Assignment4_Data621

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DATA EXPLORATION

We checked the overview of the dataset's structure while, summary() provided statistical summaries for each variable. The dataset contains 26 columns and 8161 rows.

```
# Check the structure of the dataset
str(training_df)
```

```
spc_tbl_ [8,161 x 26] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ INDEX      : num [1:8161] 1 2 4 5 6 7 8 11 12 13 ...
 $ TARGET_FLAG: num [1:8161] 0 0 0 0 0 1 0 1 1 0 ...
 $ TARGET_AMT : num [1:8161] 0 0 0 0 0 ...
 $ KIDSDRIV   : num [1:8161] 0 0 0 0 0 0 0 1 0 0 ...
 $ AGE        : num [1:8161] 60 43 35 51 50 34 54 37 34 50 ...
 $ HOMEKIDS   : num [1:8161] 0 0 1 0 0 1 0 2 0 0 ...
 $ YOJ        : num [1:8161] 11 11 10 14 NA 12 NA NA 10 7 ...
 $ INCOME     : chr [1:8161] "$67,349" "$91,449" "$16,039" NA ...
 $ PARENT1    : chr [1:8161] "No" "No" "No" "No" ...
 $ HOME_VAL   : chr [1:8161] "$0" "$257,252" "$124,191" "$306,251" ...
 $ MSTATUS    : chr [1:8161] "z_No" "z_No" "Yes" "Yes" ...
 $ SEX        : chr [1:8161] "M" "M" "z_F" "M" ...
 $ EDUCATION  : chr [1:8161] "PhD" "z_High School" "z_High School" "<High School" ...
 $ JOB        : chr [1:8161] "Professional" "z_Blue Collar" "Clerical" "z_Blue Collar" ...
 $ TRAVTIME   : num [1:8161] 14 22 5 32 36 46 33 44 34 48 ...
 $ CAR_USE    : chr [1:8161] "Private" "Commercial" "Private" "Private" ...
 $ BLUEBOOK   : chr [1:8161] "$14,230" "$14,940" "$4,010" "$15,440" ...
 $ TIF        : num [1:8161] 11 1 4 7 1 1 1 1 1 7 ...
 $ CAR_TYPE   : chr [1:8161] "Minivan" "Minivan" "z_SUV" "Minivan" ...
 $ RED_CAR    : chr [1:8161] "yes" "yes" "no" "yes" ...
 $ OLDCLAIM   : chr [1:8161] "$4,461" "$0" "$38,690" "$0" ...
```

```
$ CLM_FREQ   : num [1:8161] 2 0 2 0 2 0 0 1 0 0 ...
$ REVOKED    : chr [1:8161] "No" "No" "No" "No" ...
$ MVR_PTS    : num [1:8161] 3 0 3 0 3 0 0 10 0 1 ...
$ CAR_AGE    : num [1:8161] 18 1 10 6 17 7 1 7 1 17 ...
$ URBANICITY : chr [1:8161] "Highly Urban/ Urban" "Highly Urban/ Urban" "Highly Urban/ Urba
- attr(*, "spec")=
 .. cols(
 ..   INDEX = col_double(),
 ..   TARGET_FLAG = col_double(),
 ..   TARGET_AMT = col_double(),
 ..   KIDSDRIV = col_double(),
 ..   AGE = col_double(),
 ..   HOMEKIDS = col_double(),
 ..   YOJ = col_double(),
 ..   INCOME = col_character(),
 ..   PARENT1 = col_character(),
 ..   HOME_VAL = col_character(),
 ..   MSTATUS = col_character(),
 ..   SEX = col_character(),
 ..   EDUCATION = col_character(),
 ..   JOB = col_character(),
 ..   TRAVTIME = col_double(),
 ..   CAR_USE = col_character(),
 ..   BLUEBOOK = col_character(),
 ..   TIF = col_double(),
 ..   CAR_TYPE = col_character(),
 ..   RED_CAR = col_character(),
 ..   OLDCLAIM = col_character(),
 ..   CLM_FREQ = col_double(),
 ..   REVOKED = col_character(),
 ..   MVR_PTS = col_double(),
 ..   CAR_AGE = col_double(),
 ..   URBANICITY = col_character()
 .. )
- attr(*, "problems")=<externalptr>
```

Preliminary Data Cleaning

In this section, we reformat variable values into numeric and factor formats. Currency values are converted from a string format to a numeric format by removing $ and commas.

```r
# Remove $ and , from currency columns
# Function to clean dollar values
clean_money <- function(x) {
  as.numeric(gsub("[$,]", "", x))
}

money_vars <- c("INCOME", "HOME_VAL", "BLUEBOOK", "OLDCLAIM", "TARGET_AMT")
factor_vars <- c("TARGET_FLAG", "SEX",  "PARENT1", "MSTATUS", "URBANICITY", "REVOKED",  "RED
numeric_vars <- c("TARGET_AMT", "OLDCLAIM", "CLM_FREQ", "MVR_PTS", "CAR_AGE", "BLUEBOOK", "H

# Apply to relevant columns
clean_df <-  function(df) {

  df <- df |>
    mutate(
      JOB = as.factor(ifelse(is.na(JOB), "Unknown", as.character(JOB))),
      RED_CAR = if_else(RED_CAR == "yes", "Yes", "No"),
      URBANICITY = if_else(URBANICITY == "Highly Urban/ Urban", "Rural", "Urban")
    )

  df[money_vars] <- lapply(df[money_vars], clean_money)
  df[factor_vars] <- lapply(df[factor_vars], function(x) { as.factor(x) })
  df[numeric_vars] <- lapply(df[numeric_vars], function(x) { as.numeric(x) })

  return (df |>
    mutate(across(
      .cols = where(is.factor),
      .fns = ~ factor(sub("^z_", "", .))
    ))
  )
}

training_df <- clean_df(training_df) |>
  subset(select=-c(INDEX))
testing_df <- clean_df(testing_df)
```

Summary Statistics

We review the mean, standard deviation, and median for all numeric variables, helping us understand the data distribution and central tendencies.

Summary Stats for Numeric Variables

```
   TARGET_AMT        OLDCLAIM        CLM_FREQ         MVR_PTS
 Min.   :     0   Min.   :    0   Min.   :0.0000   Min.   : 0.000
 1st Qu.:     0   1st Qu.:    0   1st Qu.:0.0000   1st Qu.: 0.000
 Median :     0   Median :    0   Median :0.0000   Median : 1.000
 Mean   :  1504   Mean   : 4037   Mean   :0.7986   Mean   : 1.696
 3rd Qu.:  1036   3rd Qu.: 4636   3rd Qu.:2.0000   3rd Qu.: 3.000
 Max.   :107586   Max.   :57037   Max.   :5.0000   Max.   :13.000

    CAR_AGE          BLUEBOOK        HOME_VAL          INCOME
 Min.   :-3.000   Min.   : 1500   Min.   :     0   Min.   :     0
 1st Qu.: 1.000   1st Qu.: 9280   1st Qu.:     0   1st Qu.: 28097
 Median : 8.000   Median :14440   Median :161160   Median : 54028
 Mean   : 8.328   Mean   :15710   Mean   :154867   Mean   : 61898
 3rd Qu.:12.000   3rd Qu.:20850   3rd Qu.:238724   3rd Qu.: 85986
 Max.   :28.000   Max.   :69740   Max.   :885282   Max.   :367030
 NA's   :510                      NA's   :464      NA's   :445
      YOJ          HOMEKIDS         KIDSDRIV           AGE
 Min.   : 0.0   Min.   :0.0000   Min.   :0.0000   Min.   :16.00
 1st Qu.: 9.0   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:39.00
 Median :11.0   Median :0.0000   Median :0.0000   Median :45.00
 Mean   :10.5   Mean   :0.7212   Mean   :0.1711   Mean   :44.79
 3rd Qu.:13.0   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:51.00
 Max.   :23.0   Max.   :5.0000   Max.   :4.0000   Max.   :81.00
 NA's   :454                                      NA's   :6
```

Standard Deviviations for Numeric Variables

```
# A tibble: 1 x 7
  TARGET_AMT_sd KIDSDRIV_sd AGE_sd HOMEKIDS_sd YOJ_sd INCOME_sd HOME_VAL_sd
          <dbl>       <dbl>  <dbl>       <dbl>  <dbl>     <dbl>       <dbl>
1         4704.       0.512   8.63        1.12   4.09    47573.     129124.
```

```
# A tibble: 1 x 7
  TRAVTIME_sd BLUEBOOK_sd TIF_sd OLDCLAIM_sd CLM_FREQ_sd MVR_PTS_sd CAR_AGE_sd
        <dbl>       <dbl>  <dbl>       <dbl>       <dbl>      <dbl>      <dbl>
1        15.9       8420.   4.15       8777.        1.16       2.15       5.70
```

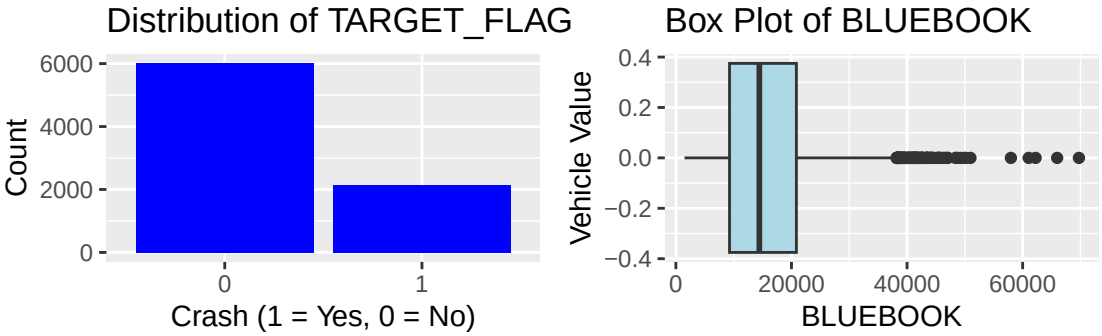
Summary Stats for Categorical Variables

```
TARGET_FLAG SEX      PARENT1    MSTATUS    URBANICITY   REVOKED    RED_CAR
0:6008      F:4375   No :7084   No :3267   Rural:6492   No :7161   No :5783
1:2153      M:3786   Yes:1077   Yes:4894   Urban:1669   Yes:1000   Yes:2378
```

```
          JOB             EDUCATION          CAR_TYPE         CAR_USE
Blue Collar :1825   <High School:1203   Minivan    :2145   Commercial:3029
Clerical    :1271   Bachelors   :2242   Panel Truck: 676   Private   :5132
Professional:1117   High School :2330   Pickup     :1389
Manager     : 988   Masters     :1658   Sports Car : 907
Lawyer      : 835   PhD         : 728   SUV        :2294
Student     : 712                       Van        : 750
(Other)     :1413
```

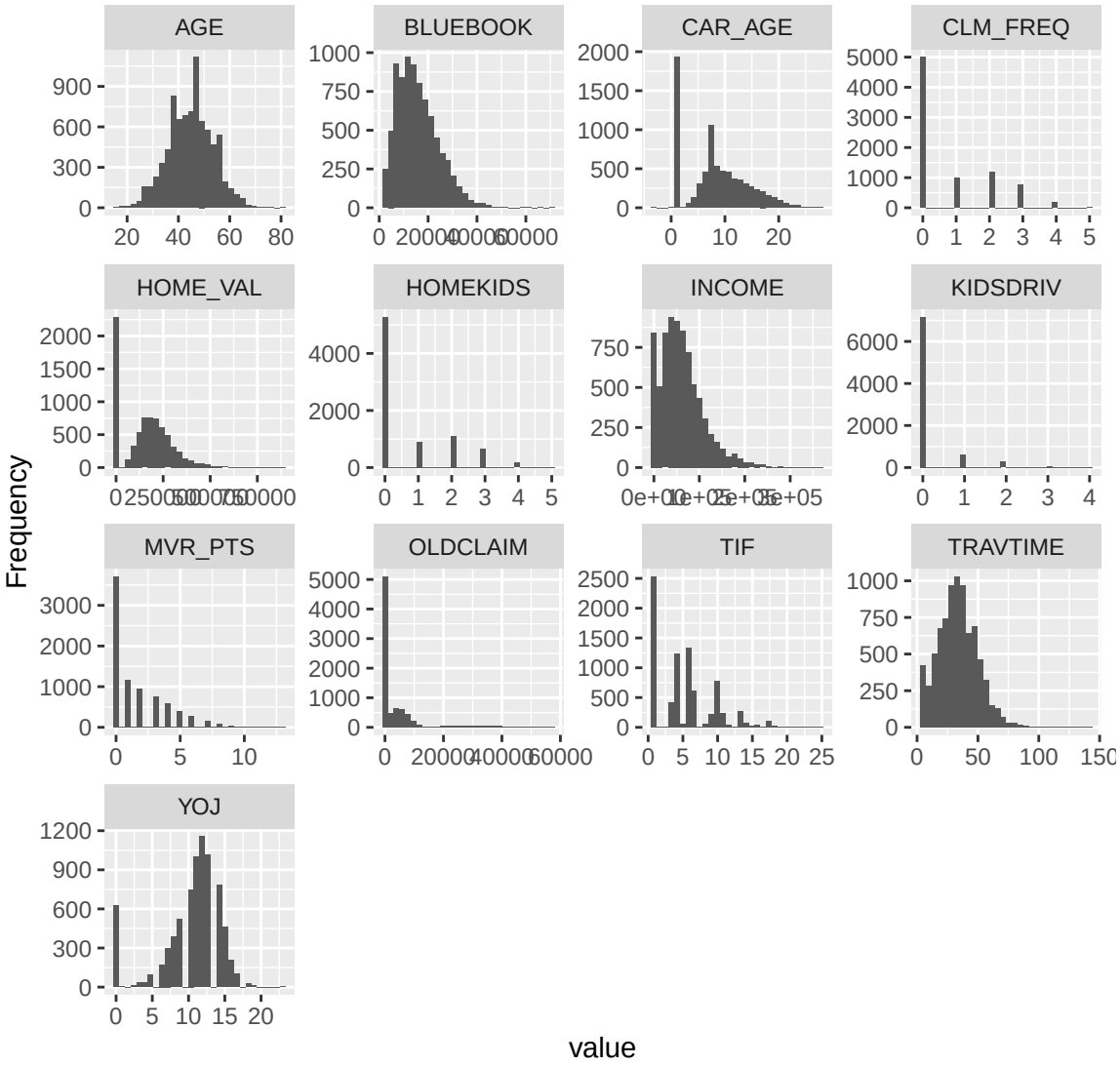
Visualizing Our Data

The first visualization is a bar chart displaying the distribution of TARGET_FLAG, helping to assess the proportion of crashes vs. non-crashes. The second visualization is a box plot for BLUEBOOK, showing the distribution and identifying potential outliers in vehicle values. TARGET_FLAG ratio of having more 0s than 1s indicates that most of the customers in the dataset did not have a crash. It's class imbalance, and it impacts the accuracy of classification models. The BLUEBOOK boxplot indicates that the variable has a strongly dominant majority of values or is long-tailed by outliers. There could be a chance that the data is non-representative, i.e., the majority of the cars have low values with few cars of high value on the tail end of the distribution.

