



## Car Price Prediction using Multiple Linear Regression

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The format of the report should follow the report structure, starting from a title page to conclusion paragraph(s). Each section must have a clear title. Make sure that there is some margin between two consecutive sections. Title, variable names, legends, etc in a plot must be clear and easy to read.

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## (I) Introduction and Background

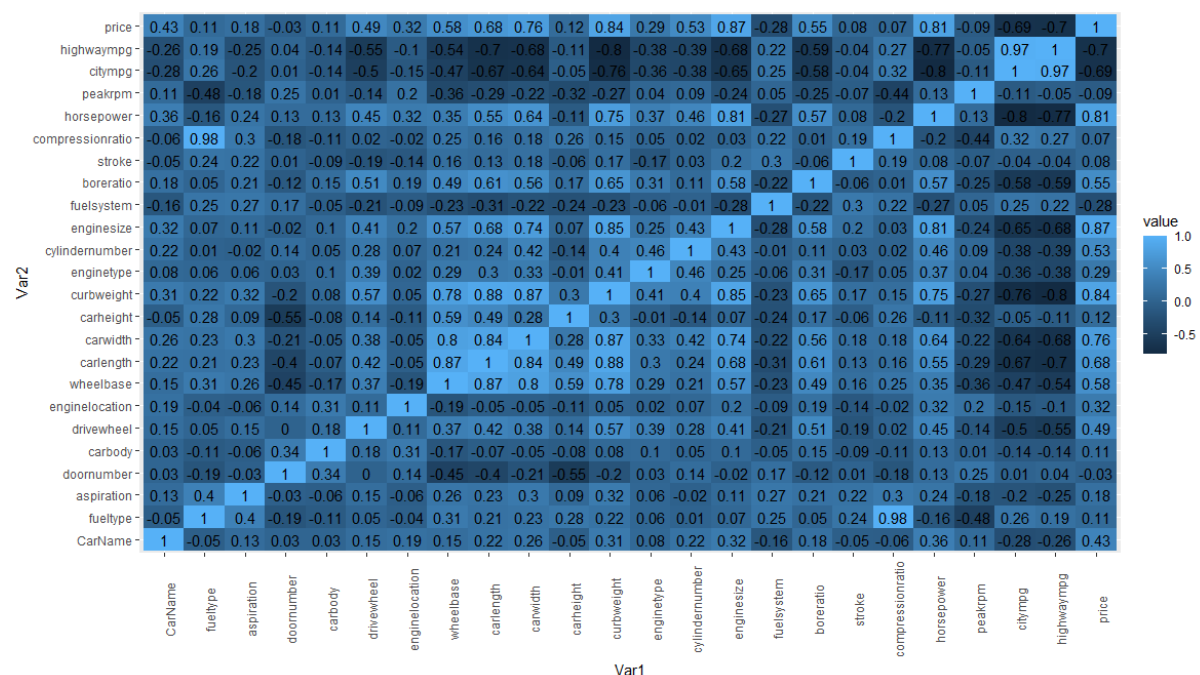
A Chinese automobile company Geely Auto aspires to enter the US market by setting up their manufacturing unit there and producing cars locally to give competition to their US and European counterparts. They have contracted an automobile consulting company to understand the factors on which the pricing of cars depends. Specifically, they want to understand the factors affecting the pricing of cars in the American market, since those may be very different from the Chinese market. The company wants to know: 1) Which variables are significant in predicting the price of a car? 2) How well do those variables describe the price of a car? Based on various market surveys, the consulting firm has gathered a large data set of different types of cars across the America market.

We are required to model the price of cars with the available independent variables. It will be used by the management to understand how exactly the prices vary with the independent variables. They can accordingly manipulate the design of the cars, the business strategy etc. to meet certain price levels. Further, the model will be a good way for management to understand the pricing dynamics of a new market.

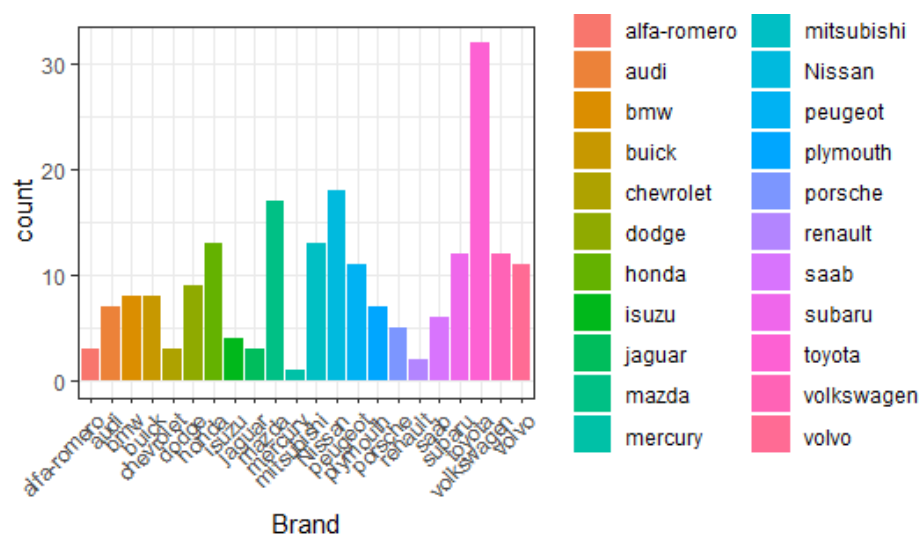
### Summary of the Data Set

We have 205 cases, 23 independent variables and 1 dependent variable. The dependent variable is car price. The independent variables are: car name, fuel type, drive wheel, engine location, engine type, cylinder number, engine size, stroke, door number, carbody, fuel system, aspiration, wheel base, car length, car width, car height, curb weight, bore ratio, compression ratio, horsepower, peak rpm, city mpg, highway mpg.

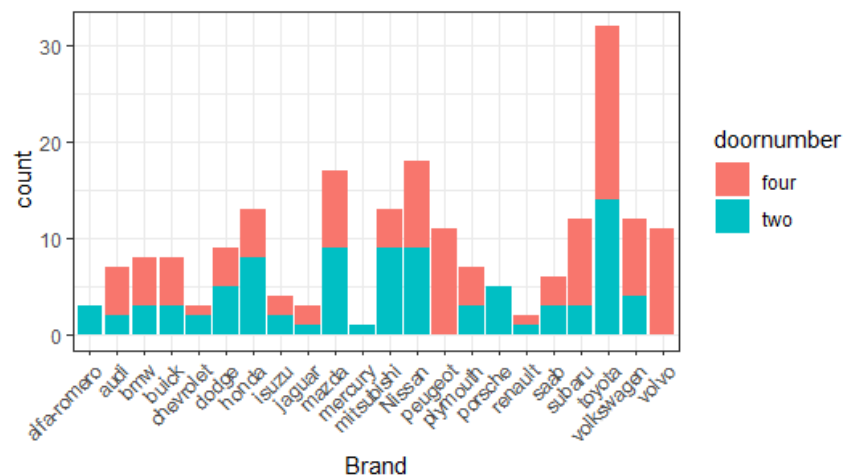
## (II) Exploratory Data Analysis



From the correlation heat map, we found that compression ratio and fuel type, city mpg and highway mpg, curve weight and horsepower are highly correlated.

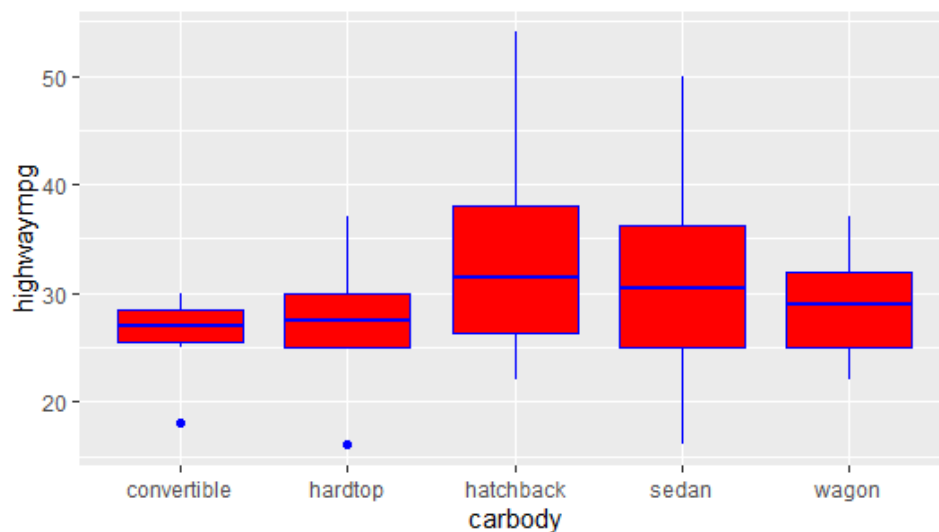


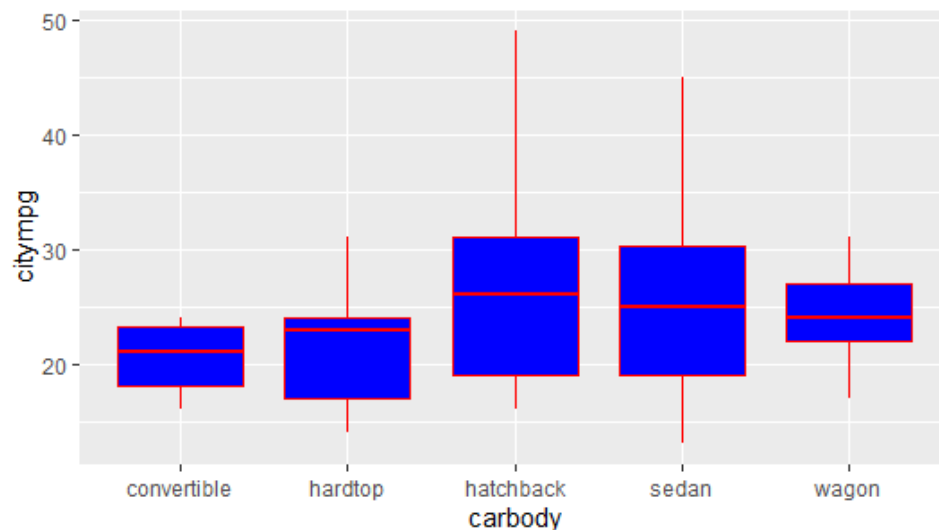
One thing we wanted to know from our dataset is which car brand was represented in our dataset the most. From plotting our histogram we found out that Toyota was represented the most then came Nissan and mazda.



Another thing we wanted to know was what was the proportion of sports cars vs non sports cars in our dataset. We looked at an insurance company's classification of a sports car and it consisted of a car having 2 doors. So we classified a sports car as a car having two doors, and so we made a histogram to see the proportion of sports cars vs non sports cars in our dataset with respect to the brand names. We see from histogram that sports cars were evenly distributed among car brands.

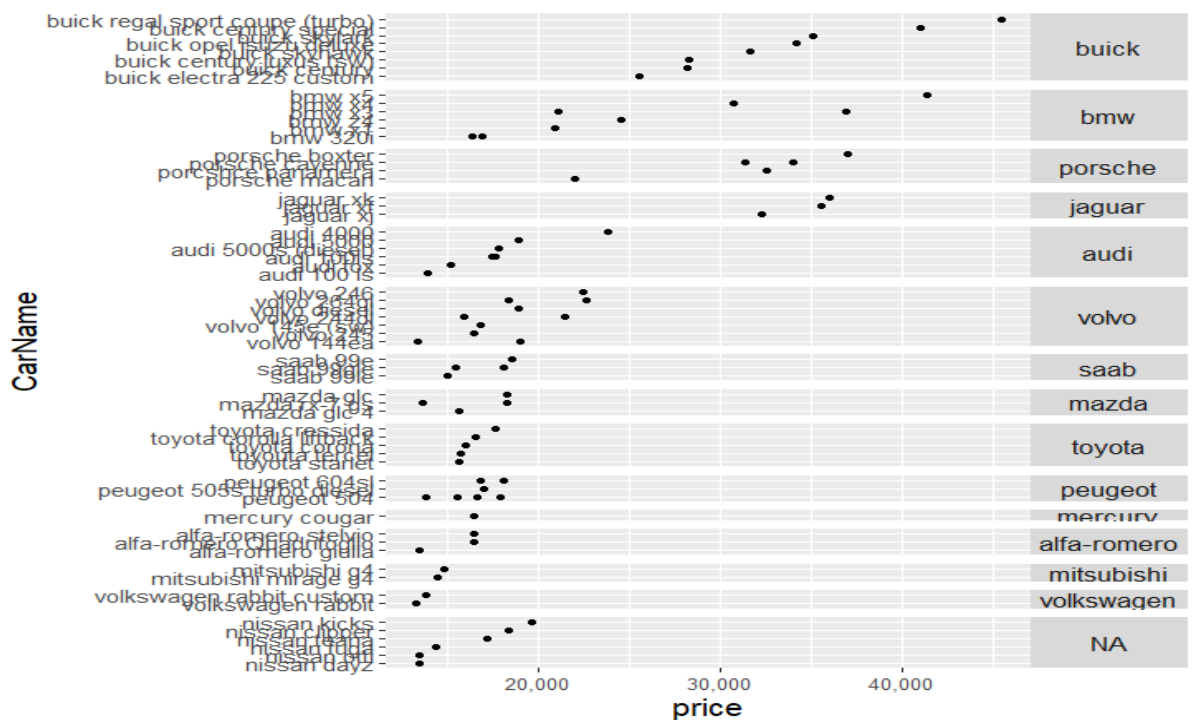
Which body type has the worst/best highway gallon per mile?





After further EDA, we create box plots of each car body's highway mpg and city mpg and the plots show us each car body's median value. These plots show which body type has the best or worst highway mpg and city mpg. Hatchback has the best highway and city mpg. Convertible has the worst highway and city mpg. After our model is complete, we could look into the highway and city mpg significance on car price.

#### Buick, BMW, Porsche & Jaguar are luxury cars



Here we graphed the prices of each brand car. We can notice here that

Buick, BMW, Porsche, and Jaguar car brands seem to be the more expensive car brands, while Volkswagen seems to be the cheapest car brands.

### Questions of Interests

1. Which variables are significantly related to a car's price?
2. Given a list of car specifications, would our model predict the requested car price and average price of cars of these specifications?
3. How much variation can our model explain the car price?

