Car Crash Prediction

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Contents

1 To build multiple linear regression and binary logistic regression models on the training data to predict the probability that a person will crash their car and also the amount of money it will cost if the person does crash their car.

Deliverables:

1. A write-up submitted in PDF format. Your write-up should have four sections. Each one is described below. You may assume you are addressing me as a fellow data scientist, so do not need to shy away from technical details.
2. Assigned predictions (probabilities, classifications, cost) for the evaluation data set. Use 0.5 threshold.
3. Include your R statistical programming code in an Appendix.

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(PerformanceAnalytics)
```

```
## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##     first, last

##
## Attaching package: 'PerformanceAnalytics'

## The following object is masked from 'package:graphics':
##
##     legend
```

```
library(imputeR)
library(VIM)
```

```
## Loading required package: colorspace
```

```
## Loading required package: grid

## Loading required package: data.table

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:xts':
##
##     first, last

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

## VIM is ready to use.
##  Since version 4.0.0 the GUI is in its own package VIMGUI.
##
##           Please use the package to use the new (and old) GUI.

## Suggestions and bug-reports can be submitted at: https://github.com/alexkowa/VIM/issues

##
## Attaching package: 'VIM'

## The following object is masked from 'package:datasets':
##
##     sleep
```

```r
library(mice)
```

```
## Warning: package 'mice' was built under R version 3.4.4

## Loading required package: lattice
```

```r
library(dummies)
```

```
## dummies-1.5.6 provided by Decision Patterns
```

```r
library(leaps)
library(ggplot2)
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

```r
library(faraway)
```

```
##
## Attaching package: 'faraway'

## The following object is masked from 'package:mice':
##
##     mammalsleep

## The following object is masked from 'package:lattice':
##
##     melanoma
```

```r
library(dplyr)
library(fastDummies)
```

```
## Warning: package 'fastDummies' was built under R version 3.4.4
```

```r
library(binr)
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-13
```

```r
library(caret)
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following object is masked from 'package:glmnet':
##
##     auc
```

```
## The following object is masked from 'package:colorspace':
##
##     coords
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
library(splines)
library(rstanarm)
```

```
## Warning: package 'rstanarm' was built under R version 3.4.4
```

```
## Loading required package: Rcpp
```

```
## Warning: package 'Rcpp' was built under R version 3.4.4
```

```
## rstanarm (Version 2.17.3, packaged: 2018-02-17 05:11:16 UTC)
```

```
## - Do not expect the default priors to remain the same in future rstanarm versions.
```

```
## Thus, R scripts should specify priors explicitly, even if they are just the defaults.
```

```
## - For execution on a local, multicore CPU with excess RAM we recommend calling
```

```
## options(mc.cores = parallel::detectCores())
```

```
## - Plotting theme set to bayesplot::theme_default().
```

```
##
## Attaching package: 'rstanarm'
```

```
## The following objects are masked from 'package:caret':
##
##     compare_models, R2
```

```r
library(corrplot)
```

```
## corrplot 0.84 loaded
```

VARIABLE NAME	DEFINITION	THEORETICAL EFFECT
INDEX	Identification Variable (do not use)	None
TARGET_FLAG	Was Car in a crash? 1=YES 0=NO	None
TARGET_AMT	If car was in a crash, what was the cost	None
AGE	Age of Driver	Very young people tend to be risky. Maybe very old people also.
BLUEBOOK	Value of Vehicle	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_AGE	Vehicle Age	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_TYPE	Type of Car	Unknown effect on probability of collision, but probably effect the payout if there is a crash
CAR_USE	Vehicle Use	Commercial vehicles are driven more, so might increase probability of collision
CLM_FREQ	# Claims (Past 5 Years)	The more claims you filed in the past, the more you are likely to file in the future
EDUCATION	Max Education Level	Unknown effect, but in theory more educated people tend to drive more safely
HOMEKIDS	# Children at Home	Unknown effect
HOME_VAL	Home Value	In theory, home owners tend to drive more responsibly
INCOME	Income	In theory, rich people tend to get into fewer crashes
JOB	Job Category	In theory, white collar jobs tend to be safer
KIDSDRIV	# Driving Children	When teenagers drive your car, you are more likely to get into crashes
MSTATUS	Marital Status	In theory, married people drive more safely
MVR_PTS	Motor Vehicle Record Points	If you get lots of traffic tickets, you tend to get into more crashes
OLDCLAIM	Total Claims (Past 5 Years)	If your total payout over the past five years was high, this suggests future payouts will be high
PARENT1	Single Parent	Unknown effect
RED_CAR	A Red Car	Urban legend says that red cars (especially red sports cars) are more risky. Is that true?
REVOKED	License Revoked (Past 7 Years)	If your license was revoked in the past 7 years, you probably are a more risky driver.
SEX	Gender	Urban legend says that women have less crashes then men. Is that true?
TIF	Time in Force	People who have been customers for a long time are usually more safe.
TRAVTIME	Distance to Work	Long drives to work usually suggest greater risk
URBANICITY	Home/Work Area	Unknown
YOJ	Years on Job	People who stay at a job for a long time are usually more safe

Figure 1: Data Definition.

1.1 Data Exploration

Describe the size and the variables in the insurance training data set. Consider that too much detail will cause a manager to lose interest while too little detail will make the manager consider that you aren't doing your job. Some suggestions are given below. Please do NOT treat this as a check list of things to do to complete the assignment. You should have your own thoughts on what to tell the boss. These are just ideas.

a. Mean / Standard Deviation / Median
b. Bar Chart or Box Plot of the data and/or Histograms
c. Is the data correlated to the target variable (or to other variables?)
d. Are any of the variables missing and need to be imputed "fixed"?

```
df =read.csv('data/insurance_training_data.csv')

eval =read.csv('data/insurance-evaluation-data.csv')
```

Below is the summary of the dataset and a quick view of the dataset.

```
summary(df)
```

```
##      INDEX         TARGET_FLAG       TARGET_AMT        KIDSDRIV
##  Min.   :    1   Min.   :0.0000   Min.   :     0   Min.   :0.0000
##  1st Qu.: 2559   1st Qu.:0.0000   1st Qu.:     0   1st Qu.:0.0000
##  Median : 5133   Median :0.0000   Median :     0   Median :0.0000
##  Mean   : 5152   Mean   :0.2638   Mean   :  1504   Mean   :0.1711
##  3rd Qu.: 7745   3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:0.0000
##  Max.   :10302   Max.   :1.0000   Max.   :107586   Max.   :4.0000
##
##       AGE           HOMEKIDS           YOJ             INCOME
##  Min.   :16.00   Min.   :0.0000   Min.   : 0.0   $0      : 615
##  1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.0           : 445
##  Median :45.00   Median :0.0000   Median :11.0   $26,840 :   4
##  Mean   :44.79   Mean   :0.7212   Mean   :10.5   $48,509 :   4
```

```
##  3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.0   $61,790 :   4
##  Max.   :81.00   Max.   :5.0000   Max.   :23.0   $107,375:   3
##  NA's   :6                        NA's   :454    (Other) :7086
##  PARENT1        HOME_VAL    MSTATUS      SEX             EDUCATION
##  No :7084   $0      :2294   Yes :4894   M  :3786   <High School :1203
##  Yes:1077           : 464   z_No:3267   z_F:4375   Bachelors    :2242
##             $111,129:   3                          Masters      :1658
##             $115,249:   3                          PhD          : 728
##             $123,109:   3                          z_High School:2330
##             $153,061:   3
##             (Other) :5391
##             JOB           TRAVTIME            CAR_USE        BLUEBOOK
##  z_Blue Collar:1825   Min.   :  5.00   Commercial:3029   $1,500 : 157
##  Clerical     :1271   1st Qu.: 22.00   Private   :5132   $6,000 :  34
##  Professional :1117   Median : 33.00                     $5,800 :  33
##  Manager      : 988   Mean   : 33.49                     $6,200 :  33
##  Lawyer       : 835   3rd Qu.: 44.00                     $6,400 :  31
##  Student      : 712   Max.   :142.00                     $5,900 :  30
##  (Other)      :1413                                      (Other):7843
##       TIF                CAR_TYPE    RED_CAR       OLDCLAIM
##  Min.   : 1.000   Minivan    :2145   no :5783   $0      :5009
##  1st Qu.: 1.000   Panel Truck: 676   yes:2378   $1,310 :   4
##  Median : 4.000   Pickup     :1389              $1,391 :   4
##  Mean   : 5.351   Sports Car : 907              $4,263 :   4
##  3rd Qu.: 7.000   Van        : 750              $1,105 :   3
##  Max.   :25.000   z_SUV      :2294              $1,332 :   3
##                                                 (Other):3134
##     CLM_FREQ      REVOKED       MVR_PTS         CAR_AGE
##  Min.   :0.0000   No :7161   Min.   : 0.000   Min.   :-3.000
##  1st Qu.:0.0000   Yes:1000   1st Qu.: 0.000   1st Qu.: 1.000
##  Median :0.0000              Median : 1.000   Median : 8.000
##  Mean   :0.7986              Mean   : 1.696   Mean   : 8.328
##  3rd Qu.:2.0000              3rd Qu.: 3.000   3rd Qu.:12.000
##  Max.   :5.0000              Max.   :13.000   Max.   :28.000
##                                               NA's   :510
##                 URBANICITY
##  Highly Urban/ Urban  :6492
##  z_Highly Rural/ Rural:1669
##
##
##
##
##
```

```r
head(df)
```

```
##   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                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
```

```r
df_original <- df

data.frame(NA_count = sapply(df_original, function(x) sum(is.na(x))))
```

```
##             NA_count
## INDEX              0
## TARGET_FLAG        0
## TARGET_AMT         0
## KIDSDRIV           0
## AGE                6
## HOMEKIDS           0
## YOJ              454
## INCOME             0
## PARENT1            0
## HOME_VAL           0
## MSTATUS            0
## SEX                0
## EDUCATION          0
## JOB                0
## TRAVTIME           0
## CAR_USE            0
## BLUEBOOK           0
## TIF                0
## CAR_TYPE           0
## RED_CAR            0
## OLDCLAIM           0
## CLM_FREQ           0
## REVOKED            0
## MVR_PTS            0
## CAR_AGE          510
## URBANICITY         0
```

Below are the inference from the summary:

1. Index feature can be removed
2. `Age,YOJ, CAR_AGE` variable has `NA` data. It needs to be handelled appropriately.

3. OLDCLAIM, BLUEBOOK,HOME_VAL, INCOME has some blank data. And it has $ sign in it. So it is considered as factor. Need to clean the data.
4. PARENT1, MSTATUS,SEX,EDUCATION,JOB,CAR_USE,CAR_TYPE,RED_CAR,REVOKED,URBANICITY is coded as categorical variable. It needs to be changed as dummy variable in the model.
5. CAR_AGE has negative value. It needs to be corrected.

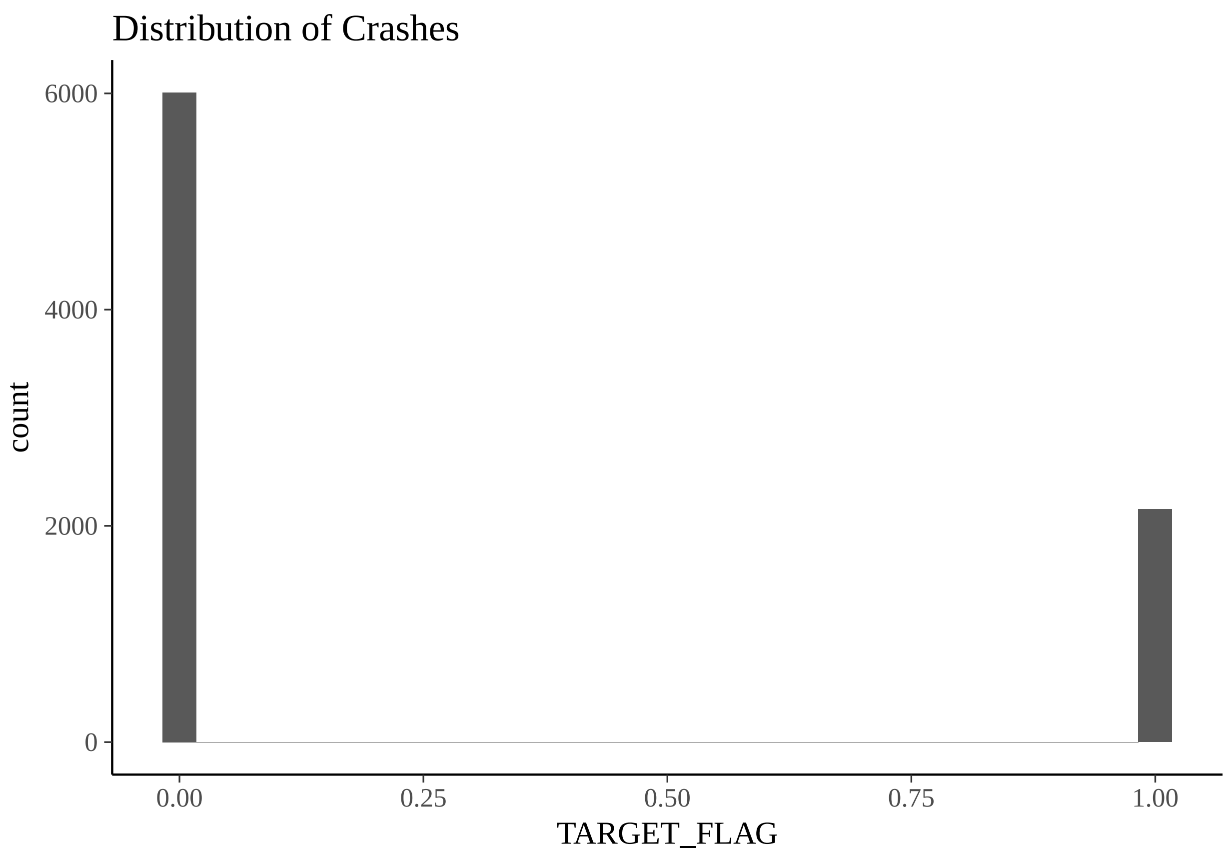
As lot of cleaning needs to be performed, we will draw necessary plots after data preparation.

1.1.1 Response variables

For this dataset, we have two response variables. They are TARGET_FLAG and TARGET_AMT. TARGET_FLAG mentions wheather the person will have a car crash or not.

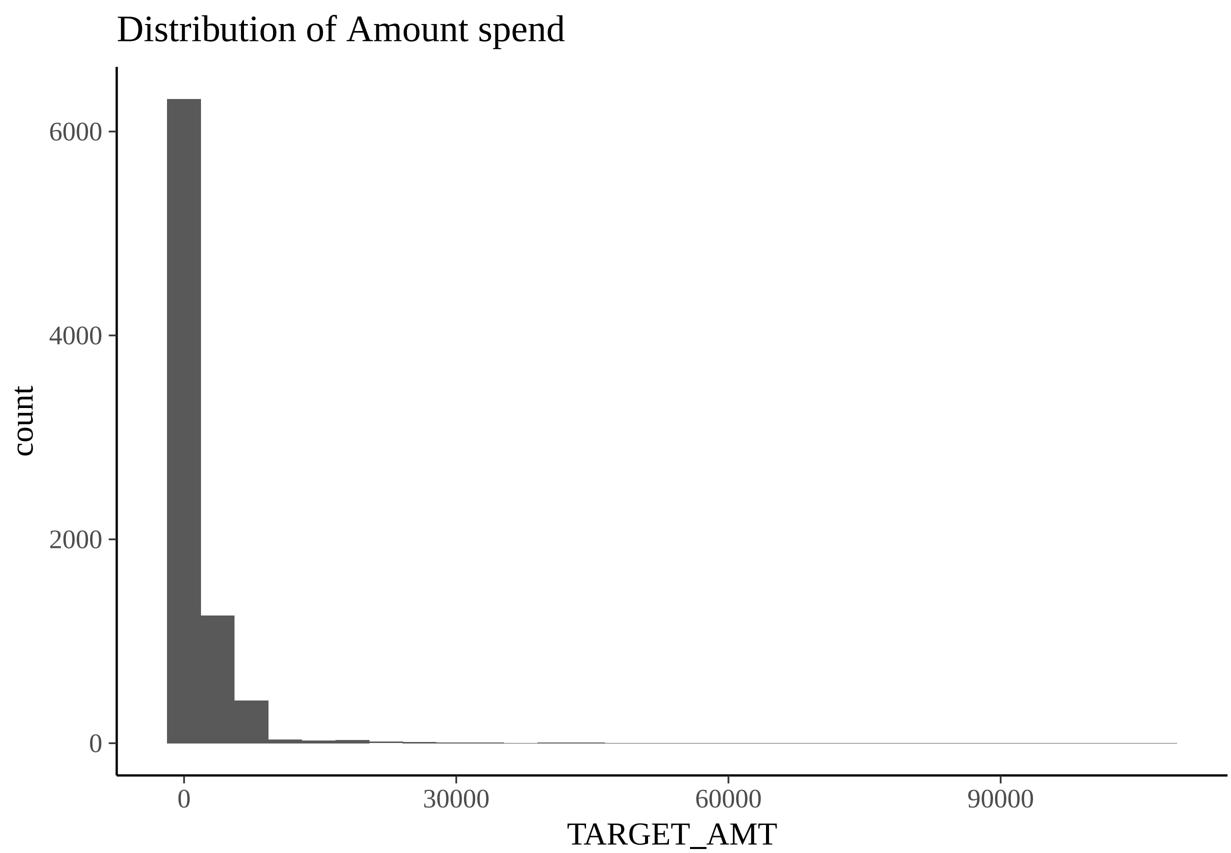
```
ggplot(df,aes(x=TARGET_FLAG)) +geom_histogram() + ggtitle('Distribution of Crashes')
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



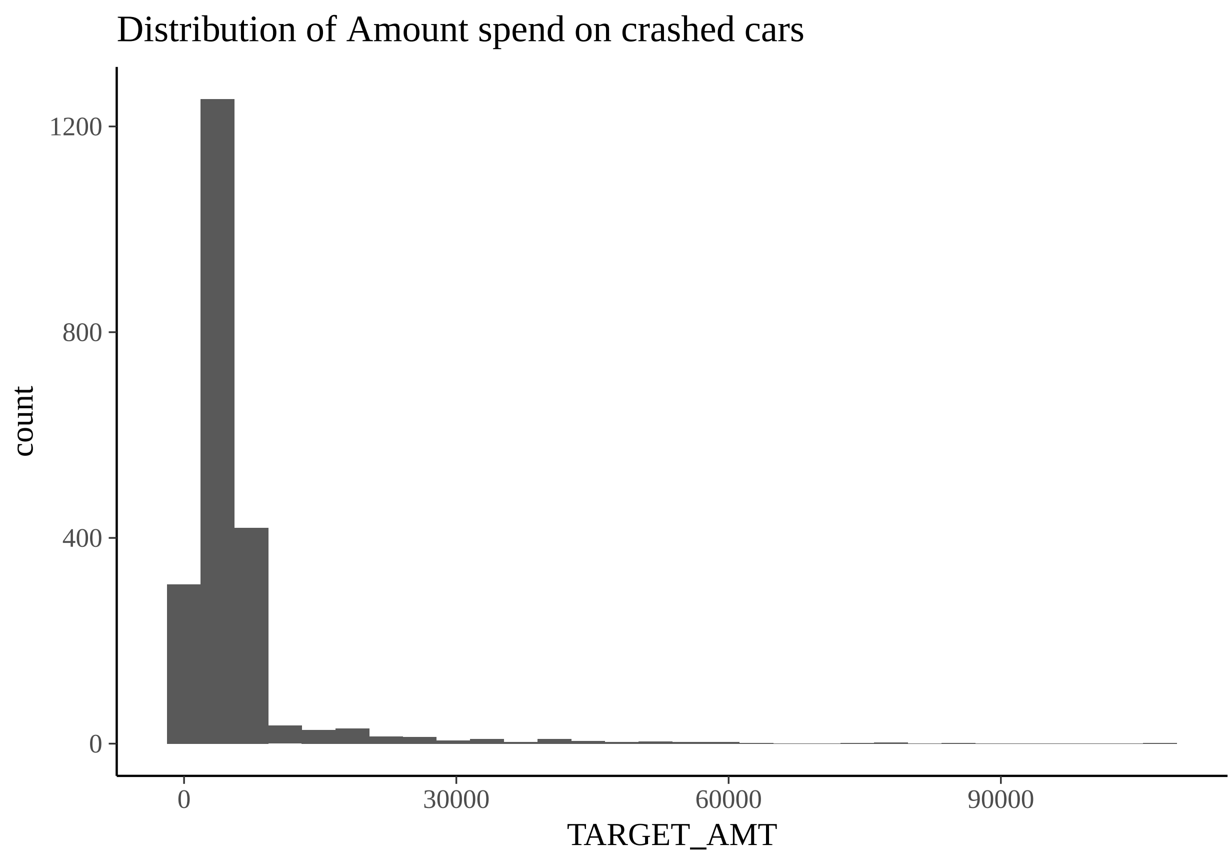

