ILLINOIS INSTITUTE OF TECHNOLOGY

# Finding the pattern behind the online shoppers purchasing intention


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**Professor - Jawahar Panchal**

**CSP571 Data Preparation and Analysis**

# Outline

# Problem Statement

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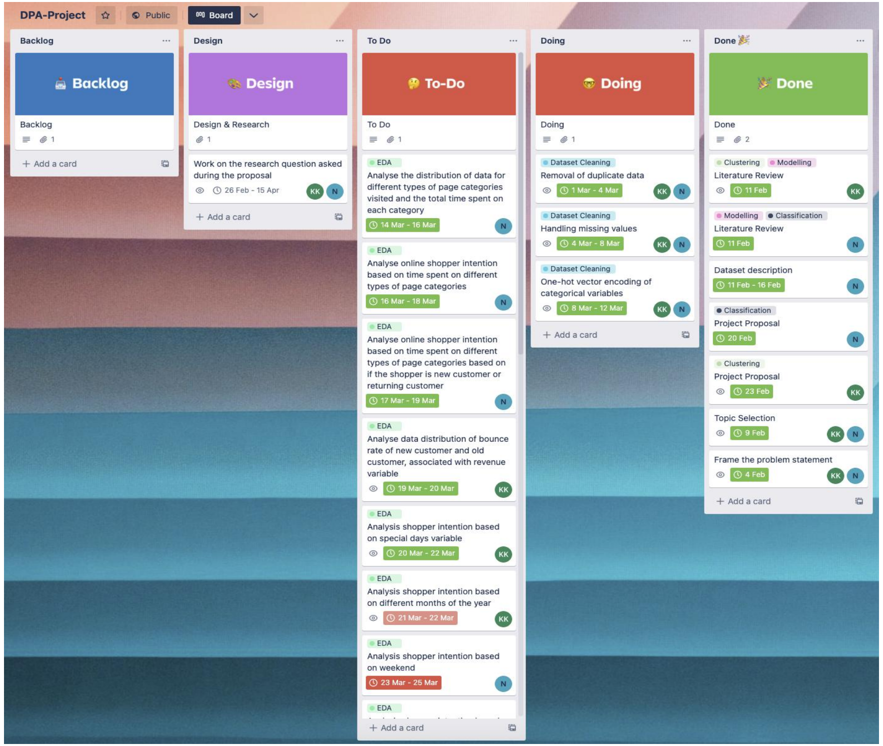
- Analyze trends in the online shoppers purchasing intention dataset using exploratory data analysis techniques, and build machine learning models to predict the purchasing intentions of visitors to a store's website both using supervised and un-supervised techniques.

# Project Planning

# Team Structure

- Naveen Raju Sreerama Raju Govinda Raju - Team Leader
- Karthik Kumar Kaiplody

# Project Planing and execution




- Used [trello](#) for the planning and keeping track of the project.
- GMM was not implemented and put to the backlog, which will be including in the future work.
- Project Repository: [DPA-Project](#)
- [Recording of the presentation](#)

# Workflow overview

## Data Collection

- Online Shopper Purchase Intenstion Dataset from UCI

## Data Preparation & Analysis

- Data cleaning.
- Data Balancing.
- Univariate, Bivariate and Multivariate analysis.

## Modelling

- Supervised Modeling
  - Naive Bayes
  - K-NN
  - Random Forest
  - SVM
  - XGBoost
- Un-supervised
  - K-means Clustering
  - DBScan Clustering
  - Hierarchical clustering

## Results & Conclusion

- Analysed conclusion.
- Model reports and evaluation.
- Future work.

# Data Sources

- The data that is being used in this project was obtained from the UC Irvine Machine Learning Repository.

- Data set contributers:

  1. C. Okan Sakar
  Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Bahcesehir University, 34349 Besiktas, Istanbul, Turkey

  2. Yomi Kastro
  Inveon Information Technologies Consultancy and Trade, 34335 Istanbul, Turke

# Data description

- The dataset consists of feature vectors belonging to 12,330 sessions.
- The dataset consists of both numerical and categorical attributes.The 'Revenue' attribute can be used as the class label.

| Attributes | |
|---|---|
| Administrative | Administrative Duration |
| Informational | Informational Duration |
| Product Related | Product Related Duration |
| Bounce rate | Exit rate |
| Page value | Special day |
| Operating system | Browser |
| Region | Traffic type |
| Visitor type | Weekend |
| Month of the year | Revenue |

# Data Preprocessing

# Data processing

- Check number of observations with NA values
- Fixing naming convention of month names in Month column

  “June” ->”Jun”
- Convert Month feature data type to factor data type
- Transforming categorical attributes(OperatingSystems, Browser, Region, TrafficType, VisitorType) into “factor” data type and then perform one-hot encoding
- Convert Revenue attribute data type to a factor.
- Transforming Boolean attributes(Weekend, Revenue ) into “int” data type
- Train - Test split : 70:30 split
- One hot encoding of train and test set

**Data balancing:**

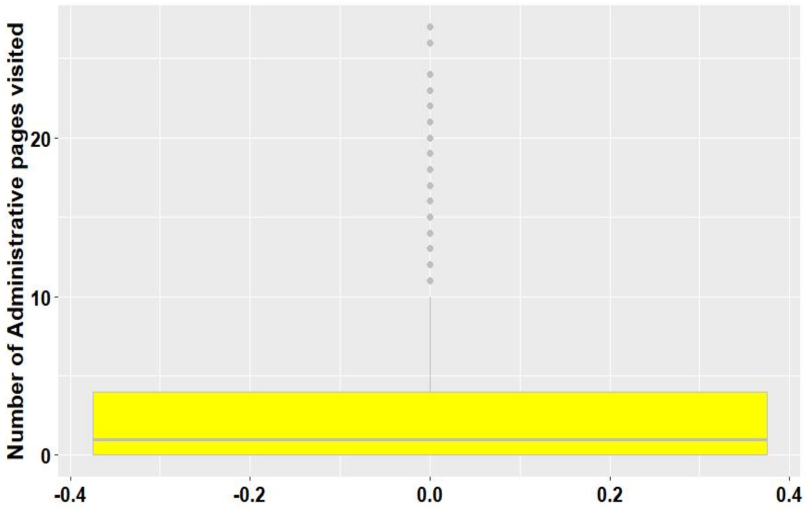
- There is huge imbalance in data set as Revenue=0 is the majority. Hence the algorithm tries to over fit on majority class.
- Number of observations with Revenue as False = 10422
- Number of observations with Revenue as True = 1908
- Here we are trying to increase minority class observations using SMOTE(Synthetic Minority Over-sampling Technique) algorithm.

