Analysis

Justin Chan and Isaac Plotkin

3/3/2022

Analysis: Final Project

Research Question and Modeling Objective

The research question we have is how to best predict car prices based on various car features in our car dataset. Therefore, our modeling objective is to create the best possible linear model from our set of features in our car dataset from Kaggle to be able to make predictions on car prices for other cars.

Description of Data and Response Variable

Data

The observations of the dataset are cars where each row is a car with the columns being various features of the car. The dataset includes 26 columns where one column is an observation index and another column is car price which is the variable we are trying to predict so we have 24 input or car features for 205 observations/cars that we can use our linear regression model.

The data was originally collected from various market surveys of different types of cars across the United States market around 1987 to learn how to price cars in China depending on the American market. There is an assumption that the cars in the data set have been randomly chosen from the set of cars in the various market surveys. Link to the dataset: https://www.kaggle.com/hellbuoy/car-price-prediction.The car dataset from Kaggle is download in the following lines of code along with downloading the packages.

```
car_data <- read_csv("~/Desktop/School/STAT108/STAT108FinalProject/data/CarPrice_Assignment.csv")
```

```
## Rows: 205 Columns: 26
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (10): CarName, fueltype, aspiration, doornumber, carbody, drivewheel, en...
## dbl (16): car_ID, symboling, wheelbase, carlength, carwidth, carheight, curb...
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
glimpse(car_data)
```

```
## Rows: 205
## Columns: 26
## $ car_ID           <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16~
## $ symboling        <dbl> 3, 3, 1, 2, 2, 2, 1, 1, 1, 0, 2, 0, 0, 0, 1, 0, 0, 0,~
## $ CarName          <chr> "alfa-romero giulia", "alfa-romero stelvio", "alfa-ro~
## $ fueltype         <chr> "gas", "gas", "gas", "gas", "gas", "gas", "gas", "gas~
## $ aspiration       <chr> "std", "std", "std", "std", "std", "std", "std", "std~
## $ doornumber       <chr> "two", "two", "two", "four", "four", "two", "four", "~
## $ carbody          <chr> "convertible", "convertible", "hatchback", "sedan", "~
## $ drivewheel       <chr> "rwd", "rwd", "rwd", "fwd", "4wd", "fwd", "fwd", "fwd~
## $ enginelocation   <chr> "front", "front", "front", "front", "front", "front",~
## $ wheelbase        <dbl> 88.6, 88.6, 94.5, 99.8, 99.4, 99.8, 105.8, 105.8, 105~
## $ carlength        <dbl> 168.8, 168.8, 171.2, 176.6, 176.6, 177.3, 192.7, 192.~
## $ carwidth         <dbl> 64.1, 64.1, 65.5, 66.2, 66.4, 66.3, 71.4, 71.4, 71.4,~
## $ carheight        <dbl> 48.8, 48.8, 52.4, 54.3, 54.3, 53.1, 55.7, 55.7, 55.9,~
## $ curbweight       <dbl> 2548, 2548, 2823, 2337, 2824, 2507, 2844, 2954, 3086,~
## $ enginetype       <chr> "dohc", "dohc", "ohcv", "ohc", "ohc", "ohc", "ohc", "~
## $ cylindernumber   <chr> "four", "four", "six", "four", "five", "five", "five"~
## $ enginesize       <dbl> 130, 130, 152, 109, 136, 136, 136, 136, 131, 131, 108~
## $ fuelsystem       <chr> "mpfi", "mpfi", "mpfi", "mpfi", "mpfi", "mpfi", "mpfi~
## $ boreratio        <dbl> 3.47, 3.47, 2.68, 3.19, 3.19, 3.19, 3.19, 3.19, 3.13,~
## $ stroke           <dbl> 2.68, 2.68, 3.47, 3.40, 3.40, 3.40, 3.40, 3.40, 3.40,~
## $ compressionratio <dbl> 9.00, 9.00, 9.00, 10.00, 8.00, 8.50, 8.50, 8.50, 8.30~
## $ horsepower       <dbl> 111, 111, 154, 102, 115, 110, 110, 110, 140, 160, 101~
## $ peakrpm          <dbl> 5000, 5000, 5000, 5500, 5500, 5500, 5500, 5500, 5500,~
## $ citympg          <dbl> 21, 21, 19, 24, 18, 19, 19, 19, 17, 16, 23, 23, 21, 2~
## $ highwaympg       <dbl> 27, 27, 26, 30, 22, 25, 25, 25, 20, 22, 29, 29, 28, 2~
## $ price            <dbl> 13495.00, 16500.00, 16500.00, 13950.00, 17450.00, 152~
```

General Description of Variables

The following is the data dictionary of our dataset that gives a clear, general description of our variables or covariates that can be used in the model. - symboling: Its assigned insurance risk rating (Categroical) - carCompany: Name of car campany (Categorical) - fueltype: Car fuel type i.e gas or diesel (Categorical) - aspiration: Aspiration used in a car (Categorical) - doornumber: Number of doors in a car (Categorical) - carbody: Body of car (Categorical) - drivewheel: Type of drive wheel(Categorical) - enginelocation: Location of car engine (Categorical) - wheelbase: Wheelbase of car (Numeric) - carlength: Length of car (Numeric) - carwidth: Width of car (Numeric) - carheight: Height of car (Numeric) - curbweight: The weight of a car withoput occupants or baggage (Numeric) - enginetype: Type of engine (Categorical) - cylindernumber: Cylinder placed in car (Categorical) - enginesize: Size of car (Numeric) - fuelsystem: Fuel Sytem of car (Categorical) - boreratio: Boreration of car (Numeric) - stroke: Stroke or volume inside the engine (Numeric) - compressionratio: compression ratio of car (Numeric) - horsepower: Horsepower (Numeric) - peakrpm: car peak rpm (Numeric) - citympg: mileage in city (Numeric) - highwaympg: milaege on highway (Numeric) - price: price of car (Numeric)

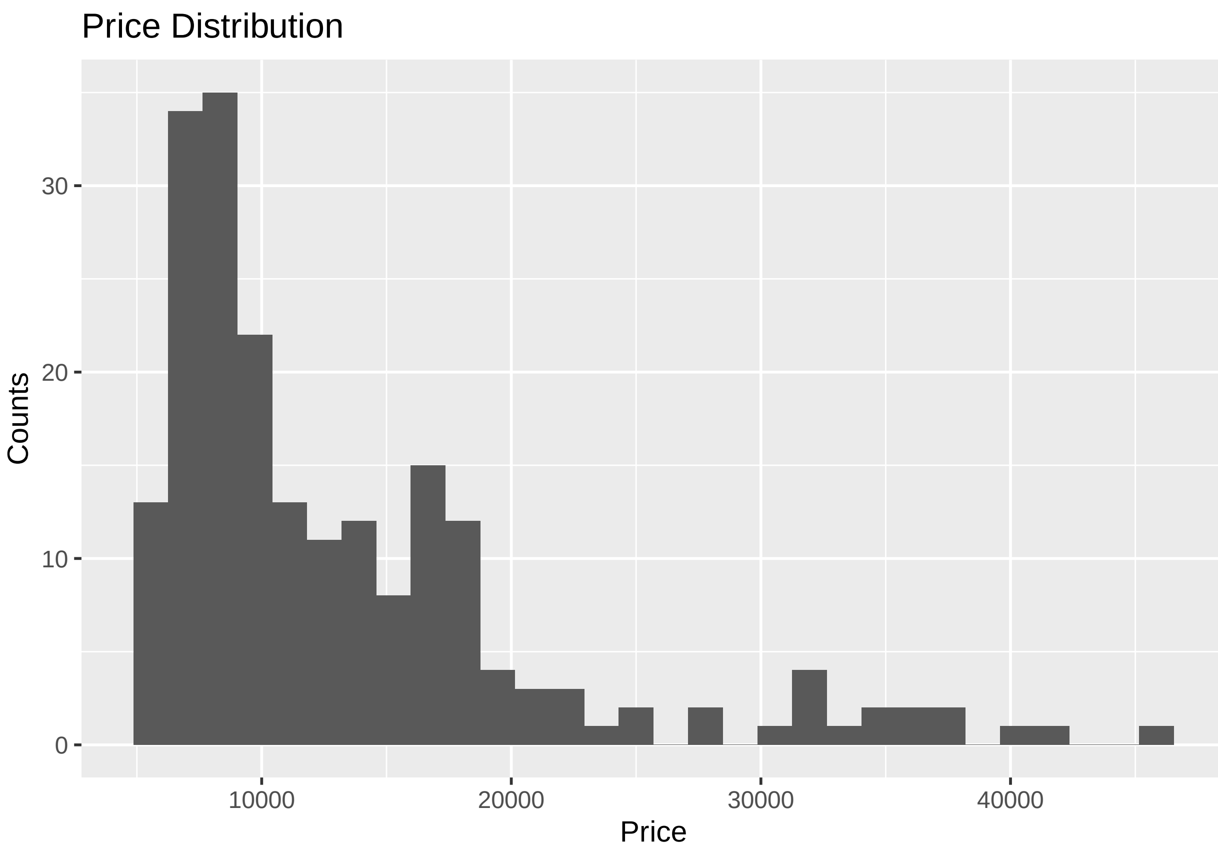
Response Variable: Price

The response variable, price, is the price of the car in our dataset. In order to be able to predict price, we performed some initial univariate analysis of price to observe its spread in the dataset.

```r
ggplot(data = car_data, aes(x = price)) +
  geom_histogram() +
```

```
  labs(x = "Price",
       y = "Counts",
       title = "Price Distribution")
```

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



The response variable, price, seems unimodal meaning that there is one peak and seems to be skewed to the right where there are many datapoints that have price around 5,000-10,000 dollars but, there are a few outliers that have price over than 25,000 dollars. To follow up with our analysis, we also created summary statistics for price to see if the statistics reflected the graph we observed.

```
car_data %>%
  summarise(min = min(price),
            q1 = quantile(price, probs = c(0.25)),
            median = median(price),
            q3 = quantile(price, probs = c(0.75)),
            max = max(price),
            iqr = IQR(price),
            mean = mean(price),
            std_dev = sd(price)
            )
```

```
## # A tibble: 1 x 8
##     min    q1 median    q3   max   iqr   mean std_dev
##   <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>  <dbl>   <dbl>
## 1  5118  7788  10295 16503 45400  8715 13277.   7989.
```

It seems like our summary statistics further support the graph where the quantiles q1 and q2 are much smaller due to the concentration of points based on the distance of min, q1, and median compared to the distance of median, q3, and max.

