Multiple Linear Regression and Binary Logistic Regression

Data 621: Homework 4 - Group 4

Sachid Deshmukh
Michael Yampol
Vishal Arora
Ann Liu-Ferrara

Nov. 15, 2019

Contents

---

1. Data Exploration

Let's load the training dataset and preview it:

```
##   INDEX TARGET_FLAG TARGET_AMT KIDSDRIV AGE HOMEKIDS YOJ   INCOME PARENT1
## 1     1           0          0        0  60        0  11  $67,349      No
## 2     2           0          0        0  43        0  11  $91,449      No
## 3     4           0          0        0  35        1  10  $16,039      No
## 4     5           0          0        0  51        0  14     <NA>      No
## 5     6           0          0        0  50        0  NA $114,986      No
## 6     7           1       2946        0  34        1  12 $125,301     Yes
##   HOME_VAL MSTATUS SEX     EDUCATION           JOB TRAVTIME    CAR_USE
## 1       $0    z_No   M           PhD  Professional       14    Private
## 2 $257,252    z_No   M z_High School z_Blue Collar       22 Commercial
## 3 $124,191     Yes z_F z_High School      Clerical        5    Private
## 4 $306,251     Yes   M  <High School z_Blue Collar       32    Private
## 5 $243,925     Yes z_F           PhD        Doctor       36    Private
## 6       $0    z_No z_F     Bachelors z_Blue Collar       46 Commercial
##   BLUEBOOK TIF   CAR_TYPE RED_CAR OLDCLAIM CLM_FREQ REVOKED MVR_PTS
## 1  $14,230  11    Minivan     yes   $4,461        2      No       3
## 2  $14,940   1    Minivan     yes       $0        0      No       0
## 3   $4,010   4      z_SUV      no  $38,690        2      No       3
## 4  $15,440   7    Minivan     yes       $0        0      No       0
## 5  $18,000   1      z_SUV      no  $19,217        2     Yes       3
## 6  $17,430   1 Sports Car      no       $0        0      No       0
##   CAR_AGE          URBANICITY
## 1      18 Highly Urban/ Urban
## 2       1 Highly Urban/ Urban
## 3      10 Highly Urban/ Urban
## 4       6 Highly Urban/ Urban
## 5      17 Highly Urban/ Urban
## 6       7 Highly Urban/ Urban
```

```
## [1] "Number of columns =  26"
```

```
## [1] "Number of rows =  8161"
```

As we can see from the preview, the training dataset has 26 columns and 8161 rows.

Let's examine the datatypes of each column:

```
## 'data.frame':    8161 obs. of  26 variables:
##  $ INDEX      : int  1 2 4 5 6 7 8 11 12 13 ...
##  $ TARGET_FLAG: int  0 0 0 0 0 1 0 1 1 0 ...
##  $ TARGET_AMT : num  0 0 0 0 0 ...
##  $ KIDSDRIV   : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ AGE        : int  60 43 35 51 50 34 54 37 34 50 ...
##  $ HOMEKIDS   : int  0 0 1 0 0 1 0 2 0 0 ...
##  $ YOJ        : int  11 11 10 14 NA 12 NA NA 10 7 ...
##  $ INCOME     : chr  "$67,349" "$91,449" "$16,039" NA ...
##  $ PARENT1    : chr  "No" "No" "No" "No" ...
##  $ HOME_VAL   : chr  "$0" "$257,252" "$124,191" "$306,251" ...
##  $ MSTATUS    : chr  "z_No" "z_No" "Yes" "Yes" ...
##  $ SEX        : chr  "M" "M" "z_F" "M" ...
##  $ EDUCATION  : chr  "PhD" "z_High School" "z_High School" "<High School" ...
##  $ JOB        : chr  "Professional" "z_Blue Collar" "Clerical" "z_Blue Collar" ...
##  $ TRAVTIME   : int  14 22 5 32 36 46 33 44 34 48 ...
##  $ CAR_USE    : chr  "Private" "Commercial" "Private" "Private" ...
##  $ BLUEBOOK   : chr  "$14,230" "$14,940" "$4,010" "$15,440" ...
##  $ TIF        : int  11 1 4 7 1 1 1 1 1 7 ...
##  $ CAR_TYPE   : chr  "Minivan" "Minivan" "z_SUV" "Minivan" ...
##  $ RED_CAR    : chr  "yes" "yes" "no" "yes" ...
##  $ OLDCLAIM   : chr  "$4,461" "$0" "$38,690" "$0" ...
##  $ CLM_FREQ   : int  2 0 2 0 2 0 0 1 0 0 ...
##  $ REVOKED    : chr  "No" "No" "No" "No" ...
##  $ MVR_PTS    : int  3 0 3 0 3 0 0 10 0 1 ...
##  $ CAR_AGE    : int  18 1 10 6 17 7 1 7 1 17 ...
##  $ URBANICITY : chr  "Highly Urban/ Urban" "Highly Urban/ Urban" "Highly Urban/ Urban" "Highly Urban/ Urban" ...
```

The following quantitative variables are currently stored as character strings:

- INCOME
- HOME_VAL
- BLUEBOOK
- OLDCLAIM

We need to convert the above variables to numeric.

The following variables are categorical, but they are not stored as factors:

- TARGET_FLAG
- Parent1
- MStatus
- Sex
- Education
- Job
- Car_Use
- Car_Type
- Red_Car
- Revoked
- Urbanicity

Linear Regression and Logistic regression algorithms work best with numerical variables.

We need to transform these variables, making them quantitative, so that we can use them for model training.

Check missing values

Let's check if any variables have missing values, i.e., values which are NULL or NA.

```
## [1] "Number of columns with missing values =  6"

## [1] "Names of columns with missing values =  AGE, YOJ, INCOME, HOME_VAL, JOB, CAR_AGE"
```

We can that there are 6 variables which have missing values:

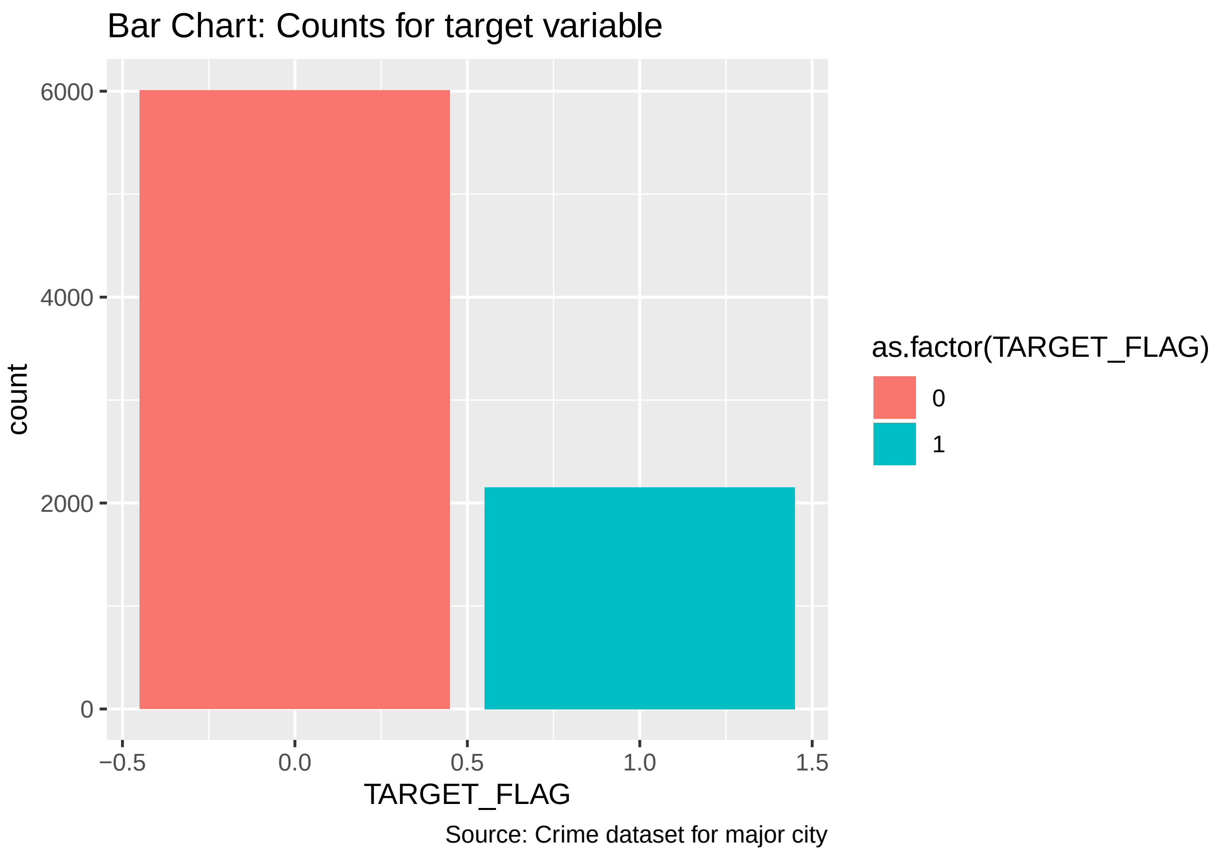
- Age
- Yoj
- Income
- Home_Val
- Job
- Car_Age

We will impute values for these variables for better model accuracy.

Check Class-Imbalance

Let's check if the training data is class-imbalanced.

A Dataset is called *class-imbalanced* when there are very few obesrvations corresponding to a minority class. This is very important in selecting model evaluation metrics.



The above barchart indicates that training dataset *is* class-imbalanced: There are fewer observations of customers who exhibit car crashes compared to observations of customers with no car crash. This makes the dataset class-imbalanced.

