Marketing Campaign Analysis

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Introduction

In this project, a thorough analysis of a retail food company's marketing campaign is presented. It aims to understand the campaign's interactions with it's target audience, find business opportunities and insights, and to propose any data-driven actions to maximize the optimal results of the campaign and generate value to the company.
Products from 5 major categories are sold: wines, rare meat products, exotic fruits, specially prepared fish, and sweet products. These can further be divided into "gold" and "regular" products. The customers can order and acquire products through 3 sales channels: physical stores, catalogs, and the company's website.

Objective(s)

The key objectives are:
1. *EDA*: explore the data to understand the characteristic features of the respondents to the previous marketing campaigns by the company, to make better execution of the forthcoming one.
2. *Regression analysis*: build a regression model to identify significant factors that influence the number of store purchases by the respondents. Also, compare the performance of the previous campaigns by their respective geographical regions.

Dataset

The dataset contains socio-demographic and firmographic features of 2,240 customers. Additionally, it contains binary flags for those customers that responded to the campaign by buying a product.

```
df <- read.csv("marketing_data.csv")
dim(df)
```

```
## [1] 2240   28
```

```
head(df)
```

```
##      ID Year_Birth  Education Marital_Status      Income Kidhome Teenhome
## 1  1826       1970 Graduation       Divorced $84,835.00        0        0
## 2     1       1961 Graduation         Single $57,091.00        0        0
## 3 10476       1958 Graduation        Married $67,267.00        0        1
## 4  1386       1967 Graduation       Together $32,474.00        1        1
## 5  5371       1989 Graduation         Single $21,474.00        1        0
## 6  7348       1958        PhD         Single $71,691.00        0        0
##   Dt_Customer Recency MntWines MntFruits MntMeatProducts MntFishProducts
```

```
## 1     6/16/14       0      189       104             379             111
## 2     6/15/14       0      464         5              64               7
## 3     5/13/14       0      134        11              59              15
## 4     5/11/14       0       10         0               1               0
## 5      4/8/14       0        6        16              24              11
## 6     3/17/14       0      336       130             411             240
##   MntSweetProducts MntGoldProds NumDealsPurchases NumWebPurchases
## 1              189          218                 1               4
## 2                0           37                 1               7
## 3                2           30                 1               3
## 4                0            0                 1               1
## 5                0           34                 2               3
## 6               32           43                 1               4
##   NumCatalogPurchases NumStorePurchases NumWebVisitsMonth AcceptedCmp3
## 1                   4                 6                 1            0
## 2                   3                 7                 5            0
## 3                   2                 5                 2            0
## 4                   0                 2                 7            0
## 5                   1                 2                 7            1
## 6                   7                 5                 2            0
##   AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2 Response Complain Country
## 1            0            0            0            0        1        0      SP
## 2            0            0            0            1        1        0      CA
## 3            0            0            0            0        0        0      US
## 4            0            0            0            0        0        0     AUS
## 5            0            0            0            0        1        0      SP
## 6            0            0            0            0        1        0      SP
```

The "Income" column in the data frame is of "chr" data type containing commas and the Dollar ($) sign. To apply any arithmetic operation on it for the analysis, it needs to be *coerced* to a numeric data type by performing string replacement.
The "Dt_Customer" column is also of "chr" data type. This needs to be coerced to "Date" type.

```
df$Income <- str_replace_all(df$Income,"([$,])", "")
df$Income <- as.numeric(df$Income)
df$Dt_Customer <- as.Date(df$Dt_Customer,format = '%m/%d/%Y')
head(df)
```

```
##      ID Year_Birth  Education Marital_Status Income Kidhome Teenhome
## 1  1826       1970 Graduation       Divorced  84835       0        0
## 2     1       1961 Graduation         Single  57091       0        0
## 3 10476       1958 Graduation        Married  67267       0        1
## 4  1386       1967 Graduation       Together  32474       1        1
## 5  5371       1989 Graduation         Single  21474       1        0
## 6  7348       1958        PhD         Single  71691       0        0
##   Dt_Customer Recency MntWines MntFruits MntMeatProducts MntFishProducts
## 1  0014-06-16       0      189       104             379             111
## 2  0014-06-15       0      464         5              64               7
## 3  0014-05-13       0      134        11              59              15
## 4  0014-05-11       0       10         0               1               0
## 5  0014-04-08       0        6        16              24              11
## 6  0014-03-17       0      336       130             411             240
##   MntSweetProducts MntGoldProds NumDealsPurchases NumWebPurchases
```

```
## 1              189          218                 1              4
## 2                0           37                 1              7
## 3                2           30                 1              3
## 4                0            0                 1              1
## 5                0           34                 2              3
## 6               32           43                 1              4
##   NumCatalogPurchases NumStorePurchases NumWebVisitsMonth AcceptedCmp3
## 1                   4                 6                 1            0
## 2                   3                 7                 5            0
## 3                   2                 5                 2            0
## 4                   0                 2                 7            0
## 5                   1                 2                 7            1
## 6                   7                 5                 2            0
##   AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2 Response Complain Country
## 1            0            0            0            0        1        0      SP
## 2            0            0            0            1        1        0      CA
## 3            0            0            0            0        0        0      US
## 4            0            0            0            0        0        0     AUS
## 5            0            0            0            0        1        0      SP
## 6            0            0            0            0        1        0      SP
```

