Homework 4

Group 1

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1 Introduction

Consumers who own a car are often required to purchase car insurance to protect themselves from serious financial repercussions of being involved in a car accident. Insurance Providers must determine the risk of offering insurance coverage to a new customer through accurate statistical models that evaluate the consumers propensity for accidents. Since Insurance Providers are motivated by collecting the maximum amount of revenue from consumers while returning the lowest amount in accident claims, statistical modeling provides Insurance Providers with insight into the consumers behavior and the most appropriate pricing schemes[1].

2 Statement of the Problem

The purpose of this report is to develop statistical models to make inference into the likelihood of a customer being involved in a car accident and the cost associated of a customer being involved in a car accident.

3 Data Exploration

3.1 Variables Explained

The variables provided in the `Insurance Training Data Set` are explained below:

Variable Code	Definition
INDEX	Identification Variable (do not use)
TARGET_FLAG	Was Car in a crash? 1=YES 0=NO
TARGET_AMT	If car was in a crash, what was the cost
AGE	Age of Driver
BLUEBOOK	Value of Vehicle
CAR_AGE	Vehicle Age
CAR_TYPE	Type of Car
CAR_USE	Vehicle Use
CLM_FREQ	# Claims (Past 5 Years)
EDUCATION	Max Education Level
HOMEKIDS	# Children at Home
HOME_VAL	Home Value
INCOME	Income
KIDSDRIV	# Driving Children
MSTATUS	Marital Status
MVR_PTS	Motor Vehicle Record Points
OLDCLAIM	Total Claims (Past 5 Years)
PARENT1	Single Parent
RED_CAR	A Red Car
REVOKED	License Revoked (Past 7 Years)
SEX	Gender
TIF	Time in Force
TRAVTIME	Distance to Work
URBANICITY	Home/Work Area
YOJ	Years on Job

[1] "Insider Information: How Insurance Companies Measure Risk - Insurance Companies.com." Insurance Companiescom. N.p., n.d. Web. 06 Nov. 2016.

3.1.1 Nominal Variables

We first look at our nominal variables and their applicable proportions. Interestingly, we see that in this data set only a quarter of the customer records indicate an accident occurred. Also, the majority of consumers in this data set have no kids at home, are married, more than a high school education but less than a PhD, use their car for private purposes, typically own a SUV or minivan, and also live in an urban environment. This provides an interesting insight to the type of customer this data set represents and should be considered when further interpreting our statistical model. Additionally, we should be mindful of any selection biases in this data set as consumers with extremely risky histories are likely to have not been extended insurance coverage.

Table 2: Table of nominal variables

Variable	**Levels**	$\mathbf{n}$	$\%$	$\sum\%$
TARGET_FLAG	0	6008	73.6	73.6
	1	2153	26.4	100.0
	all	8161	100.0	
KIDSDRIV	0	7180	88.0	88.0
	1	636	7.8	95.8
	2	279	3.4	99.2
	3	62	0.8	100.0
	4	4	0.0	100.0
	all	8161	100.0	
HOMEKIDS	0	5289	64.8	64.8
	1	902	11.1	75.9
	2	1118	13.7	89.6
	3	674	8.3	97.8
	4	164	2.0	99.8
	5	14	0.2	100.0
	all	8161	100.0	
PARENT1	No	7084	86.8	86.8
	Yes	1077	13.2	100.0
	all	8161	100.0	
MSTATUS	No	3267	40.0	40.0
	Yes	4894	60.0	100.0
	all	8161	100.0	
SEX	F	4375	53.6	53.6
	M	3786	46.4	100.0
	all	8161	100.0	
EDUCATION	Less Than High School	1203	14.7	14.7
	High School	2330	28.6	43.3
	Bachelors	2242	27.5	70.8
	Masters	1658	20.3	91.1
	PhD	728	8.9	100.0
	all	8161	100.0	
JOB	Blue Collar	1825	23.9	23.9
	Clerical	1271	16.6	40.5
	Doctor	246	3.2	43.8
	Home Maker	641	8.4	52.2
	Lawyer	835	10.9	63.1
	Manager	988	12.9	76.0
	Professional	1117	14.6	90.7
	Student	712	9.3	100.0
	all	7635	100.0	
CAR_USE	Commercial	3029	37.1	37.1
	Private	5132	62.9	100.0
	all	8161	100.0	
CAR_TYPE	Minivan	2145	26.3	26.3
	Panel Truck	676	8.3	34.6
	Pickup	1389	17.0	51.6
	Sports Car	907	11.1	62.7
	SUV	2294	28.1	90.8

Table 2: Table of nominal variables

Variable	Levels	n	%	∑%
	Van	750	9.2	100.0
	all	8161	100.0	
RED_CAR	no	5783	70.9	70.9
	yes	2378	29.1	100.0
	all	8161	100.0	
CLM_FREQ	0	5009	61.4	61.4
	1	997	12.2	73.6
	2	1171	14.3	88.0
	3	776	9.5	97.5
	4	190	2.3	99.8
	5	18	0.2	100.0
	all	8161	100.0	
REVOKED	No	7161	87.8	87.8
	Yes	1000	12.2	100.0
	all	8161	100.0	
URBANICITY	Highly Rural/ Rural	1669	20.4	20.4
	Highly Urban/ Urban	6492	79.5	100.0
	all	8161	100.0	

3.1.2 Continuous and Discrete Variables

We can see that in our continuous and discrete variables there is some additional variability. The median claim amount (`TARGET_AMT`) is 0 which would coincide with only a quarter for records indicating an accident. However, the spread is large since the average payout is only $1,504.30 but the maximum payout was $107,586.10. Surprisingly, the median `AGE` is 45 and the average `AGE` is 44.8 years, while we expected a lower average it could be due to simple selection bias in the data set source or the aging US population bringing this average higher [2]. We also noticed that an `INCOME` of $0.00 seems unwise because it is unclear how the individual would be able to cover their premium costs without parental support. Finally, we should note that the data set has as `CAR_AGE` of -3, which is impossible and will need to be removed.

There are many missing values for this portion of our data set, we have over 400 values missing for years on the job, income, home value, and car age. Due to these missing values we will need to impute to complete our statistical model.

Variable	n	Min	q_1	$\tilde{x}$	$\bar{x}$	q_3	Max	s	IQR	#NA
TARGET_AMT	8161	0	0	0	1504.3	1036	107586.1	4704.0	1036	0
TIF	8161	1	1	4	5.4	7	25.0	4.1	6	0
AGE	8155	16	39	45	44.8	51	81.0	8.6	12	6
YOJ	7707	0	9	11	10.5	13	23.0	4.1	4	454
INCOME	7716	0	28097	54028	61898.1	85986	367030.0	47572.7	57889	445
HOME_VAL	7697	0	0	161160	154867.3	238724	885282.0	129123.8	238724	464
TRAVTIME	8161	5	22	33	33.5	44	142.0	15.9	22	0
BLUEBOOK	8161	1500	9280	14440	15709.9	20850	69740.0	8419.7	11570	0
OLDCLAIM	8161	0	0	0	4037.1	4636	57037.0	8777.1	4636	0
MVR_PTS	8161	0	0	1	1.7	3	13.0	2.1	3	0
CAR_AGE	7651	-3	1	8	8.3	12	28.0	5.7	11	510

Table 3:

[2] Ortman, Jennifer M., Victoria A. Velkoff, and Howard Hogan. "An aging nation: the older population in the United States." Washington, DC: US Census Bureau (2014): 25-1140.

3.2 Imputting Missing Values

In order to address the missing values in our variables we used a non-parametric imputation method (Random Forest) using the `missForest` package. The function is particularly useful in that it can handle any type of input data and it will make as few assumptions about the structure of the data as possible.[3]

Table 2 : Imputed Descriptive Statistics
25 Variables 8161 Observations

TARGET_FLAG

n	missing	distinct	Info	Sum	Mean	Gmd
8161	0	2	0.583	2153	0.3	0.4

TARGET_AMT

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	1949	0.601	1504	2574	0	0	0	0	1036	4904	6452

```
lowest :      0.00000     30.27728     58.53106     95.56732    108.74150
highest:  73783.46592  77907.43028  78874.19056  85523.65335 107586.13616
```

KIDSDRIV

n	missing	distinct	Info	Mean	Gmd
8161	0	5	0.318	0.2	0.3

```
lowest : 0 1 2 3 4, highest: 0 1 2 3 4
```

```
0 (7180, 0.880), 1 (636, 0.078), 2 (279, 0.034), 3 (62, 0.008), 4 (4, 0.000)
```

AGE

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	66	0.999	45	10	30	33	39	45	51	56	59

```
lowest : 16 17 18 19 20, highest: 72 73 76 80 81
```

HOMEKIDS

n	missing	distinct	Info	Mean	Gmd
8161	0	6	0.723	0.7	1

```
lowest : 0 1 2 3 4, highest: 1 2 3 4 5
```

```
0 (5289, 0.648), 1 (902, 0.111), 2 (1118, 0.137), 3 (674, 0.083), 4 (164, 0.020), 5 (14,
0.002)
```

YOJ

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	446	0.991	10	4	0	5	9	11	13	14	15

```
lowest :  0.00  0.15  0.20  0.26  0.27, highest: 16.00 17.00 18.00 19.00 23.00
```

INCOME

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	7057	1	61569	50845	0e+00	5e+03	3e+04	5e+04	9e+04	1e+05	2e+05

```
lowest :      0.00      5.00      7.00     18.00     26.33
highest: 306277.00 309628.00 320127.00 332339.00 367030.00
```

PARENT1

n	missing	distinct
8161	0	2

```
No (7084, 0.868), Yes (1077, 0.132)
```

HOME_VAL

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	5570	0.978	2e+05	1e+05	0e+00	0e+00	0e+00	2e+05	2e+05	3e+05	4e+05

```
lowest :      0.000   4176.960   8196.080   8263.335   9438.009
highest: 657804.000 682634.000 738153.000 750455.000 885282.000
```

[3] Stekhoven, Daniel J., and Peter B?hlmann. "MissForest-non-parametric missing value imputation for mixed-type data." Bioinformatics 28.1 (2012): 112-118.

