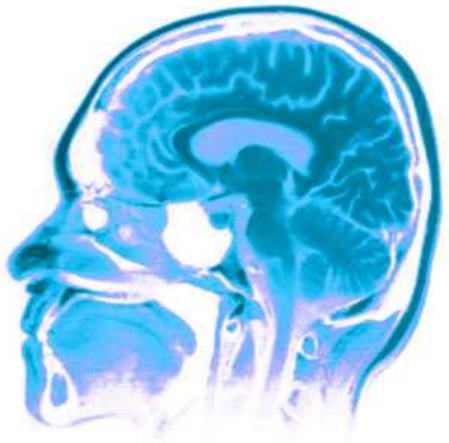


Importance sampling (IS) & Markov chain Monte Carlo (MCMC)

Nando de Freitas
March, 2013
University of British Columbia

Bayesian logistic regression

$$p(\mathbf{y}|\mathbf{X},\boldsymbol{\theta}) = \prod_{i=1}^{n} \mathrm{Ber}(y_i|\mathrm{sigm}(\mathbf{x}_i\boldsymbol{\theta})) = \prod_{i=1}^{n}\left[\frac{1}{1+e^{-\mathbf{x}_i\boldsymbol{\theta}}}\right]^{y_i}\left[1-\frac{1}{1+e^{-\mathbf{x}_i\boldsymbol{\theta}}}\right]^{1-y_i}$$

π_i

$$\pi(\theta) = -\log p(\theta|X,y) = \text{const} - \log P(y|x,\theta) - \log P(\theta) = \text{const} - \sum_{i=1}^{n} y_i \log \pi_i + (1-y_i)\log(1-\pi_i) - \frac{1}{2\sigma^2}\|\theta\|_2^2$$

We also assume a Gaussian prior

$$p(\theta) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{1}{2\sigma^2}(\theta-\mu)'(\theta-\mu)\right)$$

$\mu = 0$, θ

Posterior: $P(\theta|X,y) = \frac{1}{Z} P(y|x,\theta) P(\theta)$

$Z = \int P(y|x,\theta) P(\theta)\, d\theta$ is unknown / hard

IS

$$Z = \int P(y|\theta) P(\theta) \, d\theta$$

$$Z = \int \frac{P(y|\theta) P(\theta)}{q(\theta)} q(\theta) \, d\theta$$

$$q(\theta) = N(0, 1000)$$

$$Z = \int w(\theta) \, q(\theta) \, d\theta$$

$$\theta^{(i)} \sim q(\theta), \quad i = 1:N$$

$$Z \approx \frac{1}{N} \sum_{i=1}^{N} w(\theta^{(i)})$$

SLLN

$$P(Y_{t+1} \mid X_{t+1}, Y_{1:t}, X_{1:t}) = \int P(Y_{t+1} \mid X_{t+1}, \theta)\, P(d\theta \mid X_{1:t}, Y_{1:t})$$

$$= \int P(Y_{t+1} \mid X_{t+1}, \theta)\, P(\theta \mid X_{1:t}, Y_{1:t})\, d\theta$$

$$\approx \int P(Y_{t+1} \mid X_{t+1}, \theta)\, \frac{1}{N} \sum_{i=1}^{N} w(\theta^{(i)})\, \delta_{\theta^{(i)}}(d\theta)$$

$$\approx \frac{1}{N} \sum_{i=1}^{N} \int P(Y_{t+1} \mid X_{t+1}, \theta)\, w(\theta^{(i)})\, \delta_{\theta^{(i)}}(d\theta)$$

