Aggregate Diversity Techniques in Recommender Systems

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***Abstract* — Recommender systems are being used extensively to assist users in making right decisions in this present generation of information overload. Due to continuous exponential increase of online information and data, recommender systems are very much challenged by the issue of discovering the relevant information from this pool. As an effort to address this problem, research has been conducted to improve the recommendation quality of recommender systems. However more focus has been on improving recommendation accuracy while aggregate recommendation quality received less attention. In order to ensure that the recommendations are more useful to users, diversity has to be factored in. This will ensure that users are recommended items that they would have not been able to discover by themselves. This paper reviews some of the techniques employed to ensure aggregate diversity in recommended items.**

***Index Terms*—collaborative filtering, cross-check approach, recommendation diversity, recommender systems, ranking functions**

I. Introduction

The dependency on digital data has increased exponentially of late and has created a very complex heterogeneous online environment which makes searching of online data a nightmare to a noble user. He is usually flooded with options to consider of which he might not be able to assess timely due to lack of sufficient time or lack or experience. This problem is commonly known as information overload [1]-[3]. Recommender systems are special type of information filtering systems which attempts to assist online users by recommending items that might be of interest and useful to them [4].

Recommender systems are increasingly becoming important and applicable in various domains (e.g. movies, music, books etc.) [5], [6]. It is very vital that recommendations of recommender systems are as accurate as possible. This was made evident by Netflix with the open competition of US$1,000,000 prize for anyone who can come up with an algorithm that can beat theirs with more than 10% accuracy in predicting the items ratings [7].

However, accuracy alone does not necessarily define a quality recommendation, other aspects such as diversity, novelty, serendipity and trust have to be considered when recommending items to users [8]. This article focuses on the diversity aspect of the recommendation. There are two types of diversity; individual and aggregate diversity. The paper concentrates on aggregate diversity. The existing techniques and algorithms that attempt to address the issue of aggregate diversity are reviewed.

II. Aggregate Diversity

Recommendations need not only be accurate but also diverse to accommodate the long tail[1] items. Diversity in recommendations is divided into two; individual diversity and aggregate diversity. Individual diversity is the measure of average dissimilarity of items recommended to an individual user while aggregate diversity is the total number of distinct items recommended across all users [5]. This document is focusing on improving aggregate diversity in recommender systems.

According to Niemann and Wolpers [5], there are two lines of research that attempts to improve the aggregate diversity. The first one calculates the rating predictions using existing filtering approaches like CF[2] (collaborative filtering) then re-rank the items with the highest predicted ratings to make space for long tail items to make it to the recommendation list. The second line targets the estimation process for rarely used items. There are many recommendation techniques introduced to this far and all of them follow either the first line or the second one. We have ranking based techniques, a graph theoretic approach, combination of user-based and item-based collaborative filtering, latent class model based technique, and crosscheck approach technique.

A. Ranking based Techniques

Adomavicius and YoungOK [8] proposed an approach to improve aggregate diversity in recommender systems using ranking based techniques. These ranking techniques follow the first line of research whereby traditional filtering techniques such as CF are used first to predict the ratings of items and then items above the threshold value are ranked and then top N items are recommended to the user.

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[1]Long tail items are un popular items or less rated items
[2]Collaborative filtering is a technique used by recommender systems that recommends items that users with similar preferences have liked in the previous.

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According to Adomavicius and YoungOK [8], there are three types of ranking approaches namely; standard ranking approach, item-popularity-based ranking and parameterized ranking approach. These techniques work together and complement each other to improve aggregate diversity of recommended items.

B. Standard Ranking Approach

In this approach, the first step is to predict the unknown ratings using traditional techniques then the predicted ratings are used to support the recommendation process. The user gets recommended a list of top N items selected according to some ranking criteria. The criterion is items with highest predicted rating are the ones being recommended to the user.

This approach of recommending highly rated items improves the accuracy of the predictions but the diversity is compromised. The need to balance accuracy and diversity led to popularity based approach to compliment the standard ranking approach. The item popularity based approach was proposed.

