Homework 4

Insurance Linear and Binary Regression

Group 2

4/21/2021

Contents

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Assignment Overview

In this homework assignment, you will explore, analyze and model a data set containing approximately 8000 records representing a customer at an auto insurance company. Each record has two response variables. The first response variable, `TARGET_FLAG`, is a 1 or a 0. A "1" means that the person was in a car crash. A zero means that the person was not in a car crash. The second response variable is `TARGET_AMT`. This value is zero if the person did not crash their car. But if they did crash their car, this number will be a value greater than zero.

Your objective is 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. You can only use the variables given to you (or variables that you derive from the variables provided). Below is a short description of the variables of interest in the data set:

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: variable information

Deliverables

- 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.
- Assigned predictions (probabilities, classifications, cost) for the evaluation data set. Use 0.5 threshold.
- Include your R statistical programming code in an Appendix.

Task 1: Data Exploration

Describe the size and the variables in the insurance training data set.

```
## '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 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     : Factor w/ 6613 levels "","$0","$1,007",..: 5033 6292 1250 1 509 746 1488 315 4765 28
##  $ PARENT1    : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 2 1 1 1 1 ...
##  $ HOME_VAL   : Factor w/ 5107 levels "","$0","$100,093",..: 2 3259 348 3917 3034 2 1 4167 2 2 ...
##  $ MSTATUS    : Factor w/ 2 levels "Yes","z_No": 2 2 1 1 1 2 1 1 2 2 ...
##  $ SEX        : Factor w/ 2 levels "M","z_F": 1 1 2 1 2 2 2 1 2 1 ...
##  $ EDUCATION  : Factor w/ 5 levels "<High School",..: 4 5 5 1 4 2 1 2 2 2 ...
##  $ JOB        : Factor w/ 9 levels "","Clerical",..: 7 9 2 9 3 9 9 9 2 7 ...
##  $ TRAVTIME   : int  14 22 5 32 36 46 33 44 34 48 ...
##  $ CAR_USE    : Factor w/ 2 levels "Commercial","Private": 2 1 2 2 2 1 2 1 2 1 ...
##  $ BLUEBOOK   : Factor w/ 2789 levels "$1,500","$1,520",..: 434 503 2212 553 802 746 2672 701 135 85
##  $ TIF        : int  11 1 4 7 1 1 1 1 1 7 ...
##  $ CAR_TYPE   : Factor w/ 6 levels "Minivan","Panel Truck",..: 1 1 6 1 6 4 6 5 6 5 ...
##  $ RED_CAR    : Factor w/ 2 levels "no","yes": 2 2 1 2 1 1 1 2 1 1 ...
##  $ OLDCLAIM   : Factor w/ 2857 levels "$0","$1,000",..: 1449 1 1311 1 432 1 1 510 1 1 ...
##  $ CLM_FREQ   : int  2 0 2 0 2 0 0 1 0 0 ...
##  $ REVOKED    : Factor w/ 2 levels "No","Yes": 1 1 1 1 2 1 1 2 1 1 ...
##  $ 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 : Factor w/ 2 levels "Highly Urban/ Urban",..: 1 1 1 1 1 1 1 1 1 2 ...
```

There are 8,161 customers or observations in the insurance training data set with 26 different variables.

Sample Data from Training Data Set

```
##   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 BLUEBOOK
## 1       $0    z_No   M           PhD  Professional       14    Private  $14,230
## 2 $257,252    z_No   M z_High School z_Blue Collar       22 Commercial  $14,940
## 3 $124,191     Yes z_F z_High School      Clerical        5    Private   $4,010
## 4 $306,251     Yes   M  <High School z_Blue Collar       32    Private  $15,440
## 5 $243,925     Yes z_F           PhD        Doctor       36    Private  $18,000
## 6       $0    z_No z_F     Bachelors z_Blue Collar       46 Commercial  $17,430
##   TIF   CAR_TYPE RED_CAR OLDCLAIM CLM_FREQ REVOKED MVR_PTS CAR_AGE
## 1  11    Minivan     yes   $4,461        2      No       3      18
## 2   1    Minivan     yes       $0        0      No       0       1
## 3   4      z_SUV      no  $38,690        2      No       3      10
## 4   7    Minivan     yes       $0        0      No       0       6
## 5   1      z_SUV      no  $19,217        2     Yes       3      17
## 6   1 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
```

Data Transformation

As we can see from the above table, The training data set contains characters that will hinder our calculations so we need to remove or transform these. We will remove dollar signs from the `INCOME`, `HOME_VAL`, `BLUEBOOK`, and `OLDCLAIM` columns, and transform spaces to underscores in the `EDUCATION`, `JOB`, `CAR_TYPE`, `URBANICITY` columns.

Also the target variable `TARGET_FLAG` is actually a boolean variable. So it is better to convert it to a factor from its numeric data type.

Summary Statistics

Roughly only 25% of the customers were involved in a car crash where the cost of the crash can be up yp $107,586. Most of the drivers are middle aged and are not single parents. A little over half of the customers are married and it is about equally split between females and males. Customers drive on average half an hour to work, whereas around a third of the customers use the cars for commercial use. Most of the customers also live in urban areas and have not had their license revoked in the last 7 years.

```
##  TARGET_FLAG   TARGET_AMT        KIDSDRIV           AGE           HOMEKIDS
##  0:6008      Min.   :     0   Min.   :0.0000   Min.   :16.00   Min.   :0.0000
##  1:2153      1st Qu.:     0   1st Qu.:0.0000   1st Qu.:39.00   1st Qu.:0.0000
##              Median :     0   Median :0.0000   Median :45.00   Median :0.0000
##              Mean   :  1504   Mean   :0.1711   Mean   :44.79   Mean   :0.7212
##              3rd Qu.:  1036   3rd Qu.:0.0000   3rd Qu.:51.00   3rd Qu.:1.0000
##              Max.   :107586   Max.   :4.0000   Max.   :81.00   Max.   :5.0000
##                                                NA's   :6
##       YOJ            INCOME       PARENT1       HOME_VAL      MSTATUS
##  Min.   : 0.0   Min.   :     0   No :7084   Min.   :     0   No :3267
##  1st Qu.: 9.0   1st Qu.: 28097   Yes:1077   1st Qu.:     0   Yes:4894
##  Median :11.0   Median : 54028              Median :161160
##  Mean   :10.5   Mean   : 61898              Mean   :154867
##  3rd Qu.:13.0   3rd Qu.: 85986              3rd Qu.:238724
##  Max.   :23.0   Max.   :367030              Max.   :885282
##  NA's   :454    NA's   :445                 NA's   :464
##  SEX             EDUCATION              JOB          TRAVTIME
##  F:4375   <High School:1203   Blue Collar :1825   Min.   :  5.00
##  M:3786   Bachelors   :2242   Clerical    :1271   1st Qu.: 22.00
##           High School :2330   Professional:1117   Median : 33.00
##           Masters     :1658   Manager     : 988   Mean   : 33.49
##           PhD         : 728   Lawyer      : 835   3rd Qu.: 44.00
##                               Student     : 712   Max.   :142.00
##                               (Other)     :1413
##        CAR_USE        BLUEBOOK          TIF                CAR_TYPE
##  Commercial:3029   Min.   : 1500   Min.   : 1.000   Minivan    :2145
##  Private   :5132   1st Qu.: 9280   1st Qu.: 1.000   Panel Truck: 676
##                    Median :14440   Median : 4.000   Pickup     :1389
##                    Mean   :15710   Mean   : 5.351   Sports Car : 907
##                    3rd Qu.:20850   3rd Qu.: 7.000   SUV        :2294
##                    Max.   :69740   Max.   :25.000   Van        : 750
##
##  RED_CAR       OLDCLAIM        CLM_FREQ      REVOKED       MVR_PTS
##  no :5783   Min.   :    0   Min.   :0.0000   No :7161   Min.   : 0.000
##  yes:2378   1st Qu.:    0   1st Qu.:0.0000   Yes:1000   1st Qu.: 0.000
##             Median :    0   Median :0.0000              Median : 1.000
##             Mean   : 4037   Mean   :0.7986              Mean   : 1.696
##             3rd Qu.: 4636   3rd Qu.:2.0000              3rd Qu.: 3.000
##             Max.   :57037   Max.   :5.0000              Max.   :13.000
##
##     CAR_AGE                     URBANICITY
##  Min.   :-3.000   Highly Rural/ Rural:1669
##  1st Qu.: 1.000   Highly Urban/ Urban:6492
##  Median : 8.000
##  Mean   : 8.328
##  3rd Qu.:12.000
##  Max.   :28.000
##  NA's   :510
```