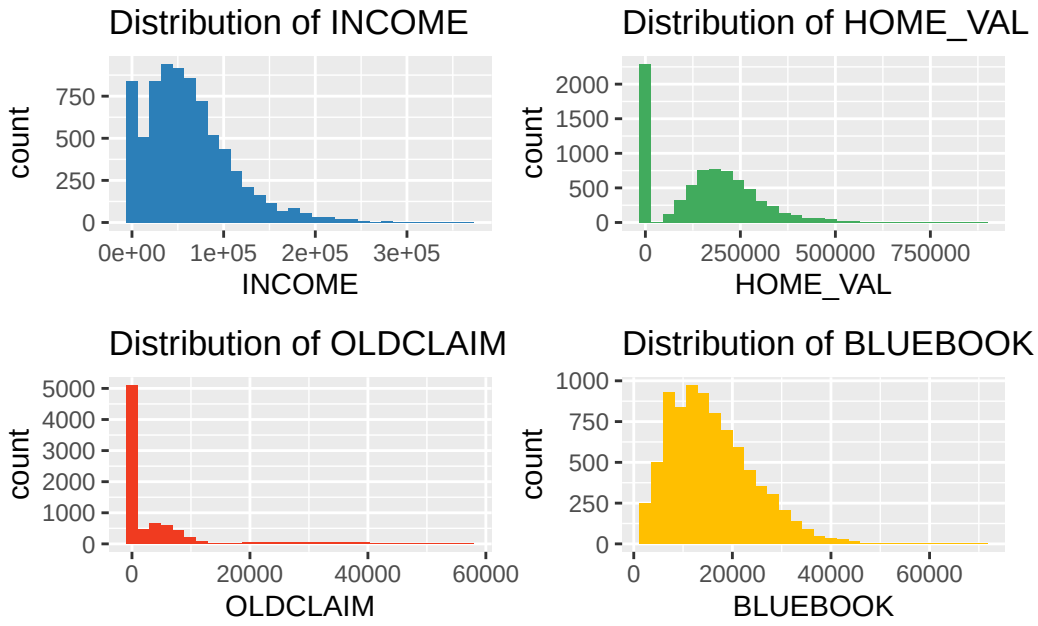


Visualize Distributions

Next we will use DataExplorer for visualize the distributions for our numberic variables. This gives mini-histograms for all numerical variables, so we can quickly spot skewness, check distribution and value ranges, and identify variables with spikes or unusual spread.



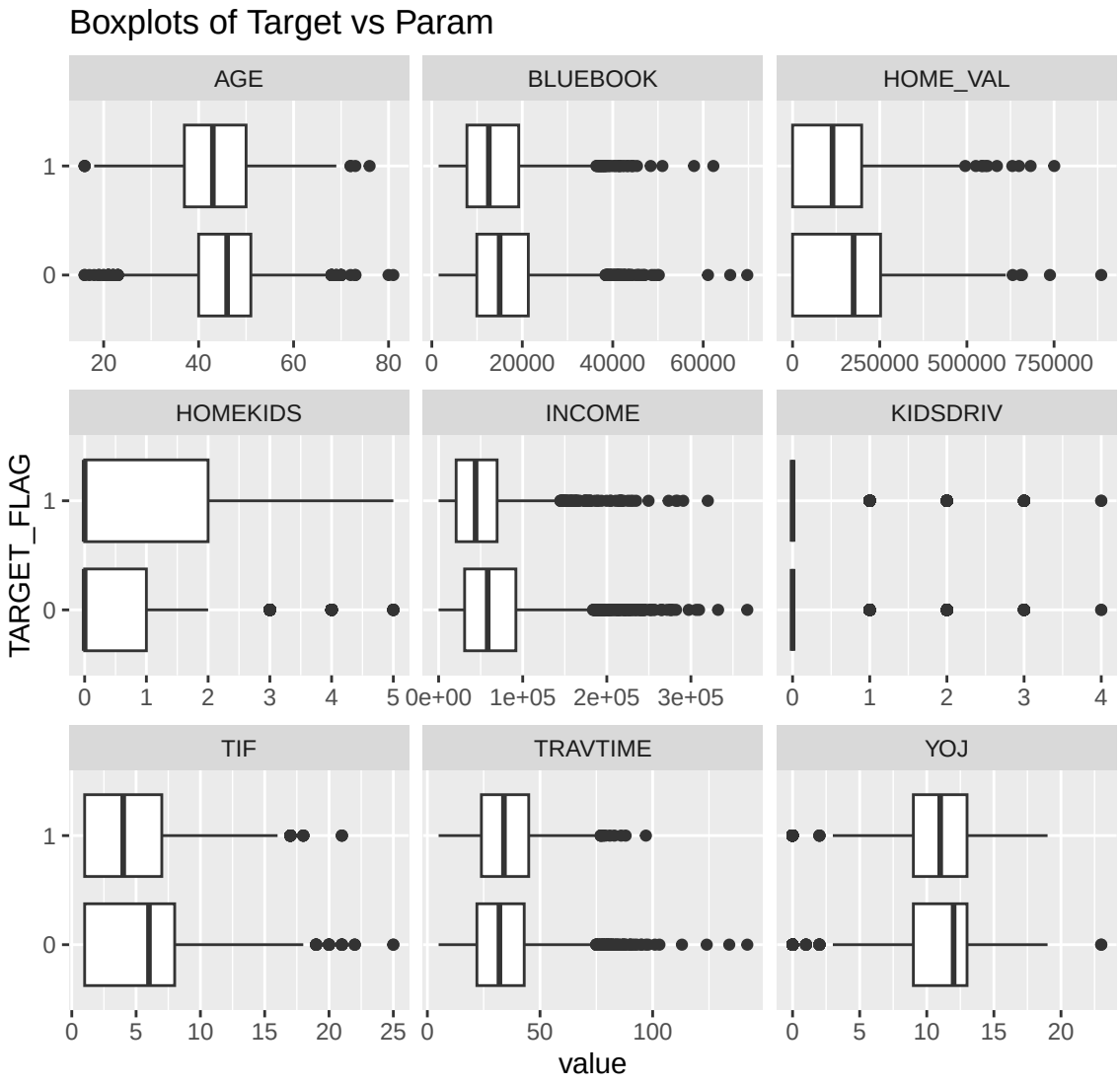
Here we focus on four variables that show skewness from their histograms that may benefit from a log transforation for when we apply a linear model. Skewness distorts relationships in regression. Log transformations may reduce skewness by compressing extreme values.



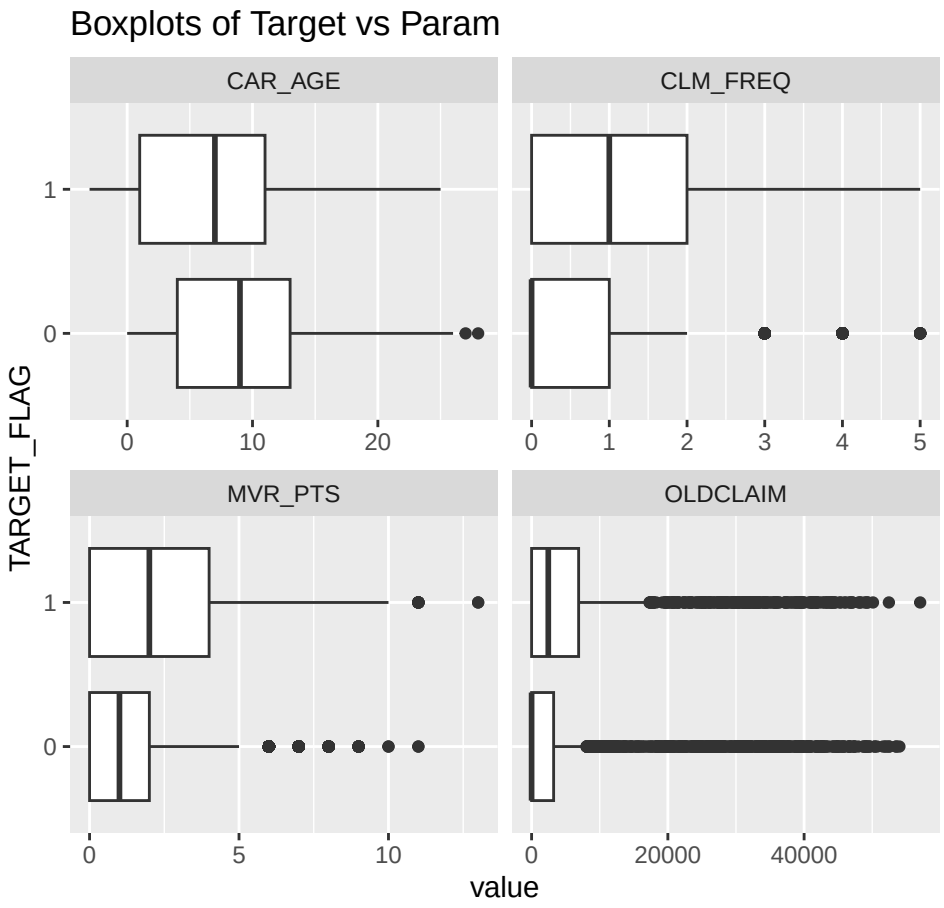

```
Skewness value for INCOME: 1.186317

Skewness value for HOME_VAL: 0.488595

Skewness value for OLDCLAIM: 3.11904

Skewness value for BLUEBOOK: 0.7942141
```

Visualizing Distributions for Numberical Variables

The boxplots on the following pages show the Interquartile Ranges for our numerical variables vs TARGET_FLAG. The IQR helps us visualize how similar/disimilar the ranges are between people who crashed (1) vs those who didn't crash (0) for each given parameter. The plots also gives us a sense of potential outliers for each parameter; we will want to look out for observations beyond the whiskers or address transform our data.

