Data 621 Homework 4: Car Insurance

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OVERVIEW

In this homework assignment, we 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 representing the cost of the crash.

Objective:

Our 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.

DATA EXPLORATION

Data Summary

The dataset consists of two data files: training and evaluation. The training dataset contains 26 columns, while the evaluation dataset contains 26. The evaluation dataset is missing columns which represent our response variables, respectively whether the person was in a car crash and the cost of the car crash if the person was in an accident. We will start by exploring the training data set since it will be the one used to generate the models.

The columns in the data set are:

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

Missing Data

An important aspect of any dataset is to determine how much, if any, data is missing. We look at all the variables to see which if any have missing data. We look at the basic descriptive statistics as well as the missing data and percentages.

We start by looking at the dataset as a whole and determine how many complete rows, that is rows with data for all predictors, do we have.

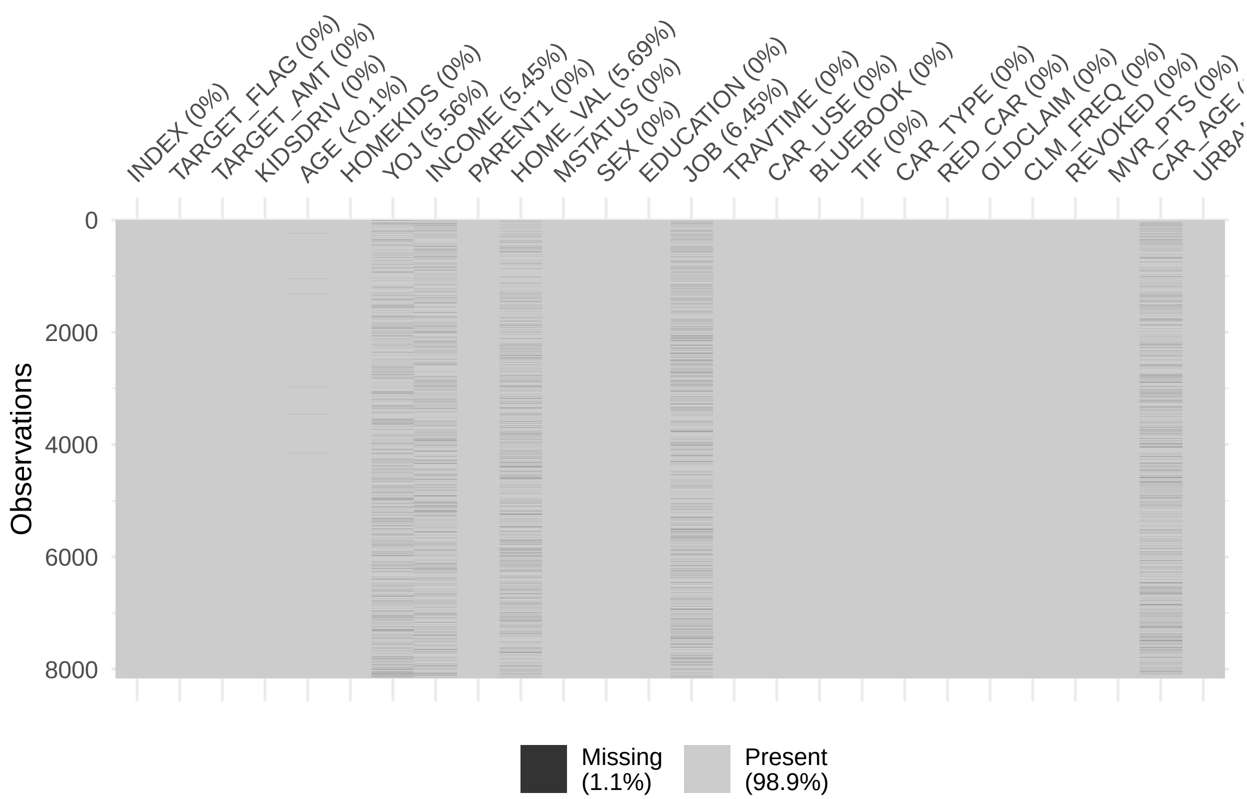
```
##    Mode   FALSE    TRUE
## logical    2116    6045
```

With these results, if we remove all rows with incomplete rows, there will be a total of 6045 rows out of 8161 .If we eliminate all non-complete rows and keep only rows with data for all the predictors in the dataset, our new dataset will results in 74% of the total dataset. We create a subset of data with complete cases only to use later in our analysis.

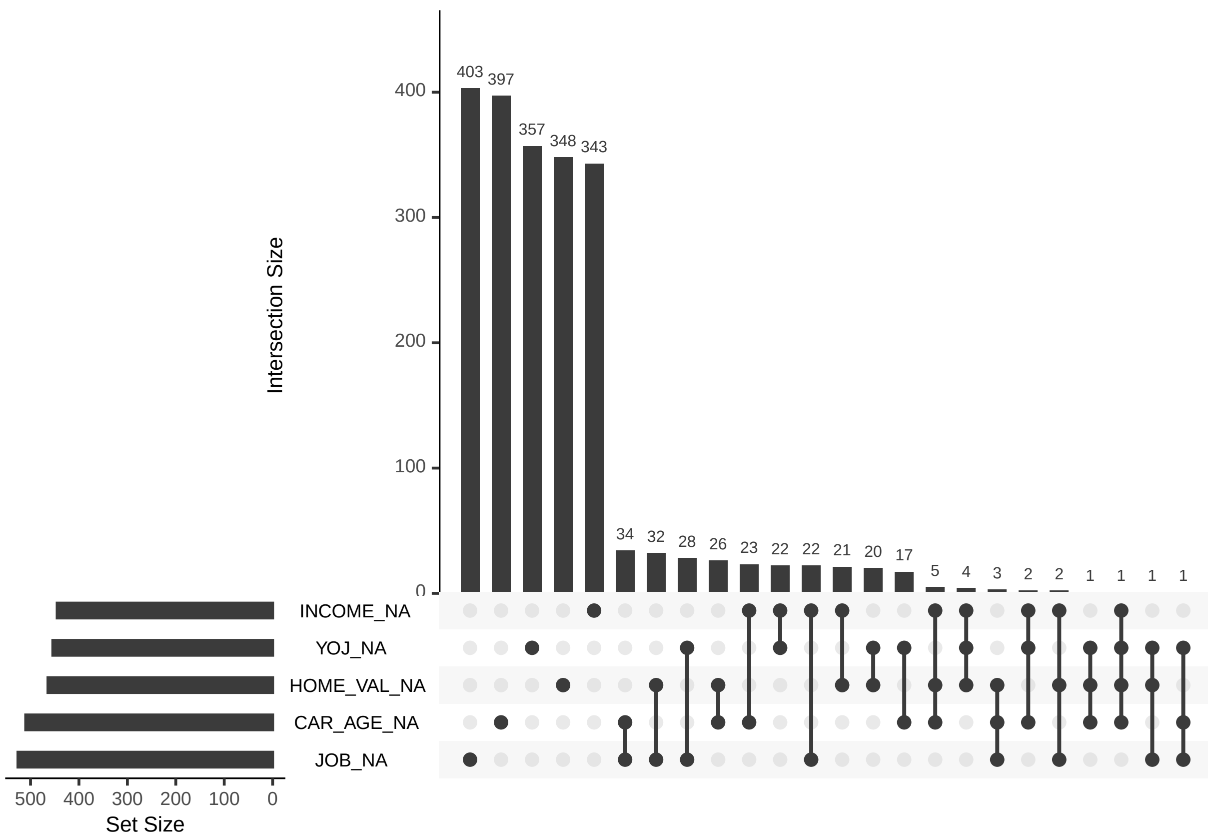
```
## Observations: 6,045
## Variables: 26
## $ INDEX       <int> 1, 2, 4, 7, 12, 13, 14, 15, 16, 19, 20, 22, 23, 24, 25,...
## $ TARGET_FLAG <int> 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0...
## $ TARGET_AMT  <dbl> 0.000, 0.000, 0.000, 2946.000, 2501.000, 0.000, 6077.00...
## $ KIDSDRIV    <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0...
## $ AGE         <int> 60, 43, 35, 34, 34, 50, 53, 43, 55, 45, 39, 42, 34, 31,...
## $ HOMEKIDS    <int> 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 3, 0, 3, 2, 1, 0, 0, 2, 1...
## $ YOJ         <int> 11, 11, 10, 12, 10, 7, 14, 5, 11, 0, 12, 11, 13, 12, 13...
## $ INCOME      <fct> "$67,349", "$91,449", "$16,039", "$125,301", "$62,978",...
## $ PARENT1     <fct> No, No, No, Yes, No, No, No, No, No, No, Yes, No, No, N...
## $ HOME_VAL    <fct> "$0", "$257,252", "$124,191", "$0", "$0", "$0", "$0", "...
## $ MSTATUS     <fct> z_No, z_No, Yes, z_No, z_No, z_No, z_No, Yes, Yes, Yes,...
## $ SEX         <fct> M, M, z_F, z_F, z_F, M, z_F, z_F, M, z_F, z_F, M, z_F, ...
## $ EDUCATION   <fct> PhD, z_High School, z_High School, Bachelors, Bachelors...
```

```
## $ JOB         <fct> Professional, z_Blue Collar, Clerical, z_Blue Collar, C...
## $ TRAVTIME    <int> 14, 22, 5, 46, 34, 48, 15, 36, 25, 48, 43, 42, 27, 48, ...
## $ CAR_USE     <fct> Private, Commercial, Private, Commercial, Private, Comm...
## $ BLUEBOOK    <fct> "$14,230", "$14,940", "$4,010", "$17,430", "$11,200", "...
## $ TIF         <int> 11, 1, 4, 1, 1, 7, 1, 7, 7, 1, 6, 6, 7, 4, 6, 6, 10, 6,...
## $ CAR_TYPE    <fct> Minivan, Minivan, z_SUV, Sports Car, z_SUV, Van, Sports...
## $ RED_CAR     <fct> yes, yes, no, no, no, no, no, no, yes, no, no, no, no, ...
## $ OLDCLAIM    <fct> "$4,461", "$0", "$38,690", "$0", "$0", "$0", "$0", "$0"...
## $ CLM_FREQ    <int> 2, 0, 2, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 2, 1, 0, 3, 0...
## $ REVOKED     <fct> No, No, No, No, No, No, No, No, Yes, No, No, No, No, No...
## $ MVR_PTS     <int> 3, 0, 3, 0, 0, 1, 0, 0, 3, 3, 0, 0, 0, 0, 0, 5, 1, 0, 2...
## $ CAR_AGE     <int> 18, 1, 10, 7, 1, 17, 11, 1, 9, 5, 13, 16, 20, 7, 1, 14,...
## $ URBANICITY  <fct> Highly Urban/ Urban, Highly Urban/ Urban, Highly Urban/...
```

But we can also look at what specific predictors are missing in our dataset. If we do this we can see how there is much more data available, as we find only 5 predictors with missing data. Data missing for these predictors also only accounts for less than 7% of the respective predictors total.



We look closer at the missing data and look at the intersection of predictors with missing data. We find that the bulk of the missing data is for predictors with no intersection with other missing predictor data.



Having this detail in missing data might be of importance when looking at models. In the next Data Preparation section we will handle these missing cases and build a data set with data for all predictors in all rows.

Data Exploration

Using TARGET_FLAG as response variables we confirm when TARGET_FLAG is 1 TARGET_AMOUNT >0 and when TARGET_FLAG is 0 when TARGET_AMOUNT = 0

```r
nrow(subset(InsTrain,TARGET_FLAG == 0))
```

```
## [1] 6008
```

```r
nrow(subset(InsTrain,TARGET_AMT == 0))
```

```
## [1] 6008
```

```r
nrow(subset(InsTrain,TARGET_FLAG > 0))
```

```
## [1] 2153
```

```r
nrow(subset(InsTrain,TARGET_AMT > 0))
```

```
## [1] 2153
```

A glimpse of the data shows that the following columns should be integers and not Factors:

- INCOME
- HOME_VAL
- BLUEBOOK
- OLDCLAIM

We display and view data with all cases and only complete cases

```
## INCOME PARENT1 HOME_VAL MSTATUS SEX EDUCATION JOB CAR_USE BLUEBOOK CAR_TYPE RED_CAR OLDCLAIM REVOKED
```

```
## Observations: 8,161
## Variables: 26
## $ INDEX       <int> 1, 2, 4, 5, 6, 7, 8, 11, 12, 13, 14, 15, 16, 17, 19, 20...
## $ TARGET_FLAG <int> 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0...
## $ TARGET_AMT  <dbl> 0.000, 0.000, 0.000, 0.000, 0.000, 2946.000, 0.000, 402...
## $ KIDSDRIV    <int> 0, 0, 0, 0, 0, 0, 0, 1, 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,...
## $ HOMEKIDS    <int> 0, 0, 1, 0, 0, 1, 0, 2, 0, 0, 0, 0, 0, 0, 0, 3, 0, 3, 2...
## $ YOJ         <int> 11, 11, 10, 14, NA, 12, NA, NA, 10, 7, 14, 5, 11, 11, 0...
## $ INCOME      <fct> "$67,349", "$91,449", "$16,039", NA, "$114,986", "$125,...
## $ PARENT1     <fct> No, No, No, No, No, Yes, No, No, No, No, No, No, No, No...
## $ HOME_VAL    <fct> "$0", "$257,252", "$124,191", "$306,251", "$243,925", "...
## $ MSTATUS     <fct> z_No, z_No, Yes, Yes, Yes, z_No, Yes, Yes, z_No, z_No, ...
## $ SEX         <fct> M, M, z_F, M, z_F, z_F, z_F, M, z_F, M, z_F, z_F, M, M,...
## $ EDUCATION   <fct> PhD, z_High School, z_High School, <High School, PhD, B...
## $ JOB         <fct> Professional, z_Blue Collar, Clerical, z_Blue Collar, D...
## $ TRAVTIME    <int> 14, 22, 5, 32, 36, 46, 33, 44, 34, 48, 15, 36, 25, 64, ...
## $ CAR_USE     <fct> Private, Commercial, Private, Private, Private, Commerc...
## $ BLUEBOOK    <fct> "$14,230", "$14,940", "$4,010", "$15,440", "$18,000", "...
## $ TIF         <int> 11, 1, 4, 7, 1, 1, 1, 1, 1, 7, 1, 7, 7, 6, 1, 6, 6, 7, ...
## $ CAR_TYPE    <fct> Minivan, Minivan, z_SUV, Minivan, z_SUV, Sports Car, z_...
## $ RED_CAR     <fct> yes, yes, no, yes, no, no, no, yes, no, no, no, no, yes...
## $ OLDCLAIM    <fct> "$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...
## $ REVOKED     <fct> No, No, No, No, Yes, No, No, Yes, No, No, No, No, Yes, ...
## $ MVR_PTS     <int> 3, 0, 3, 0, 3, 0, 0, 10, 0, 1, 0, 0, 3, 3, 3, 0, 0, 0, ...
## $ CAR_AGE     <int> 18, 1, 10, 6, 17, 7, 1, 7, 1, 17, 11, 1, 9, 10, 5, 13, ...
## $ URBANICITY  <fct> Highly Urban/ Urban, Highly Urban/ Urban, Highly Urban/...
```

We use sapply function to review which columns have NA Values. It display columns and percent of values that are missing.

```
##       INDEX TARGET_FLAG  TARGET_AMT    KIDSDRIV         AGE    HOMEKIDS
##         0.0         0.0         0.0         0.0         0.1         0.0
##         YOJ      INCOME     PARENT1    HOME_VAL     MSTATUS         SEX
##         5.6         5.5         0.0         5.7         0.0         0.0
```

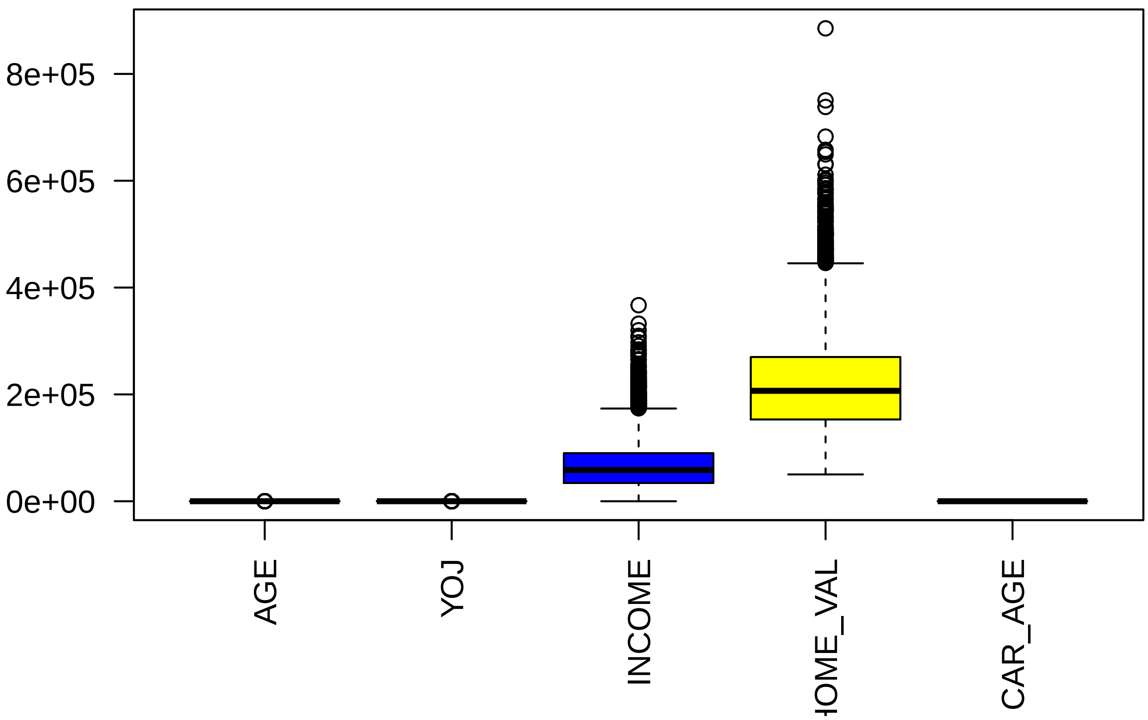
```
##   EDUCATION         JOB    TRAVTIME     CAR_USE    BLUEBOOK         TIF
##         0.0         6.4         0.0         0.0         0.0         0.0
##    CAR_TYPE     RED_CAR    OLDCLAIM    CLM_FREQ     REVOKED     MVR_PTS
##         0.0         0.0         0.0         0.0         0.0         0.0
##     CAR_AGE  URBANICITY
##         6.2         0.0
```

Data Preparation

As revealed earlier there were a list of columns that we factors that should be integers. We start by converting the columns to numeric.

```
## Observations: 8,161
## Variables: 4
## $ INCOME   <fct> "$67,349", "$91,449", "$16,039", NA, "$114,986", "$125,301...
## $ HOME_VAL <fct> "$0", "$257,252", "$124,191", "$306,251", "$243,925", "$0"...
## $ BLUEBOOK <fct> "$14,230", "$14,940", "$4,010", "$15,440", "$18,000", "$17...
## $ OLDCLAIM <fct> "$4,461", "$0", "$38,690", "$0", "$19,217", "$0", "$0", "$...
## Observations: 8,161
## Variables: 4
## $ INCOME   <int> 67349, 91449, 16039, NA, 114986, 125301, 18755, 107961, 62...
## $ HOME_VAL <int> 0, 257252, 124191, 306251, 243925, 0, NA, 333680, 0, 0, 0,...
## $ BLUEBOOK <int> 14230, 14940, 4010, 15440, 18000, 17430, 8780, 16970, 1120...
## $ OLDCLAIM <int> 4461, 0, 38690, 0, 19217, 0, 0, 2374, 0, 0, 0, 0, 5028, 0,...
```

Both boxplot and summary stats with the square root transform of Home_val and Income to confirm we can use median or mean values to replace NA values if we chose.