Exploratory Data Analaysis (EDA)

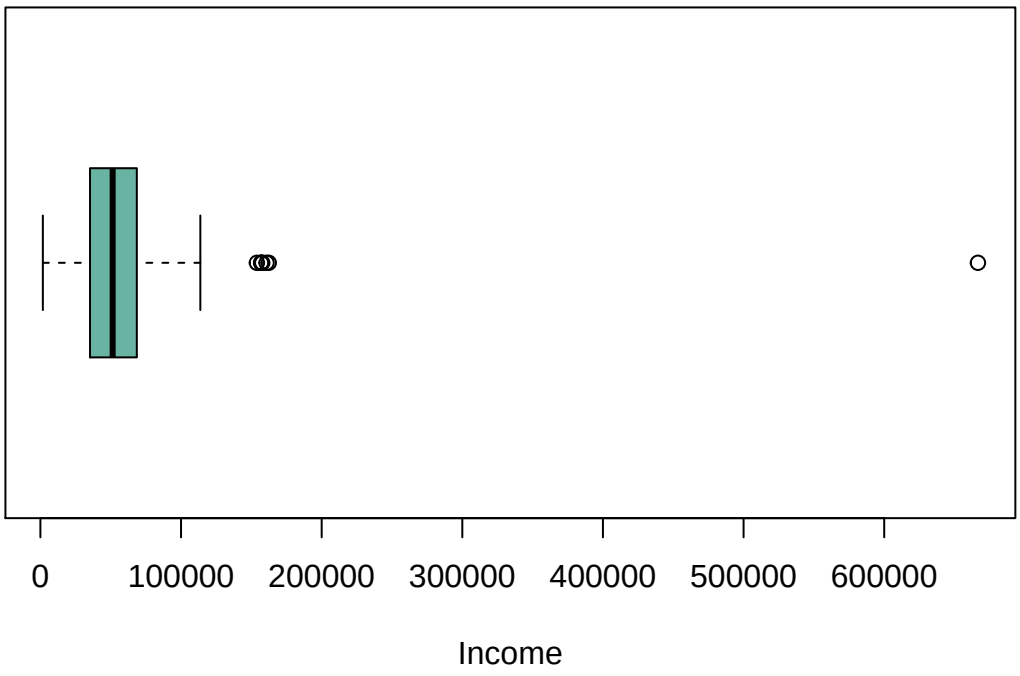
Duplicates, Outliers and Null Values Count the number of duplicate values that may be in the data frame. Also, Identify features that contain NULL values. Then, using the distribution of any such feature can help to replace the NULL value with the *median* value to avoid the effects of outliers on the imputation value.

```
sapply(df, function(df) sum(is.na(df)))
```

```
##                  ID          Year_Birth           Education      Marital_Status
##                   0                   0                   0                   0
##              Income             Kidhome            Teenhome         Dt_Customer
##                  24                   0                   0                   0
##             Recency            MntWines           MntFruits     MntMeatProducts
##                   0                   0                   0                   0
##     MntFishProducts    MntSweetProducts        MntGoldProds   NumDealsPurchases
##                   0                   0                   0                   0
##     NumWebPurchases NumCatalogPurchases   NumStorePurchases   NumWebVisitsMonth
##                   0                   0                   0                   0
##        AcceptedCmp3        AcceptedCmp4        AcceptedCmp5        AcceptedCmp1
##                   0                   0                   0                   0
##        AcceptedCmp2            Response            Complain             Country
##                   0                   0                   0                   0
```

