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Research Article

A Novel Approach to Personalized Recommender Systems Based on Multi Criteria Ratings

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Abstract: In today's market-driven world whenever the choices have to be made while buying products, we rely on recommendations from people either through word of mouth, recommendation letters, previews or reviews in the newspapers or feedback provided by other customers and surveys made on different products, etc. We live in an age of information technology with a surfeit of information to be made use of effectively. This has inevitably, led to an information overload problem which in turn has created a clear demand for automated methods which will help users locate and retrieve information with respect to their personal preferences in the best and optimal manner; resulting in the development of the Recommender System. Most of the recommender systems are model-based and use Pearson Correlation or Cosine Similarity to find the users who share the same preferences and interests. In this study, we propose two approaches which integrate the concept of multi criteria ratings into the recommender system. The results show that our approach is better than the single traditional rating system.

Keywords: Collaborative filtering, multi criteria ratings, Pearson correlation coefficient, recommender system, spearman rank correlation coefficient, weighted correlation

INTRODUCTION

The amount of data available on the internet is enormous and is constantly increasing. Some are useful, important and factual and some are false. There has been an exponential growth of information about hotels, movies, grocery shops, etc. As a consequence, this has led to an information overload problem because of which users or customers are not able to find the required information at the right place in the shortest time possible. In order to address this problem 'recommender systems' came into existence. Recommender systems are a subclass of the information filtering system that seek to predict the 'rating' or 'preference' that a user would give to an item (such as music, books etc.) or social element (e.g., people or user discussion groups) they have not yet considered, using a model built from the characteristics of an item (content-based approaches) or the user's social environment (collaborative filtering approaches) (Ricci *et al*., 2011). Recommender systems are basically classified into three categories:

- Content based filtering
- Collaborative filtering
- Hybrid approach (Balabanovic and Shoham, 1997)

Content based recommender systems recommend items confined to the users past behavior and collaborative filtering (also called as social filtering) recommends items to users with similar preferences. Hybrid approach combines both content and collaborative filtering approaches. Several techniques have been suggested to combine both these approaches. The details of these approaches can be found in (Adomavicius and Tuzhilin, 2005). There are many algorithmic techniques which have been incorporated into the recommender system. The most prominent ones are classified into the following two categories:

- Memory based approach
- Model based approach (Breese *et al*., 1998)

The memory based approach calculates recommendations based on the user's previous activities and intentions. The model based approach uses the past behavior of the user to calculate the recommendations. This approach constructs a model which is typically a statistical or machine learning model which studies the past behavior and activities of the user and then generates the recommendations. It has been proved that the model based approach is far better than the memory based approach. Collaborative filtering recommender systems can be classified based on the explicit and implicit ratings. Implicit ratings are based on the browsing behavior of the user. Time spent on a particular page would indicate the person's interest. There has been ongoing research in finding

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interesting patterns/behavior for predictions and generating recommendations. This is however, beyond the scope of this paper. Explicit ratings are usually a number given by the user normally in the range from 1 to 5 or 1 to 10. Most of the recommender systems are based on the single criteria rating and though this kind of recommender systems has been successful in many applications, in recent year's recommender systems based on multi criteria ratings are being deployed in many fields such as hospitality services, entertainment and tourism etc. In this study we propose an approach for incorporating ratings based on multi criteria in the recommender system.

MATERIALS

Recommender system based on single rating: Recommender systems, based on their applications, can be classified into three categories (Resnick and Varian, 1997) (Fig. 1):

- Movies
- News
- Web pages

The commonly used technique for generating recommendations is collaborative filtering. This is seen as "the technique" for reducing information overload and is very successful on the internet as compared to the content based filtering technique. The websites that use the collaborative filtering techniques are Amazon.com, CDnow.com and Moviefinder.com.

The term collaborative filtering was coined by Goldberg *et al*. (1992). The first recommender system called tapestry was developed by them. The tapestry is an experimental mail system developed at Xerox Palo Alto Research Centre. It was designed to support both content based and collaborative based filtering methods. It is based on Client-Server architecture. Various components like 'indexer' for parsing the documents, 'annotations store' to provide annotations associated with documents, browser which combines the functions of both a mail reader and a traditional document browser. They developed their own language for querying called TQL (Tapestry Query Language). The reason for not using SQL (Structured Query Language) for filtering documents was because of the mismatch between the relational model and tapestry model.

