Regression Models Project: Motor Trend MPG Analysis

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Executive Summary

We explore the `Motor Trend Car Road Tests` (mtcars) dataset. We'll analyze this dataset to answer the following questions.

1. "Is an automatic or manual transmission better for MPG"
2. "Quantify the MPG difference between automatic and manual transmissions"

To accomplish this, we will first determine the relationship between the covariates in the `mtcars` data. Next, we build several linear regression models and use model selection techniques to find the "best fit" model. Finally, we perform statistical inference using the "best fit"" model to determine the relationship between MPG and the transmission type after adjusting for statistically significant covariates.

We conclude that both "automatic" and "manual" transmissions have roughly equal MPG after we adjust for for Number of Cylinders, Gross Horsepower and weight. The analysis shows that MPG for a manual transmission decreases by `1.8 mpg` holding other variables constant.

Exploratory Analysis

First, lets load libraries and datasets used in the analysis.

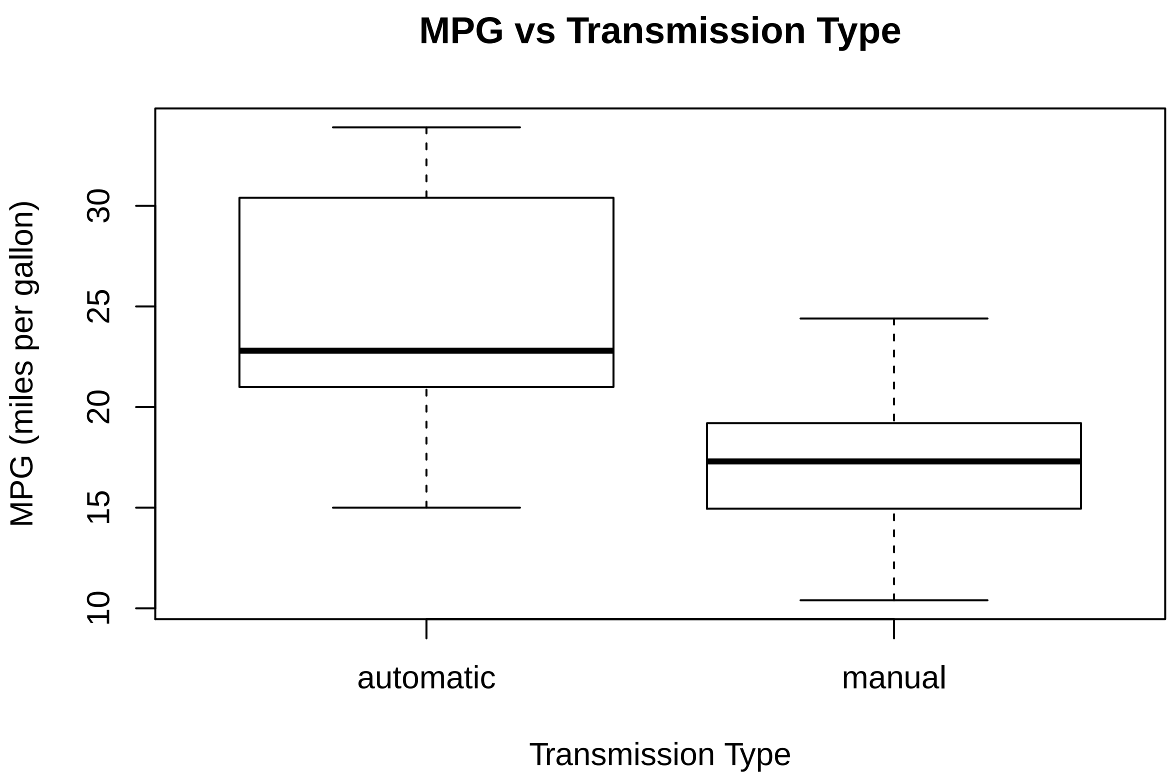
```
library(datasets)
library(ggplot2)
library(dplyr)
data("mtcars")
```