MSTATUS

n	missing	distinct
8161	0	2

No (3267, 0.4), Yes (4894, 0.6)

SEX

n	missing	distinct
8161	0	2

F (4375, 0.536), M (3786, 0.464)

EDUCATION

n	missing	distinct
8161	0	5

lowest : Bachelors High School Less Than High School Masters PhD
highest: Bachelors High School Less Than High School Masters PhD

Bachelors (2242, 0.275), High School (2330, 0.286), Less Than High School (1203, 0.147), Masters (1658, 0.203), PhD (728, 0.089)

JOB

n	missing	distinct
8161	0	8

lowest : Blue Collar Clerical Doctor Home Maker Lawyer
highest: Home Maker Lawyer Manager Professional Student

Value	Blue Collar	Clerical	Doctor	Home Maker	Lawyer	Manager
Frequency	1830	1273	254	643	865	1412
Proportion	0.224	0.156	0.031	0.079	0.106	0.173

Value	Professional	Student
Frequency	1172	712
Proportion	0.144	0.087

TRAVTIME

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	97	1	33	18	7	13	22	33	44	54	60

lowest : 5 6 7 8 9, highest: 103 113 124 134 142

CAR_USE

n	missing	distinct
8161	0	2

Commercial (3029, 0.371), Private (5132, 0.629)

BLUEBOOK

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	2789	1	15710	9354	4900	6000	9280	14440	20850	27460	31110

lowest : 1500 1520 1530 1540 1590, highest: 57970 61050 62240 65970 69740

TIF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	23	0.961	5	5	1	1	1	4	7	11	13

lowest : 1 2 3 4 5, highest: 19 20 21 22 25

CAR_TYPE

n	missing	distinct
8161	0	6

lowest : Minivan Panel Truck Pickup Sports Car SUV
highest: Panel Truck Pickup Sports Car SUV Van

Minivan (2145, 0.263), Panel Truck (676, 0.083), Pickup (1389, 0.170), Sports Car (907, 0.111), SUV (2294, 0.281), Van (750, 0.092)

RED_CAR

n	missing	distinct
8161	0	2

```
no (5783, 0.709), yes (2378, 0.291)
```

OLDCLAIM

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	2857	0.769	4037	6563	0	0	0	0	4636	9583	27090

```
lowest :     0   502   506   518   519, highest: 52507 53477 53568 53986 57037
```

CLM_FREQ

n	missing	distinct	Info	Mean	Gmd
8161	0	6	0.763	0.8	1

```
lowest : 0 1 2 3 4, highest: 1 2 3 4 5

0 (5009, 0.614), 1 (997, 0.122), 2 (1171, 0.143), 3 (776, 0.095), 4 (190, 0.023), 5 (18,
0.002)
```

REVOKED

n	missing	distinct
8161	0	2

```
No (7161, 0.877), Yes (1000, 0.123)
```

MVR_PTS

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	13	0.9	2	2	0	0	0	1	3	5	6

```
lowest :  0  1  2  3  4, highest:  8  9 10 11 13

Value          0     1     2     3     4     5     6     7     8     9    10    11    13
Frequency   3712  1157   948   758   599   399   266   167    84    45    13    11     2
Proportion 0.455 0.142 0.116 0.093 0.073 0.049 0.033 0.020 0.010 0.006 0.002 0.001 0.000
```

CAR_AGE

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	507	0.985	8	6	1	1	4	8	12	16	18

```
lowest :  0.000  1.000  2.000  2.035  2.890, highest: 24.000 25.000 26.000 27.000 28.000
```

URBANICITY

n	missing	distinct
8161	0	2

```
Highly Rural/ Rural (1669, 0.205), Highly Urban/ Urban (6492, 0.795)
```

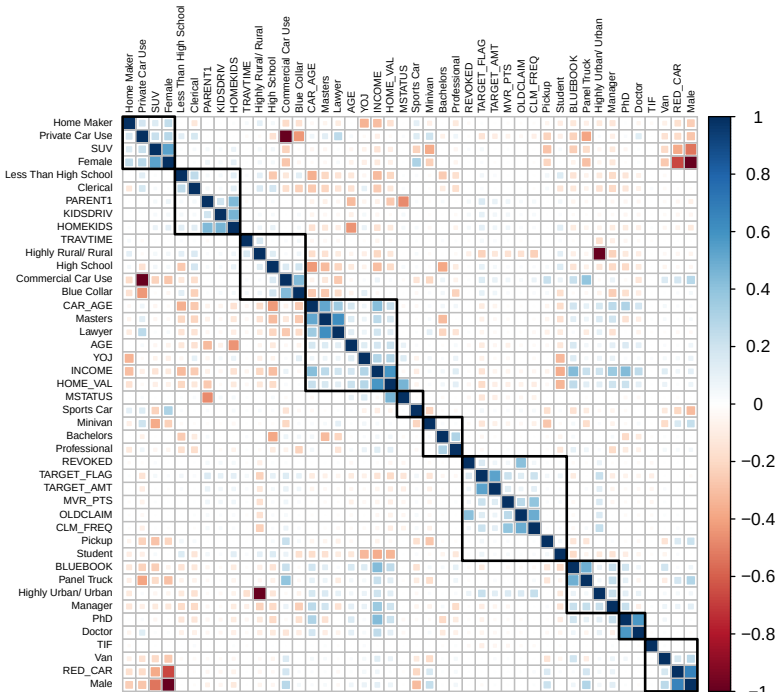


Figure 1: Correlation Plot of Training Data Set

3.3 Exploration of Variables

3.3.1 Correlation Matrix

If we widen our data set to a matrix to account for the many factors in our evaluation data set we can plot a correlation matrix. We can see some interesting patterns in the data.

- It is intuitive how both target variables have no correlation with an education level that is less than high school. If the person who wants to buy the vehicle does not have a sufficient level of education, obviously he or she would not have a high-paying job and therefore would not be able to buy the vehicle.
- Not surprisingly, the target flag variable has negative correlation with marital status. If a married couple owns the vehicle and both the husband and wife share the vehicle, each of them would have to be careful while driving it so as to not get into any accident.
- We see that the Target Flag variable is negatively correlated with bluebook value. If the bluebook value is high then that means that the car would be very expensive and the owner would likely not want to get the new car into an accident. Otherwise the owner may see their premiums increase sharply after the accident.

4 Data Transformation

4.1 Outliers Treatment

We chose winsorizing as the method to address outliers. Instead of trimming values, winsorizing uses the interquantile range to replace values that are above or below the interquantile range multiplied by a factor. Those values above or below the range multiplied by the factor are then replaced with max and min value of the interquantile range. Using the factor 2.2 for winsorizing outliers is a method developed my Hoaglin and Iglewicz and published Journal of American Statistical Association in 1987[4].

The below table is the summary results of the winsorizing of the data.

Table 4:

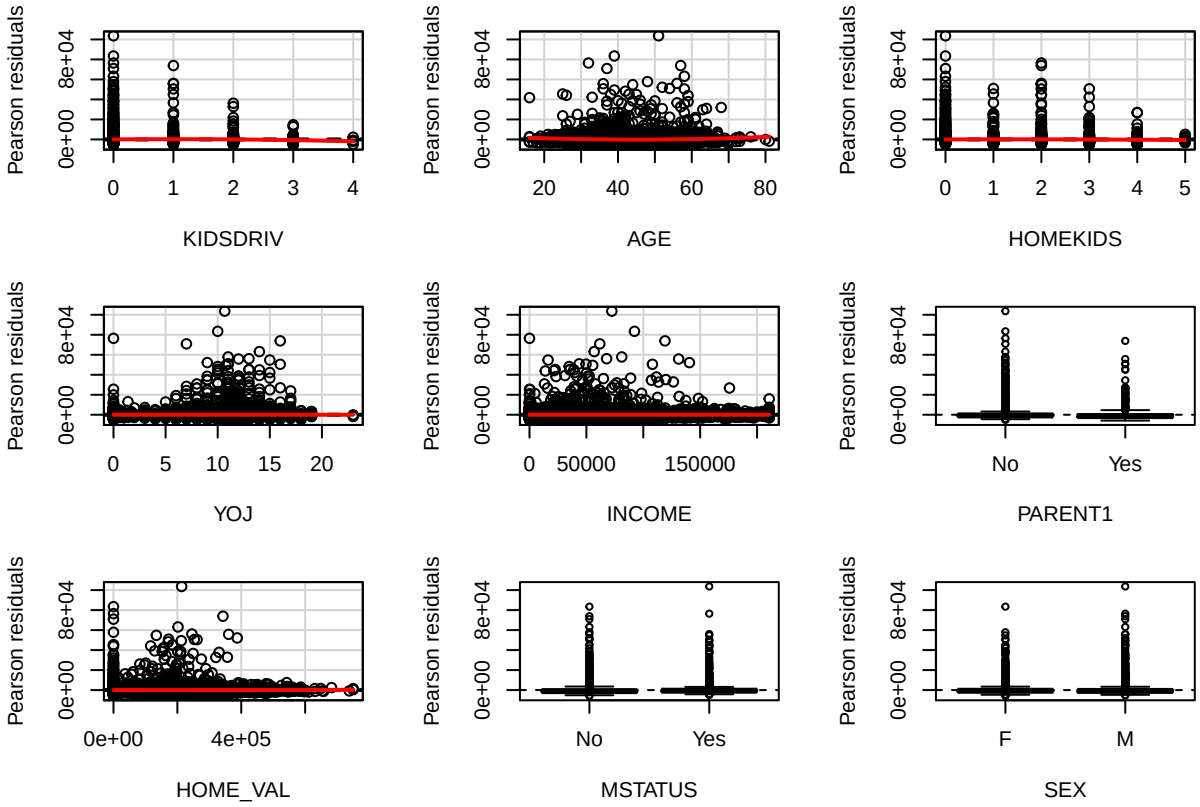
Statistic	N	Mean	St. Dev.	Min	Max
INCOME	8,161	61,225.430	45,828.110	0.000	210,660.000
HOME_VAL	8,161	154,982.200	127,401.100	0.000	750,455.000
OLDCLAIM	8,161	2,757.246	4,469.462	0	14,738
BLUEBOOK	8,161	15,696.740	8,359.971	1,500	46,250
TARGET_FLAG	8,161	0.264	0.441	0	1
TARGET_AMT	8,161	1,504.325	4,704.027	0.000	107,586.100
KIDSDRIV	8,161	0.171	0.512	0	4
AGE	8,161	44.782	8.630	16.000	81.000
HOMEKIDS	8,161	0.721	1.116	0	5
YOJ	8,161	10.498	4.037	0.000	23.000
TRAVTIME	8,161	33.486	15.908	5	142
TIF	8,161	5.351	4.147	1	25
CLM_FREQ	8,161	0.799	1.158	0	5
MVR_PTS	8,161	1.696	2.147	0	13
CAR_AGE	8,161	8.350	5.602	0.000	28.000