```
ggplot(df,aes(x=TARGET_AMT)) +geom_histogram() + ggtitle('Distribution of Amount spend')
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(df %>% filter(TARGET_FLAG==1),aes(x=TARGET_AMT)) +geom_histogram() + ggtitle('Distribution of Amo
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



1.2 Data Preparation

Different data preparation needs to be performed. We will try to clean the data one by one.

1.2.1 Data Clearning

1.2.1.1 Fixing $ value

As a first step, there are some columns which has $ symbol in the values. Lets fix it in the first step so we can have numeric values.

```
# Cleaning up the comma and $ sign in the amount columns
dollar_cleanup <- function(x) {
return(as.numeric(gsub(',','',gsub('\\$','',x))))
}

# Apply to all the applicable columns.
df[,c('OLDCLAIM', 'BLUEBOOK','HOME_VAL', 'INCOME')] = apply(df[,c('OLDCLAIM', 'BLUEBOOK','HOME_VAL', 'I


# Apply to all the applicable eval columns.
eval[,c('OLDCLAIM', 'BLUEBOOK','HOME_VAL', 'INCOME')] = apply(eval[,c('OLDCLAIM', 'BLUEBOOK','HOME_VAL'
```

1.2.1.2 Dropping Index column

As index column is not required, we will drop the index column.

```r
# Dropping Index column
df <- subset(df, select= -c(INDEX))

head(df)
```

```
##   TARGET_FLAG TARGET_AMT KIDSDRIV AGE HOMEKIDS YOJ INCOME PARENT1 HOME_VAL
## 1           0          0        0  60        0  11  67349      No        0
## 2           0          0        0  43        0  11  91449      No   257252
## 3           0          0        0  35        1  10  16039      No   124191
## 4           0          0        0  51        0  14     NA      No   306251
## 5           0          0        0  50        0  NA 114986      No   243925
## 6           1       2946        0  34        1  12 125301     Yes        0
##   MSTATUS SEX     EDUCATION          JOB TRAVTIME    CAR_USE BLUEBOOK TIF
## 1    z_No   M           PhD  Professional       14    Private    14230  11
## 2    z_No   M z_High School z_Blue Collar       22 Commercial    14940   1
## 3     Yes z_F z_High School      Clerical        5    Private     4010   4
## 4     Yes   M  <High School z_Blue Collar       32    Private    15440   7
## 5     Yes z_F           PhD        Doctor       36    Private    18000   1
## 6    z_No z_F     Bachelors z_Blue Collar       46 Commercial    17430   1
##     CAR_TYPE RED_CAR OLDCLAIM CLM_FREQ REVOKED MVR_PTS CAR_AGE
## 1    Minivan     yes     4461        2      No       3      18
## 2    Minivan     yes        0        0      No       0       1
## 3      z_SUV      no    38690        2      No       3      10
## 4    Minivan     yes        0        0      No       0       6
## 5      z_SUV      no    19217        2     Yes       3      17
## 6 Sports Car      no        0        0      No       0       7
##            URBANICITY
## 1 Highly Urban/ Urban
## 2 Highly Urban/ Urban
## 3 Highly Urban/ Urban
## 4 Highly Urban/ Urban
## 5 Highly Urban/ Urban
## 6 Highly Urban/ Urban
```

```r
df_original = df

#Evaluation
eval <- subset(eval, select= -c(INDEX))
```

Summary of the dataset after performing cleaning the amount variables.

```r
summary(df_original)
```

```
##   TARGET_FLAG       TARGET_AMT        KIDSDRIV           AGE
##  Min.   :0.0000   Min.   :     0   Min.   :0.0000   Min.   :16.00
##  1st Qu.:0.0000   1st Qu.:     0   1st Qu.:0.0000   1st Qu.:39.00
##  Median :0.0000   Median :     0   Median :0.0000   Median :45.00
##  Mean   :0.2638   Mean   :  1504   Mean   :0.1711   Mean   :44.79
##  3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:0.0000   3rd Qu.:51.00
##  Max.   :1.0000   Max.   :107586   Max.   :4.0000   Max.   :81.00
##                                                     NA's   :6
##     HOMEKIDS           YOJ           INCOME        PARENT1
##  Min.   :0.0000   Min.   : 0.0   Min.   :     0   No :7084
##  1st Qu.:0.0000   1st Qu.: 9.0   1st Qu.: 28097   Yes:1077
```

```
##  Median :0.0000   Median :11.0   Median : 54028
##  Mean   :0.7212   Mean   :10.5   Mean   : 61898
##  3rd Qu.:1.0000   3rd Qu.:13.0   3rd Qu.: 85986
##  Max.   :5.0000   Max.   :23.0   Max.   :367030
##                   NA's   :454    NA's   :445
##     HOME_VAL      MSTATUS      SEX               EDUCATION
##  Min.   :     0   Yes :4894   M  :3786   <High School :1203
##  1st Qu.:     0   z_No:3267   z_F:4375   Bachelors    :2242
##  Median :161160                          Masters      :1658
##  Mean   :154867                          PhD          : 728
##  3rd Qu.:238724                          z_High School:2330
##  Max.   :885282
##  NA's   :464
##             JOB          TRAVTIME            CAR_USE        BLUEBOOK
##  z_Blue Collar:1825   Min.   :  5.00   Commercial:3029   Min.   : 1500
##  Clerical     :1271   1st Qu.: 22.00   Private   :5132   1st Qu.: 9280
##  Professional :1117   Median : 33.00                     Median :14440
##  Manager      : 988   Mean   : 33.49                     Mean   :15710
##  Lawyer       : 835   3rd Qu.: 44.00                     3rd Qu.:20850
##  Student      : 712   Max.   :142.00                     Max.   :69740
##  (Other)      :1413
##       TIF                CAR_TYPE    RED_CAR       OLDCLAIM
##  Min.   : 1.000   Minivan    :2145   no :5783   Min.   :    0
##  1st Qu.: 1.000   Panel Truck: 676   yes:2378   1st Qu.:    0
##  Median : 4.000   Pickup     :1389              Median :    0
##  Mean   : 5.351   Sports Car : 907              Mean   : 4037
##  3rd Qu.: 7.000   Van        : 750              3rd Qu.: 4636
##  Max.   :25.000   z_SUV      :2294              Max.   :57037
##
##     CLM_FREQ      REVOKED       MVR_PTS          CAR_AGE
##  Min.   :0.0000   No :7161   Min.   : 0.000   Min.   :-3.000
##  1st Qu.:0.0000   Yes:1000   1st Qu.: 0.000   1st Qu.: 1.000
##  Median :0.0000              Median : 1.000   Median : 8.000
##  Mean   :0.7986              Mean   : 1.696   Mean   : 8.328
##  3rd Qu.:2.0000              3rd Qu.: 3.000   3rd Qu.:12.000
##  Max.   :5.0000              Max.   :13.000   Max.   :28.000
##                                               NA's   :510
##                  URBANICITY
##  Highly Urban/ Urban  :6492
##  z_Highly Rural/ Rural:1669
##
##
##
##
##
```

1.2.2 Fixing NA Values

In this dataset, there are missing values in `AGE`,`YOJ`, `CAR_AGE`, `INCOME`, `HOME_VAL` variables. Each needs to be imputed differently. Lets impute the values by each variable.

As a first step lets validate the records which are invalid or has `NA` on multiple columns.

1. We cannot have `CAR_AGE` as negative. So lets drop the observations.

2. If multiple variables like `HOMVE_VAL, INCOME, CAR_AGE, YOJ` are having NA we will drop those records.
3. Lets drop the observations which has `HOME_VAL` as NA. Because the median house value is more than the mean. If imputation is performed, then it might skew the variable. So we will drop NA records.

```
#Car Age cannot be -ve. So dropping the record
df_original <- df_original[!c(!is.na(df_original$CAR_AGE) & df_original$CAR_AGE < 0),]

# Drop records which has NA in different columns

df_original <- df_original[!c(-c(is.na(df_original$HOME_VAL)) & -c(is.na(df_original$INCOME)) & -c(is.na

df_original <- df_original[!c(-c(is.na(df_original$HOME_VAL)) & -c(is.na(df_original$INCOME)) & -c(is.na


df_original <- df_original[!c(-c(is.na(df_original$HOME_VAL)) & -c(is.na(df_original$INCOME))),]

df_original <- df_original[!c(-c(is.na(df_original$YOJ)) & -c(is.na(df_original$HOME_VAL))),]

#Drop Hom_VAL with NA records
df_original <- df_original[!c(is.na(df_original$HOME_VAL)),]


summary(df_original)
```

```
##   TARGET_FLAG       TARGET_AMT        KIDSDRIV           AGE
##  Min.   :0.0000   Min.   :     0   Min.   :0.0000   Min.   :16.00
##  1st Qu.:0.0000   1st Qu.:     0   1st Qu.:0.0000   1st Qu.:39.00
##  Median :0.0000   Median :     0   Median :0.0000   Median :45.00
##  Mean   :0.2639   Mean   :  1497   Mean   :0.1726   Mean   :44.76
##  3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:0.0000   3rd Qu.:51.00
##  Max.   :1.0000   Max.   :107586   Max.   :4.0000   Max.   :81.00
##                                                     NA's   :4
##     HOMEKIDS           YOJ            INCOME       PARENT1
##  Min.   :0.0000   Min.   : 0.00   Min.   :     0   No :6672
##  1st Qu.:0.0000   1st Qu.: 9.00   1st Qu.: 28117   Yes:1024
##  Median :0.0000   Median :11.00   Median : 54124
##  Mean   :0.7265   Mean   :10.51   Mean   : 61896
##  3rd Qu.:1.0000   3rd Qu.:13.00   3rd Qu.: 86212
##  Max.   :5.0000   Max.   :23.00   Max.   :367030
##                   NA's   :427     NA's   :412
##     HOME_VAL      MSTATUS      SEX               EDUCATION
##  Min.   :     0   Yes :4610   M  :3569   <High School :1136
##  1st Qu.:     0   z_No:3086   z_F:4127   Bachelors    :2121
##  Median :161139                          Masters      :1552
##  Mean   :154860                          PhD          : 682
##  3rd Qu.:238724                          z_High School:2205
##  Max.   :885282
##
##             JOB          TRAVTIME            CAR_USE         BLUEBOOK
##  z_Blue Collar:1723   Min.   :  5.00   Commercial:2844   Min.   : 1500
##  Clerical     :1204   1st Qu.: 22.00   Private   :4852   1st Qu.: 9358
##  Professional :1052   Median : 33.00                     Median :14450
##  Manager      : 934   Mean   : 33.52                     Mean   :15721
##  Lawyer       : 795   3rd Qu.: 44.00                     3rd Qu.:20823
##  Student      : 667   Max.   :142.00                     Max.   :69740
```

```
##  (Other)      :1321
##       TIF                 CAR_TYPE    RED_CAR       OLDCLAIM
##  Min.   : 1.000   Minivan     :2039   no :5452   Min.   :    0
##  1st Qu.: 1.000   Panel Truck: 632   yes:2244   1st Qu.:    0
##  Median : 4.000   Pickup      :1304              Median :    0
##  Mean   : 5.358   Sports Car : 855              Mean   : 4027
##  3rd Qu.: 7.000   Van         : 701              3rd Qu.: 4603
##  Max.   :25.000   z_SUV       :2165              Max.   :57037
##
##     CLM_FREQ      REVOKED       MVR_PTS          CAR_AGE
##  Min.   :0.0000   No :6753   Min.   : 0.000   Min.   : 0.000
##  1st Qu.:0.0000   Yes: 943   1st Qu.: 0.000   1st Qu.: 1.000
##  Median :0.0000              Median : 1.000   Median : 8.000
##  Mean   :0.7947              Mean   : 1.685   Mean   : 8.321
##  3rd Qu.:2.0000              3rd Qu.: 3.000   3rd Qu.:12.000
##  Max.   :5.0000              Max.   :13.000   Max.   :28.000
##                                               NA's   :474
##                  URBANICITY
##  Highly Urban/ Urban  :6118
##  z_Highly Rural/ Rural:1578
##
##
##
##
##
```

1.2.3 Imputation

As different columns `AGE`,`YOJ`, `CAR_AGE`, `INCOME`, `HOME_VAL` have NA variables, we need to fill those values with some sort of imputation. We will try different types of imputation.

1.2.3.1 KNN Imputation

Everyone driving should have a minimum age of 18. And the observations which has `NA` seems to kids. So their age should be more than 21+. `KNN` imputation will search for similar records and use the value for missing records.

```
df_knn = kNN(df_original[, !names(df_original) %in% c("TARGET_FLAG","TARGET_AMT")],variable=c('AGE','YO

df_knn <- subset(df_knn, select = -c(AGE_imp,YOJ_imp,CAR_AGE_imp,INCOME_imp,HOME_VAL_imp))

#df_knn =cbind(df_knn,TARGET_FLAG=df_original$TARGET_FLAG,TARGET_AMT=df_original$TARGET_AMT)
```

1.2.3.2 Median Imputation

Another option to perform imputation is using median. We will fill all the missing values as median value of that column.

```
df_median = df_original

df_median[, names(df_median) %in% c('AGE','YOJ', 'CAR_AGE', 'INCOME', 'HOME_VAL')]= apply(df_median[, na


df_median <- df_median[, !names(df_median) %in% c("TARGET_FLAG","TARGET_AMT")]
```

```r
#summary(df_median)
#head(df_median)

eval[, names(eval) %in% c('AGE','YOJ', 'CAR_AGE', 'INCOME', 'HOME_VAL')]= apply(eval[, names(eval) %in%


eval <- eval[, !names(eval) %in% c("TARGET_FLAG","TARGET_AMT")]
```

1.2.3.3 Mice Imputation

mice short for Multivariate Imputation by Chained Equations is an R package that provides advanced features for missing value treatment. It uses a slightly uncommon way of implementing the imputation in 2-steps, using mice() to build the model and complete() to generate the completed data. The mice(df) function produces multiple complete copies of df, each with different imputations of the missing data.

```r
#miceMod <- mice(df_original[, !names(df_original) %in% c("TARGET_FLAG","TARGET_AMT")], method="rf")  #

#df_mice <- complete(miceMod)  # generate the completed data.

#anyNA(df_mice)
```

```r
# Set the type of imputation
df_corrected =  df_median
```

