Homework 4

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November 8, 2020

1. Data Exploration

The auto insurance training dataset has 26 variables and 8161 observations. Of the variables, 24 of them are predictors for two responses: TARGET_FLAG and TARGET_AMT is numerical.

To explore the training data: - used the summary function to see means, medians, and quartiles of predictors - used str function to see the data type of each predictor - explored TARGET_FLAG in relation to some other variables such as AGE and CAR_AGE - looked at distribution of some numerical variables such as AGE and MVR_PTS

From the summary function, the TARGET_FLAG is binary and 26% of the 8161 records were accidents.

2. Data Preparation

This data was prepared to build both a binary logistic model and a multiple linear regression model. The binary logisitc model was used to predict the TARGET_FLAG response variable and the multiple linear regression model was used to predict the TARGET_AMT variable.

Thus, there was a different training dataset prepared for each model.

In both training datasets, all 948 records with at least one missing value were removed.

Then, in the multiple linear regression training dataset all records with TARGET_AMT = 0 were removed.

The training dataset for the binary logistic regression model was labelled train_df. The training dataset for the multiple linear regression model was titled train_amt_df.

3. Build Models

First, we built two models using most predictors as numerics. Then we used the step AIC function to find the best variables for each model.

One model was a Binary Logistic Regression model for the TARGET_FLAG response titled step_BLR. The second model was a Multiple Linear Regression for the TARGET_AMT response titled MLR_all_vars.

4. Select Models

To finally select a model, we used Stepwise AIC (both backward and forward) to do model selection and ended with a Binary Logistict 7661.4

Appendix

Import Libraries and Data

```
##
## Attaching package: ’dplyr’

## The following objects are masked from ’package:stats’:
##
##     filter, lag

## The following objects are masked from ’package:base’:
##
##     intersect, setdiff, setequal, union

## corrplot 0.84 loaded

##
## Attaching package: ’MASS’

## The following object is masked from ’package:dplyr’:
##
##     select

## Loading required package: lattice

## Type ’citation("pROC")’ for a citation.

##
## Attaching package: ’pROC’

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

```
# Loading the data
git_dir <- ’https://raw.githubusercontent.com/odonnell31/DATA621-HW4/main/data’
#class_data = read.csv(paste(git_dir, "/classification-output-data.csv", sep=""))
train_df = read.csv(paste(git_dir, "/insurance_training_data.csv", sep=""))
test_df = read.csv(paste(git_dir, "/insurance-evaluation-data.csv", sep = ""))
head(train_df, 2)
```

```
##   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
##   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
##   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
##            URBANICITY
## 1 Highly Urban/ Urban
## 2 Highly Urban/ Urban
```

Data Exploration & Preparation

See a summary of each column in the train_df set