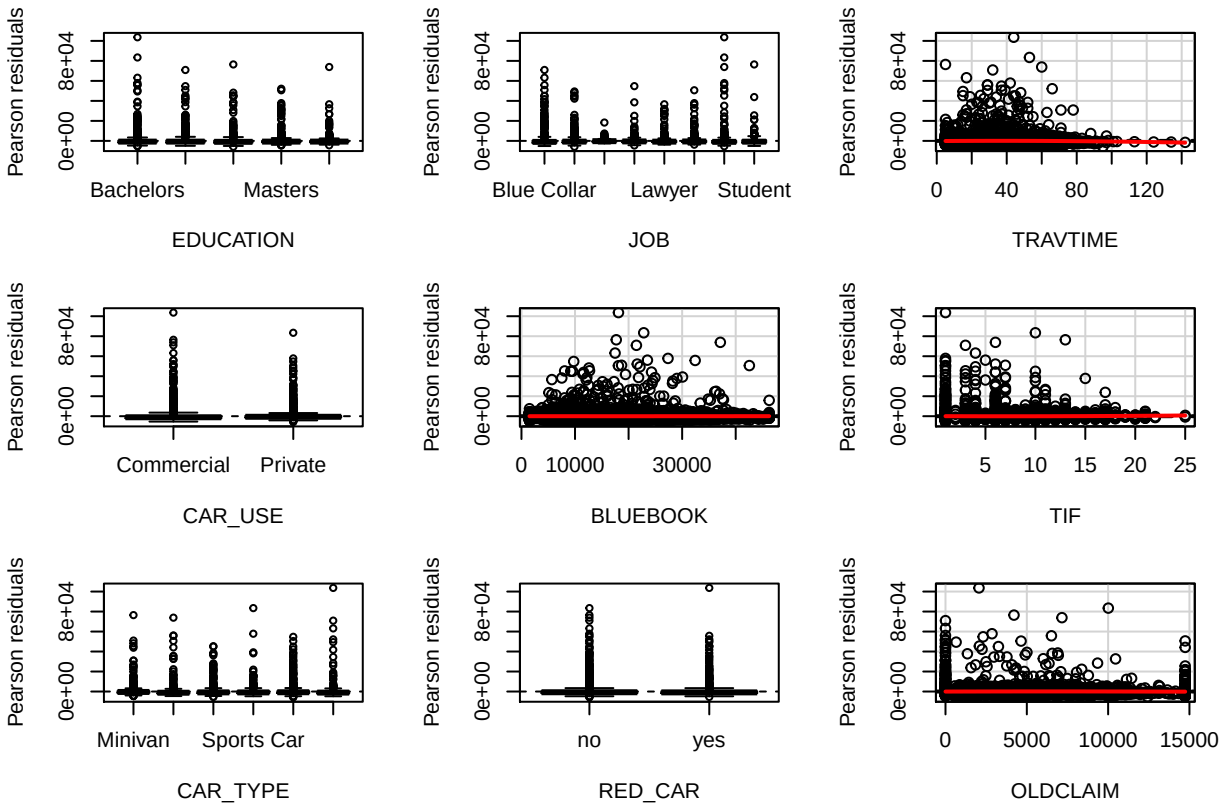
[4]Hoaglin, D. C., and Iglewicz, B. (1987), Fine tuning some resistant rules for outlier labeling, Journal of American Statistical Association, 82, 1147-1149.

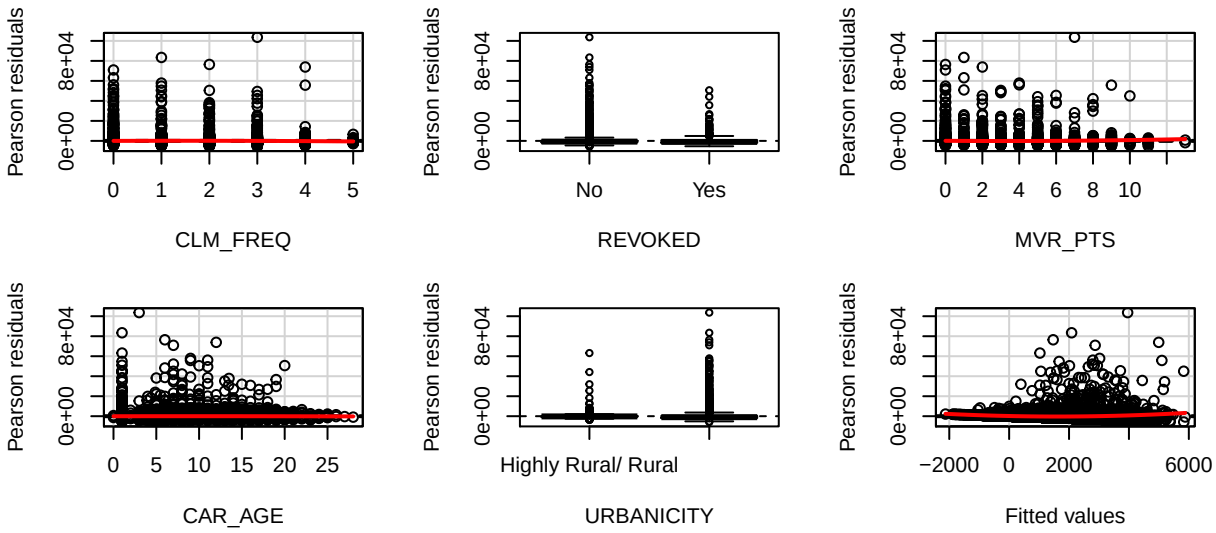
4.2 BoxCox Transformations

The Box-Cox transformations were done only on three of the input variables - income, house value, and the total number of claims during the past 5 years. These transformations were done based on the residual plots. In the residual plots, these three variables showed a great deal of non-constant variance because the plots were funnel-shaped.

Non-constant Variance Score Test Variance formula: ~ KIDSDRIV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS + SEX + EDUCATION + JOB + TRAVTIME + CAR_USE + BLUEBOOK + TIF + CAR_TYPE + RED_CAR + OLDCLAIM + CLM_FREQ + REVOKED + MVR_PTS + CAR_AGE + URBANICITY
Chisquare = 5720.739 Df = 36 p = 0




Pearson residuals
0e+00
8e+04
Bachelors
Masters
EDUCATION
Blue Collar
Lawyer
Student
JOB
0
40
80
120
TRAVTIME
Commercial
Private
CAR_USE
0
10000
30000
BLUEBOOK
5
10
15
20
25
TIF
Minivan
Sports Car
CAR_TYPE
no
yes
RED_CAR
0
5000
10000
15000
OLDCLAIM




```
##            Test stat Pr(>|t|)
## KIDSDRIV      -2.068    0.039
## AGE            4.741    0.000
## HOMEKIDS      -1.519    0.129
## YOJ            0.031    0.976
## INCOME        -0.069    0.945
## PARENT1           NA       NA
## HOME_VAL       0.528    0.597
## MSTATUS           NA       NA
## SEX               NA       NA
## EDUCATION         NA       NA
## JOB               NA       NA
## TRAVTIME      -1.328    0.184
## CAR_USE           NA       NA
## BLUEBOOK       0.130    0.896
## TIF            1.081    0.280
## CAR_TYPE          NA       NA
## RED_CAR           NA       NA
## OLDCLAIM      -1.799    0.072
## CLM_FREQ      -1.499    0.134
## REVOKED           NA       NA
## MVR_PTS        2.257    0.024
## CAR_AGE       -0.464    0.642
## URBANICITY        NA       NA
## Tukey test     8.684    0.000
```

Using the `BoxCox.lambda` function from the `forecast` package we are able to determine our necessary transformations to our independent variables.

λ	Variables
0.268842617694589	INCOME
0.505233636014921	HOME_VAL
0.456635555660553	TRAVTIME

Utilizing the below table of common transformations based on the lambda value of the BoxCox we further transform our independent variables.

