Group Number 215: Black Friday Sales Prediction

First Name	Last Name	Email (hawk.iit.edu)	Student ID
Siddhi	Kulkarni	skulkarni13@hawk.iit.edu	A20430008
Pooja	Choudhari	cpooja@hawk.iit.edu	A20425832
Sagar	Ippili	sippili@hawk.iit.edu	A20417999

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1. Introduction

Black Friday deals are the most happening events every year in US. Black Friday sales accounts to the highest revenue comparing to a regular day sale of retailers. This event leading to major revenue turnarounds, left us with many questions like amount of purchases by a consumer, kind of products majority of the consumers are interested in. Answers to these questions would help us in detecting the purchase pattern and analyzing the consumer purchase behavior. This can in return award the retailers with predictions for making important business decisions like what category of products are to be increased in the inventory and creative deals to attract more customers along with not losing the old ones.

2. Data

The black Friday dataset is the sample of transactions that are conducted on everyday basis in the Retail store. Here, we focus on knowing the costumer purchasing behavior and create classification models by predicting the amount of purchase (dependent variable) with the help of information in the dataset. The dataset consists of different columns as,

- **Age:** Categorical variable having different age groups as value, example '0-17'.
- **Gender:** Categorical variable having different Gender category as M and F.
- **City Category**: Categorical variable having the cities in three groups like A, B, C.
- **Stay_In_Current_City_Years:** Categorical variable with number of years that particular has been staying like 0,1,2.
- **Marital Status:** Categorical variable having '1' for married and '0' for unmarried.
- **Product_Category (1,2,3):** Numerical variable having specific count of purchased product. (continuous)
- **Purchase:** Numerical variable specifying the amount of purchase made. (continuous)

Link: https://www.kaggle.com/mehdidag/black-friday

3. Problems to be Solved

a) Research Problems:

We have huge data (0.5 million) and using the information, we can find which independent variable has maximum impact on dependent variable.

b) Classification Problems:

Here, the problem is a classification problem since several variables are categorical. Here, we are trying to find the impact of Product Category, Age, Gender, City Category which are dependent variables on the Customer Purchase which is a dependent variable.

c) Hypothesis Testing:

i. Hypothesis 1: Female customers are more likely to purchase more in quantity from products under 'Product_Category_1'.

ii. Hypothesis 2: Customers will purchase different number of products from Product_Category_1 and Product_Category_2.

d) Model related research problems:

i. Finding the relationship between the y-variable and other factors, i.e x-variables.

ii. Identifying which independent variables are significant on the dependent variable '**Purchase**' (y).

iii. Building different classification models on training data (80%) and make predictions on the testing data (20%), followed by comparing the accuracies of the models for choosing the best model.

4. Solutions

a) The dataset needs to be preprocessed for missing values and converting the dependent variable to a nominal variable.

b) As mentioned above, the dataset is huge having number of rows around 0.5 Million. Here, we will find solutions using Hold out evaluation by splitting dataset into training (80%) and testing (20%) datasets.

c) Perform different classification models as mentioned below:

i. Naïve Bayes classification:

- Naïve Bayes classifier is probabilistic learning process.
- To perform Naïve Bayes, we need to transform numerical data to nominal data.
- Libraries for Naïve Bayes: **naivebayes**, **Metrics**
- Features and label:

  Label: Purchase (**1** if $\mu > 9334$ and **0** if $\mu < 9334$)

  Features: Age, Gender, City Category, Stay in current city years, Marital Status, Product_Category_1, Product_Category_2, Product_Category_3

ii. **KNN Classification:**

- KNN classification is simple classification technique.
- For performing KNN we need to convert dependent variable to factor and need to normalize all the numerical variable.
- Libraries for KNN: **dummies**, **class, Metrics**
- Features and label:
  Label: Purchase (**1** if $\mu > 9334$ and **0** if $\mu < 9334$)
  Features: Age, Gender, City Category, Stay in current city years, Marital Status, Product_Category_1, Product_Category_2, Product_Category_3

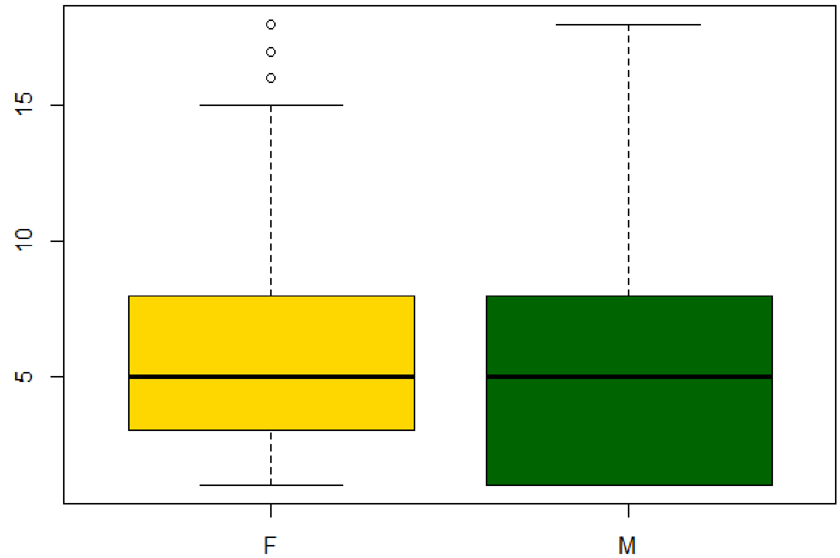
iii. **Logistic Regression:**

- Logistic regression can be performed using KNN dataset or directly the preprocessed data.
- Then build different models and find the accuracy.
- Libraries for Logistic: **caret, Metrics**
- Features and label:
  Label: Purchase (**1** if $\mu > 9334$ and **0** if $\mu < 9334$)
  Features: Age, Gender, City Category, Stay in current city years, Marital Status, Product_Category_1, Product_Category_2, Product_Category_3

d) Performing Hypothesis testing for the claims proposed.

- **Hypothesis 1:** We think that female customers are more likely to purchase more in quantity from products under 'Product_Category_1'.
- **Null Hypothesis (H_0)**: Female customers purchase more than 5 in quantity from products under Product_Category_1.
- **Alternative Hypothesis (H_a):** Female customers purchase less than 5 in quantity from products under Product_Category_1.