### Regression Method

#### Step 1:

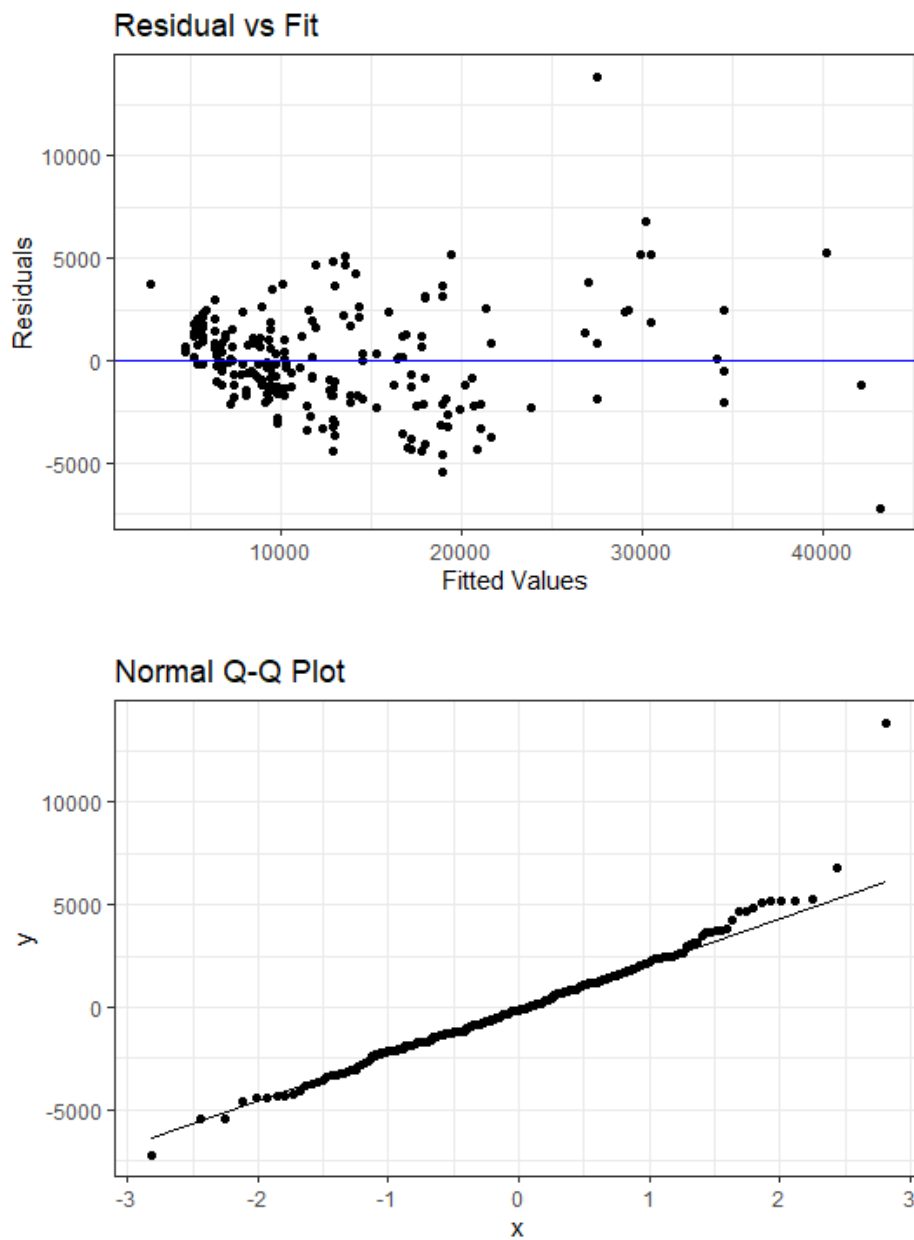
We use the Multiple Linear Regression Method to analyze which variables are significant predictors of a car's price. In order to build this model, we need to identify which of the 23 variables to include in the model. While we learned stepwise using AIC and the best subset methods for variable selection, we chose to use an alternate method, backwards stepwise regression, because our group member, Gerry, learned this method in previous courses and wanted the opportunity to apply it to our regression method. We then checked if there were any significant interaction terms to be included in our model. We were then able to determine a model:

$\text{Car price}^{\wedge}0.09 = \text{car names } x1 + \text{fuel type } 2 + \text{drive wheel } x3 + \text{engine location } x4 + \text{wheel base } x5 + \text{car width } x6 + \text{engine type } x7 + \text{cylinder number } x8 + \text{engine size } x9 + \text{stroke } x10 + \text{compression ratio } 11 + \text{horse power } x12 + \text{peak rpm } x13 + \text{car name} * \text{cylinder number}$

### (III) Regression Analysis

#### Step 2:

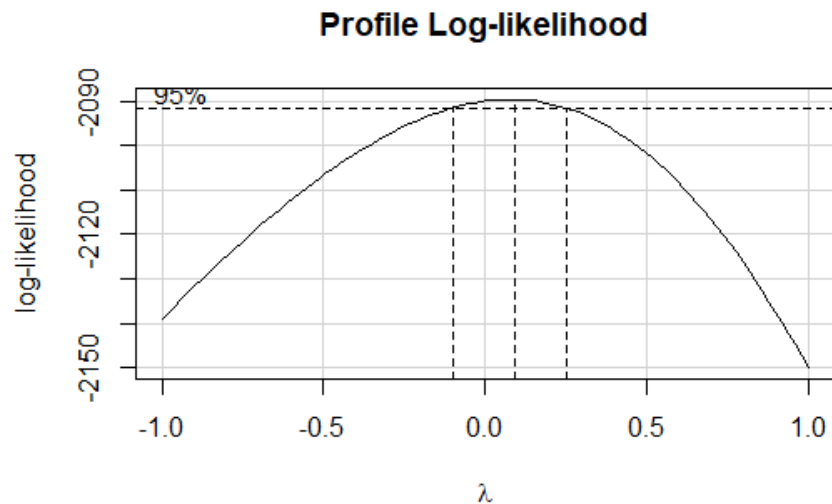
The next steps would be to perform residual analysis on our model. We check for linearity, independence, equal variance, and normality (LINE) of our residuals to make sure our model is good at analyzing our data. We find most LINE conditions are met except equal variance.



### Step 3:

To fix the unequal variance, we chose to apply the Box-Cox Method in order to find the optimal lambda to perform a power transformation on our response variable, car price.

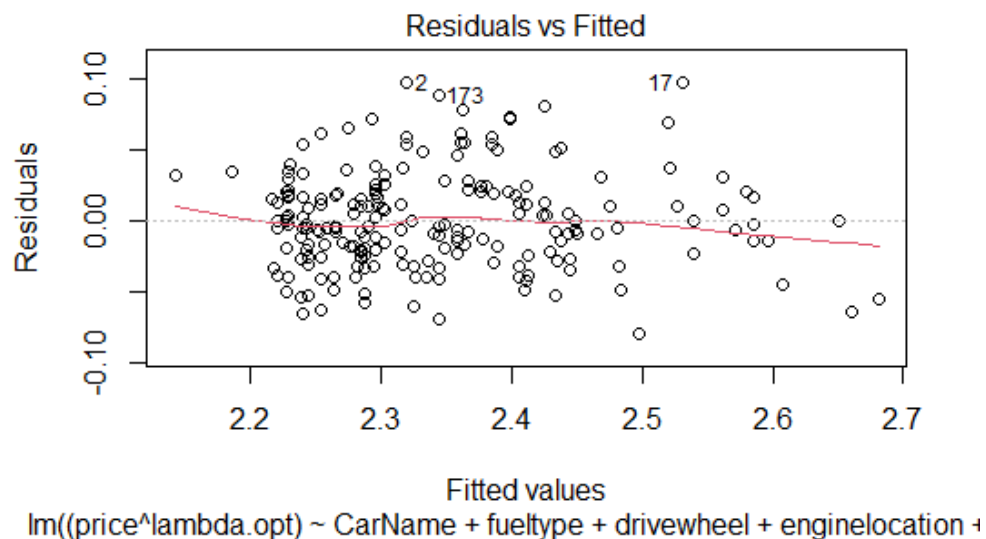


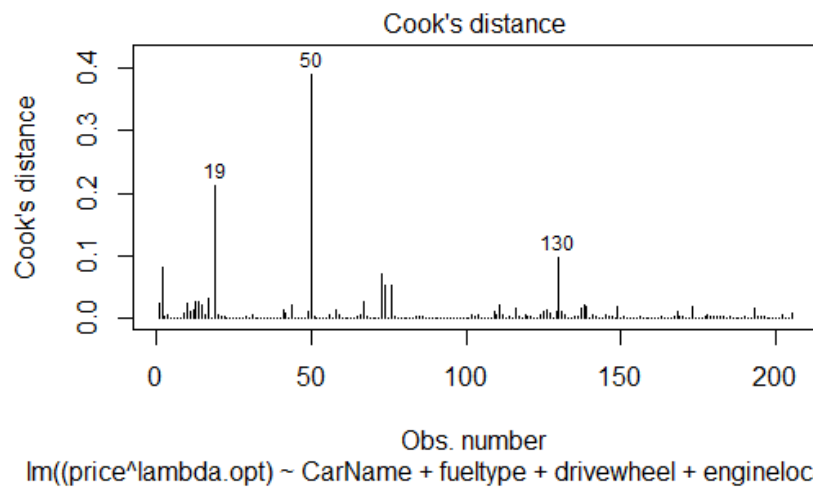
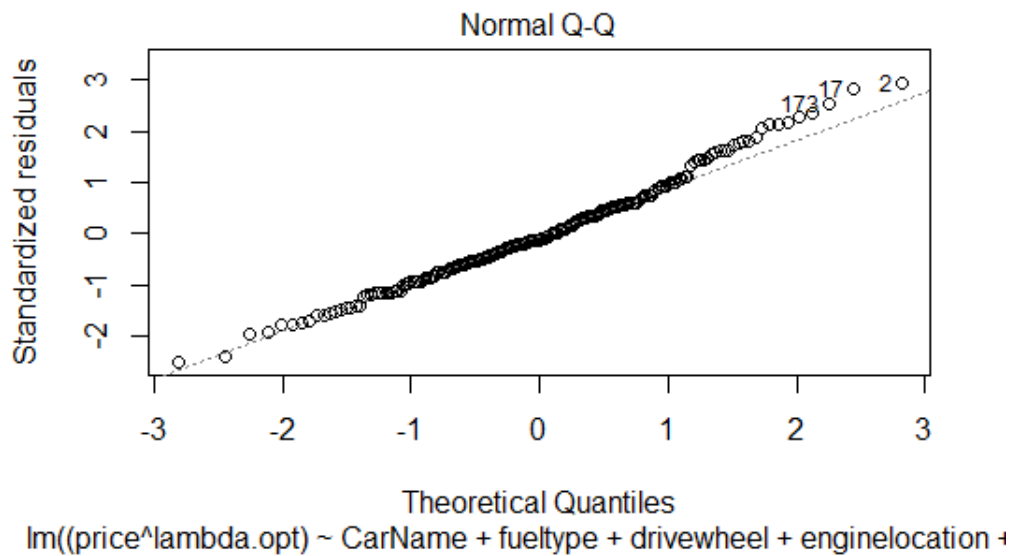


Lambda.opt = 0.09. After the power transformation, our final model is: Car price<sup>10.09</sup> = car name + fuel type + drive wheel + engine location + wheelbase + car width + engine type + cylinder number + engine size + stroke + compression ratio + horsepower + peak rpm + car name:cylinder number

#### Step 4:

We check if our power transformation affected the LINE conditions and if this final model is good for analyses and interpretations. From the residual vs. fitted plot below, we can see that the equal variance condition is satisfied now and other LINE conditions still satisfied.





In our check for high leverage points using Cook's distance, we find there are no high leverage points since Cook's distance for our plot is below 0.05

#### (IV) Results and Interpretation

## CAR PRICE PREDICTION

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```
call:
lm(formula = (price^lambda.opt) ~ CarName + fueltype + drivewheel +
  enginelocation + wheelbase + carwidth + enginetype + cylindernumber +
  enginesize + stroke + compressionratio + horsepower + peakrpm +
  CarName:cylindernumber, data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-0.080081 -0.023134 -0.004182  0.019577  0.098205

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      1.248e+00  1.494e-01   8.354 1.36e-14 ***
CarName           2.405e-03  5.379e-04   4.471 1.34e-05 ***
fueltype          9.392e-02  5.975e-02   1.572 0.117648
drivewheel        2.201e-02  5.507e-03   3.997 9.17e-05 ***
enginelocation    1.111e-01  2.526e-02   4.401 1.80e-05 ***
wheelbase         3.479e-03  8.218e-04   4.233 3.59e-05 ***
carwidth          8.973e-03  2.734e-03   3.282 0.001229 **
enginetype        -8.216e-03  2.376e-03  -3.458 0.000672 ***
cylindernumber     2.674e-02  5.604e-03   4.773 3.62e-06 ***
enginesize        5.944e-04  1.566e-04   3.796 0.000198 ***
stroke            -1.887e-02  1.014e-02  -1.860 0.064373 .
compressionratio  -3.884e-03  4.309e-03  -0.901 0.368572
horsepower         9.514e-04  1.659e-04   5.735 3.79e-08 ***
peakrpm           1.007e-05  7.880e-06   1.279 0.202611
CarName:cylindernumber -1.660e-03  4.595e-04  -3.612 0.000389 ***
---
signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03571 on 190 degrees of freedom
Multiple R-squared:  0.9,    Adjusted R-squared:  0.8926
F-statistic: 122.2 on 14 and 190 DF,  p-value: < 2.2e-16
```

Our results indicate car name was a strong predictor of car price<sup>0.09</sup>, controlling for fuel type, drive wheel, engine location, wheel base, car width, engine type, cylinder number, engine size, stroke, compression ratio, horsepower, peak rpm, and the interaction between car name and cylinder number,  $b = 2.405e-03$ ,  $SE = 5.739e-04$ ,  $t = 4.471$ ,  $p < .001$ . Also, drive wheel, engine location, wheel base, car width, engine type, cylinder number, engine size, horsepower, and the interaction between car name and cylinder number was a significant predictor of car price<sup>0.09</sup>, controlling for remaining variables. However, fuel type, engine size, stroke, compression ratio, and peak rpm were not strong predictors of car price<sup>0.09</sup>. The results highlight that car name, drive wheel, engine location, wheel base, car width, engine type, cylinder number, engine size, horsepower, and the interaction between car name and cylinder number are important for car price.

A multiple linear regression was conducted to investigate whether car name, fuel type, drive wheel, engine location, wheel base, car width, engine type, cylinder number, engine size, stroke, compression ratio, horsepower

, peak rpm, and the interaction between car name and cylinder number would predict car price. We were able to use our model to make a prediction for a car fanatic with the requested specifics: a larger size, electric Porsche with all wheel drive and higher wheelbase, for increased tire traction, and engine specifics for a larger, powerful, and efficient engine. We found a car with these specifics was (122.403, 7187.106) and the average range for this type of car is \$129.05 to \$6926.84. Our results also indicate that 89% of variation in car price can be explained by our final model which confirms our final model is a good model.

### **(V) Conclusion**

Using a multiple linear regression model, we found that car name, drive wheel, engine location, wheel base, car width, engine type, cylinder number, engine size, horsepower, and the interaction between car name and cylinder number are important for predicting car price in the American market. Thus, as a manager in Geely Auto, he or she should pay more attention to helping his or her company to design and create cars having high quality of those variables such as drive wheels and engine type. Although car name is a strong predictor of car price, and Geely Auto can not change its name to satisfy this requirement, it will be beneficial if Geely Auto can learn from other car brands about how to increase their quality and influential power by investing funding on hiring excellent engineers or advertisement.

## (VI) Appendix