EDA

Univariate

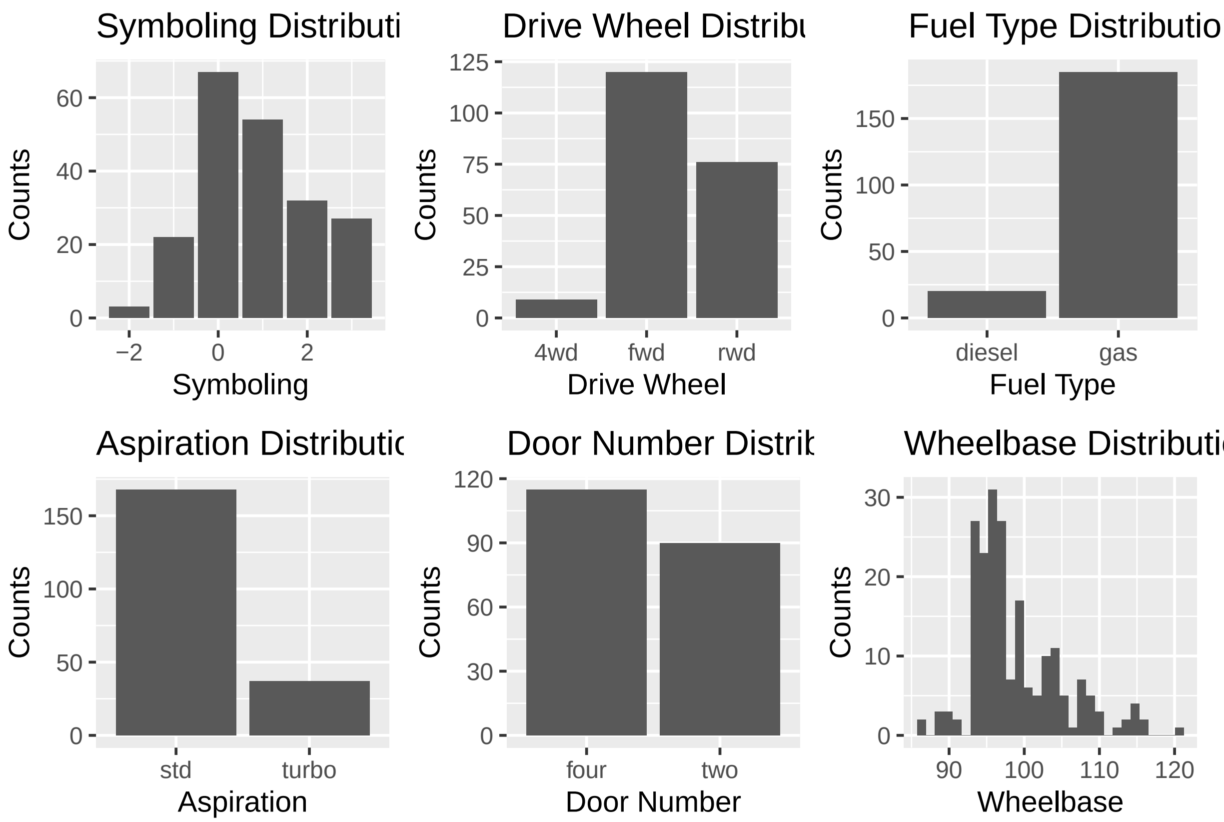
In the following code block, we plotted the 23 covariates or possible predictor variables to do a simple univariate analysis of both the categorical and continuous using bar graphs and histograms of each variable by itself. We formatted the graphs to be able to optimize for space on the pdf and still be able to see the visualization analysis for each variable.

```
p1 <- ggplot(data = car_data, aes(x = symboling)) +
  geom_bar() +
  labs(x = "Symboling",
       y = "Counts",
       title = "Symboling Distribution")

p2 <- ggplot(data = car_data, aes(x = drivewheel)) +
  geom_bar() +
  labs(x = "Drive Wheel",
       y = "Counts",
       title = "Drive Wheel Distribution")

p3 <- ggplot(data = car_data, aes(x = fueltype)) +
  geom_bar() +
  labs(x = "Fuel Type",
       y = "Counts",
       title = "Fuel Type Distribution")

p4 <- ggplot(data = car_data, aes(x = aspiration)) +
  geom_bar() +
  labs(x = "Aspiration",
       y = "Counts",
       title = "Aspiration Distribution")

p5 <- ggplot(data = car_data, aes(x = doornumber)) +
  geom_bar() +
  labs(x = "Door Number",
       y = "Counts",
       title = "Door Number Distribution")

p6 <- ggplot(data = car_data, aes(x = carbody)) +
  geom_bar() +
  labs(x = "Car Body",
       y = "Counts",
       title = "Car Body Distribution")

p7 <- ggplot(data = car_data, aes(x = CarName)) +
  geom_bar() +
  labs(x = "Car Name",
       y = "Counts",
```

```r
       title = "Car Name Distribution")

p8 <- ggplot(data = car_data, aes(x = wheelbase)) +
  geom_histogram() +
  labs(x = "Wheelbase",
       y = "Counts",
       title = "Wheelbase Distribution")

p9 <- ggplot(data = car_data, aes(x = carlength)) +
  geom_histogram() +
  labs(x = "Car Length",
       y = "Counts",
       title = "Car Length Distribution")

p10 <- ggplot(data = car_data, aes(x = carwidth)) +
  geom_histogram() +
  labs(x = "Car Width",
       y = "Counts",
       title = "Car Width Distribution")

p11 <- ggplot(data = car_data, aes(x = carheight)) +
  geom_histogram() +
  labs(x = "Car Height",
       y = "Counts",
       title = "Car Height Distribution")

p12 <- ggplot(data = car_data, aes(x = curbweight)) +
  geom_histogram() +
  labs(x = "Curb Weight",
       y = "Counts",
       title = "Curb Weight Distribution")

p13 <- ggplot(data = car_data, aes(x = enginetype)) +
  geom_bar() +
  labs(x = "Engine Type",
       y = "Counts",
       title = "Engine Type Distribution")

p14 <- ggplot(data = car_data, aes(x = cylindernumber)) +
  geom_bar() +
  labs(x = "Cylinder Number",
       y = "Counts",
       title = "Cylinder Number Distribution")

p15 <- ggplot(data = car_data, aes(x = enginesize)) +
  geom_histogram() +
  labs(x = "Engine Size",
       y = "Counts",
       title = "Engine Size Distribution")

p16 <- ggplot(data = car_data, aes(x = fuelsystem)) +
  geom_bar() +
  labs(x = "Fuel System",
```

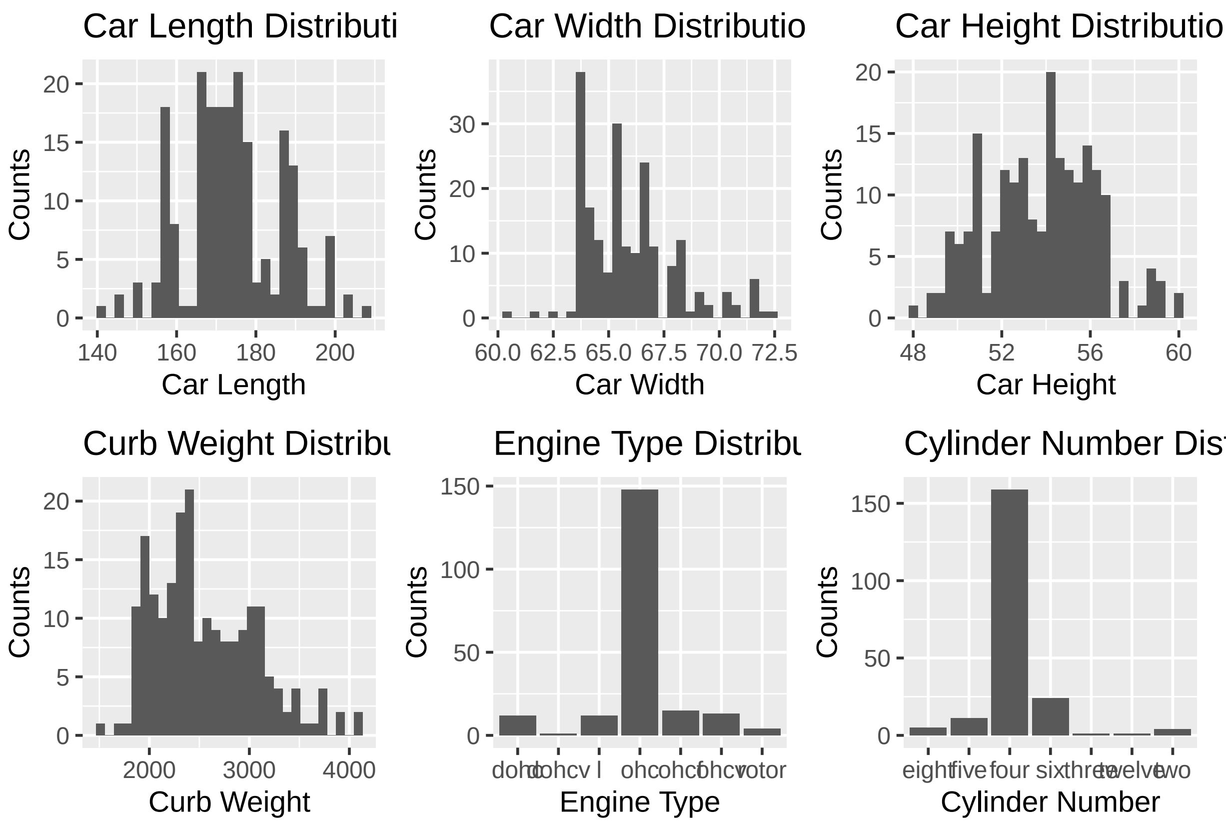
```
       y = "Counts",
       title = "Fuel System Distribution")

p17 <- ggplot(data = car_data, aes(x = boreratio)) +
  geom_histogram() +
  labs(x = "Bore Ratio",
       y = "Counts",
       title = "Bore Ratio Distribution")

p18 <- ggplot(data = car_data, aes(x = stroke)) +
  geom_histogram() +
  labs(x = "Stroke",
       y = "Counts",
       title = "Stroke Distribution")

p19 <- ggplot(data = car_data, aes(x = compressionratio)) +
  geom_histogram() +
  labs(x = "Compression Ratio",
       y = "Counts",
       title = "Compression Ratio Distribution")

p20 <- ggplot(data = car_data, aes(x = horsepower)) +
  geom_histogram() +
  labs(x = "Horsepower",
       y = "Counts",
       title = "Horsepower Distribution")

p21 <- ggplot(data = car_data, aes(x = peakrpm)) +
  geom_histogram() +
  labs(x = "Peak RPM",
       y = "Counts",
       title = "Peak RPM Distribution")

p22 <- ggplot(data = car_data, aes(x = citympg)) +
  geom_histogram() +
  labs(x = "City MPG",
       y = "Counts",
       title = "City MPG Distribution")

p23 <- ggplot(data = car_data, aes(x = highwaympg)) +
  geom_histogram() +
  labs(x = "Highway MPG",
       y = "Counts",
       title = "Highway MPG Distribution")

(p1+p2+p3)/(p4+p5+p8)
```