We will plot the boxplot to get an idea about the statements:



From the Box-Plot, we can see that the Median(q2) is equal to both the genders and we cannot come to a clear conclusion. Therefore, we will perform Z-test as follows:

```
> z.test(data$Product_Category_1,NULL,alternative = "less",mu = 5,sigma.x = sd(data$Product_Category_1),sigma.y = NULL,conf.level = 0.95)

	One-sample z-Test

data:  data$Product_Category_1
z = 57.774, p-value = 1
alternative hypothesis: true mean is less than 5
95 percent confidence interval:
       NA 5.303961
sample estimates:
mean of x 
 5.295546 
```

From the Z-test performed, we can see that the **p-value > α**, with 95% Confidence interval. Hence, we accept null hypothesis and conclude that Female customers purchase more than 5 in quantity from products under 'Product_Category_1'.

- **<u>Hypothesis 2:</u>** We think that customers will purchase different number of products from Product_Category_1 and Product_Category_2.
  - **Null Hypothesis (H_0)**: Customers will purchase same number of products from both Product_Category_1 and Product_Category_2.

- **Alternative Hypothesis (H_a):** Customers will purchase different number of products from both Product_Category_1 and Product_Category_2.

To perform the hypothesis testing, we will use Z-Test as shown:

```
> z.test(data$Product_Category_1,data$Product_Category_2,alternative="two.sided",
+ mu=0,sigma.x=sd(data$Product_Category_1),sigma.y=sd(data$Product_Category_2),conf.level=0.95)

        Two-sample z-Test

data:  data$Product_Category_1 and data$Product_Category_2
z = -590.05, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -4.561032 -4.530831
sample estimates:
mean of x mean of y
 5.295546  9.841478
```

From the Z-test performed, we can see that the **p-value < α,** with 95% Confidence interval. Hence, we reject null hypothesis and conclude that customers will purchase different number of products from both Product_Category_1 and Product_Category_2.

5. Experiments and Results

5.1. Methods and Process

We are now, going to build different classification models to predict the **Purchase**, which is our dependent variable.

5.1.1 Data Import and Data Preprocessing

1. Import data set to R.

```
> data <- read.csv("BlackFriday.csv", sep=",", header=T)
> data[1:5,]
  User_ID Product_ID Gender  Age Occupation City_Category Stay_In_Current_City_Years
1 1000001  P00069042      F 0-17         10             A                          2
2 1000001  P00248942      F 0-17         10             A                          2
3 1000001  P00087842      F 0-17         10             A                          2
4 1000001  P00085442      F 0-17         10             A                          2
5 1000002  P00285442      M  55+         16             C                         4+
  Marital_Status Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1              0                  3                 NA                 NA     8370
2              0                  1                  6                 14    15200
3              0                 12                 NA                 NA     1422
4              0                 12                 14                 NA     1057
5              0                  8                 NA                 NA     7969
> 
```

2. Replace the missing values in columns,

a. **Product_Category_2:** Replacing the missing values with mean value of the column, i.e. **9.84**.

```
> summary(data$Product_Category_2)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   2.00    5.00    9.00    9.84   15.00   18.00  166986 
> data$Product_Category_2[is.na(data$Product_Category_2)] <- 9.84
> summary(data$Product_Category_2)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  2.000   8.000   9.840   9.841  14.000  18.000 
>
```

b. **Product_Category_3:** Replacing the missing values with mean value of the column, i.e. **12.7**.

```
> summary(data$Product_Category_3)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
    3.0     9.0    14.0    12.7    16.0    18.0  373299 
> data$Product_Category_3[is.na(data$Product_Category_3)] <- 12.7
> summary(data$Product_Category_3)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   3.00   12.70   12.70   12.69   12.70   18.00 
>
```

3. Ignoring the columns '**User_ID**' and '**Product_ID**', because they are unique to themselves and have no impact on our dependent variable **'Purchase'**, followed by creating a new data set for further building classification models.

```
> data<-subset(data,select = -User_ID)
> data<-subset(data,select = -Product_ID)
> data[1:3,]
  Gender  Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F 0-17         10             A                          2              0
2      F 0-17         10             A                          2              0
3      F 0-17         10             A                          2              0
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1                  3               9.84               12.7     8370
2                  1               6.00               14.0    15200
3                 12               9.84               12.7     1422
>
```

5.1.2 Build Classification Models

1) Naïve-Bayes Classification Model:

a. Clone the data set to a new variable, '**data_nb**' to use for building Naïve-Bayes classification model.

```
> data_nb<-data
> data_nb[1:5,]
  Gender  Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F 0-17         10             A                          2              0
2      F 0-17         10             A                          2              0
3      F 0-17         10             A                          2              0
4      F 0-17         10             A                          2              0
5      M  55+         16             C                         4+              0
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1                  3               9.84               12.7     8370
2                  1               6.00               14.0    15200
3                 12               9.84               12.7     1422
4                 12              14.00               12.7     1057
5                  8               9.84               12.7     7969
>
```

b. Transform the '**Purchase**' variable into a dummy variable which has two values, i.e. **1** and **0**. Here, **1** means higher purchase [i.e. >Mean Value] amount and **0** means lower purchase [i.e. <Mean Value] amount made by a customer.

```
> summary(data_nb$Purchase)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    185    5866    8062    9334   12073   23961
> data_nb$Purchase<-ifelse(data_nb$Purchase>9334,1,0)
> data_nb$Purchase<-as.factor(data_nb$Purchase)
> head(data_nb$Purchase)
[1] 0 1 0 0 0 1
Levels: 0 1
>
```

c. Group the numerical variables using the **cut ()**, i.e.

I. 'Product_Category_1':

```
> summary(data_nb$Product_Category_1)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   1.000   5.000   5.296   8.000  18.000
> data_nb$Product_Category_1<-cut(data_nb$Product_Category_1,3)
> head(data_nb$Product_Category_1)
[1] (0.983,6.67] (0.983,6.67] (6.67,12.3]  (6.67,12.3]  (6.67,12.3]  (0.983,6.67]
Levels: (0.983,6.67] (6.67,12.3] (12.3,18]
```

II. 'Product_Category_2':

```
> summary(data_nb$Product_Category_2)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  2.000   8.000   9.840   9.841  14.000  18.000
> data_nb$Product_Category_2<-cut(data_nb$Product_Category_2,4)
> head(data_nb$Product_Category_2)
[1] (6,10]    (1.98,6] (6,10]    (10,14]  (6,10]    (1.98,6]
Levels: (1.98,6] (6,10] (10,14] (14,18]
>
```

