

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

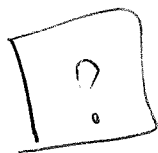
$$E \varepsilon_i = 0$$

LSM:

$$\min_{(\beta_0, \beta_1)} \sum_{i=1}^n \left[\underbrace{(y_i - (\beta_0 + \beta_1 x_i))}_{\text{RSS}} \right]^2$$

RSS

$$\log \left(\frac{p(x_i)}{1 - p(x_i)} \right) = \underbrace{\beta_0 + \beta_1 x_i}$$



$$y_i = \underbrace{\beta_0 + \beta_1 x_i}_{\varepsilon_i} + (\varepsilon_i)$$

$\varepsilon_i \sim \text{Normal}(0, \sigma^2)$

$$y_i \sim \text{Normal}(\beta_0 + \beta_1 x_i, \sigma^2)$$

• independent observations. i.e.

$\{y_i\}_{i=1}^n$ are mutually indep.

Joint distribution $\{y_i\}_{i=1}^n$

$$\prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(y_i - (\beta_0 + \beta_1 x_i))^2}{2\sigma^2}\right\}$$

the density for y_i

like likelihood function for $\{y_i\}_{i=1}^n$

$$L(\beta_0, \beta_1)$$

we want to
 $\max L(\beta_0, \beta_1)$

$$\exp \left\{ - \frac{\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2}{2\sigma^2} \right\}$$

$$\exp\{-a\} \cdot \exp\{-b\} = \exp\{-(a+b)\}$$

maximum likelihood

$$p_i = \frac{e^{\beta_0 + \beta_1 x_i}}{1 + e^{\beta_0 + \beta_1 x_i}}$$

$$\log \left(\frac{p(x_i)}{1-p(x_i)} \right) = \beta_0 + \beta_1 x_i$$

$$p_i = p(x_i) = \Pr(y_i = 1 | x_i) = E(y_i | x_i)$$

PMF for y_i

$$(x_i, y_i)$$

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$$\Pr(y_i = 1) = p_i \quad \Pr(y_i = 0) = 1 - p_i$$

$$L(\beta_0, \beta_1) = \prod_{i=1}^n p_i^{y_i} (1-p_i)^{1-y_i}$$

$$\max L(\beta_0, \beta_1)$$

$$L(\beta_0, \beta_1) = \prod_{i=1}^n p_i^{y_i} (1-p_i)^{1-y_i}$$

$$p_i = \frac{e^{\beta_0 + \beta_1 x_i}}{1 + e^{\beta_0 + \beta_1 x_i}}$$

$$\log L(\beta_0, \beta_1) = \sum_{i=1}^n \log [p_i^{y_i} (1-p_i)^{1-y_i}]$$

$$= \sum_{i=1}^n [y_i \log p_i + (1-y_i) \log (1-p_i)]$$

$$(\hat{\beta}_0, \hat{\beta}_1) \in \arg \max_{(\beta_0, \beta_1)} \log L(\beta_0, \beta_1)$$

