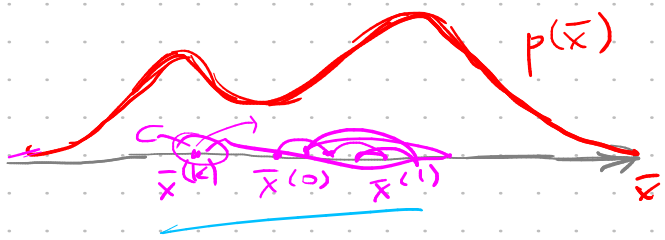


① Markov chains



$$\bar{x}^{(0)}, \bar{x}^{(1)}, \bar{x}^{(2)}, \dots$$

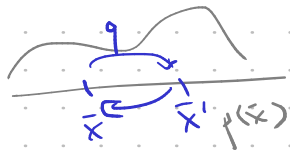
$$q^{(0)}(\bar{x}), q^{(1)}(\bar{x}), \dots, q^{(t)}(\bar{x}) \rightarrow p(\bar{x})$$

$$q(\bar{x}^{(t)} | \bar{x}^{(t-1)})$$

$$q^{(t+1)}(\bar{x}) = \int q(\bar{x} | \bar{x}') q^{(t)}(\bar{x}') d\bar{x}'$$

$$q^{(0)}, q^{(1)}, q^{(2)}, \dots, q^{(t)}, \dots \rightarrow \pi(\bar{x}) - \text{stationary distribution}$$

$$\pi(\bar{x}) : \pi(\bar{x}) = \int q(\bar{x} | \bar{x}') \pi(\bar{x}') d\bar{x}'$$



Условие
баланса: для $\forall \bar{x}, \bar{x}'$ $p(\bar{x})q(\bar{x}' | \bar{x}) = p(\bar{x}')q(\bar{x} | \bar{x}')$,

то $p(\bar{x})$ — это стационар. распределение.

$$\int q(\bar{x} | \bar{x}') p(\bar{x}') d\bar{x}' = \int p(\bar{x}) q(\bar{x}' | \bar{x}) d\bar{x}' = p(\bar{x})$$

② Metropolis-Hastings algorithm

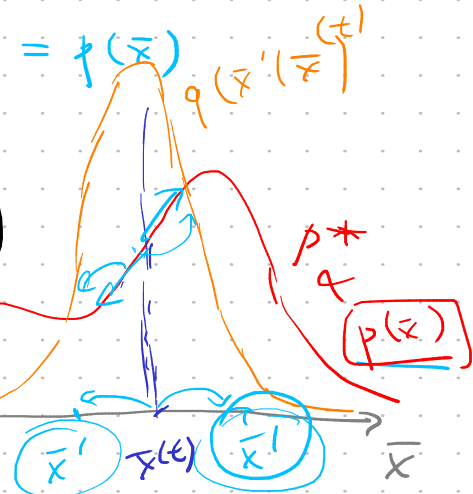
4 Markov chain $\bar{x}^{(0)}, \bar{x}^{(1)}, \dots$ $q(\bar{x}^{(t)} | \bar{x}^{(t-1)})$

