Assignment1114

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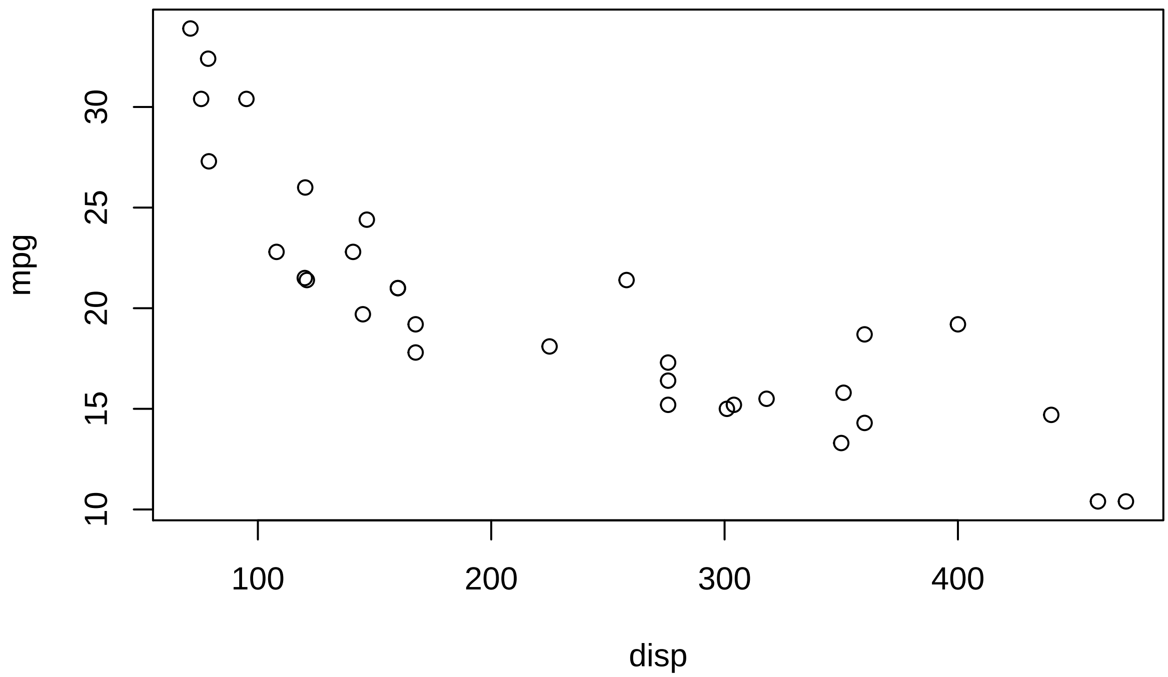
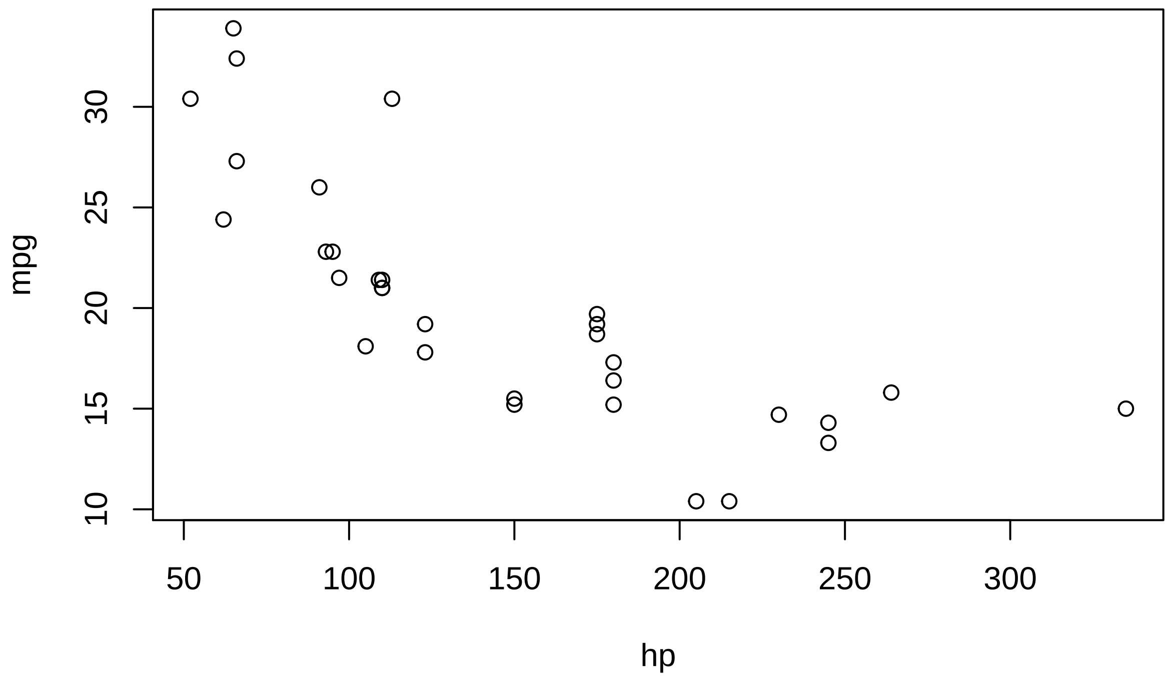
#show equation #don't show code for summary >> {r echo=FALSE}

