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Abstract:

This work investigates user online browsing and purchasing behaviors, and predicts purchasing actions during a large shopping festival in China. To improve online shopping experience for consumers, increase sales for merchants and achieve effective warehousing and delivery, we first analyse diverse online shopping behaviors based on 31 million logs generated accompanied with online shopping during a rushed sale event on 11st November, 2016. Based on the obtained user behaviours and massive data, we apply collaborative filtering based method to recommend items for different consumers, and predict whether purchase will happen. We conduct 5-fold cross validation to evaluate the collaborative filtering based recommendation method, and further identify the critical shopping behaviors that determine the precursors of purchases. As online shopping becomes a global phenomenon, findings in this study have implications on both shopping experience and sales enhancement.

1. Introduction

Holiday sales account for a significant portion of the annual revenue for many retail businesses. Understanding the browsing and purchasing patterns during such yearly shopping festivals creates opportunities for better interface designs and richer user experience. Among the rapidly growing retail sectors is e-commerce on mobile devices, contributed by an increasing number of smartphone owners who are becoming familiar with mobile purchases. Surpassing purchases made from desktop computers, mobile has already become the primary platform through which online visitors access shopping sites. According to ComScore, 63% of online shoppers in 2015 were from mobile devices as opposed to desktops, and mobile purchase are expected to grow rapidly. Despite the great potential of mobile shopping which enables anytime-anywhere purchase, however, little is known about mobile shopping behaviors due to the proprietary nature of data.

In an era of e-commerce being quite prevailing, the competition between mobile e-commerce is intense. Attributed to the grand shopping festival on 11st November (also called Double 11, Single's Day) created by Alibaba on 2009, the day gradually stands out for various Business-to-Client (B2C) e-commerce websites. Following the footsteps of Alibaba, other e-commerce websites such as JD, YiHaoDian, Suning, Gome and Amazon started offering big discounts and promotions in China on 11st November as well,. Nowadays, Double 11 has become the day when people in China celebrate the biggest shopping carnival on the Internet, similar to the Black Friday in America. The e-commerce sales on 11st November on the Internet rise from 50 million RMB in 2009 to 180 billion RMB in 2016, and are very likely to grow even higher since enterprises such as Alibaba and JingDong are now aiming at internationalizing the shopping festival Double 11 actively.

Records of sales on a single day are being made each year through this biggest shopping carnival. However, the more the sales, the more challenging it is for merchants to prepare appropriate stock, so as to guarantee the e-commerce platform will not be out of business under heavy burst traffic, and for express companies the more difficult to arrange effective deliveries. Thus, analyzing historical consumers' shopping behaviors before, on and after 11st November is essential for understanding people's shopping behaviors during this big shopping carnival, which helps increase the revenue and reputation for both merchants, express companies and e-commerce platforms such as Alibaba and JD. Nevertheless, users' online shopping behaviors are manifold. A large proportion of users spend plenty of time browsing but never pay for any items, while other users first add items to cart and pay for them after a long or short time of consideration, also there are users who request for payment and pay decidedly. To precisely recommend items to their potential buyers (cf. Kim et. al. 2016), we extract users' preference on items and temporal characteristics of their online shopping behaviors, which is based on the analysis of the logs generated when users are surfing on e-commerce websites or using shopping apps.

Based on an anonymized log dataset on 10^{th} ~ 12^{th} November with over 47k users and 236k items, we study the user online shopping behaviors. The logs studied are comprised of information on user identifier, IP address, base station identifier, browsing URL, as well as the timestamps of every action. The logs were reconstructed at the level of product pages to reveal how people access mobile shopping websites during an annual sale event on JD.com's main page, coupon pages, product pages, cart, and order action pgaes. As the data logs actions of both purchasers and non-purchasers, it provides a unique opportunity to mine common shopping behaviors related to predicting purchases during an annual sale event.

The challenge of such data-mining task lies on the complex reverse engineering efforts to understand clickstream logs and to handle noise in data without deforming any crucial patterns. In particular, clickstream logs are not guided by user feedback, thus one needs to create labels (e.g., a visitor's purchase intention) in unsupervised manners. Even the notion of session duration needs to be defined arbitrarily, as individuals engage in varying durations during the sale season (from a few seconds to several hours). We adopt varying definitions of sessions so as to be robust to under different circumstances. Furthermore, people engaged in numerous actions on the shopping site, from browsing products or main pages to ordering actions as well as editing pro les. In order to focus on predicting purchases, we identified the major actions based on their frequency and model shopper behaviors. However, this study has limitation since no information about users (e.g., gender, age) or product details could be obtained from the data. Product category information such as electronics or clothing was the only interpretable shopping context from the log data .

In this research, we conduct extensive analysis and model the mobile shopping patterns of tens of thousands of online visitors during such an annual sale event. First, we characterize online shopping users by dissecting their different online shopping steps, hesitant time duration for items, the specific time that they browse and pay on a day, etc. In addition, the popularity of an item is detected. Second, based on the observations, we extract some features to conduct item recommendations based on collaborative filtering method. With the proposed collaborative filtering based approach, the hit rate of the item recommendations is evaluated based on 5-fold cross validation. Finally, we identify the critical shopping behaviors that determine the precursors of purchases. The strength of this paper lies in testing the efficacy of several feasible precursors of purchasing actions (e.g., the effect of total browsing time, the number of clicks, product categories, and time of day in future purchases).

