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Research paper

Enhanced pareto multi-objective artificial bee colony optimization for collaborative recommender system

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Abstract

Recommender systems (RS) are systems that filter information and help users to choose products from a large amount of information available online. RS recommend satisfactory and useful products (items) like movies, music, books, and jokes to target users that they are interested in. The majority of traditional recommendation algorithms mainly concentrate on improving the performance accuracy; thus, these algorithms tend to suggest only popular items. Furthermore, diversity is another important non accuracy metric for personalized recommendations to suggest unusual or different items. To balance the conflict between accuracy and diversity, multi-objective optimization algorithms are used, which maximize these conflicting metrics simultaneously. The present article proposes an enhanced Pareto multi-objective artificial bee colony optimization algorithm for collaborative recommendation systems (EPMABC-RS). Artificial bee colony optimization is performed using the crossover operator to exchange useful information for improving local search. Important data are fully exploited, and the algorithm is expected to converge rapidly and give more accurate recommendation results. The proposed algorithm optimizes the two objective functions simultaneously and gives a set of solutions, in which no solution dominates the other in the set. Each solution suggests a distinct recommendation result to users. Decision makers can choose a recommendation according to their requirements. The findings reveal that the EPMABC algorithm is more effective in providing a set of different recommendation results with accuracy and diversity of items for the target user.

Keywords: *Pareto Optimal; Multi-Objective Recommender System; Artificial Bee Colony Optimization*.

1. Introduction

The rapid development of science and technology in recent years has led to the availability of massive amount of digital information on the Internet. Thus, the problem of information overload occurs; therefore, users are not able to obtain accurate information that they are interested in. The information overload problem can be solved using Recommender Systems (RS) by filtering irrelevant information and suggesting related items to users. To predict users' preference or interests, RS use their information history such as personal details, rating data, browsing history, purchasing details, and social networks (Face book). RS are used in online search queries like movies, books, music, and tourism.

RS can be categorized into three main types: content-based filtering method (CB), collaborative filtering method, and hybrid filtering method. CB recommends items that match with those liked by the user previously with regard to the item's content. The item contents are keywords, descriptions, categories, etc. This provides useful information on items of users' preferences [1]. For example, a restaurant-based RS follows a structured representation by using the attributes of a restaurant such as food, budget, and furnishing. Neural networks, decision trees, and vector-based methods have been used to represent the items' content profile. Collaborative filtering (CF) consists of two main steps. In the first step, the algorithm evaluates the preference behaviors of an active user and finds other users who have interests similar to those of the active user. In the second step, the preferences of the target user are predicted from the information of similar users. This method is based on the concept of discussing with our friends to take decisions such as which book to read or which movie to watch. For example, the Amazon website uses collaborative RS to recommend items to users. Traditional CF algorithms are classified into memory- and model-based methods [2]. Memory-based filtering method utilizes the complete item rating history of users to predict preferences of the target user. Similarity methods are used in these algorithms to determine the resemblance between the target user and other users. The basic and traditional similarity methods include Pearson correlation, cosine similarity, constrained Pearson correlation coefficient, and Spearman correlation. Finally, the nearest N neighbors are found for predictions. In a model-based collaborative RS, a user model is developed offline, and this model is then applied online for recommendation. Data mining methods, for example, clustering and association rule mining, are used to develop the offline model. Model-based methods require less time than memory-based ones. However, memory-based predictions are more accurate than model-based predictions. Collaborative and CB RS methods also have their own disadvantages. Therefore, hybrid RS that combine different recommendation algorithms are used [3].

The three drawbacks of traditional recommendation algorithms are sparsity, scalability, and cold start, which reduce their prediction accuracy [4]. CF is based on explicit feedback, e.g., ratings, given by users to an item. The user-item input data matrix could contain rating values for few items among all the available items. Therefore, this creates a sparse item rating matrix, over which effective similarity cannot be calculated; this affects the performance of an RS. There are millions of users, and several items are available online; therefore, an RS should have a high computational accuracy in finding the nearest neighbors. This is called the scalability issue, which affects the performance of RS. Cold start occurs when the system has a new user/new item, and no previous rating history of the user/item is found in the rating table. Accuracy is the most important performance metric in traditional RS. Traditional RS provide maximum accuracy in predicting items that might be liked by a particular user. On the other hand, accuracy-based RS recommend only popular items but not unpopular items, thus providing similar recommendations for all users [5]. They cannot provide good results on nonaccuracy indicators such as diversity and novelty. Thus, an accuracy-based method is not appropriate to suggest the most relevant and novel items to users, thus making it possibly much less useful to users. Therefore, diversity and accuracy are considered simultaneously to recommend unpopular items [6-8]. If we consider the high accuracy of RS, the diversity of recommendations will definitely decrease. Similarly, highly recommending diverse items to users may also decrease the recommendation accuracy. Because accuracy and diversity are two conflicting performance metrics for RS. Thus, a critical challenge in personalized RS is how to simultaneously maximize the accuracy and diversity. Several types of Recommendation techniques have been developed to obtain recommendation lists that are both accurate and diverse. The three performance metrics of RS, namely accuracy, novelty, and diversity, can be defined as follows:

