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A Literature Review of Empirical Studies of Recommendation Systems

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ABSTRACT
In the last twelve years, the number of web user increases, so intensely leading to intense advancement in web services which leads to enlargement the usage data at higher rates. The purpose of a recommender System is to generate meaningful recommendations to a collection of users for items or products that might interest them. Recommender systems differ in the way they analyze these data sources to develop notions of congeniality between users and items which can be used to identify well-matched pairs. The recommender system technology intentions to help users in finding items that match their personal interests. It has a successful usage in e-commerce applications to deal with problems related to information overload proficiently. In this paper, we will extensively present a survey of six existing recommendation system. The Collaborative Filtering systems analyze historical interactions alone, while Content-Based Filtering systems are based on profile attributes, Hybrid Techniques attempt to combine both of these designs, Demographic Based Recommender systems aim to categorize the user based on personal attributes and make recommendations based on demographic classes, while Knowledge-Based Recommendation attempts to suggest objects based on inferences about a user's needs and preferences, and Utility-Based Recommender systems make recommendations based on the computation of the utility of each item for the user. In this paper, we have recognized 60 research papers on recommender systems, which were published between 1971 and 2014. Finally, few research papers had an influence on research paper recommender systems in practice. We also recognized a lack of authority and long term research interest in the field, 78% of the authors published no more than one paper on research paper recommender systems, and there was miniature cooperation among different co-author groups.

Keywords
Recommendations System, Utility Based, Collaborative Filtering, Contents Based Methods, Demographic Based, Knowledge Based, Hybrid Methods, Knowledge Sources.

1. INTRODUCTION
The rapid growth of the Internet caused a matching growth of the amount of available online information that increased the essential to expand the capability of users to manage all this information. This encourages a substantial interest in specific research fields and technologies that could advantage the managing of this information overload. The technical revolution and broader network access lead to different web services ranging from education to e-shopping, web content search, social networking execution over the web [1]. In this case the domain of user search may become too high and the result might not make any context to the user search interest. This type of search may become a time taking task [2]. So the search engines and different Web services internally endow a recommender engine to filter the search for the large domain of data based on the particular user interest. The recommender engine predicts the interest of users based on user history [3]. A user history may define by link it had searched, the product it had bought, and the content of particular items catches sight of by it etc. It can use data or knowledge depending upon the analytics of the engine to predict user interest.

The latest technology designed to fight information overload is the recommender systems that initiated from cognitive science, forecasting theories, approximation theory, information retrieval, and also related to management science and consumer choice modeling in marketing [1]. A recommendation process begins with the front end of the web application sends interpellation of the user. The analytic engine receives the interpellation and retrieves usage data of that particular user. The usage data are then processed by the algorithm associated with the analytic engine to discovery similar items [4]. The items with higher proportionality with respect to user is filtered and provided as recommended opinion to the concern user.

The recommender systems used to determine the interested items for a distinguished user by employing a variety of information resources that is related to users and items [5]. The zest in this area still remains high because it is composed of a problem opulent research area and has a wealth of practical applications [1]. Recommender systems are being broadly accepted in various applications to suggest products, services, and information items to latent customers [6]. The numerous e-commerce applications join recommender systems in order to disseminate customer services, decrease customers search time and increase selling rates. For example, a wide range of companies such as the online book retailer Amazon.com [7], and news articles [8]. The hereafter recommender systems are generally classified into Collaborative Filtering, Contents-Based Methods, Demographic-Based, Knowledge-Based, Utility-Based, and Hybrid Methods [9]. In general, collaborative filtering uses an information filtering technique based on the user's previous evaluation of items or history of previous purchases [10]. In spite of the fact that, this technique has been known to reveal two major issues sparsity problem and the scalability problem [11]. In contrast, content-based filtering analyzes a set of documents rated by an individual user and uses the contents of the documents, as well as the provided ratings, to infer a user profile that can be used to recommend additional items of interest [12][13]. A hybrid Recommendation system embedded different standard recommendation models to produce its output. It can embed Content-based with the User-based or Item-based model to create a new type of algorithm.

