Int. J. Nonlinear Anal. Appl. 11 (2020) No. 1, 483-495
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2020.19127.2058

Improving the performance of video Collaborative Filtering Recommender Systems using Optimization Algorithm

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(Communicated by Madjid Eshaghi Gordji)

Abstract

The growth amount of information on the Web makes it difficult for many web users to make decision and choose either information or goods. Thus, a recommender system is an approach that helps users to obtain their needs according to her/his preference within a massive amount of information rapidly without waste of time. The main advantage of using a recommender system in any online shopping or social media like Amazon, Netflix and Facebook is to increase the percentage of overall profits, customer satisfaction and retention.

In this paper, we introduce an approach to increase the accuracy and to improve the performance of collaborative filtering recommender system. In this paper a hybrid approach is proposed to improve the performance of video collaborative filtering recommender system based on clustering and evolutionary algorithm. Proposed approach combines k-means clustering algorithm and two different evolutionary algorithms which are Accelerated Particle Swarm Optimization Algorithm (APSO) and Forest Optimization Algorithm (FOA). The main aim of this paper is to increase the accuracy of recommendation of user-based collaborative filtering video recommender system. Evaluation and computational results on the MovieLens dataset show that the proposed method has a better performance than the other related methods.

Keywords: recommender system, accelerated particle swarm optimization, forest optimization algorithm, collaborative filtering, clustering.
2010 MSC: 26D15, 26D10.

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Received: November 2019 *Revised:* January 2020

1. Introduction

We are in the midst of large amount of data and information, in which without true guidance, we may have wrong or non-optimal choices among them. The Recommender Systems (RS) are effective systems for leading users, among a huge amount of possible choices, to obtain his/her favorite and proper option (transaction), so that the considered process is personalized for each user. In fact, the recommender systems automatically simulate the same process that we utilize in our everyday lives. This is the same process that we try to find people with close proximity as well as to check them out about our choices. In this way, generally, the recommendations provided by the recommender systems can have two results as follow:

- Assists the user in making decision; for instance, it suggests choosing from among the several options ahead, and selects them.
- Improves user awareness in the context of his/her interest; for example, when giving advice to the user, he/she will become familiar with new products or new features of products that they have not already known.

Several models are utilized to suggest in the RSs, which are based on three main models [1]:

1. Collaborative Filtering (CF) Model: This model, which is the most commonly used in the recommender system, is based on the basic assumption that users who has a same taste in the past are likely to have a same taste in the future. This model has two type of methods such as neighborhood-based method and model-based method. The neighborhood-based can be defined in two ways as follow:
   - User-based CF: By statistical analyzing of information, data extracting and target user activities, neighbors of user with common interests is created. Then, by finding the closest neighbors to the target user, it suggests the user's choices based on these neighbors.
   - Item-based CF: it finds similar products with desired results, and then it generates a suggestion regarding those who like that product.
2. Content-based RS: The recommendation in content-based RS is produced by explaining the relationship between features of items. In other words, these systems collect the required information from the user through the items which they have previously observed. These systems suggest a variety of popular and unpopular items by using various intelligent techniques, such as neural networks. Besides, some of these systems utilize the link between items to discover the rules for commodity dependency and congruent items.
3. Knowledge-based RS: This system uses the user's requirement that explicitly defined by his/her to suggest items. This system can be implemented on the specific area such as home buying or antique items. This is because there is not enough user/item history in these domains and there is no available information from the user or the product.

Hybrid Recommender Systems (HRS) have also emerged and combined different models in compound systems based on the strength of their algorithms. Of course, along with content-based approaches, collaborative filtering, both individual and combined methods are still considered effective.

Data collection methods are generally divided into two categories: the first one is related to the data extracted from user behavior (Implicit data). In some applications based on collaborative filtering, the data that each user leaves in the webpage, is used to provide recommendation. The reason is that receiving a rating from users is simply not possible. Such as the process of page browsing and the duration of viewing various products provided on the website.

