between the items in the recommended list.

Then, we compare the proposed SVD-MOIA with the traditional classical method, such as user-based collaborative filtering (u-CF) and item-based collaborative filtering (i-CF)[37], matrix factorization (MF)[38]. And a comparison with another multi-objective recommendation algorithm NNIA-RS [31] is also carried out. We verify the performances of our experiments from three aspects of precision, novelty and diversity. And the minimum, maximum and average values are compared in all the recommendation lists. For MovieLens dataset, we randomly select twenty users, from 3411 to 3420 and from 5971 to 5980. For Donation Dashboard dataset, we randomly select ten users, from 111 to 120.

Table 3 shows the recommendation precision on the dataset MovieLens. The 'min', 'max', 'mean' in turn is the minimum, maximum and average value of the precision of all the recommendation lists. From table 3, it is obvious that the accuracy of SVD-MOIA is much better than other algorithms for most users. And ten users' maximum values are greater than the value of other methods. The nine users' average values are also better than others. In addition to, for

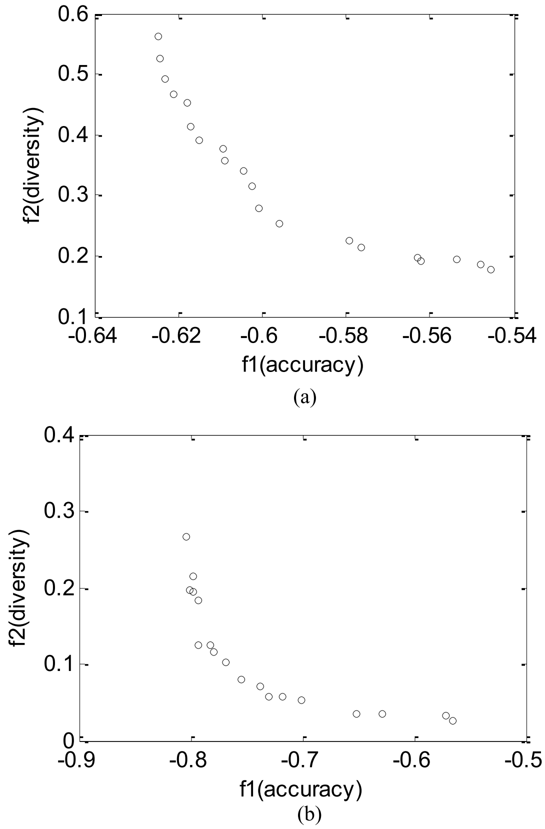

FIGURE 7. **The Pareto front of two datasets. (a) the user 3411 on the MovieLens. (b) the user 111 on the Donation Dashboard.**

3413, 3414, 3415, 3418, 3419, 3420, 5971, 5973, 5976 and 5979, these users' minimum values are also better than others.

Table 4 shows the recommendation precision on the dataset Donation Dashboard. From table 4, for user 112, the minimum, maximum and average value are better than other algorithms. Compared with NNIA-RS, for users' ID of 111, 112, 115, 118 and 119, the precision of the SVD-MOIA is significantly better. Compared with CF and MF, our proposed algorithm can generate recommendation lists with better precision, because the recommendation result of CF and MF is just one of the Pareto solutions obtained by SVD-MOIA. Not all values are higher than the comparison algorithms, but using the MOIA, it can find some good results that comparison algorithms cannot find.

We also give a mean precision of the selected users, which is illustrated in fig8. All in all, from table 3 and table 4 and fig8, we can conclude that the proposed algorithm works well in the recommendation precision. The proposed algorithm works better in Movielens than Donation Dashboard, because Movielens datasets are sparser than Donation Dashboard dataset. We use SVD to deal with spare problem, so it performs well. It can be seen that our algorithm is less than compared single objective algorithms i-CF and u-CF in Donation Dashboard dataset, because our