```
#load reshape2 package

library(reshape2)

# creating correlation matrix
corr_mat <- round(cor(data), 2)

# reduce the size of correlation matrix
melted_corr_mat <- melt(corr_mat)
head(melted_corr_mat)

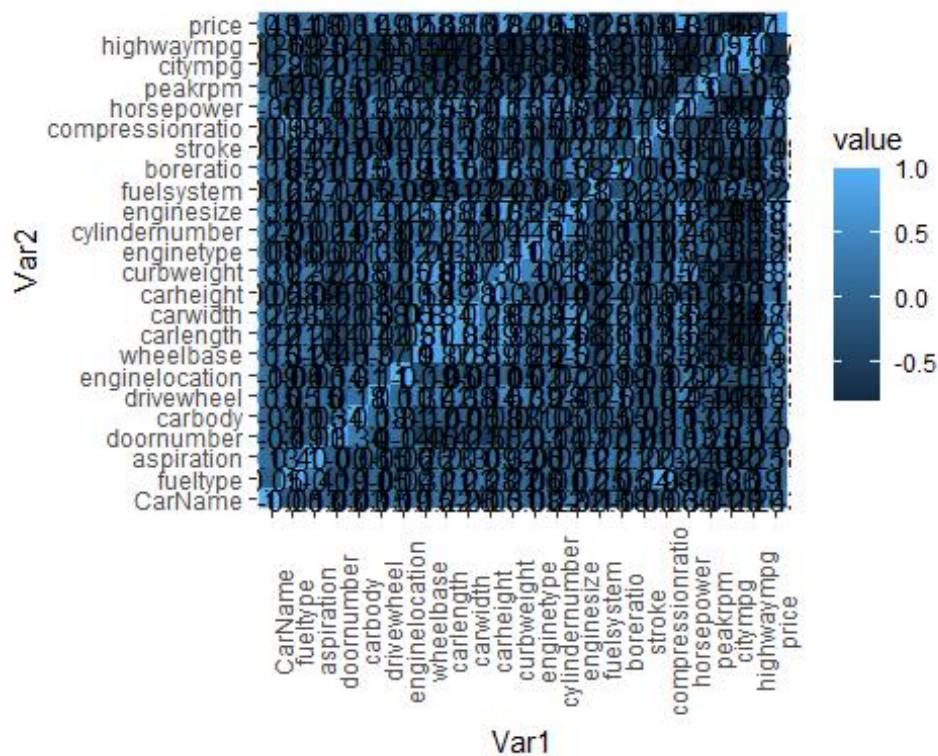
##           Var1    Var2 value
## 1    CarName CarName  1.00
## 2   fueltype CarName -0.05
## 3 aspiration CarName  0.13
## 4 doornumber CarName  0.03
## 5    carbody CarName  0.03
## 6 drivewheel CarName  0.15

# plotting the correlation heatmap
library(ggplot2)
p.dia=ggplot(data = melted_corr_mat, aes(x=Var1, y=Var2,
                                         fill=value)) +
  geom_tile() +
  geom_text(aes(Var2, Var1, label = value),
            color = "black", size = 4)

p <- p.dia +theme(axis.text.x= element_text(angle=90, size=9))
p
```

# CAR PRICE PREDICTION

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```
model <- lm(price ~., data = data)
summary(model)
```

```
##
## Call:
## lm(formula = price ~ ., data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8488.4 -1526.8  -116.5   1171.8 13542.6
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -4.796e+04  1.457e+04  -3.291  0.001199 **
## CarName       1.201e+02   3.919e+01   3.064  0.002521 **
## fueltype      1.195e+04   6.035e+03   1.980  0.049168 *
## aspiration    -4.874e+02   9.407e+02  -0.518  0.605033
## doornumber     3.278e+02   5.211e+02   0.629  0.530135
## carbody       -5.358e+00   2.396e+02  -0.022  0.982188
## drivewheel     9.921e+02   5.024e+02   1.975  0.049829 *
## enginelocation 1.144e+04   2.071e+03   5.523  1.14e-07 ***
## wheelbase     2.059e+02   9.060e+01   2.272  0.024244 *
## carlength    -2.582e+01   5.136e+01  -0.503  0.615752
## carwidth      4.611e+02   2.234e+02   2.063  0.040493 *
## carheight     5.239e+00   1.257e+02   0.042  0.966811
## curbweight    2.368e+00   1.854e+00   1.277  0.203228
```

```
## enginetype      -6.767e+02  1.929e+02  -3.508  0.000569 ***
## cylindernumber  1.393e+03  2.711e+02   5.140  7.08e-07 ***
## enginesize      8.158e+01  1.661e+01   4.913  2.00e-06 ***
## fuelsystem     -1.278e+02  1.934e+02  -0.661  0.509483
## boreratio      -7.541e+02  1.104e+03  -0.683  0.495433
## stroke         -2.329e+03  7.884e+02  -2.953  0.003559 **
## compressionratio -7.058e+02  4.241e+02  -1.664  0.097827 .
## horsepower     2.182e+01  1.753e+01   1.245  0.214752
## peakrpm        1.787e+00  6.402e-01   2.791  0.005817 **
## citympg        -1.385e+02  1.620e+02  -0.855  0.393865
## highwaympg     1.645e+02  1.502e+02   1.096  0.274693
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2660 on 181 degrees of freedom
## Multiple R-squared:  0.9017, Adjusted R-squared:  0.8892
## F-statistic: 72.15 on 23 and 181 DF,  p-value: < 2.2e-16

#Highly correlated predictors:(compression ratio,fueltype)
#(citympg,highwaympg), (curveweight,horsepower),
#load the car library
library(car)

## Loading required package: carData

#Use stepwiseRegression backwards
step(model,direction = "backward")

## Start:  AIC=3255.73
## price ~ CarName + fueltype + aspiration + doornumber + carbody +
## drivewheel + enginelocation + wheelbase + carlength + carwidth +
## carheight + curbweight + enginetype + cylindernumber + enginesize +
## fuelsystem + boreratio + stroke + compressionratio + horsepower +
## peakrpm + citympg + highwaympg
##
##              Df Sum of Sq      RSS      AIC
## - carbody      1      3536 1280473730 3253.7
## - carheight    1     12281 1280482476 3253.7
## - carlength    1    1788108 1282258303 3254.0
## - aspiration   1    1898851 1282369045 3254.0
## - doornumber   1    2799028 1283269222 3254.2
## - fuelsystem   1    3090515 1283560710 3254.2
## - boreratio    1    3300869 1283771064 3254.3
## - citympg      1    5167553 1285637748 3254.6
## - highwaympg   1    8492290 1288962485 3255.1
## - horsepower   1   10965016 1291435210 3255.5
## - curbweight   1   11536962 1292007157 3255.6
## <none>                1280470195 3255.7
```

## CAR PRICE PREDICTION

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```

## - compressionratio 1 19590167 1300060362 3256.8
## - drivewheel 1 27584885 1308055080 3258.1
## - fueltype 1 27747247 1308217442 3258.1
## - carwidth 1 30122803 1310592998 3258.5
## - wheelbase 1 36527938 1316998133 3259.5
## - peakrpm 1 55110231 1335580426 3262.4
## - stroke 1 61710022 1342180217 3263.4
## - CarName 1 66397154 1346867349 3264.1
## - enginetype 1 87080379 1367550573 3267.2
## - enginesize 1 170756113 1451226308 3279.4
## - cylindernumber 1 186912437 1467382632 3281.7
## - enginelocation 1 215823739 1496293933 3285.7
##
## Step: AIC=3253.73
## price ~ CarName + fueltype + aspiration + doornumber + drivewheel +
## enginelocation + wheelbase + carlength + carwidth + carheight +
## curbweight + enginetype + cylindernumber + enginesize + fuelsystem +
## boreratio + stroke + compressionratio + horsepower + peakrpm +
## citympg + highwaympg
##
## Df Sum of Sq RSS AIC
## - carheight 1 10654 1280484384 3251.7
## - carlength 1 1793964 1282267694 3252.0
## - aspiration 1 1896121 1282369852 3252.0
## - doornumber 1 3084586 1283558316 3252.2
## - fuelsystem 1 3098133 1283571863 3252.2
## - boreratio 1 3396448 1283870179 3252.3
## - citympg 1 5234812 1285708543 3252.6
## - highwaympg 1 8651465 1289125195 3253.1
## - horsepower 1 11420162 1291893893 3253.6
## - curbweight 1 12544265 1293017995 3253.7
## <none> 1280473730 3253.7
## - compressionratio 1 19628818 1300102549 3254.9
## - drivewheel 1 27829481 1308303212 3256.1
## - fueltype 1 27877331 1308351062 3256.1
## - carwidth 1 30121798 1310595529 3256.5
## - wheelbase 1 38843458 1319317188 3257.9
## - peakrpm 1 55380999 1335854729 3260.4
## - stroke 1 61889293 1342363023 3261.4
## - CarName 1 66561860 1347035591 3262.1
## - enginetype 1 87238958 1367712688 3265.2
## - enginesize 1 171809121 1452282851 3277.5
## - cylindernumber 1 186920878 1467394608 3279.7
## - enginelocation 1 235509823 1515983554 3286.3
##
## Step: AIC=3251.74
## price ~ CarName + fueltype + aspiration + doornumber + drivewheel +

```



```
##      enginelocation + wheelbase + carlength + carwidth + curbweight +
##      enginetype + cylindernumber + enginesize + fuelsystem + boreratio +
##      stroke + compressionratio + horsepower + peakrpm + citympg +
##      highwaympg
##
##      Df Sum of Sq      RSS      AIC
## - carlength      1   1785502 1282269887 3250.0
## - aspiration      1   1935069 1282419453 3250.0
## - doornumber      1   3106463 1283590847 3250.2
## - fuelsystem      1   3285551 1283769935 3250.3
## - boreratio       1   3405665 1283890049 3250.3
## - citympg         1   5254355 1285738739 3250.6
## - highwaympg      1   8654055 1289138439 3251.1
## - horsepower      1  11417843 1291902227 3251.6
## <none>                                1280484384 3251.7
## - curbweight      1  13118842 1293603226 3251.8
## - compressionratio 1  19876458 1300360842 3252.9
## - drivewheel      1  27898604 1308382988 3254.2
## - fueltype        1  28245660 1308730044 3254.2
## - carwidth        1  31047105 1311531489 3254.6
## - wheelbase       1  44128106 1324612490 3256.7
## - peakrpm         1  55377297 1335861681 3258.4
## - stroke          1  63168178 1343652562 3259.6
## - CarName         1  67001328 1347485712 3260.2
## - enginetype      1  92010491 1372494875 3264.0
## - enginesize      1 181265637 1461750021 3276.9
## - cylindernumber  1 187150863 1467635247 3277.7
## - enginelocation  1 244430951 1524915335 3285.5
##
## Step:  AIC=3250.02
## price ~ CarName + fueltype + aspiration + doornumber + drivewheel +
##      enginelocation + wheelbase + carwidth + curbweight + enginetype +
##      cylindernumber + enginesize + fuelsystem + boreratio + stroke +
##      compressionratio + horsepower + peakrpm + citympg + highwaympg
##
##      Df Sum of Sq      RSS      AIC
## - aspiration      1   1588156 1283858043 3248.3
## - fuelsystem      1   2686633 1284956519 3248.5
## - boreratio       1   4190642 1286460528 3248.7
## - doornumber      1   4207794 1286477681 3248.7
## - citympg         1   4385198 1286655085 3248.7
## - highwaympg      1   8465617 1290735504 3249.4
## - curbweight      1  11333389 1293603275 3249.8
## - horsepower      1  11525211 1293795097 3249.9
## <none>                                1282269887 3250.0
## - compressionratio 1  21867706 1304137593 3251.5
## - carwidth        1  29835412 1312105299 3252.7
```

```
## - fueltype          1  30056598 1312326484 3252.8
## - drivewheel        1  33031890 1315301776 3253.2
## - wheelbase         1  46383267 1328653154 3255.3
## - peakrpm           1  56804682 1339074569 3256.9
## - stroke            1  63045800 1345315687 3257.9
## - CarName           1  67132283 1349402170 3258.5
## - enginetype        1  90252314 1372522200 3262.0
## - enginesize        1 190853775 1473123661 3276.5
## - cylindernumber    1 192798443 1475068329 3276.7
## - enginelocation    1 244540892 1526810779 3283.8
##
## Step:  AIC=3248.28
## price ~ CarName + fueltype + doornumber + drivewheel + enginelocation +
##       wheelbase + carwidth + curbweight + enginetype + cylindernumber +
##       enginesize + fuelsystem + boreratio + stroke + compressionratio +
##       horsepower + peakrpm + citympg + highwaympg
##
##              Df Sum of Sq      RSS      AIC
## - fuelsystem    1   3581877 1287439920 3246.8
## - doornumber    1   3978641 1287836684 3246.9
## - boreratio     1   4160406 1288018449 3246.9
## - citympg       1   7493489 1291351531 3247.5
## - horsepower    1  10766302 1294624344 3248.0
## - curbweight    1  10803608 1294661651 3248.0
## <none>                                1283858043 3248.3
## - highwaympg    1  12653321 1296511363 3248.3
## - compressionratio 1  21932706 1305790749 3249.7
## - carwidth      1  29553526 1313411569 3250.9
## - fueltype      1  33075600 1316933643 3251.5
## - drivewheel    1  35206780 1319064822 3251.8
## - wheelbase     1  45993443 1329851485 3253.5
## - stroke        1  62445215 1346303257 3256.0
## - peakrpm       1  63875892 1347733935 3256.2
## - CarName       1  65685963 1349544005 3256.5
## - enginetype    1  89515594 1373373637 3260.1
## - cylindernumber 1 197253681 1481111724 3275.6
## - enginelocation 1 249732246 1533590289 3282.7
## - enginesize    1 297646668 1581504710 3289.0
##
## Step:  AIC=3246.85
## price ~ CarName + fueltype + doornumber + drivewheel + enginelocation +
##       wheelbase + carwidth + curbweight + enginetype + cylindernumber +
##       enginesize + boreratio + stroke + compressionratio + horsepower +
##       peakrpm + citympg + highwaympg
##
##              Df Sum of Sq      RSS      AIC
## - doornumber    1   3241195 1290681115 3245.4
```

