Assignment 4

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```r
library(tidyr)
library(dplyr)
library(caret)
library(corrplot)
```

Data Import, Preparation, and Exploration

First, let's import the training data and take a quick look.

```r
# Data import Some of the missing data is written as blank instead of NA.
# na.strings takes care of that
raw <- read.csv("https://raw.githubusercontent.com/davidblumenstiel/CUNY-MSDS-DATA-621/main/Assignment_4
    na.strings = c("", " "))

summary(raw)
```

```
##      INDEX        TARGET_FLAG       TARGET_AMT        KIDSDRIV
##  Min.   :    1   Min.   :0.0000   Min.   :     0   Min.   :0.0000
##  1st Qu.: 2559   1st Qu.:0.0000   1st Qu.:     0   1st Qu.:0.0000
##  Median : 5133   Median :0.0000   Median :     0   Median :0.0000
##  Mean   : 5152   Mean   :0.2638   Mean   :  1504   Mean   :0.1711
##  3rd Qu.: 7745   3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:0.0000
##  Max.   :10302   Max.   :1.0000   Max.   :107586   Max.   :4.0000
##
##       AGE           HOMEKIDS           YOJ            INCOME      PARENT1
##  Min.   :16.00   Min.   :0.0000   Min.   : 0.0   $0       : 615   No :7084
##  1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.0   $26,840 :   4   Yes:1077
##  Median :45.00   Median :0.0000   Median :11.0   $48,509 :   4
##  Mean   :44.79   Mean   :0.7212   Mean   :10.5   $61,790 :   4
##  3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.0   $107,375:   3
##  Max.   :81.00   Max.   :5.0000   Max.   :23.0   (Other) :7086
##  NA's   :6                        NA's   :454    NA's    : 445
##      HOME_VAL    MSTATUS      SEX              EDUCATION
##  $0      :2294   Yes :4894   M  :3786   <High School :1203
##  $111,129:   3   z_No:3267   z_F:4375   Bachelors    :2242
##  $115,249:   3                          Masters      :1658
##  $123,109:   3                          PhD          : 728
##  $153,061:   3                          z_High School:2330
##  (Other) :5391
##  NA's    : 464
```

```
##            JOB          TRAVTIME            CAR_USE        BLUEBOOK
##  z_Blue Collar:1825   Min.   :  5.00   Commercial:3029   $1,500 : 157
##  Clerical     :1271   1st Qu.: 22.00   Private   :5132   $6,000 :  34
##  Professional :1117   Median : 33.00                     $5,800 :  33
##  Manager      : 988   Mean   : 33.49                     $6,200 :  33
##  Lawyer       : 835   3rd Qu.: 44.00                     $6,400 :  31
##  (Other)      :1599   Max.   :142.00                     $5,900 :  30
##  NA's         : 526                                      (Other):7843
##       TIF                CAR_TYPE    RED_CAR       OLDCLAIM       CLM_FREQ
##  Min.   : 1.000   Minivan    :2145   no :5783   $0      :5009   Min.   :0.0000
##  1st Qu.: 1.000   Panel Truck: 676   yes:2378   $1,310 :    4   1st Qu.:0.0000
##  Median : 4.000   Pickup     :1389              $1,391 :    4   Median :0.0000
##  Mean   : 5.351   Sports Car : 907              $4,263 :    4   Mean   :0.7986
##  3rd Qu.: 7.000   Van        : 750              $1,105 :    3   3rd Qu.:2.0000
##  Max.   :25.000   z_SUV      :2294              $1,332 :    3   Max.   :5.0000
##                                                 (Other):3134
##  REVOKED       MVR_PTS          CAR_AGE                       URBANICITY
##  No :7161   Min.   : 0.000   Min.   :-3.000   Highly Urban/ Urban  :6492
##  Yes:1000   1st Qu.: 0.000   1st Qu.: 1.000   z_Highly Rural/ Rural:1669
##             Median : 1.000   Median : 8.000
##             Mean   : 1.696   Mean   : 8.328
##             3rd Qu.: 3.000   3rd Qu.:12.000
##             Max.   :13.000   Max.   :28.000
##                              NA's   :510
```

```
head(raw)
```

```
##   INDEX TARGET_FLAG TARGET_AMT KIDSDRIV AGE HOMEKIDS YOJ   INCOME PARENT1
## 1     1           0          0        0  60        0  11  $67,349      No
## 2     2           0          0        0  43        0  11  $91,449      No
## 3     4           0          0        0  35        1  10  $16,039      No
## 4     5           0          0        0  51        0  14     <NA>      No
## 5     6           0          0        0  50        0  NA $114,986      No
## 6     7           1       2946        0  34        1  12 $125,301     Yes
##   HOME_VAL MSTATUS SEX     EDUCATION           JOB TRAVTIME    CAR_USE BLUEBOOK
## 1       $0    z_No   M           PhD  Professional       14    Private  $14,230
## 2 $257,252    z_No   M z_High School z_Blue Collar       22 Commercial  $14,940
## 3 $124,191     Yes z_F z_High School      Clerical        5    Private   $4,010
## 4 $306,251     Yes   M  <High School z_Blue Collar       32    Private  $15,440
## 5 $243,925     Yes z_F           PhD        Doctor       36    Private  $18,000
## 6       $0    z_No z_F     Bachelors z_Blue Collar       46 Commercial  $17,430
##   TIF   CAR_TYPE RED_CAR OLDCLAIM CLM_FREQ REVOKED MVR_PTS CAR_AGE
## 1  11    Minivan     yes   $4,461        2      No       3      18
## 2   1    Minivan     yes       $0        0      No       0       1
## 3   4      z_SUV      no  $38,690        2      No       3      10
## 4   7    Minivan     yes       $0        0      No       0       6
## 5   1      z_SUV      no  $19,217        2     Yes       3      17
## 6   1 Sports Car      no       $0        0      No       0       7
##            URBANICITY
## 1 Highly Urban/ Urban
## 2 Highly Urban/ Urban
## 3 Highly Urban/ Urban
## 4 Highly Urban/ Urban
## 5 Highly Urban/ Urban
```

```
## 6 Highly Urban/ Urban
```

Some missing data, some factors that should be numeric and vice versa. Some of the data that should be numeric also contains dollar-signs and commas, which need to be removed prior to conversion to numeric. We'll make a function to handle this. Another thing of note is that the response variable TARGET_FLAG is unbalanced; only about 26% of the data represents crash claims.

Below the data is prepared

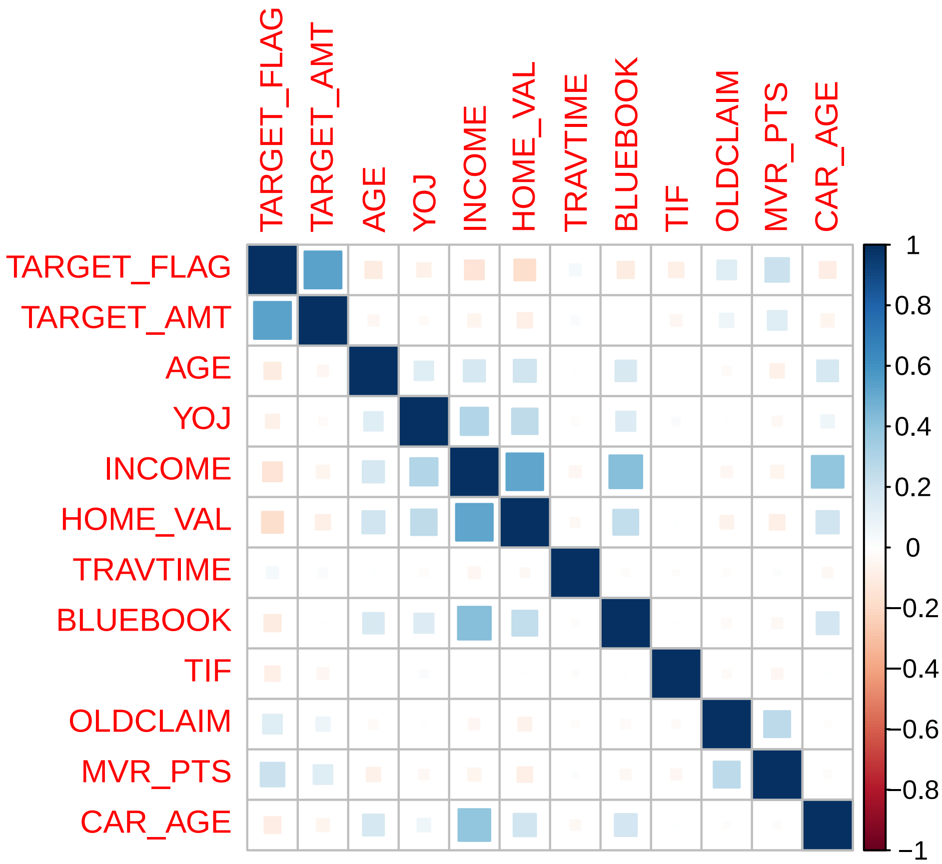
```r
fetch_and_prep <- function(url) {
    # Will take a url and return the prepaired dataset

    # Some of the missing data is written as blank instead of NA.  na.strings takes
    # care of that
    df = read.csv(url, na.strings = c("", " "))

    # Scrap the index variable
    df$INDEX <- NULL

    # Change to factor where appropriate
    df[c("KIDSDRIV", "HOMEKIDS", "CLM_FREQ")] = lapply(df[c("KIDSDRIV", "HOMEKIDS",
        "CLM_FREQ")], factor)

