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High-Performance Technique for Item Recommendation in Social Networks using Multiview Clustering

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Abstract

Recommender Systems have been widely employed in information systems over the past few decades, making it easier for each user to choose their own products based on their past behaviour. Data mining tasks and visualization tools regularly use clustering techniques in the scientific and commercial arenas. It has been shown that clustering-based methods are effective and scalable to big data sets. The accuracy and coverage of clustering-based recommender systems are, however, somewhat low. In this paper, we suggest an improved multi-view clustering method for the recommendation of items in social networks to overcome these problems. To create better partitions, the artificial Bees colony optimization algorithm (ABC) is first used to improve the initial medoids' selection. After that, users are clustered iteratively using views of both rating patterns as well as social information using multiview clustering (MVC) (i.e. trust and friendships). Ultimately, a framework is suggested for evaluating the various options. This research study suggests a novel MVC clustering approach using the ABC optimization technique. The proposed ABC-MVC algorithm's usefulness in terms of enhancing accuracy is demonstrated by experimental findings performed on a real-world dataset and it is observed that it performs better than the pre-existing techniques and baselines.

Keywords: TERMS Clustering, Collaborative Filtering, Recommendation system, Social networks, optimization, accuracy.

1 Introduction

Recommendation Systems (RSs) are required for filtering the massive flow of information flowing on the web and ostensibly exploitable by a regular user as a direct result of the exponential expansion of digital data [1]. These systems are capable of making recommendations that are suitable for user needs and preferences. RSs can generally be divided into three categories: content-based, collaborative, and hybrid systems. Without taking into consideration any information about other users, content-based filtering (CBF) predicts a user's preferences based on his or her information (gender, age, interactions on social media, etc.). Since it employs a number of processes to get the pertinent information to the person who needs it, CBF can be considered an information filtering task. Instead of searching for specific data on an incoming stream, filtering is frequently seen as the removal of undesirable data (viewed as noise) from that stream [2].

The most widely used strategy is based on an item's semantic content. Its foundations are in the field of information retrieval, and many of its guiding principles are applied here: products are recommended based on comparisons between their content and the user profile. This profile is shown as a collection of factors and weights that the user has determined to be important. This approach is straightforward, quick, and successful in traditional information retrieval models. Collaborative Filtering (CFL), one of the many recommendation algorithms, is the method most frequently used in recommender systems to give customers products that are a good fit for their tastes. The fundamental concept is that by combining the ratings of users with related interests, a prediction for a certain item can be made.

Memory-based and model-based techniques might be considered the two sub approaches of collaborative filtering based RS. The first method searches the entire database for a group of persons and items that are comparable to the target user or item. The second strategy aims to create a model (via machine learning) that describes the user's behaviour in order to anticipate his decisions. It has been demonstrated in reality that the model-based method is more effective for managing big data sets, while the memory-based approach delivers higher performance in terms of precision. Model-based techniques are also more complicated because they require training a model and adjusting a number of hyperparameters [3]. The neighborhood-based as well as model-based methods used in the collaborative filtering approach are often separated. Breese, Heckerman, and Kadie first proposed this classification in 1998. These methods are founded on the idea that similar people and similar things tend to have the same rating patterns [4]. These algorithms are still in use in many operational systems, despite ongoing research to create new ones. These algorithms are still in use in many operational systems, despite ongoing research to create new ones. These fundamental strategies typically exhibit a competitive performance while being straightforward and adaptable. They have become increasingly often used in the creation of recommender systems as a result [5].

Nevertheless, recommender systems based on clustering-based strategies provide an another approach to model-based techniques. These methods decrease the search space by grouping related people or objects together rather than breaking the rating matrix into matrices with small rankings. The majority of earlier works concentrate on grouping users and/or products based on similarities [6]. The state of the art, however, reveals that these methods have rather poor accuracy and coverage. In order to solve these problems, we created a multi-view clustering model in which users are grouped iteratively based on both rating patterns (user similarity) as well as social similarity. Similar to that, this study [7] proposes a multi-view clustering model for the recommendation in social networks.

The outcomes of this research study is summarized as follows:

1. By combining diverse clustering methods, including as Kmedoids and CLARANS, with the multiview (MVC) approach and PAM, we construct a variety of clustering-based CFL algorithms.

2. Using the ABC optimization technique, we suggest a novel MVC clustering approach.

3. To demonstrate the efficiency of the suggested MVC clustering approach in comparison to other approaches, we conduct extensive tests utilizing publically available datasets.

In our work, the initial medoids are chosen using ABC in order to produce better partitions (i.e., improving the quality of medoids in accordance with the objective function) and subsequently improve the recommendations (i.e., recommending the most suitable items to a given user). The next step involves iteratively clustering users based on perceptions of user similarity (using users' ratings of items) and social information (friendships and trust). Finally, prediction results are produced using various levels of hybridization for purposes of comparison.

The remaining sections of this study are structured as follows: On trust-based, social based as well as recommender systems based on clustering, some related research is presented in Section 2. Using an improved MVC method, Section 3 suggests a novel recommender system for products. Finally, utilizing data from the real world, experiments are carried out in Section 4. Section 5 concludes by highlighting the most significant findings and outlining some potential future study.

2 Related Works

The two primary research strands of trust and social-based recommendation as well as recommendation based on clustering techniques are used in this part to review the prior related work.

2.1 Trust and Social-based Recommendation

The study of social-based recommender systems has only recently begun, despite the fact that recommender systems have been thoroughly examined over the past ten years. In order to improve recommender systems by adding information from social networks, the authors [8] offer a matrix factorization framework with social regularization in this research. Because people who trust one another frequently have similar preferences, trust-based suggestions can enhance the efficacy of conventional recommender systems. In several recommender systems, trust particulars has been incorporated as another dimension to assist model user choice. Both forms of suggestion have combined it:

(1) using model-based methods (2) memory-based techniques. They used each user's social connections in their suggested social regularization procedures [8] in actuality. Also, one typically does not consult all of their friends before making decisions in the actual world. Instead, they might consult some friends who are knowledgeable about film reviews for movie suggestions. They may also request recommendations from a different set of friends at the same time. In this study [9], they put forth the HTPF, a novel probabilistic model that explicitly takes user attention and preference into account while making social recommendations. Many psycho-social texts highlight the significance of user attention in recommendations, and their findings indicate that user attention has a greater impact on trust relationships than user choice.

The authors [10] proposed the model HTPF with a generative process where they use social network as complemental information to deduce user's attention instead of their choice. Also, they developed a powerful stochastic Variational inference technique for their model that can handle massive data sets. Their thorough experimental findings on four real-world datasets amply supported the usefulness of their suggested approach and shown that it outperformed other social recommendation techniques. In order to address the link prediction problem, they would need to take into account users' attention as well as preferences, since attention is more susceptible to social networks.

