Linear Regression Project

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Introduction about the dataset:

The data set auto-mpg.data contains information for 398 different automobile models. Information regarding the mpg, number of cylinders, displacement, horsepower, weight, acceleration, model year, origin and car name is given. Using this data set we have created two models of linear regression to predict the mpg.

Exploratory Data Analysis & Data Preparation:

The data set contains 5 continuous variables. Horsepower has got 6 missing values which are represented as '?' in the data set. For both single variable and multi-variable linear regressions we have taken mpg as dependent variable.

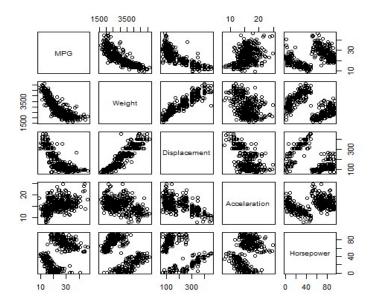
First we have given names for each column and then we have split the data into training set and test set. The training set contains first 300 observations from the original data set and test data set contains last 98 observations from the original data set.

```
names(cardata) <- c("MPG", "Cylinders", "Displacement", "Horsepower", "Weight", "Accelaration", "ModelYear", "Origin", "CarName")
```

```
cardataTraining <- cardata[1:300, ]
cardataTest <- cardata[301:398,]</pre>
```

Before proceeding further we have analyzed the pairs chart for the continuous variables to understand the relationship between them.

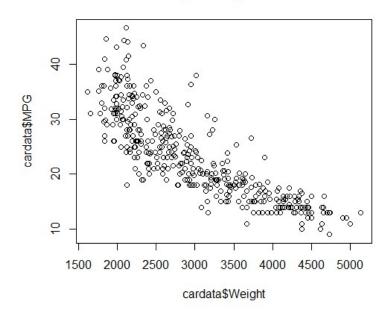
pairs(~ MPG + Weight + Displacement + Accelaration + Horsepower, data=cardata)



To understand the relationship better, we have calculated the correlation between MPG and other continuous variables weight, displacement, acceleration and horsepower. We have also made separate scatter plot for the same.

Weight vs MPG:

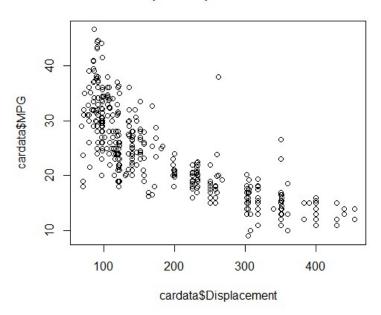
Scatterplot Weight vs MPG



Correlation between Weight and MPG is -0.8317409. Correlation suggests that weight is good candidate for linear regression

Displacement vs MPG:

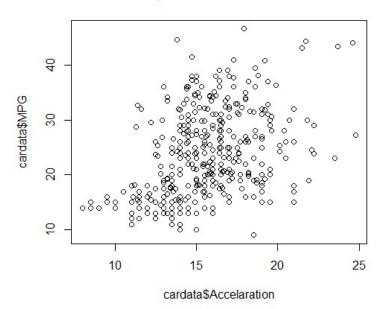
Scatterplot Displacement vs MPG



Correlation between Displacement and MPG is -0.8042028. Correlation suggests displacement may be likely candidate for linear regression. But from the scatterplot it looks like suitable for logistic regression.

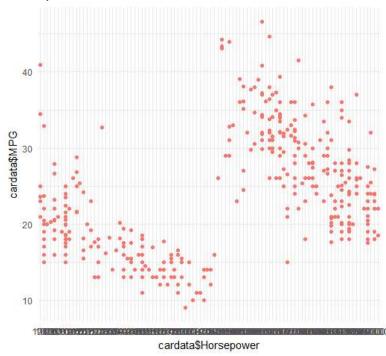
Acceleration vs MPG:

Scatterplot Acceleration vs MPG



Correlation between Acceleration and MPG is 0.4202889. Correlation number suggests there is very little correlation between acceleration and MPG.

