Confirmed quality aware recommendations using collaborative filtering and review analysis

Seema P. Nehete and
Satish R. Devane*

Datta Meghe College of Engineering,
Navi Mumbai, Maharashtra, India
Email: nehete.seema@gmail.com
Email: srdevane@yahoo.com
*Corresponding author

Abstract: Recommendation Systems (RS) save the time of users in their hectic life schedules for purchasing their interested products.RS faces challenges of data sparsity, cold start, efficiency of prediction of products and hence the proposed system is making use of Multi-Kernel Fuzzy C Means (MKFCM) clustering to group together similar users having similar age, occupation and gender into clusters. Clusters of similar users are optimised using the Fruit Fly (FF) optimisation algorithm which gives high cluster accuracy and dynamically created sub-clusters of similar users with their favourite products, overcome sparsity issue which make the analysis easy. Collaborative Filtering (CF), one of the filtering method of RS is used to predict products for target users. This RS gains user's faith by additionally performing analysis of textual reviews using optimised Artificial Neural Network (ANN) to recommend the highest quality products, thus dual tested and quality confirmed products are recommended to the user. Experimentation is done on a standard Movilense data set used by many researchers to prove the efficiency of this RS and reviews of all users are extracted from online search engines for product quality analysis before recommendation. Experimentation proves higher recall and accuracy than existing recommendation systems.

Keywords: clustering; recommendation systems; collaborative filtering; artificial neural network.

Reference to this paper should be made as follows: Nehete, S.P. and Devane, S.R. (2022) 'Confirmed quality aware recommendations using collaborative filtering and review analysis', *Int. J. Computer Applications in Technology*, Vol. 68, No. 1, pp.39–48.

Biographical notes: Seema P. Nehete is a Research Scholar and working as a Faculty in reputed Engineering College in Mumbai, India since 15 years.

Satish R. Devane is Professor in reputed Engineering College in Mumbai, India and having experience of 34 years. He completed his PhD degree from Indian Institute of Technology Bombay (IITB). He is working in Advisory Boards of Many Engineering Colleges in India.

1 Introduction

Every buyer looks for the best product for himself before purchasing as a natural human tendency. Availability of ample products and shortage of time to research about the product confuses user for purchasing. The buyers of every age group be it a teenager or old age are very busy with their hectic life schedules and hence prefer online shopping. All buyers rarely get to meet together friends, relatives due to these busy hectic schedules and lack of time, therefore they cannot physically view products purchased by each other's. Large size of data (product, movies, web series, books, songs) is available for online shopping, where buyers get confused for purchase. Buyers are not aware of actual defects in the products in which they are interested, as a result, might end up with low-quality products as they can't see the physical product on online shopping. Among a large volume of users, products and reviews available across the web, a Recommendation System (RS) helps target users, buyers for purchasing by predicting a list of products for them (Sanchez et al., 2008; Young, 2019). The RS filters similar users for target user among millions of users using filtering methods. Pazzani and Billsus (2007); Lu et al. (2010) and Bobadilla et al. (2013) already presented different filtering methods for RS. Collaborative Filtering (CF) (Suganeshwari et al., 2016), one of the filtering method of the RS is mainly used to learn a user's past purchasing history and recommend him list of products by finding similar users.

Once the target user has explored different products from similar users, many new products can be added to his taste due to the advantage of CF over another famous filtering method, content-based filtering (Pazzani and Billsus, 2007). In content-based filtering, the user may reach the wrong product at the end not as per need. CF is mainly of two types user based and item based (Shambour et al., 2020) and it makes use of ratings given by users usually in the scale of 1–5 (Chen et al., 2018; Yu et al., 2018) to their purchased products to calculate similar users with the belief that if two users have same liking in the past then they will agree in future also. Similarity measures used till now (Liji et al., 2018; Najafabadi et al., 2017) in CF are not efficient to give relevant predictions to the target user, if the data set is sparse and the user might be end up with low-quality irrelevant recommendations.

The number of nearest similar users for the target user is directly proportional to number of relevant products that need to be recommended (Zhang et al., 2017). Users who have just started online purchasing with single product will never get proper recommendations. Traditional similarity measures, due to consideration of the average rating of customers do not give recommendations to these users. From a business point of view, RS should help for adding new customers to increase revenue. In reality many product pairs have no common customers and hence item based method of recommendation used by Linden et al. (2003) is inefficient in terms of processing time and memory usage. Wu et al. (2017) required to do normalisation of customer ratings to get better results for recommendation, as a result actual ratings given by customers which shows their interest is of no use.

Lee and Lee (2014) proved that increase in number of dimensions reduce novel recommendations. McFee et al. (2012) used content-based filtering using TF-IDF but they mentioned TF-IDF on human tags decrease performance of recommendation.