    # Change to numeric where appropriate by first converting to characters, then
    # removing '$' and ',', and then converting to numeric
    df[c("INCOME", "HOME_VAL", "BLUEBOOK", "OLDCLAIM")] = lapply(df[c("INCOME", "HOME_VAL",
        "BLUEBOOK", "OLDCLAIM")], function(x) as.numeric(gsub("[,]", "", gsub("[$]",
        "", as.character(x)))))

    # Adds some more levels to factors so train and test sets have the same
    # categorical variables from:
    # https://stackoverflow.com/questions/40034750/how-to-check-if-a-factor-variable-has-only-the-level
    if ("4" %in% levels(df$KIDSDRIV) == FALSE) {
        levels(df$KIDSDRIV) = c(levels(df$KIDSDRIV), "4")
    }

    ############# NA Imputation

    # Definitely up for debate as to how to handle missing data here.  Here's one
    # take: Could also definitely use regression to impute alot of this (would
    # probably be the better option), but this is less complex

    # Income: will set to median of job type.  If job is also NA, it assumes no job
    # and income is 0
    levels(df$JOB) = c(levels(df$JOB), "Unemployed", "Unlisted")  #adds some more job options
    incomes = aggregate(INCOME ~ JOB, df, median)
    i = 0
    for (val in df$INCOME) {
        i = i + 1
        if (is.na(val)) {
            if (is.na(df[i, "JOB"])) {
                df[i, "INCOME"] = 0
                # Will also change job type to unemployed if no income or job listed
                df[i, "JOB"] = "Unemployed"
```

```
            } else {
                df[i, "INCOME"] = incomes$INCOME[incomes$JOB == df[i, "JOB"]]
            }
        }
    }

    # Job type: if job is NA but income is 0<, then it's likely they are employed;
    # set job to 'unlisted'
    df$JOB[is.na(df$JOB)] = "Unlisted"

    # Age: Set's it to median.  Not many NA's here
    df$AGE[is.na(df$AGE)] = median(df$AGE, na.rm = TRUE)

    # Years on job: Set to median of that type of job
    yearsonjob = aggregate(YOJ ~ JOB, df, median)
    i = 0
    for (val in df$YOJ) {
        i = i + 1
        if (is.na(val)) {
            df[i, "YOJ"] = yearsonjob$YOJ[yearsonjob$JOB == df[i, "JOB"]]
        }
    }

    # Home value: Will assume NA means 0 home value (does not own home).  This one is
    # up for debate
    df$HOME_VAL[is.na(df$HOME_VAL)] = 0

    # Car Age.  Will set it to the median age of that type of car.  Linear regression
    # using bluebook and cartype would be better
    carages = aggregate(CAR_AGE ~ CAR_TYPE, df, median)
    i = 0
    for (val in df$CAR_AGE) {
        i = i + 1
        if (is.na(val)) {
            df[i, "CAR_AGE"] = carages$CAR_AGE[carages$CAR_TYPE == df[i, "CAR_TYPE"]]
        }
        if (df[i, "CAR_AGE"] < 0) {
            # Someone set their car age to -3 in the training set
            df[i, "CAR_AGE"] = 0
        }

    }

    return(df)
}

url <- "https://raw.githubusercontent.com/davidblumenstiel/CUNY-MSDS-DATA-621/main/Assignment_4/insuranc

df <- fetch_and_prep(url)

summary(df)
```

```
##   TARGET_FLAG       TARGET_AMT     KIDSDRIV      AGE        HOMEKIDS
##  Min.   :0.0000   Min.   :     0   0:7180   Min.   :16.00   0:5289
##  1st Qu.:0.0000   1st Qu.:     0   1: 636   1st Qu.:39.00   1: 902
##  Median :0.0000   Median :     0   2: 279   Median :45.00   2:1118
##  Mean   :0.2638   Mean   :  1504   3:  62   Mean   :44.79   3: 674
##  3rd Qu.:1.0000   3rd Qu.:  1036   4:   4   3rd Qu.:51.00   4: 164
##  Max.   :1.0000   Max.   :107586            Max.   :81.00   5:  14
##
##       YOJ            INCOME        PARENT1       HOME_VAL      MSTATUS
##  Min.   : 0.00   Min.   :     0   No :7084   Min.   :     0   Yes :4894
##  1st Qu.: 9.00   1st Qu.: 27964   Yes:1077   1st Qu.:     0   z_No:3267
##  Median :12.00   Median : 54005              Median :151957
##  Mean   :10.53   Mean   : 60952              Mean   :146062
##  3rd Qu.:13.00   3rd Qu.: 83464              3rd Qu.:233352
##  Max.   :23.00   Max.   :367030              Max.   :885282
##
##   SEX               EDUCATION                 JOB          TRAVTIME
##  M  :3786   <High School :1203   z_Blue Collar:1825   Min.   :  5.00
##  z_F:4375   Bachelors    :2242   Clerical     :1271   1st Qu.: 22.00
##             Masters      :1658   Professional :1117   Median : 33.00
##             PhD          : 728   Manager      : 988   Mean   : 33.49
##             z_High School:2330   Lawyer       : 835   3rd Qu.: 44.00
##                                  Student      : 712   Max.   :142.00
##                                  (Other)      :1413
##        CAR_USE         BLUEBOOK          TIF              CAR_TYPE
##  Commercial:3029   Min.   : 1500   Min.   : 1.000   Minivan    :2145
##  Private   :5132   1st Qu.: 9280   1st Qu.: 1.000   Panel Truck: 676
##                    Median :14440   Median : 4.000   Pickup     :1389
##                    Mean   :15710   Mean   : 5.351   Sports Car : 907
##                    3rd Qu.:20850   3rd Qu.: 7.000   Van        : 750
##                    Max.   :69740   Max.   :25.000   z_SUV      :2294
##
##  RED_CAR       OLDCLAIM     CLM_FREQ REVOKED       MVR_PTS
##  no :5783   Min.   :    0   0:5009   No :7161   Min.   : 0.000
##  yes:2378   1st Qu.:    0   1: 997   Yes:1000   1st Qu.: 0.000
##             Median :    0   2:1171              Median : 1.000
##             Mean   : 4037   3: 776              Mean   : 1.696
##             3rd Qu.: 4636   4: 190              3rd Qu.: 3.000
##             Max.   :57037   5:  18              Max.   :13.000
##
##     CAR_AGE                        URBANICITY
##  Min.   : 0.000   Highly Urban/ Urban  :6492
##  1st Qu.: 4.000   z_Highly Rural/ Rural:1669
##  Median : 8.000
##  Mean   : 8.337
##  3rd Qu.:12.000
##  Max.   :28.000
##
```

Much better. The missing data has been imputed (details of how are in the code comments). We have lot's of variables to work with, and I'm not sure which ones are going to be meaningful. A correlation plot might give us some ideas as to how each of these variables interact. We'll Look the numeric variables.

```
corrplot(cor(df[, c(1, 2, 4, 6, 7, 9, 14, 16, 17, 20, 23, 24)], method = "pearson"),
    method = "square")
```



Not a whole lot of correlation between variables, and very little with the target variables. The only notable one here is income, bluebook, and car age which are all decently correlated. We'll examine variables further while modeling.

Modeling Crash Probability

Let's start off with a base model (all variables) for predicting whether or not there was a crash. We'll gauge performances using a holdout data-set.

```
# Train test split
set.seed(1234567890)
splitdex <- createDataPartition(df$TARGET_FLAG, p = 0.8, list = FALSE)
train <- df[splitdex, ]
validation <- df[-splitdex, ]


# Make the model
model <- glm(TARGET_FLAG ~ . - TARGET_AMT, data = train, family = "binomial")

summary(model)
```

```
##
```

```
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT, family = "binomial",
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4431  -0.7110  -0.3957   0.6768   3.1419
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -7.285e-01  3.116e-01  -2.338 0.019397 *
## KIDSDRIV1                        4.314e-01  1.278e-01   3.375 0.000738 ***
## KIDSDRIV2                        7.165e-01  1.804e-01   3.972 7.11e-05 ***
## KIDSDRIV3                        6.141e-01  3.726e-01   1.648 0.099289 .
## KIDSDRIV4                        5.543e-01  1.217e+00   0.455 0.648785
## AGE                              7.816e-04  4.676e-03   0.167 0.867244
## HOMEKIDS1                        3.492e-01  1.335e-01   2.616 0.008906 **
## HOMEKIDS2                        2.102e-01  1.311e-01   1.603 0.108854
## HOMEKIDS3                        1.978e-01  1.516e-01   1.305 0.192020
## HOMEKIDS4                        2.755e-01  2.384e-01   1.156 0.247804
## HOMEKIDS5                        1.207e+00  7.882e-01   1.532 0.125597
## YOJ                             -1.143e-02  9.708e-03  -1.178 0.238869
## INCOME                          -4.019e-06  1.256e-06  -3.200 0.001372 **
## PARENT1Yes                       2.938e-01  1.350e-01   2.176 0.029565 *
## HOME_VAL                        -7.481e-07  3.579e-07  -2.090 0.036609 *
## MSTATUSz_No                      6.243e-01  9.529e-02   6.551 5.71e-11 ***
## SEXz_F                          -2.039e-01  1.245e-01  -1.638 0.101458
## EDUCATIONBachelors              -3.614e-01  1.296e-01  -2.788 0.005299 **
## EDUCATIONMasters                -2.313e-01  1.999e-01  -1.157 0.247386
## EDUCATIONPhD                    -2.808e-02  2.387e-01  -0.118 0.906371
## EDUCATIONz_High School           7.497e-04  1.053e-01   0.007 0.994320
## JOBDoctor                       -1.048e+00  3.267e-01  -3.208 0.001335 **
## JOBHome Maker                   -1.104e-01  1.639e-01  -0.674 0.500417
## JOBLawyer                       -2.063e-01  2.073e-01  -0.995 0.319634
## JOBManager                      -1.028e+00  1.635e-01  -6.287 3.24e-10 ***
## JOBProfessional                 -2.255e-01  1.398e-01  -1.613 0.106806
## JOBStudent                      -1.586e-01  1.482e-01  -1.070 0.284404
## JOBz_Blue Collar                -1.192e-01  1.190e-01  -1.001 0.316792
## JOBUnemployed                   -1.164e+00  6.198e-01  -1.877 0.060464 .
## JOBUnlisted                     -3.938e-01  2.230e-01  -1.766 0.077388 .
## TRAVTIME                         1.433e-02  2.099e-03   6.825 8.80e-12 ***
## CAR_USEPrivate                  -7.797e-01  1.022e-01  -7.631 2.32e-14 ***
## BLUEBOOK                        -1.810e-05  5.902e-06  -3.067 0.002164 **
## TIF                             -5.345e-02  8.182e-03  -6.533 6.46e-11 ***
## CAR_TYPEPanel Truck              4.839e-01  1.821e-01   2.657 0.007879 **
## CAR_TYPEPickup                   5.385e-01  1.127e-01   4.777 1.78e-06 ***
## CAR_TYPESports Car               1.076e+00  1.451e-01   7.419 1.18e-13 ***
## CAR_TYPEVan                      6.520e-01  1.424e-01   4.579 4.68e-06 ***
## CAR_TYPEz_SUV                    8.075e-01  1.244e-01   6.492 8.48e-11 ***
## RED_CARyes                      -1.040e-01  9.670e-02  -1.075 0.282324
## OLDCLAIM                        -2.336e-05  4.766e-06  -4.903 9.46e-07 ***
## CLM_FREQ1                        6.106e-01  1.119e-01   5.455 4.90e-08 ***
## CLM_FREQ2                        7.046e-01  1.052e-01   6.695 2.16e-11 ***
## CLM_FREQ3                        6.385e-01  1.196e-01   5.338 9.38e-08 ***
```

