

~~дефекты~~
~~факторы риска~~ } \Rightarrow алгоритм некорректной выборки

— some sources factors

— не дефекты
Approximate inference

Expectation propagation

$q(\theta) \approx p(\theta | D)$
Variational approximations

Sampling

$p(\bar{x}) \quad \bar{z} \sim \text{Unif}(0,1) \rightarrow \bar{x} \sim p(\bar{x})$ ← given values
 или $p^*(x) \propto p(x)$

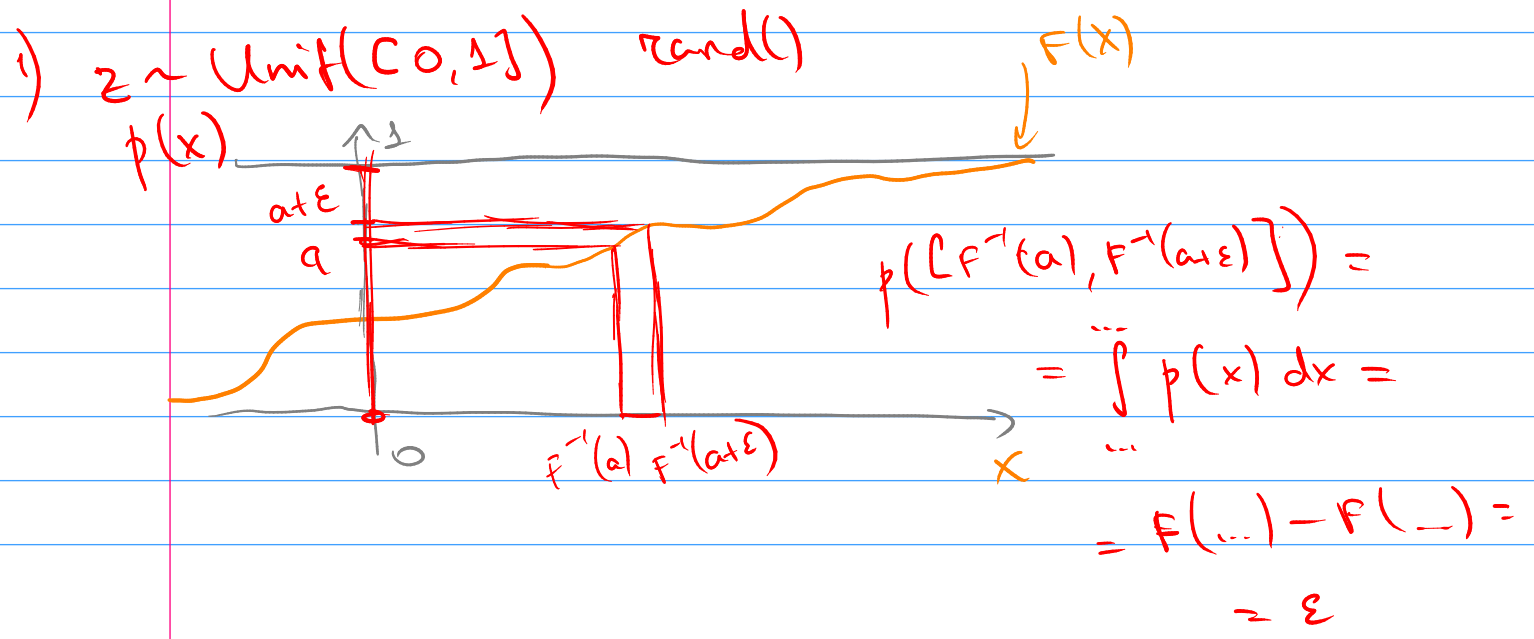
$$1) p(\bar{x} | D) = \int p(\bar{x} | \bar{\theta}) p(\bar{\theta} | D) d\bar{\theta} = \mathbb{E}_{p(\bar{\theta} | D)} [p(\bar{x} | \bar{\theta})]$$

$$\bar{\theta}^{(z)} \sim p(\bar{\theta} | D) \propto p(\bar{\theta}) p(D | \bar{\theta}) \Rightarrow \frac{1}{R} \sum_{z=1}^R p(\bar{x} | \bar{\theta}^{(z)})$$

