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ORIGINAL ARTICLE

Recommender system with grey wolf optimizer and FCM

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Abstract Recommender systems are contributing a significant aspect in information filtering and knowledge management systems. They provide explicit and reliable recommendations to the users so that user can get information about all products in e-commerce domain. In the era of big data and large complex information delivery system, it is impossible to get the right information in the online environment. In this research work, we offered a novel movie-based collaborative recommender system which utilizes the bio-inspired gray wolf optimizer algorithm and fuzzy c-mean (FCM) clustering technique and predicts rating of a movie for a particular user based on his historical data and similarity of users. Gray wolf optimizer algorithm was applied on the Movielens dataset to obtain the initial clusters, and also the initial positions of clusters are obtained. FCM is used to classify the users in the dataset by similarity of user ratings. Our proposed collaborative recommender system performed extremely well with respect to accuracy and precision. We analyzed our proposed recommender system over Movielens dataset which is available publically. Various evaluation metrics were utilized such as mean absolute error, standard deviation, precision and recall. We also compared the performance of projected system with already established systems. The experiment results delivered by proposed recommender system demonstrated that efficiency and performance are enhanced and also offered better recommendations when compared with our previous work [1].

Keywords Recommender systems · Collaborative filtering · Gray wolf optimizer · Fuzzy c-mean · Movie

1 Introduction

Recommender systems are now mostly used in all e-commerce applications and knowledge management systems. Recommender systems are responsible for delivering accurate and reliable information to the specific users [1–5]. Recommender systems collect the relevant information and preferences for the users or group of users. For example, if a new user is registered on the Amazon Web site, then recommendation engine will first try to investigate the behavior and pattern of that user, and if recommender system is unable to provide sufficient recommendations, then this type of problem is known as cold-start problem [6–8]. In this situation, the system is unaware of the new user's choices and likes, but as soon as the user spends the time on the Web site and browses the web pages of Amazon Web site, then he will get the recommendation of the products which he likes. Various applications and business applications such as tourism, entertainment, web intelligence and online shopping have seen the power of recommender system, and still it is moving toward its mature phase. RSs work on the various filtering procedures such as collaborative filtering (CF), context based, content based (CB), hybrid and social based. CF approach is the most widely used tactic which is adopted by the recommender systems [9–13]. In the CF-based system, the recommendation is suggested on the basis rating provided by the users. For example, if users have given the ratings to an e-commerce Web site of various items such as camera, washing machine and juicer mixer, then recommender system will suggest the products

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to consumers. In the CB filtering, the decision relies on the choices which were done in the past [14–16]. If a person purchased a computer, then RS will probably suggest the products which are related to computer only, because RS will learn the behavior of this individual. In the demographic-based recommender system, the recommendations are provided by the various factors related to the human such as country, age, sex and location [17–19]. Nowadays hybrid-based recommender systems are working well in the e-commerce and web intelligence applications as they used the combination of the demographic filtering, CB filtering and CF with various computational intelligence, machine learning technologies and algorithms [20–22]. To optimize the recommended results is always a challenging task, especially in which different domains have been applied such as data mining, computational intelligence and machine learning. The bio-inspired algorithms are most respectable and efficient in data optimization. There are also other proficient bio-inspired algorithms such as genetic algorithm (GA), artificial immune system (AIS), ant colony optimization (ACO), artificial bee colony (ABC), fish swarm algorithm (FSA), bacteria foraging optimization (BFO) and differential evolution. These algorithms have shown better outcomes in other domains such as bioinformatics, image processing, operation management and data mining. These algorithms can be applied in recommender systems for expert recommendations. We have used GWO, a bio-inspired algorithm which is based on the gray wolves [23–26]. The meta-heuristics algorithm describes the behavior of wolves by analyzing their hunting and leadership tactics, and these actions are performed by the numerous types of wolves (carnivores animal) breeds such as β, δ, α and Ω. A clustering approach, FCM, is employed with the meta-heuristic GWO. GWO has been applied to various engineering domains such as optical engineering, physics (pressure, heat, tension), fluid dynamics, medical data (breast cancer, lymphography) and voting. Fuzzy c-means clustering technique is based on the features that it delivers diverse membership degree of each and every individual which concerned distinct clusters [27–30]. We first applied the GWO on the Movielens dataset from which we get the initial location of clusters. By taking these initial positions of clusters, FCM is employed which classifies the user in the dataset by utilizing similarity of user ratings. We divided the dataset as training and test data into the ratio of 70:30. The major contribution of this research work is:

