# Retail Store Case Study Report for the Black Friday sale

**Group No.**: Group 18

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**Executive Summary:** The dataset contains data from a retail store that would like to understand the purchasing habits of their customers so that they can offer a personalized list of products that would interest their customers. We impute the missing data and perform EDA. We use machine learning in order to build a prediction model that will predict a customers purchase amount. A list of machine learning models is compiled and built using tenfold repeated cross validation with three repeats. These models include a glm model, a glmnet model, a linear regression model, a GBM model and a treebag model. The model that produced the best median RMSE was the gbm model. This model produced a median RMSE of 3002.142. In order to increase sales, there are two possible solutions. First to market the products to the part of the demographic that doesn't shop at the given retail store. The second to market products to the part of the demographic that buys the products based on their purchase history and future purchase predictions.

# I. Background and Introduction

A retail store would like to understand the purchasing habits of its customers so that they can offer customized list of products that would interest those customers.

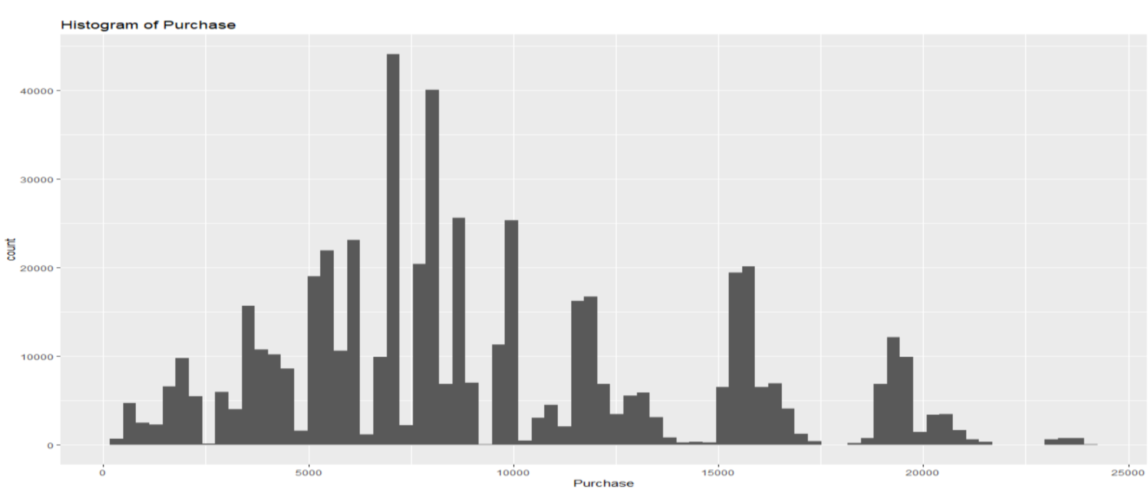
The report will explore a month's worth of sales data from the store. The variable of interest in this report is amount purchased in the last month. The data also contains the demographic information including age, gender, occupation, city, category, stay in current city and marital status. Additionally, the dataset also contains product information including ID and different product category information.

Using this information, a machine learning model will be built that will predict purchase amount based on the customer's demographics and the categories of the product and the store will have information they need to offer customers the products they need.

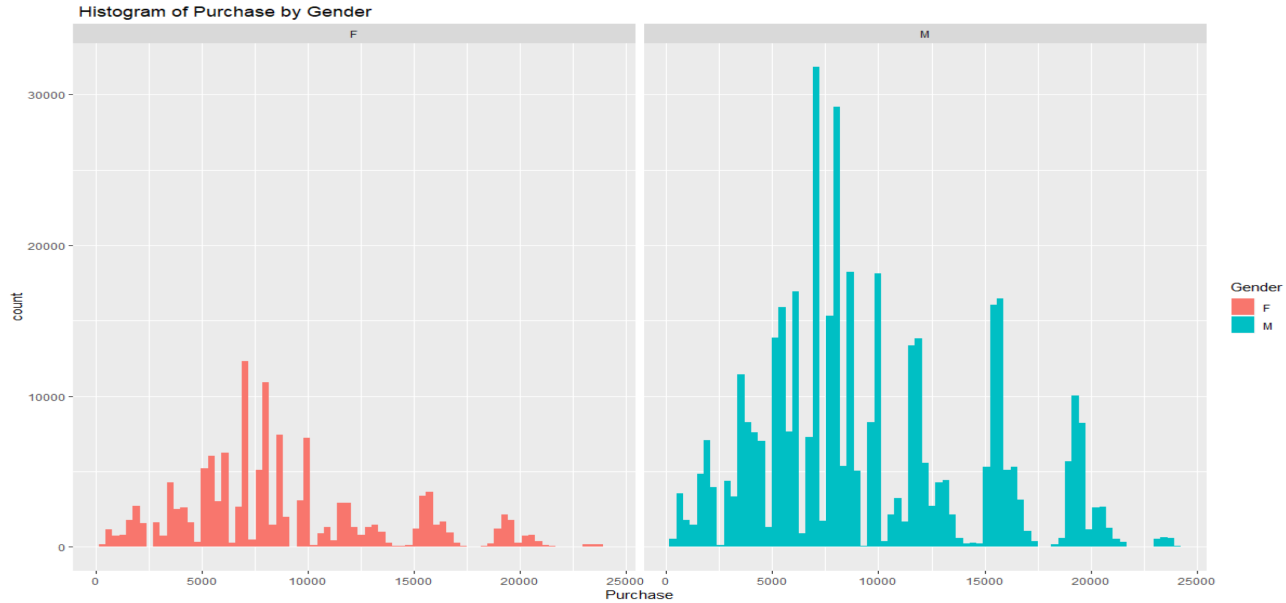
# II. Data Exploration and Visualization

The first step in exploring the data is loading the required libraries. The dataframe has 12 variables and 550068 observations. Inspecting the data reveals that every variable other than Purchase is a categorical variable. The columns that require changing to factor variables Marital_Status, Occupation, User_ID, Product_Category_1, Product_Category_2 and Product_Category_3.

