Data 621 - HW4

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5/2/2021

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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:

Response Variables:

VARIABLE NAME	DEFINITION	THEORETICAL EFFECT
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

Explanatory Variables:

VARIABLE NAME	DEFINITION	THEORETICAL EFFECT
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

Data Exploration

```
## Rows: 8,161
## Columns: 26
## $ INDEX       <int> 1, 2, 4, 5, 6, 7, 8, 11, 12, 13, 14, 15, 16, 17, 19, 20, 2~
## $ TARGET_FLAG <int> 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1~
## $ TARGET_AMT  <dbl> 0.000, 0.000, 0.000, 0.000, 0.000, 2946.000, 0.000, 4021.0~
## $ KIDSDRIV    <int> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
## $ AGE         <int> 60, 43, 35, 51, 50, 34, 54, 37, 34, 50, 53, 43, 55, 53, 45~
## $ HOMEKIDS    <int> 0, 0, 1, 0, 0, 1, 0, 2, 0, 0, 0, 0, 0, 0, 0, 3, 0, 3, 2, 1~
## $ YOJ         <int> 11, 11, 10, 14, NA, 12, NA, NA, 10, 7, 14, 5, 11, 11, 0, 1~
## $ INCOME      <chr> "$67,349", "$91,449", "$16,039", "", "$114,986", "$125,301~
## $ PARENT1     <chr> "No", "No", "No", "No", "No", "Yes", "No", "No", "No", "No~
## $ HOME_VAL    <chr> "$0", "$257,252", "$124,191", "$306,251", "$243,925", "$0"~
## $ MSTATUS     <chr> "z_No", "z_No", "Yes", "Yes", "Yes", "z_No", "Yes", "Yes",~
## $ SEX         <chr> "M", "M", "z_F", "M", "z_F", "z_F", "z_F", "M", "z_F", "M"~
## $ EDUCATION   <chr> "PhD", "z_High School", "z_High School", "<High School", "~
## $ JOB         <chr> "Professional", "z_Blue Collar", "Clerical", "z_Blue Colla~
## $ TRAVTIME    <int> 14, 22, 5, 32, 36, 46, 33, 44, 34, 48, 15, 36, 25, 64, 48,~
## $ CAR_USE     <chr> "Private", "Commercial", "Private", "Private", "Private", ~
## $ BLUEBOOK    <chr> "$14,230", "$14,940", "$4,010", "$15,440", "$18,000", "$17~
## $ TIF         <int> 11, 1, 4, 7, 1, 1, 1, 1, 1, 7, 1, 7, 7, 6, 1, 6, 6, 7, 4, ~
## $ CAR_TYPE    <chr> "Minivan", "Minivan", "z_SUV", "Minivan", "z_SUV", "Sports~
## $ RED_CAR     <chr> "yes", "yes", "no", "yes", "no", "no", "no", "yes", "no", ~
## $ OLDCLAIM    <chr> "$4,461", "$0", "$38,690", "$0", "$19,217", "$0", "$0", "$~
## $ CLM_FREQ    <int> 2, 0, 2, 0, 2, 0, 0, 1, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 2~
## $ REVOKED     <chr> "No", "No", "No", "No", "Yes", "No", "No", "Yes", "No", "N~
## $ MVR_PTS     <int> 3, 0, 3, 0, 3, 0, 0, 10, 0, 1, 0, 0, 3, 3, 3, 0, 0, 0, 0, ~
## $ CAR_AGE     <int> 18, 1, 10, 6, 17, 7, 1, 7, 1, 17, 11, 1, 9, 10, 5, 13, 16,~
## $ URBANICITY  <chr> "Highly Urban/ Urban", "Highly Urban/ Urban", "Highly Urba~
```

There are 8161 observation in the training dataset having 21 feature variables and 2 target variables.

```
##   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

##      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   Length:8161
##  1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.0   Class :character
##  Median :45.00   Median :0.0000   Median :11.0   Mode  :character
##  Mean   :44.79   Mean   :0.7212   Mean   :10.5
##  3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.0
##  Max.   :81.00   Max.   :5.0000   Max.   :23.0
##  NA's   :6                        NA's   :454
##    PARENT1            HOME_VAL           MSTATUS              SEX
##  Length:8161        Length:8161        Length:8161        Length:8161
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   EDUCATION             JOB               TRAVTIME        CAR_USE
##  Length:8161        Length:8161        Min.   :  5.00   Length:8161
##  Class :character   Class :character   1st Qu.: 22.00   Class :character
##  Mode  :character   Mode  :character   Median : 33.00   Mode  :character
##                                        Mean   : 33.49
##                                        3rd Qu.: 44.00
##                                        Max.   :142.00
##
##    BLUEBOOK              TIF           CAR_TYPE           RED_CAR
##  Length:8161        Min.   : 1.000   Length:8161        Length:8161
##  Class :character   1st Qu.: 1.000   Class :character   Class :character
##  Mode  :character   Median : 4.000   Mode  :character   Mode  :character
##                     Mean   : 5.351
##                     3rd Qu.: 7.000
##                     Max.   :25.000
##
##    OLDCLAIM           CLM_FREQ        REVOKED            MVR_PTS
##  Length:8161        Min.   :0.0000   Length:8161        Min.   : 0.000
##  Class :character   1st Qu.:0.0000   Class :character   1st Qu.: 0.000
##  Mode  :character   Median :0.0000   Mode  :character   Median : 1.000
##                     Mean   :0.7986                      Mean   : 1.696
##                     3rd Qu.:2.0000                      3rd Qu.: 3.000
##                     Max.   :5.0000                      Max.   :13.000
```

```
##
##     CAR_AGE        URBANICITY
##  Min.   :-3.000   Length:8161
##  1st Qu.: 1.000   Class :character
##  Median : 8.000   Mode  :character
##  Mean   : 8.328
##  3rd Qu.:12.000
##  Max.   :28.000
##  NA's   :510
```

There are several recurring issues with some columns: all columns containing money amounts have incomptaible punctuation and characters. Also, categorical variables neeed to be changed to factors and their factor names edited for intelligibility.

```
##   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       HOME_VAL
##  Min.   :0.0000   Min.   : 0.0   Min.   :     0   No :7084   Min.   :     0
##  1st Qu.:0.0000   1st Qu.: 9.0   1st Qu.: 28097   Yes:1077   1st Qu.:     0
##  Median :0.0000   Median :11.0   Median : 54028              Median :161160
##  Mean   :0.7212   Mean   :10.5   Mean   : 61898              Mean   :154867
##  3rd Qu.:1.0000   3rd Qu.:13.0   3rd Qu.: 85986              3rd Qu.:238724
##  Max.   :5.0000   Max.   :23.0   Max.   :367030              Max.   :885282
##                   NA's   :454    NA's   :445                 NA's   :464
##  MSTATUS    SEX                    EDUCATION               JOB
##  No :3267   F:4375   Bachelors            :2242   Blue Collar :1825
##  Yes:4894   M:3786   High School          :2330   Clerical    :1271
##                      Less than High School:1203   Professional:1117
##                      Masters              :1658   Manager     : 988
##                      PhD                  : 728   Lawyer      : 835
##                                                   Student     : 712
##                                                   (Other)     :1413
##     TRAVTIME           CAR_USE        BLUEBOOK          TIF
##  Min.   :  5.00   Commercial:3029   Min.   : 1500   Min.   : 1.000
##  1st Qu.: 22.00   Private   :5132   1st Qu.: 9280   1st Qu.: 1.000
##  Median : 33.00                     Median :14440   Median : 4.000
##  Mean   : 33.49                     Mean   :15710   Mean   : 5.351
##  3rd Qu.: 44.00                     3rd Qu.:20850   3rd Qu.: 7.000
##  Max.   :142.00                     Max.   :69740   Max.   :25.000
##
##         CAR_TYPE    RED_CAR       OLDCLAIM        CLM_FREQ      REVOKED
##  Minivan    :2145   no :5783   Min.   :    0   Min.   :0.0000   No :7161
##  Panel Truck: 676   yes:2378   1st Qu.:    0   1st Qu.:0.0000   Yes:1000
##  Pickup     :1389              Median :    0   Median :0.0000
##  Sports Car : 907              Mean   : 4037   Mean   :0.7986
##  SUV        :2294              3rd Qu.: 4636   3rd Qu.:2.0000
##  Van        : 750              Max.   :57037   Max.   :5.0000
##
##     MVR_PTS          CAR_AGE                    URBANICITY
```

```
##  Min.   : 0.000   Min.   :-3.000   Highly Rural/ Rural:1669
##  1st Qu.: 0.000   1st Qu.: 1.000   Highly Urban/ Urban:6492
##  Median : 1.000   Median : 8.000
##  Mean   : 1.696   Mean   : 8.328
##  3rd Qu.: 3.000   3rd Qu.:12.000
##  Max.   :13.000   Max.   :28.000
##                   NA's   :510
```

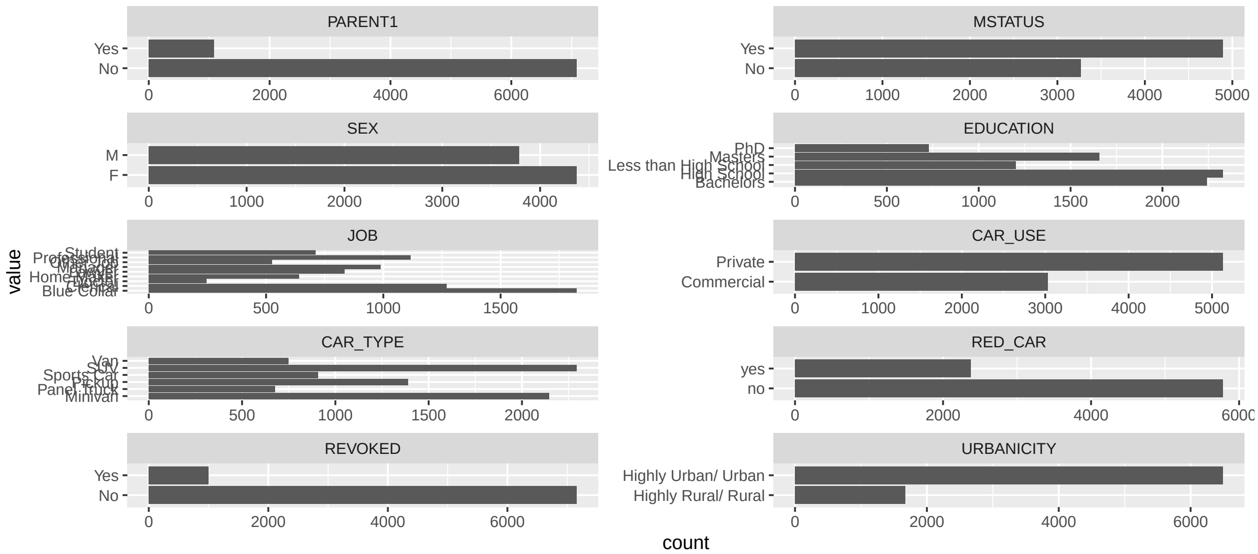
The fixed dataframe now only includes columns that are numeric or factors. Car age appears to have some values less than 1, including a negative values. These will be changed to the mode of 1.

Categorical variables

```
## [1] "PARENT1"
## [1] "No"  "Yes"
## [1] "MSTATUS"
## [1] "No"  "Yes"
## [1] "SEX"
## [1] "F" "M"
## [1] "EDUCATION"
## [1] "Bachelors"             "High School"           "Less than High School"
## [4] "Masters"               "PhD"
## [1] "JOB"
## [1] "Blue Collar"  "Clerical"     "Doctor"       "Home Maker"   "Lawyer"
## [6] "Manager"      "Other Job"    "Professional" "Student"
## [1] "CAR_USE"
## [1] "Commercial" "Private"
## [1] "CAR_TYPE"
## [1] "Minivan"     "Panel Truck" "Pickup"      "Sports Car"  "SUV"
## [6] "Van"
## [1] "RED_CAR"
## [1] "no"  "yes"
## [1] "REVOKED"
## [1] "No"  "Yes"
## [1] "URBANICITY"
## [1] "Highly Rural/ Rural" "Highly Urban/ Urban"
```

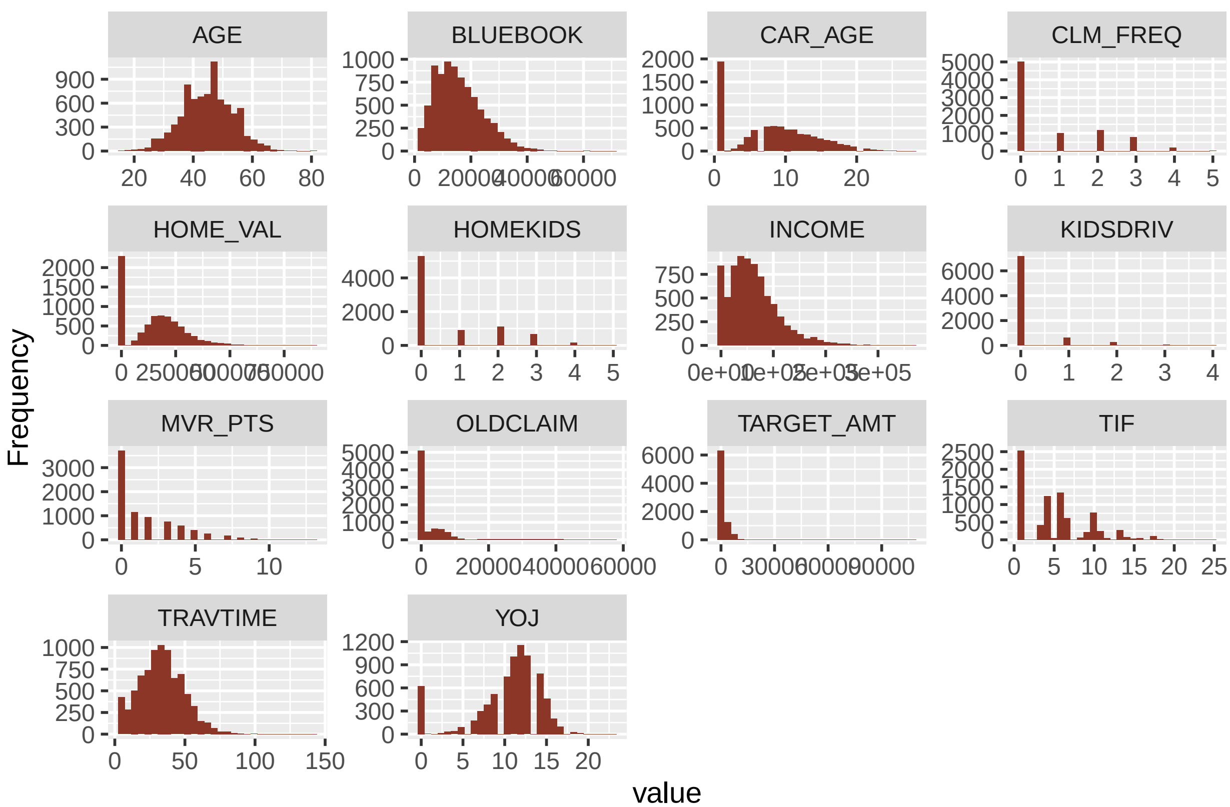
Looking at categorical variables, most of the columns are binary.

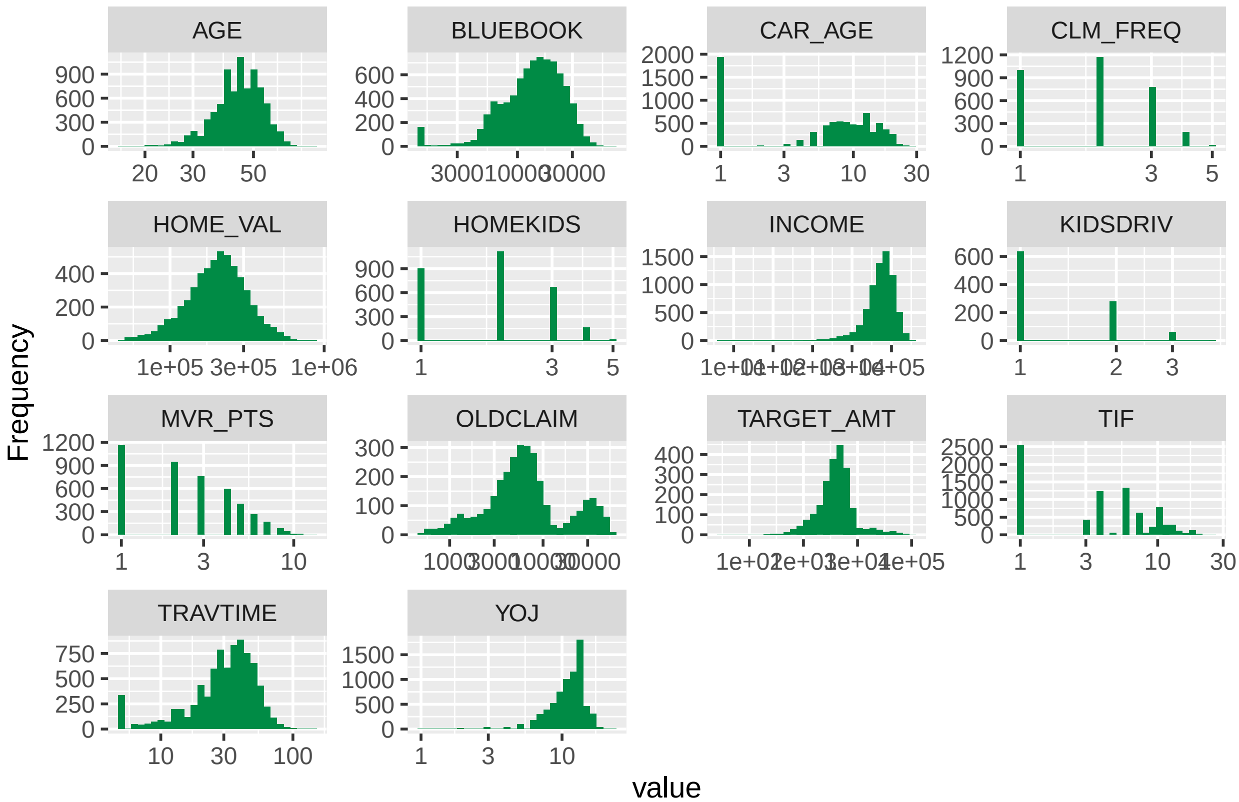
Below graphs shows the distribution of all categorical predictors.



Numeric Variables

Below 2 graphs shows the distribution of numeric variables. The red graphs are on normal scale and the green ones are on log10 scale. Many numeric variables feature the value of zero as a mode.

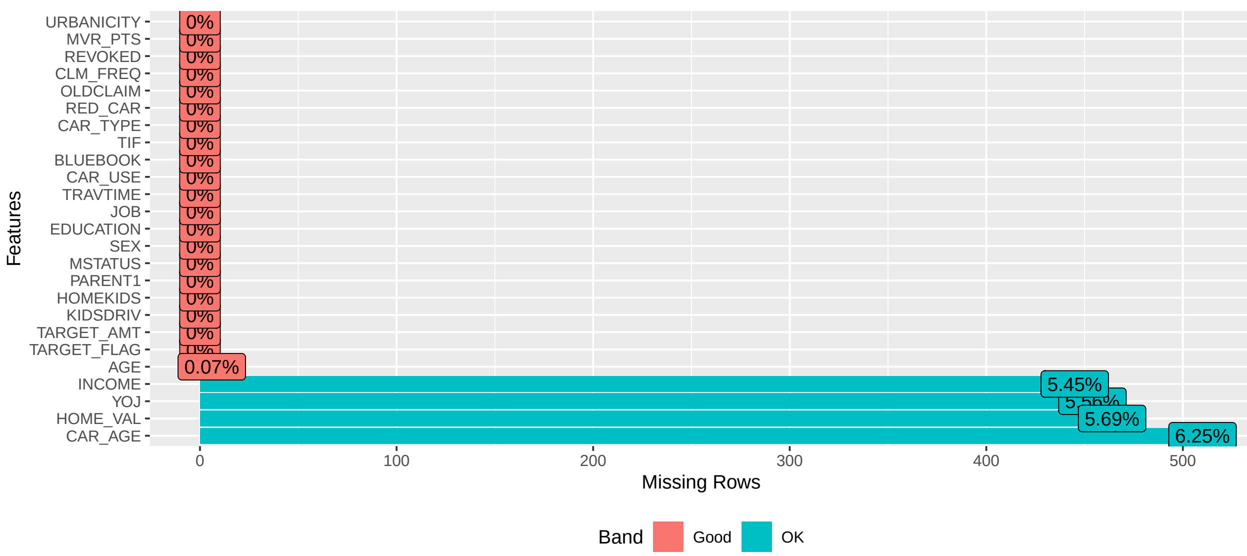




Missing Values

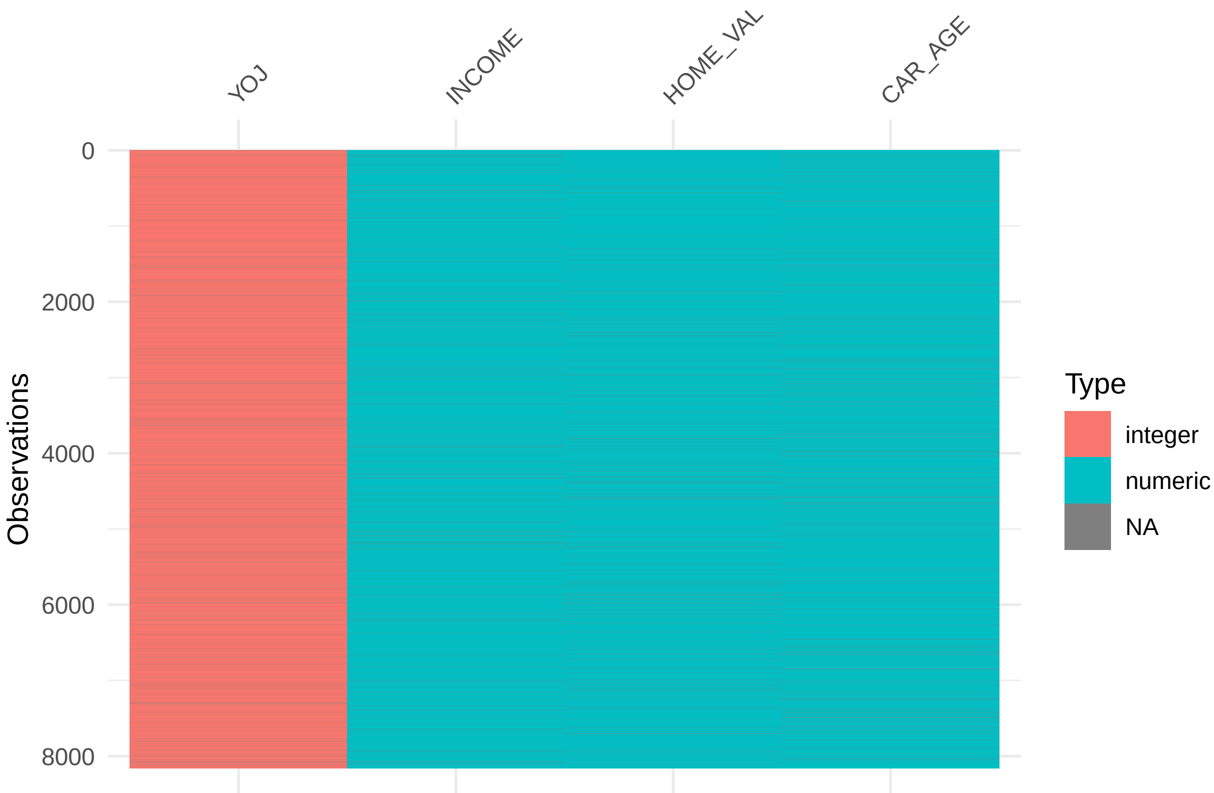
Here are columns having missing values coded as NA:

```
##    AGE YOJ INCOME HOME_VAL CAR_AGE
## 1    6 454    445      464     510
```




```
## TARGET_FLAG  TARGET_AMT    KIDSDRIV         AGE    HOMEKIDS         YOJ
##       0.000       0.000       0.000       0.001       0.000       0.056
##      INCOME     PARENT1    HOME_VAL     MSTATUS         SEX   EDUCATION
##       0.055       0.000       0.057       0.000       0.000       0.000
```

