

$$p(\theta|x) = \frac{p(x|\theta) \cdot p(\theta)}{\int p(x|\theta) p(\theta) d\theta} = \frac{p(x, \theta)}{\int p(x, \theta) d\theta}$$

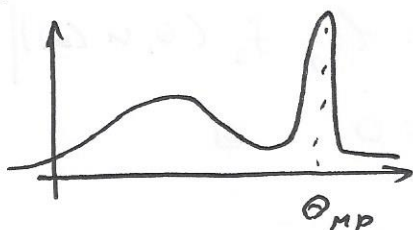
$$1) \theta_{MP} = \underset{\theta}{\operatorname{argmax}} p(\theta|x) \quad \text{точечные оценки}$$

$$\underset{\hat{\theta}}{\operatorname{argmin}} l(\theta, \hat{\theta})$$

$$1) l(\theta, \hat{\theta}) = \|\theta - \hat{\theta}\|^2$$

$$2) l(\theta, \hat{\theta}) = |\theta - \hat{\theta}|$$

$$3) l(\theta, \hat{\theta}) = I[\theta \neq \hat{\theta}]$$



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Сопрежённость распределения вероятностей

$$\odot \quad p(x|\theta) \sim \mathcal{A}(\theta)$$

$$p(\theta) \sim \mathcal{B}(\beta) \quad \text{сопряжённые} \quad p(\theta|x) \sim \mathcal{B}(\beta')$$

conjugate distribution

Тогда интеграл $\int p(x|\theta) p(\theta) d\theta$ берётся аналитически

$$\odot p(x|\mu) \sim \mathcal{N}(x|\mu, 1)$$

$$p(x|\mu) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2} + x\mu - \frac{\mu^2}{2}\right)$$

$$p(\mu) \sim \exp(-a\mu^2 + b\mu + c), \quad a > 0$$

$$p(\mu) \sim \mathcal{N}(\mu|m, s^2), \quad p(\mu|x) ?$$

$$\odot p(x|\mu) \sim \mathcal{N}(x|\mu_0, \beta^{-1})$$

$$p(x|\mu) = \frac{\sqrt{\beta}}{\sqrt{2\pi}} \exp\left(-\frac{\beta x^2}{2}\right)$$

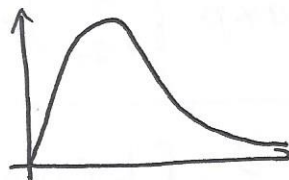
$$p(\mu) \sim \exp(-\beta a) \cdot \beta^c \cdot \frac{1}{\Gamma(a, c)}$$

$$\beta^{-1} \quad a > 0, \quad c > -1, \quad \beta > 0$$

$$p(\mu) \sim \Gamma(\beta|\alpha, \theta) = \frac{\theta^\alpha}{\Gamma(\alpha)} \cdot \beta^{\alpha-1} \exp(-\theta\beta)$$

$$a, \theta \geq 0, \quad \beta > 0$$

$$p(\beta|x) \sim \Gamma(\beta|\alpha', \theta')$$



$$\odot p(x|\mu, \beta^{-1}) \neq \mathcal{N}(x|\mu, \beta^{-1}), \quad p(\mu, \beta) ?$$

$$p(x|\mu, \beta^{-1}) = \frac{\sqrt{\beta}}{\sqrt{2\pi}} \exp\left(-\frac{\beta}{2} x^2 + \beta \mu x - \beta \frac{\mu^2}{2}\right) \quad \text{стр 1}$$

$$p(x|\mu, \beta^{-1}) ; \quad p(\mu, \beta^{-1}) \neq p(\mu) \cdot p(\beta^{-1}) \Rightarrow p(\mu, \beta|x) \neq p(\mu) p(\beta)$$

$$p(\mu, \beta) \sim N(\mu, \beta | m, \lambda, a, b) = \\ = N(\mu | m, (\lambda \beta)^{-1}) \Gamma(\beta | a, b) = p(\mu | \beta) p(\beta)$$

III Критерий факторизации (Фиттер)

