mtcars Analysis

Overview

The data from mtcars will be looked at and analyzed to determine the relationship between the miles per gallon and whether or not the cars are automatic or manual.

Exploratory Analysis

The data is first loaded and converted to factors

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.1.3
```

```
require(gridExtra)
```

```
## Loading required package: gridExtra
```

```
## Warning: package 'gridExtra' was built under R version 3.1.3
```

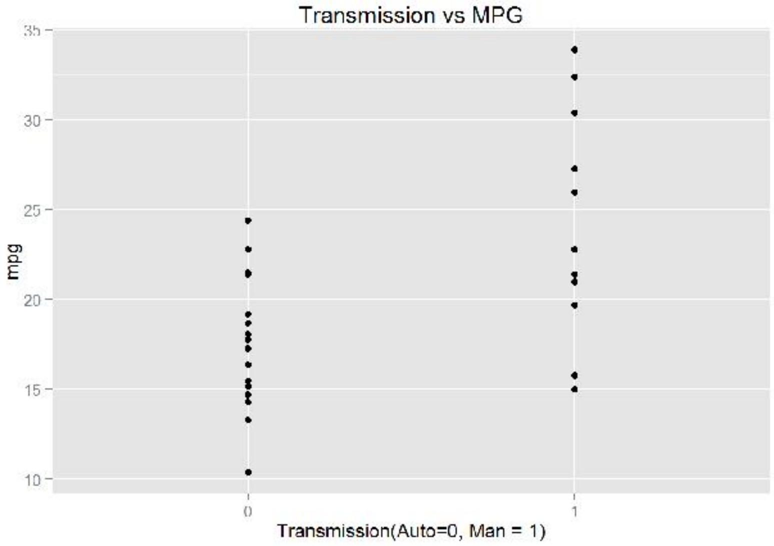
```
## Loading required package: grid
```

```
data(mtcars)

mtcars$am = as.factor(mtcars$am)
mtcars$cyl = as.factor(mtcars$cyl)
mtcars$gear = as.factor(mtcars$gear)
mtcars$carb = as.factor(mtcars$carb)
mtcars$vs = as.factor(mtcars$vs)

auto = subset(mtcars, mtcars$am == 0)
man = subset(mtcars, mtcars$am == 1)
```

A quick plot is setup in order to see how the data is distributed amonst transmission and mpg



As can be seen in the figure above, manual cars appear to have a higher maximum mpg and minimum mpg. The range in mpg widely varies amongst manual cars compared to automatic.

```
t.test(man$mpg, auto$mpg)
```

```
##
##  Welch Two Sample t-test
##
## data:  man$mpg and auto$mpg
## t = 3.7671, df = 18.332, p-value = 0.001374
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##   3.209684 11.280194
## sample estimates:
## mean of x mean of y
##  24.39231  17.14737
```

In addition, as can be seen in the two item T test of both the manual and automatic transmissions, there is a 95% confidence interval of 3.21-11.28 showing that there is likely to be some difference between manual and automatic transmissions. The p value is low enough to reject the notion that there is no difference between mpg amongst transmissions and that manual is better for mpg than automatic. In addition, the difference in the means can be easily seen with manual have an average mpg of 24.39 and automatic have an anverage of 17.1

Regression modeling

```
model1 <- lm(mpg ~ ., data=mtcars)
summary(model1)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5087 -1.3584  0.0948  0.7745  4.6251
##
## Coefficients: (1 not defined because of singularities)
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 22.84530   19.99148   1.143   0.2711
## cyl6         2.64870    3.04089   0.871   0.3975
## cyl8        -0.33616    7.15954  -0.047   0.9632
## disp         0.03555    0.03190   1.114   0.2827
## hp           0.07051    0.03943   1.788   0.0939 .
## drat         1.18283    2.48348   0.476   0.6407
## wt           4.52978    2.53875   1.784   0.0946 .
## qsec         0.36784    0.93540   0.393   0.6997
## vs1          1.93085    2.87126   0.672   0.5115
## am1          1.21212    3.21355   0.377   0.7113
## gear4        1.11435    3.79952   0.293   0.7733
## gear5        2.52840    3.73636   0.677   0.5089
## carb         1.03577    1.19437   0.867   0.3995
## carb2       -2.01510    2.20142  -0.915   0.3745
## carb3        0.91809    3.40346   0.273   0.7885
## carb4        1.31590    1.89037   0.697   0.4965
## carb6       -0.70150    4.25377  -0.165   0.8713
## carb8             NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.833 on 15 degrees of freedom
## Multiple R-squared:  0.8931, Adjusted R-squared:  0.779
## F-statistic:  7.83 on 16 and 15 DF,  p-value: 0.000124
```

A preliminary linear model on the mtcars dataset blindly checking the effect other variables would have on the mpg shows that mpg is not highly dependent on any of the independent variables. However, the coffecient of am is about 2.52023 which means that assuming all other variables remain constant, as the value goes higher(car is manual), there is a greater effect on the mpg. The next model will try using only cofficients which are higher than 1.

