
Gradient-free Hamiltonian Monte Carlo with Efficient Kernel exponential families

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Abstract

We propose *Kamiltonian Monte Carlo (KMC)*, a gradient-free adaptive MCMC algorithm based on Hamiltonian Monte Carlo (HMC). On target densities where HMC is unavailable due to intractable gradients, KMC adaptively learns the target’s gradient structure by fitting an exponential family model in a Reproducing Kernel Hilbert Space. Computational costs are reduced by two novel efficient approximations to this gradient. While being asymptotically exact, KMC mimics HMC in terms of sampling efficiency and offers substantial mixing improvements to state-of-the-art gradient free samplers. We support our claims with experimental studies on both toy and real-world applications, including Approximate Bayesian Computation and exact-approximate MCMC.

1 Introduction

Estimating expectations using Markov Chain Monte Carlo (MCMC) is a fundamental approximate inference technique in Bayesian statistics. MCMC itself can be computationally demanding, and the expected estimation error depends directly on the correlation between successive points in the Markov chain. Therefore, MCMC efficiency can be achieved by taking large steps with high probability.

Hamiltonian Monte Carlo (HMC) [1] is an MCMC algorithm that improves efficiency by exploiting gradient information. It simulates particle movement along the contour lines of a dynamical system which is constructed from the target density. Projections of these trajectories cover wide parts of the target’s support, and the probability of accepting a move along a trajectory is often close to one. Remarkably, this property is mostly invariant to dimensionality. Thus, HMC is often superior to random walk methods, which need to decrease their step size at a much faster rate to maintain a reasonable acceptance probability with increasing dimension [1, Sec. 4.4].

Unfortunately, for a large class of problems, gradient information is not available. For example, in Pseudo-Marginal MCMC (PM-MCMC) [2, 3], the posterior density does not have an analytic expression even up to a normalising constant, e.g. in Bayesian Gaussian Process classification [4]. Therefore, it can only be estimated at any given point. A related context is MCMC for Approximate Bayesian Computation (ABC-MCMC), where a Bayesian posterior has to be approximated through repeated simulation from a likelihood model [5, 6]. In both cases, plain HMC cannot be applied, leaving random walk methods as the only mature alternative. Recently, there have been efforts to mimic HMC’s behaviour using stochastic gradients from mini-batches in Big Data [7], or stochastic finite differences in ABC [8]. However, stochastic gradient based HMC methods often suffer from low acceptance rates or additional bias that is hard to quantify [9].

Random walk methods can be tuned by proposing local steps whose scaling matches the target density. For example, Adaptive Metropolis-Hastings (AMH) [10, 11] is based on learning the global linear scaling of a target density from the history of the Markov chain. Yet, for densities with non-linear support across components, this approach does not work very well. Recently, [12] introduced

a Kernel Adaptive Metropolis-Hastings (KAMH) algorithm, with proposals locally aligned to the target density. By adaptively learning target covariance in a Reproducing Kernel Hilbert Space (RKHS), KAMH achieves improved sampling efficiency.

In this paper, we extend the idea of using kernel methods to learn efficient proposal distributions [12]. Rather than *locally* smoothing the target density, however, we estimate its gradients *globally*. More precisely, we fit an (unnormalised) infinite dimensional exponential family model in a RKHS via score matching [13, 14]. This is a non-parametric method to model the log unnormalised target density as an RKHS function, and has been shown to approximate a rich class of density functions arbitrarily well. More importantly, the method has been empirically observed to be relatively robust to increasing dimensionality – in sharp contrast to classical kernel density estimation, [15, Sec. 6.5]. A Gaussian Process (GP) was also used in [16] as an emulator of the target density in order to speed up HMC, however this work requires access to the log target density in closed form, to provide training points for the GP regressor.

We require our adaptive algorithm to be computationally efficient, as it deals with high-dimensional MCMC chains of growing length. Thus, we develop two novel approximations to the infinite dimensional exponential family model. The first approximation, *score matching lite*, is based on computing the solution in terms of a lower dimensional, yet growing, subspace in the RKHS. KMC with score matching lite (*KMC lite*) is geometrically ergodic on the same class of targets as standard random walks. The second approximation uses a finite dimensional feature space (*KMC finite*), combined with the random Fourier features framework of [17]. This results in an extremely efficient online estimator that allows to use all of the Markov chain history, at the cost of decreased efficiency when initialised in the tails. A choice between KMC lite and KMC finite will ultimately depend on the ability to initialise the sampler within high-density regions of the target density; alternatively the two approaches could be combined.

Experiments show that KMC inherits the efficiency of HMC, and therefore mixes significantly better than state-of-the-art gradient-free adaptive samplers on a number of target densities, including on synthetic examples, and when used in PM-MCMC and ABC-MCMC.

Paper outline: In Section 2, we place our contribution in the context of previous work and cover HMC basics. Section 3 introduces Hamiltonian dynamics induced by kernel exponential families. Section 4 contains our approximate estimators of the log density and its gradient, and Section 5 applies these results to obtain our Kamiltonian Monte Carlo algorithm. We demonstrate the efficiency of KMC in a number of experiments in Section 6.