The GROUPLENS Project (Korstan *et al*., 1997; Resnick *et al*., 1994) designed, implemented and evaluated a collaborative filtering system for usenet news which is a discussion group service on the internet. It is also based on Client-Server architecture. This recommender system is based on single criterion rating. The rating is a number from 1 to 5 with 1 being lowest. For predicting scores for new users they used Pearson Correlation Coefficient for calculating weights.

A Recommender System called RINGO was developed by (Shardanand and Maes, 1995). The system makes personalized recommendations for music albums and artists. They describe a technique for making personalized recommendations to users based on the similarities between the common interests of the target user with all other users. There are many techniques for calculating the similarities among the user profiles. The most prominent ones are Cosine Similarity and Pearson Correlation Coefficient. To calculate Cosine similarity and Pearson Correlation Coefficient, let the target user be U_a and the set of items be $P = \{P_1, P_2....P_n\}$. The Cosine Similarity between user U_a and user U_b is given by:

$$Sim(U_a, U_b) = \frac{\sum_{k=1}^{n} R_{ak} \ R_{bk}}{\sqrt{\sum_{k=1}^{n} R^2_{ak}} \sqrt{\sum_{k=1}^{n} R^2_{bk}}} \tag{1}$$

where, R_{ak} is the rating given by the User U_a for an item P_k.

The Pearson Correlation Coefficient between user U_a and User U_b is given by:

$$Sim(U_a, U_b) = \frac{\sum_{k=1}^{n} (R_{ak} - \bar{R}_a)(R_{bk} - \bar{R}_b)}{\sqrt{\sum_{k=1}^{n} (R_{ak} - \bar{R}_a)^2} \sqrt{\sum_{k=1}^{n} (R_{bk} - \bar{R}_b)^2}} \tag{2}$$

where,

$$\bar{R}_a = \frac{\sum_{k=1}^{n} R_{ak}}{n} \text{ is the average rating for user } U_a. \tag{3}$$

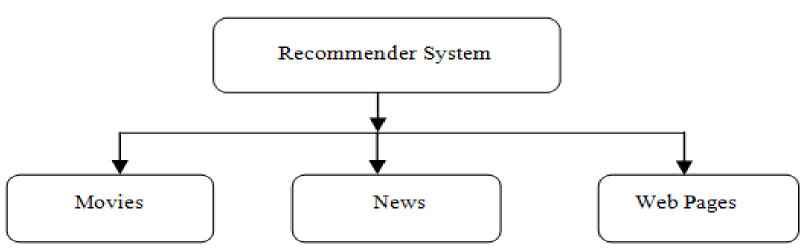

Fig. 1: Categories of recommender system

The Cosine Similarity and Pearson Correlation Coefficient range from -1 to +1 with -1 being negatively correlated i.e., no similarity between the users and +1 being positively correlated i.e., there is a strong similarity between the users with Pearson Correlation Coefficient performing better than the cosine similarity (Breese *et al*., 1998). They introduced a constraint on Pearson correlation coefficient as discussed in (Korstan *et al*., 1997; Resnick *et al*., 1994) by neglecting the negative values. Since the rating is from 1 to 7, anything above the average is considered to be positive correlation. For producing recommendations to the user, the improvised Pearson correlation coefficient computed the correlation between the target user and all the neighboring users. The users whose correlation was greater than the prescribed threshold were selected.

Recommender system based on multi criteria ratings: One of the first advancements in the area of recommender systems based on multi criteria ratings was developed by (Adomavicius and Kwon, 2007). They proposed new techniques for incorporating multi criteria ratings in recommender systems. The two new approaches introduced in their work are the similarity based approach and aggregation function based approach. For calculating the similarity between the users or items, they used Chebyshev distance metric and took the minimum of cosine similarity metric. Since the overall rating is dependent on the single ratings, they argued that an overall rating is some function of single rating. They used linear regression model for assigning weights to calculate the overall rating for the user.

Liu *et al*. (2011) proposed a personalized recommender system by clustering the users with preference lattice based on partial orders. They assumed that some criteria will be dominant from others. These dominant criteria will be different for different users. The recommendation output for a user is based on the ratings given by the users from the same cluster or nearby clusters. They proposed three approaches for incorporating the concept of multi criteria ratings:

- Using the aggregate function
- Using overall ratings
- Combining clusters with collaborative filtering

They used Hasse diagram to represent the various clusters.

