Data 621 Group 2 HW 4: Insurance

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Problem Definition

The objective is to build multiple linear regression and binary logistic regression models on the training data to predict the probability that a person will crash their car and also the amount of money it will cost if the person does crash their car.

Dataset Definition

```
##    VARIABLE.NAME                            DEFINITION
## 1          INDEX     Identification Variable (do not use)
## 2    TARGET_FLAG           Was Car in a crash? 1=YES 0=NO
## 3     TARGET_AMT If car was in a crash, what was the cost
## 4            AGE                           Age of Driver
## 5       BLUEBOOK                        Value of Vehicle
## 6        CAR_AGE                             Vehicle Age
## 7       CAR_TYPE                             Type of Car
## 8        CAR_USE                             Vehicle Use
## 9       CLM_FREQ                 # Claims (Past 5 Years)
## 10     EDUCATION                     Max Education Level
## 11      HOMEKIDS                      # Children at Home
## 12      HOME_VAL                              Home Value
## 13        INCOME                                  Income
## 14           JOB                            Job Category
## 15      KIDSDRIV                      # Driving Children
## 16       MSTATUS                          Marital Status
## 17       MVR_PTS               Motor Vehicle Record Points
## 18      OLDCLAIM                 Total Claims (Past 5 Years)
## 19       PARENT1                           Single Parent
## 20       RED_CAR                               A Red Car
## 21       REVOKED             License Revoked (Past 7 Years)
## 22           SEX                                  Gender
## 23           TIF                           Time in Force
## 24      TRAVTIME                        Distance to Work
## 25    URBANICITY                         Home/Work Area
## 26           YOJ                            Years on Job
##                                                                                  THEORETICAL.EFFECT
## 1                                                                                              None
## 2                                                                                              None
## 3                                                                                              None
## 4                                         Very young people tend to be risky. Maybe very old people also.
## 5      Unknown effect on probability of collision, but probably effect the payout if there is a crash
## 6      Unknown effect on probability of collision, but probably effect the payout if there is a crash
## 7      Unknown effect on probability of collision, but probably effect the payout if there is a crash
## 8                   Commercial vehicles are driven more, so might increase probability of collision
## 9             The more claims you filed in the past, the more you are likely to file in the future
## 10                  Unknown effect, but in theory more educated people tend to drive more safely
## 11                                                                                   Unknown effect
```

```
## 12                                             In theory, home owners tend to drive more responsibly
## 13                                             In theory, rich people tend to get into fewer crashes
## 14                                                     In theory, white collar jobs tend to be safer
## 15                           When teenagers drive your car, you are more likely to get into crashes
## 16                                                       In theory, married people drive more safely
## 17                            If you get lots of traffic tickets, you tend to get into more crashes
## 18 If your total payout over the past five years was high, this suggests future payouts will be high
## 19                                                                                    Unknown effect
## 20       Urban legend says that red cars (especially red sports cars) are more risky. Is that true?
## 21           If your license was revoked in the past 7 years, you probably are a more risky driver.
## 22                           Urban legend says that women have less crashes then men. Is that true?
## 23                            People who have been customers for a long time are usually more safe.
## 24                                                  Long drives to work usually suggest greater risk
## 25                                                                                           Unknown
## 26                                   People who stay at a job for a long time are usually more safe
```

DATA EXPLORATION

Let's start with a glimpse of the data

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

And, here's the summary for all the variables in the dataset:

```
##   TARGET_FLAG     TARGET_AMT        KIDSDRIV         AGE        HOMEKIDS
##  Min.   :0.00   Min.   :     0   Min.   :0.0   Min.   :16   Min.   :0.0
##  1st Qu.:0.00   1st Qu.:     0   1st Qu.:0.0   1st Qu.:39   1st Qu.:0.0
##  Median :0.00   Median :     0   Median :0.0   Median :45   Median :0.0
##  Mean   :0.26   Mean   :  1504   Mean   :0.2   Mean   :45   Mean   :0.7
```