C. Item-Popularity-Based Ranking

Item popularity based ranking works exactly like standard approach in prediction stage. They only differ when it comes to the recommendation stage. Item-popularity as the name suggests, considers the popularity of items before recommending them. That is it ranks items according to their popularity from less popular to more popular. The popularity of an item is given by the number of total ratings it has. The higher number of ratings means that the item is known to a number of users.

This was proved to improve the aggregate diversity of recommended items. However this comes at the expenses of accuracy loss. That is why another technique is needed to address these trade off between accuracy and diversity, hence the introduction of parameterised ranking approach.

D. Parameterized Ranking Approach

Parameterized ranking approach parameterize the other ranking approaches by introducing a ranking threshold $T_R \in [T_H, T_{\max}]$ (where $T_{\max}$ is the largest possible rating on the rating scale, e.g., $T_{\max}$ = 5 and T_H is the minimum acceptable threshold value). This is to offer the user a flexibility to choose a certain level of recommendation accuracy and diversity. In general, for any given ranking function $rank_x(i),$ this threshold T_R is used to create a parameterized version of that function $rank_x(i, T_R)$. The formal representation is illustrated below.

$$rank_x(i, T_R) = \begin{cases} rank_x(i), if R^*(u,i) \in [T_R, T_{\max}] \\ \alpha_u + rank_{standard}(i), if R^*(u,i) \in [T_H, T_R] \end{cases}$$

where $\alpha_u = \max rank_x(i)$.

Items that are predicted above T_R are ranked according to $rank_x(i)$, while items that are below T_R are ranked according to the standard ranking approach. All items that are above T_R are ranked ahead of all items that are below T_R .

E. Graph Theoretic Approach

Adomavicius and Young Ok [9] came up with yet another approach to address the aggregate diversity in recommender systems and they called it a graph-theoretic approach. The recommendation step is carried out using the standard ranking approach discussed in the previous section.

This approach formulates the problem of maximizing diversity as a well known *max-flow problem* in graphs [10]. It translates users and items as vertices or nodes and an association of user and item as an edge. An edge from user to item exists if and only if item *(i)* has been predicted to be relevant for user (*u*). Each edge is assumed to have a capacity $c(e) = 1$ and can be assigned an integer flow of 1 only if the item *(i)* is actually recommended to user *(u)* as part of top-N recommendations and 0 otherwise. This is illustrated in Fig. 1. These assumptions result in a situation where maximum flow value will be equal to the largest possible number of recommendations that can be made from among available items. In this case no user can be recommended more than maximum capacity of an edge and no item can be counted more than once.

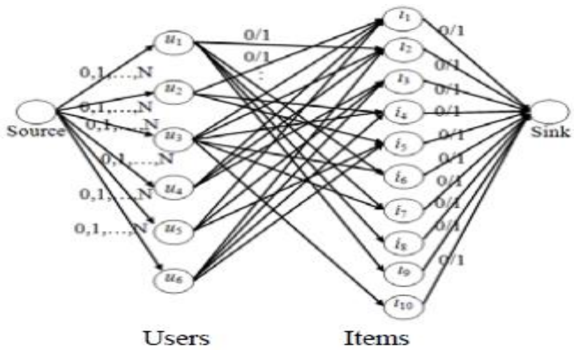

Figure 1. Max flow problem [11].

This is precisely the definition of the *diversity-in-top-N* metric. Therefore finding the maximum flow will be indeed finding the recommendations that yield maximum diversity.

The graph theoretic approach algorithm yields better accuracy-diversity results as compared to item re-ranking approaches, however this improvement come at the cost of computational complexity.

F. Latent Class Model based Technique

Suzuki, Mikawa and Goto [12] came up with the latent class model in 2012. In this approach, user preferences are predicted by a probabilistic latent space model called Aspect Model (AM). A set of items is written formally as

$$X = \{X_i; 1 \le i \le I\} \quad (1)$$

And users as

$$Y = \{Y_j; 1 \le j \le J\} \quad (2)$$

A set of (X_i, Y_j) represents the event that a user Y_j purchased an item X_i. This model introduces one latent class, and a set of latent classes for both users and items is defined as

$$Z = \{Z_k; 1 \le k \le K\} \qquad (3)$$

This model assumes that similar users and similar items are grouped together and a user or item can have more than one group. The probability of set (X_i, Y_j) is calculated using (4).

$$P(X_i, Y_j) = \sum_K P(Z_k) P(X_i \mid Z_k) P(Y_i \mid Z_k) \qquad (4)$$

The corresponding graphical model for this equation is shown in Fig. 2 below.

