Relationship Between Automatic and Manual Transmission on MPG

Summary:

Motor Trend, an automobile trend magazine is interested in exploring the relationship between a set of variables and miles per gallon (MPG) outcome. I will analyze the mtcars dataset from the 1974 Motor Trend US magazine to answer the following questions:

(1). Is automatic or manual transmission better for miles per gallon (MPG)?

(2). What is the MPG difference between automatic and manual transmissions?

Using simple linear regression analysis, Ie determine that there is a signficant difference between the mean MPG for automatic and manual transmission cars. Manual transmissions achieve a higher value of MPG compared to automatic transmission. This increase is approximately 1.8 MPG when switching from an automatic transmission to a manual one, with all else held constant.

Data Processing

We begin by loading in the mtcars dataset and transforming certain variables into factors.

```
data(mtcars)
mtcars$cyl  <- factor(mtcars$cyl)
mtcars$vs   <- factor(mtcars$vs)
mtcars$gear <- factor(mtcars$gear)
mtcars$carb <- factor(mtcars$carb)
mtcars$am   <- factor(mtcars$am,labels=c("Automatic","Manual"))
```

Exploratory Data Analysis

I explore various relationships between variables of interest. First, I plotted the relationship between all the variables of the mtcars dataset. I learned from this plot that the variables cyl, disp, hp, drat, wt, vs and am have a strong correlation with mpg (Appendix - Figure 1).

In this analysis, I am interested in the effects of car transmission type on mpg (Appendix - Figure 2). So, I look at the distribution of mpg for each level of AM (Automatic or Manual) by plotting a box plot. This plot depicts that manual transmissions tend to have higher MPG. This data is further analyzed and discussed in regression analysis section by fitting a linear model.

Regression Analysis

In this section, I build a linear regression models using different variables in order to find the best fit and compare it with the base model using Analysis of Variance(ANOVA). After model selection, I also performed analysis of residuals.

```
initialmodel <- lm(mpg ~ ., data = mtcars)
bestmodel <- step(initialmodel, direction = "both")
## Start:  AIC=76.4
## mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb
##
##        Df Sum of Sq    RSS    AIC
## - carb  5   13.5989 134.00 69.828
## - gear  2    3.9729 124.38 73.442
## - am    1    1.1420 121.55 74.705
## - qsec  1    1.2413 121.64 74.732
## - drat  1    1.8208 122.22 74.884
## - cyl   2   10.9314 131.33 75.184
## - vs    1    3.6299 124.03 75.354
## <none>               120.40 76.403
## - disp  1    9.9672 130.37 76.948
## - wt    1   25.5541 145.96 80.562
## - hp    1   25.6715 146.07 80.588
##
## Step:  AIC=69.83
## mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear
##
##        Df Sum of Sq    RSS    AIC
## - gear  2    5.0215 139.02 67.005
## - disp  