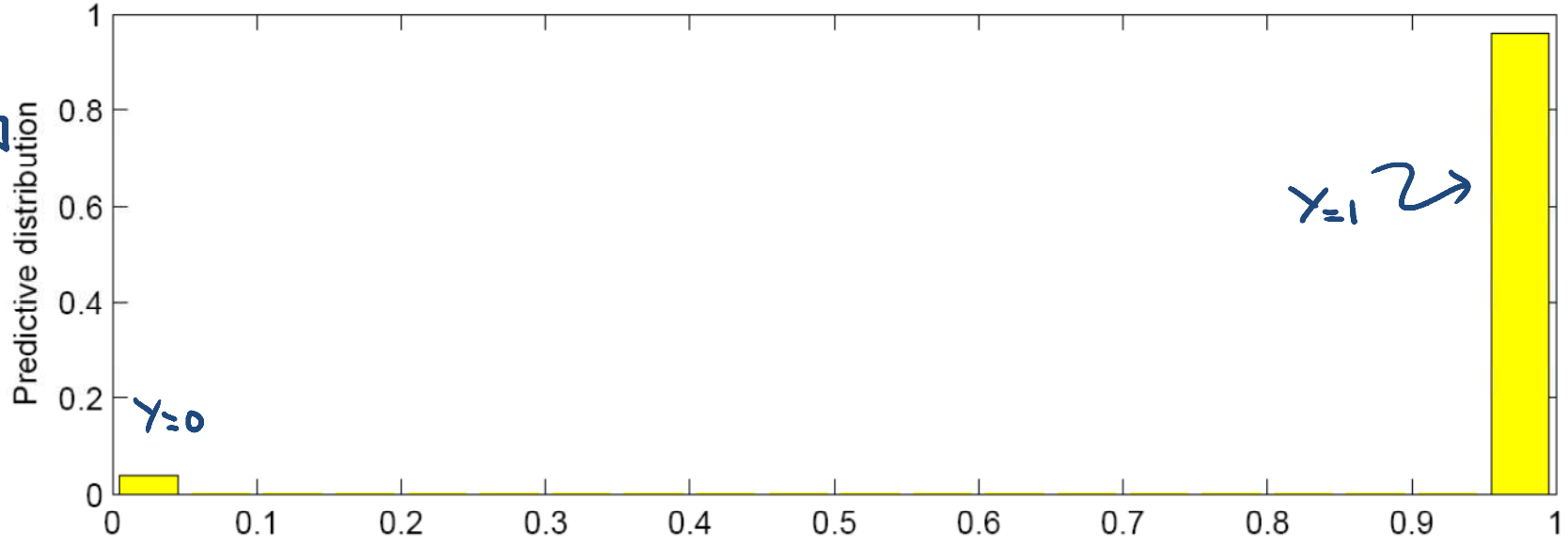
$$\approx \frac{1}{N} \sum_{i=1}^{N} \underbrace{P(Y_{t+1} \mid X_{t+1}, \theta^{(i)})}_{\text{likelihood}}\, w(\theta^{(i)})$$

Example: Logistic Regression

$$p(y_{T+1}|x_{1:T+1}) = \int_{\Theta} p(y_{T+1}|x_{T+1},\theta)p(\theta|x_{1:T},y_{1:T})d\theta$$

$$p(y_{T+1}|x_{1:T+1}) = \frac{1}{N}\sum_{i=1}^{N} p(y_{T+1}|x_{T+1},\theta^{(i)})$$

$\theta^{(i)} \sim P(\theta|x_{1:T},y_{1:T})$



Un-normalized IS

$$p(\theta \mid D) = \frac{1}{Z} p(D \mid \theta)\, p(\theta) = \frac{p(D \mid \theta)\, p(\theta)}{\int p(D \mid \theta)\, p(\theta)\, d\theta}$$

D = data

$$p(y_{t+1} \mid x_{t+1}, D)$$

$$= p(y_{t+1} \mid x_{1:t+1}, y_{1:t}) = \frac{1}{Z} \int p(y_{t+1} \mid x_{t+1}, \theta)\, p(D \mid \theta)\, p(\theta)\, d\theta$$