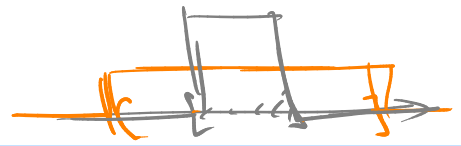
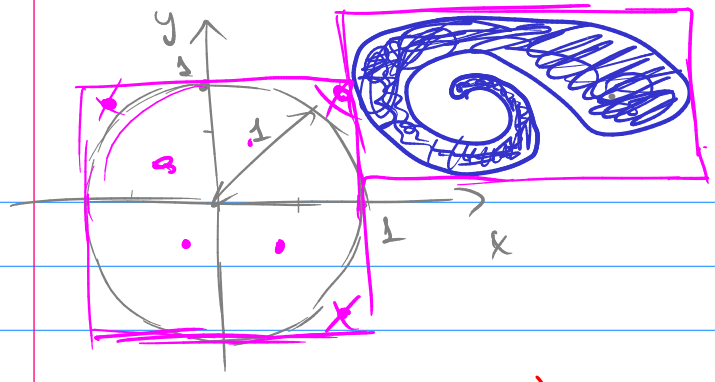
$$2) Q(\bar{\theta}, \bar{\theta}^{(m)}) = \int p(z | x, \bar{\theta}^{(m)}) \ln p(x, z | \bar{\theta}) dz =$$

$$= \mathbb{E}_{p(z | x, \bar{\theta}^{(m)})} [\ln p(x, z | \bar{\theta})] \approx \frac{1}{R} \sum_{z=1}^R \ln p(x, z^{(z)} | \bar{\theta})$$