Common Box-Cox Transformations[5] [6]

λ	Y'
-2	$Y^{-2} = \frac{1}{Y^2}$
-1	$Y^{-1} = \frac{1}{Y^1}$
-0.5	$Y^{-0.5} = \frac{1}{\sqrt{(Y)}}$
0	$\log(Y)$
.25	$\sqrt[4]{Y}$
0.5	$Y^{0.5} = \sqrt{(Y)}$
1	$Y^1 = Y$
2	Y^2

Lambda values were truncated to the nearest tenth that match a common transformation as per the below table.

variable	variable transformation
INCOME	$\sqrt[4]{INCOME}$
HOME VAL	$\sqrt{(HOME\ VAL)}$
TRAVTIME	$\sqrt{TRAVTIME}$

[5] By Understanding Both the Concept of Transformation and the Box-Cox Method, Practitioners Will Be Better Prepared to Work with Non-normal Data. . "Making Data Normal Using Box-Cox Power Transformation." ISixSigma. N.p., n.d. Web. 29 Oct. 2016.

[6] "Which Variance Inflation Factor Should I Be Using: $textGVIF$ or $textGVIF^{1/(2cdottextdf)}$?" R. N.p., n.d. Web. 13 Nov. 2016.

5 Models Built

5.1 Logistic Regressions 1 - Backwards Selection Method

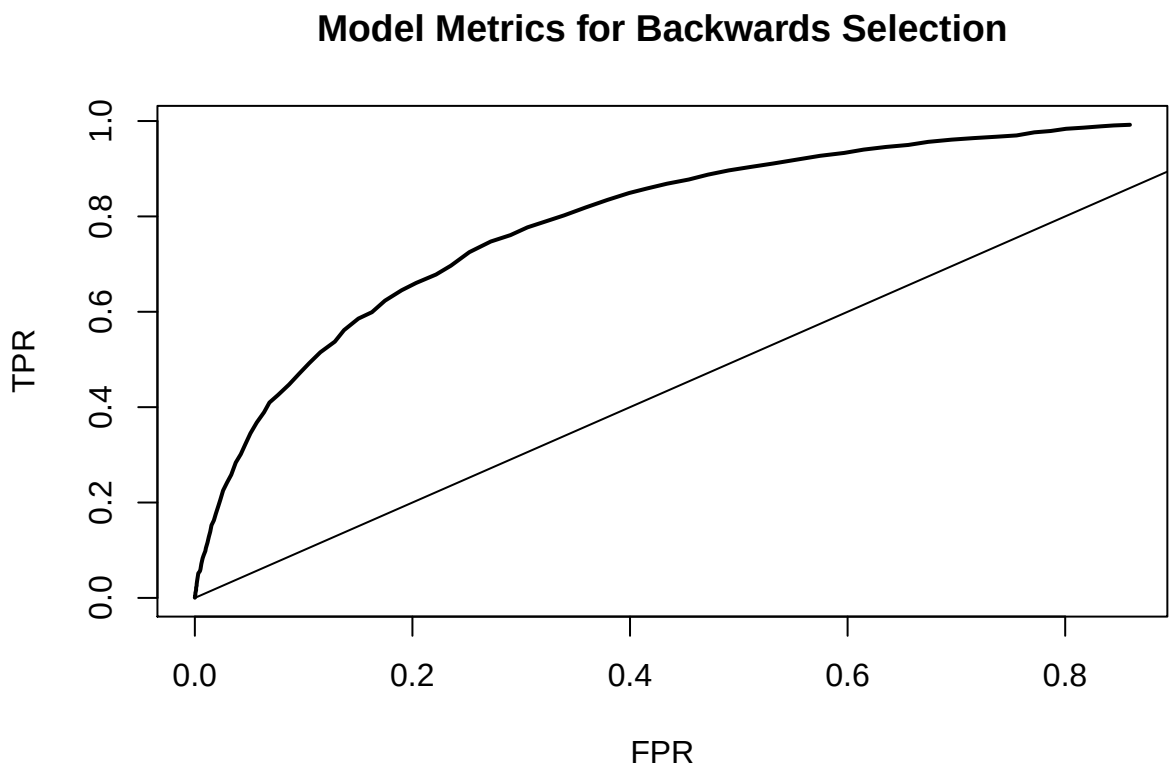
In the backwards selection model, the resulting AIC was 7,703.13. All of the variables remain except the age of the driver, sex, whether the car was red or not, number of kids at home, car use, and car age. Zero correlation for bluebook value is a result of our transformations. As the bluebook value increases, the log likelihood that the vehicle gets into a crash decreases.

Table 6:

	fullModel
Constant	0.113*** (0.037)
KIDSDRIV	0.065*** (0.009)
I(INCOMEˆ(1/4))	−0.008*** (0.002)
PARENT1Yes	0.085*** (0.015)
I(sqrt(HOME_VAL))	−0.0001*** (0.00003)
MSTATUSYes	−0.059*** (0.012)
EDUCATIONHigh School	0.062*** (0.013)
EDUCATIONLess Than High School	0.054*** (0.016)
EDUCATIONMasters	0.024 (0.017)
EDUCATIONPhD	0.041* (0.022)
JOBClerical	0.012 (0.016)
JOBDoctor	−0.134*** (0.036)
JOBHome Maker	−0.053** (0.025)
JOBLawyer	−0.051* (0.026)
JOBManager	−0.136*** (0.019)
JOBProfessional	−0.028 (0.018)
JOBStudent	−0.069*** (0.023)
I(sqrt(TRAVTIME))	0.023*** (0.003)
CAR_USEPrivate	−0.126*** (0.014)
BLUEBOOK	−0.00000*** (0.00000)
TIF	−0.008*** (0.001)
CAR_TYPEPanel Truck	0.069*** (0.022)
CAR_TYPEPickup	0.073*** (0.015)
CAR_TYPESports Car	0.133*** (0.016)
CAR_TYPESUV	0.096*** (0.012)
CAR_TYPEVan	0.081*** (0.018)
OLDCLAIM	−0.00000** (0.00000)
CLM_FREQ	0.031*** (0.005)
REVOKEDYes	0.139*** (0.014)
MVR_PTS	0.021*** (0.002)
URBANICITYHighly Urban/ Urban	0.299*** (0.012)
N	8,161
Log Likelihood	−3,820.565
Akaike Inf. Crit.	7,703.130
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

5.1.1 Model Metrics for Backwards Selection

We first use an established threshold of .50 to determine our best possible threshold.



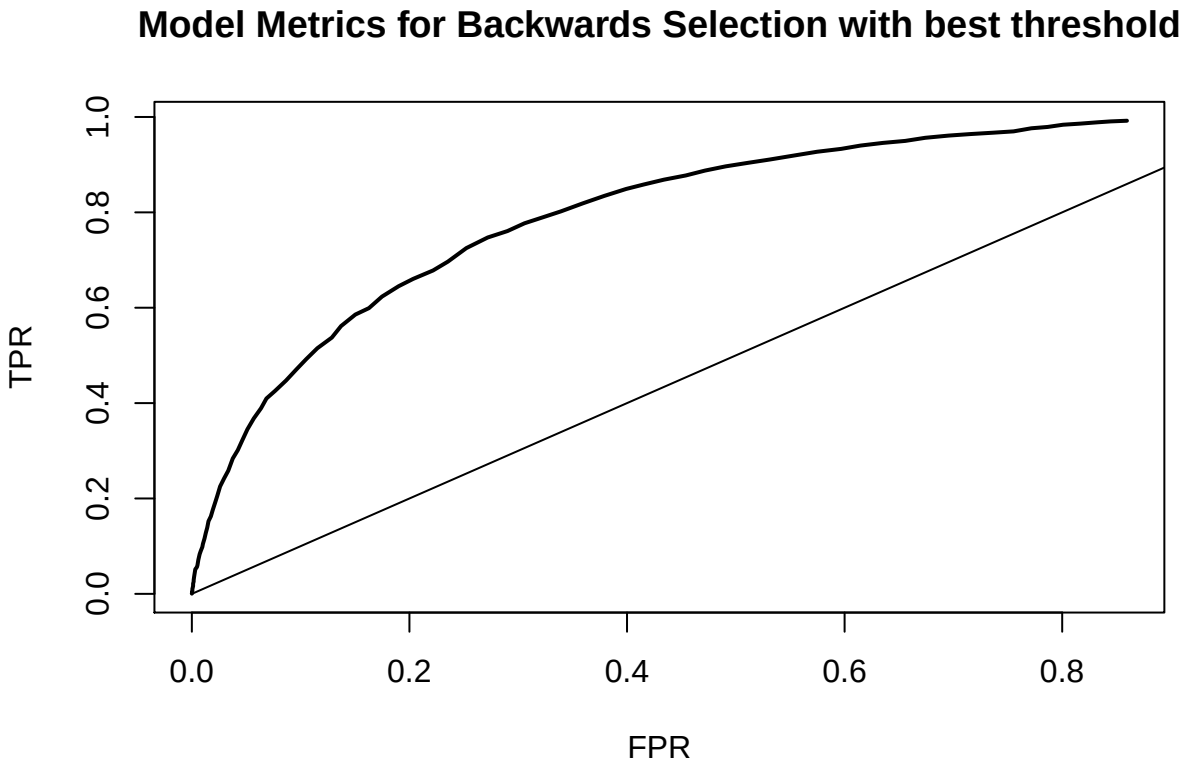
	Act-Pos	Act-Neg
Pred-Pos	792	1361
Pred-Neg	342	5666

	Model Metrics for Backwards Selection
accuracy	0.791
classif.error	0.209
precision	0.698
sensitivity	0.368
specificity	0.943
f1score	0.482
auc	0.672
best.threshold	0.320
aic	7703.130
CVError	0.151

Our previous results indicate that .320 would be the best threshold for this model so we re-run our metrics using this threshold.

