Stay Some More and Buy? Modeling the Effects of Visit Time on Online Shopping Purchases

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Abstract

Research in online commerce is heavily focused on identifying and understanding the factors that drive behaviors of users, since such findings can have immediate and direct impact on the sales volumes. One of the long-established principles in the field have been that the more time a prospective customer spends in a visit, the more likely is the purchase decision. Meanwhile, the annual growth of mobile commerce (20-35%) is even higher than of e-commerce in general (15-20%), and many established beliefs about web users' behavior are shifting. In our paper we build two simple models with datasets available through Kaggle repository, to explore the effect of visit time on purchase decisions and online shop's revenues. The results suggest that the time spent on mobile app did have moderate effect on the sales (R^2 = 0.249), while time spent on website was not significant at all. The F1-score in the classification model for the visitors' buy / no buy decision was also rather low, at 0.342. Correspondingly, we discuss some other related factors that could be used to enhance the quality of the models and presumably improve the online sales. Thus our results might be of interest to both machine learning specialists and to electronic commerce or marketing practitioners.

Keywords [1]

Machine learning, e-commerce, m-commerce, user behavior

1. Introduction

Every year the number of Internet users is increasing, which leads to an increase in the volume of online purchases (e-commerce) by 15-20% annually [1], which far exceeds the growth of traditional brick-and-mortar commerce. The reported main reasons for choosing shopping online are: low prices, time savings and convenience [2]. Correspondingly, a solid share of today's research in e-commerce seeks for the ways to increase online shopping revenue, particularly through better understanding of online behavior of users.

In conventional stores, it is generally very difficult to get information about the number of visitors, the time spent in the store, where the customers come from, etc. On the contrary, modern web analytic systems allow obtaining such information easily for e-shops. The main metric for online stores is the number of sales, that is, user reaching the final product order or check-out page [3]. To track this, various systems for collecting statistics are utilized, such as Yandex.Metrica, Google Analytics and some others.

Visit duration has long been considered a key performance metric in e-commerce, enhancing conversion rate and reflecting loyalty to the e-tailor. In a study from 2015 [4], data from 94 online stores underwent statistical analysis (in SPSS software) and several hypotheses were tested, with the overall goal to measure financial return on website visit duration. The PLS (General Partial Least Squares) simulations obtained did not show a relationship between website ranking and visit duration,

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but in general a convincing model of user purchase decision-making has been devised. In an even more established study [5], the authors proposed a type II tobit model, which showed the visitors' decisions to continue browsing or leave the website, as well as the length of time spent viewing each of the pages. The results suggested that the propensity of visitors to continue browsing changed dynamically, depending on the depth of the site visit, and the number of repeat visits. In [6], the authors investigated several groups of factors influencing the duration of a website visit. A random effects model was employed to determine the influence of these factors on the visit duration and the number of pages viewed by the user. The results suggested that older people and women spent more time at websites, while the sites that featured lots of advertisements got lower visit times from most studied user demographic groups.

The results of the above and similar research works have been considered helpful in improving (optimizing) e-commerce websites, to achieve longer average visit durations and presumably enhance sales. As we mentioned above, the "time on site" metric has been important in online commerce for already two decades, the reasoning being as follows. The longer a user has spent in the online store, the more interested she is in the products of this site [7], and this interest should lead to a purchase. But not only website browsing habits change; also in the past several years in has been repeatedly noted that mobile commerce is growing even faster than e-commerce, with the reported annual growth of 20-35% [8]. Mobile devices are already used in more than half visits to online stores, and the sales are expected to catch up [9]. However, whether the factors affecting purchase-making behavior of prospective online customers who use mobile applications are the same as for websites is currently underexplored in research work that came to our attention.

The research objective of our paper is investigating how the time spent by users in online stores affects their income. For this end, we test two hypotheses:

1. Does the time spent by the user on online store website affect the purchases (income from a customer)?
2. Does the time spent by the user in m-commerce mobile application affect the income?

In our study, we relied on two openly available datasets that we describe in the following Section. In Section 3, we test the hypotheses using SPSS Statistics software[2] and report the results. Finally, we discuss the findings and make the conclusions.