$u(x)$ — достаточная статистика \Leftrightarrow

$$\exists p(x|\theta) = f_1(x) f_2(\theta) f_3(\theta, u(x))$$

$$\square \log p(x|\theta) = \log f_1(x) + \log f_2(\theta) + \log f_3(\theta, u(x)) \Big|_{\frac{\partial}{\partial \theta}} = 0 \\ \frac{\partial}{\partial \theta} \log f_2(\theta) + \frac{\partial}{\partial \theta} \log f_3(\theta, u(x)) = 0 \quad \blacksquare$$

Экспоненциальный класс распределений.

Достаточные статистики.

○ Параметрическое семейство $p(x|\theta)$ принадлежит экспоненциальному классу распределений, если

$$p(x|\theta) = \frac{h(x)}{g(\theta)} \exp(\theta^T u(x))$$

$$h(x) \geq 0, u(x) - \forall \theta\text{-и} \quad g(\theta) = \int h(x) \exp(\theta^T u(x)) dx$$

$$N(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2} + \frac{x\mu}{\sigma^2} - \frac{\mu^2}{2\sigma^2}\right)$$

$$\theta_1 = -\frac{1}{2\sigma^2}, u_1(x) = x^2, h(x) = 1,$$

$$\theta_2 = \frac{\mu}{\sigma^2}, u_2(x) = x, g^{-1}(\theta) = \exp\left(-\frac{\mu^2}{2\sigma^2}\right) \cdot \frac{1}{\sqrt{2\pi}\sigma},$$

$$\sigma^2 = -\frac{1}{2\theta_1}, \mu = \theta_2 \sigma^2 = -\frac{\theta_2}{2\theta_1}, \frac{\mu}{\sigma^2} = \frac{\theta_2}{2}$$

$$g^{-1}(\theta) = \exp\left\{\frac{\theta_2^2}{4\theta_1}\right\} \cdot \frac{\sqrt{2\theta_1}}{\sqrt{2\pi}}; \quad \theta_1, \theta_2 - \text{естественные параметры}$$

$$\frac{\partial g(\theta)}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \int h(x) \exp(\theta^T u(x)) dx = \int h(x) \theta_j^T u_j(x) \cdot \exp(\theta^T u(x)) dx =$$

$$= g(\theta) \int \frac{h(x) u_j(x) \exp(\theta^T u(x))}{g(\theta)} dx = g(\theta) \int \frac{h(x) \exp(\theta^T u(x))}{g(\theta)} u_j(x) dx =$$

$$= g(\theta) \mathbb{E} u_j(x), \quad \mathbb{E} u_j(x) = \frac{1}{g(\theta)} \frac{\partial g(\theta)}{\partial \theta_j}$$

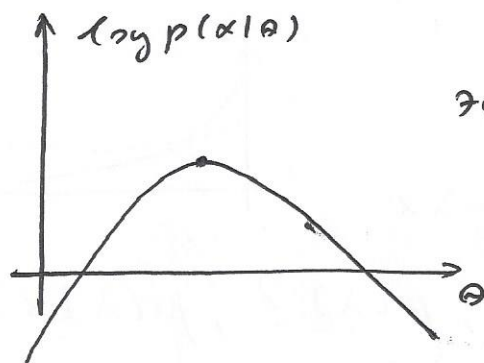
$$\mathbb{E} u_j(x) = \frac{\partial}{\partial \theta_j} \log g(\theta)$$

аналогично $\text{cov}(u_j(x), u_i(x)) = \frac{\partial^2 \log g(\theta)}{\partial \theta_j \partial \theta_i} \quad (\text{стр } 2)$