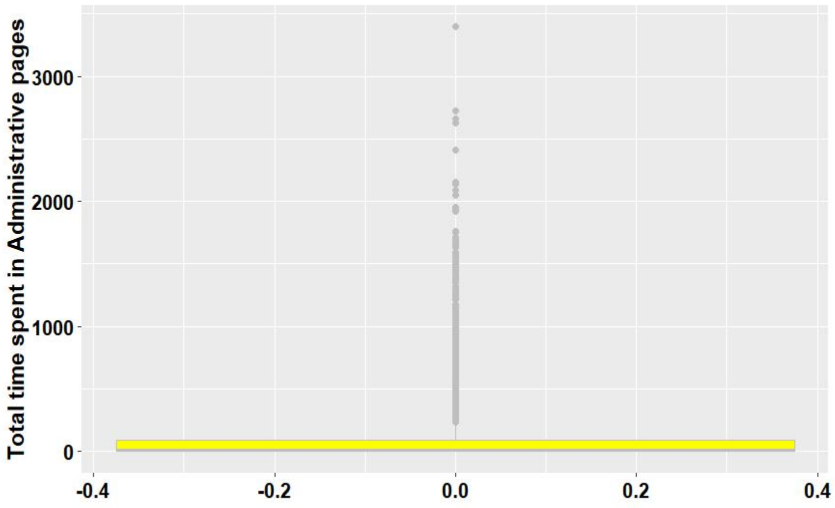
# Data Analysis

# Data Analysis

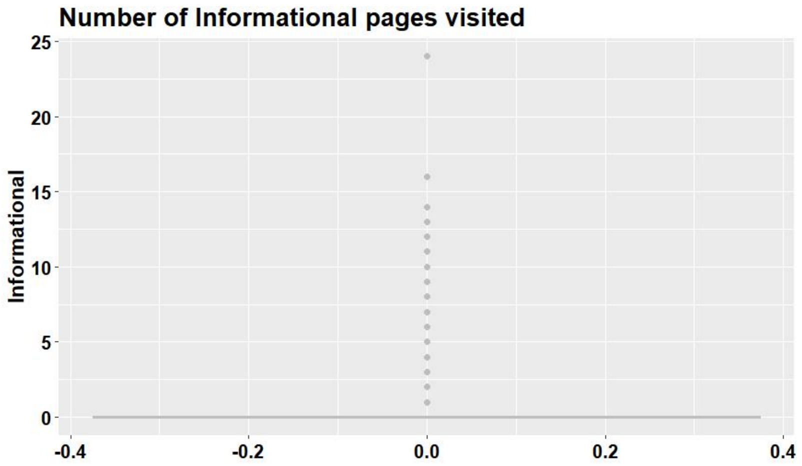
1) Exploring data distribution of different page category and time spent in it.

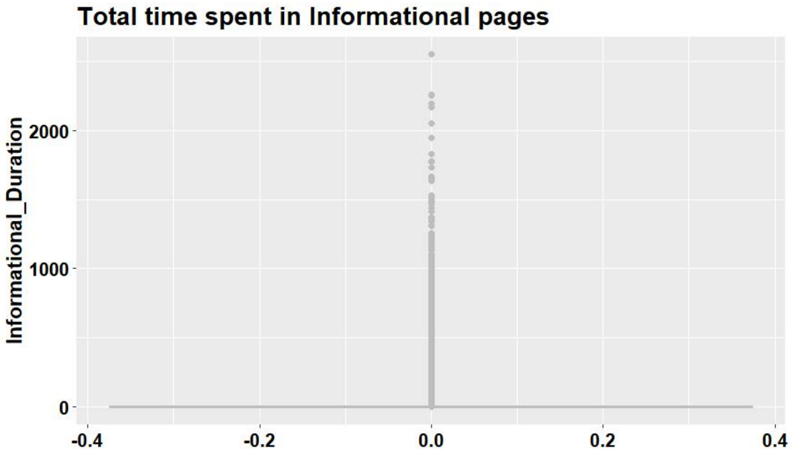
a) Exploring data pattern of "Administrative" and "Administrative_Duration"



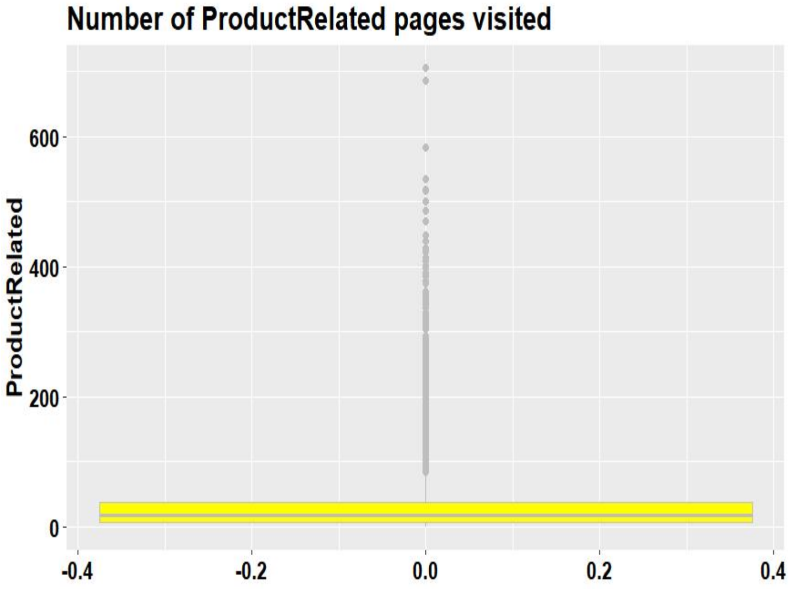



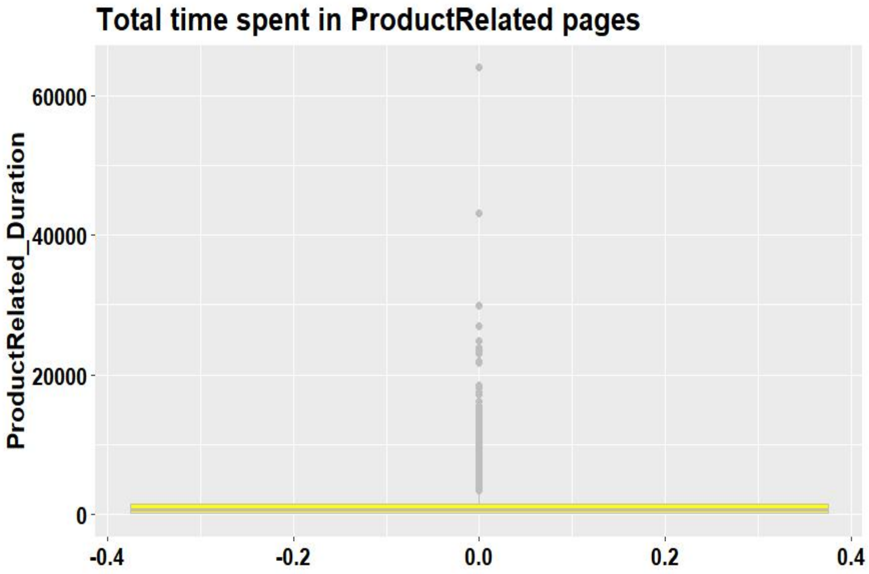
## b) Exploring data pattern of "Informational" and "Informational_Duration"



