Data 621

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Abstract

In this homework assignment, you will explore, analyze and model a data set containing approximately 8000 records representing a customer at an auto insurance company. Each record has two response variables. The first response variable, TARGET_FLAG, is a 1 or a 0. A “1” means that the person was in a car crash. A zero means that the person was not in a car crash. The second response variable is TARGET_AMT. This value is zero if the person did not crash their car. But if they did crash their car, this number will be a value greater than zero.

Keywords: insurance, data621

Data Exploration

```
knitr::opts_chunk$set(echo = TRUE)
library(e1071)
library(dplyr)
```

```
##
## 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
```

```
library(purrr)
library(tidyr)
library(ggplot2)
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(FactoMineR)
```

```
## Warning: package 'FactoMineR' was built under R version 3.4.4
```

```
library(VIF)
library(knitr)
library(kableExtra)
```

```
## Warning: package 'kableExtra' was built under R version 3.4.4
```

```
library(Hmisc)
```

```
## Loading required package: lattice
```

```
## Loading required package: survival
```

```
## Loading required package: Formula
```

```
## Warning: package 'Formula' was built under R version 3.4.4
```

```
##
## Attaching package: 'Hmisc'
```

```
## The following objects are masked from 'package:dplyr':
##
##     src, summarize
```

```
## The following object is masked from 'package:e1071':
##
##     impute
```

```
## The following objects are masked from 'package:base':
##
##     format.pval, units
```

```
library(pROC)
```

```
## Warning: package 'pROC' was built under R version 3.4.4
```

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

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

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

```
library(binr)

# read data
train = read.csv(file="data/insurance_training_data.csv")
dim(train)
```

```
## [1] 8161   26
```

```
#transform data

#this step is necessary in order to analyze data as it is not clean
currencyconv = function(input) {
  out = sub("\\$", "", input)
  out = as.numeric(sub(",", "", out))
  return(out)
}

# Replace spaces with underscores
underscore = function(input) {
  out = sub(" ", "_", input)
  return(out)
}


train = as.tbl(train) %>%
  mutate_at(c("INCOME","HOME_VAL","BLUEBOOK","OLDCLAIM"),
            currencyconv) %>%
  mutate_at(c("EDUCATION","JOB","CAR_TYPE","URBANICITY"),
            underscore) %>%
  mutate_at(c("EDUCATION","JOB","CAR_TYPE","URBANICITY"),
            as.factor) %>%
  mutate(TARGET_FLAG = as.factor(TARGET_FLAG))

#check data
summary(train) %>% kable() %>% kable_styling()
```

INDEX </th>	TARGET_FLAG	TARGET_AMT	KIDSDRIV </th>	AGE </th>	HOMEKIDS </th>	YOJ </th>	INCOME </th>	PARENT1	HOME_VAL </th>	MSTATUS	SEX	
Min. : 1	0:6008	Min. : 0	Min. :0.0000	Min. :16.00	Min. :0.0000	Min. : 0.0	Min. : 0	No :7084	Min. : 0	Yes :4894	M :3786	<H
1st Qu.: 2559	1:2153	1st Qu.: 0	1st Qu.:0.0000	1st Qu.:39.00	1st Qu.:0.0000	1st Qu.: 9.0	1st Qu.: 28097	Yes:1077	1st Qu.: 0	z_No:3267	z_F:4375	Ba
Median	NA	Median : 0	Median	Median	Median	Median	Median	NA	Median	NA	NA	M

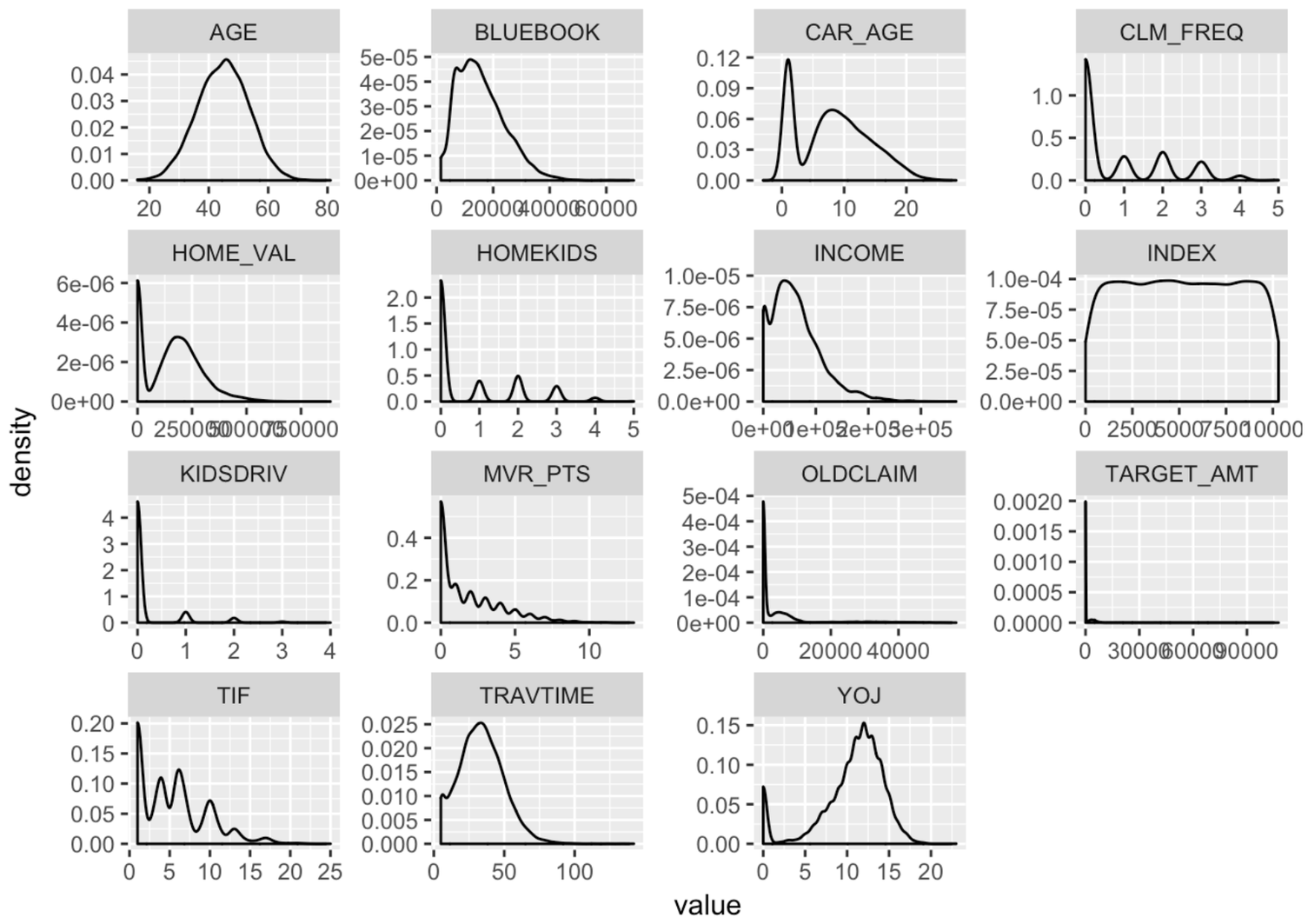
: 5133			:0.0000	:45.00	:0.0000	:11.0	: 54028		:161160		
Mean : 5152	NA	Mean : 1504	Mean :0.1711	Mean :44.79	Mean :0.7212	Mean :10.5	Mean : 61898	NA	Mean :154867	NA	NA	Ph
3rd Qu.: 7745	NA	3rd Qu.: 1036	3rd Qu.:0.0000	3rd Qu.:51.00	3rd Qu.:1.0000	3rd Qu.:13.0	3rd Qu.: 85986	NA	3rd Qu.:238724	NA	NA	z_
Max. :10302	NA	Max. :107586	Max. :4.0000	Max. :81.00	Max. :5.0000	Max. :23.0	Max. :367030	NA	Max. :885282	NA	NA	NA
NA	NA	NA	NA	NA's :6	NA	NA's :454	NA's :445	NA	NA's :464	NA	NA	NA

```
sapply(train, function(x) sum(is.na(x))) %>% kable() %>% kable_styling()
```

	x
INDEX	0
TARGET_FLAG	0
TARGET_AMT	0
KIDSDRIV	0
AGE	6
HOMEKIDS	0
YOJ	454
INCOME	445
PARENT1	0
HOME_VAL	464
MSTATUS	0
SEX	0
EDUCATION	0
JOB	0
TRAVTIME	0
CAR_USE	0
BLUEBOOK	0
TIF	0
CAR_TYPE	0
RED_CAR	0
OLDCLAIM	0
CLM_FREQ	0
REVOKED	0
MVR_PTS	0
CAR_AGE	510
URBANICITY	0

```
# library(UpSetR)
#
# train %>% as_shadow_upset() %>% upset()


ntrain<-select_if(train, is.numeric)
ntrain %>%
  keep(is.numeric) %>%                     # Keep only numeric columns
  gather() %>%                             # Convert to key-value pairs
  ggplot(aes(value)) +                     # Plot the values
    facet_wrap(~ key, scales = "free") +   # In separate panels
    geom_density()
```

```
## Warning: Removed 1879 rows containing non-finite values (stat_density).
```



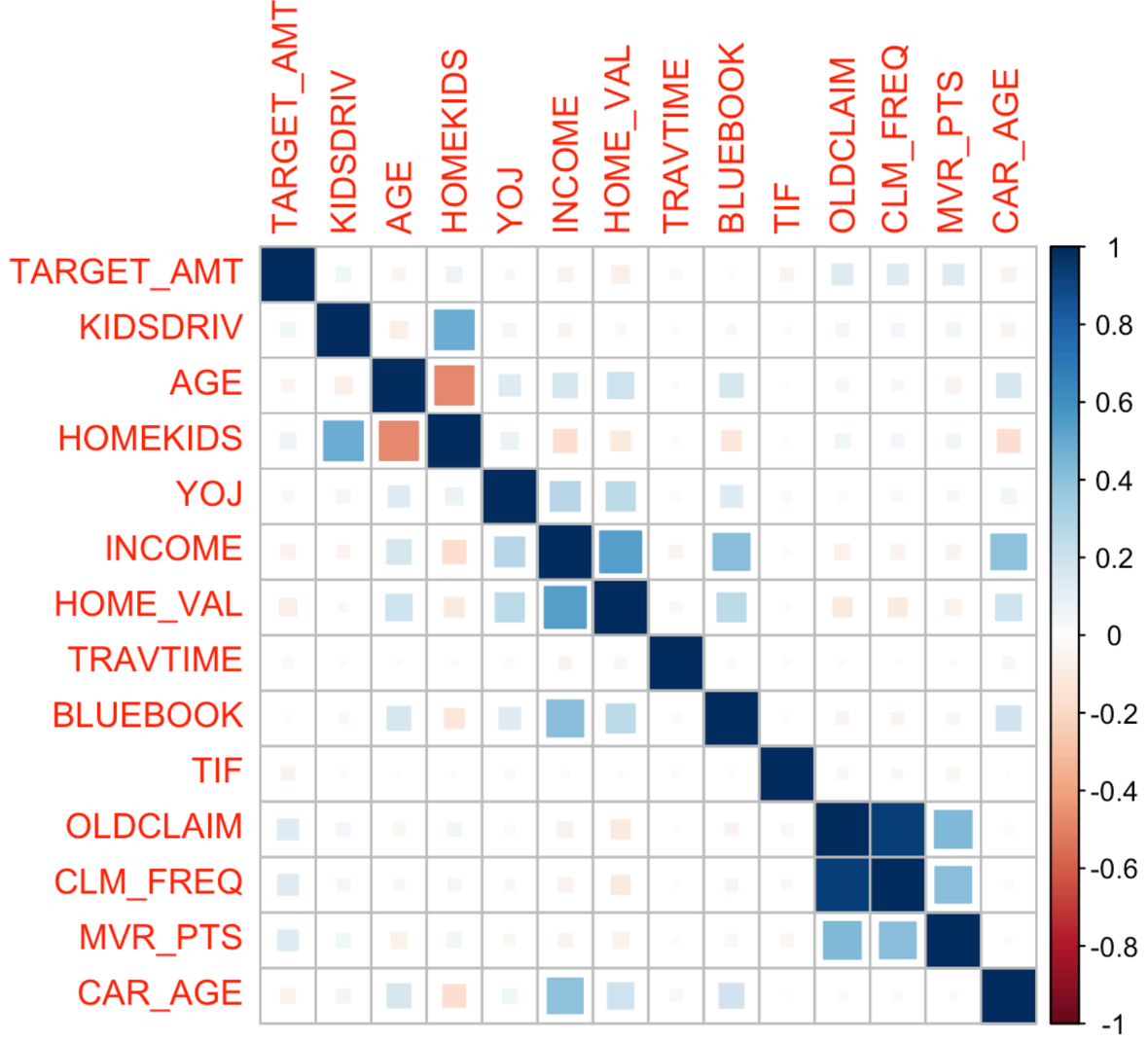

```
#
# trainnum <- dplyr::select_if(train, is.numeric)
#
# rcorr(as.matrix(trainnum))
# corrplot(cor(trainnum), method="square")
#
# # correlation test 1
# cor.test(trainnum$HOME_VAL,trainnum$INCOME,method="pearson")
#
# #NOT significant ignore
```

