Model of Personal Discount Sensitivity in Recommender Systems

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Abstract. Recommender systems help users to encounter information or items that are of interest to them. Prior work on recommender systems has focused on eliciting preferences for items and neglected the personal traits in discount sensitivity. In this paper, we propose a recommender system that incorporates the influence of discounts. The effectiveness of the model is verified using a public retail dataset. The discount-sensitive model increased recommendation accuracy and modeling personal differences in this sensitivity further improved it. In order to specify the characteristics of discount sensitivity, the correlations between discount sensitivity and other traits of users and items are also investigated. The results show that discount sensitivity is positively correlated with item popularity and negatively correlated with persistence in purchase behaviors.

Keywords: Consumer Psychology, Personality, Price Promotion, Grocery Shopping, Retail Business, Collaborative Filtering, Matrix Factorization, Diversity

1 Introduction

Recommender systems help people find interesting information in the age of “information overload”. These systems learn the preference of each user from their past interactions with items and then predict which items will be attractive to them. Vast number of research studies have been dedicated to the advancement of recommendation algorithms and the exploration of their application fields [1, 2].

Recommender systems are beneficial not only for end-users but also for business operators. Ecommerce businesses increase their sales by recommending commercial goods [3]. Currently, the use of recommendation engines is prevalent in online shops.

While research on recommendations has mainly focused on the prediction of item preferences, users’ choices are not always determined by item preferences alone. In retail business, shop owners often offer bargains to attract customers. Consumers are sensitive to this price variation, when they make purchasing decisions.

Recently, recommender systems have started to incorporate various psychological aspects of users to fulfill users’ needs in more depth [4]. The discount sensitivity of each user is one of these aspects that differs among users.

In this work, we propose a recommendation model with personalized discount sensitivity, extending the state-of-the-art recommender algorithm. We also analyzed the correlations between discount sensitivity and other personal attributes. This paper is an extended version of the work presented at the Third Workshop on Emotions and Personality in Personalized Systems [5].

In the next section, we review prior work related to this study. In Section 3, we explain the proposed model. Section 4 and 5 present the experimental procedures and results, respectively. Section 6 describes the correlation of discount sensitivity to other features. Finally, we summarize and conclude this research in Section 7.

2 Related Work

The effect of price promotion has been explored extensively in the field of marketing science [6, 7], and recently, some recommendation studies [8, 9, 10, 11, 12] have taken into account the influence of price. For instance, a hybrid recommender system for supermarkets including discount information was proposed in [8]. Price has also been personalized using a multi-armed Bandit in [9], depending on three classes of consumers; those who buy an item regardless of promotions, those who buy an item if it is discounted, and those who do not buy the item even if it is discounted. The price range of each item has been incorporated into topic models to learn intrinsic user characteristics concerning prices [10] and the item choice within a category has also been predicted, given the effect of price cuts [11]. Further, the consumer responses to bundled discounts have been modeled, accounting for the correlation of item preferences [12]. Our work is different from these studies in that it combines user preference and discount sensitivity in a unified model that learns them simultaneously.

The relationship between personality and recommendation has also attracted interest. Personality can be predicted implicitly [13] and acquired personality can be used to guess item preferences [14, 15]. It has been found that like-logs in social networking services are correlated with personality [13]. Personality similarity has been used for tackling the difficulty in estimating the preference of new users [14]. Behaviors in micro blog services are indicators of personality and useful for brand preference elicitation [15]. Active learning for preference elicitation can leverage personality to acquire ratings efficiently [16]. Personality has been found to be correlated not only to item preference, but also to diversity preference [17, 18]. For instance, diversity in movie recommendation was adjusted by personality in [17], and how personality influences the preference of diversity types was investigated in [18]. We regard discount sensitivity as an aspect of personality and investigate its relationship with diversity preference.

Recommendation model with discount sensitivity can be seen as an instance of multi-criteria recommender systems [19], composed of two criteria, item preference and discount preference. In addition, discount can be regarded as one of the contexts and our model can be contextualized also in context-aware recommender systems [20]. Relevant contexts depend on domains; in tourism, for example, distance, time available, crowdedness, and knowledge of the surroundings are effective contexts [21].

