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A Multi-population Genetic Algorithm for Multiobjective Recommendation System

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***Abstract*—Nowadays, recommendation systems (RSs) have been widely used in many real-world applications. However, traditional recommendation techniques mainly aim at improving recommendation accuracy, while other metrics to measure the performance of the RSs are not considered. In this paper, a multiobjective recommendation model that considers different metrics, including accuracy, diversity, and novelty of recommendations is established. Compared with recommendation models that only consider accuracy, this model can recommend more different items with higher diversity and more fresh items with higher novelty to enhance the long-term performance of RSs. Moreover, to efficiently solve this multiobjective recommendation model, a multi-population genetic algorithm (MPGA), which follows the multiple populations for multiple objectives (MPMO) framework, is proposed. As far as we know, it is the first time that the advanced MPMO framework is used in RSs. We conduct comparison experiments on three real-world datasets with three state-of-the-art multiobjective recommendation algorithms and two traditional multiobjective evolutionary algorithms. The experimental results indicate that the performance of MPGA is better than all the compared methods.**

Keywords—multiobjective evolutionary algorithms (MOEAs), recommendation system, multiple populations for multiple objectives

I. INTRODUCTION

With the rapid development of society and Internet, there have been a large amount of items and information, which are still growing exponentially. Therefore, it is hard for human beings to find the items that they really need and it is also hard to expose all the valuable items to different users. Recommendation systems (RSs) [1], which can provide guidance for users to choose items, have attracted increasing attention.

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At present, lots of recommendation techniques have been proposed, such as content-based methods [2], collaborative filtering methods [3], and hybrid methods [4]. The content-based methods recommend items mainly through matching the interests of users with the characteristics of items and the interests of users are usually summarized based on the items already chose by this user. Collaborative filtering methods mainly include two working fashions. One is that it would recommend the items chosen by similar users to the target users, which is named as user-based collaborative filtering (User-based-CF). Another one is that it would recommend items similar to the items already chosen by the target user, which is named as item-based collaborative filtering. The hybrid methods are the combination of two or several techniques. In addition, the knowledge graph can also be used to excavate the information of the input data, and improve the recommendation accuracy [5].

However, these traditional recommendation techniques only focus on improving recommendation accuracy. The diversity and novelty of recommendation are not considered. Items that are rated by many users would be recommended frequently and other items cannot be exposed enough, which hurts the long-term performance of RSs. The RSs may also suffer from the cold-start problem.

In order to overcome the above-mentioned problems, some works model the RSs as a multiobjective problem and measure the performance of RSs from different aspects with different metrics. Considering the high effectiveness and efficiency of evolutionary computation [6]-[8], various kinds of multiobjective evolutionary algorithms (MOEAs) are proposed to deal with the models of multiobjective RSs. For example, Zuo *et al.* [9] proposed a MOEA-ProbS method, which was a combination of MOEA and probabilistic spreading algorithm (ProbS). Accuracy and Diversity were considered as two objectives to be optimized by this method. Cui *et al.* [10] designed a new probabilistic genetic operator and proposed the PMOEA to optimize two objectives, including accuracy and diversity. Wei *et al.* [11] focused on the commercial RSs and proposed a hybrid probabilistic MOEA (HP-MOEA) to optimize two objectives, i.e., the total profit and novelty. Zhao *et al.* [12] explicitly considered the interest and profit from both customers and merchants and proposed the cooperative-competitive evolutionary algorithm to optimize three objectives, i.e., the needs of customers, the expectations of merchants, and constraint functions.

Most of these existing multiobjective recommendation algorithms are based on the non-dominated genetic algorithm II (NSGA-II) [16], which is a widely applicable MOEA.

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However, the NSGA-II variants are sometimes not efficient in multiple or many objectives optimization, and many efficient MOEAs have been proposed in the decade, such as algorithms based on multiple populations for multiple objectives framework (MPMO) [18]. To be more specific, two representative MPMO-based algorithms, i.e., coevolutionary multiswarm particle swarm optimization algorithm proposed by Zhan *et al.* [18] and coevolutionary particle swarm optimization algorithm proposed by Liu *et al.* [19] for multi-objective optimization and many-objective optimization respectively, have shown high effectiveness on multiple benchmarks compared with NSGA-II and other traditional MOEAs. Yang *et al.* have developed another MPMO-based algorithm [20] that achieves considerable results. Moreover, the algorithms based on the MPMO framework have also shown competitive performance on various real-world problems, such as cloud workflow scheduling [21], supply chain configuration [22], airline crew rostering [23], job-shop scheduling [24], vehicle routing [25], and cold chain logistics scheduling [26]. In order to further verify the performance of MPMO-based methods and promote the process of multiobjective RSs, we utilize the MPMO framework to solve the multiobjective RSs problem. As far as we know, it is the first time that the MPMO framework is used in multiobjective RSs.