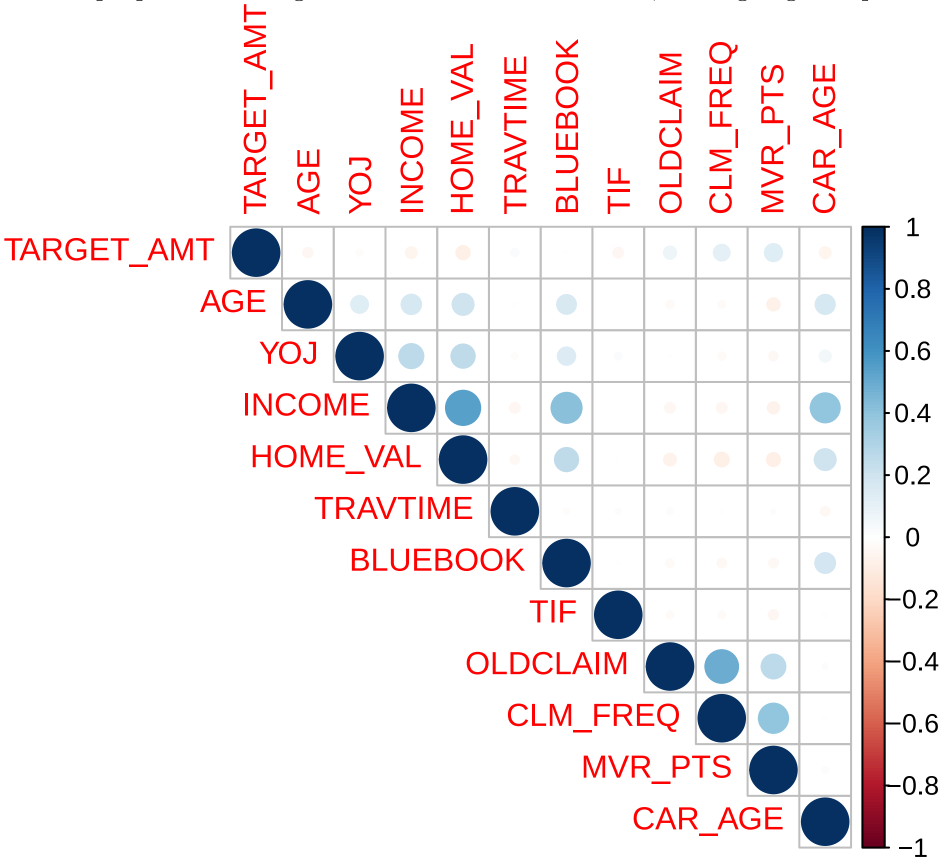
```
##          JOB    TRAVTIME     CAR_USE    BLUEBOOK         TIF    CAR_TYPE
##        0.000       0.000       0.000       0.000       0.000       0.000
##      RED_CAR    OLDCLAIM    CLM_FREQ     REVOKED     MVR_PTS     CAR_AGE
##        0.000       0.000       0.000       0.000       0.000       0.062
##   URBANICITY
##        0.000
```



Four variables have missing values, however there doesn't appear to be a pattern and it's safe to assume they're missing at random.

Correlation

For the purposes of seeing correlation between variables, we're going to replace NA values with the median.



It's clear there are some positive correlations between the following variables:
* **Income** & **Home value**: 0.54
* **Income** & **Bluebook**: 0.42
* **Income** & **Car age**: 0.39
* **Claim Frequency** & **Old claims**: 0.50
* **Claim Frequence** & **MVR_PTS**:0.39

Data Preparation

Removing TARGET_FLAG

Our multiple linear regression model will be predicting the amount of money someone receives if they crash, so we will be removing the variable *TARGET_FLAG*

Handling Missing Data - Multiple Linear Regression

For the multiple linear regression, we're going to assume that the NULL values will take the median value for the variable.

Transforming Variables - Multiple Linear Regression

There some variables that are not normally distributed so we're going to try using a log transformation later to see if that creates a better model. For a few variables with values, 0, we added 1 to avoid negative infinity when taking the log of those variables. This will not alter our modeling results significantly.

Zeroes in Home Value

It seems from the histogram above, that the mode of the variable HOME_VAL is 0. Given that, the distribution seems normal if we remove 0s and that the difference between 0 and the number that appears next on the axis is significant, we are assuming that 0 indicates missing values for HOME_VAL. Therefore, we will convert 0s to NAs in HOME_VAL prior to imputing missing values for Binary Logistic Regression Model 3 below.

Addressing Zeroes using Binning

The histograms for several variables indicate that there many with an overrepresentation of 'zero' values. Some of the worst offenders include CAR_AGE, HOME_VAL, HOMEKIDS, KIDSDRIV, OLDCLAIM, TIF, and YOJ. INCOME also has many 'zero' or very low values, and also similar to CAR_AGE and HOME_VAL because, omitting zero, the rest of the distributions appear to be skewed, approximately normal distributions. To avoid problems with interpretation, the 4th model will consider these continuous variables as categorical variables defined as a number range.

```
##   TARGET_FLAG       TARGET_AMT          AGE            INCOME        PARENT1
##  Min.   :0.0000   Min.   :     0   Min.   :16.00   Min.   :     0   No :7084
##  1st Qu.:0.0000   1st Qu.:     0   1st Qu.:39.00   1st Qu.: 28097   Yes:1077
##  Median :0.0000   Median :     0   Median :45.00   Median : 54028
##  Mean   :0.2638   Mean   :  1504   Mean   :44.79   Mean   : 61898
##  3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:51.00   3rd Qu.: 85986
##  Max.   :1.0000   Max.   :107586   Max.   :81.00   Max.   :367030
##                                    NA's   :6       NA's   :445
##  MSTATUS    SEX                       EDUCATION               JOB
##  No :3267   F:4375   Bachelors            :2242   Blue Collar :1825
##  Yes:4894   M:3786   High School          :2330   Clerical    :1271
##                      Less than High School:1203   Professional:1117
##                      Masters              :1658   Manager     : 988
##                      PhD                  : 728   Lawyer      : 835
##                                                   Student     : 712
##                                                   (Other)     :1413
##     TRAVTIME             CAR_USE        BLUEBOOK            CAR_TYPE
##  Min.   :  5.00   Commercial:3029   Min.   : 1500   Minivan    :2145
##  1st Qu.: 22.00   Private   :5132   1st Qu.: 9280   Panel Truck: 676
##  Median : 33.00                     Median :14440   Pickup     :1389
##  Mean   : 33.49                     Mean   :15710   Sports Car : 907
##  3rd Qu.: 44.00                     3rd Qu.:20850   SUV        :2294
##  Max.   :142.00                     Max.   :69740   Van        : 750
##
##  RED_CAR       CLM_FREQ      REVOKED       MVR_PTS
##  no :5783   Min.   :0.0000   No :7161   Min.   : 0.000
##  yes:2378   1st Qu.:0.0000   Yes:1000   1st Qu.: 0.000
##             Median :0.0000              Median : 1.000
##             Mean   :0.7986              Mean   : 1.696
##             3rd Qu.:2.0000              3rd Qu.: 3.000
##             Max.   :5.0000              Max.   :13.000
##
##                URBANICITY     CAR_AGE_BIN        HOME_VAL_BIN   HAS_HOME_KIDS
##  Highly Rural/ Rural:1669   New     :1938   Zero        :2294   Has kids:2872
##  Highly Urban/ Urban:6492   Like New:  66   $0-$50k     :   0   No kids :5289
##                             Average :3775   $50k-$150k  :1274
##                             Old     :1872   $150k-$250k:2445
##                             NA's    : 510   Over $250k  :1684
```

```
##                                             NA's       : 464
##
##             HAS_KIDSDRIV    OLDCLAIM_BIN              TIF_BIN
##  Has kids driving: 981   Zero    :5009   Zero             :   0
##  No kids driving :7180   $0-$3k  : 584   Less than 1 year:2533
##                          $3k-$6k : 970   1-4 years       :1672
##                          $6k-$9k : 720   4-7 years       :2013
##                          Over $9k: 878   Over 7 years    :1943
##
##
##                  YOJ_BIN
##  Zero               : 625
##  Less than 10 years :2313
##  Between 10-15 years:4425
##  Over 15 years      : 344
##  NA's               : 454
##
##
##   TARGET_FLAG TARGET_AMT AGE INCOME PARENT1 MSTATUS SEX             EDUCATION
## 1           0          0  60  67349      No      No   M                   PhD
## 2           0          0  43  91449      No      No   M           High School
## 3           0          0  35  16039      No     Yes   F           High School
## 4           0          0  51     NA      No     Yes   M Less than High School
## 5           0          0  50 114986      No     Yes   F                   PhD
## 6           1       2946  34 125301     Yes      No   F             Bachelors
##            JOB TRAVTIME    CAR_USE BLUEBOOK   CAR_TYPE RED_CAR CLM_FREQ REVOKED
## 1 Professional       14    Private    14230    Minivan     yes        2      No
## 2  Blue Collar       22 Commercial    14940    Minivan     yes        0      No
## 3     Clerical        5    Private     4010        SUV      no        2      No
## 4  Blue Collar       32    Private    15440    Minivan     yes        0      No
## 5       Doctor       36    Private    18000        SUV      no        2     Yes
## 6  Blue Collar       46 Commercial    17430 Sports Car      no        0      No
##   MVR_PTS          URBANICITY CAR_AGE_BIN HOME_VAL_BIN HAS_HOME_KIDS
## 1       3 Highly Urban/ Urban         Old         Zero       No kids
## 2       0 Highly Urban/ Urban         New   Over $250k       No kids
## 3       3 Highly Urban/ Urban     Average   $50k-$150k      Has kids
## 4       0 Highly Urban/ Urban     Average   Over $250k       No kids
## 5       3 Highly Urban/ Urban         Old  $150k-$250k       No kids
## 6       0 Highly Urban/ Urban     Average         Zero      Has kids
##       HAS_KIDSDRIV OLDCLAIM_BIN          TIF_BIN             YOJ_BIN
## 1 No kids driving      $3k-$6k     Over 7 years Between 10-15 years
## 2 No kids driving         Zero Less than 1 year Between 10-15 years
## 3 No kids driving     Over $9k        1-4 years  Less than 10 years
## 4 No kids driving         Zero        4-7 years Between 10-15 years
## 5 No kids driving     Over $9k Less than 1 year                <NA>
## 6 No kids driving         Zero Less than 1 year Between 10-15 years
```

Build Models

Model1

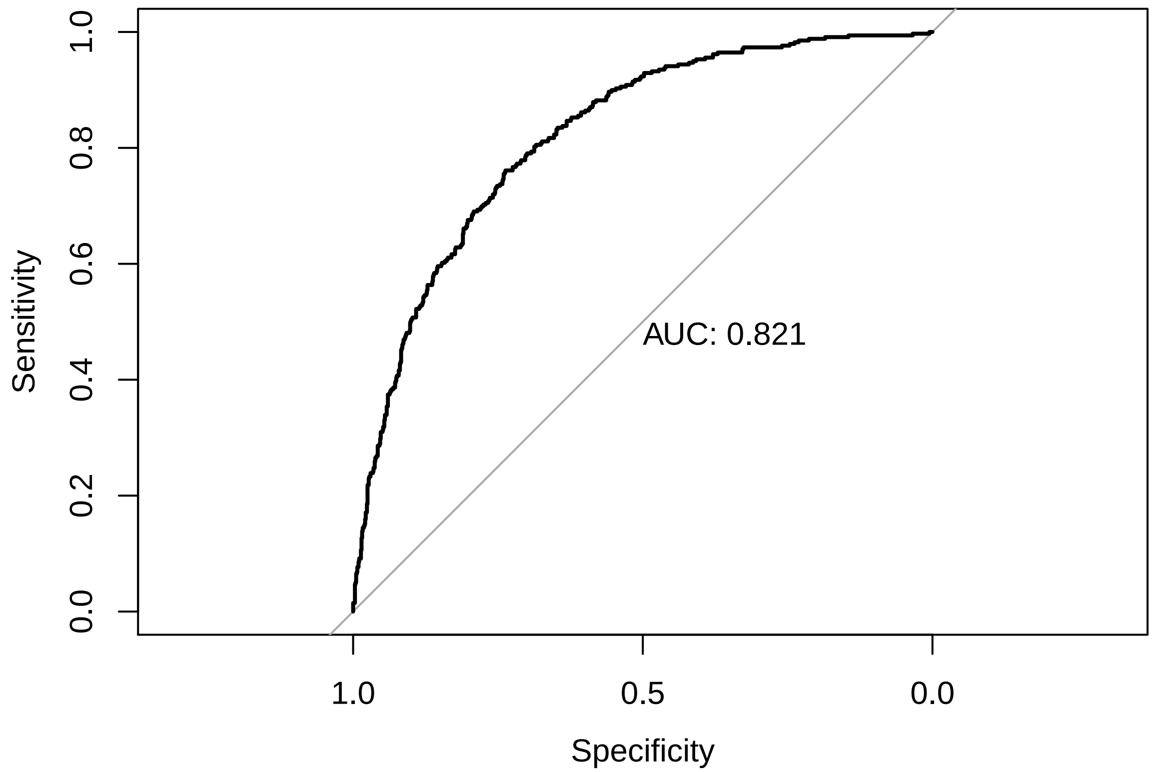
The first model to consider includes all given variables and does not impute any values.

```
##
```

```
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = insurance_fix)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5843  -0.7124  -0.3998   0.6195   3.1633
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -2.881e+00  3.199e-01  -9.005  < 2e-16 ***
## KIDSDRIV                        3.385e-01  6.908e-02   4.900 9.57e-07 ***
## AGE                            -3.665e-03  4.531e-03  -0.809 0.418503
## HOMEKIDS                        3.349e-02  4.176e-02   0.802 0.422588
## YOJ                            -1.071e-02  9.589e-03  -1.117 0.263837
## INCOME                         -2.988e-06  1.260e-06  -2.371 0.017738 *
## PARENT1Yes                      4.337e-01  1.225e-01   3.541 0.000398 ***
## HOME_VAL                       -1.301e-06  3.899e-07  -3.337 0.000848 ***
## MSTATUSYes                     -4.389e-01  9.666e-02  -4.541 5.61e-06 ***
## SEXM                            1.914e-01  1.241e-01   1.543 0.122880
## EDUCATIONHigh School            3.716e-01  1.020e-01   3.645 0.000268 ***
## EDUCATIONLess than High School  3.724e-01  1.306e-01   2.852 0.004342 **
## EDUCATIONMasters                2.887e-02  1.607e-01   0.180 0.857462
## EDUCATIONPhD                    2.617e-01  2.054e-01   1.274 0.202597
## JOBClerical                     2.052e-01  1.193e-01   1.720 0.085428 .
## JOBDoctor                      -5.011e-01  3.136e-01  -1.598 0.110084
## JOBHome Maker                  -8.529e-02  1.750e-01  -0.487 0.625972
## JOBLawyer                      -1.923e-02  2.126e-01  -0.090 0.927939
## JOBManager                     -8.826e-01  1.595e-01  -5.534 3.13e-08 ***
## JOBOther Job                   -3.071e-01  2.117e-01  -1.450 0.146938
## JOBProfessional                -1.066e-01  1.360e-01  -0.784 0.433062
## JOBStudent                     -1.370e-01  1.497e-01  -0.915 0.359966
## TRAVTIME                        1.562e-02  2.118e-03   7.374 1.66e-13 ***
## CAR_USEPrivate                 -8.256e-01  1.040e-01  -7.935 2.10e-15 ***
## BLUEBOOK                       -2.101e-05  5.885e-06  -3.570 0.000357 ***
## TIF                            -5.318e-02  8.241e-03  -6.453 1.10e-10 ***
## CAR_TYPEPanel Truck             6.097e-01  1.807e-01   3.374 0.000740 ***
## CAR_TYPEPickup                  5.246e-01  1.136e-01   4.619 3.85e-06 ***
## CAR_TYPESports Car              1.128e+00  1.450e-01   7.784 7.05e-15 ***
## CAR_TYPESUV                     8.518e-01  1.241e-01   6.866 6.59e-12 ***
## CAR_TYPEVan                     6.335e-01  1.421e-01   4.460 8.21e-06 ***
## RED_CARyes                     -1.227e-01  9.685e-02  -1.267 0.205139
## OLDCLAIM                       -1.180e-05  4.375e-06  -2.698 0.006977 **
## CLM_FREQ                        1.953e-01  3.183e-02   6.136 8.46e-10 ***
## REVOKEDYes                      8.644e-01  1.035e-01   8.354  < 2e-16 ***
## MVR_PTS                         1.143e-01  1.528e-02   7.485 7.16e-14 ***
## CAR_AGE                        -7.075e-03  8.448e-03  -0.837 0.402334
## URBANICITYHighly Urban/ Urban   2.313e+00  1.241e-01  18.640  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7445.1  on 6447  degrees of freedom
```

```
## Residual deviance: 5764.7  on 6410  degrees of freedom
##   (1713 observations deleted due to missingness)
## AIC: 5840.7
##
## Number of Fisher Scoring iterations: 5
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 862 188
##          1  77 149
##
##                Accuracy : 0.7923
##                  95% CI : (0.769, 0.8143)
##     No Information Rate : 0.7359
##     P-Value [Acc > NIR] : 1.650e-06
##
##                   Kappa : 0.4026
##
##  Mcnemar's Test P-Value : 1.406e-11
##
##             Sensitivity : 0.9180
##             Specificity : 0.4421
##          Pos Pred Value : 0.8210
##          Neg Pred Value : 0.6593
##              Prevalence : 0.7359
##          Detection Rate : 0.6755
##    Detection Prevalence : 0.8229
##       Balanced Accuracy : 0.6801
##
##        'Positive' Class : 0
##
```



Model2

The second model imputes values using the 'mice' library using classification and regression trees. We will use glm.mids() that applies glm() to a multiply imputed data set.

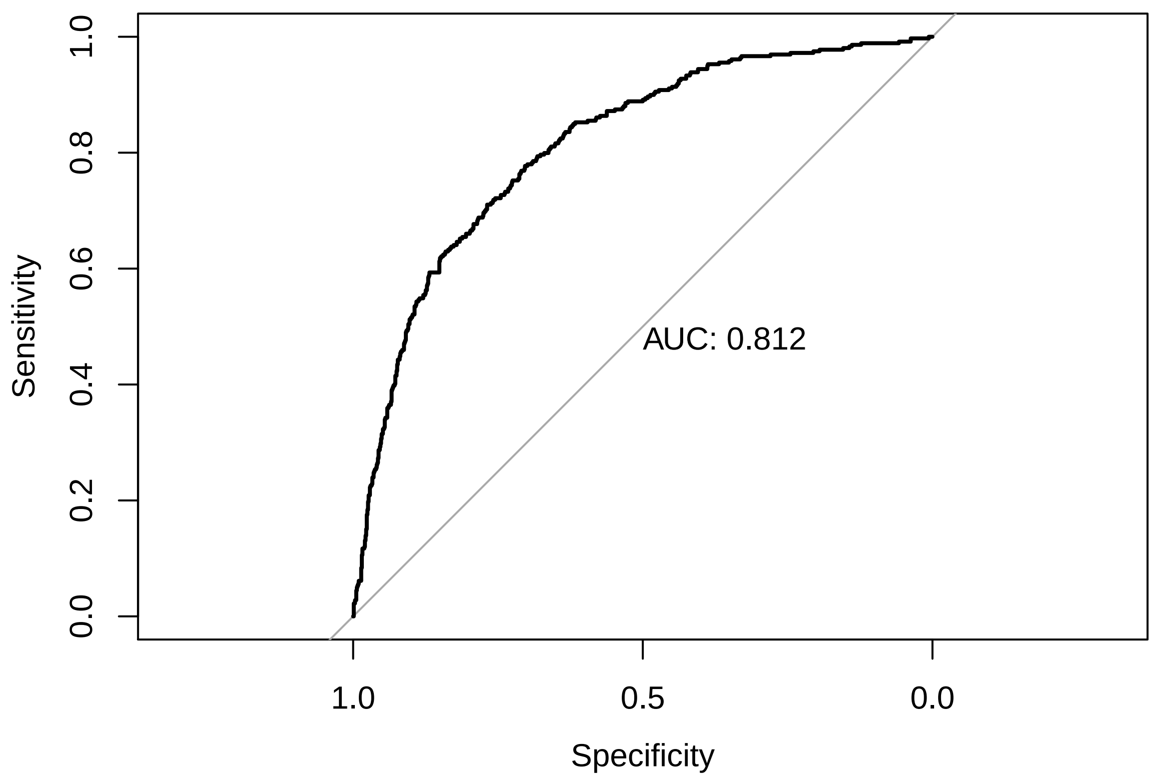
```
##
##  iter imp variable
##   1   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   2   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   3   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   4   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   5   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
```

```
## call :
## glm.mids(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = insurance_impute)
##
## call1 :
## mice(data = insurance_fix, m = 1, method = "cart")
##
## nmis :
## TARGET_FLAG  TARGET_AMT    KIDSDRIV         AGE    HOMEKIDS         YOJ
##           0           0           0           6           0         454
##      INCOME     PARENT1    HOME_VAL     MSTATUS         SEX   EDUCATION
##         445           0         464           0           0           0
##         JOB    TRAVTIME     CAR_USE    BLUEBOOK         TIF    CAR_TYPE
##           0           0           0           0           0           0
##     RED_CAR    OLDCLAIM    CLM_FREQ     REVOKED     MVR_PTS     CAR_AGE
##           0           0           0           0           0         510
##  URBANICITY
```

```
##          0
##
## analyses :
## [[1]]
##
## Call:  glm(formula = formula, family = family, data = complete(data,
##     i))
##
## Coefficients:
##                   (Intercept)                       KIDSDRIV
##                    -2.896e+00                      3.840e-01
##                           AGE                       HOMEKIDS
##                    -6.800e-04                      5.566e-02
##                           YOJ                         INCOME
##                    -1.784e-02                     -3.413e-06
##                    PARENT1Yes                       HOME_VAL
##                     3.802e-01                     -1.293e-06
##                    MSTATUSYes                           SEXM
##                    -4.818e-01                      8.755e-02
##           EDUCATIONHigh School  EDUCATIONLess than High School
##                     3.765e-01                      3.506e-01
##              EDUCATIONMasters                   EDUCATIONPhD
##                     1.187e-01                      2.530e-01
##                   JOBClerical                      JOBDoctor
##                     9.534e-02                     -7.712e-01
##                JOBHome Maker                      JOBLawyer
##                    -1.305e-01                     -2.040e-01
##                    JOBManager                   JOBOther Job
##                    -8.666e-01                     -3.031e-01
##               JOBProfessional                     JOBStudent
##                    -1.459e-01                     -1.525e-01
##                      TRAVTIME                  CAR_USEPrivate
##                     1.462e-02                     -7.552e-01
##                      BLUEBOOK                            TIF
##                    -2.042e-05                     -5.558e-02
##           CAR_TYPEPanel Truck                 CAR_TYPEPickup
##                     5.559e-01                      5.547e-01
##            CAR_TYPESports Car                    CAR_TYPESUV
##                     1.023e+00                      7.681e-01
##                   CAR_TYPEVan                     RED_CARyes
##                     6.174e-01                     -1.227e-02
##                      OLDCLAIM                       CLM_FREQ
##                    -1.378e-05                      1.965e-01
##                    REVOKEDYes                        MVR_PTS
##                     8.870e-01                      1.133e-01
##                       CAR_AGE   URBANICITYHighly Urban/ Urban
##                    -5.686e-03                      2.391e+00
##
## Degrees of Freedom: 8160 Total (i.e. Null);  8123 Residual
## Null Deviance:       9418
## Residual Deviance: 7292  AIC: 7368
```