3 Discount-Sensitive Model

We extended the Bayesian personalized ranking (BPR) model [22] with matrix factorization (MF) [23] to incorporate personalized discount effects. In Subsection 3.1, we present a preliminary analysis of personal difference in discount sensitivity, which motivated us to develop a recommendation algorithm that includes it. Subsection 3.2 introduces the MF of item preferences in BPR, and Subsection 3.3 presents our extensions.

3.1 Individual Difference of Discount Sensitivity

The effects of price promotions can be different among users and items. Our preliminary analysis of a public retail dataset (described in Section 4.1) is in accordance with this hypothesis.

We compared the purchase behaviors of two users under various price promotion conditions in Fig. 1, which shows the distributions of purchase counts for various discount rates. The user in the left panel tends to buy at regular prices, and probably has low discount sensitivity. The user in the right panel appears to search for discounted items, and thus should have high discount sensitivity.

We also investigated the difference of the discount effect on items. Fig. 2 shows the purchase rates of two items at different discount rates. We define purchase rate as the number of purchases divided by the number of visiting users on each day. The left and the right panels show the characteristics for different items in different categories and the blue lines show linear regressions. Discounts increase sales for both items, but they increase them more for the right item, that is, the discount sensitivity of the right item is much higher than that of the left item.

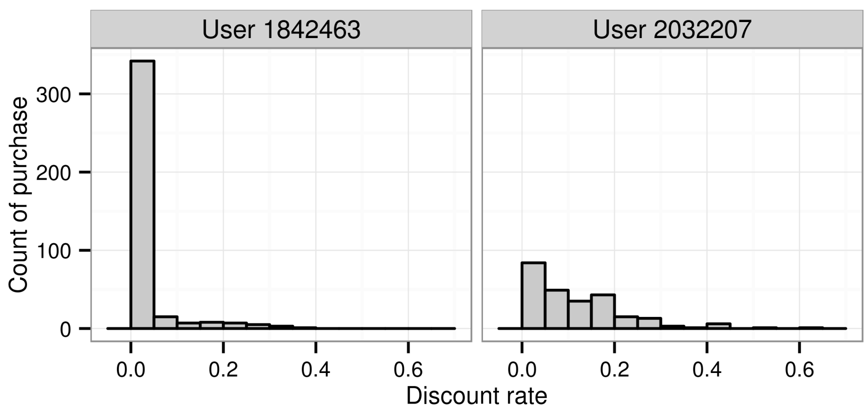

Fig. 1. Discount rate distributions of purchased items.

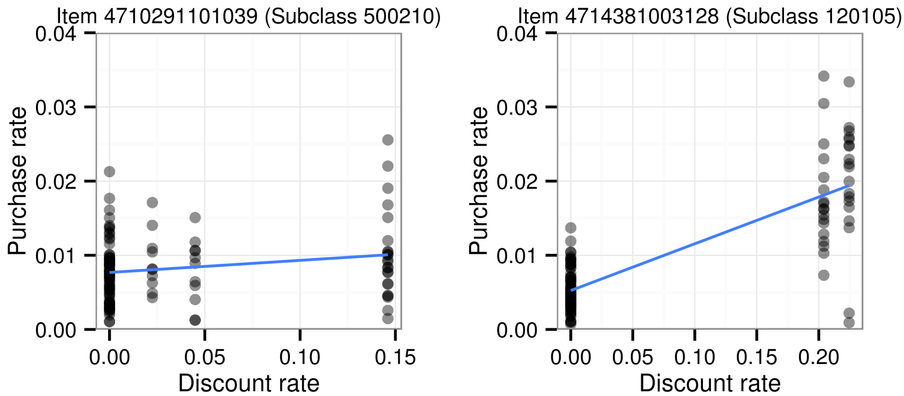

Fig. 2. Discount rate dependence of purchase rates.

3.2 MF of Item Preference

Collaborative filtering is a recommendation technique that predicts item preference of a user from the preferences of similar items and similar users [24]. To overcome the sparsity of feedback data of users for items, MF is commonly used in collaborative filtering [23].

MF decomposes preference into the latent factors of users and items. Adding biases for item preference, the valuation of user u to item i can be expressed as [23]:

$$v_{ui} = \mu + b_i + b_u + q_i^T p_u, \tag{1}$$

where μ is a bias common to all items and users, b_i is an item-specific bias, and b_u is a user-specific bias. Futher, q_i is the latent factor of item i and p_u is the latent factor of user u.

