E-Commerce Customer Churn Analysis and Prediction

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Introduction

Customer churn was, and still is, a very important concept in contemporary marketing that should not be ignored (Jahromi, Stakhovych, & Ewing, 2014). Customer churn or customer attrition refers to the loss of customers. It is the percentage of customers that have stopped using a company's product or service over a certain period of time. Lost customers also mean lost revenue which is why it is so important for companies to know in advance which customers will churn in the near future.

Many small and relatively new companies are struggling due to the economic effects of COVID-19 and are wanting to find new/innovative ways to hold onto their loyal customer. With data science being such a hot topic they might want to use it to help them with their decision making. It is best to use machine learning with very large datasets, which these companies might not have.

The focus of this data analysis project will be to predict customer churn of an up-and-coming E-Commerce company that has a relatively small dataset. They want to use this analysis/prediction to plan what incentives and/or other retention offers to offer to prevent this from happening. This will need to be done keeping the chances of overfitting in mind and what can be done if such happens.

For predictive modelling three algorithms will be used to predict which customers will churn in the near future:

- Logistic Regression
- Random Forest
- XGBoost
- SVM

Literature Review

Many companies, from pre-pandemic times, were starting to realize that they should focus more on retaining their current customers while attracting new ones. For this, customers that are about to leave/churn need to be identified so that they can be targeted with tailored incentives (points, discounts, etc.) or other retention offers (coupons, etc.) (Jahromi, Stakhovych, & Ewing, 2014).

With so many companies losing customers during the COVID-19 Pandemic due to economic concerns, such as high unemployment rate (Ranchhod & Daniels, 2021), more of such analysis and predictions are needed to keep current customers to be able to walk towards the path of recovery (Mulcahy, 2020). With many countries being in lockdown and preventing consumers to shop in store all shopping is being done online.

Many businesses have seen significant increases during the COVID-19 pandemic along with a high churn rate (Rachmawati, 2021). This is possibly because searching and comparing products/offers/deals at competing stores simultaneously is much more easier to do online. Loyal customers that would not have bothered or were not able to check what competitors are offering pre-pandemic, are doing so now. These are also the customers that produce higher revenue and margins than new customers. This makes it even more crucial to understand loyal customers and prevent them from churning by developing innovative marketing strategies and improve customer satisfaction (Cao, Yu, & Zhang, 2015).

Dataset

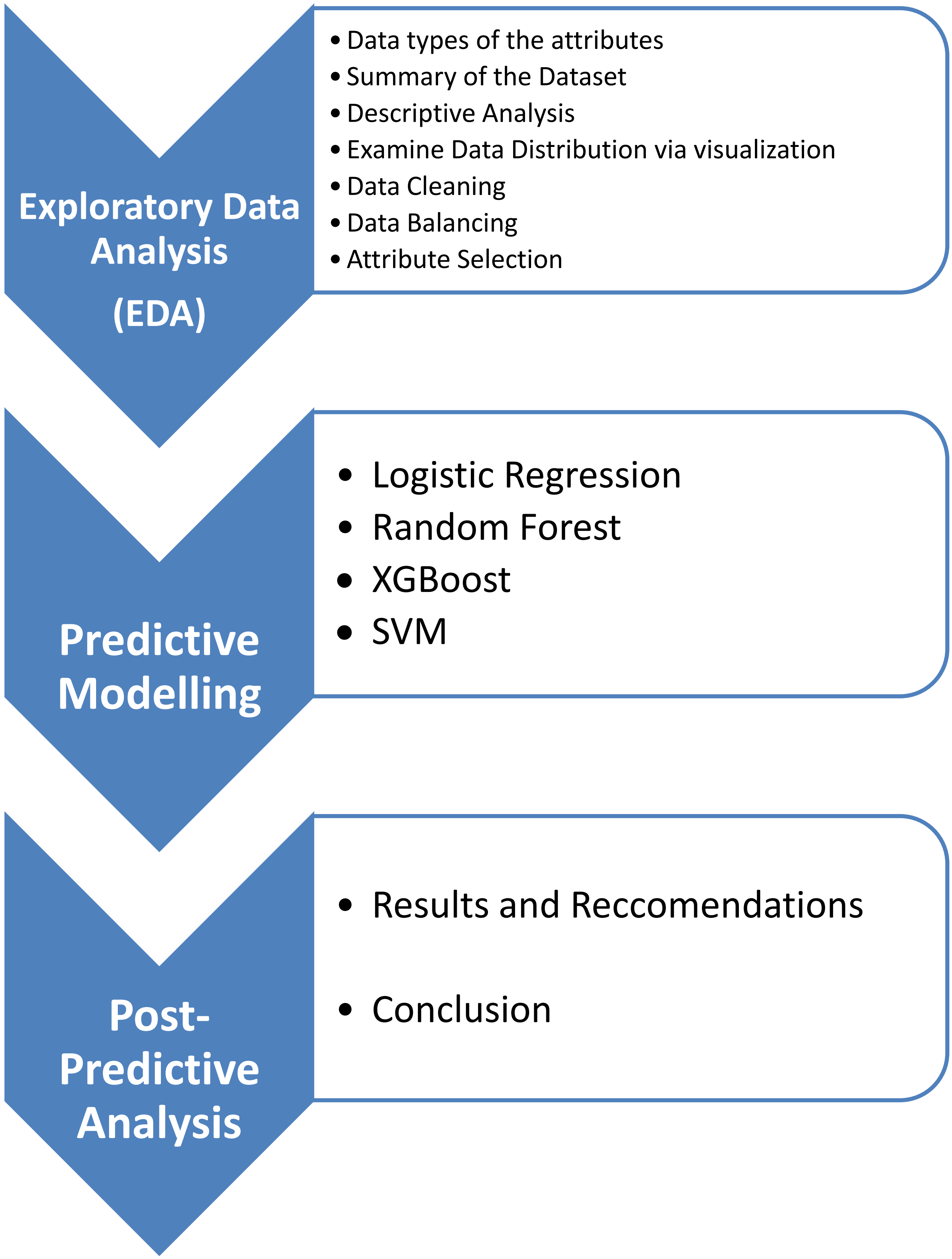
The dataset used for this project was curated by Ankit Verma and obtained from Kaggle. This small sample of 5630 rows was taken from the database of an e-commerce company sometime during 2019 (when the company was approx. 4 years old). Each row representing a separate customer. It was then modified by the curator to give it the current shape. The dataset has information on a wide range of customers including, but not limited to, those who have been customers since the inception of the company to the ones recently acquired.