Forthcoming Demographic Based Recommender systems aim to classify the user based on personal attributes and make recommendations based on demographic classes, while Knowledge-Based Recommendation attempts to suggest objects based on inferences about a user's necessity and preferences, and Utility-Based Recommender systems make recommendations based on the computation of the utility of each item for the user. Currently, recommender systems remain a snappy area of research, intersecting several sub-disciplines of statistics, machine learning, data mining and information retrievals [6]. The applications have been pursued in diverse domains ranging from recommending web pages to music, books, movies and other consumer products. The intention of a recommender system from a broad perspective is to provide improved and useful recommendations that make users happy by propitiate user needs. The needs of users are dissimilar [14].

2. RELATED WORK

Recommendation systems revulsion the way inanimate websites communicate with their users. Rather than endowing a static experience in which users search for and potentially buy products, recommender systems increase interaction to provide an invaluable experience. Recommender systems identify recommendations [1] autonomously for individual users based on past purchases and searches, and on other users' behavior. For examples recommendations are not hard to find in our day-to-day activities [6]. We may read movie reviews in a magazine or online hotel reviews [2] on the Internet to take the plunge what movies to watch or in which hotel to stay. Occasionally, we even accept recommendations from a librarian to decide which book to choose by discussing our interest [3] and current mood. Normally, people like to seek recommendations from friends or associates when they do not have enough information to decide which books to read, movies to watch, hotels or restaurants to book etc.

The people love to share their liking regarding books, movies, hotels or restaurants [5]. Recommender systems attempt to create a technological proxy which produces the recommendation automatically based on user's previous preferences. The assumption behind many recommender systems is that a good way to produce personalized recommendations for a user is to identify people with the same interests and recommend items that may interest these like-minded people. In this portion we briefly present some of the research literature related [6] to recommender systems in general, recommendation system, and evaluation of recommender systems. Recommender systems can be broadly categorized in six different ways [15] collaborative filtering, contents-based methods, Demographic-based, Knowledge-based, Utility based, and hybrid methods.

First, collaborative filtering uses only user-item rating matrix for predicting unappreciated preference [16]. It can be categorized into a memory-based collaborative filtering, which contains the whole matrix on memory [11], and model-based collaborative filtering, building a model of estimation [17]. The most emphatic memory-based algorithms known so far are item-based collaborative filtering. A short time ago, making use of matrix factorization, a kind of model-based approach, is known as the most proficient and accurate, in particular after those approaches won the Netflix prize in 2009. The content-based methods, on the other hand, recommend [13] items based on their characteristics as well as specific preferences of a user [15]. Additionally Pazzani [18] studied this approach in depth, including how to build user and item profiles [19]. The Demographic filtering recommender systems aim to categorize the user based on personal attributes such as their education, age, occupation, and/or gender, to learn the kinship between a single item and the type of people who like it [20] and make recommendations based on demographic class. The Knowledge-based recommender systems use knowledge about users and products to pursue a knowledge-based approach to generating a recommendation, reasoning about what products con commingle verges the user's requirements [21]. The Utility-based recommender systems make recommendations based on the computation of the utility of each item for the user. Utility-based recommendation techniques use features of items as background data, adduce utility functions over items for users to describe user liking, and apply the function to determine the rank of items for a user [22].

Last category, hybrid approach, tries to combine both collaborative and content-based recommendation. Koren [23] suggested effectively combining rating information and user, item profiles for more accurate recommendation. Major part of the large-scale commercial and social websites recommend options, such as products or people to connect with, to users. Recommendation engines sort through massive amounts of data to [15] know potential user preferences. Recommender systems have concentrated on recommending media items such as movies, but recently they have been extended to the academy. It seems as though recommender systems are very popular in commercial applications these days, it is still difficult to assess them due to the lack of standard methods. The conventional recommender systems [24] were usually introduced in Human-Computer Interaction community, so they have been assessed by user study. This approach is still used, especially for verifying improvement in terms of user experience.