```
# view a summary of all columns
summary(train_df)
```

```
##      INDEX        TARGET_FLAG       TARGET_AMT        KIDSDRIV
##  Min.   :    1   Min.   :0.0000   Min.   :     0   Min.   :0.0000
##  1st Qu.: 2559   1st Qu.:0.0000   1st Qu.:     0   1st Qu.:0.0000
##  Median : 5133   Median :0.0000   Median :     0   Median :0.0000
##  Mean   : 5152   Mean   :0.2638   Mean   :  1504   Mean   :0.1711
##  3rd Qu.: 7745   3rd Qu.:1.0000   3rd Qu.:  1036   3rd Qu.:0.0000
##  Max.   :10302   Max.   :1.0000   Max.   :107586   Max.   :4.0000
##
##       AGE           HOMEKIDS           YOJ          INCOME
##  Min.   :16.00   Min.   :0.0000   Min.   : 0.0   Length:8161
##  1st Qu.:39.00   1st Qu.:0.0000   1st Qu.: 9.0   Class :character
##  Median :45.00   Median :0.0000   Median :11.0   Mode  :character
##  Mean   :44.79   Mean   :0.7212   Mean   :10.5
##  3rd Qu.:51.00   3rd Qu.:1.0000   3rd Qu.:13.0
##  Max.   :81.00   Max.   :5.0000   Max.   :23.0
##  NA's   :6                        NA's   :454
##    PARENT1            HOME_VAL           MSTATUS              SEX
##  Length:8161        Length:8161        Length:8161        Length:8161
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   EDUCATION             JOB              TRAVTIME        CAR_USE
##  Length:8161        Length:8161        Min.   :  5.00   Length:8161
##  Class :character   Class :character   1st Qu.: 22.00   Class :character
##  Mode  :character   Mode  :character   Median : 33.00   Mode  :character
##                                        Mean   : 33.49
##                                        3rd Qu.: 44.00
##                                        Max.   :142.00
##
##    BLUEBOOK              TIF         CAR_TYPE             RED_CAR
##  Length:8161        Min.   : 1.000   Length:8161        Length:8161
##  Class :character   1st Qu.: 1.000   Class :character   Class :character
##  Mode  :character   Median : 4.000   Mode  :character   Mode  :character
##                     Mean   : 5.351
##                     3rd Qu.: 7.000
##                     Max.   :25.000
##
##    OLDCLAIM            CLM_FREQ        REVOKED             MVR_PTS
##  Length:8161        Min.   :0.0000   Length:8161        Min.   : 0.000
##  Class :character   1st Qu.:0.0000   Class :character   1st Qu.: 0.000
##  Mode  :character   Median :0.0000   Mode  :character   Median : 1.000
##                     Mean   :0.7986                      Mean   : 1.696
##                     3rd Qu.:2.0000                      3rd Qu.: 3.000
##                     Max.   :5.0000                      Max.   :13.000
```

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

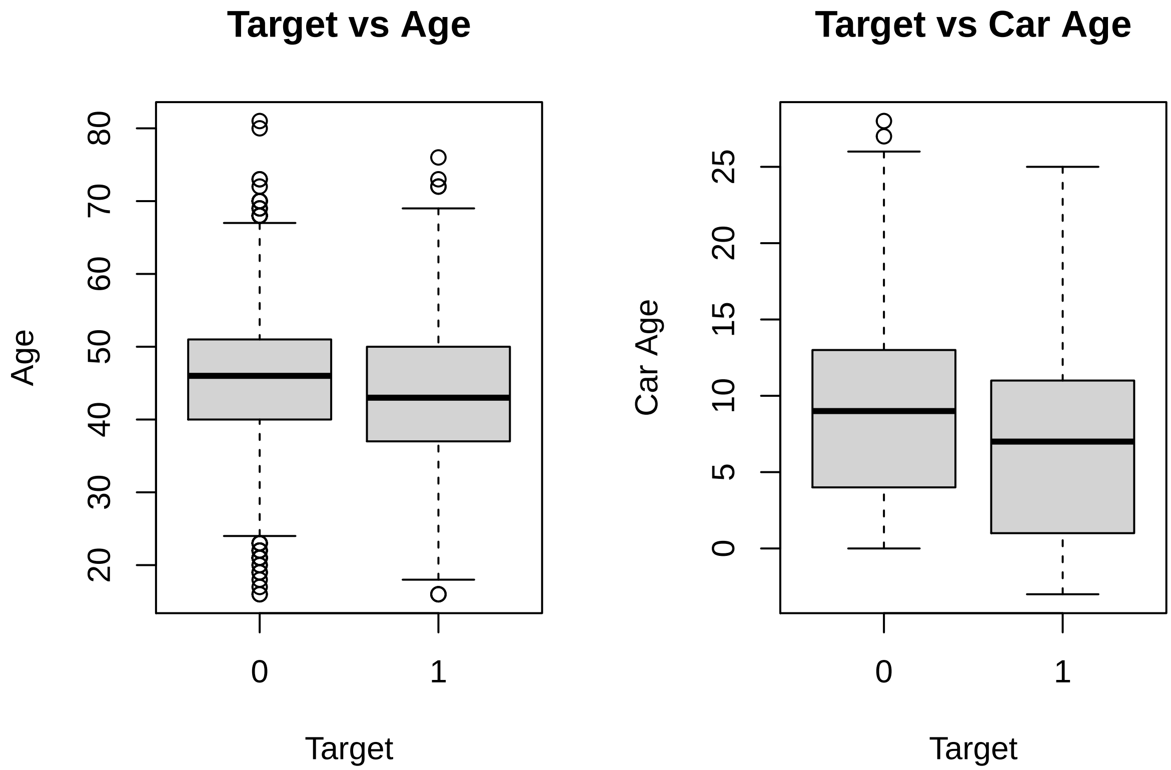
Look at the data type of each variable

