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An Approach to Design and Development Recommender System

Samir N Ajani[1*], Lokesh M Heda[2], Santosh Kumar Sahu[3], Manish M Motghare[4]

[1]Dept.of Computer Science and Engineering, Shri Ramdeobaba College of Engineering and Management , Nagpur, India
[2]Dept. of Electronics Engineering, Shri Ramdeobaba College of Engineering and Management , Nagpur, India
[3]Dept. of Computer Application, Shri Ramdeobaba College of Engineering and Management , Nagpur, India
[4]Dept. of Computer Application, Shri Ramdeobaba College of Engineering and Management , Nagpur, India

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ABSTRACT- Each day we are surrounded by any number of decisions to make. Which book should I read next? Which movie to watch? Which book to read? Which blog to follow? Or which item to buy? Finding the appropriate choice is like finding a needle in a haystack. Increasingly, we use the web and online resources to help us make a decision. As our decision making is transported and conducted in the online sphere, the use of recommendation systems has become essential in daily life. Recommendation systems have been studied and developed for more than two and a half decades. Within this period, a variety of algorithms has been developed for various application domains. The major breakthrough in development of recommender system was in 2006 when Netflix announced the $1 million to whoever improved the accuracy of his existing system called Cinematch by 10%in a machine learning and data mining competition for movie rating prediction.

Keywords: *Recommender System, content-based, collaborative filtering, knowledge based filtering, IoT.*

1. Introduction

Recommender system is a tool that used to predict what a user may or may not like among a list of given items. Recommendation systems are a pretty interesting alternative to search fields, as recommendation engines help users discover products or content that they may not come across otherwise. This makes recommendation engines a great part of web sites and services such as facebook, YouTube, Amazon, and more. Recommendation engines work ideally in one of two ways. It can rely on the properties of the items that a user likes, which are analyzed to determine what else the user may like or it can rely on the likes and dislikes of other users, which the recommendation engine then uses to compute a similarity index between users and recommend items to them accordingly. It is also possible to combine both these methods to build amuch more robust recommendation engine.

Recommender systems have developed in parallel with the web. Web 3.0 boosts the need of more accurate Recommender systems that have been developed concurrently with the web. Recommender systems are vibrant tool for addressing issues of the information overload from the internet. Its evolution has accompanied the evolution and generation of the web. recommender systems developed in the first generation used traditional web sources to collect information which is content-based data from purchased or used products, demographic data collected in users records and memory-based data collected from users item preferences. The 2G of recommender systems extensively use the web 2.0 by gathering social information (e.g., friends, followers, followed, trusted users)[1]. The third generation of recommender systems will use the web 3.0 through information provided by the integrated devices on the IoT. The use of location information already incorporated in many recommender systems will be followed by data from devices and sensors, which will be widely used (e.g., real-time health signals, RFID, food habits, online local weather parameters such as temperature and pressure).

2. Related Work

Recommendation systems stem from the needs of users. It holds interesting scientific questions, as it combine aspects from human-computer interaction, information retrieval and machine learning domains. Based on how unknown ratings are predicted, recommendationtechniques can be classified into four general categories:content-based, collaborative filtering, knowledge based and hybrid.content-based methods recommend items by matchinguser profile features with item features [5], customer's buying patterns in rating data are analyze in order tomake predictions in collaborative filtering[9],demographic filtering [2]recommendations based on the principlethat individuals with certain common personal attributes (gender,age, country, etc.) will also have common preferences,Knowledge-based (KB) recommendation offers rating basedon knowledge about the users, items and/or their relationships[1]and hybridmethods combinations content-based,demographic filteringand collaborative techniques to make prediction in rating data

[11]. Among differentrecommendation approaches, collaborative filteringtechniques have been most widely used, largely becausethey are domain independent, require minimal, if any,information about user and item features, yet they can stillachieve accurate predictions [14].In a typical setting of collaborative filtering recommendersystems, users' preferences for items are modeledvia numeric ratings. Thus, the recommendation problem isreduced to the problem of estimating ratings for the itemsthat have not been seen by a user and this estimation is usuallybased on the other available ratings given by this andor other users.