For logistic regression, we can't rely on model metrics like *Accuracy* because of this.

Since the dataset is class-imbalanced, we will give more importance to *Precision*, *Recall* and *ROC AUC* for evaluating logistic regression models.

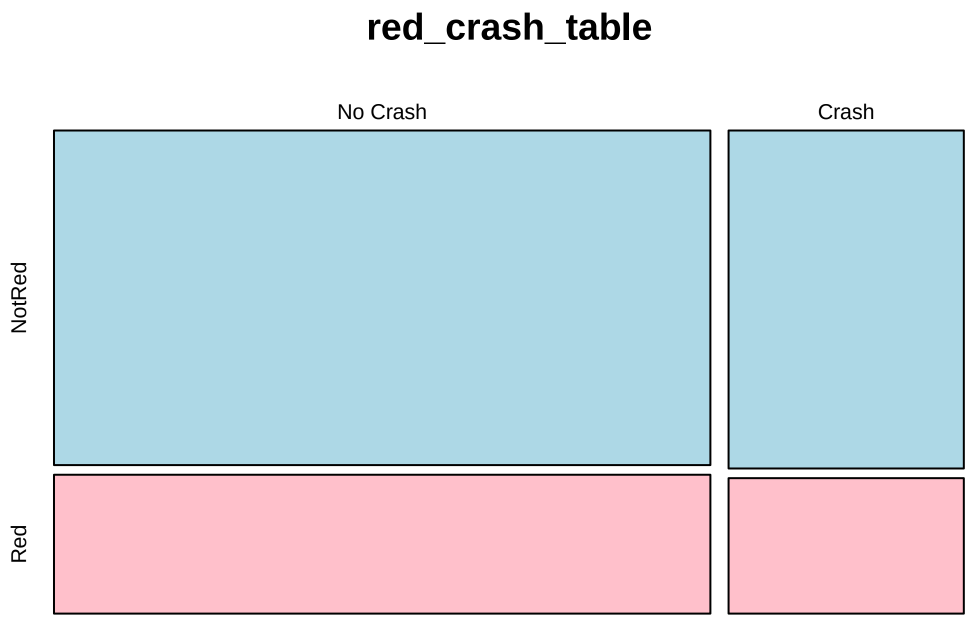
Red-colored cars

Let's check if Red colored cars crash more frequently:

Counts of car crashes vs. red or not red

```
##
##              NotRed  Red
##   No Crash     4246 1762
##   Crash        1537  616
```

Mosaicplot of car crashes vs. red or not red



Proportions of car crashes vs. red or not red

```
##
##               NotRed        Red
##   No Crash 0.52027938 0.21590491
##   Crash    0.18833476 0.07548095
```

What percent of cars which did (or, didn't) crash were red?

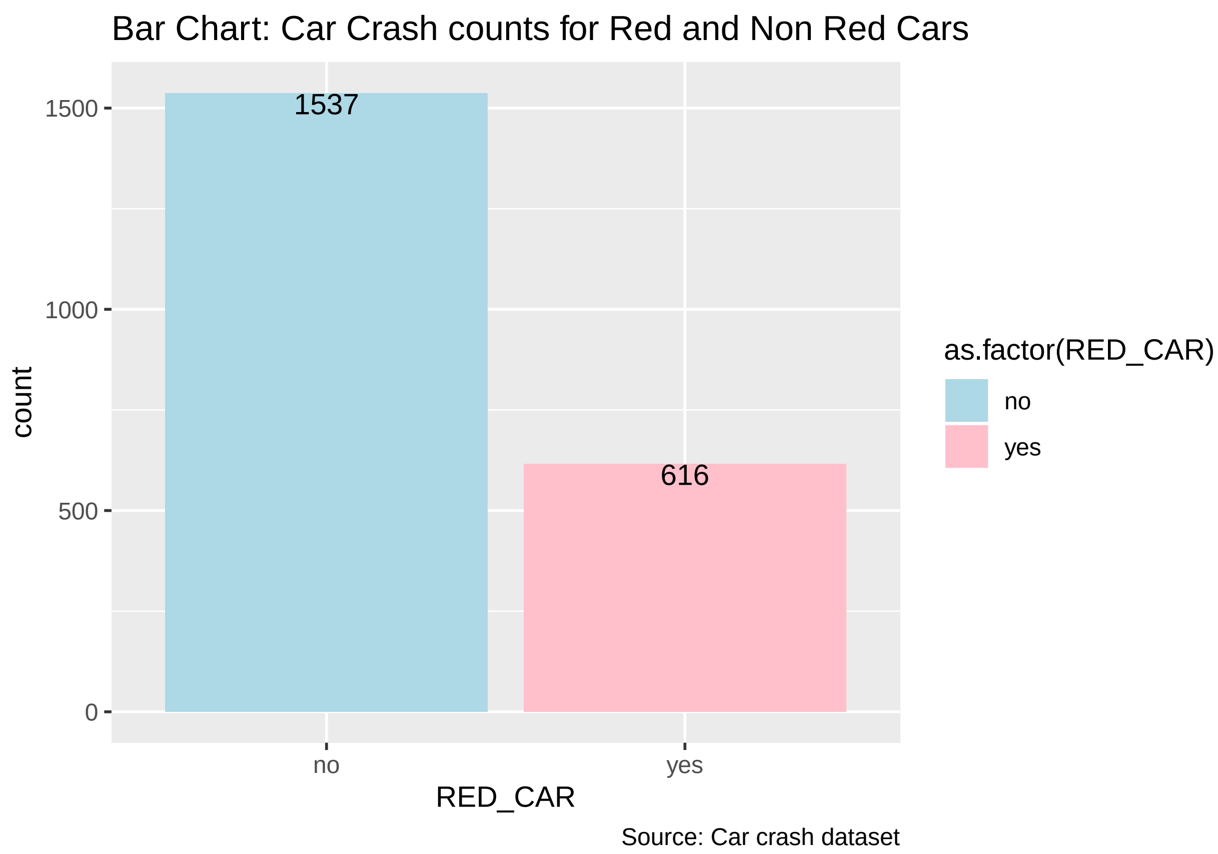
```
##
##              NotRed       Red
##   No Crash 0.7067244 0.2932756
##   Crash    0.7138876 0.2861124
```

What percent of cars of each color (Red, non-Red) crashed?

```
##
##              NotRed       Red
##   No Crash 0.7342210 0.7409588
##   Crash    0.2657790 0.2590412
```

Perform a chi-sq test to determine whether there is a difference in proportions

```
## Number of cases in table: 8161
## Number of factors: 2
## Test for independence of all factors:
##  Chisq = 0.3939, df = 1, p-value = 0.5303
```



Bar Chart: Car Crash counts for Red and Non Red Cars
1500
1000
500
0
count
1537
616
no
yes
RED_CAR
as.factor(RED_CAR)
no
yes
Source: Car crash dataset

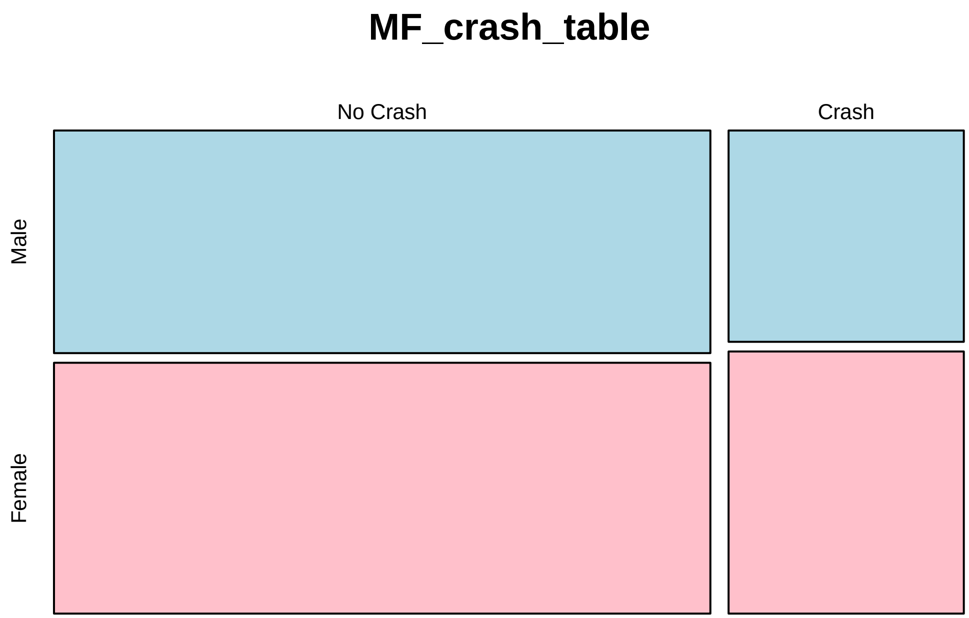
Women vs. Men

Let's check whether women are safer drivers compared to men:

Counts of car crashes vs. Male/Female

```
##
##              Male Female
##   No Crash 2825   3183
##   Crash     961   1192
```

Mosaicplot of car crashes vs. Male/Female



Proportions of car crashes vs. Male/Female

```
##
##                  Male    Female
##   No Crash 0.3461586 0.3900257
##   Crash    0.1177552 0.1460605
```

What percent of cars which did (or, didn't) crash were driven by Male vs. Female drivers?