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

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

- if $a \geq 1$ then accept $\bar{x}^{(t+1)} = \bar{x}'$

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



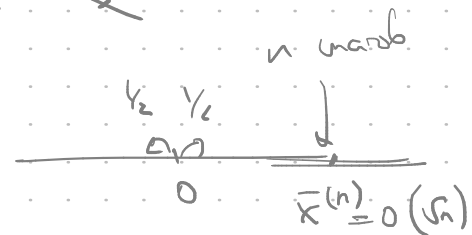
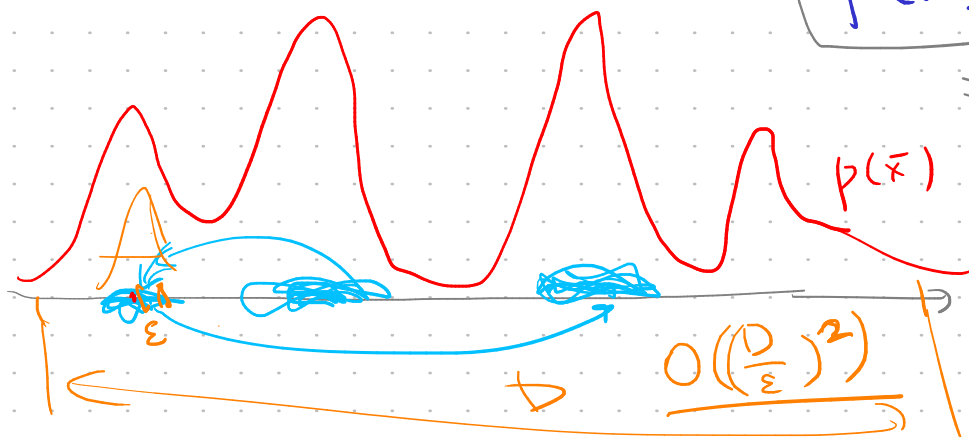
$$\forall \bar{x}, \bar{x}' \quad p(\bar{x}) \cdot p_{MC}(\bar{x}' | \bar{x}) \neq p(\bar{x}') p_{MC}(\bar{x} | \bar{x}')$$

тогда $a(\bar{x}' | \bar{x}) \geq 1$ $p_{MC}(\bar{x}' | \bar{x}) = q(\bar{x}' | \bar{x})$

$$p_{MC}(\bar{x} | \bar{x}') = q(\bar{x} | \bar{x}') \cdot a(\bar{x}, \bar{x}')$$

$$p(\bar{x})q(\bar{x}'|\bar{x}) \neq p(\bar{x}')q(\bar{x}|\bar{x}') \cdot \frac{p^*(\bar{x})}{p^*(\bar{x}')} \cdot \frac{q(\bar{x}'|\bar{x})}{q(\bar{x}|\bar{x}')}$$

$$= \frac{p(\bar{x})}{p(\bar{x}')}$$



$$N(\bar{x}|\bar{\mu}, \epsilon)$$

$$\bar{\mu} \sim p(\bar{\mu}|D) \propto p(\bar{\mu}) \cdot p(D|\bar{\mu})$$

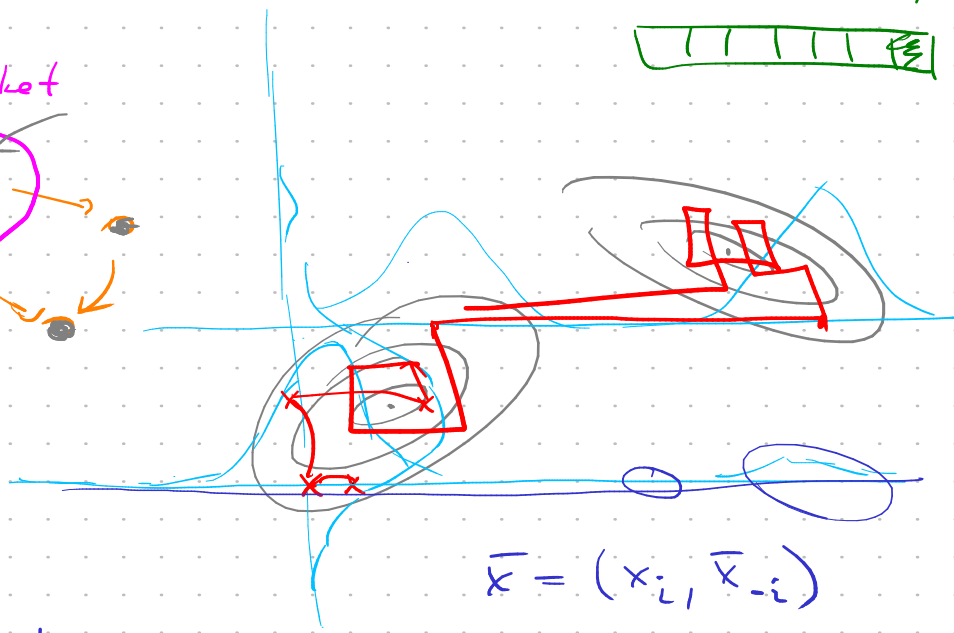
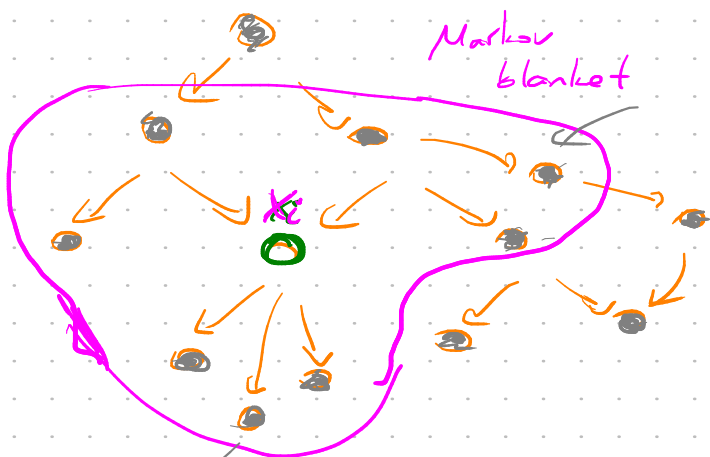
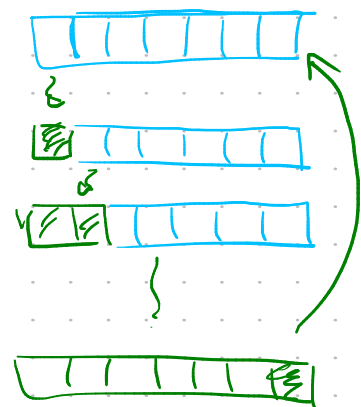
$$\bar{x} \sim p(\bar{x}|D) = \int p(\bar{x}|\bar{\mu}) p(\bar{\mu}|D) d\bar{\mu} \approx \frac{1}{L} \sum_{r=1}^L p(\bar{x}|\bar{\mu}^{(r)})$$