$\log g(\theta)$ - выпуклая ф-ция

$$\log p(x|\theta) = \log h(x) - \log g(\theta) + \theta^T u(x)$$

выпуклая ф-ция \Leftarrow const выпуклая линейная



эвристическая численная оптимизация

$$X = (x_1, \dots, x_n) \sim p(x|\theta)$$

$$\log p(X|\theta) = \sum_{i=1}^n \log p(x_i|\theta) = \sum_{i=1}^n \log h(x_i) - n \log g(\theta) + \theta^T \sum_{i=1}^n u_i(x_i) \rightarrow \max_{\theta}$$

$$-n \frac{\partial \log g(\theta)}{\partial \theta_j} + \sum_{i=1}^n u_i(x_i) = 0$$

$$\frac{\partial}{\partial \theta_j} \log g(\theta) = \frac{1}{n} \sum_{i=1}^n u_i(x_i) \approx \mathbb{E} u_i$$

$$\Downarrow \mathbb{E} u_i(x)$$

$\mathbb{E} u_i(x)$ model	$=$	$\mathbb{E} u_i(x)$ data
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сопряжённое распределение

$$p(x|\theta) = \frac{h(x)}{g(\theta)} \exp(\theta^T u(x))$$

$$p(\theta|\eta, \gamma) = \exp(\theta^T \eta) \frac{1}{g^{\gamma}(\theta)} \frac{1}{Z(\eta, \gamma)}$$

$$p(\theta|\eta, \gamma, X) \propto p(x|\theta) \cdot p(\theta|\eta, \gamma) = \prod_{i=1}^n h(x_i) \cdot \frac{1}{g^{\gamma}(\theta)} \cdot \exp(\theta^T (\sum_{i=1}^n u(x_i))) \cdot \exp(\theta^T \eta) \cdot \frac{1}{g^{\gamma}(\theta)} \cdot \frac{1}{Z(\eta, \gamma)} =$$

$$= \exp(\theta^T (\sum_{i=1}^n u(x_i) + \eta)) \frac{1}{g^{n+\gamma}(\theta)} \frac{\prod_{i=1}^n h(x_i)}{Z(\eta, \gamma)}$$

$$\eta' = \eta + \sum_{i=1}^n u(x_i)$$

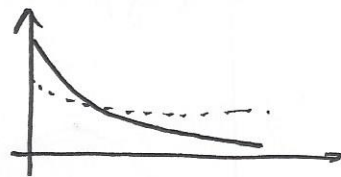
$$\gamma' = \gamma + n$$

$$p(\theta|X, \eta, \gamma) = p(\theta|\eta', \gamma')$$

$$p(\theta | x, y, z) = p(\theta | z', y') \quad \underline{09.09.16 \text{ Лекция семинар}}$$

сопряжённые распределения
экспоненциальные семейства.

$$p(\theta | x) = \frac{p(x | \theta) p(\theta)}{\int p(x | \theta) p(\theta) d\theta}$$



$$① \quad x \sim \exp(\lambda), \quad p(x) = \lambda e^{-\lambda x}$$

x_1, \dots, x_n - выборка, λ_{ML} ? , $p(\lambda)$? , $p(\lambda | x)$? , $E p(\lambda | x)$?

$$\mathcal{L}(\theta | x, \theta) = \prod_{i=1}^n p(x_i | \lambda) = \prod_{i=1}^n \lambda e^{-\lambda x_i}$$

$$\log \mathcal{L}(x, \theta) = \sum_{i=1}^n x_i (\log \lambda - \lambda x_i)$$

$$\frac{\partial \log \mathcal{L}(x, \theta)}{\partial \lambda} = - \sum_{i=1}^n x_i + n \lambda = 0, \quad \lambda = \frac{n}{\sum_{i=1}^n x_i}$$

$$p(\lambda) = G(\lambda | a, b) = \frac{b^a}{\Gamma(a)} \lambda^{a-1} e^{-b\lambda}$$

$$p(x | \lambda) \cdot p(\lambda) = \left(\prod_{i=1}^n \lambda e^{-\lambda x_i} \right) \frac{b^a}{\Gamma(a)} \lambda^{a-1} e^{-b\lambda} = \frac{b^a}{\Gamma(a)} \lambda^{n+a-1} e^{-\lambda(\sum_{i=1}^n x_i + b)}$$

