Week 6 Regression Report Sample

For this sample report, I'll use a portion of R's built-in data set `mtcars`. I created a data file with five of the variables from that set for the purposes of this sample report.

Question

Can we predict the mpg of a car from its engine displacement, horsepower, weight, and number of gears?

Understanding the Data

After loading the data, R created the following summary.

```
      mpg             disp             hp               wt
 Min.   :10.40   Min.   : 71.1   Min.   : 52.0   Min.   :1.513
 1st Qu.:15.43   1st Qu.:120.8   1st Qu.: 96.5   1st Qu.:2.581
 Median :19.20   Median :196.3   Median :123.0   Median :3.325
 Mean   :20.09   Mean   :230.7   Mean   :146.7   Mean   :3.217
 3rd Qu.:22.80   3rd Qu.:326.0   3rd Qu.:180.0   3rd Qu.:3.610
 Max.   :33.90   Max.   :472.0   Max.   :335.0   Max.   :5.424
      gear
 Min.   :3.000
 1st Qu.:3.000
 Median :4.000
 Mean   :3.688
 3rd Qu.:4.000
 Max.   :5.000
```

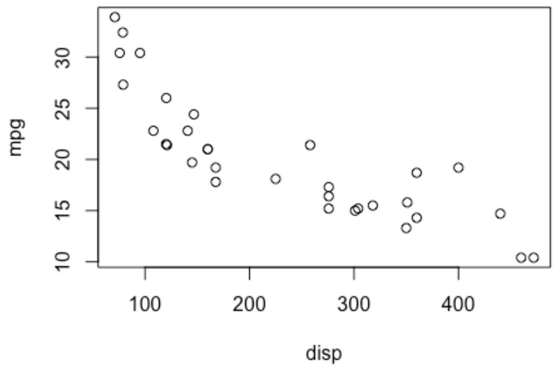
The variable `gear` only has three values which seems to suggest that we should treat it as a categorical variable, not numerical. We specified that gear is a factor in R.

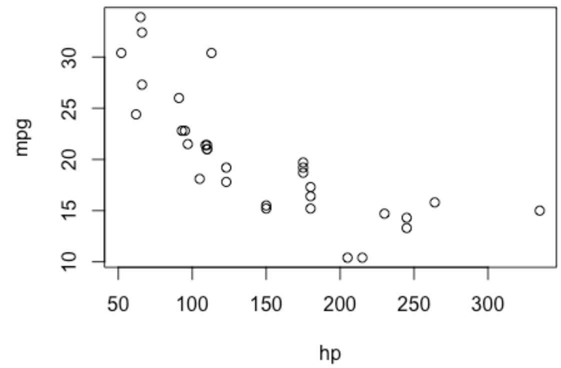
We check the correlation between the other variables.

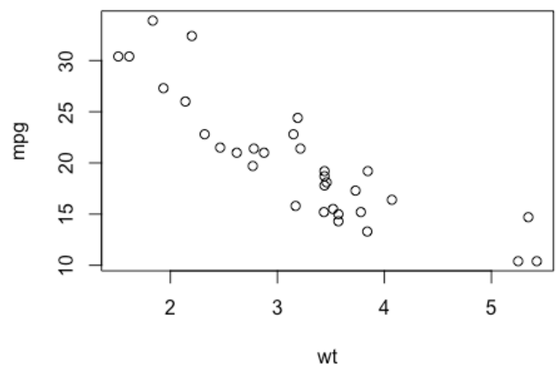
```
            mpg       disp         hp         wt
mpg   1.0000000 -0.8475514 -0.7761684 -0.8676594
disp -0.8475514  1.0000000  0.7909486  0.8879799
hp   -0.7761684  0.7909486  1.0000000  0.6587479
wt   -0.8676594  0.8879799  0.6587479  1.0000000
```

These all seem to have fairly strong linear relationships to `mpg`.

We will produce the scatterplots now.

