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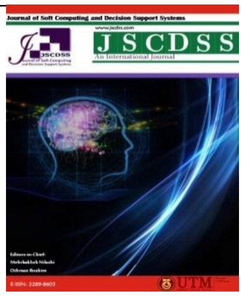

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A Multi-Criteria Recommender System for Tourism Using Fuzzy Approach

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Abstract

Recommender Systems have been widely used in Information and Communication Technology (ICT). The main reason for this extensive use is to decrease the problem of information explosion. Collaborative Filtering techniques, which attempt to predict what information will meet a user's needs based on data coming from similar users, are becoming increasingly popular as ways to combat information overload. Collaborative Filtering techniques usage has shown significant advantages in tourism service recommendations. Accuracy improvement of Collaborative Filtering techniques for tourism recommender systems has been an important issue in the previous studies. Therefore, this study aims to improve the recommendation accuracy of Collaborative Filtering techniques for tourism recommender systems. In this study, the method of recommendation is developed using fuzzy C-means algorithm for user-based and item-based models. Two similarity measures, Pearson Correlation and Cosine, are used for similarity calculations of users and items in both user-based and item-based models. Mean Absolute Error (MAE) is then used as an evaluation metric to show the accuracy improvement of proposed method. The experimental results on TripAdvisor dataset with several comparisons are presented to show the enhancement of proposed method predictive accuracy. The experimental results demonstrated that the user-based model of recommendation which uses fuzzy C-means algorithm remarkably improves the recommendation predictive accuracy with MAE=0.72 in relation to the item-based recommendation model with MAE=0.73. Since the proposed recommender system improves the accuracy of Collaborative Filtering techniques, the recommender system will be a promising recommendation method for item recommendation task in tourism domain.

Keywords: Recommender systems, Tourism, Multi-Criteria, Fuzzy clustering

1. Introduction

The application of Information and Communication Technologies (ICT), specifically the internet, by human being is growing day by day (Zhang et al., 2014). People are more relied to internet for performing their tasks and solve their problems (Bilge and Kaleli, 2014). It provides information for thousands of users, who are seeking new products and services, and make available the comparison between different brands and companies (LoStorto, 2013).

Although the availability of various options that internet provides, has its own advantages, but recent statics claim that providing several choices for users or online customers is not only inconvenient but also it damage users' state of well-being (Ricci et al., 2011). The availability of various options is called information overload (Nilashi et al., 2014b) or information explosion (Lucas et al., 2013). This problem is one of the side effects of massive development of internet and it causes difficulty for users to find proper information, tailored to their needs and interests (Cramer et al., 2008).

To eliminate the problem of information overload and enhance customer relationship, the application of Recommender Systems has increased impressively, because they have proved to be helpful in facing information overload (Ricci et al., 2011; Nilashi et al., 2014a) and increase user satisfaction (Vahid et al., 2016; Pu et al., 2012., Finn et al., 2009).

Recommender Systems help online users in decision making and buying process in e-commerce settings (Jannach et al., 2012; Nilashi et al., 2014a,b; Nilashi et al., 2015a,b). Application of Recommender Systems leads to higher level of user satisfaction, due to the fact that recommenders help user to make decisions with higher quality between options that are less general and more tailored to their needs and preferences, in a limited knowledge constraints, less time consuming and less effort requiring procedure (Zhang et al., 2014; Pu and Chen, 2010).

One of the most recent applications of Recommender Systems has occurred in context of tourism industry. It has been noticed in last decades that tourism is a very important industry due to its significant profitability for countries (Agarwal, 2013). It is affirmed by World Travel & Tourism Council, that nearly 11% of the worldwide GDP (Gross Domestic Product) is allocated to travel and tourism domain (Lucas et al., 2013).

Introduction of internet to the travel and tourism industry has dramatically changed the way of searching for information. Travellers rely on travel websites and online booking platforms to find required information (Jannach, et al, 2014; Vladimirov, 2012).

In 2013, Tripadvisor reported as World Wide Web's hugest website in domain of travel, where information about approximately one million accommodations is available and more than 200 million users visit the website per month. The most favourable feature of the website however, is the customer's reviews about their experiences. More than 100 million reviews are available at the website (Jannach et al., 2014). The website also permits users to rate their feedback in a multi-criteria scale, which covers several factors such as cleanliness, service or value for money (Nilashi et al., 2014b).

Due to the complexity of context, tourism industry tremendously benefit employment of artificial intelligence, Decision Support Systems, in particular Recommender Systems (Lucas et al., 2013). In the mentioned context, Recommender Systems are applied to aid travellers during their research for a destination and process of planning their trip (Jannach et al., 2014).

In order to give users suggestions and predict their favourable items, Recommender Systems usually build a database on matrix of users and items. However, since the growth of internet, the number of users, searching for items has massively increased as well as the number of items provided by vendors. Due to this progressing number, Recommender Systems require more time for computation and more space for storage (Ricci et al., 2011). Time and space difficulties have caused several problems and persuaded researchers to pursue a new solution, since lower computation time enhances the efficiency of recommenders. Also, requiring smaller database is more economic.