3. RECOMMENDER SYSTEMS FUNCTION

This is presumably the most important function of a commercial recommendation system, i.e., to be able to sell an additional set of items compared to those usually sold without any kind of recommendation. This objective is achieved because the recommended items are likely to suit the user's needs and wants. An additional major function [6] of a recommendation system is to enable the user to select items that might be [10] hard to find without a precise recommendation. A well designed recommendation system can also make better the experience of the user with the site or the application. The user will quest the recommendations interesting, relevant and, with a properly designed human-computer interaction, she will also enjoy using the system. A user should be stalwart to a web site which, when visited, recognizes the old customer and treats him as a valuable visitor [25]. This is a normal feature of a recommendation system since many recommendation systems compute recommendations, leveraging the information acquired from the user in previous interactions, e.g., her ratings of items. A further important function of a recommendation system, which can be leveraged in many other applications, is the description of the user's preferences, someone collected explicitly or predicted by the system. The service provider may then decide to re-use this knowledge for a number of other intentions, such as improving the management of the item's stock or production.

4. DATA AND KNOWLEDGE SOURCES IN RECOMMENDATION SYSTEM

Recommendation systems are information processing systems that actively gather several kinds of data in order to build their recommendations. Data is the first instance about the items to suggest and the users who will receive these recommendations. However the data and knowledge sources available for recommender systems can be very diverse, ultimately, whether they can be exploited or not depends on the recommended technique. The data used by the recommendation system, refers to three kinds of objects: items, users, and transactions. The Items are the objects that are recommended. Items may be characterized by their complexity and their value or utility. The value of an item may be positive if the item is useful for the user or negative if the item is not convenient and the user made a wrong decision when selecting it [26]. The users of a recommendation system may have very miscellaneous goals and characteristics. In order to personalize the recommendations and the human-computer Interaction [27], recommendation system exploit a range of information about the users. This information can be structured in various ways and again the [28] selection of what information to model depends on the recommended technique. We normally refer to a transaction as a recorded interaction between a user and the recommendation system. The transactions are logged-like data that store essential information generated during the human-computer interaction and which [29] are useful for the generation algorithm that the system is using. In the transaction model, the system collects the various requests-responses, and may accordingly learn to modify its interaction strategy by observing the outcome of the recommendation process.

5. RECOMMENDATION SYSTEM TECHNIQUES

This paper presents several different types of recommender systems that vary in terms of the addressed domain, the knowledge used, but especially in regard to the recommendation algorithm. Conclusively, provide a first overview of the different types of recommender systems, and briefly introduce the distinguished between six different classes of recommendation approaches [30].

5.1 Collaborative Filtering

The term collaborative filtering (CF) was coined in 1992 by Goldberg et al., who proposed that information filtering can be more emphatic when humans are involved in the filtering process [31]. The concept of collaborative filtering as it is understood nowadays was introduced two years later by Resnick et al. [32]. Their theory was that users like what like-minded users like, where two users were considered like-minded when they rated items alike. When like-minded users were identified, items that one user rated positively were recommended to the other user, and vice versa. Compared to Content-based filtering, collaborative filtering offers three advantages. First, collaborative filtering is content independent, i.e. no error-prone item processing is required [33]. Second, because humans do the ratings, collaborative filtering takes into account real quality assessments [34]. In the end, collaborative filtering is supposed to provide serendipitous recommendations because recommendations are not based on item symmetry but on user symmetry.