Accuracy: It specifies the degree of match between the top-N items and the preferences of the user.

Novelty: It indicates how much novel the top-N items are to the user.

Diversity: It shows how the suggested items are different from each other on the top-k items.

In this article, a multi-objective RS is proposed using the traditional CF method with multi-objective ABC algorithm to obtain diverse recommendation lists without decreasing the accuracy of the system.

The following are the main highlights of the present study:

1) The optimization technique artificial bee colony (ABC) is employed for the first time in multi-objective RS. The uniform crossover operator is implemented for the onlooker bee to exchange useful data, thus improving both the diversity of solution space and the performance of the Recommendation algorithm.
2) The findings yielded by the suggested algorithm are compared with the results obtained by some traditional Recommendation techniques, and the suggested algorithm showed improved performance as compared to the other methods.

This article has the following structure. Section 2 details previous studies on CF and multi-objective Recommender algorithms. Section 3 explains the concept of CF-based RS. In Section 4, we propose a multi-objective RS using ABC optimization algorithm. Section 5 validates how the suggested algorithm performs on the MovieLens dataset, and the obtained findings are compared with those of the other existing methods. Lastly, Section 6 summarizes the study and provides suggestions for future investigations.

2. Related studies

Various methods have been suggested to obtain novel and diverse items simultaneously. In [9-11], the authors pointed out these two objectives and highlighted the significance of a good RS. McNee [9] showed that an accuracy-based method is unfavorable for RS. The main drawback of this method is that it focuses more on accuracy than diversity. Accuracy-based method suggests similar or popular products. But, it is definitely not sufficient for a providing a good RS. Zhou [10] developed a new network-based inference RS that eliminates redundant correlations, thus providing better diversity and popularity as well as accuracy than existing Collaborative methods. Castells [11] explained two features, namely ranking sensitivity and relevance awareness, to model user-item interaction for calculating novelty and diversity. Ma et al. [12] developed an algorithm based on bidirectional transfer to find a solution for the conflict problem. Belem et al. [13] proposed a tag RS by using a novel diversification method to solve the diversity problem. Panniello [14] compared many context-aware RS in terms of accuracy and diversity to determine which performs better. Ziegler et al. [15] estimated the diversity value by using the dissimilarity rank method. Bobadilla et al. [16] provided an overall outline of accuracy and nonaccuracy metrics. Zhang [17] proposed a trust region algorithm, which improves diversity and accuracy simultaneously. Adomavicius [18] introduced many item ranking methods for providing recommendations that are both diverse and accurate. Zhou [19] proposed a hybrid HeatS algorithm to improve simultaneously the diversity and accuracy. By using integrated diffusion on user-item-tag tripartite graphs, Zhang and Zhou [20] developed an RS. Rodriguez proposed [21] an RS that enhances the utility of the system by using additional relevance features in an additional stage. Hurley [22] proposed a multi-objective RS that considers the diversity and similarity as the objectives. Ribeiro [23] proposed a hybrid algorithm using the weighted combination of existing algorithms considering the parameters of accuracy, diversity, and novelty. Zhou et al. [24] proposed two heat diffusion algorithms to solve the accuracy–diversity tradeoff problem. Mikeli [25] proposed a model-based RS using multiple criteria. Shi [26] introduced a Markovian graph-based RS with transition probabilities that satisfy accuracy, diversity, similarity, and long tail objectives.