3 Gibbs sampling

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

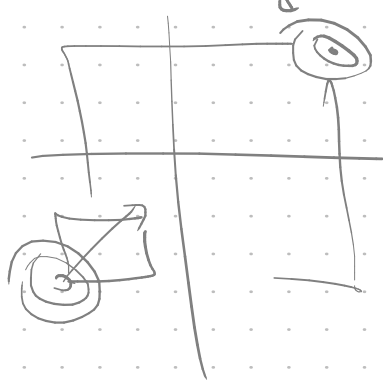
- init $\bar{x}^{(0)}$
- repeat:
- for $i=1 \dots n$:

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



- $i-i$ was!

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



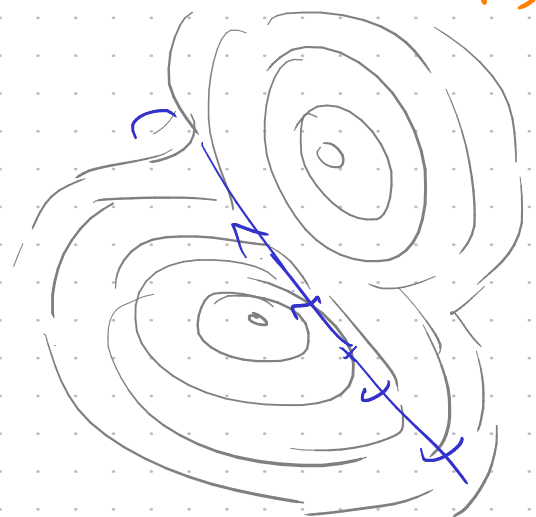
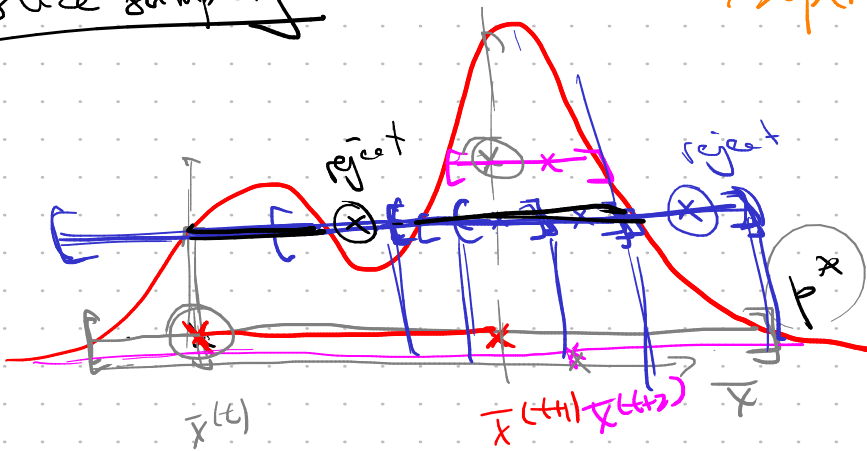
$$a(\bar{x}', \bar{x}) = \frac{p^*(\bar{x}')}{p^*(\bar{x})} \cdot \frac{q(\bar{x} | \bar{x}')}{q(\bar{x}' | \bar{x})} = \frac{p(x_i' | \bar{x}_{-i}')}{p(x_i | \bar{x}_{-i})} \cdot \frac{p(x_i | \bar{x}_{-i}')}{p(x_i' | \bar{x}_{-i}')} = 1$$