TABLE 3. **Precision on movielens.**

User'ID	i-CF	u-CF	MF	NNIA-RS			SVD-MOIA		
				min	max	mean	min	max	mean
3411	0.4	0.1	0.3	0.1	0.4	0.2	0.2	**0.5**	0.380
3412	0	0.1	0.1	0	0.1	0.093	0.1	**0.4**	**0.270**
3413	0.1	0.1	0	0	0.1	0.093	**0.3**	**0.5**	**0.400**
3414	0.3	0.1	0.1	0.1	0.5	0.255	**0.6**	**0.8**	**0.711**
3415	0	0.1	0	0.1	0.2	0.135	**0.4**	**0.6**	**0.510**
3416	0.2	0	0.2	0	0.2	0.035	0	0	0
3417	0.2	0.1	0	0.1	0.3	0.165	0	0.2	0.095
3418	0	0	0	0	0	0	**0.1**	**0.2**	**0.165**
3419	0.1	0	0	0	0.1	0.018	**0.2**	**0.4**	**0.305**
3420	0	0.1	0.1	0	0	0	**0.2**	**0.3**	**0.230**
5971	0	0	0	0	0.2	0.023	**0.4**	**0.6**	**0.518**
5972	0.3	0.3	0.2	0.1	0.3	0.018	0	0.2	0.075
5973	0	0	0	0	0	0	**0.1**	**0.3**	**0.160**
5974	0	0	0	0	0.2	0.078	0	0.1	0.012
5975	0	0	0	0.2	0.2	0.2	0.1	0.2	0.145
5976	0	0	0	0	0	0	**0.3**	0.5	**0.461**
5977	0	0	0	0	0.1	0.02	0	0	0
5978	0.2	0.4	0.3	0.1	0.4	0.248	0.2	0.3	0.217
5979	0	0	0	0	0	0	**0.2**	0.5	**0.380**
5980	0.1	0.2	0.1	0	0.1	0.028	0.1	0.4	**0.270**

TABLE 4. **Precision on donation dashboard.**

				NNIA-RS			SVD-MOIA		
User'Id	i-CF	u-CF	MF	min	min	mean	min	max	mean
111	0.3	0.2	0.1	0	0.2	0.1225	0.1	0.6	0.265
112	0	0	0	0	0	0	**0.2**	0.6	**0.426**
113	0.2	0.3	0.1	0	0.2	0.0775	0	0.1	0.015
114	0.2	0.3	0.1	0.1	0.4	0.265	0	0.3	0.185
115	0.2	0.2	0.2	0	0.2	0.01	0	0.4	0.105
116	0.2	0.2	0.1	0.1	0.2	0.1025	0	0.4	0.165
117	0.3	0.3	0.3	0.2	0.4	0.23	0	0.6	0.250
118	0.6	0.6	0.2	0	0.2	0.1175	0.3	0.6	0.456
119	0.2	0.2	0.1	0	0.1	0.0525	0	0.5	0.158
120	0.5	0.4	0	0.4	0.5	0.3275	0	0.1	0.085

algorithm does not blindly purse precision, it also considers diversity.

Table 5 shows the recommendation novelty on the dataset MovieLens. Compared with i-CF, u-CF and MF, for users' number of 3411, 3414, 3415, 3416, 3420, 5971, 5972, 5973, 5794, 5975, 5976, 5980, the proposed SVD-MOIA gets a smaller novelty values. And for more than half of the users, SVD-MOIA works better than NNIA-RS on novelty.

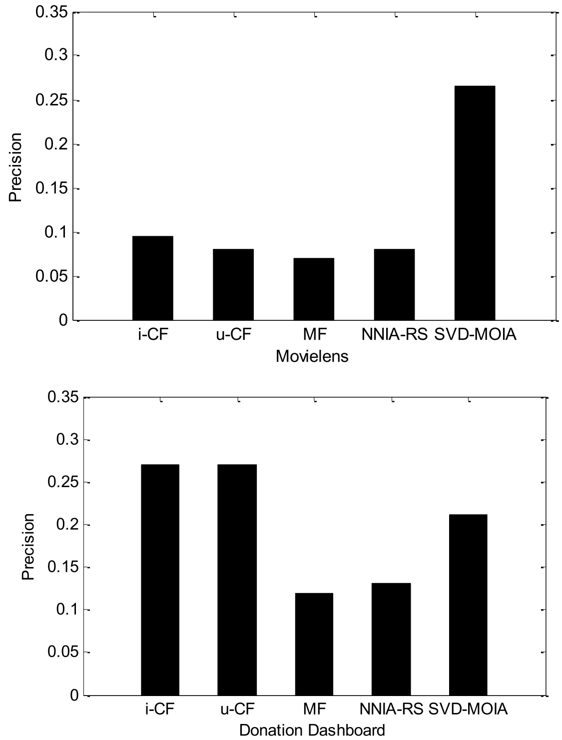

FIGURE 8. Precision of different algorithm.