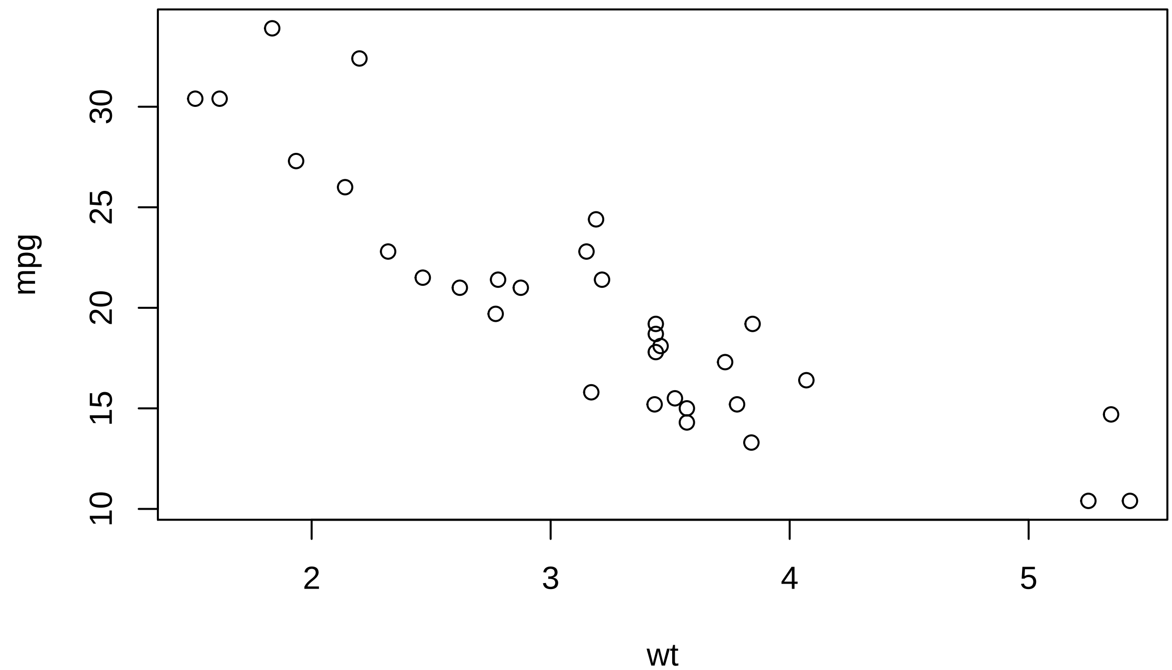
Dependant Variable (Response): mpg Independant Variables (Predictor): disp, hp, wt

First to look into the relationship between the variables we look into the plots:





mpg
30
25
20
15
10
50
100
150
200
250
300
hp



From this, we can assume that mpg and the other variables are in a negative relationship. Next we create a linear model regression with the variables, with mpg as the response variable to see how much each variables contribute in predicting mpg.

```r
stp1<-lm(mpg~disp+hp+wt, data=mtcars)
```

The summary:

```
##
## Call:
## lm(formula = mpg ~ disp + hp + wt, data = mtcars)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -3.891 -1.640 -0.172  1.061  5.861
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 37.105505   2.110815  17.579  < 2e-16 ***
## disp        -0.000937   0.010350  -0.091  0.92851
## hp          -0.031157   0.011436  -2.724  0.01097 *
## wt          -3.800891   1.066191  -3.565  0.00133 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.639 on 28 degrees of freedom
```

```
## Multiple R-squared:  0.8268, Adjusted R-squared:  0.8083
## F-statistic: 44.57 on 3 and 28 DF,  p-value: 8.65e-11
```

The mathematical equation for this is:

mpg = 37.105505 + (-0.000937) * disp + (-0.031157) * hp + (-3.800891) * wt

With this equation we are able to predict the mileage per gallon depending on the disp, hp, wt variables.

However, as disp does not have a significance under 0.05, we leave it out in the next step.

```r
stp2<-lm(mpg~hp+wt, data=mtcars)
```

The summary:

```
##
## Call:
## lm(formula = mpg ~ hp + wt, data = mtcars)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -3.941 -1.600 -0.182  1.050  5.854
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 37.22727    1.59879  23.285  < 2e-16 ***
## hp          -0.03177    0.00903  -3.519  0.00145 **
## wt          -3.87783    0.63273  -6.129 1.12e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.593 on 29 degrees of freedom
## Multiple R-squared:  0.8268, Adjusted R-squared:  0.8148
## F-statistic: 69.21 on 2 and 29 DF,  p-value: 9.109e-12
```

Both variables have a significance level of 99% (p-value < 0.01).

Now we will see how much the variables effect mpg not individually but paired.

```r
stp3<-lm(mpg~hp*wt,data=mtcars)
```

The summary:

```
##
## Call:
## lm(formula = mpg ~ hp * wt, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0632 -1.6491 -0.7362  1.4211  4.5513
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 49.80842    3.60516  13.816 5.01e-14 ***
```

```
## hp          -0.12010    0.02470  -4.863 4.04e-05 ***
## wt          -8.21662    1.26971  -6.471 5.20e-07 ***
## hp:wt        0.02785    0.00742   3.753 0.000811 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.153 on 28 degrees of freedom
## Multiple R-squared:  0.8848, Adjusted R-squared:  0.8724
## F-statistic: 71.66 on 3 and 28 DF,  p-value: 2.981e-13
```

We can see that hp and wt together have a positive relationship to mpg, but the significance level is lower than when calculated individually. Therefore, the interaction between hp and wt can be statistically less significant to consider into the equation.

The final equation of step 3 model looks like this:

mpg = 49.80 + (-0.12010)* hp + (-8.21662) * wt + (0.02785) *(hp:wt)

A change in the value of wt would make the biggest change in the value of mpg.