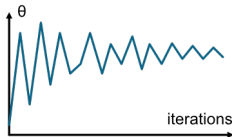




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Coupled Markov chains with applications to Approximate Bayesian Computation for model based clustering

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likelihood

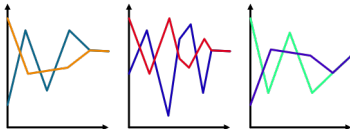
intractable



**Unbiased Markov chain
Monte Carlo methods with
couplings**

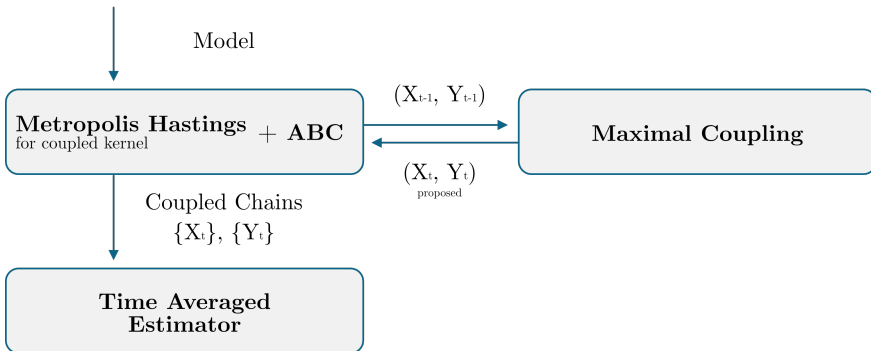


**Approximate Bayesian
Computation**



The complete method: MCMC + Couplings + ABC

Implementation



Maximal coupling

Maximal coupling between two distributions p and q

- sample $X \sim p$;
- sample $W|X \sim \mathcal{U}\{[0, p(X)]\}$;
- if $W \leq q(X)$ then output (X, X) , otherwise:
 - ① sample $Y \sim q$;
 - ② sample $W^*|Y \sim \mathcal{U}\{[0, q(Y)]\}$ until $W^* > p(Y)$
 - ③ output (X, Y) .

Output

Distribution of a pair of random variables X, Y that maximizes $\mathbb{P}(X = Y)$ subject to the marginal constraints $X \sim p$ and $Y \sim q$

Metropolis Hastings with couplings and ABC

Model

$$Y_i | \mu, \sigma^2 \stackrel{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$$

$$\mu \sim \mathcal{N}(\mu_0, \sigma_0^2)$$

$$\sigma^2 \sim \text{InvGa}(a, b)$$

$$\mu_0 = 8, \quad \sigma_0^2 = 4$$

$$a = b = 1$$

Initialization

set $\theta = (\mu, \sigma^2)$

for $k=1,2$:

until $K_h(||s_k^{(0)} - s_{obs}||) > 0$:

- sample $\theta_k^{(0)} \sim \pi(\theta)$
- simulate n_{obs} observations $y_{ki} \sim \mathcal{N}(\mu^{(0)}, \sigma^{2(0)})$ from maximal coupling
- compute $s_k^{(0)} = S(y_k)$;

Iterations

for $i = 1, \dots, M$:

given $\theta^{(i-1)} = (\mu^{(i-1)}, \sigma^{2(i-1)})$

- generate $[\theta_1^{(i)}, \theta_2^{(i)}]$ from a maximal coupling given $[\theta_1^{(i-1)}, \theta_2^{(i-1)}]$;
- for $k=1,2$:
 - ① simulate n_{obs} observations $y_k^{(i)} \sim \mathcal{N}(\mu^{(i)}, \sigma^{2(i)})$ from maximal coupling;
 - ② compute $s_k^{(i)} = S(y_k)$;
 - ③ accept $\theta_k^{(i)}$ with probability

$$\frac{K_h(\|s_k^{(i)} - s_{obs}\|) \pi(\theta_k^{(i)})}{K_h(\|s_k^{(i-1)} - s_{obs}\|) \pi(\theta_k^{(i-1)})}$$

Output

for $k= 1,2$

$$\mu_k^{(1)}, \dots, \mu_k^{(M)} \sim \pi_{ABC}(\mu|y_{obs});$$

$$\sigma_k^{2(1)}, \dots, \sigma_k^{2(M)} \sim \pi_{ABC}(\sigma|y_{obs}).$$

Summary statistics: Sample mean, Sample Variance

Distance: L^2 -norm

Kernel: $K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$, $K_h(u) = \frac{K(\frac{u}{h})}{h}$

Proposal distribution: $\begin{bmatrix} \mu^* \\ \log(\sigma^{2*}) \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu^{(i)} \\ \log(\sigma^{2(i)}) \end{bmatrix}, 0.1^2 \cdot \mathcal{I} \right)$

Summary statistics: Sample mean, Sample Variance

Distance: L^2 -norm

Kernel: $K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$, $K_h(u) = \frac{K(\frac{u}{h})}{h}$

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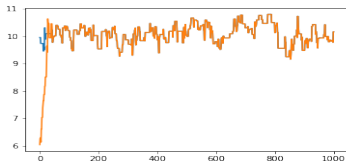
Dataset

