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Research Article

A REVIEW OF RECOMMENDER SYSTEM: FROM PAST TO THE FUTURE

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Abstract

Last decade and half had been witnessed to an unprecedented expansion of Internet. This has resulted in data overloading; due to which it has become an increasing problem for retrieving useful information from internet. Users searching for products or content have endless number of Web pages to navigate and require enormous efforts, requires judgmental aptitude and intuitiveness to extract meaningful information from the enormous data. Recommender systems are meant to be an important solution to the data overload and skewed information problem that persists today in World Wide Web. The job of the recommender system is to provide the consumer with a selection of products or content which suit his/her needs so that the user need not browse through enormous number of web pages. Recommender system has undergone a lot of improvements in last two decades in terms of accuracy in output and has been an intense area of research in recent times. This paper discusses the various improvements in the field of recommender system from the past to the present and also explores the future research trends.

Keywords: Context; Recommender System; Collaborative Filtering; Trust network.

I. Introduction

Internet has been perhaps the most outstanding innovation in the field of communication and information technology. In the last decade or so there had been an unprecedented expansion of internet and web contents. This has also created the problem of information overloading. Recommender system attempts to address that issue. Recommender systems have become a widely used tool for Web applications. In an environment where there are an infinite number of Web sites for consumers to choose from, the competition is fierce. If a Web site can offer a consumer, an automated and intelligent system which generates personalized recommendations, this would definitely provide a competitive advantage and also ease out the effort required on part of the user. There are many different types and uses for recommender systems. The recommended items can range from online-shopping products, to a suggested course for a student, or a particular kind of medical care / doctor for a patient. Recommender systems use various types of information to generate a recommendation, such as, past purchase records, click stream analysis, user profiles, explicit ratings of items, or social network information. Recommender systems use various methods to process the input data, and output recommendations to the user. The recommender systems are broadly categorized in to two types: Content based and collaborative filtering. Content based recommender systems operate by comparing description of recommendable items. This type of recommender system relies on rich content description of items those are being recommended. Here items may be products or services. A content-based movie recommender system will typically operate on information such as actors, directors, category of movie (action, drama etc), producers and so on. This information will be checked against the predefined preference of a user to determine the movie to be recommended to the user. This type of recommender system requires a lot of information processing pertaining to each item detail. Also it requires the availability of each item description. Collaborative filtering based recommender system uses a different approach. It is based on the observation that in real life scenario, people typically rely on the friends who have similar taste or preferences. It is built on the assumption that a possible way to determine interesting content for a user, is to find other users who have similar interest, and then recommend item that those similar users liked. Collaborative filtering also has major shortcomings. A major problem with traditional collaborative filtering based recommender system is data sparseness. Cold start problem is also one of the major weaknesses of collaborative filtering based recommender system. There are many approaches to overcome these issues by using trust network based recommender system, hybrid recommender systems to improve the recommendation accuracy and overcoming data sparseness issue. Default average voting, filterbots techniques etc. are used to address the cold start problem. There are many improvements to the Recommender System and continue to be an active area of research to further enhance the usability and accuracy.

The paper is organized as follows, Section II discusses related works. Initial developments in recommender system are presented in section III. In Section IV, outline the present scenarios, section V gives the future trends in the field of Recommender Systems, Finally, conclusion of the paper is given in section VI.

II. Related Works

In this section we review some of the works related to various approaches to Recommender System (RS). A lot of work has been done in the area of RS in general. The collaborative filtering, content based and Hybrid approaches and the issues of Recommender System are explained in the survey done by Adomavicius and Tuzhilin [1]. The new algorithm for increasing the accuracy of collaborative Filtering is discussed by Herlocker, Konstan et. Al in [2]. A new filtering technique combing collaborative Filtering and Content Based filter is discussed by Q. Li and B. Kim in [3]. Context aware RS is discussed by G. Adomavicius and Alexander Tuzhilin in [4]. Their work details about modeling contextual information in RS. They also describe contextual pre-filtering, post-filtering and Contextual modeling. In [4], they mention about possibility of combining post-filter, pre-filtering and contextual modeling in order to achieve higher accuracy in RS output. Matthias, Gernot Bauer explore the design space of RS for mobile applications and describe different dimensions and techniques for capturing the users, the items, the contexts etc. in [5]. Sofiane Abbar, Mokrane and Stephane in [6], present an approach based on data personalization and Personal Access Model that provides a set of personalization services. Daniar Asanov in [12] discusses different types of traditional approaches as well as modern approaches to RS. They also discussed the main challenges in RS. Chang E, Thomson P et. al in [15], discusses the dynamic and fuzzy nature of trust and their impact. John O'Donovan & Barry Smyth discusses the impact of trust in Recommender System in [14]. Different computational models for trust are also discussed.

