IJIRMET ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
Vol. 2, Issue 4, April 2017

A Survey based on Recommendation Techniques

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Abstract - ***Nowadays, the increasing growth of e-commerce sites i.e. flipkart, amazon, ebay etc. which create ratings, comments and feedback of buyers which lift new application area for recommendation system. Although research on recommendation system has increased significantly over the past 10 years. To help the customer, many e-commerce companies are also developing their recommendation system to help their buyers to choose products more efficiently. The consumer can get advantages by receiving some information about the item which they are likely to buy. Due to this process, the business can get profit with an increasing of its sale. This paper gives some overview of about recommender system and depicts the present patterns of proposal techniques that are for the most part characterized into three classifications: content based, collaborative filtering and hybrid. These paper also describe the challenges of current recommendation method.***

Key words: **Recommendation system, collaborative filtering, content based filtering, hybrid, Matrix Factorization**

I. INTRODUCTION

Now a day's popularization of the internet and quick usage of E-commerce site the recommender system become more popular. Recommendations are a part of everyday life where people rely on external knowledge to make decisions about an artifact of interest [1][2]. Recommendation system recommends interested items to buyers based on available information such as previous usage patterns, and features of the product them. In general recommendation system directly helps active user to find product, item and services (such as music, movie, products, digital products, electronics and websites). For pulling customer they have to filter all the products to narrow down the search space and recommend most fitting items to them. Albeit a wide range of ways to deal with the recommender frameworks have been produced in the previous couple of years, the enthusiasm for this territory still stays high because of developing interest on viable applications, which can give customized proposals and manage data over-burden. In its most regular definition, the suggestion issue is decreased to the issue of evaluating appraisals for the things that have not been seen by the client. Commonly, a recommender system[3] looks at a client portrayal to some reference components, and tries to envision the "rating" or "inclination" that a client would provide for a thing they had not yet considered. These elements might be from the data thing (the content based approach) or the client's social condition (the collaborative filtering). The recommender framework apply information mining strategies and expectation calculations to foresee client's enticement on data ,item and administrations client.

Over the past periods, various approaches for building recommender systems have been created [3]; collaborative filtering has been a very productive approach in both exploration and practice in recommendation system, and in information filtering and web approach. To recommend product recommendation engine uses different recommendation algorithms. According to the type of feature to be used to recommend items to users these algorithms can be categorized into six different ways: Content-based filtering (CB), Collaborative Filtering (CF), and Hybrid recommendation techniques. There is a need to develop recommendation system which aids to grow sell of items, to enlarge customers satisfaction by better understand actually what they need, increase user loyalty. Recommendation system provides personalized suggestion based on users' past behavior and or similarities between users' and products' profiles. A recommender framework incorporates typically three stages, i.e. procuring inclination from clients' info information, figuring the proposal utilizing appropriate strategies, lastly showing the suggestion results to clients

II. RECOMMENDATION TECHNIQUES

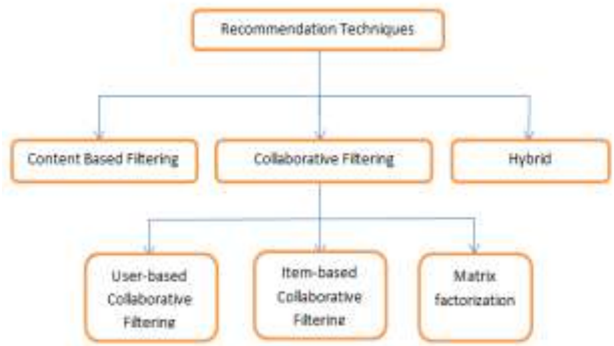

Fig. 1 Different Recommendation Technique

A. Collaborative Filtering

Collaborative filtering is popular and widely used technique in RS. Recommendation system recommends product based on highest ratings of similar users. For example, in a product recommendation application, Collaborative filtering system tries to discover other similarity invested clients and after that suggests the product will be most likely to be purchase by them. Collaborative Filtering can be divided into various categories, such as: a) User-based Collaborative Filtering, b) Item-based Collaborative Filtering, c) Matrix Factorization.