# c) Exploring data pattern of “Product Related” and “Product Related Duration”



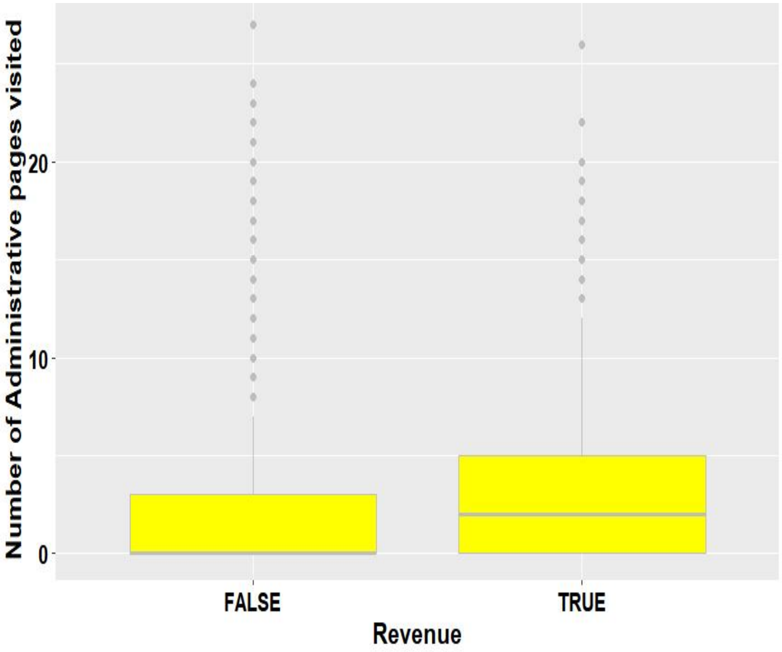



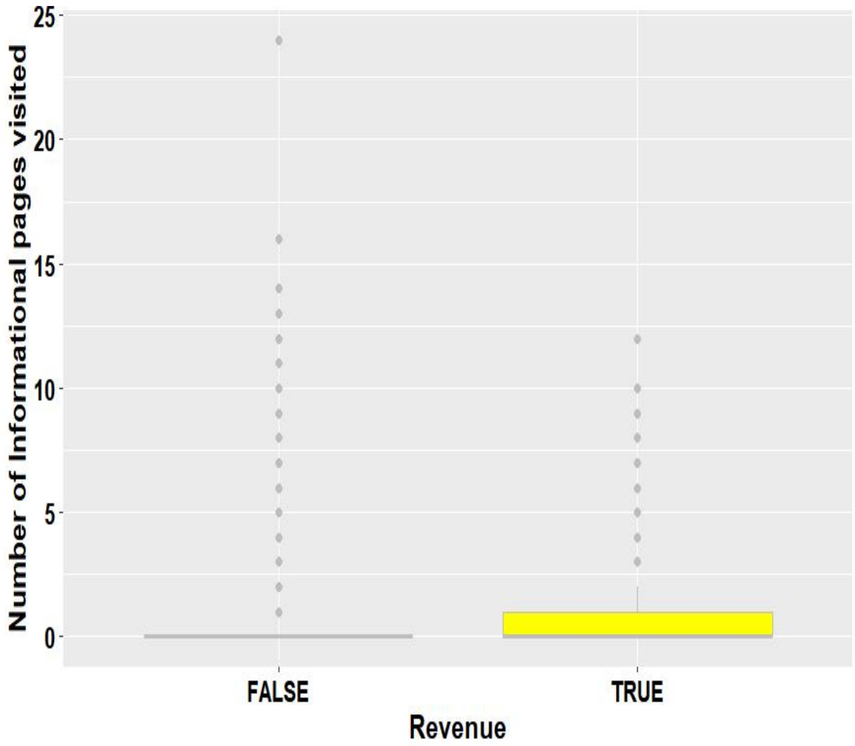
# Summary

- Analysing number of page visit of 3 different page categories it clearly says that customers are interested more in Product related pages rather than knowing information of the product in detail.

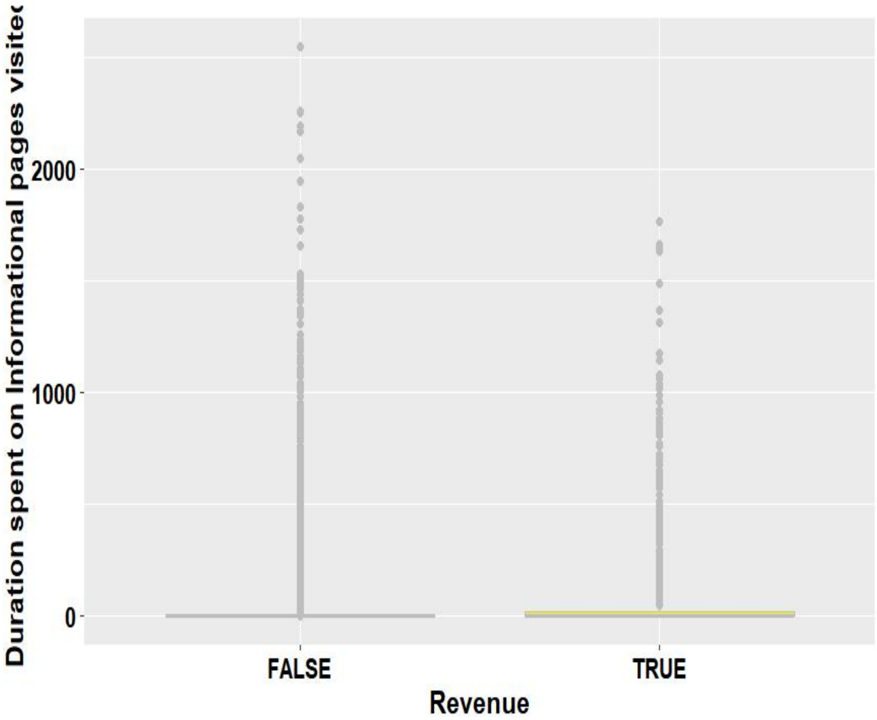
- Analysing total time spent in 3 different page categories, it clearly says that customers spend most of the time in product related pages whereas they are not interested in spending time in information related pages.

2)Exploring the data distribution of different page categories versus the target variable Revenue, as well as the time spent on each page category versus the target variable Revenue.

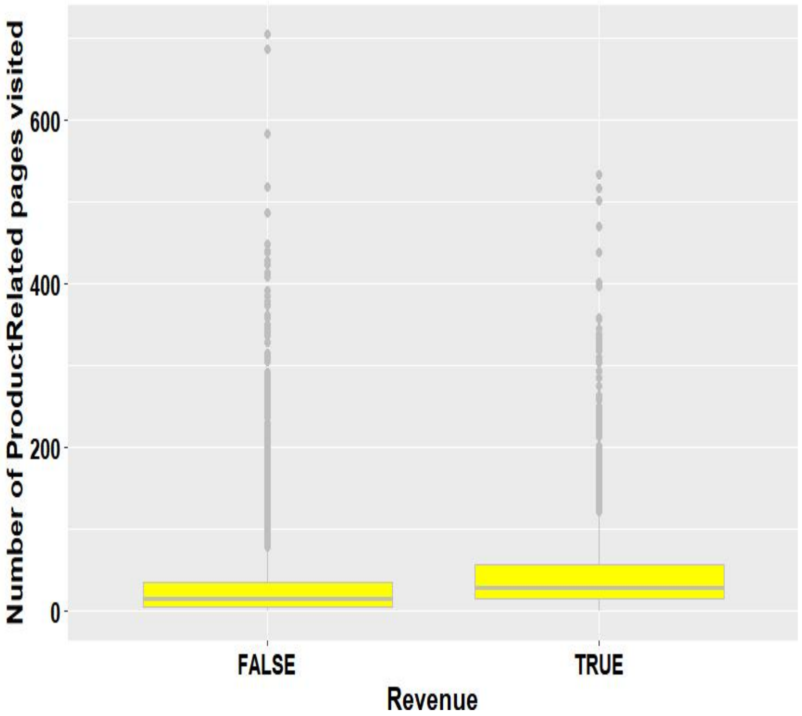


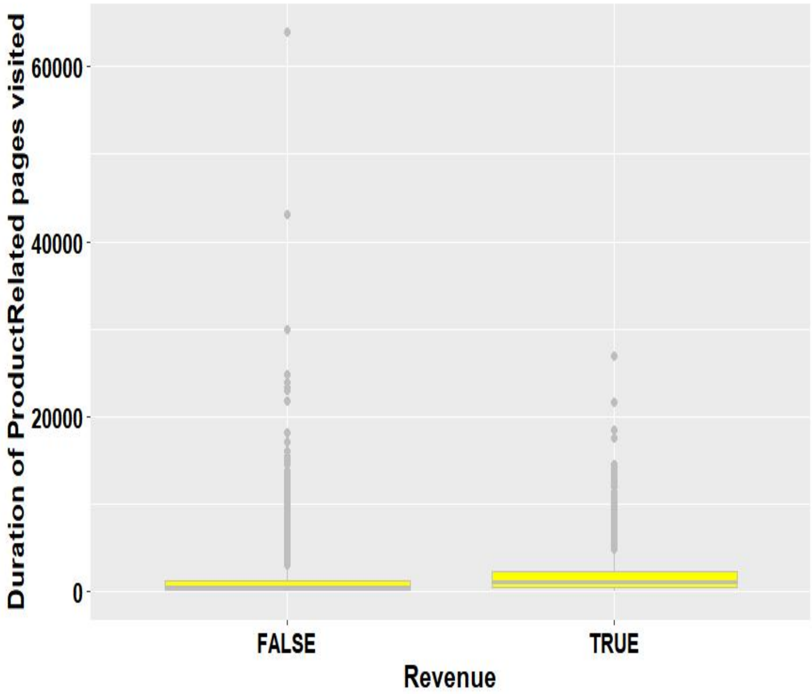
25
20
15
10
5
0
Number of Informational pages visited
FALSE
TRUE
Revenue