III. Initial Developments in Recommender System

Traditionally recommender systems are of two broad categories: Content Based and Collaborative filtering.

Content Based RS:Content-based filtering also referred to as cognitive filtering, recommends items based on a comparison between the content of the items and a user profile. The content of each item is represented as a set of descriptors, typically the words that describes an item. The user profile is represented with the same terms and built up by analyzing the content of items which have been seen by the user. In this approach description of each item is given by a number of terms that characterizes the item. For example, a content-based movie recommender system will typically operate on information such as actors, directors, category of movie (action, drama etc), producers and so on. These parameters will be checked against the predefined preference of a user to determine the movie to be recommended to the user. This type of recommender system requires a lot of information processing pertaining to each item detail. Also it requires the availability of each item description. Content-based techniques are limited by the features that are explicitly associated with the objects that these systems recommend. Therefore, in order to have a sufficient set of features, the content must either be in a form that can be parsed automatically by a computer (e.g., text), or the features should be assigned to items manually. Information retrieval techniques work well in extracting features from text documents, but the same does not work in all domains and areas. For example, automatic feature extraction methods are much harder to apply to the multimedia data, e.g., graphical images, audio and video streams. By analyzing a movie video by computer, it is very difficult to describe the features in terms of actors, type, producers etc. Moreover, it is not always practically feasible to assign attributes manually due to limitations of resources and time. Another problem associated with limited content analysis is that, if two different items are represented by the same set of features, they are not distinguishable. If two text based documents use the same terms and keywords, content based recommender system will not be able to distinguish between a well written and a badly written article, hence the whole purpose of recommendation will be lost and quality of recommender system output will eventually be poor.

Collaborative Filtering (CF):Collaborative filtering is a traditional method used in recommender system. The fundamental assumption behind this approach is that other similar users' opinion can be selected and combined in such a way as to provide a reasonable prediction of active user's preference. It is built on the assumption that a possible way to determine interesting content for a user, is to find other users who have similar interest, and then recommend item that those similar users liked. So a neighborhood of similar users are formed, all these users are assumed to have similar taste and preferences. There are various types of CF, user-based CF and item-based CF. User-based approach was proposed in the end of 1990s by the professor of University of Minnesota Jonathan L.Herlocker. In the user-based approach, the users perform the main role. The users with similar taste/reference join into one group. Various approaches have been used to compute the similarity between users in collaborative recommender systems. In most of these approaches, the similarity between two users is based on their ratings of items that both users have rated. The most common approaches to similarity calculations are correlation- and cosine-based. Recommendations are given to user based on ratings of items by other users of the same group, with whom he/she shares common preferences. If the item was positively rated by the community/ group, it will be recommended to the user. Thus in the user-based approach the items that were already rated by the user before play an important role in searching a group that shares appreciations with him. In item-based CF, a slightly different method is used, the fact that the taste of users remains constant or change very slightly, similar items build neighborhoods based on appreciations (good ratings) of users. Here the Recommender System will generate recommendation of similar items to the user which he would prefer. Both these approaches have many short comings such as data sparseness, cold start problem etc.

I. Present Approaches & Methods Used In Rs

A. Context – aware Recommender System

As discussed in [4], context has many definitions and is a multidimensional concept that has been studied across different research disciplines including Computer Science, Cognitive Science, linguistic, philosophy, psychology and organizational context. Since context has been studied in multiple disciplines, each of them view the context in their own way and are different from each other. We will try to understand the term context specifically in the domain of RS. In the case of RS, context parameters are heavily dependent on whether it is a movie RS or a Tourist RS etc. In movie RS, the contexts are typically: Day of watching, Place (Theatre) of watching, Time of Watching, Seasonal info (during festival etc.), companion (friends, family etc), Important pre & post events. In Tourist RS, the contexts are typically: Holiday details, last Tour date & place, companion, Important pre & post events.

