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Recommender System And Ranking Techniques: A Survey

Antony Taurshia.A
Post Graduate Student Karunya University
Coimbatore, India

S.Deepa Kanmani
Assistant Professor Karunya University
Coimbatore, India

ABSTRACT

Recommender system is a subset of information filtering system that predicts the rating a user would give to an item and recommends those items to the user. There are different ways in which recommendations can be made. The success of recommender system depends on the usefulness of the system. The usefulness can be measured in terms of accuracy, diversity, flexibility, serendipity and reliability. Most of the recommender system have focused on improving recommendation accuracy, but diversity is overlooked. In this paper several recommendation techniques and ranking techniques that improve the aggregate diversity of recommendations have been explored.

Keywords:- Accuracy, aggregate diversity, individual diversity, recommendtation.

1. INTRODUCTION

There are vast amount of information available and the recommender system is proven to be useful in extracting information and making useful recommendation to users. Recommender system plays an important role in electronic commerce. It inceases sales by recommending items and it allows users to make decisions such as which item to buy. Item is termed as what the system recommends to users such as movies, books. For example Amazon.com uses recommender system for recommending books to users. Mostly recommender systems work based on the ratings given by user. Rating is user's preference for an item. Rating directly given by the user is called known rating. In order to provide recommendations to users the following two tasks are performed.

Rating prediction: The ratings of unrated items are predicted (i.e predicted rating) from the information available.

Ranking: The rated items are ranked and then recommended to users to maximize the user's utility.

There are several recommendation techniques like collaborative filtering, content based, hybrid. Content based recommender system uses history of user's preferences for recommending items. Collaborative filtering recommender system recommends items based on preferences of similar users. Hybrid recommender system uses a combination of recommender system for recommending items. So far used recommender system have focused only on improving recommendation accuracy. This causes overspecialization which leads to frustration of the user. Some of the researches have focused on improving individual diversity. This paper explores several ranking approaches that increases the aggregate diversity in recommender system.

This paper is organized as follows. Section 2 includes a discussion on key concepts and section 3 includes a discussion on several recommendation techniques and section 4 gives a discussion of several ranking approaches and section 5 gives the conclusion.

2. KEY CONCEPTS

This consist of several keywords about the recommender system.

2.1 Recommendation

Recommendation is the suggestion given by system to user like suggestion for books in Amazon.com and movies in Netflix.

2.2 Accuracy

Accuracy is how well a recommender system make predictions. Accuracy can be calculated as truly highly ranked items divided by highly ranked items.

2.3 Individual Diversity

Individual diversity is the diversity in the individual user's recommendation list.

2.4 Aggregate Diversity

Aggregate diversity is the diversity in recommendation list across all users.

3. RECOMMENDATION TECHNIQUES

This section briefly discuss several recommendation techniques.

3.1 Content Based Recommendation

Content based recommender system [6] recommend items based on user profile information and item description. User's profile contains information like description about the type of items that interest the user and the history of user's interaction with the recommender system. Items information are stored in a database with its attributes. The key component of content based recommendation is classification learning algorithm that creates a user model from the user history. This recommender system is capable of introducing new items to user. It can also provide explanation for recommending items. The user has to fill profile details mandatorily inorder to get recommendations.

3.2 Collaborative Filtering Recommendation

Collaborative filtering recommender system [4] recommends items based on the past preferences of similar users. First the user gives the preferences by rating the items. Based on the users ratings the system finds the similar users. With the similar users the ratings of unrated items are predicted and recommended to users. There are several approaches of collaborative filtering technique. Active filtering uses peer-to-peer approach, people who have similar interest rate products. Passive filtering approach uses implicit information like user's action for recommendation. Item-based filtering system uses item-item relationship for recommendation.

The collaborative filtering technique can be memory based or model based.

Memory based CF: Heuristic based techniques recommend items based on the past activites of users.

Model based CF: This technique learns a predictive model based on the past user activities using statistical or machine learning model.

The system should have enough ratings for recommending items as it is fully dependent on rating. This is called ramp up problem.

3.3 Knowledge Based Recommendation

This technique uses the knowledge about products and users needs for making recommendations. Recommendation is made by matching the similarity between user's preference and product description. It does not suffer from ramp up problem since it does not depend on the ratings given by user. This system needs a database and needs to be updated for making useful recommendations.

3.4 Outside The Box Recommendation

The problem of overspecialization is overcome using OTB recommendations [3], [5] and helps to make fresh discoveries. This technique uses a concept called item region. Region (i.e the "box") is defined as the group of similar items. Regions are created based on similarity distances between items. Stickiness is user's familiarity to a region. Based on the stickiness the system finds items that are not familiar to the user and recommends those items. This technique increases the novelty.

3.5 Graph Based Recommendation

Most of the recommender system use two dimensional information like user and item. Homogeneous and heterogeneous graphs [8] can be used which provides the capability to deal with multidimensional information like user's intensions. A graph-theoretic approach [9] based on maximum flow or maximum bipartite computations represent user and item as vertices and the flow is calculated. This technique improves aggregate diversity of recommendations. One of the major drawback with the graph-based approach is when the input data becomes large it becomes tedious to rebuild graph.

3.6 Hybrid Recommendation

Hybrid recommendation uses a combination of recommendation technique. Content based recommendation and collaborative filtering recommendation is the commonly used combination. Both the system suffers from ramp up problem. The disadvantages in both the techniques can be overcome by combining them in parallel or cascade. Both the rating and the profile data can be used for finding recommendations. This technique improves the recommendation accuracy but diversity is not considered.

4. RANKING TECHNIQUES

This section includes several ranking techniques [1], [2] in recommender system to improve aggregate diversity.