Missing Values

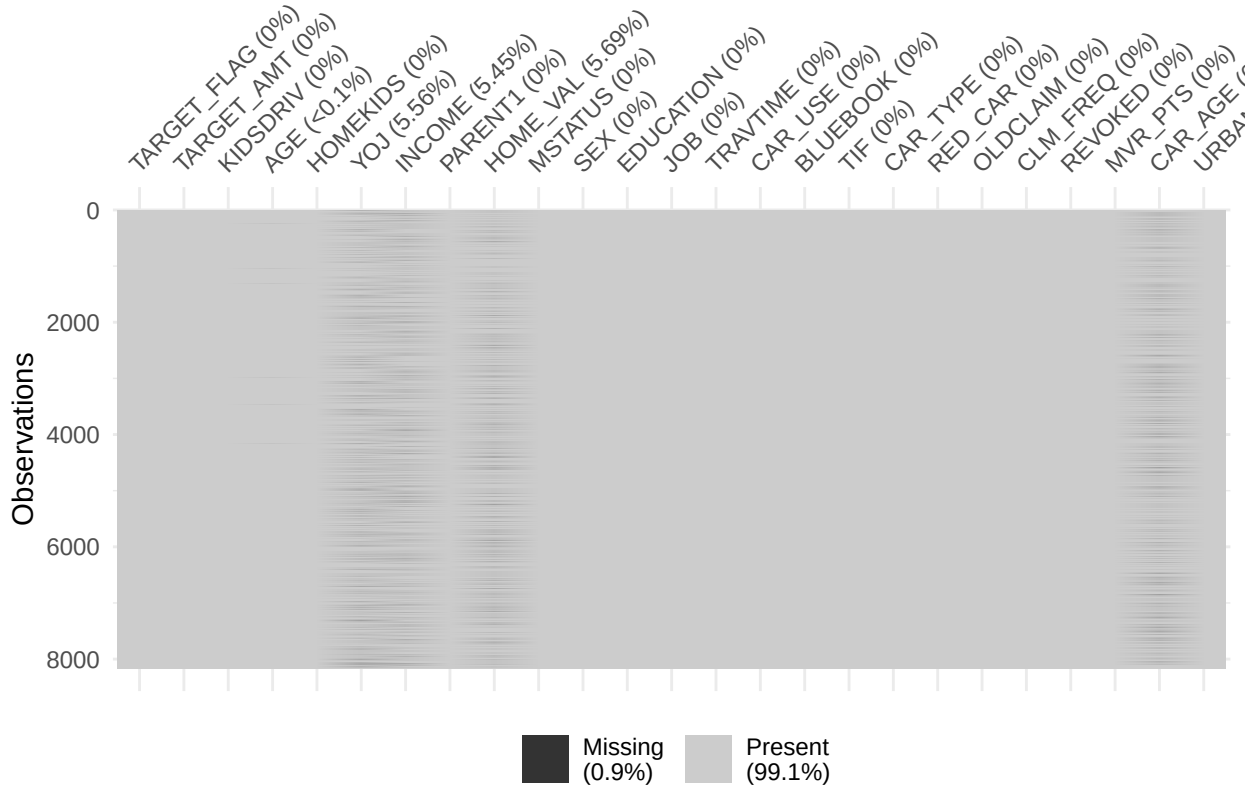
```
sapply(training_set, function(x) sum(is.na(x))) %>% sort(decreasing = TRUE) %>% kable() %>% kable_styli
```

	x
CAR_AGE	510
HOME_VAL	464
YOJ	454
INCOME	445
AGE	6
TARGET_FLAG	0
TARGET_AMT	0
KIDSDRIV	0
HOMEKIDS	0
PARENT1	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
URBANICITY	0

As we can see from the above table of missing values, three variables contain missing values. The "CAR_AGE" variable has the largest amount of missing variables (510), followed by "HOME_VALUE" (464), YOJ" (454), "INCOME"(445) and finally "AGE" (6).

Below is a visual representation of the missing data.

```
vis_miss(training_set)
```

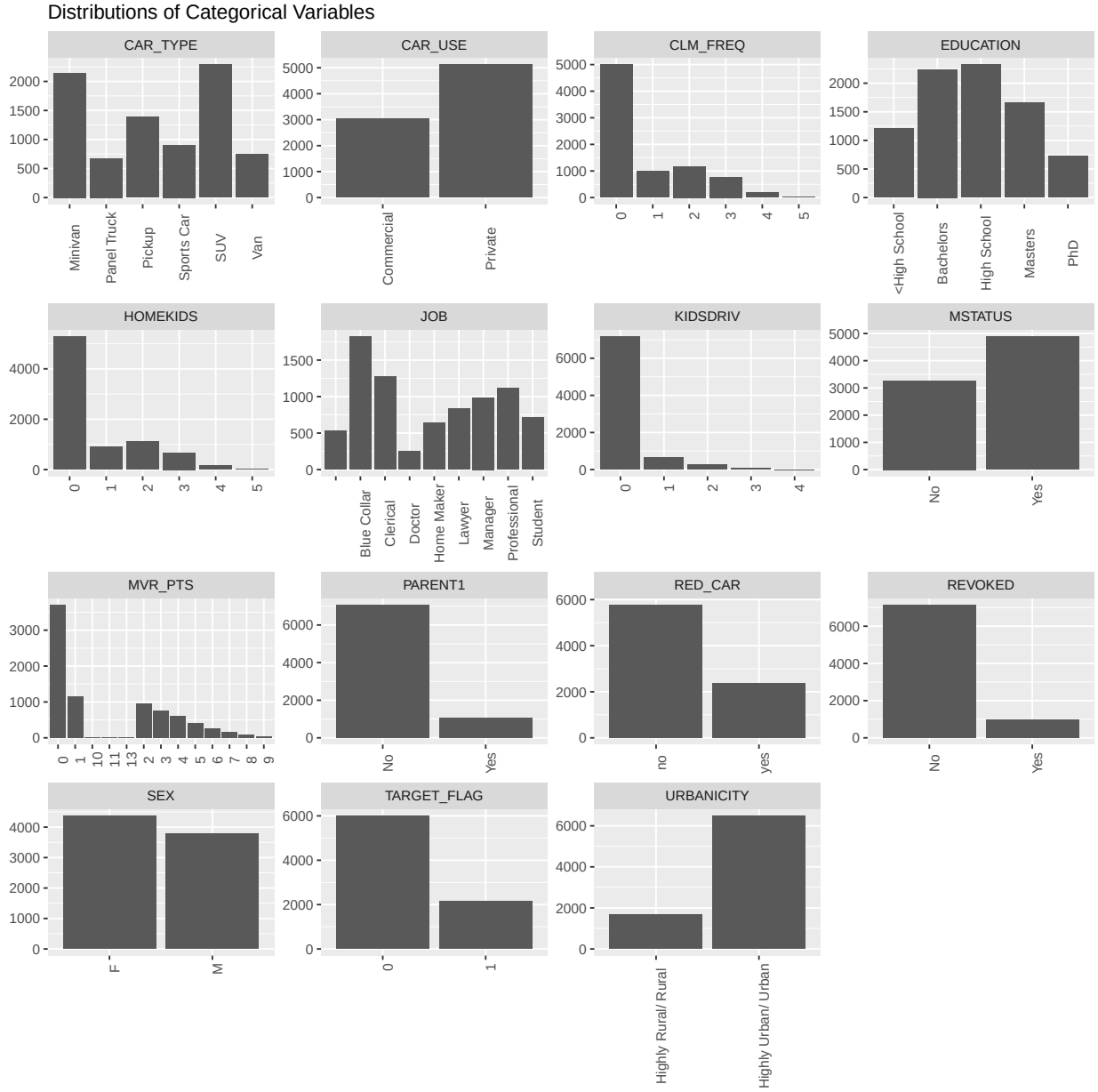


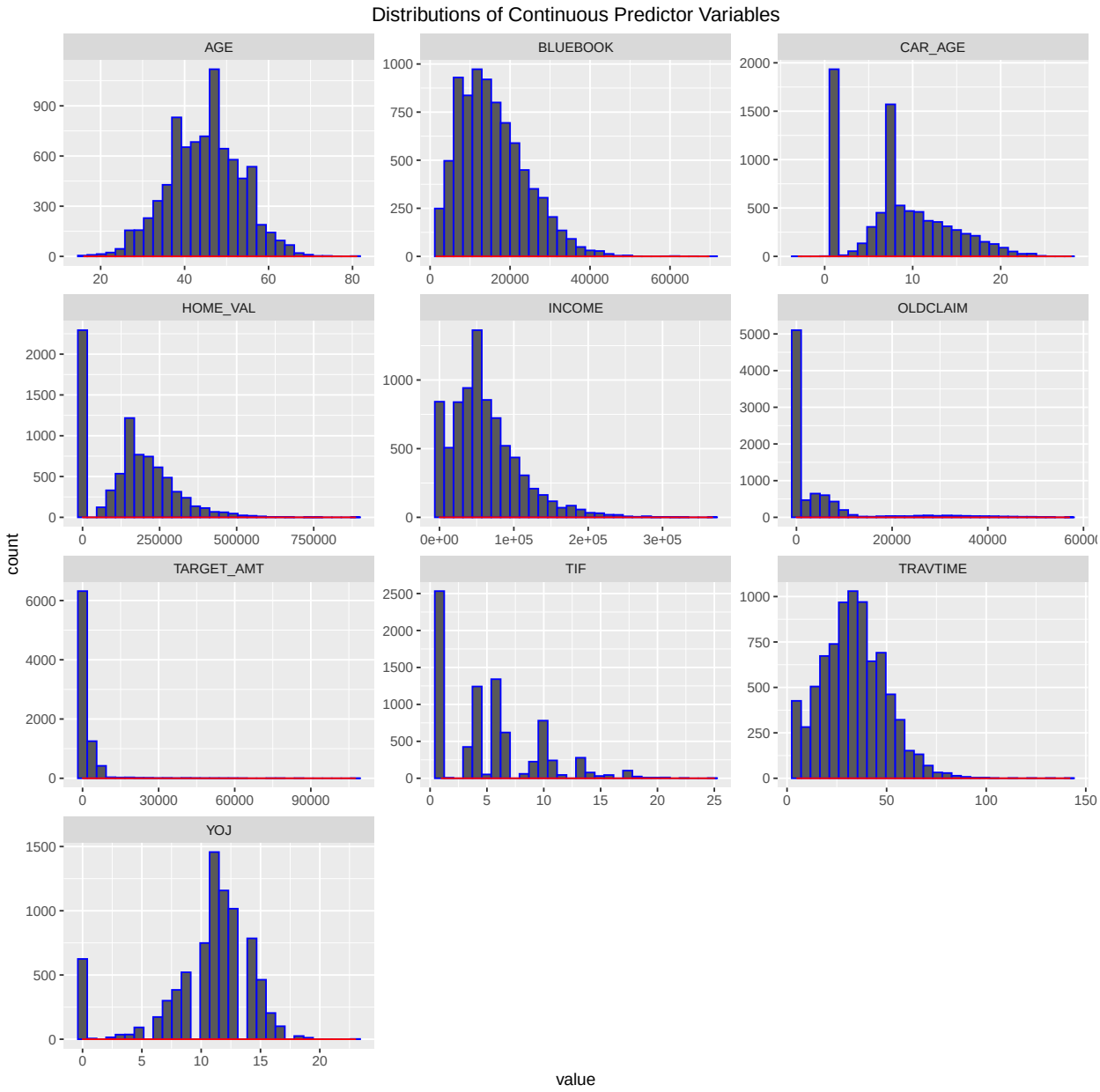
Impute Missing Values

Data is imputed using the medians of the missing variables.