1.2.4 Imputation of Categorical Variable

JOB variable has some blank values. As it is a text column, we cannot use previous methods. We will just create a new job category as Other.

```r
# Convert to char for updating empty value to others
df_corrected$JOB = as.character(df_corrected$JOB)
df_corrected[df_corrected$JOB =='',]$JOB ='Other'



# Convert the necessary categorical columns to factor and add amoutn columns
df_corrected$KIDSDRIV = as.integer(df_corrected$KIDSDRIV)
df_corrected$HOMEKIDS = as.integer(df_corrected$HOMEKIDS)
df_corrected$JOB = as.factor(df_corrected$JOB)

df_corrected<-cbind(df_corrected,TARGET_FLAG=df_original$TARGET_FLAG,TARGET_AMT=df_original$TARGET_AMT)
summary(df_corrected)
```

```
##     KIDSDRIV           AGE           HOMEKIDS           YOJ
##  Min.   :0.0000   Min.   :16.00   Min.   :0.0000   Min.   : 0.00
##  1st Qu.:0.0000   1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.00
##  Median :0.0000   Median :45.00   Median :0.0000   Median :11.00
##  Mean   :0.1726   Mean   :44.76   Mean   :0.7265   Mean   :10.53
##  3rd Qu.:0.0000   3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.00
##  Max.   :4.0000   Max.   :81.00   Max.   :5.0000   Max.   :23.00
##
##      INCOME       PARENT1       HOME_VAL       MSTATUS      SEX
##  Min.   :     0   No :6672   Min.   :     0   Yes :4610   M  :3569
```

```
##  1st Qu.: 29696   Yes:1024   1st Qu.:     0   z_No:3086   z_F:4127
##  Median : 54124              Median :161139
##  Mean   : 61480              Mean   :154860
##  3rd Qu.: 83429              3rd Qu.:238724
##  Max.   :367030              Max.   :885282
##
##          EDUCATION                JOB           TRAVTIME
##  <High School :1136   z_Blue Collar:1723   Min.   :  5.00
##  Bachelors    :2121   Clerical     :1204   1st Qu.: 22.00
##  Masters      :1552   Professional :1052   Median : 33.00
##  PhD          : 682   Manager      : 934   Mean   : 33.52
##  z_High School:2205   Lawyer       : 795   3rd Qu.: 44.00
##                       Student      : 667   Max.   :142.00
##                       (Other)      :1321
##        CAR_USE        BLUEBOOK          TIF                CAR_TYPE
##  Commercial:2844   Min.   : 1500   Min.   : 1.000   Minivan    :2039
##  Private   :4852   1st Qu.: 9358   1st Qu.: 1.000   Panel Truck: 632
##                    Median :14450   Median : 4.000   Pickup     :1304
##                    Mean   :15721   Mean   : 5.358   Sports Car : 855
##                    3rd Qu.:20823   3rd Qu.: 7.000   Van        : 701
##                    Max.   :69740   Max.   :25.000   z_SUV      :2165
##
##  RED_CAR       OLDCLAIM        CLM_FREQ      REVOKED       MVR_PTS
##  no :5452   Min.   :    0   Min.   :0.0000   No :6753   Min.   : 0.000
##  yes:2244   1st Qu.:    0   1st Qu.:0.0000   Yes: 943   1st Qu.: 0.000
##             Median :    0   Median :0.0000              Median : 1.000
##             Mean   : 4027   Mean   :0.7947              Mean   : 1.685
##             3rd Qu.: 4603   3rd Qu.:2.0000              3rd Qu.: 3.000
##             Max.   :57037   Max.   :5.0000              Max.   :13.000
##
##     CAR_AGE                         URBANICITY    TARGET_FLAG
##  Min.   : 0.000   Highly Urban/ Urban  :6118   Min.   :0.0000
##  1st Qu.: 4.000   z_Highly Rural/ Rural:1578   1st Qu.:0.0000
##  Median : 8.000                                Median :0.0000
##  Mean   : 8.301                                Mean   :0.2639
##  3rd Qu.:12.000                                3rd Qu.:1.0000
##  Max.   :28.000                                Max.   :1.0000
##
##    TARGET_AMT
##  Min.   :     0
##  1st Qu.:     0
##  Median :     0
##  Mean   :  1497
##  3rd Qu.:  1036
##  Max.   :107586
##
```

```r
#Eval
# Convert to char for updating empty value to others
eval$JOB = as.character(eval$JOB)
eval[eval$JOB =='',]$JOB ='Other'
```

```r
# Convert the necessary categorical columns to factor and add amount columns
eval$KIDSDRIV = as.integer(eval$KIDSDRIV)
eval$HOMEKIDS = as.integer(eval$HOMEKIDS)
eval$JOB = as.factor(eval$JOB)
```

1.2.5 Feature Engineering and Transformation

We need to perform some transformations and add new features on the input dataset. This will provide more information to the model.

1.2.5.1 Binary Variables Creation

We will convert add some binary variables. This information has been provided in the question. Below variables will be added to the dataset.

1. New variable can have kids or No kids.
2. Education less than High school and greater than high school, so creating a binary variable.
3. In theory, home owners tend to drive more responsibly - So creating a binary variable.
4. If Old claims are performed, then he has higher chances of crash - creating a binary variable.
5. If CLM_FREQ is hig, then there are higher chaces of crash.
6. If a home ownership is there, then less chances of crash.

```r
df_transformed <-df_corrected

df_transformed$KIDSDRIV_BIN <- if_else(df_transformed$KIDSDRIV>0,0,1)
df_transformed$HOMEKIDS_BIN <- if_else(df_transformed$HOMEKIDS>0,0,1)
df_transformed$OLDCLAIM_BIN <- if_else(df_transformed$OLDCLAIM>0,1,0)
#df_transformed$CLM_FREQ_BIN <- if_else(df_transformed$CLM_FREQ>0,1,0)
df_transformed$EDUCATION <- if_else(df_transformed$EDUCATION =='<High School',0,1)
df_transformed$HOME_OWN <- if_else(df_transformed$HOME_VAL>0,0,1)

summary(df_transformed)
```

```
##     KIDSDRIV           AGE           HOMEKIDS            YOJ
##  Min.   :0.0000   Min.   :16.00   Min.   :0.0000   Min.   : 0.00
##  1st Qu.:0.0000   1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.00
##  Median :0.0000   Median :45.00   Median :0.0000   Median :11.00
##  Mean   :0.1726   Mean   :44.76   Mean   :0.7265   Mean   :10.53
##  3rd Qu.:0.0000   3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.00
##  Max.   :4.0000   Max.   :81.00   Max.   :5.0000   Max.   :23.00
##
##      INCOME       PARENT1       HOME_VAL       MSTATUS      SEX
##  Min.   :     0   No :6672   Min.   :     0   Yes :4610   M  :3569
##  1st Qu.: 29696   Yes:1024   1st Qu.:     0   z_No:3086   z_F:4127
##  Median : 54124              Median :161139
##  Mean   : 61480              Mean   :154860
##  3rd Qu.: 83429              3rd Qu.:238724
##  Max.   :367030              Max.   :885282
##
##    EDUCATION                  JOB          TRAVTIME            CAR_USE
##  Min.   :0.0000   z_Blue Collar:1723   Min.   :  5.00   Commercial:2844
##  1st Qu.:1.0000   Clerical     :1204   1st Qu.: 22.00   Private   :4852
##  Median :1.0000   Professional :1052   Median : 33.00
##  Mean   :0.8524   Manager      : 934   Mean   : 33.52
```

```
##  3rd Qu.:1.0000   Lawyer       : 795   3rd Qu.: 44.00
##  Max.   :1.0000   Student      : 667   Max.   :142.00
##                   (Other)      :1321
##     BLUEBOOK          TIF                CAR_TYPE    RED_CAR
##  Min.   : 1500   Min.   : 1.000   Minivan    :2039   no :5452
##  1st Qu.: 9358   1st Qu.: 1.000   Panel Truck: 632   yes:2244
##  Median :14450   Median : 4.000   Pickup     :1304
##  Mean   :15721   Mean   : 5.358   Sports Car : 855
##  3rd Qu.:20823   3rd Qu.: 7.000   Van        : 701
##  Max.   :69740   Max.   :25.000   z_SUV      :2165
##
##     OLDCLAIM        CLM_FREQ      REVOKED       MVR_PTS
##  Min.   :    0   Min.   :0.0000   No :6753   Min.   : 0.000
##  1st Qu.:    0   1st Qu.:0.0000   Yes: 943   1st Qu.: 0.000
##  Median :    0   Median :0.0000              Median : 1.000
##  Mean   : 4027   Mean   :0.7947              Mean   : 1.685
##  3rd Qu.: 4603   3rd Qu.:2.0000              3rd Qu.: 3.000
##  Max.   :57037   Max.   :5.0000              Max.   :13.000
##
##     CAR_AGE                        URBANICITY    TARGET_FLAG
##  Min.   : 0.000   Highly Urban/ Urban  :6118   Min.   :0.0000
##  1st Qu.: 4.000   z_Highly Rural/ Rural:1578   1st Qu.:0.0000
##  Median : 8.000                                Median :0.0000
##  Mean   : 8.301                                Mean   :0.2639
##  3rd Qu.:12.000                                3rd Qu.:1.0000
##  Max.   :28.000                                Max.   :1.0000
##
##    TARGET_AMT      KIDSDRIV_BIN     HOMEKIDS_BIN     OLDCLAIM_BIN
##  Min.   :     0   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:     0   1st Qu.:1.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :     0   Median :1.0000   Median :1.0000   Median :0.0000
##  Mean   :  1497   Mean   :0.8794   Mean   :0.6463   Mean   :0.3833
##  3rd Qu.:  1036   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :107586   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##     HOME_OWN
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.2981
##  3rd Qu.:1.0000
##  Max.   :1.0000
##
```

```r
#Eval
eval$KIDSDRIV_BIN <- if_else(eval$KIDSDRIV>0,0,1)
eval$HOMEKIDS_BIN <- if_else(eval$HOMEKIDS>0,0,1)
eval$OLDCLAIM_BIN <- if_else(eval$OLDCLAIM>0,1,0)
#eval$CLM_FREQ_BIN <- if_else(eval$CLM_FREQ>0,1,0)
eval$EDUCATION <- if_else(eval$EDUCATION =='<High School',0,1)
eval$HOME_OWN <- if_else(eval$HOME_VAL>0,0,1)
```

As a next step, we will also transform INCOME varaiable to different bins. We will split into three parts, low income class, middle class and high income.

```
cuts = bins(df_transformed$INCOME,target.bins = 3, minpts = 1000)


print(cuts$binct)
```

```
##      [0, 38666]  [38668, 71121] [71141, 367030]
##            2566            2565            2565
```

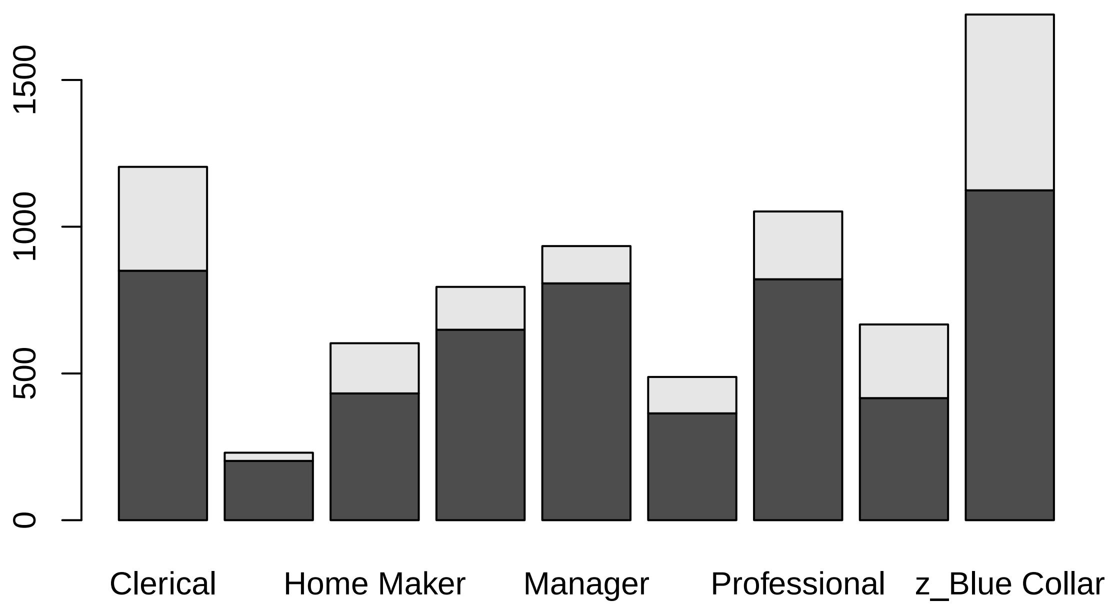
```
df_transformed$INCOME_BIN <- if_else(df_transformed$INCOME>0 & df_transformed$INCOME<=37092,0,if_else(df

#Eval
eval$INCOME_BIN <- if_else(eval$INCOME>0 & eval$INCOME<=37092,0,if_else(eval$INCOME>37092 & eval$INCOME
```

1.2.5.2 JOB analysis

Job plays a major role in accidents. Genearlly a person in white-collar is less likely to have an accident compared to blue-collar or a car driver. Because white-collar person works in a secured office and may not travel much.

Below is the distribution of the accidents. Doctors are very less likely to cause an accident.

```
barplot(table(df_transformed[,c('TARGET_FLAG','JOB')]))
```



We can group all the white-collar and blue-collar jobs. Here 'Clerical','Doctor','Lawyer','Manager','Professional','Other' are considered as white-collar job. We will convert all the values as white collar and leave out Home_maker and students.

```
df_transformed$JOB = as.character(df_transformed$JOB)

df_transformed[df_transformed$JOB %in% c('Clerical','Doctor','Lawyer','Manager','Professional','Other')


#Eval
eval$JOB = as.character(eval$JOB)

eval[eval$JOB %in% c('Clerical','Doctor','Lawyer','Manager','Professional','Other'),]$JOB ='White_Colla
```

1.2.6 Correlation Charts

1.2.6.1 TARGET_FLAG Plots

As a next step we will draw some correlation matrix and analyze individual charts. As the dataset has many variables, we will spilt it into different plots.

```
# Charts for Target_Flage

#for(i in seq(1,35,by=5)){
#chart.Correlation(cbind(df_transformed[,c(i:(i+5))], TARGET_FLAG = df_transformed[,c('TARGET_FLAG')]),
#}
```

Above plots suggests that there are some room for improvemnt by performing binning.

```
#TARGET_AMT charts

#for(i in seq(1,35,by=5)){
#chart.Correlation(cbind(df_transformed[,c(i:(i+5))], TARGET_AMT = df_transformed[,c('TARGET_AMT')]),hi
#}
```

1.2.7 Numerical variables transformation

Some of the other predictor variables are not correctly distributed. So we might need to perform transformations to correct the variables.

```
log_transform <- function(x) {
  return(log(x))
}

# Apply to all the applicable columns.
#df_transformed[,c('INCOME','TRAVTIME', 'BLUEBOOK','TIF')] = apply(df_transformed[,c('INCOME','TRAVTIME
```

1.2.8 Adding Dummy Variables

As a next step, there are different factor variables with text. Those need to be converted to dummy variables. This is an important step in preparing the dataset.

Finally we have created dummy variables for all the factor predictor variables. We have also performed the drop-off step. This dummy variables inclusion has increased the variable count.

```
#Creating dummies function

create_dummies_replaced <- function(df_corrected, sel_cols){
```

```
  df_dummy <- dummy_cols(df_corrected,select_columns = sel_cols,remove_first_dummy = TRUE)
  return(df_dummy[,!(names(df_dummy) %in% sel_cols)])
}


df_transformed <- create_dummies_replaced(df_transformed,c('SEX','PARENT1','EDUCATION','MSTATUS','INCOM

# Target_flag
df_transformed_target_flg <- df_transformed %>% dplyr::select(-TARGET_AMT)


#EVal

eval <- create_dummies_replaced(eval,c('SEX','PARENT1','EDUCATION','MSTATUS','INCOME_BIN',  'JOB','CAR_
```

1.2.9 Correlation matrix

Below is the correlation matrix of the dataset.

```
cormat <- as.matrix(cor(df_transformed, use = "pairwise.complete.obs"))

#corrplot(cormat, method = "color",tl.cex = 0.7, addCoef.col = "black", addCoefasPercent = FALSE)


zdf <- as.data.frame(as.table(cormat))

with(zdf,zdf[order(Freq,decreasing = TRUE),]) %>%  data.frame() %>% filter(Var1!=Var2) %>% head()
```

```
##           Var1         Var2      Freq
## 1 OLDCLAIM_BIN     CLM_FREQ 0.8693796
## 2     CLM_FREQ OLDCLAIM_BIN 0.8693796
## 3   RED_CAR_no      SEX_z_F 0.6675273
## 4      SEX_z_F   RED_CAR_no 0.6675273
## 5 OLDCLAIM_BIN     OLDCLAIM 0.5813259
## 6     OLDCLAIM OLDCLAIM_BIN 0.5813259
```

1.2.10 TRAN TEST Split

As a final step before we build our models, we need to validate the models which we will build. However, there is no test dataset. We will split the dataset into two parts and use the test dataset to validate our model.

```
set.seed(40)
#Random numbers
randomobs <- sample(seq_len(nrow(df_transformed_target_flg)), size = floor(0.7 * nrow(df_transformed_ta

# Train dataset
train <- df_transformed_target_flg[randomobs,]

#Test dataset
test <- df_transformed_target_flg[-randomobs,]
```

1.3 Build Models and evaluation

After performing all the data cleaning, transformations and feature engineering, we will build different models on car crash classification and cost of an accident(regression).

