Prediction of Online Customers' Purchasing Intention

Team Name: YZman

Team Member: Xiayi Ye, Chenxing Zhai

Team web page: https://github.com/zcx10025/DM-Project

Abstract

Today, the use of big data technology has penetrated into every area of our daily life, especially in the field of e-commerce. Understanding customer preferences and buying habits, predicting customer buying intentions are useful for business decisions, such as accurate delivery of advertising, network traffic analysis, market trends and etc. So we choose this topic to explore how big data technology works on prediction of online customers' purchasing intention.

After preprocessing, exploratory data analysis and feature selection, we will build two models to predict whether a visit will end with a transaction. A comparison of the two models will also be included.

Introduction:

The rapid development of e-commerce is inseparable from the advancement of big data technology. Analysis of customers' behavior, purchasing intention and their preference are useful for business decision. For example, after you buy a computer at Amazon, next time you enter Amazon, it will automatically recommend some products related to computer to you, such as keyboard, mouse and so on. After we grasp many big data technologies this semester, we have a new understanding of online shopping. So we choose this topic to explore how big data technology predict online shoppers' purchase intention. Through this topic, we can not only understand the analysis method of e-commerce from the perspective of a consumer, but also evaluate which consumers have a strong willingness to purchase from the perspective of a merchant.

Our goal is to build two models to predict whether a visit will be finalized with a transaction with this data set. If our model is precision enough, perhaps it can really be used in reality to predict the customers' purchasing intention. Because this will be a classification problem, so I decide to use confusion matrix to evaluate our model.

Data set and features:

We download the data set from UCI Machine Learning Repository. The link is : https://archive.ics.uci.edu/ml/datasets/Online+Shoppers+Purchasing+Intention+Dataset#

The dataset consists of 10 numerical, 8 categorical attributes and 12,330 rows. Description of them is below:

Name	Description	Type
Administrative	Number of administrative pages visited by the visitor	Numeric
Administrative Duration	Total time spent on administrative pages by the visitor	Numeric
Informational	Number of informational pages visited by the visitor	Numeric
Informational Duration	Total time spent on informational pages by the visitor	Numeric
Product Related	Number of product related pages visited by the visitor	Numeric
Product Related Duration	Total time spent on product related pages by the visitor	Numeric
Bounce Rate	Bounce rate of the pages visited by the visitor	Numeric
Exit Rate	Exit rate of the pages visited by the visitor	Numeric
Page Value	Value of the page visited by the visitor	Numeric

Special Day	Measure how close the day of the visit is to a special day	Numeric
Month	The day of the visit is in which month	Categorical
Operating System	Operating system version of the visitor	Categorical
Browser	Browser type of the visitor	Categorical
Region	Region where the visit is located	Categorical
Traffic Type	Ways for visitors to visit the web page	Categorical
Visitor Type	Whether the visitor is a new visitor, returning visitor or other	Categorical
Weekend	Indicate whether the day of the visit is weekend	Categorical
Revenue	Indicate whether this visit become a transaction finally	Categorical

Tools:

We plan to use R for our project. Packages like “caret”, “ggplot2” and “corrplot” can be used to preprocess the data and do some exploration analysis. We want to build several classification model and make a prediction, so package “e1071”, “randonForest” and “neuralnet” may be included.

Related work (Literature Review):

[1] Yi Jin Lima, Abdullah Osmanb, Shahrul Nizam Salahuddinc, Abdul Rahim Romled, Safizal Abdullahe, 2015. Factors Influencing Online Shopping Behavior: The Mediating Role of Purchase Intention.

Available： https://www.sciencedirect.com/science/article/pii/S2212567116000502#bibl0005

Summary: When customers have a good impression of the product and feel that it is useful, their willingness to buy it will increase significantly. However, customers' doubts about the standardization of products on the website can adversely affect purchase behavior. In addition, if the customer subconsciously feels that the product is useful, then they do not care whether to buy online or offline. In a nutshell, the wishes of customers determine whether they will buy online.