$$= \frac{p(\bar{x}_{-i}) p(x_i' | \bar{x}_{-i})}{p(\bar{x}_{-i}') p(x_i | \bar{x}_{-i}')} \cdot \frac{p(x_i | \bar{x}_{-i}')}{p(x_i' | \bar{x}_{-i}')} = 1$$

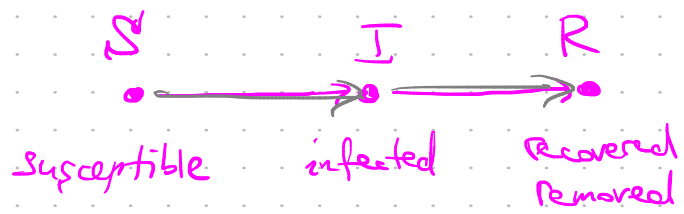


④ slice sampling

$$x \sim p(x) \Leftrightarrow (x, y) \sim \text{Unif}(\text{trap } p^*)$$



⑤ SIR models



$$X = \{x_1, x_2, \dots, x_N\}$$

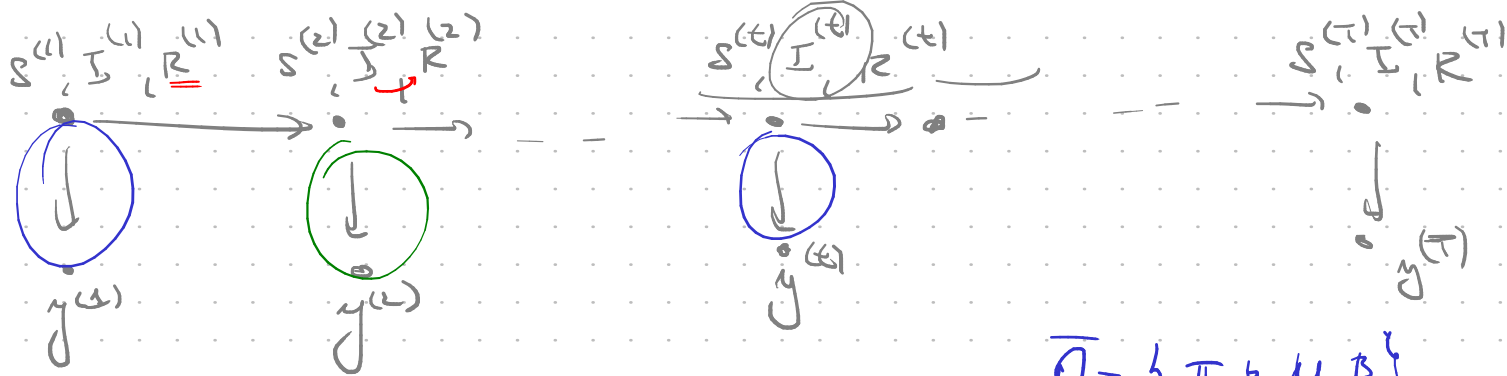
$$x_i^{(t)} \in \{S, I, R\}$$

$$y = \{y^{(1)}, y^{(2)}, \dots, y^{(T)}\}$$

bootstrapping to approx. t

$$S^{(t)} = \#\{i | x_i^{(t)} = S\}$$

$$I^{(t)}, R^{(t)} \quad \forall t \quad S^{(t)} + I^{(t)} + R^{(t)} = N$$



$$\Theta = \{\pi, p, \mu, \beta\}$$

Параметры модели:

