

$$f\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$L(\theta|X) = f(x_1, x_2, \dots, x_n | \theta)$$

$$= \prod_{i=1}^n f(x_i | \theta)$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$= \left(\frac{1}{\sqrt{2\pi}\sigma^2}\right)^{n/2} \times \prod_{i=1}^n e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$\log(L(\theta|X)) = \frac{-n}{2} \log(2\pi\sigma^2)$$

$$+ \log e^{-\left(\frac{(x_1 - \mu)^2 + (x_2 - \mu)^2 + \dots + (x_n - \mu)^2}{2\sigma^2}\right)}$$

$$= \frac{-n}{2} \log(2\pi\sigma^2) - \sum_{i=1}^n \frac{(x_i - \mu)^2}{2\sigma^2}$$

$$\frac{\partial \log(L(\theta|x))}{\partial \mu} = 0$$

$$0 - \left(\frac{\sum x_i - n\mu}{\sigma^2} \right) = 0$$

$$\Rightarrow \mu = \frac{\sum_{i=1}^n x_i}{n}$$

$$\frac{\partial \log(L(\theta|x))}{\partial \sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

For Regression

$$y_i \sim N(\overset{X^T \theta}{\cancel{\theta}}, \sigma^2).$$

~~$L(\theta)$~~ y_i are iid

$$L(\theta; X|Y) = P(y_1, \dots, y_n | x_1, \dots, x_n; \theta)$$

$$= \prod_{i=1}^n p(y_i | x_i; \theta)$$

$$= \left(\frac{1}{\sqrt{2\pi}\sigma} \right)^n e^{-\frac{\sum (y_i - \overset{x_i \theta^T}{\cancel{\theta x_i}})^2}{2\sigma^2}}$$

$$= (2\pi\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} (Y - X\theta)^T (Y - X\theta)}.$$

$$\log(L(\theta; X|Y)) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (Y - X\theta)^T (Y - X\theta).$$

$$\frac{\partial \log(L(\cdot))}{\partial \theta} = 0$$

$$0 = \frac{1}{2\sigma^2} [0 - 2X^T Y + X^T X \theta]$$

$$\Rightarrow \theta = (X^T X)^{-1} X^T Y.$$

Note

$$\sum_{i=1}^n a_i^2 = A^T A.$$