Actually star ratings are calculated as average of ratings given by users to their purchased products which are provided by the e-commerce website; do not show all negative textual reviews of products that might have experiences of dissatisfied customers for the same product. These negative textual reviews help to decide the quality of the product, as a result if we think of using only opinion mining of reviews for recommendation (Sharma et al., 2015) then user interest cannot be learned properly and might end with overspecialisation which irritates user Several approaches and systems for the recommendation were developed (Sharma et al., 2015; Kumari et al., 2015; McFee et al., 2012; Adomavicius and Tuzhilin, 2005) but very few have focused on the integration of analysis of textual negative reviews available on internet along with customer ratings in the recommendation process. From 2000 till 2019, (Jebaseeli and Kirubakaran, 2012; Sun et al., 2011), we found only a few studies relevant to quality-aware product recommendations using sentiment analysis of reviews (Zhang et al., 2013) and hence conform solution is required to overcome problems of recommendation system and to give relevant quality recommendations to target user (Shambour et al., 2020; Khusro et al., 2016). Clustering with proper optimisation algorithm (Mangat, 2012; Chen et al., 2018) and CF, along with analysis of textual reviews can give efficient solution for RS (Xiao et al., 2015). Therefore a clustering-based CF approach for recommendation system is proposed in this research, which next aims at analysing positive and negative reviews of products that need to be recommended to users. The RS uses Multi-Kernel Fuzzy C Means (MKFCM) clustering to narrow down the volume of users to search for similar users. The clusters of users are optimised using Fruit Fly (FF) optimisation algorithm. Technically, this RS is enacted around two stages. In the first stage, users are clustered using user's attributes. Then heterogeneous sub-clusters are created with dynamic clustering that collect together users with their favourite products to overcome data sparsity issue. At the second stage, a CF algorithm with new improved similarity measure which work with ratings given by users to their purchased products is imposed on the clusters which gives efficient solution to cold start problem. Resultant predicted products from CF will undergo feature extraction and review analysis using optimised Artificial Neural Network (ANN), before a final prediction.

The main contributions of this paper to give conform solution to the problems of recommendation system are as follows:

1) Aims at Scalability: in this, entire customer base is clustered using optimised ensemble clustering algorithm and hence similarity calculation for CF will be done in each cluster easily. Here modified MKFCM algorithm using average of linear and sigmoid kernels is proposed for efficient clustering. Clustering has problem of initial centroid selection to get accurate clusters. Optimised Fruit Fly algorithm provides best solution among five calculated solutions to get correct initial centroids.

2) Aims at data sparsity and cold start: many users hesitate to give ratings, hence data set becomes sparse. Evolutionary clustering algorithm proposed here provides solution to data sparsity by clustering users and his favourite items together. New user is having no purchased history and it is difficult to predict his taste and hence similar users .Our proposed clustering assign new user correctly to his age group with the assumption similar age people has same taste and thinking. Similarity between users for CF is correctly calculated using proposed novel similarity measure.

3) Aims at analysis of negative reviews: in this method item reviews are extracted from all real time websites. User reviews provide user's opinion about the item. Every item has positive and negative impact on all users. If these low-quality products specified by negative opinions are recommended to users, then RS will lose faith of users' on system. Therefore, before recommending item finally to the user negative impact is considered using optimal ANN algorithm.

4) To prove efficiency of proposed method Movilense standard data set is used. Experimentation proves this novel algorithm outperforms existing recommender systems on the basis of different evaluation measures precision, recall and *F*-measure.

The rest of the paper is organised as, Section 2 gives an idea about the literature survey and Section 3 explains the proposed methodology followed by results and discussion in Section 4.

2 Related work

Literature survey is done in four parts.

2.1 Clustering and fruit fly

The FF optimisation algorithm is found in 2011. It is first used for clustering optimisation by Xing and Meng (2015) in 2015. The algorithm is easy for computation with less number of input parameters than all available swarm optimisation algorithms. Authors have proposed shock factor for smell concentration value and tested initial range position on 10 data sets. The authors confirmed high precision, *F*-measure, and Dunn's index. Author (Zhou et al., 2017) proposed a clustering algorithm based on FF concept. FF algorithm is used to calculate cut-off distance and cluster centres. Authors shown that FF optimisation converges fast and helps in correct clustering on seven UCI repository data sets.

Zeng et al. (2017) used multi-kernel fuzzy clustering for Multiview data efficiently. Authors used collaborative learning for individual views and multi kernels for the combination of all views in common kernel space. The authors tested the algorithm on synthesis data sets and proved that MKFCM obtained stable results than other existing clustering algorithms.

Huang et al. (2012) stated that with proper kernel tricks fuzzy c means can be improved to get non spherical clusters. Selecting kernel or combination of kernels is difficult for effective clustering. Authors proposed MKFCM with kernel-learning setting. They analysed multiple kernels and adjusted kernel weights to prove MKFCM is more resilient to unreliable kernels and unpredictable features.

Gu and Wu (2018) stated that due to mentioned problems of harmony search algorithm is not efficient to find global solution for optimisation problems. Ren et al. (2015) analysed different optimisation algorithms like artificial bee colony (ABC) algorithm, Biogeography-Based Optimisation (BBO), Differential Evolution (DE) algorithm, Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) algorithm for thrust allocation problem and concluded that population size and evaluation number affect performance of all these algorithms.

2.2 Dynamic clustering

Chen et al. (2018) used heterogeneous-clustering and CF. Users and their favourite products are clustered together and then CF is applied for giving recommendations to the active user. The author experimented on movielense and CiaoDVD data set and obtained good performance of CF. Liji et al., (2018) used dynamic clustering for clustering users as per their states which are calculated from user features. Authors showed user states are changing as time evolves and become stable at some certain values. Authors have clustered users using stable states. This dynamic clustering on movilense data set results in high precision and recall.