There are 20 unique numeric, qualitative and binary attributes within this dataset:

1. **CustomerID:** Unique customer ID's
2. **Churn:** Churn class attribute with binary values (1 for churn and 0 for not churn)
3. **Tenure:** Tenure of customer in organization
4. **PreferredLoginDevice:** Preferred login device
5. **CityTier:** City tier
6. **WarehouseToHome:** Distance in between warehouse to home of customer
7. **PreferredPaymentMode:** Preferred payment method
8. **Gender:** Gender of customer
9. **HourSpendOnApp:** Number of hours spend on mobile application or website
10. **NumberOfDeviceRegistered:** Total number of devices registered per customer
11. **PreferedOrderCat:** Preferred order category of customer in the previous month
12. **SatisfactionScore:** Satisfactory score of customer on service
13. **MaritalStatus:** Marital status of customer
14. **NumberOfAddress:** Total number of addresses
15. **Complain:** Any complaint raised in the previous month
16. **OrderAmountHikeFromlastYear:** Percentage increase in order from last year
17. **CouponUsed:** Total number of coupons used in the previous month
18. **OrderCount:** Total number of orders placed in the previous month
19. **DaySinceLastOrder:** Days since last order
20. **CashbackAmount:** Average cashback in the previous month

I am interested in analyzing the "Churn" attribute given "1", which identifies those customers that have churned to try to predict what lead them to churn and why.

Approach


Exploratory Data Analysis
(EDA)
• Data types of the attributes
• Summary of the Dataset
• Descriptive Analysis
• Examine Data Distribution via visualization
• Data Cleaning
• Data Balancing
• Attribute Selection
Predictive Modelling
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• SVM
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• Conclusion

Step 1: Exploratory Data Analysis (EDA)

[Link of my Github]

Data types of the Attributes

```
CustomerID                 : int [1:5630] 50001 50002 50003 50004 50005 50006 50007 50008 50009 50010 ...
Churn                      : num [1:5630] 1 1 1 1 1 1 1 1 1 1 ...
Tenure                     : num [1:5630] 4 NA NA 0 0 0 NA NA 13 NA ...
PreferredLoginDevice       : chr [1:5630] "Mobile Phone" "Phone" "Phone" "Phone" ...
CityTier                   : num [1:5630] 3 1 1 3 1 1 3 1 3 1 ...
WarehouseToHome            : num [1:5630] 6 8 30 15 12 22 11 6 9 31 ...
PreferredPaymentMode       : chr [1:5630] "Debit Card" "UPI" "Debit Card" "Debit Card" ...
Gender                     : chr [1:5630] "Female" "Male" "Male" "Male" ...
HourSpendOnApp             : num [1:5630] 3 3 2 2 NA 3 2 3 NA 2 ...
NumberOfDeviceRegistered   : num [1:5630] 3 4 4 4 3 5 3 3 4 5 ...
PreferedOrderCat           : chr [1:5630] "Laptop & Accessory" "Mobile" "Mobile" "Laptop & Accessory" ...
SatisfactionScore          : num [1:5630] 2 3 3 5 5 5 2 2 3 3 ...
MaritalStatus              : chr [1:5630] "Single" "Single" "Single" "Single" ...
NumberOfAddress            : num [1:5630] 9 7 6 8 3 2 4 3 2 2 ...
Complain                   : num [1:5630] 1 1 1 0 0 1 0 1 1 0 ...
OrderAmountHikeFromlastYear: num [1:5630] 11 15 14 23 11 22 14 16 14 12 ...
CouponUsed                 : num [1:5630] 1 0 0 0 1 4 0 2 0 1 ...
OrderCount                 : num [1:5630] 1 1 1 1 1 6 1 2 1 1 ...
DaySinceLastOrder          : num [1:5630] 5 0 3 3 3 7 0 0 2 1 ...
CashbackAmount             : num [1:5630] 160 121 120 134 130 ...
```