2. Method

2.1. The Dataset Description

The first dataset that we used was *Online Shopper's intentions*, openly accessible through Kaggle [10]. The dataset consists of 10 numeric and 8 categorical attributes for a total of 12,330 sessions. They have been collected for a single website using Google Analytics. The times spent by users in various webpages (administrative, informational, etc.) available in this dataset were independent variables in our study. The dependent variable was the Revenue, which corresponds to the visitor's purchasing decision and have binary values (TRUE / FALSE). In Table 1 we show some records and columns from the *Online Shopper's intentions* as an example.

The second dataset that we used in the study was the *Linear Regression E-commerce Dataset,* also from the Kaggle repository [11]. This dataset contains data about customers who buy clothes online, in an e-shot that also offers advice on style and clothing. Customers come to the store, have sessions / meetings with a personal stylist, and then they can go home and order the clothes of their choice either through the mobile app or through the website. The dataset consists of eight attributes, making up a total of 500 different customer data. Our independent variables were the time spent on the site and the time spent in the mobile application. The dependent variable was the store's annual income (purchases) from the customer (note, that unlike in the first dataset, in the second the dependent variable was rational scale). In Table 2 we present some extracts from the *Linear Regression E-commerce Dataset* as an example.

[2] https://www.ibm.com/ru-ru/products/spss-statistics

Table 1
Data samples from the *Online Shopper's intentions* dataset

Time Duration in Administrative Page	Time Duration in Informational Page	Time Duration in Product-Related Page	Revenue
29.75	0	1410.43	FALSE
0	0	124	FALSE
0	0	0	FALSE
0	56	0	FALSE
0	0	0	FALSE
122	40	3154.97	TRUE
396.5	0	415.5	FALSE
238.58	119.5	2933.7	TRUE
0	0	411.92	TRUE

Table 2
Data samples from the *Linear Regression E-commerce Dataset*

Time on App	Time on Website	Yearly Amount Spent
12.65565	39.57767	587.9511
11.10946	37.26896	392.2049
11.33028	37.1106	487.5475
13.71751	36.72128	581.8523
12.79519	37.53665	599.4061
12.02693	34.47688	637.1024
11.36635	36.68378	521.5722
12.35196	37.37336	549.9041
13.38624	37.5345	570.2004

2.2. User Behavior Modeling

User behavioral models are subdivided into short-term and long-term models. The construction of the long-term models is mainly required for their further application (for example, for use in recommender systems). Long-term behavior describes relatively stable user preferences based on an extensive history. The short term models describe a user's current activity and his / her actual intentions. Each type of models has its own advantages and shortcomings – for instance, long-term models can collapse when a web resource is updated, which happens rather often nowadays [12].

Since the datasets that we employ in our research involve relatively extensive user history, they should correspond to long-term behavioral model. As a particular method we used for the analysis of the two datasets, logistic and linear regressions were chosen, in accordance to the data structure, particularly the binary dependent variable of the *Online Shopper's intentions* dataset.

Logistic regression is a form of multiple regression, whose general purpose is to analyze the relationship between multiple independent variables (also called regressors or predictors) and a dependent variable. Binary logistic regression is applied when the dependent variable is binary – i.e. it can take only two values. The independent variables are generally interval or rational scale, which is exactly our case for the duration times. Through the use of logistic regression, it is possible to estimate the probability that an event will occur for a particular subject (sick / healthy, loan repayment / default, etc.) [13]. The quality of logistic regression models is characterized with parameters that correspond to data classification tasks: Precision, Recall, Specificity, Sensitivity, etc. (more detailed information can be found e.g. in [14]). The F1-score was calculated using the traditional harmonic mean formulation:

$$F_1 = 2\frac{Precision * Recall}{Precision + Recall} \quad (1)$$

Linear regression, which we naturally employed for the *Linear Regression E-commerce Dataset*, is used in statistical analysis and machine learning to describe the effect that one or several independent variables (factors, regressors) have on a dependent (explained) variable. All variables are rational or interval scale, which both the time and the annual revenue conform to, and the effect is expressed as a linear dependence function. The quality of linear regression model is an extensive research topic, but we in our current study used the widely recognized R-squared and significance metrics.

