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A New Model for Predicting the Probability of Product Return in Online Shopping

Ehram Safari [a], Seyedeh OmSalameh Pourhashemi [b], Mohsen Gharahkhani [c]

[a] ICT Research Institute (Iran Telecommunication Research Center), Tehran, Iran
[b] Islamic Azad University Central Tehran Branch, Tehran, Iran
[c] Department of Finance, Iranian E-Institute of Higher Education, Tehran, Iran

*** Corresponding author email address**: pourhashemi1986@gmail.com

Abstract

One of the current important issues for online stores regarding online shopping is customer satisfaction from online shopping. Many of the customers who purchase their products online from electronic stores are not satisfied with the products they receive. Some of the reliable online stores follow the policy of "product returns" to increase their customers' satisfaction. According to this policy, if the customers are not satisfied with the products they have received, they can return them to the store under predetermined conditions. Therefore, the purpose of this paper is to present a model based on the factors influencing online customers' satisfaction during online shopping. The presented model in this study is based on the data obtained from eBay Store using data mining and SPSS Modeler. Using this method and well-known algorithms such as CHAID and C&R Tree, and C5.0, a model is created that can predict the order returns at high accuracy. The investigations showed that the values of cross-validation for the accuracy of the models created by CHAID, C&R Tree and C5.0 algorithms on the data set of the three algorithms were 78.6 – 80.1 percent, which confirmed the accuracy of the final model. Research results showed that prediction of the probability of product returns is, in fact, in line with the estimation of the maximum logical costs which determine the logical number of messages and call duration for any product with specific profit and cost so that product returns can be prevented.

Keywords: Online shopping, Data mining, Satisfaction, Product return

1. Introduction

Nowadays, one of the important business challenges among most of the sellers is product return by users. Product returns by users are different from product returns from retailers (to the manufacturer) and it ends by the consumers stopping using the product (usually after several months or years). The cost of returning the customers is considerable (Asadi, Nilashi, Husin, & Yadegaridehkordi, 2017; Ng & Stevens, 2015). In the past, the return fee among electronic retailers such as computer sellers was common by mail orders (Chu, Gerstner, & Hess, 1998). However, nowadays, almost all great retailers present a full refund. The retailers generally believe that a full refund is the best return policy considering the considerable costs of following such a policy.

Online shopping is one of the newest and most popular types of shopping in the present era (Abumalloh, Ibrahim, & Nilashi, 2020; Nilashi et al., 2020). Many people shop online due to different reasons such as being busy or long distances. However, the main problem with this type of shopping is the fact that the products are intangible and they cannot be examined closely, which leads to the customers' dissatisfaction when the products are delivered in most cases. Some of the reliable online stores are willing to take back their products from dissatisfied customers to increase their customers' satisfaction (Ahani, Nilashi, Ibrahim, Sanzogni, & Weaven, 2019; Asadi, Abdullah, Safaei, & Nazir, 2019; Asadi, Hussin, & Dahlan, 2018; Asadi, Nilashi, et al., 2019; Asadi et al., 2020; Samad et al., 2020; Yadegaridehkordi, Iahad, & Asadi, 2015), which apart from losses for the store will lead to a waste of time, paying extra costs and customers' dissatisfaction.

Product return is one of the main problems in stores, especially online stores. Accordingly, the model that will be presented in the present study can be used by recommender systems or individuals at online stores to reduce the product returns to a significant level. Recommender systems can test the products that they want to recommend to the customers based on their profile and shopping background (Nilashi, bin Ibrahim, & Ithnin, 2014; Nilashi, bin Ibrahim, Ithnin, & Sarmin, 2015; Nilashi, Jannach, bin Ibrahim, Esfahani, & Ahmadi, 2016). In case the model output confirms lack of product return, then the recommendations will be provided for the customers with a higher degree of confidence and in case a customer orders a product whose return is positive according to the model, the customer can be called before sending the product and more details can be provided for him/her regarding the purchased product. Using this model, online stores can be able to detect the orders that might be returned and consequently, eliminate the grounds for customer dissatisfaction and make the customers loyal and buy products again. It is noteworthy that the obtained satisfaction can be a great success for stores because it provides the grounds for the customers repurchase, increases their loyalty, and reduce the risks of sales. The present study is mainly focused on the dataset of the eBay store. eBay is selected as the data source because its products include similar products with different return documents (i.e. full refund and no refund) that are presented by various sellers mainly small to medium-size. This study evaluates (1) the prediction of product return according to the target variables, (2) investigation of the effect of product specifications such as color, price, size, production date, manufacturer and product code on product return, (3) investigation of the effect of factors such as customer profile such as date of birth, current city, customer type (male, female, factory, etc.) and custom code on product return, and (4) investigation of the effect of the date of order and delivery date to a customer on product return. The rest of the paper is organized as follows. Section 2 presents a review of the related literature. Section 3 introduces the method of data collection and tools. Section 4 presents the research variables. Section 5 presents the stages of data analysis and section 6 analyzes the research results. Section 7 presents the main findings and suggestions for further studies.

