Auto Insurance Data Assignment

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CUNY SPS Data 621

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Abstract

This assignment focused on analyzing data from an insurance auto company. The dataset contains over 8,000 records that encompass their policy holders. The data set has 26 variables, 2 outcome and 24 predictor, of different types such as continuous or factor type variables. The purpose for this assignment is to analyze the data, perform any data manipulation / clean-up and build three (3) binary logistic regression and three (3) multiple linear regression models using only the data (or derivatives thereof) to predict if the region is above or below the median crime rate. The chosen model provided an AIC = 7384.4 and R^2 = 0.2879.

Keywords: insurance, data621

Auto Insurance Data Assignment

The following is the analysis and write-up based upon my interpretation of the data and predict if an individual is likely to have an accident, and then if they do, what the claim amount may be.

Data Exploration

The purpose of this step is to get a 'feel' for the dataset. The following information describes the data from different angles including completeness, statistical summaries, visuals to determine the shape and effect of each variable and other items deemed pertinent.

Summary Statistics

The first step is to look at the data to determine some items including completeness and the shape of each variable. The following are the results of summarizing the data in a table and the visualization of each variables density function (PDF).

Table 1

Summary Statistics for Moneyball Training Data

VARIABLE	MIN	1Q	MEDIAN	MEAN	3Q	MAX	NA
INDEX	1	2559	5133	5152	7745	10302	
TARGET_FLAG	4.17222222	1.53680556					
TARGET_AMT	0	0	0	1504	1036	107586	
KIDSDRIV	0	0	0	0.1711	0	4	
AGE	16	39	45	44.79	51	81	6
HOMEKIDS	0	0	0	0.7212	1	5	
YOJ	0	9	11	10.5	13	23	454
INCOME	0	28097	54028	61898	85986	367030	445
PARENT1	No:7084	Yes:1077					
HOME_VAL	0	0	161160	154867	238724	885282	464
MSTATUS	Yes:4894	z_No:3267					
SEX	M:3786	z_F:4375					
EDUCATION	<High_School:1203	Bachelors:2242	Masters:1658	PhD:728	z_High_School:2330		
JOB	z_Blue_Collar:1825	Clerical:1271	Professiol:1117	Mager:988	Lawyer:835	Student:712	(Other):1413
TRAVTIME	5	22	33	33.49	44	142	
CAR_USE	Commercial:3029	Private:5132					
BLUEBOOK	1500	9280	14440	15710	20850	69740	
TIF	1	1	4	5.351	7	25	
CAR_TYPE	Minivan:2145	Panel_Truck:676	Pickup:1389	Sports_Car:907	Van:750	z_SUV:2294	

RED_CAR	no:5783	yes:2378					
OLDCLAIM	0	0	0	4037	4636	57037	
CLM_FREQ	0	0	0	0.7986	2	5	
REVOKED	No:7161	Yes:1000					
MVR_PTS	0	0	1	1.696	3	13	
CAR_AGE	-3	1	8	8.328	12	28	510
URBANICITY	Highly_Urban/Urban:6492		z_Highly_Rural/Rural:1669				