Traditional recommender systems usually compute the similarity using two-dimensional user-item matrix. They did not take into consideration contextual information which affects and influence the decisions. The contextual information is time, location, companions, weather, and so on. Considering context information as one system design factor is necessary for producing more accurate recommendations. Adomavicius and Tuzhilin proposed a multidimensional approach to incorporate contextual information into the design of recommender systems Adomavicius et al. (2005).

They also proposed a multidimensional rating estimation method based on the reduction based approach, and tested their methods on a movie recommendation application that took time, place, and companion contextual information into consideration. Here, recommendations are generated using only the ratings made in the same context of the target prediction. However, in fact, it is rarely the same context occurs in the future but instead the similar context. The disadvantage of that method is the increase of data sparsity. Yap et al. (2007) exploit a different way of incorporating contextual information and tries to improve prediction accuracy using a Content Based (CB) approach. The authors model the context as additional descriptive features of the user and build a Bayesian Network to make a prediction.

They increase the accuracy even with noisy and incomplete contextual information. Umberto and Michele have analysed post filtering, pre filtering and contextual modeling for context-aware recommender system. There are research done on selecting relevant context features, relevant contexts increases the accuracy of recommender system while the irrelevant ones actually degrades the performance both in terms of output accuracy and computational load.

Ante Odic et al. in [19], describes different methods for elicitation of relevant context selection for a movie recommender system.

Rhul Gupta et al. in [20] points out the naïve Bayes classifiers and SVD for context aware recommender system. Feature reduction for product recommendation is given in [21].

B. Trust – Network based Recommender System

In order to overcome the limitations of Collaborative Filtering based Recommender system, in recent years there have been a lot of concentrated research in trust network based recommender system. In trust based recommender strategy, the neighborhood formation is done based on trust relationships between the users. In real world when looking for a recommendation for a movie or tourist spot, we often turn to our friends. A particular friend may not be reliable for all types of recommendation. Here, recommendation partners should have similar taste and preferences and also they need to be trustworthy. Social trust is very complex and depends on many factors which make it difficult to model the same in a computational system. There are many factors which influence trust, e.g.; relationship with the person, psychological factors, influence of others' opinion etc. There are many definition of trust that falls into many categories. Marsh in [22] has formalized trust definition in computational sense, taking into account both social and technological aspects. Krishten Mori in [10], has elaborated the concept of trust in recommender system and brought out various aspects of trust network in recommender system, including the trust metric and reputation metrics. There are three main properties of trust that are relevant to developing trust-based recommender system models: transitivity, asymmetry, and personalization. The idea of transitivity is that social trust can be passed between people. For example, A trusts B, and B highly trusts C, even though A does not know C, A could still derive some sense of trustworthiness for C. However, trust is not perfectly transitive in the mathematical sense, because it would not be the case that A highly trusts C, a person A has no previous interactions with. There has been lot of research in modeling the transitivity of trust, also referred to as trust propagation. Guha et al. [23] developed a formal framework of trust propagation schemes. Their framework assumes that users explicitly state trust values in other users. They have also introduced the notion of distrust and the propagation of distrust. The asymmetric property of trust is very important. If two people are involved in a relationship, the trust which they hold for one another will not necessarily be identical. Because individuals are so unique in their terms of their personal experiences, backgrounds, and histories, it is easy to understand the asymmetric nature of trust. In the application to collaborative filtering, trust differs from similarity, in that similarity is symmetric. This is an important difference because trust allows users to form additional connections which were not possible with similarity values. The last property is personalization of trust. Trust is a subjective, personal opinion. Two people often have very different opinions about the trustworthiness of the same person. Personalization plays an important role in making recommendations to a user. Personalization of trust greatly affects the accuracy of a recommender system. Computational models based on trust is given in [14].