2.3 Collaborative filtering and similarity measures

Wu ett al. (2017) given a new similarity measure based on preferences uniformity of two users. The author has shown the proposed method is efficient than existing similarity measures. Liu et al (2014) also proposed a new user similarity model called New Heuristic Similarity Measure (NHSM) to improve accuracy. Authors make use of normalissation to differentiate all users by searching minute differences in their similarities. Bobaldia et al. (2012) calculated singularities for every product. He has considered agreement, and disagreements between users. Here, the author has shown improvements in the recommendation quality.

2.4 Textual review analysis

On the literature survey, it is found that RSs based on ratings cannot test the quality of products.

Textual reviews are needed to confirm the quality of products. Sentiment-aware recommendation considers reviews given by customers to assess the quality of products. A survey is done on sentiment aware recommendations.

Despotovic and Tanikic (2017) used an artificial neural network with a sigmoid activation function to analyse microblogs. Authors compared results with naive Bayes, Maximum entropy and SVM techniques and obtained good performance. Vilares et al. (2017) used syntax-based rules for semantic calculation and review analysis. They created dependency tree using compositional operations and semantic rules. They provided future scope to extract semantic rules between different objects.

Many papers on sentiment analysis of product reviews are surveyed by Jebaseeli and Kirubakaran (2012). They mentioned that people take opinions of other people as their reviews about products before purchasing. Opinion mining classifies product reviews positive, negative and neutral using natural processing techniques. Analysis of different features of products using reviews plays important help to users for purchasing products.

Sharma et al. (2015) used analysis of textual reviews to recommend hotels to users. They extracted reviews of previous users based on multiple criterias. Using different NLP techniques they created item-feature-user matrix from extracted reviews instead of only from star ratings. Authors used collaborative approach for extracting reviews as from users who belong to same geographical locations along with previous visited users. Different steps like pre-processing, extraction of features, assignment of polarity and generation of utility matrix before final recommendation are used.

Kumari et al. (2015.) given personalised book recommendations by analysing textual reviews. They stored reviews of every item in the document D according to different features and classify them into positive and negative classes using mining of opinions. For every item store every feature as positive or negative using count of positive reviews. They found user's interest using his past textual reviews and filtered sored reviews according to his interested features for final recommendations.

The literature survey concludes that existing clustering methods have given low cluster accuracy and overlapping clusters. Clustering accuracy is dependent on initial centroids. If initial centroids are not accurate, millions of users end up in the wrong clusters, therefore there is a need for optimised clustering. The clusters should be accurate to find the most similar users. Traditional similarity measures of CF face the problem of data sparsity and cold start so predicts irrelevant product list and lost user's faith in the system. Only a few papers worked on sentiment aware recommendation. Before purchasing the product every user wants quality confirmation of interested product, so review analysis is needed and very important before recommending the products.

3 Proposed method

The proposed system of RS with CF needs user information and user's rating for the past purchased product as input. For accurate clustering, RS uses an improved objective function of multi-kernel fuzzy clustering (MKFCM).MKFCM gives accurate clustering because of the correct and best initial centroids for clusters. Best centroids are calculated using the proposed fitness function of the FF optimisation algorithm. Once accurate clusters are calculated, the sparse utility matrix problem of CF is solved by the evolutionary heterogeneous clustering of users and products. Heterogeneous clustering creates a filled utility matrix of users and their favourite product's ratings. The new improved similarity measure is used to give recommendations to the single product purchased user and new users. Product quality analysis before the recommending the product is very important. This RS fetches textual reviews from online search engines and analyses using the proposed optimal Artificial Neural Network (ANN). The RS gives three main methods – Optimised MKFCM clustering for clustering users, CF and Online Review analysis using optimal ANN. In this RS, we proposed an improved objective function of MKFCM with the fitness function of FF optimisation, new similarity measure for CF, and textual review analysis using activation function of optimal ANN. Proposed methods are explained in the following section. For explanation, the paper denotes the number of users by X and the number of products by P.

3.1 Optimised multiple kernel fuzzy c-means clustering (MKFCM) for clustering users

Clustering is an important step in the RS. Different clustering methods are used by researchers, among them FCM is better with the expense of a large number of iterations. Clustering should be accurate and results are expected in a short time for millions of users.

Kernel methods can be used to get accurate clustering with less number of iterations. Kernel methods have the advantage of mapping data by easy separations into the correct structure. The sigmoid kernel has the additional advantage of good performance. The RS uses MKFCM which is an extension to Fuzzy c means which is a combination of linear and sigmoid kernels. The objective function of traditional FCM is given in equation (1).

$$F = \sum_{i=1}^{x} \sum_{j=1}^{y} \xi_{ij}^{m} \left\| \phi(U_i) - \phi(C_j) \right\|^2 \tag{1}$$

where U represents user and C represents cluster centre, x – Number of users, y – Number of clusters and ξ_{ij} – Cluster membership of user i to cluster j. In traditional FCM if we elaborate on the term $\left\| \phi(U_i) - \phi(C_j) \right\|^2$, it is given by equation (2).

$$\left\| \phi(U_i) - \phi(C_j) \right\|^2 = K(U_i, U_i) + (C_j, C_j) - 2K(U_i, C_j) \tag{2}$$

If we put $K(U_i, U_i) = 1$ and $K(C_j, C_j) = 1$ then the above equation (1) can be written as eqn.3 and using multi-kernel we get,

$$F = 2 \sum_{i=1}^{x} \sum_{j=1}^{y} \xi_{ij}^{m} \left(1 - MK(U_i, C_j)\right) \tag{3}$$

where Mk=Avg (Linear, sigmoid).