Appendix 1 shows the `mtcars` dataset has 11 variables. Let's change the `am` variable to a factor. This will make the `R` output show the strings 'automatic' where `am == 1` and 'manual' where `am == 0`. We also make `cyl` a factor since its values are only `4` and `6`.

```
mtcars <- mutate(mtcars,
                 am=factor(ifelse(am==1, 'automatic', 'manual')),
                 cyl=as.factor(cyl))
table(mtcars$am)
```

```
##
## automatic    manual
##        13        19
```

The boxplot below shows the group mean is `24.4 mpg` for 'automatic' transmissions and `17.14 mpg` for 'manual' transmissions. The difference in the group means seem significant. However, we will show that the difference is less significant after we adjust for other variables.



Model Selection

Before we can characterize the relationship between mpg and the transmission type (am), we must first search for other variables that can distort, or confound the relationship between the mpg and am. The analysis performed in **Appendix 2** shows that cyl, disp, hp, drat, wt all significantly change the am coeffient when included in a linear model with am. In **Appendix 3**, we generate nested models for am plus these 5 variables then evaluate them using nested likelihood ratio tests.

The "best fit" model includes: am, cyl, hp and wt.

```
best_fit <- lm(mpg ~ am + cyl + hp + wt, data=mtcars)
r_squared <- round(summary(best_fit)$adj.r.squared, digits=3)*100
```

The r.squared value for this model indicates that 84% of the total variablity is explained by the linear relationship between the outcome mpg and the predictors am, cyl, hp and wt.

Finally, in **Appendix 4** we plot the residuals to search for a pattern in the versus the fitted (yhat) values. The plot shows a slight curve in the values - but nothing too bad.

Automatic Vs. Manual Comparison

Now that we have a model containing the necessary covariates, let's calculate the change in mpg for transmission type after adjusting for Number of Cylinders (cyl), Gross Horsepower (hp) and weight (wt). The results show that the mpg for a manual transmission decreases by 1.80 mpg holding other variables constant.

```
summary(best_fit)$coef
```

```
##                Estimate Std. Error   t value     Pr(>|t|)
## (Intercept) 35.51753528 2.03171034 17.481594 6.811749e-16
## ammanual    -1.80921138 1.39630450 -1.295714 2.064597e-01
## cyl6        -3.03134449 1.40728351 -2.154040 4.068272e-02
## cyl8        -2.16367532 2.28425172 -0.947214 3.522509e-01
## hp          -0.03210943 0.01369257 -2.345025 2.693461e-02
## wt          -2.49682942 0.88558779 -2.819404 9.081408e-03
```

However, the confidence interval for `am` ranges from `-4.6` to `1.06`. Because it includes 0, we cannot reject the null hypothesis after adjusting for Number of Cylinders (`cyl`), Gross Horsepower (`hp`) and weight (`wt`). Therefore, we conclude that both “automatic” and “manual” transmissions have roughly equal MPG after we adjust for `cyl`, `hp` and `wt`.

```r
confint(best_fit)
```

```
##                   2.5 %       97.5 %
## (Intercept) 31.34129487 39.693775694
## ammanual    -4.67935639  1.060933628
## cyl6        -5.92405718 -0.138631806
## cyl8        -6.85902199  2.531671342
## hp          -0.06025492 -0.003963941
## wt          -4.31718120 -0.676477640
```

Conclusion

We conclude that both “automatic” and “manual” transmissions have roughly equal MPG after we adjust for for Number of Cylinders (`cyl`), Gross Horsepower (`hp`) and weight (`wt`). The analysis shows that the `mpg` for a manual transmission decreases by `1.8 mpg` holding other variables constant.