Data Preparation

```
# impute data for missing values
# use column mean for calculation

train$AGE[is.na(train$AGE)] <- mean(train$AGE, na.rm=TRUE)
train$YOJ[is.na(train$YOJ)] <- mean(train$YOJ, na.rm=TRUE)
train$HOME_VAL[is.na(train$HOME_VAL)] <- mean(train$HOME_VAL, na.rm=TRUE)
train$CAR_AGE[is.na(train$CAR_AGE)] <- mean(train$CAR_AGE, na.rm=TRUE)

train$INCOME[is.na(train$INCOME)] <- mean(train$INCOME, na.rm=TRUE)

#get complete cases
train <- train[complete.cases(train),]

train2<-train

# # transform data using log for skewed HOMEKIDS, MVR_PTS, OLDCLAIM, TIF, KIDSDRIVE and CLM_FREQ

train$HOMEKIDS <- log(train$HOMEKIDS+1)
train$MVR_PTS <- log(train$MVR_PTS+1)
train$OLDCLAIM <- log(train$OLDCLAIM+1)
train$TIF <- log(train$TIF+1)
train$KIDSDRIV <- log(train$KIDSDRIV+1)
train$CLM_FREQ <- log(train$CLM_FREQ+1)


#remove rad per correlation in prior section

train <- train[, !(colnames(train) %in% c("INDEX"))]
#
# #create variable
# train$new <- train$tax / (train$medv*10)
#
trainnum <- dplyr::select_if(train, is.numeric)

rcorr(as.matrix(trainnum))
```

```
##            TARGET_AMT KIDSDRIV   AGE HOMEKIDS   YOJ INCOME HOME_VAL
## TARGET_AMT       1.00     0.06 -0.04     0.07 -0.02  -0.06    -0.08
## KIDSDRIV         0.06     1.00 -0.08     0.49  0.05  -0.05    -0.02
## AGE             -0.04    -0.08  1.00    -0.47  0.13   0.18     0.20
## HOMEKIDS         0.07     0.49 -0.47     1.00  0.08  -0.16    -0.11
## YOJ             -0.02     0.05  0.13     0.08  1.00   0.27     0.26
## INCOME          -0.06    -0.05  0.18    -0.16  0.27   1.00     0.54
## HOME_VAL        -0.08    -0.02  0.20    -0.11  0.26   0.54     1.00
## TRAVTIME         0.03     0.01  0.01    -0.01 -0.02  -0.05    -0.03
## BLUEBOOK         0.00    -0.02  0.16    -0.11  0.14   0.42     0.25
## TIF             -0.05    -0.01  0.00     0.00  0.02  -0.01     0.00
## OLDCLAIM         0.13     0.05 -0.04     0.05 -0.02  -0.07    -0.11
## CLM_FREQ         0.13     0.04 -0.03     0.04 -0.02  -0.05    -0.10
## MVR_PTS          0.13     0.05 -0.07     0.06 -0.03  -0.05    -0.07
## CAR_AGE         -0.06    -0.05  0.17    -0.15  0.06   0.39     0.20
##            TRAVTIME BLUEBOOK   TIF OLDCLAIM CLM_FREQ MVR_PTS CAR_AGE
## TARGET_AMT     0.03     0.00 -0.05     0.13     0.13    0.13   -0.06
## KIDSDRIV       0.01    -0.02 -0.01     0.05     0.04    0.05   -0.05
## AGE            0.01     0.16  0.00    -0.04    -0.03   -0.07    0.17
## HOMEKIDS      -0.01    -0.11  0.00     0.05     0.04    0.06   -0.15
## YOJ           -0.02     0.14  0.02    -0.02    -0.02   -0.03    0.06
## INCOME        -0.05     0.42 -0.01    -0.07    -0.05   -0.05    0.39
## HOME_VAL      -0.03     0.25  0.00    -0.11    -0.10   -0.07    0.20
## TRAVTIME       1.00    -0.02 -0.01    -0.01     0.00    0.01   -0.04
## BLUEBOOK      -0.02     1.00 -0.01    -0.04    -0.04   -0.04    0.18
## TIF           -0.01    -0.01  1.00    -0.03    -0.02   -0.04    0.00
## OLDCLAIM      -0.01    -0.04 -0.03     1.00     0.93    0.44   -0.02
## CLM_FREQ       0.00    -0.04 -0.02     0.93     1.00    0.41   -0.01
## MVR_PTS        0.01    -0.04 -0.04     0.44     0.41    1.00   -0.01
## CAR_AGE       -0.04     0.18  0.00    -0.02    -0.01   -0.01    1.00
##
## n= 8161
##
##
## P
##            TARGET_AMT KIDSDRIV AGE    HOMEKIDS YOJ    INCOME HOME_VAL
## TARGET_AMT             0.0000   0.0002 0.0000   0.0585 0.0000 0.0000
## KIDSDRIV   0.0000              0.0000 0.0000   0.0000 0.0000 0.0577
## AGE        0.0002     0.0000          0.0000   0.0000 0.0000 0.0000
## HOMEKIDS   0.0000     0.0000   0.0000         0.0000 0.0000 0.0000
## YOJ        0.0585     0.0000   0.0000 0.0000         0.0000 0.0000
## INCOME     0.0000     0.0000   0.0000 0.0000   0.0000        0.0000
## HOME_VAL   0.0000     0.0577   0.0000 0.0000   0.0000 0.0000
## TRAVTIME   0.0115     0.5499   0.6342 0.4230   0.1362 0.0000 0.0018
## BLUEBOOK   0.6712     0.0415   0.0000 0.0000   0.0000 0.0000 0.0000
## TIF        0.0000     0.3832   0.9404 0.6725   0.0498 0.4889 0.7280
## OLDCLAIM   0.0000     0.0000   0.0004 0.0000   0.0987 0.0000 0.0000
## CLM_FREQ   0.0000     0.0000   0.0054 0.0002   0.0272 0.0000 0.0000
## MVR_PTS    0.0000     0.0000   0.0000 0.0000   0.0033 0.0000 0.0000
## CAR_AGE    0.0000     0.0000   0.0000 0.0000   0.0000 0.0000 0.0000
##            TRAVTIME BLUEBOOK TIF    OLDCLAIM CLM_FREQ MVR_PTS CAR_AGE
## TARGET_AMT 0.0115   0.6712   0.0000 0.0000   0.0000   0.0000  0.0000
## KIDSDRIV   0.5499   0.0415   0.3832 0.0000   0.0000   0.0000  0.0000
## AGE        0.6342   0.0000   0.9404 0.0004   0.0054   0.0000  0.0000
## HOMEKIDS   0.4230   0.0000   0.6725 0.0000   0.0002   0.0000  0.0000
## YOJ        0.1362   0.0000   0.0498 0.0987   0.0272   0.0033  0.0000
## INCOME     0.0000   0.0000   0.4889 0.0000   0.0000   0.0000  0.0000
## HOME_VAL   0.0018   0.0000   0.7280 0.0000   0.0000   0.0000  0.0000
## TRAVTIME            0.1246   0.2945 0.6009   0.7501   0.5405  0.0009
## BLUEBOOK   0.1246            0.5420 0.0001   0.0003   0.0007  0.0000
## TIF        0.2945   0.5420          0.0147   0.0408   0.0006  0.9927
## OLDCLAIM   0.6009   0.0001   0.0147          0.0000   0.0000  0.0787
## CLM_FREQ   0.7501   0.0003   0.0408 0.0000           0.0000  0.2247
## MVR_PTS    0.5405   0.0007   0.0006 0.0000   0.0000          0.4250
## CAR_AGE    0.0009   0.0000   0.9927 0.0787   0.2247   0.4250
```

```
corrplot(cor(trainnum), method="square")
```




```
cor.test(trainnum$HOMEKIDS,trainnum$AGE,method="pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  trainnum$HOMEKIDS and trainnum$AGE
## t = -48.338, df = 8159, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.4885252 -0.4547891
## sample estimates:
##       cor
## -0.4718298
```

```
train2<-train
```

Build Models LOGIT TARGET_FLAG

```
#MODEL 1
logit <- glm(formula = TARGET_FLAG ~ . - TARGET_AMT, data=train, family = "binomial" (link="logit"))

summary(logit)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT, family = binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5262  -0.7180  -0.3983   0.6545   3.1455
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -7.942e-01  3.293e-01  -2.412 0.015880 *
## KIDSDRIV                         6.821e-01  1.103e-01   6.185 6.21e-10 ***
## AGE                              4.736e-05  4.078e-03   0.012 0.990734
## HOMEKIDS                         1.513e-01  8.300e-02   1.823 0.068320 .
## YOJ                             -1.353e-02  8.578e-03  -1.577 0.114756
## INCOME                          -3.457e-06  1.076e-06  -3.212 0.001317 **
## PARENT1Yes                       3.295e-01  1.144e-01   2.881 0.003970 **
## HOME_VAL                        -1.323e-06  3.419e-07  -3.871 0.000109 ***
## MSTATUSz_No                      5.146e-01  8.493e-02   6.059 1.37e-09 ***
## SEXz_F                          -8.929e-02  1.120e-01  -0.797 0.425327
## EDUCATIONBachelors              -3.720e-01  1.154e-01  -3.223 0.001267 **
## EDUCATIONMasters                -2.803e-01  1.785e-01  -1.570 0.116405
## EDUCATIONPhD                    -1.496e-01  2.135e-01  -0.701 0.483401
## EDUCATIONz_High_School           2.111e-02  9.487e-02   0.222 0.823945
## JOBClerical                      3.986e-01  1.963e-01   2.030 0.042359 *
## JOBDoctor                       -4.227e-01  2.662e-01  -1.588 0.112286
## JOBHome_Maker                    2.049e-01  2.099e-01   0.976 0.328988
## JOBLawyer                        1.172e-01  1.693e-01   0.692 0.488652
## JOBManager                      -5.616e-01  1.712e-01  -3.280 0.001038 **
## JOBProfessional                  1.673e-01  1.782e-01   0.939 0.347724
## JOBStudent                       2.038e-01  2.140e-01   0.953 0.340799
## JOBz_Blue_Collar                 3.101e-01  1.853e-01   1.674 0.094190 .
## TRAVTIME                         1.483e-02  1.880e-03   7.890 3.02e-15 ***
## CAR_USEPrivate                  -7.604e-01  9.172e-02  -8.291  < 2e-16 ***
## BLUEBOOK                        -2.079e-05  5.255e-06  -3.956 7.63e-05 ***
## TIF                             -3.257e-01  4.138e-02  -7.869 3.56e-15 ***
## CAR_TYPEPanel_Truck              5.701e-01  1.613e-01   3.533 0.000410 ***
## CAR_TYPEPickup                   5.578e-01  1.007e-01   5.540 3.03e-08 ***
## CAR_TYPESports_Car               1.031e+00  1.298e-01   7.942 2.00e-15 ***
## CAR_TYPEVan                      6.158e-01  1.264e-01   4.872 1.10e-06 ***
## CAR_TYPEz_SUV                    7.787e-01  1.111e-01   7.007 2.43e-12 ***
## RED_CARyes                      -5.766e-03  8.631e-02  -0.067 0.946741
## OLDCLAIM                         6.763e-03  1.697e-02   0.398 0.690300
## CLM_FREQ                         3.160e-01  1.277e-01   2.474 0.013363 *
## REVOKEDYes                       7.242e-01  8.184e-02   8.850  < 2e-16 ***
## MVR_PTS                          2.808e-01  4.202e-02   6.682 2.35e-11 ***
## CAR_AGE                         -1.807e-03  7.530e-03  -0.240 0.810372
## URBANICITYz_Highly_Rural/ Rural -2.371e+00  1.130e-01 -20.989  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7308.4  on 8123  degrees of freedom
## AIC: 7384.4
##
## Number of Fisher Scoring iterations: 5
```

```
exp(logit$coefficients)
```

```
##                   (Intercept)                      KIDSDRIV
##                    0.45194170                    1.97796637
##                           AGE                      HOMEKIDS
##                    1.00004736                    1.16334008
##                           YOJ                         INCOME
##                    0.98656280                    0.99999654
##                   PARENT1Yes                      HOME_VAL
##                    1.39023185                    0.99999868
##                  MSTATUSz_No                        SEXz_F
##                    1.67300058                    0.91457630
##           EDUCATIONBachelors               EDUCATIONMasters
##                    0.68933598                    0.75559308
##                 EDUCATIONPhD         EDUCATIONz_High_School
##                    0.86104231                    1.02133113
##                  JOBClerical                     JOBDoctor
##                    1.48969494                    0.65526320
##                JOBHome_Maker                     JOBLawyer
##                    1.22734502                    1.12438495
##                  JOBManager                JOBProfessional
##                    0.57030294                    1.18213072
##                  JOBStudent               JOBz_Blue_Collar
##                    1.22609195                    1.36361825
##                    TRAVTIME                CAR_USEPrivate
##                    1.01494543                    0.46747121
##                    BLUEBOOK                             TIF
##                    0.99997921                    0.72204512
##           CAR_TYPEPanel_Truck                 CAR_TYPEPickup
##                    1.76835639                    1.74677458
##            CAR_TYPESports_Car                    CAR_TYPEVan
##                    2.80272210                    1.85105526
##                 CAR_TYPEz_SUV                     RED_CARyes
##                    2.17863803                    0.99425108
##                     OLDCLAIM                       CLM_FREQ
##                    1.00678601                    1.37166999
##                    REVOKEDYes                        MVR_PTS
##                    2.06310705                    1.32420339
##                       CAR_AGE URBANICITYz_Highly_Rural/ Rural
##                    0.99819493                    0.09334636
```

```
logitscalar <- mean(dlogis(predict(logit, type = "link")))
logitscalar * coef(logit)
```

```
##                   (Intercept)                       KIDSDRIV
##                 -1.158016e-01                   9.945167e-02
##                           AGE                       HOMEKIDS
##                  6.904809e-06                   2.206017e-02
##                           YOJ                          INCOME
##                 -1.972543e-03                  -5.040064e-07
##                    PARENT1Yes                       HOME_VAL
##                  4.803969e-02                  -1.929523e-07
##                   MSTATUSz_No                         SEXz_F
##                  7.503592e-02                  -1.301990e-02
##             EDUCATIONBachelors                EDUCATIONMasters
##                 -5.424472e-02                  -4.086324e-02
##                   EDUCATIONPhD          EDUCATIONz_High_School
##                 -2.181469e-02                   3.077558e-03
##                    JOBClerical                      JOBDoctor
##                  5.811519e-02                  -6.163603e-02
##                  JOBHome_Maker                      JOBLawyer
##                  2.986941e-02                   1.709406e-02
##                     JOBManager                JOBProfessional
##                 -8.188439e-02                   2.439650e-02
##                     JOBStudent                JOBz_Blue_Collar
##                  2.972047e-02                   4.522137e-02
##                        TRAVTIME                  CAR_USEPrivate
##                  2.163050e-03                   -1.108755e-01
##                         BLUEBOOK                             TIF
##                 -3.030737e-06                  -4.748519e-02
##              CAR_TYPEPanel_Truck                  CAR_TYPEPickup
##                    8.311836e-02                   8.132789e-02
##                CAR_TYPESports_Car                     CAR_TYPEVan
##                    1.502692e-01                   8.978260e-02
##                     CAR_TYPEz_SUV                     RED_CARyes
##                    1.135413e-01                  -8.406609e-04
##                         OLDCLAIM                         CLM_FREQ
##                    9.861172e-04                   4.607979e-02
##                      REVOKEDYes                          MVR_PTS
##                    1.055966e-01                   4.094471e-02
##                         CAR_AGE URBANICITYz_Highly_Rural/ Rural
##                  -2.634331e-04                  -3.457765e-01
```

```
confint.default(logit)
```

```
##                                        2.5 %        97.5 %
## (Intercept)                     -1.439652e+00 -1.487526e-01
## KIDSDRIV                         4.659328e-01  8.982056e-01
## AGE                             -7.944409e-03  8.039120e-03
## HOMEKIDS                        -1.137668e-02  3.139672e-01
## YOJ                             -3.034002e-02  3.283437e-03
## INCOME                          -5.565742e-06 -1.347510e-06
## PARENT1Yes                       1.052923e-01  5.536488e-01
## HOME_VAL                        -1.993393e-06 -6.532553e-07
## MSTATUSz_No                      3.481541e-01  6.810835e-01
## SEXz_F                          -3.088261e-01  1.302374e-01
## EDUCATIONBachelors              -5.982429e-01 -1.458101e-01
## EDUCATIONMasters                -6.301049e-01  6.960026e-02
## EDUCATIONPhD                    -5.680126e-01  2.687893e-01
## EDUCATIONz_High_School          -1.648411e-01  2.070547e-01
## JOBClerical                      1.374718e-02  7.833955e-01
## JOBDoctor                       -9.444515e-01  9.901495e-02
## JOBHome_Maker                   -2.064601e-01  6.161667e-01
## JOBLawyer                       -2.145962e-01  4.490685e-01
## JOBManager                      -8.971700e-01 -2.260052e-01
## JOBProfessional                 -1.819185e-01  5.165555e-01
## JOBStudent                      -2.155551e-01  6.232188e-01
## JOBz_Blue_Collar                -5.304572e-02  6.733290e-01
## TRAVTIME                         1.114967e-02  1.852002e-02
## CAR_USEPrivate                  -9.401775e-01 -5.806575e-01
## BLUEBOOK                        -3.108426e-05 -1.048713e-05
## TIF                             -4.067786e-01 -2.445566e-01
## CAR_TYPEPanel_Truck              2.538386e-01  8.862624e-01
## CAR_TYPEPickup                   3.604241e-01  7.551178e-01
## CAR_TYPESports_Car               7.762439e-01  1.284938e+00
## CAR_TYPEVan                      3.680626e-01  8.634492e-01
## CAR_TYPEz_SUV                    5.608898e-01  9.965101e-01
## RED_CARyes                      -1.749296e-01  1.633986e-01
## OLDCLAIM                        -2.650452e-02  4.003069e-02
## CLM_FREQ                         6.565860e-02  5.663993e-01
## REVOKEDYes                       5.638194e-01  8.846068e-01
## MVR_PTS                          1.984459e-01  3.631762e-01
## CAR_AGE                         -1.656445e-02  1.295105e-02
## URBANICITYz_Highly_Rural/ Rural -2.592883e+00 -2.149994e+00
```