Traditional FCM is not having the advantage of kernels and result in low cluster accuracy. To gain higher cluster accuracy, improved objective function with an average of sigmoid and linear kernels are taken as shown in equation (3). MKFCM proves more efficient than all other clustering algorithms. Centroid updation is done to reach accurate clusters with less iteration.

Millions of users make purchases worldwide at all times. Clustering groups together similar users so that a large database of users can be handled efficiently. In this paper, we have analysed different clustering algorithms and found improved clustering accuracy by MKFCM. It is found that the calculated average of linear and sigmoid kernel gives better accuracy. Also, MKFCM is protected from unrelated features added by different kernels and automatically adjust the kernel weights. For any clustering algorithm, centroids are needed to be chosen correctly. Many algorithms randomly generate these centroids initially. Cluster accuracy is highly dependent on these initial centroids. Therefore this RS uses the FF optimisation algorithm to get initial and best centroids.

3.1.1 FF optimisation

Many algorithms of swarm intelligence cluster analysis are available where the proposed optimised FF is simple among them with less number of input parameters. To get the correct initial and best cluster centroids, the FF optimisation algorithm is used which gives better cluster accuracy. The Fruit fly algorithm is implemented in the way flies search for their food. These fruit flies are intelligent than other birds as they have a good sense of smell and perception quality. The fruit flies fastly reach to the food and find similar food to the food they have reached efficiently. This behaviour is used to find the best cluster centres and accurate clusters having similar users in this research. The FF optimisation algorithm is proposed with an improved fitness function to get higher cluster accuracy. Using FF optimisation we get different solutions out of which one best solution is selected which gives the best cluster accuracy. This solution gives correct initial and best centroids, using that optimum clusters are created. FF optimisation is done by the following equation (4).

The RS uses Distance Within-Cluster (DWC) and Distance between Clusters (DBC) for calculating cluster fitness. From each FF, one solution is given. In the solution, if DWC is minimum and DBC is maximum, then clusters are accurate. In this way, each FF gives different clusters with different cluster centres. For different cluster centres, given by each FF, aggregation of DBC is done.

$$Fitness = \frac{DWC}{1 + \beta * DBC / DWC} \tag{4}$$

where

$$DWC = \sum_{j=i}^{Y} \sum_{i=1}^{X} D\left(U_i, C_j\right) \tag{5}$$

$$DBC = \sum_{i=i}^{Y} \sum_{j=1}^{Y} D\left(C_i, C_j\right) \tag{6}$$

β-scaling factor=1.

According to minimum DWC and maximum DBC, every FF solutions are ranked. The solution with maximum DBC and minimum DWC is considered as the final solution. Final and best centroids will be taken from FF which has searched optimal clusters. These cluster centres will work as initial cluster centroids for multiple fuzzy c means clustering.

3.1.2 Evolutionary heterogeneous clustering

MKFCM clustering groups together similar users according to user details. The user purchases different products frequently. These products should be considered to calculate similar users. Also at different states, user's tastes might change and dynamic clustering identifies these changes. The proposed system uses dynamic clustering. The dynamic clustering called as evolutionary heterogeneous clustering creates sub-clusters of users and products under each homogeneous cluster of users. The idea is that the user and only his most favourite and certified products are combined using an utility matrix as per the Kuramoto model. Utility matrix has ratings given by users to their purchased products. This sub-clustering reduces millions of user-products to a small subset of users and their most favourite products. This gives ignore sparse values and concentrates on the target user and his similar users. Thus for recommendation CF can concentrate the exact set of users and products.

3.2 Finding most similar users using CF

In this research, we have analysed different traditional similarity measures and found the following problems:

1) Cosine and adjusted cosine does not take into consideration only ratings given to common products between users, but it considers all ratings given by user to all products.
2) Jaccard considers common products between users and gives only 2 values of similarity 1 and 0.5.
3) If two users are have commonly purchased products and both have given the same ratings to these products then also Pearson, cosine and adjusted cosine give different similarity values of these users with the third user.
4) For new users and sparse data, these similarity measures failed to give a solution.
5) Tested *F*-measure accuracy for these similarity measures which is not satisfying.

To overcome all the above problems proposed RS finds out the most similar users for every target user. It calculates the similarity between two different users using the new measure given in equation (7). In equation (7), numerator gives deviation of maximum rating among both the users for the common products with the span of the mean of ratings of both the users. Denominator considers only the maximum rating for the common product between user pair, because of that user with less product purchase history and new users get the most similar users.

$$sim\left(u_x, u_y\right) = \frac{\sqrt{\sum_{n \in N} \left| \max\left(r_{u_x n}, r_{u_y n}\right) - r_{u_x u_y} \right|}^{2}}{\sqrt{N} * \max\left(r_{u_x n}, r_{u_y n}\right)} \tag{7}$$

where u_x, u_y two different users, $r_u u_y = \left(5 - \left(r_u x + r_u y\right)/2\right)$, N – common products rated by u_x and u_y, $r_{ux,un}$ and $r_{uy,un}$ – user $u_x's$ and $u_y's$ rating to common product n and $\overline{r_{u_x}}$ and $\overline{r_{uy}}$ common purchased product rating's average for users u_x and u_y Using this similarity list of products is predicted for the target user.

