

Modelo de regresión

Sea el modelo de regresión

$$t_n = \phi(x_n) w^T + \eta_n, \text{ con } \{t_n \in \mathbb{R}, x_n \in \mathbb{R}^p\}_{n=1}^N, w \in \mathbb{R}^q,$$

$$\phi: \mathbb{R}^p \rightarrow \mathbb{R}^q, q \geq p \text{ y } \eta_n \sim N(\eta_n | 0, \sigma^2).$$

Presente el problema de optimización [inferencia] y la solución del mismo para los modelos

$$t_n = \phi(x_n) w^T + \eta_n$$

$$\eta_n \sim N(\eta_n | 0, \sigma^2)$$

por hipótesis $E[\eta_n] = 0$ y $\text{Var}(\eta_n) = \sigma^2$

entonces

$$t_n \sim N(E[\eta_n]; \text{Var}(\eta_n)).$$

$$E[t_n] = E[\phi(x_n) w^T + \eta_n]$$

$$= E[\phi(x_n) w^T] + \underbrace{E[\eta_n]}_0 \rightarrow \text{por hip}$$

$$= \phi(x_n) w^T$$

$$\text{Var}(t_n) = \text{Var}(\phi(x_n) w^T + \eta_n)$$

$$= \text{Var}(\cancel{\phi(x_n) w^T}^0) + \text{Var}(\eta_n)$$

$$= \sigma^2.$$

luego se concluye que $t_n \sim N(\phi(x_n) w^T; \sigma^2)$

$$f(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t_n - \mu)^2}{2\sigma^2}}$$

$$f(t_n) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t_n - \phi(x_n)w^T)^2}{2\sigma^2}}$$

$$\textcircled{2} L(\phi(x_n), w^T/x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t_n - \phi(x_n)w^T)^2}{2\sigma^2}} \dots \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t_n - \phi(x_n)w^T)^2}{2\sigma^2}}$$

$$L(\phi(x_n), w^T/x) = \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^n e^{-\frac{\sum_{n=1}^N (t_n - \phi(x_n)w^T)^2}{2\sigma^2}}$$

$$\ln L(\phi(x_n), w^T/x) = n \ln \left(\frac{1}{\sqrt{2\pi}\sigma}\right) - \frac{\sum_{n=1}^N (t_n - \phi(x_n)w^T)^2}{2\sigma^2}$$

$$\frac{\partial \ln L(\phi(x_n), w^T/x)}{\partial w^T} = 0 - \frac{\sum_{n=1}^N 2(t_n - \phi(x_n)w^T)(-\phi(x_n))}{2\sigma^2}$$

$$\Rightarrow \sum_{n=1}^N (t_n - \phi(x_n)w^T)(\phi(x_n)) = 0$$

$$\Rightarrow \sum_{n=1}^N (\phi(x_n)^T t_n - \hat{w} \cdot \phi(x_n) \phi(x_n)^T) = 0$$

$$\Rightarrow \sum_{n=1}^N \phi(x_n)^T t_n - \sum_{n=1}^N \phi(x_n) \phi(x_n)^T \cdot \hat{w} = 0$$

$$\hat{w}_{n.v.} = \frac{\sum_{n=1}^N \phi(x_n)^T t_n}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T}$$

$$\textcircled{2} \quad \frac{\partial l(\phi(x_n), w^T/x)}{\partial \phi(x_n)} = 0 = \frac{\sum_{n=1}^N x(t_n - \phi(x_n)w^T)(-w^T)}{x^2}$$

$$\Rightarrow \sum_{n=1}^N (t_n w^T - \phi(x_n) w^T \cdot w^T) = 0$$

$$\Rightarrow \sum_{n=1}^N t_n^T \cdot w - \hat{\phi}(x_n) \sum_{n=1}^N w \cdot w = 0$$

$$\Rightarrow t_n^T \sum_{n=1}^N w = \hat{\phi}(x_n) \sum_{n=1}^N w^2 = 0$$

$$\hat{\phi}(x_n)_{m.v.} = \frac{\sum_{n=1}^N t_n^T \cdot w}{\sum_{n=1}^N w^2}$$

$$\hat{\phi}(x_n)_{m.v.} = \frac{\sum_{n=1}^N t_n^T \left(\frac{\sum_{n=1}^N \phi(x_n)^T t_n}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T} \right)}{\sum_{n=1}^N \left(\frac{\sum_{n=1}^N \phi(x_n)^T t_n}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T} \right)^2}$$

por tanto, \hat{w} y $\hat{\phi}(x_n)$ son los estimadores de máxima verosimilitud de w^T y $\phi(x_n)$.

