RegMods Assignment

Summary

Manual transmission better for MPG (miles per gallon) than automatic transmission. We did a multivariate regression to improve estimate of transmission types on MPG.

Data Processing

```
data(mtcars)

mtcars$cyl <- as.factor(mtcars$cyl)
mtcars$vs <- as.factor(mtcars$vs)
mtcars$gear <- factor(mtcars$gear)
mtcars$carb <- factor(mtcars$carb)
mtcars$am <- factor(mtcars$am,labels=c('Automatic','Manual'))
str(mtcars)
```

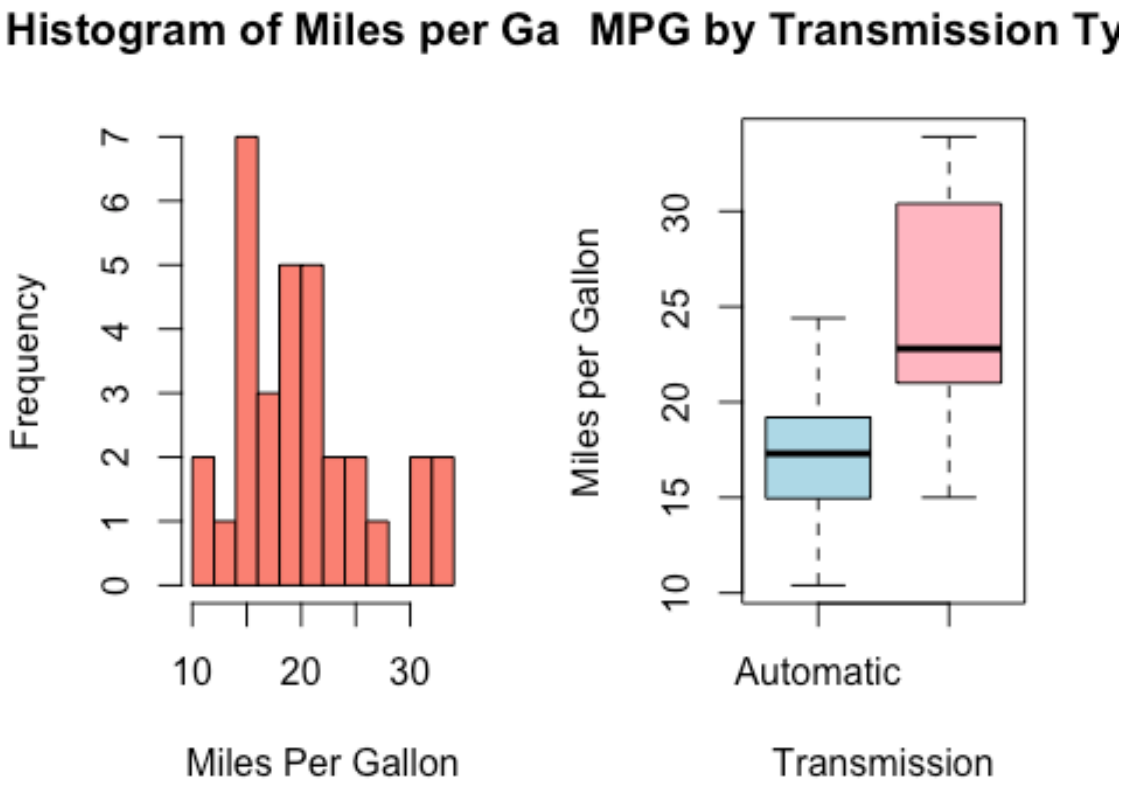
```
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ cyl : Factor w/ 3 levels "4","6","8": 2 2 1 2 3 2 3 1 1 2 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : Factor w/ 2 levels "0","1": 1 1 2 2 1 2 1 2 2 2 ...
##  $ am  : Factor w/ 2 levels "Automatic","Manual": 2 2 2 1 1 1 1 1 1 1 ...
##  $ gear: Factor w/ 3 levels "3","4","5": 2 2 2 1 1 1 1 2 2 2 ...
##  $ carb: Factor w/ 6 levels "1","2","3","4",..: 4 4 1 1 2 1 4 2 2 4 ...
```

EDA

Do a boxplot to examine car transmission types on mpg. We can say there is increase in mpg for manual transmission vs automatic transmission. Also, plot histogram to check for normal curve.

```
par(mfrow = c(1, 2))
# Histogram with Normal Curve
x <- mtcars$mpg
h <- hist(x, breaks=10, col="salmon", xlab="Miles Per Gallon",
        main="Histogram of Miles per Gallon")

boxplot(mpg~am, data = mtcars,
        col = c("light blue", "light pink"),
        xlab = "Transmission",
        ylab = "Miles per Gallon",
        main = "MPG by Transmission Type")
```