The second category is data from the user itself (Explicit Data), in which users may allow the system to provide more suggestions that are specific by specifying their preferences when purchasing previous items and giving ratings to each one. In other words, when buying the goods, users register their opinion by giving feedback in the system. The RS uses this information in its future recommendations and suggests products in accordance to the user's interests. The extracted data from the user itself is much more accurate than the extracted data from the user's behavior, as the user declares his opinion accurately.

In general, a recommender systems goal is to make users happy by satisfying their requirements and increase producers benefit by selling more products.

Evolutionary algorithms are based on the main evolutionary theory of Charles Darwin. The way the evolutionary mechanisms are implemented varies considerably; however, the basic idea behind all these variations is similar. Evolutionary algorithms are characterized by the existence of a population of individuals exposed to environmental pressure, which leads to natural selection, i.e. the survival of the fittest, and in turn the increase of the average fitness of the population. Fitness is the measure of the degree of adaptation of an organism to its environment; the bigger the fitness is, the more the organism is fit and adapted to the environment. In general, evolutionary algorithms focus only on a subset of mechanisms defined over the biological evolutionary process [2].

The main purpose of the present study is to improve the performance of video Collaborative filtering recommender systems by using K-means for clustering similar users and an evolutionary algorithm for optimizing the K-means result, reduce the Mean Absolute Error (MAE) value in comparison with similar research and increases the accuracy of recommendation. In this paper, the collaborative filtering model, which is the most commonly used method in this area with explicit data, is utilized to recommend Top-K video to users.

The article structure is as follow: we introduce the related works in Section 2. Section 3 describes our proposed system. The Section 4 and Section 5 are related to the evaluation and the experimental results compared to related works, respectively. Finally, conclusions and possible future works are explained in Section 6 and Section 7.

2. Related works

With growing the online business, e-learning, user communication and sharing, and the advent of social networks, the necessity to design and implement recommender systems is undeniable. To do so, several algorithms have been used, most of which are based on the collaborative filtering algorithms.

Overall, the aim of these research is to design a recommender system that uses data mining algorithms such as clustering algorithms and evolutionary algorithms based on the basic methods of recommender system which have been mentioned in the previous section, improve precision and quality of the system.

In the middle of 1990s, study on recommender systems was introduced as an independent branch of research, and the reason for this interest was the desire of researchers to solve the problem of recommender methods, which was utilized in the initial approach to search in the vast amount of information problem. The capability of computers to provide recommendations was determined as early as the history of computers. Grundy, a computer librarian, was an early step towards automated auto-recommender systems [25]. This librarian was a relatively simple recommender that grouped users using hard-coded information about the various book genres to generate recommendations. This work is considered as the initial entry into the RS field.

In the early 1990s, the collaborative filtering model were developed as a way to manage the vast amount of online information space. Tapestry was a collaborative manual filtration system, which allows the user to query for items in an information area such as email based on the opinions and other actions of users [7]. This required the efforts of its users, but it allowed them to control the reactions of the previous readers to a part of the correspondence to determine their relationship with them.

It is worthwhile to mention that after the automated collaborative filtering models, the automatic location of related ideas and their accumulation were generated to give the recommends. In this way, GroupLens uses this technique to define Usenet articles that may be of interest to a particular user [17]. Users only needed to score or use other ways to give explicit feedback. The system combines these with other users' scores or actions to generate personalized results. Note that by such systems, users are not able to get any direct information from other users' opinions. Moreover, they do not need to know what other users or other items are in order to receive suggestions.

During this period, advisory and collaborative filtering models became a topic of interest among researchers in the fields of human-computer interactions, machine learning and data retrieval. This interest may lead to the generation of a number of recommender systems for a variety of backgrounds, including Ringo for Music [26], the BellCore video recommender for videos [10], and Jester for the jokes [8]. Outside of the computer world, the marketing field has analyzed recommender for their ability to increase sales and improve customer experience.

