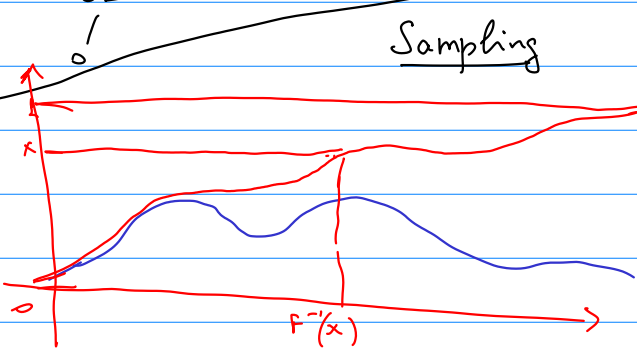
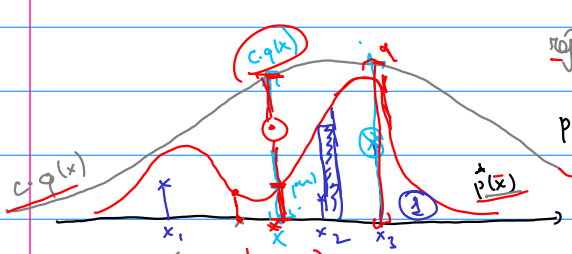
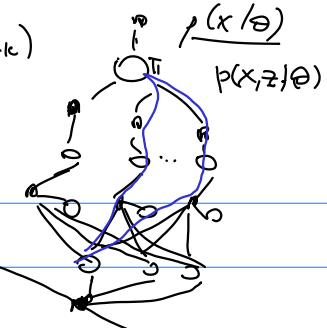
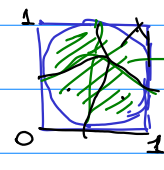


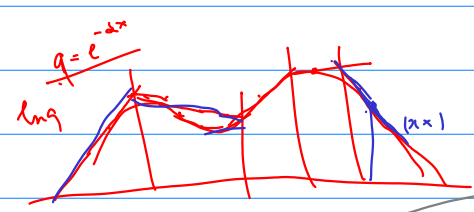
$$f(x) = \prod_{i=1}^n f_i(x_i) \quad \sum_{x_1, \dots, x_n} p(x_1, \dots, x_n) = p(x_i)$$



$$\int f(x)p(x)dx \approx \frac{1}{N} \sum_{k=1}^N f(x_k)$$



rejection sampling
 $p^*(x) \propto p(x)$



$$\bar{x} \sim q(\bar{x}) = p(x_1) p(x_2|x_1) p(x_3|x_2, x_3) \dots$$

$$\bar{x} \sim p(x_1, \dots, x_n) = p(x_1) p(x_2|x_1) \dots p(x_n|x_1, \dots, x_{n-1})$$

importance sampling

likelihood weighted sampling

$$\bar{x}, x_1, x_2, x_3, x_4 \sim q$$

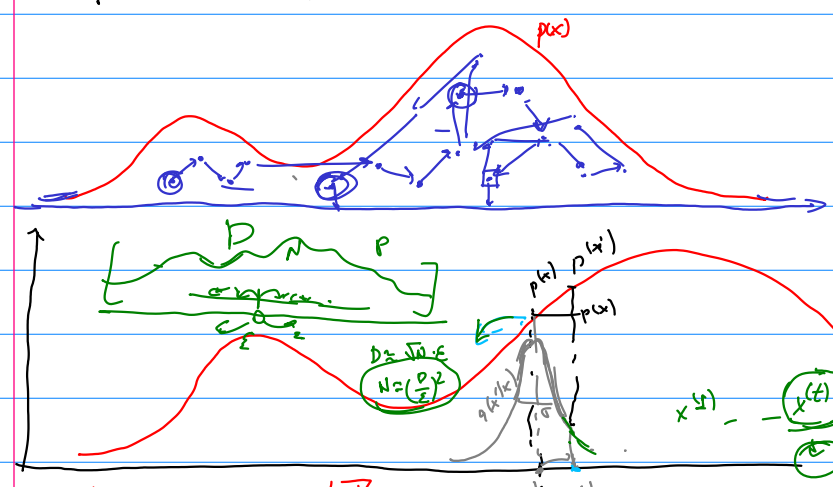
$$f(\bar{x}) \cdot \prod_{x \in \text{evidence}} p(x|\text{par}(x))$$

$$p(\bar{x}, x_1, x_2, x_3) \propto p(\bar{x}) p(x_1, x_2, x_3)$$

$$E f \approx \left[\frac{1}{N} \sum_{k=1}^N f(x_k) \right]$$

$$\int f(x)p(x)dx = \int f(x) \frac{p(x)}{q(x)} q(x) dx \approx \frac{1}{N} \sum_{k=1}^N f(x_k) \frac{p(x_k)}{q(x_k)}$$

Markov Chain Monte Carlo (MCMC)



Metropolis-Hastings:

- repeat:
- sample $x' \sim q(x'|x)$
 - if $p(x') > p(x)$ accept x'
 - if $p(x') \leq p(x)$ accept x' with prob. $\alpha = \frac{p(x')}{p(x)} \cdot \frac{q(x|x')}{q(x'|x)}$
- else $x' = x$

accept x'

$$A \pi = \bar{\pi} \quad x^{(1)}, x^{(2)}, \dots, x^{(t)}$$

$$T(x, x') \cdot p(x) = T(x', x) \cdot p(x)$$

gen. Sanchez:

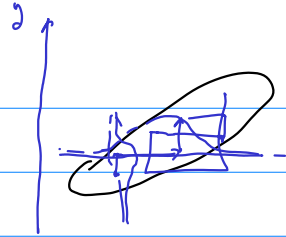
$$p(x) \propto \int T(x, x') p(x') dx = p(x) \int T(x, x') dx$$

$$\frac{q(x'|x) \cdot p(x)}{p(x')} \cdot \frac{q(x|x')}{q(x'|x)}$$

Gibbs sampling

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

$\bar{x}^{(0)}$
 $x_1 \sim p(x_1 | \bar{x}_{-1}^{(0)})$
 $x_2 \sim p(x_2 | x_1, \bar{x}_{-2}^{(0)})$
 $x_3 \sim p(x_3 | x_1, x_2, \dots)$



$N(\mu, \Sigma) \approx q_i(z_i) \cdot q_i(z_i)$

$KL(q||p) \rightarrow \min$ $q_i(z_i) = N(z_i | \mu_i, \Sigma_i)$
 $\mu = (\mu_1, \dots, \mu_n)$
 $\Sigma = (\Sigma_1, \dots, \Sigma_n)$

$KL(p||q) \rightarrow \min$

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

$x_i' \sim p(x_i' | \bar{x}_{-i})$

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

$q(\bar{x}' | \bar{x})$

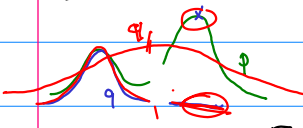
$q(\bar{x}') > p(\bar{x}) \rightarrow \text{accept } x'$

$p(\bar{x}') < p(\bar{x}) \rightarrow \text{accept w/ prob.}$

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

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

$J(f) = \int_{-\infty}^{+\infty} f(x) p(x) dx \rightarrow \min$
 EM: $p(x|\theta) \rightarrow \max$ | $p(x, z|\theta) \rightarrow \max$



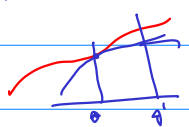
$p(x, z|\theta) = p(z|x, \theta) p(x|\theta)$

$\ln p(x, z|\theta) = \ln p(z|x, \theta) + \ln p(x|\theta)$

$E_{q(z)}[\ln p(x|\theta)] = E_{q(z)}[\ln p(x, z|\theta) - \ln p(z|x, \theta)] + \int \ln q(z) q(z) dz$

$\ln p(x|\theta) = \int \ln p(x, z|\theta) q(z) dz - \int \ln p(z|x, \theta) q(z) dz =$

$\ln p(x|\theta) = \int \ln \frac{p(x, z|\theta)}{q(z)} q(z) dz - \int \ln \frac{p(z|x, \theta)}{q(z)} q(z) dz =$
 $= \ln(q|\theta) + KL(q||p(z|x, \theta)) - \int \ln \frac{p(z|x, \theta)}{q(z)} q(z) dz$



$\ln p(x|\theta) \geq \ln(q|\theta) - \frac{1}{\theta} \rightarrow \max$

subback-leibler

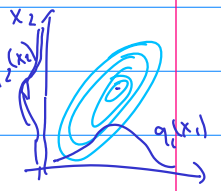
$KL(q||p) = \int \ln \frac{q}{p} q dx$
 $= E_q \ln \frac{q}{p}$

$KL(q||p) \geq 0$
 $KL(q||p) = 0 \Leftrightarrow q = p$

$KL(p||q) = - \int \ln \frac{q}{p} p dx$

$\mu_1 = \mu_2 - \lambda_1 d_1 (\mu_2 - \mu_1)$
 $\mu_2 = \mu_2 - \lambda_2 d_2 (\mu_2 - \mu_1)$

$\ln q_i^* = E_{z_i} \ln p(x_i, z_i)$



$q_i^*(x_i) \approx p(x_i, z_i)$
 $\ln q_i^* = E_{x_i} \ln p(x_i, z_i)$

$p(x, z) = p(x) p(z|x)$

$\ln p(x, z) - \ln p(z|x) = \ln p(x)$

$\int \ln \frac{p(x, z)}{q(z)} q(z) dz - \int \ln \frac{p(z|x)}{q(z)} q(z) dz = \ln p(x)$

$\ln(q) + KL(q||p(z|x)) = \ln p(x)$

$\ln(q) \leq \ln p(x)$ - variational lower bound

$E_x [\text{const} - \frac{1}{2} (\bar{x} - \bar{\mu})^T \Lambda (\bar{x} - \bar{\mu})] = \frac{1}{2} [(x_1 - \mu_1)^T \Lambda_{11} (x_1 - \mu_1) + E_{x_2} (x_1 - \mu_1)^T \Lambda_{12} (x_1 - \mu_1) + 2 E_{x_2} (x_1 - \mu_1)^T \Lambda_{12} (x_2 - \mu_2)]$

$L(q) = \int \ln \frac{p(x, z)}{q(z)} q(z) dz \rightarrow \max$

$q(z) = \prod_{z_i \in \mathcal{Z}} q_i(z_i)$ $\Pi q_i \approx p(z|x)$

$\int \ln \frac{p(x, z)}{\Pi q_i} \cdot \Pi q_i dz_1 \dots dz_n = - \int \ln q_i \Pi q_i dz = - \int \ln q_i q_i dz =$

$= \int \ln p(x, z) \cdot \Pi q_i dz - \int \ln \Pi q_i \cdot \Pi q_i dz =$

$E_{z_i} \ln p(x, z) = \ln p(x, z)$

$\max_{q_i} L(q) = \text{const} + \int \ln \tilde{p} q_i dz_i - \int \ln q_i q_i dz_i = \text{const} + \int \ln \frac{\tilde{p}}{q_i} q_i dz_i = KL(q, \tilde{p})$