$q(\theta)$ ← $Q(\mu, \sigma^2 I)$

$$= \frac{\int p(y_{t+1} \mid x_{t+1}, \theta)\, p(D \mid \theta)\, p(\theta)\, \frac{q(\theta)}{q(\theta)}\, d\theta}{\int p[D \mid \theta]\, p(\theta)\, \frac{q(\theta)}{q(\theta)}\, d\theta}$$

$$= \frac{\int p(y_{t+1} \mid x_{t+1}, \theta)\, w(\theta)\, q(\theta)\, d\theta}{\int w(\theta)\, q(\theta)\, d\theta} = \frac{\frac{1}{N} \sum_{i=1}^{N} w(\theta^{(i)})\, p(y_{t+1} \mid x_{t+1}, \theta^{(i)})}{\frac{1}{N} \sum_{j=1}^{N} w(\theta^{(j)})}$$

$$= \sum_{i=1}^{N} \tilde{w}(\theta^{(i)})\, p(y_{t+1} \mid x_{t+1}, \theta^{(i)})$$

$$\tilde{w}^i = \frac{w^i}{\sum_j w^j}$$

MCMC

Detailed Balance:

If $\int_{x_t} \pi(x_t)\, P(x_{t+1} | x_t) = \int_{x_t} \pi(x_{t+1})\, P(x_t | x_{t+1})$

$= \pi(x_{t+1}) \int_{x_t} P(x_t | x_{t+1}) = 1$

Integrating over x_t yields

$$\int_{x_t} \pi(x_t)\, P(x_{t+1} | x_t) = 1\, \pi(x_{t+1})$$

Which is the ergodic behaviour we want.

Now we have a sufficient condition for designing $P(x_{t+1} | x_t)$ so as to get samples from π

MCMC: Metropolis-Hastings

- Initialise $x^{(0)}$.
- For $i = 0$ to $N - 1$
  - Sample $u \sim U_{[0,1]}$.
  - Sample $x^\star \sim q(x^\star | x^{(i)})$.
  - If $u < A(x^{(i)}, x^\star) = \min\left\{1, \frac{p(x^\star)q(x^{(i)}|x^\star)}{p(x^{(i)})q(x^\star|x^{(i)})}\right\}$

