Coursera: Regression Models Course Project

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December 19, 2014

Executive Summary

I work for Motor Trend (MT), a magazine about the automobile industry. Looking at a data set of a collection of cars, MT is interested in exploring the relationship between vehicle attributes and miles per gallon (MPG). Two specific areas (below) are summarized for you, followed by a detailed explanation of our conclusions.

Is an automatic or manual transmission better for MPG?

Our analysis shows that a manual transmission correlates with increased fuel efficiency. Transmission alone is not the best way to increase fuel efficiency. Here are some other possibilities discovered in the data.

1) The number of cylinders in a car may have more impact. A 4-cylinder car can commonly have up to 10 mpg increase over an 8-cylinder vehicle. Average MPG ranges between 15 and 26 mpg for highest and lowest cylinder counts, respectively.

2) Combining an Inline-engine and fewer Carburetors with a Manual tranmission may also help increase MPG. On average, these cars may get up to 29 MPG, with typical manual transmissions . Toyota Corolla, Fiat, and Datsun do well here.

Quantify the MPG difference between automatic and manual transmissions.

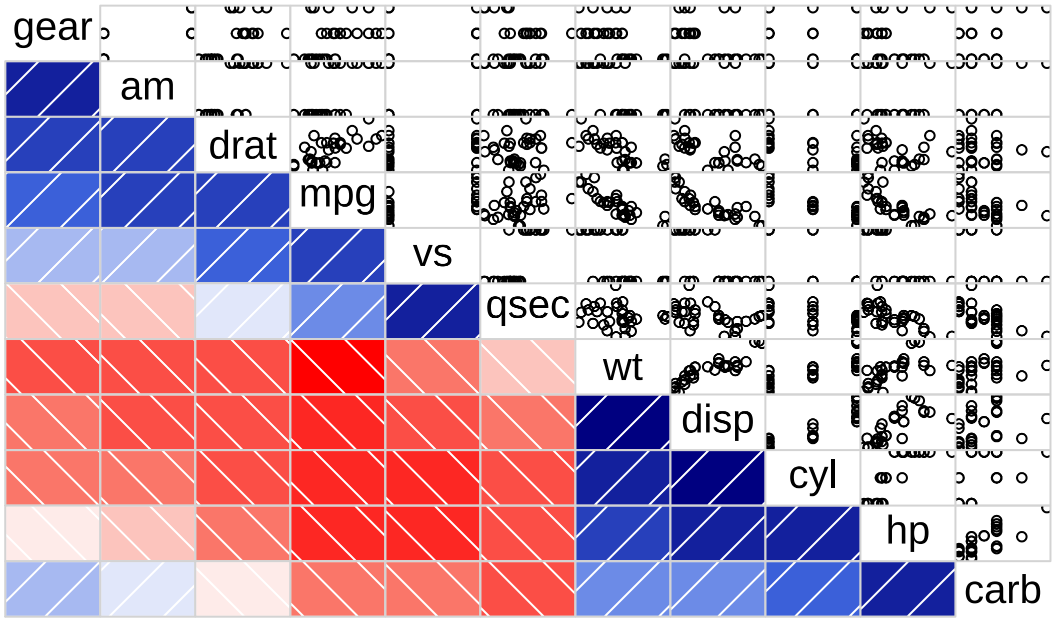
Using a model that considers only engine type (V or Inline) and the number of Carburetors, we can quantify the mpg increase simply by choosing a manual transmission. If we train the same model on two mutually exclusive data sets (automatic versus manual transmission), we see that a *manual transmission get more than 7 mpg better fuel efficiency*. Switching to an Inline engine has a more positive effect on automatics (+4.34 mpg), but that is insufficient to overtake the manual transmission. In fact, our model suggests that a manual transmission could opt for more power by switching to a V-engine and dual Carbs and still likely outperform the fuel efficiency of the average automatic (if they weren't racing or hauling loads).

```r
at <- mtcars[mtcars$am==0,c("mpg","vs","carb")]; lm_at <- lm(mpg ~ ., at)
mt <- mtcars[mtcars$am==1,c("mpg","vs","carb")]; lm_mt <- lm(mpg ~ ., mt)
coef(lm_at); coef(lm_mt)
```

```
## (Intercept)          vs        carb
##   19.461710    4.347200   -1.430825
```

```
## (Intercept)          vs        carb
##   26.738430    3.772314   -1.497521
```

Model Design



Thoughts on Correlation:

- MPG is positively correlated with Manual transmission (am), Rear-axle ratio (drat), and an Inline engine (vs)
- MPG is negatively correlated with Vehicle weight (wt), Engine Displacement (disp), Cylinder count(cyl), and Horsepower (hp)
- MPG is lightly correlated with Gear count (gear), Carburetor count (carb), and Quarter-mile time (qsec)
- Weight may have colinearity with issues with Gear count, Transmission type, and Rear-axle ratio
- Engine Displacement may have correlation

Thoughts on Coefficients (grain of salt required - this is a kitchen sink model, after all) :

- Increased Weight, Carburetor count, and Horsepower result in less MPG (matches intuition)
- Increased Displacement, Straight engine, More gears, Rear axle ratio, and Manual transmission result in higher MPG (matches intuition)
- The coefficients of Quarter-mile time and Cylinders do "not" match intuition as both should likely have negative impact on MPG

Thoughts on Colinearity :

- Variance inflation factors all reasonably high, indicating problems (we expect this for a kitchen sink model)
- Weight is correlated with most items on the list, and we find that it has Heteroskedascity issues with mpg (see Appendix)

Appendix: Exploratory Data Analysis (output grossly reduced to meet 5 page requirement)

Omitted Variables (due to 5-page limit) :: disp, drat, hp, qsec, gear

Critical Variables

mpg :: Miles/(US) gallon

Our Dependent Variable.

cyl :: Number of cylinders

Larger, more powerful vehicles typically have more cylinders. More cylinders typically means more fuel-per-second consumed in modern cars (and more horsepower), but have a negative impact on mpg.

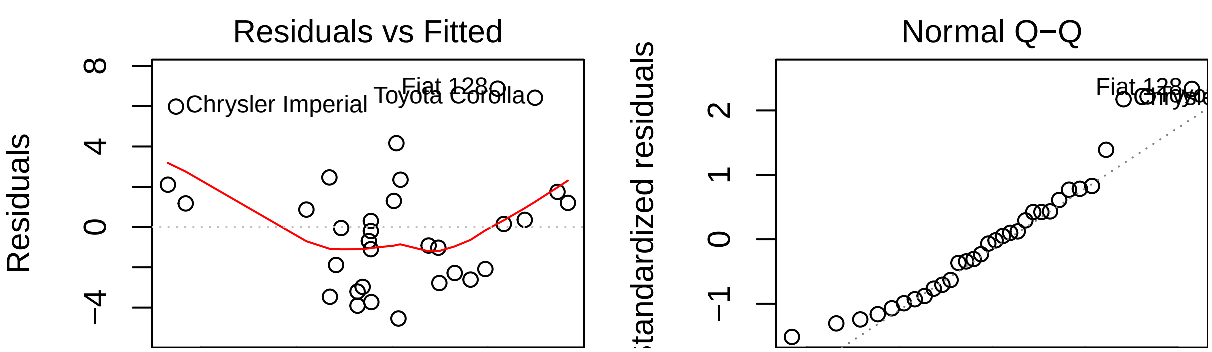
```
#...Model and output interesting EDA
fit <- lm(mpg ~ cyl, mtcars)
summary(fit)$r.squared
```

```
## [1] 0.72618
```

wt :: Weight (lb/1000)

Weight of vehicle expressed in units of 1k lbs. Note that Weight's residual plot shows non-random U-shape (i.e. Heteroskedasticity)

```
fit <- lm(mpg ~ wt, mtcars)
par(mfrow=c(1,2),mar=c(0,5,15,0))
plot(fit,which=c(1,2))
```



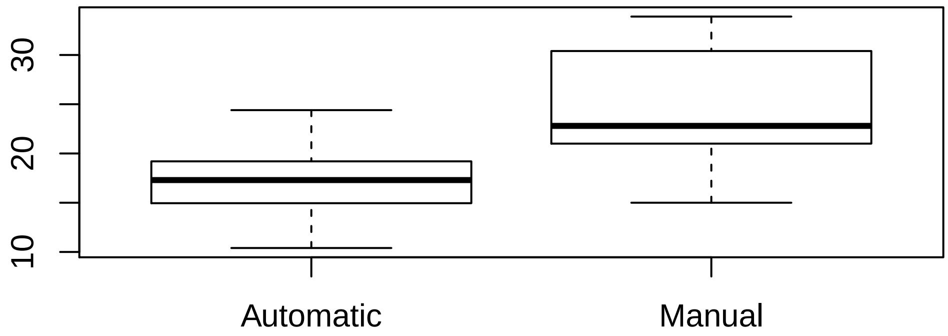
am :: Transmission (0 = automatic, 1 = manual)

Manual transmission should help mpg (based on Consumer Reports research)

```
fit <- lm(mpg ~ am, mtcars)
summary(fit)$r.squared
```