```
## - boreratio      1  5095184 1292535104 3245.7
## - citympg        1  8823231 1296263152 3246.2
## - curbweight     1  9886829 1297326749 3246.4
## - horsepower     1 12412455 1299852375 3246.8
## <none>           1287439920 3246.8
## - highwaympg     1 14440544 1301880464 3247.1
## - compressionratio 1 18881537 1306321457 3247.8
## - fueltype       1 29537562 1316977482 3249.5
## - carwidth       1 30979014 1318418934 3249.7
## - drivewheel     1 38423494 1325863414 3250.9
## - wheelbase      1 52410200 1339850120 3253.0
## - peakrpm        1 60778645 1348218565 3254.3
## - CarName        1 68083130 1355523050 3255.4
## - stroke         1 72477744 1359917664 3256.1
## - enginetype     1 89928225 1377368145 3258.7
## - cylindernumber 1 194190618 1481630538 3273.6
## - enginelocation 1 250923005 1538362925 3281.3
## - enginesize      1 306172631 1593612552 3288.6
##
## Step: AIC=3245.36
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
##       carwidth + curbweight + enginetype + cylindernumber + enginesize +
##       boreratio + stroke + compressionratio + horsepower + peakrpm +
##       citympg + highwaympg
##
##           Df Sum of Sq      RSS      AIC
## - boreratio      1  5355090 1296036204 3244.2
## - curbweight     1  8062940 1298744055 3244.6
## - citympg        1  8100099 1298781214 3244.6
## <none>           1290681115 3245.4
## - highwaympg     1 13179278 1303860393 3245.4
## - horsepower     1 13797813 1304478927 3245.5
## - compressionratio 1 19774283 1310455398 3246.5
## - fueltype       1 31013983 1321695098 3248.2
## - carwidth       1 33587245 1324268359 3248.6
## - drivewheel     1 42922560 1333603675 3250.1
## - wheelbase      1 49578007 1340259122 3251.1
## - peakrpm        1 61759804 1352440919 3252.9
## - CarName        1 69618472 1360299587 3254.1
## - stroke         1 70187794 1360868908 3254.2
## - enginetype     1 86995585 1377676700 3256.7
## - cylindernumber 1 195289786 1485970901 3272.2
## - enginelocation 1 247873863 1538554978 3279.4
## - enginesize      1 324940068 1615621183 3289.4
##
## Step: AIC=3244.21
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
```

```
##      carwidth + curbweight + enginetype + cylindernumber + enginesize +
##      stroke + compressionratio + horsepower + peakrpm + citympg +
##      highwaympg
##
```

	Df	Sum of Sq	RSS	AIC
## - citympg	1	6595370	1302631574	3243.3
## - curbweight	1	9208443	1305244647	3243.7
## - horsepower	1	11839004	1307875209	3244.1
## - highwaympg	1	12307515	1308343719	3244.1
## <none>			1296036204	3244.2
## - compressionratio	1	19752771	1315788975	3245.3
## - carwidth	1	30637881	1326674085	3247.0
## - fueltype	1	30907659	1326943863	3247.0
## - drivewheel	1	38372036	1334408241	3248.2
## - wheelbase	1	47303966	1343340170	3249.6
## - stroke	1	67486772	1363522976	3252.6
## - CarName	1	69777346	1365813551	3253.0
## - peakrpm	1	74525984	1370562189	3253.7
## - enginetype	1	95977314	1392013518	3256.9
## - cylindernumber	1	238352457	1534388661	3276.8
## - enginelocation	1	242551421	1538587625	3277.4
## - enginesize	1	320581460	1616617664	3287.5

```
## Step: AIC=3243.25
```

```
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
##      carwidth + curbweight + enginetype + cylindernumber + enginesize +
##      stroke + compressionratio + horsepower + peakrpm + highwaympg
##
```

	Df	Sum of Sq	RSS	AIC
## - highwaympg	1	6769710	1309401284	3242.3
## - curbweight	1	11576889	1314208463	3243.1
## <none>			1302631574	3243.3
## - compressionratio	1	18943460	1321575034	3244.2
## - horsepower	1	19036783	1321668357	3244.2
## - fueltype	1	28623406	1331254980	3245.7
## - carwidth	1	32791489	1335423063	3246.3
## - drivewheel	1	34716184	1337347758	3246.6
## - wheelbase	1	43752560	1346384134	3248.0
## - stroke	1	64190786	1366822360	3251.1
## - peakrpm	1	71137869	1373769443	3252.2
## - CarName	1	72705256	1375336830	3252.4
## - enginetype	1	97237786	1399869360	3256.0
## - cylindernumber	1	235717985	1538349559	3275.3
## - enginelocation	1	260344860	1562976434	3278.6
## - enginesize	1	319925313	1622556887	3286.3

```
## Step: AIC=3242.31
```

```
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
##   carwidth + curbweight + enginetype + cylindernumber + enginesize +
##   stroke + compressionratio + horsepower + peakrpm
##
##           Df Sum of Sq      RSS      AIC
## - curbweight      1   6305113 1315706397 3241.3
## <none>                        1309401284 3242.3
## - compressionratio 1   13467224 1322868508 3242.4
## - horsepower      1   16561341 1325962625 3242.9
## - fueltype        1   23490972 1332892257 3244.0
## - drivewheel      1   31529586 1340930870 3245.2
## - carwidth        1   32050301 1341451585 3245.3
## - wheelbase       1   43044770 1352446054 3246.9
## - stroke          1   60657845 1370059129 3249.6
## - peakrpm         1   65106516 1374507800 3250.3
## - CarName         1   81425601 1390826885 3252.7
## - enginetype      1   94136483 1403537767 3254.5
## - cylindernumber  1  228993988 1538395272 3273.4
## - enginelocation  1  256270109 1565671393 3277.0
## - enginesize      1  337948289 1647349573 3287.4
##
## Step:  AIC=3241.3
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
##   carwidth + enginetype + cylindernumber + enginesize + stroke +
##   compressionratio + horsepower + peakrpm
##
##           Df Sum of Sq      RSS      AIC
## <none>                        1315706397 3241.3
## - compressionratio 1   17628383 1333334780 3242.0
## - horsepower      1   25839112 1341545509 3243.3
## - fueltype        1   30601932 1346308329 3244.0
## - carwidth        1   46974022 1362680419 3246.5
## - drivewheel      1   56610752 1372317149 3247.9
## - stroke          1   58433177 1374139575 3248.2
## - peakrpm         1   63788631 1379495028 3249.0
## - wheelbase       1   70042664 1385749061 3249.9
## - enginetype      1   87913403 1403619800 3252.6
## - CarName         1   88897396 1404603793 3252.7
## - cylindernumber  1  222851923 1538558320 3271.4
## - enginelocation  1  250876662 1566583059 3275.1
## - enginesize      1  453850116 1769556513 3300.1
##
## Call:
## lm(formula = price ~ CarName + fueltype + drivewheel + enginelocation +
##   wheelbase + carwidth + enginetype + cylindernumber + enginesize +
##   stroke + compressionratio + horsepower + peakrpm, data = data)
```

```
##
## Coefficients:
##      (Intercept)      CarName      fueltype      drivewheel
##      -53534.637      132.029      9242.231      1149.270
##      enginelocation      wheelbase      carwidth      enginetype
##      11194.717      192.613      520.832      -609.407
##      cylindernumber      enginesize      stroke      compressionratio
##      1377.244      91.229      -2147.224      -505.609
##      horsepower      peakrpm
##      23.616      1.749

#AIC=3241.3

model2 = lm(price ~ CarName + fueltype + drivewheel + enginelocation +
             wheelbase + carwidth + enginetype + cylindernumber + enginesize +
             stroke + compressionratio + horsepower + peakrpm, data = data)

summary(model2)

##
## Call:
## lm(formula = price ~ CarName + fueltype + drivewheel + enginelocation +
##      wheelbase + carwidth + enginetype + cylindernumber + enginesize +
##      stroke + compressionratio + horsepower + peakrpm, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
##     -9141    -1500     -244     1267    14084
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -5.353e+04  1.083e+04  -4.943 1.68e-06 ***
## CarName        1.320e+02  3.675e+01   3.592 0.000417 ***
## fueltype       9.242e+03  4.385e+03   2.108 0.036360 *
## drivewheel     1.149e+03  4.009e+02   2.867 0.004613 **
## enginelocation 1.119e+04  1.855e+03   6.035 8.11e-09 ***
## wheelbase      1.926e+02  6.040e+01   3.189 0.001670 **
## carwidth       5.208e+02  1.994e+02   2.611 0.009735 **
## enginetype     -6.094e+02  1.706e+02  -3.572 0.000448 ***
## cylindernumber 1.377e+03  2.421e+02   5.688 4.77e-08 ***
## enginesize      9.123e+01  1.124e+01   8.117 5.74e-14 ***
## stroke        -2.147e+03  7.372e+02  -2.913 0.004013 **
## compressionratio -5.056e+02  3.161e+02  -1.600 0.111314
## horsepower     2.362e+01  1.219e+01   1.937 0.054250 .
## peakrpm        1.749e+00  5.748e-01   3.043 0.002672 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2625 on 191 degrees of freedom
## Multiple R-squared:  0.8989, Adjusted R-squared:  0.8921
## F-statistic: 130.7 on 13 and 191 DF,  p-value: < 2.2e-16

#Adjusted R-squared:  0.8921
#model2 is our best model so far.

# Estimate Std. Error t value Pr(>|t|)
# (Intercept)      -5.353e+04  1.083e+04  -4.943 1.68e-06 ***
#  CarName          1.320e+02  3.675e+01   3.592 0.000417 ***
#  fueltype         9.242e+03  4.385e+03   2.108 0.036360 *
#  drivewheel       1.149e+03  4.009e+02   2.867 0.004613 **
#  enginelocation   1.119e+04  1.855e+03   6.035 8.11e-09 ***
#  wheelbase        1.926e+02  6.040e+01   3.189 0.001670 **
#  carwidth         5.208e+02  1.994e+02   2.611 0.009735 **
#  enginetype       -6.094e+02  1.706e+02  -3.572 0.000448 ***
#  cylindernumber   1.377e+03  2.421e+02   5.688 4.77e-08 ***
#  enginesize       9.123e+01  1.124e+01   8.117 5.74e-14 ***
#  stroke           -2.147e+03  7.372e+02  -2.913 0.004013 **
#  compressionratio -5.056e+02  3.161e+02  -1.600 0.111314
# horsepower        2.362e+01  1.219e+01   1.937 0.054250 .
# peakrpm           1.749e+00  5.748e-01   3.043 0.002672 **

# We want to check interaction terms

library(MASS)

# We want to check if the model2 check the LINE checkmarks.
```

```

#plot(model2)

#we can check for potential significant interaction terms before doing any transfo
rmations.

add1(model2, ~. + fueltype*CarName + drivewheel*CarName + enginelocation*CarName +
      wheelbase*CarName + carwidth*CarName + enginetype*CarName + cylindernumber*
CarName + enginesize*CarName +
      stroke*CarName + compressionratio*CarName + horsepower*CarName + peakrpm*Ca
rName, test = 'F')

## Single term additions
##
## Model:
## price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
##       carwidth + enginetype + cylindernumber + enginesize + stroke +
##       compressionratio + horsepower + peakrpm
##
##              Df Sum of Sq      RSS      AIC F value    Pr(>F)
## <none>                        1315706397 3241.3
## CarName:fueltype             1    189737 1315516660 3243.3  0.0274 0.868694
## CarName:drivewheel           1   18228257 1297478140 3240.4  2.6693 0.103956
## CarName:enginelocation        0         0 1315706397 3241.3
## CarName:wheelbase            1   44752587 1270953810 3236.2  6.6902 0.010442 *
## CarName:carwidth             1   29892597 1285813800 3238.6  4.4171 0.036898 *
## CarName:enginetype           1   48585730 1267120667 3235.6  7.2852 0.007579 **
## CarName:cylindernumber        1   28371156 1287335241 3238.8  4.1873 0.042104 *
## CarName:enginesize           1   44438659 1271267738 3236.3  6.6417 0.010720 *
## CarName:stroke               1    1436145 1314270252 3243.1  0.2076 0.649160
## CarName:compressionratio      1    1076328 1314630069 3243.1  0.1556 0.693721
## CarName:horsepower           1   38213746 1277492651 3237.3  5.6835 0.018110 *
## CarName:peakrpm              1    1263459 1314442939 3243.1  0.1826 0.669606
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#The results are amazing to see, I would have expected for all interactions to be
significant
#but based on the interaction terms only wheelbase, carwidth, enginetype, cylindernum
ber, enginesize, horsepower are
significant.

model3 = update(model2, ~.+CarName:cylindernumber)
summary(model3)

##
## Call:
## lm(formula = price ~ CarName + fueltype + drivewheel + enginelocation +

```

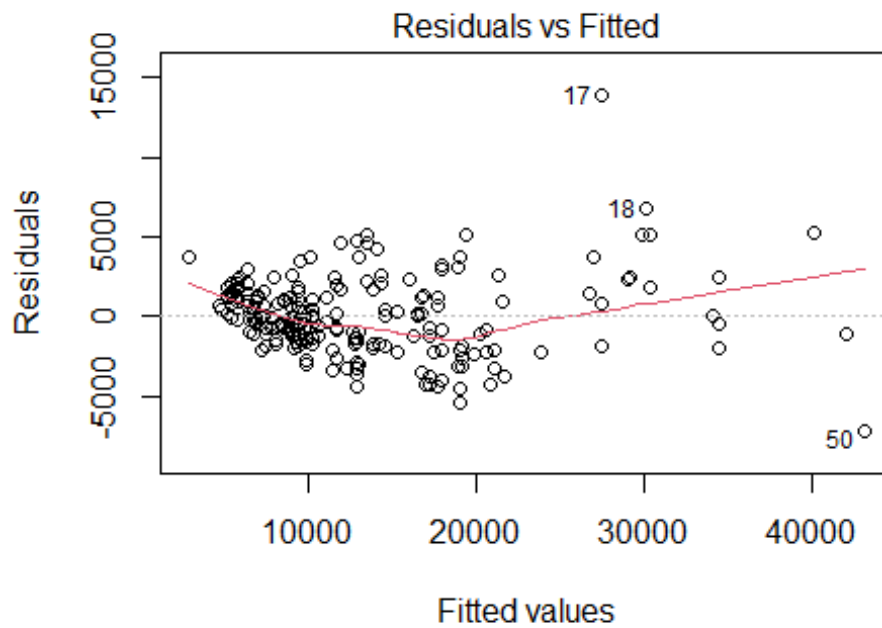