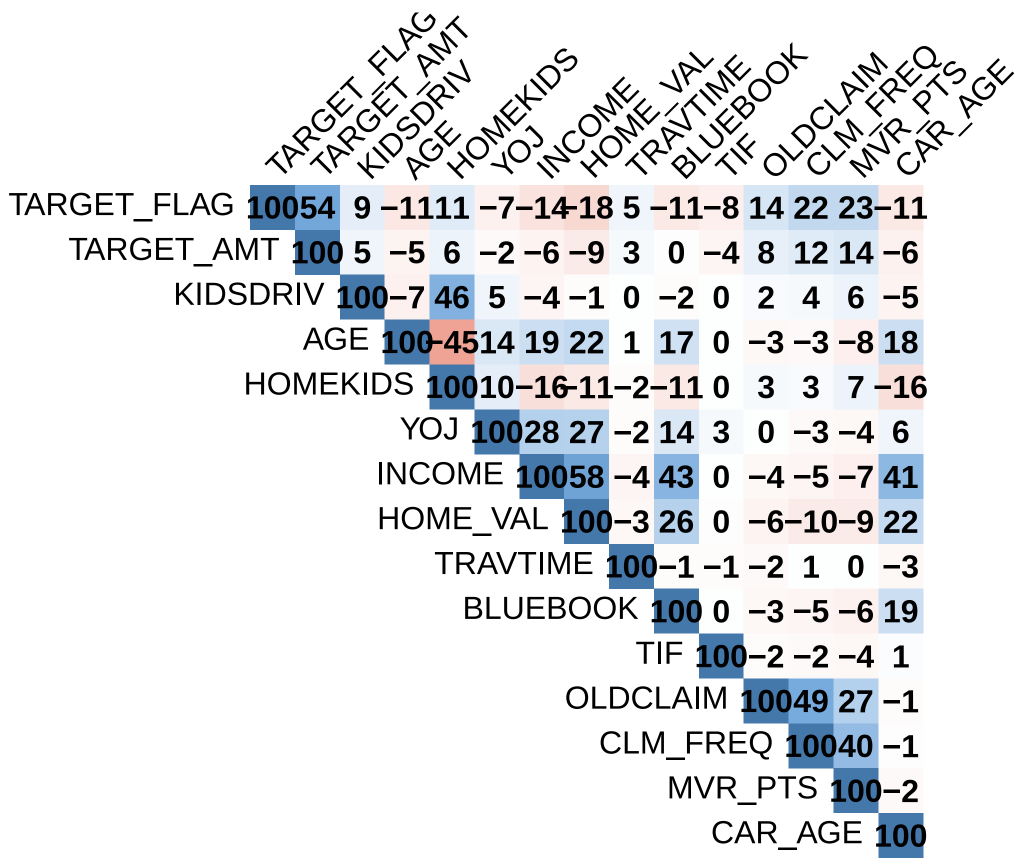
```
##  3rd Qu.:1.00   3rd Qu.:  1036   3rd Qu.:0.0   3rd Qu.:51   3rd Qu.:1.0
##  Max.   :1.00   Max.   :107586   Max.   :4.0   Max.   :81   Max.   :5.0
##                                                NA's   :6
##       YOJ           INCOME      PARENT1        HOME_VAL     MSTATUS
##  Min.   : 0    $0      : 615   No :7084   $0      :2294   Yes :4894
##  1st Qu.: 9            : 445   Yes:1077           : 464   z_No:3267
##  Median :11    $26,840 :   4              $111,129:   3
##  Mean   :10    $48,509 :   4              $115,249:   3
##  3rd Qu.:13    $61,790 :   4              $123,109:   3
##  Max.   :23    $107,375:   3              $153,061:   3
##  NA's   :454   (Other) :7086              (Other) :5391
##   SEX              EDUCATION               JOB          TRAVTIME
##  M  :3786   <High School :1203   z_Blue Collar:1825   Min.   :  5
##  z_F:4375   Bachelors    :2242   Clerical     :1271   1st Qu.: 22
##             Masters      :1658   Professional :1117   Median : 33
##             PhD          : 728   Manager      : 988   Mean   : 33
##             z_High School:2330   Lawyer       : 835   3rd Qu.: 44
##                                  Student      : 712   Max.   :142
##                                  (Other)      :1413
##        CAR_USE        BLUEBOOK         TIF             CAR_TYPE
##  Commercial:3029   $1,500 : 157   Min.   : 1.0   Minivan    :2145
##  Private   :5132   $6,000 :  34   1st Qu.: 1.0   Panel Truck: 676
##                    $5,800 :  33   Median : 4.0   Pickup     :1389
##                    $6,200 :  33   Mean   : 5.4   Sports Car : 907
##                    $6,400 :  31   3rd Qu.: 7.0   Van        : 750
##                    $5,900 :  30   Max.   :25.0   z_SUV      :2294
##                    (Other):7843
##  RED_CAR       OLDCLAIM       CLM_FREQ    REVOKED       MVR_PTS
##  no :5783   $0     :5009   Min.   :0.0   No :7161   Min.   : 0.0
##  yes:2378   $1,310 :   4   1st Qu.:0.0   Yes:1000   1st Qu.: 0.0
##             $1,391 :   4   Median :0.0              Median : 1.0
##             $4,263 :   4   Mean   :0.8              Mean   : 1.7
##             $1,105 :   3   3rd Qu.:2.0              3rd Qu.: 3.0
##             $1,332 :   3   Max.   :5.0              Max.   :13.0
##             (Other):3134
##     CAR_AGE                    URBANICITY
##  Min.   :-3    Highly Urban/ Urban  :6492
##  1st Qu.: 1    z_Highly Rural/ Rural:1669
##  Median : 8
##  Mean   : 8
##  3rd Qu.:12
##  Max.   :28
##  NA's   :510
```

The summary on the data identifies the following variables with missing values (and counts)
1. AGE (6)
2. YOJ (454)
3. INCOME (445)
4. HOME_VAL (464)
5. CAR_AGE (510)

Also, based on the summary and the ranges for `Min` and `Max`, the data seems to be pretty clean and valid with no invalid outliers (except for some negative values in `CAR_AGE`). The currency data for variables, `INCOME`, `HOME_VAL`, `BLUEBOOK`, `OLDCLAIM`, got loaded as factors instead of numeric and therefore needs to be *"fixed"*. After the conversion to numeric values, the summary for these variables, below, also shows that the data seems valid, having appropriate ranges.

```
##      INCOME          HOME_VAL         BLUEBOOK        OLDCLAIM
##  Min.   :     0   Min.   :     0   Min.   : 1500   Min.   :    0
##  1st Qu.: 28097   1st Qu.:     0   1st Qu.: 9280   1st Qu.:    0
##  Median : 54028   Median :161160   Median :14440   Median :    0
##  Mean   : 61898   Mean   :154867   Mean   :15710   Mean   : 4037
##  3rd Qu.: 85986   3rd Qu.:238724   3rd Qu.:20850   3rd Qu.: 4636
##  Max.   :367030   Max.   :885282   Max.   :69740   Max.   :57037
##  NA's   :445      NA's   :464
```

Now let's see how numerical data is correlated to the target variables and to each other, based on the chart below.



Based on the chart, there are some cases with significant percentage of correlation. However such parings of correlated values are expected. For example, `KIDSDRIV` is expected to be correlated to `HOMEKIDS` and high `INCOME` would correlate with higher values of `HOME_VAL` and `BLUEBOOK`. Such correlation may not be addressed right away as we still need to prepare and possibly transform the data. Also, some of the correlated values may fall off during model selection.

