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## COMPARATIVE STUDY OF CONVENTIONAL AND RECIPROCAL RECOMMENDATION **SYSTEM**

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Abstract: Recommendation systems provide an intelligent way to navigate through an ocean of options available at users' disposal and present information that they perceive to be useful and worth trying out. Recommender Systems (RS) are assistance in the form of software, tools or algorithms that may guide a target user in making decision by proposing him recommendations based on his interests. In conventional recommendation system we have active elements on one side (Person) and passive elements in others side (Products). Success is determined by only one side (user-side) who is seeking recommendation, but the other way is not possible. Reciprocal recommendation is a special case of recommendation system where both sides we have active participants (people) and their mutual agreement is mandatory for a successful relation. Many social websites' core task is to recommend people to people.

The objective of this article is to do a comparative study of conventional and reciprocal recommendation system and study the domain of applications and the approaches used for the implementation in the recommendation system.

Keywords - recommendation system, conventional recommendation system, reciprocal recommendation system

#### 1. INTRODUCTION

In the digital age, users are presented with plethora of options to choose from. To direct a user, recommender frameworks are a way to battle this data over-burden and provide suggestions to users, customized to their preference and profile. Availability of users' data has elevated the need of development of technologies to analyze and extract useful information. A typical example of this trend is personalized recommendation system. In the last few years, the growth of various platform controlling high volumes of user profiles information has expanded the use of recommender system. Recommender Systems are assistance in the form of software, tools or algorithms that may guide a target user in making decision by proposing him recommendations based on his interests [1]. Recommendation system has found applications in almost every e-commerce website. Reciprocal recommendation is a special case of recommendation system where both sides we have active participants (people) and their mutual agreement is mandatory for a successful relation. Users' interest is the pivot in any reciprocal recommendation system.

#### 1.1. Recommendation System

Pizatto et. al. [2] defined that recommender systems are assistance in the form of software, tools or algorithms that may guide a target user in making decision by proposing him recommendations based on his interests. A recommendation system is a subclass of information filtering system whose objective is to predict the preference of a user. It is one of the most popular applications of machine learning technologies.

## 1.2. Reciprocal Recommendation

The concept of reciprocal recommendation was first coined by Pizzato et al. [2] who applied it in the domain of Online-dating. Most of the people-to-people recommendations, especially the 1-to-1, which aimed at creating relationships, are reciprocal wherein both parties are free to express their likes-dislikes. Under a reciprocal recommender, both the user and the item represent people. People on both sides of the recommendation system have equal weightage, wherein preferences of both must be satisfied. Many social websites' core task is to recommend people to people. Various level of matching such as person to person in online dating websites, job applicants with employers and mentors with mentees are nothing but examples of such recommendations.

#### APPROACHES FOR RECOMMENDATION SYSTEM

There are many criteria which differentiate recommenders from one-another. But the techniques like content-based, collaborative-filtering, hybrid, etc used to generate the recommendations, are most common to distinguish between them. Let's deep dive into the details of the approaches most used.

#### • Content-based (CB):

In Content-based approach, the recommendation is mainly based on the content of the users' profile and his preferences explicitly specified. Principally, comparison is done between user profile and candidate items in order to discover the items to be recommended. Items are generally represented by an attribute set together with their weight which denotes its relevance [1]. Users' preferences and values of the attributes are considered for computational approaches. In the fuzzy base model of Online Indian Matchmaking system (OIMS), a person is given recommendations based solely on his profile content where he explicitly specifies the qualities that he is looking for in his desired partner.

But, the major issue with the content-based recommender system is that it suffers from overspecialization. Hence, it recommends only those items which are very similar to those that the user already knows.