Note: Source: insurance-training-data.csv

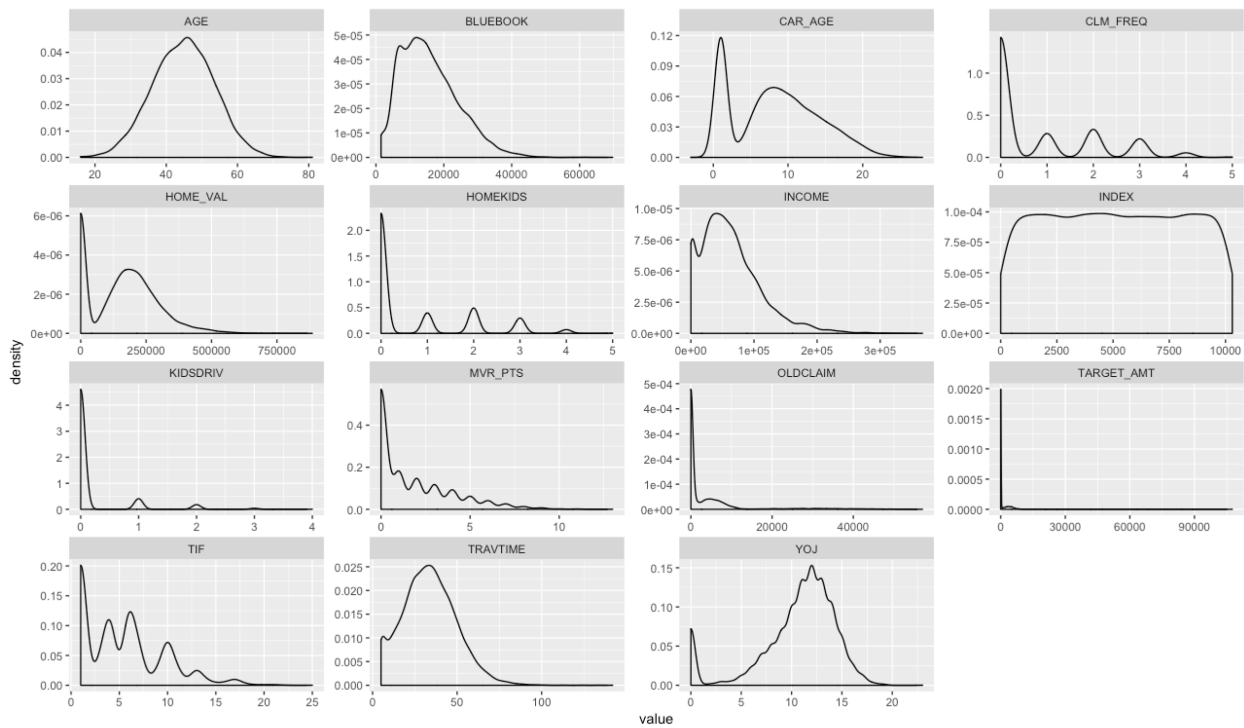


Figure 1. PDF for Each Dataframe Variable.

In looking at both, Table 1, Figure 1 and Appendix B (correlation matrix) together, we can note specific items that may skew our model building results.

NA: These incomplete cases will cause any correlation exercise to be incorrect or not possible. There are a few ways to deal with NAs including imputing the missing data or ignoring the variable altogether. For the purposes of this analysis, the variable CAR_AGE, INCOME, HOME_VALUE and AGE have missing information. The highest offender is CAR_AGE with about 5% of the data missing while others are much lower than that.

PDF: Figure 1 shows the PDF of each variable, this allows us to see if the data is normal or not. For the numeric variables, four (4) variables (AGE, YOJ, TRAVTIME and INCOME) shows the typical normal density function but all others like ***CLM_FREQ*** show left skewness and others show bimodality (CAR_AGE). For the purposes of this analysis, the variables HOMEKIDS, MVR_PTS, OLDCLAIM, TIF, KIDSDRIVE and CLM_FREQ will be log transformed to remove the effects of skewness. All other variables were left as is because the shape didn't warrant it.

Correlation: We look for correlated variables that we can make decisions on and determine which variable might be closely related to others either due to collinearity or other underlying factors that are visible at first glance in the dataset. Correlated variables bloat the model and don't produce any more insight than ignoring one of the two that show correlation. In our data, none of the variables show any particular correlation that would be cause for alarm and would require removal in order to avoid collinearity.

Data Preparation

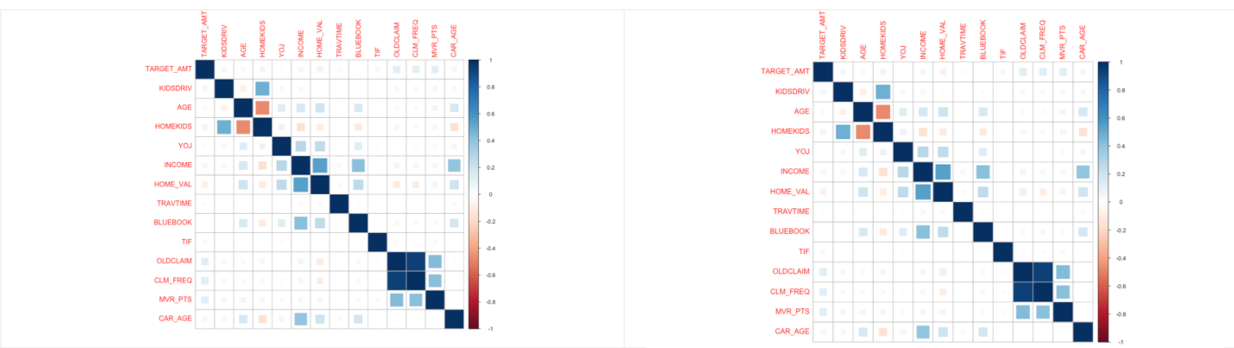
The purpose of this step is to take the findings from the exploration and transform the data as needed. The following information describes the transformations done in order to prepare the data for model building and model selection.

NA: All missing values were imputed using the mean within each column even though it is not the most adequate for this data. The nearest neighbor method would have been more valid by using another variable to bin, but there was concern about causing bias due to calculating the mean on variables that have inherit bias in them (such as education). Therefore, the mean for the entire dataset (excluding NA values) was used for this analysis.

Log Transformation: For this dataset, six (6) variables were transformed that were deemed overtly skewed in comparison to other variables in the dataset. HOMEKIDS, MVR_PTS, OLDCLAIM, TIF, KIDSDRIVE and CLM_FREQ were the variables transformed using the log base 10 function, for example for the TIF column the transformation was *log(train$* TIF*+1)*. The value 1 was added in order to ensure that values of 0 continue to be 0 after the transformation (as $\log_{10}(0)$ is not possible).