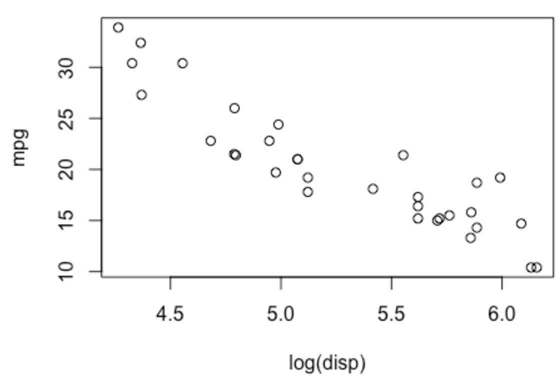




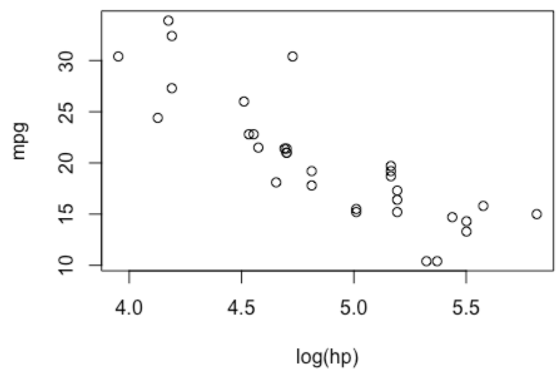


Displacement and horsepower both show some non-linearity. We will transform both and then attempt to build the model.

First we transform `disp` with a log function and store this in a new variable, `log_disp`. The new scatterplot is below.



Next we transform hp with the log function and store this in a variable log_hp. The new scatterplot is below.



These scatterplots show a much more linear relationship. We check the correlation coefficients to verify and see the following values:

```
                mpg   log_disp     log_hp         wt
mpg       1.0000000 -0.9071119 -0.8487707 -0.8676594
log_disp -0.9071119  1.0000000  0.8617723  0.8845389
log_hp   -0.8487707  0.8617723  1.0000000  0.7158277
wt       -0.8676594  0.8845389  0.7158277  1.0000000
```

The correlation coefficients for mpg with both log_disp and log_hp have increased.

Building the Model

Finally we are ready to generate our model. We initially use all variables then use backward elimnation to remove unnecessary variables. Our process eliminates gear, then log_disp, leaving us with the following model.

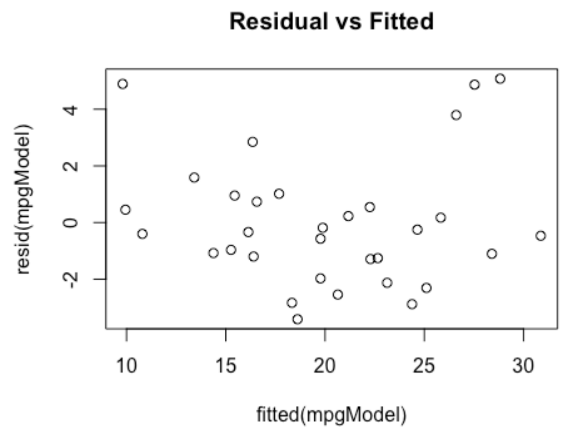
```

Call:
lm(formula = mpg ~ log_hp + wt)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.4130 -1.2642 -0.3679  0.7902  5.0780 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  59.5709     4.9769  11.970 9.64e-13 ***
log_hp       -5.9218     1.2658  -4.678 6.20e-05 ***
wt           -3.2856     0.6148  -5.344 9.74e-06 ***
---
```

