# Abstract

I have been tasked with developing a logistic regression and a multiple linear regression that will determine (1) the likelyhood that a policy holder will make a claim on their car and (2) given that a claim is made, how much will it cost. Using both of these models we will be able to set rates for car insurance based on a number of predictors ranging from income, distance to work or number of kids at home. Their are 8161 observations in the training set with 23 predictors. There are 2 response variables, the binary value indicating whether a claim was made and a numeric value indicating the cost of said cliam.

I will develop three logistic regression models, explore each, and ultimately select the strongest model to use on the evaluation set. I will then develop two multiple linear regressions, explore both, and select the strongest model to use on the evaluation set.

I will begin by exploring the data set as a whole and then each individual predictor.

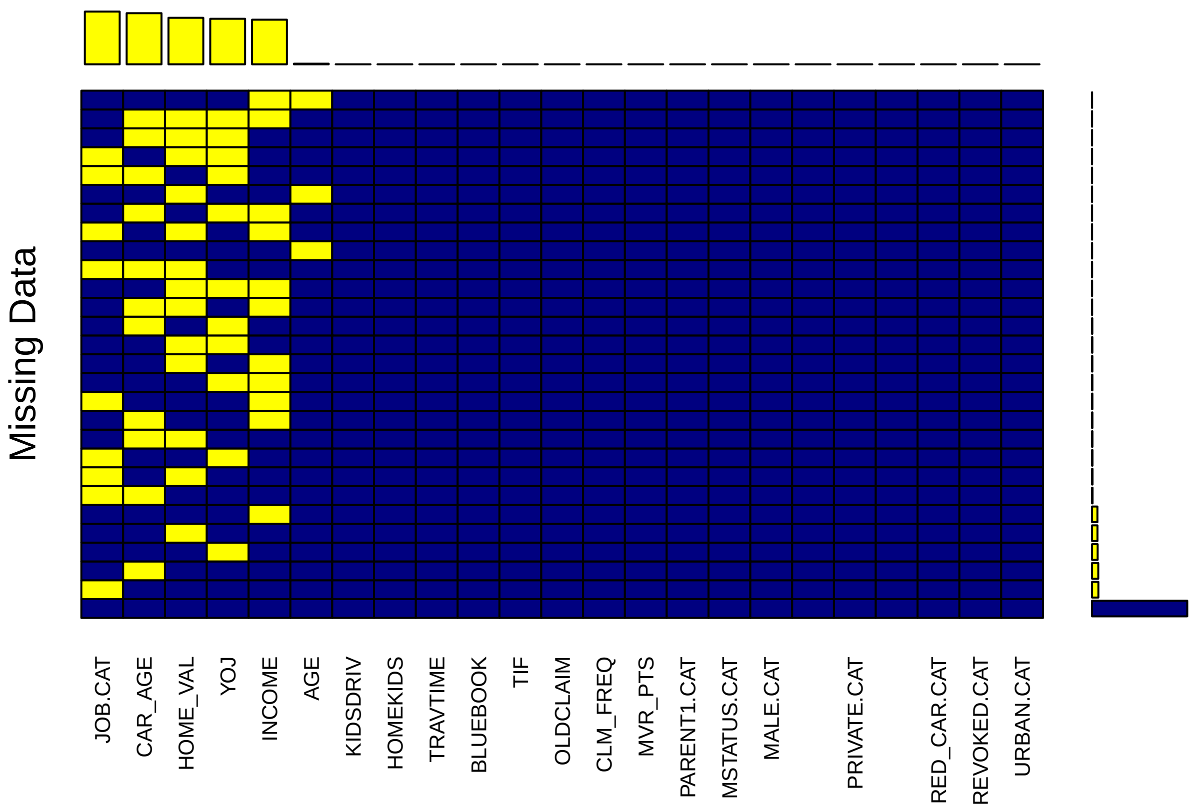

# Data Exploration

Initial inspection of the data shows a small number of missing values in AGE, YOJ, INCOME, HOME_VAL, CAR_AGE and JOB.CAT. Considering the small number of missing values, it is reasonble to impute them. The below plot shows the distribution of the missing values.

```
insurance %>%
  map_dbl(~sum(is.na(.))/nrow(insurance)) %>%
  kable()
```

| | x |
|---|---|
| TARGET_FLAG | 0.0000000 |
| TARGET_AMT | 0.0000000 |
| KIDSDRIV | 0.0000000 |
| AGE | 0.0007352 |
| HOMEKIDS | 0.0000000 |
| YOJ | 0.0556304 |
| INCOME | 0.0545276 |
| HOME_VAL | 0.0568558 |
| TRAVTIME | 0.0000000 |
| BLUEBOOK | 0.0000000 |
| TIF | 0.0000000 |
| OLDCLAIM | 0.0000000 |
| CLM_FREQ | 0.0000000 |
| MVR_PTS | 0.0000000 |
| CAR_AGE | 0.0624923 |
| PARENT1.CAT | 0.0000000 |
| MSTATUS.CAT | 0.0000000 |
| MALE.CAT | 0.0000000 |
| EDUCATION.CAT | 0.0000000 |
| JOB.CAT | 0.0644529 |
| PRIVATE.CAT | 0.0000000 |
| CAR_TYPE.CAT | 0.0000000 |
| RED_CAR.CAT | 0.0000000 |
| REVOKED.CAT | 0.0000000 |
| URBAN.CAT | 0.0000000 |

```
VIM::aggr(insurance[, c(-1, -2)], col=c('navyblue', 'yellow'),
          numbers=TRUE, sortVars=TRUE,
          labels=names(insurance[, c(-1, -2)]), cex.axis=.7,
          gap=3, ylab=c('Missing Data', 'Pattern'), combined=TRUE)
```




```
##
##  Variables sorted by number of missings:
##      Variable Count
##       JOB.CAT   526
##       CAR_AGE   510
##      HOME_VAL   464
##           YOJ   454
##        INCOME   445
##           AGE     6
##      KIDSDRIV     0
##      HOMEKIDS     0
##      TRAVTIME     0
##      BLUEBOOK     0
##           TIF     0
##      OLDCLAIM     0
##      CLM_FREQ     0
##       MVR_PTS     0
##   PARENT1.CAT     0
##   MSTATUS.CAT     0
##      MALE.CAT     0
##  EDUCATION.CAT     0
```

```
##    PRIVATE.CAT     0
##   CAR_TYPE.CAT     0
##    RED_CAR.CAT     0
##    REVOKED.CAT     0
##      URBAN.CAT     0
```

I will use the mice library to partition the data. Once complete I will create a new data frame that has the imputed values.

```
set.seed(123)
imputed.data <- mice::mice(insurance[, c(-1, -2)], m=5, maxit=50, method='pmm', seed=500, printFlag=FALS
insurance.complete <- cbind(insurance[, c(1, 2)], complete(imputed.data, 1))
```

I will partition the data into a training set (80%) and a testing set (20%), seperate from the evaluation set that I will use on the selected model. After partitioning the data, I will use 10-fold cross-validation in training my models. About 25% of the customers in the full training set made a claim. This will be reflected in the partition.

```
set.seed(1)
part <- caret::createDataPartition(insurance.complete$TARGET_FLAG, p=0.8, list=FALSE)
log.training <- insurance.complete[, -2] %>%
  filter(row_number() %in% part)
log.testing <- insurance.complete[, -2] %>%
  filter(!row_number() %in% part)
```

With all the values imputed, I am ready to start my initial exploration of the predictors. I created two functions to help with this analysis.

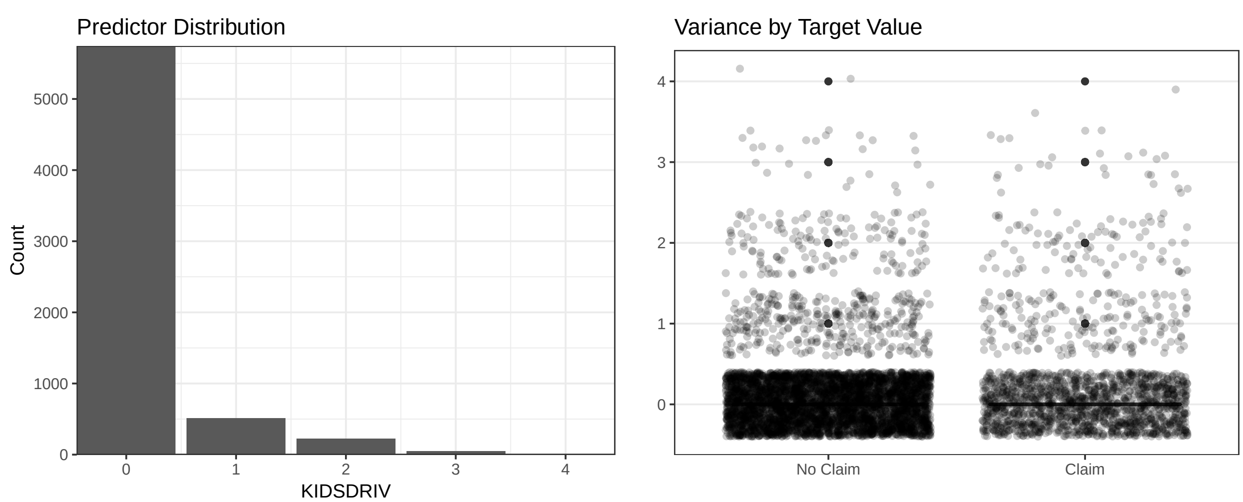
```
Predictor.Discrete.Disp <- function(x){
  require(gridExtra)
  plot.1 <- ggplot(log.training, aes_string(x)) +
    geom_bar() +
    labs(y = 'Count',
    title = 'Predictor Distribution') +
    theme_bw() +
    scale_x_continuous(expand = c(0, 0)) +
    scale_y_continuous(expand = c(0, 0, 0.05, 0.05))

  plot.2 <-
    log.training %>%
    mutate(TARGET_FLAG = factor(TARGET_FLAG)) %>%
    ggplot(aes_string('TARGET_FLAG', x)) +
    geom_boxplot() +
    geom_jitter(alpha=0.2) +
    theme_bw() +
    labs(x='',
         y='',
         title='Variance by Target Value') +
    scale_x_discrete(labels = c('No Claim', 'Claim')) +
    theme(panel.grid.minor = element_blank(),
          panel.grid.major.x = element_blank())

  grid.arrange(plot.1, plot.2, ncol=2)
}

Predictor.Disp <- function(x){
```

```
  require(gridExtra)
  plot.1 <- ggplot(log.training, aes_string(x)) +
    geom_density() +
    labs(y = 'Density',
    title = 'Predictor Distribution') +
    theme_bw() +
    scale_x_continuous(expand = c(0, 0)) +
    scale_y_continuous(expand = c(0, 0, 0.05, 0.05))

  plot.2 <-
    log.training %>%
    mutate(TARGET_FLAG = factor(TARGET_FLAG)) %>%
    ggplot(aes_string('TARGET_FLAG', x)) +
    geom_boxplot() +
    geom_point(alpha=0.2) +
    theme_bw() +
    labs(x='',
         y='',
         title='Variance by Target Value') +
    scale_x_discrete(labels = c('No Claim', 'Claim')) +
    theme(panel.grid.minor = element_blank(),
          panel.grid.major.x = element_blank())

  grid.arrange(plot.1, plot.2, ncol=2)
}
```

## KIDSDRIV

### The number of kids that drive the car on the policy

This predictor is discrete with values ranging only from 0 to 4. It is heavily skewed with most cars having 0 kid drivers. Examining the table of values, it appears that having any number of kid driver's results in a higher likelyhood of making a claim.



