Learning To Re-Rank For Multistakeholder Recommendations

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Abstract. Recommender Systems are personalized applications aiming to assist decision making by a list of tailored recommendations. Traditional recommender systems only focus on addressing the objective of the end users whose decisions ultimately determine the deal of the recommendation systems. However, the customer of the recommendations is not the only party whose needs should be represented. The needs of multiple stakeholders should be taken into account. In this paper, we are considering re-rank functions that are designed to balance end-user and online retailer needs. A variety of methodological approaches of different complexities are explored to incorporate profit information into recommenders and to balance preference and profitability. Taking the above factors into consideration, we tackle the problem balancing two sides by proposing a novel algorithm-Preference with Revenue Recommendation (PRR). Extensive experiments conducted on real world dataset indicate our method can be done with a marginal or no loss in ranking accuracy.

1. Introduction

Recommender systems (RSs) have been successfully applied to help millions of users finding items to meet their tastes[1]. These systems provide recommendations based on some existing information such as user's preferences, preferences of other users and purchase history of each user. RSs are popularly being employed to a number of applications, including e-commerce(e.g. Amazon, eBay), online streaming(e.g. Netflix, Pandora), social networks(e.g. Facebook, Twitter), tourism(e.g. Tripadvisor) and restaurant (e.g. Yelp), and they have become indispensable tools because of the volume of overwhelming content[2].

Traditional RSs produce a list of recommendations to satisfy the needs and interests of the end user. It is entirely appropriate to keep customers or viewers high loyalty and retention. However, the receiver of the recommendations may not be the only stakeholder in the recommendation outcome. Other stakeholders like the sellers, the system need to be considered when these perspectives differ from those of customers[3]. For example, in the reciprocal recommendation, both the user and the item models represent people, the date will be successful when each side is satisfied, therefore, it is necessary to consider the utilities of two parties to produce accurate recommendations. In the advertising area, user preferences and advertisers interests should be both taken into account. In that case, advertisement should be recommended to target users who have the possibility to purchase[4].
Sole focus on the end users’ preference hampers profitability for the provider. Sellers or providers would not make use of recommendation systems if they believed such systems were not making profits for them. What is needed is a shift in focus, considering not only the users’ considerations but also the perspectives and utilities of multiple stakeholders. Adding the provider as a stakeholder allows marketing to be integrated throughout the recommendation process[5-6].

There is a wide variety of potential ways that RSs can take a provider’s perception into account, such as increasing sales, revenues, user engagement. Sometimes, a business may wish to highlight products that are more profitable or that are currently on sale. Such profit-oriented goals may revolve around the capability of RSs to influence the behavior of the users by stimulating more or different sales or by keeping the users involved with the service[7]. These profit-oriented goals can easily be in conflict with end users’ needs, since the recommendation service might no longer be simply suggesting items with the expected highest utility for the consumer but rather explicitly taking into account the retailers’ own business-oriented considerations. Therefore, achieving the proper balance between the two sides constitutes an important and interesting research question[8].

In this paper, we mainly focus on the specific topic of profit awareness in RSs, aiming to learn the impact of the probability of users buying an item in a rank list. We incorporate some direct purchase information into the recommendation algorithm. The purchase record including the price of a recommended item, with or without a discount, the amount of discount, preferential amount, etc.

We assume a user will select his action from a limited number of options (purchase items which he/she have bought in history) and the system merely recommends a certain action (based on a certain model or algorithm). We believe that the purchase list can illustrate preference of the buyers to a certain degree. Therefore, our work mainly focus on evaluating the utility of different methods taking multistholder perspective, it is different from classic RSs which recommend a limited number of options from a large corpus and make the highest accuracy. Our algorithm supplies a ranked list of items which can balance the preference of buyers and the revenue of the sellers. The main work as follows:

Step 1: In order to maximize the probability that a user accepts a recommendation, three models were adopted to verify the prediction effect.

Step 2: This stage is based on Step 1. The best prediction model was used to provide users with Top-N items. Specially, we process the data into users groups, for each group, we provide recommendations from 1 to N.

