Models

Merlise Clyde

September 1, 2017

Problem Setting

Data:

- Observe for each case i (Y_i, X_i)
- Response or dependent variable Y_i
- Predictor(s) or **independent** variable X_i

Goals:

- Exploring distribution of $p(y|X = x)$ as a function of x
- Understanding the mean in Y as a function of x :
  $E(Y \mid X = x) = f(X)$

Special cases:

- regression (normal Y) or additive error model
- classification (binary or Bernoulli Y where probability $p(Y = 1 \mid X)$ depends on x)
- other exponential family models
  - Poisson regression (counts)
  - Gamma regression (continous, positive)
- Survival models

Additive Error Model

- Assume $E[\epsilon_i] = 0$ for $i = 1, \ldots, n$,

$$Y_i = f(X_i) + \epsilon_i$$

- Regression function $E(Y \mid x) = f(x)$
- ideal or optimal predictor of Y given $X = x$
- minimizes $E[(Y - g(x))^2 \mid X = x]$ over all functions $g(x)$ at all points $X = x$ **Show**
- for prediction $\epsilon = Y - f(x)$ is *irreducible error* as even if we know $f(x)$ there are still errors in predicting Y
- for any estimator $\hat{f}(x)$ we have

$$E[(Y - \hat{f}(x))^2 \mid X = x] = \underbrace{(f(x) - \hat{f}(x)))^2}_{\textit{Reducible}} + \underbrace{\mathrm{Var}(\epsilon)}_{\textit{Irreducible}}$$

Linear Regression

- Taylors series expansion of regression function about point x_0

$$f(x_i) = f(x_0) + f'(x_0)(x_i - x_0) + \text{ Remainder}$$

  leads to locally linear approximation

$$Y_i = \beta_0 + X_i\beta_1 + \varepsilon_i$$

- ε_i : errors (sampling/measurement errors ϵ, lack of fit)

Regression in Matrix Notation

Simple Linear Regression:

$$Y_i = \beta_0 + x_i\beta_1 + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \beta_1 + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\beta + \varepsilon$$

Big Picture:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \overset{iid}{\sim} N(0, \sigma^2)$$

- Estimate parameters $(\boldsymbol{\beta}, \sigma)$
- interpretation of parameters: $\boldsymbol{\beta}, \sigma$
- assess model fit — adequate? good? if inadequate, how?
- move to more complicated model?
- predict new ("future") responses at new $x_{n+1}, \ldots$
- how much variability does X explain?
- how important is X is predicting Y

Body Fat Data

- For a group of 252 male subjects, various body measurements were obtained
- An accurate measurement of the percentage of body fat is recorded for each
- Goal is to use the other body measurements as a proxy for predicting body fat
- Understand how changing one measurement may lead to changes in Bodyfat

Data

```r
library(BAS)
data(bodyfat)  #from BAS   help(bodyfat)
dim(bodyfat)
```

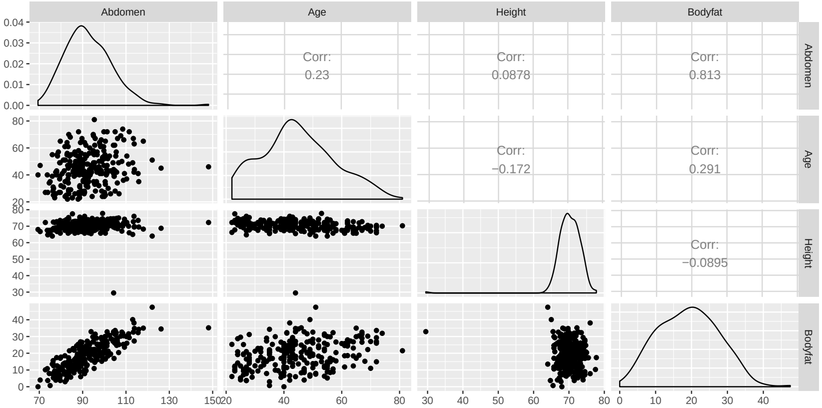
```
## [1] 252  15
```

```r
summary(bodyfat)  # anything strange ?
```

```
##     Density          Bodyfat            Age            Weight
##  Min.    :0.995   Min.    : 0.00   Min.    :22.00   Min.    :118.
##  1st Qu.:1.041   1st Qu.:12.47   1st Qu.:35.75   1st Qu.:159.
##  Median :1.055   Median :19.20   Median :43.00   Median :176.
##  Mean    :1.056   Mean    :19.15   Mean    :44.88   Mean    :178.
##  3rd Qu.:1.070   3rd Qu.:25.30   3rd Qu.:54.00   3rd Qu.:197.
##  Max.    :1.109   Max.    :47.50   Max.    :81.00   Max.    :363.
##      Height            Neck            Chest            Abdomen
##  Min.    :29.50   Min.    :31.10   Min.    : 79.30   Min.    : 69
##  1st Qu.:68.25   1st Qu.:36.40   1st Qu.: 94.35   1st Qu.: 84
##  Median :70.00   Median :38.00   Median : 99.65   Median : 90
##  Mean    :70.15   Mean    :37.99   Mean    :100.82   Mean    : 92
```