2. Review of the Related Literature

Many researchers have studied the subject of product returns. They investigated numerous models according to the optimal return policies under the title of different properties of product, market, and consumer. As an example, in a study, Shulman, Coughlan, and Savaskan (2009) studied the exclusive retailers who sold multiple products, while Hsiao and Chen (2012) examined a more extensive concept of quality risk including product uncertainty which is a common reason for product returns. The full refund value is considerable among eBay consumers. Although the amount is not as much as expected, it is significantly lower than 20 to 30 percent for the catalogs and retail store products estimated by Anderson, Hansen, and Simester (2009) and Heiman, Just, McWilliams, and Zilberman (2015). De, Hu, and Rahman (2013) studied the effect of different product-based technologies and product returns. The data sets provide accurate information that the customers using technologies before purchasing such as using an online zoom tool leads to fewer product returns, while using images replacing a product are accompanied by more product returns.

In their study, Shang, Pekgün, Ferguson, and Galbreth (2017) investigated how familiar online consumers are with the product return value. They investigated eBay in their study. Results showed that the value of full refund policy for the consumers might not be what they expect and this will lead to a lot of heterogeneity among buyers with different online purchasing experiences. In another study, Sahoo, Dellarocas, and Srinivasan (2018) investigated the effect of online product examination on product returns. In their study, they showed that compared to more examining and presence of useful comments of other users, the products being accessible will lead to fewer product returns after the customer has controlled the products and other related factors. Besides, in another study, Sahoo, Srinivasan, and Dellarocas (2013) investigated the effect of online examination on product returns and net sales. They stated that less probably, online accessibility of the product is less correlated to product returns after having controlled the customer, products, channels, and other related factors.

3. Data Collection and Research Instruments

Data mining was used in this study (Bagherifard, Rahmani, Rafe, & Nilashi, 2018; Nilashi, 2016; Nilashi et al., 2018). The data was first cleaned and normalized using SQL and Excel and then determined through classification and training. In the following, the model was extracted from Train data using SPSS Modeler. In this software, a default stream of the binary classification was created and was considered as the primary model, to begin with. Only a number of the variables available in the data were considered in these streams. Also, only one percent of the data was first used due to the shortage of memory.

To investigate whether the importance level of variables such as customer age, customer gender, product color, etc. affect the product returns, the Variable Importance was used in SPSS Modeler. According to the outputs of the module, the variables with higher importance were used in the final model and then the model was tested using Test data to determine the accuracy of the model in the prediction of probable product returns.

4. Research Variables

In this section, research variables are presented in two categories of primary and derived variables which will be described in detail in the following.

4.1. Primary Variables

The variables presented in Table 1 are the primary variables obtained from the eBay store. The target variable in this study is the return shipment which is a binary variable with only two modes of zero and one; the value one for this variable means product return or the return of the product by the customer and the value zero means the product is accepted or absence of product return by the customer.

4.2. Derived Variables

The derived variables (see Table 2) are created to help the data mining process.

