Potential of Next Generation Recommender Systems: A Survey on the State of the Art Developments and Possible Expansions

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Abstract – In recent years, as a matter of fact, Recommender Systems (RS) have changed the way of interaction significantly between the netizens and the World Wide Web. These systems are developed by carefully observing, studying and analyzing the walkthrough of the netizens such as implicit feedback (user clicks), explicit feedback (ratings, opinions on various trending issues or topics, reviews and other options). The most important and vital part of the recommender system is to recognize user's personalized preferences from the user's browsing history or by studying user's profile information. This paper aims to perform an orderly audit and review of existing recommendation approaches and depicts the present age and describes various limitations of current methods & discuss possible future developments and expansions, further how it can be applicable to even broader range of domains. The extensions may include improvement of identifying and understanding the right users and items, embedding contextual information, overcome the language barrier with the help of cross-lingual approach, promoting Multicriteria ratings, handling missing data with a minimum number of attributes or properties, and a provision for more flexible and less proactive types of recommendations.

Keywords: Personalised Preferences, Contextual Information, Multicriteria Ratings, Cross-Lingual.

1. INTRODUCTION

In the current era due to wide availability of Internet and the use of social networking sites like YouTube, Facebook, Instagram, and many E-commerce websites like Amazon, Flipkart, Myntra etc. generates overloaded of information to the netizens but at the same time searching in the overcrowded data becomes very complex and involves lot of challenges for the data filtering process. For example, there is a huge number of movies in Netflix, a collection of millions of books in Amazon, more than 10 billion page collection in Facebook, petabytes of videos on YouTube etc. It becomes a very cumbersome to the users to find what the user is actually looking for. To some extent search engines solves the problem, however, personalized information is yet to be solved extensively.

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This need leads to the development of Recommender Systems. These are effective tools for filtering and sorting the required products, items, or information. They take the advantage of browsing history of the users, opinions from the various community of people to help individuals more effectively by recommending content to the users after processing an enormous available set of choices. There are several recommender systems employing different algorithms, approaches, and methods that are used to address some challenges based on the application where it is being used. Basically, there are two types of approaches to develop recommender systems [1]. i. Content-Based Filtering, ii. Collaborative Filtering. Based on the requirement we can combine these two approaches also. These two are used as a base model for most of the advanced systems. More advanced systems are using context-aware, semantic approaches to improve the accuracy of the system. Semantic search in the sense, instead of looking for based on the matching of keywords, it will look for contextual data such as time, place, and who and how data is generated etc. are used to determine the contextual meaning in the words during the search. Some of the recent and advanced systems are using optimization techniques, particle swarm optimization to make better recommendations.

2. CONSTRUCTION OF THE LEARNING SYSTEM

The most general way of representing the information or knowledge for constructing recommender system is depicted in figure 1.

		Items				
		1	2	3	….	M
	1	4	3	2		1
	2					
	3		5		4	
Users	..			5	1	
	..				5	
	..	4		5	4	2
	N	5			2	2

FIGURE 1. USER (VS) ITEM: USER RATING MATRIX, WHERE EACH CELL REPRESENTING THE RATING OF PARTICULAR USER (U) FOR AN ITEM (I).

Users given a rating and his preferences are represented in a Matrix format, where N users(u) and M items (i). Each cell (u, i) represents the rating given to an item i by the user u. In most of the cases, User matrix is sparse because many of the users won't rate the items. The RS job is to predict rating [1] where the user not rated. In this process, only active users will be considered. The space S of possible items is generally very large [4], ranging in hundreds of thousands or even millions of items in some applications and the user space can also be very large—millions in some cases.

3. BACKGROUND: TRADITIONAL RECOMMENDER SYSTEMS

Have you ever amused how the "Videos you may like" are suggested during your watch on YouTube, how the "mobile applications you may like are recommended to you" when you install applications in Google play store? This feature recommends you based on your browsing history in YouTube, Google play store. These suggestions are more specific to you only, and it may vary from other users based on their interest, usage, and history. Recommender Systems by analysing the past browsing history of the netizens or users of the specific applications in the web or mobile, then the system will perceive suggestions consequently to the users. These systems usually recommend suggestions based on the type of techniques that are implemented by the classification (Figure 2) Recommender Systems.