The 'Income' column contains 24 NULL values. It can be replaced by the median Income.

```
boxplot(df$Income , col="#69b3a2" , xlab="Income",horizontal = TRUE)
```




```
# Set the outlier, which may be a data entry error, in the Income column to N/A.
df <- df %>%
  mutate_at(vars(Income), na_if, 666666)
max(df$Income,na.rm = TRUE)
```

```
## [1] 162397
```

```
# Set the n/a entries in Income to the median income.
df$Income[is.na(df$Income)]<-median(df$Income,na.rm = TRUE)
# check for duplicate values
sum(anyDuplicated(df))
```

```
## [1] 0
```

There are no duplicate values in the data frame.

Feature Engineering Review a list of variables in the data frame which can be combined to create new useful variables for the analysis.

```
str(df)
```

```
## 'data.frame':    2240 obs. of  28 variables:
##  $ ID                 : int  1826 1 10476 1386 5371 7348 4073 1991 4047 9477 ...
```

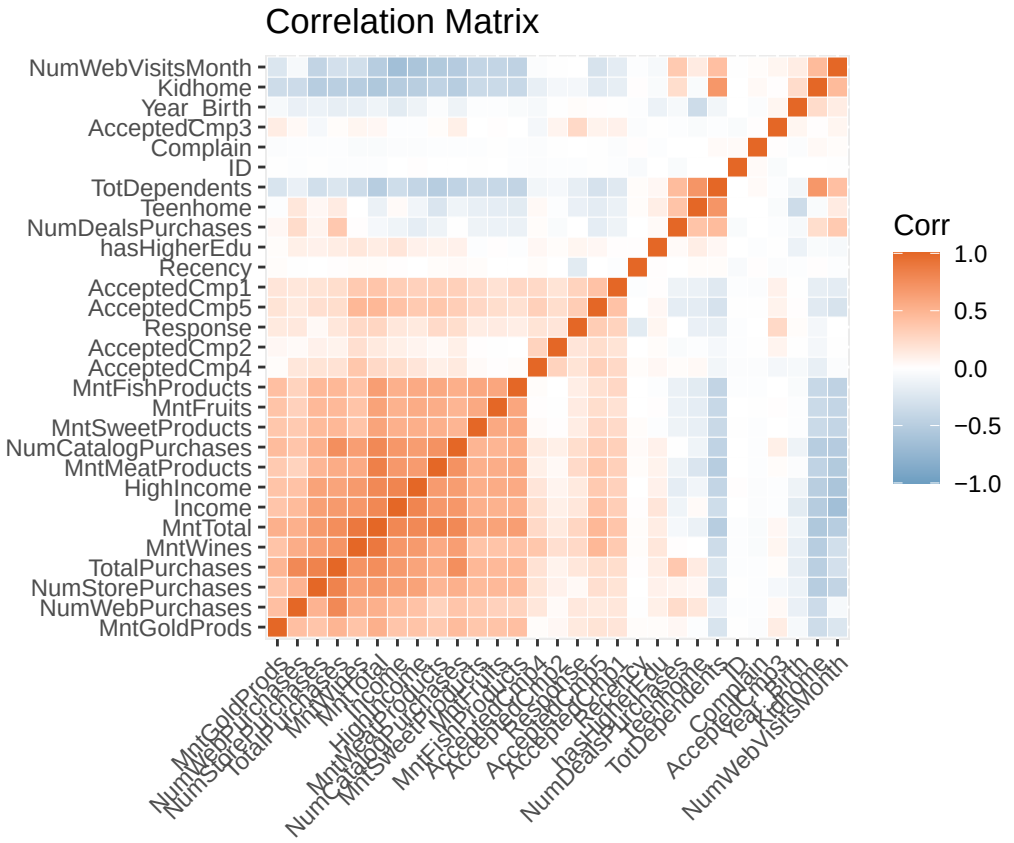
```
##  $ Year_Birth         : int  1970 1961 1958 1967 1989 1958 1954 1967 1954 1954 ...
##  $ Education          : chr  "Graduation" "Graduation" "Graduation" "Graduation" ...
##  $ Marital_Status     : chr  "Divorced" "Single" "Married" "Together" ...
##  $ Income             : num  84835 57091 67267 32474 21474 ...
##  $ Kidhome            : int  0 0 0 1 1 0 0 0 0 0 ...
##  $ Teenhome           : int  0 0 1 1 0 0 0 1 1 1 ...
##  $ Dt_Customer        : Date, format: "0014-06-16" "0014-06-15" ...
##  $ Recency            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ MntWines           : int  189 464 134 10 6 336 769 78 384 384 ...
##  $ MntFruits          : int  104 5 11 0 16 130 80 0 0 0 ...
##  $ MntMeatProducts    : int  379 64 59 1 24 411 252 11 102 102 ...
##  $ MntFishProducts    : int  111 7 15 0 11 240 15 0 21 21 ...
##  $ MntSweetProducts   : int  189 0 2 0 0 32 34 0 32 32 ...
##  $ MntGoldProds       : int  218 37 30 0 34 43 65 7 5 5 ...
##  $ NumDealsPurchases  : int  1 1 1 1 2 1 1 1 3 3 ...
##  $ NumWebPurchases    : int  4 7 3 1 3 4 10 2 6 6 ...
##  $ NumCatalogPurchases: int  4 3 2 0 1 7 10 1 2 2 ...
##  $ NumStorePurchases  : int  6 7 5 2 2 5 7 3 9 9 ...
##  $ NumWebVisitsMonth  : int  1 5 2 7 7 2 6 5 4 4 ...
##  $ AcceptedCmp3       : int  0 0 0 0 1 0 1 0 0 0 ...
##  $ AcceptedCmp4       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp5       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp1       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp2       : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ Response           : int  1 1 0 0 1 1 1 0 0 0 ...
##  $ Complain           : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Country            : chr  "SP" "CA" "US" "AUS" ...
```

