Adaptive MCMC

5th July 2023

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MCMC Overview

Goal: obtain a Markov chain $X_1, X_2, \ldots$ with transition P on $\mathcal{X} \subset \mathbb{R}^d$ that has stationary distribution π ("π-ergodicity"[1]).

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$$I(f) = \int_{\mathcal{X}} f(x)\pi(dx)$$

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(though perhaps ignoring the first few samples $X_1, \ldots, X_{i_0}$ for some $i_0 \in \mathbb{N}$ as *burn-in* to allow the chain to mix sufficiently and reach the distribution π).

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Metropolis-Hastings[2] (MH) at each step $i = 0, 1, \ldots$:

1. Propose $Y_{i+1} \sim q(X_i, \cdot)$
2. Set $X_{i+1} = Y_{i+1}$ with probability

$$\alpha(X_i, Y_{i+1}) = \min\left(1, \frac{\pi(Y_{i+1})q(Y_{i+1}, X_i)}{\pi(X_i)q(X_i, Y_{i+1})}\right),$$

   otherwise $X_{i+1} = X_i$.

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E.g. Normal Symmetric Random Walk Metropolis (N-SRWM):

$$q_\theta(X_i, Y_{i+1}) = \mathcal{N}(Y_{i+1}; X_i, \theta^2 I_d)$$

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for some $\theta > 0$. The corresponding estimator $\hat{I}_N^\theta(f)$ has high variance for values of θ that are too small or too large (the same can happen with non-isotropic proposal covariances in place of $\theta^2 I_d$).

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Some theoretical results exist for the optimal proposals in different scenarios:

- e.g. using a multivariate random walk

$$Y_{i+1} \sim \mathcal{N}(X_i, 2.38^2 C/d)$$

where d is the dimension of $\mathcal{X}$ and C is the covariance of the target distribution π, which is a mixture of Gaussians (or just has a large dimension d)[3].

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- Eventually we want to stop adapting and use the same θ for all steps (at least with high probability).

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Ensuring π-ergodicity

In order to achieve π-ergodicity of our adaptive process, so that

$$|\mathbb{E}(f(X_i)) - \mathbb{E}_\pi(f(X))| \to 0$$

as $i \to \infty$ for any $f : \mathcal{X} \to \mathbb{R}$, we require[4]:

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   - are small with high probability, or
   - take place with probability $p(i) \to 0$ as $i \to \infty$ (e.g. stop adapting after τ steps).
3. Containment: Times from X_i to stationary distribution π are bounded in probability as $i \to \infty$. (This is usually achieved as a result of the two conditions above, depending on how diminishing adaptation is achieved.)

[4] Gareth O Roberts and Jeffrey S Rosenthal 2005.

WLLN (for bounded functions)

Under stationarity, adaptation and containment we get:

$$\frac{\lim_{n\to\infty}\sum_{i=1}^{n} f(X_i)}{n} = \pi(f)$$

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(But, convergence for all $\mathbf{L^1}$ functions does not follow[5].)

[5] Yang 2008.

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- Andrieu and Thoms 2008—"vanishing adaptation" (i.e. no adaptation after a certain step $\tau \in \mathbb{N}$) is sufficient for containment.

Convergence towards π

Assume we have a subset of "good" values $\mathcal{K} \subset \Theta$ for which containment is ensured (i.e. for which there is a common drift function), and let σ be the first time i at which $\theta_i \notin \mathcal{K}$ (this may be infinity).

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Then under certain conditions[6] (satisfied by N-SRWM), with "smoothly decaying" step-sizes $|\theta_i - \theta_{i-1}| \leq \gamma_i$ (e.g. $\gamma_i = i^{-\alpha}, \alpha > 0$), there exists a constant $C' > 0$ such that for all $i \geq 1$ and $|f| \leq 1$:

$$|\mathbb{E}[(f(X_i) - \mathbb{E}_\pi(f)) \underbrace{\mathbb{I}\{\sigma \geq i\}}_{\substack{\text{only consider} \\ \theta_i \in \mathcal{K}}}]| < C'\gamma_i.$$

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That is, whilst θ doesn't leave $\mathcal{K}$, convergence to π occurs at a rate of at least $\{\gamma_i\}$—and doesn't not require convergence of $\{\theta_i\}$!