The majority of CF-based methods focus on item rating-based prediction that recommends the top-N items for a user. These algorithms satisfy the accuracy metric because it recommends items that have a high rating value. But, they do not assure on nonaccuracy metrics of recommendations. Only a very few algorithms that consider both these metrics have been proposed for RS. In this paper, we minimize the problem by proposing the Pareto-based efficiency method, which is used in economics theory. That is, one action (objective) does not affect other actions. The same idea is utilized in developing multi-objective RS, which give different recommendations to users. Every recommendation result is a balance result between the two conflicting objectives. Recently, a large number of multi-objective algorithms such as MOEA/D [27] and NSGA-II [28] have been proposed. We design a multi-objective ABC optimization with the traditional collaborative filtering method that optimizes the two objective functions, namely diversity and accuracy, simultaneously.

Traditional CF algorithms provide only one solution at a time, while the multi-objective RS provides a set of different solutions at a time, and each solution represents a unique set of recommended suggestions. This allows the decision makers or target users to select one suitable recommendation result among the various suggestions. A previous study on related work revealed that only very few studies have been conducted on multi-objective RS. This motivated us to apply multi-objective ABC optimization for the first time in solving the multi-objective conflicting problems of an RS. Thus, in this study, we improve the Pareto multi-objective ABC optimization algorithm with the crossover operator. This improves the pareto-optimal solutions of RS in terms of different parameters such as precision, novelty, and diversity.

3. Collaborative recommender system

In this section, we explain the basics of item similarity calculation, prediction, and top-N recommender system.

3.1. Introduction of collaborative filtering recommender system

Most of famous online website systems like Amazon use the CF technique because of the simple framework of CF. As already mentioned traditional CF algorithm is further classified into two types: model-based and memory-based methods. Each method has its individual features. Model-based methods can solve the sparsity issue. But, the development of the model is expensive. Memory-based algorithms can decrease the scalability problem and can be easily implemented than model-based algorithms. Memory-based methods are further categorized into methods based on user and item. User-based CF algorithms are designed on information of neighboring users who have identical interests. The user-based CF algorithm first determines how much the target user is similar to all other users. From this similarity value, the k nearest neighbors for the target user are found. Finally, the item ratings are predicted by using the neighbors' average ratings. Cosine similarity is the commonly used method for similarity computation. Item-based CF algorithm is identical to user-based algorithm; however, in the latter, the similarity value is calculated between items, whereas in the former, it is calculated between users.

3.1.1. Item-based collaborative filtering

Item-based CF is a widely used technique for RS. It is also called as the nearest neighbor recommendation algorithm [29]. The steps of item-based CF are described below.

3.1.1.1. Computation of item similarity

In similarity computation, an important step in item-based CF, the extent of similarity between two items is calculated using items' rating values. The traditional similarity methods are cosine- and correlation-based similarity methods.
The similarity between items i and j is estimated by cosine similarity and is determined as follows:

$$S_{i,j} = \frac{r_i \cdot r_j}{|r_i| \cdot |r_j|} \quad (1)$$

Where $S_{i,j}$ is the similarity between the items i and j and r_i and r_j are the rating vectors of items i and j, respectively.

3.1.1.2. Prediction

After obtaining the similarity between the target item and other items, the ratings are predicted from the weighted sum of k nearest items' ratings.
The rating predicted for an item 'i' is calculated as follows:

$$P_{u,i} = \frac{\sum_{j \in N} (S_{i,j} X r_{u,i})}{\sum_{j \in N} |S_{i,j}|} \quad (2)$$

Where N is the number of neighbors for item i, $P_{u,i}$ is the prediction of item i for user u, $S_{i,j}$ denotes the similarity extent between items j, and I and $r_{u,i}$ indicates the rating of item i given by user u.

3.1.1.3. Rating prediction of top-n recommender system

The RS output can be obtained in two steps:
1. Prediction 2. Recommendation
Prediction: It predicts the rating of unrated items for the target user.
Recommendation: The top-N recommendations are suggested to the target user according to their prediction scores. The recommender results should be most liked by the user. The top-N recommendations do not need a rating value for each item.

4. The proposed method

In this section, we explain the proposed multi-objective ABC optimization-based recommendation algorithm.