'Mnt...' variables can be summed to create a 'MntTotal', representing the total amount spent by a customer in all the years as a customer. 'Num...Purchases' variables can be summed to create a 'TotalPurchases' Variable. A 'TotDependents' variable can be created by adding together 'Kidhome' and 'Teenhome'. Customers with higher education and income of more than $60,000 can also be used to create two new variables.

```
# Total amount spent by far
df <- mutate(df, MntTotal = MntWines + MntFruits + MntMeatProducts + MntFishProducts + MntSweetProducts
df$MntTotal <- as.numeric(df$MntTotal)

# Total number of purchases by far
df <- mutate(df, TotalPurchases = NumDealsPurchases + NumWebPurchases + NumCatalogPurchases + NumStorePu

# Total number of dependents
df <- mutate(df, TotDependents = Kidhome + Teenhome)

# High income individuals
df <- mutate(df, HighIncome = Income > 60000)
df$HighIncome <- as.numeric(df$HighIncome)
# Customers with Higher Education
df <- mutate(df, hasHigherEdu = Education %in% c('Graduation', 'PhD', 'Master'))
df$hasHigherEdu <- as.numeric(df$hasHigherEdu)
```

```
# Subset of the data frame with only numeric variables
corrdf <- df[,sapply(df,is.numeric)]
```

```r
# correlation matrix of the variables
corrMatrix <- cor(corrdf)
ggcorrplot(corrMatrix, title = "Correlation Matrix",
  hc.order = TRUE,
  outline.color = "white",
  ggtheme = ggplot2::theme_gray,
  colors = c("#6D9EC1", "white", "#E46726"))+
 theme(axis.text.x = element_text(angle = 45, vjust = 1,
    size = 9, hjust = 1),axis.text.y = element_text(size = 9))
```



Plots and Patterns

Plotting the correlation matrix of the features helps in identifying patterns or cluster in the data. Positive correlations between features appear orange, negative correlations appear blue, and no correlation appears white in the colored matrix above.

Findings:

• Total Amount and Total Purchases:

- Total amount spent (MntTotal) and other 'Mnt' features, along with total purchases and other 'Purchases' features, are positively correlated with Income.

