Getting the Timing Right: Leveraging Category Inter-purchase Times to Improve Recommender Systems

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ABSTRACT

In the marketing domain, models of grocery buying behavior consider purchase incidence as a key dimension. However, in recommender systems, timing is often subsumed under contextual information and has received little attention yet. For this reason, we analyze the relation between the timing of a recommendation and its acceptance across different product categories. Our study is based on a real-world deployment of an in-store recommendation system in the brick-and-mortar grocery industry. We base our analysis on transaction data of more than 100,000 unique users and more than four million product recommendations. Our findings suggest that the success of a recommendation significantly depends on the inter-purchase time within the respective category. Different sensitivities across product categories further stress the importance of timing and its interplay with category characteristics within the context of recommender systems. The insights gained in this study enable retailers to improve scheduling recommendations and target promotions more efficiently.

CCS Concepts

•**Information systems** → **Computational advertising;** *Data mining;* Data analytics; •**Applied computing** → **Online shopping;**

Keywords

inter-purchase times; category; retail; fast moving consumer goods

1. INTRODUCTION

Customer purchase decisions, both online and in-store, are to a great extent influenced by recommendations. They might either be proactively inquired by customers seeking advice from family, friends or sales staff or provided by retailers leveraging their customers' past browsing or purchasing behaviors. In the latter scenario, a customer's interest in buying in a particular category at a particular time is not evident and needs to be inferred indirectly—a task often performed by automated recommender systems [2]. Consequently, recommender systems need to solve two questions in order to provide meaningful recommendations: First, whether or not to recommend a product to a particular customer and second, when to recommend it—thus, getting the timing right [12]. In contrast to common retailer promotions that target whole customer segments based on average category inter-purchase times, personalized recommendations enable the promotion of specific products based on individual preferences regarding product and timing decisions.

In this paper, the success of a recommendation—as indicated by the redemption of personalized in store price-off promotions—is modeled as a function of category inter-purchase times. We find that inter-purchase times significantly influence the acceptance of recommendations and that the effect further depends on the respective product category. Particularly, in many fast moving categories, there is an optimal point in time for a product recommendation. Thus, incorporating category inter-purchase times can improve the accuracy of recommendations by up to 6 %[1]. Furthermore, we show that the optimal point in time for a recommendation does not coincide with average category inter-purchase times. Thus, recommendations can influence individual inter-purchase times. Our findings contribute to the efficiency of personalized promotions and their successful implementation within recommendation schedules in the retailing industry.

2. RELATED WORK

Traditionally, research on recommender systems has focused on developing distinct approaches for recommending products or services to users of a particular recommender system. For this reason, content-based [10], collaborative-filtering [8] and hybrid approaches [4] have been advanced, incorporating information of the current system user, of similar peers or a combination of both. Yet, independently of the underlying approach, recommender systems have traditionally aimed at answering the two-dimensional question of what to recommend to whom [12]. More recently, however, research has begun to further leverage context as a multidimensional feature. Such context-aware recommender systems incorporate all kinds of contextual information depending on the dimensions of the respective question [1].

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[1]As measured by the increase of correctly classified redemptions.

