FEEDBACK BASED LOCATION AWARE RECOMMENDER SYSTEM

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ABSTRACT

Conventional recommender systems neither consider item location nor the user location to recommend the items of user's choice. In online purchasing Feedback Based Recommender Systems(FBLARS) considers both the user as well as item location to recommend the items to the users. Existing recommender systems used to recommend the items to the users by considering the parameters like (user, item ,rating) that are ill-equipped to provide location based recommendations. The FBLARS considers the parameters like(user, item, rating, item location, user location) to provide location based recommendations to the users. FBLARS uses Item Based Collaborative Filtering to provide recommendations. It uses a travel distance filtering technique to exploit the user locations without effecting the scalability as well as the quality of recommendation and avoids access to all the items in a large search space.

Keywords: FBLARS, Items, Location, Scalability, Rating, User

I. INTRODUCTION

Recommender systems generally try to provide what the most suitable products or services are, based on the user's preferences and constraints. In order to complete such a computational task, recommender systems collect from users their preferences, which are either explicitly expressed, e.g., as ratings for products, or are inferred by interpreting user actions. Recommender system development initiated from a simple observation: individuals often rely on recommendations provided by others in making routine, daily decisions[1,2]. "Item" is the general term used to denote what the system recommends to users. Traditional recommender systems neither consider item location nor user location. FBLARS is a location based recommendation system gives recommendation by considering following parameters like[3] (user, uloc, ratings, item) where uloc is user location,(user, rating, item, iloc) where iloc is the location of item and (user, uloc, rating, item, iloc) . FBLARS uses travel distance filtering technique that avoids exhaustive access to all spatial items. It uses pyramid maintenance data structure to represent huge data in a efficient manner.

II. METHODS

2.1 Content-Based Filtering

In content based filtering the system learns to recommend items that are similar to the ones that the user liked in the past[6]. The similarity of items is calculated based on the features associated with the compared items. For example, if a user has positively rated a movie that belongs to the comedy genre, then the system can learn to recommend other movies from this genre. Content-based filtering systems are designed mostly to recommend text-based items, the content in these systems is usually described with keywords.

2.2 Collaborative Filtering

2.2.1 The Collaborative Filtering Works as Follows [4]

- User preferences are considered from large search space.
- Using similarity count the similarity between the subgroup of the user and the user who are seeking recommendation is considered.
- Predicted rating is calculated using similarity count in order to find what may be the rating of the user who has not yet rated the item which is already rated by the different user.

Collaborative filtering is the most widely used technique for recommendation[10].

2.3 Two Types of Collaborative Filtering are [4]

- Memory based collaborative filtering.
- Model based collaborative filtering.

2.3.1 Memory Based Collaborative Filtering

This method uses the matrix of user ratings for items of the entire database to find users that are similar to the active user, and use their preferences to predict ratings for the active user.

2.3.2 Model Based Collaborative Filtering

This method extracts some information from dataset and uses that as a "model" to make recommendations without having to use complete dataset every time. It first develops a model of user ratings. Then computes the expected value of a user prediction , given his/her ratings on other items.

2.4 Item Based Collaborative Filtering

The task of item based collaborative filtering algorithm to find item likeliness is of two forms[6]:

2.4.1 Prediction

A numerical value, expressing the predicted likeliness of an item the user hasn't expressed his/her opinion about.

2.4.2 Recommendation

A list of N items the active user will like the most (Top-N recommendations).

The Fig 1 shows the item based collaborative filtering approach[5].

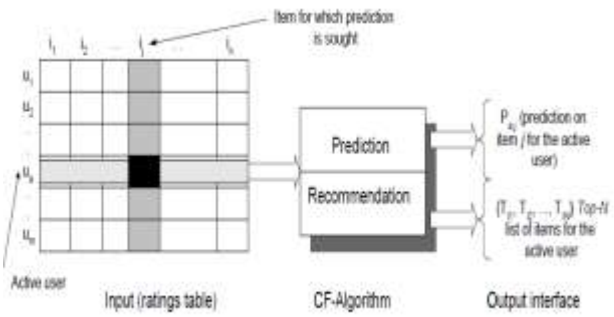

Fig 1 Item Based Collaborative Filtering approach

The item based similarity is found through cosine similarity using the formula:

$$sim(i_p, i_q) = \frac{\vec{i_p} \cdot \vec{i_q}}{||\vec{i_p}|| \, ||\vec{i_q}||}$$

The adjusted cosine similarity is given by :

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \bar{R_u})(R_{u,j} - \bar{R_u})}{\sqrt{\sum_{u \in U}(R_{u,i} - \bar{R_u})^2}\sqrt{\sum_{u \in U}(R_{u,j} - \bar{R_u})^2}}.$$

III. MODEL BUILDING

This iteration calculates the similarity score *sim(ip,iq)* for each set of objects ip and iq that have at least one common rating by the same user. Where R and U are the number of ratings and users, List L ,only the most similar items with the highest similarity score

3.1 The Pearson Correlation is Given by

$$w_{i,j} = \frac{\sum_{u \in U}(r_{u,i} - \bar{r}_i)(r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U}(r_{u,i} - \bar{r}_i)^2}\sqrt{\sum_{u \in U}(r_{u,j} - \bar{r}_j)^2}}$$

where U is the set of all users who have rated both items i and j, ru,i is the rating of user u on item i, and ¯ri is the average rating of the ith item across users. Figure below shows item based collaborative filtering model generation.