```
## CLM_FREQ4                          7.665e-01  1.994e-01   3.844 0.000121 ***
## CLM_FREQ5                          1.768e+00  6.541e-01   2.703 0.006870 **
## REVOKEDYes                         9.876e-01  1.045e-01   9.451  < 2e-16 ***
## MVR_PTS                            9.985e-02  1.567e-02   6.371 1.87e-10 ***
## CAR_AGE                           -8.920e-03  8.463e-03  -1.054 0.291885
## URBANICITYz_Highly Rural/ Rural -2.232e+00  1.213e-01 -18.404  < 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: 7566.3  on 6528  degrees of freedom
## Residual deviance: 5846.3  on 6479  degrees of freedom
## AIC: 5946.3
##
## Number of Fisher Scoring iterations: 5
```

This model finds many of the variables significant in predicting crashes, however there are some that should be removed as they aren't predictive. Let's see how it performs on the validation set.

```
make.predictions <- function(model, test, threshold = 0.5) {


    test_pred_probs = predict(model, test, type = "response")

    test$predict_prob = test_pred_probs

    # Took most of this next line from:
    # https://www.r-bloggers.com/2020/05/binary-logistic-regression-with-r/
    test$predicted = as.factor(ifelse(test_pred_probs >= threshold, 1, 0))

    return(test[, c("predict_prob", "predicted")])

}
predictions <- make.predictions(model, validation, threshold = 0.5)



library(pROC)
```

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

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

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

```
confusionMatrix(predictions$predicted, as.factor(validation$TARGET_FLAG), positive = "1")
```

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

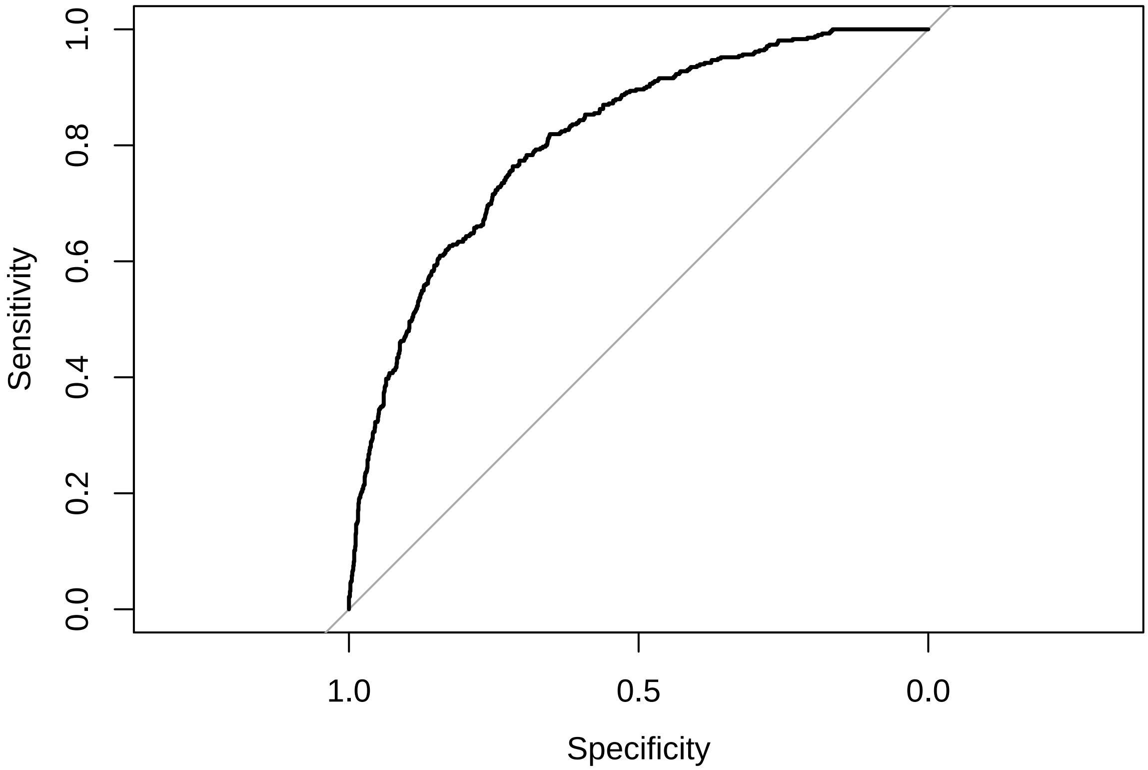
```
##
##           Reference
## Prediction    0    1
##          0 1113  232
##          1  104  183
##
##                Accuracy : 0.7941
##                  95% CI : (0.7737, 0.8135)
##     No Information Rate : 0.7457
##     P-Value [Acc > NIR] : 2.553e-06
##
##                   Kappa : 0.3957
##
##  Mcnemar's Test P-Value : 4.256e-12
##
##             Sensitivity : 0.4410
##             Specificity : 0.9145
##          Pos Pred Value : 0.6376
##          Neg Pred Value : 0.8275
##              Prevalence : 0.2543
##          Detection Rate : 0.1121
##    Detection Prevalence : 0.1759
##       Balanced Accuracy : 0.6778
##
##        'Positive' Class : 1
##
```

```
proc = roc(as.factor(validation$TARGET_FLAG), predictions$predict_prob)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
plot(proc)
```




```
print(proc$auc)
```

```
## Area under the curve: 0.8115
```

This model has a decent accuracy, but isn't terribly useful. If you recall, the data-set has about 74% cases of no crash; this only does a little better than predicting no crash for each instance. There are also a lot of variables that aren't very predictive.

Let's try a LASSO model. LASSO will rid us of some of the coefficients and hopefully help us put together a better model.

```
#I'm copying alot of this from the last assignment

library(glmnet)  #Was a helpful guide: https://web.stanford.edu/~hastie/glmnet/glmnet_alpha.html
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loaded glmnet 4.1-1
```

```r
#There are random elements to this, but I'm not sure where (relaxed fit?)
set.seed(1234567890)


#Data prep.  Needs to be in matrix format
#Took code from here: https://stackoverflow.com/questions/35437411/error-in-predict-glmnet-function-not
train_X <- model.matrix(~.-TARGET_FLAG -TARGET_AMT,data=train)
train_Y <- train$TARGET_FLAG

val_X = model.matrix(~.-TARGET_FLAG -TARGET_AMT,data=validation)

#Makes a series of crossvalidated glmnet models for 100 lambda values (default)
#lamba values are constants that define coefficient shrinkage.
LASSO_crash_model <- cv.glmnet(x = train_X,   #Predictor variables
                      y = train_Y,
                      family = "binomial", #Has it do logistic regression
                      nfolds = 20, #k fold cv
                      type.measure = "class",  #uses missclassification error as loss
                      alpha = 1) #Alpha = 1 is lasso.

