Online Shoppers Purchasing Intention

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Introduction

As internet penetration and accessibility increase, the number of digital buyers keeps climbing every year, creating tremendous opportunities for developing more useful analytics to drive business decisions. This project explores *Online Shoppers Purchasing Intention Dataset* which contains e-commerce user information. It consists of 12330 rows where each row represents a session that belongs to a different user in a 1-year period to avoid any tendency to a specific campaign, special day, user profile, or period. The dataset consists of 10 numeric variables and 8 categorical variables.

The numeric variables are:

- `Administrative` : Number of pages visited by the visitor about account management
- `Administrative Duration` : Total amount of time (in seconds) spent by the visitor on account management related pages
- `Informational` : Number of pages visited by the visitor about Web site, communication and address information of the shopping site
- `Informational Duration` : Total amount of time (in seconds) spent by the visitor on informational pages
- `Product Related` : Number of pages visited by visitor about product related pages
- `Product-Related Duration` : Total amount of time (in seconds) spent by the visitor on product related pages
- `Bounce Rate` : Average bounce rate value of the pages visited by the visitor
- `Exit Rate` : Average exit rate value of the pages visited by the visitor
- `Page Value` : Average page value of the pages visited by the visitor
- `Special Day` : Closeness of the site visiting time to a special day

The categorical variables are:

- `Operating system` : Operating system of the visitor
- `Browser` : Browser of the visitor
- `Region` : Geographic region from which the session has been started by the visitor
- `Traffic type` : Traffic source by which the visitor has arrived at the Web site (e.g., banner, SMS, direct)
- `Visitor type` : Whether the visitor is a New Visitor, a Returning Visitor or Other
- `Weekend` : Whether the date of the visit is weekend
- `Month` : Month of the visit
- `Revenue` : Whether the visit has been finalized with a transaction

For data preparation, except for turning binary variables into factors and removing rows that contain NAs, we made no change to the raw data when building models and making analyses.

Research Questions

Given the data, we aim at addressing features of online shoppers that could potentially have an impact on the purchasing results. We will examine 3 research questions:

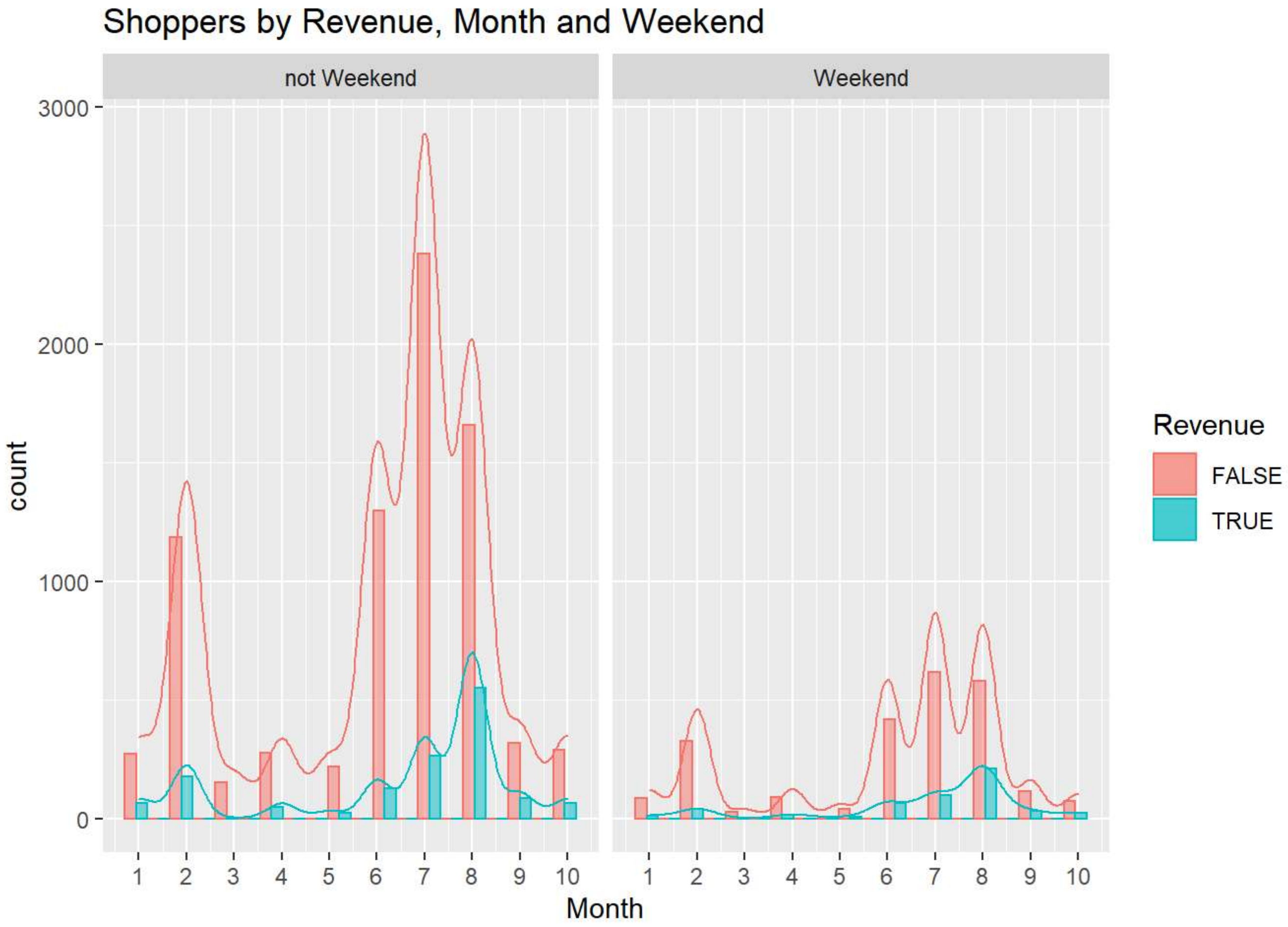
1. What is the relationship between features related to timing (`Weekend` , `Month` , and `special Day`) and revenue generation?
2. Is there an impact of visitor type(new, returning, other) on whether revenue will be generated?
3. How do some web metric(`BounceRates` , `Administrative_Duration` , `PageValues` , and `productRelated`) influence revenue generation?