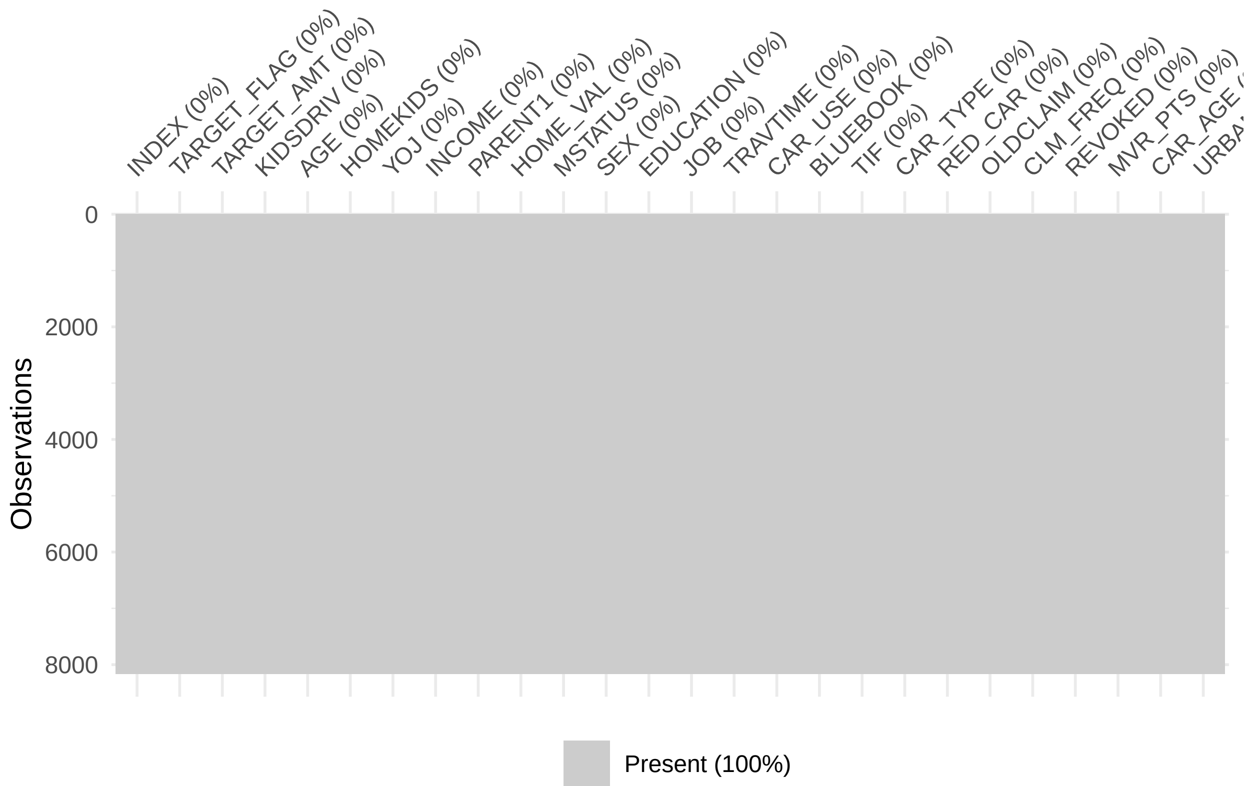



```
##          vars    n      mean       sd median   trimmed      mad   min    max
## AGE         1 8155     44.79     8.63     45     44.83     8.90    16     81
## YOJ         2 7707     10.50     4.09     11     11.07     2.97     0     23
## INCOME      3 7101  67258.94 45810.25  58438  61952.41 39533.53     5 367030
## HOME_VAL    4 5403 220620.68 96145.72 206692 211487.81 85498.58 50223 885282
## CAR_AGE     5 7651      8.33     5.70      8      7.96     7.41    -3     28
##           range  skew kurtosis      se
## AGE          65 -0.03    -0.06    0.10
## YOJ          23 -1.20     1.18    0.05
## INCOME   367025  1.30     2.50  543.63
## HOME_VAL 835059  1.09     1.97 1308.01
## CAR_AGE      31  0.28    -0.75    0.07
```

We next replace all NA values with mean values for cases that are missing values, we impute the JOBs variable for now (although we will reconsider whether omitting these rows is better) and rerun sapply function to confirm there are no longer any missing values.

```
##       INDEX TARGET_FLAG  TARGET_AMT    KIDSDRIV         AGE    HOMEKIDS
##         0.0         0.0         0.0         0.0         0.1         0.0
##         YOJ      INCOME     PARENT1    HOME_VAL     MSTATUS         SEX
##         5.6        13.0         0.0        33.8         0.0         0.0
##   EDUCATION         JOB    TRAVTIME     CAR_USE    BLUEBOOK         TIF
##         0.0         6.4         0.0         0.0         0.0         0.0
##    CAR_TYPE     RED_CAR    OLDCLAIM    CLM_FREQ     REVOKED     MVR_PTS
##         0.0         0.0         0.0         0.0         0.0         0.0
```

```
##     CAR_AGE  URBANICITY
##         6.2         0.0
```




```
##          vars    n      mean       sd    median   trimmed      mad   min    max
## AGE         1 8161     44.79     8.62     45.00     44.83     8.90    16     81
## YOJ         2 8161     10.50     3.98     11.00     11.05     2.97     0     23
## INCOME      3 8161  67258.94 42731.37  66367.00  62497.52 36362.25     5 367030
## HOME_VAL    4 8161 220620.68 78227.99 220620.68 214305.03 41344.79 50223 885282
## CAR_AGE     5 8161      8.33     5.52      8.33      7.98     5.44    -3     28
##           range  skew kurtosis     se
## AGE          65 -0.03    -0.06   0.10
## YOJ          23 -1.24     1.42   0.04
## INCOME   367025  1.40     3.32 473.02
## HOME_VAL 835059  1.34     4.50 865.95
## CAR_AGE      31  0.29    -0.60   0.06
```

We have this way derived a dataset with no missing values. We can use this set of data for our modeling design. We chose to work with this data as opposed to the first "complete" set in which rows with missing data were eliminated.

Build Model

Modeling design will be divided in two phases. First we will design a model to predict if the person is in a car crash, that is predict TARGET_FLAG. In a second phase, we will predict TARGET_AMT, the cost of the crash.

TARGET_FLAG Modeling

This response variable being binary, 0 or 1, we will be looking at logistic regression models to find a good fit. We will start with a naive model with all the predictors included as a baseline. First approach will be to simply the model by reducing the predictors used. We will look at several model metrics such as AIC, BIC. We will also include confusion tables and ROC plot to better understand each model.

Model 1: all predictors

We start out with a straightforward logit logistical regression with all predictors included. As a note, we need to make sure we do not include the TARGET_AMT response variable in our model as a predictor.

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - INDEX - TARGET_AMT, family = binomial(link = "logit"),
##     data = InsTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5548  -0.7184  -0.4032   0.6346   3.1472
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -4.750e-01  2.748e-01  -1.728 0.083915 .
## KIDSDRIV                         3.847e-01  6.101e-02   6.306 2.87e-10 ***
## AGE                             -8.588e-04  4.011e-03  -0.214 0.830483
## HOMEKIDS                         5.680e-02  3.720e-02   1.527 0.126829
## YOJ                             -1.914e-02  8.888e-03  -2.154 0.031261 *
## INCOME                          -2.155e-06  1.162e-06  -1.855 0.063585 .
## PARENT1Yes                       3.795e-01  1.095e-01   3.467 0.000526 ***
## HOME_VAL                        -9.005e-07  5.908e-07  -1.524 0.127471
## MSTATUSz_No                      6.329e-01  7.272e-02   8.703  < 2e-16 ***
## SEXz_F                          -7.739e-02  1.118e-01  -0.692 0.488791
## EDUCATIONBachelors              -4.599e-01  1.144e-01  -4.018 5.86e-05 ***
## EDUCATIONMasters                -5.141e-01  1.532e-01  -3.357 0.000789 ***
## EDUCATIONPhD                    -4.617e-01  1.880e-01  -2.456 0.014063 *
## EDUCATIONz_High School          -1.365e-02  9.467e-02  -0.144 0.885335
## JOBDoctor                       -7.034e-01  2.656e-01  -2.648 0.008092 **
## JOBHome Maker                   -6.625e-02  1.425e-01  -0.465 0.642047
## JOBLawyer                       -1.851e-01  1.616e-01  -1.146 0.251943
## JOBManager                      -9.248e-01  1.356e-01  -6.822 8.98e-12 ***
## JOBProfessional                 -2.485e-01  1.215e-01  -2.045 0.040901 *
## JOBStudent                      -2.503e-03  1.301e-01  -0.019 0.984651
## JOBz_Blue Collar                -1.727e-01  1.049e-01  -1.645 0.099934 .
## TRAVTIME                         1.464e-02  1.878e-03   7.791 6.64e-15 ***
## CAR_USEPrivate                  -7.768e-01  9.085e-02  -8.550  < 2e-16 ***
## BLUEBOOK                        -2.204e-05  5.235e-06  -4.210 2.56e-05 ***
## TIF                             -5.561e-02  7.333e-03  -7.583 3.37e-14 ***
## CAR_TYPEPanel Truck              4.823e-01  1.577e-01   3.058 0.002230 **
## CAR_TYPEPickup                   5.241e-01  9.983e-02   5.250 1.52e-07 ***
## CAR_TYPESports Car               1.022e+00  1.297e-01   7.883 3.20e-15 ***
## CAR_TYPEVan                      5.776e-01  1.251e-01   4.618 3.87e-06 ***
## CAR_TYPEz_SUV                    7.609e-01  1.112e-01   6.842 7.83e-12 ***
## RED_CARyes                      -1.577e-03  8.608e-02  -0.018 0.985383
## OLDCLAIM                        -1.404e-05  3.902e-06  -3.598 0.000320 ***
```

```
## CLM_FREQ                         1.992e-01  2.847e-02   6.997 2.62e-12 ***
## REVOKEDYes                       8.955e-01  9.104e-02   9.837  < 2e-16 ***
## MVR_PTS                          1.152e-01  1.357e-02   8.489  < 2e-16 ***
## CAR_AGE                         -5.591e-04  7.516e-03  -0.074 0.940704
## URBANICITYz_Highly Rural/ Rural -2.383e+00  1.129e-01 -21.103  < 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: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7327.1  on 8124  degrees of freedom
## AIC: 7401.1
##
## Number of Fisher Scoring iterations: 5
```

From the model's summary itself we see that there are several predictors which are not statistically relevant, which suggest a simpler model should be possible. We build a second model without the non-significant predictors.

Model 2: reduced predictors

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - INDEX - TARGET_AMT - AGE - INCOME -
##     JOB - BLUEBOOK - CAR_AGE - RED_CAR, family = binomial(link = "logit"),
##     data = InsTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4982  -0.7289  -0.4194   0.6476   3.1224
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -6.275e-01  1.842e-01  -3.406 0.000658 ***
## KIDSDRIV                         3.483e-01  5.950e-02   5.854 4.79e-09 ***
## HOMEKIDS                         9.058e-02  3.372e-02   2.687 0.007219 **
## YOJ                             -2.828e-02  7.362e-03  -3.842 0.000122 ***
## PARENT1Yes                       3.696e-01  1.077e-01   3.432 0.000598 ***
## HOME_VAL                        -2.108e-06  4.702e-07  -4.483 7.38e-06 ***
## MSTATUSz_No                      6.213e-01  7.191e-02   8.641  < 2e-16 ***
## SEXz_F                          -2.529e-01  8.790e-02  -2.878 0.004007 **
## EDUCATIONBachelors              -7.334e-01  9.571e-02  -7.663 1.82e-14 ***
## EDUCATIONMasters                -8.017e-01  1.049e-01  -7.642 2.14e-14 ***
## EDUCATIONPhD                    -9.544e-01  1.391e-01  -6.864 6.70e-12 ***
## EDUCATIONz_High School          -1.246e-01  9.123e-02  -1.366 0.172010
## TRAVTIME                         1.496e-02  1.866e-03   8.017 1.08e-15 ***
## CAR_USEPrivate                  -8.298e-01  7.286e-02 -11.388  < 2e-16 ***
## TIF                             -5.428e-02  7.270e-03  -7.466 8.26e-14 ***
## CAR_TYPEPanel Truck              1.106e-01  1.317e-01   0.839 0.401223
## CAR_TYPEPickup                   5.561e-01  9.698e-02   5.734 9.81e-09 ***
## CAR_TYPESports Car               1.208e+00  1.201e-01  10.053  < 2e-16 ***
## CAR_TYPEVan                      4.075e-01  1.186e-01   3.435 0.000592 ***
## CAR_TYPEz_SUV                    9.573e-01  1.017e-01   9.411  < 2e-16 ***
```

```
## OLDCLAIM                        -1.403e-05  3.862e-06  -3.632 0.000281 ***
## CLM_FREQ                         2.006e-01  2.824e-02   7.104 1.21e-12 ***
## REVOKEDYes                       9.037e-01  9.019e-02  10.021  < 2e-16 ***
## MVR_PTS                          1.205e-01  1.347e-02   8.946  < 2e-16 ***
## URBANICITYz_Highly Rural/ Rural -2.283e+00  1.119e-01 -20.400  < 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: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7425.7  on 8136  degrees of freedom
## AIC: 7475.7
##
## Number of Fisher Scoring iterations: 5
```

The new model has a slightly higher AIC which would tells us the first model is slightly less complex.

