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A survey on recommendation system

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Abstract: *In this paper, we give a brief introduction about recommendation systems, components of recommendation systems i.e. items, users and user-item matching algorithms, various approaches of recommendation systems i.e. Collaborative filtering (people-to-people correlation) approach, Content-based recommendation approach, Demographic recommendation approach, Social network-based recommendation approach, Hybrid recommendation approach and Context-based recommendation approach, We also explain various application areas of recommendation systems (e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services) and challenges.*
Keywords: *Applications, approaches, challenges, Content, context, collaborative filtering, demographic and hybrid based recommendation.*

I. Introduction

The fast growth and diversity of information available on the internet and development of various e-commerce services frequently overwhelmed users, leading them not to take right decisions [1]. The availability of huge number of options instead providing benefit, starts decreasing users' well-being known as the [3] Paradox of Choice (Schwartz, 2009). Recently, recommendation system has proved itself to be a valuable means because of their ability to present right items to the right users. Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user [1, 2]. The suggestions relate to various decision-making processes, such as what items to buy, what music to listen to, or what online news to read.

Recommendation system is the system that is capable of analysing user visits and by analysing these visits produces suitable suggestions to him/her in the future. Suggestions are basically the similar results that are supposed to be the match of the users taste. They help the users to take decisions. Basically, they reduce the overload of the data. Recommendations can be personal if it the system capturing the interest of a single user and based on his/her taste provides suggestion to him/her. These are personal in the sense that they are not same to every user. And if the recommendation system captures the interest of the large user set and then starts making suggestion to users like due to popularity of some item or product from the wide range of users. These types of recommendations are said to be public recommendations or impersonal recommendations [1, 4].

By the definition of the recommendation system it is clear that there would be something that captures users behaviour and by analysing that behaviour it would results in future predictions. The thing that provides this capability to a these system is said to be "user modeling" or "user profile". User profile or user modeling is the basic unit of every kind of recommendation system [4]. The system stores information about the user's behaviour into the user profile. The information is about user's most frequent visits, top searches etc.

II. Background

Recommendation system development started from simple observations of day to day life. Individuals often depend on suggestions given by others [1]. For example an individual commonly rely on what his friend suggest when selecting a novel to read; when selecting a movie to watch individuals rely on movie reviews or when a friend recommends song to listen; In arrange marriages also a family person suggests a suitable match. Therefore for mimicking this behaviour in software, recommendation systems were developed. According to Joseph Huttner (2009) The first recommender system, Tapestry, was developed at the Xerox Palo Alto Research Centre and is described in a 1992 issue of the Communications of the ACM9 [5]. The motivation for Tapestry was rapid use of electronic mail, which resulted in "users being inundated by a huge stream of incoming documents". Following Tapestry's lead, Amazon's first thought in constructing a recommender system was that based on the active user's buying history, the recommender system would find other users with similar buying patterns, and then recommend those other users' highly-rated items. Formally, this is called user-to-user collaborative filtering - "user-to-user" because users are matched to one another and "collaborative filtering" because the algorithm relies on historical purchasing data to determine which users are similar.

III. Components In Recommendation System

Mostly any recommendation system composed of 3 major components [6] i.e. users (users of the recommendation system which may have different goals and characteristics), items (items are the objects that are recommended to the users or the information that is used for recommending relevant items) and user-item matching algorithms (information retrieval techniques that help in finding relevant items for relevant users).

3.1 Items

The information that is used by the recommender system for recommending right items to a user is considered as item. But mostly items are the final results that are proposed to the user. These final results can have positive value or negative value for a user [1]. Positive value depicts that the item is of user's interest and if the item is not of user's interest than its value is considered as negative. Moreover, whenever a user is consuming any item than it not only involves monetary cost but also the cognitive cost i.e. the effort in finding the item [1]. Hence, recommender systems should reduce the cognitive cost for the item.

Example: In case of music recommendation system, Items defines all the basic information that is used in MIR (music information retrieval) [6, 13]. In 2005, Pachet described the music metadata into three class i.e. editorial metadata (the cover name, composer, title, or genre etc.), cultural metadata (Similarity between music items) and acoustic metadata (Beat, tempo, pitch, instrument, mood etc.) [7]. Here, we can say that recommendation system uses the properties and features (title, genre, beat, tempo, instrument etc. in above example) of the item (i.e. music) for recommendation.

3.2 Users

Users of the recommendation system (as mentioned above), which may have different goals and characteristics. A good recommender system should meet various user requirements. Recommendation system exploits information about the user for meet user requirements using various recommendation techniques [1]. However, gathering user information is expensive task. Expensive in terms of both effort, cost. User profile or user modeling is the core unit of any recommendation system [4]. The system stores information about the user's behaviour in user profile. The information is about user's most frequent visits, top searches, age, location etc. User modeling depicts the difference in the user profile.

