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CONVERGENCE SPEED AND APPROXIMATION ACCURACY OF NUMERICAL MCMC

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Abstract

When implementing Markov Chain Monte Carlo (MCMC) algorithms, perturbation caused by numerical errors is sometimes inevitable. This paper studies how the perturbation of MCMC affects the convergence speed and approximation accuracy. Our results show that when the original Markov chain converges to stationarity fast enough and the perturbed transition kernel is a good approximation to the original transition kernel, the corresponding perturbed sampler has fast convergence speed and high approximation accuracy as well. Our convergence analysis is conducted under either the Wasserstein metric or the χ^2 metric, both are widely used in the literature. The results can be extended to obtain non-asymptotic error bounds for MCMC estimators. We demonstrate how to apply our convergence and approximation results to the analysis of specific sampling algorithms, including Random walk Metropolis, Metropolis adjusted Langevin algorithm with perturbed target densities, and parallel tempering Monte Carlo with perturbed densities. Finally, we present some simple numerical examples to verify our theoretical claims.

Keywords: Bayesian inverse problems; Markov Chain Monte Carlo; convergence speed; perturbation analysis

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1. Introduction

Markov Chain Monte Carlo (MCMC) is one of the main sampling methods in Bayesian statistics. Given a target density π with respect to Lebsegue measure on $\mathbb{R}^d$, an MCMC algorithm often simulates a Markov chain $(X_n)_{n\geq 0}$, with transition kernel P, such that π is its corresponding invariant measure. Under some generic conditions, the distribution of X_n converges to π geometrically quickly. This indicates the existence of some mixing time n_0, such

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that the distribution of X_n is close to π when $n > n_0$. In other words, given a test function $f : \mathbb{R}^d \to \mathbb{R}$, we can use the following approximation:

$$\mathbb{E}f(X_n) \approx \mathbb{E}^\pi f(X) := \int f(x)\pi(x)dx. \tag{1}$$

In practice, this allows us to approximate the average of a test function $\mathbb{E}^\pi f(X)$ using the temporal average of the Markov chain:

$$F_n := \frac{1}{n}\sum_{i=1}^{n} f(X_{n_0+i}). \tag{2}$$

The efficiency of the approximation scheme (2) is largely determined by the convergence speed of the Markov Chain $(X_n)_{n\geq 0}$ to π or the mixing time n_0. In particular, it will take $O(n_0)$ iterations to produce an approximately independent sample. In this context, convergence analysis has been a key component in the MCMC literature (see, for example, Section 4.1 of [1, 27]).

When implementing MCMC on complicated target densities, it is often the case that we can simulate only a perturbed Markov chain $(\widehat{X}_n)_{n\geq 0}$ with transition kernel $\widehat{P}$. This is mainly due to two reasons:

(i) The transition kernel P cannot be simulated directly. For example, if $(X_n)_{n\geq 0}$ is described by a stochastic differential equation (SDE) evaluated at a countable set of time points, using numerical schemes like the Euler–Maruyama method will induce discretization errors.

(ii) We do not have direct access to $\pi(x)$ or its derivatives. This is quite common in Bayesian inverse problems [40], where the target density can be written as

$$\pi(x) \propto p_0(x)\exp\left(-\tfrac{1}{2}\|G(x)-y\|^2\right). \tag{3}$$

In (3), p_0 is the prior density of the unknown parameter x, G describes the data-generating process, and y is the observed data. In many cases, G is formulated through an involved partial differential equation, and we can compute only an approximation of it, $\widehat{G}$ [5, 7, 21]. The corresponding "numerical" density becomes

$$\widehat{\pi}(x) \propto p_0(x)\exp\left(-\tfrac{1}{2}\|\widehat{G}(x)-y\|^2\right). \tag{4}$$

In other settings, we may have access to $\pi(x)$, but accurate evaluation of its gradient $\nabla\pi(x)$ may not be accessible since it often involves highly dimensional adjoint models. If we want to use gradient-based MCMC, e.g. Metropolis Adjusted Langevin Algorithm (MALA), we can use only an approximately correct proposal. However, the Metropolis–Hastings step can guarantee that the target density remains the same, i.e. $\widehat{\pi} = \pi$.

In the above-mentioned scenarios, we run an MCMC $(\widehat{X}_n)_{n\geq 0}$ with transition kernel $\widehat{P}$ and target density $\widehat{\pi}$, which is the invariant measure of $(\widehat{X}_n)_{n\geq 0}$. In both scenarios (1) and (2) listed above, we would like to approximate $\mathbb{E}^\pi f(X)$ using

$$\mathbb{E}f(\widehat{X}_{n_0}) \quad \text{or} \quad \widehat{F}_n = \frac{1}{n}\sum_{i=1}^{n} f(\widehat{X}_{n_0+i}). \tag{5}$$

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There are two key questions to address when using estimators of the form (5): The first question concerens the convergence speed of $(\widehat{X}_n)_{n\geq 0}$ toward its invariant measure $\widehat{\pi}$, which determines the efficiency of the estimators in (5). In particular, if we use D to denote some metric between two distributions and use ν to denote the distribution of $\widehat{X}_0$, we are interested in how quickly $D(\nu\widehat{P}^n, \widehat{\pi})$ converges to zero. The second question concerns approximation accuracy, which can be measured by either the distance between the two invariant measures, $D(\widehat{\pi}, \pi)$ or the distance between the distribution of $\widehat{X}_n$ and π, $D(\nu\widehat{P}^n, \pi)$. For MCMC based on $(\widehat{X}_n)_{n\geq 0}$ to achieve fast convergence and high approximation accuracy, we need to impose the following two high-level conditions (these conditions will be made more precise in our subsequent development) [1]:

(1) $\widehat{P}$ is a good approximation of P.

(2) $(X_n)_{n\geq 0}$ converges to its invariant measure π quickly enough.

Condition 1 is necessary because if $\widehat{P}$ is not a good approximation of P, $\widehat{\pi}$ is unlikely to be close to π, and the convergence property of $(X_n)_{n\geq 0}$ will not be useful in inferring the convergence property of $(\widehat{X}_n)_{n\geq 0}$. Condition 2 is also necessary. Otherwise, the approximation error may increase with the number of iterations. For example, one can think of an unstable autoregressive sequence in which numerical errors often increase exponentially with the number of iterations. Since Condition 1 involves only the one-step transition kernels, it is easier to fulfill. Hence, it is reasonable to study Condition 2 first and then formulate a version of Condition 1 that is compatible with the corresponding Condition 2.

In the literature on Markov chains, convergence to stationarity is often studied using one of two frameworks. The main differences between the two frameworks are the metrics and the analytical tools involved. The first type of metric are the Wasserstein metrics [31]. The associated convergence results are often termed "geometric ergodicity." Establishing convergence under the Wasserstein metrics often involves finding an appropriate Lyapunov function V and constructing an appropriate coupling [28]. For simplicity, we will call this framework **Wasserstein convergence**. The second framework uses the χ^2 distance [3] (or KL-divergence as in [45]). Establishing convergence under the χ^2 distance often involves functional analysis or other partial differential equation (PDE) tools such as Poincaré inequality and log Sobolev inequality. For simplicity, we will refer to this framework as the "χ^2 **convergence**".

Establishing Wasserstein convergence is often viewed as being more intuitive, as it involves a standard Lyapunov function and coupling construction. Establishing χ^2 convergence can be weaker, but it often provides tighter quantification, especially in high-dimensional settings. For example, for the unadjusted Langevin algorithm, [9] uses Wasserstein convergence, and the analysis works only for a fixed dimension; [11, 45] use χ^2 convergence, and the analysis works in high-dimensional settings. We also note that these two frameworks are related: In particular, on one hand, under suitable regularity conditions, geometric ergodicity leads to the existence of a spectral gap and, hence, χ^2 convergence (see, for example, Proposition 2.8 in [21]; see also [19] for a more complete discussion of the connection). On the other hand, under proper regularity conditions, convergence under the χ^2 distance leads to convergence under the total variation distance.

We discuss both frameworks in this paper because for some Markov chains, we may have knowledge of only one form of convergence. For example, to the best of our knowledge, the parallel tempering methods are studied only under the χ^2 distance [12, 46]. Preconditioned Crank–Nicolson algorithms are studied only under the Wasserstein distance

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[21]. The unadjusted Langevin algorithm was first studied under the Wasserstein distance [14, 16] and was later studied under the KL divergence [45]. While there might be theoretical value to establishing convergence in both metrics, doing so is practically unnecessary. In this paper, we assume the convergence of $(X_n)_{n\geq 0}$ under either the Wasserstein distance or the χ^2 distance, and we then study the convergence of $(\widehat{X}_n)_{n\geq 0}$ under one of the two metrics accordingly. We address the question not only qualitatively but also quantitatively in order to establish bounds for the convergence speed and the approximation accuracy of $(\widehat{X}_n)_{n\geq 0}$.

1.1. Related literature

The approximation and convergence questions we study here are fundamental for MCMC and have been studied in various settings before. Most existing works focus on specific approximation schemes. For example, [6, 35] study ergodicity of $\widehat{P}$ if $\widehat{P}(x, A) = P(x, h^{-1}(A))$ for some round-off function h. [22] studies the ergodicity property of finite-rank, nonnegative, sub-Markov kernels in relation to the ergodicity property of the original Markov kernel. [4] studies the convergence and approximation problems of an adaptive subsampling approach under the assumption of uniform ergodicity. [30] studies the approximation problem for Monte Carlo within Metropolis algorithms. In general, there is a lack of a unified framework.

To provide a comprehensive overview of how perturbation of MCMC affects the approximation accuracy and convergence speed, we put together four sets of results. First, we study the approximation problem under the Wasserstein distance, i.e. the ergodicity framework. The corresponding result (Theorem 1) is taken directly from [38]. Approximation accuracy—i.e. bounds for the difference between the nth step distributions of the perturbed chain and the original chain, under the Wasserstein distance—has also been studied in [25, 34, 39] under similar but arguably stronger assumptions. For example, [39] requires the perturbed chain to remain close to the original Markov chain uniformly over a bounded number of iterations, while we require controlling the errors of only one-step transition kernels. [34] focuses on MCMC algorithms with the subsampling type of errors. It requires the existence of a subset $\hat{G}$ in which both the unperturbed and the perturbed chains remain with a high probability and there is a uniform bound on the errors of one-step transition kernels on $\hat{G}$. [25] requires the Markov chains to be uniformly ergodic, which limits the applicability of the results to non-compact-state spaces. Second, we study the convergence problem under the Wasserstein distance. The corresponding result (Theorem 2) is new but follows from similar lines of analysis as in [38]. The papers [24, 34] also analyze the convergence of the perturbed chain, under only the total variation distance, however (and thus requires uniform ergodicity rather than geometric ergodicity). The convergence problem has also been studied in [18], but [18] does not quantify how the convergence rate depends on the perturbation size. Third and fourth, we study the convergence and the approximation problems under the χ^2 distance. The recent work [32] studies the approximation accuracy and the convergence rate of $\widehat{P}$ under the χ^2 distance. Compared to our work, [32] requires stronger assumptions. For example, [32] requires $\widehat{P}$ to be $L_2(\pi) \to L_2(\pi)$, which can be difficult to verify in practice.

As just reviewed, many existing works focus on studying the approximation problem. The convergence problem is less studied. However, it is worth pointing out that most of these approximation results show only

$$D(\nu\widehat{P}^n, \pi) = O(\rho^n + \epsilon),$$

where ρ is the convergence rate of P and ϵ is the difference between P and $\widehat{P}$. Because ϵ is nonzero, this does not directly imply the convergence of $D(\nu\widehat{P}^n, \widehat{\pi})$ to zero. Moreover, if one

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has a convergence result, e.g. $D(\nu\widehat{P}^n, \widehat{\pi}) = O(\hat{\rho}^n)$ for some $\hat{\rho} \in (0, 1)$, and if $\widehat{\pi}$ has an explicit smaller approximation error $D(\pi, \widehat{\pi}) = o(\epsilon)$, using triangular inequality, we can establish a tighter upper bound for $D(\nu\widehat{P}^n, \pi)$.

Lastly, while the connection between the Wasserstein convergence and the MCMC sampling error is well known, most results are asymptotic, i.e. in the form of the central limit theorem [26]. Non-asymptotic error bounds are more useful in practice [27]. Our work provides a comprehensive list of finite-sample performance quantifications for numerical MCMC samplers. We demonstrate that our results can be easily applied to the analysis of various algorithms in Sections 4 and 5.

1.2. Notations

For a probability measure μ on $\mathbb{R}^d$, we define

$$\mu f = \int_{\mathbb{R}^d} f(x)\mu(dx), \quad \text{var}_\mu f = \int_{\mathbb{R}^d} (f(x) - \mu f)^2 \mu(dx).$$

We also use $\mu(dx)$ to denote the corresponding density function. For μ-squared integrable functions $f, g : \Omega \to \mathbb{R}$, we define the inner product with respect to μ as

$$\langle f, g\rangle_\mu = \int_{\mathbb{R}^d} f(x)g(x)\mu(dx).$$

Then, $\|f\|_\mu^2 = \langle f, f\rangle_\mu = \int_{\mathbb{R}^d} f(x)^2\mu(dx)$. In what follows, we omit $\mathbb{R}^d$ from the integral notation when it is clear from the context. For a transition kernel P, we define

$$\mu P(A) = \int P(x, A)\mu(dx).$$

For a measurable function f, we define $\delta_x Pf = Pf(x) = \int f(y)P(x, dy)$. We say that P is symmetric with respect to π if for any measurable functions f, g,

$$\langle Pf, g\rangle_\pi = \langle f, Pg\rangle_\pi.$$

Lastly, we denote C as a generic constant whose value can change from line to line.