4.1. Multi-objective ABC optimization

The recommendation problem is considered as a multi-objective problem in recent years, and a multi-objective RS gives more comparable results than single-objective RS. Studies on multi-objective RS are very few. In this paper, we attempt to use the multi-objective ABC optimization method in RS. Karaboga introduced the ABC optimization meta-heuristic algorithm in 2005 [30], and this algorithm depends on the smart foraging behavior of honey bee swarms. The basic ABC algorithm provides good results in optimization because of its several advantages such as memory, local search, and solution improvement mechanism. The artificial bee colony involves three groups: employed bees, onlooker bees, and scout bees, which perform different jobs by working together. Employed bees randomly search new food sources (solutions) by interaction with their neighbors. If a new food source is of better quality than the previous one, then the former replaces the latter. Then, onlooker bees select one of these food sources according to their quality (fitness value) exploited by employed bees and improve the quality of such food sources. Scout bees perform exploration procedure to search the poorest food sources, which are yet to be optimized in few cycles, and reinitialize them.

4.2. Proposed EPMABC-RS

The proposed EPMABC-RS gives a different recommendation list to each user. The architecture of the suggested algorithm is given in Fig. 1. The proposed EPMABC-RS algorithm has two main steps: (1) item rating prediction and (2) EPMABC-RS.

4.2.1. Item rating prediction

An item-based CF algorithm first predicts the unrated items and then provides a recommendation list to each user. A detailed explanation is provided in section 3.1.1.

4.2.2. EPMABC-RS

After item rating prediction, EPMABC-RS is used to optimize the recommendation results, which have better diversity and accuracy. Then, it provides different recommendation lists to the target user.

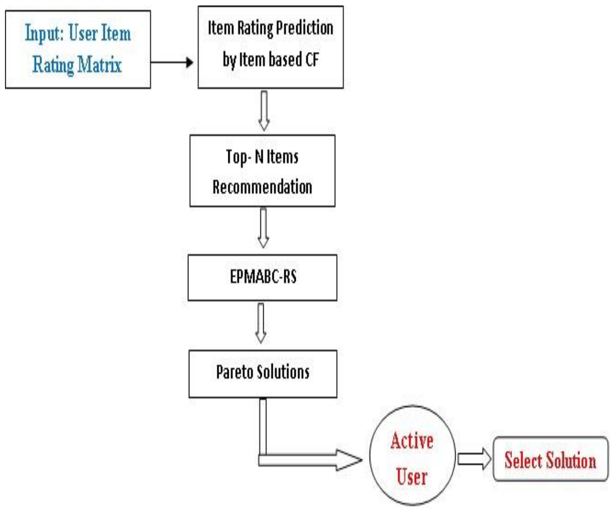

Fig. 1: Architecture of Proposed Approach.

4.2.2.1. Objective functions

Multi-objective algorithms depend on the objective functions. In this proposed framework, two conflicting objectives are considered, namely diversity and accuracy, to get a good recommendation list. The former is the sum of ratings of items given in the recommendation list, and the latter objective function measures the diversity of items (unpopularity).
Objective function of Accuracy:
The traditional CF methods recommend items depending on the predicted ratings. The accuracy metric measures the popularity of recommendation results. The objective function of accuracy is defined in Eq. (3).

$$F_1 = \sum_{i=1}^{k} \hat{r}_{u,i} \quad (3)$$

Where k represents the length of the recommendation list for a user and $\hat{r}_{u,i}$ is the predicted rating of item 'i' by user u.
Objective function of Diversity:
Recently, several RS use non accuracy measures for prediction. For example, the diversity metric measures the unpopularity of recommendation results. A diversity-based RS might find something new to the user that might be liked by him/her. The objective function of diversity is given as

$$F_2 = \sum_{j=1}^{k} \frac{1}{\mu_i(\sigma_i+1)^2} \quad (4)$$

Where μ_i and σ_i are the mean and variance of ratings of item j (rated by all users), respectively.
Optimization problem is formulated by combining the above two objective functions. These objective functions must be maximized simultaneously. The above two objective functions with CF can give an optimal recommendation results in terms of accuracy and diversity. The Objective function is formulated as follows.

$$\begin{cases} \text{Max} F_1 = \sum_{i=1}^{k} \hat{r}_{u,i} \\ \text{Max } F2 = \sum_{j=1}^{k} \frac{1}{\mu_i(\sigma_i+1)^2} \end{cases} \quad (5)$$

4.2.2.2. Population initialization

Item-based CF predicts the unrated items of the target user. In our proposed method, each food source functions to resolve the problem and the three types of forager bees are analogous to the three different search phases of the algorithm.
Every food source is represented as $X = \{x_1, x_2, x_k\}$, where $x_i \in [1, L]$. Every element indicates the item ID in CF-L. k is the length of the final recommendation. Thus, each food source represents a recommendation list. The individual representation of a food source is shown in Fig. 2.
Every item in the food source must be different and not repeated. The initial population is generated using a random method by using Eq. (6).

$$x_{id} = \rho b_d + rand(0,1) \cdot (ub_d - \rho b_d) \quad (6)$$

54	4	23	116	70	18	48	43	98	271

Fig. 2: Individual Representation of EPMABC-RS.