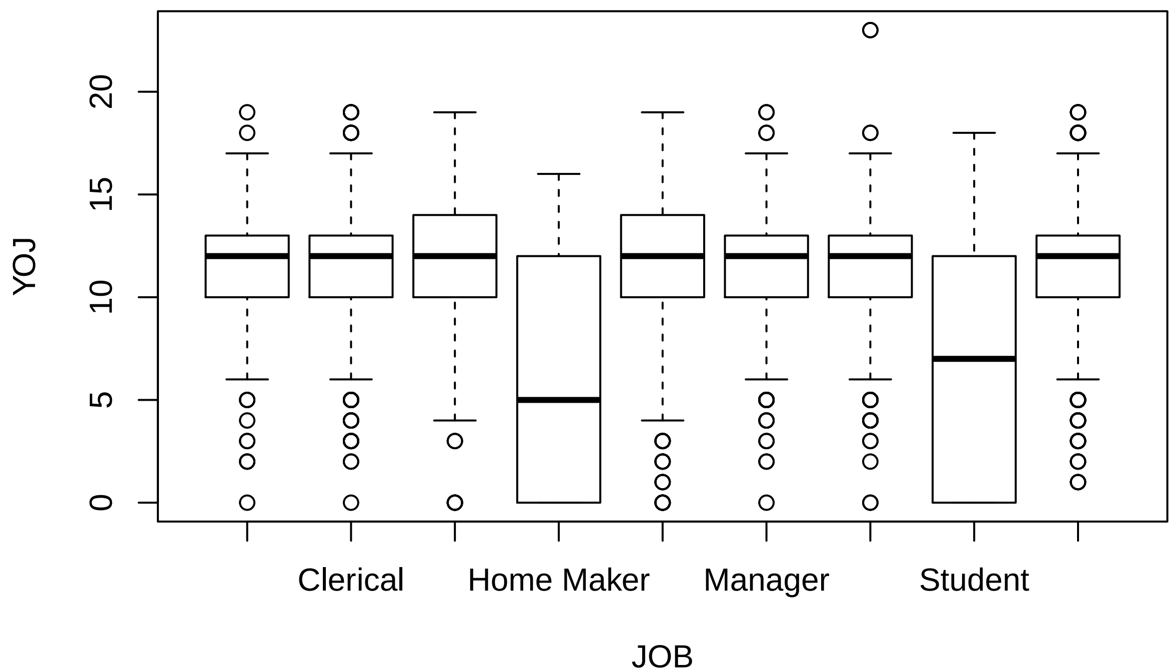
DATA PREPARATION

`AGE` Variable

Assigning a medium age would be appropriate given that there are only 6 records with missing values. Also those records either indicate having kids at home and/or being married and so assigning median age of 45 would seem reasonable.

`YOJ` (Years on Job) Variable

For the `YOJ` variable it would make sense to see how it is distributed accross different job types. Below the `boxplot` and aggregation table, against the `JOB` variable, show that the median values may be drastically different among different jobs. Therefore, assigning median values per job type rather than just the single, overall median value would be more appropriate.



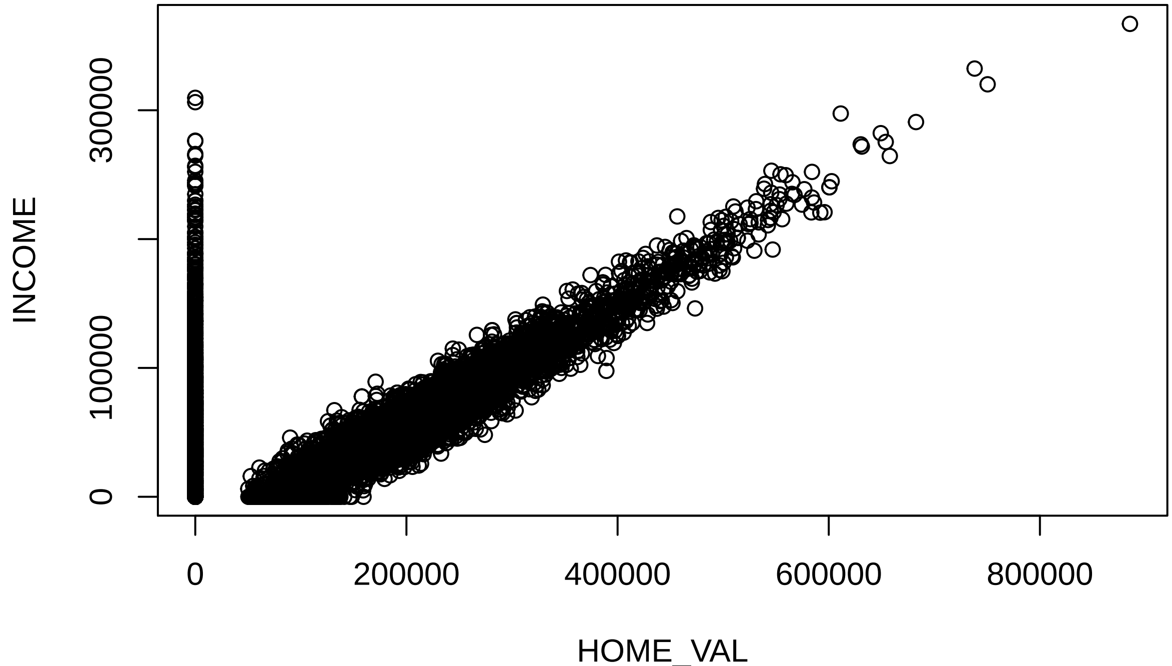

```
##             JOB YOJ
## 1                12
## 2      Clerical  12
## 3        Doctor  12
## 4    Home Maker   5
## 5        Lawyer  12
## 6       Manager  12
## 7  Professional  12
## 8       Student   7
## 9 z_Blue Collar  12
```

`CAR_AGE` Variable

Car age has some invalid negative values. We can assign them to `NA` and then deal with them as missing values. To deal with missing values of `CAR_AGE`, it may be a good idea to find a correlation with `BLUEBOOK` value and derive approximate values for the age. However, for this we would require knowing the make and model of the cars. Given that this information is not available to us and that it is considerable number of rows with the missing values, it may be best to simply asign median age.

`INCOME` and `HOME_VAL` Variables

Both the `INCOME` and the `HOME_VAL` variables have missing values. However there are only 33 instances where both variables jointly are missing values. Otherwise, individually, these variables have over 400 missing values. It would be no surprise, however, that the two variables are positively correlated, because the higher the income, the more expesive a home value can be expected. The plot below does show this correlation indeed.



Given such correlation, it may be possible to come up with an impute strategy where the two variables can help each other. We will be making an assumption here that the `HOME_VAL` variable with value of 0 is considered to indicate that someone is not a home owner. Therefore, we can design to execute the following strategy for imputing these two variables:
1. For the 33 instances where both are missing, randomly assign a value to `HOME_VAL` variable choosing between 0 and median home value.
2. Build a simple linear model to predict income values based on the home value (i.e. where home value > 0). Any predicted negative amounts should be changed to 0.
3. Use median income for the remaining missing income values.
4. Finally, to avoid having two highly correlated variables, replace `HOME_VAL` variable with a new variable called, `HOME_OWN`, by transforming the `HOME_VAL` variable to a 0 or 1 binary indicator (0=*not a home owner*). Any missing values are to be randomly assigned to 0 or 1.

Before moving on, it would also make sense to create a new variable, `INCOME_CLASS`, by transforming the `INCOME` variable from being a continuous numeric variable into a categorical 3 level **(LOW, MID, HIGH)** variable. Using `INCOME` variable with exact numerical values, would not make sense as a predictor for the kind of responses we want to predict. Also, it would help us to deal with cases where income is entered as 0 value.

To create the 3 category levels, we used Inter-Quartile ranges, where below 25% would rank as `LOW`, above 75% would rank as `HIGH` and the rest is `MID`.