Example: User Profile Modeling [6, 8] Celma suggested that the user profile can be categorized into three domains: demographic, geographic, and psychographic. Demographic features contain information about Age, marital status, gender etc. Geographic features contain information about Location, city, country etc. Psychographic features contain information about Stable and fluid attributes. Stable attribute are life longer like interests, lifestyle, personality etc. whereas Fluid attributes are for short time period like mood, attitude, opinions etc.

3.3 User-item matching algorithms

In order to perform its core function i.e. identifying the relevant items for the user, a recommendation system must predict that an item is worthy to recommend [1]. So to do this, the system must be able to find out the utility of some of the items, or make comparisons of the utilities of the items, and then decide what items to recommend based on these comparisons. There are different types of recommendation approaches exist that we will explain in the next section.

IV. Approaches In Recommendation System

There are various types of techniques that are followed by recommenders based on their domains or requirements. Most popular of these are collaborative recommendations or community based recommendations, content based recommendations, knowledge based recommendations and hybrid recommendations techniques.

4.1 Collaborative filtering-based recommendation approach

It is the most famous and highly implemented technique in recommendation system. Collaborative filtering has another famous name known as "people-to-people correlation" [1]. As the name itself specifies that it involves collaboration of people that help in recommendation. Collaborating filtering-based systems find similar users whose previous history strongly correlates with the active user [4]. Active user is the present user whom the system will provide recommendation. Similar users are the users who have common taste or similar purchase history as that of the active user [4].

4.1.1 Cold-Start problem

For this approach, it is necessary to have sufficient information, such as user ratings and reviews. But sometimes due to lack of such information a major problem comes known as "Cold-Start problem" [11]. It is due to the existence of new user or new item that does not have any previous history. In such cases, recommendation system cannot provide accurate recommendation as there is not enough information available to analyze.

4.1.2 Popularity-bias

One more limitation of collaborative filtering approach based recommendation systems is “popularity-bias”. [8, 11] This problem arose from the Long Tail phenomenon (Anderson, 2008), which states that maximum number of the users consume very few but famous items while few number of users consume less famous items. Since collaborative filtering depends on the preferences of the people to generate recommendations, it leads to poor diversity of recommended items (as mostly people prefer to consume only famous items). [11] E.g. Celma showed that the music industry follows the long tail phenomenon (Celma & Cano, 2008).

4.2 Content-based recommendation approach

In this approach, system analyses the user previous actions (items that the user visits in the past). [1] Recommendation system recommends the items that the user liked in the past. The similarity of the items is calculated based on the features associated with the compared items. Hence, the name content, as the content of the item is the criteria to find similar item that will be recommended by the system. [6, 12] For example in case of music recommendation systems the content associated with the music is editorial information (genre, artist, title etc.), acoustic metadata (Beat, tempo, pitch, instrument, mood etc.). Unlike collaborative filtering approach, content based do not have problem of cold-start and popularity-bias.

4.3 Demographic recommendation approach

In this approach, recommendations are generated on the basis of user demographic profile [1]. Demographic profile contains the demographic information about the user. The information is about user’s age, gender, job area, nationalities, language, region etc. It is assumed that different demographic niches would obtain different recommendations [1]. For example many website provide customized suggestions according to a user’s age.

4.4 Social network-based recommendation techniques

Drastic development of social networking tools on the internet leads to the usage of social networking analysis in recommender systems. Recommendation systems helps in providing ability to make user busy with other users through social interactions like online friends, group chats etc. hence making user experience more interactive [9]. To generate recommendations users social ties are used [9]. It helps in the cases when there is data sparse problem generally in collaborative filtering approach. Trust factor is considered very important in this approach [9]. Trust depicts an initiative suggestion of one user to another. It tells how well a user trust on another user regarding some item or taste. Trust and user similarity has positive correlation in online communities. Many researchers did various studies on integrating trust into recommendation systems. Trust-based approaches provide increase generation of recommendations with accuracy. However, there are various other alternatives used for filtering and user preference prediction other than trust like “co-authorship” relation, physical context, social tags, and social bookmarks [9].

4.5 Hybrid recommender systems

In this approach, recommendations are generated by the combination of above mentioned techniques. Its aim is to exploits the advantage of each one of these techniques [1]. For example, collaborative filtering approach have disadvantage of cold start problem (due to the introduction of new items as they have no ratings) but in content based approach items are recommended on the basis of item description which is easily available. Hybrid system helps to increase the overall performance of the system.

4.6 Context aware recommendation systems

All the above recommendation systems approaches models only long-term preferences of the users and none of them consider short-term preferences [11]. Traditional recommendation systems do not take into account user situation. Context is a multifaceted concept that has been studied across different research disciplines (computer science, cognitive science, linguistics, philosophy, psychology) [1]. Since context has been studied in multiple disciplines, each discipline tends to take its own idiosyncratic view that is somewhat different from other disciplines and is more specific than the standard generic dictionary definition of context as “conditions or circumstances which affect something”[1]. Context aware recommendation system is a rising technique in the field of recommendation system that generates recommendations by take into account user short-term preferences by using information of different contexts. Context aware recommendation systems explored different context information, such as region, time, emotional state, physiological state, running pace, weather etc. For example, Many music recommendation systems have been developed that takes contextual information like text [11], daily activities [10] etc. to provide accurate recommendations.

