

WS

$$x_0 \sim \mathcal{N}(\mu, \sigma^2) - \text{KOP}$$

$$m \sim \mathcal{N}(\mu_0, \sigma_0^2)$$

$$\frac{1}{\sigma^2} \sim \Gamma(\alpha, \beta)$$

$$a) p(x, m, \sigma^2 | \alpha, \beta, \mu_0, \sigma_0^2) = \prod_{i=1}^n \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right) \cdot \frac{1}{\sigma_0 \sqrt{2\pi}} \exp\left(-\frac{(m - \mu_0)^2}{2\sigma_0^2}\right) \cdot \frac{\alpha^\beta (\frac{1}{\sigma^2})^{\beta-1}}{\Gamma(\beta)} e^{-\frac{\alpha}{\sigma^2}}$$

$$= \prod_{i=1}^n \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right) \cdot \frac{1}{\sigma_0 \sqrt{2\pi}} \exp\left(-\frac{(m - \mu_0)^2}{2\sigma_0^2}\right) \cdot \frac{\alpha^\beta (\frac{1}{\sigma^2})^{\beta-1}}{\Gamma(\beta)} e^{-\frac{\alpha}{\sigma^2}}$$

$$b) p(\mu, \sigma^2 | x, \alpha, \beta, \mu_0, \sigma_0^2) =$$

$$= \frac{p(x | \mu, \sigma^2; \alpha, \beta, \mu_0, \sigma_0^2) \cdot p(\mu, \sigma^2 | \alpha, \beta, \mu_0, \sigma_0^2)}{p(x | \alpha, \beta, \sigma_0^2, \mu_0)}$$

$$= \frac{\prod_{i=1}^n p(x_i | \mu, \sigma^2, m) p(\mu | \mu_0, \sigma_0^2) \cdot p(\frac{1}{\sigma^2} | \alpha, \beta)}{\int_{\mu, \sigma^2} \prod_{i=1}^n \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right) \cdot p(\mu | \mu_0, \sigma_0^2) \cdot p(\frac{1}{\sigma^2} | \alpha, \beta) \cdot d\mu d\sigma^2}$$

Унитарна ре гласна от k, σ^2
 и он отбелязва за репрезентативна
 функция и не може да бъде
 протегнута.

Видове:

$$f(x, \sigma^2) = \frac{1}{\sigma^2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right)$$

$$\sim \prod_{i=1}^n \left(\frac{1}{\sigma^2}\right) \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right)$$

$$= \exp\left[-\frac{1}{2\sigma^2} (n - \mu)^2\right] \cdot \left(\frac{1}{\sigma^2}\right)^{n-1} \cdot \exp\left[-\frac{1}{2\sigma^2}\right] =$$

$$= \left|\frac{1}{\sigma^2}\right| = \sigma^{\frac{n}{2} + \beta - 1} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 - \right.$$

$$\left. - \frac{1}{2\sigma^2} (n - \mu)^2 - \alpha \sigma^2\right] = \sigma^{\frac{n}{2} + \beta - 1}$$

$$\cdot \exp\left(-\frac{1}{2} n \cdot ((x^2 - 2x\mu + \mu^2) + s^2) - \right.$$

$$\left. - \frac{1}{2\sigma^2} (n^2 - 2n\mu + \mu^2) - \alpha \sigma^2\right] =$$

$$= \sigma^{\frac{n}{2} + \beta - 1} \exp\left[-\frac{1}{2} n s^2 - \alpha \sigma^2\right]$$

$$= \exp\left(-\left(\frac{1}{2} n + \frac{1}{2\sigma^2}\right) n^2 + (n \cdot 2x + \frac{\mu}{\sigma^2}) n - \right.$$

$$-\frac{\mu \sigma^2}{2} z - \frac{\mu_0^2}{2\sigma_0^2} \beta \sim$$

$$\sim \Gamma\left(\frac{1}{\sigma^2} \mid \frac{\mu}{2} \sigma^2 + \alpha, \frac{\mu}{2} + \beta\right) \cdot \frac{N(\mu_0, \sigma_0^2)}{\left(\frac{\mu}{2} + \frac{1}{\sigma_0^2}\right)}$$

$$\cdot N\left(\mu \mid \frac{\frac{\mu \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2}}{\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2}}, \frac{1}{\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2}}\right) \cdot N(\mu_0, \sigma_0^2)$$