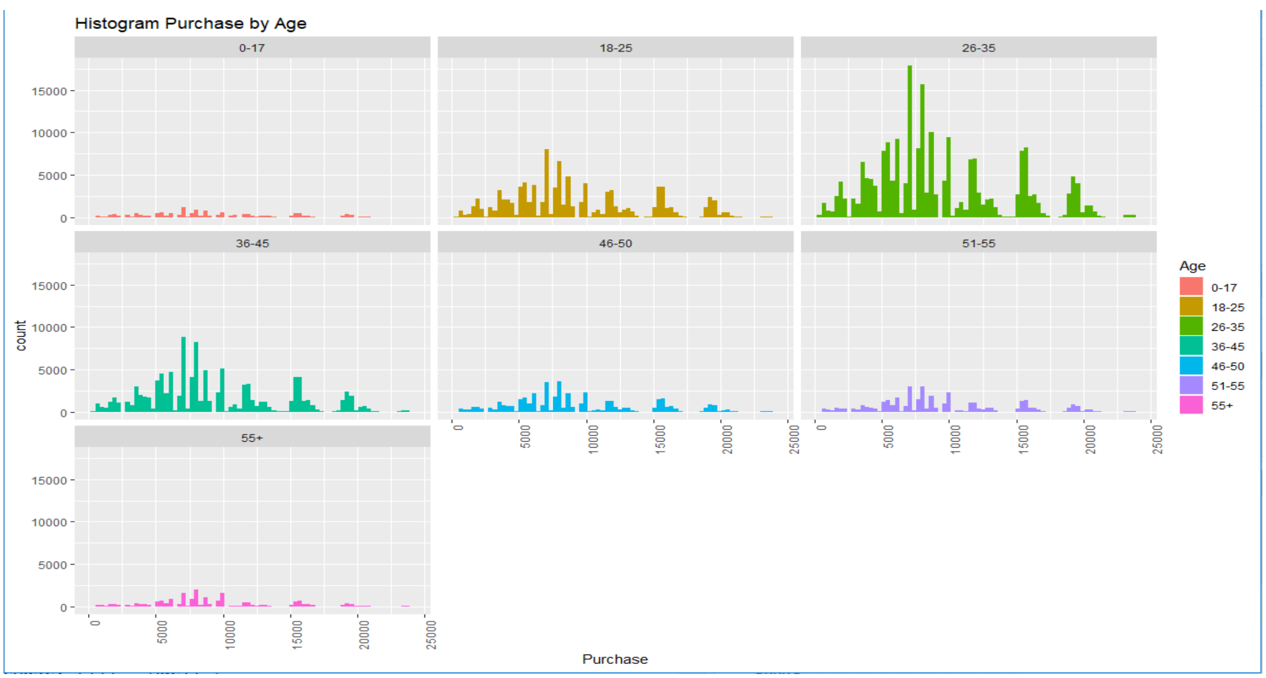
Another problem with data is that Product_Category_2 and Product_Category_3 have missing values. These columns contain categorical data, so it won't be appropriate to use median or kNN imputation. All the missing values are imputed as 0.



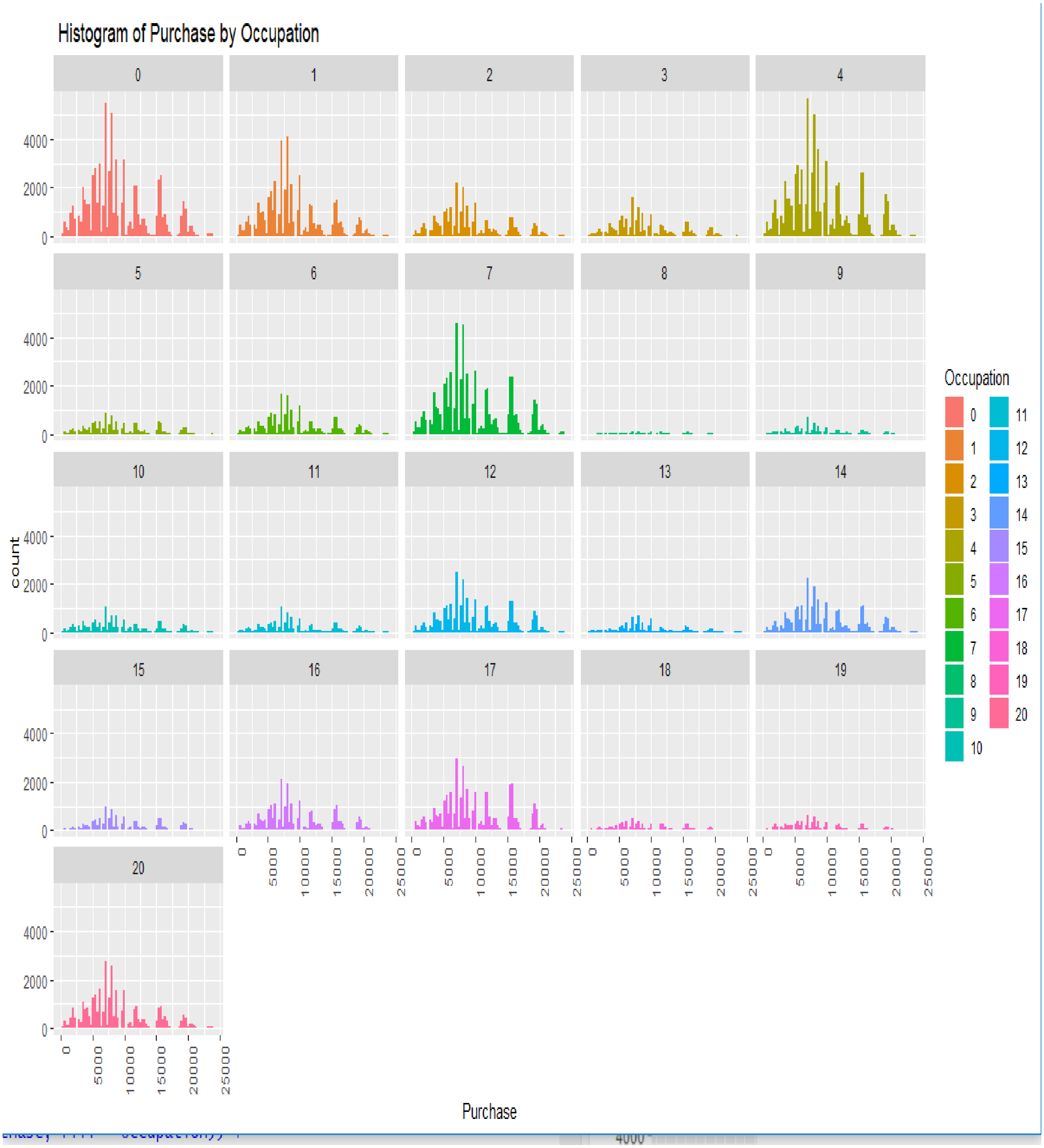

The target variable Purchase has an almost Gaussian distribution. A histogram of the purchase variable shows a unimodal curve that has a positive skew which explains why the mean of purchase amount variable is larger than the median of purchase amount variable.



