

# Linear Regression - MLE

(1)

5/8/26

Can do EM for  
• Latent weights  
• Multiple lines  
(line membership)  
• Missing data

$$y = w^T x + \epsilon$$

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

$$y = n \times 1$$

$$x = n \times m$$

$$w = 1 \times m$$

$$y = n \times 1$$

$$X = n \times m$$

$$w = 1 \times m$$

$$p(y|x, w, \sigma^2) = \mathcal{N}(y | w^T x, \sigma^2)$$

$$\mathcal{N}(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

$$\ln \mathcal{N}(\mu, \sigma^2) = -\frac{1}{2} \ln(2\pi\sigma^2) - \frac{(x-\mu)^2}{2\sigma^2}$$

$$= -\frac{1}{2} \ln 2\pi - \frac{1}{2} \ln \sigma^2 - \frac{(x-\mu)^2}{2\sigma^2}$$

$$= -\frac{1}{2} \ln 2\pi - \ln \sigma - \frac{(x-\mu)^2}{2\sigma^2}$$

$$\ln p(y|x, w, \sigma^2) = -\frac{1}{2} \ln 2\pi - \ln \sigma - \frac{(y - w^T x)^2}{2\sigma^2}$$

$$\ln \mathcal{L}(w, \sigma^2) = \ln \prod_{i=1}^n p(y_i | x_i, w, \sigma^2) = \sum_{i=1}^n \ln p(y_i | x_i, w, \sigma^2)$$

$$\Rightarrow \sum_{i=1}^n -\frac{1}{2} \ln 2\pi - \ln \sigma - \frac{(y_i - w^T x_i)^2}{2\sigma^2}$$

$$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial}{\partial w} \sum_{i=1}^n -\frac{(y_i - w^T x_i)^2}{2\sigma^2} = -\frac{1}{2\sigma^2} \sum_{i=1}^n \frac{\partial}{\partial w} (y_i - w^T x_i)^2$$

$$\frac{\partial}{\partial w} (y_i - w^T x_i)^2 = 2(y_i - w^T x_i)(-x_i)$$

$$\frac{\partial \mathcal{L}}{\partial w} = -\frac{1}{2\sigma^2} \sum_{i=1}^n -2(y_i - w^T x_i)(x_i) = \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - w^T x_i)(x_i)$$

$$\frac{\partial \mathcal{L}}{\partial w} = 0 \Rightarrow \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - w^T x_i)(x_i) = 0 \Rightarrow \sum_{i=1}^n (y_i - w^T x_i)(x_i) = 0$$

$$\Rightarrow \sum_{i=1}^n y_i x_i - \sum_{i=1}^n (w^T x_i) x_i = 0 \Rightarrow \sum_{i=1}^n y_i x_i = \sum_{i=1}^n (w^T x_i) x_i$$

(2)

$$\frac{\partial \mathcal{L}}{\partial \omega} = 0 \Rightarrow \sum^n y_n = \sum^n (\omega^T x)(x) \Rightarrow X^T y = X^T X \omega \Rightarrow \text{Normal equations.}$$

$$\boxed{\omega = (X^T X)^{-1} X^T y}$$

↔

$$\frac{\partial \mathcal{L}}{\partial \sigma} = \frac{\partial}{\partial \sigma} \sum^n \left[ \underbrace{-\frac{1}{2} \ln 2\pi}_{\frac{\partial}{\partial \sigma} = 0} - \ln \sigma - \frac{(y - \omega^T x)^2}{2\sigma^2} \right]$$

$$\Rightarrow \sum^n \left[ \frac{\partial}{\partial \sigma} - \ln \sigma - (y - \omega^T x)^2 \frac{\partial}{\partial \sigma} \frac{1}{2\sigma^2} \right]$$

$$= \sum^n \left[ -\frac{1}{\sigma} - (y - \omega^T x)^2 \left( -\frac{1}{\sigma^3} \right) \right] = 0$$

$$\Rightarrow \sum^n -\frac{1}{\sigma} = \sum^n \frac{(y - \omega^T x)^2}{\sigma^3} \Rightarrow \frac{1}{\sigma} = \frac{1}{\sigma^3} \sum^n (y - \omega^T x)^2$$

$$\Rightarrow \sigma^2 = \sum^n (y - \omega^T x)^2$$

$$\sigma = \frac{\sqrt{\sum^n (y - \omega^T x)^2}}{\sqrt{N}} = \frac{1}{\sqrt{N}} \sqrt{\sum^n (y - \omega^T x)^2}$$

$$\boxed{\sigma^2 = \frac{1}{N} \sum^n (y - \omega^T x)^2}$$