Horsepower vs MPG:



Horsepower data contains missing values. So we are not able to compute correlation between horsepower and MPG. But from the scatterplot it looks like horsepower is an unlikely candidate for linear regression.

From the above charts and correlation we chose weight as a predictor of MPG for the single variable linear regression as it has the most correlation and linearity out of the four continuous variables.

Correlation suggests weight and mpg are negatively correlated.

Building Single –Variable Linear Regression model:

cardataLinReg <- Im(MPG ~ Weight, data = cardataTraining)</pre>

Summary of model:

```
Call:
lm(formula = MPG ~ Weight, data = cardataTraining)
Residuals:
   Min
         10 Median
                          3Q
                                Max
-9.1077 -1.8842 -0.0333 1.7275 15.1232
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 40.3879027 0.63688<u>0</u>4
                                63.41 <2e-16 ***
         <2e-16 ***
Weight
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 2.992 on 298 degrees of freedom
Multiple R-squared: 0.7741, Adjusted R-squared: 0.7733
F-statistic: 1021 on 1 and 298 DF, p-value: < 2.2e-16
```

Predicting MPG based on the model:

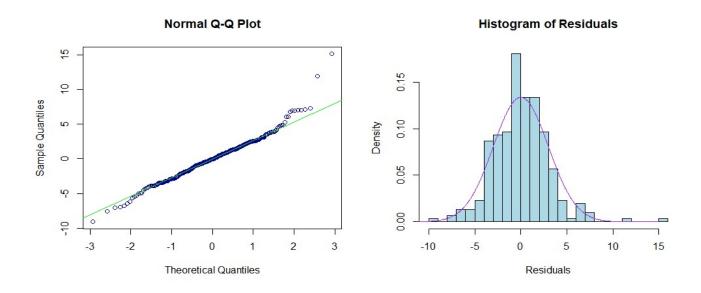
Based on the model built we used the intercept, coefficients and weight from test data set we have predicted MPG.

```
predicted_y_sv_cardata <- cardataLinReg$coefficients[1] +
    cardataLinReg$coefficients[2] * cardataTest$Weight</pre>
```

Calculating Model Error:

```
sv_modelerror <- cardataTest$MPG - predicted_y_sv_cardata</pre>
```

Histogram and QQ-Plot of Residuals



From the qq plot and the histogram of residuals it is clear that the residuals are normally distributed. Therefore it is proved that model is fitting exactly as it is expected.

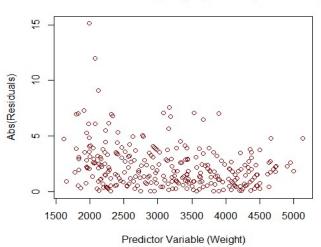
Plots for Residuals:

```
plot(cardataTraining$Weight, cardataLinReg$residuals,
    col = "Dark Green",
    main = "Predictor Variable (Weight) vs. Residuals",
    xlab = "Predictor Variable (Weight)",
    ylab = "Residuals")
plot(cardataTraining$Weight, abs(cardataLinReg$residuals),
    col = "Dark Red",
    main = "Predictor Variable (Weight) vs. Abs(Residuals)",
    xlab = "Predictor Variable (Weight)",
    ylab = "Abs(Residuals)")
```

Predictor Variable (Weight) vs. Residuals

Selding 10 - 1500 2000 2500 3000 3500 4000 4500 5000 Predictor Variable (Weight)

Predictor Variable (Weight) vs. Abs(Residuals)



Building Multi-variable Linear Regression:

Before building a multi variable linear regression we normalized the continuous variables weight, displacement, acceleration to get all the variables in same scale.