- We proposed a novel efficient collaborative movie recommender system by adopting a new meta-heuristic algorithm.
- We employed a bio-inspired meta-heuristic algorithm, such as gray wolf optimizer (GWO).
- The clustering process was boosted with the utilization of fuzzy c-means clustering technique.
- The proposed recommender system was evaluated on Movielens dataset.
- We employed MAE, standard deviation, precision and recall for analyzing the behavior of the system.
- The proposed recommender system performed superiorly as it delivered MAE as 0.68 and performed efficiently with respect to time.
- We compared our proposed RS with the already established systems in which proposed recommender system shows superior outcomes.

This research work is structured into several segments, for example, Sect. 2 discusses the relevant work; Sect. 3 demonstrates the projected system. Section 4 is related to experiments and results, and finally, Sect. 5 shows the summary and possible gaps in the proposed work.

2 Related work

Recommender system has demonstrated a significant impact in e-commerce business since last two decades. Intelligent systems are recommending the products to the users based on their past behavior and by analyzing performance in the online environment. A method was offered for guessing the likes of the users by the help of collaborative filtering and matrix factorization [13]. Nowadays data are available in tremendous form, and it is now uncontrollable and hard to analyze from it because now it has turned into big data. Various business intelligence and web-based companies required the relevant information from these big data so that they can understand the customers need according to the market demand. A research study was performed for prediction ratings jobs in group recommender systems [31]. In the group recommendation systems, behavior and pattern of similar users are clustered in a collective group and then collectively analyzed the prediction of a particular group. Researchers offered four different types of group recommender systems out of which three were built according to the existing methodologies, and the last one was applied in a different environment that avoided the data sparsity problem. In the similar area of research of group recommender system, a recommender system was produced which took the involvement of each member presented in particular group and weighted them accordingly [32]. For the justification of their concepts, authors proposed a model named as MCS model with the help of matrix factorization technique and then detected the importance of the contribution of each user presented in the group. Tagging is an essential trait of an online social RS in which the performance of the system is enhanced, but there are several issues which are responsible for delaying the performance of the tag-based recommender system such as ambiguity, sparsity and redundancy. These such issues were taken into consideration and an algorithm was presented which relied on the deep neural networks and formed a system which had an abstract form of a tag-based recommender system [33]. A literature survey based on interactive recommender system was accomplished by researchers in which they focused on serious problems of recommender systems such as collaborative filtering, contextual information, controllability, diversity and cold start [34]. In the recommender systems, sometimes the information of the users is not complete and has some missing and faulty information because these impact recommender systems failed to understand what products should be recommended. Based on these errors and mistakes, some authors termed it as natural noise in the recommender system [35]. This natural noise was reduced and managed by presenting a system which employed the fuzzy-based methods and provided an efficient recommender system. Evolutionary computation is an emerging research area which is applied to the different interdisciplinary areas of computer science, web technologies and electronics. A survey was conducted for the involvement of evolutionary computation in the recommender system and tracked down the areas of information retrieval, knowledge management and web personalization [36]. Authors considered the papers which were based on recent technologies and themes of RS. They furthermore examined the issues of recommender systems such as novelty, diversity and serendipity. Authors categorized and explained the research work done so far, with evolutionary computation, genetic algorithm, evolutionary programming, genetic programming, feature weighting approaches, clustering-based methodologies and latent models. As soon as recommender system influence is increasing on big data, then online social networks are also growing tremendously in which the products reviews and ratings are shared by online users who can be friends or strangers. Various Web sites such as Flickr, Amazon and Flipkart have millions of users, and they exchange their experiences, lifestyle involvements, check-ins or point of interests, product ratings and reviews. In this regard for web social networks, a study was performed which categorized the social information into three major parts such as social web search, social search and social recommender systems [37]. They also sub-divided all these components majorly into the indexing, result ranking, query recommendations, social content search, collaborative search, user recommendation, item recommendation and topics recommendations. Recommender systems apart from the recommendation to online recommendation have a significant impact on other domains also which are essential for activities such as web intelligence and information retrieval from big data. The researchers performed a study related to the application of recommender systems in other substantial domains and categorized them as electronic (government, resource services commerce, shopping, library, business, learning, tourism and group activities) [38]. In the similar type of study, the performance and behavior of recommender system were analyzed in the e-learning environments [39]. They suggested and examined the techniques for recommender systems as association rule mining, content based, matrix factorization, tensor factorization and collaborative filtering. Another literature survey was conducted by the authors in which they deeply studied the recommender systems [40]. They studied the recommender systems on the various important factors such as evaluation procedures, offline and online evaluation with different types of accuracy issues. We analyzed the behavior of users who have rated the movie on the scale 1 to 5 and demonstrated that our proposed system is better than the other existing systems. A collaborative recommender system was presented with the utilization of genetic algorithm in which researchers focused on the various similarity measures [41]. A literature review of the bio-inspired algorithm was conducted, in which author surveyed various important swarm algorithms with their applications [42]. A new meta-heuristic algorithm was named as kidney-inspired and considered four components [43]. Recommender systems for groups are productive and effectual in nature because information can be shared very easily and fastly. A group recommender system was designed to analyze the sentiments of human in online microblogs in which authors focused on the TV and movies applications [44]. A similar work related to the mining of news was presented by the researchers in which they adopted fuzzy systems [45]. A multi-objective system was introduced in which authors proposed a new evolutionary algorithm for long tail recommendations [46]. A tag-based recommender system based on the deep neural network was offered by authors in which they utilized the two Last.Fm and Delicious [47]. An evolutionary algorithm was proposed which was based on the discretization and cut points. This algorithm followed the multivariate tactic and chromosome deduction methodology with the utilization of various benchmark datasets [48].