Based on the above-mentioned consideration, we establish a multiobjective recommendation model and propose a multi-population genetic algorithm (MPGA) that also follows the MPMO framework. To sum up, the contributions of this paper are as follows:

1) In the problem formulation aspect, we formalize the RS problem as a multiobjective problem. Moreover, a novel multiobjective recommendation model is established to measure the accuracy, diversity, and novelty of recommendations.

2) In the algorithm design aspect, we propose the novel MPGA to solve the established model and deal with the recommendation problem. To the best of our knowledge, it is the first time that MPMO is used in multiobjective RSs.

3) In the application aspect, we verify the performance of the proposed MPGA on three datasets. These three datasets cover different real-world applications.

The remainder of this paper is organized as follows. Section II details the related work of multiobjective RSs. Section III describes the novel multiobjective recommendation model. Section IV presents the proposed MPGA. Section V verifies the performance of the proposed MPGA through experiments. Finally, Section VI concludes this paper.

II. Related Work

In this section, recent works related to multiobjective RSs are reviewed from the aspects of RSs and MOEAs respectively.

A. Recommendation Systems

RSs mainly aim at finding items that users would enjoy and recommend these items to users. In order to recommend accurately, users' interest and ratings of some items are used as training data and analyzed. A rating matrix is frequently used to represent the training data, with a row representing a user, a column representing an item, and an entry representing the rating if the rating is known. Many entries in the rating matrix may be unknown because some users may only rate a few items.

RSs can excavate more information from users' previous ratings and construct the predicted rating matrix. Traditional recommendation algorithms would recommend items with the highest predicted ratings to the target user. The User-based-CF [27], one of the widely adopted methods, would first calculate the similarity relationship between users through metrics such as cosine similarity. For example, the cosine similarity between user a and user b can be described as

$$sim_{a,b} = \frac{r_a \times r_b}{|r_a| \times |r_b|} \tag{1}$$

where a and b are two different users, r_a and r_b are their rating vectors on all the items.

After that, the predicted rating $pr_{a,i}$ of a for an unrated item i can be calculated based on ratings of a's k most similar users, described as

$$pr_{a,i} = \frac{\sum_{b \in S_{a,k}} sim_{a,b} \times r_{b,i}}{\sum_{b \in S_{a,k}} sim_{a,b}} \tag{2}$$

where $S_{a,k}$ represents the set of k users who have the highest similarity to a and $r_{b,i}$ is the rating of user b for item i.

B. Multiobjective Evolutionary Algorithms

Multiobjective evolutionary algorithms are used to solve problems with two or more objectives. Moreover, these objectives are often conflicting with each other. A minimization multiobjective optimization problem can be formulated as

$$\begin{aligned} &Minimize\ F(x) = \{f_1(x), f_2(x), ... f_M(x)\} \\ &Subject\ to\ x = (x_1, x_2, ..., x_n) \in R^n \end{aligned} \tag{3}$$

where x represents the decision vector in the decision space R^n and $F(x)$ represents the objective vector in the objective space R^M.

Algorithms that are based on the MPMO framework have shown high effectiveness and efficiency to solve the multiobjective optimization problem. MPMO-based algorithms maintain multiple populations and each population is updated according to one corresponding objective and would not be confused by other objectives. Therefore, different populations can search different regions of the Pareto front with the guidance of different objectives. In addition, an archive is utilized to store excellent solutions such as Pareto optimal solutions from different populations and so as to help the multiple populations to generate more promising solutions through evolution operators.

III. Multiobjective Recommendation Model

A multiobjective recommendation model is established in this paper, and three objectives, i.e., accuracy, diversity, and novelty are considered. These three objectives conflict with each other. For example, recommending items that are evaluated with high ratings by some users to other users who have similar preferences can reach high recommendation accuracy. However, the recommendation diversity would be low because that duplicate items are recommended to different users. In addition, in order to deal with the cold-start problem and recommend fresh items to users, the novelty is considered as an objective of this model. Moreover, in order to treat these three objectives equally, we transform these objectives into minimization functions and normalize these three objectives.