The collaborative filtering algorithms are generally sorted into two classes: memory based and model based. The memory-based algorithm predicts the votes of the active user on a target item as a weighted average of the votes given for that item by other users. The model-based algorithm views the problem as calculating the expected value of a vote from a probabilistic perspective and uses the users' preferences to learn a model. As usual problem of collaborative filtering in the domain of research-paper recommender systems is sparse. The Vellino [35] compared the implicit ratings on Mendeley (research papers) and Netflix (movies), and found that sparsity on Netflix was three orders of magnitude lower than on Mendeley. This is caused by the different ratio of users and items. In domains like movie recommendations, there are typically few items and many users.

Item-based collaborative filtering usually offers preferable resistance to data sparsity problem than user-based collaborative filtering. It is because in practice there are more items were rated by common users than users' rate common items. In baseline predictors collaborative filtering models try to capture the interactions between users and items that produce the different rating values. In spite of, much of the observed rating values are due to the effects associated with either users or items, autonomously of their interaction. Next, denote by μ the overall average rating. A baseline prediction for an unknown rating rui is denoted by bui and accounts for the user and item effects. The parameters bu and bi indicate the observed deviations of user u and item i, respectively, from the average.

$$b_{ui} = \mu + b_u + b_i$$

For example, suppose that we want a baseline predictor for the rating of the movie Furious Seven by user perwej. Now, say that the average rating over all movies, μ, is 4.1 stars. Furthermore, Furious Seven is better than an average movie, so it tends to be rated 0.8 stars above the average. On the other hand, perwej is a critical user, who tends to rate 0.4 stars lower than the average. Thus, the baseline predictor for Furious Seven rating by perwej would be 4.5 stars by calculating 4.1−0.4+0.8. In order to estimate bu and bi one can solve the least squares issue.

$$\min_{b_*} \sum_{(u,i)\in\mathcal{K}} (r_{ui} - \mu - b_u - b_i)^2 + \lambda_1\left(\sum_u b_u^2 + \sum_i b_i^2\right)$$

This way, the first term $\Sigma(u,i)\in K(r_{ui} - \mu + b_u + b_i)2$ strives to find b_u's and b_i's that fit the given ratings. The regularizing term – λ_1 ($\Sigma_u b^2_u + \Sigma_i b^2_i$) avoids over fitting by penalizing the magnitudes of the parameters. This least square problem can be solved impartially efficiently by the method of stochastic gradient descent. There are further critiques of collaborative filtering. The computing time for collaborative filtering tends to be higher than for content-based filtering [36]. Collaborative filtering is normally less scalable and be in need of more offline data processing than Content-based filtering. The collaborative filtering creates similar users sensed that collaborative filtering dictates opinions [37].

5.2 Contents-Based Methods

The Content-based filtering (CBF) is one of the most widely used and researched recommendation approaches [38]. The Content-based filtering is the user modeling process, in which the interests of users are presupposing from the items that users interacted with. Items are usually textual, for instance emails or web pages [39]. Interaction is typically established through actions, such as downloading, buying, authoring, or

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tagging an item. Items are represented by a content model containing the items' features.

Typically, content-based filtering techniques to match items to users through classifier-based approaches or nearest-neighbor methods. In classifier-based approaches each user is allied with a classifier as a profile. The classifier takes an item as its input and then concludes whether the item is preferred by allied users based on the item contents [18]. On the contrary, content-based filtering techniques based on nearest-neighbor methods store all items a user has rated in their user profile. In order to determine the user's interests in a concealed item, one or more items in the user profile with contents that are closest to the concealed item are allocated, and based on the user's preferences to these discovered neighbor items the user's preferences to the concealed item can be stimulated [26][18].

The Content-based filter systems need proper techniques for representing the items and producing the user profile, and some action plan for comparing the user profile with the item represents. The high level architecture of a content based recommender system is depicted in figure 1.