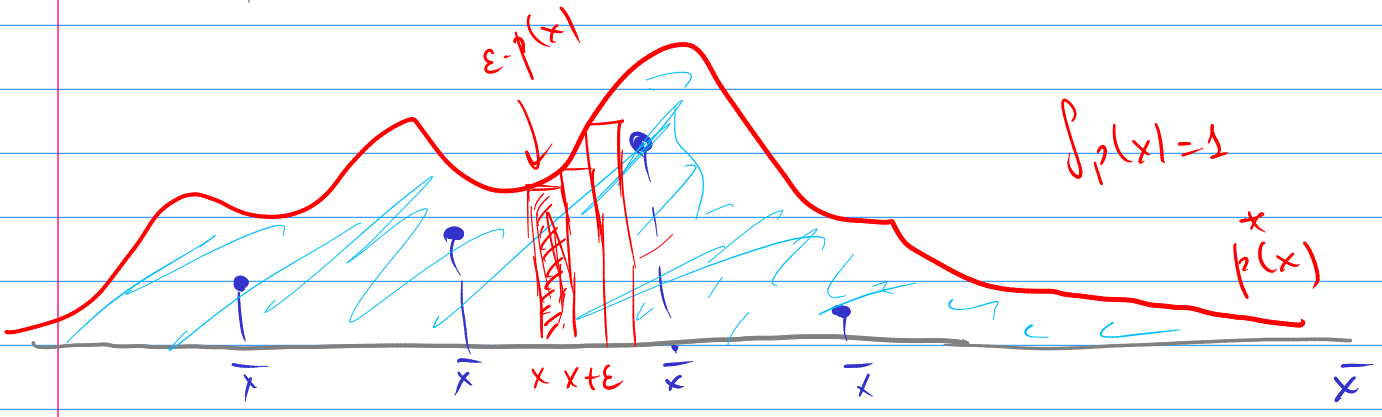
Monte-Carlo EM



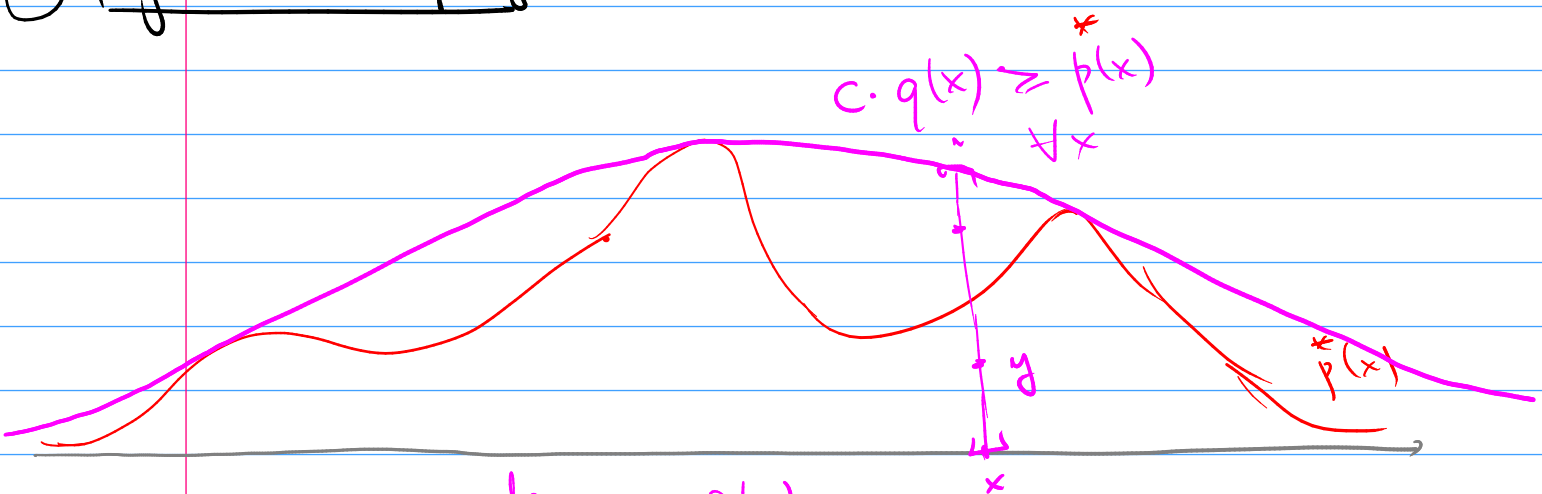
2)



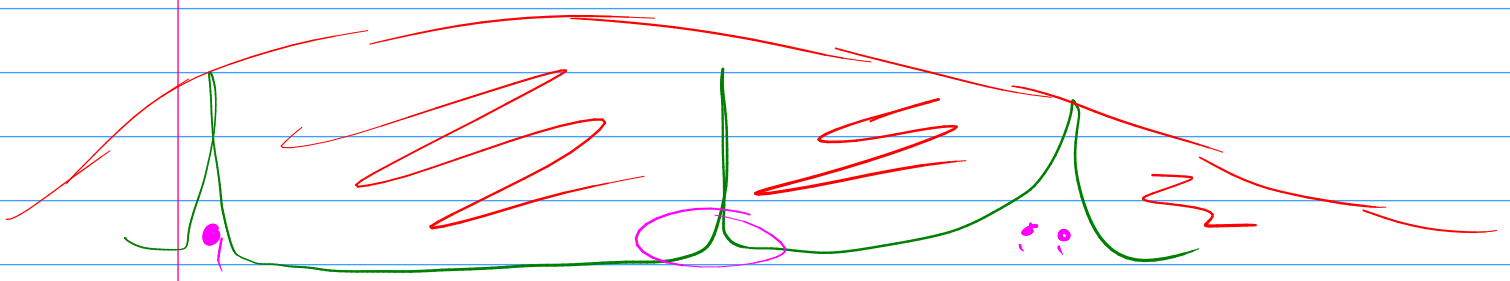
3)