III. 'Product_Category_3':

```
> summary(data_nb$Product_Category_3)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   3.00   12.70   12.70   12.69   12.70   18.00
> data_nb$Product_Category_3<-cut(data_nb$Product_Category_3,4)
> head(data_nb$Product_Category_3)
[1] (10.5,14.2] (10.5,14.2] (10.5,14.2] (10.5,14.2] (10.5,14.2] (10.5,14.2]
Levels: (2.98,6.75] (6.75,10.5] (10.5,14.2] (14.2,18]
>
```

d. Check the entire data set after grouping

```
> head(data_nb)
  Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F  0-17         10             A                          2              0
2      F  0-17         10             A                          2              0
3      F  0-17         10             A                          2              0
4      F  0-17         10             A                          2              0
5      M   55+         16             C                         4+              0
6      M 26-35         15             A                          3              0
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1       (0.983,6.67]             (6,10]        (10.5,14.2]        0
2       (0.983,6.67]           (1.98,6]        (10.5,14.2]        1
3        (6.67,12.3]             (6,10]        (10.5,14.2]        0
4        (6.67,12.3]            (10,14]        (10.5,14.2]        0
5        (6.67,12.3]             (6,10]        (10.5,14.2]        0
6       (0.983,6.67]           (1.98,6]        (10.5,14.2]        1
> 
```

e. Dataset being very large (approx. 500 thousand records), we will split data into train data and test data for hold-out evaluation later.

```
> index.data_nb<-sample(1:nrow(data_nb),size=round(0.8*nrow(data_nb)))
> train.data_nb<-data_nb[index.data_nb,]
> test.data_nb<-data_nb[-index.data_nb,]
> head(train.data_nb)
       Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
170762      M 36-45          2             A                          2              0
11935       M 26-35          0             C                          1              0
305395      M 46-50         12             C                          1              1
487998      M 36-45         17             C                          3              0
159734      M 18-25          0             B                          1              0
390377      F 46-50         16             A                          1              1
       Product_Category_1 Product_Category_2 Product_Category_3 Purchase
170762        (6.67,12.3]            (10,14]        (10.5,14.2]        0
11935        (0.983,6.67]            (14,18]        (10.5,14.2]        1
305395        (6.67,12.3]             (6,10]        (10.5,14.2]        0
487998        (6.67,12.3]             (6,10]        (10.5,14.2]        0
159734       (0.983,6.67]             (6,10]        (10.5,14.2]        1
390377       (0.983,6.67]            (10,14]        (10.5,14.2]        0
> head(tes.data_nb)
Error in head(tes.data_nb) : object 'tes.data_nb' not found
> head(test.data_nb)
   Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
2       F  0-17         10             A                          2              0
4       F  0-17         10             A                          2              0
19      M 36-45          1             B                          1              1
21      M 26-35         12             C                         4+              1
28      M 26-35         17             C                          0              0
30      F 36-45          1             B                         4+              1
   Product_Category_1 Product_Category_2 Product_Category_3 Purchase
2        (0.983,6.67]           (1.98,6]        (10.5,14.2]        1
4         (6.67,12.3]            (10,14]        (10.5,14.2]        0
19       (0.983,6.67]            (10,14]          (14.2,18]        1
21       (0.983,6.67]            (10,14]        (10.5,14.2]        0
28       (0.983,6.67]            (10,14]        (10.5,14.2]        0
30       (0.983,6.67]           (1.98,6]        (6.75,10.5]        1
> 
```

f. Build the Naïve-Bayes classification model.

```
> model_nb<-naive_bayes(Purchase~.,train.data_nb)
> pred_nb<-predict(model_nb,test.data_nb)
> head(predict(model_nb,test.data_nb,type="prob"))
             0          1
[1,] 0.4773295 0.52267053
[2,] 0.9418721 0.05812791
[3,] 0.5076089 0.49239106
[4,] 0.7416757 0.25832425
[5,] 0.7383431 0.26165689
[6,] 0.1365317 0.86346833
> library(Metrics)
> accuracy(test.data_nb$Purchase,pred_nb)
[1] 0.7089057
> |
```

From the Naïve-Bayes model, we can see that the accuracy is **0.7089057**.

g. Try building different Naïve-Bayes classification models by categorizing the numerical variables in to different number of groups using the 'cut ()'.

I. Product_Category_1 with 3, Product_Category_2 with 2 and Product_Category_3 with 4 groups each.

```
> data_nb<-data
> data_nb<-subset(data,select = -User_ID)
> data_nb<-subset(data_nb,select = -Product_ID)
> data_nb$Purchase<-ifelse(data_nb$Purchase>9334,1,0)
> data_nb$Purchase<-as.factor(data_nb$Purchase)
> head(data_nb)
  Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F  0-17         10             A                          2              0
2      F  0-17         10             A                          2              0
3      F  0-17         10             A                          2              0
4      F  0-17         10             A                          2              0
5      M   55+         16             C                         4+              0
6      M 26-35         15             A                          3              0
> data_nb$Occupation<-as.factor(data$Occupation)
> data_nb$Marital_Status<-as.factor(data_nb$Marital_Status)
> data_nb$Product_Category_1<-cut(data_nb$Product_Category_1,3)
> data_nb$Product_Category_2<-cut(data_nb$Product_Category_2,2)
> data_nb$Product_Category_3<-cut(data_nb$Product_Category_3,4)
> index.data_nb<-sample(1:nrow(data_nb),size=round(0.8*nrow(data_nb)))
> train.data_nb<-data_nb[index.data_nb,]
> test.data_nb<-data_nb[-index.data_nb,]
> model_nb<-naive_bayes(Purchase~.,train.data_nb)
> pred<-predict(model_nb,test.data_nb)
> head(predict(model_nb,test.data_nb,type="prob"))
             0         1
[1,] 0.2617788 0.7382212
[2,] 0.6622482 0.3377518
[3,] 0.8389146 0.1610854
[4,] 0.7349300 0.2650700
[5,] 0.3308822 0.6691178
[6,] 0.7090515 0.2909485
> accuracy(test.data_nb$Purchase,pred)
[1] 0.6986467
```

From the above Naïve-Bayes model, we can see that the accuracy is <u>0.6986467</u>.