We also examine whether visiting the shopping site prior to the sale event or browsing a coupon page is indicative of future purchases. Our important findings are summarized as follows,

(1) Our study provides a first of a kind view on mobile purchase patterns over a shopping event.

(2) We show that an ISP is able to parse specific human actions through requested URLs and use it to study user behavior. Therefore, this study is based on clickstreams, which include various browsing details.

(3) This study is a multi-platform study. Choices of different platforms may lead to quite different behaviors. For example, although only about 39% users chose native app, they contributed 56% of all purchases.

(4) We find that item recommendations based on collaborative filtering is efficient, and the identified characteristic in shopping behaviours can predict the purchases with high accuracy.

The rest of this article is organized as follows. In Section 2, we describe the dataset we utilize in this article. Section 3 gives some statistical analysis from the perspective of users and items, respectively. In Section 4, we propose a collaborative filtering based approach to recommend items to consumers and a purchase prediction method. After representing some related works in e-commence and recommendation systems in Section 5, we finally conclude this article in Section 6.

2. Motivation and Dataset Description

2.1 Motivation

For online retailers, understanding user's purchasing behaviors is a significant problem. Many researchers have been focusing on the purchasing behaviors of online shoppers since 1999. Their researches are based on Pinterest data. They studied both long-term (in days) and short-term one (in minutes or hours) purchasing behavior. One major purpose of these works aimed at finding factors that have influence on purchasing behaviors. It turns out demographic factors, product categories, whether or not the user look at product info and other browsing behaviors, interest in ads, percentages of each action type, price of product, time information, as well as many other factors, are helpful for purchase prediction.

In 2017, at least three purchase prediction competitions have been launched in China. JData1 is held by JD.com, competition2 is held by vip.com, and Instacart Market Basket Analysis 3. Especially, JData offers more than half a million RMB of rewards for competitors, which is almost as much as the highest reward on Kaggle.

Both of these competitions focus on purchase prediction on particular categories during an upcoming week, which is a long-term purchase prediction problem. Participants of such competitions usually do a lot of exploration data analysis to discover strong predictors. They use algorithms based on gradient boosting decision trees to combine these predictors. Besides, ensemble methods are popular when making final predictions.

We collected a particular dataset during a Double 11 shopping festival, when people take much shorter time than usual to make purchase decision. As our data is collected by ISP though we have entire records from cellphone , user records from PC are not available, compared with data from website owner. Thus our data is not quite precise for long-term human behavior study. In this paper, we mainly focus on people's short-term shopping behaviors. Besides, we compare the user behaviors before the shopping festival and after the festival. Through these differences, we are able to carry out recommendation and predict the actions of purchase. Specifically, we model our short-term purchase prediction problem as a simple classification-learning problem. We remove all ordering actions from sessions of user activity and label these sessions as purchase or non-purchase. From the behavior sequence in each session we are able to extract many features that are relative to purchase behavior.

2.2 Dataset

Our dataset includes an anonymized online shopping logs of 47,906 users involving 236,809 items. 581,430 entries record users' online shopping behaviours through JD websites/apps on November 10,11 and 12 in 2016. Each entry consists of anonymized user id, timestamp, action type and item id. The timestamp is the time when the action recorded in this entry happened, formatted in GMT+8. Action types refer to browsing, adding to cart and ordering. We obtain this dataset through cleaning the flow record data offered by one of the main network operators in China collected using deep packet inspection (DPI) technology. We chose to study all traffic flows to and from www.JD.com, one of the largest e-commerce retailers in China. The DPI technology can be used to resolve the traffic flow contents from packet headers. Extractable information typically includes the requested web link (URL) and timestamp. The URLs toward the JD.com site were structured such that we could identify meaningful information from the URL itself such as product IDs, product category IDs, and user action types. While this study is limited to understanding patterns occurring on a single website, we expect the key shopping behaviors observed from data would be similar to that seen in other shopping websites during the shopping festival.

The traffic flows indicated that people accessed the JD.com shopping website through different platforms. The most prominent ones were third-party apps (e.g. WeChat), native Jingdong app, and mobile web browsers, as listed below:

• Third-party apps is the kind of platform where most users access JD.com. Among all third-party apps, WeChat is the most popular. As the most popular social network in China which accounted for 51% of all visitors (cf. Yin 2016),WeChat offers pages for online stores through which people can browse items and order them conveniently without native shopping apps.

• The native Jingdong app was the next popular platform, accounting for 39% of all visitors. The native Jingdong app generated the most amount of traffic (accounting 57% of all flows), indicating visitors on Jingdong app are heavy users of the Jingdong shopping site.

• Mobile web browser was the third most popular way to access, accounting for 15% of all visitors.