Finally, in the late 1990s, the commercial recommender technology began to emerge. The Amazon.com website is one of the most popular application of recommender systems. Based on the purchase and visit history, and the item that the user observed, they recommend some items to the user.

As its introduction by Amazon, the recommender technology has often been embedded in many e-commerce and online systems based on peer-based filtering. A significant motivation to do so is to increase sales volumes, customers may buy a product if it is recommended to them, but otherwise it may not buy that product. Many companies, such as Net Perceptions and Strands, recommend online retailers to provide both technology and service [21].

Recommender system models are not limited to the collaborative filtering model and includes content-based approaches based on information retrieval methods, Bayesian inference, and case-based reasoning. These methods take into account the content or the main features of the items to be recommended, instead of using users' scoring patterns.

The aim of Netflix Prize in 2006 was to compete researcher with a recommender algorithm that could beat Netflix's CineMatch algorithm with 10% improvement in offline tests [9]. The Million Dollar Prize represents the value that vendors place on the recommendations for accuracy. This has led to a wide range of activities in this field, both the academic environment and other enthusiasts.

Hsu et al. developed a combination of two methods based on network structure and a correlation filter to provide a kind of recommender system [12]. Huang et al. described the user duality graph of a product for the presentation of a recommender system, and ultimately considered the answer to collaborative filtering for their problem [11]. Chen and Fong also looked at the concept of trust between individuals to use it in filtering users on the Facebook social network [12].

Konow et al. also provided a kind of simple recommender system by applying combined data filtering, based on the frequency of product visits [16]. In addition, Gallego and Huecas, with customer clustering, based on the profile information and transactions that the customer performed, recommended the product to the cluster users using the mobile banking system [4].

Kolomvatsos et al. presented a model in which algorithms such as descriptive algorithms, decision trees, and random categorization algorithms were implemented using similarity criteria for recommending videos to users [15]. They also carried out evaluations on the Movielens Collection.

Luiz et al. proposed a combined approach to enhance system efficiency and solve the cold start problem, combining collaborative filtering and demographic information [19]. In their research, they used Clustering-Co combined algorithms and machine learning to solve the cold start problem, and evaluations were performed on Netflix, Jester, Movielens datasets.

Due to the low importance of challenges such as scalability, distribution and user trust in comparison with users and videos cold start problem, in all of the research that has been done so far, these challenges have been solved through preprocessing, clustering and categorization operations. Jian Wei et al utilized a collaborative filtering system and deep learning method to recommend video suggestions and fix the cold start problem in collaborative filtering systems [29]. They did their own experiments on the lens movie data from UTF-X.

Viktoratos et al. used a combination of knowledge-based and community-based rules to help cope with the cold start of users in the areas of informed text-providing [28].

Recommender systems do a wide domain search to find the most suitable product for each active user. Since evolutionary algorithms are suitable for problems with large search space, they can have a significant role in the structure of these systems. There are various kinds of evolutionary algorithms. Some of them are simulated from animal or plants behavior, such as BVOA [6] that can optimize the accuracy of system based on the behavior of BrunsVigea flower and have considerable impact on this field. The other example is artificial bee colony algorithm which is an optimization algorithm based on the intelligent foraging behavior of honeybee swarm [27].

Katarya presented a method for recommending the video using the metaheuristic artificial bee algorithm [13]. Metre and Deshmukh described the different challenges associated with multidimensional data clustering and scope of research on optimizing the clustering problems using PSO. They also propose a strategy to use hybrid PSO variant for clustering multidimensional numerical, text and image data [22]. In another research, Arie et al. proposed the utilization of PSO in Convolutional Neural Networks (CNNs), which is one of the basic methods in deep learning. The use of PSO on the training process aims to optimize the results of the solution vectors on CNN in order to improve the recognition accuracy [24].