V. Application Area Of Recommendation System

5.1 E-government recommendation systems

The fast growth of e-government services leads to information overload causes businesses and citizens taking poor choices [9]. Recommendation systems address this problem. E-government recommendation system includes government-to-citizen, government-to-business services.

5.1.1 Government-to-citizen service recommendation

To support citizens in their access to personalized and adapted services supplied by public administration offices, a multi-agent system was presented by De Meo et al. [14].

5.1.2 Government-to-business service recommendation

A recommender system called Smart Trade Exhibition Finder developed which recommends suitable trade exhibitions to businesses [9].

5.2 E-business recommendation systems

There are many recommendation systems that have been developed for e-business applications. Some system provides recommendations to individual customers known as business to consumer system. There are other recommendation system also exist that provide recommendations about products and services to business users, which are business to business systems [9]. A telecom recommendation system is there to support telecom companies in recommending suitable products and services to their business and individual customers [9].

5.3 E-commerce/e-shopping recommendation systems

In the last few years, there are many recommendation systems that have been developed to provide support to online individual customers [9]. E-shopping is a highly popular field of e-commerce. The largest e-commerce websites, such as Amazon and eBay also uses recommender systems.

5.4 E-library recommendation systems

There are many recommendation systems that have been developed in digital library applications to help users find and select information and knowledge sources [9]. To provide better personalized e-library services, a system called CYCLADES was developed [9]. Porcel et al. developed a recommender system to recommend research resources in University Digital Libraries [15]. The hybrid Recommendation approach is commonly used in the e-library recommendation systems.

5.5 E-learning recommendation systems

This type of recommendation 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) [9]. Many e-learning recommendation systems have been developed from past ten years. E.g. A personalized e-learning material recommender system was proposed in the work of Lu [16].

5.6 E-tourism recommendation systems

E-tourism recommender systems are designed to provide suggestions for tourists for transportation, restaurants and accommodation [9].

5.7 E-resource service recommendation systems

Typical applications of recommender systems in resource services are Tag, TV program, webpage, news, document, video, music, and movie recommendation [9].

VI. Challenges

There are many challenges in the field of recommendation systems here we are explaining some of the challenges are:

6.1 Algorithms scalability with big and real-world datasets

As the research in the development of recommendation system is growing day by day, a major issue comes into existence is how to implement recommendation techniques in real world systems and how to solve the problem of large and dynamic datasets. Sometimes an algorithm works well when tested offline on small dataset but becomes inefficient when used on large real world datasets [1].

6.2 Proactive recommendation systems

Proactive recommendation systems generate recommendations automatically without explicitly asked. A recommendation system can become proactive if it detects implicit requests hence can predict not only know what to recommend but when and how push recommendation [1].

6.3 Privacy preserving recommender systems

Recommendation systems extract user data to generate personal recommendations. Therefore, there is a need to protect this user data from unauthorized access [1].

Distributed recommender systems that operate in open networks: Majority of recommendation system follows client-server architecture which can suffer from all problems of centralized systems. Cloud or grid computing can provide opportunity to use more robust and flexible models for recommendation systems [1].

6.4 Diversity of the items recommended to a target user

User will get better recommendations if there is diversity in the items included. There are many situations when user wants to explore diverse items. So there is a need to define the type of the diversity and how to combine diversity goal with accuracy recommendation [1].

6.5 Integrating of long-term and short-term user references in the process of building recommendation list

Usually recommendation system considers long term preferences of the user and build user model on the basis of it. Now-a-days many recommendation systems are developing that considers short-term preferences of the user also. Short-term preference depends on the current situation of the user (e.g. context based recommendation system). New research is needed to build hybrid models that can correctly decide to drift or not toward the contingent user's preferences when there is enough evidence to suggest that the user's short-term preferences are departing from the long-term ones [1].

6.6 Recommendation systems that optimize a sequence of recommendations

Recommendation systems have emerged in the attempt to quality improvement of recommendation generated by the systems based on a simple approach: a one-time request/response. Recommendation systems can be further enhanced by implementing learning capabilities that can optimize not only the items that are recommended but also how the dialogue between the user and the system must unfold in different situations [1].

6.7 Recommenders designed to operate in mobile devices and usage contexts

Many recommendation requests are expected to be made when the user is moving e.g., at shops or hotels in a visited city. This necessitates "mobilizing" the user interface and to design computational solutions that can efficiently use the still limited resources (computational power and size of screen) of the mobile devices [1].

VII. Conclusion

Recommendation systems proved themselves to be a best solution for addressing problem of the information overload. They help in making decisions by preserving time and energy. Future work will focus on enhancement of the existing methods and algorithms used so that the recommendation systems predictions and recommendations quality can be improved.

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