II. **Product_Category_1 with 6, Product_Category_2 with 6 and Product_Category_3 with 2 groups each.**

```
> data_nb<-data_nb_new
> data_nb$Product_Category_2<-cut(data_nb$Product_Category_2,6)
> data_nb$Product_Category_3<-cut(data_nb$Product_Category_3,6)
> data_nb$Product_Category_1<-cut(data_nb$Product_Category_1,2)
> index.data_nb<-sample(1:nrow(data_nb),size=round(0.8*nrow(data_nb)))
> train.data_nb<-data_nb[index.data_nb,]
> test.data_nb<-data_nb[-index.data_nb,]
> model_nb<-naive_bayes(Purchase~.,train.data_nb)
> pred<-predict(model_nb,test.data_nb)
> accuracy(test.data_nb$Purchase,pred)
[1] 0.7030089
```

From the above Naïve-Bayes model, we can see that the accuracy is 0.7030089.

III. **Product_Category_1 with 8, Product_Category_2 with 8 and Product_Category_3 with 6 groups each.**

```
> data_nb<-data_nb_new
> data_nb$Product_Category_3<-cut(data_nb$Product_Category_3,8)
> data_nb$Product_Category_2<-cut(data_nb$Product_Category_2,8)
> data_nb$Product_Category_1<-cut(data_nb$Product_Category_1,6)
> index.data_nb<-sample(1:nrow(data_nb),size=round(0.8*nrow(data_nb)))
> train.data_nb<-data_nb[index.data_nb,]
> test.data_nb<-data_nb[-index.data_nb,]
> model_nb<-naive_bayes(Purchase~.,train.data_nb)
> pred<-predict(model_nb,test.data_nb)
> accuracy(test.data_nb$Purchase,pred)
[1] 0.7899735
```

From the above Naïve-Bayes model, we can see that the accuracy is 0.7899735.

IV. **Product_Category_1 with 8, Product_Category_2 with 8 and Product_Category_3 with 8 groups each.**

```
> data_nb<-data_nb_new
> data_nb$Product_Category_3<-cut(data_nb$Product_Category_3,8)
> data_nb$Product_Category_2<-cut(data_nb$Product_Category_2,8)
> data_nb$Product_Category_1<-cut(data_nb$Product_Category_1,8)
> index.data_nb<-sample(1:nrow(data_nb),size=round(0.8*nrow(data_nb)))
> train.data_nb<-data_nb[index.data_nb,]
> test.data_nb<-data_nb[-index.data_nb,]
> model_nb<-naive_bayes(Purchase~.,train.data_nb)
> pred<-predict(model_nb,test.data_nb)
> accuracy(test.data_nb$Purchase,pred)
[1] 0.8362275
```

From the above Naïve-Bayes model, we can see that the accuracy is 0.8362275.

From the above built different Naïve-Bayes models, we can achieve a highest accuracy of **0.8362275**. Hence, we can consider this model as the best among the Naïve-Bayes Classification models built above.

2) KNN classification Model:

a. Clone the data set to a new variable, ‘data_knn’ to use for building KNN classification model.

```
> data_knn<-data
> data_knn[1:5,]
  Gender  Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F 0-17         10             A                          2              0
2      F 0-17         10             A                          2              0
3      F 0-17         10             A                          2              0
4      F 0-17         10             A                          2              0
5      M  55+         16             C                         4+              0
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1                  3               9.84               12.7     8370
2                  1               6.00               14.0    15200
3                 12               9.84               12.7     1422
4                 12              14.00               12.7     1057
5                  8               9.84               12.7     7969
> |
```

b. Transform the ‘**Purchase**’ variable into a dummy variable which has two values, i.e **1** and **0**. Here, **1** means higher purchase [i.e >Mean Value] amount and **0** means lower purchase [i.e <Mean Value] amount made by a customer.

```
> summary(data_knn$Purchase)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    185    5866    8062    9334   12073   23961
> data_knn$Purchase<-ifelse(data_knn$Purchase>9334,1,0)
> data_knn$Purchase<-as.factor(data_knn$Purchase)
> head(data_knn$Purchase)
[1] 0 1 0 0 0 1
Levels: 0 1
> |
```

c. Create the dummy variables to the categorical variables ‘Gender’, ‘Age’, ‘Occupation’, ‘City_Category’, ‘Stay_In_Current_City_Years’, ‘Marital_Status’.

```
> library(dummies)
dummies-1.5.6 provided by Decision Patterns

> data_knn<-dummy.data.frame(data_knn,names=c("Gender","Age","Occupation","City_Category","Stay_In_Current_City_Years","Marital_Status"))
> head(data_knn)
  GenderF GenderM Age0-17 Age18-25 Age26-35 Age36-45 Age46-50 Age51-55 Age55+ Occupation0 Occupation1 Occupation2 Occupation3 Occupation4
1       1       0       1        0        0        0        0        0      0           0           0           0           0           0
2       1       0       1        0        0        0        0        0      0           0           0           0           0           0
3       1       0       1        0        0        0        0        0      0           0           0           0           0           0
4       1       0       1        0        0        0        0        0      0           0           0           0           0           0
5       0       1       0        0        0        0        0        0      1           0           0           0           0           0
6       0       1       0        0        1        0        0        0      0           0           0           0           0           0
  Occupation7 Occupation8 Occupation9 Occupation10 Occupation11 Occupation12 Occupation13 Occupation14 Occupation15 Occupation16 Occupati
1           0           0           0            1            0            0            0            0            0            0
2           0           0           0            1            0            0            0            0            0            0
3           0           0           0            1            0            0            0            0            0            0
4           0           0           0            1            0            0            0            0            0            0
5           0           0           0            0            0            0            0            0            0            1
6           0           0           0            0            0            0            0            0            1            0
  Occupation19 Occupation20 City_CategoryA City_CategoryB City_CategoryC Stay_In_Current_City_Years0 Stay_In_Current_City_Years1 Stay_In_(
1            0            0              1              0              0                           0                           0
2            0            0              1              0              0                           0                           0
3            0            0              1              0              0                           0                           0
4            0            0              1              0              0                           0                           0
5            0            0              0              0              1                           0                           0
```