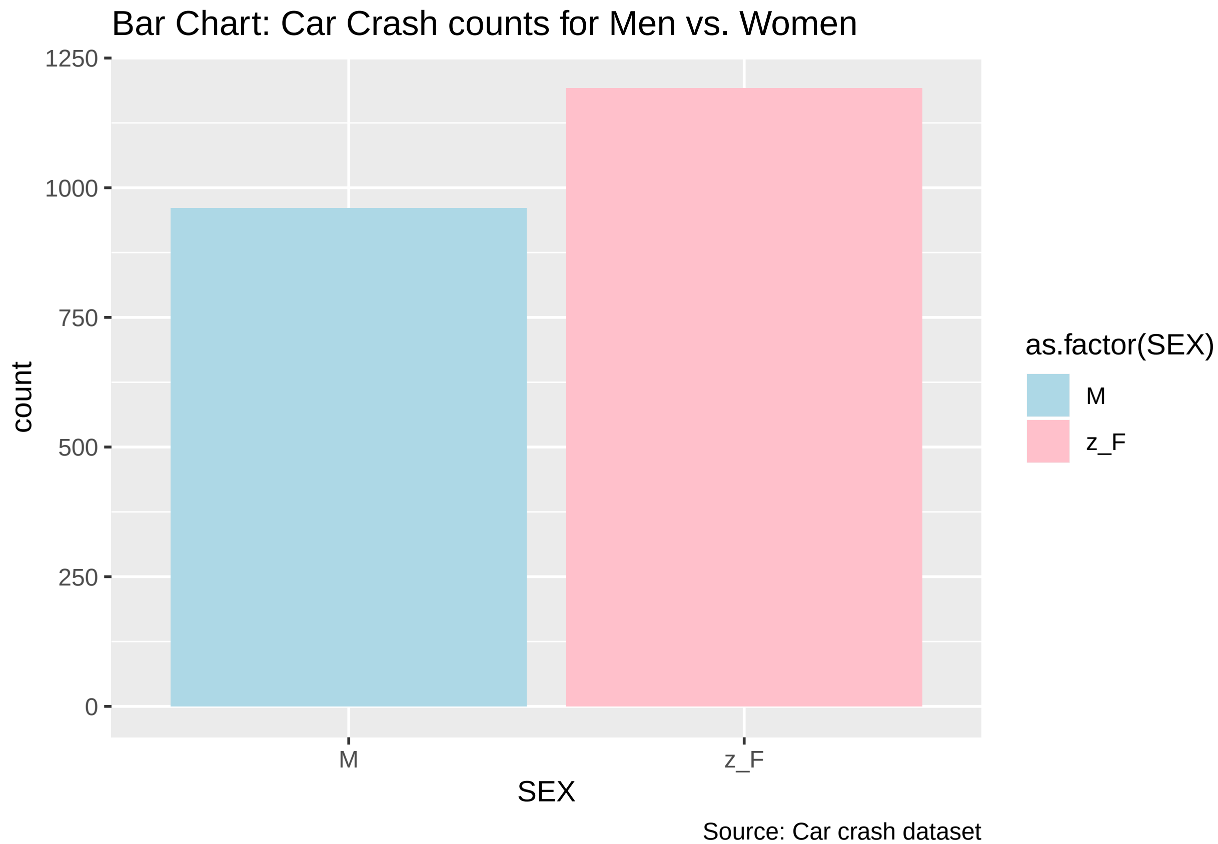
```
##
##                Male    Female
##   No Crash 0.4702064 0.5297936
##   Crash    0.4463539 0.5536461
```

What percent of cars driven by Men crashed? By Women?

```
##
##                Male    Female
##   No Crash 0.7461701 0.7275429
##   Crash    0.2538299 0.2724571
```

Perform a chi-sq test to determine whether there is a significant difference in proportions:

```
## Number of cases in table: 8161
## Number of factors: 2
## Test for independence of all factors:
##  Chisq = 3.626, df = 1, p-value = 0.05688
```



While the above bar tables and chart show that women appear to have more car crashes compared to men, the χ^2 test indicates that the data is not significantly different at 95% confidence.

Thus, we cannot reject the null hypothesis H_0: Men and women drivers experience accidents at the same frequency.

2. Data Preparation

Encode Parent1 variable. No = 0 and Yes = 1

```
train.df$PARENT1 = ifelse(train.df$PARENT1 == 'No', 0, 1)
train.df$PARENT1 = as.numeric(train.df$PARENT1)
table(train.df$PARENT1)
```

```
##
##    0    1
## 7084 1077
```

Encode MStatus variable. No = 0 and Yes = 1

```
train.df$MSTATUS = ifelse(train.df$MSTATUS == 'z_No', 0, 1)
train.df$MSTATUS = as.numeric(train.df$MSTATUS)
table(train.df$MSTATUS)
```

```
##
##    0    1
## 3267 4894
```

Encode Sex variable. Male = 0 and Female = 1

```
train.df$SEX = ifelse(train.df$SEX == 'M', 0, 1)
train.df$SEX = as.numeric(train.df$SEX)
table(train.df$SEX)
```

```
##
##    0    1
## 3786 4375
```

Encode Education variable.

```r
train.df$EDUCATION = as.numeric(factor(train.df$EDUCATION,
                                       order = TRUE,
                                       levels = c("<High School", "z_High School",
                                                  "Bachelors", "Masters", "PhD")))
table(train.df$EDUCATION)
```

```
##
##    1    2    3    4    5
## 1203 2330 2242 1658  728
```

Encode Job variable.

```r
train.df$JOB = as.numeric(factor(train.df$JOB,
                                 order = TRUE,
                                 levels = c("Student", "Home Maker",
                                            "z_Blue Collar", "Clerical", "Professional",
                                            'Manager', 'Lawyer', 'Doctor')))
table(train.df$JOB)
```

```
##
##    1    2    3    4    5    6    7    8
##  712  641 1825 1271 1117  988  835  246
```

Encode Car_Use variable. Private = 0 and Commercial = 1

```r
train.df$CAR_USE = ifelse(train.df$CAR_USE == "Private", 0, 1)
train.df$CAR_USE  = as.numeric(train.df$CAR_USE)
table(train.df$CAR_USE)
```

```
##
##    0    1
## 5132 3029
```

Encode CAR_TYPE variable.

```r
train.df$CAR_TYPE = as.numeric(factor(train.df$CAR_TYPE,
                                      order = TRUE,
                                      levels = c("Minivan", "z_SUV", "Van",
                                                 "Pickup", "Panel Truck", 'Sports Car')))
table(train.df$CAR_TYPE)
```

```
##
##    1    2    3    4    5    6
## 2145 2294  750 1389  676  907
```

Encode Red_car variable. No = 0 and Yes = 1

```r
train.df$RED_CAR = ifelse(train.df$RED_CAR == "no", 0, 1)
train.df$RED_CAR  = as.numeric(train.df$RED_CAR)
table(train.df$RED_CAR)
```

```
##
##    0    1
## 5783 2378
```

Encode Revoked variable. No = 0 and Yes = 1

```r
train.df$REVOKED = ifelse(train.df$REVOKED == "No", 0, 1)
train.df$REVOKED  = as.numeric(train.df$REVOKED)
table(train.df$REVOKED)
```

```
##
##    0    1
## 7161 1000
```

Encode Urban city variable. Rural = 0 and Urban = 1

```r
train.df$URBANICITY = ifelse(train.df$URBANICITY == "z_Highly Rural/ Rural", 0, 1)
train.df$URBANICITY  = as.numeric(train.df$URBANICITY)
table(train.df$URBANICITY)
```

```
##
##    0    1
## 1669 6492
```

Convert Income, Home_val, BlueBook, oldClaim Variable to quantitative variable

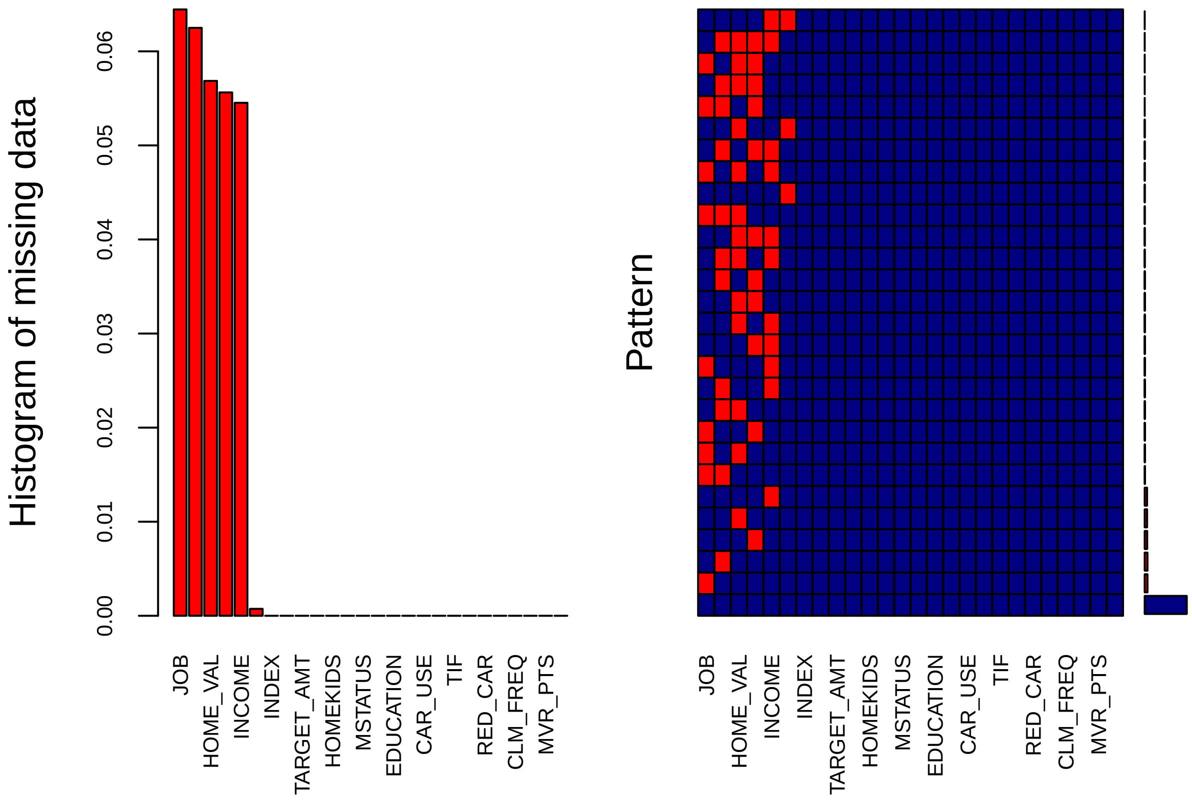
DATA IMPUTATION

Let's do data imputation for columns with missing values.