3 Proposed recommender system

In this segment, we will present the projected RS which is assimilated by the FCM and gray wolf optimizer. The fuzzy c-mean is well-known clustering algorithm which is applied to the Movielens dataset. The gray wolf optimizer was used in our work as it performed efficiently and delivered superior result in the optimization process when compared to other meta-heuristic methodologies [24].

In Fig. 1, we demonstrated the workflow of our anticipated RS in which first the Movielens dataset is

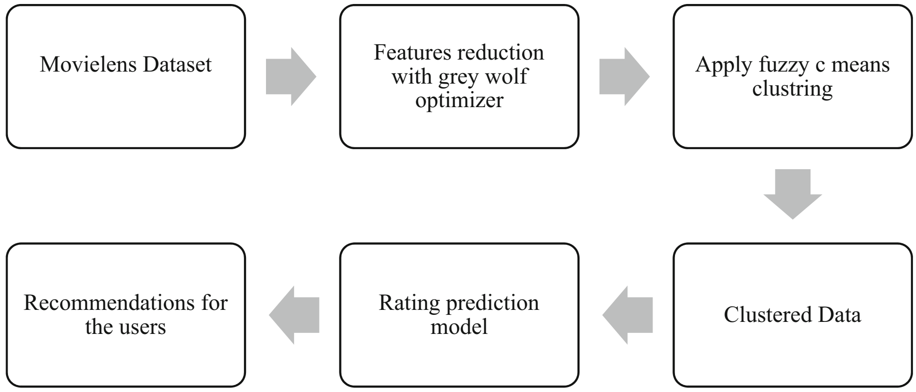

Fig. 1 Workflow of proposed collaborative movie recommender system

engaged and then gray wolf optimizer is applied to find the initial locations of the clusters. When we received the initial positions with the help of gray wolf optimizer, then FCM is used to classify the users in Movielens dataset by applying similarity of the user ratings. The useful recommendations are delivered to the users who received the effects of FCM and gray wolf optimizer.

Fig. 2 Pseudocode of proposed collaborative movie recommender system

1. Load the GWO culture X_i (i = 1, 2, ..., n) // X_i represents random cluster positions in Movielens dataset.
2. Initialize r, R, and Q // r, R and Q are coefficient points.
3. Estimate the appropriateness of each explorer negotiator
4. X_α =finest explorer negotiator
5. X_β =2nd finest explorer negotiator
6. X_δ =3rd finest explorer negotiator
7. While (z < Most number of iterations) // z represents current iteration.
   - 7.1 for respective explorer negotiator
     - 7.1.1 Refresh the spot of the present explorer negotiator.
   - 7.2 end for
   - 7.3 Refresh r, R and Q.
   - 7.4 Determine the appropriateness of entire explorer negotiators.
   - 7.5 Refresh X_α, X_β, & X_δ
   - 7.6 z=z+1
8. end while
9. Return X_α // represents positions of centroids given by the grey wolf optimizer for Movielens data.
10. Randomly select cluster centre // Fuzzy c-means.