Variable Creation: For this dataset, no new variables were created. There was an option use binning to create a new variable such as the CAR_AGE where flagging new cars as 1 vs those older than a specific amount of years as 0 could have been done but was decided against. There are enough varied variables in the data set to see how the models behave.

Correlation Check: Once these manipulations are done, a side-by-side comparison of the correlations matrix is done to ensure no inadvertent effects to the data.



Before	After

Figure 2. Correlation Comparison Before and After.

As can be noted, there were no real strong correlations before and no correlations after that warrant removal of any variables.

Model Building for Outcome Variable TARGET_FLAG

The purpose of this step is to take the modified dataset and begin exploring potential models that will be used on the final dataset provided. The following information describes the three (3) models built for this step and the relevant analysis to provide reasons for model selection in the next step.

MODEL 1

The first model takes in the data as manipulated in step two. In this first model, we have an AIC of 7384.4. The data in Table 2, shows that the model has an accuracy of 79.3%.

```
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
```

Variable Interpretation:

(Intercept)	-0.1158016	JOBDoctor	-0.06163603
KIDSDRIV	0.09945167	JOBHome_Maker	0.02986941
AGE	6.90481E-06	JOBLawyer	0.01709406
HOMEKIDS	0.02206017	JOBManager	-0.08188439
YOJ	-0.001972543	JOBProfessional	0.0243965
INCOME	-5.04006E-07	JOBStudent	0.02972047
PARENT1Yes	0.04803969	JOBz_Blue_Collar	0.04522137
HOME_VAL	-1.92952E-07	TRAVTIME	0.00216305
MSTATUSz_No	0.07503592	CAR_USEPrivate	-0.1108755
SEXz_F	-0.0130199	BLUEBOOK	-3.03074E-06
EDUCATIONBachelors	-0.05424472	TIF	-0.04748519
EDUCATIONMasters	-0.04086324	CAR_TYPEPanel_Truck	0.08311836
EDUCATIONPhD	-0.02181469	CAR_TYPEPickup	0.08132789
EDUCATIONz_High_School	0.003077558	CAR_TYPESports_Car	0.1502692
JOBClerical	0.05811519	CAR_TYPEVan	0.0897826
CAR_TYPEz_SUV	0.1135413	MVR_PTS	0.04094471
RED_CARyes	-0.000840661	CAR_AGE	-0.000263433
OLDCLAIM	0.000986117	URBANICITYz_Highly_Rural/Rural	-0.3457765
CLM_FREQ	0.04607979		
REVOKEDYes	0.1055966		

Table 2. *Confusion Matrix Model 1*

True \ Pred	0	1
0	5,550	458
1	1,235	918

No variables seem peculiar expect for URBANCITY, this variable stands out with its coefficient at -0.35% chance that a policy holder will be in an accident (less likely) when they live in rural area (less cars, less opportunities for accidents). As this is a correct interpretation of the variable, for now, this variable will be left in.