1    0.9934 135.00 68.064
## - drat  1    1.1854 135.19 68.110
## - vs    1    3.6763 137.68 68.694
## - cyl   2   12.5642 146.57 68.696
## - qsec  1    5.2634 139.26 69.061
## <none>               134.00 69.828
## - am    1   11.9255 145.93 70.556
## - wt    1   19.7963 153.80 72.237
## - hp    1   22.7935 156.79 72.855
## + carb  5   13.5989 120.40 76.403
##
## Step:  AIC=67
## mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am
##
##        Df Sum of Sq    RSS    AIC
## - drat  1    0.9672 139.99 65.227
## - cyl   2   10.4247 149.45 65.319
## - disp  1    1.5483 140.57 65.359
## - vs    1    2.1829 141.21 65.503
## - qsec  1    3.6324 142.66 65.830
## <none>               139.02 67.005
## - am    1   16.5665 155.59 68.608
## - hp    1   18.1768 157.20 68.937
## + gear  2    5.0215 134.00 69.828
## - wt    1   31.1896 170.21 71.482
## + carb  5   14.6475 124.38 73.442
```

```
##
## Step:  AIC=65.23
## mpg ~ cyl + disp + hp + wt + qsec + vs + am
##
##        Df Sum of Sq    RSS    AIC
## - disp  1    1.2474 141.24 63.511
## - vs    1    2.3403 142.33 63.757
## - cyl   2   12.3267 152.32 63.927
## - qsec  1    3.1000 143.09 63.928
## <none>              139.99 65.227
## + drat  1    0.9672 139.02 67.005
## - hp    1   17.7382 157.73 67.044
## - am    1   19.4660 159.46 67.393
## + gear  2    4.8033 135.19 68.110
## - wt    1   30.7151 170.71 69.574
## + carb  5   13.0509 126.94 72.095
##
## Step:  AIC=63.51
## mpg ~ cyl + hp + wt + qsec + vs + am
##
##        Df Sum of Sq    RSS    AIC
## - qsec  1     2.442 143.68 62.059
## - vs    1     2.744 143.98 62.126
## - cyl   2    18.580 159.82 63.466
## <none>              141.24 63.511
## + disp  1     1.247 139.99 65.227
## + drat  1     0.666 140.57 65.359
## - hp    1    18.184 159.42 65.386
## - am    1    18.885 160.12 65.527
## + gear  2     4.684 136.55 66.431
## - wt    1    39.645 180.88 69.428
## + carb  5     2.331 138.91 72.978
##
## Step:  AIC=62.06
## mpg ~ cyl + hp + wt + vs + am
##
##        Df Sum of Sq    RSS    AIC
## - vs    1     7.346 151.03 61.655
## <none>              143.68 62.059
## - cyl   2    25.284 168.96 63.246
## + qsec  1     2.442 141.24 63.511
## - am    1    16.443 160.12 63.527
## + disp  1     0.589 143.09 63.928
## + drat  1     0.330 143.35 63.986
## + gear  2     3.437 140.24 65.284
## - hp    1    36.344 180.02 67.275
## - wt    1    41.088 184.77 68.108
## + carb  5     3.480 140.20 71.275
##
## Step:  AIC=61.65
## mpg ~ cyl + hp + wt + am
##
##        Df Sum of Sq    RSS    AIC
## <none>              151.03 61.655
## - am    1     9.752 160.78 61.657
## + vs    1     7.346 143.68 62.059
## + qsec  1     7.044 143.98 62.126
```

```
## - cyl   2    29.265 180.29 63.323
## + disp  1     0.617 150.41 63.524
## + drat  1     0.220 150.81 63.608
## + gear  2     1.361 149.66 65.365
## - hp    1    31.943 182.97 65.794
## - wt    1    46.173 197.20 68.191
## + carb  5     5.633 145.39 70.438
```