Before, moving on to building models, let's take the final look and validate the summary of the data. Note, that `INCOME` and `HOME_VAL` were replaced by `INCOME_CLASS` and `HOME_OWN` variables, respectively.

```
##   TARGET_FLAG      TARGET_AMT         KIDSDRIV          AGE          HOMEKIDS
```

```
##  Min.   :0.00   Min.   :     0   Min.   :0.0   Min.   :16   Min.   :0.0
##  1st Qu.:0.00   1st Qu.:     0   1st Qu.:0.0   1st Qu.:39   1st Qu.:0.0
##  Median :0.00   Median :     0   Median :0.0   Median :45   Median :0.0
##  Mean   :0.26   Mean   :  1504   Mean   :0.2   Mean   :45   Mean   :0.7
##  3rd Qu.:1.00   3rd Qu.:  1036   3rd Qu.:0.0   3rd Qu.:51   3rd Qu.:1.0
##  Max.   :1.00   Max.   :107586   Max.   :4.0   Max.   :81   Max.   :5.0
##
##       YOJ       PARENT1    MSTATUS      SEX              EDUCATION
##  Min.   : 0.0   No :7084   Yes :4894   M  :3786   <High School :1203
##  1st Qu.: 9.0   Yes:1077   z_No:3267   z_F:4375   Bachelors    :2242
##  Median :12.0                                     Masters      :1658
##  Mean   :10.5                                     PhD          : 728
##  3rd Qu.:13.0                                     z_High School:2330
##  Max.   :23.0
##
##             JOB          TRAVTIME         CAR_USE        BLUEBOOK
##  z_Blue Collar:1825   Min.   :  5   Commercial:3029   Min.   : 1500
##  Clerical     :1271   1st Qu.: 22   Private   :5132   1st Qu.: 9280
##  Professional :1117   Median : 33                     Median :14440
##  Manager      : 988   Mean   : 33                     Mean   :15710
##  Lawyer       : 835   3rd Qu.: 44                     3rd Qu.:20850
##  Student      : 712   Max.   :142                     Max.   :69740
##  (Other)      :1413
##       TIF               CAR_TYPE    RED_CAR       OLDCLAIM
##  Min.   : 1.0   Minivan    :2145   no :5783   Min.   :    0
##  1st Qu.: 1.0   Panel Truck: 676   yes:2378   1st Qu.:    0
##  Median : 4.0   Pickup     :1389              Median :    0
##  Mean   : 5.4   Sports Car : 907              Mean   : 4037
##  3rd Qu.: 7.0   Van        : 750              3rd Qu.: 4636
##  Max.   :25.0   z_SUV      :2294              Max.   :57037
##
##     CLM_FREQ   REVOKED       MVR_PTS        CAR_AGE
##  Min.   :0.0   No :7161   Min.   : 0.0   Min.   : 0.0
##  1st Qu.:0.0   Yes:1000   1st Qu.: 0.0   1st Qu.: 4.0
##  Median :0.0              Median : 1.0   Median : 8.0
##  Mean   :0.8              Mean   : 1.7   Mean   : 8.3
##  3rd Qu.:2.0              3rd Qu.: 3.0   3rd Qu.:12.0
##  Max.   :5.0              Max.   :13.0   Max.   :28.0
##
##                  URBANICITY      HOME_OWN     INCOME_CLASS
##  Highly Urban/ Urban  :6492   Min.   :0.00   HIGH:2040
##  z_Highly Rural/ Rural:1669   1st Qu.:0.00   LOW :2040
##                               Median :1.00   MID :4081
##                               Mean   :0.69
##                               3rd Qu.:1.00
##                               Max.   :1.00
##
```

BUILD MODELS

To model prediction of the quantitative variable, `TARGET_AMT`, we started off with a simple linear model including all the variables. Progressing with stepwise, backward elimination, we arrived at our first model with reduced set of variables which are statistically significant. Here's the summary of this `LM` model.

```
##
```

```
## Call:
## lm(formula = TARGET_AMT ~ . - TARGET_FLAG - RED_CAR - YOJ - AGE -
##     HOMEKIDS - EDUCATION - HOME_OWN - OLDCLAIM - BLUEBOOK - SEX,
##     data = m1.data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -5763  -1697   -756    341 103683
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        701.99     340.69    2.06  0.03938 *
## KIDSDRIV                           376.06     102.08    3.68  0.00023 ***
## PARENT1Yes                         639.02     176.51    3.62  0.00030 ***
## MSTATUSz_No                        596.81     119.32    5.00  5.8e-07 ***
## JOBClerical                        387.52     290.98    1.33  0.18298
## JOBDoctor                         -322.84     376.10   -0.86  0.39070
## JOBHome Maker                      275.73     335.53    0.82  0.41122
## JOBLawyer                          202.46     286.09    0.71  0.47915
## JOBManager                        -647.04     266.98   -2.42  0.01539 *
## JOBProfessional                    196.57     266.23    0.74  0.46031
## JOBStudent                         303.66     329.97    0.92  0.35746
## JOBz_Blue Collar                   326.47     266.05    1.23  0.21983
## TRAVTIME                            11.95       3.22    3.71  0.00021 ***
## CAR_USEPrivate                    -729.91     156.98   -4.65  3.4e-06 ***
## TIF                                -46.91      12.17   -3.85  0.00012 ***
## CAR_TYPEPanel Truck                565.05     243.07    2.32  0.02012 *
## CAR_TYPEPickup                     382.00     168.03    2.27  0.02303 *
## CAR_TYPESports Car                 775.83     182.90    4.24  2.2e-05 ***
## CAR_TYPEVan                        671.03     204.20    3.29  0.00102 **
## CAR_TYPEz_SUV                      509.08     138.86    3.67  0.00025 ***
## CLM_FREQ                           106.91      48.83    2.19  0.02858 *
## REVOKEDYes                         447.98     154.91    2.89  0.00384 **
## MVR_PTS                            172.16      25.80    6.67  2.7e-11 ***
## CAR_AGE                            -28.16      11.23   -2.51  0.01220 *
## URBANICITYz_Highly Rural/ Rural -1659.46     139.33  -11.91  < 2e-16 ***
## INCOME_CLASSLOW                    460.24     206.89    2.22  0.02614 *
## INCOME_CLASSMID                    413.54     139.27    2.97  0.00299 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4550 on 8134 degrees of freedom
## Multiple R-squared:  0.0693, Adjusted R-squared:  0.0663
## F-statistic: 23.3 on 26 and 8134 DF,  p-value: <2e-16
```

Following similar progression for predicting the binary outcome of the `TARGET_FLAG` variable, here's the summary of the binomial logistic regression model.