Figure 1

Summary of the Dataset

```
   CustomerID         Churn             Tenure       PreferredLoginDevice     CityTier      WarehouseToHome
 Min.    :50001   Min.    :0.0000   Min.   : 0.00   Length:5630           Min.   :1.000   Min.   :  5.00
 1st Qu.:51408   1st Qu.:0.0000   1st Qu.: 2.00   Class :character      1st Qu.:1.000   1st Qu.:  9.00
 Median :52816   Median :0.0000   Median : 9.00   Mode  :character      Median :1.000   Median : 14.00
 Mean   :52816   Mean   :0.1684   Mean   :10.19                         Mean   :1.655   Mean   : 15.64
 3rd Qu.:54223   3rd Qu.:0.0000   3rd Qu.:16.00                         3rd Qu.:3.000   3rd Qu.: 20.00
 Max.   :55630   Max.   :1.0000   Max.   :61.00                         Max.   :3.000   Max.   :127.00
                                  NA's   :264                                           NA's   :251
 PreferredPaymentMode    Gender           HourSpendOnApp  NumberOfDeviceRegistered PreferedOrderCat
 Length:5630          Length:5630        Min.   :0.000   Min.   :1.000            Length:5630
 Class :character     Class :character   1st Qu.:2.000   1st Qu.:3.000            Class :character
 Mode  :character     Mode  :character   Median :3.000   Median :4.000            Mode  :character
                                         Mean   :2.932   Mean   :3.689
                                         3rd Qu.:3.000   3rd Qu.:4.000
                                         Max.   :5.000   Max.   :6.000
                                         NA's   :255
 SatisfactionScore MaritalStatus      NumberOfAddress     Complain      OrderAmountHikeFromlastYear
 Min.   :1.000     Length:5630        Min.   : 1.000   Min.   :0.0000   Min.   :11.00
 1st Qu.:2.000     Class :character   1st Qu.: 2.000   1st Qu.:0.0000   1st Qu.:13.00
 Median :3.000     Mode  :character   Median : 3.000   Median :0.0000   Median :15.00
 Mean   :3.067                        Mean   : 4.214   Mean   :0.2849   Mean   :15.71
 3rd Qu.:4.000                        3rd Qu.: 6.000   3rd Qu.:1.0000   3rd Qu.:18.00
 Max.   :5.000                        Max.   :22.000   Max.   :1.0000   Max.   :26.00
                                                                        NA's   :265
   CouponUsed        OrderCount      DaySinceLastOrder CashbackAmount
 Min.   : 0.000   Min.   : 1.000   Min.   : 0.000    Min.   :  0.0
 1st Qu.: 1.000   1st Qu.: 1.000   1st Qu.: 2.000    1st Qu.:145.8
 Median : 1.000   Median : 2.000   Median : 3.000    Median :163.3
 Mean   : 1.751   Mean   : 3.008   Mean   : 4.543    Mean   :177.2
 3rd Qu.: 2.000   3rd Qu.: 3.000   3rd Qu.: 7.000    3rd Qu.:196.4
 Max.   :16.000   Max.   :16.000   Max.   :46.000    Max.   :325.0
 NA's   :256      NA's   :258      NA's   :307
```

Figure 2

Examine Data Distribution

Box plots to show outliers, minimum value, lower quartile (Q1), median value (Q2), upper quartile (Q3), and maximum value in the data set.