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Table 1
Primary research variables

Variable	Description	Minimum	Maximum
Order Item ID	Order Number		
Order Date	Order Date	2012/01/04	2013/03/31
Delivery Date	Delivery Date	2012/03/04	2013/22/07
Item ID	Product ID	1	3070
Size	Other Products	--	--
Color	Product Color	--	--
Manufacturer ID	Manufacturer ID	1	166
Price	Product Price	3.4	999
Customer ID	Customer ID	6	86610
Salutation	Customer Type (Household, Male, Female, Company)	--	--
Date Of Birth	Customer Date of Birth	1912/07/10	2005/19/12
State	Customer State	--	--
Creation Date	Production Date	2011/16/2	2013/3/31
Return Shipment	Product Return Status	0	1

Table 2
Derived variables

Derived variable	Description	Minimum	Maximum
Sen	Customer Age	6	99
Ttdeliver (time to deliver)	Time-to-Delivery (days)	0	175
SeneMahsul	Product's Age (days)	1	887
Size2	Size uniformization	--	--
Color2	Color placements	--	--
DeliverdYN	Blank or non-blank delivery date	0	1
State2	Numbering customers' states	1	16
Salutation2	Numbering customer types (male, female, company, etc.)	1	5
Sen2	Age group categorization (old, young, etc.)	--	--

5. Data Mining Steps

Data mining and creating an accurate and efficient model is not possible using raw or primary data. The data includes inconsistencies, outliers caused by intentional and unintentional human errors and noises, etc. which need to be solved. Accordingly, data preprocessing is of great importance. The major steps in data preprocessing include data cleaning, data integration, data reduction, and data conversion. The measures taken to implement these steps are presented in Table 3.

Table 3
Description of data mining steps

A) Data Cleaning	The following steps were taken regarding data cleaning:

Missing Values	The fields with no values will be examined. The number of the rows with blank delivery dates was 6413 and none of them were returned. Therefore, they were deleted from the rows as follows.
	
	`delete FROM [dm2].[dbo].[train$]`
	`where deliveryDate is null`
	
	The rows with unknown dates of birth were identified as follows.
	
	`SELECT distinct customerID`
	`FROM [el].[dbo].[train]`
	`where dateOfBirth='?'`
	`order by customerID`

An International Journal JSCDSS
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Table 3
Description of data mining steps (Cont.)

<table>
<tr><td>Deleting noise</td><td>The interval between ordering products and delivering them to the customer and the repetition number of each interval was obtained using the following code:

<code>SELECT count([delivery]), delivery
FROM [dm2].[dbo].[train$]
group by delivery</code>

Investigating the intervals between ordering and delivering, it was observed that some intervals were negative. The negative intervals mean the delivery was made before the orders were set which indicates an error in recording the date of order or delivery to the customer. The number of negative cases was less than 200. The values were replaced and corrected by the average positive values. The following code was used to see the distribution of delivery time:

<code>SELECT count([delivery]) as count_of_cases, delivery
FROM [dm2].[dbo].[train$]
where delivery>20
group by delivery
order by delivery</code>

The values above 70 or 80 days were reduced in a specific and consistent trend and do not follow the outlier behavior. Therefore, the data was not deleted and was included in the calculation of the average delay in product delivery. The following code was used to examine the average delay in the deliveries:

<code>SELECT avg(delivery)
FROM [dm2].[dbo].[train$]
where delivery>=0</code>

the average value of the delays in delivering customer orders equals 7.6 and since there was not much data in the intervals above 50 to 120, the average was rounded down and 7 was taken as the average value. Then the value of the interval between ordering and delivering or the negative delivery delays was updated and the negative values were replaced by 7. Besides, the rows where the delivery dates were before the product was sent were updated and the delivery dates were changed according to the following code to seven days after the order.

<code>update [dm2].[dbo].[train$]
set
[dm2].[dbo].[train$].[deliveryDate]=DATEADD("day",7,[orderDate])
where [dm2].[dbo].[train$].delivery<0</code></td></tr>
<tr><td>Finding and Deleting Outliers</td><td>This type of data might occur due to noise and/or intentional or unintentional human error. Some of the important measures taken for detecting and deleting outliers are an investigation of the derived variable of delivery delays (the interval between orders to delivery). The following code was used to see the distribution of delivery time.

