Week3

Dhruv

2018-01-29

```r
#imports
library(ISLR)
library(ggplot2)
library(MASS)
library(dplyr)
library(car)
library(stats)
library(knitr)
```

```r
#Import Data
auto = Auto
```

```r
#Explore Data
str(auto)
```

```
## 'data.frame':    392 obs. of  9 variables:
##  $ mpg         : num  18 15 18 16 17 15 14 14 14 15 ...
##  $ cylinders   : num  8 8 8 8 8 8 8 8 8 8 ...
##  $ displacement: num  307 350 318 304 302 429 454 440 455 390 ...
##  $ horsepower  : num  130 165 150 150 140 198 220 215 225 190 ...
##  $ weight      : num  3504 3693 3436 3433 3449 ...
##  $ acceleration: num  12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
##  $ year        : num  70 70 70 70 70 70 70 70 70 70 ...
##  $ origin      : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ name        : Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231 14 161 141 54 223 241 2
```

```r
summary(auto)
```

```
##       mpg          cylinders      displacement     horsepower
##  Min.   : 9.00   Min.   :3.000   Min.   : 68.0   Min.   : 46.0
##  1st Qu.:17.00   1st Qu.:4.000   1st Qu.:105.0   1st Qu.: 75.0
##  Median :22.75   Median :4.000   Median :151.0   Median : 93.5
##  Mean   :23.45   Mean   :5.472   Mean   :194.4   Mean   :104.5
##  3rd Qu.:29.00   3rd Qu.:8.000   3rd Qu.:275.8   3rd Qu.:126.0
##  Max.   :46.60   Max.   :8.000   Max.   :455.0   Max.   :230.0
##
##      weight      acceleration        year           origin
##  Min.   :1613   Min.   : 8.00   Min.   :70.00   Min.   :1.000
##  1st Qu.:2225   1st Qu.:13.78   1st Qu.:73.00   1st Qu.:1.000
##  Median :2804   Median :15.50   Median :76.00   Median :1.000
##  Mean   :2978   Mean   :15.54   Mean   :75.98   Mean   :1.577
##  3rd Qu.:3615   3rd Qu.:17.02   3rd Qu.:79.00   3rd Qu.:2.000
##  Max.   :5140   Max.   :24.80   Max.   :82.00   Max.   :3.000
##
##                  name
##  amc matador       :  5
##  ford pinto        :  5
##  toyota corolla    :  5
##  amc gremlin       :  4
```

```
##  amc hornet        :  4
##  chevrolet chevette:  4
##  (Other)           :365
```

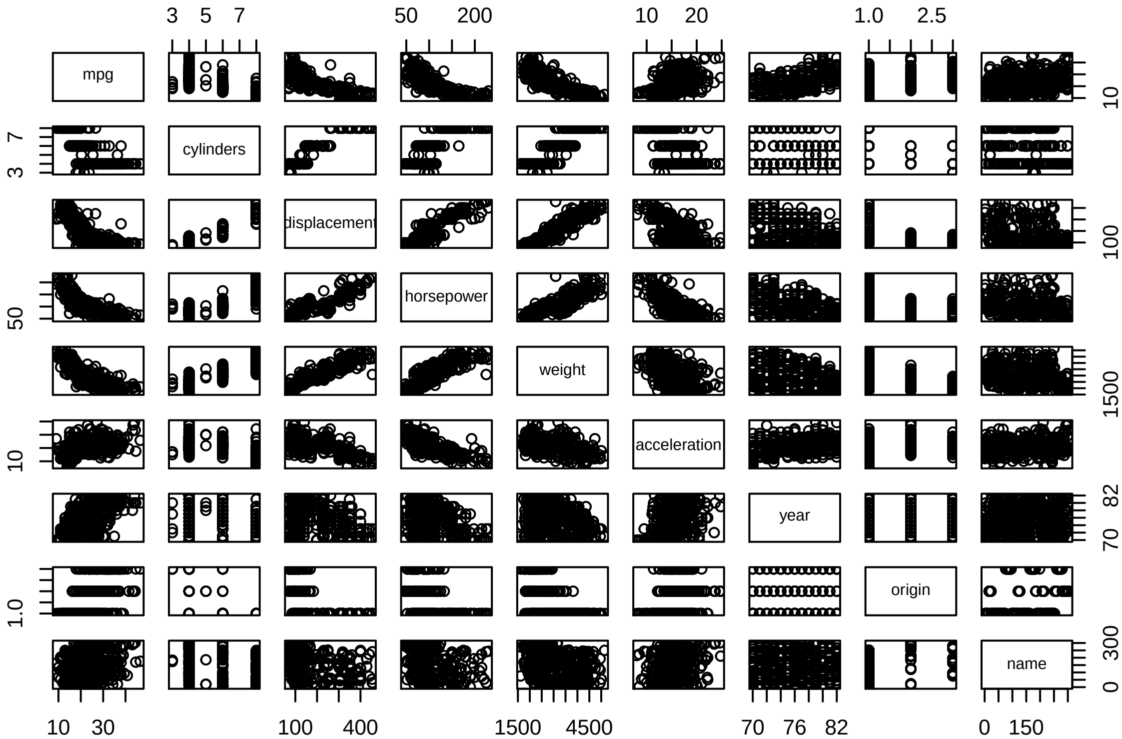
```r
colnames(auto)
```

```
## [1] "mpg"          "cylinders"    "displacement" "horsepower"
## [5] "weight"       "acceleration" "year"         "origin"
## [9] "name"
```

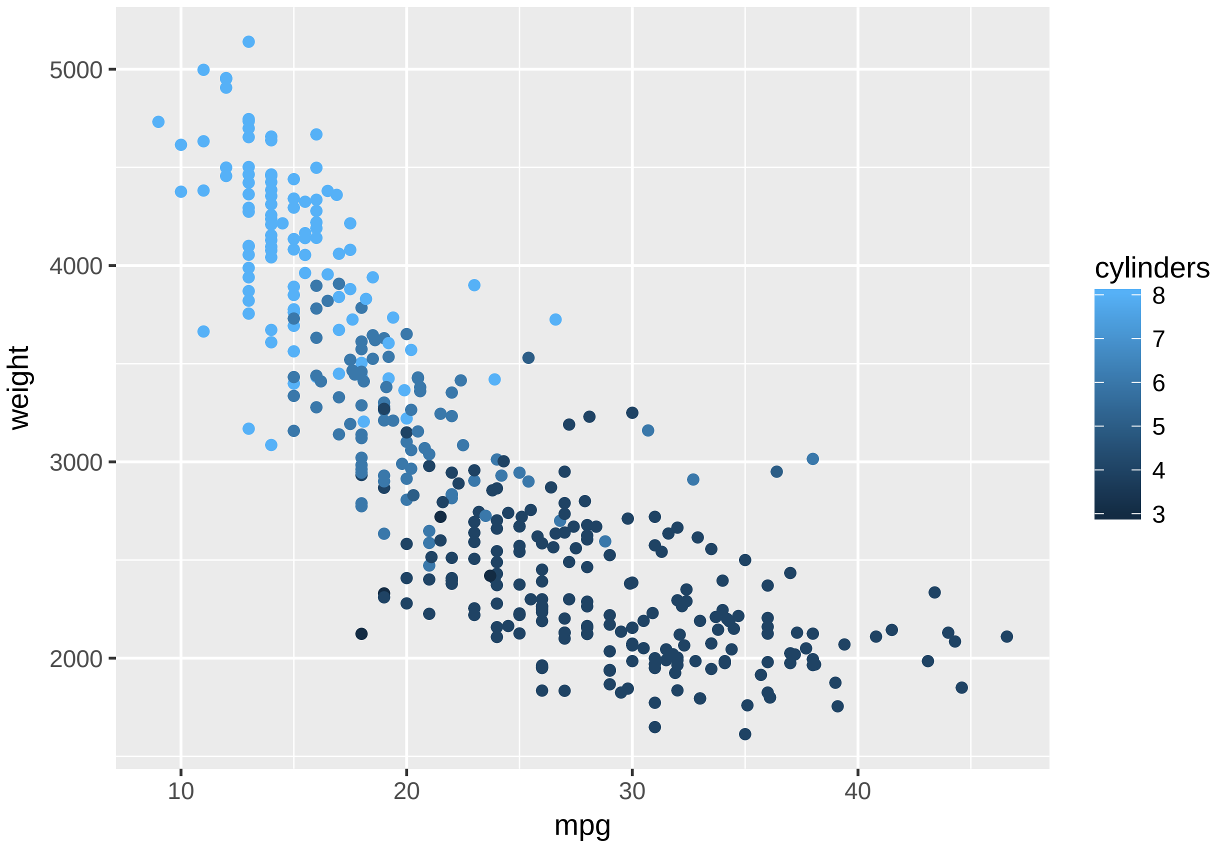
```r
head(auto, n=10)
```

```
##    mpg cylinders displacement horsepower weight acceleration year origin
## 1   18         8          307        130   3504         12.0   70      1
## 2   15         8          350        165   3693         11.5   70      1
## 3   18         8          318        150   3436         11.0   70      1
## 4   16         8          304        150   3433         12.0   70      1
## 5   17         8          302        140   3449         10.5   70      1
## 6   15         8          429        198   4341         10.0   70      1
## 7   14         8          454        220   4354          9.0   70      1
## 8   14         8          440        215   4312          8.5   70      1
## 9   14         8          455        225   4425         10.0   70      1
## 10  15         8          390        190   3850          8.5   70      1
##                         name
## 1  chevrolet chevelle malibu
## 2          buick skylark 320
## 3         plymouth satellite
## 4              amc rebel sst
## 5                ford torino
## 6           ford galaxie 500
## 7           chevrolet impala
## 8          plymouth fury iii
## 9           pontiac catalina
## 10        amc ambassador dpl
```