d. Extract numerical variables and normalize the selected data [scaling].

```
> numeric.vars.knn = sapply(data_knn,is.numeric)
> data_knn[numeric.vars.knn] <- lapply(data_knn[numeric.vars.knn],scale)
> head(data_knn)
     GenderF    GenderM    Age0-17   Age18-25   Age26-35   Age36-45   Age46-50
1  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.4999519 -0.3005111
2  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.4999519 -0.3005111
3  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.4999519 -0.3005111
4  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.4999519 -0.3005111
5 -0.5710567  0.5710567 -0.1677122 -0.4710879 -0.8154179 -0.4999519 -0.3005111
6 -0.5710567  0.5710567 -0.1677122 -0.4710879  1.2263628 -0.4999519 -0.3005111
  Occupation5 Occupation6 Occupation7 Occupation8 Occupation9 Occupation10 Occu
1   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025    6.4488003   -
2   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025    6.4488003   -
3   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025    6.4488003   -
4   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025    6.4488003   -
5   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025   -0.1550673   -
6   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025   -0.1550673   -
  Occupation18 Occupation19 Occupation20 City_CategoryA City_CategoryB City_Ca
1   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0.8532733      -0.
2   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0.8532733      -0.
3   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0.8532733      -0.
4   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0.8532733      -0.
5   -0.1108463   -0.1256246   -0.2553648     -0.6067059     -0.8532733       1.
6   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0.8532733      -0.
  Stay_In_Current_City_Years2 Stay_In_Current_City_Years3 Stay_In_Current_City_
1                   2.0988099                  -0.4582973                     -
2                   2.0988099                  -0.4582973                     -
3                   2.0988099                  -0.4582973                     -
4                   2.0988099                  -0.4582973                     -
5                  -0.4764596                  -0.4582973                      
6                  -0.4764596                   2.1819857                     -
  Product_Category_3 Purchase
1        0.004042377        0
2        0.574222766        1
3        0.004042377        0
```

e. Dataset being very large (approx. 500 thousand records), we will split data into train data and test data for hold-out evaluation later.

```
> set.seed(123)
> test.index<-1:107515
> train.data_knn<-data_knn[-test.index,]
> test.data_knn<-data_knn[test.index,]
> train.Purchase<-data_knn$Purchase[-test.index]
> test.Purchase<-data_knn$Purchase[test.index]
> head(train.data_knn)
          GenderF   GenderM    Age0-17   Age18-25   Age26-35
107516 -0.5710567 0.5710567 -0.1677122 -0.4710879 -0.8154179
107517 -0.5710567 0.5710567 -0.1677122 -0.4710879 -0.8154179
107518 -0.5710567 0.5710567 -0.1677122 -0.4710879  1.2263628
107519 -0.5710567 0.5710567 -0.1677122 -0.4710879  1.2263628
107520 -0.5710567 0.5710567 -0.1677122 -0.4710879  1.2263628
107521 -0.5710567 0.5710567 -0.1677122 -0.4710879  1.2263628
       Occupation5 Occupation6 Occupation7 Occupation8 Occupa
107516   -0.151006  -0.1956641   2.8809129 -0.05331976   -0.10
107517   -0.151006  -0.1956641   2.8809129 -0.05331976   -0.10
107518   -0.151006  -0.1956641  -0.3471115 -0.05331976   -0.10
107519   -0.151006  -0.1956641  -0.3471115 -0.05331976   -0.10
107520   -0.151006  -0.1956641  -0.3471115 -0.05331976   -0.10
107521   -0.151006  -0.1956641  -0.3471115 -0.05331976   -0.10
       Occupation17 Occupation18 Occupation19 Occupation20 Ci
107516   -0.2800306   -0.1108463   -0.1256246   -0.2553648
107517   -0.2800306   -0.1108463   -0.1256246   -0.2553648
107518   -0.2800306   -0.1108463   -0.1256246   -0.2553648
107519   -0.2800306   -0.1108463   -0.1256246   -0.2553648
107520   -0.2800306   -0.1108463   -0.1256246   -0.2553648
```

```
> head(test.data_knn)
    GenderF    GenderM    Age0-17   Age18-25   Age26-35    Age
1  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.49
2  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.49
3  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.49
4  1.7511363 -1.7511363  5.9625827 -0.4710879 -0.8154179 -0.49
5 -0.5710567  0.5710567 -0.1677122 -0.4710879 -0.8154179 -0.49
6 -0.5710567  0.5710567 -0.1677122 -0.4710879  1.2263628 -0.49
  Occupation5 Occupation6 Occupation7 Occupation8 Occupation9
1   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
2   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
3   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
4   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
5   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
6   -0.151006  -0.1956641  -0.3471115 -0.05331976  -0.1076025
  Occupation18 Occupation19 Occupation20 City_CategoryA City_C
1   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0
2   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0
3   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0
4   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0
5   -0.1108463   -0.1256246   -0.2553648     -0.6067059     -0
6   -0.1108463   -0.1256246   -0.2553648      1.6482419     -0
  Stay_In_Current_City_Years2 Stay_In_Current_City_Years3 Stay
1                   2.0988099                  -0.4582973
2                   2.0988099                  -0.4582973
3                   2.0988099                  -0.4582973
4                   2.0988099                  -0.4582973
```

f. Calculate the Accuracy of the KNN Classification models and find the best model.

```
> library(Metrics)
> accuracy(test.Purchase,knn.1)
[1] 0.9862159
> knn.5<-knn(train.data_knn,test.data_knn,train.Purchase,k=5)
> accuracy(test.Purchase,knn.5)
[1] 0.9556248
> knn.15<-knn(train.data_knn,test.data_knn,train.Purchase,k=15)
> accuracy(test.Purchase,knn.15)
[1] 0.910366
```

The largest accuracy of the KNN model is **0.9862** at **K=1**.

3) Logistic Regression Model:

a. Clone the data set to a new variable, 'data_lg' to use for building Logistic Regression model

```
> data_lg<-data
> data_lg[1:5,]
  Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F  0-17         10             A                          2              0
2      F  0-17         10             A                          2              0
3      F  0-17         10             A                          2              0
4      F  0-17         10             A                          2              0
5      M   55+         16             C                         4+              0
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1                  3               9.84               12.7     8370
2                  1               6.00               14.0    15200
3                 12               9.84               12.7     1422
4                 12              14.00               12.7     1057
5                  8               9.84               12.7     7969
> 
```

b. Transform the '**Purchase**' variable into a dummy variable which has two values, i.e **1** and **0**. Here, **1** means higher purchase [i.e >Mean Value] amount and **0** means lower purchase [i.e <Mean Value] amount made by a customer.

```
> summary(data_lg$Purchase)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    185    5866    8062    9334   12073   23961 
> data_lg$Purchase<-ifelse(data_lg$Purchase>9334,1,0)
> data_lg$Purchase<-as.factor(data_lg$Purchase)
> head(data_lg$Purchase)
[1] 0 1 0 0 0 1
Levels: 0 1
> 
```