2.2 Recommendation based on Clustering

It has been shown that clustering-based methods are effective and scalable to big data sets. They can reduce the sparsity of rating data as a dimension-reduction technique [11]. Subsequent studies claimed that by using a more sophisticated clustering strategy, accuracy might be increased much further and could even exceed the other CFL approaches. In [12], a weighted clustering approach-based incremental CF system is proposed. With a little amount of processing, this method seeks to deliver high-quality recommendations. How to account for ongoing changes in user preferences and behaviour is an intriguing topic with corporate recommendation systems. The nearest neighbour query range is not favorable to a real-time recommendation is not a fair solution, and the standard collaborative filtering recommendation method is very sparse because the user changes over time and is not a good predictor of user interest. Simply said, traditional recommender systems that are CFL and CBF based lack any idea of time. This could become a problem if consumers use commercial systems long enough to experience major behavioral changes. So, one potential drawback of this research [13] is that it only took into account circumstances involving ratings as well as trust, even if it may be simple to extend or revise it in order to incorporate more information sources. They used a rather straightforward way to calculate continuous trust levels, which was another shortcoming.

A multi-view clustering was developed by Alizadeh and Sheugh [14] which was based on Euclidian distance. A multi-content clustering CFL model-based web item recommendation system was put forth in [15]. In order to make an acceptable recommendation, many viewpoints, including user ratings and comments, have been taken into account. In addition, user preferences have been examined using historical interaction features and extra behaviour features. A multiview clustering recommendation method that includes extra social data (friendship, trust, and influence) has just been created. The value of combining these traits and their advantageous effects on hybrid recommendation were shown by this investigation. In [16], a fuzzy C-means clustering strategy based model-based CF is taken into consideration. The authors suggested an altered cuckoo search technique to optimize the data points in every cluster so as to deliver an effective suggestion because model-based CFL suffers from a greater error rate and requires more iterations for convergence.

The authors of this study [17] used a preference model to convert the countable raw ratings into actual numbers in order to achieve this rating refinement. They improved the effect of user clustering by using the sparrow search method and adding item kinds to the similarity calculation in order to locate comparable users. The results showed that the proposed technique was superior in terms of accuracy and correlation when compared to comparable heuristic-based CFs. The performance of the proposed CFL based on a preference model and sparrow search was compared with that of related heuristic-based CFLs.

This study [18] developed a hybrid framework of fuzzy c-means clustering and particle swarm optimization to identify significant user-item subgroups for CF. By contrasting the significance of using user-item subgroups in CF for computing prediction score with standard CF models like maximum margin matrix factorization, probabilistic matrix factorization, and item-based models. By taking advantage of particle swarm optimization's globalized searching behaviour, the particle swarm optimization method is employed to direct fuzzy c-means centroids towards the ideal subspace. Once highly linked user-item subgroups have been identified, any unique collaborative filtering is used to determine each user's prediction score for the subgroup. The top N suggestion items are determined using the final prediction score of each user, which is calculated from all of the subgroups to which the user belongs. By setting the initial centroid of the clusters to the closest optimal solutions, the population-based optimisation algorithm in this proposed approach helps the fuzzy c-means clustering find highly connected user-item subgroups.

The associated research supported the idea that adding social data to CFL can increase the accu-

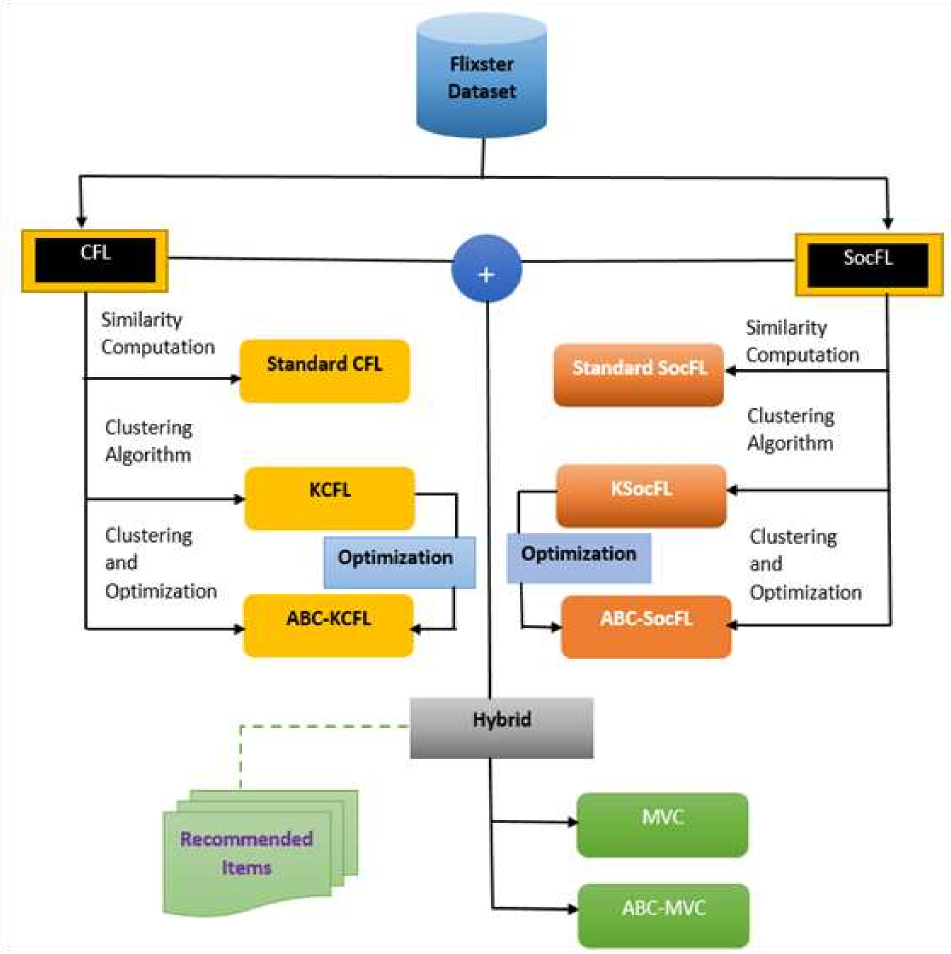


Figure 1: Proposed work

racy of recommendation. Multi-view clustering approach has been used in several research due to the comparatively low accuracy of clustering-based techniques. Finally, as per the survey, recommender systems have not made use of efficient multiview-based clustering techniques. This encourages us to create an optimal strategy that can resolve these problems and provide superior divisions.

3 Methodlogy

An overview of the suggested recommendation approach is shown in Figure 1. Several methodologies have been employed for CFL, social filtering (SocFL) as well as hybrid filtering (HybFL). UCFL, KCFL, ABC-KCFL designations are referred to the basic user-based CFL, clustering-based CFL and optimized clustering-based CFL utilizing the artificial Bees colony optimization algorithm (ABC) respectively. The regular SocFL, the clustering-based SocFL, as well as optimized clustering-based SocFL utilizing ABC are represented by the SocFL, KSocFL, and ABC-KSocFL algorithms, respectively.