1) $R^{(1)} = 0, p(x_i^{(1)} = I) = \pi, p(x_i^{(1)} = S) = 1 - \pi$

2) $p(x_i^{(t)} \in y^{(t)} | x_i^{(t)} = I) = p$

$$p(y^{(t)} | I^{(t)}, p) = \text{Binom}(y^{(t)} | I^{(t)}, p)$$

3) $p(x_i^{(t+1)} = R | x_i^{(t)} = I) = \mu$

— " — I — " — = $1 - \mu$

4) $p(\text{заболевает на } \Delta \text{ контактах}) = \beta$

$$p(x_i^{(t+1)} = S | x_i^{(t)} = S) = (1 - \beta) I^{(t)}$$

— " — I — " — = $1 - (1 - \beta) I^{(t)}$

$$p(x_i^{(t+1)} | x_i^{(t)}) = \begin{matrix} & \begin{matrix} S & I & R \end{matrix} \\ \begin{matrix} S \\ I \\ R \end{matrix} & \begin{pmatrix} (1-\beta) I^{(t)} & 1-(1-\beta) I^{(t)} & 0 \\ 0 & 1-\mu & \mu \\ 0 & 0 & 1 \end{pmatrix} \end{matrix}$$

6 Inference in SIR

$$p(x, y | \Theta) = p(x^{(1)} | \pi) p(y^{(1)} | x^{(1)}, p) p(x^{(2)} | x^{(1)}, \beta, \mu) \dots p(y^{(T)} | x^{(T)}, \beta)$$

$$= \left[\pi^{I^{(1)}} (1-\pi)^{S^{(1)}} \right] \left[\binom{I^{(1)}}{y^{(1)}} p^{y^{(1)}} (1-p)^{I^{(1)}-y^{(1)}} \right] \dots =$$

$$= \pi^{I^{(1)}} (1-\pi)^{S^{(1)}} \cdot \left[\prod_{t=1}^T \binom{I^{(t)}}{y^{(t)}} p^{y^{(t)}} (1-p)^{I^{(t)}-y^{(t)}} \right] \left[\prod_{t=1}^T \prod_{j=1}^N p(x_j^{(t+1)} | x_j^{(t)}, \mu, \beta, I_j^{(t)}) \right]$$

$$p(y|\bar{\theta}) = \int p(y|x, \bar{\theta}) p(x|\bar{\theta}) dx = \mathbb{E}_{p(x|\bar{\theta})} [p(y|x, \bar{\theta})] \approx \frac{1}{R} \sum_{r=1}^R p(y|x_{(r)}, \bar{\theta})$$

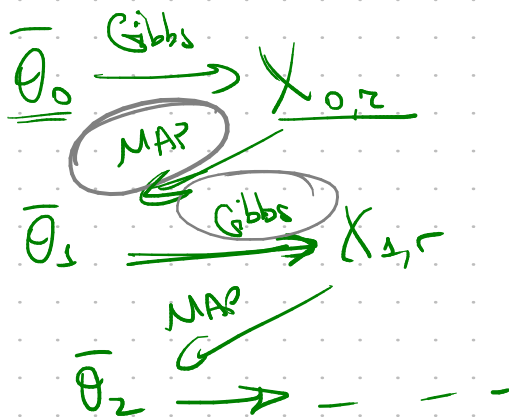
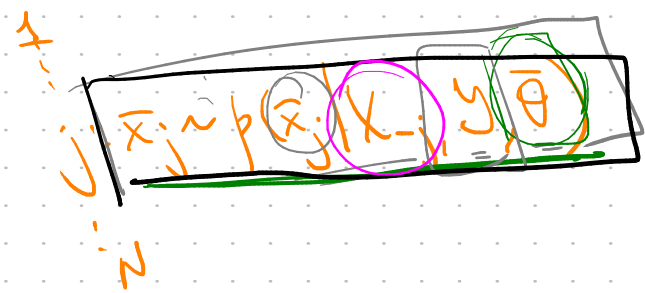
$\bar{\theta} \rightarrow \max$