3.3 Quality analysis of product using textual reviews extracted from online search engines

Textual review analysis is required to recommend quality confirmed products. The proposed method is used to give quality recommendations to the target user. This method is a dual confirmation to give quality recommendations. To recommend a list of products to target users CF is used with ratings of most similar users, but reviews given by all other users need to be analysed to decide the quality and ranking of recommended products. This proposed method extracts all online reviews from all search engines for every product predicted in CF for the target user. Here, for active user's interesting products, we have checked the quality of products by analysing positive and negative reviews given by all users. The optimised ANN algorithm is used to perform textual review analysis. Then based on positive and negative review scores, predicted products in the list according to quality are recommended to the user.

4 Algorithm

The proposed RS works in five main steps. Millions of users and a large number of items are available online, user clustering helps in an optimised way of analysing users. Heterogeneous clustering evolves as the liking of user changes or if users purchase new items. CF finds similar taste users together and predicts a selection list for users. Textual review analysis arranges the selected list according to best reviews. Finally, the top-N recommendation list is predicted for the user after dual testing. The algorithm for the proposed system is mentioned in Figure 1.

The five steps of algorithm are elaborated further.

Step 1: User clustering

Users are clustered together using user details such as occupation, gender and age number as input. Age and gender are taken as numeric, while the occupation is mapped among 0 to *n*. The distance of input data is calculated from the centroid of clusters using equation (8).

$$\text{Distance}\left(\text{user, centroid}\right) = \left(\left(u_a - c_a\right)^2 + \left(u_g - c_g\right)^2 + \left(u_o - c_o\right)^2\right)^{1/2} \tag{8}$$

Initial and best centroid (ca, cg, cc) are for the occupation, gender and age number attributes of the user and searched using FF optimisation algorithm explained in the above section. Then, optimised MKFCM is applied to get accurate clusters.

Step 2: Hetrogeneous evolutionary clustering

In this step sub-clusters of each user, cluster are formed. User and their favourite products are grouped using heterogeneous evolutionary clustering.

Step 3: Prediction of the list of products

In every heterogeneous cluster of users and products, the similarity between two different users is found using the proposed formula given in equation (7)

Using the highest similarity, most similar people are found for the target user. A list of products is predicted for target users from their most similar users.

Step 4: Online textual review analysis

For every product of top-N, textual reviews are searched and extracted from online search engines. Pre-processing of these reviews is done. The predicted score of each product is calculated using the optimised ANN algorithm.

Step 5: Final quality recommendation

All the products in the predicted list of target users are ranked using a predicted score based on reviews. Finally, quality recommendations are given to the target user.

Figure 1 Algorithm for optimum personalised confirmed quality aware recommendation

```
Input-user details(age,gender,occupation),utility matrix,K
Output-Recommendation list
1.//user clustering
  1.1.//First find best cluster centroids
     1.1.1 Repeat
          a.for every FF do
               a.1 find the distance between each user and cluster centroid given by FF according to
                   Eqn.5
             a.2 calculate fitness function with the formula given in eqn.4
          b. end for
     1.1.2 until minimum intracluster distance found from cluster centroids
  1.2 for each user u do
     1.2.1 Calculate distance between each user and best initial cluster centroid searched from FF by
          eqn.8
  1.3 end for
2. //Heterogeneous evolutionary clustering
  2.1 for each user cluster
     2.1.1 Create subcluster of the user and their favorite items
  2.2 end for
3. //CF-Prediction of the list of products
   3.1 for each subcluster of user and item
     3.1.1 Find the most similar users using eqn.7
   3.2 end for
   3.3 Create a top-N prediction list for the target user using CF
4.// Online Textual review analysis
  4.1 for every predicted product of top-N for target user
     4.1.1 Extract online reviews from different search engines
     4.1.2 Perform pre-processing and analysis of reviews
     4.1.3 Predict the score of each review using the optimized neural network
  4.2 end for
5. Recommend top-N products based on prediction score
```

5 Results and discussion

The data set of MovieLens (https://grouplens.org/datasets/movielens/100k/) is used in our experiments. It contains 1 lac ratings given by 943 users to 1682 movies. Train and test data set is given in standard data set as base and test set. Here for every test user, 80% of his purchased products are taken into the training data set, and the remaining 20% are taken into the test set for the same users. Like this Movilense data set is divided into five different combinations of the train and test data from u1 to u5 base and test sets. All five test sets contain different users. To evaluate the performance of the proposed method we considered all five base and test sets as five-fold cross-validation and took the average.