Where 'i' represents the index of solution with range i=1, 2… solutions and'd' is the dimension index of each solution with range d=1, 2…D.
In our work, D is the length of recommendation and is set as 10, and rand (0, 1) is a uniformly distributed real random number over [0-1]. ρb_d and ub_d are the lower and upper bounds of solutions.

4.2.2.3. Employed bee Phase

The employed bee phase applies the exploitation search procedures to produce novel food sources in the neighboring area of a given food source.
The neighboring food sources are found using Eq. (7).

$$V_{id} = x_{id} + Q_{id} \cdot (x_{id} - x_{kd}) \quad (7)$$

Where k is a random neighbor, which is different from 'i', x_{id} is the old solution, d is the randomly selected dimension, and Q_{id} is the range of values in the interval [-1, 1].
Subsequently, the efficiency of the new food source is calculated using objective functions, and the greedy method is applied to the original and new food sources. The better ones will be stored in the memory.

4.2.2.4. Onlooker bee phase

In the traditional ABC algorithm, the onlooker bees collect the data shared by the employee bees on food sources and select a food source according to the probability in terms of the fitness value of the solution. The probability is estimated using Eq. (8) as given below:

$$Pi = \frac{f(x_i)}{\sum_{i=1}^{NS} f(x_i)} \quad (8)$$

Where $f(x_i)$ is the fitness of solution i and NS is the total number of solutions.
Because the random selection method is not effective, we use the crossover operation for effective information exchange for providing better neighborhood solutions. The crossover operation has the following steps. After choosing the food sources using probability, each onlooker bee generates a new food source in the neighboring area by using the crossover operator, as shown in Fig. 3.This improves its spatial search capabilities. Finally, the method of greedy selection is used for the original and new food sources. If the new solution fits better than the current solution, then the new one is used as a replacement; otherwise, the current solution is retained. The crossover point is the 4th element.

Parent 1

54	4	23	116	70	18	48	43	98	271

Parent 2

43	37	2	53	11	97	10	9	1	4

Child 1

54	4	23	53	11	97	10	43	98	271

Child 2

43	37	2	116	70	18	48	9	1	4

Fig. 3: Illustration of the Crossover Operation. Given Two Food Sources Are Selected as (Recommendation Lists) Parent1 and Parent2, respectively, and the Child Food Sources Child 1 and Child 2 are created by the Crossover Operation.

4.2.2.5. Scout bee phase

For a maximum number of iterations, any solution that is unable to update itself is regarded as an abandoned solution, and that solution is called as scout bee. The control parameter for scout bee is defined as a trial or limit. Such abandoned food sources are replaced with new solutions randomly, thus improving the population diversity (exploration) to a certain level.

$$\text{Limit} = (SN*D) \quad (9)$$

Where 'D' is the dimension of the problem and 'SN' is the number of food sources or employed bees.
This process is repeated until a Convergence criteria is satisfied such as a Maximum Iteration Count (200).

5. Experimental studies

5.1. Data set

Our proposed method EPMABC-RS is evaluated for performance and compared with traditional item-based CF methods. The Movie Lens dataset, a popular and publicly available dataset, is used to test the efficiency of EPMABC-RS.

5.2. Experiment settings

Table 1 lists the parameters studied in our experiments. MATLAB is used to run the experiments. The population size (SN) and the Maximum Iteration Count (MIC) was 100,200 respectively. 'N' is the number of neighbors for active user to recommend items.

Table 1: Parameters

Parameter	Meaning	Value
L	Length of the CF recommendation list	50
k	Length of the final recommendation list	10
SN	Size of the population	100
MIC	Maximum Iteration Count	200
N	Number of neighbors	10

5.3. Performance metrics

Different parameters are used to verify the performance of a Recommendation algorithm. The parameters of precision, diversity, and novelty are used to measure the performance of the proposed EPMABC-RS.