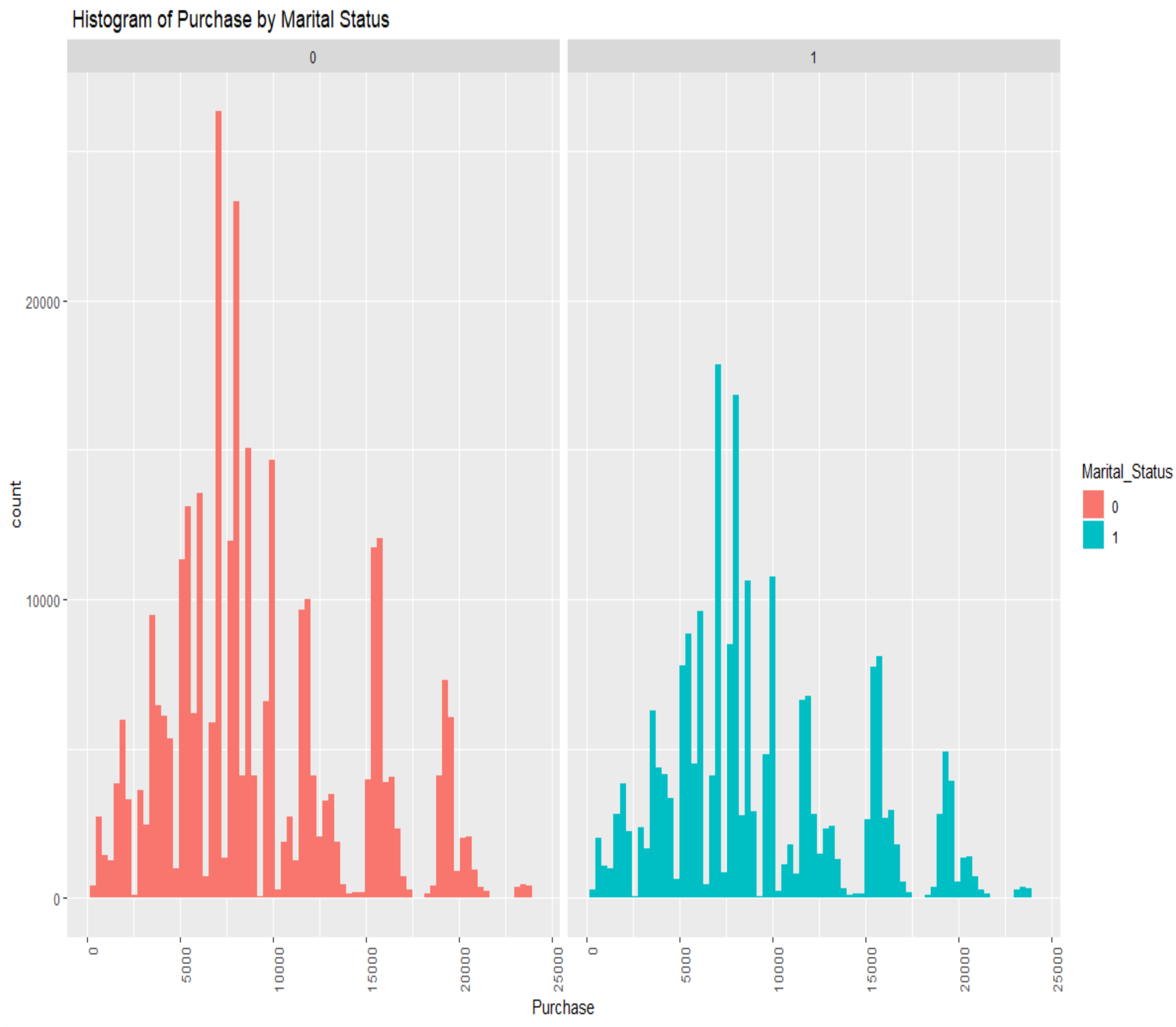

On average the men spend more money on purchase than women. This last conclusion is more reasonable since the percentage of male buyers is higher than female buyers. Further, men shopped for more products than women.



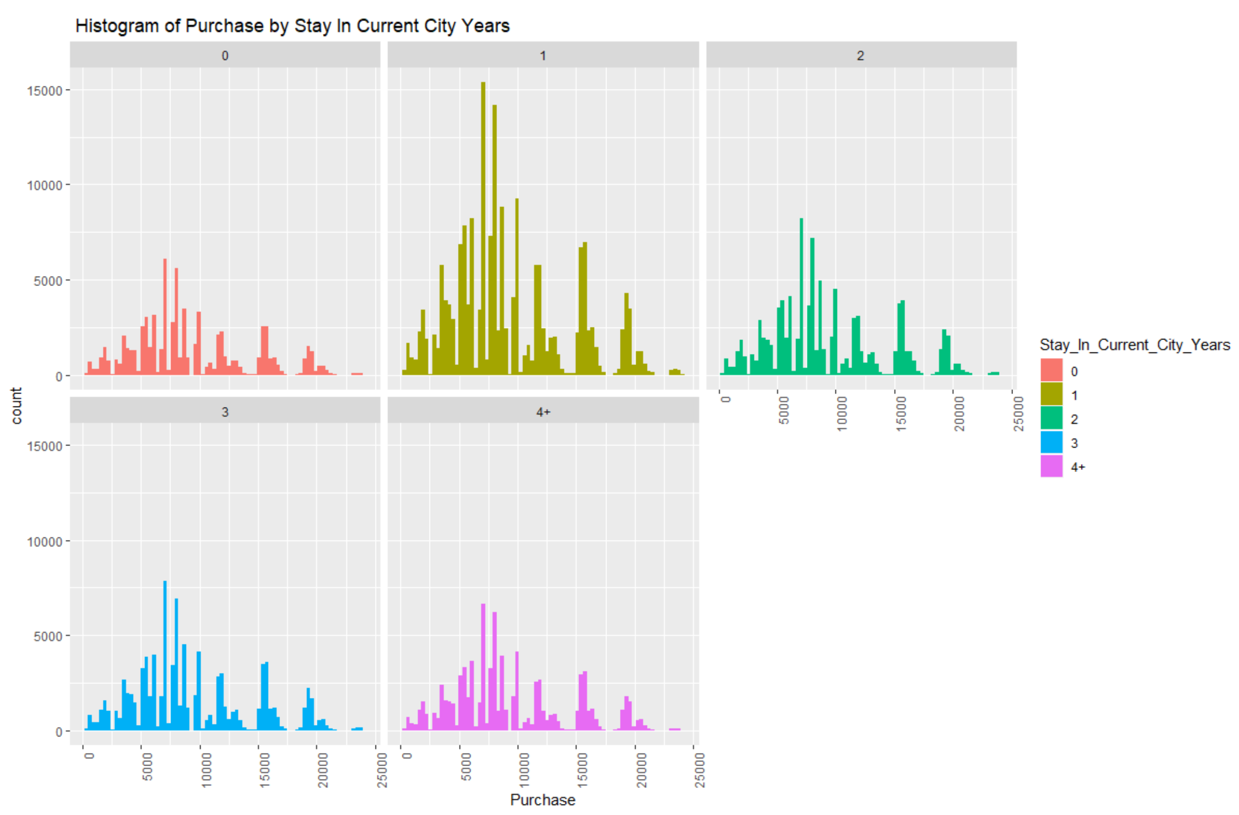

Curiously, on average customer with more than 50 years old are the ones who spent the most.