C. Hybrid Methods in Recommender System

Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with some other technique in an attempt to avoid the ramp-up problem. Hybrid methods are described in [24]. Table I shows some of the combination methods those are being implemented.

Table I: Hybrid RS Methods.

Hybrid Method	Description
Weighted	The scores of several recommendation techniques are combined together to produce a single recommendation.
Switching	The system switches between recommendation techniques depending on the situation. The issue of this hybrid is selecting one recommender among candidates. This selection is made according to the situation it is experiencing. The criterion for the selection like confidence value or external criteria should exist and the components might have different performance with different situations
Mixed	Each component of this hybrid should be able to produce recommendation lists with ranks and the core algorithm of mixed hybrid merges them into a single ranked list. The challenge here is how the new rank scores should be produced.
Feature combination	Features from different recommendation data sources are thrown together into a single recommendation algorithm
Cascade	One recommender refines the recommendations given by another.
Feature augmentation	Output from one technique is used as an input feature to another
Meta-level	The model learned by one recommender is used as input to another.

Content boosted collaborative filtering is detailed in [25].

Hybrid methods are used to combine different recommendation methods in one or more ways as listed above, in order to achieve more accurate recommender output. Hybrid of trust based system with content based methods is developed.

II. Future Trends IN recommender System

Recommender system has been an active area of research for a decade or so and continues to be an interesting research domain. Although recommender systems has witnessed unprecedented improvements starting from very primitive content based and collaborative filtering methods, a lot of research is going on to further enhance the output accuracy and improvements in all dimensions of recommender system. The search is focused on various areas to make the RS more and more useable and practical in real life scenarios. The following are some of the areas of RS where there are itense research going on and these efforts are surely shaping the future of recommender systems.

Privacy: Privacy preserving RS is one of the major challenges towards developing a practical RS. There are various real life situations where getting input data is not easy and at times extremely difficult for the recommender system to make a reliable recommendation. There are various reasons for that. In the case of systems like medical recommendation system, availability of input data are in sparse as medical history is often treated as personal, confidential information. As a result of these, developing a reliable medical recommender system or any such system which requires data that is considered to be private and confidential is extremely difficult. In [26], an approach towards privacy preserving RS is detailed that makes use of Homomorphic cryptography to achieve the same.

Recommendation list Diversity: Most research into recommending items has been towards the accuracy of predicted ratings. There are also other factors those have been identified as important to users. One such factor is the diversity of items in the recommendation list. In a user survey aimed at evaluating the effect of diversification on user satisfaction, it is found that it had a positive effect on overall satisfaction even though accuracy of the recommendations was affected adversely [27]. There is a great need for a shift in focus that is related to the functionality offered by recommender systems that can exploit directly the usage data, and add more value to the user.

Dynamics in User interest: Human beings have varied interest and most importantly this interest is dynamic. Recommender system needs to adapt to this dynamism. Most personalization systems tend to use a static profile of the user. However user interests are not static, changing with time and context. Few systems have attempted to handle the dynamics within the user profile. The behavior of users varies over time and it should affect the construction of models. A Recommender system should be able to adapt to the user's behavior, when this changes.

Data Sparseness & Cold start: In many of the practical dataset, it has been found that data sparseness is a major issue, many of the recommender algorithms makes this issue worse and cold start problem is becoming a deterrent for the RS usage. There are many research initiatives towards eliminating data sparseness using singular value decomposition.

Adaptive and scalable RS: Although the accuracy of RS is being enhanced, the computing requirements are also becoming more and more complex. Scalable RS has become an impending need towards practical use-case scenarios and indeed an area of focused research.

Collaborative RS: Recommender systems need to collaborate among themselves in order to increase the accuracy of RS and also increase the scope of RS. These collaborative RSs would be linked to each other over a simplified but standard interface and would be complementary to each other.

Conclusions

In this paper, we have briefly reviewed various methods and approaches in Recommender System in present scenario starting from the traditional ones, also future research trends in RS are brought out. This review would be helpful and beneficial to the research community to focus on various issues pertaining to RS. In future course, we will focus on context aware recommender system and explore various efficient approaches to context selection along with other future trends in RS, in order to make RS more accurate and practically useable.

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