We think that each user has a unique collection of characteristics, such as ratings of resources, a list of friends, and information about who they may trust. The calculation of collaborative and social distance determines how similar two users are: **Collaborative:** The Pearson correlation function is used to determine how similar two users, p and q, are based on their assessment histories. The following equation (1) is used to determine the distance $D_{sim}(p, q)$ between two users, p and q

$$D_{sim}(p, q) = 1 - Sim_{pearson}(p, q) \tag{1}$$

Social: Two features, friendship and trust have been utilised to ascertain the social interaction between users [19].

(1) Degree of Friendship: Using the Jaccard formula (2), Two users' levels of friendship are determined using (3).

$$Friendship(p, q) = \frac{|F_p \cap F_q|}{|F_p \cup F_q|} \tag{2}$$

Where F_p denotes friends of p and F_q denotes friends of q The distance $D_{Friendship}(p, q)$ is computed using (3)

$$D_{Friendship}(p, q) = 1 - Friendship(p, q) \tag{3}$$

(2) Degree of Trust: There are numerous algorithms available for calculating trust. The six-level technique [20] has been chosen, which determines how much users, p and q, trust one another by taking a distance of six into account as shown in equation (4).

$$D_{Trust}(p, q) = 1 - Trust(p, q) \tag{4}$$

3.1 Social and Collaborative RSs

We adopted the user-user based advice for the traditional CFL and opted for a memory-based CFL method. Using user ratings on things, the system provides the option of finding the ideal neighbours for a certain user in this method. As previously mentioned, we used the Pearson correlation method to determine how similar users were. On the other hand, the conventional SocFL takes into account elements of friendship and trust when determining the social distance [21]. The social distance was calculated using a weighted formula (5).

$$D_{Soc} = \beta_1 * D_{trust} + \beta_2 * D_{Friendship} \tag{5}$$

Where, β_1 represents weight related to Trust and β_2 represents weight related to Friendship and also, $\beta_1 + \beta_2 = 1$

The pseudocode of SocFL is shown in algorithm 1.

Algorithm 1 SocFL

Input: User :P_a, Distance: $DT_{friendship}$ DT_{Trust} , $Item_i$: Item, K is the count of nearest neighbors for prediction consideration

Output: Prediction $P_a, Item_i$

Compute DT_{Soc}using the weighted formula shown in equation (5)

Clustering configuration on DT_{Soc} is generated

Choose K nearest neighbors with respect to DT_{Soc}

Based on KNN assessments, apply Prediction $P_a, Item_i$

3.2 Social Recommendation and Clustering-based CFL technique

The clustering-based CFL technique (KCFL) uses a clustering approach to identify the community of the active user p. Users' assessments from the same cluster will serve as the foundation for the prediction. The Kmedoids technique has been chosen.

The Partitioning Around Medoid (PAM) algorithm [22], which is the most popular realization of the K-Medoid clustering, and the Clustering Large Applications Based upon Randomized Search (CLARANS) algorithm [23] are two different variants of the K-medoids algorithm that we have implemented. The PAM-based CFL enables predictions based on clusters produced by the PAM algorithm's application. PAM uses a greedy search method, which is quicker than an exhaustive search but may not yield the best result. The PAM-based CFL is shown in algorithm 2.

The clustering based SocFL (KSocFL) is similar to KCFL by considering D_{soc} by D_{sim}

Algorithm 2 . PAM-based CFL

Input: Active User P_a, D_{sim},$Item_i$,N:number of medoids
Output: user P_a prediction on $Item_i$
Choose random K medoids sets ($Initial\_Medoids$)
Apply PAM with $Initial\_Medoids$ using D_{sim}
Identify cluster of P_a
Prediction $(P_a, Item_i)$

3.3 SocFL and ABC clustering based CFL technique

As the Kmedoids clustering method relies on a random selection of medoids, we will use the ABC meta-heuristic to choose the initial medoids more effectively. The steps followed in ABC clustering based CFL is as follows:

1. Using the user-item rating matrix, determine$P_a's$ distances from the other users, and then enter the results in the D_sim
2. Choose one of the Kmedoids, CLARANS or PAM partitioning clustering algorithms.
3. Use the ABC for the medoids selection to obtain the best available reference solution.
4. Measure the separations between users and medoids.
5. Produce the ultimate clustering arrangement.
6. Determine the user's active P_a community
7. The prediction formula is applied.

3.4 Recommendation of Hybrid Technique

The weighted hybrid technique (WHybFL) computes the total similarity between two users as follows by combining the interests-based similarity of users along with their social similarity weight as shown in (6).

$$Sim_{Hyb}(p_1, p_1) = \alpha * Sim_{pearson}(p_1, p_2) + \beta * Sim_{soc}(p_1, p_2) \tag{6}$$

Where α and β represents weights expressing priority level such that $\alpha + \beta = 1$. D_{Hybis} the hybrid distance and it is computed using equation (7).

$$D_{Hyb} = \alpha * D_{sim} + (1 - \alpha) * D_soc \tag{7}$$

Similar to how WHybFL and KCFL are combined, Clustering-based hybrid technique (KHybFL) combines both KCFL and KSocFL algorithms. This algorithm has two possible variants: one that combines the CFL with social information on friendship and trust (KCFLSoc), and the other that only considers trust information (KCFLTrust). KHybFL is carried out as follows:

1. Using D_{Hyb}, determine the separations between p_a and other users.
2. Create a final clustering configuration.
3. Find the cluster that contains the current user.
4. Calculate the predictions using the harmonic average weighted method while taking the users of the cluster that contains p_{ainto} account.

The ABC-KCFL and ABC-KSocFL algorithms are used with the KHybFL in the weighted optimized clustering-based hybrid method. The main distinction is that the clusters produced in this instance have been refined using the ABC metaheuristic.

Table 1: Flixster Dataset description

Attributes	Total #
Users	5000
Items	13527
Ratings	264540
Trust	2898
Density	0.39

4 Results and Discussion

To assess the proposed improved MVC clustering-based recommendation strategy, we performed empirical trials. It has been researched how applying ABC optimization for clustering using various algorithms (KCFL, KSocFL, and KHybFL) adds value and how the optimized MVC approach compares to baselines and related work. These are the two key research concerns that have been examined. The studies were conducted with the help of the Flixster real-world data collection. The trust information is collected on the movie sharing as well as from the discovery website Flixster.com. The description of the dataset is shown in table 1. There are about 5000 users, 13527 items, 264540 ratings with density of 0.39.

