Covering Diversification and Fairness for Better Recommendation (Short Paper)

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Abstract. Smart applications are appealing an accurate matching between users and items, in which recommendation technologies are applied widely. Since recommendation serve for two roles, namely users and items, accuracy is not the only focus, the diversification and fairness should also be paid more attention for improving recommendation performance. The tradeoff among the accuracy, diversification and fairness on recommendation is bringing a big challenge. This paper proposed a novelty recommendation model to ensure the recommendation performance, which introduces a multi-variate linear regression model to cooperate with the collaborative filtering method. This study utilizes an improved similarity metrics to discover the closeness between users and item categories under the help of the collaborative filtering methods, and exploits the micro attribute information of items by a multi-variate linear regression model to decide the final recommended items. The experimental results show that our proposed method can provide better recommendation accuracy, diversification and fairness than the recommendation based on pure collaborative filtering method.

Keywords: Diversified recommendation · Recommendation fairness · Recommendation evaluation

1 Introduction

Many smart services, copious merchandise, and other items are being pushed to users by mobile applications, electronic commerce, etc. The accompanying challenge is how to discover those items matching users' real needs. The classical recommendation methods transform users' historical information into a

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vector model for describing users or items, and then apply a similarity computation based on the vector model to find those similar users/items for a specific user/item, who are finally exploited to predict scores for this specific user/item. But those micro recommendation factors, such as item attributes, can often play an important role for recommendation acceptance. On the other hand, users often have diversified requirements, but the strict ranking mechanism for recommendation limits the recommendation diversification. For example, when a movie fan is labelled by a tag of action movie, most of the items in his/her recommendation list will be action movies. In addition, from the angel of the recommended items, each item wish to gain the recommendation opportunities, but the global ranking often causes that most of items can not be recommended for a low prediction score or less attention, the recommendation fairness are not introduced well.

This paper put forward a novelty recommendation model to provide both recommendation diversification and recommendation fairness, which also considers the item attributes for improving recommendation performance. The major contribution of this paper is to make full use of both users' historical information and item attributes to design a novelty recommendation strategy, the former is responsible for predicting those missing scores and then deciding the concrete item categories that have a high relevance with users, and the latter is applied to obtain the final recommended items in the limited categories by a multivariate linear regression model. The proposed recommendation strategy gains better recommendation performance when giving consideration on both recommendation diversification and fairness.

2 Related Work

Two popular recommendation strategies are recommendation based on collaborative strategy and recommendation based on classification-aided decision. Collaborative filtering is the most classical recommendation technology driven by collaborative strategy, which includes user-based collaborative recommendation [1], item-based collaborative recommendation [2,3] and model-based collaborative recommendation [4–6]. Their primary strategy is to model users/items as vector model and then to apply similarity metrics to find similar objects for identifying those items well matched with users. Computing efficiency is also a focus of recommendation based on collaborative filtering, [7] realizes a distributed and scalable collaborative filtering algorithm on cloud computing platform.

Classification-driven recommendation often uses classification results to generate recommendation lists. [8] proposes a novelty information entropy metric, which is based on a new split criterion and a new construction method of decision trees and can avoid local optimums. [9] introduces multi-label classification for approximate nearest neighbor search, which obtains better prediction accuracy for large label space. [10] put forwards a method that can extend random forest to any data set and obtains better performance on multi-dimensional data sets than traditional random forest methods. [11] introduces the recommendation technology for location-based services.

3 Problem Statement

In this section, we will discuss the problem about recommendation covering diversification and faireness. Usually, recommendation diversification requires that a user should enjoy items in different categories, and recommendation fairness requires that each item should have enough opportunities to be recommended. The traditional recommendation problem is that you have a set of ratings S that are done on a set of items I by a group of users U, you should output a list of items RI for a specific user u, in which each item $i \in RI$ has a high predicted rating for the user u than those items $j \in I \wedge j \notin RI$.

In order to give consideration to both recommendation diversification and fairness, a set of categories, C, are introduced to our recommendation problem, each item $i \in I$ belongs to a specific category $c \in C$. The attributes of items, which can show the popularity of items, such as sales, price, etc., are also covered for recommendation. The recommended items depends on a function $T(u, c)$ which tells the closeness between a user u and a category c, namely those items that will be recommended should satisfy two conditions, one is that the item should be in the categories that have a high score on closeness with the specific user u, and the other is that the item should have a high predicted rating for the user u in its category. The formal definition for recommendation covering diversification and fairness can be defined as Definition 1.