Hypotheses Testing

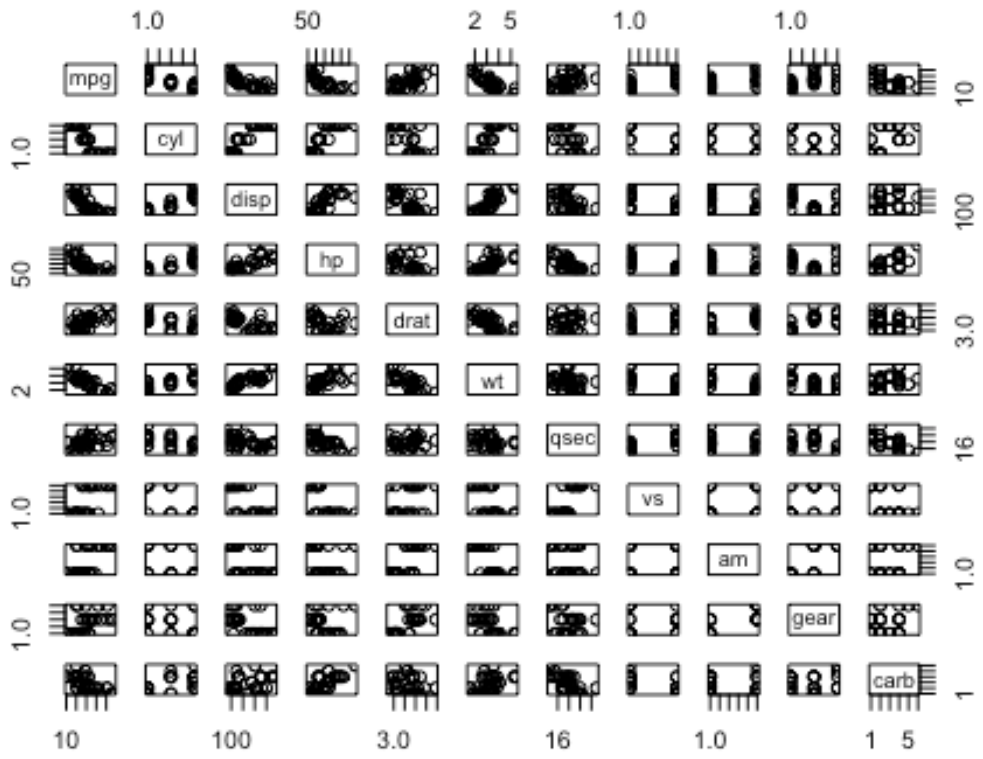
Seems that mean MPG of manual transmission cars is 7.24 MPGs higher than that of automatic transmission cars. We need to check whether this is a significant difference. Set alpha-value at 0.5 and run a t-test to find out.

```
autoData <- mtcars[mtcars$am == "Automatic",]
manualData <- mtcars[mtcars$am == "Manual",]
t.test(autoData$mpg, manualData$mpg)

##
##  Welch Two Sample t-test
##
## data:  autoData$mpg and manualData$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:
##  -11.280194  -3.209684
## sample estimates:
## mean of x mean of y
##  17.14737  24.39231
```

Regression Analysis

```
pairs(mtcars)
```




```
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
```

Based on pairwise correlation of variables with mpg, we see that there is little linear correlation between mpg and the variables qsec, gear, and carb.

Model building and selection

Model1 explains variation less (adjusted R Square: 0.3385) compared to Model2 (adjusted R Square: 0.8066). However, Model1's am variable give lower p-value (less than 0.05) whereas no variable in the model2 gives lower p-value than 0.05 (due to overfitting). Therefore, we use the step method to iterate over the variables and obtain the best model.

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

```
##
## Call:
## lm(formula = mpg ~ am, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.3923 -3.0923 -0.2974  3.2439  9.5077
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   17.147      1.125  15.247 1.13e-15 ***
## am             7.245      1.764   4.106 0.000285 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.902 on 30 degrees of freedom
## Multiple R-squared:  0.3598, Adjusted R-squared:  0.3385
## F-statistic: 16.86 on 1 and 30 DF,  p-value: 0.000285
```

```
model2 <- lm(mpg~., data = mtcars)
summary(model2)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4506 -1.6044 -0.1196  1.2193  4.6271
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 12.30337   18.71788   0.657   0.5181
## cyl         -0.11144    1.04502  -0.107   0.9161
## disp         0.01334    0.01786   0.747   0.4635
## hp          -0.02148    0.02177  -0.987   0.3350
## drat         0.78711    1.63537   0.481   0.6353
## wt          -3.71530    1.89441  -1.961   0.0633 .
## qsec         0.82104    0.73084   1.123   0.2739
## vs           0.31776    2.10451   0.151   0.8814
## am           2.52023    2.05665   1.225   0.2340
## gear         0.65541    1.49326   0.439   0.6652
## carb        -0.19942    0.82875  -0.241   0.8122
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.65 on 21 degrees of freedom
## Multiple R-squared:  0.869,  Adjusted R-squared:  0.8066
## F-statistic: 13.93 on 10 and 21 DF,  p-value: 3.793e-07
```