Distributions

Having established that there are no missing values in the dataset, we will now take a look at the distribution profiles for each of the predictor variables. This will help us to decide which variables we should include in our final models.





Looking at the above distribution plots, we observe that there are a lot of skewed variables.

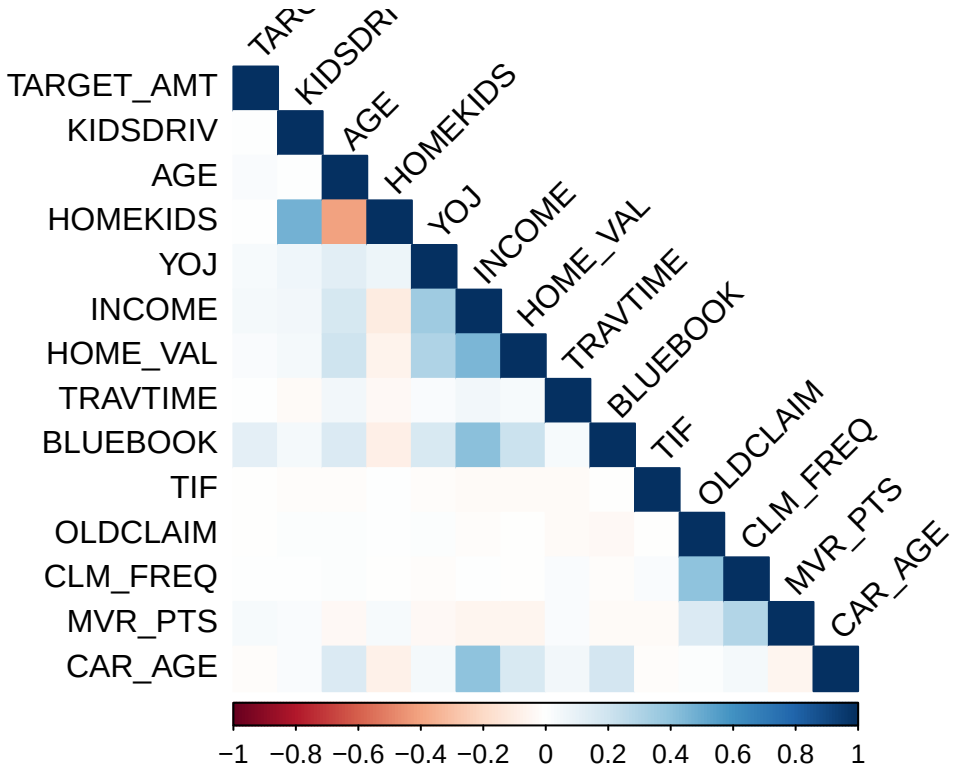
Table 1: Correlation of numeric predictors with the Target Amount

	.
TARGET_AMT	1.0000000
BLUEBOOK	0.1180862
INCOME	0.0440837
MVR_PTS	0.0398112
YOJ	0.0331754
HOME_VAL	0.0297703
AGE	0.0277963
CAR_AGE	-0.0131175
TIF	-0.0060110
OLDCLAIM	-0.0056563
TRAVTIME	0.0051768
CLM_FREQ	0.0019608
HOMEKIDS	0.0004689
KIDSDRIV	0.0000184

Correlations

In order to run correlations, we first filter the training dataset for just the records where there was an actual accident and a non-zero insurance claim. This is because the existence of a claim is conditional on the occurrence of an accident. If we take the entire dataset for analyzing the correlation between the claim amount and the numeric variable, we would get skewed results.

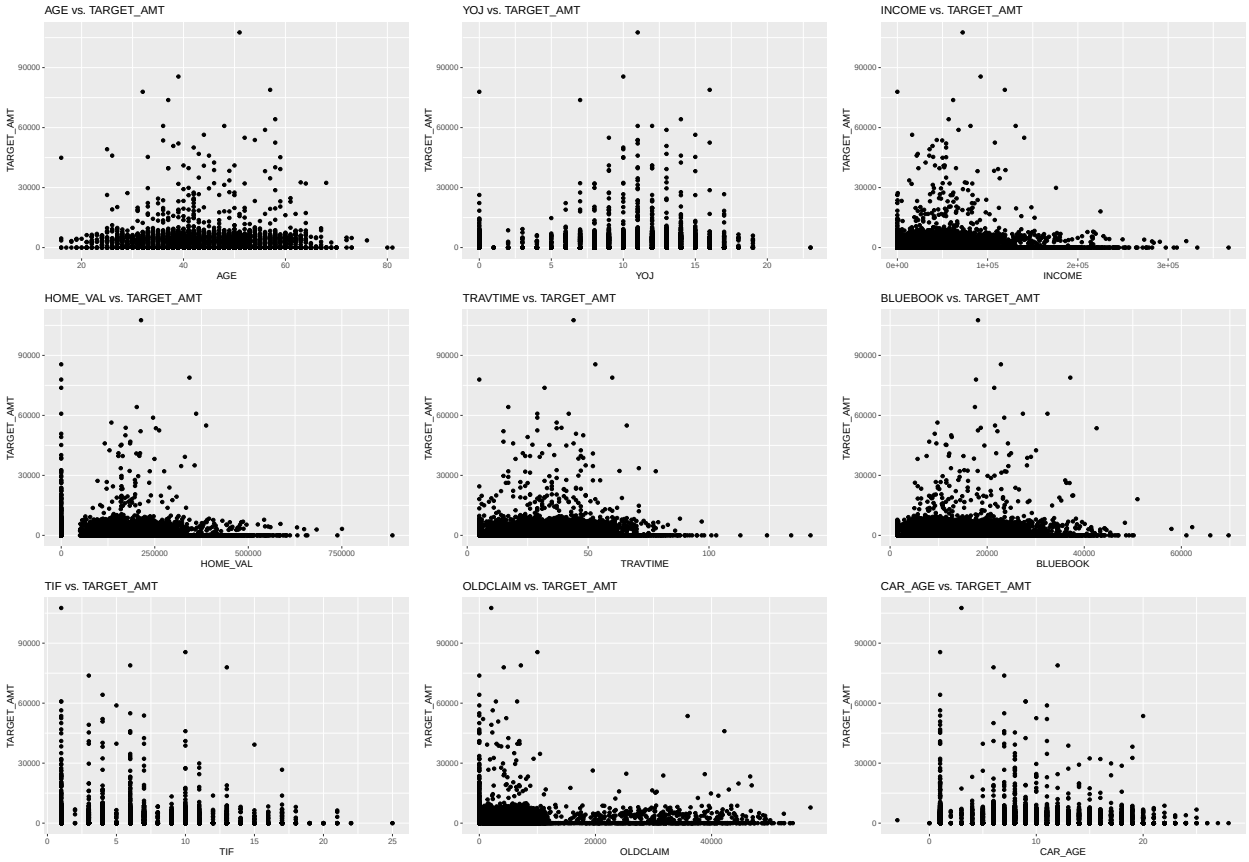
After we filter the records to those with `TARGET_FLAG` =1, then we further filter the columns to retain only the numeric predictor variables. In this case, that would result in the `TARGET_AMT` as the response variable, and the following numeric predictor variables:`AGE`,`BLUEBOOK`,`CAR_AGE`,`CLM_FREQ`,`HOMEKIDS`,`HOME_VAL`,`INCOME`,`KIDSDRIV`, `MVR_PTS`,`TIF`,`TRAVTIME`, `OLD_CLAIM`,`YOJ`.



According to the correlation table and plot above, there is relatively higher correlation between the `TARGET_AMT` and the `BLUEBOOK` value. We would have expected to see some correlation between the TARGET_AMT and the AGE of the vehicle, but that doesn't seem to be the case here. In any case, the age of the car would factor into the `BLUEBOOK` value, so including both variables in a linear model with `TARGET_AMT` is likely to introduce multi-collinearity.

Variable Plots

Scatter plots of each variable versus the target variable.



Task 2: Data Preparation

Describe how you have transformed the data by changing the original variables or creating new variables.

Variable transformations (such as log, square root, quadratic, inverse, etc) will be applied during model building. Also, variables that were created or refactored will also be included in the model building process.