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



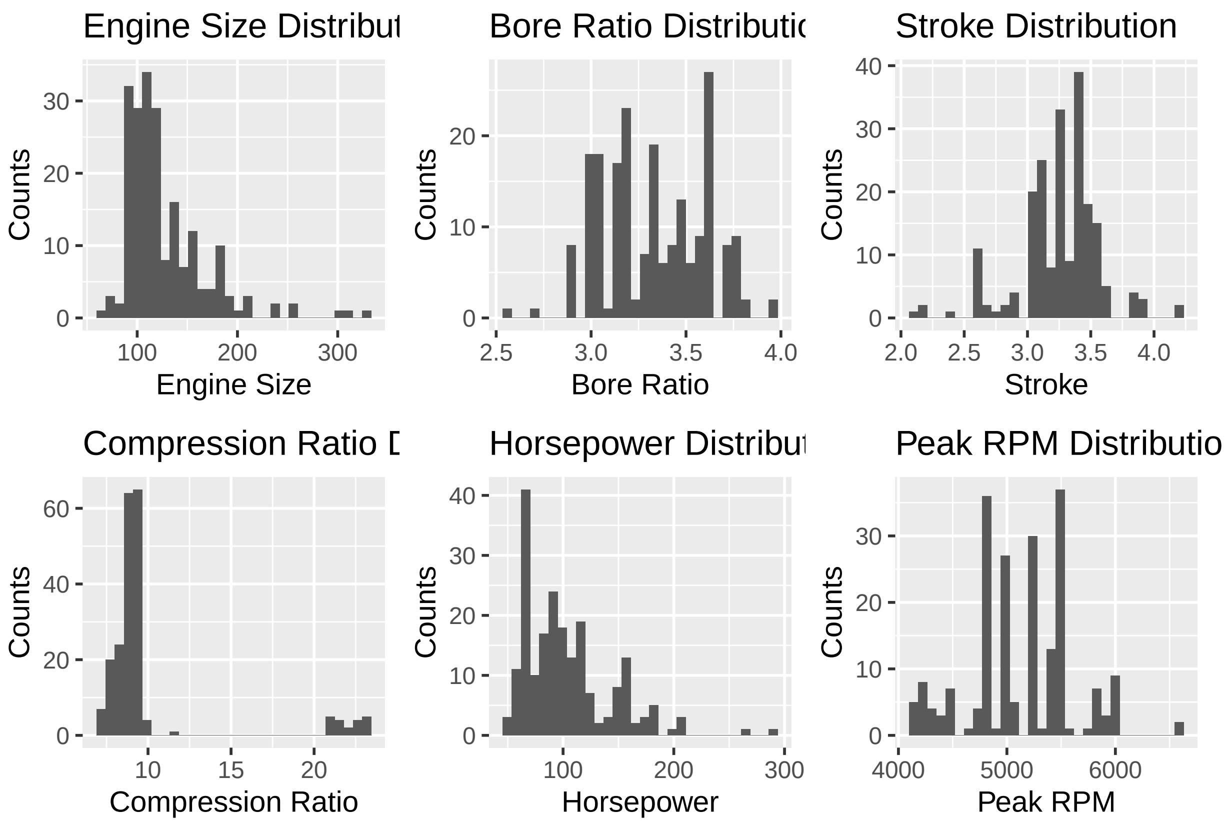

```
(p9+p10+p11)/(p12+p13+p14)
```

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



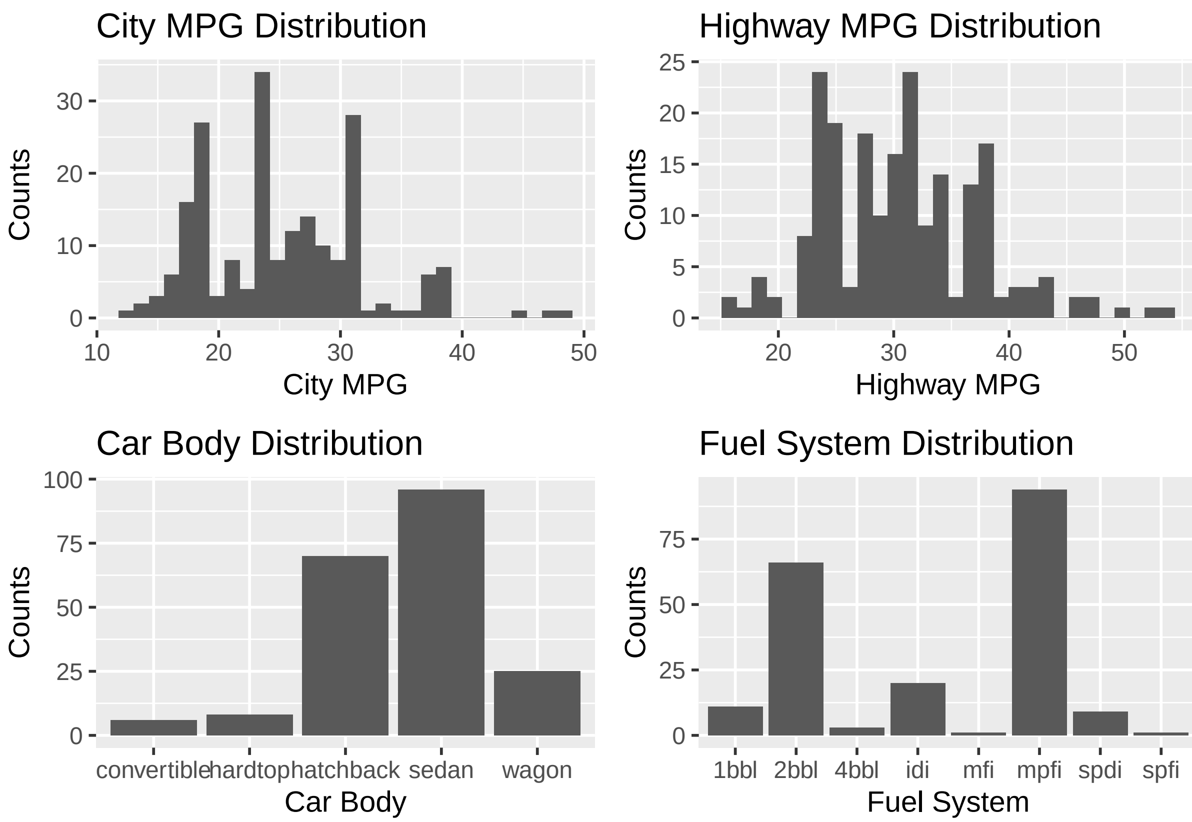

```
(p15+p17+p18)/(p19+p20+p21)
```

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

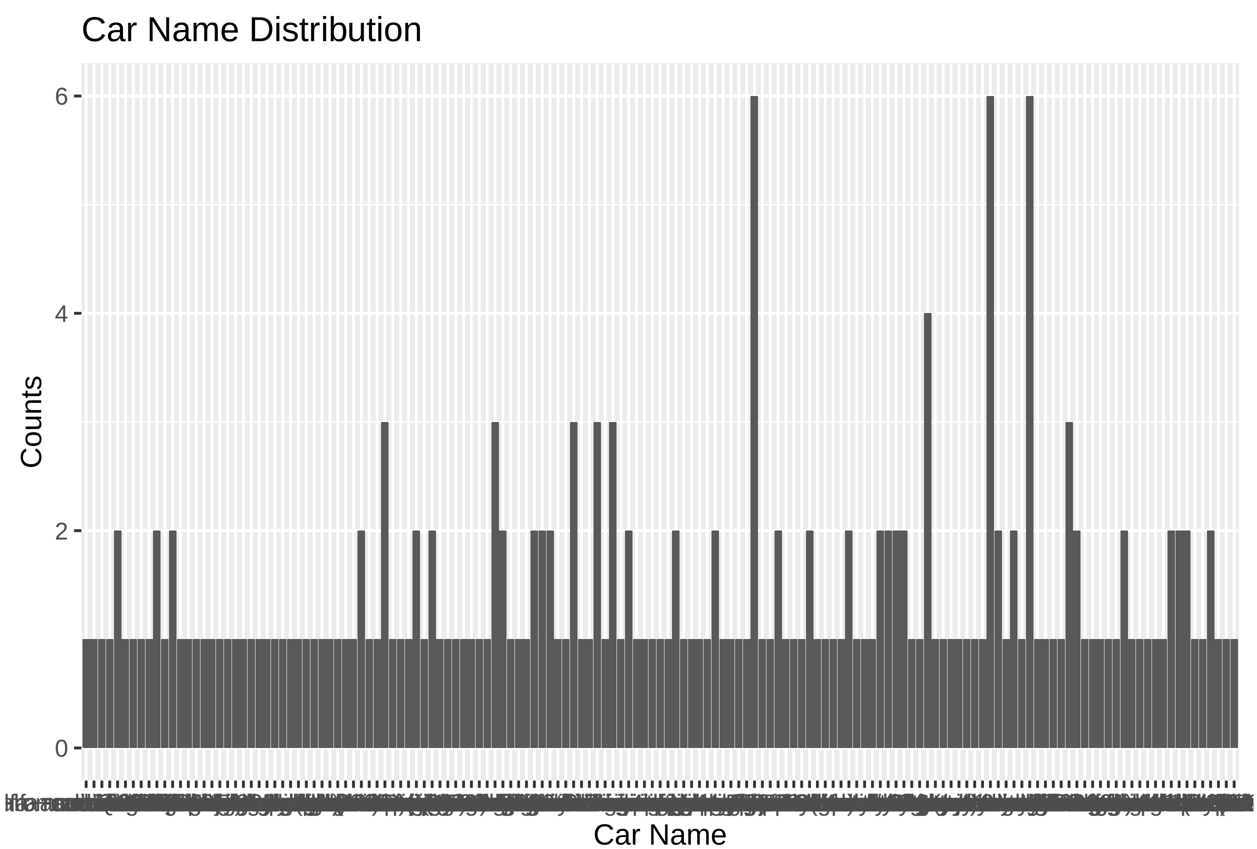



```
(p22+p23)/(p6 + p16)
```

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


City MPG Distribution
Counts
0
10
20
30
10
20
30
40
50
City MPG
Highway MPG Distribution
Counts
0
5
10
15
20
25
20
30
40
50
Highway MPG
Car Body Distribution
Counts
0
25
50
75
100
convertible
hardtop
hatchback
sedan
wagon
Car Body
Fuel System Distribution
Counts
0
25
50
75
1bbl
2bbl
4bbl
idi
mfi
mpfi
spdi
spfi
Fuel System

```
p7
```