#Predicts the probability that the target variable is 1
#setting lambda.min uses the lambda value with the minimum mean cv error (picks the best model)
predictions <- predict(LASSO_crash_model,
                       newx = val_X,
                       type = "response",
                       s=LASSO_crash_model$lambda.min)

#Print's the coefficients the model uses
print(coef.glmnet(LASSO_crash_model, s = LASSO_crash_model$lambda.min))
```

```
## 51 x 1 sparse Matrix of class "dgCMatrix"
##                                       1
## (Intercept)                -5.250675e-01
## (Intercept)                 .
## KIDSDRIV1                   4.004334e-01
## KIDSDRIV2                   6.022020e-01
## KIDSDRIV3                   3.750049e-01
## KIDSDRIV4                   .
## AGE                        -1.970173e-03
## HOMEKIDS1                   1.127480e-01
## HOMEKIDS2                   8.943491e-03
## HOMEKIDS3                   .
## HOMEKIDS4                   .
## HOMEKIDS5                   6.983762e-01
## YOJ                        -2.818820e-03
## INCOME                     -4.486304e-06
## PARENT1Yes                  4.372747e-01
## HOME_VAL                   -8.072571e-07
## MSTATUSz_No                 4.555423e-01
## SEXz_F                      .
## EDUCATIONBachelors         -2.265760e-01
## EDUCATIONMasters           -1.409287e-01
## EDUCATIONPhD                .
```

```
## EDUCATIONz_High School           4.804993e-02
## JOBDoctor                       -5.221588e-01
## JOBHome Maker                    .
## JOBLawyer                        .
## JOBManager                      -7.076978e-01
## JOBProfessional                 -2.577050e-03
## JOBStudent                       .
## JOBz_Blue Collar                 .
## JOBUnemployed                   -3.127200e-01
## JOBUnlisted                      .
## TRAVTIME                         1.153808e-02
## CAR_USEPrivate                  -7.382597e-01
## BLUEBOOK                        -1.502443e-05
## TIF                             -4.324628e-02
## CAR_TYPEPanel Truck              8.110495e-02
## CAR_TYPEPickup                   2.243845e-01
## CAR_TYPESports Car               6.476230e-01
## CAR_TYPEVan                      2.647144e-01
## CAR_TYPEz_SUV                    4.358309e-01
## RED_CARyes                       .
## OLDCLAIM                        -8.416885e-06
## CLM_FREQ1                        3.508672e-01
## CLM_FREQ2                        4.517532e-01
## CLM_FREQ3                        3.700698e-01
## CLM_FREQ4                        4.119322e-01
## CLM_FREQ5                        9.728506e-01
## REVOKEDYes                       7.367550e-01
## MVR_PTS                          1.034423e-01
## CAR_AGE                         -1.337527e-02
## URBANICITYz_Highly Rural/ Rural -1.963756e+00
```

Fewer variables, but still quite a few. The coefficients tend to make some sense. For instance, one is more likely to crash if they have more kids driving, have more prior claims, drive more, and have more record points. One is less likely to crash however if they are older, have more years at their job, earn more income, have a pricier car, are more educated, are unemployed (more careful), and use their own car. One could probably boil down a lot of these variables to a 'responsibility' metric; things like age and prior claims could all play into it. Red cars, on the other hand, don't make a meaningful difference (lucky us).

Let's see how the model performs.

```r
confusionMatrix(as.factor(ifelse(predictions >= 0.5, 1, 0)), as.factor(validation$TARGET_FLAG),
    positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1141  258
##          1   76  157
##
##                Accuracy : 0.7953
##                  95% CI : (0.7749, 0.8147)
##     No Information Rate : 0.7457
##     P-Value [Acc > NIR] : 1.436e-06
```

```
##
##                   Kappa : 0.3692
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.3783
##             Specificity : 0.9376
##          Pos Pred Value : 0.6738
##          Neg Pred Value : 0.8156
##              Prevalence : 0.2543
##          Detection Rate : 0.0962
##    Detection Prevalence : 0.1428
##       Balanced Accuracy : 0.6579
##
##        'Positive' Class : 1
##
```

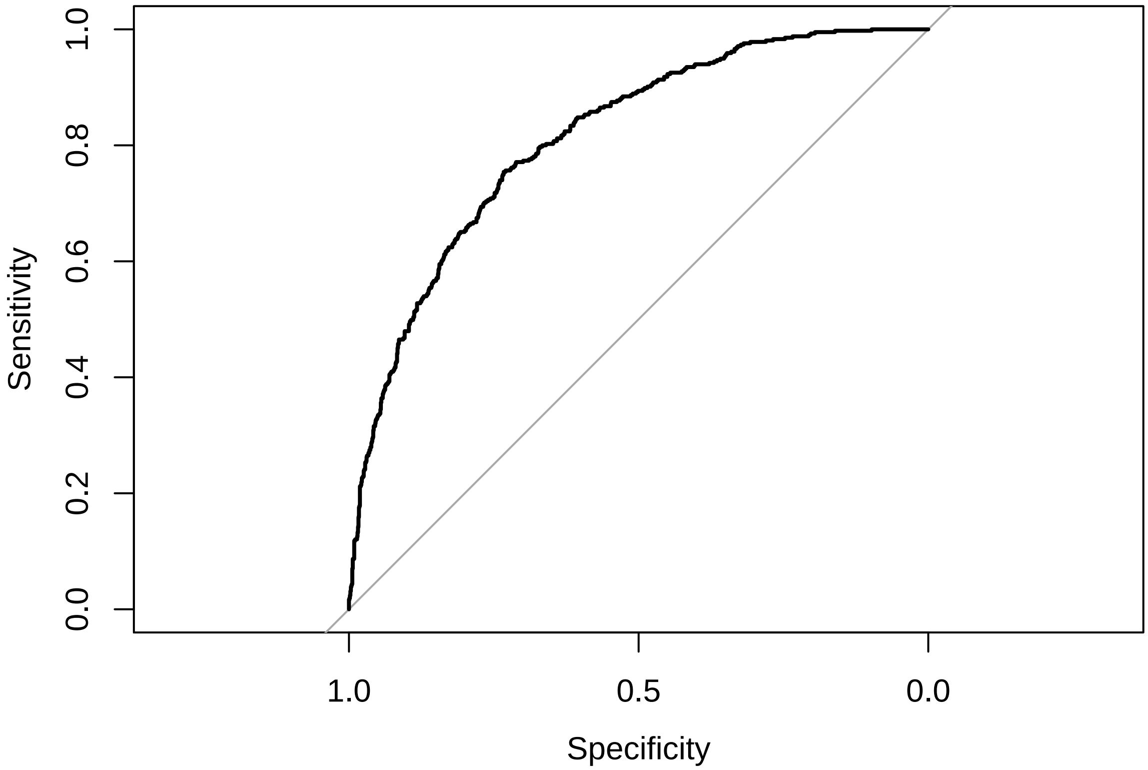
```r
proc = roc(validation$TARGET_FLAG, predictions)
```

```
## Setting levels: control = 0, case = 1
```

```
## Warning in roc.default(validation$TARGET_FLAG, predictions): Deprecated use a
## matrix as predictor. Unexpected results may be produced, please pass a numeric
## vector.
```

```
## Setting direction: controls < cases
```

```r
plot(proc)
```




```
print(proc$auc)
```

```
## Area under the curve: 0.8133
```

It's able to get rid of a few without predictors negatively impacting the accuracy or AUC much. One other thing to consider is that this model finds fewer false positives, but more false negatives. That said, it's not really any more accurate than the base model on the whole, and is only about an additional 5% better than just guessing no crash for all cases.

Modeling Payout

Now we need to predict how much those who were predicted to crash actually get. I suspect the payout is proportional to both the value of the car and how damaging the crash is. The value of the car is one of the variables (Bluebook), and I suspect the damage might correlate to some of the other variables like the type of car and various 'responsibility' type measures. We'll see if any of the models confirm my suspicions.

There are two different ways to go about selecting the data we want to use to train this: use data from all cases where there was a crash, or only use data where we predicted a crash. Using all cases of crashes might be better at predicting the payout from crashes for the population, but using only predicted cases might be a more practical fit. Let's try it with all cases, using a basic multiple linear regression model, and LASSO again to try to get the number of predictors down.

Below is a basic multiple regression model

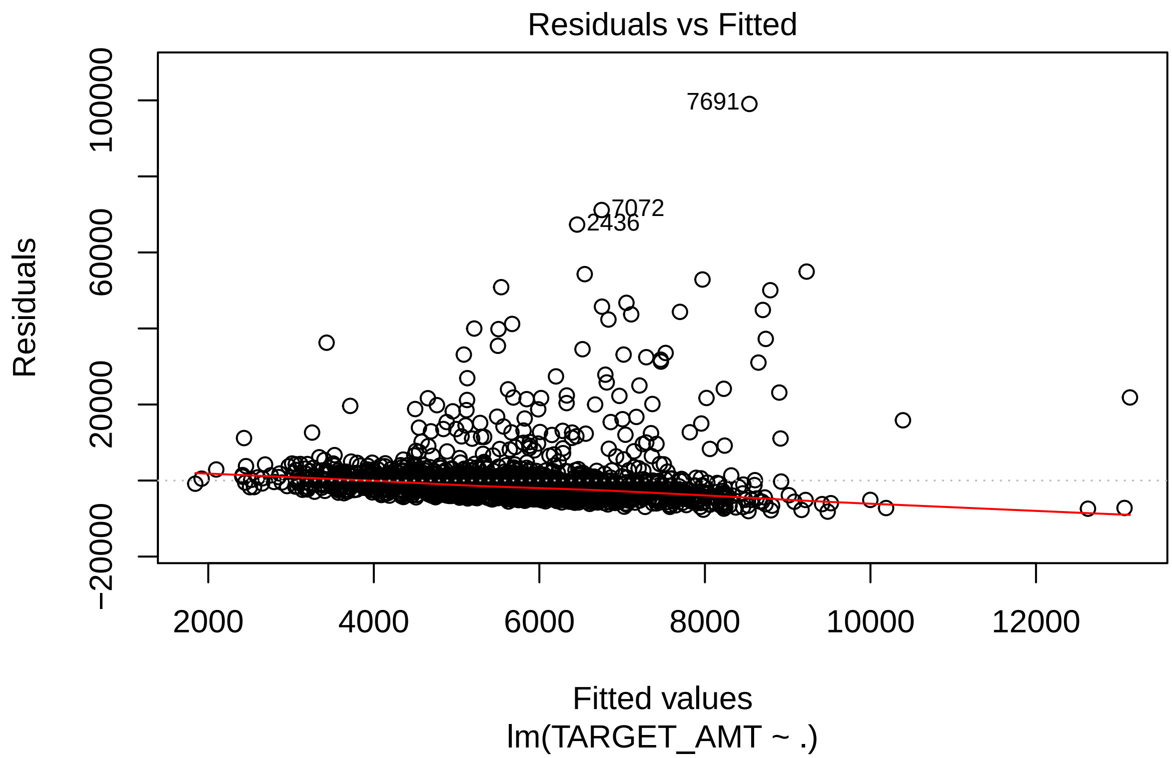
```r
# Select only instances where a crash occured
all_crash <- subset(df, TARGET_FLAG == 1)
all_crash$TARGET_FLAG <- NULL

set.seed(987654321)

