

30.09.16 думо

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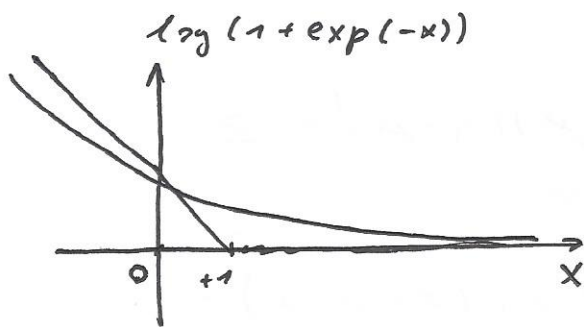
$$x \in \mathbb{R}^d, t \in \{-1, 1\}$$

$$p(T, w | X) = p(T | X, w) p(w) = \prod_{i=1}^n \frac{1}{1 + \exp(-t_i w^T x_i)} \cdot N(w | 0, \bar{\Sigma})$$

$$\log p(w | X, T) = \log \frac{p(T | X, w) p(w)}{\int p(T | X, w) p(w) dw} \propto \log \prod_{i=1}^n \frac{1}{1 + \exp(-t_i w^T x_i)} +$$

$$+ \log p(w) + \text{const} \rightarrow \max_w \quad (\text{дальше градиент})$$

$$\sum_{i=1}^n \log(1 + \exp(-t_i w^T x_i)) + \frac{\alpha}{2} \|w\|^2 \rightarrow \min_w$$



дальше градиент

$$x_i \rightarrow (\varphi_1(x_i) \dots \varphi_k(x_i))$$

$$\varphi_j(x_i) = \exp(-\sigma \|x_i - x_j\|^2)$$

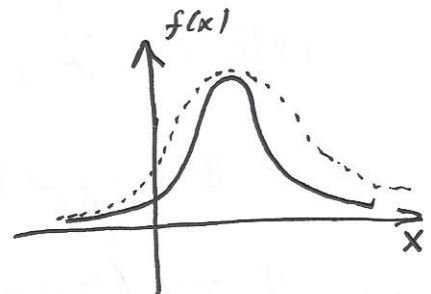
$$\varphi_j(x) = \exp(-\sigma \|x - x_j\|^2)$$

$$p(T, w | X) = p(T | X, w) \cdot p(w | A) = \prod_{i=1}^n \frac{1}{1 + \exp(-t_i w^T x_i)} \cdot$$

$$\cdot N(w | 0, \bar{A}^{-1}), \quad A = \begin{pmatrix} \alpha_1 & & \\ & \ddots & \\ & & \alpha_d \end{pmatrix}$$

$$p(T | X, A) = \int p(T | X, w) p(w | A) dw =$$

$$= \int \prod_{i=1}^n \frac{1}{1 + \exp(-t_i w^T x_i)} \cdot N(w | 0, \bar{A}^{-1}) dw$$



нормализация

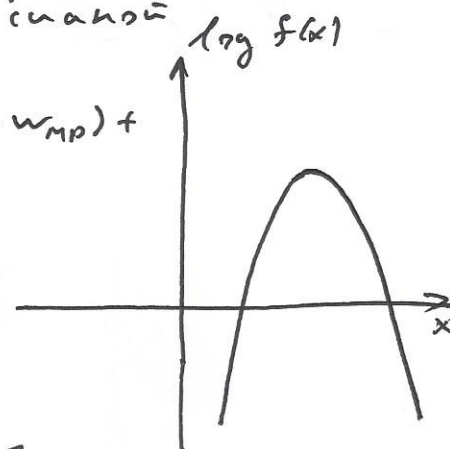
$$\log Q(w) = \log Q(w_{mp}) + \nabla \log Q(w_{mp})^T (w - w_{mp}) +$$

