Multi-criteria Recommender Systems: An overview of the state-of-the-art

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ABSTRACT

Internet has taken over the people of current era such that the users are immensely dependent upon the knowledge and services it provides to them. It leaves the users with tremendous confusion in making choices among the available overloaded information.Recommender systems have proved to be a saviour to this problem created by overabundant knowledgeavailable to users.Multi-criteria RSs (MCRS) are being categorized and researched upon with many different organizing system in order to enhance the accuracy and performance of RSs with respect to traditional RSs. The purpose of this paper is to accumulate and facilitate the viewer researchers with a good portion of work that is done to improve the process of recommendation in the field of MCRS. We survey the state-of-the-art methodologies and try to provide a thorough review of grafted approaches, challenges and drawbacks of various research works accomplished in this area of RSs.

Keywords- *Recommender Systems, Multi-criteria ratings, collaborative filtering, optimization.*

1. Introduction

Recommender Systems are the web-based software tools which are designed to mitigate the severity of increasing information overload problem. A plethora of data is available on the internet which is growing incredibly with each second. Internet has become a breath to the life support system of its users. Any kind of information that anyone wants to access from anywhere is now a days easily available on internet. The reliability of users and trust on the system has become a vital need for the providers. To pen down their thoughts or to buy any big or small product or to get knowledge about any field, people are accessing internet. The users want to get their most desired products in a very less amount of time. And therefore, researchers have been doing valuable work in both industry and academia to develop new intelligent techniques to overcome this problem of information overload.Recommender Systems (RSs) are one of the intelligent solutions to this problem of dealing with the large amount of data [7]. It is a tool which eases the ability of decision-making for its various users. RSs predict the items which are most probable to be liked by the users with respect to their past preferences and then generate the recommendations accordingly increasing customer satisfaction and faith in e-commerce.It also reduces the e-commerce time complexity problem and helps by retrieving the most relevant piece of information among a large set of available items [8]. Most of theweb applications use RSs to provide efficient and accurate recommendations to its users. Some of the famous applications using RSs include Netflix, Facebook, Amazon, Twitter, YouTube, LinkedIn, Google+ etc.

Based on their area of recommendation, there are few major types of RSs: Group-based Recommendation system [38, 39], Trust-based recommender system [41, 42], Multi-criteria Recommender Systems [6, 11, 14], Context-aware Recommender system [43].

In large number of personalized applications, the traditional single-criteria rating RSs are being used. While, in order to come up with better decisions, it is essential to possess sufficient amount of information about the object to be rated or to be predicted and recommended to the user.

RSs are usually classified into following categories [1,9,10]:

Content-Based recommendations: It uses content-based filtering approach which aims to find the items similar to the items that the user has liked in the past. They view the recommendation problem as finding related items to a set of items.

Collaborative filtering recommendations: The user will be recommended items that people of similar tastes and preferences liked in the past.

Demographic recommendations:classifies the user according to their personal profile attributes known as their demographic features such as age, gender, nationality, etc. and makes recommendations based on them. Example Grundy system which was developed to support book searches in library [11]

Hybrid approach: Recommendations are made by combining any of the aforementioned recommendation types, resulting in an increase in recommendation quality addressing the shortcomings of each type and overcoming it with the advantages of the other type [12, 13].

In the field of RSs, most widely used filtering technique is the Collaborative Filtering (CF) approach for recommendation. Base of this approach depends solely on the similarity between users according to their past preferences. It encourages the idea that if two users have similar preferences of item in their past then it is highly probable that the items liked by one user will also be liked by the other one due to their high similarity aspect. Therefore, it focuses on finding similar peers to the active user (the one to whom recommendation is to be provided) for providing recommendation.

Recommender Systems basically performs a three-phase process incorporating:

1. **Similarity computation-** In this phase, the major concern is to evaluate the most similar neighbours of the active user. Generally, most of the RSs use Collaborative Filtering approaches to calculate the similarity between various users and thereafter carrying out the best k neighbours.
2. **Neighbourhood formation and Prediction-** In this phase, RS estimates the rating that the active user would provide to unknown items, based on the ratings given to those particular items by its neighbours.
3. **Recommendation-** After predicting the unknown ratings, items which are predicted to get highest ratings among all and therefore most probable to be liked by the active user are selected and finally recommended to the active user.

Recommender systems have become an increasingly significant research field since mid-1990s with a tremendous growth in the usage and dependency on internet. Almost all possible areas like music, movies, medicine, shopping, education etc. have gathered an eye over the inclusion of RSs for its better productivity and increasingusers with higher level of satisfaction.RSs require the user to input data in any of the two ways either implicitly or explicitly. Explicit ratings are provided by each user using one or more ordinal or qualitative scales while implicit preferences seek to avoid this bottleneck by deducing the users browsing behaviour [29]. For example the time spent by a user on a products webpage. As mentioned above, there are various recommendation techniques incorporated in RSs to improve the process of recommendation. Among all the prescribed techniques, Collaborative filtering is the most widely used approach among RSs where the basis of recommendation is the similarity between the users such as the users who carry most similar preferences becomes the source of predicting item ratings and then recommending the best rated items to the other one.

Table 1 includes some of the important definitions related to Recommender systems provided by different researchers in their respective research works.

1.1 Collaborative Filtering Approach

The term 'collaborative filtering' was first devised by Goldberg to describe an email filtering system called *Tapestry* which allowed users to rate messages as good or bad or attach text annotations [2]. Tapestry was the first recommendation support system which was built at Xerox®Parc and it was pretty good at providing recommendations but also had a major drawback that the users had to write complicated queries [3]. The first system generating and providing automated personalized recommendation is GroupLens system [4, 5].Collaborative recommendations can be categorized into two main groups: *memory-based (or heuristic method)* and *model-based.* In memory-based approach, the previously rated items by the most similar users are used to predict any unknown item rating, usually computed as an aggregation of ratings provided by the users to that item [53,54]. On the other hand, model-based approach constructs a predictive model to calculate the overall rating a user would give to any unknown item, from the observed multi-criteria ratings [1, 6, 55].Collaborative Filtering algorithms are based on the concept of similarity which defines that how close the users are and hence how much their preferences match or resemble to each other's preferences.

The similarity sim (u,u´) between any two users u and u´ can be calculated using different methods:

Let R(u,i) be the set of ratings provided by user u to item i where R (u,i) = ($r_\circ$, r_1, r_2…,r_k) and for another user u´ let it be R (u´,i)= ($r_\circ'$,r_1',…r_k'). Distance function d (u,u´) is carried out using [6,14]:

- Manhattan distance: $\sum_{i=0}^{k} |r_i - r_i'|$;

  (1)

- Euclidean distance: $\sqrt{\sum_{i=0}^{k} | r_i - r_i' |^2}$;

  (2)

Now, d(u,u´) between two users is: $d(u,u') = 1/|I(u,u')| * \sum_{i\in I(u,u')}(R(u,i), R(u',i))$

(3)

Here, I(u,u´) denotes the set of items rated by both u and u´.