AIC Step Method Model 3

Another way of selecting which predictors to use in the model is by calculating the AIC of the model. This metric is similar to the adjusted R-square of a model in that it penalizes models with more predictors over simpler model with few predictors. We use Stepwise function in r to find the lowest AIC with different predictors.

```
## Start:  AIC=7401.13
## TARGET_FLAG ~ (INDEX + TARGET_AMT + KIDSDRIV + AGE + HOMEKIDS +
##     YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION +
##     JOB + TRAVTIME + CAR_USE + BLUEBOOK + TIF + CAR_TYPE + RED_CAR +
##     OLDCLAIM + CLM_FREQ + REVOKED + MVR_PTS + CAR_AGE + URBANICITY) -
##     INDEX - TARGET_AMT
##
##              Df Deviance    AIC
## - RED_CAR     1   7327.1 7399.1
## - CAR_AGE     1   7327.1 7399.1
## - AGE         1   7327.2 7399.2
## - SEX         1   7327.6 7399.6
## <none>            7327.1 7401.1
## - HOMEKIDS    1   7329.4 7401.4
## - HOME_VAL    1   7329.5 7401.5
## - INCOME      1   7330.6 7402.6
## - YOJ         1   7331.8 7403.8
## - PARENT1     1   7339.2 7411.2
## - OLDCLAIM    1   7340.3 7412.3
## - BLUEBOOK    1   7345.2 7417.2
## - EDUCATION   4   7356.1 7422.1
## - KIDSDRIV    1   7366.9 7438.9
## - CLM_FREQ    1   7375.4 7447.4
## - JOB         7   7390.8 7450.8
## - TIF         1   7386.8 7458.8
## - TRAVTIME    1   7388.0 7460.0
## - MVR_PTS     1   7399.8 7471.8
## - CAR_USE     1   7401.4 7473.4
```

```
## - MSTATUS     1   7402.8 7474.8
## - CAR_TYPE    5   7415.2 7479.2
## - REVOKED     1   7422.2 7494.2
## - URBANICITY  1   7971.7 8043.7
##
## Step:  AIC=7399.13
## TARGET_FLAG ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME + CAR_USE +
##     BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED +
##     MVR_PTS + CAR_AGE + URBANICITY
##
##              Df Deviance    AIC
## - CAR_AGE     1   7327.1 7397.1
## - AGE         1   7327.2 7397.2
## - SEX         1   7327.7 7397.7
## <none>            7327.1 7399.1
## - HOMEKIDS    1   7329.4 7399.4
## - HOME_VAL    1   7329.5 7399.5
## - INCOME      1   7330.6 7400.6
## - YOJ         1   7331.8 7401.8
## - PARENT1     1   7339.2 7409.2
## - OLDCLAIM    1   7340.3 7410.3
## - BLUEBOOK    1   7345.2 7415.2
## - EDUCATION   4   7356.1 7420.1
## - KIDSDRIV    1   7366.9 7436.9
## - CLM_FREQ    1   7375.4 7445.4
## - JOB         7   7390.9 7448.9
## - TIF         1   7386.8 7456.8
## - TRAVTIME    1   7388.0 7458.0
## - MVR_PTS     1   7399.8 7469.8
## - CAR_USE     1   7401.4 7471.4
## - MSTATUS     1   7402.9 7472.9
## - CAR_TYPE    5   7415.3 7477.3
## - REVOKED     1   7422.2 7492.2
## - URBANICITY  1   7971.7 8041.7
##
## Step:  AIC=7397.13
## TARGET_FLAG ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME + CAR_USE +
##     BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED +
##     MVR_PTS + URBANICITY
##
##              Df Deviance    AIC
## - AGE         1   7327.2 7395.2
## - SEX         1   7327.7 7395.7
## <none>            7327.1 7397.1
## - HOMEKIDS    1   7329.5 7397.5
## - HOME_VAL    1   7329.5 7397.5
## - INCOME      1   7330.6 7398.6
## - YOJ         1   7331.8 7399.8
## - PARENT1     1   7339.2 7407.2
## - OLDCLAIM    1   7340.3 7408.3
## - BLUEBOOK    1   7345.2 7413.2
## - EDUCATION   4   7365.8 7427.8
```

```
## - KIDSDRIV    1   7366.9 7434.9
## - CLM_FREQ    1   7375.4 7443.4
## - JOB         7   7390.9 7446.9
## - TIF         1   7386.8 7454.8
## - TRAVTIME    1   7388.0 7456.0
## - MVR_PTS     1   7399.8 7467.8
## - CAR_USE     1   7401.4 7469.4
## - MSTATUS     1   7402.9 7470.9
## - CAR_TYPE    5   7415.3 7475.3
## - REVOKED     1   7422.3 7490.3
## - URBANICITY  1   7971.8 8039.8
##
## Step:  AIC=7395.18
## TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + YOJ + INCOME + PARENT1 +
##     HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME + CAR_USE +
##     BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED +
##     MVR_PTS + URBANICITY
##
##              Df Deviance    AIC
## - SEX         1   7327.7 7393.7
## <none>            7327.2 7395.2
## - HOME_VAL    1   7329.5 7395.5
## - HOMEKIDS    1   7330.1 7396.1
## - INCOME      1   7330.7 7396.7
## - YOJ         1   7332.1 7398.1
## - PARENT1     1   7339.5 7405.5
## - OLDCLAIM    1   7340.4 7406.4
## - BLUEBOOK    1   7345.7 7411.7
## - EDUCATION   4   7365.8 7425.8
## - KIDSDRIV    1   7367.8 7433.8
## - CLM_FREQ    1   7375.4 7441.4
## - JOB         7   7391.1 7445.1
## - TIF         1   7386.8 7452.8
## - TRAVTIME    1   7388.0 7454.0
## - MVR_PTS     1   7400.0 7466.0
## - CAR_USE     1   7401.4 7467.4
## - MSTATUS     1   7403.2 7469.2
## - CAR_TYPE    5   7415.5 7473.5
## - REVOKED     1   7422.3 7488.3
## - URBANICITY  1   7972.5 8038.5
##
## Step:  AIC=7393.74
## TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + YOJ + INCOME + PARENT1 +
##     HOME_VAL + MSTATUS + EDUCATION + JOB + TRAVTIME + CAR_USE +
##     BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM + CLM_FREQ + REVOKED +
##     MVR_PTS + URBANICITY
##
##              Df Deviance    AIC
## <none>            7327.7 7393.7
## - HOME_VAL    1   7330.1 7394.1
## - HOMEKIDS    1   7330.6 7394.6
## - INCOME      1   7331.3 7395.3
## - YOJ         1   7332.6 7396.6
## - PARENT1     1   7339.9 7403.9
```

```
## - OLDCLAIM    1   7340.9 7404.9
## - BLUEBOOK    1   7354.0 7418.0
## - EDUCATION   4   7366.4 7424.4
## - KIDSDRIV    1   7368.4 7432.4
## - CLM_FREQ    1   7376.1 7440.1
## - JOB         7   7391.2 7443.2
## - TIF         1   7387.4 7451.4
## - TRAVTIME    1   7388.7 7452.7
## - MVR_PTS     1   7400.4 7464.4
## - CAR_USE     1   7401.8 7465.8
## - MSTATUS     1   7403.7 7467.7
## - REVOKED     1   7423.1 7487.1
## - CAR_TYPE    5   7433.7 7489.7
## - URBANICITY  1   7973.3 8037.3
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + YOJ + INCOME +
##     PARENT1 + HOME_VAL + MSTATUS + EDUCATION + JOB + TRAVTIME +
##     CAR_USE + BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM + CLM_FREQ +
##     REVOKED + MVR_PTS + URBANICITY, family = binomial(link = "logit"),
##     data = InsTrain)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5546  -0.7187  -0.4041   0.6353   3.1526
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -5.106e-01  2.178e-01  -2.345 0.019047 *
## KIDSDRIV                        3.823e-01  6.002e-02   6.370 1.88e-10 ***
## HOMEKIDS                        5.820e-02  3.452e-02   1.686 0.091808 .
## YOJ                            -1.934e-02  8.772e-03  -2.205 0.027427 *
## INCOME                         -2.171e-06  1.161e-06  -1.869 0.061576 .
## PARENT1Yes                      3.804e-01  1.090e-01   3.491 0.000481 ***
## HOME_VAL                       -9.027e-07  5.898e-07  -1.531 0.125877
## MSTATUSz_No                     6.331e-01  7.264e-02   8.716  < 2e-16 ***
## EDUCATIONBachelors             -4.625e-01  1.077e-01  -4.293 1.76e-05 ***
## EDUCATIONMasters               -5.204e-01  1.335e-01  -3.899 9.66e-05 ***
## EDUCATIONPhD                   -4.712e-01  1.731e-01  -2.721 0.006501 **
## EDUCATIONz_High School         -1.446e-02  9.436e-02  -0.153 0.878209
## JOBDoctor                      -6.976e-01  2.651e-01  -2.632 0.008499 **
## JOBHome Maker                  -8.113e-02  1.406e-01  -0.577 0.563927
## JOBLawyer                      -1.849e-01  1.610e-01  -1.148 0.251040
## JOBManager                     -9.240e-01  1.352e-01  -6.833 8.32e-12 ***
## JOBProfessional                -2.488e-01  1.214e-01  -2.050 0.040397 *
## JOBStudent                     -4.305e-03  1.299e-01  -0.033 0.973563
## JOBz_Blue Collar               -1.714e-01  1.049e-01  -1.634 0.102164
## TRAVTIME                        1.464e-02  1.878e-03   7.796 6.39e-15 ***
## CAR_USEPrivate                 -7.756e-01  9.080e-02  -8.542  < 2e-16 ***
## BLUEBOOK                       -2.383e-05  4.700e-06  -5.070 3.97e-07 ***
## TIF                            -5.559e-02  7.332e-03  -7.583 3.39e-14 ***
## CAR_TYPEPanel Truck             5.273e-01  1.467e-01   3.594 0.000326 ***
## CAR_TYPEPickup                  5.228e-01  9.974e-02   5.242 1.59e-07 ***
```

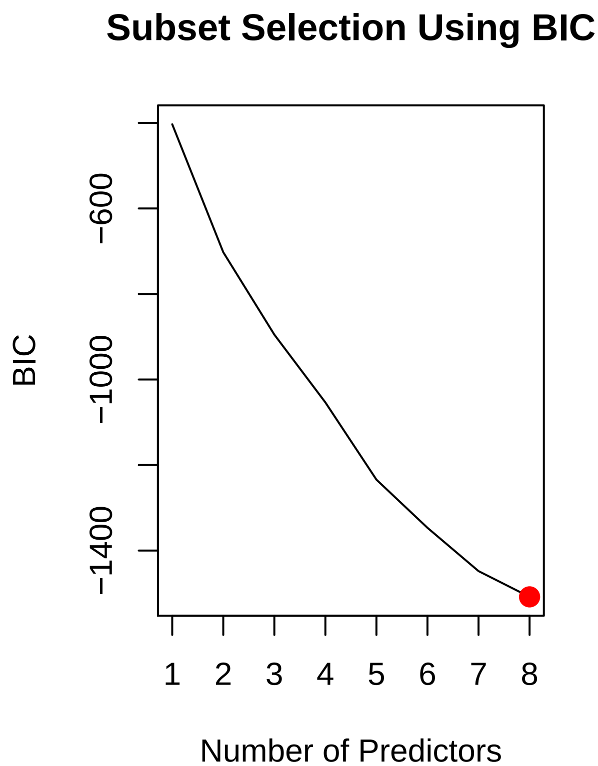
```
## CAR_TYPESports Car               9.666e-01  1.073e-01   9.007  < 2e-16 ***
## CAR_TYPEVan                      6.030e-01  1.208e-01   4.993 5.96e-07 ***
## CAR_TYPEz_SUV                    7.069e-01  8.587e-02   8.232  < 2e-16 ***
## OLDCLAIM                        -1.404e-05  3.902e-06  -3.599 0.000320 ***
## CLM_FREQ                         1.993e-01  2.846e-02   7.002 2.52e-12 ***
## REVOKEDYes                       8.966e-01  9.102e-02   9.850  < 2e-16 ***
## MVR_PTS                          1.152e-01  1.356e-02   8.494  < 2e-16 ***
## URBANICITYz_Highly Rural/ Rural -2.385e+00  1.129e-01 -21.115  < 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: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7327.7  on 8128  degrees of freedom
## AIC: 7393.7
##
## Number of Fisher Scoring iterations: 5
```

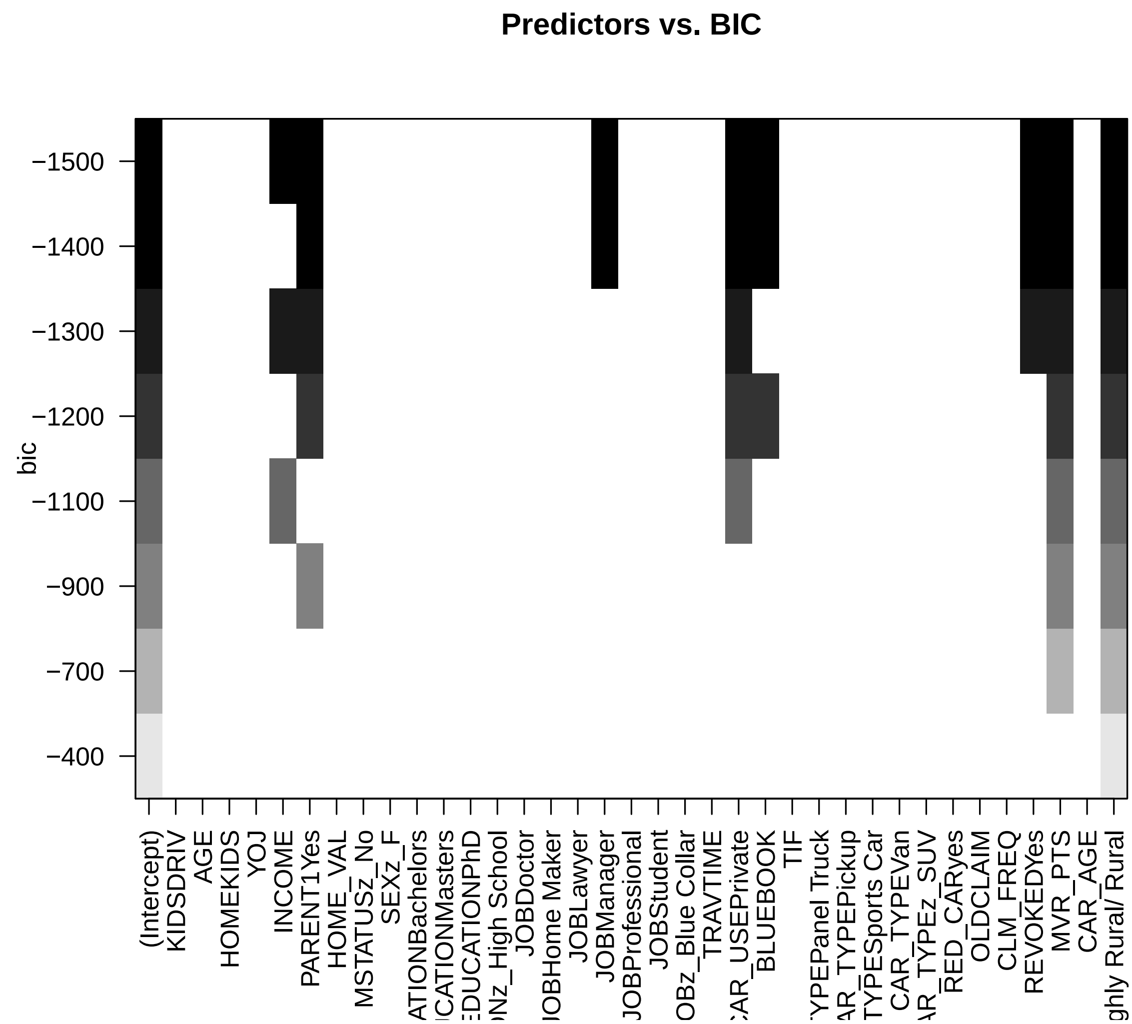
This reduces the predictors used to 25 from 30. The AIC is reduced from 7401.13 (our original general model) to 7393.7, just slightly and but we benefit by having a simpler model less prone to overfitting.

Also, the predictors in the model now are all significant (under 0.05 pr level) and all but one under .02 or very significant. Which is much improved over the first model.

BIC Method Model 4

To determine the number of predictors and which predictors to be used we will use the Bayesian Information Criterion (BIC).


Subset Selection Using BIC
BIC
−600
−1000
−1400
1
2
3
4
5
6
7
8
Number of Predictors



The plot on the right shows that the number of predictors with the lowest BIC are `PARENT` , `HOMEVAL`, `CAR_USE`, 'CAR_TYPE', 'REVOKED', 'MVR_PTS', 'CAR_AGE' and 'URBANICITY'. We will use those predictors to build the next model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.1597	0.1313	-1.216	0.224
PARENT1Yes	0.9546	0.07901	12.08	1.33e-33
HOME__VAL	-3.982e-06	4.656e-07	-8.553	1.198e-17
CAR__USEPrivate	-0.8658	0.06761	-12.81	1.536e-37
CAR__TYPEPickup	0.5309	0.09354	5.676	1.381e-08
CAR__TYPESports Car	1.015	0.1012	10.04	1.059e-23
CAR__TYPEVan	0.3784	0.1136	3.332	0.0008625
CAR__TYPEz__SUV	0.7943	0.0809	9.818	9.434e-23
REVOKEDYes	0.7583	0.07981	9.501	2.082e-21
MVR__PTS	0.1574	0.01282	12.28	1.137e-34
URBANICITYz__Highly Rural/ Rural	-2.022	0.1077	-18.77	1.286e-78
CAR__AGE	-0.03381	0.005697	-5.934	2.95e-09

(Dispersion parameter for binomial family taken to be 1)

Null deviance:	8639 on 7484 degrees of freedom
Residual deviance:	7144 on 7473 degrees of freedom

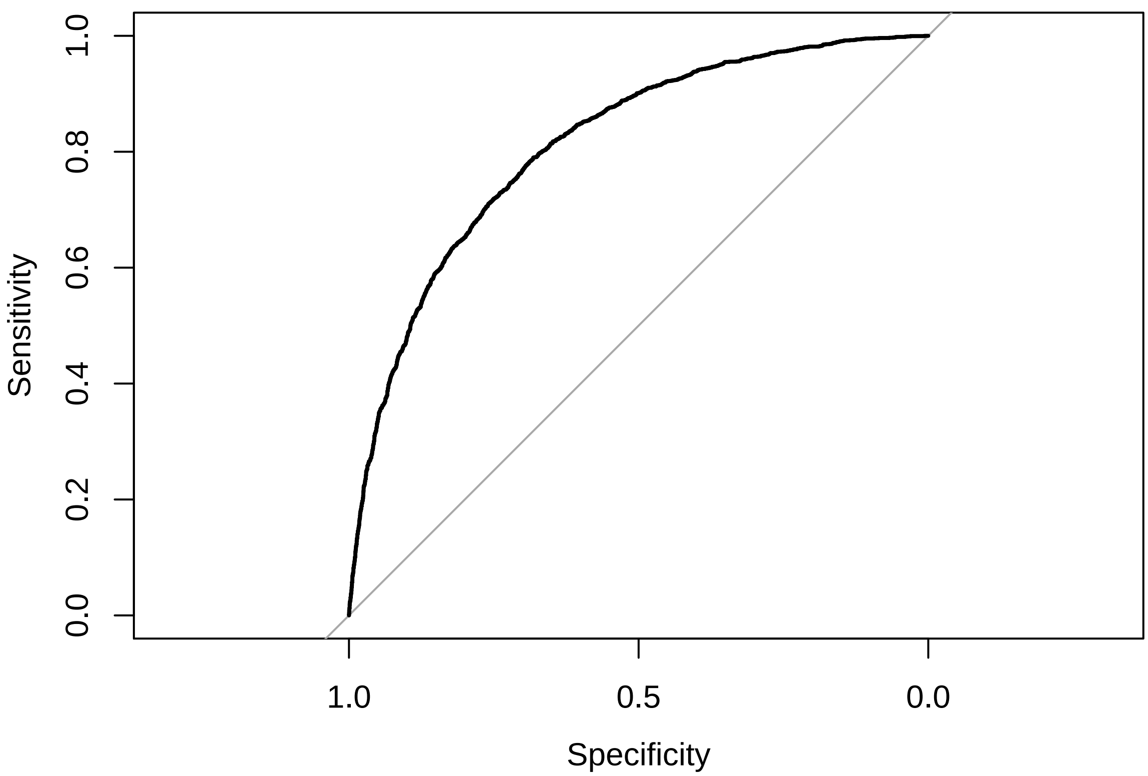
Select Model

Compare Model Statistics

Model 1 - General Model

ROC Curve

The ROC Curve helps measure true positives and true negative. A high AUC or area under the curve tells us the model is predicting well.