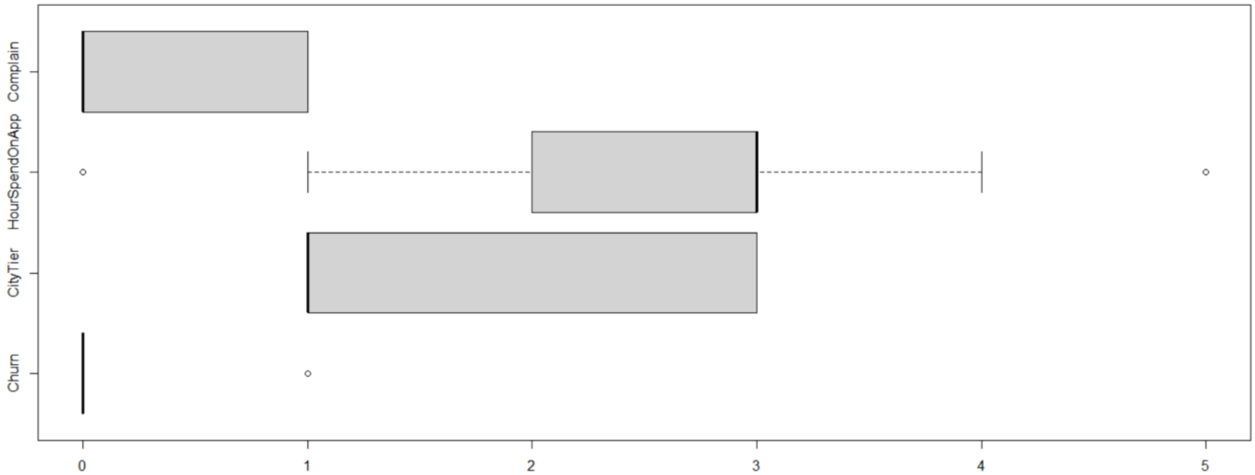


Figure 3

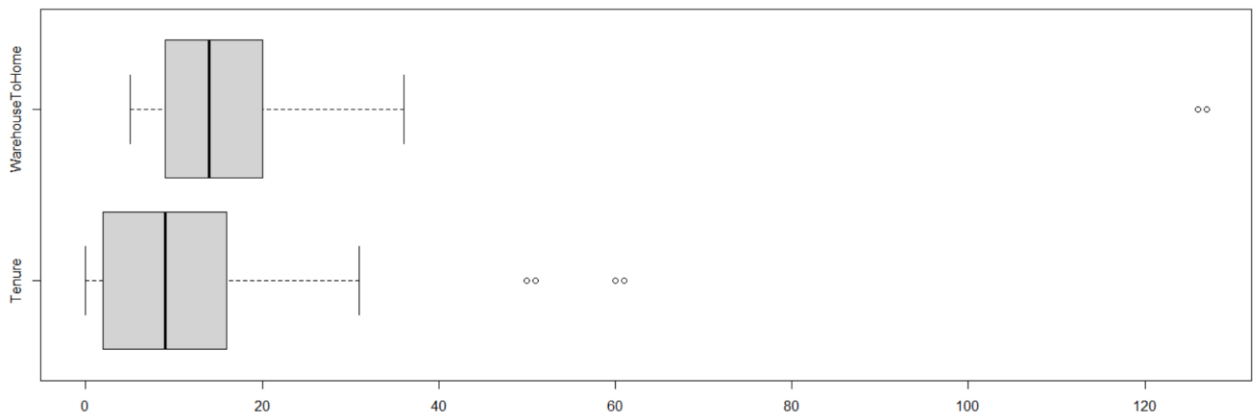


Figure 4

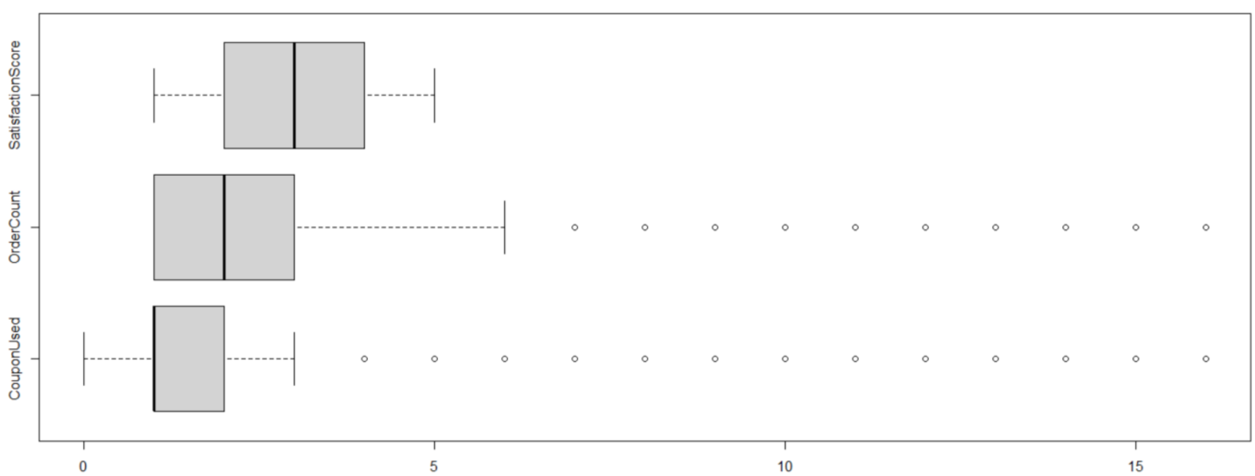


Figure 5

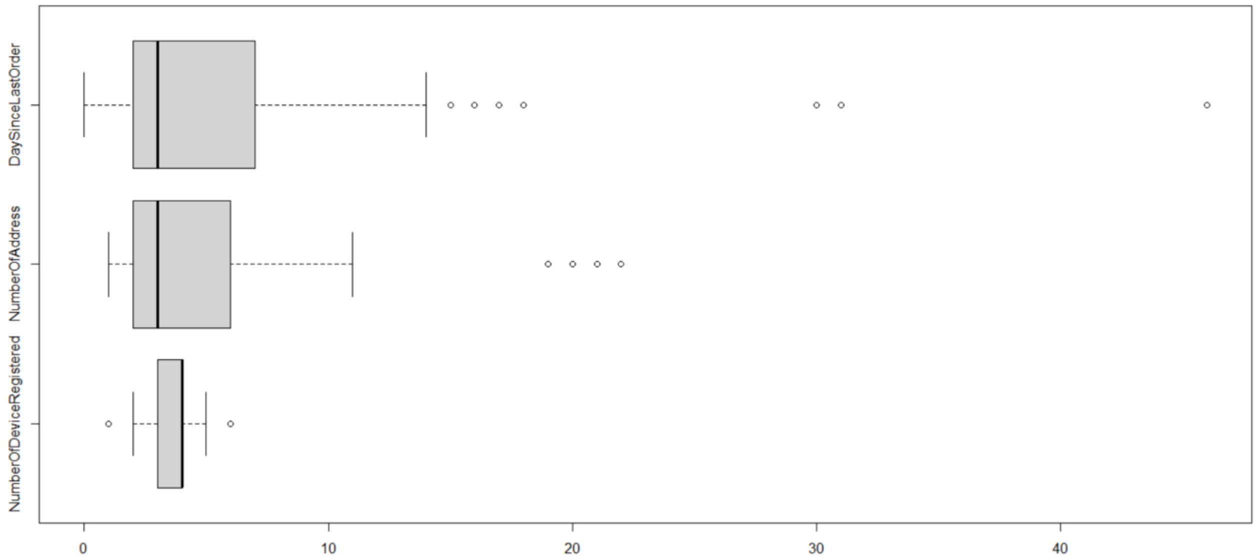
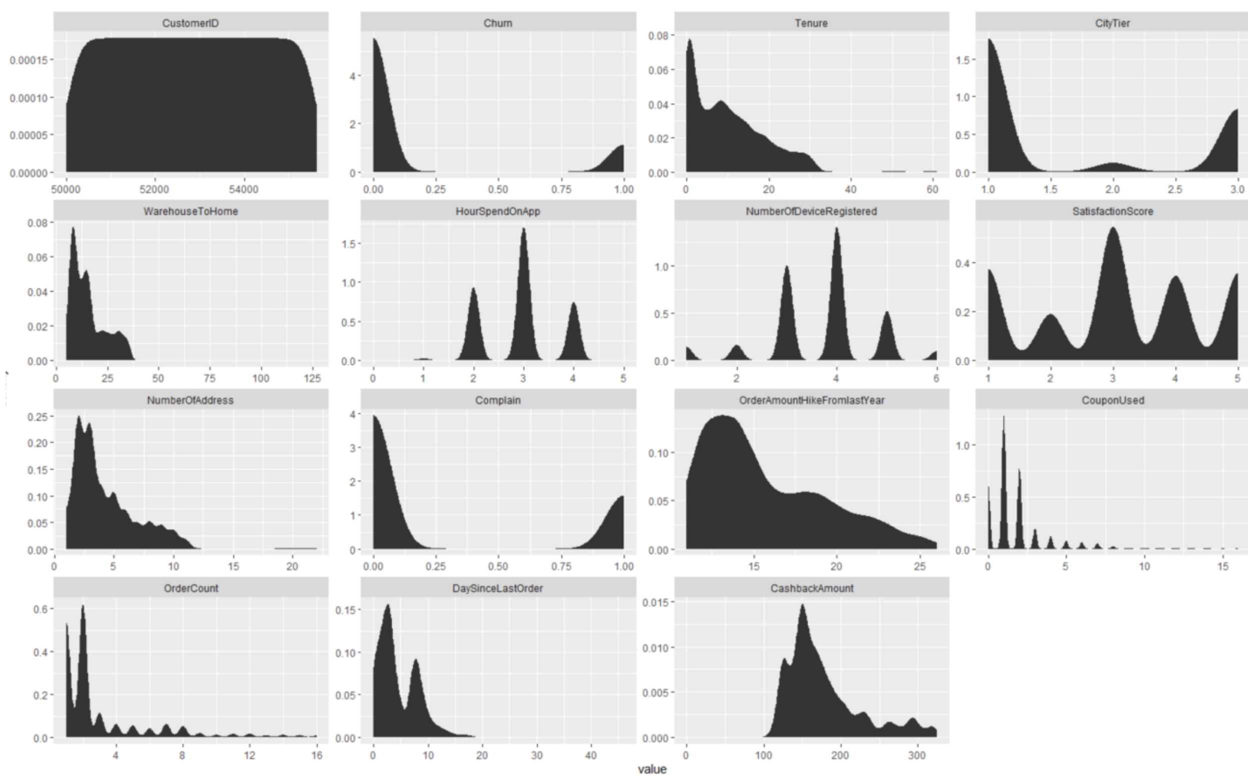