F matrix represents an association between clusters for Movielens dataset of users.

11. Load F= [f_{lm}] matrix, F(0)
12. Estimate the f_{lm} using:

$$f_{lm}^{m} = 1 \Big/ \sum_{k=1}^{c} \left[\frac{\|(X_l - c_m)\|}{\|(X_l - c_k)\|} \right]^{\frac{2}{n-1}}$$ // represents association between i^{th} and j^{th} cluster in Movielens.

13. set k=0
14. At k-step: determine the midpoints B(k)=[c_m] with F(k)

$$b_m = \frac{\sum_{l=1}^{N} f_{lm}^{n} \cdot x_l}{\sum_{l=1}^{N} f_{lm}^{n}}$$ // represents the new position of the jth cluster for Movielens dataset.

15. Refresh F(k), F(k+1)

$$f_{lm}^{m} = 1 \Big/ \sum_{k=1}^{c} \left[\frac{\|(X_l - c_m)\|}{\|(X_l - c_k)\|} \right]^{\frac{2}{n-1}}$$

16. If || F(k+1) - F(k)||< ε, then discontinue; else go back to step 12.
17. Return newly formed clusters and cluster centers for the Movielens users.

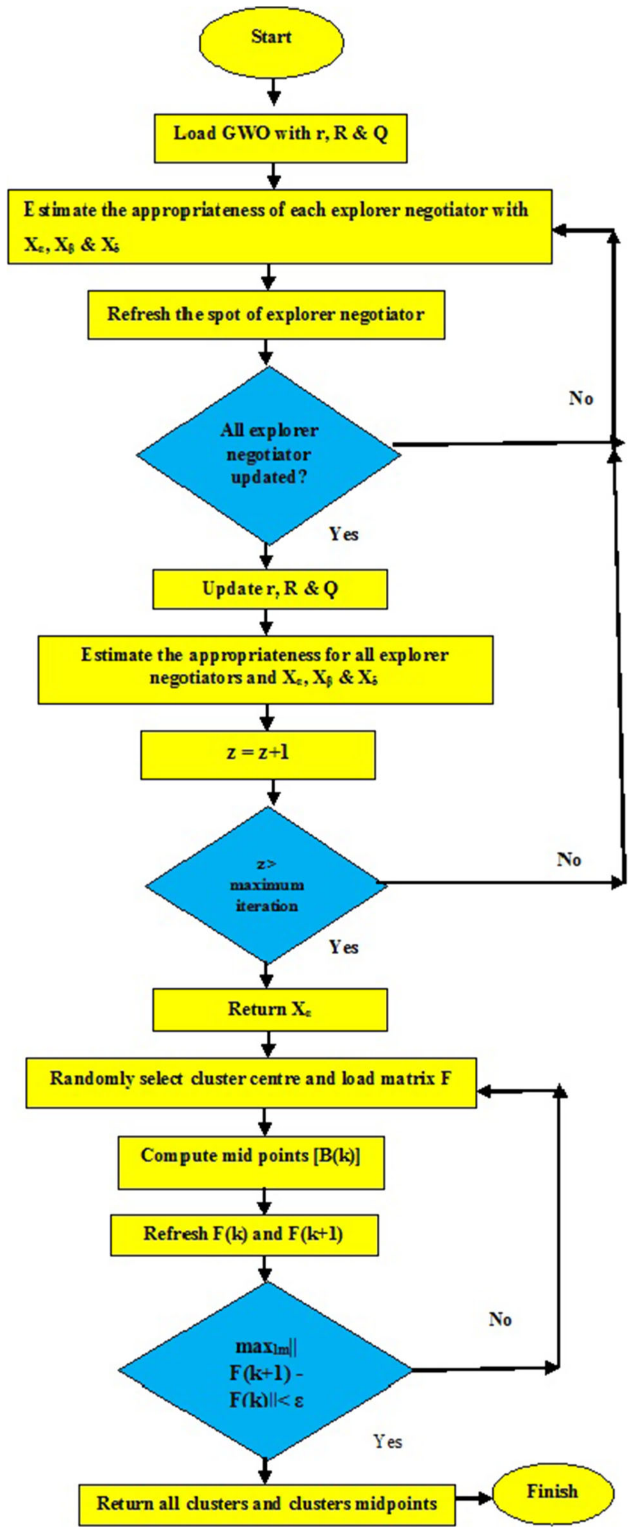

Fig. 3 Detailed flowchart of proposed collaborative movie recommender system

In Fig. 2, we demonstrated the pseudocode of our proposed recommender system, where initial data are loaded in GWO culture with three explorer negotiators and FCM is applied finally. Whereas in Fig. 3, we have demonstrated the detailed working flow process with all three coefficient points such as r, R and Q which are valid for clusters. Figures 2 and 3 demonstrate the proposed recommender system in which first Movielens data are initialized. With the help of gray wolf optimizer, features of movies in which users have rated them are initialized. Then, we estimated the appropriateness of respective explorer negotiator and designated as finest according to their positions. Then, we refreshed the spots of recent explorer negotiator. We will check whether all the