5.1.1.1 Model Metrics for Backwards Selection with best threshold

Model Metrics using best threshold of .320.



	Act-Pos	Act-Neg
Pred-Pos	1609	544
Pred-Neg	1634	4374

	Model Metrics for Backwards Selection with best threshold
accuracy	0.733
classif.error	0.267
precision	0.496
sensitivity	0.747
specificity	0.728
f1score	0.596
auc	0.672
best.threshold	0.320
aic	7703.130
CVError	0.151

5.1.2 Multicollinearity for Backwards Selection

We square `GVIF^(1/(2*Df))` [7] in order to use the VIF threshold of 5 for multicollinearity. Here in our subset selection model we find that no variable exceeds our pre-established threshold of 5 for multicollinearity.

rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
KIDSDRIV	1.077479	1	1.038017	1.077479
I(INCOME^(1/4))	3.304651	1	1.817870	3.304651
PARENT1	1.411265	1	1.187967	1.411265
I(sqrt(HOME_VAL))	2.092827	1	1.446661	2.092827
MSTATUS	2.011783	1	1.418373	2.011783
EDUCATION	6.358805	4	1.260149	1.587976
JOB	25.249598	7	1.259392	1.586069
I(sqrt(TRAVTIME))	1.033131	1	1.016431	1.033131
CAR_USE	2.409493	1	1.552254	2.409493
BLUEBOOK	1.671435	1	1.292840	1.671435
TIF	1.007070	1	1.003529	1.007070
CAR_TYPE	2.488834	5	1.095468	1.200050
OLDCLAIM	2.191933	1	1.480518	2.191933
CLM_FREQ	2.074773	1	1.440407	2.074773
REVOKED	1.199983	1	1.095437	1.199983
MVR_PTS	1.237482	1	1.112422	1.237482
URBANICITY	1.247372	1	1.116858	1.247372

[7] "Which Variance Inflation Factor Should I Be Using: $textGVIF$ or $textGVIF^{1/(2cdottextdf)}$?" R. N.p., n.d. Web. 13 Nov. 2016.

5.2 Logistic Regression 2 - Forwards Selection Method

In the forwards selection model, the resulting AIC was 7,712.07. All of the variables remain in the model.

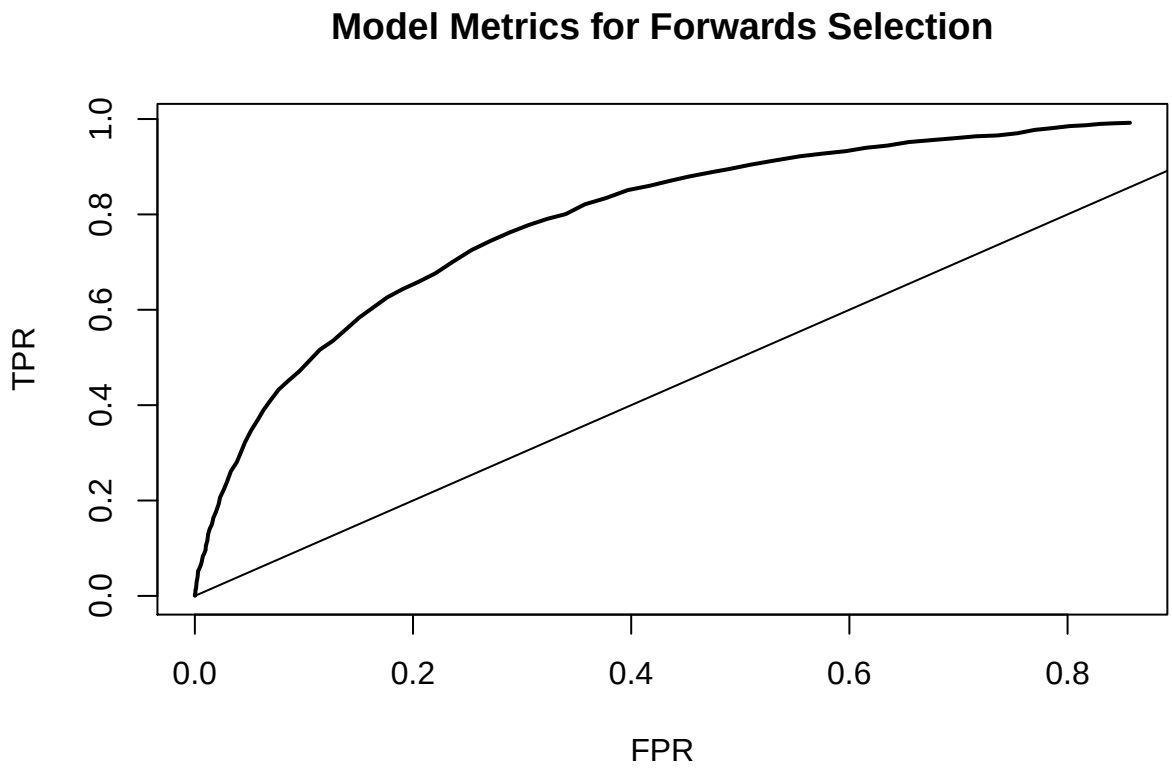
Table 12:

	fullModel
Constant	0.123** (0.048)
KIDSDRIV	0.062*** (0.010)
AGE	−0.0004 (0.001)
HOMEKIDS	0.004 (0.006)
YOJ	0.001 (0.002)
I(INCOMEˆ(1/4))	−0.009*** (0.002)
PARENT1Yes	0.075*** (0.017)
I(sqrt(HOME_VAL))	−0.0001*** (0.00003)
MSTATUSYes	−0.063*** (0.013)
SEXM	0.014 (0.016)
EDUCATIONHigh School	0.059*** (0.014)
EDUCATIONLess Than High School	0.049*** (0.018)
EDUCATIONMasters	0.028 (0.018)
EDUCATIONPhD	0.046** (0.023)
JOBClerical	0.010 (0.016)
JOBDoctor	−0.132*** (0.037)
JOBHome Maker	−0.051** (0.025)
JOBLawyer	−0.049* (0.026)
JOBManager	−0.134*** (0.019)
JOBProfessional	−0.027 (0.018)
JOBStudent	−0.070*** (0.023)
I(sqrt(TRAVTIME))	0.023*** (0.003)
CAR_USEPrivate	−0.126*** (0.014)
BLUEBOOK	−0.00000*** (0.00000)
TIF	−0.008*** (0.001)
CAR_TYPEPanel Truck	0.063*** (0.024)
CAR_TYPEPickup	0.074*** (0.015)
CAR_TYPESports Car	0.141*** (0.019)
CAR_TYPESUV	0.104*** (0.015)
CAR_TYPEVan	0.077*** (0.018)
RED_CARyes	−0.005 (0.013)
OLDCLAIM	−0.00000** (0.00000)
CLM_FREQ	0.031*** (0.005)
REVOKEDYes	0.138*** (0.014)
MVR_PTS	0.021*** (0.002)
CAR_AGE	−0.001 (0.001)
URBANICITYHighly Urban/ Urban	0.299*** (0.012)
N	8,161
Log Likelihood	−3,819.035
Akaike Inf. Crit.	7,712.070

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

5.2.1 Model Metrics for Forwards Selection

We first use an established threshold of .50 to determine our best possible threshold.



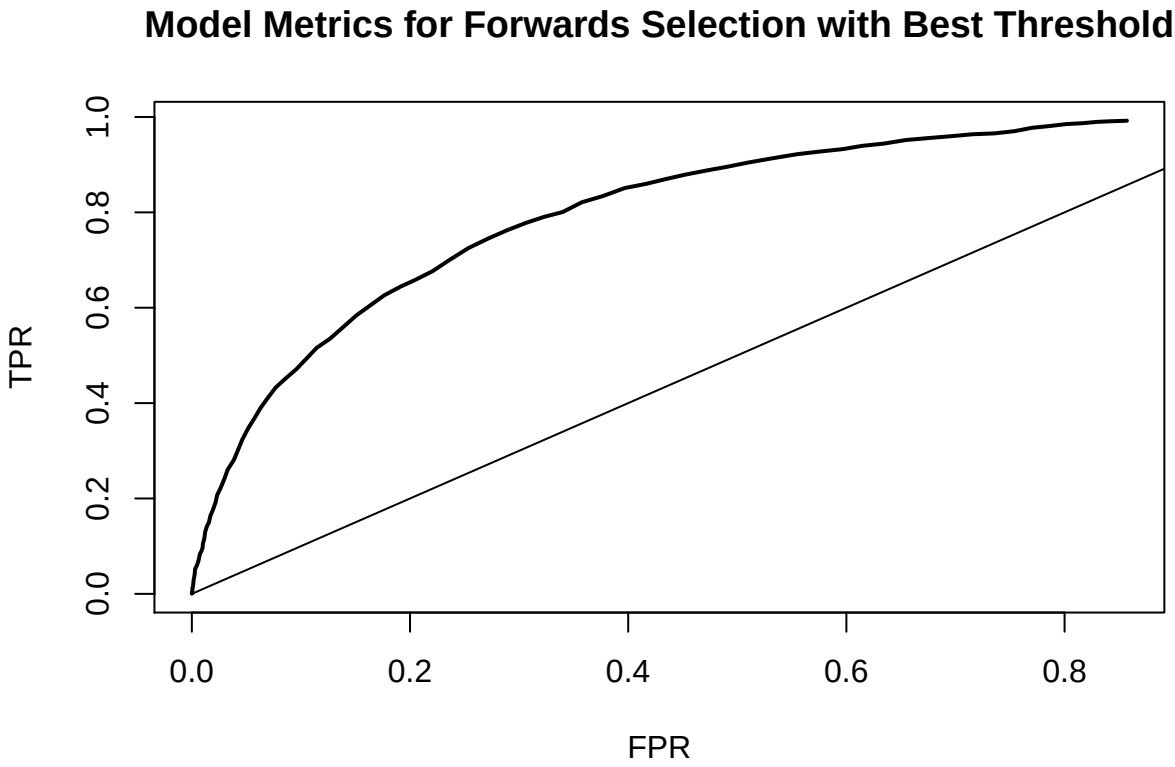
	Act-Pos	Act-Neg
Pred-Pos	797	1356
Pred-Neg	348	5660

	Model Metrics for Forwards Selection
accuracy	0.791
classif.error	0.209
precision	0.696
sensitivity	0.370
specificity	0.942
f1score	0.483
auc	0.670
best.threshold	0.310
aic	7712.070
CVError	0.151

Our previous results indicate that .310 would be the best threshold for this model so we re-run our metrics using this threshold.