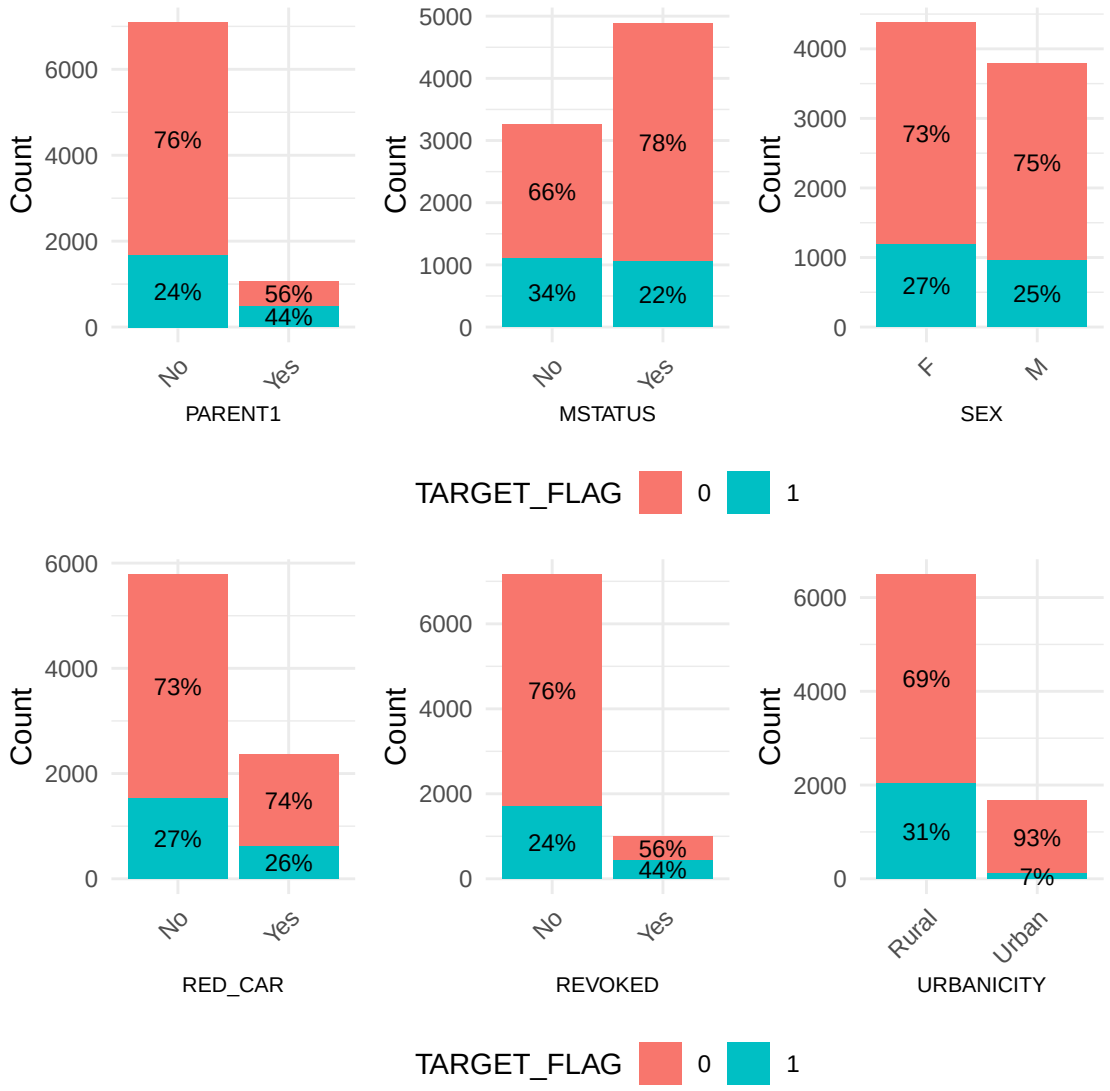


Our boxplots show that there is good difference between the medians for MVR_PTS (motor vehicle record points), HOME_VAL (home value), and TIF (time in force) for crashers and non-crashes and moderate differences for INCOME, YOJ (years on Job) and CAR_AGE. CLM_FREQ (claim frequency) how high variation but this is likely due to the disproportionate number of claims from crashers versus non-crashers who may be processing other claim types outside of automotive vehicle accidents.



Visualizing Distributions for Categorical Variables

Visualizing the distributions of out categorical variables helps ensure variables are treated as discrete categories, not continuous numbers.



Key takeaways:

PARENT1 - greater percentage of parents crashed their cars vs. non-parents (though smaler total number)

REVOKED - greater percentage of people whose license was revoked in the last 7 years crashed their cars vs. others (though smaler total number)

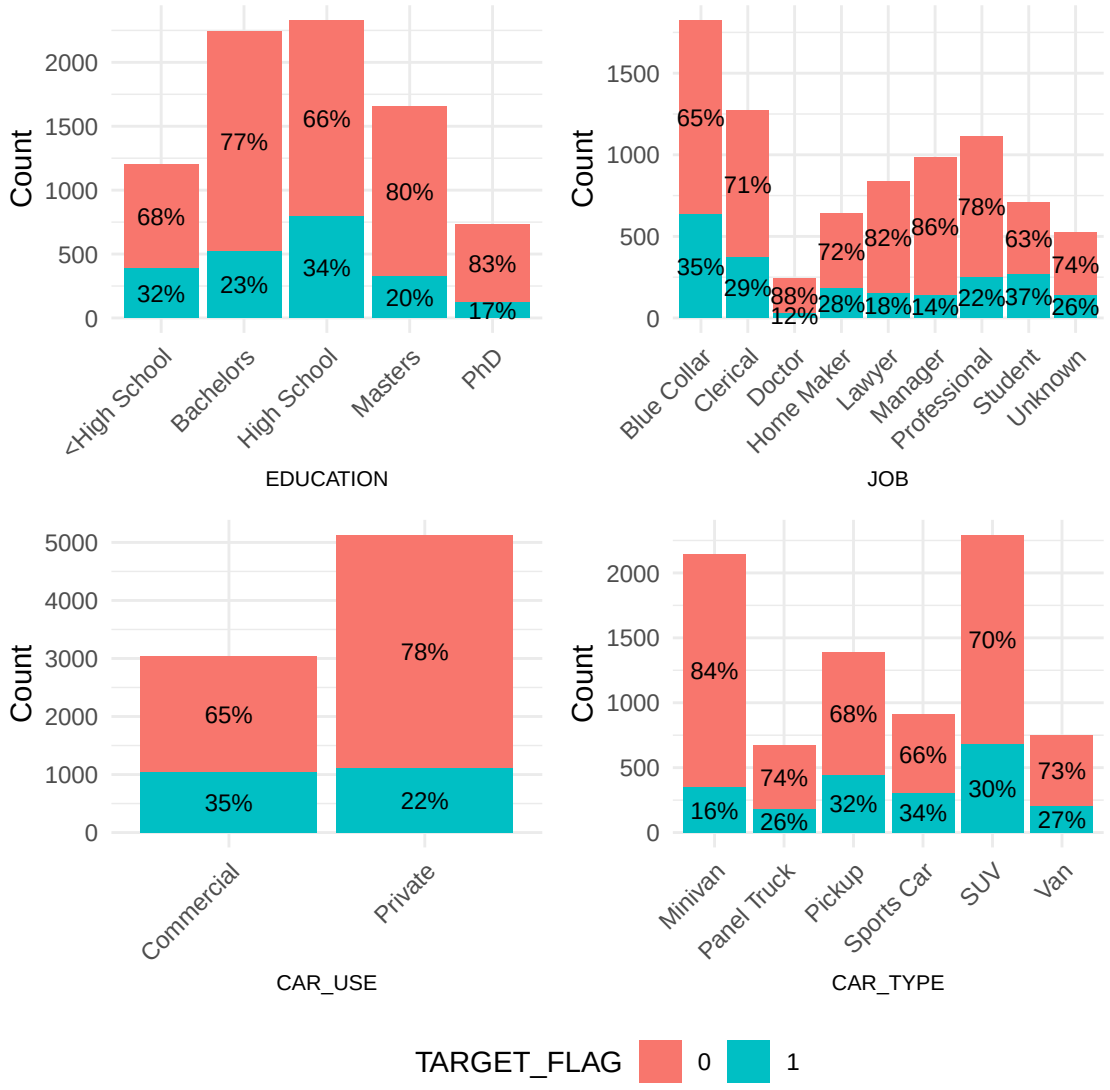
EDUCATION - High School graduates had the highest number of crashes among all educational groups; a higher percentage of high school graduates were also in a crash when compared to the breakdown of other groups.

JOB - Blue collar workers had the highest number of crashes among all job groups; a higher percentage of blue collar workers were also in a crash when compared to the breakdown of

other groups.

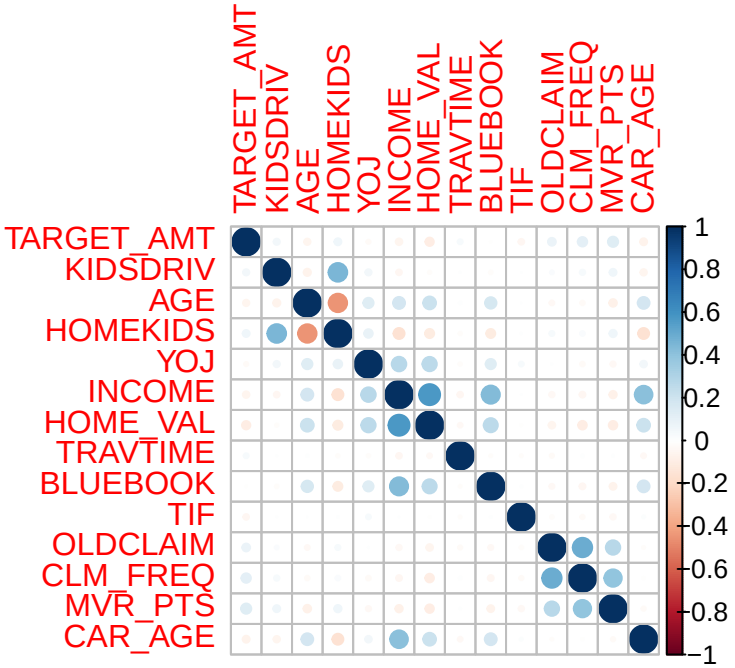
CAR_USE - A similar number of commerical and private policy holders that were involved in a crash, though private policies accounted for a smaller percentage of crashes within that group.

CARTYPE - SUV's had highest total number of crashes among all vehicle types and the second highest percentage when compared to other groups



Correlation Analysis

The correlation plot provides a graphical impression of the relationship between different numerical variables of the data set. The size and color of the circles convey the strength of the relationship. Dark blue circles indicate strong positive relationships, which predict that if one variable is increasing, so will the other. Dark red circles on the other hand produce negative high correlations, where the rise of one variable is accompanied by a fall in the other. Light-colored circles show weak or no correlation.



Plots suggest that TARGET_FLAG is not strongly correlated with most of the numeric features. Hence, no numeric feature is particularly useful to a customer to make a claim. What it says is perhaps claims will be predicted more accurately with a more advanced method, i.e., interactions, categorical features, or non-linear models.

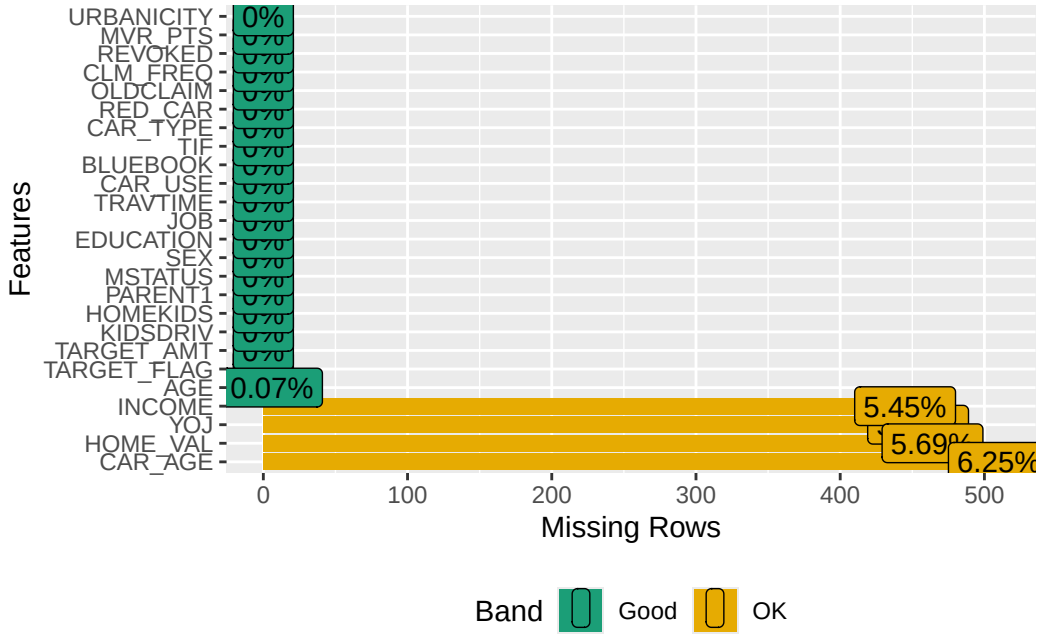
Moreover, some variables such as MVR_PTS (Motor Vehicle Record Points) and CLM_FREQ (Claim Frequency) show high positive correlation. As would be expected—more holders of violations file more claims. Also, correlations such as AGE and HOMEKIDS or KIDSDRIV reflect older people with children at home, a typical demographic pattern.

Knowledge of such relationships is helpful in model building and data preparation. Correlated variables cause multicollinearity in regression models, necessitating extra work in the form of variance inflation factor (VIF) testing to eliminate redundant information. Target_FLAG correlations also imply that other transformations, engineered features, or other sources of data might be helpful in enhancing predictiveness.

Missing Value Analysis

Missing values show that the data have missing values in relatively high counts of major variables, and most missing values exist in JOB (526 missing), CAR_AGE (510 missing), HOME_VAL (464 missing), INCOME (445 missing), YOJ (454 missing), and AGE (6 missing). Missing values may produce bias or weaken the ability of the model to predict unless appropriately handled.

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



Missing values for large numbers for variables like JOB and HOME_VAL mean the work details weren't reported for certain customers or home values weren't reported. Missing values for YOJ and INCOME may be for self-employed or the ones having the wrong job history. For CAR_AGE, missing values may be for new acquisitions or lease of automobiles where the age wasn't reported.

Depending on the count of missing values, different imputation methods will be needed. Quantitative features like AGE, INCOME, and CAR_AGE can be imputed with median to remove the impact of outliers, while features like JOB may require one extra "Unknown" value. Additionally, making missing value indicators for features like HOME_VAL will enable the model to learn missing value patterns and enhance the predictive power. Closing gaps like these in an efficient way is vital to achieve model reliability and precision.