    $x^{(i+1)} = x^\star$

    else

    $x^{(i+1)} = x^{(i)}$

$x^{(i)}$

e.g. $\pi(x) = \frac{P(x)}{Z}$

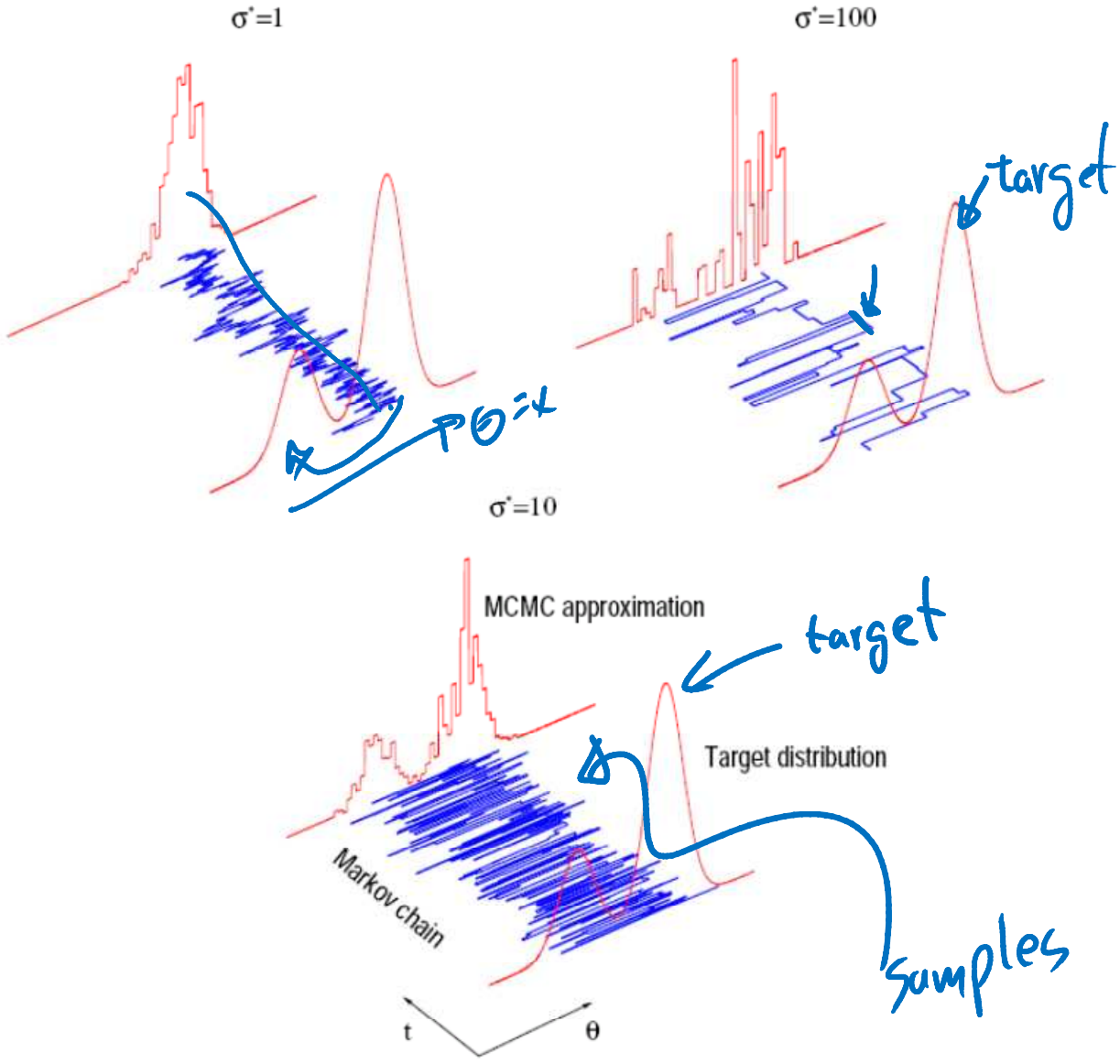
$x^* = x^{(i)} + N(0, \sigma^2)$

posterior

0.8

$x^{(i+1)}$

MCMC: Choosing the Right Proposal



MCMC: Theory

Kernel:

$$T = K(x, B) = \begin{cases} q(B|x)\, A(x, B) & x \notin B \\ 1 - \int_{x' \in \{\mathcal{X} \setminus B\}} q(x'|x) A(x, x') & x \in B \end{cases}$$

Prob of going from x to interval B.

all space minus B

$$\therefore \quad K(x, B) = q(B|x) A(x, B) + \Pi_{x \in B} \left\{ 1 - q(B|x) A(x, B) - \int_{x' \in \{\mathcal{X} \setminus B\}} q(x'|x) A(x, x') \right\}$$

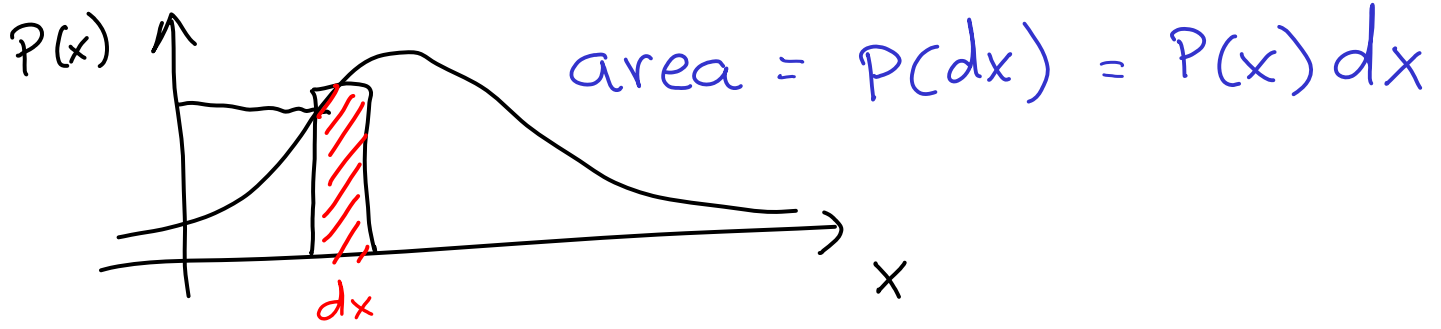
$$K(x, B) = q(B|x) A(x, B) + \Pi_{x \in B} \left\{ 1 - \int_{x' \in \mathcal{X}} q(x'|x) A(x, x') \right\}$$