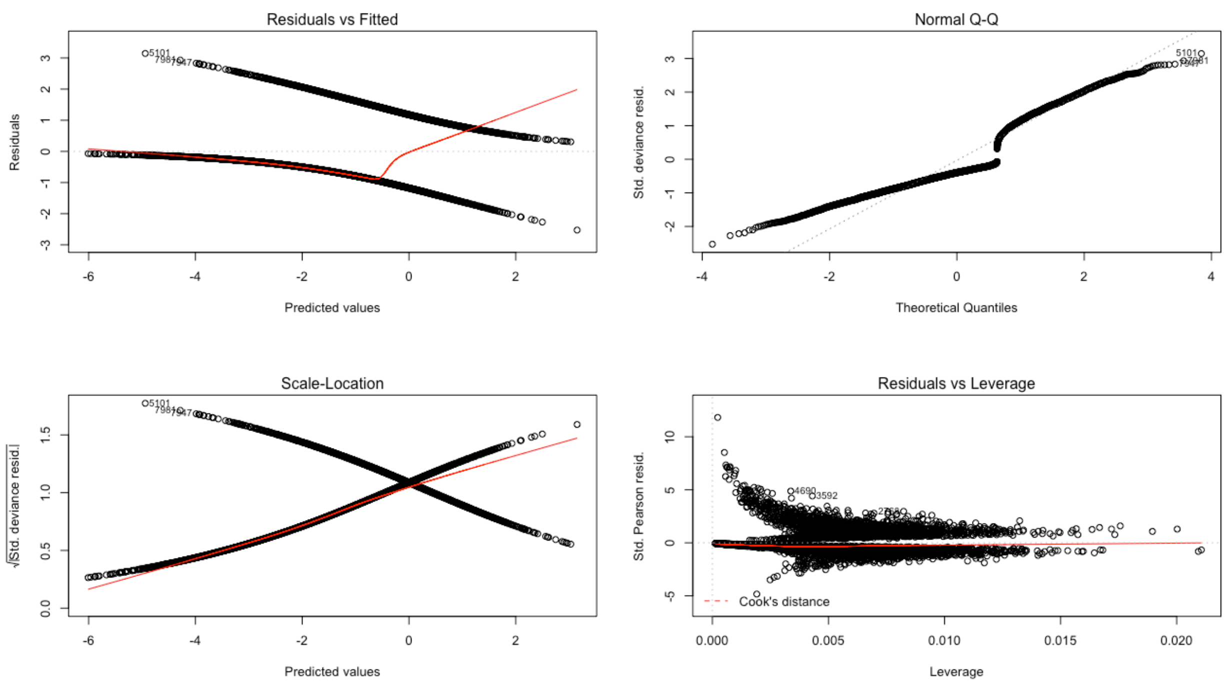


Figure 3. Model 1 (TARGET_FLAG) Plots.

For this model, we can see that the Normal Q-Q plot shows a unique charactersis not only on the tails but also in the middle, this is due to the binary flag. However, in looking at the residucals we see heteroskedastic behavior.

MODEL 2

The second model only takes into account the variables noted of significance from Model 1 (p-value < 0.05). In this second model, we have an AIC of 7376.8. The data in Table 3, shows that the model has an accuracy of 79.0%.

```
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
```

Variable Interpretation:

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

Table 3. *Confusion Matrix Model 2*

True \ Pred	0	1
0	5,541	467
1	1,247	906

In this model, although the AIC dropped, the accuracy also dropped by 0.3% vs Model 1. No variables seem peculiar expect for URBANCITY, this variable stands out with its coefficient at -0.35% chance that a policy holder will be in an accident (less likely) when they live in rural area (less cars, less opportunities for accidents). As this is a correct interpretation of the variable, for now, this variable will be left in.

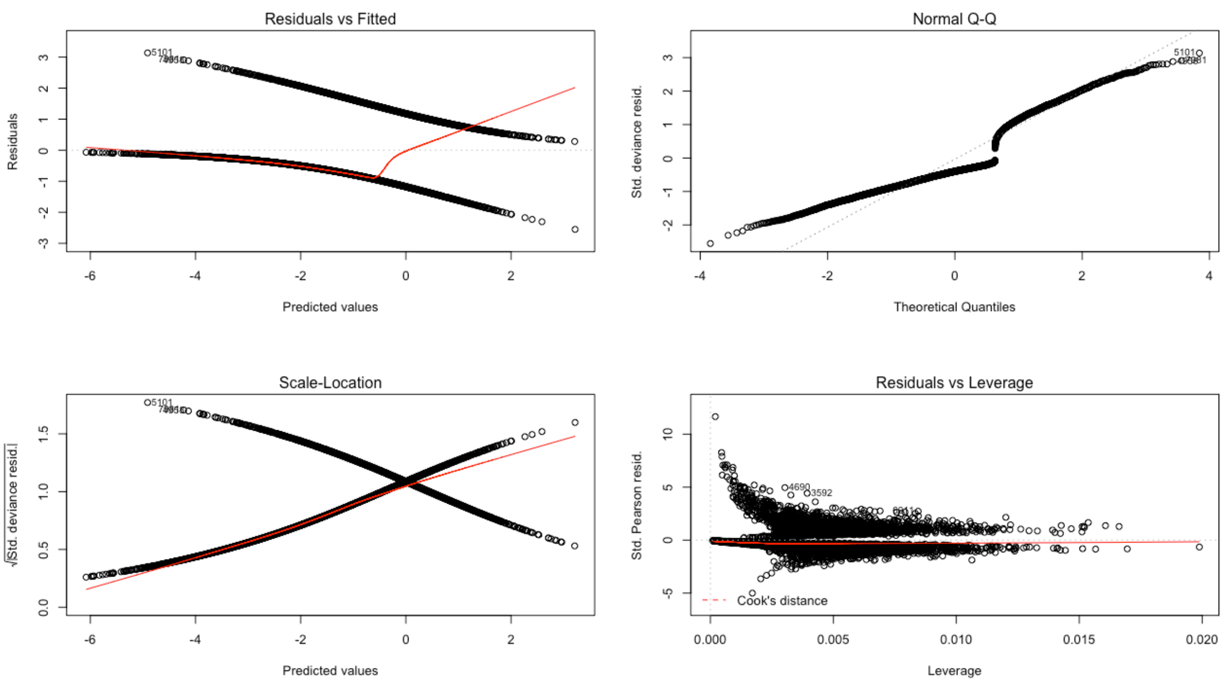


Figure 4. Model 2 (TARGET_FLAG) Plots.

For this model, we can see that the Normal Q-Q plot shows unique characters is not only on the tails but also in the middle, this is due to the binary flag. However, in looking at the residuals we see heteroskedastic behavior. There is no major change to the first model.