Bayesian personalized ranking (BPR) is a pairwise learning framework [22], that can be adopted for various recommendation tasks [25, 26]. In BPR, probability that user u buys item i and does not buy item j is expressed as a sigmoid function of rating difference between i and j:

$$p(i \in I_u^+ \wedge j \in I \setminus I_u^+) = \frac{1}{(1+\exp(-x_{uij}))}. \tag{2}$$

$$\begin{aligned} x_{uij} &= v_{ui} - v_{uj} \\ &= b_i - b_j + (q_i - q_j)^T p_u. \end{aligned} \tag{3}$$

Here, I_u^+ are items for which a user gives positive feedback (e.g., purchase), and $I \setminus I_u^+$ are items for which the user gives no feedback. Note that μ and b_u are irrelevant in the BPR setting, and hence the scope of the parameters is as follows.

$$\Theta = \{b_i, q_i, p_u \mid i \in I, u \in U\}. \tag{4}$$

Training data for BPR is composed of user-item triplets:

$$D_S \equiv \{(u,i,j) \mid i \in I_u^+ \wedge j \in I \setminus I_u^+\}. \tag{5}$$

Each triple corresponds to the observation that a user prefers item i over item j. The log-likelihood of this observation is calculated as:

$$\begin{aligned} L &\equiv \ln p(\Theta \mid D_S) \\ &= \ln p(D_S \mid \Theta) p(\Theta) - \ln p(D_S) \end{aligned} \tag{6}$$

BPR optimizes model parameter Θ by maximizing log likelihood L under training data D_S. Assuming a normal distribution with zero mean and diagonal covariance for priors $p(\Theta)$, the gradient of the log likelihood becomes the following.

$$\frac{\partial L}{\partial \Theta} = \sum_{(u,i,j) \in D_S} \frac{\exp(-x_{uij})}{1+\exp(-x_{uij})} \bullet \frac{\partial}{\partial \Theta} x_{uij} - \lambda_\Theta \Theta. \tag{7}$$

In this study, stochastic gradient descent was used, as in the original paper [22], and the update rule is:

$$\Theta \leftarrow \Theta + \alpha \left(\frac{\exp(-x_{uij})}{1+\exp(-x_{uij})} \bullet \frac{\partial}{\partial \Theta} x_{uij} - \lambda_\Theta \Theta \right). \tag{8}$$

3.3 Discount Sensitive Extensions

We assumed that item valuation comes from the preference for the item itself and the preference for discount. The preference for discount can be formalized as the product of the discount rate and discount sensitivity. In order to personalize discount sensitivity, we introduced an item-specific bias and a user-specific bias. Considering the possibility that the combination of a user and an item influences discount sensitivity, we also added latent factors for the user and item. Equation (1) is therefore extended to:

$$\begin{aligned} v_{ui} &= \mu + b_i + b_u + q_i^T p_u \\ &\quad + d_i(\mu^d + b_i^d + b_u^d + (q_i^d)^T p_u^d), \end{aligned} \tag{9}$$

where d_i denotes the discount rate of an item i. Terms μ^d, b_i^d, b_u^d, q_i^d, p_u^d are discount sensitivity terms, which are proportionality coefficients that drive up the valuation in response to the discount. Specifically, μ^d is a bias common to all items and users, which shows the general effect of discounts, b_i^d and b_u^d represent discount sensitivity biases for item i and user u, respectively, and p_u^d and q_i^d respectively correspond to the latent factors of user u and item i.

Including these terms, the rating difference in Equation (3) becomes:

$$\begin{aligned} x_{uij} &= b_i - b_j + (q_i - q_j)^T p_u \\ &+ d_i(\mu^d + b_i{}^d + b_u{}^d) - d_j(\mu^d + b_j{}^d + b_u{}^d) \\ &+ (d_i q_i{}^d - d_j q_j{}^d)^T p_u{}^d . \end{aligned} \tag{10}$$

As a result, the optimized parameter Θ changes, as follows:

$$\Theta = \{b_i, q_i, p_u, \mu^d, b_i^d, b_u^d, q_i^d, p_u^d \mid i \in I, u \in U\}. \tag{11}$$

Training data then include the discount rate of each item on the day of shopping S.

$$D_S \equiv \{(u, i, j, d_{i,s}, d_{j,s}) \mid i \in I_u{}^+ \wedge j \in I \setminus I_u{}^+ \wedge s \in S\}. \tag{12}$$

These training data justify the change of item selection depending on price. For example, user u could have bought item i instead of j when discount $d_{i,s} > d_{j,s}$ and on another day, user u could have bought item j instead of i when discount $d_{j,s} > d_{i,s}$.