A. Accuracy

The first objective of this multiobjective recommendation model is to measure the accuracy of recommendations. However, we cannot access the real ratings during the training stage. Therefore, the predicted ratings are used instead. In this paper, we calculate the predicted ratings through the User-based-CF technique described in Section II-A. Suppose that the predicted rating between the user u and the item i is pr_{ui}, the accuracy of recommendations is the sum of the predicted ratings of all users and the recommendation list related to each user, described as

$$Accuracy = \frac{\sum_{u \in U} \sum_{i \in L} pr_{ui}}{|U| \times |L|} \tag{4}$$

where U is the set of users and L is the recommendation list that contains items.

B. Diversity

The second objective of this recommendation model is to measure the diversity. In order to expose more items, i.e., recommend as many different items as possible, the coverage of items in the recommendation list is adopted to measure the diversity, described as

$$Diversity = \frac{N_d}{|U| \times |L|} \tag{5}$$

where N_d is the number of different items that are recommended to all the users in the recommendation lists.

C. Novelty

The third objective of this recommendation model is to measure the novelty of recommendations. Traditional RS may encounter the cold start problem because there are no ratings for fresh items and the predicted ratings of these fresh items are also not available. To establish an RS with high performance in the long run, we consider these fresh items and measure them through the novelty, described as

$$Novelty = \frac{N_f}{|U| \times |L|} \tag{6}$$

where N_f is the number of fresh items that are recommended to all the users in the recommendation lists.

D. Normalization

In order to fairly measure the effect of these three objectives and calculate the real values of crowding distances, we normalized the objectives to have a scale of [0, 1]. In order to better calculate the hypervolume contribution, we transform these three objective functions into minimization functions by subtracting the objective function value from 1.

IV. PROPOSED MPGA METHOD

A. The Framework of MPGA

In this paper, RS is modeled as a multiobjective problem and a multiobjective recommendation model is established. In order to deal with the model, we incorporate MPMO framework with GA and propose the MPGA. To our best knowledge, it is the first time the MPMO framework is used in multiobjective RSs. Based on the MPMO framework, MPGA maintains an archive and three populations for three

Algorithm 1 MPGA

Begin
Initialize the size of each population SN = 33, objective number M = 3;
The total size of multiple population $N = SN * M$;
Initialize feasible Population P based on the training data;
Evaluate P on all the objectives;
Archive $Ar = P$;
For gen = 1 to 1000 **Do**
    Trial population TP = **Genetic Operator** (P, Ar);
    Trial archive TAr = **Genetic Operator** (Ar, Ar);
    Evaluate TP and TAr on all the objectives;
    P = **Population Update** (P, TP);
    Ar = **Archive Update** (Ar, TP, TAr);
End for
Output the Pareto non-dominated solutions from Ar as the result.
End

corresponding objectives. The pseudocode of MPGA is shown in **Algorithm 1**. The multiple populations and the archive are initialized, as described in Section IV-B. After that, MPGA approaches the Pareto front through iterations. There are mainly three steps in each iteration. First, the trial multiple populations and the trial archive are generated through the genetic operators based on the multiple populations and the archive respectively, as described in Section IV-C. Second, the multiple populations are updated to preserve the solutions that are excellent on the corresponding single objective, which can enhance the local search ability of the algorithm, described in Section IV-D. Third, the archive is updated to preserve the solutions that are excellent on three objectives, which can enhance the global search ability of the algorithm, described in Section IV-E.

B. Initialization

In MPGA, we encode the individual as a matrix. Each row in the matrix represents the recommendation list associated with a user, and each entry is an item recommended to this user. Therefore, an individual is a possible solution to recommend items to users. In addition, it should be noticed that there are two constraints when constructing the matrix. One constraint is that one item cannot be recommended to one user twice. Another constraint is that the rated item by a user cannot be recommended to this user. In MPGA, for the multiple populations, we initialize all the individuals randomly under these two constraints. Moreover, the archive is updated to preserve the individuals in the initialized multiple populations.

C. Genetic Opeators

In MPGA, genetic operators, i.e., crossover operator and mutation operator, are used to generate trial multiple populations and trial archive based on the original multiple populations and archive respectively.

