Understanding Multi-Channel Customer Behavior in Retail

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ABSTRACT

Online shopping is gaining popularity. Traditional retailers with physical stores adjust to this trend by allowing their customers to shop online as well as offline, in-store. Increasingly, customers can browse and purchase products across multiple shopping channels. Understanding how customer behavior relates to the availability of multiple shopping channels is an important prerequisite for many downstream machine learning tasks, such as recommendation and purchase prediction. However, previous work in this domain is limited to analyzing single-channel behavior only.

In this paper, we provide the first insights into multi-channel customer behavior in retail based on a large sample of 2.8 million transactions originating from 300,000 customers of a food retailer in Europe. Our analysis reveals significant differences in customer behavior across online and offline channels, for example with respect to the repeat ratio of item purchases and basket size. Based on these findings, we investigate the performance of a next basket recommendation model under multi-channel settings. We find that the recommendation performance differs significantly for customers based on their choice of shopping channel, which strongly indicates that future research on recommenders in this area should take into account the particular characteristics of multi-channel retail shopping.

CCS CONCEPTS

• Information systems → Recommender systems; **Online shopping**.

KEYWORDS

Customer behavior; next basket recommendation

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1 INTRODUCTION

The emergence of e-commerce in recent years has encouraged retailers with physical stores to provide the possibility of online shopping for their customers in addition to in-store (offline) shopping. Customers do not only buy goods via multiple shopping channels, but they can also leverage the online channel for exploring the product inventory, comparing products, and saving products for later purchases, before shopping offline. In addition, the data generated via online shopping provides a further opportunity for personalizing the shopping experience through recommendation [1, 11].

The ease of use of online shopping translates into a rapidly growing market share of e-commerce solutions, even in industries such as fashion. This growth is not cannibalistic – most customers who purchase goods online also purchase in-store (offline) [2]. The addition of an online channel does not isolate the offline channel. Instead, it creates a multi-channel shopping experience for customers in retail sectors like grocery, cosmetics, and apparel.

Understanding customer behavior in retail serves as a basis for many downstream machine learnings tasks, such as recommending products and predicting purchases. While there are numerous studies examining user behavior in online shopping platforms, little is known about multi-channel customer behavior. Previous work relies mainly on click stream data [3, 5, 10, 13, 17, 18, 21]. Other sources of customer behavior include transaction data [15], digital receipts of online purchases extracted from emails [9], transaction logs of a bank [16], or search logs of a commercial product search engine [12]. However, these studies utilize data from a single shopping channel only, and do not explore multi-channel customer behavior. So far, multi-channel customer behavior has mostly been studied in the marketing and retail research literature [1, 2, 4, 7, 8]. These studies rely on perceptions gathered via interviews and customer surveys, in order to model, e.g., lock-in effects or physical store surface needs. Yet, perceptions are often different from actions, and these works do not consider actual transaction data from customers.

In this paper, we provide the first study on multi-channel customer behavior in retail. Based on a sample of 2.8 million transactions from 300,000 customers, gathered from a food retailer with multiple physical stores and two online platforms, we provide a first picture of customer behavior in a multi-channel retail setting. To this end, we group the customers into three groups, namely *online-only*, *offline-only*, and *multi-channel* customers, based on their choice of shopping channels (Section 2). We first compare the shopping behavior of these customer groups in Section 3. We find that the tendency to purchase previously bought products, defined as repeat behavior ratio, is higher for online-only customers. Zooming in on multi-channel customers, our analysis reveals that there is little overlap in online and offline baskets of multi-channel customers; they use each channel for different sets of items. Our analysis further indicates that online baskets are larger, and contain items from more diverse product categories.