```
model2 <- lm(mpg ~ . - cyl - disp - hp - wt - qsec - carb, data=mtcars)
summary(model2)
```

```
##
## Call:
## lm(formula = mpg ~ . - cyl - disp - hp - wt - qsec - carb, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.4446 -1.3311  0.3815  1.7763  5.0663
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  14.9284     6.3091   2.350  0.02695 *
## drat          1.8453     1.8617   0.990  0.33159
## vs1           2.1866     1.7894   1.222  0.23311
## am1           3.4187     2.0136   1.698  0.10195
## gear4         2.4647     2.6494   0.931  0.36094
## gear5         3.6200     3.0971   1.169  0.25351
## carb         -1.8524     0.4976  -3.723  0.00101 **
##
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.897 on 25 degrees of freedom
## Multiple R-squared:  0.8136, Adjusted R-squared:  0.7689
## F-statistic: 18.19 on 6 and 25 DF,  p-value: 5.078e-08
```

```
anova(model1, model2)
```

```
## Analysis of Variance Table
## 
## Model 1: mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb + 
##     car
## Model 2: mpg ~ (cyl + disp + hp + drat + wt + qsec + vs + am + gear + 
##     carb + car) - cyl - disp - hp - wt - qsec - car
##   Res.Df    RSS  Df Sum of Sq      F Pr(>F)
## 1     15 120.40                            
## 2     25 209.85 -10    -89.45 1.1144 0.4116
```

Model2 was built with high coffecients however, as we can see using anova, the new model is not significantly different from the first one.

```
data(mtcars)
sort(cor(mtcars)[1,])
```

```
##         wt        cyl       disp         hp       carb       qsec 
## -0.8676594 -0.8521620 -0.8475514 -0.7761684 -0.5509251  0.4186840 
##       gear         am         vs       drat        mpg 
##  0.4802848  0.5998324  0.6640389  0.6811719  1.0000000
```

The correlation of the data is checked to see which variables are related to mpg. wt, cyl, disp, and hp all appear to be highly correlated to mpg. disp and cyl appear correlated to one another and would be as higher cylinders in a engine would be capable of greater displacement. wt and hp would generally be typical logical guesses to indicators of mpg.

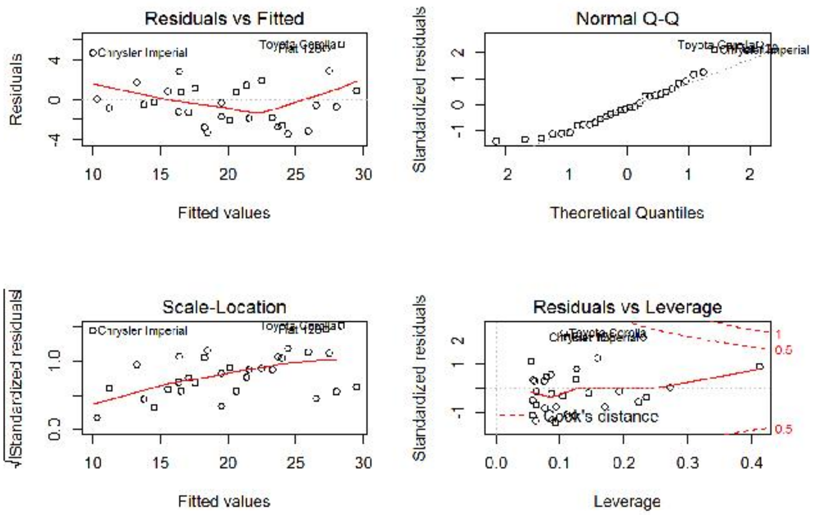
```
model3 <- lm(mpg ~ am + wt + hp, data=mtcars)
summary(model3)
```

```
## 
## Call:
## lm(formula = mpg ~ am + wt + hp, data = mtcars)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -3.4221 -1.7924 -0.3788  1.2249  5.5317 
## 
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 34.002875   2.642659  12.867 2.82e-13 ***
## am           2.083710   1.376420   1.514 0.141268    
## wt          -2.878575   0.904971  -3.181 0.003574 ** 
## hp          -0.037479   0.009605  -3.902 0.000546 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 2.538 on 28 degrees of freedom
## Multiple R-squared:  0.8399, Adjusted R-squared:  0.8227 
## F-statistic: 48.96 on 3 and 28 DF,  p-value: 2.908e-11
```

```
anova(model1, model3)
```

```
## Analysis of Variance Table
## 
## Model 1: mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb + 
##     car
## Model 2: mpg ~ am + wt + hp
##   Res.Df    RSS  Df Sum of Sq      F Pr(>F)
## 1     15 120.40                            
## 2     28 180.29 -13   -59.888 0.5739 0.8394
```

Model3 is not signficantly better than using every variable however, it’s variables in determining the mpg are individually much more significant to determing the mpg.



In addition, the residuals appear normally distributed on the Q-Q graph, and there are no obvious patterns on the residuals vs fitted on the distribution of residuals.