Appendix

Appendix 1: mtcars summary

```r
summary(mtcars)
```

```
##       mpg             cyl             disp             hp       
##  Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0  
##  1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5  
##  Median :19.20   Median :6.000   Median :196.3   Median :123.0  
##  Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7  
##  3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0  
##  Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0  
##       drat             wt             qsec             vs        
##  Min.   :2.760   Min.   :1.513   Min.   :14.50   Min.   :0.0000  
##  1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000  
##  Median :3.695   Median :3.325   Median :17.71   Median :0.0000  
##  Mean   :3.597   Mean   :3.217   Mean   :17.85   Mean   :0.4375  
##  3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000  
##  Max.   :4.930   Max.   :5.424   Max.   :22.90   Max.   :1.0000  
```

```
##          am          gear            carb      
##  automatic:13   Min.   :3.000   Min.   :1.000  
##  manual   :19   1st Qu.:3.000   1st Qu.:2.000  
##                 Median :4.000   Median :2.000  
##                 Mean   :3.688   Mean   :2.812  
##                 3rd Qu.:4.000   3rd Qu.:4.000  
##                 Max.   :5.000   Max.   :8.000
```

Appendix 2: covariate selection

Let's "get our hands dirty" and quantify the percentage change in the `am` coefficient when we adjust for all other variables. The output shows that `cyl`, `disp`, `hp`, `drat`, `wt` all change the `am` coeffient by greater than +/- 25%

```r
# baseline
a <- summary(lm(mpg ~ am, data=mtcars))$coef[2]

# calc percent change in the baseline for each covariate
rbind(
  c('baseline', 'cyl', 'disp', 'hp', 'drat', 'wt', 'qsec', 'vs', 'gear', 'carb'),
  round(c((a-a)/a,
    100 * (a - summary(lm(mpg ~ am + cyl, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + disp, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + hp, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + drat, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + wt, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + qsec, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + vs, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + gear, data=mtcars))$coef[2])/a,
    100 * (a - summary(lm(mpg ~ am + carb, data=mtcars))$coef[2])/a
  ), digits=2)
)
```

```
##      [,1]       [,2]    [,3]    [,4]    [,5]    [,6]     [,7]     [,8]   
## [1,] "baseline" "cyl"   "disp"  "hp"    "drat"  "wt"     "qsec"   "vs"   
## [2,] "0"        "64.67" "74.69" "27.16" "61.25" "100.33" "-22.52" "16.26"
##      [,9]   [,10]  
## [1,] "gear" "carb" 
## [2,] "1.43" "-5.63"
```