The best model obtained from the above computations shows that variables, cyl, wt and hp as confounders and am as the independent variable. Details of the model are depicted below.

```
summary(bestmodel)
##
## Call:
## lm(formula = mpg ~ cyl + hp + wt + am, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9387 -1.2560 -0.4013  1.1253  5.0513
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.70832    2.60489  12.940 7.73e-13 ***
## cyl6        -3.03134    1.40728  -2.154  0.04068 *
## cyl8        -2.16368    2.28425  -0.947  0.35225
## hp          -0.03211    0.01369  -2.345  0.02693 *
## wt          -2.49683    0.88559  -2.819  0.00908 **
## amManual     1.80921    1.39630   1.296  0.20646
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.41 on 26 degrees of freedom
## Multiple R-squared:  0.8659, Adjusted R-squared:  0.8401
## F-statistic: 33.57 on 5 and 26 DF,  p-value: 1.506e-10
```

The adjusted R-squared value of 0.84 which is the maximum obtained considering all combinations of variables. From these results I concluded that more than 84% of the variability is explained by the above model.

I also compared the base model with only AM as the predictor variable and the best model which I obtained above containing the confounder variables.

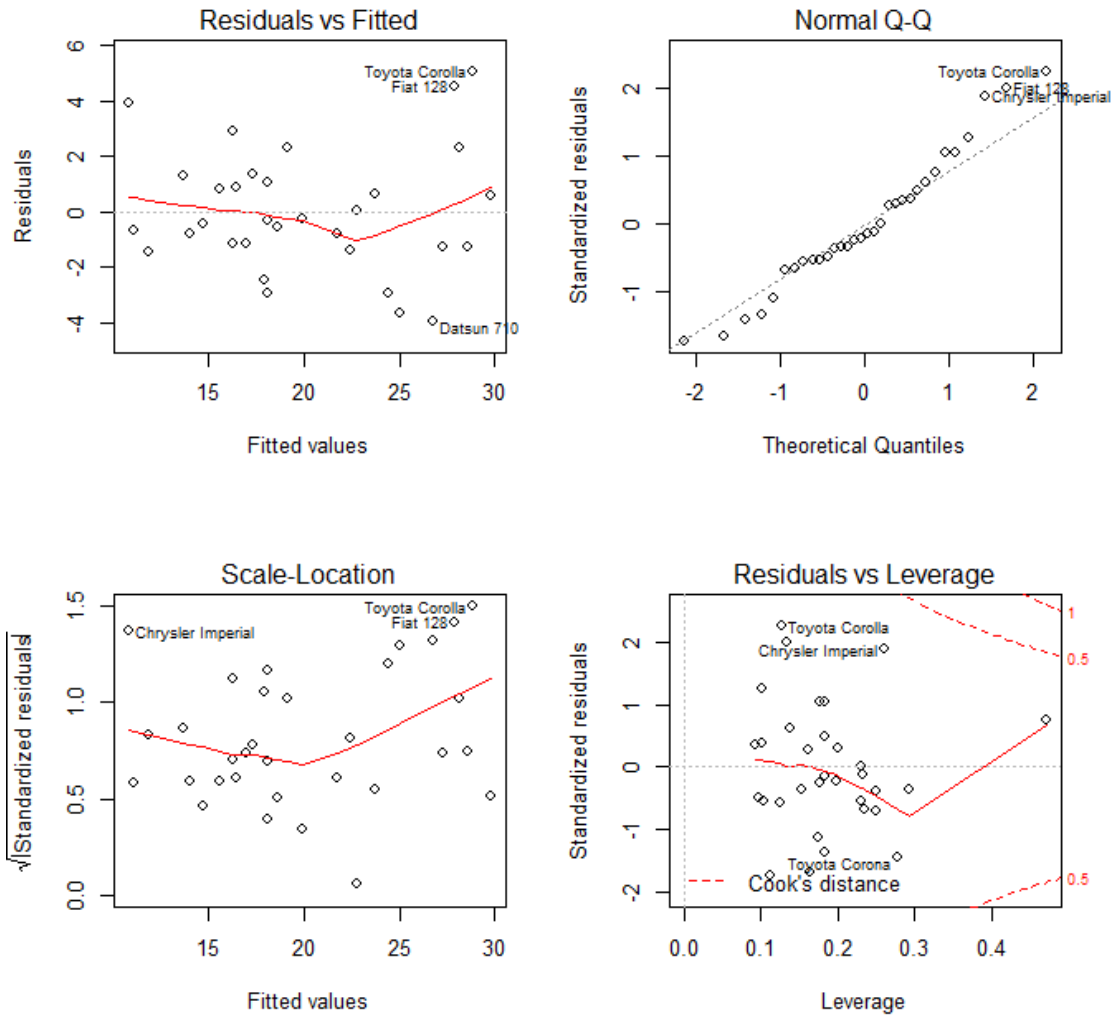
```
basemodel <- lm(mpg ~ am, data = mtcars)
anova(basemodel, bestmodel)
## Analysis of Variance Table
##
## Model 1: mpg ~ am
## Model 2: mpg ~ cyl + hp + wt + am
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1     30 720.90
## 2     26 151.03  4    569.87 24.527 1.688e-08 ***
## ---
## Signif.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

Looking at the above results, the p-value obtained is highly significant and we reject the null hypothesis that the confounder variables cyl, hp and wt don't contribute to the accuracy of the model.

Model Residual and Diagnostics

In this section, I have the residual plots of the regression model along with the computation of regression diagnostics for the liner model. This excercise helped me in examining the residuals and finding leverage points to find any potential problems with the model.

```
par(mfrow=c(2, 2))
plot(bestmodel)
```



The following observations are made from the above plots:
(1).The points in the Residuals vs. Fitted plot are randomly scattered on the plot that verifies the independence condition.

(2). The Normal Q-Q plot consists of the points which mostly fall on the line indicating that the residuals are normally distributed.

(3). The Scale-Location plot consists of points scattered in a constant band pattern, indicating constant variance.

(4).There are some distinct points of interest (outliers or leverage points) in the top right of the plots that may indicate values of increased leverage of outliers.

In the following section, I showed the computation regression diagnostics of the model to find out these leverage points. I computed top three points in each case of influence measures. The data points with the most leverage in the fit that can be found by looking at the hatvalues() and those that influence the model coefficients the most are given by the dfbetas() function.