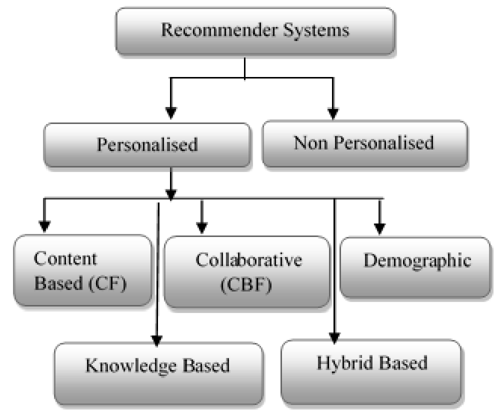

FIGURE 2. CLASSIFICATION OF RECOMMENDER SYSTEMS

Personalised Recommender Systems

For example, Mr. David visits an online e-commerce web store like Flipkart, Amazon, and Myntra to buy a product and performs search operation. Since David is already registered user, the system will first search the previous orders by him and searches the most popular or trending product of the same specifications. An online store with most advanced e-commerce techniques will also be applied to suggest a most personalized item. If the user, adds some products to his cart, then the suggestion engine will consider those products also during the recommendation process. Thus, the system is continuously observing and updating knowledge about the user and his actions and analyse, refine all these things and then recommends personalized suggestions.

The relatively matured concept and techniques of recommender systems in E-commerce can be applied to library database design and implementation to develop personalized recommender system for university students [5].

3.1 Content-Based Filtering (CBF)

Recommendations are based on the content of items rather than other user's opinion. This type of systems will consider the user's profile which is created during the account creation. This information includes user age, gender, location, and his preferences on various things. Usually, during the account creation, the recommender systems will do the basic survey to get this profile information. The system compares the items which are already positively rated by the user and which are the items not rated and which negatively rated and search for the similar choices (Figure 4). Those items which are similar to the positively rated one are recommended. These systems also work with user profile inf which was created at the account cre erally, when a user creating his profile the will make a survey [10] to fetch some more information about a user in order to avoid the cold - start problem.

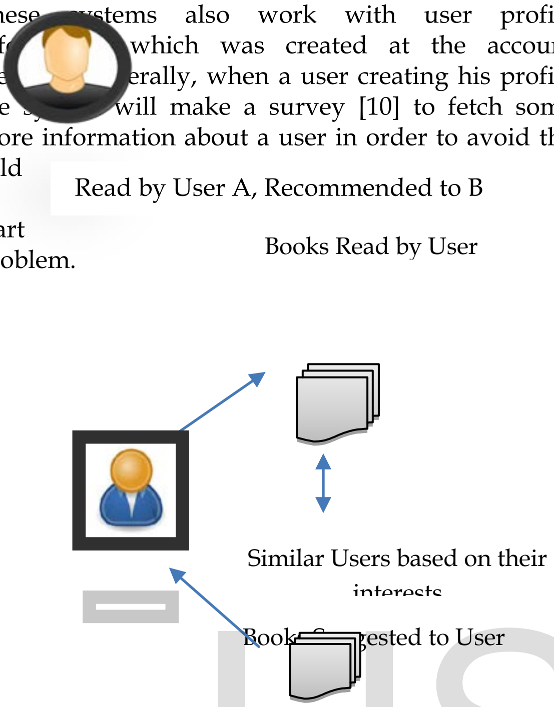

FIGURE 3. CONTENT- BASED RECOMMENDER SYSTEM

The advantage of this type of system is only that particular user's data is enough, and there will be no data scarcity issue. The disadvantage is content analysis is essential to define the item, if more features are available of that particular user, then it takes more time to analyse.

3.2 Collaborative filtering (CF)

The basic idea behind the collaborative system is to find the users who are having the similar preferences and qualities to offer recommendations. It is the main technique for personalized recommendations [18]. The main functionality of CF (figure 4) is to produce personalized suggestions based on the preferences of users. The main idea is to explore the association between users and items based on the rating given by particular users. Basic Assumption is that, the users with similar interests have common preferences. Collaborative filtering approach is mostly used by e-commerce [12] web sites like Amazon, Flipkart etc.