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Monte Carlo Error

Bias for a single sample X_i:

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It can then be proved that there exist constants $A(\gamma, \mathcal{K})$ and $B(\gamma, \mathcal{K})$ such that for any $n \geq 1$ the error is bounded as:

$$\sqrt{\mathbb{E}\left[\left|\frac{1}{n}\sum_{i=1}^{n} f(X_i) - \mathbb{E}_\pi(f))\right|^2 \mathbb{I}\{\sigma \geq i\}\right]} \leq \underbrace{\frac{A(\gamma, \mathcal{K})}{\sqrt{n}}}_{\text{standard Monte Carlo error}} + \underbrace{B(\gamma, \mathcal{K})\frac{\sum_{i=1}^{n}\gamma_i}{n}}_{\text{price paid for adaptation}}$$

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(So if $\gamma_i = i^{-\alpha}$, $\alpha \in (0, 1)$, then $\frac{\sum_{i=1}^{n}\gamma_i}{n} \sim \frac{N^{-\alpha}}{1-\alpha}$, meaning there is no loss in rate of convergence for $\alpha \geq 1/2$.)

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  Can have faster convergence for high-dimensional proposals than RWM.

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RWM: $q(X, dX) = \mathcal{N}(X, s_d\boldsymbol{\Sigma})$

Theoretical result[9]: for a wide range of target distributions, optimal proposal for RWM is with $\boldsymbol{\Sigma} = C$ and $s_d = 2.38^2/d$ where d is the dimension of $\mathcal{X}$ and C is the covariance of π.

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$$\hat{C}_i = \begin{cases} \hat{C}_0 & i \leq i_0 \\ s_d \mathrm{cov}(X_0, ..., X_{i-1}) + s_d \epsilon I_d & i > i_0 \end{cases}$$

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where $s_d > 0$ is a scale factor, $\epsilon > 0$ is a small constant (used to avoid singularity of $\hat{C}_i$—particularly in multimodal posteriors—and required for Haario's proof of AM's π-ergodicity).

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AM: Efficient Updates

Using the fact that

$$\mathrm{cov}(X_0, ..., X_i) = \frac{1}{i}\left(\sum_{k=0}^{i} X_k^T X_k - (i+1)\bar{X}_i \bar{X}_k^T\right),$$

where $\bar{X}_i = \frac{1}{i}\sum_{k=0}^{i} X_k$, we can update $\hat{C}_i$ incrementally[11]:

$$\hat{C}_{i+1} = \frac{i-1}{i}\hat{C}_i + \frac{s_d}{i}(i\bar{X}_{i-1}\bar{X}_{i-1}^T - (i+1)\bar{X}_i\bar{X}_{i-1}^T + X_i X_i^T + \epsilon I_d).$$

[11](I *think* that this is essentially the same as the "Rao-Blackwellised AM algorithm" presented by Andrieu and Thoms 2008.)

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Then we can use Robbins-Monro style updates to optimise $\theta = s_d$ such that $\alpha_i(\theta) \to \alpha^*$ as $i \to \infty$.

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where $L \in \mathbb{N}$, $Y_{i,1}, ..., Y_{i,L} \sim q_\theta(X_i, \cdot)$ are IID and

$$\bar{\alpha}_i(\theta) = \frac{1}{L}\sum_{l=1}^{L} \min\left(1, \frac{\pi(Y_{i,l})q_\theta(Y_{i,l}, X_i)}{\pi(X)q_\theta(X_i, Y_{i,l})}\right).$$

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Intuition:

- if $\bar{\alpha}_i(\theta)$ is too high ($\bar{\alpha}_i(\theta) - \alpha^* > 0$), make proposal tighter by reducing $\theta = s_d$,
- if $\bar{\alpha}_i(\theta)$ is too low ($\bar{\alpha}_i(\theta) - \alpha^* < 0$), make proposal wider by increasing $\theta = s_d$.