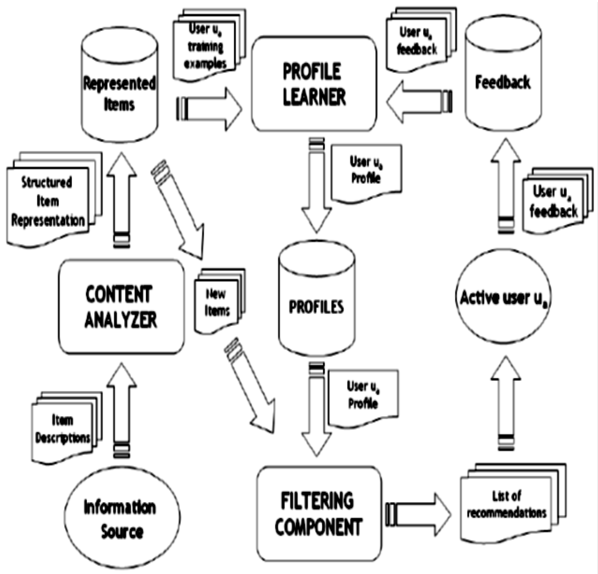

Figure 1. The architecture of Content-based Recommender

In the content analyzer when information has no structure some kind of pre-processing step is needed to extract structured episodic information. The main responsibility of the component is to represent the content of items coming from information sources in a form suitable for the next processing steps. The data items are analyzed by feature extraction techniques in order to shift item representation of the original information space to the target one. Thereupon profile learner this module collects data representative of the user preferences and tries to generalize this data, in order to construct the user profile. Ordinarily, the generalization strategy is comprehension through machine learning techniques which are able to dissert a model of user interests, starting from items liked or disliked in the past [40]. Hereafter filtering component this module exploits the user profile to suggest relevant items by matching the profile representation against that of items to be recommended. The result is a binary or continuous relevance judgment putted using some equality metrics [41], the latter case resulting in a ranked list of potential engrossing items. This technique is also less dominated by the cold-start problem which is one of the major weaknesses of the collaborative filtering based recommenders.

5.3 Demographic-Based

The Demographic Based recommender systems's intention to categorize the user based on personal attributes and make recommendations based on demographic classes. An early example of this kind of system was Grundy [42] that recommended books based on personal information gathered through an interactive dialogue. The user's responses were matched opposed to a library of manually assembled user stereotypes. Approximately more recent recommender systems have also taken this approach. [43], for example, uses demographic groups from marketing research to suggest a range of products and services. A short survey is used to gather the data for user categorization. In other systems, machine learning is used to arrive at a classifier based on demographic data [20]. The representation of demographic information in a user model can vary substantially. The Rich's system used handcrafted attributes with numeric confidence values [25]. The Pazzani's model uses Winnow to extract features from users' home pages that are predictive of liking certain restaurants [18]. Demographic techniques form "people-to-people" correlations like collaborative ones, but use different data [44]. The avail of a demographic approach is that it may not require a history of user ratings of the type needed by collaborative and content-based techniques. In spite of, there are some shortcomings of demographic filtering recommenders because they create user profiles by classifying users using stereotyped descriptors [42] and recommend the same items to users with similar demographic profiles. As each user is different, these recommendations might be too general [26] and lousy in quality. Accurately demographic filtering based recommenders do not provide any individual adaptation regarding interest changes [26]. Nevertheless, an individual user's interests tend to shift over time, so the user profile needs to conform to change which is normally available in collaborative filtering and content based recommenders as both of them take users' preference data as input for recommendation making.

5.4 Knowledge-based

The Knowledge-based recommendation endeavors to suggest objects based on inferences about a user's needs and preferences. In some intellect, all recommendation techniques could be described as doing some kind of inference. The Knowledge-based approaches are eminent in that they have functional knowledge; they have knowledge about how a particular item meets a particular user need, and can consequently reason about the relationship between a need and a possible recommendation [45]. The user profile can be any knowledge structure that supports this presumption. In the convenient case, as in Google, it may simply be the query that the user has formulated. In others, it may be a more detailed representation of the user's needs [46]. The penetration system and several other recent systems [47] employ techniques from case-based reasoning for knowledge-based recommending.