Figure 6

Density plots to see the Distribution of all the Variables



Frequency table of all the columns that have character data types

```
Character_Data %>% count(PreferredLoginDevice)
A tibble: 3 x 2
PreferredLoginDevice     n
<chr>                <int>
Computer              1634
Mobile Phone          2765
Phone                 1231
Character_Data %>% count(PreferredPaymentMode)
A tibble: 7 x 2
PreferredPaymentMode     n
<chr>                <int>
Cash on Delivery       149
CC                     273
COD                    365
Credit Card           1501
Debit Card            2314
E wallet               614
UPI                    414
Character_Data %>% count(Gender)
A tibble: 2 x 2
Gender     n
<chr>  <int>
Female  2246
Male    3384
Character_Data %>% count(PreferedOrderCat)
A tibble: 6 x 2
PreferedOrderCat       n
<chr>              <int>
Fashion              826
Grocery              410
Laptop & Accessory  2050
Mobile               809
Mobile Phone        1271
Others               264
Character_Data %>% count(MaritalStatus)
A tibble: 3 x 2
MaritalStatus     n
<chr>         <int>
Divorced        848
Married        2986
Single         1796
```

Figure 7

Total number of missing values in each column

```
      CustomerID                     Churn                    Tenure       PreferredLoginDevice
               0                         0                       264                          0
        CityTier           WarehouseToHome      PreferredPaymentMode                     Gender
               0                       251                         0                          0
   HourSpendOnApp  NumberOfDeviceRegistered         PreferedOrderCat          SatisfactionScore
             255                         0                         0                          0
    MaritalStatus            NumberOfAddress                  Complain OrderAmountHikeFromlastYear
               0                         0                         0                        265
      CouponUsed                OrderCount          DaySinceLastOrder             CashbackAmount
             256                       258                       307                          0
```

Figure 8

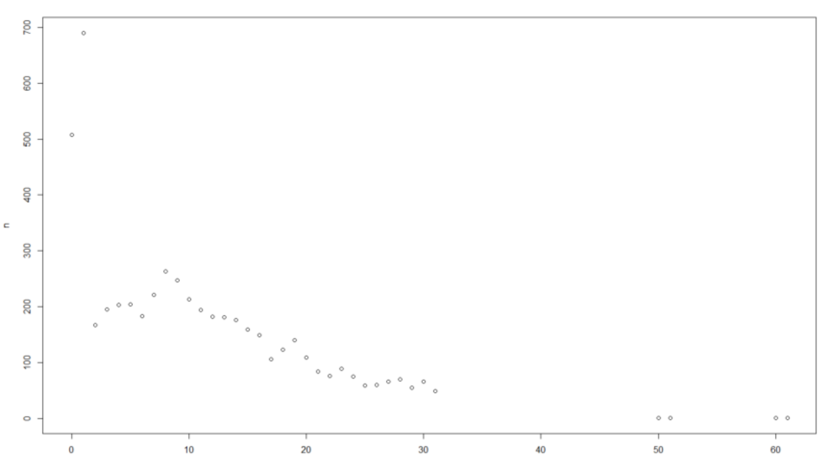
Data Cleaning: Character Variables

Since the following categories have the same meaning they will be cleaned by choosing one of the two:

1) Mobile Phone and Phone: Mobile Phone
2) CC and Credit Card: Credit Card
3) Cash on Delivery and COD: Cash on Delivery

Data Cleaning: Numeric Variables

When trying to remove all rows with missing values only 3774 rows remained and 1856 rows were removed. With the dataset already being too small and skewed I decided to clean it and keep as many of the rows as possible, if not all, by replacing missing values with the median value.