# Train test split
splitdex <- createDataPartition(all_crash$TARGET_AMT, p = 0.8, list = FALSE)
crash_train <- all_crash[splitdex, ]
crash_validation <- all_crash[-splitdex, ]

base_model_payout <- lm(TARGET_AMT ~ ., crash_train)
summary(base_model_payout)
```

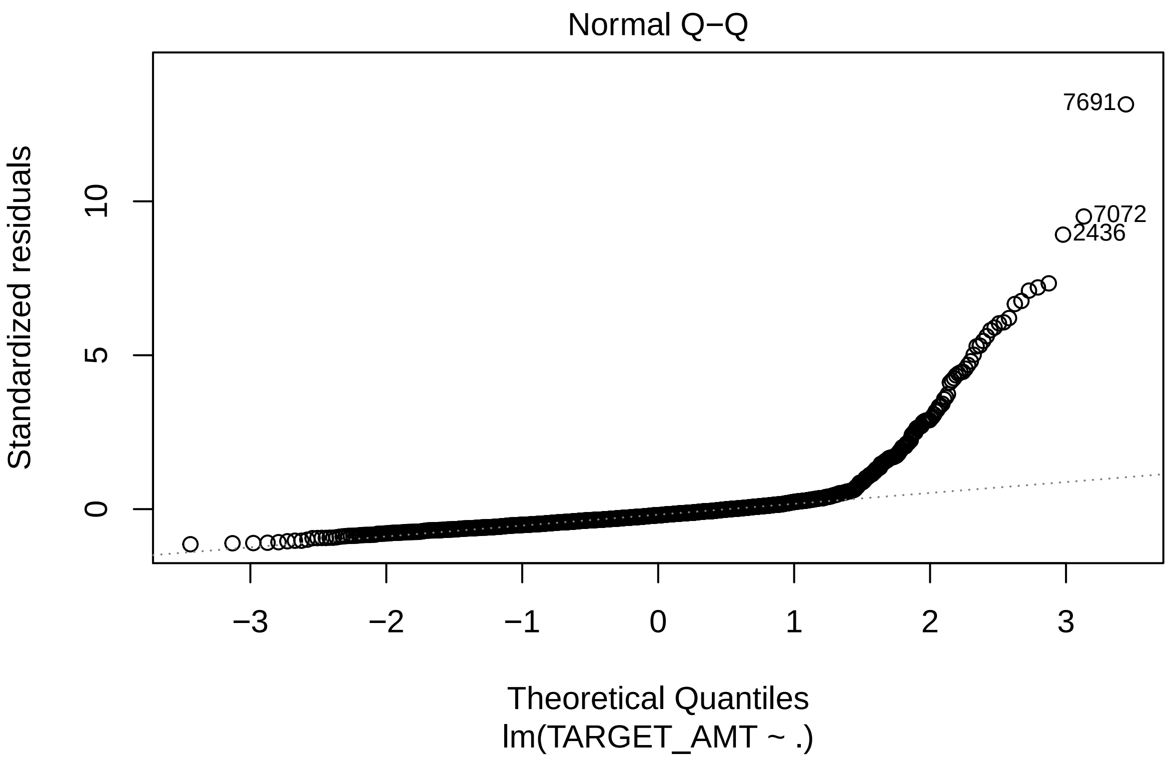
```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = crash_train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -8176  -3148  -1495    433  99049
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     4.146e+03  1.725e+03   2.403  0.01636 *
## KIDSDRIV1                      -3.985e+02  6.909e+02  -0.577  0.56422
## KIDSDRIV2                      -2.965e+02  9.223e+02  -0.321  0.74790
## KIDSDRIV3                      -3.186e+02  1.736e+03  -0.184  0.85439
## KIDSDRIV4                      -1.256e+01  8.668e+03  -0.001  0.99884
## AGE                             3.440e+01  2.438e+01   1.411  0.15853
## HOMEKIDS1                       7.239e+02  7.642e+02   0.947  0.34369
## HOMEKIDS2                       1.145e+03  7.457e+02   1.536  0.12469
## HOMEKIDS3                       5.769e+02  8.334e+02   0.692  0.48889
## HOMEKIDS4                       3.760e+02  1.248e+03   0.301  0.76317
## HOMEKIDS5                       9.646e+02  3.924e+03   0.246  0.80586
## YOJ                             3.049e+01  5.627e+01   0.542  0.58803
## INCOME                         -1.177e-02  7.775e-03  -1.514  0.13032
## PARENT1Yes                     -1.203e+02  7.478e+02  -0.161  0.87223
## HOME_VAL                        2.517e-03  2.144e-03   1.174  0.24073
## MSTATUSz_No                     7.875e+02  5.677e+02   1.387  0.16558
## SEXz_F                         -1.199e+03  7.248e+02  -1.654  0.09839 .
## EDUCATIONBachelors              1.866e+01  7.052e+02   0.026  0.97889
## EDUCATIONMasters                7.616e+02  1.203e+03   0.633  0.52687
## EDUCATIONPhD                    7.218e+02  1.477e+03   0.489  0.62515
## EDUCATIONz_High School         -3.847e+02  5.683e+02  -0.677  0.49855
## JOBDoctor                      -3.661e+02  2.053e+03  -0.178  0.85850
## JOBHome Maker                  -1.157e+02  9.378e+02  -0.123  0.90180
## JOBLawyer                       3.565e+02  1.303e+03   0.274  0.78441
## JOBManager                     -6.846e+02  1.054e+03  -0.650  0.51592
## JOBProfessional                 6.015e+02  8.083e+02   0.744  0.45686
## JOBStudent                     -1.091e+02  8.298e+02  -0.131  0.89543
## JOBz_Blue Collar               -1.708e+02  6.519e+02  -0.262  0.79332
## JOBUnemployed                   4.695e+03  4.005e+03   1.172  0.24124
```

```
## JOBUnlisted                      -2.672e+02  1.363e+03  -0.196  0.84460
## TRAVTIME                         -1.348e+01  1.236e+01  -1.090  0.27578
## CAR_USEPrivate                   -9.268e+02  5.826e+02  -1.591  0.11182
## BLUEBOOK                          9.757e-02  3.389e-02   2.879  0.00403 **
## TIF                              -3.109e+01  4.756e+01  -0.654  0.51336
## CAR_TYPEPanel Truck              -5.352e+02  1.051e+03  -0.509  0.61061
## CAR_TYPEPickup                   -4.017e+02  6.576e+02  -0.611  0.54137
## CAR_TYPESports Car                3.379e+02  8.260e+02   0.409  0.68253
## CAR_TYPEVan                       1.325e+02  8.632e+02   0.153  0.87807
## CAR_TYPEz_SUV                     7.561e+02  7.376e+02   1.025  0.30547
## RED_CARyes                       -1.970e+02  5.517e+02  -0.357  0.72101
## OLDCLAIM                          2.603e-02  2.779e-02   0.937  0.34904
## CLM_FREQ1                        -4.273e+02  6.205e+02  -0.689  0.49114
## CLM_FREQ2                        -5.675e+02  5.908e+02  -0.961  0.33691
## CLM_FREQ3                         8.426e+01  6.481e+02   0.130  0.89658
## CLM_FREQ4                        -1.269e+03  1.015e+03  -1.250  0.21140
## CLM_FREQ5                        -1.521e+03  3.171e+03  -0.480  0.63155
## REVOKEDYes                       -1.113e+03  6.015e+02  -1.851  0.06435 .
## MVR_PTS                           1.305e+02  7.767e+01   1.680  0.09312 .
## CAR_AGE                          -5.468e+01  4.841e+01  -1.130  0.25885
## URBANICITYz_Highly Rural/ Rural  6.260e+02  8.860e+02   0.707  0.47995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7613 on 1675 degrees of freedom
## Multiple R-squared:  0.03043,    Adjusted R-squared:  0.002062
## F-statistic: 1.073 on 49 and 1675 DF,  p-value: 0.3408
```

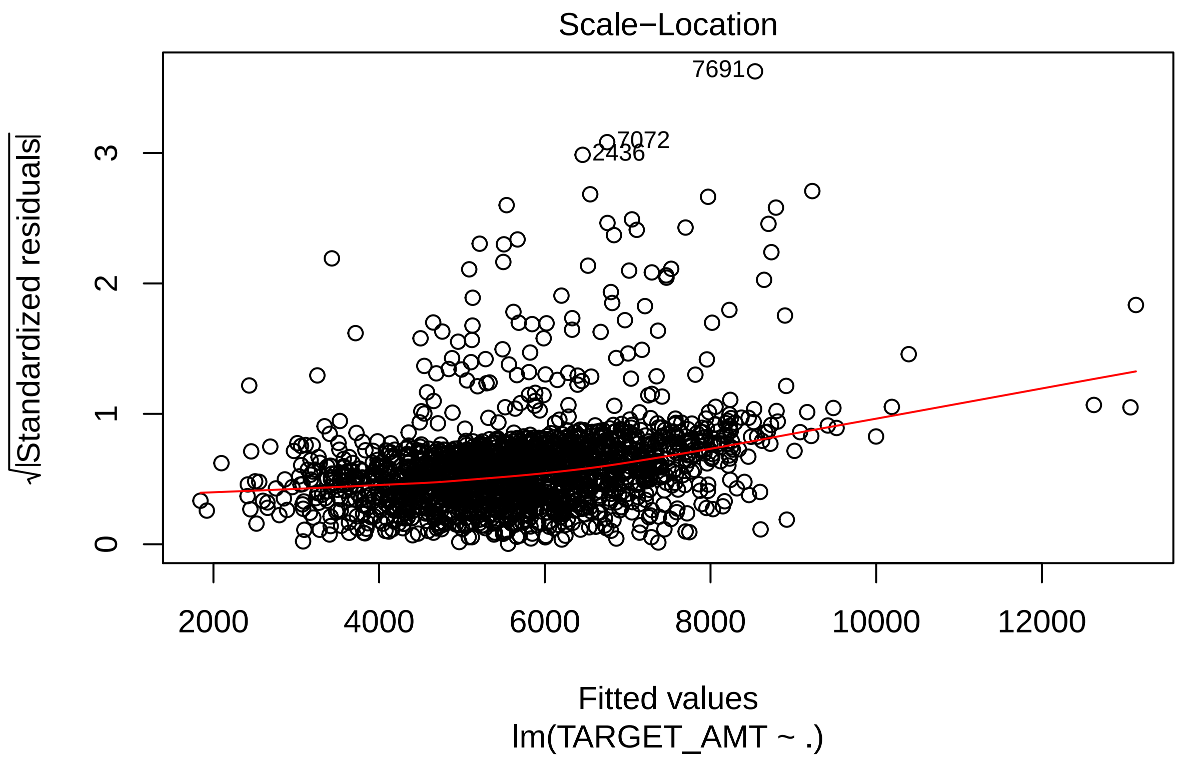
```r
plot(base_model_payout)
```