1.3. Organization

We start by developing general results for the Wasserstein convergence in Section 2 and the χ^2 convergence in Section 3. We demonstrate how to apply these frameworks on two popular Metropolis–Hastings–MCMC algorithms in Section 4 and on the more involved parallel tempering algorithm in Section 5. Finally, in Section 6, we verify our claims numerically on a Bayesian inverse problem, which tries to infer the initial condition and the model parameters in the predator–prey system.

2. Wasserstein Convergence

We start our discussion with the Wasserstein convergence. Following [38], we first introduce the metric we use and the notion of ergodicity. For a lower semi-continuous function $V : \mathbb{R}^d \to [1, \infty]$, we define

$$d_V(x, y) = (V(x) + V(y))1_{x \neq y}. \tag{6}$$

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For two probability measures μ and ν on $\mathbb{R}^d$, we define

$$\|\mu - \nu\|_V = \sup_{|f| \le V} \left| \int f(x)(\mu(dx) - \nu(dx)) \right|.$$

It can be shown that $\|\mu - \nu\|_V = W_{d_V}(\mu, \nu)$ where W denotes the Wasserstein distance (Lemma 3.1 in [38]). If we use the constant function $V(x) = 1$, this gives the well-known total variation distance, i.e.

$$\|\mu - \nu\|_{TV} = \sup_{|f| \le 1} \left| \int f(x)(\mu(dx) - \nu(dx)) \right|.$$

Note that using $V(x) = 1$ neglects the location information of x. This location information can be crucial for problems with unbounded domains.

In general, for problems with unbounded domains, one often chooses V to be a Lyapunov function. Given a Markov chain X_n with transition kernel P, which we will write together as (X_n, P) for short, we say $V : \mathbb{R}^d \to [1, \infty)$ is a Lyapunov function if there exist $\lambda \in (0, 1)$ and $L > 0$ such that

$$PV(x) = \int P(x, dy)V(y) \le \lambda V(x) + L, \tag{7}$$

and the sublevel sets of V are compact. The choice of V depends on the Markov chain and the target density. It can often be chosen as $\|x\|^2$ or $-\log \pi(x)$ or as functions of certain moments; see, for example, [20, 21, 38].

If π is the invariant measure of X_n, we say X_n is geometrically ergodic under $\|\cdot\|_V$ (see Theorem 16.1 in [31]) if there are constants $\rho \in (0, 1)$ and $C_0 \in (0, \infty)$, such that for any $n \in \mathbb{Z}^+$,

$$\|\delta_x P^n - \pi\|_V \le C_0 \rho^n V(x). \tag{8}$$

We refer to ρ as the ergodicity coefficient. Note that the smaller the value of ρ, the faster the convergence to stationarity. From (8), using the triangle inequality, we obtain an equivalent definition of geometric ergodicity, which requires that for any x and y,

$$\|\delta_x P^n - \delta_y P^n\|_V \le C_0' \rho^n d_V(x, y). \tag{9}$$

The equivalence can be seen from

$$\|\delta_x P^n - \pi\|_V \le \int \pi(dy)\|\delta_x P^n - \delta_y P^n\|_V \le C_0' \rho^n (V(x) + \pi V) \le C_0 \rho^n V(x). \tag{10}$$

where $C_0 = C_0'(1 + \pi V)$.

The approximation problem under Wasserstein distance has been studied in [38]. We present one of their main results here, which is related to our subsequent development. Interested readers can find more general discussion in the original work.

Theorem 1. (Corollary 3.3 in [38]) *Suppose (X_n, P) is geometrically ergodic, i.e., as in (9). Suppose $\widehat{V}$ is a Lyapunov function for $(\widehat{X}_n, \widehat{P})$ in the sense of (7) and that*

$$\|\delta_x P - \delta_x \widehat{P}\|_V \le \epsilon \widehat{V}(x). \tag{11}$$

Then, for some constant C, we have

$$\|\delta_x P^n - \delta_x \widehat{P}^n\|_V \le C\epsilon \frac{1 - \rho^n}{1 - \rho} \left(\widehat{V}(x) + \frac{L}{1 - \lambda} \right). \tag{12}$$

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The bound in (12) and the triangular inequality give us an approximation error bound

$$\|\delta_x \widehat{P}^n - \pi\|_V \leq \|\delta_x P^n - \delta_x \widehat{P}^n\|_V + \|\delta_x P^n - \pi\|_V \leq C'(\epsilon + \rho^n)(\widehat{V}(x) + V(x))$$

for some constant C'.

Remark 1. By restricting our attention to distance functions of the form (6), we focus on a specific form of Wasserstein distance due to its connection to geometric ergodicity. The work [38] also studies the approximation problem under a more general form of Wasserstein ergodicity (see Theorem 3.1 in [38]).

Note that the right-hand side of (12) is not converging to zero as $n \to 0$. Thus, it cannot help us learn the ergodicity of $\widehat{X}_n$ or whether $\widehat{X}_n$ has a unique invariant measure. The next result shows that ergodicity can be obtained with essentially the same conditions as Theorem 1 (note that condition (8) leads to (13) through (10)).

Theorem 2. *Suppose V is a Lyapunov function for P in the sense of (7). In addition, assume there exist $N \in \mathbb{Z}^+$ and $\rho \in (0, 1)$, such that for any $n \geq N$,*

$$\|\delta_x P^n - \delta_y P^n\|_V \leq \rho^n d_V(x, y). \tag{13}$$

Lastly, there is an $\epsilon_0 > 0$, and the following holds for some $\epsilon \in (0, \epsilon_0]$,

$$\|\delta_x P - \delta_x \widehat{P}\|_V \leq \epsilon V(x). \tag{14}$$

Then, V is a Lyapunov function for $\widehat{P}$ as well with

$$\widehat{P}V(x) \leq (\lambda + \epsilon)V(x) + L.$$

Moreover, $\widehat{X}_n$ has a unique invariant measure $\widehat{\pi}$ and there exist $C_1, D_1 \in (0, \infty)$ independent of ϵ, such that

$$\|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \leq C_1(\rho + D_1\epsilon)^n d_V(x, y).$$

In Theorem 2, ϵ_0 is chosen such that $\lambda + \epsilon_0 < 1$ and $\rho + D_1\epsilon_0 < 1$. Theorem 2 indicates that if P is geometrically ergodic with ergodicity coefficient ρ and if $\widehat{P}$ is ϵ-close to P as characterized by (14), $\widehat{P}$ is also geometrically ergodic. Moreover, the ergodicity coefficient of $\widehat{P}$ is bounded above by $\rho + D_1\epsilon$.

In statistical applications, we are more interested in turning convergence results into error bounds for the Monte Carlo estimators. The central limit theorem of ergodic Markov chains was studied in [26, 44], which provide asymptotic error quantifications. In practice, non-asymptotic bounds for finite values of n may be more desirable. The following proposition appeared in [27, 37]. We provide an explicit statement here to show the variance bound along with a simple proof for self-completeness. For simplicity, we assume the Markov chain is initialized with the invariant measure, i.e. $\widehat{X}_0 \sim \widehat{\pi}$, so a burn-in period is not necessary.

Proposition 1. *Suppose $\|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \leq \widehat{\rho}^n d_V(x, y)$ for some $\widehat{\rho} \in (0, 1)$. Then, for any f that is 1-Lipschitz under $\|\cdot\|_V$,*

$$\left|\delta_x \widehat{P}^n f - \widehat{\pi} f\right| \leq \widehat{\rho}^n (V(x) + \widehat{\pi} V).$$

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In addition, if we use $\hat{f}_M = \frac{1}{M}\sum_{k=1}^{M} f(\widehat{X}_k)$ *as an estimator of* $\widehat{\pi} f$ *starting from* $\widehat{X}_0 \sim \widehat{\pi}$,

$$\mathbb{E}_{\widehat{\pi}}\left[(\hat{f}_M - \widehat{\pi} f)^2\right] \leq \frac{2}{(1-\widehat{\rho})M}\mathbb{E}_{\widehat{\pi}}\Big[|f(\widehat{X}_0)|(V(\widehat{X}_0) + \widehat{\pi} V)\Big].$$

In many applications, we are interested in the properties of $\widehat{\pi}$ on compact regions. In these scenarios, the associated test functions will be bounded, and 1-Lipschitz will be under $\|\cdot\|_V$. To learn tail properties of $\widehat{\pi}$ such as intermittency, the test functions often need to grow with $\|x\|$. In order to apply Proposition 2, we would need the Lyapunov function V to grow at a similar scale.

3. χ^2 convergence

In this section, we discuss convergence under the χ^2 divergence. We first introduce some notations. For a transition kernel P and density μ, we define

$$\|P\|_\mu = \max_{f:0<\|f\|_\mu<\infty} \frac{\|Pf\|_\mu}{\|f\|_\mu},$$

where $\|f\|_\mu^2 = \langle f, f\rangle_\mu$. For two probability measures μ and ν on $\mathbb{R}^d$, where ν is absolutely continuous with respect to μ, we define the χ^2 divergence of ν from μ as:

$$D_{\chi^2}(\nu\|\mu) = \int \left(\frac{\nu(x)}{\mu(x)} - 1\right)^2 \mu(x)dx = \int \frac{\nu(x)^2}{\mu(x)}dx - 1.$$

For a transition kernel P that is reversible with respect to π, the spectral gap of P is defined as [21]

$$\kappa(P) = 1 - \sup\left\{\frac{\|Pf - \pi f\|_\pi^2}{\|f - \pi f\|_\pi^2} : f \in L^2(\pi), \operatorname{var}_\pi f \neq 0\right\}. \tag{15}$$

Note that by repeatedly applying (15), we have for any $f \in L^2(\pi)$

$$\|P^n f - \pi f\|_\pi^2 \leq (1-\kappa(P))^n \|f - \pi f\|_\pi^2.$$

Thus, the larger the spectral gap, the more quickly X_n converges to its invariant measure.

Remark 2. An alternative definition of the spectral gap takes the form [2, 3]

$$\kappa_a(P) = \inf\left\{\frac{\langle f, (I-P)f\rangle_\pi}{\operatorname{var}_\pi f} : f \in L^2(\pi), \operatorname{var}_\pi f \neq 0\right\}.$$

Note that these two spectral gaps are related through $1 - \kappa(P) = (1 - \kappa_a(P))^2$.

3.1. General χ^2 approximation and convergence

Theorem 3. *Our first result assumes that* (X_n, P) *has a spectral gap and that* $\widehat{P}$ *is a close approximation of* P*: Suppose* P *is a reversible transition kernel with invariant measure* π *and a spectral gap* $\kappa(P) > 0$ *in the sense of (15). There is an* $\epsilon_0 > 0$ *such that for any transition kernel* $\widehat{P}$ *satisfying* $\|P - \widehat{P}\|_\pi \leq \epsilon < \epsilon_0$ *and any* $a \in (0, 1)$*, there exists a constant* C *that may depend on* $\kappa(P)$ *such that the following holds with* $\widehat{\kappa} = (1-a)\kappa(P) - \frac{C\epsilon^2}{a} \in (0, 1)$*:*

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(i) *For any* $f \in L^2(\pi)$,

$$\|\widehat{P}^n f - \pi \widehat{P}^n f\|_\pi^2 \leq (1-\widehat{\kappa})^n \mathrm{var}_\pi f$$

(ii) $\widehat{P}$ *has an invariant measure* $\widehat{\pi}$, *which satisfies*

$$|(\widehat{\pi} - \pi \widehat{P}^n) f|^2 \leq C\epsilon^2 (1-\widehat{\kappa})^n \mathrm{var}_\pi f.$$

Moreover, $D_{\chi^2}(\widehat{\pi}\|\pi) \leq C\epsilon^2$.

In Theorem 3, ϵ_0 is chosen such that $\hat{\kappa} \in (0,1)$. Theorem 3 indicates that if $\widehat{P}$ and P are ϵ-close to each other as quantified by $\|\widehat{P} - P\|_\pi \leq \epsilon$, then $\widehat{P}$ has a stationary distribution $\widehat{\pi}$. Moreover, $\widehat{\pi}$ and π are ϵ-close to each other as quantified by $D_{\chi^2}(\widehat{\pi}\|\pi) \leq C\epsilon^2$. We also note that showing that $\|\widehat{P}^n f - \pi \widehat{P}^n f\|_\pi^2 \leq (1-\widehat{\kappa})^n \mathrm{var}_\pi f$ is different than finding the spectral gap of $\widehat{P}$, since the latter would need a similar inequality but with π replaced by $\widehat{\pi}$. In other words, Theorem 3 does not provide a spectral gap for $\widehat{P}$. On the other hand, we can obtain error bounds for Monte Carlo estimators using the bounds established in Theorem 3:

Proposition 2. *Under the same conditions as those in Theorem 3, for any* $f \in L^2(\pi)$ *and any initial distribution* $\widehat{X}_0 \sim \nu \ll \pi$, *there exists a constant* C *such that*

$$\left|\nu \widehat{P}^n f - \widehat{\pi} f\right|^2 \leq (1-\widehat{\kappa})^n \mathrm{var}_\pi(f) \left(\sqrt{D_{\chi^2}(\nu\|\pi) + 1} + C\epsilon\right)^2.$$

In addition, if f *is bounded, there exists a constant* C *such that*

$$\mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi} f)^2] \leq \frac{C}{M(1-(1-\widehat{\kappa})^{1/4})} \sqrt{\mathrm{var}_{\widehat{\pi}}(f) \mathrm{var}_\pi(f)},$$

where $\hat{f}_M = \frac{1}{M}\sum_{k=1}^M f(\widehat{X}_k)$.

Remark 3. [32] provides a result similar to the first claim in Theorem 3 (see Lemma A.6 in [32]). But it requires stronger assumptions on $\widehat{P}$, namely, it requires that $\widehat{P}$ is ergodic and aperiodic and that it is a mapping from $L_2(\pi)$ to $L_2(\pi)$. Our result does not require these assumptions.