Detailed balance :

$$\pi(A)\,K(A,B) = \pi(B)\,K(B,A)$$

$$\int_{x\in A} \pi(dx)\,K(x,B) = \int_{y\in B} \pi(dy)\,K(y,A)$$

Note: $\int f(x)\,p(x)\,dx \equiv \int f(x)\,p(dx)$



Variations of Metropolis-Hastings

$$\min\left\{1, \frac{P(x^*)}{P(x^{(i)})} \frac{q(x^{(i)}|x^*)}{q(x^*|x^{(i)})}\right\}$$

$$x^* = x^{(i)} + N(0, \sigma^2)$$

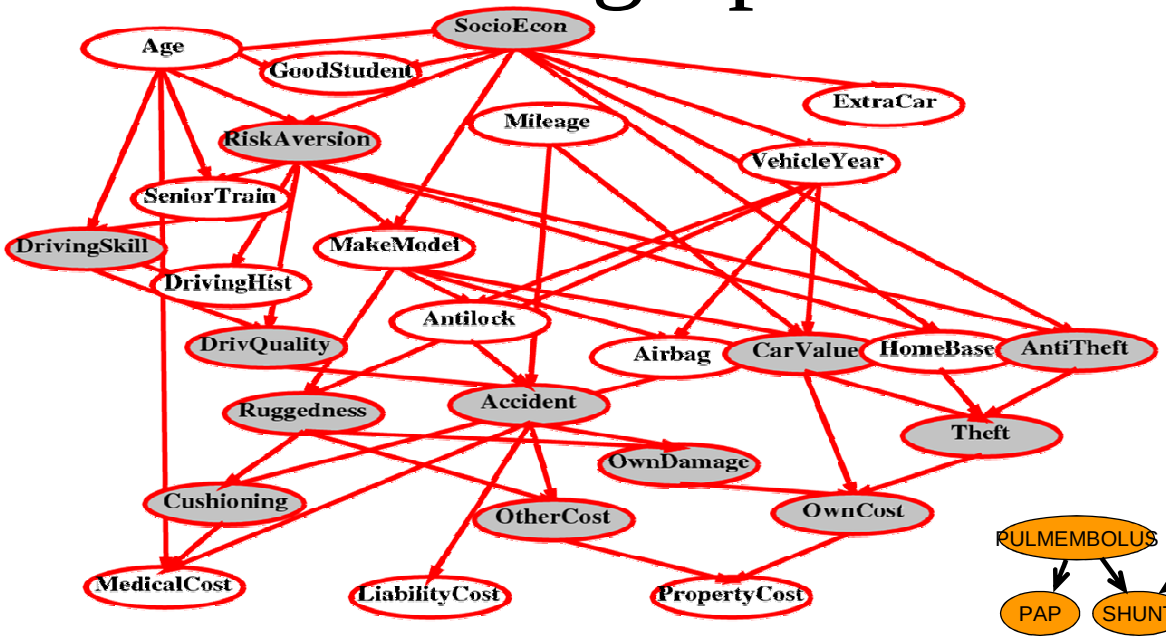
$$q(x^{(i)}|x^*) \propto e^{-\|x^* - x^{(i)}\|^2/\sigma^2}$$