DATA PREPARATION

Create Flags

```
# Create binary flags for missing values (1 = missing, 0 = not missing)
training_df <- training_df %>%
  mutate(
    YOJ_MISSING = ifelse(is.na(YOJ), 1, 0),
    INCOME_MISSING = ifelse(is.na(INCOME), 1, 0),
    HOME_VAL_MISSING = ifelse(is.na(HOME_VAL), 1, 0),
    CAR_AGE_MISSING = ifelse(is.na(CAR_AGE), 1, 0),
    JOB_MISSING = ifelse(JOB == "Unknown", 1, 0)
  )
```

Handling Missing Values

Missing values in key numeric columns (AGE, YOJ, INCOME, HOME_VAL, and CAR_AGE) are replaced with their respective medians. Data is preserved and no biased. We then convert YOJ, INCOME, HOME_VAL, and CAR_AGE into numeric to make it easier for managing in the list of upcoming transformations.

In addition, binary flags (YOJ_MISSING, INCOME_MISSING, HOME_VAL_MISSING, CAR_AGE_MISSING, JOB_MISSING) are built to indicate missing values in variables. This allows for models to detect missingness as a predictor.

```
training_df$AGE[is.na(training_df$AGE)] <- median(training_df$AGE, na.rm = TRUE)
training_df$YOJ[is.na(training_df$YOJ)] <- median(training_df$YOJ, na.rm = TRUE)
training_df$INCOME[is.na(training_df$INCOME)] <- median(training_df$INCOME, na.rm = TRUE)
training_df$HOME_VAL[is.na(training_df$HOME_VAL)] <- median(training_df$HOME_VAL, na.rm = TRU
training_df$CAR_AGE[is.na(training_df$CAR_AGE)] <- median(training_df$CAR_AGE, na.rm = TRUE)

colSums(is.na(training_df))
```

```
     TARGET_FLAG       TARGET_AMT         KIDSDRIV              AGE
               0                0                0                0
        HOMEKIDS              YOJ           INCOME          PARENT1
               0                0                0                0
        HOME_VAL          MSTATUS              SEX        EDUCATION
               0                0                0                0
             JOB         TRAVTIME          CAR_USE         BLUEBOOK
               0                0                0                0
             TIF         CAR_TYPE          RED_CAR         OLDCLAIM
               0                0                0                0
        CLM_FREQ          REVOKED          MVR_PTS          CAR_AGE
               0                0                0                0
      URBANICITY      YOJ_MISSING   INCOME_MISSING HOME_VAL_MISSING
               0                0                0                0
 CAR_AGE_MISSING      JOB_MISSING
               0                0
```

Feature Engineering

Some of the new features aim to capture meaningful relationships in the data:

AVG_CLAIM: This is the feature that is created by dividing OLDCLAIM by CLM_FREQ so as to be able to interpret average payout per claim.

HIGH_RISK_CAR: Certain types of cars (e.g., "Sports Car", "Luxury SUV") are designated as high-risk by encoding them with a binary value of 1.

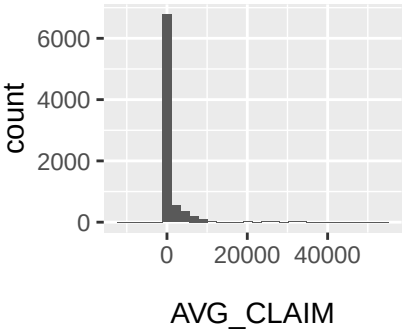
```r
# Convert CAR_AGE and OLDCLAIM to numeric to avoid errors
training_df$CLM_FREQ <- as.numeric(training_df$CLM_FREQ)
training_df$OLDCLAIM <- as.numeric(training_df$OLDCLAIM)

# Ensure no division by zero when creating CLAIMS_PER_YEAR
training_df <- training_df %>%
  mutate(
    AVG_CLAIM = ifelse(!is.na(CLM_FREQ) & CLM_FREQ > 0, OLDCLAIM / CAR_AGE, OLDCLAIM)
  )

# Create a binary flag for high-risk car types
training_df <- training_df %>%
  mutate(
    HIGH_RISK_CAR = ifelse(CAR_TYPE %in% c("Sports Car", "Luxury SUV"), 1, 0)
  )
```

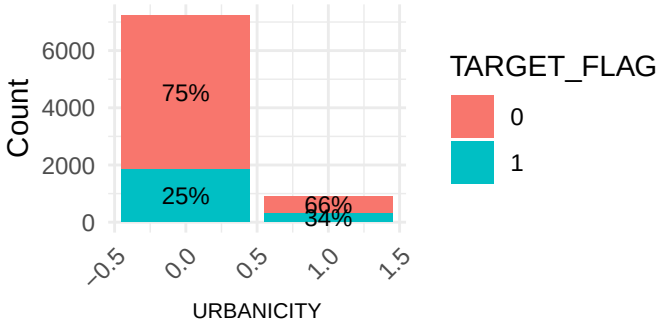
```
glimpse(training_df$AVG_CLAIM)
```

```
 num [1:8161] 248 0 3869 0 1130 ...
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
Warning: Removed 2 rows containing non-finite outside the scale range
(`stat_bin()`).
```





Transform data

Skewed numerical attributes are log-transformed to stabilize their distributions:

LOG_BLUEBOOK (log-transformed value of the vehicle),

LOG_OLDCLAIM (log-transformed old claims),

LOG_INCOME (log-transformed income). NA values are substituted with a small positive constant (0.01) before applying the log transformation to prevent computation errors.

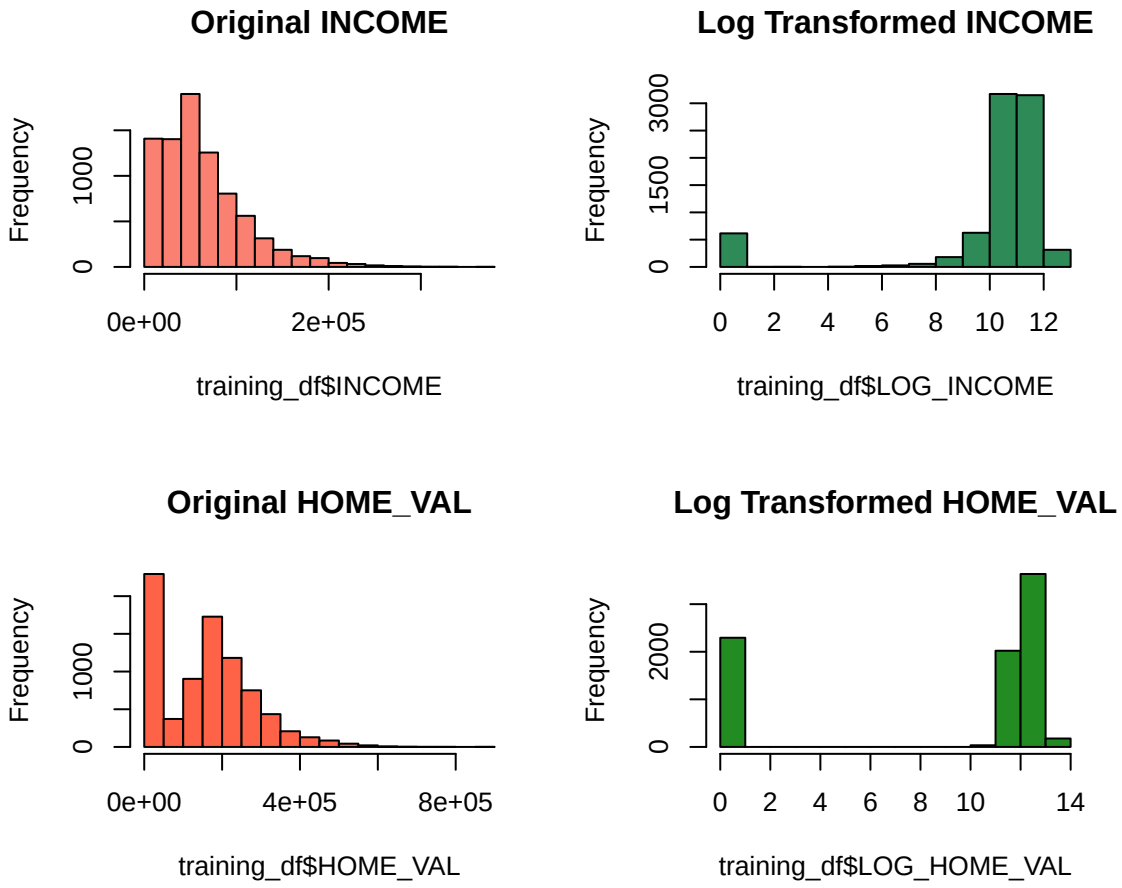
LOG_HOME_VAL (log-transformed home value)

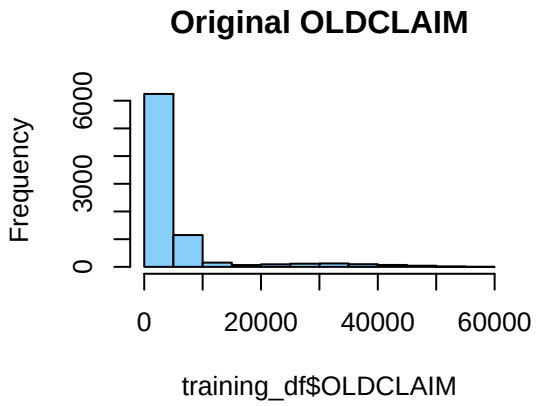
```
# Handle NA values before log transformation
training_df <- training_df %>%
  mutate(
    BLUEBOOK = ifelse(is.na(BLUEBOOK), 0.01, BLUEBOOK),
    OLDCLAIM = ifelse(is.na(OLDCLAIM), 0.01, OLDCLAIM),
    INCOME = ifelse(is.na(INCOME), 0.01, INCOME),
    HOME_VAL = ifelse(is.na(INCOME), 0.01, HOME_VAL),
    LOG_BLUEBOOK = log1p(BLUEBOOK),
    LOG_OLDCLAIM = log1p(OLDCLAIM),
```

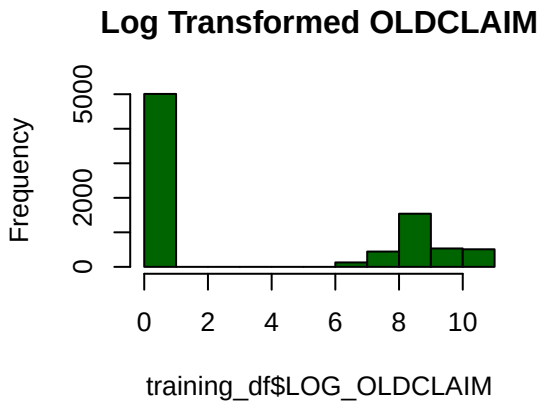
```
    LOG_INCOME = log1p(INCOME),
    LOG_HOME_VAL = log1p(HOME_VAL)
  )
```

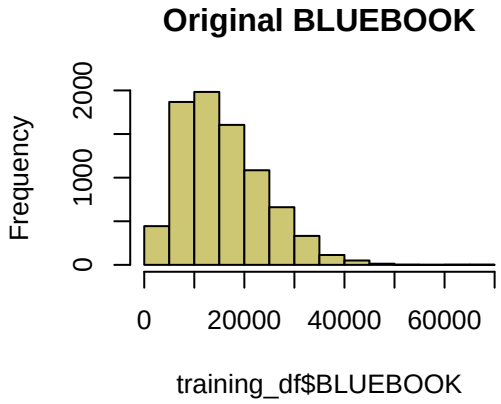
Compare Before and After Transformation

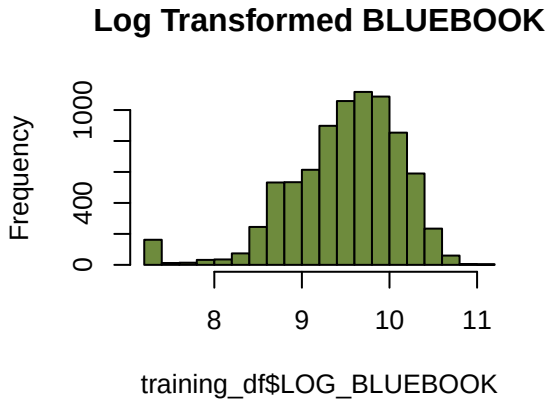
The charts below show the distributions for the values of the INCOME, HOME_VAL, OLDCLAIM, and BLUEBOOK parameters before and after applying a log transformation.





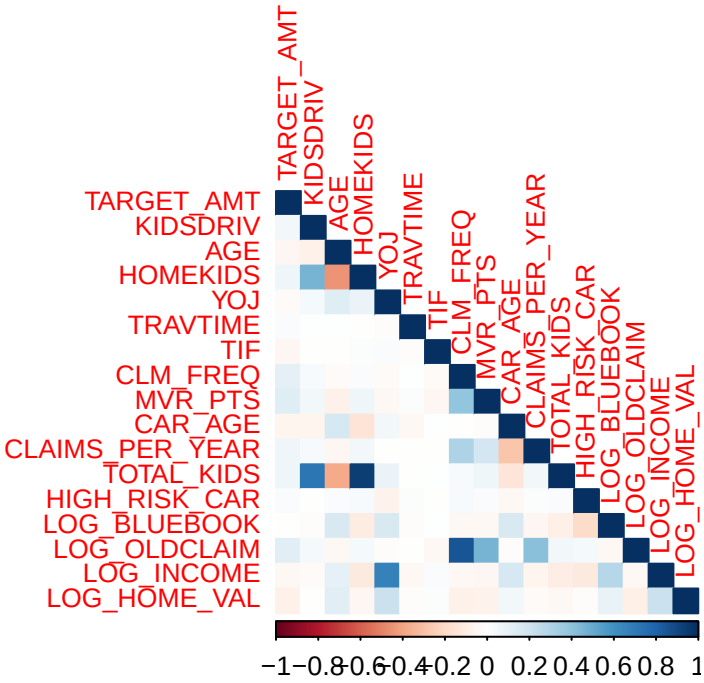






Check Variable Correlations (Multicollinearity Insight)

This updated Correlation Matrix shows correlation values for all numerical values including our log transformed values and our new variables. The matrix below shows that there is high correlation between LOG_OLDCLAIM and CLM_FREQ (Claim frequency) and LOG_INCOME and YOJ (Years on Job). There is moderate correlation between our HOMEKIDS, KIDSDRV (Kids driving) and AGE.