Research Question 1

To start with, we would like to look at the overall relationship between time features and revenue. More specifically, we would investigate how `Weekend` , `Month` and `Special Day` can impact `Revenue` making.

We begin by showing a bar chart with density curves on counts to see how `Revenue` is impacted by `Weekend` and `Month` .

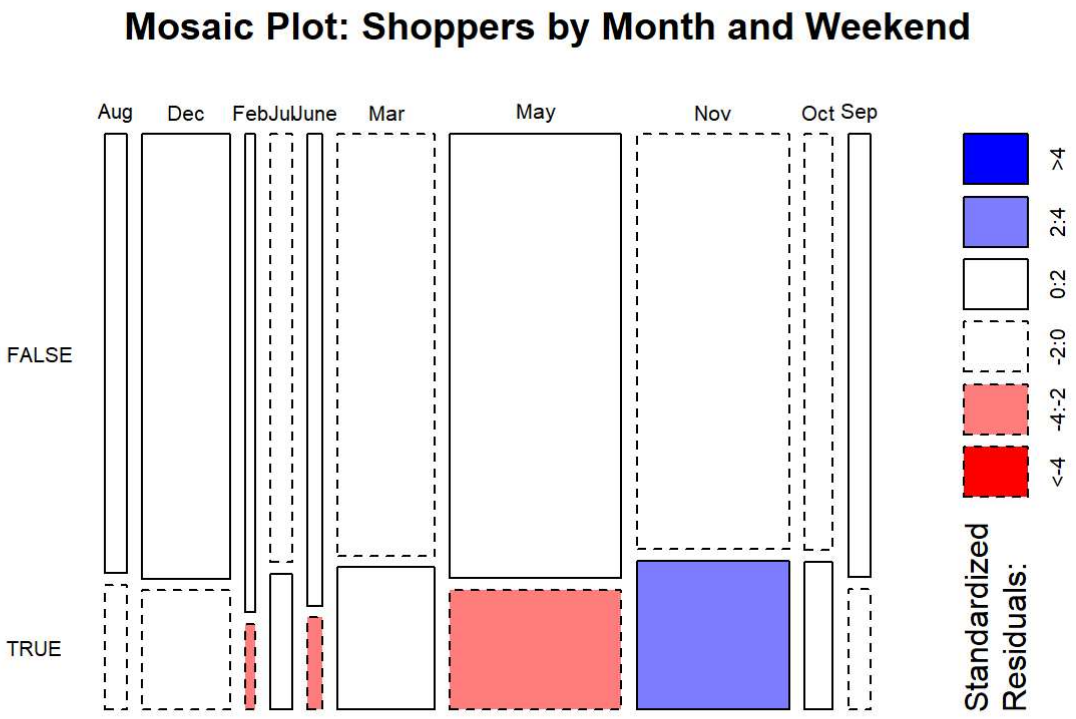
Relationship between Revenue, Month and Weekend



From the graph above, we can first visualize the distribution of month by looking at height of bars on both facets. On March, May, November and December, we see the more online shopper visits, and there is no record for Jan and very few for April. Then, looking at height for different colored bars, we see that there are always more shopper visits without revenue than revenue. Also, we see that for both facet, meaning no matter it's weekend or not, there are more shopper visits with revenue made on non-weekends than weekends.

Independence between Month and Weekend

Also, we are interested in seeing the amount of visits regardless of revenue, but purely on Month and Weekend. We use a mosaic plot to visualize the relationship between online visits of `Month` and `Weekend` .