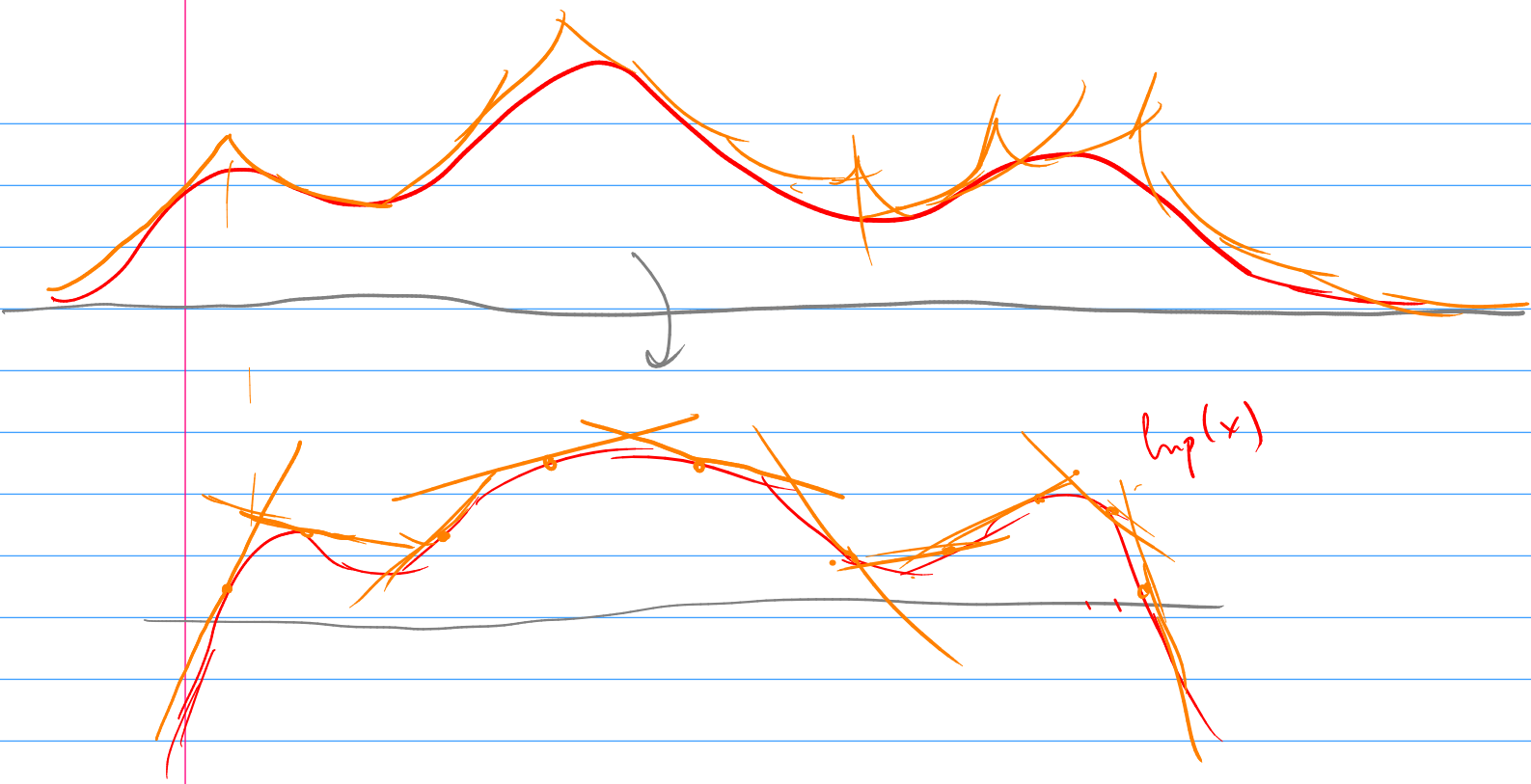


① Rejection sampling



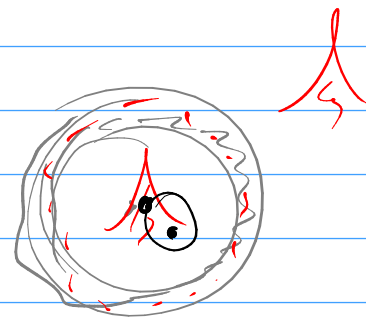
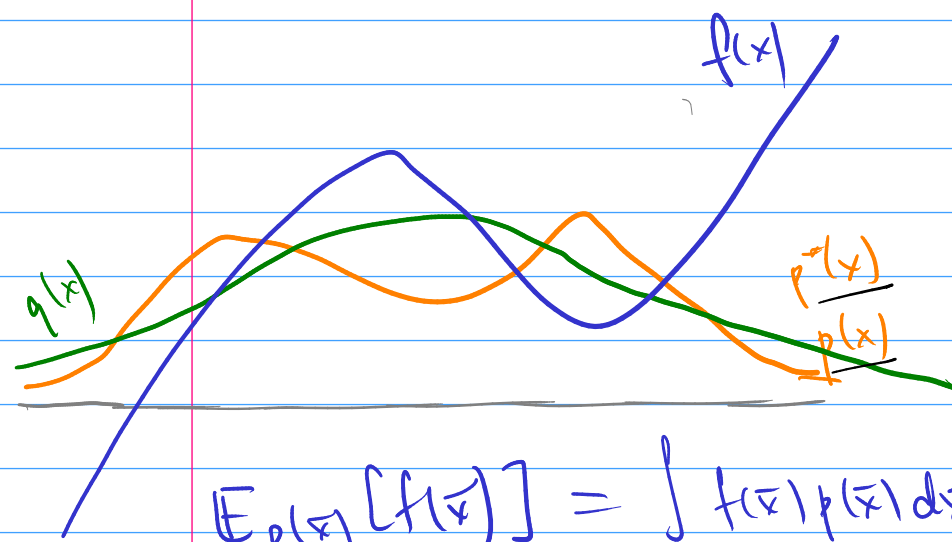
- sample $x \sim q(x)$
- sample $y \sim [0, c \cdot q(x)]$
- if $y > p(x)$ reject
- else accept x