The crossover operator used in MPGA is an extension of the standard uniform crossover operator. Each individual is generated based on two parent individuals A and B. As for the trial multiple populations, A is an individual randomly selected from the corresponding population and B is an individual randomly selected from the archive. As for the trial archive, A and B are two individuals randomly selected from the archive.

The process of crossover operator is described in Fig. 1, and only one row is shown for focus and simplicity. When MPGA generates an individual C based on A and B, the process is carried out row by row. For each row, first, the items

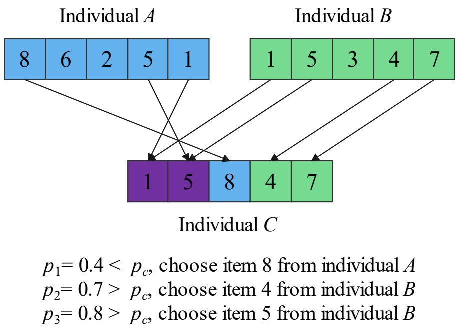

Fig. 1. The process of crossover operator.

appeared in the recommendation lists of both A and B are inherited to the recommendation list of the individual C. In this case, item 1 and item 5 are inherited. Then, if a random number in [0, 1] is smaller than the crossover probability p_c, an item in A is inherited to the individual C. Otherwise, an item in B is inherited. This step is conducted iteratively to fill in the recommendation list of the individual C. In this case, three random numbers are generated and compared with p_c in order to choose three items to fill in the recommendation list, i.e., $p_1 = 0.4 < p_c$ and item 8 from individual A is chosen, $p_2 = 0.7 > p_c$ and item 4 from individual B is chosen, and $p_3 = 0.8 > p_c$ and item 7 from individual B is chosen.

In MPGA, the single-point mutation operator is conducted after the crossover operator. For each row in an individual, an item is randomly selected. If a random number in [0, 1] is smaller than the mutation probability p_m, this item is discarded and another available item is selected under the constraints described in Section IV-B. Otherwise, the item would not be changed. The pseudocode of the genetic operator is given in **Algorithm 2**.

D. Population Update

In MPGA, after generating trial individuals based on the multiple populations, the multiple populations are updated to preserve the excellent individuals. For each population that aims at optimizing one corresponding objective, all the individuals in this population and all the individuals in the corresponding trial population are merged and sorted according to the corresponding objective. And half of the individuals with better objective value in the merged list are inserted into the new population. The pseudocode of the population update is given in **Algorithm 3**.

E. Archive Update

In MPGA, we merge all the individuals in the original archive, trial multiple populations, and trial archive together. The non-dominated ranking method [13] is adopted to sort the individuals in the merge list. Then, add the individuals in the first non-dominated front into the new archive. If the number of individuals in the new archive is less than the maximum size, the individuals in the next non-dominated front are added until the number of individuals in the new archive is equal to or greater than the maximum size of the archive. If the number of individuals in the new archive is greater than the maximum size of the archive, some individuals are deleted based on the crowding distance [14] to ensure the diversity of the archive individuals. In this paper, the archive maximum size is the same as the sum of the size of three populations for simplicity. The pseudocode of the archive update is given in **Algorithm 4**.

Algorithm 2 Genetic Operator (P_1, P_2)

```
Begin
Trial population TP = ∅;
For i = 1 to N Do
    Generate a random number a in range [0, 1];
    Generate a random number b in range [0, 1];
    Individual A = P_{1,a};
    Individual B = P_{2,b};
    Individual C = crossover and mutation operator between A and B;
    TP = TP ∪ {C};
End for
Return TP;
End
```

Algorithm 3 Population Update (P, TP)

```
Begin
Population P* = ∅;
For i = 1 to M Do
    MP = Merge the i^th population of P and i^th population of TP;
    Sort MP based on the i^th objective function;
    BMP = Half of individuals in MP with better i^th objective value;
    P* = P* ∪ BMP;
End for
Return P*;
End
```

Algorithm 4 Archive Update (Ar, TP, TAr)

```
Begin
Archive Ar* = ∅;
MP = Merge Ar, TP, and TAr together;
{F_1, F_2, …, F_n} = Non-dominated sort MP;
Initialize i = 0;
While |Ar*| < N Do
    Ar* = Ar* ∪ F_i;
    i = i + 1;
End while
If |Ar*| > N Then
    Delete some individuals from Ar* based on crowding distance;
End if
Return Ar*;
End
```

V. Experimental Analysis

In this section, the experimental datasets are first described. Then, the experiment is set up. After that, the parameter settings of the proposed MPGA and the compared algorithms are given, and the experimental results are shown and analyzed. Last, the conflicting relationship of multiobjective recommendation model is verified.

