# Regression: MotorTrend MPG

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## Executive Summary

We were asked by Motor Trend to help understand the relationship between a number of variables, predictors, and miles-per-gallon (MPG), outcome, Specifically, were are asked to answer the following two questions:

- Is an automatic or manual transmission better for MPG?
- Quantify the MPG difference between automatic and manual transmissions"

By performing regression analysis, we obtained a model indicating a 1.81 mpg increase with switching from an automatic to manual. The analysis provided below supports this conclusion.

## Data Processing

Use data(mtcars) to load the R dataset into the current enviromnent.

```
data(mtcars)
mtcars2 <- mtcars
mtcars2$am <- as.factor(mtcars2$am)
mtcars2$cyl <- as.factor(mtcars2$cyl)
```

## Exploratory Data Analysis

To obtain a high-level insight to the relationship of the different variables in the data set, we created a panel plot and correlation matrix (see Appendix: Figure 1 & Figure 2) to understand the relationships. We find that the variables cyl, disp, hp, and wt have the strongest relationship with mpg.

## Regression Analysis

Here we look build and compare various regression models to identify a model that best fits data. We use several metrics to evaluate our model fit, including: adjusted r-square, residual squared error (sigma), and p-values. We also use ANOVA and an analysis of the residuals to evaluate the model.

### Regression Models

Approached building mdoels by selecting variables likely contribute significantly to predicting MPG.

```
fit1 <- lm(mpg ~ am, data = mtcars2)
fit10 <- lm(mpg ~ ., data = mtcars2)
bestfit <- step(fit10, direction = "both")   ## stepwise process to identify best fit

## Obtained by manually adding / removing variables (using correlations as guide)
fit3 <- lm(mpg ~ am + wt + cyl, data = mtcars2)
fit4 <- lm(mpg ~ am + wt + cyl + hp, data = mtcars2)
```

### Comparison of Regression Models

Two comparisons performed to evaluate the best model. The first is a comparison of the r.square and p-value for each model. Then, we perform ANOVA test to evaluate whether model is significantly better.

Exhbit 1: R.Square, Sigma, and P-value Comparisons

```
##     model r.squared adj.r.squared  sigma statistic p.value df
## 1    fit1    0.3598        0.3385 4.9020   16.8603   3e-04  2
## 2    fit3    0.8375        0.8134 2.6032   34.7917   0e+00  5
## 3    fit4    0.8659        0.8401 2.4101   33.5712   0e+00  6
## 4 bestfit    0.8497        0.8336 2.4588   52.7496   0e+00  4
## 5   fit10    0.8816        0.8165 2.5819   13.5381   0e+00 12
```

Exhibit 2: ANOVA

```
## Analysis of Variance Table
##
## Model 1: mpg ~ am
## Model 2: mpg ~ am + wt + cyl
## Model 3: mpg ~ am + wt + cyl + hp
##   Res.Df    RSS Df Sum of Sq       F    Pr(>F)
## 1     30 720.90
## 2     27 182.97  3    537.93 30.8692 1.008e-08 ***
## 3     26 151.03  1     31.94  5.4991   0.02693 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

# Residuals & Diagnostics

Understanding residuals is critical to understanding how well the regression model fits the data. The different plots (see Appendix: Figure 3) provide some insight to how closely the regression line fits the data. Although a few “outlier” points noted, the results seem to validate model fit.

1. Residuals vs Fitted: This plot shows if residuals have non-linear patterns. Want to see that the residuals are fairly well-distributed around the fitted line, and no particular pattern exists.
2. Normal Q-Q: This plot shows if residuals are normally distributed. It’s good fit if residuals are lined closely the straight dashed line.
3. Scale-Location: Use to check the assumption of equal variance (homoscedasticity). Ideally, we would see points that are equally spread around a horizontal line along the entire range of predictors.
4. Cooks distance: The purpose of this plot is identify may be considered outliers. The “Cooks distance” is considerably different from others. These points may be influential against the regression line, changing intercept and/or slope.

## High Leverage/Influential Data Points

We use the function influence.measures() to help identify points/observations that may need to be considered.