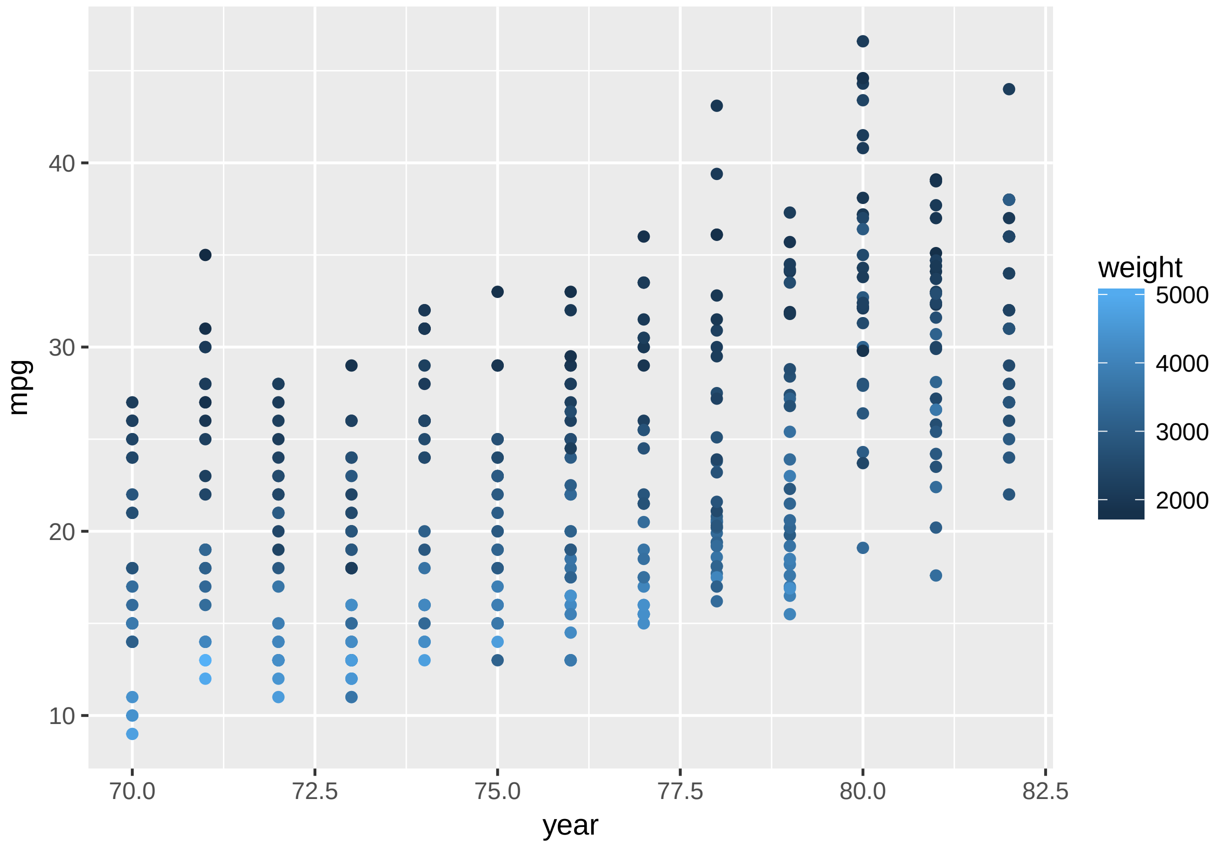
```r
#Explore Data
plot(auto)
```




```r
#Relationship between mpg and displacement, horsepower, weight, year
ggplot(auto, aes(x = mpg, y = weight)) + geom_point(aes(color = cylinders))
```



```
#Heavier cars have more cylinders, lighter vehicles have less cylinders and give more mpg
ggplot(auto, aes(x = year, y = mpg)) + geom_point(aes(color = weight))
```




```
#over a short span of 12 years, the weight of the cars has reduced by approximately 3000lbs, and mpg ha
#This is a significant rise, enough to investigate the reason for such a spike, manufacturing technique
```

```
autoModel1 = lm(mpg ~ cylinders + horsepower + weight + displacement + year + acceleration, data = auto)
summary(autoModel1)
```

```
##
## Call:
## lm(formula = mpg ~ cylinders + horsepower + weight + displacement +
##     year + acceleration, data = auto)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.6927 -2.3864 -0.0801  2.0291 14.3607
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.454e+01  4.764e+00  -3.051  0.00244 **
## cylinders    -3.299e-01  3.321e-01  -0.993  0.32122
## horsepower   -3.914e-04  1.384e-02  -0.028  0.97745
## weight       -6.795e-03  6.700e-04 -10.141  < 2e-16 ***
## displacement  7.678e-03  7.358e-03   1.044  0.29733
## year          7.534e-01  5.262e-02  14.318  < 2e-16 ***
## acceleration  8.527e-02  1.020e-01   0.836  0.40383
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.435 on 385 degrees of freedom