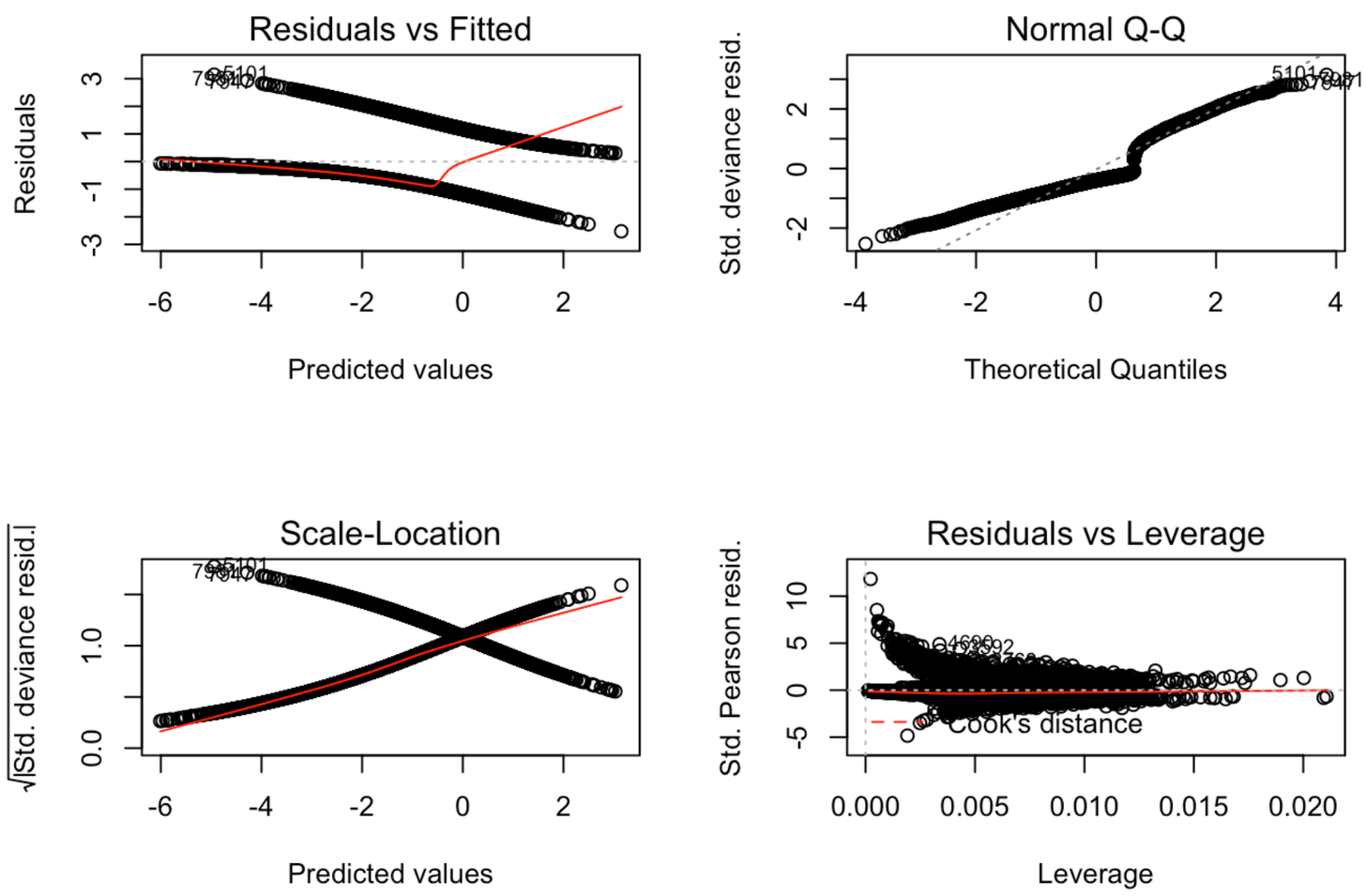
```
predlogit <- predict(logit, type="response")
train2$pred1 <- predict(logit, type="response")
summary(predlogit)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.002449 0.077438 0.201727 0.263816 0.403524 0.958860
```