Task 3: Build Models

Using the training data, build at least three different binary logistic regression models, using different variables (or the same variables with different transformations).

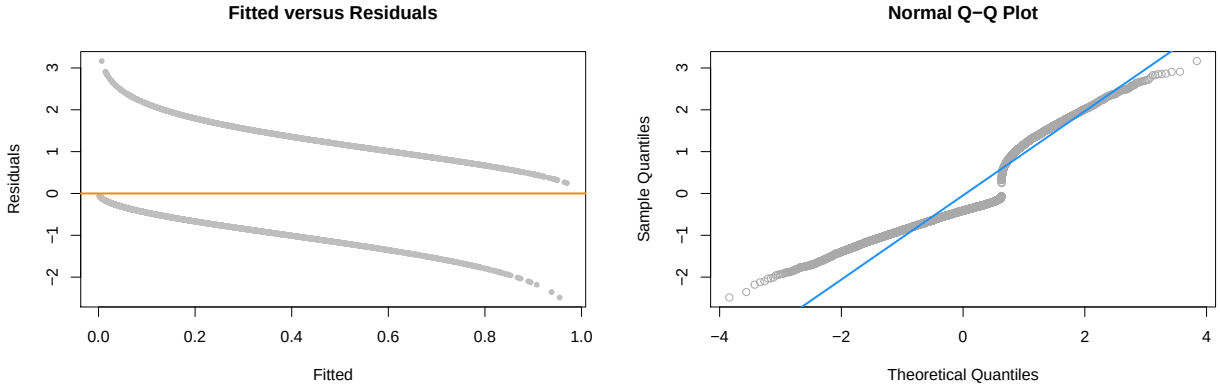
Binary Logistic Regression

Model 1

- `EDUCATION` was grouped as "College" and "No College"
- `AGE` was grouped as "Under 25" and "25 and Over"
- `JOB` was grouped as "Careered" and "Not Careered"
- `MINIVAN` grouped the `CAR_TYPE` as "yes" or "no" if it was a minivan
- `RED_CAR`, `CAR_AGE`, `SEX`, `YOJ` , `HOMEKIDS` were removed due to high p value

```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + AGE + INCOME + PARENT1 +
##     HOME_VAL + MSTATUS + EDUCATION + JOB + TRAVTIME + CAR_USE +
##     BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ + REVOKED + MVR_PTS +
##     URBANICITY + MINIVAN, family = "binomial", data = .)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4872  -0.7243  -0.4116   0.6333   3.1652
##
## Coefficients:
##                                    Estimate    Std. Error z value
## (Intercept)                   -2.5384959056  0.1776677325 -14.288
## KIDSDRIVyes                    0.6968909256  0.0875701855   7.958
## AGEUnder 25                    0.7441640781  0.2774639894   2.682
## INCOME                        -0.0000038457  0.0000009847  -3.905
## PARENT1Yes                     0.4133399254  0.0946701431   4.366
## HOME_VAL                      -0.0000011871  0.0000003309  -3.588
## MSTATUSYes                    -0.4897519101  0.0789660463  -6.202
## EDUCATIONNo College            0.5091517578  0.0684335720   7.440
## JOBNot Careered                0.1932319833  0.0794187358   2.433
## TRAVTIME                       0.0150436632  0.0018676816   8.055
## CAR_USEPrivate                -0.7798798062  0.0637471094 -12.234
## BLUEBOOK                      -0.0000258798  0.0000039580  -6.539
## TIF                           -0.0552053607  0.0072966926  -7.566
## OLDCLAIM                      -0.0000140356  0.0000038716  -3.625
## CLM_FREQ                       0.1976855328  0.0282840192   6.989
## REVOKEDYes                     0.9049111771  0.0904723959  10.002
## MVR_PTS                        0.1182584323  0.0135563565   8.723
## URBANICITYHighly Urban/ Urban  2.3406979757  0.1128027392  20.750
## MINIVANyes                    -0.6739533263  0.0738433531  -9.127
##                                             Pr(>|z|)
## (Intercept)                   < 0.0000000000000002 ***
## KIDSDRIVyes                   0.000000000000001747 ***
## AGEUnder 25                                0.007318 **
## INCOME                        0.000094095841950242 ***
## PARENT1Yes                    0.000012648083830509 ***
```

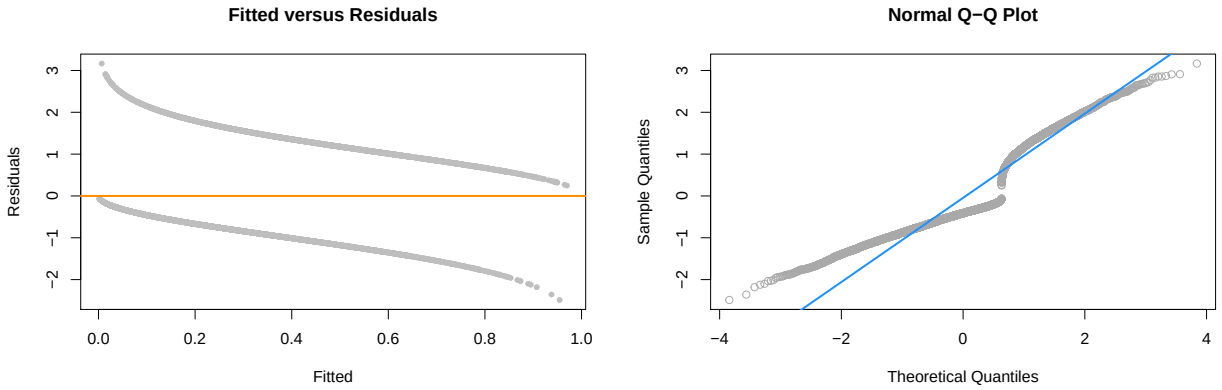
```
## HOME_VAL                                0.000334 ***
## MSTATUSYes                  0.000000000557299288 ***
## EDUCATIONNo College         0.000000000000100619 ***
## JOBNot Careered                         0.014971 *
## TRAVTIME                    0.000000000000000797 ***
## CAR_USEPrivate              < 0.0000000000000002 ***
## BLUEBOOK                    0.000000000062104046 ***
## TIF                         0.000000000000038547 ***
## OLDCLAIM                                0.000289 ***
## CLM_FREQ                    0.000000000002762585 ***
## REVOKEDYes                  < 0.0000000000000002 ***
## MVR_PTS                     < 0.0000000000000002 ***
## URBANICITYHighly Urban/ Urban < 0.0000000000000002 ***
## MINIVANyes                  < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7366.3  on 8142  degrees of freedom
## AIC: 7404.3
##
## Number of Fisher Scoring iterations: 5
```



Model 2

```
##
## Call:
## glm(formula = TARGET_FLAG ~ INCOME + PARENT1 + HOME_VAL + MSTATUS +
##     EDUCATION + TRAVTIME + CAR_USE + TIF + CAR_TYPE + REVOKED +
##     URBANICITY, family = binomial(link = "logit"), data = training_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2151  -0.7437  -0.4504   0.7317   3.0341
##
## Coefficients:
##                                    Estimate    Std. Error z value
## (Intercept)                   -2.5097700872  0.1754970690 -14.301
## INCOME                        -0.0000057209  0.0000009443  -6.058
## PARENT1Yes                     0.6633559231  0.0888177757   7.469
## HOME_VAL                      -0.0000015424  0.0000003245  -4.754
## MSTATUSYes                    -0.3742337414  0.0763556681  -4.901
## EDUCATIONBachelors            -0.5921668518  0.0956906561  -6.188
## EDUCATIONHigh School          -0.0809393935  0.0896475530  -0.903
## EDUCATIONMasters              -0.6094601110  0.1071458499  -5.688
## EDUCATIONPhD                  -0.6227665192  0.1443151490  -4.315
## TRAVTIME                       0.0156280286  0.0018302862   8.539
## CAR_USEPrivate                -0.8987050507  0.0716420077 -12.544
## TIF                           -0.0566834590  0.0071612998  -7.915
## CAR_TYPEPanel Truck            0.2714278527  0.1280630609   2.119
## CAR_TYPEPickup                 0.5634830682  0.0953288916   5.911
## CAR_TYPESports Car             1.0726682146  0.1025601762  10.459
## CAR_TYPESUV                    0.8268973605  0.0823284992  10.044
## CAR_TYPEVan                    0.5223542406  0.1154076129   4.526
## REVOKEDYes                     0.7609781315  0.0782622562   9.723
## URBANICITYHighly Urban/ Urban  2.4740662702  0.1088123580  22.737
##                                          Pr(>|z|)
## (Intercept)                   < 0.0000000000000002 ***
## INCOME                         0.00000000137465496 ***
## PARENT1Yes                     0.00000000000008097 ***
## HOME_VAL                       0.00000199866822317 ***
## MSTATUSYes                     0.00000095257208772 ***
## EDUCATIONBachelors             0.00000000060798914 ***
## EDUCATIONHigh School                         0.367
## EDUCATIONMasters               0.00000001284339097 ***
## EDUCATIONPhD                   0.00001593695169238 ***
## TRAVTIME                      < 0.0000000000000002 ***
## CAR_USEPrivate                < 0.0000000000000002 ***
## TIF                            0.00000000000000247 ***
## CAR_TYPEPanel Truck                          0.034 *
## CAR_TYPEPickup                 0.00000000340167224 ***
## CAR_TYPESports Car            < 0.0000000000000002 ***
## CAR_TYPESUV                   < 0.0000000000000002 ***
## CAR_TYPEVan                    0.00000600628479796 ***
## REVOKEDYes                    < 0.0000000000000002 ***
## URBANICITYHighly Urban/ Urban < 0.0000000000000002 ***
## ---
```