The knowledge used by a knowledge-based recommender system can also take many forms. Google uses information about the links between web pages to argue prominence and authoritative value. Knowledge-based recommender systems actually help users find out and thereby understand an information space. Users are an essential part of the knowledge discovery process, extended their information needs in the course of interacting with the system. The needs only have general knowledge about the set of items and only an informal knowledge of one's needs; the system knows about the tradeoffs, category boundaries, and useful search policy in the domain. Knowledge-based systems tend to work superior than others at the beginning of their deployment, but if they are not furnished with learning components they may be surpassed by other shallow methods that can seize the opportunity the logs of the human computer interaction.

5.5 Utility-based

The Utility-based recommender systems make recommendations based on the computation of the usefulness of each item for the user. Utility-based recommendation techniques use features of items as background data, educe utility functions over items for users to describe user preferences, and apply the function to determine the rank of items for a user [48]. The user profile consequently been the utility function that the system has derived from the user, and the system employs constraint satisfaction techniques to locate the best match. Utility-based recommenders do not endeavor to build long-term generalizations about their users, but rather base their advice on an evaluation of the match between a user's need and the set of options at hand.

The e-commerce site, Persona Logic has different techniques for arriving at a user-specific utility function and applying it to the objects under consideration [49]. The benefit of utility-based recommendations are that they do not face issue involving new users, new items, and sparsity [48]. The main issue here is how a utility function for each user should be created. The user must build a complete liking function and weigh each attribute's necessity. This frequently leads to a valuable burden of interaction. Consequently, determining how to make accurate recommendations with little user effort is a critical issue in designing utility-based recommender systems. The convenience of utility-based recommendation is that it can factor non-product attributes, such as vendor credibility and product availability, into the utility computation, making it possible for example to trade off price against delivery schedule for a user who has an instant necessity.

5.6 Hybrid recommender systems

The hybrid recommendation systems are a mix of single recommendation systems as sub-components. This hybrid approach was introduced to cope with a difficulty of conventional recommendation systems. The hybrid recommender system is composed of two or more diverse recommendation techniques, and the basic rationale is to gain preferable performance with little of the deficiency of any individual technique, as well as to incorporate various data sets to produce recommendations with higher precision and perfection. The first hybrid recommender system Burke's was developed in hybrid recommender systems combines two or more recommendation techniques to gain superior performance with little of the deficiency of any individual one [50]. Ordinarily, collaborative filtering is integrated with some other technique in an attempt to avoid the ramp-up problem. Depending on the domain and data characteristics, dissimilar types of combinations might produce dissimilar outputs. The further down describes several hybridization techniques that come into consideration to merge collaborative filtering and content-based filtering recommenders [51].

The Weighted hybridization probably the most straightforward architecture of a hybrid system is a weighted one. In view of this item are scored separately by both incorporated recommender, whereas the final output is a linear combination of the intermediate results. Typically, empiric means are used to determine the best weights for each component. Note that content-based recommenders are able to make prediction on any item, but collaborative recommender can only score an item if there are peer users who have rated it.

In Mixed hybridization many domains it is impracticable to receive an item score by both recommenders, because either rating matrix or content spaces are too sparse. Mixed hybridization techniques generate a self-sufficient set of recommendations for each component, and join the ranked candidates before being shown to the user. Nevertheless, merging the predicted items of both recommenders makes it difficult to evaluate the improvement about the individual components. Hereafter Switching hybridization, some hybrid systems consist of more than two recommendation components with different underlying collaborative filtering or content-based filtering approaches. Time and again recommenders are ordered, and if the first one cannot produce a recommendation with high confidence, then the next one is proven, and so on. On the other hand, other switching hybrids might select single recommenders according to the type of user of the item. However, this method supposes that some reliable switching criterion is available. In the Feature Combination hybridization Systems that follow the feature combination approach only employ one recommendation component, which is endorsed by a second passive component. Alternatively processing the features of the contributing component separately, they are injected into the algorithm of the genuine recommender. In Cascade hybridization the concept of cascade hybrids is akin to feature enhancement techniques. In spite of this, cascade models make candidate pick solely with the primary recommender, and employ the secondary recommender simply to refine item scores. For example, items that were equally scored by the main component might be re-ranked employing the secondary component.