Which columns have missing values, and what is a missing pattern?

Let's leverage VIM package to get this information:

```
## Warning in plot.aggr(res, ...): not enough vertical space to display
## frequencies (too many combinations)
```



```
##
##  Variables sorted by number of missings:
##     Variable       Count
##          JOB 0.064452886
##      CAR_AGE 0.062492342
##     HOME_VAL 0.056855777
##          YOJ 0.055630437
##       INCOME 0.054527631
##          AGE 0.000735204
##        INDEX 0.000000000
##  TARGET_FLAG 0.000000000
##   TARGET_AMT 0.000000000
##     KIDSDRIV 0.000000000
##     HOMEKIDS 0.000000000
##      PARENT1 0.000000000
##      MSTATUS 0.000000000
##          SEX 0.000000000
##    EDUCATION 0.000000000
##     TRAVTIME 0.000000000
##      CAR_USE 0.000000000
##     BLUEBOOK 0.000000000
##          TIF 0.000000000
##     CAR_TYPE 0.000000000
##      RED_CAR 0.000000000
##     OLDCLAIM 0.000000000
##     CLM_FREQ 0.000000000
##      REVOKED 0.000000000
##      MVR_PTS 0.000000000
##   URBANICITY 0.000000000
```

From the above missing values pattern, we can see that most of the observations do not have missing values.

Non-missing values are shown in blue. This is good news, thus we can assert good quality of the data.

Let's use the mice package to impute missing values

MICE: "Multivariate Imputation by Chained Equations"

The **mice** package implements a method to deal with missing data.
The package creates multiple imputations (replacement values) for multivariate missing data.
The method is based on Fully Conditional Specification, where each incomplete variable is imputed by a separate model.
The MICE algorithm can impute mixes of continuous, binary, unordered categorical and ordered categorical data.
In addition, MICE can impute continuous two-level data, and maintain consistency between imputations by means of passive imputation.
Many diagnostic plots are implemented to inspect the quality of the imputations.

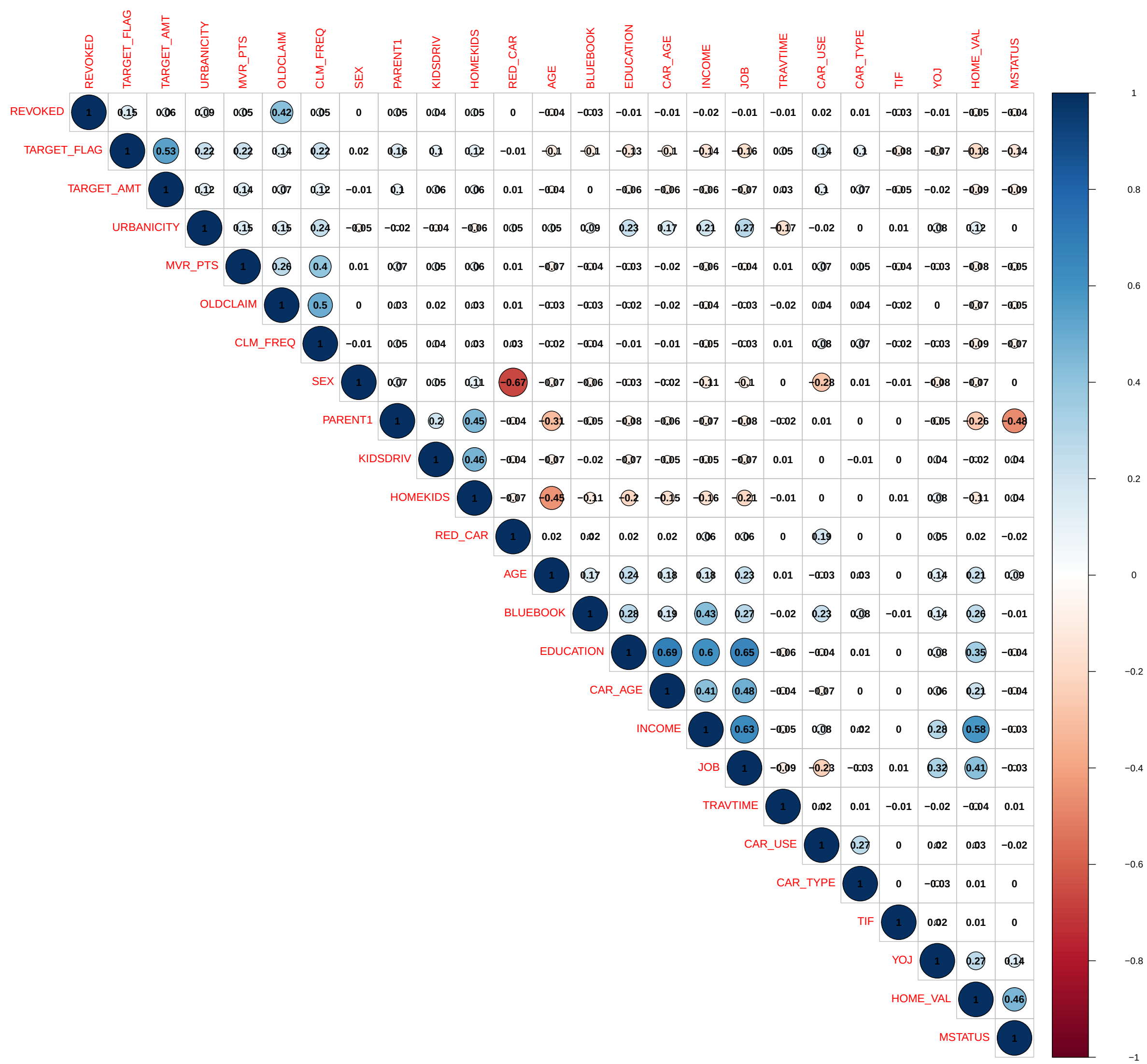
```
##
##  iter imp variable
##   1   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   1   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   9   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   9   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
```