[2] Dai, H., Wang, L., Li, Y., Nie, Z., Wen, J. R., & Zhao, L. (2010). *U.S. Patent No. 7,831,685*. Washington, DC: U.S. Patent and Trademark Office.
Available: https://patents.google.com/patent/US7831685B2/en

Summary: The data extracted from the web browser or search behavior can be used to detect users' browsing or search intent. The article mentions that machine learning can automatically detect and classify online users' business intent based on these data. Therefore, the related advertisement can be matched with the user or potential user who has the purchase intention to increase revenue.

Preprocessing

According to the data set, we need to change the type of the 8 categorical predictors and the output variable into factor first. Then we use the function "preProcess" to preprocess the data. Method is "range", which means we scale the numerical predictor to a 0–1 scale. The formula is: $v' = \left(\frac{v - min_A}{max_A - min_A}\right)$.

Below is the result after we finish the preprocessing:

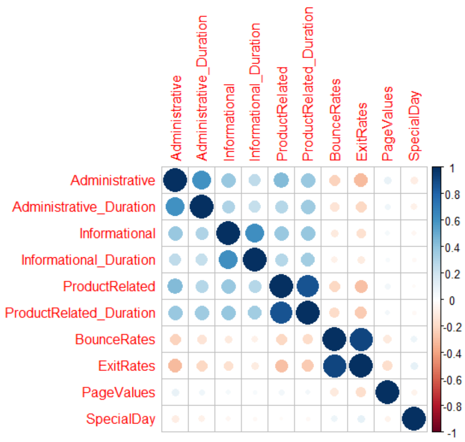
```
> str(df)
'data.frame':   12330 obs. of  18 variables:
 $ Administrative         : num  0 0 0 0 0 ...
 $ Administrative_Duration: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Informational          : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Informational_Duration : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ProductRelated         : num  0.00142 0.00284 0.00142 0.00284 0.01418 ...
 $ ProductRelated_Duration: num  0.00 1.00e-03 0.00 4.17e-05 9.81e-03 ...
 $ BounceRates            : num  1 0 1 0.25 0.1 ...
 $ ExitRates              : num  1 0.5 1 0.7 0.25 ...
 $ PageValues             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ SpecialDay             : num  0 0 0 0 0 0 0.4 0 0.8 0.4 ...
 $ Month                  : Factor w/ 10 levels "Aug","Dec","Feb",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ OperatingSystems       : Factor w/ 8 levels "1","2","3","4",..: 1 2 4 3 3 2 2 1 2 2 ...
 $ Browser                : Factor w/ 13 levels "1","2","3","4",..: 1 2 1 2 3 2 4 2 2 4 ...
 $ Region                 : Factor w/ 9 levels "1","2","3","4",..: 1 1 9 2 1 1 3 1 2 1 ...
 $ TrafficType            : Factor w/ 20 levels "1","2","3","4",..: 1 2 3 4 4 3 3 5 3 2 ...
 $ VisitorType            : Factor w/ 3 levels "New_Visitor",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ Weekend                : Factor w/ 2 levels "FALSE","TRUE": 1 1 1 1 2 1 1 2 1 1 ...
 $ Revenue                : Factor w/ 2 levels "FALSE","TRUE": 1 1 1 1 1 1 1 1 1 1 ...
```