After looking at all the graphs, we wanted to see the summary statistics of the univariate variables so we ran the summary method to see the individual statistics of each of our possible covariates.

```
summary(car_data)
```

```
##      car_ID      symboling          CarName            fueltype
##  Min.   :  1   Min.   :-2.0000   Length:205         Length:205
##  1st Qu.: 52   1st Qu.: 0.0000   Class :character   Class :character
##  Median :103   Median : 1.0000   Mode  :character   Mode  :character
##  Mean   :103   Mean   : 0.8341
##  3rd Qu.:154   3rd Qu.: 2.0000
##  Max.   :205   Max.   : 3.0000
##   aspiration         doornumber          carbody           drivewheel
##  Length:205         Length:205         Length:205         Length:205
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##  enginelocation       wheelbase        carlength        carwidth
##  Length:205         Min.   : 86.60   Min.   :141.1   Min.   :60.30
##  Class :character   1st Qu.: 94.50   1st Qu.:166.3   1st Qu.:64.10
##  Mode  :character   Median : 97.00   Median :173.2   Median :65.50
##                     Mean   : 98.76   Mean   :174.0   Mean   :65.91
##                     3rd Qu.:102.40   3rd Qu.:183.1   3rd Qu.:66.90
##                     Max.   :120.90   Max.   :208.1   Max.   :72.30
##    carheight       curbweight    enginetype         cylindernumber
```

```
##  Min.   :47.80   Min.   :1488   Length:205         Length:205        
##  1st Qu.:52.00   1st Qu.:2145   Class :character   Class :character  
##  Median :54.10   Median :2414   Mode  :character   Mode  :character  
##  Mean   :53.72   Mean   :2556                                        
##  3rd Qu.:55.50   3rd Qu.:2935                                        
##  Max.   :59.80   Max.   :4066                                        
##    enginesize     fuelsystem          boreratio        stroke     
##  Min.   : 61.0   Length:205         Min.   :2.54   Min.   :2.070  
##  1st Qu.: 97.0   Class :character   1st Qu.:3.15   1st Qu.:3.110  
##  Median :120.0   Mode  :character   Median :3.31   Median :3.290  
##  Mean   :126.9                      Mean   :3.33   Mean   :3.255  
##  3rd Qu.:141.0                      3rd Qu.:3.58   3rd Qu.:3.410  
##  Max.   :326.0                      Max.   :3.94   Max.   :4.170  
##  compressionratio   horsepower       peakrpm        citympg     
##  Min.   : 7.00    Min.   : 48.0   Min.   :4150   Min.   :13.00  
##  1st Qu.: 8.60    1st Qu.: 70.0   1st Qu.:4800   1st Qu.:19.00  
##  Median : 9.00    Median : 95.0   Median :5200   Median :24.00  
##  Mean   :10.14    Mean   :104.1   Mean   :5125   Mean   :25.22  
##  3rd Qu.: 9.40    3rd Qu.:116.0   3rd Qu.:5500   3rd Qu.:30.00  
##  Max.   :23.00    Max.   :288.0   Max.   :6600   Max.   :49.00  
##    highwaympg        price      
##  Min.   :16.00   Min.   : 5118  
##  1st Qu.:25.00   1st Qu.: 7788  
##  Median :30.00   Median :10295  
##  Mean   :30.75   Mean   :13277  
##  3rd Qu.:34.00   3rd Qu.:16503  
##  Max.   :54.00   Max.   :45400
```

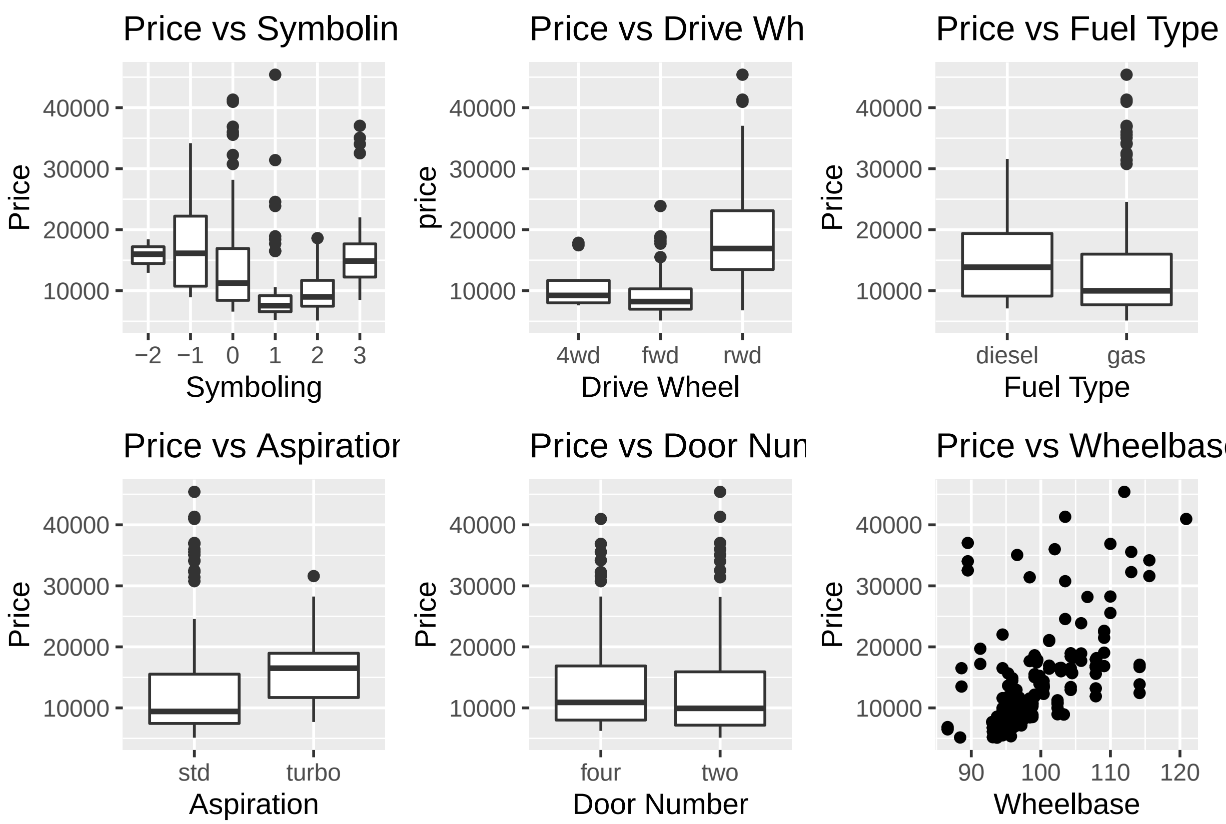
From these visualizations and statistics, we found the general distributions of each individual covariate which is always good to know before modeling. As we move into bivariate analysis, we want to see how these distributions change when including price values to plot against them. ## Bivariate For bivariate analysis, we wanted to analyze each covariate vs price to see the relationship between each one to be able to see first if a covariate could be use to distinguish price values for cars and see if there is a linear relationship between the predictor variable and our response variable. The following block of code gives us price vs each individual covariate using box plots and scatterplots for categorical and continuous variables.

```
b1 <- ggplot(data = car_data, aes(x = as.factor(symboling), y = price)) +
  geom_boxplot() +
  labs(x = "Symboling",
       y = "Price",
       title = "Price vs Symboling")

b2 <- ggplot(data = car_data, aes(x = drivewheel, y = price)) +
  geom_boxplot() +
  labs(x = "Drive Wheel",
       y = "price",
       title = "Price vs Drive Wheel")

b3 <- ggplot(data = car_data, aes(x = fueltype, y = price)) +
  geom_boxplot() +
  labs(x = "Fuel Type",
       y = "Price",
       title = "Price vs Fuel Type")
```

