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User Adoption Tendency Modeling for Social Contextual Recommendation

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ABSTRACT: Most of studies on the existing recommender system for Netflix-style sites (scenarios with explicit user feedback) focus on rating prediction, but few have systematically analyzed users' motivations to make decisions on which items to rate. In this paper, the authors study the difficult and challenging task Item Adoption Prediction (IAP) for predicting the items users will rate or interact with. It is not only an important supplement to previous works, but also a more realistic requirement of recommendation in this scenario. To recommend the items with high Adoption Tendency, the authors develop a unified model UATM based on the findings of Marketing and Consumer Behavior. The novelty of the model in this paper includes: First, the authors propose a more creative and effective optimization method to tackle One-Class Problem where only the positive feedback is available; second, the authors systematically and conveniently integrate the user adoption information (both explicit and implicit feedbacks included) and the social contextual information with quantitatively characterizing different users' personal sensitivity to various social contextual influences.

Keywords: recommender system, context-awareness, collaborative ranking, behavior modeling

1 INTRODUCTION

Social network, as an effective medium for users to share information, has become more and more important and popular. For those social review sites such as Douban and Epinions, users can exchange their preference by assigning ratings on the watched items such as movies, books, music or adding the unwatched but appealing items to the wish list. However, the number of users and items becomes so large that it is hard for users to find either the watched items or appealing items. Therefore, the recommender system as an Information Filtering technique has effectively met the needs.

There are two basic tasks in the area of recommendation. For the scenarios where users' explicit feedbacks like rating are available, the recommendation list is generated by ranking all the items in a descending order of the predicted ratings. Thus, Rating Prediction which recovers the missing ratings is the key issue. By assuming that the rating scores reflect users' preference, these methods are used to help the user find the items which will be assigned good feedback then. However, the user preference feedback is based on the prerequisite that the items (movies) have been watched in the past or will be watched in the future. The issue is that for the unrated items we don't know what users have watched as well as what users will watch. This generates the urgent requirement for another fundamental task: The item Adoption Prediction (IAP for short), which predicts the items that will be adopted (for example, watched movies or movies to be watched).

In fact, IAP is not only an important supplement to previous works, but also a more realistic requirement of recommender systems. The review sites whose contents are generated by users, recommending the items that users will adopt can directly improve interactivity and enhance user's participation. And the users whose purposes of surfing on the review sites are either to rate and review items or to find the right items for themselves to watch, recommending the watched or appealing items that can meet their needs. Briefly speaking, in this recommendation scenario, IAP is of great significance since it can both boost sites' popularity and foster users' satisfaction. Thus, recommending the items that users will adopt should be a more crucial issue than recommending those who will give a high score if having adopted. This motivates us to address IAP problem for social review sites.

To address these challenges, in this paper, we propose the User Adoption Tendency Model which is coined as UATM. The goal of our model is to recommend the items users will adopt, namely the items a given user will rate or interact with in the future. Assuming that user behaviors are affected by the user personal preference (the user preference factor) and external environment conditions (the social contextual influence), our model generates the recommendation list by ranking all the items in a descending order of the computed Adoption Tendency Score.

2 RELATED WORK

Our research is substantially different from the previous works which either focus on rating prediction in

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the scenarios with user explicit feedbacks[6, 7], or cast the recommendation task as user adoption predictions in the scenarios without explicit feedbacks[4, 9].

One-Class Problem is the main challenge of IAP. An intuitive idea is given to introduce negative examples from missing data. Existing approaches can be broadly classified into two categories: One is to randomly sample negative samples from the missing data [2, 8], and another is to treat all the missing data as negative samples with adding weights on them [8].

The information Integration is another challenge to build more accurate recommender system. Social information is utilized to better shape the user latent space typically. For example, [6] makes a recommendation by adding additional social regularization terms in MF to constrain the user latent feature vectors to be similar to his or her friends' average latent features. [12] proposes a category-specific social trust influence weight which outlines several variants of weighting friends within circles based on their inferred expertise levels. And the contextual information has also been recognized as an important factor[5, 11].

3 FRAMEWORK

Definition: The Adoption Tendency Score ($ATS_{i,j}$) reflects the tendency for user i to adopt the item j. The higher ATS is, the higher probability for user to adopt is. $ATS_{i,j} = P_{i,j} \bullet I_{ij}$, where $P_{i,j}$ and I_{ij} respectively represent the user personal factors and the environmental influence factors.

As the user personal factors followed with MF-based methods, we assume that how much a target user i likes the given item j depends on the user latent feature U_i and the item latent feature V_j. Finally, $P_{i,j} = U_i \cdot V_j$.