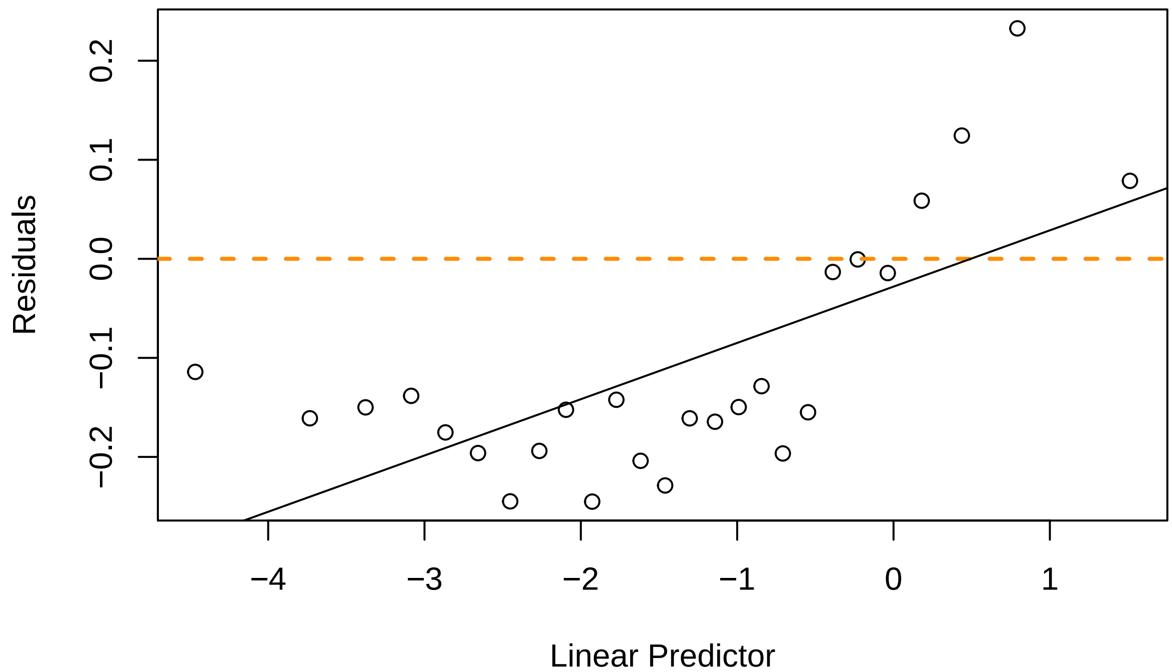


The AUC value of 0.81, tells us this model predicted values are accurate.

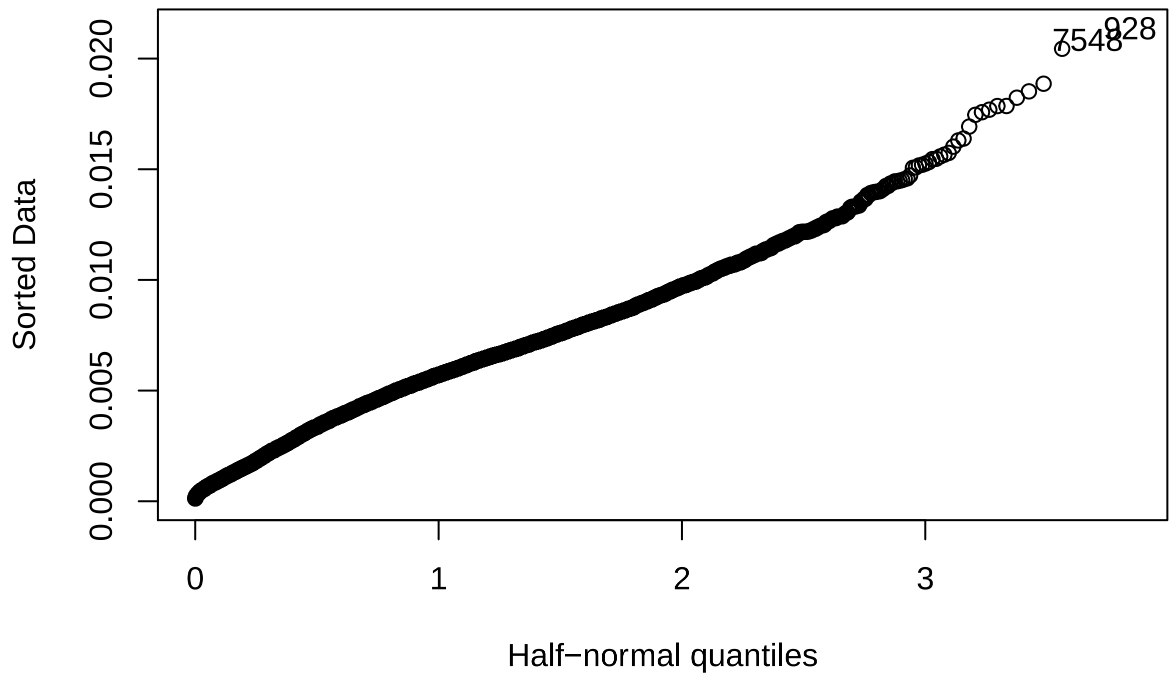
Confusion Matrix

```
##
## targethat    0    1
##          0 5554 1249
##          1  454  904
```

Create a binned diagnostic plot of residuals vs prediction There are definite patterns here, which bear investigating.

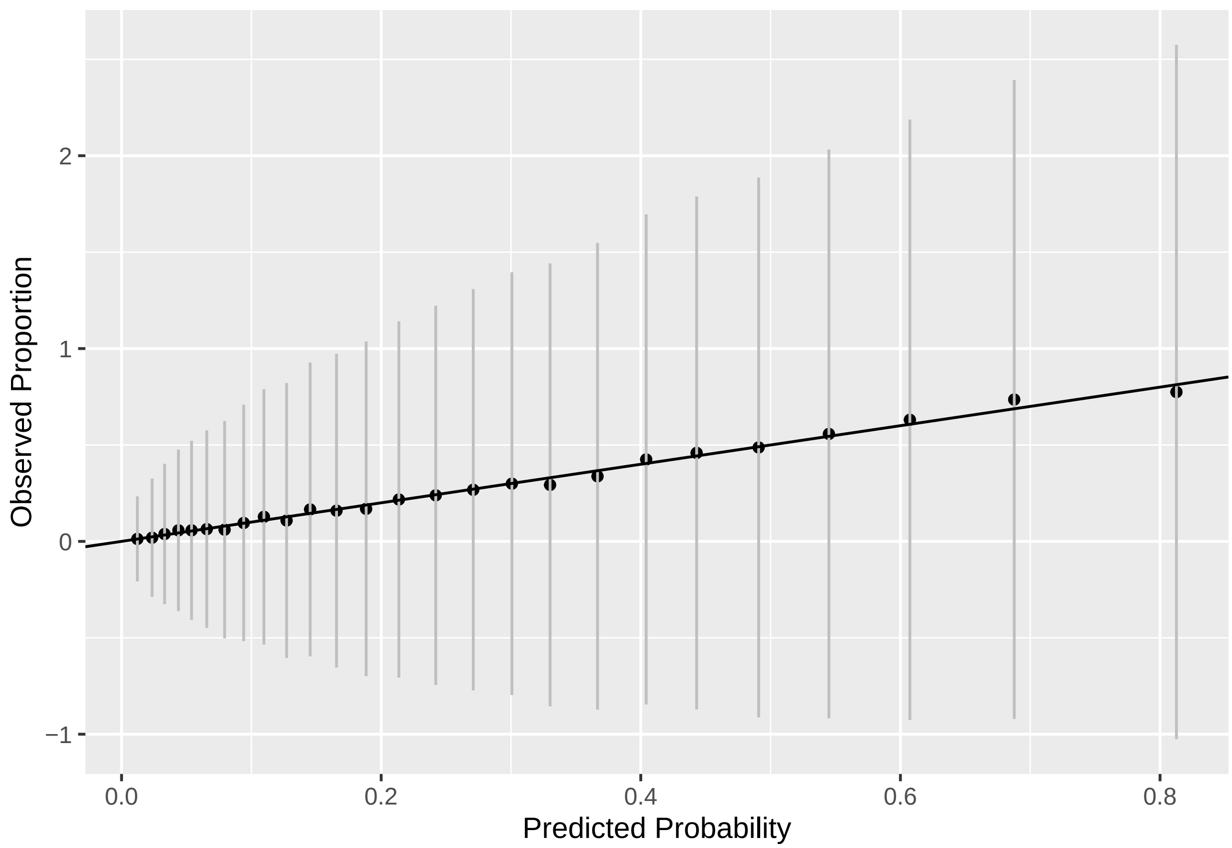


Plot leverages.



We don't see any strong outliers with the leverage plot. The points identified (3608,5686) are essentially in the plot of the line formed, so they are not likely pulling our model in any direction.

Plot Goodness of fit

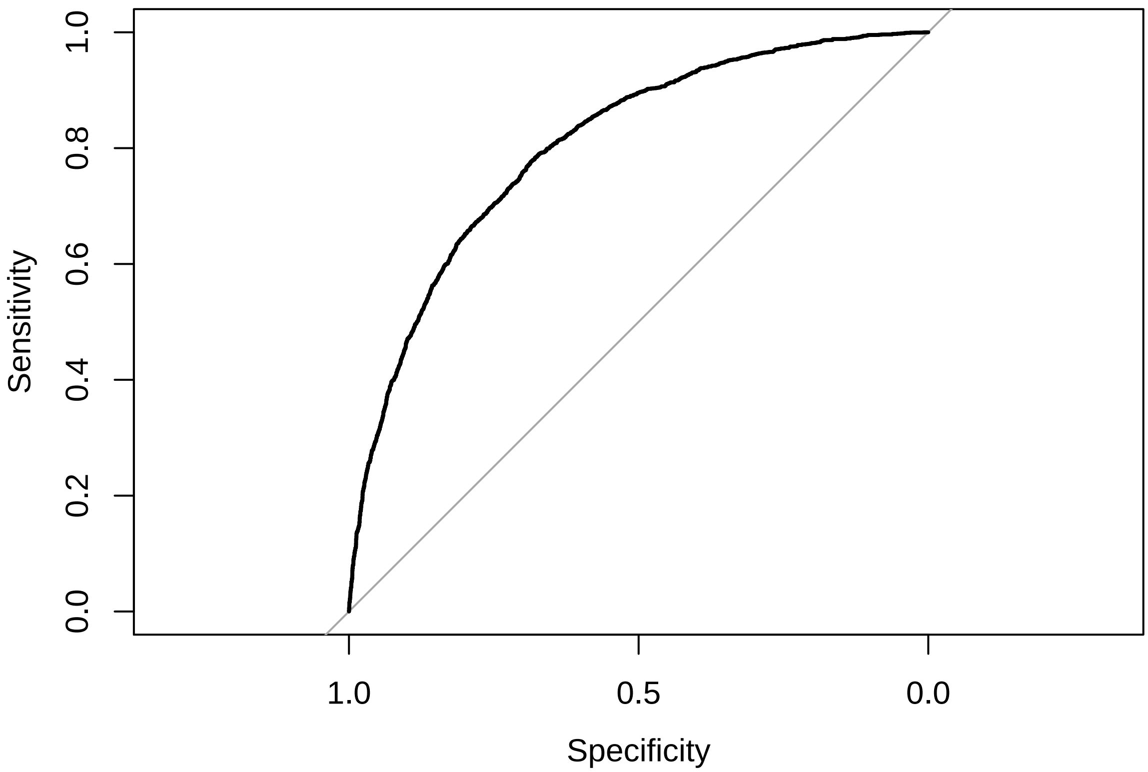


We see that our predictors fall close to the line.

Model 2 - Reduced General Model

ROC Curve

The ROC Curve helps measure true positives and true negative. A high AUC or area under the curve tells us the model is predicting well.

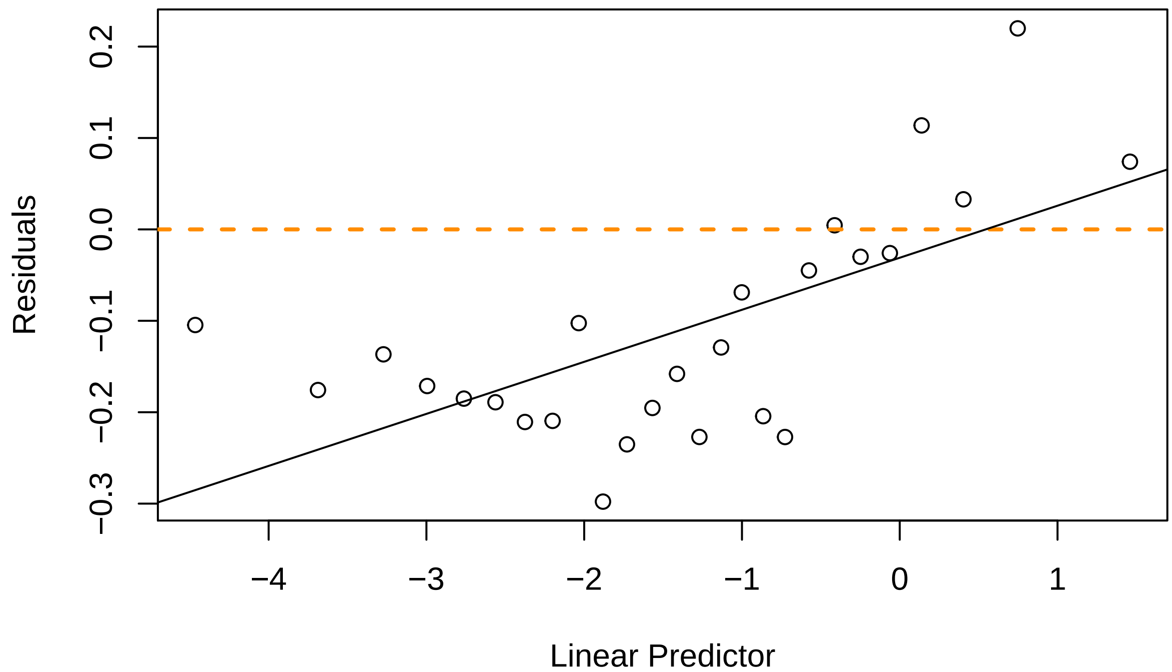


The AUC value of 0.8, tells us this model predicted values are curate.

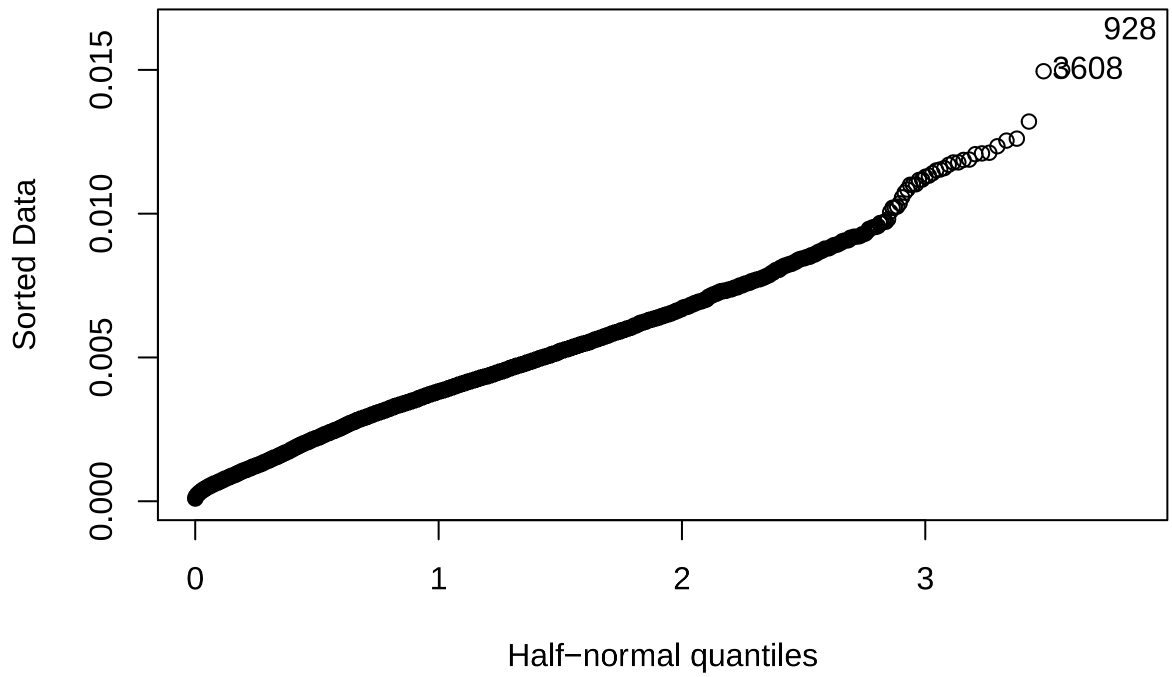
Confusion Matrix

```
##
## targethat    0    1
##         0 5559 1296
##         1  449  857
```

Create a binned diagnostic plot of residuals vs prediction There are definite patterns here, which bear investigating.