MODEL 3

The third model is a reduced model. This dataset has a lot of variables, that from can be seen are secondary in nature to the true intent of the model. Is the policy holder in an accident and what was the value? This can be answered using the most basic items that are there. KIDSDRIVE and TRAVTIME affect who drives and the distance of travel, and then INCOME and HOME_VAL to see if income and home value (higher risk of assets being seized in an accident) vs those who aren't high income earners or homeowners. In this third model, we have an AIC of 9031.1. The data in Table 3, shows that the model has an accuracy of 73.6%.

```
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
```

Variable Interpretation:

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

Table 4. *Confusion Matrix Model 3*

True \ Pred	0	1
0	5,937	71
1	2086	67

The increase in AIC is expected and shows that the model does no better than flipping a coin and therefore is not an appropriate model or this exercise. This means that other variables such as Job, Education and other policy holder specific items do impact the chances of an accident and thereby filing a claim. In this case, Model With this in mind, Model 1 so far seems the most appropriate so far.

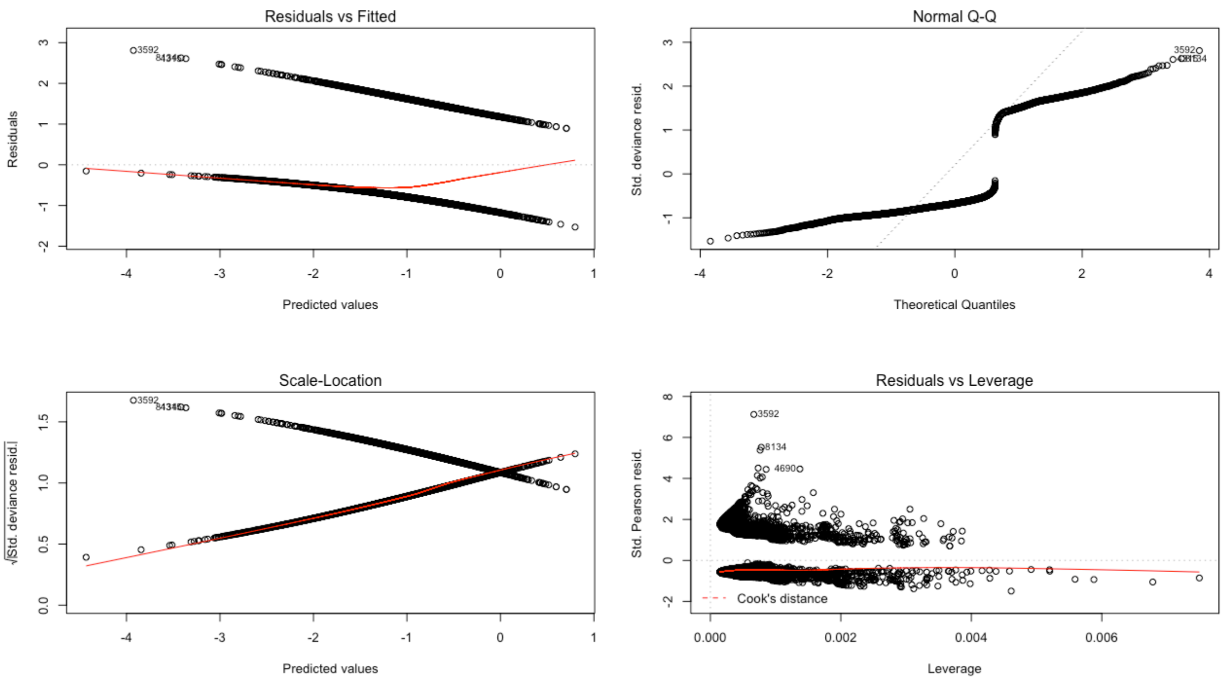


Figure 5. Model 3. (TARGET_FLAG) Plots.

For this model, we can see that the Normal Q-Q plot is completely different than the others. This is due to the lack of variables to help explain the TARGET_FLAG variable. This is also apparent in the unique shape of the residuals as they no longer sho any shape but cluster around -1 and 2.

Model Building for Outcome Variable TARGET_AMT

The purpose of this step is to take the modified dataset and begin exploring potential models that will be used on the final dataset provided. The following information describes the three (3) models built for this step and the relevant analysis to provide reasons for model selection in the next step.