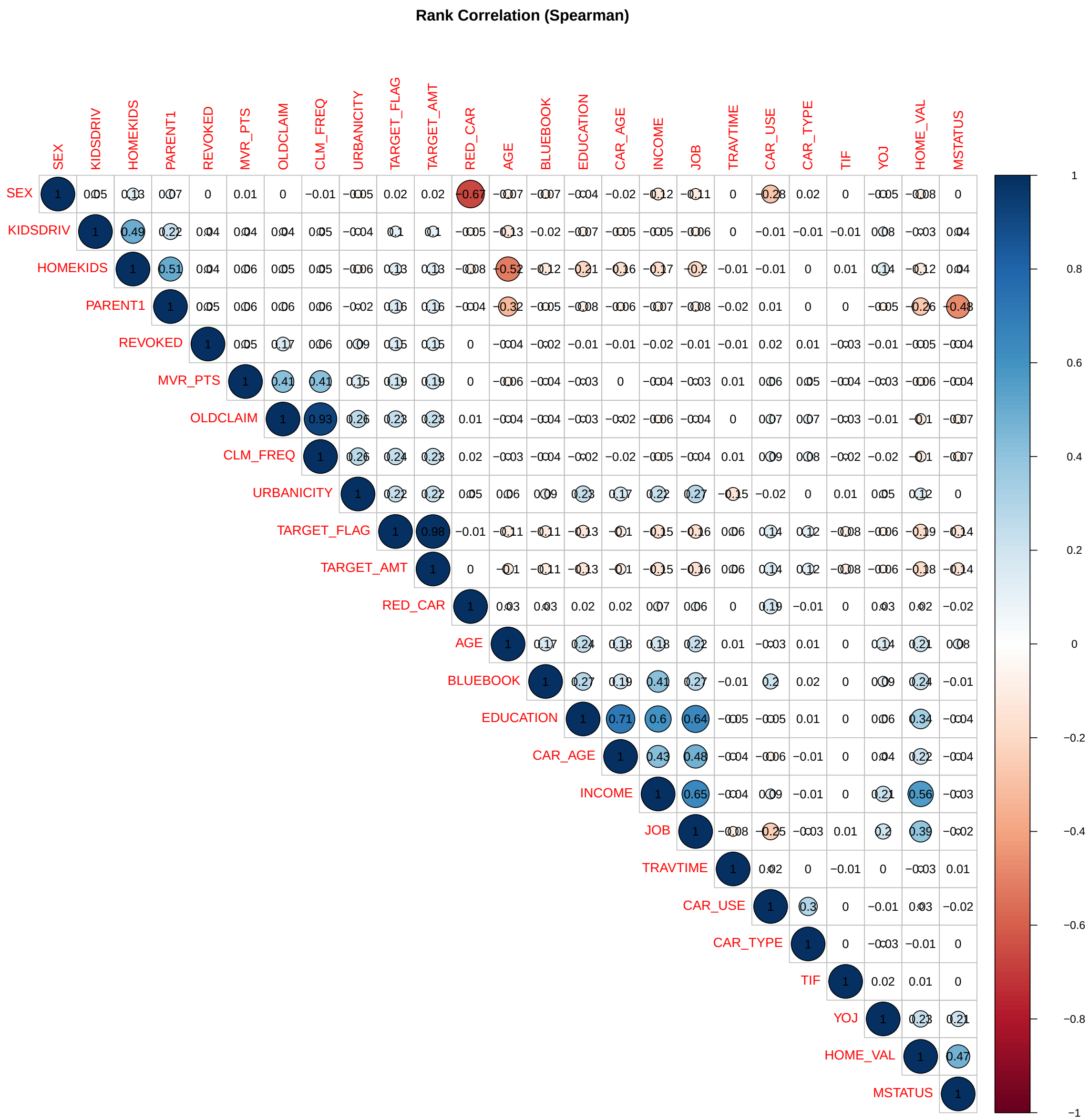
Check for correlated variables

The variables which are highly correlated carry similar information and can affect model accuracy. Highly correlated variables also impact estimation of model coefficients. Let's determine which variables in the training datasets are highly correlated to each other.

```
  trainmatrix <- as.matrix(train.df)
# The first column, "Index", is not useful, so drop it
  trainmatrix <- trainmatrix[,-1]
  res2<-rcorr(trainmatrix)
  respearson=rcorr(trainmatrix,type = "pearson")
  resspearman=rcorr(trainmatrix,type = "spearman")
  res3 <- cor(trainmatrix)
```

Rank Correlation (Pearson)




Rank Correlation (Spearman)
SEX
KIDSDRIV
HOMEKIDS
PARENT1
REVOKED
MVR_PTS
OLDCLAIM
CLM_FREQ
URBANICITY
TARGET_FLAG
TARGET_AMT
RED_CAR
AGE
BLUEBOOK
EDUCATION
CAR_AGE
INCOME
JOB
TRAVTIME
CAR_USE
CAR_TYPE
TIF
YOJ
HOME_VAL
MSTATUS
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1

From the above correlation graph we can see that target variable `TARGET_FLAG` is highly correlated with following variables

- **REVOKED: License Revoked**
- **MVR_PTS: Motor Vehicle Record Points**
- **OLD_CLAIM: Total Claims**
- **CLAIM_FREQ: Claim Frequency**
- **URBANICITY: Home/Work Area**
- **JOB: Job**
- **INCOME: Income**
- **HOME_VAL: Home Value**
- **MSTATUS: Maritial Status**
- **CAR_USE: Use of car**

In addition to above variables, following variables are important for `TARGET_AMT` output variable

- **BLUEBOOK: Value of vehicle**
- **CAR_AGE: Age of car**
- **CAR_TYPE: TType of car**

Add interaction terms to our dataset

3. Build Models - Logistic Regression

Model fitting and evaluation

For model evaluation we will use train/test split technique. Since the goal of the exercise is to predict car crashes, we will build a high recall model

High Recall Model

***High recall model* focuses on identifying the maximum possible positive instances. In this case it means we are optimizing our model to identify as many potential car crash targets as possible. Note that sometimes this can come at the cost of *precision*, where we might get high number of false positives.**

Model Evaluation Metrics

Definitions:

- **TP** : Stands for "True Positives"
- **TN** : Stands for "True Negatives"
- **FP** : Stands for "False Positives"
- **FN** : Stands for "False Negatives"

We will use following metrics for model evaluation and comparison:

- **ROC AUC** : AUC - ROC curve is a performance measurement for the classification problem at various thresholds. ROC is a probability curve, and AUC ("Area Under the Curve") represents the degree or measure of separability.
  - It tells how much the model is capable of distinguishing between classes.
  - The higher the AUC, the better the model.
- **Model Accuracy** : Accuracy is one metric for evaluating classification models.
  - Informally, accuracy is the ***fraction of predictions our model got right.***
  - Formally, accuracy has the following definition: $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$
- **Model Recall** : Recall is a metric that focuses on ***how many true positives*** are identified from ***total positive observations*** in the data set.
  - False Negatives (FN) are positive observations which our model failed to identify, and reduce the recall.
  - Formally, recall has following definition: $Recall = \frac{TP}{TP+FN}$.
- **Model Precision** : Precision is a metric that focuses on ***how many observations are truly positive*** out of the total number of cases which the model ***identified as positive***.
  - False Positives (FP) are negative observations which our model misidentified as positive, and reduce the precision.
  - Formally, precision has following definition : $Precision = \frac{TP}{TP+FP}$.

Building the models

Now that we are clear on our model fitting and evaluation method (Train test split) ,and also have model evaluation metrics (Recall) which we will use to compare the model effectiveness, we are all set to build different models and assess their performance.

We will build three different models and compare them using above mentioned model metrics.

1. **Let's build a model with important predictors, as per above analysis:**

- **REVOKED: License Revoked**
- **MVR_PTS: Motor Vehicle Record Points**
- **OLD_CLAIM: Total Claims**
- **CLAIM_FREQ: Claim Frequency**
- **URBANICITY: Home/Work Area**
- **JOB: Job**
- **INCOME: Income**
- **HOME_VAL: Home Value**
- **MSTATUS: Maritial Status**
- **CAR_USE: Use of car**
- **CAR_TYPE: Type of Car**

1. **Model with selected important variables**

```
model.metrix = model.fit.evaluate("target ~ INCOME + HOME_VAL + MSTATUS  + JOB + CAR_USE + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED + MVR_
print.model.matrix("Base Model", model.metrix)
```

```
## [1] "Printing Metrix for model:  Base Model"
## [1] "AUC : 0.781038017616685"
## [1] "Accuracy : 0.768068599428338"
## [1] "Recall : 0.287650602409639"
## [1] "Precision : 0.667832167832168"
```

2. **Model with all the predictors, plus transformed variables**

We will add new variables to the model

```
model.metrix = model.fit.evaluate("target ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS+ SEX + EDUCATION + JOB
print.model.matrix("Interaction Term", model.metrix)
```

```
## [1] "Printing Metrix for model:  Interaction Term"
## [1] "AUC : 0.794767304512163"
## [1] "Accuracy : 0.775826868109432"
## [1] "Recall : 0.337349397590361"
## [1] "Precision : 0.672672672672673"
```

3. Model with balanced training set

Since we know that data is class-imbalanced, we will use ROSE package and leverage synthetic data generation technique to balance the training data.

```
train.data.balanced <- ROSE(target ~ ., data = train.data, seed = 1)$data
model.metrix = model.fit.evaluate("target ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS+ SEX + EDUCATION + JOB
print.model.matrix("Class Balanced", model.metrix)
```

```
## [1] "Printing Metrix for model:  Class Balanced"
## [1] "AUC : 0.790119300732339"
## [1] "Accuracy : 0.746835443037975"
## [1] "Recall : 0.635542168674699"
## [1] "Precision : 0.5275"
```

From the above results we can see that model which uses all the variables along with newly added interaction term and which has class balance data performs better. We will use this model for prediction.

4. Model coefficient analysis

```
fit = glm(formula = "target ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS+ SEX + EDUCATION + JOB + TRAVTIME +

summary(fit)
```

```
##
## Call:
## glm(formula = "target ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS+ SEX + EDUCATION + JOB + TRAVTIME + CAR
##     data = train.df.class)
##
```