Lakiotaki *et al*. (2011) proposed a hybrid framework that incorporates various techniques from the field of decision support system with the collaborative filtering approach. As pointed out by (Manouselis and Costopoulou, 2007) multi criteria ratings are useful in the decision making process. Multi Criteria Decision Analysis (MCDA) is truly a well established field in the area of decision science which helps the decision makers to analyze and support their decisions. They are useful in recommender systems also by helping the user take decisions. They used UTA algorithm which is Disaggregation-Aggregation framework algorithm to analyze user's cognitive decision policy. The UTA algorithm was given preference over other preferential structures.

Jannach *et al*. (2012) proposed a recommender system based on multi criteria ratings. They proposed new methods to incorporate multi criteria ratings into recommender systems to improve predictive accuracy. The concept of aggregate function as proposed by (Adomavicius and Kwon, 2007) is being used in this study also but they have used Support Vector Regression to determine the relation between the ratings and overall ratings. They have built a regression function not only for every item but also for every user. They have used Gradient Descent Algorithm to calculate the weights required for the overall ratings. They argue that while rating, the users are more interested in the features of the particular attribute. Not all features are required to determine the overall rating. The most prominent features are used to build the feature selection strategy to improve the accuracy of the recommender systems when the rating dimension is huge.

METHODOLOGY

Incorporating multi criteria ratings in traditional recommender systems: Traditional recommender system users normally use single rating for a particular product. They are of the form as proposed by (Adomavicius and Kwon, 2007):

$$R : \text{Users} \times \text{Product} \rightarrow R_0 \tag{4}$$

where, $\text{Users} \times \text{Product}$ is a matrix representing the rating given by the user for a particular product. R_0 is a positive number in the range from 1 to 5. R is a function to be estimated based on R_0 for the new user. In contrast to single rating recommender system, the recommender system based on multi criteria ratings consists of n ratings and the rating function is of the form as proposed by (Adomavicius and Kwon, 2007):

$$R : \text{Users} \times \text{Product} \rightarrow R_0 \times R_1 \times R_2 \times \quad \times R_n \tag{5}$$

As compared to a recommender system based on single rating, the recommender system based on multi criteria rating will have n+1 ratings. The 'n' criteria and an overall rating, based on these 'n' criteria. Let us consider an example from a Restaurant Domain (Fig. 2).

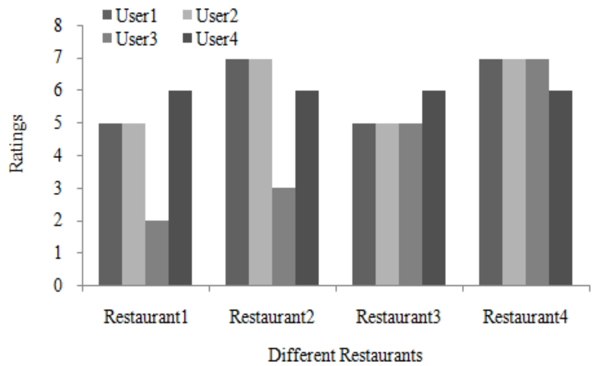

Fig. 2: Recommender system based on single rating

In the above table we have 4 users and 4 restaurants. So if the recommender system has to predict which restaurant user U1 would like then it will see all the ratings which have been given by other users for different restaurants. In the above table we see that U2 is closest to U1. Now let us consider the same example with multi criteria ratings. The four main criteria considered are location, ambience, price and food quality.

When the user rates an item based on the factors involved, we see that U1 has similar preferences as U4 unlike in a single rating system where we had U1 with similar preferences as U2 and U3.

The objective of a recommender system is to provide users choices that will best match their preference. Thus incorporating multi criteria ratings into a recommender system is beneficial as we know the user's exact preference and not just some arbitrary value. In multi criteria ratings we have 'n' ratings; we therefore require new techniques to calculate the overall rating to optimize the accuracy and performance of the recommendations.

The two approaches introduced by (Adomavicius and Kwon, 2007) are the similarity based approach and aggregation based approach. In a traditional single criterion recommender system we predict the rating for user 'u' on product P_i based on the ratings provided by different users for the same product. In order to calculate the similarities between the user's various measures such as Pearson-Correlation Coefficient, Spearman Rank Correlation, Vector Similarity, Entropy, Mean-Squared can be used. Any standard metric to measure distance can also be used to calculate the similarities among the users. The aggregate function based approach assumes that not all criteria are important to calculate the overall rating to give the top N recommendations to the user. If we take an example as considered in Fig. 2, some users may give priority to price, location and ambience and some users may give importance to food quality, location and price. Thus we see that there is a relationship that exists between the overall rating and the individual 'n' ratings.