2000
1000
0
Duration spent on Informational pages visitec
FALSE
TRUE
Revenue



Number of ProductRelated pages visited
600
400
200
0
FALSE
TRUE
Revenue

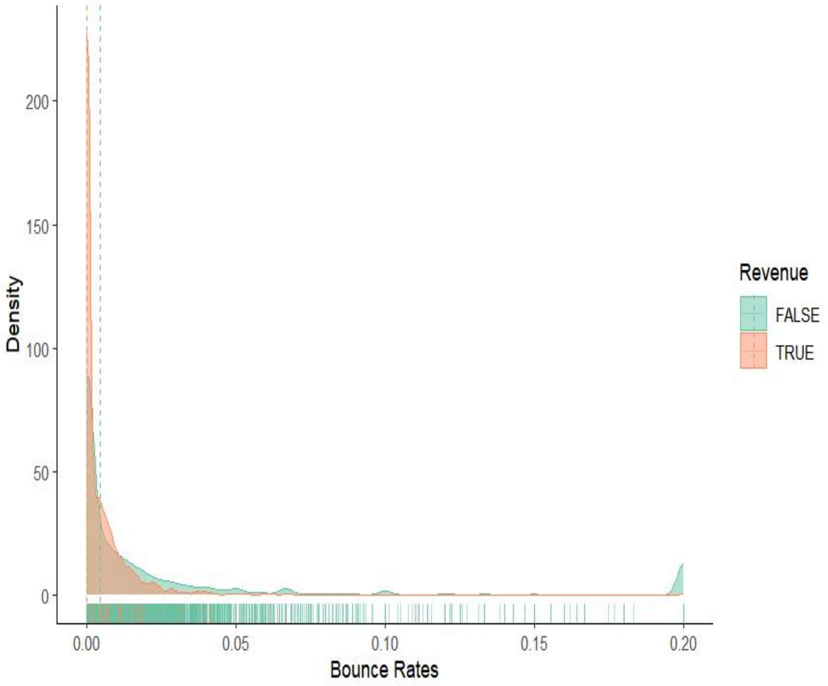



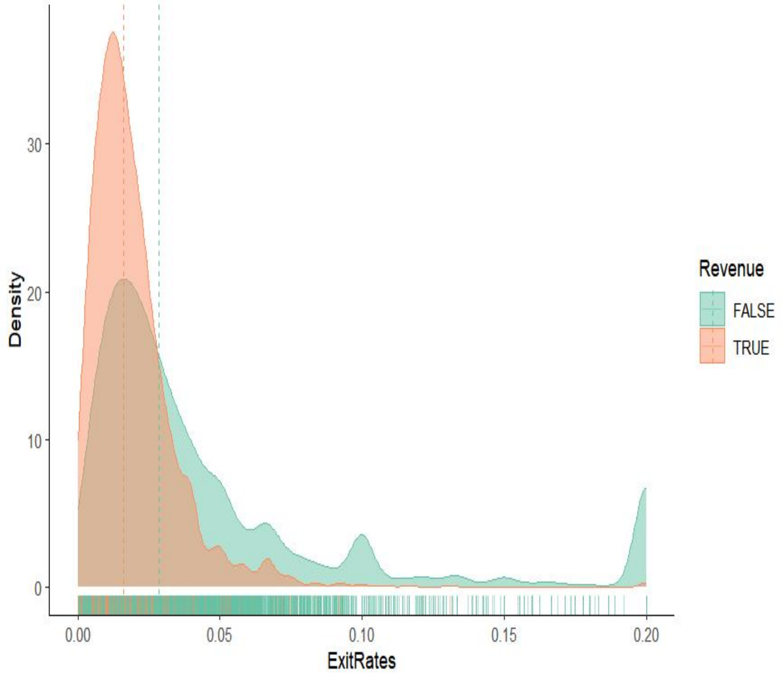
Duration of ProductRelated pages visited
60000
40000
20000
0
FALSE
TRUE
Revenue

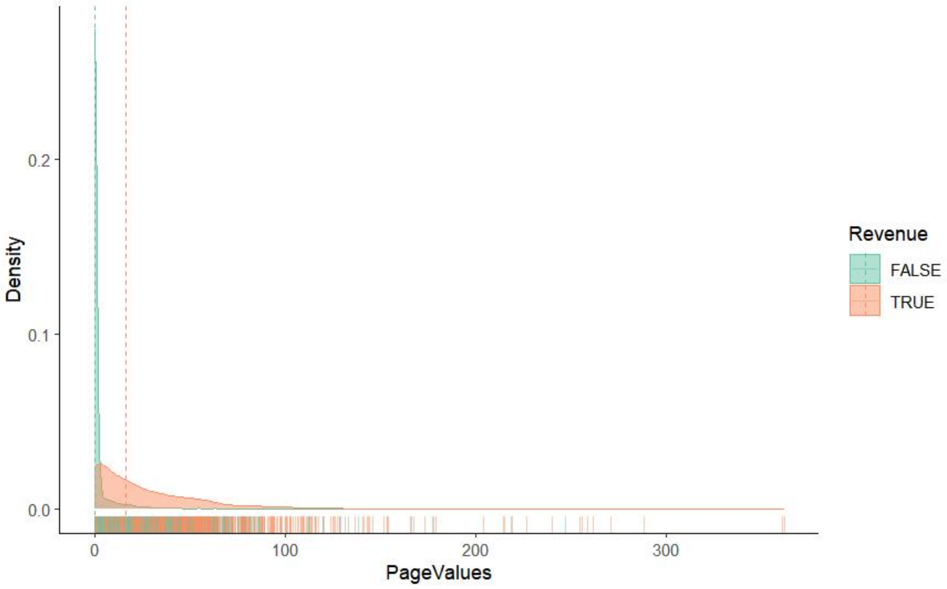
# Summary

- People who end up buying will mostly visit administrative page and spend almost 1min.
- People who end up not buying will mostly not visit administrative page.
- People are least interested in visiting informational page.
- People who end up buying will mostly visit product related page and spend almost 18mins.
- People who will end up buying will mostly visit product related page and spend almost 8.5mins.
- But people who end up buying will visit more product related than the ones who don't.

## 3) “***<u>Bounce Rates”, “Exit Rates” and “Page Values”</u>*** features versus the target variable Revenue respectively.