In the studies conducted in realm of Recommender Systems, Collaborative Filtering techniques are to date, the most applied and most successful techniques. This widespread application of Collaborative Filtering although develops the technique, but however reveals some potential challenges (Sarwar et al.,2011), or as Cho et al. (2002) call them, limitations. Several studies in the literature prove the success of Collaborative Filtering methods and their ability to provide accurate recommendation, nevertheless it also illustrate that Collaborative Filtering methods suffer from some particular vulnerabilities. Since the aim of this study is to enhance the accuracy of recommendation in Collaborative Filtering methods, it is necessary to first identify problematic areas and by solving the problems, increase in the accuracy of recommendation will be achieved.

The first problem Collaborative Filtering methods is Data sparsity which refers to data insufficiency in the matrix of user-item (Ahn, 2008). Data sparsity is considered as one of the most critical issues and it happens when the number of rating provided by users which a recommender requires for formulating prediction is much lesser than the number of available ratings .In other words, there are a high number of items to user ratio (Xiaoyuan Su et al. 2007). As the result, the recommender will not be able to provide very qualified suggestions.

Since most of recommenders depends on rating provided explicitly by users, in order to perform and since users usually do not and cannot rate all the item in a system (Lucas et al., 2013), hence there is a large number of value missed in the database of user-item matrix, and this sparse database influence the accuracy of prediction generated by Recommender Systems (Nilashi et al., 2014b).

The sparsity problem develops its complexity for the systems that pass their early stages (Xiaoyuan Su al.2008), and even in a long term run, the ratings of a user, even an active user, do not cover all the items and in addition new items are added regularly and new users also join to the system and increase the number of sparse data (Ahn, 2008). As an example millions of catalogue items available at Amazon.com that only 1% of them equals to more than 10,000 items, users obviously would not be able to experience them all (Linden et al ., 2003).

Thus data sparsity can significantly bound the performance of Collaborative Filtering methods (Zhang et al., 2014) Therefore, it is necessary to research in new recommender methods to improve the problem of data sparsity by suggesting new solution and successively enhance the accuracy of recommendation.

One of the other problems perceived by Recommender Systems is the need for a large space in data base for being able to save all the user and item data, and therefore spending too much time while computing the prediction. Requiring large pace and long calculation time is also called Scalability problem (Lucas et al., 2013). As an example in the context of E-commerce, there might millions numbers of users as well as millions number of catalogue items. Therefore the need for time and space generate complex and expensive problems (Linden et al., 2003).

The problem of scalability appears in Memory based methods, which requires high computational time, and the time expands as the number of users and item in the system grows. Model based methods, on the other hand, do not suffer from this problem, since their model of recommendation is built offline and only when users access the system, the model is applied, thus no extra time is required for calculating the recommendation (Lucas et al., 2013).

Lack of Accuracy happens as the direct result of spars and unscalable database. Accuracy of recommendation that a system provides to its user, so far has been noticed as the most important factor in the literature that determines the level of quality and wellbeing of a Recommender System. To date various researches focused to propose models and algorithms to improve the level of accuracy. Any attempt to reduce the impact of data sparsity and database scalability result in improving the accuracy. Attempting to improve the accuracy has been the goal in works of Jannach et al. (2014).

According to literature, several attempts are accomplished to overcome any of the mentioned problems. Many have tried to hybridize different recommendation

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techniques in order to minimize the disadvantages and emphasize advantages of each technique to achieve the maximum possible performance. For example Burke (2002) has defined in detail several possible hybridization methods such as weighted, switching, mixed, cascade, meta-level, feature combination and feature augmentation. Bostandjiev et al. (2012) also propose a hybrid Recommender System which combine predictions from several platforms and provide an interactive system for users which is more accurate and interactive. Hybrid methods are also applied in tourism domain to solve problem of sparsity and grey-sheep. For instance Lucas et al. (2010) have proposed a hybrid recommendation approach using data mining techniques such as classification and association techniques.

To solve the sparsity problem, Lee et al. (2004) tried to discover hidden similarities in Collaborative Filtering. In their study Zhang et al. (2014) proposed a user preference derived algorithm. To enhance the accuracy Jannach et al. (2014) proposed a multi-dimensional customer rating in their study. Bilge and Kaleli (2014) used a multi criteria item–based framework to overcome the problem of scalability.

The mentioned problems do not involve solely the users and customers. Online E-commerce retailors and service providers are also affected, since customers are not able to find them easily, or in case of communication, the customer-vendor relation does not retain. Hence, for advancing in competitive advantage and retain a formidable relationship with customers, online E-commerce retailors and service providers should search for new solutions and techniques (Subramanian et al., 2014).

From a vast investigation on the literature, it can be claimed that, different type of techniques are used to overcome the problems of sparsity and scalability and enhance the prediction accuracy. Traditional Collaborative Filtering techniques utilize Pearson's correlation or cosine-based similarities (Ahn, 2008).

