

# 12: Multiple linear regression [2.3, 3, 3.4]

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Notation:

independent units of observation

$$i = 1, \dots, n \quad \leftarrow (y_i, x_i^T) \quad \leftarrow \begin{matrix} \text{p-vector} \\ \text{p-vector} \end{matrix}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \underbrace{Y}_{n \times 1} \quad \leftarrow \begin{matrix} \text{random variable} \\ \text{vector of responses} \end{matrix} \quad \leftarrow \begin{matrix} \text{rent} \\ \text{wages} \end{matrix}$$

$$\begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{bmatrix} = \underbrace{X}_{n \times p} \quad \leftarrow \begin{matrix} \text{fixed} \\ \text{design matrix} \end{matrix}$$

rows = observations  
cols = covariates

parameters of interest

$$\underbrace{\beta}_{(p \times 1)} \quad \text{vector of regression coeff (parameter)}$$

unknown

main focus to find  $\beta$  estimate

$$\underbrace{\varepsilon}_{(n \times 1)} \quad \text{random vector}$$

unknown & unobserved

Model:

$$Y = X\beta + \varepsilon \quad \leftarrow \varepsilon \sim N_n(0, \sigma^2 I)$$

$$y_i = x_i^T \beta + \varepsilon_i \quad \leftarrow \begin{matrix} \varepsilon_i \sim N(0, \sigma^2) \\ \varepsilon_i, \varepsilon_j \text{ independent} \end{matrix}$$

1

Other model assumptions:

Full rank:  $\text{rank}(X) = p$

$X$  where  $n \gg p$   
 $n \times p$

number of lin. indep. columns.

Identifiability problems when not full rank.

Distribution of  $Y_i$

$$Y_i = X_i^T \beta + \varepsilon_i \leftarrow N(0, \sigma^2)$$

$\uparrow \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_p X_{pi}$

$$Y_i \sim N(X_i^T \beta, \sigma^2)$$



$$E(Y_i) = E(X_i^T \beta + \varepsilon_i) = X_i^T \beta + \underbrace{E(\varepsilon_i)}_0$$

$$\text{Var}(Y_i) = \text{Var}(X_i^T \beta + \varepsilon_i) = \sigma + \sigma^2$$

$Y_i, Y_j$  will be independent since  $\varepsilon_i$  and  $\varepsilon_j$  is indep.

$$Y \sim N_n(X\beta, \sigma^2 I)$$

$n \times 1$

but, we could have written

$$Y_i \sim N(\mu_i, \sigma^2)$$

$\uparrow$  per. of interest       $\nwarrow$  nuisance       $\swarrow$  distribution of response

$$\eta_i = x_i^T \beta \quad \leftarrow \text{linear predictor} \quad \text{(lin pred.)}$$

$$\mu_i = \eta_i \quad \leftarrow \text{connection } \mu_i \text{ and } \eta_i$$

$\xrightarrow{\text{mean}}$