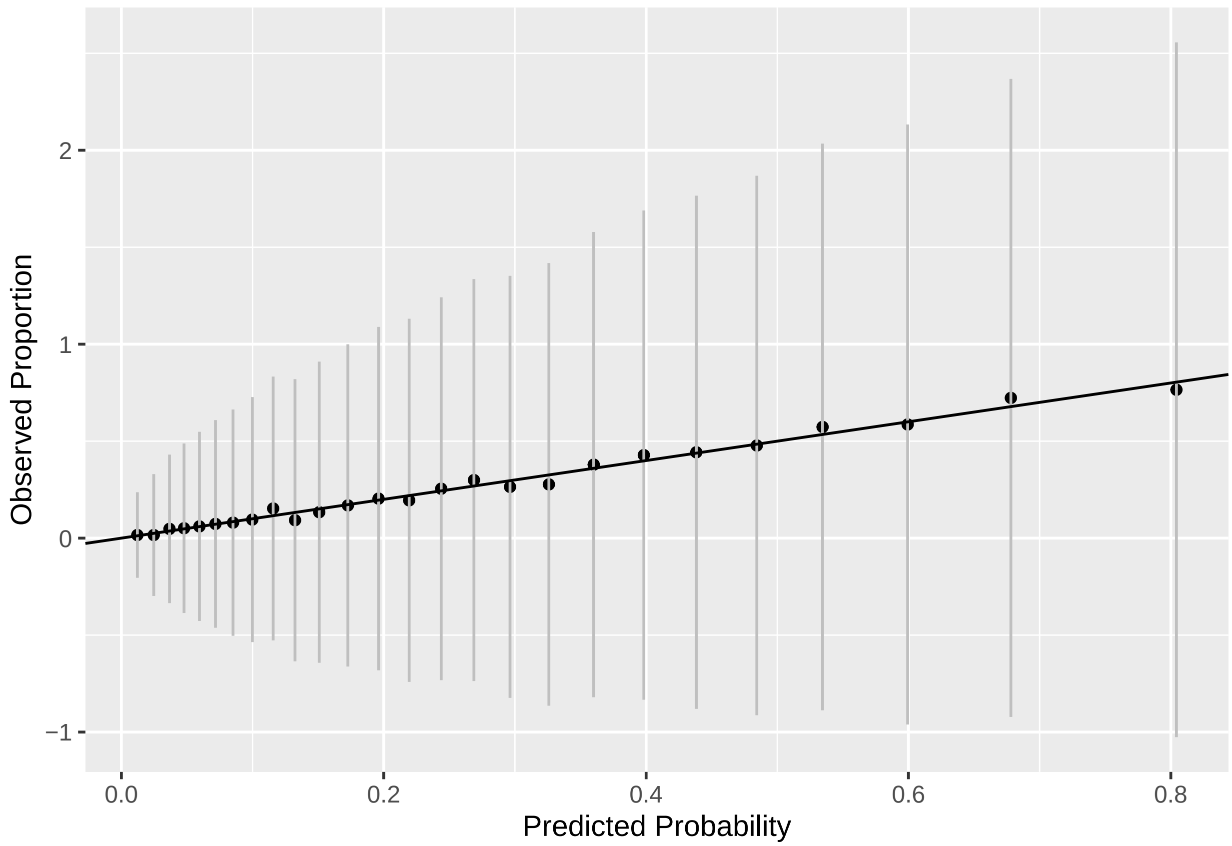


Plot leverages.



We don't see any strong outliers with the leverage plot. The points identified (3608,5686) are essentially in the plot of the line formed, so they are not likely pulling our model in any direction.

Plot Goodness of fit

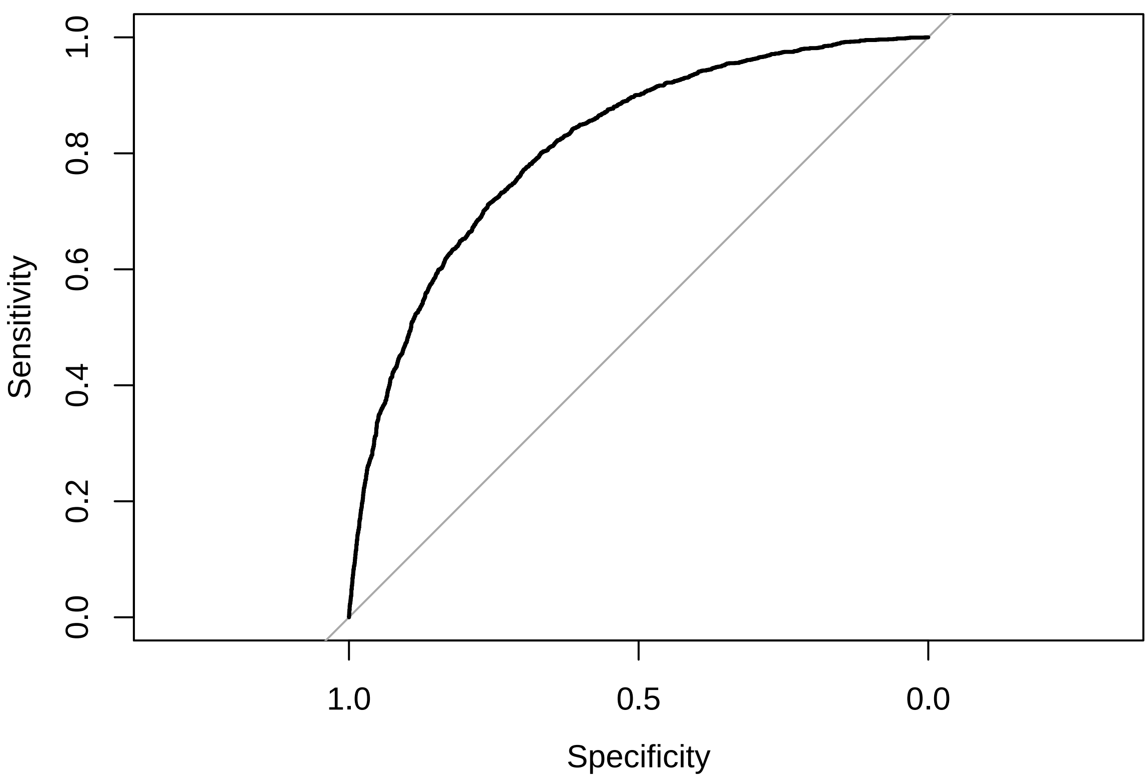


We see that our predictors fall close to the line.

Model 3 - Step AIC Model

ROC Curve

The ROC Curve helps measure true positives and true negative. A high AUC or area under the curve tells us the model is predicting well.

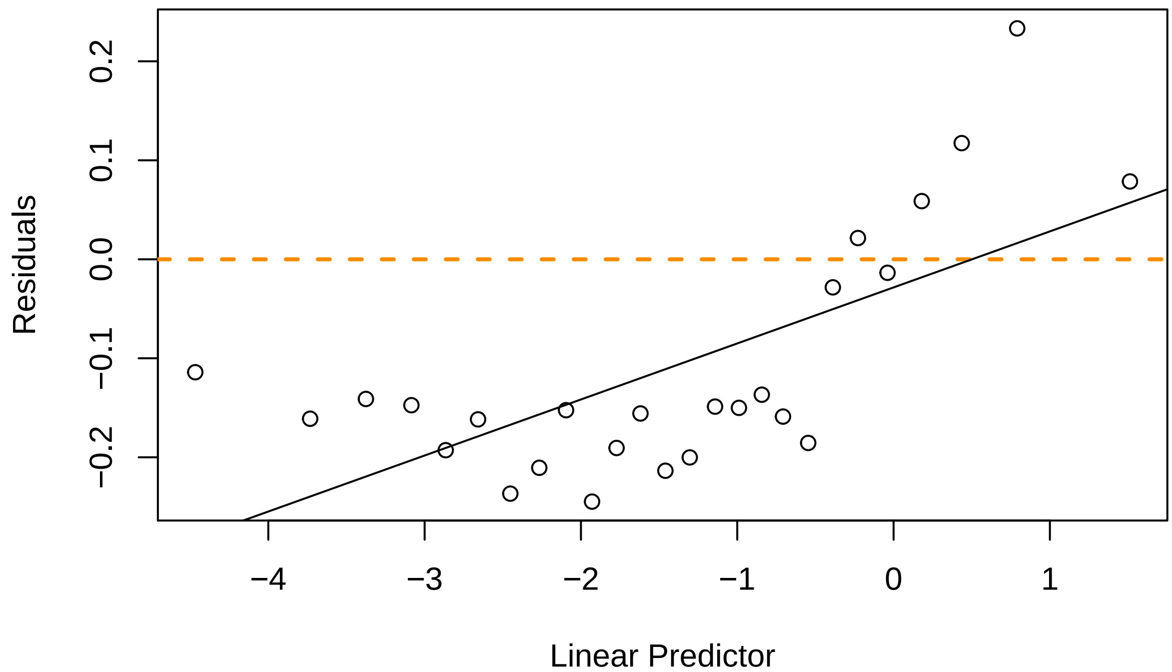


The AUC value of 0.81, tells us this model predicted values are accurate.

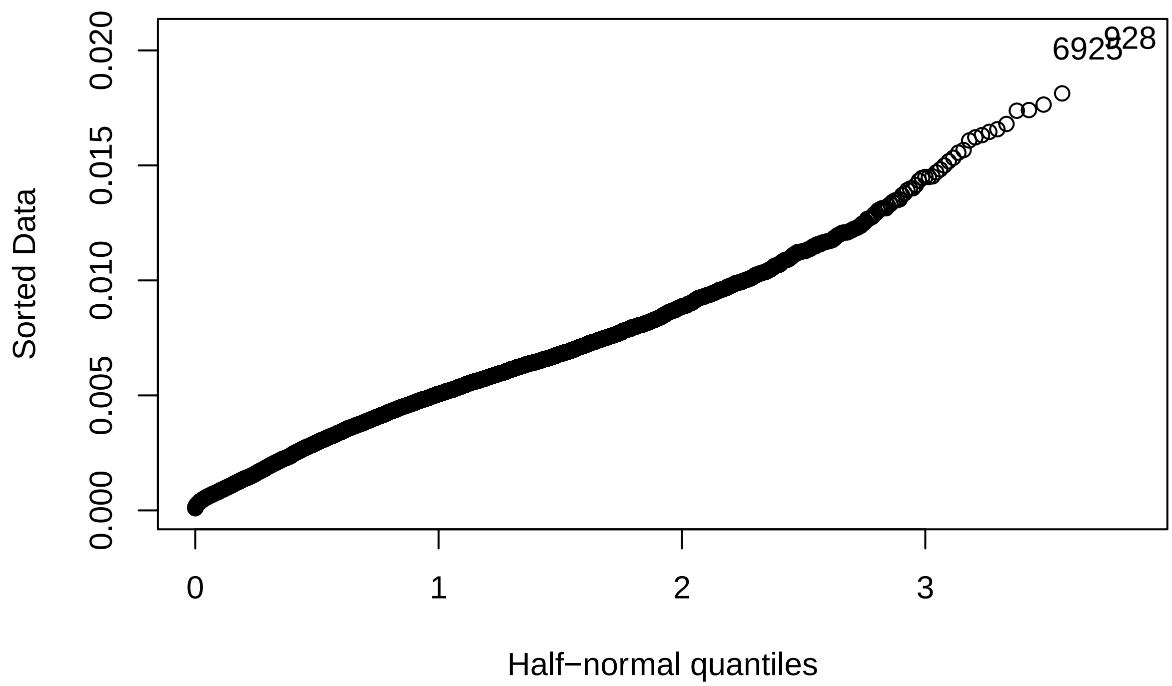
Confusion Matrix

```
##
## targethat    0    1
##          0 5555 1246
##          1  453  907
```

Create a binned diagnostic plot of residuals vs prediction There are definite patterns here, which bear investigating.

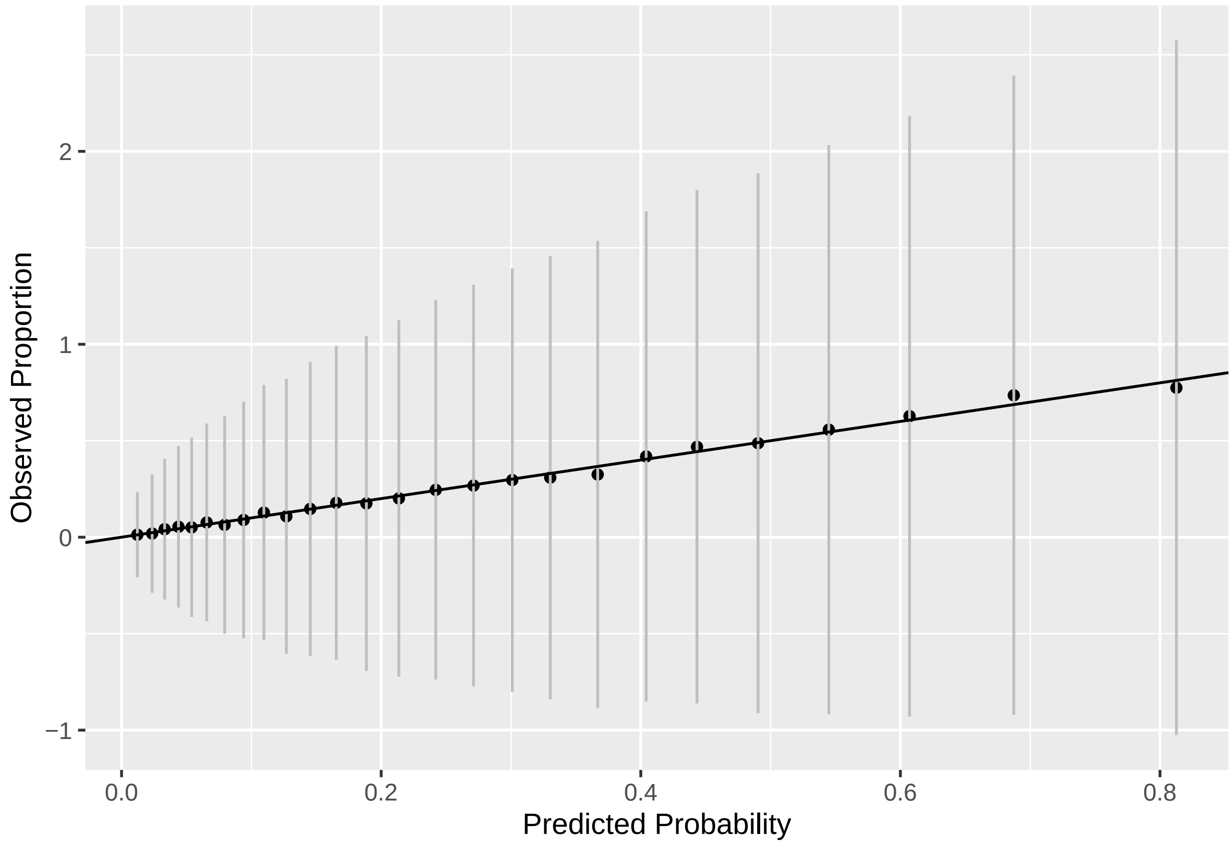


Plot leverages.



We don't see any strong outliers with the leverage plot. The points identified (3608,5686) are essentially in the plot of the line formed, so they are not likely pulling our model in any direction.

Plot Goodness of fit

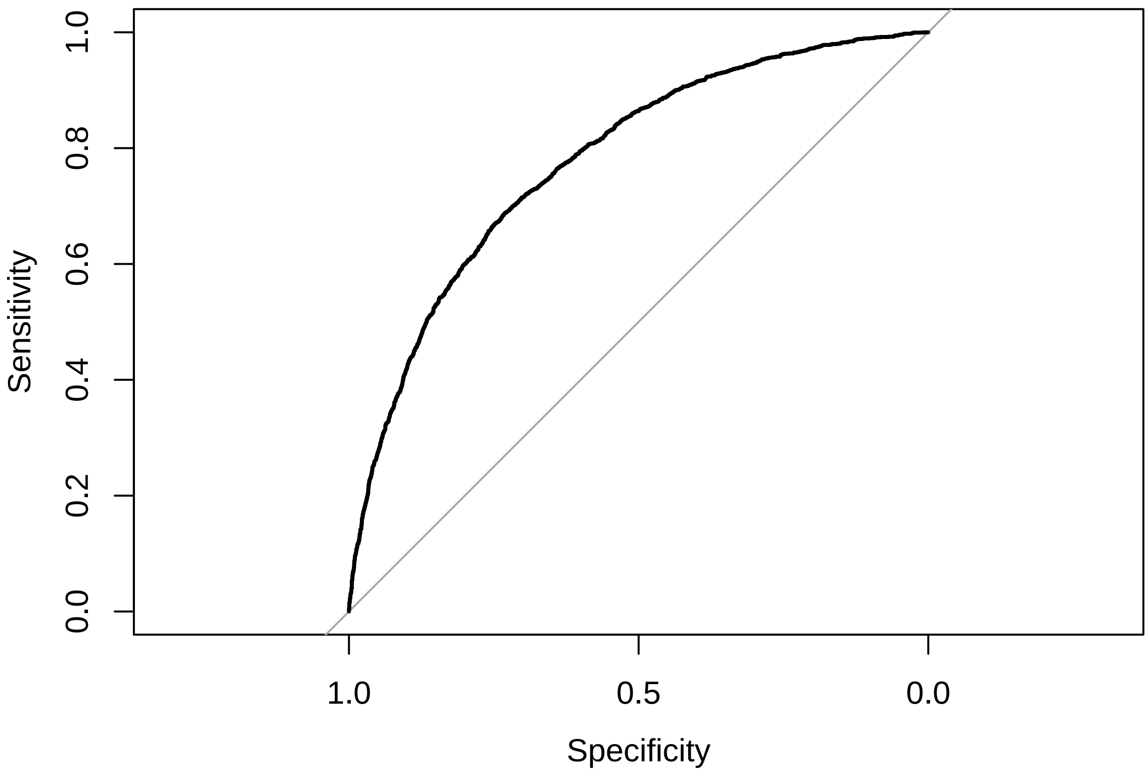


We see that our predictors fall close to the line.