While the webpage designs may appear similar across these platforms, the choice of platforms leads to entirely different user experience. For example, payment takes fewer clicks and hence easier on apps than on mobile browsers. The remainder of this paper presents the characteristics of shopping behaviors seen across all the platforms unless specified. Usually, there are three steps before users complete a transaction through online shopping. First, users browse the website, search and find items of interest. Then, they add possible items to buy to cart. Finally, users make decisions on what to buy, submit payment requests and complete payments. In our dataset, 98.4% of users browse items, 20.9% of users add items to cart, and 17.9% of users make orders, while 95.6% of items are browsed, 7.39% of items are added to cart, and 4.56% of items are ordered, as shown in Table 1. However, not all consumers follow the steps—browsing, adding to cart, and ordering to make a deal. As shown in Figure 1, only 9.80% of users browse, add items to cart and then make orders. 75.2% of users only browse, 11.4% of users browse and add to cart without buying anything, implying 86.6% of users are window shopping. On the other hand, 8.52% of users browse and make orders without adding items to cart. Meanwhile, not all items are browsed and added to cart before they are ordered. 91.3% of items are only browsed, while 3.23% of items are browsed and added to cart, and 0.168% of items are browsed and added to cart before ordered.

Table 1 Basic information about action types of users and on items.

Action types	Users	Items
Browsing	47124 (98.4%)	226355 (95.6%)
Adding to cart	10011 (20.9%)	17512 (7.39%)
Ordering	8568 (17.9%)	10808 (4.56%)

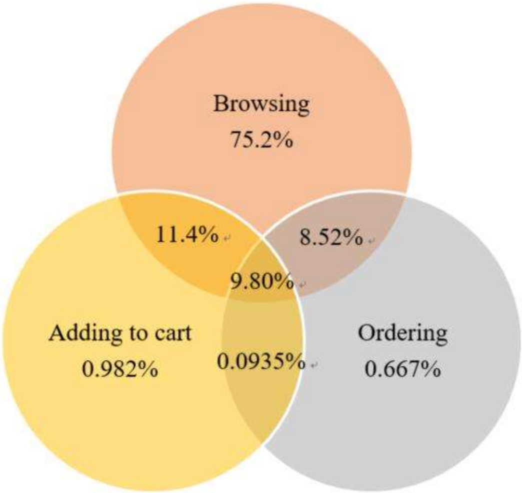


Figure 1 Distribution of users of different online shopping behaviours.

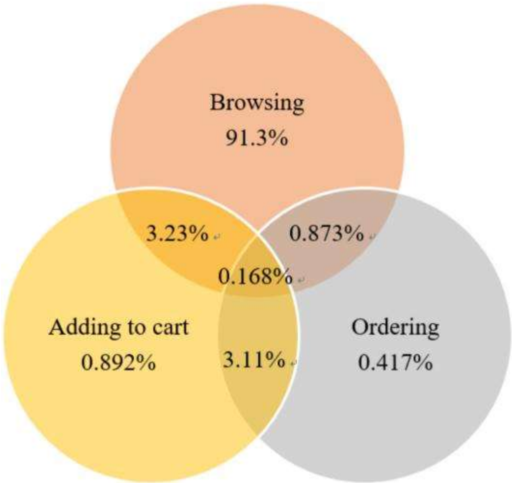


Figure 2 Distribution of items browsed, added to cart and ordered.

3. Characteristics of Online Shopping Behaviours

Since many shops on the e-commerce platform and the platform itself offer great discounts and promotions on 11st November, in this section, we utilize our dataset to answer the following questions: (1) What is the impact of discounts and promotions on the online sales? (2) How do discounts and promotions influence the shopping behaviour patterns of users? (3) How do discounts and promotions affect the popularity of items? Specially, we examine the sales variation (3.1), shopping behaviour patterns of users (3.2), and the popularity of items (3.3) before, on, and after the Double 11.

3.1 Sales Variation

To reveal the impact of discounts and promotions on the sales of online shopping, we investigate the number of users browsing, adding to cart, ordering, as well as the number of items browsed, added to cart, and ordered before, on, and after 11st November. As shown in Table 2, the number of users surfing on the online shopping website or using the app is the greatest on 11st November\, and drops significantly on 12th November. This implies that discounts and promotions play an important role in attracting users. \ The number of users ordering on 11st November is over twice that on November 10, and over four times that on 12th November. The situation is almost the same in terms of the number of items ordered on November 11 compared to that on November 10 and 12. Furthermore, the numbers of ordering, browsing, and adding to cart vary with time in a day, and the variation curves on November 10, 11, and 12 are totally different. Meanwhile, browsing is a much more frequent behaviour than adding to cart and ordering.

Figure 3 shows the number of ordering per half an hour on November 10, 11, and 12, respectively. The peak ordering time slice on 11st November is between 00:30 and 00:59, with 1306 orders, compared with 145 orders in the same time slice on November 10 and 228 orders on 12th November. The peak ordering time slice on November 10 is between 23:30 and 23:59, with peak ordering number as 557, which is less than 50% of the maximum on 11st November. The peak ordering number on November 12 is even less, with 228 orders between 00:30 and 00:59 . The influence of online shopping carnival starts from half an hour before 11st November till half an hour later on November 12. Meanwhile, the distribution of browsing and adding to cart behaviour on November 10, 11, and 12 is different from that of ordering. The numbers of accumulative browsing and adding to cart reach peak between 23:30 and 00:00 on 10th November before the greatest discounts and promotions start (as shown in Figure 4 and Figure 5). The number of ordering, browsing, and adding to cart reach a local maxima at around 10:30am, owing to the fact that some merchants offer discounts and promotions until 10:00am instead of 00:00 on 11st November.

Table 2 Number of users and involving items before, on, and after 11st November.

