Regression Model Course Project

Patihe Suip

December 21, 2015

Project Executive Summary

In this project we are to analyze the Motor Trend magazine in exploring the relationship between a set of variables and miles per gallon (MPG) outcome. We will analyze the mtcars dataset from the 1974 Motor Trend US magazine and they are interested in the following two questions:

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

By using simple linear regression analysis, can be determine that 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 was increase is approximately 1.8 MPG when switching from an automatic transmission to a manual, with all else held constant.

Setting-up The Environment

setwd("D:\Data Scientist\Regression models\Regression Project")

Data Processing and Transformation

We loading the datasets mtcars and transforming key fields into factors, in the following section.

```
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 The Data Analysis

First we look at the relationships between mpg and other variables in the dataset, by plotting the scatterplot comparing each pair of variables (see Figure 1 in Appendix).

By Looking at the pairwise scatterplot, we conclude that the following variables are correlated to mpg: - cyl, disp, hp, drat, wt, vs, am and carb. These relationships will be considered when fitting a linear model.

The area of interest is beween am and mpg. An initil check is done at looking at the distribution of mpg for each of the two levels of am (Automation and Manual). This is shown in Figure 2 in Appendix.

By this finding we see that manual transmission have higher mpg value.

Regression Analysis

After that we build linear regression using different variables in order to find the best fit. These are all compared to the initial model that includes all variables.

Model Building and Selection

Based on initial model includes all variables as predictors of mpg. Then we perform stepwise model selection in order to select significant predictors for the final, best model.The step function will perform this selection by calling lm repeatedly to build multiple regression models and select the best variables from them using both forward selection and backward elimination methods using AIC algorithm. This ensures that we have included useful variables while omitting ones that do not contribute significantly to predicting mpg.

```
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 we see that in addition to am, cyl, hp, and wt are all also important variables in predicting mpg, with am as the independent variable while the rest as confounding varaibles.

```r
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 above model adjusted R-squared R^2 value of 0.84 which is the maximum obtained considering all combinations of variables this conclude that more than 84% of the variability is explained by the above model.

We compare the base model with only am as the predictor variable and the best model which we obtained above containing confounder variables also.

```
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 p-value of the best model is very low, meaning that we can confidently reject the null hypothesis that these additional variables do not contribute to the model fit. This is consistent with the previous result that set the best model as it is.

Model Residuals and Diagnostics

This section have the residual plots (see Appendix figure 3) of our regression model along with computation of regression diagnostics for our liner model. This excercise helped us in examining the residuals and finding leverage points to find any potential problems with the model. Following the residual plots (in Appendix):-

-Points in the Residuals vs. Fitted plot are randomly scattered on the plot that verifies the independence condition.

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

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

-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.

We computation of some regression diagnostics of our model to find out these leverage points. We compute top three points in each case of influence measures. The data points with the most leverage in the fit 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
```

Inference

We perform a t-test on the two subsets of mpg data: manual and automatic transmissions. This test assumes that they are each normally distributed and tests the null hypothesis that they come from the same distribution. By default, this performs a two-sided test with ??=0.05 and assuming unequal variances. The t-test results clearly allow us to reject 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
```

Conclusion

Based on the observations from our best fit model, we can conclude that:

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

-mpg will decrease by 2.5 (adjusted by hp, cyl, and am) for every 1000 lb increase in wt

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

-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: Pair plots for mtcars datase

```
pairs(mtcars)
```