3. Results

3.1. The Online Shopper's Intention Dataset

First, we analyzed the *Online Shopper's intention* dataset, in which three independent variables are involved: 1) the time of working with the administrative part of the site, 2) the time of working with the information part of the site, and 3) the time of working with the product pages. In the dataset, 12112 records (98.2%) turned out being valid. The dependent binary variable, the site's income, takes the value TRUE or FALSE: whether the user made a purchase during this session or not. The regression model was built using the stepwise Forward LR method.

When a model was built, with a cut-off value of 0.5 (default) the percentage of cases correctly classified into observed categories was 84.4. However, the classes in the dataset are unbalanced: only 1875 (15.5%) visitors had made a purchase (TRUE), while 10,237 (84.5%) did not (FALSE). So we varied cut-off values (0.45, 0.4, 0.35, 0.3, 0.25, 0.2, etc.), obtaining the resulting Precision and Recall as presented in Table 3. Notably, at the cut-off value level of 0.15, the Accuracy of our model began to decline rapidly (by 11.6% compared to the cut-off value of 0.2). The lowest threshold of the cut-off value adjustment that we performed was 0.12, as Precision had achieved 1 at this level, the Accuracy however being already rather poor, at 15.5. The maximum F1-score value (0.342) was found for the cut-off value of 0.14.

In Fig. 1 we present the Precision-Recall curve for the model, corresponding to the considered cutoff values. In Fig. 2 we also show the ROC-curve – although it's more suited for the case of the balanced classes, we decided to include it for the illustrative purposes. The area under the curve is 0.681.

As the quality of the classification model is relatively low, we can conclude that our hypothesis "the time spent by the user on the website of the online store affects the purchase (income)" is not supported much. The three considered time values failed to considerably improve over the "null" predictor that would just predict TRUE for 15.5% of the classified cases.

3.2. The Linear Regression E-commerce Dataset

The next dataset that we analyzed was the *Linear Regression E-commerce Dataset*, for which we used the pairwise linear regression method. The multiple regression method was inappropriate because the independent variables are highly collinear with each other, as can be seen in Fig. 3. We built the first model in which we used the *Time on App* as the independent variable (the time the user spent in the application during the year), and the *Yearly Amount Spent* (the sum of the user's purchases for the entire year) as the dependent variable.

The results of the linear regression analyses for the two independent variables are presented in Table 4. The $R^2 = 0.249$ for the *Time on App* is not very high, but it is considerably higher than $R^2 < 0.01$ for the *Time on Website* variable, which was also not statistically significant. In the regression equation for Time on App, the constant was not statistically significant ($p = 0.608$), which is in line with the conceptual reasoning that zero time spent in online store cannot result in any revenue from such a user. Still, we employ the regression analysis that includes the constant, for the sake of comparability. In Fig. 4 we show the linear regression plot for the *Time on App* model.

Table 3
The quality indicators of the logistic regression model (*Online Shopper's intention* dataset)

Cut-off value	Accuracy	Precision	Recall	F1-score
0.5	84.4	$\frac{24}{1875}$=0.0128	$\frac{24}{68}$=0.353	0.025
0.45	84.3	$\frac{31}{1875}$=0.0165	$\frac{31}{91}$=0.34	0.032
0.4	84.2	$\frac{45}{1875}$=0.024	$\frac{45}{131}$=0.343	0.045
0.35	84	$\frac{65}{1875}$=0.0346	$\frac{65}{193}$=0.336	0.063
0.3	83.6	$\frac{98}{1875}$=0.052	$\frac{98}{302}$=0.325	0.09
0.25	83	$\frac{173}{1875}$=0.092	$\frac{173}{534}$=0.323	0.144
0.2	80	$\frac{382}{1875}$=0.204	$\frac{382}{1317}$=0.29	0.239
0.19	79	$\frac{430}{1875}$=0.229	$\frac{430}{1528}$= 0.281	0.253
0.18	77.6	$\frac{489}{1875}$= 0.261	$\frac{489}{1822}$=0.268	0.265
0.17	75.7	$\frac{583}{1875}$=0.311	$\frac{583}{2238}$= 0.261	0.283
0.16	72.7	$\frac{712}{1875}$=0.38	$\frac{712}{2858}$= 0.249	0.301
0.15	68.4	$\frac{885}{1875}$=0.472	$\frac{885}{3724}$=0.24	0.316
0.14	61.7	$\frac{1207}{1875}$=0.644	$\frac{1207}{5175}$= 0.233	**0.342**
0.13	46.7	$\frac{1640}{1875}$=0.875	$\frac{1640}{7858}$= 0.209	0.337
0.12	15.5	$\frac{1875}{1875}$=1	$\frac{1875}{12112}$=0.155	0.268