Our paper continues to follow the same method as proposed by (Adomavicius and Kwon, 2007) but have used other techniques to improve the accuracy of recommendations.
Our contributions can be summarized as follows:

- Instead of using Pearson Correlation Coefficient or cosine based similarity as used by (Adomavicius and Kwon, 2007) we have used Spearman Rank Correlation in below section. The reason being Spearman Rank Correlation coefficient does not assume linear interval scale in their computations like Pearson Correlation and also, it does not rely on model assumptions (Herlocker *et al*., 1999). We compute the measure of correlation between the ranks given by the user instead of ratings.
- We argue that user tastes change over time, so we have introduced a weighted correlation approach in below section to calculate weights based on the time stamp.

Proposed recommender system based on multi criteria ratings: This section describes how the Recommender system works. We take the dataset consisting of multi criteria ratings and search for similarities among the users using Spearman Rank Correlation, Euclidean Distance Metric and Karl Pearson Correlation. This clustering approach will give us the common users based on the individual criteria. In the Weighed Correlation Approach we derive a formula for assigning weights to each criterion depending on the time stamp. Together both the approaches will find the recommended list of products.

Clustering based on spearman rank correlation: In this section we present a novel approach of clustering the users based on Spearman Rank Correlation. In order to calculate the similarities among users, we have used Spearman Rank Correlation Coefficient. We convert the ratings into ranks by giving the highest (smallest) observation rank 1. The next observation is given rank 2 and so on. Let $(x_1, y_1), (x_2, y_2) ----- (x_n, y_n)$ be the ranks of 'n' individual for the two characteristics A and B. Let $d_i = x_i - y_i$ denote the difference between ranks of the ith individual for two characteristic (ratings). Whenever there is a tie while assigning the ranks we use the correction factor $\frac{m\,(m^2-1)}{12}$ where m is the number of times an item is repeated. This correction factor is to be added for each repeated value in both the series.

The steps for calculating similarities among the users are as follows:

Step 1: Calculate the mean of both the series i.e.:

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \text{ and } \overline{Y} = \frac{\sum_{i=1}^{n} Y_i}{n}$$

Step 2: Calculate the quantity $D = \overline{X} - \overline{Y}$.

Step 3: $\rho_{a,u}$ is the similarity between the active user a and the neighboured user u defined by Spearman Rank Correlation Coefficient:

$$\rho_{a,u} = 1 - \frac{6\sum_{k=1}^{n} D^2}{n(n^2-1)} \quad (6)$$

Step 4: If there is a tie in ranks then the correction factor is used:

$$\rho_{a,u} = 1 - \frac{6\left[\sum_{k=1}^{n} D^2 + m(m^2-1)\right]}{n(n^2-1)} \quad (7)$$

The value of $\rho_{a,u}$ lies between -1 and +1. If the value of $\rho_{a,u}$ is closer to +1 then there is a high correlation/similarity among the uses and -1 denotes there is no correlation/similarity among the users. Here we assume the window size to be 3.

Combining clusters based on individual ratings: Here we assume that user U has given an overall rating r_0 and has multi criteria ratings r_1, r_2... r_n. Then (n+1) similarities can be obtained by using the Spearman Rank Correlation. Sim_0 (U_a, U_b) represents the similarity based on overall rating, Sim_1 (U_a, U_b) represents the similarity based on the first criterion and so on. Thus total similarity is given by:

$$Clust_{tot}(U_a, U_b) = \frac{1}{n+1}\sum_{k=0}^{n} Sim_k(U_a, U_b) \quad (8)$$

We have also used the standard distance metric Euclidean Metric to calculate the distance between the users:

$$d_i(U_a, U_b) = \sqrt{\sum_{k=1}^{n}(r_k - r'_k)} \quad (9)$$

The overall distance between users is given by:

$$Tot\_Dist(U_a, U_b) = \frac{1}{C(U_a, U_b)}\sum_{k \in C} d_k(U_a, U_b) \quad (10)$$

where, C (U_a, U_b) denotes the set of products that both the users rated.