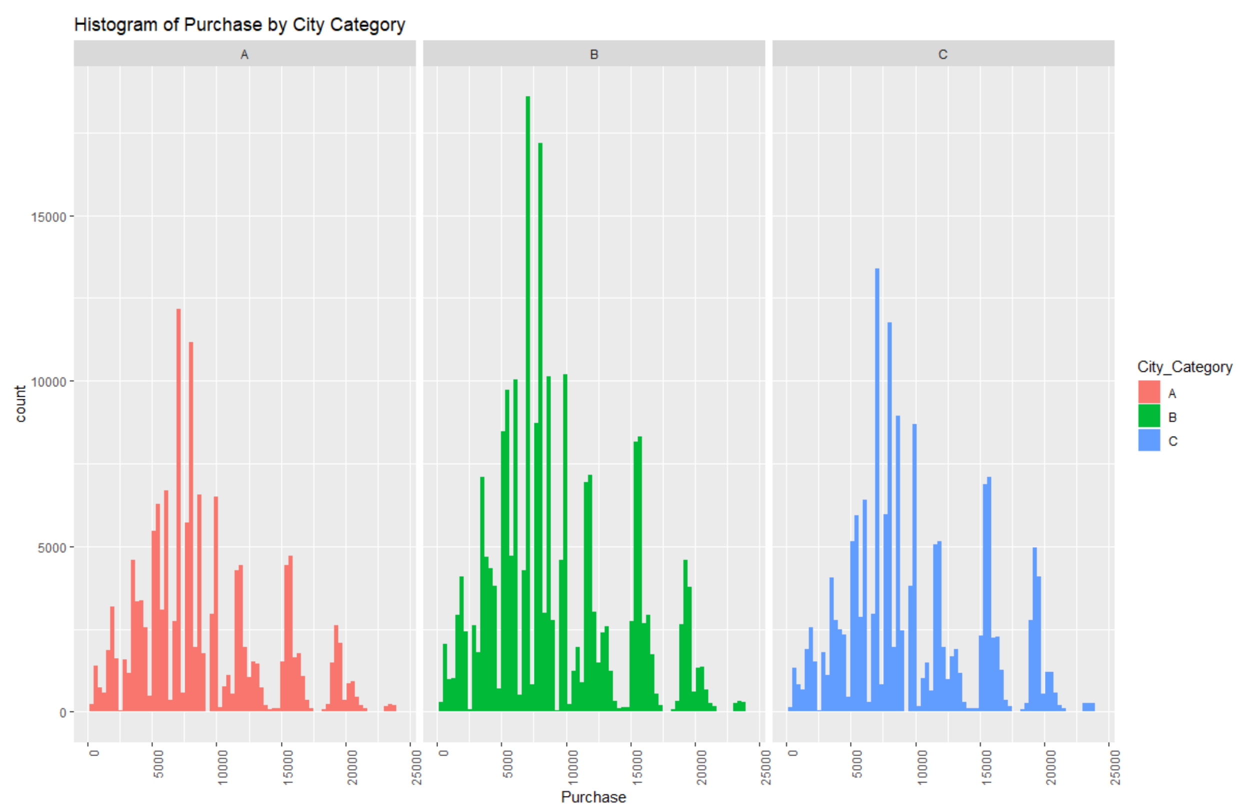

There are some occupations which have higher representations, but the amount each user spends on average is the same for all occupations.




On average an individual customer tends to spend the same amount independently if his/her is married or not.




The longest someone is living in that city the less prone they are to buy new things. Hence, if someone is new in town and needs a great number of new things for their house that they'll take advantage of the low prices in Black Friday to purchase all the things needed.




We see that city type ‘B’ had the highest number of purchases registered. However, the city whose buyers spend the most is city type ‘C’.

After fully cleaning the data the cleaned dataset is examined. It reveals that the median purchase amount for the last month was $8,047. In addition, it shows that the mean was $9,264. The minimum purchase amount was $12 and the maximum purchase amount was $23,961.

## III. Data Preparation and Preprocessing

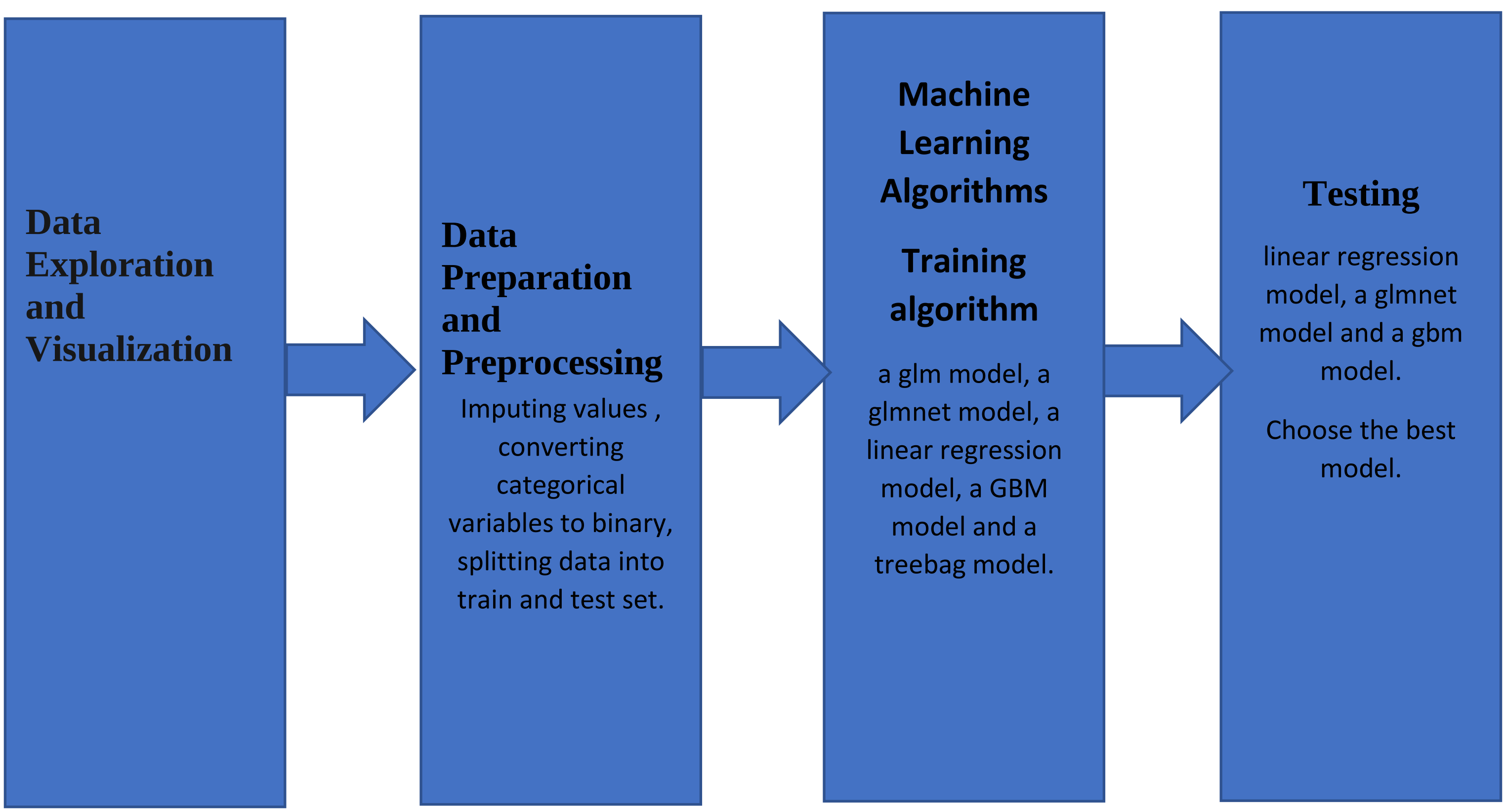
The columns with categorical variables are changed to numeric variables. These include Marital_Status, Occupation, User_ID, Product_Category2, Product_Category_3. The columns Product_Category_2 and Product_Category_3 have missing values. We impute the nan values to 0.