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction   0   1
##          0 878 190
##          1  70 136
##
##                Accuracy : 0.7959
##                  95% CI : (0.7727, 0.8177)
##     No Information Rate : 0.7441
##     P-Value [Acc > NIR] : 8.412e-06
##
##                   Kappa : 0.3905
##
##  Mcnemar's Test P-Value : 1.582e-13
##
##             Sensitivity : 0.9262
##             Specificity : 0.4172
##          Pos Pred Value : 0.8221
##          Neg Pred Value : 0.6602
##              Prevalence : 0.7441
##          Detection Rate : 0.6892
##    Detection Prevalence : 0.8383
##       Balanced Accuracy : 0.6717
##
##        'Positive' Class : 0
##
```



Model 3

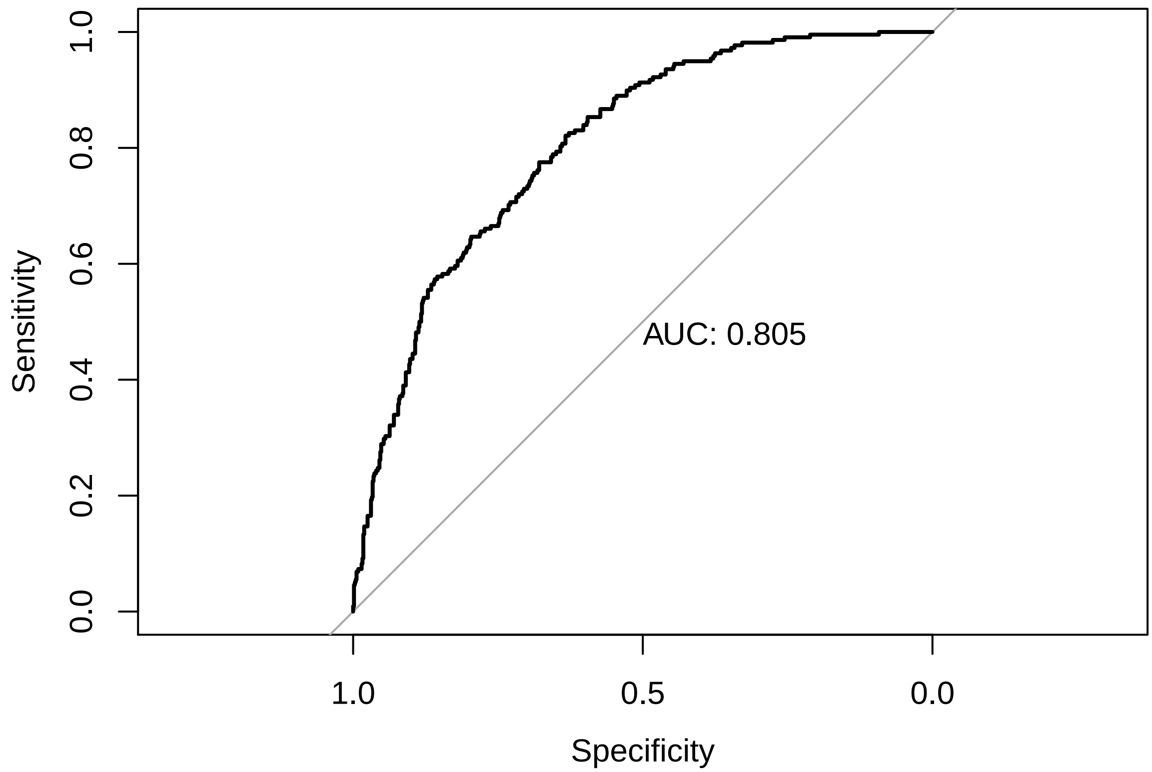
Now we will replicate the model above to see if our assumption about treating 0s in HOME_VAL as missing data, yields a better model fit.

```
##
##  iter imp variable
##   1   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   2   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   3   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   4   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE
##   5   1  AGE  YOJ  INCOME  HOME_VAL  CAR_AGE

## call :
## glm.mids(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = insurance_impute2)
##
## call1 :
## mice(data = insurance_fix2, m = 1, method = "cart")
##
## nmis :
## TARGET_FLAG  TARGET_AMT    KIDSDRIV         AGE    HOMEKIDS         YOJ
##           0           0           0           6           0         454
##      INCOME     PARENT1    HOME_VAL     MSTATUS         SEX   EDUCATION
##         445           0        2758           0           0           0
##         JOB    TRAVTIME     CAR_USE    BLUEBOOK         TIF    CAR_TYPE
##           0           0           0           0           0           0
##     RED_CAR    OLDCLAIM    CLM_FREQ     REVOKED     MVR_PTS     CAR_AGE
##           0           0           0           0           0         510
##  URBANICITY
##           0
##
## analyses :
## [[1]]
##
## Call:  glm(formula = formula, family = family, data = complete(data,
##     i))
##
## Coefficients:
##                  (Intercept)                          KIDSDRIV
##                   -2.920e+00                         3.863e-01
##                          AGE                          HOMEKIDS
##                   -2.083e-03                         5.737e-02
##                          YOJ                            INCOME
##                   -1.598e-02                        -5.084e-06
##                   PARENT1Yes                          HOME_VAL
##                    3.585e-01                        -4.278e-08
##                   MSTATUSYes                              SEXM
##                   -6.449e-01                         7.930e-02
##          EDUCATIONHigh School  EDUCATIONLess than High School
##                    4.095e-01                         3.924e-01
##              EDUCATIONMasters                      EDUCATIONPhD
##                    9.530e-02                         2.425e-01
##                  JOBClerical                         JOBDoctor
##                    9.797e-02                        -7.434e-01
```

```
##                JOBHome Maker                           JOBLawyer
##                   -1.180e-01                          -2.033e-01
##                   JOBManager                        JOBOther Job
##                   -8.532e-01                          -2.962e-01
##              JOBProfessional                          JOBStudent
##                   -1.489e-01                          -5.974e-02
##                     TRAVTIME                      CAR_USEPrivate
##                    1.462e-02                          -7.546e-01
##                     BLUEBOOK                                 TIF
##                   -1.992e-05                          -5.572e-02
##          CAR_TYPEPanel Truck                      CAR_TYPEPickup
##                    5.418e-01                           5.527e-01
##           CAR_TYPESports Car                         CAR_TYPESUV
##                    1.028e+00                           7.653e-01
##                  CAR_TYPEVan                          RED_CARyes
##                    6.128e-01                          -4.897e-03
##                     OLDCLAIM                            CLM_FREQ
##                   -1.395e-05                           1.989e-01
##                   REVOKEDYes                             MVR_PTS
##                    8.933e-01                           1.138e-01
##                      CAR_AGE   URBANICITYHighly Urban/ Urban
##                    3.030e-04                           2.396e+00
##
## Degrees of Freedom: 8160 Total (i.e. Null);  8123 Residual
## Null Deviance:       9418
## Residual Deviance: 7307  AIC: 7383
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 666 116
##          1  53  58
##
##                Accuracy : 0.8108
##                  95% CI : (0.7835, 0.8359)
##     No Information Rate : 0.8052
##     P-Value [Acc > NIR] : 0.3547
##
##                   Kappa : 0.3009
##
##  Mcnemar's Test P-Value : 1.849e-06
##
##             Sensitivity : 0.9263
##             Specificity : 0.3333
##          Pos Pred Value : 0.8517
##          Neg Pred Value : 0.5225
##              Prevalence : 0.8052
##          Detection Rate : 0.7458
##    Detection Prevalence : 0.8757
##       Balanced Accuracy : 0.6298
##
##        'Positive' Class : 0
##
```



Model 4

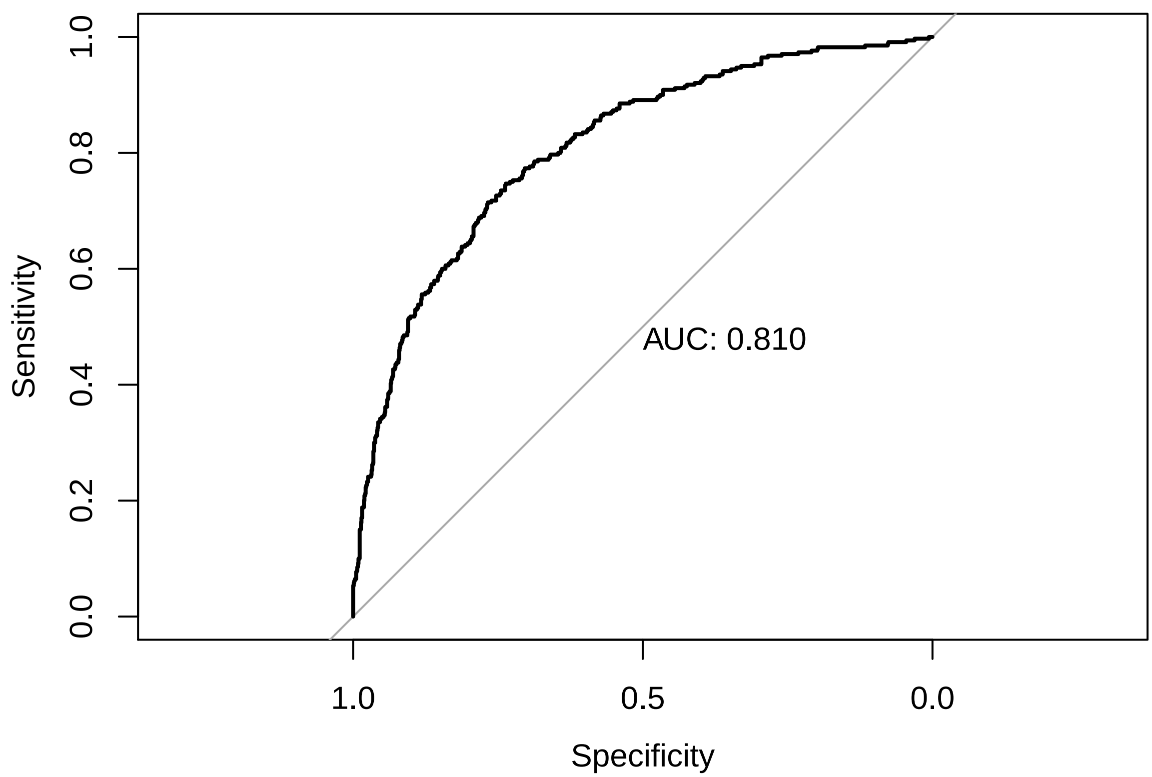
```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = insurance_bins)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4626  -0.7053  -0.3955   0.6199   3.1398
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -1.797e+00  3.584e-01  -5.013 5.36e-07 ***
## AGE                             -2.185e-03  4.754e-03  -0.459 0.645876
## INCOME                          -2.814e-06  1.344e-06  -2.094 0.036240 *
## PARENT1Yes                       2.826e-01  1.374e-01   2.057 0.039716 *
## MSTATUSYes                      -4.613e-01  1.046e-01  -4.408 1.04e-05 ***
## SEXM                             1.923e-01  1.249e-01   1.540 0.123660
## EDUCATIONHigh School             3.623e-01  1.022e-01   3.545 0.000393 ***
## EDUCATIONLess than High School  3.819e-01  1.300e-01   2.937 0.003312 **
## EDUCATIONMasters                -5.378e-04  1.664e-01  -0.003 0.997421
## EDUCATIONPhD                     2.007e-01  2.092e-01   0.959 0.337374
## JOBClerical                      1.937e-01  1.213e-01   1.597 0.110252
## JOBDoctor                       -4.930e-01  3.153e-01  -1.564 0.117906
## JOBHome Maker                   -2.461e-01  1.915e-01  -1.285 0.198816
## JOBLawyer                       -6.033e-03  2.145e-01  -0.028 0.977560
## JOBManager                      -8.712e-01  1.609e-01  -5.413 6.18e-08 ***
## JOBOther Job                    -3.073e-01  2.131e-01  -1.442 0.149177
```

```
## JOBProfessional               -9.770e-02  1.369e-01  -0.714 0.475349
## JOBStudent                    -4.025e-01  1.690e-01  -2.381 0.017254 *
## TRAVTIME                       1.617e-02  2.135e-03   7.572 3.66e-14 ***
## CAR_USEPrivate                -8.233e-01  1.048e-01  -7.855 4.00e-15 ***
## BLUEBOOK                      -2.099e-05  5.904e-06  -3.555 0.000378 ***
## CAR_TYPEPanel Truck            6.416e-01  1.818e-01   3.530 0.000415 ***
## CAR_TYPEPickup                 5.401e-01  1.141e-01   4.734 2.21e-06 ***
## CAR_TYPESports Car             1.113e+00  1.460e-01   7.625 2.43e-14 ***
## CAR_TYPESUV                    8.572e-01  1.249e-01   6.864 6.72e-12 ***
## CAR_TYPEVan                    6.329e-01  1.429e-01   4.428 9.51e-06 ***
## RED_CARyes                    -1.138e-01  9.730e-02  -1.170 0.242142
## CLM_FREQ                       5.041e-02  5.036e-02   1.001 0.316827
## REVOKEDYes                     8.822e-01  1.024e-01   8.619  < 2e-16 ***
## MVR_PTS                        9.784e-02  1.588e-02   6.163 7.15e-10 ***
## URBANICITYHighly Urban/ Urban  2.289e+00  1.249e-01  18.321  < 2e-16 ***
## CAR_AGE_BINLike New           -1.338e-01  3.469e-01  -0.386 0.699741
## CAR_AGE_BINAverage            -1.262e-01  8.393e-02  -1.503 0.132808
## CAR_AGE_BINOld                -1.346e-01  1.290e-01  -1.044 0.296614
## HOME_VAL_BIN$50k-$150k        -3.229e-01  1.266e-01  -2.551 0.010744 *
## HOME_VAL_BIN$150k-$250k       -3.035e-01  1.089e-01  -2.787 0.005324 **
## HOME_VAL_BINOver $250k        -5.742e-01  1.330e-01  -4.316 1.59e-05 ***
## HAS_HOME_KIDSNo kids          -2.294e-01  1.149e-01  -1.996 0.045923 *
## HAS_KIDSDRIVNo kids driving   -4.551e-01  1.114e-01  -4.085 4.41e-05 ***
## OLDCLAIM_BIN$0-$3k             4.055e-01  1.614e-01   2.513 0.011983 *
## OLDCLAIM_BIN$3k-$6k            3.729e-01  1.479e-01   2.522 0.011683 *
## OLDCLAIM_BIN$6k-$9k            5.461e-01  1.555e-01   3.512 0.000445 ***
## OLDCLAIM_BINOver $9k           3.841e-02  1.549e-01   0.248 0.804231
## TIF_BIN1-4 years              -2.044e-01  9.180e-02  -2.226 0.025982 *
## TIF_BIN4-7 years              -4.302e-01  8.854e-02  -4.859 1.18e-06 ***
## TIF_BINOver 7 years           -5.787e-01  9.156e-02  -6.320 2.62e-10 ***
## YOJ_BINLess than 10 years     -5.332e-01  1.659e-01  -3.214 0.001307 **
## YOJ_BINBetween 10-15 years    -5.828e-01  1.605e-01  -3.631 0.000282 ***
## YOJ_BINOver 15 years          -3.052e-01  2.154e-01  -1.417 0.156469
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7445.1  on 6447  degrees of freedom
## Residual deviance: 5718.0  on 6399  degrees of freedom
##   (1713 observations deleted due to missingness)
## AIC: 5816
##
## Number of Fisher Scoring iterations: 5
```

This and the consequent model considers all binned variables plus old variables.

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 862 196
##          1  65 167
##
##                Accuracy : 0.7977
```

```
##                 95% CI : (0.7747, 0.8193)
##    No Information Rate : 0.7186
##    P-Value [Acc > NIR] : 4.259e-11
##
##                  Kappa : 0.438
##
## Mcnemar's Test P-Value : 8.499e-16
##
##            Sensitivity : 0.9299
##            Specificity : 0.4601
##         Pos Pred Value : 0.8147
##         Neg Pred Value : 0.7198
##             Prevalence : 0.7186
##         Detection Rate : 0.6682
##   Detection Prevalence : 0.8202
##      Balanced Accuracy : 0.6950
##
##       'Positive' Class : 0
##
```



Model 5

The next model provides a combination of imputation and binning.

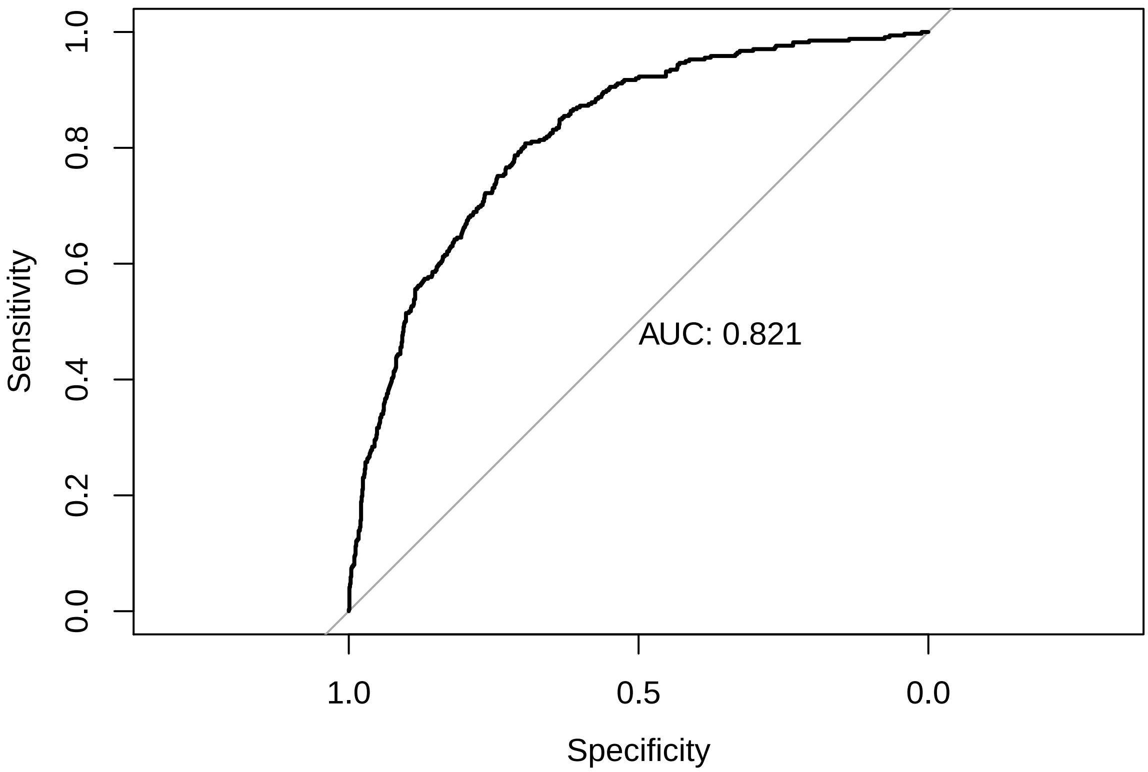
```
##
## iter imp variable
##  1   1  AGE  INCOME  CAR_AGE_BIN  HOME_VAL_BIN  YOJ_BIN
##  2   1  AGE  INCOME  CAR_AGE_BIN  HOME_VAL_BIN  YOJ_BIN
##  3   1  AGE  INCOME  CAR_AGE_BIN  HOME_VAL_BIN  YOJ_BIN
##  4   1  AGE  INCOME  CAR_AGE_BIN  HOME_VAL_BIN  YOJ_BIN
```

```
##   5   1  AGE  INCOME  CAR_AGE_BIN  HOME_VAL_BIN  YOJ_BIN
## call :
## glm.mids(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = insurance_binned_impute)
##
## call1 :
## mice(data = insurance_bins, m = 1, method = "cart")
##
## nmis :
##   TARGET_FLAG    TARGET_AMT           AGE        INCOME       PARENT1
##             0             0             6           445             0
##       MSTATUS           SEX     EDUCATION           JOB      TRAVTIME
##             0             0             0             0             0
##       CAR_USE      BLUEBOOK      CAR_TYPE       RED_CAR      CLM_FREQ
##             0             0             0             0             0
##       REVOKED       MVR_PTS    URBANICITY   CAR_AGE_BIN  HOME_VAL_BIN
##             0             0             0           510           464
## HAS_HOME_KIDS  HAS_KIDSDRIV  OLDCLAIM_BIN       TIF_BIN       YOJ_BIN
##             0             0             0             0           454
##
## analyses :
## [[1]]
##
## Call:  glm(formula = formula, family = family, data = complete(data,
##     i))
##
## Coefficients:
##                    (Intercept)                              AGE
##                     -1.734e+00                       -7.178e-04
##                         INCOME                       PARENT1Yes
##                     -3.449e-06                        2.461e-01
##                     MSTATUSYes                             SEXM
##                     -5.170e-01                        9.158e-02
##            EDUCATIONHigh School  EDUCATIONLess than High School
##                      3.891e-01                        3.798e-01
##                EDUCATIONMasters                     EDUCATIONPhD
##                      1.073e-01                        2.039e-01
##                    JOBClerical                        JOBDoctor
##                      8.246e-02                       -7.537e-01
##                  JOBHome Maker                        JOBLawyer
##                     -2.709e-01                       -2.062e-01
##                     JOBManager                     JOBOther Job
##                     -8.592e-01                       -3.156e-01
##                JOBProfessional                       JOBStudent
##                     -1.531e-01                       -3.632e-01
##                       TRAVTIME                    CAR_USEPrivate
##                      1.488e-02                       -7.493e-01
##                       BLUEBOOK              CAR_TYPEPanel Truck
##                     -2.023e-05                        5.765e-01
##                 CAR_TYPEPickup              CAR_TYPESports Car
##                      5.616e-01                        1.011e+00
##                    CAR_TYPESUV                      CAR_TYPEVan
##                      7.750e-01                        6.148e-01
```

```
##                      RED_CARyes                         CLM_FREQ
##                      -3.817e-03                        5.084e-02
##                      REVOKEDYes                          MVR_PTS
##                       8.913e-01                        9.843e-02
##  URBANICITYHighly Urban/ Urban               CAR_AGE_BINLike New
##                       2.369e+00                        1.287e-01
##              CAR_AGE_BINAverage                   CAR_AGE_BINOld
##                      -6.374e-02                       -7.366e-02
##         HOME_VAL_BIN$50k-$150k          HOME_VAL_BIN$150k-$250k
##                      -3.077e-01                       -2.663e-01
##         HOME_VAL_BINOver $250k              HAS_HOME_KIDSNo kids
##                      -5.013e-01                       -2.195e-01
##    HAS_KIDSDRIVNo kids driving               OLDCLAIM_BIN$0-$3k
##                      -5.669e-01                        3.926e-01
##            OLDCLAIM_BIN$3k-$6k               OLDCLAIM_BIN$6k-$9k
##                       3.579e-01                        4.999e-01
##           OLDCLAIM_BINOver $9k                 TIF_BIN1-4 years
##                       2.028e-02                       -1.924e-01
##               TIF_BIN4-7 years              TIF_BINOver 7 years
##                      -4.310e-01                       -5.888e-01
##      YOJ_BINLess than 10 years      YOJ_BINBetween 10-15 years
##                      -5.673e-01                       -6.194e-01
##           YOJ_BINOver 15 years
##                      -4.101e-01
##
## Degrees of Freedom: 8160 Total (i.e. Null);  8112 Residual
## Null Deviance:       9418
## Residual Deviance: 7250  AIC: 7348

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 889 186
##          1  74 150
##
##                Accuracy : 0.7998
##                  95% CI : (0.777, 0.8213)
##     No Information Rate : 0.7413
##     P-Value [Acc > NIR] : 4.533e-07
##
##                   Kappa : 0.4146
##
##  Mcnemar's Test P-Value : 5.822e-12
##
##             Sensitivity : 0.9232
##             Specificity : 0.4464
##          Pos Pred Value : 0.8270
##          Neg Pred Value : 0.6696
##              Prevalence : 0.7413
##          Detection Rate : 0.6844
##    Detection Prevalence : 0.8276
##       Balanced Accuracy : 0.6848
##
```

```
##        'Positive' Class : 0
##
```



Multiple Linear Regression

Model 1

Below code shows output for preliminary regression modelling insurance payout given that a claim has been predicted. R-squared values are very low, but this assumes that a correct prediction from the binary logistic model has been made.