$$+ \frac{1}{2} (w - w_{mp})^T \nabla \nabla \log Q(w_p) (w - w_{mp})$$

$$- \nabla \nabla \log Q(w_p) = \Sigma^{-1}$$

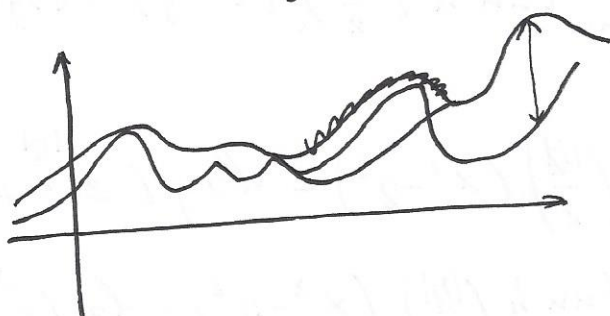
$$\int Q(w) dw = \int Q(w_{mp}) \exp\left(-\frac{1}{2} (w - w_{mp})^T \Sigma^{-1} (w - w_{mp})\right) dw =$$

$$= (2\pi)^{\frac{d}{2}} \sqrt{\det \Sigma} Q(w_{mp})$$

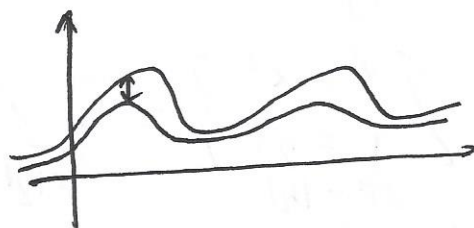


$$\log p(T|X, A) = \log Q(w_{MP}) - \frac{1}{2} \log \det(-\nabla \nabla \log Q(w_{MP})) \rightarrow \max_{w_{MP}}$$

$$d_i^{new} = \frac{1 - d_i^{old} \sum_{j,i}}{Q_i^2}; \quad w_{MP} = \operatorname{argmax}_w p(T|X, w) p(w|A)$$



произвольные

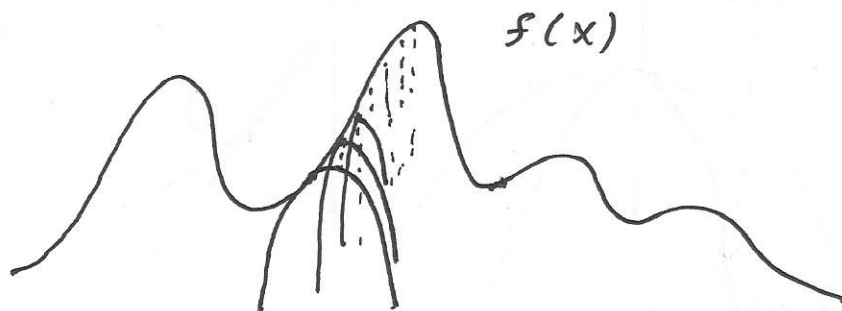


максимизация
и минимизация

обоснованность:

$$\log Q(w_{MP}) - \frac{1}{2} \log \det(-\nabla \nabla \log Q(w_{MP})) \rightarrow \max_A$$

максимизация



$$\{g(x, \beta)\}$$

$$1) g(x, \beta) \leq f(x) \quad \forall x, \beta$$

$$2) \forall x_0 \exists \beta_0: g(x_0, \beta_0) = f(x_0)$$

итерационная оптими-
зация вариационных
и минимизация

$$\int Q(w, A) dw \geq \int h(w, \beta, A) dw = I(\beta, A) \rightarrow \max$$

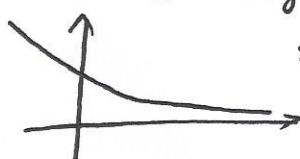
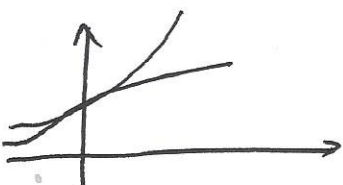
произведение гауссиан \leftrightarrow произведение сигмоидных функций и.
комбинатор вариационных и минимизация

$$\log \frac{1}{1 + \exp(-x)} = -\log(1 + \exp(-x)) = \text{логистическая}$$

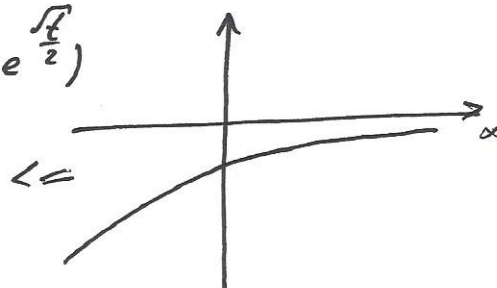
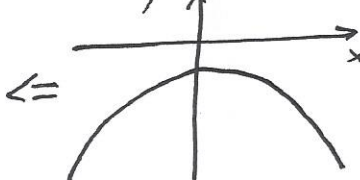
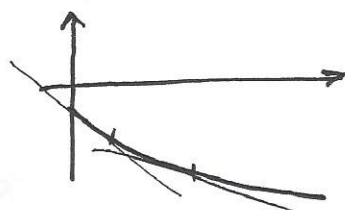
$$= -\log(e^{-\frac{x}{2}}(e^{\frac{x}{2}} + e^{-\frac{x}{2}})) =$$