Although it has been realized that focusing on multi criteria approaches instead of single criteria would result in a more accurate recommendation, but majority of scholars in the literature are concentrated on Collaborative Filtering techniques that take into account only one overall rating criteria (Nilashi et al., 2014b). Current study though, is focused to continue a multi criteria approach, in order to enhance the accuracy and resolve the problems of sparsity and scalability. Thus the database of the study is not a typical database containing a matrix of user–item, in which the overall users' ratings of items are available. To achieve the objective of current study, multi-criteria ratings are available.

The main contribution of the study is the application of Fuzzy Clustering means for clustering data. Study on the literature shows that, several researches with similar scope were accomplished by using various data mining and recommendation techniques. However, applying Fuzzy C-means have remained rare and unregularly, although Fuzzy methods have proved to be efficient on reducing sparsity problems (Nilashi et al., 2014b).

2. Literature review

2.1 Recommender Systems

Recommender Systems are called by different names. They are also introduced as the result of studies in various fields. For instance, Nilashi et al. (2014b) consider them representing of information retrieval and information filtering for facing information overload, while Zhang et al. (2014) claims that Recommender Systems apply knowledge discovery techniques such as data mining and machine learning in order to realize interests of users. Burk (2007) calls Recommender Systems as personalized information provider agent.

According to Ahn (2008), since they can generate personalized recommendation to customers, the Up-selling and Cross-selling of online stores have boosted up significantly. Lucas et al. (2013) also define Recommender Systems as a competitive advantage in the electronic business market which leads to enhancing customer satisfaction. Jannach et al. (2012) admit that, due to their ability to increase customer satisfaction, Recommender Systems successively are capable of enhancing customer loyalty and sales. Thus, as the result of their significant profitability, Recommender Systems today have evolved into an essential asset in E-commerce settings (Nilashi et al., 2014b).

Recommender Systems, in course of time, might be attached to several other studies such as cognitive science, approximation theory, information retrieval and forecasting theories (Adomavicius and Tuzhilin, 2005), but they started their independence as a subject of interest in 1990's (Konstan and Riedl, 2012). In a simple explanation, Bordogna and Pasi (2010) introduce Recommender Systems as systems that provide relevant information according to users' particular requirements in an effortless and effectual process.

According to techniques they employ for generating suggestions, Recommender Systems are divided in several categories such as Collaborative Filtering (CF) approach, Content-Based (CB) approach, and Hybrid approaches. Zhang et al. (2014) added also Network- Based (NB) approach. Among all, Collaborative Filtering (CF) is mentioned as the most commonly used and reputed approach (Nilashi et al., 2014b; Lucas et al., 2013; Bilge and Kaleli, 2014; Jannach et al., 2012). This approach is that much popular and used that Lee et al. (2004) claim the term Recommender Systems can be referred and replaced as Collaborative Filtering and vice versa.

2.2 Collaborative Filtering techniques

Collaborative Filtering techniques also called learning-based technique by Burke (2007) are counted as recommender techniques which are used in the greatest extent, especially in online stores. The core concept of the technique relies on the similarities between users, saved in a large database. In time of recommendation, the system checks the preferences of a particular target user about an

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item, with other similar users (Ahn, 2008; Burke, 2007; Nilashi et al., 2014b).

As it was mentioned, the recommender gives a user recommendation based on preferences of other users, who have explicitly expressed them by means of rating items. Thus, ratings provided by a large network of users for items are the basic component for Collaborative Filtering techniques (Nilashi et al., 2014b; Jannach et al., 2012; Jannach et al., 2014).

In Collaborative Filtering methods, it is assumed by default that if users express resembling preferences, thus they would likely choose same or similar items to each other (Zhang et al., 2014). Results of researchers in literature demonstrate that Collaborative Filtering can identify cross-genre niches (Burke, 2007) and suggest a meaningful recommendation based on the data of a large user database which is new and unfamiliar for the user (Jannach et al., 2014).

2.3 Multi-Criteria Recommender Systems

To date, most of Recommender Systems conduct a single rating approach in order to provide recommendation for users. This two dimensional approach, focuses on the overall rating provided by users and attempt to suggest items to users based on the similarity that exist between their overall rating history. Although, the traditional single-rating approach so far had a smooth performance, but ever since the appearance of multi-criteria recommendation techniques, one can perceive the result of single criteria systems, less accurate (Adomavicius et al.,2011). Thus several new studies are trying to propose new model in this area in order to improve the accuracy of the recommendation.

In order to picture the performance of Collaborative Filtering Recommender Systems, it is required that concept of rating and users be explained. Rating is an act by which users explicitly indicate their idea and taste regarding a particular item. In a single-criteria centric system, users are able to only give one rating value which would be their overall rating, however, in a multi-criteria centric Recommender System, user are allowed to rate different attributes of one unique item And give different rate to different aspect of that item (Sanchez et al., 2011).