MODEL 1

The first model takes in the data as manipulated in step two (with variables imputed and removed). In this first model, we have an $R^2 = 0.2879$ and p-value < 0.05. The data in Figure 3, shows that there is not heteroscedastic and has a positive trend on the predicted vs fitted values.

```
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
```

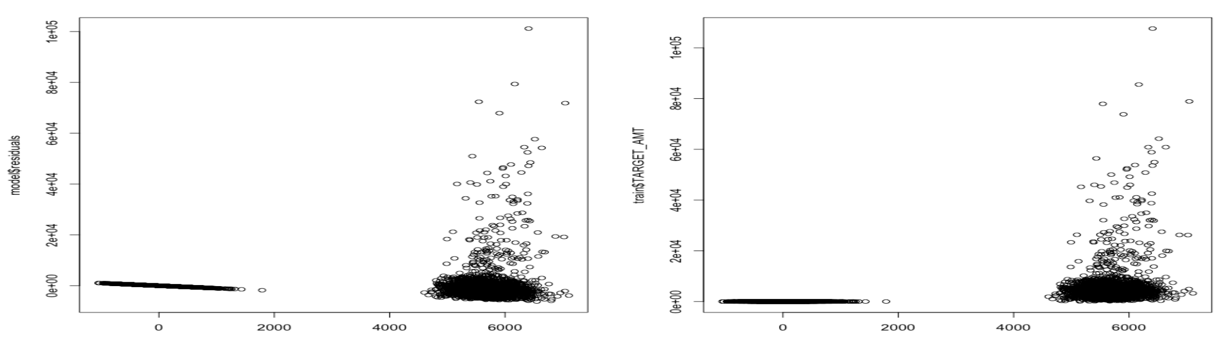


Figure 7. Model Check for Residual Shape and Model vs. Actuals

What is peculiar in the results however, are that some variables have factor that is counterintuitive to the expected impact on TARGET_AMT. As an example, JOB has varying signs for jobs that are high paying and would cause the thought that they have more expensive cars and therefore when they are in an accident the amount would be higher than others For now, all variablees will be left in.

MODEL 2

The second model only takes into account the variables noted of significance from Model 1 (p-value < 0.05). This means that BLUEBOOK, REVOKED, MVR_PTS and CAR_AGE would be the the only variables to be used in Model 2. In this second model, we have an R^2 = 0.2886 and p-value < 0.05 which is only a marginal improvement in the model capability.

```
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
```

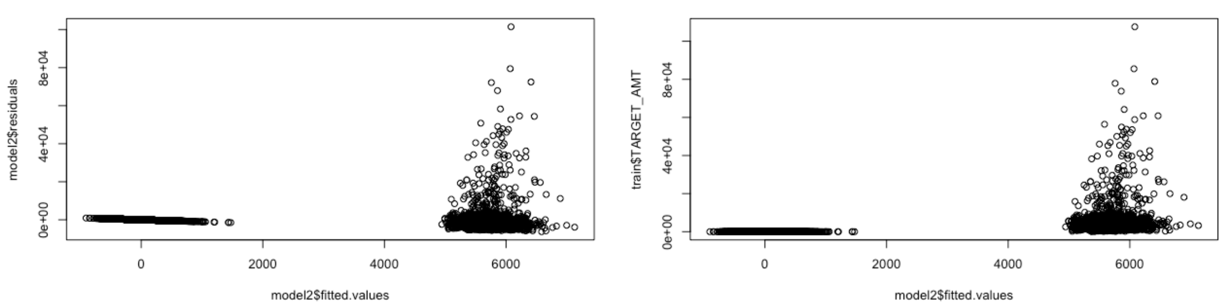


Figure 8. Model 2 Plots (Residuals vs Fitted and QQ)

MODEL 3

The third model takes the same variables used in the Model 3 from the TARGET_FLAG model building. In this third model, we have an $R^2 = 0.1047$ and p-value < 0.05 which is not an improvement in the model capability.

```
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
```

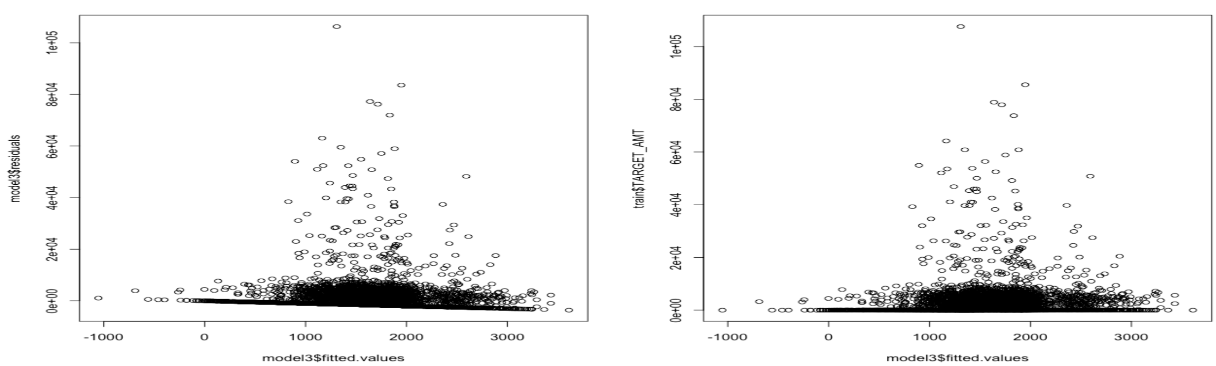


Figure 5. Model 3 Plots (Residuals vs Fitted and QQ)

Similar to the models from the TARGET_FLAG exercise, the numerous amount of variables do have an impact in the value of the claim when there is an accident. This means that solely looking at variables that are correlated to driving behavior are not enough to explain the outcome variables. With this in mind, Model 1 is also the most appropriate for the TARGET_AMT variable just like it was in the TARGET_FLAG variable.