```
leverage <- hatvalues(bestmodel)
tail(sort(leverage),3)
##       Toyota Corona Lincoln Continental       Maserati Bora
##           0.2777872           0.2936819           0.4713671
influential <- dfbetas(bestmodel)
tail(sort(influential[,6]),3)
## Chrysler Imperial          Fiat 128     Toyota Corona
##         0.3507458         0.4292043         0.7305402
```

Looking at the above results, we notice that our analysis was correct, these are the same cars as mentioned in the residual plots.

Statistical Inference

In this section, I performed a t-test on the two subsets of mpg data: manual and automatic transmission assuming that the transmission data has a normal distribution and tests the null hypothesis that they come from the same distribution. Based on the t-test results, I rejected the null hypothesis that the mpg distributions for manual and automatic transmissions are the same.

```
t.test(mpg ~ am, data = mtcars)
##
##  Welch Two Sample t-test
##
## data:  mpg by am
## 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 in group Automatic    mean in group Manual
##                17.14737                24.39231
```

Conclusions

Based on the analysis done in this project, we can conclude that:

(1). Cars with Manual transmission get 1.8 more miles per gallon compared to cars with Automatic transmission. (1.8 adjusted for hp, cyl, and wt).

(2).mpg will decrease by 2.5 for every 1000 lb increase in wt.

(3). mpg decreases negligibly (only 0.32) with every increase of 10 in hp.

(4). If number of cylinders, cyl increases from 4 to 6 and 8, mpg will decrease by a factor of 3 and 2.2 respectively (adjusted by hp, wt, and am).

Appendix

Figure 1 - Pairs plot for the “mtcars” dataset

```
pairs(mpg ~ ., data = mtcars)
```

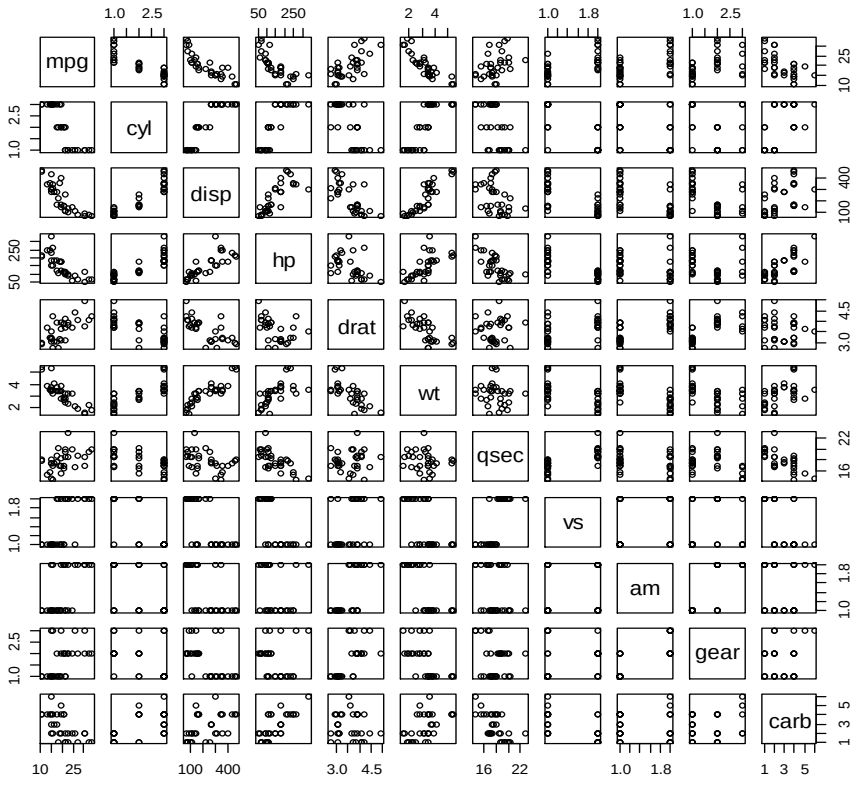


Figure 2 - Boxplot of miles per gallon by transmission type

```
boxplot(mpg ~ am, data = mtcars, col = (c("red","blue")), ylab = "Miles Per
                    Gallon", xlab = "Transmission Type")
```