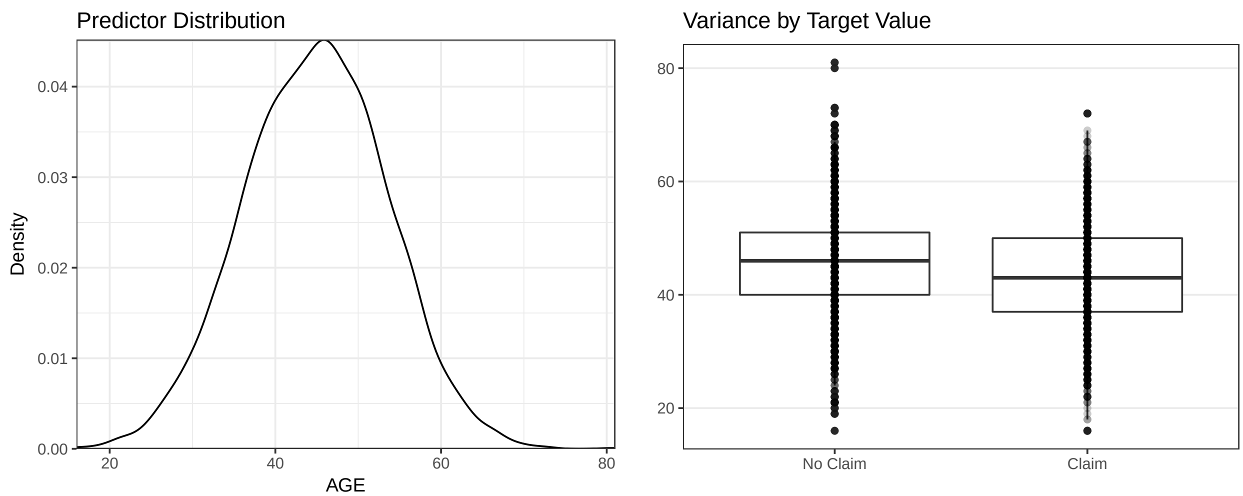

```
##          TARGET
## KIDSDRIV    0    1
```

```
##          0 4315 1429
##          1  329  180
##          2  136   86
##          3   25   26
##          4    2    2
```

# AGE

### Age of the Driver

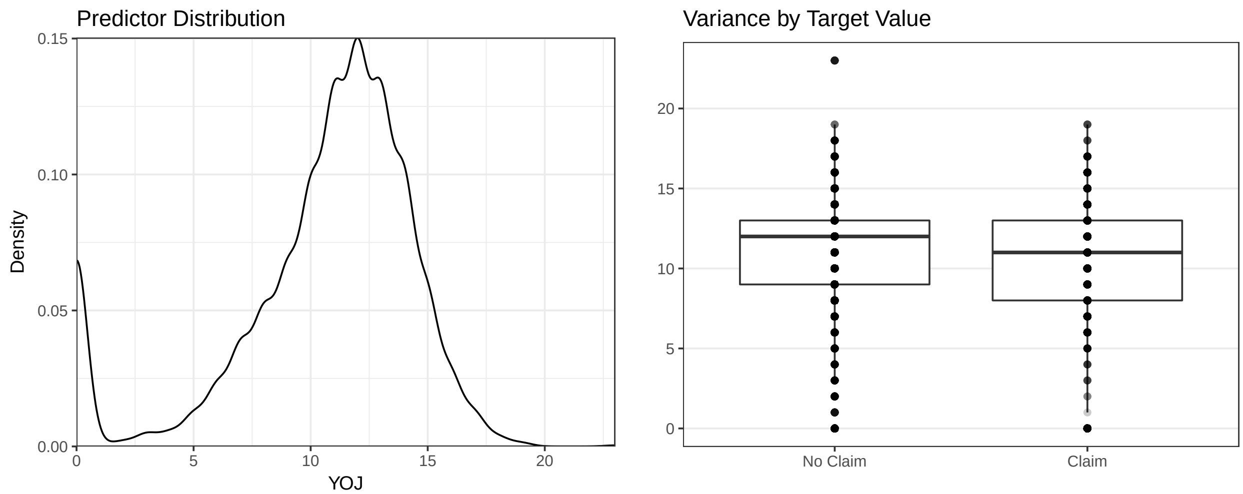
Age has a nice, normal distribution centered around 45. The distribution based on whether a claim is made or not is nearly identical. This leads me to believe that age will not be helpful in determining the likelyhook of making a claim.




# YOJ

### Years On Job

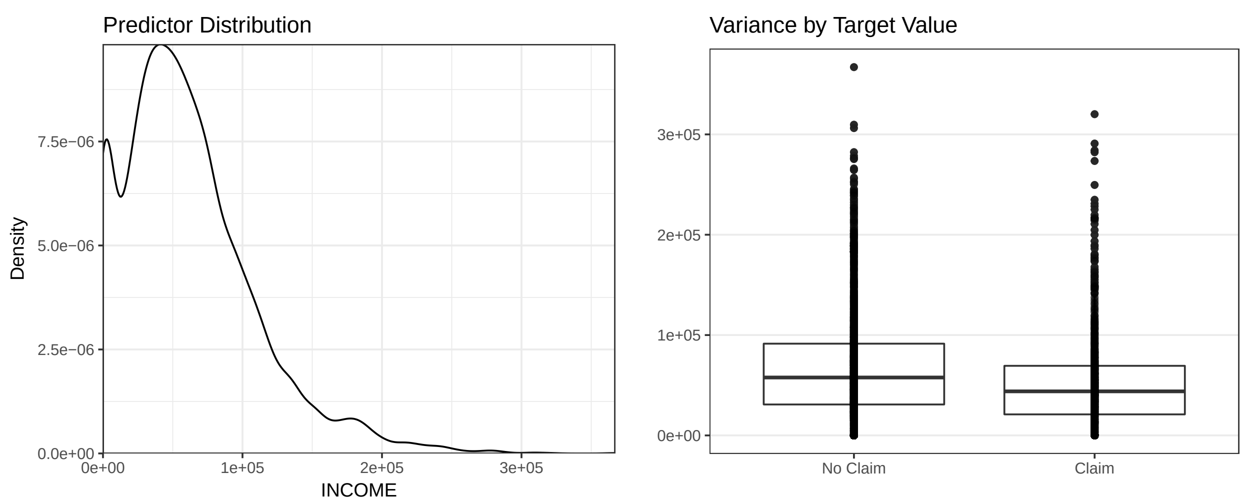
This predictor is nearly normal other than people who are currently unemployed. The distribution when seperated by predictor shows no meanginful difference. It is unlikely that we will use this variable.




## INCOME

### Yearly Income

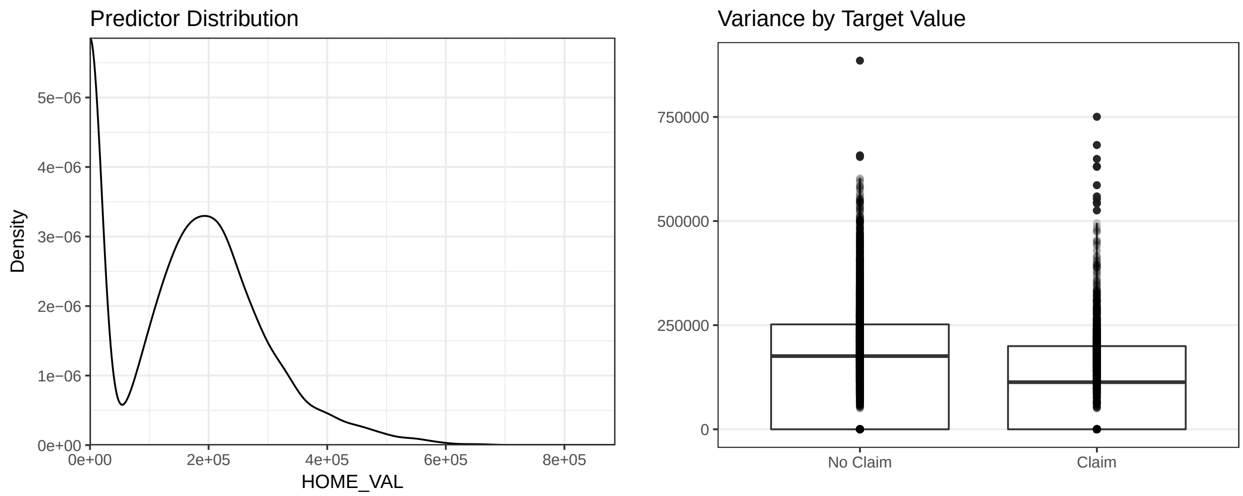
Income is, just like in the general population, heavily skewed. This is represented in the boxplot as well as there are numerous upper outliers in both cases. The correlation between YOJ and INCOME is not as large as one might imagine.




## HOME_VAL

### Value of Home

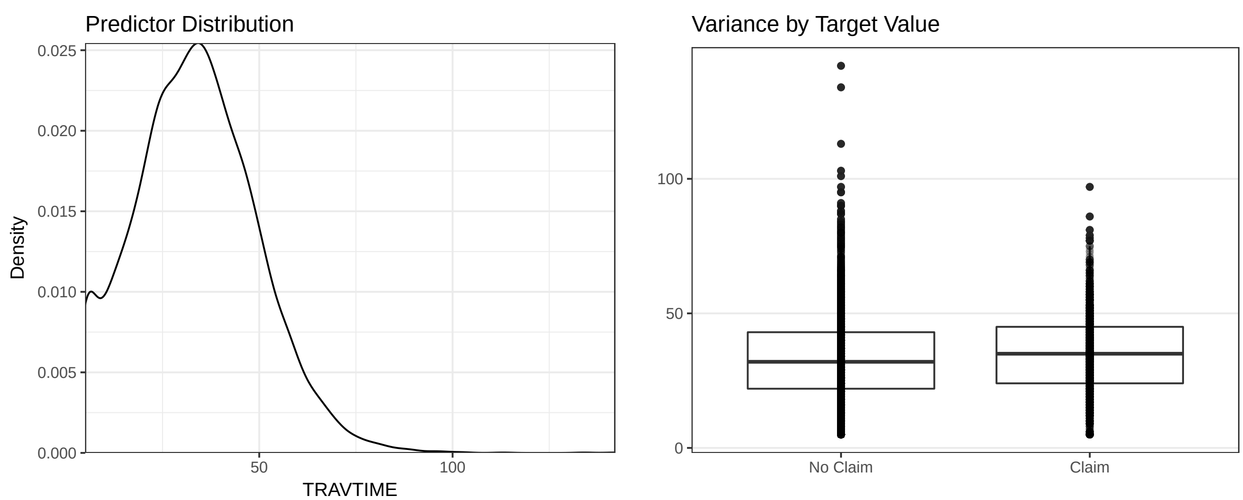
Usefullness of this predictor may be dented by the large number of people who do not own a home. It may be worth considering seperating this into a categorical variable represnting whether or not someone owns a home. The value of the home may be captured by INCOME.