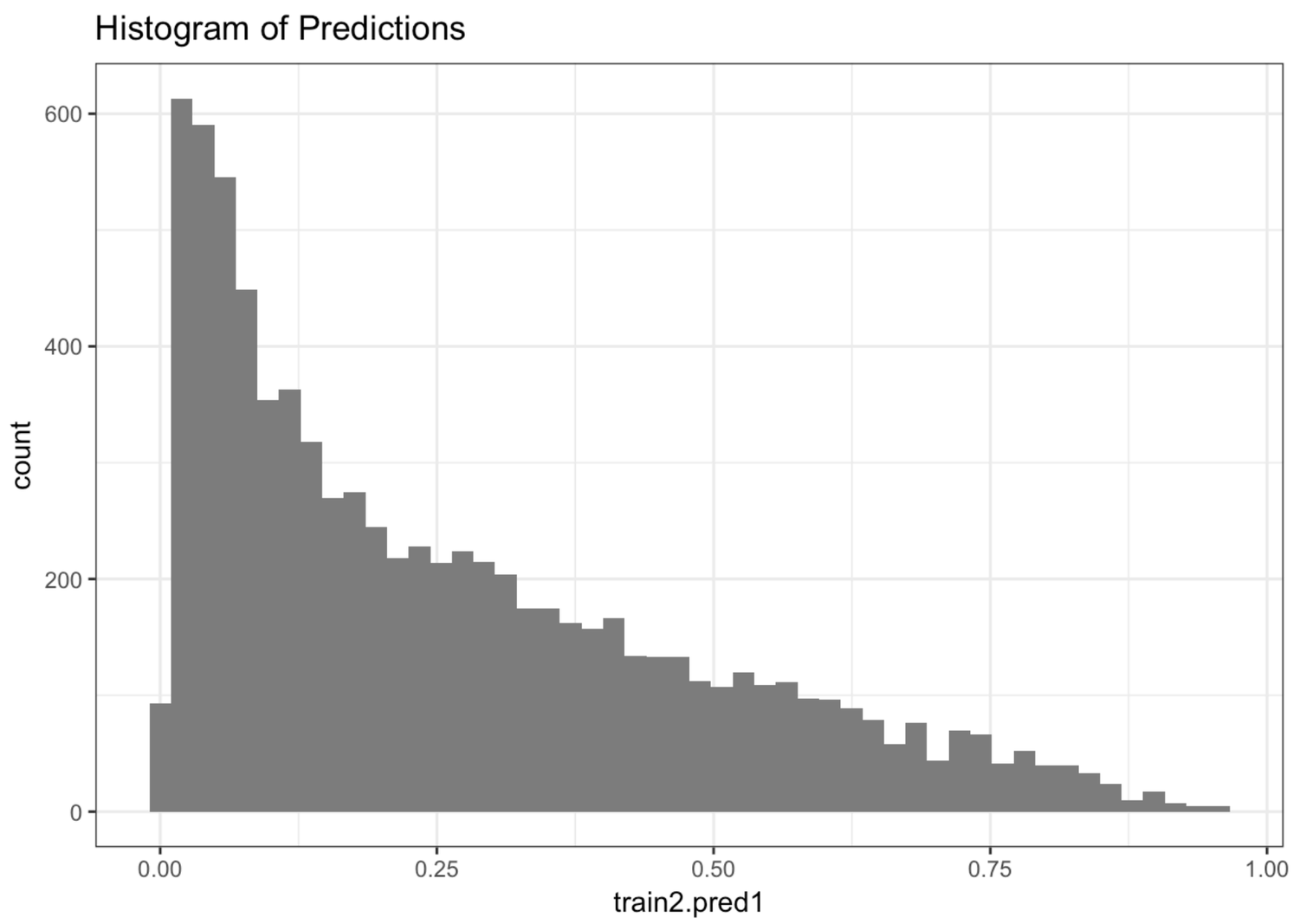
```
table(true = train$TARGET_FLAG, pred = round(fitted(logit)))
```

```
##     pred
## true    0    1
##    0 5532  476
##    1 1251  902
```

```
#plots for Model 1
par(mfrow=c(2,2))
plot(logit)
```




```
data.frame(train2$pred1) %>%
    ggplot(aes(x = train2.pred1)) +
    geom_histogram(bins = 50, fill = 'grey50') +
    labs(title = 'Histogram of Predictions') +
    theme_bw()
```




```
plot.roc(train$TARGET_FLAG, train2$pred1)

#extract variables that are significant and rerun model
sigvars <- data.frame(summary(logit)$coef[summary(logit)$coef[,4] <= .05, 4])
sigvars <- add_rownames(sigvars, "vars")
```

```
## Warning: Deprecated, use tibble::rownames_to_column() instead.
```

```
colist<-dplyr::pull(sigvars, vars)
# colist<-colist[2:11]
colist<-c("KIDSDRIV","INCOME","PARENT1","HOME_VAL","MSTATUS","EDUCATION","JOB","TRAVTIME","CAR_USE","BLUEBOOK","T
IF","CAR_TYPE","CLM_FREQ","REVOKED","MVR_PTS","URBANICITY")

idx <- match(colist, names(train))
trainmod2 <- cbind(train[,idx], train2['TARGET_FLAG'])

#MODEL 2
logit2 <- glm(TARGET_FLAG ~ ., data=trainmod2, family = "binomial" (link="logit"))
summary(logit2)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ ., family = binomial(link = "logit"),
##     data = trainmod2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5523  -0.7190  -0.3985   0.6497   3.1365
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -8.728e-01  2.620e-01  -3.332 0.000863 ***
## KIDSDRIV                       7.664e-01  9.775e-02   7.841 4.48e-15 ***
## INCOME                        -3.552e-06  1.071e-06  -3.317 0.000910 ***
## PARENT1Yes                     4.476e-01  9.451e-02   4.736 2.18e-06 ***
## HOME_VAL                      -1.367e-06  3.407e-07  -4.012 6.03e-05 ***
## MSTATUSz_No                    4.766e-01  7.969e-02   5.981 2.22e-09 ***
## EDUCATIONBachelors            -3.839e-01  1.086e-01  -3.534 0.000409 ***
## EDUCATIONMasters              -3.062e-01  1.612e-01  -1.899 0.057514 .
## EDUCATIONPhD                  -1.761e-01  1.997e-01  -0.882 0.377940
## EDUCATIONz_High_School         1.682e-02  9.450e-02   0.178 0.858752
## JOBClerical                    4.011e-01  1.962e-01   2.044 0.040930 *
## JOBDoctor                     -4.251e-01  2.658e-01  -1.599 0.109770
## JOBHome_Maker                  2.561e-01  2.038e-01   1.257 0.208790
## JOBLawyer                      1.091e-01  1.690e-01   0.646 0.518557
## JOBManager                    -5.704e-01  1.711e-01  -3.335 0.000854 ***
## JOBProfessional                1.578e-01  1.781e-01   0.886 0.375433
## JOBStudent                     2.732e-01  2.104e-01   1.299 0.194092
## JOBz_Blue_Collar               3.064e-01  1.852e-01   1.654 0.098047 .
## TRAVTIME                       1.471e-02  1.877e-03   7.837 4.61e-15 ***
## CAR_USEPrivate                -7.623e-01  9.158e-02  -8.324  < 2e-16 ***
## BLUEBOOK                      -2.321e-05  4.715e-06  -4.922 8.56e-07 ***
## TIF                           -3.257e-01  4.135e-02  -7.875 3.41e-15 ***
## CAR_TYPEPanel_Truck            6.226e-01  1.505e-01   4.137 3.53e-05 ***
## CAR_TYPEPickup                 5.528e-01  1.006e-01   5.497 3.86e-08 ***
## CAR_TYPESports_Car             9.746e-01  1.074e-01   9.077  < 2e-16 ***
## CAR_TYPEVan                    6.466e-01  1.220e-01   5.301 1.15e-07 ***
## CAR_TYPEz_SUV                  7.218e-01  8.585e-02   8.407  < 2e-16 ***
## CLM_FREQ                       3.624e-01  5.464e-02   6.631 3.33e-11 ***
## REVOKEDYes                     7.349e-01  8.022e-02   9.161  < 2e-16 ***
## MVR_PTS                        2.863e-01  4.138e-02   6.920 4.51e-12 ***
## URBANICITYz_Highly_Rural/ Rural -2.373e+00  1.129e-01 -21.024  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418.0  on 8160  degrees of freedom
## Residual deviance: 7314.8  on 8130  degrees of freedom
## AIC: 7376.8
##
## Number of Fisher Scoring iterations: 5
```

```
exp(logit2$coefficients)
```

```
##                   (Intercept)                      KIDSDRIV
##                    0.41776744                    2.15209411
##                        INCOME                     PARENT1Yes
##                    0.99999645                    1.56455092
##                      HOME_VAL                  MSTATUSz_No
##                    0.99999863                    1.61063279
##             EDUCATIONBachelors             EDUCATIONMasters
##                    0.68119924                    0.73624403
##                EDUCATIONPhD          EDUCATIONz_High_School
##                    0.83855457                    1.01695952
##                JOBClerical                    JOBDoctor
##                    1.49341342                    0.65370747
##               JOBHome_Maker                    JOBLawyer
##                    1.29192357                    1.11527301
##                JOBManager               JOBProfessional
##                    0.56527588                    1.17097642
##                JOBStudent              JOBz_Blue_Collar
##                    1.31419704                    1.35848308
##                  TRAVTIME                CAR_USEPrivate
##                    1.01482211                    0.46658415
##                  BLUEBOOK                             TIF
##                    0.99997679                    0.72205023
##           CAR_TYPEPanel_Truck              CAR_TYPEPickup
##                    1.86373779                    1.73806537
##            CAR_TYPESports_Car                 CAR_TYPEVan
##                    2.65019303                    1.90901065
##                 CAR_TYPEz_SUV                    CLM_FREQ
##                    2.05810528                    1.43671851
##                    REVOKEDYes                       MVR_PTS
##                    2.08518827                    1.33154581
## URBANICITYz_Highly_Rural/ Rural
##                    0.09320986
```

```
logit2scalar <- mean(dlogis(predict(logit2, type = "link")))
logit2scalar * coef(logit2)
```

```
##                     (Intercept)                        KIDSDRIV
##                   -1.274002e-01                    1.118714e-01
##                          INCOME                       PARENT1Yes
##                   -5.185070e-07                    6.533249e-02
##                        HOME_VAL                     MSTATUSz_No
##                   -1.994968e-07                    6.956953e-02
##               EDUCATIONBachelors               EDUCATIONMasters
##                   -5.603494e-02                   -4.469269e-02
##                    EDUCATIONPhD          EDUCATIONz_High_School
##                   -2.570038e-02                    2.454692e-03
##                    JOBClerical                      JOBDoctor
##                    5.854023e-02                   -6.204783e-02
##                   JOBHome_Maker                      JOBLawyer
##                    3.738562e-02                    1.592436e-02
##                    JOBManager                 JOBProfessional
##                   -8.326286e-02                    2.303837e-02
##                    JOBStudent                JOBz_Blue_Collar
##                    3.988064e-02                    4.471824e-02
##                      TRAVTIME                  CAR_USEPrivate
##                    2.147590e-03                   -1.112694e-01
##                      BLUEBOOK                               TIF
##                   -3.387609e-06                   -4.753412e-02
##               CAR_TYPEPanel_Truck                CAR_TYPEPickup
##                    9.087371e-02                    8.068389e-02
##                CAR_TYPESports_Car                   CAR_TYPEVan
##                    1.422595e-01                    9.437697e-02
##                   CAR_TYPEz_SUV                      CLM_FREQ
##                    1.053534e-01                    5.289110e-02
##                      REVOKEDYes                         MVR_PTS
##                    1.072616e-01                    4.179488e-02
## URBANICITYz_Highly_Rural/ Rural
##                   -3.463539e-01
```

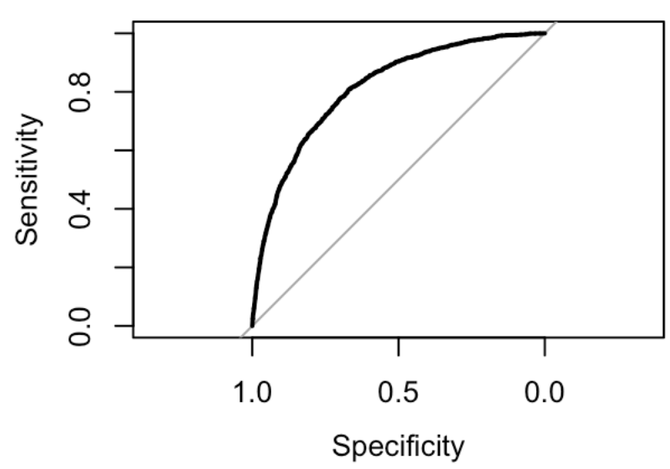
```
predlogit2 <- predict(logit2, type="response")
train2$pred2 <- predict(logit2, type="response")

summary(predlogit2)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.002282 0.077191 0.202256 0.263816 0.403691 0.961502
```

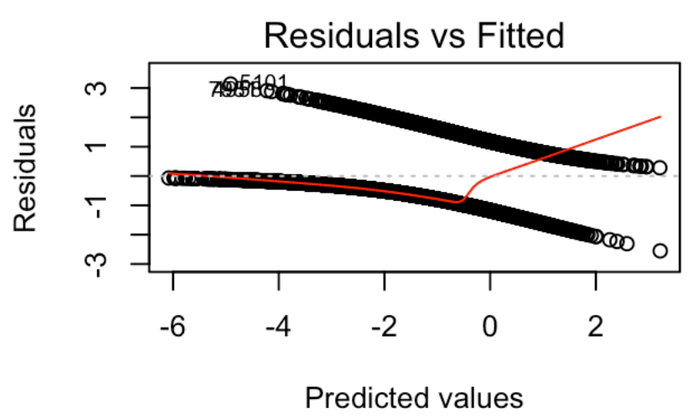
```
table(true = train$TARGET_FLAG, pred = round(fitted(logit2)))
```

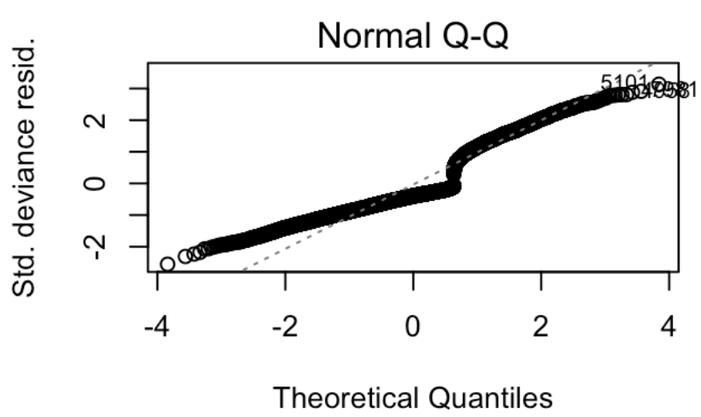
```
##     pred
## true    0    1
##    0 5541  467
##    1 1247  906
```

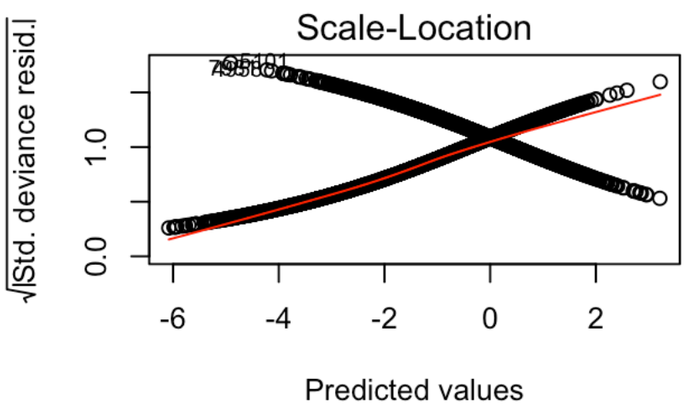
```
#plots for Model 2
par(mfrow=c(2,2))
```