100 samples generated from a Gaussian distribution:

$$Y_{obs} \sim \mathcal{N}(\mu_{obs}, \sigma_{obs}^2)$$

$$\mu_{obs} = 10, \sigma_{obs}^2 = 3$$

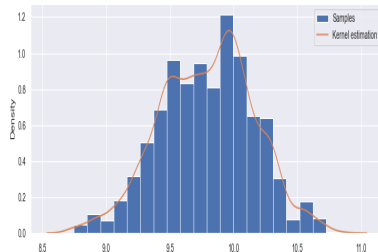
Single coupled chains



Samplings from all accepted chains

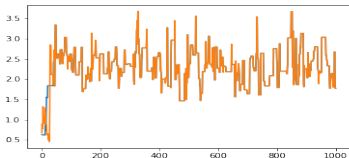


Sampling histogram with estimated distribution

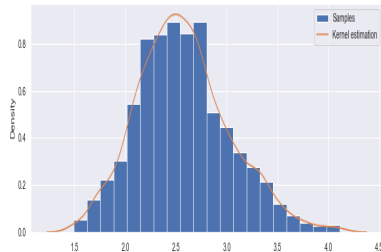


Time Averaged Estimators mean obtained: $\mathbb{E}[H_{k:m}(X_\mu, Y_\mu)] \simeq 9.8$

Single coupled chains



Sampling histogram with estimated distribution



Samplings from all accepted chains



Time Averaged Estimators mean obtained: $\mathbb{E}[H_{k:m}(X_{\sigma^2}, Y_{\sigma^2})] \simeq 2.56$

Numerical experiment: g-and-k distribution

Quantile function

$$r \in (0, 1) \mapsto a + b \left(1 + 0.8 \left(\frac{1 - \exp(-g \cdot z(r))}{1 + \exp(-g \cdot z(r))} \right) \right) (1 + z(r)^2)^k \cdot z(r)$$

where $z(r)$ is the r -th quantile of the standard Normal distribution.

Prior distributions

$$a \sim \mathcal{U}([0, 10])$$

$$b \sim \mathcal{U}([0, 10])$$

$$g \sim \mathcal{U}([0, 10])$$

$$k \sim \mathcal{U}([0, 10])$$

Summary statistics: 10 quantiles

Distance: L^2 – norm

Kernel:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}, \quad K_h(u) = \frac{K(\frac{u}{h})}{h}$$

Dataset

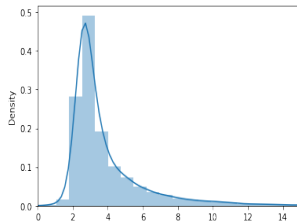
100 samples generated as follows:

$$a_{obs} = 3, b_{obs} = 1, g_{obs} = 2, k_{obs} = 0.5$$

$$y_{obs} \sim \text{quantilefunction}(z(r), \theta_{obs})$$

$$z(r) \sim \mathcal{N}(0, 1)$$

Quantile distribution: y_{obs}



Initialization

given $\theta = (a, b, g, k)$

for $k=1,2$:

Untill $K_h(\|s_k^{(0)} - s_{obs}\|) > 0$:

- Generate $\theta_k^{(0)} \sim \mathcal{U}([0, 10]^4)$ from prior density.
- Generate $z(r) \sim \mathcal{N}(0, 1)$
- Generate a sample of n_{obs} observations such that $y_k \sim \text{quantilefunction}(z(r), \theta_k^0)$
- Compute $s_k^{(0)} = S(y_k)$

Iterations

for i in $(1, \dots, M)$:

- generate $\theta_1^{(i)}, \theta_2^{(i)}$ from $\text{maximalcoupling}(\theta_1^{(i-1)}, \theta_2^{(i-1)})$
- simulate n_{obs} observations $y_1^{(i)}, y_2^{(i)}$ from maximal coupling
- Compute the summaries $s_k^{(i)} = S(y_k^{(i)})$
- Accept $\theta_k^{(i)}$ with probability

$$\frac{Kh(\|s_k^{(i)} - s_{obs}\|)\pi(\theta_k^{(i)})}{Kh(\|s_k^{(i-1)} - s_{obs}\|)\pi(\theta_k^{(i-1)})}$$

otherwise $\theta_k^{(i)} = \theta_k^{(i-1)}$;

Iterations

for i in $(1, \dots, M)$:

Couplings

for j in $(1, \dots, n_{obs})$:

- ① $z^{(i,j)}(r) \sim \mathcal{N}(0, 1)$

- ② generate:

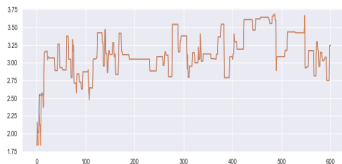
$$y_1^{(ij)} \sim \text{quantilefunction}(z^{(i,j)}(r), \theta_1^{(i-1)})$$

$$y_2^{(ij)} \sim \text{quantilefunction}(z^{(i,j)}(r), \theta_2^{(i-1)})$$

$$\kappa n(\|S_k^{(i)} - S_{obs}\|) \pi(\theta_k^{(i-1)})$$

otherwise $\theta_k^{(i)} = \theta_k^{(i-1)}$;

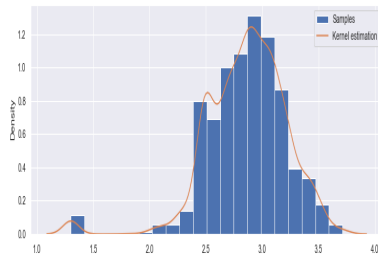
Single coupled chains



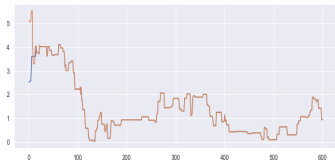
Samplings from all accepted chains



Sampling histogram with estimated distribution



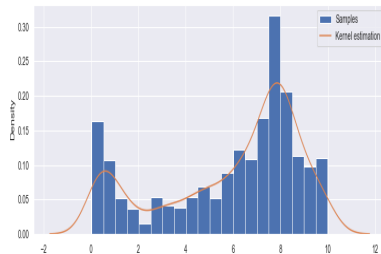
Single coupled chains



Samplings from all accepted chains



Sampling histogram with estimated distribution



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