The environmental Influence Factor: Social contextual environment can also influence the user decision-making process. Assume that we have extracted social contextual features (The detail feature extraction discussion is beyond this paper). $F_{j,k}^{(i)}$is the *k*th features of item j with respect to user i. For example, when the *k*th feature is “Friends”, $F_{j,k}^{(i)}$ can be the number of the user i's friends who adopted the item j. When the *k*th feature refers to “Genres=Horror”, then $F_{j,k}^{(i)}$ =1 if the item j is a horror movie, or 0 otherwise. Then, we normalize each feature value to [0, 1]. To quantitatively capture the different sensitivity to various features for each user, we develop a latent factor S. $S_{i,k}$ is used to describe the sensitivity of the user i to the *k*th feature. Finally, the environmental influence is shown as follows:

$$I_{i,j} = \sum_k S_{i,k} \cdot F_{j,k}^{(i)}.$$

As the motivation mentioned earlier, we propose a unified recommendation framework for IAP to model the user decision-making process by leveraging explicit and implicit feedbacks, social contextual information embedded in the social network. The framework of our model is illustrated in Figure 1. Thereinto, the ATS of user i that has on item j can be formally denoted as follows:

$$A = P \odot I = U^T V \odot S^T F \quad (1)$$

4 USER ADOPTION TENDENCY MODEL

4.1 *Random UATM (r-UATM)*

Assumption 1: For a given user, the ATS of positive samples (adopted items) are greater than the ATS of the negative samples (rejected items).

This assumption makes collaborative ranking [2, 9] applicable to IAP. Our intuition can be encoded as a problem of rank optimization. Given a user i and two items which are m and n, we use the following pairwise model to define the probability that an item m ranks before an item n according to the ATS:

$$P(rank(m) < rank(n)|i) = \frac{1}{1+e^{-(A_{im}-A_{in})}} \quad (2)$$

Where, A_{im} and A_{in} are the ATS of user i that have on item m and n respectively. For our optimization problem, the pair set D can be defined as follows:

$$D = \{< i, m, n > | m \in Pos(i), n \in Neg(i)\} \quad (3)$$

Where Pos(i) is the positive set which consists of items adopted by the user i, and Neg(i) is the negative set which consists of items rejected by the user i. Our optimization task is to maximize the probability that the positives rank before the negatives. As we know, we can't explicitly get the negatives, namely the items that the user won't adopt in the future. All we have is either positive or unobserved. Based on the statistics on the real-world dataset among the unobserved samples, the number of the negatives is far greater than that of the positives. Hence, we use sampling technique to get negatives in the training procedure. Finally, to maximize the probability in Eq.(2), it is equivalent to minimize the objective function shown as follows:

$$\underset{S,U,V}{argmin} \sum_{<i,m,n> \in D} ln(1+e^{-(A_{im}-A_{in})}) + Regularization \quad (4)$$

4.2 *Prototype UATM (p-UATM)*

The first objective which we propose to some extent is used to solve the problem brought by no-negative samples. And we may simultaneously introduce the noise as well. Even though the probability that the negative samples we obtain through random sampling are the items that user won't adopt is very high, we still probably mistaken assign the items adopted in the future to negative samples. Hence, in order to tackle this problem, we propose another objective function in Eq.(5) with the following assumption.

Assumption 2: For a given user, the ATS of the adopted item is greater than average ATS of the unobserved items. The greater ATS of the item which surpasses the average of the unobserved items, the higher probability that the user adopts the item is.

This assumption is consistent with application scenarios since the number of negatives is far greater than that of positives. With this assumption, our recommendation task can be converted to the rank problem of the positive samples with the unobserved samples instead of the negative samples. To maximize the probability that the ATS of the adopted items which are greater than average ATS of the unobserved items, it is equivalent to minimize the objective function in Eq.(5):

$$\underset{S,U,V}{argmin} \sum_{<i,j>\in O} ln(1+e^{-\Delta_{ij}}) + Regularization \quad (5)$$

Where $O = \{< i,j > |user\ i\ adopted\ item\ j\}$ is the observed adoption set, and $\Delta_{ij} = A_{ij} - \overline{A_i}$. A_{ij} is the ATS of the adopted item, and $\overline{A_i}$ which serves as a negative prototype that can be calculated by the average ATS of the unobserved items. The objective function enables us to avoid explicitly introducing negative samples. The advantages will be verified in the experiments.