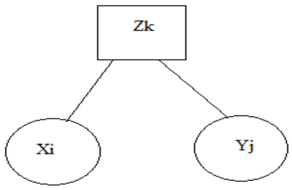

Figure 2. A graphical model for AM [12]

The probabilities; $P(Z_k)$, $P(X_i \mid Z_k)$ and $P(Y_i \mid Z_k)$ are the parameters of the multinomial distributions which can be estimated by the EM algorithms.

The purchase probability is predicted by calculating the estimator of the joined probability

$$\hat{P}(X_i \mid Y_j) = \frac{\hat{P}(X_i, Y_j)}{\sum_{x_i} \hat{P}(X_i, Y_j)} \qquad (5)$$

This approach showed increase in diversity, however the tradeoff between accuracy and diversity remained an issue to be addressed.

G. *Crosscheck Approach Technique*

Crosscheck approach was proposed by Nagaraj and the rest of his crew [13]. Their approach is to categorise items into groups such as technology, sport, literature, media, others, etc, which are also called circles. Users join categories in order of their preference and a user can be associated with more than one categories.

Items belonging to a certain category are rated either high or low by the members of that category. There is a category called 'others' where any user can go through same information items related to the category in which he is not primarily interested. The system has to keep track of user's history up to a certain period of time in order to recommend him other related items.

The top-N items recommended to each user are obtained in this way; first the system collects ratings of users to a particular item. And then checks if that user has rated the item before. If the user has rated the item, it means he is aware of the items existence so the item is not recommended to the user instead other items are recommended.

Users are recommended items which are not related to their category in 'others' category and the items in this category must be high rated information items irrespective of the category. This category shows the items related to all other categories except the categories in which a particular user is a member. This will result in a large number of long tail items and the diversity can be achieved by recommending those items.

The items are crosschecked before recommended to the user to ensure that he has never rated the items before and to check as to how many distinct items are recommended to different users in each category. Also the popularity of those items is taken into consideration to ensure that long-tail items are pushed into the recommendation list.

For the users who are new to the system, the system recommends most popular categories or circles along with 'others' category as a default rather than recommending information items.

H. *A Multi-attributed Hybrid Re-ranking Technique*

Patil and Wagh [14] came up with their own technique to address the issue of aggregate diversity. They called their technique a Multi-attributed hybrid Re-ranking technique. In this technique, they used collaborative filtering method to predict the ratings of items and multi-attributed hybrid contend based approach (MCBRT) for re ranking the most relevant items found through standard ranking. They used MoviLense dataset for experiments and their items were movies. The architecture of their systems is shown in Fig. 3.

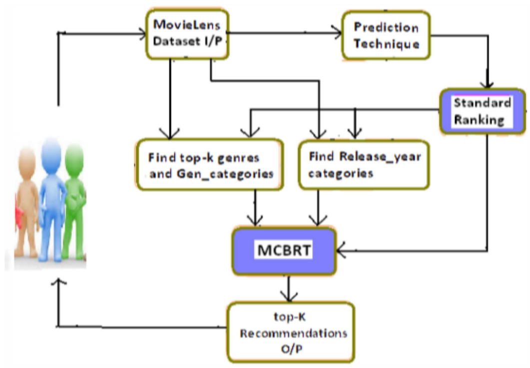

Figure 3. System architecture [14]

TABLE I. LOGICAL OR TO MANIPULATE FINAL CATEGORIES

Movieid	23	107	56	78	301	211	590
Predicted Rating	4.8	4.78	4.62	4.10	4.08	3.74	3.44
Genre category	H'	H'	H'	O'	O'	H'	O'
Release_year category	O''	H''	H''	H''	O''	H''	O''
Final category	H	H	H	H	O	H	O

Multi-attributed hybrid MCBRT considers more than one attributes of contents to achieve higher aggregate diversity as compared to MCBRT which considers a single attribute [15]. They used input tables such as the one shown in Table I in the dataset to list top-N favourite genres for each user. Then they categorised all movies obtained after standard ranking into Genre and Release-year categories.