Parvina et al proposed a CF method to predict missing ratings accurately, which called TCFACO [23]. It included three main steps. In the first step, users were ranked considering available rating values and social trust relationships. In the next step, the ACO method was utilized to assign proper weight values to users to show how they were similar to the target user. Then, a set of top similar users was filter out in the third step to be used in predicting unknown ratings for the target user.

Chen et al. presented a CF recommendation algorithm based on user correlation and evolutionary clustering [3]. Firstly, score matrix was preprocessed with normalization and dimension reduction. Based on the processed data, clustering principle was generated and dynamic evolutionary clustering was implemented. Secondly, the search for the nearest neighbors with highest similar interest was considered.

Laishram et al proposed a hybrid framework based on PSO and Fuzzy C-Means clustering that optimized the searching behavior of user-item subgroups in CF [18]. In their paper the objective was to explore CF that considered only user-item subgroups which included only similar subset of users based on a subset of items.

3. The structure of proposed system

In the proposed system, first the active users cluster into k clusters according to their historical transaction using K-means algorithm, then by using evolutionary algorithms such as APSO and

FOA, this clustering will optimized. Afterwards, an optimized clustering will be used to determine the closest cluster to the target user and recommend the Top-K video to her/him based on the user preferences of this cluster.

Figure (1) shows the general scheme of the proposed recommender system.

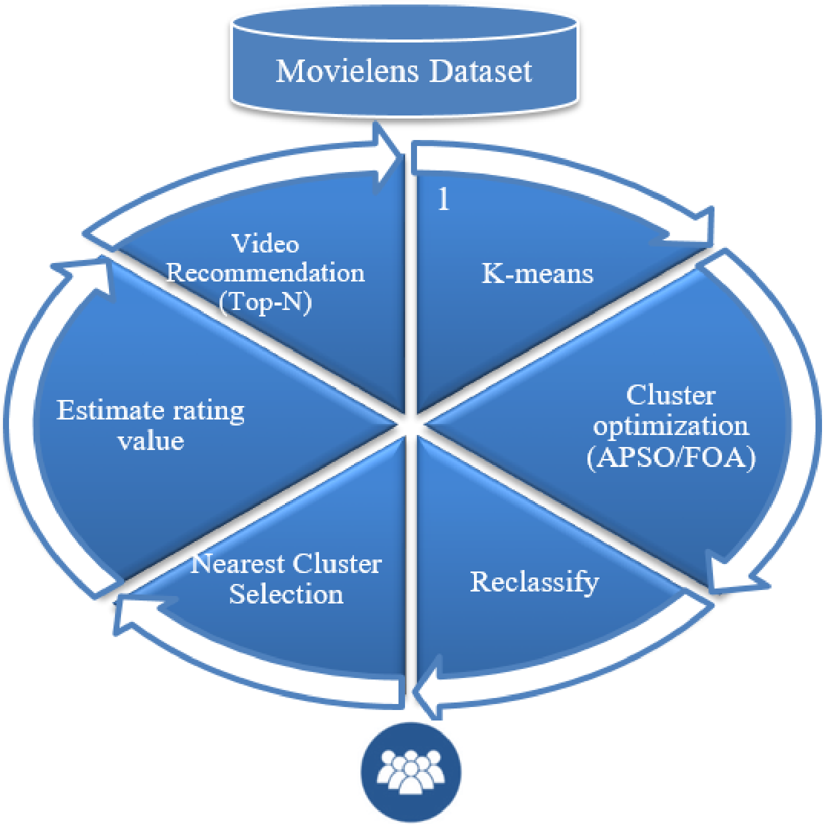

Figure 1: General schema of proposed system

In the following, the steps of the Figure (1) are explained.

3.1. K-means clustering

McQueen, a sociologist and mathematician in 1965, developed the k-means clustering technique [20]. The K-means method is one of the methods for data clustering in data mining and the clustering responses in this method may be accomplished by minimizing or maximizing the target function.

This method, despite its simplicity, is a basic method for many clustering methods (such as fuzzy clustering) and it is a monolithic and flat method.