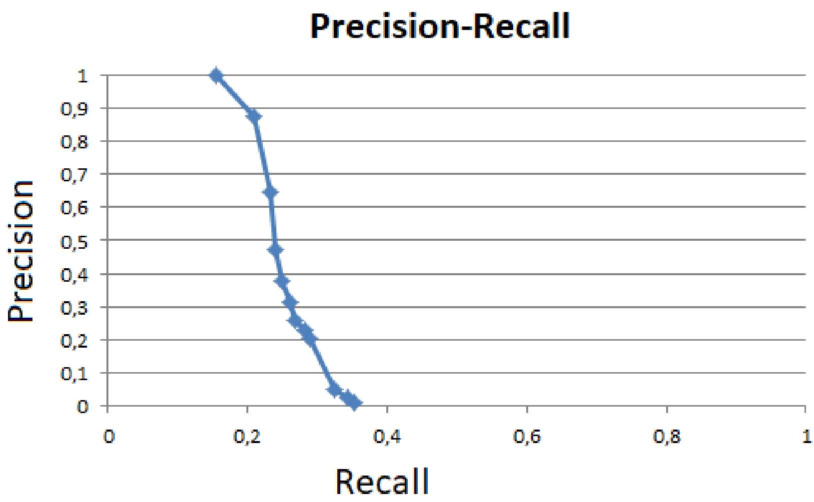

Figure 1: The Precision-Recall curve for the logistic model (dataset 1)

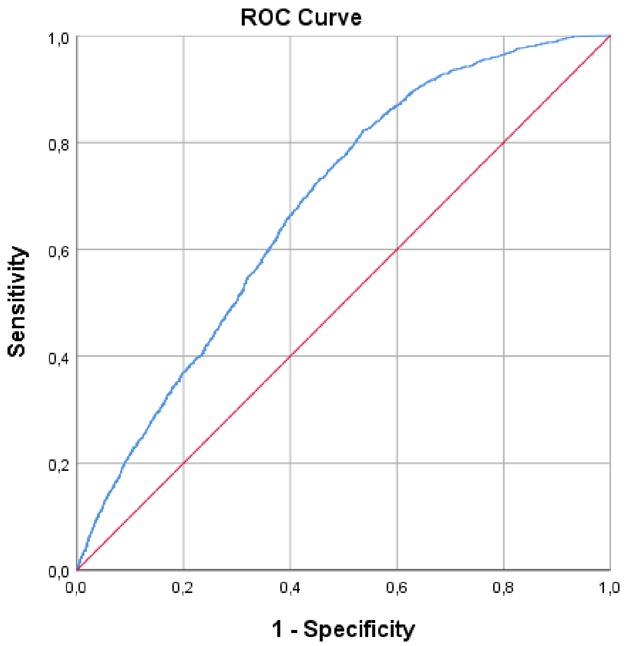

Figure 2: The ROC curve for the logistic model (dataset 1)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Time on Website	-,044[b]	-1,132	,258	-,051	,993

a. Dependent Variable: Yearly Amount Spent

b. Predictors in the Model: (Constant), Time on App

Figure 3: Excluded variables in the analysis of the dataset 2

Table 4

Results of the *Linear Regression E-commerce Dataset* analysis

Independent variable	Statistics	Beta	R^2
Time on App	$F_{1,498} = 165$, $p < 0.001$	0.499	0.249
Time on Website	$F_{1,498} = 0.003$, $p = 0.953$	-0.003	0.000007

4. Discussion and Conclusions

The linear regression analysis results presented in Table 4 suggest that the *Time on App* variable much better explains the dependent variable than the *Time on Website*. Hence, it can be assumed that time spent on an app is more likely to result in a purchase than time spent on a website. So, the hypothesis 1 (impact of time on websites) should be rejected, as the classification model in the dataset 1 was weak and *Time on Website* was not significant in the dataset 2. The hypothesis 2 (impact of time on mobile apps) can be confirmed, as *Time on App* was significant in the dataset 2, even though the $R^2 = 0.249$ was low.