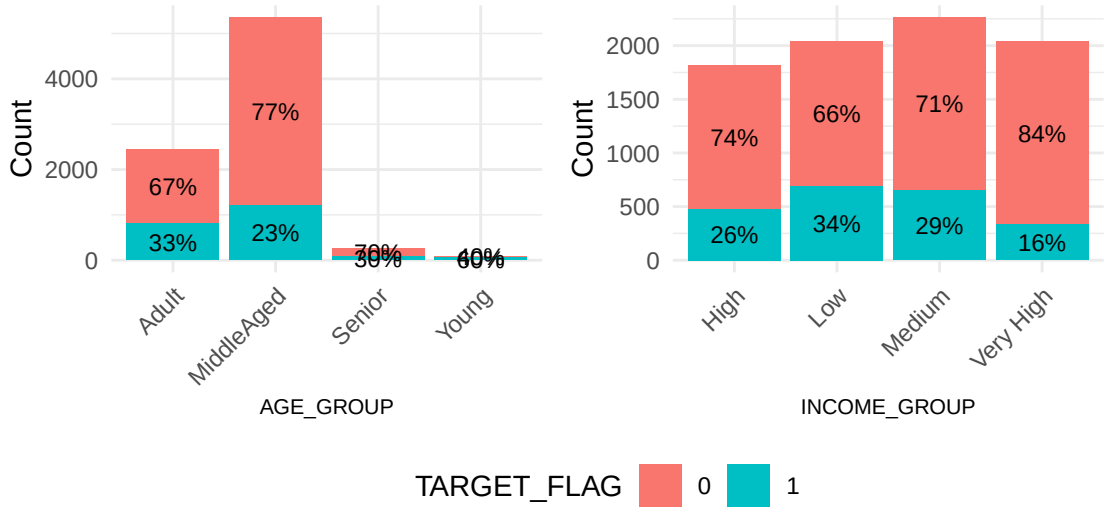
Categorical Groupings

Categorical groupings are created to reduce numerical variables: AGE_GROUP: Four age groups—Young (25), Adult (26-40), Middle-Aged (41-60), and Senior (>60)—categorize individuals.

INCOME_GROUP: Income is divided into four quantile-based groups (Low, Medium, High, Very High) such that there is an equal share of income levels.

```
# Transform data by putting it into buckets using case_when
training_df <- training_df %>%
  mutate(
    AGE_GROUP = case_when(
      AGE <= 25 ~ "Young",
      AGE > 25 & AGE <= 40 ~ "Adult",
      AGE > 40 & AGE <= 60 ~ "MiddleAged",
      AGE > 60 ~ "Senior",
      TRUE ~ NA_character_  # Handle missing values
    )
  )
```

```r
# Fix Income Grouping - Ensure proper quantile calculation
income_quantiles <- quantile(training_df$INCOME, probs = seq(0, 1, 0.25), na.rm = TRUE)

training_df <- training_df %>%
  mutate(
    INCOME_GROUP = case_when(
      INCOME <= income_quantiles[2] ~ "Low",
      INCOME > income_quantiles[2] & INCOME <= income_quantiles[3] ~ "Medium",
      INCOME > income_quantiles[3] & INCOME <= income_quantiles[4] ~ "High",
      INCOME > income_quantiles[4] ~ "Very High",
      TRUE ~ NA_character_
    )
  )
```



Creating New Features:

To capture relationships between features more effectively, new ratio-based features are formed:

CLAIMS_INCOME_RATIO: Indicates the proportion of old claims relative to income.

VEHICLE_VALUE_TO_INCOME: Indicates how cheap the vehicle is relative to income.

CLAIMS_TO_MVR_PTS: Prior claims quantity per vehicle record to indicate the severity of prior offenses.

Also an estimated risk score by averaging important risk indicators (MVR_PTS, CLM_FREQ, HIGH_RISK_CAR, and REVOKED). The risk score forms a composite measure of the subject's risk level.

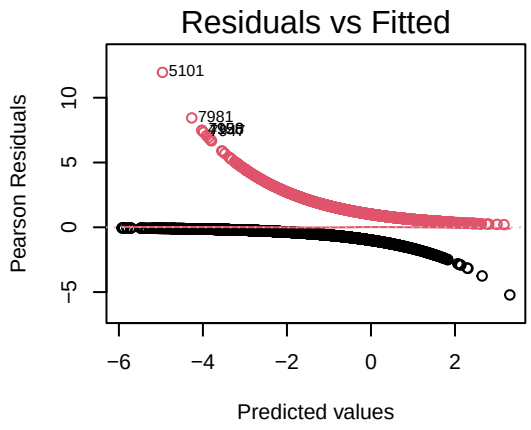
```r
# Ensure no division by zero when creating ratios
training_df <- training_df %>%
  mutate(
    CLAIMS_INCOME_RATIO = ifelse(INCOME > 0, OLDCLAIM / INCOME, NA),
    VEHICLE_VALUE_TO_INCOME = ifelse(INCOME > 0, BLUEBOOK / INCOME, NA),
    CLAIMS_TO_MVR_PTS = ifelse(MVR_PTS > 0, OLDCLAIM / MVR_PTS, NA)
  )

# Create a risk score by combining various indicators
training_df <- training_df %>%
  mutate(
    RISK_SCORE = (MVR_PTS * 0.4) + (CLM_FREQ * 0.3) + (HIGH_RISK_CAR * 0.2) + (REVOKED * 0.1)
  )
```

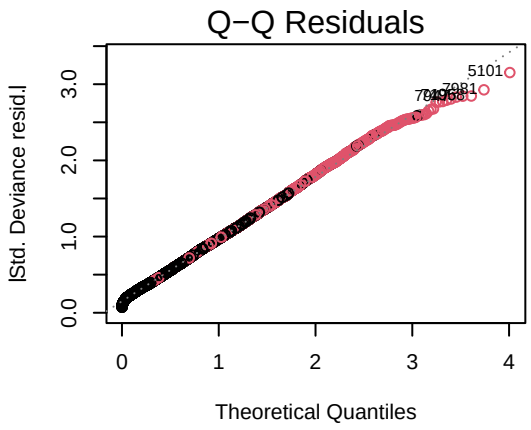
Checking for Outliers

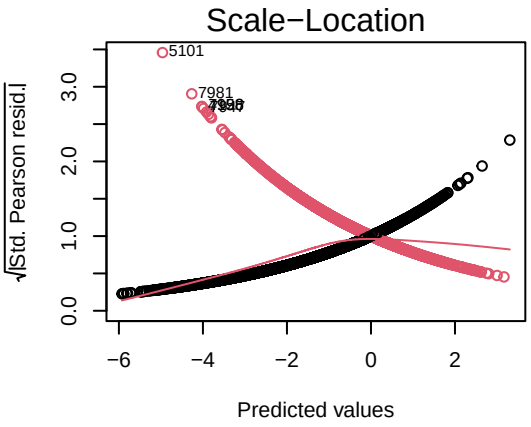
We will fit a base model that includes all 23 original variables without any transformations. We will use this model to check for outliers using the Cook's Distance test. Below we see the output of the 10 observations with the highest Cook's Distance values.

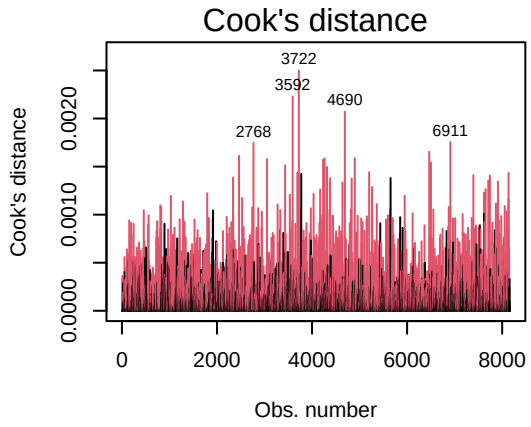
```
Rows: 10
Columns: 7
$ index      <int> 3722, 3592, 4690, 6911, 2768, 6465, 2464, 4898, 4265, 3051
$ .fitted    <dbl> -2.966839, -2.994046, -3.217335, -2.104933, -1.810303, -3.2~
$ .resid     <dbl> 2.456430, 2.466948, 2.552103, 2.107090, 1.980821, 2.563574,~
$ .hat       <dbl> 0.004839881, 0.004203504, 0.003133085, 0.007998736, 0.01061~
$ .sigma     <dbl> 0.9474993, 0.9474961, 0.9474687, 0.9476024, 0.9476355, 0.94~
$ .cooksd    <dbl> 0.002498889, 0.002227328, 0.002071025, 0.001755391, 0.00174~
$ .std.resid <dbl> 2.462396, 2.472149, 2.556111, 2.115568, 1.991422, 2.566696,~
```

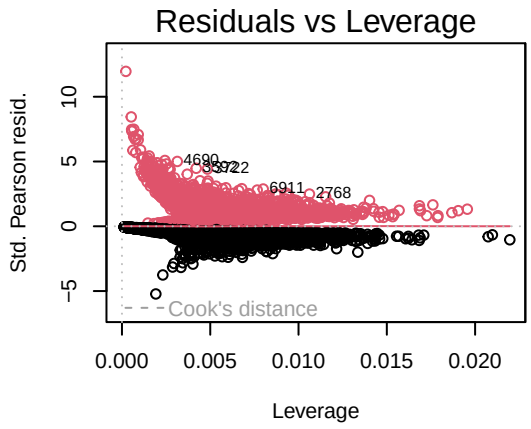
The diagnostic plots on the following page show that point 5101 stands out in our Residuals vs. Fitted and Scale Location plots. However, when take a closer look at some our other diagnostic plots and we don't see this point within the 10 highest Cook's distance values. Our Cook's distance values and respective plot shows that none of our points is an extreme outlier. Examining our Cook's distance vs Leverage plot doesn't present evidence of the presence of outliers with high leverage.

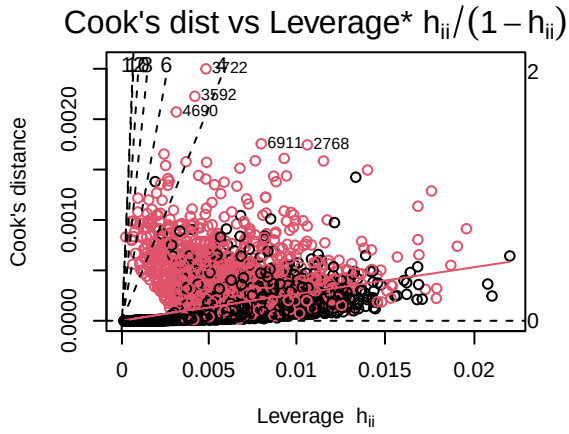

Residuals vs Fitted
Pearson Residuals
Predicted values
5101
7981


Q−Q Residuals
|Std. Deviance resid.|
Theoretical Quantiles
5101
7981


Scale−Location
√|Std. Pearson resid.|
Predicted values
5101
7981


Cook's distance
Cook's distance
Obs. number
3722
3592
4690
2768
6911


Residuals vs Leverage
Std. Pearson resid.
Leverage
Cook's distance
4690
6911
2768


Cook's dist vs Leverage* h_ii/(1 − h_ii)
Cook's distance
Leverage h_ii
3722
3592
4690
6911
2768

MODEL BUILDING

Binary Logistic Regression Models for TARGET_FLAG

We use glm() with family = binomial for logistic regression. This model predicts the probability of a crash (1). We are predicting TARGET_FLAG (binary: 1 = made a claim, 0 = no claim).

