Incorporating Curiosity into Personalized Ranking for Collaborative Filtering (Student Abstract)

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Abstract

Curiosity affects the users' selections of the items, and it motivates them to explore the items regardless of their preferences. This phenomenon is particularly common in the social networks. However, the existing social-based recommendation methods neglect users' curiosity in the social networks, and it may cause the accuracy decease in recommendation. What's more, only focusing on simulating the users' preferences can lead to information cocoons. In order to tackle the problems, we propose a Curiosity Enhanced Bayesian Personalized Ranking (CBPR) model. Our model makes full use of the theories of psychology to model the users' curiosity aroused when facing different opinions. The experimental results on two public datasets demonstrate the advantages of our CBPR model over the existing models.

Introduction

Curiosity is the intrinsic motivation for exploration (Wu and Miao 2013). Especially in social scenario, users are curious about the new information about how other people behave, feel, and think (Wu et al. 2016). For example, Bob's friends have different opinions about a movie, which may arouse the feeling of uncertainty and make Bob curious. This curiosity may urge him to see the movie and explore the reasons for the disagreement even though the movie is not his type. Since the users' curiosity can affect their selections, it is more sensible to take into account the users' curiosity when recommending items for them.

Although the existing social-based recommendation methods achieve great performance, most of them do not fully exploit the psychological characteristics of people in the social networks (Zhao, McAuley, and King 2014). They only employ one characteristic that the users and their friends tend to have similar preference and recommend the items their friends prefer for the user. However, they ignore that the decision one makes is not only influenced by the users' preference but also the users' curiosity in the social networks. Therefore, failure to consider the curiosity during recommendation may lead to a decrease in the accuracy of the recommender system. Even worse, only focusing on the users' preference can result in recommending similar items without diversity, and thus the users can easily get bored.

To solve the above problems, we propose a Curiosity Enhanced Bayesian Personalized Ranking (CBPR) model which incorporates the users' curiosity to the recommender system. Based on the psychologist Berlyne's theory (Berlyne 1960), we provide a method to quantify the curiosity of a user for an item by measuring the uncertainty stimulus. The uncertainty stimulus is one of the main factors that induce curiosity. Specifically, the uncertainty stimulus is calculated using the information entropy on the users' friends. Apart from direct friends, we also consider the influence of the indirect friends on the curiosity of the user.

Proposed Methodology

Notation There is a set of users denoted by U, and a set of items denoted by I. $|U| = m$, $|I| = n$. For each user, all items I can be split into three parts, Positive feedback P_u which are the set of items that user u have behaviors, Curiosity feedback C_u which are the set of items that not chosen by the user u but may attract their curiosity, and Negative feedback N_u which are the set of items that user u does not choose and may have no curiosity about them.

Model Assumption A user would prefer the items from positive feedback to negative feedback, and the items from curiosity feedback to negative feedback. $x_{ui} \geq x_{uj}, x_{uk} \geq x_{uj}, i \in P_u, k \in C_u, j \in N_u$, where x_{ui}, x_{uk} and x_{uj} represent a user u's interest on the items i, j, k from the positive feedback, curiosity feedback and negative feedback.

Modeling of Curiosity Uncertainty stimulus is one of the key factors that can induce curiosity, and we quantify the curiosity of a user by measuring the uncertainty stimulus. We formally define the user u's uncertainty for item i using information entropy as $si^{un}_{u,i} = -\sum_{r=1}^{R} p^r_{u,i} \log p^r_{u,i}$ following psychologist Berlyne's theories (Berlyne 1960), where R is a set and denotes all possible response around user u, such as his friends' different ratings from 1 to 5, and $p^r_{u,i}$ denotes the probability of each response for item i. We use softmax function to calculate $p^r_{u,i} = \frac{\exp(w^r_{u,i})}{\sum_{r=1}^{R} \exp(w^r_{u,i})}$, where $w^r_{u,i}$ refers to user u' s weight of each possible response r for item i, formulated as $w^r_{u,i} = \sum_{d=1}^{D} \left[e^{-\mu d} \times \frac{N^r_{v,i}}{N_{v,i}} \right]$, where

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$v \in U_u^d$ and D represents the farthest social network layer. U_u^d denotes user u's friends in layer d. For example, friends in layer 1 are the direct friends of user u. Friends in layer 2 are the direct friends of the direct friends of user u. $N_{v,i}$ and $N_{v,i}^r$ denote the number of user u's friends in layer d who give any response on item i, and the number of user u's friends in layer d who give response r (such as friend v gives 5 score rating) on item i. μ is information spread coefficient, and term $e^{-\mu d}$ is used to depict that information spread is decaying with the social network layer d.