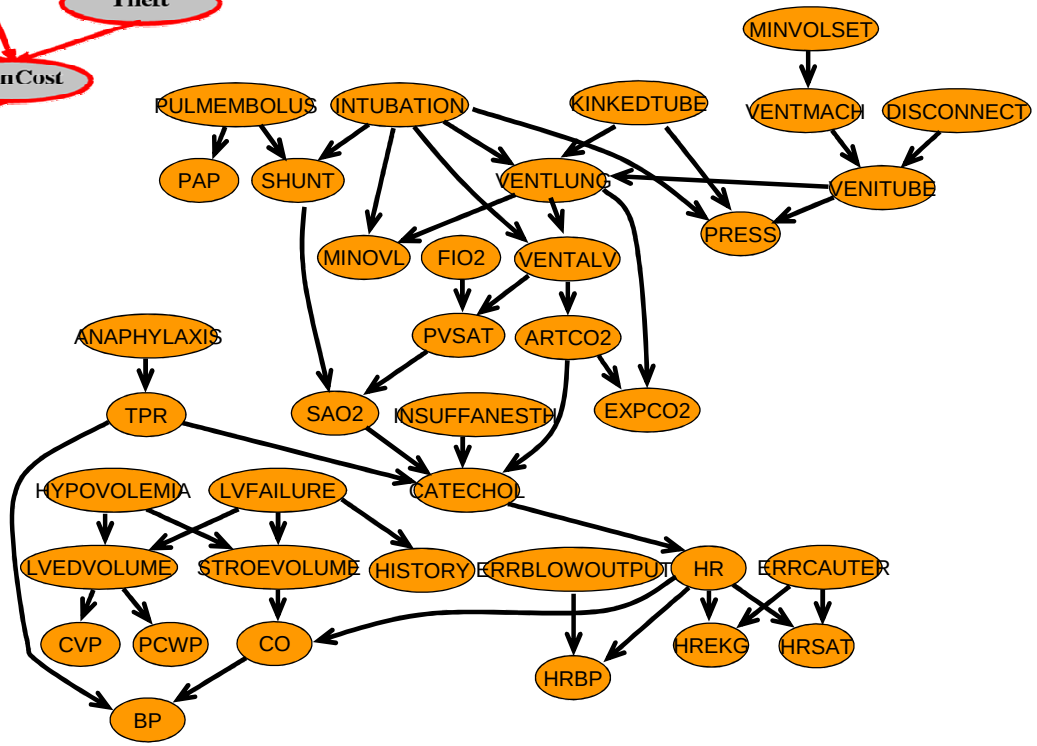
$$q(x^*|x^{(i)}) \propto e^{-\|x^{(i)} - x^*\|^2/\sigma^2}$$

$$\min\left\{1, \frac{P(x^*)^{1/T}}{P(x^{(i)})^{1/T}}\right\}$$

If anneal with T, concentrate on peaks of P(x)

Extending MH to directed probabilistic graphical models

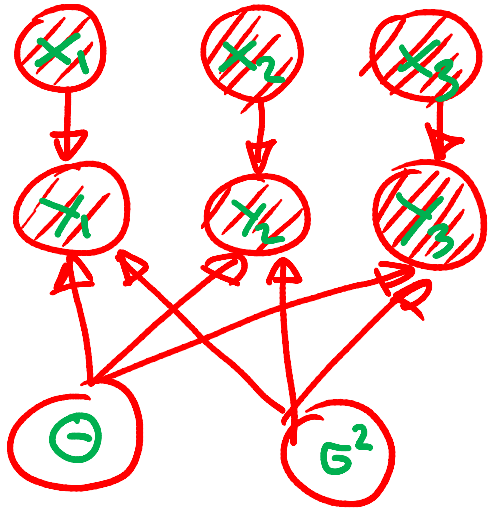




Bayesian graphical models and Gibbs

$$P(\sigma^2) = IG(a, b)$$
$$P(\theta) = N(0, \delta^2 I)$$
$$P(y_i | x_i, \theta) = N(x\theta, \sigma^2)$$

$\equiv$



GIBBS:

FOR $i = 1$ to Nsamples

$$\theta^{(i+1)} \sim P(\theta | \sigma^{2(i)}, x, y)$$
$$\sigma^{2(i+1)} \sim P(\sigma^2 | \theta^{(i)}, x, y)$$

END

Gibbs Sampling

Choose the following proposal:

$$q(x^{\star}|x^{(i)}) = \begin{cases} p(x_j^{\star}|x_{-j}^{(i)}) & \text{If } x_{-j}^{\star} = x_{-j}^{(i)} \\ 0 & \text{Otherwise.} \end{cases}$$

where $x_{-j} = \{x_1, \ldots, x_{j-1}, x_{j+1}, \ldots, x_n\}$.