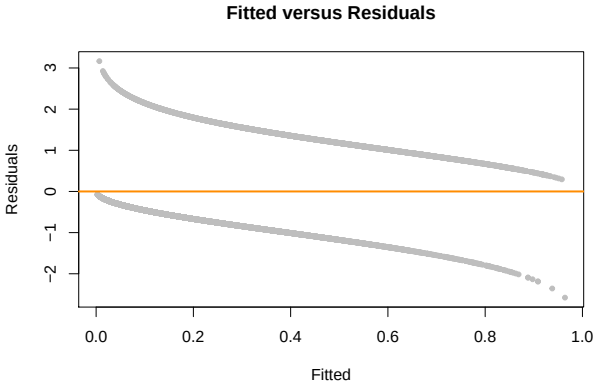
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418  on 8160  degrees of freedom
## Residual deviance: 7635  on 8142  degrees of freedom
## AIC: 7673
##
## Number of Fisher Scoring iterations: 5
```

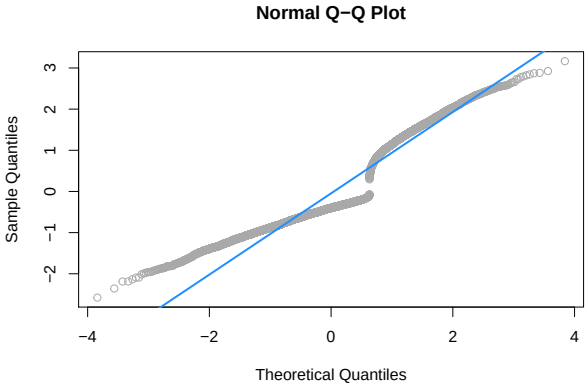


Model 3

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT - INCOME, family = "binomial",
##     data = training_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5795  -0.7115  -0.4005   0.6204   3.1652
##
## Coefficients:
##                                    Estimate    Std. Error z value
## (Intercept)                    -3.0679518334  0.3373699802  -9.094
## KIDSDRIV                        0.3830469969  0.0611286396   6.266
## AGE                            -0.0004733507  0.0040185220  -0.118
## HOMEKIDS                        0.0484593218  0.0370831235   1.307
## YOJ                            -0.0132936551  0.0085550583  -1.554
## PARENT1Yes                      0.3980213607  0.1094482892   3.637
## HOME_VAL                       -0.0000016541  0.0000003205  -5.162
## MSTATUSYes                     -0.4382163188  0.0819322446  -5.349
## SEXM                            0.0869811203  0.1119515249   0.777
## EDUCATIONBachelors             -0.4336590913  0.1143016429  -3.794
## EDUCATIONHigh School           -0.0036236357  0.0947363450  -0.038
## EDUCATIONMasters               -0.3600356708  0.1773934832  -2.030
## EDUCATIONPhD                   -0.3334875706  0.2079105373  -1.604
## JOBBlue Collar                  0.3637218921  0.1848138578   1.968
## JOBClerical                     0.5159560435  0.1938419886   2.662
## JOBDoctor                      -0.4214004991  0.2662130405  -1.583
## JOBHome Maker                   0.4146033637  0.2023150912   2.049
## JOBLawyer                       0.1442181947  0.1688899097   0.854
## JOBManager                     -0.5273877157  0.1708828315  -3.086
## JOBProfessional                 0.2034688816  0.1779215166   1.144
## JOBStudent                      0.3607450708  0.2095168920   1.722
## TRAVTIME                        0.0144384980  0.0018825719   7.670
## CAR_USEPrivate                 -0.7555539047  0.0916823913  -8.241
## BLUEBOOK                       -0.0000231194  0.0000052013  -4.445
## TIF                            -0.0550026436  0.0073328336  -7.501
## CAR_TYPEPanel Truck             0.5567027529  0.1615875110   3.445
## CAR_TYPEPickup                  0.5575279306  0.1006672494   5.538
## CAR_TYPESports Car              1.0271619017  0.1298242768   7.912
## CAR_TYPESUV                     0.7707255522  0.1112524500   6.928
## CAR_TYPEVan                     0.6103712250  0.1263398360   4.831
## RED_CARyes                     -0.0086544858  0.0863095906  -0.100
## OLDCLAIM                       -0.0000137280  0.0000039072  -3.514
## CLM_FREQ                        0.1966864045  0.0285294183   6.894
## REVOKEDYes                      0.8851089489  0.0912284023   9.702
## MVR_PTS                         0.1144788910  0.0135971123   8.419
## CAR_AGE                        -0.0020306511  0.0075320244  -0.270
## URBANICITYHighly Urban/ Urban   2.3853025598  0.1127354597  21.158
##                                          Pr(>|z|)
## (Intercept)                    < 0.0000000000000002 ***
## KIDSDRIV                        0.00000000036985964 ***
## AGE                                         0.906232
```

```
## HOMEKIDS                                  0.191289
## YOJ                                       0.120210
## PARENT1Yes                                0.000276 ***
## HOME_VAL                          0.00000024477789715 ***
## MSTATUSYes                        0.00000008867596153 ***
## SEXM                                      0.437186
## EDUCATIONBachelors                        0.000148 ***
## EDUCATIONHigh School                      0.969489
## EDUCATIONMasters                          0.042398 *
## EDUCATIONPhD                              0.108715
## JOBBlue Collar                            0.049063 *
## JOBClerical                               0.007774 **
## JOBDoctor                                 0.113434
## JOBHome Maker                             0.040433 *
## JOBLawyer                                 0.393150
## JOBManager                                0.002027 **
## JOBProfessional                           0.252795
## JOBStudent                                0.085107 .
## TRAVTIME                          0.00000000000001726 ***
## CAR_USEPrivate                   < 0.0000000000000002 ***
## BLUEBOOK                          0.00000879282137125 ***
## TIF                               0.00000000000006339 ***
## CAR_TYPEPanel Truck                       0.000571 ***
## CAR_TYPEPickup                    0.00000003053784090 ***
## CAR_TYPESports Car                0.00000000000000253 ***
## CAR_TYPESUV                       0.00000000000427684 ***
## CAR_TYPEVan                       0.00000135722253494 ***
## RED_CARyes                                0.920128
## OLDCLAIM                                  0.000442 ***
## CLM_FREQ                          0.00000000000541836 ***
## REVOKEDYes                       < 0.0000000000000002 ***
## MVR_PTS                          < 0.0000000000000002 ***
## CAR_AGE                                   0.787466
## URBANICITYHighly Urban/ Urban < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7307.8  on 8124  degrees of freedom
## AIC: 7381.8
##
## Number of Fisher Scoring iterations: 5
```

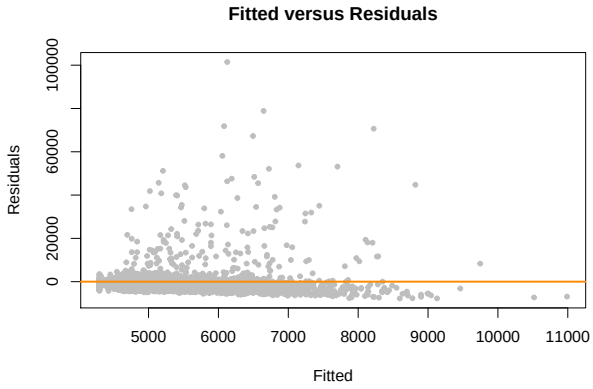

Fitted versus Residuals
Residuals
Fitted
−2
−1
0
1
2
3
0.0
0.2
0.4
0.6
0.8
1.0

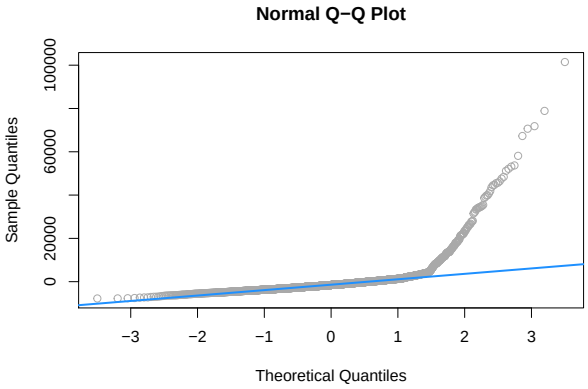

Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
−2
−1
0
1
2
3
−4
−2
0
2
4

Multiple Linear Regression

Model 4 Here we run a linear regression (for the records that represent an actual accident) i.e. TARGET_FLAG=1, between the TARGET_AMT and the BLUEBOOK variable.