$$= \frac{b^a}{\Gamma(a)} \lambda^n \cdot e^{-\lambda \sum_{i=1}^n x_i} \cdot \lambda^{a-1} \cdot e^{-b\lambda} = \frac{b^a}{\Gamma(a)} \lambda^{n+a-1} e^{-\lambda(\sum_{i=1}^n x_i + b)}$$

$$= G(\lambda | n+a, \sum_{i=1}^n x_i + b) = G(\lambda | a', b') = p(\lambda | x)$$

$$a' = n+a, \quad b' = b + \sum_{i=1}^n x_i$$

$$E p(\lambda | x) = \frac{n+a}{\sum_{i=1}^n x_i + b} = \frac{a}{b} \frac{b}{\sum x_i + b} + \frac{n}{\sum x_i} \frac{\sum x_i}{\sum x_i + b} =$$

$$= \lambda_{p2} w + \lambda_{ML} (1-w)$$

$$② \quad x \sim \text{Bern}(q)$$

x	0	1
p(x)	1-q	q

$$p(x) =$$

$$x_1, \dots, x_n \sim \text{Bern}(q)$$

$$1) \quad p(x | q) = \prod_{i=1}^n q^{x_i} (1-q)^{1-x_i}$$

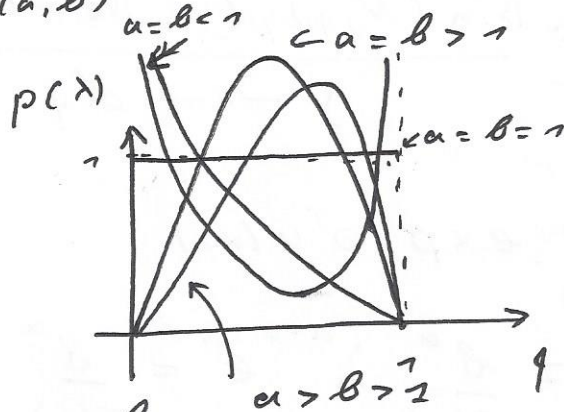
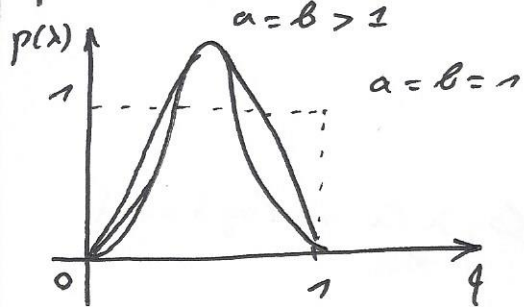
$$2) \quad p(k | N, q) = \binom{N}{k} q^k (1-q)^{N-k}$$

$$3) \quad p(k | q, 2) = \binom{k}{k+2-1} q^k (1-q)^2$$

Сокращенный prior ?

$$p(q) = q^{a-1} (1-q)^{b-1} \frac{1}{B(a,b)}, \quad a > 0, b > 0$$

β -распределение



$$\mathbb{E} p = \frac{a}{a+b}, \quad \mathbb{D} p = \frac{ab}{(a+b)^2(a+b+1)}$$

$$\frac{1}{B(a,b)} = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}, \quad C_N^k = \frac{N!}{k!(N-k)!}$$

$$p(q|x) = \text{Beta}(q|a', b')$$

$$q^{k+a-1} (1-q)^{b+N-k-1}, \quad a' = k+a, \quad b' = b+N-k$$

$$\mathbb{E} p = \frac{k+a}{b+N-k}$$

$$\begin{cases} \frac{a}{a+b} = \mu \\ \frac{ab}{(a+b)^2(a+b+1)} = \sigma \end{cases}$$

$$\frac{a}{\mu} = a+b, \quad b = \frac{a}{\mu} - a$$

$$\frac{a^2 \left(\frac{1}{\mu} - 1 \right)}{\left(a + a \left(\frac{1}{\mu} - 1 \right) \right) \left(a + a \left(\frac{1}{\mu} - 1 \right) + 1 \right)} = \sigma$$