5.2.1.1 Model Metrics for Forwards Selection with best threshold

Model Metrics using best threshold of .310.



	Act-Pos	Act-Neg
Pred-Pos	1641	512
Pred-Neg	1734	4274

	Model Metrics for Forwards Selection with Best Threshold
accuracy	0.725
classif.error	0.275
precision	0.486
sensitivity	0.762
specificity	0.711
f1score	0.594
auc	0.670
best.threshold	0.310
aic	7712.070
CVError	0.151

Model Metrics for Forwards Selection with Best Threshold

5.2.2 Multicollinearity for Forwards Selection

We square `GVIF^(1/(2*Df))` in order to use the VIF threshold of 5 for multicollinearity. Here in our subset selection model we find that no variable exceeds our pre-established threshold of 5 for multicollinearity.

rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
KIDSDRIV	1.325344	1	1.151236	1.325344
AGE	1.487782	1	1.219747	1.487782
HOMEKIDS	2.136050	1	1.461523	2.136050
YOJ	2.043591	1	1.429542	2.043591
I(INCOME^(1/4))	4.626874	1	2.151017	4.626874
PARENT1	1.844294	1	1.358048	1.844294
I(sqrt(HOME_VAL))	2.115696	1	1.454543	2.115696
MSTATUS	2.204211	1	1.484659	2.204211
SEX	3.324170	1	1.823231	3.324170
EDUCATION	8.969420	4	1.315514	1.730578
JOB	26.685061	7	1.264376	1.598647
I(sqrt(TRAVTIME))	1.033912	1	1.016814	1.033912
CAR_USE	2.409933	1	1.552396	2.409933
BLUEBOOK	2.065326	1	1.437124	2.065326
TIF	1.007641	1	1.003813	1.007641
CAR_TYPE	5.489500	5	1.185641	1.405745
RED_CAR	1.814257	1	1.346944	1.814257
OLDCLAIM	2.193395	1	1.481011	2.193395
CLM_FREQ	2.076612	1	1.441045	2.076612
REVOKED	1.200779	1	1.095800	1.200779
MVR_PTS	1.239981	1	1.113544	1.239981
CAR_AGE	2.166209	1	1.471805	2.166209
URBANICITY	1.248323	1	1.117284	1.248323

5.3 Logistic Regression 3 - Subset Selection Method

5.3.1 Subset Variable Selection

Using the `leaps` package and the `regsubsets` function we are able to subset our independent variables by looking at the best model for each predictor.

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)
KIDSDRIV								*
AGE								
HOMEKIDS								
YOJ								
I(INCOMEˆ(1/4))					*	*	*	*
PARENT1Yes					*	*	*	
I(sqrt(HOME_VAL))		*	*	*				
MSTATUSYes								*
SEXM								
EDUCATIONHigh School								
EDUCATIONLess Than High School								
EDUCATIONMasters								
EDUCATIONPhD								
JOBClerical								
JOBDoctor								
JOBHome Maker								
JOBLawyer								
JOBManager							*	*
JOBProfessional								
JOBStudent								
I(sqrt(TRAVTIME))								
CAR_USEPrivate				*	*	*	*	*
BLUEBOOK								
TIF								
CAR_TYPEPanel Truck								
CAR_TYPEPickup								
CAR_TYPESports Car								
CAR_TYPESUV								
CAR_TYPEVan								
RED_CARyes								
OLDCLAIM								
CLM_FREQ								
REVOKEDYes						*	*	*
MVR_PTS			*	*	*	*	*	*
CAR_AGE								
URBANICITYHighly Urban/ Urban	*	*	*	*	*	*	*	*

5.3.2 Subset Model

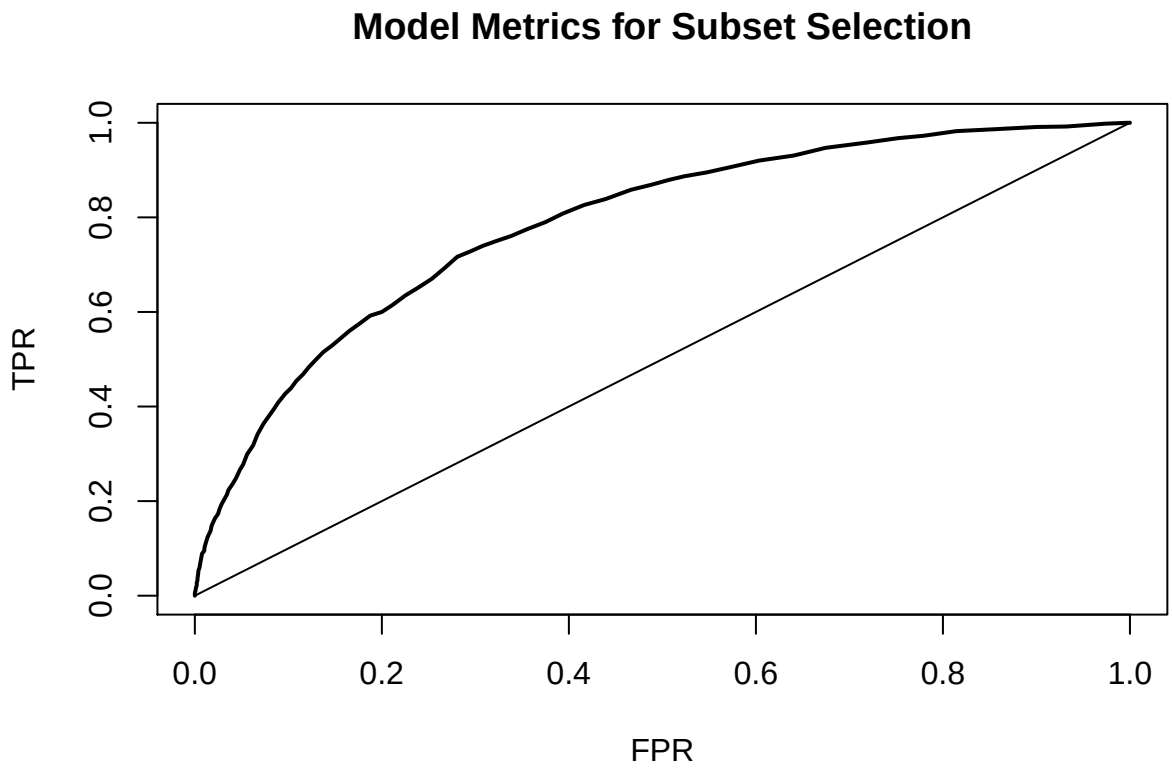
The variables as indicated in column 8 of the previous table will be further implement into our subset selection model in the following table. In the subset selection model, the resulting AIC was 7,708.37. Very few of the variables remained. These variables were number of kids driving, income, marital status, job category, car use, whether the license was revoked or not, urbanicity, and motor vehicle record points. In this model, the target variable has a stronger correlation with urbanicity than it does in the other logistic models.

Table 19:

	TARGET_FLAG
Constant	−1.135*** (0.185)
KIDSDRIV	0.469*** (0.052)
I(INCOMEˆ(1/4))	−0.085*** (0.010)
MSTATUSYes	−0.748*** (0.057)
JOBClerical	0.148 (0.099)
JOBDoctor	−0.972*** (0.218)
JOBHome Maker	−0.422*** (0.156)
JOBLawyer	−0.467*** (0.121)
JOBManager	−0.955*** (0.096)
JOBProfessional	−0.398*** (0.099)
JOBStudent	−0.343** (0.144)
CAR_USEPrivate	−0.725*** (0.070)
REVOKEDYes	0.753*** (0.078)
MVR_PTS	0.151*** (0.012)
URBANICITYHighly Urban/ Urban	2.283*** (0.109)
N	8,161
Log Likelihood	−3,839.185
Akaike Inf. Crit.	7,708.369
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

5.3.3 Model Metrics for Subset Selection

We first use an established threshold of .50 to determine our best possible threshold.