- Total number of purchases in all three categories of ways to purchase - store, web and catalog - are also positively correlated with Income and *negatively* correlated with the 'TotDependents'.

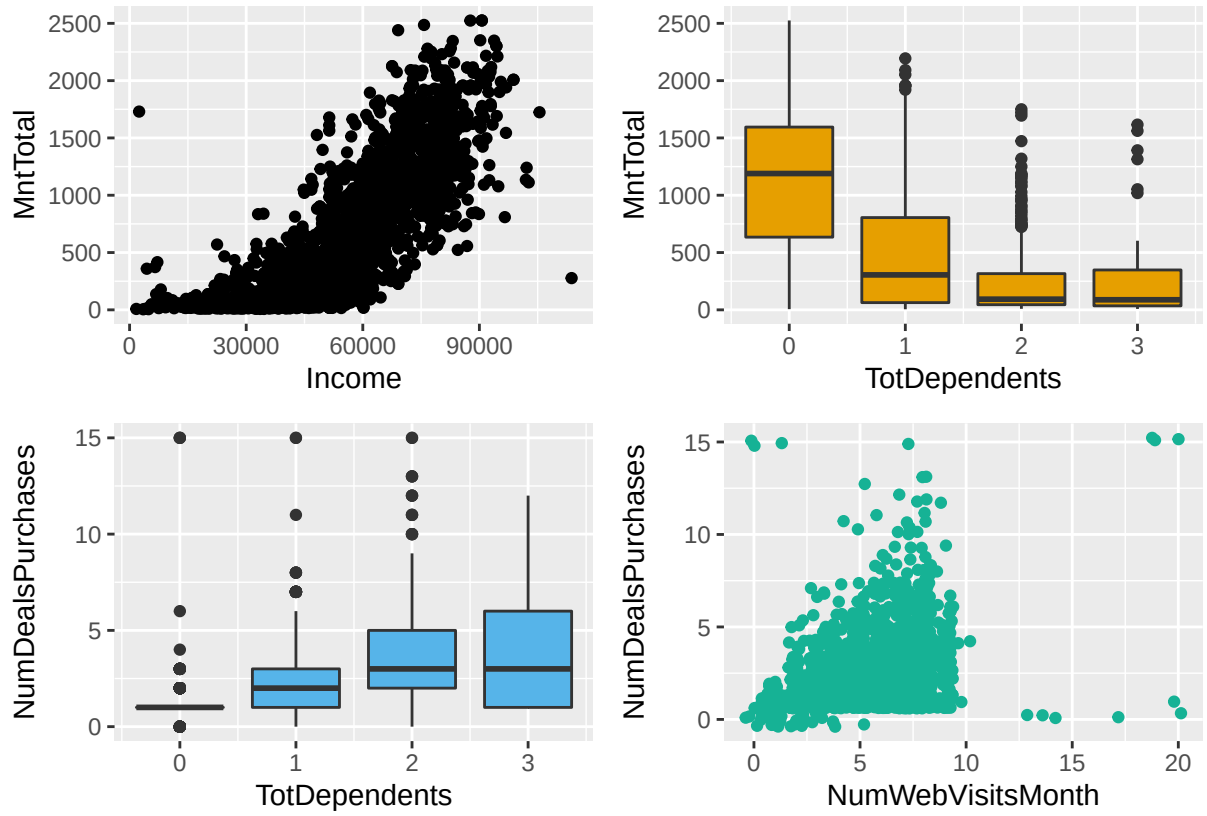
• NumDealsPurchases correlation

- 'NumDealsPurchases' is positively correlated with 'NumWebVisitsMonth', 'NumWebPurchases', and 'TotDependents'. *This suggests that customers with dependents prefer buying online with deals on products.*

• Anomalies:

- 'Income' seems to suggest a positive, but week, correlation with 'Response' to previous advertising campaigns.

```r
plot1 <- ggplot(subset(df,Income<150000),aes(x=Income,y=MntTotal)) + geom_point()

plot2 <- ggplot(df,aes(x=TotDependents,y=MntTotal,group=TotDependents)) + geom_boxplot(fill = "#E69F00"

plot3 <- ggplot(df,aes(x=TotDependents,y=NumDealsPurchases,group=TotDependents)) + geom_boxplot(fill="#

plot4 <- ggplot(df,aes(x=NumWebVisitsMonth,y=NumDealsPurchases,group=NumWebPurchases)) + geom_point(pos

wrap_plots(plot1, plot2, plot3, plot4)
```



Regreesion Analysis

In order to gain further insight into what features explain the "Response" variable, denoting the response of the customers to the previous campaign, Logistic regression analysis is to be performed to help in classifying what factors lead the audience to respond to the advertising.

