

WED NOV 15

WEEK 8

HW & DUE THURS (TOMORROW) 11:59 PM
NEXT HW DUE TUES (HW 8)

FINAL (TAKE HOME) DUE
FRI FINALS WEEK

GLM's, NONLINEAR MODELS

Review: Linear models

(MODEL, ^{DATA} ESTIMATION, PERFORMANCE)
GOALS?

DATA
MODEL

$$\begin{matrix} y_1 \\ \vdots \\ y_n \end{matrix} \quad \begin{bmatrix} x_{11} & & x_{1k} \\ x_{21} & & \\ \vdots & & \\ x_{n1} & & x_{nk} \end{bmatrix} \quad \underline{X}$$

$n \times 1 \qquad n \times k$

$$E[y_i] = b_1 x_{i1} + b_2 x_{i2} + \dots + b_k x_{ik}$$

$$E[Y] = Xb \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_k \end{bmatrix}$$

y, X observed
 b is unknown parameters
Goal: Find estimates of b

Linear model

$$Y = Xb + \sum_{n \times 1}$$

$$\varepsilon \sim N(0, \sigma^2 I)_{n \times n}$$

$\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n$ independent
 $N(0, \sigma^2)$

$$Y \sim N(Xb, \sigma^2 I)$$

Goals: Estimates of $b \rightarrow$ MLE / LEAST-SQUARES
(SAME FOR NORMAL)

ONCE ESTIMATED b , what good is it?

Make predictions:

If you want to predict y for
 $x_1^*, x_2^*, \dots, x_k^*$

$$y_i \quad \hat{y}_i \rightarrow b_1 x_{i1} + \dots + b_k x_{ik}$$

$$\frac{1}{n} \sum (y_i - \hat{y}_i)^2 = \text{MSE} = \text{est of } \sigma^2$$

estimate of how well model fits data

Generalized Linear Model

$$\eta_i = (X\beta)_i \quad \text{linear predictor}$$

Ingredients to GLM

(1) DISTRIB OF RESPONSE y_i

$$y_i = \begin{cases} 1 & \text{w.p. } p_i \\ 0 & 1-p_i \end{cases}$$

$$E y_i = p_i$$

$$y_i \sim \text{Bernoulli}(p_i)$$

$$E y_i = p_i$$

(2) $g(E y_i) = \text{linear predictor } \eta_i = (X\beta)_i$

$$X = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}$$

$$X \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} a + b x_1 \\ \vdots \\ a + b x_n \end{bmatrix}$$

$$\eta_i = +5 - x_i$$

(here $a = 5$ $b = -1$)

$$p_i = \frac{1}{1 + e^{-\eta_i}}$$

Likelihood function

i^{th} data point

$$\theta_i = a + b a_i + c s_i$$

$$p(y_i | p_i)$$

$$p_i = \frac{1}{1 + e^{-\theta_i}}$$

$$y_i = \begin{cases} 1 \\ 0 \end{cases}$$

$$p(1 | p_i) = p_i$$

$$p(0 | p_i) = 1 - p_i$$

$$p(y_i | p_i) = p_i^{y_i} (1 - p_i)^{1 - y_i}$$

$$-\log p(y_i | p_i) = -y_i \log p_i - (1 - y_i) \log (1 - p_i)$$

$$-l(a, b, c) = \sum_i -\log p(y_i | p_i)$$

minimize to find a, b, c

$$y_i = 2 + \cos(t_i) + \epsilon_i \quad \epsilon_i \sim N(0, \sigma^2)$$

$$y_i = a + b \underbrace{\cos(t_i)}_{x_i} + \epsilon_i \quad a, b \text{ unknown}$$

CLAIM: Can use what we know to est a, b

$$y_i = a + b x_i + \epsilon_i \quad \text{linear model}$$

est a, b least-squares

$$y = X\beta + \epsilon$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

LEAST-SQUARES
SOL'N
FOR MATRIX
LINEAR MODEL