c. Split data into train data and test data.

```
> train.index<-createDataPartition(data_lg$Purchase,p=0.8,list=FALSE)
> train.data_lg<-data_lg[train.index,]
> test.data_lg<-data_lg[-train.index,]
> head(train.data_lg)
  Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
1      F  0-17         10             A                          2              0
3      F  0-17         10             A                          2              0
4      F  0-17         10             A                          2              0
6      M 26-35         15             A                          3              0
7      M 46-50          7             B                          2              1
8      M 46-50          7             B                          2              1
  Product_Category_1 Product_Category_2 Product_Category_3 Purchase
1                  3               9.84               12.7        0
3                 12               9.84               12.7        0
4                 12              14.00               12.7        0
6                  1               2.00               12.7        1
7                  1               8.00               17.0        1
8                  1              15.00               12.7        1
> head(test.data_lg)
   Gender   Age Occupation City_Category Stay_In_Current_City_Years Marital_Status
2       F  0-17         10             A                          2              0
5       M   55+         16             C                         4+              0
14      M 26-35         20             A                          1              1
22      M 26-35         12             C                         4+              1
26      M 26-35         17             C                          0              0
30      F 36-45          1             B                         4+              1
   Product_Category_1 Product_Category_2 Product_Category_3 Purchase
2                   1               6.00               14.0        1
5                   8               9.84               12.7        0
14                  1               2.00                5.0        1
22                  8               9.84               12.7        1
26                  6               8.00               12.7        1
30                  2               4.00                8.0        1
> 
```

d. Build full logistic model using ‘glm()’.

```
> model_lg_full<-glm(as.factor(Purchase)~.,data=train.data_lg,family=binomial())
> summary(model_lg_full)

Call:
glm(formula = as.factor(Purchase) ~ ., family = binomial(), data = train.data_lg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6622  -0.9797  -0.7115   1.0496   2.4619

Coefficients:
                              Estimate Std. Error  z value Pr(>|z|)
(Intercept)                  0.3255572  0.0291102   11.184  < 2e-16 ***
GenderM                      0.2224393  0.0078314   28.404  < 2e-16 ***
Age18-25                     0.1153657  0.0215789    5.346 8.98e-08 ***
Age26-35                     0.1945145  0.0209692    9.276  < 2e-16 ***
Age36-45                     0.2572174  0.0215513   11.935  < 2e-16 ***
Age46-50                     0.2499432  0.0236833   10.554  < 2e-16 ***
Age51-55                     0.3814411  0.0241499   15.795  < 2e-16 ***
Age55+                       0.3456951  0.0264662   13.062  < 2e-16 ***
Occupation                   0.0023126  0.0005136    4.502 6.72e-06 ***
City_CategoryB               0.0651329  0.0082552    7.890 3.02e-15 ***
City_CategoryC               0.2675380  0.0088579   30.203  < 2e-16 ***
Stay_In_Current_City_Years1  0.0159197  0.0106084    1.501 0.133440
Stay_In_Current_City_Years2  0.0184713  0.0118245    1.562 0.118262
Stay_In_Current_City_Years3 -0.0022555  0.0120262   -0.188 0.851233
Stay_In_Current_City_Years4+ 0.0322954  0.0123173    2.622 0.008743 **
Marital_Status              -0.0245683  0.0071527   -3.435 0.000593 ***
Product_Category_1          -0.1728760  0.0011102 -155.722  < 2e-16 ***
Product_Category_2          -0.0486791  0.0008902  -54.686  < 2e-16 ***
Product_Category_3           0.0073419  0.0014769    4.971 6.65e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 579321  on 430061  degrees of freedom
Residual deviance: 529299  on 430043  degrees of freedom
AIC: 529337

Number of Fisher Scoring iterations: 4

>
```

e. Build a base model with one x-variable.

```
> model_lg_base<-glm(as.factor(Purchase)~Gender,data=train.data_lg,family=binomial())
> summary(model_lg_base)

Call:
glm(formula = as.factor(Purchase) ~ Gender, family = binomial(),
    data = train.data_lg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0405  -1.0405  -0.9281   1.3208   1.4491

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.619282   0.006449  -96.03   <2e-16 ***
GenderM      0.288398   0.007366   39.15   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 579321  on 430061  degrees of freedom
Residual deviance: 577765  on 430060  degrees of freedom
AIC: 577769

Number of Fisher Scoring iterations: 4
```