Since collaborative techniques are based on similarities between the users and not the distance between the users, we use the simple technique of taking the similarity as the inverse of the total distance, i.e.:

$$Clust(U_a, U_b) = \frac{1}{1 + Tot\_Dist\,(U_a, U_b)} \quad (11)$$

where,

$$Clust(U_a, U_b) = \begin{cases} 0 \text{ if } Tot\_Dist(U_a, U_b) \to \infty \\ 1 \text{ if } Tot\_Dist(U_a, U_b) \to 0 \end{cases} \quad (12)$$

If the user has not rated a product based on the cluster group to which it belongs, a common rating will be given. In this way sparsity can be reduced.

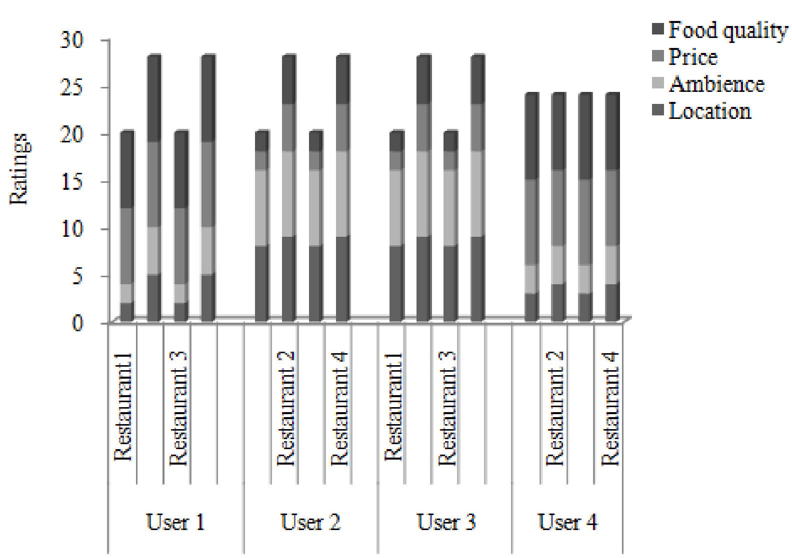

Fig. 3: Recommender system based on multi criteria ratings

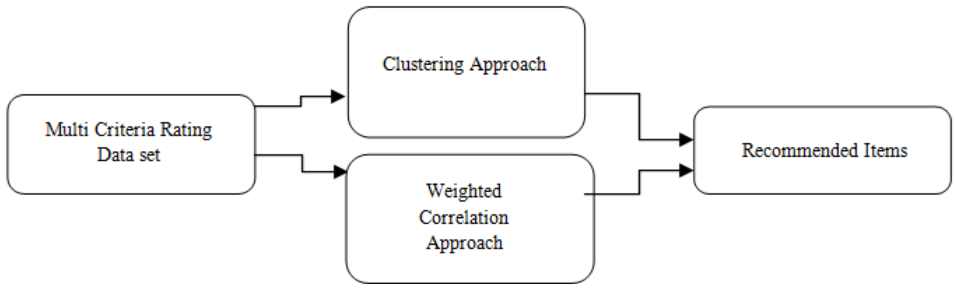

Fig. 4: Recommender system work flow

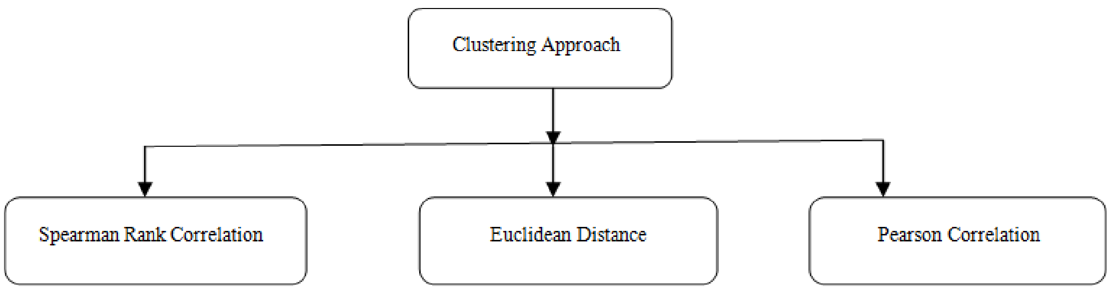

Fig. 5: Clustering approach

Weighted correlation approach: We assume that not all criteria are important to calculate the overall rating to give the top N recommendations to the user. If we take an example as considered in Fig. 3, some users may give priority to price, location and ambience and some users may give importance to food quality, location and price. Thus we see that there is a relationship that exists between the overall rating and the individual 'n' ratings. We assume that each criterion has its own importance and user tastes changes from day to day. For example, today the user may give importance to ambience and food and tomorrow the user may give importance to service and rooms, etc (Fig. 4 and 5).