	Tenure	n
1	0	508
2	1	690
3	2	167
4	3	195
5	4	203
6	5	204
7	6	183
8	7	221
9	8	263
10	9	247
11	10	213
12	11	194
13	12	182
14	13	181
15	14	176
16	15	159
17	16	149
18	17	106
19	18	123
20	19	140
21	20	109
22	21	84
23	22	76
24	23	89
25	24	75
26	25	59
27	26	60
28	27	66
29	28	70
30	29	55
31	30	66
32	31	49
33	50	1
34	51	1
35	60	1
36	61	1
37	NA	264

Figure 9

For Tenure which is the tenure of each customer with the organization since its inception. I decided to fill in the N/A's with 0's keeping in mind that the company has only been around for 4 years and the tenure of majority of its customers are 1 year or less.

Density plots to see the Distribution of all the Variables after Cleaning

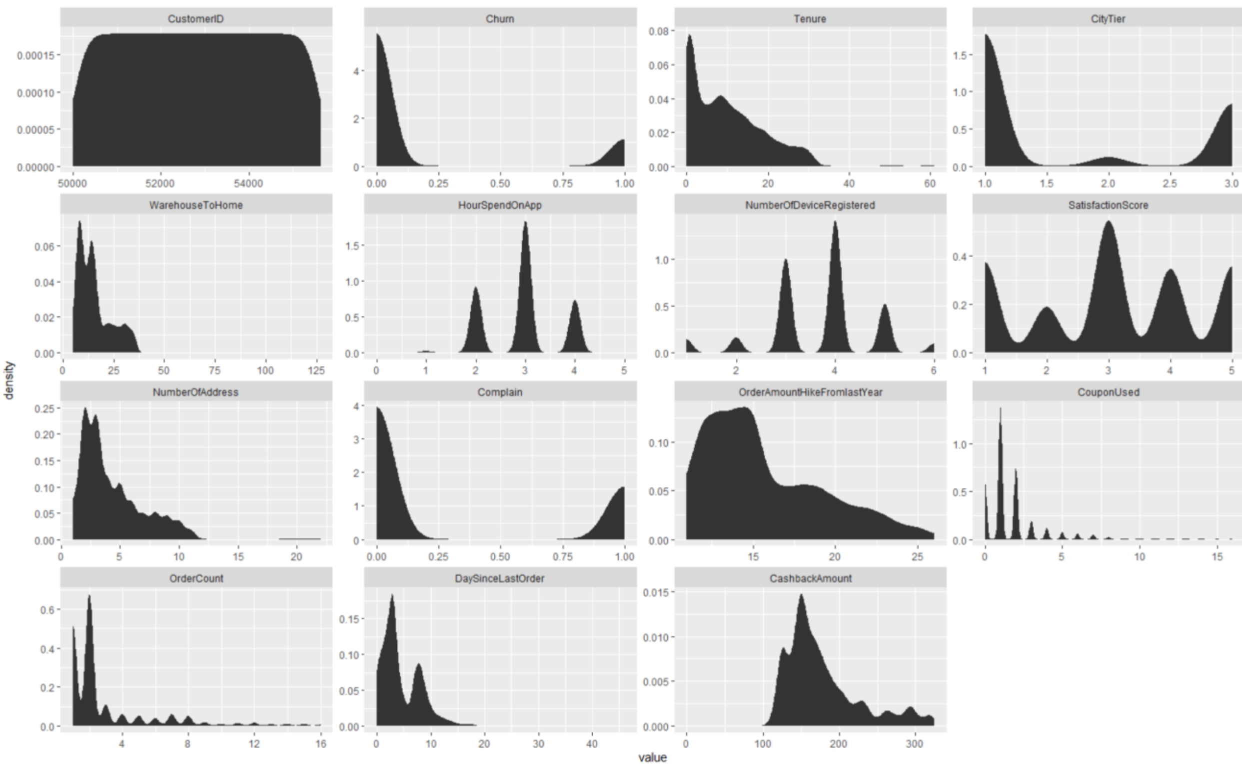


Figure 10

Data Cleaning: Removal of Outliers

CustomerID is removed as it does not provide any information.

Attributes that have outliers:

HourSpendOnApp: The 3 customers who spent 5 hours on the app or website did not churn and will not help in predicting if customers are leaving after spending hours on the app or website. So they are removed.

WarehouseToHome: The 2 customers who live the furthest from the warehouse did not churn so this will not help in predicting if distance from the warehouse could be a reason for customers leaving. So they are removed.

Tenure: The 4 customers who have been with the company for over 50 months have not churned. This will not help in predicting why such loyal customers are leaving. Due to the company being only 4 years old and 50 – 60 months being 4.2 – 5 years these accounts could be belong to founders, employees or even test accounts belonging to the company. So they are removed.

OrderCount: There are quite a few customers who churned even after placing many orders. Only the customers who churned and are OrderCount outliers are kept so we can try to predict what is causing customers to leave even after placing many orders.

CouponUsed: There are quite a few customers who churned after using 4 or more coupons. Only the customers who churned and are CouponUsed outliers are kept so we can try to predict what is causing customers to leave even after using so many coupons. This will also help us to predict if customers are only purchasing from this company when they have a coupon and leaving when there are none available for a long period of time.

NumberOfAddress: 2 out of the 4 outlier customers who had bought from (or sent to) 19 or more addresses churned. Neither one of them are the tenure outliers. The 2 NumberOfAddress outliers that churned are kept to help us predict why they churned after buying from or sending to so many addresses.

DaySinceLastOrder: Only 1 of the outlier customers churned so this will not help us to predict a customer who is about to churn. So they are removed.