## Multiple R-squared:  0.8093, Adjusted R-squared:  0.8063
## F-statistic: 272.2 on 6 and 385 DF,  p-value: < 2.2e-16
```

```
#weight and year are very significant.

#Determine coliniarity
fitvif <- lm(mpg ~ cylinders+displacement+horsepower+weight+acceleration+year, data = auto)
show(vif(fitvif))
```

```
##    cylinders displacement   horsepower       weight acceleration
##    10.633049    19.641683     9.398043    10.731681     2.625581
##         year
##     1.244829
```

```
#displacement has the highest VIF (above ~10)
```

```
#variable selection
#using stepwise selection
fit <- lm(mpg ~ cylinders+displacement+horsepower+weight+acceleration+year, data = auto)
step <- stepAIC(fit, direction="both", trace=FALSE)
summary(step)$coeff
```

```
##                 Estimate   Std. Error    t value      Pr(>|t|)
## (Intercept) -14.347253018 4.0065185631  -3.580978  3.856624e-04
## weight       -0.006632075 0.0002145559 -30.910708 8.361624e-107
## year          0.757318281 0.0494726873  15.307806  9.772260e-42
```

```
summary(step)$r.squared
```

```
## [1] 0.8081803
```

```
#shows adjusted R^2 to be 80%, meaning weight and year explain 80% of the variation in mpg. (Adequate m
```

```
#test each parameter via nested likelihood ratio test
fit1 <- lm(mpg ~ weight, data = auto)
fit2 <- lm(mpg ~ weight+year, data = auto)
fit3 <- lm(mpg ~ weight+year+cylinders, data = auto)
fit4 <- lm(mpg ~ weight+year+cylinders+horsepower, data = auto)
fit5 <- lm(mpg ~ weight+year+cylinders+horsepower+acceleration, data = auto)
anova(fit1, fit2, fit3, fit4, fit5)
```

```