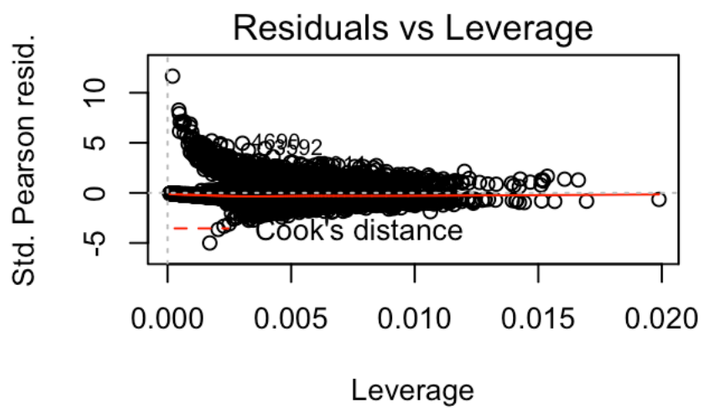



```
plot(logit2)
```

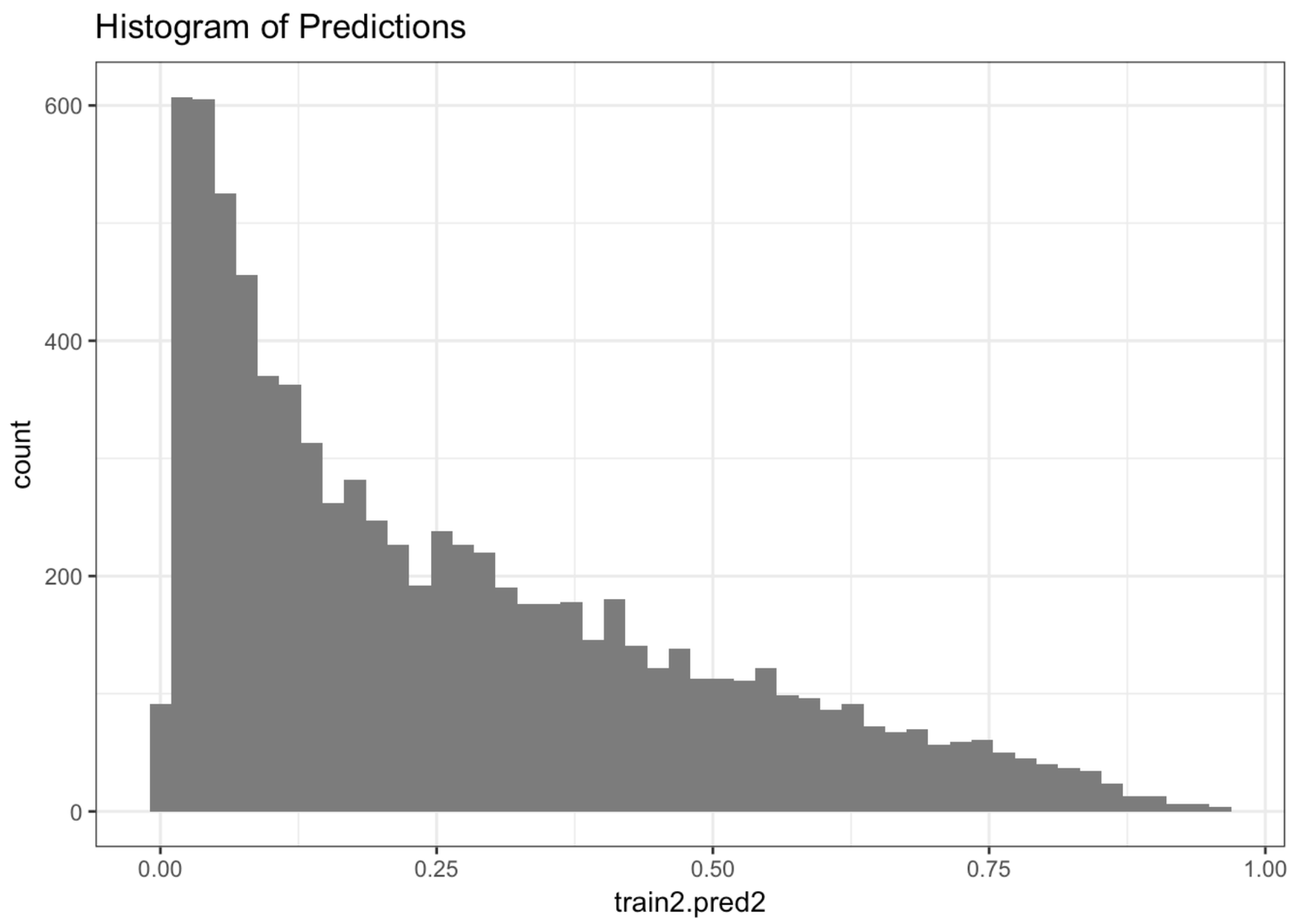









```
data.frame(train2$pred2) %>%
    ggplot(aes(x = train2.pred2)) +
    geom_histogram(bins = 50, fill = 'grey50') +
    labs(title = 'Histogram of Predictions') +
    theme_bw()
```




```
plot.roc(train$TARGET_FLAG, train2$pred2)

#MODEL 3
#PC Model no racial bias
logit3 <- glm(TARGET_FLAG ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME, data=train, family = "binomial" (link="logit
"))
summary(logit3)
```

```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME,
##     family = binomial(link = "logit"), data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5299  -0.8217  -0.6749   1.2315   2.8090
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.876e-01  7.305e-02  -9.412  < 2e-16 ***
## KIDSDRIV     7.266e-01  8.115e-02   8.953  < 2e-16 ***
## INCOME      -3.497e-06  6.826e-07  -5.123 3.01e-07 ***
## HOME_VAL    -2.972e-06  2.499e-07 -11.895  < 2e-16 ***
## TRAVTIME     5.880e-03  1.598e-03   3.679 0.000234 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 9418.0  on 8160  degrees of freedom
## Residual deviance: 9021.1  on 8156  degrees of freedom
## AIC: 9031.1
##
## Number of Fisher Scoring iterations: 4
```

```
exp(logit3$coefficients)
```

```
## (Intercept)    KIDSDRIV      INCOME    HOME_VAL    TRAVTIME
##   0.5028055   2.0679778   0.9999965   0.9999970   1.0058969
```

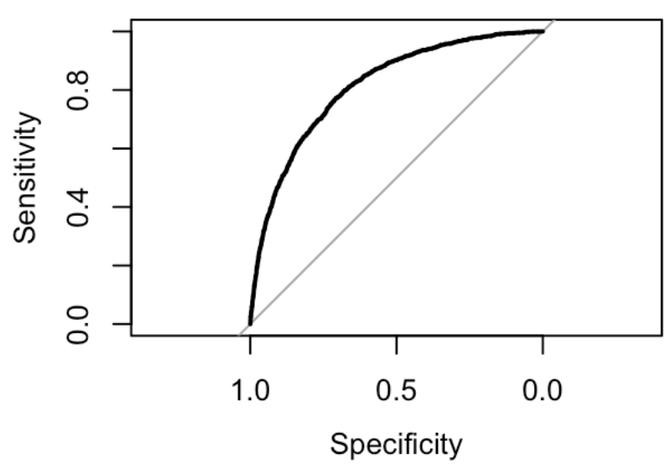
```
predlogit3 <- predict(logit3, type="response")
train2$pred3 <- predict(logit3, type="response")
summary(predlogit3)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.01176 0.19679 0.25557 0.26382 0.32927 0.68970
```

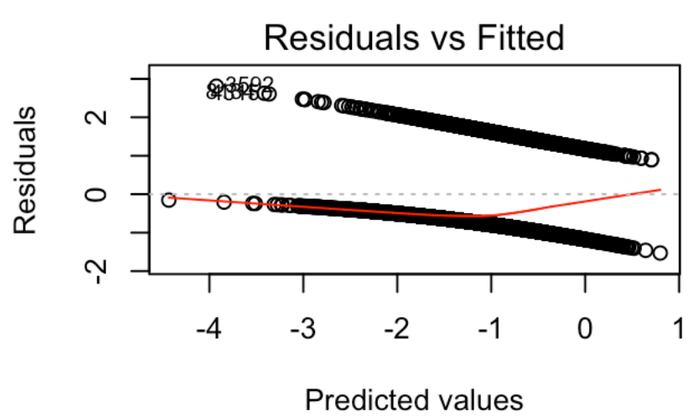
```
table(true = train$TARGET_FLAG, pred = round(fitted(logit3)))
```

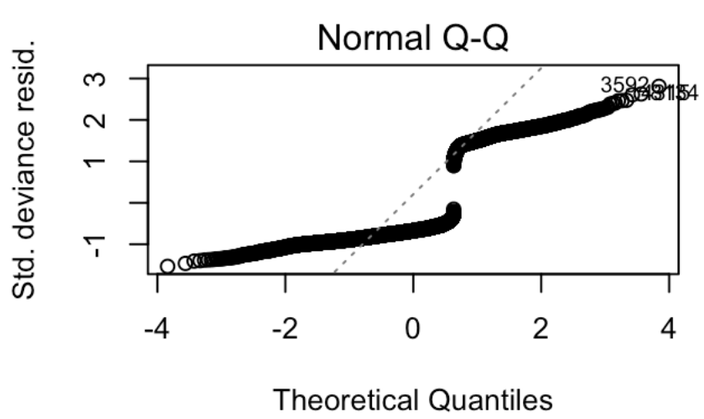
```
##      pred
## true    0    1
##    0 5937   71
##    1 2086   67
```

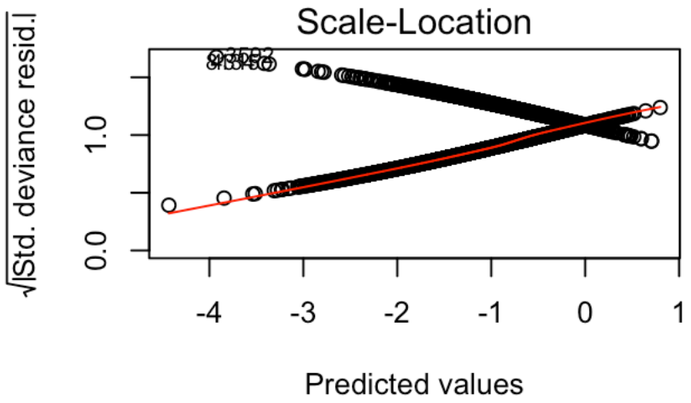
```
#plots for Model 3
par(mfrow=c(2,2))
```

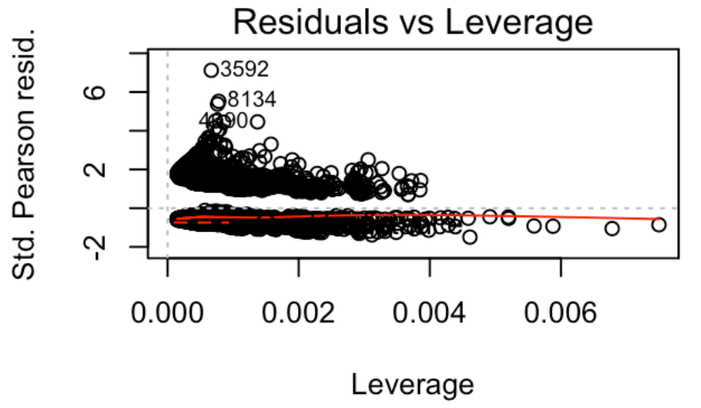



```
plot(logit3)
```

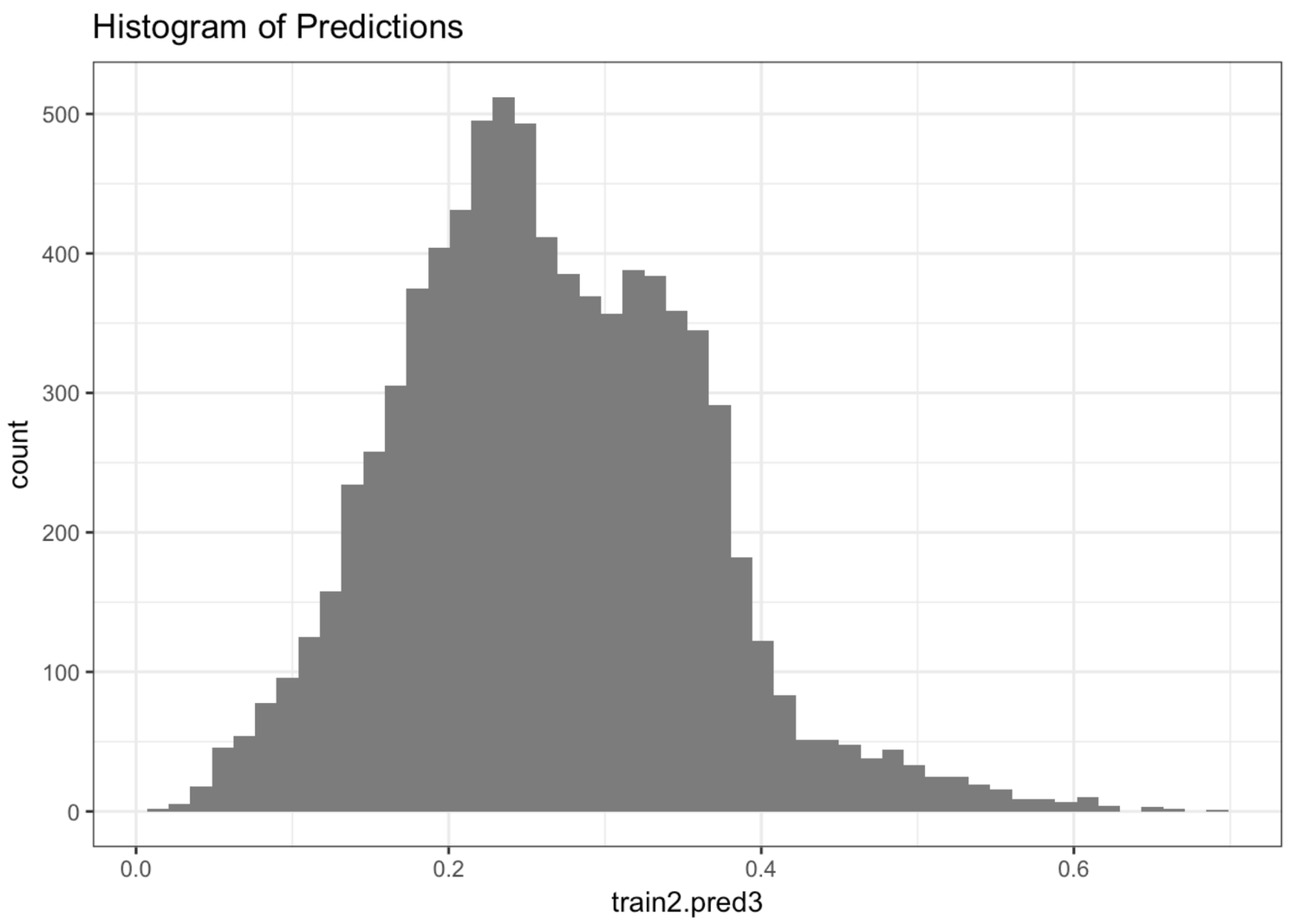









```
data.frame(train2$pred3) %>%
    ggplot(aes(x = train2.pred3)) +
    geom_histogram(bins = 50, fill = 'grey50') +
    labs(title = 'Histogram of Predictions') +
    theme_bw()
```




```
plot.roc(train$TARGET_FLAG, train2$pred3)

logit3scalar <- mean(dlogis(predict(logit3, type = "link")))
logit3scalar * coef(logit3)
```

```
##   (Intercept)      KIDSDRIV        INCOME      HOME_VAL      TRAVTIME
## -1.271908e-01  1.344090e-01 -6.468917e-07 -5.498016e-07  1.087668e-03
```

```
round(logitscalar * coef(logit),2)
```