```
## Warning: not plotting observations with leverage one:
##   390
```

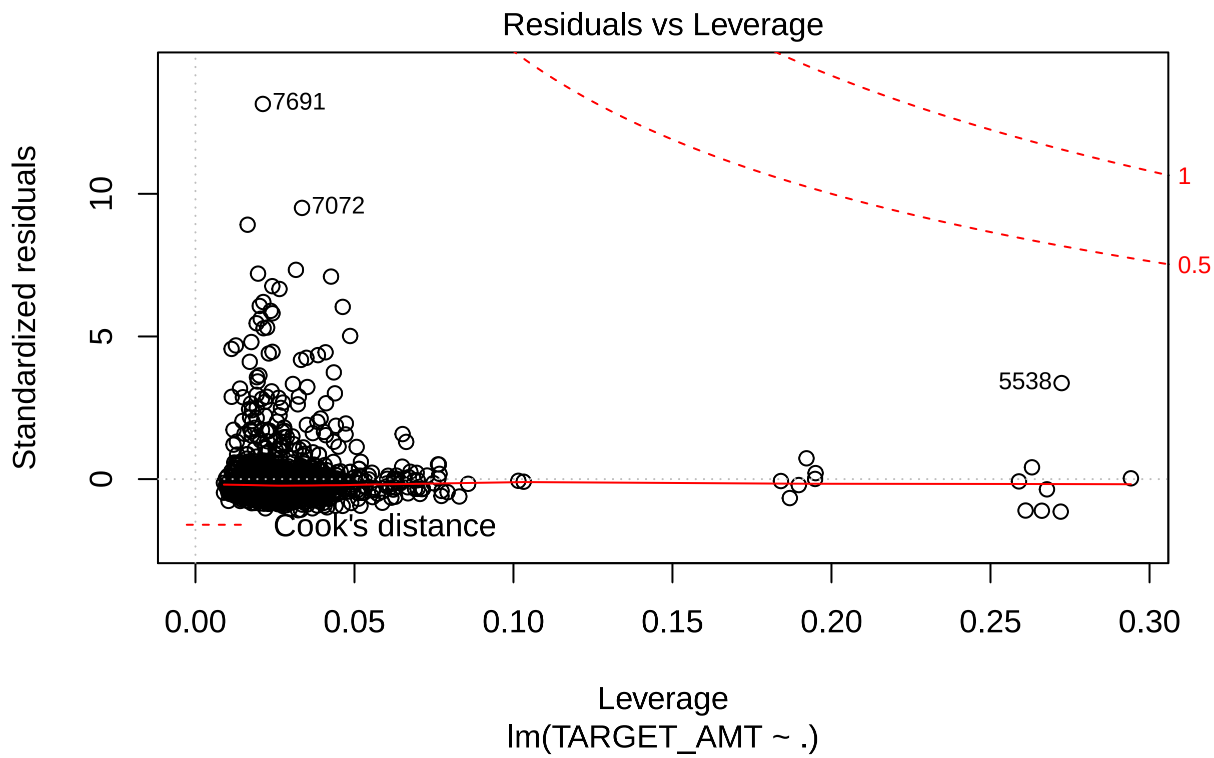

Residuals vs Fitted
Residuals
-20000
20000
60000
100000
7691
7072
2436
2000
4000
6000
8000
10000
12000
Fitted values
lm(TARGET_AMT ~ .)




```
## Warning: not plotting observations with leverage one:
##   390
```



Scale−Location
√|Standardized residuals|
0
1
2
3
7691
7072
2436
2000
4000
6000
8000
10000
12000
Fitted values
lm(TARGET_AMT ~ .)



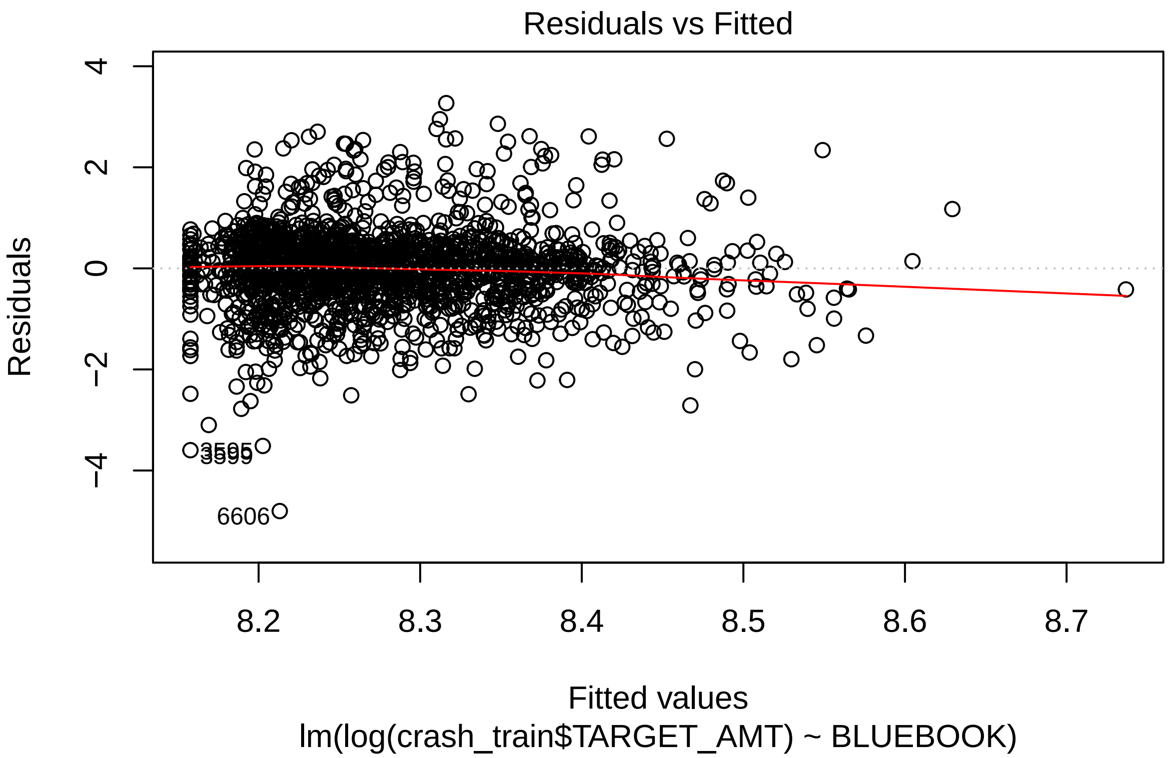
Yeah, pretty bad. This probably does not meet the assumptions of linear regression either. The only significant predictor here is Bluebook, which I suspected would be one of them, but not the only one. This model does not provide any evidence for my suspicions regarding the role of 'damage' in the payout. One big problem with this model is the residuals are have a significant right-skew. The response variable also has a right skew; let's fix that and see if it helps. We'll also only Bluebook as the predictor variable.

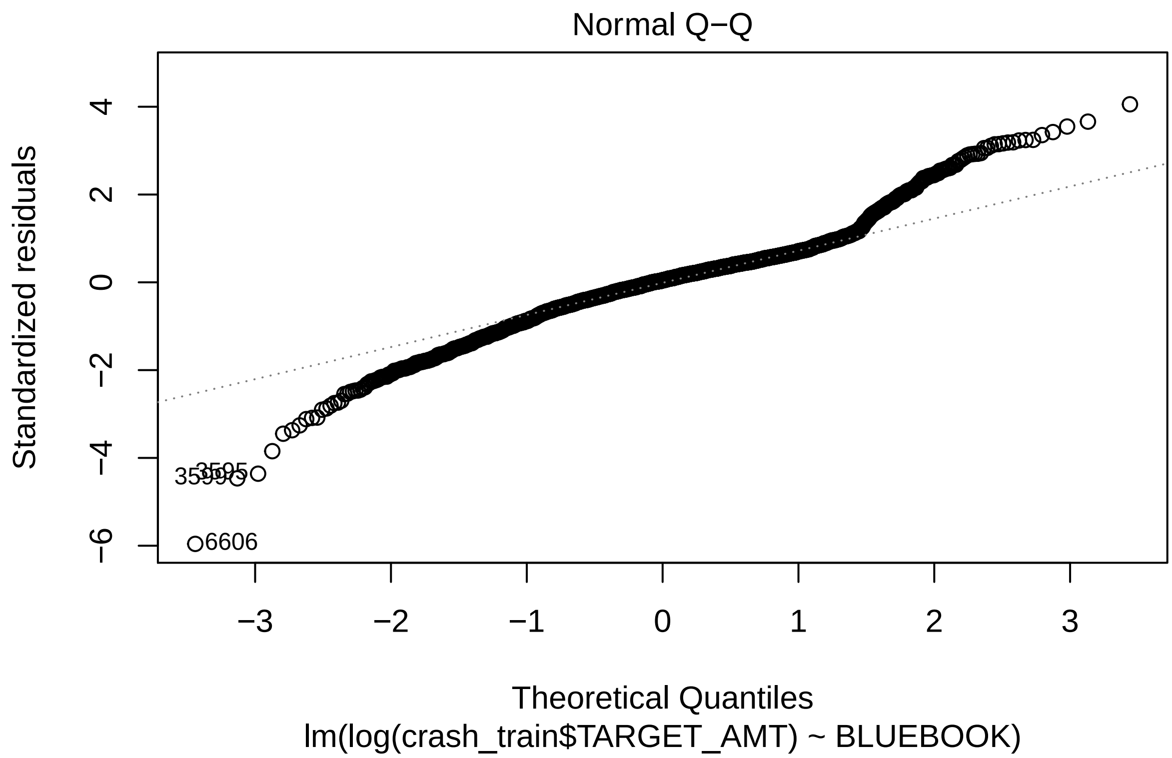
```
# Transforms the response variable first
bluebook_model_payout <- lm(log(crash_train$TARGET_AMT) ~ BLUEBOOK, crash_train)
summary(bluebook_model_payout)
```