In traditional techniques with single-criterion core concept, it is automatically assumed that two users have a same taste when their overall rating upon an item is similar. However, it has been noticed that two users can give a same overall rating to a particular item, but their opinion about different attribute of that item might vary significantly.

It is proved that the degree of importance regarding each quality factor is a relative subject and depends to each and every individual. For example in the mentioned tourism context, a business traveller might have the same rating about a hotel with a young solo traveller, while their rating about attributes such as sleep quality or value for money vary (Nilashi et al., 2014b). Having the ability to express needs and preferences in a multi-criteria way allow users to meet their expectations, more effectively (Jannach et al., 2011). To clear the concept, it is necessary to explain that, overall rating is the one and final opinion of a user regarding an item, but multi-component ratings, as Nilashi et al. (2014b) call it, means rating different value of different attribute of an item, separately.

It has turned into a recent trend to apply a multi-criteria rating approach instead of being solely concentrated on users' overall rating. Where R_0 is the set of possible overall ratings and R_i indicates the possible rating for each criterion i shows the number of criteria. The matrix is famous as a user-item matrix where the size of matrix is defined as $n \times m$ where n is the number of users and m indicate the number of items. Each cell of this matrix is dedicated to the rating of a specific user about a specific item. This user ratings matrix is typically sparse, as most users do not rate most items (Melville and Sindhwani, 2010).

The idea behind multi-criteria rating approach is still the same as a similarity measurement that leads to prediction function in an ordinary single-criterion approach, but instead a more specific outcome is expected. Each user is given an ID, same as each item. Not only the overall rating of the user to an item is shown, but also rating per each single criterion is shown as well. For example the overall rating provided by user U_2 for item I_2 is 5 but its rating for location criteria is 3 and for cleanliness criteria is also 3. It demonstrates a set of rating provided by 2 users about different attributes of 2 different hotels including value for money, room, location and cleanness. Users are also able to give an overall rating to each hotel.

Similarity measure is considered as one of the significant approach in data mining and recommendation system in the phase of data pre-processing. There are various alternations in the application of similarity measures in recommendation techniques, but in Collaborative Filtering similarity measure is usually used to calculate the taste of two users (Ricci et al., 2011) and their similarity of rating history.

By Pearson correlation measures, similarity is considered as the degree of a linear dependence between two variables. Thus, the ratings of two users can be imagined as a vector in an m-dimensional space, and compute similarity based on the cosine of the angle between them (Melville and Sindhwani, 2010).

Measuring similarity in multi-criteria studies has shown that in Collaborative Filtering techniques, with multi criteria approach correlation based similarity and linear regression are providing accurate results (Adomavicius and Kwon, 2007). This branch of techniques usually perform on nearest-neighbour recommendation technique as the basis considering a single criteria approach, while in new studies, it is suggested to gather the value of similarity either obtained in single criteria approach or by multi criteria distance approaches and predict the recommendation by summing up similarities with aggregation function based methods (Nilashi et al., 2014b).

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2.4 User-based recommendation and Item-based recommendation

User-based Collaborative Filtering is in fact the traditional definition of Collaborative Filtering, in which the focus is on the similarity of preferences in the user community. Item-based Collaborative Filtering, on the other hand is a filtering approach that instead of being focused on users is mainly concentrated on items and similarities that exist between items (Ahn, 2008).

Item-based Collaborative Filtering, in the literature is announced as a solution to the problem of scalability, existing usually in User-based Collaborative Filtering. Since the number of users in a database is increasing constantly and the core concept of User-based Collaborative Filtering is to search this ever growing number, scalability problem arise as a significant obstacle. The core concept of Item-based Collaborative Filtering is to calculate similarities between items with this assumption that if given users are interested in a given item, they will be interested in similar items as well (Nilashi et al., 2014b).

Because of search for similarity between users' rating and taste, for a database with large number of users and items, User based Collaborative Filtering algorithms do not perform outstandingly, because searching for similar users is a complex computation. Thus item-to-item Collaborative Filtering or Item–based Collaborative Filtering methods were suggested, which instead of searching for similarity between users, they search for items similar to those items that users have rated before. It is proved to be faster and providing more accurate recommendations. In this approach, similarity between pairs of items *i* and *j* is computed offline using Pearson correlation (Nilashi et al., 2014b).

Previous attempts accomplished in the literature demonstrate that, studies are usually focused on either User-based Filtering techniques or Item–based approaches. However, new researches demonstrate that, instead of depending on only one of these techniques and trying to achieve an overall weight, gaining the weight for each individual item can provide more accurate results.

In an optimized approach, regression function can be learned for each user and then, combine the results of weights for each user and each item with the weight of prediction. Regression method for User-based is learnable, in same way as Item-based regression methods. Difference exists solely on the way of dividing data.

Being dependent only on user-based techniques, specially does not satisfy users with few item rated and since the number of existing rating is relatively superior to the number of users, therefore combining the two approach leads to advantage of each method support the deficiencies of the other.