```
## wheelbase + carwidth + enginetype + cylindernumber + enginesize +
## stroke + compressionratio + horsepower + peakrpm + CarName:cylindernumber,
## data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7168.8 -1611.7  -132.5   1380.1  13861.7
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -4.989e+04  1.089e+04  -4.582 8.31e-06 ***
## CarName         1.616e+02  3.921e+01   4.121 5.62e-05 ***
## fueltype        8.748e+03  4.356e+03   2.009 0.046003 *
## drivewheel      1.036e+03  4.015e+02   2.579 0.010655 *
## enginelocation  1.105e+04  1.841e+03   6.003 9.66e-09 ***
## wheelbase       1.933e+02  5.991e+01   3.227 0.001475 **
## carwidth        4.704e+02  1.993e+02   2.360 0.019284 *
## enginetype     -6.854e+02  1.732e+02  -3.957 0.000107 ***
## cylindernumber  2.053e+03  4.085e+02   5.027 1.15e-06 ***
## enginesize      9.628e+01  1.142e+01   8.433 8.33e-15 ***
## stroke        -2.372e+03  7.393e+02  -3.208 0.001571 **
## compressionratio -4.644e+02  3.141e+02  -1.479 0.140914
## horsepower      2.334e+01  1.209e+01   1.930 0.055130 .
## peakrpm         1.605e+00  5.744e-01   2.794 0.005734 **
## CarName:cylindernumber -6.855e+01  3.350e+01  -2.046 0.042104 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2603 on 190 degrees of freedom
## Multiple R-squared:  0.9011, Adjusted R-squared:  0.8938
## F-statistic: 123.7 on 14 and 190 DF,  p-value: < 2.2e-16

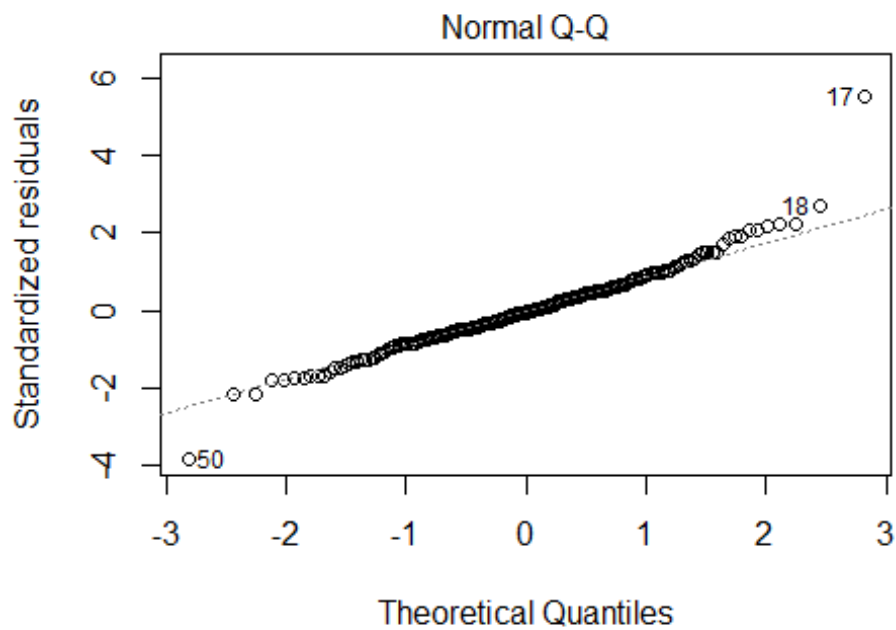
anova(model2,model3)

## Analysis of Variance Table
##
## Model 1: price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
## carwidth + enginetype + cylindernumber + enginesize + stroke +
## compressionratio + horsepower + peakrpm
## Model 2: price ~ CarName + fueltype + drivewheel + enginelocation + wheelbase +
## carwidth + enginetype + cylindernumber + enginesize + stroke +
## compressionratio + horsepower + peakrpm + CarName:cylindernumber
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1     191 1315706397
## 2     190 1287335241   1  28371156 4.1873 0.0421 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

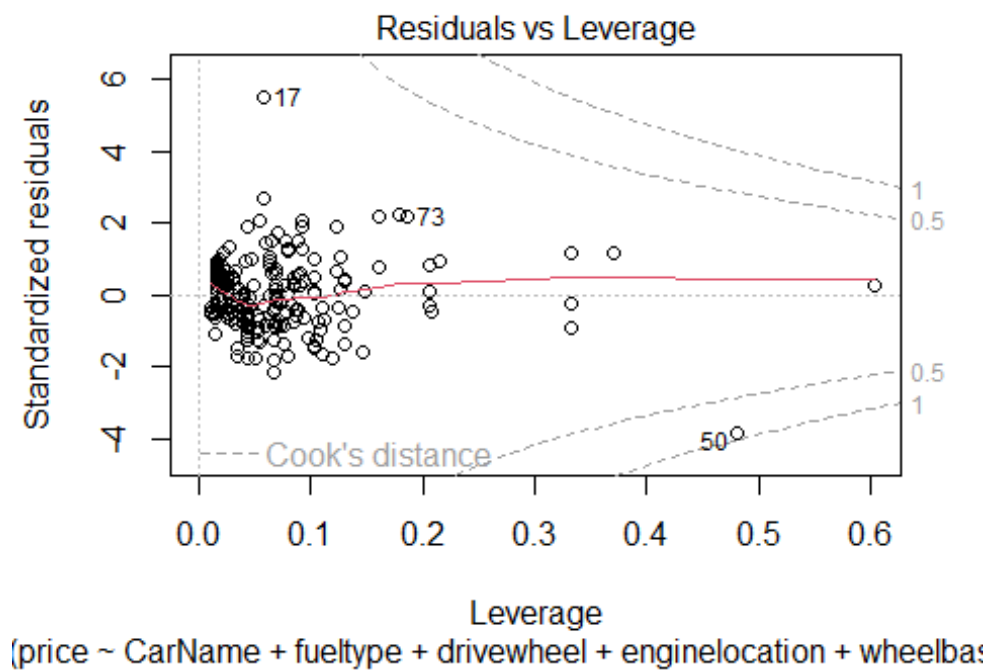
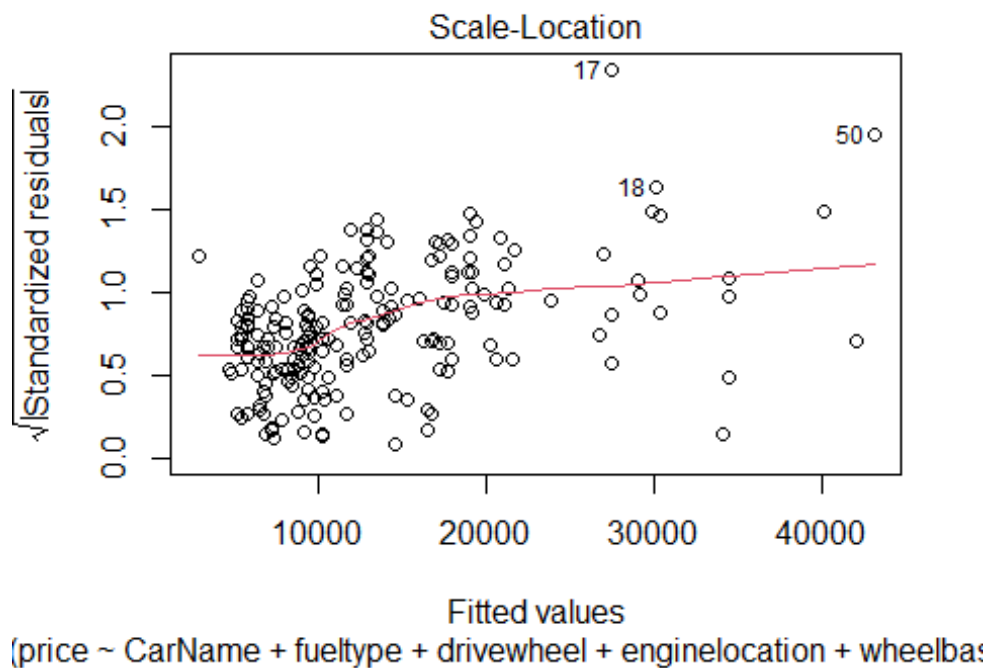
```
plot(model13)
```



(price ~ CarName + fueltype + drivewheel + enginelocation + wheelba:



(price ~ CarName + fueltype + drivewheel + enginelocation + wheelba:



*#In the residual vs Fitted plot we see a fanning pattern*  
*#In the QQ plot we see a non normality.*

```
library(broom)
```

*#Another way to plot these graphs are:*

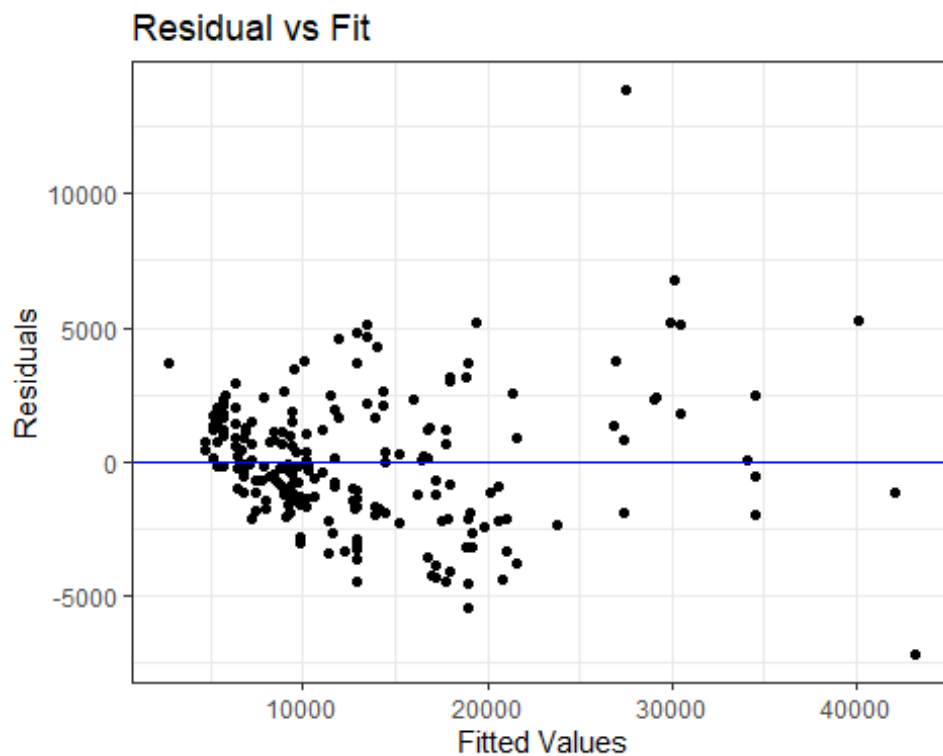
```

mod_table = augment(model3)
names(mod_table)

## [1] "coefficients" "residuals" "effects" "rank"
## [5] "fitted.values" "assign" "qr" "df.residual"
## [9] "xlevels" "call" "terms" "model"

ggplot(mod_table, aes(x = .fitted, y = .resid)) +
  geom_point() +
  geom_hline(yintercept = 0, colour = 'blue') +
  labs(x = 'Fitted Values', y = 'Residuals') +
  ggtitle('Residual vs Fit') +
  theme_bw()

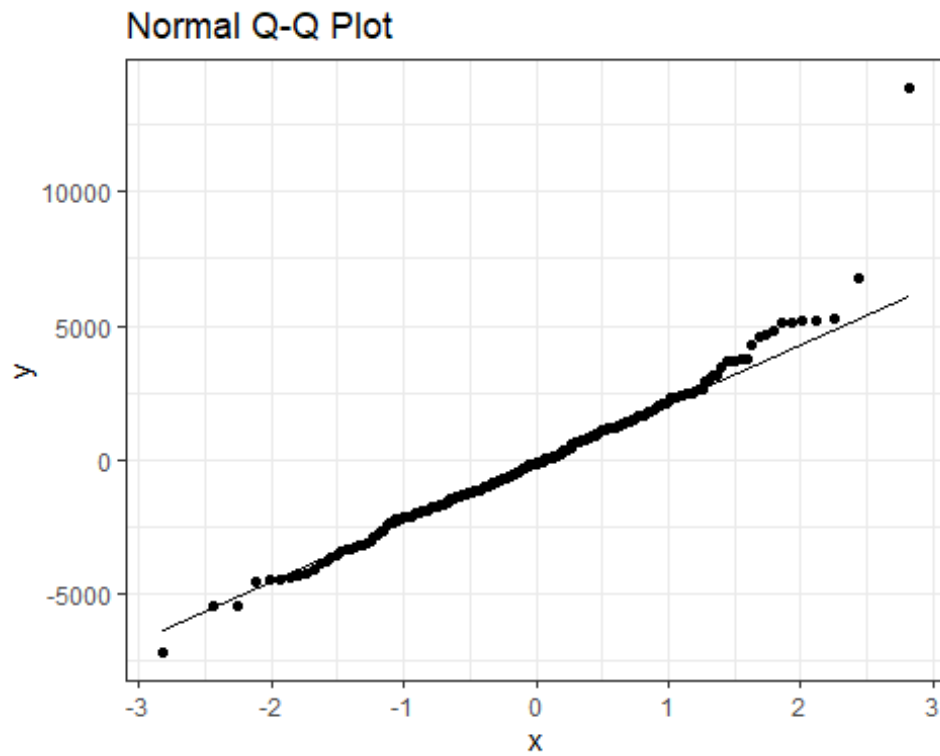
```



```

#Here we see a fanning pattern
#We need to transform the y-variable
ggplot(mod_table, aes(sample = .resid)) +
  stat_qq() +
  stat_qq_line() +
  ggtitle('Normal Q-Q Plot') +
  theme_bw()

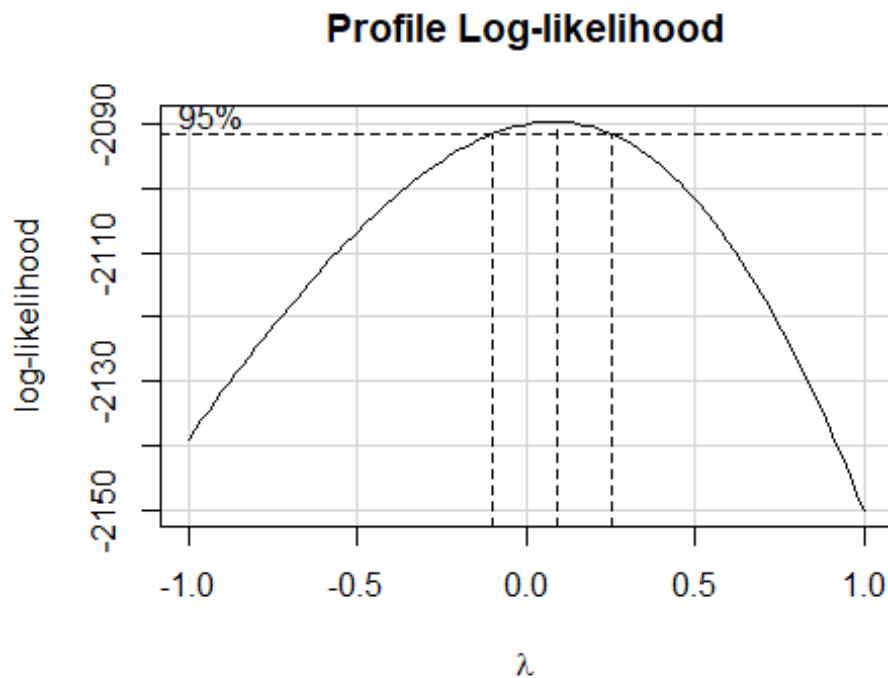
```



```
shapiro.test(resid(model3))  
  
##  
## Shapiro-Wilk normality test  
##  
## data: resid(model3)  
## W = 0.95893, p-value = 1.191e-05
```