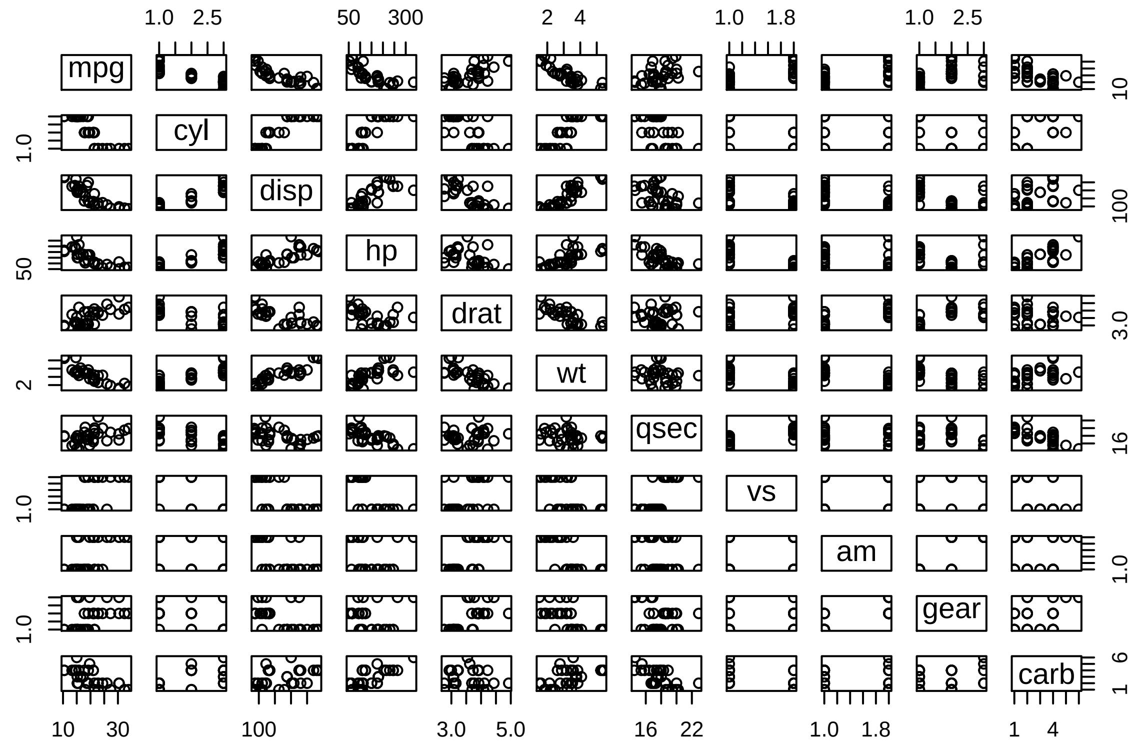


Figure 2: Boxplot of Miles per Gallon (MPG) by Transmission Type (AM)