```r
# data type of predictors
str(train_df)
```

```
## 'data.frame':    8161 obs. of  26 variables:
##  $ INDEX      : int  1 2 4 5 6 7 8 11 12 13 ...
##  $ TARGET_FLAG: int  0 0 0 0 0 1 0 1 1 0 ...
##  $ TARGET_AMT : num  0 0 0 0 0 ...
##  $ KIDSDRIV   : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ AGE        : int  60 43 35 51 50 34 54 37 34 50 ...
##  $ HOMEKIDS   : int  0 0 1 0 0 1 0 2 0 0 ...
##  $ YOJ        : int  11 11 10 14 NA 12 NA NA 10 7 ...
##  $ INCOME     : chr  "$67,349" "$91,449" "$16,039" "" ...
##  $ PARENT1    : chr  "No" "No" "No" "No" ...
##  $ HOME_VAL   : chr  "$0" "$257,252" "$124,191" "$306,251" ...
##  $ MSTATUS    : chr  "z_No" "z_No" "Yes" "Yes" ...
##  $ SEX        : chr  "M" "M" "z_F" "M" ...
##  $ EDUCATION  : chr  "PhD" "z_High School" "z_High School" "<High School" ...
##  $ JOB        : chr  "Professional" "z_Blue Collar" "Clerical" "z_Blue Collar" ...
##  $ TRAVTIME   : int  14 22 5 32 36 46 33 44 34 48 ...
##  $ CAR_USE    : chr  "Private" "Commercial" "Private" "Private" ...
##  $ BLUEBOOK   : chr  "$14,230" "$14,940" "$4,010" "$15,440" ...
##  $ TIF        : int  11 1 4 7 1 1 1 1 1 7 ...
##  $ CAR_TYPE   : chr  "Minivan" "Minivan" "z_SUV" "Minivan" ...
##  $ RED_CAR    : chr  "yes" "yes" "no" "yes" ...
##  $ OLDCLAIM   : chr  "$4,461" "$0" "$38,690" "$0" ...
##  $ CLM_FREQ   : int  2 0 2 0 2 0 0 1 0 0 ...
##  $ REVOKED    : chr  "No" "No" "No" "No" ...
##  $ MVR_PTS    : int  3 0 3 0 3 0 0 10 0 1 ...
##  $ CAR_AGE    : int  18 1 10 6 17 7 1 7 1 17 ...
##  $ URBANICITY : chr  "Highly Urban/ Urban" "Highly Urban/ Urban" "Highly Urban/ Urban" "Highly Urban/
```

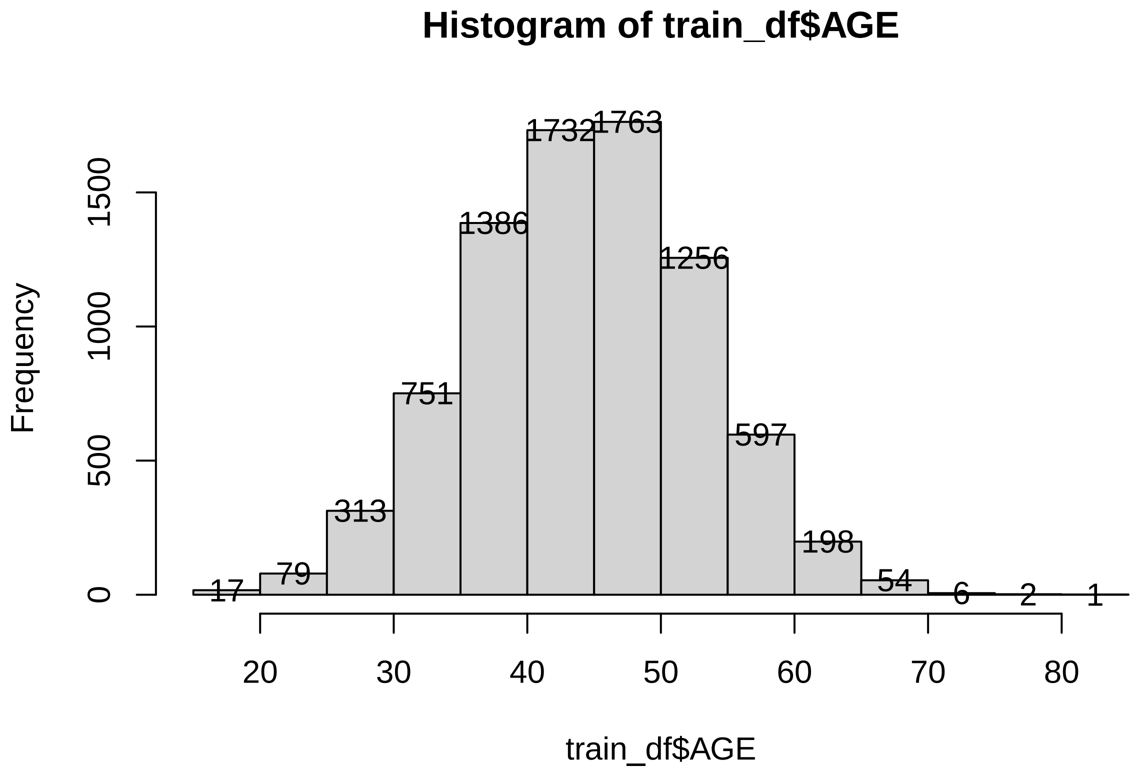
Look at the relationship between TARGET_FLAG and some of the numerical variables.