explorer negotiators are refreshed or not; if they are not updated, then again we will refresh the spot of existing explorer negotiator. After this process, all the coefficients points r, R and Q are updated, and appropriateness value of all the explorer negotiator is calculated which is present in the form of users, who have rated the movies. After the implementation of gray wolf optimization in Movielens dataset, then users' centers of a particular cluster are selected randomly. The results generated by grey wolf optimization technique were later on adopted by FCM. A membership matrix is initialized, and then, center vectors are calculated. Membership matrices are updated with the help of user rating and movie ratings which are retrieved by the vectors. Finally, all the clusters and clusters centers are returned with effective ratings which are estimated by the help of a mean absolute error, precision and recall.

Table 1 Assessment of state of the art methods with different metrics

Method/system	MAE	SD	Precision	Recall
K-means	0.7	0.62	0.53	0.43
PCA-K-means	0.64	0.73	0.57	0.48
K-means-improved	0.69	0.65	0.52	0.42
SOM-cluster	0.79	0.08	0.31	0.23
FCM	0.77	0.53	0.49	0.38
UPCC	0.83	0.67	0.17	0.28
KM-PSO-FCM	0.74	0.77	0.54	0.41
PCA-SOM	1.96	1.15	0.16	0.15
PCA-GAKM	0.92	0.18	0.49	0.33
GAKM-cluster	0.78	0.13	0.37	0.45
PCA	1.99	1.48	0.19	0.22
Proposed	0.68	0.54	0.55	0.49

4 Experiment outcomes and investigation

In this segment, we will discuss the analysis of experiments of the projected RS which was performed on the Movielens dataset (http://grouplens.org/datasets/movielens/). We performed all these experiments on the system which has a configuration as Intel I3 processor, 8 GB RAM and Python 2.7.10 environment.