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK, data = training_set_numeric)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7757  -3083  -1541    295 101459
##
## Coefficients:
##               Estimate Std. Error t value             Pr(>|t|)
## (Intercept) 4131.65436  329.48405  12.540 < 0.0000000000000002 ***
## BLUEBOOK       0.11017    0.01997   5.515          0.000000039 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7691 on 2151 degrees of freedom
## Multiple R-squared:  0.01394,    Adjusted R-squared:  0.01349
## F-statistic: 30.42 on 1 and 2151 DF,  p-value: 0.000000039
```

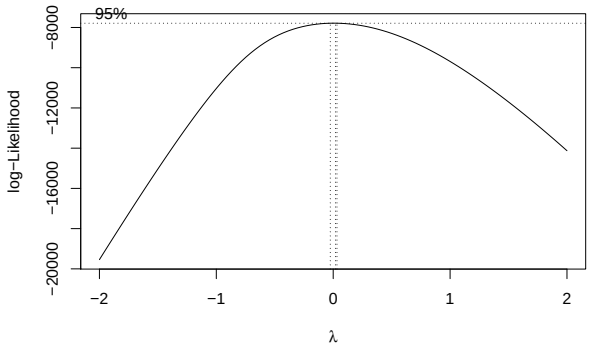


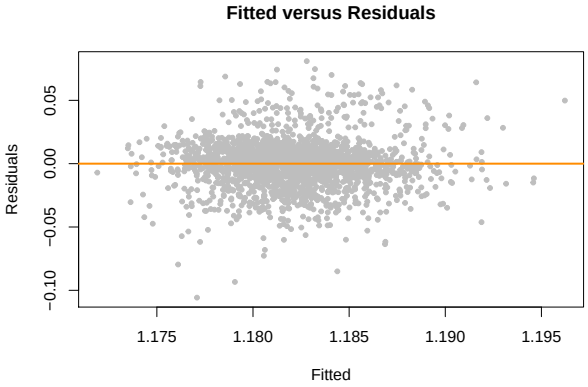


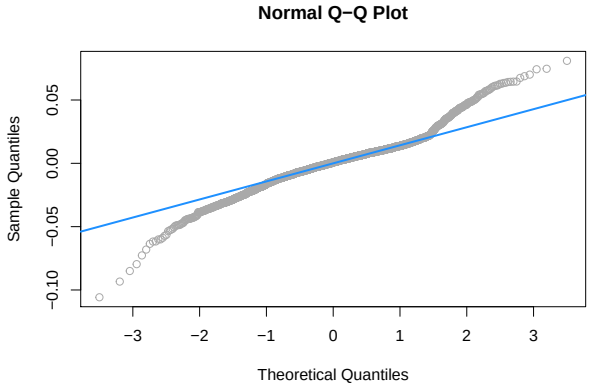
Model 5 Using the Boxcox method for linear model.

```
##
## Call:
## lm(formula = TARGET_AMT^(1) ~ ., data = data)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.105762 -0.009634  0.000749  0.009599  0.080927
##
## Coefficients:
##                                     Estimate      Std. Error t value
## (Intercept)                      1.174097356347  0.004994461397 235.080
## KIDSDRIV                        -0.000766473804  0.000795200280  -0.964
## AGE                              0.000045046895  0.000053353774   0.844
## HOMEKIDS                         0.000558959294  0.000520290239   1.074
## YOJ                             -0.000022475456  0.000123521645  -0.182
## INCOME                          -0.000000031826  0.000000016935  -1.879
## PARENT1Yes                       0.000574179574  0.001475101290   0.389
## HOME_VAL                         0.000000003635  0.000000005075   0.716
## MSTATUSYes                      -0.002348666282  0.001239526656  -1.895
## SEXM                             0.002268833851  0.001648695394   1.376
## EDUCATIONBachelors              -0.000694956993  0.001611004017  -0.431
## EDUCATIONHigh School             0.000181505648  0.001292348608   0.140
## EDUCATIONMasters                 0.003601788764  0.002720875911   1.324
## EDUCATIONPhD                     0.005937436887  0.003293860792   1.803
## JOBBlue Collar                   0.001502882033  0.002878623843   0.522
## JOBClerical                      0.001311249797  0.003021539147   0.434
## JOBDoctor                       -0.001035979944  0.004426297830  -0.234
## JOBHome Maker                   -0.001188889198  0.003180809525  -0.374
## JOBLawyer                       -0.000275474113  0.002585417744  -0.107
## JOBManager                       0.000404067259  0.002677330932   0.151
## JOBProfessional                  0.002547884962  0.002836000195   0.898
## JOBStudent                       0.000493947066  0.003229747475   0.153
## TRAVTIME                        -0.000006113871  0.000027832363  -0.220
## CAR_USEPrivate                  -0.000342473962  0.001310185426  -0.261
## BLUEBOOK                         0.000000287558  0.000000076694   3.749
## TIF                             -0.000046975803  0.000106792688  -0.440
## CAR_TYPEPanel Truck              0.000009851578  0.002412559681   0.004
## CAR_TYPEPickup                   0.000676285873  0.001499046060   0.451
## CAR_TYPESports Car               0.001400828129  0.001884367093   0.743
## CAR_TYPESUV                      0.002215842438  0.001674775528   1.323
## CAR_TYPEVan                     -0.000284207621  0.001935958933  -0.147
## RED_CARyes                       0.000495668458  0.001247007441   0.397
## OLDCLAIM                         0.000000105747  0.000000056854   1.860
## CLM_FREQ                        -0.000860607923  0.000396908405  -2.168
## REVOKEDYes                      -0.002298635135  0.001297695301  -1.771
## MVR_PTS                          0.000355027712  0.000172119610   2.063
## CAR_AGE                         -0.000058375161  0.000110405223  -0.529
## URBANICITYHighly Urban/ Urban    0.001352819972  0.001899489885   0.712
##                                            Pr(>|t|)
## (Intercept)                    < 0.0000000000000002 ***
## KIDSDRIV                                   0.335219
## AGE                                        0.398594
```

```
## HOMEKIDS                                  0.282801
## YOJ                                       0.855635
## INCOME                                    0.060343 .
## PARENT1Yes                                0.697132
## HOME_VAL                                  0.473873
## MSTATUSYes                                0.058254 .
## SEXM                                      0.168924
## EDUCATIONBachelors                        0.666235
## EDUCATIONHigh School                      0.888321
## EDUCATIONMasters                          0.185726
## EDUCATIONPhD                              0.071597 .
## JOBBlue Collar                            0.601667
## JOBClerical                               0.664356
## JOBDoctor                                 0.814968
## JOBHome Maker                             0.708613
## JOBLawyer                                 0.915157
## JOBManager                                0.880052
## JOBProfessional                           0.369070
## JOBStudent                                0.878463
## TRAVTIME                                  0.826151
## CAR_USEPrivate                            0.793815
## BLUEBOOK                                  0.000182 ***
## TIF                                       0.660070
## CAR_TYPEPanel Truck                       0.996742
## CAR_TYPEPickup                            0.651932
## CAR_TYPESports Car                        0.457325
## CAR_TYPESUV                               0.185956
## CAR_TYPEVan                               0.883300
## RED_CARyes                                0.691049
## OLDCLAIM                                  0.063029 .
## CLM_FREQ                                  0.030249 *
## REVOKEDYes                                0.076651 .
## MVR_PTS                                   0.039265 *
## CAR_AGE                                   0.597044
## URBANICITYHighly Urban/ Urban             0.476418
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01932 on 2115 degrees of freedom
## Multiple R-squared:  0.02649,    Adjusted R-squared:  0.009457
## F-statistic: 1.555 on 37 and 2115 DF,  p-value: 0.01792
```


95%
log−Likelihood
−8000
−12000
−16000
−20000
−2
−1
0
1
2
λ


Fitted versus Residuals
Residuals
0.05
0.00
−0.05
−0.10
1.175
1.180
1.185
1.190
1.195
Fitted


Normal Q−Q Plot
Sample Quantiles
0.05
0.00
−0.05
−0.10
−3
−2
−1
0
1
2
3
Theoretical Quantiles

Task 4: Select Models

Decide on the criteria for selecting the best binary logistic regression model.

Error Calculations

Model 1 Confusion Matrix

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5570 1277
##          1  438  876
##
##                Accuracy : 0.7899
##                  95% CI : (0.7809, 0.7986)
##     No Information Rate : 0.7362
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.3817
##
##  Mcnemar's Test P-Value : < 0.00000000000000022
##
##             Sensitivity : 0.9271
##             Specificity : 0.4069
##          Pos Pred Value : 0.8135
##          Neg Pred Value : 0.6667
##              Prevalence : 0.7362
##          Detection Rate : 0.6825
##    Detection Prevalence : 0.8390
##       Balanced Accuracy : 0.6670
##
##        'Positive' Class : 0
##
```

Model 2 Confusion Matrix

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5582 1382
##          1  426  771
##
##                Accuracy : 0.7785
##                  95% CI : (0.7693, 0.7874)
##     No Information Rate : 0.7362
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.3349
##
##  Mcnemar's Test P-Value : < 0.00000000000000022
##
##             Sensitivity : 0.9291
##             Specificity : 0.3581
##          Pos Pred Value : 0.8016
##          Neg Pred Value : 0.6441
##              Prevalence : 0.7362
##          Detection Rate : 0.6840
##    Detection Prevalence : 0.8533
##       Balanced Accuracy : 0.6436
##
##        'Positive' Class : 0
##
```

Model 3 Confusion Matrix

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5561 1230
##          1  447  923
##
##                Accuracy : 0.7945
##                  95% CI : (0.7856, 0.8032)
##     No Information Rate : 0.7362
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.4011
##
##  Mcnemar's Test P-Value : < 0.00000000000000022
##
##             Sensitivity : 0.9256
##             Specificity : 0.4287
##          Pos Pred Value : 0.8189
##          Neg Pred Value : 0.6737
##              Prevalence : 0.7362
##          Detection Rate : 0.6814
##    Detection Prevalence : 0.8321
##       Balanced Accuracy : 0.6772
##
##        'Positive' Class : 0
##
```