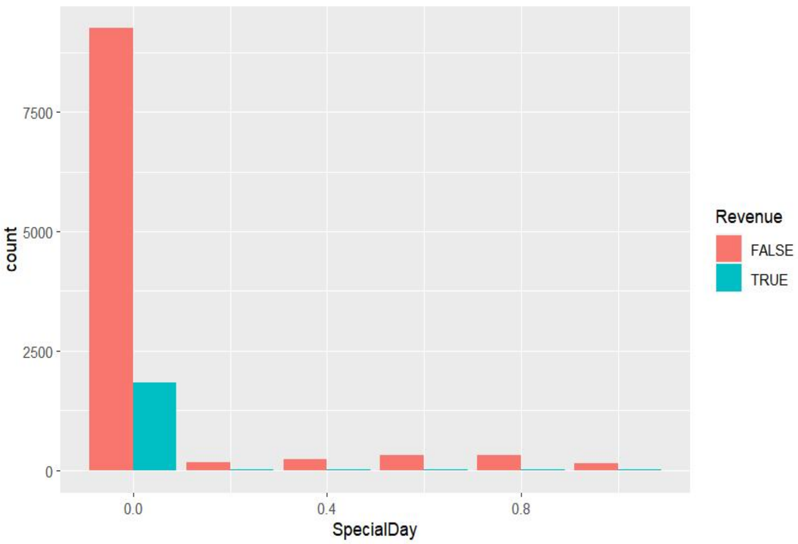





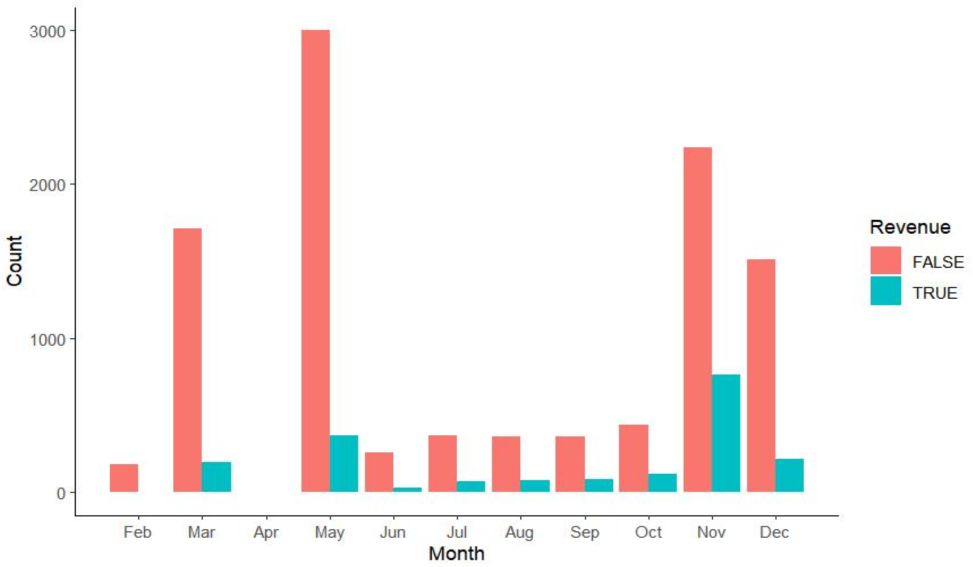

# Summary

- There is no noticeable disparity in Bounce Rates between customers who made a purchase and those who did not.
- However, customers who ended up making a purchase had lower Exit Rates on average, indicating that they were more likely to remain on the website's pages.
- Additionally, customers who did not make a purchase had significantly lower Page Values, suggesting that they spent less time on related pages.

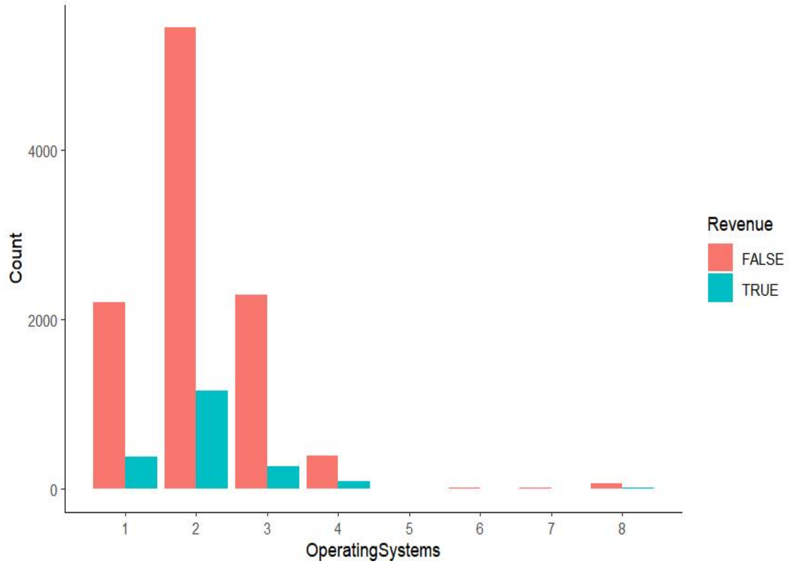
4) “Special Day” features versus the target variable Revenue



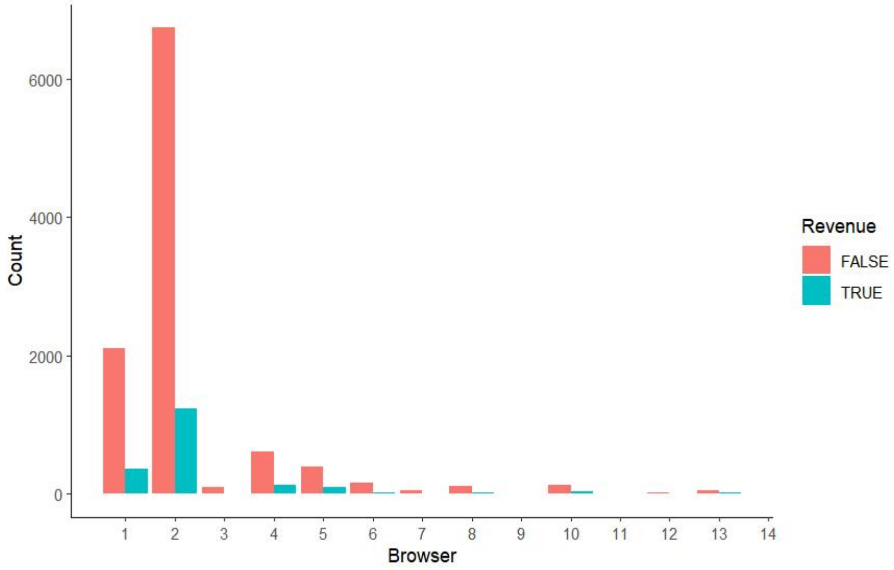

5) “Month” features versus the target variable Revenue.



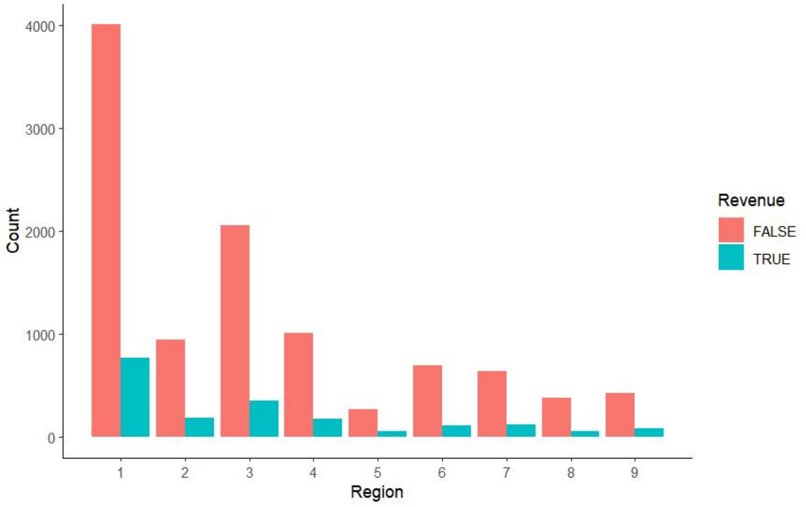
6) “Operating Systems” features versus the target variable Revenue.



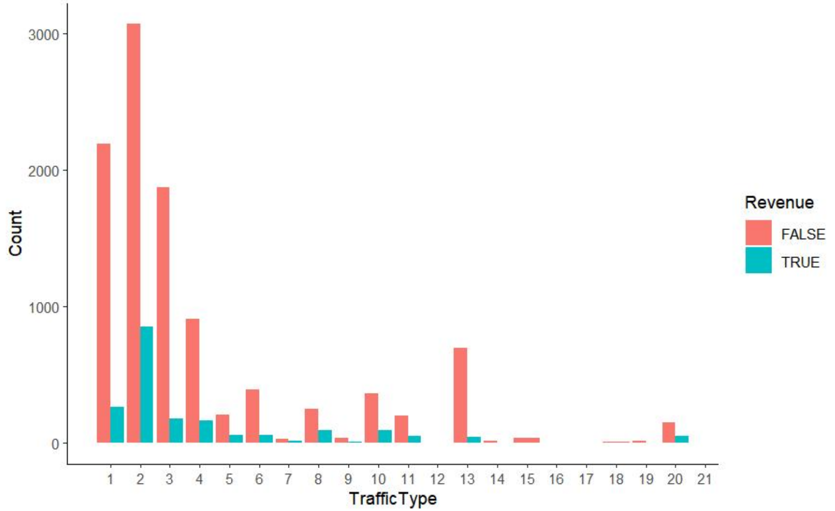

7) “Browser” features versus the target variable Revenue.