Day	Users			Items		
10th November	21,878	Browsing	21572 (98.6%)	99,332	Browsed	95773 (96.4%)
		Adding to cart	3909(17.9%)		Added to cart	6410 (6.45%)
		Ordering	2647 (12.1%)		Ordered	1508 (1.52%)
11st November	28,377	Browsing	27737 (97.7%)	129,480	Browsed	123457 (95.3%)
		Adding to cart	5952 (21.0%)		Added to cart	10677 (8.25%)
		Ordering	5527 (19.5%)		Ordered	3400 (2.63%)
12th November	9,705	Browsing	9528 (98.2%)	50,078	Browsed	48001 (95.9%)
		Adding to cart	1756 (18.1%)		Added to cart	3174 (6.34%)
		Ordering	1360 (14.0%)		Ordered	941 (1.88%)

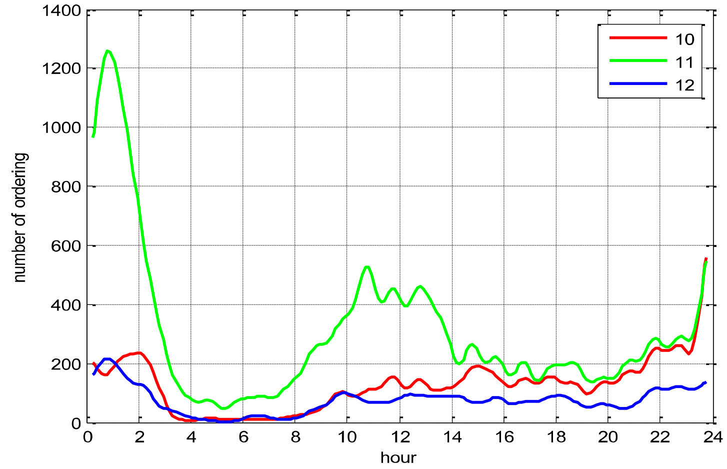


Figure 3 Number of ordering per half an hour on 10th to 12th November .

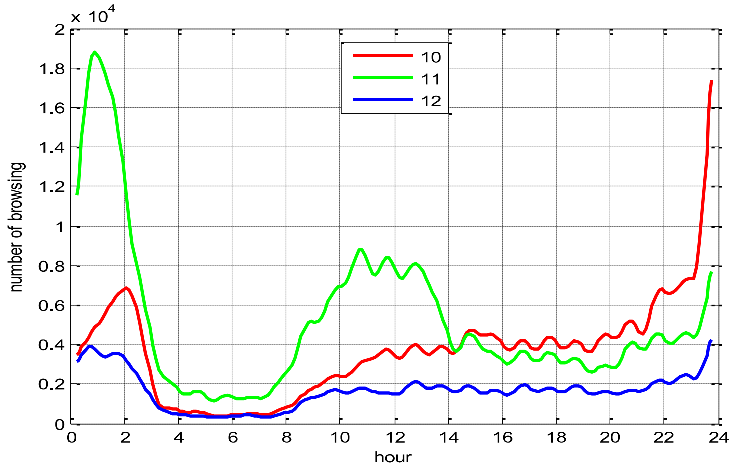


Figure 4 Number of browsing per half an hour on 10th to 12th November .

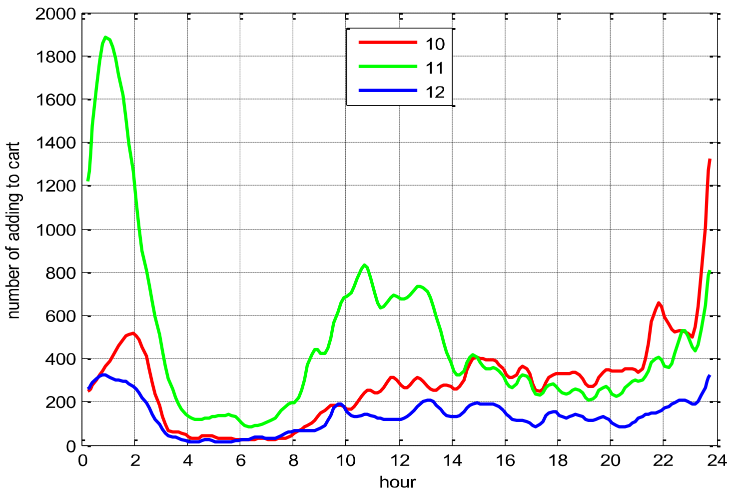


Figure 5 Number of adding to cart per half an hour on 10th to 12th November .

3.2 Shopping Behaviour Patterns of Users

To answer how the discounts and promotions influence the shopping behaviour patterns of users, we analyse the number of items each user orders, and the average time the user spends on each action when they are online shopping on 11st November, compared to results on 10th and 12th November. Figure 6 shows the Cumulative Distribution Function (CDF) curves of the number of items that one user orders. 80% of users order no more than 3 items on 10th and 12th November, while 80% of users order no more than 4 items on 11st November. Meanwhile, users who buy the most on November 11 buy 35 items, while users who buy the most buy 27 and 29 items on 10th and 12th November, respectively. Big discounts and promotions on 11st November stimulate the purchasing desire of some users. Figure 7 shows the CDF curves of the average browsing time and times before one user add an item to cart. Figure 7 (a) shows 80% of users browse no more than 7 times before they add an item to cart, on November 10 th, 11 th, or 12 th. Some users browse as many as 218.5 times on average before they add an item to cart on 11st November, while someusers browse as many as 225 times on average before they add an item to cart on 10th November. In comparison, users browse at most 131 times on average before adding an item to cart on 12th November, which can be explained by the fact that there are not so many attractive items to users since most users have bought most items they want on 11st November. Figure 7 (b) shows the CDF curve of the average browsing times before one user makes an order. 90% of users spend no more than 22.15 minutes on average browsing before they make orders on 11st November, while the average time spent on browsing is no more than 12.75 minutes on 10th November , and 14.45 minutes on 12th November. This can be explained by the fact that there can be different merchants offering different discounts and promotions on similar items, and that many consumers are tend to shop around before making their final decisions.

