

How do we obtain the values
of $\beta = [\beta_0, \beta_1, \dots, \beta_{p-1}]^T$

$$X = \begin{bmatrix} x_{00} & x_{01} & \dots & x_{0p-1} \\ \vdots & \vdots & & \vdots \\ x_{m-10} & - & - & x_{m-1p-1} \end{bmatrix}$$

$$Y \rightarrow Y(X) = f(X) + \epsilon$$

$$\epsilon \sim N(0, \sigma^2)$$

\downarrow mean value $\mu = 0$

i.i.d = independent and identically distributed

$$f(x) \simeq \tilde{y}(x) \rightarrow \tilde{y}_i = \tilde{y}(x_i)$$

$$Y = X\beta + \epsilon \quad \tilde{y} = X\beta$$

How do we find β ?

optimizing/minimizing a
function called the
cost/cost function

In Linear regression:

$$\text{Cost function} = C(\beta; X)$$

$$= \frac{1}{2} \sum_{i=1}^{n-1} (y_i - \tilde{y}_i)^2 = \text{MSE}$$

$$\begin{aligned}
 &= \frac{1}{n} \left[(y - \tilde{y})^T (y - \tilde{y}) \right] \\
 &= \frac{1}{n} \left[(y - X\beta)^T (y - X\beta) \right] \\
 &= \frac{1}{n} \sum_{i=0}^{n-1} (y_i - x_{i,*} \beta)^2
 \end{aligned}$$

$$\min_{\beta \in \mathbb{R}^p} \left[(y - X\beta)^T (y - X\beta) \right]$$

$$\frac{\partial C(\beta)}{\partial \beta_j} = \frac{\partial}{\partial \beta_j} \left[\sum_{i=0}^{n-1} (y_i - \beta_0 x_{i0} - \beta_1 x_{i1} - \beta_2 x_{i2} - \dots - \beta_j x_{ij} - \beta_{p-1} x_{i,p-1})^2 \right]$$

$$x_{i,*} \beta = x_{i0} \beta_0 + x_{i1} \beta_1 + \dots + x_{i,p-1} \beta_{p-1}$$

$$\begin{bmatrix} x_{00} & x_{01} & \dots & x_{0,p-1} \\ x_{10} & x_{11} & \dots & x_{1,p-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n-1,0} & x_{n-1,1} & \dots & x_{n-1,p-1} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{p-1} \end{bmatrix}$$

$$\frac{\partial C}{\partial \beta_j} = 0 = -2 \sum_{i=0}^{n-1} x_{ij} (y_i - \beta_0 x_{i0} - \beta_1 x_{i1} - \dots - \beta_j x_{ij} - \beta_{p-1} x_{i,p-1})$$

$$- \beta_p (x'_{p-1})$$

\Rightarrow in Matrix vector form;

$$\frac{\partial C}{\partial \beta} = 0 = X^T (y - X\beta)$$

$$= X^T X \beta = X^T y$$

$X \in \mathbb{R}^{n \times p}$ $X^T \in \mathbb{R}^{p \times n}$
 $y \in \mathbb{R}^n$

if we can invert $X^T X$

$$\Rightarrow \beta = \underbrace{(X^T X)^{-1}}_{\text{known}} X^T y$$

