Segmentation of Online Shoppers through Web Analytics

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**Abstract**

New economic activity has emerged because of the rising popularity of internet purchasing. It's critical to comprehend customer intent if you want to compete in the fiercely competitive world of online shopping. To survive in this fast-paced, fiercely competitive world, it is essential to understand what drives customer intention. People now often search online for the products they need and make purchases through online transactions. It has simplified and improved their quality of life.

Companies now have a strong need to understand the behaviours and goals of customers who are showing interest in online shopping. In this project, we have examined the success of customer transaction through classification algorithms, Decision Tree and KNN classifiers were developed to forecast whether or not a consumer browsing an online store's webpages will make a purchase. Further the results from those methods are compared with respect to the accuracy to find which method is preferred for classification.

**Keywords**

Normalisation, Discretization, Histogram, Box Plot, Decision Trees, KNN Classifier, Decision Trees, Confusion Matrix

**Introduction**

The recent phenomenon of online shopping is in spree across the world. So, it is important for any ecommerce company to sell the right product to the right customers using in-depth web analytics and data mining algorithms. To find the prospects and intended buyers, the most crucial step in marketing is to identify the demand in the market and provide the right product to them based on the insights of customer visit through various websites. Most consumers just browse e-commerce websites to learn more about a product and check its availability. This information may help business to analyze and get an idea regarding which kind of product a consumer will be interested to purchase based on their searches and by proposing those items to each customer’s interest benefiting both the firm and the customers.

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**Objective**

The project’s main goal is to predict the Online shopper Purchase intention. It is crucial to predict consumers' purchasing intentions so that retention strategies, such as promoting items, may be used to turn prospective customers into buyers. However, more importantly for the business it is needed to identify the right customers for higher profitability and increasing sales. ​

The purpose of this project is to take advantage of the web-analytics data accumulated in the form of browser history or views for e-commerce company in each session by the shoppers/users during their online visits. This data is used in the project to identify different customer segments and classify the target users’ intent to buy.

**Literature Review**

The first study [1] relates to the requirement to put up a model that predicts the visitor's purchase intent as soon as the e-commerce website is viewed. The benefit of this is that the danger of website abandonment that comes with each visit is eliminated. Finding the best suitable machine learning technique to do this was the difficult problem. Three classification methods—naive Bayes, C4.5, and random forest—have been researched to address the issue at hand. Each classifier's performance and scalability have been enhanced by oversampling. Based on the findings of comparison and experimentation, the random forest classifier is effective as a balanced classifier that can meet the needs of the challenge.

The Internet and information technologies have significantly changed how businesses operate. Businesses are investing heavily in e-commerce applications, but it is difficult for them to assess the effectiveness of their e-commerce systems. The measuring difficulties of the new e-commerce environment can be met by adapting the DeLone & McLean Information Systems Success Model [2]. The modified model's six dimensions provide a condensed framework for classifying the e-commerce success measures that have been found in the literature. How the model may be used to direct the discovery and specification of e-commerce success measures is illustrated by two case cases.

The intention of customers to purchase online during the information-gathering phase is examined in this article [3]. The study specifically considers three crucial factors that are likely to have an impact on consumer intentions: purchasing channel convenience, product type attributes, and perceived pricing of the item are the first three. The findings show that product type and convenience have an impact on consumers' intentions to purchase online. Customers are more likely to purchase online when they consider physical shopping to be cumbersome. Also, customers' desire to purchase online is stronger when they believe the product is a search good rather than an experience good.

In this study [4], the customer's purchase intention is forecasted using empirical data collected from online consumers to create a more accurate prediction model. To forecast whether a consumer will make a purchase or not, several classification algorithms have been examined, including Decision Tree, Random Forest, Naive Bayes, and SVM. To improve the performance of these algorithms, several ensemble approaches were used. According to the study, Random Forest is the best method for predicting a customer's propensity to buy. Also, this method can predict with the best accuracy, 90.34%, when gradient boosting is used. This work is distinctive in that it applies ensemble approaches to this dataset.

The most common page tagging method used to assess the visibility of online portals is Google Analytics. The study's goal [5] was to apply Google Analytics' approach to the Uva Wellassa University (UWU) library's Web Portals, which comprise its Home Page (HP), Online Public Access Catalogue (OPAC), and Institutional Repository (IR). During the research period, it was discovered that 366756 local and international visitors browsed UWU's online resources. With 53,078 visits (15.82%), the USA is the most popular nation at the UWU e. Repository, followed by the Netherlands with 14,044 (4.78%) and France with 15,775 (4.70%).