1.3.1 TARGET_FLAG - Crash prediction

Car crash is an a binary response variable. Whether the crash happened or not. Our Models has to predict the binary variable. So these type of models will be a classification problem.

```
outcomeName <- 'TARGET_FLAG'
predictorsNames <- names(train)[names(train) != outcomeName]
```

1.3.1.1 Model 1 - GLM Stepwise selection

We will create a GLM binomial model with `logit` link function. As there are different variables which not statistcially significant, we will perform backward stepwise variable reduction.

```
model_11_transformed_dummies = glm(TARGET_FLAG ~ ., train, family=binomial(link = 'logit'))

model_11_backward = step(model_11_transformed_dummies,direction = 'backward',trace=FALSE)
```

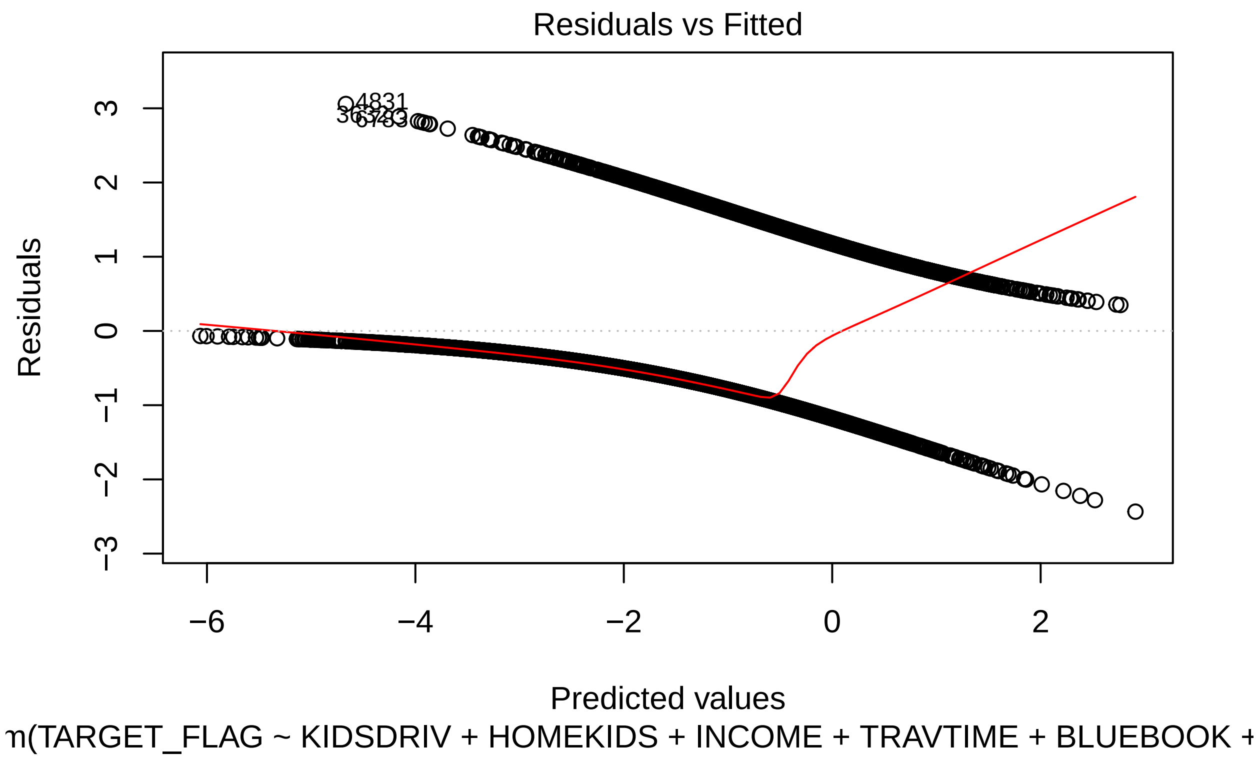
Below are the different evaluation metrics we will perform to validate the model.

```
summary(model_11_backward)
```

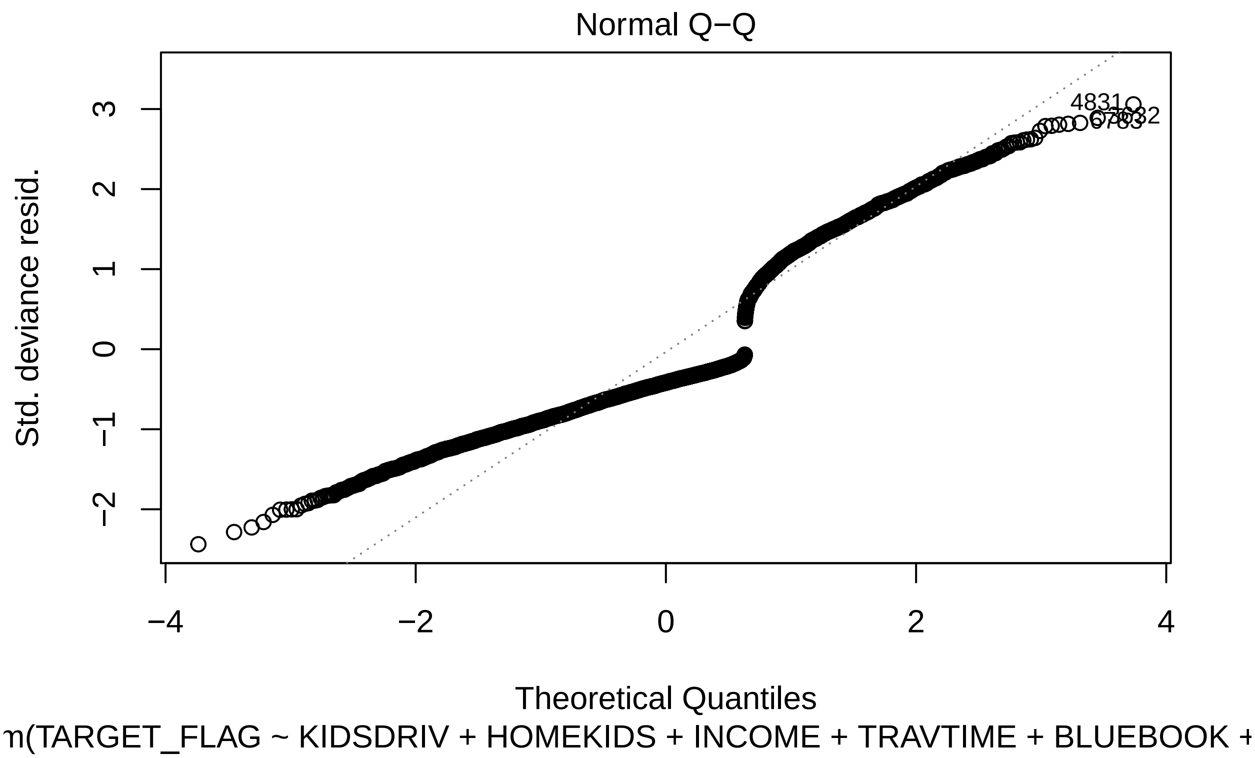
```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + INCOME + TRAVTIME +
##     BLUEBOOK + TIF + OLDCLAIM + MVR_PTS + CAR_AGE + HOMEKIDS_BIN +
##     OLDCLAIM_BIN + HOME_OWN + PARENT1_Yes + EDUCATION_0 + MSTATUS_Yes +
##     INCOME_BIN_0 + CAR_USE_Commercial + CAR_TYPE_z_SUV + `CAR_TYPE_Sports Car` +
##     CAR_TYPE_Van + `CAR_TYPE_Panel Truck` + CAR_TYPE_Pickup +
##     REVOKED_Yes + `URBANICITY_z_Highly Rural/ Rural`, family = binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4343  -0.7295  -0.4164   0.6618   3.0583
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                        -8.189e-01  2.524e-01  -3.244 0.001179
## KIDSDRIV                            2.839e-01  7.216e-02   3.934 8.36e-05
## HOMEKIDS                           -1.151e-01  6.405e-02  -1.797 0.072324
## INCOME                             -7.705e-06  1.114e-06  -6.919 4.56e-12
## TRAVTIME                            1.546e-02  2.284e-03   6.770 1.29e-11
## BLUEBOOK                           -2.483e-05  5.813e-06  -4.272 1.94e-05
## TIF                                -5.009e-02  9.014e-03  -5.557 2.74e-08
## OLDCLAIM                           -1.688e-05  5.125e-06  -3.295 0.000986
## MVR_PTS                             9.799e-02  1.737e-02   5.640 1.70e-08
## CAR_AGE                            -2.254e-02  7.431e-03  -3.033 0.002418
## HOMEKIDS_BIN                       -4.775e-01  1.634e-01  -2.923 0.003469
## OLDCLAIM_BIN                        5.125e-01  9.612e-02   5.332 9.72e-08
## HOME_OWN                            2.948e-01  9.380e-02   3.143 0.001675
```

```
## PARENT1_Yes                          2.877e-01  1.471e-01   1.957 0.050396
## EDUCATION_0                          3.491e-01  1.101e-01   3.170 0.001525
## MSTATUS_Yes                         -4.965e-01  1.073e-01  -4.626 3.73e-06
## INCOME_BIN_0                        -1.427e-01  9.601e-02  -1.487 0.137125
## CAR_USE_Commercial                   9.426e-01  8.878e-02  10.618  < 2e-16
## CAR_TYPE_z_SUV                       6.484e-01  1.022e-01   6.347 2.20e-10
## `CAR_TYPE_Sports Car`                8.281e-01  1.322e-01   6.265 3.72e-10
## CAR_TYPE_Van                         5.110e-01  1.457e-01   3.508 0.000452
## `CAR_TYPE_Panel Truck`               5.050e-01  1.722e-01   2.932 0.003366
## CAR_TYPE_Pickup                      3.687e-01  1.196e-01   3.083 0.002052
## REVOKED_Yes                          9.009e-01  1.127e-01   7.997 1.28e-15
## `URBANICITY_z_Highly Rural/ Rural` -2.213e+00  1.381e-01 -16.028  < 2e-16
##
## (Intercept)                        **
## KIDSDRIV                           ***
## HOMEKIDS                           .
## INCOME                             ***
## TRAVTIME                           ***
## BLUEBOOK                           ***
## TIF                                ***
## OLDCLAIM                           ***
## MVR_PTS                            ***
## CAR_AGE                            **
## HOMEKIDS_BIN                       **
## OLDCLAIM_BIN                       ***
## HOME_OWN                           **
## PARENT1_Yes                        .
## EDUCATION_0                        **
## MSTATUS_Yes                        ***
## INCOME_BIN_0
## CAR_USE_Commercial                 ***
## CAR_TYPE_z_SUV                     ***
## `CAR_TYPE_Sports Car`              ***
## CAR_TYPE_Van                       ***
## `CAR_TYPE_Panel Truck`             **
## CAR_TYPE_Pickup                    **
## REVOKED_Yes                        ***
## `URBANICITY_z_Highly Rural/ Rural` ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6218.4  on 5386  degrees of freedom
## Residual deviance: 4903.3  on 5362  degrees of freedom
## AIC: 4953.3
##
## Number of Fisher Scoring iterations: 5
```

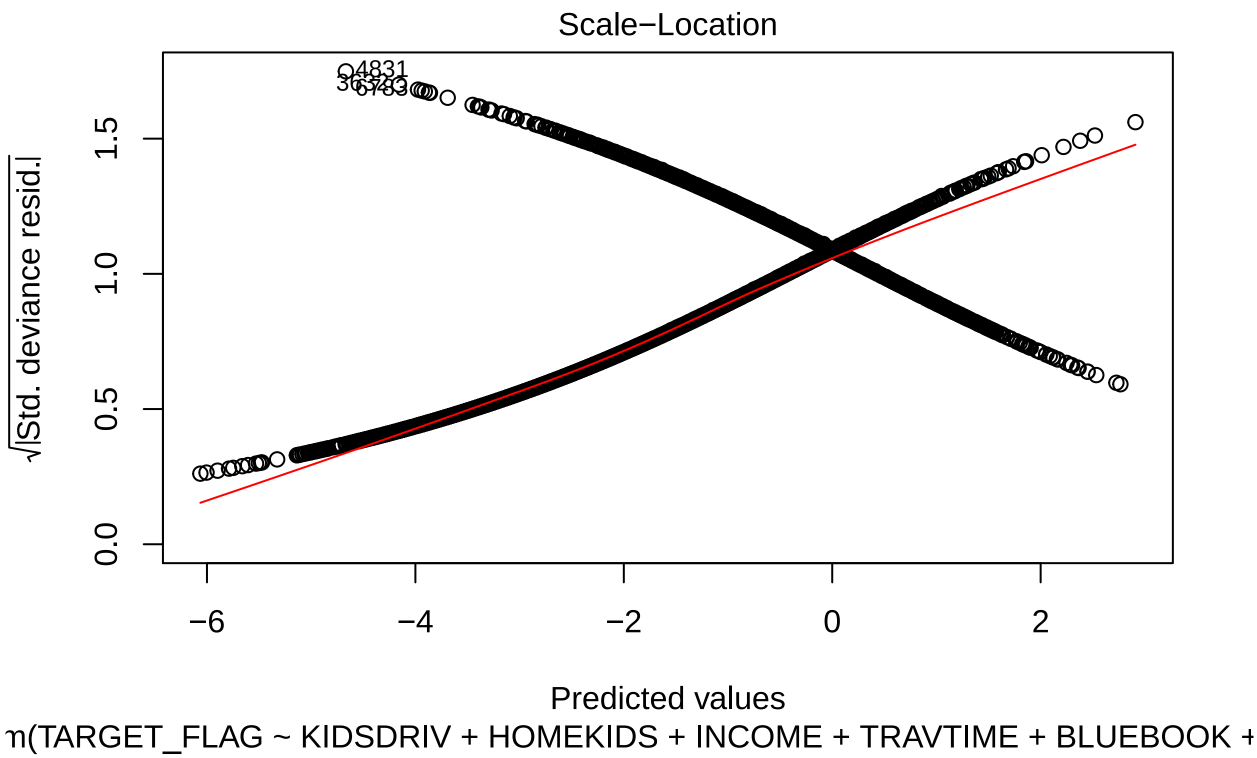
```
plot(model_11_backward)
```

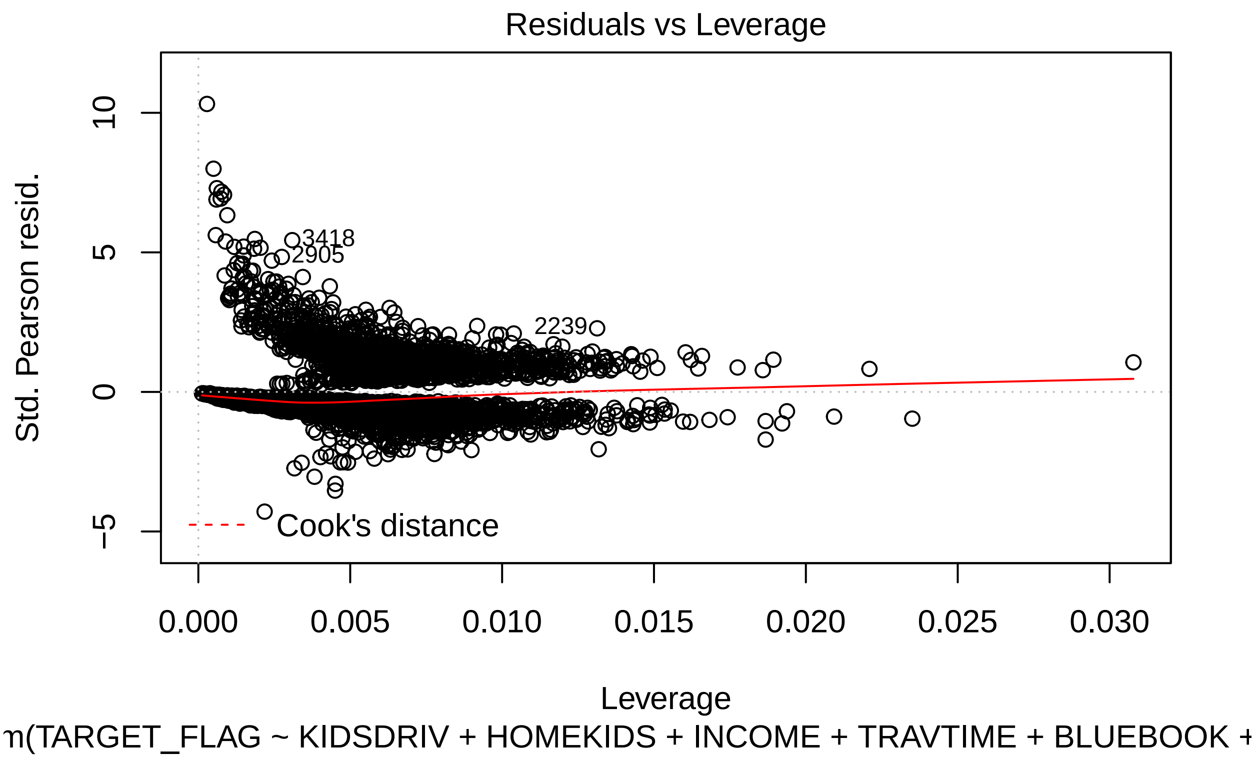


Residuals vs Fitted
Residuals
Predicted values
4831
36723
6733
3
2
1
0
−1
−2
−3
−6
−4
−2
0
2
m(TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + INCOME + TRAVTIME + BLUEBOOK +

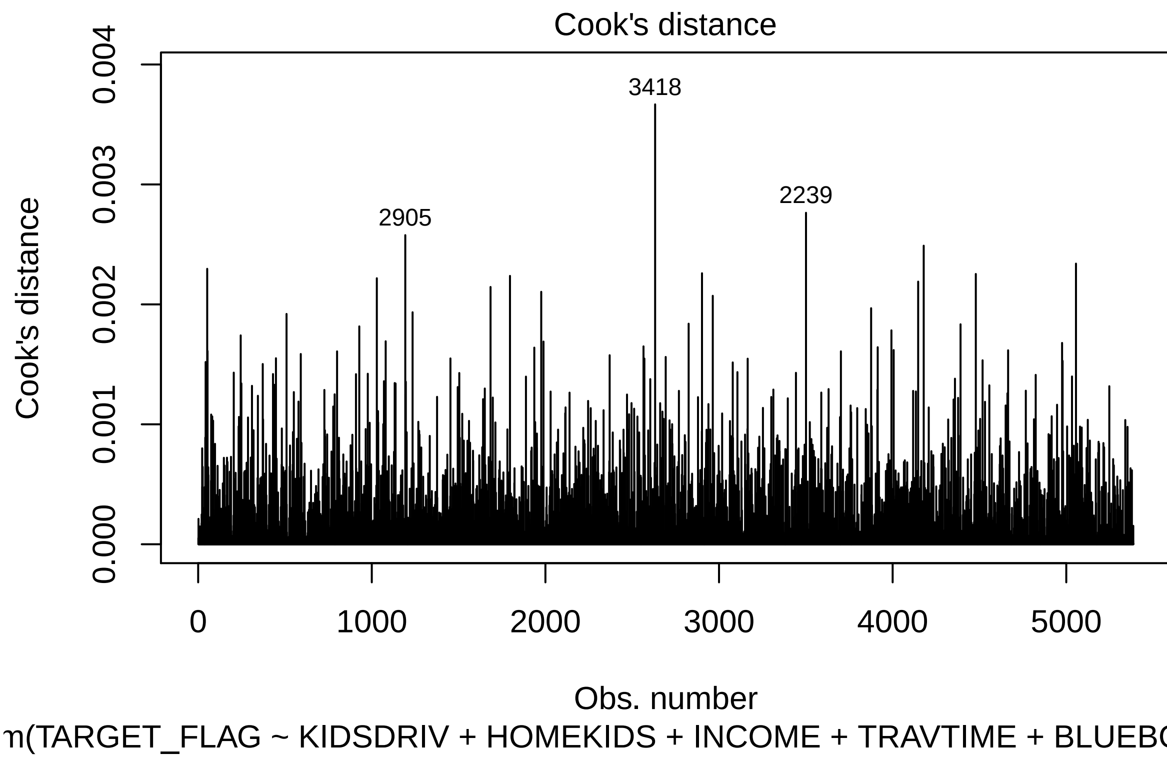


Normal Q−Q
Std. deviance resid.
Theoretical Quantiles
lm(TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + INCOME + TRAVTIME + BLUEBOOK +
4831
6783


