Discount Sensitivity – Are We All Equal?

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The high adoption of smart mobile devices among consumers is an opportunity for e-commerce retailers to increase their sales by recommending consumers with real time, personalized coupons which take into account the specific contextual situation of the consumer [5]. While context-aware recommender systems (CARS) have been widely analyzed [1,2] personalized pricing or discount optimization in recommender systems to improve recommendations' accuracy and commercial KPIs has hardly been researched [7]. This paper studies how to model user-item personalized discount sensitivity and incorporate it into a real time contextual recommender system in a way which can be integrated into a commercial service. We propose a novel approach for modeling user-item personalized discount sensitivity in a sparse data scenario, and present a new CARS algorithm (CBRF) which combines co-clustering [3,4] and random forest [6] to incorporate the personalized discount sensitivity.

We conducted an experimental study with real consumers and mobile discount coupons to evaluate our solution. In this experience, less attractive coupons were offered with higher discount. We defined two features, which model the user and item independent discount sensitivity: du_u the probability of a user u to consume a coupon with a discount level d, and di_i the probability of an item i to be consumed utilizing a coupon with discount level d. The new features are expressed by

$$du_u(d) = \frac{\sum_{r_{uic1..d..ck} \epsilon R, r=1} 1}{\sum_{r_{uic1..d..ck} \epsilon R} 1} \qquad di_i(d) = \frac{\sum_{r_{uic1..d..ck} \epsilon R, r=1} 1}{\sum_{r_{uic1..d..ck} \epsilon R} 1}$$

here, the nominator counts the number of consumed coupons with discount level d which were recommended to user u or recommended item i, and the denominator counts the overall number of coupons with discount level d which were recommended to user u or recommended item i. We identified three typical consumer types: the high discount sensitive consumer who has a higher probability of consuming a coupon as the discount level increases, the medium discount sensitive consumer whose consumption probability dependency on the discount level varies and is not monotonic, and the low discount sensitive consumer who surprisingly has a lower probability of consuming the coupon as the discount level increases and the attractiveness of the coupon's restaurant decreases. Figure 1 presents discount sensitivity curves for the three typical consumer types.

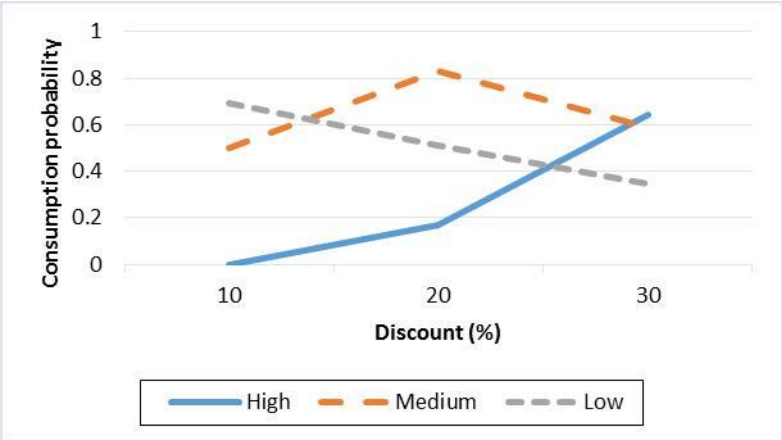

Figure 1. Typical consumer types in respect to discount sensitivity

We compared the CBRF algorithm to the common matrix factorization with context (MFC) algorithm. The experimental results (as described in Figure 2) suggest that incorporating personalized discount sensitivity significantly improves the consumption prediction accuracy and that the suggested CBRF algorithm provides better prediction results for this use case.

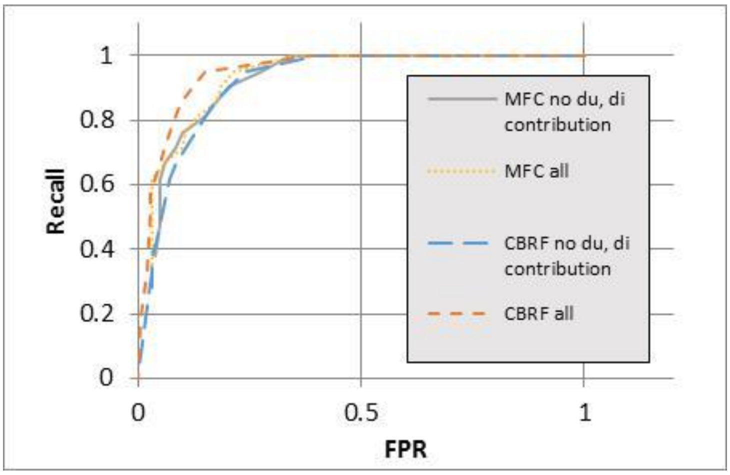

Figure 2. Contribution of discount sensitivity for CBRF and MFC algorithm consumption prediction

The contribution of this research is three-fold:

- We propose a novel approach for modeling personal discount sensitivity of users and items in coupon recommendation in a sparse data scenario.

- We incorporate personalized discount sensitivity into the CARS model for mobile coupon consumption prediction.
- We present a new CARS algorithm based on co-clustering with random forest in each cell (CBRF) to effectively incorporate personal discount sensitivity for coupon consumption prediction. We evaluate the CBRF algorithm's prediction accuracy and show that it provides better prediction accuracy than the common matrix factorization with context (MFC) algorithm when incorporating personal discount sensitivity.

This is the first research which shows that consumers respond differently to discount levels applied to various product segments. Our results demonstrate the potential of modeling consumer-product discount sensitivity for pricing or discount optimization. We submitted a paper to JASIST on January 2016.

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