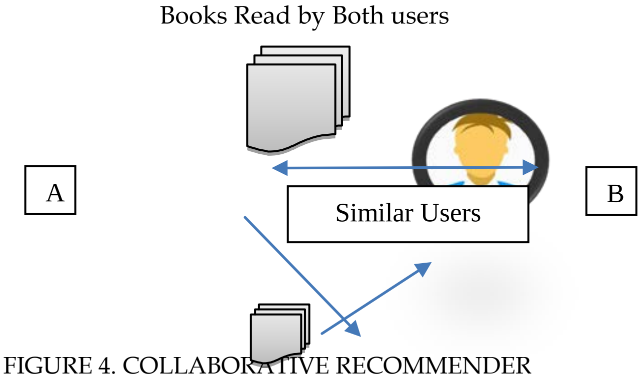

FIGURE 4. COLLABORATIVE RECOMMENDER SYSTEMS

This kind of systems mainly suffers from two issues, one is implicit feedback (user mouse clicks and ordered items) it leads to the problem of scarcity, the second issue is, as these systems follows only linear models. These issues highly influences the learning process [19, 21] and hence it affects the performance of the system [18]. This can also be extended to Web recommendations. A netizens may have heterogeneous information which is generally dynamic nature. This information overload makes it crucial for the netizens to access personalized information that leads to the need for powerful automated web personalization tools for "Web Recommendation" [20 & 23] which is primarily aimed at deriving right information at right time. The recommendation process by combining the user clustering and item clustering with collaborative filtering will give more scalable and more accurate than the traditional one.

3.3 Demographic Filtering Systems

This type of systems uses demographic information such as age, gender, educational qualifications, job status, place etc. of the people for identifying the type of user. In this model, the product features are not at all considered, only the demographic information is used for recommendation process. But, in practice, the process of collecting such information [2] involves the person's acceptance, since the system is collecting personal information, the user may not willing to give because they are much concern about privacy and security.

3.4 Knowledge-based Recommender Systems

This type of systems are applied to specific kind of domain only. For example, buying a flat, land etc. are not frequently purchased by the people so such kind of things have very few ratings. Time is also vital constraint when it comes to technological products.

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These systems essentially use explicit knowledge about the user preferences and contextual information. The below (Table 1.) Illustrates the comparison between these methods, type of input it is taking, strengths and weakness of these methods are listed.

RS Filtering Approach	Prerequisite	Input Data	Process	Strengths & Weakness
Collaborative	Rating from Users U for the Items I	Ratings of the items	it tries to identify users who are similar to the users in U	Weaknesses - Cold Start, Data scarcity, it uses Linear Models to learn about user - item relations Strength: Domain Knowledge is Not Required
Content-Based Filtering	Features of the Items (I)	Ratings of the items	It classifies the items based on the features of the given items.	Weaknesses: More Data is required to get better results. Strength: Implicit Feedback (Users Mouse Clicks)
Demographic	Demographic Attribute values about U and I	Demographic Attribute values about U and I	It explores all the users that are demographically similar to Users U.	Strength: Can be applied to any kind of domain
Knowledge-Based	Features of the items and Knowledge of these items regarding how much extent it gives satisfaction to user needs	Description of the User requirements and his interests	It creates facts and rules like inferences between users and items.	Weakness: User preferences may not be Constant, it may change over the course of time.

TABLE 1. COMPARISON BETWEEN RS METHODS AND THEIR STRENGTHS & WEAKNESSES

3.5 Hybrid Recommender Systems

It uses a combination of Content-Based and Collaborative Filtering [3] and other types of systems. Robin Burke [13] had brought out a taxonomy of hybrid recommender Systems categorizing them. Even though these methods are already applied and implemented in several domains, but still there is a need to upgrade the learning mechanism. The learning mechanism must consider wider set of attributes, and gains knowledge in deeper level. By employing hybrid clustering algorithm for user clustering and supporting active use by a range of rated relevant recommendations [20] will improve the results comparatively. The below is the list of several approaches which are already applied to the learning mechanism:

a. Bayesian networks: This is a type of Probabilistic Graphical Model that can be used to build models from data or from expert's opinion. These type of networks can be applied in various domains like prediction, large patterns, and anomaly patterns and their detection, diagnostics, automated insight, reasoning, time series prediction and decision making under uncertainty. These systems contain probabilistic models representing random variables and conditional dependencies in a Directed Acyclic Graph (DAG). It is a graph which contains directed links and no cycles. These networks are also referred to as Bayes nets, Belief networks and sometimes Causal networks.

b. Association Rules: It is a process to find the frequent patterns, associations, correlations, and casual structures that exist in the given data sets. The main aim is to find the association rules which enable the users to predict the occurrence of a particular item based on the occurrence of another item in the same transaction. That is, there is a chance of occurring of these two items in many transactions. Finding such a kind of rules is referred to as an Association Rule Mining.

c. Clustering*:* It is one of the data mining technique(s) that group the given set of elements or objects into a number of classes. Here, the basic condition is to maximize the similarity among the items of the same class or group. This Data Mining concept can be applied to Learning System of RS. Cluster Analysis is the process of finding "natural" groups based on some similarity measure and objects together [24].

d. Genetic Algorithms: The basic idea is, to get the better output we need to keep on change the input or population. First, we need to define initial population and then define a function that classifies the items based on the properties. It is an optimization technique to find globally acceptable solutions, for that purpose, it performs iteratively which combine the interim solutions. This kind of algorithm is suitable for personalized recommendations.

e. Semantics*:* Semantic web provides a common language that allows data to be shared between applications and allows reusability. In semantic web recommendation approach, the recommendation process is generally based on concept diagram [8].