#### • Collaborative Filtering (CF):

It is the most popularly used approach for implicit feedback recommender system which is based on inter-user comparison. It gives recommendations based on similar users' taste and interest. It believes that if a given user agrees with some other users in the past then in future also the recommendation coming from these users will be relevant and useful for the given user. It uses the known preferences of a group of similar users to determine the unknown preferences of a given user. Collaborative filtering technique can be classified as user-based and item-based. In the user-based approach, only those items are being recommended to a user which is liked by similar users. While in the item-based approach, those items are being recommended which are similar to items being liked by the user in the past. Collaborative filtering systems are generally classified into either memory-based or model-based approaches. However, scalability and sparsity are two major problem in this technique.

#### Community-based recommender systems:

This type of system recommends items based on the preferences of the user's friends. This approach follows the principle according to which people tend to rely more on recommendations from their friends than on recommendations from similar but anonymous individuals.

#### Demographic recommender systems:

This type of system recommends items based on the demographic profile of the user. The assumption is that different recommendations should be generated for different demographic niches. An example of demographic recommender at work could be the display of ads to users depending on the country they are accessing the system or the language they are speaking.

#### • Knowledge Based (KB) recommender system:

Knowledge-based systems recommend items based on specific domain knowledge about how certain item features meet users' needs and preferences and, ultimately, how the item is useful for the user. In such systems a similarity function estimates how much the user needs (problem description) match the recommendations (solutions of the problem).

#### Hybrid approach:

The popular hybrid approaches are solution to the problems of collaborative and content-based systems. Since both content-based method and collaborative approach have some shortcomings, a mixed approach is used. Even a very good recommender system is incapable of addressing the diverse needs of its heterogeneous users. Hybrid recommendation algorithms finds its most important application in solving the cold-start problem [3] by integrating the content and collaborative data so that even a new user which has never got rating before, can be recommended. In a similar fashion, a new user who has not given rating can also get recommendation.

Hybridization can be done by methods like weighting, switching, mixed, cascading, feature combination etc. Nowadays, the sources of information are very diverse in nature, hence more emphasis is given on hybrid recommender system as they have the ability to integrate information from heterogeneous sources.

## 3. COMPARATIVE STUDY OF APPLICATIONS OF CONVENTIONAL AND RECIPROCAL RECOMMENDATION

#### 3.1 Applications of Conventional

There are many applications which are based on the traditional recommendation system. We will present some key applications from various domain which uses conventional recommendation system.

## • E-governance Recommendation Systems

Electronic government (e-government) refers to the use of the Internet and other information and communication technologies to support governments in providing improved information and services to citizens and businesses. The rapid growth of e-government has caused information overload, leaving businesses and citizens unable to make effective choices from the range of information to which they are exposed, hamper the effectiveness of e-government services, and difficulties in locating the right information for the right users will increasingly impact on the loyalty of users.

Various applications of e-government recommender systems, in particular e-government Web interface personalization and adaptation and e-government service recommendation is available, which include government-to-citizen (G2C) and government-to-business (G2B) services.

To support government to effectively recommend the proper business partners (e.g., international buyers, agents, distributors, and retailers) to individual businesses (e.g., exporters), a recommender system called BizSeeker [7] was developed. Business users can obtain a recommendation list of potential business partners from BizSeeker.

## • E-business Recommendation Systems

Many recommender systems have been developed for e-business applications. Some systems focus on recommendations generated to individual customers, which are business-to-consumer (B2C) systems, while others aim to provide recommendations about products and services to business users, which are business-to-business (B2B) systems. E-commerce/e-shopping recommender systems refer to recommender systems for B2C applications.

To help catalog administrators in B2B marketplaces maintain up-to-date product databases, an ontology-based product-recommender system was presented [8] in which keyword-based, ontology and Bayesian belief network techniques are used to generate recommendations.

To help business user's selected trusted online auction sellers, a recommender system was designed [9] in which trading relationships are used to calculate the level of recommendations. Recommender systems were also applied in digital ecosystems where agents negotiate services on behalf of a number of small companies [10].

To build stable digital business ecosystems by means of improved collective intelligence, a model of negotiation-style dynamics from the point of view of computational ecology was introduced in [10], which inspires an ecosystem monitor and a novel negotiation-style recommender.