*#We can try box-cox method*

```
library(car)  
mod.boxcox = boxCox(model3, lambda = seq(-1, 1, length=10))
```



```
lambda.opt = mod.boxcox$x[which.max(mod.boxcox$y)] #find the optimal lambda
lambda.opt

## [1] 0.09090909

model4 = lm((price^lambda.opt) ~ CarName + fueltype + drivewheel + enginelocation +
            wheelbase + carwidth + enginetype + cylindernumber + enginesize +
            stroke + compressionratio + horsepower + peakrpm + CarName:cylindernumber,
            data = data)
summary(model4)

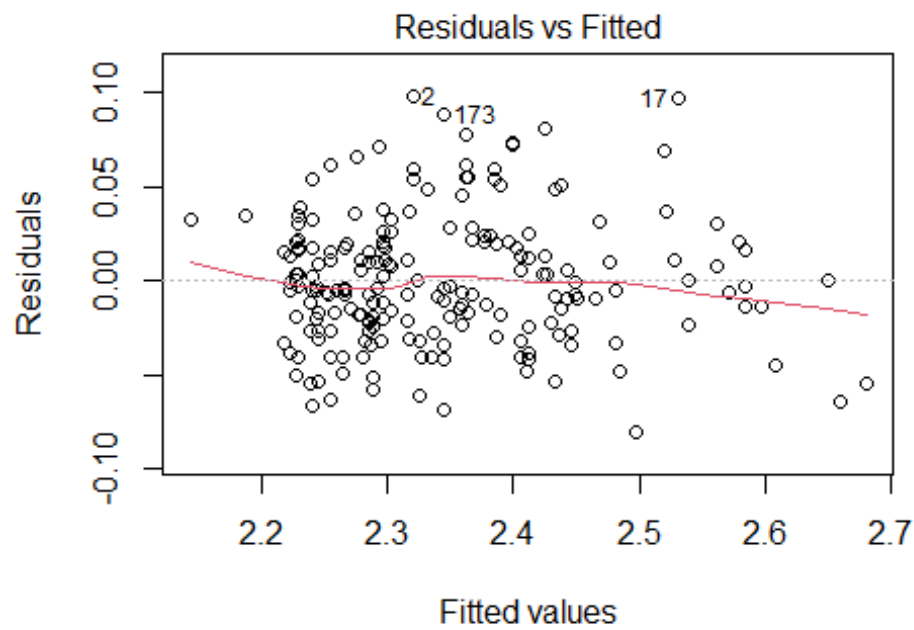
##
## Call:
## lm(formula = (price^lambda.opt) ~ CarName + fueltype + drivewheel +
##     enginelocation + wheelbase + carwidth + enginetype + cylindernumber +
##     enginesize + stroke + compressionratio + horsepower + peakrpm +
##     CarName:cylindernumber, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.080081 -0.023134 -0.004182  0.019577  0.098205
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
```

```

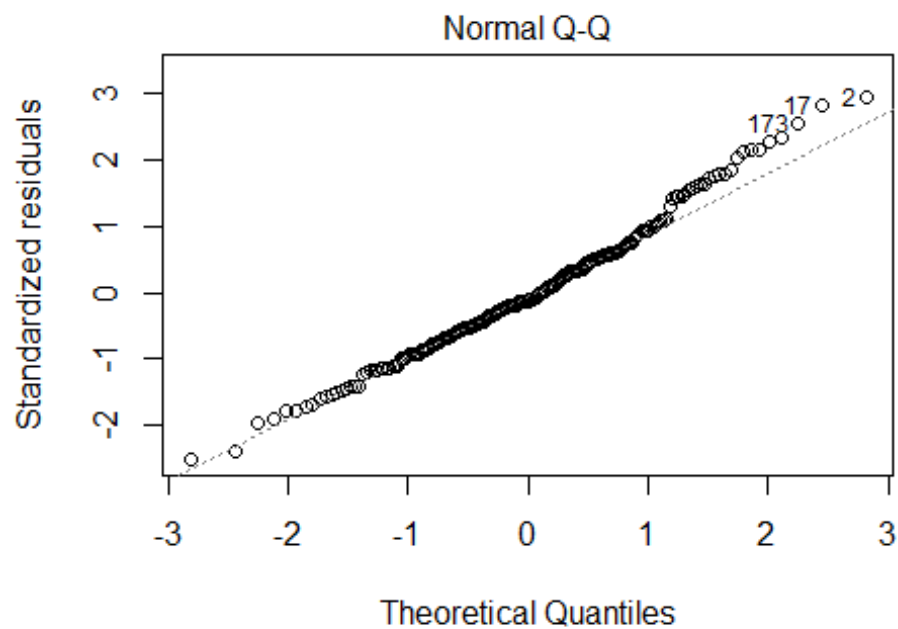
## (Intercept)          1.248e+00  1.494e-01   8.354 1.36e-14 ***
## CarName              2.405e-03  5.379e-04   4.471 1.34e-05 ***
## fueltype             9.392e-02  5.975e-02   1.572 0.117648
## drivewheel          2.201e-02  5.507e-03   3.997 9.17e-05 ***
## enginelocation       1.111e-01  2.526e-02   4.401 1.80e-05 ***
## wheelbase            3.479e-03  8.218e-04   4.233 3.59e-05 ***
## carwidth             8.973e-03  2.734e-03   3.282 0.001229 **
## enginetype          -8.216e-03  2.376e-03  -3.458 0.000672 ***
## cylindernumber       2.674e-02  5.604e-03   4.773 3.62e-06 ***
## enginesize           5.944e-04  1.566e-04   3.796 0.000198 ***
## stroke              -1.887e-02  1.014e-02  -1.860 0.064373 .
## compressionratio    -3.884e-03  4.309e-03  -0.901 0.368572
## horsepower           9.514e-04  1.659e-04   5.735 3.79e-08 ***
## peakrpm             1.007e-05  7.880e-06   1.279 0.202611
## CarName:cylindernumber -1.660e-03  4.595e-04  -3.612 0.000389 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03571 on 190 degrees of freedom
## Multiple R-squared:  0.9, Adjusted R-squared:  0.8926
## F-statistic: 122.2 on 14 and 190 DF, p-value: < 2.2e-16

plot(model4)

```

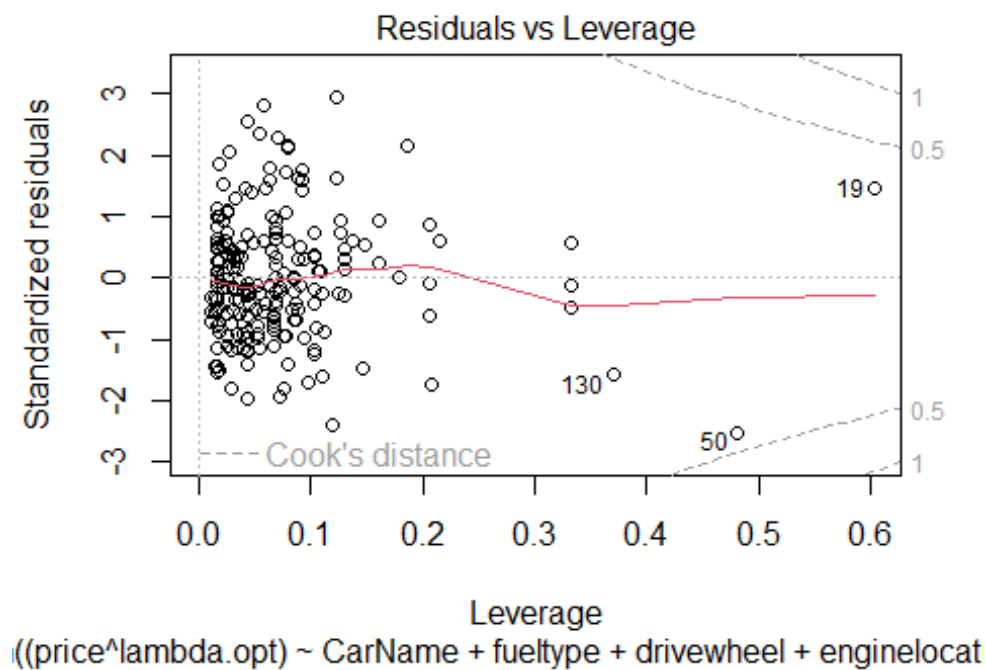
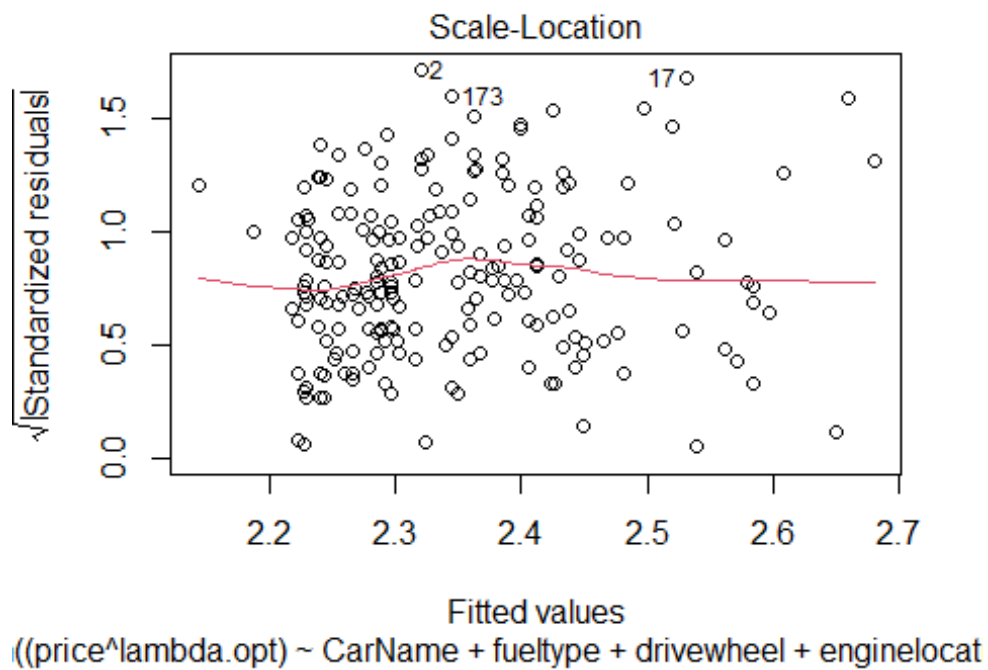


((price<sup>lambda.opt</sup>) ~ CarName + fueltype + drivewheel + engine locat

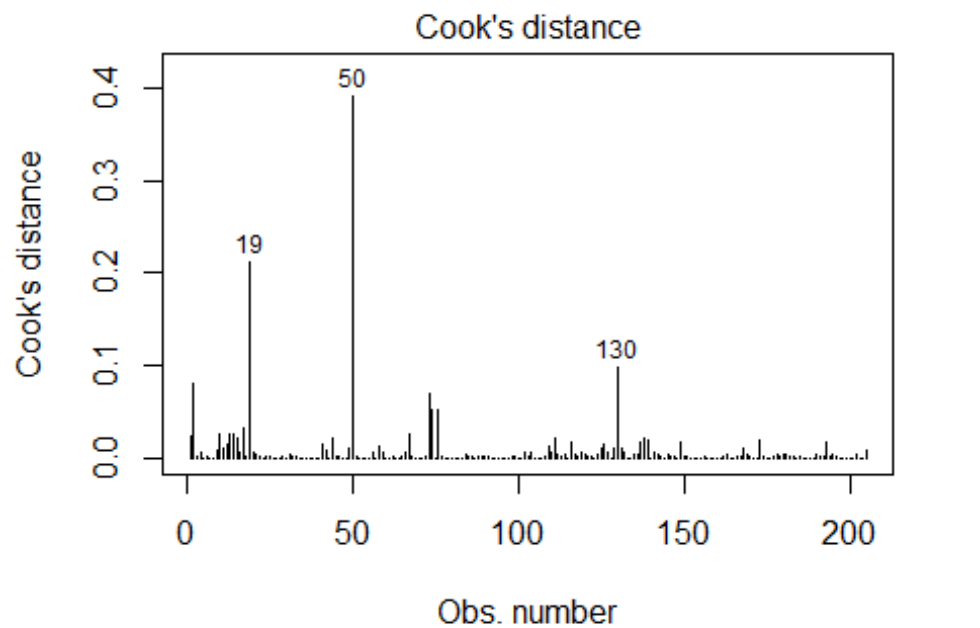


((price<sup>lambda.opt</sup>) ~ CarName + fueltype + drivewheel + engine locat





```
plot(model14, which = 4)
```