## TRAVTIME

### Distance to Work

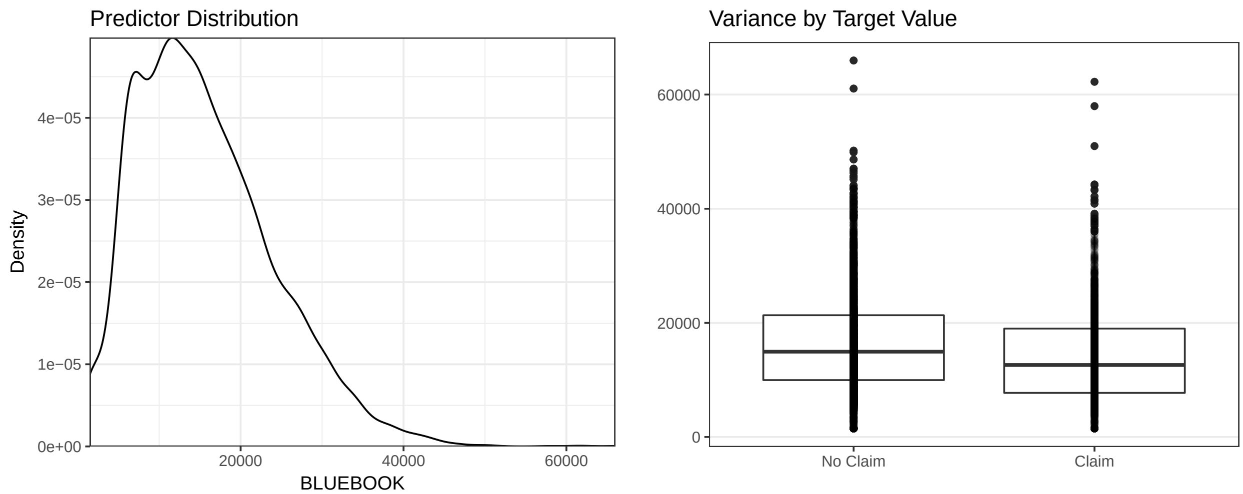
The distance travelled to work is fairly normal and the boxplots show only a subtle increase in the likelyhood of making a claim.




## BLUEBOOK

### Value of Vehicle

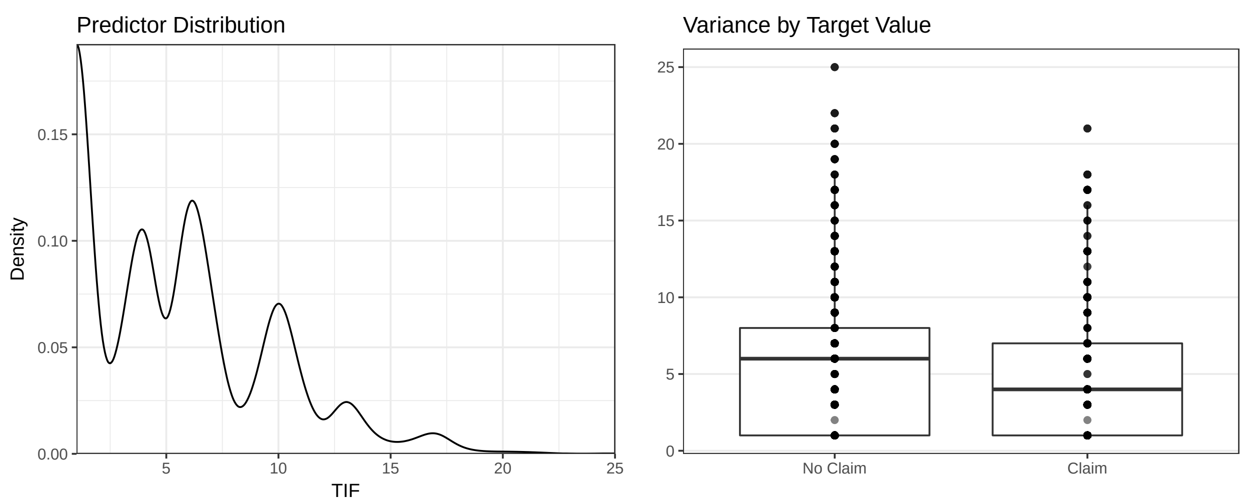
The boxplot indicates that those making a claim have a car that is lower in value. Could this be that more expensive cars are driven more carefully due to their cost or is this a confounding variable that once again measures INCOME?




# TIF

## Length of Stay with Company

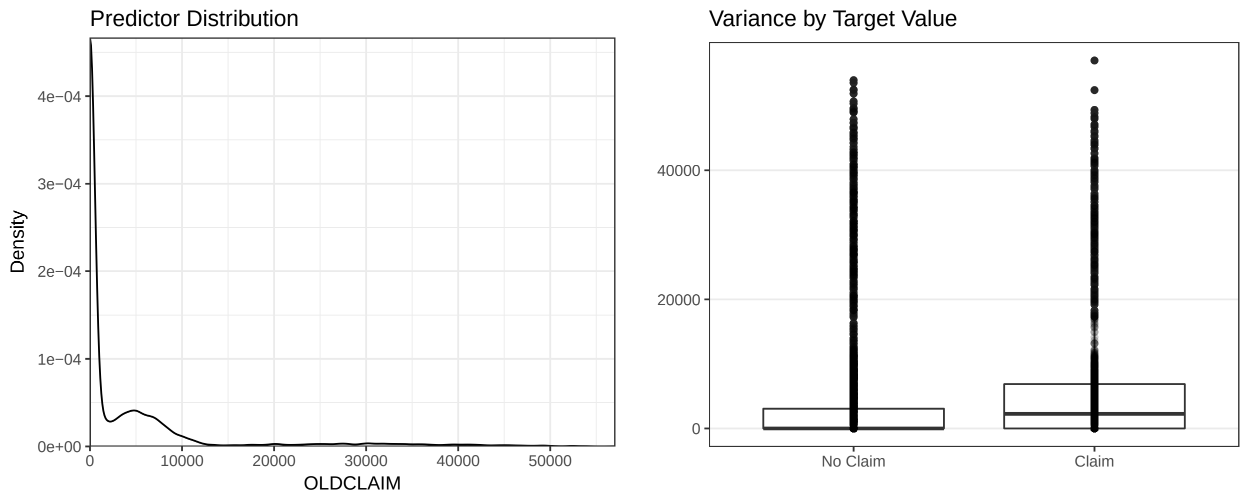
The density plot of this predictor indicates that it could be considered as discrete. There appears to be a significant decrease in the likelyhood of making a claim the longer the person has been with the company. That is, safe drivers tend to stay safe.




# OLDCLAIM

## Claims cost made in the Past 5 Years

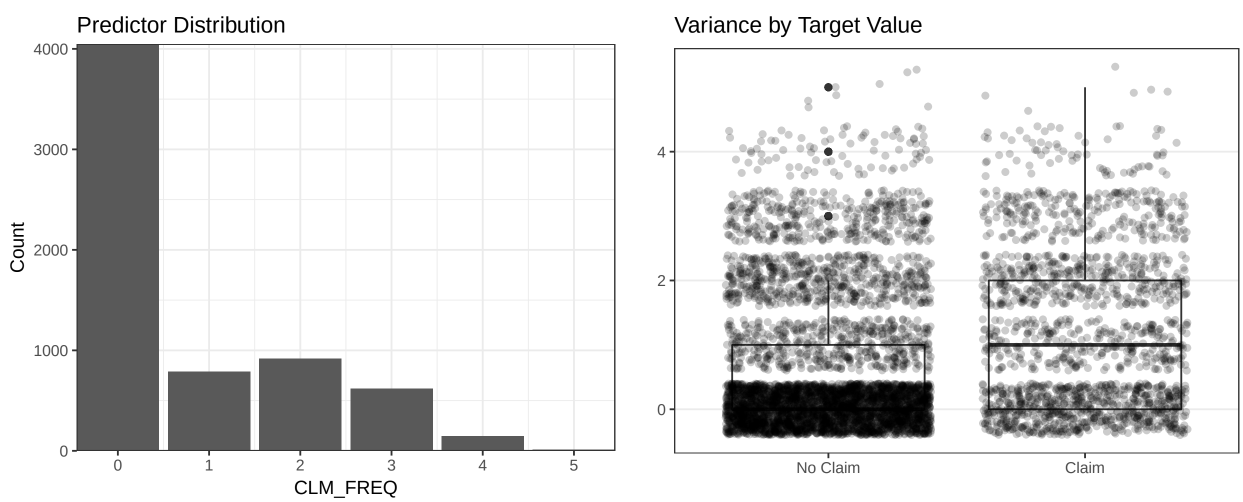
Heavily, heavily skewed predictor. Most people do not make claims.




## CLM_FREQ

### Number of claims made in the Past 5 Years

This predictor appears to be highly significant against people who have made a past claim. That is, people who have made a claim in the past 5 years are very likely to make another claim.

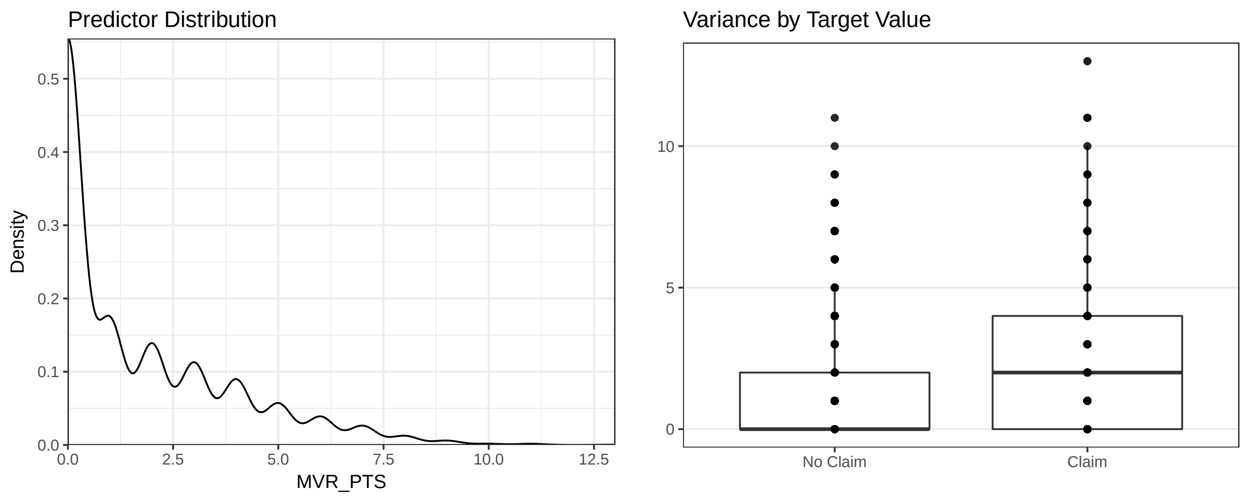



```
##     TARGET
## MALE    0    1
##    0 2537  968
##    1 2270  755
```

## MVR_PTS

### Motor Vehicle Record Points

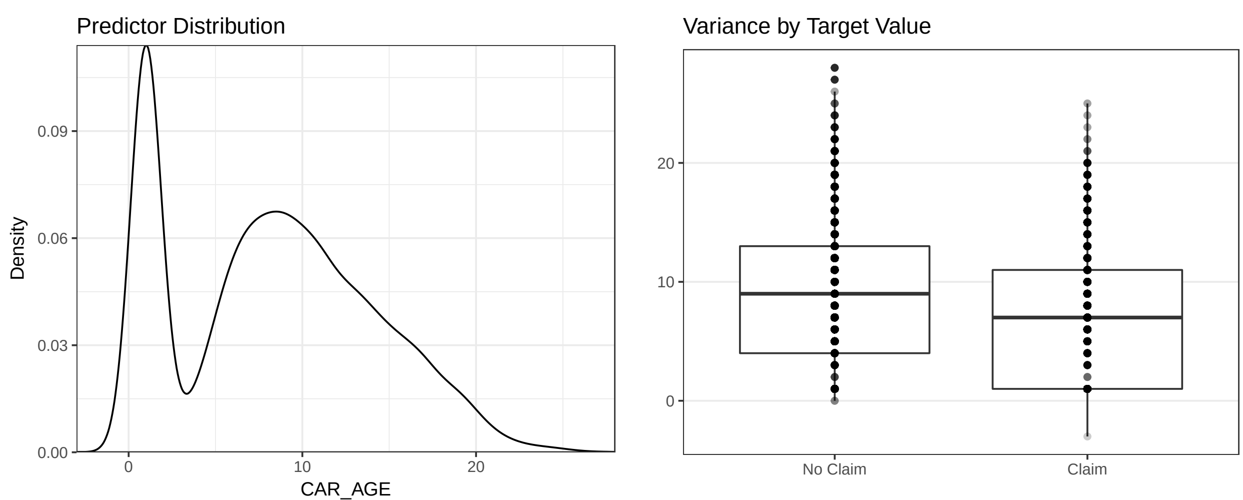
This predictor can be seen as a proxy for how safe a driver someone is. Receiving points on a license indicates that the driver has likely been caught speeding, tailgating or other dangerous driving activities. The boxplot indicates that this variable is likely to be highly significant.




