Report on auto-mpg Data Set

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Abstract

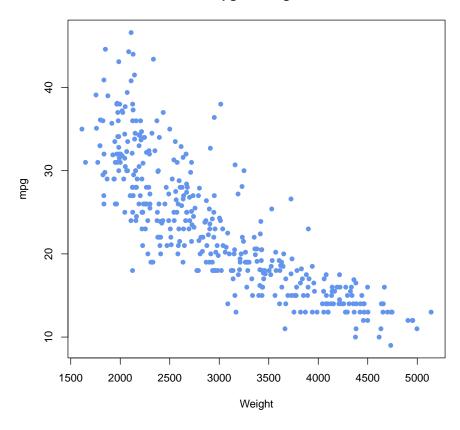
The dataset auto-mpg.csv, comes from the 1983 American Statistical Association Exposition. The response variable of interest is fuel consumption, measured in miles per gallon. Other attributes of cars like the weight, horsepower, number cylinders, and acceleration time were also recorded for each car. We will study the relationship between mpg and weight (in lbs).

We first load the dataset and view the first few entries as well as run a summary:

```
##
                       car.name mpg weight
## 1 chevrolet chevelle malibu
                                       3504
## 2
             buick skylark 320
                                       3693
## 3
            plymouth satellite
                                       3436
## 4
                 amc rebel sst
                                       3433
## 5
                   ford torino
                                 17
                                       3449
## 6
              ford galaxie 500
                                       4341
                                 15
##
      car.name
                                             weight
##
    Length:398
                        Min. : 9.00
                                                :1613
                                        Min.
    Class : character
##
                        1st Qu.:17.50
                                         1st Qu.:2224
##
    Mode :character
                        Median :23.00
                                         Median:2804
##
                        Mean
                               :23.51
                                         Mean
                                                :2970
##
                        3rd Qu.:29.00
                                         3rd Qu.:3608
##
                        Max. :46.60
                                        Max. :5140
```

We can plot a mpg vs. weight scatterplot and find out the relationship between the two variables.

mpg vs. weight



Looking at the plot, we find that a linear model would be a good fit for the dataset. We thus fit a linear model to the data:

```
##
## Call:
## lm(formula = df$mpg ~ df$weight)
##
## Residuals:
##
      Min
                1Q Median
                                3Q
                                       Max
## -12.012 -2.801 -0.351
                             2.114 16.480
##
## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 46.3173644 0.7952452
                                       58.24
                                               <2e-16 ***
## df$weight
               -0.0076766 0.0002575
                                      -29.81
                                               <2e-16 ***
```

```
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ##

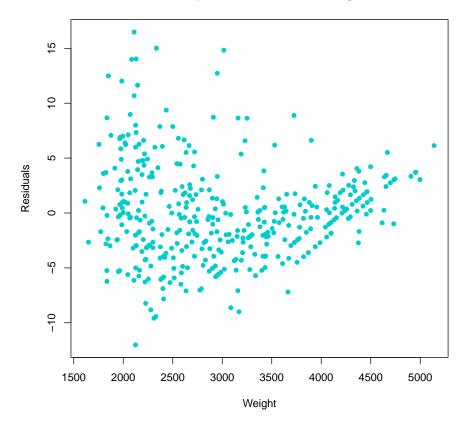
## Residual standard error: 4.345 on 396 degrees of freedom

## Multiple R-squared: 0.6918, Adjusted R-squared: 0.691

## F-statistic: 888.9 on 1 and 396 DF, p-value: < 2.2e-16
```

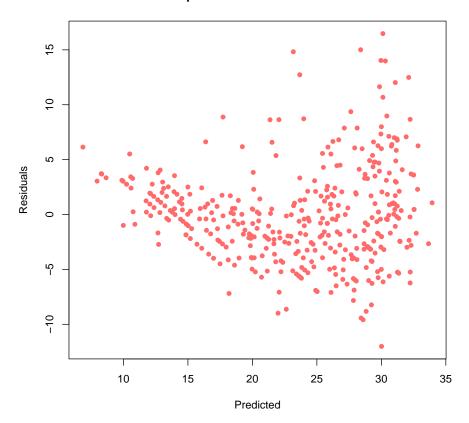
To look at whether our simple linear model assumption is right or not, we might plot the residuals on the y-axis and the predictor variables on the x-axis. The resultant plot is:

Scatterplot of Residuals vs. Weight



We observe that the plot shows a stepped pattern which gives evidence that the simple-linear part in the simple linear model is wrong. Also, the there is a changing width which also points to the fact that the model is mis-specified. Thus, we either need more predictor variables, or a different model, or both. We can derive a similar result using the residual vs predicted value plot:

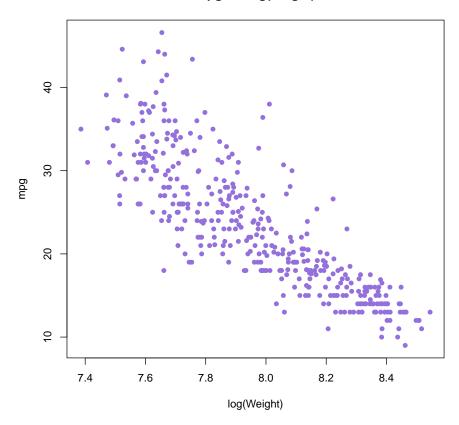
Scatterplot of Residuals vs. Predicted



We observe that this plot is more similar to the previous one. The reason being the predicted values are a function of the covariates and thus, the graphs are similar.