$$X = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_j, \dots, \bar{x}_N)$$

$$(x_j^{(1)}, x_j^{(2)}, \dots, x_j^{(r)})$$

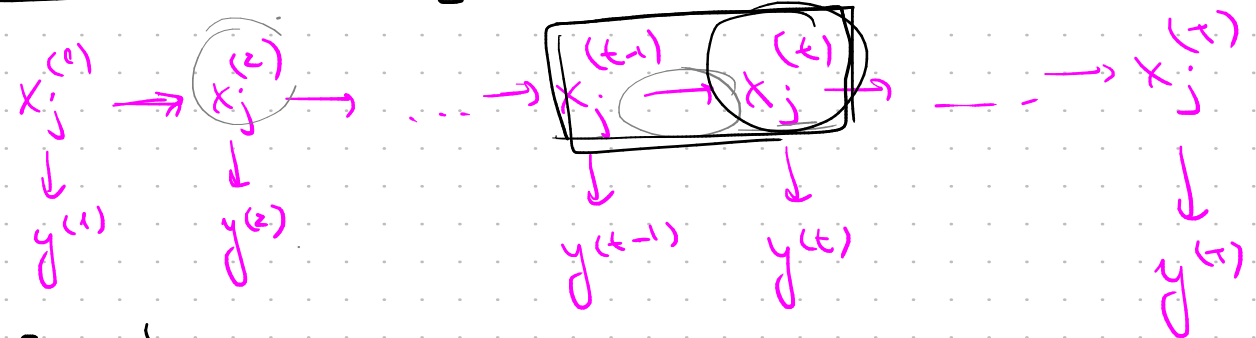
EM

Gibbs sampling:



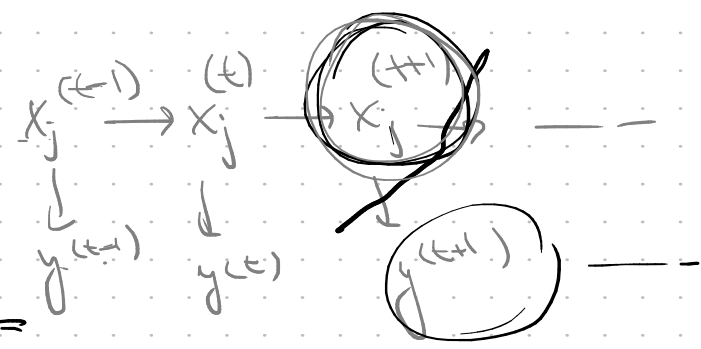
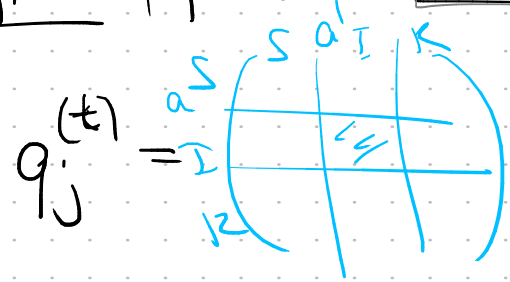
⑦ Stochastic Viterbi algorithm

$$\bar{x}_j \sim p(\bar{x}_j | X_{-j}, y, \bar{\theta})$$



$$a, a' \in \{S, I, R\}$$

$$q_{j,a,a'}^{(t)} = p(x_j^{(t)} = a, x_j^{(t+1)} = a' | y^{(1)} \dots y^{(t)}, X_{-j}, \bar{\theta})$$



$$x_j^{(t)} \sim p(x_j^{(t)} = a | x_j^{(t+1)} = a', y, X_{-j}, \bar{\theta}) = p(x_j^{(t)} = a | x_j^{(t+1)} = a', y^{(1)} \dots y^{(t)}, X_{-j}, \bar{\theta})$$