Source	Definition	Year
[16]	Collaborative filtering (CF) is the process of filtering or evaluating items through the opinions of other people. CF technology brings together the opinions of large interconnected communities on the web, supporting filtering of substantial quantities of data.	2007
[17]	In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients.	1997
[2]	Recommender systems apply data mining techniques and prediction algorithms to predict users' interest on information, products and services among the tremendous amount of available items.	2010
[6]	While the overall rating that a user gives to an item provides the information regarding *how much* the user liked the item, multi-criteria ratings provide some insights regarding *why* the user liked the item as much as she did.	2007
[18]	Multi-criteria recommender systems are one of the RSs which utilize users' multiple ratings on different aspects of the items (ie, multi-criteria ratings) to predict user preferences.	2017
[19]	MCDA aims at giving the decision maker a recommendation, in other words aiding the decision maker in the so called decision making process, concerning a set of objects, actions, alternatives, items etc, evaluated on multiple points of view, which are roughly referred as criteria (attributes, features, variables etc).	2011
[20]	Recommender systems systems apply data analysis techniques to the problem of helping users nd the items they would like to purchase at E-Commerce sites by producing a predicted likeliness score or a list of top{N recommended items for a given user	2001
[21]	Multi-criteria decision analysis provide better understanding of inherent features of decision problem, promote the role of participants in decision making processes, facilitate compromise and collective decisions and provide a good platform to understanding the perception of models' and analysts' in a realistic scenario.	2004
[22,23,24]	Recommender Systems (RSs) are software tools and techniques that provide suggestions for items that are most likely of interest to a particular user	1994,1997, 2015
[25]	The provision of personalized shopping recommendations in online stores has shown to be a valuable way to help customers find interesting items and to consequently increase customer loyalty and sales. Recent studies, for example, showed that using a recommender system (RS) can lead to increased sales volumes in the short term and in the long term or help to increase sales diversity by directing customers to other parts of the available product catalogue.	2012
[26]	Multi-criteria ratings can represent more complex preferences of each user and thus help to	2011

	improve the quality of recommendations.	
[27]	Multi-criteria ratings allow users to express more differentiated opinions by allowing separate ratings for different aspects or dimensions of an item.	2012
[28]	A new extension of traditional collaborative filtering schemes takes into account not only how much a user likes an item, but also why she likes the item by collecting multi-criteria preferences focusing on distinctive features of the items. These multi-criteria collaborative filtering systems have the potential to improve recommender system accuracy since they reveal multiple views of users on products.	2019

Table 1: Definitions related to Recommender systems and Multi-criteria RS

The two most common methods used to calculate the similarity between users are Pearson correlation based and cosine based similarity methods [14]:

- Pearson correlation-based:

$$sim(u,u') = \frac{\sum_{i\in I(u,u')}(R(u,i)-\overline{R(u)})(R(u',i)-\overline{R(u')})}{\sqrt{\sum_{i\in I(u,u')}(R(u,i)-\overline{R(u)})^2}\sqrt{\sum_{i\in I(u,u')}(R(u',i)-\overline{R(u')})^2}}$$

(4)

- Cosine-based:

$$sim(u,u') = \frac{\sum_{i\in I(u,u')}R(u,i)R}{\sqrt{\sum_{i\in I(u,u')}R(u,i)^2}\sqrt{\sum_{i\in I(u,u')}R(u',i)^2}}$$

(5)

After obtaining similarities between the users, next task is to get the top-k neighbours of the active user (to whom recommendation is to be provided). Users having highest similarity with the active user are considered as itsTop-k neighbours and are further used for predicting the items ratings that the active user will give to an item he has not seen yet but is seen by his most similar users and therefore are most probable to be liked by the active user too. Most commonly average of the ratings provided by the neighbours is taken to calculate the predicted ratings.Based on the predicted ratings of unseen items, the best top N items with highest predicted ratings are recommended to the user.

CF systems have certain drawback and limitations facing data sparsity problem, scalability and cold start problem etc [15,16]. With the emerging huge amount of work of CF systems these problems have also been tried to get overcome by various researchers.

2. Background

Traditional RSs operates in the two-dimensional *User* x *Item* matrix where the overall rating of an item R_0 given by a user u on any item i is represented as

$$R: Uses \times Item \rightarrow R_o.$$

Multi-criteria ratings on the other hand consider user's preferences more specifically and represent the individual criteria ratings given to that particular item by the user. Let's say there are *k* numbers of criteria or aspects of the item, and then the prospect of rating item will be elaborated as

$$R: User \times Item \rightarrow R_0 \times R_1 \times R_2 \times \ldots \times R_k.$$

In mid 1990s, RS emerged as an independent research area when the recommendation problems which explicitly rely on rating structure were being focussed upon. Basic RS involves single rating to the available items. Let's take an example of a simple recommender system which includes 5 users'$u_1 \ldots u_5$and 5 items $i_{1\ldots}i_5$ where each has provided a rating on the scale of 1-10.

As seen in figure 1, it seems that ratings provided by user u_2 and u_3 are most similar to those provided by the active user u_1 (target user) also indicating that u_2 and $u_3$areits nearest neighbours (true peers). Hence, the unknown rating to item i_5 that would be given by u_1 will be calculated using the ratings given by its neighbours u_2 and u_3 which thus led the target rating to be predicted as “9”.

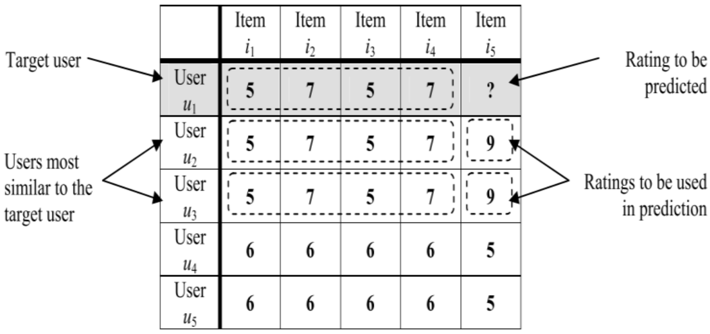

Figure 1: Single-rating recommender system [6]

Now, consider the above mentioned scenario in a multi-criteria rating system where each item is being categorized into its four specific criteria on which every user has provided its specific ratings. If we consider a movie RS and that each of these items shown in figure 1, as movies where each movie includes 4 criteria for example let it be movie genre, direction, acting, story. The ratings provided to these criteria in a multi-criteria RS are as shown below in Figure 2.

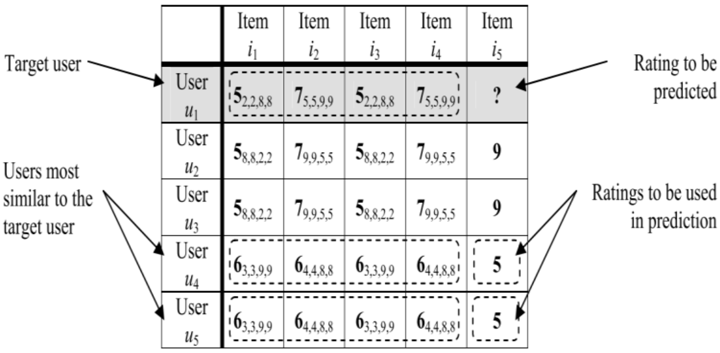

Figure 2: Multi-criteria rating recommender system [6]

Extending each single rating into multi-criteria ratings by incorporating ratings provided by users to different criteria of the item or movie, the nearest neighbours of the active (target) user seems to have changed totally. Concentrating on the criteria ratings, it can be seen that no matter user u_2 and u_3 share exact same single rating with u_1 but analysing more accurately user u_4 and u_5 share more similar likeness to u_1 while rating each criteria of the movie or item. Therefore, the rating of the unseen item i_5 of target user u_1 will be predicted using the ratings provided by its actual nearest neighbours u_4 and $u_{5.}$

Single rating RS shows that *how much* the user like or dislike an item, while on the other hand being more specific to knowledge multi-criteria RS answers that *why* the user has liked or disliked the item that much. And thus we can say the additional information provided by the multi-criteria ratings could help to improve the quality of recommendation as it will be able to provide more specific preferences of the user.

Multi-criteria Recommender Systems are one of the most widely used Recommenders due to its detailed preference learning notion which helps to improve the quality of recommendations provided to user.In this paper, an over view of various algorithms which use multi-criteria ratings are being discussed. Each type of recommender system included in this study is deliberated with a discussion on the highlights about the system. It also spots the crucial concern seeking issue of security and reliability in recommendations. Finally, the challenges that are being faced by multi-criteria recommenders are thrown some light upon, to give an idea about the scope of further research in this field.

3. Literature Survey: Multi-criteria Recommender Systems

Multi-criteria collaborative filtering schemes allow modelling the user predilection in a more expound manner by collecting ratings on various aspects of an item or service. The importance of MCRS is well high lightened in various previous literatures and recently many RSs have been incorporating multi-criteria ratings for producing better quality of recommendation.