3.2. Spectral gap with density ratio bounds

In this section, we show that stronger results can be established if we can bound the ratio between the invariant densities π and $\widehat{\pi}$. Such a bound is assessable if we have an explicit characterization of $\widehat{\pi}$. For example, in Bayesian inverse problems, $\pi(x) \propto p_0(x)\exp(-\frac{1}{2}\|G(x) - y\|^2)$, while $\widehat{\pi}(x) \propto p_0(x)\exp(-\frac{1}{2}\|\widehat{G}(x) - y\|^2)$. In this case, a density ratio bound can be obtained if $\|G(x) - \widehat{G}(x)\|$ is bounded. This is practically feasible by using an accurate numerical approximation of G; and the approximation error can be estimated by the grid size or Galerkin truncation used in the numerical scheme (see, for example, [23]). Similar assumptions have also been imposed in existing Bayesian computation literature; see, for example, [5].

Theorem 4. *Suppose* P *and* $\widehat{P}$ *are two reversible transition kernels with invariant densities* π *and* $\widehat{\pi}$ *respectively. We further assume that* $\pi(x)/\widehat{\pi}(x) \in [(1+\epsilon)^{-1}, 1+\epsilon]$, *and that* $\|P - \widehat{P}\|_\pi \leq \epsilon$. *Then there exists a universal constant* C *such that*

$$\kappa(\widehat{P}) \geq \kappa(P) - C\epsilon.$$

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Note that for ϵ small enough, $\kappa(P) - C\epsilon > 0$. Based on the spectral gap, we have the following non-asymptotic Monte Carlo error bound:

Proposition 3. *Suppose $(\widehat{X}_n, \widehat{P})$ has a spectral gap $\widehat{\kappa}$. Suppose the initial distribution is ν, i.e. $\widehat{X}_0 \sim \nu$. Then*

$$\left|\mathbb{E}f(\widehat{X}_n) - \widehat{\pi}f\right|^2 \leq (1-\widehat{\kappa})^n \mathrm{var}_{\widehat{\pi}} f(D_{\chi^2}(\nu\|\widehat{\pi}) + 1).$$

In addition, if $\nu = \widehat{\pi}$, then for $\hat{f}_M = \frac{1}{M}\sum_{k=1}^{M}$, we have

$$\mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi}f)^2] \leq \frac{2}{M(1-(1-\widehat{\kappa})^{1/2})}\mathrm{var}_{\widehat{\pi}}[f].$$

Note that Proposition 3 is not a new result. A more delicate central limit theorem version of it can be found as Theorem 4.4 of [21]. We provide a short proof of the proposition in the Appendix B for self-completeness.

Before we conclude our discussion of the χ^2 convergence, we remark that even though the condition $\|P - \widehat{P}\|_\pi \leq \epsilon$ is reasonable for the spectral gap analysis, it can be hard to verify directly in some applications. To remedy this issue, the next proposition shows that we can bound $\|P - \widehat{P}\|_\pi$ through a bound for $\|\delta_x P - \delta_x \widehat{P}\|_{TV}$, which can be easier to obtain using coupling techniques.

Proposition 4. *Suppose there exists a π-measurable function $V : \mathbb{R}^d \to [1, \infty)$ such that $\|\delta_x P - \delta_x \widehat{P}\|_{TV} \leq \epsilon V(x)$. In addition, suppose $\frac{1}{a} \leq \pi(x)/\hat{\pi}(x) \leq a$ for some constant $a > 0$. Then*

$$\|P - \widehat{P}\|_\pi \leq \sqrt{2(1+a^2)}\sqrt{\epsilon}\|V\|_\pi^{1/2}.$$

4. Application: Metropolis–Hastings MCMC on perturbed densities

Random walk Metropolis (RWM) and Metropolis adjusted Langevin algorithm (MALA) are two popular MCMC samplers when it comes to sampling a generic density π. Many existing works have already studied their spectral gap under suitable conditions on π [15, 21, 36]. When implementing these samplers, it is often the case that we have access only to an approximation of π, which we denote as $\widehat{\pi}$. In this section, we will demonstrate how to apply our analysis framework to establish proper bounds for the spectral gap of the "numerical" RWM and MALA.

In fact, we can develop some general results for the Metropolis–Hastings (MH) type of Monte Carlo algorithm. Assume the proposals are given by some smooth transition density $R(x, x')$. Due to the possibility of rejection, MH Monte Carlo transition densities w.r.t. Lebesgue measure can be written as $P(x, x') = \gamma(x)\delta_x(x') + \beta(x, x')$ with

$$\beta(x, x') = \min\left\{\frac{\pi(x')R(x', x)}{\pi(x)}, R(x, x')\right\}, \quad \gamma(x) = 1 - \int \beta(x, x')dx'. \tag{16}$$

The perturbed transition density can be written as $\widehat{P}(x, x') = \hat{\gamma}(x)\delta_x(x') + \widehat{\beta}(x, x')$. We provide some sufficient conditions under which the difference between P and $\widehat{P}$ is of order ϵ.

Lemma 1. *If the transition density is of the form $P(x, x') = \gamma(x)\delta_x(x') + \beta(x, x')$ with $\nu(x)P(x, x') = \nu(x')P(x', x)$, suppose that $\widehat{P}(x, x') = \hat{\gamma}(x)\delta_x(x') + \hat{\beta}(x, x')$ with*

$$|\hat{\gamma}(x) - \gamma(x)| \leq C\epsilon \ \text{ and } \ (1 - C\epsilon)\beta(x, x') \leq \hat{\beta}(x, x') \leq (1 + C\epsilon)\beta(x, x').$$

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for some constant $C \in (0, \infty)$. *Then there exists a constant* $C_1 \in (0, \infty)$ *such that* $\|P - \widehat{P}\|_v \leq C_1\epsilon$.

4.1. Random walk Metropolis

RWM considers implementing the MH procedure on random walk proposals. That is, we use

$$R(x, x') = \frac{1}{(2\pi h)^{d/2}} \exp\left(-\frac{1}{4h}\|x' - x\|^2\right)$$

in (16). It is worth noting that using a perturbed density $\widehat{\pi}$ does not affect this proposal.

Proposition 5. *For RWM, there is an* $\epsilon_0 > 0$ *so that for any* $\epsilon < \epsilon_0$ *and* $\sup_x |\log \pi(x) - \log \hat{\pi}(x)| \leq C\epsilon$, *there is a constant* C_1 *so that*

$$\|P_{RWM} - \widehat{P}_{RWM}\|_\pi \leq C_1\epsilon.$$

If the original RWM has a spectral gap and if $\sup_x |\log \pi(x) - \log \hat{\pi}(x)| \leq C\epsilon$, then Proposition 5, together with Theorem 4, implies that the perturbed RWM has a proper spectral gap as well. In practice, an estimate of ϵ can be obtained by analyzing the numerical scheme used; see Section 3.2 for more details.

4.2. Metropolis adjusted Langevin algorithm

MALA considers implementing the MH procedure on proposals following the Langevin diffusion. That is, we use

$$R(x, x') = \frac{1}{(4\pi h)^{d/2}} \exp\left(-\frac{1}{4h}\|x' - x - h\nabla \log \pi(x)\|^2\right)$$

in (16). Using a perturbed density $\widehat{\pi}$ does change this proposal. We discuss the perturbation in two separate cases. In particular, we shall verify that the condition $\|P_{MALA} - \widehat{P}_{MALA}\|_\pi \leq \epsilon$ holds under appropriate assumptions on $\widehat{\pi}$ in the two cases. Then, if P_{MALA} has a spectral gap, the numerical sampler $\widehat{P}_{MALA}$ has a proper spectral gap as well.

4.2.1. *Bounded domain* When the support of π and $\widehat{\pi}$ is bounded, the analysis is quite straightforward with Lemma 1.

Proposition 6. *For MALA, there is an* $\epsilon_0 > 0$ *so that for any* $\epsilon < \epsilon_0$, *if* $\sup_x |\log \pi(x) - \log \hat{\pi}(x)| \leq C\epsilon$, $\sup_x \|\nabla \log \pi(x) - \nabla \log \hat{\pi}(x)\| \leq C\epsilon$ *and if the support of* π *and* $\widehat{\pi}$ *is bounded, then*

$$\|P_{MALA} - \widehat{P}_{MALA}\|_\pi = O(\epsilon).$$

4.2.2. *Unbounded support* When the support of the density is unbounded, directly bounding $\|P_{MALA} - \widehat{P}_{MALA}\|_\pi$ becomes difficult. Instead, we consider establishing $\|\delta_x P - \delta_x \widehat{P}\|_{TV} = O(\epsilon)$.

Proposition 7. *For MALA, if* $\log \pi$ *is Lipschitz,* $\sup_x |\log \pi(x) - \log \hat{\pi}(x)| \leq L_\pi\epsilon$ *and, moreover,* $\sup_x \|\nabla \log \pi(x) - \nabla \log \widehat{\pi}(x)\| \leq L_\pi\epsilon$, *for any* $\delta > 0$, *there exists* $C_\delta \in (0, \infty)$ *such that for* $h < (\frac{5L_\pi}{\delta} + 20L_\pi)^{-1}$,

$$\|\delta_x P - \delta_x \widehat{P}\|_{TV} \leq C_\delta\epsilon \exp(\delta\|x\|^2).$$

When $\pi(x)$ is sub-Gaussian, we can find a $\delta > 0$ such that $V(x) = \exp(\delta\|x\|^2)$ is L_2-integrable under π. Then Proposition 4 indicates that $\|P - \widehat{P}\|_\pi = O(\sqrt{\epsilon})$.

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5. Application: Parallel Tempering with Perturbed Densities

In this section, we demonstrate how to apply our framework to parallel tempering (PT) algorithms [17, 42, 43]. These algorithms are also referred to as the replica exchange methods [11, 13, 41]. Compared with regular MCMC samplers like RWM and MALA, PT tries to sample a multiple-tempered version of the target density. Such a design can improve the convergence rate on densities with multiple isolated modes.

To implement PT, a sequence of distributions $\pi_0, \ldots, \pi_K$ is considered, where the last one is the target density $\pi_K = \pi$. The first density, π_0, is usually a distribution that is easy to draw samples from. The intermediate distributions, π_k's $1 \le k \le K-1$, are set up so that the two neighboring densities are similar to each other. A common choice for the intermediate distributions is to consider interpolations between π_K and π_0:

$$\pi_k(x) \propto \pi^{\beta_k}(x)\pi_0^{1-\beta_k}(x),$$

where $0 = \beta_0 < \beta_1 < \ldots < \beta_K = 1$ is a sequence of parameters. PT intends to generate samples from the product density

$$\Pi = \pi_0 \times \pi_1 \times \cdots \times \pi_K \text{ on } \mathbb{R}^{d(K+1)}.$$

To do so, its iterations consist of $K+1$ parts, i.e. $X_n = (X_n^0, \ldots, X_n^K)$, and the updating rule is given by the following two steps:

(i) Update each X_n^k to X_{n+1}^k according to a transition kernel M_k, whose stationary distribution is π_k. In practice, M_k is often taken as the transition kernel obtained by repeating the RWM or MALA update for t_k steps. That is, $M_k = P_{RWM}^{t_k}$ or $M_k = P_{MALA}^{t_k}$.

(ii) Pick an index $k \in \{0, \ldots, K-1\}$ uniformly at random, and swap the values of X_{n+1}^k and X_{n+1}^{k+1} with probability $\alpha_k(X_{n+1}^k, X_{n+1}^{k+1})$, where

$$\alpha_k(x, x') = \min\left\{1, \frac{\pi_k(x')\pi_{k+1}(x)}{\pi_k(x)\pi_{k+1}(x')}\right\}.$$

The pseudo-code of PT is given in Algorithm 1.

The exchange procedure can be described by the transition probability on $R^{(K+1)d} \times R^{(K+1)d}$:

$$Q_k(x, x) = 1 - \alpha_k(x^k, x^{k+1}), \quad Q_k(x, S_k(x)) = \alpha_k(x^k, x^{k+1}),$$

where $S_k(x) = (x^0, \ldots, x^{k-1}, x^{k+1}, x^k, x^{k+2}, \ldots, x^K)$. With a little change of notation, we write the transition kernel as Q_k as well; i.e. $Q_k f(x) = Q_k(x, x)f(x) + Q_k(x, S_k(x))f(S_k(x))$. The transition kernel of PT can then be written as

$$P = (M_0 \otimes \cdots \otimes M_K)\left(\frac{1}{K}\sum_{\mathbf{k}\in\{0,\ldots,K-1\}} Q_k\right), \tag{17}$$

where the direct product of two transition kernels is given by

$$M_0 \otimes M_1 f(x^0, x^1) = \int\int M_0(x^0, y^0)M_1(x^1, y^1)f(y^0, y^1)dy^0dy^1.$$

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Algorithm 1 Parallel Tempering

Input: Replica counts K, target densities π_k for $k = 0, \ldots, K$, transition kernels M_k targeting π_k.
Output: $(x_t^k)_{t=0,\ldots,T_k,k=0,\ldots,K}$ as samples from π_k
Initialize x_0^k for all k
for $t = 0$ to T **do**
  for $k = 0$ to K **do** %Run MCMC at each level.
    Generate $x_{t+1}^k \sim M_k(x_t^k, \cdot)$.
  end for
  %Consider swapping at a random level.
  Let k be a random index in $\{0, \ldots, K-1\}$
  Let U be a random sample from Unif[0, 1]
  if $U < a_k(x_{t+1}^k, x_{t+1}^{k+1})$ **then**
    $(x_{t+1}^k, x_{t+1}^{k+1}) = (x_{t+1}^{k+1}, x_{t+1}^k)$
  end if
end for

The spectral gap of P in (17) has been studied in [46]. Assuming the state space can be partitioned into $\mathbb{R}^d = \cup_{i=1}^J A_j$, it is shown that $\kappa(P)$ can be seen as the product of three elements: (1) the maximal spectral gap when sampling π_k, $k \geq 1$, constrained on one piece, A_j; (2) the spectral gap when sampling π_0 using M_0; and (3) the density ratio $\pi_k(A_j)/\pi_{k+1}(A_j)$. In particular, if π_0 is easy to sample, π_k is not very different from π_{k+1}, and the sampling of π_k constrained on A_j is efficient, then PT can be highly efficient. When implementing PT numerically, we may not have access to the exact values of π_k but only an ϵ-approximation, which we denote as $\widehat{\pi}_k$. Then the corresponding PT uses a sampler $\widehat{M}_k$, with invariant measure $\widehat{\pi}_k$ at each replica, while the exchange probability is given by

$$\widehat{\alpha}_k(x, x') = \min\left\{1, \frac{\widehat{\pi}_k(x')\widehat{\pi}_{k+1}(x)}{\widehat{\pi}_k(x)\widehat{\pi}_{k+1}(x')}\right\}.$$

The corresponding transition kernel can be written as

$$\widehat{P} = \left(\widehat{M}_0 \otimes \cdots \otimes \widehat{M}_K\right)\left(\frac{1}{K}\sum_{\mathbf{k}\in\{0,\ldots,K-1\}} \widehat{Q}_k\right).$$

It is natural to ask whether this numerical PT will inherit the spectral gap of P. The next result, together with Theorem 4, indicate that under appropriate regularity conditions on $\widehat{\pi}_k$'s, the numerical PT also has a proper spectral gap.