Through this study [6] Ryanair's clickthrough rates climbed by 200% and its bounce rate dropped by 18% simultaneously thanks to Web Analytics, which helped to better understand visitor behaviour and utilise the information at hand. Dara Brady, the head of advertising at Ryanair, claimed that by altering the homepage design, they were able to boost traffic to other pages by 16% and quadruple their income through individualised email marketing.

In this study [7], it is shown that using session data from an e-commerce environment, it is possible to develop a machine learning model to forecast purchase conversion. Despite the dataset's high level and aggregated characteristics, it was still able to identify signals that may aid in solving our prediction challenge. A more detailed dataset, such as a user's unique page history during a session, may enhance performance. It could be difficult to implement a real-time machine learning model for this use case. In order to achieve a "early win," it was advised to start with straightforward rule-based triggers on crucial parameters like PageValues and BounceRates before switching to a machine learning model to further increase conversion rate.

This study [8] examined and assessed the possibilities for extracting monthly stationarity from a conditioned time series of bounce rates using a benchmark dataset. When a time series is analysed for the magnitude of changes in analytics and forecasting, controlling for stationarity is a key challenge. The method can be helpful in evaluating marketing initiatives by utilising the proper transformations and a novel technique for computing the stationary distance. By using measurements of variations in the placements of local maxima points throughout the segmentation of the conditioned series, the benchmark test results from the experimental portion of this study demonstrate the extremely clear and logical periodicity of the presented approach.

**Methodology**

Data mining techniques enable businesses to better understand their customers’ needs and behaviors, which can lead to more effective marketing strategies and increased sales. This project involves dataset with both numerical and categorical data. Prior to additional handling, data cleaning, and pre-processing steps are implemented on these records to discard the insignificant information.

In this experimental study to identify the Online shopper purchase intention we need to segment the market to find the Target group beforehand. Classification algorithms can be used to predict whether a customer is likely to make a purchase based on their behavior and characteristics. Popular classification algorithms that can be applied to the Online Shoppers Purchasing Intention Dataset include Decision trees and KNN classifier.

Decision trees and KNN classifier are used to create models that predict whether a customer will make a purchase based on features such as the duration of their visit, the number of pages they viewed, and the type of device they used to access the website. The choice of algorithm depends on the characteristics of the dataset, the size of the dataset, the desired level of accuracy, and the computational resources available. Using both these algorithms we were able to achieve more comprehensive analysis of the data.

**Attributes of the Dataset:**

1. Administrative – *How many times views were there for the Administrator pages of the website by each visitor in one session.****Datatype – Ratio (Integer)***​
2. Administrative\_Duration – *The time duration spent by each visitor while viewing the Admin pages in that session.****Datatype – Ratio (Float)***​
3. Informational- *How many times views were there for the Informational pages of the website by each visitor in one session.****Datatype – Ratio (Integer)***​
4. Informational\_Duration - *The time duration spent by each visitor while viewing the Informational pages in that session.****Datatype – Ratio (Float)***​
5. ProductRelated - *How many times views were there for the Product Related pages of the website by each visitor in one session.****Datatype – Ratio (Integer)***​
6. ProductRelated\_Duration - *The time duration spent by each visitor while viewing the Product Related pages in that session.****Datatype – Ratio (Float)***​
7. BounceRates – Average % of viewers who entered the site by that type of webpage/s and exited the website without triggering any other page. ***Datatype – Ratio (Float)***​
8. ExitRates – Average % of viewers who exited the webpage from that type of webpage/s irrespective of the entry page to the website. ***Datatype – Ratio (Float)***​
9. PageValues – Average value (CAD $) of the type of webpages before a viewer completing a transaction. ***Datatype – Ratio (Float)***​
10. SpecialDay – On a special day like ‘Canada Day’ or ‘Christmas’ the weightage goes higher if the day of visit is nearer to those special days. ***Datatype – Ratio (Float)***​
11. Month – Month of the visit for that session. **Datatype – Nominal (String)**​
12. OperatingSystems – From which OS the viewer has visited the webpage/s (i.e., Windows 10, Windows 11, Android, Mac etc.). ***Datatype – Categorical (Integer)***​
13. Browser – *Which Browser the visitor has used.****Datatype – Categorical (Integer)***​
14. Region – *The region/province in Canada from where the visitor has accessed the website.****Datatype – Categorical (Integer)***​
15. TrafficType – *Higher the traffic of the website at the time of the session, larger the number.****Datatype – Categorical (Integer)***​
16. VisitorType – *Returning visitor, New visitor or Others (visitors like internal employees or undefined visitors).****Datatype – Categorical (Integer)***​
17. Weekend – *Whether the visitors visited the site over weekend or weekday.****Datatype - Categorical (Boolean)***​
18. Revenue **(Class)**– *Whether the session ended up with final transaction which would be considered as revenue.****Datatype – Categorical (Boolean)***​

