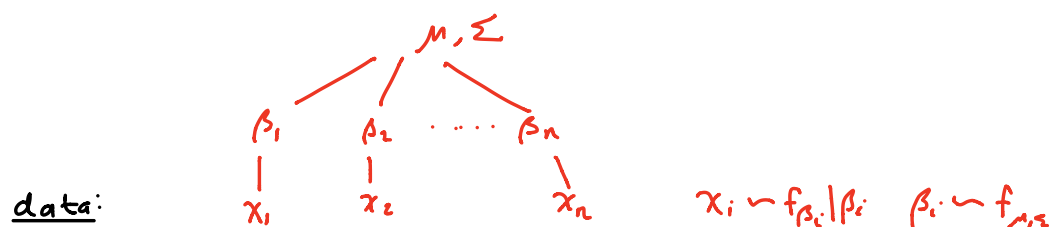


Consensus Monte Carlo

Scott et. al. (2013)

C. Li et al. (2017)

Consider the Hierarchical Model



$$\pi(\beta_1, \beta_2, \dots, \beta_n, \mu, \Sigma | x_{1:n})$$

Idea send $\beta_1, \dots, \beta_{50}$ to the first core

$\beta_{51}, \dots, \beta_{100}$ to the second
 \vdots

Rank: Parallel Gibbs with communication is still inefficient.
 with respect to the # of cores

Consensus Monte Carlo

Take $\bar{x} = x_1, \dots, x_n$ and split into $\bar{x}_j = x_{j,1}, \dots, x_{j,m}$ for $j \in [K]$ s.t. $mk = n$.

model: $f_{\theta}(x)$

posterior: $\pi_j(\theta | \bar{x}_j) \propto p(\theta) \prod_{s=1}^m f_{\theta}(x_{js})$

prior: $p(\theta)$

$$\bar{\pi}(\theta | \bar{x}) \propto p(\theta) \prod_{s=1}^n f_{\theta}(x_s)$$

$$\propto p(\theta) \prod_{k=1}^K f_{\theta}(x_{k:n})$$

$$\propto \prod_{k=1}^K p(\theta)^{1/K} f_{\theta}(\bar{x}_k)$$

$$= \prod_{k=1}^K \pi_k(\theta | \bar{x}_k).$$

Clearly the assumption here is the small subsetting of the data.

Question: Can we sample from $\bar{\pi}(\cdot | \bar{x})$ given samples from $\pi_j(\cdot | \bar{x}_j)$.

Main idea: let $f_i \sim N(\mu_i, C_i)$ $i=1,2$ and consider the density

$$\bar{f}(x) \propto f_1(x) f_2(x) \propto \exp \left[-\frac{1}{2} (x-\mu_1)^T C_1^{-1} (x-\mu_1) - \frac{1}{2} (x-\mu_2)^T C_2^{-1} (x-\mu_2) \right]$$

$$\propto \exp \left\{ -\frac{1}{2} (x-\bar{\mu})^T \bar{C}^{-1} (x-\bar{\mu}) \right\}$$

$$\bar{C}^{-1} = (C_1^{-1} + C_2^{-1})^{-1} \bar{\mu} = (C_1^{-1} + C_2^{-1})^{-1} [C_1^{-1} \mu_1 + C_2^{-1} \mu_2]$$

Furthermore if $x_1 \sim N(\mu_1, C_1)$ $x_2 \sim N(\mu_2, C_2)$

$$\bar{x} = (C_1^{-1} + C_2^{-1})^{-1} [C_1^{-1} x_1 + C_2^{-1} x_2] \sim N(\bar{\mu}, \bar{C})$$

Consensus MC:

(*) In parallel: draw $\{\theta_k^{(s)}; s=1, \dots, S\}$ for each $k \in [K]$

• mcmc sample from $\pi_k(\cdot | \bar{x}_k)$

(**) For $s=1, \dots, S$ combine $\theta_1^{(s)} \dots \theta_K^{(s)}$

$$\theta^{(s)} = \left(\sum_{k=1}^K \hat{C}_k^{-1} \right) \left(\sum_{k=1}^K \hat{C}_k^{-1} \theta_k^{(s)} \right)$$

when \hat{C}_k is covariance of $\bar{\pi}_k(\cdot | \bar{x}_k)$

Simple, Accurate, & Scalable Post-Interval Estimation

Setup: $\bar{X} = X_{1:n}$, split $\bar{X}_1, \dots, \bar{X}_K$ $X_k = X_{k,1:m}$

$$\bar{\pi}_k(\theta | \bar{x}_k) \propto p(\theta) \underbrace{\left[\prod_{s=1}^m f_\theta(X_{k,s}) \right]}_{\text{data cloning}}^K$$

Q: How to use samples from $\bar{\pi}_k(\cdot | \bar{x}_k)$ to sample from $\bar{\pi}(\cdot | \bar{x})$

Idea: take average? Q: How?

Take barycenter in a metric space

$$P_2(\Theta) = \left\{ \mu \in \Theta : \int \|x\|_2^2 \mu(dx) < \infty \right\}$$

$$\| \mu - \nu \|_{W_2} = \left\{ \inf_{\gamma \in \Gamma(\mu, \nu)} \int \|x - y\|_{W_2}^2 \gamma(dx, dy) \right\}^{1/2} \stackrel{\text{def}}{=} W_2(\mu, \nu)$$

$\Gamma(\mu, \nu)$ set of all measures on $\Theta \times \Theta$ with marginals

(μ, ν) .

Then the average is given by

$$\bar{\pi}(\cdot | \bar{x}) \stackrel{\text{def}}{=} \argmin_{\mu} \sum_{k=1}^K W_2^2(\mu, \bar{\pi}_k(\cdot | \bar{x}_k))$$

Remember given x_1, \dots, x_n $\bar{x} = \argmin_{b \in \mathbb{R}} \sum_{i=1}^n (x_i - b)^2$

In \mathbb{R} : $w_2(\mu, \nu) = \left(\int |F_\mu^{-1}(t) - F_\nu^{-1}(t)|^2 dt \right)^{1/2} = \|F_\mu^{-1} - F_\nu^{-1}\|_2$

$$= \left(\int |F_\mu(x) - F_\nu(x)|^2 dx \right)^{1/2}$$

As $\|\cdot\|_2$ has an associated inner product,

$$\bar{\pi}(\cdot | \bar{x}) = \left(\frac{1}{K} \sum_{k=1}^K \pi_j^{-1}(\cdot | \bar{x}_j) \right)^{-1}$$