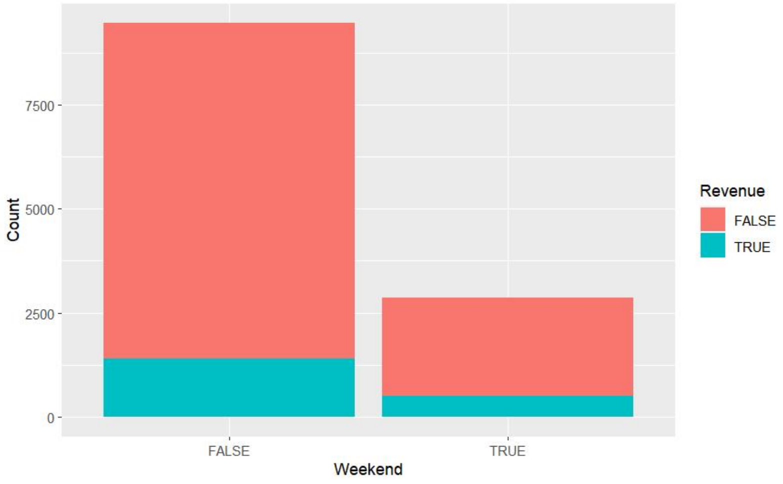
8)“Region” features versus the target variable Revenue.



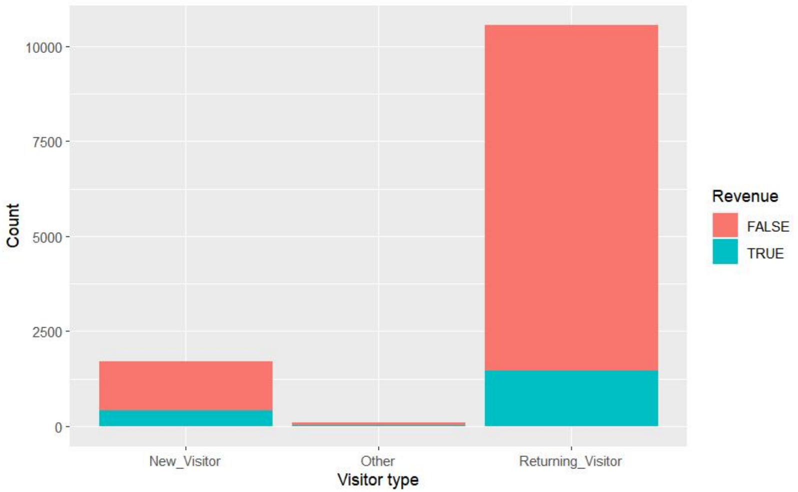

9)“Traffic Type” features versus the target variable Revenue.



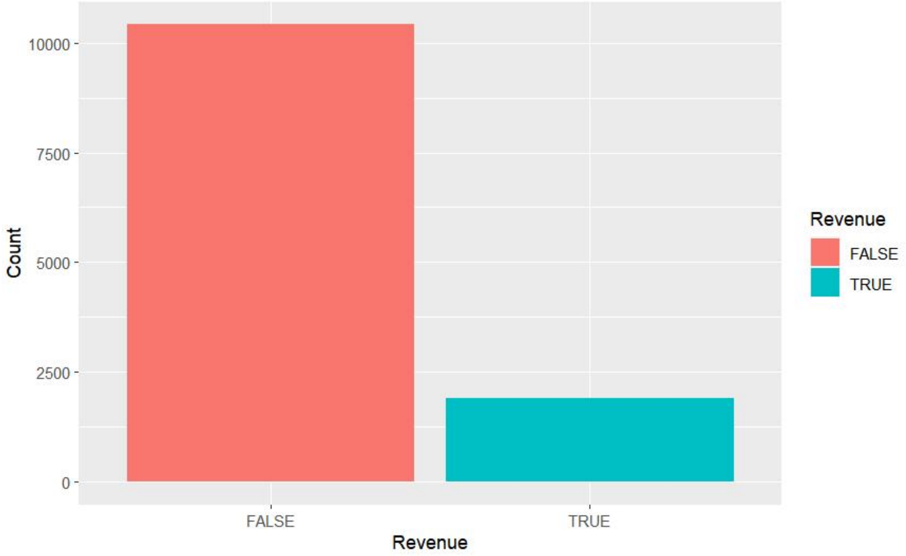
10)"Weekend" features versus the target variable Revenue.




11)"Visitor Type" features versus the target variable Revenue.



# 12) Data distribution of “Revenue” feature




| FALSE | TRUE |
|---|---|
| 10422 | 1908 |

# Supervised

# Model Training and Results

1) Naive Bayes

Results:

One hot encoding data

Average accuracy: 75.6%

| Prediction | Reference | |
|---|---|---|
| | 0 | 1 |
| 0 | 31.6 | 6.0 |
| 0 | 18.4 | 44.0 |

Data without one-hot encoding

Average accuracy: 84.5%

| Prediction | Reference | |
|---|---|---|
| | 0 | 1 |
| 0 | 84.5 | 15.5 |
| 0 | 0 | 0 |

## 2) k-Nearest Neighbor

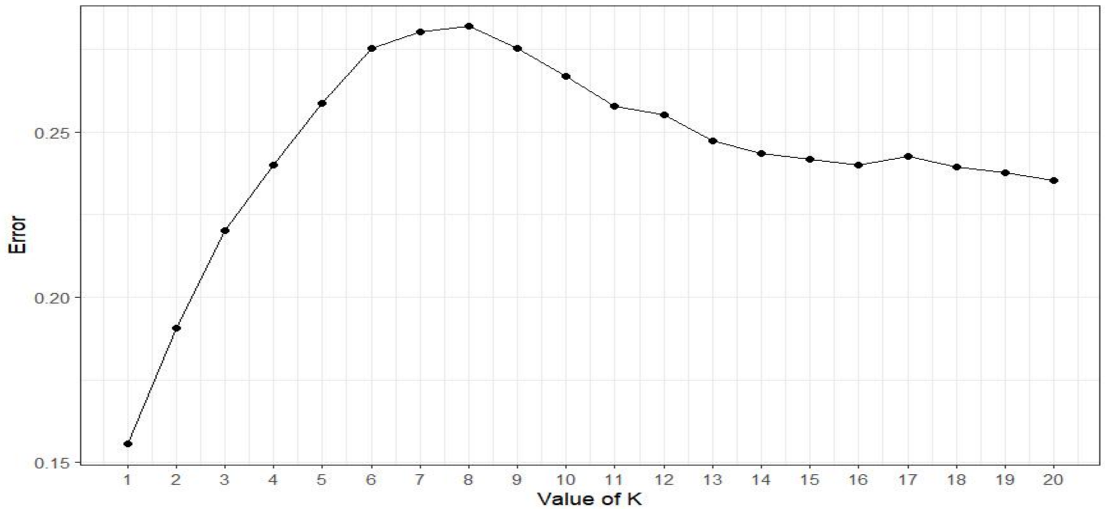
Trained on one-hot encoded dataset

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 2847  296
         1  280  277
                                          
               Accuracy : 0.8443          
                 95% CI : (0.8322, 0.8559)
    No Information Rate : 0.8451          
    P-Value [Acc > NIR] : 0.5652          
                                          
                  Kappa : 0.3984          
                                          
 Mcnemar's Test P-Value : 0.5320          
                                          
            Sensitivity : 0.9105          
            Specificity : 0.4834          
         Pos Pred Value : 0.9058          
         Neg Pred Value : 0.4973          
             Prevalence : 0.8451          
         Detection Rate : 0.7695          
   Detection Prevalence : 0.8495          
      Balanced Accuracy : 0.6969          
                                          
       'Positive' Class : 0               
```

# Visualizing KNN with different k values(number of nearest neighbor)

- Lowest error with k=1



# 3) Random Forest

## Results:

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 2955  189
         1  172  384

               Accuracy : 0.9024
                 95% CI : (0.8924, 0.9118)
    No Information Rate : 0.8451
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.6227

 Mcnemar's Test P-Value : 0.3997

            Sensitivity : 0.9450
            Specificity : 0.6702
         Pos Pred Value : 0.9399
         Neg Pred Value : 0.6906
             Prevalence : 0.8451
         Detection Rate : 0.7986
   Detection Prevalence : 0.8497
      Balanced Accuracy : 0.8076

       'Positive' Class : 0

Thus accuracy of random forest is 89.81%
```