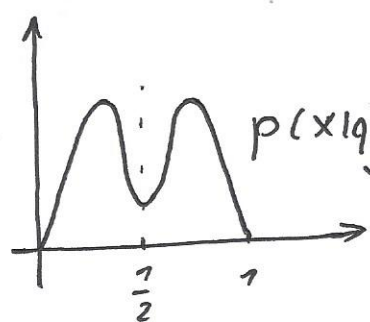
$$\frac{a \left(\frac{1}{\mu} - 1 \right)}{\left(1 + \left(\frac{1}{\mu} - 1 \right) \right) \left(a + a \left(\frac{1}{\mu} - 1 \right) + 1 \right)} = \sigma$$

$$\frac{a\gamma}{(1+\gamma)(a+a\gamma+1)} = \sigma$$

$$a\gamma = \sigma(a+a\gamma+1+a\gamma+a\gamma^2+\gamma)$$

$$a\gamma = \sigma a + 2a\gamma\sigma + \sigma + a\gamma^2\sigma + \sigma\gamma +$$

$$a(\sigma + 2\gamma\sigma + \gamma^2\sigma - \gamma) = -\sigma - \sigma\gamma$$



$$w_1 \text{Beta}(a_1, b_1) + w_2 \text{Beta}(a_2, b_2)$$

$$p(x|q) = \frac{\text{Bin}(N, q) \cdot (w_1 \text{Beta}(a_1, b_1) + w_2 \text{Beta}(a_2, b_2))}{\int \text{Bin}(N, q) \cdot (w_1 \text{Beta}(a_1, b_1) + w_2 \text{Beta}(a_2, b_2)) dq}$$

$$p(x|\theta) = \frac{h(x)}{g(\theta)} \exp(\theta^T u(x))$$

$$(4) G(\lambda|a, b) = \frac{\theta^a}{\Gamma(a)} \lambda^{a-1} e^{-\lambda \theta} = \frac{\theta^a}{\Gamma(a)} e^{\log \lambda (a-1) \log \lambda - \theta \lambda}$$

$$\theta = \begin{bmatrix} a-1 \\ -\theta \end{bmatrix}, u(\lambda) = \begin{bmatrix} \log \lambda \\ \lambda \end{bmatrix}, g(\theta) = \frac{\Gamma(a+1)}{\Gamma(a) (-\theta_2)^{a+1}}$$

$$\mathbb{E} u(\lambda) =$$

$$\mathbb{E} \frac{\log \lambda}{g(\theta)} = \frac{\partial}{\partial \theta_1} \left(\log \frac{\Gamma(a+1)}{(-\theta_2)^{a+1}} \right) = \frac{\partial}{\partial \theta_1} (\log \Gamma(a+1) -$$

$$-(a+1) \log(-\theta_2)) = \psi(a+1) - \log(-\theta_2)$$

$$\psi(x) - \text{gamma gamma gamma}, \log(x - \frac{1}{2}) \leq \psi(x) \leq \log(x)$$

$$\mathbb{E} \lambda = \frac{\partial}{\partial \theta_2} (\log \Gamma(a+1) - (a+1) \log(-\theta_2)) = - \frac{a+1}{\theta_2} = \frac{a}{b}$$

$$(5) p(x|q) = C_N^x q^x (1-q)^{N-x} = \frac{N!}{x!(N-x)!} C_N^x e^{x \log q + (N-x) \log(1-q)} =$$

$$= C_N^x \cdot e^{N \log(1-q)} \cdot e^{x \log q - x \log(1-q)} = C_N^x (1-q)^N e^{x \log \frac{q}{1-q}}$$

$$\theta = \log \frac{q}{1-q}, u(x) = x, h(x) = C_N^x$$

$$e^\theta = \frac{q}{1-q}, (1-q)e^\theta = q, q(1+e^\theta) = 1, q = \frac{1}{1+e^\theta}$$

$$g(\theta) = \left(1 - \frac{1}{1+e^\theta}\right)^N = \left(\frac{e^\theta}{1+e^\theta}\right)^N$$