

$$\begin{aligned}
 \log(p(\mathbf{z})) &= \log(p(\mathbf{y}|\mathbf{x})p(\mathbf{x})) = \log(p(\mathbf{y}|\mathbf{x})) + \log(p(\mathbf{x})) \\
 &= \log \left[\frac{1}{(2\pi)^{D/2} |\mathbf{L}^{-1}|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) \right] \right] \\
 &\quad + \log \left[\frac{1}{(2\pi)^{M/2} |\mathbf{\Delta}|} \exp \left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) \right] \right] \\
 &= -\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) - \frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) + \text{cte.}
 \end{aligned}$$

Ejercicio: Determine el término cte.

Sea $\mathbf{z} = [\mathbf{x}, \mathbf{y}]$ la pdf conjunta en log se puede representar como:

$$p(\mathbf{z}) = p(\mathbf{x}, \mathbf{y}) = p(\mathbf{y}|\mathbf{x})p(\mathbf{x})$$

$$\log(p(\mathbf{z})) = \log(p(\mathbf{y}|\mathbf{x})) + \log(p(\mathbf{x}))$$

$$\begin{aligned}
 &= \log \left(\frac{1}{(2\pi)^{D/2} |\mathbf{L}^{-1}|^{1/2}} \cdot \exp \left(-\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) \right) \right) \\
 &\quad + \log \left(\frac{1}{(2\pi)^{M/2} |\mathbf{\Delta}|^{1/2}} \cdot \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) \right) \right)
 \end{aligned}$$

$$= \log \left(\exp \left(-\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) \right) \right)$$

$$+ \log \left(\exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) \right) \right)$$

$$+ \log \left(\frac{1}{(2\pi)^{D/2} |\mathbf{L}^{-1}|^{1/2}} \right) + \log \left(\frac{1}{(2\pi)^{M/2} |\mathbf{\Delta}|^{1/2}} \right)$$

$$\begin{aligned}
 &= -\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) - \frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) \\
 &\quad - \log((2\pi)^{D/2} |\mathbf{L}^{-1}|^{1/2}) - \log((2\pi)^{M/2} |\mathbf{\Delta}|^{1/2})
 \end{aligned}$$

$$\begin{aligned}
 &= -\frac{1}{2} (\mathbf{y} - \mathbf{Ax} - \mathbf{b})^T \mathbf{L} (\mathbf{y} - \mathbf{Ax} - \mathbf{b}) - \frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Delta} (\mathbf{x} - \boldsymbol{\mu}) \\
 &\quad - \log((2\pi)^{(D+M)/2} |\mathbf{L}^{-1}|^{1/2} |\mathbf{\Delta}|^{1/2})
 \end{aligned}$$

constante

Ejercicio: Sea $t_n = \mathbf{w}^T \phi(x_n) + \eta$;

con $\mathbf{w} \sim p(\mathbf{w}) = \mathcal{N}(\mathbf{w} | \mathbf{m}_0, \mathbf{S}_0)$ y $\eta \sim p(\eta) = \mathcal{N}(\eta | 0, \mathbf{B}^{-1})$

Demuestre que $p(\mathbf{w} | \mathbf{t}) = \mathcal{N}(\mathbf{w} | \mathbf{m}_N, \mathbf{S}_N)$

$$\mathbf{m}_N = \mathbf{S}_N (\mathbf{S}_0^{-1} \mathbf{m}_0 + \beta \Phi^T \mathbf{t}) \in \mathbb{R}^Q$$

$$\mathbf{S}_N^{-1} = \mathbf{S}_0^{-1} + \beta \Phi^T \Phi \in \mathbb{R}^{Q \times Q}$$

$$\Phi = [\phi(x_1), \phi(x_2), \dots, \phi(x_N)]^T \in \mathbb{R}^{N \times Q}; \quad \mathbf{t} = [t_1, t_2, \dots, t_N]^T \in \mathbb{R}^N$$

$$\mathbf{w} \in \mathbb{R}^Q$$

$$\beta \in \mathbb{R}^+$$

Para esto vamos a tener en cuenta el teorema de Bayes para variables Gaussianas que nos dice

$$\text{Sea } p(\mathbf{x}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}^{-1})$$

$$\text{y } p(\mathbf{y} | \mathbf{x}) = \mathcal{N}(\mathbf{y} | \mathbf{A}\mathbf{x} + \mathbf{b}, \mathbf{L}^{-1})$$

entonces

$$p(\mathbf{x} | \mathbf{y}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_{\mathbf{x}|\mathbf{y}}, \boldsymbol{\Sigma}_{\mathbf{x}|\mathbf{y}})$$

donde

$$\boldsymbol{\mu}_{\mathbf{x}|\mathbf{y}} = (\boldsymbol{\Sigma} + \mathbf{A}^T \mathbf{L} \mathbf{A})^{-1} (\mathbf{A}^T \mathbf{L} (\mathbf{y} - \mathbf{b}) + \boldsymbol{\Sigma} \boldsymbol{\mu})$$

$$\boldsymbol{\Sigma}_{\mathbf{x}|\mathbf{y}} = (\boldsymbol{\Sigma} + \mathbf{A}^T \mathbf{L} \mathbf{A})^{-1}$$

- Primero, hallemos qui n es $p(\mathbf{t} | \mathbf{w}^T \Phi, \mathbf{B}^{-1} \mathbf{I})$