Study on the literature demonstrates that most of the previous researches are mainly focused on user-based Collaborative Filtering and make effort to find users with similarity to their neighbours and recommend them suitable items based on the similarity between users. Although proposed algorithms in this section work reasonably, but still data is hard to scale and the database is rather spars, thus the recommendations are not accurate enough. Several studies have proposed Item-based Collaborative approaches as a solution to cover up the gap. For example, in a study conducted by Karypis (2001), it is claimed that Item-based algorithms work 28 times faster than User-based Collaborative Filtering. Also, in terms of quality of recommendation, Item-based algorithms provide recommendation with quality up to 27% better.

In Item-based techniques instead of users, first the similarity between items must be identified. Addressing the problem of sparsity and scalability by applying Item-based techniques is also conducted by Xue et al. (2005) in a cluster-based study. Usage of Item-based Collaborative Filtering algorithms for overcoming the problem of sparsity and scalability is also mentioned by Sarwar et al. (2001). In their study computing similarity between items and an Item-based algorithm is represented as a solution to the common problem of User-based Collaborative Filtering approach.

2.5 Fuzzy Clustering

Clustering helps us identify customer segments with similar tastes in the literature, a large variety of clustering techniques have been proposed. Some of these approaches like *k*-means algorithm are very popular (Nilashi et al., 2014). Fuzzy Clustering which uses the fuzzy logic (Nilashi et al., 2011; Nilashi and Ibrahim, 2013) has become popular recently. By means of fuzzy logic a user can be assigned to more than one cluster with different belonging degree and receive recommendation from more than one group (Lucas et al., 2013) .

Fuzzy Clustering means is one of the clustering techniques with ability to put one piece of data into two or more numbers of clusters. The method is highly applicable in pattern recognition. The *k*-means algorithm is a very efficient algorithm in case of large data sets. Fuzzy versions of the *k*-means algorithm, known as fuzzy C-means allow each piece of data to be a member of all clusters instead of being distinctly member of one particular cluster.

At first process, the degree of membership for a user or an item is calculated. Then the centre of cluster is calculated. The user matrix is then updated based on the result of cluster centres, at the end, users or items are clustered based on their degree of membership to each cluster.

In fuzzy C-means, data are assigned to cluster with a Membership Function (MF). This fact is representing the fuzzy state of the algorithm. For doing that, it is only needed to build an appropriate matrix named U with factors between 0 and 1, and represent the degree of membership between data and centres of clusters.

Fuzzy C-means performs similarly with *k*-means algorithms, but with the difference that fuzzy C-means is able to hold values between 0 and 1. It means that Fuzzy C-means do not follow a strict definition for clustering data and datum can be stored in clusters by percentage. There is a slight line that can define every datum may belong to

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several clusters with different values of the membership coefficient. Fig. 1 depicts a flowchart of fuzzy C-means clustering implementation.

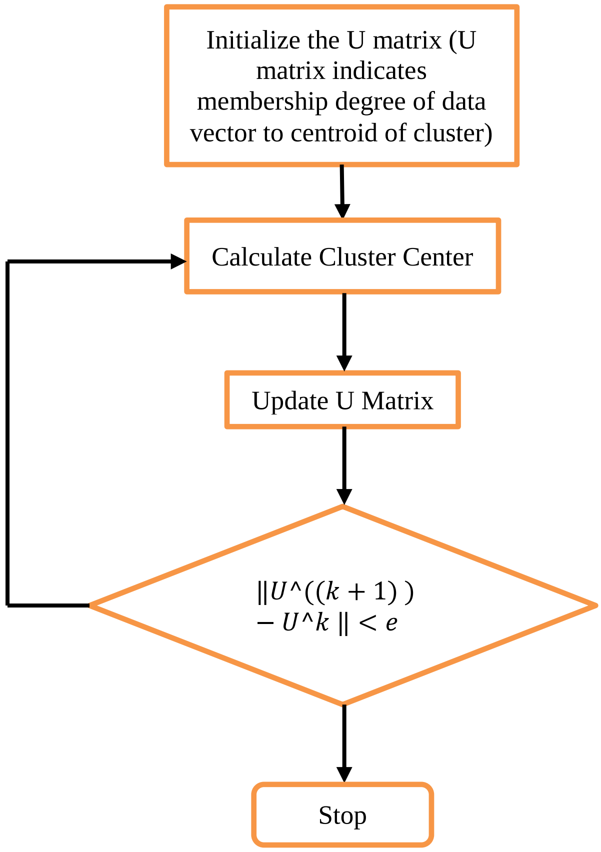

Fig. 1. Fuzzy C-means method

3. Methodology

Since the objective of the current research is to increase the accuracy of recommendation in Collaborative Filtering techniques by solving sparsity and scalability problems, first it is needed to evaluate the quality of result. A baseline standard is required so this fact can be understood whether the objectives are met or not.

As it is stated by Jannach et al. (2013), in the realm of Recommender Systems, the quality of recommendation and the performance of the system are commonly measured according to accuracy metrics.