4.1 Performance Metrics

Mean absolute error (MAE) as well as root-mean-squared error (RMSE) are two common metrics used in model evaluation. Equations(8) and (9) are utilized to determine the MAE and RMSE for a sample of n observations. yi denotes the realized value , $\hat{y}$ denotes the predicted value and y denotes the mean of the realized values [23], [24],[25]

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(|y_i - \hat{y}_i|) \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

We looked examined how optimization affected several clustering-based recommendation methods. Using the Flixster and Kmedoids algorithms, where K is the number of clusters and ranges from 10 to 100, this evaluation was conducted. Figure 2 demonstrates that ABC-KCFL performs better than KCFL. The optimal selection of starting medoids permits an enhancement of clustering so as to boosts the suggestion accuracy

As shown in Figure.3, KSocFL optimization improves performance when taking into account the two types of information (social), they are trust as well as trust with friendship.

We compared the clustering-based hybrid algorithms KCFLT and KCFLSoc to the corresponding ABC-KCFLT and ABC-KCFLSoc algorithms in order to assess the effects of optimization on each algorithm.

The outcomes show that employing ABC over clustering-based recommendation algorithms is advantageous. Figure.4 demonstrates that ABC-KCFLSoc produces recommendations with a higher degree of accuracy.

4.2 MVC clustering technique contribution on the optimization

The two types of information (i.e., trust and trust with friendship) were taken into consideration as we have compared the ABC-MVC algorithm to the baselines as well as related studies. Figure 5 displays the outcomes of ABC-MVC-Trust utilizing Flixster1 with the clustering algorithms Kmedoids and CLARANS. With this analysis, we were able to demonstrate how well the ABC-MVC algorithm performed, achieving a better MAE value of 0.646 for K = 70 with Kmedoids and 0.650 for K = 19

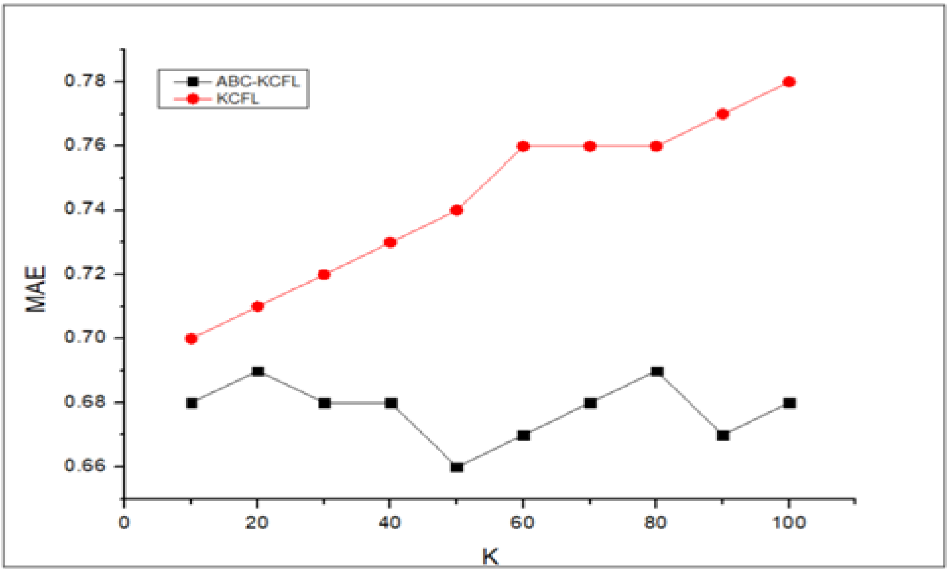


Figure 2: MAE rates of ABC-KCFL and KCFL

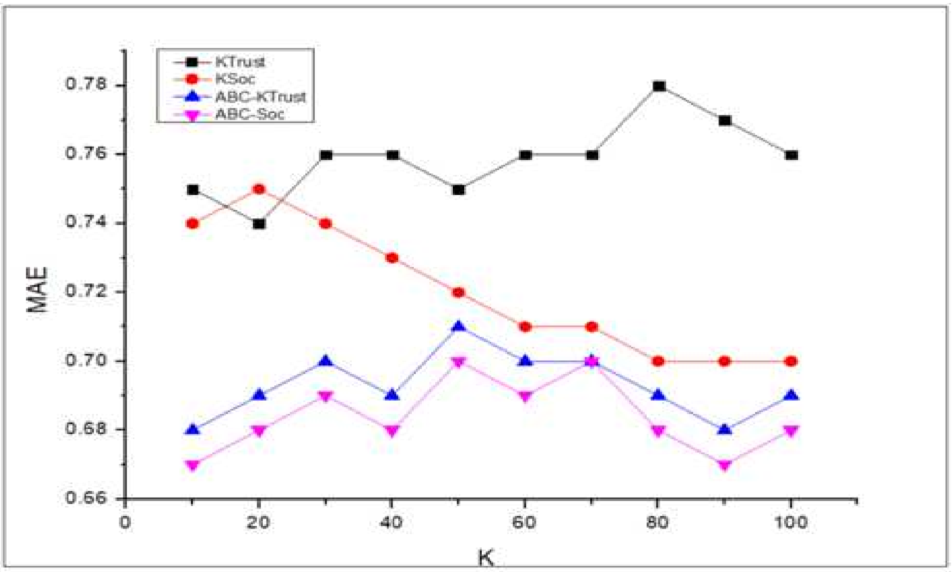


Figure 3: MAE rates of KTrust/KSoc and ABC-KTrust/ABC-Soc

with CLARANS for the ABC-MVC-Trust method. With the MVC-Trust algorithm, the MAE values are equal to 0.672 and 0.664, respectively, for the same numbers of clusters K. It is clear that the KCFLT algorithm performs better than these algorithms, KCFL and KTrust, and also demonstrated that the KCFL's recommendation accuracy has increased as a result of the integration of the Trust information. Nevertheless, the MVC still outperforms KCFLT hybridization, indicating the role played by multiview clustering. The ABC-MVC algorithm proves its efficacy by enhancing MVC performance as a result of the carefully chosen initial medoids prior to the multiview clustering.

We conducted the same assessment, taking social information into account (trust and friendship). Similar to Figure.5, Figure.6 shows the outcomes of ABC-MVC-Soc utilizing Flixster1 with the clustering algorithms Kmedoids and CLARANS. The collected results support the earlier assessment for all the algorithms, all of which have advanced in the same direction.