4.3 *Behavioral regularization*

Based on the intuition that historical rating scores can be used to reflect preference and historical adoptions that can be used to reflect personal sensitivity to various social contextual features, we embed them into the objective function by introducing the rating matrix R and the adoption behavior matrix B to respectively constrain P and S. Where R_{ij} is the user i's rating score on item j and B_{pq} is the ratio of user p's adoptions at feature q (For example, if 30% of adopted movies are horror movies, then the sensitive value is 0.3). With behavioral regularization we can extend the Eq. (5) as follows:

$$\underset{S,U,V}{argmin} \sum_{<i,j>\in O} ln(1+e^{-\Delta_{ij}}) + \lambda_1||P-R||_F^2 + \lambda_2||S-B||_F^2 \quad (6)$$

Where, $||\cdot||_F^2$ is the Frobenius norm and λ_1, λ_2 are the tuning parameters. To avoid over-fitting, we introduce the following global regularization term which constitutes a constraint of the complexity of S, U, and V:

$$\begin{aligned}&\underset{S,U,V}{argmin} \sum_{<i,j>\in O} ln(1+e^{-\Delta_{ij}}) + \lambda_1||P-R||_F^2 \\ &+\lambda_2||S-B||_F^2 + \lambda_3||S||_F^2 + \lambda_4||U||_F^2 + \lambda_5||V||_F^2\end{aligned} \quad (7)$$

A local minimum of the objective function given by Eq. (7) can be found by performing gradient descent in S, U, and V, which are iteratively updated.

5 EXPERIMENT

5.1 *Dataset description*

We use the version of Douban dataset shared by Erheng Zhong and so on [13]. The original data consists of 5257666 adoptions between 33561 users and 87081 movies. It also has the relationships among the users. To obtain rich contextual information, we further select webpages of the relative movies from Douban website and extract 566 social contextual features in total, including Friends (1), Popularity (1), Quality (1), Freshness (300), Genres (37), Language (130) and Location (96). The trivial process of feature extraction is omitted for limited space. Furthermore, we discard the movies which we fail to select their property information and remove the users who are suspected as spammer (which means adopting mass movies within a limited time). Finally, we collect 4270761 adoptions between 32948 users and 40212 movies.

5.2 *Experimental protocol*

Different from the task of traditional movie recommendation, our task is to recommend movies which will be adopted in the future. To simulate the real application scenarios, our model and all baselines are required to predict the user adoption behavior in the future according to the historical behavior. For Douban dataset, we partition the dataset into 3 parts: the test set which including the adoptions in the last month (Oct. 2011), the validation set which including the data in Sep. 2011, and the training set consists of the others(before Sep. 1, 2011). We use the validation set to tune the parameters of our models and all the baselines. And then, we utilize the tuned parameters to train models on training-validation set. Since we cannot treat all the items that have no feedbacks in the test(validation) set as irrelevant/negative ones, we adopt a conventional widely-used evaluation strategy [3, 11]. For each user in test (validation) set, we randomly select 40 movies that have no feedback as irrelevant items and construct a candidate list which includes these 40 movies together with those positive ones. The goal is to rank the movies which users really adopted in front of the randomly sampled ones. We use four standards and popular evaluation metrics to measure and compare the performance of various recommendation models:

$$Precision@n = \frac{\#\ of\ adoptions\ in\ Top\ n\ list}{n}$$

$$Recall@n = \frac{\#\ of\ adoptions\ in\ Top\ n\ list}{\#\ of\ total\ adoptions}$$

$$F1@n = \frac{2 \times Precision@n \times Recall@n}{Precision@n + Recall@n}$$

$$AP_i@n = \frac{\sum_{n=1}^{N} Precision@n \times I(n)}{\#\ of\ adoptions\ of\ user\ i}$$

Where N is the length of recommendation list and

I(n) is the indicator function returning 1 if the n-th recommended item is adopted by i or 0 otherwise. Mean Average Precision (MAP) can be obtained by averaging AP of all the users.

We compare the proposed methods with baseline methods: Item-based CF [10], User-based CF, BMF, KDDCUP07 [4], SoReg [6], SoCo [5], CTR [2], and some reduction versions of UATM.

5.3 *Results*

Note that all the metrics evaluate the performance of Top-N recommendation. Thus, we plot the values of the metrics with different N.