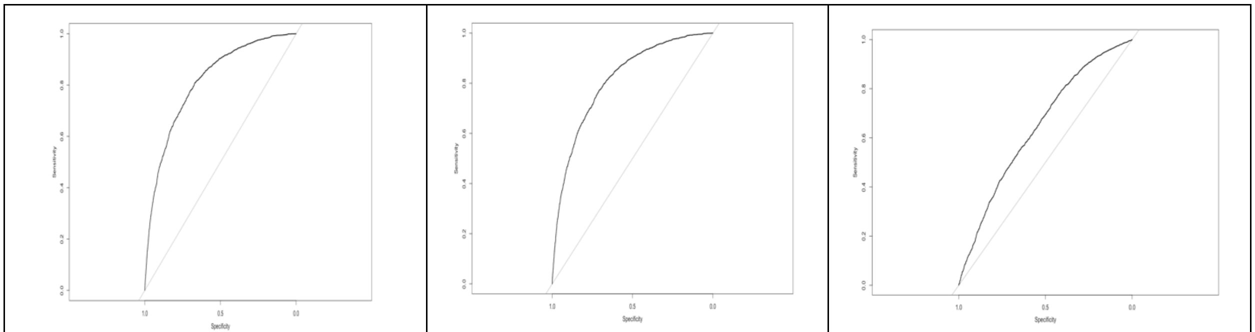
METHODOLOGY

Familiarity with the dataset subject is low and therefore the methodology will be more closely related to the statistical information presented. In this case, a combination of three (3) factors (AIC, Percent Accuracy, and ROC Curve) will be the criteria to select the model for the TARGET_FLAG variable and one (1) factor (R^2) for the TARGET_AMT variable. The reason for this is that the significance of each variable is high in Model 1 through 3 as the adjustments for correlation and log transformations were already taken care of in Step 2 of the process. If Step 2 had not been done, then it would have been hidden in the model building and taken care of between Model 1 and Model 2. In addition, because this is a binary predictive exercise accuracy is also important for this exercise as seen in Table 5 below.

Table 5. *Model Criteria Selection*

OUTCOME VARIABLE	Criteria	Model 1 (All Variables)	**Model 2 (Significant Variables Only)**	Model 3 (Politically Correct)
TARGET_FLAG	AIC	7384.4	7376.8	9031.1
	Accuracy %	79.3%	79.0%	73.6%
TARGET_AMT	R^2	0.2879%	0.2886%	0.01047%

Of importance also is the ROC Curves for each model which tell us if the model predictive capability is better than just chance (a coin-toss at 50/50). In looking at each curve blow in Figure 3, we can see that the ROC curve for model 1 has a better smoother transition in comparison to Model 1 and Model 2. Overall, the ROC curve for Model 1 trends to the upper left quadrant in a more evenly distributed manner versus the other two.



Model 1	Model 2	Model 3

Figure 6. ROC Curves for Each Model (Model 1 through 3) for TARGET_FLAG.

With this in mind, Model 1 is best model with an AIC of 7384.4 for the TARGET_FLAG variable and Model 1 is the best model for the TARGET_AMT variable.

TEST DATA

The dataset had 2,141 entries and 26 columns and was modified to fit the final variables and scaling used in Model 1 from above. This means that the same process of adjustments and log transformations was done in order to be able to use the model correctly. The final predicted values are based upon a normalized value from the test data. The data is shown as follows with the corresponding summaries for the spread of the data.

Table 6. *Predicted Statistics vs Summary of Model 1 Predicted Values for TARGET_FLAG*

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

Table 6 above is only meant as a comparison but it does highlight that the test data has a higher set of values that would be deemed 0 (that there is no claim). The spread of the data for test is also a lot tighter than the training values which may be a function of cases in the test data. The data might have more of TARGET_FLAG = 0 or 1 which would skew the results.

Table 7. *Predicted Statistics vs Summary of TARGET_AMT in Training Data*

	Predicted (Test)			Train
	fit	lwr	upr	Actual
Min.	-1206.17	-1870.4	-542	0
1st	-255.615	-782.6	256.4	0
Median	-22.708	-538.1	478.1	0
Mean	-8.173	-540.5	524.1	1,504
3rd	223.762	-303.8	774.3	1,036
Max.	1251.287	521.4	1998.7	107,586

Table 7 is only meant as a comparison but it does highlight that the training data doesn't fall in the anywhere in the upper / lower limits except in the minimum values. The spread of the data for training is also a lot tighter than the predicted values which an issue in the method of normalizing the test data. This might indicate why the training and predicted values aren't more closely aligned.