Additionally, by examining the outcomes of the two prior evaluations (Figures 5 and 6), we can conclude that the MVC-Soc and ABC-MVC-Soc algorithms, which combine friendship and trust information, outperformed the MVC-Trust and ABC-MVC-Trust algorithms for Kmedoids and CLARANS algorithms. Using Kmedoids, we were able to improve the MAE value for the ABC-MVC-Soc method

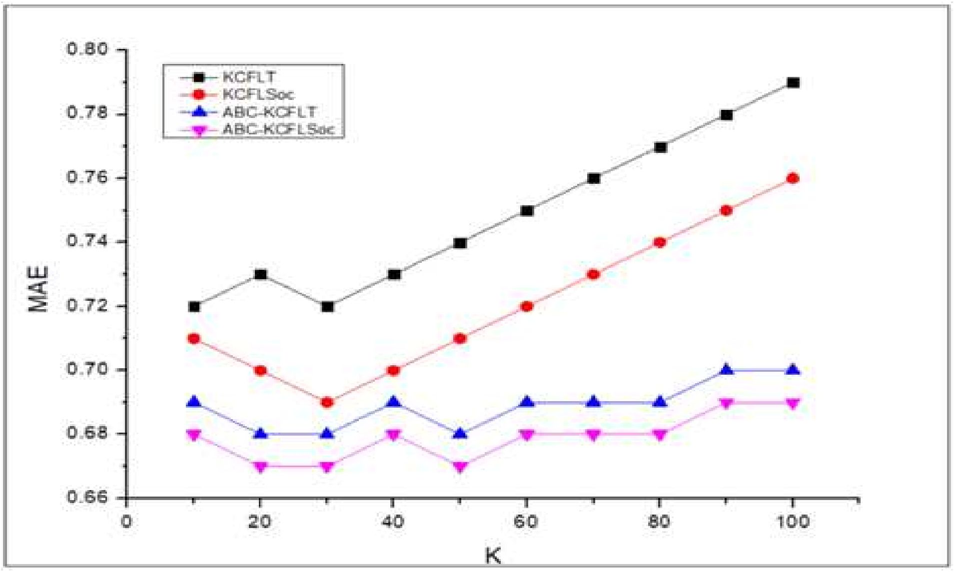


Figure 4: MAE rates of KTrust/KSoc and ABC-KTrust/ABC-Soc

from 0.6910 to 0.6501 with K value equal to 70. Similar to this, for CLARANS, we achieved reasonably good MAE value of 0.625 with K value equal to 7 for the ABC-MVC-Soc algorithm compared to the MAE value of 0.660 with MVC-Soc.

4.3 Discussions

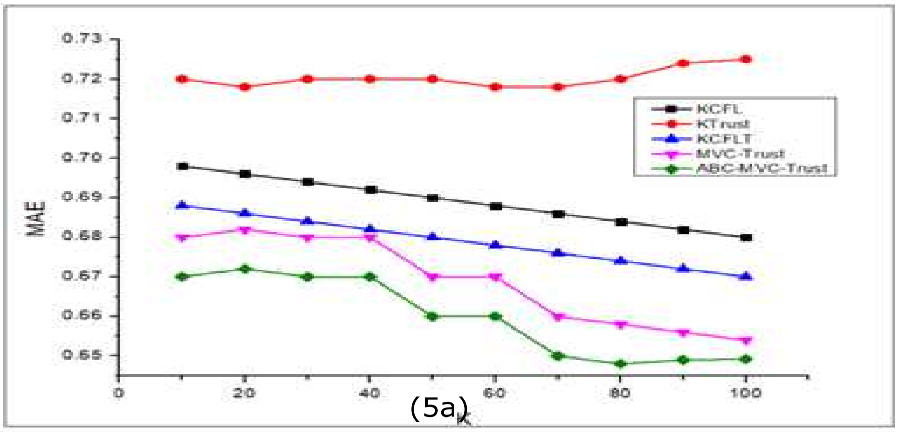
The outcomes of the trials show how optimization benefits all clustering-based recommendation algorithms. In comparison to KCFL, KTrust, KSocFL, KCFLT, and KCFLSoc, we found that ABC-KCFL, ABC-KTrust, ABC-KSocF, ABC-KCFLT, and ABC-KCFLSoc all had the best recommendation accuracy. On the other hand, the evaluation shows that ABC-MVC outscored all of these algorithms and that the MVC algorithm fared better than the other baselines. The MVC technique for both the Kmedoids and CLARANS algorithms was improved by the optimized initial medoids selection. By employing several MVC algorithm variations, this result is still valid. Also, all previous analyses demonstrate that CLARANS algorithm outperforms K-medoids and also, social information (friendship and trust) considerably increased all algorithms' ability to make accurate recommendations (MVC and ABC-MVC). This clearly shows that how MVC-Soc and ABC-MVC-Soc perform better than MVC-Trust and ABC-MVC-Trust. Figure 7 presents comparison of the clustering algorithms in brief.

Figure.8 depicts the trust and social features comparison of the clustering algorithms. It is clearly observed that ABC-MVC-Soc has outperformed compared to all other models.

Finally, KCFLSoc and KNN-CFLSoc are compared with MVC and ABC-MVC approaches. The findings obtained supported the efficiency of our concept when compared to hybrid recommendation systems based on supervised and unsupervised categorization. The benefit of the best partitioning is that it groups individuals according to how collaboratively and socially similar they are to one another, leading to the most accurate forecasts for these users. This claim is supported by the fact that we received the best evaluation results for the metrics MAE and RMSE.

The summary of the complete findings with regard to the best and average RMSE and MAE values is shown in Table.2. While Best-MAE is the minimum MAE and Best-RMSE is the least RMSE value acquired by varying the number of clusters "K". A-MAE is the average of the MAE and A-RMSE is the average of the RMSE values. The clustering-based techniques have been implemented using the Kmedoids algorithm. From Table.2, it is observed that ABC-MVC-Soc has the Best MAE value of 0.6501 and ABC-MVC-Trust has the Best MAE value of 0.6492. Similarly, ABC-MVC-Soc has the Best RMSE value of 0.8001 and ABC-MVC-Trust has the Best RMSE value of 0.8202.

The studies were also conducted on Film Trust real-world data collection. The description of the dataset is shown in Table.3. There are about 5000 users, 13527 items, 264540 ratings with density of



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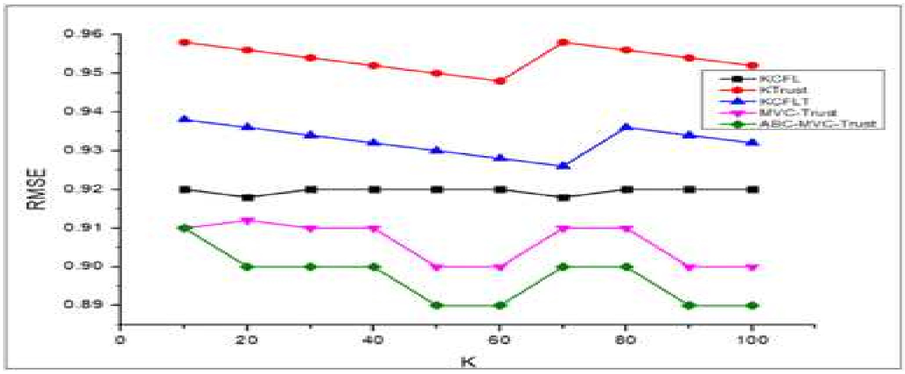