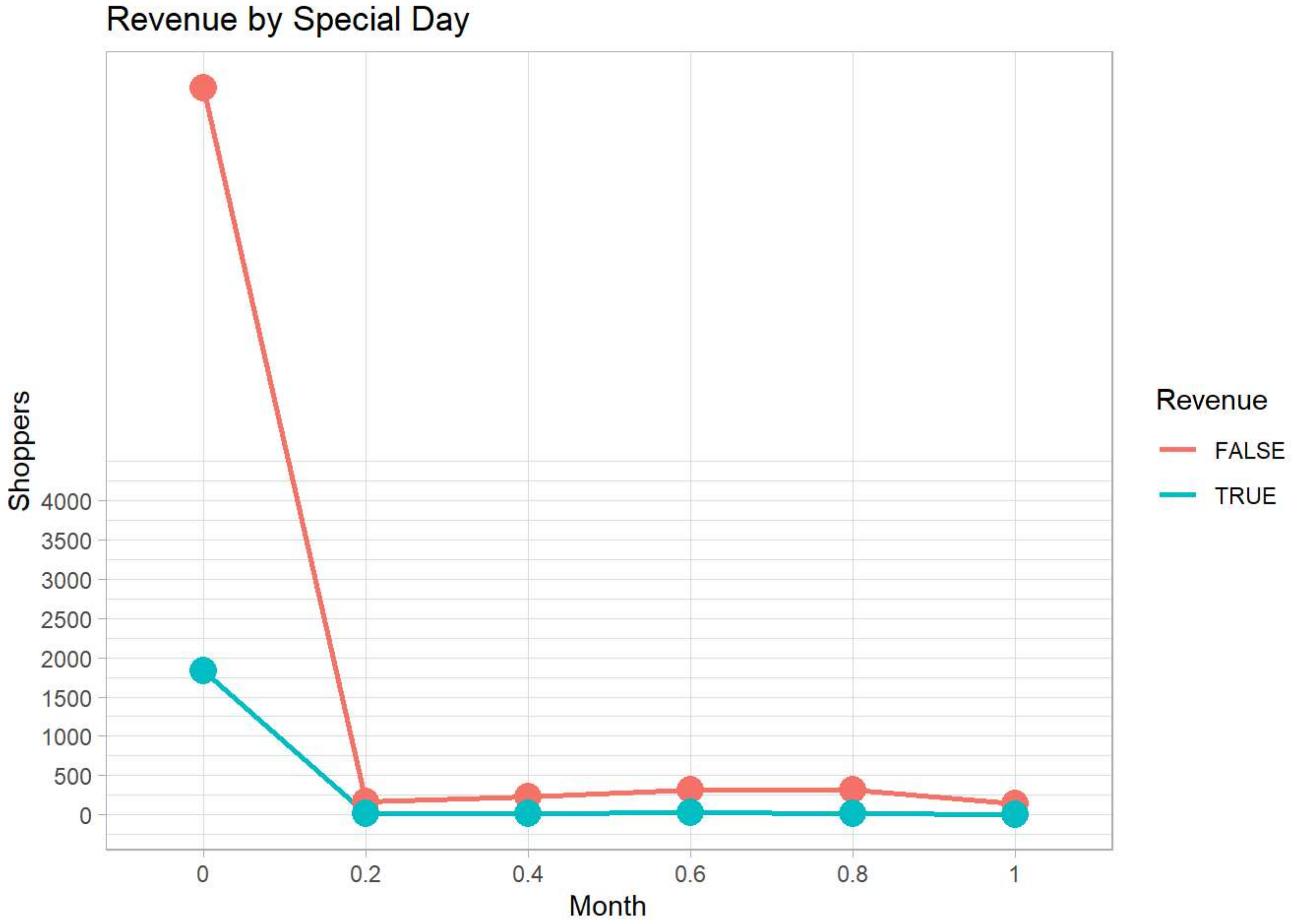


In the mosaic plot above, the width of the rectangles is proportional to a marginal distribution, and the height is proportional to a conditional distribution. Thus, from the above plots, we can easily assess the marginal distribution of `Month` by looking at widths, and conditional distribution given `Weekend` by looking at heights.

Now we analyze the mosaic plot, it appears that there are significantly more online shoppers on `November` 's `Weekend` than we would expect under the null hypothesis of independence, and significantly less online shoppers on `Feburuary` , `June` , `May` 's `Weekend` than we would expect under the null hypothesis of independence. Thereby suggesting that we should reject the null hypothesis, i.e., we would conclude that `Month` and `Weekend` are not independent for online shoppers data.

Revenue by Special Day

Meanwhile, we would also like to see whether there is a relationship between `Revenue` and `Special Day`. Thus, we used a line plot to visualize the Conditional distribution of `Special Day` given `Revenue`.