5.3.1. Precision

Precision represents the proportion of recommended items relevant to a user from the total items in the final recommendation list. The more is the precision of a recommendation algorithm, the more accurate are the results provided by the RS. Precision is calculated as given below:

$$Precision = \frac{N_{ri}}{K} \quad (10)$$

Where K is the length of the recommendation list and Nr_i is the number of relevant items in the top k recommendation list.

5.3.2. Diversity

Diversity measures the average rarity of items in the recommendation list and can be calculated as follows:

$$d = \frac{1}{k(k-1)} \sum_{a \neq b} s(a, b) \quad (11)$$

Where k is the length of the recommendation list, and s(a, b) is the similarity extent between items a and b in the recommendation list. The suggested recommendation lists are more diverse (different), if the intra-user diversity has a low value.

5.3.3. Novelty

Novelty is described as the average degree of recommended items. Novelty is defined on the basis of popularity and is calculated using Eq. (12)

$$Novelty = \frac{1}{L} \sum_{i \in R_t} d_i \quad (12)$$

In the above equation, L represents the length of the recommendation list, d_i is the degree of item 'i', and R_t is the final recommendation list. The lower the popularity value, the higher is the novelty of the recommendation.

5.4. Experimental results

We use the proposed EPMABC-RS on the Movie Lens dataset [31], which is available on the Group lens website (http://www.grouplens.org/). This dataset consists of 943 users on 1682 movies with 1, 00, 000 ratings (1–5), and each user has rated up to 20 movies. The performance of EPMABC-RS is investigated by partitioning the entire MovieLens dataset into 80% and 20% of training and test data, respectively. In CF, the number of nearest neighbors for an active user is set as 10. The latent factors in matrix factorization (MF) and PureSVD are set as 20. Our proposed method can provide a number of recommendation lists to the target user. Table 2 shows recommendation lists for the first 10 users of EPMABC-RS. It is shown that the proposed RS generates only one recommendation list for the fourth user and more than 25 recommendation results for all other users. The Pareto front of EPMABC-RS of the sixth user is shown in Fig. 4. It gives 26 different recommendation results to the sixth user of MovieLens. Each point in the figure represents a different recommendation result. Every result is a tradeoff between the two objective functions. The point 'b 'which is on the right corner in Fig. 4. has the highest accuracy, but lowest diversity. The result 'a' which is on the left corner has the highest diversity, but accuracy is poor. The algorithm is evaluated for performance by comparing with those of existing Recommendation algorithms: (1) user-based (u-CF), (2) item-based (i-CF), and (3) matrix factorization algorithms.
u-CF and i-CF algorithms are the traditional RS algorithms. The MF method [32] represents both users and items in the same joint latent factor space.

Table 2: Number of Recommendations to the First 10 Users

Number of solutions										
ID	1	2	3	4	5	6	7	8	9	10
Movie Lens	49	48	53	1	45	26	48	55	25	31

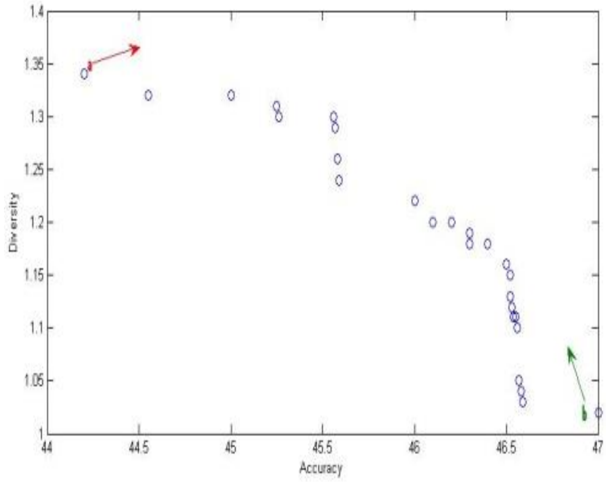

Fig. 4: Pareto Results of the Sixth User.