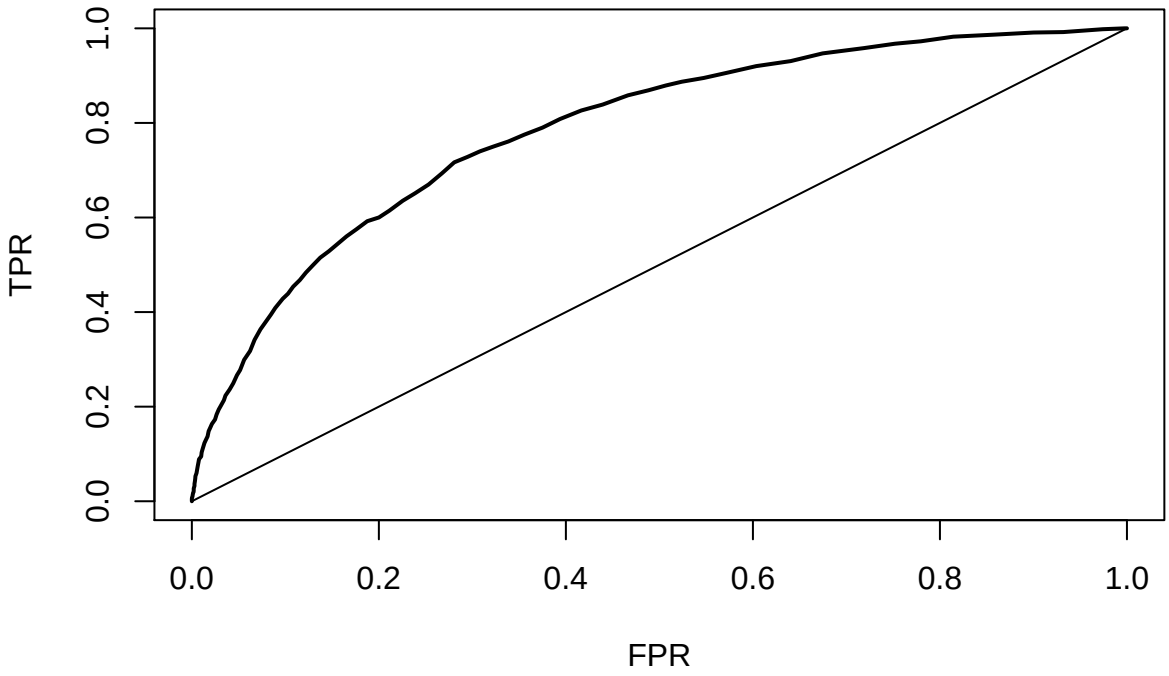


	Act-Pos	Act-Neg
Pred-Pos	783	1370
Pred-Neg	441	5567

	Model Metrics for Subset Selection
accuracy	0.778
classif.error	0.222
precision	0.640
sensitivity	0.364
specificity	0.927
f1score	0.464
auc	0.786
best.threshold	0.280
aic	7708.369
CVError	0.154

5.3.3.1 Model Metrics for Subset Selection with best threshold

Model Metrics using best threshold of .280.



	Act-Pos	Act-Neg
Pred-Pos	1543	610
Pred-Neg	1686	4322

	Model Metrics for Subset Selection with Best Threshold
accuracy	0.719
classif.error	0.281
precision	0.478
sensitivity	0.717
specificity	0.719
f1score	0.573
auc	0.786
best.threshold	0.280
aic	7708.369
CVError	0.154

5.3.4 Multicollinearity for Subset Selection

We square `GVIF^(1/(2*Df))` in order to use the VIF threshold of 5 for multicollinearity. Here in our subset selection model we find that no variable exceeds our pre-established threshold of 5 for multicollinearity.

rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
KIDSDRIV	1.022204	1	1.011041	1.022204
I(INCOME^(1/4))	3.012788	1	1.735739	3.012788
MSTATUS	1.026972	1	1.013396	1.026972
JOB	4.435051	7	1.112262	1.237126
CAR_USE	1.491887	1	1.221428	1.491887
REVOKED	1.004182	1	1.002089	1.004182
MVR_PTS	1.011248	1	1.005608	1.011248
URBANICITY	1.084428	1	1.041359	1.084428

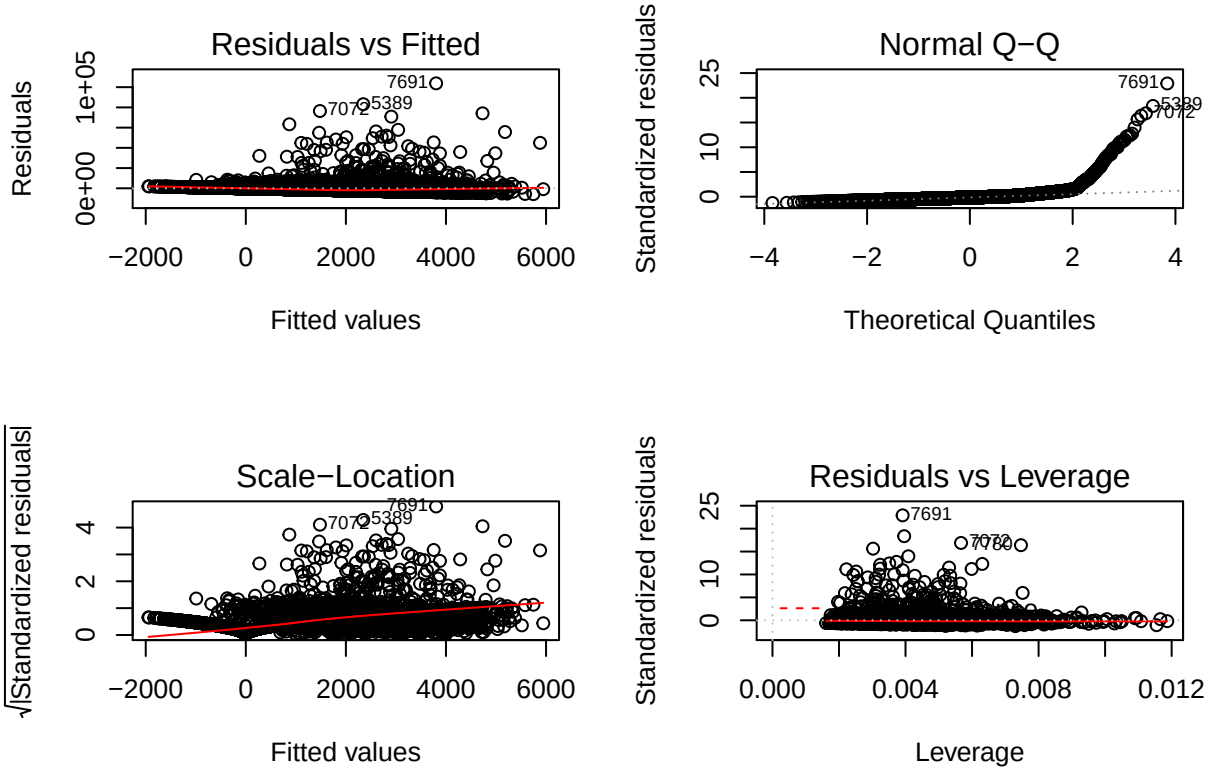
5.4 Linear Regression 1 - Backwards Selection

In the backwards linear regression model, the variables eliminated were The target variable has the strongest correlation with the urbanicity. Due to our transformation of the income variable, income does have some correlation now with the target amount. Before our tranformation there was no correlation at all between these two variables.

Table 25:

	bkFitStep
Constant	155.127 (483.701)
KIDSDRIV	373.748*** (102.021)
I(INCOMEˆ(1/4))	−42.613** (18.400)
PARENT1Yes	651.686*** (176.724)
I(sqrt(HOME_VAL))	−0.513 (0.328)
MSTATUSYes	−472.060*** (145.552)
SEXM	354.488** (160.980)
EDUCATIONHigh School	179.812 (158.771)
EDUCATIONLess Than High School	275.395 (206.053)
EDUCATIONMasters	359.220* (208.987)
EDUCATIONPhD	652.657** (268.258)
JOBClerical	54.342 (191.096)
JOBDoctor	−1,228.175*** (428.452)
JOBHome Maker	−316.777 (298.794)
JOBLawyer	−346.133 (304.717)
JOBManager	−1,036.446*** (224.812)
JOBProfessional	11.033 (210.674)
JOBStudent	−465.695* (273.834)
I(sqrt(TRAVTIME))	131.435*** (34.969)
CAR_USEPrivate	−824.416*** (161.514)
BLUEBOOK	0.014 (0.009)
TIF	−47.715*** (12.166)
CAR_TYPEPanel Truck	283.655 (275.805)
CAR_TYPEPickup	397.622** (170.505)
CAR_TYPESports Car	1,035.523*** (216.328)
CAR_TYPESUV	775.037*** (178.442)
CAR_TYPEVan	519.314** (212.581)
CLM_FREQ	106.214** (48.786)
REVOKEDYes	430.516*** (154.861)
MVR_PTS	170.200*** (25.800)
CAR_AGE	−27.881** (13.204)
URBANICITYHighly Urban/ Urban	1,676.140*** (139.142)
N	8,161
R^2	0.072
Adjusted R^2	0.068
Residual Std. Error	4,541.097 (df = 8129)
F Statistic	20.227*** (df = 31; 8129)
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