We also modified the sampling scheme of the training data. First, we chose a user randomly and selected a shopping day on which the user visited the shop. Next, we selected item i from the items purchased by the user on that day, and item j from the items not purchased by the user. As we explain later in Subsection 4.2, items on the shelf might vary each day. As a result, the sampling of j should be confined to items existing on the day.

4 Experimental Conditions

In this section, we explain experimental conditions. First, we describe the dataset used in this study. We next detail the specifics of training and evaluation. In Subsection 4.3, the tested models and accuracy metrics are specified.

4.1 Dataset

We used the Ta-Feng dataset [27], which contains the transaction logs of a retail shop. This shop sells a wide range of merchandise, from food and grocery items to office supplies and furniture [27]. The transaction logs include user IDs, item IDs, dates, and prices. The records cover a period of four months. The name of the items and subclasses are not published; however, items are categorized into subclasses, and a subclass ID is assigned to each item ID.

We extracted the unit prices of items on each day. The item price was the same on the same day, in most cases. When multiple prices existed on one day, we picked the median price as the day price. The discount rates of each item on each day were calculated as:

$$1 - \frac{the\ day\ price}{\max(prices\ of\ the\ item)}. \tag{13}$$

We used a dense subset of the Ta-Feng data, extracting the data of users that visited the shop 10 times or more and items that sold 100 times or more. This subset comprises 7.4% of the users and 7.6% of the items, and includes 16.2% of the records. The basic statistics of the original Ta-Feng data and extracted data are summarized in Table 1.

Table 1. Statistics of the Ta-Feng dataset and extracted dataset.

Data	#records	#users	#items	#subclasses
Original	817741	32266	23812	2012
Extracted	132168	2373	1802	373

4.2 Training and Evaluations

Of the 120 days coverd by the dataset, we used the last 10 days for evaluation and the other 110 days for training, considering that learning precedes prediction in real scenarios. There was at least one purchase log for all the extracted users in the training subset. In contrast, only 1,850 users had purchase histories in the test subset. Evaluations were conducted on these partial users, although the parameters of all the extracted users were learned in the training phase.

The items on the shelf changed every day. We assumed that items with at least one purchase record on a certain day were on the shelf on that day. Of the 1,802 selected items, 1,087 items on average were sold each day. At the evaluation stage, we selected the recommended items of each day from the items on the shelf on that day. We did not exclude items purchased during training periods from the recommended items. In contrast to movie or book consumption, repeat purchase is common in grocery shopping and increasing repeat purchases by recommendations is also beneficial for retailers. Furthermore, predicting repeat purchase is a non-trivial task, as item choice is affected by the price discounts and the availability of items on each day.

4.3 Accuracy Comparison

We compared the conventional MF model with several types of discount sensitive models: MF with non-personalized discount sensitivity (MF-DS(NP)), MF with personalized discount sensitivity (MF-DS(P)), and MF with personalized and user-item-interactional discount sensitivity (MF-DS(PI)).

We used the area under the curve (AUC), precision and recall as evaluation metrics. We initially calculated the metrics for each user on each day. We next calculated the per-user average over the testing period. The statistical significance of the difference in accuracy among different models was verified for user-by-user pairs of metrics using the Wilcoxon signed rank test. As a representative value, we further took the average of all users for each model.

5 Evaluation Results

We evaluated our models for various matrix dimensions (Subsection 5.1). Detailed comparisons of each model and the results of the significance tests are shown in Subsection 5.2. We adjust the data density to verify the effectiveness of our models under different densities in Subsection 5.3.

5.1 Comparison for Various Matrix Dimensions

We evaluated the AUC of MF and MF-DS(PI) at matrix dimensions ranging from 3 to 300. Fig. 3 shows results. The discount sensitive models improved the AUC at all dimensions.