Scale−Location
4831
3633
6783
√|Std. deviance resid.|
0.0
0.5
1.0
1.5
−6
−4
−2
0
2
Predicted values
m(TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + INCOME + TRAVTIME + BLUEBOOK +




```
plot(model_11_backward,which = c(4))
```

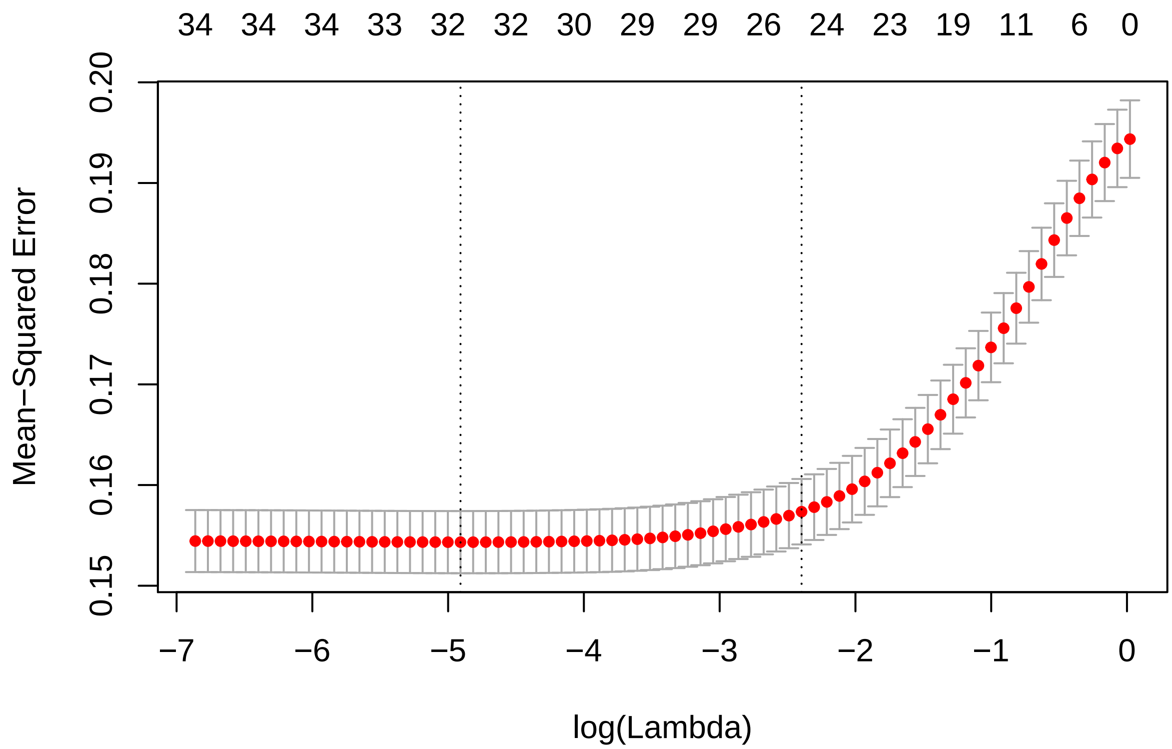



```
# Predicted prob
prediction_model11_prob = predict(model_11_backward,test[,predictorsNames], type='response')

#Predicted class
predicted_model11 = if_else(prediction_model11_prob>=0.5, 1,0)


#print(confusionMatrix(data = predicted_model11, reference = test[,outcomeName],positive = "1"))

#ROC Curve
#roc_model11 <- roc(TARGET_FLAG ~ prediction_model11_prob, data = test)
#auc_model11 <- round(roc_model11$auc, 4)


#plot(roc_model11, legacy_axes =TRUE, col="blue", main = paste0("Model L1 ROC","\n","AUC : ",auc_model1
```

1.3.1.2 Model 2- Lasso Binary regression using GLMNET

In this type of model, we will create a LASSO binary regression using GLMNET package. In this approach, we will shrink the variable coefficents to 0 by selecting the appropirate lambda value.

```
X = as.matrix(train %>% dplyr::select(-TARGET_FLAG))
X_test = as.matrix(test %>% dplyr::select(-TARGET_FLAG))

model21_glmmod <- cv.glmnet(X,y=train[,outcomeName], alpha=0.1)
plot(model21_glmmod)
```




```r
# Predicted prob
predict_glmnet.prob = predict(model21_glmmod,X_test,type='response',s=model21_glmmod$lambda.min)

#Predicted class
predicted = if_else(predict_glmnet.prob>=0.5, 1,0)


print(confusionMatrix(data = predicted, reference = test[,outcomeName],
                positive = "1"))
```

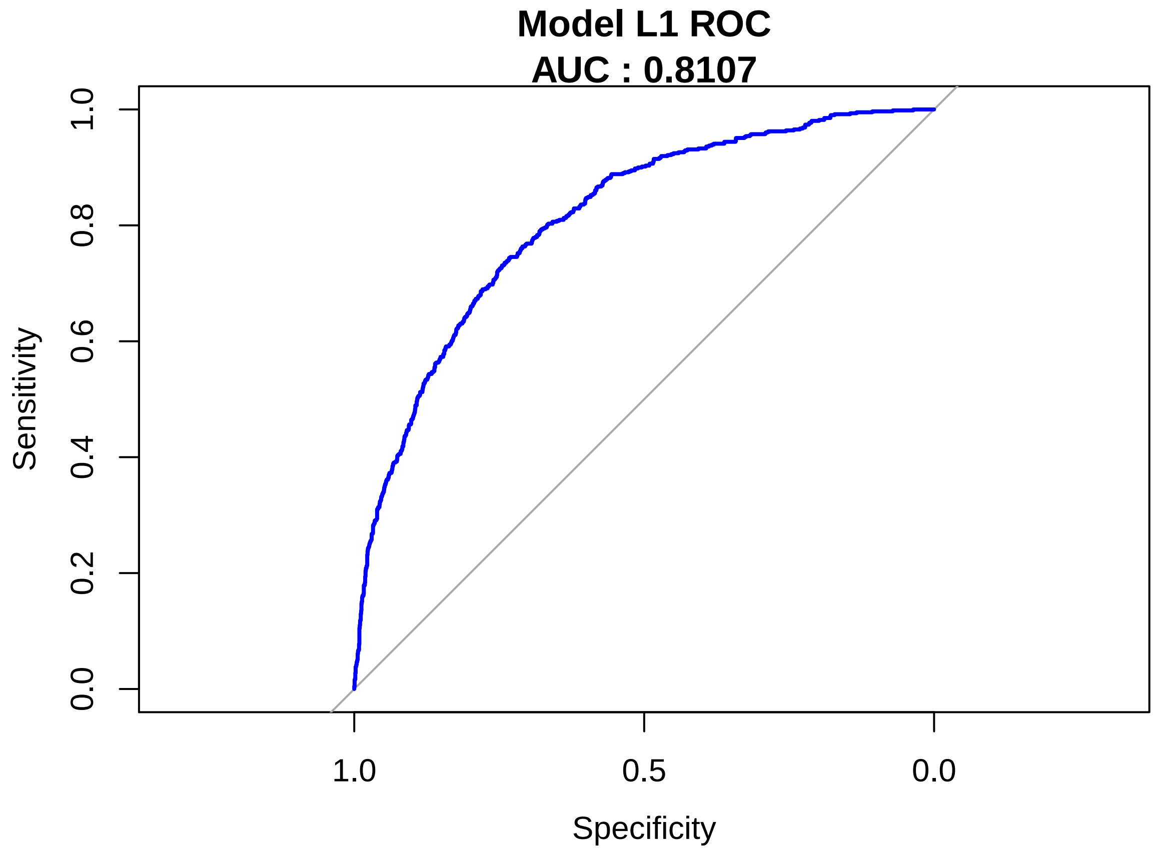
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1616  403
##          1   84  206
##
##                Accuracy : 0.7891
##                  95% CI : (0.7719, 0.8056)
##     No Information Rate : 0.7362
##     P-Value [Acc > NIR] : 2.162e-09
##
##                   Kappa : 0.3472
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.33826
```

```
##          Specificity : 0.95059
##       Pos Pred Value : 0.71034
##       Neg Pred Value : 0.80040
##           Prevalence : 0.26375
##       Detection Rate : 0.08922
## Detection Prevalence : 0.12560
##    Balanced Accuracy : 0.64442
##
##     'Positive' Class : 1
##
```

```
#ROC Curve
model21_glmmod_roc <- roc(TARGET_FLAG ~ predict_glmnet.prob, data = test)
```

```
## Warning in roc.default(response, m[[predictors]], ...): Deprecated use
## a matrix as predictor. Unexpected results may be produced, please pass a
## numeric vector.
```

```
model21_glmmod_auc <- round(model21_glmmod_roc$auc, 4)


plot(model21_glmmod_roc, legacy_axes =TRUE, col="blue", main = paste0("Model L1 ROC","\n","AUC : ",model
```



1.3.1.3 Model 3 - Bayesian Logistic Regression

In this model, we will run Bayesian type logistic regression. Bayesian model calculates the prior and posterior probability using Markov Chain Monte Carlo(MCMC) method.

`rstanarm` package provides functions to run Bayesian type models.

```
#t_prior =student_t(df=35, location = 0, scale = 2.5)

#model_31_bayseian_scaled <- stan_glm(TARGET_FLAG ~ . ,data=train ,family=binomial(link='logit'), prior

#linpred <- posterior_linpred(model_31_bayseian_scaled)
#preds <- posterior_linpred(model_31_bayseian_scaled, transform=TRUE)
#pred <- colMeans(preds)
#pr <- as.integer(pred >= 0.5)

#confusionMatrix(data = pr,reference = train$TARGET_FLAG, positive = "1")
```

1.3.2 TARGET_AMT - COST prediction

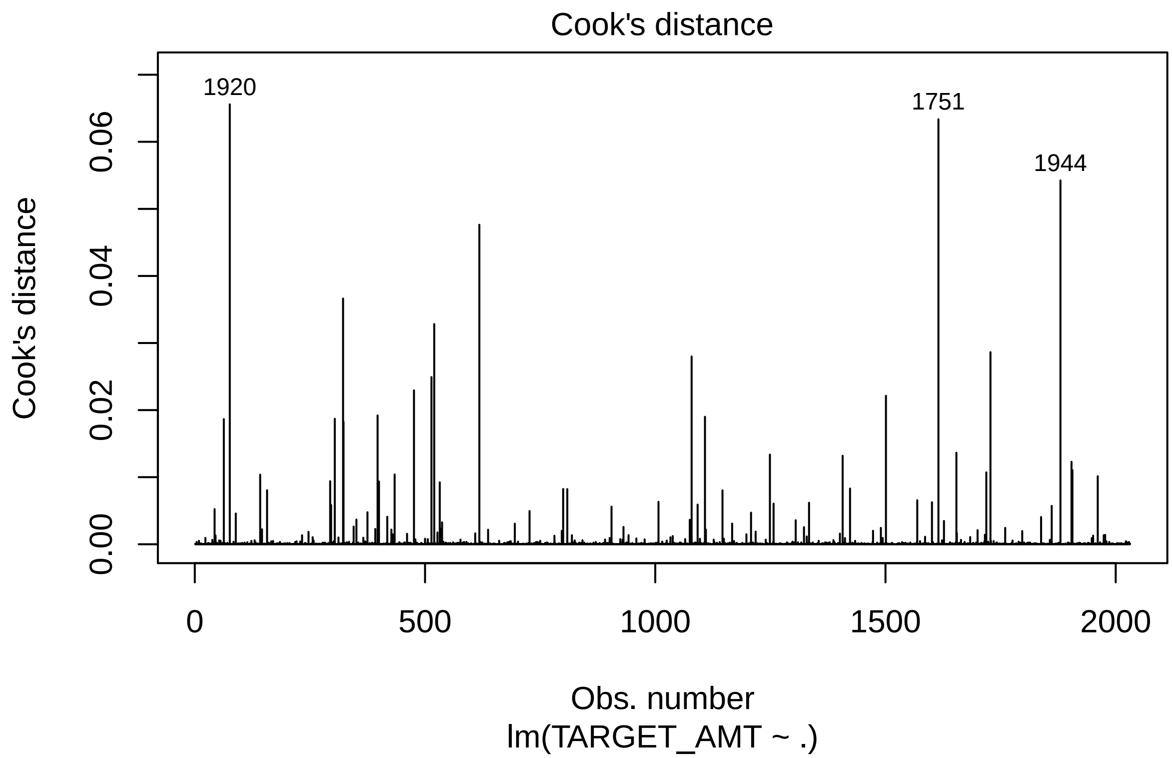
Previously we have predicted the car crash using the available variables. As a next step, if the accident happens, we will build models to predict the cost of car to pay for that accident.

```
df_transformed_target_amt <- df_transformed %>% filter(TARGET_FLAG==1) %>% dplyr::select(-TARGET_FLAG)


#Random numbers target
randomobs_amt <- sample(seq_len(nrow(df_transformed_target_amt)), size = floor(1 * nrow(df_transformed_

# Train dataset
train_target_amt <- df_transformed_target_amt [randomobs_amt,]

#Test dataset
test_target_amt <- df_transformed_target_amt[-randomobs_amt,]
```

1.3.2.1 Model 1 - Stepwise selection

As a inital step we will build a simple stepwise model as a base. This will have all the variables and automatic stepwise selection process.

```
# General model
model_11_amt_step <- lm(TARGET_AMT ~ ., train_target_amt)


# Remove outliers
outliers_remove <- function(x,test_model){
  rownames(x) <- NULL
  outliers <- cooks.distance(test_model)
  plot(test_model,which = c(4))
  print(as.numeric(row.names(data.frame(c(tail(sort(outliers),3))))))
  x <- x[-as.numeric(row.names(data.frame(c(tail(sort(outliers),3))))),]
  return(x)
}


# Remove outliers
model_12_amt_step_outliers <- lm(TARGET_AMT ~ ., outliers_remove(train_target_amt,model_11_amt_step))
```




```
## [1] 1944 1751 1920
```

```r
# Summary
summary(model_12_amt_step_outliers)
```

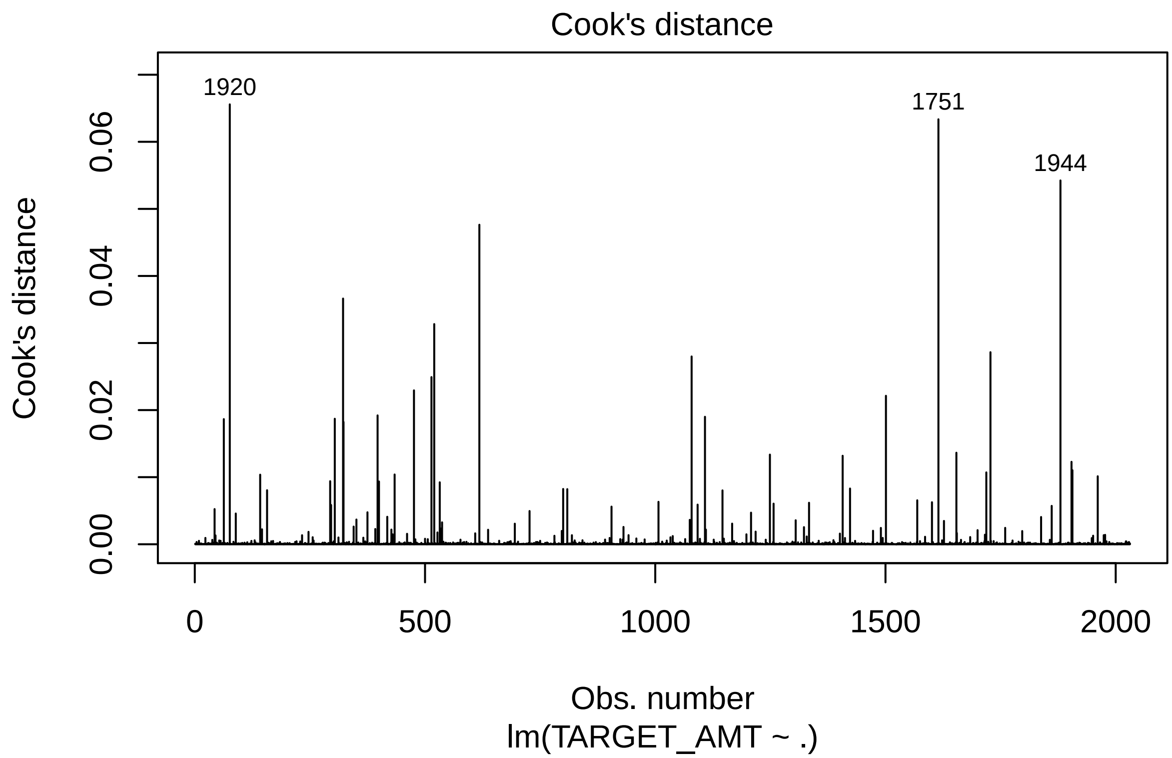
```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = outliers_remove(train_target_amt,
##     model_11_amt_step))
##
## Residuals:
##    Min      1Q Median      3Q     Max
##  -9619   -3181  -1511     499  100148
##
## Coefficients:
##                                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)                           5.432e+03  1.852e+03   2.934  0.00339
## KIDSDRIV                             -8.752e+02  6.608e+02  -1.324  0.18553
## AGE                                   1.754e+01  2.285e+01   0.767  0.44289
## HOMEKIDS                              6.690e+01  3.046e+02   0.220  0.82616
## YOJ                                   3.770e+01  6.003e+01   0.628  0.53006
## INCOME                               -4.202e-03  8.616e-03  -0.488  0.62579
## HOME_VAL                             -7.677e-04  3.761e-03  -0.204  0.83829
## TRAVTIME                              4.878e+00  1.149e+01   0.425  0.67123
## BLUEBOOK                              1.350e-01  3.200e-02   4.217 2.59e-05
## TIF                                  -8.000e+00  4.416e+01  -0.181  0.85624
## OLDCLAIM                              2.446e-02  2.554e-02   0.958  0.33825
```