3.1 Multi-criteria Decision Making Problem

Decision making is basically a psychological phenomenon regarded as a cognitive process leading to select the most likable course of action among a number of available alternatives. Considering different choices or course of actions which conflict to a substantial extent is called Multi-criteria Decision Making (MCDM). According to Gandibleuxet. al[31], MCDM consists mostly of two branches, multiple criteria optimization and multi-criteria decision analysis (MCDA).MCDM came up as a promising field of study since the early 1970's, when the focus was on theories of multiple objective linear programming [33,34]. In 1990's, many pioneering ideas including fuzzy multiple objective programming [35], evolutionary algorithms in multiple criteria such as Pareto-based and Non-Pareto based techniques [31, 81], vector optimization, linear programming with multiple objective functions [32], goal programming for decision making [38], data envelopment analysis in MCDM had begun to edge the field.On the other hand, Multi-criteria Decision Analysis aims to help the decision makers in unifying and blending the information in such a way that leads to make them a confident decision, minimizing the potential for post-decision regret by providing satisfaction towards all criteria being taken into account [36, 37]. Roy's [14, 30] methodology inculcates four steps while evaluating a decision making problem:

1. *Defining the object of decision:* It is, defining the set of items for which the decision has to be made and the causeof the decision. It refers to the concept of decision problematic which is of four types namely Choice, Sorting, Ranking and Description.
2. *Defining Family of Criteria*: It defines that the performance of items depends on a certain set of criteria which may refer to as multiple features or attributes of an item or multiple dimensions over which the item is evaluated. A consistent family of criteria is required to make rational decisions. There are basically four types of criteria in MCDM [44]:

- *Measurable*-criteria ratings are provided as a quantified measurement on some standard evaluation scale.
- *Ordinal*- qualitative or descriptive scale is used to define an ordered set of values.
- *Probabilistic*- probability distribution is used to represent the uncertainty in evaluation of criteria.
- *Fuzzy*-criteria ratings are provided in an interval of qualitative or descriptive scale.

3. *Developing a Global Preference Model:* In order to express the preferences among the alternatives of items, a Global Preference Model is developed to aggregate the values of criteria,which according to [44, 45] can be categorized into Multi-Attribute Utility Theory (MAUT) [46], Multi-Objective Optimization models finding Pareto optimal solutions [47], Outranking Relational Models in which all the items are compared to each other pair-wise [48] and Preference disaggregation models [49].

Discussion

Many research studies have indicated that recommendation is neither just a single decision making problem nor it can be considered as a group decision making problem [11]. There are various decision making problems and each single user has an impact on the recommendations provided to some other user. Since, there are multiple features of an item leading it to possess multiple criteria and making it difficult for the user to make an accurate decision regarding that item, this leads to MCDM problems. Thus, engaging MCDM modelling will allow the use of more complex yet better recommendation methodologies such as multi-objective optimization [1], taking linear combinations of multiple criteria to reduce the problem into single-criteria one, optimizing the criterion using various machine learning techniques like Pareto-optimal solutions and fetching the most optimal solutions [81,82].

3.2 Multi-Criteria recommendation as Data Query

In Multi-Criteria RSs each user gives ratings to multiple criteria of any item or product in order to express higher degree of preference on various aspects of the item. Difficulty arises when there are criteria which are conflicting with each other in nature.For eg.Zagat's guide [51] provides food, décor, service as the three criteria on which a restaurant is being rated in a recommendation system and if the food of a restaurant may be very good but the décor is elementaryand service is also not satisfactory or if two of the criteria are up to user's expectations but the one which was most preferable for him was weak, in such cases conflicting criteria become problem for the process of recommendation. Therefore, in practice, an alternative may be better than the other one with respect to one criterion and weak or worst in terms of other criterion. The possible solutions involve, applying weights to all the criteria reflecting the importance it has for any particular user. Different solutions to multi-criteria optimization problem in multi-criteria decision analysis (MCDA) take a linear weighted combination of multiple criteria to reduce the problem.In [50], Lee and Teng proposed an opinion that the weights of different criteria differs with different user and also changes with time. As in, for some users decor may be the most important aspect to choose a restaurant while for others food may be at prior. Also, it is not necessary that a person who doesn't bother about high price dine-in on special occasions such as birthdays or anniversaries may not be wishing to go for a normal price dine-in on normal days. Thus, weights of criteria are time-variant leading to a notion that in multi-criteria recommendation, it is very difficult to get an optimal candidate having best ratings for all the criteria. As stated in a research work [50], multi-criteria recommendations are a *data query* problem and thus skyline query algorithms can be used for solving the conflicting multiple criteria problem.A *Skyline* is a subset of points which are not being dominated by any other point and thus by depicting the non-dominated users in a d-dimensional space, it creates a skyline connecting the best points together and also getting preferable results for recommendation.

Discussion

It seems to be an appealing idea to recommend that set of items to the user which contains the best performance on specific criteria which is at the topmost preference for a user, instead of recommending those set of items with Top-N utility values [11].Using the concept of Skyline Query for multi-criteria recommendation helps to sort out the conflicts within the criteria ratings on an item. It states that recommendation cannot be formulated as an optimization problem due to these criteria conflicts rather skyline queries proved to be more feasible in practical applications.

3.3 Multi-criteria recommendation using Criteria Chains

In order to alleviate the problem of overloaded information and provide a better assistance to user's decision making process, Multi-Criteria RSsare being experimented using different methodologies one of which is very innovatively projected by Zheng [55] in his recent work which proposed "Criteria Chains". It tries to integrate the dependency of multiple criteria ratings into process of prediction, hence leading to improve the quality of recommendation.*Classifier Chains* [56] forms the basis to learn the notion of Criteria chains. The concept behind classifier chains is to be able to learn the binary predictions i.e. 0 or 1 for each label in shape of a chain. The first label is derived using the features in the data. And its prediction is going to be added as an extra feature for predicting the second label and similarly the label predictions are added as additional features to derive the next label and so on until complete labels are predicted.

Let's take the Zagat's guide data [51] also mentioned in previous section including food-décor-service as the three criteria to a restaurant. Firstly, the sequence of the chain is defined, e.g., "Food-service-décor". Now, we predict active user u_1's rating on food for a restaurant say R_1 according to the *User x Rating*matrix.After that, we take u_1's predicted rating on food for R_1 restaurant as input to predict his rating on service for R_1 restaurant, since it lies on the second position in the already defined criteria chain. At last, we will take the predicted ratings on food and service as inputs to predict u_1's rating on Service for R_1 restaurant.

Taking predicted criteria ratings as inputs to the other criteria in chain turn out to be a challenge in criteria chains recommendation process which is resolved by undertaking criteria preferences as contextual information and using context-aware recommendation algorithms to calculate the predicted criteria ratings in the procedure.

Three recommendation models for multi-criteria recommendations are built by using criteria chain preferences as context information:

1. **Criteria Chains- Aggregation Model (CCA):** The context aware recommendation algorithm used in this model is context-aware matrix factorization (CAMF) [57]. After which Aggregation based approach is used to build a linear hybrid of user and item specific models.
2. **Criteria Chains- Contextual Model (CCC):** In this model, the predicted multiple ratings are considered as contextual circumstances and user's overall rating is predicted based on CAMF algorithm.
3. **Criteria –Independent Contextual Model (CIC):** In this model, all the predicted criteria ratings are treated individually without considering their dependencies on each other and finally viewing all these predicted ratings as contexts to predict user's overall rating based on CAMF algorithm.

Discussion

The experiments demonstrated on TripAdvisor and YahooMovies using CCA and CCC approaches for recommendation definitely won to prove the remarkable improvement in the quality of prediction in multi-criteria recommendation [55].CCC happens to outperform then the other compared approaches since it views all the predicted multi-criteria ratings as contextual information. The procedure of predicting multiple criteria ratings can be viewed and taken as a context suggestion problem [81, 82]. Moreover, criteria chains can allow incorporating any context-aware recommendation algorithm while dealing with criteria dependencies.