## CAR_AGE

** Age of the Vehicle **

This predictor is bimodal, indicating that most cars are either brand new or quite old. There is one data point that is clearly mislabeled as it indicates the car is -3 years old. This will be corrected to 0. There is no indication whether 0, 3 or some other number is the correct choice but considering it is one value amongst many 10s of thousands it is unlikely to have any meaningful effect on the regression.




## MALE.CAT

### Categorical 0 is Female, 1 if Male

This variable was derived from SEX, just to make the variable's meaning more clear. There appears to be no meanginful difference when considering the gender of the driver.

```
##      TARGET
## MALE    0    1
##    0 2537  968
```

```
##    1 2270  755
```

## EDUCATION.CAT

### Categorical representing max education level

This variable will need to be monitoring as it may be correlated with INCOME or YOJ.

```
##               TARGET
## EDUCATION         0    1
##   <High School  662  312
##   Bachelors    1390  433
##   High School  1209  625
##   Masters      1069  256
##   PhD           477   97
```

## PRIVATE.CAT

### Categorical 0 is commerical, 1 if private

This variable was derived from CAR_USE, just to make the variable's meaning more clear.

```
##        TARGET
## PRIVATE    0    1
##       0 1587  826
##       1 3220  897
```

## CAR_TYPE.CAT

### Categorical representing the car's type

Certain cars are popular with more aggressive or less safe drivers. This may assist in identifying the likelyhood of making a claim.

```
##              TARGET
## CAR_TYPE         0    1
##   Minivan     1433  272
##   Panel Truck  395  132
##   Pickup       778  360
##   Sports Car   476  227
##   SUV         1291  574
##   Van          434  158
```

## RED_CAR.CAT

### Categorical 0 if not Red, 1 if Red

Urban legend states that red cars stand out to police officers and are thus more likely to get pulled over or find themselves in perilous situations.

```
##        TARGET
## RED_CAR    0    1
##       0 3392 1232
##       1 1415  491
```

### REVOKED.CAT

#### Categorical 0 is license not revoked, 1 is revoked

The table's distribution paints a bleak picture that customers who have previously lost their license are likely to be in future accidents.

```
##         TARGET
## REVOKED    0    1
##       0 4363 1387
##       1  444  336
```

### URBAN.CAT

#### Categorical 0 is not urban home/work area, 1 is urban home/work area

This variable can be seen as a proxy for whether the driver frequently uses highways. Urban driving is more likely to result in making a claim, but highway claims are more likely to be expensive. (Collisions at 25mph are obviously less damaging than at 65mph).

```
##       TARGET
## URBAN    0    1
##     0 1261   89
##     1 3546 1634
```

## Logistic Regression

### Model 1

For the first model, I will consider only the categorical variables. This model has the advantage of being the most easily interpretable and the easiest to calculate for future customers.

I began by adding in all the categorical predictors and then examining which, if any, should be removed from the regression. I considered 5 different methods for model selection. [SEE APPENDIX]

**drop1** suggested keeping all the predictors

**AIC** suggested dropping RED_CAR.CAT

**BIC** suggested dropping RED_CAR.CAT

**lasso** suggested dropping RED_CAR.CAT along with specific values from JOB and CAR_TYPE, which is not recommended.

**manual selection** suggested RED_CAR only

Based on the above 5 methods, the final version of model 1 will only drop RED_CAR.CAT

```
ctrl <- trainControl(method='repeatedcv', number=10, savePredictions=TRUE)
model.1 <- train(TARGET_FLAG ~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT +
                   JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT + REVOKED.CAT + URBAN.CAT,
                 data=log.training, method='glm', family='binomial',
                 trControl=ctrl, tuneLength=5)
summary(model.1)
```

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

```
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0413  -0.7562  -0.4541   0.7786   3.0499
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -2.80573    0.18682 -15.019  < 2e-16 ***
## PARENT1.CAT1                0.63961    0.09926   6.444 1.17e-10 ***
## MSTATUS.CAT1               -0.57838    0.07285  -7.939 2.04e-15 ***
## MALE.CAT1                   0.23577    0.09622   2.450  0.01427 *
## EDUCATION.CATBachelors     -0.62693    0.11291  -5.552 2.82e-08 ***
## `EDUCATION.CATHigh School` -0.11482    0.10149  -1.131  0.25789
## EDUCATION.CATMasters       -0.89400    0.14913  -5.995 2.04e-09 ***
## EDUCATION.CATPhD           -0.95240    0.17335  -5.494 3.93e-08 ***
## JOB.CATClerical             0.17628    0.10885   1.620  0.10532
## JOB.CATDoctor              -0.57962    0.26943  -2.151  0.03146 *
## `JOB.CATHome Maker`         0.34218    0.14056   2.434  0.01492 *
## JOB.CATLawyer               0.10660    0.17783   0.599  0.54887
## JOB.CATManager             -0.63456    0.13586  -4.671 3.00e-06 ***
## JOB.CATProfessional        -0.05117    0.12167  -0.421  0.67407
## JOB.CATStudent              0.31480    0.11943   2.636  0.00839 **
## PRIVATE.CAT1               -0.81476    0.09660  -8.435  < 2e-16 ***
## `CAR_TYPE.CATPanel Truck`   0.09198    0.15288   0.602  0.54739
## CAR_TYPE.CATPickup          0.58310    0.10804   5.397 6.77e-08 ***
## `CAR_TYPE.CATSports Car`    1.25444    0.13242   9.473  < 2e-16 ***
## CAR_TYPE.CATSUV             1.05847    0.11044   9.584  < 2e-16 ***
## CAR_TYPE.CATVan             0.42118    0.13174   3.197  0.00139 **
## REVOKED.CAT1                0.72426    0.08764   8.264  < 2e-16 ***
## URBAN.CAT1                  2.44877    0.12114  20.215  < 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: 7536.3  on 6529  degrees of freedom
## Residual deviance: 6197.0  on 6507  degrees of freedom
## AIC: 6243
##
## Number of Fisher Scoring iterations: 5
```

## Model 2

For the second model, I will begin by adding in every single predictor, running the regression and then iteratively remove terms based on my analysis. [SEE APPENDIX]

**drop1** suggested keeping all the predictors

**AIC** suggested dropping AGE, YOJ, CAR_AGE, MALE.CAT, RED_CAR

**BIC** suggested dropping AGE, YOJ, CAR_AGE, MALE.CAT, JOB, RED_CAR

**lasso** suggested dropping nothing

**manual selection** suggested dropping RED_CAR, AGE, YOJ, CAR_AGE, MALE.CAT, HOMEKIDS

Based on the above 5 methods, the final verison of model 2 will drop AGE, YOJ, CAR_AGE, MALE.CAT and RED_CAR.CAT

```
ctrl <- trainControl(method='repeatedcv', number=10, savePredictions=TRUE)
model.2 <- train(TARGET_FLAG ~ . -AGE -YOJ -CAR_AGE -MALE.CAT -RED_CAR.CAT,
                 data=log.training, method='glm', family='binomial',
                 trControl=ctrl, tuneLength=5)
summary(model.2)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6557  -0.7083  -0.3859   0.6274   3.1720
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -2.671e+00  2.220e-01 -12.032  < 2e-16 ***
## KIDSDRIV                      3.784e-01  6.763e-02   5.595 2.20e-08 ***
## HOMEKIDS                      4.616e-02  3.798e-02   1.215 0.224250
## INCOME                       -3.587e-06  1.222e-06  -2.936 0.003329 **
## HOME_VAL                     -1.554e-06  3.908e-07  -3.978 6.95e-05 ***
## TRAVTIME                      1.531e-02  2.121e-03   7.219 5.24e-13 ***
## BLUEBOOK                     -2.401e-05  5.335e-06  -4.500 6.80e-06 ***
## TIF                          -5.476e-02  8.177e-03  -6.697 2.13e-11 ***
## OLDCLAIM                     -1.563e-05  4.467e-06  -3.500 0.000466 ***
## CLM_FREQ                      2.053e-01  3.211e-02   6.393 1.63e-10 ***
## MVR_PTS                       1.263e-01  1.531e-02   8.250  < 2e-16 ***
## PARENT1.CAT1                  3.999e-01  1.225e-01   3.265 0.001096 **
## MSTATUS.CAT1                 -5.049e-01  9.555e-02  -5.284 1.26e-07 ***
## EDUCATION.CATBachelors       -4.422e-01  1.205e-01  -3.669 0.000243 ***
## `EDUCATION.CATHigh School`   -4.240e-02  1.056e-01  -0.402 0.688001
## EDUCATION.CATMasters         -5.440e-01  1.624e-01  -3.350 0.000807 ***
## EDUCATION.CATPhD             -3.494e-01  2.009e-01  -1.739 0.082036 .
## JOB.CATClerical               7.080e-02  1.147e-01   0.617 0.537148
## JOB.CATDoctor                -6.667e-01  2.834e-01  -2.352 0.018653 *
## `JOB.CATHome Maker`          -3.165e-02  1.551e-01  -0.204 0.838327
## JOB.CATLawyer                 4.623e-02  1.852e-01   0.250 0.802937
## JOB.CATManager               -6.036e-01  1.424e-01  -4.238 2.25e-05 ***
## JOB.CATProfessional          -5.747e-02  1.273e-01  -0.452 0.651612
## JOB.CATStudent               -1.151e-01  1.355e-01  -0.849 0.395752
## PRIVATE.CAT1                 -8.021e-01  1.003e-01  -8.000 1.25e-15 ***
## `CAR_TYPE.CATPanel Truck`     5.008e-01  1.704e-01   2.939 0.003295 **
## CAR_TYPE.CATPickup            5.038e-01  1.128e-01   4.468 7.90e-06 ***
## `CAR_TYPE.CATSports Car`      9.719e-01  1.220e-01   7.968 1.61e-15 ***
## CAR_TYPE.CATSUV               7.777e-01  9.607e-02   8.095 5.73e-16 ***
## CAR_TYPE.CATVan               6.225e-01  1.374e-01   4.529 5.92e-06 ***
## REVOKED.CAT1                  8.325e-01  1.028e-01   8.099 5.54e-16 ***
## URBAN.CAT1                    2.470e+00  1.279e-01  19.312  < 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: 7536.3  on 6529  degrees of freedom
## Residual deviance: 5797.9  on 6498  degrees of freedom
## AIC: 5861.9
##
## Number of Fisher Scoring iterations: 5
```

## Model 3

Examining the diagnostic plots for model 2 indicates that there are a number of predictors that may require a quadratic term. For the final model I will add in all these potential quadratic terms and select a model from there.