After imputing the nan values, we check the spread of Product_Category_1, Product_Category_2, Product_Category_3. Then we calculate the standard deviation of purchase. Then we find the final summary of the data.

After fully cleaning the data the cleaned dataset is examined. The median purchase amount for the last month was $8,047. Additionally, the mean was $9,264. The minimum purchase amount was $12 and the maximum purchase amount was $23,961.

## IV. Data Mining Techniques and Implementation

- This report uses machine learning in order to build a prediction model that will predict a customer's purchase amount. The first step to building this model is removing the `User_ID` and `Product_ID` columns as these variables have zero variance. Each `Product_ID` and each `User_ID` will be particular to the customer or product.
- After these near zero variance variables were removed, a sample was selected from the data. This sample was selected because this dataset is large. Fortunately, a large sample of the data should be enough to represent the data accurately and to build a machine learning model. The sample that was selected was selected randomly. The sample size 10% of the data. Once the sample is selected, the next step in building the model can be performed.
- Next the sampled data was partitioned. 70% of the sample was selected randomly to be the `train` set. The `train` set is the data that will be used to build the algorithm. The other 30% of the sample was assigned to the `test` set. The `test` set will be used to test the accuracy of the model.
- Once the sample is partitioned, a list of machine learning algorithms using different methods is compiled. These algorithms were built using ten-fold repeated cross-validation with three repeats. The models created include a glm model, a glmnet model, a linear regression model, a GBM model and a treebag model.
- Next, three ensemble models were created. These ensemble models included a linear regression model, a glmnet model and a gbm model. Each model also used ten-fold cross-validation repeated three times. All three of these models proved to be better predictors than any of the other models alone.



## V. Performance Evaluation

- Once the sample is partitioned, a list of machine learning algorithms using different methods is compiled. These algorithms were built using ten-fold repeated cross-validation with three repeats. The model that produced the best median RMSE was the gbm model. This model produced a median RMSE of 3002.142. Using this model would produce fairly accurate predictions. However, creating an ensemble model using these models should produce even greater accuracy.
- Next, three ensemble models were created. These ensemble models included a linear regression model, a glmnet model and a gbm model. Each model also used ten-fold cross-validation repeated three times. All three of these models proved to be better predictors than any of the other models alone. The gbm model produced an RMSE of 2980.54. The linear model produced an RMSE of 2993.22 and the glmnet model produced an RMSE of 2993.751.
- Once the different models were used to make predictions, it is discovered the the glmnet stack produced the best predictions. This model produced an RMSE of 3085.436. Therefore, it was the model used to make the final predictions for the `testing` dataset.

## VI. Discussion and Recommendation

There are a few conclusions that can be made using the analysis in this paper.

- The first conclusion is that even when broken down into different demographics, the median purchase made by customers does not fluctuate much. It didn't matter if the group was male, female, young, old, married or unmarried, the median purchase by the customers hovered around $8000.
- However, some groups were more present than others. Males shopped more than females. The marital status 0 shopped more than the marital status 1. Unfortunately, which label mean married, and which label means unmarried is unknown. Also, customers between the ages of 18 and 45 shopped the most. The age range 26-35 had the highest turnout. Additionally, people who only lived in their city for a year shopped a lot.

There are two different ways that the retail store could increase their sales.

- First, to advertise to groups that do not shop much. Further research has to be done in order to come up with a targeted marketing campaign.
- The other option will be to target the customers that shop often offer customized list of products that would interest those customers.

Finally, the models were tested to find the model that makes the best predictions. When analyzing the data from the testing model, it is revealed that the `Product_Category_1`, `Product_Category_2` and `Product_Category_3` variables have new levels. These new variables will present a problem when making predictions. Therefore, the original models needed to be revisited and these variables were left as numeric variables after 0 was imputed for the missing values.

The glmnet stack produced the best predictions. This model produced an RMSE of 3085.436. Therefore, it was the model used to make the final predictions for the `testing` dataset.

## VII. Summary

The dataset contains data from ABC Private Limited that would like to understand the purchasing habits of their customers so that they can offer a personalized list of products that would interest their customers.

We impute the missing data and perform EDA. Then we split the data into train data and test data. We use machine learning in order to build a prediction model that will predict a customers purchase amount. A list of machine learning models is compiled and built using tenfold repeated cross validation with three repeats. These models include a glm model, a glmnet model, a linear regression model, a GBM model and a treebag model. The model that produced the best median RMSE was the gbm model. This model produced a median RMSE of 3002.142.

We then create three ensemble models which include a  linear regression model, a glmnet model and a gbm model. Each model uses ten-fold cross-validation repeated three times. The gbm model produced an RMSE of 2980.54. The linear model produced an RMSE of 2993.22 and the glmnet model produced an RMSE of 2993.751. The glmnet stack produced the best results so this model was used to produce the final predictions for the training dataset.

## Appendix: R Code for use case study

```
install.packages("dplyr")

library(dplyr)

library(ggplot2)

install.packages("caret")

library(caret)

install.packages("caretEnsemble")

library(caretEnsemble)

library(VIM)

install.packages("gridExtra")

library(gridExtra)

install.packages("glmnet")
```

library(glmnet)

#loading data

black_friday <-read.csv("BlackFriday.csv")

#Previewing Data

head(black_friday)

**Output-**

```
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+
6 1000003   P00193542      M  26-35         15             A
3
  Marital_Status Product_Category_1 Product_Category_2 Product_Category_3 Pur
chase
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
6              0                  1                  2                 NA
15227
```

#Understanding the structure of data

str(black_friday)

**Output-**

```
'data.frame':   537577 obs. of  12 variables:
 $ User_ID                   : int  1000001 1000001 1000001 1000001 1000002 1
000003 1000004 1000004 1000004 1000005 ...
 $ Product_ID                : Factor w/ 3623 levels "P00000142","P00000242",
..: 671 2375 851 827 2733 1830 1744 3319 3597 2630 ...
 $ Gender                    : Factor w/ 2 levels "F","M": 1 1 1 1 2 2 2 2 2
2 ...
 $ Age                       : Factor w/ 7 levels "0-17","18-25",..: 1 1 1 1
7 3 5 5 5 3 ...
 $ Occupation                : int  10 10 10 10 16 15 7 7 7 20 ...
 $ City_Category             : Factor w/ 3 levels "A","B","C": 1 1 1 1 3 1 2
2 2 1 ...
 $ Stay_In_Current_City_Years: Factor w/ 5 levels "0","1","2","3",..: 3 3 3 3
5 4 3 3 3 2 ...
```

```
 $ Marital_Status            : int  0 0 0 0 0 0 1 1 1 1 ...
 $ Product_Category_1        : int  3 1 12 12 8 1 1 1 1 8 ...
 $ Product_Category_2        : int  NA 6 NA 14 NA 2 8 15 16 NA ...
 $ Product_Category_3        : int  NA 14 NA NA NA NA 17 NA NA NA ...
 $ Purchase                  : int  8370 15200 1422 1057 7969 15227 19215 158
54 15686 7871 ...
```