#### • E-commerce/E-shopping recommender systems

In the last few years, a number of unique e-shopping recommender systems have been developed to provide guidelines to online individual customers. E-shopping is a specialized and highly popular field of e-commerce.

Amazon and eBay: Many of the largest commerce websites, such as Amazon and eBay, already use recommender systems to help their customers find products to purchase . In these B2C e-commerce websites, products can be recommended based on the top overall sellers, customer demographics, or an analysis of the past buying behavior of the customer as a prediction for future buying behavior.

The wasabi personal shopper: a case-based recommender system [11] is a domain-independent database browsing tool designed for online information access, particularly for electronic product catalogs. Fuzzy techniques are also employed in CB e-shopping recommender systems; for example, Cao and Li [12] developed a fuzzy-based recommender system for products made up of different components.

Mobile-based recommender systems: With the increasing use of mobile phones and the advances in wireless networks, recommender systems are not only available for Web users but are also being provided to mobile users as mobile-based recommender systems. Lawrence et al. [13] designed a mobile personalized recommender system to suggest new products to supermarket shoppers, who use Personal Digital Assistants (PDAs) to compose and transmit their orders to the store where they are assembled for subsequent pickup.

#### • E-library Recommendation Systems

Digital libraries are collections of digital materials, and services delivered to user. In e-library application recommender systems are very useful for the selection of digital material and information.

Fab, part of the Stanford University Digital Library Project, was reported [15]. It is a hybrid recommender system which combines both the CB and CF recommendation techniques.

To provide better personalized e-library services, a system called CYCLADES (http://www.ercim.org/cyclades), was presented [16]. CYCLADES provides an integrated environment for individual users and group users (communities) in a highly personalized and flexible way. The recommendation algorithms rely on both personalized information organization and users' opinions and use CB and CF methods separately and in combination.

Porcel et al. [14] researched and developed a recommender system to recommend research resources in University Digital Libraries (UDL A fuzzy linguistic recommender system was proposed in which multi-granular Fuzzy Linguistic Modeling (FLM) was used to represent and handle flexible information by means of linguistic labels, and a hybrid recommender system that combines both CB and CF approaches was presented.

#### • E-learning Recommendation Systems

This type of recommender system usually aims to assist learners to choose the courses, subjects and learning materials that interest them, as well as their learning activities (such as in-class lecture or online study group discussion)

Zaiane [17] proposed an approach to build a software agent that uses data mining techniques such as association rule mining to construct a model that represents online user behaviors, and used this model to suggest activities or shortcuts. The suggestions generated assist learners to better navigate online material by finding relevant resources more quickly using the recommended shortcuts.

Lu [18] suggested a personalized e-learning material recommender system (PLRS). Once a learning material database or a learning activity database is created and a learner's registration information is obtained by the system, the PLRS uses a computational analysis model to identify an individual's learning requirement and then uses matching rules to generate a recommendation of learning materials (or activities) for the learner.

A recommender system prototype module designed for integration into a commercial adaptive e-learning system called IWT [19] and a recommendation methodology was defined to recommend learning goals and generate learning experiences for learners. The recommendation methodology applies a hybrid recommendation approach which consists of three steps: concept mapping, concept utility estimation and upper level learning goals (ULLG) utility estimation.

#### • E-tourism Recommendation Systems

E-tourism recommender systems are designed to provide suggestions for tourists. Some systems focus on attractions and destinations, while others offer tour plans that include transportation, restaurants and accommodation.

A recommender system called Entrée to recommend restaurants based on KB approaches was proposed by Burke et al. [20]. The knowledge was collected from users and retrieved by Entrée to find similar choices by refining such search criteria as price and taste. By combining Content Filtering into Knowledge Based a better Entrée recommendation system was developed by Burke [6] in which assessments of users also became criteria.