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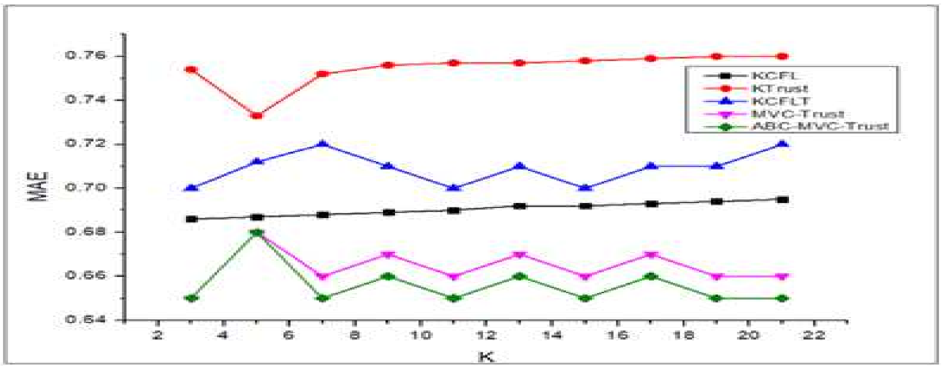

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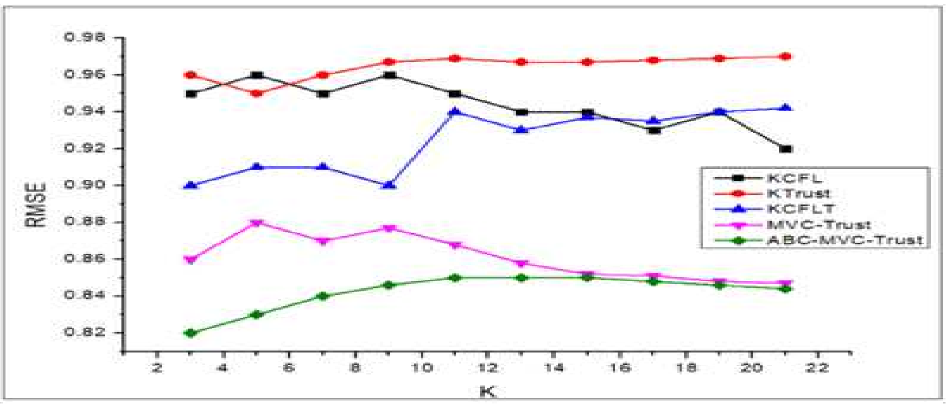
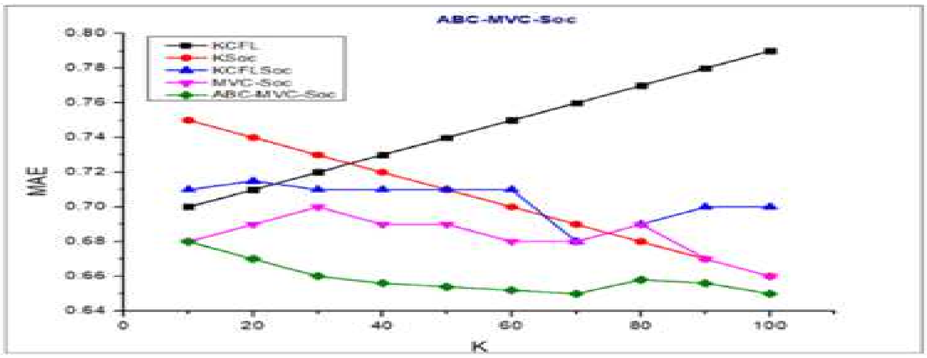


(5d)

Figure 5: (5a)Flixster Trust (MAE) Medoids (5b)Flixster Trust (RMSE) Medoids (5c)Flixster Trust (MAE) CLARANS (5d)Flixster Trust(RMSE) CLARANS



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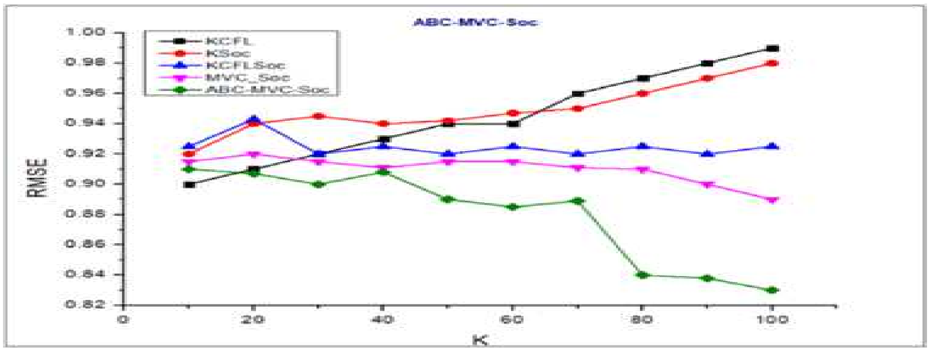

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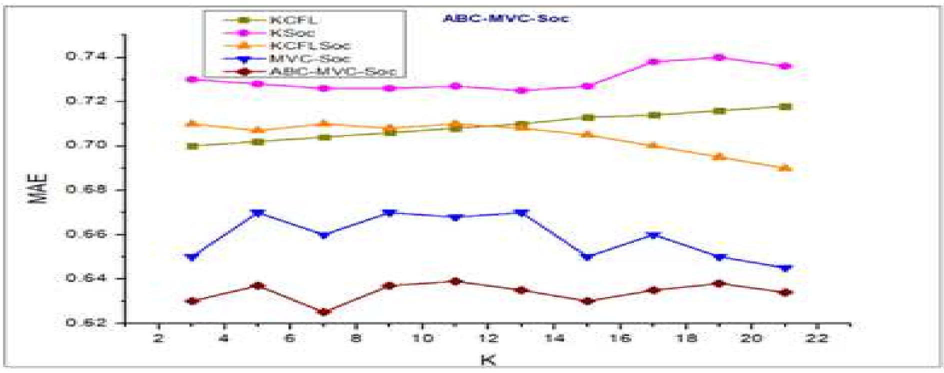