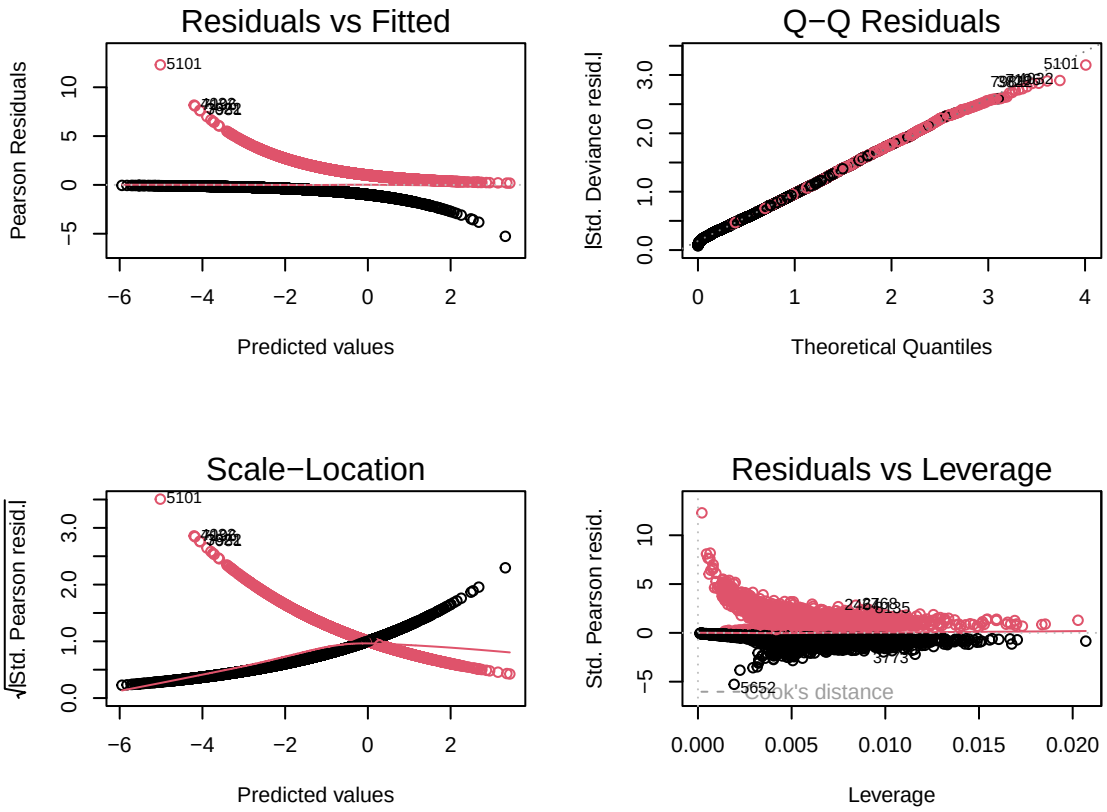
Model 1: Log Transformed Model

The log transformed model includes 19 our original variables and uses four log transformed variables: LOG_BLUEBOOK, LOG_HOME_VAL, LOG_INCOME, LOG_OLDCLAIM.

```
Call:
glm(formula = TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_AGE + CAR_TYPE +
    CAR_USE + CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL +
    LOG_INCOME + JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM +
    PARENT1 + RED_CAR + REVOKED + SEX + TIF + TRAVTIME + URBANICITY +
    YOJ, family = binomial, data = training_df)

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)           3.0401191  0.6189290   4.912 9.02e-07 ***
AGE                  -0.0034867  0.0040448  -0.862 0.388684
LOG_BLUEBOOK         -0.3107452  0.0589589  -5.271 1.36e-07 ***
CAR_AGE              -0.0009956  0.0075215  -0.132 0.894697
CAR_TYPEPanel Truck   0.4874984  0.1501870   3.246 0.001171 **
CAR_TYPEPickup        0.5885180  0.1005952   5.850 4.91e-09 ***
CAR_TYPESports Car    1.0265903  0.1279633   8.023 1.04e-15 ***
CAR_TYPESUV           0.8080301  0.1076172   7.508 5.99e-14 ***
CAR_TYPEVan           0.6195414  0.1251736   4.949 7.44e-07 ***
CAR_USEPrivate       -0.7543996  0.0920903  -8.192 2.57e-16 ***
CLM_FREQ              0.0903450  0.0434843   2.078 0.037742 *
EDUCATIONBachelors   -0.4107709  0.1147459  -3.580 0.000344 ***
EDUCATIONHigh School  0.0265010  0.0954495   0.278 0.781285
EDUCATIONMasters     -0.3611188  0.1777855  -2.031 0.042234 *
EDUCATIONPhD         -0.3871715  0.2067055  -1.873 0.061060 .
HOMEKIDS              0.0241261  0.0374774   0.644 0.519737
LOG_HOME_VAL         -0.0291342  0.0069015  -4.221 2.43e-05 ***
LOG_INCOME           -0.0937313  0.0176949  -5.297 1.18e-07 ***
JOBClerical           0.1404673  0.1056664   1.329 0.183734
JOBDoctor            -0.7776908  0.2861833  -2.717 0.006579 **
```

```
JOBHome Maker        -0.2547855  0.1646928  -1.547 0.121855
JOBLawyer            -0.2227525  0.1877111  -1.187 0.235355
JOBManager           -0.9057062  0.1397265  -6.482 9.05e-11 ***
JOBProfessional      -0.1722614  0.1196742  -1.439 0.150031
JOBStudent           -0.3997931  0.1461271  -2.736 0.006220 **
JOBUnknown           -0.3927425  0.1845650  -2.128 0.033342 *
KIDSDRIV              0.4036578  0.0612752   6.588 4.47e-11 ***
MSTATUSYes           -0.4812207  0.0866989  -5.550 2.85e-08 ***
MVR_PTS               0.1020655  0.0140545   7.262 3.81e-13 ***
LOG_OLDCLAIM          0.0225774  0.0124662   1.811 0.070128 .
PARENT1Yes            0.3747205  0.1096208   3.418 0.000630 ***
RED_CARYes           -0.0149001  0.0863243  -0.173 0.862961
REVOKEDYes            0.7000443  0.0814072   8.599  < 2e-16 ***
SEXM                  0.1102954  0.1081743   1.020 0.307914
TIF                  -0.0545220  0.0073385  -7.430 1.09e-13 ***
TRAVTIME              0.0148258  0.0018877   7.854 4.03e-15 ***
URBANICITYUrban      -2.3978262  0.1138054 -21.070  < 2e-16 ***
YOJ                   0.0202910  0.0108561   1.869 0.061611 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 9418  on 8160  degrees of freedom
Residual deviance: 7289  on 8123  degrees of freedom
AIC: 7365

Number of Fisher Scoring iterations: 5
```

Diagnostics Plots



Model 2: Stepwise Selected Log Transformed Model

We applied backward selection to the Log Transformed Model (model 1) to obtain a simplified model that removes the majority of the variables with little statistical significance. while trying to find a low AIC value. The AIC value for model 2 is 7357.7 while our original log transformed model had an AIC value of 7364.97. AIC is just one measure that we will use to evaluate and select our final model in section 4 of this work, but it is worth noting here as a preliminary point of comparison as we build our models.

```
Start:  AIC=7364.97
TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_AGE + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL + LOG_INCOME +
    JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 +
    RED_CAR + REVOKED + SEX + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- CAR_AGE       1   7289.0 7363.0
```

```
- RED_CAR       1   7289.0 7363.0
- HOMEKIDS      1   7289.4 7363.4
- AGE           1   7289.7 7363.7
- SEX           1   7290.0 7364.0
<none>              7289.0 7365.0
- LOG_OLDCLAIM  1   7292.2 7366.2
- YOJ           1   7292.5 7366.5
- CLM_FREQ      1   7293.3 7367.3
- PARENT1       1   7300.7 7374.7
- LOG_HOME_VAL  1   7306.9 7380.9
- EDUCATION     4   7314.1 7382.1
- LOG_BLUEBOOK  1   7316.5 7390.5
- LOG_INCOME    1   7317.5 7391.5
- MSTATUS       1   7319.4 7393.4
- KIDSDRIV      1   7332.4 7406.4
- MVR_PTS       1   7342.1 7416.1
- TIF           1   7346.2 7420.2
- TRAVTIME      1   7350.9 7424.9
- JOB           8   7366.2 7426.2
- CAR_USE       1   7357.1 7431.1
- REVOKED       1   7361.7 7435.7
- CAR_TYPE      5   7382.7 7448.7
- URBANICITY    1   7926.6 8000.6

Step:  AIC=7362.99
TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_TYPE + CAR_USE + CLM_FREQ +
    EDUCATION + HOMEKIDS + LOG_HOME_VAL + LOG_INCOME + JOB +
    KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + RED_CAR +
    REVOKED + SEX + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- RED_CAR       1   7289.0 7361.0
- HOMEKIDS      1   7289.4 7361.4
- AGE           1   7289.7 7361.7
- SEX           1   7290.0 7362.0
<none>              7289.0 7363.0
- LOG_OLDCLAIM  1   7292.3 7364.3
- YOJ           1   7292.5 7364.5
- CLM_FREQ      1   7293.3 7365.3
- PARENT1       1   7300.7 7372.7
- LOG_HOME_VAL  1   7306.9 7378.9
- EDUCATION     4   7319.7 7385.7
- LOG_BLUEBOOK  1   7316.5 7388.5
```

```
- LOG_INCOME    1   7317.6 7389.6
- MSTATUS       1   7319.4 7391.4
- KIDSDRIV      1   7332.4 7404.4
- MVR_PTS       1   7342.1 7414.1
- TIF           1   7346.2 7418.2
- TRAVTIME      1   7350.9 7422.9
- JOB           8   7366.2 7424.2
- CAR_USE       1   7357.2 7429.2
- REVOKED       1   7361.7 7433.7
- CAR_TYPE      5   7382.8 7446.8
- URBANICITY    1   7926.6 7998.6

Step:  AIC=7361.02
TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_TYPE + CAR_USE + CLM_FREQ +
    EDUCATION + HOMEKIDS + LOG_HOME_VAL + LOG_INCOME + JOB +
    KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED +
    SEX + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- HOMEKIDS      1   7289.4 7359.4
- AGE           1   7289.8 7359.8
- SEX           1   7290.2 7360.2
<none>              7289.0 7361.0
- LOG_OLDCLAIM  1   7292.3 7362.3
- YOJ           1   7292.5 7362.5
- CLM_FREQ      1   7293.3 7363.3
- PARENT1       1   7300.8 7370.8
- LOG_HOME_VAL  1   7306.9 7376.9
- EDUCATION     4   7319.8 7383.8
- LOG_BLUEBOOK  1   7316.5 7386.5
- LOG_INCOME    1   7317.6 7387.6
- MSTATUS       1   7319.4 7389.4
- KIDSDRIV      1   7332.5 7402.5
- MVR_PTS       1   7342.1 7412.1
- TIF           1   7346.2 7416.2
- TRAVTIME      1   7350.9 7420.9
- JOB           8   7366.4 7422.4
- CAR_USE       1   7357.2 7427.2
- REVOKED       1   7361.7 7431.7
- CAR_TYPE      5   7383.0 7445.0
- URBANICITY    1   7926.6 7996.6

Step:  AIC=7359.43
```

```
TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_TYPE + CAR_USE + CLM_FREQ +
    EDUCATION + LOG_HOME_VAL + LOG_INCOME + JOB + KIDSDRIV +
    MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED + SEX +
    TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- SEX           1   7290.5 7358.5
- AGE           1   7290.9 7358.9
<none>              7289.4 7359.4
- LOG_OLDCLAIM  1   7292.7 7360.7
- CLM_FREQ      1   7293.7 7361.7
- YOJ           1   7293.8 7361.8
- PARENT1       1   7305.9 7373.9
- LOG_HOME_VAL  1   7307.4 7375.4
- EDUCATION     4   7320.2 7382.2
- LOG_BLUEBOOK  1   7317.0 7385.0
- LOG_INCOME    1   7319.4 7387.4
- MSTATUS       1   7319.8 7387.8
- MVR_PTS       1   7342.6 7410.6
- TIF           1   7346.5 7414.5
- KIDSDRIV      1   7347.2 7415.2
- TRAVTIME      1   7351.2 7419.2
- JOB           8   7366.8 7420.8
- CAR_USE       1   7357.7 7425.7
- REVOKED       1   7362.4 7430.4
- CAR_TYPE      5   7383.6 7443.6
- URBANICITY    1   7926.8 7994.8

Step:  AIC=7358.54
TARGET_FLAG ~ AGE + LOG_BLUEBOOK + CAR_TYPE + CAR_USE + CLM_FREQ +
    EDUCATION + LOG_HOME_VAL + LOG_INCOME + JOB + KIDSDRIV +
    MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED + TIF +
    TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- AGE           1   7291.7 7357.7
<none>              7290.5 7358.5
- LOG_OLDCLAIM  1   7293.8 7359.8
- CLM_FREQ      1   7294.9 7360.9
- YOJ           1   7294.9 7360.9
- PARENT1       1   7306.9 7372.9
- LOG_HOME_VAL  1   7308.4 7374.4
- EDUCATION     4   7321.4 7381.4
```

```
- LOG_INCOME    1   7320.7 7386.7
- MSTATUS       1   7321.0 7387.0
- LOG_BLUEBOOK  1   7326.6 7392.6
- MVR_PTS       1   7343.6 7409.6
- TIF           1   7347.6 7413.6
- KIDSDRIV      1   7347.9 7413.9
- TRAVTIME      1   7352.5 7418.5
- JOB           8   7367.7 7419.7
- CAR_USE       1   7358.5 7424.5
- REVOKED       1   7363.8 7429.8
- CAR_TYPE      5   7400.2 7458.2
- URBANICITY    1   7928.3 7994.3

Step:  AIC=7357.71
TARGET_FLAG ~ LOG_BLUEBOOK + CAR_TYPE + CAR_USE + CLM_FREQ +
    EDUCATION + LOG_HOME_VAL + LOG_INCOME + JOB + KIDSDRIV +
    MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED + TIF +
    TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
<none>              7291.7 7357.7
- LOG_OLDCLAIM  1   7295.0 7359.0
- YOJ           1   7295.6 7359.6
- CLM_FREQ      1   7296.0 7360.0
- LOG_HOME_VAL  1   7309.9 7373.9
- PARENT1       1   7312.9 7376.9
- EDUCATION     4   7323.0 7381.0
- LOG_INCOME    1   7321.1 7385.1
- MSTATUS       1   7321.4 7385.4
- LOG_BLUEBOOK  1   7329.5 7393.5
- MVR_PTS       1   7345.4 7409.4
- TIF           1   7348.6 7412.6
- KIDSDRIV      1   7348.8 7412.8
- TRAVTIME      1   7353.2 7417.2
- JOB           8   7370.3 7420.3
- CAR_USE       1   7359.4 7423.4
- REVOKED       1   7365.3 7429.3
- CAR_TYPE      5   7400.6 7456.6
- URBANICITY    1   7931.1 7995.1


Call:
```

```
glm(formula = TARGET_FLAG ~ LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + LOG_HOME_VAL + LOG_INCOME + JOB +
    KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED +
    TIF + TRAVTIME + URBANICITY + YOJ, family = binomial, data = training_df)

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)          3.215131   0.549675   5.849 4.94e-09 ***
LOG_BLUEBOOK        -0.338298   0.054800  -6.173 6.69e-10 ***
CAR_TYPEPanel Truck  0.533434   0.143997   3.704 0.000212 ***
CAR_TYPEPickup       0.587607   0.100499   5.847 5.01e-09 ***
CAR_TYPESports Car   0.950929   0.107973   8.807  < 2e-16 ***
CAR_TYPESUV          0.739915   0.085747   8.629  < 2e-16 ***
CAR_TYPEVan          0.651315   0.121822   5.346 8.97e-08 ***
CAR_USEPrivate      -0.751293   0.092016  -8.165 3.22e-16 ***
CLM_FREQ             0.089724   0.043461   2.064 0.038973 *
EDUCATIONBachelors  -0.419593   0.107943  -3.887 0.000101 ***
EDUCATIONHigh School 0.023430   0.095139   0.246 0.805470
EDUCATIONMasters    -0.381190   0.160061  -2.382 0.017241 *
EDUCATIONPhD        -0.419251   0.192054  -2.183 0.029037 *
LOG_HOME_VAL        -0.029360   0.006897  -4.257 2.07e-05 ***
LOG_INCOME          -0.093978   0.017465  -5.381 7.41e-08 ***
JOBClerical          0.145110   0.105466   1.376 0.168855
JOBDoctor           -0.783083   0.285877  -2.739 0.006158 **
JOBHome Maker       -0.277361   0.163372  -1.698 0.089560 .
JOBLawyer           -0.235519   0.187401  -1.257 0.208838
JOBManager          -0.916285   0.139426  -6.572 4.97e-11 ***
JOBProfessional     -0.181549   0.119448  -1.520 0.128537
JOBStudent          -0.392047   0.145675  -2.691 0.007119 **
JOBUnknown          -0.394500   0.184473  -2.139 0.032474 *
KIDSDRIV             0.418492   0.055100   7.595 3.08e-14 ***
MSTATUSYes          -0.461593   0.084059  -5.491 3.99e-08 ***
MVR_PTS              0.102545   0.014041   7.303 2.81e-13 ***
LOG_OLDCLAIM         0.022779   0.012461   1.828 0.067558 .
PARENT1Yes           0.435845   0.094725   4.601 4.20e-06 ***
REVOKEDYes           0.704002   0.081371   8.652  < 2e-16 ***
TIF                 -0.054339   0.007335  -7.408 1.29e-13 ***
TRAVTIME             0.014768   0.001886   7.829 4.91e-15 ***
URBANICITYUrban     -2.401382   0.113860 -21.091  < 2e-16 ***
YOJ                  0.020598   0.010437   1.974 0.048429 *
---
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: 7291.7  on 8128  degrees of freedom
AIC: 7357.7

Number of Fisher Scoring iterations: 5


[1] 7357.708
```