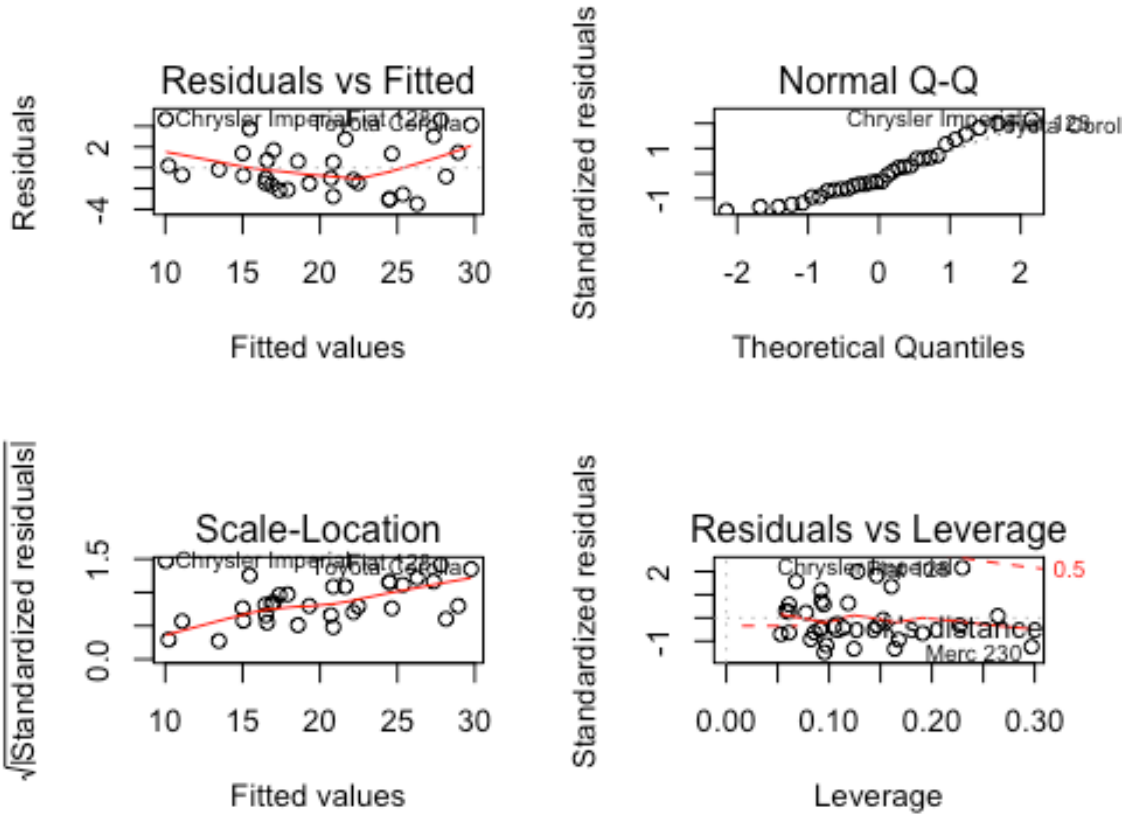
```r
best <- step(model2, direction = "both", trace = FALSE)
summary(best)
```

```
##
## Call:
## lm(formula = mpg ~ wt + qsec + am, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4811 -1.5555 -0.7257  1.4110  4.6610
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.6178     6.9596   1.382 0.177915
## wt           -3.9165     0.7112  -5.507 6.95e-06 ***
## qsec          1.2259     0.2887   4.247 0.000216 ***
## am            2.9358     1.4109   2.081 0.046716 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.459 on 28 degrees of freedom
## Multiple R-squared:  0.8497, Adjusted R-squared:  0.8336
## F-statistic: 52.75 on 3 and 28 DF,  p-value: 1.21e-11
```

Residual diagnostics

Residual are normally distributed and homoskedastic. So, we can report the estimates from our report.

```r
par(mfrow = c(2,2))
plot(best)
```


Residuals vs Fitted
Residuals
Fitted values
Chrysler Imperial
Toyota Corolla
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
0.5
Merc 230