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT - RED_CAR - CAR_AGE -
##     AGE - SEX - YOJ - HOMEKIDS, family = "binomial", data = m1.data)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
```

```
## -2.653  -0.713  -0.399   0.620   3.122
##
## Coefficients:
##                                    Estimate  Std. Error z value Pr(>|z|)
## (Intercept)                     -1.64388176  0.27108699   -6.06  1.3e-09
## KIDSDRIV                         0.42047088  0.05512343    7.63  2.4e-14
## PARENT1Yes                       0.46849335  0.09458862    4.95  7.3e-07
## MSTATUSz_No                      0.45490974  0.08124354    5.60  2.2e-08
## EDUCATIONBachelors              -0.39075897  0.11086616   -3.52  0.00042
## EDUCATIONMasters                -0.29321537  0.16266967   -1.80  0.07146
## EDUCATIONPhD                    -0.25113320  0.19727451   -1.27  0.20301
## EDUCATIONz_High School           0.01134349  0.09703778    0.12  0.90694
## JOBClerical                      0.44380935  0.19575939    2.27  0.02338
## JOBDoctor                       -0.37605077  0.26521918   -1.42  0.15622
## JOBHome Maker                    0.35293999  0.20742628    1.70  0.08885
## JOBLawyer                        0.12048069  0.16900535    0.71  0.47592
## JOBManager                      -0.54455136  0.17089932   -3.19  0.00144
## JOBProfessional                  0.17614403  0.17811604    0.99  0.32270
## JOBStudent                       0.25156675  0.21736104    1.16  0.24712
## JOBz_Blue Collar                 0.33188709  0.18516868    1.79  0.07308
## TRAVTIME                         0.01449743  0.00188336    7.70  1.4e-14
## CAR_USEPrivate                  -0.76146222  0.09177385   -8.30  < 2e-16
## BLUEBOOK                        -0.00002345  0.00000469   -5.00  5.8e-07
## TIF                             -0.05506541  0.00734992   -7.49  6.8e-14
## CAR_TYPEPanel Truck              0.59093603  0.15104960    3.91  9.1e-05
## CAR_TYPEPickup                   0.55243910  0.10073318    5.48  4.2e-08
## CAR_TYPESports Car               0.96777800  0.10757655    9.00  < 2e-16
## CAR_TYPEVan                      0.65732099  0.12227714    5.38  7.6e-08
## CAR_TYPEz_SUV                    0.70455030  0.08612020    8.18  2.8e-16
## OLDCLAIM                        -0.00001400  0.00000391   -3.58  0.00034
## CLM_FREQ                         0.19534957  0.02853821    6.85  7.6e-12
## REVOKEDYes                       0.89386562  0.09128901    9.79  < 2e-16
## MVR_PTS                          0.11310570  0.01360641    8.31  < 2e-16
## URBANICITYz_Highly Rural/ Rural -2.40270092  0.11304749  -21.25  < 2e-16
## HOME_OWN                        -0.31291914  0.07990033   -3.92  9.0e-05
## INCOME_CLASSLOW                  0.64073955  0.12659663    5.06  4.2e-07
## INCOME_CLASSMID                  0.45398756  0.08836191    5.14  2.8e-07
##
## (Intercept)                     ***
## KIDSDRIV                        ***
## PARENT1Yes                      ***
## MSTATUSz_No                     ***
## EDUCATIONBachelors              ***
## EDUCATIONMasters                .
## EDUCATIONPhD
## EDUCATIONz_High School
## JOBClerical                     *
## JOBDoctor
## JOBHome Maker                   .
## JOBLawyer
## JOBManager                      **
## JOBProfessional
## JOBStudent
## JOBz_Blue Collar                .
```

```
## TRAVTIME                          ***
## CAR_USEPrivate                    ***
## BLUEBOOK                          ***
## TIF                               ***
## CAR_TYPEPanel Truck               ***
## CAR_TYPEPickup                    ***
## CAR_TYPESports Car                ***
## CAR_TYPEVan                       ***
## CAR_TYPEz_SUV                     ***
## OLDCLAIM                          ***
## CLM_FREQ                          ***
## REVOKEDYes                        ***
## MVR_PTS                           ***
## URBANICITYz_Highly Rural/ Rural ***
## HOME_OWN                          ***
## INCOME_CLASSLOW                   ***
## INCOME_CLASSMID                   ***
## ---
## 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: 7292.6  on 8128  degrees of freedom
## AIC: 7359
##
## Number of Fisher Scoring iterations: 5
```

We'd like to see if we can possibly enhance and build additional models. Looking at both models, it appears that having a job as a Manager has the most statistical signfinicanse for our predictions. In both cases, the coefficients are negative, which seems to suggest that if you're a manager, then you're more likely to be a more responsible and a less risky driver. This made for an unanticipated, but a reasonable discovery, nevertheless. So, it may be a good idea to simplify the `JOB` predictor into a binary category of "Not Manager" and "Manager".

This resulted in `LM` [`TARGET_AMT`] model, where all the remaing variables are being significant as shown in the summary below.

```
##
## Call:
## lm(formula = TARGET_AMT ~ KIDSDRIV + PARENT1 + MSTATUS + JOB +
##     TRAVTIME + CAR_USE + TIF + CAR_TYPE + CLM_FREQ + REVOKED +
##     MVR_PTS + CAR_AGE + URBANICITY + INCOME_CLASS, data = m2.data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -5737  -1705   -763    346 103586
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        954.56     244.44    3.91  9.5e-05 ***
## KIDSDRIV                           382.80     101.97    3.75  0.00018 ***
## PARENT1Yes                         662.28     175.92    3.76  0.00017 ***
## MSTATUSz_No                        580.94     119.01    4.88  1.1e-06 ***
## JOBManager                        -836.38     161.65   -5.17  2.3e-07 ***
```