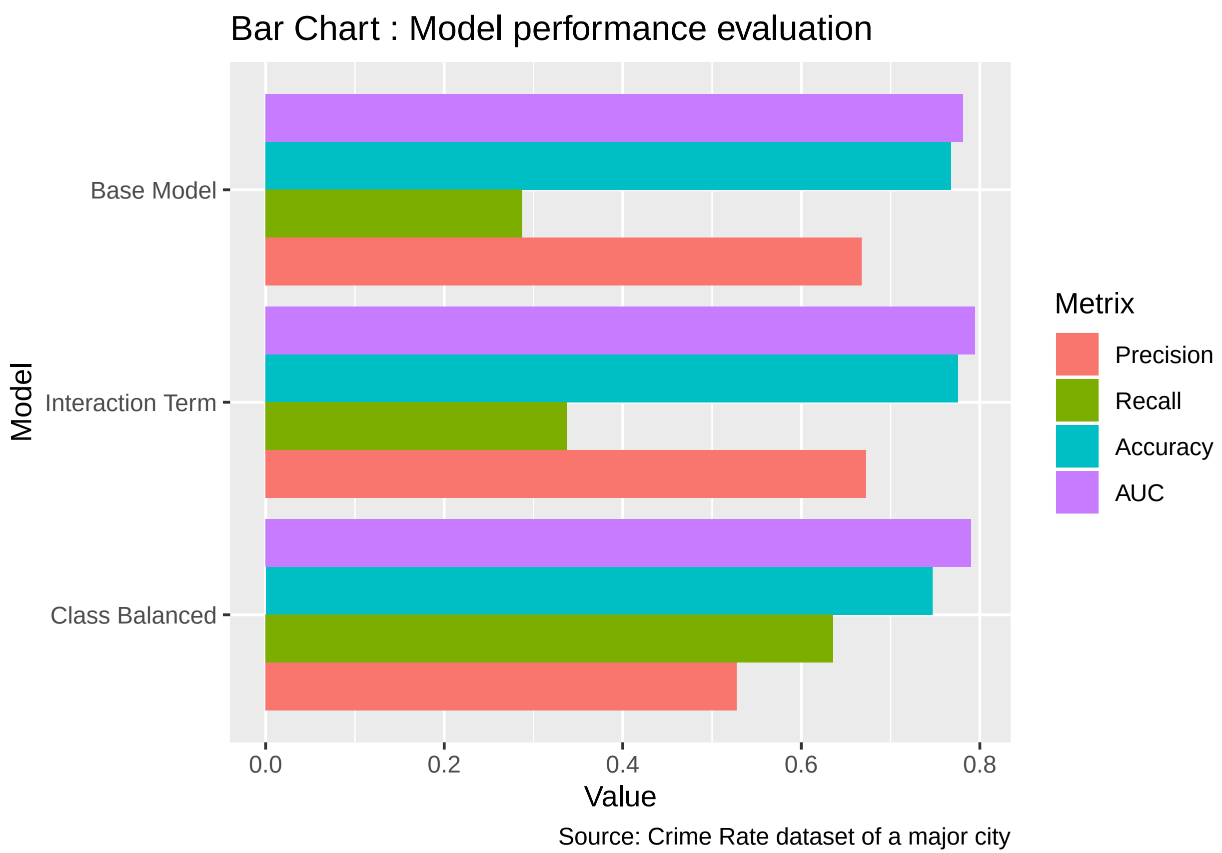
```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9871  -0.2812  -0.1128   0.2871   1.1862
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     2.192e-01  9.737e-02   2.251 0.024417 *
## KIDSDRIV        6.135e-02  9.760e-03   6.286 3.42e-10 ***
## AGE             1.039e-03  1.501e-03   0.692 0.488812
## HOMEKIDS        5.686e-03  5.618e-03   1.012 0.311566
## YOJ             2.048e-04  1.284e-03   0.160 0.873257
## INCOME         -7.131e-07  1.705e-07  -4.182 2.91e-05 ***
## PARENT1         6.852e-02  1.735e-02   3.950 7.88e-05 ***
## HOME_VAL        1.524e-07  9.602e-08   1.587 0.112449
## MSTATUS        -6.807e-02  1.280e-02  -5.319 1.07e-07 ***
## SEX             1.856e-01  1.522e-01   1.219 0.222801
## EDUCATION      -3.203e-02  8.504e-03  -3.766 0.000167 ***
## JOB            -1.491e-02  5.132e-03  -2.906 0.003674 **
## TRAVTIME        2.008e-03  2.763e-04   7.267 4.00e-13 ***
## CAR_USE         1.188e-01  1.127e-02  10.545  < 2e-16 ***
## BLUEBOOK       -4.058e-06  5.880e-07  -6.901 5.54e-12 ***
## TIF            -7.678e-03  1.044e-03  -7.356 2.07e-13 ***
## CAR_TYPE        1.722e-02  2.707e-03   6.362 2.10e-10 ***
## RED_CAR        -9.730e-03  1.278e-02  -0.762 0.446373
## OLDCLAIM       -2.398e-06  6.373e-07  -3.762 0.000170 ***
## CLM_FREQ        3.378e-02  4.717e-03   7.162 8.65e-13 ***
## REVOKED         1.592e-01  1.486e-02  10.712  < 2e-16 ***
## MVR_PTS         3.603e-02  4.883e-03   7.378 1.77e-13 ***
## CAR_AGE        -8.086e-04  1.058e-03  -0.764 0.444658
## URBANICITY      2.823e-01  1.178e-02  23.958  < 2e-16 ***
## JOB_EDU         2.232e-02  1.370e-02   1.629 0.103341
## MVR_PTS_Trans -4.242e-02  1.352e-02  -3.137 0.001713 **
## HOME_INCOME    -6.314e-04  1.770e-04  -3.568 0.000362 ***
## AGE_SEX        -4.151e-02  3.990e-02  -1.040 0.298173
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1519754)
##
```

```
##     Null deviance: 1585  on 8160  degrees of freedom
## Residual deviance: 1236  on 8133  degrees of freedom
## AIC: 7814.2
##
## Number of Fisher Scoring iterations: 2
```

The following conclusions can be drawn from model coefficients

- **KidsDriv: As number of kids driver increses log odds of car crash also increases**
- **Age: Not very significant in predicting car crash**
- **HomeKids: Not very significant in predicting car crash**
- **YOJ: Not very significant in predicting car crash**
- **Income: As Income increases log odds of car crash decreases**
- **Home_Val: Not very important for predicting car crash**
- **MStatus: If you are married, it decreases the log odds of car crash**
- **Education: As education increases log odds of car crash decreases**
- **Jobs: Higher the job level less likely the log odds of car crash**
- **Travtime: Longer the travel time increases the log odds of car crash**
- **Car Use: Commercial cars have more risk compared to private cars**
- **BlueBook: As the cost of cars increases log odds of car crash decreases**
- **TIF: Longer the people are in force less risky it becomes**
- **Red_Car: As expected a car being red doesn't contribute to car crash**
- **Clm_Freq, Revoked and Mvr_Pts: As expected all these variables increases the risk of car crash**
- **Urbanicity : Interestigly Work area is more prone to car crashes than home area**

From the above analysis it is demonstrated that model-3, which uses all the variables along with newly added interaction term and which has class-balanced data, performs better. We will use this model for prediction. The below bar chart shows different models and helps us to compare them on the basis of model metrics.



4. Build Models - Multiple Linear Regression

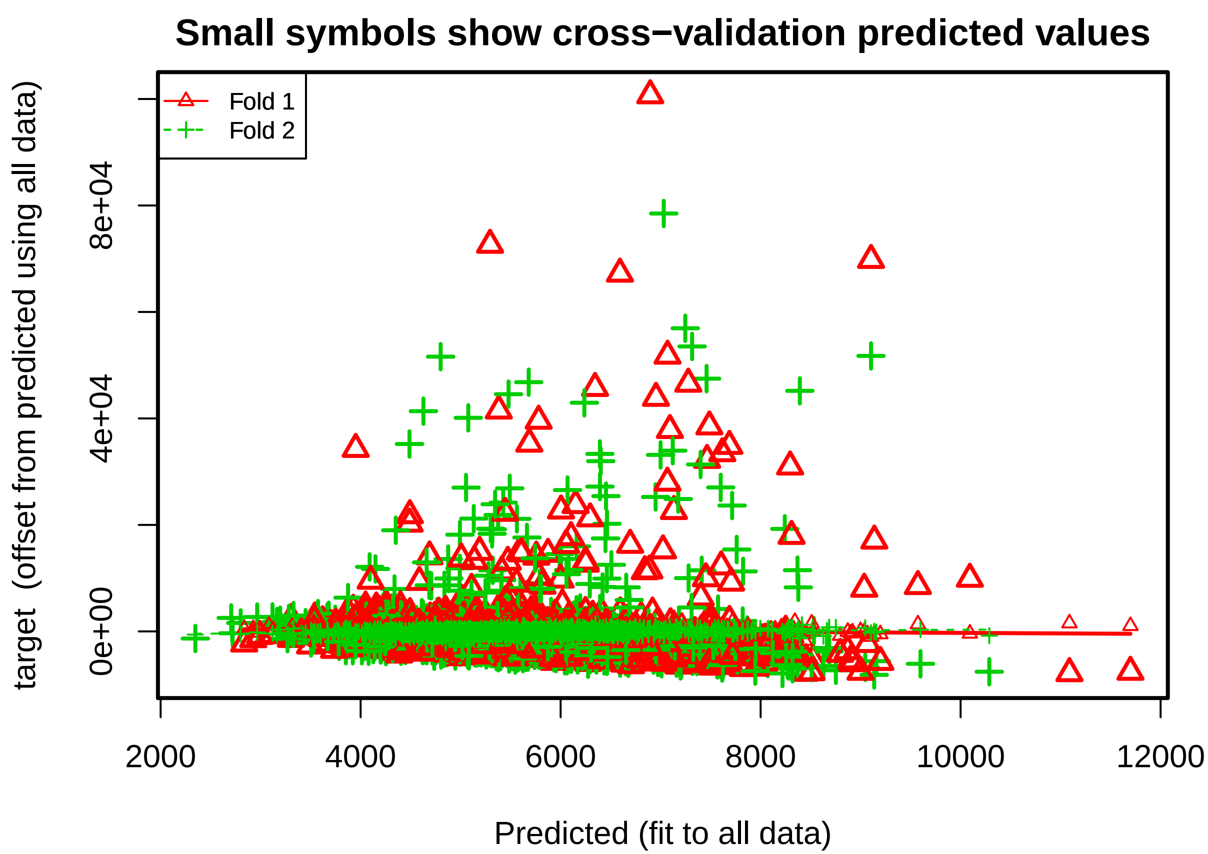
For Linear regression model we will use the cross validation technique. We will use Root Mean Square Error (RMSE) as a model evaluation metric. The model with the lower RMSE will be the best model.