We use uncertainty stimulus $si_{u,i}^{un}$ as the curiosity score. Based on Wundt Curve, too little uncertainty stimulus will cause boredom (Xu et al. 2019). Therefore, we set a threshold γ to filter the incurious items and only select the items whose uncertainty stimulus is above the threshold into the curiosity feedback C_u. The users' curiosity feedback set is $C_u = \{i \in (I - P_u) | si_{u,i}^{un} \geq \gamma\}$.

Learning the CBPR We try to minimize the objective function of CBPR bellow:

$$\mathcal{O} = \sum_u \left[\sum_{i \in P_u} \sum_{j \in N_u} - \ln \sigma(x_{uij}) + \sum_{k \in C_u} \sum_{j \in N_u} - \ln \sigma(x_{ukj}) \right] + \lambda_\Theta \left\| \Theta \right\|^2 \tag{1}$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$, $x_{uij} = x_{ui} - x_{uj}$ and $x_{ukj} = x_{uk} - x_{uj}$. For any item $l \in I$, the rating of user u for item l is $x_{ul} = W_u V_l^T + b_l$, where the vector W_u represents the user u, the vector V_l represents the item l, and b_l represent the bias of item l. W $\in \mathbb{R}^{m*f}$, $V \in \mathbb{R}^{n*f}$, $b \in \mathbb{R}^n$ and f is the latent factor numbers. Parameter set $\Theta = \{W, V, b\}$ and $\lambda_\Theta \left\| \Theta \right\|^2$ is a L2-norm regulation. The objective is to maximize the difference of the item ratings between P_u and N_u and between C_u and N_u. The optimization problem of the objective function above can be solved by the stochastic gradient descent with bootstrap sampling of training triples following (Rendle et al. 2009). The model parameters are updated as follows:

$$\Theta \leftarrow \Theta + \alpha \left(\frac{e^{-x_{uij}}}{1+e^{-x_{uij}}} \cdot \frac{\partial}{\partial \Theta} x_{uij} + \frac{e^{-x_{ukj}}}{1+e^{-x_{ukj}}} \cdot \frac{\partial}{\partial \Theta} x_{ukj} - \lambda_\Theta \Theta \right) \tag{2}$$

where $\alpha > 0$ is the learning rate.

Item Recommendation We generate a candidate list for the target user u. It contains K items with the highest ranking scores which can be calculated by $\hat{x}_{ul} = W_u V_l^T + b_l$.

Experiments

Datasets FilmTrust and CiaoDVDs[1] are both social datasets, which are crawled from the FilmTrust website in 2011 and the Dvd Ciao website in 2013 respectively.

Baseline Methods We compare our models with several state-of-the-art recommendation baselines models, including Pop, RankSGD (Jahrer and Töscher 2012), BPR (Rendle et al. 2009), SBPR (Zhao, McAuley, and King 2014) and UC (Wu, Liu, and Miao 2017)

[1]https://guoguibing.github.io/librec/datasets.html

Methods	FilmTrust		CiaoDVDs	
	P@10	R@10	P@10	R@10
Pop	0.1382	0.3245	0.0105	0.0375
RankSGD	0.1654	0.2706	0.0070	0.0214
BPR	0.3458	0.6066	0.0120	0.0426
SBPR	0.3362	0.5890	0.0120	0.0402
UC	0.3279	0.5512	0.0117	0.0373
CBPR	**0.3506**	**0.6248**	**0.0152**	**0.0519**

Table 1: Evaluation results

Results We use Precision at 10 (P@10), Recall at 10 (R@10) to evaluate the recommendation performance. The results are shown in Table 1. We can see that our model significantly outperforms the state of the art methods. It proves that except users' preference, curiosity also affects the users' selection of the items. By considering the users' curiosity, our model can predict the users' behaviour more accurately.

Conclusion

The users' curiosity plays a crucial role in the users' selection. In this paper, we propose the CBPR method which integrates curiosity into recommendation in the social networks. Particularly, we provide a way to measure the curiosity by modeling the uncertainty stimulus and incorporate it into the BPR model. Comprehensive experiments on two real-world social datasets show the effectiveness of our model.

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