Eventually Meta-Level hybridization this kind of hybrids employs a model learned by the contributing recommender as input for the genuine one. In spite of the fact that the general schematic of meta-level hybrids reminds on feature enhancement techniques, there exists a valuable difference between both approaches. As an alternative supplying the actual recommender with additional features, a meta-level, contributing recommender provides a completely new recommendation space. Though, it is not always inevitably practicable to produce a model that fits the recommendation logic of the primary component [51].

6. RECOMMENDATION SYSTEM PROPERTIES

In this segment we review a range of properties that are commonly considered when deciding which recommendation approach to select also showing several properties regarding to the techniques that are being used for generating recommendations [5]. In prediction precision is by [29] far the most discussed property in the recommendation system literature. At the fundamental of the vast majority of recommender systems gag prediction engine. This engine may predict user opinions over items or the probability of usage. A fundamental imagination in a recommender system is that a system that provides more immaculate predictions will be preferred by the user. Hereby, numerous researchers set out to find algorithms that provide superior predictions. Again confidence in the recommendation can be defined as the system's trust in its recommendations or predictions. As we have noted above, collaborative filtering recommenders tend to make better their precision [12] as the amount of data over items grows. Accordingly, the confidence in the predicted property typically also grows with the amount of data.

In the trust as long as confidence is the system trust in its ratings, in trust we mention here to the user's trust in the system recommendation. For example, it may be profitable for the system to recommend a few items that the user already knows and likes. This way, even though the users advantage no value from this recommendation, she notices that the system provides suitable recommendations, which may increase her trust in the system recommendations for undetermined items. Hereafter in utility [20] several e - commerce websites employ a recommendation system in order to ameliorate their revenue by, e.g., enhancing cross-sell. In such cases the recommendation engine can be judged by the revenue that it generates for the website. In usual, we can define various types of utility functions that the recommender tries to optimize. In risk some cases a recommendation may be linked with a potential risk. For example, when recommending stocks for purchase, users may desire to be risk-averse, preferring stocks that have a lower expected growth, but also a lower risk of collapsing. To the other side users may [24] be risk-seeking, preferring stocks that have a potentially high, even if less likely, profit. In case we may wish to estimate not only the value generated from a recommendation, but also to minimize the risk.

In the serendipity is a measure of how astounding the victorious recommendations are. For example, if the user has rated positively many movies where a certain star actor appears, recommending the new movie that the actor may be novel, because the user may not know about it, but is hardly surprising [39]. Naturally, random recommendations may be very astounding, and we consequently need to balance serendipity with precision. In the privacy a collaborative filtering system, a [26] user willingly makes known his preferences over items to the system in the expectation of getting useful recommendations. It is important for most users that their liking stays private, that no third party can use the recommendation system to learn something about the likes of a distinctive user.

Eventually, in scalability recommender systems are designed to help users navigate in large [29] collections of items, one of the aims of the designers of such systems is to scale up to real data sets. Actually, it is often the case that algorithms trade other properties, such as precision or coverage, for providing intense results even for spacious data sets consisting of millions of items.

7. THE CHALLENGES AND LIMITATIONS OF RECOMMENDATION SYSTEMS

In this paper several techniques used in a recommender system experiences some of the obstacles that may be described in terms of basic problems as the scalability of the algorithms with large and real world data sets. As the research on basic techniques progresses and matures, it becomes clear that a fundamental issue for recommendation systems is to sort out how to embed the basic recommended techniques in real operational systems and how to deal with massive and dynamic sets of data produced by the interactions of users with items. Recently developed approaches and large-scale evaluation studies are needed [52].