Pairs Plots

```r
library(GGally)
ggpairs(bodyfat, columns=c(8,3,5,2))
```



Ordinary Least Squares

- OLS estimates of parameters β_0 and β minimize sum of squared errors
  - $$\sum_{i=1}^{n}(Y_i - (\beta_0 + X_i\beta_1))^2$$
  - $$L(\boldsymbol{\beta}) = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^T(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$$
- OLS estimate of $\boldsymbol{\beta}$
  - $$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$$
- Ad Hoc
- Equivalent to Maximum Likelihood Estimates with assumption that errors are iid Normal (Model based)

Summarizing Model Fit

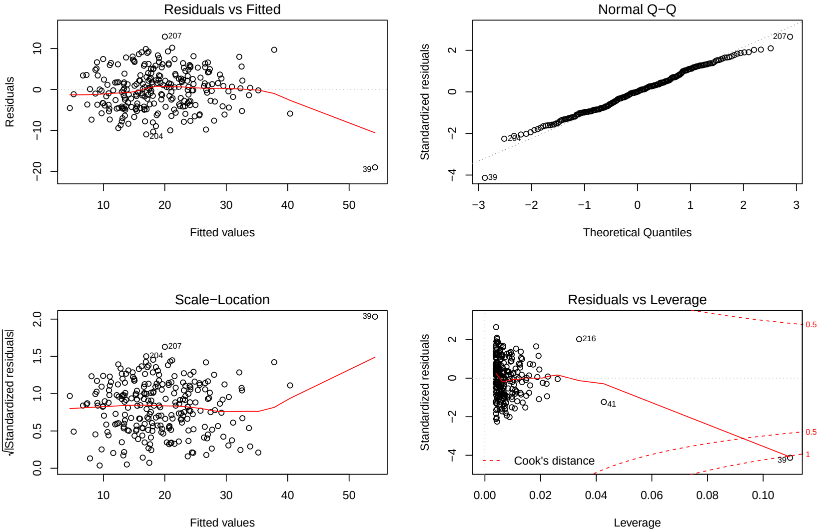
- Fitted values
$$\hat{Y}_i = x_i^T \hat{\beta}$$
- Residuals (estimates of errors)
$$e_i = Y_i - \hat{Y}_i = \hat{\epsilon}_i$$
- Sum of Squared Errors
$$\mathrm{SSE} = \sum e_i^2$$
- measures remaining residual variation in response
- MSE = SSE/(n -2) (or more generally $n - p$) is an estimate of σ^2
- degrees of freedom n-p

Fitting Models in R

```r
bodyfat.lm = lm(Bodyfat ~ Abdomen, data=bodyfat)
summary(bodyfat.lm)   #summary of regression output
```

```
##
## Call:
## lm(formula = Bodyfat ~ Abdomen, data = bodyfat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.0160  -3.7557   0.0554   3.4215  12.9007
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -39.28018    2.66034  -14.77   <2e-16 ***
## Abdomen       0.63130    0.02855   22.11   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
##
## Residual standard error: 4.877 on 250 degrees of freedom
## Multiple R-squared:  0.6617, Adjusted R-squared:  0.6603
```

Residual Plots



Diagnostic Plots

- Residuals versus fitted values
- Normal Quantile: check normality of residuals or look for heavier tails than normal where observed quantiles are larger than expected under normality
- Scale-Location plot:
  Detect if the spread of the residuals is constant over the range of fitted values. (Constant variance with mean)
- standardized residuals versus leverage with contours of Cook's distance: shows influential points where points greater than 1 or 4/n are considered influential
- Case 39 appears to be influential!

Hat Matrix

- predictions

$$\hat{Y} = X\hat{\beta} = X(X^TX)^{-1}X^TY$$

$$H = X(X^TX)^{-1}X^T$$

- Hat Matrix or Projection Matrix
  - idempotent $HH = H$
  - symmetric
  - leverage values are the diagonal elements h_{ii}

$$\hat{Y}_i = h_{ii}Y_i + \sum_{i \neq j} h_{ij}Y_j$$

$$0 \leq h_{ii} \leq 1$$

- leverage values near 1 imply $\hat{Y}_i = Y_i$
- potentially influential
- measure of how far x_i is from center of data

Residual Analysis

- residuals

$$e = Y - \hat{Y} = (I - H)Y$$

$$\mathrm{var}(e_i) = \hat{\sigma}^2(1 - h_{ii})$$

- Standardize:

$$r_i = e_i / \sqrt{\mathrm{var}(e_i)}$$

- if leverage is near 1 then residual is near 0 and variance is near 0 and r_i is approximately 0 (may not be helpful)

Cook's Distance

Measure of influence of case i on predictions

$$D_i = \frac{\| Y - \hat{Y}_{(i)} \|^2}{\hat{\sigma}^2 \, p}$$

after removing the ith case

Easier way to calculate

$$D_i = \frac{e_i^2}{\hat{\sigma}^2 p} \left[\frac{h_{ii}}{(1 - h_{ii})^2} \right],$$

$$D_i = \frac{r_{ii}}{p} \frac{h_{ii}}{1 - h_{ii}}$$

Model Assessment

- Always look at residual plots!
- Check constant variance, outliers, influence, normality assumption
- Treat e_i as ‘`new data'' -- look at structure, other predictorsavplots`‘
- Case 39 looks influential!

How should we proceed?