When a recommender system is used in a commercial context, it should ideally benefit both customers and retailers. While the former improve or facilitate their decision making [8], the latter are enabled to improve targeting and exploit cross- and up-selling opportunities [12]. Ultimately aiming at influencing consumer buying behavior [2], recommender systems should thus take into account the different dimensions of the underlying decision. Grocery purchase decisions are usually modeled as consisting of three dimensions, purchase incidence, brand choice and purchase quantity [7, 3]. Hence, customer purchases simultaneously cover the questions when to buy in a certain product category, which brand to buy and how much to buy. First, purchase volumes are assumed to be driven by household size, inventory levels, consumption rates as well as in-store and price promotions [7, 3]. The second dimension, brand choice, coincides with the main purpose of recommender systems and thus has been extensively covered in the respective literature [8]. The decision whether or not to buy a certain brand is driven by the entire product attributes including price. Finally, the last dimension, describes the timing of a purchase which depends on consumption rates, inventory levels as well as in-store and price promotions [7, 3]. From a retailer perspective, recommendations are personalized promotions that allow for a precise targeting of single customers and can thus be used in order to influence any of the three dimensions of the customer purchase decision. Retailers can try to influence the timing of a purchase by providing customers with recommendations. The aspired purchase acceleration increases sales if customers do not only engage in stockpiling but adapt their consumption levels accordingly [9]. This is eventually dependent on the underlying product category and its characteristics. Moreover, well-timed promotional recommendations can be used to encourage store switching. Thus, customers would be expected to relocate purchases from competitors' stores to the focus retailer [11]. Overall, the timing of recommendations should receive a greater amount of attention in research on recommender systems, especially in industries where products are regularly re-bought and categories are described by distinct purchasing cycles as in the grocery industry.

3. METHOD AND DATA

In order to analyze the influence of category-specific inter-purchase times on the success of recommendations, an empirical study of real-world transaction and recommendation data has been conducted at a brick-and-mortar grocery retailer. The results of the empirical analysis shall be used in order to answer the following questions: (1) Is there a category-specific optimal point in time for a product recommendation? (2) Can recommendations be used to influence individual inter-purchase times? (3) Does incorporating inter-purchase times have a positive effect on the redemption of a recommendation? The in-store recommendation system that has been studied for this purpose provides customers with personalized product recommendations in the form of tailored price promotions. Customers can receive these personalized recommendations when they enter the store by scanning their loyalty card at special in-store kiosk terminals. The terminal then prints a list of tailored price promotions for every customer. Promotions are chosen from a specific set of currently active campaigns, which retailers and manufacturers can define to target specific consumers. The specific underlying algorithm is subject to our partner's secrecy. On a high level, campaigns are assigned using a dynamic scoring model estimating redemption probabilities based on a similiarty measure between a user's historic shopping baskets, the promoted products and an individual price-off derived from user heterogeneity in price sensitivity. Inter-purchase times are not considered in the scoring algorithm. Campaigns are then assigned to users maximizing total expected revenue constrained to specific campaign goal fulfillment criteria and filters. At the checkout promotions are automatically redeemed when the customer's loyalty card is scanned. As the loyalty program is completely anonymous, no demographic information is provided by the customers. In the following, we analyze transaction data that was collected in 2015 over a period of two months in more than 100 stores in a big European city. Our sample includes more than 100,000 unique users as well as more than four million product recommendations, out of which we analyze more than 500,000. The categorization we use is provided by a large market research organization. We limit our analysis to the top ten most recommended campaigns in our sample and pick four fast-moving categories which are regularly purchased—namely bread, cola, milk and curd—for a more specific analysis. These are used for an examination of our proposed research questions. Ultimately, this allows us to identify and illustrate different patterns in the adoption and timing of recommendations.

3.1 Category Redemption Rates and Inter-purchase Times

To quantify the impact of inter-purchase times on category level redemptions, we conduct a linear regression of category redemption rates (abbreviated as RR) on the predictor "time since the last category purchase" (subsequently abbreviated as $TSLP$). In order to account for a potentially nonlinear relationship between inter-purchase times and redemption rates, we add a quadratic and cubic term of our $TSLP$ variable to the regression. We hypothesize that for most categories c there is an optimal point in time for a recommendation that will correspond to the average category inter-purchase time. We expect recommendations made much earlier (low $TSLP$) to be penalized as customers inventory will not be low enough to induce another category purchase. Furthermore, we also expect lower redemption rates for customers that have not made purchases in the respective category for a long time (high $TSLP$). These could either have purchased at a competitor's store or become uninterested in the category itself.