**Data Cleansing and Manipulation**

The data from UCI repository is having 18 attributes including one class variable of “Revenue”. It is assigned under ‘my\_data’ in R. As a part of data cleansing and manipulation, after looking at the structure of ‘my\_data’ it was realized that each attribute is having different data-types including integer, number, character etc. To keep them uniformed first we converted the character type attributes like ‘Month’ or ‘VisitorType’ into factors such as 1 to 12 and 1 to 3 respectively.

Furthermore, the ‘VIsitorType’ 3 or Others in actual dataset were not defined as internal visits by employees or some other internal customers in in our case and those data were present for 85 rows. However, as they would not have given any insights and even might be misleading in terms of creating an outlier, we have omitted those 85 rows from our data.

We have also uniformed our data by changing the data type as factors from integers for other categorical values like Browser, OperatingSystems, Region, TrafficType – for better results in classifications methods which would be used later.

**Normalization**

Once our data is cleaned and ready for further usage, the normality is checked for those attributes which were integer or numeric data-types. As most of the columns had mean and mode quite far from each other and from ‘quantile’ the data were highly skewed, they needed to get normalised. We needed to normalize all the attributes which were numeric or integer for the improvement of results. Here, we name our data as ‘my\_data\_norm’.

There were total 10 numeric attributes starting from Administration to SpecialDay which were normalized based on Min-Max Normalisation method. Later the normalization range checked by ‘lapply’ to ensure the data for each attribute is ranging from 0 to 1.

**Scatter Plot -Visualisation**

* **Scatter Plot & Correlation:** Further to our data mining method we considered three attributes to check how they are related to the fourth attribute of ‘PageValues’. Those three attributes which were considered to check were ‘BounceRates’, ‘ExitRates’ and ‘SpecialDay’. As the attribute ‘PageValues’ refers to the value of a webpage depending upon whether that page led consumers for any transaction thereafter, we thought of validating the data through scatterplot and Lowess line with relationship with earlier said three attributes. Pearson correlation coefficient was also measured for all of them. We found the following graphs along with the correlation coefficient results –

Chart, scatter chart

Description automatically generated  
Figure 1: Pagevalues vs BounceRates

Chart

Description automatically generated

Figure 2: Pagevalues vs ExitRates

Chart, histogram

Description automatically generated

Figure 3: Pagevalues vs SpecialDay

* **Pearson Correlation Coefficient**

BounceRates~PageValues = -0.1205702, ExitRates~PageValues = -0.1756431, SpecialDay~PageValues = -0.06405728

* **Insights**

So, from these graphs and correlation coefficient we validate that PageValues are going to be less if there are high BounceRates or ExitRates and that is expected as well although the correlation is not strong, but it shows the negativity.

However, which surprises us the most is that the PageValues relationship is also negatively correlated with SpecialDay. This means the transactions of different webpages are more when the day of visiting the website is not nearer to any special day like ‘Valentine’s Day’ or ‘Good Friday’ etc. Although the coefficient is very less but it is worth to re-check with some other sample data, but it raises a question about the product demands through this ecommerce site during special days (probably due to lack of promotion).

**Discretization**

After doing the normalization of numeric data we found that the page duration attributes, i.e., ‘Administrative\_Duration’, ‘ProductRelated\_Duration’ and ‘Informational\_Duration’ these three attributes would add more value and insights if we consider them as discrete variables of ‘Low’, ‘Medium’, ‘High’ and ‘Very High’ values rather than continuous values while doing Decision Trees or KNN classification method.

Therefore, in the next step we have discretized them further based on ‘Intervals’ by Equal-width (distance) partitioning method. And we named our data thereafter as ‘my\_data\_discretized’. Going forward all our classification methods would be done on this data. The structure of the data is mentioned here:

Text

Description automatically generated with low confidence

Figure 4: Structure of the Dataset

**Decision Trees**

Decision Trees are effective supervised machine learning algorithms that can handle both classification and regression tasks. The tests on each characteristic are represented at the nodes, the results of this operation are represented at the branches, and the class labels are represented at the leaf nodes. It is characterised by nodes and branches. To compute the likely results of various options, it employs a tree-like model. Due to their simplicity in understanding and use, these tree-based algorithms are popular. In addition, this algorithm's predictive models are seen to have decent accuracy and strong stability, which makes them strong algorithms that can successfully fit large datasets.