In our proposed system, each point is equivalent to a user and the goal is to cluster users according to their historical data. In our proposed system, the number of required clusters (center points) was defined by testing the system with different values.

3.2. Clustering Optimization

There are many online users and application of recommender systems in different fields, is increased. Thus, the best way to choose similar users from this large dataset is to utilize the soft computing techniques and to take advantage of evolutionary algorithms.

Particle Swarm Optimization Algorithm (PSO) introduced by Kennedy and Eberhart in 1995 [14] is one of the most widely used evolutionary algorithms. Some of its benefits are as follow:

- Its implementation is relatively simple.
- Its population size is low, so initializing will be easier.
- Number of parameters is low. Therefore, the amount of processing memory required less.
- There is little chance of being trapped locally (Dependent on proper determination of parameters).
- It has exploration and exploitation.

One of the disadvantages is that the particle speed decreases with increasing number of repetitions and converges to the best results. On the other hand, this algorithm is mainly utilized for problems associated with binary decisions.

To accelerate the convergence of the PSO, a simplified version of it, called APSO, is developed [30]. In this algorithm, only the best global situation is considered. Our proposed system used APSO for optimizing the clusters. In our system, each particle in APSO is equivalent to a user in the form of a vector α, with the length of the number of videos in the dataset, and each α_j component in this vector is initialized with the user rating to j^{th} video.

In proposed system, Eq. (3.1) is used to update the particle speed and Eq. (3.2) is used to prevent early convergence.

$$\nu_i^{t+1} = \nu_i^t + \beta(g^* - x_i^t) + \alpha\varepsilon_t \tag{3.1}$$

$$\alpha = \alpha_0\gamma^t \tag{3.2}$$

Where β represents the degree of attractiveness of the best global position and the value is from a set $[0, 1]$. When the value close to 1, the convergence rate will increase. α is a random parameter and γ is a control parameter.

In Eq. (3.1), the first part indicates the current position of the i^{th} user. The second part is equivalent to the social component of the user, which directs to the best global position, and the third part indicates a random motion in the search space.

To prevent early convergence, α can be varied and gradually reduce its value by using the second Equation.

According to these mentioned Equations, there are both exploration calculations (using random values) and exploitation (best positioning). The combination of these two, will usually lead to global optimization. The particle faces a fundamental trade-off between exploitation and exploration. Too little exploration can prevent the particle from ever converging to the optimal solution, while too much exploration can prevent the particle from gaining near-optimal payoff in a timely fashion.

At first, the initial values of the parameters α and β are determined. Then the initial population with N particles is generated randomly, the fitness function is calculated for each population particle, and the best is chosen. The APSO module of our proposed system is implemented in an iterative manner, and each particle position is updated using the previous equations. This process continues until the termination conditions are reached, and eventually the best particle will be introduced as the output.

Forest Optimization Algorithm (FOA) was proposed in 2014 by Ghaemi and Feizi-Derakhshi. It is an evolutionary algorithm which is inspired from trees seeding procedure that some of seeds fall on the land just under the tree. While, other seeds in widespread areas by natural procedures like water and wind movement and animals that feed on seeds or fruits and scatter the seeds to the different places that spread out the forest trees territory [5].

The result in [5] show, FOA needs less number of evaluations to reach to a specific level of accuracy in comparison with GA and PSO; Also the results showed the superiority of FOA to both GA and PSO, because FOA needs less number of evaluations and it has high level of accuracy in comparison with GA and PSO.

This algorithm which has been used in the proposed system, consists of three main steps. The first one is local seeding of the trees, next step is the population limiting and the last step is the global seeding of the trees.

In the proposed system, the solution will be equivalent to a tree in the forest. To do optimization, the solution may include all cluster centers. When the Forest algorithm terminates, the best obtained solution is formed in the form of cluster centers.