```
## Potentially influential observations of
##   lm(formula = mpg ~ am + wt + cyl + hp, data = mtcars2) :
##
##                     dfb.1_ dfb.am1 dfb.wt dfb.cyl6 dfb.cyl8 dfb.hp dffit
## Lincoln Continental  0.16  -0.09   -0.19   0.06     0.04     0.04  -0.22
## Maserati Bora       -0.18   0.04   -0.09  -0.14    -0.25     0.53   0.70
##                     cov.r   cook.d hat
## Lincoln Continental  1.74_*  0.01   0.29
## Maserati Bora        2.10_*  0.08   0.47
```

# Statistical Inference

To provide additional perspective on the strength of the model in predicting, a comparison of the actual MPG to the fitted mpg and associated 95% confidence interval to look at how well the model estimated results. While there are a few instances (see Appendix: Figure 4) where the actual MPG falls outside the

95% confidence interval, a majority fit the model.

# Conclusion

The regression model, fit4, provides the best fit, explaining 84% of the changes in MPG. Outline of coefficients:
1. Intercept [33.71] - estimate of MPG for an average wt & hp car with 4 cyl car and automatic transmission
2. am1 - MPG increases 1.81 mpg for switching to a manual transmission, all else equal
3. wt - reduces MPG by 2.5 for a 1 unit (1,000 lbs) change in the weight of a car, all else equal
4. cyl6 - a switch from a 4 cyl to 6 cyl decreases MPG by 3.03, all else equal
5. cyl8 - a switch from a 4 cyl to 8 cyl decreases MPG by 2.16, all else equal (less than 6 cyl?) 6. hp - a 1 unit change in hp reduces MPG by 0.03, all else equal

## Regression Coefficients

```
## (Intercept)         am1          wt        cyl6        cyl8          hp
##       33.71        1.81       -2.50       -3.03       -2.16       -0.03
```

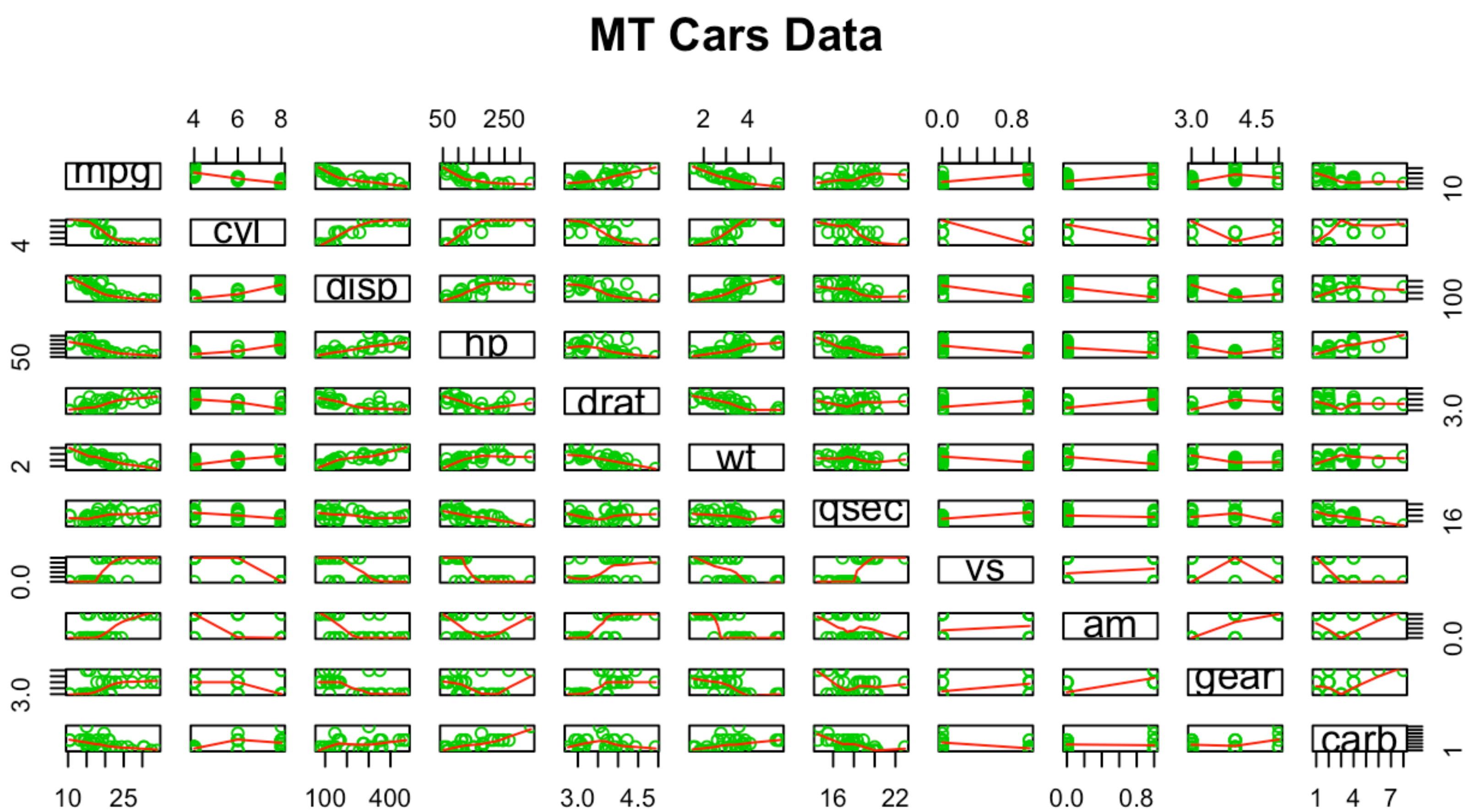
Although there may more that can be learned about interaction between cyl (cyl8) and hp, this model produces a fairly reliable approach to predicting the MPG of a car. With a larger population and/or more detailed look at values within a variable, it may be possible to create a better model. This creates the risk of overfitting to reduce residuals, but not necessarily improving the applicability of the model.

# Appendix

## Figure 1: Illustrate the relationship of each variable

A panel plot of the relationship of each variable to another within the 'mtcars' data set.