Model 4 - Rep BIC Model

ROC Curve

The ROC Curve helps measure true positives and true negative. A high AUC or area under the curve tells us the model is predicting well.

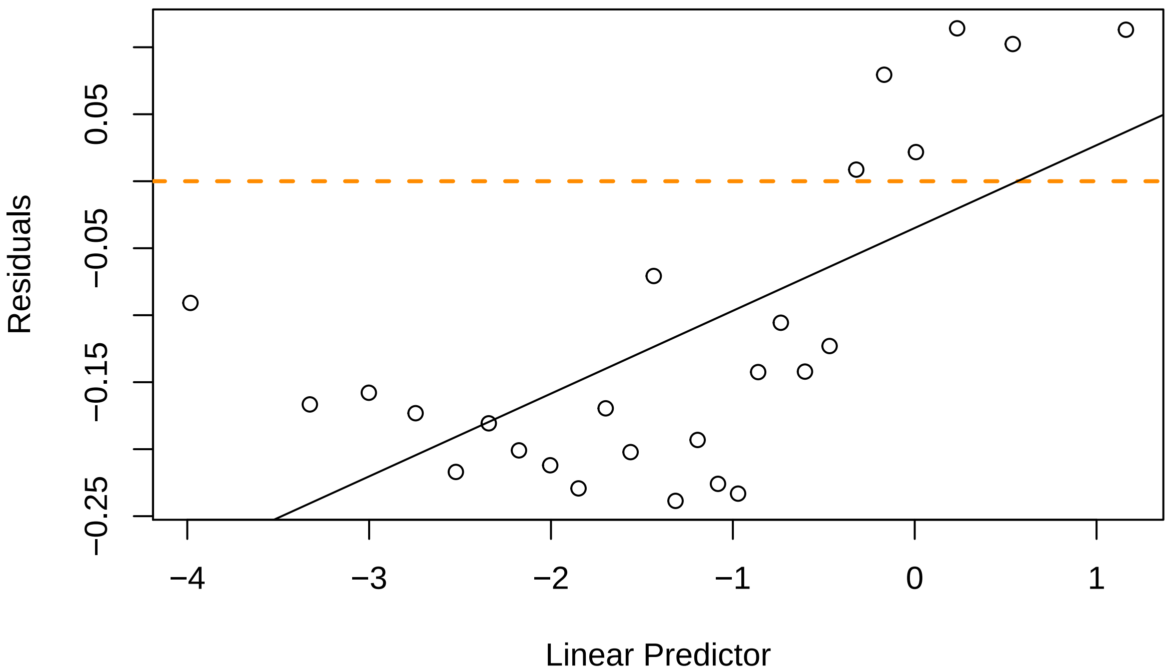


The AUC value of 0.78, tells us this model predicted values are accurate.

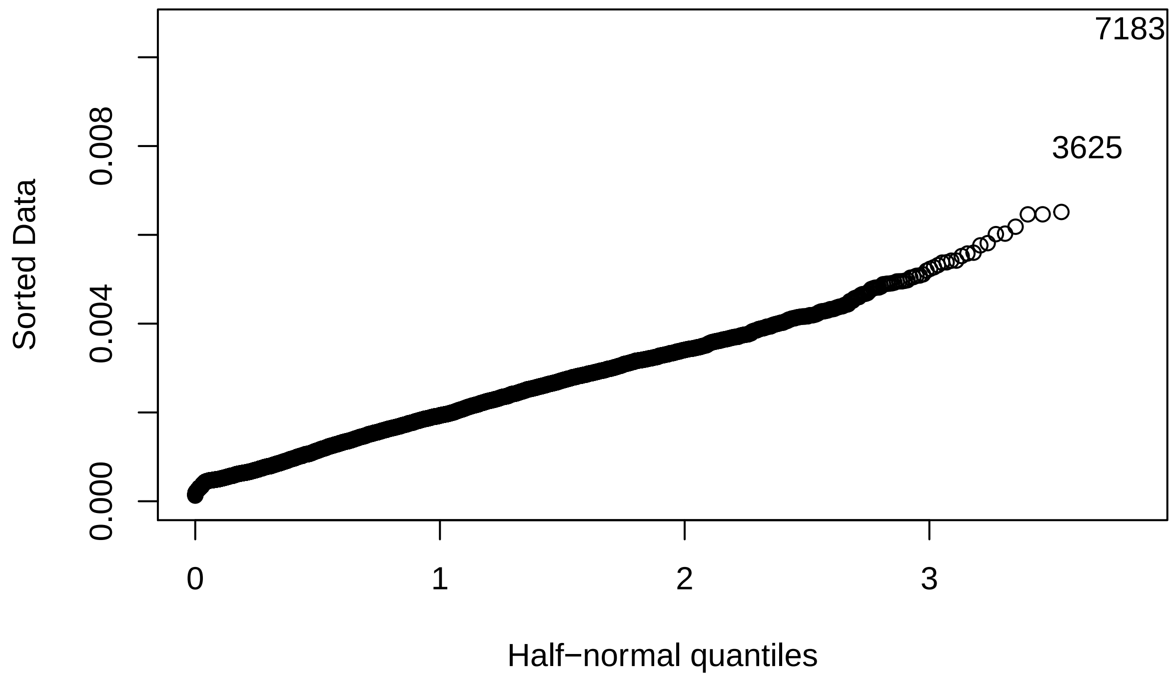
Confusion Matrix

```
##
## targethat    0    1
##         0 5139 1329
##         1  371  646
```

Create a binned diagnostic plot of residuals vs prediction There are definite patterns here, which bear investigating.

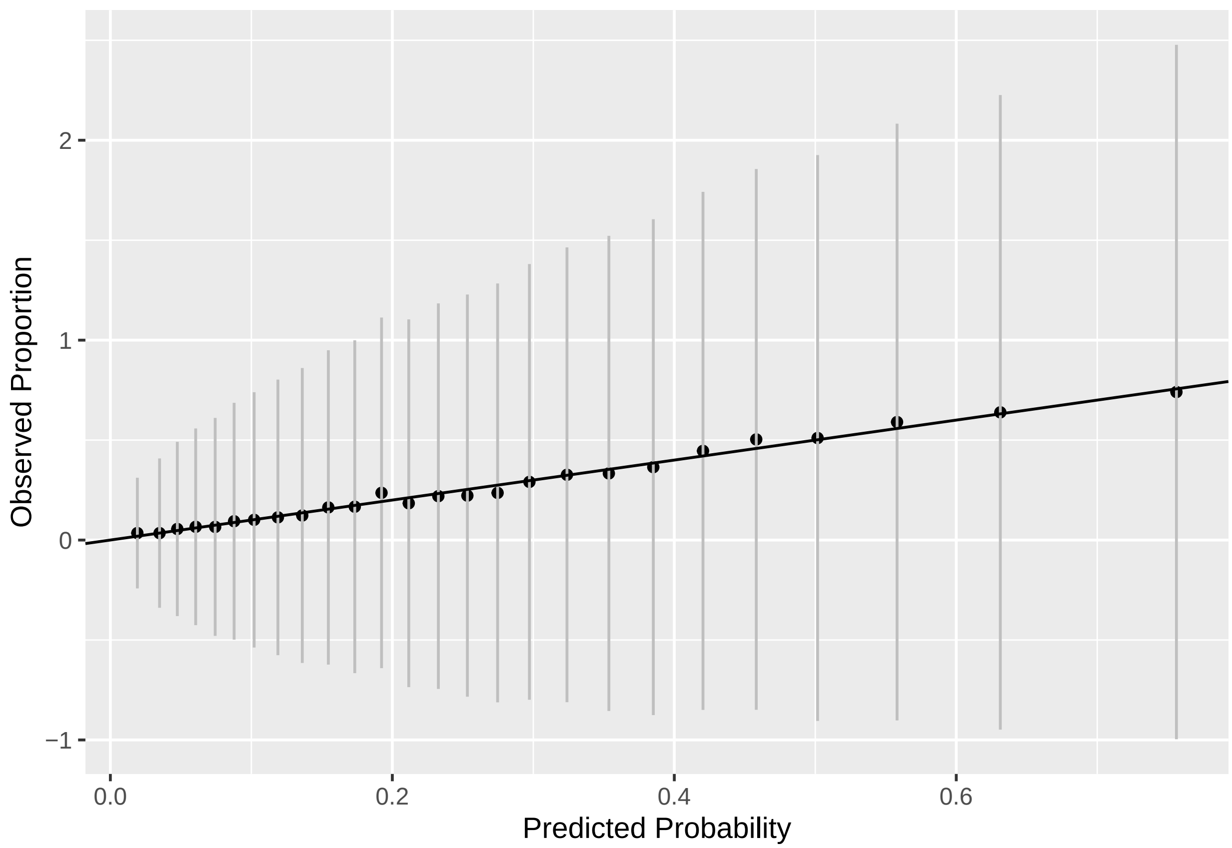


Plot leverages.



We don't see any strong outliers with the leverage plot. The points identified (3608,5686) are essentially in the plot of the line formed, so they are not likely pulling our model in any direction.

Plot Goodness of fit



We see that our predictors fall close to the line.

Pick the best regression model

Metric	Model 1	Model 2	Model 3	Model 4
AIC	7401.1283155	7475.6655813	7393.7376519	7168.2891998
BIC	7660.3918291	7650.843631	7624.9726775	7251.3370753

With 4 models computed, we select the model with the lowest combination of AIC and BIC. The the table we can see the model to pick is model 3.

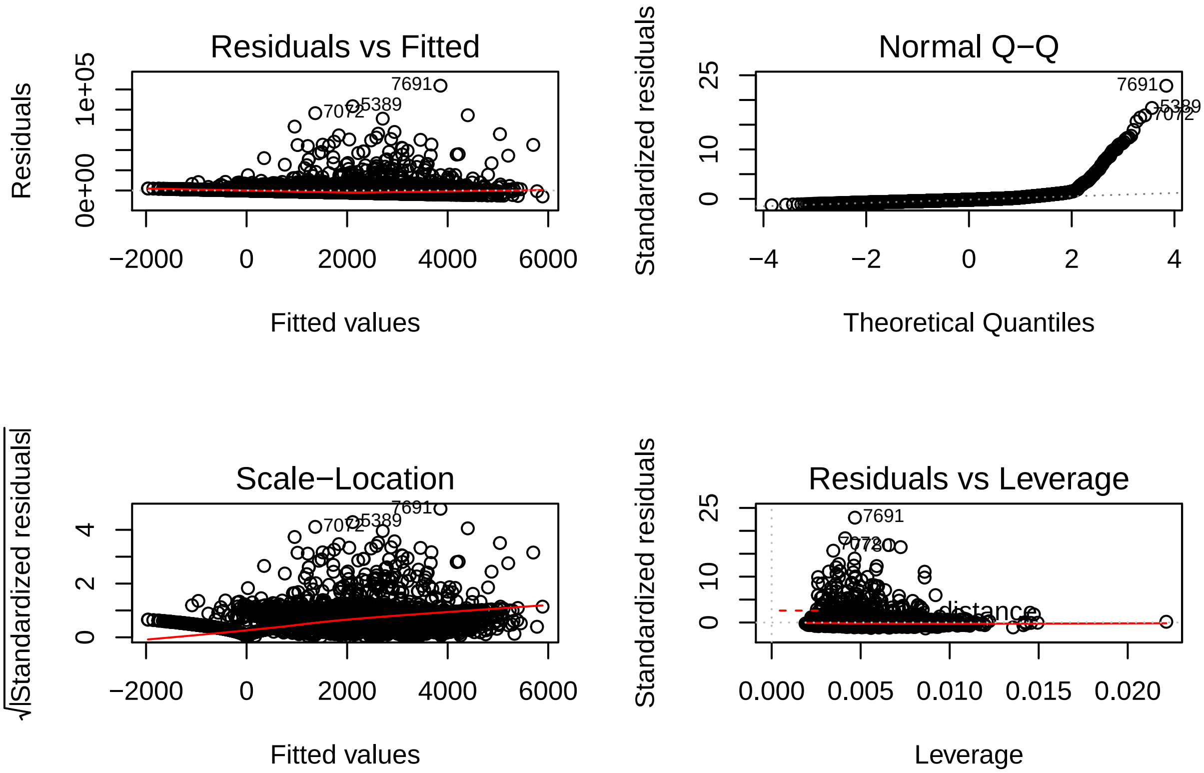
TARGET_AMT Modeling

Model 1: all predictors

Same as with the logistic model before, we start with a model that includes all predictors

```
##
## Call:
## lm(formula = TARGET_AMT ~ . - TARGET_FLAG, data = InsTrain)
##
## Residuals:
##    Min     1Q Median     3Q    Max
```

```
##  -5887  -1705   -762    340 103729
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     1.728e+03  4.874e+02   3.545 0.000395 ***
## INDEX                           5.912e-04  1.695e-02   0.035 0.972179
## KIDSDRIV                        3.143e+02  1.132e+02   2.777 0.005498 **
## AGE                             6.023e+00  7.064e+00   0.853 0.393912
## HOMEKIDS                        8.755e+01  6.557e+01   1.335 0.181875
## YOJ                            -1.500e+01  1.558e+01  -0.963 0.335611
## INCOME                         -3.815e-03  2.007e-03  -1.901 0.057371 .
## PARENT1Yes                      5.761e+02  2.024e+02   2.846 0.004435 **
## HOME_VAL                       -5.116e-04  9.887e-04  -0.517 0.604880
## MSTATUSz_No                     6.231e+02  1.254e+02   4.969 6.86e-07 ***
## SEXz_F                         -3.613e+02  1.838e+02  -1.966 0.049383 *
## EDUCATIONBachelors             -3.318e+02  2.025e+02  -1.638 0.101447
## EDUCATIONMasters               -2.261e+02  2.664e+02  -0.849 0.396011
## EDUCATIONPhD                   -1.204e+01  3.225e+02  -0.037 0.970227
## EDUCATIONz_High School         -1.187e+02  1.715e+02  -0.692 0.488993
## JOBDoctor                      -7.980e+02  4.030e+02  -1.980 0.047738 *
## JOBHome Maker                  -4.945e+01  2.494e+02  -0.198 0.842812
## JOBLawyer                      -9.920e+01  2.749e+02  -0.361 0.718167
## JOBManager                     -9.034e+02  2.257e+02  -4.003 6.32e-05 ***
## JOBProfessional                -2.168e+01  2.122e+02  -0.102 0.918646
## JOBStudent                     -1.169e+02  2.356e+02  -0.496 0.619786
## JOBz_Blue Collar               -1.020e+02  1.890e+02  -0.540 0.589356
## TRAVTIME                        1.207e+01  3.224e+00   3.745 0.000182 ***
## CAR_USEPrivate                 -8.186e+02  1.629e+02  -5.024 5.17e-07 ***
## BLUEBOOK                        1.342e-02  8.609e-03   1.559 0.119094
## TIF                            -4.835e+01  1.218e+01  -3.968 7.30e-05 ***
## CAR_TYPEPanel Truck             1.558e+02  2.708e+02   0.575 0.565184
## CAR_TYPEPickup                  3.366e+02  1.695e+02   1.986 0.047021 *
## CAR_TYPESports Car              1.019e+03  2.179e+02   4.677 2.96e-06 ***
## CAR_TYPEVan                     4.651e+02  2.115e+02   2.199 0.027895 *
## CAR_TYPEz_SUV                   7.457e+02  1.794e+02   4.157 3.25e-05 ***
## RED_CARyes                     -4.248e+01  1.491e+02  -0.285 0.775670
## OLDCLAIM                       -1.064e-02  7.439e-03  -1.430 0.152812
## CLM_FREQ                        1.437e+02  5.505e+01   2.611 0.009048 **
## REVOKEDYes                      5.574e+02  1.736e+02   3.212 0.001324 **
## MVR_PTS                         1.764e+02  2.592e+01   6.806 1.07e-11 ***
## CAR_AGE                        -2.682e+01  1.280e+01  -2.095 0.036209 *
## URBANICITYz_Highly Rural/ Rural -1.647e+03  1.391e+02 -11.841  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4546 on 8123 degrees of freedom
## Multiple R-squared:  0.07032,    Adjusted R-squared:  0.06609
## F-statistic: 16.61 on 37 and 8123 DF,  p-value: < 2.2e-16
```

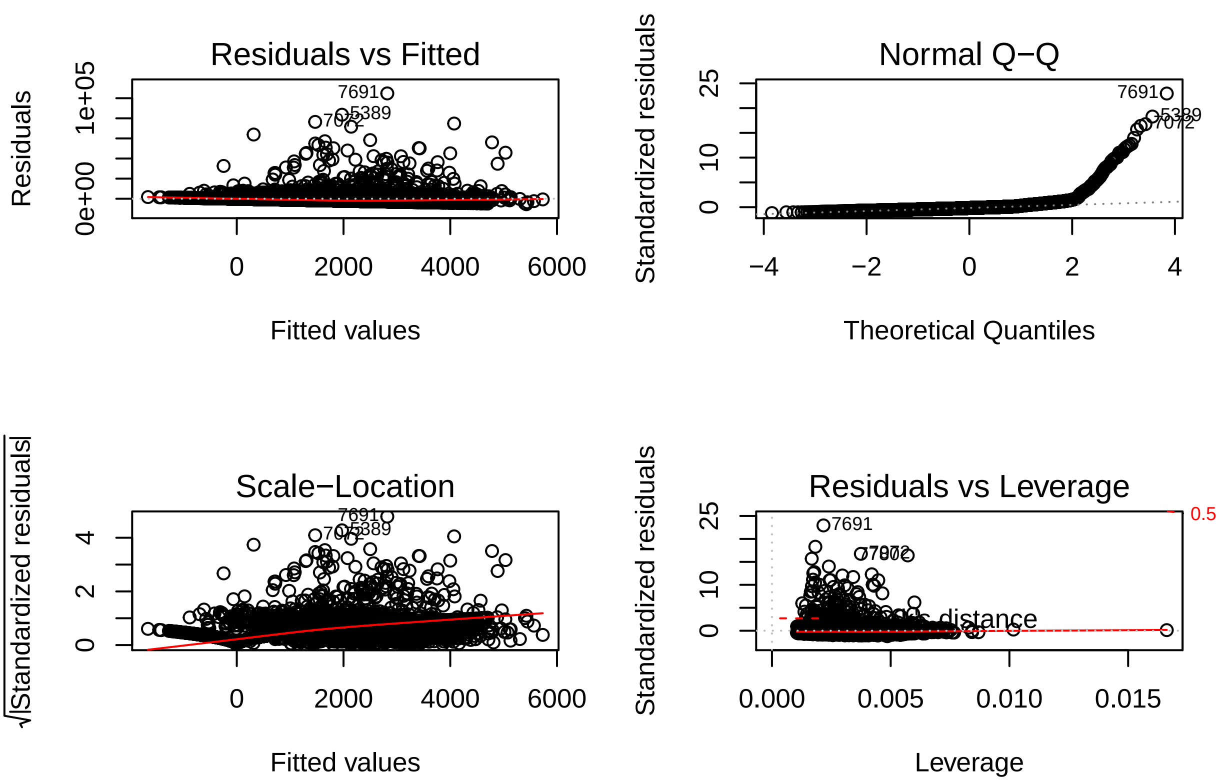


This model shows an adj R^2 as 0.28, and F-statistic of 87.86 with a small p-value. The result is not a very good model showing a very low R^2. We also observe several parameters which are not very significant. We try a second model without these parameters, although we do not expect it so be much better that this first model.