Proposition 8. *Suppose that for each replica, if the target distribution satisfies* $\sup_x |\log \widehat{\pi}_k(x) - \log \pi_k(x)| \leq \epsilon$ *and the transition kernel satisfies* $\|P_k - \widehat{P}_k\|_{\pi_k} \leq \epsilon$, *then the transition kernel of PT satisfies the following for some constant C:*

$$\|P - \widehat{P}\|_{\Pi} \leq C\epsilon.$$

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Before we prove Proposition 8, we first prove two auxiliary lemmas. The first lemma shows that different compositions of approximated transition kernels yield approximation kernels of similar accuracy. In particular, it helps us establish the condition $\|P_k - \widehat{P}_k\|_{\pi_k} \le \epsilon$ in Proposition 8 if we use $M_k = P_{RWM}^{t_k}$ or $M_k = P_{MALA}^{t_k}$.

Lemma 2

(i) *For two transition kernels R and S, both with invariant measure ν, if $\|R - \widehat{R}\|_\nu \le C\epsilon$ and if $\|S - \widehat{S}\|_\nu \le C\epsilon$, then there is a constant C' so that*

$$\|RS - \widehat{R}\widehat{S}\|_\nu \le C'\epsilon.$$

(ii) *For two transition kernels R_1 and R_2, with invariant measure ν_1 and ν_2 respectively, if $\|R_1 - \hat{R}_1\|_{\nu_1} \le C\epsilon$ and if $\|R_2 - \hat{R}_2\|_{\nu_2} \le C\epsilon$, then there is a constant C' so that*

$$\|R_1 \otimes R_2 - \widehat{R}_1 \otimes \widehat{R}_2\|_\nu \le C'\epsilon,$$

where $\nu = \nu_1 \times \nu_2$ is the joint invariance distribution.

(iii) *For n transition kernels $S_1, S_2, \ldots, S_n$, all with invariant measure ν, if $\|S_i - \widehat{S}_i\|_\nu \le C\epsilon$ for $i = 1, \ldots, n$, then for $U = \frac{1}{n}\sum_{i=1}^n S_i$ and $\widehat{U} = \frac{1}{n}\sum_{i=1}^s \widehat{S}_i$, there is a constant C' so that*

$$\|U - \widehat{U}\|_\nu \le C'\epsilon.$$

The second lemma establishes proper bounds for the swapping transition.

Lemma 3. *Let Q be a transition probability of form*

$$Q(x, S(x)) = a(x, S(x)), \quad Q(x, x) = 1 - a(x, S(x)),$$

where $S(x)$ is some given map. Suppose Q is reversible with a density ν, i.e.

$$\nu(x)Q(x, S(x)) = \nu(S(x))Q(S(x), x).$$

Similarly, let $\widehat{Q}$ denote the transition probability of the form

$$\widehat{Q}(x, S(x)) = \widehat{a}(x, S(x)), \quad \widehat{Q}(x, x) = 1 - \widehat{a}(x, S(x)),$$

reversible with $\widehat{\nu}$. If for some constant C, $(1 - C\epsilon)a(x, S(x)) \le \widehat{a}(x, S(x)) \le (1 + C\epsilon)a(x, S(x))$, then

$$\|(Q - \widehat{Q})f\|_\nu \le 2C\epsilon\|f\|_\nu.$$

6. Numerical examples

In this section, we present some numerical examples based on the predator–prey system to illustrate the theoretical results developed in the preceding sections.

6.1. Predator–prey system

We consider inferring the parameters of a system of ordinary differential equations (ODEs) that models the predator–prey system [29]. Denoting the populations of prey and predator by

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(γ_p, γ_q), the populations change over time according to the pair of coupled ODEs is

$$\begin{aligned}\frac{d\gamma_p}{dt} &= r\gamma_p\left(1-\frac{\gamma_p}{K}\right) - s\left(\frac{\gamma_p\,\gamma_q}{w+\gamma_p}\right),\\ \frac{d\gamma_q}{dt} &= u\left(\frac{\gamma_p\,\gamma_q}{w+\gamma_p}\right) - v\gamma_q,\end{aligned} \tag{18}$$

with initial conditions $\gamma_p(0)$ and $\gamma_q(0)$. r, K, a, s, u, and v are model parameters that control the dynamics of the populations of prey and predator. In the absence of the predator, the population of prey evolves according to the logistic equation, which is characterized by r and K. In the absence of the prey, the population of the predator has an exponential decay rate v. The additional parameters s, w, and u characterize the interaction between the predator population and the prey population.

In the inference problem, we want to estimate both the model parameters and the initial conditions. In this case, we have $d = 8$ and denote

$$\theta = (\gamma_p(0), \gamma_q(0), r, K, a, s, u, v).$$

A commonly used prior for this problem is a uniform distribution over a hypercube $(a_1, b_1) \times \cdots \times (a_d, b_d)$ (see e.g. [33]). Here we set $a_i = 10^{-3}$ and $b_i = 2 \times 10^2$ for all i. Noisy observations of both $\gamma_p(t;\theta)$ and $\gamma_q(t;\theta)$ at times regularly spaced at $m = 20$ time points in $t \in [2, 40]$ are used to infer θ. This defines a so-called forward model,

$$F(\theta) = [\gamma_p(t_1;\theta), \gamma_q(t_1;\theta), \ldots, \gamma_p(t_m;\theta), \gamma_q(t_m;\theta)],$$

that maps a given parameter θ to the observables. The observables are perturbed with independent Gaussian observational errors with mean zero and variance 4. A "true" parameter

$$\theta_{\text{true}} = [50, 5, 0.6, 100, 1.2, 25, 0.5, 0.3]^\top$$

is used to generate the synthetic observed data set, which is denoted by y. The trajectories of $\gamma_p(t;\theta_{\text{true}})$ and $\gamma_q(t;\theta_{\text{true}})$ together with the synthetic data set are shown in Figure 1.

To prevent rejections caused by proposal samples that fall outside of the hypercube, we further consider the prior distribution as the pushforward of the standard Gaussian measure, with the probability density function

$$p_0(x) = (2\pi)^{-d/2}\exp\left(-\frac{1}{2}\|x\|^2\right)$$

under a diffeomorphic transformation $T : \mathbb{R}^d \to \mathbb{R}^d$ that maps each coordinate

$$\theta_i = T_i(x_i) = a_i + \frac{b_i - a_i}{\sqrt{2\pi}}\int_{-\infty}^{x_i}\exp\left(-\frac{1}{2}z^2\right)dz.$$

In other words, $p_0(x)$ is the prior distribution for the transformed parameter $x = T^{-1}(\theta)$. Writing $G(x) = F(T(x))$, our goal is to characterize the posterior distribution

$$\pi(x) \propto p_0(x)\exp\left(-\frac{1}{8}\|G(x) - y\|^2\right).$$

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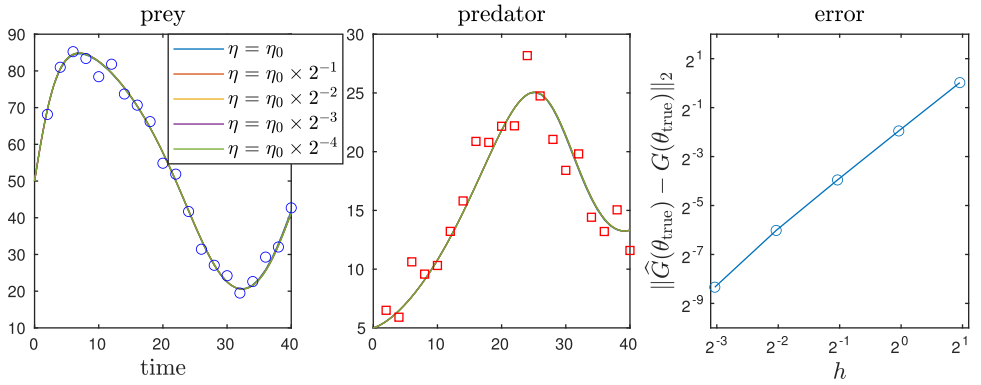


FIGURE 1. Left and middle: the trajectories of $\gamma_p(t;\theta_{\text{true}})$ and $\gamma_q(t;\theta_{\text{true}})$ computed using the second-order Runge–Kutta method, with different time step size η. Right: the L_2 error of the model outputs with different time step sizes η. Here $G(\theta_{\text{true}})$ is computed using $\eta = \eta_0 \times 2^{-6}$. The trajectories computed by the time step size $\eta = \eta_0 \times 2^{-6}$ are used to generate a synthetic data set. The observed data sets of the prey and the predator are shown as circles and squares, respectively.

The system of ODEs in (18), and hence the function $G(x)$, has to be numerically solved by some ODE solvers. Here we use the second-order explicit Runge–Kutta method, with time step size η, to solve (18). As shown in Figure 1, the trajectories of $\gamma_p(t;\theta_{\text{true}})$ and $\gamma_q(t;\theta_{\text{true}})$ converge as $\eta \to 0$ at a rate of $O(\eta^2)$ (see [8] for a detailed analysis). The numerical solver, which is characterized by the step size η, defines the approximate model $\widehat{G}(x)$ and the approximate posterior density $\widehat{\pi}(x)$. Figure 2 shows the estimated marginal distributions (using Algorithm 1) of perturbed posteriors defined by various time step sizes. Here we observe that as h decreases, the estimated marginal distributions almost overlap each other, which suggests that the perturbed distributions converge as the discretized model $\widehat{G}$ converges.

6.2. MCMC results

To validate the theoretical results of Metropolis–Hasting MCMC on perturbed densities in Section 4, we first simulate the RWM algorithm with invariant densities $\widehat{\pi}(x)$ defined by various time step sizes, as shown in Figure 1. All the Markov chains in this set of simulation experiments are generated using the same Gaussian random walk proposal distribution. The box plots of the integrated autocorrelation times (IACTs) of the resulting Markov chains are shown in Figure 3. Then we simulate MALA with invariant densities $\widehat{\pi}(x)$ defined by the same set of time step sizes. The box plots of the resulting IACTs are shown in Figure 4. Again, all the Markov chains are generated using the same proposal distribution. For both algorithms, we simulate each Markov chain for 10^6 iterations after discarding burn-in samples and repeat the simulation for 20 times with different initial states to produce the box plots. As established in our theoretical analysis, for both algorithms the resulting Markov chains targeting various approximate posterior densities produce similar IACTs.

To validate the theoretical results on the parallel tempering with perturbed densities in Section 5, we simulate Algorithm 1 with the same Gaussian random walk as in RWM. For each of the invariant densities $\widehat{\pi}(x)$ defined by various time step sizes, we set $K = 4$, and the intermediate distributions take the form

$$\widehat{\pi}_k(x) \propto p_0(x) \exp\left(-\frac{\beta_k}{8}\|\widehat{G}(x) - y\|^2\right),$$

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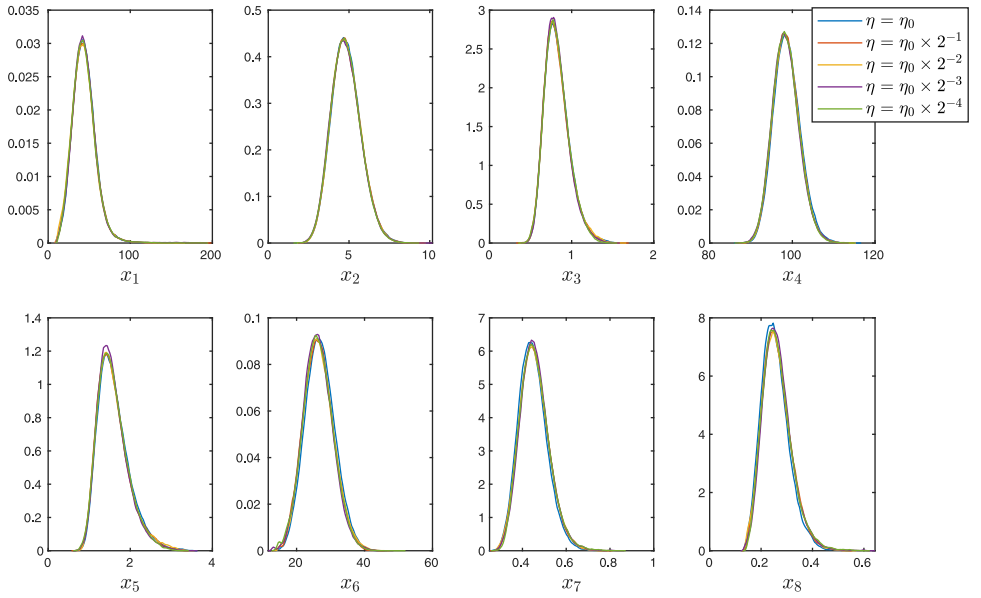


FIGURE 2. Marginal distributions of perturbed posteriors defined by various time step sizes.