`((price^lambda.opt) ~ CarName + fueltype + drivewheel + engine locat`

```
rs = rstandard(model4)
which(rs > 3)

## named integer(0)

#We see no influential points

#potential prediction and confidence intervals
library(dplyr)

##
## Attaching package: 'dplyr'

## The following object is masked from 'package:MASS':
##
##   select

## The following object is masked from 'package:car':
##
##   recode

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

# CAR PRICE PREDICTION

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```
new_data = data %>% select (CarName, fueltype, drivewheel , enginelocation ,
                           wheelbase ,carwidth, enginetype,cylindernumber,engine
size ,
                           stroke , compressionratio , horsepower ,peakrpm, price)
new_data
```

##	CarName	fueltype	drivewheel	enginelocation	wheelbase	carwidth	enginetype
## 1	18	0	1	0	88.6	64.1	3
## 2	18	0	1	0	88.6	64.1	3
## 3	18	0	1	0	94.5	65.5	2
## 4	12	0	0	0	99.8	66.2	0
## 5	12	0	2	0	99.4	66.4	0
## 6	12	0	0	0	99.8	66.3	0
## 7	12	0	0	0	105.8	71.4	0
## 8	12	0	0	0	105.8	71.4	0
## 9	12	0	0	0	105.8	71.4	0
## 10	12	0	2	0	99.5	67.9	0
## 11	11	0	1	0	101.2	64.8	0
## 12	11	0	1	0	101.2	64.8	0
## 13	11	0	1	0	101.2	64.8	0
## 14	11	0	1	0	101.2	64.8	0
## 15	11	0	1	0	103.5	66.9	0
## 16	11	0	1	0	103.5	66.9	0
## 17	11	0	1	0	103.5	67.9	0
## 18	11	0	1	0	110.0	70.9	0
## 19	16	0	0	0	88.4	60.3	4
## 20	16	0	0	0	94.5	63.6	0
## 21	16	0	0	0	94.5	63.6	0
## 22	9	0	0	0	93.7	63.8	0
## 23	9	0	0	0	93.7	63.8	0
## 24	9	0	0	0	93.7	63.8	0
## 25	9	0	0	0	93.7	63.8	0
## 26	9	0	0	0	93.7	63.8	0
## 27	9	0	0	0	93.7	63.8	0
## 28	9	0	0	0	93.7	63.8	0
## 29	9	0	0	0	103.3	64.6	0
## 30	9	0	0	0	95.9	66.3	0
## 31	3	0	0	0	86.6	63.9	0
## 32	3	0	0	0	86.6	63.9	0
## 33	3	0	0	0	93.7	64.0	0
## 34	3	0	0	0	93.7	64.0	0
## 35	3	0	0	0	93.7	64.0	0
## 36	3	0	0	0	96.5	64.0	0
## 37	3	0	0	0	96.5	63.9	0
## 38	3	0	0	0	96.5	65.2	0
## 39	3	0	0	0	96.5	65.2	0

## CAR PRICE PREDICTION

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## 40	3	0	0	0	96.5	65.2	0
## 41	3	0	0	0	96.5	62.5	0
## 42	3	0	0	0	96.5	65.2	0
## 43	3	0	0	0	96.5	66.0	0
## 44	17	0	1	0	94.3	61.8	0
## 45	17	0	0	0	94.5	63.6	0
## 46	17	0	0	0	94.5	63.6	0
## 47	17	0	1	0	96.0	65.2	0
## 48	19	0	1	0	113.0	69.6	3
## 49	19	0	1	0	113.0	69.6	3
## 50	19	0	1	0	102.0	70.6	2
## 51	2	0	0	0	93.1	64.2	0
## 52	2	0	0	0	93.1	64.2	0
## 53	2	0	0	0	93.1	64.2	0
## 54	2	0	0	0	93.1	64.2	0
## 55	2	0	0	0	93.1	64.2	0
## 56	2	0	1	0	95.3	65.7	5
## 57	2	0	1	0	95.3	65.7	5
## 58	2	0	1	0	95.3	65.7	5
## 59	2	0	1	0	95.3	65.7	5
## 60	2	0	0	0	98.8	66.5	0
## 61	2	0	0	0	98.8	66.5	0
## 62	2	0	0	0	98.8	66.5	0
## 63	2	0	0	0	98.8	66.5	0
## 64	2	1	0	0	98.8	66.5	0
## 65	2	0	0	0	98.8	66.5	0
## 66	2	0	1	0	104.9	66.1	0
## 67	2	1	1	0	104.9	66.1	0
## 68	10	1	1	0	110.0	70.3	0
## 69	10	1	1	0	110.0	70.3	0
## 70	10	1	1	0	106.7	70.3	0
## 71	10	1	1	0	115.6	71.7	0
## 72	10	0	1	0	115.6	71.7	2
## 73	10	0	1	0	96.6	70.5	2
## 74	10	0	1	0	120.9	71.7	2
## 75	10	0	1	0	112.0	72.0	2
## 76	21	0	1	0	102.7	68.0	0
## 77	4	0	0	0	93.7	64.4	0
## 78	4	0	0	0	93.7	64.4	0
## 79	4	0	0	0	93.7	64.4	0
## 80	4	0	0	0	93.0	63.8	0
## 81	4	0	0	0	96.3	65.4	0
## 82	4	0	0	0	96.3	65.4	0
## 83	4	0	0	0	95.9	66.3	0
## 84	4	0	0	0	95.9	66.3	0
## 85	4	0	0	0	95.9	66.3	0
## 86	4	0	0	0	96.3	65.4	0

## CAR PRICE PREDICTION

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## 87	4	0	0	0	96.3	65.4	0
## 88	4	0	0	0	96.3	65.4	0
## 89	4	0	0	0	96.3	65.4	0
## 90	1	0	0	0	94.5	63.8	0
## 91	1	1	0	0	94.5	63.8	0
## 92	1	0	0	0	94.5	63.8	0
## 93	1	0	0	0	94.5	63.8	0
## 94	1	0	0	0	94.5	63.8	0
## 95	1	0	0	0	94.5	63.8	0
## 96	1	0	0	0	94.5	63.8	0
## 97	1	0	0	0	94.5	63.8	0
## 98	1	0	0	0	94.5	63.8	0
## 99	1	0	0	0	95.1	63.8	0
## 100	1	0	0	0	97.2	65.2	0
## 101	1	0	0	0	97.2	65.2	0
## 102	1	0	0	0	100.4	66.5	2
## 103	1	0	0	0	100.4	66.5	2
## 104	1	0	0	0	100.4	66.5	2
## 105	1	0	1	0	91.3	67.9	2
## 106	1	0	1	0	91.3	67.9	2
## 107	1	0	1	0	99.2	67.9	2
## 108	7	0	1	0	107.9	68.4	4
## 109	7	1	1	0	107.9	68.4	4
## 110	7	0	1	0	114.2	68.4	4
## 111	7	1	1	0	114.2	68.4	4
## 112	7	0	1	0	107.9	68.4	4
## 113	7	1	1	0	107.9	68.4	4
## 114	7	0	1	0	114.2	68.4	4
## 115	7	1	1	0	114.2	68.4	4
## 116	7	0	1	0	107.9	68.4	4
## 117	7	1	1	0	107.9	68.4	4
## 118	7	0	1	0	108.0	68.3	4
## 119	13	0	0	0	93.7	63.8	0
## 120	13	0	0	0	93.7	63.8	0
## 121	13	0	0	0	93.7	63.8	0
## 122	13	0	0	0	93.7	63.8	0
## 123	13	0	0	0	93.7	63.8	0
## 124	13	0	0	0	103.3	64.6	0
## 125	13	0	1	0	95.9	66.3	0
## 126	15	0	1	0	94.5	68.3	0
## 127	15	0	1	1	89.5	65.0	1
## 128	15	0	1	1	89.5	65.0	1
## 129	15	0	1	1	89.5	65.0	1
## 130	15	0	1	0	98.4	72.3	6
## 131	20	0	0	0	96.1	66.5	0
## 132	20	0	0	0	96.1	66.6	0
## 133	14	0	0	0	99.1	66.5	0

## CAR PRICE PREDICTION

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## 134	14	0	0	0	99.1	66.5	0
## 135	14	0	0	0	99.1	66.5	0
## 136	14	0	0	0	99.1	66.5	0
## 137	14	0	0	0	99.1	66.5	3
## 138	14	0	0	0	99.1	66.5	3
## 139	5	0	0	0	93.7	63.4	1
## 140	5	0	0	0	93.7	63.6	1
## 141	5	0	2	0	93.3	63.8	1
## 142	5	0	0	0	97.2	65.4	1
## 143	5	0	0	0	97.2	65.4	1
## 144	5	0	0	0	97.2	65.4	1
## 145	5	0	2	0	97.0	65.4	1
## 146	5	0	2	0	97.0	65.4	1
## 147	5	0	0	0	97.0	65.4	1
## 148	5	0	0	0	97.0	65.4	1
## 149	5	0	2	0	96.9	65.4	1
## 150	5	0	2	0	96.9	65.4	1
## 151	0	0	0	0	95.7	63.6	0
## 152	0	0	0	0	95.7	63.6	0
## 153	0	0	0	0	95.7	63.6	0
## 154	0	0	0	0	95.7	63.6	0
## 155	0	0	2	0	95.7	63.6	0
## 156	0	0	2	0	95.7	63.6	0
## 157	0	0	0	0	95.7	64.4	0
## 158	0	0	0	0	95.7	64.4	0
## 159	0	1	0	0	95.7	64.4	0
## 160	0	1	0	0	95.7	64.4	0
## 161	0	0	0	0	95.7	64.4	0
## 162	0	0	0	0	95.7	64.4	0
## 163	0	0	0	0	95.7	64.4	0
## 164	0	0	1	0	94.5	64.0	0
## 165	0	0	1	0	94.5	64.0	0
## 166	0	0	1	0	94.5	64.0	3
## 167	0	0	1	0	94.5	64.0	3
## 168	0	0	1	0	98.4	65.6	0
## 169	0	0	1	0	98.4	65.6	0
## 170	0	0	1	0	98.4	65.6	0
## 171	0	0	1	0	98.4	65.6	0
## 172	0	0	1	0	98.4	65.6	0
## 173	0	0	1	0	98.4	65.6	0
## 174	0	0	0	0	102.4	66.5	0
## 175	0	1	0	0	102.4	66.5	0
## 176	0	0	0	0	102.4	66.5	0
## 177	0	0	0	0	102.4	66.5	0
## 178	0	0	0	0	102.4	66.5	0
## 179	0	0	1	0	102.9	67.7	3
## 180	0	0	1	0	102.9	67.7	3

## CAR PRICE PREDICTION

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## 181	0	0	1	0	104.5	66.5	3
## 182	0	0	1	0	104.5	66.5	3
## 183	6	1	0	0	97.3	65.5	0
## 184	6	0	0	0	97.3	65.5	0
## 185	6	1	0	0	97.3	65.5	0
## 186	6	0	0	0	97.3	65.5	0
## 187	6	0	0	0	97.3	65.5	0
## 188	6	1	0	0	97.3	65.5	0
## 189	6	0	0	0	97.3	65.5	0
## 190	6	0	0	0	94.5	64.2	0
## 191	6	0	0	0	94.5	64.0	0
## 192	6	0	0	0	100.4	66.9	0
## 193	6	1	0	0	100.4	66.9	0
## 194	6	0	0	0	100.4	66.9	0
## 195	8	0	1	0	104.3	67.2	0
## 196	8	0	1	0	104.3	67.2	0
## 197	8	0	1	0	104.3	67.2	0
## 198	8	0	1	0	104.3	67.2	0
## 199	8	0	1	0	104.3	67.2	0
## 200	8	0	1	0	104.3	67.2	0
## 201	8	0	1	0	109.1	68.9	0
## 202	8	0	1	0	109.1	68.8	0
## 203	8	0	1	0	109.1	68.9	2
## 204	8	1	1	0	109.1	68.9	0
## 205	8	0	1	0	109.1	68.9	0

##	cylindernumber	enginesize	stroke	compressionratio	horsepower	peakrpm
## 1	0	130	2.680	9.00	111	5000
## 2	0	130	2.680	9.00	111	5000
## 3	1	152	3.470	9.00	154	5000
## 4	0	109	3.400	10.00	102	5500
## 5	2	136	3.400	8.00	115	5500
## 6	2	136	3.400	8.50	110	5500
## 7	2	136	3.400	8.50	110	5500
## 8	2	136	3.400	8.50	110	5500
## 9	2	131	3.400	8.30	140	5500
## 10	2	131	3.400	7.00	160	5500
## 11	0	108	2.800	8.80	101	5800
## 12	0	108	2.800	8.80	101	5800
## 13	1	164	3.190	9.00	121	4250
## 14	1	164	3.190	9.00	121	4250
## 15	1	164	3.190	9.00	121	4250
## 16	1	209	3.390	8.00	182	5400
## 17	1	209	3.390	8.00	182	5400
## 18	1	209	3.390	8.00	182	5400
## 19	6	61	3.030	9.50	48	5100
## 20	0	90	3.110	9.60	70	5400
## 21	0	90	3.110	9.60	70	5400