Genre category manipulates movies based on genre attribute of the movie. For a movie to be accepted as a Home category (H), its genre should have been listed as one of the top-N liking genres else it is accepted as 'Other' category (O).

Release-year category is manipulated based on the release year attribute of the movie and the user's age. Depending on this attributes a movie can be categorised as home category (H) or other category (O). As shown from Table I, logical OR operation was performed on Genre categories and Release-year category values. The Final category was found to be either Home category or 'Other' category (O).

From the perspective of both attributes, this process takes care of a movie being completely strange for that user. They finally used those categories values for re-ranking purposes so that the complete strangeness of movie should not result in decreasing accuracy significantly. This is illustrated in Fig. 3. It can be seen that movies 23, 107 and 56 are replaced by next movies 590, 122 and 700 respectively. But for maintaining accuracy, it can be too risky to include movies like 122 and 700 which have low values of predictions. Ranking threshold can be used to achieve the flexibility to decide required accuracy and diversity levels.

However, although the accuracy loss is negligible in this approach, the set back of this approach is that it creates a very complex system.

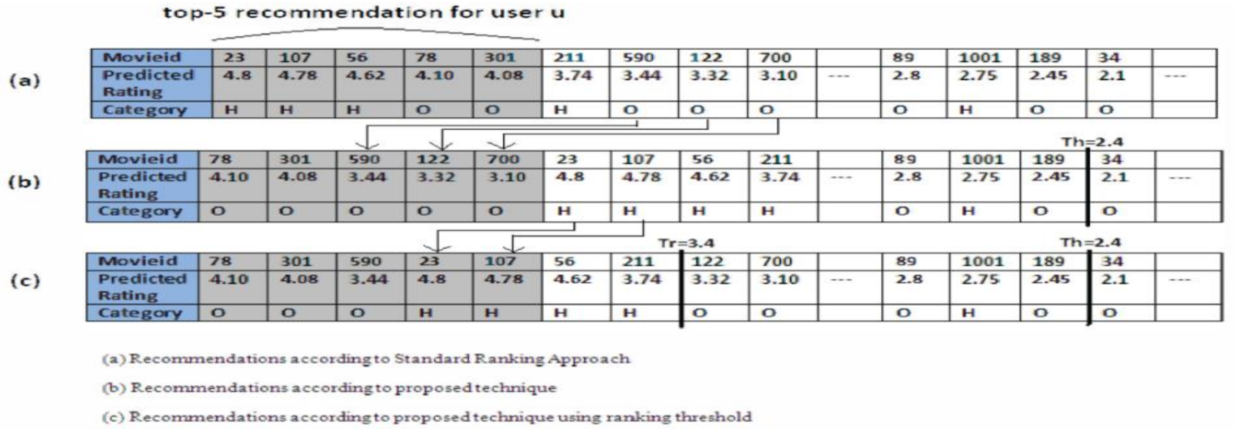

Figure 4. General idea of proposed re-ranking technique multi-attributed hybrid MCBRT with respect to standard ranking [14]

III. CONCLUSION

The important goal of recommender systems is to recommend relevant and useful items to users. These have to be items that would be otherwise difficult for users to find by themselves without the aid of the system. Generally diversity in recommender systems enhances personalised recommendations while at the same time ensuring that long-tail items are also included in the recommendation list.

This document reviewed some of the common algorithms employed to ensure aggregate diversity in recommended items. It has been noticed that these algorithms work on one of the two major phases of recommendation process. That is, they either seeks to improve the prediction of items rating or they improve the ranking of candidate items.

However the trade-off between accuracy and diversity is still an open issue that challenges a lot of algorithms. This is because the more the system tries to recommend accurate items, the more it concentrates on well known and rated items. This on the other hand affects the diversity. When trying to cater for diversity, accuracy is compromised. Therefore more algorithms needs to be researched that will enhance both the diversity and the accuracy of recommended items.

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