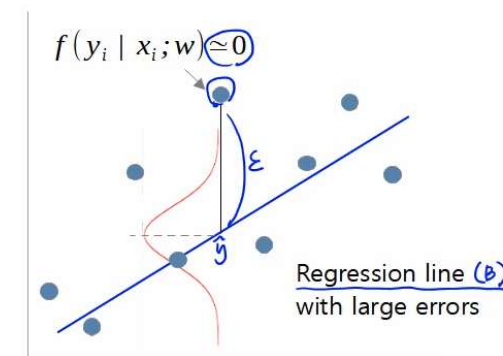
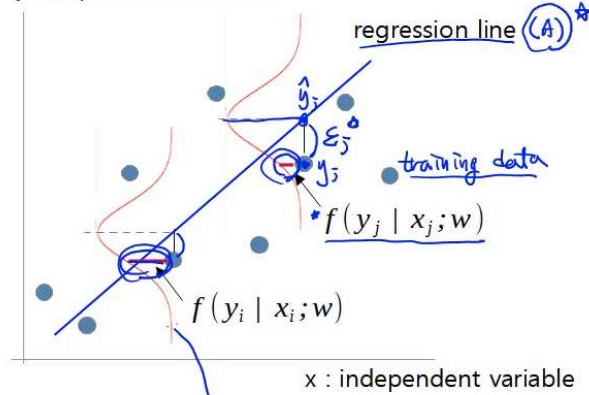


■ Estimating a regression line using the Maximum Likelihood Estimates (MLE)

- Suppose we know the data consists of values drawn from $(y=wx+b+\epsilon)$ ϵ is independent, identically distributed, and normally distributed.
- What are the parameter values w and b for which the observed data have the greatest probability?
- This can be solved with MLE, and the result is the same as the Least Squares Method.

y : dependent variable



$$\hat{y}_i = w_1 x_{1,i} + w_2 x_{2,i} + \dots + w_k x_{k,i} + b \quad \epsilon \sim \mathcal{N}(0, \sigma^2) \quad \text{log likelihood function}$$

$$f(y_i | x_i; w, b) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y_i - \hat{y}_i)^2}{2\sigma^2}\right) \quad \log(L(w, b)) = \sum_{i=1}^N \log(f(y_i | x_i; w, b))$$

$$\max_{w, b} L(w, b) = \prod_{i=1}^N f(y_i | x_i; w, b) \quad \leftarrow \text{likelihood function}$$

$$\max_{w, b} \log(L(w, b)) = N \log \frac{1}{\sqrt{2\pi}\sigma} - \frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

- Maximize log likelihood

$$\max_{w, b} \log(L(w, b)) = \max_{w, b} \left(- \sum_i (y_i - \hat{y}_i)^2 \right)$$

- Minimize squared error = least squares method

$$\max_{w, b} \left(- \sum_i (y_i - \hat{y}_i)^2 \right) \rightarrow \min_{w, b} \sum_i (y_i - \hat{y}_i)^2$$

- Maximizing the log-likelihood is equivalent to minimizing the squared error.