First, I will clean the data by dropping redundant columns in the dataset that are not needed in the regression model

```r
df <- subset(df,select = -c(ID, Year_Birth, Dt_Customer))
view(df)
```

Next, split the data into two random subsets with a ratio of 70:30. The larger subset is to be used for training the model and the rest of the data is for evaluating model estimates.

```r
set.seed(42)
sampleSplit <- sample.split(Y=df$Response, SplitRatio=0.7)
trainSet <- subset(x=df, sampleSplit==TRUE)
testSet <- subset(x=df, sampleSplit==FALSE)

model <- glm(Response ~.,family=binomial(link='logit'),data=trainSet)
summary(model)
```

```
##
## Call:
## glm(formula = Response ~ ., family = binomial(link = "logit"),
##     data = trainSet)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3659  -0.3979  -0.2265  -0.1046   3.3429
##
## Coefficients: (4 not defined because of singularities)
##                            Estimate   Std. Error z value            Pr(>|z|)
## (Intercept)             11.17285242 882.74395780   0.013            0.989901
## EducationBasic          -0.75581972   0.87102182  -0.868            0.385537
## EducationGraduation      0.52810811   0.40082098   1.318            0.187649
## EducationMaster          0.85737386   0.44802543   1.914            0.055662
## EducationPhD             1.19755581   0.43242113   2.769            0.005616
## Marital_StatusAlone    -14.19380885 882.74463942  -0.016            0.987171
## Marital_StatusDivorced -14.26632194 882.74371435  -0.016            0.987106
## Marital_StatusMarried  -15.48009310 882.74367210  -0.018            0.986009
## Marital_StatusSingle   -14.20083149 882.74369232  -0.016            0.987165
## Marital_StatusTogether -15.24924606 882.74369483  -0.017            0.986217
## Marital_StatusWidow    -13.53658537 882.74376693  -0.015            0.987765
## Marital_StatusYOLO     -13.58966391 882.74495914  -0.015            0.987717
## Income                  -0.00000905   0.00001118  -0.809            0.418237
## Kidhome                  0.21032631   0.26994957   0.779            0.435902
## Teenhome                -1.12467190   0.24640170  -4.564 0.00000500963995910
## Recency                 -0.02802246   0.00360531  -7.773 0.00000000000000769
## MntWines                 0.00016101   0.00048425   0.333            0.739509
## MntFruits                0.00265933   0.00316870   0.839            0.401329
## MntMeatProducts          0.00293096   0.00061522   4.764 0.00000189676412172
## MntFishProducts         -0.00275549   0.00236363  -1.166            0.243701
## MntSweetProducts         0.00169818   0.00277596   0.612            0.540707
## MntGoldProds             0.00528676   0.00206416   2.561            0.010431
## NumDealsPurchases        0.22738186   0.06209036   3.662            0.000250
## NumWebPurchases          0.05210549   0.04105275   1.269            0.204358
## NumCatalogPurchases      0.09791708   0.05345431   1.832            0.066983
## NumStorePurchases       -0.17248960   0.04518564  -3.817            0.000135
## NumWebVisitsMonth        0.28670651   0.06140932   4.669 0.00000302995806872
## AcceptedCmp3             2.08635793   0.27248679   7.657 0.00000000000001907
## AcceptedCmp4             1.65339851   0.34157600   4.840 0.00000129513124812
## AcceptedCmp5             1.67395765   0.36139869   4.632 0.00000362349069849
## AcceptedCmp1             1.31947918   0.34226346   3.855            0.000116
## AcceptedCmp2             0.95186935   0.65637019   1.450            0.147002
## Complain                 0.21812645   1.12216177   0.194            0.845878
## CountryCA               -0.06524827   0.43977413  -0.148            0.882053
```

```