## CAR PRICE PREDICTION

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## 22	0	90	3. 230	9. 41	68	5500
## 23	0	90	3. 230	9. 40	68	5500
## 24	0	98	3. 390	7. 60	102	5500
## 25	0	90	3. 230	9. 40	68	5500
## 26	0	90	3. 230	9. 40	68	5500
## 27	0	90	3. 230	9. 40	68	5500
## 28	0	98	3. 390	7. 60	102	5500
## 29	0	122	3. 460	8. 50	88	5000
## 30	0	156	3. 900	7. 00	145	5000
## 31	0	92	3. 410	9. 60	58	4800
## 32	0	92	3. 410	9. 20	76	6000
## 33	0	79	3. 070	10. 10	60	5500
## 34	0	92	3. 410	9. 20	76	6000
## 35	0	92	3. 410	9. 20	76	6000
## 36	0	92	3. 410	9. 20	76	6000
## 37	0	92	3. 410	9. 20	76	6000
## 38	0	110	3. 580	9. 00	86	5800
## 39	0	110	3. 580	9. 00	86	5800
## 40	0	110	3. 580	9. 00	86	5800
## 41	0	110	3. 580	9. 00	86	5800
## 42	0	110	3. 580	9. 00	101	5800
## 43	0	110	3. 580	9. 10	100	5500
## 44	0	111	3. 230	8. 50	78	4800
## 45	0	90	3. 110	9. 60	70	5400
## 46	0	90	3. 110	9. 60	70	5400
## 47	0	119	3. 230	9. 20	90	5000
## 48	1	258	4. 170	8. 10	176	4750
## 49	1	258	4. 170	8. 10	176	4750
## 50	5	326	2. 760	11. 50	262	5000
## 51	0	91	3. 150	9. 00	68	5000
## 52	0	91	3. 150	9. 00	68	5000
## 53	0	91	3. 150	9. 00	68	5000
## 54	0	91	3. 150	9. 00	68	5000
## 55	0	91	3. 150	9. 00	68	5000
## 56	4	70	3. 255	9. 40	101	6000
## 57	4	70	3. 255	9. 40	101	6000
## 58	4	70	3. 255	9. 40	101	6000
## 59	4	80	3. 255	9. 40	135	6000
## 60	0	122	3. 390	8. 60	84	4800
## 61	0	122	3. 390	8. 60	84	4800
## 62	0	122	3. 390	8. 60	84	4800
## 63	0	122	3. 390	8. 60	84	4800
## 64	0	122	3. 390	22. 70	64	4650
## 65	0	122	3. 390	8. 60	84	4800
## 66	0	140	3. 160	8. 00	120	5000
## 67	0	134	3. 640	22. 00	72	4200
## 68	2	183	3. 640	21. 50	123	4350



## CAR PRICE PREDICTION

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## 69	2	183	3.640	21.50	123	4350
## 70	2	183	3.640	21.50	123	4350
## 71	2	183	3.640	21.50	123	4350
## 72	3	234	3.100	8.30	155	4750
## 73	3	234	3.100	8.30	155	4750
## 74	3	308	3.350	8.00	184	4500
## 75	3	304	3.350	8.00	184	4500
## 76	0	140	3.120	8.00	175	5000
## 77	0	92	3.230	9.40	68	5500
## 78	0	92	3.230	9.40	68	5500
## 79	0	92	3.230	9.40	68	5500
## 80	0	98	3.390	7.60	102	5500
## 81	0	110	3.460	7.50	116	5500
## 82	0	122	3.460	8.50	88	5000
## 83	0	156	3.860	7.00	145	5000
## 84	0	156	3.860	7.00	145	5000
## 85	0	156	3.860	7.00	145	5000
## 86	0	122	3.460	8.50	88	5000
## 87	0	122	3.460	8.50	88	5000
## 88	0	110	3.460	7.50	116	5500
## 89	0	110	3.460	7.50	116	5500
## 90	0	97	3.290	9.40	69	5200
## 91	0	103	3.470	21.90	55	4800
## 92	0	97	3.290	9.40	69	5200
## 93	0	97	3.290	9.40	69	5200
## 94	0	97	3.290	9.40	69	5200
## 95	0	97	3.290	9.40	69	5200
## 96	0	97	3.290	9.40	69	5200
## 97	0	97	3.290	9.40	69	5200
## 98	0	97	3.290	9.40	69	5200
## 99	0	97	3.290	9.40	69	5200
## 100	0	120	3.470	8.50	97	5200
## 101	0	120	3.470	8.50	97	5200
## 102	1	181	3.270	9.00	152	5200
## 103	1	181	3.270	9.00	152	5200
## 104	1	181	3.270	9.00	152	5200
## 105	1	181	3.270	9.00	160	5200
## 106	1	181	3.270	7.80	200	5200
## 107	1	181	3.270	9.00	160	5200
## 108	0	120	3.190	8.40	97	5000
## 109	0	152	3.520	21.00	95	4150
## 110	0	120	3.190	8.40	97	5000
## 111	0	152	3.520	21.00	95	4150
## 112	0	120	2.190	8.40	95	5000
## 113	0	152	3.520	21.00	95	4150
## 114	0	120	2.190	8.40	95	5000
## 115	0	152	3.520	21.00	95	4150

## CAR PRICE PREDICTION

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## 116	0	120	3.190	8.40	97	5000
## 117	0	152	3.520	21.00	95	4150
## 118	0	134	3.210	7.00	142	5600
## 119	0	90	3.230	9.40	68	5500
## 120	0	98	3.390	7.60	102	5500
## 121	0	90	3.230	9.40	68	5500
## 122	0	90	3.230	9.40	68	5500
## 123	0	98	3.230	9.40	68	5500
## 124	0	122	3.460	8.50	88	5000
## 125	0	156	3.860	7.00	145	5000
## 126	0	151	3.110	9.50	143	5500
## 127	1	194	2.900	9.50	207	5900
## 128	1	194	2.900	9.50	207	5900
## 129	1	194	2.900	9.50	207	5900
## 130	3	203	3.110	10.00	288	5750
## 131	0	132	3.900	8.70	90	5100
## 132	0	132	3.900	8.70	90	5100
## 133	0	121	3.070	9.31	110	5250
## 134	0	121	3.070	9.30	110	5250
## 135	0	121	2.070	9.30	110	5250
## 136	0	121	3.070	9.30	110	5250
## 137	0	121	3.070	9.00	160	5500
## 138	0	121	3.070	9.00	160	5500
## 139	0	97	2.360	9.00	69	4900
## 140	0	108	2.640	8.70	73	4400
## 141	0	108	2.640	8.70	73	4400
## 142	0	108	2.640	9.50	82	4800
## 143	0	108	2.640	9.50	82	4400
## 144	0	108	2.640	9.00	94	5200
## 145	0	108	2.640	9.00	82	4800
## 146	0	108	2.640	7.70	111	4800
## 147	0	108	2.640	9.00	82	4800
## 148	0	108	2.640	9.00	94	5200
## 149	0	108	2.640	9.00	82	4800
## 150	0	108	2.640	7.70	111	4800
## 151	0	92	3.030	9.00	62	4800
## 152	0	92	3.030	9.00	62	4800
## 153	0	92	3.030	9.00	62	4800
## 154	0	92	3.030	9.00	62	4800
## 155	0	92	3.030	9.00	62	4800
## 156	0	92	3.030	9.00	62	4800
## 157	0	98	3.030	9.00	70	4800
## 158	0	98	3.030	9.00	70	4800
## 159	0	110	3.350	22.50	56	4500
## 160	0	110	3.350	22.50	56	4500
## 161	0	98	3.030	9.00	70	4800
## 162	0	98	3.030	9.00	70	4800

## CAR PRICE PREDICTION

43

## 163	0	98	3.030	9.00	70	4800
## 164	0	98	3.030	9.00	70	4800
## 165	0	98	3.030	9.00	70	4800
## 166	0	98	3.080	9.40	112	6600
## 167	0	98	3.080	9.40	112	6600
## 168	0	146	3.500	9.30	116	4800
## 169	0	146	3.500	9.30	116	4800
## 170	0	146	3.500	9.30	116	4800
## 171	0	146	3.500	9.30	116	4800
## 172	0	146	3.500	9.30	116	4800
## 173	0	146	3.500	9.30	116	4800
## 174	0	122	3.540	8.70	92	4200
## 175	0	110	3.350	22.50	73	4500
## 176	0	122	3.540	8.70	92	4200
## 177	0	122	3.540	8.70	92	4200
## 178	0	122	3.540	8.70	92	4200
## 179	1	171	3.350	9.30	161	5200
## 180	1	171	3.350	9.30	161	5200
## 181	1	171	3.350	9.20	156	5200
## 182	1	161	3.350	9.20	156	5200
## 183	0	97	3.400	23.00	52	4800
## 184	0	109	3.400	9.00	85	5250
## 185	0	97	3.400	23.00	52	4800
## 186	0	109	3.400	9.00	85	5250
## 187	0	109	3.400	9.00	85	5250
## 188	0	97	3.400	23.00	68	4500
## 189	0	109	3.400	10.00	100	5500
## 190	0	109	3.400	8.50	90	5500
## 191	0	109	3.400	8.50	90	5500
## 192	2	136	3.400	8.50	110	5500
## 193	0	97	3.400	23.00	68	4500
## 194	0	109	3.400	9.00	88	5500
## 195	0	141	3.150	9.50	114	5400
## 196	0	141	3.150	9.50	114	5400
## 197	0	141	3.150	9.50	114	5400
## 198	0	141	3.150	9.50	114	5400
## 199	0	130	3.150	7.50	162	5100
## 200	0	130	3.150	7.50	162	5100
## 201	0	141	3.150	9.50	114	5400
## 202	0	141	3.150	8.70	160	5300
## 203	1	173	2.870	8.80	134	5500
## 204	1	145	3.400	23.00	106	4800
## 205	0	141	3.150	9.50	114	5400
##	price					
## 1	13495.00					
## 2	16500.00					
## 3	16500.00					

## CAR PRICE PREDICTION

44

## 4	13950.00
## 5	17450.00
## 6	15250.00
## 7	17710.00
## 8	18920.00
## 9	23875.00
## 10	17859.17
## 11	16430.00
## 12	16925.00
## 13	20970.00
## 14	21105.00
## 15	24565.00
## 16	30760.00
## 17	41315.00
## 18	36880.00
## 19	5151.00
## 20	6295.00
## 21	6575.00
## 22	5572.00
## 23	6377.00
## 24	7957.00
## 25	6229.00
## 26	6692.00
## 27	7609.00
## 28	8558.00
## 29	8921.00
## 30	12964.00
## 31	6479.00
## 32	6855.00
## 33	5399.00
## 34	6529.00
## 35	7129.00
## 36	7295.00
## 37	7295.00
## 38	7895.00
## 39	9095.00
## 40	8845.00
## 41	10295.00
## 42	12945.00
## 43	10345.00
## 44	6785.00
## 45	8916.50
## 46	8916.50
## 47	11048.00
## 48	32250.00
## 49	35550.00
## 50	36000.00

## CAR PRICE PREDICTION

45

##	51	5195.00
##	52	6095.00
##	53	6795.00
##	54	6695.00
##	55	7395.00
##	56	10945.00
##	57	11845.00
##	58	13645.00
##	59	15645.00
##	60	8845.00
##	61	8495.00
##	62	10595.00
##	63	10245.00
##	64	10795.00
##	65	11245.00
##	66	18280.00
##	67	18344.00
##	68	25552.00
##	69	28248.00
##	70	28176.00
##	71	31600.00
##	72	34184.00
##	73	35056.00
##	74	40960.00
##	75	45400.00
##	76	16503.00
##	77	5389.00
##	78	6189.00
##	79	6669.00
##	80	7689.00
##	81	9959.00
##	82	8499.00
##	83	12629.00
##	84	14869.00
##	85	14489.00
##	86	6989.00
##	87	8189.00
##	88	9279.00
##	89	9279.00
##	90	5499.00
##	91	7099.00
##	92	6649.00
##	93	6849.00
##	94	7349.00
##	95	7299.00
##	96	7799.00
##	97	7499.00

## CAR PRICE PREDICTION

46

```
## 98 7999.00
## 99 8249.00
## 100 8949.00
## 101 9549.00
## 102 13499.00
## 103 14399.00
## 104 13499.00
## 105 17199.00
## 106 19699.00
## 107 18399.00
## 108 11900.00
## 109 13200.00
## 110 12440.00
## 111 13860.00
## 112 15580.00
## 113 16900.00
## 114 16695.00
## 115 17075.00
## 116 16630.00
## 117 17950.00
## 118 18150.00
## 119 5572.00
## 120 7957.00
## 121 6229.00
## 122 6692.00
## 123 7609.00
## 124 8921.00
## 125 12764.00
## 126 22018.00
## 127 32528.00
## 128 34028.00
## 129 37028.00
## 130 31400.50
## 131 9295.00
## 132 9895.00
## 133 11850.00
## 134 12170.00
## 135 15040.00
## 136 15510.00
## 137 18150.00
## 138 18620.00
## 139 5118.00
## 140 7053.00
## 141 7603.00
## 142 7126.00
## 143 7775.00
## 144 9960.00
```

## CAR PRICE PREDICTION

47

```
## 145 9233.00
## 146 11259.00
## 147 7463.00
## 148 10198.00
## 149 8013.00
## 150 11694.00
## 151 5348.00
## 152 6338.00
## 153 6488.00
## 154 6918.00
## 155 7898.00
## 156 8778.00
## 157 6938.00
## 158 7198.00
## 159 7898.00
## 160 7788.00
## 161 7738.00
## 162 8358.00
## 163 9258.00
## 164 8058.00
## 165 8238.00
## 166 9298.00
## 167 9538.00
## 168 8449.00
## 169 9639.00
## 170 9989.00
## 171 11199.00
## 172 11549.00
## 173 17669.00
## 174 8948.00
## 175 10698.00
## 176 9988.00
## 177 10898.00
## 178 11248.00
## 179 16558.00
## 180 15998.00
## 181 15690.00
## 182 15750.00
## 183 7775.00
## 184 7975.00
## 185 7995.00
## 186 8195.00
## 187 8495.00
## 188 9495.00
## 189 9995.00
## 190 11595.00
## 191 9980.00
```

## CAR PRICE PREDICTION

48

```
## 192 13295.00
## 193 13845.00
## 194 12290.00
## 195 12940.00
## 196 13415.00
## 197 15985.00
## 198 16515.00
## 199 18420.00
## 200 18950.00
## 201 16845.00
## 202 19045.00
## 203 21485.00
## 204 22470.00
## 205 22625.00

model4 = lm((price^lambda.opt) ~ CarName + fueltype + drivewheel + enginelocation
+
            wheelbase + carwidth + enginetype + cylindernumber + enginesize +
            stroke + compressionratio + horsepower + peakrpm + CarName:cylindern
umber,
            data = new_data)

new = data.frame(CarName=15, fueltype = 1, drivewheel = 0,
                 enginelocation= 0, wheelbase = 100, carwidth = 7,
                 cylindernumber = 5, enginesize = 250, stroke = 3,
                 compressionratio = 17, horsepower = 18, peakrpm = 4150, enginetype=0)
predict(model4, new, interval = 'prediction', level = 0.95)

##          fit          lwr          upr
## 1 1.882564 1.541358 2.22377
 #(1.541358 2.22377)
predict(model4, new, interval = 'confidence', level = 0.95)

##          fit          lwr          upr
## 1 1.882564 1.548707 2.216421
 #(1.548707 2.216421)
```