Definition 1. Recommendation covering diversification and fairness *Given a set of items I, a set of categories C, a group of users U and their ratings on items S, and a function $T(u, c)$ for computing the closeness between users and categories. The constraints are that each item $i \in I$ belongs to a category $c \in C$, and each item also has some attributes to show their popularity, such as sales, price, etc. Each score $s \in S$ is a triple, $<u, i, g>$, to show a real number g, namely the rating on the item i exerted by the user u. Recommendation covering diversification and fairness aims at finding those close categories with a specific user u by $T(u, c)$ and then applying the predicted rating and their popular attributes to decide those output items for each found category.*

In the above definition, recommendation diversification is provided by computing the closeness between users and categories, which can ensure that the items in different categories can be output, and recommendation fairness is improved by the final recommendation decision on the popular attributes of items.

4 Recommendation Model and Proposed Method

4.1 Recommendation Framework

In order to improve the recommendation diversification and recommendation fairness, we design a recommendation framework that is composed of four parts. The first step is to design the similarity metrics to find the similar users, and the second step is to provide a closeness function $T(u, c)$ and to compute the closeness between users and categories. The third step is to introduce multi-variate linear regression on the item attributes to compute their popularity, which will also consider the recommended times and the corresponding recommendation weights for each item, and the top-n popular items in top-m close categories will be initially filtered out. The final step is responsible for computing the global weights of the filtered items from the third step and outputting top-k items. The recommendation framework is illustrated in Fig. 1.

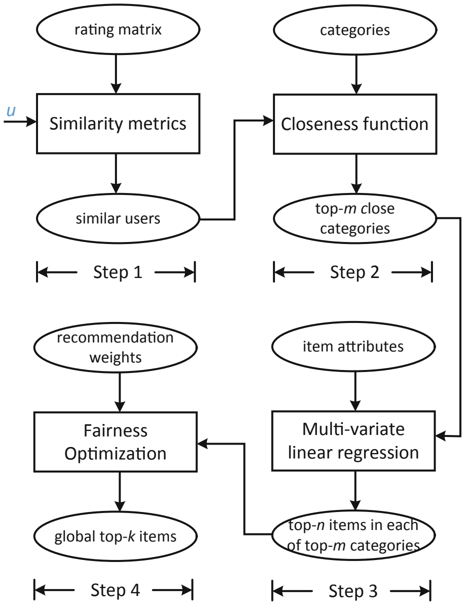

Fig. 1. The recommendation framework.

4.2 Computing Closeness Between Users and Categories

The part is responsible for finding similar users and then computing the closeness between users and categories. In order to find those similar users, we introduce weighted common scoring items $w_{ab}(i)$, which is based on the item similarity matrix H_{nn}. H_{nn} is constructed from the rating matrix by computing the similarity of any item vectors, $w_{ab}(i)$ is defined as Formula 1.

$$w_{ab}(i) = \frac{Max(|I(a \cap b)|, \gamma)}{\gamma} * \frac{(r_{a,i} + r_{b,j})}{2} * \frac{\sum_{g_j \in G_{ab} \wedge j \neq i} h_{i,j}}{n-1} \tag{1}$$

I is a set of items. $I(a \cap b)$ denotes the number of those items which are bought by both user a and user b. γ is a constant represented by a positive integer. $r_{a,i}$ denotes the rating that user a assigns to an item i. Obviously, $\frac{r_{a,i}+r_{b,i}}{2}$ is to increase the weights of those items that are assigned a high rating by both a and b, and to reduce the weights of those items that are assigned a low rating by a and b.

G_{ab} is an item set holding those items that are rated by both a and b, and n is the cardinal number of G_{ab}. $\sum_{g_j \in G_{ab} \wedge j \neq i} h_{i,j}$ is to sum all similarity between the specific item i and all items $j \in G_{ab} \wedge j \neq i$. The above value is used to indicate whether a category is a common preference of both user a and user b. Intuitively, a big value output by $\sum_{g_j \in G_{ab} \wedge j \neq i} h_{i,j}$ means that the category holding the item i have more common items with G_{ab}, and this category is more likely to be a preference for user a and user b. $w_{ab}(i)$ can compute the weights for similarity between a and b based on those corresponding item similarity. Depending on the weights contributed by $w_{ab}(i)$, we can define the Pearson Correlation Coefficient between user a and user b as Formula 2.

$$Sim(a,b,w) = \frac{cov(R_a, R_b; w)}{\sigma(R_a; w)\sigma(R_b; w)}$$
$$= \frac{\sum_{g_i \in G_{ab}} w_{ab}(i)(r_{a,i} - m(a;w))(r_{b,i} - m(b;w))}{\sqrt{\sum_{g_i \in G_{ab}} w_{ab}(i)(r_{a,i} - m(a;w))^2}\sqrt{\sum g_i \in G_{ab} w_{ab}(i)(r_{b,i} - m(b;w))^2}} \tag{2}$$