There are different types of Decision Trees, in this project we have chosen Conditional Inference Trees. The package used for Conditional Inference Trees is **“party”** and the syntax is **ctree(formula, data)**. This type of decision tree is renowned for its adaptability and solid foundations since it recursively separates the response variables using a conditional inference framework.

**KNN Classifier**

One approach for supervised non-linear classification is KNN, also known as K Nearest Neighbor. KNN is a non-parametric method, meaning it makes no assumptions about the distribution or underlying data. It is one of the most straightforward and extensively used algorithms that depends on its k value (neighbours). A new data point is categorised into the target class using the K Nearest Neighbour supervised learning technique based on the attributes of its surrounding data points.

The KNN algorithm's algorithm is as follows:

* K defines the number of neighbours.
* Choose the neighbour with the K-number.
* Take the K Nearest Neighbor of the farthest unknown data point.
* Count the number of data points in each category among the K-neighbors.
* The category with the most neighbours should get the new data point.

**Attribute Selection**

One of the core components of the decision tree algorithm is the attribute selection approach. It is a measuring tool that decides which variable will split data into subsets higher up the tree. The decision to use strategic splits has a significant impact on the tree's correctness. The tree uses a variety of techniques to divide a node into sub-nodes, which improves the node's overall clarity with regard to the target variable. In this project the attribute which is considered is **“Revenue”.**

**Experiment setup**

**Dataset**

The data set used for this project is obtained from UCI repository and the name of the data set is **“Online shoppers purchasing intention dataset”**, the data set comprises the visit pattern of the visitors of the webpage for the ecommerce company. It includes 12330 sessions for the visitors, 17 attributes of their visit pattern and 1 class/target variable which is **‘Revenue’**.

|  |  |  |  |
| --- | --- | --- | --- |
| **Data Set** | **Instances** | **Attributes** | **Classes** |
| Online shoppers purchasing intention dataset | 12330 | 18 | 1 |

Table 1: Details of Dataset

The data set has been split as train and test datasets. The splitting was done in the ratio as listed below.

1. 70:30
2. 80:20

The library used for data Split for Decision Tree in this Project is **“caTools”**. The method **split()** from the package **"caTools"** is used to divide the data into Train and Test.

|  |  |  |
| --- | --- | --- |
| **Split Ratio** | **Instances in Train dataset** | **Instances in Test dataset** |
| 70:30 | 8571 | 3674 |
| 80:20 | 9796 | 2449 |

Table 2: Details of number of examples in each training/test set

**(Evaluation Metrics)**

The evaluation metrics for both classifiers considered and measured for this project are accuracy, sensitivity, and specificity. These results were based on the Confusion Matrix

Sensitivity: It is a measure of a prediction model's capacity to choose examples of a specific class from a data set.

Specificity: It measures the accuracy of a class's predictions, including both true positive and false positive results for the class under consideration.

Accuracy: It is the percentage of the total number of correctly predicted events that occurred.

**Results**

**Decision Tree**

**Visualization of Decision Tree**

**Chart

Description automatically generated**

Figure 5: Decision Tree generated with the date with Split Ratio 70/30

**Chart, scatter chart

Description automatically generated**

Figure 6: Decision Tree generated with the date with Split Ratio 80/20

**Evaluation Metrics from Decision Tree Classifier**

**Reference Reference**

**Prediction 1 2 1 2**

**1 323 120 208 83**

**2 245 2986 170 1988**

|  |  |  |
| --- | --- | --- |
|  | 70 – 30 Split | 80 – 20 Split |
| Accuracy | 0.9007 | 0.8967 |
| 95% CI | (0.8905, 0.9101) | (0.884, 0.9085) |
| No Information Rate | 0.8454 | 0.8457 |
| P-Value [Acc > NIR] | < 2.2e-16 | 1.184e-13 |
| Kappa | 0.5824 | 0.5632 |
| Mcnemar's Test P-Value | 8.558e-11 | 6.417e-08 |
| Sensitivity | 0.56866 | 0.55026 |
| Specificity | 0.96137 | 0.95992 |
| Pos Pred Value | 0.72912 | 0.71478 |
| Neg Pred Value | 0.92417 | 0.92122 |
| Prevalence | 0.1546 | 0.15435 |
| Detection Rate | 0.08792 | 0.08493 |
| Detection Prevalence | 0.12058 | 0.11882 |
| Balanced Accuracy | 0.76501 | 0.75509 |
| Positive' Class | 1 | 1 |

Table 3: Evaluation Metrics of DecisionTree

**Visualization of KNN Classifier**

**Evaluation Metrics from KNN Classifier**

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