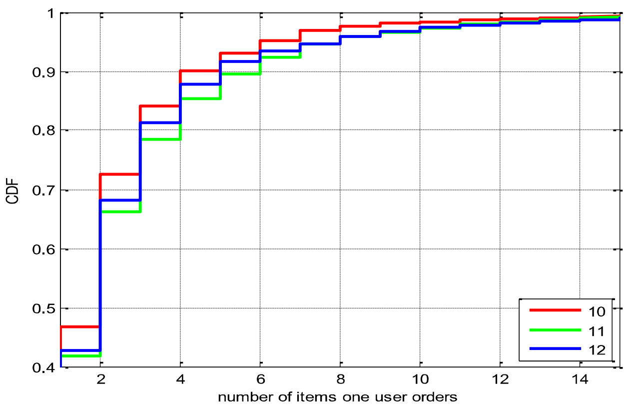
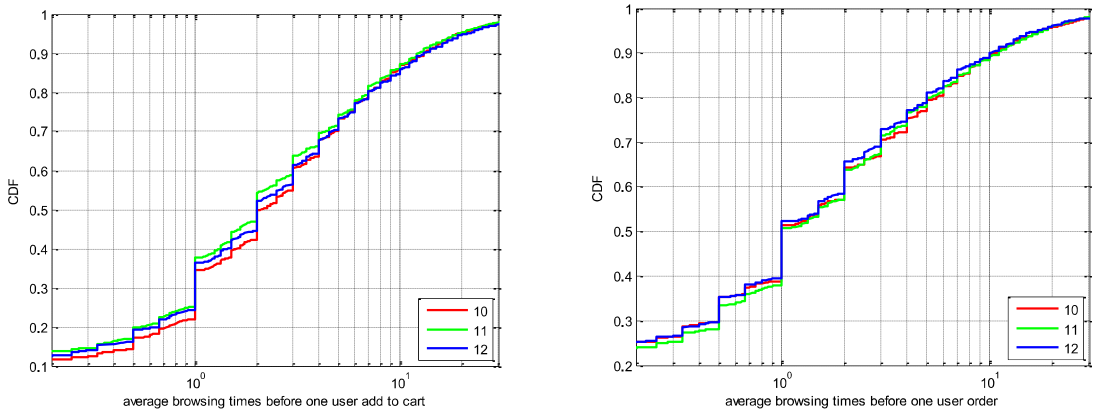


Figure 6 CDF curves of the number of items that one user orders on 10th to 12th November .



(a) (b)

Figure 7 CDF curves of the average browsing times before one user adds an item to cart and make an order on 10th to 12th November.

3.3 Popularity of Items

Figure 8 displays the number of concurrent shoppers on JD.com binned by the hour, which shows a peak starting a few hours prior to the sale event (i.e., 11PM on November 10th to 2AM on November 11th). The temporal pattern demonstrates mobile shoppers rushed to the site anticipating substantial sales on the Singles' Day. Sales marked record high for JD.com in 2016, where nearly one out of every 10 visitors purchased at least one item during the three-day period.

To investigate how discounts and promotions affect the popularity of items, we analyse the times that one item is ordered on 10th to 12th November, respectively. As shown in Figure 9, 80% of items are ordered no more than 3 times during the period. Nevertheless, the most popular item is ordered 5204 times on 11rd November, while the most popular item is ordered 2061 times on November 10 and 1091 times on 12th November. Discounts and promotions are beneficial for rising the sales of items substantially.