## Analysis of Variance Table
##
## Model 1: mpg ~ weight
## Model 2: mpg ~ weight + year
## Model 3: mpg ~ weight + year + cylinders
## Model 4: mpg ~ weight + year + cylinders + horsepower
## Model 5: mpg ~ weight + year + cylinders + horsepower + acceleration
##   Res.Df    RSS Df Sum of Sq        F Pr(>F)
## 1    390 7321.2
## 2    389 4569.0  1   2752.28 233.1726 <2e-16 ***
## 3    388 4564.0  1      4.96   0.4200 0.5173
## 4    387 4562.4  1      1.60   0.1357 0.7128
## 5    386 4556.2  1      6.19   0.5247 0.4693
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#note the spike in sum of squares when we run fit2 (weight + year)
```

```r
#final Model
finalfit <- lm(mpg ~ weight+year, data = auto)
summary(finalfit)$coef
```

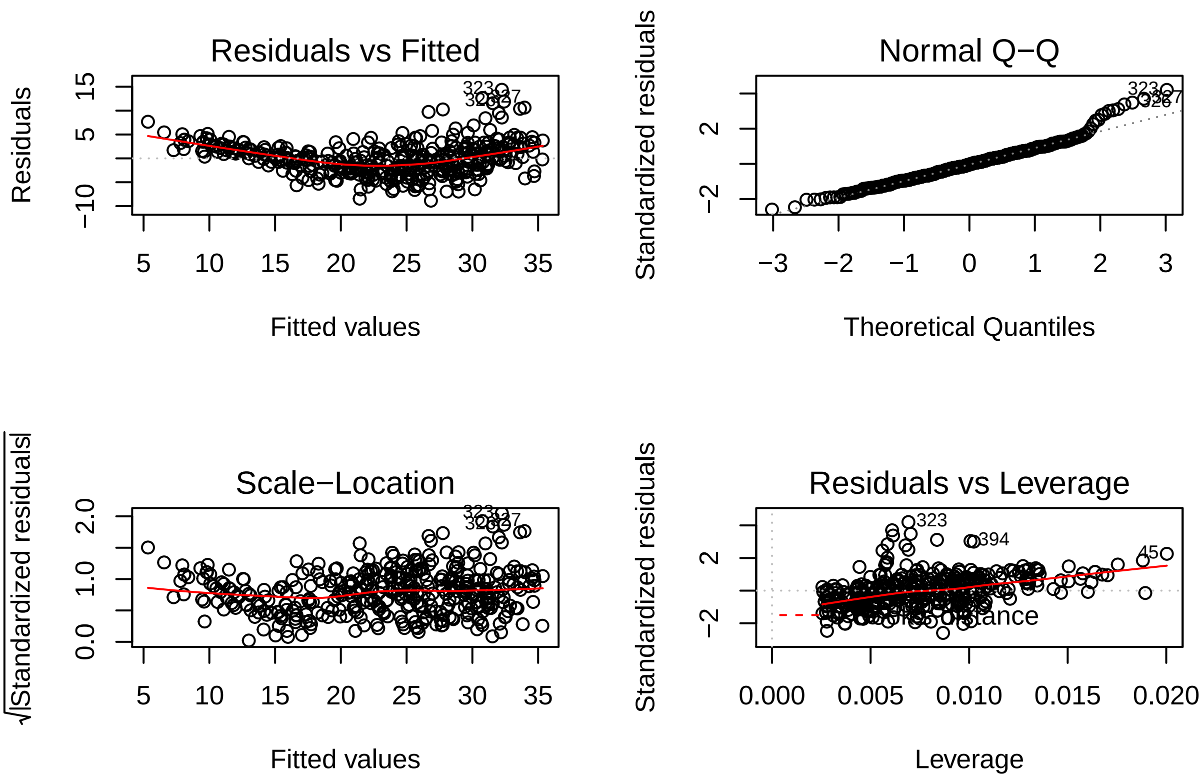
```
##                 Estimate   Std. Error    t value      Pr(>|t|)
## (Intercept) -14.347253018 4.0065185631  -3.580978  3.856624e-04
## weight       -0.006632075 0.0002145559 -30.910708 8.361624e-107
## year          0.757318281 0.0494726873  15.307806  9.772260e-42
```

```r
#detect colliniarity
fitvif <- lm(mpg ~ weight+year, data = auto)
show(vif(fitvif))
```

```
##   weight     year
## 1.105651 1.105651
```

```r
#we are okay ( no values above ~10)
```

```r
#residual plot
par(mfrow=c(2,2))
plot(fitvif)
```




```r
#The visibility of a distinct pattern in our residual plot indicates that further transformation can be
#It was interesting to see how much of an effect year has over the mpg of a car. Although we lack the d
# Many emissions requirements were stiffened which forced car manufacturures to reduce gasoline consump
#Although a simple dataset, it was an excellent adventure into feature selection based on basic investi
```