Model Comparison

```
##                            Model 1 Model 2 Model 3
## accuracy                    0.7899  0.7785  0.7945
## classification error rate   0.2101  0.2215  0.2055
## precision                   0.6667  0.6441  0.6737
## sensitivity                 0.9271  0.9291  0.9256
## specificity                 0.4069  0.3581  0.4287
## F1 score                    0.5053  0.4603  0.5240
## AUC                         0.6670  0.6436  0.6772
```

Model of Choice

We picked Models 3 and 4 because they had the best results. Model 3 had the highest AUC and the best accuracy. `URBANICITY` had the highest affect on the model which makes sense because there are more crashes in cities compared to rural areas. Model 4 had a higher adjusted R^2 compared to Model 5.

```
##   TARGET_FLAG TARGET_AMT KIDSDRIV AGE HOMEKIDS YOJ INCOME PARENT1 HOME_VAL
## 1           0   6552.017        0  48        0  11  52881      No        0
## 2           0   6217.110        1  40        1  11  50815     Yes        0
## 3           0   4781.638        0  44        2  12  43486     Yes        0
## 4           0   5148.493        0  35        2  11  21204     Yes        0
## 5           0   5830.425        0  59        0  12  87460      No        0
## 6           0   6958.532        0  46        0  14  54028      No   207519
##   MSTATUS SEX   EDUCATION          JOB TRAVTIME    CAR_USE BLUEBOOK TIF
## 1      No   M   Bachelors      Manager       26    Private    21970   1
## 2      No   M High School      Manager       21    Private    18930   6
## 3      No   F High School  Blue Collar       30 Commercial     5900  10
## 4      No   M High School     Clerical       74    Private     9230   6
## 5      No   M High School      Manager       45    Private    15420   1
## 6     Yes   M   Bachelors Professional        7 Commercial    25660   1
##      CAR_TYPE RED_CAR OLDCLAIM CLM_FREQ REVOKED MVR_PTS CAR_AGE
## 1         Van     yes        0        0      No       2      10
## 2     Minivan      no     3295        1      No       2       1
## 3         SUV      no        0        0      No       0      10
## 4      Pickup      no        0        0     Yes       0       4
## 5     Minivan     yes    44857        2      No       4       1
## 6 Panel Truck      no     2119        1      No       2      12
##            URBANICITY
## 1 Highly Urban/ Urban
## 2 Highly Urban/ Urban
## 3 Highly Rural/ Rural
## 4 Highly Rural/ Rural
## 5 Highly Urban/ Urban
## 6 Highly Urban/ Urban
```