Onward privacy preserving recommender systems exploits user data to generate personalized recommendations. In the attempt to build increasingly preferable recommendations, they collect as much user data as possible [53]. This will clearly have a negative influence on the privacy of the users and the users may start feeling that the system realize too much about their true preferences [54]. In the Sparsity problem stated simply, most users do not rate most items and hence the user ratings matrix are typically very sparse. This is a problem for collaborative filtering systems, since it decreases the likelihood of finding a set of user with similar ratings. This problem usually occurs when a system has a very high item-to-user ratio, or the system is in the initial stages of use. This issue can reduce by using additional domain information [55] or making assumptions about the data generation process that allows for the high-quality allegation. The numerous researchers have attempted to alleviate this problem still this area demands more research. In the Cold Start problem new items and new users pose a valuable challenge to recommender systems. Jointly, these problems are referred to as the cold start problem. The first of these problems arises in collaborative filtering systems, where an item cannot be recommended so long as some user has rated it before. This problem applies not only to new items, but also to obscure items, which is particularly harmful to users with eclectic tastes. As such the new-item problem is also often referred to as the first-rater problem. Because content-based approaches [56] do not rely on ratings from other users, they can be used to produce recommendations for all items, provided attributes of the items are available. In fact, the content-based predictions of similar users can also be used to further make better predictions for the active user.

In Generic user models and cross domain recommender systems are able to mediate user data through dissimilar systems and application domains. Using generic user model techniques, single recommendation systems can put forward recommendations about a variety of items [57]. This is in general not possible for general recommendation systems which can combine more techniques in a hybrid approach, but cannot comfortably gain from user preferences collected in one domain to generate recommendations in a different one. In the Fraud recommender systems are being increasingly adopted by commercial websites, they have started to play a valuable role in affecting the profitability of sellers. This has led to many conscienceless vendors engaging in different forms of fraud to game recommender systems for their benefit. Typically, they endeavor to inflate the perceived desirability of their own products (push attacks) or lower the ratings of their competitors (nuke attacks). These types of attack have been extensively studied as shilling attacks or profile injection attacks. According to such attacks usually involve setting up dummy profiles, and assume different amounts of knowledge about the system [58].

In mobilizing the recommenders designed to operate on mobile devices and usage contexts [59]. Mobile computing is emerging as the most natural platform for personal computing. Numerous recommendation requests are likely to be made when the user is on the move, e.g., at shops or hotels in a visited city [60]. This necessitates “mobilizing” the user interface and to design computing solutions that can efficiently use the still limited resources of the mobile devices.

8. CONCLUSION AND FUTURE WORK

In this paper, we have presented a novel, literature review on recommendation systems. Recommendation systems are software tools and techniques confer counsel for items to be of use to a user. The counsel relates to various decision making processes, such as what items to buy, what music to listen to, or what online news to read. Recommendation systems have developed in parallel with the web. The recommender systems technology, efficient significant favorable outcome in a broad range of applications and potentially a powerful searching and recommending technique. The paper presents an overview of the field of recommender systems and delineates the current generation of recommendation techniques that are usually classified into the following six main categories: Collaborative Filtering, Contents-Based Methods, Demographic-Based, Knowledge-Based, Utility-Based, and Hybrid Methods. In this paper, we are delineating recommender systems function and data and knowledge sources in recommendation system as well as recommendation system properties. This paper is also showing several challenges and limitations regarding to the techniques that are being used for generating recommendations. In this paper, we have identified 60 research papers on recommender systems, which were published between 1971 and 2014, to perceive the trend of recommender systems respective research and to provide practitioners and researchers with comprehension and future direction on recommender systems. Conclusively, we hope that the issues presented in this paper would advance the consideration in the recommender systems community about the next generation of recommendation technologies.

9. REFERENCES

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