4.1 Standard Approach

This is the commonly used approach for ranking the items in recommender system. The predicted rating is ranked from highest to lowest.

$$rank_{standard}(i) = R^*(u,i)^{-1}$$

where $R^*(u,i)$ is the predicted rating. The power of -1 indicates that the items with highest predicted ratings are recommended to user. This approach increases the accuracy in recommender system but not diversity.

4.2 Item Popularity Based Approach

Item popularity based approach ranks items based on the popularity of the item from lowest to highest. The number of users who have rated the item gives the popoularity of the item.

$$rank_{Itempop}(i) = |U(i)|,$$

$$where\ U(i) = \{u \in U \mid \exists R(u,i)\}$$

$R(u,i)$ is the known rating given by user u to item i. This approach increases the diversity in recommender system.

4.3 Reverse Predicted Rating Approach

This approach ranks the items based on the predicted rating value from lowest to highest.

$$rank_{RevPred}(i) = R^*(u,i)$$

4.4 Item Average Rating

This approach ranks the items based on the average of the known ratings.

$$rank_{AvgRating}(i) = \overline{R(i)},$$

$$\text{where } \overline{R(i)} = \frac{1}{|U(i)|} \sum_{u \in U(i)} R(u,i)$$

$U(i)$ is the set of all users who have rated item i.

4.5 Item Absolute Likeability

This approach ranks the items according to how many users liked the item.

$$rank_{AbsLike}(i) = |U_H(i)|,$$
$$\text{where } U_H(i) = \{u \in U(i) | R(u,i) \geq T_H\}$$

4.6 Item Relative Likeability

This approach ranks items according to the percentage of the users who really liked an item among all users who rated them.

$$rank_{RelLike}(i) = |U_H(I)|/|U(i)|$$

4.7 Item Rating Variance

This approach ranks items according to the rating variance of users who rated the item.

$$rank_{ItemVar}(i) = \frac{1}{|U(i)|} \sum_{u \in U(i)} (R(u,i) - \overline{R(I)})^2$$

4.8 Neighbours' Rating Variance

This approach ranks items according to the rating variance of neighbors of a particular user for a particular item. The closest neighbors of user u among the users who rated the particular item i, denoted by u'

$$rank_{NeighborVar}(i) = \frac{1}{|U(i) \cap N(u)|} \sum_{\acute{u} \in (U(i) \cap N(u))} R(\acute{u},i) - \overline{R_u(i)})^2$$

N(u) is the set of nearest neighbours of user u.

4.9 Random Ranking Approach

Ranking the items randomly can also improve the diversity compared to the standard ranking approach.

$$Rank_{Random}(i) = Random(0{,}1)$$

where Random(0,1) is a function that generates uniformly distributed random numbers in the [0, 1] interval.

4.10 Parameterized Ranking Approaches

The several ranking approaches can be parameterized using "rating threshold" TR which belongs to [TH,Tmax] where TH is the predicted rating threshold and Tmax is the maximum rating in the rating scale.

$$rank_x(i, T_R) = \begin{cases} rank_x(i), & \text{if } R^*(u,i) \in [T_R, T_{max}\} \\ Remove\ item, & \text{if } R^*(u,i) \in [T_H, T_R) \end{cases}$$

TR can be used for ranking and filtering purposes. This approach cannot provide all *N* recommendations for each user, but it can be filled using other recommendation strategies.

5 CONCLUSION

Recommendation techniques used so far focus on improving recommendation accuracy but diversity is never considered. This paper briefly discuss several recommendation techniques and studies several ranking approaches that improves diversity with minimal accuracy loss. This also includes parametrized ranking approach that provides a threshold value to adjust the level of accuracy and diversity. Thus the ranking approaches can provide consistent and robust improvements in diversity with different recommendation techniques.

REFERENCES

[1] Gediminas. A., and Youngok.K., "Overcoming Accuracy-Diversity Tradeoff in Recommender Systems: A Variance-Based Approach." Proceedings of the 18th Workshop on Information Technology and Systems (WITS'08), Paris, France, 2008.

[2] Gediminas. A., and Youngok. K., "Toward More Diverse Recommendations: Item Re-Ranking Methods for Recommender Systems." 19th Workshop on Information Technology and Systems (WITS'09), Phoenix, Arizona,2009.

[3] Zeinab. A., Sihem. A.Y., Lakshmanan. V.S., Sergei. V., Cong. Y., "Getting recommender systems to think outside the box." 285-288 RecSys, 2009.

[4] Herlocker. J.L., Konstan. J.A., Terveen. L.G., and Riedl. J., "Evaluating Collaborative Filtering Recommender Systems," ACM Transactions on Information Systems, 22(1), pp. 5-53, 2004.

[5] Amer-Yahia. S., Lakshmanan. L.V.S., Vassilvitskii. SS., Yu. C., "Battling Predictability and Overconcentration in Recommender Systems." IEEE Data Eng. Bulletin,33-40, 2009.

[6] Michael J. Pazzani and Daniel Billsus, "Content-Based Recommendation Systems. ", 325-341, 2007.

[7] Sangkeun. L, "A generic graph-based multidimensional recommendation framework and its implementations." WWW (Companion Volume) 161-166, 2011.

[8] Gediminas. A., and Youngok. K., "Maximizing Aggregate Recommendation Diversity: A Graph-Theoretic Approach" Workshop on Novelty and Diversity in Recommender Systems, held in conjunction with ACM RecSys, 2011.

[9] Fatih. A., Aysenur. B., "Enhancing Accuracy of Hybrid Recommender Systems through Adapting the Domain Trends."ACM RecSys'10 PRSAT Workshop, 2010.