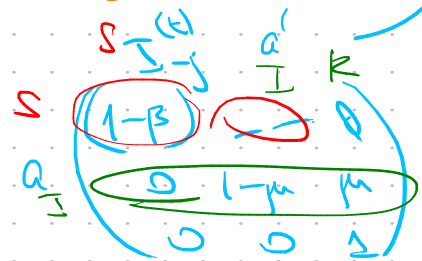
$$q_{j,a,a'}^{(t)} = p(x_j^{(t)}=a, x_j^{(t+1)}=a' | y^{(t)} - y^{(t+1)}, -) \propto$$

$$\propto p(x_j^{(t)}=a, x_j^{(t+1)}=a', y^{(t)} | y^{(t)} - y^{(t+1)}, -) =$$

$$= \underbrace{p(x_j^{(t)}=a | y^{(t)} - y^{(t+1)})}_{\text{"}} \cdot \underbrace{p(y^{(t)} | x_j^{(t)}=a, -)}_{\text{Binom}(y^{(t)} | 1-j + [a=1], \beta)} \cdot \underbrace{p(x_j^{(t+1)}=a' | x_j^{(t)}=a, -)}_{\text{Binom}(a' | 1-j + [a=1], \beta)}$$

$$\sum_{a''} p(x_j^{(t)}=a, x_j^{(t+1)}=a'' | -)$$

$$= \sum_{a''} q_{j,a'',a}^{(t+1)}$$



Sampling:

$$- Q_j^{(t)} = a \left(- q_{j,a,a'}^{(t)} - \right) Q_j^{(t)}$$

- sample $x_j^{(t)}, x_j^{(t+1)}, \dots, x_j^{(T)}$

$$x_j^{(t)} \sim p(x_j^{(t)}=a | y, x_{-j}, \theta) = \sum_{a'} q_{j,a,a'}^{(t)}$$

$$x_j^{(t)} \sim p(x_j^{(t)}=a | x_j^{(t+1)}=a', y, x_{-j}, \bar{\theta}) \propto q_{j,a,a'}^{(t)}$$

- output $(x_j^{(t)} - x_j^{(T)})$

$$\bar{\theta} = (\pi, \mu, \beta)$$

⑧ Learning

$$p(\bar{\theta} | x, y) \propto p(\bar{\theta}) p(x, y | \bar{\theta})$$

$$p(\pi) p(\mu) p(\beta)$$

$$p(\pi) = \text{Beta}(\pi | a_{\pi}, b_{\pi}) \propto \pi^{a_{\pi}-1} (1-\pi)^{b_{\pi}-1}$$

1) Init $\bar{\theta}, X$

2) for $j=1, \dots, N, 1, \dots, N, \dots$

(i) $\bar{x}_j \sim \text{Gibbs}$

(ii) replace $\bar{x}_j$ b X

(iii) every M steps update $\bar{\theta}$ from X

$$\log p(\theta | X, y) = \text{const} + \underbrace{(a_\pi - 1) \log \pi + (b_\pi - 1) \log(1 - \pi)}_{\pi} + \underbrace{\sum_{t=1}^T \log \pi + \sum_{t=1}^T \log(1 - \pi)}_{\pi} + \underbrace{(a_\beta - 1) \log \beta + (b_\beta - 1) \log(1 - \beta)}_{\beta} + \underbrace{\sum_{t=1}^T (y^{(t)} \log \beta + (1 - y^{(t)}) \log(1 - \beta))}_{\beta} + (a_\mu - 1) \log \mu + (b_\mu - 1) \log(1 - \mu) + \sum_{j=1}^N \sum_{t=1}^{T-1} \left([x_j^{(t)} = I, x_j^{(t+1)} = R] \log \mu + [x_j^{(t)} = I, x_j^{(t+1)} = I] \log(1 - \mu) \right)$$

$$+ (a_\beta - 1) \log \beta + (b_\beta - 1) \log(1 - \beta) + \sum_{j=1}^N \sum_{t=1}^{T-1} \left([x_j^{(t)} = I, x_j^{(t+1)} = R] \cdot I^{(t)} \cdot \log(1 - \beta) + [x_j^{(t)} = R, x_j^{(t+1)} = I] \cdot \textcircled{?} \right)$$