1)User-based Collaborative Filtering

In the user-based collaborative proceed; the users attain the prime role. User-based algorithms work over the entire user database to make predictions. If certain major part of the customers has the similar taste then they join into one class. Recommendations are given to customer based on analysis of items by other users from the same class, with whom he/she shares common taste. If the item was confidently rated by the group, it will be recommended to the user[3]. Based on ratings user recommend top rated or top viewing products which have not been rated by common current user. For a new user if the system is not able to find any user like them then it recommends most-liked products.

2) Item-based Collaborative Filtering

To recommend a product, item comparison matrix can be produced. It first recognizes that how many items are rated or viewed by active user. Then search for similarities between those rated items and searching best closest item which have same number of ratings. Currently, Amazon operates Item- based collaborative filtering for recommends related/similar items. Item and User similarity calculated based on cosine similarity formula, Where, $\vec{}$ is all users who rating Item and $\vec{}$ is all users who rating Item B. Item based filtering is widely known by Amazon.com.

Here, are the primary steps of item-based filtering:

1. First is construct item-relationships.
2. Make use of the item-relationships, the system can predict the user's flavor.

3)Matrix Factorization

The Matrix Factorization (MF) plays a major role in the Collaborative Filtering recommender system. Matrix Factorization is the only one model based approach which is produced highly accurate results. It is used to reduce the user- item feature information. It converts item and users to the same latent factor Space, Latent space tries to describe ratings by characterizing both items and users on factors automatically inferred from user feedback [10]. It is more preferred for large publicly available dataset but it is quite difficult.

The Matrix Factorization techniques are usually more fruitful because they allow user to find the latent features underlying the interactions between users and items. Matrix Factorization is essentially a numerical tool for playing around with matrices, and is in this manner pertinent in number of spaces where one

II.Principal Component Analysis(PCA)

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Where,

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III.Probabilistic Matrix Factorization(PMF) IV.
Non-Negative Matrix Factorization(NMF)

I. Singular value Decomposition(SVD)

Singular value decomposition is the more powerful dimension reduction technique of matrix factorization. The key issue in an SVD decomposition is to find a lower dimension feature space [14].
SVD of an m × n matrix A is of the form[4][14] :

$$SVD(A) = U \sum V^T$$

Where,
U and V are m × m and n × n orthogonal matrices
∑ is the m ×n singular orthogonal matrix with non-negative elements
An m × m matrix U is called orthogonal if equals to an m × m identity matrix. The diagonal elements in Σ (σ1, σ2, σ3, …… σn) are called the singular values of matrix A. Usually, the singular values are placed in the descending order in Σ. The column vectors of U and V are called the left singular vectors and the right singular vectors respectively [4,14,16].

II. Principal component analysis (PCA)

The Principal Component Analysis (PCA) is also the powerful technique of dimensionality reduction and is a particular realization of the Matrix Factorization(MF) approach[18]. PCA is a measurable method that uses an orthogonal transformation to change over an arrangement of perceptions of potentially associated factors into an arrangement of values of linearly uncorrelated factors called principal components [16].

III. Probabilistic Matrix Factorization(PMF)

The Probabilistic Matrix Factorization (PMF) is a probabilistic linear model with Gaussian observation noise [21]. The user preference matrix is represented as the product of tow lower-rank user and item matrices in Probabilistic Matrix Factorization (PMF). Suppose we have N users and M movies. Let Rij be the rating value of user i for movie j, Ui and Vj represent D-dimensional user-specific and movie-specific latent feature vectors respectively[21].

Then the conditional distribution over the observed ratings $R \in \mathbb{R}^{N\times M}$ and the prior distributions over $U \in \mathbb{R}^{D\times N}$ and $V \in \mathbb{R}^{D\times M}$ are given by in [21]:

$N(X|\mu,\sigma^2)$ denotes the Gaussian distribution with mean **μ** and variance **$\sigma^2 I_{ij}$** is the indicator variable that is equal to **1** if user ***i*** rated movie ***j*** and equal to **0** otherwise.