б) Да дадено, т.н. априорно-
 независими, и даден репликацион
 модел, и априорно-независими
 и даден — ~~независими~~ репликацион

$N(\mu_0, \sigma^2) \cdot P(\alpha, \beta) \sim N(\mu, \sigma^2, \alpha, \beta) \Rightarrow$
 и даден репликацион модел
 и даден репликацион модел.

Затова то е корисно.

$$2). \quad q(\mu, \sigma^2) = q(\mu)q(\sigma^2)$$

$$\begin{aligned} \log q(\mu) &\sim \log p(\mu, \sigma^2 / \sigma, \alpha, \beta, \mu_0, \sigma_0^2) \sim \\ &\sim \log \left[-\frac{1}{2} \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \mu^2 - 2\mu \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right) + \right. \\ &\quad \left. + \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) + \log \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \right] = \\ &= -\frac{1}{2} \mu^2 \cdot \frac{1}{\sigma^2} - 2\mu \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right) + \\ &+ \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 + \log \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \Rightarrow \\ &\Rightarrow q(\mu) \sim \sqrt{\frac{1}{\sigma^2} \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 + \frac{1}{\sigma^2}} \exp \left(-\frac{1}{2} \mu^2 \cdot \frac{1}{\sigma^2} - 2\mu \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right) + \right. \\ &\quad \left. + \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 + \log \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \right) \Rightarrow \end{aligned}$$

$$\begin{aligned} &\Rightarrow q(\mu) \sim \sqrt{\frac{1}{\sigma^2} \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 + \frac{1}{\sigma^2}} \exp \left(-\frac{1}{2} \mu^2 \cdot \frac{1}{\sigma^2} - 2\mu \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right) + \right. \\ &\quad \left. + \left(\frac{\mu_0 \sigma}{\sigma^2} + \frac{\mu_0}{\sigma_0^2} \right)^2 + \log \left(\frac{\mu}{\sigma^2} + \frac{1}{\sigma_0^2} \right) \right) \Rightarrow \end{aligned}$$

$$1) p(\beta, \lambda) = \prod_{i=1}^n \lambda \exp(-\lambda \beta_i) =$$

$$= \lambda^n \exp\left(-\lambda \sum_{i=1}^n \beta_i\right)$$

$$p(\lambda | \beta, \alpha) = \frac{p(\beta | \lambda) \cdot p(\lambda | \alpha)}{\int p(\beta | \lambda) p(\lambda | \alpha) d\lambda} \Rightarrow$$

$$\Rightarrow p(\lambda | \beta, \alpha) \sim \lambda^n \exp\left(-\lambda \sum_{i=1}^n \beta_i\right) \cdot p(\lambda | \alpha)$$

$$p(\lambda | \alpha) \sim \Gamma(\alpha | 1, \frac{1}{\alpha}) \Rightarrow$$

$$\Rightarrow p(\lambda | \alpha) \sim \alpha \exp(-\alpha \lambda)$$

$$\Rightarrow p(\lambda | \beta, \alpha) \sim \lambda^n \exp\left(-\lambda \left(\sum_{i=1}^n \beta_i + \alpha\right)\right)$$

$$\Rightarrow p(\lambda | \beta, \alpha) \sim \Gamma(\lambda | n+1, \frac{1}{\sum \beta_i + \alpha})$$

\Rightarrow Conjugated.