$RMSE = \sqrt{\sum [ActualValue - PredictedValue]^2}$

1. **Model with selected important variables**

```
model.metrix = lm.cv("target ~ INCOME + HOME_VAL + MSTATUS  + JOB + CAR_USE + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED + MVR_PTS + URBANIC
```

```
## Warning in CVlm(data = input.data, form.lm = formula(form), m = 2, plotit = "Residual", :
##
##  As there is >1 explanatory variable, cross-validation
##  predicted values for a fold are not a linear function
##  of corresponding overall predicted values.  Lines that
##  are shown for the different folds are approximate
```



```r
print.rmse(model.metrix$output)
```

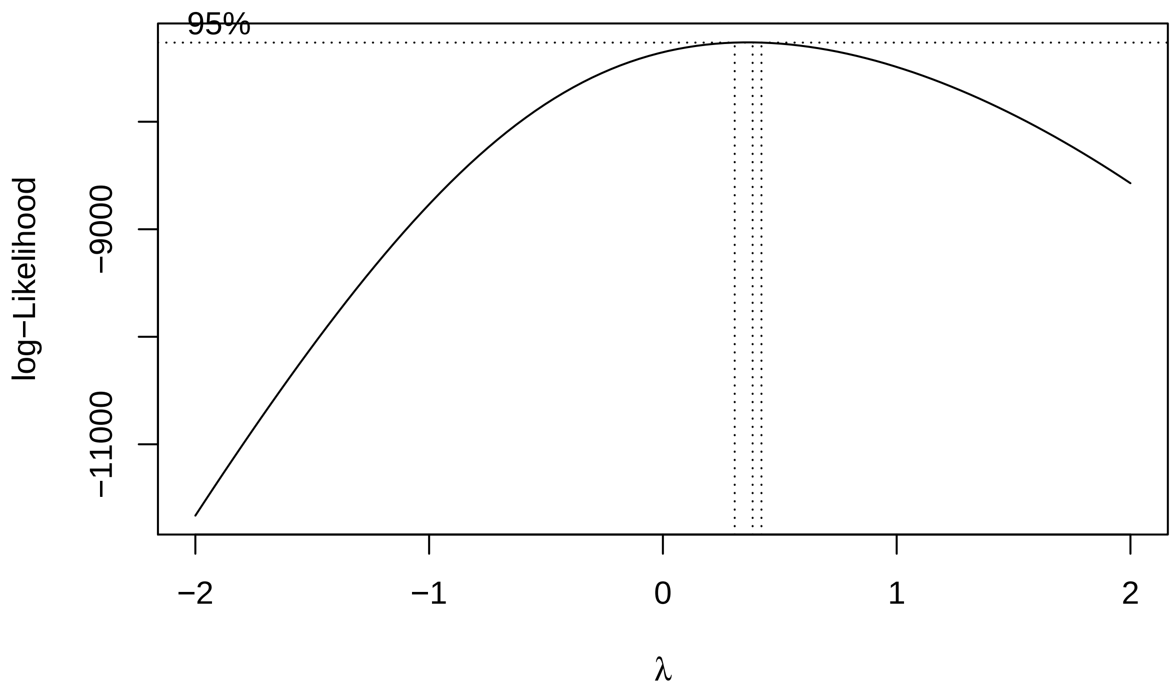
```
## [1] "Root Mean Square =  355315.14804385"
```

From the above residual plot we can see that residuals are y-axis imbalanced and heterogeneous.

2. Model with BoxCox transformation along with logarithmic transformation of output variable.

We are also selecting fewer variables, as per important regression coefficients.

```r
bc <- boxcox(train.df.reg$BLUEBOOK ~ log(train.df.reg$target))
```



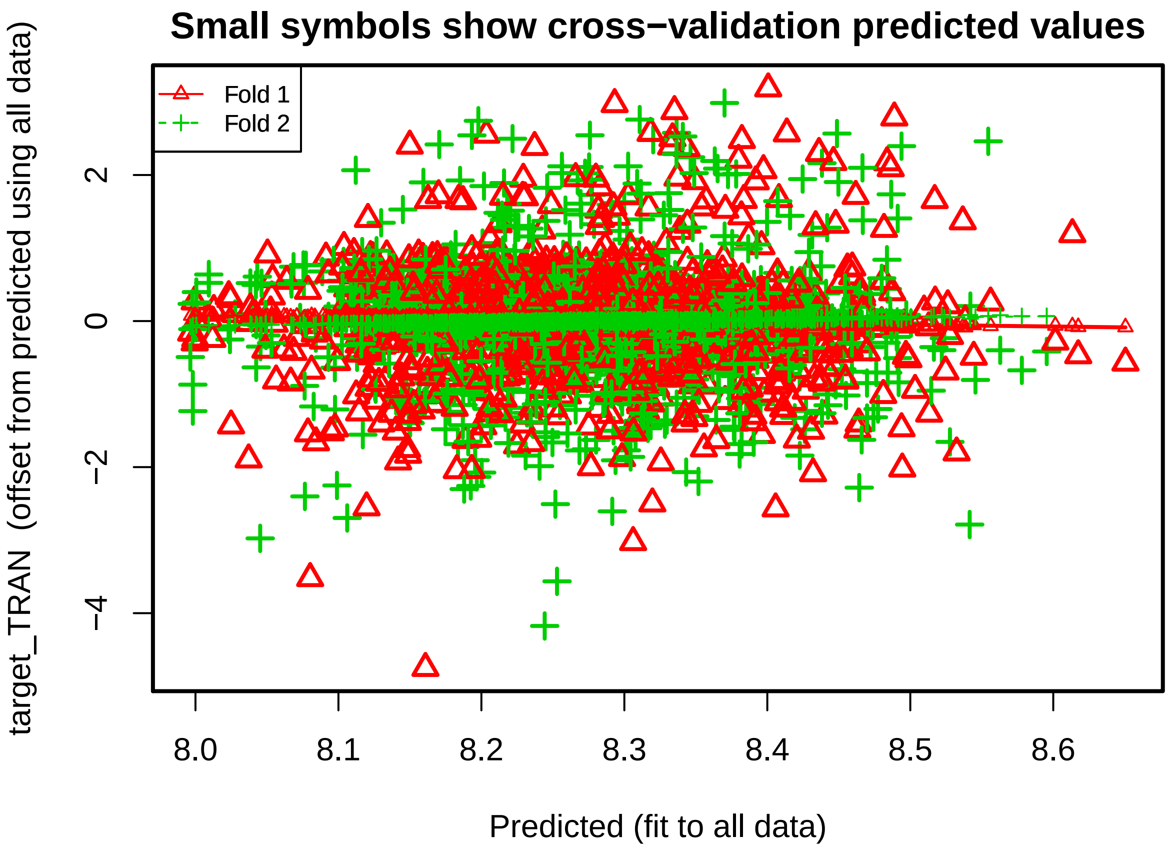

```
lambda <- bc$x[which.max(bc$y)]

train.df.reg$target_TRAN = log(train.df.reg$target)
train.df.reg$BLUEBOOK_TRAN = (train.df.reg$BLUEBOOK^lambda -1)/lambda

model.metrix = lm.cv("target_TRAN ~ BLUEBOOK_TRAN + MVR_PTS + CAR_AGE + CAR_TYPE", train.df.reg)
```

```
## Warning in CVlm(data = input.data, form.lm = formula(form), m = 2, plotit = "Residual", :
##
##  As there is >1 explanatory variable, cross-validation
```

```
##  predicted values for a fold are not a linear function
##  of corresponding overall predicted values.  Lines that
##  are shown for the different folds are approximate
```




```r
model.metrix$output$Predicted = exp(model.metrix$output$Predicted)
print.rmse(model.metrix$output)
```

```
## [1] "Root Mean Square =  366286.69929848"
```

The above residual plot looks better. It is balanced on both axes and homogeneous.

We can see that model with the Box-Cox transformation along with target variable logarithmic transformation gives us higher RMSE compared to the model with important variables. However, the difference in RMSE is not that big and in general it is always best practice to select the model with fewer variables to avoid overfitting. For this reason we will choose the second model (Model with Box-Cox transformation with fewer variables) for prediction.

3. Regression model coefficient analysis

```
fit = lm(target_TRAN ~ BLUEBOOK_TRAN + MVR_PTS + CAR_AGE + CAR_TYPE + REVOKED + SEX, train.df.reg)
summary(fit)
```

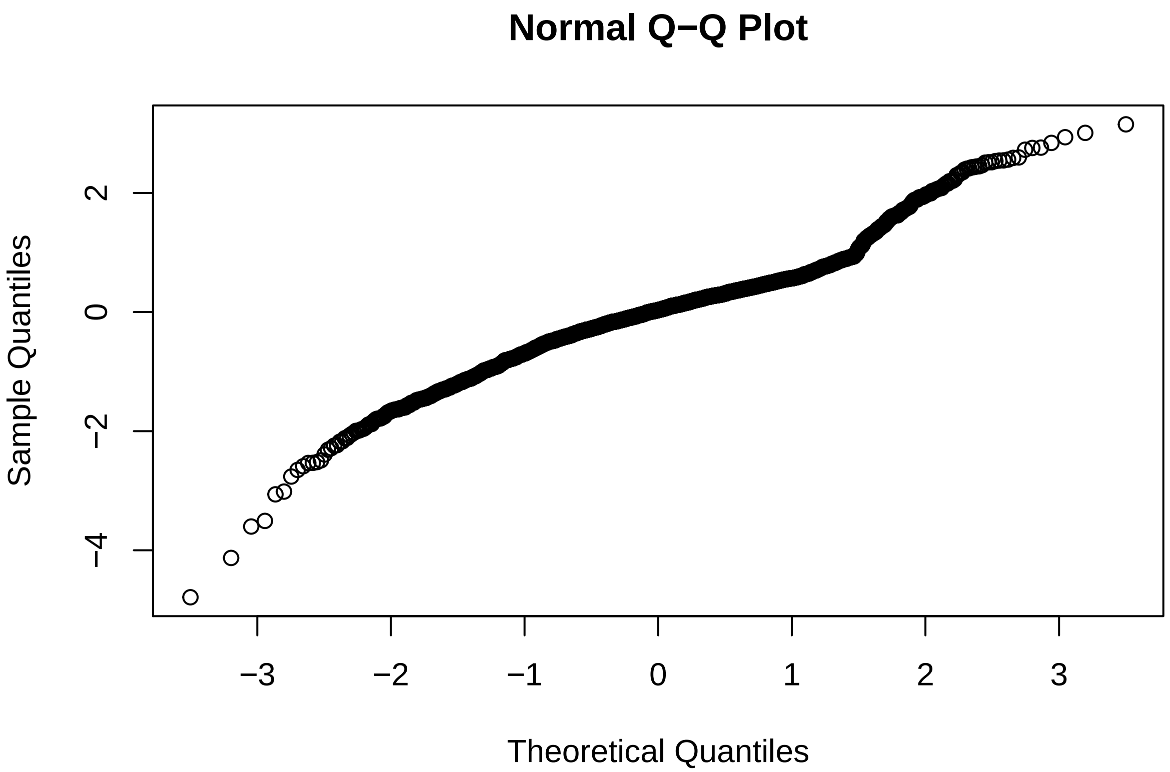
```
##
## Call:
## lm(formula = target_TRAN ~ BLUEBOOK_TRAN + MVR_PTS + CAR_AGE +
##     CAR_TYPE + REVOKED + SEX, data = train.df.reg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7888 -0.4018  0.0342  0.4030  3.1519
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    7.865e+00  8.550e-02  91.983  < 2e-16 ***
## BLUEBOOK_TRAN  4.232e-03  7.686e-04   5.506  4.1e-08 ***
## MVR_PTS        1.395e-02  6.753e-03   2.066   0.0389 *
## CAR_AGE        3.301e-05  3.216e-03   0.010   0.9918
## CAR_TYPE       2.532e-03  1.054e-02   0.240   0.8102
## REVOKED       -2.926e-02  4.300e-02  -0.681   0.4962
## SEX           -5.424e-02  3.511e-02  -1.545   0.1226
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8062 on 2146 degrees of freedom
## Multiple R-squared:  0.01838,    Adjusted R-squared:  0.01564
## F-statistic: 6.699 on 6 and 2146 DF,  p-value: 4.857e-07
```