In this section we propose a novel approach of assigning weights to each criterion. We consider the overall rating as a function of individual ratings where the individual ratings are calculated by assigning weight which is a function of transaction history:

$$R = f(r_1, r_2......r_n) \tag{13}$$

The entire transaction history is split into n equal parts. In each part the highest rated criteria assigned by the user is taken into consideration. The weights of each criterion are obtained as follows:

$$W = \frac{T_c}{n} \tag{14}$$

where, T_c is the highest number of transactions for particular criteria over that period of time and n is the total number of transactions. This weighted criterion will give K most similar users.

The overall ratings is given by:

$$R = \frac{\frac{\sum_{i=1}^{n} W_i \rho_i}{N}}{K} \tag{15}$$

where,

- W_i = The weight of each criterion obtained from the previous step
- ρ_i = The Spearman Correlation Coefficient obtained from the clustering approach
- N = Total number of criteria
- K = Similar users based on the transaction (Fig. 6)

RESULTS AND DISCUSSION

We have used Tripadvisor.co.uk dataset for our experiments. A large number of feedback ratings are available in this dataset. The dataset has ratings of 5 individual criteria namely, value, location, cleanliness, rooms and service. All the individual ratings and overall ratings are range from 1 to 5, with 5 being excellent. We have used 1000 users and 100 hotels with a time stamp from 1 to 1000. We have the option of splitting the time stamp with any value. Based on the timestamp we split the data set with 90% as training set and remaining 10% for evaluating the proposed approaches. We have also split the data set with 80% as training set and remaining 20% for evaluating the proposed approaches. The comparative results are shown in Fig. 7 to 9, respectively. By varying the test