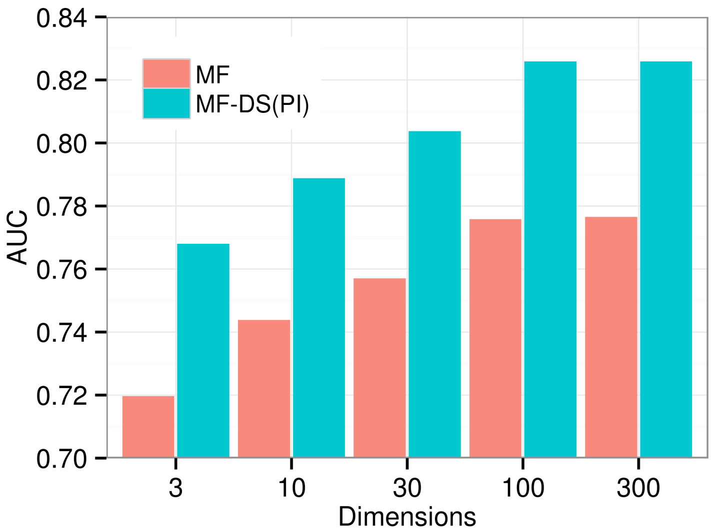

Fig. 3. AUCs of MF and MF-DS(PI) at different matrix dimensions.

5.2 Detailed Comparison of Models

We next conducted a detailed comparison of conventional MF, MF-DS(NP), MF-DS(P), and MF-DS(PI). We calculated precision (P) and recall (R) when the number of items recommended by the system is 1, 10, and 100. In most conditions, MF-DS(NP) outperformed MF and MF-DS(P) achieved further improvement. MF-DS(PI) tends to increase accuracy, though not always significantly.

Table 2. Accuracy comparison of algorithms at 30 matrix dimensions. Marks * and ** indicate statistically significant differences on the Wilcoxon signed rank test with $p < 0.1$ and $p < 0.01$, respectively. MF-DS(NP) was compared with MF, MF-DS(P) was compared with MF-DS(NP), and MF-DS(PI) was compared with MF-DS(P).

Dimension 30	AUC	P/R (1 item)	P/R (10 items)	P/R (100 items)
MF	0.7571	0.1467/ 0.0586	0.0624/ 0.2323	0.0152/ 0.4726
MF-DS(NP)	0.8012**	0.1666*/ 0.0661*	0.0570/ 0.2171	0.0165**/ 0.5247**
MF-DS(P)	0.8030**	0.2210**/ 0.0878**	0.0638**/ 0.2425**	0.0170**/ 0.5341**
MF-DS(PI)	0.8038	0.2226/ 0.0923*	0.0649*/ 0.2450*	0.0170/ 0.5387

Table 3. Accuracy comparison of algorithms at 100 matrix dimensions. Marks * and ** indicate statistically significant differences on the Wilcoxon signed rank test with $p < 0.1$ and $p < 0.01$, respectively. MF-DS(NP) was compared with MF, MF-DS(P) was compared with MF-DS(NP), and MF-DS(PI) was compared with MF-DS(P).

Dimension 100	AUC	P/R (1 item)	P/R (10 items)	P/R (100 items)
MF	0.7758	0.1993/ 0.0812	0.0792/ 0.2805	0.0172/ 0.5191
MF-DS(NP)	0.8198**	0.1984/ 0.0812	0.0646/ 0.2411	0.0184**/ 0.5705**
MF-DS(P)	0.8242**	0.2337**/ 0.0959**	0.0737**/ 0.2698**	0.0188**/ 0.5836**
MF-DS(PI)	0.8259*	0.2463**/ 0.1000*	0.0721/ 0.2639	0.0191**/ 0.5875*

5.3 Comparison at Various Data Densities

In order to confirm the universality of the discount sensitive effect, we adjusted the data density. Density is defined by the ratio of purchased item-user pairs to all item-user pairs. Note that the data density of the extracted data in Table 1 is 0.024 and experiments in Subsection 5.1 and 5.2 were conducted at this density. Fig. 4 shows the AUCs of MF and MF-DS(PI) at different densities. MF-DS(PI) improved the AUC for all densities and tends to be more effective on denser datasets.