A context-aware recommender system, CATIS [21] was developed to recommends tourist accommodation, restaurants and attractions. The context is dynamically collected by a context manager. A collection of Web services provided by an application server is used to gather user context information. The recommendations are generated by combining the user query and the user context information from the application server.

A mobile-based recommender system called SMARTMUSEUM [22], suggests users with recommendations for sites and objects on those sites on their mobile phones. In this system, an ontology-based personalization, annotation, and information filtering framework was developed.

## 3.2 Applications of Reciprocal Recommendation System

#### • Online Indian Matchmaking System (OIMS)

Web-based dating sites have nowadays become very popular and important platforms for people to look for partners for numerous benefits that it provides [4]. Unlike traditional user-item recommendations where the system is tailored to the need of just one side or party for matching items (e.g., books, products, etc.) with user's interests and likeness, the aim of recommendation system for online dating is to match people whose interests mutually coincide in and hence likely to communicate with each other. In this section a detailed study has been done on this class of recommenders in the field of online matchmaking system.

Marital sites are progressively transforming into a superior alternative for the new era in their search for potential mates. The result is positively large as it gives a worldwide selection of lakhs of individuals cutting crosswise over age, professions, religions, and groups. The intelligence, openness and thus adequacy of the online medium make it a favoured medium for finding a life partner.

An iterative framework is proposed for reciprocal recommendation to help users to shortlist marriage partners according to his preferences.

In OIMS, the main objective is to find a partner, for which one user is being recommended to a different user having common interests and matching preferences. Any proposal given in an internet-based matchmaking situation should consider the priorities and requirements of both the parties before being referred to each other. One person initiates communication based on his priorities, but the success depends on the likeness of the opposite party as well. Unless both the parties show interest in each-other a successful relationship can't be built.

A major contribution by Pizzato et al. [2] is that they developed the techniques RECON [4]. Another major contribution in techniques was CCR [23]. Koprinska and Yacef [5] gives a detailed insight into the characteristics of Reciprocal recommendation. Several recommenders designed for online dating based on collaborative filtering methods, but the proposed method did not use the profile information of a candidate and his ideal partner such as his age, occupation etc. which must be used for generating efficient recommendations. To overcome this issue, content-based recommendation system was used [24]. But it was noted that the user's actual behaviour was contrary to explicit information that they had provided. Although this was not intentional but happens due to lack of self-understanding, craving for better option or compromising on their preferences if they find some more promising / exciting options.

To overcome this problem Pizzato et al. [25] captured users' implicit behavior to provide recommendation. Alanazi et al. [24] introduced a model for person-to-person recommendations using Hidden Markov Model which easily collects the temporal changes of users' actions and thus produces better customized suggestions based on the users' behavior.

Zenebe and Norcio [26] has introduced similarity measures, namely interest similarity and attractiveness similarity, to compute the compatibility score. Interest similarity refers to similarity between two people who have send messages to the same users. Attractiveness similarity refers to similarity between two persons who have received message from same users.

Kim et al. [3] proposed content-boosted recommender for web-based dating. Their main emphasis was to handle problem of cold-start users.

Wayne et al. [27] have used collaborative filtering for deploying a model for online dating and used decision trees to overcome the problem of favoring popular users which is a major issue with collaborative methods.

PMI-IR [28] is a simple unsupervised learning algorithm for identifying synonyms which uses Pointwise Mutual Information and information retrieval to measure the similarity of pair of words and uses a large source of data; i.e.; world wide web. A second famous approach is Latent Semantic Analysis (LSA) [29] which uses Singular Value Decomposition (SVD) to find the semantic representation of words. Islam and Inkpen [30] proposed Second Order Co-occurrence PMI (SOC-PMI) which makes use of Pointwise Mutual Information to arrange the set of significant neighbor words of the two selected words.

Online Indian Matrimonial system plays a vital role in suggesting life partners and is being relied by millions of Indians globally.