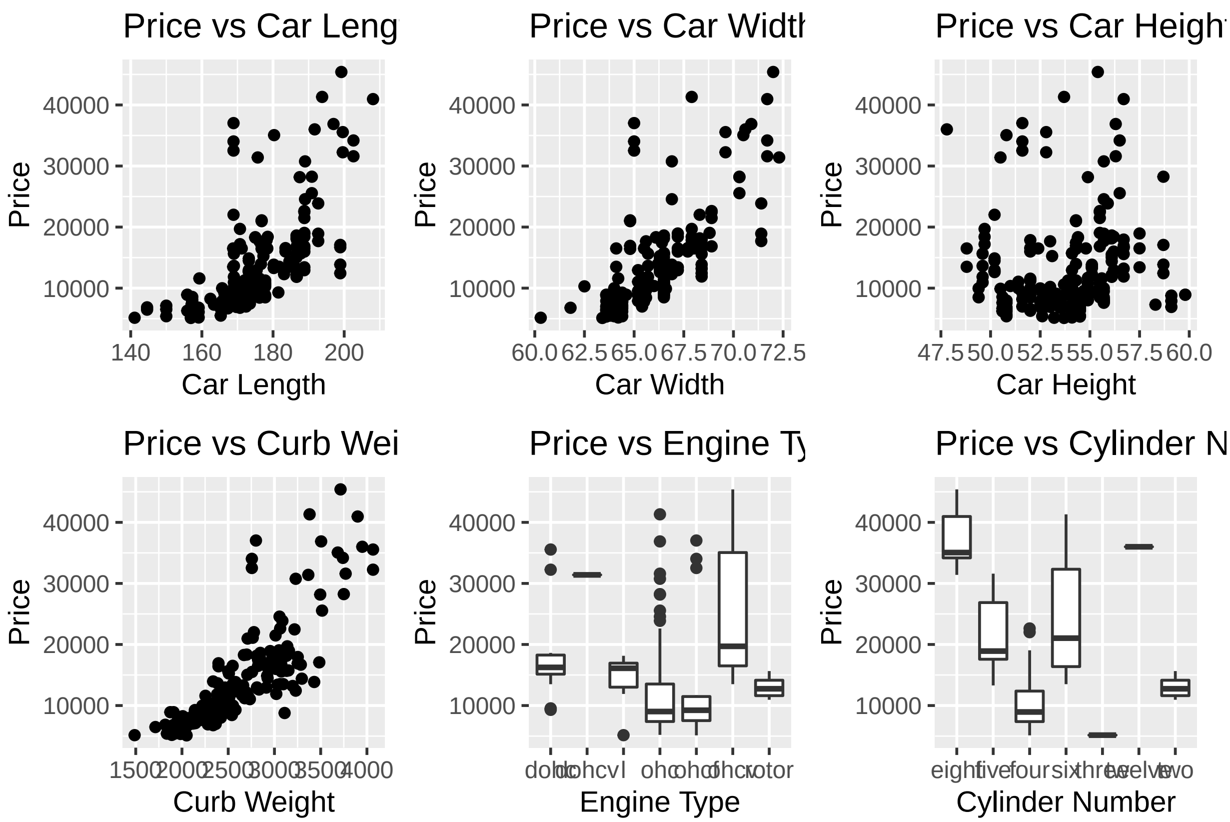
```r
b4 <- ggplot(data = car_data, aes(x = aspiration, y = price)) +
  geom_boxplot() +
  labs(x = "Aspiration",
       y = "Price",
       title = "Price vs Aspiration")

b5 <- ggplot(data = car_data, aes(x = doornumber, y = price)) +
  geom_boxplot() +
  labs(x = "Door Number",
       y = "Price",
       title = "Price vs Door Number")

b6 <- ggplot(data = car_data, aes(x = carbody, y = price)) +
  geom_boxplot() +
  labs(x = "Car Body",
       y = "Price",
       title = "Price vs Car Body")

b7 <- ggplot(data = car_data, aes(x = CarName, y = price)) +
  geom_boxplot() +
  labs(x = "Car Name",
       y = "Price",
       title = "Price vs Car Name")

b8 <- ggplot(data = car_data, aes(x = wheelbase, y = price)) +
  geom_point() +
  labs(x = "Wheelbase",
       y = "Price",
       title = "Price vs Wheelbase")

b9 <- ggplot(data = car_data, aes(x = carlength, y = price)) +
  geom_point() +
  labs(x = "Car Length",
       y = "Price",
       title = "Price vs Car Length")

b10 <- ggplot(data = car_data, aes(x = carwidth, y = price)) +
  geom_point() +
  labs(x = "Car Width",
       y = "Price",
       title = "Price vs Car Width")

b11 <- ggplot(data = car_data, aes(x = carheight, y = price)) +
  geom_point() +
  labs(x = "Car Height",
       y = "Price",
       title = "Price vs Car Height")

b12 <- ggplot(data = car_data, aes(x = curbweight, y = price)) +
  geom_point() +
  labs(x = "Curb Weight",
       y = "Price",
       title = "Price vs Curb Weight")
```

```
b13 <- ggplot(data = car_data, aes(x = enginetype, y = price)) +
  geom_boxplot() +
  labs(x = "Engine Type",
       y = "Price",
       title = "Price vs Engine Type")

b14 <- ggplot(data = car_data, aes(x = cylindernumber, y = price)) +
  geom_boxplot() +
  labs(x = "Cylinder Number",
       y = "Price",
       title = "Price vs Cylinder Number")

b15 <- ggplot(data = car_data, aes(x = enginesize, y = price)) +
  geom_point() +
  labs(x = "Engine Size",
       y = "Price",
       title = "Price vs Engine Size")

b16 <- ggplot(data = car_data, aes(x = fuelsystem, y = price)) +
  geom_boxplot() +
  labs(x = "Fuel System",
       y = "Price",
       title = "Price vs Fuel System")

b17 <- ggplot(data = car_data, aes(x = boreratio, y = price)) +
  geom_point() +
  labs(x = "Bore Ratio",
       y = "Price",
       title = "Price vs Bore Ratio")

b18 <- ggplot(data = car_data, aes(x = stroke, y = price)) +
  geom_point() +
  labs(x = "Stroke",
       y = "Price",
       title = "Price vs Stroke")

b19 <- ggplot(data = car_data, aes(x = compressionratio, y = price)) +
  geom_point() +
  labs(x = "Compression Ratio",
       y = "Price",
       title = "Price vs Compression Ratio")

b20 <- ggplot(data = car_data, aes(x = horsepower, y = price)) +
  geom_point() +
  labs(x = "Horsepower",
       y = "Price",
       title = "Price vs Horsepower")

b21 <- ggplot(data = car_data, aes(x = peakrpm, y = price)) +
  geom_point() +
  labs(x = "Peak RPM",
       y = "Price",
       title = "Price vs Peak RPM")
```

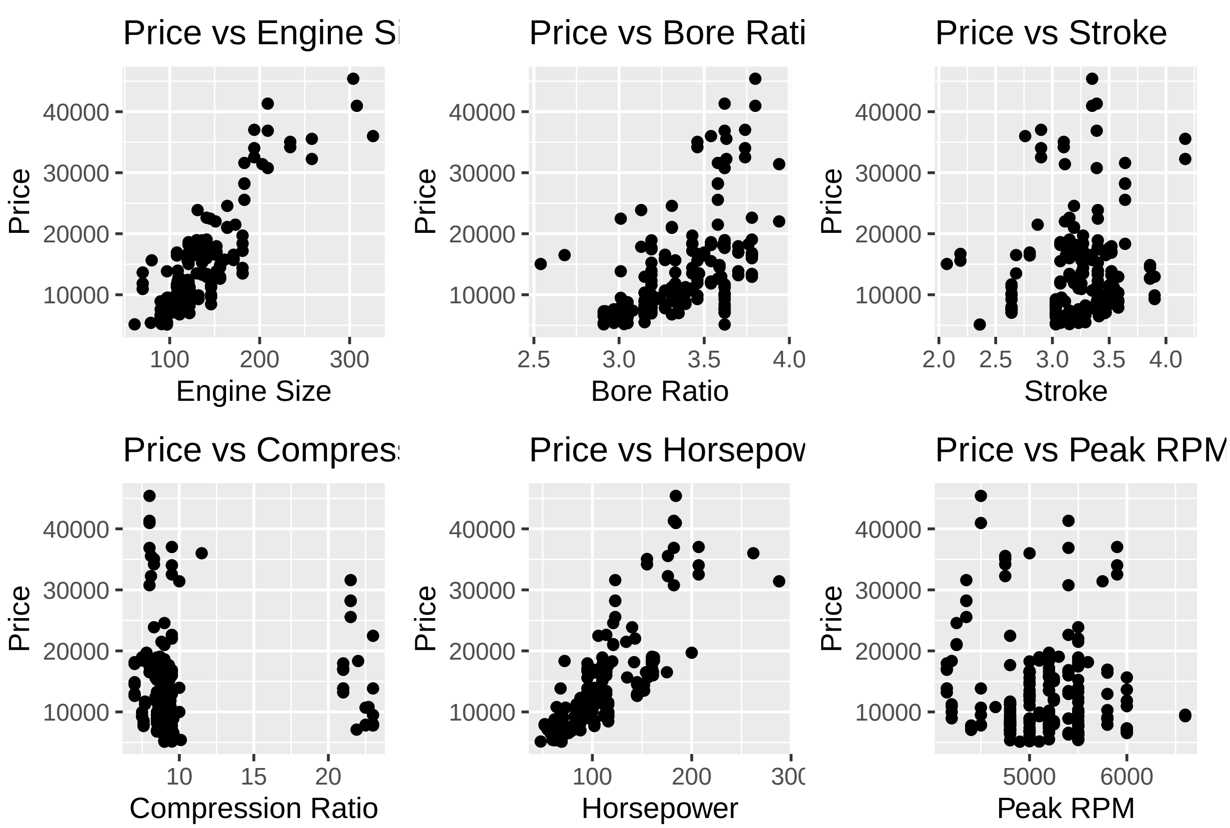
```
b22 <- ggplot(data = car_data, aes(x = citympg, y = price)) +
  geom_point() +
  labs(x = "City MPG",
       y = "Price",
       title = "Price vs City MPG")

b23 <- ggplot(data = car_data, aes(x = highwaympg, y = price)) +
  geom_point() +
  labs(x = "Highway MPG",
       y = "Price",
       title = "Price vs Highway MPG")

(b1+b2+b3)/(b4+b5+b8) # Wheelbase, symboling, drive wheel, aspiration
```



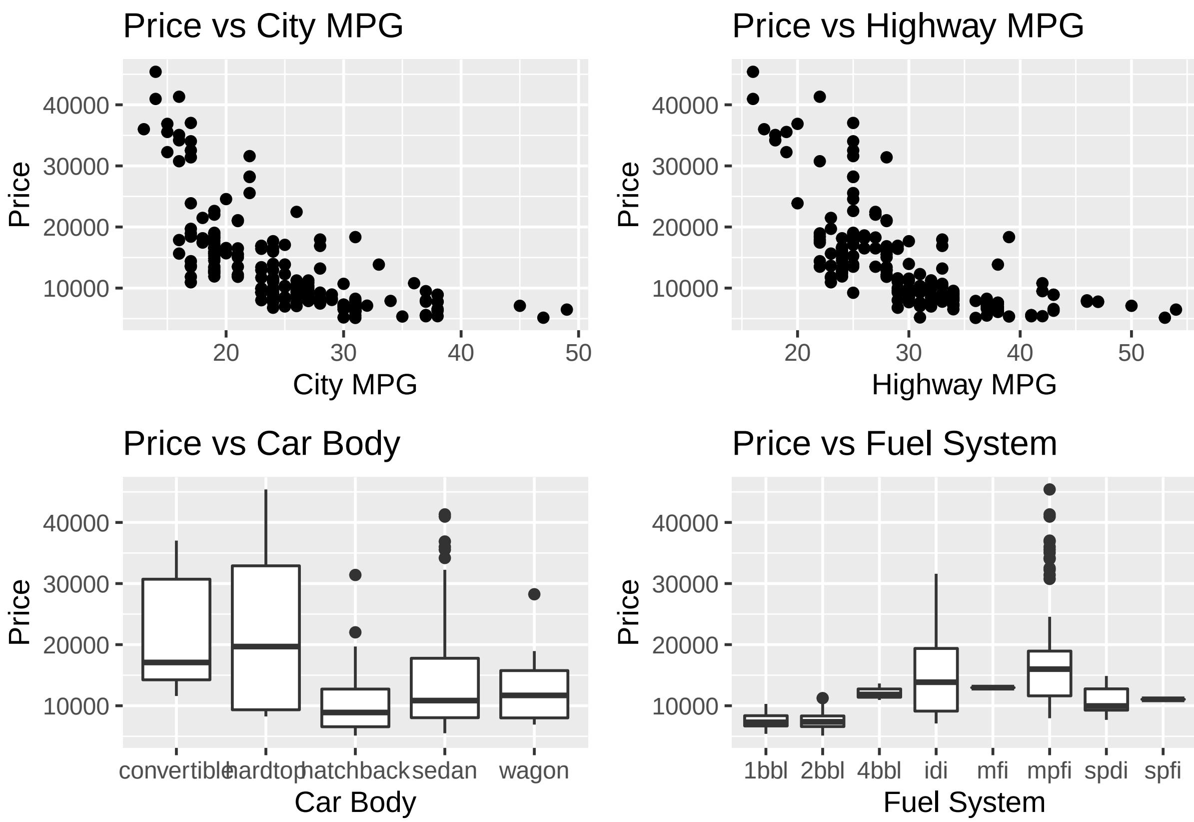

```
(b9+b10+b11)/(b12+b13+b14) # Cylinder num, curb weight, car length, car width
```