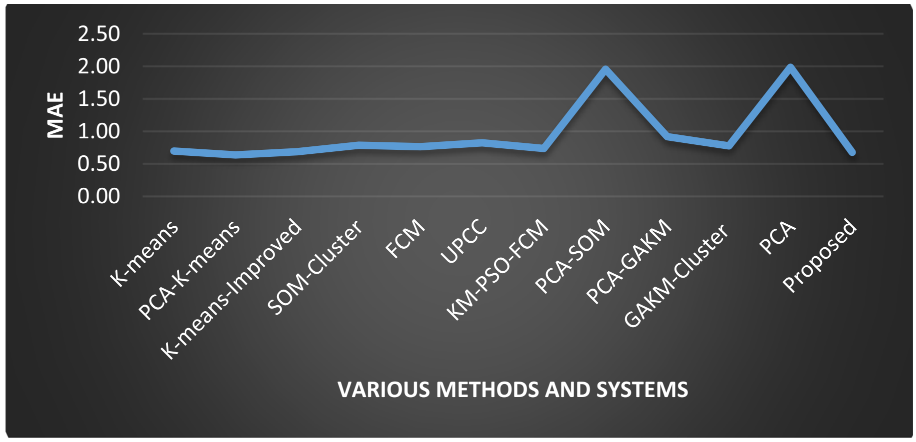

Fig. 4 Comparison of various methods and systems for MAE

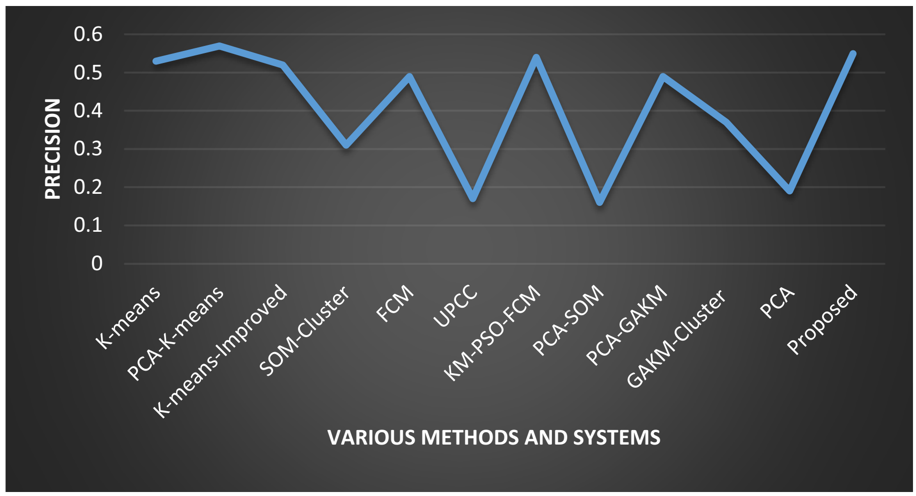

Fig. 5 Comparison of various methods and systems for precision

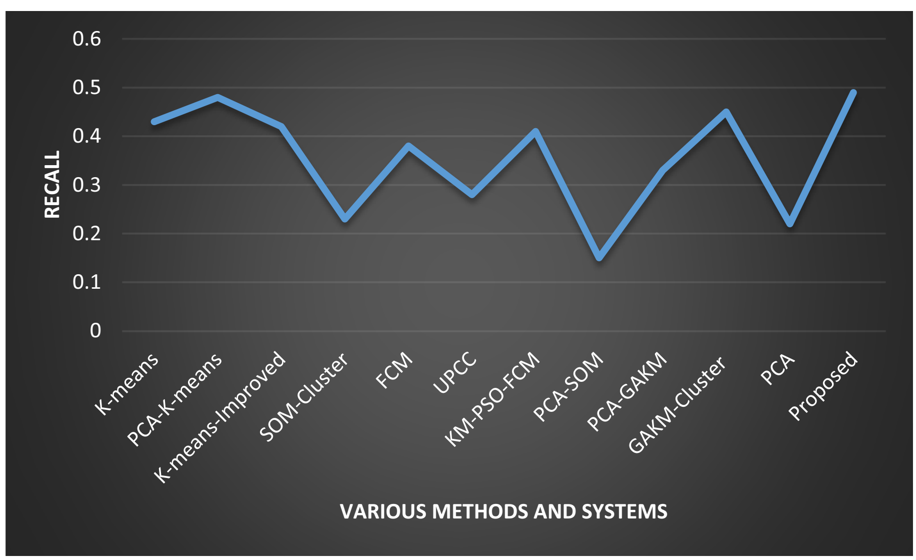

Fig. 6 Comparison of various methods and systems for recall

4.1 Dataset and evaluation procedures

For the evaluation of our proposed recommender system, we considered the Movielens dataset which is available publically. The University of Minnesota collected the dataset for the GroupLens research project. The Movielens dataset contains the 100, 000 ratings (1–5) and 943 users who have rated 1682 movies. Every user from 943 has