$$= \frac{x}{2} - \log(e^{\frac{|x|}{2}} + e^{-\frac{|x|}{2}})$$

четная ф-ция



$$-\log(e^{\frac{|x|}{2}} + e^{-\frac{|x|}{2}}) = \begin{cases} t = x^2 \\ |x| = \sqrt{t} \end{cases} = -\log(e^{-\frac{\sqrt{t}}{2}} + e^{\frac{\sqrt{t}}{2}})$$



$$f(x) ; g(x, z) = f(z) + f'(z)(x - z)$$

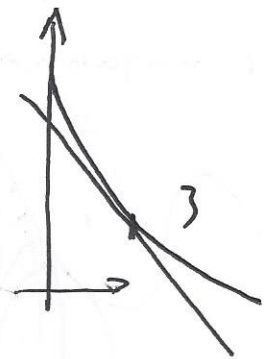
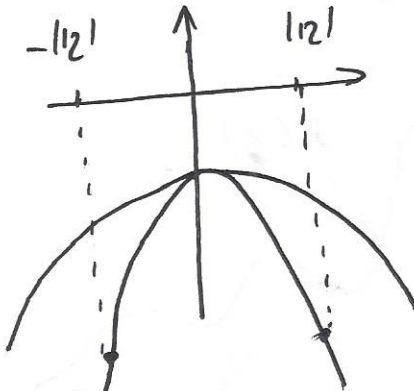
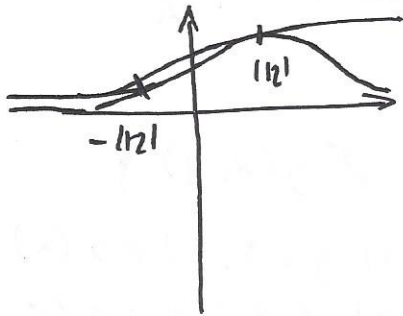
$$\ln \log'(e^{-\frac{\sqrt{t}}{2}} + e^{\frac{\sqrt{t}}{2}}) = \frac{e^{\frac{\sqrt{t}}{2}} - e^{-\frac{\sqrt{t}}{2}}}{e^{-\frac{\sqrt{t}}{2}} + e^{\frac{\sqrt{t}}{2}}} \cdot \frac{1}{4\sqrt{t}}$$

$$-\log(e^{-\frac{\sqrt{t}}{2}} + e^{\frac{\sqrt{t}}{2}}) \geq -\frac{1}{4\sqrt{t}} \tanh\left(\frac{\sqrt{t}}{2}\right)(t - z) - \log(e^{-\frac{\sqrt{z}}{2}} + e^{\frac{\sqrt{z}}{2}})$$

$$= \left\{ \begin{array}{l} t = x^2 \\ z = b^2 \\ \sqrt{z} = |b| \end{array} \right\} = -\frac{1}{4|b|} \tanh\left(\frac{|b|}{2}\right)(x^2 - b^2) - \log(e^{-\frac{|b|}{2}} + e^{\frac{|b|}{2}})$$

$$-\log(1 + e^{-x}) \geq \frac{x}{2} - \frac{1}{4|b|} \tanh\left(\frac{|b|}{2}\right)(x^2 - b^2) - \log(e^{-\frac{|b|}{2}} + e^{\frac{|b|}{2}})$$

$$\frac{1}{1 + e^{-x}} \geq \frac{1}{e^{\frac{|b|}{2}} + e^{-\frac{|b|}{2}}} \cdot \exp\left(\frac{x}{2} - \frac{1}{4|b|} \tanh\left(\frac{|b|}{2}\right)(x^2 - b^2)\right)$$