Appendix 3: model selection

We generate nested models for these `5` variables using and evaluate them using a nested likelihood ratio tests. The results show that models 2, 4 and 6 have the greatest significance. This suggests that `disp` and `drat` should be excluded from the model.

```r
fit1 <- lm(mpg ~ am, data=mtcars)
fit2 <- lm(mpg ~ am + cyl, data=mtcars)
fit3 <- lm(mpg ~ am + cyl + disp, data=mtcars)
fit4 <- lm(mpg ~ am + cyl + disp + hp, data=mtcars)
fit5 <- lm(mpg ~ am + cyl + disp + hp + drat, data=mtcars)
fit6 <- lm(mpg ~ am + cyl + disp + hp + drat + wt, data=mtcars)
anova(fit1, fit2, fit3, fit4, fit5, fit6)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ am
## Model 2: mpg ~ am + cyl
## Model 3: mpg ~ am + cyl + disp
## Model 4: mpg ~ am + cyl + disp + hp
## Model 5: mpg ~ am + cyl + disp + hp + drat
## Model 6: mpg ~ am + cyl + disp + hp + drat + wt
##   Res.Df    RSS Df Sum of Sq       F   Pr(>F)
## 1     30 720.90
## 2     28 264.50  2    456.40 36.4876 5.28e-08 ***
## 3     27 230.46  1     34.04  5.4421  0.02837 *
## 4     26 183.04  1     47.42  7.5822  0.01106 *
## 5     25 182.38  1      0.66  0.1052  0.74847
## 6     24 150.10  1     32.28  5.1614  0.03234 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

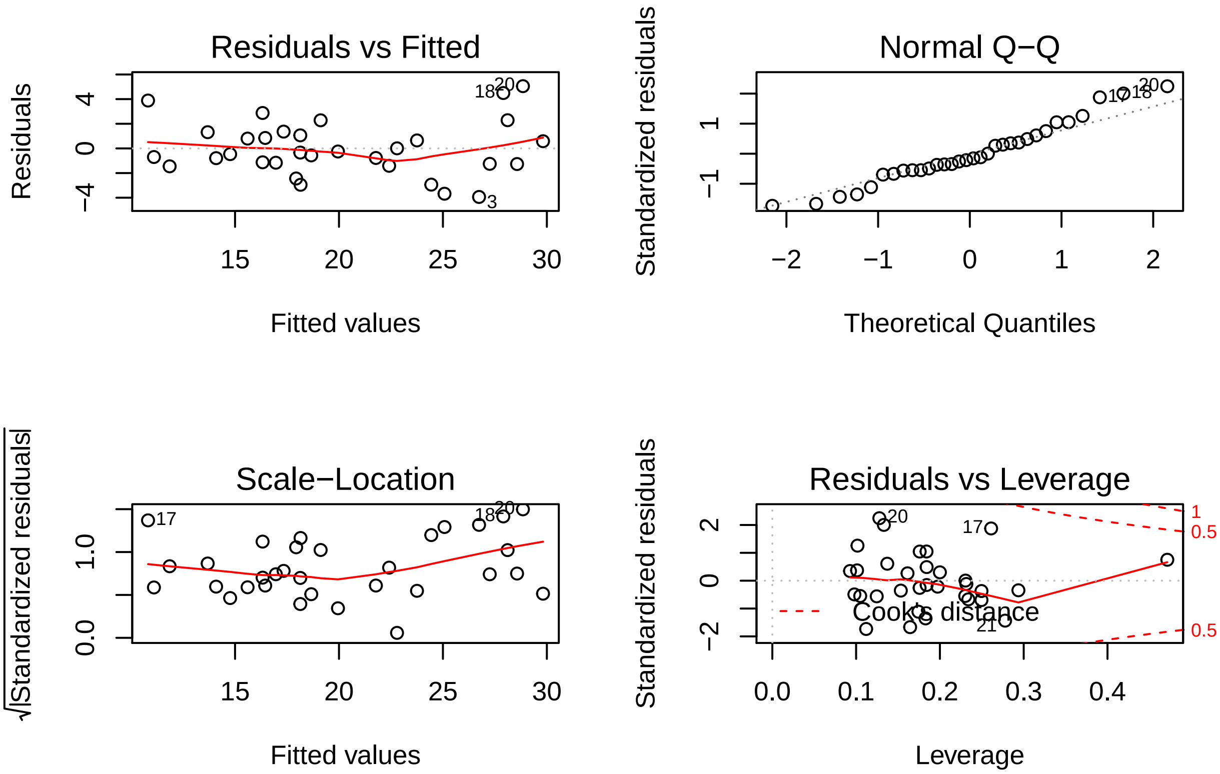
The comparison below shows that a model with the variables: `am`, `cyl`, `hp` and `wt` is a better fit than a model containing only `am`. This is our "best fit" model.

```r
fit1 <- lm(mpg ~ am, data=mtcars)
fit7 <-   lm(mpg ~ am + factor(cyl) + hp + wt, data=mtcars)
anova(fit1, fit7)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ am
## Model 2: mpg ~ am + factor(cyl) + hp + wt
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1     30 720.90
## 2     26 151.03  4    569.87 24.527 1.688e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Appendix 4: residual plot for final model

Finally, we plot the residuals (top left) to search for a pattern in the residuals vs the fitted (yhat) values.


Residuals vs Fitted
Residuals
Fitted values
−4
0
4
15
20
25
30
18
20
3
Normal Q−Q
Standardized residuals
Theoretical Quantiles
−1
1
−2
−1
0
1
2
17
18
20
Scale−Location
√|Standardized residuals|
Fitted values
0.0
1.0
15
20
25
30
17
18
20
Residuals vs Leverage
Standardized residuals
Leverage
−2
0
2
0.0
0.1
0.2
0.3
0.4
20
17
21
Cook's distance
1
0.5
0.5