AM: Generic Robbins-Monro Updates

Generic Robbins-Monro updates for any suitable parameterisation θ of the proposal q_θ:

$$\theta_{i+1} = \theta_i - \gamma_i H(\theta_i, X_0, \ldots, Y_i, X_i, Y_{i+1}, X_{i+1})$$

for some $H : \Theta \times \mathcal{X}^{1+2(i+1)} \to \Theta$ (note we have access to discarded proposals Y_k).

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(In the previous slide, $\Theta = \mathbb{R}^+$ and $H(\theta_i, X_0, \ldots, Y_i, X_i, Y_{i+1}, X_{i+1}) = \bar{\alpha}_i(\theta) - \alpha^*$.)

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Moment matching: With $\mu_\pi, \mathbf{\Sigma}_\pi$ the true mean and covariance of π and $\mu(\theta), \mathbf{\Sigma}(\theta)$ are the empirical mean and covariance, try to find θ for which

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Under certain conditions, this can be shown[12] to be equivalent to minimising the KL, in which case we end up with

$$H(X, \theta) = \nabla_\theta \log \frac{\pi(X)}{q_\theta(X)}$$

[12] Andrieu and Moulines 2006.

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- Not sure this is very promising: no guarantee $\exists\theta$ s.t. $q_\theta = \pi$.
- But, we could use several separate (Gaussian) proposals for different parts of π (e.g. for each latent r.v.) and tune these each with VI (with optional covariance scaling factors).

AM: A stopping rule

Stop adaptation once we see that

$$\frac{1}{n}\sum_{i=1}^{n} H(\theta_i, X_{i+1})$$

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"More principled statistical rules relying on the CLT can also be suggested, but we do not expand on this here"[13].

[13] Andrieu and Thoms 2008.

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3. Various automatic choices based on θ_i and X_i given a predefined function $\gamma : [0, \infty) \to [0, \infty)$. Typically based on the idea that alternating signs of $H(\theta, X)$ tend to suggest θ_i is oscillating around a solution. E.g.:

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   - Same as above[15] but with separately derived step sizes for each component of θ.

[14] Andrieu and Thoms 2008.

[15] Delyon and Juditsky 1993.

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- Online EM algorithm version that uses Gaussian mixture proposals[17].

[16] Andrieu and Thoms 2008.
[17] Andrieu and Moulines 2006.

Metropolis-Adjusted Langevin Algorithm (MALA)

Perform AM as before (and all the variations that we've covered), but with a Langevin proposal (thus using drift function $\nabla \log \pi(X)$):

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Popular variation: Truncated drift MALA (T-MALA)[18]—solves some of MALA's convergence problems by truncating the drift function to avoid "bad" values of θ.

$$\nabla \log \pi(X) \mapsto \frac{\delta}{\max(\delta, |\nabla \log \pi(X)|)} \nabla \log \pi(X)$$

where $\delta > 0$.

[18] Atchadé 2006.

A Quick Comparison of the Methods

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- RWM is very robust to a wide variety of distributions, with component-wise versions/Metropolis-within-Gibbs being at least as good (when sensibly scaled).
- Full multivariate RWM tends to converge to the same proposals as component-wise/MwG proposals, but often more slowly.

Table of Contents

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RWM satisfies these, as does (T-)MALA, so we should be able to use the adaptive schemes discussed above.

Massively Parallel Adaptive MCMC

Recall the two main adaptive strategies (leading to functions H):

1. Try to reach a target acceptance rate α^* by adapting s_d in the AM algorithm.
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So both adaptive schemes seem promising (and hopefully not too complicated), both with RWM and (T-)MALA proposals.

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- But in general it seems that RWM and MALA are the most popular proposal types.
- In particular, the basic AM algorithm (and its variations) seems like a good starting point for massively parallel adaptive MCMC.

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