5.1 Evaluation metrics

Before suggesting list of products to users, the RS predicts ratings for recommended products of the target user. From recommended list of products, if a user actually purchases the product and the predicted rating of that product matches the real rating given by user, then prediction and recommendation are accurate. In the standard data set, the test set gives the user's favourite products. So the RS is accurate if the predicted list of products is having maximum products from the test set of the user. On this concept first n recommended products are classified as relevant and not relevant. For such binary classification precision (Cremonesi et al., 2010) and recall (Fouss et al.., 2007) metrics are used which will analyse actual purchased and predicted products by RS. Precision is validating how many relevant products are recommended in first N products and given by formula in equation (9).

$$\text{Precision} = \frac{\begin{array}{c}\text{Number of relevant}\\ \text{products recommended} @ N\end{array}}{N} \tag{9}$$

The recall is validating in first N products, how many relevant products are recommended out of the total number of relevant products. Recall can be stated as in equation (10)

$$\text{Recall} = \frac{\begin{array}{c}\text{Number of relevant products}\\ \text{in first } N \text{ recommendation list}\end{array}}{\text{Total number of relevant products in test set}} \tag{10}$$

Both measures should attain high value for good performance. One more evaluation criteria called F-measure is used which gives an accuracy of recommendation. F-measure is as given in equation (11).

$$F\text{-measure} = 2*(P*R)/(P+R) \tag{11}$$

To have better recommendation accuracy, F-measure should be high.

5.2 Experimentation

The increase in the number of recommended products and the number of nearest neighbours, affect the precision and recall metrics. In this paper, we have analysed the efficiency of proposed algorithm with the existing algorithms.

5.2.1 Performance analysis of MKFCM

The proposed MKFCM algorithm of user clustering for top-N recommended products is compared with two existing algorithms Evolutionary heterogeneous clustering-CF (Chen et al., 2018) and PR-ACMF (Liji et al., 2018). All these algorithms attained good performance, but are very much calculative and complicated. Also we have compared proposed algorithm with traditional k-means clustering having 3, 8 and 15 clusters. The precision, recall and F-measure for mentioned algorithms are given in Table 1. From the Table1 it can be seen that proposed MKFCM algorithm outperforms than all existing algorithms. For Top-4 and Top-6 products K-means 3 and PR-ACMF have same recall, but our proposed algorithm perform better than both. For all clustering algorithms including our proposed algorithm precision goes on decreasing as Top-N products increased but recall and F-measure increase as top-N increases.

5.2.2 Performance analysis of proposed similarity measure

RS uses new similarity measure to find the similarity between two different users. The standard data set is having sparse data. To overcome the sparsity of the data set we proposed evolutionary heterogeneous clustering which creates sub-clusters of every user cluster. As sub-clusters are less sparse than the overall data set, new proposed similarity measures outperform traditional similarity measures as shown in Table 2. For all traditional similarity measures including our proposed similarity measure, precision goes on decreasing as the number of recommended products are increased. Recall and F-measure is increased as top-N products increases. For top-10 products new similarity measure performs very well. As the number of top-N products is increased, our similarity measure performed very efficiently than other measures. Using the proposed similarity measure, users with single or less product purchase history are properly getting most similar users and hence recommendations as compared to existing measures.

Table 1 Comparison of MKFCM with existing algorithms

Evaluation Metrics	*Precision*					*Recall*					*F-measure*				
Method	*Top-N*					*Top-N*					*Top-N*				
	2	*4*	*6*	*8*	*10*	*2*	*4*	*6*	*8*	*10*	*2*	*4*	*6*	*8*	*10*
kmeans3	92.71	91.74	90.94	90.4	90.03	8.48	16.2	23.03	29.07	34.47	15.47	27.36	36.48	43.68	49.51
kmeans8	92.18	91.23	90.49	90	89.66	8.43	16.1	22.91	28.94	34.32	15.37	27.2	36.31	43.48	49.3
kmeans15	91.58	90.92	90.37	89.9	89.57	8.38	16.06	22.88	28.92	34.29	15.28	27.12	36.26	43.44	49.25
EHC-CF	92.28	91.43	90.65	90.1	89.65	8.43	16.14	22.95	29	34.32	15.39	27.26	39.37	43.56	49.3
PRACMF	93.21	91.78	91.11	90.4	90.1	8.52	16.2	23.03	29.08	34.5	15.55	27.36	36.55	43.69	49.61
PROP	93.68	92.02	91.44	90.9	90.22	9.03	16.52	23.62	29.33	34.62	16.48	28.02	37.54	44.35	50.04

Table 2 Comparison of proposed similarity measure with existing measures

Evaluation Metrics	*Precision*					*Recall*					*F-measure*				
Method	*Top-N*					*Top-N*					*Top-N*				
	10	*12*	*14*	*16*	*18*	*10*	*12*	*14*	*16*	*18*	*10*	*12*	*14*	*16*	*18*
cos	89.91	89.37	89.19	88.8	88.6	34.4	39.09	43.39	47.19	50.7	49.44	54.04	58.02	61.27	64.14
pcc	89.06	88.7	88.44	88.3	87.99	34.1	38.8	43.04	46.89	50.35	48.97	53.65	57.54	60.88	63.69
acos	89.28	88.89	88.63	88.3	88.15	38.9	38.88	43.12	46.94	50.44	49.09	53.74	57.65	60.95	63.81
icos	89.95	89.39	89.2	88.9	88.65	34.4	39.16	43.42	47.23	50.72	49.5	54.15	58.41	61.68	64.52
prop	90.23	90.06	89.65	89.1	89.31	39.1	39.92	44.12	47.96	51.27	54.57	55.32	59.14	62.35	65.14

Table 3 Comparison of traditional ANN and optimised ANN on textual reviews

Evaluation Metric	*F-measure*				
Method	*Top-N*				
	10	*12*	*14*	*16*	*18*
ANN	70.3	71.21	71.51	71.7	72.51
Optimized ANN	71.36	72.3	72.45	73	73.52

5.2.3 Performance analysis of optimised ANN

For quality recommendations, we have analysed online reviews of all users. In this paper, we have compared the proposed method with traditional ANN for performance analysis. Review analysis works on real data extracted from online search engines. New reviews are extracted for all target users. This real-time review analysis is compared by using traditional and proposed optimised ANN. The optimised ANN method works efficiently than traditional ANN as shown in Table 3. The proposed optimised method works efficiently when reviews are considered for top-10 and more products.