The observed differences between customer groups can affect the performance of models that are designed for downstream prediction tasks based on customer behavior (Section 4). As a case study, we investigate the Next Basket Recommendation (NBR) task, where the goal is to predict items that a customer will purchase in their future basket, given their previous shopping baskets. Existing approaches to NBR rely on data from a single shopping channel only, and do not consider multi-channel settings [6, 14, 19]. We examine the performance of a standard NBR model, namely PersonalTopK, for different customer groups and different channels of the future basket. NBR performance differs significantly for different customer groups, with the online-only customers receiving the best and offline-only customers receiving the worst overall performance. For multi-channel customers, the performance heavily depends on the channel type for the target basket, and choosing the correct target channel has the potential to boost NBR performance. Overall, our experiments indicate that the NBR task is not trivial for multi-channel settings; a single model is not able to achieve the same performance for different customer groups. Our findings serve as a call for follow-up research on designing recommendation models that explicitly model the characteristics of multi-channel retail.

In summary, we provide the following contributions.

- To the best of our knowledge, we provide the first study of multi-channel customer behavior in retail, based on a large sample of 2.8 million transactions from 300,000 customers of a food retailer in Europe with physical stores, an online shop and a mobile application (Section 2).
- Our analysis of the transaction logs of different customer groups indicates that online-only, offline-only, and multi-channel customers have different shopping behavior across multiple dimensions, such as repeat ratio and basket size (Section 3).
- In experiments with a standard next basket recommendation model, it underperforms for multi-channel customers (compared to online-only customers), indicating the need for approaches that explicitly model the multi-channel context (Section 4).

2 DATASET DESCRIPTION

Our work is based on proprietary transaction data from a large food retailer in Europe, with a number of physical stores, an online website, and a mobile application. The same product inventory is offered on all channels. Customers can get a loyalty card either in-store or online, and can use that card for their shopping across all channels. A customer can be tracked across offline and online channels if they use their loyalty card at the cashier in-store, and use the same card when buying online. A customer needs to be identified to fulfill the order in the online channel, while this is not the case for in-store shopping (offline).

Sampling of customers based on channel preferences. In order to understand multi-channel customer behavior, we select an eight week period of time as the *transaction period*, and define three groups of customers based on their channel preferences during the transaction period: (1) *offline-only customers* who conducted only offline transactions and no online transaction, (2) *online-only customers* who have only online transactions and no offline transactions, and (3) *multi-channel customers* who conducted both online and offline transactions.

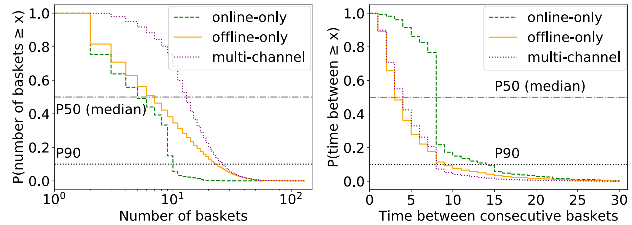

Figure 1: Cumulative distribution of the number of baskets (left) and the time between consecutive baskets (in days, right) per customer.

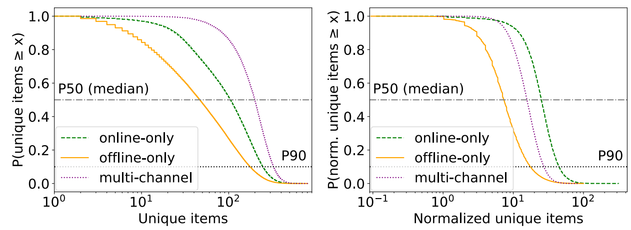

Figure 2: Cumulative distribution of the number of unique items (left), and normalized unique items (right) per customer.

Extraction of transaction data. We first filter the data to retain only customers with a loyalty card so as to be able to track customers, both within and across channels. Next, we sample 100,000 customers at random from each group, and extract their transactions during our period of interest. Each transaction in the data is marked as either online or offline, and represents a basket with one or multiple products, purchased by a customer. The sample of online-only customers has 500K corresponding transactions, while the sample for offline-only customers comprises of 900K transactions. The multi-channel customers undertook 1.4M transactions with a similar online/offline ratio.

3 UNDERSTANDING CUSTOMER BEHAVIOR

We first focus on similarities and differences in the behavior of all three customer groups, and then consider multi-channel customers. We also study the characteristics of online and offline baskets.