3.4 Clustering in Multi-Criteria Recommender Systems

Clustering can be spoken of as a methodology in which data sets are partitioned into subsets whose in-class (intra-class) members are "highly similar" to each other in some sense and cross-class (inter-class) members are "dissimilar" to each other on the corresponding sense, putting the whole weight of any computational method on the term *"similarity"*[58]. Clustering is being applied to collaborative filtering recommender systems in order to enhance the scalability issue of RSs [59, 60]. Clustering is an unsupervised learning data mining algorithm which aims at minimizing the intra-class distance while maximizing the inter-class distances between the data sets.

In [66], a research focussed on improving the predictive accuracy of MRCS was proposed, including new recommendation hybridapproach using Adaptive Neuro-fuzzy Inference system (ANFIS) and Self organizing Map (SOM) where SOM generates high quality clusters of dataset and ANFIS for discovering fuzzy rules using user's ratings in dataset, generating Membership Function (MF), prediction.

Modalities refer to different types of information such as image features (colour, shape, texture etc.), texts or usages. Grouping of objects with variety of modalities is called multi-model clustering. In [68], from a training set of users, a set of clusters is made and whenever a new user arrives, he is been assigned to one of the clusters on the basis of initially accessed pages. The pages being accessed by the users, who were already there in that cluster, will be recommended to the new user or else the user will be assigned to the nearest cluster according to the aggregated cosine similarity being calculated over its content. The clustering in this work is based on the multi-model information. Multi-model clustering can also be used for node aggregation by grouping the nodes together. While, Nilashi et. al. in their proposed work [69], introduced a new recommendation technique aiming at improving the accuracy of MCRS. The research method projected in [69] uses Classification and Regression Tree (CART) and Expectation Maximization (EM) to increase the accuracy of recommendation. It also worked upon the interdependencies of multiple criteria in datasets and dimensionality reduction using Principal Component Analysis (PCA).In [85], hierarchical agglomerative clustering is applied to social tagging system to cluster users together, on the basis of similarity in tags.In this survey, we have briefed below few of the Multi-criteria RSs which have incorporated the idea of clustering.

3.4.1 Multi-criteriarecommendation based on clustering user preferences

In [61], a novel approach to MCRS is introduces which cluster users in accordance to their preferences over criteria of an item. Since, it is stated by many of the researches in RSs field that different users uphold different importance to different criteria of an item and therefore, it is necessary to provide these more valuable criteria a significant prominence. The significant criteria are the ones which can even affect the overall rating of the system as it is assumed that overall rating is highly related to the significant criteria ratings [62]. An aggregation function is used to determine the overall rating of an item a user has provided by using criteria ratings of the item [6].

Let the function be $R_0 = f(R_1, R_2 \ldots R_k)$.

In order to obtain the significant criteria, [61] used the statistical technique "linear least squares regression" as aggregation function. Only criteria which pass the significance level are taken as significant criteria.

Clustering of users is done on the basis of significant criteria. Users with similar significant criteria preferences are more likable to share similar predictive behaviour.For eg if there are five criteria on which a user can rate a hotel namely service, ambience, price, rooms, facilities. If a user u_1 prefers ambience then he will be added to ambience cluster, while user u_2 according to his preference will be added to price cluster. But, there will be other clusters too which with more than one or two significant criteria and this lead to the formation of cross-table to get better understanding.As shown below in Table 2.

	Service (S)	Ambience (A)	Price (P)	Rooms (R)	Facilities (F)
User u_1			x		
User u_2				X	
User u_3	X	X	x		
User u_4				X	X

Table 2: User Criteria Preference cross-table

The clusters here are ordered partially in an abstract structure in the form of lattice as shown in figure 2. A partial ordered set satisfies the condition that "x is related to y under R", where R denotes binary relation containing all the pairs of points which are related to each other under R. Here, x and y are similar or close to each other only if they are comparable in a way that $x \leq y$ or $y \leq x$. As shown in the example, the starting point is a cluster in which all the five criteria themselves are considered as significant and every user belongs to only one cluster. Figure 3 depicts a criteria preference lattice drawn as a Hasse diagram but only a small portion of all the connections have been shown. It indicates that in this example the clustersin higher lower level seems to be more close than the one which are at the same levels or adjacent to each other.Prediction of unknown ratings for any user is done on the basis of clustering approach explained herewith,and therefore rankings of items are predicted from the users which belong to the same cluster or close clusters. Based on the past feedback about the item or service from users, the predicted can be done using threeapproaches- aggregation function of criteria, aggregation from total rating, combining clustering and collaborative filtering [61].

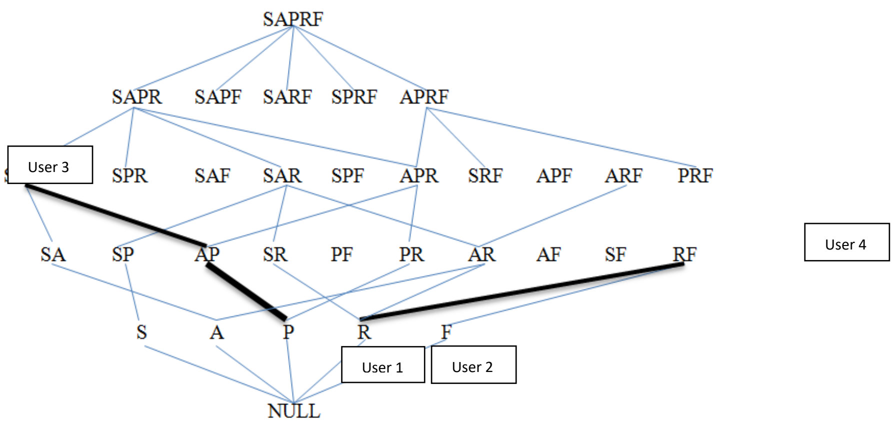

Figure 3: Criteria Preference Lattice drawn as Hasse Diagram [63]

Non-linear regression function can be used to discover the significant criteria considering users who may have rated many items and hence challenging the assumption of overall rating being related to criteria ratings in a linear fashion.

3.4.2 Relevant Set Correlation Clustering in MCRS

Clustering in multi-criteria rating RS involves the improvement in scalability of the system without causing any hindrance to its predictive accuracy.Clustering when combined to MCRS represents not only the groups of users with similar ratings but also provides the similar reasons for these ratings. In [64], the author proposed to use novel clustering algorithm which is the relevant set-correlation (RSC) model in multi-criteria recommendation focusing and addressing few shortcomings of MCRS including the dependency on any particular similarity metric, or the assumption that the individual criteria are not dependent on each other. The RSC model clusters many variant types of data points may it be numeral, image data or categorical. The RSC model utilizes the shared neighbour clustering technique [69] in which the closeness or similarity between any two entities is dependent on the amount of neighbours (relevant sets) in common.It employs a ranking function "oracle" to provide a ranked list of similar users and thus form the clusters of users. Users in the ranked list are then compared to evaluate the similar ones such that two users are said to be similar if they share a big sum of neighbours.

3.4.3 A Collaborative Filtering based Multi-criteria recommendation system using EM clustering and PCA-ANFIS

Multi-criteria based CF enlarges the probability of delivering better recommendations to users by taking into account their preferences in multiple aspects and therefore proves to be a level up technique to assist the recommendations in tourism.In [70], a hybrid method for hotel recommendation is proposed using EM clustering model [71, 72], PCA for dimensionality problem and to reduce the interdependency issues among criteria in multi-criteria ratings. Adaptive Neuro-Fuzzy Inference System (ANFIS) is used in collaboration to learn the prediction models for items and users in every cluster.As shown in figure 4, the model consists of two phase offline and online where all the above mentioned techniques are used sequentially for recommendation process of a multi-criteria system.