д) Обоснование:

$$p(t|\alpha) = \int_{-\infty}^{\infty} p(t|\lambda) p(\lambda|\alpha) d\lambda = \\ = \int_0^{\infty} \lambda^n \exp\left(-\lambda \sum_{i=1}^n t_i\right) \alpha e^{-\alpha \lambda} d\lambda =$$

$$\frac{\partial p}{\partial \alpha} = \int_0^{\infty} \lambda^n \exp\left(-\lambda \sum_{i=1}^n t_i\right) (e^{-\alpha \lambda} - \alpha^2 e^{-\alpha \lambda}) d\lambda = \\ = (1 - \alpha^2) \int_0^{\infty} \lambda^n \exp\left(-\lambda \left(\sum_{i=1}^n t_i + \alpha\right)\right) d\lambda =$$

$$= \frac{(1 - \alpha^2)}{\left(\sum_{i=1}^n t_i + \alpha\right)^{n+2}} \int_0^{\infty} u^n \exp(-u) du =$$

$$= \frac{\Gamma(n+2) (1 - \alpha^2)}{\left(\sum_{i=1}^n t_i + \alpha\right)^{n+2}} = 0 \Rightarrow \alpha = 1.$$

$$p(y, w | A, X) = \mathcal{N}(w | 0, A^{-1}) \prod_{j=1}^m p(y_j | x_j, w),$$

$$p(y_j = 1) = \frac{1}{1 + \exp(-w^T x_j)} = \sigma(w^T x_j).$$

$$A = \text{diag}(\alpha_j)$$

$$A = \arg \max_A p(y_0 | X_0, A)$$

$$a) p(y, w | A, X) = p(y | w, A) \cdot p(w | A) =$$

$$= \left[\prod_{j=1}^m p(y_j | x_j, w) \right] \cdot \mathcal{N}(w | 0, A^{-1}) =$$

$$= \left[\prod_{j=1}^m (1 - p(y_j = 1))^{1-y_j} (p(y_j = 1))^{y_j} \right] \cdot$$

$$\mathcal{N}(w | 0, A^{-1}) =$$

$$= \frac{|\det A|}{(\sqrt{2\pi})^n} \exp\left(-\frac{w^T A w}{2}\right) \cdot \prod_{j=1}^m \left[\frac{1}{1 + \exp(-w^T x_j)} \right]^{y_j} \cdot \left(\frac{\exp(-w^T x_j)}{1 + \exp(-w^T x_j)} \right)^{1-y_j}$$

$$\cdot \prod_{j=1}^m \left(\frac{1}{1 + \exp(-w^T x_j)} \right)^{y_j} \cdot \left(\frac{\exp(-w^T x_j)}{1 + \exp(-w^T x_j)} \right)^{1-y_j}$$

Діагональні. не звичайно ~~можливо~~
~~можливо~~ $p(w_j, \dots) = p(\cdot)$

в Різницевій економії беруть зваж.
 w_j

$$w^T(\text{diag } \alpha) w = (\alpha_1 w_1, \dots, \alpha_n w_n)^T w =$$

$$= \sum_{j=1}^n \alpha_j w_j^2 \Rightarrow \text{Реш } \alpha_j \geq 0 \text{ можливе.}$$

можливо для $w_j \Rightarrow \boxed{\alpha_j \geq 0}$

$$Q(p(y, w | x, A)) \geq L(w, A, \xi) = \frac{\sqrt{\det A}}{(2\pi)^n}$$

$$\cdot \exp\left(-\frac{1}{2} w^T A w\right) \prod_{i=1}^n \left[G(\xi_i) \cdot \exp\left\{-\frac{2G(\xi_i)-1}{4\xi_i} (w^T x_i x_i^T w - \xi_i^2)\right\} + \frac{y_i w^T x_i - \xi_i}{2} \right] = \frac{\sqrt{\det A}}{(2\pi)^n} \prod_{i=1}^n G(\xi_i) \cdot$$

$$\cdot \exp\left\{-\frac{2G(\xi_i)-1}{4\xi_i} (w^T x_i x_i^T w - \xi_i^2)\right\} + \frac{y_i w^T x_i - \xi_i}{2}$$

$$\cdot \exp\left\{-\frac{2G(\xi_i)-1}{4\xi_i} (w^T x_i x_i^T w - \xi_i^2)\right\} \exp\left\{-\frac{1}{2} w^T A w\right\}$$

$$A = A + \sum_{i=1}^n \frac{2G(\xi_i)-1}{2\xi_i} x_i x_i^T; R = \frac{1}{2} \sum_{i=1}^n y_i x_i$$