IV. Non-Negative Matrix Factorization(PMF)

Non-negative matric factorization (NMF) was first proposed by Paatero and Tapper in 1994 and was significantly famous by Lee and Seung (Lee and Seung, 1999), also called as non- negative matrix approximation. NMF is a group of algorithms in multivariate analysis and linear algebra where a matrix X is factorized into two matrices P and O, with the property that all three matrices have no negative elements [14].

Let the input data matrix $X = (x_1, x_2, \ldots\ldots, x_n)$ contain a collection of n data vectors as columns. We consider factorization of the form:

$$X \approx PQ^T$$

Where, $X \in \mathbb{R}^{N\times M}$, $P \in \mathbb{R}^{D\times N}$ and $Q \in \mathbb{R}^{D\times M}$

B. Content Based Filtering

IJIRMET ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
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The content-based recommender system examines the content of a certain item depending on its type and will try to study the paralles among the items that the user has greatest rated. Then, depending on the analysis, the system will discover items with greatest degree of similarity to the user's preferences. Standard approach for content-based [1] recommender systems are those who offer with items with textual information, such as documents, web sites or films descriptions.

In a more detailed manner, consider the content of an item profiles and a set of attributes characterizing items which represent extracted features from the item s. Hence, the content can be represented as a vector of length *n* representing the extracted features: Content(c_j)=(k_{1j},k_{2j},…,k_{nj}), where k_{1j} represents the value for the given feature *l* out of the *w* features. Based on the item profile vector, Content Based Profile = (k_{c1},k_{c2},…,k_{cn}) which is similar to users is a vector of weights where each weight represents the importance of each feature extracted for a certain user c. Similar to collaborative filtering, similarity measures can be used to find the highest scoring item, or probabilistic techniques can be employed to estimate if a certain item belongs to a certain class of users and thus, the problem becomes a classification problem where one can make use of generative approaches that rely on maximum likelihood [2][10]. The features of the item will be used to compute the conditional probabilities.

C. Hybrid Recommendation System

The both technique collaborative filtering and content based filtering combine in this approach. Hybrid system combining techniques and tries to use the advantages of collaborative filtering to fix the disadvantages of content based filtering. For example, a CF method is affected from new-item problems, i.e., they cannot recommend items which may have no ratings. This does not limit content-based approaches since the prediction for new items is based on their information (features) that are usually easily available.

III. CHALLENGES OF RS SYSTEM

1) Sparsity Problem

Sparsity problem is the key issue faced by recommender system and data sparsity has very impact on the quality of recommendation. Generally, data of system like last.fm is display in form of user-item matrix, occupy by scores given to music and as no. of users and items grow the matrix dimensions and sparsity evolves [20]. The main logic behind data sparsity is that most users do not rate almost all of the items and the obtained ratings are usually sparse. Collaborative filtering is suffering from this problem because it is based on with the rating matrix in most study.

2) Cold Start Problem

Cold start problem refers to the condition when a new user or item just come in to the system. It basically deals with three kinds of problem and they are: new user problem, new item problem and new system problem. In such study, it is really tough to give recommendation as in case of new user, there are very fewer details about user that is accessible and also for a new item, no ratings are generally accessible and thus collaborative filtering cannot make helpful recommendations in case of new item as well as new user. However, content based methods can give recommendation in case of new item as they do not based on any past rating information of other users to recommend the item.

3) Scalability

Scalability is the property of system that indicates the ability to handle bigger amount details in a graceful manner. With vast growth in information over internet, it is clear that the recommender systems are having an exploding market of data and so this is a great challenge to handle with consistently growing demand. Some of the recommender system algorithm offers with the computations which increase with growing number of users and items. In CF computations develop exponentially and get expensive, sometimes leading to incorrect results. Methods proposed for handling this scalability problem and speeding up suggestion formulation are based on approximation mechanisms. Whether or not they improve performance, quite often bring accuracy reduction [19].

IV. CONCLUSION

Collaborative Filtering (CF) is a powerful technique used in Recommendation System (RS). CF technique suffers from problem with large dataset and sparseness in rating matrix. In this paper we have studied different methods of recommendation system and challenges also.

From this survey we can say that, collaborative filtering is most used approach in recommendation system. Matrix factorization method of collaborative filtering is able to handle massive data set and sparseness problem in matrix.

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