$$RR_c(TSLP) = k_{c,0} + k_{c,1} \cdot TSLP + k_{c,2} \cdot TSLP^2 + k_{c,3} \cdot TSLP^3 \qquad (1)$$

Table 1 summarizes the results of the regression described in equation 1 for our four selected categories, while Figure 1 illustrates the corresponding fitted redemption rates. Apart from the category cola, all categories exhibit a characteristic inverse u-shape, indicating the existence of an optimal point in time for a category recommendation. For milk and curd, average inter-purchase times without promotion are higher than the optimal points in time for a recommendation. Thus, in these categories recommendations might trigger purchase acceleration. In the case of the category cola, this effect might even be so strong that redemptions

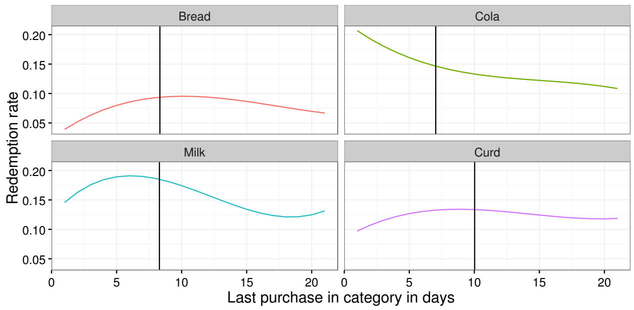

Figure 1: Comparing fitted redemption rates to avg. category inter-purchase times without promotions

are highest right after a category purchase.

Table 1: Summary of regression results

	Dependent variable:			
	RR			
	Bread	Cola	Milk	Curd
$TSLP$	0.016***	−0.017***	0.025***	0.013***
	(0.005)	(0.005)	(0.005)	(0.004)
$TSLP^2$	−0.001**	0.001*	−0.003***	−0.001**
	(0.001)	(0.001)	(0.001)	(0.0004)
$TSLP^3$	0.00002	−0.00002	0.0001***	0.00003*
	(0.00002)	(0.00002)	(0.00002)	(0.00001)
Constant	0.024*	0.223***	0.123***	0.085***
	(0.013)	(0.014)	(0.014)	(0.010)
R^2	0.625	0.843	0.823	0.543
Adjusted R^2	0.559	0.816	0.792	0.462
F Statistic	9.445***	30.540***	26.386***	6.725***
Note:		*p<0.1; **p<0.05; ***p<0.01		

3.2 Changes in Individual Inter-purchase Times

In order to determine whether recommendations have an influence on individual category inter-purchase times, we split individual purchases, distinguishing category purchases that are affected by promotions from those that are not. In a first scenario, purchases are only affected by promotions when a promotion is redeemed during that particular purchase. In a second case, we also account for stockpiling, by including the purchase directly following a purchase on promotion into the promotion sample. In this way, we determine average inter-purchase times with and without promotional redemptions, considering only those customers for whom both inter-purchase times can be calculated.[2] Using two-sided Kolmogorov-Smirnov tests ($p<0.05$), we analyze the average inter-purchase times in both scenarios. In the first case, we find significant differences in average inter-purchase times for all categories. In the second scenario, accounting for stockpiling, we find significant differences in average inter-purchase times for all categories except for curd, where customers might engage in stockpiling when redeeming a promotion.

[2]It should further be noted that purchase volumes are not accounted for as we only focus on purchase incidence.

3.3 Improving Redemption Classification

In order to test the validity of our findings we randomly split our data in an estimation and validation sample (2:1) and then train two different logistic regressions. The first model only uses the scoring values ($SCORE$) provided by our research partner, also accounting for the magnitude of the individual price discount. Our model extension additionally includes a variable that indicates the deviation of the $TSLP$ variable from the optimal recommendation time, derived in our previous regression model. We allow the coefficient of this feature to vary depending on whether the recommendation was provided too early (d_{early}) or too late (d_{late}).