A. Experimental Datasets

We evaluate our methods on three datasets, i.e., MovieLens-1M (ML-1M), Last.FM, and Jester Dataset4. These three datasets vary significantly in user number, item number, and sparsity. Sparsity is the known user-item relation over the total user-item pairs. Therefore, these three datasets can measure the robustness of the method in different sparse applications, as described in TABLE I:

1) ML-1M (https://grouplens.org/datasets/movielens/1m/): this dataset

TABLE I
PROPERTIES OF THE THREE DATASETS

Datasets	Users	Items	Relations	Sparsity
MovieLens-1M	6040	3952	1000209	4.19e-02
Last.FM	1892	17632	92834	2.78e-03
JesterDataset4	7699	158	106489	8.75e-02

contains 1000209 anonymous ratings of 3952 movies (items) provided by 6040 users. The data is collected from the MovieLens website. The rating ranges from 1 to 5 and a higher rating means that the user likes this movie better.

2) Last.FM (https://grouplens.org/datasets/hetrec-2011/): this dataset consists of 1892 users, 17632 artists, and 92834 listening relations between users and listened artists (items). The data is collected from the Last.FM online music website. The rating is the number of listen for each relation and a higher rating means that the user likes this artist better.

3) Jester Dataset4 [16]: This dataset contains 7699 users, 158 jokes (items), and 106489 anonymous ratings of jokes by users of the Jester joke recommendation system. The data is collected from April 2015 to Nov 2019. The rating ranges from -10 to 10 and a higher rating means that the user like this joke better.

In order to better deal with the data in these three datasets, we apply a normalization process to the ratings. To be specific, we scale the ratings to [-1, 1], where a negative value means dislike and a positive value means like. Besides, an item is defined as a fresh item if it is rated by fewer than 5 users.

B. Experiment Setup

To set up the experiment, the dataset should be divided into training set and test set. In this paper, for each dataset, 80% of the data is randomly selected as the training set, and the rest makes up the test set.

In addition, the hypervolume [28] is adopted as the performance metric, which is a widely used metric to compare different MOEAs. The hypervolume of the non-dominated solution set can assess the portion of the objective space that is covered by these solutions. It should be noticed that the reference point is set as (1,1,1) in this experiment. Therefore, we can determine if one solution set is superior than the other through hypervolume.

C. Parameter Settings and Experimental Results

In order to validate the effectiveness of the proposed MPGA, we compare the proposed MPGA with various kinds of algorithms. Generally speaking, these comparison algorithms can be classified into two categories, i.e., multiobjective recommendation algorithms and MOEAs. All the algorithms are implemented on a PC with Core i7, 8GB RAM, Windows 11, and are compiled with Python 3.8.10.

1) Multiobjective Recommendation Algorithms: Three novel multiobjective algorithms that are designed for recommender systems, i.e., MOEA-ProbS [10], PMOEA [11], and HP-MOEA [12], are selected for comparison.

2) MOEAs: Two representative MOEAs, i.e., NSGA-II [17] and NSGA-III [18], are implemented to optimize the proposed multiobjective recommendation model and tested on the datasets.

The parameter settings of these algorithms are given in TABLE II. N is the size of population if only one population is maintained, and N is the total size of multiple populations if two or more populations are maintained. For MPGA, the size of each population is set as 33 and the total size of three populations is 99. T is the maximum generation size, in order to keep the number of function evaluation times the same among all the algorithms, T is set as 1000 for MPGA and set as 2000 for other algorithms. L is the length of recommendation list, p_m is the crossover probability, k is the number of similar users who are used in User-based-CF, p_c is the mutation probability, p_n is the number of parents used in the crossover operator for PMOEA.