**drop1** suggested keeping all the predictors

**AIC** suggested dropping AGE, HOMEKIDS^2, YOJ, MVR_PTS, CAR_AGE, MALE.CAT, RED_CAR

**BIC** suggested dropping KIDSDRIV^2, AGE, HOMEKIDS, HOMEKIDS^2, YOJ, CLM_FREQ^2, MVR_PTS, CAR_AGE, MALE.CAT, JOB.CAT, RED_CAR.CAT

I will be more aggresive with this final model and select the BIC suggestion.

```
log.training <- log.training %>%
  mutate(MVR_PTS2 = MVR_PTS*MVR_PTS)
ctrl <- trainControl(method='repeatedcv', number=10, savePredictions=TRUE)
model.3 <- train(TARGET_FLAG ~ . -AGE -HOMEKIDS -YOJ -MVR_PTS -CAR_AGE -MALE.CAT
                 -JOB.CAT -RED_CAR.CAT,
                 data=log.training, method='glm', family='binomial',
                 trControl=ctrl, tuneLength=5)
summary(model.3)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6049  -0.7208  -0.4035   0.5997   3.1553
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -2.530e+00  2.120e-01 -11.935  < 2e-16 ***
## KIDSDRIV                     4.080e-01  6.191e-02   6.590 4.41e-11 ***
## INCOME                      -4.010e-06  1.126e-06  -3.563 0.000366 ***
## HOME_VAL                    -1.444e-06  3.782e-07  -3.818 0.000135 ***
## TRAVTIME                     1.554e-02  2.113e-03   7.352 1.95e-13 ***
## BLUEBOOK                    -2.434e-05  5.306e-06  -4.588 4.47e-06 ***
## TIF                         -5.386e-02  8.142e-03  -6.615 3.71e-11 ***
## OLDCLAIM                    -1.514e-05  4.433e-06  -3.415 0.000639 ***
## CLM_FREQ                     2.122e-01  3.176e-02   6.681 2.37e-11 ***
## PARENT1.CAT1                 4.780e-01  1.055e-01   4.529 5.93e-06 ***
## MSTATUS.CAT1                -4.777e-01  9.038e-02  -5.285 1.26e-07 ***
## EDUCATION.CATBachelors      -5.739e-01  1.097e-01  -5.230 1.70e-07 ***
## `EDUCATION.CATHigh School` -9.378e-02  1.028e-01  -0.913 0.361479
## EDUCATION.CATMasters        -6.542e-01  1.235e-01  -5.299 1.17e-07 ***
## EDUCATION.CATPhD            -6.556e-01  1.696e-01  -3.867 0.000110 ***
```

```
## PRIVATE.CAT1                 -8.460e-01  8.255e-02 -10.248  < 2e-16 ***
## `CAR_TYPE.CATPanel Truck`    4.577e-01  1.628e-01   2.812 0.004921 **
## CAR_TYPE.CATPickup           4.725e-01  1.104e-01   4.279 1.87e-05 ***
## `CAR_TYPE.CATSports Car`     9.672e-01  1.207e-01   8.016 1.09e-15 ***
## CAR_TYPE.CATSUV              7.820e-01  9.520e-02   8.214  < 2e-16 ***
## CAR_TYPE.CATVan              5.879e-01  1.355e-01   4.338 1.44e-05 ***
## REVOKED.CAT1                 8.376e-01  1.022e-01   8.198 2.45e-16 ***
## URBAN.CAT1                   2.437e+00  1.278e-01  19.067  < 2e-16 ***
## MVR_PTS2                     1.920e-02  2.247e-03   8.542  < 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: 7536.3  on 6529  degrees of freedom
## Residual deviance: 5832.6  on 6506  degrees of freedom
## AIC: 5880.6
##
## Number of Fisher Scoring iterations: 5
```

## Model Selection

$R^2$ does not exist for logistic regression in the traditional sense. However, there are a number of so called pseudo $R^2$ terms that can be analized. This is a good starting point for identifying the relative strength of each model.

```
model.1.diag <- glm(TARGET_FLAG ~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT +
                      JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
                   REVOKED.CAT + URBAN.CAT, data=log.training, family=binomial)
model.2.diag <- glm(TARGET_FLAG ~ . -AGE -YOJ -CAR_AGE -MALE.CAT -RED_CAR.CAT,
                    data=log.training, family=binomial)
model.3.diag <- glm(TARGET_FLAG ~ . -AGE -HOMEKIDS -YOJ - MVR_PTS -CAR_AGE -MALE.CAT
                    -JOB.CAT -RED_CAR.CAT +I(MVR_PTS^2), data=log.training, family=binomial)
data_frame(name=names(pscl::pR2(model.1.diag)), value=pscl::pR2(model.1.diag)) %>%
  spread(1, 2) %>%
  kable()
```

| G2 | llh | llhNull | McFadden | r2CU | r2ML |
|---|---|---|---|---|---|
| 1339.287 | -3098.525 | -3768.168 | 0.1777106 | 0.2708375 | 0.1854321 |

```
data_frame(name=names(pscl::pR2(model.2.diag)), value=pscl::pR2(model.2.diag)) %>%
  spread(1, 2) %>%
  kable()
```

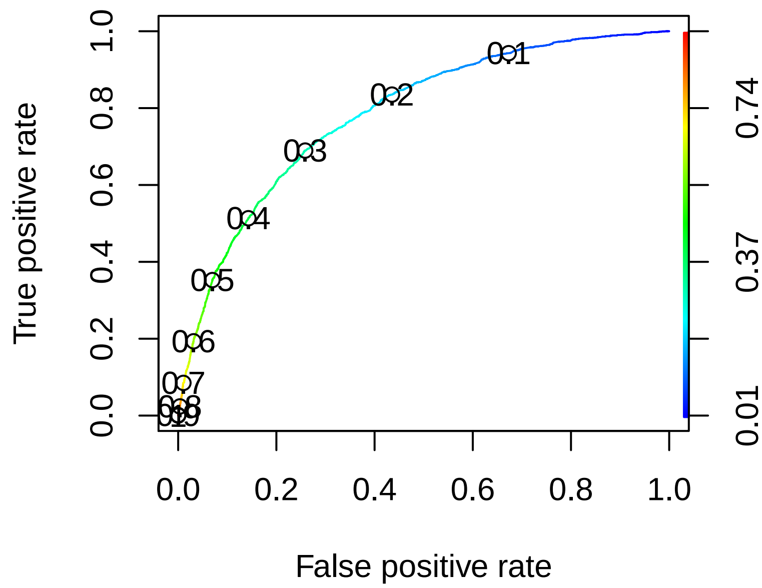
| G2 | llh | llhNull | McFadden | r2CU | r2ML |
|---|---|---|---|---|---|
| 1744.125 | -2896.106 | -3768.168 | 0.2314287 | 0.3423573 | 0.234399 |

```
data_frame(name=names(pscl::pR2(model.3.diag)), value=pscl::pR2(model.3.diag)) %>%
  spread(1, 2) %>%
  kable()
```

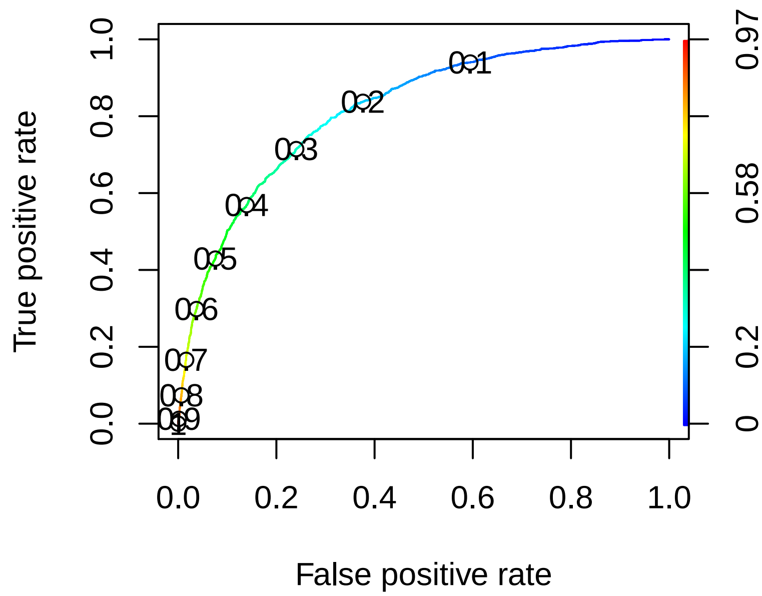
| G2 | llh | llhNull | McFadden | r2CU | r2ML |
|---|---|---|---|---|---|
| 1703.709 | -2916.314 | -3768.168 | 0.226066 | 0.335415 | 0.2296458 |

The first model is the weakest while the second and third are close in their psuedo-$R^2$. Next, we will examine the ROC curve to determine a good cutoff point for categorization against the testing data. All three models appear to have between 0.5 to 0.4 as a good compromise.

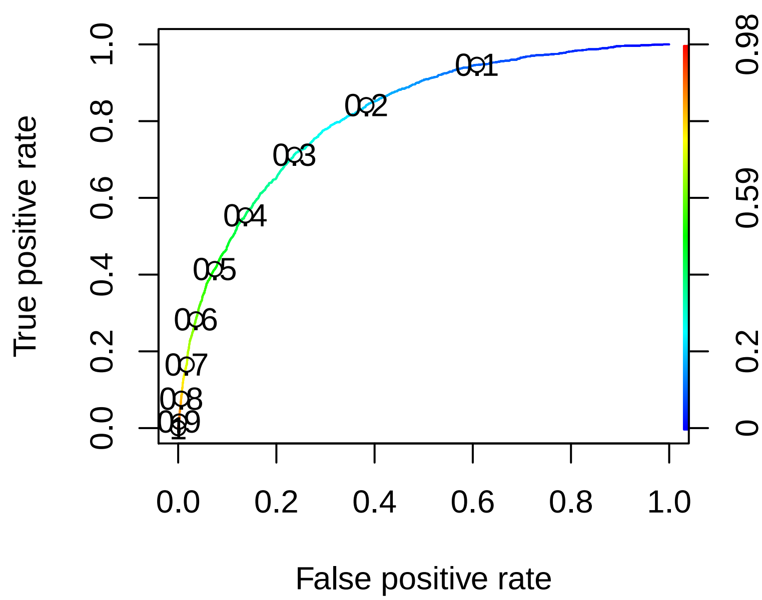
```
ROCRPred <- prediction(predict(model.1.diag, type='response'), log.training$TARGET_FLAG)
ROCRPref <- performance(ROCRPred, 'tpr', 'fpr')
plot(ROCRPref, colorize=TRUE, print.cutoffs.at = seq(0.1, by=0.1))
```




```
ROCRPred <- prediction(predict(model.2.diag, type='response'), log.training$TARGET_FLAG)
ROCRPref <- performance(ROCRPred, 'tpr', 'fpr')
plot(ROCRPref, colorize=TRUE, print.cutoffs.at = seq(0.1, by=0.1))
```




```r
ROCRPred <- prediction(predict(model.3.diag, type='response'), log.training$TARGET_FLAG)
ROCRPref <- performance(ROCRPred, 'tpr', 'fpr')
plot(ROCRPref, colorize=TRUE, print.cutoffs.at = seq(0.1, by=0.1))
```