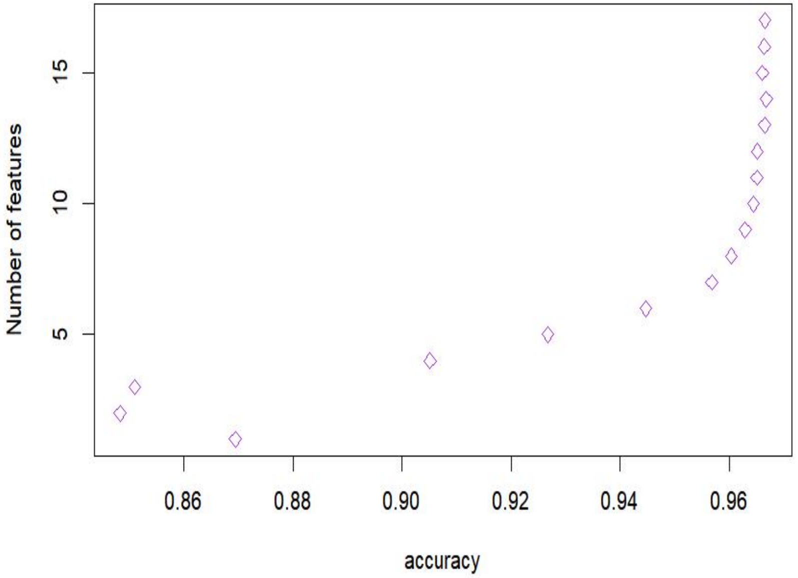
## Recursive Feature Elimination

| | Attribute | Accuracy |
|---|---|---|
| 14 | Region | 0.9667576 |
| 17 | Weekend | 0.9665521 |
| 13 | Browser | 0.9664835 |
| 16 | VisitorType | 0.9664151 |
| 15 | TrafficType | 0.9660722 |
| 12 | OperatingSystems | 0.9651126 |
| 11 | Month | 0.9651125 |
| 10 | SpecialDay | 0.9644273 |
| 9 | PageValues | 0.9629195 |
| 8 | ExitRates | 0.9603834 |
| 7 | BounceRates | 0.9568190 |
| 6 | ProductRelated_Duration | 0.9446862 |
| 5 | ProductRelated | 0.9267302 |
| 4 | Informational_Duration | 0.9051401 |
| 1 | Administrative | 0.8694320 |
| 3 | Informational | 0.8509948 |
| 2 | Administrative_Duration | 0.8483216 |

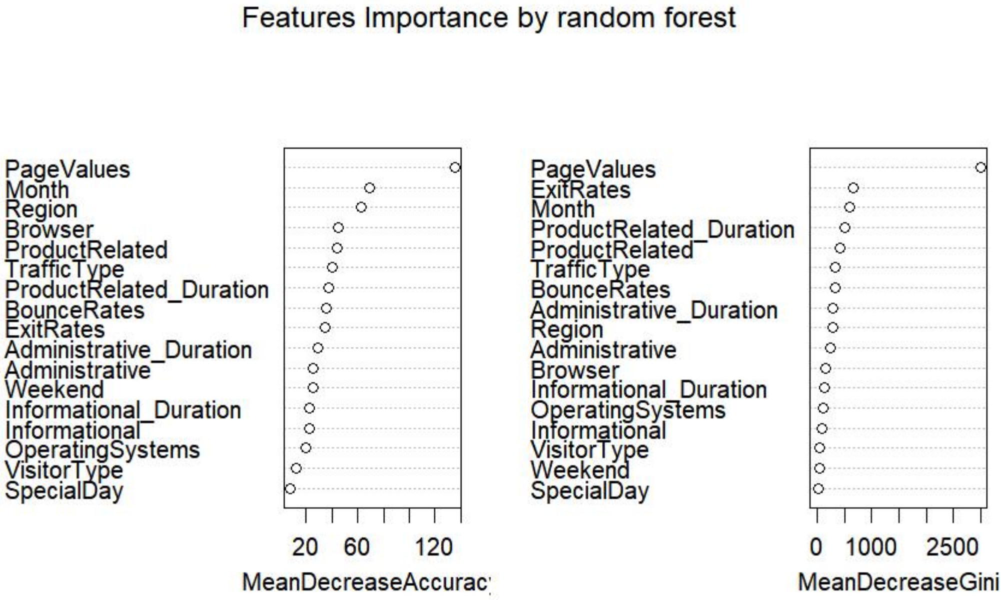
# Feature variable importance table

| Feature variable importance table | MeanDecreaseAccuracy |
|---|---|
| Administrative | 25.740664 |
| Administrative_Duration | 29.428259 |
| Informational | 22.772219 |
| Informational_Duration | 22.896964 |
| ProductRelated | 44.383527 |
| ProductRelated_Duration | 37.415946 |
| BounceRates | 35.813305 |
| ExitRates | 34.568105 |
| PageValues | 135.122725 |
| SpecialDay | 8.007717 |
| Month | 68.915250 |
| OperatingSystems | 19.990634 |
| Browser | 45.293001 |
| Region | 62.972472 |
| TrafficType | 39.930089 |
| VisitorType | 12.686405 |
| Weekend | 25.540213 |

Number of features vs Accuracy plot




Variable importance plot



# Random forest trained on top 10 features

## Results

```
            Reference
Prediction     0    1
         0  2933  190
         1   194  383

               Accuracy : 0.8962
                 95% CI : (0.8859, 0.9059)
    No Information Rate : 0.8451
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.6046

 Mcnemar's Test P-Value : 0.8783

            Sensitivity : 0.9380
            Specificity : 0.6684
         Pos Pred Value : 0.9392
         Neg Pred Value : 0.6638
             Prevalence : 0.8451
         Detection Rate : 0.7927
   Detection Prevalence : 0.8441
      Balanced Accuracy : 0.8032

       'Positive' Class : 0
```

## Top 10 features

PageValues
Month
Region
Browser
ProductRelated
TrafficType
ProductRelated_Duration
BounceRates
ExitRates Administrative_Duration

# 4) Support Vector Machine

- Kernel : Linear

  Result

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 2794  121
         1  333  452

               Accuracy : 0.8773
                 95% CI : (0.8663, 0.8877)
    No Information Rate : 0.8451
    P-Value [Acc > NIR] : 1.453e-08

                  Kappa : 0.5928

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.8935
            Specificity : 0.7888
         Pos Pred Value : 0.9585
         Neg Pred Value : 0.5758
             Prevalence : 0.8451
         Detection Rate : 0.7551
   Detection Prevalence : 0.7878
      Balanced Accuracy : 0.8412

       'Positive' Class : 0
```

Kernel : Radial

Result

```
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 2824  120
         1  303  453

               Accuracy : 0.8857
                 95% CI : (0.875, 0.8958)
    No Information Rate : 0.8451
    P-Value [Acc > NIR] : 8.165e-13

                  Kappa : 0.6136

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9031
            Specificity : 0.7906
         Pos Pred Value : 0.9592
         Neg Pred Value : 0.5992
             Prevalence : 0.8451
         Detection Rate : 0.7632
   Detection Prevalence : 0.7957
      Balanced Accuracy : 0.8468