f. Build a stepwise forward model.

```
> model_lg_fwd<-step(model_lg_base,scope=list(upper=model_lg_full,lower=~1),direction="forward",trace=T)
Start:  AIC=577769.4
as.factor(Purchase) ~ Gender

                          Df Deviance    AIC
+ Product_Category_1       1   534227 534233
+ Product_Category_2       1   559375 559381
+ City_Category            2   576216 576224
+ Product_Category_3       1   576723 576729
+ Age                      6   577612 577628
+ Occupation               1   577699 577705
+ Stay_In_Current_City_Years  4   577739 577751
<none>                         577765 577769
+ Marital_Status           1   577765 577771

Step:  AIC=534232.8
as.factor(Purchase) ~ Gender + Product_Category_1

                          Df Deviance    AIC
+ Product_Category_2       1   531142 531150
+ City_Category            2   533015 533025
+ Age                      6   533594 533612
+ Product_Category_3       1   534066 534074
+ Occupation               1   534169 534177
+ Marital_Status           1   534205 534213
+ Stay_In_Current_City_Years  4   534203 534217
<none>                         534227 534233

Step:  AIC=531149.6
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2

                          Df Deviance    AIC
+ City_Category            2   529914 529926
+ Age                      6   530434 530454
+ Occupation               1   531080 531090
+ Product_Category_3       1   531112 531122
+ Marital_Status           1   531117 531127
+ Stay_In_Current_City_Years  4   531116 531132
```

```
<none>                            531142 531150

Step:  AIC=529926.4
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category

                             Df Deviance    AIC
+ Age                         6   529367 529391
+ Occupation                  1   529871 529885
+ Product_Category_3          1   529885 529899
+ Marital_Status              1   529901 529915
+ Stay_In_Current_City_Years  4   529899 529919
<none>                            529914 529926

Step:  AIC=529391.4
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category + Age

                             Df Deviance    AIC
+ Product_Category_3          1   529343 529369
+ Occupation                  1   529347 529373
+ Marital_Status              1   529356 529382
+ Stay_In_Current_City_Years  4   529355 529387
<none>                            529367 529391

Step:  AIC=529368.6
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category + Age + Product_Category_3

                             Df Deviance    AIC
+ Occupation                  1   529322 529350
+ Marital_Status              1   529331 529359
+ Stay_In_Current_City_Years  4   529331 529365
<none>                            529343 529369

Step:  AIC=529350.1
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category + Age + Product_Category_3 + Occupation


                             Df Deviance    AIC
+ Marital_Status              1   529310 529340
+ Stay_In_Current_City_Years  4   529310 529346
<none>                            529322 529350

Step:  AIC=529340.3
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category + Age + Product_Category_3 + Occupation + Marital_Status

                             Df Deviance    AIC
+ Stay_In_Current_City_Years  4   529299 529337
<none>                            529310 529340

Step:  AIC=529336.5
as.factor(Purchase) ~ Gender + Product_Category_1 + Product_Category_2 +
    City_Category + Age + Product_Category_3 + Occupation + Marital_Status +
    Stay_In_Current_City_Years
```

```
> summary(model_lg_fwd)

Call:
glm(formula = as.factor(Purchase) ~ Gender + Product_Category_1 +
    Product_Category_2 + City_Category + Age + Product_Category_3 +
    Occupation + Marital_Status + Stay_In_Current_City_Years,
    family = binomial(), data = train.data_lg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6622  -0.9797  -0.7115   1.0496   2.4619

Coefficients:
                              Estimate Std. Error  z value Pr(>|z|)
(Intercept)                  0.3255572  0.0291102   11.184  < 2e-16 ***
GenderM                      0.2224393  0.0078314   28.404  < 2e-16 ***
Product_Category_1          -0.1728760  0.0011102 -155.722  < 2e-16 ***
Product_Category_2          -0.0486791  0.0008902  -54.686  < 2e-16 ***
City_CategoryB               0.0651329  0.0082552    7.890 3.02e-15 ***
City_CategoryC               0.2675380  0.0088579   30.203  < 2e-16 ***
Age18-25                     0.1153657  0.0215789    5.346 8.98e-08 ***
Age26-35                     0.1945145  0.0209692    9.276  < 2e-16 ***
Age36-45                     0.2572174  0.0215513   11.935  < 2e-16 ***
Age46-50                     0.2499432  0.0236833   10.554  < 2e-16 ***
Age51-55                     0.3814411  0.0241499   15.795  < 2e-16 ***
Age55+                       0.3456951  0.0264662   13.062  < 2e-16 ***
Product_Category_3           0.0073419  0.0014769    4.971 6.65e-07 ***
Occupation                   0.0023126  0.0005136    4.502 6.72e-06 ***
Marital_Status              -0.0245683  0.0071527   -3.435 0.000593 ***
Stay_In_Current_City_Years1  0.0159197  0.0106084    1.501 0.133440
Stay_In_Current_City_Years2  0.0184713  0.0118245    1.562 0.118262
Stay_In_Current_City_Years3 -0.0022555  0.0120262   -0.188 0.851233
Stay_In_Current_City_Years4+ 0.0322954  0.0123173    2.622 0.008743 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 579321  on 430061  degrees of freedom
Residual deviance: 529299  on 430043  degrees of freedom
AIC: 529337

Number of Fisher Scoring iterations: 4

>
```

g. Build a stepwise backward model using the full model built previously.

```
> model_lg_bwd<-step(model_lg_full,direction="backward",trace=T)
Start:  AIC=529336.5
as.factor(Purchase) ~ Gender + Age + Occupation + City_Category +
    Stay_In_Current_City_Years + Marital_Status + Product_Category_1 +
    Product_Category_2 + Product_Category_3

                             Df Deviance    AIC
<none>                            529299 529337
- Stay_In_Current_City_Years  4   529310 529340
- Marital_Status              1   529310 529346
- Occupation                  1   529319 529355
- Product_Category_3          1   529323 529359
- Age                         6   529816 529842
- Gender                      1   530112 530148
- City_Category               2   530352 530386
- Product_Category_2          1   532321 532357
- Product_Category_1          1   557414 557450
> summary(model_lg_bwd)

Call:
glm(formula = as.factor(Purchase) ~ Gender + Age + Occupation +
    City_Category + Stay_In_Current_City_Years + Marital_Status +
    Product_Category_1 + Product_Category_2 + Product_Category_3,
    family = binomial(), data = train.data_lg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6622  -0.9797  -0.7115   1.0496   2.4619

Coefficients:
                              Estimate Std. Error  z value Pr(>|z|)
(Intercept)                  0.3255572  0.0291102   11.184  < 2e-16 ***
GenderM                      0.2224393  0.0078314   28.404  < 2e-16 ***
Age18-25                     0.1153657  0.0215789    5.346 8.98e-08 ***
Age26-35                     0.1945145  0.0209692    9.276  < 2e-16 ***
Age36-45                     0.2572174  0.0215513   11.935  < 2e-16 ***
Age46-50                     0.2499432  0.0236833   10.554  < 2e-16 ***
Age51-55                     0.3814411  0.0241499   15.795  < 2e-16 ***
Age55+                       0.3456951  0.0264662   13.062  < 2e-16 ***
Occupation                   0.0023126  0.0005136    4.502 6.72e-06 ***
City_CategoryB               0.0651329  0.0082552    7.890 3.02e-15 ***
City_CategoryC               0.2675380  0.0088579   30.203  < 2e-16 ***
Stay_In_Current_City_Years1  0.0159197  0.0106084    1.501 0.133440
Stay_In_Current_City_Years2  0.0184713  0.0118245    1.562 0.118262
Stay_In_Current_City_Years3 -0.0022555  0.0120262   -0.188 0.851233
Stay_In_Current_City_Years4+ 0.0322954  0.0123173    2.622 0.008743 **
Marital_Status              -0.0245683  0.0071527   -3.435 0.000593 ***
Product_Category_1          -0.1728760  0.0011102 -155.722  < 2e-16 ***
Product_Category_2          -0.0486791  0.0008902  -54.686  < 2e-16 ***
Product_Category_3           0.0073419  0.0014769    4.971 6.65e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 579321  on 430061  degrees of freedom
Residual deviance: 529299  on 430043  degrees of freedom
AIC: 529337

Number of Fisher Scoring iterations: 4
```

h. Use AIC as metric to conclude a better model.

Using AIC as metric: From the above build stepwise forward and backward models, we can see that both the approaches suggest the same model, which is similar to full model.