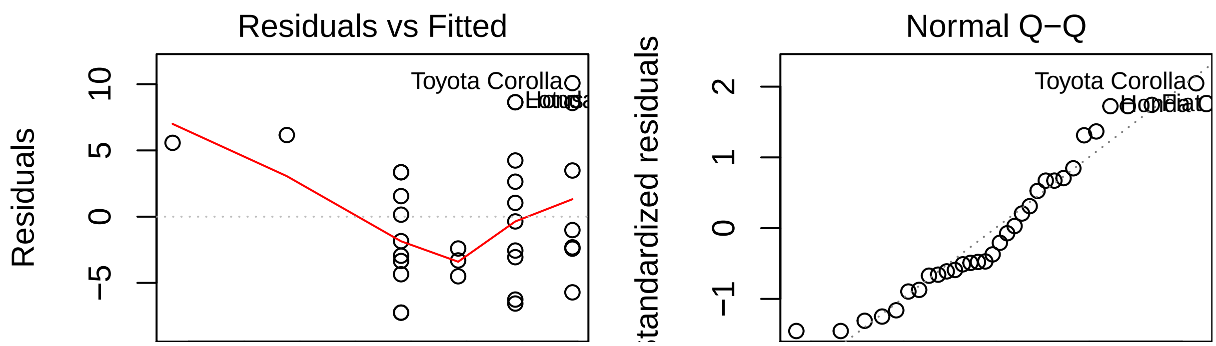
```
## [1] 0.3597989
```

```r
par(mfrow=c(1,1),mar=c(8,5,8,5))
boxplot(mtcars$mpg~mtcars$am,names=c("Automatic","Manual"))
```



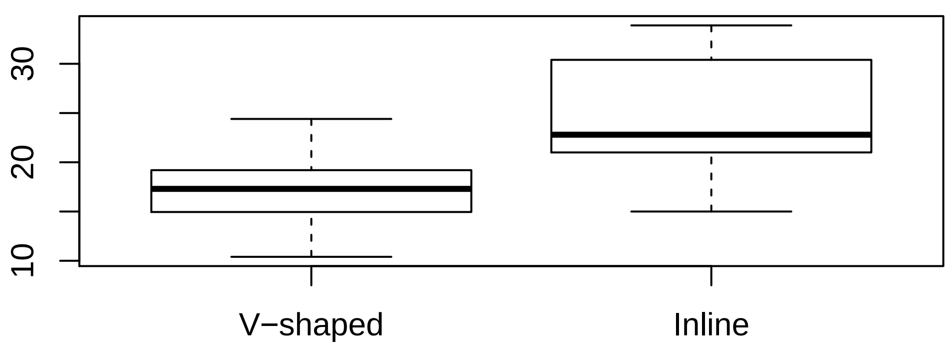
carb :: Number of carburetors

Number of carbs decreases fuel efficiency



vs :: V-shaped or Straight (Inline) engine shape

Inline engine increases fuel efficiency



Modeling

Remove Heteroskedastic, Colinear, and Uncorrelated variables

- Coefficients match intuition, but P-values for T-stats are much to large to give confidence
- Variance Inflation Factors are also reasonably large

```
mtcars_1 <- mtcars[,c("mpg","drat","vs","am","gear","carb")]
model_1 <- lm(mpg ~ ., mtcars_1)
sqrt( vif(model_1) )
```

```
##     drat       vs       am     gear     carb
## 1.685073 1.484628 1.887650 2.076755 1.495089
```

(Selected Model) Remove Gear and Drat due to correlation

- Coefficients match research and individual trends
- p-values and variable inflation factors are appropriately small
- No significant colinearity issues
- No Heteroskedasticity issues

```
mtcars_3 <- mtcars[,c("mpg","vs","am","carb")]
model_3 <- lm(mpg ~ ., mtcars_3)
s <- summary(model_3)
s$coefficients
```

```
##              Estimate Std. Error   t value     Pr(>|t|)
## (Intercept) 19.517399  1.6090815 12.129528 1.155904e-12
## vs           4.195736  1.3245867  3.167581 3.695735e-03
## am           6.797956  1.1014890  6.171606 1.154742e-06
## carb        -1.430783  0.4081085 -3.505890 1.552505e-03
```

```
s$r.squared
```

```
## [1] 0.7818462
```

```
sqrt(vif(model_3))
```

```
##       vs       am     carb
## 1.254946 1.033173 1.239088
```

Remove VS since it correlates with am and carb

Thoughts :: R^2 took a dive, so removing VS was not necessary

```
mtcars_5 <- mtcars[,c("mpg","am","carb")]
model_5 <- lm(mpg ~ ., mtcars_5)
summary(model_5)$r.squared
```

```
## [1] 0.7036726
```