Besides, for users' ID of 3411, 3414, 3415, 3416, 5974, 5975, SVD-MOIA has better mean values of novelty than other algorithms. Table 6 shows the novelty on the dataset Donation Dashboard. All the users have achieved a better novelty with SVD-MOIA.

We give a mean novelty of the selected users, which is illustrated in fig9. From the discussion of the above two datasets, the proposed SVD-MOIA improves the novelty of the recommendation lists.

Table 7 shows the recommendation diversity on the dataset MovieLens. Table 8 shows the recommendation diversity on the dataset Donation Dashboard. We also give a mean diversity of the selected users, which is illustrated in fig10.The similarity calculation of items is based on the feature vectors of the items in this paper, and the other literatures are based on the rating matrix. The two calculation methods are a little different. However, it can be seen from the experimental results that the algorithm proposed in this paper has a good performance on the diversity.

From the above discussions, it can be seen that the proposed algorithm performs well in most cases, because it not only pursues accuracy but also novelty and diversity. we can conclude that the proposed SVD-MOIA keeps good recommendation accuracy in most cases, even better than other algorithms. And at the same time, it improves the novelty and diversity of recommendation lists to meet the various needs of users. For example, users number of 3414, 3415 in the dataset MovieLens and user number of 112 in the dataset Donation Dashboard, the algorithm performs better than others algorithms in all metrics of accuracy, novelty and diversity.

All in all, the outputs of the proposed algorithm are a number of Pareto solutions, which stand for the recommendation list for a target user. For each target user, the algorithm generates different recommendation lists. The experimental results show that our proposed algorithm can get a better result compared with the available methods. SVD is effective in dealing with sparse rating matrix and ensure the

TABLE 5. Novelty on movielens.

User-ID	i-CF	u-CF	MF	NNIA-RS			SVD-MOIA		
				min	max	mean	min	max	mean
3411	1357.4	615.2	1771.1	637.1	944	764.9	349.5	619.2	**482.7**
3412	641.9	657.6	941.1	226.4	751	482	637.4	1086.6	856.5
3413	556.3	695.6	562.1	350.6	903.7	535.7	638	924	770.7
3414	1079.5	670.5	1737.1	351.4	1059.1	644.7	389.1	817.4	**552.1**
3415	648.4	1009.2	812.6	645.8	1304.1	948.2	265.1	525.3	**385.2**
3416	489	690.2	1363.8	43.7	928.9	344.2	161.2	258.8	**205.8**
3417	691.1	1100.4	61	96.5	672.3	352	167.9	516.5	322.9
3418	310	595	961.2	348.1	736.1	522.2	700.5	1258.8	985.5
3419	690.8	637.2	369.4	89.9	359.4	181.1	271.4	946.9	483.4
3420	224.9	591.9	533	158.7	439	314.9	216.2	785.5	449.7
5971	969.6	567.6	1486.7	106.2	966.8	373.2	296.6	577.7	422.2
5972	886.9	856	1191	288.3	869.9	479.2	687.7	997.7	805.6
5973	499.1	977.2	763.3	22.7	930.9	175.8	264.9	483.2	410.5
5974	970.5	776.2	1137.5	565.2	944.7	736.8	436.8	753.5	**573.7**
5975	387.1	642.7	307.4	669.2	914.5	790.1	301.2	432.3	**368.9**
5976	283.5	784.9	663.9	84	356	219.8	196	268.3	235.4
5977	950.4	985.4	55.1	431.2	1141.9	697.7	137.8	227.8	183.2
5978	466	951.6	932	442.2	1073.7	770.2	553.2	690.5	603.8
5979	1184.5	776.9	46.4	310.3	898.3	553.9	349.5	619.2	482.6
5980	935.5	942.8	1065.4	40	819	382.7	637.4	1086.6	856.5

TABLE 6. Novelty on donation dashboard.