$I^{(t)}$ коэффициент $\Rightarrow \geq 1$ по определению

$$\textcircled{?} = \left(\underbrace{E[\text{\# кол-во } I \text{ за } t \text{ шагов}]}_{I^{(t)}} \cdot \log \beta + \underbrace{E[\text{\# кол-во } R \text{ за } t \text{ шагов}]}_{I^{(t)} \left(1 - \frac{\beta}{1 - (1 - \beta)^{I^{(t)}}} \right)} \cdot \log(1 - \beta) \right)$$

$$I^{(t)} \cdot p(\text{закон } I \text{ за } t \text{ шагов} | \text{закон } I) = I^{(t)} \cdot \frac{\beta}{1 - (1 - \beta)^{I^{(t)}}}$$

$$p(\pi | \dots) = \text{Beta}(a'_\pi, b'_\pi)$$

$$a'_\pi = a_\pi + I^{(1)} \quad b'_\pi = b_\pi + I^{(1)}$$

$$a'_\beta = a_\beta + \sum_t y^{(t)}$$

$$b'_\beta = b_\beta + \sum_t (1 - y^{(t)})$$

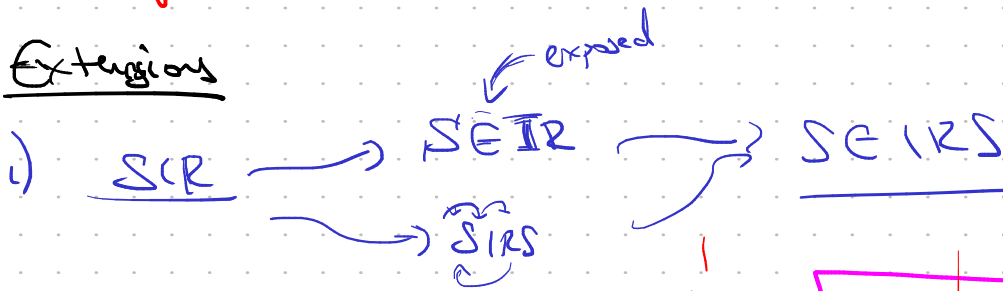
$$a'_\mu = a_\mu + [\text{\# перекл. } I \rightarrow R]$$

$$b'_\mu = b_\mu + [\text{\# перекл. } I \rightarrow I]$$

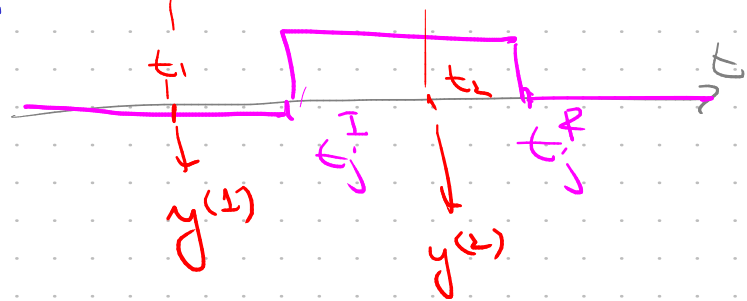
$$a'_\beta = a_\beta + \sum_{j=1}^N \sum_{t=1}^{T-1} [x_j^{(t)} = I, x_j^{(t+1)} = R] \cdot I^{(t)} \cdot \frac{\beta}{1 - (1 - \beta)^{I^{(t)}}}$$

$$b'_\beta = b_\beta + \sum_{j=1}^N \sum_{t=1}^{T-1} [x_j = S] \left([x_j = S] \cdot \bar{I}^{(t)} + [x_j = I] \cdot \bar{I}^{(t)} \left(1 - \frac{\beta_{14}}{1 - (1 - \beta_{14}) \bar{I}^{(t)}} \right) \right)$$

9) Extensions



2) Continuous time



3) Модель заражения