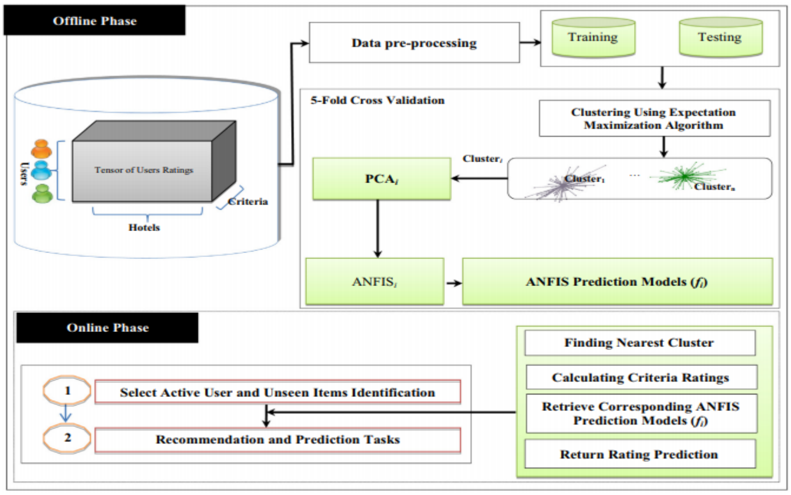

Figure 4: PCA-ANFIS model for the multi-criteria CF [70].

Discussion

Clustering in Multi-criteria RSs which has been counted in this survey has clearly shown significant improvement in the performance of RS.While, there can be a lot of scope in future to examine various clustering techniques in RSs to challenge the data sparcity problem in MCRS, missing information in datasets, membership of users in clusters etc. Hybrid algorithms can be used to cope up with various disadvantages of user or item based algorithms in clustering.

3.5 Multi-criteria optimization

An optimization problem refers to finding out the best optimal solution among the set of all feasible solutions.Let's see an example in figure 5 where Zubi has to buy a new car with his preferences being best possible low price and low fuel consumption. We have 4 different choices or alternatives which are Ford Figo, Volkswagen Polo, Toyota Etios and Chevrolet Beat with three criteria namely price, fuel consumption and power. Criteria values of the four items in a two-dimensional coordinate system, we can see that Ford Figo and ToyotoEtios are the two best choices since they are both lower in price and consume less fuel compared to other two.

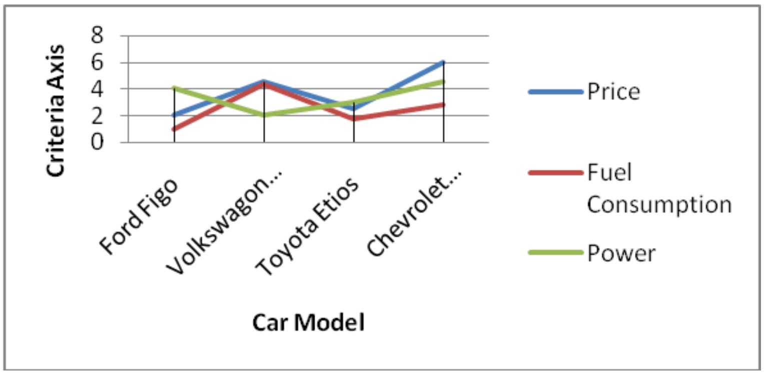

Figure 5: Multi-criteria optimization example

Thus, we call also say that these two are the optimal solutions for this MCDM problem. Some of the approaches which address multi-criteria optimization (MCO) problemsand can be used to incorporate in RSs are discussed in [1] and mentioned below:

- Reducing the multi-criteria problem into a single rating problem by linear combination;
- To find the Pareto Optimal solution;
- The most important criterion can be optimized converting the other remaining ones into constraints;
- Applying various machine learning techniques such as genetic algorithm to learn the fittest or the best criteria among all, in order to thus find out the better predictions and recommendations.

Discussion

There are a lot of optimization algorithms in machine learning which can be utilized to MCRS for improving the efficiency and accuracy of the RS. For e.g. Genetic algorithm is widely used in the field of RSs which mimics the procedure of natural selection in order to generate solutions to optimization problem using techniques like selection and mutation, crossovers, inheritance, extracting the best individuals among population set and creating the new and better ones. Particle Swarm Optimization (PSO) is another technique which was inspired by observing the behaviour of social animals like flocking of birds, fish schooling. It is used to attain the weights of various features of the items for active user and can be used to fine-tune a profile-matching algorithm [92]. Likewise, many other machine learning algorithms can also be used to optimize the results of a RS and enhancing its performance.

3.6 Pareto optimal recommendations

Multi-criteria RSs involve multiple conflicting criteria which simultaneously are intended to compete with each other for finding out the most likable preference of user. There are different objectives but it is not possible to fetch one single solution which can satisfy all the objectives at the same time. For these conflicting objectives, there has to be a Pareto optimal solution. This approach provides with a number of good items from large number of available candidates. Data envelopment analysis (DEA) find outs the best performers among all the available criteria in the items without requiring a priori weights for each criteria [14] and using linear programming to identify the best set of weights for each decision making unit, determining the reduced set of items with best ratings within all criteria.Skyline queries, as described above also provide the pareto optimal points in the form of skyline points.

Ortega et al. [90]stated that; *"A solution x is called Pareto optimal, Pareto efficient or non-inferior, if none of the objective functions can be improved in value without degrading some of the other objective values or say if no other feasible* solution *exists, which takes a lower value in some objective without causing a simultaneous increase in at least some other one."*The main motive of the work is to filter out or eliminate the less representative users from the k-neighbours and keep the most promising ones to carry on with more accurate and efficient prediction and recommendation. The whole procedure is carried out in four phases:

- Selecting the non-dominated users
- Similarity computation and neighbourhood formation
- Item prediction
- Item recommendation

We say that user *x* dominates user *y* with respect to target user *u*, if the following expression is satisfied.

$$x >_u y \leftrightarrow \forall i_c \in I_u : d(r_{u,i}, r_{x,i}) \le d(r_{u,i}, r_{y,i}) \wedge \exists j \in I_u | \forall I_c \in I_u : d(r_{u,j}, r_{x,j}) < d(r_{u,j}, r_{y,j}) \quad (7)$$

Where,$I_u = \{i \in I | r_{u,i} \neq \bullet\}$ is the set of items rated by the user u, $i_c = \{c \in i | r_{u,i} \neq \bullet\}$ be the criteria rating given in an item i rated by the user *u*. And $d(r_{u,i}, r_{x,i})$ is the absolute difference between the ratings provided by*u* and *x* to the item i.

Users who are being dominated by the dominating users do not show higher similarity with the target user as compared to the non-dominated users and therefore, the dominated users can be eliminated. Now, the non-dominated users are filtered to get out the top-k neighbours of target/active using various similarity computation techniques. Finally, the Top-k users are used for prediction and recommendation of the items to target user.

Discussion

Shown above is a brief notion about using the concept of pareto dominance in MCRS. Recommendation techniques which have been developed for RSs with single ratings could possibly be used for MCRS too.DEA or frontier analysis, Skyline data queries can be used to find out the best points or say items which are not dominated by any other itemin the dataset.Some hybrid recommendation techniques can also be utilized into multi-criteria recommendations to enhance its performance.

4.Managing Security and Privacy

Recommender Systems are emerging as one of the most important feature of any internet applicationswhich provide better understanding to its users regarding their access to the available plethora of information.With every advancement in technology comes a matter of concern regarding its user's privacy and security. Some RSs like Amazon.com provide automated personalized results to user while others like Epinion's.com is non-automated and operated manually by the users who need to go through the reviews given by other users on the site manually before making a conclusive judgement about an item.

RSs necessitate at least two types of trust from its users [73]:

- In order to understand the user preference well and provide good recommendations, the recommenders require considerable amount of information about users. Hence, the users must be able to trust the integrity of RSs for their private information.
- Users must be able to rely on the accuracy of recommendations being provided to them by the RSs.