Model 3: Using Categorical Groupings

For model 3, we substituted AGE and INCOME with our categorically grouped variables AGE_GROUP and INCOME_GROUP and used all of the other predictors from our Log Transformed model. We again used backward selection to obtaina simplified model. This model yields an AIC value of 7327.1

```
Start:  AIC=7335.06
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_AGE + CAR_TYPE +
    CAR_USE + CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL +
    INCOME_GROUP + JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM +
    PARENT1 + RED_CAR + REVOKED + SEX + TIF + TRAVTIME + URBANICITY +
    YOJ

               Df Deviance    AIC
- CAR_AGE       1   7251.1 7333.1
- SEX           1   7251.2 7333.2
- HOMEKIDS      1   7251.3 7333.3
- RED_CAR       1   7251.3 7333.3
- YOJ           1   7252.8 7334.8
<none>              7251.1 7335.1
- LOG_OLDCLAIM  1   7254.3 7336.3
- CLM_FREQ      1   7255.3 7337.3
- PARENT1       1   7260.0 7342.0
- EDUCATION     4   7271.5 7347.5
- LOG_HOME_VAL  1   7267.8 7349.8
- INCOME_GROUP  3   7279.6 7357.6
- MSTATUS       1   7279.8 7361.8
- LOG_BLUEBOOK  1   7280.0 7362.0
- AGE_GROUP     3   7284.9 7362.9
- MVR_PTS       1   7298.0 7380.0
- JOB           8   7315.1 7383.1
```

```
- KIDSDRIV      1   7302.8 7384.8
- TIF           1   7311.0 7393.0
- TRAVTIME      1   7313.2 7395.2
- CAR_USE       1   7322.0 7404.0
- CAR_TYPE      5   7331.3 7405.3
- REVOKED       1   7324.7 7406.7
- URBANICITY    1   7889.9 7971.9

Step:  AIC=7333.07
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL + INCOME_GROUP +
    JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 +
    RED_CAR + REVOKED + SEX + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- SEX           1   7251.2 7331.2
- HOMEKIDS      1   7251.3 7331.3
- RED_CAR       1   7251.3 7331.3
- YOJ           1   7252.8 7332.8
<none>              7251.1 7333.1
- LOG_OLDCLAIM  1   7254.3 7334.3
- CLM_FREQ      1   7255.3 7335.3
- PARENT1       1   7260.0 7340.0
- LOG_HOME_VAL  1   7267.8 7347.8
- EDUCATION     4   7274.7 7348.7
- INCOME_GROUP  3   7279.6 7355.6
- MSTATUS       1   7279.8 7359.8
- LOG_BLUEBOOK  1   7280.0 7360.0
- AGE_GROUP     3   7284.9 7360.9
- MVR_PTS       1   7298.0 7378.0
- JOB           8   7315.1 7381.1
- KIDSDRIV      1   7302.8 7382.8
- TIF           1   7311.1 7391.1
- TRAVTIME      1   7313.2 7393.2
- CAR_USE       1   7322.0 7402.0
- CAR_TYPE      5   7331.4 7403.4
- REVOKED       1   7324.8 7404.8
- URBANICITY    1   7889.9 7969.9

Step:  AIC=7331.25
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL + INCOME_GROUP +
    JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 +
```

```
    RED_CAR + REVOKED + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- RED_CAR       1   7251.4 7329.4
- HOMEKIDS      1   7251.5 7329.5
- YOJ           1   7253.0 7331.0
<none>              7251.2 7331.2
- LOG_OLDCLAIM  1   7254.5 7332.5
- CLM_FREQ      1   7255.4 7333.4
- PARENT1       1   7260.2 7338.2
- LOG_HOME_VAL  1   7268.0 7346.0
- EDUCATION     4   7274.9 7346.9
- INCOME_GROUP  3   7279.9 7353.9
- MSTATUS       1   7280.1 7358.1
- AGE_GROUP     3   7285.5 7359.5
- LOG_BLUEBOOK  1   7284.9 7362.9
- MVR_PTS       1   7298.1 7376.1
- JOB           8   7315.2 7379.2
- KIDSDRIV      1   7303.0 7381.0
- TIF           1   7311.2 7389.2
- TRAVTIME      1   7313.5 7391.5
- CAR_USE       1   7322.1 7400.1
- REVOKED       1   7325.0 7403.0
- CAR_TYPE      5   7339.0 7409.0
- URBANICITY    1   7890.2 7968.2

Step:  AIC=7329.38
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + HOMEKIDS + LOG_HOME_VAL + INCOME_GROUP +
    JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 +
    REVOKED + TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- HOMEKIDS      1   7251.6 7327.6
- YOJ           1   7253.1 7329.1
<none>              7251.4 7329.4
- LOG_OLDCLAIM  1   7254.6 7330.6
- CLM_FREQ      1   7255.5 7331.5
- PARENT1       1   7260.4 7336.4
- LOG_HOME_VAL  1   7268.1 7344.1
- EDUCATION     4   7275.1 7345.1
- INCOME_GROUP  3   7280.0 7352.0
- MSTATUS       1   7280.1 7356.1
```

```
- AGE_GROUP     3   7285.6 7357.6
- LOG_BLUEBOOK  1   7285.6 7361.6
- MVR_PTS       1   7298.3 7374.3
- JOB           8   7315.6 7377.6
- KIDSDRIV      1   7303.2 7379.2
- TIF           1   7311.3 7387.3
- TRAVTIME      1   7313.6 7389.6
- CAR_USE       1   7322.3 7398.3
- REVOKED       1   7325.1 7401.1
- CAR_TYPE      5   7348.8 7416.8
- URBANICITY    1   7890.2 7966.2

Step:  AIC=7327.58
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + LOG_HOME_VAL + INCOME_GROUP + JOB +
    KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED +
    TIF + TRAVTIME + URBANICITY + YOJ

               Df Deviance    AIC
- YOJ           1   7253.1 7327.1
<none>              7251.6 7327.6
- LOG_OLDCLAIM  1   7254.9 7328.9
- CLM_FREQ      1   7255.7 7329.7
- PARENT1       1   7264.3 7338.3
- LOG_HOME_VAL  1   7268.3 7342.3
- EDUCATION     4   7275.5 7343.5
- INCOME_GROUP  3   7280.1 7350.1
- MSTATUS       1   7280.9 7354.9
- AGE_GROUP     3   7288.0 7358.0
- LOG_BLUEBOOK  1   7285.9 7359.9
- MVR_PTS       1   7298.6 7372.6
- JOB           8   7316.0 7376.0
- TIF           1   7311.4 7385.4
- TRAVTIME      1   7313.7 7387.7
- KIDSDRIV      1   7318.1 7392.1
- CAR_USE       1   7322.6 7396.6
- REVOKED       1   7325.6 7399.6
- CAR_TYPE      5   7349.2 7415.2
- URBANICITY    1   7890.3 7964.3

Step:  AIC=7327.13
TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE + CAR_USE +
    CLM_FREQ + EDUCATION + LOG_HOME_VAL + INCOME_GROUP + JOB +
```

```
    KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED +
    TIF + TRAVTIME + URBANICITY

               Df Deviance    AIC
<none>              7253.1 7327.1
- LOG_OLDCLAIM  1   7256.3 7328.3
- CLM_FREQ      1   7257.4 7329.4
- PARENT1       1   7265.3 7337.3
- LOG_HOME_VAL  1   7270.2 7342.2
- EDUCATION     4   7276.8 7342.8
- INCOME_GROUP  3   7282.1 7350.1
- MSTATUS       1   7284.5 7356.5
- AGE_GROUP     3   7289.7 7357.7
- LOG_BLUEBOOK  1   7288.2 7360.2
- MVR_PTS       1   7300.8 7372.8
- JOB           8   7317.4 7375.4
- TIF           1   7313.4 7385.4
- TRAVTIME      1   7315.1 7387.1
- KIDSDRIV      1   7319.0 7391.0
- CAR_USE       1   7324.8 7396.8
- REVOKED       1   7327.1 7399.1
- CAR_TYPE      5   7351.1 7415.1
- URBANICITY    1   7891.3 7963.3


Call:
glm(formula = TARGET_FLAG ~ AGE_GROUP + LOG_BLUEBOOK + CAR_TYPE +
    CAR_USE + CLM_FREQ + EDUCATION + LOG_HOME_VAL + INCOME_GROUP +
    JOB + KIDSDRIV + MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 +
    REVOKED + TIF + TRAVTIME + URBANICITY, family = binomial,
    data = training_df)

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)           2.572422   0.557326   4.616 3.92e-06 ***
AGE_GROUPMiddleAged  -0.232349   0.066678  -3.485 0.000493 ***
AGE_GROUPSenior       0.300307   0.171924   1.747 0.080683 .
AGE_GROUPYoung        0.899643   0.249159   3.611 0.000305 ***
LOG_BLUEBOOK         -0.330860   0.055608  -5.950 2.68e-09 ***
CAR_TYPEPanel Truck   0.567336   0.145279   3.905 9.42e-05 ***
CAR_TYPEPickup        0.574791   0.101034   5.689 1.28e-08 ***
CAR_TYPESports Car    0.888626   0.110084   8.072 6.90e-16 ***
```

```
CAR_TYPESUV             0.714288   0.086206   8.286  < 2e-16 ***
CAR_TYPEVan             0.677169   0.122795   5.515 3.50e-08 ***
CAR_USEPrivate         -0.773510   0.092124  -8.396  < 2e-16 ***
CLM_FREQ                0.089701   0.043394   2.067 0.038722 *
EDUCATIONBachelors     -0.392148   0.112751  -3.478 0.000505 ***
EDUCATIONHigh School    0.011398   0.097157   0.117 0.906612
EDUCATIONMasters       -0.283303   0.163842  -1.729 0.083787 .
EDUCATIONPhD           -0.261605   0.196787  -1.329 0.183722
LOG_HOME_VAL           -0.028499   0.006924  -4.116 3.85e-05 ***
INCOME_GROUPLow         0.141398   0.116152   1.217 0.223472
INCOME_GROUPMedium     -0.006093   0.086433  -0.070 0.943804
INCOME_GROUPVery High  -0.437946   0.095255  -4.598 4.27e-06 ***
JOBClerical             0.078247   0.110581   0.708 0.479193
JOBDoctor              -0.677301   0.286587  -2.363 0.018111 *
JOBHome Maker           0.027213   0.155355   0.175 0.860948
JOBLawyer              -0.194872   0.188377  -1.034 0.300912
JOBManager             -0.878295   0.140440  -6.254 4.00e-10 ***
JOBProfessional        -0.148125   0.120502  -1.229 0.218983
JOBStudent             -0.153824   0.141134  -1.090 0.275751
JOBUnknown             -0.351367   0.185572  -1.893 0.058302 .
KIDSDRIV                0.450473   0.055226   8.157 3.44e-16 ***
MSTATUSYes             -0.470878   0.083387  -5.647 1.63e-08 ***
MVR_PTS                 0.097055   0.014099   6.884 5.84e-12 ***
LOG_OLDCLAIM            0.022180   0.012473   1.778 0.075372 .
PARENT1Yes              0.344280   0.098548   3.494 0.000477 ***
REVOKEDYes              0.707333   0.081595   8.669  < 2e-16 ***
TIF                    -0.056154   0.007371  -7.618 2.58e-14 ***
TRAVTIME                0.014841   0.001890   7.854 4.03e-15 ***
URBANICITYUrban        -2.397969   0.113729 -21.085  < 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: 7253.1  on 8124  degrees of freedom
AIC: 7327.1

Number of Fisher Scoring iterations: 5


[1] 7327.134
```