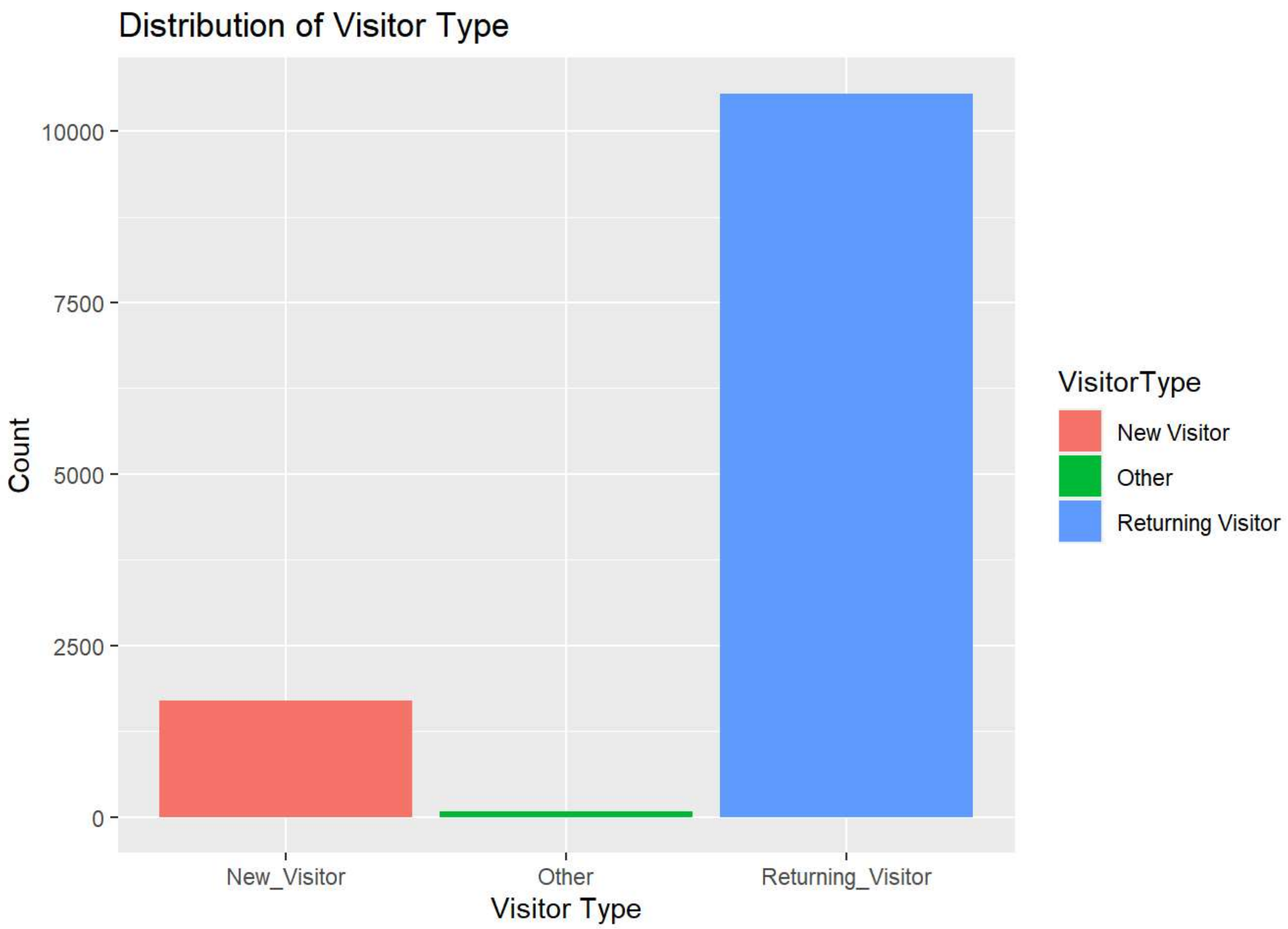


From the above graph, we can see that most online shoppers visit the website on Non-special day occasions. And there is a slight increase in visits around special day index = from 0.2 to 0.6, which corresponds to from 4 days to 2 days prior to a special day. This phenomenon might be caused by needs for special day gifts and there is a decrease from special day index = from 0.6 to 1, which might be caused by shipping and handling time for the product.