Table 2: Summary of classification estimation and validation results

	Dependent variable:			
	Redemption			
	Milk		Cola	
	Standard	Extended	Standard	Extended
$SCORE$	1.440***	1.344***	2.672***	2.476***
	(0.045)	(0.045)	(0.207)	(0.207)
d_{early}		−0.040***		
		(0.011)		
d_{late}		−0.014***		−0.014***
		(0.001)		(0.001)
Constant	−2.116***	−1.825***	−2.401***	−1.953***
	(0.019)	(0.026)	(0.026)	(0.030)
Observations	30,881	30,881	33,032	33,032
LL	−11,770	−11,559	−10,762	−10,471
AIC	23,545	23,126	21,529	20,949
Recall	0.123	0.141	0.035	0.061
		(+14.6 %)		(+74 %)
Precision	0.524	0.540	0.339	0.345
		(+3.1 %)		(+1.8 %)
Prevalence	0.136	0.136	0.090	0.090
Balanced Accuracy	0.553	0.561	0.514	0.524
Note:		*p<0.1; **p<0.05; ***p<0.01		

We report the quality of our models on the hidden evaluation set for the two categories with the best model fit in our previous regression analysis: milk and cola. Table 1 summarizes the results of our classification model. Our standard model provides similar results for milk as obtained in previous studies within the retailing industry [6]. By incorporating the distance to the optimal recommendation time, we are able to improve precision[3] by 3.1 % and recall[4] by 14.6 % compared to the standard model. For the category cola we can increase recall by 74 %, however precision can only be marginally increased by 1.8 %. We believe that our extended model can only marginally improve the correct classification in the second category due to the monotonous relationship between $TSLP$ and overall redemption rates as indicated in Figure 1 and Table 1. Furthermore, we are able to get similar precision improvements for the remaining two categories (bread 6.6 % and curd 2.4 %).

4. CONCLUSION AND FUTURE WORK

Purchase incidence is one of the key pillars of every customer choice decision [7, 3]. Yet, so far it has only received marginal attention in the context of recommender systems. However, as commercial recommendations ultimately aim at influencing customer choices [2], purchase incidence should be incorporated when a recommendation is made. For this reason, we have analyzed customer data from an in-store recommendation system at a brick-and-mortar grocery retailer that provides customers with tailored price promotions. Our findings support the view that recommender systems should not only focus on the product or service to recommend but also on the timing of the recommendation [12]. Regarding the first research question we find that in many fast moving categories, there exists an optimal point in time for a recommendation which maximizes its acceptance among customers. In particular, we show that considering this optimum and category-specific individual inter-purchase times, has a positive effect on the success of recommendations, increasing precision by up to 6 %. Thus, secondly, incorporating this additional information improves recommender systems. Moreover, we find that the optimal point in time for a recommendation precedes the average category inter-purchase time for most categories, indicating accelerated category purchases. Finally, with respect to the third research question, it can be concluded that recommendations can influence individual inter-purchase times.

Altogether, the findings we present in this paper emphasize the importance of incorporating category-specific inter-purchase times when making product recommendations. Yet, as the data we have used for our analyses is limited to two months, we cannot account for any seasonal effects that might affect category inter-purchase times throughout the year. Therefore, it will be worthwhile to extend the observation period in order to capture seasonality and model dynamic inter-purchase times. Furthermore, as we do not use scanner data but transaction data of a single retailer instead, we cannot directly account for category purchases at competitors' stores and for inventory building. However, in further analyses deviations from predicted parametric inter-purchase times could help to indicate consumers' shopping at other retailers [5]. This individual risk could be modeled with the help of further identifiers based on past purchases and category characteristics. Finally, these opportunities for further research will help to improve the timing of recommendations and design recommender systems that better address the needs of individual customers while leveraging category-specific inter-purchase times.

[3]Precision: Share of correctly classified as redeemed divided by share of all classified as redeemed.
[4]Recall: Share of correctly classified as redeemed divided by all observed redemptions (also hit-rate).

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