Model 2: Significant predictors

```
##
## Call:
## lm(formula = TARGET_AMT ~ +AGE + EDUCATION + REVOKED + MVR_PTS +
##     JOB + YOJ + CLM_FREQ + HOME_VAL + URBANICITY + PARENT1 +
##     MSTATUS + TRAVTIME + BLUEBOOK, data = InsTrain)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -5426  -1685   -762    231 104766
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    8.602e+02  3.888e+02   2.212 0.026983 *
## AGE                            6.055e+00  6.519e+00   0.929 0.353029
## EDUCATIONBachelors            -3.005e+02  1.843e+02  -1.631 0.102943
## EDUCATIONMasters              -3.921e+02  2.269e+02  -1.728 0.083988 .
## EDUCATIONPhD                  -2.272e+02  2.832e+02  -0.802 0.422482
## EDUCATIONz_High School         4.008e+01  1.647e+02   0.243 0.807697
## REVOKEDYes                     5.263e+02  1.555e+02   3.384 0.000719 ***
## MVR_PTS                        1.908e+02  2.590e+01   7.369 1.89e-13 ***
```

```
## JOBDoctor                         -1.121e+03  3.979e+02  -2.818 0.004850 **
## JOBHome Maker                     -9.377e+01  2.451e+02  -0.383 0.702049
## JOBLawyer                         -4.025e+02  2.689e+02  -1.496 0.134568
## JOBManager                        -1.009e+03  2.247e+02  -4.492 7.15e-06 ***
## JOBProfessional                   -1.416e+02  2.116e+02  -0.669 0.503241
## JOBStudent                         2.289e+02  2.285e+02   1.002 0.316516
## JOBz_Blue Collar                   2.877e+02  1.695e+02   1.697 0.089718 .
## YOJ                               -6.070e+00  1.481e+01  -0.410 0.681963
## CLM_FREQ                           1.437e+02  4.896e+01   2.935 0.003346 **
## HOME_VAL                          -1.486e-03  8.013e-04  -1.855 0.063629 .
## URBANICITYz_Highly Rural/ Rural -1.568e+03  1.395e+02 -11.242  < 2e-16 ***
## PARENT1Yes                         8.668e+02  1.802e+02   4.810 1.54e-06 ***
## MSTATUSz_No                        5.094e+02  1.204e+02   4.231 2.35e-05 ***
## TRAVTIME                           1.223e+01  3.238e+00   3.777 0.000160 ***
## BLUEBOOK                           9.345e-03  6.611e-03   1.414 0.157475
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4571 on 8138 degrees of freedom
## Multiple R-squared:  0.05819,    Adjusted R-squared:  0.05565
## F-statistic: 22.86 on 22 and 8138 DF,  p-value: < 2.2e-16
```



This model shows an adj R^2 as 0.056, and F-statistic of 22.86 with a small p-value.

Using the reduced predictors, let's now do a stepwise regression:

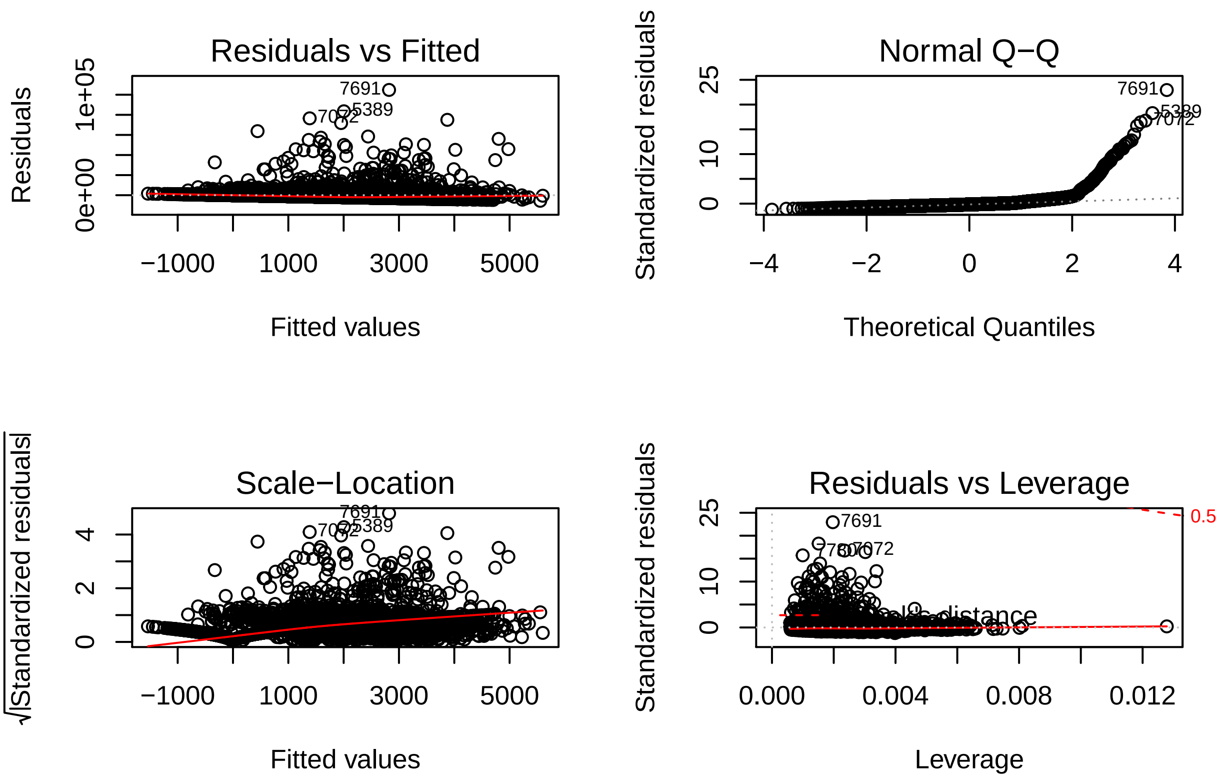
Model 3: Stepwise Regression

```
## Start:  AIC=137577.4
## TARGET_AMT ~ +AGE + EDUCATION + REVOKED + MVR_PTS + JOB + YOJ +
##     CLM_FREQ + HOME_VAL + URBANICITY + PARENT1 + MSTATUS + TRAVTIME +
##     BLUEBOOK
##
##              Df  Sum of Sq        RSS    AIC
## - YOJ         1    3509293 1.7006e+11 137576
## - AGE         1   18026179 1.7007e+11 137576
## - EDUCATION   4  154037045 1.7021e+11 137577
## <none>                     1.7006e+11 137577
## - BLUEBOOK    1   41765295 1.7010e+11 137577
## - HOME_VAL    1   71907597 1.7013e+11 137579
## - CLM_FREQ    1  179988338 1.7024e+11 137584
## - REVOKED     1  239252115 1.7030e+11 137587
## - TRAVTIME    1  298134916 1.7035e+11 137590
## - MSTATUS     1  374117944 1.7043e+11 137593
## - PARENT1     1  483407044 1.7054e+11 137599
## - JOB         7 1186770595 1.7124e+11 137620
## - MVR_PTS     1 1134624808 1.7119e+11 137630
## - URBANICITY  1 2640997262 1.7270e+11 137701
##
## Step:  AIC=137575.6
## TARGET_AMT ~ AGE + EDUCATION + REVOKED + MVR_PTS + JOB + CLM_FREQ +
##     HOME_VAL + URBANICITY + PARENT1 + MSTATUS + TRAVTIME + BLUEBOOK
##
##              Df  Sum of Sq        RSS    AIC
## - AGE         1   16550382 1.7008e+11 137574
## - EDUCATION   4  153627889 1.7021e+11 137575
## - BLUEBOOK    1   41120143 1.7010e+11 137576
## <none>                     1.7006e+11 137576
## - HOME_VAL    1   72557883 1.7013e+11 137577
## - CLM_FREQ    1  180284088 1.7024e+11 137582
## - REVOKED     1  239230021 1.7030e+11 137585
## - TRAVTIME    1  297722480 1.7036e+11 137588
## - MSTATUS     1  398431642 1.7046e+11 137593
## - PARENT1     1  479908120 1.7054e+11 137597
## - JOB         7 1194946049 1.7125e+11 137619
## - MVR_PTS     1 1138469809 1.7120e+11 137628
## - URBANICITY  1 2638652491 1.7270e+11 137699
##
## Step:  AIC=137574.4
## TARGET_AMT ~ EDUCATION + REVOKED + MVR_PTS + JOB + CLM_FREQ +
##     HOME_VAL + URBANICITY + PARENT1 + MSTATUS + TRAVTIME + BLUEBOOK
##
##              Df  Sum of Sq        RSS    AIC
## - EDUCATION   4  152052323 1.7023e+11 137574
## <none>                     1.7008e+11 137574
## - BLUEBOOK    1   45832097 1.7012e+11 137575
## - HOME_VAL    1   68168845 1.7014e+11 137576
## - CLM_FREQ    1  183048294 1.7026e+11 137581
## - REVOKED     1  237194155 1.7031e+11 137584
## - TRAVTIME    1  299955129 1.7038e+11 137587
## - MSTATUS     1  407190173 1.7048e+11 137592
## - PARENT1     1  468406609 1.7054e+11 137595
```

```
## - JOB         7 1179606130 1.7126e+11 137617
## - MVR_PTS     1 1129124172 1.7121e+11 137626
## - URBANICITY  1 2630482199 1.7271e+11 137698
##
## Step:  AIC=137573.6
## TARGET_AMT ~ REVOKED + MVR_PTS + JOB + CLM_FREQ + HOME_VAL +
##     URBANICITY + PARENT1 + MSTATUS + TRAVTIME + BLUEBOOK
##
##              Df  Sum of Sq        RSS    AIC
## - BLUEBOOK    1   32875890 1.7026e+11 137573
## <none>                     1.7023e+11 137574
## - HOME_VAL    1  119051672 1.7035e+11 137577
## - CLM_FREQ    1  181086747 1.7041e+11 137580
## - REVOKED     1  241380620 1.7047e+11 137583
## - TRAVTIME    1  292522009 1.7052e+11 137586
## - MSTATUS     1  387615210 1.7062e+11 137590
## - PARENT1     1  485655803 1.7071e+11 137595
## - MVR_PTS     1 1137578413 1.7137e+11 137626
## - JOB         7 1790035008 1.7202e+11 137645
## - URBANICITY  1 2578301343 1.7281e+11 137694
##
## Step:  AIC=137573.2
## TARGET_AMT ~ REVOKED + MVR_PTS + JOB + CLM_FREQ + HOME_VAL +
##     URBANICITY + PARENT1 + MSTATUS + TRAVTIME
##
##              Df  Sum of Sq        RSS    AIC
## <none>                     1.7026e+11 137573
## - HOME_VAL    1   95590131 1.7036e+11 137576
## - CLM_FREQ    1  178112068 1.7044e+11 137580
## - REVOKED     1  237961372 1.7050e+11 137583
## - TRAVTIME    1  293078406 1.7055e+11 137585
## - MSTATUS     1  393037079 1.7065e+11 137590
## - PARENT1     1  476844375 1.7074e+11 137594
## - MVR_PTS     1 1131360137 1.7139e+11 137625
## - JOB         7 1781608903 1.7204e+11 137644
## - URBANICITY  1 2593045561 1.7285e+11 137695
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ REVOKED + MVR_PTS + JOB + CLM_FREQ +
##     HOME_VAL + URBANICITY + PARENT1 + MSTATUS + TRAVTIME, data = InsTrain)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -5553  -1689   -758    210 104765
##
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      1.158e+03  2.268e+02   5.106 3.36e-07 ***
## REVOKEDYes                       5.246e+02  1.555e+02   3.374 0.000744 ***
## MVR_PTS                          1.903e+02  2.587e+01   7.357 2.07e-13 ***
## JOBDoctor                       -1.202e+03  3.378e+02  -3.559 0.000374 ***
## JOBHome Maker                   -1.700e+02  2.227e+02  -0.763 0.445339
## JOBLawyer                       -6.757e+02  2.156e+02  -3.135 0.001727 **
```

```
## JOBManager                      -1.170e+03  2.081e+02  -5.621 1.97e-08 ***
## JOBProfessional                 -2.957e+02  1.951e+02  -1.516 0.129666
## JOBStudent                       2.284e+02  2.154e+02   1.060 0.289019
## JOBz_Blue Collar                 2.416e+02  1.656e+02   1.459 0.144644
## CLM_FREQ                         1.428e+02  4.893e+01   2.919 0.003521 **
## HOME_VAL                        -1.569e-03  7.339e-04  -2.138 0.032512 *
## URBANICITYz_Highly Rural/ Rural -1.548e+03  1.390e+02 -11.138  < 2e-16 ***
## PARENT1Yes                       8.206e+02  1.718e+02   4.776 1.82e-06 ***
## MSTATUSz_No                      5.129e+02  1.183e+02   4.336 1.47e-05 ***
## TRAVTIME                         1.212e+01  3.237e+00   3.744 0.000182 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4572 on 8145 degrees of freedom
## Multiple R-squared:  0.05706,    Adjusted R-squared:  0.05532
## F-statistic: 32.86 on 15 and 8145 DF,  p-value: < 2.2e-16
```



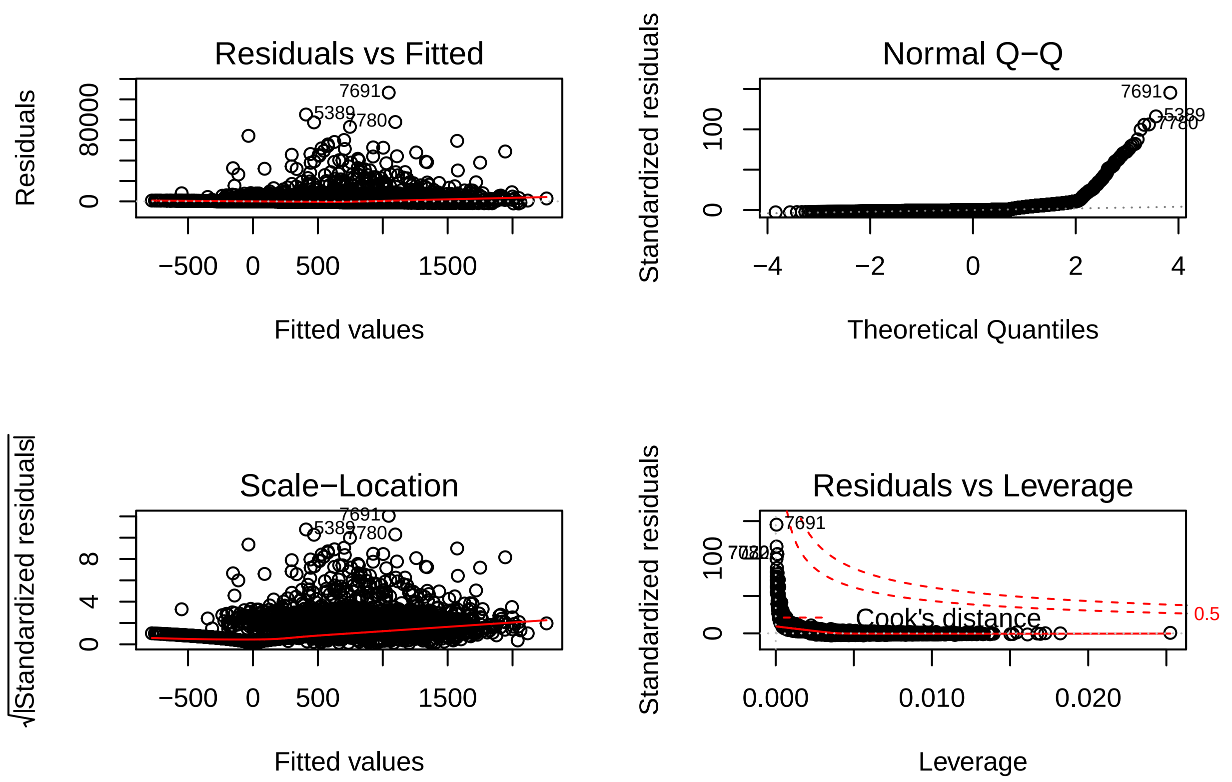
This model shows an adj R^2 as 0.055, and F-statistic of 32.86 with a small p-value. As expected this model isn't any better than the first one. It is simpler, but its performance is basically the same. What we do notice, and very visible in the Q-Q plot, is that these seem to be a high number of data points distance from the normal. This suggest a different kind of model.