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = mlr_crash)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -9657  -3165  -1474    574  76279
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     4.075e+03  1.809e+03   2.253   0.0244 *
## KIDSDRIV                       -1.771e+02  3.556e+02  -0.498   0.6185
## AGE                             5.833e-01  2.351e+01   0.025   0.9802
## HOMEKIDS                        2.752e+02  2.295e+02   1.199   0.2306
## YOJ                             1.917e+01  5.463e+01   0.351   0.7256
## INCOME                         -1.510e-02  7.821e-03  -1.930   0.0537 .
## PARENT1Yes                     -9.951e+01  6.469e+02  -0.154   0.8778
## HOME_VAL                        2.230e-03  2.268e-03   0.984   0.3255
## MSTATUSYes                     -1.387e+03  5.662e+02  -2.450   0.0144 *
```

```
## SEXM                             1.816e+03  7.167e+02   2.534   0.0114 *
## EDUCATIONHigh School            -8.578e+02  5.772e+02  -1.486   0.1374
## EDUCATIONLess than High School -1.712e+02  7.149e+02  -0.239   0.8108
## EDUCATIONMasters                 6.457e+02  1.048e+03   0.616   0.5380
## EDUCATIONPhD                     2.938e+03  1.282e+03   2.293   0.0220 *
## JOBClerical                     -1.143e+03  6.452e+02  -1.772   0.0766 .
## JOBDoctor                       -3.784e+03  1.998e+03  -1.894   0.0584 .
## JOBHome Maker                   -1.046e+03  9.995e+02  -1.047   0.2954
## JOBLawyer                       -6.243e+02  1.323e+03  -0.472   0.6370
## JOBManager                      -1.788e+03  1.042e+03  -1.716   0.0864 .
## JOBOther Job                    -4.589e+02  1.304e+03  -0.352   0.7250
## JOBProfessional                  7.702e+02  7.712e+02   0.999   0.3181
## JOBStudent                      -1.059e+03  8.089e+02  -1.309   0.1905
## TRAVTIME                         4.108e+00  1.234e+01   0.333   0.7393
## CAR_USEPrivate                  -2.737e+02  5.849e+02  -0.468   0.6399
## BLUEBOOK                         1.486e-01  3.376e-02   4.402 1.14e-05 ***
## TIF                             -5.847e+00  4.695e+01  -0.125   0.9009
## CAR_TYPEPanel Truck             -2.619e+02  1.053e+03  -0.249   0.8036
## CAR_TYPEPickup                   3.003e+02  6.627e+02   0.453   0.6505
## CAR_TYPESports Car               1.951e+03  8.262e+02   2.361   0.0183 *
## CAR_TYPESUV                      1.657e+03  7.363e+02   2.251   0.0245 *
## CAR_TYPEVan                     -2.228e+02  8.588e+02  -0.259   0.7953
## RED_CARyes                      -3.138e+02  5.511e+02  -0.569   0.5692
## OLDCLAIM                         5.024e-02  2.528e-02   1.987   0.0471 *
## CLM_FREQ                        -2.048e+02  1.749e+02  -1.171   0.2416
## REVOKEDYes                      -1.259e+03  5.850e+02  -2.152   0.0315 *
## MVR_PTS                          8.937e+01  7.564e+01   1.182   0.2375
## CAR_AGE                         -9.797e+01  4.878e+01  -2.009   0.0447 *
## URBANICITYHighly Urban/ Urban   5.991e+01  8.182e+02   0.073   0.9416
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7586 on 1665 degrees of freedom
##   (450 observations deleted due to missingness)
## Multiple R-squared:  0.04273,    Adjusted R-squared:  0.02145
## F-statistic: 2.009 on 37 and 1665 DF,  p-value: 0.000334
```

The R^2 value is very low, around 4%, and many of the variables are not significant.

Model 2

Using our log transformation on certain variables, the results are slightly worse.

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8045  -3199  -1526    438  99546
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     -9715.099   4630.184  -2.098   0.0360 *
## KIDSDRIV                         -186.329    320.282  -0.582   0.5608
```

```
## AGE                             544.526    882.174   0.617   0.5371
## HOMEKIDS                        187.340    209.948   0.892   0.3723
## YOJ                               8.150     61.050   0.133   0.8938
## INCOME                           22.840     96.307   0.237   0.8126
## PARENT1Yes                      331.308    588.943   0.563   0.5738
## HOME_VAL                         58.650     38.287   1.532   0.1257
## MSTATUSYes                     -868.702    509.343  -1.706   0.0882 .
## SEXM                           1212.639    630.947   1.922   0.0547 .
## EDUCATIONHigh School           -457.376    505.973  -0.904   0.3661
## EDUCATIONLess than High School   51.500    635.038   0.081   0.9354
## EDUCATIONMasters                548.316    883.446   0.621   0.5349
## EDUCATIONPhD                   1658.219   1088.609   1.523   0.1278
## JOBClerical                     -85.075    581.159  -0.146   0.8836
## JOBDoctor                     -2759.504   1870.439  -1.475   0.1403
## JOBHome Maker                   -73.493    941.671  -0.078   0.9378
## JOBLawyer                      -249.977   1173.707  -0.213   0.8314
## JOBManager                    -1310.356    904.347  -1.449   0.1475
## JOBOther Job                   -529.041   1140.250  -0.464   0.6427
## JOBProfessional                 509.067    684.161   0.744   0.4569
## JOBStudent                      317.311    799.632   0.397   0.6915
## TRAVTIME                        -51.921    299.067  -0.174   0.8622
## CAR_USEPrivate                 -345.492    522.462  -0.661   0.5085
## BLUEBOOK                       1398.356    328.055   4.263 2.11e-05 ***
## TIF                             -14.903     42.536  -0.350   0.7261
## CAR_TYPEPanel Truck             -29.775    881.064  -0.034   0.9730
## CAR_TYPEPickup                 -136.236    596.552  -0.228   0.8194
## CAR_TYPESports Car             1011.268    735.029   1.376   0.1690
## CAR_TYPESUV                     677.040    643.223   1.053   0.2927
## CAR_TYPEVan                     135.500    762.155   0.178   0.8589
## RED_CARyes                     -192.707    497.240  -0.388   0.6984
## OLDCLAIM                          7.773     67.902   0.114   0.9089
## CLM_FREQ                        -67.375    232.751  -0.289   0.7722
## REVOKEDYes                     -765.210    422.770  -1.810   0.0704 .
## MVR_PTS                         126.448     70.048   1.805   0.0712 .
## CAR_AGE                        -380.023    263.152  -1.444   0.1489
## URBANICITYHighly Urban/ Urban    31.111    755.064   0.041   0.9671
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7695 on 2115 degrees of freedom
## Multiple R-squared:  0.02941,    Adjusted R-squared:  0.01244
## F-statistic: 1.732 on 37 and 2115 DF,  p-value: 0.004147
```

Model 3: Backwards Elimination

Now let's use backwards elimination to remove some of variables that are not significant.

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8045  -3199  -1526    438  99546
##
```

```
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -9715.099   4630.184  -2.098   0.0360 *
## KIDSDRIV                        -186.329    320.282  -0.582   0.5608
## AGE                              544.526    882.174   0.617   0.5371
## HOMEKIDS                         187.340    209.948   0.892   0.3723
## YOJ                                8.150     61.050   0.133   0.8938
## INCOME                            22.840     96.307   0.237   0.8126
## PARENT1Yes                       331.308    588.943   0.563   0.5738
## HOME_VAL                          58.650     38.287   1.532   0.1257
## MSTATUSYes                      -868.702    509.343  -1.706   0.0882 .
## SEXM                            1212.639    630.947   1.922   0.0547 .
## EDUCATIONHigh School            -457.376    505.973  -0.904   0.3661
## EDUCATIONLess than High School    51.500    635.038   0.081   0.9354
## EDUCATIONMasters                 548.316    883.446   0.621   0.5349
## EDUCATIONPhD                    1658.219   1088.609   1.523   0.1278
## JOBClerical                      -85.075    581.159  -0.146   0.8836
## JOBDoctor                      -2759.504   1870.439  -1.475   0.1403
## JOBHome Maker                    -73.493    941.671  -0.078   0.9378
## JOBLawyer                       -249.977   1173.707  -0.213   0.8314
## JOBManager                     -1310.356    904.347  -1.449   0.1475
## JOBOther Job                    -529.041   1140.250  -0.464   0.6427
## JOBProfessional                  509.067    684.161   0.744   0.4569
## JOBStudent                       317.311    799.632   0.397   0.6915
## TRAVTIME                         -51.921    299.067  -0.174   0.8622
## CAR_USEPrivate                  -345.492    522.462  -0.661   0.5085
## BLUEBOOK                        1398.356    328.055   4.263 2.11e-05 ***
## TIF                              -14.903     42.536  -0.350   0.7261
## CAR_TYPEPanel Truck              -29.775    881.064  -0.034   0.9730
## CAR_TYPEPickup                  -136.236    596.552  -0.228   0.8194
## CAR_TYPESports Car              1011.268    735.029   1.376   0.1690
## CAR_TYPESUV                      677.040    643.223   1.053   0.2927
## CAR_TYPEVan                      135.500    762.155   0.178   0.8589
## RED_CARyes                      -192.707    497.240  -0.388   0.6984
## OLDCLAIM                           7.773     67.902   0.114   0.9089
## CLM_FREQ                         -67.375    232.751  -0.289   0.7722
## REVOKEDYes                      -765.210    422.770  -1.810   0.0704 .
## MVR_PTS                          126.448     70.048   1.805   0.0712 .
## CAR_AGE                         -380.023    263.152  -1.444   0.1489
## URBANICITYHighly Urban/ Urban     31.111    755.064   0.041   0.9671
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7695 on 2115 degrees of freedom
## Multiple R-squared:  0.02941,    Adjusted R-squared:  0.01244
## F-statistic: 1.732 on 37 and 2115 DF,  p-value: 0.004147
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME +
##     PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME +
##     CAR_USE + BLUEBOOK + TIF + CAR_TYPE + RED_CAR + CLM_FREQ +
##     REVOKED + MVR_PTS + CAR_AGE + URBANICITY, data = mlr_crash_transf)
##
```

```
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8055  -3195  -1534    449  99520
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -9703.231   4627.944  -2.097   0.0361 *
## KIDSDRIV                        -186.712    320.190  -0.583   0.5599
## AGE                              543.441    881.917   0.616   0.5378
## HOMEKIDS                         187.371    209.899   0.893   0.3721
## YOJ                                8.449     60.979   0.139   0.8898
## INCOME                            22.822     96.285   0.237   0.8127
## PARENT1Yes                       328.742    588.379   0.559   0.5764
## HOME_VAL                          58.642     38.278   1.532   0.1257
## MSTATUSYes                      -869.123    509.211  -1.707   0.0880 .
## SEXM                            1213.494    630.756   1.924   0.0545 .
## EDUCATIONHigh School            -457.887    505.835  -0.905   0.3655
## EDUCATIONLess than High School    51.393    634.890   0.081   0.9355
## EDUCATIONMasters                 543.613    882.285   0.616   0.5379
## EDUCATIONPhD                    1652.076   1087.033   1.520   0.1287
## JOBClerical                      -82.867    580.703  -0.143   0.8865
## JOBDoctor                      -2765.994   1869.144  -1.480   0.1391
## JOBHome Maker                    -69.836    940.909  -0.074   0.9408
## JOBLawyer                       -242.197   1171.465  -0.207   0.8362
## JOBManager                     -1307.098    903.688  -1.446   0.1482
## JOBOther Job                    -522.305   1138.465  -0.459   0.6464
## JOBProfessional                  511.708    683.613   0.749   0.4542
## JOBStudent                       319.696    799.174   0.400   0.6892
## TRAVTIME                         -52.423    298.965  -0.175   0.8608
## CAR_USEPrivate                  -347.085    522.155  -0.665   0.5063
## BLUEBOOK                        1398.320    327.978   4.263  2.1e-05 ***
## TIF                              -14.956     42.524  -0.352   0.7251
## CAR_TYPEPanel Truck              -33.151    880.365  -0.038   0.9700
## CAR_TYPEPickup                  -137.900    596.236  -0.231   0.8171
## CAR_TYPESports Car              1012.421    734.788   1.378   0.1684
## CAR_TYPESUV                      676.299    643.040   1.052   0.2930
## CAR_TYPEVan                      135.417    761.977   0.178   0.8590
## RED_CARyes                      -194.931    496.745  -0.392   0.6948
## CLM_FREQ                         -46.161    140.797  -0.328   0.7431
## REVOKEDYes                      -756.269    415.397  -1.821   0.0688 .
## MVR_PTS                          128.158     68.418   1.873   0.0612 .
## CAR_AGE                         -379.748    263.080  -1.443   0.1490
## URBANICITYHighly Urban/ Urban     31.696    754.871   0.042   0.9665
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7693 on 2116 degrees of freedom
## Multiple R-squared:  0.02941,    Adjusted R-squared:  0.0129
## F-statistic: 1.781 on 36 and 2116 DF,  p-value: 0.003007
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + INCOME +
##     PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME +
```

```
##     CAR_USE + BLUEBOOK + TIF + CAR_TYPE + RED_CAR + CLM_FREQ +
##     REVOKED + MVR_PTS + CAR_AGE + URBANICITY, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8028  -3203  -1530    439  99526
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     -9802.39    4571.21  -2.144   0.0321 *
## KIDSDRIV                         -190.69     318.83  -0.598   0.5498
## AGE                               565.15     867.68   0.651   0.5149
## HOMEKIDS                          193.93     204.45   0.949   0.3430
## INCOME                             30.91      76.57   0.404   0.6865
## PARENT1Yes                        329.39     588.22   0.560   0.5756
## HOME_VAL                           58.81      38.25   1.538   0.1243
## MSTATUSYes                       -860.73     505.48  -1.703   0.0888 .
## SEXM                             1215.25     630.48   1.927   0.0541 .
## EDUCATIONHigh School             -456.40     505.60  -0.903   0.3668
## EDUCATIONLess than High School     57.35     633.28   0.091   0.9278
## EDUCATIONMasters                  544.42     882.06   0.617   0.5372
## EDUCATIONPhD                     1651.22    1086.76   1.519   0.1288
## JOBClerical                       -81.44     580.48  -0.140   0.8884
## JOBDoctor                       -2766.26    1868.71  -1.480   0.1389
## JOBHome Maker                     -71.81     940.58  -0.076   0.9392
## JOBLawyer                        -244.04    1171.12  -0.208   0.8350
## JOBManager                      -1307.12     903.48  -1.447   0.1481
## JOBOther Job                     -524.53    1138.09  -0.461   0.6449
## JOBProfessional                   508.91     683.16   0.745   0.4564
## JOBStudent                        321.71     798.86   0.403   0.6872
## TRAVTIME                          -53.43     298.81  -0.179   0.8581
## CAR_USEPrivate                   -344.52     521.71  -0.660   0.5091
## BLUEBOOK                         1400.31     327.59   4.275    2e-05 ***
## TIF                               -15.01      42.51  -0.353   0.7241
## CAR_TYPEPanel Truck               -39.29     879.05  -0.045   0.9644
## CAR_TYPEPickup                   -138.62     596.07  -0.233   0.8161
## CAR_TYPESports Car               1008.47     734.06   1.374   0.1696
## CAR_TYPESUV                       676.28     642.89   1.052   0.2929
## CAR_TYPEVan                       129.97     760.79   0.171   0.8644
## RED_CARyes                       -195.58     496.61  -0.394   0.6938
## CLM_FREQ                          -46.05     140.76  -0.327   0.7436
## REVOKEDYes                       -753.35     414.77  -1.816   0.0695 .
## MVR_PTS                           128.13      68.40   1.873   0.0612 .
## CAR_AGE                          -380.42     262.97  -1.447   0.1482
## URBANICITYHighly Urban/ Urban      32.33     754.68   0.043   0.9658
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7691 on 2117 degrees of freedom
## Multiple R-squared:  0.0294, Adjusted R-squared:  0.01335
## F-statistic: 1.832 on 35 and 2117 DF,  p-value: 0.002154
```

```
##
## Call:
```

```
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + INCOME +
##     PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME +
##     CAR_USE + BLUEBOOK + TIF + CAR_TYPE + RED_CAR + CLM_FREQ +
##     REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8029  -3200  -1530    442  99526
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9767.63    4497.57  -2.172   0.0300 *
## KIDSDRIV                       -191.06     318.64  -0.600   0.5488
## AGE                             563.91     866.99   0.650   0.5155
## HOMEKIDS                        193.78     204.37   0.948   0.3432
## INCOME                           30.97      76.54   0.405   0.6858
## PARENT1Yes                      329.24     588.07   0.560   0.5756
## HOME_VAL                         58.77      38.23   1.537   0.1244
## MSTATUSYes                     -859.38     504.37  -1.704   0.0886 .
## SEXM                           1214.56     630.13   1.927   0.0541 .
## EDUCATIONHigh School           -456.51     505.48  -0.903   0.3666
## EDUCATIONLess than High School   57.49     633.13   0.091   0.9277
## EDUCATIONMasters                544.35     881.85   0.617   0.5371
## EDUCATIONPhD                   1651.00    1086.49   1.520   0.1288
## JOBClerical                     -83.04     579.13  -0.143   0.8860
## JOBDoctor                     -2764.75    1867.94  -1.480   0.1390
## JOBHome Maker                   -71.56     940.34  -0.076   0.9393
## JOBLawyer                      -244.07    1170.84  -0.208   0.8349
## JOBManager                    -1305.71     902.66  -1.447   0.1482
## JOBOther Job                   -523.68    1137.64  -0.460   0.6453
## JOBProfessional                 508.32     682.86   0.744   0.4567
## JOBStudent                      318.99     796.14   0.401   0.6887
## TRAVTIME                        -54.22     298.16  -0.182   0.8557
## CAR_USEPrivate                 -344.51     521.58  -0.661   0.5090
## BLUEBOOK                       1400.54     327.47   4.277 1.98e-05 ***
## TIF                             -14.97      42.49  -0.352   0.7246
## CAR_TYPEPanel Truck             -38.22     878.48  -0.044   0.9653
## CAR_TYPEPickup                 -138.32     595.89  -0.232   0.8165
## CAR_TYPESports Car             1008.24     733.87   1.374   0.1696
## CAR_TYPESUV                     676.31     642.74   1.052   0.2928
## CAR_TYPEVan                     130.50     760.51   0.172   0.8638
## RED_CARyes                     -195.48     496.49  -0.394   0.6938
## CLM_FREQ                        -45.73     140.53  -0.325   0.7449
## REVOKEDYes                     -752.87     414.51  -1.816   0.0695 .
## MVR_PTS                         128.21      68.36   1.875   0.0609 .
## CAR_AGE                        -380.35     262.91  -1.447   0.1481
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7689 on 2118 degrees of freedom
## Multiple R-squared:  0.0294, Adjusted R-squared:  0.01382
## F-statistic: 1.887 on 34 and 2118 DF,  p-value: 0.001515

##
```

```
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + INCOME +
##     PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + CAR_USE +
##     BLUEBOOK + TIF + CAR_TYPE + RED_CAR + CLM_FREQ + REVOKED +
##     MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7928  -3193  -1536    437  99511
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9919.35    4418.51  -2.245   0.0249 *
## KIDSDRIV                       -190.38     318.54  -0.598   0.5501
## AGE                             561.46     866.69   0.648   0.5172
## HOMEKIDS                        193.67     204.33   0.948   0.3433
## INCOME                           30.55      76.49   0.399   0.6896
## PARENT1Yes                      332.46     587.67   0.566   0.5716
## HOME_VAL                         58.96      38.20   1.543   0.1229
## MSTATUSYes                     -860.93     504.18  -1.708   0.0879 .
## SEXM                           1212.02     629.83   1.924   0.0544 .
## EDUCATIONHigh School           -453.99     505.17  -0.899   0.3689
## EDUCATIONLess than High School   59.11     632.92   0.093   0.9256
## EDUCATIONMasters                542.00     881.56   0.615   0.5387
## EDUCATIONPhD                   1647.94    1086.12   1.517   0.1293
## JOBClerical                     -81.79     578.96  -0.141   0.8877
## JOBDoctor                     -2761.12    1867.40  -1.479   0.1394
## JOBHome Maker                   -74.69     939.97  -0.079   0.9367
## JOBLawyer                      -239.16    1170.26  -0.204   0.8381
## JOBManager                    -1301.37     902.14  -1.443   0.1493
## JOBOther Job                   -517.79    1136.92  -0.455   0.6488
## JOBProfessional                 508.69     682.70   0.745   0.4563
## JOBStudent                      322.09     795.78   0.405   0.6857
## CAR_USEPrivate                 -348.16     521.08  -0.668   0.5041
## BLUEBOOK                       1398.46     327.19   4.274    2e-05 ***
## TIF                             -14.75      42.47  -0.347   0.7284
## CAR_TYPEPanel Truck             -39.82     878.24  -0.045   0.9638
## CAR_TYPEPickup                 -136.54     595.68  -0.229   0.8187
## CAR_TYPESports Car             1009.62     733.66   1.376   0.1689
## CAR_TYPESUV                     673.92     642.46   1.049   0.2943
## CAR_TYPEVan                     133.45     760.16   0.176   0.8607
## RED_CARyes                     -197.06     496.30  -0.397   0.6914
## CLM_FREQ                        -46.24     140.47  -0.329   0.7421
## REVOKEDYes                     -751.98     414.39  -1.815   0.0697 .
## MVR_PTS                         128.03      68.34   1.873   0.0611 .
## CAR_AGE                        -381.09     262.82  -1.450   0.1472
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7688 on 2119 degrees of freedom
## Multiple R-squared:  0.02938,    Adjusted R-squared:  0.01427
## F-statistic: 1.944 on 33 and 2119 DF,  p-value: 0.001059