<code>SELECT count([delivery]) as count_of_cases, delivery
FROM [dm2].[dbo].[train$]
where delivery>20
group by delivery
order by delivery</code>

Results indicated that the intervals above 70 or 80 days are not considered outlier data because their frequency has reduced continuously. Nothing has been deleted from these values and they have been included in the calculation of the average value. Moreover, the following code was used to check outlier dates not to exist:

<code>select deliverydate, COUNT(delivery dates) as c
from [dm2].[dbo].[train$]
group by deliveryDate
order by c</code></td></tr>
<tr><td>B) Data Integration</td><td>The value of the sizes was different. The size of some clothes was based on numerical values and the size of others was based on string values. Also, the size definition was not consistent in different clothes. As an example, the size 40 is sometimes equal to medium and sometimes it is equal to XXL, which depends on the product. To solve this problem, the sizes were first integrated and then the sizes close to each other were merged to have fewer size variations.</td></tr>
<tr><td>C) Data Conversion and Discretization</td><td>The following steps were taken regarding data cleaning:</td></tr>
</table>

An International Journal JSCDSS
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Table 3
Description of data mining steps (Cont.)

Creating Derived Variables	Many derived variables were created in this study and the creation of some of them are presented in the following:
	One of the variables that can be achieved from the data is the time to delivery or ttdeliver that is obtained via the following code:
	
	`alter table [dm2].[dbo].[train$]`
	`add ttdeliver int`
	`update [dm2].[dbo].[train$]`
	`set ttdeliver =`
	`(select`
	`DATEDIFF("dd",b.[orderDate] ,b.[ttdeliverDate] )`
	`FROM [dm2].[dbo].[train$] as b`
	`where b.orderItemID=a.orderItemID`
	`)`
	`FROM [dm2].[dbo].[train$] as a`

Conducting Rollup on Derived Variables	The two derived variables of state2 and salutation2 were created to increase the data processing speed. The state variable represents the current city of the customers and the salutation variable includes different types of customers numbered in state2 and salutation2 variables and the string variables are replaced by numerical values.
Changing Specific Color Names to Common Names and Deleting the Missing Values	The name of specific colors was changed to common color names and was used as color2. Also, the colors with no values were determined and deleted.
D) Data Reduction	One of the techniques by which the great volume of data can be shown in smaller sizes is the data clustering technique. The k-means clustering technique is used in this paper. This method uses the silhouette index to investigate cluster separation and the consistency of the content in each cluster. Using the silhouette index it was found that the clustering was not of good quality. Accordingly, the clustering was discarded.
E) Data Auditing	Information analysis and evaluation are used to identify and correct the barriers, repeatability, and shortage of information.
F) Determining the Type of Variables	
G) Data Classification	Different classification algorithms were used for binary classification in the model. The reason for using the binary classification was the banality of the target variable or the return shipment which has two values of zero and one. First the classification algorithm of each one was separately presented in the table and the results were examined. Some classifications had negative effects, some had not quite a good effect and some had a positive effect on the obtained accuracy. Then the ensemble method was used. This method used many classifications simultaneously which significantly increased the final accuracy.

6. Results Analysis

Results showed that the highest accuracy was related to the SVM algorithm with a value of 64.999 percent followed by the logical regression and Bayes classifier algorithms. Considering the accuracy of 64.999 percent obtained for this model, the aforementioned accuracy will be achieved in the following as the model is completed; otherwise, the applied changes have to be deleted for harming the accuracy. The input volume in the present project was great and the memory problem was solved and it was allowed to use all the data. However, the run time of the algorithms increased. Accordingly, the two derived variables of state2 and salutation2 were created to reduce the run time of the algorithms. The "state" variable includes the customer's living city and the "salutation" variable includes customer types. The variables "state2" and "salutation2" were numbered. Other derived variables were created and used along with the primary variables in the model for higher efficiency and using the input variables better. Some of the created variables include product age and deliveredYN. Also, corrections were applied to the color and size variables and the results were a reduction in the diversity of the colors and the integration of the available sizes in different standards. After applying the corrections and changes to the data and model, the model was implemented again by selecting the majority of binary classification algorithms. The accuracy of the output algorithms significantly increased after the corrections and changes. Therefore, the changes were maintained due to their positive effect on the value of the output accuracy. The output obtained from the implementation of the model only shows the results of the three classification algorithms of CHAID, C5, and C&R Tree. The accuracy of the three algorithms was also observed to have a significant increase and the highest value was 79.231 percent, which was related to the C5 classifier. To apply the changes on the default settings of the classification algorithms and investigating the effect of the changes on the accuracy of the model, each classification algorithm was tested separately by applying different settings, which had no significant effect on the accuracy of the models and showed that the default settings resulted in the optimal values for the algorithms.