Here, $m(b;w)$ corresponds to the average value of all weighted ratings that are done on each item of G_{ab} by a, which is defined as Formula 3.

$$m(a;w) = \frac{\sum_{g_i \in G_{ab}} w_{ab}(i) r_{a,i}}{\sum_{g_i \in G_{ab}} w_{ab}(i)} \tag{3}$$

According to both item ratings and user similarity, the closeness between users and categories can be defined as Formula 4.

$$T_{a,c_k} = \frac{\sum_{i=1}^{n} r_{a,c_{k,i}}}{\sum_{j=1}^{m} \sum_{i=1}^{n} r_{a,c_{j,i}}} + Sim(a,b,w) \frac{\sum_{i=1}^{n} r_{b,c_{k,i}}}{\sum_{j=1}^{m} \sum_{i=1}^{n} r_{b,c_{j,i}}} \tag{4}$$

The expected rating of i contributed by a, namely $p_{a,i}$, can be computed as Formula 5.

$$p_{a,i} = \overline{r_a} + \frac{\sum_{b \in NSIM_a} sim(a,b,w) \times (r_{b,i} - \overline{r_b})}{\sum_{b \in NSIM_a} sim(a,b,w)} \tag{5}$$

$NSIM_a$ corresponds to the set holding the nearest neighbors of user a. $\overline{r_a}$ and $\overline{r_b}$ represent the average rating contributed by a and b respectively.

4.3 Ranking Items on Diversification

In this section, we introduce a multi-variate linear regression model to cooperate with collaborative filtering method for further optimization on recommendation outputs, in which both users macro behavior information and their micro attribute information are given a full consideration. When we obtain the closeness between users and categories, the attributes of those items in the top-k categories will be input into the multi-variate linear regression, which is defined as Formula 6.

$$F = f(x_{i,j}) = \omega^T x_{i,j} + d \tag{6}$$

Here, $x_{i,j}$ denotes the j_{th} attribute of the i_{th} item, such as sales, price, rating, etc. F can be understood as the quantitative popularity of items. The least square approach is used for deciding the optimal parameters of the regression model, and the minimal Euclidean distance is used as the evaluation metric.

The rating of each item on popularity, F, can be computed by the least square method. For giving consideration to the fairness of those unrecommended items, we introduce the item rating on the fairness, which is defined by both the recommendation times of items and the item rating on popularity and expressed as Formula 7. In Formula 7, the recommendation times of items is denoted as $times$, F is the item rating on popularity and FS is just the item rating on the recommendation fairness. The rating on the recommendation fairness aims at making those items in the long tail to gain the referral opportunities, which can avoid the recommendation overfitting effectively.

$$FS = \frac{log(2)}{log(1 + times)} F \tag{7}$$

4.4 A Comprehensive Ranking Algorithm

This section will design a comprehensive ranking algorithm based on the information provided by both the multi-variate linear regression model, which makes recommendation contributions by micro item information, and the collaborative filtering method. The great advantage for our proposed recommendation algorithm is that it can make the tradeoff among the recommendation accuracy, diversification and fairness. The whole recommendation process is presented in Algorithm 1.

5 Experiments and Analysis

In this section, we designed experiments on the real data set to verify our proposed recommendation method. The data set is an open data set on shopping and is composed of 12,000 records contributed by 213 users on 2352 items. The data set covers 18 categories, and each record consists of the following information, *title*, *category*, *sales*, *price*, and *rating*. All program is coded in Python and Matlab.

$$Accuracy = \frac{RightNum}{OutputNum} \tag{8}$$

$$Coverage = \frac{OutputCategories}{AllCategories} \tag{9}$$

$$Fairness = \frac{2 * Accuracy * Coverage}{Accuracy + Coverage} \tag{10}$$

Algorithm 1. *A Comprehensive Recommendation Algorithm*

Input: user a and b,
user-item rating matrix R,
common rating item set G_{ab},
item similarity matrix H_{nn},
Output: the top-k recommended item list
$p = 0, G_1 = G_{ab}$;
get g_i from G_1, $G_1 = G_1 - g_i, p++$;
repeat
  $G_2 = G_{ab}, w_{ab}(i) = 0, q = 1$;
  repeat
    get $h_{i,k}$ from H, $i \neq k \wedge g_k \in G_2$;
    $q++, G_2 = G_2 - g_k$;
    $w_{ab}(i) = w_{ab}(i) + h_{i,k}$;
  until $q \geq |G_{ab}|$
  $w_{ab}(i) = \frac{w_{ab}(i)}{n-1} * \frac{Max(|I(a \cap b)|, \gamma)}{\gamma} * \frac{(r_{a,i} + r_{b,j})}{2}$;
until $p \geq |G_{ab}|$
computing the weighted average $m(a; w)$ by Formula 3;
computing the similarity between users $Sim(a, b, w)$ by Formula 2;
computing the closeness between users and categories T_{a,c_k} by Formula 4;
computing the prediction rating between users and items $p_{a,i}$ by Formula 5;
computing the linear regression scoring of each item F by Formula 6;
computing the final recommendation score of each item FS by Formula 7;
generating the final top-k items according to the FS value of each item in each category;
return top-k items.