```
##
## Call:
## lm(formula = log(crash_train$TARGET_AMT) ~ BLUEBOOK, data = crash_train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8027 -0.4065  0.0374  0.3890  3.2699
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 8.144e+00  3.868e-02 210.535  < 2e-16 ***
## BLUEBOOK    9.531e-06  2.341e-06   4.071 4.89e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8064 on 1723 degrees of freedom
```

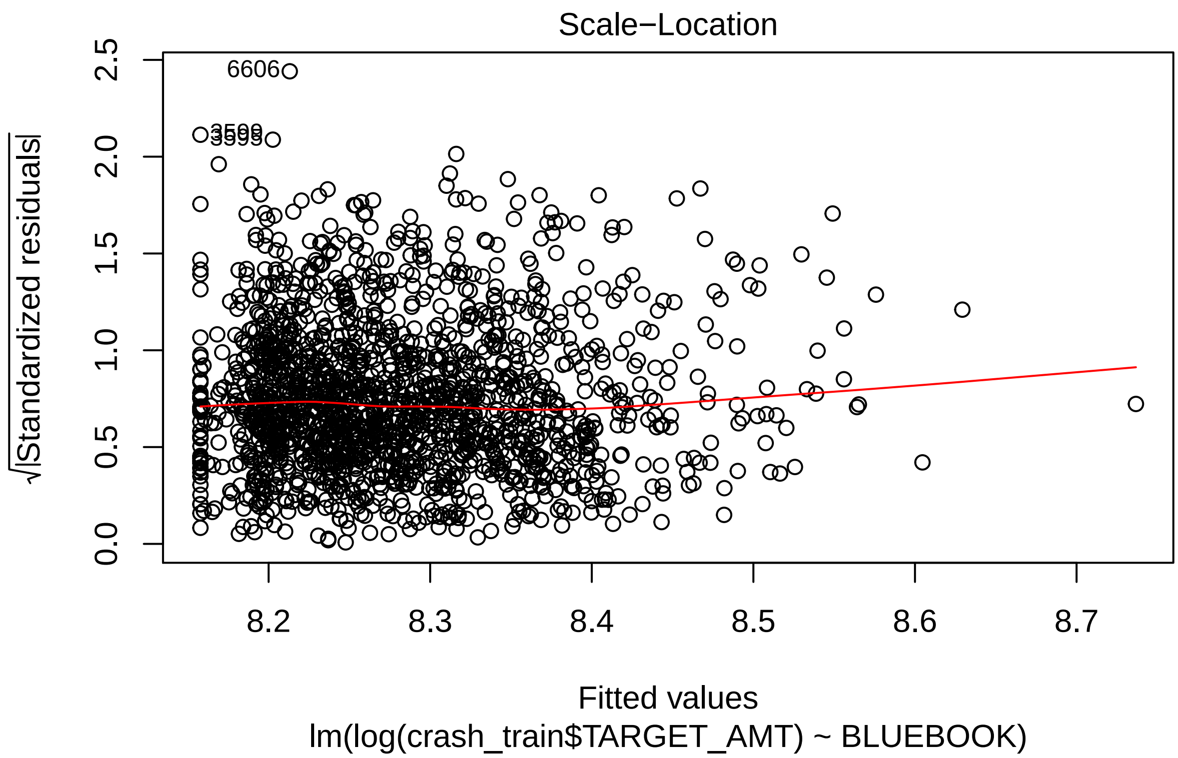
```
## Multiple R-squared:  0.009527,   Adjusted R-squared:  0.008953
## F-statistic: 16.57 on 1 and 1723 DF,  p-value: 4.891e-05
```

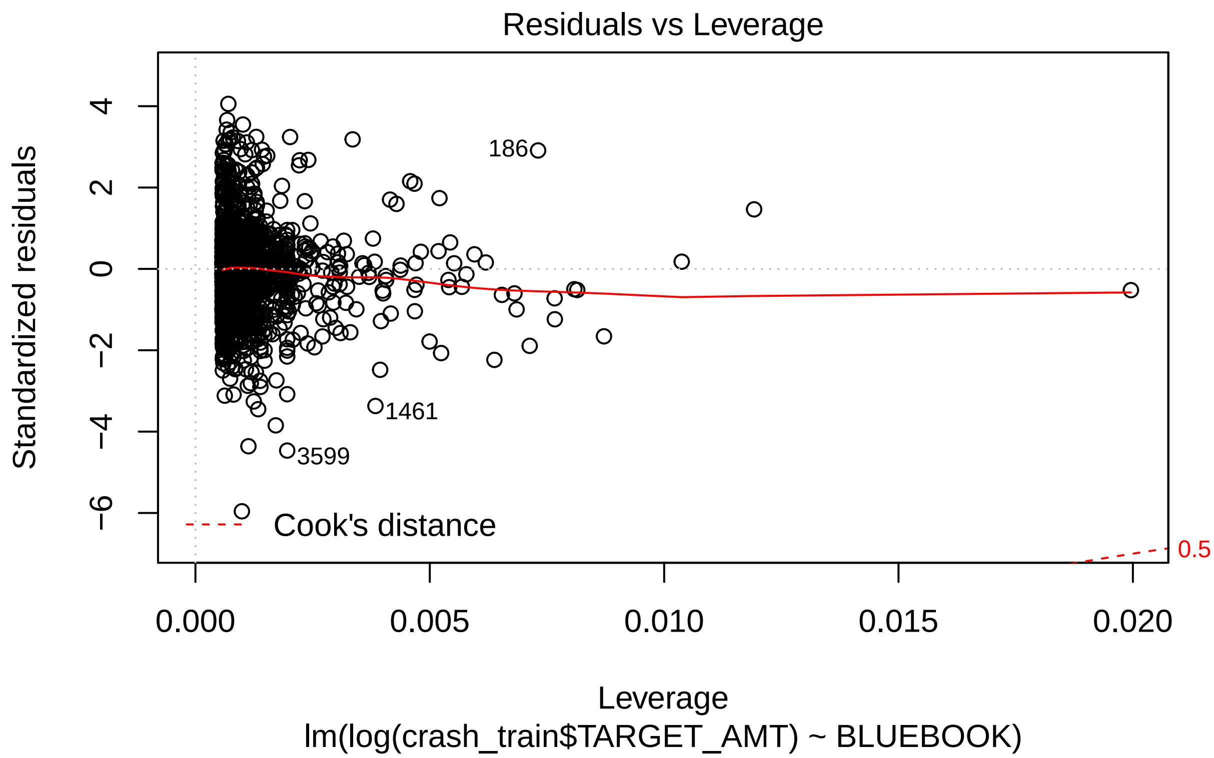
```r
plot(bluebook_model_payout)
```





Normal Q−Q
Standardized residuals
4
2
0
−2
−4
−6
3595
3599
6606
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(log(crash_train$TARGET_AMT) ~ BLUEBOOK)


Scale−Location
6606
3599
3599
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
8.2
8.3
8.4
8.5
8.6
8.7
Fitted values
lm(log(crash_train$TARGET_AMT) ~ BLUEBOOK)




```
# Finds how well the predictions match up to the actual validation data Also
# reverses the log transformation after predictions are made
fit <- lm(exp(predict(bluebook_model_payout, crash_validation[, 2:24])) ~ crash_validation$TARGET_AMT)
plot(exp(predict(bluebook_model_payout, crash_validation[, 2:24])) ~ crash_validation$TARGET_AMT)
abline(0, 1, col = "red")
```