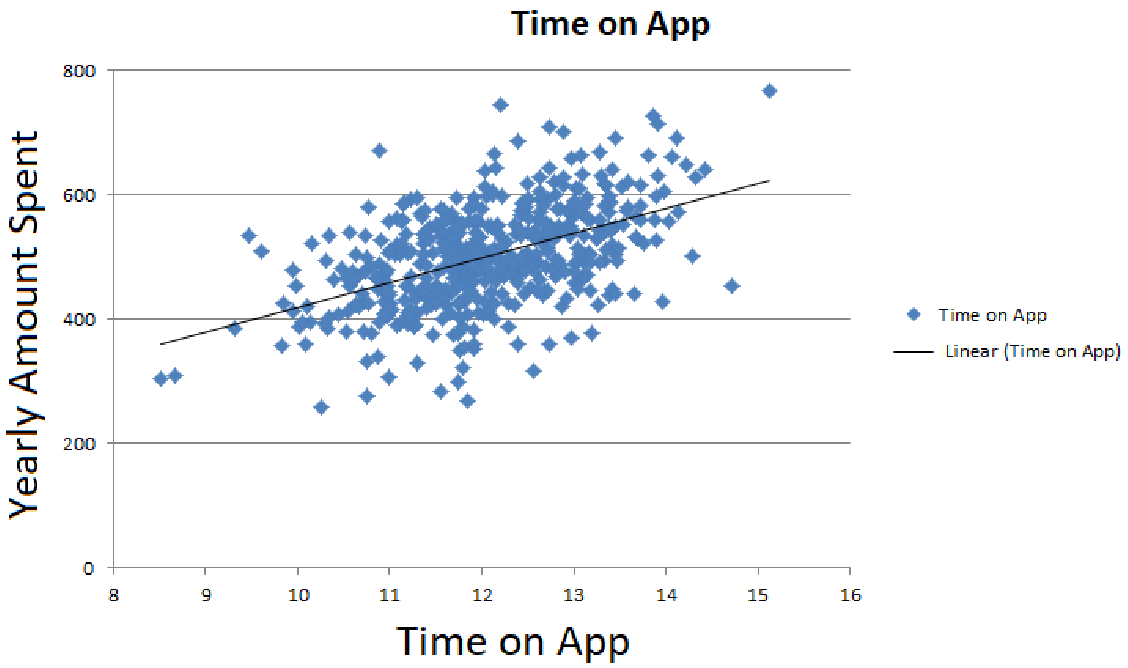

Figure 4: Linear regression plot for the dataset 2 (significant independent variable)

The low share of variance explained by the time in the online store revenue suggests the effect of other important factors. Among the factors related to online store visits, we can note the week day of the visit, whether the visit is a repeated one, the user's region, etc. These deserve further exploration to improve the models for the dataset 2. In turn, our classification model for dataset 1 (F1 = 0.342) may foremost suffer from lack of consideration of repeated visits. That is, in one visiting session the user could obtain all the necessary information for the purchase decision-making, while the actual purchase can be made during the next, shorter visit.

However, the general outcome of the study is consistent with some related research, e.g. in [15] the authors conducted a study comparing purchases on a website and in a mobile application. The results of the data analysis showed that customers feel more comfortable using mobile applications for online shopping than on the website, in terms of ease of search, ease of access and so on. This may suggest an ongoing shift of customers' purchases towards m-commerce, whereas websites (browsed on desktop machines) are visited for other purposes. In any case, we would like to highlight that the time spent in online stores still is still an important indicator of their operation, even if an indirect one. First, it positively contributes to maintaining the interest of users in the store, which can lead to potential purchases [16]. Second, the duration of a visit to a website is an important factor that should be considered when placing advertisements, which will lead to additional profits [17]. On the other hand, it might be exactly the excessive web advertisements that reduce usability and aesthetical impression of websites and push users towards using mobile apps. The consideration of these mixed effects in the online store user behavior models are among our further research plans.

We would also like to note that our study was very much limited in the number of online stores that were affected. In both *Online Shopper's intentions* and the *Linear Regression E-commerce* datasets, the data for only one (though different) online store is presented. Correspondingly, a study of much larger scale is necessary before generalizing our conclusions.

5. Acknowledgment

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