5.2.4 Cold start

RSs suffer from a cold start problem. RSs fail to give quality recommendations to a new user as he has no history. The proposed system solves this cold start issue. A new user is allocated to a respective user cluster according to his age, gender and occupation. Then, this user goes to evolutionary heterogeneous clustering and CF. For this, we considered the default highest rating for all products which are purchased by other users in the same cluster having the same age, gender and occupation combination. Then, target new users get quality and appropriate recommendations. This solution acquires user trust in the RS.

6 Conclusion and future work

Clustering is important to improve the scalability of the CF algorithm. It reduces millions of users into different small clusters. These clusters can be handled efficiently than entire user data in this RS using MKFCM. Other than available methods, this RS used a dynamic heterogeneous clustering to deal with sparse values in the data. The sub-clusters are evolved as a user makes a new purchase or if the user's taste changes with time. CF works around the new similarity measure. The proposed new similarity measure used, only ratings of common products purchased between different users which must be considered actually to calculate similarity. Our RS is more efficient with high recall and recommendation accuracy as compared to *k*-means, EHC-CF, PRACMF.

As Top-N products increase, precision is decreased for all algorithms but note that *F*-measure and recall rise. The proposed similarity measure performs very well for the top-10 items. As the number of top-N products has risen, our measure of similarity has been very successful compared to other measures. Using the proposed similarity measure, users with single or less product purchasing history are properly getting most similar users and thus recommendations as opposed to current existing measures. This RS has given better solution to cold start problem by assigning user properly to his age group cluster.

Review analysis is important for quality confirmation before final recommendation. This RS extracts real-time textual reviews of products from online search engines to analyse quality. Negative reviews confirm the low-quality features of products, such products may not be recommended to the target user and hence this RS gives guarantee of giving good quality personalised recommendations The analysis shows that the optimised ANN gives an accurate review classification compared to traditional ANN. An optimum personalised RS is provided in this work which gives dual confirmation to target users about recommended products first by CF and second by review analysis for quality.

In future this work can be extended by collecting feature wise rating for every product from the user, so that user interest and expectation can be learned clearly. Though reviews are given by user, they are not covering opinion about all features of product. Hence, combination of user's detailed ratings and reviews with his contextual information on social websites will give best solution to RS.

References

Adomavicius, G. and Tuzhilin, A. (2005) 'Toward the next generation of recommender systems: a survey of the state-oF-the-art and possible extensions', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 17, No. 6, pp.734–749.

Bobadilla, J. et al. (2013) 'Recommender systems survey', *Knowledge-Based Systems*, Vol. 46, pp.109–132.

Bobadilla, J., Ortega, F. and Hernando, A. (2012) 'A CF similarity measure based on singularities', *Information Processing and Management*, Vol. 48, No. 2, pp.204–217.

Chen, J., Wang, H. and Yan, Z. (2018) 'Evolutionary heterogeneous clustering for rating prediction based on user CF', *Swarm and Evolutionary Computation*, Vol. 38, pp.35–41.

Cremonesi, P., Koren, Y. and Turrin, R. (2010) 'Performance of recommender algorithms on top-n recommendation tasks', *Proceedings of the 4th ACM Conference on Recommender Systems*, pp.39–46.

Despotovic, V. and Tanikic, D. (2017) 'Sentiment analysis of microblogs using multilayer feed-forward artificial neural networks', *Computing and Informatics*, Vol. 36, No. 5, pp.1127–1142.

Fouss, F. et al. (2007) 'Random-walk computation of similarities between nodes of a graph with application to collaborative recommendation', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 19, No. 3, pp.355–369.

Gu, J. and Wu, D. (2018) 'A random distribution harmony search algorithm', *10th International Conference on Advanced Computational Intelligence (ICACI)*, IEEE, China.

Huang, H., Chuang, Y. and Chen, C. (2012) 'Multiple kernel fuzzy clustering', *Proceedings of the IEEE Transactions on Fuzzy Systems*, Vol. 20, No. 1, pp.120–134. Doi: 10.1109/TFUZZ.2011.2170175.

Jebaseeli, A.N. and Kirubakaran, E. (2012) 'A survey on sentiment analysis of (product) reviews', *International Journal of Computer Applications*, Vol. 47, No. 11.

Khusro, S., Ali, Z. and Ullah, I. (2016) 'Recommender systems: issues, challenges, and research opportunities', in Kim, J.K. and Joukov, N. (Eds): *Information Science and Applications (ICISA'16)*, Springer Singapore, Singapore, pp.1179–1189.

Kumari, P., Tewari, A.S. and Barman, A.G. (2015) 'Personalised book recommendation system based on opinion mining technique', *Global Conference on Communication Technologies (GCCT)*, IEEE, India.