Appendix

```
# ============================================================================================
# Load Required Libraries
# ============================================================================================

knitr::opts_chunk$set(echo = TRUE, warning = FALSE, include = TRUE)

# Load required libraries.
library(tidyverse)
library(caret)
library(pROC)
library(grid)
library(Amelia)
library(ggplot2)
library(kableExtra)
library(corrplot)
library(reshape2)
library(e1071)
library(visdat)
library(mice)
library(MASS)


# ============================================================================================
# Load The Datasets and Look at the Structure of the Data
# ============================================================================================

# Pull in the provided crime training and evaluation datasets.
training_set <- read.csv('https://raw.githubusercontent.com/Jagdish16/CUNY_DATA_621/main/homework_4/insu
evaluation_set <- read.csv('https://raw.githubusercontent.com/Jagdish16/CUNY_DATA_621/main/homework_4/in

# List the structure of the training dataset.
str(training_set)


# ============================================================================================
# Summarize the Training Data
# ============================================================================================

# Summarize the training dataset.
summary(training_set)

# ============================================================================================
# Cleaning Data
# ============================================================================================

training_set <- training_set %>%
  # remove the index variable
  dplyr::select(-INDEX) %>%
  # remove characters such aS $ | , | _Z
  mutate_all(~ str_remove_all(., "\\$|,|z_")) %>%
  # convert spaces to underscores
  # mutate_all(~ str_replace_all(., " ", "_")) %>%
```

```
  # convert types automatically from chr type
  type.convert(.) %>%
  # convert TARGET_FLAG to factor
  mutate(TARGET_FLAG = as.factor(TARGET_FLAG))

 evaluation_set <- evaluation_set %>%
  # remove the index variable
  dplyr::select(-INDEX) %>%
  # remove characters such aS $ | , | _Z
  mutate_all(~ str_remove_all(., "\\$|,|z_")) %>%
  # convert spaces to underscores
  # mutate_all(~ str_replace_all(., " ", "_")) %>%
  # convert types automatically from chr type
  type.convert(.) %>%
  # convert TARGET_FLAG to factor
  mutate(TARGET_FLAG = as.factor(TARGET_FLAG))

# ============================================================================================
# Check for Missing Values
# ============================================================================================

# Check for missing values using the Amelia package's missmap() function.
sapply(training_set, function(x) sum(is.na(x))) %>% sort(decreasing = TRUE) %>% kable() %>% kable_stylin

As we can see from the above table of missing values, three variables contain missing values. The "CAR_A

Below is a visual representation of the missing data.

vis_miss(training_set)

\clearpage

# ============================================================================================
# Imputing Missing Values
# ============================================================================================

training_set <- training_set %>%
  mutate(AGE = ifelse(is.na(AGE),median(training_set$AGE, na.rm =TRUE),AGE),
         YOJ = ifelse(is.na(YOJ),median(training_set$YOJ, na.rm =TRUE), YOJ),
         INCOME = ifelse(is.na(INCOME),median(training_set$INCOME, na.rm =TRUE), INCOME),
         HOME_VAL = ifelse(is.na(HOME_VAL),median(training_set$HOME_VAL, na.rm =TRUE), HOME_VAL),
         CAR_AGE = ifelse(is.na(CAR_AGE),median(training_set$CAR_AGE, na.rm =TRUE), CAR_AGE))


# ============================================================================================
# Distribution Plots
# ============================================================================================

# Using the Dplyr package, massage the data by removing the target value prior
# to plotting a histogram for each predictor variable.
training_set %>%
  mutate(CLM_FREQ = as.factor(CLM_FREQ),
         HOMEKIDS = as.factor(HOMEKIDS),
         KIDSDRIV = as.factor(KIDSDRIV),
```

```
        MVR_PTS = as.factor(MVR_PTS)) %>%
  select_if(is.factor) %>%
  gather(variable, value) %>%
  ggplot(., aes(x = value)) +
  geom_histogram(bins = 25, stat = 'count') +
  labs(title = 'Distributions of Categorical Variables') +
  facet_wrap(~variable, scales ="free", ncol = 4) +
  labs(x = element_blank(), y = element_blank()) +
  theme(axis.text.x = element_text(angle = 90))

training_set %>%
  mutate(CLM_FREQ = as.factor(CLM_FREQ),
         HOMEKIDS = as.factor(HOMEKIDS),
         KIDSDRIV = as.factor(KIDSDRIV),
         MVR_PTS = as.factor(MVR_PTS)) %>%
  select_if(negate(is.factor)) %>%
  gather(variable, value) %>%
  ggplot(., aes(x = value)) +
  geom_histogram(bins = 30, color = 'blue') +
  labs(title = 'Distributions of Continuous Predictor Variables') +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_density(aes(x = value), color = 'red') +
  facet_wrap(. ~variable, scales = 'free', ncol = 3)

# ================================================================================
# Data Correlation Table and Matrix Plot
# ================================================================================

training_set_claims = training_set%>%filter(TARGET_FLAG==1)
training_set_numeric<-select_if(training_set_claims,is.numeric)
correlation_table <- cor(training_set_numeric, method = 'pearson', use = 'complete.obs')[,1]
correlation_table %>%
  as.data.frame() %>%
  arrange(desc(abs(.))) %>%
  kable(caption = 'Correlation of numeric predictors with the Target Amount') %>%
  kable_styling(bootstrap_options = c("striped", "hover"))

# ================================================================================
# Scatter Plots of Each Variable Versus the Target Variable
# ================================================================================

# Scatter plots for each of the variables against the target.
col_size = dim(training_set)[2]
cols = training_set %>%
  mutate(CLM_FREQ = as.factor(CLM_FREQ),
         HOMEKIDS = as.factor(HOMEKIDS),
         KIDSDRIV = as.factor(KIDSDRIV),
         MVR_PTS = as.factor(MVR_PTS)) %>%
  select_if(negate(is.factor)) %>%
  names(.)
for (col in cols[2:10]) {
  plot = training_set %>%
    ggplot(aes_string(x = col, y = 'TARGET_AMT')) +
    geom_point(stat = 'identity') +
```

```
    labs(title = paste(col,'vs.','TARGET_AMT'))
    print(plot)
}

# ========================================================================================
# Model One
# ========================================================================================

- `EDUCATION` was grouped as "College" and "No College"
- `AGE` was grouped as "Under 25" and "25 and Over"
- `JOB` was grouped as "Careered" and "Not Careered"
- `MINIVAN` grouped the `CAR_TYPE` as "yes" or "no" if it was a minivan
- `RED_CAR`, `CAR_AGE`, `SEX`, `YOJ` , `HOMEKIDS` were removed due to high p value

options(scipen = 999)
model1 <- training_set %>%
  mutate(EDUCATION = ifelse(EDUCATION=="Bachelors" |EDUCATION=="Masters"|EDUCATION=="PhD",
                            "College","No College"),
         AGE = ifelse(AGE < 25, "Under 25", "Over 25"),
         JOB = ifelse(JOB=="Student" | JOB =="Home Maker" | JOB =="Clerical", "Not Careered", "Careered
         MINIVAN = as.factor(ifelse(CAR_TYPE == "Minivan", "yes", "no")),
         KIDSDRIV = as.factor(ifelse(KIDSDRIV == 0, "no", "yes")),
         ) %>%

  glm(TARGET_FLAG ~ KIDSDRIV + AGE  + INCOME + PARENT1 + HOME_VAL + MSTATUS +
        EDUCATION + JOB + TRAVTIME + CAR_USE + BLUEBOOK + TIF + OLDCLAIM +
        CLM_FREQ + REVOKED + MVR_PTS + URBANICITY + MINIVAN, family= "binomial", data = .)

summary(model1)

plot(fitted(model1), resid(model1), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Fitted versus Residuals")
abline(h = 0, col = "darkorange", lwd = 2)
qqnorm(resid(model1), main = "Normal Q-Q Plot", col = "darkgrey")
qqline(resid(model1), col = "dodgerblue", lwd = 2)


# ========================================================================================
# Model Two
# ========================================================================================

options(scipen = 999)
model2 = glm(TARGET_FLAG ~ INCOME +
             PARENT1 + HOME_VAL +
             MSTATUS + EDUCATION +
             TRAVTIME + CAR_USE +
             TIF + CAR_TYPE +
             REVOKED + URBANICITY,
             data = training_set, family = binomial(link = 'logit'))
summary(model2, digits = 2)


plot(fitted(model1), resid(model1), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Fitted versus Residuals")
```

```
abline(h = 0, col = "darkorange", lwd = 2)
qqnorm(resid(model1), main = "Normal Q-Q Plot", col = "darkgrey")
qqline(resid(model1), col = "dodgerblue", lwd = 2) col = "dodgerblue", lwd = 2)
```

```
# ============================================================================================
# Model Three
# ============================================================================================

model3 = glm(TARGET_FLAG~.-TARGET_AMT-INCOME,training_set,family ='binomial')

summary(model3)

plot(fitted(model3), resid(model3), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Fitted versus Residuals")
abline(h = 0, col = "darkorange", lwd = 2)
qqnorm(resid(model3), main = "Normal Q-Q Plot", col = "darkgrey")
qqline(resid(model3), col = "dodgerblue", lwd = 2)


# ============================================================================================
# Model Four
# ============================================================================================

Here we run a linear regression (for the records that represent an actual accident) i.e. TARGET_FLAG=1,

model4 = lm(TARGET_AMT ~ BLUEBOOK, data = training_set_numeric)

summary(model4)

plot(fitted(model4), resid(model4), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Fitted versus Residuals")
abline(h = 0, col = "darkorange", lwd = 2)
qqnorm(resid(model4), main = "Normal Q-Q Plot", col = "darkgrey")
qqline(resid(model4), col = "dodgerblue", lwd = 2)

# ============================================================================================
# Model Five
# ============================================================================================

data <- training_set %>% filter(TARGET_FLAG == 1)
data <- data[-1]
b <- boxcox(TARGET_AMT ~ . , data = data)


lamda <- b$x
lik <- b$y
bc <- cbind(lamda, lik)
l <- bc[order(-lik),][1,1]


model5 <- lm(TARGET_AMT^(l) ~ . , data = data)

summary(model5)

plot(fitted(model5), resid(model5), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Fitted versus Residuals")
abline(h = 0, col = "darkorange", lwd = 2)
qqnorm(resid(model5), main = "Normal Q-Q Plot", col = "darkgrey")
```

```
qqline(resid(model5), col = "dodgerblue", lwd = 2)

# ========================================================================================
# Model Selection
# ========================================================================================

# Function that creates a vector of binary values based on threshold.
to_binary = function(arr,thresh) {
  binary = c()
  for (i in arr) {
    if (i >= thresh) {
      binary = c(binary, 1)
    }
    else {
      binary = c(binary, 0)
    }
  }
  return(binary)
}

# Predictions based on a threshhold of 0.5.
predictions = training_set[c('target')]
predictions$model1 = to_binary(predict(model1,type ='response'),0.5)
predictions$model2 = to_binary(predict(model2,type ='response'),0.5)
predictions$model3 = to_binary(predict(model3,type ='response'),0.5)
head(predictions)
```

```
# ================================================================================
# Error Calculations
# ================================================================================

predictions = predictions %>%
  mutate(target = as.factor(target),
         model1 = as.factor(model1),
         model2 = as.factor(model2),
         model3 = as.factor(model3)
         )

# Model 1.
confusionMatrix(predictions$model1,predictions$target)

# Model 2.
confusionMatrix(predictions$model2,predictions$target)

# Model 3.
confusionMatrix(predictions$model3,predictions$target)
```

```
# ================================================================================
# Model Comparison
# ================================================================================

accuracy <- function(df,col1,col2) {
  true = df[,col1]
  predict = df[,col2]
  # total events
  len = length(true)
  # total correct predictions
  correct = 0
  for (i in seq(len)){
    if (true[i] == predict[i]){
      correct = correct + 1
    }
  }
  # accuracy
  return (correct/len)
}
class_error_rate <- function(df,col1,col2) {
  true = df[,col1]
  predict = df[,col2]
  # total events
  len = length(true)
  # total errors
  error = 0
  for (i in seq(len)){
    if (true[i] != predict[i]){
      error = error + 1
    }
  }
  # error rate
  return (error/len)
}
precision <- function(col1, col2) {
  # Calculate the total number of true positives in the dataset.
  true_positive <- sum(col1 == 1 & col2 == 1)
  # Calculate the total number of false positives in the dataset.
  false_positive <- sum(col1 == 0 & col2 == 1)
  # Perform the precision calculation and round the result to 2 decimal places.
  prediction_precision <- true_positive / (true_positive + false_positive)
  return(prediction_precision)
}
sensitivity <- function(col1, col2) {

  true_positive <- sum(col1 == 1 & col2 == 1)
  false_negative <- sum(col1 == 1 & col2 == 0)

  sensitivity<- true_positive / (true_positive + false_negative)

  return(sensitivity)
}
specificity <- function(col1, col2) {
```

```
  true_negative <- sum(col2 == 0 & col1 == 0)
  false_positive <- sum(col2 == 1 & col1 == 0)

  specificity <- true_negative / (true_negative + false_positive)

  return(specificity)
}
f1_score <- function(col1, col2) {
  sens <- sensitivity(col1, col2)
  prec <- precision(col1, col2)
  f1 <- 2 * sens * prec / (prec+sens)
  return(f1)
}
roc_model1 <- roc(predictions$TARGET_FLAG, as.numeric(predictions$model1))
roc_model2 <- roc(predictions$TARGET_FLAG, as.numeric(predictions$model2))
roc_model3 <- roc(predictions$TARGET_FLAG, as.numeric(predictions$model3))
#accuracy
acc <- c(accuracy(predictions,'TARGET_FLAG','model1'), accuracy(predictions,'TARGET_FLAG','model2'),
         accuracy(predictions,'TARGET_FLAG','model3'))
#classification error rate
class_error <- c(class_error_rate(predictions,'TARGET_FLAG','model1'),
                 class_error_rate(predictions,'TARGET_FLAG','model2'),
                 class_error_rate(predictions,'TARGET_FLAG','model3'))
#precision
prec <- c(precision(predictions$TARGET_FLAG, predictions$model1),
          precision(predictions$TARGET_FLAG, predictions$model2),
          precision(predictions$TARGET_FLAG, predictions$model3))
#specificity
spec <- c(specificity(predictions$TARGET_FLAG, predictions$model1),
          specificity(predictions$TARGET_FLAG, predictions$model2),
          specificity(predictions$TARGET_FLAG, predictions$model3))
#sensitivity
sens <- c(sensitivity(predictions$TARGET_FLAG, predictions$model1),
          sensitivity(predictions$TARGET_FLAG, predictions$model2),
          sensitivity(predictions$TARGET_FLAG, predictions$model3))
#f1 score
f1 <- c(f1_score(predictions$TARGET_FLAG, predictions$model1),
        f1_score(predictions$TARGET_FLAG, predictions$model2),
        f1_score(predictions$TARGET_FLAG, predictions$model3))
#AUC
a_u_c <- c(auc(roc_model1), auc(roc_model2), auc(roc_model3))
model_comparison <- rbind(acc, class_error, prec, spec, sens, f1, a_u_c) %>%
  as.data.frame() %>%
  magrittr::set_rownames(c('accuracy', 'classification error rate', 'precision', 'sensitivity',
                 'specificity', 'F1 score', 'AUC')) %>%
  magrittr::set_colnames(c('Model 1', 'Model 2', 'Model 3')) %>%
  round(., 4)
model_comparison

# ================================================================================
# Evaluating Dataset
# ================================================================================
```

```
- Picked Models 2 and 4 because they had the best results

evaluation_set = evaluation_set%>%
  mutate(AGE = ifelse(is.na(AGE),median(training_set$AGE, na.rm =TRUE),AGE),
         YOJ = ifelse(is.na(YOJ),median(training_set$YOJ, na.rm =TRUE), YOJ),
         INCOME = ifelse(is.na(INCOME),median(training_set$INCOME, na.rm =TRUE), INCOME),
         HOME_VAL = ifelse(is.na(HOME_VAL),median(training_set$HOME_VAL, na.rm =TRUE), HOME_VAL),
         CAR_AGE = ifelse(is.na(CAR_AGE),median(training_set$CAR_AGE, na.rm =TRUE), CAR_AGE))
evaluation_set$TARGET_FLAG = to_binary(predict(model2,evaluation_set,type = "response"),0.5)
evaluation_set$TARGET_AMT = predict(model4,evaluation_set)
head(evaluation_set)
```