```
pairs(mtcars, panel = panel.smooth, main = "MT Cars Data", col = 3)
```




## Figure 2: Correlation Factor Matrix

```
mtcars.cor <- round(cor(mtcars), 3)
mtcars.cor
```

```
##         mpg    cyl   disp     hp   drat     wt   qsec     vs     am   gear
## mpg   1.000 -0.852 -0.848 -0.776  0.681 -0.868  0.419  0.664  0.600  0.480
## cyl  -0.852  1.000  0.902  0.832 -0.700  0.782 -0.591 -0.811 -0.523 -0.493
## disp -0.848  0.902  1.000  0.791 -0.710  0.888 -0.434 -0.710 -0.591 -0.556
## hp   -0.776  0.832  0.791  1.000 -0.449  0.659 -0.708 -0.723 -0.243 -0.126
## drat  0.681 -0.700 -0.710 -0.449  1.000 -0.712  0.091  0.440  0.713  0.700
## wt   -0.868  0.782  0.888  0.659 -0.712  1.000 -0.175 -0.555 -0.692 -0.583
## qsec  0.419 -0.591 -0.434 -0.708  0.091 -0.175  1.000  0.745 -0.230 -0.213
## vs    0.664 -0.811 -0.710 -0.723  0.440 -0.555  0.745  1.000  0.168  0.206
## am    0.600 -0.523 -0.591 -0.243  0.713 -0.692 -0.230  0.168  1.000  0.794
## gear  0.480 -0.493 -0.556 -0.126  0.700 -0.583 -0.213  0.206  0.794  1.000
## carb -0.551  0.527  0.395  0.750 -0.091  0.428 -0.656 -0.570  0.058  0.274
##        carb
## mpg  -0.551
## cyl   0.527
## disp  0.395
## hp    0.750
## drat -0.091
## wt    0.428
## qsec -0.656
## vs   -0.570
## am    0.058
## gear  0.274
## carb  1.000
```