The other method used to increase the accuracy is the ensemble method of classification algorithms. Because the three algorithms of CHAID, C5, and C&R Tree were shown as the best classification algorithms in model output,

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the ensemble method was used to combine these three algorithms. There are multiple methods to combine the results of these algorithms. The method used in the present study is the reliability-based weighting (SRBW) technique because the accuracy obtained from this technique is higher than that obtained from other techniques. In this method, each algorithm has a specific weight proportionate with its reliability. These weights are added up at each unique result and the result with the higher weight is considered as the final result of the ensemble technique. The result of investigating the accuracy of the final model was 80.15 percent. A total number of 283.478, 81.237, and 40.590 records were used for training, testing, and evaluation, respectively. The important variables of the ensemble model were also determined and the most effective predicted variable was return shipment that was applied in the ensemble model. The "Price" variable (the primary variable representing the product price) was the most important variable and the "item ID" variable (the primary variable representing the customer's current city) was the least important variable in determining the value of the target variable. Other variables such as color2 and deliverYN are not influential variables in predicting.

6.1. Investigation of the Combination of Holdout and Accuracy Metric Methods

First, the data were randomly divided according to the holdout method into three categories of training, testing, and validation. Then the value of accuracy was estimated for each category. The value of accuracy for testing and validation was not significantly different from the value of accuracy for training, which shows the appropriate efficiency of the model.

6.2. Investigation of the Combination of Cross-Validation and Accuracy Metric

Each of the CHAID, C5, and C&R Tree algorithms was evaluated by this method. The values of cross-validation for these algorithms lied in the range of 78.6 and 80.1, which confirmed the accuracy of the final model. When selecting this validation method, the holdout or partitioning evaluations are not performed anymore. Investigating the cross-validation showed that the accuracy value obtained from cross-validation (78.19 percent) is very close to the accuracy value of the ensemble method of classification algorithms (80.15 percent), which confirms its correctness.

7. Conclusion and Suggestions for Further Studies

The current study presented a model to predict the probability of product returns at a high accuracy so that the results can be used to determine the maximum amount of reasonable costs to prevent the return of the orders. The model presented in this study was based on the data obtained from the eBay store. According to the results, the first hypothesis stating that the product return can be predicted according to the research variables was confirmed. Besides, research findings show that the product specifications influence predicting its return. Therefore, the second hypothesis is confirmed. However, the significance and effectiveness of each of the specifications are different. According to research results, the product specifications in the order from the most important to the least important ones are: price, size, manufacturer, color, product age, and product code. The production date variable which refers to the date the product was created, does not directly affect the prediction and is not considered an influential specification. However, it influences the prediction indirectly and by the derived variable "product age" which refers to the production date until the order is placed for it. Apart from the product specifications, customer specifications also affect the prediction of product returns. Therefore, the third hypothesis is also confirmed. The significance of each customer specification is also different. Customer specifications in terms of significance are: age, age 2, customer type, customer's current city, customer type 2, customer code, and current city 2. The variables age, age 2, customer type 2, and current city 2 are derived from the primary variables. The customer birth date variable was not influential in product returns. However, the variables derived from it including the age and age2 were influential variables and it shows the indirect effect of this factor on product return. Although the variables of order date and product delivery were introduced in hypothesis four, the variable derived from these two primary variables called ttdeliver was influential in prediction. Hence, the fourth hypothesis is confirmed. It is noteworthy that another variable derived from the primary variable of a delivery date was created called deliveredYN, which cannot be seen among the variables affecting the final model. It can be stated that although some of the variables in each hypothesis were not influential variables on the model output, most of them were influential directly or through the variables derived from them. Therefore, all research hypotheses were confirmed. However, the effect of some variables was partially rejected and it was found that the influential variables do not share the same level of significance. Suggestions for further studies are presented in the following:

i. Data mining on data with more and diverse variables and to include more aspects of online shopping and presenting a model more comprehensive than the model presented in this paper.
ii. Designing a recommender system based on the final model achieved from the present study such that the products with the least probability of return are recommended to the customers.
iii. Data mining on data to predict and detect the best seller products in stores that can be very effective in the pre-ordering and inventory processes.
iv. One of the eBay store features is C2C sales among users. Creating a model for second-hand product shopping among the website users can be investigated in further studies.

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v. The use of other machine learning techniques such as ensemble and incremental machine learning techniques.

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