Finally, I will create a confusion matrix for each model against the testing data.

```
predictions <- ifelse(predict(model.1, newdata=log.testing, type='prob')[2] < 0.4, 0, 1)
caret::confusionMatrix(table(predicted=predictions, actual = log.testing$TARGET_FLAG))
```

```
## Confusion Matrix and Statistics
##
##          actual
## predicted    0    1
##         0 1010  203
##         1  191  227
##
##                Accuracy : 0.7584
##                  95% CI : (0.7369, 0.779)
##     No Information Rate : 0.7364
##     P-Value [Acc > NIR] : 0.02227
##
##                   Kappa : 0.3722
##  Mcnemar's Test P-Value : 0.57946
##
##             Sensitivity : 0.8410
##             Specificity : 0.5279
##          Pos Pred Value : 0.8326
##          Neg Pred Value : 0.5431
##              Prevalence : 0.7364
##          Detection Rate : 0.6193
##    Detection Prevalence : 0.7437
##       Balanced Accuracy : 0.6844
##
##        'Positive' Class : 0
##
```

```
predictions <- ifelse(predict(model.2, newdata=log.testing, type='prob')[2] < 0.4, 0, 1)
caret::confusionMatrix(table(predicted=predictions, actual = log.testing$TARGET_FLAG))
```

```
## Confusion Matrix and Statistics
##
##          actual
## predicted    0    1
##         0 1012  180
##         1  189  250
##
##                Accuracy : 0.7738
##                  95% CI : (0.7527, 0.7939)
##     No Information Rate : 0.7364
##     P-Value [Acc > NIR] : 0.0002795
##
##                   Kappa : 0.4212
##  Mcnemar's Test P-Value : 0.6770710
##
##             Sensitivity : 0.8426
##             Specificity : 0.5814
##          Pos Pred Value : 0.8490
##          Neg Pred Value : 0.5695
##              Prevalence : 0.7364
##          Detection Rate : 0.6205
```

```
##    Detection Prevalence : 0.7308
##       Balanced Accuracy : 0.7120
##
##        'Positive' Class : 0
##
```

```
log.testing <- log.testing %>%
  mutate(MVR_PTS2 = MVR_PTS*MVR_PTS)
predictions <- ifelse(predict(model.3, newdata=log.testing, type='prob')[2] < 0.4, 0, 1)
caret::confusionMatrix(table(predicted=predictions, actual = log.testing$TARGET_FLAG))
```

```
## Confusion Matrix and Statistics
##
##          actual
## predicted    0    1
##         0 1010  189
##         1  191  241
##
##                Accuracy : 0.767
##                  95% CI : (0.7457, 0.7873)
##     No Information Rate : 0.7364
##     P-Value [Acc > NIR] : 0.002449
##
##                   Kappa : 0.4008
##  Mcnemar's Test P-Value : 0.959087
##
##             Sensitivity : 0.8410
##             Specificity : 0.5605
##          Pos Pred Value : 0.8424
##          Neg Pred Value : 0.5579
##              Prevalence : 0.7364
##          Detection Rate : 0.6193
##    Detection Prevalence : 0.7351
##       Balanced Accuracy : 0.7007
##
##        'Positive' Class : 0
##
```

Based on all the available diagnostics, I will select **model 2**. It has consistently produces the highest quality predictions.

## LINEAR REGRESSION

# APPENDIX

## LOGISTIC REGRESSION

### Model 1 Selection

```
model.1.full <- glm(TARGET_FLAG ~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT +
                      JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
```

```r
                      RED_CAR.CAT + REVOKED.CAT + URBAN.CAT, family=binomial, data=log.training)
drop1(model.1.full)
```

| | Df | Deviance | AIC |
|---|---|---|---|
| | NA | 6196.277 | 6244.277 |
| PARENT1.CAT | 1 | 6238.009 | 6284.009 |
| MSTATUS.CAT | 1 | 6258.423 | 6304.423 |
| MALE.CAT | 1 | 6199.063 | 6245.063 |
| EDUCATION.CAT | 4 | 6266.443 | 6306.443 |
| JOB.CAT | 7 | 6265.210 | 6299.210 |
| PRIVATE.CAT | 1 | 6268.689 | 6314.689 |
| CAR_TYPE.CAT | 5 | 6323.457 | 6361.457 |
| RED_CAR.CAT | 1 | 6197.050 | 6243.050 |
| REVOKED.CAT | 1 | 6263.184 | 6309.184 |
| URBAN.CAT | 1 | 6836.627 | 6882.627 |

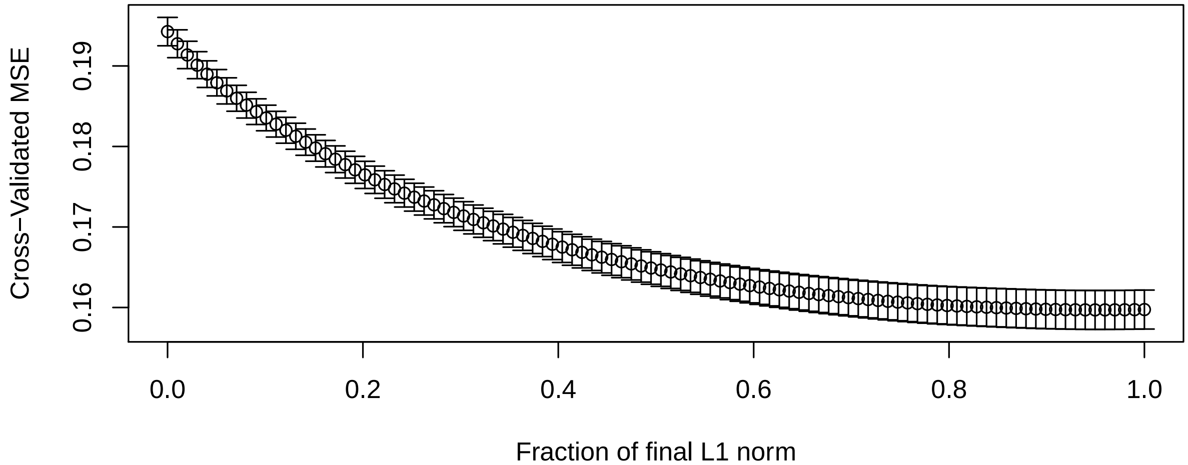
```r
MASS::stepAIC(model.1.full, trace=0)
```

```
##
## Call:  glm(formula = TARGET_FLAG ~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT +
##     EDUCATION.CAT + JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT + REVOKED.CAT +
##     URBAN.CAT, family = binomial, data = log.training)
##
## Coefficients:
##              (Intercept)              PARENT1.CAT1
##                 -2.80573                   0.63961
##             MSTATUS.CAT1                 MALE.CAT1
##                 -0.57838                   0.23577
##   EDUCATION.CATBachelors  EDUCATION.CATHigh School
##                 -0.62693                  -0.11482
##     EDUCATION.CATMasters          EDUCATION.CATPhD
##                 -0.89400                  -0.95240
##         JOB.CATClerical             JOB.CATDoctor
##                  0.17628                  -0.57962
##        JOB.CATHome Maker             JOB.CATLawyer
##                  0.34218                   0.10660
##          JOB.CATManager       JOB.CATProfessional
##                 -0.63456                  -0.05117
##          JOB.CATStudent              PRIVATE.CAT1
##                  0.31480                  -0.81476
##  CAR_TYPE.CATPanel Truck        CAR_TYPE.CATPickup
##                  0.09198                   0.58310
##   CAR_TYPE.CATSports Car           CAR_TYPE.CATSUV
##                  1.25444                   1.05847
##          CAR_TYPE.CATVan              REVOKED.CAT1
##                  0.42118                   0.72426
##               URBAN.CAT1
##                  2.44877
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6507 Residual
## Null Deviance:       7536
## Residual Deviance: 6197  AIC: 6243
```

```
MASS::stepAIC(model.1.full, k=log(nrow(log.training)), trace=0)
```

```
##
## Call:  glm(formula = TARGET_FLAG ~ PARENT1.CAT + MSTATUS.CAT + EDUCATION.CAT +
##     JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT + REVOKED.CAT + URBAN.CAT,
##     family = binomial, data = log.training)
##
## Coefficients:
##             (Intercept)              PARENT1.CAT1
##                -2.64083                   0.62287
##            MSTATUS.CAT1    EDUCATION.CATBachelors
##                -0.58112                  -0.63460
## EDUCATION.CATHigh School      EDUCATION.CATMasters
##                -0.11741                  -0.90163
##        EDUCATION.CATPhD          JOB.CATClerical
##                -0.98037                   0.17777
##           JOB.CATDoctor          JOB.CATHome Maker
##                -0.56865                   0.31235
##           JOB.CATLawyer            JOB.CATManager
##                 0.10457                  -0.63257
##     JOB.CATProfessional            JOB.CATStudent
##                -0.05546                   0.32244
##            PRIVATE.CAT1   CAR_TYPE.CATPanel Truck
##                -0.81017                   0.16522
##       CAR_TYPE.CATPickup    CAR_TYPE.CATSports Car
##                 0.59304                   1.10501
##          CAR_TYPE.CATSUV           CAR_TYPE.CATVan
##                 0.91069                   0.47154
##            REVOKED.CAT1                URBAN.CAT1
##                 0.72789                   2.45024
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6508 Residual
## Null Deviance:       7536
## Residual Deviance: 6203  AIC: 6247
```

```
set.seed(123)
model.1.lasso <- lars(model.matrix(~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT
                                   + JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
                                     RED_CAR.CAT + REVOKED.CAT + URBAN.CAT, log.training),
                      as.numeric(log.training$TARGET_FLAG))
cvlmod <- cv.lars(model.matrix(~ PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT +
                                 JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
                                 RED_CAR.CAT + REVOKED.CAT + URBAN.CAT, log.training),
                  as.numeric(log.training$TARGET_FLAG))
```




```
predict(model.1.lasso, s=0.9494949, type='coef', mode='fraction')$coef
```

```
##              (Intercept)              PARENT1.CAT1              MSTATUS.CAT1
##             0.0000000000              0.1213647128             -0.0874451342
##                MALE.CAT1   EDUCATION.CATBachelors EDUCATION.CATHigh School
##             0.0220785941             -0.0879004191             -0.0010461384
##      EDUCATION.CATMasters         EDUCATION.CATPhD         JOB.CATClerical
##            -0.1263733918             -0.1422308833              0.0236443618
##           JOB.CATDoctor          JOB.CATHome Maker          JOB.CATLawyer
##            -0.0914008251              0.0505833464             -0.0004754156
##          JOB.CATManager       JOB.CATProfessional         JOB.CATStudent
##            -0.1175211570             -0.0163205022              0.0488848878
##            PRIVATE.CAT1   CAR_TYPE.CATPanel Truck      CAR_TYPE.CATPickup
##            -0.1310238177             -0.0051469131              0.0767786518
##    CAR_TYPE.CATSports Car           CAR_TYPE.CATSUV        CAR_TYPE.CATVan
##             0.1742879086              0.1463183928              0.0477593605
##             RED_CAR.CAT1              REVOKED.CAT1              URBAN.CAT1
##             0.0095991727              0.1333193452              0.3180415792
```