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

Residual standard error: 2.339 on 29 degrees of freedom
Multiple R-squared:  0.8591,    Adjusted R-squared:  0.8494
F-statistic: 88.44 on 2 and 29 DF,  p-value: 4.542e-13
```

Both of the remaining variables and the model overall are significant.

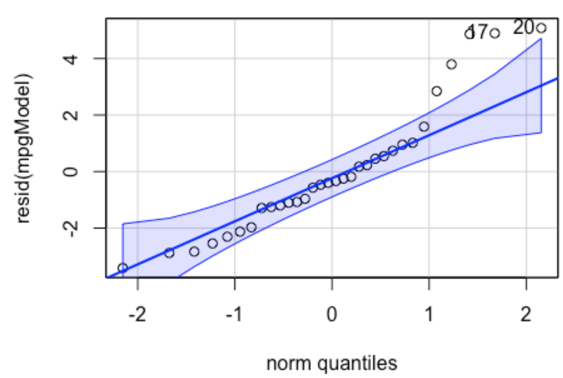
Model Assumptions

We will check model assumptions to see if any more transformations are necessary.



There seems to be some nonlinearity, but the variance seems roughly equal. This is a somewhat worrisome plot.

The qqPlot below shows several points on the large end that leave the dashed lines. This combined with the residual plot above indicates a data transformation would be helpful.



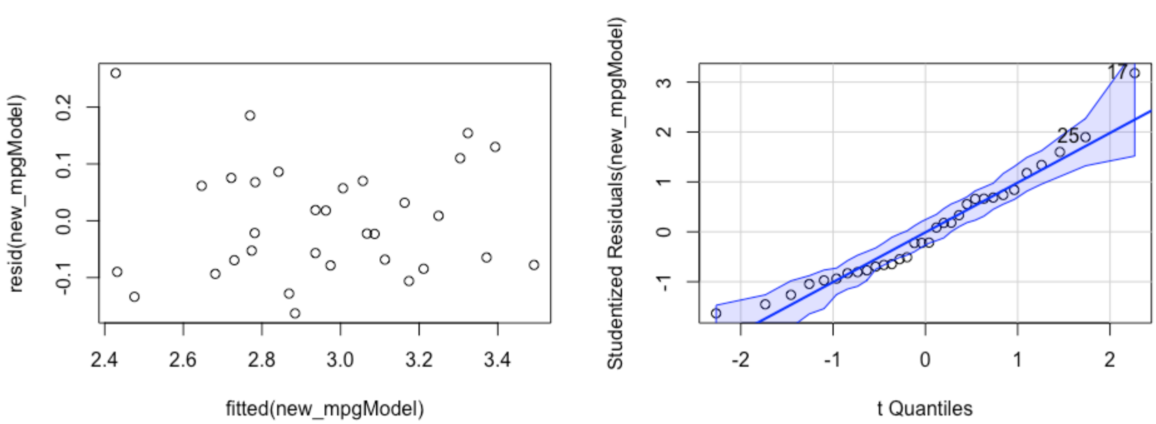
We will perform a `log` transformation on the response variable and create a new variable `log_mpg`.

With this transformed variable, the linear model now looks like this:

```
Call:
lm(formula = log_mpg ~ log_hp + wt)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.16296 -0.07799 -0.02210  0.06837  0.25985 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.83167    0.22198  21.766  < 2e-16 ***
log_hp      -0.26566    0.05646  -4.706 5.75e-05 ***
wt          -0.17942    0.02742  -6.543 3.63e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1043 on 29 degrees of freedom
Multiple R-squared:  0.8852,	Adjusted R-squared:  0.8773 
F-statistic: 111.8 on 2 and 29 DF,  p-value: 2.338e-14
```

So far the model looks better with a slightly larger adjusted R-squared and even smaller p-values for several of the variables.

We now check the model assumptions with residual plots.



These both seem improved. There is no more non-linearity in the residual plot. The normal-probability plot has most of the points very close to the straight line. This seems to be the best model we can construct from this dataset.

Conclusion

Overall the model meets all assumptions and the R-squared value is rather high at 88%. We should be confident in using this model to predict mpg for cars based on their weight and horsepower.