Model 4: Using One-Hot Encoded Params

Building off of the predictors we obtained in model 3, uses one-hot encoded predictors for AGE_GROUP, INCOME_GROUP, EDUCATION, and JOB to remove predictors with little statistical significance from our model. Our AIC value has increased a bit to 7354.6 but our model is slightly simpler.

```
Call:
glm(formula = TARGET_FLAG ~ AGE_GROUPMiddleAged + LOG_BLUEBOOK +
    CAR_AGE + CAR_TYPE + CAR_USE + CLM_FREQ + EDUCATIONBachelors +
    LOG_HOME_VAL + `INCOME_GROUPVery High` + JOBManager + KIDSDRIV +
    MSTATUS + MVR_PTS + LOG_OLDCLAIM + PARENT1 + REVOKED + TIF +
    TRAVTIME + URBANICITY + YOJ, family = binomial, data = df_training_one_hot)

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              2.967478   0.523193   5.672 1.41e-08 ***
AGE_GROUPMiddleAged     -0.320530   0.062697  -5.112 3.18e-07 ***
LOG_BLUEBOOK            -0.347126   0.054152  -6.410 1.45e-10 ***
CAR_AGE                 -0.022936   0.005723  -4.008 6.13e-05 ***
CAR_TYPEPanel Truck      0.473037   0.135014   3.504 0.000459 ***
CAR_TYPEPickup           0.538859   0.097886   5.505 3.69e-08 ***
CAR_TYPESports Car       0.898541   0.106904   8.405  < 2e-16 ***
CAR_TYPESUV              0.711022   0.084830   8.382  < 2e-16 ***
CAR_TYPEVan              0.610915   0.119539   5.111 3.21e-07 ***
CAR_USEPrivate          -0.800728   0.070734 -11.320  < 2e-16 ***
CLM_FREQ                 0.081032   0.043068   1.881 0.059906 .
EDUCATIONBachelors      -0.252133   0.067815  -3.718 0.000201 ***
LOG_HOME_VAL            -0.026950   0.006316  -4.267 1.98e-05 ***
`INCOME_GROUPVery High` -0.630592   0.080374  -7.846 4.30e-15 ***
JOBManager              -0.777864   0.105977  -7.340 2.14e-13 ***
KIDSDRIV                 0.449855   0.054944   8.187 2.67e-16 ***
MSTATUSYes              -0.433265   0.080233  -5.400 6.66e-08 ***
MVR_PTS                  0.099115   0.013984   7.088 1.36e-12 ***
LOG_OLDCLAIM             0.025009   0.012395   2.018 0.043617 *
PARENT1Yes               0.391078   0.097158   4.025 5.69e-05 ***
REVOKEDYes               0.704209   0.081123   8.681  < 2e-16 ***
TIF                     -0.054918   0.007339  -7.483 7.28e-14 ***
TRAVTIME                 0.015043   0.001880   8.000 1.25e-15 ***
URBANICITYUrban         -2.333909   0.112827 -20.686  < 2e-16 ***
YOJ                     -0.012554   0.007470  -1.681 0.092856 .
---
```

```
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: 7304.6  on 8136  degrees of freedom
AIC: 7354.6

Number of Fisher Scoring iterations: 5

[1] 7354.647
```

Model 5: Using Engineered Features

Uses CLAIMS_PER_YEAR, TOTAL_KIDS, HIGH_RISK_CAR

```
Call:
glm(formula = TARGET_FLAG ~ HIGH_RISK_CAR + AGE_GROUPMiddleAged +
    `INCOME_GROUPVery High` + CAR_AGE + CLM_FREQ + EDUCATIONBachelors +
    LOG_HOME_VAL + +JOBManager + KIDSDRIV + MSTATUS + MVR_PTS +
    CLAIMS_PER_YEAR + TOTAL_KIDS + REVOKED + TIF + TRAVTIME +
    URBANICITY + YOJ, family = binomial, data = df_training_one_hot)

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)             -9.133e-02  1.298e-01  -0.704  0.48163
HIGH_RISK_CAR            3.384e-01  8.678e-02   3.900 9.63e-05 ***
AGE_GROUPMiddleAged     -3.397e-01  6.355e-02  -5.346 8.99e-08 ***
`INCOME_GROUPVery High` -6.666e-01  7.692e-02  -8.666  < 2e-16 ***
CAR_AGE                 -3.575e-02  5.898e-03  -6.061 1.35e-09 ***
CLM_FREQ                 1.907e-01  2.569e-02   7.423 1.15e-13 ***
EDUCATIONBachelors      -1.951e-01  6.579e-02  -2.966  0.00302 **
LOG_HOME_VAL            -2.790e-02  6.162e-03  -4.527 5.97e-06 ***
JOBManager              -8.856e-01  1.039e-01  -8.526  < 2e-16 ***
KIDSDRIV                 3.092e-01  7.827e-02   3.950 7.81e-05 ***
MSTATUSYes              -5.336e-01  7.054e-02  -7.564 3.91e-14 ***
MVR_PTS                  1.183e-01  1.323e-02   8.938  < 2e-16 ***
CLAIMS_PER_YEAR         -1.712e-05  6.180e-06  -2.770  0.00561 **
TOTAL_KIDS               8.871e-02  3.042e-02   2.916  0.00355 **
REVOKEDYes               8.117e-01  8.184e-02   9.918  < 2e-16 ***
TIF                     -5.075e-02  7.158e-03  -7.089 1.35e-12 ***
```

```
TRAVTIME                  1.435e-02  1.834e-03   7.825 5.06e-15 ***
URBANICITYUrban          -2.212e+00  1.100e-01 -20.110  < 2e-16 ***
YOJ                      -2.097e-02  7.262e-03  -2.888  0.00388 **
---
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: 7609.2  on 8142  degrees of freedom
AIC: 7647.2

Number of Fisher Scoring iterations: 5


[1] 7647.163
```

Model : MQ's Logit model

```
Call:
glm(formula = TARGET_FLAG ~ CAR_TYPE + CAR_USE + EDUCATION +
    INCOME_LOG + JOB + KIDSDRIV + MSTATUS + MVR_PTS + OLDCLAIM_LOG +
    PARENT1 + REVOKED + TIF + TRAVTIME + URBANICITY + YOJ, family = binomial,
    data = insurance_training_clean)

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)          -0.037801   0.209808  -0.180  0.85702
CAR_TYPEPanel Truck   0.294173   0.138090   2.130  0.03315 *
CAR_TYPEPickup        0.638988   0.099535   6.420 1.37e-10 ***
CAR_TYPESports Car    1.050250   0.106206   9.889  < 2e-16 ***
CAR_TYPESUV           0.801973   0.084784   9.459  < 2e-16 ***
CAR_TYPEVan           0.523990   0.119397   4.389 1.14e-05 ***
CAR_USEPrivate       -0.726693   0.091465  -7.945 1.94e-15 ***
EDUCATIONBachelors   -0.460832   0.107359  -4.292 1.77e-05 ***
EDUCATIONHigh School  0.007735   0.094752   0.082  0.93494
EDUCATIONMasters     -0.418406   0.159187  -2.628  0.00858 **
EDUCATIONPhD         -0.476026   0.190371  -2.501  0.01240 *
INCOME_LOG           -0.102679   0.017360  -5.915 3.33e-09 ***
JOBClerical           0.166126   0.104873   1.584  0.11318
JOBDoctor            -0.796151   0.283724  -2.806  0.00501 **
```

```
JOBHome Maker        -0.279879   0.162823  -1.719  0.08563 .
JOBLawyer            -0.273406   0.186521  -1.466  0.14270
JOBManager           -0.929191   0.138762  -6.696 2.14e-11 ***
JOBProfessional      -0.202469   0.118749  -1.705  0.08819 .
JOBStudent           -0.143442   0.137864  -1.040  0.29812
JOBUnknown           -0.383798   0.183417  -2.092  0.03639 *
KIDSDRIV              0.415107   0.054748   7.582 3.40e-14 ***
MSTATUSYes           -0.651828   0.070222  -9.282  < 2e-16 ***
MVR_PTS               0.103963   0.013958   7.448 9.44e-14 ***
OLDCLAIM_LOG          0.044326   0.007301   6.071 1.27e-09 ***
PARENT1Yes            0.435929   0.094070   4.634 3.59e-06 ***
REVOKEDYes            0.690271   0.080397   8.586  < 2e-16 ***
TIF                  -0.054047   0.007303  -7.401 1.35e-13 ***
TRAVTIME              0.014774   0.001877   7.872 3.48e-15 ***
URBANICITYUrban      -2.385583   0.113518 -21.015  < 2e-16 ***
YOJ                   0.018746   0.010393   1.804  0.07128 .
---
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: 7352.5  on 8131  degrees of freedom
AIC: 7412.5

Number of Fisher Scoring iterations: 5
```

Interpreting the Output: Significant p-values (< 0.05) indicate variables that are strong predictors of making a claim.

Model Significance with Deviance Test

```r
null_dev <- logit_model$null.deviance
resid_dev <- logit_model$deviance
df_diff <- logit_model$df.null - logit_model$df.residual
p_val <- 1 - pchisq(null_dev - resid_dev, df_diff)

cat("Model significance p-value:", p_val)
```

```
Model significance p-value: 0
```

```r
# Check each variable
anova(logit_model, test = "Chisq")
```

```
Analysis of Deviance Table

Model: binomial, link: logit

Response: TARGET_FLAG

Terms added sequentially (first to last)

             Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         8160     9418.0
CAR_TYPE      5   180.07      8155     9237.9 < 2.2e-16 ***
CAR_USE       1   179.75      8154     9058.1 < 2.2e-16 ***
EDUCATION     4   113.92      8150     8944.2 < 2.2e-16 ***
INCOME_LOG    1    43.86      8149     8900.4 3.530e-11 ***
JOB           8    48.18      8141     8852.2 9.108e-08 ***
KIDSDRIV      1    66.54      8140     8785.6 3.435e-16 ***
MSTATUS       1   175.98      8139     8609.7 < 2.2e-16 ***
MVR_PTS       1   270.65      8138     8339.0 < 2.2e-16 ***
OLDCLAIM_LOG  1   167.72      8137     8171.3 < 2.2e-16 ***
PARENT1       1    19.27      8136     8152.0 1.135e-05 ***
REVOKED       1    94.14      8135     8057.9 < 2.2e-16 ***
TIF           1    50.13      8134     8007.8 1.439e-12 ***
TRAVTIME      1    16.43      8133     7991.3 5.041e-05 ***
URBANICITY    1   635.59      8132     7355.7 < 2.2e-16 ***
YOJ           1     3.27      8131     7352.5   0.07064 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Run Assumption Tests Using Residuals

Assumption Testing – Logistic

Multicollinearity: Variance Inflation Factor

```r
vif(logit_model)
```

```
                 GVIF Df GVIF^(1/(2*Df))
CAR_TYPE     1.904825  5        1.066561
CAR_USE      2.458052  1        1.567818
EDUCATION    7.321883  4        1.282560
INCOME_LOG   3.584614  1        1.893308
JOB         27.351174  8        1.229733
KIDSDRIV     1.091199  1        1.044605
MSTATUS      1.462453  1        1.209319
MVR_PTS      1.230555  1        1.109304
OLDCLAIM_LOG 1.255965  1        1.120698
PARENT1      1.434180  1        1.197573
REVOKED      1.012436  1        1.006199
TIF          1.008860  1        1.004420
TRAVTIME     1.037331  1        1.018494
URBANICITY   1.151000  1        1.072847
YOJ          2.153507  1        1.467483
```

Explanation: VIF $>$ 5 or 10 indicates multicollinearity. Remove or combine correlated variables.

Linear Regression Models for TARGET_AMT

MODEL EVALUATION