Then we have split the dataset into training data set and test data set mod_cardata_train <- mod_cardata[1:300,] mod cardata test <- mod cardata[301:398,]

Then we built 4 different models using different combinations of explanatory variables to predict MPG and explored the summary of those model to choose better combination of explanatory variables.

```
multi_val_reg1 <- lm(MPG ~ norm_wt + norm_disp, data = mod_cardata_train)
multi_val_reg2 <- lm(MPG ~ norm_wt + norm_disp + norm_acc, data =
mod_cardata_train)
multi_val_reg3 <- lm(MPG ~ norm_disp + norm_acc, data = mod_cardata_train)
multi_val_reg4 <- lm(MPG ~ norm_wt + norm_acc, data = mod_cardata_train)
```

Summary of multi – variable linear regression:

```
Call:
lm(formula = MPG ~ norm_wt + norm_disp, data = mod_cardata_train)
Residuals:
   Min
            1Q Median
                           3Q
                                 Max
-9.4362 -1.8464 -0.1621 1.6470 15.2024
Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 21.8453 0.1743 125.347 <2e-16 ***
          -4.1929 0.4465 -9.390 <2e-16 ***
norm_wt
norm_disp
           -1.1827
                     0.4458 -2.653 0.0084 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 2.963 on 297 degrees of freedom
Multiple R-squared: 0.7793, Adjusted R-squared: 0.7778
F-statistic: 524.5 on 2 and 297 DF, p-value: < 2.2e-16
```

We chose the first model (Weight & Displacement as explanatory variable) because out of the four models this is the model with more significance for the explanatory variables.

Predicting MPG based on the model:

```
pred_y_mv_cardata1 <- multi_val_reg1$coefficients[1] +
    multi_val_reg1$coefficients[2]*mod_cardata_test$norm_wt +
    multi_val_reg1$coefficients[3]*mod_cardata_test$norm_disp</pre>
```

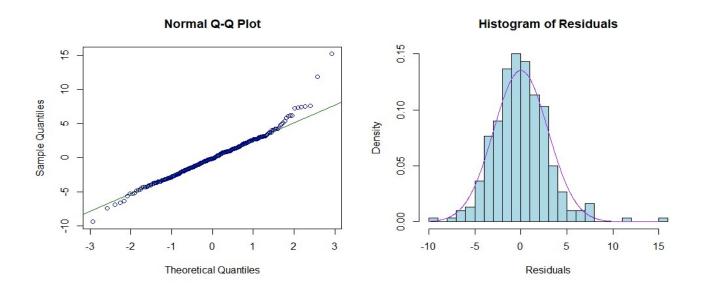
Calculating Model Error:

mv_modelerror <- mod_cardata_test\$MPG - pred_y_mv_cardata1</pre>

Histogram and QQ-Plot of Residuals:

```
hist(multi_val_reg1$residuals, breaks = 30, probability = T, main="Histogram of Residuals", xlab = "Residuals", col = "light blue") x <- seq(-10, 15, length = 1000) y <- dnorm(x, mean = mean(multi_val_reg1$residuals),sd = sd(multi_val_reg1$residuals)) lines(x,y,col="Purple")
```

qqnorm(multi_val_reg1\$residuals, col="Dark Blue")
qqline(multi_val_reg1\$residuals, col="Dark Green")



From the qq plot and the histogram of residuals it is clear that the residuals are normally distributed. Therefore it is proved that model is fitting exactly as it is expected.

Plots for Residuals:

```
plot (mod cardata train$norm wt, multi val reg1$residuals,
   col = "Dark Blue", main = "Residuals vs. Weight",
  xlab = "Weight", ylab = "Residuals")
plot (mod_cardata_train$norm_disp, multi_val_reg1$residuals,
   col = "Dark Blue", main = "Residuals vs. Displacement",
  xlab = "Displacement", ylab = "Residuals")
plot(mod_cardata_train$norm_wt, abs(multi_val_reg1$residuals),
   col = "Dark Blue", main = "Abs. Residuals vs. Weight",
   xlab = "Weight", ylab = "Abs. Residuals")
plot(mod cardata train$norm disp, abs(multi val reg1$residuals),
   col = "Dark Blue", main = "Abs. Residuals vs. Displacement",
   xlab = "Displacement", ylab = "Abs. Residuals")
              Residuals vs. Displacement
                                                                  Residuals vs. Weight
    9
                                                     9
Residuals
                                                 Residuals
                                                     40
                                                     LQ.
                                                     9
                   0
                                      2
                                                              -1
                      Displacement
                                                                         Weight
            Abs. Residuals vs. Displacement
                                                                Abs. Residuals vs. Weight
Abs. Residuals
                                                 Abs. Residuals
                                                     9
```