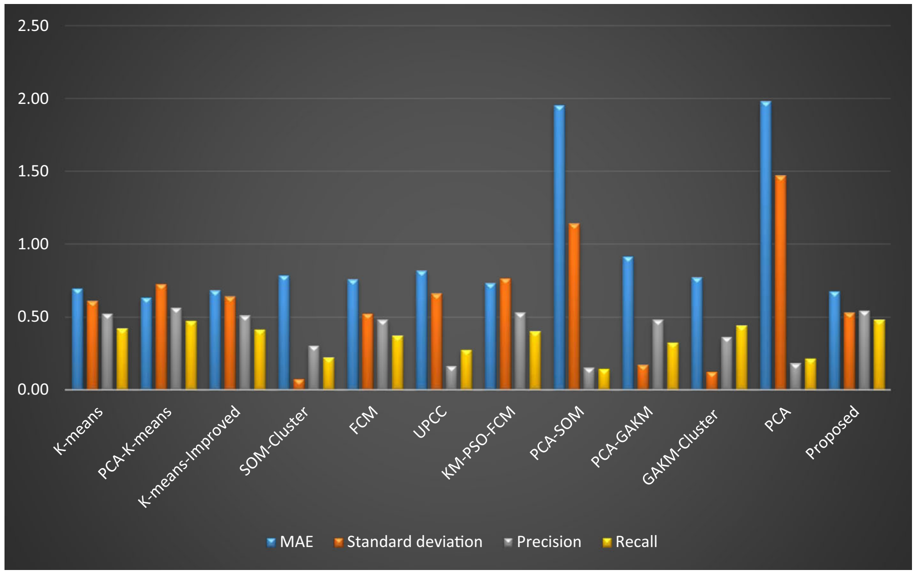

Fig. 7 Comparison of the state of art methods and systems with various metrics

rated at least 20 movies. To understand the behavior of the user's recommendation quality, we adopted some evaluation matrices. We calculated means absolute error (MAE) which is the most popular metric to understand the conduct of a recommender system. We also calculated the precision and recall for the proposed system, so that we can analyze the interest of users in a particular movie or collection of movies.

$$\mathrm{MAE} = \frac{\sum \| o_{gh} - s_{gh} \|}{G} \tag{1}$$

G = entire amount of expected movies, o_{gh} = expected value for user g on item h, s_{gh} = real rating.

$$\mathrm{Precision} = \left| \frac{\mathrm{Interesting} \cap \mathrm{Top}N}{N} \right| \tag{2}$$

$$\mathrm{Recall} = \left| \frac{\mathrm{Interesting} \cap \mathrm{Top}N}{|\mathrm{Interesting}|} \right| \tag{3}$$

If the MAE value is small, then prediction accuracy is superior. And if precision and recall values are high, then recommender system's prediction accuracy is better.

4.2 Results

In this segment, we mentioned the outcomes and comparisons which were performed on various already existing systems by adopting Movielens dataset of 100 K.

In Table 1, we have compared proposed system with other existing systems. The proposed system has a mean absolute error as 0.68, which is much better than PCA and PCA-SOM methods. K-means, PCA-K-means, K-means-improved, SOM-Cluster, FCM, KM-PSO-FCM and GAKM-Cluster have MAE ranges from 0.64 to 0.78. Some of the methods did not respond well, for example, SOM-Cluster, UPCC, PCA-GAKM, PCA-SOM, and PCA has 0.79, 0.83, 0.92, 1.96 and 1.99, respectively. As far as other evaluation metrics is concerned such as standard deviation, precision and recall, our proposed system also delivered enhanced results.

In Figs. 4, 5 and 6, comparisons of different systems are compared by MAE, precision and recall, respectively.

In Fig. 7, all evaluation metrics such as mean absolute error, standard deviation, precision and recall are compared for the different existing systems and the proposed system.

So we concluded from Fig. 7 and Table 2 that our proposed system performed well with valuable recommendations and performance for the Movielens dataset.

Table 2 Comparison of speed of different methods and systems for Movielens dataset

Method	Time (in seconds)
K-means	24.75
PCA-K-means	67.56
K-means-improved	23.48
SOM-cluster	89.11
FCM	42.67
UPCC	181.23
KM-PSO-FCM	140.43
PCA-SOM	152.89
PCA-GAKM	31.25
GAKM-cluster	332.31
PCA	19.65
Proposed	66.45

5 Conclusion and future work

Recommender systems are helpful for the organizations and e-commerce business in such manner that they help the users to choose relevant products from billions of products. Similarly, companies will get to know their customer more in depth such as their behaviors, likes and patterns. We have presented a new and efficient collaborative movie-based recommender system. Our proposed recommender system performed superiorly when compared with already existing systems. As suggested, recommender system delivered the mean absolute error, standard deviation, precision and recall as 0.68, 0.54, 0.55 and 0.49, respectively. The performance of proposed system with respect to time is also superior as compared to existing systems. As far as future work is a concern, we will apply this system by including demographic features, sentiments, machine learning and big data environment. We can also enhance the quality of our proposed recommender system by including some important factors such as privacy, trust within the group, contextual information and application of hybrid systems.

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