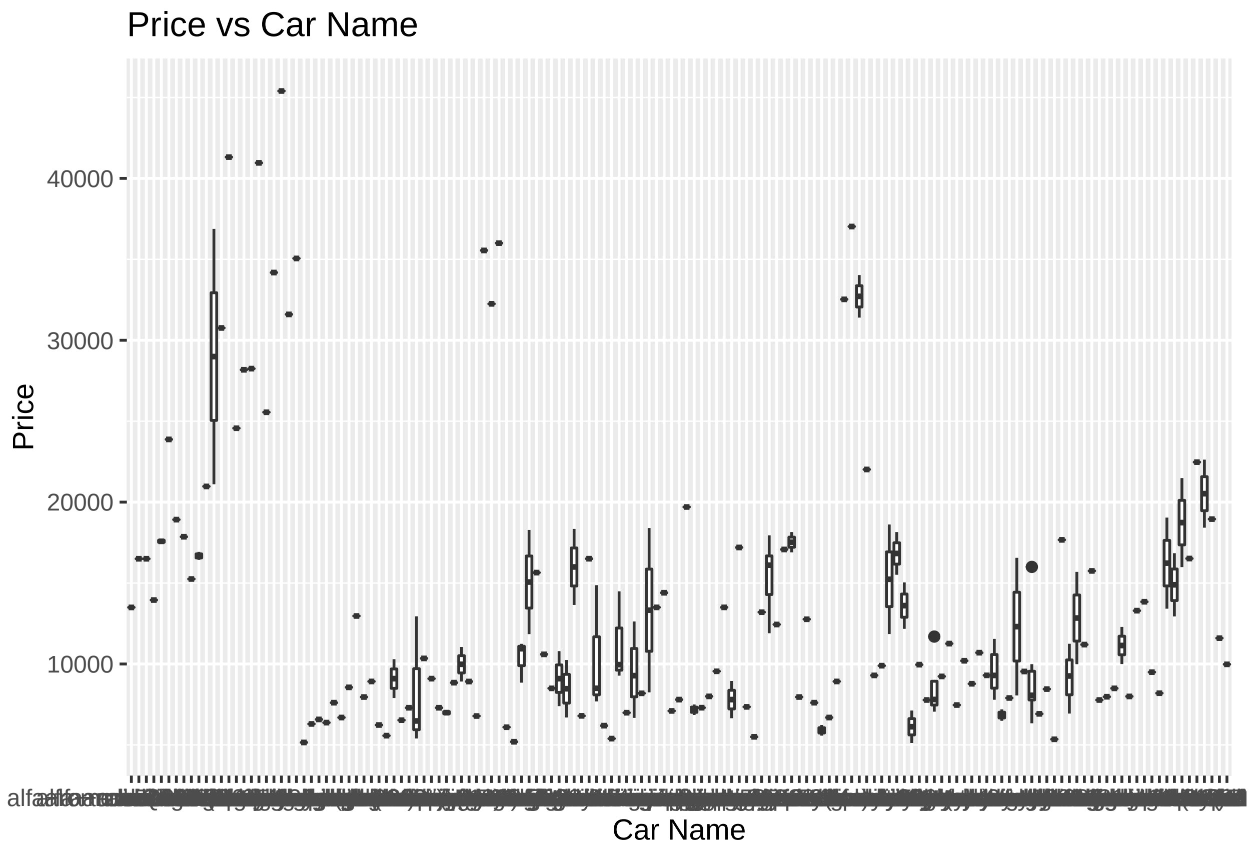

```
(b15+b17+b18)/(b19+b20+b21) # Engine size, horsepower, bore ration
```



```r
(b22+b23)/(b6 + b16) # fuel system, city mpg, highway mpg
```




```r
b7
```

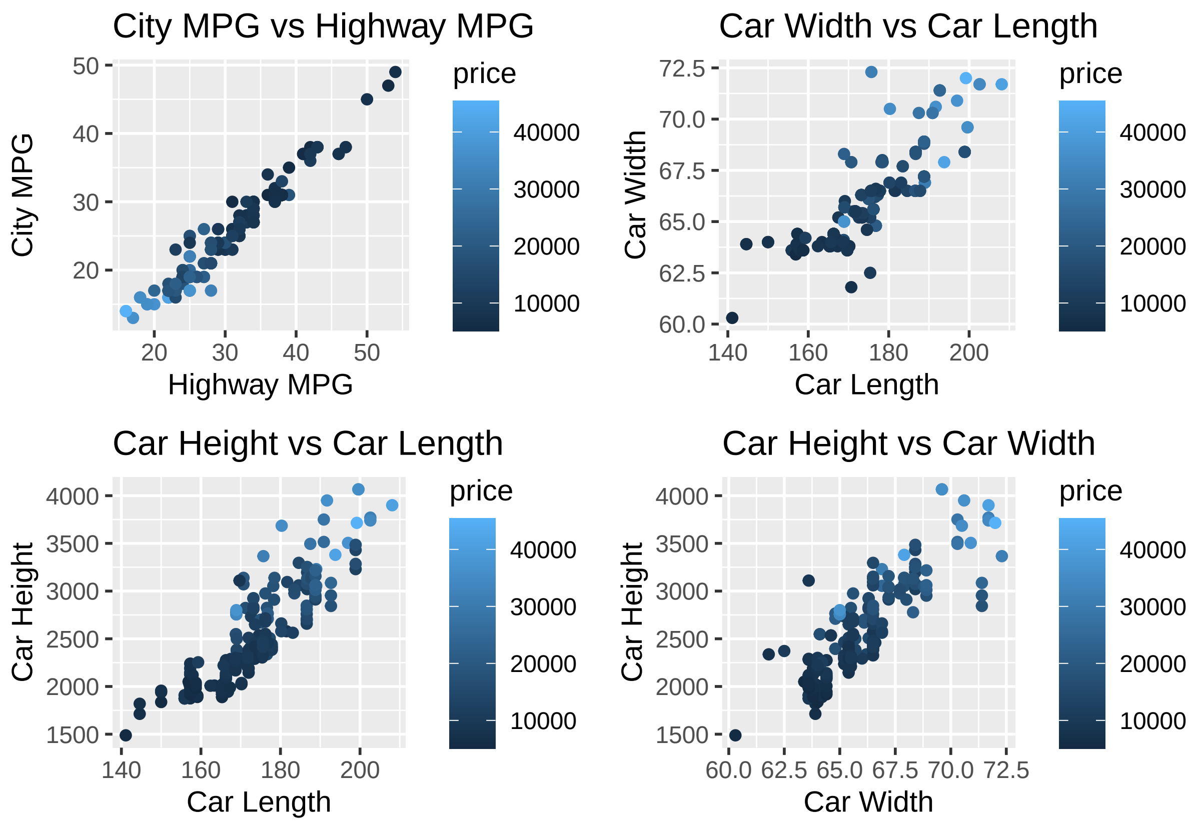


When choosing initial variables to choose for our linear model, we wanted to find scatterplots that had a clear linear relationship and boxplots where categories had different median values and price ranges. From our first six graphs, symboling and drivewheel had categories that had different distributions for price which allowed them to be our possible covariates. Aspiration and wheelbase seemed pretty reasonable to be covariates so they were also allowed to continue on the next stage. The rest of the covariates, fueltype and doornumber, were left out due to the minimal difference between their categories in boxplots. The next six graphs were analyzed where carlength, carwidth, and curb weight had the most clear linear relationship from the scatterplots so they were still considered as candidates while car height seemed to have a weak linear relationship and was eliminated. From the boxplots, it seemed like the cylindernumber had each of its field to have their unique distributions for price which allowed it to continue as a possible covariate while engine type seemed to have much more outliers that caused more overlapping of price ranges across categories which meant it would be left out of further analysis. For the next six graphs, the scatterplots that looked like they had a linear relationship were allowed to be further analyzed as possible covariates in our model, including enginesize, boreratio, and horsepower. The other three predictor variables, compressionratio, stroke, and peakrpm did not seem to have any linear relationship with price which meant they were excluded as candidates as covariates. The next four graphs presented citympg and highwaympg to have a decreasing relationship between price which is a linear relationship and allowed to be continued for further analysis. Fuelsystem also seemed that it could be possible to be used as a covariate based on a bit of the spread across the categories but, carbody categories had to have quite a bit of overlapping across categories which caused the elimination of further analysis. The last graph, carName had both make and model of each car which only had a count of one car in each bin which would seem to perform well but, it seemed that there would be a too large spread to be effective to estimate price. Essentially, there were too many categories to be able to predict price and the model should not want to be overfit which could occur with the various categories among carname so that was excluded from further analysis.

Multivariate

Mutlivariate analysis was to determine if there was interactions between particular covariates specifically the ones we believed that would be used in the model and seemed to be associate with each other. The multivariate analysis we did was against highwaympg and citympg since there were miles per gallon variables and would probably be associated with each other. In addition to these two covariates, it was believed that carlength, carwidth, and curbweight would also have interactions since the bigger the car, generally the bigger the width, length and weight of the car. The following blocks of code plots the covariates in scatterplots against each other since they are continuous variables which price colored, with lighter blue representing high car price and dark blue being low car prices.

```
m1 <- ggplot(data = car_data, aes(x = highwaympg, y = citympg, color = price)) +
  geom_point() +
  labs(x = "Highway MPG",
       y = "City MPG",
       title = "City MPG vs Highway MPG")


m2 <- ggplot(data = car_data, aes(x = carlength, y = carwidth, color = price)) +
  geom_point() +
  labs(x = "Car Length",
       y = "Car Width",
       title = "Car Width vs Car Length")

m3 <- ggplot(data = car_data, aes(x = carlength, y = curbweight, color = price)) +
  geom_point() +
  labs(x = "Car Length",
       y = "Car Height",
       title = "Car Height vs Car Length")

m4 <- ggplot(data = car_data, aes(x = carwidth, y = curbweight, color = price)) +
  geom_point() +
  labs(x = "Car Width",
       y = "Car Height",
       title = "Car Height vs Car Width")

(m1+m2)/(m3+m4)
```



Due to the clear relationships between citympg and highwaympg, car height and car length, and car height and car width, these interactions may be something to consider when creating the linear model. Car width and car length seemed to have the weakest relationship but, should still be considered when making the model.