```r
par(mfrow=c(1,2))
# plot response variable "target" against predictor variable "age" and "car_age"
boxplot(AGE ~ TARGET_FLAG, train_df,
        main="Target vs Age",
        xlab="Target",
        ylab="Age")
boxplot(CAR_AGE ~ TARGET_FLAG, train_df,
        main="Target vs Car Age",
        xlab="Target",
        ylab="Car Age")
```

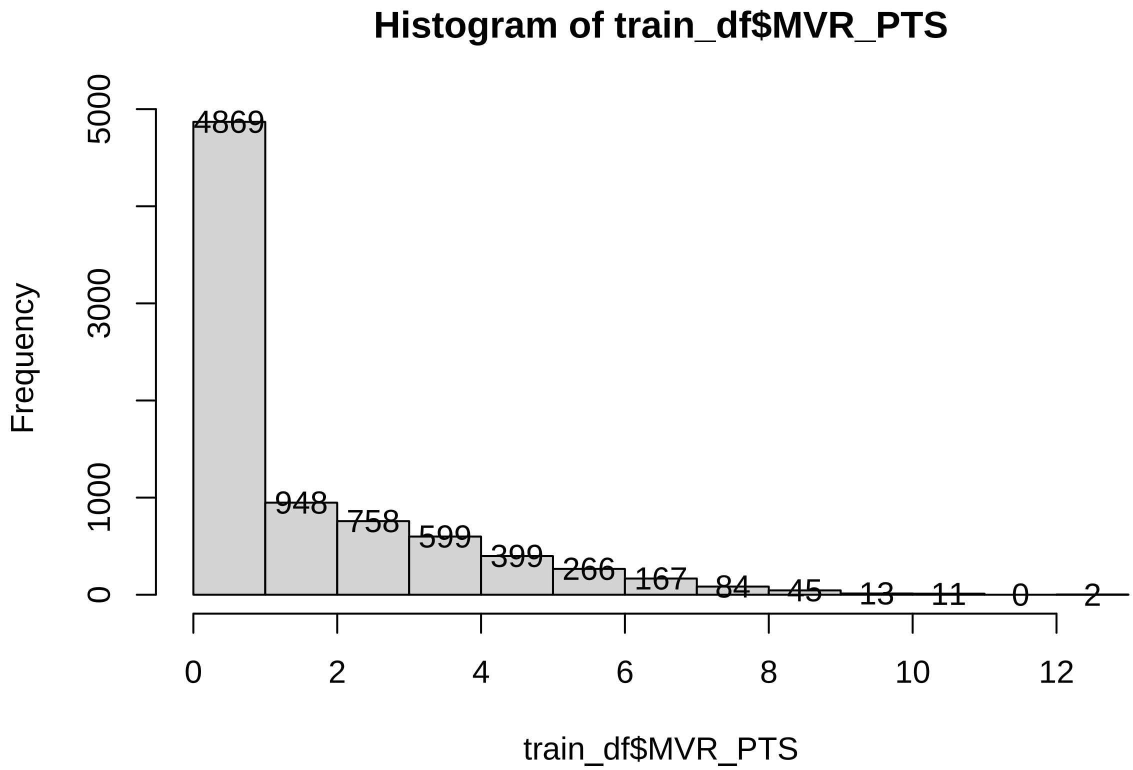


Look at the distribution of some numerical variables.

```
h <- hist(train_df$AGE)
text(h$mids,h$counts,labels=h$counts)
```



```
h <- hist(train_df$MVR_PTS)
text(h$mids,h$counts,labels=h$counts)
```



Check for NA's

```
has_NA = names(which(sapply(train_df, anyNA)))
has_NA
```

```
## [1] "AGE"     "YOJ"     "CAR_AGE"
```

Remove rows with NA's train_df will be used for binary logistic regression model

```
train_df <- train_df[complete.cases(train_df), ]
```

Create train_amt_df dataframe for multiple linear regression model

```
train_amt_df <- subset(train_df, TARGET_AMT > 0)
summary(train_amt_df$TARGET_FLAG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       1       1       1       1       1       1
```

Modeling

1) Binary Logistic Regression