## Model 2 Selection

```
model.2.full <- glm(TARGET_FLAG ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME +
                      HOME_VAL + TRAVTIME + BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ +
                      MVR_PTS + CAR_AGE + PARENT1.CAT + MSTATUS.CAT + MALE.CAT +
                      EDUCATION.CAT + JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
                      RED_CAR.CAT + REVOKED.CAT + URBAN.CAT, data=log.training, family=binomial)
drop1(model.2.full)
```

| | Df | Deviance | AIC |
|---|---|---|---|
| | NA | 5794.729 | 5868.729 |
| KIDSDRIV | 1 | 5825.885 | 5897.885 |
| AGE | 1 | 5795.377 | 5867.377 |

| | Df | Deviance | AIC |
|---|---|---|---|
| HOMEKIDS | 1 | 5795.842 | 5867.842 |
| YOJ | 1 | 5796.558 | 5868.558 |
| INCOME | 1 | 5802.724 | 5874.724 |
| HOME_VAL | 1 | 5809.702 | 5881.702 |
| TRAVTIME | 1 | 5847.488 | 5919.488 |
| BLUEBOOK | 1 | 5809.055 | 5881.055 |
| TIF | 1 | 5840.861 | 5912.861 |
| OLDCLAIM | 1 | 5807.171 | 5879.171 |
| CLM_FREQ | 1 | 5835.207 | 5907.207 |
| MVR_PTS | 1 | 5862.213 | 5934.213 |
| CAR_AGE | 1 | 5794.819 | 5866.819 |
| PARENT1.CAT | 1 | 5804.437 | 5876.437 |
| MSTATUS.CAT | 1 | 5820.708 | 5892.708 |
| MALE.CAT | 1 | 5794.750 | 5866.750 |
| EDUCATION.CAT | 4 | 5813.004 | 5879.004 |
| JOB.CAT | 7 | 5831.347 | 5891.347 |
| PRIVATE.CAT | 1 | 5859.021 | 5931.021 |
| CAR_TYPE.CAT | 5 | 5865.533 | 5929.533 |
| RED_CAR.CAT | 1 | 5794.850 | 5866.850 |
| REVOKED.CAT | 1 | 5858.895 | 5930.895 |
| URBAN.CAT | 1 | 6345.545 | 6417.545 |

```r
MASS::stepAIC(model.2.full, trace=0)
```

```
##
## Call:  glm(formula = TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + YOJ + INCOME +
##     HOME_VAL + TRAVTIME + BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ +
##     MVR_PTS + PARENT1.CAT + MSTATUS.CAT + EDUCATION.CAT + JOB.CAT +
##     PRIVATE.CAT + CAR_TYPE.CAT + REVOKED.CAT + URBAN.CAT, family = binomial,
##     data = log.training)
##
## Coefficients:
##              (Intercept)                   KIDSDRIV
##               -2.550e+00                  3.739e-01
##                 HOMEKIDS                        YOJ
##                5.603e-02                 -1.403e-02
##                   INCOME                   HOME_VAL
##               -3.404e-06                 -1.539e-06
##                 TRAVTIME                   BLUEBOOK
##                1.536e-02                 -2.364e-05
##                      TIF                   OLDCLAIM
##               -5.456e-02                 -1.553e-05
##                 CLM_FREQ                    MVR_PTS
##                2.054e-01                  1.255e-01
##             PARENT1.CAT1               MSTATUS.CAT1
##                3.923e-01                 -4.920e-01
##   EDUCATION.CATBachelors  EDUCATION.CATHigh School
##               -4.421e-01                 -4.212e-02
##     EDUCATION.CATMasters           EDUCATION.CATPhD
##               -5.408e-01                 -3.541e-01
##          JOB.CATClerical              JOB.CATDoctor
##                7.109e-02                 -6.796e-01
```

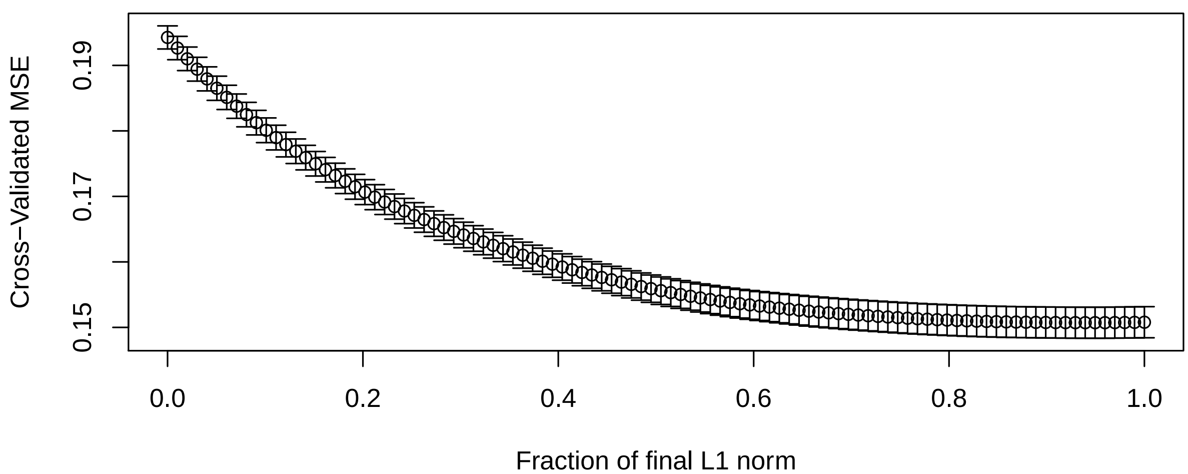
```
##       JOB.CATHome Maker            JOB.CATLawyer
##              -1.060e-01                3.385e-02
##          JOB.CATManager      JOB.CATProfessional
##              -6.089e-01               -6.452e-02
##          JOB.CATStudent             PRIVATE.CAT1
##              -1.775e-01               -7.964e-01
##  CAR_TYPE.CATPanel Truck       CAR_TYPE.CATPickup
##               4.998e-01                5.065e-01
##   CAR_TYPE.CATSports Car          CAR_TYPE.CATSUV
##               9.704e-01                7.782e-01
##          CAR_TYPE.CATVan             REVOKED.CAT1
##               6.174e-01                8.315e-01
##               URBAN.CAT1
##               2.474e+00
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6497 Residual
## Null Deviance:       7536
## Residual Deviance: 5796  AIC: 5862
```

```
MASS::stepAIC(model.2.full, k=log(nrow(log.training)), trace=0)
```

```
##
## Call:  glm(formula = TARGET_FLAG ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME +
##     BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ + MVR_PTS + PARENT1.CAT +
##     MSTATUS.CAT + EDUCATION.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
##     REVOKED.CAT + URBAN.CAT, family = binomial, data = log.training)
##
## Coefficients:
##              (Intercept)                 KIDSDRIV
##              -2.593e+00                4.041e-01
##                   INCOME                 HOME_VAL
##              -4.002e-06               -1.472e-06
##                 TRAVTIME                 BLUEBOOK
##               1.557e-02               -2.435e-05
##                      TIF                 OLDCLAIM
##              -5.334e-02               -1.559e-05
##                 CLM_FREQ                  MVR_PTS
##               2.036e-01                1.310e-01
##              PARENT1.CAT1             MSTATUS.CAT1
##               4.801e-01               -4.755e-01
##   EDUCATION.CATBachelors  EDUCATION.CATHigh School
##              -5.773e-01               -1.005e-01
##     EDUCATION.CATMasters          EDUCATION.CATPhD
##              -6.551e-01               -6.588e-01
##             PRIVATE.CAT1   CAR_TYPE.CATPanel Truck
##              -8.501e-01                4.477e-01
##       CAR_TYPE.CATPickup    CAR_TYPE.CATSports Car
##               4.673e-01                9.633e-01
##          CAR_TYPE.CATSUV          CAR_TYPE.CATVan
##               7.785e-01                5.822e-01
##             REVOKED.CAT1               URBAN.CAT1
##               8.430e-01                2.432e+00
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6506 Residual
## Null Deviance:       7536
```

```
## Residual Deviance: 5837  AIC: 5885
```

```
set.seed(123)
model.2.lasso <- lars(model.matrix(~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + HOME_VAL +
                                     TRAVTIME + BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ +
                                     MVR_PTS + CAR_AGE + PARENT1.CAT + MSTATUS.CAT +
                                     MALE.CAT + EDUCATION.CAT + JOB.CAT +
                                     PRIVATE.CAT + CAR_TYPE.CAT + RED_CAR.CAT + REVOKED.CAT +
                                     URBAN.CAT, log.training), as.numeric(log.training$TARGET_FLAG))
cvlmod <- cv.lars(model.matrix(~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + HOME_VAL +
                                 TRAVTIME + BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ +
                                 MVR_PTS + CAR_AGE + PARENT1.CAT + MSTATUS.CAT + MALE.CAT +
                                 EDUCATION.CAT + JOB.CAT +
                                 PRIVATE.CAT + CAR_TYPE.CAT + RED_CAR.CAT + REVOKED.CAT +
                                 URBAN.CAT, log.training), as.numeric(log.training$TARGET_FLAG))
```




```
cvlmod$index[which.min(cvlmod$cv)]
```

```
## [1] 0.9494949
```

```
predict(model.2.lasso, s=0.9292929, type='coef', mode='fraction')$coef
```

```
##              (Intercept)              KIDSDRIV                   AGE
##             0.000000e+00          5.723853e-02         -4.911684e-04
##                 HOMEKIDS                   YOJ                INCOME
##             5.099281e-03         -2.040275e-03         -4.039648e-07
##                 HOME_VAL              TRAVTIME              BLUEBOOK
##            -1.930173e-07          1.992438e-03         -2.696929e-06
##                      TIF              OLDCLAIM              CLM_FREQ
##            -7.500450e-03         -2.215477e-06          3.313635e-02
##                  MVR_PTS               CAR_AGE           PARENT1.CAT1
##             2.287662e-02         -7.243079e-04          7.881198e-02
##             MSTATUS.CAT1             MALE.CAT1  EDUCATION.CATBachelors
##            -6.689047e-02          0.000000e+00         -5.902253e-02
## EDUCATION.CATHigh School    EDUCATION.CATMasters       EDUCATION.CATPhD
##             2.609209e-03         -6.785259e-02         -4.929497e-02
```

```
##         JOB.CATClerical             JOB.CATDoctor        JOB.CATHome Maker
##            1.263407e-02             -7.684859e-02             0.000000e+00
##           JOB.CATLawyer            JOB.CATManager      JOB.CATProfessional
##            0.000000e+00             -9.334725e-02            -4.739336e-03
##          JOB.CATStudent              PRIVATE.CAT1  CAR_TYPE.CATPanel Truck
##           -8.742197e-03             -1.262808e-01             2.559194e-02
##      CAR_TYPE.CATPickup  CAR_TYPE.CATSports Car           CAR_TYPE.CATSUV
##            5.385015e-02              1.229269e-01             9.723174e-02
##         CAR_TYPE.CATVan               RED_CAR.CAT1             REVOKED.CAT1
##            5.790253e-02              1.359614e-04             1.352238e-01
##              URBAN.CAT1
##            2.942721e-01
```