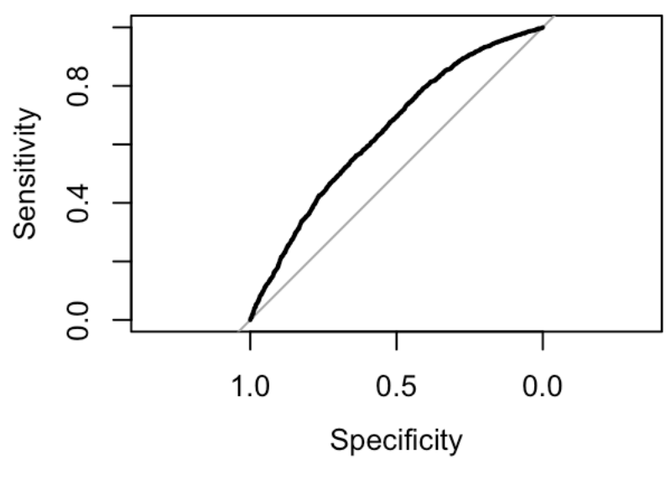
```
##                      (Intercept)                          KIDSDRIV
##                            -0.12                              0.10
##                              AGE                          HOMEKIDS
##                             0.00                              0.02
##                              YOJ                            INCOME
##                             0.00                              0.00
##                       PARENT1Yes                          HOME_VAL
##                             0.05                              0.00
##                      MSTATUSz_No                            SEXz_F
##                             0.08                             -0.01
##                EDUCATIONBachelors                EDUCATIONMasters
##                            -0.05                             -0.04
##                      EDUCATIONPhD           EDUCATIONz_High_School
##                            -0.02                              0.00
##                       JOBClerical                         JOBDoctor
##                             0.06                             -0.06
##                     JOBHome_Maker                         JOBLawyer
##                             0.03                              0.02
##                       JOBManager                    JOBProfessional
##                            -0.08                              0.02
##                       JOBStudent                   JOBz_Blue_Collar
##                             0.03                              0.05
##                         TRAVTIME                    CAR_USEPrivate
##                             0.00                             -0.11
##                         BLUEBOOK                              TIF
##                             0.00                             -0.05
##                CAR_TYPEPanel_Truck                   CAR_TYPEPickup
##                             0.08                              0.08
##                CAR_TYPESports_Car                      CAR_TYPEVan
##                             0.15                              0.09
##                     CAR_TYPEz_SUV                      RED_CARyes
##                             0.11                              0.00
##                         OLDCLAIM                         CLM_FREQ
##                             0.00                              0.05
##                       REVOKEDYes                          MVR_PTS
##                             0.11                              0.04
##                          CAR_AGE URBANICITYz_Highly_Rural/ Rural
##                             0.00                             -0.35
```

```
round(logit2scalar * coef(logit2),2)
```

```
##                   (Intercept)                      KIDSDRIV
##                         -0.13                          0.11
##                        INCOME                     PARENT1Yes
##                          0.00                          0.07
##                      HOME_VAL                   MSTATUSz_No
##                          0.00                          0.07
##             EDUCATIONBachelors              EDUCATIONMasters
##                         -0.06                         -0.04
##                  EDUCATIONPhD        EDUCATIONz_High_School
##                         -0.03                          0.00
##                   JOBClerical                    JOBDoctor
##                          0.06                         -0.06
##                 JOBHome_Maker                    JOBLawyer
##                          0.04                          0.02
##                    JOBManager                JOBProfessional
##                         -0.08                          0.02
##                   JOBStudent                JOBz_Blue_Collar
##                          0.04                          0.04
##                     TRAVTIME                 CAR_USEPrivate
##                          0.00                         -0.11
##                     BLUEBOOK                           TIF
##                          0.00                         -0.05
##            CAR_TYPEPanel_Truck                CAR_TYPEPickup
##                          0.09                          0.08
##             CAR_TYPESports_Car                   CAR_TYPEVan
##                          0.14                          0.09
##                  CAR_TYPEz_SUV                      CLM_FREQ
##                          0.11                          0.05
##                     REVOKEDYes                       MVR_PTS
##                          0.11                          0.04
## URBANICITYz_Highly_Rural/ Rural
##                         -0.35
```

```
round(logit3scalar * coef(logit3),2)
```

```
## (Intercept)    KIDSDRIV      INCOME    HOME_VAL    TRAVTIME
##       -0.13        0.13        0.00        0.00        0.00
```

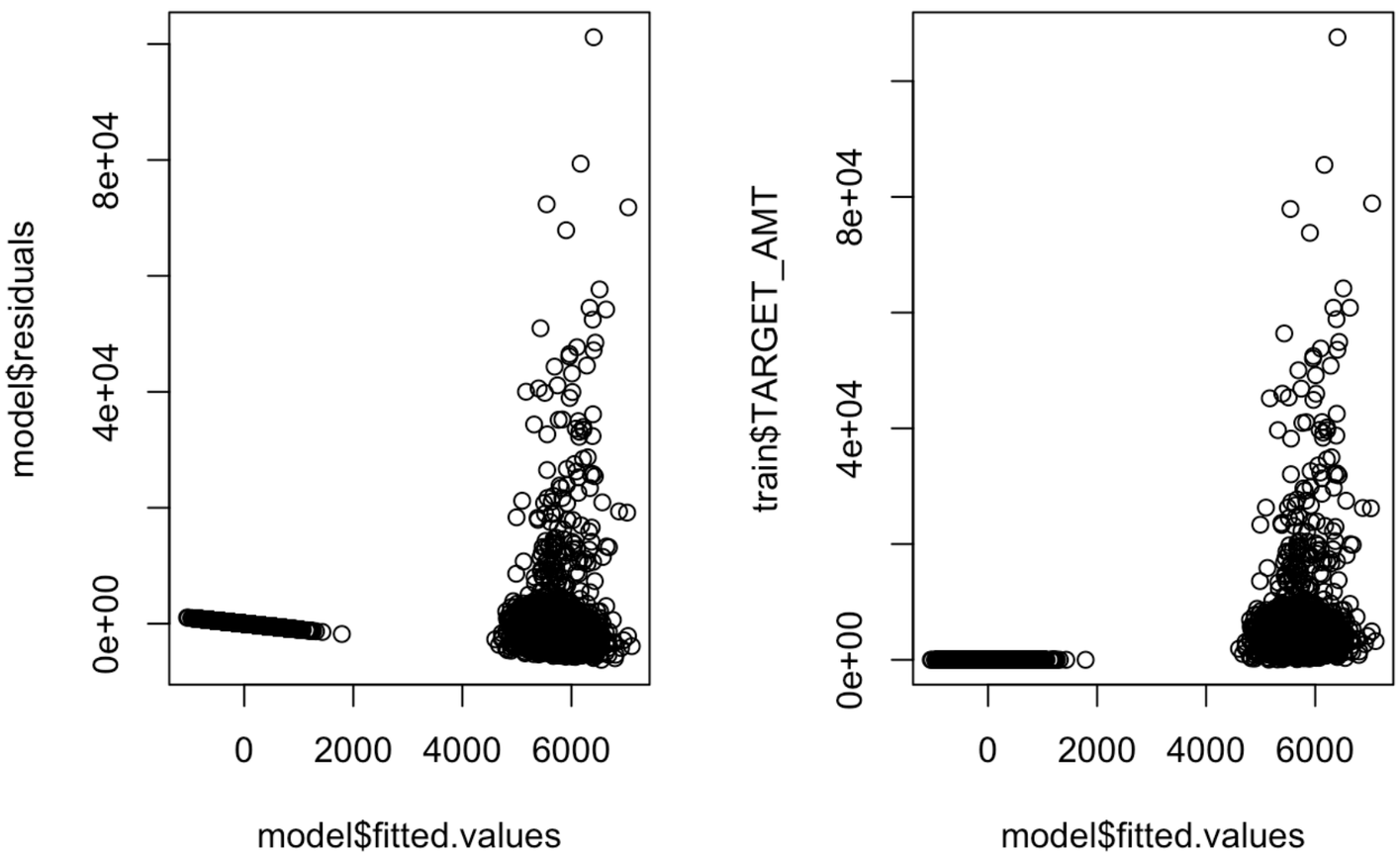


Build Models GENERAL TARGET_AMT

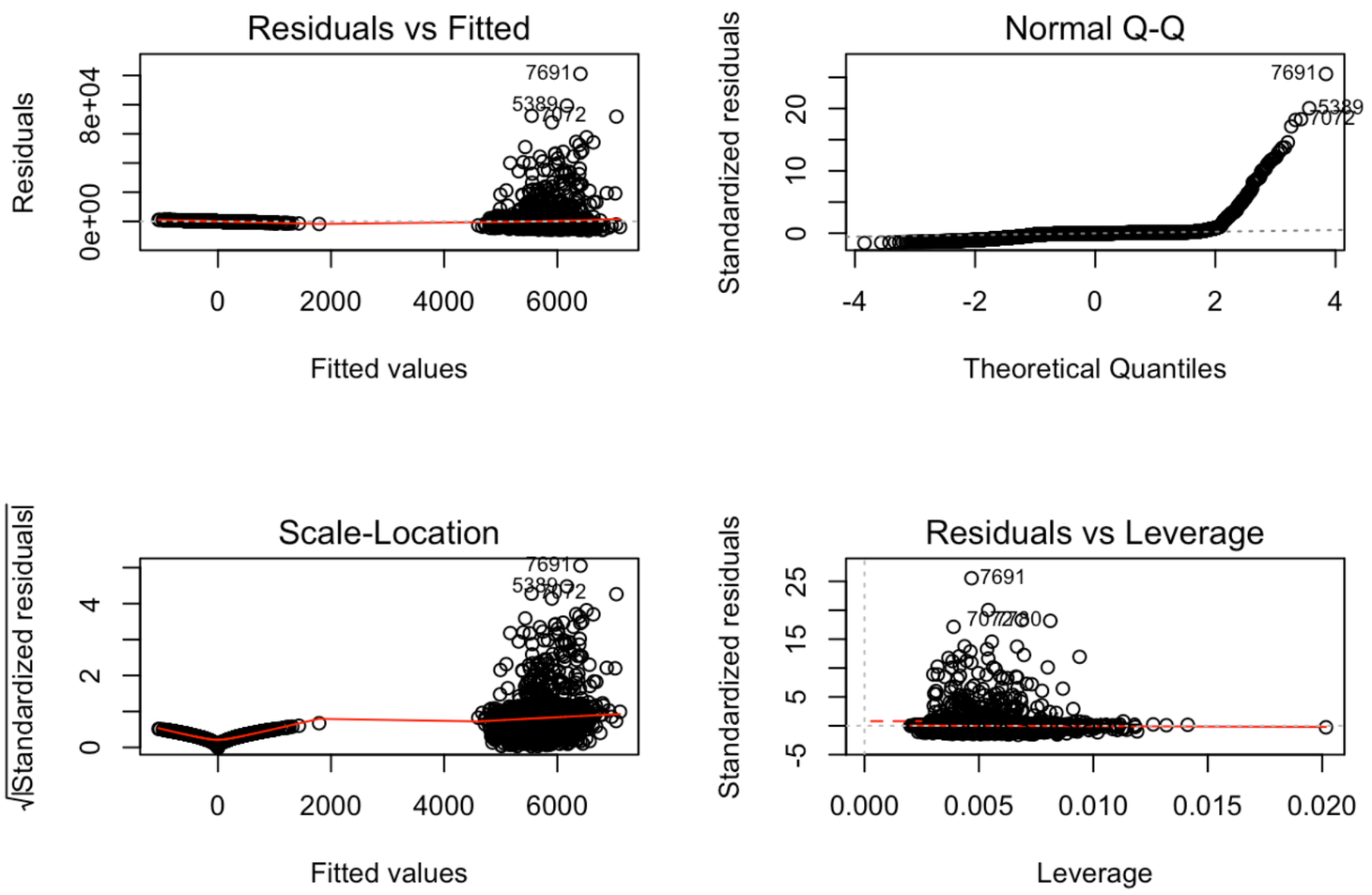
```
#MODEL 1
model <- lm(TARGET_AMT ~ ., data=train)
summary(model)
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -6234   -465    -58    243 101178
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -5.975e+02  5.010e+02  -1.193   0.2331
## TARGET_FLAG1                   5.707e+03  1.134e+02  50.329  < 2e-16 ***
## KIDSDRIV                      -2.216e+01  1.781e+02  -0.124   0.9010
## AGE                            6.145e+00  6.271e+00   0.980   0.3272
## HOMEKIDS                       9.215e+01  1.256e+02   0.733   0.4633
## YOJ                            7.685e+00  1.319e+01   0.583   0.5601
## INCOME                        -2.258e-03  1.577e-03  -1.431   0.1524
## PARENT1Yes                     1.209e+02  1.830e+02   0.661   0.5088
## HOME_VAL                       3.864e-04  5.165e-04   0.748   0.4545
## MSTATUSz_No                    1.770e+02  1.282e+02   1.381   0.1673
## SEXz_F                        -2.896e+02  1.606e+02  -1.804   0.0713 .
## EDUCATIONBachelors             6.823e+01  1.790e+02   0.381   0.7031
## EDUCATIONMasters               2.235e+02  2.620e+02   0.853   0.3937
## EDUCATIONPhD                   4.283e+02  3.110e+02   1.377   0.1685
## EDUCATIONz_High_School        -1.243e+02  1.502e+02  -0.828   0.4077
## JOBClerical                   -8.406e+00  2.984e+02  -0.028   0.9775
## JOBDoctor                     -2.812e+02  3.571e+02  -0.788   0.4310
## JOBHome_Maker                 -7.045e+01  3.185e+02  -0.221   0.8249
## JOBLawyer                      7.660e+01  2.582e+02   0.297   0.7667
## JOBManager                    -1.265e+02  2.521e+02  -0.502   0.6158
## JOBProfessional                1.733e+02  2.698e+02   0.642   0.5206
## JOBStudent                    -1.306e+02  3.266e+02  -0.400   0.6892
## JOBz_Blue_Collar               5.187e+01  2.813e+02   0.184   0.8537
## TRAVTIME                       5.682e-01  2.824e+00   0.201   0.8405
## CAR_USEPrivate                -9.993e+01  1.443e+02  -0.693   0.4886
## BLUEBOOK                       2.944e-02  7.536e-03   3.906 9.45e-05 ***
## TIF                           -1.653e+01  6.277e+01  -0.263   0.7922
## CAR_TYPEPanel_Truck           -5.880e+01  2.430e+02  -0.242   0.8088
## CAR_TYPEPickup                -3.318e+01  1.493e+02  -0.222   0.8241
## CAR_TYPESports_Car             2.098e+02  1.910e+02   1.099   0.2720
## CAR_TYPEVan                    9.709e+01  1.865e+02   0.521   0.6026
## CAR_TYPEz_SUV                  1.621e+02  1.571e+02   1.032   0.3021
## RED_CARyes                    -2.696e+01  1.302e+02  -0.207   0.8360
## OLDCLAIM                       4.079e+00  2.908e+01   0.140   0.8884
## CLM_FREQ                      -8.551e+01  2.210e+02  -0.387   0.6989
## REVOKEDYes                    -2.991e+02  1.385e+02  -2.160   0.0308 *
## MVR_PTS                        1.396e+02  6.716e+01   2.079   0.0376 *
## CAR_AGE                       -2.520e+01  1.118e+01  -2.254   0.0242 *
## URBANICITYz_Highly_Rural/ Rural  2.987e+01  1.272e+02   0.235   0.8143
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3970 on 8122 degrees of freedom
## Multiple R-squared:  0.2912, Adjusted R-squared:  0.2879
## F-statistic:  87.8 on 38 and 8122 DF,  p-value: < 2.2e-16
```

```
par(mfrow=c(1,2))
plot(model$residuals ~ model$fitted.values)
plot(model$fitted.values,train$TARGET_AMT)
```




```
par(mfrow=c(2,2))
plot(model)
```