       'Positive' Class : 0
```

# 5) XG Boost

Training parameters

a)objective = "binary:logistic"

b)eta = 0.3

c)max_depth = 6

d)eval_metric = "auc"

e)Nrounds = 100

f)Early stopping rounds = 10

| | | | | |
|---|---|---|---|---|
| [1] | train | auc:0.940757 | test | auc:0.909651 |
| [2] | train | auc:0.949137 | test | auc:0.918012 |
| [3] | train | auc:0.952685 | test | auc:0.922717 |
| [4] | train | auc:0.954565 | test | auc:0.926051 |
| [5] | train | auc:0.957042 | test | auc:0.926611 |
| [6] | train | auc:0.958906 | test | auc:0.927626 |
| [7] | train | auc:0.961152 | test | auc:0.927922 |
| [8] | train | auc:0.963121 | test | auc:0.927406 |
| [9] | train | auc:0.963852 | test | auc:0.926375 |
| [10] | train | auc:0.965559 | test | auc:0.925545 |
| [11] | train | auc:0.967358 | test | auc:0.925664 |
| [12] | train | auc:0.969143 | test | auc:0.924629 |
| [13] | train | auc:0.970182 | test | auc:0.924950 |
| [14] | train | auc:0.970923 | test | auc:0.924509 |
| [15] | train | auc:0.973319 | test | auc:0.923537 |
| [16] | train | auc:0.974383 | test | auc:0.923199 |
| [17] | train | auc:0.975294 | test | auc:0.923111 |

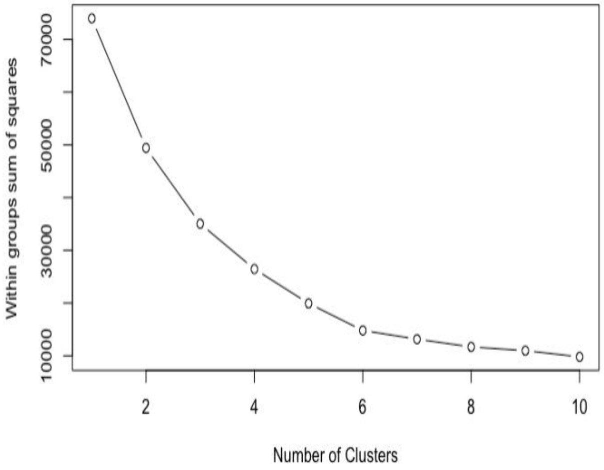
Stopping. Best iteration:

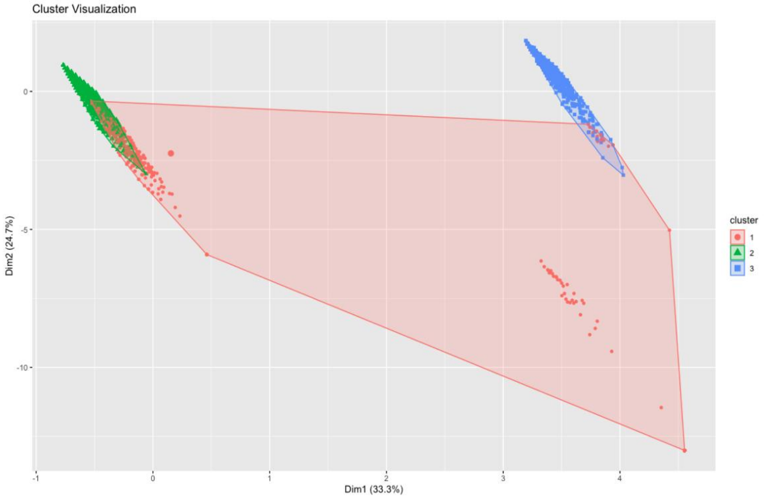
[7] train-auc:0.961152 test-auc:0.927922

# Un-supervised Learning

# K-Means Clustering

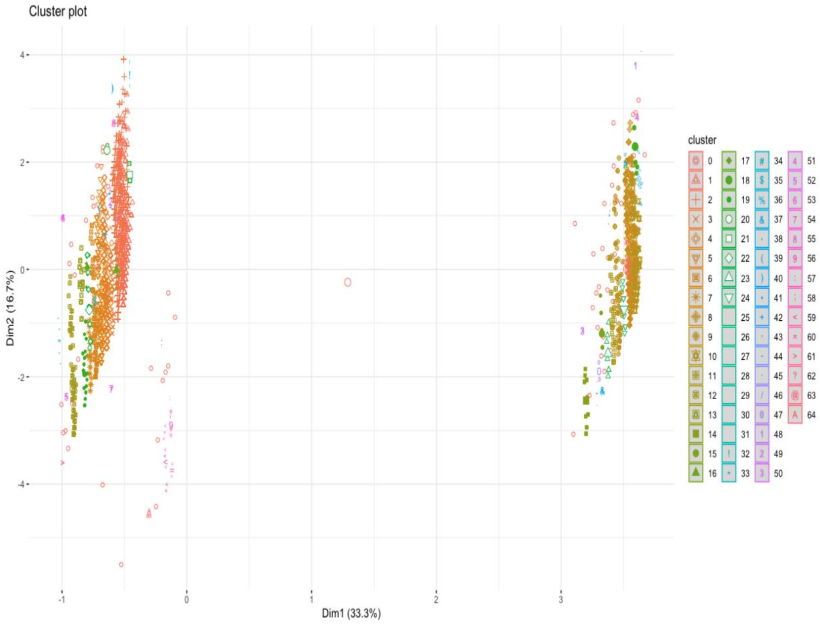
Clusters has been identified using Elbow method, and from the clustered plot we can say that most of the data can be clustered into 3 clusters.



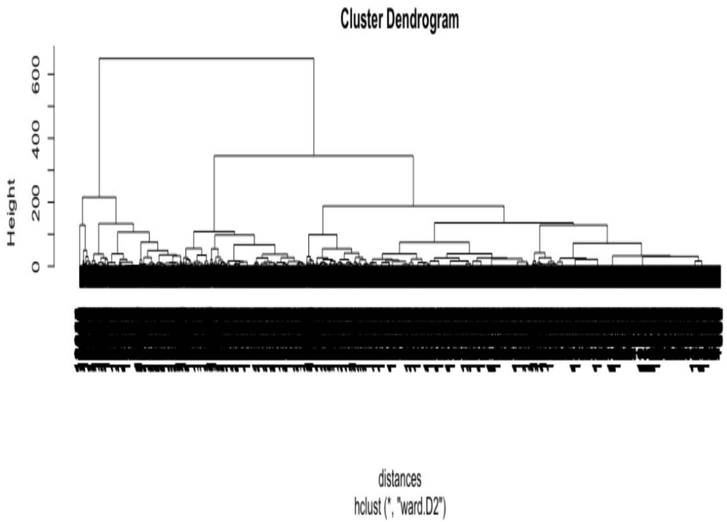
# DBScan Clustering

- As name says this is a density-based clustering algorithm that groups data points into clusters based on their density. DBSCAN is particularly useful for datasets with irregular shapes and noises. But our dataset was mostly without the noises and hence the results were as below



# Hierarchical clustering:

- This is another unsupervised learning algorithm that clusters data points into a tree-like structure based on the similarity between them. Hierarchical clustering can be either agglomerative (bottom-up) or divisive (top-down).



# Future Work

# Future Work

- We would plan to work more on the data gathering, we did look into it but couldn't find the similar datasets.
- Work on couple more research question for example, "How does web metrics influence the revenue."
- Will explore and try to implement MLOps best practices by designing and creating a end-to-end pipelines.
- Would explore Gaussian Mixture Models for the clustering and also analyse the clusters indepth.

# Conculsion

# Conclusion

- Analysing number of page visit of 3 different page categories it clearly says that customers are interested more in Product related pages rather than knowing information of the product in detail.
- Revenue is generated by the customers who visit the product page and spend more time on it, which intuitively mean whom ever spends more time on administrative and informational page will only hop around rather than end up buying.
- Discounts can be given to the ones who spend more time on Product related page.
- There is no noticeable disparity in Bounce Rates between customers who made a purchase and those who did not.
- However, customers who ended up making a purchase had lower Exit Rates on average, indicating that they were more likely to remain on the website's pages.
- Additionally, customers who did not make a purchase had significantly lower Page Values, suggesting that they spent less time on related pages.

# Bibliography


- [1]. https://jurnal-ppi.kominfo.go.id/index.php/jppi/article/view/341
- [2]. Real-time prediction of online shoppers' purchasing intention using multilayer perceptron and LSTM recurrent neural networks [ https://link.springer.com/article/10.1007/s00521-018-3523-0 ]
- [3]. Data Clustering: A Review [ https://dl.acm.org/doi/pdf/10.1145/331499.331504 ]
- [4]. A Comparison Study of Credit Card Fraud Detection: Supervised versus Unsupervised [ https://arxiv.org/pdf/1904.10604.pdf ]
- [5].Real-Time Prediction of Online Shoppers Purchasing Intention Using Random Forest [ https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7256375/ ].

# Thank You