

Байесовский подход для регрессии

$$y \sim \mathcal{N}(y | \mathbf{w}^T \mathbf{x}, \sigma^2) \leftarrow \text{lin. regr.}$$

$$\mathcal{N}(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$$

$$\tau = \frac{1}{\sigma^2} - \text{precision}$$

$$\mathcal{N}(x | \mu, \tau) = \sqrt{\frac{\tau}{2\pi}} e^{-\frac{\tau}{2}(x-\mu)^2}$$

$$\mathcal{N}(x_1, \dots, x_n | \mu, \tau) = \left(\frac{\tau}{2\pi}\right)^{n/2} e^{-\frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2}$$

① $\tau = \text{const}, \mu = ?$

$$\log p(D | \mu) = \text{const} - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2$$

$$p(\mu) = \mathcal{N}(\mu | \mu_0, \tau_0) = \sqrt{\frac{\tau_0}{2\pi}} e^{-\tau_0/2 (\mu - \mu_0)^2}$$

$$\log p(\mu | D) = \text{const} - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2 - \frac{\tau_0}{2} (\mu - \mu_0)^2 =$$

$$= \text{const} - \frac{1}{2} \mu^2 (\tau_0 + \tau \cdot n) + \mu (\tau_0 \mu_0 + \tau \cdot \sum_i x_i) =$$

$$= \text{const} - \frac{\tau_0 + \tau n}{2} \left(\mu - \frac{\tau_0 \mu_0 + \tau \cdot \sum x_i}{\tau_0 + \tau n} \right)^2$$

$$p(\mu | x_1, \dots, x_n) = \mathcal{N}\left(\mu \mid \frac{\tau_0 \mu_0 + \tau \cdot \sum x_i}{\tau_0 + \tau n}, \tau_0 + \tau n\right)$$

$$\tau_n = \tau_0 + \tau \cdot n$$

$$\frac{1}{\sigma_n^2} = \frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}$$

② $\mu = \text{const}, \tau = ?$

$$\log p(D | \tau) = \text{const} + \frac{n}{2} \log \tau - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2$$

$$p(\tau | d_0, \beta_0) = \frac{\beta_0^{d_0}}{\Gamma(d_0)} \tau^{d_0-1} e^{-\beta_0 \tau}$$

gamma distribution
 $\tau \in (0, +\infty)$

$$\log p(\tau | x_1, \dots, x_n) = \text{const} + \frac{n}{2} \log \tau - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2 + (d_0 - 1) \tau - \beta_0 \tau$$

$$p(\tau | x_1, \dots, x_n) = \text{Gamma}\left(\tau \mid d_0 + \frac{n}{2}, \beta_0 + \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^2\right)$$

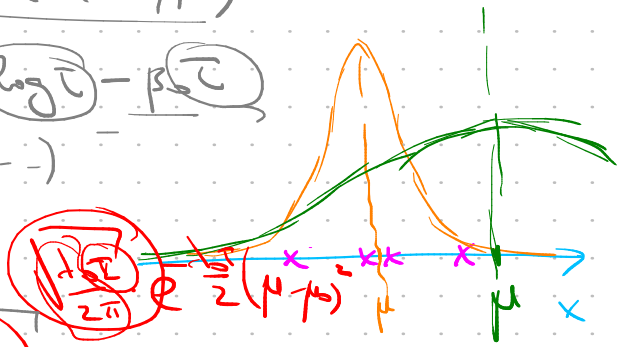
3) $\mu, \tau = ?$ $\log p(x_1 \dots x_n | \mu, \tau) = \text{Const} + \frac{n}{2} \log \tau - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2$
 $p(\mu, \tau) = ?$

$$p(\mu, \tau) = p(\mu) p(\tau) = \mathcal{N}(\mu | \mu_0, \tau_0) \text{Gam}(\tau | \alpha_0, \beta_0)$$

$$\log p(\mu, \tau) = \text{Const} - \frac{\tau_0}{2} (\mu - \mu_0)^2 + (\alpha_0 - 1) \log \tau - \beta_0 \tau$$

$\text{Gam}(\alpha_0, \beta_0) \quad \mathcal{N}(\mu_0, \tau_0) \quad \mathcal{N}(\mu_0, \tau_0) \quad \text{Gam}(-, -)$

$$p(\mu, \tau) = p(\tau) p(\mu | \tau) = p(\mu) p(\tau | \mu)$$



$$p(\mu, \tau) = \text{Gam}(\tau | \alpha_0, \beta_0) \cdot \mathcal{N}(\mu | \mu_0, \lambda_0 \tau)$$

$$\log p(\mu, \tau) = \text{Const} + (\alpha_0 - 1) \log \tau - \beta_0 \tau + \frac{1}{2} \log \tau - \frac{\lambda_0 \tau}{2} (\mu - \mu_0)^2$$