Comparison of customer groups. We consider the users' purchase frequency in both channels. Fig. 1 depicts the cumulative distribution of the number of baskets and the time between consecutive baskets (in days) for online-only, offline-only, and multi-channel customers. We observe that multi-channel customers have the highest number of baskets, and online-only customers have the lowest. Offline-only and multi-channel customers have a similar behavior with respect to shopping times, with a median of three days between consecutive baskets, and a 90% percentile of seven days. The distribution is different for online-only customers: the average time between consecutive baskets is longer, with a median of seven days. This seven day interval is frequent for a large number of online customers, partly because of the possibility of selecting a fixed day for delivery for a series of online baskets.

On top of the number of purchases, we also seek insights into the quantity and variety of items purchased. Fig. 2 shows the cumulative distribution of the number of unique items that a customer has purchased during their shopping history, and the normalized unique items, defined as the number of unique items divided by the number

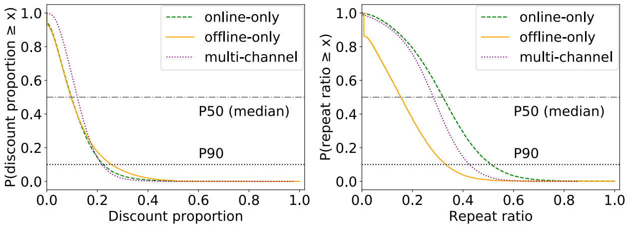

Figure 3: Cumulative distribution of the discount proportion (left) and the repeat ratio (right) for different groups of customers.

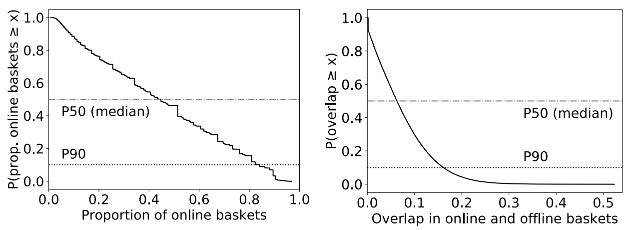

Figure 4: Cumulative distribution of the proportion of online baskets (left) and the overlap in items purchased online and offline (right) for multi-channel customers.

of baskets. Offline-only customers have the smallest number of unique items and normalized items; while multi-channel customers have the highest number of unique items, online-only customers have purchased more unique items when the number of baskets is considered. We conjecture that easy access to the full catalogue plus the ease of home delivery leads to this increase in diversity.

As the loyalty card allows for discounts, it is of interest to know how different customer groups behave with regard to promotions. Fig. 3 shows the cumulative distribution of the discount proportion (defined as the amount of discount per basket divided by basket value) and the repeat ratio (defined as the number of unique items divided by the total number of items purchased across baskets) for different groups of customers. All customers are similar w.r.t. the discount proportion, online-only customers have the highest repeat ratio, and offline-only customers have the lowest.

Behavior of multi-channel customers. Do multi-channel users prefer a shopping channel? Fig. 4 (left) depicts the cumulative distribution of the proportion of online baskets, defined as the number of online baskets divided by the total number of both online and offline baskets, per customer. For roughly half of the multi-channel customers, online baskets are in the majority, while for the other half offline baskets are dominant, so there is no clear preference.

Next, we want to know whether multi-channel customers use the two channels for the same purchases. Fig. 4 (right) plots the cumulative distribution of the overlap in items purchased online and offline for multi-channel customers, calculated as the Jaccard index of online and offline item sets. The overlap between online and offline baskets is minimal for the majority of customers; for 90% of them, the overlap is less than 0.16. This implies that while multi-channel customers purchase both online and offline baskets, they use each channel for purchasing a separate set of products. Finally, we investigate when multi-channel customers are more susceptible to prefer one channel over the other. We find that offline shopping peaks on Fridays and Saturdays, while online shopping has a uniform distribution across week days. We also observe a