Taking the log transformation of the covariate, we obtaing the following graph:

mpg vs. log(weight)



This is a straight line once again, which suggests that the regression is not linear, but rather exponential. It also suggests that the normality assumption of the error terms was false previously.

We once again fit a linear regression on this transformed data and see if the residuals satisfy the normality assumption:

```
##
## lm(formula = df$mpg ~ log(df$weight))
##
## Residuals:
##
        Min
                  1Q
                       Median
                                     3Q
                                             Max
##
  -12.4676 -2.6558
                      -0.2669
                                 1.9333 15.9770
##
## Coefficients:
##
                  Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 210.5270 5.9763 35.23 <2e-16 ***

## log(df$weight) -23.5032 0.7506 -31.31 <2e-16 ***

## ---

## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1

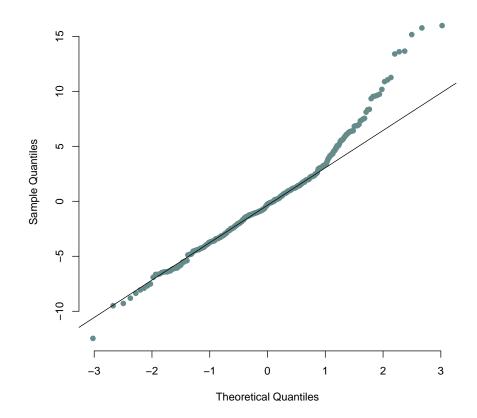
##

## Residual standard error: 4.198 on 396 degrees of freedom

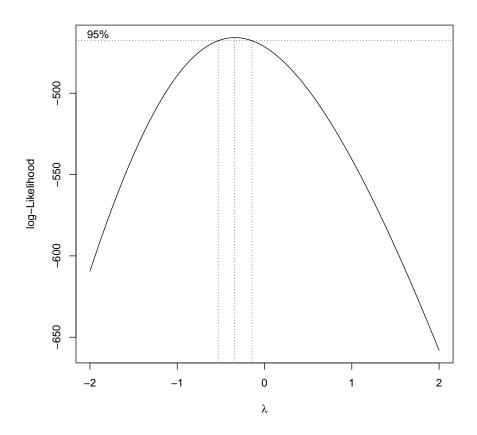
## Multiple R-squared: 0.7123, Adjusted R-squared: 0.7116

## F-statistic: 980.4 on 1 and 396 DF, p-value: < 2.2e-16
```

Normal Q-Q Plot



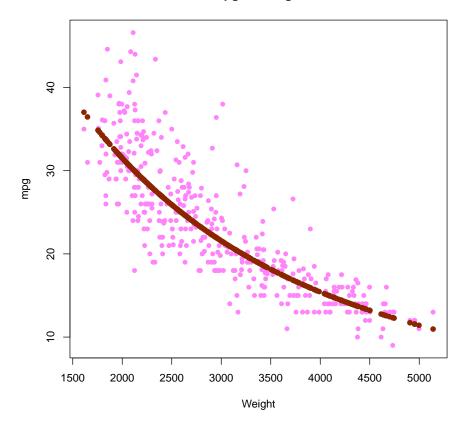
As anticipated, the residuals do not satisfy the normality assumption. Finally, we might use the Box-Cox transformation and refit our model using the appropriate transformation:



[1] -0.3434343

We finally plot our Box-Cox transformed model with our estimated lambda:

mpg vs. weight



Among the three models, the Box-Cox transformed model looks the best fit. The slope of the model infers that if the weight is changed by one unit measure, on an average the mpg would change by (in units):

```
## df$weight
## -0.0001239117
```

We can verify if the association between weight and mpg is linear or not. The null hypothesis being that the correlation is 0 with the alternative being that the correlation is not 0. Under the null hypothesis, the test statistic is

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \sim t_{n-2}$$

where r: sample correlation coefficient and n: number of observations.

We accept the null hypothesis if our p-value of the test > 0.05 else we reject the null hypothesis. In case the null hypothesis is rejected then we might assume that the association between our variables is linear. We apply a correlation test on the variables and the result we obtained are as follows:

```
##
## Pearson's product-moment correlation
##
## data: df$weight and df$bc.mpg
## t = -37.449, df = 396, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.9029842 -0.8593671
## sample estimates:
## cor
## -0.8830687</pre>
```

We observe that the p-value for this test is:

```
## [1] 3.390755e-132
```

which is less than our minimum threshold for accepting the null hypothesis. Thus, with 0.05 level of significance, we reject the null hypothesis that the correlation is 0. Thus, we may safely assume that the there is some level of linear association between our variables.

Further, we might want to find a 90% confidence interval for β ^ of our fitted model. We find that the required confidence interval is:

```
## 5 % 95 %
## df$weight -0.0001293669 -0.0001184565
```

This tells us that if we find the estimated beta 100 times, in 90 of those, our beta would fall within this range.