Study on the literature demonstrates that, there are several other metrics to evaluate a Recommender System. One of the factors to evaluate performance of a Recommender is Precision, which demonstrate the number of correct recommendation compare to the overall recommended items. Mean Absolute Error (MAE) is another metric, which shows the average of difference that exists between real rating of users and prediction of recommender. Recall is another measure that illustrates the number of correct recommendation in comparison with the number of all liked items.

Coverage is another factor that measures the number of predicted items in contrast to the number of all items in the data set. F-measure is another factor to measure quality and quantity of the recommendation which is the combination of precision and recall. Root Mean Square Error (RMSE) is another measurement factor, which this study will employ in order to evaluate the accuracy of the resulted recommendations (Jannach et al., 2014; Nilashi et al., 2014b).

After adjusting a proper set of evaluation metrics, data must be prepared. The data set used in this study consists of 5000 json files. Every single one of these json files is the rates provided by a user for several hotels. Thus there are 5000 users in this data set. The preparation of data set has been done in several steps.

At first by usage of a code written in Java all 5000 json files was combined. At next step, the files that have been made are parsed in order to create a table with the exact number of rates. In fact each row is dedicated to one vote. Elements such as username, hotel name and ID and the rates given to every feature of a hotel are each saved in a row. This action is done by using a code written in C++.

At this point, in the table, repetitious rows are spotted meaning that some votes have been repeated for a single user. Hence all these repetitious rows were eliminated. This will help to eliminate the redundancy of data and later on the process is easier and lighter.

A user×hotel table was created for single criteria analysis. In this table $T_{i,j}$ stands for the overall rate that the user i has given to hotel *j*. Also in order to conduct a multi-criteria analysis a user×hotel×criteria matrix was created. In this matrix $T_{i,j,k}$ stands for a rate that the user *i* provides for hotel *j* to the criteria *k*.

Rows filled by users whose number of vote is below the threshold was eliminated from the table. The number assigned to threshold in single criteria study is 40, meaning that users with number of votes below 40 are eliminated while the execution of the algorithm. 283 users have rated over 40 hotels, thus they remain in the table. In case of multi-criteria study, this control is applied to every single criterion. This will solve the problem of sparsity to some extent.

After the data set is cleaned a part of data should be trained in order to obtain the most accurate model with least error value. The rest of the data also should be reserved for testing in order to achieve the same goal. The logic of train and test in single criteria approach is to put for each user parts of its rates in train set and put the rest in test. In multi criteria approach the same practice is applied on each criterion.

After eliminating users who have not provided enough votes and the hotels with insufficient information, there are hotels with some criteria that have been remained unrated by users. The solution to fill these empty values is to use a permanent or constant value for replacement to fill these null values. Some different assumptions are considered and the effectiveness of these assumptions will be specified according to the outcomes.

Some assumptions for accuracy of predicting user's interest toward a hotel were considered. For instance all criterions are independent and there is no actual

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dependency between them and in case of lack of rate for a specific criterion, the average rates of other users in its cluster can be used to fill it. Also if there would be one empty value for specific criteria of a hotel, average rate of other users in its cluster about that criterion will be used.

3.1 Offline and Online phase of Recommendation

In this study, same as other studies the whole recommendation process takes place in two off-line and on-line phases. In off-line phase data is trained and tested in a various number of combinations of possibilities. No matter what algorithm or technique is used, the best case which represents lower value of error is learned. When the proposed model is learned it is applied on the trained data. Once the user submits a new rating in the online phase, the system must recommend user an item accordingly to the trained model. In both single and multi-criteria methods, after applying the algorithm to all the different cases, according to the value of error, the best scenario will be chosen. The offline phase runs based on this optimized option and the model is constructed.

The same practice is applied in online phase and *n*number of best case User-based propositions and numbers of best case Item-based propositions are generated for a current user. Then among all the suggestions, n_1 proposition from User-based approach and n_2 Proposition from Item-based approach are recommended to user, where $n=n_1+n_2$. For choosing among proposed options, the weighted average of both User-based approach and Item-based approach is calculated.

3.2 Design of Multi criteria model

To design a multi criteria model, several approaches might be applied. The method used in this study is as follow: At first by developing an approximator, the relationship between criteria rates and overall rates was gathered. Then for every user/item that is supposed to be tested, same as single criteria model, there was a separate prediction for every criteria. Using the correlation between criteria ratings and overall ratings, the overall for every user/item is predicted. The error value of the overall is obtained. Same as single criteria modelling, the accuracy metric to evaluate the error value is MAE. Like single criteria modelling, this method runs at several cases in order to obtain the best result in terms of number of clusters, number of nearest neighbour, the fuzzy performance or crisp.

The regression at first phase is applied using feed-forward artificial neural network. For a more accurate prediction given by neural network, the regression for all the users is not done simultaneously. First users are divided to 5 clusters using fuzzy C-means algorithm. Then for every single cluster an approximator is created. At third step, in order to test user, it will be referenced to the approximator of the cluster.