TABLE II
PARAMETER SETTINGS OF ALGORITHMS

Algorithms	Parameter settings
MPGA	$N = 99$, $T = 1000$, $L = 5$, $p_m = 1/L$, $k = 20$, $p_c = 0.5$
MOEA-ProbS	$N = 100$, $T = 2000$, $L = 5$, $p_m = 1/L$, $k = 20$, $p_c = 0.8$
PMOEA	$N = 100$, $T = 2000$, $L = 5$, $p_m = 1/L$, $k = 20$, $p_n = 5$
HP-MOEA	$N = 100$, $T = 2000$, $L = 5$, $p_m = 1/L$, $k = 20$
NSGA-II	$N = 100$, $T = 2000$, $L = 5$, $p_m = 1/L$, $k = 20$, $p_c = 0.5$
NSGA-III	$N = 100$, $T = 2000$, $L = 5$, $p_m = 1/L$, $k = 20$, $p_c = 0.5$

The proposed MPGA is compared with three multiobjective recommendation algorithms (i.e., MOEA-ProbS, PMOEA, and HP-MOEA) and two MOEAs (i.e., NSGA-II and NSGA-III) on three datasets. Each algorithm is run 30 times independently, and TABLE III records the mean values and standard deviations of hypervolume. The algorithm with higher mean hypervolume value and lower standard deviations indicate that this algorithm is better. The highest mean values and lowest standard deviations for each dataset are also highlighted in bold. From TABLE III, it is clear that the proposed MPGA achieves the highest mean values on all the three datasets and the lowest standard deviations on two datasets. It indicates that the proposed MPGA can outperform all the compared algorithms on these three datasets and that MPGA is robust.

D. Conflicting Relationship of multiobjective RS model

The multiobjective RS model proposed in this paper includes three objectives, i.e., accuracy, diversity, and novelty. The conflicting relationship between any two objectives should be verified. Therefore, we use the parallel coordinate plot [29] to analyze the conflicting relationship of these three objectives, which is a frequently used technique to visualize high-dimensional multivariate data. Fig. 2 shows the parallel coordinate plot of MPGA on dataset MovieLens-1M. Similar results can be obtained for other algorithms and other datasets. From Fig. 2, it is clear that line segments between any two objectives are crossed, which indicates that any two objectives of the proposed multiobjective RS model are conflict.

VI. CONCLUSIONS

In this paper, we establish a novel multiobjective recommendation model and propose the MPGA algorithm to deal with it. It is the first time to use the MPMO framework in multiobjective RS as far as we know. The proposed MPGA

TABLE III
HYPERVOLUME VALUES OF ALL ALGORITHMS FOR THREE DATA SETS

Dataset	MPGA		MOEA-ProbS		PMOEA		HP-MOEA		NSGA-II		NSGA-III	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
MovieLens-1M	**0.7140**	**0.0065**	0.4556	0.0582	0.5027	0.0256	0.6848	0.0071	0.6957	0.0088	0.6042	0.0250
Last.FM	**0.5863**	0.0202	0.5690	0.0174	0.5443	**0.0143**	0.5805	0.0180	0.5785	0.0209	0.4727	0.0367
JesterDataset4	**0.5678**	**0.0092**	0.3266	0.0266	0.3815	0.0246	0.5644	0.0120	0.5563	0.0144	0.4459	0.0203

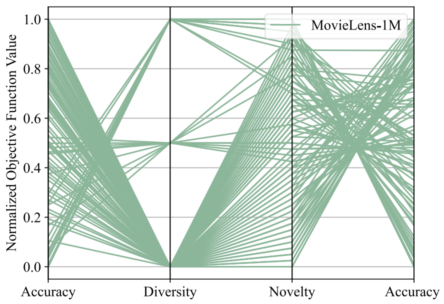

Fig. 2. The parallel coordinate plot of MPGA on dataset MovieLens-1M.

uses the designed genetic operators to generate promising solutions for multiple populations and archive. Moreover, the multiple populations are updated with the guidance of one corresponding objective, and the archive is updated based on the non-dominated sort and crowding distance. The proposed MPGA is tested on three real-world datasets and compared with three multiobjective recommendation algorithms and two traditional MOEAs. Experimental results show that MPGA can outperform these three multiobjective recommendation algorithms and these two MOEAs on the hypervolume contribution, which can verify the robust and excellent performance of MPGA.

Our future work mainly includes two aspects. On one aspect, we will further improve the performance of MPGA by combing MPGA with some mathematical methods or deep learning techniques [30]. On the other aspect, we will assess MPGA on more datasets with different sparsity, and compare MPGA with more methods.

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