$$\prod_{i=1}^n \sigma(t_i w^T x_i) \geq \prod_{i=1}^n l(t_i w^T x_i, \eta_i)$$

$$\int \sigma(t_i w^T x_i) N(w | 0, A^{-1}) dw \geq \int \prod_{i=1}^n l(t_i w^T x_i, \eta_i) N(w | 0, A^{-1}) dw$$

$$= \Phi(A, \vec{\eta}) \longrightarrow \max_{A, \eta}$$

$$p(x) = N(x | \mu, \Sigma)$$

$$p(y|x) = N(y | \mu Ax, \Gamma)$$

$$p(y) ? \quad \mathbb{E}y = A\mu, \quad \text{ID}y = A^T \Sigma A^T + \Gamma$$

$$y = Ax + \varepsilon, \quad \varepsilon \sim N(\varepsilon | 0, \Gamma)$$

$$\{x_n, t_n\}_{n=1}^N, \quad x \in \mathbb{R}^d, \quad t \in \mathbb{R}$$

$$p(t, w | X, A, \beta) = \prod_i N(t_i | x_i^T w, \beta^{-1}) \cdot N(w | 0, \bar{A}^{-1})$$

$$A = \alpha I, \quad A = \text{diag}(\alpha_1, \dots, \alpha_d)$$

$$\log p(t_{t_2} | X_{t_2}, A, \beta) \rightarrow \max_{A, \beta}$$

$$\int p(t_{t_2} | X_{t_2}, w, \beta) p(w | A, \beta, X_{t_2}, t_{t_2}) dw$$

$$\text{evidence} \quad T_{t_2} | X_{t_2}, A, \beta \sim N(0, \beta^{-1} I + X_{t_2} \bar{A}^{-1} X_{t_2}^T)$$

$$-\frac{1}{2} \log \det(\beta^{-1} I + X \bar{A}^{-1} X^T) - \frac{1}{2} T^T (\beta^{-1} I + X \bar{A}^{-1} X^T)^{-1} T$$

упрощения матрицы:

$$(A + UCV)^T = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}$$

$$\det(X + AB) = \det X \cdot \det(I + B X^{-1} A)$$

$$\log \det(\underbrace{\beta^{-1} I}_{X'} + \underbrace{X}_{A'} \underbrace{\bar{A}^{-1}}_{B'}) = \log \det \beta^{-1} I + \log \det(I + \beta X^T X \bar{A}^{-1}) =$$

$$= \log \beta^{-n} + \log \det(I + \beta X^T X \bar{A}^{-1}) = -n \log \beta + \log \det(I + \beta X^T X \bar{A}^{-1})$$

$$= -n \log \beta + \log \det(A + \beta X^T X) \bar{A}^{-1} = -n \log \beta - \log \det \Sigma -$$

$$- \log \det A \quad \{ \mu = \beta \Sigma X^T T, \quad \Sigma = (\beta X^T X + A)^{-1} \}$$

$$- \frac{\beta}{2} \|x\|^2 - \frac{1}{2} \mu^T A \mu = - \frac{\beta}{2} \|x\|^2 - \frac{1}{2} \mu^T \Sigma X^T T - \frac{1}{2} \beta^2 T^T X \Sigma A \Sigma X^T T$$

$$\Sigma X^T T = - \frac{1}{2} (\beta X \Sigma X^T T - T)^T (\beta X \Sigma X^T T - T) - \frac{1}{2} \beta^2 T^T X \Sigma A \Sigma X^T T$$

$$\frac{1}{2} \log \det \Sigma + \frac{n}{2} \log \beta + \frac{1}{2} \log \det A - \frac{\beta}{2} \|x\|^2 - \frac{1}{2} \mu^T A \mu$$

$$\begin{aligned}
 p(t | X, X_{t_2}, t_{t_2}, A, \beta) &= \int p(t | X, w, \beta) \cdot p(w | X_{t_2}, t_{t_2}, A, \beta) dw = \\
 &= \int N(t | Xw, \beta^T I) \cdot N(w | \mu, \Sigma) dw = \\
 &= N(t | X\mu, \beta^T I + X \Sigma X^T) \\
 &\begin{cases} N(t | X\mu, \beta^T I) \end{cases}, \text{ если вместо интегрирования} \\
 &\quad \text{точечная оценка.}
 \end{aligned}$$