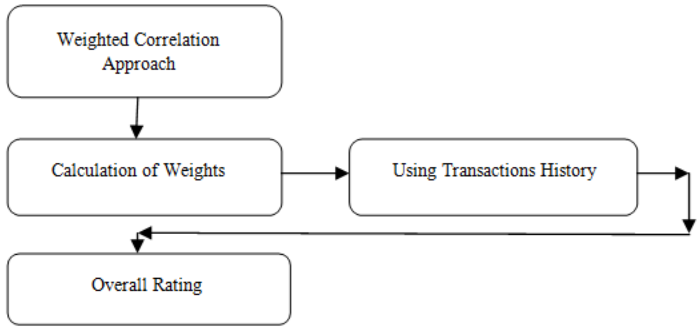

Fig. 6: Weighted correlation approach

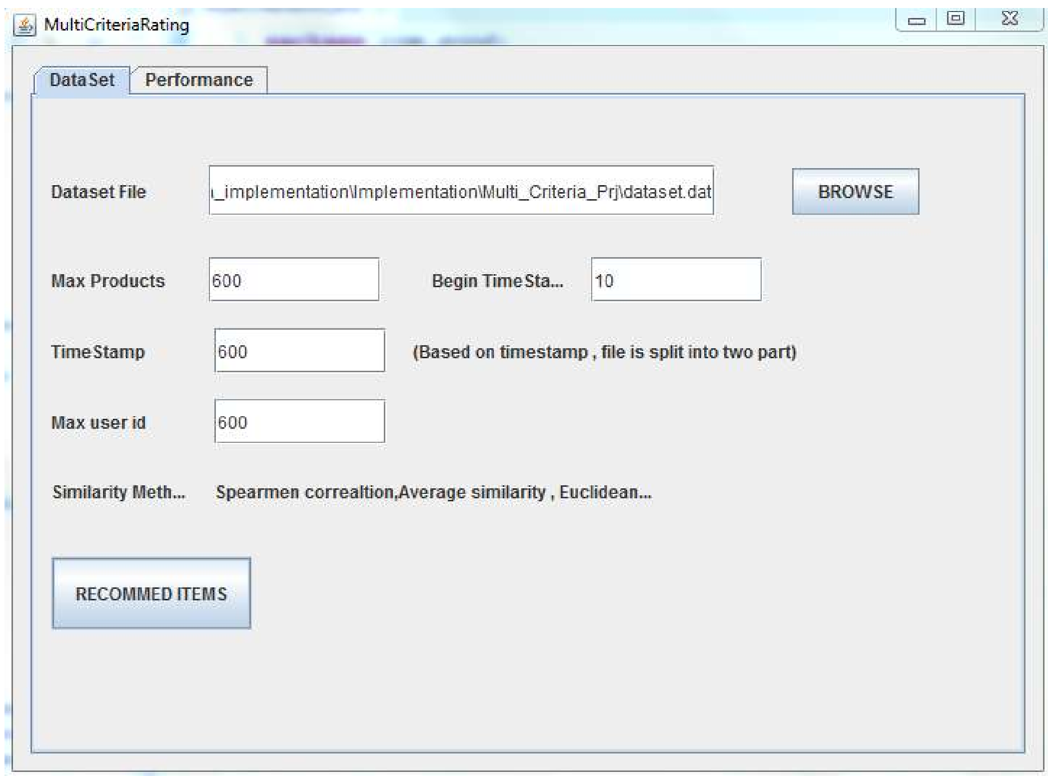

Fig. 7: Multi criteria recommender system with time stamp: 600

data set we see that the MAE value of the proposed approach is lower as compared to the other recommender approaches as shown in Fig. 7.

Evaluation metric: For evaluating the accuracy of the different approaches, we have used Mean Absolute Error (MAE). MAE is one of the most commonly used statistical accuracy metric (Hyndman and Koehler, 2005). It is the measure of average absolute deviation between the predicted rating and the user's true rating. The lower the MAE, the more accurate is the prediction:

$$MAE = \frac{\sum_{i=1}^{N} p_i - q_i}{N} \tag{16}$$

where, N is the number of ratings.

CONCLUSION

Most Recommender systems based on single rating are successful in various ecommerce sites but the utilization of ratings based on multi criteria improves the accuracy and the prediction of the recommender systems. In this study we have discussed two approaches that will incorporate multi criteria ratings into the recommender systems. The clustering approach and the weighted correlation approach. The experimental results were carried out on the real world dataset called Tripadvisor.co.uk. The dataset has ratings of 5 individual criteria namely, value, location, cleanliness, rooms and service. The results show that