In the year 2006, Lam et.al raised the question of risks involved in the process of recommendation, the concern of protecting the private information from any kind of unwanted exposure.In the year 1987, Robert hacker's movie rental historywas leaked, after which the Video Privacy Protection Act was passed in 1988, to protect the disclosure of someone's personal detail without consent.

In [74],Almazro et.al stated that the privacy risks and security from exposure of personal information should be a matter of concern for users while dealing with recommender systems. They said that in order to take advantages of personalized recommendation, user first need to register for creating an account which requires personal details like name, gender, address, mobile number, email id, birth date etc. Disclosure of identity is the primary type of riskto be focused, since Quasi-identifiers which can be correlated with some other quasi-identifiers to create a unique identifier and thus leading into personal identifying information [73].

Another security related issue being confronted by RSs include manipulation from producers or spiteful users [75]. In order to increase the recommendation of some item, the ratings can be manipulated. Dellarocas et.al [76] has shown that even the popular RSs such as Amazon and eBay are being manipulated.When the RS's recommendation for any item is being influenced or manipulated by submitting biased ratings to the system, this type of attack is known as *Shilling Attack*, which is one of the most talked aboutattack for biasing the predictions of RSs.

Few types of attacks

- *Push attack*- In this type of attack the malicious user intends to decrease the ratings of all the items which does not lie in its target item-set and therefore making the items of target item-set good for recommendations.
- *Nuke attack*- In nuke attacks, the ratings of items other than the target item-set may be increased, to make the target item-set look like unwanted and decrease its chances of being recommended to users.
- *RandomBot*- It can be called as a filterbot in which the items outside the target item-set are randomly given maximum or minimum ratings according to the intentions of the malicious attacker.
- *AverageBot*- In this type of attack, the attacker needs to have the knowledge about the average rating for each item in the dataset. The attacker rates the items other than the target item-set, following a normal distribution with a mean equal to average rating for that item [80].

- *Sybil attack*-In this attack, a malicious user creates severalfakeuser accounts with an intention of increasing or decreasing the recommendation of another user or item.

In [77], Jin et.al reviewed the malicious behaviour of Online Social Network (OSN) users. In terms of social media, Facebook comes under the top most used RSs by today's generation. Gao et. al [78] studied a data set which included more than 187 million wall messages within 3.5 million users of Facebook and found 200,000 wall posts as malicious which were originated from 57,000 malicious accounts.In Sybil attacks, a malicious attacker builds several fake accounts in order to interrupt and corrupt the recommendation system, were found to be the most common attacks in OSNs.There are various schemes have been proposed to diminish Sybil attack such as *SybilGaurd*, *Sybillimit*, *SybilInfer* and *SumUp* [77].Spectral Clustering algorithm is used in [79] to detect shilling attacks in RSs, by formulating a submatrix optimization problem and transforming it into graph. The clustering algorithm is applied to solve the min-cut problem in the unbalanced structured graph. The experiment carried out using *MovieLens* datasetshowed that the method outperformed for several attack models.

Discussion

Security is definitely one of the major concerns for users who question the privacy, reliability and accuracy of their preferences while using RSs. Hence, robust and effective trust based recommendation algorithms must be made to deal with these concerned security issues of millions of users.Trust has been an alarming challenge which is catching the eyes of researchers in the field of RSs. Trust-aware Recommender Systems [87, 88, 89] helps to mitigate the cold-start problem in RSs, it filters fake profiles and thus robust to malicious attacks [86] while building up a trust network is very important for users in order to enjoy more significant recommendations.

5. Challenges in Multi-criteria Recommender Systems

5.1 Increasing intrusiveness- This era is leading towards a generation of technology where human involvement is totally intended to reduce the manpower to its lowest level, increasing the automatic machine power to rule and handle the workload of humans. Although, RSs have reduced the problem of information overload to a wide extent, still providing the ratings manually to their experienced items also seems to be a tedious task for many of the users. Therefore, users would be more satisfied if they did not have to rate each and every criteria of an item in multi-criteria recommender systems. Hence, it is required that the RSs incorporate the intrinsic implicit models to automatically learn the ratings being given by the users to various items according to their past preferences.

5.2 Increased dataset size and scalability issue- When it comes to multiple criteria rating, it is obvious that the dataset will also be multiple times larger as compared to single rating recommender system. Zagat's restaurant, Yahoo! Movies, Goibibo hotels provide multiple criteria datasets which contain ratings on various restaurants, movies and hotels with respect to different criterion and thus making it very huge in size. Thus, increase in space complexityis also required to be looked upon and reduced. Also, the data may not always be in numerical form rather it may be available in contextual form. In such cases context-aware recommender systems can be used to efficiently deal with the process of recommendation

5.3 Incorporating multi-criteria ratings into Context-aware and group recommendation RSs-Multi-criteria recommender systems include ratings which are given to multiple criteria of an item. It is obvious that MCRSs provide more specific idea about user preferences and this special feature can be utilized in collaboration with the other types of RSs which provides ratings on the basis of different contexts or where the recommendation is to be provided to a group of people who share similar preferences. Creating a hybrid recommender system using various efficient algorithms can also be helpful in improving the recommendations.

5.4 Dealing with trust based issues-Security is the major concern of users when they provide their personal information to RSs for maintain their preference dataset. Also, users should be able to find the recommendations more relative to their interests and worth it according to their choices. For this purpose it is necessary that the RSs should be able to build up a strong trust factor to its users, by providing more desirable recommendations as options and at the same time also maintaining the security of every individual's data. Trust based Recommender systems are able to show improvement in system's accuracy, efficiency and scalability [91].

5.5 Choosing best set of criteria for item evaluation- Most of the MCRSs requires its users to provide rating multiple criteria of an item at a single level say genre, special effects, story in a movie. These criteria can further be divided into sub-criteria to understand the user preferences more specifically. For e.g. Genre can be comedy, horror, romance, thriller but thriller can also be divided into romantic thriller, horror thriller, and suspense thriller. Techniques like analytic hierarchy process can be used to

6. Conclusion and Future scope

This review paper throws light on different type algorithms which uses multi-criteria ratings and aim to enhance the efficiency and accuracy of Multi-criteria recommender systems. It also brings into concern the serious security issues and challenges that are being faced by the users who seek recommendations from RSs. For any researcher who is willing to work under the field of multi-criteria recommendations would hopefully find some major areas which can be taken to experiment upon in future as MCRS is becoming a new area of interest attracting many eyes recommendations have taken up to be an essential need of each user using internet and coping up with the problem of information overload. This survey completely aims to provide an essential basic review of the work that hasbeen done in the field of MCRSs and hence, facilitating the awareness about the areas with a willing scope of improvement according to the interest of researcher.

REFERENCES

1. Adomavicius, G., &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 & Data Engineering*, (6), 734-749.
2. Almazro, D., Shahatah, G., Albdulkarim, L., Kherees, M., Martinez, R., &Nzoukou, W. (2010). A survey paper on recommender systems. *arXiv preprint arXiv:1006.5278*.
3. Deshpande, M., &Karypis, G. (2004). Item-based top-n recommendation algorithms. *ACM Transactions on Information Systems (TOIS)*, *22*(1), 143-177.
4. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., &Riedl, J. (1994, October). GroupLens: an open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work*(pp. 175-186). ACM.
5. Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., &Riedl, J. (1997). GroupLens: applying collaborative filtering to Usenet news. *Communications of the ACM*, *40*(3), 77-87.
6. Adomavicius, G., & Kwon, Y. (2007). New recommendation techniques for multicriteria rating systems. *IEEE Intelligent Systems*, *22*(3).
7. Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-based systems*, *46*, 109-132.
8. Wasid, M., & Ali, R. (2017). Use of Soft Computing Techniques for Recommender Systems: An Overview. In *Applications of Soft Computing for the Web* (pp. 61-80). Springer, Singapore.
9. Balabanović, M., &Shoham, Y. (1997). Fab: content-based, collaborative recommendation. *Communications of the ACM*, *40*(3), 66-72.
10. Van Setten, M. (2005). Supporting people in finding information: hybrid recommender systems and goal-based structuring.
11. Manouselis, N., &Costopoulou, C. (2007). Analysis and classification of multi-criteria recommender systems. *World Wide Web*, *10*(4), 415-441.
12. Li, Y., Lu, L., &Xuefeng, L. (2005). A hybrid collaborative filtering method for multiple-interests and multiple-content recommendation in E-Commerce. *Expert systems with applications*, *28*(1), 67-77.
13. Bostandjiev, S., O'Donovan, J., &Höllerer, T. (2012, September). TasteWeights: a visual interactive hybrid recommender system. In *Proceedings of the sixth ACM conference on Recommender systems* (pp. 35-42). ACM.

