Modeling User Behavior in Recommender Systems based on Maximum Entropy

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ABSTRACT

We propose a model for user purchase behavior in online stores that provide recommendation services. We model the purchase probability given recommendations for each user based on the maximum entropy principle using features that deal with recommendations and user interests. The proposed model enable us to measure the effect of recommendations on user purchase behavior, and the effect can be used to evaluate recommender systems. We show the validity of our model using the log data of an online cartoon distribution service, and measure the recommendation effects for evaluating the recommender system.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications—*Data Mining*; H.3.3 [**Information Storage and Retrieval**]: Information Retrieval and Search—*Information Filtering*

General Terms

Algorithms,Experimentation

Keywords

recommendation, user model, maximum entropy principle

1. INTRODUCTION

Recommender systems are widely used by online stores because they can improve user convenience and store profits. Recommendations would change user behavior, and it is important for online stores to understand user behavior when items are recommended. If online stores know the degree of change in purchase behavior brought about by recommendations, they can predict the degree to which the recommendations can increase cross-sell. Although a number of user behavior models have been proposed, they do not consider the effect of recommendations.

In this paper, we propose a model for user behavior in online stores that provide recommendation services based on the maximum entropy principle. The maximum entropy principle is a method for estimating a probabilistic distribution that satisfies all the constraints in the given data while maximizing the entropy [2]. In our model, we estimate purchase probabilities for each user given recommendations under the constraints present in the purchase log data. One of the advantages of the maximum entropy principle is that we can integrate arbitrary features in the model. We integrate user interest information and recommendation information for a user behavior model by employing the maximum entropy principle.

From the log data, our model can estimate the degree of change in purchase probabilities induced by recommendations. We call this degree of change the *recommendation effect*. It is difficult to evaluate recommender systems [1]. Most recommender systems have been evaluated in terms of their accuracy in predicting ratings or next purchase items. However, the high predictive accuracy of the recommendations does not necessarily imply good recommendations. Those recommendations are likely to recommend ordinary items that users are already aware of. Although other factors, such as novelty or serendipity [3] have been proposed for use in evaluating recommender systems, it is difficult to measure them quantitatively. The recommendation effect estimated with our model can be used to evaluate the recommender system itself. The recommendation effect can be different for different users. Some users are more likely to purchase items than others when recommended. We estimate the recommendation effect for each user. We evaluate our model using real log data, and we estimate the recommendation effect and the difference among users. To the best of our knowledge, this is the first report describing the recommendation effect in relation to individual users in a real online store.

2. USER BEHAVIOR MODEL WITH RECOMMENDATIONS

Let $\boldsymbol{S} = \{s_j\}_{j=1}^{V}$ be a set of items, and $r(u) \subset \boldsymbol{S}$ be a set of recommended items. Based on the maximum entropy principle, we estimates $P(s|u, r(u))$, which is the probability that user u purchases item s when an item set $r(u)$ is recommended.

The item that a user purchases depends on the recommended items and the user interests. We use two types of features to model user purchase behavior. The first is whether item s is recommended to user u or not:

$$z(r(u), s) = \begin{cases} 1 & \text{if } s \in r(u), \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The second is related to user interest. We used first-order Markov transitions $s_i \rightarrow s_j$ as interest features, since the last purchased item most reveals the interest [2]:

$$y_{ij}(u,s) = \begin{cases} 1 & \text{if item } s_i \text{ is the last purchased} \\ & \text{item of user } u \text{ and } s = s_j, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

With the maximum entropy principle, the probability that user u purchases item s when item set $r(u)$ is recommended can be modeled as follows:

$$P(s|u,r(u)) = \frac{1}{Z(u,r(u))} \exp\Big(\sum_{i,j} \alpha_{ij} y_{ij}(u,s) + \phi z(r(u),s)\Big), (3)$$

where $Z(u,r(u)) = \sum_k \exp(\sum_{i,j} \alpha_{ij} y_{ij}(u,s_k) + \phi z(r(u),s_k))$ is the normalization term, and $\boldsymbol{\alpha} = \{\alpha_{ij}\}$ and ϕ are unknown parameters to be estimated. Note that only one α_{ij} in the summation is effective for a given pair of (u,s). Since the purchase probability is increased $\exp(\phi)$ times by the recommendation $r(u)$, ϕ represents the recommendation effect. Some users are likely to be affected by recommendations, and others are not. Therefore, we estimate the recommendation effect ϕ_n for each user u_n. The unknown parameter $\boldsymbol{\alpha}$ and ϕ_n can be estimated by maximizing the log likelihood.