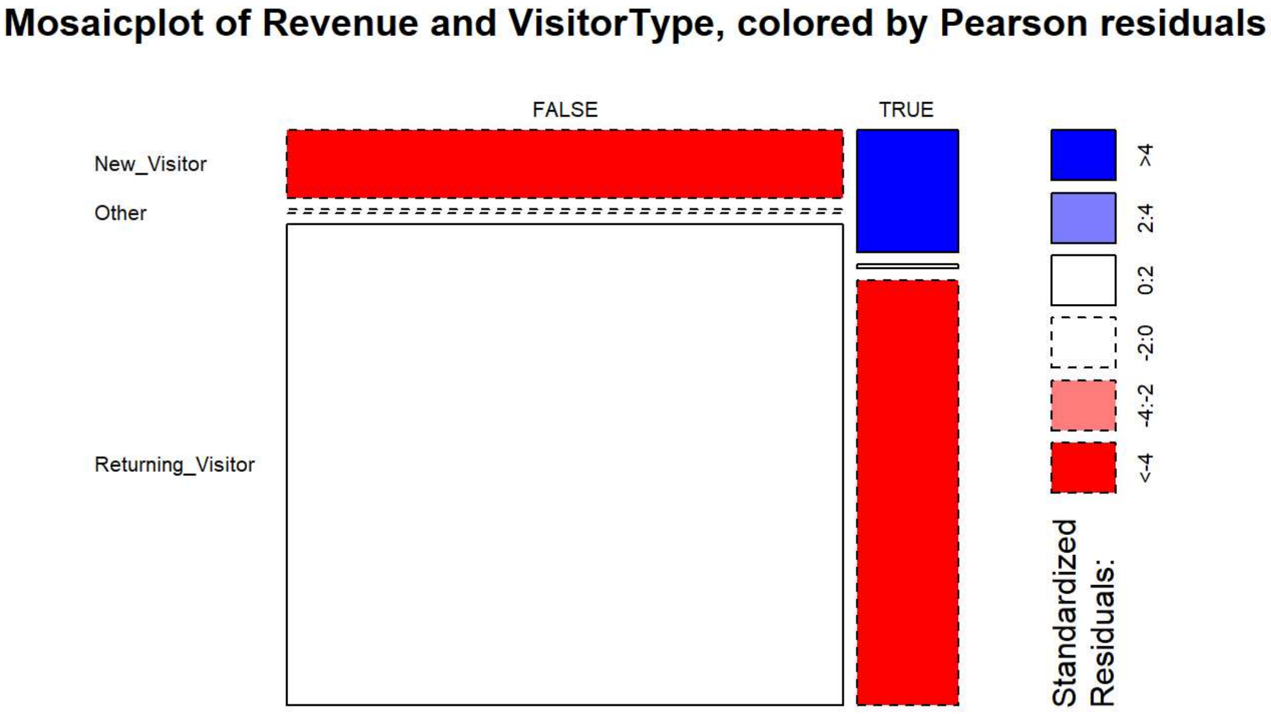
Research Question 2

We would like to better understand whether the type of shoppers could have an impact on revenue generation. By doing so, businesses would be able to identify and target potential buyers more accurately using different approaches such as pop-up advertisements. Specifically, we looked at the variables `Revenue` and `VisitorType`.

First, we constructed a bar chart of `VisitorType` to assess the marginal distribution of `VisitorType` and have a better understanding of our variable in interest. From the graph, we can see that returning visitors have the highest count, followed by new visitors, and visitors from Other category have the lowest count.



Then, we moved on to investigate the relationship between `Revenue` and `VisitorType` . Here we use a mosaic plot to assess the independence of the variables. From the mosaic plot, we see the cell of new visitors who have made a purchase is colored blue, which means this cell has observed counts that are significantly higher than what we would expect under independence. Besides, we noticed that the cell of new visitors who did not make a purchase and the cell of returning visitors who have made a purchase are colored red, which means this cell has observed counts that are significantly lower than what we would expect under independence. Thus, we say that `VisitorType` and `Revenue` are dependent on each other and new visitors are more likely to move forward with a transaction.



Although it seemed that visitor type and revenue are not independent, we couldn't make any statistical conclusions just based on observing the above graph. We need to conduct additional statistical tests to have enough evidence. Since we are dealing with two categorical variables, we would use the chi-square test to test whether `Revenue` and `VisitorType` are truly dependent. Since the p-value is less than 0.05, we conclude that `VisitorType` and `Revenue` are not independent which further validates our previous interpretation of the mosaic plot.

```
## 
##  Pearson's Chi-squared test
## 
## data:  table(online$Revenue, online$VisitorType)
## X-squared = 135.25, df = 2, p-value < 2.2e-16
```

In conclusion, we say that there is an impact of Visitor type on whether there will be revenue generated or not. We also found that the new visitors are more likely to make a purchase than the other two types of visitors. Businesses should try to utilize different approaches to target each type of visitor in order to generate more revenue.

Research Question 3

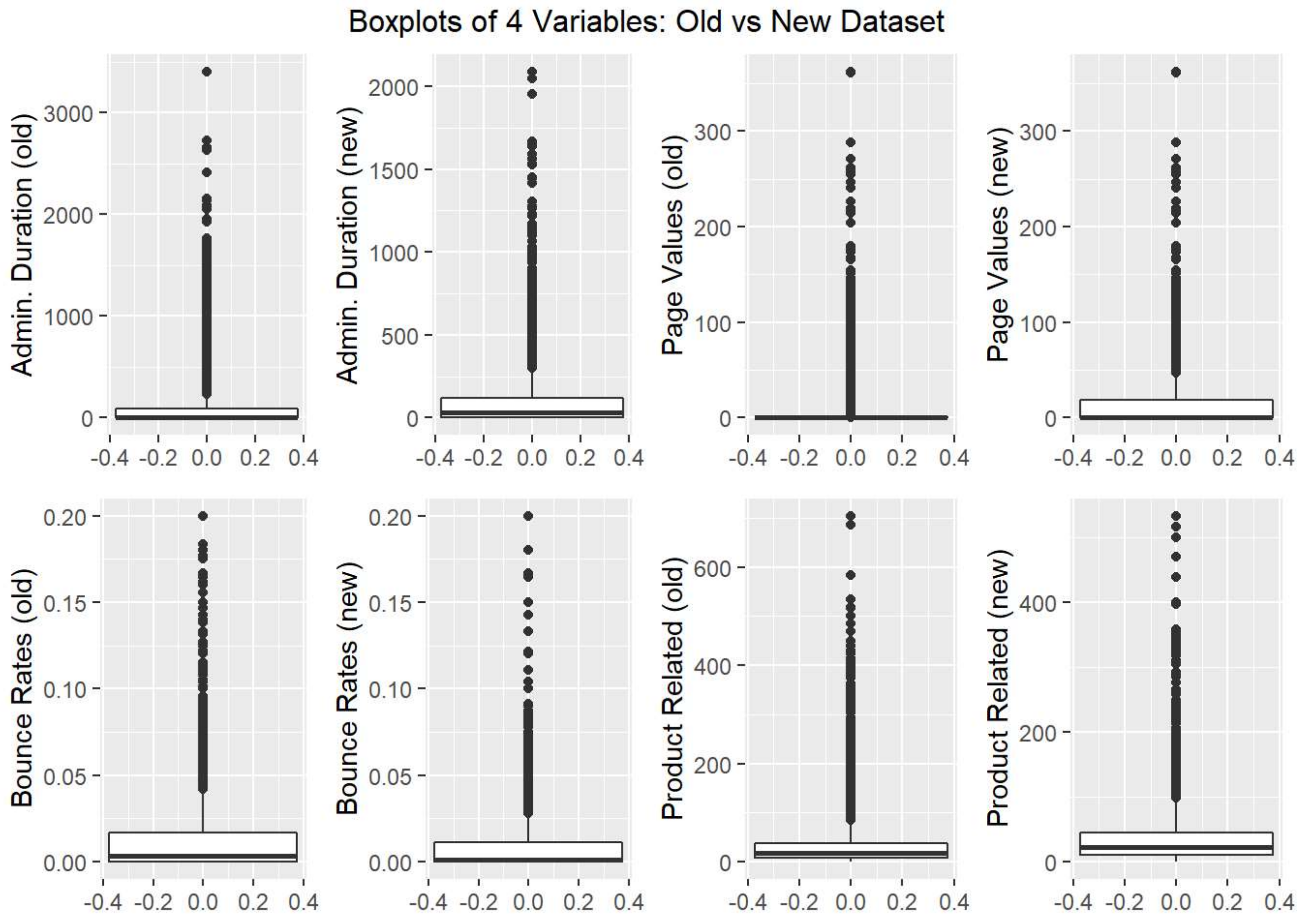
In this section, we are interested how other web metrics of individual visitors affect revenue generation. To be more concise, we will investigate in the relationship of some quantitative variables, such as `Administrative_Duration` , `PageValues` , `BounceRates` , and `ProductRelated` , with `Revenue.` When we look at the dataset, there are 10422 observations with no revenue and 1908 observations with revenue. To deal with such an unbalanced dataset, we adopted a wide-accepted technique called resampling. It consists of removing samples from the majority class.

```
## # A tibble: 2 × 2
##   Revenue     n
##   <fct>   <int>
## 1 FALSE   10422
## 2 TRUE     1908
```