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

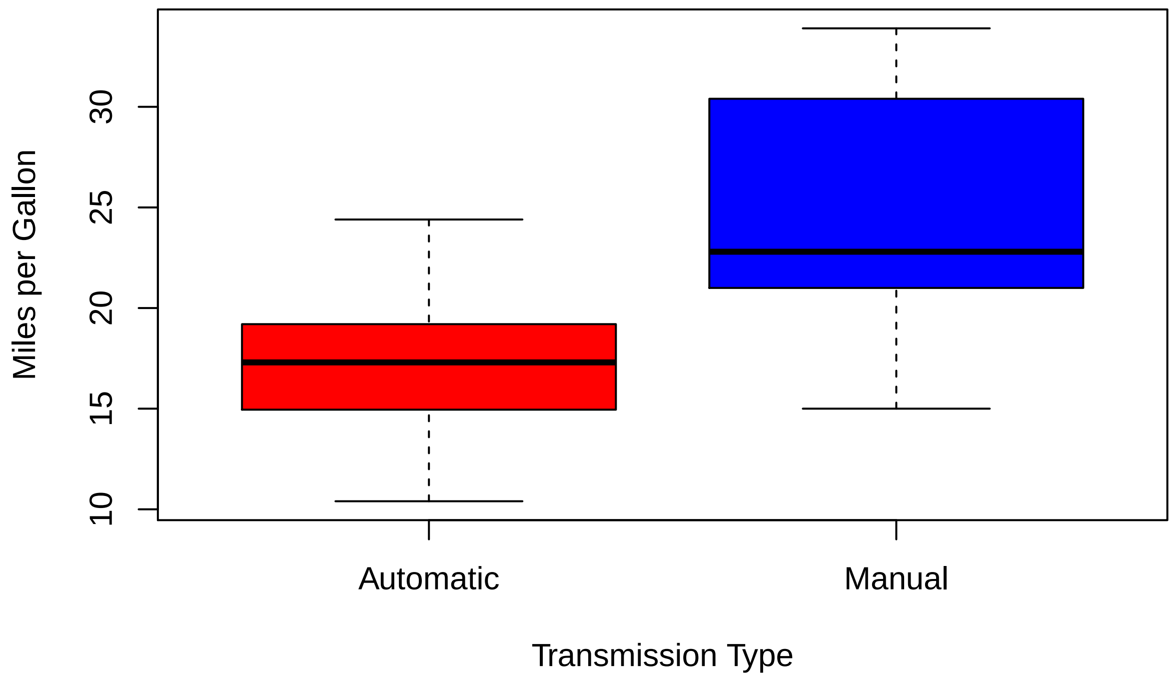
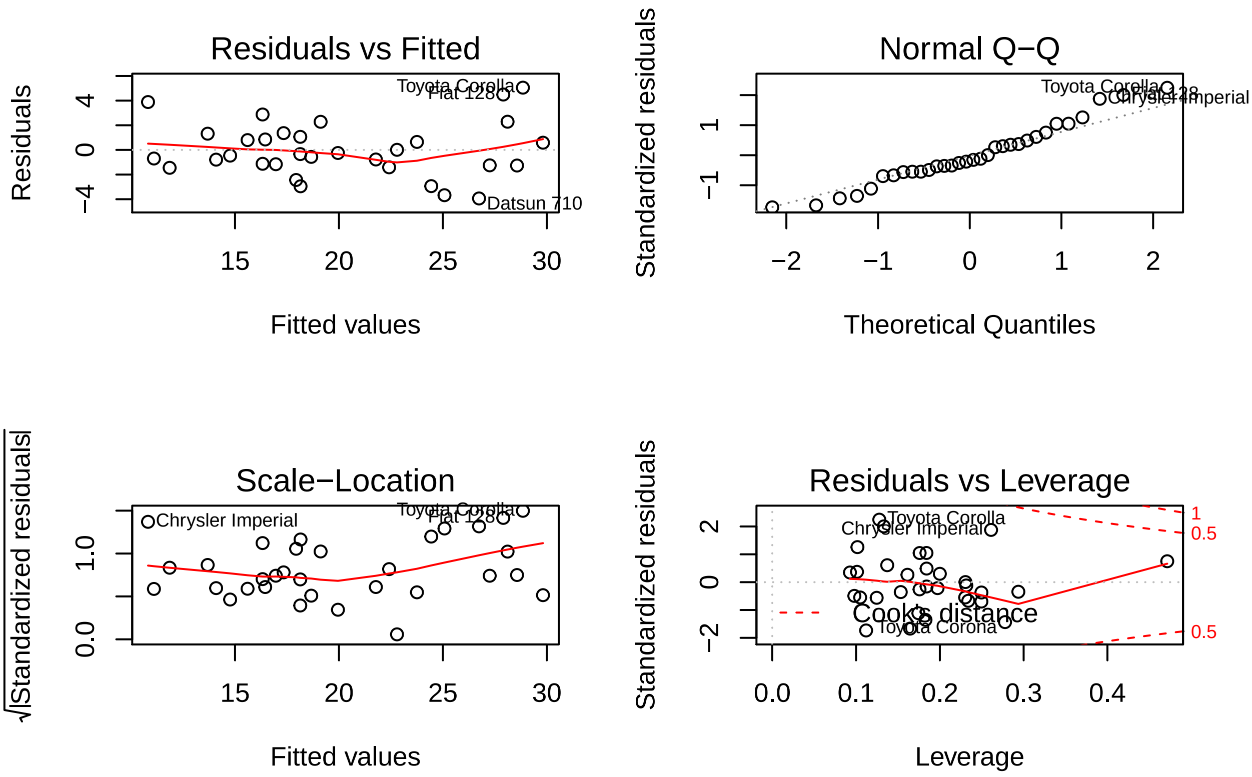


Figure 3: Residual Plots

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


Residuals vs Fitted
Residuals
Fitted values
Toyota Corolla
Fiat 128
Datsun 710
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Chrysler Imperial
Scale−Location
√|Standardized residuals|
Residuals vs Leverage
Leverage
Cook's distance
Toyota Corona