#summarising data

summary(black_friday)

**Output-**

```
   User_ID            Product_ID     Gender        Age           Occupation
City_Category
 Min.   :1000001   P00265242:  1858   F:132197   0-17 : 14707   Min.   : 0.00
0   A:144638
 1st Qu.:1001495   P00110742:  1591   M:405380   18-25: 97634   1st Qu.: 2.00
0   B:226493
 Median :1003031   P00025442:  1586              26-35:214690   Median : 7.00
0   C:166446
 Mean   :1002992   P00112142:  1539              36-45:107499   Mean   : 8.08
3
 3rd Qu.:1004417   P00057642:  1430              46-50: 44526   3rd Qu.:14.00
0
 Max.   :1006040   P00184942:  1424              51-55: 37618   Max.   :20.00
0
                   (Other)  :528149              55+  : 20903
 Stay_In_Current_City_Years Marital_Status   Product_Category_1 Product_Categ
ory_2
 0 : 72725                  Min.   :0.0000   Min.   : 1.000     Min.   : 2.00
 1 :189192                  1st Qu.:0.0000   1st Qu.: 1.000     1st Qu.: 5.00
 2 : 99459                  Median :0.0000   Median : 5.000     Median : 9.00
 3 : 93312                  Mean   :0.4088   Mean   : 5.296     Mean   : 9.84
 4+: 82889                  3rd Qu.:1.0000   3rd Qu.: 8.000     3rd Qu.:15.00
                            Max.   :1.0000   Max.   :18.000     Max.   :18.00
                                                                NA's   :16698

6
 Product_Category_3    Purchase
 Min.   : 3.0       Min.   :  185
 1st Qu.: 9.0       1st Qu.: 5866
 Median :14.0       Median : 8062
 Mean   :12.7       Mean   : 9334
 3rd Qu.:16.0       3rd Qu.:12073
 Max.   :18.0       Max.   :23961
 NA's   :373299
```

#Changing Numeric Variables to Categorical Variables

black_friday$Marital_Status <- factor(black_friday$Marital_Status)

black_friday$Occupation <- factor(black_friday$Occupation)

black_friday$User_ID <- factor(black_friday$User_ID)

black_friday$Product_Category_2 <- factor(black_friday$Product_Category_2)

black_friday$Product_Category_3 <- factor(black_friday$Product_Category_3)

#new summary of data

summary(black_friday)

**Output-**

```
    User_ID             Product_ID      Gender        Age           Occupation
City_Category
 1001680:  1025    P00265242:  1858    F:132197   0-17 : 14707   4        : 70862
A:144638
 1004277:   978    P00110742:  1591    M:405380   18-25: 97634   0        : 68120
B:226493
 1001941:   898    P00025442:  1586               26-35:214690   7        : 57806
C:166446
 1001181:   861    P00112142:  1539               36-45:107499   1        : 45971
 1000889:   822    P00057642:  1430               46-50: 44526   17       : 39090
 1003618:   766    P00184942:  1424               51-55: 37618   20       : 32910
 (Other):532227    (Other)  :528149               55+  : 20903   (Other):222818
 Stay_In_Current_City_Years Marital_Status Product_Category_1 Product_Categor
y_2
 0 : 72725                  0:317817       Min.   : 1.000     8       : 63058
 1 :189192                  1:219760       1st Qu.: 1.000     14      : 54158
 2 : 99459                                 Median : 5.000     2       : 48481
 3 : 93312                                 Mean   : 5.296     16      : 42602
 4+: 82889                                 3rd Qu.: 8.000     15      : 37317
                                           Max.   :18.000     (Other):124975
                                                              NA's    :166986

 Product_Category_3    Purchase
 16       : 32148     Min.   :  185
 15       : 27611     1st Qu.: 5866
 14       : 18121     Median : 8062
 17       : 16449     Mean   : 9334
 5        : 16380     3rd Qu.:12073
 (Other): 53569       Max.   :23961
 NA's    :373299
```

#spread of Product categories

table(black_friday$Product_Category_1)

**Output-**

```
     1       2       3       4       5       6       7       8       9      10      11
12      13
138353  23499   19849   11567  148592  20164    3668  112132    404    5032   23960
3875    5440
    14      15      16      17      18
  1500    6203    9697     567    3075
```

table(black_friday$Product_Category_2)

**Output-**

```
    2      3      4      5      6      7      8      9     10     11     12     13     14
15     16
48481   2835  25225  25874  16251    615  63058   5591   2991  13945   5419  10369  54158
37317  42602
   17     18
13130   2730
```

table(black_friday$Product_Category_3)

**Output-**

```
3      4      5      6      8      9     10     11     12     13     14     15     16
17     18
  600   1840  16380   4818  12384  11414   1698   1773   9094   5385  18121  27611  32148
16449   4563
```

#imputing 0 for missing values in Product_Category_2 & Product_category_3

black_friday$Product_Category_2 <- as.numeric(black_friday$Product_Category_2)

black_friday[is.na(black_friday$Product_Category_2), "Product_Category_2"] <- 0

black_friday$Product_Category_3 <- as.numeric(black_friday$Product_Category_3)

black_friday[is.na(black_friday$Product_Category_3), "Product_Category_3"] <- 0

#standard deviation of Purchase

sd(black_friday$Purchase)

**Output-**

```
[1] 4981.022
```

#final summary of data

summary(black_friday)