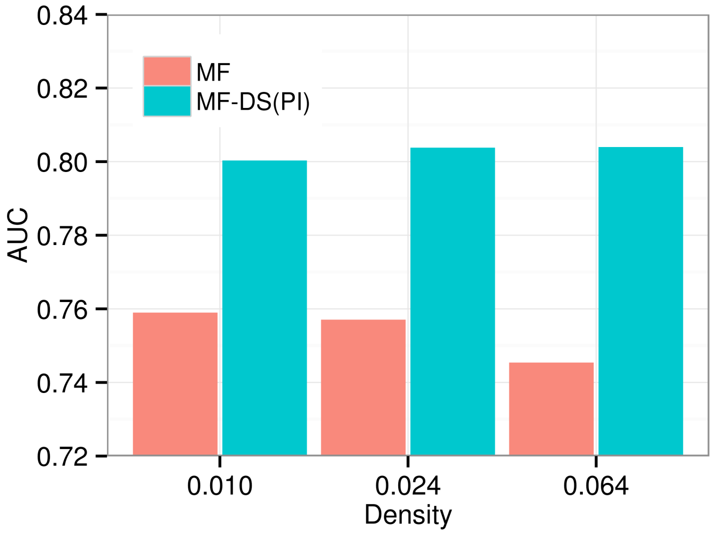

Fig. 4. AUC of MF and MF-DS(PI) at different data densities.

6 Analysis of Discount Sensitivity

In this section, we investigate the discount sensitivity bias of users and items in MF-DS(P).

6.1 User Profile and Discount Sensitivity

The Ta-Feng dataset includes customer residence areas and ages. We analyzed the influence of these factors on discount sensitivity.

The left panel of Fig. 5 portrays the distribution of the discount sensitivity biases of users for respective residence areas. Areas are sorted in order of distance to the shop. The width of the shape expresses the density of the distribution at each vertical value of the discount sensitivity bias. The correlation coefficient r is 0.098 and the statistical significance level p is 6.9×10^{-6}. A weak but significant tendency was found in which users from distant areas responded to discounts more strongly. Distant users might be prone to compensate for their transportation costs with good deals on purchases. We also investigated age-dependence, but no effect was observed.

We hypothesized that users with a strong tendency to buy particular items (item persistence) might react to discounts differently. We believe that persistence is closely related to personality. For instance, persistence is most likely correlated positively with neuroticism and negatively with openness and agreeableness. Personal item persistence was extracted from repeat purchases of users within the same category. In [28], the propensity for diversity, which is the inverse of item persistence, was measured using entropy. We used entropy as an indicator of the weakness of a user's item persistence.

We first calculated the per-user subclass-level entropy and took the average for each user as:

$$H(u) = -\frac{1}{C}\sum_{c \in C}\sum_{i \in I_c} r_{i,u} \log r_{i,u}, \tag{14}$$

where I_c denotes the item set in a specific item subclass category, and r_i represents repeat purchase density, defined as the number of purchases for item i divided by the total purchases of the subclass category. A subclass purchased less than four times was omitted from the summation. Low entropy in a subclass means that a user has strong persistence in that subclass and tends to buy specific items. High entropy in a subclass means that a user does not care about differences among items in the subclass and tends to buy various items. The average entropy over categories, defined as Equation (14), represents whether the user is generally picky or not.

The right panel of Fig. 5 presents the relation of entropy and discount sensitivity bias of users. Discount sensitivity increases as entropy increases. The correlation coefficient r was 0.12 and the statistical significance level p was 3.2×10^{-7}. The result indicates that users without persistence tend to select discounted items, which is reasonable considering that picky users do not like another item regardless of the price offered.

We constructed a linear regression model for the discount sensitivity bias of users from the residence area and the entropy. Estimated coefficients are positive (0.024 for residence area and 0.044 for entropy) and significant (the p-values are 4.5×10^{-5} for residence area and 3.9×10^{-5} for entropy). The root mean square error (RMSE) of the prediction is 0.2462 for 10-fold cross validation, an improvement of the value of 0.2482, acquired from the mean estimate.