```
## TRAVTIME                         12.09      3.22    3.76  0.00017 ***
## CAR_USEPrivate                 -767.31    127.11   -6.04  1.6e-09 ***
## TIF                             -46.57     12.16   -3.83  0.00013 ***
## CAR_TYPEPanel Truck             495.98    226.91    2.19  0.02886 *
## CAR_TYPEPickup                  359.65    165.09    2.18  0.02940 *
## CAR_TYPESports Car              770.42    181.77    4.24  2.3e-05 ***
## CAR_TYPEVan                     635.81    200.32    3.17  0.00151 **
## CAR_TYPEz_SUV                   505.31    137.87    3.67  0.00025 ***
## CLM_FREQ                        106.01     48.78    2.17  0.02981 *
## REVOKEDYes                      455.72    154.77    2.94  0.00324 **
## MVR_PTS                         172.80     25.78    6.70  2.2e-11 ***
## CAR_AGE                         -35.43     10.00   -3.54  0.00040 ***
## URBANICITYz_Highly Rural/ Rural -1618.30    136.98  -11.81  < 2e-16 ***
## INCOME_CLASSLOW                 577.11    162.44    3.55  0.00038 ***
## INCOME_CLASSMID                 503.20    132.03    3.81  0.00014 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4540 on 8141 degrees of freedom
## Multiple R-squared:  0.0687, Adjusted R-squared:  0.0666
## F-statistic: 31.6 on 19 and 8141 DF,  p-value: <2e-16
```

When applied to the binomial model, the newly transformed `JOB` variable resulted in higher significance for the `EDUCATION` variable for levels higher than "High School". Here's the summary of the model illustrating this point.

```
##
## Call:
## glm(formula = TARGET_FLAG ~ . - TARGET_AMT - RED_CAR - CAR_AGE -
##     AGE - SEX - YOJ - HOMEKIDS, family = "binomial", data = m2.data)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.628  -0.716  -0.404   0.627   3.086
##
## Coefficients:
##                                 Estimate  Std. Error z value Pr(>|z|)
## (Intercept)                   -1.36203781  0.19497870   -6.99  2.8e-12
## KIDSDRIV                       0.42353521  0.05505973    7.69  1.4e-14
## PARENT1Yes                     0.47752810  0.09426868    5.07  4.1e-07
## MSTATUSz_No                    0.46534287  0.07911482    5.88  4.1e-09
## EDUCATIONBachelors            -0.46401538  0.10037063   -4.62  3.8e-06
## EDUCATIONMasters              -0.50377477  0.11044375   -4.56  5.1e-06
## EDUCATIONPhD                  -0.60660549  0.14451783   -4.20  2.7e-05
## EDUCATIONz_High School        -0.01472772  0.09345119   -0.16  0.87477
## JOBManager                    -0.73996857  0.10688555   -6.92  4.4e-12
## TRAVTIME                       0.01457661  0.00188068    7.75  9.1e-15
## CAR_USEPrivate                -0.77136605  0.07419175  -10.40  < 2e-16
## BLUEBOOK                      -0.00002328  0.00000467   -4.99  6.2e-07
## TIF                           -0.05458259  0.00733851   -7.44  1.0e-13
## CAR_TYPEPanel Truck            0.56639337  0.14358965    3.94  8.0e-05
## CAR_TYPEPickup                 0.54408026  0.09862463    5.52  3.5e-08
## CAR_TYPESports Car             0.97487941  0.10657827    9.15  < 2e-16
## CAR_TYPEVan                    0.64463003  0.11991647    5.38  7.6e-08
## CAR_TYPEz_SUV                  0.71046634  0.08539649    8.32  < 2e-16
```

```
## OLDCLAIM                         -0.00001384  0.00000391   -3.54  0.00040
## CLM_FREQ                          0.19475093  0.02848108    6.84  8.0e-12
## REVOKEDYes                        0.89277669  0.09117292    9.79  < 2e-16
## MVR_PTS                           0.11282457  0.01357618    8.31  < 2e-16
## URBANICITYz_Highly Rural/ Rural -2.38695129  0.11288009  -21.15  < 2e-16
## HOME_OWN                         -0.27951415  0.07376091   -3.79  0.00015
## INCOME_CLASSLOW                   0.70120636  0.10765310    6.51  7.3e-11
## INCOME_CLASSMID                   0.48731993  0.08756661    5.57  2.6e-08
##
## (Intercept)                     ***
## KIDSDRIV                        ***
## PARENT1Yes                      ***
## MSTATUSz_No                     ***
## EDUCATIONBachelors              ***
## EDUCATIONMasters                ***
## EDUCATIONPhD                    ***
## EDUCATIONz_High School
## JOBManager                      ***
## TRAVTIME                        ***
## CAR_USEPrivate                  ***
## BLUEBOOK                        ***
## TIF                             ***
## CAR_TYPEPanel Truck             ***
## CAR_TYPEPickup                  ***
## CAR_TYPESports Car              ***
## CAR_TYPEVan                     ***
## CAR_TYPEz_SUV                   ***
## OLDCLAIM                        ***
## CLM_FREQ                        ***
## REVOKEDYes                      ***
## MVR_PTS                         ***
## URBANICITYz_Highly Rural/ Rural ***
## HOME_OWN                        ***
## INCOME_CLASSLOW                 ***
## INCOME_CLASSMID                 ***
## ---
## 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: 7304.8  on 8135  degrees of freedom
## AIC: 7357
##
## Number of Fisher Scoring iterations: 5
```

Interestingly, and is likely to be expected, the higher the education level, the more negative the coefficients' trend is. This again suggests that more educated people tend to be less likely to end up with a car accident. Therefore, similar to how we transformed the `JOB` variable, it made sense to transform `EDUCATION` to just two values, "Lower" and "Higher" ("Higher" standing for Bachelors and above). And again we ended up with a model where all the remaing variables ended up being significant.

```
##
## Call:
## glm(formula = TARGET_FLAG ~ KIDSDRIV + PARENT1 + MSTATUS + EDUCATION +
```