14. Adomavicius, G., & Kwon, Y. (2015). Multi-criteria recommender systems. In *Recommender systems handbook*(pp. 847-880). Springer, Boston, MA.
15. Ekstrand, M. D., Riedl, J. T., &Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends® in Human–Computer Interaction*, *4*(2), 81-173.
16. Schafer, J. B., Frankowski, D., Herlocker, J., &Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web* (pp. 291-324). Springer, Berlin, Heidelberg.
17. Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56-58.
18. Zheng, Y. (2017, April). Situation-aware multi-criteria recommender system: using criteria preferences as contexts. In *Proceedings of the Symposium on Applied Computing* (pp. 689-692). ACM.
19. Lakiotaki, K., Matsatsinis, N. F., &Tsoukias, A. (2011). Multicriteria user modeling in recommender systems. *IEEE Intelligent Systems*, *26*(2), 64-76.
20. Sarwar, B., Karypis, G., Konstan, J., &Riedl, J. (2001, April). Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web* (pp. 285-295). ACM.
21. Pohekar, S. D., &Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—a review. *Renewable and sustainable energy reviews*, *8*(4), 365-381.
22. Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56-58.
23. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., &Riedl, J. (1994, October). GroupLens: an open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work*(pp. 175-186). ACM.
24. Ricci, F., Rokach, L., &Shapira, B. (2015). Recommender systems: introduction and challenges. In *Recommender systems handbook* (pp. 1-34). Springer, Boston, MA.
25. Jannach, D., Karakaya, Z., &Gedikli, F. (2012, June). Accuracy improvements for multi-criteria recommender systems. In *Proceedings of the 13th ACM conference on electronic commerce* (pp. 674-689). ACM.
26. Shambour, Q., & Lu, J. (2011, August). A hybrid multi-criteria semantic-enhanced collaborative filtering approach for personalized recommendations. In *Proceedings of the 2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology-Volume 01* (pp. 71-78). IEEE Computer Society.
27. Fuchs, M., &Zanker, M. (2012, September). Multi-criteria ratings for recommender systems: an empirical analysis in the tourism domain. In *International Conference on Electronic Commerce and Web Technologies* (pp. 100-111). Springer, Berlin, Heidelberg.
28. Turk, A. M., & Bilge, A. (2019). Robustness analysis of multi-criteria collaborative filtering algorithms against shilling attacks. *Expert Systems with Applications*, *115*, 386-402.
29. Oard, D. W., & Kim, J. (1998, July). Implicit feedback for recommender systems. In *Proceedings of the AAAI workshop on recommender systems* (Vol. 83). WoUongong.
30. Roy, B. (2013). *Multicriteria methodology for decision aiding*(Vol. 12). Springer Science & Business Media.
31. Gandibleux, X. (Ed.). (2006). *Multiple criteria optimization: state of the art annotated bibliographic surveys* (Vol. 52). Springer Science & Business Media.
32. Benayoun, R., De Montgolfier, J., Tergny, J., &Laritchev, O. (1971). Linear programming with multiple objective functions: Step method (STEM). *Mathematical programming*, *1*(1), 366-375.
33. Zeleny, M. (2012). *Linear multiobjective programming* (Vol. 95). Springer Science & Business Media.
34. Hartley, R. (1985). Linear multiple objective programming. In *Mathematics of Multi Objective Optimization* (pp. 157-177). Springer, Vienna.
35. Zimmermann, H. J. (1978). Fuzzy programming and linear programming with several objective functions. *Fuzzy sets and systems*, *1*(1), 45-55.
36. Belton, V., & Stewart, T. (2002). *Multiple criteria decision analysis: an integrated approach*. Springer Science & Business Media.
37. Tamiz, M., Jones, D., & Romero, C. (1998). Goal programming for decision making: An overview of the current state-of-the-art. *European Journal of operational research*, *111*(3), 569-581.

38. Baatarjav, E. A., Phithakkitnukoon, S., &Dantu, R. (2008, November). Group recommendation system for facebook. In *on the move to meaningful internet systems: OTM 2008 workshops* (pp. 211-219). Springer, Berlin, Heidelberg.
39. Kim, J. K., Kim, H. K., Oh, H. Y., &Ryu, Y. U. (2010). A group recommendation system for online communities. *International Journal of Information Management*, *30*(3), 212-219.
40. Anderson, R. M., Borgs, C. H., Chayes, J. T., Feige, U. M., Flaxman, A., Kalai, A. T., ... &Tennenholtz, M. (2011). *U.S. Patent No. 7,991,841*. Washington, DC: U.S. Patent and Trademark Office.
41. Kant, V., &Bharadwaj, K. K. (2013). Fuzzy computational models of trust and distrust for enhanced recommendations. *International Journal of Intelligent Systems*, *28*(4), 332-365.
42. Anderson, R. M., Borgs, C. H., Chayes, J. T., Feige, U. M., Flaxman, A., Kalai, A. T., ... &Tennenholtz, M. (2011). *U.S. Patent No. 7,991,841*. Washington, DC: U.S. Patent and Trademark Office.
43. Adomavicius, G., &Tuzhilin, A. (2011). Context-aware recommender systems. In *Recommender systems handbook*(pp. 217-253). Springer, Boston, MA.
44. Jacquet-Lagreze, E., &Siskos, Y. (2001). Preference disaggregation: 20 years of MCDA experience. *European Journal of Operational Research*, *130*(2), 233-245.
45. Pardalos, P. M., Siskos, Y., &Zopounidis, C. (Eds.). (2013). *Advances in multicriteria analysis* (Vol. 5). Springer Science & Business Media.
46. Mateo, J. R. S. C. (2012). Multi-attribute utility theory. In *Multi Criteria Analysis in the Renewable Energy Industry* (pp. 63-72). Springer, London.
47. Goel, T., Vaidyanathan, R., Haftka, R. T., Shyy, W., Queipo, N. V., & Tucker, K. (2007). Response surface approximation of Pareto optimal front in multi-objective optimization. *Computer methods in applied mechanics and engineering*, *196*(4-6), 879-893.
48. De Smet, Y., &Eppe, S. (2009, April). Multicriteria relational clustering: the case of binary outranking matrices. In *International Conference on Evolutionary Multi-Criterion Optimization* (pp. 380-392). Springer, Berlin, Heidelberg.
49. Jacquet-Lagreze, E., &Siskos, Y. (2001). Preference disaggregation: 20 years of MCDA experience. *European Journal of Operational Research*, *130*(2), 233-245.
50. Lee, H. H., &Teng, W. G. (2007, August). Incorporating multi-criteria ratings in recommendation systems. In *Information Reuse and Integration, 2007. IRI 2007. IEEE International Conference on* (pp. 273-278). IEEE.
51. Zagat Survey, https://www.zagat.com/.
52. Breese, J. S., Heckerman, D., &Kadie, C. (1998, July). Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence* (pp. 43-52). Morgan Kaufmann Publishers Inc..
53. Manouselis, N., &Costopoulou, C. (2007). Experimental analysis of design choices in multiattribute utility collaborative filtering. *International Journal of Pattern Recognition and Artificial Intelligence*, *21*(02), 311-331.
54. Delgado, J., & Ishii, N. (1999). Memory-based weighted majority prediction. In *SIGIR Workshop Recomm. Syst. Citeseer*.
55. Zheng, Y. (2017, March). Criteria chains: a novel multi-criteria recommendation approach. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces* (pp. 29-33). ACM.
56. Read, J., Pfahringer, B., Holmes, G., & Frank, E. (2011). Classifier chains for multi-label classification. *Machine learning*, *85*(3), 333.
57. Baltrunas, L., Ludwig, B., & Ricci, F. (2011, October). Matrix factorization techniques for context aware recommendation. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 301-304). ACM.
58. Jarvis, R. A., & Patrick, E. A. (1973). Clustering using a similarity measure based on shared near neighbors. *IEEE Transactions on computers*, *100*(11), 1025-1034.
59. Nnadi, N. J. (2009, October). Applying relevant set correlation clustering to multi-criteria recommender systems. In *Proceedings of the third ACM conference on Recommender systems* (pp. 401-404). ACM.
60. Si, L., & Jin, R. (2003). Flexible mixture model for collaborative filtering. In *Proceedings of the 20th International Conference on Machine Learning (ICML-03)* (pp. 704-711).