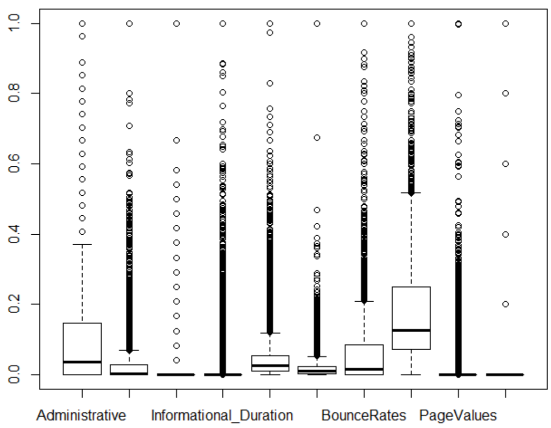
```
> summary(df)
 Administrative     Administrative_Duration Informational      Informational_Duration ProductRelated      ProductRelated_Duration
 Min.   :0.00000   Min.   :0.000000        Min.   :0.00000   Min.   :0.00000        Min.   :0.000000   Min.   :0.000000
 1st Qu.:0.00000   1st Qu.:0.000000        1st Qu.:0.00000   1st Qu.:0.00000        1st Qu.:0.009929   1st Qu.:0.002878
 Median :0.03704   Median :0.002207        Median :0.00000   Median :0.00000        Median :0.025532   Median :0.009362
 Mean   :0.08575   Mean   :0.023779        Mean   :0.02098   Mean   :0.01352        Mean   :0.045009   Mean   :0.018676
 3rd Qu.:0.14815   3rd Qu.:0.027438        3rd Qu.:0.00000   3rd Qu.:0.00000        3rd Qu.:0.053901   3rd Qu.:0.022887
 Max.   :1.00000   Max.   :1.000000        Max.   :1.00000   Max.   :1.00000        Max.   :1.000000   Max.   :1.000000

  BounceRates        ExitRates          PageValues         SpecialDay            Month       OperatingSystems    Browser         Region
 Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   May    :3364   2      :6601     2      :7961   1      :4780
 1st Qu.:0.00000   1st Qu.:0.07143   1st Qu.:0.00000   1st Qu.:0.00000   Nov    :2998   1      :2585     1      :2462   3      :2403
 Median :0.01556   Median :0.12578   Median :0.00000   Median :0.00000   Mar    :1907   3      :2555     4      : 736   4      :1182
 Mean   :0.11096   Mean   :0.21536   Mean   :0.01628   Mean   :0.06143   Dec    :1727   4      : 478     5      : 467   2      :1136
 3rd Qu.:0.08406   3rd Qu.:0.25000   3rd Qu.:0.00000   3rd Qu.:0.00000   Oct    : 549   8      :  79     6      : 174   6      : 805
 Max.   :1.00000   Max.   :1.00000   Max.   :1.00000   Max.   :1.00000   Sep    : 448   6      :  19     10     : 163   7      : 761
                                                                         (Other):1337   (Other):  13     (Other): 367   (Other):1263
  TrafficType               VisitorType     Weekend        Revenue
 2      :3913   New_Visitor      : 1694   FALSE:9462   FALSE:10422
 1      :2451   Other            :   85   TRUE :2868   TRUE : 1908
 3      :2052   Returning_Visitor:10551
 4      :1069
 13     : 738
 10     : 450
 (Other):1657
```

Exploratory Data Analysis

We created correlation coefficient graph and boxplot for the numeric variables. According to the plots below, we can say that the number of pages viewed by the user has a high correlation with the length of time spent on the page. Also we find that there are too many outliers in column “Informational_Duration” and “SpecialDay”.





Models

We plan to build two models. One is based on random forest and the other is based on neural network. We will compare and analyze these three models to get their own advantages and disadvantages. So far, we have successfully established a model based on random forest. According to the confusion matrix, the accuracy is about 90%.

Before we build our first model, we use function "step" to run a feature selection. According to the result, "ProductRelated_Duration + ExitRates + PageValues + Month + TrafficType + VisitorType" is the best feature combination. So we decide to build two models based on different feature combination. One is the combination of all the features and the other is the combination obtained by function "step". We split the data, 60% for training and 40% for testing. Then we run our model in R.

Results and discussion

Below is the confusion matrix of our first model:

All the features are used:

```
          Reference
Prediction FALSE TRUE
     FALSE  4007  328
     TRUE    161  435

               Accuracy : 0.9008
```

Best feature combination obtained by "step":

```
          Reference
Prediction FALSE TRUE
     FALSE  3994  312
     TRUE    174  451

               Accuracy : 0.9014
```

It seems that the best combination obtained by "step" is more accurate.

Conclusions