② Importance sampling

$E_{p(\bar{x})} [f(\bar{x})] = ?$



$$E_{p(\bar{x})} [f(\bar{x})] = \int f(\bar{x}) p(\bar{x}) d\bar{x} = \int f(\bar{x}) \frac{p(\bar{x})}{q(\bar{x})} q(\bar{x}) d\bar{x} =$$

$$= E_{q(\bar{x})} \left[f \cdot \frac{p}{q} \right] \stackrel{\bar{x}^{(2)} \sim q(\bar{x})}{\approx} \frac{1}{R} \sum_{r=1}^R f(\bar{x}^{(r)}) \frac{p(\bar{x}^{(r)})}{q(\bar{x}^{(r)})}$$

$p(\bar{x}) = \frac{1}{Z_p} p^*(\bar{x})$

$E_p [f] =$

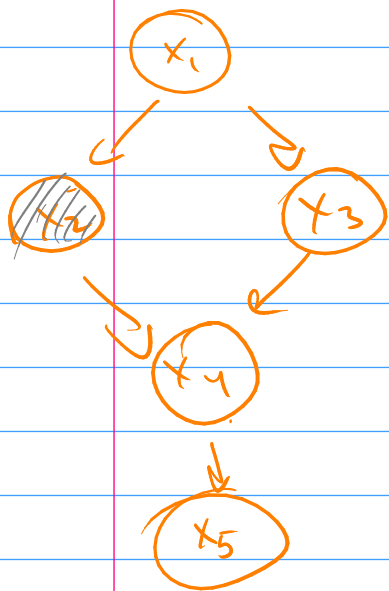
$q(\bar{x}) = \frac{1}{Z_q} q^*(\bar{x})$

$= E_q \left[f \cdot \frac{p}{q} \right] = E_q \left[f \cdot \frac{p^*(\bar{x})}{q^*(\bar{x})} \cdot \frac{Z_q}{Z_p} \right]$

↑ importance weights

$$\frac{z_p}{z_q} = \int \frac{1}{z_q} p^*(\bar{x}) d\bar{x} = \int p^*(\bar{x}) \frac{q(\bar{x})}{q^*(\bar{x})} d\bar{x} =$$

$$= E_q \left[\frac{p^*}{q^*} \right] \approx \frac{1}{R} \sum_{i=1}^R \frac{p^*(\bar{x}^{(i)})}{q^*(\bar{x}^{(i)})}$$



$$p(x_1 - x_5) = p(x_1) p(x_2|x_1) p(x_3|x_1)$$

$$p(x_4|x_2, x_3) p(x_5|x_4)$$

$x_1, x_3, x_4, x_5 \sim p(x_1, x_3, x_4, x_5 | x_2)$?

Rejection sampling: $x_1 - x_5 \sim p(x_1 - x_5)$

Importance sampling:

$$E_p[f] = E_q \left[f \cdot \frac{p}{q} \right] \approx \frac{1}{R} \sum_{i=1}^R \frac{p(\bar{x}^{(i)})}{q(\bar{x}^{(i)})} f(\bar{x}^{(i)})$$

q: $x_1 \sim p(x_1), x_3 \sim p(x_3|x_1), x_4 \sim p(x_4|x_2, x_3), x_5 \sim p(x_5|x_4)$