##
```

```
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK +
##     TIF + CAR_TYPE + RED_CAR + CLM_FREQ + REVOKED + MVR_PTS +
##     CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7925  -3197  -1545    443  99526
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  -9694.85    4381.75  -2.213   0.0270 *
## KIDSDRIV                      -185.98     318.29  -0.584   0.5591
## AGE                            564.77     866.48   0.652   0.5146
## HOMEKIDS                       192.47     204.26   0.942   0.3462
## PARENT1Yes                     326.40     587.36   0.556   0.5785
## HOME_VAL                        59.53      38.17   1.560   0.1190
## MSTATUSYes                    -866.79     503.87  -1.720   0.0855 .
## SEXM                          1214.06     629.69   1.928   0.0540 .
## EDUCATIONHigh School          -457.37     505.00  -0.906   0.3652
## EDUCATIONLess than High School   39.79     630.95   0.063   0.9497
## EDUCATIONMasters               551.82     881.04   0.626   0.5312
## EDUCATIONPhD                  1658.08    1085.60   1.527   0.1268
## JOBClerical                    -97.88     577.44  -0.170   0.8654
## JOBDoctor                    -2783.28    1866.21  -1.491   0.1360
## JOBHome Maker                 -292.97     764.65  -0.383   0.7017
## JOBLawyer                     -254.76    1169.38  -0.218   0.8276
## JOBManager                   -1308.39     901.79  -1.451   0.1470
## JOBOther Job                  -521.56    1136.66  -0.459   0.6464
## JOBProfessional                502.63     682.39   0.737   0.4615
## JOBStudent                     129.67     633.27   0.205   0.8378
## CAR_USEPrivate                -337.81     520.33  -0.649   0.5163
## BLUEBOOK                      1408.77     326.11   4.320 1.63e-05 ***
## TIF                            -15.27      42.44  -0.360   0.7191
## CAR_TYPEPanel Truck            -30.76     877.77  -0.035   0.9721
## CAR_TYPEPickup                -125.32     594.89  -0.211   0.8332
## CAR_TYPESports Car            1007.17     733.49   1.373   0.1699
## CAR_TYPESUV                    682.65     641.96   1.063   0.2877
## CAR_TYPEVan                    139.30     759.87   0.183   0.8546
## RED_CARyes                    -199.44     496.16  -0.402   0.6878
## CLM_FREQ                       -46.11     140.44  -0.328   0.7427
## REVOKEDYes                    -752.76     414.30  -1.817   0.0694 .
## MVR_PTS                        126.28      68.18   1.852   0.0642 .
## CAR_AGE                       -380.99     262.76  -1.450   0.1472
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7686 on 2120 degrees of freedom
## Multiple R-squared:  0.02931,    Adjusted R-squared:  0.01466
## F-statistic:     2 on 32 and 2120 DF,  p-value: 0.0007551
```

```
##
## Call:
```

```
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK +
##     TIF + CAR_TYPE + RED_CAR + REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7934  -3210  -1541    443  99469
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9717.22    4380.30  -2.218   0.0266 *
## KIDSDRIV                       -187.09     318.20  -0.588   0.5566
## AGE                             560.79     866.21   0.647   0.5174
## HOMEKIDS                        192.96     204.21   0.945   0.3448
## PARENT1Yes                      327.70     587.22   0.558   0.5769
## HOME_VAL                         59.68      38.16   1.564   0.1180
## MSTATUSYes                     -868.05     503.75  -1.723   0.0850 .
## SEXM                           1215.55     629.54   1.931   0.0536 .
## EDUCATIONHigh School           -455.67     504.87  -0.903   0.3669
## EDUCATIONLess than High School   42.80     630.75   0.068   0.9459
## EDUCATIONMasters                546.87     880.72   0.621   0.5347
## EDUCATIONPhD                   1655.60    1085.35   1.525   0.1273
## JOBClerical                     -98.34     577.31  -0.170   0.8648
## JOBDoctor                     -2814.40    1863.41  -1.510   0.1311
## JOBHome Maker                  -294.97     764.46  -0.386   0.6996
## JOBLawyer                      -238.46    1168.08  -0.204   0.8383
## JOBManager                    -1296.96     900.93  -1.440   0.1501
## JOBOther Job                   -517.27    1136.35  -0.455   0.6490
## JOBProfessional                 503.33     682.25   0.738   0.4607
## JOBStudent                      131.22     633.12   0.207   0.8358
## CAR_USEPrivate                 -335.11     520.16  -0.644   0.5195
## BLUEBOOK                       1409.19     326.04   4.322 1.62e-05 ***
## TIF                             -15.71      42.41  -0.370   0.7111
## CAR_TYPEPanel Truck             -29.39     877.58  -0.033   0.9733
## CAR_TYPEPickup                 -127.40     594.74  -0.214   0.8304
## CAR_TYPESports Car             1000.79     733.08   1.365   0.1723
## CAR_TYPESUV                     683.27     641.82   1.065   0.2872
## CAR_TYPEVan                     143.65     759.59   0.189   0.8500
## RED_CARyes                     -202.05     495.99  -0.407   0.6838
## REVOKEDYes                     -754.20     414.19  -1.821   0.0688 .
## MVR_PTS                         119.70      65.16   1.837   0.0663 .
## CAR_AGE                        -385.16     262.40  -1.468   0.1423
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7685 on 2121 degrees of freedom
## Multiple R-squared:  0.02926,    Adjusted R-squared:  0.01507
## F-statistic: 2.062 on 31 and 2121 DF,  p-value: 0.0005236
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK +
##     CAR_TYPE + RED_CAR + REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
```

```
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7929  -3210  -1538    442  99523
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9820.06    4370.60  -2.247   0.0248 *
## KIDSDRIV                       -186.88     318.14  -0.587   0.5570
## AGE                             563.78     866.00   0.651   0.5151
## HOMEKIDS                        192.10     204.16   0.941   0.3468
## PARENT1Yes                      332.02     586.99   0.566   0.5717
## HOME_VAL                         59.66      38.15   1.564   0.1180
## MSTATUSYes                     -859.82     503.16  -1.709   0.0876 .
## SEXM                           1216.81     629.40   1.933   0.0533 .
## EDUCATIONHigh School           -457.18     504.75  -0.906   0.3652
## EDUCATIONLess than High School   41.75     630.61   0.066   0.9472
## EDUCATIONMasters                542.75     880.47   0.616   0.5377
## EDUCATIONPhD                   1653.85    1085.12   1.524   0.1276
## JOBClerical                    -104.83     576.93  -0.182   0.8558
## JOBDoctor                     -2798.33    1862.52  -1.502   0.1331
## JOBHome Maker                  -294.00     764.30  -0.385   0.7005
## JOBLawyer                      -232.83    1167.74  -0.199   0.8420
## JOBManager                    -1294.47     900.72  -1.437   0.1508
## JOBOther Job                   -520.50    1136.08  -0.458   0.6469
## JOBProfessional                 499.74     682.04   0.733   0.4638
## JOBStudent                      134.49     632.93   0.212   0.8317
## CAR_USEPrivate                 -323.75     519.14  -0.624   0.5329
## BLUEBOOK                       1409.68     325.97   4.325  1.6e-05 ***
## CAR_TYPEPanel Truck             -22.29     877.19  -0.025   0.9797
## CAR_TYPEPickup                 -125.55     594.59  -0.211   0.8328
## CAR_TYPESports Car              997.34     732.87   1.361   0.1737
## CAR_TYPESUV                     680.38     641.64   1.060   0.2891
## CAR_TYPEVan                     146.89     759.39   0.193   0.8466
## RED_CARyes                     -200.26     495.87  -0.404   0.6864
## REVOKEDYes                     -751.21     414.03  -1.814   0.0698 .
## MVR_PTS                         120.49      65.11   1.851   0.0644 .
## CAR_AGE                        -384.91     262.35  -1.467   0.1425
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7683 on 2122 degrees of freedom
## Multiple R-squared:  0.0292, Adjusted R-squared:  0.01547
## F-statistic: 2.127 on 30 and 2122 DF,  p-value: 0.0003608
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK +
##     CAR_TYPE + REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7921  -3209  -1542    438  99449
```

```
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9915.44    4363.36  -2.272   0.0232 *
## KIDSDRIV                       -184.70     318.03  -0.581   0.5615
## AGE                             578.39     865.07   0.669   0.5038
## HOMEKIDS                        192.45     204.12   0.943   0.3459
## PARENT1Yes                      333.44     586.86   0.568   0.5700
## HOME_VAL                         59.81      38.14   1.568   0.1170
## MSTATUSYes                     -860.83     503.05  -1.711   0.0872 .
## SEXM                           1104.16     564.11   1.957   0.0504 .
## EDUCATIONHigh School           -450.55     504.38  -0.893   0.3718
## EDUCATIONLess than High School   48.79     630.25   0.077   0.9383
## EDUCATIONMasters                548.71     880.18   0.623   0.5331
## EDUCATIONPhD                   1666.91    1084.42   1.537   0.1244
## JOBClerical                     -97.36     576.52  -0.169   0.8659
## JOBDoctor                     -2807.36    1862.02  -1.508   0.1318
## JOBHome Maker                  -292.72     764.14  -0.383   0.7017
## JOBLawyer                      -234.95    1167.50  -0.201   0.8405
## JOBManager                    -1300.32     900.42  -1.444   0.1489
## JOBOther Job                   -535.77    1135.23  -0.472   0.6370
## JOBProfessional                 502.88     681.86   0.738   0.4609
## JOBStudent                      129.31     632.67   0.204   0.8381
## CAR_USEPrivate                 -327.47     518.96  -0.631   0.5281
## BLUEBOOK                       1412.50     325.83   4.335 1.53e-05 ***
## CAR_TYPEPanel Truck             -34.26     876.52  -0.039   0.9688
## CAR_TYPEPickup                 -129.40     594.40  -0.218   0.8277
## CAR_TYPESports Car             1000.28     732.69   1.365   0.1723
## CAR_TYPESUV                     688.83     641.18   1.074   0.2828
## CAR_TYPEVan                     142.73     759.17   0.188   0.8509
## REVOKEDYes                     -748.97     413.91  -1.809   0.0705 .
## MVR_PTS                         119.73      65.07   1.840   0.0659 .
## CAR_AGE                        -383.29     262.26  -1.461   0.1440
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7682 on 2123 degrees of freedom
## Multiple R-squared:  0.02912,    Adjusted R-squared:  0.01586
## F-statistic: 2.196 on 29 and 2123 DF,  p-value: 0.0002469
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + AGE + HOMEKIDS + HOME_VAL +
##     MSTATUS + SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK + CAR_TYPE +
##     REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8001  -3182  -1544    429  99508
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -9645.55    4336.73  -2.224   0.0262 *
## KIDSDRIV                       -177.34     317.72  -0.558   0.5768
```

```
## AGE                               522.09     859.24   0.608   0.5435
## HOMEKIDS                          244.05     182.77   1.335   0.1819
## HOME_VAL                           59.37      38.13   1.557   0.1196
## MSTATUSYes                      -1008.08     431.08  -2.338   0.0195 *
## SEXM                             1101.07     563.99   1.952   0.0510 .
## EDUCATIONHigh School             -443.57     504.15  -0.880   0.3791
## EDUCATIONLess than High School     50.65     630.14   0.080   0.9359
## EDUCATIONMasters                  533.07     879.61   0.606   0.5446
## EDUCATIONPhD                     1656.38    1084.09   1.528   0.1267
## JOBClerical                       -96.79     576.43  -0.168   0.8667
## JOBDoctor                       -2822.82    1861.53  -1.516   0.1296
## JOBHome Maker                    -291.98     764.02  -0.382   0.7024
## JOBLawyer                        -211.22    1166.57  -0.181   0.8563
## JOBManager                      -1282.01     899.70  -1.425   0.1543
## JOBOther Job                     -519.14    1134.67  -0.458   0.6473
## JOBProfessional                   518.77     681.18   0.762   0.4464
## JOBStudent                        126.15     632.54   0.199   0.8419
## CAR_USEPrivate                   -322.17     518.79  -0.621   0.5347
## BLUEBOOK                         1415.19     325.74   4.345 1.46e-05 ***
## CAR_TYPEPanel Truck               -44.90     876.18  -0.051   0.9591
## CAR_TYPEPickup                   -133.98     594.25  -0.225   0.8216
## CAR_TYPESports Car               1007.48     732.47   1.375   0.1691
## CAR_TYPESUV                       690.69     641.06   1.077   0.2814
## CAR_TYPEVan                       134.90     758.92   0.178   0.8589
## REVOKEDYes                       -754.18     413.75  -1.823   0.0685 .
## MVR_PTS                           120.97      65.02   1.860   0.0630 .
## CAR_AGE                          -379.67     262.15  -1.448   0.1477
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7680 on 2124 degrees of freedom
## Multiple R-squared:  0.02898,    Adjusted R-squared:  0.01618
## F-statistic: 2.264 on 28 and 2124 DF,  p-value: 0.0001746
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ AGE + HOMEKIDS + HOME_VAL + MSTATUS +
##     SEX + EDUCATION + JOB + CAR_USE + BLUEBOOK + CAR_TYPE + REVOKED +
##     MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8078  -3178  -1530    459  99524
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     -9136.73    4239.16  -2.155   0.0312 *
## AGE                               400.50     831.03   0.482   0.6299
## HOMEKIDS                          189.67     154.61   1.227   0.2200
## HOME_VAL                           59.59      38.12   1.563   0.1181
## MSTATUSYes                      -1006.39     431.00  -2.335   0.0196 *
## SEXM                             1106.98     563.80   1.963   0.0497 *
## EDUCATIONHigh School             -436.94     503.93  -0.867   0.3860
## EDUCATIONLess than High School     51.04     630.04   0.081   0.9354
```

```
## EDUCATIONMasters                 511.06     878.58   0.582   0.5608
## EDUCATIONPhD                    1645.52    1083.74   1.518   0.1291
## JOBClerical                      -88.08     576.12  -0.153   0.8785
## JOBDoctor                      -2799.95    1860.77  -1.505   0.1325
## JOBHome Maker                   -279.85     763.59  -0.366   0.7140
## JOBLawyer                       -190.63    1165.80  -0.164   0.8701
## JOBManager                     -1314.95     897.62  -1.465   0.1431
## JOBOther Job                    -510.27    1134.37  -0.450   0.6529
## JOBProfessional                  510.66     680.91   0.750   0.4534
## JOBStudent                       132.06     632.35   0.209   0.8346
## CAR_USEPrivate                  -335.48     518.16  -0.647   0.5174
## BLUEBOOK                        1409.23     325.51   4.329 1.57e-05 ***
## CAR_TYPEPanel Truck              -51.81     875.95  -0.059   0.9528
## CAR_TYPEPickup                  -139.97     594.06  -0.236   0.8138
## CAR_TYPESports Car              1016.08     732.19   1.388   0.1654
## CAR_TYPESUV                      699.27     640.78   1.091   0.2753
## CAR_TYPEVan                      143.98     758.63   0.190   0.8495
## REVOKEDYes                      -765.21     413.21  -1.852   0.0642 .
## MVR_PTS                          120.13      64.99   1.848   0.0647 .
## CAR_AGE                         -374.75     261.96  -1.431   0.1527
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7679 on 2125 degrees of freedom
## Multiple R-squared:  0.02883,    Adjusted R-squared:  0.01649
## F-statistic: 2.337 on 27 and 2125 DF,  p-value: 0.0001215
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOMEKIDS + HOME_VAL + MSTATUS + SEX +
##     EDUCATION + JOB + CAR_USE + BLUEBOOK + CAR_TYPE + REVOKED +
##     MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8151  -3184  -1523    459  99553
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -7876.66    3336.17  -2.361   0.0183 *
## HOMEKIDS                         160.41     142.16   1.128   0.2593
## HOME_VAL                          60.39      38.08   1.586   0.1129
## MSTATUSYes                      -987.07     429.06  -2.301   0.0215 *
## SEXM                            1132.80     561.15   2.019   0.0436 *
## EDUCATIONHigh School            -436.65     503.84  -0.867   0.3862
## EDUCATIONLess than High School    58.18     629.75   0.092   0.9264
## EDUCATIONMasters                 528.50     877.68   0.602   0.5471
## EDUCATIONPhD                    1672.96    1082.05   1.546   0.1222
## JOBClerical                     -107.99     574.53  -0.188   0.8509
## JOBDoctor                      -2761.44    1858.72  -1.486   0.1375
## JOBHome Maker                   -263.45     762.69  -0.345   0.7298
## JOBLawyer                       -163.91    1164.27  -0.141   0.8881
## JOBManager                     -1310.21     897.41  -1.460   0.1444
## JOBOther Job                    -506.24    1134.14  -0.446   0.6554
```

```
## JOBProfessional                 522.82     680.32   0.768   0.4423
## JOBStudent                      129.66     632.22   0.205   0.8375
## CAR_USEPrivate                 -331.96     518.02  -0.641   0.5217
## BLUEBOOK                       1432.35     321.90   4.450 9.04e-06 ***
## CAR_TYPEPanel Truck             -68.44     875.11  -0.078   0.9377
## CAR_TYPEPickup                 -139.29     593.95  -0.235   0.8146
## CAR_TYPESports Car             1045.93     729.43   1.434   0.1517
## CAR_TYPESUV                     731.48     637.17   1.148   0.2511
## CAR_TYPEVan                     139.25     758.43   0.184   0.8543
## REVOKEDYes                     -757.71     412.84  -1.835   0.0666 .
## MVR_PTS                         119.52      64.97   1.840   0.0660 .
## CAR_AGE                        -374.56     261.91  -1.430   0.1528
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7678 on 2126 degrees of freedom
## Multiple R-squared:  0.02873,    Adjusted R-squared:  0.01685
## F-statistic: 2.419 on 26 and 2126 DF,  p-value: 8.117e-05
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOMEKIDS + HOME_VAL + MSTATUS + SEX +
##     EDUCATION + JOB + BLUEBOOK + CAR_TYPE + REVOKED + MVR_PTS +
##     CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8303  -3189  -1522    430  99678
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -8109.987   3315.783  -2.446   0.0145 *
## HOMEKIDS                         156.882    142.037   1.105   0.2695
## HOME_VAL                          61.055     38.057   1.604   0.1088
## MSTATUSYes                      -991.309    428.947  -2.311   0.0209 *
## SEXM                            1125.415    560.949   2.006   0.0450 *
## EDUCATIONHigh School            -433.541    503.748  -0.861   0.3895
## EDUCATIONLess than High School   -39.142    611.076  -0.064   0.9489
## EDUCATIONMasters                 528.314    877.554   0.602   0.5472
## EDUCATIONPhD                    1680.341   1081.838   1.553   0.1205
## JOBClerical                     -274.495    512.351  -0.536   0.5922
## JOBDoctor                      -3026.832   1811.747  -1.671   0.0949 .
## JOBHome Maker                   -452.065    703.509  -0.643   0.5206
## JOBLawyer                       -419.505   1093.662  -0.384   0.7013
## JOBManager                     -1497.993    848.098  -1.766   0.0775 .
## JOBOther Job                    -596.233   1125.255  -0.530   0.5963
## JOBProfessional                  348.994    623.820   0.559   0.5759
## JOBStudent                        80.140    627.392   0.128   0.8984
## BLUEBOOK                        1446.868    321.058   4.507 6.95e-06 ***
## CAR_TYPEPanel Truck              121.834    823.083   0.148   0.8823
## CAR_TYPEPickup                    -7.405    557.076  -0.013   0.9894
## CAR_TYPESports Car              1029.205    728.861   1.412   0.1581
## CAR_TYPESUV                      723.797    636.964   1.136   0.2559
## CAR_TYPEVan                      263.545    733.104   0.359   0.7193
```

```
## REVOKEDYes                      -747.782    412.490  -1.813   0.0700 .
## MVR_PTS                          122.581     64.785   1.892   0.0586 .
## CAR_AGE                         -376.213    261.859  -1.437   0.1509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7677 on 2127 degrees of freedom
## Multiple R-squared:  0.02854,    Adjusted R-squared:  0.01712
## F-statistic:   2.5 on 25 and 2127 DF,  p-value: 5.655e-05
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOMEKIDS + HOME_VAL + MSTATUS + SEX +
##     EDUCATION + BLUEBOOK + CAR_TYPE + REVOKED + MVR_PTS + CAR_AGE,
##     data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8096  -3207  -1527    378 100059
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -8094.118   3197.807  -2.531   0.0114 *
## HOMEKIDS                        142.794    141.266   1.011   0.3122
## HOME_VAL                         55.348     34.571   1.601   0.1095
## MSTATUSYes                     -910.378    410.811  -2.216   0.0268 *
## SEXM                           1133.015    552.890   2.049   0.0406 *
## EDUCATIONHigh School           -427.565    474.626  -0.901   0.3678
## EDUCATIONLess than High School  -70.085    567.078  -0.124   0.9017
## EDUCATIONMasters                 29.144    556.698   0.052   0.9583
## EDUCATIONPhD                    552.367    780.792   0.707   0.4794
## BLUEBOOK                       1433.180    313.328   4.574 5.06e-06 ***
## CAR_TYPEPanel Truck             245.320    787.406   0.312   0.7554
## CAR_TYPEPickup                   -0.581    554.157  -0.001   0.9992
## CAR_TYPESports Car              952.486    727.235   1.310   0.1904
## CAR_TYPESUV                     664.736    635.728   1.046   0.2959
## CAR_TYPEVan                     281.676    720.588   0.391   0.6959
## REVOKEDYes                     -681.358    411.172  -1.657   0.0976 .
## MVR_PTS                         127.543     64.525   1.977   0.0482 *
## CAR_AGE                        -365.036    261.332  -1.397   0.1626
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7675 on 2135 degrees of freedom
## Multiple R-squared:  0.02527,    Adjusted R-squared:  0.01751
## F-statistic: 3.256 on 17 and 2135 DF,  p-value: 7.297e-06
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOMEKIDS + HOME_VAL + MSTATUS + SEX +
##     BLUEBOOK + CAR_TYPE + REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7893  -3212  -1557    410 100200
```

```
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -8654.216   3095.823  -2.795  0.00523 **
## HOMEKIDS              135.427    140.861   0.961  0.33645
## HOME_VAL               58.351     34.436   1.694  0.09032 .
## MSTATUSYes           -963.913    407.931  -2.363  0.01822 *
## SEXM                 1116.708    552.118   2.023  0.04324 *
## BLUEBOOK             1452.995    311.031   4.672 3.18e-06 ***
## CAR_TYPEPanel Truck   314.423    783.769   0.401  0.68834
## CAR_TYPEPickup         -2.979    553.431  -0.005  0.99571
## CAR_TYPESports Car    959.028    725.935   1.321  0.18661
## CAR_TYPESUV           638.714    634.744   1.006  0.31441
## CAR_TYPEVan           336.811    717.794   0.469  0.63895
## REVOKEDYes           -697.721    410.676  -1.699  0.08947 .
## MVR_PTS               129.059     64.464   2.002  0.04541 *
## CAR_AGE              -226.895    209.010  -1.086  0.27779
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7671 on 2139 degrees of freedom
## Multiple R-squared:  0.02439,    Adjusted R-squared:  0.01846
## F-statistic: 4.114 on 13 and 2139 DF,  p-value: 9.195e-07
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOMEKIDS + HOME_VAL + MSTATUS + SEX +
##     BLUEBOOK + REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7506  -3167  -1547    392 100397
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7682.75    2396.42  -3.206  0.00137 **
## HOMEKIDS      126.65     140.53   0.901  0.36755
## HOME_VAL       59.05      34.40   1.717  0.08621 .
## MSTATUSYes   -948.00     407.02  -2.329  0.01995 *
## SEXM          666.22     335.54   1.986  0.04721 *
## BLUEBOOK     1410.39     255.13   5.528 3.63e-08 ***
## REVOKEDYes   -695.80     409.88  -1.698  0.08973 .
## MVR_PTS       128.90      64.30   2.005  0.04512 *
## CAR_AGE      -217.32     208.65  -1.042  0.29775
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7667 on 2144 degrees of freedom
## Multiple R-squared:  0.02321,    Adjusted R-squared:  0.01957
## F-statistic: 6.369 on 8 and 2144 DF,  p-value: 3.381e-08
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOME_VAL + MSTATUS + SEX + BLUEBOOK +
##     REVOKED + MVR_PTS + CAR_AGE, data = mlr_crash_transf)
```