**Output-**

```
    User_ID           Product_ID       Gender        Age           Occupation
City_Category
 1001680:  1025   P00265242:  1858   F:132197   0-17 : 14707   4      : 70862
A:144638
 1004277:   978   P00110742:  1591   M:405380   18-25: 97634   0      : 68120
B:226493
 1001941:   898   P00025442:  1586              26-35:214690   7      : 57806
C:166446
 1001181:   861   P00112142:  1539              36-45:107499   1      : 45971
 1000889:   822   P00057642:  1430              46-50: 44526   17     : 39090
 1003618:   766   P00184942:  1424              51-55: 37618   20     : 32910
 (Other):532227   (Other)  :528149              55+  : 20903   (Other):222818
 Stay_In_Current_City_Years Marital_Status Product_Category_1 Product_Categor
y_2
 0 : 72725                  0:317817       Min.   : 1.000     Min.   : 0.000
 1 :189192                  1:219760       1st Qu.: 1.000     1st Qu.: 0.000
 2 : 99459                                 Median : 5.000     Median : 4.000
 3 : 93312                                 Mean   : 5.296     Mean   : 6.096
 4+: 82889                                 3rd Qu.: 8.000     3rd Qu.:13.000
```

```
                                             Max.   :18.000     Max.   :17.000

 Product_Category_3    Purchase
 Min.   : 0.000     Min.   :  185
 1st Qu.: 0.000     1st Qu.: 5866
 Median : 0.000     Median : 8062
 Mean   : 2.999     Mean   : 9334
 3rd Qu.: 5.000     3rd Qu.:12073
 Max.   :15.000     Max.   :23961
```

```
#Histogram of Purchase Column

ggplot(black_friday, aes(x = Purchase)) +

  geom_histogram(bins = 75) +

  labs(title= "Histogram of Purchase")

#Histogram of Purchase column vs Gender

ggplot(black_friday, aes(x = Purchase, fill = Gender)) +

  geom_histogram(bins = 75) +

  facet_grid(. ~ Gender) +

  labs(title= " Histogram of Purchase by Gender")

#Histogram of Purchase vs Age

ggplot(black_friday, aes(x = Purchase, fill = Age)) +

  geom_histogram(bins = 75) +

  facet_wrap(~ Age) +

  labs(title= "Histogram Purchase by Age") +

  theme(axis.text.x = element_text(angle = 90, hjust = 1))

#Histogram of Purchase vs occupation

ggplot(black_friday, aes(x = Purchase, fill = Occupation)) +

  geom_histogram(bins = 75) +

  facet_wrap(~ Occupation) +

  labs(title= " Histogram of Purchase by Occupation") +

  theme(axis.text.x = element_text(angle = 90, hjust = 1))

#Histogram of Purchase vs Marital Status

ggplot(black_friday, aes(x = Purchase, fill = Marital_Status)) +

  geom_histogram(bins = 75) +
```

```
  facet_wrap(~ Marital_Status) +
  labs(title= " Histogram of Purchase by Marital Status") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
#Histogram of Purchase vs stay in current city
ggplot(black_friday, aes(x = Purchase, fill = Stay_In_Current_City_Years)) +
  geom_histogram(bins = 75) +
  facet_wrap(~ Stay_In_Current_City_Years) +
  labs(title= " Histogram of Purchase by Stay In Current City Years") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
# Histogram of purchase vs city
ggplot(black_friday, aes(x = Purchase, fill = City_Category)) +
  geom_histogram(bins = 75) +
  facet_wrap(~ City_Category) +
  labs(title= "Histogram of Purchase by City Category") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
# removing Nearzerovariables
bfm <- black_friday %>%
  select(-User_ID, -Product_ID)
#New Summary of data
summary(bfm)
```

**Output-**

```
Gender        Age            Occupation     City_Category Stay_In_Current_City
_Years
 F:132197   0-17 : 14707   4       : 70862   A:144638      0 : 72725
 M:405380   18-25: 97634   0       : 68120   B:226493      1 :189192
            26-35:214690   7       : 57806   C:166446      2 : 99459
            36-45:107499   1       : 45971                 3 : 93312
            46-50: 44526   17      : 39090                 4+: 82889
            51-55: 37618   20      : 32910
            55+  : 20903   (Other):222818
 Marital_Status Product_Category_1 Product_Category_2 Product_Category_3    P
urchase
 0:317817       Min.   : 1.000     Min.   : 0.000     Min.   : 0.000     Min.
:   185
 1:219760       1st Qu.: 1.000     1st Qu.: 0.000     1st Qu.: 0.000     1st
Qu.: 5866
                Median : 5.000     Median : 4.000     Median : 0.000     Medi
an : 8062
```

```
                Mean   : 5.296     Mean   : 6.096     Mean   : 2.999     Mean
: 9334
                3rd Qu.: 8.000     3rd Qu.:13.000     3rd Qu.: 5.000     3rd
Qu.:12073
                Max.   :18.000     Max.   :17.000     Max.   :15.000     Max.
:23961
```

#Sampling data

```
set.seed(366284)

bf_sample <- createDataPartition(y = bfm$Purchase,

                                  p = 0.1, list=FALSE)

bf_sample <- bfm[bf_sample, ]
```

#Summary of data after sampling

```
summary(bf_sample)
```

**Output-**

```
Gender      Age          Occupation    City_Category Stay_In_Current_City_Ye
ars
 F:13231   0-17 : 1461   4      : 7206   A:14170       0 : 7371
 M:40528   18-25: 9854   0      : 6830   B:22924       1 :18909
           26-35:21456   7      : 5811   C:16665       2 : 9883
           36-45:10743   1      : 4543                 3 : 9283
           46-50: 4587   17     : 3753                 4+: 8313
           51-55: 3676   20     : 3194
           55+  : 1982   (Other):22422
 Marital_Status Product_Category_1 Product_Category_2 Product_Category_3    P
urchase
 0:31860        Min.   : 1.000     Min.   : 0.000     Min.   : 0.000     Min.
:  187
 1:21899        1st Qu.: 1.000     1st Qu.: 0.000     1st Qu.: 0.000     1st
Qu.: 5866
                Median : 5.000     Median : 4.000     Median : 0.000     Medi
an : 8062
                Mean   : 5.275     Mean   : 6.083     Mean   : 2.998     Mean
: 9322
                3rd Qu.: 8.000     3rd Qu.:13.000     3rd Qu.: 5.000     3rd
Qu.:12073
                Max.   :18.000     Max.   :17.000     Max.   :15.000     Max.
:23961
```

#Partitiong data

```
inTrain <- createDataPartition(y = bf_sample$Purchase,

                          p = 0.7, list=FALSE)

train <- bf_sample[inTrain, ]

test <- bf_sample[-inTrain, ]
```

#Caretlists

control <- trainControl(method = "repeatedcv", number = 10, repeats = 3, savePredictions = TRUE, classProbs = TRUE)

algorithmList <- c('glm', 'glmnet', 'lm', 'treebag', 'gbm')

models <- caretList(Purchase ~ ., train, trControl = control, methodList = algorithmList)

#Testing Models Predictive Accuracy

results <- resamples(models)

summary(results)

**Output-**

```
Call:
summary.resamples(object = results)

Models: glm, glmnet, lm, treebag, gbm
Number of resamples: 30

MAE
            Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
glm     3485.460 3519.948 3549.570 3545.918 3564.789 3632.974    0
glmnet  3482.270 3518.128 3550.788 3545.017 3563.229 3630.118    0
lm      3485.460 3519.948 3549.570 3545.918 3564.789 3632.974    0
treebag 2325.749 2349.966 2362.541 2365.365 2380.083 2412.726    0
gbm     2251.340 2270.762 2285.390 2284.204 2295.808 2334.849    0

RMSE
            Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
glm     4538.443 4567.629 4619.134 4616.301 4636.954 4776.629    0
glmnet  4538.934 4569.171 4618.632 4616.074 4636.011 4775.831    0
lm      4538.443 4567.629 4619.134 4616.301 4636.954 4776.629    0
treebag 3014.020 3060.813 3071.443 3075.707 3091.464 3139.114    0
gbm     2937.196 2970.188 2988.407 2989.460 3001.792 3056.735    0

Rsquared
             Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
glm     0.1075230 0.1240033 0.1349418 0.1326547 0.1400529 0.1547559    0
glmnet  0.1074201 0.1243869 0.1351358 0.1327726 0.1407449 0.1551233    0
lm      0.1075230 0.1240033 0.1349418 0.1326547 0.1400529 0.1547559    0
treebag 0.5969730 0.6098720 0.6145313 0.6148684 0.6204068 0.6389329    0
gbm     0.6174413 0.6345896 0.6375504 0.6373552 0.6420593 0.6611509    0
```