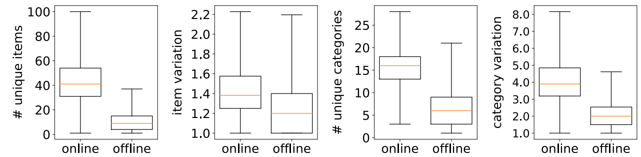

Figure 5: Distribution of the variation in terms of items and item categories for online and offline baskets.

decline in shopping on Sundays for both online and offline channels. We further look at the patterns underlying the selection of a channel for shopping. We consider the channel switch probability for multi-channel customers. The probability is exactly equal to 0.5 for 20% of customers; these customers may or may not select a different channel for their next basket with an equal chance. Roughly 40% of customers change their channel with a probability of less than 0.5, and 10% of customers change their channel almost after every basket. This indicates that predicting the next channel for the customer is not trivial.

Comparison of online and offline baskets. Each transaction in the data represents a basket of products purchased at a time by a customer. How do baskets purchased online compare to those purchased offline? Fig. 5 shows the distribution of the number of unique items and unique item categories in a basket, the basket variation (defined as the basket size divided by the number of unique items), and the basket category variation (defined as the basket size divided by the number of unique item categories) for online and offline baskets. While online baskets contain more unique items and more unique item categories, there is not much difference in basket variation and basket category variation; this is a hint that the difference in the distribution of the number of unique items and the number of unique item categories in online and offline baskets is mostly caused by the larger basket size in the online channel.

4 NEXT BASKET RECOMMENDATION

We have observed important differences in purchasing behavior between the three groups of customers. We hypothesize that ignoring the shopping channel can hurt the performance of downstream machine learning tasks. In this section, we present a case study to investigate this hypothesis. In particular, we study the performance of a prominent Next Basket Recommendation (NBR) model in the multi-channel context. The goal of an NBR model is to predict the set of items that a customer will purchase in their next basket, given their purchase history [6, 14, 19]. Formally, given the history of baskets for customer u defined as $B^u = \{B_1^u, B_2^u, \dots, B_n^u\}$, where B_i^u is a basket of items defined as $B_i^u = \{x_1, x_2, \dots, x_t\}$, and $x_i \in X$ denotes an item from the whole item set X, the goal is to predict the items in the next basket of the customer, i.e., B_{n+1}^u. For the basket history B^u, the recommendation model assigns a score to all items $x_i \in X$, and the top-k items are returned as the candidate items for the next basket recommendation.

We investigate the NBR task for different types of customers in multi-channel retail. We use a simple but powerful recommendation model, namely PersonalTopK, that has been shown to perform on par with complex state-of-the-art methods [6]. PersonalTopK recommends the most frequent k items that appear in the past baskets of a given customer as the prediction for the next basket.

Experimental setup. We experiment with our transaction logs, pick a week as the test week, and consider all customers that have

Table 1: Experimental results for next basket recommendation using the PersonalTopK model.

Prediction target	$k=10$			$k=20$			$k=50$		
	Recall	nDCG	PHR	Recall	nDCG	PHR	Recall	nDCG	PHR
Online-only customers	0.1582	0.5873	0.9743	0.2459	0.4993	0.9882	0.3988	0.4564	0.9939
Offline-only customers	0.1773	0.2716	0.7331	0.2435	0.2664	0.7998	0.3448	0.2951	0.8664
Multi-channel customers	0.1282	0.3696	0.7688	0.1950	0.3292	0.8242	0.3085	0.3124	0.8838
Multi-channel customers, online target basket	0.1431	0.5946	0.9816	0.2265	0.5068	0.9916	0.3677	0.4372	0.9968
Multi-channel customers, offline target basket	0.1163	0.1891	0.5981	0.1697	0.1867	0.6899	0.2609	0.2123	0.7931
Multi-channel customers, target channel known	0.1373	0.3808	0.7882	0.2027	0.3387	0.8369	0.3095	0.3191	0.8846

a basket in the test week as candidate test customers, with their first basket in the test week as the target basket to predict. We only consider customers that have over 10 baskets in the previous seven weeks as our test customers, and leverage the baskets from the previous seven weeks as training data. We partition the test customers into three groups based on their shopping channels in the training data. We are left with 15K offline-only, 52K multi-channel, and 3K online-only customers. For the multi-channel customers, around 50% of the target baskets are online and 50% are offline.