NumberOfDeviceRegistered: The outlier value 6 is not too far from the upper quartile of 4 only the outliers that churned are kept.

By keeping some of the outlier customers that churned this also helped to slightly balance the dataset.

Correlation Between all Numerical Variables

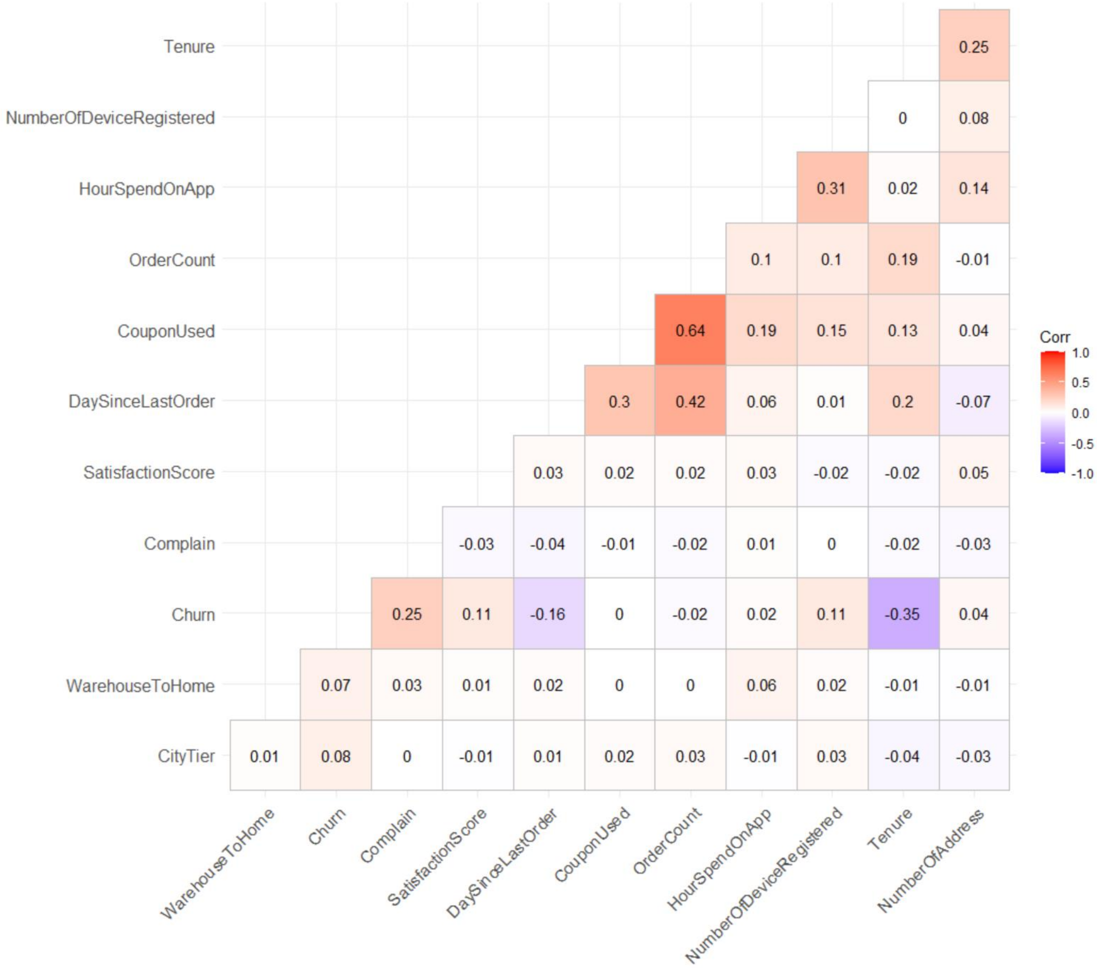


Figure 11

Step 2: Predictive Modelling

Used the predictive modeling process of taking known results to create, process, and validate 3 models used to predict future outcomes.

- Logistic Regression
- Random Forest
- XGBoost
- SVM

Since the dataset does not have a balanced number for Churn (the class label). The dataset was split into train and test sets in a way that preserved the same proportions of examples in each class as observed in the original dataset by using stratified train-test split (Brownlee, 2020).

Unbalanced Training Set Before Feature Selection						
	AUC	ROC	Sensitivity	Specificity	Accuracy	Used Pythagoras Theorem sqrt((1-sensitivity)^2 +(1-specificity) ^{2}) for ROC
Logistic Regression	0.91	0.93	0.62	0.94	0.88	
Logistic Regression 3 CV	0.78	0.93	0.62	0.94	0.88	
Logistic Regression 10 CV	0.78	0.93	0.62	0.94	0.88	
Random Forest	0.93	0.53	0.87	0.99	0.97	
XG Boost	Error Msg	Error Msg	Error Msg	Error Msg	Error Msg	
SVM	0.78	0.93	0.61	0.95	0.88	

Logistic Regression

```
      overall                             names
1  15.4672286                            Tenure
20 13.8074763                          Complain
23 10.8844500                        OrderCount
19  9.5215805                   NumberOfAddress
13  7.8845866 PreferedOrderCatLaptop & Accessory
16  7.1628743                 SatisfactionScore
11  6.6816474          NumberOfDeviceRegistered
25  6.2829319                    CashbackAmount
15  5.4556494            PreferedOrderCatOthers
24  5.2672018                 DaySinceLastOrder
14  5.0062298      PreferedOrderCatMobile Phone
4   4.7985264                   WarehouseToHome
2   4.2586489   PreferredLoginDeviceMobile Phone
9   3.9099808                        GenderMale
18  3.9086288               MaritalStatusSingle
12  3.6013938           PreferedOrderCatGrocery
3   3.5394664                          CityTier
5   3.2852522    PreferredPaymentModeCredit Card
8   1.9978538           PreferredPaymentModeUPI
6   1.9351764     PreferredPaymentModeDebit Card
10  1.5004684                     HourSpendOnApp
17  0.8367842              MaritalStatusMarried
7   0.5932768      PreferredPaymentModeE wallet
21  0.4999718       OrderAmountHikeFromlastYear
22  0.1834274                        CouponUsed
```