Data Resampling

To begin with the analysis, we will do resampling to better visualize whether the four variables are distributed differently depending on revenue generation. Notice that in the current dataset there are far more data without revenue generated than with revenue. With this end, we randomly undersample the original data without revenue so that the size of data with and without revenue are roughly equal.

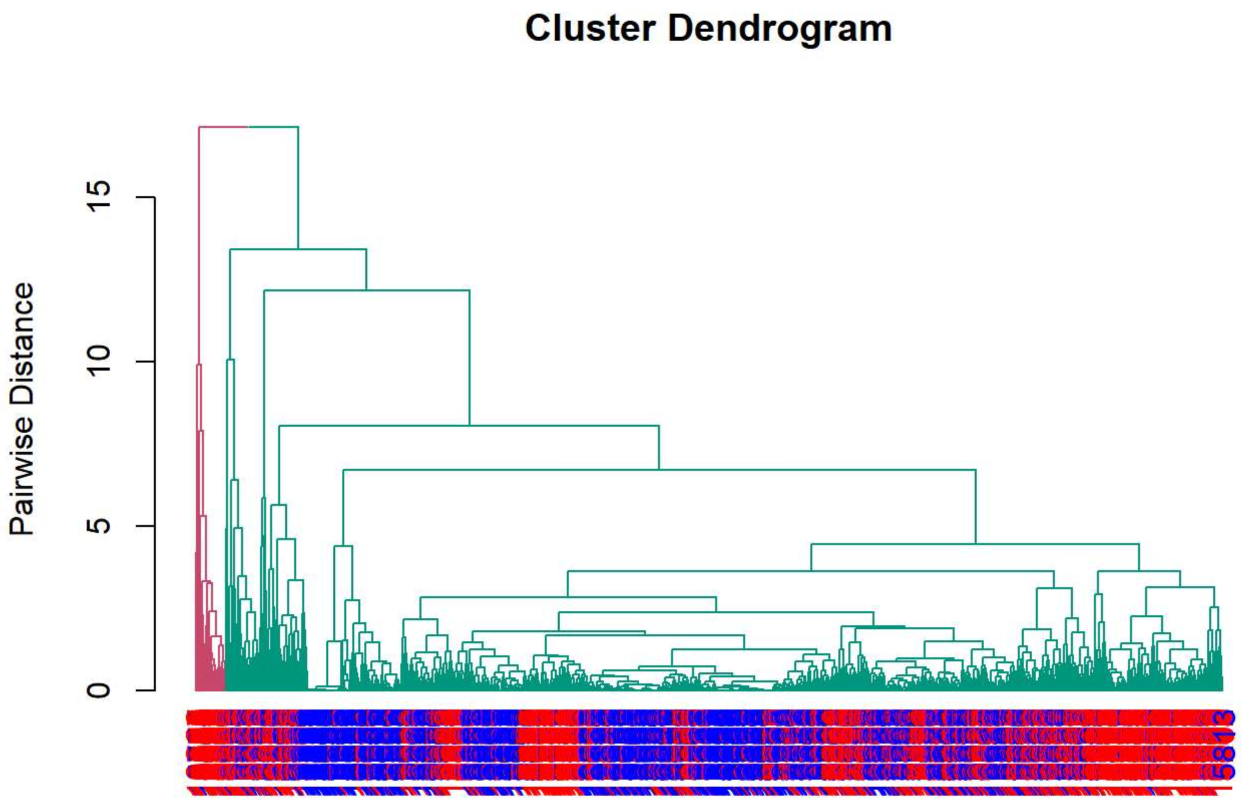
Next, we want to make sure that undersampling the majority class doesn't lead to underfitting, i.e. the new sample fails to capture the general pattern in the data. We create side-by-side boxplots for all the four quantitative variables to compare their distributions between the original and the new dataset.