```
## CLM_FREQ                          -1.156e+02  2.469e+02  -0.468  0.63966
## MVR_PTS                            1.312e+02  7.355e+01   1.784  0.07465
## CAR_AGE                           -4.845e+01  3.797e+01  -1.276  0.20208
## KIDSDRIV_BIN                      -1.373e+03  1.110e+03  -1.238  0.21603
## HOMEKIDS_BIN                      -1.723e+02  8.569e+02  -0.201  0.84062
## OLDCLAIM_BIN                       6.395e+01  7.001e+02   0.091  0.92723
## HOME_OWN                          -8.011e+02  8.815e+02  -0.909  0.36358
## SEX_z_F                           -1.562e+03  6.807e+02  -2.294  0.02189
## PARENT1_Yes                        3.839e+01  7.006e+02   0.055  0.95630
## EDUCATION_0                        4.185e+02  5.247e+02   0.798  0.42521
## MSTATUS_Yes                       -1.015e+03  5.682e+02  -1.786  0.07419
## INCOME_BIN_2                       8.296e+01  5.419e+02   0.153  0.87835
## INCOME_BIN_0                      -4.899e+02  5.078e+02  -0.965  0.33476
## `JOB_z_Blue Collar`               -2.164e+02  5.136e+02  -0.421  0.67356
## `JOB_Home Maker`                  -1.280e+02  8.207e+02  -0.156  0.87609
## JOB_Student                       -8.274e+01  7.981e+02  -0.104  0.91745
## CAR_USE_Commercial                 4.917e+02  5.283e+02   0.931  0.35213
## CAR_TYPE_z_SUV                     1.055e+03  6.945e+02   1.519  0.12891
## `CAR_TYPE_Sports Car`              1.323e+03  7.787e+02   1.700  0.08935
## CAR_TYPE_Van                       4.169e+01  8.003e+02   0.052  0.95846
## `CAR_TYPE_Panel Truck`            -4.533e+02  9.888e+02  -0.458  0.64669
## CAR_TYPE_Pickup                   -5.787e+01  6.229e+02  -0.093  0.92598
## RED_CAR_no                         3.383e+01  5.178e+02   0.065  0.94792
## REVOKED_Yes                       -9.183e+02  5.490e+02  -1.672  0.09459
## `URBANICITY_z_Highly Rural/ Rural` -6.785e+01  7.829e+02  -0.087  0.93095
##
## (Intercept)                       **
## KIDSDRIV
## AGE
## HOMEKIDS
## YOJ
## INCOME
## HOME_VAL
## TRAVTIME
## BLUEBOOK                          ***
## TIF
## OLDCLAIM
## CLM_FREQ
## MVR_PTS                           .
## CAR_AGE
## KIDSDRIV_BIN
## HOMEKIDS_BIN
## OLDCLAIM_BIN
## HOME_OWN
## SEX_z_F                           *
## PARENT1_Yes
## EDUCATION_0
## MSTATUS_Yes                       .
## INCOME_BIN_2
## INCOME_BIN_0
## `JOB_z_Blue Collar`
## `JOB_Home Maker`
## JOB_Student
## CAR_USE_Commercial
```

```
## CAR_TYPE_z_SUV
## `CAR_TYPE_Sports Car`              .
## CAR_TYPE_Van
## `CAR_TYPE_Panel Truck`
## CAR_TYPE_Pickup
## RED_CAR_no
## REVOKED_Yes                        .
## `URBANICITY_z_Highly Rural/ Rural`
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7773 on 1992 degrees of freedom
## Multiple R-squared:  0.0284, Adjusted R-squared:  0.01133
## F-statistic: 1.664 on 35 and 1992 DF,  p-value: 0.008865
```

Created model is not very good for this particular dataset. As the response variable is skewed, we will transform the response variable and perform then create a model.

```
log_transform <- function(x) {
  return(log(x))
}


train_target_amt_income = train_target_amt

train_target_amt_income$INCOME=train_target_amt_income$INCOME+0.00001

# Apply to all the applicable columns.
train_target_amt_income[,c('INCOME','TRAVTIME', 'BLUEBOOK','TIF')] = apply(train_target_amt_income[,c('


train_target_amt_nooutlier <- outliers_remove(train_target_amt_income,model_11_amt_step)
```




```
## [1] 1944 1751 1920
```

```r
# Remove outliers
model_13_amt_step_outliers_log <- lm(log(TARGET_AMT) ~ ., train_target_amt_nooutlier)


model_14_amt_step = step(model_13_amt_step_outliers_log,trace = FALSE)

summary(model_14_amt_step)
```

```
##
## Call:
## lm(formula = log(TARGET_AMT) ~ BLUEBOOK + OLDCLAIM + CLM_FREQ +
##     MVR_PTS + SEX_z_F + MSTATUS_Yes + REVOKED_Yes, data = train_target_amt_nooutlier)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.6947 -0.3971  0.0304  0.4082  3.2350
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.785e+00  2.601e-01  26.089  < 2e-16 ***
## BLUEBOOK     1.641e-01  2.712e-02   6.050 1.73e-09 ***
## OLDCLAIM     4.954e-06  2.404e-06   2.060   0.0395 *
## CLM_FREQ    -3.262e-02  1.672e-02  -1.951   0.0512 .
## MVR_PTS      1.571e-02  7.280e-03   2.158   0.0310 *
## SEX_z_F     -5.725e-02  3.600e-02  -1.591   0.1119
```

```
## MSTATUS_Yes -6.449e-02  3.567e-02  -1.808   0.0707 .
## REVOKED_Yes -8.923e-02  5.467e-02  -1.632   0.1028
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.802 on 2020 degrees of freedom
## Multiple R-squared:  0.02546,    Adjusted R-squared:  0.02208
## F-statistic: 7.538 on 7 and 2020 DF,  p-value: 5.443e-09
```

Above model is better than the previous model. However, it has only less variables and the adjusted R2 is not very high. We will try other models and see.

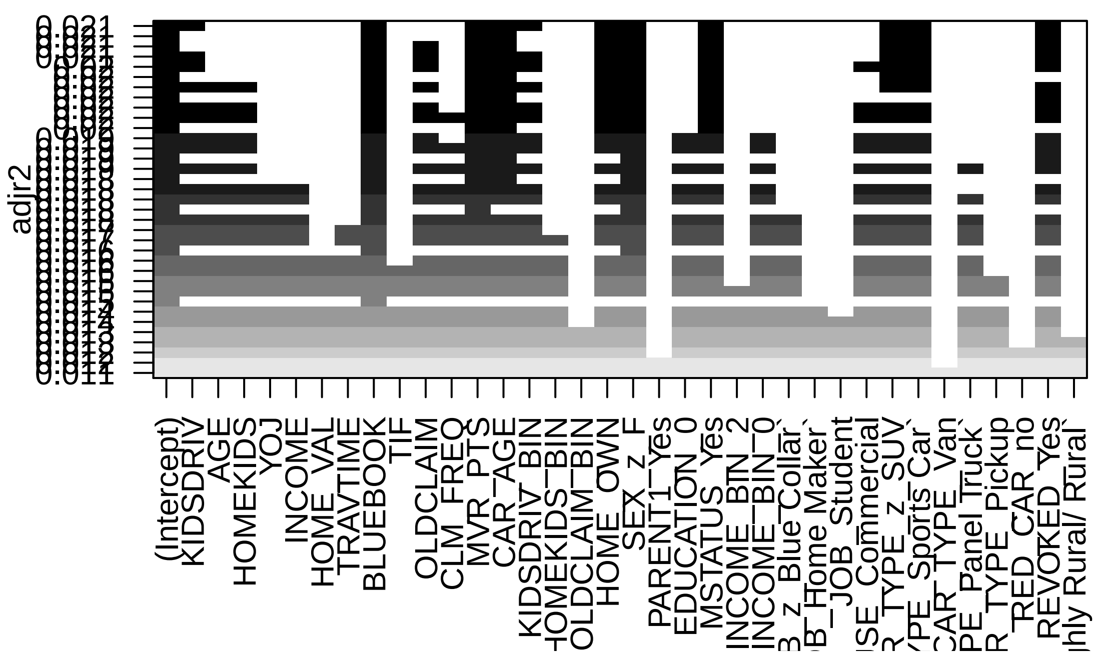
1.3.2.2 Model 2 - Regsubsets

In this model, we will perform automatic selection of the variables using `regsubsets`.

```
model_21_regfit <- regsubsets(TARGET_AMT ~ .,train_target_amt,nvmax = 35)

model_21_regfit_summary <- summary(model_21_regfit)

print(paste0('Adjusted R2:',max(model_21_regfit_summary$adjr2)))
```

```
## [1] "Adjusted R2:0.0207120371661899"
```

```
plot(model_21_regfit,scale='adjr2')
```



Automatic selection of variables did not improve much on the adj-R2. We will try other different models.

1.3.2.3 Model 3 - Ridge Regression

In this attempt, we will perform Ridge regression. Ridge regression uses L2 regulaization and reduces the coeffecients.

```
set.seed(825)
fitControl <- trainControl(method = "cv",number = 10)
# Set seq of lambda to test
lambdaGrid <- expand.grid(lambda = 10^seq(10, -2, length=100))

model_21_ridge <- train(TARGET_AMT ~ .,train_target_amt, method='ridge', lambda=10)

model_21_ridge
```

```
## Ridge Regression
##
## 2031 samples
##   35 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 2031, 2031, 2031, 2031, 2031, 2031, ...
## Resampling results across tuning parameters:
##
##   lambda  RMSE      Rsquared     MAE
##   0e+00   8061.362  0.004439284  3876.282
##   1e-04   8061.312  0.004440042  3876.194
##   1e-01   8041.648  0.004880798  3841.835
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was lambda = 0.1.
```

It seems the results are not signficant. Rsquared has not immproved much. So this is also not the best model.

1.3.2.4 Model 4 - Regression Splines

This time we will try a nonlinear model with regression splines. Splines provide a way to smoothly interpolate between fixed points called knots.

```
knots <- quantile(train_target_amt$BLUEBOOK)

model_41_splines <- lm( TARGET_AMT ~ factor(SEX_z_F) + factor(MSTATUS_Yes) + factor(REVOKED_Yes) +bs(BLU

model_41_splines_summary <- summary(model_41_splines)


pred_splines = predict(model_41_splines,newdata = train_target_amt[,predictorsNames])
```

```
## Warning in predict.lm(model_41_splines, newdata = train_target_amt[,
## predictorsNames]): prediction from a rank-deficient fit may be misleading
```

```
# Splines - 6487
rmse = sqrt(mean((train_target_amt$TARGET_AMT - pred_splines)^2))

print(paste0("Adjusted R2: ",model_41_splines_summary$adj.r.squared))
```

```
## [1] "Adjusted R2: 0.081990025388321"
```

```
print(paste0("F-statistic: ",model_41_splines_summary$fstatistic))
```

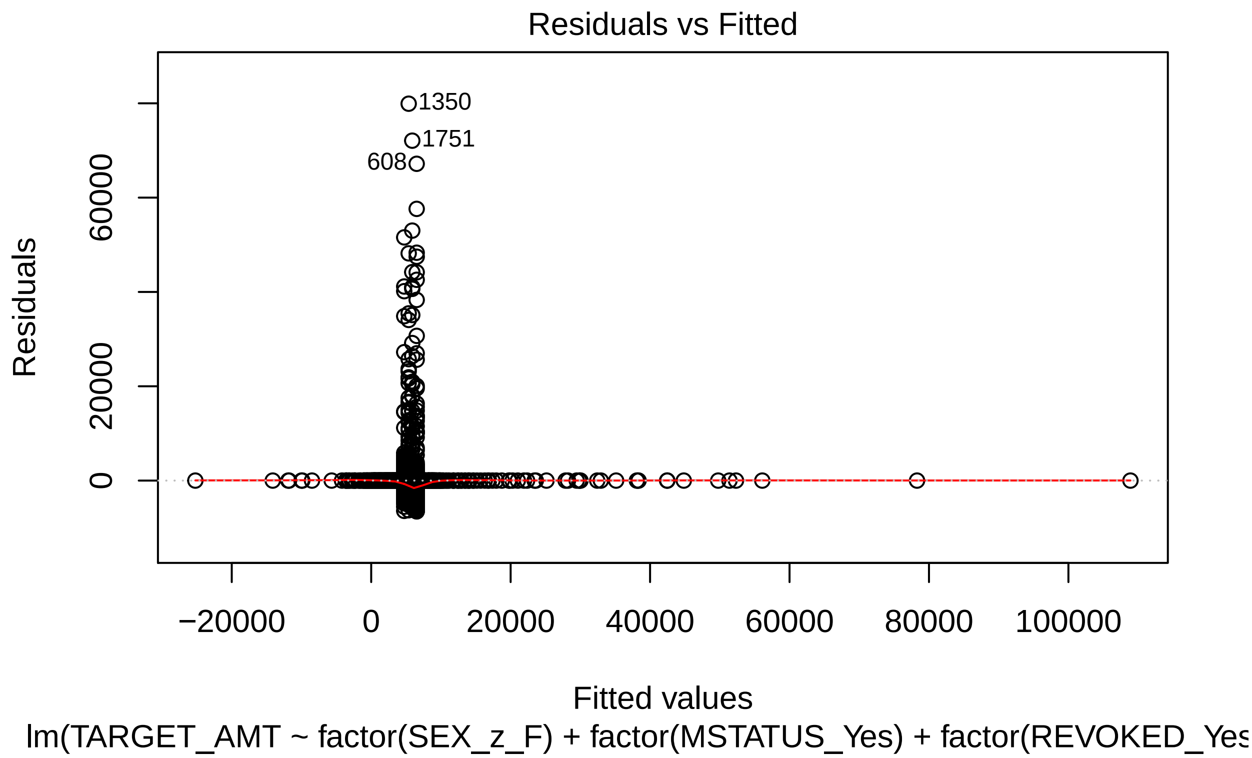
```
## [1] "F-statistic: 1.27387454516885" "F-statistic: 662"
## [3] "F-statistic: 1368"
```

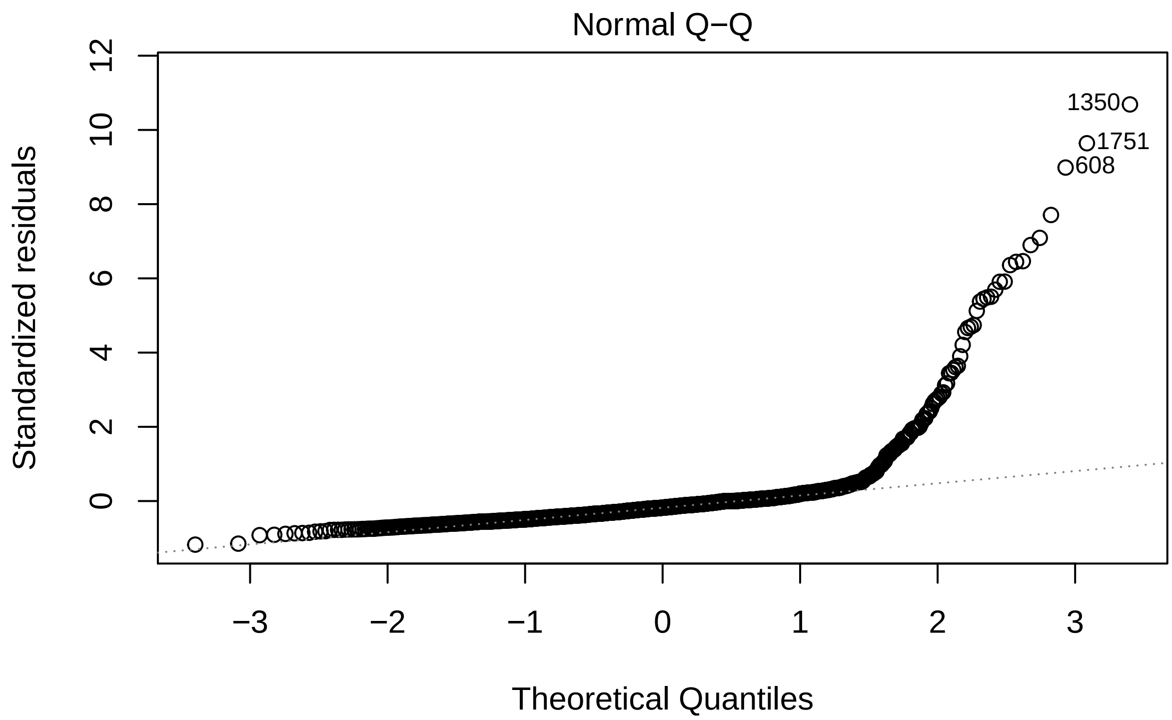
```
print(paste0("RMSE: ",rmse))
```

