Regression Models

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Motor Trend, a magazine for the automative industry is interested in exploring the relationship between a set of variables and miles per gallon (mpg) as the outcome. They are interested in the following questions, - "Is an automatic or manual transmission better for MPG" - "Quantify the MPG difference between automatic and manual transmissions"

Given is a dataset named mtcars, the goal here is to develop a model with explains the relationship between the variables and mpg. We will build multiple regression models and select the one which has the best outcome.

```
# Loading the required libraries
library(ggplot2)
library(datasets)
library(gridExtra)

#Loading the dataset
data(mtcars)

#Converting the numeric variables to factors
mtcars$cyl <- as.factor(mtcars$cyl)
mtcars$vs <- as.factor(mtcars$vs)
mtcars$am <- as.factor(mtcars$am)
mtcars$gear <- as.factor(mtcars$gear)
mtcars$carb <- as.factor(mtcars$carb)
names(mtcars)[9] <- "Transmission"
levels(mtcars$Transmission) <- c("Automatic","Manual")
```

```
#Regression Model-1 : mpg as outcome and 'am' as the variable
fit_am <- lm(mpg ~ Transmission, data=mtcars)
summary(fit_am)
```

```
##
## Call:
## lm(formula = mpg ~ Transmission, 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 ***
## TransmissionManual    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
```

- In this model, the transmission variable is significant as expected with a p-value of 0.000285. However, this model fails to explain the variance and explains only 33.8% of it. We now try to find a better model and include all variables.

```
#Regression Model-2 : mpg as outcome with all input variables
fit_all <- lm(mpg ~ ., data=mtcars)
summary(fit_all)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5087 -1.3584 -0.0948  0.7745  4.6251
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        23.87913   20.06582   1.190   0.2525
## 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
## TransmissionManual  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
## carb2              -0.97935    2.31797  -0.423   0.6787
## carb3               2.99964    4.29355   0.699   0.4955
## carb4               1.09142    4.44962   0.245   0.8096
## carb6               4.47757    6.38406   0.701   0.4938
## carb8               7.25041    8.36057   0.867   0.3995
## ---
## 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
```

- In this regression model, we include all variables. This model does explain the variance better (77.9%) but doesn't have any significant variable. We will try to change the model and find the significant variables with the backward selection technique.

```
#Regression Model-3 : Backward selection to identify the significant variables
fit_back <- step(fit_all, k=log(nrow(mtcars)))
```

```
summary(fit_back)
```

```
##
```

```
## Call:
## lm(formula = mpg ~ wt + qsec + Transmission, 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 ***
## TransmissionManual   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
```

- With the backward technique, we have identified the variables wt, qsec and Transmission type as the significant variables. This model also explains most of the variance (83.3%). We will select this regression model for quantifying the mpg difference.

"Is an automatic or manual transmission better for MPG"

- As per out third model, we expect a *improvement* in mpg with manual transmission. The boxplot also shows that the mean mpg for manual is better than the mean mpg for automatic transmission.

"Quantify the MPG difference between automatic and manual transmissions"

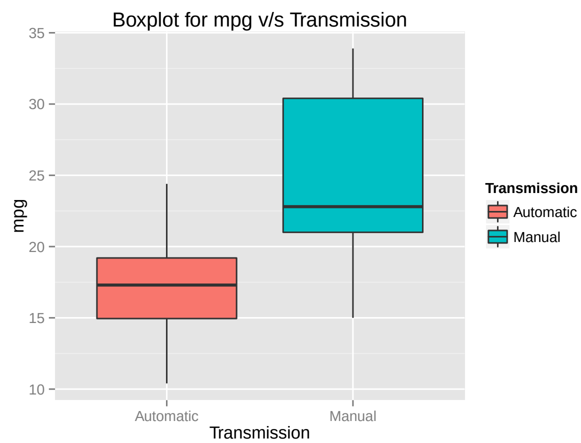
- While selecting the 3rd model, the difference in mpg for manual transmission and automatic transmission is 2.93 mpg (Here the weight wt(lbs/1000) and qsec is kept constant).

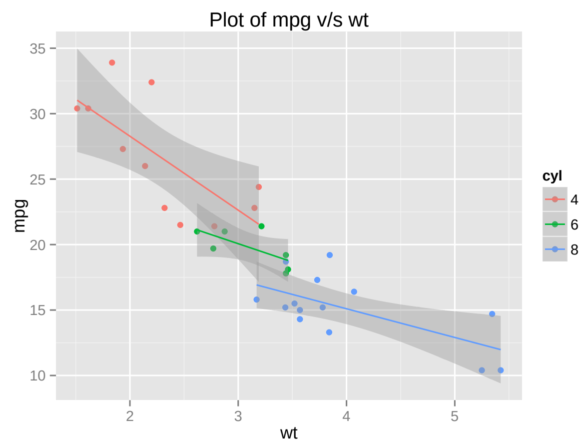
Figures:

```r
# Plot for the relation between mpg and Transmission
g <- ggplot(mtcars, aes(x=Transmission, y=mpg))
g <- g + geom_boxplot(aes(fill=Transmission))
g <- g + labs(title = "Boxplot for mpg v/s Transmission")

g2 <- ggplot(mtcars, aes(x=wt, y=mpg))
g2 <- g2 + geom_point(aes(colour=cyl))
g2 <- g2 + geom_smooth(method=lm, aes(colour=cyl))
g2 <- g2 + labs(title="Plot of mpg v/s wt")

grid.arrange(g, g2, ncol=2)
```






```r
# Plot for for final selection model
par(mfrow = c(2,2))
plot(fit_back)
```