From the graph above, we can see that the distributions of `Administrative_Duration` , `BounceRates` , and `ProductRelated` are roughly equal between the two datasets. In terms of `PageValues` , we observe that although the distributions between two datasets are different, this can be explained by the extreme right-skewness in the original dataset.

Clusters and Distances

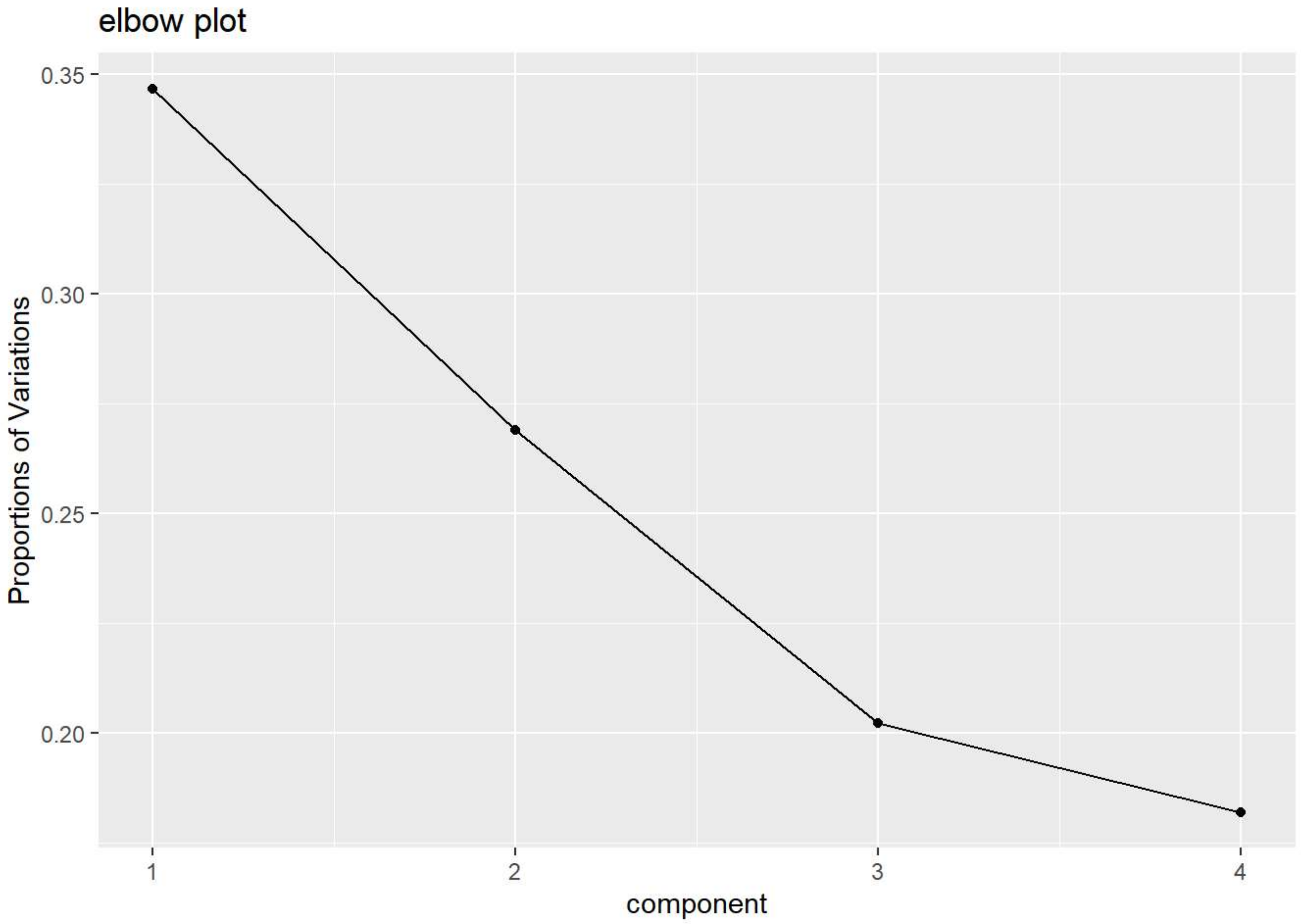
We will then investigate how the overall distances in the four variables among the data differ depending on how whether revenue is generated for a certain visit. To do this, we create a dendrogram using complete-linkage as clustering method, with the leaves colored by revenue generated. In this case, the `red` leaves represented the data with revenue, while `blue` leaves represent the data without revenue.