```
## [1] "RMSE: 6487.29566076278"
```

```
plot(model_41_splines)
```

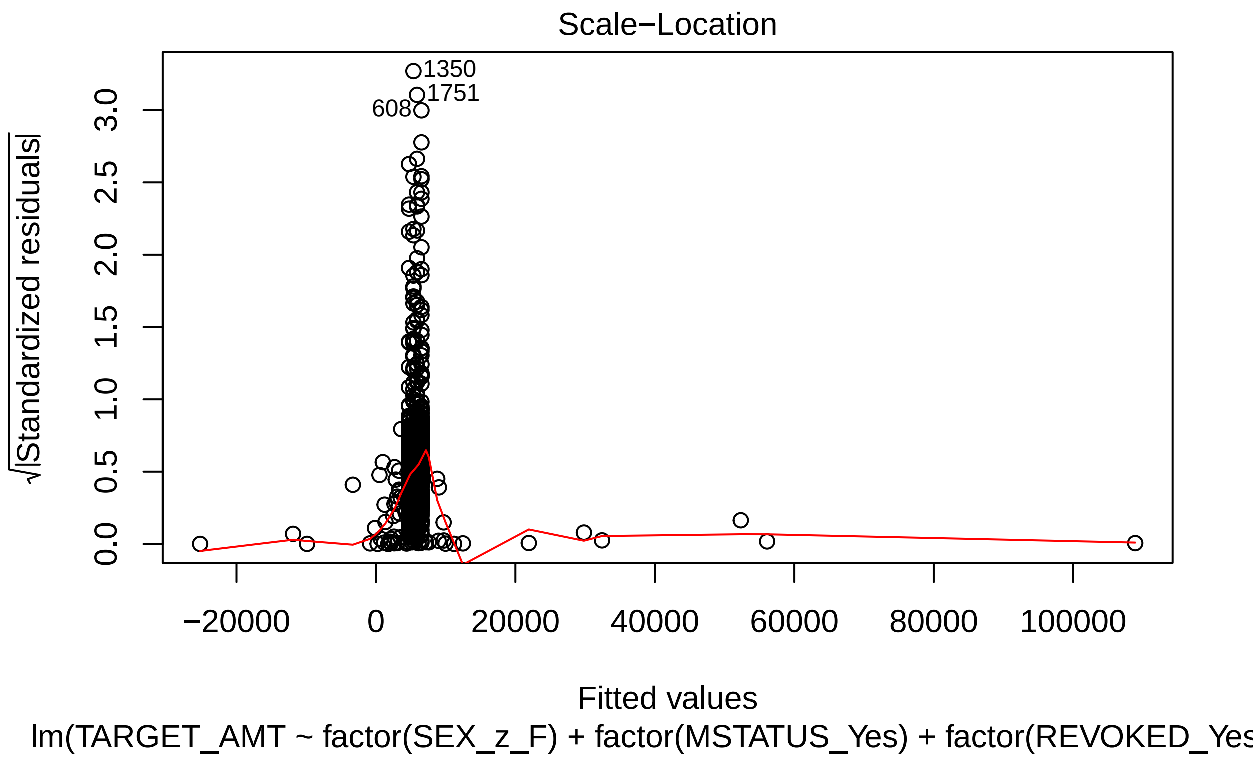
```
## Warning: not plotting observations with leverage one:
##   13, 18, 20, 39, 41, 49, 52, 59, 65, 66, 83, 87, 92, 96, 101, 102, 104, 105, 117, 118, 121, 128, 13
```





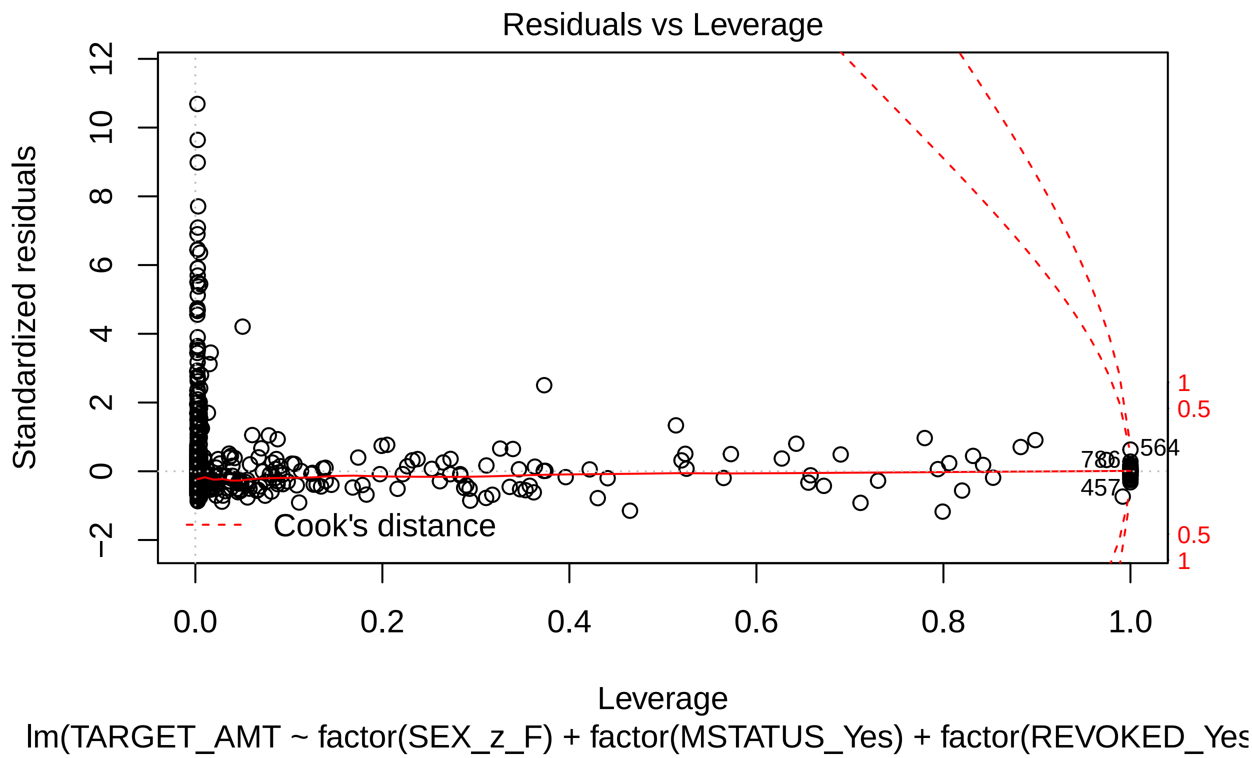
lm(TARGET_AMT ~ factor(SEX_z_F) + factor(MSTATUS_Yes) + factor(REVOKED_Yes

```
## Warning: not plotting observations with leverage one:
##   13, 18, 20, 39, 41, 49, 52, 59, 65, 66, 83, 87, 92, 96, 101, 102, 104, 105, 117, 118, 121, 128, 13
```

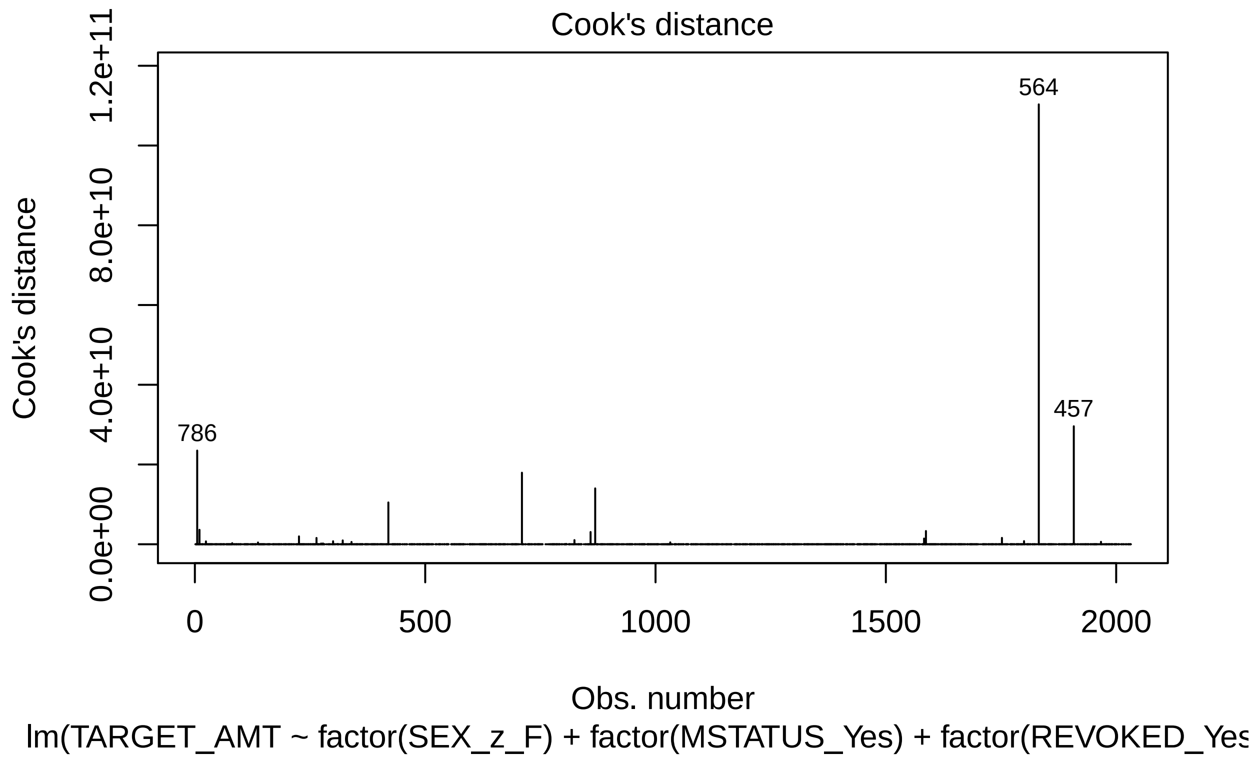



```
## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced
```

```
## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced
```




```r
plot(model_41_splines,which = c(4))
```



Above model is build from the base model from stepwise selection. When we add splines, then we get better adjusted R2 compared to other models. However, the residual plots show that there is some autocorrelation. So we will reject this model.

1.4 Model Selection

We have build different models and evaluated them. In this section, we will select the final model and add other metrics to it.

1.4.1 TARGET_FLAG Model

We have build basic model, stepwise model, Lasso logistic regression and regsubsets model. It seems stepwise model is performing good and more interpretable. Lets analyze the model further.

```
summary(model_11_backward)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + INCOME + TRAVTIME +
##     BLUEBOOK + TIF + OLDCLAIM + MVR_PTS + CAR_AGE + HOMEKIDS_BIN +
##     OLDCLAIM_BIN + HOME_OWN + PARENT1_Yes + EDUCATION_0 + MSTATUS_Yes +
##     INCOME_BIN_0 + CAR_USE_Commercial + CAR_TYPE_z_SUV + `CAR_TYPE_Sports Car` +
##     CAR_TYPE_Van + `CAR_TYPE_Panel Truck` + CAR_TYPE_Pickup +
##     REVOKED_Yes + `URBANICITY_z_Highly Rural/ Rural`, family = binomial(link = "logit"),
##     data = train)
##
```

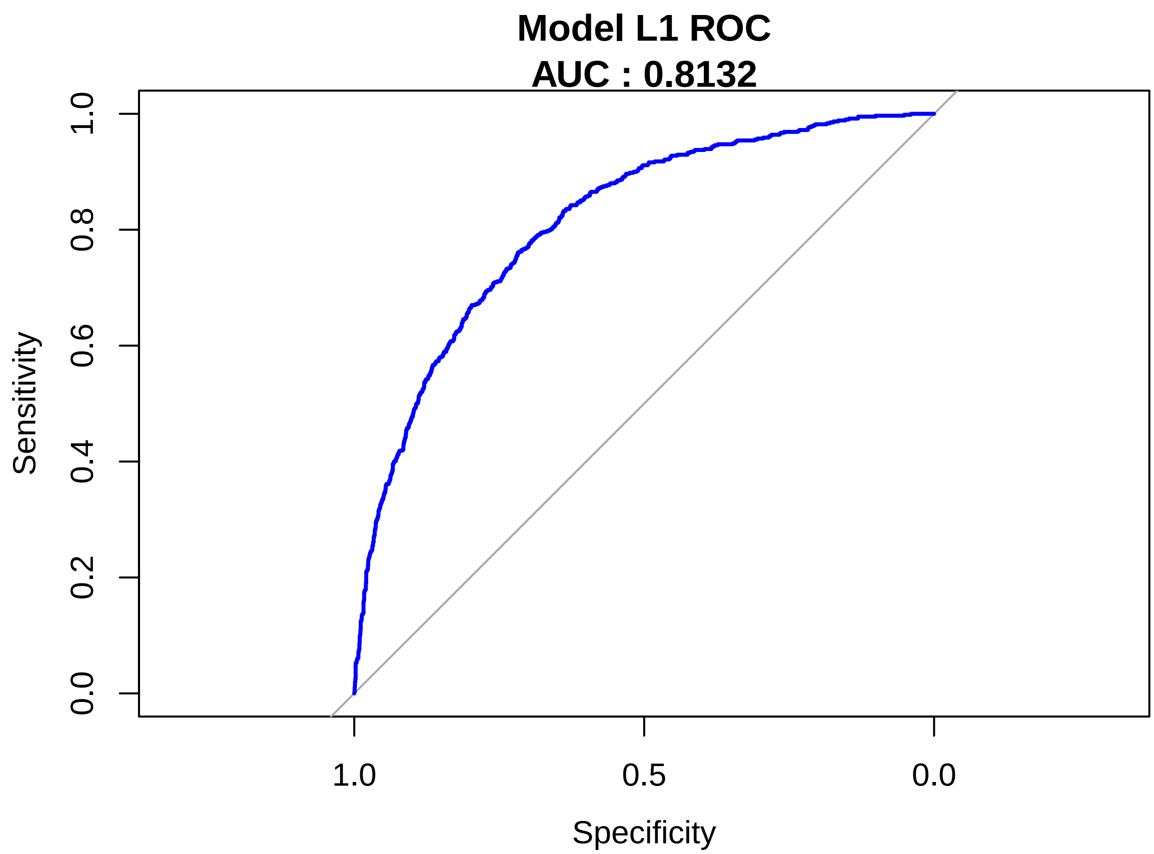
```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4343  -0.7295  -0.4164   0.6618   3.0583
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                        -8.189e-01  2.524e-01  -3.244 0.001179
## KIDSDRIV                            2.839e-01  7.216e-02   3.934 8.36e-05
## HOMEKIDS                           -1.151e-01  6.405e-02  -1.797 0.072324
## INCOME                             -7.705e-06  1.114e-06  -6.919 4.56e-12
## TRAVTIME                            1.546e-02  2.284e-03   6.770 1.29e-11
## BLUEBOOK                           -2.483e-05  5.813e-06  -4.272 1.94e-05
## TIF                                -5.009e-02  9.014e-03  -5.557 2.74e-08
## OLDCLAIM                           -1.688e-05  5.125e-06  -3.295 0.000986
## MVR_PTS                             9.799e-02  1.737e-02   5.640 1.70e-08
## CAR_AGE                            -2.254e-02  7.431e-03  -3.033 0.002418
## HOMEKIDS_BIN                       -4.775e-01  1.634e-01  -2.923 0.003469
## OLDCLAIM_BIN                        5.125e-01  9.612e-02   5.332 9.72e-08
## HOME_OWN                            2.948e-01  9.380e-02   3.143 0.001675
## PARENT1_Yes                         2.877e-01  1.471e-01   1.957 0.050396
## EDUCATION_0                         3.491e-01  1.101e-01   3.170 0.001525
## MSTATUS_Yes                        -4.965e-01  1.073e-01  -4.626 3.73e-06
## INCOME_BIN_0                       -1.427e-01  9.601e-02  -1.487 0.137125
## CAR_USE_Commercial                  9.426e-01  8.878e-02  10.618  < 2e-16
## CAR_TYPE_z_SUV                      6.484e-01  1.022e-01   6.347 2.20e-10
## `CAR_TYPE_Sports Car`               8.281e-01  1.322e-01   6.265 3.72e-10
## CAR_TYPE_Van                        5.110e-01  1.457e-01   3.508 0.000452
## `CAR_TYPE_Panel Truck`              5.050e-01  1.722e-01   2.932 0.003366
## CAR_TYPE_Pickup                     3.687e-01  1.196e-01   3.083 0.002052
## REVOKED_Yes                         9.009e-01  1.127e-01   7.997 1.28e-15
## `URBANICITY_z_Highly Rural/ Rural` -2.213e+00  1.381e-01 -16.028  < 2e-16
##
## (Intercept)                        **
## KIDSDRIV                           ***
## HOMEKIDS                           .
## INCOME                             ***
## TRAVTIME                           ***
## BLUEBOOK                           ***
## TIF                                ***
## OLDCLAIM                           ***
## MVR_PTS                            ***
## CAR_AGE                            **
## HOMEKIDS_BIN                       **
## OLDCLAIM_BIN                       ***
## HOME_OWN                           **
## PARENT1_Yes                        .
## EDUCATION_0                        **
## MSTATUS_Yes                        ***
## INCOME_BIN_0
## CAR_USE_Commercial                 ***
## CAR_TYPE_z_SUV                     ***
## `CAR_TYPE_Sports Car`              ***
## CAR_TYPE_Van                       ***
## `CAR_TYPE_Panel Truck`             **
```

```
## CAR_TYPE_Pickup                    **
## REVOKED_Yes                        ***
## `URBANICITY_z_Highly Rural/ Rural` ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6218.4  on 5386  degrees of freedom
## Residual deviance: 4903.3  on 5362  degrees of freedom
## AIC: 4953.3
##
## Number of Fisher Scoring iterations: 5
```

```
print(confusionMatrix(data = predicted_model11, reference = test[,outcomeName],positive = "1"))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1570  358
##          1  130  251
##
##                Accuracy : 0.7887
##                  95% CI : (0.7714, 0.8051)
##     No Information Rate : 0.7362
##     P-Value [Acc > NIR] : 2.913e-09
##
##                   Kappa : 0.3815
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.4122
##             Specificity : 0.9235
##          Pos Pred Value : 0.6588
##          Neg Pred Value : 0.8143
##              Prevalence : 0.2638
##          Detection Rate : 0.1087
##    Detection Prevalence : 0.1650
##       Balanced Accuracy : 0.6678
##
##        'Positive' Class : 1
##
```

```
#ROC Curve
roc_model11 <- roc(TARGET_FLAG ~ prediction_model11_prob, data = test)
auc_model11 <- round(roc_model11$auc, 4)


plot(roc_model11, legacy_axes =TRUE, col="blue", main = paste0("Model L1 ROC","\n","AUC : ",auc_model11
```



So the model perfoms well on the test dataset. Similar transformations needs to be performed on new dataset and predict the car crash.

1.4.2 TARGET_AMT Model

We have build basic model, stepwise model, regsubsets, ridge regression and regression splines model. By comparing ll the models, we can see stepwise model and regression splines model are performing better. However, all the models seems to do fairly bad. As the TARGET_AMT is fairly complex, I'll select the general linear regression with reduced variables.