3. EXPERIMENTAL RESULTS

We evaluated our model in terms of predictive accuracies of next purchase items under a certain recommendation provided using the log data of an online cartoon distribution service for cell-phones in Japan. In this online store, five cartoons are recommended that are chosen manually by human experts on each cartoon distribution page.

We compared following three models: no effect model, uniform effect model, and individual effect model. *No effect model* assumes the recommendation effect $\phi = 0$, which uses only user interests for features as same as conventional user models. *Uniform effect model* has uniform recommendation effects ϕ for all users. *Individual effect model* has the recommendation effects ϕ_n for each user u_n. We first estimated parameters about user interests $\boldsymbol{\alpha}$ using the log data without recommendations, and used the parameters $\boldsymbol{\alpha}$ for all three models. The log data consisted of 23,354 users, 218,231 transactions, and 128 items. Next, we estimated the average recommendation effect ϕ for all users using the log data with recommendations and used the parameters ϕ for the uniform effect model. The log data consisted of 44,338 users, 604,673 transactions. Finally, we estimated recommendation effects for each user ϕ_n with a Gaussian prior with mean ϕ and variance $1/\eta$. We used $\eta = 1$. The test data was the last item of each user in the log data with recommendations, that was excluded in the estimation.

For the evaluation measurements, we used the predictive accuracies of N-best items. Table 1 shows the results. The accuracy of the individual effect model is higher than that of the others. This result shows that estimating the individual recommendation effect is important in terms of predicting purchase behavior. The average recommendation effect was $\phi = 0.24$. This means that the purchase probability is increased $1.27 (= \exp(0.24))$ times by recommendations, and the recommendations lead to increased purchases. Figure 1 shows a histogram of users with recommendation effect ϕ_n estimated in the individual effect model. This figure can be viewed to characterize the recommendations used in the online store. It has two peaks at around $\phi_n = 0.1$ and 0.8. The recommendations did not change purchase behaviors of users around $\phi_n = 0.1$, and this might be because they were recommended ordinary items that the users would purchase even without recommendations. On the other hand, the recommendations affected purchase behaviors of users around and above $\phi_n = 0.8$, and the one reason might be their high serendipity.

Table 1: Predictive accuracies of N-best items (%).

N	1	2	3	4	5
No effect model	17.4	24.9	33.9	39.8	42.1
Uniform effect model	17.4	24.9	34.2	39.8	44.6
Individual effect model	**17.6**	**26.3**	**35.8**	**41.5**	**45.1**

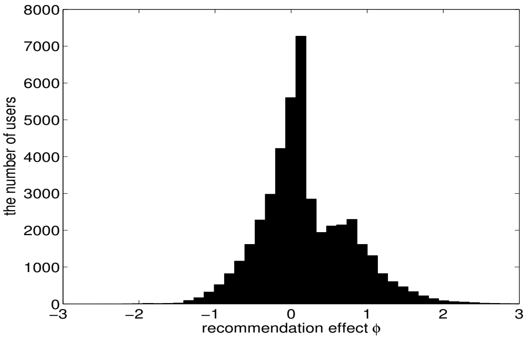

Figure 1: Histogram of users with recommendation effect ϕ_n in the individual effect model.

4. CONCLUSION

In this paper, we proposed a model for user behavior in online stores that provide recommendation services. We estimates the probability of purchasing an item given recommendations for each user based on the maximum entropy principle. Using our model, we can measure the recommendation effects. In the experiments, we showed the validity of our model using the log data of a real online store. We used simple features to model user interests. We need to improve our user behavior model using other features, such as user demographic information, and content information. We would like to evaluate our model further by applying it to other online stores.

5. REFERENCES

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