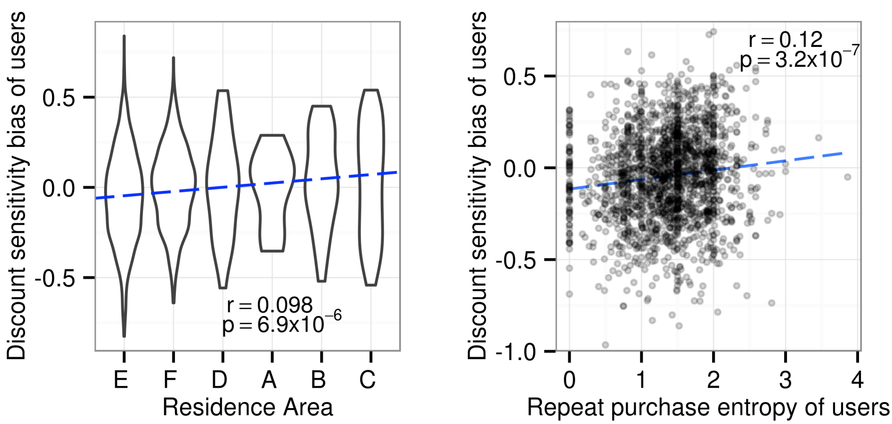

Fig. 5. Correlations of user discount sensitivity biase with user attributes. The residence area in the left plot are ordered according to distance from the shop.

6.2 Item Profile and Discount Sensitivity

We examined the correlation between the preference bias of items and discount sensitivity bias of items. The left panel of Fig. 6 shows that a positive correlation was found among the variables, where the correlation coefficient r is 0.38. The preference bias of items is similar to item popularity. Therefore, this result suggests that the discounts of popular items are more appealing in general.

It is well known in the field of marketing research that frequent and deep discounts will change consumers' reference price and diminish discount sensitivity [6, 7]. We confirmed this effect by comparing the average discount rates of various items and their discount sensitivity biases. As shown in the right panel of Fig. 6, the correlation coefficient r is -0.17, and a negative correlation was found among the variables.

We then created a linear regression model for item discount sensitivity bias from the popularity and the mean discount. Estimated coefficients are positive (0.186) for the popularity and negative (-0.436) for the mean discount. Both coefficients are significant (the p-values are 2×10^{-16} for the popularity and 1.4×10^{-9} for the mean discount). The RMSE of the prediction is 0.204 for 10-fold cross validation, an improvement on the value of 0.222, acquired from the mean estimate.

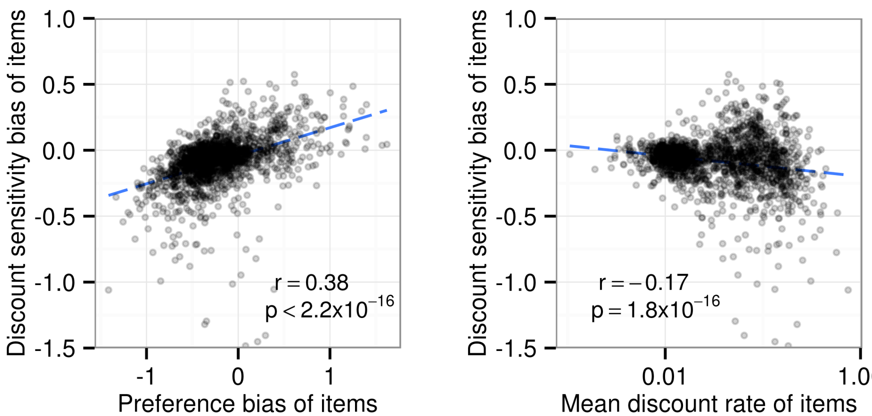

Fig. 6. Correlations of discount sensitivity biase of items with item attributes.

7 Conclusion

In this paper, we proposed a recommendation model that incorporates the price discount effect. Personalized discount sensitivity was introduced into the conventional MF. The proposed model enhances the AUC, precision and recall in a retail shopping dataset. The results demonstrate that personalized discount sensitivity is a crucially important component in recommender systems in the retail domain.

We analyzed the personal difference of discount sensitivity in relation to user and item attributes. Item discount sensitivities are correlated with item popularity and mean discount rate, and user discount sensitivities are correlated with the distance to the shop and users' item persistence. We believe that persistence is closely related to personality and these findings contribute to the understanding of personality.

In future work, we plan to extend our model with personality. Combining purchase records and personality information, discount sensitivity can be estimated from personality. Cross-item effects (e.g., how the purchase of a discounted item affects the purchase of another item) have been investigated in marketing science [6, 7]. The fusion of other consumer psychologies and recommendation algorithms is another potential direction for future research.

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