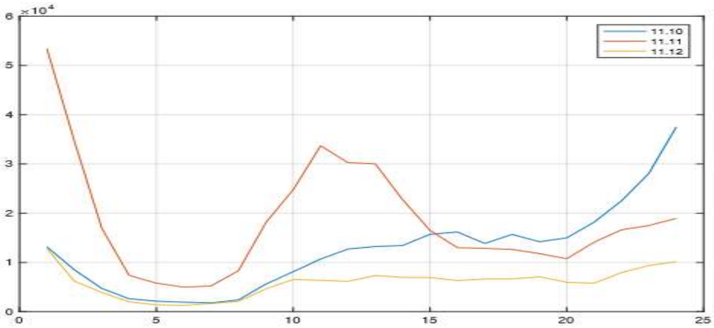


Figure 8 Hourly clicks prior to and during the shopping festival

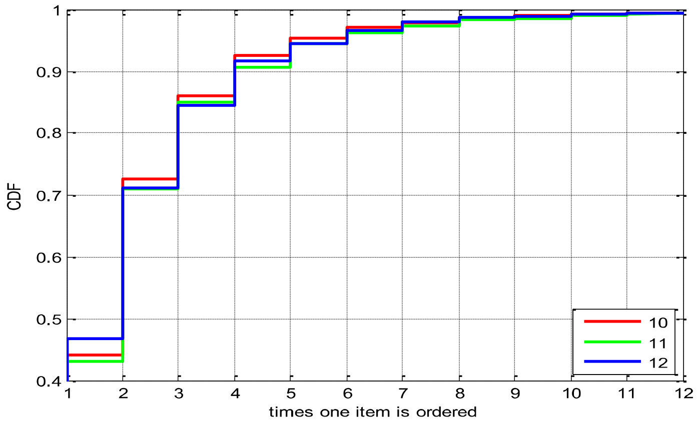


Figure 9 CDF curve of the times that one item is ordered on 10th to 12th November.

4. Collaborative Filtering Based Recommendation

In this section, we aim to recommend items to users based on their historical ordering records. We pre-process the utilized dataset to generate the purchasing matrix, which contains 3821 users as columns and 5564 items as rows. The values of the elements in this matrix is either 0 or 1, where 0 means the user did not buy the item, while 1 means the user bought the item. There are 6166 elements with non-zero values in this matrix. The data sparsity problem is very severe in this task. We conduct the K-fold Cross Validation (K-CV) method to evaluate the performance of the recommendation method applied in this article, where K is set to be 5. The purchasing matrix is randomly divided into 5 parts, where each part is used as the testing set once, and the other four parts left are used as the training set. We utilize the functional module in MyMediaLite 3.11version (cf. Gantner et. al. 2011) to complete the item prediction from positive-only implicit feedback, applying matrix factorization method WR-MF (cf. Hu et. al. 2009). Parameters in WR-MF method such as numFactors is set to be 10, and regularization is set to be 0.0015. We evaluate the performance of the collaborative filtering based approach in terms of Precision@k and Recall@k, which are defined as follows (cf. Li et. al. 2016):

$$\text{Precision}@k = \frac{1}{N}\sum_{i=1}^{N}\frac{S_i(k)\cap T_i}{k},$$

$$\text{Recall}@k = \frac{1}{N}\sum_{i=1}^{N}\frac{S_i(k)\cap T_i}{|T_i|},$$

where $S_i(k)$ represents the set of top k items recommended to user i, T_i represents the set of items bought by user i in the testing dataset, $|T_i|$ represents the number of elements in the set T_i.

The performance of the collaborative filtering based approach is shown in Table 3. From the results, we can see that it is hard to do recommendation for any signal items. Thus, we are motivated to identify features contributing to users' purchase behavior,which can be further utilized in purchase prediction. During a short-term shopping festival, most people decide whether they would purchase something within a short time. Therefore, in this paper we mainly focus on short-term human behavior modelling . In studying Internet browsing behaviour, it's common to treat a user's behavior as several sessions. Each session represents an activity from login to logout. Many studies shows that user's browsing activity is most probably finished, if the user haven't sent anymore request in 20 minutes. Besides, we assume once people place an order, they will no longer concern about the ordered products in this activity. Based on the above assumptions, we divide a user's whole click stream into sessions by 20 minutes interval threshold as well as timestamps of ordering actions. Figure 10 shows the distribution of session length, where35% of sessions consists of only one action. The session length of purchaser and non-purchaser follow quite different distribution. It is easy to be observe that when a user have intent to buy something, he would take more time and more clicks to look into a series of products. Thus, we evaluate the occurrence of purchasing behavior by the following factors.

Table 3 The performance of the collaborative filtering based approach

	Precision@5	**Precision@10**	**Recall@5**	**Recall@10**
Fold 0	0.01418	0.01170	0.02827	0.03357
Fold 1	0.01315	0.01131	0.02442	0.03051
Fold 2	0.01426	0.01155	0.02935	0.03527
Fold 3	0.01411	0.01169	0.02813	0.03441
Fold 4	0.01316	0.01129	0.02511	0.03145

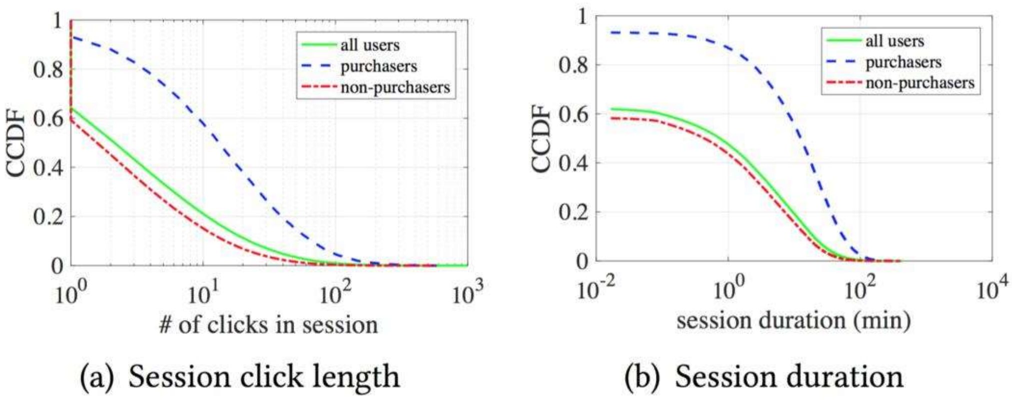


Figure 10 Distribution of session length. Purchaser means the session consists one ordering action at least.