The neural network layers used here are 10, which are obtained after running in several methods and comparing the outcome of each running. The algorithm to train the neural network is Levenberg-Marquardt. The percentage for train data, test data and the validation is: 70, 15, and 15. The function used to evaluate the error value is MAE in a training rate of 0.01.

4. Findings and results

In fuzzy C-means, the dependency of users to cluster is of no importance but the degree of membership to a cluster plays role. According to their degree of involvement they can participate in item recommendation. In calculating the value of prediction, first clusters with degree of membership greater than 2 are characterized. For clusters lacking this degree the value of zero will be adjusted.

By assumption that clusters which have zero degree of membership will not participate in calculation, the degree of membership is normalized and then the normalized value will replace the previous value (Verma et al., 2013).

In MATLAB, several set of possibilities run. For instance, fuzzy C-means algorithm is once used with Correlation metric and User-based model and *k*-means is also used with Correlation metric and User-based model. The comparison between two set of possibilities shows that the application of fuzzy C-means with Correlation and User-based model, shows the lowest MAE equal to 0.45 when the number of clusters is 9 and the number of nearest neighbours is 3. However the application of *k*-means with Correlation metric and User-based model shows the lowest MAE equal to 0.565 when the number of clusters is 5 and the number of nearest neighbours is 3. Also when the number of cluster is 5, the MAE is equal to 0.46. Thus, it is understood that using fuzzy c-means with Correlation metric gives a better result than using *k*-means algorithm.

If considering the metrics and the clustering method invariant while changing the two parameters of numbers of nearest neighbours and numbers of clusters, the value of prediction error will change. To do so, the model problem has been implemented in several modes. In comparison between fuzzy C-means and clustering using *k*-means, fuzzy C-means shows better results comparing to the result of *k*-means algorithm. Comparison between Item-based and User-based model demonstrate that the data set used for User-based model shows a lower value of MAE error compare to item-based model. Fig. 2 demonstrates Comparison of error in user-based approach with cosine metric and correlation metric. Fig. 3 shows comparison of the output of the algorithm in item-based approach with two different clustering.

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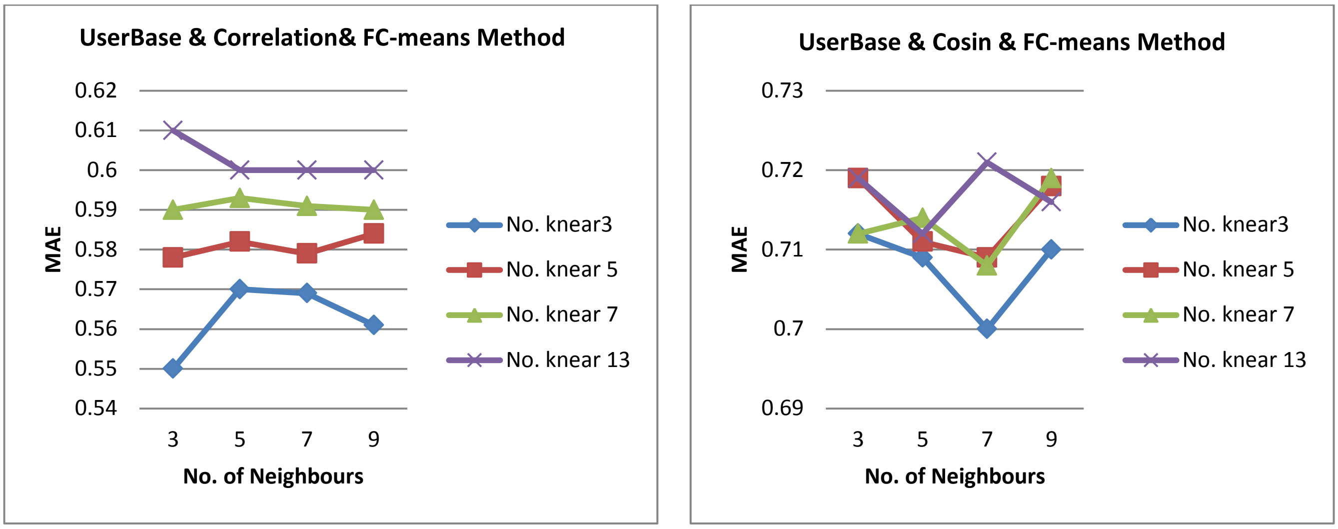

Fig. 2. Comparing error in user-based approach with cosine metric and correlation metric