$$A = A + \sum_{i=1}^n \frac{2G(\xi_i)-1}{2\xi_i} x_i x_i^T; R = \frac{1}{2} \sum_{i=1}^n y_i x_i$$

$$c) p(y|x, \theta) = \int p(y, w|x, \theta) dw \approx$$

$$\approx \int L(w, A, \xi) dw = \tilde{L}(A, \xi)$$

$$\tilde{L}(A, \xi) \rightarrow \max_{A, \xi}$$

E-var:

$$q(y) = p(y|x, w) = \prod_{n=1}^m p(y_n | x_n, \theta)$$

M-var:

$$E_{q(y)} \log p(x, y|w) \rightarrow \max_{\theta}, \theta_2(A, \xi)$$

E-var:

$$p(y|x, w) = \frac{\prod_{n=1}^m p(x_n | y_n, w) p(y_n)}{\int \prod_{n=1}^m p(x_n | y_n, \theta) p(y_n) dy_n}$$

$$\approx \prod_{n=1}^m p(y_n, A_n, w) \Rightarrow$$

$$\Rightarrow q(y_n) = \mathcal{N}(y_n | \mu_n, \Sigma_n)$$

Max:

$$\text{Bayes} \log p(x, y | A, \sigma) \rightarrow \max_{A, \sigma}$$

$$\hat{A}(A, \sigma) = (V, \sigma)$$

$$\log p(x, y | V, \sigma) = \log \prod_{n=1}^m p(x_n, y_n | V, \sigma) =$$

$$= \log \prod_{n=1}^m \left\{ \frac{1}{R^2} \exp \left(-\frac{1}{2\sigma^2} (x_n - Vy_n)^T (x_n - Vy_n) \right) \right\} p(y_n) =$$

$$= \log \sum_{n=1}^m \log \left\{ \frac{1}{R^2} \exp \left(-\frac{1}{2\sigma^2} (x_n^T x_n - 2y_n^T V^T x_n + y_n^T V^T V y_n) \right) \right\} p(y_n) = \log p(y) + \text{const.}$$

$$+ \sum_{n=1}^m \left(-\frac{1}{2\sigma^2} (-2y_n^T V^T x_n + y_n^T V^T V y_n) \right)$$

$$\frac{\partial}{\partial \sigma} \log p(y, x | V, \sigma) = \sum \left(-\frac{1}{2\sigma^2} (-2x_n y_n^T + 2Vy_n y_n^T) \right) = 0$$

$$E(y_n) \cdot \sum_{n=1}^m \left(-\frac{1}{2\sigma^2} (-2x_n y_n^T + 2Vy_n y_n^T) \right) = 0$$

$$\sum_{n=1}^m E(y_n) (-y_n y_n^T) + E(y_n) (Vy_n y_n^T) = 0$$

$$\sum_{n=0}^m |E_{q(y_n)} x_n y_n^T| = \sqrt{\sum_{n=0}^m |E_{q(y_n)} y_n y_n^T|} =$$

$$\sqrt{\left(\sum_{n=0}^m |E_{q(y_n)} x_n y_n^T\right) \left(\sum_{n=0}^m |E_{q(y_n)} y_n y_n^T\right)^{-1}}$$

$$\sqrt{\left(\sum_{n=0}^m x_n |E_{q(y_n)} y_n^T\right) \left(\sum_{n=0}^m |E_{q(y_n)} y_n y_n^T\right)^{-1}}$$

By Bayes:

$$q(y_n) = \mathcal{N}(y_n | \mu_n, \Sigma_n)$$

$$|E_{q(y_n)} y_n = \mu_n$$

$$|E_{q(y_n)} y_n y_n^T = \Sigma_n + \mu_n \mu_n^T$$

$$\frac{\partial}{\partial \theta} : |E_{q(y_n)} y_n^T V^T V y_n = |E_{q(y_n)} \text{tr}(y_n^T V^T V y_n)$$

$$= \text{tr}(|E_{q(y_n)} y_n y_n^T V^T V)$$