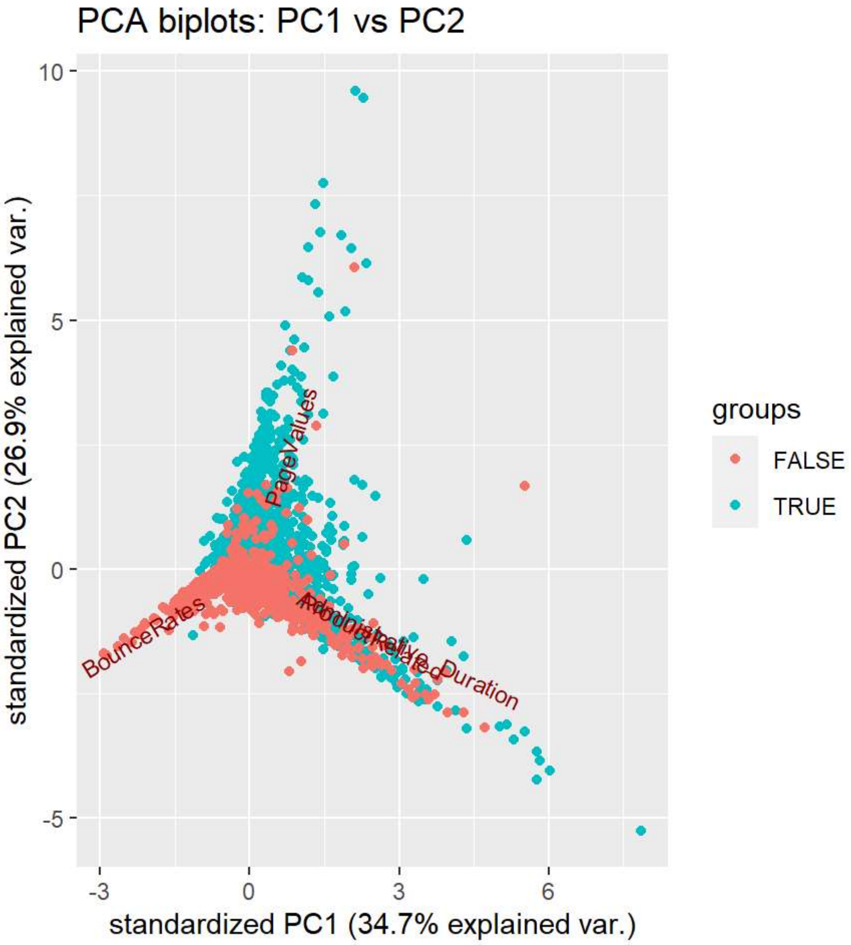
From the dendrogram above, we observe that the left cluster tend to have visits with revenue generated. This indicate that some visits within 17 dendrogram distance generating revenues tend to have similar web metrics in terms of `Administrative_Duration` , `Pagevalues` , `BounceRates` , and `ProductRelated`. From the right cluster, we cannot draw any clear conclusion as because of the strong noises.

Dimension Reduction

Given that we are analyzing a 4-dimensional dataset, we will do principal component analysis to reduce the data into lower dimensions. To know how many components explain the majority of the total variations, we create an elbow plot as below.



As the elbow plot suggests, the first two principal components explain over 60% of the total variations. Thus, for the next part, we will investigate how the four variables are associated with the first two principal components. To visualize the relationship, we create the following biplot with data points colored by whether there is revenue generated:



From the biplot above, we observe that although there isn't a clear relationship between the first principal component and `Revenue` , higher values of the second principal component are associated with higher likelihood of revenue. Also, we find that `BounceRates` tend to be negatively associated with the first two principal components, while `PageValues` is positively associated withe the first two principal components. In terms of `ProductRelated` and `Administrative_Duration` , they are positively associated with the first principal component, but are both negatively associated with the second principal component. To infer from this, web visits with revenue generated may have lower `BounceRates` and higher `PageValues.` The relationship between `Revenue` and `Administrative_Duration` and `ProductRelated` tend to be unclear from the two dimensions.

In conclusion, from clustering based on distances, we find that web metrics for visits with revenue generated tend to be similar in terms of `Administrative_Duration` , `ProductRelated` , `PageValues` , and `BounceRates` , while such similarity seems unclear for web visits without revenue. Moreover, by dimension-reduction for the four variables, we find that `Revenue` tends to be positively associated with the second principal component. Also, we observe that `BounceRates` and `PageValues` are positively and negatively associated with `Revenue` , respectively.

Conclusion

In this project, we have shown that, first, time variables have some impact on visits and revenue making. People tend to make online visits on some months' weekends more frequently than others, indicated by dependency between Weekend and Month variables. We also found that more visits and revenue are made on weekdays than on weekends. And people do not seem to make more visits and purchases near special days. Furthermore, we discovered that the types of visitors and purchasing behavior depend on each other. More specifically, new visitors are more likely to make a purchase than returning visitors. Finally, we find that web metrics for visits with revenue generated tend to be similar in terms of Administrative_Duration, ProductRelated, PageValues, and BounceRates. At the same time, such similarity seems unclear for web visits without revenue.

Besides our three research questions, there were additional questions that this project has not answered. First, future research should take a look at the geographical feature `Region` since the shopping styles could vary in different areas. Another topic of interest would be `Traffic Type` to see the source by which the visitor has arrived at the Web site. It can be beneficial for the business to choose the best way of advertising. Last but not least, classification models using machine learning techniques such as K nearest neighbors, Logistic regression, Support Vector Machine, and decision trees can be used to identify purchasing and non-purchasing customers more accurately. The capability of segmenting people into ‘likely to purchase’ and ‘unlikely to purchase’ groups would facilitate optimization in all aspects of the business from product recommendation, and sales promotion strategies to operations management.