Logistic Regression 3 CV

```
                                        Overall
Tenure                                   100.00
Complain                                  94.97
OrderCount                                72.35
NumberOfAddress                           64.70
`PreferedOrderCatLaptop & Accessory`      52.31
SatisfactionScore                         43.91
NumberOfDeviceRegistered                  39.19
CashbackAmount                            37.76
DaySinceLastOrder                         33.87
PreferedOrderCatOthers                    33.58
`PreferedOrderCatMobile Phone`            32.15
WarehouseToHome                           29.66
CityTier                                  22.50
MaritalStatusSingle                       22.44
`PreferredPaymentModeCredit Card`         20.50
`PreferredLoginDeviceMobile Phone`        20.24
GenderMale                                19.45
PreferedOrderCatGrocery                   17.27
PreferredPaymentModeUPI                   13.81
`PreferredPaymentModeDebit Card`          13.19
```

Logistic Regression 10 CV

```
                                        Overall
Tenure                                   100.00
Complain                                  94.97
OrderCount                                72.35
NumberOfAddress                           64.70
`PreferedOrderCatLaptop & Accessory`      52.31
SatisfactionScore                         43.91
NumberOfDeviceRegistered                  39.19
CashbackAmount                            37.76
DaySinceLastOrder                         33.87
PreferedOrderCatOthers                    33.58
`PreferedOrderCatMobile Phone`            32.15
WarehouseToHome                           29.66
CityTier                                  22.50
MaritalStatusSingle                       22.44
`PreferredPaymentModeCredit Card`         20.50
`PreferredLoginDeviceMobile Phone`        20.24
GenderMale                                19.45
PreferedOrderCatGrocery                   17.27
PreferredPaymentModeUPI                   13.81
`PreferredPaymentModeDebit Card`          13.19
```

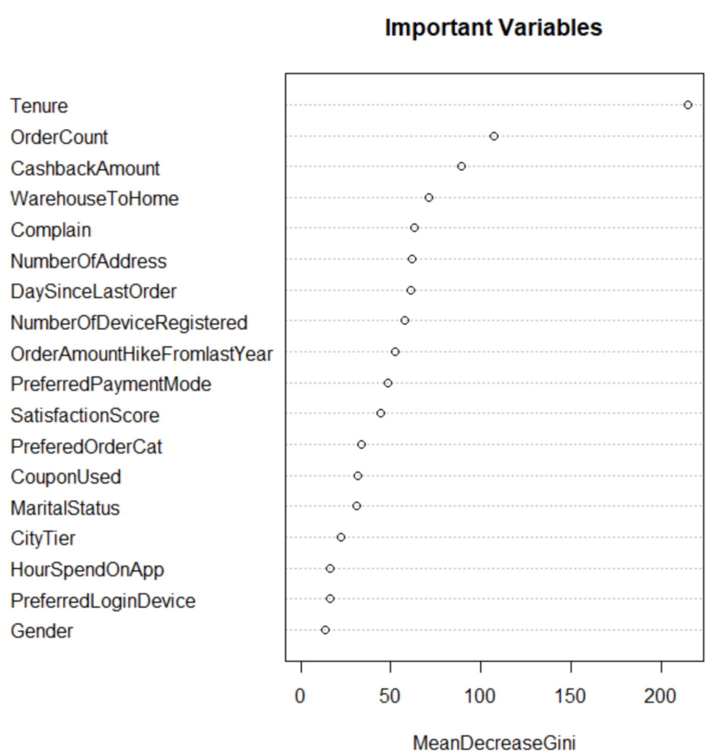
Random Forest

"The out-of-bag (oob) error estimate

In random forests, there is no need for cross-validation or a separate test set to get an unbiased estimate of the test set error. It is estimated internally, during the run, as follows:

Each tree is constructed using a different bootstrap sample from the original data. About one-third of the cases are left out of the bootstrap sample and not used in the construction of the kth tree.

Put each case left out in the construction of the kth tree down the kth tree to get a classification. In this way, a test set classification is obtained for each case in about one-third of the trees. At the end of the run, take j to be the class that got most of the votes every time case n was oob. The proportion of times that j is not equal to the true class of n averaged over all cases is the oob error estimate. This has proven to be unbiased in many tests." (Breiman & Cutler) So cross-validation techniques will not be used for the random forest model.



XGBoost

Still in the process of troubleshooting error messages.

SVM

Performs very well with limited amount of data to analyze.

Still in the process of finding a way to create a table or graph to display the important variables for this model.

Step 3: Post-Predictive Analysis

Due to the dataset being relatively small all the models are overfitting.

Recommendations

At the moment, continuing to collect more data is recommended to prevent this overfitting.

Conclusion

Since collecting more data is not possible for the scope of this project balancing the training set and feature selection will be used to see if it helps with the overfitting.

The training set will be balanced using Safe-Level-SMOTE (Safe-Level-Synthetic Minority Over-Sampling Technique) as some outliers will be kept for some of the attributes.

Attributes will be selected before and after balancing the training set.

The models will be compared by:

1) Unbalanced Training Set Before Feature Selection
2) Unbalanced Training Set After Feature Selection
3) Balanced Training Set Before Feature Selection
4) Balanced Training Set After Feature Selection

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