```
# Prediction on the train dataset
pred_splines = predict(model_14_amt_step,newdata = train_target_amt[,predictorsNames])

# Splines - 6487
rmse = sqrt(mean((train_target_amt$TARGET_AMT - pred_splines)^2))

print(paste0("Adjusted R2: ",summary(model_14_amt_step)$adj.r.squared))
```

```
## [1] "Adjusted R2: 0.0220804007438259"
```

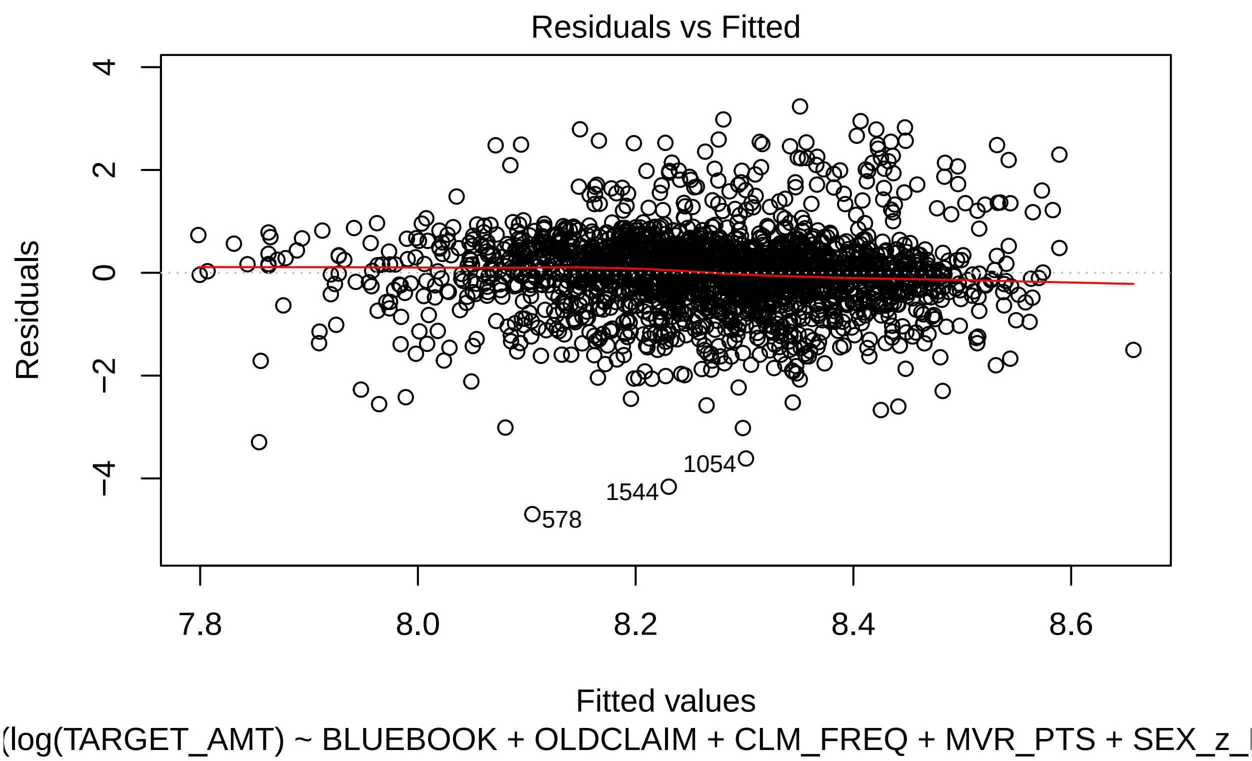
```
print(paste0("F-statistic: ",summary(model_14_amt_step)$fstatistic[1]))
```

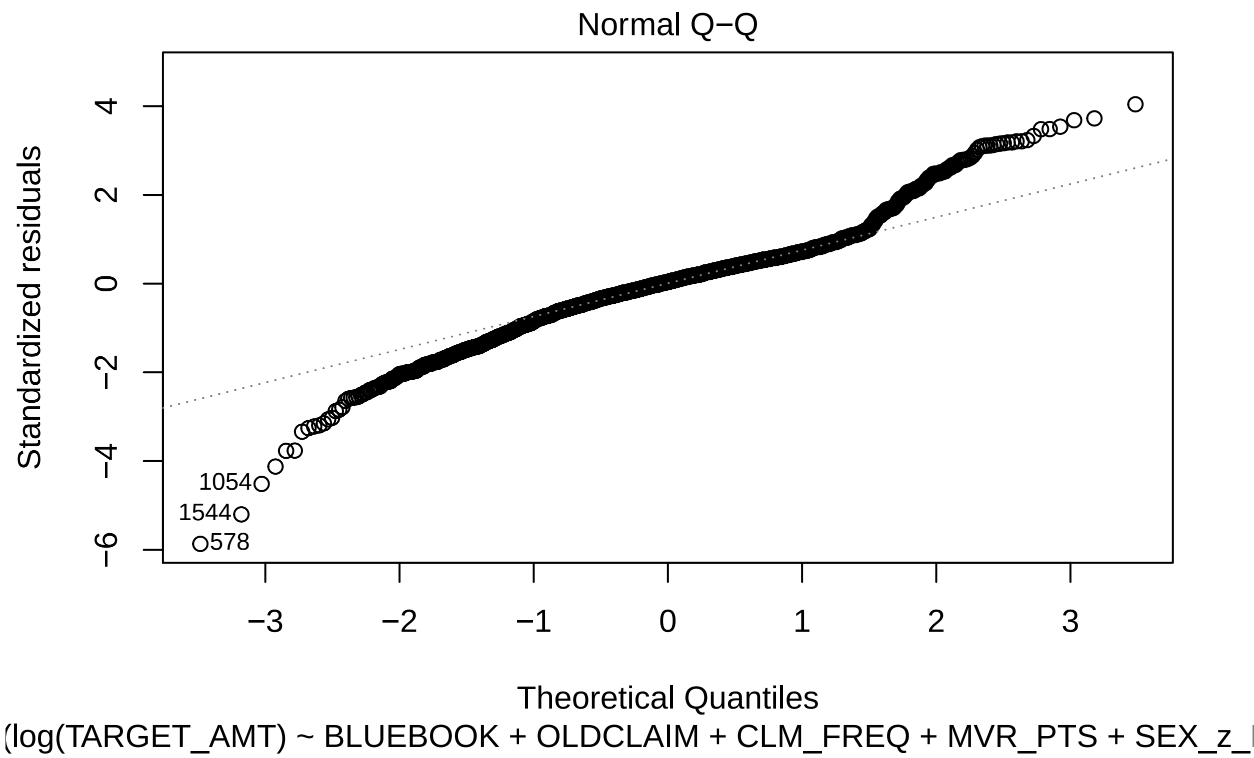
```
## [1] "F-statistic: 7.53821969790011"
```

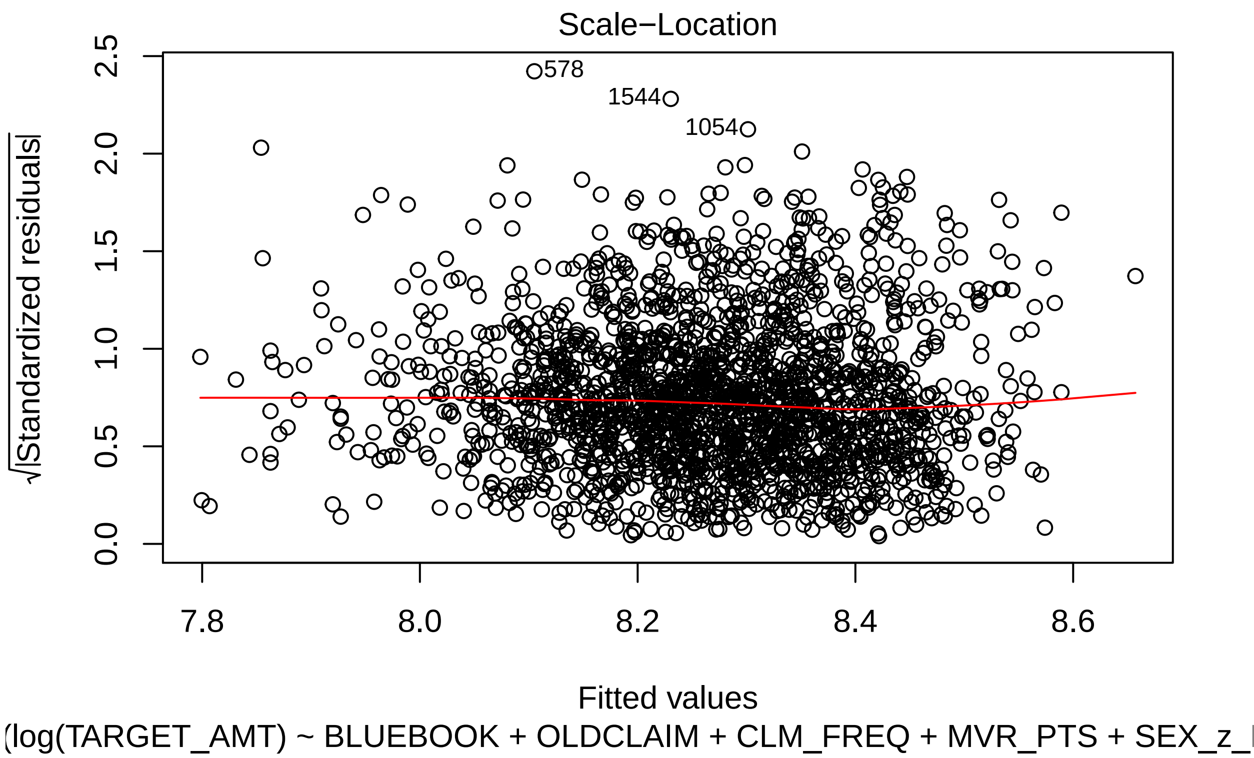
```
print(paste0("RMSE: ",rmse))
```

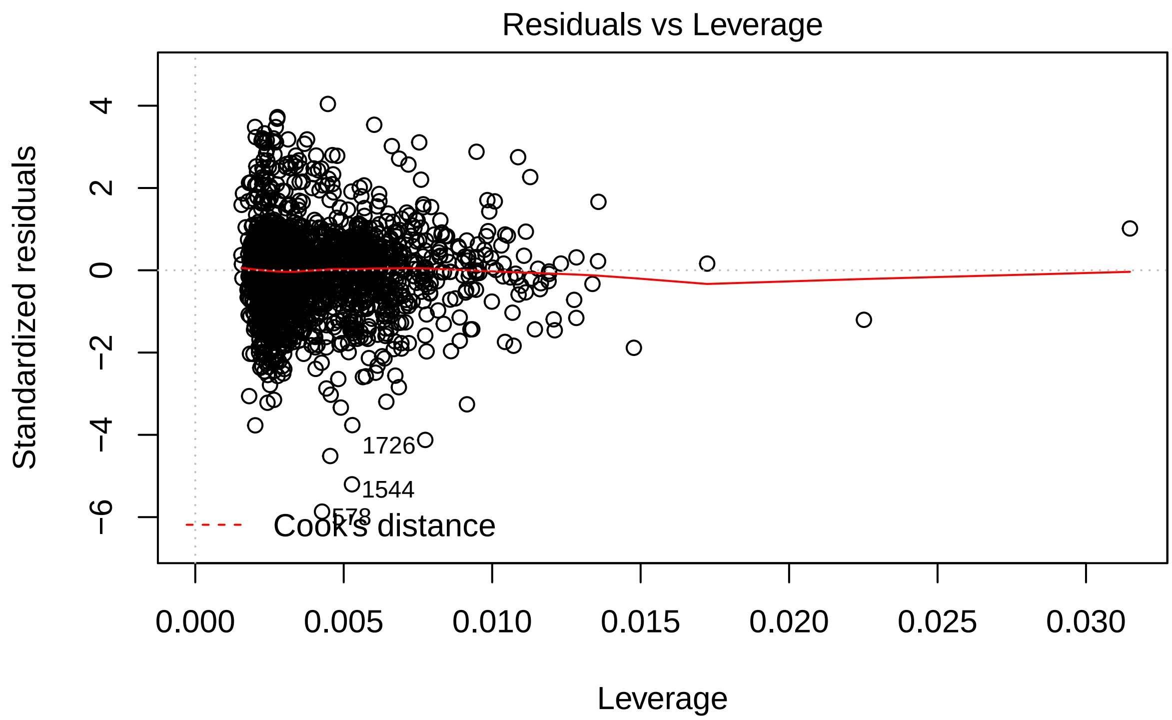
```
## [1] "RMSE: 8447.76961249729"
```

```r
plot(model_14_amt_step)
```



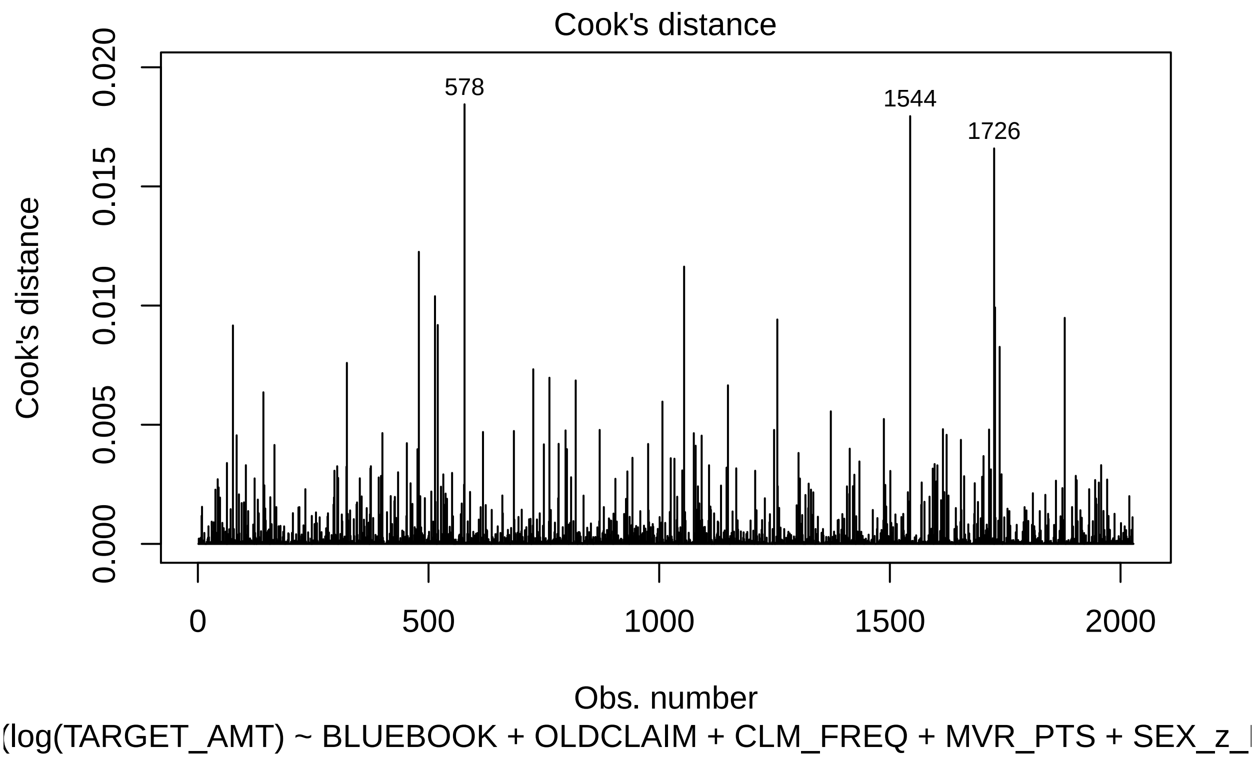

Normal Q−Q
Standardized residuals
4
2
0
−2
−4
−6
1054
1544
578
−3
−2
−1
0
1
2
3
Theoretical Quantiles
(log(TARGET_AMT) ~ BLUEBOOK + OLDCLAIM + CLM_FREQ + MVR_PTS + SEX_z_


Scale−Location
578
1544
1054
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
7.8
8.0
8.2
8.4
8.6
Fitted values
(log(TARGET_AMT) ~ BLUEBOOK + OLDCLAIM + CLM_FREQ + MVR_PTS + SEX_z_



(log(TARGET_AMT) ~ BLUEBOOK + OLDCLAIM + CLM_FREQ + MVR_PTS + SEX_z_I

```
plot(model_14_amt_step,which = c(4))
```



1.5 Prediction of evaluation dataset

Finally we will predict the values of evaluation dataset using the models which we freezed.

1.5.1 Target Flag

```
# Adding to balance the columns
eval$CAR_TYPE_Van =0

# Predicted prob
prediction_eval_flag = predict(model_11_backward,eval, type='response')

#Predicted class
predicted_model11 = if_else(prediction_model11_prob>=0.5, 1,0)
table(predicted_model11)
```

```
## predicted_model11
##    0    1
## 1928  381
```

We are predicting there will be around 381 crashes.

1.5.2 Target Amt

```
# Prediction on the train dataset
eval_prediction = predict(model_14_amt_step,newdata = eval)

#Average Target amount
mean(eval_prediction)
```

```
## [1] 2544.552
```

1.6 Summary

1. We have performed data cleaning on the necessary columsn.
2. Performed a detailed exploratory data analysis.
3. Transformed the variables and added additional features.
4. Build various models for predicting TARGET_FLAG and TARGET_AMT.
5. Evaluated various metrics on the dataset and predicted the evaluation datasets.