5.1 Experimental Evaluation

We introduce the recommendation accuracy and the category coverage as the evaluation metrics, which are defined in Formulas 8 and 9. Here, **OutputNum** denotes the number of the recommended items by our proposed method, and **RightNum** denotes the number of items that should be recommended and also are in the output list. **AllCategories** denotes the total number of the categories covering all items, and **OutputCategories** denotes the number of the categories that are related with those recommended and accepted items. Both accuracy and coverage are merged into the fairness for recommendation, which is a trade-off between the recommendation accuracy and recommendation coverage and is defined in Eq. 10. Cross validation is introduced for experimental evaluation, the ratio between the training set and the testing set is 8 to 2.

5.2 Experimental Results and Analysis

We made an experimental comparison between our proposed method (abbr. CTT) and the collaborative filtering method(abbr. CF), and the experimental results are presented in Figs. 2, 3 and 4. Our proposed method has a slight fall in the recommendation accuracy than the collaborative filtering method, but outperforms the collaborative filtering method on both the recommendation coverage and the recommendation fairness. The reason of a lower accuracy by our method is due that we reduce the recommendation time of those popular items that are covered by those categories with high closeness to users. The above measure contributes a little to the higher coverage and fairness, on the other hand, the integration of classification and micro attributes is very helpful to improve the recommendation performance.

We also designed a group of experiments to verify the recommendation performance under different data volume, and the experimental results are presented in Figs. 5, 6 and 7. When increasing the amount of data, both the recommendation accuracy and coverage have an obvious rising, which is due that more data can contribute more accurate relationships between users and items. But when the data amount becomes bigger, the recommendation fairness shows a small decrease, which is because the number of the recommended items is fixed though the base of the candidate items becomes bigger.

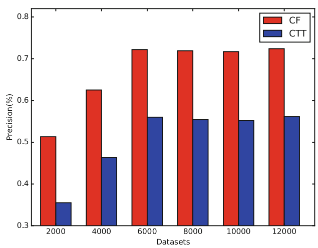

Fig. 2. Performance Comparison on Precision

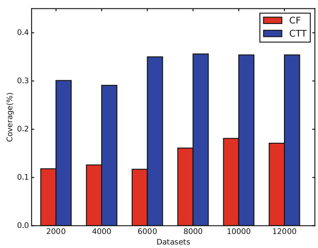

Fig. 3. Performance Comparison on Coverage

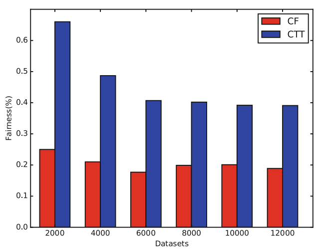

Fig. 4. Performance Comparison on Fairness

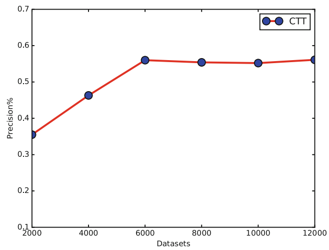

Fig. 5. Performance Comparison on Precision

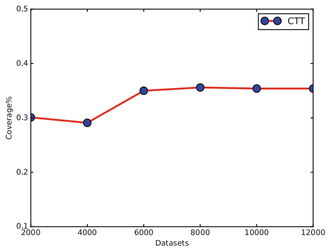

Fig. 6. Coverage

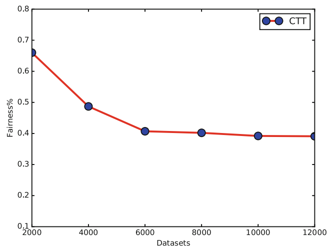

Fig. 7. Fairness

6 Conclusions

This paper provided an integration mechanism between the multi-variate linear regression and the collaborative filtering method for improving the recommendation performance, which presents a good performance for balancing the recommendation accuracy, diversification and fairness. The multi-variate linear regression model is responsible for considering the micro attributes of items to generate the final recommendation results in each category contributed by the collaborative filtering methods. The unification of macro users' behavior information and micro item attribute information make great contributions for improving recommendation accuracy, diversification and fairness.

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