Model 4: Weighted coefficients

We build a Hubber weighted model to account for the distant points observed in the previous models.

```
##
```

```
## Call: rlm(formula = TARGET_AMT ~ . - TARGET_FLAG, data = InsTrain,
##     maxit = 40)
## Residuals:
##      Min       1Q   Median       3Q      Max
##  -2047.0   -492.2   -133.3    503.8 106540.0
##
## Coefficients:
##                                  Value     Std. Error t value
## (Intercept)                       676.8268   94.2063    7.1845
## INDEX                              -0.0001    0.0033   -0.0153
## KIDSDRIV                          139.0172   21.8765    6.3546
## AGE                                -0.0529    1.3652   -0.0387
## HOMEKIDS                            8.7242   12.6732    0.6884
## YOJ                                -8.8665    3.0102   -2.9455
## INCOME                             -0.0009    0.0004   -2.2019
## PARENT1Yes                        274.0114   39.1159    7.0051
## HOME_VAL                            0.0001    0.0002    0.7054
## MSTATUSz_No                       169.7873   24.2341    7.0061
## SEXz_F                            -26.5180   35.5257   -0.7464
## EDUCATIONBachelors               -168.5739   39.1421   -4.3067
## EDUCATIONMasters                 -173.2367   51.4839   -3.3649
## EDUCATIONPhD                     -190.1227   62.3261   -3.0505
## EDUCATIONz_High School             11.8464   33.1433    0.3574
## JOBDoctor                        -146.8373   77.8923   -1.8851
## JOBHome Maker                       7.0630   48.1974    0.1465
## JOBLawyer                         -82.4219   53.1218   -1.5516
## JOBManager                       -281.5451   43.6208   -6.4544
## JOBProfessional                   -88.4633   41.0165   -2.1568
## JOBStudent                         -9.3306   45.5270   -0.2049
## JOBz_Blue Collar                  -83.1141   36.5182   -2.2760
## TRAVTIME                            3.9424    0.6230    6.3281
## CAR_USEPrivate                   -300.8995   31.4928   -9.5546
## BLUEBOOK                           -0.0052    0.0017   -3.1514
## TIF                               -15.6168    2.3549   -6.6317
## CAR_TYPEPanel Truck                30.2631   52.3424    0.5782
## CAR_TYPEPickup                    130.2403   32.7521    3.9765
## CAR_TYPESports Car                278.0083   42.1038    6.6029
## CAR_TYPEVan                        93.9587   40.8706    2.2989
## CAR_TYPEz_SUV                     199.0489   34.6674    5.7417
## RED_CARyes                         -2.1157   28.8124   -0.0734
## OLDCLAIM                           -0.0043    0.0014   -2.9666
## CLM_FREQ                           55.3530   10.6402    5.2023
## REVOKEDYes                        387.5239   33.5434   11.5529
## MVR_PTS                            63.4666    5.0093   12.6697
## CAR_AGE                            -0.1901    2.4742   -0.0768
## URBANICITYz_Highly Rural/ Rural -550.0751   26.8871  -20.4587
##
## Residual standard error: 733.5 on 8123 degrees of freedom
```



The models doesn't seem to help with weighted coefficients, we still see the effects of several datapoints in the data.

Pick the best regression model

Metric	Model 1	Model 2	Model 3	Model 4
AIC	1.606635×10^5	1.607393×10^5	1.6073514×10^5	1.6133706×10^5
BIC	1.6093677×10^5	1.6090748×10^5	1.6085426×10^5	1.6161034×10^5

With 4 models computed, we select the model with the lowest combination of AIC and BIC. The model to pick is model 3.

Conclusion

For both the logistic regression and linear regressions we picked model 3. Results for the logistic regression were rather good, but the linear regression doesn't seem to be a good model, even when using weighted coefficients.

APPENDIX

Code used in analysis

```r
knitr::opts_chunk$set(echo = FALSE, warning = FALSE)
require(knitr)
library(ggplot2)
library(tidyr)
library(MASS)
library(psych)
library(kableExtra)
library(dplyr)
library(faraway)
library(gridExtra)
library(reshape2)
library(leaps)
library(pROC)
library(caret)
library(naniar)
library(pander)
library(pROC)
#Get the data. Added na.strings to add na for records that have a blank value
InsTrain <- read.csv("insurance_training_data.csv",na.strings="",header=TRUE)
InsEval <- read.csv("insurance-evaluation-data.csv",na.strings="",header=TRUE)
InsEval <- subset(InsEval, select=-c(TARGET_FLAG,TARGET_AMT))
InsEval <- read.csv("insurance-evaluation-data.csv",na.strings="",header=TRUE)
ins1 <- describe(InsTrain, na.rm = F)
ins1$na_count <- sapply(InsTrain, function(y) sum(length(which(is.na(y)))))
ins1$na_count_perc <- sapply(InsTrain, function(x) round(sum(is.na(x))/nrow(InsTrain)*100,1))
colsTrain<-ncol(InsTrain)
colsEval<-ncol(InsEval)
missingCol<-colnames(InsTrain)[!(colnames(InsTrain) %in% colnames(InsEval))]
cc<-summary(complete.cases(InsTrain))
cInsTrain<-subset(InsTrain, complete.cases(InsTrain))
cc
glimpse(cInsTrain)
#sapply(InsTrain, function(x) round(sum(is.na(x))/nrow(InsTrain)*100,1))
vis_miss(InsTrain)
gg_miss_upset(InsTrain)
nrow(subset(InsTrain,TARGET_FLAG == 0))
nrow(subset(InsTrain,TARGET_AMT == 0))
nrow(subset(InsTrain,TARGET_FLAG > 0))
nrow(subset(InsTrain,TARGET_AMT > 0))
cat(colnames(InsTrain[ sapply(InsTrain, is.factor)]), "\n\n")
glimpse(InsTrain)
sapply(InsTrain, function(x) round(sum(is.na(x))/nrow(InsTrain)*100,1))
c<-c('INCOME','HOME_VAL','BLUEBOOK','OLDCLAIM')
if(c %in% colnames(InsTrain)){

  glimpse(InsTrain[,(c)])
  InsTrain[,c] <- sapply(InsTrain[,(c)],
                         function(x) as.integer(gsub('[$,]','',as.character(x))))

  glimpse(InsTrain[,(c)])

} else {
```

```
  cat("Please review your selection of columns:", c)

}
# AGE YOJ INCOME HOME_VAL CAR_AGE
InsTrain$INCOME <- na_if(InsTrain$INCOME, 0)
InsTrain$HOME_VAL <- na_if(InsTrain$HOME_VAL, 0)
r <- colnames(InsTrain[ sapply(InsTrain, function(x) return(anyNA(x) && is.integer(x)))])
boxplot(InsTrain[,r],names = r,las = 2,col = c("orange","red", "blue", "yellow", "brown", "green"))
describe(subset(InsTrain, select =r))
sapply(InsTrain, function(x) round(sum(is.na(x))/nrow(InsTrain)*100,1))
InsTrain[,r] <- replace_na(InsTrain[,r], as.list(colMeans(InsTrain[,r], na.rm = TRUE)))

# Jobs could be analyzed more before imputing
Jobs <- summary(InsTrain$JOB)
JobsMode <- Jobs[which.max(Jobs)]
# ifelse(JobsMode[[1]]  / nrow(InsTrain) > 2.5*(Jobs["NA's"][[1]] / nrow(InsTrain)),
InsTrain$JOB <- replace_na(InsTrain$JOB, names(JobsMode))#,
#na.omit(InsTrain)
#summary(InsTrain$JOB)
vis_miss(InsTrain)
describe(subset(InsTrain, select =r))
#View(InsTrain)
m1<-glm(TARGET_FLAG~.-INDEX-TARGET_AMT,data=InsTrain,family="binomial"(link="logit"))
summary(m1)
m2<-glm(TARGET_FLAG~.-INDEX-TARGET_AMT-AGE-INCOME-JOB-BLUEBOOK-CAR_AGE-RED_CAR,data=InsTrain,family="bin
summary(m2)
m3 <- step(m1)
summary(m3)
InsTrainM4<-InsTrain[ , !(names(InsTrain) %in% c('INDEX','TARGET_AMT'))]
regfit.full <- regsubsets(factor(TARGET_FLAG) ~ ., data=InsTrainM4)
par(mfrow = c(1,2))
reg.summary <- summary(regfit.full)
plot(reg.summary$bic, xlab="Number of Predictors", ylab="BIC", type="l", main="Subset Selection Using BI
BIC_num <- which.min(reg.summary$bic)
points(BIC_num, reg.summary$bic[BIC_num], col="red", cex=2, pch=20)
plot(regfit.full, scale="bic", main="Predictors vs. BIC", asp = 10)
InsTrains <-subset(InsTrain, PARENT1='YES',CAR_TYPE %in% c('Minivan','Pickup','Sports Car','Van','z_SUV
m4 <- glm(TARGET_FLAG ~ PARENT1 + HOME_VAL + CAR_USE + CAR_TYPE + REVOKED + MVR_PTS + URBANICITY + CAR_A
InsTrains$predicted_m3<- predict(m4, InsTrains, type='response')
InsTrains$target_m4$target <- ifelse(InsTrains$predicted_m4>0.5, 1, 0)
pander::pander(summary(m4))
targethat<-predict(m1,type="response")
g<-roc(TARGET_FLAG~targethat,data=InsTrain)
plot(g)
targethat[targethat<0.5]<-0
targethat[targethat>=0.5]<-1
table(targethat,InsTrain$TARGET_FLAG)
InsMut <- mutate(InsTrain, Residuals = residuals(m1), linPred = predict(m1))
grpIns <- group_by(InsMut, cut(linPred, breaks=unique(quantile(linPred, (0:25/26)))))
diagIns <- summarise(grpIns, Residuals = mean(Residuals), linPred = mean(linPred))
plot(Residuals ~ linPred, data = diagIns, xlab="Linear Predictor")
abline(h = 0, lty = 2, col = "darkorange", lwd = 2)
abline(lm(Residuals ~ linPred, data = diagIns))
```

```r
halfnorm(hatvalues(m1))
linPred <- predict(m1)
InsMut <- mutate(InsTrain, predProb = predict(m1, type = "response"))
grpIns <- group_by(InsMut, cut(linPred, breaks = unique(quantile(linPred, (0:25)/26))))
#hosmer-lemeshow stat
hlDf <- summarise(grpIns, y= sum(TARGET_FLAG), pPred=mean(predProb), count = n())
hlDf <- mutate(hlDf, se.fit=sqrt(pPred * (1-(pPred)/count)))
ggplot(hlDf,aes(x=pPred,y=y/count,ymin=y/count-2*se.fit,ymax=y/count+2*se.fit)) +
    geom_point()+geom_linerange(color=grey(0.75))+geom_abline(intercept=0,slope=1) +
    xlab("Predicted Probability") +
    ylab("Observed Proportion")
targethat<-predict(m2,type="response")
g<-roc(TARGET_FLAG~targethat,data=InsTrain)
plot(g)
targethat[targethat<0.5]<-0
targethat[targethat>=0.5]<-1
table(targethat,InsTrain$TARGET_FLAG)
InsMut <- mutate(InsTrain, Residuals = residuals(m2), linPred = predict(m2))
grpIns <- group_by(InsMut, cut(linPred, breaks=unique(quantile(linPred, (0:25/26)))))
diagIns <- summarise(grpIns, Residuals = mean(Residuals), linPred = mean(linPred))
plot(Residuals ~ linPred, data = diagIns, xlab="Linear Predictor")
abline(h = 0, lty = 2, col = "darkorange", lwd = 2)
abline(lm(Residuals ~ linPred, data = diagIns))
halfnorm(hatvalues(m2))
linPred <- predict(m2)
InsMut <- mutate(InsTrain, predProb = predict(m2, type = "response"))
grpIns <- group_by(InsMut, cut(linPred, breaks = unique(quantile(linPred, (0:25)/26))))
#hosmer-lemeshow stat
hlDf <- summarise(grpIns, y= sum(TARGET_FLAG), pPred=mean(predProb), count = n())
hlDf <- mutate(hlDf, se.fit=sqrt(pPred * (1-(pPred)/count)))
ggplot(hlDf,aes(x=pPred,y=y/count,ymin=y/count-2*se.fit,ymax=y/count+2*se.fit)) +
    geom_point()+geom_linerange(color=grey(0.75))+geom_abline(intercept=0,slope=1) +
    xlab("Predicted Probability") +
    ylab("Observed Proportion")
targethat<-predict(m3,type="response")
g<-roc(TARGET_FLAG~targethat,data=InsTrain)
plot(g)
targethat[targethat<0.5]<-0
targethat[targethat>=0.5]<-1
table(targethat,InsTrain$TARGET_FLAG)
InsMut <- mutate(InsTrain, Residuals = residuals(m3), linPred = predict(m3))
grpIns <- group_by(InsMut, cut(linPred, breaks=unique(quantile(linPred, (0:25/26)))))
diagIns <- summarise(grpIns, Residuals = mean(Residuals), linPred = mean(linPred))
plot(Residuals ~ linPred, data = diagIns, xlab="Linear Predictor")
abline(h = 0, lty = 2, col = "darkorange", lwd = 2)
abline(lm(Residuals ~ linPred, data = diagIns))
halfnorm(hatvalues(m3))
linPred <- predict(m3)
InsMut <- mutate(InsTrain, predProb = predict(m3, type = "response"))
grpIns <- group_by(InsMut, cut(linPred, breaks = unique(quantile(linPred, (0:25)/26))))
#hosmer-lemeshow stat
hlDf <- summarise(grpIns, y= sum(TARGET_FLAG), pPred=mean(predProb), count = n())
hlDf <- mutate(hlDf, se.fit=sqrt(pPred * (1-(pPred)/count)))
```

```
ggplot(hlDf,aes(x=pPred,y=y/count,ymin=y/count-2*se.fit,ymax=y/count+2*se.fit)) +
    geom_point()+geom_linerange(color=grey(0.75))+geom_abline(intercept=0,slope=1) +
    xlab("Predicted Probability") +
    ylab("Observed Proportion")
targethat<-predict(m4,type="response")
g<-roc(TARGET_FLAG~targethat,data=InsTrains)
plot(g)
targethat[targethat<0.5]<-0
targethat[targethat>=0.5]<-1
table(targethat,InsTrains$TARGET_FLAG)
InsMut <- mutate(InsTrains, Residuals = residuals(m4), linPred = predict(m4))
grpIns <- group_by(InsMut, cut(linPred, breaks=unique(quantile(linPred, (0:25/26)))))
diagIns <- summarise(grpIns, Residuals = mean(Residuals), linPred = mean(linPred))
plot(Residuals ~ linPred, data = diagIns, xlab="Linear Predictor")
abline(h = 0, lty = 2, col = "darkorange", lwd = 2)
abline(lm(Residuals ~ linPred, data = diagIns))
halfnorm(hatvalues(m4))
linPred <- predict(m4)
InsMut <- mutate(InsTrains, predProb = predict(m4, type = "response"))
grpIns <- group_by(InsMut, cut(linPred, breaks = unique(quantile(linPred, (0:25)/26))))
#hosmer-lemeshow stat
hlDf <- summarise(grpIns, y= sum(TARGET_FLAG), pPred=mean(predProb), count = n())
hlDf <- mutate(hlDf, se.fit=sqrt(pPred * (1-(pPred)/count)))
ggplot(hlDf,aes(x=pPred,y=y/count,ymin=y/count-2*se.fit,ymax=y/count+2*se.fit)) +
    geom_point()+geom_linerange(color=grey(0.75))+geom_abline(intercept=0,slope=1) +
    xlab("Predicted Probability") +
    ylab("Observed Proportion")
m1AIC <- AIC(m1)
m1BIC <- BIC(m1)
m2AIC <- AIC(m2)
m2BIC <- BIC(m2)
m3AIC <- AIC(m3)
m3BIC <- BIC(m3)
m4AIC <- AIC(m4)
m4BIC <- BIC(m4)
InsTrain<-InsTrain[ , !(names(InsTrain) %in% c('predicted_m3','target_m4'))]
lm1<-lm(TARGET_AMT~.-TARGET_FLAG,InsTrain)
summary(lm1)
par(mfrow = c(2,2))
plot(lm1)
lm2 <- lm(TARGET_AMT ~ +AGE +EDUCATION +REVOKED +MVR_PTS +JOB +YOJ +CLM_FREQ +HOME_VAL +URBANICITY +PARE
summary(lm2)
par(mfrow = c(2,2))
plot(lm2)
lm3 <- step(lm2)
summary(lm3)
par(mfrow = c(2,2))
plot(lm3)
lm4<-rlm(TARGET_AMT~.-TARGET_FLAG,InsTrain,maxit=40)
summary(lm4)
par(mfrow = c(2,2))
plot(lm4)
lm1AIC <- AIC(lm1)
```

```r
lm1BIC <- BIC(lm1)
lm2AIC <- AIC(lm2)
lm2BIC <- BIC(lm2)
lm3AIC <- AIC(lm3)
lm3BIC <- BIC(lm3)
lm4AIC <- AIC(lm4)
lm4BIC <- BIC(lm4)
# TJ
c<-c('INCOME','HOME_VAL','BLUEBOOK','OLDCLAIM')
if(c %in% colnames(InsEval)){

  glimpse(InsEval[,(c)])
  InsEval[,c] <- sapply(InsEval[,(c)],
                        function(x) as.integer(gsub('[$,]','',as.character(x))))

  glimpse(InsEval[,(c)])

} else {

  cat("Please review your selection of columns:", c)

}
eval_plm<-predict(lm3,InsEval)
write.csv(eval_plm,"predicted_eval_values_Target_Amt.csv")
eval_p<-predict(m3,InsEval, type = "response")
write.csv(eval_p,"predicted_eval_values_Target_Flag.csv")
```