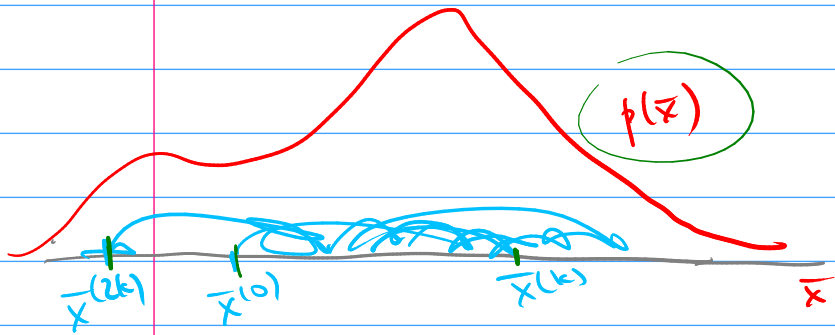
$$p(x_1, x_3, x_4, x_5 | x_2) \propto \frac{p(x_1, x_2, \dots, x_5)}{p(x_2|x_1)} = p(x_1) p(x_2|x_1) \dots$$

$$q(x_1, x_2, x_5) = p(x_1) p(x_2|x_1) - p(x_5|x_4)$$

$$E_p[f] \approx \frac{1}{R} \sum_{i=1}^R f(x^{(i)}) \cdot \prod_{x_i \in \text{evidence}} p(x_i | \text{par}(x_i))$$

likelihood weighted sampling

MCMC - Markov Chain Monte Carlo



$$x_1, x_2, \dots, x_k, \dots$$

$$q(x_k | x_{k-1}) = q(x_{k-1} | x_k)$$

$$q^{(0)}(\bar{x}), \quad q^{(1)}(\bar{x}) = \int T(\bar{x}; \bar{x}') q^{(0)}(\bar{x}') d\bar{x}'$$

$$q^{(1)}(\bar{x}) = A q^{(0)}(\bar{x})$$

$$q^{(0)}, q^{(1)}, q^{(2)}, \dots \rightarrow \pi(\bar{x}) = \int T(\bar{x}; \bar{x}') \pi(\bar{x}') d\bar{x}'$$

↑
stationary distrib.

Условие Деталя: если $\forall x, x'$ $p(x)T(x'; x) = p(x')T(x; x')$,
то $p(x)$ - stationary distrib. для T

$$p(\bar{x}) \stackrel{?}{=} \int T(\bar{x}; \bar{x}') p(\bar{x}') d\bar{x}' \stackrel{?}{=} \int p(\bar{x}) T(\bar{x}'; \bar{x}) d\bar{x}' = p(\bar{x})$$

Metropolis - Hastings algorithm

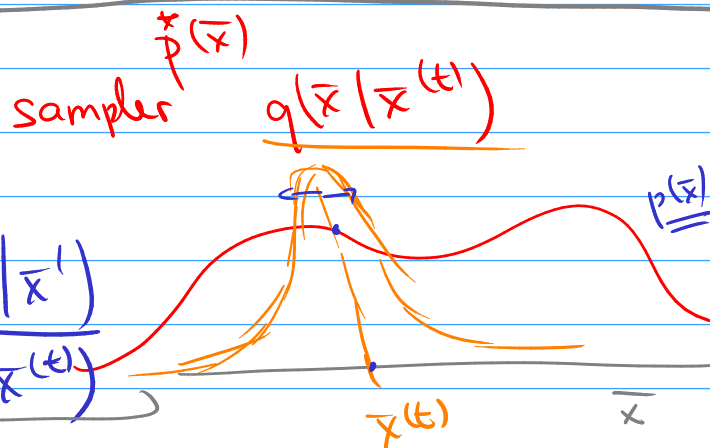
Markov chain: $\bar{x}^{(t)}$

$$- \bar{x}' \sim q(\bar{x}' | \bar{x}^{(t)})$$

$$- a(\bar{x}', \bar{x}^{(t)}) = \frac{p^*(\bar{x}')}{p^*(\bar{x}^{(t)})} \cdot \frac{q(\bar{x}^{(t)} | \bar{x}')}{q(\bar{x}' | \bar{x}^{(t)})}$$

$$- \text{if } a \geq 1 \quad \bar{x}^{(t+1)} := \bar{x}^{(t)}$$

$$\text{else } \bar{x}^{(t+1)} := \begin{cases} \bar{x}' & \text{с вероятностью } a \\ \bar{x}^{(t)} & \text{с вероятностью } 1-a \end{cases}$$