5.4.1 Linear Regression 1 - Backwards Selection Model Metrics



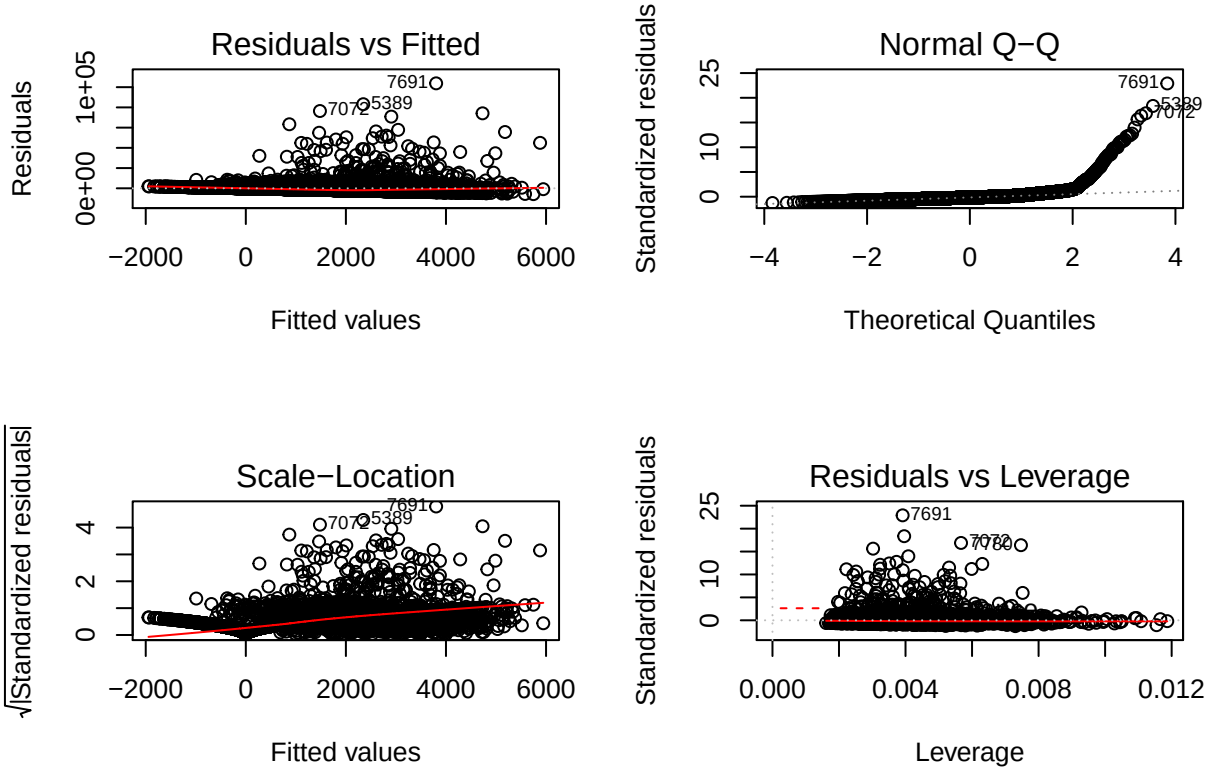
5.5 Linear Regression 2 - Forwards Selection

In the forwards linear regression model, the variables eliminated were the same as the variables eliminated in the backwards linear regression. Additionally, we removed `HOME_VAL` and `BLUEBOOK` because they did not appear to be significant in the previous model. Just like the previous model, the target variable has the strongest correlation with urbanicity.

Table 26:

	fwdFitstep
Constant	357.964 (460.236)
MVR_PTS	170.557*** (25.795)
URBANICITYHighly Urban/ Urban	1,674.581*** (139.164)
JOBClerical	61.164 (190.906)
JOBDoctor	−1,209.748*** (428.237)
JOBHome Maker	−318.806 (298.826)
JOBLawyer	−338.710 (304.616)
JOBManager	−1,029.965*** (224.758)
JOBProfessional	11.612 (210.556)
JOBStudent	−377.477 (267.863)
MSTATUSYes	−601.849*** (119.319)
CAR_USEPrivate	−829.337*** (161.487)
KIDSDRIV	376.869*** (102.025)
CAR_TYPEPanel Truck	463.358* (248.511)
CAR_TYPEPickup	362.629** (169.180)
CAR_TYPESports Car	923.236*** (204.203)
CAR_TYPESUV	668.781*** (164.957)
CAR_TYPEVan	591.351*** (207.143)
TIF	−47.827*** (12.168)
I(sqrt(TRAVTIME))	132.590*** (34.970)
PARENT1Yes	642.156*** (176.701)
I(INCOMEˆ(1/4))	−44.237** (17.867)
REVOKEDYes	434.916*** (154.857)
CAR_AGE	−27.498** (13.203)
CLM_FREQ	107.285** (48.754)
SEXM	247.621* (146.601)
EDUCATIONHigh School	185.762 (158.504)
EDUCATIONLess Than High School	284.796 (205.740)
EDUCATIONMasters	356.364* (209.019)
EDUCATIONPhD	651.012** (268.056)
N	8,161
R^2	0.071
Adjusted R^2	0.068
Residual Std. Error	4,541.888 (df = 8131)
F Statistic	21.448*** (df = 29; 8131)
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

5.5.1 Linear Regression 2 - Forwards Selection Model Metrics



6 Selected Models

6.1 Logistic Regression Selected

Logistic Regression Model Metrics

Out of all the logistic models, the Subset Selection Model rated the best due to the highest accuracy. The AIC for this model was not the lowest. However, the difference between this AIC (7708.37) and the lowest AIC (7703.13) is not too much.

	Model Metrics for Forwards Selection	Model Metrics for Subset Selection	Model Metrics for Backwards Selection with best threshold
accuracy	0.725	0.778	0.733
classif.error	0.275	0.222	0.267
precision	0.486	0.640	0.496
sensitivity	0.762	0.364	0.747
specificity	0.711	0.927	0.728
f1score	0.594	0.464	0.596
auc	0.670	0.786	0.672
best.threshold	0.310	0.280	0.320
aic	7712.070	7708.369	7703.130
CVError	0.151	0.154	0.151

Our Final Logistic Model (Subset Selection Method):

$$\begin{aligned}\log(TARGETFLAG) = & -469 * KIDSDRIV + -0.085 * I(INCOME^(1/4)) + -0.748 * MSTATUSYes \\ & + 0.148 * JOBClerical + -0.972 * JOBDoctor + -0.421 * JOBHomeMaker \\ & + -0.466 * JOBLawyer + -0.954 * JOBManager + -0.398 * JOBProfessional \\ & + -0.343 * JOBStudent + -0.725 * CAR_USEPrivate + 0.752 * REVOKEDYes \\ & + 0.151 * MVR_PTS + 2.282672 * URBANICITYHighlyUrban/Urban + -1.135467\end{aligned}$$

6.2 Linear Regression Selected

In the linear models rendered, some of the correlation coefficients do make sense. For example, in both models, it would make sense for a student to have to pay less in a car crash due to the fact that the student would spend more time studying and less time on the road. It would also make sense for urbanicity to affect the cost during a car crash because in urban areas, there are more people and pedestrians and the probability of people getting killed in a car crash would be very high as opposed to rural areas where there would be less pedestrians.

6.3 Predictions using Final Model on Evaluation Data Set

The below table represents our predictions as indicated in column `eval.predResp` using our final model using the provided evaluation data set.

7 Appendix A

7.1 Session Info

- R version 3.3.2 (2016-10-31), `x86_64-w64-mingw32`
- Locale: `LC_COLLATE=English_United States.1252`, `LC_CTYPE=English_United States.1252`, `LC_MONETARY=English_United States.1252`, `LC_NUMERIC=C`, `LC_TIME=English_United States.1252`
- Base packages: base, datasets, graphics, grDevices, methods, parallel, stats, utils
- Other packages: abc 2.1, abc.data 1.0, bibtex 0.4.0, boot 1.3-18, car 2.1-3, corrplot 0.77, data.table 1.9.6, doParallel 1.0.10, dplyr 0.5.0, e1071 1.6-7, foreach 1.4.3, forecast 7.3, Formula 1.2-1, ggplot2 2.1.0, glmulti 1.0.7, highlight 0.4.7, Hmisc 4.0-0, iterators 1.0.8, itertools 0.1-3, knitcitations 1.0.7, knitr 1.15, lattice 0.20-34, leaps 2.9, locfit 1.5-9.1, magrittr 1.5, MASS 7.3-45, matrixStats 0.51.0, missForest 1.4, nnet 7.3-12, pacman 0.4.1, pracma 1.9.5, purrr 0.2.2, quantreg 5.29, randomForest 4.6-12, readr 1.0.0, rJava 0.9-8, scales 0.4.1, SparseM 1.74, stargazer 5.2, stringr 1.1.0, survival 2.40-1, tibble 1.2, tidyr 0.6.0, tidyverse 1.0.0, timeDate 3012.100, xlsx 0.5.7, xlsxjars 0.6.1, xtable 1.8-2, zoo 1.7-13
- Loaded via a namespace (and not attached): acepack 1.4.1, assertthat 0.1, bitops 1.0-6, chron 2.3-47, class 7.3-14, cluster 2.0.5, codetools 0.2-15, colorspace 1.3-0, DBI 0.5-1, digest 0.6.10, evaluate 0.10, foreign 0.8-67, fracdiff 1.4-2, grid 3.3.2, gridExtra 2.2.1, gtable 0.2.0, highr 0.6, htmlTable 1.7, htmltools 0.3.5, httr 1.2.1, latticeExtra 0.6-28, lazyeval 0.2.0, lme4 1.1-12, lubridate 1.6.0, Matrix 1.2-7.1, MatrixModels 0.4-1, mgcv 1.8-16, minqa 1.2.4, munsell 0.4.3, nlme 3.1-128, nloptr 1.0.4, pbkrtest 0.4-6, plyr 1.8.4, quadprog 1.5-5, R6 2.2.0, RColorBrewer 1.1-2, Rcpp 0.12.7, RCurl 1.95-4.8, RefManageR 0.13.0, RJSONIO 1.3-0, rmarkdown 1.1, rpart 4.1-10, splines 3.3.2, stringi 1.1.2, tools 3.3.2, tseries 0.10-35, XML 3.98-1.5, yaml 2.1.13