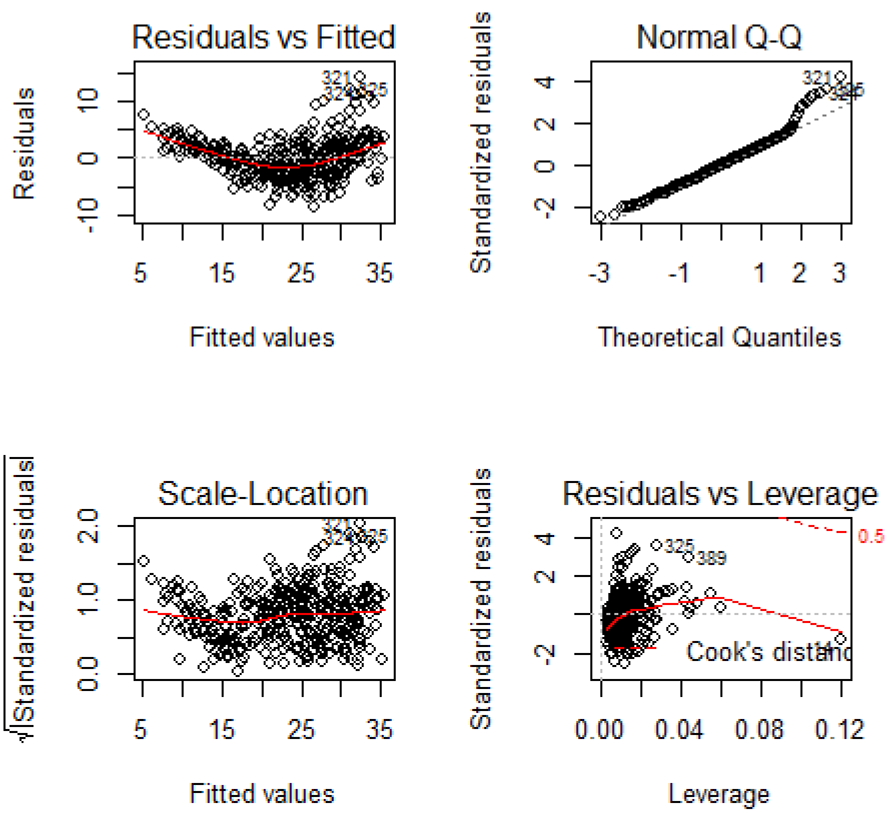
 # Dr. M. Baron, Statistical Machine Learning class, STAT-427/627

REGRESSION DIAGNOSTICS

 # Let's change the folder to the one where we have data

```
> setwd("C:\Users\baron\627\data")
> load("Auto.rda")
> names(Auto)
[1] "mpg"          "cylinders"    "displacement"
[4] "horsepower"   "weight"       "acceleration"
[7] "year"         "origin"       "name"

> attach(Auto)
> reg=lm(mpg ~ year + acceleration + horsepower + weight)
> par(mfrow=c(2,2))
> plot(reg)
```



 # STUDENTIZED RESIDUALS AND OUTLIERS

```
> t = rstudent(reg)

> plot(t)

> t[ abs(t) > 3 ]
```

```
     243       321       324       325       328       382
3.338459 4.272284 3.446234 3.651403 3.236226 3.024362
```

 # Which of these residuals can be considered as outliers?
 # Compare with the Bonferroni-adjusted quantile from t-distribution.

```
> qt( 0.05/2/392, 387 )
[1] -3.870293

> t[ abs(t) > abs(qt( 0.05/392/2, 387 )) ]
     321
4.272284
```

 # Testing NORMALITY

```
> shapiro.test(t)

        Shapiro-Wilk normality test

data:  t
W = 0.97109, p-value = 5.101e-07
```

 # Also look at the Normal Q-Q plot above. Shapiro-Wilk statistic W measures how close the graph is to a straight line.

 # Testing HOMOSCEDASTICITY (constant variance). This is the Breausch-Pagan test.

```
> ncvTest(reg)
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 22.04621    Df = 1     p = 2.66165e-06
```

 # INFLUENTIAL DATA

```
> infl = influence(reg)
```

 # Gives hat diagonals H_{ii}, the vector of coefficients (without the ith case), s = RMSE (without the ith case)

```
> leverage = infl$hat
> plot(leverage)
> 5/length(mpg)
[1] 0.0127551
> summary(infl$hat)
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
0.002781 0.007543 0.010640 0.012760 0.014740 0.120500

> leverage[ leverage > 0.03 ]

> infl$coefficients
```

```
> infl$sigma
```

ADDITIONAL PACKAGE "CAR" (Go to "Packages" tab and choose "car")

```
> library(car)

> outlierTest(reg)
    rstudent unadjusted p-value Bonferonni p
321 4.272284          2.4397e-05    0.0095635

> cook = cooks.distance(reg)
> plot(cook)
```

The Cook's distance measures the effect of deleting the i-th observation

```
> influence.measures(reg)
```

Besides the Cook's distance, it calculates DFBETS, DFFITS, and other measures of influence

VARIANCE INFLATION FACTORS

```
> vif(reg)
        year acceleration   horsepower       weight
    1.228910     2.519844     8.813443     5.303347
```