### • Reciprocal Recommendation Process in Job Recommendation system

In this digital era, most people use internet to find jobs. But due to presence of large number of jobs being posted online, it becomes a complicated task to shortlist the right ones. According to a report by International Association of Employment Web Sites, there are more than 60,000 employment sites which are busy catering to job seekers, employers and recruiters worldwide. Reasons for the excessive use of online resources are pretty evident. Not only it facilitates extended reach and in turn attracts a larger number of individuals, but also enables faster processing as well as tracking of greater number of applications that too, more cost-effectively. Thus, it has greatly affected the way companies hire candidates.

With reference to job recommendation system (asymmetric system), it helps jobseeker to give job recommendation suiting his profile and his preferences and also generates recommendations (suitable candidates) for recruiter that are in accordance with the requirement of jobs being posted by him.

Rafter and Smyth [31] proposed the first Job recommendation system. First reciprocal recommender for recruitment was proposed by Malinowski et al. [32] whose research in the field of Job recommendation system emphasizes on the need of reciprocity. They constructed two recommenders. The objective of the first one was to recommend job seekers (i.e. their résumés/profiles) to job opening of a particular employer/recruiter. The second part of the framework recommended job openings to job seekers. The two recommender systems were assessed separately and demonstrated satisfactory prediction accuracy outputs. But the major drawback was that the recommendation was totally based on explicit preferences and the users' explicit preference was expressed in binary form. The degree of preferences of a user for each attribute was not measured hence efficiency was not high.

Hongtao et al. [33] gave a reciprocal recommendation methodology for the field of recruitment and gave the calculation method of users' preference and the measurement method of similarity. The proposed algorithm combines benefits of both the explicit preference and implicit preference of user and can find the users characteristic and interest much more accurately. But the drawback is that they have not considered his personal information like his marital status, kids/dependent and current location in the process of recommendation. From practical point of view of a user, these parameters play very important role in assessing any job.

Paparrizos et al. [34] used CB approach to predict the next job of a job-seeker completely based on his profile information. Musale et al. [35] proposed job recommendation for campus placement using only CB approach. Yuan et al. [36] used deep-learning approach to design a model for job-recommendation. Shalaby et al. [37] used graph-based approach to overcome the problem of sparsity and scalability in Job recommendation system.

#### 4. CONCLUSION

Recommender Systems (RS) are assistance in the form of software, tools or algorithms that may guide a target user in making decision by proposing him recommendations based on his interests. Various application and approaches have been analysed in a domain like e-commerce, e-Learning, e-Governance, Tourism etc. The dominant model for such recommendation system is to

provide a user with recommendations of items likely to be of interest to the user. Following are important findings of conventional recommender systems

- The typical recommendation approaches, such as CF, CB and KB, still play a dominant role in almost all kinds of application, but hybrid recommender systems are more popular than single recommendation technique-based systems for avoiding the drawbacks of individual recommendation approaches
- e-learning recommender systems have highly applied knowledge-based methods,
- e-resource recommendation systems use more CF methods;
- Some new recommendation techniques, such as the social network-based recommender system and context awarenessbased recommender system, have played an increasingly important role in recent application developments;
- Hybrid recommender systems are more popular than single recommendation technique-based systems for avoiding the drawbacks of individual recommendation approaches

Several societal services including like match making, online dating, social media networking, Job recruitment, mainly trying to match people of having same mindset. The success of these services and the user experience with them often depends on their ability to match users. Reciprocal Recommender Systems (RRS) arose to facilitate this process by identifying users who are a potential match for each other, based on information provided by them. These systems are inherently more complex than user-item recommendation approaches and unidirectional user recommendation services, since they need to take into account both users' preferences towards each other in the recommendation process. This entails not only predicting accurate preference estimates as classical recommenders do, but also defining adequate fusion processes for aggregating user-to-user preferential information. This comparative study has presented a snapshot analysis of the extant literature to summarize the state-of-the-art reciprocal recommendation system research to date, focusing on the fundamental features that differentiate it from other conventional recommender systems.

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