Step 3: To illustrate the potential trade-off between recommendation preference and profit optimization, we test different algorithms on the same dataset, algorithms including Maximization Users Preference Recommendation (MUPR), Maximization Revenue Recommendation (MRR), Preference with Revenue Recommendation (PRR).

2. Model

We aimed to learn the maximize probability of purchase from a list of user features. Three models were employed to test the effect, models including a plain latent factor model Factorization Machine (FM), Deep Neural Networks (DNN) and the Factorization-Machine based neural network (DeepFM)[14]. FM have great success in discovering new low dimensional interactions, DNN are able to discover high-order feature combination, while DeepFM combining FM and DNN simultaneously share low-order and high-order interactions. Without extensive feature engineering, we achieved good effectiveness and efficiency by the aforementioned models, DeepFM was the best. DeepFM prediction model:

\[ \hat{y} = \text{sigmoid}(y_{FM} + y_{DNN}) \]  

Where \( \hat{y} \in (0,1) \) is the predicted possibility of user purchase, \( y_{FM} \) is the output of FM part, while \( y_{DNN} \) is the DNN component.
Based on the best output of the model, we leveraged the prediction of DeepFM as the input of the TOP-N recommendation. We adopted three methods MUPR, MRR and PRR to evaluate the recommendation taking multiple objectives into consideration.

In order to evaluate the effectiveness of recommendation, Ground Truth Ideal Discounted Cumulative Gain (IDCG) was used as the valuation Indicator and TOP-N items was recommended. NDCG was computed by the out of Discounted Cumulative Gain (DCG) divided by Ideal Discounted Cumulative Gain (IDCG). The ranking algorithm as follows:

\[ \text{NDCG@}N = \frac{\text{DCG}}{\text{IDCG}} = \frac{\sum_{i=1}^{N} 2^{\text{VAL}_i} - 1}{\sum_{i=1}^{N} 2^{\text{REAL}_i} - 1} \]

(2)

Where N is the number of recommended items, VAL is the order of predict value, whereas REAL is the Ground Truth order.

In MUPR model, we chose the highest user preference as recommendation items. In our experiment, the Ground Truth IDCG was each user’s purchase number list sorted from high to low and normalized. In MRR, we took the revenue as the only indicator to recommend, the most profitable one is pushed to the top of the list. PRR was a multi-object and MultiStakeholder task, the most preference for the users and maximized revenue for the provider were in consideration. We leveraged Least square function to fit the most relevant items of customers and the most profitable for providers, and training model with mean square error. Compared with the previous two methods, our model has a good effect on the data set, and has little difference with the recommendation of ground truth top-N.

\[ \hat{y} = \alpha \cdot \text{VAL} + \beta \cdot \text{REV} + \varepsilon \]

(3)

Where \( \alpha, \beta \) are parameters for training, \( \varepsilon \) is bias, REV is the real revenue of providers.

3. Dataset and Experiments

We conducted experiments on a real word dataset, data were collected from online delicacy takeout service website (ODTS). The ODTS corpus contained 5330 users, 5025 items and 617,531 transaction records, of which 43.03% were females and 56.97% were males. Explicit feedbacks were scarce and not always available, but implicit ones were relatively easy to gain from users behavior history, such as purchase records.

In order to learn the impact of the items rank on the likelihood of the users buying a item, sufficient records should be employed, so we removed all prices from the dataset where the number of user transactions was lower than 15. Cross-validation is used to estimate the performance of different algorithms. The validation datasets are randomly divided into training and test sets with a 75/25 splitting ratio. We compare the performance of different models (FM, DNN, DeepFM) on ODTS. For each model, we set the number of epoch to 100, the number of boosting iterations to 1000, and swept the values of learning rate 0.1.