#Building Ensembles

stack_glmnet <- caretStack(models, method = "glmnet", trControl = trainControl(method = "repeatedcv", number = 10, repeats = 3, savePredictions = TRUE))

stack_glmnet

**Output-**

```
A glmnet ensemble of 2 base models: glm, glmnet, lm, treebag, gbm

Ensemble results:
glmnet

112896 samples
     5 predictor

No pre-processing
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 101605, 101607, 101606, 101608, 101607, 101607, ...
Resampling results across tuning parameters:

  alpha  lambda      RMSE      Rsquared   MAE
  0.10     7.91216  2983.289  0.6376127  2272.499
  0.10    79.12160  2989.662  0.6361456  2287.714
  0.10   791.21601  3024.374  0.6322548  2324.677
  0.55     7.91216  2983.326  0.6376066  2272.668
  0.55    79.12160  2987.479  0.6367646  2283.953
  0.55   791.21601  3052.332  0.6336604  2340.524
  1.00     7.91216  2983.396  0.6375926  2273.063
  1.00    79.12160  2985.634  0.6372954  2278.291
  1.00   791.21601  3087.687  0.6372954  2359.101

RMSE was used to select the optimal model using the smallest value.
The final values used for the model were alpha = 0.1 and lambda = 7.91216.
```

#testing model

predictions_glmnet <- predict(stack_glmnet, test)

error <- predictions_glmnet - test$Purchase

#calculation rmse

sqrt(mean(error^2))

**Output-**

```
[1] 3046.695
```

#Linear Regresson emsemble

stack_lm <- caretStack(models, method = "lm", trControl = trainControl(method = "repeatedcv", number = 10, repeats = 3, savePredictions = TRUE))

stack_lm

**Output-**

```
A lm ensemble of 2 base models: glm, glmnet, lm, treebag, gbm
```

```
Ensemble results:
Linear Regression

112896 samples
     5 predictor

No pre-processing
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 101607, 101607, 101606, 101605, 101606, 101607, ...
Resampling results:

  RMSE      Rsquared   MAE
  2982.541  0.6378372  2270.224

Tuning parameter 'intercept' was held constant at a value of TRUE
```

#testing model by prediction

predictions_lm <- predict(stack_lm, test)

error <- predictions_lm - test$Purchase

sqrt(mean(error^2))

**Output-**

```
[1] 3045.509
```

#GBM Ensemble

stack_gbm <- caretStack(models, method = "gbm", trControl = trainControl(method = "repeatedcv", number = 10, repeats = 3, savePredictions = TRUE))

stack_gbm

**Output-**

```
A gbm ensemble of 2 base models: glm, glmnet, lm, treebag, gbm

Ensemble results:
Stochastic Gradient Boosting

112896 samples
     5 predictor

No pre-processing
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 101605, 101607, 101608, 101607, 101605, 101606, ...
Resampling results across tuning parameters:

  interaction.depth  n.trees  RMSE      Rsquared   MAE
  1                   50      3004.177  0.6365599  2313.764
  1                  100      2974.843  0.6397946  2262.229
  1                  150      2973.575  0.6400149  2259.403
  2                   50      2976.227  0.6396986  2266.802
  2                  100      2971.281  0.6405699  2257.859
  2                  150      2969.886  0.6408985  2255.887
  3                   50      2972.973  0.6402641  2261.679
```

```
  3                   100      2969.574  0.6409731  2256.350
  3                   150      2968.344  0.6412601  2254.258

Tuning parameter 'shrinkage' was held constant at a value of 0.1
Tuning
 parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 150, interaction.depth = 3
, shrinkage =
 0.1 and n.minobsinnode = 10.
```

#testing model by gbm

predictions_gbm <- predict(stack_gbm, test)

error <- predictions_gbm - test$Purchase

sqrt(mean(error^2))

**Output-**

```
[1] 3029.206
```

#Importing testing data

testing <- read.csv("BlackFriday.csv")

#Converting Data

testing$Marital_Status <- factor(testing$Marital_Status)

testing$Occupation <- factor(testing$Occupation)

testing$User_ID <- factor(testing$User_ID)

#Imputing 0 for missing values in Product_Category_2,Product_Category_3

testing$Product_Category_2 <- as.numeric(testing$Product_Category_2)

testing[is.na(testing$Product_Category_2), "Product_Category_2"] <- 0

testing$Product_Category_3 <- as.numeric(testing$Product_Category_3)

testing[is.na(testing$Product_Category_3), "Product_Category_3"] <- 0

#Removing nonzero values

testing_sub <- testing %>%

  select(-User_ID, -Product_ID)

summary(testing_sub)

**Output-**

```
Gender        Age           Occupation     City_Category Stay_In_Current_City
_Years
 F:132197   0-17 : 14707   4      : 70862   A:144638      0 : 72725
 M:405380   18-25: 97634   0      : 68120   B:226493      1 :189192
            26-35:214690   7      : 57806   C:166446      2 : 99459
            36-45:107499   1      : 45971                 3 : 93312
            46-50: 44526   17     : 39090                 4+: 82889
            51-55: 37618   20     : 32910
            55+  : 20903   (Other):222818
 Marital_Status Product_Category_1 Product_Category_2 Product_Category_3    P
urchase
 0:317817       Min.   : 1.000     Min.   : 0.000     Min.   : 0.000     Min.
:  185
 1:219760       1st Qu.: 1.000     1st Qu.: 0.000     1st Qu.: 0.000     1st
Qu.: 5866
                Median : 5.000     Median : 5.000     Median : 0.000     Medi
an : 8062
                Mean   : 5.296     Mean   : 6.785     Mean   : 3.872     Mean
: 9334
                3rd Qu.: 8.000     3rd Qu.:14.000     3rd Qu.: 8.000     3rd
Qu.:12073
                Max.   :18.000     Max.   :18.000     Max.   :18.000     Max.
:23961
```

#Final testing

testing_predictions_glmnet <- predict(stack_glmnet, testing_sub)

testing$Purchase <- testing_predictions_glmnet

submission_glmnet <- testing[, c("User_ID", "Product_ID", "Purchase")]

dim(submission_glmnet)

**Output-**

```
[1] 537577      3
```

head(submission_glmnet)

**Output-**

```
User_ID Product_ID  Purchase
1 1000001   P00069042  9871.534
```

```
2 1000001  P00248942 14974.791
3 1000001  P00087842  1267.045
4 1000001  P00085442  1077.683
5 1000002  P00285442  7871.378
6 1000003  P00193542 13070.109
```

write.csv(submission_glmnet, "black_friday_predictions.csv",

row.names = FALSE)

**Output-**

black_friday_predicti
ons.csv

**https://drive.google.com/open?id=1ByLQ0vBFv7VZxmHxCwwlFrQ8kz7J0ks7**

## VII. Citations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