User'Id	i-CF	u-CF	MF	NNIA-RS			SVD-MOIA		
				min	max	mean	min	max	mean
111	258	271.1	320.6	230.8	289.1	254.4	176.3	233.4	**198.1**
112	232.1	269.8	314.4	224.4	298.8	257.6	180	268.9	**207.7**
113	343.3	321.4	301	192.8	296.2	241.5	175.9	271.4	**213.1**
114	246.6	299.1	349.2	230.1	271.8	245.2	183.7	301.8	**242.2**
115	288.8	269.9	325.9	205.9	307.7	243.8	174.6	268.4	**208.7**
116	257.4	272.9	354.7	204	278.6	250.3	176.9	266.5	**207.8**
117	292.3	290.2	356.5	213.4	277.5	249.7	181.3	327.6	**249.1**
118	267.7	255.6	322.3	214.5	285.7	249.7	177.8	212.5	**186.4**
119	233.6	253.4	314.9	221.6	293.8	251.9	173.4	251.2	**196.4**
120	299	300.4	348.1	227.1	276.4	249.2	181	271.7	**211.6**

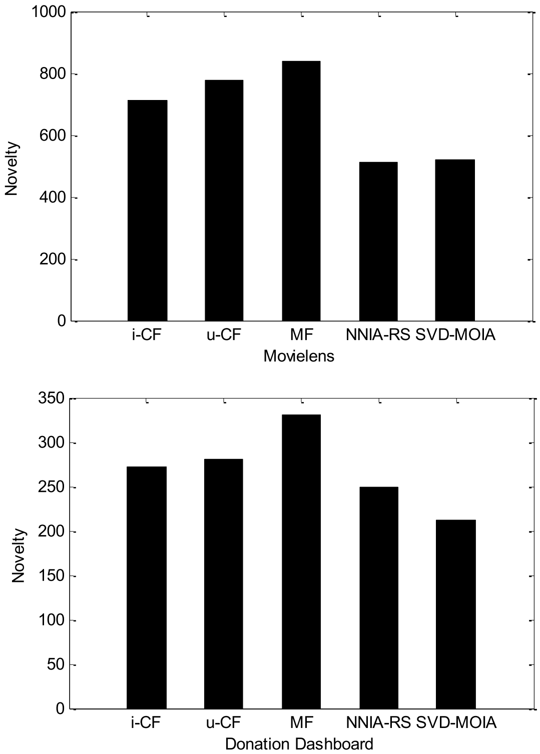

FIGURE 9. Novelty of different algorithm.

TABLE 7. Diversity on movielens.

User'Id	i-CF	u-CF	MF	NNIA-RS			SVD-MOIA		
				min	max	mean	min	max	mean
3411	0.485	0.462	0.485	0.381	0.486	0.438	0.176	0.55	**0.322**
3412	0.489	0.329	0.486	0.448	0.488	0.466	0.079	0.392	**0.214**
3413	0.486	0.337	0.488	0.464	0.488	0.473	0.252	0.452	**0.334**
3414	0.487	0.481	0.484	0.311	0.487	0.402	0.05	0.244	**0.106**
3415	0.488	0.477	0.488	0.476	0.487	0.482	0.129	0.213	**0.158**
3416	0.387	0.427	0.48	0.271	0.482	0.371	0.048	0.126	**0.081**
3417	0.488	0.478	0.439	0.358	0.489	0.435	0.132	0.358	**0.235**
3418	0.227	0.393	0.483	0.159	0.488	0.329	0.092	0.324	**0.183**
3419	0.388	0.475	0.398	0.237	0.481	0.365	0.178	0.485	**0.326**
3420	0.489	0.466	0.453	0.448	0.487	0.466	0.092	0.373	**0.221**
5971	0.313	0.447	0.484	0.042	0.486	0.259	0.141	0.229	**0.177**
5972	0.486	0.43	0.478	0.406	0.486	0.448	0.104	0.244	**0.167**
5973	0.314	0.38	0.48	0.041	0.487	0.25	0.114	0.345	**0.220**
5974	0.486	0.465	0.486	0.295	0.487	0.389	0.128	0.348	**0.201**
5975	0.392	0.468	0.387	0.386	0.488	0.439	0.087	0.263	**0.151**
5976	0.487	0.474	0.448	0.346	0.489	0.419	0.088	0.221	**0.129**
5977	0.487	0.468	0.416	0.479	0.489	0.483	0.049	0.178	**0.097**
5978	0.488	0.395	0.486	0.297	0.483	0.39	0.147	0.28	**0.189**
5979	0.488	0.36	0.416	0.461	0.488	0.474	0.176	0.55	**0.322**
5980	0.302	0.478	0.489	0.098	0.486	0.297	0.079	0.392	**0.214**