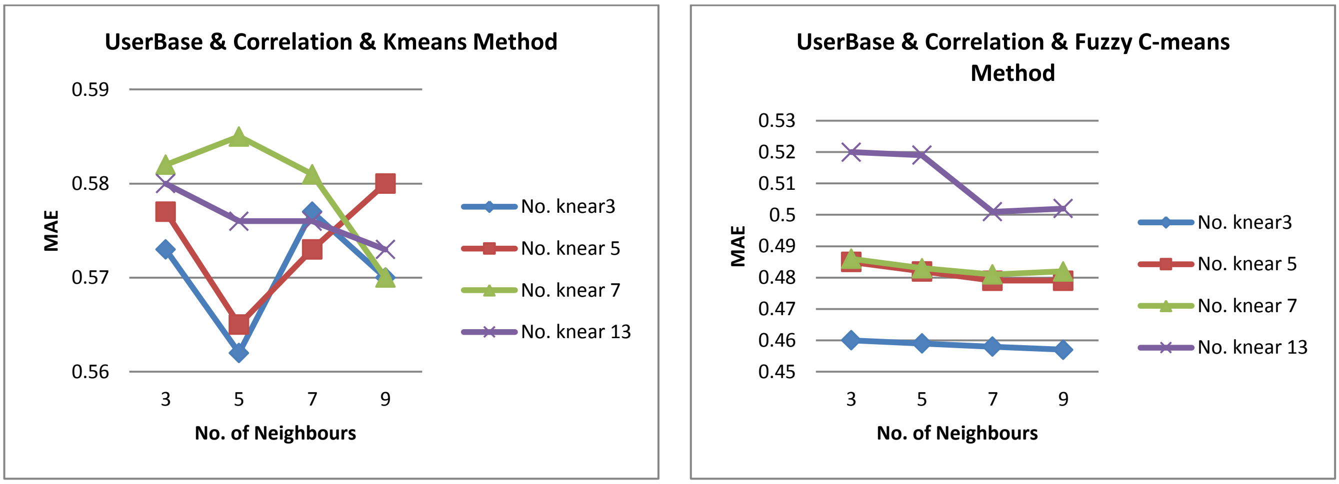

Fig. 3. Comparison of the output of the algorithm in item-based approach with two different clustering

The comparison between two set of possibilities, where fuzzy C-means algorithm is once used with Cosine similarity metric and once with Correlation metric and for both the User-based model is applied shows that the application of Fuzzy C-means with Cosine and User-based model shows the lowest MAE equal to 0.70 when the number of clusters is 7 and the number of nearest neighbours is 3. However the application of Fuzzy C-means with Correlation metric and User-based model shows the lowest MAE equal to 0.55 when the number of clusters is 9 and the number of nearest neighbours is 3. The MAE also when the number of cluster is 7 is equal to 0.57. It is understood that using Correlation metric gives a better result.

For estimating and recommending items that are not rated by users, the nearest distance between item and the centre of cluster is used. The MAE value for each number of clusters using Cosine similarity metric and Item-based approach at each run is different. The lower MAE value is the more accurate prediction and it happened when the number of clusters is 3 and the number of neighbours is 7 the lowest MAE obtained is 0.725.

5. Conclusion

This study was conducted to enhance the performance of Recommender Systems by enhancing performance of system in both offline and online phases. The goal was to show this enhancement by elevating the accuracy of the recommended item, resolving sparsity of the database and helping it to face the problem of scalability while working with large databases. Study also aimed to enhance the accuracy of the recommended item by combining both User-based and Item-based approach in online phase, instead of applying only one approach which is common in other studies of the literature.

The data set was gathered from ratings provided by users of Tripadvisor website. And another main goal of the study was to apply a multi criteria model instead of single criteria in order to give a more realistic recommendation to users.

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To achieve the goals, fuzzy C-means algorithms alongside *k*-means algorithms were applied to various numbers of clusters. Several set of possibilities were ran in MATLAB in order to calculate the best possible case and use it as the base model on offline phase and train the data set according to that. Also, Cosine and Pearson correlation approaches were applied in order to calculate the value of error for every set of possibilities.

As it can be seen fuzzy C-means algorithm used by correlation demonstrates lower error value for both Users-based approach and Item-based approach. It is necessary to mention that number of clusters and number of nearest neighbours are assumed 3.

For resolving the problem of sparsity this study proposes a solution. In some table cells where the rate of the user is not given, there is -1. All of these cells must be filled with a value because the value of zero will cause an unreal error. This happens due to the comparison of zero which is the lowest rate given by users, with other values such as 4 or 5. Thus these cells will be filled with the average of the rates of other users. In multi-criteria approach, same practice will be applied to each criterion. It is to be considered that this averaging practice for each cluster of users will be applied separately. For applying single criteria and multi-criteria study proves that applying multi criteria recommendation not only enhance the accuracy of recommendation but also helps it to be more realistic and near to users' interests. For applying user-based approach and item-based approach at online phase study proves that user-based approach tends to give a more accurate and optimal weight, however very slightly.

All in all, the study was able to meet the entire desired goal and prove that the proposed model to train data in offline phase and applying user–based approach in online phase will enhance the accuracy of recommendation, while working on the dataset in offline phase helps to overcome sparsity and scalability.

Finding of the study can contribute to the enhancement of recommendation technique even in a very small scale. The result would be beneficial not only for the users of web services but also for other parties such as hotel managers and stakeholders who can concentrate on their online services and better understand of their customers' need without investing great value of money. This also can help them to improve their relationship with customers without financing for advertisement.

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