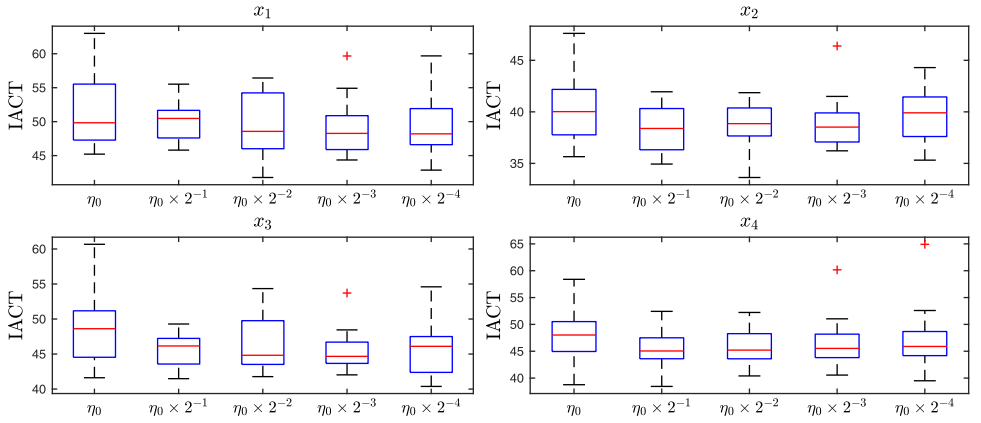


FIGURE 3. Box plots of integrated autocorrelation times (IACTs) of the first four parameter Markov chains simulated by the RWM algorithm. Here, 20 realizations of Markov chains are used to estimate the IACT.

where $\beta_k = 1 + \alpha^{-K} - \alpha^{-k}$ with $\alpha = 1.3$ and $k = \{0, 1, 2, 3, 4\}$. Here β_k is an increasing sequence such that $\beta_K = 1$. The same Gaussian random walk is used across all replicas to simulate the Markov chain. The box plots of the IACTs of resulting Markov chains are shown in Figure 5. Similar to the previous experiments, the resulting Markov chains targeting various approximate posterior densities produce similar IACTs. Furthermore, we noticed that the IACTs of Algorithm 1 are smaller than those of the RMW and MALA algorithm, which suggests that Algorithm 1 has a better mixing rate.

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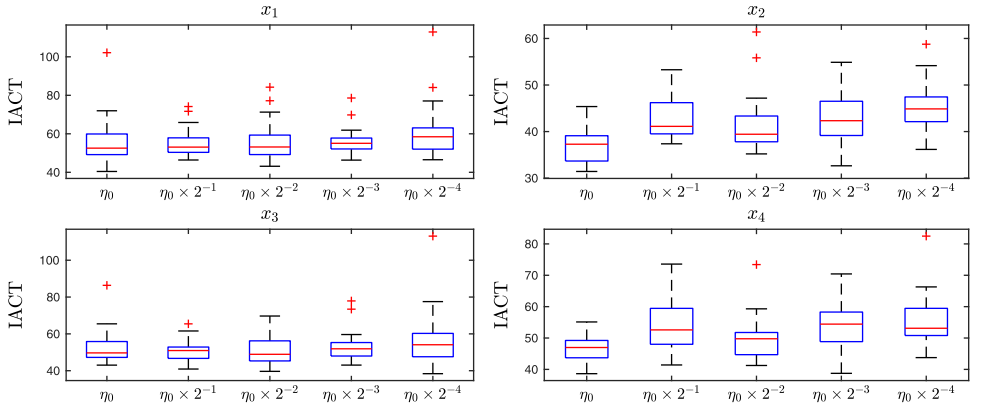


FIGURE 4. Box plots of integrated autocorrelation times (IACTs) of the first four parameter Markov chains simulated by the MALA algorithm. Here, 20 realizations of Markov chains are used to estimate the IACT.

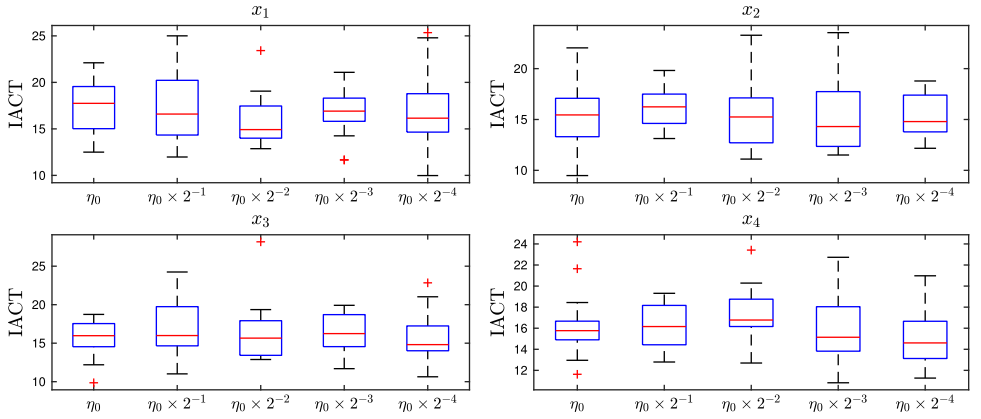


FIGURE 5. Box plots of integrated autocorrelation times (IACTs) of the first four parameters of Markov chains simulated by Algorithm 1. Here, 20 realizations of Markov chains are used to estimate the IACT.

7. Conclusion

In this paper, we quantify the convergence speed and the approximation accuracy of numerical MCMC samplers under two general frameworks: ergodicity and spectral gap. Our results can be easily applied to study the efficiency and accuracy of various sampling algorithms. In particular, we demonstrate how to apply our framework to study Metropolis–Hasting MCMC algorithms and parallel tempering Monte Carlo algorithms. These results are validated by numerical simulations on a Bayesian inverse problem based on the predator–prey model.

In the applications in Sections 4 and 5, we assume that we can approximate the target transition kernels with some uniform accuracy guarantees. In some problems with unbounded domains, this can be difficult to achieve. It would be interesting to relax such requirements to the ones assumed in [10].

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Appendix A. Proof for the Wasserstein convergence

Proof of Theorem 2. Let Q be the optimal coupled measure between $\delta_x P$ and $\delta_x \widehat{P}$ from the Kantorovich–Rubinstein theorem. Then

$$\begin{aligned} |PV(x) - \widehat{P}V(x)| &= \left| \int Q_x(dx', dy')(V(x') - V(y')) \right| \\ &\leq \left| \int Q_x(dx', dy')(V(x') + V(y'))1_{x' \neq y'} \right| = \|\delta_x P - \delta_x \widehat{P}\|_V. \end{aligned}$$

Next, as $\|\delta_x P - \delta_x \widehat{P}\|_V \leq \epsilon V(x)$, we have

$$|PV(x) - \widehat{P}V(x)| \leq \epsilon V(x).$$

In addition, because V is a Lyapunov function under P,

$$\widehat{P}V(x) \leq PV(x) + \epsilon V(x) \leq (\lambda + \epsilon)V(x) + L.$$

As $(\lambda + \epsilon) \in (0, 1)$ for ϵ small enough, V is a Lyapunov function under $\widehat{P}$ with parameters $\lambda + \epsilon$ and L.

We next establish a bound for $\|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V$, $x \neq y$ using

$$\|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \leq \|\delta_x \widehat{P}^n - \delta_x P^n\|_V + \|\delta_x P^n - \delta_y P^n\|_V + \|\delta_y P^n - \delta_y \widehat{P}^n\|_V. \tag{19}$$

For $\|\delta_x \widehat{P}^n - \delta_x P^n\|_V$, by Theorem 1, we have

$$\|\delta_x \widehat{P}^n - \delta_x P^n\|_V \leq \frac{C\epsilon}{1-\rho} \left(V(x) + \frac{L}{1-\lambda-\epsilon} \right) \leq C\epsilon V(x)$$

for some C because $V(x) \geq 1$. A similar bound holds for $\|\delta_y P^n - \delta_y \widehat{P}^n\|_V$ as well—i.e.

$$\|\delta_y P^n - \delta_y \widehat{P}^n\|_V \leq \frac{C\epsilon}{1-\rho} \left(V(y) + \frac{L}{1-\lambda-\epsilon} \right) \leq C\epsilon V(y).$$

For any $l \leq N$, Let $D_1 = \frac{C}{N\rho^{2N-1}}$. Then (19) leads to

$$\begin{aligned} \|\delta_x \widehat{P}^{l+N} - \delta_y \widehat{P}^{l+N}\|_V &\leq \rho^{l+N} d_V(x, y) + C\epsilon(V(x) + V(y)) \\ &= \left(\rho^{l+N} + C\epsilon \right) d_V(x, y) \leq (\rho + D_1\epsilon)^{l+N} d_V(x, y), \end{aligned} \tag{20}$$

where the last inequality follows from $(a+b)^N > a^N + Na^{N-1}b$ for all $a, b > 0$, which comes from Taylor expansion.

Next, let $\widehat{Q}^k_{x,y}$ be the optimal coupled measure between $\delta_x \widehat{P}^{kN}$ and $\delta_y \widehat{P}^{kN}$. Then

$$\begin{aligned} \|\delta_x \widehat{P}^{kN} - \delta_y \widehat{P}^{kN}\|_V &\leq \int \widehat{Q}^{k-1}_{x,y}(dx', dy') \|\delta_{x'} \hat{P}^N - \delta_{y'} \hat{P}^N\|_V \\ &\leq \int \widehat{Q}^{k-1}_{x,y}(dx', dy')(\rho + D_1\epsilon)^N d_V(x', y') \\ &\leq (\rho + D_1\epsilon)^{kN} d_V(x, y). \end{aligned} \tag{21}$$

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For any $n \geq N$, we can write $n = kN + N + l$, for $k, l \in \mathbb{Z}_0^+$, and

$$\begin{aligned}\|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V &\leq \int \widehat{Q}^k_{x,y}(dx', dy')\|\delta_{x'}\hat{P}^{N+l} - \delta_{y'}\hat{P}^{N+l}\|_V \\ &\leq C_1(\rho + D_1\epsilon)^{N+l} \int \widehat{Q}^k_{x,y}(dx', dy') d_V(x', y') \text{ by (20)} \\ &\leq C_1(\rho + D_1\epsilon)^{l+kN+N} d_V(x, y) \text{ by (21)} \\ &= C_1(\rho + D_1\epsilon)^n d_V(x, y).\end{aligned}$$

Lastly, we show that $\widehat{P}$ has a unique invariant measure $\widehat{\pi}$. Fix a point x, considering a sequence $\{\delta_x \widehat{P}^n, n = 1, 2, \ldots\}$. Note that

$$\begin{aligned}\|\delta_x \widehat{P}^n - \delta_x \widehat{P}^{n+1}\|_V &\leq \int \|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \widehat{P}(x, dy) \\ &\leq C_1(\rho + D_1\epsilon)^n \mathbb{E}[d_V(x, \widehat{X}_1)] \\ &\leq C_1(\rho + D_1\epsilon)^n [(\lambda + 1 + \epsilon)V(x) + L].\end{aligned}$$

This implies that $\delta_x \widehat{P}^n$ is a Cauchy sequence in d_V as well as the total variation distance. Since the sublevel sets of V are compact and $\delta_x \widehat{P}^n V$ remains bounded, it is a tight sequence. Therefore, the sequence has a limit, which we denote by π_x. Next, we show that $\pi_x = \pi_y$:

$$\|\pi_x - \pi_y\|_V \leq \|\pi_x - \delta_x \widehat{P}^n\|_V + \|\delta_y \widehat{P}^n - \pi_y\|_V + \|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \to 0 \text{ as } n \to 0.$$

Proof of Proposition 1. For the first claim, let $Q^n_{x,y}$ be the the optimal coupled measure between $\delta_x \widehat{P}^n$ and $\delta_y \widehat{P}^n$ for any $x, y \in \mathbb{R}^d$. Then

$$\begin{aligned}|\delta_x \widehat{P}^n f - \widehat{\pi} f| &= |\delta_x \widehat{P}^n f - \widehat{\pi} \widehat{P}^n f| \\ &\leq \int |\delta_x \widehat{P}^n f - \delta_y \widehat{P}^n f| \widehat{\pi}(dy) \\ &\leq \int \int Q^n_{x,y}(dx', dy') |f(x') - f(y')| \widehat{\pi}(dy) \\ &\leq \int \|\delta_x \widehat{P}^n - \delta_y \widehat{P}^n\|_V \widehat{\pi}(dy) \\ &\leq \widehat{\rho}^n \int d_V(x, y) \widehat{\pi}(dy) \leq \widehat{\rho}^n (V(x) + \widehat{\pi} V).\end{aligned} \tag{22}$$

For the second claim, note that for any f with $\widehat{\pi} f = 0$, we have

$$\begin{aligned}\mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi} f)^2] &= \frac{1}{M^2} \mathbb{E}_{\widehat{\pi}} \left[\sum_{j,k=1}^{M} f(\widehat{X}_j) f(\widehat{X}_k) \right] \\ &\leq \frac{2}{M^2} \mathbb{E}_{\widehat{\pi}} \left[\sum_{j=1}^{M} |f(\widehat{X}_j)| \sum_{k=0}^{\infty} |f(\widehat{X}_{j+k})| \right] \\ &= \frac{2}{M} \mathbb{E}_{\widehat{\pi}} \left[|f(\widehat{X}_0)| \mathbb{E} \left[\sum_{k=0}^{\infty} |f(\widehat{X}_k)| \middle| \widehat{X}_0 \right] \right] \text{ since } \widehat{X}_j \sim \widehat{\pi}\end{aligned}$$

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$$\leq \frac{2}{M}\mathbb{E}_{\widehat{\pi}}\left[|f(\widehat{X}_0)|\sum_{k=0}^{\infty}\widehat{\rho}^k(V(\widehat{X}_0)+\widehat{\pi}V)\right] \text{ from (22)}$$
$$\leq \frac{2}{(1-\widehat{\rho})M}\mathbb{E}_{\widehat{\pi}}\Big[|f(\widehat{X}_0)|(V(\widehat{X}_0)+\widehat{\pi}V)\Big].$$

Appendix B. Proof for the χ^2 convergence

Proof of Theorem 3. We will write $\kappa = \kappa(P)$ for short.
For **Claim 1,** first note that

$$\begin{aligned}
\mathrm{var}_\pi(\widehat{P}f) &= \frac{1}{2}\int \left(\widehat{P}f(x)-\widehat{P}f(y)\right)^2\pi(dx)\pi(dy)\\
&= \frac{1}{2}\int \left(Pf(x)-Pf(y)+(P-\widehat{P})f(y)-(P-\widehat{P})f(x)\right)^2\pi(dx)\pi(dy)\\
&\leq \left(\frac{1}{2}+\frac{a\kappa}{2}\right)\int (Pf(x)-Pf(y))^2\pi(dx)\pi(dy) \qquad (23)\\
&\quad + \left(\frac{1}{2}+\frac{1}{2a\kappa}\right)\int \left((P-\widehat{P})f(x)-(P-\widehat{P})f(y)\right)^2\pi(dx)\pi(dy)\\
&\leq (1+a\kappa)\mathrm{var}_\pi(Pf)+\left(2+\frac{2}{a\kappa}\right)\int ((P-\widehat{P})f(x))^2\pi(dx).
\end{aligned}$$

Here we used $AB \leq \frac{a\kappa}{2}A^2 + \frac{2}{a\kappa}B^2$ to get the first inequality.