recommended accuracy, and MOIA is ideal for optimization of two conflicting goals of accuracy and diversity in recommendation system.

TABLE 8. Diversity on donation dashboard.

User'Id	i-CF	u-CF	MF	NNIA-RS			SVD-MOIA		
				min	max	mean	min	max	mean
111	0.443	0.438	0.446	0.392	0.451	0.419	0.038	0.383	**0.179**
112	0.436	0.452	0.441	0.391	0.449	0.418	0.043	0.427	**0.191**
113	0.437	0.458	0.428	0.391	0.449	0.418	0.051	0.453	**0.224**
114	0.44	0.433	0.449	0.409	0.453	0.426	0.046	0.436	**0.221**
115	0.433	0.428	0.44	0.389	0.452	0.415	0.044	0.409	**0.167**
116	0.436	0.439	0.446	0.393	0.444	0.417	0.046	0.406	**0.181**
117	0.436	0.439	0.452	0.389	0.454	0.416	0.044	0.475	**0.247**
118	0.436	0.437	0.454	0.288	0.448	0.417	0.049	0.303	**0.121**
119	0.438	0.451	0.45	0.39	0.452	0.418	0.047	0.428	**0.173**
120	0.447	0.448	0.449	0.408	0.453	0.426	0.039	0.272	**0.127**

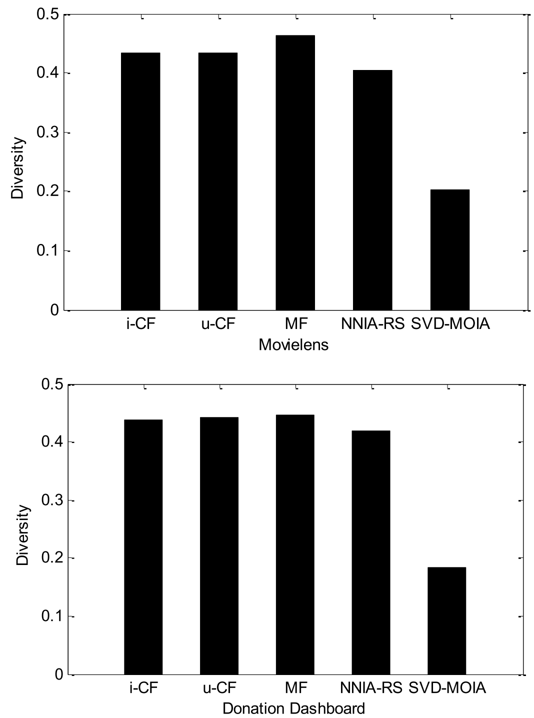

FIGURE 10. Diversity of different algorithm.

V. CONCLUSION

In this paper, we not only consider the recommendation accuracy but also recommendation diversity. To deal with accuracy-diversity dilemma of recommendation system, we model the recommendation system as a multi-objective problem, and propose a recommendation algorithm based on SVD (singular value decomposition) and MOIA (multi-objective immune algorithm), called SVD-MOIA. First, SVD is used to generate the candidate recommendation lists because the rating matrix is rather sparser, then MOIA is used to optimize the conflicting goal of accuracy and diversity. Experimental results show that the proposed algorithm increases the recommendation diversity to solve the accuracy-diversity dilemma and get a better trade-off of accuracy and diversity. For a target user, the proposed algorithm can provide the recommendation list with different weights of accuracy and diversity in only one run to meet user's demand.

However, the work is far from enough. There is still much work for improvement of diversity. In addition, there are still many problems to be solved for the SVD of large datasets. We still have a lot of steps to move forward.

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