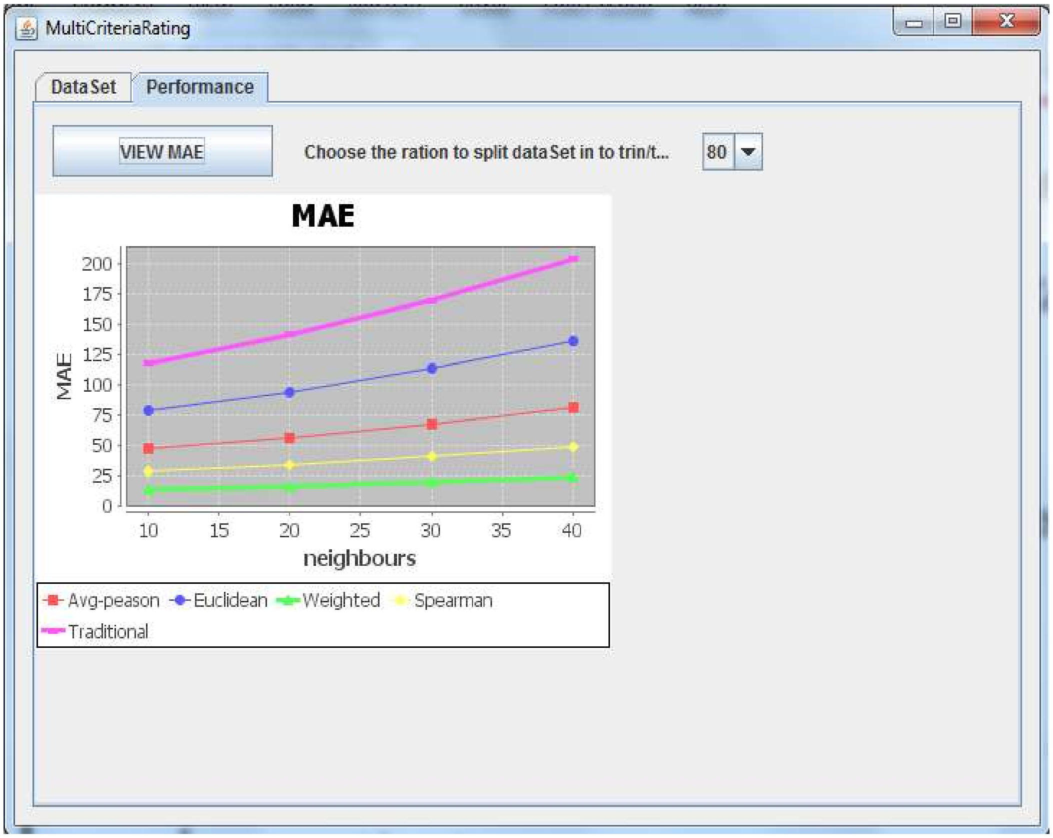

Fig. 8: Results of various approaches (ratio 80:20)

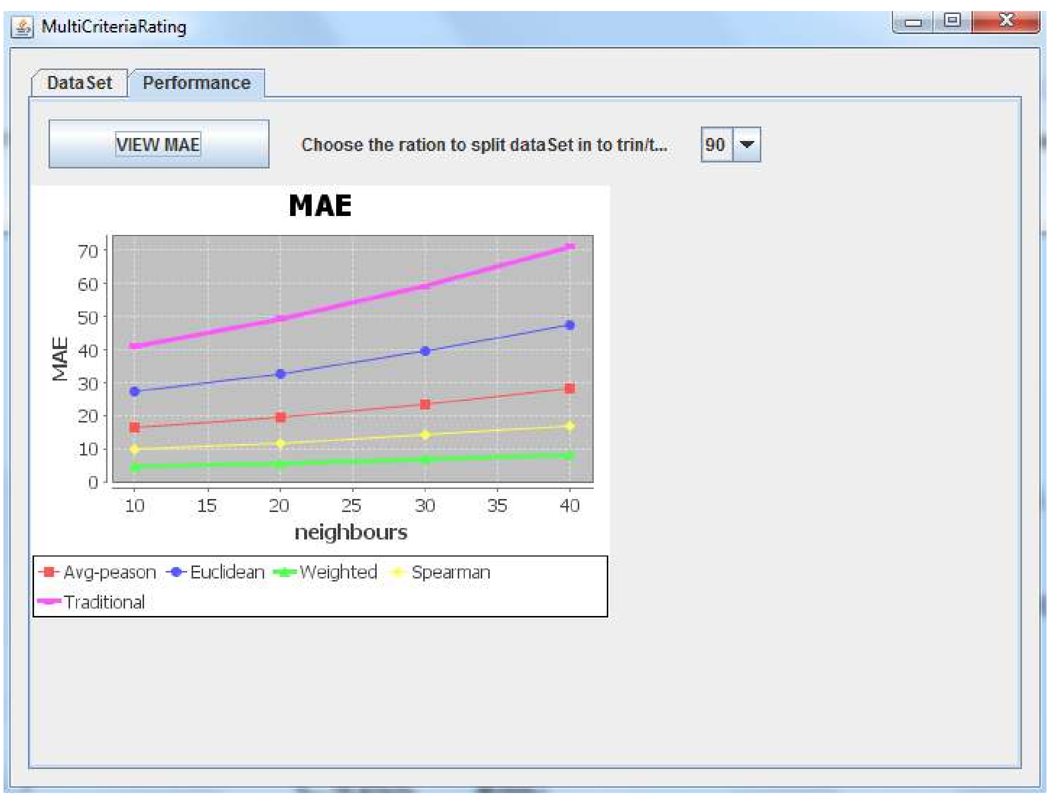

Fig. 9: Results of various approaches (ratio 90:10)

the weighted correlation approach has the least MAE. This shows that incorporating multi criteria ratings in the recommender system improves the accuracy and quality of the recommender systems. The area of recommender systems is a vast emerging area in the world of ecommerce. There is a need for developing more techniques for improving the accuracy and quality of recommender systems. Many ecommerce applications recommend a list of items to the users like recommending vacation packages to the customers, restaurants, etc., are two dimensional in nature i.e., users and items. This may not be sufficient as the customer preferences may largely depend on various factors. For example, if we have to provide recommendations to the customers based on recommending the vacation packages to them, then we should take into consideration the time when they would like to go. Also, it may not be sufficient in many applications to recommend individual items to individual users but rather categories of items to certain types of users. Thus for future work, we are planning to incorporate the concept of multidimensionality in recommender systems.

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