```
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7364  -3150  -1572    412 100285
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7400.44    2375.76  -3.115  0.00186 **
## HOME_VAL       57.02      34.32   1.661  0.09682 .
## MSTATUSYes   -914.64     405.32  -2.257  0.02413 *
## SEXM          637.15     333.97   1.908  0.05655 .
## BLUEBOOK     1395.31     254.57   5.481 4.73e-08 ***
## REVOKEDYes   -677.87     409.37  -1.656  0.09790 .
## MVR_PTS       130.71      64.27   2.034  0.04209 *
## CAR_AGE      -227.51     208.34  -1.092  0.27495
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7667 on 2145 degrees of freedom
## Multiple R-squared:  0.02284,    Adjusted R-squared:  0.01966
## F-statistic: 7.164 on 7 and 2145 DF,  p-value: 1.71e-08
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ HOME_VAL + MSTATUS + SEX + BLUEBOOK +
##     REVOKED + MVR_PTS, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7435  -3176  -1595    386 100375
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7489.85    2374.46  -3.154  0.00163 **
## HOME_VAL       55.56      34.30   1.620  0.10540
## MSTATUSYes   -887.80     404.59  -2.194  0.02832 *
## SEXM          653.55     333.65   1.959  0.05026 .
## BLUEBOOK     1358.16     252.30   5.383 8.12e-08 ***
## REVOKEDYes   -682.24     409.37  -1.667  0.09575 .
## MVR_PTS       133.92      64.20   2.086  0.03711 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7667 on 2146 degrees of freedom
## Multiple R-squared:  0.0223, Adjusted R-squared:  0.01957
## F-statistic: 8.158 on 6 and 2146 DF,  p-value: 9.631e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ MSTATUS + SEX + BLUEBOOK + REVOKED +
##     MVR_PTS, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7042  -3176  -1561    401 100457
```

```
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7646.12    2373.39  -3.222  0.00129 **
## MSTATUSYes   -510.63     331.01  -1.543  0.12306
## SEXM          652.64     333.77   1.955  0.05067 .
## BLUEBOOK     1400.78     251.02   5.580  2.7e-08 ***
## REVOKEDYes   -710.83     409.15  -1.737  0.08247 .
## MVR_PTS       128.56      64.14   2.004  0.04516 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7670 on 2147 degrees of freedom
## Multiple R-squared:  0.02111,    Adjusted R-squared:  0.01883
## F-statistic: 9.258 on 5 and 2147 DF,  p-value: 9.836e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ SEX + BLUEBOOK + REVOKED + MVR_PTS,
##     data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7317  -3180  -1617    423 100195
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8002.80    2362.86  -3.387  0.00072 ***
## SEXM          645.74     333.85   1.934  0.05322 .
## BLUEBOOK     1411.85     251.00   5.625  2.1e-08 ***
## REVOKEDYes   -690.94     409.08  -1.689  0.09136 .
## MVR_PTS       129.43      64.16   2.017  0.04378 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7672 on 2148 degrees of freedom
## Multiple R-squared:  0.02002,    Adjusted R-squared:  0.0182
## F-statistic: 10.97 on 4 and 2148 DF,  p-value: 8.306e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ SEX + BLUEBOOK + MVR_PTS, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7181  -3173  -1607    348 100329
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8153.34    2362.20  -3.452 0.000568 ***
## SEXM          648.01     333.99   1.940 0.052483 .
## BLUEBOOK     1412.22     251.11   5.624 2.11e-08 ***
## MVR_PTS       131.00      64.18   2.041 0.041360 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 7676 on 2149 degrees of freedom
## Multiple R-squared:  0.01872,    Adjusted R-squared:  0.01735
## F-statistic: 13.66 on 3 and 2149 DF,  p-value: 7.883e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7511  -3151  -1545    328 100673
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8251.14    2363.18  -3.492  0.00049 ***
## BLUEBOOK     1453.68     250.36   5.806 7.33e-09 ***
## MVR_PTS       130.32      64.22   2.029  0.04256 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7681 on 2150 degrees of freedom
## Multiple R-squared:  0.017,  Adjusted R-squared:  0.01609
## F-statistic: 18.59 on 2 and 2150 DF,  p-value: 9.889e-09
```

Model 4: Forward Elimination

Now let's use forward addition to add of variables one at a time.

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7181  -3173  -1607    348 100329
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8153.34    2362.20  -3.452 0.000568 ***
## BLUEBOOK     1412.22     251.11   5.624 2.11e-08 ***
## MVR_PTS       131.00      64.18   2.041 0.041360 *
## SEXM          648.01     333.99   1.940 0.052483 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7676 on 2149 degrees of freedom
## Multiple R-squared:  0.01872,    Adjusted R-squared:  0.01735
## F-statistic: 13.66 on 3 and 2149 DF,  p-value: 7.883e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS,
##     data = mlr_crash_transf)
##
## Residuals:
```

```
##    Min     1Q Median     3Q    Max
##  -6912  -3152  -1537    329 100585
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7813.51    2372.55  -3.293  0.00101 **
## BLUEBOOK     1401.56     251.14   5.581  2.7e-08 ***
## MVR_PTS       130.20      64.16   2.029  0.04256 *
## SEXM          654.74     333.93   1.961  0.05004 .
## MSTATUSYes   -492.51     331.00  -1.488  0.13691
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7674 on 2148 degrees of freedom
## Multiple R-squared:  0.01973,    Adjusted R-squared:  0.0179
## F-statistic: 10.81 on 4 and 2148 DF,  p-value: 1.127e-08
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS +
##     HOME_VAL, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7317  -3147  -1567    342 100494
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7643.27    2373.65  -3.220   0.0013 **
## BLUEBOOK     1357.01     252.40   5.376 8.43e-08 ***
## MVR_PTS       135.73      64.22   2.113   0.0347 *
## SEXM          655.60     333.78   1.964   0.0496 *
## MSTATUSYes   -887.17     404.76  -2.192   0.0285 *
## HOME_VAL       58.03      34.28   1.693   0.0907 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7670 on 2147 degrees of freedom
## Multiple R-squared:  0.02104,    Adjusted R-squared:  0.01876
## F-statistic: 9.227 on 5 and 2147 DF,  p-value: 1.057e-08
```

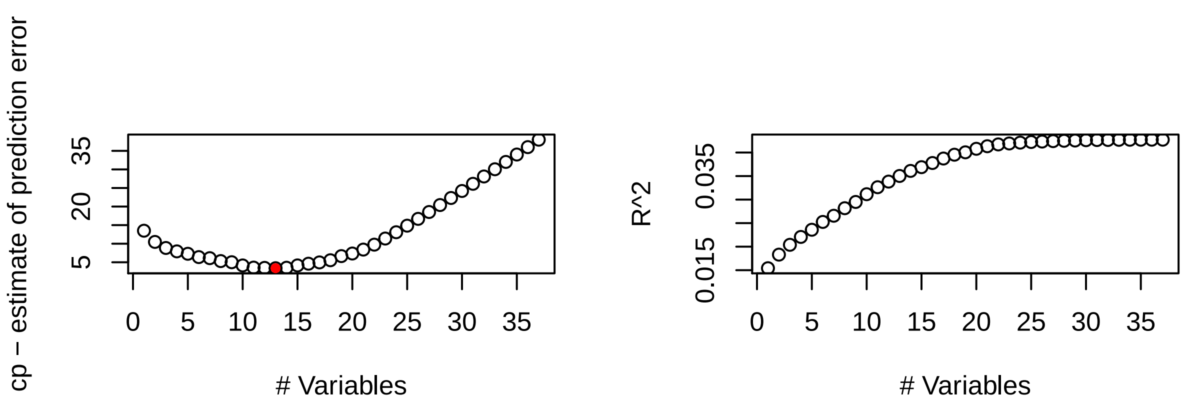
```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS +
##     HOME_VAL + REVOKED, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7435  -3176  -1595    386 100375
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7489.85    2374.46  -3.154  0.00163 **
## BLUEBOOK     1358.16     252.30   5.383 8.12e-08 ***
## MVR_PTS       133.92      64.20   2.086  0.03711 *
```

```
## SEXM          653.55     333.65   1.959  0.05026 .
## MSTATUSYes   -887.80     404.59  -2.194  0.02832 *
## HOME_VAL       55.56      34.30   1.620  0.10540
## REVOKEDYes   -682.24     409.37  -1.667  0.09575 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7667 on 2146 degrees of freedom
## Multiple R-squared:  0.0223, Adjusted R-squared:  0.01957
## F-statistic: 8.158 on 6 and 2146 DF,  p-value: 9.631e-09
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS +
##     HOME_VAL + REVOKED + CAR_AGE, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7364  -3150  -1572    412 100285
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7400.44    2375.76  -3.115  0.00186 **
## BLUEBOOK     1395.31     254.57   5.481 4.73e-08 ***
## MVR_PTS       130.71      64.27   2.034  0.04209 *
## SEXM          637.15     333.97   1.908  0.05655 .
## MSTATUSYes   -914.64     405.32  -2.257  0.02413 *
## HOME_VAL       57.02      34.32   1.661  0.09682 .
## REVOKEDYes   -677.87     409.37  -1.656  0.09790 .
## CAR_AGE      -227.51     208.34  -1.092  0.27495
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7667 on 2145 degrees of freedom
## Multiple R-squared:  0.02284,    Adjusted R-squared:  0.01966
## F-statistic: 7.164 on 7 and 2145 DF,  p-value: 1.71e-08
```

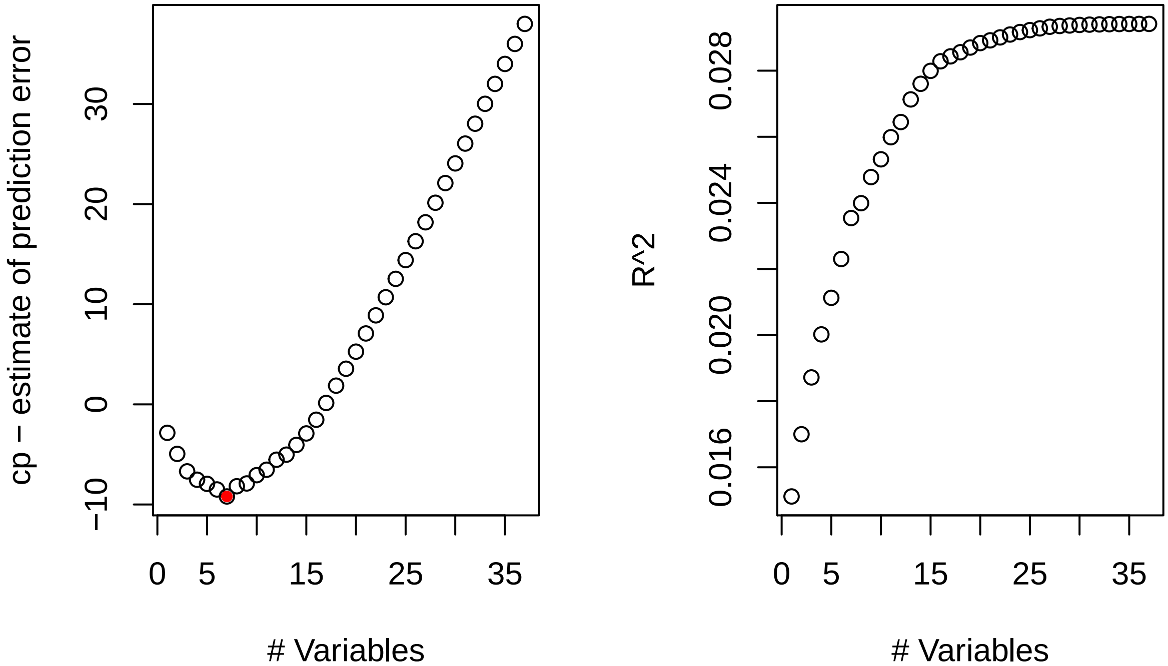
Model 5: Picking the best model using Leaps

The function, *regsubsets()*, will go through iterations to find the best model using parameters = 1,2,3,4,… n. Here we see the model with 13 variables (represented by the red dot) had the lowest cp, which indicates the best model. The R^2 remains to be around 3.5% from about 13 variables and higher, which is extremely low.



Model 6:

Using the regsubsets function and our data that includes log transformations, we see it suggests a model with 7 variables is best look at the cp value.



Using the transformed variables, we will choose the model that has 7 parameters since the R^2 value doesn't change by much as the number of parameters increases. This gives us the following equation:

```
##     (Intercept)      MSTATUSYes    EDUCATIONPhD       JOBDoctor      JOBManager
##    4857.7855103    -866.2249453    2008.6181953   -3283.3214513   -1358.0216839
## JOBProfessional        BLUEBOOK         CAR_AGE
##    1083.6185705       0.1127877     -67.5694404
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ MSTATUS + JOB + BLUEBOOK + CAR_AGE +
##     EDUCATION, data = mlr_crash_transf)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -7308  -3123  -1531    374 100678
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       -5467.5     2656.6  -2.058   0.0397 *
## MSTATUSYes                         -491.1      334.2  -1.470   0.1418
## JOBClerical                        -306.4      510.7  -0.600   0.5486
## JOBDoctor                         -2863.7     1806.9  -1.585   0.1131
## JOBHome Maker                      -710.4      681.5  -1.042   0.2973
## JOBLawyer                          -605.8     1087.2  -0.557   0.5774
## JOBManager                        -1531.3      845.0  -1.812   0.0701 .
## JOBOther Job                       -449.7     1104.0  -0.407   0.6838
## JOBProfessional                     316.3      622.3   0.508   0.6112
## JOBStudent                         -279.7      573.6  -0.488   0.6258
```

```
## BLUEBOOK                          1342.2      268.7   4.996 6.33e-07 ***
## CAR_AGE                           -439.1      261.4  -1.680   0.0932 .
## EDUCATIONHigh School              -539.8      502.5  -1.074   0.2829
## EDUCATIONLess than High School   -116.7      609.6  -0.191   0.8482
## EDUCATIONMasters                   534.5      877.3   0.609   0.5424
## EDUCATIONPhD                      1618.9     1080.7   1.498   0.1343
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7687 on 2137 degrees of freedom
## Multiple R-squared:  0.02142,    Adjusted R-squared:  0.01455
## F-statistic: 3.118 on 15 and 2137 DF,  p-value: 4.575e-05
```

Model 7

For this model, we used the log transformation of the response variable and a combination of predictors. Here is the model that yielded the best results:

```
##
## Call:
## lm(formula = log(TARGET_AMT) ~ MSTATUS + SEX + BLUEBOOK + CLM_FREQ +
##     MVR_PTS + EDUCATION, data = mlr_crash_transf)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7062 -0.4084  0.0422  0.4048  3.2688
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      6.78059    0.25943  26.136  < 2e-16 ***
## MSTATUSYes                      -0.07614    0.03488  -2.183   0.0292 *
## SEXM                             0.05556    0.03503   1.586   0.1128
## BLUEBOOK                         0.15326    0.02712   5.652  1.8e-08 ***
## CLM_FREQ                        -0.02297    0.01457  -1.577   0.1150
## MVR_PTS                          0.01766    0.00705   2.505   0.0123 *
## EDUCATIONHigh School             0.06214    0.04575   1.358   0.1745
## EDUCATIONLess than High School  0.06322    0.05455   1.159   0.2466
## EDUCATIONMasters                 0.08379    0.05693   1.472   0.1412
## EDUCATIONPhD                     0.13885    0.08042   1.726   0.0844 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.804 on 2143 degrees of freedom
## Multiple R-squared:  0.0251, Adjusted R-squared:  0.02101
## F-statistic: 6.131 on 9 and 2143 DF,  p-value: 1.473e-08
```

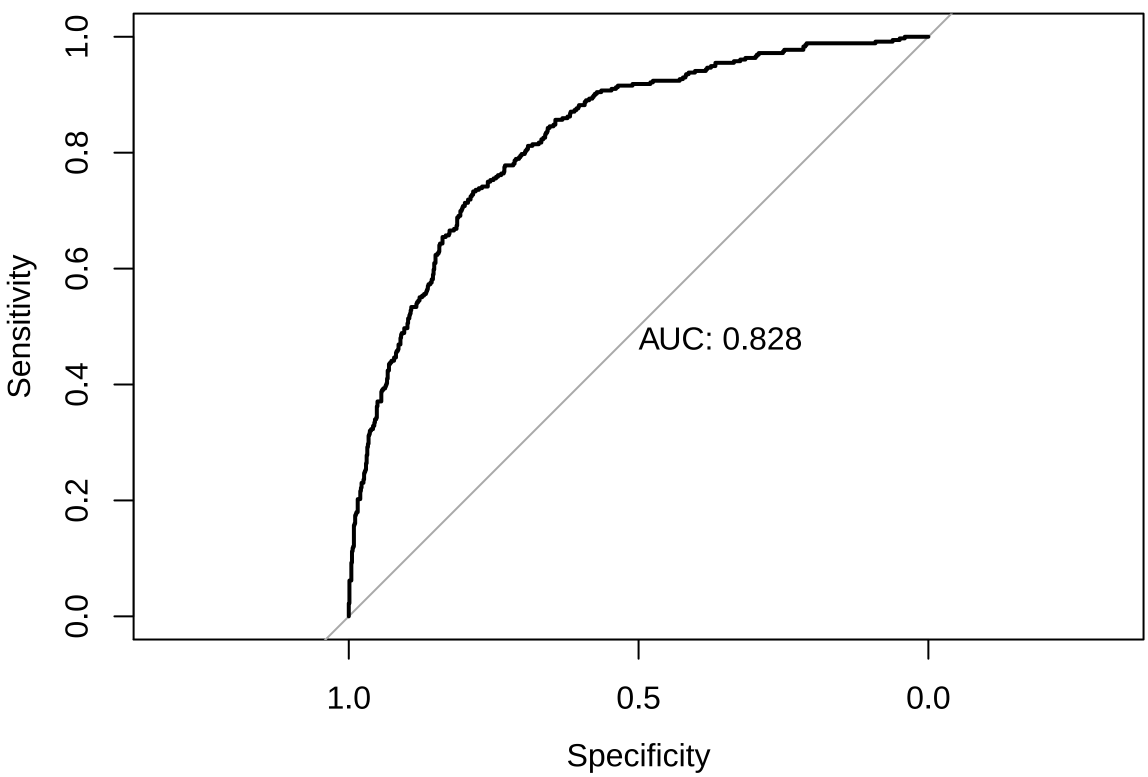
Select Models & Prediction

Binary Logistic Regression

Based on the peformance diagnostics, model 4 or our binned model performs the best. AIC is 5816 and here are the other performance diagnostics:

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction   0   1
##          0 880 195
##          1  85 134
##
##                Accuracy : 0.7836
##                  95% CI : (0.7602, 0.8058)
##     No Information Rate : 0.7457
##     P-Value [Acc > NIR] : 0.0008298
##
##                   Kappa : 0.3587
##
##  Mcnemar's Test P-Value : 7.318e-11
##
##             Sensitivity : 0.9119
##             Specificity : 0.4073
##          Pos Pred Value : 0.8186
##          Neg Pred Value : 0.6119
##              Prevalence : 0.7457
##          Detection Rate : 0.6801
##    Detection Prevalence : 0.8308
##       Balanced Accuracy : 0.6596
##
##        'Positive' Class : 0
##
```

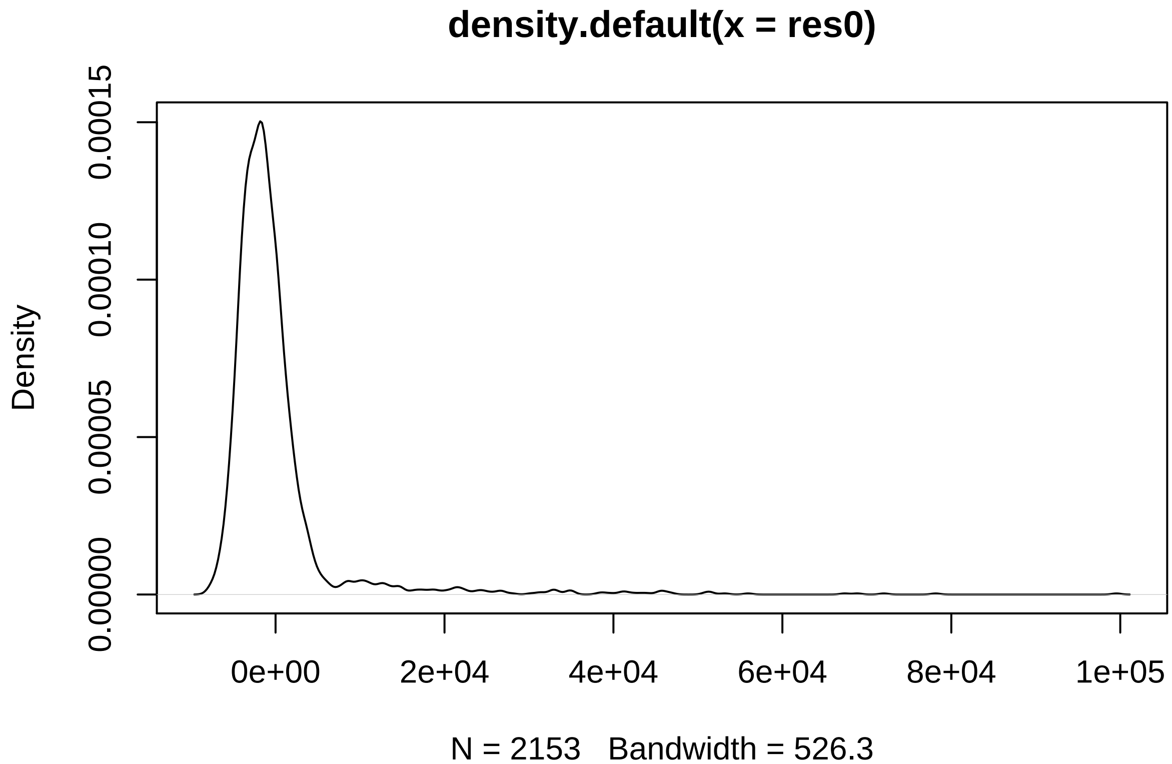


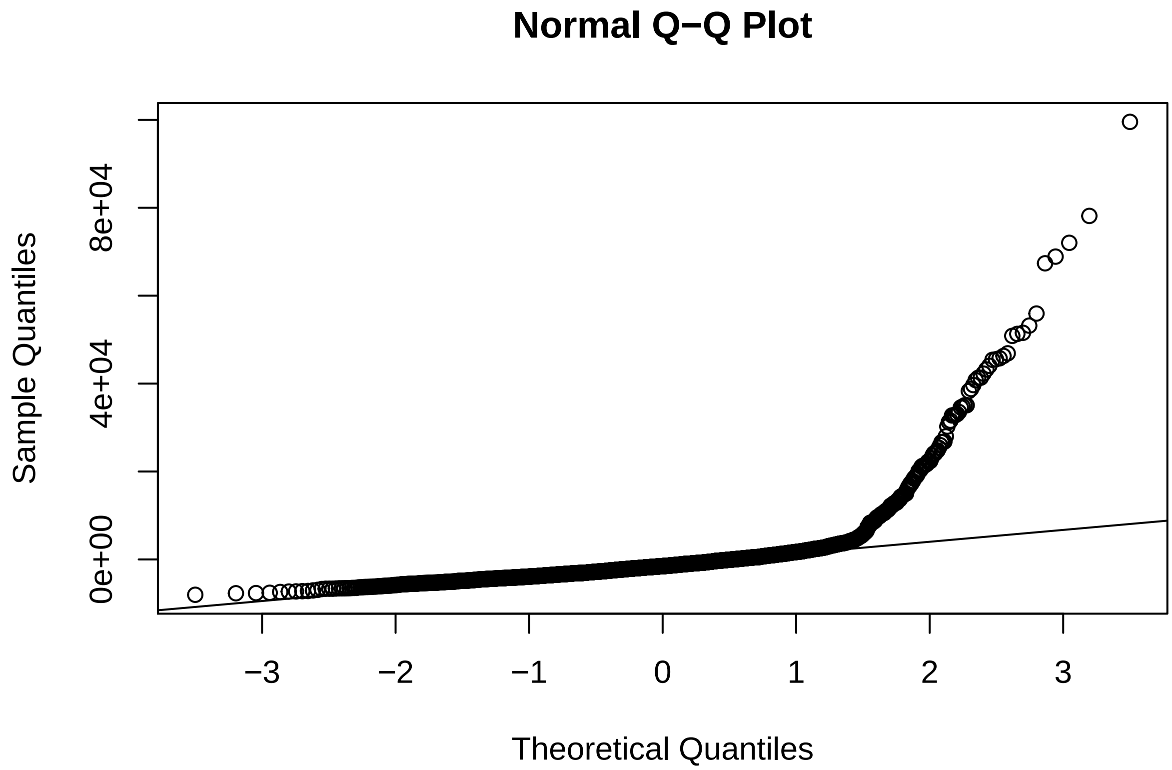
Multiple Linear Regression

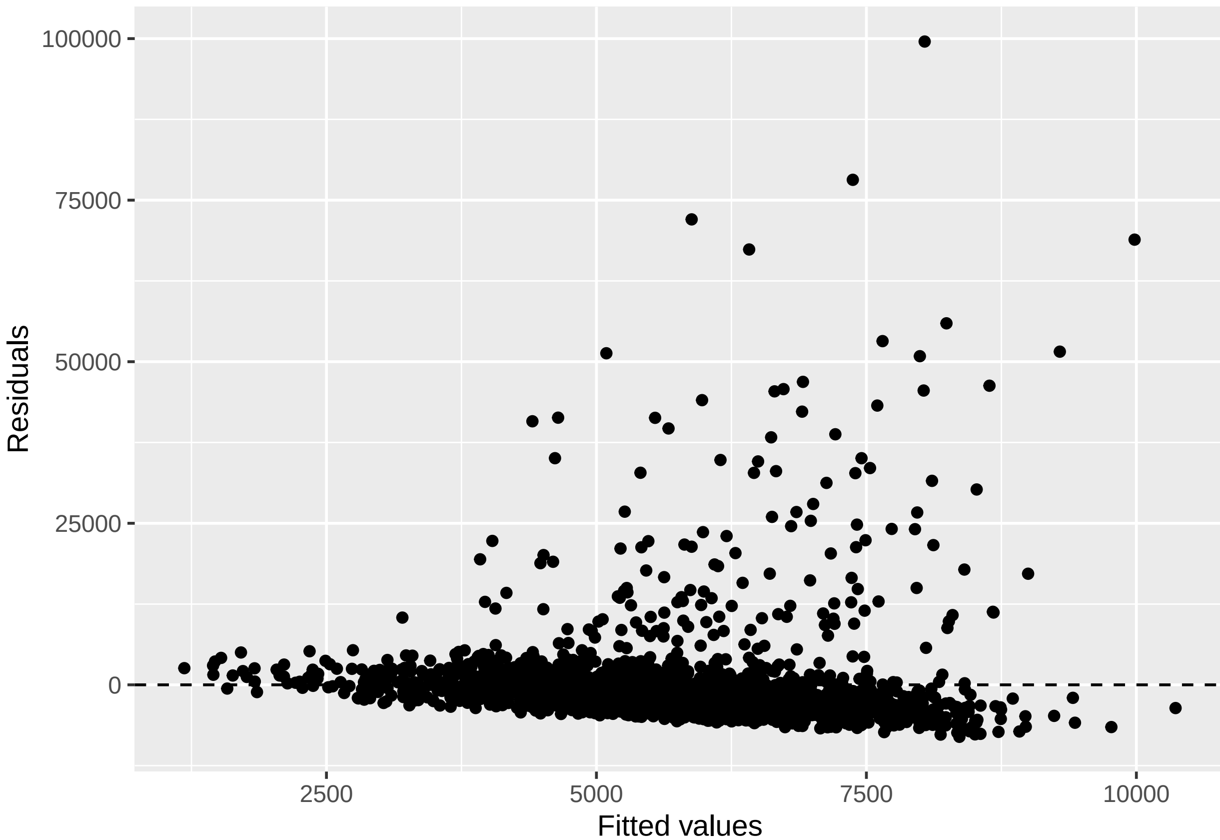
We will look at the diagnostic plot for the two models that had the highest adjusted r^2. Particularly model 1(with all variables minus TARGET_FLAG) and model 7 (log of response variable and a combination of predictors).

Model 1

Model 1 had an adjusted r^2 of 0.02145 and is significant. Here is the diagnostic plot for model 1



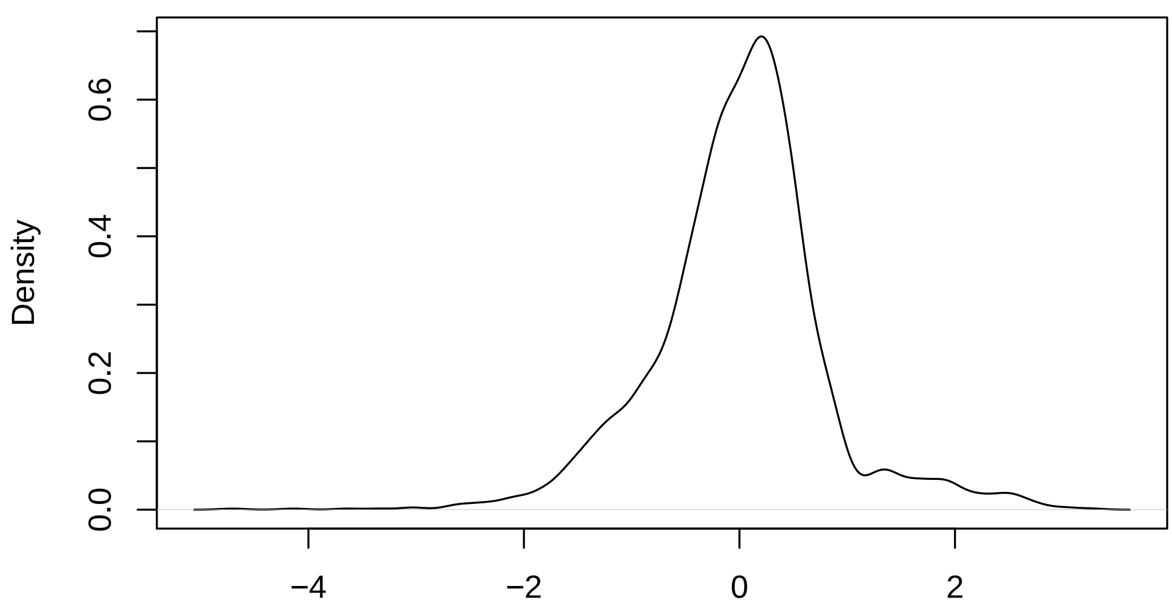




The density plot seems skewed and the qq plot deviates quite a bit.

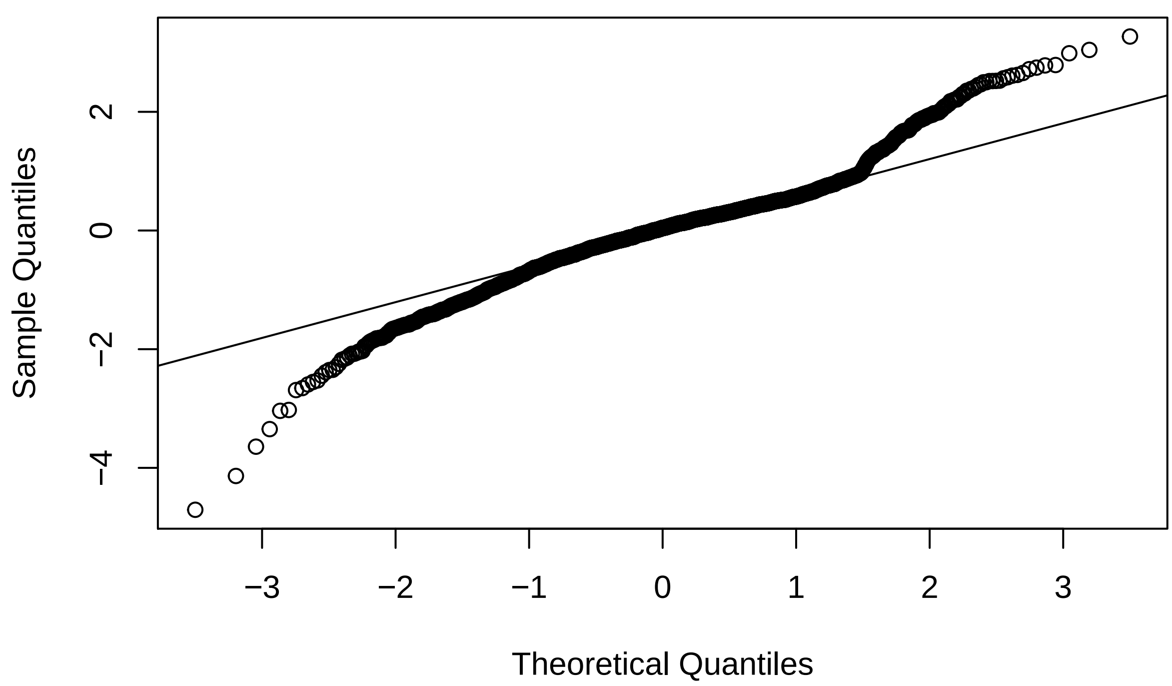
Model 7

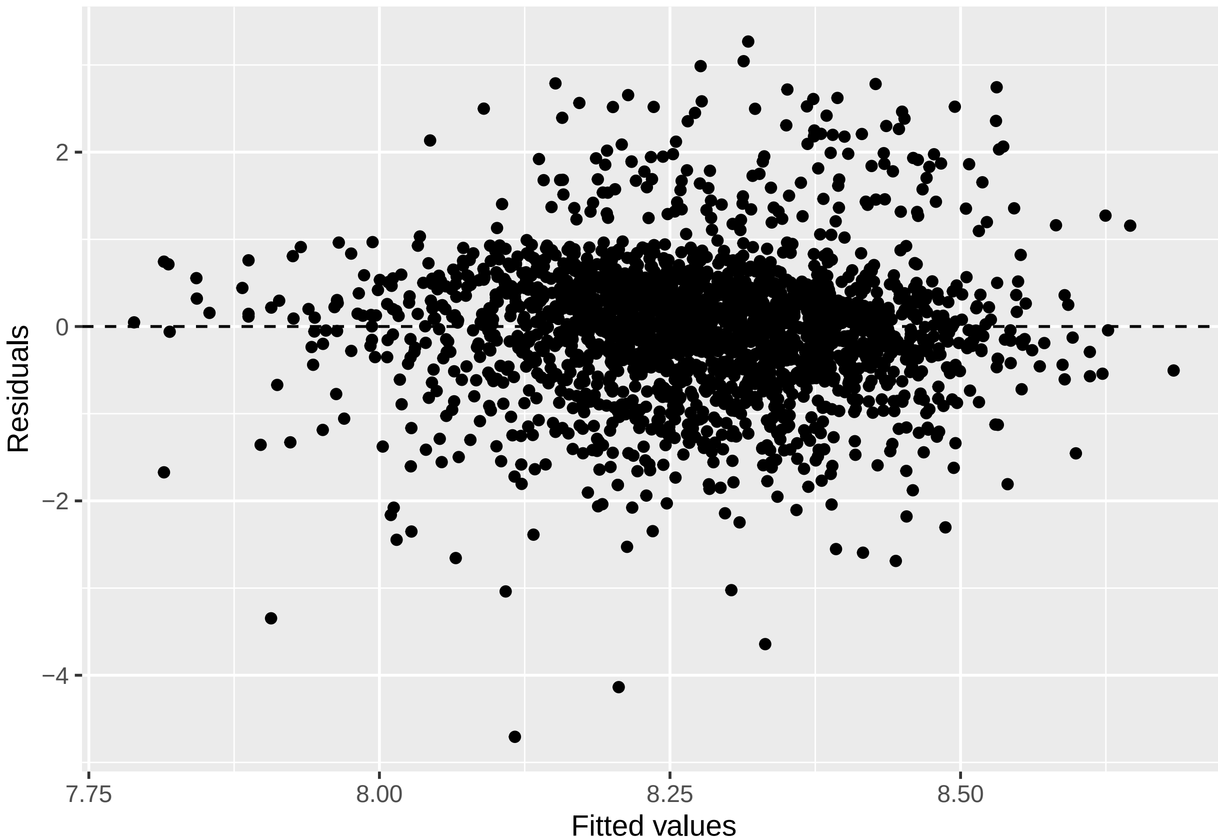
Model 7 had an adjusted r^2 of 0.02158 and is significant density.default(x = res0)



N = 2153 Bandwidth = 0.1177

Normal Q−Q Plot





The density and qqplot for model 7 seem somewhat normally distributed. The residual plot indicates homoscedasticity.

Prediction

```
## predicted_flag_bin
##    0    1
## 5337 1111
```

```
## predicted_amt2
##                0 236.563937331378 236.583059129324 236.586911059253
##             7050                1                1                1
## 236.588374348008 236.618567800217 236.639886586829 236.650517024196
##                1                1                1                1
## 236.666228109109 236.680518823897 236.693942533297 236.694517055668
##                1                1                1                1
## 236.709888189348  236.71217556486  236.73197315084 236.733494351473
##                1                1                1                1
## 236.739001222665 236.746711192303 236.768811369856 236.782809601628
##                1                1                1                1
## 236.786029097308 236.793057169133 236.795152892136 236.813629150445
##                1                1                1                1
## 236.815397804792 236.853934318856 236.859249537539 279.623178522203
##                1                1                1                1
## 305.746405082491 324.062675345335 342.466540605108 365.482545811332
##                1                1                1                1
## 380.696781460324    386.850134888 416.101141301053 417.654884091719
##                1                1                1                1
```

```
## 428.276728495385 454.327928747418 498.729564409365 532.402168591273
##                1                1                1                1
## 549.358172460297 552.447608109474 561.498115567589 564.841591548708
##                1                1                1                1
## 581.662040648804 589.206087835678 593.797036191213 604.602223795272
##                1                1                1                1
## 612.095641399929 616.770647501632 619.976025006175 621.326527968014
##                1                1                1                1
## 627.498811976283 635.087741416078 635.097988983583 635.128373653145
##                1                1                1                1
## 638.214441507918 650.492859416711 650.592606486795 665.828997663872
##                1                1                1                1
## 665.858552136897 665.859632555789 666.005199885929 668.878874949939
##                1                1                1                1
## 672.013618417714 679.506844369862 696.418555724399 696.487285255517
##                1                1                1                1
## 696.510450635901 696.521528399944  696.56621943551 711.698116301255
##                1                1                1                1
## 711.767478701776 711.773049594627 711.829819140254 711.836399885403
##                1                1                1                1
## 711.846014360691 711.857234536491 713.396267794833 717.881088658769
##                1                1                1                1
## 727.098551517454 727.187035715922 727.243678065853 734.899133938319
##                1                1                1                1
## 739.413558516032  740.93791775457 742.556011953446 742.561518824638
##                1                1                1                1
##  757.78595868735 757.791082253525 757.793668656989 757.914883470377
##                1                2                1                1
## 762.375507775788 765.448741659593  766.98923820669 770.132090165183
##                1                1                1                1
## 773.106592718168 773.140196883411 773.223174210687 776.218177350495
##                1                1                1                1
## 776.310321826384 782.380506274276 788.480884174377  788.53254536989
##                1                1                1                1
## 788.543360464157 791.423245850874 793.193303017467  803.69298074658
##                1                1                1                1
## 803.705324037088 803.772596824387 803.834440472624 803.896398041239
##                1                1                1                1
## 812.866656987298 812.988745351009  814.48134047314 816.065198072525
##                1                1                1                1
## 819.059562233149  819.11912505081 819.122152236013 819.150632835081
##                1                1                1                1
## 819.173606562957 819.184628525794 819.238733728532 823.848861793891
##                1                1                1                1
## 825.179311495583 829.876019253761 834.394194495739 834.399509714423
##                1                1                1                1
## 834.404882844985 834.481023752944 834.492734609204 834.499762681029
##                1                1                1                1
## 835.973875207211 839.082283697642 843.681908521329 845.110015679882
##                1                1                1                1
## 849.771464331554 849.820189843277 851.348932838298 854.421150760023
##                1                1                1                1
## 855.917981339914 858.965512680623 862.135445971087 864.976980158608
##                1                1                1                1
```

```
##  865.10127205592 865.115263742756 865.121467727824 865.121652384724
##                1                1                1                1
## 865.131209398807 865.131273855621 868.140503253403 868.182848343612
##                1                1                1                1
##  877.41811866818 880.435073686818 880.454238180581 880.537215507857
##                1                1                1                1
## 885.004761167618  885.05494342316  886.53773896243 889.759126579838
##                1                1                1                1
##  895.68736105638 895.703306712431 895.713995061676 895.731653570868
##                1                1                1                1
## 895.735320393224 895.743364427128 895.744870411699 895.764241774032
##                1                1                1                1
## 895.808683245212 895.811461301184 895.836530752063 897.290000279666
##                1                1                1                1
## 898.848297747712 898.867669110045 901.718626120345 903.305070123194
##                1                1                1                1
## 903.364818048427 903.481399540946  910.88950908903 911.098235057438
##                1                1                2                1
## 911.104822347522 911.106328332093 911.157797875098 914.191905506406
##                1                1                1                1
## 915.694563088469 918.713549373296 918.717216195652 924.867094453481
##                1                1                1                1
## 926.250775356916 926.286284027808 926.307602814421 926.418869088256
##                1                1                1                1
## 926.446028359652 926.455251309471 926.469002087528 926.479746237979
##                2                1                1                1
## 926.486333528063 926.501590290692 926.505640433583 938.632159831474
##                1                1                1                1
## 941.650136699158 941.659893586203  953.97557593766 957.005640421685
##                1                1                1                1
## 957.051652334249 957.106084605644 957.123302333096 957.202470426259
##                1                1                1                1
##  958.56120907451 959.966400417066 963.199626086428 967.824683845759
##                1                1                1                1
## 972.301396218978 972.418616690681  972.45247042031 976.985526115508
##                1                1                1                1
## 984.687037254324 986.274874232725 987.592475776771 987.729438033248
##                1                1                1                1
## 987.729636246211 987.737595780236 987.776593807652 987.780700707683
##                1                1                1                1
## 987.783543235987 987.783734888496 989.143994737379 989.178679321514
##                1                1                1                1
## 989.291643232429 990.720888721753 992.245964894418  995.38949918588
##                1                1                1                1
## 999.937037248375 1002.90734726223 1003.01348996989 1003.08076275719
##                1                1                1                1
## 1003.11367802901 1003.16905530315 1004.55140011352 1006.23847995284
##                1                1                1                1
## 1009.21537725678 1010.73090341097 1013.75101935544 1018.28222889203
##                1                1                1                1
## 1018.31627383901 1020.02651905871 1021.59551142094 1023.03722739646
##                1                1                1                1
## 1024.39001773381  1024.4477339577   1026.144555468  1029.0835493501
##                1                1                1                1
```

```
## 1029.14886816818 1032.07259829204 1032.08659652381 1033.60583219617
##                1                1                1                1
## 1033.66412294243 1033.67070368758 1036.75355204667 1036.76589533718
##                1                1                1                1
## 1046.01702681792 1047.37557381366 1047.44108428426 1047.49342737758
##                1                1                1                1
##  1049.0007026293 1049.03785406294  1053.6050681493 1053.62551993052
##                1                1                1                1
##  1056.6743656033 1064.25817213488 1064.28343323827 1075.16461933853
##                1                1                1                1
## 1076.67120635479 1079.62265724048 1079.68367680196 1082.67018858119
##                1                1                1                1
## 1084.31292010481 1085.64026468188 1085.67596457012  1088.9081742774
##                1                1                1                1
## 1090.19780008952 1090.39696082339 1094.90899021499 1095.09108217811
##                1                1                1                1
## 1099.69145335642   1101.081715005 1107.27697274115 1110.23557844368
##                1                1                1                1
## 1110.26659620546   1110.344557342 1111.74792845597 1114.93355172832
##                1                1                1                1
## 1120.90818098729 1122.48506842673 1122.52589231631  1124.0817166433
##                1                1                1                1
## 1125.63152275077 1125.64772451614 1127.22797974998 1128.59778961734
##                1                1                1                1
## 1133.28221854182 1133.33399993742 1134.87899395409 1136.41101435667
##                1                1                1                1
## 1137.88696693168 1137.90589051667 1139.38001003846 1142.57031543727
##                1                1                1                1
## 1147.06214915697 1147.09335857126 1147.14639855565 1148.65468976945
##                1                1                1                1
## 1150.24963423915 1156.22348210718 1156.26152794079 1160.83633898776
##                1                1                1                1
## 1170.03678231644 1171.67887486088 1171.72620810111 1174.75330287666
##                1                1                1                1
## 1180.78215797361 1186.92304091508 1186.94785469179  1190.1092387098
##                1                1                1                1
## 1191.57437573988 1196.22045391584 1199.22323841977 1202.23406047061
##                1                1                1                1
## 1203.72322988646 1203.77387511989  1211.4651386912 1211.49234721887
##                1                1                1                1
## 1214.55038180125 1217.52196388651  1217.5342427202 1217.68512526903
##                1                1                1                1
##  1219.0521640605 1220.71772691576 1225.27615152495  1225.2963964376
##                1                1                1                1
##  1226.7653209408 1228.32076239793 1232.79658600476  1235.9608904905
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## 4247.68282198251 4253.82478443151 4256.72833409953 4265.98067319486
##                1                1                1                1
## 4284.24864351166  4284.3681454719 4311.90187859343  4311.9861209965
##                1                1                1                1
## 4324.13581233523 4338.07555173904 4354.92307395065 4370.19604767258
##                1                1                1                1
##   4389.949159474 4431.58358253917 4445.17383944665 4491.30104854334
##                1                1                1                1
## 4535.53864927245 4612.21010817592 4616.94523807711 4633.76447134217
##                1                1                1                1
##  4644.4754246343 4656.79129863827 4670.49953655875 4673.67541816012
##                1                1                1                1
## 4679.66516222063 4710.38434769361 4737.87264445433 4757.97637471879
##                1                1                1                1
##  4764.0976299658  4828.4676972326 4836.07642425837 4875.91984915979
##                1                1                1                1
## 4882.01383142232  4977.1085269479 5081.15205703001 5211.53770115873
##                1                1                1                1
## 5220.89997068822 5249.89471250412 5407.72535576869 5447.52350856724
##                1                1                1                1
## 5524.12232155285 5697.44338458309 5968.56129888332 5997.84034678921
##                1                1                1                1
##  6152.4616121133 6958.67142067345
##                1                1
```

Code Appendix

```
knitr::opts_chunk$set(echo=FALSE, error=FALSE, warning=FALSE, message=FALSE)