Table 3 presents the excellence of the proposed scheme evaluated on the MovieLens dataset. "Maxi" and "mini" indicate the maximum and minimum values of all the recommendation lists, respectively. "Mean" is the average precision of all the recommendation lists for a user. Only the fifth user's average mean value of our algorithm is better than the values of the existing algorithms. But the proposed EPMABC-RS has better precision than the existing algorithms: the maximum values obtained for the third, fifth, and tenth users in the proposed method are higher than those obtained in other methods. The precision of our algorithm is equal or less than those of other CF algorithms for other users. The conclusion is that the recommendation results of u-CF, i-CF, and MF methods are just one among those of the Pareto solutions obtained by EPMABC-RS.
The diversity of our algorithm and other methods is given in Table 4. Only four users have their mean values of EPMABC-RS less than those of existing methods. The first, sixth, and ninth users are

recommended more diverse lists by EPMABC-RS than those by the other methods. Because its diversity values are less than other methods.

Table 3: Precision Metric on Movie Lens Dataset

Movie Lens				EPMABC-RS		
User Id	u-CF	i-CF	MF	Mini	Maxi	mean
1	0.4	0.3	0.2	0.1	0.3	0.2
2	0	0	0	0	0.1	0.013
3	0.1	0.4	0.2	0.1	**0.5**	0.214
4	0	0.1	0	0	0	0
5	0.1	0.1	0	0.1	**0.5**	**0.255**
6	0.5	0.2	0.3	0.1	0.2	0.078
7	0.3	0.3	0.1	0.1	0.3	0.180
8	0	0.2	0.1	0	0.1	0.02
9	0.1	0	0.2	0	0.1	0.09
10	0.4	0.4	0.3	0.5	**0.6**	0.34

Table 4: Diversity Metric on Movie Lens Database

Movie Lens				EPMABC-RS		
User Id	u-CF	i-CF	MF	Mini	Maxi	mean
1	0.042	0.038	0.41	**0.013**	0.1	0.057
2	0.123	0.213	0.137	0.121	0.14	**0.094**
3	0.1	0.2	0.2	0.1	0.5	0.3
4	0.084	0.09	0.05	0.113	0.113	0.113
5	0.118	0.218	0.345	0.063	0.021	**0.092**
6	0.023	0.029	0.019	**0.005**	0.082	0.042
7	0.056	0.057	0.059	0.022	0.089	**0.045**
8	0.024	0.025	0.192	0	0.026	**0.006**
9	0.073	0.061	0.031	**0.072**	0.123	0.09
10	0.4	0.21	0.03	0.5	0.6	0.54

Table 5: Novelty Metric on Movie Lens Dataset

Movie Lens				EPMABC-RS		
User Id	u-CF	i-CF	MF	Mini	Maxi	mean
1	98.1	111.2	431.2	18.9	119.7	**84.61**
2	81.8	78.2	291.2	**67.8**	115	91.87
3	21.8	18.2	35.7	150.1	151.2	**12.32**
4	210.2	281	423.6	151.1	150.4	**141.1**
5	53.8	87.2	115.2	32	66.9	**51.09**
6	139.22	149.2	189.0	51.8	128	**78.3**
7	82.9	71.2	192.7	48.0	130.2	**75.9**
8	149.7	152.1	192.1	71.2	176.2	**109.3**
9	71.3	56.2	45.9	40.2	101.8	**70.2**
10	182	187	132	153.7	192.3	192.4

The novelty of the developed algorithm is compared with those of the existing methods on the MovieLens dataset, and Table 5 shows the results. With the exception of the second user of MovieLens, the mean value of our proposed method is less than those of all other methods. This proves that the proposed method makes more novel recommendations with good accuracy and diversity.

The comparison results reveal that the proposed method can predict some users' preferences which the traditional methods could not predict. The greatest novelty of our method can recommend unpopular items to users. Artificial bee colony optimization is performed using the crossover operator to exchange useful information for improving local search. Important data are fully exploited, and the algorithm is expected to converge rapidly and give more accurate recommendation results. The main contribution of EPMABC-RS is that it provides a set of recommendation lists to a user at one time with diverse and novel recommendations. But the majority of traditional recommendation algorithms suggest only one recommendation lists at a time.

6. Conclusion

We have proposed the Pareto-based ABC optimization algorithm for developing multi-objective RS. The proposed method provides recommendation lists with good prediction accuracy and diversity. The ABC exploitation search procedure is enhanced using the crossover operator for improving the diversity space. This algorithm can give different recommendation results for the target user. The decision maker can choose a recommendation according to their requirements. The proposed algorithm was used on the Movie Lens dataset, and the findings revealed that the algorithm is efficient to recommend diverse items. Our framework can be improved in the future especially by further enhancing the diversity of the algorithm and by including multiple objectives in Recommendations.

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