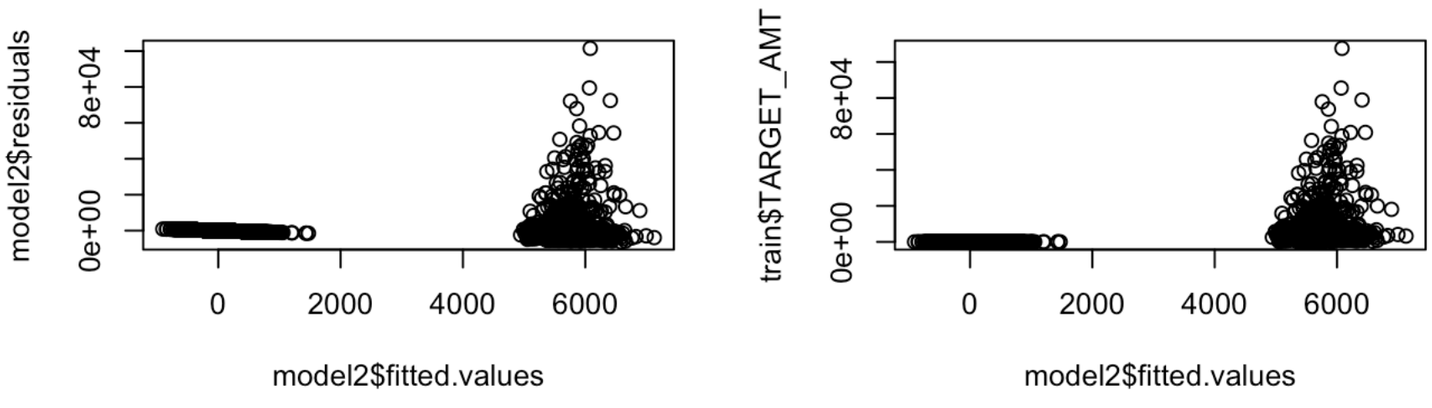

```
#extract variables that are significant and rerun model
sigvars <- data.frame(summary(model)$coef[summary(model)$coef[,4] <= .05, 4])
sigvars <- add_rownames(sigvars, "vars")
```

```
## Warning: Deprecated, use tibble::rownames_to_column() instead.
```

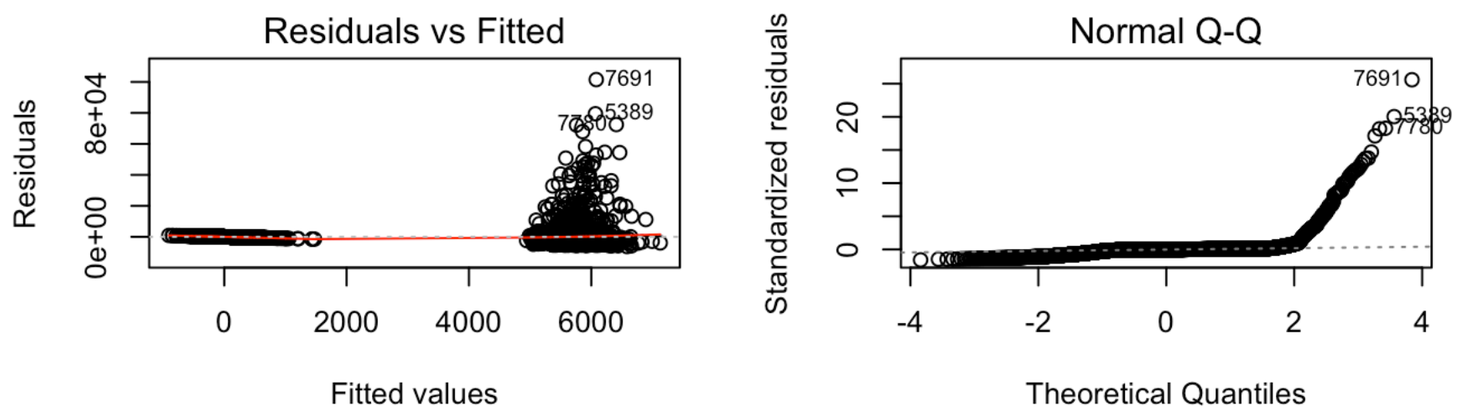
```
colist<-dplyr::pull(sigvars, vars)
colist<-c("TARGET_FLAG","BLUEBOOK","REVOKED","MVR_PTS","CAR_AGE")

idx <- match(colist, names(train))
trainmod2 <- cbind(train[,idx], train['TARGET_AMT'])

#MODEL 2
model2<-lm(TARGET_AMT ~ ., data=trainmod2)

summary(model2)
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = trainmod2)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -6269   -378    -34    192 101505
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -4.315e+02  1.206e+02  -3.579 0.000347 ***
## TARGET_FLAG1  5.735e+03  1.036e+02  55.334  < 2e-16 ***
## BLUEBOOK      3.010e-02  5.328e-03   5.649 1.67e-08 ***
## REVOKEDYes   -2.874e+02  1.356e+02  -2.120 0.034021 *
## MVR_PTS       1.309e+02  6.101e+01   2.145 0.031986 *
## CAR_AGE      -1.291e+01  8.122e+00  -1.590 0.111894
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3968 on 8155 degrees of freedom
## Multiple R-squared:  0.289,  Adjusted R-squared:  0.2886
## F-statistic: 662.9 on 5 and 8155 DF,  p-value: < 2.2e-16
```

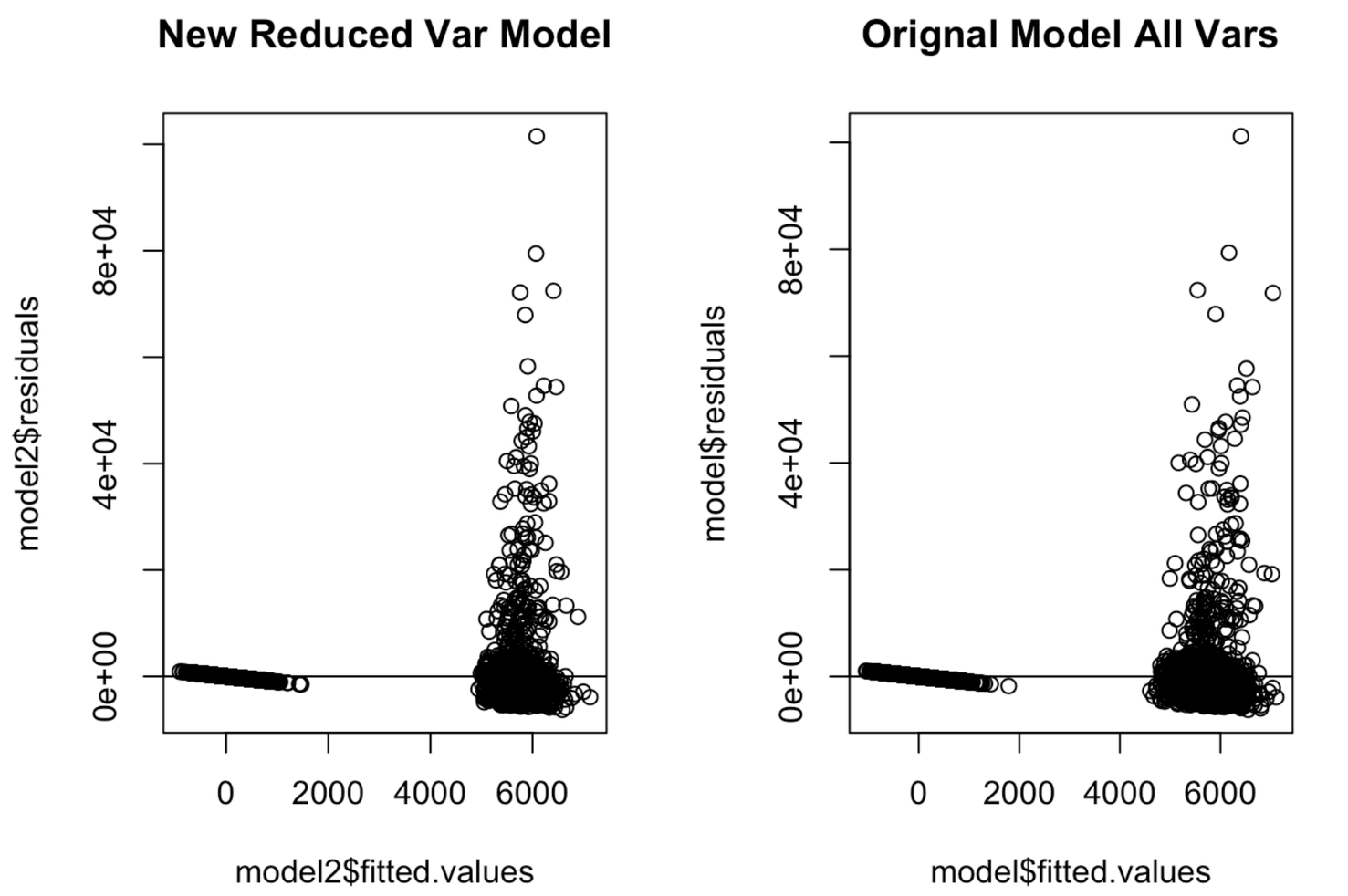
```
par(mfrow=c(2,2))
plot(model2$residuals ~ model2$fitted.values)
plot(model2$fitted.values,train$TARGET_AMT)


par(mfrow=c(2,2))
```




```
plot(model2)
```