In general, the information about the users and items are present in the form of textual form in nature. Using keywords and tags, won't give specific meaning and won't improve the efficiency of the recommendation system all the time. Sometimes, keywords may give different meaning in different context, so depending completely on a keyword will not give accurate results. So, the system must understand the semantics and the context where it is being applied.

4. REVIEW OF MODERN RECOMMENDER SYSTEMS APPROACHES AND LATEST FINDINGS

4.1 Context-Aware approach

A context is a dynamic feature of items and filters out the items that do not match the given specific moment of time. The contextual information may include the location of the user, the identity of people, date, and time with am/pm, season, temperature and the environment. Such a kind of information always plays a key role in recommendation process [20-22] and modelling the user behaviour with respect to the given context. This information is useful, because, some people will purchase items only in the evening and during weekends and night time only, in such context this information is more dependable. The system which uses such information for suggesting items/products is termed as Context-Aware Systems. These methods can be divided into Pre-Filtering, post-Filtering and Context Modelling [15]. Pre-Filtering and Post-Filtering methods require supervision and fine-tuning in all steps of recommendation [16]. A context as a dynamic feature of items and filter out the items that do not match a specific context [17]. According to survey by G. Adomavicius and A. Tuzhilin [22] these can be done in three-step process namely pre-filtering, post-filtering and context modeling. Some works [23-24] have applied tree-based partition with matrix factorization.

4.2 Semantic-based approach

Semantic search is a kind of data searching technique in which a search query aims in finding not only keyword matchings' but also essentially determine in which context [14] the user is searching the meanings of the keywords. By default, any search engine is configured to perform a search operation by using tags and keyword. In general, the information about the users and items are present in the form of textual form in nature. Using [17] keywords and tags, won't give specific meaning and won't improve the efficiency of the recommendation system all the time. Sometimes, keywords may give different meaning in different context, so depending completely on a keyword will not give accurate results. So, the system must understand the semantics and the context where it is being applied is a crucial part.

4.3 Cross-Lingual Approach

Due to the rapid development of World Wide Web, the world becomes a global village, anybody can get the access anything from any corner of the world. But, the only hurdle is to language. Different countries will have different native languages [2], so getting recommendations for the items/products which have the information in their own local langue/mother tongue. So, the systems must be developed in such a way to read, analyse understand and suggest users, even the descriptions or ratings are not in their mother tongue or unaware of that specific languages. During the development of recommender systems, if one can able to include semantic approach models and tools like language translators, it is possible to make language-independent systems, so that, such systems can able to handle and overcome the burden and barrier of languages.

4.4 Application of Reinforcement Learning

Recommender systems employee reinforcement learning for product recommendations. It also uses Markov Decision Process (MDP) model for sequential decision problems, which are random in nature. It is widely used in applications where an autonomous agent is influencing its surrounding environment through actions [7] (for example, a navigating robot). An MDP consist of-of four-tuple: (S, A, Rwd, tri) where S is a set of states, A is a set of actions, Rwd is a reward function that assigns a real value to each state/action pair, and tr is the state-transition function, which provides the probability of a transition between every pair of states given each action

4.5 An Ontology-Based Recommender System for Semantic Search Operations

An ontology is an explicit specification of a conceptualization formally represented knowledge. Ontology is a systematic account of Existence [9]. These are one of the basis of the Semantic Web. They can also be used to share knowledge like the structure of the web, domain knowledge, and any explicit information. Ontologies help to extend RS to a multi-class environment and thus allow knowledge-based approaches. Semantic search, Contextual approach combined together and called as Ontology-based Search or Logic approach is the one of the newest. In general it is consider two major attributes namely Precision and Recall as measures indices for information filtering and retrieval purpose and then used for evaluating prototype results to improve the search process.