Next, note that

$$(1+a\kappa)\mathrm{var}_\pi(Pf(X)) \leq (1+a\kappa)(1-\kappa)\mathrm{var}_\pi f \leq (1-(1-a)\kappa)\mathrm{var}_\pi f. \qquad (24)$$

Let $\Delta f(x) = f(x) - \pi f$. Then,

$$\mathbb{E}_\pi\left[\left((P-\widehat{P})f(X)\right)^2\right] = \mathbb{E}_\pi\left[\left((P-\widehat{P})\Delta f(X)\right)^2\right] \leq \epsilon^2\|\Delta f\|_\pi^2 = \epsilon^2\mathrm{var}_\pi f. \qquad (25)$$

Plugging the bounds (24) and (25) into (23), we have

$$\mathrm{var}_\pi(\widehat{P}f) \leq \left(1-(1-a)\kappa+\frac{(2a\kappa+2)\epsilon^2}{a\kappa}\right)\mathrm{var}_\pi f.$$

Using induction with $C = 2 + 2/\kappa$, we find

$$\mathrm{var}_\pi(\widehat{P}^n f) \leq \left(1-(1-a)\kappa+\frac{C\epsilon^2}{a}\right)^n \mathrm{var}_\pi f.$$

For **Claim 2,** first note that

$$\begin{aligned}
\left|\int \widehat{P}f(x)\pi(dx)-\pi f\right| &= \left|\int (\widehat{P}-P)f(x)\pi(dx)\right|\\
&= \left|\int (\widehat{P}-P)\Delta f(x)\pi(dx)\right| \text{ recall that } \Delta f(x) = f(x)-\pi f\\
&\leq \left(\int \left((\widehat{P}-P)\Delta f(x)\right)^2\pi(dx)\right)^{1/2}\\
&= \|(P-\widehat{P})\Delta f\|_\pi \leq \epsilon\sqrt{\mathrm{var}_\pi f}.
\end{aligned}$$

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Then, because $\int Pg(x)\pi(dx) = \int g(x)\pi(dx)$ for any function g,

$$\left|\int (\widehat{P}^{n+1} - \widehat{P}^n)f(x)\pi(dx)\right| = \left|\int (\widehat{P} - P)(\widehat{P}^n f)(x)\pi(dx)\right| \\ \leq \epsilon\sqrt{\mathrm{var}_\pi(\widehat{P}^n f)} \leq \epsilon(1-\widehat{\kappa})^{n/2}\sqrt{\mathrm{var}_\pi f},$$

from Claim 1. Let $\mu_n = \pi\widehat{P}^n$ and $f = \mathrm{sgn}(\mu_{n+1} - \mu_n)$. Because $\mathrm{var}_\pi f \leq \mathbb{E}_\pi |f|^2 = 1$,

$$\|\mu_{n+1} - \mu_n\|_{TV} = \left|\int (\widehat{P}^{n+1} - \widehat{P}^n)f(x)\pi(dx)\right| \leq \epsilon(1-\widehat{\kappa})^{n/2}\sqrt{\mathrm{var}_\pi f} \leq \epsilon(1-\widehat{\kappa})^{n/2}.$$

Thus, μ_n is a Cauchy sequence under the total variation metric, which implies that the sequence has a limit $\widehat{\pi}$ and that

$$|(\widehat{\pi} - \mu_n)f| \leq \sum_{k=n}^{\infty} |(\mu_{k+1} - \mu_k)f| \leq \frac{\epsilon(1-\widehat{\kappa})^{n/2}}{1-(1-\widehat{\kappa})^{1/2}}\sqrt{\mathrm{var}_\pi f}$$

When letting $n = 0$, we have

$$|\widehat{\pi}f - \pi f| \leq \frac{\epsilon}{1-(1-\widehat{\kappa})^{1/2}}\sqrt{\mathrm{var}_\pi f} \tag{26}$$

Consider $f = \widehat{\pi}/\pi$. $D_{\chi^2}(\widehat{\pi}\|\pi) = |\widehat{\pi}f - \pi f| = \mathrm{var}_\pi f$. Combining this with (26), we have

$$D_{\chi^2}(\widehat{\pi}\|\pi) \leq \frac{\epsilon^2}{(1-(1-\widehat{\kappa})^{1/2})^2}.$$

Proof of Proposition 2. For the first claim, we note that

$$|\nu\widehat{P}^n f - \pi\widehat{P}^n f| \leq \int \frac{\nu(x)}{\pi(x)}\pi(dx)|\widehat{P}^n f(x) - \pi\widehat{P}^n f| \\ \leq \sqrt{\int \left(\frac{\nu(x)}{\pi(x)}\right)^2 \pi(dx)}\sqrt{\int |\widehat{P}^n f(x) - \pi\widehat{P}^n f|^2\pi(dx)} \\ \leq \sqrt{D_{\chi^2}(\nu\|\pi) + 1} \times (1-\hat{\kappa})^{n/2}\sqrt{\mathrm{var}_\pi f} \text{ by Theorem 3.}$$

Meanwhile,

$$|(\widehat{\pi} - \pi\widehat{P}^n)f| \leq C\epsilon(1-\hat{\kappa})^{n/2}\sqrt{\mathrm{var}_\pi f} \text{ by Theorem 3.}$$

By triangular inequality,

$$|\nu\widehat{P}^n f - \widehat{\pi}f| \leq |\nu\widehat{P}^n f - \pi\widehat{P}^n f| + |\pi\widehat{P}^n f - \widehat{\pi}f| \\ \leq (1-\widehat{\kappa})^{n/2}\sqrt{\mathrm{var}_\pi f}\left(\sqrt{D_{\chi^2}(\nu\|\pi) + 1} + C\epsilon\right).$$

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For the second part, we first note that for any f with $\widehat{\pi} f = 0$, we have

$$\begin{aligned}
\mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi} f)^2] &= \frac{1}{M^2}\mathbb{E}_{\widehat{\pi}}\left[\sum_{j,k=1}^{M} f(\widehat{X}_j) f(\widehat{X}_k)\right] \\
&\leq \frac{2}{M^2}\mathbb{E}_{\widehat{\pi}}\left[\sum_{j=1}^{M} |f(\widehat{X}_j)| \sum_{k=0}^{\infty} |f(\widehat{X}_{j+k})|\right] \\
&= \frac{2}{M}\sum_{k=0}^{\infty} \mathbb{E}_{\widehat{\pi}}\left[|f(\widehat{X}_0)||f(\widehat{X}_k)|\right] \\
&\leq \frac{2}{M}\sqrt{\mathbb{E}_{\widehat{\pi}}[f(\widehat{X}_0)^2]} \sum_{k=0}^{\infty} \sqrt{\mathbb{E}_{\widehat{\pi}}[(\widehat{P}^k f(\widehat{X}_0))^2]}.
\end{aligned}$$

Next,

$$\begin{aligned}
\mathrm{var}_{\widehat{\pi}}(\widehat{P}^k f) &= \widehat{\pi}(\widehat{P}^k f)^2 \\
&\leq \widehat{\pi}(\widehat{P}^k f - \pi \widehat{P}^k f)^2 \\
&\leq \pi(\widehat{P}^k f - \pi \widehat{P}^k f)^2 + \frac{\epsilon}{1-(1-\widehat{\kappa})^{1/2}}\sqrt{\mathrm{var}_{\pi}[(\widehat{P}^k f - \pi \widehat{P}^k f)^2]} \text{ by (26)} \\
&\leq (1-\widehat{\kappa})^k \mathrm{var}_{\pi}(f) + \frac{\epsilon}{1-(1-\widehat{\kappa})^{1/2}}\sqrt{\mathrm{var}_{\pi}[(\widehat{P}^k f - \pi \widehat{P}^k f)^2]} \text{ by Theorem 3.}
\end{aligned}$$

Because $\sup_x |f(x)| \leq C$ for some $C \in (0, \infty)$, $\sup_x |\widehat{P}^k f(x)| \leq C$ and $\sup_x |(\widehat{P}^k - \pi \widehat{P}^k) f(x)| \leq 2C$. Then

$$\pi(\widehat{P}^k f - \pi \widehat{P}^k f)^4 \leq 4C^2 \pi(\widehat{P}^k f - \pi \widehat{P}^k f)^2 \leq 4C^2(1-\widehat{\kappa})^k \mathrm{var}_{\pi} f \text{ by Theorem 3.}$$

Thus,

$$\mathrm{var}_{\widehat{\pi}}(\widehat{P}^k f) \leq (1-\widehat{\kappa})^k \mathrm{var}_{\pi}(f) + \frac{\epsilon}{1-(1-\widehat{\kappa})^{1/2}} 2C(1-\widehat{\kappa})^{\frac{k}{2}}\sqrt{\mathrm{var}_{\pi} f}$$

and we can further find a constant C' such that

$$\mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi} f)^2] \leq \frac{C'}{M(1-(1-\widehat{\kappa})^{1/4})}\sqrt{\mathrm{var}_{\widehat{\pi}} f \ \mathrm{var}_{\pi} f}.$$

Proof of Theorem 4. To simplify the notation, let κ denote the spectral gap of P and let $\widehat{\kappa}$ denote the spectral gap of $\widehat{P}$. By the definition of spectral gap, i.e. (15), we have

$$\widehat{\kappa} = \min_f \frac{\langle f, (I - \widehat{P}^2) f\rangle_{\widehat{\pi}}}{\mathrm{var}_{\widehat{\pi}} f}.$$

First, note that

$$\begin{aligned}
\mathrm{var}_{\widehat{\pi}} f &= \mathbb{E}_{\widehat{\pi}}[(f - \widehat{\pi} f)^2] \\
&\leq \mathbb{E}_{\widehat{\pi}}[(f - \pi f)^2] \\
&\leq (1+\epsilon)\mathbb{E}_{\pi}[(f - \pi f)^2] \\
&= (1+\epsilon)\mathrm{var}_{\pi} f.
\end{aligned} \tag{27}$$

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We next establish two useful bounds:

$$\begin{aligned} |\langle f, (I-P^2)f\rangle_{\widehat{\pi}} - \langle f, (I-P^2)f\rangle_{\pi}| &\le \int |f(x)(I-P^2)f(x)|\epsilon\pi(dx) \\ &\le \epsilon\|f\|_{\pi}\|(I-P^2)f\|_{\pi} \le \epsilon\|f\|_{\pi}^2, \end{aligned} \tag{28}$$

and

$$\begin{aligned} |\langle f, (\widehat{P}^2-P^2)f\rangle_{\widehat{\pi}}| &\le \|f\|_{\widehat{\pi}}\|(\widehat{P}^2-P^2)f\|_{\widehat{\pi}} \\ &\le (1+\epsilon)^2\|f\|_{\pi}\|(\widehat{P}^2-P^2)f\|_{\pi} \\ &\le (1+\epsilon)^2\|f\|_{\pi}(2\|(\widehat{P}-P)Pf\|_{\pi} + \|(\widehat{P}-P)^2f\|_{\pi}) \\ &\le (1+\epsilon)^2\|f\|_{\pi}(2\epsilon\|Pf\|_{\pi} + \epsilon\|(\widehat{P}-P)f\|_{\pi}) \\ &\le (1+\epsilon)^2\|f\|_{\pi}(2\epsilon\|f\|_{\pi} + \epsilon^2\|f\|_{\pi}) \\ &\le 3(1+\epsilon)^2\epsilon\|f\|_{\pi}^2 \\ &\le C\epsilon\|f\|_{\pi}^2. \end{aligned} \tag{29}$$

Then

$$\begin{aligned} |\langle f, (I-\widehat{P}^2)f\rangle_{\widehat{\pi}}| &\ge |\langle f, (I-P^2)f\rangle_{\widehat{\pi}}| - |\langle f, (\widehat{P}^2-P^2)f\rangle_{\widehat{\pi}}| \text{ by triangular inequality} \\ &\ge |\langle f, (I-P^2)f\rangle_{\widehat{\pi}}| - C\epsilon\|f\|_{\pi}^2 \text{ by the bound in (29)} \\ &\ge |\langle f, (I-P^2)f\rangle_{\pi}| - |\langle f, (I-P^2)f\rangle_{\pi} - \langle f, (I-P^2)f\rangle_{\widehat{\pi}}| - C\epsilon\|f\|_{\pi}^2 \\ &\ge |\langle f, (I-P^2)f\rangle_{\pi}| - C\epsilon\|f\|_{\pi}^2 - C\epsilon\|f\|_{\pi}^2 \text{ by the bound in (28)} \\ &\ge \langle f, (I-P^2)f\rangle_{\pi} - C\epsilon\mathrm{var}_{\pi}f. \end{aligned} \tag{30}$$

Combining (27) and (30), we have $\widehat{\kappa} \ge \kappa - C\epsilon$.