```
##     JOB + TRAVTIME + CAR_USE + BLUEBOOK + TIF + CAR_TYPE + OLDCLAIM +
##     CLM_FREQ + REVOKED + MVR_PTS + URBANICITY + HOME_OWN + INCOME_CLASS,
##     family = "binomial", data = m2.data)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.628  -0.715  -0.403   0.624   3.093
##
## Coefficients:
##                                   Estimate  Std. Error z value Pr(>|z|)
## (Intercept)                    -1.39365183  0.17802928   -7.83  4.9e-15
## KIDSDRIV                        0.42489689  0.05505366    7.72  1.2e-14
## PARENT1Yes                      0.48481026  0.09399290    5.16  2.5e-07
## MSTATUSz_No                     0.46352806  0.07908214    5.86  4.6e-09
## EDUCATIONHigher                -0.47796109  0.06734712   -7.10  1.3e-12
## JOBManager                     -0.73632334  0.10652564   -6.91  4.8e-12
## TRAVTIME                        0.01464420  0.00187958    7.79  6.6e-15
## CAR_USEPrivate                 -0.77890540  0.07082992  -11.00  < 2e-16
## BLUEBOOK                       -0.00002358  0.00000466   -5.06  4.1e-07
## TIF                            -0.05462146  0.00733775   -7.44  9.8e-14
## CAR_TYPEPanel Truck             0.55706558  0.14206518    3.92  8.8e-05
## CAR_TYPEPickup                  0.53876300  0.09799882    5.50  3.8e-08
## CAR_TYPESports Car              0.97162796  0.10650276    9.12  < 2e-16
## CAR_TYPEVan                     0.64102054  0.11938629    5.37  7.9e-08
## CAR_TYPEz_SUV                   0.70870257  0.08533342    8.31  < 2e-16
## OLDCLAIM                       -0.00001377  0.00000390   -3.53  0.00042
## CLM_FREQ                        0.19403670  0.02845286    6.82  9.1e-12
## REVOKEDYes                      0.89291768  0.09114237    9.80  < 2e-16
## MVR_PTS                         0.11291398  0.01357383    8.32  < 2e-16
## URBANICITYz_Highly Rural/ Rural -2.38486200  0.11289515  -21.12  < 2e-16
## HOME_OWN                       -0.27655442  0.07370860   -3.75  0.00018
## INCOME_CLASSLOW                 0.73071213  0.10376338    7.04  1.9e-12
## INCOME_CLASSMID                 0.51565503  0.08365183    6.16  7.1e-10
##
## (Intercept)                    ***
## KIDSDRIV                       ***
## PARENT1Yes                     ***
## MSTATUSz_No                    ***
## EDUCATIONHigher                ***
## JOBManager                     ***
## TRAVTIME                       ***
## CAR_USEPrivate                 ***
## BLUEBOOK                       ***
## TIF                            ***
## CAR_TYPEPanel Truck            ***
## CAR_TYPEPickup                 ***
## CAR_TYPESports Car             ***
## CAR_TYPEVan                    ***
## CAR_TYPEz_SUV                  ***
## OLDCLAIM                       ***
## CLM_FREQ                       ***
## REVOKEDYes                     ***
## MVR_PTS                        ***
## URBANICITYz_Highly Rural/ Rural ***
```

```
## HOME_OWN                        ***
## INCOME_CLASSLOW                 ***
## INCOME_CLASSMID                 ***
## ---
## 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: 7306.1  on 8138  degrees of freedom
## AIC: 7352
##
## Number of Fisher Scoring iterations: 5
```

SELECT MODELS

For both types of models (linear and logistic), the selection came down to the last versions of the models generated after all of the variable reductions and tranformations took place. In case of `LM` model the *Adjusted R-squared* value was slightly improved in the latest model. The bottom line is that the selection was mainly due to favoring more of a simpler model, with less variables, rather than due to statistical evaluations as those were very similar between the model versions.

APPENDIX - R statistical programming code

```r
library(knitr)
library(kableExtra)
library(plyr)
library(tidyverse)
library(corrplot)
library(reshape2)
library(ggplot2)

# Load dataset definition
url <- 'insurance_dataset_definition.csv'
ds <- read.csv(url, header = TRUE);
ds

# Load training dataset
url <- 'insurance_training_data.csv'
df <- read.csv(url, header = TRUE, row.names = 'INDEX')
head(df)
summary(df)

# Parse Numerical Data
# INCOME
df$INCOME <- parse_number(as.character(df$INCOME))
# HOME_VAL
df$HOME_VAL <- parse_number(as.character(df$HOME_VAL))
# BLUEBOOK
df$BLUEBOOK <- parse_number(as.character(df$BLUEBOOK))
# OLDCLAIM
df$OLDCLAIM <- parse_number(as.character(df$OLDCLAIM))
df %>% select(INCOME, HOME_VAL, BLUEBOOK, OLDCLAIM) %>% summary()
```

```r
# Show Correlation
cor.data <- df %>% select(TARGET_FLAG,TARGET_AMT,KIDSDRIV,AGE,HOMEKIDS,
                          YOJ,INCOME,HOME_VAL,TRAVTIME,BLUEBOOK,TIF,OLDCLAIM,
                          CLM_FREQ,MVR_PTS,CAR_AGE) %>% na.omit() %>%  cor()
col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD", "#4477AA"))
corrplot(cor.data, method = "shade", shade.col = NA, tl.col = "black",
         tl.srt = 45, col = col(200), addCoef.col = "black", cl.pos = "n",
         order = "original", type = "upper", addCoefasPercent = T)

# impute AGE with median value
median_age <- summary(df$AGE)[['Median']]
df[is.na(df$AGE),]['AGE'] <- median_age

# Box Plot of YOJ over JOB
plot(YOJ ~ JOB, df)
aggregate(YOJ ~ JOB, df, median)
# Imputing YOJ with median value per job
df_tmp <- df %>% group_by(JOB) %>%
  mutate(NEW_YOJ = median(YOJ, na.rm = TRUE)) %>%
  select(JOB, YOJ, NEW_YOJ)
df[is.na(df$YOJ),]$YOJ <- df_tmp[is.na(df_tmp$YOJ),]$NEW_YOJ

# Impute `CAR_AGE` missing values
df$CAR_AGE[which(df$CAR_AGE < 0)] <- NA
median_car_age <- summary(df$CAR_AGE)[['Median']]
df[is.na(df$CAR_AGE),]['CAR_AGE'] <- median_car_age

# Transform INCOME and HOME_VAL
nrow_na <- nrow(df[is.na(df$INCOME) & is.na(df$HOME_VAL),])
plot(INCOME~HOME_VAL, df)
# 1
median_home_val <- summary(df$HOME_VAL)[['Median']]
df[is.na(df$INCOME) & is.na(df$HOME_VAL),]$HOME_VAL <- sample(c(0, median_home_val),
                                                              size=nrow_na, replace = T)
# 2
lm_data <- df[df$HOME_VAL > 0,]
lm1 <- lm(INCOME~HOME_VAL, data = lm_data)
lm1.predict <- predict(lm1, newdata = df[is.na(df$INCOME) & df$HOME_VAL > 0,]['HOME_VAL'])
df[is.na(df$INCOME) & df$HOME_VAL > 0,]$INCOME <- lm1.predict
rm(lm_data, lm1)
# deal with negative values
df[!is.na(df$INCOME) & df$INCOME < 0,]$INCOME <- 0
# 3
median_income <- summary(df$INCOME)[['Median']]
df[is.na(df$INCOME),]$INCOME <- median_income
# 4
df$HOME_OWN <- ifelse(df$HOME_VAL > 0, 1, 0)
# deal with missing values
nrow_na <- nrow(df[is.na(df$HOME_OWN),])
df[is.na(df$HOME_OWN),]$HOME_OWN <- sample(c(0, 1), size=nrow_na, replace = T)