Conclusion

Six (6) models were presented (3 for TARGET_FLAG and 3 for TARGET_AMT) after exploring and manipulating the data as necessary. With using a multi-criteria approach for this exercise, it became clear that the Model 1 was selected and provided an AIC of 7384.4 for TARGET_FLAG and a R^2=0.2879 for TARGET_AMT which was basically using all the variables presented in the dataset. If more time were available, the creation of new variables would be explored to create more factored variables instead of continuous variables that were presented and could have provided better insight into the data set.

Appendix A: R Code

```
---
title: "Data 621"
author: 'Cesar Espitia HW #4'
date: "7/8/2018"
output: html_document
---

## 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


```{r dataexploration}
knitr::opts_chunk$set(echo = TRUE)
library(e1071)
library(dplyr)
library(purrr)
library(tidyr)
library(ggplot2)
library(corrplot)
library(FactoMineR)
library(VIF)
library(knitr)
library(kableExtra)
library(Hmisc)
library(pROC)
library(binr)

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


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

# 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()
#
# 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

```{r datapreparation}

# 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))
corrplot(cor(trainnum), method="square")
cor.test(trainnum$HOMEKIDS,trainnum$AGE,method="pearson")

train2<-train


```




## Build Models LOGIT TARGET_FLAG
```{r buildmodelslogit}

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

summary(logit)
exp(logit$coefficients)
logitscalar <- mean(dlogis(predict(logit, type = "link")))
logitscalar * coef(logit)

confint.default(logit)

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

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

#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")
colist<-dplyr::pull(sigvars, vars)
# colist<-colist[2:11]
colist<-
c("KIDSDRIV","INCOME","PARENT1","HOME_VAL","MSTATUS","EDUCATION","JOB","TRAVTIME","CAR_USE","BLUEBOOK","TIF","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)
exp(logit2$coefficients)
logit2scalar <- mean(dlogis(predict(logit2, type = "link")))
logit2scalar * coef(logit2)

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

summary(predlogit2)

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

#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)
exp(logit3$coefficients)

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

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

#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)

round(logitscalar * coef(logit),2)
round(logit2scalar * coef(logit2),2)
round(logit3scalar * coef(logit3),2)
` ` `


## Build Models GENERAL TARGET_AMT
` ` `{r buildmodels, include=TRUE}

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

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")
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)


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)

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
```{r selectmodels}

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


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)

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

```
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)

summary(model)
```

```
```

Appendix B: CORRELATION MATRIX

	INDEX	TARGET_AMT	KIDSDRIV	AGE	HOMEKIDS	YOJ	INCOME	HOME_VAL	TRAVTIME	BLUEBOOK	TIF	OLDCLAIM	CLM_FREQ	MVR_PTS	CAR_AGE
INDEX	0	0.9572	0.1594	0.0022	0.9962	0.0189	0.4385	0.2881	0.0372	0.2089	0.4053	0.9091	0.0898	0.4765	0.9513
TARGET_AMT	0.9572	0	0	0.0002	0	0.0525	0	0	0.0115	0.6712	0	0	0	0	0
KIDSDRIV	0.1594	0	0	0	0	0.0001	0	0.0825	0.4455	0.0516	0.8574	0.0653	0.0008	0	0
AGE	0.0022	0.0002	0	0	0	0	0	0	0.6342	0	0.9952	0.0082	0.0296	0	0
HOMEKIDS	0.9962	0	0	0	0	0	0	0	0.5128	0	0.2859	0.0069	0.008	0	0
YOJ	0.0189	0.0525	0.0001	0	0	0	0	0	0.1369	0	0.0296	0.7936	0.0209	0.0009	0
INCOME	0.4385	0	0	0	0	0	0	0	0	0	0.9276	0	0	0	0
HOME_VAL	0.2881	0	0.0825	0	0	0	0	0	0.0018	0	0.8564	0	0	0	0
TRAVTIME	0.0372	0.0115	0.4455	0.6342	0.5128	0.1369	0	0.0018	0	0.1246	0.2945	0.0818	0.5535	0.3384	0.0008
BLUEBOOK	0.2089	0.6712	0.0516	0	0	0	0	0	0.1246	0	0.6242	0.0077	0.001	0.0004	0
TIF	0.4053	0	0.8574	0.9952	0.2859	0.0296	0.9276	0.8564	0.2945	0.6242	0	0.0473	0.0375	0.0002	0.4969
OLDCLAIM	0.9091	0	0.0653	0.0082	0.0069	0.7936	0	0	0.0818	0.0077	0.0473	0	0	0	0.2417
CLM_FREQ	0.0898	0	0.0008	0.0296	0.008	0.0209	0	0	0.5535	0.001	0.0375	0	0	0	0.4151
MVR_PTS	0.4765	0	0	0	0	0.0009	0	0	0.3384	0.0004	0.0002	0	0	0	0.0817
CAR_AGE	0.9513	0	0	0	0	0	0	0	0.0008	0	0.4969	0.2417	0.4151	0.0817	0