## Model 3 Selection

```
model.3.full <- glm(TARGET_FLAG ~ KIDSDRIV + I(KIDSDRIV ^ 2) + AGE + HOMEKIDS +
                      I(HOMEKIDS ^ 2) + YOJ + INCOME + HOME_VAL + TRAVTIME + BLUEBOOK +
                      TIF + OLDCLAIM + CLM_FREQ + I(CLM_FREQ ^ 2) + MVR_PTS + I(MVR_PTS ^ 2) +
                      CAR_AGE + PARENT1.CAT + MSTATUS.CAT + MALE.CAT + EDUCATION.CAT + JOB.CAT +
                      PRIVATE.CAT + CAR_TYPE.CAT + RED_CAR.CAT + REVOKED.CAT +
                      URBAN.CAT, data=log.training, family=binomial)
drop1(model.3.full)
```

| | Df | Deviance | AIC |
|---|---|---|---|
| | NA | 5781.167 | 5863.167 |
| KIDSDRIV | 1 | 5788.018 | 5868.018 |
| I(KIDSDRIV^2) | 1 | 5781.500 | 5861.500 |
| AGE | 1 | 5781.530 | 5861.530 |
| HOMEKIDS | 1 | 5783.051 | 5863.051 |
| I(HOMEKIDS^2) | 1 | 5782.358 | 5862.358 |
| YOJ | 1 | 5783.111 | 5863.111 |
| INCOME | 1 | 5789.711 | 5869.711 |
| HOME_VAL | 1 | 5794.815 | 5874.815 |
| TRAVTIME | 1 | 5833.679 | 5913.679 |
| BLUEBOOK | 1 | 5795.568 | 5875.568 |
| TIF | 1 | 5827.674 | 5907.674 |
| OLDCLAIM | 1 | 5797.943 | 5877.943 |
| CLM_FREQ | 1 | 5801.231 | 5881.231 |
| I(CLM_FREQ^2) | 1 | 5786.990 | 5866.990 |
| MVR_PTS | 1 | 5781.876 | 5861.876 |
| I(MVR_PTS^2) | 1 | 5786.662 | 5866.662 |
| CAR_AGE | 1 | 5781.205 | 5861.205 |
| PARENT1.CAT | 1 | 5786.976 | 5866.976 |
| MSTATUS.CAT | 1 | 5809.044 | 5889.044 |
| MALE.CAT | 1 | 5781.173 | 5861.173 |
| EDUCATION.CAT | 4 | 5799.959 | 5873.959 |
| JOB.CAT | 7 | 5817.394 | 5885.394 |
| PRIVATE.CAT | 1 | 5843.400 | 5923.400 |
| CAR_TYPE.CAT | 5 | 5851.549 | 5923.549 |
| RED_CAR.CAT | 1 | 5781.345 | 5861.345 |
| REVOKED.CAT | 1 | 5849.739 | 5929.739 |
| URBAN.CAT | 1 | 6312.472 | 6392.472 |

```
MASS::stepAIC(model.3.full, trace=0)
```

```
##
## Call:  glm(formula = TARGET_FLAG ~ KIDSDRIV + HOMEKIDS + I(HOMEKIDS^2) +
##     YOJ + INCOME + HOME_VAL + TRAVTIME + BLUEBOOK + TIF + OLDCLAIM +
##     CLM_FREQ + I(CLM_FREQ^2) + I(MVR_PTS^2) + PARENT1.CAT + MSTATUS.CAT +
##     EDUCATION.CAT + JOB.CAT + PRIVATE.CAT + CAR_TYPE.CAT + REVOKED.CAT +
##     URBAN.CAT, family = binomial, data = log.training)
##
## Coefficients:
##              (Intercept)                  KIDSDRIV
##               -2.501e+00                 3.641e-01
##                 HOMEKIDS             I(HOMEKIDS^2)
##                1.945e-01                -4.214e-02
##                      YOJ                    INCOME
##               -1.416e-02                -3.544e-06
##                 HOME_VAL                  TRAVTIME
##               -1.467e-06                 1.536e-02
##                 BLUEBOOK                       TIF
##               -2.352e-05                -5.497e-02
##                 OLDCLAIM                  CLM_FREQ
##               -1.891e-05                 4.330e-01
##            I(CLM_FREQ^2)              I(MVR_PTS^2)
##               -6.565e-02                 1.734e-02
##              PARENT1.CAT1              MSTATUS.CAT1
##                3.197e-01                -5.224e-01
##   EDUCATION.CATBachelors  EDUCATION.CATHigh School
##               -4.328e-01                -3.060e-02
##     EDUCATION.CATMasters          EDUCATION.CATPhD
##               -5.246e-01                -3.163e-01
##          JOB.CATClerical             JOB.CATDoctor
##                5.827e-02                -6.947e-01
##        JOB.CATHome Maker             JOB.CATLawyer
##               -1.216e-01                 2.454e-02
##           JOB.CATManager       JOB.CATProfessional
##               -6.187e-01                -7.278e-02
##           JOB.CATStudent              PRIVATE.CAT1
##               -1.827e-01                -7.849e-01
##  CAR_TYPE.CATPanel Truck        CAR_TYPE.CATPickup
##                5.142e-01                 5.095e-01
##   CAR_TYPE.CATSports Car           CAR_TYPE.CATSUV
##                9.679e-01                 7.743e-01
##          CAR_TYPE.CATVan              REVOKED.CAT1
##                6.268e-01                 8.684e-01
##               URBAN.CAT1
##                2.453e+00
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6495 Residual
## Null Deviance:       7536
## Residual Deviance: 5783  AIC: 5853
```

```
MASS::stepAIC(model.3.full, k=log(nrow(log.training)), trace=0)
```

```
##
```

```
## Call:  glm(formula = TARGET_FLAG ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME +
##     BLUEBOOK + TIF + OLDCLAIM + CLM_FREQ + I(MVR_PTS^2) + PARENT1.CAT +
##     MSTATUS.CAT + EDUCATION.CAT + PRIVATE.CAT + CAR_TYPE.CAT +
##     REVOKED.CAT + URBAN.CAT, family = binomial, data = log.training)
##
## Coefficients:
##              (Intercept)                  KIDSDRIV
##               -2.530e+00                 4.080e-01
##                   INCOME                  HOME_VAL
##               -4.010e-06                -1.444e-06
##                 TRAVTIME                  BLUEBOOK
##                1.554e-02                -2.434e-05
##                      TIF                  OLDCLAIM
##               -5.386e-02                -1.514e-05
##                 CLM_FREQ              I(MVR_PTS^2)
##                2.122e-01                 1.920e-02
##              PARENT1.CAT1              MSTATUS.CAT1
##                4.780e-01                -4.777e-01
##   EDUCATION.CATBachelors  EDUCATION.CATHigh School
##               -5.739e-01                -9.378e-02
##     EDUCATION.CATMasters          EDUCATION.CATPhD
##               -6.542e-01                -6.556e-01
##              PRIVATE.CAT1   CAR_TYPE.CATPanel Truck
##               -8.460e-01                 4.577e-01
##       CAR_TYPE.CATPickup    CAR_TYPE.CATSports Car
##                4.725e-01                 9.672e-01
##          CAR_TYPE.CATSUV           CAR_TYPE.CATVan
##                7.820e-01                 5.879e-01
##              REVOKED.CAT1                URBAN.CAT1
##                8.376e-01                 2.437e+00
##
## Degrees of Freedom: 6529 Total (i.e. Null);  6506 Residual
## Null Deviance:       7536
## Residual Deviance: 5833  AIC: 5881
```

## DIAGNOSTICS

## LOGISTIC REGRESSION

Multi-collinearity is not an issue for any of the three models.

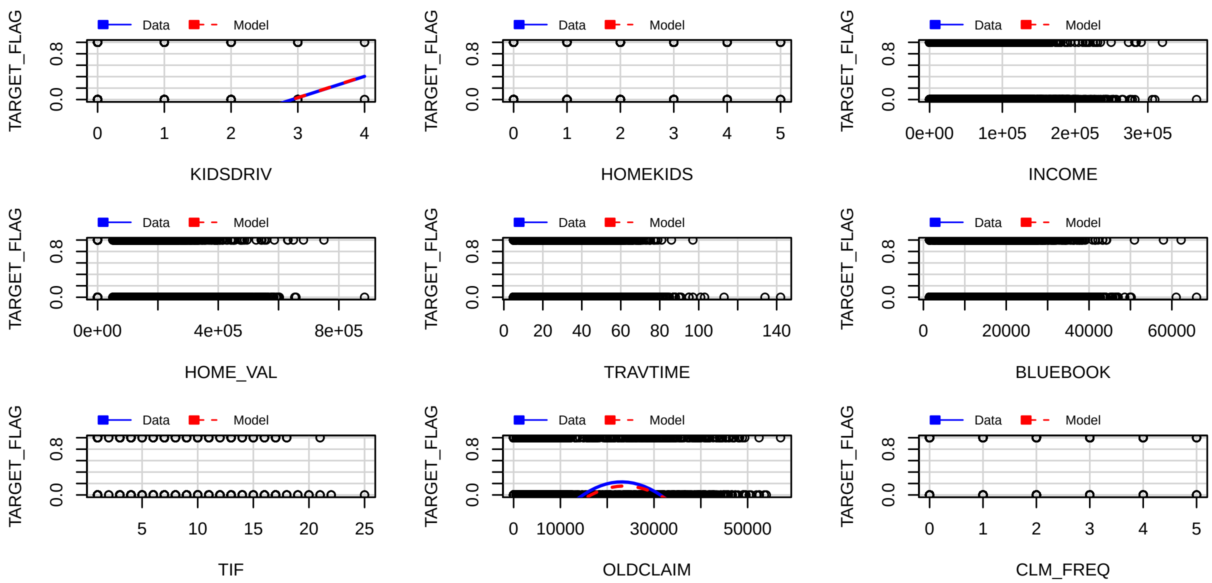
```
car::vif(model.2.diag)
```

```
##                   GVIF Df GVIF^(1/(2*Df))
## KIDSDRIV      1.309855  1        1.144489
## HOMEKIDS      1.828832  1        1.352343
## INCOME        2.616859  1        1.617671
## HOME_VAL      2.032597  1        1.425692
## TRAVTIME      1.039361  1        1.019491
## BLUEBOOK      1.740927  1        1.319442
## TIF           1.010203  1        1.005088
## OLDCLAIM      1.655198  1        1.286545
## CLM_FREQ      1.473428  1        1.213849
## MVR_PTS       7.481396  1        2.735214
```

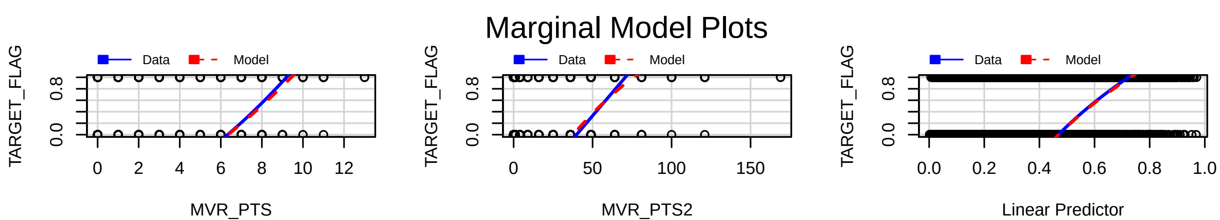
```
## PARENT1.CAT    1.897780  1        1.377599
## MSTATUS.CAT    2.135983  1        1.461500
## EDUCATION.CAT  5.091979  4        1.225634
## JOB.CAT        7.906833  7        1.159159
## PRIVATE.CAT    2.319325  1        1.522933
## CAR_TYPE.CAT   2.558079  5        1.098478
## REVOKED.CAT    1.293346  1        1.137254
## URBAN.CAT      1.138633  1        1.067067
## MVR_PTS2       7.217232  1        2.686491
```

Finally, I have the mmps plots to demonstrate a good fit.

```
car::marginalModelPlots(model.2.diag)
```




```
## Warning in mmps(...): Interactions and/or factors skipped
```



## LINEAR REGRESSION