# create INCOME_CLASS
sum_income <- summary(df$INCOME)
```

```r
low_income_ub <- sum_income[['1st Qu.']]
high_income_lb <- sum_income[['3rd Qu.']]
rm(sum_income)
df$INCOME_CLASS <- as.factor(case_when(
  df$INCOME < low_income_ub ~ 'LOW',
  df$INCOME > high_income_lb ~ 'HIGH',
  TRUE ~ 'MID'))

# validate new model summary
df_train <- select(df, -'INCOME', -'HOME_VAL')
summary(df_train)

## Build Models
# Build first LM
m1.data <- df_train
m1.lm <- lm(TARGET_AMT ~ . -TARGET_FLAG-RED_CAR-YOJ-AGE-HOMEKIDS-EDUCATION-HOME_OWN
            -OLDCLAIM-BLUEBOOK-SEX, data = m1.data)
summary(m1.lm)

# Build first Logistic Model
b1.lm <- glm(formula = TARGET_FLAG ~ . -TARGET_AMT-RED_CAR-CAR_AGE-AGE-SEX-YOJ-HOMEKIDS,
             family = "binomial", data = m1.data)
summary(b1.lm)

# Transform JOB variable
m2.data = m1.data
m2.data$JOB <- factor(ifelse(m2.data$JOB != "Manager", "Not Manager", "Manager"),
                      levels = c("Not Manager", "Manager"))
# Build second LM
m2.lm <- lm(TARGET_AMT ~ . -TARGET_FLAG-RED_CAR-YOJ-AGE-HOMEKIDS-EDUCATION-HOME_OWN
            -OLDCLAIM-BLUEBOOK-SEX, data = m2.data)
m2.lm <- update(m2.lm, .~. -TARGET_FLAG-RED_CAR-YOJ-AGE-HOMEKIDS-EDUCATION-HOME_OWN
                -OLDCLAIM-BLUEBOOK-SEX, data = m2.data)
summary(m2.lm)

# Build second Logistic Model
b2.lm <- glm(formula = TARGET_FLAG ~ . -TARGET_AMT-RED_CAR-CAR_AGE-AGE-SEX-YOJ-HOMEKIDS,
             family = "binomial", data = m2.data)
summary(b2.lm)

# Tranform EDUCATION variable
m2.data$EDUCATION <- mapvalues(m2.data$EDUCATION,
                               c("<High School", "Bachelors", "Masters",
                                 "PhD", "z_High School"),
                               c("Lower", "Higher", "Higher", "Higher", "Lower"))

# Build third Logistic Model
b2.lm <- glm(formula = TARGET_FLAG ~ . -TARGET_AMT-RED_CAR-CAR_AGE-AGE-SEX-YOJ-HOMEKIDS,
             family = "binomial", data = m2.data)
b2.lm <- update(b2.lm, .~. -TARGET_AMT-RED_CAR-CAR_AGE-AGE-SEX-YOJ-HOMEKIDS,
                data = m2.data)
summary(b2.lm)
```

PREDICTIONS - R statistical programming code

```
# Load Data
url <- './insurance-evaluation-data.csv'
df.fin <- read.csv(url, header = TRUE, row.names = 'INDEX')
df <- df.fin

## Prepare Data
# Transform EDUCATION
df$EDUCATION <- mapvalues(df$EDUCATION,
                          c("<High School", "Bachelors", "Masters", "PhD", "z_High School"),
                          c("Lower", "Higher", "Higher", "Higher", "Lower"))

# Transform JOB
df$JOB <- factor(ifelse(df$JOB != "Manager", "Not Manager", "Manager"),
                 levels = c("Not Manager", "Manager"))
levels(df$JOB)

# Parse INCOME
df$INCOME <- parse_number(as.character(df$INCOME))

# Parse HOME_VAL
df$HOME_VAL <- parse_number(as.character(df$HOME_VAL))

# Parse BLUEBOOK
df$BLUEBOOK <- parse_number(as.character(df$BLUEBOOK))

# Parse OLDCLAIM
df$OLDCLAIM <- parse_number(as.character(df$OLDCLAIM))

# Impout missing CAR_AGE
df[is.na(df$CAR_AGE),]['CAR_AGE'] <- median_car_age

# Impute missing INCOME data
# 1
nrow_na <- nrow(df[is.na(df$INCOME) & is.na(df$HOME_VAL),])
df[is.na(df$INCOME) & is.na(df$HOME_VAL),]$HOME_VAL <- sample(
  c(0, median_home_val), size=nrow_na, replace = T)

# 2
lm_data <- df[df$HOME_VAL > 0,]
lm1.predict <- predict(lm1, newdata = df[is.na(df$INCOME) & df$HOME_VAL > 0,]['HOME_VAL'])
df[is.na(df$INCOME) & df$HOME_VAL > 0,]$INCOME <- lm1.predict
# deal with negative values
df[!is.na(df$INCOME) & df$INCOME < 0,]$INCOME <- 0

# 3
df[is.na(df$INCOME),]$INCOME <- median_income

# 4
df$HOME_OWN <- ifelse(df$HOME_VAL > 0, 1, 0)
# deal with missing values
nrow_na <- nrow(df[is.na(df$HOME_OWN),])
df[is.na(df$HOME_OWN),]$HOME_OWN <- sample(c(0, 1), size=nrow_na, replace = T)
```

```r
summary(df$HOME_OWN)

# Create INCOME_CLASS
df$INCOME_CLASS <- as.factor(case_when(
  df$INCOME < low_income_ub ~ 'LOW',
  df$INCOME > high_income_lb ~ 'HIGH',
  TRUE ~ 'MID'))

# str(df)
# summary(df)

m.predict <- predict(m2.lm, newdata = df)
b.predict <- predict(b2.lm, newdata = df)

df.fin$TARGET_FLAG <- ifelse(b.predict > .5, 1, 0)
df.fin$TARGET_AMT <- m.predict
df.fin[df.fin$TARGET_FLAG == 0,]$TARGET_AMT <- ''
write.csv(df.fin, "insurance-evaluation-data-completed.csv")
```