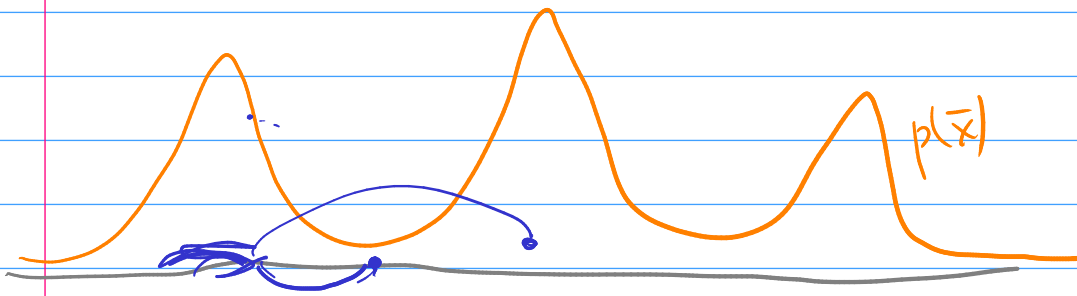
$$a(\bar{x}, \bar{x}') = \frac{1}{a(\bar{x}', \bar{x})}$$

$$p(\bar{x}) \prod (\bar{x}' | \bar{x}) \stackrel{?}{=} p(\bar{x}') \prod (\bar{x} | \bar{x}')$$

$$a(\bar{x}' | \bar{x}) \stackrel{?}{=} 1$$

$$p(\bar{x}) \cdot q(\bar{x}' | \bar{x}) \stackrel{?}{=} p(\bar{x}') q(\bar{x} | \bar{x}') \cdot a(\bar{x}, \bar{x}')$$

$$\cancel{p(\bar{x}) q(\bar{x}' | \bar{x})} \stackrel{?}{=} \cancel{p(\bar{x}') q(\bar{x} | \bar{x}')} \cdot \frac{p^*(\bar{x})}{p^*(\bar{x}')} \cdot \frac{q(\bar{x}' | \bar{x})}{q(\bar{x} | \bar{x}')}$$



$$p(\bar{\theta} | D) \propto p(\bar{\theta}) \cdot \prod_n p(\bar{x}_n | \bar{\theta})$$

Gibbs sampling

$$p(\bar{x}) = p(x_1, x_2, \dots, x_n)$$

- loop over k:

- loop over i = 1..n:

$$x_i^{(k+1)} \sim p(x_i^{(k+1)} | x_1^{(k+1)}, \dots, x_{i-1}^{(k+1)}, x_{i+1}^{(k)}, \dots, x_n^{(k)})$$

$$\begin{matrix} x_1^{(1)} & \dots & x_n^{(1)} \\ x_1^{(2)} & x_1^{(1)} & \dots & x_n^{(1)} \end{matrix}$$

$$(x_1^{(2)} \dots x_{n-1}^{(2)} x_n^{(2)}) \rightarrow \bar{x}^{(2)}$$



$$q(x'_i | \bar{x}) = \begin{cases} 0, & \bar{x}'_{-i} \neq \bar{x}_{-i} \\ p(x'_i | \bar{x}_{-i}), & \bar{x}'_{-i} = \bar{x}_{-i} \end{cases}$$

$$\begin{aligned} a(\bar{x}'_i, \bar{x}) &= \frac{p(\bar{x}')}{p(\bar{x})} \frac{q(\bar{x} | \bar{x}')}{q(\bar{x}' | \bar{x})} = \frac{p(\bar{x}')}{p(\bar{x})} \frac{p(x_i | \bar{x}_{-i})}{p(x'_i | \bar{x}_{-i})} \\ &= \frac{p(\bar{x}'_i | \bar{x}'_{-i}) p(\bar{x}'_{-i})}{p(\bar{x}_i | \bar{x}_{-i}) p(\bar{x}_{-i})} \cdot \frac{p(x_i | \bar{x}_{-i})}{p(x'_i | \bar{x}_{-i})} = 1 \end{aligned}$$

Slice sampling

$\bar{x} \sim p(\bar{x}) \Leftrightarrow (\bar{x}, u) \sim \text{Unit}(\text{product } p(\bar{x}))$

- $u \sim \text{Unit}(0, p(\bar{x}))$
 - $\bar{x} \sim p(\bar{x} | u)$