5. DISCUSSION

In this survey y, many articles regarding recommender systems were studied. These articles carefully analysed and classified on the basis of recommendation type, application area, type of data mining technique used, accuracy and performance measures. This analysis reveals various notable information.

i. Recommendation Approaches: CB filtering systems suggest items based on the previously ordered or purchased items. Items with a high degree of similarity with the user profile and preferences will be suggested as recommendations. On the other hand, CF works based on the preferences of like-minded people's interests. This filtering system further can be classified as user based and item based approach. In user-based filtering, a user will get the recommendation from the items which are liked by likeminded user's preferences. On the other hand, Item-based approach, the user will get the details based on the purchases of likeminded people. In both cases, only active users will be considered in the recommendation process. These Active users will be selected based on weighted average of the ratings by the users. If only a few ratings are considered then it leads to scarcity.

ii. Recommender Systems Domain*:* Survey reveals that recommender systems are been applied in several domains like E-commerce (online stores), entertainment, various social forums, social networking sites, on discussion platforms etc. In real-world applications, dynamic and real-time recommendations always play a vital role. It is important to note that, these systems play a key and prominent role in next-generation recommender systems, in domains like farming, government policies, academic institutions, and universities.

iii. Data Mining Techniques:

Clustering, Collaborative Filtering's matrix factorization, KNN have widely used data mining techniques in implementing the RS.

Classification and Clustering are very simple techniques and adaptable to many datasets [21]. Matrix Factorization [19] is a process used to find the feature association between users and items. It is an approach that complex matrix operations are simplified and perform an operation on decomposed matrices. Widely used methods are LU and QR matrix decomposition. The issue with MF is, it reduces dimensions, which inevitably results in loss of user-item interactions. KNN is the best method to collect user ratings, user activities, user information from various social networking sites.

iv. Recommendation Types: Generally recommendations by the system is based on the user's profile and considering his history. For instance, the online store uses User & Item relation to analyse the user's interest on what type of items he purchasing frequently. The interaction between user and item can be either implicit or explicit too. Recommender system can also be implemented in other domains like academics, farming related things like crops recommendations, medical domain. To sum up the whole story, the type of interactions possible are includes, user to items, user to user, items to tags or keywords, user to tags are possible.

RS can also be applied in Online Forums like Quora, Askme, and Yahoo. Usually, these forums are the best place to share the knowledge by posting the questions and different opinions, due to the increase in posting number of questions and opinions at the same time it degrades the performance. This problem leads to the development of recommender systems to find the respondents from a range of expert users based on his or her own knowledge.

V. Analysing the Performance: The recommendations given by system can be evaluated by a variety of metrics to measure the efficiency of the system. The most frequent measures in any domain include time complexity and memory complexity. Time requirement implies the amount of time it is taking to generate suggestions and memory requirement implies, the amount of memory it consumes to perform required operations for generating predictions and recommendations. In the survey, it is noticed that precision and recall are considered as evaluation metrics. Precision means it is the efficiency of the relevant items which are recommended by the system.

6. POTENTIAL CHALLENGES

i. Cold-Start

It is of two types, cold start of new items and new users. Cold start problem for an item occurs when we don't have enough previous ratings [2] related to that item. It is a challenging task to suggest items to new users since the system don't have any historical information related to that particular user and his profile is empty and not rated anytime yet.

ii. Scalability

As the numbers of users and items raise more and more, the system essentially require sufficient physical resources in order to give the most accurate recommendations. When the load is more on the system, accordingly the system resources are needed to increase, if not the efficiency and performance will drastically fall down. The basic solution is to increase physical resources [2] of the system to handle new items and users at the same level.

iii. Scarcity

This kind of problem occurs due to lack of enough information [2]. For example, few products purchased by users through an online store like Amazon and gave ratings to only a few of the items. Such kind of circumstances will lead Scarcity problem.

iv. Static

As the users preferences will change dynamically it is very difficult to reflect the user's preferences in real-world scenario. RS may deal with single criteria ratings and the methods are inflexible since they are "hard-wired" into the systems by the vendors. Many systems are intrusive in nature, i.e., they require explicit feedback from the user and significant level of user involvement. It is impractical to elicit many ratings from the user.

7. CONCLUSION

Recommender Systems are already developed and applied in various domains and made a significant impact in the real world. CBF and CF techniques are the basic approaches to all the existing systems. In this survey, the following are noticed, many more advanced approaches like Context-Aware, Semantic-based, Cross-Lingual , Reinforcement Learning and deep Reinforcement are being developed and are more effective, accurate and efficient than existing approaches can be applied to a broader range of domains as well. Contextual, Semantic and Cross-Lingual approaches can be made as an integral part of RS so that these systems will accelerate and polished suggestions. In this paper, various challenges and limitations are also discussed. These systems are not limited to only computers and mobile devices, but we can apply it to various other domains like medical, education, farming, government policies and to create expert recommender systems for day to day activities as well. This leads to the development of more domain-specific recommendation systems. Statistical, machine learning, information retrieval, and other techniques that have made a significant effect in the process of advanced state-of-the-art recommender systems in comparison to early recommender systems. All these advanced state of the art techniques will help us to research and encourage us to develop more advanced Recommender Systems.

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