Modeling Approach

The modeling approach we decided that would be best would be to use the fourteen covariates that seemed to have a linear relationship between car price from our bivariate analysis would be used in a linear model. A multivariate linear model was used because our outcome of car price was continuous which would make sense to have a linear model to be able to predict car price with multiple covariates. We wanted to use AIC and BIC of each model to determine our model selection of which variables would be best to be used in the linear model since we do not want to overfit our model and would penalize for extra variables. We wanted to search all posible model so we used the method dredge() from the MuMIn package to be able to create all the possible models from our covariartes and order them by AIC and BIC values.

```
full.model <- lm(price ~ wheelbase+symboling+drivewheel+aspiration+cylindernumber+curbweight*carlength*
dredge(full.model, rank = "AICc")
```

```
## Fixed term is "(Intercept)"
```

```
...
## Global model call: lm(formula = price ~ wheelbase + symboling + drivewheel + aspiration +
##     cylindernumber + curbweight * carlength * carwidth + enginesize +
##     horsepower + boreratio + fuelsystem + citympg * highwaympg,
##     data = car_data, na.action = "na.fail")
## ---
...
```

```
dredge(full.model, rank = "BIC")
```

```
## Fixed term is "(Intercept)"
```

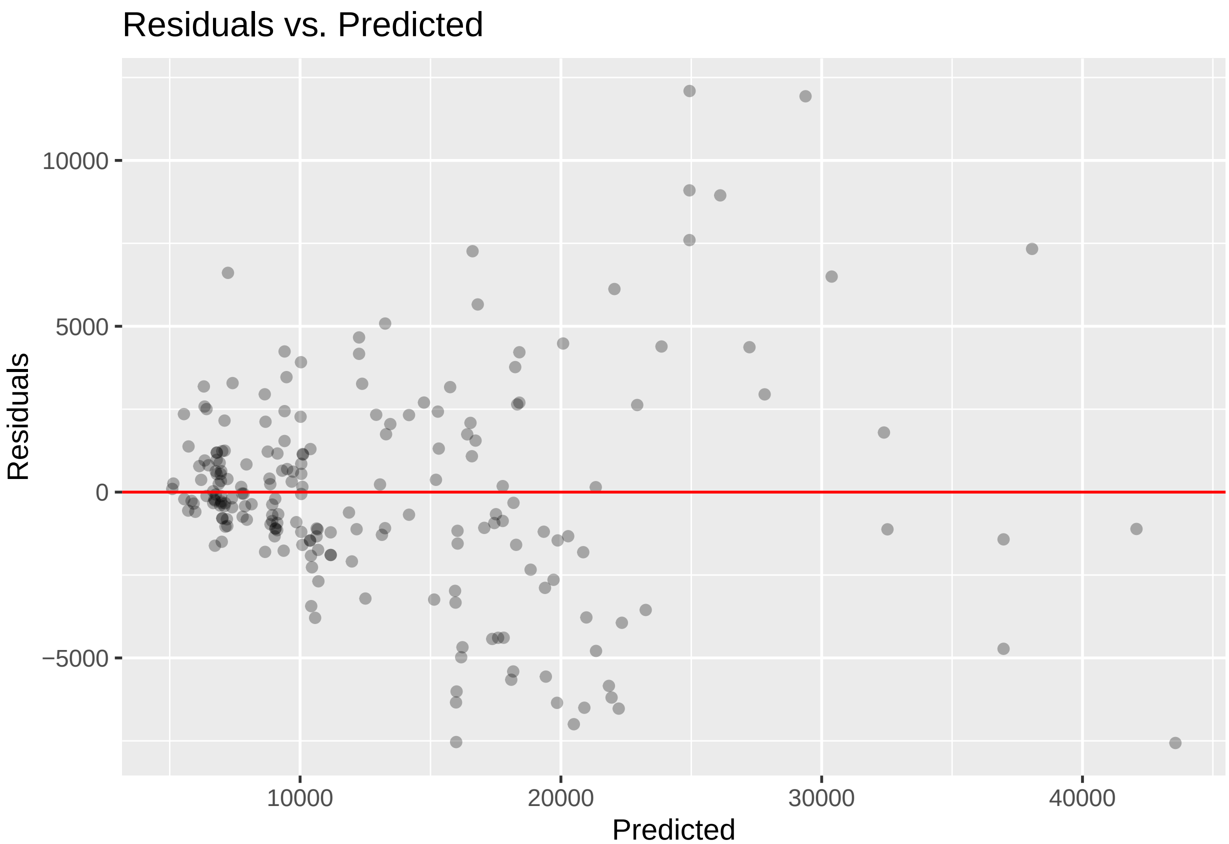
```
...
## Global model call: lm(formula = price ~ wheelbase + symboling + drivewheel + aspiration +
##     cylindernumber + curbweight * carlength * carwidth + enginesize +
##     horsepower + boreratio + fuelsystem + citympg * highwaympg,
##     data = car_data, na.action = "na.fail")
## ---
...
```

```
# AIC
# 1 carlength, curbweight, citympg, cylindernumber, drivewheel, enginesize, highwaympg, horsepower, car
# 2 carlength, curbweight, citympg, cylindernumber, drivewheel, enginesize, highwaympg, horsepower, whe
# 3 carlength, curbweight, citympg, cylindernumber, drivewheel, enginesize, fuelsystem, highwaympg, hor
# 4 carlength, curbweight, citympg, cylindernumber, drivewheel, enginesize, fuelsystem, highwaympg, hor
# 5 carlength, curbweight, cylindernumber, drivewheel, enginesize, highwaympg, horsepower, wheelbase, c
#
#
# BIC
# 1 carlength, curbweight, drivewheel, enginesize, horsepower, carlength:curbweight
# 2 carlength, curbweight, drivewheel, enginesize, horsepower, wheelbase, carlength:curbweight
# 3 carlength, curbweight, drivewheel, enginesize, horsepower, symboling, carlength:curbweight
# 4 boreratio, carlength, curbweight, drivewheel, enginesize, horsepower, carlength:curbweight
# 5 carlength, curbweight, citympg, drivewheel, enginesize, highwaympg, horsepower, carlength:curbweigh
#
# 1 carwidth, drivewheel, enginesize, horsepower
# 2 carwidth, cylindernumber, drivewheel, enginesize, horsepower
# 3 cylindernumber, drivewheel, enginesize, horsepower, wheelbase
# 4 carlength, cylindernumber, drivewheel, enginesize, horsepower
# 5 boreratio, carwidth, drivewheel, enginesize, horsepower
```

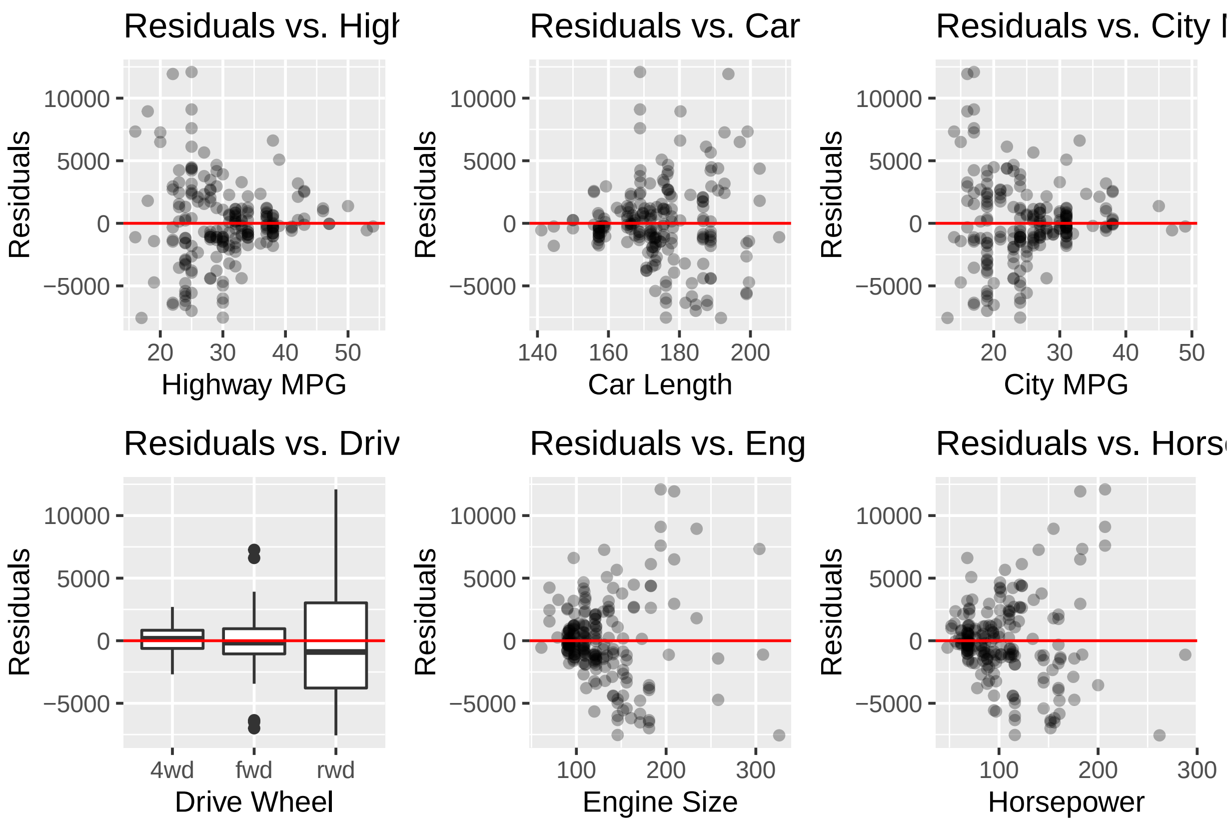
```
final.model <- lm(price ~ carlength*curbweight+citympg+drivewheel+enginesize+highwaympg+horsepower, car
tidy(final.model, conf.int = TRUE) %>%
  kable(format = "markdown", digits = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	60903.482	17906.787	3.401	0.001	25587.643	96219.320
carlength	-380.101	98.530	-3.858	0.000	-574.423	-185.779
curbweight	-29.539	6.990	-4.226	0.000	-43.326	-15.753
citympg	-387.043	185.084	-2.091	0.038	-752.066	-22.019
drivewheelfwd	-1800.403	1268.908	-1.419	0.158	-4302.948	702.143
drivewheelrwd	423.462	1251.586	0.338	0.735	-2044.921	2891.845
enginesize	72.936	13.482	5.410	0.000	46.347	99.525
highwaympg	348.714	169.546	2.057	0.041	14.335	683.093
horsepower	54.240	14.074	3.854	0.000	26.483	81.996
carlength:curbweight	0.176	0.037	4.711	0.000	0.102	0.249

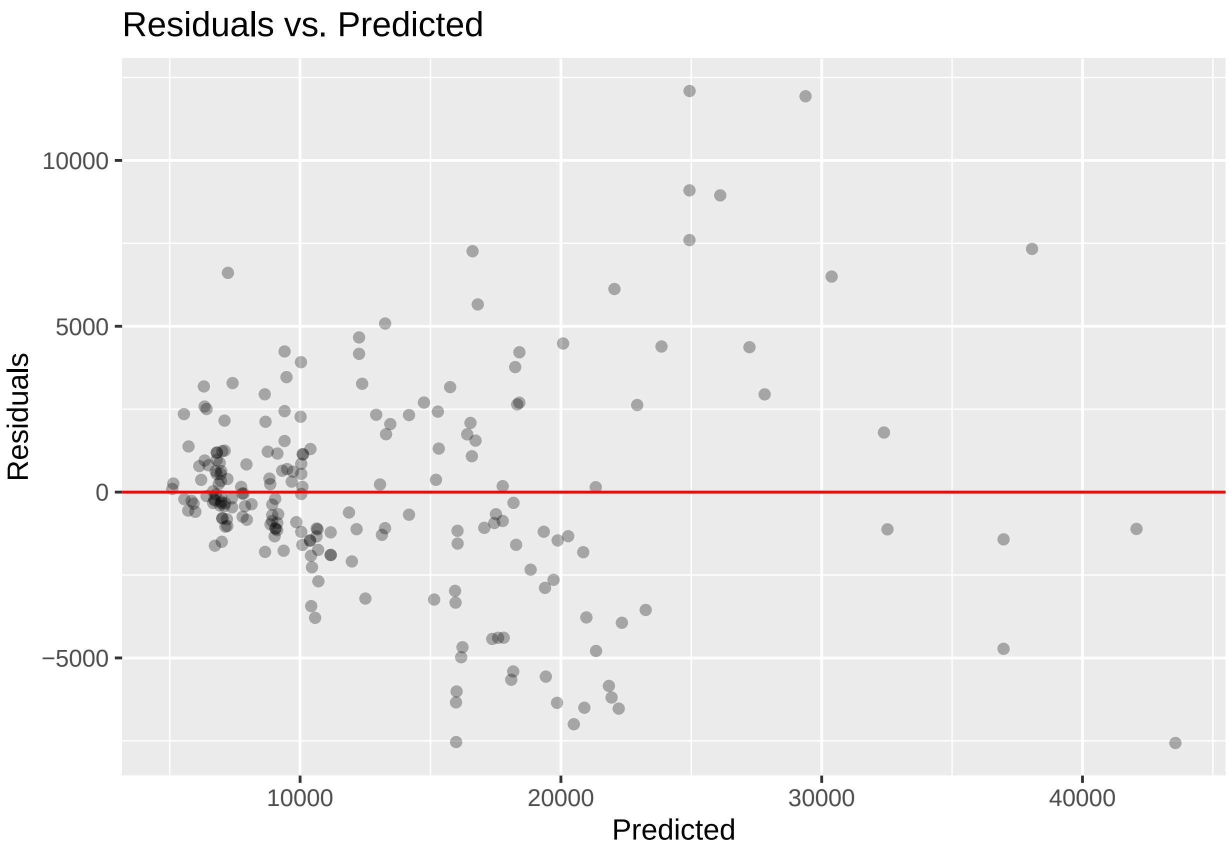
```r
car_aug <- augment(final.model)
l1 = ggplot(data = car_aug, aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Predicted", y = "Residuals", title = "Residuals vs. Predicted")