Lee, K. and Lee, K. (2014) 'Using dynamically promoted experts for music recommendation', *IEEE Transactions on Multimedia*, Vol. 16, No. 5, pp.1201–1210.

Liji, U., Chai, Y. and Chen, J. (2018) 'Improved personalized recommendation based on user attributes clustering and score matrix filling', *Computer Standards and Interfaces*, Vol. 57, pp.59–67.

Linden, G., Smith, B. and York, J. (2003) Amazon.com: recommendations item-to-item collaborative filtering', *IEEE Internet Computing*, Vol. 7, No. 1, pp.76–80.

Liu, H. et al. (2014) 'A new user similarity model to improve the accuracy of CF', *Knowledge-Based Systems*, Vol. 56, pp.156–166.

Lu, J. et al. (2010) 'BizSeeker: a hybrid semantic RS for personalized government-to-business e-services', *Internet Research*, Vol. 20, No. 3, pp.342–365.

Mangat, V. (2012) 'Survey on particle swarm optimization based clustering analysis', *Swarm and Evolutionary Computation*, Springer, Berlin, Heidelberg, pp.301–309.

McFee, B., Barrington, L. and Lanckriet, G. (2012) 'Learning content similarity for music recommendation', *IEEE Transactions on Audio, Speech, and Language Processing*, Vol. 20, No. 8, pp.2207–2218.

Najafabadi, M.K., Mahrin, M.N., Chuprat, S. and Md Sarkan, H. (2007) 'Improving the accuracy of collaborative filtering recommendations using clustering association rules mining on implicit data', *Computers in Human Behaviour*, Vol. 67, pp.113–128.

Pazzani, M.J. and Billsus, D. (2007) 'Content-based recommendation systems', *The Adaptive Web*, Springer, Berlin, Heidelberg, pp.325–341.

Ren, F. et al. (2015) 'A comparative study of population-based optimisation algorithms for thrust allocation in dynamic positioning system', *International Journal of Modelling, Identification and Control*, Vol. 23, No. 2, pp.101–111.

Sanchez, M., Moreno, M.N., Segrera, S. and Lopez, V. (2008) 'Framework for the development of a personalised recommender system with integrated web-mining functionalities', *International Journal of Computer Applications in Technology*, Vol. 33, No. 4, pp.312–319.

Shambour, Q.Y., Abu-Alhaj, M.M. and Al-Tahrawi, M.M. (2020) 'A hybrid collaborative filtering recommendation algorithm for requirements elicitation', *International Journal of Computer Applications in Technology*, Vol. 63, Nos. 1/2, pp.135–146.

Sharma, Y., Bhatt, J. and Magon, R. (2015) 'A multi-criteria review-based hotel recommendation system', *IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, IEEE, UK.

Suganeshwari, G. and Syed Ibrahim, S.P. (2016) 'A survey on collaborative filtering based recommendation system', in Vijayakumar, V. and Neelanarayanan, V. (Eds): *Proceedings of the 3rd International Symposium on Big Data and Cloud Computing Challenges (ISBCC16')*, Springer International Publishing, Cham, pp.503–518.

Sun, J. et al. (2011) 'Opinion comparison between internet forums and customer reviews', *International Journal of Computer Applications in Technology*, Vol. 40, Nos. 1/2, pp.107–113.

Vilares, D., Gomez-Rodr˜oguez, C. and Alonso, M.A. (2017) 'Universal, unsupervised (rule-based), uncovered sentiment analysis', *Knowledge-Based Systems*, Vol. 118, pp.45–55.

Wu, X., Cheng, B. and Chen, J. (2017) 'Collaborative filtering service recommendation based on a novel similarity computation method', *IEEE Transactions on Services Computing*, Vol. 10, No. 3, pp.352–365.

Wu, X., Huang, Y. and Wang, S. (2017) 'A new similarity computation method in CF based RS', *Proceedings of the IEEE 86th Vehicular Technology Conference (VTC-Fall)*, IEEE, pp.1–5.

Xiao, W. et al. (2015) 'Clustering algorithm based on FF optimization', *Proceedings of the International Conference on Rough Setsand Knowledge Technology*, Springer, Cham.

Young, P. (2019) 'Recommender technologies and emerging applications', *Advanced Methodologies and Technologies in Network Architecture, Mobile Computing, and Data Analytics*, IGI Global, Hershey, PA, USA, pp.458–470.

Yu, Y. et al. (2018) 'Joint user knowledge and matrix factorization for recommender systems', *World Wide Web*, Vol. 21, No. 4, pp.1141–1163.

Zeng, S. et al. (2017) 'A unified collaborative multikernel fuzzy clustering for multiview data', *IEEE Transactions on Fuzzy Systems*, Vol. 26, No. 3, pp.1671–1687.

Zhang, S. et al. (2017) 'Efficient kNN classification with different numbers of nearest neighbors', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 29, No. 5, pp.1774–1785.

Zhang, W., Ding, G., Chen, L., Li, C. and Zhang, C. (2013) 'Generating virtual ratings from Chinese reviews to augment online recommendations', *ACM Transactions on Intelligent System Technology*, Vol. 4, pp.1–17.

Zhou, R. et al. (2017) 'Improved FF optimization algorithm-based density peak clustering and its applications', *Tehnicki vjesnik*, Vol. 24, No. 2, pp.473–480.