61. Liu, L., Mehandjiev, N., &Xu, D. L. (2011, October). Multi-criteria service recommendation based on user criteria preferences. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 77-84). ACM.
62. Zhang, Y., Zhuang, Y., Wu, J., & Zhang, L. (2009). Applying probabilistic latent semantic analysis to multi-criteria recommender system. *Ai Communications*, *22*(2), 97-107.
63. Davey, B. A., & Priestley, H. A. (2002). *Introduction to lattices and order*. Cambridge university press.
64. Nnadi, N. J. (2009, October). Applying relevant set correlation clustering to multi-criteria recommender systems. In *Proceedings of the third ACM conference on Recommender systems* (pp. 401-404). ACM.
65. Jarvis, R. A., & Patrick, E. A. (1973). Clustering using a similarity measure based on shared near neighbors. *IEEE Transactions on computers*, *100*(11), 1025-1034.
66. Nilashi, M., bin Ibrahim, O., &Ithnin, N. (2014). Hybrid recommendation approaches for multi-criteria collaborative filtering. *Expert Systems with Applications*, *41*(8), 3879-3900.
67. Nilashi, M., Jannach, D., bin Ibrahim, O., &Ithnin, N. (2015). Clustering-and regression-based multi-criteria collaborative filtering with incremental updates. *Information Sciences*, *293*, 235-250.
68. Schuetze, H., Pitkow, J. E., Pirolli, P. L., Chi, E. H., & Li, J. (2003). *U.S. Patent No. 6,567,797*. Washington, DC: U.S. Patent and Trademark Office.
69. Nilashi, M., Esfahani, M. D., Roudbaraki, M. Z., Ramayah, T., & Ibrahim, O. (2016). A multi-criteria collaborative filtering recommender system using clustering and regression techniques. *Journal of Soft Computing and Decision Support Systems*, *3*(5), 24-30.
70. Nilashi, M., bin Ibrahim, O., Ithnin, N., &Sarmin, N. H. (2015). A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. *Electronic Commerce Research and Applications*, *14*(6), 542-562.
71. Mitra, P., Pal, S. K., &Siddiqi, M. A. (2003). Non-convex clustering using expectation maximization algorithm with rough set initialization. *Pattern Recognition Letters*, *24*(6), 863-873.
72. Jung, Y. G., Kang, M. S., &Heo, J. (2014). Clustering performance comparison using K-means and expectation maximization algorithms. *Biotechnology & Biotechnological Equipment*, *28*(sup1), S44-S48.
73. Lam, S., Frankowski, D., &Riedl, J. (2006). Do you trust your recommendations? An exploration of security and privacy issues in recommender systems. *Emerging trends in information and communication security*, 14-29.
74. Almazro, D., Shahatah, G., Albdulkarim, L., Kherees, M., Martinez, R., &Nzoukou, W. (2010). A survey paper on recommender systems. *arXiv preprint arXiv:1006.5278*.
75. Chirita, P. A., Nejdl, W., &Zamfir, C. (2005, November). Preventing shilling attacks in online recommender systems. In *Proceedings of the 7th annual ACM international workshop on Web information and data management* (pp. 67-74). ACM.
76. Lam, S. K., &Riedl, J. (2004, May). Shilling recommender systems for fun and profit. In *Proceedings of the 13th international conference on World Wide Web* (pp. 393-402). ACM.
77. Jin, L., Chen, Y., Wang, T., Hui, P., &Vasilakos, A. V. (2013). Understanding user behavior in online social networks: A survey. *IEEE Communications Magazine*, *51*(9), 144-150.
78. Gao, H., Hu, J., Wilson, C., Li, Z., Chen, Y., & Zhao, B. Y. (2010, November). Detecting and characterizing social spam campaigns. In *Proceedings of the 10th ACM SIGCOMM conference on Internet measurement* (pp. 35-47). ACM.
79. Zhang, Z., &Kulkarni, S. R. (2014, July). Detection of shilling attacks in recommender systems via spectral clustering. In *Information Fusion (FUSION), 2014 17th International Conference on* (pp. 1-8). IEEE.
80. Chirita, P. A., Nejdl, W., &Zamfir, C. (2005, November). Preventing shilling attacks in online recommender systems. In *Proceedings of the 7th annual ACM international workshop on Web information and data management* (pp. 67-74). ACM.
81. Ortega, F., SáNchez, J. L., Bobadilla, J., &GutiéRrez, A. (2013). Improving collaborative filtering-based recommender systems results using Pareto dominance. *Information Sciences*, *239*, 50-61.
82. Ribeiro, M. T., Ziviani, N., Moura, E. S. D., Hata, I., Lacerda, A., &Veloso, A. (2015). Multiobjectivepareto-efficient approaches for recommender systems. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *5*(4), 53.

83. Zheng, Y., Mobasher, B., & Burke, R. (2016, July). User-oriented context suggestion. In *Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization*(pp. 249-258). ACM.
84. Zheng, Y., Mobasher, B., & Burke, R. (2014, August). Context recommendation using multi-label classification. In *Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)-Volume 02* (pp. 288-295). IEEE Computer Society.
85. Shepitsen, A., Gemmell, J., Mobasher, B., & Burke, R. (2008, October). Personalized recommendation in social tagging systems using hierarchical clustering. In *Proceedings of the 2008 ACM conference on Recommender systems* (pp. 259-266). ACM.
86. Abbasi, M. A., Tang, J., & Liu, H. (2014). Trust-aware recommender systems. *Machine Learning book on computational trust, Chapman & Hall/CRC Press*.
87. Massa, P., &Avesani, P. (2007, October). Trust-aware recommender systems. In *Proceedings of the 2007 ACM conference on Recommender systems* (pp. 17-24). ACM.
88. Massa, P., &Avesani, P. (2007, October). Trust-aware recommender systems. In *Proceedings of the 2007 ACM conference on Recommender systems* (pp. 17-24). ACM.
89. Guo, G., Zhang, J., Thalmann, D., Basu, A., &Yorke-Smith, N. (2014, March). From ratings to trust: an empirical study of implicit trust in recommender systems. In *Proceedings of the 29th Annual ACM Symposium on Applied Computing* (pp. 248-253). ACM.
90. Ortega, F., SáNchez, J. L., Bobadilla, J., &GutiéRrez, A. (2013). Improving collaborative filtering-based recommender systems results using Pareto dominance. *Information Sciences*, *239*, 50-61.
91. O'Donovan, J., & Smyth, B. (2005, January). Trust in recommender systems. In *Proceedings of the 10th international conference on Intelligent user interfaces* (pp. 167-174). ACM.
92. Ujjin, S., & Bentley, P. J. (2003, April). Particle swarm optimization recommender system. In *Swarm Intelligence Symposium, 2003. SIS'03. Proceedings of the 2003 IEEE* (pp. 124-131). IEEE.