- Cart. The design of shopping cart is directly for the convenience of ordering. Thus, we could almost say an add-to-cart action is strongly related to a purchase intent. Quantitatively, our data shows 23% purchasing sessions have cart actions. Although the ratio is not very high in absolute value, it's much higher than 7% of non-purchase sessions.

- Session lengths. Intuitively, people would spend more time and effort if they really want to purchase something on the website. So in general we believe a longer session implies a higher probability for ordering. Basically, we show that the session length distributions are quite different between purchasing sessions and non-purchasing sessions.

- Event page browsing. Since most consumers are attracted to the website by sales events, we would like to discover if browsing on event pages would be typical to people's purchase decision.

- Number of browsed products. When people really want to purchase something, they would usually compare several products and choose one. So we suppose the more browsing actions a session have, the more probable it would be ended by an ordering action.

- Platform. We suppose people have different degrees of purchase inclinations on JD.com via different platforms. In general, purchase rate on native JD app is twice more than that on other platforms. We suppose browsing specific product pages means that the visitor is seriously looking for something to buy. Therefore, we compare the number of buyers versus the number of visitors who have browsed at least one product page. The ratios of JD app and third-party apps are nearly equal, and are twice as much as that of mobile web browser.

- Date. In Section 4, we've already introduced how the sales events on each of the 3 days were held. We can simply treat the three days as one day before the festival, on the festival, and then one day after the festival. We've shown that traffic of the three day days is quite different in amount (see Figure 10). In general, there are more activities on 11^{th} , compared with 10^{th} and 12^{th}. Meanwhile, it turns out that the rate of purchases on 12^{th} is higher than 10^{th}I, which can be explained in two ways. Firstly, on 10^{th}, people were more likely to prepare for the upcoming shopping festival by looking for things they would buy, and they would wait until the shopping festival actually began. The fact also explains why the session lengths on 10th are the longest. Secondly, some of JD's coupons were still available on 12^{th}, and since 12^{th} was the deadline date, many people would purchase things by using these last minute coupons for discounts.

- Time within a day. There are two reasons that may cause the influence of time on people's ordering behaviour. Firstly, some sales event last for several hours during the shopping festival. Seconly, 11^{th} the Singles' Day was a Friday, which means people had to go to work on that day. Thus, the time of a day is related to the probability of purchase.

Now, with the given session's statistics (number of clicks, users, duration per product category), we design several machine learning methods to carry out the prediction. We down sample our data in order to have same amount of purchasing sessions and non-purchasing sessions. As there are many different kinds of features, we choose logistic regression classifier and apply 5-fold cross validation. Logistic regression is a regression model where the Dependent Variable (DV) is categorical. It covers the case of a binary dependent variable—that is, where it can take only two values, "0" and "1", which represent outcomes such as pass/fail, win/lose, alive/dead or healthy/sick. Cases where the dependent variable has more than two outcome categories may be analysed in multinomial logistic regression, or, if the multiple categories are ordered, in ordinal logistic regression. The performance of our prediction is given as the AUC (cf. Fawcett 2006), which is defined as follows.

- AUC: area under the curve (mathematically known as the definite integral) is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming "positive" ranks higher than "negative"). In practice, it is possible to calculate the AUC by using an average of a number of trapezoidal approximations.

Based on the above defined metric, we show the prediction results in a specific category in Figure 11. From the results, we can observe that our prediction accuracy is above 75% in all of the cases. The accuracy achieves about 84% when the category is phone. Generally, there is not so much difference between different types of shopping items. On the other hand, it also demonstrates the use of the session level indicators is ideal for predicting the purchase action. Thus, we conclude that the method we proposed can predict the purchase action with high accuracy.

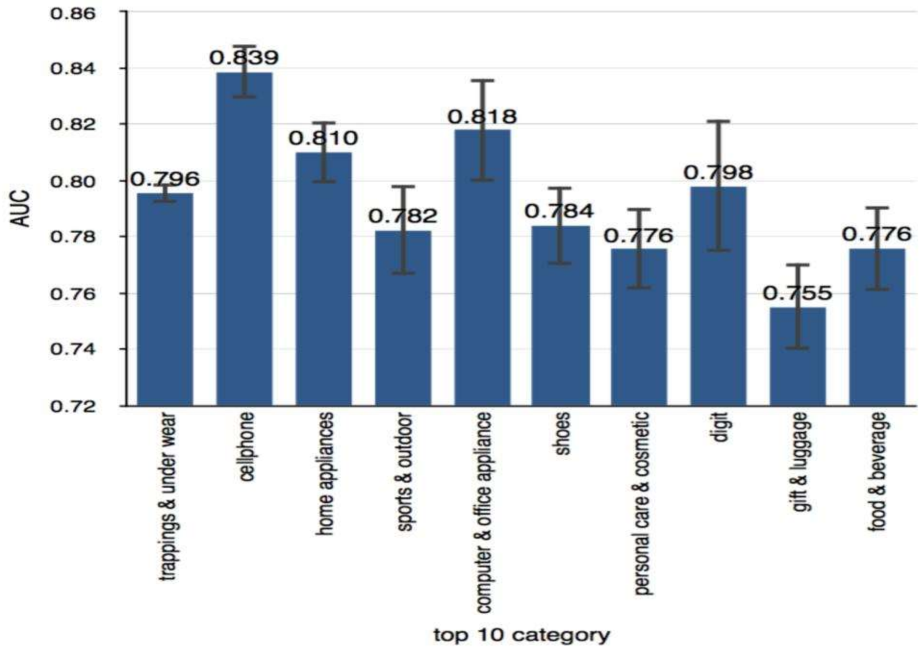


Figure 11 The AUC of ROC for purchase prediction in a specific category.