Proof of Proposition 3. For the first claim,

$$\begin{aligned} |\nu\widehat{P}^n f - \widehat{\pi}f| &= |\nu\widehat{P}^n f - \widehat{\pi}\widehat{P}^n f| \\ &\le \int \frac{\nu(x)}{\widehat{\pi}(x)}\widehat{\pi}(x)|\widehat{P}^n f(x) - \widehat{\pi}\widehat{P}^n f|dx \\ &\le \sqrt{\int \left(\frac{\nu(x)}{\widehat{\pi}(x)}\right)^2 \widehat{\pi}(x)dx}\sqrt{\int |\widehat{P}^n f(x) - \widehat{\pi}\widehat{P}^n f|^2\widehat{\pi}(x)dx} \\ &\le \sqrt{D_{\chi^2}(\nu\|\widehat{\pi}) + 1} \times (1-\hat{\kappa})^{n/2}\sqrt{\mathrm{var}_{\widehat{\pi}}f}. \end{aligned}$$

For the second part, we first note that if we replace f with $f - \widehat{\pi}f$, with a little change in notation, we have

$$\begin{aligned} \mathbb{E}_{\widehat{\pi}}[(\hat{f}_M - \widehat{\pi}f)^2] &= \frac{1}{M^2}\mathbb{E}_{\widehat{\pi}}\left[\sum_{j,k=1}^{M} f(\widehat{X}_j)f(\widehat{X}_k)\right] \\ &\le \frac{2}{M^2}\mathbb{E}_{\widehat{\pi}}\left[\sum_{j=1}^{M}|f(\widehat{X}_j)|\sum_{k=0}^{\infty}|f(\widehat{X}_{j+k})|\right] \\ &= \frac{2}{M}\sum_{k=0}^{\infty}\mathbb{E}_{\widehat{\pi}}\left[|f(\widehat{X}_0)||f(\widehat{X}_k)|\right] \end{aligned}$$

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$$\leq \frac{2}{M}\sqrt{\mathbb{E}_{\widehat{\pi}}[f(\widehat{X}_0)^2]}\sum_{k=0}^{\infty}\sqrt{\mathbb{E}_{\widehat{\pi}}[(\widehat{P}^k f(\widehat{X}_0))^2]}$$
$$\leq \frac{2}{M}\sqrt{\mathbb{E}_{\widehat{\pi}}[f(\widehat{X}_0)^2]}\sum_{k=0}^{\infty}(1-\widehat{\kappa})^{k/2}\sqrt{\mathrm{var}_{\widehat{\pi}} f}$$
$$= \frac{2}{M(1-(1-\widehat{\kappa})^{1/2})}\mathrm{var}_{\widehat{\pi}} f$$

Proof of Proposition 4. Let Q_x be the optimal coupled measure between $\delta_x P$ and $\delta_x \widehat{P}$. Then

$$|(\delta_x P - \delta_x \widehat{P})f| \leq \int Q_x(dx', dy')|f(x') - f(y')|$$
$$= \int Q_x(dx', dy')(|f(x') - f(y')|)1_{x' \neq y'}.$$

Next

$$\|(P-\hat{P})f\|_\pi^2 = \int \pi(dx)|(\delta_x P - \delta_x \widehat{P})f|^2$$
$$\leq \int \pi(dx)\left(\int Q_x(dx', dy')(|f(x') - f(y')|)1_{x' \neq y'}\right)^2$$
$$\leq \left(\int \pi(dx)Q_x(dx', dy')\left(2f(x')^2 + 2f(y')^2\right)\right)\left(\int \pi(dx)Q_x(dx', dy')1_{x' \neq y'}\right)$$
$$\leq 2\left(\langle \pi P, f^2\rangle + \langle \pi \widehat{P}, f^2\rangle\right)\left(\epsilon \int \pi(dx)V(x)\right)$$
$$\leq 2\epsilon\left(\langle \pi, f^2\rangle + a\langle \widehat{\pi}\widehat{P}, f^2\rangle\right)(\pi V)$$
$$\leq 2\epsilon\left(1+a^2\right)\|f\|_\pi^2\|V\|_\pi.$$

Appendix C. Verification for Metropolis–Hastings MCMC

We first present an auxiliary lemma, which is well known:

Lemma 4. *Suppose a transition kernel P is reversible with invariant measure π. Then $\|P\|_\pi \leq 1$.*

Proof We first note that

$$\int f(x)^2\pi(dx) - \int \pi(dx)f(x)f(y)P^2(x, dy)$$
$$= \frac{1}{2}\int \pi(dx)f(x)^2P^2(x, dy) + \frac{1}{2}\int \pi(dx)f(y)^2P^2(x, dy) - \int \pi(dx)f(x)f(y)P^2(x, dy)$$
$$= \frac{1}{2}\int \pi(dx)(f(x)-f(y))^2P^2(x, dy) \geq 0.$$

Thus,

$$\int f(x)^2\pi(dx) \geq \int \pi(dx)f(x)f(y)P^2(x, dy) = \|Pf\|_\pi^2.$$

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Proof of Lemma 1. For any density of the form $\mu(x) = \nu(x)s(x)$, we have

$$\begin{aligned}
|\mu(P-\widehat{P})f| &\le \int \mu(x)|\alpha(x)-\hat{\alpha}(x)||f(x)|dx + \int \mu(x)|\beta(x,x')-\hat{\beta}(x,x')||f(x')|dx'dx \\
&\le C\epsilon \int \mu(x)|f(x)|dx + C\epsilon \int \mu(x)\beta(x,x')|f(x')|dx'dx \\
&\le C\epsilon \int \mu(x)|f(x)|dx + C\epsilon \int \mu(x)P(x,x')|f(x')|dx'dx \\
&= C\epsilon \int \nu(x)s(x)|f(x)|dx + C\epsilon \int \nu(x)s(x)P(x,x')|f(x')|dx'dx \\
&\le C\epsilon\|s\|_\nu\|f\|_\nu + C\epsilon\|s\|_\nu\|Pf\|_\nu \\
&\le 2C\epsilon\|s\|_\nu\|f\|_\nu \text{ by Lemma 4.}
\end{aligned}$$

Next, taking $\mu \propto |(P-\widehat{P})f|\nu$, we have

$$\|(P-\widehat{P})f\|_\nu^2 \le 2C\epsilon\|(P-\widehat{P})f\|_\nu\|f\|_\nu,$$

which further implies that there is a C_1 such that $\|P-\widehat{P}\|_\nu \le C_1\epsilon$.

Proof of Proposition 5. We denote the acceptance probabilities for the original process and the perturbed process as

$$b(x,x') = \frac{\pi(x')}{\pi(x)} \wedge 1 \text{ and } \hat{b}(x,x') = \frac{\hat{\pi}(x')}{\hat{\pi}(x)} \wedge 1$$

respectively. Since for any positive numbers a, b, c, d,

$$\min\{a/b, c/d\} \le \frac{a\wedge c}{b\wedge d} \le \max\{a/b, c/d\},$$

and since $\exp(-C\epsilon) \le \pi(x)/\hat{\pi}(x) \le \exp(C\epsilon)$, we have

$$\exp(-2C\epsilon)b(x,x') < \hat{b}(x,x') < \exp(2C\epsilon)b(x,x').$$

Using the fact that $\beta(x,x') = R(x,x')b(x,x')$ and $\hat{\beta}(x,x') = R(x,x')\hat{b}(x,x')$, we have

$$\exp(-2C\epsilon)\beta(x,x') < \hat{\beta}(x,x') < \exp(2C\epsilon)\beta(x,x').$$

In addition, for $\alpha(x) = \int R(x,x')(1-b(x,x'))dx'$ and $\hat{\alpha}(x) = \int R(x,x')(1-\hat{b}(x,x'))dx'$,

$$|\alpha(x)-\hat{\alpha}(x)| \le \int R(x,x')|b(x,x')-\hat{b}(x,x')|dx' \le C\epsilon.$$

By Lemma 1, we can find a C_1 such that

$$\|P_{RWM} - \widehat{P}_{RWM}\|_\pi \le C_1\epsilon.$$

Proof of Proposition 6. Note that

$$R(x,x') = \frac{1}{(4\pi h)^{d/2}} \exp\left(-\frac{1}{4h}\|x'-x-\nabla\log\pi(x)h\|^2\right),$$

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and

$$\widehat{R}(x, x') = \frac{1}{(4\pi h)^{d/2}} \exp\left(-\frac{1}{4h}\|x' - x - \nabla \log \hat{\pi}(x)h\|^2\right).$$

As $|\nabla \log \widehat{\pi}(x) - \nabla \log \pi(x)| \le C\epsilon$ and the support is bounded, we can enlarge the value of C so that

$$(1 - C\epsilon)R(x, x') \le \widehat{R}(x, x') \le (1 + C\epsilon)R(x, x'),$$

Let the acceptance probability be

$$\begin{aligned} b(x, x') &= \frac{\pi(x') \exp\left(-\frac{1}{4h}\|x - x' + \nabla \log \pi(x')h\|^2\right)}{\pi(x) \exp\left(-\frac{1}{4h}\|x' - x + \nabla \log \pi(x)h\|^2\right)} \wedge 1 \\ &= \left\{\exp\left(\log \pi(x') - \log \pi(x) - \frac{1}{2}\langle x - x', \nabla \log \pi(x') - \nabla \log \pi(x)\rangle\right)\right. \\ &\quad \left.\times \exp\left(\frac{h}{4}\left[\|\nabla \log \pi(x')\|^2 - \|\nabla \log \pi(x)\|^2\right]\right)\right\} \wedge 1 \end{aligned}$$

Similarly, we define

$$\begin{aligned} \hat{b}(x, x') &= \frac{\hat{\pi}(x') \exp\left(-\frac{1}{4h}\|x - x' + \nabla \log \hat{\pi}(x')h\|^2\right)}{\hat{\pi}(x) \exp\left(-\frac{1}{4h}\|x' - x + \nabla \log \hat{\pi}(x)h\|^2\right)} \wedge 1 \\ &= \left\{\exp\left(\log \hat{\pi}(x') - \log \hat{\pi}(x) - \frac{1}{2}\langle x - x', \nabla \log \hat{\pi}(x') - \nabla \log \hat{\pi}(x)\rangle\right)\right. \\ &\quad \left.\times \exp\left(\frac{h}{4}\left[\|\nabla \log \hat{\pi}(x')\|^2 - \|\nabla \log \hat{\pi}(x)\|^2\right]\right)\right\} \wedge 1 \end{aligned}$$

Since $|\log \pi(x) - \log \widehat{\pi}_k(x)| \le C\epsilon$, $\|\nabla \log \pi(x) - \nabla \log \widehat{\pi}_k(x)\| \le C\epsilon$, and the support is bounded, we can further enlarge C such that

$$(1 - C\epsilon)b(x, x') \le \hat{b}(x, x') \le (1 + C\epsilon)b(x, x').$$

Lastly, for $\beta(x, x') = R(x, x')b(x, x')$ and $\hat{\beta}(x, x') = \hat{R}(x, x')\hat{b}(x, x')$,

$$(1 - C\epsilon)\beta(x, x') \le \hat{\beta}(x, x') \le (1 + C\epsilon)\beta(x, x').$$

In addition, for $\alpha(x) = \int R(x, x')(1 - b(x, x'))dx'$ and $\hat{\alpha}(x) = \int \hat{R}(x, x')(1 - \hat{b}(x, x'))dx'$,

$$\begin{aligned} |\alpha(x) - \hat{\alpha}(x)| &\le \int |R(x, x') - \hat{R}(x, x')|(1 - b(x, x'))dx' \\ &\quad + \int \hat{R}(x, x')|b(x, x') - \hat{b}(x, x')|dx' \\ &\le C\epsilon \int R(x, x')dx' + C\epsilon \int \hat{R}(x, x')dx' = 2C\epsilon \end{aligned}$$

By Lemma 1, we have a constant C_1 such that

$$\|P_{MALA} - \widehat{P}_{MALA}\|_\pi \le C_1\epsilon.$$

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Proof of Proposition 7. The transition kernel of MALA takes the form

$$P(x, y) = \alpha(x)\delta_x(y) + \beta(x, y)$$

where

$$\beta(x, y) = \frac{\pi(y)}{\pi(x)} q(y, x) \wedge q(x, y) = a(x, y) \wedge q(x, y),$$

with

$$q(x, y) = \frac{1}{(2\pi h)^{d/2}} \exp\left(-\frac{1}{4h}\|y - x - \nabla \log \pi(x)h\|^2\right), \; a(x, y) = \frac{\pi(y)}{\pi(x)} q(y, x),$$

and $\alpha(x) = 1 - \int \beta(x, dy)$. Similarly, we can write $\widehat{P}(x, y) = \widehat{\alpha}(x)\delta_x(y) + \widehat{\beta}(x, y)$ when using the perturbed target density $\widehat{\pi}$.