Minimos Cuadrados

$$t_n = \phi(x_n) w^T + \eta_n$$

$$\eta_n \sim N(\eta_n | 0, \sigma^2)$$

$$E = \sum_{n=1}^N (t_n - \phi(x_n) w^T)^2$$

$$E(\eta_n) = 0$$

$$\frac{\partial E}{\partial w^T} = \sum_{n=1}^N 2(t_n - \phi(x_n) w^T) (-\phi(x_n))$$

$$\Rightarrow -2 \sum_{n=1}^N (t_n \phi(x_n) - w^T \phi(x_n)^2) = 0$$

$$\Rightarrow \sum_{n=1}^N (t_n \phi(x_n) - \hat{w}^T \phi(x_n)^2) = 0$$

$$\Rightarrow \sum_{n=1}^N t_n \phi(x_n) - \hat{w}^T \sum_{n=1}^N \phi(x_n)^2 = 0$$

$$\hat{w} = \frac{\sum_{n=1}^N t_n \phi(x_n)^T}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T}$$

$$\hat{\phi}(x_n) = \frac{t_n \sum_{n=1}^N \left(\frac{\sum_{n=1}^N t_n \phi(x_n)^T}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T} \right)}{\sum_{n=1}^N \left(\frac{\sum_{n=1}^N t_n \phi(x_n)^T}{\sum_{n=1}^N \phi(x_n) \phi(x_n)^T} \right)^2} \quad \checkmark$$

Con la segunda derivada \hat{w} y $\hat{\phi}(x_n)$ son los estimadores de un minimo.

Minimos Cuadrados Regularizados

$$t_n = \phi(x_n) w^T + \eta_n \quad \eta_n \sim N(\eta_n | 0, \sigma^2)$$

$$l(\phi(x_n), w^T | x_n) = \frac{\sum_{n=1}^N (t_n - \phi(x_n) w^T)^2 + \lambda |w|^2}{2 \sigma^2}$$

$$= \frac{\sum_{n=1}^N 2(t_n - \phi(x_n) w^T)(-\phi(x_n)) + 2\lambda w}{2 \sigma^2}$$

$$\Rightarrow \sum_{n=1}^N (t_n - \phi(x_n) w^T) \phi(x_n) + \lambda w = 0$$

$$\Rightarrow \sum_{n=1}^N (t_n \phi(x_n)^T - w \phi(x_n) \phi(x_n)^T) + \lambda w = 0$$

$$\Rightarrow \sum_{n=1}^N t_n \phi(x_n)^T - w \sum_{n=1}^N \phi(x_n) \phi(x_n)^T + \lambda w = 0$$

$$\Rightarrow \sum_{n=1}^N t_n \phi(x_n)^T = w \left(\sum_{n=1}^N \phi(x_n) \phi(x_n)^T + \lambda I \right)$$

$$\hat{w}_{M.V.} = \sum_{n=1}^N t_n \phi(x_n)^T \left(\sum_{n=1}^N \phi(x_n) \phi(x_n)^T + \lambda I \right)^{-1}$$

Modelo Máximo a-posteriori

$$P(\phi(x_n), w^T, \underline{x}) \propto P(t_n / \underline{x}, w^T) P(w^T)$$

$$\log P(w^T / t_n, \phi(x_n) / \underline{x}) \approx L \left(\prod_{n=1}^N N(t_n / \phi(x_n) w^T, \sigma_n^2) \prod_{n=1}^N N(n_n / 0, \sigma_n^2) \right)$$

$$= L \left[\prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{(t_n - \phi(x_n) w^T)^2}{2\sigma_n^2}} \right] + L \left[\prod_{n=1}^N N(n_n / 0, \sigma_n^2) \right] \quad (*)$$

$$+ L \left(\prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{\|n_n - 0\|^2}{2\sigma_n^2}} \right)$$

$$= (*) + L \left(\prod_{n=1}^N \frac{1}{(\sqrt{2\pi\sigma_n^2})^{1/2}} \right) + L \left(e^{-\frac{\sum |n_n|^2}{2\sigma_n^2}} \right)$$

$$= (*) + L \left(\frac{1}{(\sqrt{2\pi\sigma_n^2})^{N/2}} \right) + L \left(e^{-\frac{\sum |n_n|^2}{2\sigma_n^2}} \right)$$

$$= (*) - \frac{N}{2} [\log(2\pi) + \log(\sigma_n^2)] - \frac{\sum |n_n|^2}{2\sigma_n^2}$$

$$= -\frac{N}{2} [\log(2\pi) + \log(\sigma_n^2)] - \frac{\|t_n - \phi(x_n) w^T\|^2}{2\sigma_n^2}$$

$$- \frac{N}{2} [\log(2\pi) + \log(\sigma_n^2)] - \frac{\|n_n\|^2}{2\sigma_n^2}$$

$$= MA - \left[\frac{2\sigma_n^2}{2\sigma_n^2} \|t_n - \phi(x_n) w^T\|^2 + \frac{2\sigma_n^2}{2\sigma_n^2} \|n_n\|^2 \right] + Cte$$

$$= Min \left[\|t_n - \phi(x_n) w^T\|^2 + \|n_n\|^2 \right] + Cte$$

$$\lambda = \frac{\sigma_n^2}{\sigma_n^2} \hat{w}_{MAP} = \left(\phi(x_n)^T \phi(x_n) + \frac{\sigma_n^2}{N} I \right)^{-1} \phi(x_n)^T t_n \rightarrow w_{n.c.r}$$