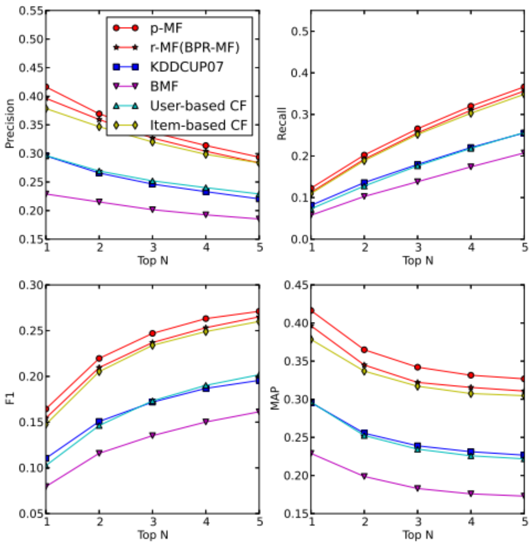

Figure 1. Performance comparison over 4 metrics for theoptimization objective

Optimization Objective In order to verify the advantage of the proposed optimization objective, we conduct this experiment without utilizing any social and contextual information. As is exhibited in Figure 1, the proposed p-MF model consistently outperforms the other methods over all the metrics. The performance of BMF is the worst among all the approaches, which verifies that the optimization objective of rating prediction is not consistent with our recommendation scenarios. Different from BMF, the method which won KDDCup07 is a tailor made for IAP. However, the performance is not as good as expected since it regards all the missing ratings as negatives and the optimization objective is to minimize the RMSE on the binary matrix. User-based CF and Item-based CF achieve relatively good performance since they naturally recommend popular items. Nevertheless, it is hard to further incorporate social and contextual information into these methods. Finally, although r-MF (BPR-MF) is comparable with the proposed p-MF, it is clear that introducing a negative prototype is of value to further boost the performance.

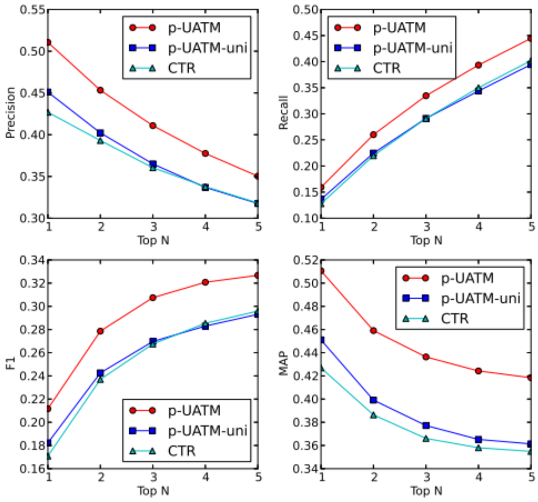

Figure 2. Performance comparison over 4 metrics for the user sensitivity modeling

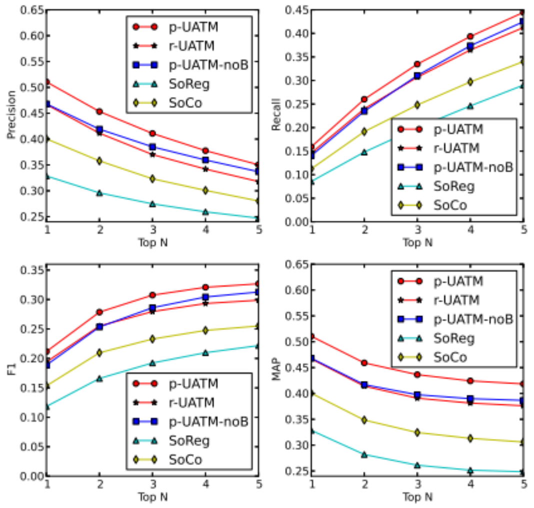

Figure 3. Performance comparison over 4 metrics for the unified model

User Sensitivity Modeling Another innovation of our proposed models is quantitatively characterizing the social contextual influence on different users. We provide a comparison of three approaches which identically derive the optimization objective from Collaborative Ranking: The p-UATM models user's personal sensitivity; the modified version of p-UATM uniformly characterizes the average sensitivity of all the users; and the CTR estimates the global influence of various social contextual explicit features in a linear combination model. Thus, the comparison can be focused on the different granularity of sensitivity modeling. Figure 2 shows that the improvement of our proposed model over the two baselines is obvious. This provides strong evidence that the personalized sensitivity factor is indeed useful to improve the quality of recommendation Compared with the CTR, the p-UATM-uni achieves only slightly better precision, which indicates that the average sensitivity without personalization can make limited contributions.

Unified Model To the best of our knowledge, there is no existing work which tackles the IAP integrating adoption information and the social contextual information in similar scenarios. We adapt the state-of-the-art social contextual recommendation methods for rating prediction to IAP by training them on a binary adoption matrix. The comparison results are shown in Figure 3. SoReg which only considers the social relationships performs the worst. Although it is reported that SoCo clearly outperforms SoReg for rating prediction task, SoCo works poorly in this situation. As what we have observed, both the UATM and its variations have a more significant improvement than others. More specifically, the p-UATM consistently performs better than the r-UATM over all various N, which demonstrate the effectiveness and necessity of utilizing negative prototype again. The observation that the p-UATM outperforms the p-UATM-noB supports the importance to utilize the user historical behavior information.

6 CONCLUSION

Our research improves the understanding of the challenging but realistic recommendation task IAP. By modeling user's motivation to adopt items, we propose a unified model UATM which systematically integrates the user explicit feedback, the user implicit feedback, and the social contextual information. The novelty of the proposed method includes: First, the optimization objective with solid probabilistic derivation for tackling One-Class Problem; and Second, the users' personal sensitivity modeling to various social contextual influence. Extensive experiments demonstrate that both the new optimization objective and user sensitivity modeling can greatly boost the recommendation performance.

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