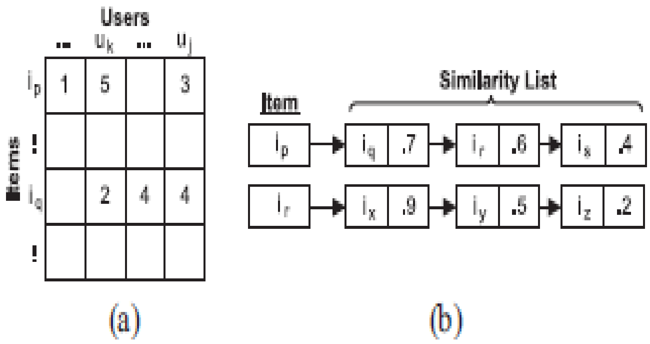

Fig 2 Item Based Collaborative Filtering Model Generation

3.2 Hybrid Filtering

Hybrid filtering combines collaborative and content-based methods, which helps to avoid certain limitations of content-based and collaborative systems **[8]**.

3.2.1 FBLARS System Architecture

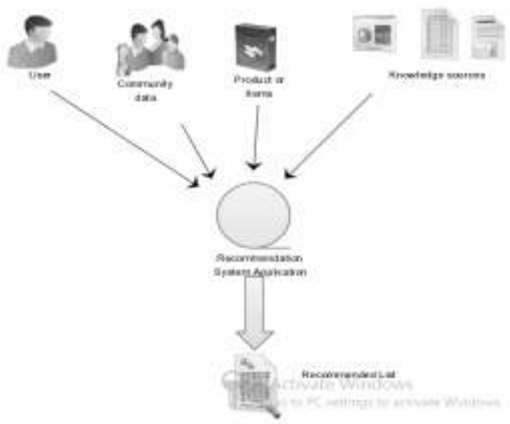

Fig 3 FBLARS Architecture

User in online purchasing purchases the item of his/her choice and rates the particular item. Using the community opinion the new user will get recommendations through collaborative filtering.

IV. ALGORITHMS

4.1 Item Based Collaborative filtering

Item based collaborative filtering recommends items by considering the similarity between the co-rated items through cosine similarity.

4.2 Maintenance Algorithm

As time goes by, new users, ratings, and items will be added to the system. This new data will both increase the size of the collaborative filtering models maintained in the pyramid cells[9], as well as alter recommendations produced from each cell. To account for these changes, FBLARS performs maintenance on a cell-by-cell basis.

4.3 Travel Penalty Algorithm for Spatial Items

Query processing for spatial items using the *travel penalty* technique[7] employs a single system-wide item-based collaborative filtering model to generate the top-k recommendations by ranking each spatial item i for a querying user u based on $RecScore(u, i)$, computed as:

$$RecScore(u, i) = P(u, i) - TravelPenalty(u, i).$$

$P(u, i)$ is the standard item-based CF predicted rating of item i for user u. $TravelPenalty(u, i)$ is the road network travel distance between u and i normalized to the same value range as the rating scale.

V. EXPERIMENTAL RESULTS

The paper is implemented in java. Item based Collaborative filtering as well as travel distance filtering algorithm is been implemented to provide location based recommendations to the user . The present work takes user id, user location ,product id, product location and the user rating for the product they have already purchased. The system provides the recommended products to the querying user by considering item as well as the user location. FBLARS first applies the item based collaborative filtering to find the similarity between the co-rated items and then calculates the predicted rating using the similarity count to predict the rating of the product that are not rated by the querying users.

5.1 Performance

FBLARS Provides increased performance compared to the conventional recommender system as it considers location based ratings it avoids exhaustive access to all the items in the large search space. Hence increases the performance to the greater extent.

5.2 Scalability

FBLARS is scalable compared to conventional recommender systems. The implementation of FBLARS with travel distance filtering makes the system scalable without affecting the quality of location based recommendation.

5.3 Quality Analysis

The recommendation quality increases to a greater extent as travel distance filtering is used along with the item based collaborative filtering.

VI. CONCLUSION

FBLARS is a location based recommender system which provides recommendations to the querying users by considering both item as well as user location without sacrificing the quality of recommendation. It uses item based collaborative filtering along with travel distance filtering which avoids exhaustive access to all spatial items. FBLARS is more efficient and scalable compared to existing recommender systems and provides high quality of recommendation.

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