We evaluate the NBR performance using Recall@k, nDCG@k, and PHR@k [6, 20]. Recall is widely used in NBR, measuring how many of the items in the target basket are present in the predicted items for the next basket. nDCG is a ranking based measure which takes into account the order of items. PHR (Personal Hit Rate) measures the ratio of customers whose predicted baskets contain the items appearing in the target basket, evaluating the performance at customer level. All measures are averaged across the predicted baskets for all test users. We report the metrics for $k \in \{10, 20, 50\}$.

Results and discussion. Table 1 contains the results of the PersonalTopK recommendation model. PersonalTopK performs surprisingly well across all metrics and basket sizes, compared to common datasets used for evaluating the NBR task [6, 20]. This highlights the importance of personal history in our dataset. The performance for online-only customers is superior to offline-only customers, across all metrics and basket sizes, except Recall@10. The difference in performance is substantial; improvements range from 55% to 116% in terms of nDCG and 15% to 33% in terms of PHR. The performance for multi-channel customers is lower than for online-only customers with a large margin across metrics and basket sizes. The decrease in performance ranges from 19% to 23% in recall, 32% to 37% in nDCG, and 11% to 21% in PHR. The performance for multi-channel customers is higher than for offline-only customers, except in Recall. This is in line with our finding on the repeat ratio from the customer behavior analysis in the previous section; online-only customers have the most repeated behavior, followed by multi-channel and offline-only customers. The importance of personal history differs for different types of customers.

Next, we zoom in on multi-channel customers, and distinguish between multi-channel customers with an online vs. an offline target basket. In cases where the target basket is online, NBR performance is substantially better across all metrics and basket sizes, ranging from 23% to 41% in recall, 106% to 214% in nDCG and 26% to 64% in PHR. This is inline with the previous results; online baskets are easier to predict for the PersonalTopK model due to stronger repeated behavior. The NBR performance for multi-channel customers with an offline target basket is lower than for offline-only customers with a large margin (ranging from 24% to 34% in recall, 28% to 30% in nDCG and 8% to 18% in PHR), across all metrics and basket sizes. This means that the online baskets of these customers are not very helpful in predicting the items in the offline target basket. This is probably caused by the fact that the candidate items pool becomes large with the addition of items purchased in the online channel, which adds noise in predicting the offline target basket. However, this is not the case for the customers with an online target basket in general. While some metrics (Recall@10, Recall@20, Recall@50 and nDCG@50) are marginally lower for multi-channel customers with an online basket compared to online-only customers, the rest of the metrics are improved. This indicates that the offline baskets of multi-channel customers are not necessarily misleading the recommendation of online baskets.

We further consider an oracle version of PersonalTopK for the multi-channel customers, where we assume that the channel for the target basket of customers is known, and where we only consider data from the correct target channel for computing the most frequent items. NBR performance in this context is superior to the performance for multi-channel customers. This means that knowing the target channel can improve the performance of an NBR model, even for one as simple as PersonalTopK. We still observe a large difference compared to the best performing group, namely online-only customers. Hence, there is a huge potential for improving the performance of NBR for multi-channel customers.

5 CONCLUSION

We presented the first study on customer behavior in a multi-channel setting in retail, where customers can use both online (web shop, mobile application) and offline (physical store) channels for shopping. We based our analysis on a sample of 2.8 million transactions originating from 300,000 customers of a food retailer in Europe. We revealed significant differences in customer behavior across online and offline channels, for example w.r.t. basket size and the repeat ratio of item purchases. Based on these findings, we investigated the performance of a downstream prediction task under multi-channel settings, namely next basket recommendation. The recommendation performance differs significantly for customers based on their choice of shopping channel. This strongly indicates that future research on recommenders in this area should take into account the particular characteristics of multi-channel retail shopping.

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