Then the acceptance is:

$$A(x^{(i)}, x^{\star}) = \min\left\{1, \frac{p(x^{\star})q(x^{(i)}|x^{\star})}{p(x^{(i)})q(x^{\star}|x^{(i)})}\right\} = 1.$$

- Initialise $x_{1:n}^{(0)}$.
- For $i = 0$ to $N - 1$
  - Sample $x_1^{(i+1)} \sim p(x_1 | x_2^{(i)}, x_3^{(i)}, \ldots, x_n^{(i)})$.
  - Sample $x_2^{(i+1)} \sim p(x_2 | x_1^{(i+1)}, x_3^{(i)}, \ldots, x_n^{(i)})$.

    $\vdots$
  - Sample

    $x_j^{(i+1)} \sim p(x_j | x_1^{(i+1)}, \ldots, x_{j-1}^{(i+1)}, x_{j+1}^{(i)}, \ldots, x_n^{(i)})$.

    $\vdots$
  - Sample $x_n^{(i+1)} \sim p(x_n | x_1^{(i+1)}, x_2^{(i+1)}, \ldots x_{n-1}^{(i+1)})$.

Gibbs Sampling For Graphical models

A large-dimensional joint distribution is factored into a directed graph that encodes the conditional independencies in the model. In particular, if $x_{pa(j)}$ denotes the parent nodes of node x_j, we have

$$p(x) = \prod_j p(x_j|x_{pa(j)}).$$

It follows that the full conditionals simplify as follows

$$p(x_j|x_{-j}) = p(x_j|x_{pa(j)}) \prod_{k \in ch(j)} p(x_k|x_{pa(k)})$$

where $ch(j)$ denotes the children nodes of x_j.

Auxiliary Variable Samplers

- It is often easier to sample from an augmented distribution $p(x, u)$, where u is an auxiliary variable, than from $p(x)$.
- It is possible to obtain marginal samples $x^{(i)}$ by sampling $(x^{(i)}, u^{(i)})$ according to $p(x, u)$ and, then, ignoring the samples $u^{(i)}$.
- This very useful idea was proposed in the physics literature (Swendsen and Wang, 1987).

Hybrid (Hamiltonian) Monte Carlo

- The idea is to exploit gradient information.
- Define the extended target distribution:

$$p(x, u) = p(x)N(u; 0, I_{n_x}).$$

- Introduce the gradient vector: $\Delta(x) = \partial \log p(x)/\partial x$
- Introduce the parameters ρ and L.
- Next we "leapfrog".

- Sample $v \sim U_{[0,1]}$ and $u^\star \sim N(0, I_{n_x})$.
- Let $x_0 = x^{(i)}$ and $u_0 = u^\star + \rho\Delta(x_0)/2$.
- For $l = 1, \ldots, L$, take steps

$$x_l = x_{l-1} + \rho u_{l-1}$$
$$u_l = u_{l-1} + \rho_l \Delta(x_l)$$

where $\rho_l = \rho$ for $l < L$ and $\rho_L = \rho/2$.

- If $v < A = \min\left\{1, \frac{p(x_L)}{p(x^{(i)})} \exp\left(-\frac{1}{2}(u_L^{\mathrm{T}} u_L - u^{\star\mathrm{T}} u^\star)\right)\right\}$

$$(x^{(i+1)}, u^{(i+1)}) = (x_L, u_L)$$

else $$(x^{(i+1)}, u^{(i+1)}) = (x^{(i)}, u^\star)$$