We prove the proposition by showing that

$$\int |q(x, y) - \hat{q}(x, y)|dy \le C\epsilon \text{ and } \int |a(x, y) - \widehat{a}(x, y)|dy \le C\epsilon \exp(\delta x^2). \tag{31}$$

In particular, note that $a \wedge q - \widehat{a} \wedge \widehat{q} \in \{a - \hat{a}, q - \hat{q}, a - \hat{q}, \hat{a} - q\}$, which further implies that

$$|a \wedge q - \widehat{a} \wedge \widehat{q}| \le |a - \widehat{a}| + |q - \widehat{q}|.$$

Thus, if the bounds in (31) hold, then

$$\begin{aligned}
\|\delta_x P - \delta_x \widehat{P}\|_{TV} &= \int |\beta(x, y) - \widehat{\beta}(x, y)|dy + |\alpha(x) - \widehat{\alpha}(x)| \\
&\le 2 \int |\beta(x, y) - \widehat{\beta}(x, y)|dy \\
&\le 2 \int |a(x, y) - \widehat{a}(x, y)|dy + 2 \int |q(x, y) - \widehat{q}(x, y)|dy \\
&\le 2C\epsilon(1 + \exp(\delta x^2)).
\end{aligned}$$

In order to obtain the first part of (31), note that by the intermediate value theorem, $|\exp(a) - \exp(b)| \le |\exp(a) + \exp(b)||a - b|$ holds for any a, b, so we can bound

$$\begin{aligned}
|q(x, y) - \hat{q}(x, y)| \le& \frac{1}{4}|q(x, y) + \hat{q}(x, y)|\|\nabla \log \pi(x) - \nabla \log \widehat{\pi}(x)\| \\
&(\|y - x - h\nabla \log \pi(x)\| + \|y - x - h\nabla \log \widehat{\pi}(x)\|) \\
\le& \frac{C\epsilon}{4}|q(x, y) + \hat{q}(x, y)| \left(\|y - x - h\nabla \log \pi(x)\| + \|y - x - h\nabla \log \widehat{\pi}(x)\|\right).
\end{aligned} \tag{32}$$

Note that $q(x, y)$ is the proposal density of y. Thus,

$$\begin{aligned}
&\int q(x, y) \left(\|y - x - h\nabla \log \pi(x)\| + \|y - x - h\nabla \log \widehat{\pi}(x)\|\right) dy \\
&\le \int q(x, y) \left(2\|y - x - h\nabla \log \pi(x)\| + Ch\epsilon\right) dy \\
&\le Ch\epsilon + 2\sqrt{\int q(x, y)\|y - x - h\nabla \log \pi(x)\|^2 dy} = Ch\epsilon + 2\sqrt{2hd}.
\end{aligned}$$

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Similarly,

$$\int \hat{q}(x,y)\left(\|y-x-h\nabla\log\pi(x)\|+\|y-x-h\nabla\log\widehat{\pi}(x)\|\right)dy \le Ch\epsilon+2\sqrt{2hd}.$$

Therefore, we use (32) and find a larger C such that

$$\int |q(x,y)-\hat{q}(x,y)|dy \le C\epsilon.$$

To handle the second part of (31), we use $|\exp(a)-\exp(b)| \le |\exp(a)+\exp(b)||a-b|$ again and find

$$\begin{aligned}
&|a(x,y)-\widehat{a}(x,y)|\\
=&\left|\frac{\pi(y)}{\pi(x)}q(y,x)-\frac{\widehat{\pi}(y)}{\widehat{\pi}(x)}\hat{q}(y,x)\right|\\
\le&\frac{1}{4}\left|\frac{\pi(y)}{\pi(x)}q(y,x)+\frac{\widehat{\pi}(y)}{\widehat{\pi}(x)}\hat{q}(y,x)\right|\Bigg(|\log\pi(x)-\log\widehat{\pi}(x)|+|\log\pi(y)-\log\widehat{\pi}(y)|\\
&+\|\nabla\log\pi(y)-\nabla\log\widehat{\pi}(y)\|\left(\|y+h\nabla\log\pi(y)-x\|+\|y+h\nabla\log\widehat{\pi}(y)-x\|\right)\Bigg)\\
\le&\frac{C\epsilon}{4}\left|\frac{\pi(y)}{\pi(x)}q(y,x)+\frac{\widehat{\pi}(y)}{\widehat{\pi}(x)}\hat{q}(y,x)\right|\left(2+\left(\|y+h\nabla\log\pi(y)-x\|+\|y+h\nabla\log\widehat{\pi}(y)-x\|\right)\right).
\end{aligned}$$

Note that the first part can be bounded by

$$\begin{aligned}
&\int \frac{\pi(y)}{\pi(x)}q(y,x)\left(C+\left(\|y+h\nabla\log\pi(y)-x\|+\|y+h\nabla\log\widehat{\pi}(y)-x\|\right)dx\right.\\
\le&\int \frac{\pi(y)}{\pi(x)}q(y,x)\left(C+h\epsilon+2\|y+h\nabla\log\pi(y)-x\|\right)dx\\
=&\int \frac{\pi(y)}{(2\pi h)^{d/4}\pi(x)}\sqrt{q(y,x)}\cdot(2\pi h)^{d/4}\sqrt{q(y,x)}\left(C+h\epsilon+2\|y+h\nabla\log\pi(y)-x\|\right)dx
\end{aligned}$$

For $\frac{\pi(y)}{\pi(x)}(2\pi h)^{-d/4}\sqrt{q(y,x)}$, we can bound it by

$$\begin{aligned}
&\frac{1}{(2\pi h)^{d/4}}\frac{\pi(y)}{\pi(x)}\sqrt{q(y,x)}\\
=&\frac{1}{(2\pi h)^{d/2}}\exp\left(\log\pi(y)-\log\pi(x)-\frac{1}{8h}\|y+h\nabla\log\pi(y)-x\|^2\right)\\
\le&\frac{1}{(2\pi h)^{d/2}}\exp\left(\langle\nabla\log\pi(w),y-x\rangle-\frac{1}{8h}\|y-x\|^2-\frac{1}{4}\langle\nabla\log\pi(y),y-x\rangle\right)\text{ for some }w\\
\le&\frac{1}{(2\pi h)^{d/2}}\exp\left(\frac{5L_\pi}{4}\|y-x\|(\|x\|+\|y-x\|+C)-\frac{1}{8h}\|y-x\|^2\right)\text{ by Lipschitzness of }\nabla\log\pi\\
\le&\frac{1}{(2\pi h)^{d/2}}\exp\left(\left(\frac{5L_\pi}{16\delta}+\frac{5L_\pi}{4}-\frac{1}{8h}\right)\|y-x\|^2+\delta\|x\|^2+10L_\pi^2C^2\right)\\
\le&\frac{1}{(2\pi h)^{d/2}}\exp\left(-\frac{1}{16h}\|y-x\|^2+\delta\|x\|^2+10L_\pi^2C^2\right)\text{ as }h<\left(\tfrac{5L_\pi}{\delta}+20L_\pi\right)^{-1}.
\end{aligned}$$

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For $(2\pi h)^{d/4}\sqrt{q(y,x)}\,(C+h\epsilon+2\|y+h\nabla\log\pi(y)-x\|)$, first note that we can find a larger C such that

$$\begin{aligned}&(2\pi h)^{d/4}\sqrt{q(y,x)}\|y+h\nabla\log\pi(y)-x\|\\&=\exp\left(-\frac{1}{8h}\|y+h\nabla\log\pi(y)-x\|^2\right)\|y+h\nabla\log\pi(y)-x\|\le C.\end{aligned}$$

Combining these two upper bounds, we can find a C_1 such that

$$\int\frac{\pi(y)}{\pi(x)}q(y,x)\,(C+h\epsilon+2\|y+h\nabla\log\pi(y)-x\|)\,dx\le C_1\exp(\delta\|x\|^2).$$

Similarly, we can show that

$$\begin{aligned}&\int\frac{\widehat{\pi}(y)}{\widehat{\pi}(x)}\hat{q}(y,dx)\,(C+(\|y+h\nabla\log\pi(y)-x\|+\|y+h\nabla\log\widehat{\pi}(y)-x\|)\\&\le\int\frac{\widehat{\pi}(y)}{\widehat{\pi}(x)}\hat{q}(y,dx)\,(C+h\epsilon+2\|y+h\nabla\log\widehat{\pi}(y)-x\|)\le C\exp(\delta\|x\|^2).\end{aligned}$$

Thus, $\int|a(x,y)-\widehat{a}(x,y)|dy\le C\epsilon\exp(\delta x^2)$ for some C. This concludes the proof of (35) and our claim.

Appendix D. Verification for the parallel tempering algorithm

Proof of Lemma 2. For claim 1, note that for any $\|f\|_\nu\le 1$,

$$\begin{aligned}\|RSf-\widehat{R}\widehat{S}f\|_\nu&\le\|R(S-\widehat{S})f\|_\nu+\|(R-\widehat{R})\widehat{S}f\|_\nu\\&\le\|(S-\widehat{S})f\|_\nu+C\epsilon\|\widehat{S}f\|_\nu\text{ by Lemma 4}\\&\le C\epsilon\|f\|_\nu+C\epsilon\|(\widehat{S}-S)f\|_\nu+C\epsilon\|Sf\|_\nu\\&\le(2C+C^2\epsilon)\epsilon\|f\|_\nu\text{ by Lemma 4.}\end{aligned}$$

For claim 2, we first note that

$$R_1\otimes R_2=(R_1\otimes I)(I\otimes R_2)$$

We will show that

$$\|(R_1\otimes I)-(\widehat{R}_1\otimes I)\|_\nu=\|((R_1-\widehat{R}_1)\otimes I)\|_\nu\le C\epsilon.$$

For any $f(x,y)$, we define

$$g(x,y):=((R_1-\widehat{R}_1)\otimes I)f(x,y)$$

Then for each fixed y, since $\|R_1-\widehat{R}_1\|_{\nu_1}\le C\epsilon$,

$$\int g(x,y)^2\nu_1(x)dx\le C^2\epsilon^2\int f(x,y)^2\nu_1(x)dx$$

Thus,

$$\|g\|_\nu^2=\int g(x,y)^2\nu_1(x)\nu_2(y)dxdy\le C^2\epsilon^2\int\int f(x,y)^2\nu_1(x)\nu_2(y)dxdy=C^2\epsilon^2\|f\|_\nu^2.$$

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Similarly, we can show that

$$\|(I \otimes R_2) - (I \otimes \widehat{R}_2)\|_\nu = \|I \otimes (R_2 - \widehat{R}_2)\|_\nu \leq C\epsilon.$$

From claim 1, we can find a C' so that

$$\|R_1 \otimes R_2\|_\nu = \|(R_1 \otimes I)(I \otimes R_2)\|_\nu \leq C'\epsilon.$$

For claim 3, by triangular inequality, we have

$$\|U - \widehat{U}\|_\nu \leq \frac{1}{n}\sum_{i=1}^{n} \|S_i - \widehat{S}_i\|_\nu \leq C\epsilon.$$

Proof of Lemma 3. Denote $x' = S(x)$. For any density of form $\mu(x) = s(x)\nu(x)$, we have

$$\begin{aligned}
|\mu(Q - \widehat{Q})f| &\leq \int \mu(x)|a(x,x') - \widehat{a}(x,x')||f(x)|dx + \int \mu(x)|a(x,x') - \widehat{a}(x,x')||f(x')|dx \\
&\leq C\epsilon \int \mu(x)|f(x)|dx + C\epsilon \int \mu(x)a(x,x')|f(x')|dx \\
&\leq C\epsilon \int s(x)\nu(x)|f(x)|dx + C\epsilon \int s(x)\nu(x)(Q(x,x)|f(x)| + Q(x,x')|f(x')|)dx \\
&\leq C\epsilon\|s\|_\nu\|f\|_\nu + C\epsilon\|s\|_\nu\|Q|f|\|_\nu \\
&\leq 2C\epsilon\|s\|_\nu\|f\|_\nu.
\end{aligned}$$

Taking $\mu(x) \propto |(Q - \widehat{Q})f(x)|\nu(x)$, we have the result.

Proof of Proposition 8. Recall that

$$P = MQ, \quad M = (M_0 \otimes \cdots \otimes M_K), \quad Q = \left(\frac{1}{K}\sum_{k\in\{0,\ldots,K-1\}} Q_{k,k+1}\right).$$

and

$$\widehat{P} = \widehat{M}\widehat{Q}, \quad \widehat{M} = \left(\widehat{M}_0 \otimes \cdots \otimes \widehat{M}_K\right), \quad \widehat{Q} = \left(\frac{1}{K}\sum_{k\in\{0,\ldots,K-1\}} \widehat{Q}_{k,k+1}\right).$$

Since M is a product of M_k, Lemma 2 claim 2 indicates that $\|M - \widehat{M}\|_\Pi \leq C_1\epsilon$ for some C_1. Then note that if $a \leq CA$, $b \leq CB$, then $\min\{a,b\} \leq C\min\{A,B\}$ so the acceptance probability of $Q_{k,k+1}$ and $\widehat{Q}_{k,k+1}$ satisfies

$$\frac{\alpha_k(x,x')}{\widehat{\alpha}_k(x,x')} \leq \sup_{x,x'}\left\{\frac{\pi_k(x')\pi_{k+1}(x)\widehat{\pi}_k(x)\widehat{\pi}_{k+1}(x')}{\widehat{\pi}_k(x')\widehat{\pi}_{k+1}(x)\pi_k(x)\pi_{k+1}(x')}\right\} \leq (1 + C_1\epsilon)^4 \leq 1 + D\epsilon$$

for some constant D. Then Lemma 3 indicates that $\|Q_{k,k+1} - \widehat{Q}_{k,k+1}\|_\Pi \leq C_2\epsilon$ for some C_2 and Lemma 2 claim 3 indicates that for some C_3,

$$\|Q - \widehat{Q}\|_\Pi \leq C_3\epsilon.$$

Finally, we use claim 1 from Lemma 2 and find that $\|P - \widehat{P}\|_\Pi \leq C'\epsilon$ for some C'.

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There were no competing interests that arose during the preparation or publication process of this article to declare.

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