Como $\eta = t_n - \mathbf{w}^T \Phi(x_n)$ entonces

$$\mathcal{N}(\eta | 0, \mathbf{B}^{-1}) = \mathcal{N}(t_n - \mathbf{w}^T \Phi(x_n) | 0, \mathbf{B}^{-1})$$

$$= \mathcal{N}(t_n | \mathbf{w}^T \Phi(x_n), \mathbf{B}^{-1})$$

Por lo tanto,

$$t_n \sim \mathcal{N}(t_n | \omega^T \Phi(x_n), B^{-1}) \rightarrow \mathbf{t} \sim \mathcal{N}(\mathbf{t} | \omega^T \Phi, B^{-1} \mathbf{I})$$

- Notamos que tenemos las dos hipótesis del teorema

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}^{-1})$$

$$p(\boldsymbol{\omega}) = \mathcal{N}(\boldsymbol{\omega} | \mathbf{M}_0, \mathbf{S}_0)$$

$$p(\mathbf{y} | \mathbf{x}) = \mathcal{N}(\mathbf{y} | \mathbf{A}\mathbf{x} + \mathbf{b}, \mathbf{L}^{-1})$$
$$\text{y } \mathbf{t} = \mathcal{N}(\mathbf{t} | \omega^T \Phi, B^{-1} \mathbf{I})$$

Lo que está en rojo es para ver el teorema en nuestro ejercicio

Así que lo podemos aplicar

$$p(\mathbf{x} | \mathbf{y}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_{\mathbf{x}|\mathbf{y}}, \boldsymbol{\Sigma}_{\mathbf{x}|\mathbf{y}})$$

$$p(\boldsymbol{\omega} | \mathbf{t}) = \mathcal{N}(\boldsymbol{\omega} | \mathbf{M}_N, \mathbf{S}_N)$$

donde

$$\boldsymbol{\Sigma}_{\mathbf{x}|\mathbf{y}} = (\boldsymbol{\Lambda} + \mathbf{A}^T \mathbf{L} \mathbf{A})^{-1}$$

(Varianza)

$$\mathbf{S}_N = \boldsymbol{\Sigma}_{\boldsymbol{\omega}|\mathbf{t}} = (\mathbf{S}_0 + \Phi^T \mathbf{B} \mathbf{I} \Phi)^{-1}$$

$$\boldsymbol{\mu}_{\mathbf{x}|\mathbf{y}} = (\boldsymbol{\Lambda} + \mathbf{A}^T \mathbf{L} \mathbf{A})^{-1} (\mathbf{A}^T \mathbf{L} (\mathbf{y} - \mathbf{b}) + \boldsymbol{\Lambda} \boldsymbol{\mu})$$

(Media)

$$\mathbf{M}_N = \boldsymbol{\mu}_{\boldsymbol{\omega}|\mathbf{t}} = (\mathbf{S}_0^{-1} + \Phi^T \mathbf{B} \mathbf{I} \Phi)^{-1} (\Phi^T \mathbf{B} \mathbf{I} (\mathbf{t} - \mathbf{0}) + \mathbf{S}_0^{-1} \mathbf{M}_0)$$

$$\mathbf{M}_N = \boldsymbol{\mu}_{\boldsymbol{\omega}|\mathbf{t}} = (\mathbf{S}_0^{-1} + \Phi^T \mathbf{B} \mathbf{I} \Phi)^{-1} (\mathbf{B} \Phi^T \mathbf{t} + \mathbf{S}_0^{-1} \mathbf{M}_0)$$

$$\mathbf{M}_N = \boldsymbol{\mu}_{\boldsymbol{\omega}|\mathbf{t}} = \mathbf{S}_N (\mathbf{B} \Phi^T \mathbf{t} + \mathbf{S}_0^{-1} \mathbf{M}_0)$$

Ejercicio:

Demuestre que la predictiva toma la forma:

$$p(t^* | \mathcal{L}, \phi, w) = \int p(t^* | w) p(w | \mathcal{L}) dw$$

$$p(t^* | \mathcal{L}, \phi, w) = \mathcal{N}(t^* | m_N^T \phi(x^*), \sigma_N^2(x^*))$$

$$\sigma_N^2(x^*) = \frac{1}{\beta} + \phi(x^*)^T S_N \phi(x^*) \in \mathbb{R}^+$$

Vamos a analizar este ejercicio desde la marginalización de la predictiva aplicando un resultado del procedimiento del teorema de Bayes para variables Gaussianas

Si $p(x) = \mathcal{N}(x | \mu, \Sigma^{-1})$ y $p(y|x) = \mathcal{N}(y | Ax + b, C^{-1})$

entonces

$$p(y) = \mathcal{N}(y | \mu_y, \Sigma_{yy}) = \mathcal{N}(y | b + A\mu, C^{-1} + A\Sigma^{-1}A^T)$$

En nuestro ejercicio tenemos que

$$\eta = t^* - w^T \phi(x^*) \sim \mathcal{N}(t^* - w^T \phi(x^*) | 0, B^{-1})$$

$$\Rightarrow p(t^* | w) = \mathcal{N}(t^* - w^T \phi(x^*) | 0, B^{-1}) \\ = \mathcal{N}(t^* | \phi(x^*) w, B^{-1})$$

Además, del ejercicio anterior sabemos que

$$p(w | \mathcal{L}) = \mathcal{N}(w | \mu_{m|\mathcal{L}}, \Sigma_{m|\mathcal{L}}) = \mathcal{N}(w | m_N, S_N)$$

Por lo tanto,

$$p(t^* | \mathbf{t}, \omega) = \mathcal{N}(t^* | \Phi(x^*) \mathbf{M}_N, \mathbf{B}^{-1} + \Phi(x^*)^T \mathbf{S}_N \Phi(x^*))$$