5. Related Works

Research on consumer behaviour modelling in e-commerce dates back to the early occurrence of e-commerce websites. Consumer behaviour modelling then was conducted for predicting the acceptance of e-commerce (cf. Pavlou 2003) and appropriate goods stocking (cf. Hristoski et. al. 2007). More recently, browsing (cf. He et. al. 2015), ordering (cf. Wu et. al. 2015) and repeat ordering behaviours (cf. Liu et. al. 2016) of consumers are investigated to predict sales and recommend items to their potential buyers. In our work, we investigate the average browsing times before one user adds an item to cart and make an order before, on and after the big shopping festival.

Another line of related works focus on recommendation systems widely used in e-commerce field to improve cross-selling (cf. Kamakura 2014), increase customers' loyalty (cf. Liu et. al. 2016) and realize deep personalization (cf. Zou et. al. 2017). Studies have investigated users' consumption intention from various aspects such as social media (cf. Ding et. al. 2015), cursor movement (cf. Huang et. al. 2011) and advertising target (cf. Farahat et. al. 2012). This work is different from previous works since we investigate the impact of big sales and promotions proposed by almost all e-commerce websites on the same day. Influence on the variations of sales, users' consuming patterns and popularity of items are studied in our work.

The third line of related works focus on the machine learning techniques applied in the recommendation system. The main category of techniques are collaborative filtering (cf. Schafer et. al. 2007), content based (cf. Pazzani and Billsus 2007), knowledge based (cf. Nguyen et. al. 2014) and hybrid (cf. Zhang et. al. 2016). Collaborative filtering based approaches are further classified into memory based and model based. Memory based collaborative filtering can be realized with user-based algorithm (cf. Zhu et. al. 2009) or item-based algorithm (cf. Sarwar et. al. 2001), while model based collaborative filtering approaches are realized by matrix factorization (cf. Ma 2013) such as Singular Value Decomposition (SVD) (cf. Koren and Volinsky 2009). In this work, we apply collaborative filtering based method to recommend items for consumers, and 5-fold cross validation method is used to evaluate the performance of the method.

6. Discussion

The findings in this article give us insights in how to recommend products to their potential buyers and predict the actions of purchases. For example, since people would spend more time and effort if they really intent to purchase something on the website, e-commence website could recommend and bring the products again into the views of users who have browsed them for a long time but hesitantly to buy. Since people prefer to compare prices between different e-commence website, it is beneficial for the e-commence company to show the higher prices of rival website on its own page of the same product when design the product page on shopping festivals. Since peak traffic always occur half an hour after the big discounts start, to alleviate the burden of logistics and website servers, it is better to set multiple discount time during a day. Our insightful findings in this article could give many constructive suggestions for merchants, logistics companies and e-commence companies to increase their incomings and working efficiency.

7. Conclusions and Future Work

In this article, we investigate how the big discounts and promotions offered on November 11st influence the sales of e-commerce websites, consumers' online shopping behaviours and the popularity of items based on the logs cleaned from the DPI dataset. The sales of e-commerce are stimulated sharply by discounts and promotions. We find that the sales per half an hour reach the peak at 00:30 and 10:30am on November 11st that are half an hour later than the time that big discounts and promotions start. Customers are more likely to shop around on the website before they make orders. The last conclusion is that the sales of the most popular items on November 11st could be increased several times. We also apply a collaborative filtering based approach to recommend items to users, and five-fold cross validation is conducted to evaluate the effectiveness of the proposed method. Moreover, we test the efficacy of several feasible precursors of purchasing actions (e.g., the effect of total browsing time, the number of clicks, product categories, and time of day in future purchases) by examining whether visiting the shopping site prior to the sale event or browsing a coupon page is indicative of future purchases.

The effect of holidays and shopping season to retails is critical. By far being the busiest shopping season of the year and this period can determine the difference between profit and loss for the year for many retailers. Mobile clearly is the big story. Despite accounting for a smaller overall percentage of spending, hence have an outsize impact on retail sales growth. In terms of traffic, mobile outpaced desktop retail traffic by a factor of 2 and was higher also on the Cyber Monday, when online retailers promote exceptional bargains immediately following the Thanksgiving holiday weekend in the US.

In our future work, we plan to make use of shopping data within the WeChat app from an information diffusion perspective. WeChat is a social network where information is shared among social ties (cf. Zhang et. al. 2017) that agree to be mutual friends. People can forward shopping links to their social relationships, upon which a diffusion of information can occur. We did not look into such cases nor proximity of information search behavior, where two connected individuals may search for similar items on the JD.com shopping site. To further improve the accuracy of recommendation and prediction of purchase actions, advanced techniques such as deep learning and transfer learning can be applied into these tasks. We leave these issues as future work.

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