The fitness function in both APSO and FOA algorithm equals the similarity of the members of each cluster to each other, which is calculated using Euclidean distance for each particle. As the length of all vectors in the search space is the same (unit vectors), the results of using the Euclidean or cosine spacing will be the same for measuring the similarity of two vectors.

3.3. The rest steps of the proposed system

For the distance measurement, we used Euclidean function. By computing the distance between the active user and each center of clusters, the proposed system decides which cluster the user will belong to.

By obtaining optimized clusters and detecting active user clusters, the scalability problem is solved. Therefore, the collaborative filtering model is applied only to the users within the cluster, and thus the sparsity problem which is one of the most important problems that recommender systems have, will be solved. In fact, active user neighbors are obtained from users within the selected cluster for the active user, and by optimizing the clusters, users who are more similar to the active user are placed in her/him cluster and the accuracy of system recommendations is increased. Missing values of the active user, which are scores related to the video that the active user has not seen yet, are predicted based on the users score within the active user cluster. So, once user was assigned to one cluster, system predict expected ratings for unseen videos and select the topN rated videos to recommend them to the active user.

4. Evaluation

To evaluate the performance of the proposed system, the MAE (Mean Absolute Error) metric is used, which is one of the most common evaluation criteria in this field and is calculated using Eq. (4.1).

$$MAE = (|R_{ij} - P_{ij}|)/M \tag{4.1}$$

Where M is the number of videos; R_{ij} and P_{ij} are the actual score and the predicted rating for user i for the j^{th} video, respectively.

In this paper, the $100,000$ version of the publically available Movielens Collection is used ($http://grouplens.org/datasets/movielens/$). This dataset includes 943 users and $1,682$ videos in which each user rating for a video ranging from 1 to 5. It is worth noting that each user has scored at least 20 videos. In addition, this dataset contains simple demographic information such as age, gender, and occupation.

The dataset of this collection is in four columns of userId, movieId, rating and timestamp, in which they are first arranged in the order of userId, and then based on movieId. The structure of this dataset is illustrated in Figure (2).

1	userId	movieId	rating	timestamp
2	1	1	4.0	964982703
3	1	3	4.0	964981247
4	1	6	4.0	964982224
5	1	47	5.0	964983815
6	1	50	5.0	964982931
7	1	70	3.0	964982400
8	1	101	5.0	964980868
9	1	110	4.0	964982176
10	1	151	5.0	964984041
11	1	157	5.0	964984100
12	1	163	5.0	964983650
13	1	216	5.0	964981208

Figure 2: Small part of Movielens dataset

Before comparing our system with similar methods, it is necessary to adjust the values of the APSO parameters. The parameters α_0, γ, L, N, and T, are respectively equivalent to the initial random parameter, control parameter, particle length (the number of videos in the data set), population size, and maximum number of iterations. The corresponding values of the parameters are presented in the Table (1).

Table 1: The value of the APSO parameters

Parameter	**Value**
α_0	0.10
γ	0.91
L	1682
N	5
T	15

Also the values of the FOA parameters should be adjusted. The parameters t, N, L, T, LSC and GSC, are equivalent to the Number of iterations, Initial population size, Life time, Transfer rate, Local seeding change and Global seeding change, respectively. The corresponding values of the parameters are presented in the Table (2).

5. Experimental Results

For the issue of recommending the most suitable videos to users in our proposed system, the idea behind the proposed method is to find users with similar taste as a candidate set. This set of candidates includes all users in the target users cluster that has scored at least 20 videos.

As the evolutionary algorithms produce different results at each run and the results of the k-means are different due to the sensitivity to the initial location of the cluster centers at each run, proposed system is repeated for 20 runs, and the average results of these 20 runs are reported.

Table 2: The value of the FOA parameters

Parameter	Value
t	20
N	5
L	10
T	5
LSC	20%
GSC	10%

As mentioned before, K-means is very sensitive to the number of clusters (k). Hence, this algorithm is implemented with different values for k. Finally, 5 was considered as the number of clusters. The results of this experiment can be seen in Figure (3).