l2 = ggplot(data = car_aug, aes(x = carlength, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Car Length", y = "Residuals", title = "Residuals vs. Car Length")

l3 = ggplot(data = car_aug, aes(x = citympg, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "City MPG", y = "Residuals", title = "Residuals vs. City MPG")

l4 = ggplot(data = car_aug, aes(x = drivewheel, y = .resid)) +
  geom_boxplot() +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Drive Wheel", y = "Residuals", title = "Residuals vs. Drive Wheel")

l5 = ggplot(data = car_aug, aes(x = enginesize, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Engine Size", y = "Residuals", title = "Residuals vs. Engine Size")

l6 = ggplot(data = car_aug, aes(x = horsepower, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Horsepower", y = "Residuals", title = "Residuals vs. Horsepower")

l7 = ggplot(data = car_aug, aes(x = highwaympg, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Highway MPG", y = "Residuals", title = "Residuals vs. Highway MPG")

(l1)
```




```
(17+12+13)/(14+15+16)
```

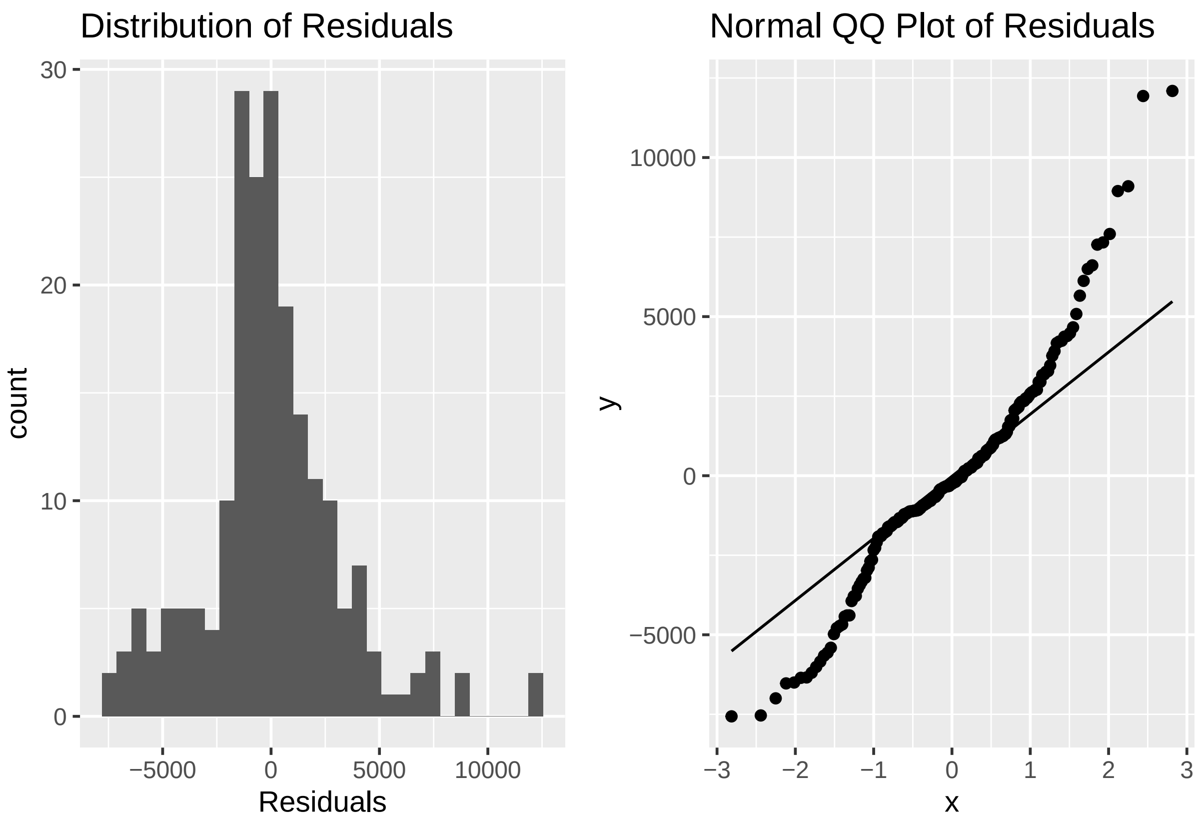



```
ggplot(data = car_aug, aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Predicted", y = "Residuals", title = "Residuals vs. Predicted")
```

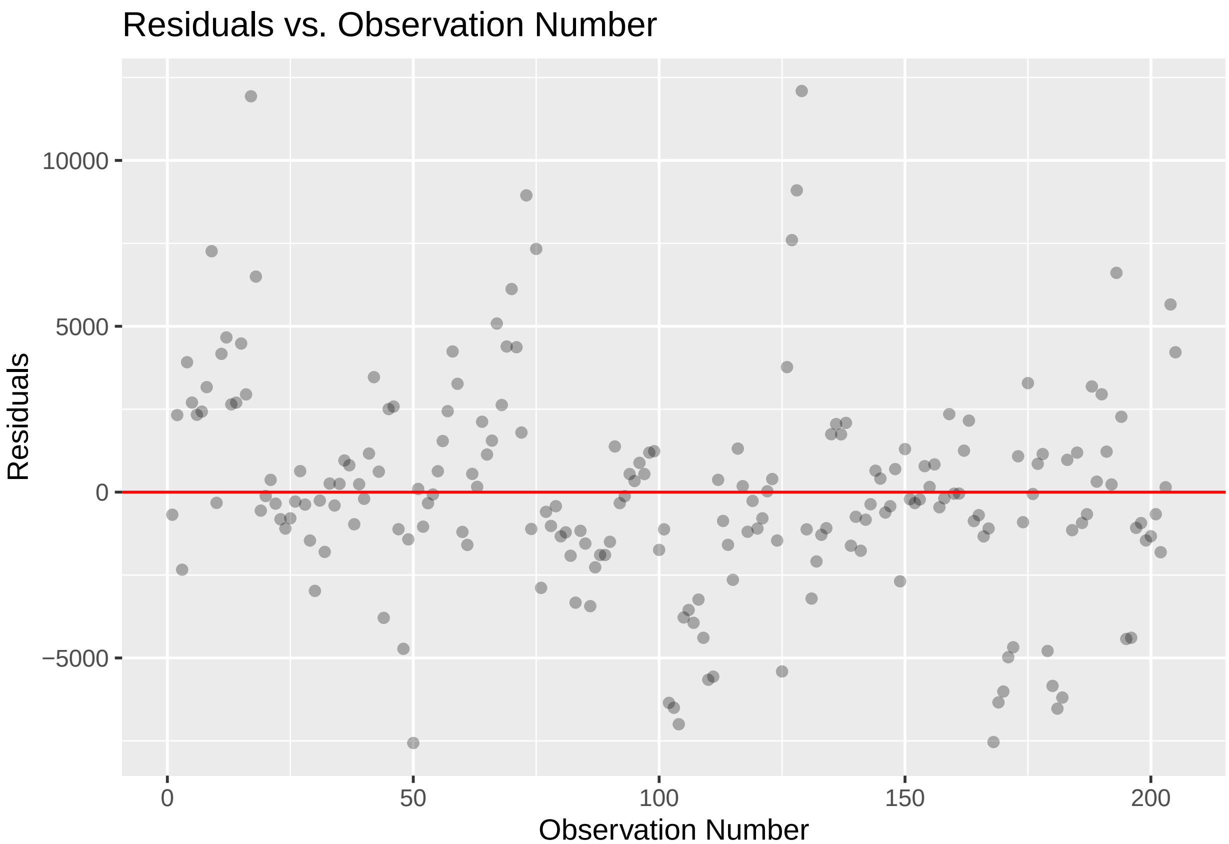



```
n1 = ggplot(data = car_aug, aes(x = .resid)) +
  geom_histogram() +
  labs(x = "Residuals", title = "Distribution of Residuals")

n2 = ggplot(data = car_aug, aes(sample = .resid)) +
  stat_qq() +
  stat_qq_line() +
  labs(title = "Normal QQ Plot of Residuals")

n1+n2
```

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




```
car_aug <- car_aug %>%
  mutate(obs_num = 1:nrow(car_aug))
ggplot(data = car_aug, aes(x = obs_num, y = .resid)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red") +
  labs(x = "Observation Number",
       y = "Residuals",
       title = "Residuals vs. Observation Number")
```



Residuals vs. Observation Number
Residuals
10000
5000
0
−5000
0
50
100
150
200
Observation Number