# Libraries


library(stringr)
library(tidyr)
library(DataExplorer)
library(dplyr)
library(visdat)
library(pROC)
library(mice)
library(corrplot)
library(MASS)
library(caret)
library(e1071)
library(rbin)

library(GGally)
library(ggplot2)
library(readr)
library(reshape2)
library(purrr)
library(leaps)

set.seed(2012)


insurance <- read.csv('https://raw.githubusercontent.com/hillt5/DATA_621/master/HW4/insurance_training_d
insurance_test <- read.csv('https://raw.githubusercontent.com/hillt5/DATA_621/master/HW4/insurance_train
glimpse(insurance)
head(insurance)
summary(insurance)
insurance_fix <- dplyr::select(insurance, -INDEX)

insurance_fix$HOME_VAL <- substr(insurance_fix$HOME_VAL, 2, nchar(insurance_fix$HOME_VAL)) # remove the
insurance_fix$HOME_VAL <- as.numeric(str_remove_all(insurance_fix$HOME_VAL, "[[:punct:]]")) # remove th

insurance_fix$BLUEBOOK<- substr(insurance_fix$BLUEBOOK , 2, nchar(insurance_fix$BLUEBOOK ))
insurance_fix$BLUEBOOK<- as.numeric(str_remove_all(insurance_fix$BLUEBOOK,"[[:punct:]]"))

insurance_fix$INCOME  <- substr(insurance_fix$INCOME, 2, nchar(insurance_fix$INCOME))
insurance_fix$INCOME <- as.numeric(str_remove_all(insurance_fix$INCOME, "[[:punct:]]"))

insurance_fix$OLDCLAIM <- substr(insurance_fix$OLDCLAIM, 2, nchar(insurance_fix$OLDCLAIM))
insurance_fix$OLDCLAIM <- as.numeric(str_remove_all(insurance_fix$OLDCLAIM, "[[:punct:]]"))


insurance_fix$MSTATUS = as.factor(str_remove(insurance_fix$MSTATUS, 'z_')) #several variables have a a 
insurance_fix$PARENT1 = as.factor(str_remove(insurance_fix$PARENT1, 'z_'))
```

```
insurance_fix$EDUCATION = str_replace(insurance_fix$EDUCATION, '<', 'Less than ') #change < to less tha
insurance_fix$SEX= as.factor(str_remove(insurance_fix$SEX, 'z_'))
insurance_fix$EDUCATION = as.factor(str_remove(insurance_fix$EDUCATION, 'z_'))
insurance_fix$JOB[insurance_fix$JOB == ""] <- 'Other Job' #recode blank spaces as 'Other Job'
insurance_fix$JOB = as.factor(str_remove(insurance_fix$JOB, 'z_'))
insurance_fix$CAR_USE = as.factor(str_remove(insurance_fix$CAR_USE, 'z_'))
insurance_fix$CAR_TYPE = as.factor(str_remove(insurance_fix$CAR_TYPE, 'z_'))
insurance_fix$URBANICITY = as.factor(str_remove(insurance_fix$URBANICITY, 'z_'))
insurance_fix$REVOKED = as.factor(str_remove(insurance_fix$REVOKED, 'z_'))
insurance_fix$RED_CAR = as.factor(str_remove(insurance_fix$RED_CAR, 'z_'))

summary(insurance_fix)

insurance_fix$CAR_AGE[insurance_fix$CAR_AGE <1] <- 1
cat_cols = c()
j <- 1
for (i in 4:ncol(insurance_fix)) {
  if (class((insurance_fix[,i])) == 'factor') {
      print(names(insurance_fix[i]))
      print(levels(insurance_fix[,i]))
      cat_cols[j]=names(insurance_fix[i])
      j <- j+1
  }

}



ins_fact <-  insurance_fix[cat_cols]
ins_factm <- melt(ins_fact, measure.vars = cat_cols, variable.name = 'metric', value.name = 'value')

ggplot(ins_factm, aes(x = value)) +
  geom_bar() +
  scale_fill_brewer(palette = "Set1") +
  facet_wrap( ~ metric, nrow = 5L, scales = 'free') + coord_flip()
plot_histogram(insurance_fix, geom_histogram_args = list("fill" = "tomato4"))

plot_histogram(insurance_fix, scale_x = "log10", geom_histogram_args = list("fill" = "springgreen4"))
# check columns having missing values
insurance_fix %>% summarise_all(funs(sum(is.na(.)))) %>% select_if(~any(.)>0)
plot_missing(insurance_fix)

round(colSums(is.na(insurance_fix))/nrow(insurance_fix),3)

vis_dat(insurance_fix %>% dplyr:: select(YOJ, INCOME, HOME_VAL, CAR_AGE))



numer_data <- insurance_fix[,c('TARGET_AMT','AGE','YOJ','INCOME','HOME_VAL','TRAVTIME','BLUEBOOK','TIF'

AGE_MEDIAN <- median(filter(insurance_fix,AGE > 0)$AGE)
INCOME_MEDIAN <- median(filter(insurance_fix,INCOME > 0)$INCOME)
YOJ_MEDIAN <- median(filter(insurance_fix,YOJ > 0)$YOJ)
```

```r
HOME_VAL_MEDIAN <- median(filter(insurance_fix,HOME_VAL > 0)$HOME_VAL)
CAR_AGE_MEDIAN <- median(filter(insurance_fix,CAR_AGE > 0)$CAR_AGE)


numer_data <- numer_data %>% dplyr::mutate(AGE = replace_na(AGE,AGE_MEDIAN),
                             INCOME = replace_na(INCOME,INCOME_MEDIAN),
                             YOJ = replace_na(YOJ,YOJ_MEDIAN),
                             HOME_VAL = replace_na(HOME_VAL,HOME_VAL_MEDIAN),
                             CAR_AGE = replace_na(CAR_AGE,CAR_AGE_MEDIAN))
corrplot(cor(numer_data),type="upper")

mlr_crash <- subset(filter(insurance_fix,TARGET_FLAG==1),select = -c(TARGET_FLAG))

mlr_crash_fix_na <- mlr_crash

AGE_MEDIAN <- median(filter(mlr_crash_fix_na,AGE > 0)$AGE)
INCOME_MEDIAN <- median(filter(mlr_crash_fix_na,INCOME > 0)$INCOME)
YOJ_MEDIAN <- median(filter(mlr_crash_fix_na,YOJ > 0)$YOJ)
HOME_VAL_MEDIAN <- median(filter(mlr_crash_fix_na,HOME_VAL > 0)$HOME_VAL)
CAR_AGE_MEDIAN <- median(filter(mlr_crash_fix_na,CAR_AGE > 0)$CAR_AGE)

mlr_crash_fix_na <- mlr_crash_fix_na %>% dplyr::mutate(AGE = replace_na(AGE,AGE_MEDIAN),
                             INCOME = replace_na(INCOME,INCOME_MEDIAN),
                             YOJ = replace_na(YOJ,YOJ_MEDIAN),
                             HOME_VAL = replace_na(HOME_VAL,HOME_VAL_MEDIAN),
                             CAR_AGE = replace_na(CAR_AGE,CAR_AGE_MEDIAN))
mlr_crash_transf <- mlr_crash_fix_na
mlr_crash_transf$AGE <- log(mlr_crash_transf$AGE)
mlr_crash_transf$BLUEBOOK <- log(mlr_crash_transf$BLUEBOOK)
mlr_crash_transf$CAR_AGE <- log(mlr_crash_transf$CAR_AGE + 1)
mlr_crash_transf$HOME_VAL <- log(mlr_crash_transf$HOME_VAL + 1)
mlr_crash_transf$INCOME <- log(mlr_crash_transf$INCOME + 1)
mlr_crash_transf$OLDCLAIM <- log(mlr_crash_transf$OLDCLAIM + 1)
mlr_crash_transf$TRAVTIME <- log(mlr_crash_transf$TRAVTIME)

insurance_fix2 <- insurance_fix
insurance_fix2$HOME_VAL <-ifelse(insurance_fix2$HOME_VAL == 0, NA, insurance_fix2$HOME_VAL)
insurance_bins <- insurance_fix %>%
  mutate(CAR_AGE_BIN=cut(CAR_AGE, breaks=c(-Inf, 1, 3, 12, Inf), labels=c("New","Like New","Average", '
  mutate(HOME_VAL_BIN=cut(HOME_VAL, breaks=c(-Inf, 0, 50000, 150000, 250000, Inf), labels=c("Zero", "$0
  mutate(HAS_HOME_KIDS = as.factor(case_when(HOMEKIDS == 0 ~ 'No kids', HOMEKIDS > 0 ~ ('Has kids')))) %
  mutate(HAS_KIDSDRIV = as.factor(case_when(KIDSDRIV == 0 ~ 'No kids driving', KIDSDRIV > 0 ~ 'Has kids
  mutate(OLDCLAIM_BIN =cut(OLDCLAIM, breaks=c(-Inf, 0, 3000, 6000, 9000, Inf), labels=c("Zero","$0-$3k"
  mutate(TIF_BIN =cut(TIF, breaks=c(-Inf, 0, 1, 4, 7, Inf), labels=c("Zero","Less than 1 year", "1-4 yea
  mutate(YOJ_BIN =cut(YOJ, breaks=c(-Inf, 0, 10, 15, Inf), labels=c("Zero","Less than 10 years", 'Betwe
  dplyr::select(-c(CAR_AGE, HOME_VAL, HOMEKIDS, KIDSDRIV, OLDCLAIM, TIF, YOJ)) #drop the binned feature

summary(insurance_bins)
head(insurance_bins)


insurance_logistic_model <- glm(insurance_fix, family = 'binomial', formula = TARGET_FLAG~.-TARGET_AMT)
```

```r
summary(insurance_logistic_model)

get_cv_performance <- function(data_frame, model, split = 0.8) {  ### input is dataframe for partitioni
  n <- ncol(data_frame) #number of columns in original dataframe
  train_control <- trainControl(method="repeatedcv", number=10, repeats=3)
  trainIndex <- createDataPartition(data_frame[,n], p=split, list=FALSE)
  data_train <- data_frame[trainIndex,]
  data_test <- data_frame[-trainIndex,]

  x_test <- data_test[,2:n] #explanatory variables
  y_test <- data_test[,1]  #response variable
  predictions <- predict(model, x_test, type = 'response')

  return(confusionMatrix(data = (as.factor(as.numeric(predictions>0.5))), reference = as.factor(y_test)

  return(plot(roc(y_test, predictions),print.auc=TRUE))

}
get_roc <- function(data_frame, model, split = 0.8) {  ### input is dataframe for partitioning, model a
  n <- ncol(data_frame) #number of columns in original dataframe
  train_control <- trainControl(method="repeatedcv", number=10, repeats=3)
  trainIndex <- createDataPartition(data_frame[,n], p=split, list=FALSE)
  data_train <- data_frame[trainIndex,]
  data_test <- data_frame[-trainIndex,]

  x_test <- data_test[,2:n] #explanatory variables
  y_test <- data_test[,1]  #response variable
  predictions <- predict(model, x_test, type = 'response')
  return(plot(roc(y_test, predictions),print.auc=TRUE))

}

get_cv_performance(insurance_fix, insurance_logistic_model)
get_roc(insurance_fix, insurance_logistic_model)



insurance_impute <- mice(insurance_fix, method = 'cart', m = 1)

imputed_lm <- glm.mids(data = insurance_impute, formula = TARGET_FLAG ~.-TARGET_AMT, family = 'binomial


imputed_lm


get_cv_performance(insurance_fix, imputed_lm$analyses[[1]])
get_roc(insurance_fix, imputed_lm$analyses[[1]])



insurance_impute2 <- mice(insurance_fix2, method = 'cart', m = 1)
imputed_lm2 <- glm.mids(data = insurance_impute2, formula = TARGET_FLAG ~.-TARGET_AMT, family = 'binomia
imputed_lm2
```

```r
get_cv_performance(insurance_fix2, imputed_lm2$analyses[[1]])
get_roc(insurance_fix2, imputed_lm2$analyses[[1]])



binned_lm <- glm(data = insurance_bins, formula = TARGET_FLAG ~.-TARGET_AMT, family = 'binomial')


summary(binned_lm)


get_cv_performance(insurance_bins, binned_lm)
get_roc(insurance_bins, binned_lm)

insurance_binned_impute <- mice(insurance_bins, method = 'cart', m = 1)

binned_imputed_lm <- glm.mids(data = insurance_binned_impute, formula = TARGET_FLAG ~.-TARGET_AMT, famil


binned_imputed_lm


get_cv_performance(insurance_bins, binned_imputed_lm$analyses[[1]])
get_roc(insurance_bins, binned_imputed_lm$analyses[[1]])

mlr<- lm(TARGET_AMT ~ . ,data=mlr_crash)
summary(mlr)
mlr<- lm(TARGET_AMT ~ . ,data=mlr_crash_transf)
summary(mlr)
mlr1 <- lm(TARGET_AMT ~ . ,data=mlr_crash_transf)
summary(mlr1)
mlr2 <- update(mlr1,TARGET_AMT~. - OLDCLAIM)
summary(mlr2)
mlr3 <- update(mlr2,TARGET_AMT~. - YOJ)
summary(mlr3)
mlr4 <- update(mlr3,TARGET_AMT~. - URBANICITY)
summary(mlr4)
mlr5 <- update(mlr4,TARGET_AMT~. - TRAVTIME)
summary(mlr5)
mlr6 <- update(mlr5,TARGET_AMT~. - INCOME)
summary(mlr6)
mlr7 <- update(mlr6,TARGET_AMT~. - CLM_FREQ)
summary(mlr7)
mlr8 <- update(mlr7,TARGET_AMT~. - TIF)
summary(mlr8)
mlr9 <- update(mlr8,TARGET_AMT~. - RED_CAR)
summary(mlr9)
mlr10 <- update(mlr9,TARGET_AMT~. - PARENT1)
summary(mlr10)
mlr11 <- update(mlr10,TARGET_AMT~. - KIDSDRIV)
summary(mlr11)
mlr12 <- update(mlr11,TARGET_AMT~. - AGE)
summary(mlr12)
```

```r
mlr13 <- update(mlr12,TARGET_AMT~. - CAR_USE)
summary(mlr13)
mlr14 <- update(mlr13,TARGET_AMT~. - JOB)
summary(mlr14)
mlr15 <- update(mlr14,TARGET_AMT~. - EDUCATION)
summary(mlr15)
mlr16 <- update(mlr15,TARGET_AMT~. - CAR_TYPE)
summary(mlr16)
mlr17 <- update(mlr16,TARGET_AMT~. - HOMEKIDS)
summary(mlr17)
mlr18 <- update(mlr17,TARGET_AMT~. - CAR_AGE)
summary(mlr18)
mlr19 <- update(mlr18,TARGET_AMT~. - HOME_VAL)
summary(mlr19)
mlr20 <- update(mlr19,TARGET_AMT~. - MSTATUS)
summary(mlr20)
mlr21 <- update(mlr20,TARGET_AMT~. - REVOKED)
summary(mlr21)
mlr22 <- update(mlr21,TARGET_AMT~. - SEX)
summary(mlr22)
mlr_fwd <- lm(TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX ,data= mlr_crash_transf)
summary(mlr_fwd)

mlr_fwd <- lm(TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS ,data= mlr_crash_transf)
summary(mlr_fwd)

mlr_fwd <- lm(TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS + HOME_VAL,data= mlr_crash_transf)
summary(mlr_fwd)

mlr_fwd <- lm(TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS + HOME_VAL + REVOKED,data= mlr_crash_trans
summary(mlr_fwd)

mlr_fwd <- lm(TARGET_AMT ~ BLUEBOOK + MVR_PTS + SEX + MSTATUS + HOME_VAL + REVOKED + CAR_AGE,data= mlr_
summary(mlr_fwd)
mlr_full <- regsubsets(TARGET_AMT ~ . ,data=mlr_crash, nvmax=NULL)
mlr_summary<- summary(mlr_full)
par(mfrow=c(2,2))
plot(mlr_summary$cp,xlab = "# Variables", ylab = "cp - estimate of prediction error")
points(13,mlr_summary$cp[13],pch=20,col="red")
plot(mlr_summary$rsq,xlab = "# Variables", ylab = "R^2")

mlr_full_transf <- regsubsets(TARGET_AMT ~ . ,data=mlr_crash_transf, nvmax=NULL)
mlr_summary_transf <- summary(mlr_full_transf)

par(mfrow=c(1,2))
plot(mlr_summary_transf$cp,xlab = "# Variables", ylab = "cp - estimate of prediction error")
points(7,mlr_summary_transf$cp[7],pch=20,col="red")
plot(mlr_summary_transf$rsq,xlab = "# Variables", ylab = "R^2")
coef(mlr_full,7)
model_6 <- lm(TARGET_AMT ~ MSTATUS +JOB+ BLUEBOOK + CAR_AGE+EDUCATION, data = mlr_crash_transf)
summary(model_6)
model_log <- lm(log(TARGET_AMT) ~ MSTATUS+SEX+ BLUEBOOK + CLM_FREQ + MVR_PTS+EDUCATION, data = mlr_crash
summary(model_log)
```

```
get_cv_performance(insurance_bins, binned_lm)
get_roc(insurance_bins, binned_lm)
res0 <- resid(mlr)
plot(density(res0))
qqnorm(res0)
qqline(res0)
ggplot(data = mlr, aes(x = .fitted, y = .resid)) +
  geom_jitter() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals")
res0 <- resid(model_log)
plot(density(res0))
qqnorm(res0)
qqline(res0)
ggplot(data = model_log, aes(x = .fitted, y = .resid)) +
  geom_jitter() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals")
insurance_fix3 <- dplyr::select(insurance_test, -INDEX)

insurance_fix3$HOME_VAL <- substr(insurance_fix3$HOME_VAL, 2, nchar(insurance_fix3$HOME_VAL)) # remove
insurance_fix3$HOME_VAL <- as.numeric(str_remove_all(insurance_fix3$HOME_VAL, "[[:punct:]]")) # remove

insurance_fix3$BLUEBOOK<- substr(insurance_fix3$BLUEBOOK , 2, nchar(insurance_fix3$BLUEBOOK ))
insurance_fix3$BLUEBOOK<- as.numeric(str_remove_all(insurance_fix3$BLUEBOOK,"[[:punct:]]"))

insurance_fix3$INCOME  <- substr(insurance_fix3$INCOME, 2, nchar(insurance_fix3$INCOME))
insurance_fix3$INCOME <- as.numeric(str_remove_all(insurance_fix3$INCOME, "[[:punct:]]"))

insurance_fix3$OLDCLAIM <- substr(insurance_fix3$OLDCLAIM, 2, nchar(insurance_fix3$OLDCLAIM))
insurance_fix3$OLDCLAIM <- as.numeric(str_remove_all(insurance_fix3$OLDCLAIM, "[[:punct:]]"))

insurance_fix3$MSTATUS = as.factor(str_remove(insurance_fix3$MSTATUS, 'z_')) #several variables have a
insurance_fix3$PARENT1 = as.factor(str_remove(insurance_fix3$PARENT1, 'z_'))
insurance_fix3$EDUCATION = str_replace(insurance_fix3$EDUCATION, '<', 'Less than ') #change < to less t
insurance_fix3$SEX= as.factor(str_remove(insurance_fix3$SEX, 'z_'))
insurance_fix3$EDUCATION = as.factor(str_remove(insurance_fix3$EDUCATION, 'z_'))
insurance_fix3$JOB[insurance_fix3$JOB == ""] <- 'Other Job' #recode blank spaces as 'Other Job'
insurance_fix3$JOB = as.factor(str_remove(insurance_fix3$JOB, 'z_'))
insurance_fix3$CAR_USE = as.factor(str_remove(insurance_fix3$CAR_USE, 'z_'))
insurance_fix3$CAR_TYPE = as.factor(str_remove(insurance_fix3$CAR_TYPE, 'z_'))
insurance_fix3$URBANICITY = as.factor(str_remove(insurance_fix3$URBANICITY, 'z_'))
insurance_fix3$REVOKED = as.factor(str_remove(insurance_fix3$REVOKED, 'z_'))
insurance_fix3$RED_CAR = as.factor(str_remove(insurance_fix3$RED_CAR, 'z_'))
insurance_fix3$CAR_AGE[insurance_fix3$CAR_AGE <1] <- 1
insurance_bins2 <- insurance_fix3 %>%
  mutate(CAR_AGE_BIN=cut(CAR_AGE, breaks=c(-Inf, 1, 3, 12, Inf), labels=c("New","Like New","Average", '
  mutate(HOME_VAL_BIN=cut(HOME_VAL, breaks=c(-Inf, 0, 50000, 150000, 250000, Inf), labels=c("Zero", "$0
  mutate(HAS_HOME_KIDS = as.factor(case_when(HOMEKIDS == 0 ~ 'No kids', HOMEKIDS > 0 ~ ('Has kids')))) %
  mutate(HAS_KIDSDRIV = as.factor(case_when(KIDSDRIV == 0 ~ 'No kids driving', KIDSDRIV > 0 ~ 'Has kids
  mutate(OLDCLAIM_BIN =cut(OLDCLAIM, breaks=c(-Inf, 0, 3000, 6000, 9000, Inf), labels=c("Zero","$0-$3k"
```

```r
  mutate(TIF_BIN =cut(TIF, breaks=c(-Inf, 0, 1, 4, 7, Inf), labels=c("Zero","Less than 1 year", "1-4 yea
  mutate(YOJ_BIN =cut(YOJ, breaks=c(-Inf, 0, 10, 15, Inf), labels=c("Zero","Less than 10 years", 'Betwe
  dplyr::select(-c(CAR_AGE, HOME_VAL, HOMEKIDS, KIDSDRIV, OLDCLAIM, TIF, YOJ)) #drop the binned feature

mlr_crash2 <- subset(filter(insurance_fix2,TARGET_FLAG==1),select = -c(TARGET_FLAG))
mlr_crash_fix_na2 <- mlr_crash2
AGE_MEDIAN <- median(filter(mlr_crash_fix_na2,AGE > 0)$AGE)
INCOME_MEDIAN <- median(filter(mlr_crash_fix_na2,INCOME > 0)$INCOME)
YOJ_MEDIAN <- median(filter(mlr_crash_fix_na2,YOJ > 0)$YOJ)
HOME_VAL_MEDIAN <- median(filter(mlr_crash_fix_na2,HOME_VAL > 0)$HOME_VAL)
CAR_AGE_MEDIAN <- median(filter(mlr_crash_fix_na2,CAR_AGE > 0)$CAR_AGE)

mlr_crash_fix_na2 <- mlr_crash_fix_na2 %>% dplyr::mutate(AGE = replace_na(AGE,AGE_MEDIAN),
                             INCOME = replace_na(INCOME,INCOME_MEDIAN),
                             YOJ = replace_na(YOJ,YOJ_MEDIAN),
                             HOME_VAL = replace_na(HOME_VAL,HOME_VAL_MEDIAN),
                             CAR_AGE = replace_na(CAR_AGE,CAR_AGE_MEDIAN))
mlr_crash_transf2 <- mlr_crash_fix_na2
mlr_crash_transf2$AGE <- log(mlr_crash_transf2$AGE)
mlr_crash_transf2$BLUEBOOK <- log(mlr_crash_transf2$BLUEBOOK)
mlr_crash_transf2$CAR_AGE <- log(mlr_crash_transf2$CAR_AGE + 1)
mlr_crash_transf2$HOME_VAL <- log(mlr_crash_transf2$HOME_VAL + 1)
mlr_crash_transf2$INCOME <- log(mlr_crash_transf2$INCOME + 1)
mlr_crash_transf2$OLDCLAIM <- log(mlr_crash_transf2$OLDCLAIM + 1)
mlr_crash_transf2$TRAVTIME <- log(mlr_crash_transf2$TRAVTIME)

predicted_amt <- predict(model_log, insurance_bins2)
predicted_amt2 = predicted_amt
predicted_amt2[] = 0

predicted_flag = predict(binned_lm, insurance_bins2, type = "response")
predicted_flag_bin = ifelse(predicted_flag > 0.5, 1, 0)

for (i in 1:length(predicted_amt)) {
  if(predicted_flag_bin[i] == 0 | is.na(predicted_flag_bin[i])) {
    predicted_amt2[i] = 0
  } else {
    predicted_amt2[i] = predicted_amt[i]
  }

}
table(predicted_flag_bin)
table(predicted_amt2)
```