## CountryGER              -0.07047488   0.53087673  -0.133            0.894390
## CountryIND              -0.76365126   0.53836530  -1.418            0.156056
## CountryME               15.09790720 882.74356920   0.017            0.986354
## CountrySA               -0.17701780   0.42684238  -0.415            0.678351
## CountrySP               -0.16051249   0.37773118  -0.425            0.670882
## CountryUS               -1.07290856   0.61334191  -1.749            0.080242
## MntTotal                         NA           NA      NA                  NA
## TotalPurchases                   NA           NA      NA                  NA
## TotDependents                    NA           NA      NA                  NA
## HighIncome               0.19176026   0.40380402   0.475            0.634869
## hasHigherEdu                     NA           NA      NA                  NA
##
## (Intercept)
## EducationBasic
## EducationGraduation
## EducationMaster         .
## EducationPhD            **
## Marital_StatusAlone
## Marital_StatusDivorced
## Marital_StatusMarried
## Marital_StatusSingle
## Marital_StatusTogether
## Marital_StatusWidow
## Marital_StatusYOLO
## Income
## Kidhome
## Teenhome                ***
## Recency                 ***
## MntWines
## MntFruits
## MntMeatProducts         ***
## MntFishProducts
## MntSweetProducts
## MntGoldProds            *
## NumDealsPurchases       ***
## NumWebPurchases
## NumCatalogPurchases     .
## NumStorePurchases       ***
## NumWebVisitsMonth       ***
## AcceptedCmp3            ***
## AcceptedCmp4            ***
## AcceptedCmp5            ***
## AcceptedCmp1            ***
## AcceptedCmp2
## Complain
## CountryCA
## CountryGER
## CountryIND
## CountryME
## CountrySA
## CountrySP
## CountryUS               .
## MntTotal
## TotalPurchases
```

```
## TotDependents
## HighIncome
## hasHigherEdu
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1321.45  on 1567  degrees of freedom
## Residual deviance:  793.33  on 1527  degrees of freedom
## AIC: 875.33
##
## Number of Fisher Scoring iterations: 13
```

```
# Do Anova test
anova(model, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: Response
##
## Terms added sequentially (first to last)
##
##
##                     Df Deviance Resid. Df Resid. Dev             Pr(>Chi)
## NULL                                 1567    1321.45
## Education            4   13.331      1563    1308.11            0.0097686 **
## Marital_Status       7   35.877      1556    1272.24 0.000007646060066843 ***
## Income               1   20.482      1555    1251.76 0.000006020828321304 ***
## Kidhome              1    0.454      1554    1251.30            0.5005548
## Teenhome             1   42.214      1553    1209.09 0.000000000081807239 ***
## Recency              1   58.741      1552    1150.35 0.000000000000017982 ***
## MntWines             1   61.816      1551    1088.53 0.000000000000003772 ***
## MntFruits            1    0.082      1550    1088.45            0.7740870
## MntMeatProducts      1   18.535      1549    1069.91 0.000016679284382077 ***
## MntFishProducts      1    4.325      1548    1065.59            0.0375580 *
## MntSweetProducts     1    0.709      1547    1064.88            0.3998125
## MntGoldProds         1   18.008      1546    1046.87 0.000022002658370788 ***
## NumDealsPurchases    1   11.695      1545    1035.18            0.0006267 ***
## NumWebPurchases      1    1.470      1544    1033.71            0.2253019
## NumCatalogPurchases  1    6.669      1543    1027.04            0.0098080 **
## NumStorePurchases    1   35.442      1542     991.60 0.000000002627746591 ***
## NumWebVisitsMonth    1   28.230      1541     963.37 0.000000107708998320 ***
## AcceptedCmp3         1   62.259      1540     901.11 0.000000000000003011 ***
## AcceptedCmp4         1   53.153      1539     847.95 0.000000000000308485 ***
## AcceptedCmp5         1   27.775      1538     820.18 0.000000136247514216 ***
## AcceptedCmp1         1   15.246      1537     804.93 0.000094368867506171 ***
## AcceptedCmp2         1    2.456      1536     802.47            0.1170593
## Complain             1    0.051      1535     802.42            0.8211929
## Country              7    8.864      1528     793.56            0.2625368
## MntTotal             0    0.000      1528     793.56
## TotalPurchases       0    0.000      1528     793.56
```

```
## TotDependents        0    0.000      1528     793.56
## HighIncome           1    0.226      1527     793.33           0.6348538
## hasHigherEdu         0    0.000      1527     793.33
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Running the regression tells us that Education, Teenhome, and Recency have extremely low p-value at 5% threshold, suggesting a strong association of these features of affecting the log-probability of response of the individuals to the advertising. Furthermore, MntMeatProducts and AcceptedCmp3 are also considerable variable in the model.