```r
# preliminary exploration with one predictor
model1 <- glm(formula = TARGET_FLAG ~ AGE, family = binomial(), data = train_df)
summary(model1)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ AGE, family = binomial(), data = train_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0712  -0.8017  -0.7376   1.4215   2.0219
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.184991   0.140255   1.319    0.187
## AGE         -0.027504   0.003141  -8.756   <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: 8303.6  on 7212  degrees of freedom
## Residual deviance: 8225.7  on 7211  degrees of freedom
## AIC: 8229.7
##
## Number of Fisher Scoring iterations: 4
```

Binary Logistic Regression Model with more variables

```r
BLR_all_vars = glm(TARGET_FLAG ~ AGE +
                   CAR_AGE +
                   MVR_PTS +
                   YOJ +
                   CLM_FREQ +
                   TIF, family = binomial(), data = train_df)
summary(BLR_all_vars)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ AGE + CAR_AGE + MVR_PTS + YOJ + CLM_FREQ +
##     TIF, family = binomial(), data = train_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8003  -0.7558  -0.6057   0.9552   2.4008
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.004828   0.162509   0.030 0.976299
## AGE         -0.019102   0.003313  -5.766 8.12e-09 ***
## CAR_AGE     -0.037685   0.005134  -7.341 2.12e-13 ***
## MVR_PTS      0.152214   0.013185  11.544  < 2e-16 ***
## YOJ         -0.023014   0.006747  -3.411 0.000648 ***
## CLM_FREQ     0.302335   0.024479  12.351  < 2e-16 ***
## TIF         -0.042139   0.007117  -5.921 3.21e-09 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8303.6  on 7212  degrees of freedom
## Residual deviance: 7647.6  on 7206  degrees of freedom
## AIC: 7661.6
##
## Number of Fisher Scoring iterations: 4
```

Step through AIC scores to find best model

```
step_BLR = stepAIC(BLR_all_vars)
```

```
## Start:  AIC=7661.59
## TARGET_FLAG ~ AGE + CAR_AGE + MVR_PTS + YOJ + CLM_FREQ + TIF
##
##            Df Deviance    AIC
## <none>          7647.6 7661.6
## - YOJ       1   7659.1 7671.1
## - AGE       1   7681.1 7693.1
## - TIF       1   7683.7 7695.7
## - CAR_AGE   1   7702.5 7714.5
## - MVR_PTS   1   7781.4 7793.4
## - CLM_FREQ  1   7796.8 7808.8
```

```
summary(step_BLR)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ AGE + CAR_AGE + MVR_PTS + YOJ + CLM_FREQ +
##     TIF, family = binomial(), data = train_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8003  -0.7558  -0.6057   0.9552   2.4008
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.004828   0.162509   0.030 0.976299
## AGE         -0.019102   0.003313  -5.766 8.12e-09 ***
## CAR_AGE     -0.037685   0.005134  -7.341 2.12e-13 ***
## MVR_PTS      0.152214   0.013185  11.544  < 2e-16 ***
## YOJ         -0.023014   0.006747  -3.411 0.000648 ***
## CLM_FREQ     0.302335   0.024479  12.351  < 2e-16 ***
## TIF         -0.042139   0.007117  -5.921 3.21e-09 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8303.6  on 7212  degrees of freedom
## Residual deviance: 7647.6  on 7206  degrees of freedom
## AIC: 7661.6
##
## Number of Fisher Scoring iterations: 4
```

2) Multiple Linear Regression

Multiple Linear Regression models with many variables

```
MLR_all_vars = lm(TARGET_AMT ~ AGE +
                  CAR_AGE +
                  MVR_PTS +
                  YOJ +
                  CLM_FREQ +
                  TIF, data = train_amt_df)
summary(MLR_all_vars)
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ AGE + CAR_AGE + MVR_PTS + YOJ + CLM_FREQ +
##     TIF, data = train_amt_df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -6127  -3068  -1561    142  79965
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4636.72     920.08   5.039 5.11e-07 ***
## AGE            15.56      18.58   0.837    0.402
## CAR_AGE       -24.37      32.32  -0.754    0.451
## MVR_PTS       112.96      71.34   1.583    0.114
## YOJ            50.51      39.47   1.280    0.201
## CLM_FREQ     -135.92     148.13  -0.918    0.359
## TIF           -14.20      44.46  -0.319    0.749
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7618 on 1886 degrees of freedom
## Multiple R-squared:  0.003076,   Adjusted R-squared:  -9.516e-05
## F-statistic:  0.97 on 6 and 1886 DF,  p-value: 0.444
```