

MON NOV 6

PCA REVIEW

HW DUE TOMORROW DISC

LINEAR MODELS

$$z = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}_{n \times 1} \quad \text{cov}(z)_{i,j} = \text{cov}(z_i, z_j) = \mathbb{E}[(z_i - \mathbb{E}z_i)(z_j - \mathbb{E}z_j)]$$

$z$  is a random vector  
 $n \times 1$

$A$  is  $k \times n$  matrix

$$\text{cov}(Az) = A \underbrace{\text{cov}(z)}_{n \times n} A^T$$

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

$k \times 1$  random vector

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_5 \end{bmatrix} \quad z_1, z_2, z_3, z_4, z_5 \text{ indep } N(0,1)$$
$$\Sigma = \text{cov}(z)_{i,j} = 0 \quad i \neq j$$

$$\text{cov}(z) = \Sigma = A \Sigma A^T$$

$$X = \begin{bmatrix} x_{11} & \dots & x_{15} \\ x_{21} & & x_{25} \\ \vdots & & \vdots \\ x_{r1} & & x_{r5} \end{bmatrix}$$

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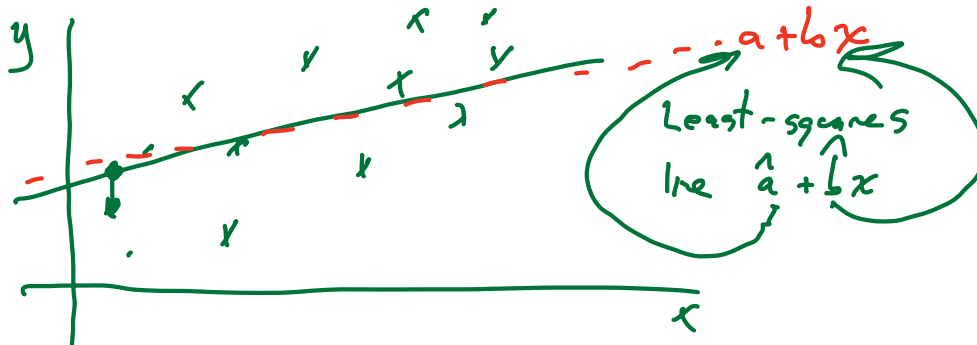
LINEAR MODELS

$(X, Y)$  HAS SOME JOINT DISTRIBUTION

BEFORE: MOTIVATION

BIVARIATE DATA

$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$



$$r_i = y_i - a + bx_i$$

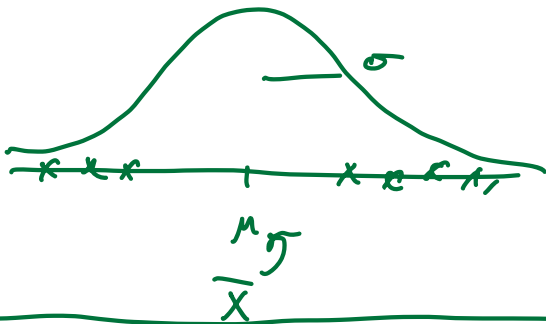
least-squares line: pick  $a, b$  to minimize  $\sum_{i=1}^n r_i^2 = f(a, b)$   
 least-square line is just data summary

ONE MODEL FOR DATA  $a, b$  unknown to us

$$y_i = a + bx_i + \varepsilon_i \quad \varepsilon_1, \varepsilon_2, \dots \text{IID } N(0, \sigma^2)$$

$\swarrow \quad \searrow \quad \nearrow$   
 $a, b, \varepsilon_i$  unknown

Goal: use the data to estimate  $a, b$



Random variable world  $(x, y)$  some joint distribution  
 $(Y = a + bX + \varepsilon)$

Find  $\hat{y} = a + bX$  so that  $\hat{y}$  is a good guess at  $y$

$$E(Y - \hat{y})^2 = \text{MSE}$$

we (design  $\hat{y}$ ) so that  
~~What~~ should  $E\hat{y} = EY$

Suppose  $\tilde{y}$  is an estimator of  $Y$

$$E\tilde{y} - EY = \beta \neq 0$$

$$\begin{aligned} \text{Let } \hat{y} &= \tilde{y} - \beta & E\hat{y} &= E\tilde{y} - \beta = \\ & & &= EY \end{aligned}$$

CLAIM:  $MSE(\hat{Y}) \leq MSE(\tilde{Y})$

$$MSE(\hat{Y}) = E(\hat{Y} - Y)^2$$

$$= E[(\hat{Y} - \tilde{Y} + \tilde{Y} - Y)^2]$$

$$= E[(\hat{Y} - \tilde{Y})^2 + 2(\hat{Y} - \tilde{Y})(\tilde{Y} - Y) + (\tilde{Y} - Y)^2]$$

$$= E[(\hat{Y} - \tilde{Y})^2] + 2E[(\hat{Y} - \tilde{Y})(\tilde{Y} - Y)] + E[(\tilde{Y} - Y)^2]$$

$$= \beta^2 - 2\beta E[\hat{Y} - Y] + MSE(\tilde{Y})$$

$$= \beta^2 - 2\beta (E[\hat{Y}] - E[Y]) + MSE(\tilde{Y})$$

$$MSE(\hat{Y}) = -\beta^2 + MSE(\tilde{Y})$$

$$\Rightarrow MSE(\hat{Y}) \leq MSE(\tilde{Y})$$

Moral: we should always take  $\hat{Y}$  so that  $E\hat{Y} = EY$

without loss of generality assume  $EY = EX = 0$   
(Ex: show that general case follows)

$$\hat{Y} = aX + b$$

$$E\hat{Y} = EY = 0$$

$$E\hat{Y} = aE(X) + b = b$$

$$\Rightarrow b = 0$$

$$\hat{Y} = aX$$

Question: How to choose  $a$ ?

$$\begin{aligned}
 \text{MSE}(\hat{Y}) &= E[(aX - Y)^2] \\
 &= E[a^2 X^2 - 2aXY + Y^2] \\
 &= a^2 E[X^2] - 2a E[XY] + E[Y^2] \\
 &= a^2 \text{Var}(X) - 2a \text{Cov}(X, Y) + \text{Var}(Y)
 \end{aligned}$$

minimize wrt  $a$

$$a = \frac{\text{SD}(Y)}{\text{SD}(X)} \text{COR}(X, Y) \quad \rightarrow \quad \frac{\text{Cov}(X, Y)}{\text{SD}(X) \text{SD}(Y)}$$

Empirical version of this:  $(x_1, y_1), \dots, (x_n, y_n)$

It should not surprise you that the least-squares line has

$$\hat{a} = \frac{s_y}{s_x} \rho_{xy}$$

← sample SD of  $y_1, \dots, y_n$   
 ← sample correlation  
 ← sample SD of  $x_1, \dots, x_n$

$$\hat{b} = \bar{y} - a \bar{x}$$

$$\frac{\frac{1}{n-1} \sum (x_i - \bar{x})(y_i - \bar{y})}{\text{SD}_x \text{SD}_y}$$

$$\begin{aligned}
 \hat{y}_i &= \text{fitted value} \\
 &= \hat{a} + \hat{b} x_i
 \end{aligned}$$

$$\begin{aligned}
 \rho_{xy} &= \text{strength linear relationship} \\
 \rho_{xy} &= \pm 1 \text{ if data on line} \\
 |\rho_{xy}| &< 1
 \end{aligned}$$