$$\log p(\mu, \tau | x_1 \dots x_n) = \text{Const} + \frac{n}{2} \log \tau - \frac{\tau}{2} \sum_{i=1}^n (x_i - \mu)^2 + (\alpha_0 - 1) \log \tau - \beta_0 \tau + \frac{1}{2} \log \tau - \frac{\lambda_0 \tau}{2} (\mu - \mu_0)^2 =$$

$$= \text{Const} + (\alpha_0 + \frac{n}{2} - 1) \log \tau + \frac{1}{2} \log \tau - \frac{\tau}{2} \left(\lambda_0 (\mu - \mu_0)^2 + \sum_{i=1}^n (x_i - \mu)^2 \right) - \beta_0 \tau$$

$$\lambda_0 (\mu^2 - 2\mu\mu_0 + \mu_0^2) + (n \cdot \mu^2 - 2\mu \cdot \sum_{i=1}^n x_i + \sum_{i=1}^n x_i^2) =$$

$$= (\lambda_0 + n) \mu^2 - 2\mu(\lambda_0 \mu_0 + \sum_{i=1}^n x_i) + \lambda_0 \mu_0^2 + \sum_{i=1}^n x_i^2 =$$

$$= (\lambda_0 + n) \left(\mu - \frac{\lambda_0 \mu_0 + \sum_{i=1}^n x_i}{\lambda_0 + n} \right)^2 + \lambda_0 \mu_0^2 + \sum_{i=1}^n x_i^2 - \frac{(\lambda_0 \mu_0 + \sum_{i=1}^n x_i)^2}{\lambda_0 + n}$$

$$= \text{Const} + (\alpha_n - 1) \log \tau + \frac{1}{2} \log \tau - \frac{(\alpha_n \tau)}{2} \left(\mu - \frac{\lambda_n \mu_n + \sum_{i=1}^n x_i}{\lambda_n + n} \right)^2 - \frac{\tau}{2} \left(\frac{\lambda_n \mu_n^2 + \sum_{i=1}^n x_i^2 - (\lambda_n \mu_n + \sum_{i=1}^n x_i)^2}{\lambda_n + n} \right) - \beta_n \tau$$

$\alpha_n \quad \lambda_n \quad \beta_n$

$$p(\mu, \tau | x_1 \dots x_n) = \text{Gam}(\tau | \alpha_n, \beta_n) \cdot \mathcal{N}(\mu | \mu_n, \lambda_n \tau), \text{ see}$$

$$\alpha_n = \alpha_0 + n/2 \quad \beta_n = \beta_0 + \lambda_0 \mu_0^2 + \sum x_i^2 - \frac{(\lambda_0 \mu_0 + \sum x_i)^2}{\lambda_0 + n}$$

$$\mu_n = \frac{\lambda_0 \mu_0 + \sum x_i}{\lambda_0 + n}, \quad \lambda_n = \lambda_0 + n$$

$$(4) \quad p(\mu | x_1, \dots, x_n) = \int_0^\infty p(\mu, \tau | x_1, \dots, x_n) d\tau =$$

$$= \int_0^\infty \text{Gam}(\tau | \alpha_n, \beta_n) \cdot \mathcal{N}(\mu | \mu_n, \lambda_n \tau) d\tau =$$

$$= \text{Const.} \int_0^\infty \tau^{\alpha_n - 1} e^{-\beta_n \tau} \cdot \tau^{1/2} e^{-\frac{\lambda_n \tau}{2} (\mu - \mu_n)^2} d\tau$$

$$= \text{Const.} \int_0^\infty \tau^{(\alpha_n + 1/2) - 1} \cdot e^{-\tau \left(\beta_n + \frac{\lambda_n}{2} (\mu - \mu_n)^2 \right)} d\tau =$$

$$= \text{Const.} \cdot \frac{\Gamma(\alpha_n + 1/2)}{\left(\beta_n + \frac{\lambda_n}{2} (\mu - \mu_n)^2 \right)^{\alpha_n + 1/2}} = p(\mu | x_1, \dots, x_n)$$

degrees of freedom
↓
 $-\frac{\alpha+1}{2}$

Student's t-distribution

$$p(x) = \text{Const.} \cdot \left(1 + \frac{x^2}{\sigma^2} \right)^{-\frac{\alpha+1}{2}}$$

(5) Predictive distribution

$$p(x | x_1, \dots, x_n) = \int_0^\infty \int_{-\infty}^\infty \mathcal{N}(x | \mu, \tau) \cdot \text{Gam}(\tau | \alpha_n, \beta_n) \mathcal{N}(\mu | \mu_n, \lambda_n \tau) d\mu d\tau$$

$$\int \mathcal{N}(x | \mu) \mathcal{N}(\mu | \mu_n, \lambda_n \tau) d\mu = \mathcal{N}(x | \mu', \tau')$$

$$= \int_0^\infty \mathcal{N}(x | \mu', \tau') \cdot \text{Gam}(\tau | \alpha_n, \beta_n) d\tau = \text{Student}(x | \dots)$$