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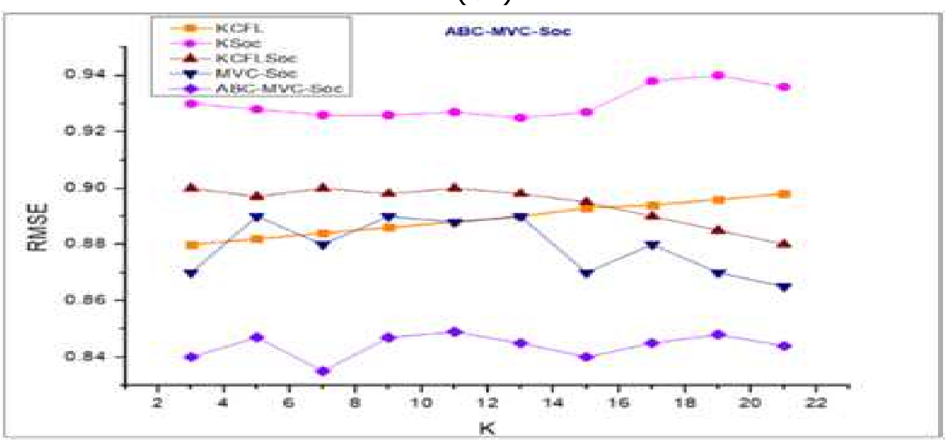


(6d)

Figure 6: (6a)Flixster Trust (MAE) Medoids (6b)Flixster Trust (RMSE) Medoids (6c)Flixster Trust(MAE) CLARANS (6d)Flixster Trust(RMSE) CLARANS

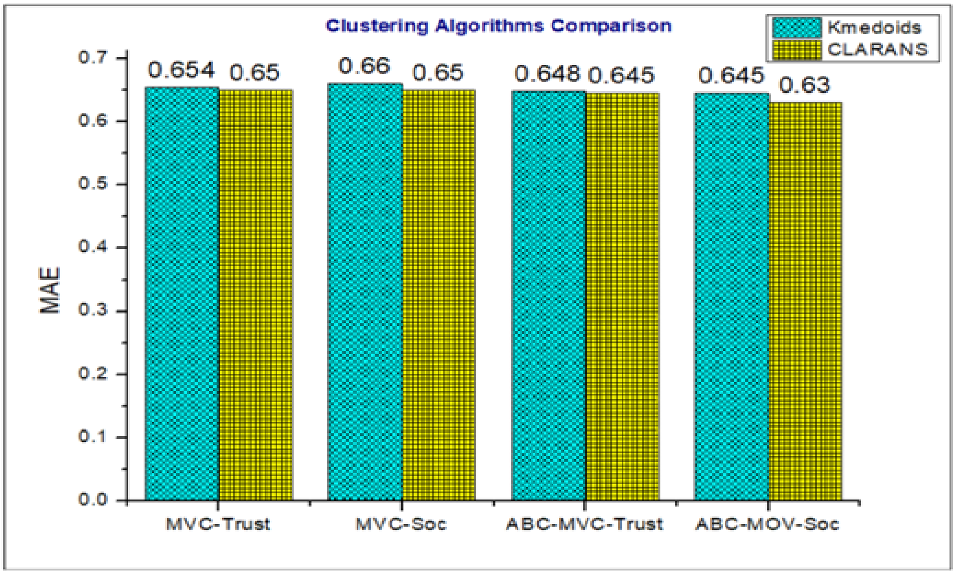


Figure 7: Comparison of Clustering Algorithms

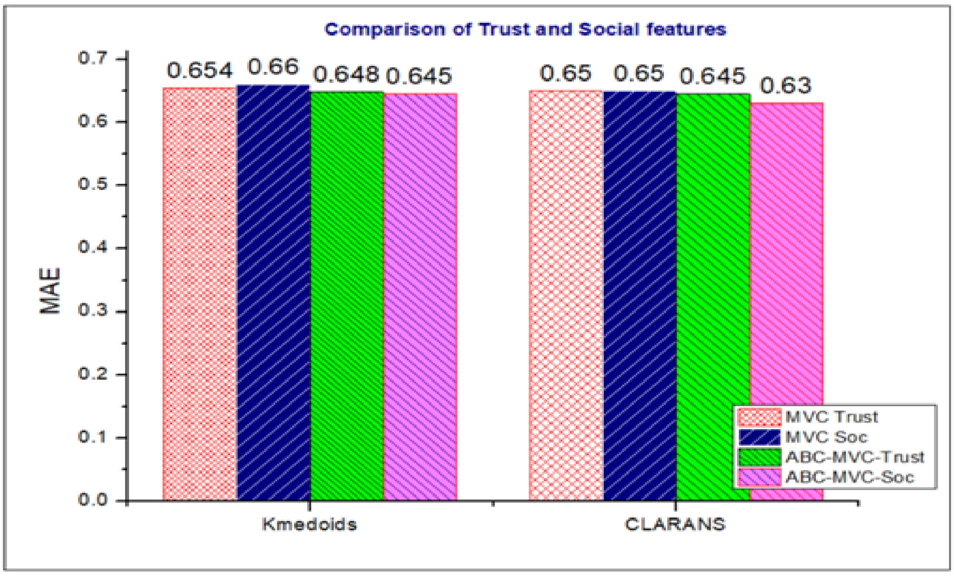


Figure 8: Comparison of social and trust features

0.39

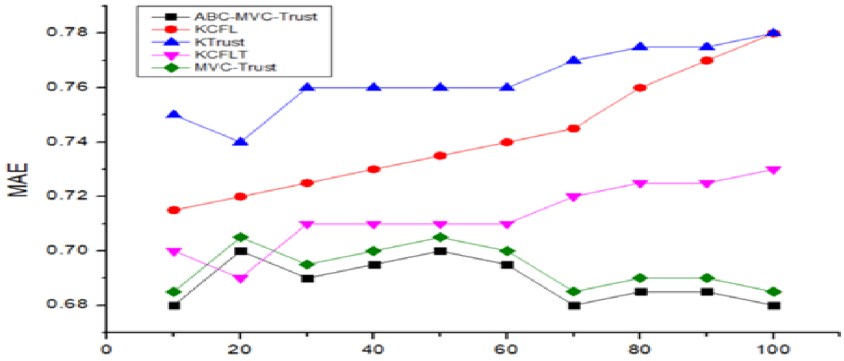
The two types of social information (trust / trust and friendship) were taken into consideration as we compared the ABC-MVC algorithm to the baselines and related studies on the Film Trust dataset. The outcomes of ABC-MVC-Trust employing Film Trust's Kmedoids and CLARANS clustering algorithms are shown in Figure 9. Through this assessment, we were able to demonstrate the ABC-MVC algorithm's effectiveness, which resulted in a better MAE score. On the other hand, it is clear that the KCFLT algorithm performs better than the two algorithms, KCFL and KTrust, demonstrating that the KCFL's recommendation accuracy has increased as a result of the integration of the Trust information. The MVC still outperforms KCFLT hybridization, highlighting the value of multiview clustering. The ABC-MVC algorithm proves its efficacy by enhancing MVC performance as a result of the carefully chosen initial medoids prior to the multiview clustering.