Figure 3: MAE for different values of k

Furthermore, APSO has been implemented with different values for the generation parameter, and the best results for the parameter T is chosen. The results of these performances are also shown in Figure (4).

Finally, regarding the values obtained for the parameters, in order to evaluate the proposed method, it has been tested on the standard dataset which was introduced previously. Given that the results of the proposed system can be different at each run, the execution of this algorithm is repeated for 20 times and the average result is shown in Table (3).

Table 3: Results from the proposed method

	KM-APSO	KM-FOA
Time (second)	237.221	313.102
MAE	0.686	0.672

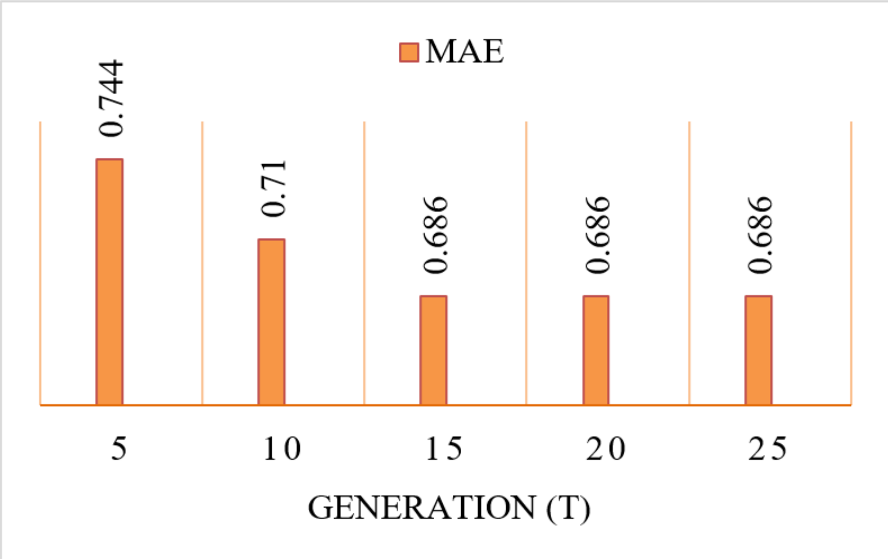

Figure 4: MAE for different values of T

As can be seen in the previous Table, although the MAE of the combination of K-Means and FOA is slightly lower, it has reached the final result over a longer period of time.

Table (4), shows that the proposed method has a more accurate prediction than similar methods.

Table 4: MAE of the proposed method and similar methods ($k = 5$)

Method	MAE
PCA-GAKM [13]	0.79
PCA-SOM [13]	0.82
SOM-CLUSTER [13]	0.819
UPCC [13]	0.825
k-means cluster [13]	0.825
PCA-k-means [13]	0.85
GAKM CLUSTER [13]	0.815
ABC-KM [13]	0.773
KM-APSO	**0.686**
KM-FOA	**0.672**

According to the previous table, the proposed method was able to significantly increase the accuracy, comparing with previous studies.

6. Conclusion

One of the most popular systems that have been considered by researchers from the past decade up to now is the video recommender system. Considering the large amount of information, providing the most attractive items (videos) to users is one of the most important issues in this regard.

The main aim of this paper was to improve the accuracy and performance of video recommender system based on collaborative filtering method in finding similar users and tastes. In the proposed method, the combination of the k-means clustering method and evolutionary algorithms were used for this purpose.

Considering the results of the experiments performed on the proposed method using the standard dataset and the introduced evaluation criteria, it can be seen that this method has a better performance in recommending the video to users than the similar methods performed in this area and increased the accuracy of recommendation.

Although FOA and APSO (which is a simplified version of the PSO) are good in comparison with other evolutionary algorithms, they are not generally fast algorithms. As this section can be used offline, it does not slow down the process. However, at the certain intervals, the results should be updated with respect to the changes. In this regard, efforts to improve the speed of this system will be among the upcoming work in this area.

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