Model	AIC
Full Logistic Regression Model	**529337**
Stepwise Forward LG Model	**529337**
Stepwise Backward LG Model	**529337**

i. Calculate the Accuracy of the final Logistic Regression model using '**train()**'.

```
> model_lg_fit<-train(as.factor(Purchase)~.,data=train.data_lg,method="glm",family="binomial")
> pred<-predict(model_lg_fit,newdata=test.data_lg)
> accuracy(pred,test.data_lg$Purchase)
[1] 0.7606567
> |
```

The accuracy of the Logistic Regression model built is **0.7606567**.

5.2. Evaluations and Results

5.2.1 Evaluate Best Classification Model

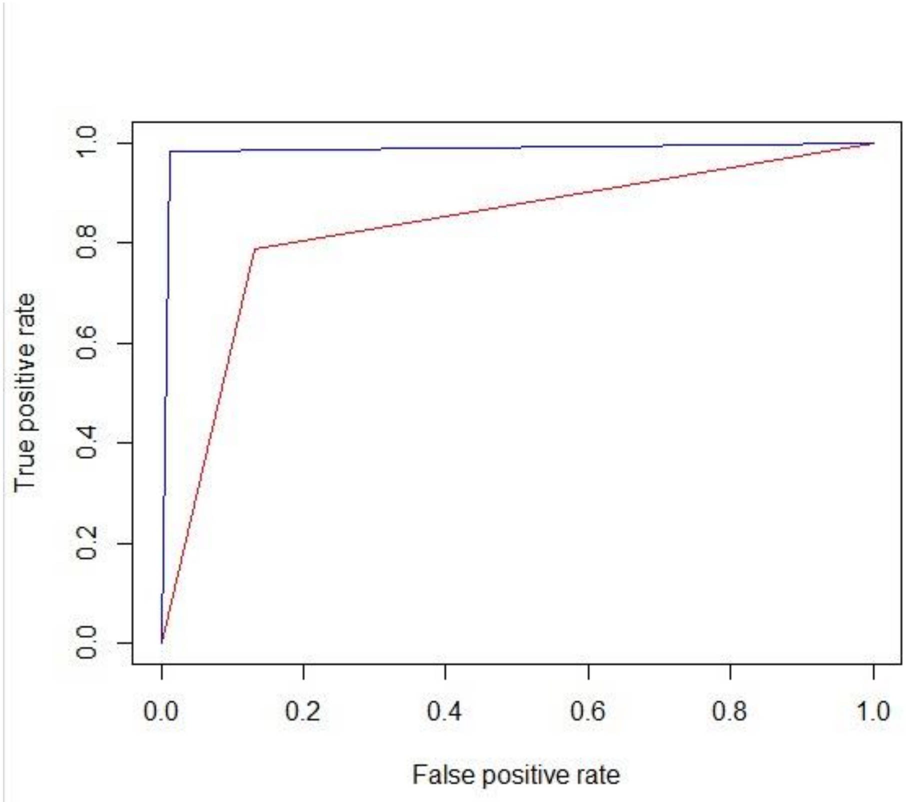
- We build three different classification models to predict the black Friday sale purchase amount.
- Accuracies of all the three models are as shown in the table.

Model	AIC
Naïve-Bayes Classification	**0.8362275**
KNN Classification (K=1)	**0.9862159**
Logistic Regression Model	**0.7606567**

- Finally, we consider the **KNN Classification** model the best, which make predictions with the highest accuracy, i.e. **0.9862159 ~ 98.62%**

5.2.2 Validation of Best Model

- We chose KNN Classification model as the best model among the built models.
- We further validated this model using the Area Under the Curve value.
  a. AUC is considered very powerful measure for classification.
  b. Library ROCR is used to draw AUC curve.
  c. The closer the curve to the left uppermost side of the plot, the better is the model. In the above plot we can see that the curve has reached the uppermost left corner of the plot, hence the model is better.




```
> prediction_val_nb = prediction(as.numeric(pred),as.numeric(test.data_nb$Purchase))
> performance_nb = performance(prediction_val_nb,"tpr","fpr")
> plot(performance_nb,col="blue")
```

```
> knn.1<-knn(train.data_knn,test.data_knn,train.Purchase,k=1)
> prediction_val_knn <- prediction(as.numeric(knn.1),as.numeric(test.data_knn$Purchase))
> performance_knn = performance(prediction_val_knn,"tpr","fpr")
> plot(performance_nb,col = "red")
> plot(performance_knn,add = TRUE,col = "blue")
>
```

```
> AUC_knn = max(attr(performance_knn,"y.values")[[1]]-(attr(performance_knn,"x.values")[[1]]))
> AUC_knn
[1] 0.9715863
> AUC_nb = max(attr(performance_nb,"y.values")[[1]]-(attr(performance_nb,"x.values")[[1]]))
> AUC_nb
[1] 0.6582353
>
```

- Here, the **AUC** = **0.9715**, which is very near to 1. Hence, we can say that the **KNN Classification** model is best model chosen.

5.3. Findings

We will summarize some of the findings we found during our study as follows:

1) The following hypothesis were proven:

i. Female customers purchase more than 5 in quantity from products under 'Product_Category_1'.
ii. Customers will purchase different number of products from both Product_Category_1 and Product_Category_2.

2) We have built multiple classification models to predict the Purchase, (which is our dependent variable) on the training data and found that KNN Classification model is predicting with the highest accuracy of **0.9862159 ~ 98.62%**, using Hold-Out evaluation.
3) We validated best model using Area Under Curve value. The value we got was **0.9715.**

6. Conclusions and Future Work

6.1. Conclusions

The ulterior motive of this project is to help the retailers to predict the customer's purchase (higher or lower) on a Black Friday sale, that would help in predicting which gender of a person would buy more and which category of products are high in demand.

Hence, for a given data that includes gender, city category, stay in current city, product categories, our model will predict the possibility for a customer to make higher purchase with **98.62%** accuracy.

6.2. Limitations

1) If the dataset has yearly Black Friday Sales with dates (daily/monthly), we could have performed time series analysis to identify trends and predict future purchase amount along with seasonality effects (if any).
2) Dataset includes generic naming convention for the product categories and is the very reason we are unable to give a name to the products that were in the highest demand and constitute for the majority sales on Black Friday.

6.3. Potential Improvements or Future Work

In future, we can work on logistic regression model and improve the performance. Also, we can perform different Machine Learning techniques like decision tree, random forest and SVM to achieve better accuracy.