Table 2: Comparison of MAE and RMSE of different algorithms

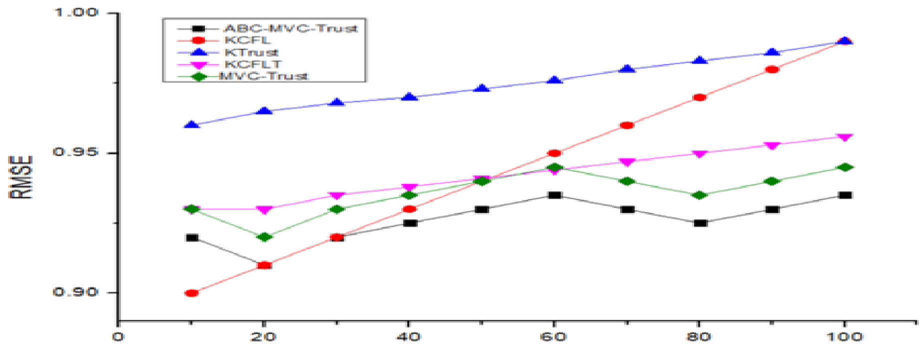
Approaches	RMSE		MAE	
	A- RMSE	Best-RMSE	A-MAE	Best MAE
MV-Trust [Guo, 15]	0.9024	0.9125	0.6894	0.6888
MVC-Soc	0.9013	0.8951	0.6852	0.6825
KCFL	0.9597	0.9080	0.7492	0.7110
KNN-CFL[Sarwar, 01]	1.0238	0.9165	0.7718	0.7010
K-Trust	0.9566	0.9433	0.7562	0.7401
K-Soc	0.9464	0.9321	0.7234	0.7002
K-NN-Soc	0.9386	0.9210	0.7501	0.7402
KCFLT	0.9490	0.9424	0.7309	0.7200
KCFLSoc	0.9486	0.9400	0.7003	0.6900
KNN-CFLSoc	0.9401	0.9312	0.7604	0.7500
ABC-KCFLT	0.9318	0.9208	0.6902	0.6800
ABC-KCFLSoc	0.9286	0.9102	0.7302	0.7200
ABC-MVC-Trust	0.8230	0.8202	0.6512	0.6492
ABC-MVC-Soc	0.8107	0.8001	0.6620	0.6501

Table 3: Film Trust Dataset description

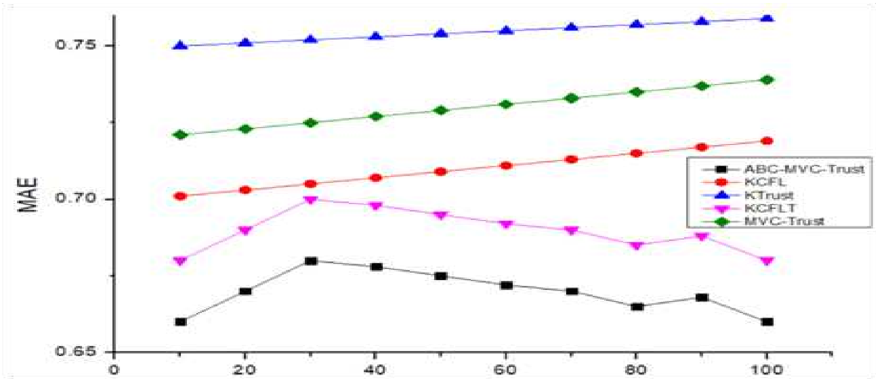
Attributes	Total #
Users	1508
Items	2071
Ratings	35497
Trust	2853
Density	1.14



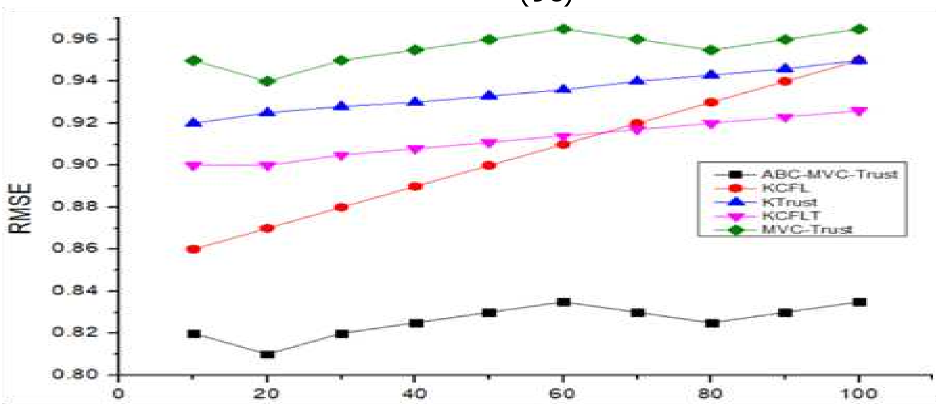
(9a)



(9b)



(9c)



(9d)

Figure 9: (9a)Film Trust (MAE) KMedoids,(9b)Film Trust (RMSE) Kmedoids,(9c)Film Trust (MAE) CLARANS,(9d)Film Trust (RMSE) CLARANS

5 Conclusion and Future work

In this research, we suggested an improved multiview clustering recommendation method for social networks, in which the people are repeatedly clustered based on views of social data and rating patterns. For the social filtering, we have taken into account information on friendship and trust. The artificial Bees colony optimization approach is used to optimize the multiview clustering. Furthermore, taken into consideration are several clustering techniques like K medoids as well as CLARANS. The proposed study demonstrated that the ABC-MVC-Soc has outperformed the MVC-Soc and the ABC-MVC-Trust has outperformed the MVC-Trust. The assessments have additionally demonstrated that the CLARANS algorithm outperformed Kmedoids and that the accuracy of recommendations increases when more social information-related variables are used. Finally, it would be very much interesting to incorporate additional dimensions into our MVC clustering approach in order to further increase the recommendation accuracy namely semantic view, user preferences etc., The outcomes from the Flixster database are encouraging. Yet, there are various methods to expand on our strategy: We are confident that other domains will benefit from our strategy as well. Additional characteristics might be taken into account, such as user credibility and influence within the social network. It would also be intriguing to think about using implicit trust relationships to enhance user trust data. In addition, factors like user authority and social network influence might be taken into consideration. It would also be interesting to consider how to improve user trust data by employing implicit trust relationships. It is crucial to test how well our strategy for dealing with cold-start users works. Many weighted combinations of the factors relating to the social and hybrid algorithms have been empirically evaluated. The accuracy of the recommendations should increase if the values of these weights are automatically optimized, particularly if we combine many features to represent social information and other techniques, like semantic filtering.

Data Availability

The Data used to support the findings of this study are included within the article.

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The research carried out has not received funds from any organizations.

Conflict of interest

The authors declare no conflict of interest.

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