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

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y - x^T w)^2}{2\sigma^2}\right)$$

For n independent observations, joint log-likelihood function will be:

$$L(w, \sigma^2) = \sum_{i=1}^{n} \log\left[\frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left(-\frac{(y^{(i)} - x^{(i)^T} w)^2}{2\sigma^2}\right)\right]$$

$$= \sum_{i=1}^{n} \left[\log(2\pi\sigma^2)^{-1/2} + \log \exp\left(-\frac{(y^{(i)} - x^{(i)^T} w)^2}{2\sigma^2}\right)\right]$$

$$= \frac{-n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} (y^{(i)} - x^{(i)^T} w)^2$$

Deriving log-likelihood function w.r.t 'w':

$$\frac{\partial L}{\partial w} = -\frac{1}{\cancel{2}\sigma^2} \sum_{i=1}^{n} \cancel{2}(y^{(i)} - x^{(i)^T} w) \times (-x^{(i)})$$

$$= \frac{1}{\sigma^2} \sum_{i=1}^{n} x^{(i)} (y^{(i)} - x^{(i)^T} w)$$

Set derivative to zero (maximization condition)

$$0 = \frac{1}{\sigma^2} \sum_{i=1}^{n} x^{(i)} (y^{(i)} - x^{(i)^T} w)$$

$$0 = \sum_{i=1}^{n} x^{(i)} y^{(i)} - x^{(i)} x^{(i)^T} w$$

$$\sum_{i=1}^{n} x^{(i)} \cdot x^{(i)^T} w = \sum_{i=1}^{n} x^{(i)} y^{(i)}$$

$$\therefore \boxed{w = \left[\sum_{i=1}^{n} (x^{(i)} x^{(i)T})\right]^{-1} \times \sum_{i=1}^{n} x^{(i)} y^{(i)}}$$

Now, deriving log-likelihood w.r.t 'σ^2'

$$\frac{\partial L}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^{n} \left(y^{(i)} - x^{(i)^T} w \right)^2$$

Set derivative to zero (maximization condition)

$$0 = \frac{-n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^{n} \left(y^{(i)} - x^{(i)^T} w \right)^2$$

$$\frac{n}{\cancel{2}\sigma^2} = \frac{1}{\cancel{2}\sigma^4} \sum_{i=1}^{n} \left(y^{(i)} - x^{(i)^T} w \right)^2$$

$$\therefore \boxed{\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} \left(y^{(i)} - x^{(i)^T} w \right)^2}$$