Interestingly, we can see that only two variables are statistically significant and contributing towards target amount prediction:

- **BLUEBOOK** : Value of car is very important factor in determining claim amount. This perfectly makes sense.
- **MVR_PTS** : Number of traffic tickets is next important variable. Note that coefficient is positive which indicates pay-out amount increases with the number of ticket violations. This makes sense because it indicates that the more traffic violations, the more careless the driver, which translates to a higher risk of expensive accidents, thus the higher insurance payout. We will use this model since this is giving us lower RMSE indicating better model fit.

3. Regression model residiual analysis

```
qqnorm(fit$residuals)
```



From the residual normality plots we can see that residuals are normally distributed. This satisfies the normality assumption of residuals for multiple regression model.

5. Select Models

1. Read evaluation data and clean. Create required interaction terms

```
##
##  iter imp variable
##   1   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   1   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   9   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   9   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
```

```
## Warning: Number of logged events: 2
```

Logistic Regression

For Logistic regression we will use Model-3, which uses the balanced dataset using Synthetic Data Generation technique (SMOTE) and also leverages other variables to determine risk of car crashes.

```r
model.formula = "target ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS+ SEX + EDUCATION + JOB + TRAVTIME + CAR_


model <- glm(formula = model.formula, family = "binomial", data = train.data.balanced)



predicted <- predict(model, newdata = testing,type="response")
lables = ifelse(predicted > 0.5, 1, 0)

testing$TARGET_FLAG_Proba = round(predicted,1)
testing$TARGET_FLAG = lables
testing = data.frame(testing)
#write.table(testing, "./Data/PredictedOutcome.csv", row.names = FALSE, sep=",")
```

Multiple Linear Regression

For multiple linear regression we will use the second model, which uses Box-Cox transformation and fewer variables. Even though RMSE is lower, we are sticking to this model due to fewer variables and improved explainability.

```r
model.formula = "target_TRAN ~ BLUEBOOK_TRAN + MVR_PTS + CAR_AGE + CAR_TYPE"


model <- lm(formula = model.formula,  data = train.df.reg)



predicted <- predict(model, newdata = testing)
testing$TARGET_AMT = testing$TARGET_FLAG * exp(predicted)
testing = data.frame(testing)
write.table(testing, "./Data/PredictedOutcome.csv", row.names = FALSE, sep=",")
```

6. Appendix

Train Test Split Validation Code

```r
model.fit.evaluate <- function(model.formula, train.data, test.data) {
  auclist = NULL
  accuracylist = NULL
  recalllist = NULL
  precisionlist = NULL
  k =1
  set.seed(123)

  training <-train.data
  testing.org<-test.data

  testing = testing.org[1:nrow(testing.org), names(testing.org)[names(testing.org) != 'target']]

  model <- glm(formula = model.formula,
               family = "binomial", data = training)
  predicted <- predict(model, newdata = testing,type="response")
  pred <- prediction(predicted, testing.org$target)
  ind = which.max(round(slot(pred, 'cutoffs')[[1]],1) == 0.5)
  perf <- performance(pred, measure = "tpr", x.measure = "fpr")

  auc.tmp <- performance(pred,"auc");
  auc <- as.numeric(auc.tmp@y.values)
  auclist[k] = auc

  acc.perf = performance(pred, measure = "acc")
  acc = slot(acc.perf, "y.values")[[1]][ind]
  accuracylist[k] = acc

  prec.perf = performance(pred, measure = "prec")
  prec = slot(prec.perf, "y.values")[[1]][ind]
  precisionlist[k] = prec

  recall.perf = performance(pred, measure = "tpr")
  recall = slot(recall.perf, "y.values")[[1]][ind]
  recalllist[k] = recall
```

```
  return(list("AUC" = mean(auclist), "Accuracy" = mean(accuracylist),  "Recall" = mean(recalllist), "Precision" = mean(precisionlist)))
}

df.metrix <<- NULL
print.model.matrix = function(model.name, matrixobj)
{

  print(paste("Printing Metrix for model: ", model.name))
  for(i in 1 : length(matrixobj))
  {
    df = data.frame("Model" = model.name, "Metrix"=names(matrixobj)[[i]], "Value" = matrixobj[[i]])
    df.metrix <<- rbind(df, df.metrix)
    print(paste(names(matrixobj)[[i]], ":", matrixobj[[i]]))
  }

}
```

Linear Regression Cross Validation Code

```
lm.cv = function(form,input.data)
{
  out <- CVlm(data = input.data, form.lm = formula(form),m=2,plotit= "Residual", printit = FALSE)
  cv.rmse <- sqrt(attr(out,"ms"))
  return(list('output' = out))
}
print.rmse = function(output.df)
{
  rss = sum((output.df$target - output.df$Predicted)^2)
  print(paste('Root Mean Square = ', sqrt(rss)))
}
```

Evaluation data cleanup code

```
testing = read.csv("./Data/insurance-evaluation-data.csv", stringsAsFactors = FALSE, na.strings=c("NA","NaN", " ", ""))

testing$PARENT1 = ifelse(testing$PARENT1 == 'No', 0, 1)
testing$PARENT1 = as.numeric(testing$PARENT1)
```

```
testing$MSTATUS = ifelse(testing$MSTATUS == 'z_No', 0, 1)
testing$MSTATUS = as.numeric(testing$MSTATUS)
testing$SEX = ifelse(testing$SEX == 'M', 0, 1)
testing$SEX = as.numeric(testing$SEX)
testing$EDUCATION = as.numeric(factor(testing$EDUCATION, order = TRUE, levels = c("<High School", "z_High School", "Bachelors", "Masters",
testing$JOB = as.numeric(factor(testing$JOB, order = TRUE, levels = c("Student", "Home Maker", "z_Blue Collar", "Clerical", "Professional"
testing$CAR_USE = ifelse(testing$CAR_USE == "Private", 0, 1)
testing$CAR_USE  = as.numeric(testing$CAR_USE)
testing$CAR_TYPE = as.numeric(factor(testing$CAR_TYPE, order = TRUE, levels = c("Minivan", "z_SUV", "Van", "Pickup", "Panel Truck", 'Sport
testing$RED_CAR = ifelse(testing$RED_CAR == "no", 0, 1)
testing$RED_CAR  = as.numeric(testing$RED_CAR)
testing$REVOKED = ifelse(testing$REVOKED == "No", 0, 1)
testing$REVOKED  = as.numeric(testing$REVOKED)
testing$URBANICITY = ifelse(testing$URBANICITY == "z_Highly Rural/ Rural", 0, 1)
testing$URBANICITY  = as.numeric(testing$URBANICITY)

testing = apply(testing[], 2, function(x) ConvertQuantitative(x)) %>%data.frame()
comp.data <- mice(testing,m=2,maxit=10,meth='pmm',seed=500)
```

```
##
##  iter imp variable
##   1   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   1   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   2   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   3   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   4   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   5   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   6   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   7   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   8   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   9   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
```

```
##   9   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   1  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
##   10   2  AGE  YOJ  INCOME  HOME_VAL  JOB  CAR_AGE
```

```
## Warning: Number of logged events: 2
```

```
testing = complete(comp.data)
testing = testing[, !names(testing) %in% c('Index', 'TARGET_FLAG', 'TARGET_AMT')]

testing$JOB_EDU =  round(log(testing$JOB * testing$EDUCATION))
testing$HOME_INCOME = log(1+ testing$HOME_VAL) * log(1 + testing$INCOME)
testing$MVR_PTS_Trans = round(log(1+ testing$MVR_PTS))
testing$AGE_SEX =log(1 + testing$AGE) * (1+testing$SEX)
testing$BLUEBOOK_TRAN = (testing$BLUEBOOK^lambda -1)/lambda
```