```r
summary(fit)
```

```
##
## Call:
## lm(formula = exp(predict(bluebook_model_payout, crash_validation[,
##     2:24])) ~ crash_validation$TARGET_AMT)
##
## Residuals:
##    Min      1Q Median     3Q    Max
## -485.2 -250.6  -68.3  172.6 2048.2
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 3.907e+03  1.896e+01 206.008  < 2e-16 ***
## crash_validation$TARGET_AMT 7.550e-03  1.898e-03   3.978 8.17e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 322.7 on 426 degrees of freedom
## Multiple R-squared:  0.03582,    Adjusted R-squared:  0.03355
## F-statistic: 15.82 on 1 and 426 DF,  p-value: 8.167e-05
```

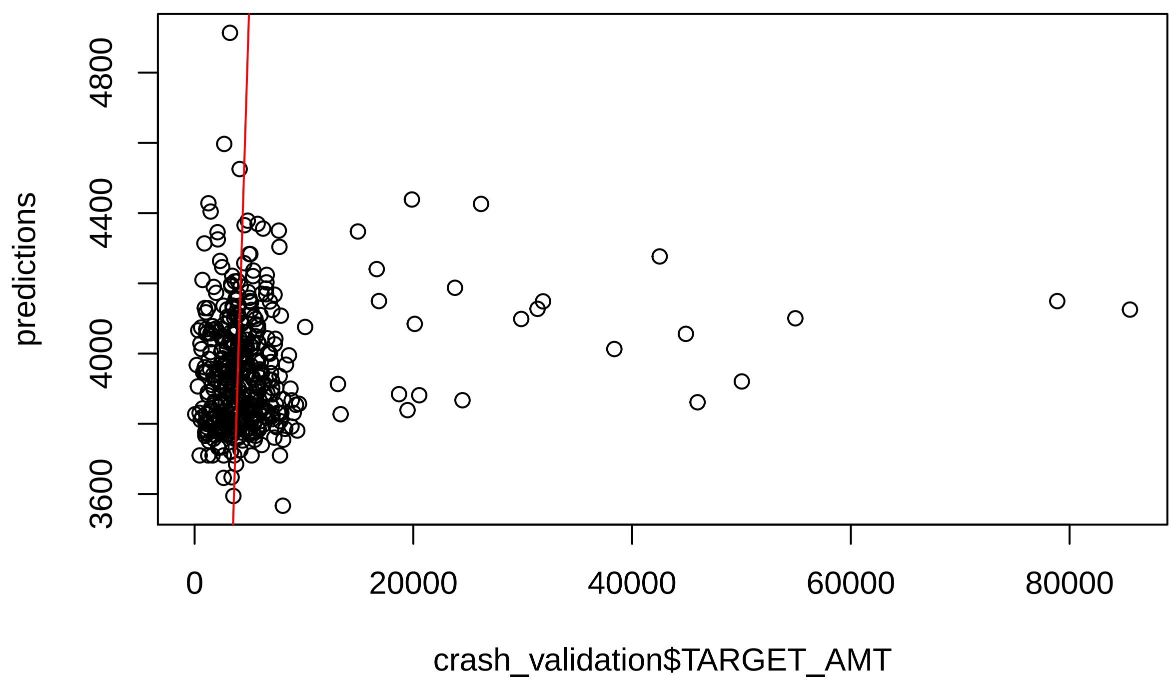
The residuals look much better after a log transformation, but the model is still only weekly predictive, and cannot predict high payouts (>$5000) well at all. Many variables such as car age and type will directly play into the bluebook value, and are implicated in this model as well. Let's try using LASSO to reduce the number of coefficients (it seems like only one or a handful are useful) and see if it comes up with a better model.

```
set.seed(0987654321)


#Data prep.  Needs to be in matrix format
#Took code from here: https://stackoverflow.com/questions/35437411/error-in-predict-glmnet-function-not
crash_train_X <- model.matrix(~. -TARGET_AMT,data=crash_train)

#Needs a log transformation
crash_train_Y <- log(crash_train$TARGET_AMT)

crash_val_X = model.matrix(~. -TARGET_AMT,data=crash_validation)

#Makes a series of crossvalidated glmnet models for 100 lambda values (default)
#lamba values are constants that define coefficient shrinkage.
LASSO_payout_model <- cv.glmnet(x = crash_train_X,   #Predictor variables
                      y = crash_train_Y,
                      nfolds = 10, #k fold cv
                      type.measure = "mse",  #uses mean squared error as loss
                      alpha = 1) #Alpha = 1 is lasso.

#setting lambda.min uses the lambda value with the minimum mean cv error (picks the best model).  also
predictions <- exp(predict(LASSO_payout_model, newx = crash_val_X, s=LASSO_payout_model$lambda.min))

#Print's the coefficients the model uses
print(coef.glmnet(LASSO_payout_model, s = LASSO_payout_model$lambda.min))
```

```
## 51 x 1 sparse Matrix of class "dgCMatrix"
##                                       1
## (Intercept)                8.211314e+00
## (Intercept)                .
## KIDSDRIV1                  .
## KIDSDRIV2                  .
## KIDSDRIV3                  .
## KIDSDRIV4                  .
## AGE                        .
## HOMEKIDS1                  .
## HOMEKIDS2                  .
## HOMEKIDS3                  .
## HOMEKIDS4                  .
## HOMEKIDS5                  .
## YOJ                        .
## INCOME                     .
## PARENT1Yes                 .
## HOME_VAL                   .
## MSTATUSz_No                .
## SEXz_F                     .
## EDUCATIONBachelors         .
## EDUCATIONMasters           .
## EDUCATIONPhD               .
## EDUCATIONz_High School     .
## JOBDoctor                  .
```

```
## JOBHome Maker                     .
## JOBLawyer                         .
## JOBManager                        .
## JOBProfessional                   .
## JOBStudent                        .
## JOBz_Blue Collar                  .
## JOBUnemployed                     .
## JOBUnlisted                       .
## TRAVTIME                          .
## CAR_USEPrivate                    .
## BLUEBOOK                          4.975035e-06
## TIF                               .
## CAR_TYPEPanel Truck               .
## CAR_TYPEPickup                    .
## CAR_TYPESports Car                .
## CAR_TYPEVan                       .
## CAR_TYPEz_SUV                     .
## RED_CARyes                        .
## OLDCLAIM                          .
## CLM_FREQ1                         .
## CLM_FREQ2                         .
## CLM_FREQ3                         .
## CLM_FREQ4                        -6.530999e-02
## CLM_FREQ5                         .
## REVOKEDYes                        .
## MVR_PTS                           .
## CAR_AGE                           .
## URBANICITYz_Highly Rural/ Rural   .
```

```r
plot(predictions ~ crash_validation$TARGET_AMT)
abline(0, 1, col = "red")
```




```r
fit <- lm(predictions ~ crash_validation$TARGET_AMT)

summary(fit)
```

```
##
## Call:
## lm(formula = predictions ~ crash_validation$TARGET_AMT)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -389.60 -127.59  -30.15   93.20  972.98
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                3.930e+03  9.822e+00 400.105  < 2e-16 ***
## crash_validation$TARGET_AMT 3.281e-03  9.831e-04   3.338 0.000918 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 167.1 on 426 degrees of freedom
## Multiple R-squared:  0.02549,    Adjusted R-squared:  0.0232
## F-statistic: 11.14 on 1 and 426 DF,  p-value: 0.0009185
```

This is a very similar model to the Bluebook model. The only other bit LASSO adds in here is if there have been 4 claims (fairly rare) then you the payout is less. Also similar to the bluebook model, it doesn't work well, especially for predicting high payouts. The Bluebook model does better when comparing the fit of predicted values vs actual values on the validation set.

As to the theory that Payout = Car-Value X Damage, we can confirm that car-value (bluebook) does play a significant role, but are unable to confirm that the amount of damage done has any affect. This could be because either damage does not have a role, or the variables we have are unable to predict the amount of damage done.

Selecting Models and Making Predictions

We'll be using the LASSO model to predict whether or not there was a crash, and the bluebook model to predict how much the payout was. When evaluated on a holdout set, both classification models are similar statistics wise (similar accuracy, AUC, etc), but the LASSO model is simpler and slightly more accurate. Of the payout prediction models, it appears the variables just aren't very predictive of cost, with the exception of Bluebook (car value), which makes sense. A simple linear regression model with Bluebook and an intercept only out performed the others in terms of R^2 as evaluated on how well the predictions on a holdout set fit the real costs. The residual plots for the bluebook model were also permissible, owing in great part to the log transformation of the response variable.

Below the test set is imported, prepared, and predictions are made. The predictions then saved locally.

```r
url <- "https://raw.githubusercontent.com/davidblumenstiel/CUNY-MSDS-DATA-621/main/Assignment_4/insuranc

test <- fetch_and_prep(url)

# Not sure why, but this needs slighly different prep than the validation set
test_X <- model.matrix(~., data = test[, 3:25])

# Predicts probability of crash
predictions <- data.frame(predict(LASSO_crash_model, newx = test_X, type = "response",
    s = LASSO_crash_model$lambda.min))
colnames(predictions) <- "crash_probability"

# If probability of a crash is >50% then it lists as crash (1), otherwise no
# crash (0)
predictions <- predictions %>% mutate(class = as.factor(round(crash_probability)))

# If there's a crash, then it assigns a predicted cost for the payout, otherwise
# it sets it to 0

# There are probably better ways to do this than overwriting
predictions["cost"] <- exp(predict(bluebook_model_payout, test))
predictions$cost[predictions$class == 0] <- 0

# Save predictions locally
write.csv(predictions, file = "predictions.csv")
```