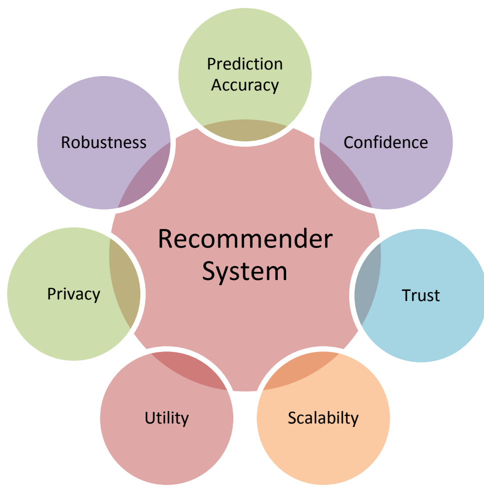

Fig: Characteristics of Recommender System.

3. Proposed Approach:

Our model for a recommender system incorporates social information as well as information collected by the integrated devices on IoT. The loT (Internet of Things) is a network of Internet enabled objects, together with web services that interact with these objects. Underlying the Internet of Things are technologies such as RPID (radio frequency identification), sensors, and smart phones. At the same time, social networks have become an indispensable part of this process. People from all over the globe use them on a daily basis to get input from people and sources they trust. When people spend time on social networks, they leave valuable information about themselves. This has attracted the attention of researchers and professionals from numerous academic and commercial fields. As recommendations are one domain that has witnessed widespread change due to social networks, there is an obvious interest in the field of social inspired recommender system.

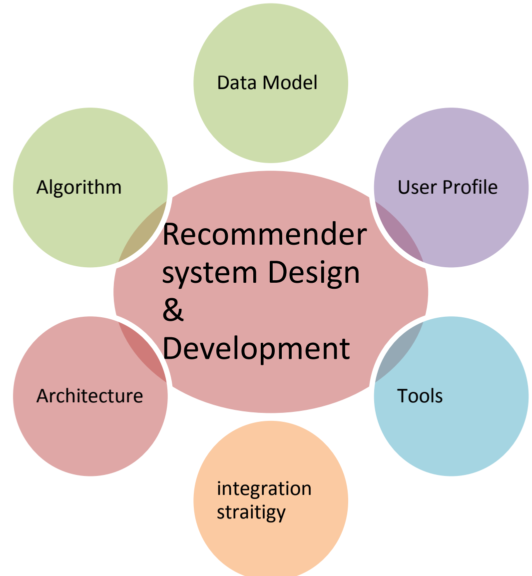

Figure: Design issues of Recommender system.

4. Prediction Accuracy Measures:

- **mean absolute error**
- **accuracy**
- **coverage**

In order to measure the accuracy of the rating by a RS, it isusual to use the calculation of some of the most common predictionerror metrics, amongst which the Mean Absolute Error(MAE) and its related metrics: mean squared error, root meansquared error, and normalized mean absolute error stand out.

5. Benefits

- **Engage Shoppers:**

Shoppers become more engaged in the site when personalized product recommendations are made. They are able to delve more deeply into the product line without having to perform search after search.

- **Convert Shoppers to Customers:**

Converting shoppers into customers takes a special touch. Personalized interactions from a recommendation engine show your customer that he is valued as an individual. In turn, this engenders his loyalty.

- **Increase Average Order Value:**

Average order values typically go up when a recommendation engine in uses to display personalized options. Advanced metrics and reporting can definitively show the effectiveness of a campaign.

- **Increase Number of Items per Order:**

In addition to the average order value rising, the number of items per order also typically rises when a recommendation engine is employed. When the customer is shown options that meet his interest, he is more likely to add items to his purchase.

In future my research work will help naiveusers, elder persons who have little knowledge about internet search and hand held devices like highly configured cell phones,tablets, etc.

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