Figure 3: Regression Model Residuals

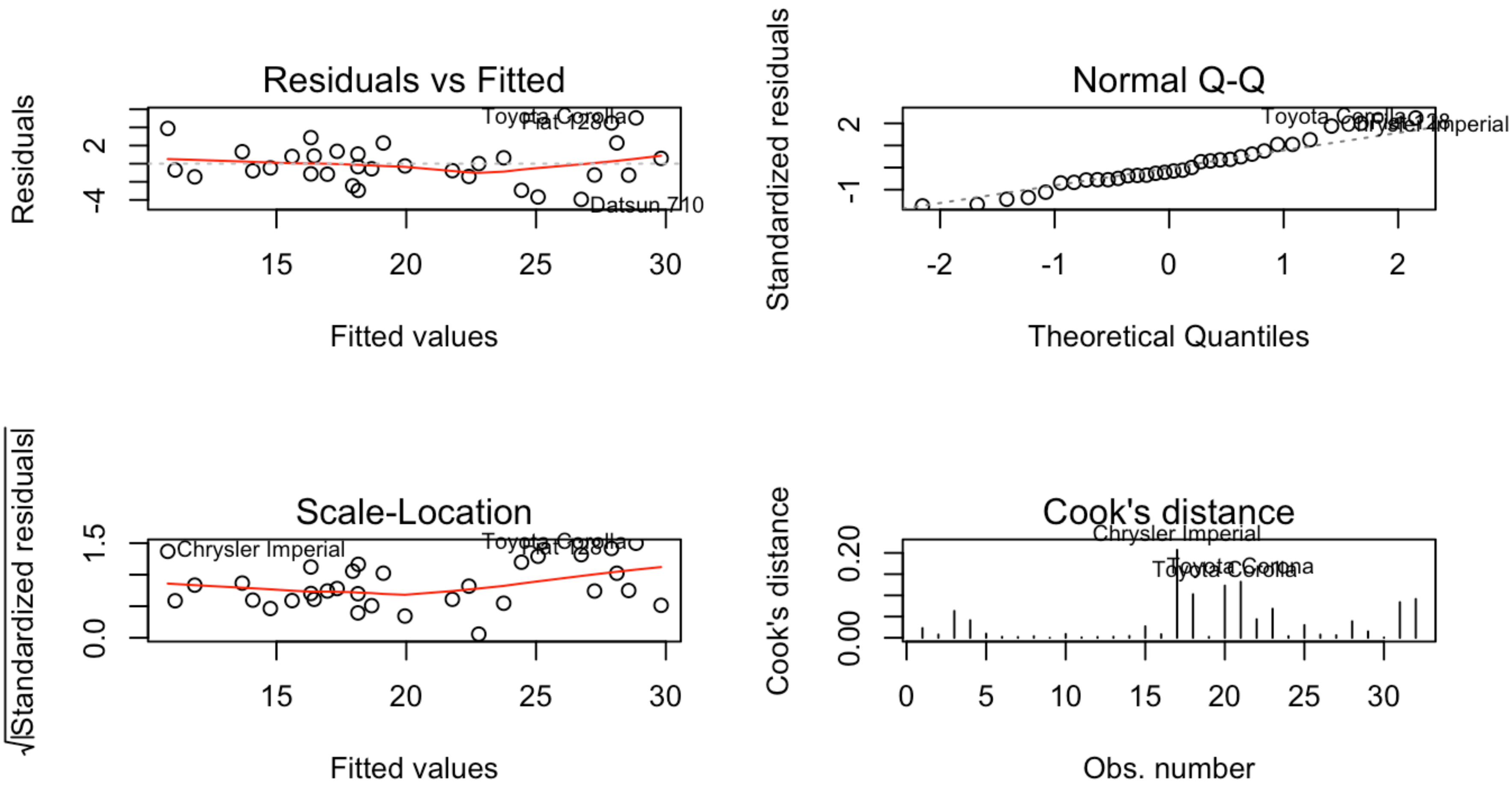



Figure 4: Regression Model Observations outside Confidence Interval

```
fit4.confint <- round(predict(fit4, mtcars2, interval = "confidence", level = 0.95),
2)
actual <- mtcars2[,1]
fit4.compare <- as.data.frame(cbind(actual, fit4.confint))
fit4.compare$outlier <- ifelse(fit4.compare$actual < fit4.compare$lwr | fit4.compare$
actual > fit4.compare$upr, "Y","N")
fit4.outlier <- subset(fit4.compare, outlier == "Y")
select(fit4.outlier, actual, fit, lwr, upr)
```

```
##                   actual   fit   lwr   upr
## Datsun 710          22.8 26.74 25.08 28.40
## Hornet 4 Drive      21.4 19.12 16.99 21.24
## Chrysler Imperial   14.7 10.81  8.28 13.35
## Fiat 128            32.4 27.91 26.10 29.71
## Toyota Corolla      33.9 28.85 27.08 30.62
## Toyota Corona       21.5 24.44 21.83 27.05
## Dodge Challenger    15.5 17.94 15.87 20.01
## AMC Javelin         15.2 18.15 16.03 20.27
## Pontiac Firebird    19.2 16.33 14.75 17.90
## Lotus Europa        30.4 28.11 26.03 30.19
## Volvo 142E          21.4 25.08 23.07 27.09
```