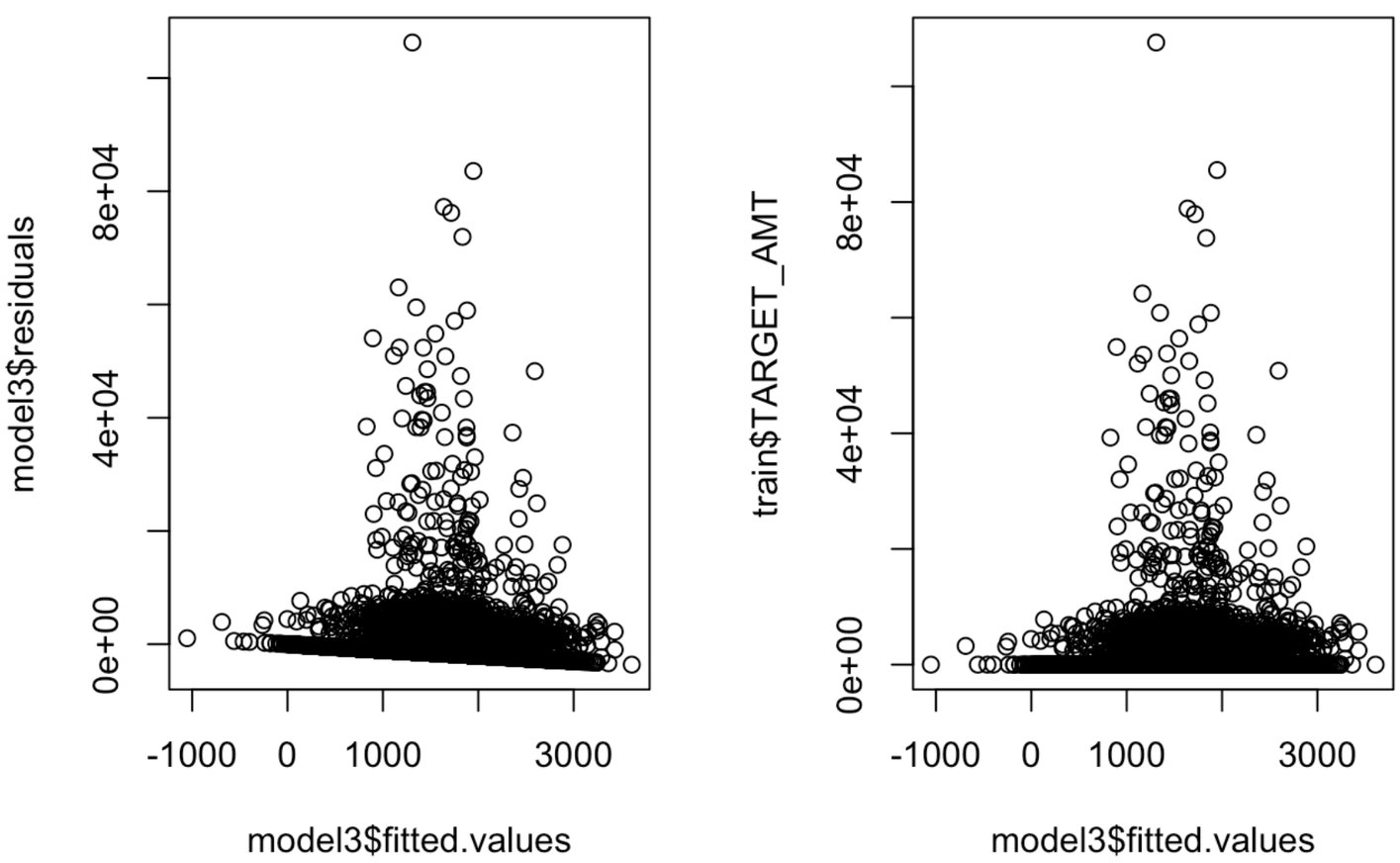

```
par(mfrow=c(1,2))
plot(model2$residuals ~ model2$fitted.values, main="New Reduced Var Model")
abline(h = 0)
plot(model$residuals ~ model$fitted.values, main="Orignal Model All Vars")
abline(h = 0)
```



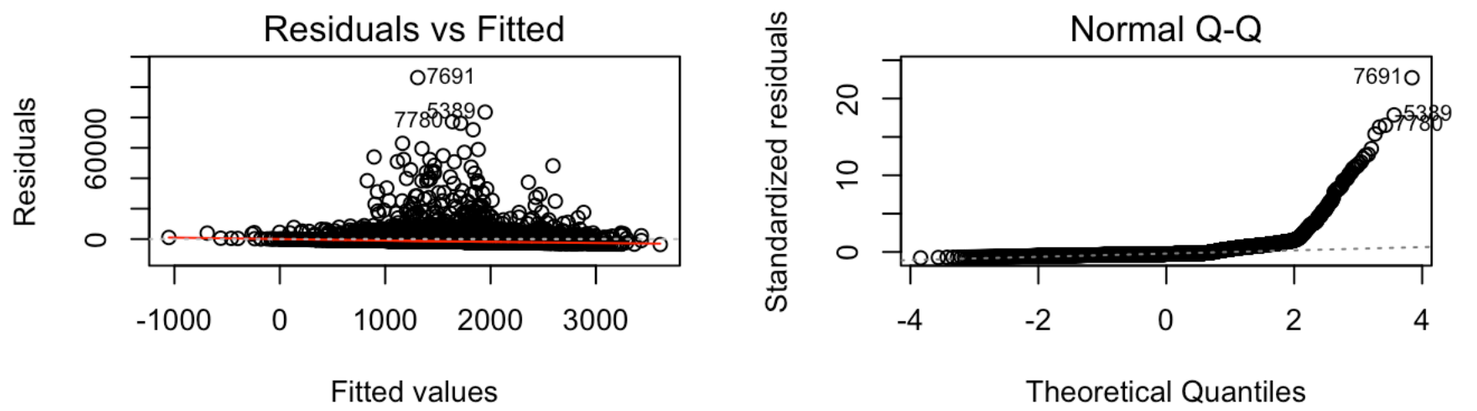

```
#MODEL 3
#remove variables with opposite coefficients

model3<-lm(TARGET_AMT ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME, data=train)
summary(model3)
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + INCOME + HOME_VAL + TRAVTIME,
##     data = train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -3610  -1652  -1239   -318 106277
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.680e+03  1.470e+02  11.426  < 2e-16 ***
## KIDSDRIV     9.172e+02  1.789e+02   5.126 3.03e-07 ***
## INCOME      -1.242e-03  1.336e-03  -0.930   0.3522
## HOME_VAL    -2.809e-03  4.920e-04  -5.710 1.17e-08 ***
## TRAVTIME     7.234e+00  3.260e+00   2.219   0.0265 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4679 on 8156 degrees of freedom
## Multiple R-squared:  0.01096,    Adjusted R-squared:  0.01047
## F-statistic: 22.59 on 4 and 8156 DF,  p-value: < 2.2e-16
```

```
par(mfrow=c(1,2))
plot(model3$residuals ~ model3$fitted.values)
plot(model3$fitted.values,train$TARGET_AMT)
```




```
par(mfrow=c(2,2))
plot(model3)
```



Select Models

```
test = read.csv(file="data/insurance-evaluation-data.csv")
test2<- test
dim(test)
```

```
## [1] 2141   26
```

```
test$TARGET_AMT <- 0
test$TARGET_FLAG <- 0

test = as.tbl(test) %>%
  mutate_at(c("INCOME","HOME_VAL","BLUEBOOK","OLDCLAIM"),
            currencyconv) %>%
  mutate_at(c("EDUCATION","JOB","CAR_TYPE","URBANICITY"),
            underscore) %>%
  mutate_at(c("EDUCATION","JOB","CAR_TYPE","URBANICITY"),
            as.factor) %>%
  mutate(TARGET_FLAG = as.factor(TARGET_FLAG))

# impute data for missing values
# use column mean for calculation

test$HOMEKIDS <- log(test$HOMEKIDS+1)
test$MVR_PTS <- log(test$MVR_PTS+1)
test$OLDCLAIM <- log(test$OLDCLAIM+1)
test$TIF <- log(test$TIF+1)
test$KIDSDRIV <- log(test$KIDSDRIV+1)
test$CLM_FREQ <- log(test$CLM_FREQ+1)

# use column mean for calculation

test$AGE[is.na(test$AGE)] <- mean(test$AGE, na.rm=TRUE)
test$YOJ[is.na(test$YOJ)] <- mean(test$YOJ, na.rm=TRUE)
test$HOME_VAL[is.na(test$HOME_VAL)] <- mean(test$HOME_VAL, na.rm=TRUE)
test$CAR_AGE[is.na(test$CAR_AGE)] <- mean(test$CAR_AGE, na.rm=TRUE)

test$INCOME[is.na(test$INCOME)] <- mean(test$INCOME, na.rm=TRUE)

#get complete cases


#remove rad per correlation in prior section

test <- test[, !(colnames(test) %in% c("INDEX"))]



TARGET_FLAG <- predict(logit, newdata = test, type="response")

y_pred_num <- ifelse(TARGET_FLAG > 0.5, 1, 0)
y_pred <- factor(y_pred_num, levels=c(0, 1))
summary(y_pred)
```

```
##    0    1
## 1776  365
```

```
rbind(round(summary(predlogit),4), round(summary(TARGET_FLAG),4)) %>% kable()
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0024	0.0774	0.2017	0.2638	0.4035	0.9589
0.0031	0.0777	0.2183	0.2708	0.4102	0.9464

```
test$TARGET_FLAG <- as.factor(test$TARGET_FLAG)

test2 <- test[, !(colnames(test) %in% c("TARGET_FLAG"))]
TARGET_AMT<- predict(model, newdata = test, interval='confidence') #data from scaling originally to get to actual wins
summary(TARGET_AMT)
```

```
##       fit                 lwr               upr
##  Min.   :-1206.170   Min.   :-1870.4   Min.   :-542.0
##  1st Qu.: -255.615   1st Qu.: -782.6   1st Qu.: 256.4
##  Median :  -22.708   Median : -538.1   Median : 478.1
##  Mean   :   -8.173   Mean   : -540.5   Mean   : 524.1
##  3rd Qu.:  223.762   3rd Qu.: -303.8   3rd Qu.: 774.3
##  Max.   : 1251.287   Max.   :  521.4   Max.   :1998.7
```

```
summary(model)
```

```
##
## Call:
## lm(formula = TARGET_AMT ~ ., data = train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -6234   -465    -58    243 101178
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -5.975e+02  5.010e+02  -1.193   0.2331
## TARGET_FLAG1                   5.707e+03  1.134e+02  50.329  < 2e-16 ***
## KIDSDRIV                      -2.216e+01  1.781e+02  -0.124   0.9010
## AGE                            6.145e+00  6.271e+00   0.980   0.3272
## HOMEKIDS                       9.215e+01  1.256e+02   0.733   0.4633
## YOJ                            7.685e+00  1.319e+01   0.583   0.5601
## INCOME                        -2.258e-03  1.577e-03  -1.431   0.1524
## PARENT1Yes                     1.209e+02  1.830e+02   0.661   0.5088
## HOME_VAL                       3.864e-04  5.165e-04   0.748   0.4545
## MSTATUSz_No                    1.770e+02  1.282e+02   1.381   0.1673
## SEXz_F                        -2.896e+02  1.606e+02  -1.804   0.0713 .
## EDUCATIONBachelors             6.823e+01  1.790e+02   0.381   0.7031
## EDUCATIONMasters               2.235e+02  2.620e+02   0.853   0.3937
## EDUCATIONPhD                   4.283e+02  3.110e+02   1.377   0.1685
## EDUCATIONz_High_School        -1.243e+02  1.502e+02  -0.828   0.4077
## JOBClerical                   -8.406e+00  2.984e+02  -0.028   0.9775
## JOBDoctor                     -2.812e+02  3.571e+02  -0.788   0.4310
## JOBHome_Maker                 -7.045e+01  3.185e+02  -0.221   0.8249
## JOBLawyer                      7.660e+01  2.582e+02   0.297   0.7667
## JOBManager                    -1.265e+02  2.521e+02  -0.502   0.6158
## JOBProfessional                1.733e+02  2.698e+02   0.642   0.5206
## JOBStudent                    -1.306e+02  3.266e+02  -0.400   0.6892
## JOBz_Blue_Collar               5.187e+01  2.813e+02   0.184   0.8537
## TRAVTIME                       5.682e-01  2.824e+00   0.201   0.8405
## CAR_USEPrivate                -9.993e+01  1.443e+02  -0.693   0.4886
## BLUEBOOK                       2.944e-02  7.536e-03   3.906 9.45e-05 ***
## TIF                           -1.653e+01  6.277e+01  -0.263   0.7922
## CAR_TYPEPanel_Truck           -5.880e+01  2.430e+02  -0.242   0.8088
## CAR_TYPEPickup                -3.318e+01  1.493e+02  -0.222   0.8241
## CAR_TYPESports_Car             2.098e+02  1.910e+02   1.099   0.2720
## CAR_TYPEVan                    9.709e+01  1.865e+02   0.521   0.6026
## CAR_TYPEz_SUV                  1.621e+02  1.571e+02   1.032   0.3021
## RED_CARyes                    -2.696e+01  1.302e+02  -0.207   0.8360
## OLDCLAIM                       4.079e+00  2.908e+01   0.140   0.8884
## CLM_FREQ                      -8.551e+01  2.210e+02  -0.387   0.6989
## REVOKEDYes                    -2.991e+02  1.385e+02  -2.160   0.0308 *
## MVR_PTS                        1.396e+02  6.716e+01   2.079   0.0376 *
## CAR_AGE                       -2.520e+01  1.118e+01  -2.254   0.0242 *
## URBANICITYz_Highly_Rural/ Rural  2.987e+01  1.272e+02   0.235   0.8143
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3970 on 8122 degrees of freedom
## Multiple R-squared:  0.2912, Adjusted R-squared:  0.2879
## F-statistic:  87.8 on 38 and 8122 DF,  p-value: < 2.2e-16
```