```
# Predict the value of Response on the test set
fitted.results <- predict(model,newdata=testSet,type='response')
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

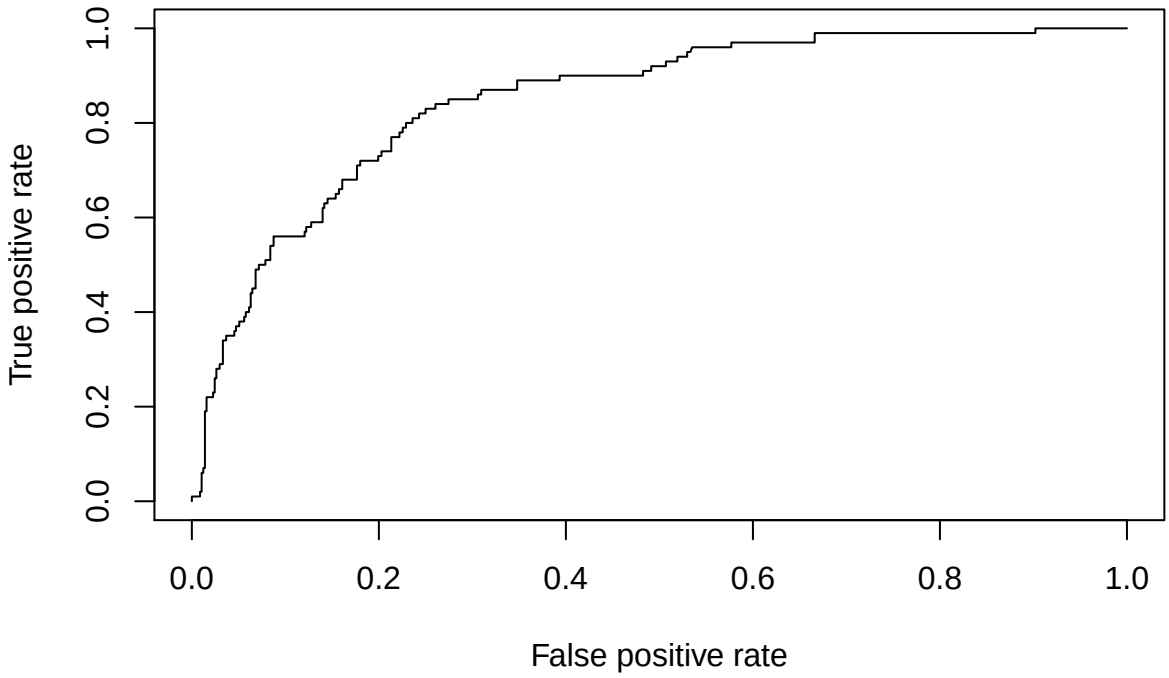
```
fitted.results <- ifelse(fitted.results > 0.5,1,0)
misClasificError <- mean(fitted.results != testSet$Response)
print(paste('Accuracy',1-misClasificError))
```

```
## [1] "Accuracy 0.864583333333333"
```

```
# Compute the AUC (Area Under the ROC Curve)
p <- predict(model, newdata=testSet, type="response")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
pr <- prediction(p, testSet$Response)
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
```




```
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
auc
```

```
## [1] 0.8493794
```

The predicted values from the model gives us the accuracy of 0.86, which is quite good. Additionally, after plotting ROC, the evaluated AUC for the model is 0.84. As a rule of thumb, a model with good predictive ability should have an AUC closer to 1, so our model is fairly accurate.

Conclusion

• The response to the campaign is positively correlated with income and negatively correlated with kids/teens.
• The analysis showed that the best selling products are meat and wine. I suggest that the company invest in boosting the sales of rest of the product line.
• Number of dependents and number of web visits are positively correlated with the number of deals purchases, so I suggest targeting ads with online offers to homes with kids/teens.