As shown in Fig. 1, FM fluctuates slightly between 0.1 and 0.2, but there is no downward trend. DNN decreased rapidly between 0-40 epoch, 40-100 epoch tended to be stable and kept around 0.11. Compared with DNN, DeepFM decreases more sharply. It reaches the local minimum RMSE at epoch 20, fluctuates slightly at 40-60 epoch, decreases continuously after 60 epoch, and reaches the optimum at 100 epoch. It clearly illustrates that DNN and DeepFM have better prediction result after training, maybe the features in ODTS have high-order interactions than low dimensional ones.
In the Step 2 ranking stage, each user was recommended 5,10,20 items respectively. We did not recommend more items because of the limited dataset and the relatively stable user taste. We applied the final prediction result of DeepFM to the rank step, that was the MUPR. While in the revenue maximizing settings all items were sorted from high to low by user groups, then ranking step continued. Whereas simply recommending those items with the highest profit for customers is probably in almost all cases not the optimal strategy, as users might start to distrust a recommendation service when its suggestions are not considered useful. Generally, we can hypothesize that in many domains there is a trade-off between suggesting items that are the most profitable for the providers and suggesting those that are considered the most relevant for the user. The third method was designed base on aforementioned thoughts, in our PRR design, both the customer’s preference and the supplier’s profitability are into account.

Fig. 1. RMSE of three models.

Fig. 2. The NDCG distribution of different algorithms.

Fig.2 shows the performance of three different Models (MostRelative for MUPR, MaxRevenue for MRR, MultistakeholderModel for PRR) for TOP-10 items recommendation. MUPR is evenly distributed between 0.8 and 1.0, and 343 users ndcg value reaches 0.6-0.7. This is in the case of fully considering user preferences, without considering other stakeholders. In contrast, the NDCG distribution of MRR is not ideal. From the bar chart, we can see that the number of users less than NDCG 0.5 is quite large, more than the sum of users of all other distributions. This recommendation
effect has far deviated from the user preferences. The recommendation scheme based on this model may not be accepted by users. The third recommended scheme PRR gradually shows an upward trend in the range of 0.5 to 0.9, and reaches a stable level in the range of 0.9 to 1.0, which is similar to the number of users in the previous range. At the same time, the number of users in the lower NDCG value range is also small, which is less than 500. The recommendation scheme generated under this model, on the one hand, considers the customer's preferences to the maximum extent, and also considers the maximum benefit of the provider, which belongs to the multistakeholder recommendation mode. This method is also easy to be accepted by end users.

In order to compare and verify the impact of the number of different recommended commodities on NDCG, we also recommend top-5, top-10 and top-20 items, as shown in TABLE1.

| TABLE I. NDCG RANK OF DIFFERENT MODEL |
|---------------------------------------|
| Mean NDCG of Three Models             |
| NDCG@5                  | MUPR | MRR | PRR |
| 0.6437                        | 0.1490 | 0.6045 |
| NDCG@10                     | 0.6991 | 0.1825 | 0.6772 |
| NDCG@20                     | 0.8050 | 0.3091 | 0.7997 |

The above table illustrates the effect of different recommended online items under different models. The value of MUPR is always the largest among the three models, and it shows an upward trend with the increase of the purpose of the recommendation. This is reasonable because with the increase of recommended commodities, the probability that users can choose their favorite commodities also increases. However, in the experiment, we did not test more than 20 items, as we are based on the historical data of user shopping and the user's taste is relatively stable, and we will not try too many different products.

Nevertheless, for MRR, as shown in Fig.2, the recommended effectiveness of the model is not ideal. Compared with the MRR of 5 recommended products, NDCG is only 0.1490, and 20 recommended products is 0.3091, which is almost 0.5 lower than that of MUPR at the same level.

As mentioned above, PRR model can well fit the preferences of multiple stakeholders of users and providers. At the same time, with the increase of the number of recommended items, the recommendation effect also shows an obvious upward trend. The gap between PRR and MUPR is 0.0053 in top-20. It is proved that the model is effective in considering multiple stakeholders and multiple objectives.

4. Conclusion
In this work, we have proposed a novel learning-to-re-rank approach for solving multistakeholder recommendation problems. We have addressed the difficult task of learning a linear combination of potentially conflicting stakeholder objectives by defining a novel Preference with Revenue Recommendation algorithm. Experimental results on the ODTS dataset suggest that our approach is effective in solving this problem, it delivers the best performance trade-off for customers and online providers under consideration.

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