2 Background and Previous Work

Let the domain of interest \mathcal{X} be a compact¹ subset of \mathbb{R}^d , and denote the unnormalised *target* density on \mathcal{X} by π . We are interested in constructing a Markov chain $x_1 \rightarrow x_2 \rightarrow \dots$ such that $\lim_{t \rightarrow \infty} x_t \sim \pi$. By running the Markov chain for a long time T , we can consistently approximate any expectation w.r.t π . Markov chains are constructed using the Metropolis-Hastings algorithm, which at the current state x_t draws a point from a proposal mechanism $x^* \sim Q(\cdot|x_t)$, and sets $x_{t+1} \leftarrow x^*$ with probability $\min(1, [\pi(x^*)Q(x_t|x^*)]/[\pi(x_t)Q(x^*|x_t)])$, and $x_{t+1} \leftarrow x_t$ otherwise. In this paper, we generally assume that π is intractable², i.e. that we can neither evaluate $\pi(x)$ nor³ $\nabla \log \pi(x)$ for any x , but can compute unbiased estimates of $\pi(x)$. Replacing $\pi(x)$ with an unbiased estimator results in PM-MCMC [2, 3], which asymptotically remains exact (*exact-approximate inference*).

(Kernel) Adaptive Metropolis-Hastings In the absence of $\nabla \log \pi$, the usual choice of Q is a random walk, i.e. $Q(\cdot|x_t) = \mathcal{N}(\cdot|x_t, \Sigma_t)$. A popular choice of the scaling is $\Sigma_t \propto I$. When the (unknown) scale of the target density is not uniform across dimensions, or if there are strong correlations, the original AMH algorithm [10, 11] improves mixing by adaptively learning global covariance structure of π from the history of the Markov chain. For cases where the local scaling does not match the global covariance structure of π , for instance when the support of the target is highly nonlinear, KAMH [12] improves mixing by learning the target covariance structure in a

¹The compactness restriction is imposed to satisfy the assumptions in [13].

²Unavailable due to analytic intractability, as opposed to computationally expensive in the Big Data context.

³Throughout the paper ∇ denotes the gradient operator wrt. to x .

RKHS. KAMH proposals are Gaussian with a covariance that matches the local covariance of π around the current state x_t , without requiring access to $\nabla \log \pi$.

Hamiltonian Monte Carlo Hamiltonian Monte Carlo (HMC) often overcomes random walk behaviour by utilising deterministic, measure-preserving maps to generate efficient Markov transitions that [1, 18]. Starting from the negative log unnormalised target density, referred to as the *potential energy* $U(q) \propto -\log \pi(q)$, we introduce an auxiliary *momentum* variable $p \sim \exp(-K(p))$ with $p \in \mathcal{X}$. The joint distribution of (p, q) is then proportional to $\exp(-H(p, q))$, where $H(p, q) := K(p) + U(q)$ is called the *Hamiltonian*. $H(p, q)$ defines a *Hamiltonian flow*, parametrised by a trajectory length $t \in \mathbb{R}$, which is a map $\phi_t^H : (p, q) \mapsto (p^*, q^*)$ for which $H(p^*, q^*) = H(p, q)$ for any $t \in \mathbb{R}$. This allows construction of π -invariant Markov chains: for a chain at state $q = x_t$, we repeatedly (i) re-sample $p' \sim \exp(-K(\cdot))$, and then (ii) apply the Hamiltonian flow for time t , giving $(p^*, q^*) = \phi_t^H(p', q)$. The flow can be generated by the *Hamiltonian operator*

$$\hat{H} := \frac{\partial K}{\partial p} \frac{\partial}{\partial q} - \frac{\partial U}{\partial q} \frac{\partial}{\partial p} =: \hat{K} + \hat{U}. \quad (1)$$

In practice, \hat{H} is usually unavailable and we need to resort to approximations. Here, we limit ourselves to the leap-frog integrator; see [1] for details. To correct for discretisation error, a Metropolis acceptance procedure can be applied: starting from (p', q) , the end-point of the approximate trajectory is accepted with probability $\min[1, \exp(-H(p^*q^*) + H(q, p'))]$. HMC is often able to propose distant, uncorrelated moves with a high acceptance probability.

Intractable densities In many cases the gradient of $\log \pi(q) = -U(q)$ is unavailable, leaving random-walk based methods as the state-of-the-art [12, 11]. KMC aims to overcome random-walk behaviour, so as to obtain significantly more efficient sampling [1].

3 Kernel Induced Hamiltonian Dynamics

KMC replaces the potential energy operator \hat{U} in (1) by a kernel induced surrogate \hat{U}_k computed from the history of the Markov chain. As we will see, this surrogate does not require gradients of the log-target density. The surrogate induces a kernel Hamiltonian flow, which can be numerically simulated using standard leap-frog integration. As with the discretisation error in HMC, any deviation of the kernel induced flow to the true flow is corrected via a Metropolis acceptance procedure. Consequently, the stationary distribution of the Markov chain will remain correct.⁴

Infinite Exponential Families in a RKHS We construct a kernel induced potential energy surrogate whose gradients match the gradients of the true potential energy \hat{U} in (1), or $\log \pi(x)$, but without accessing π or $\nabla \pi$ directly. We fit an infinite dimensional exponential family model [13] of the form

$$\exp(\langle f, k(x, \cdot) \rangle_{\mathcal{H}} - A(f)). \quad (2)$$

Here \mathcal{H} is a RKHS of real valued functions on \mathcal{X} . The RKHS has a uniquely associated symmetric, positive definite *kernel* $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$, which satisfies $f(x) = \langle f, k(x, \cdot) \rangle$ for any $f \in \mathcal{H}$, [19]. The canonical feature map $k(\cdot, x) \in \mathcal{H}$ here takes the role of the *sufficient statistics* while $f \in \mathcal{H}$ are the *natural parameters*, and $A(f) := \log \int_{\mathcal{X}} \exp(\langle f, k(x, \cdot) \rangle_{\mathcal{H}}) dx$ is the cumulant generating function. (2) defines broad class of densities: when universal kernels are used, the family is dense in the space of continuous densities on compact domains, with respect to the Total Variation, KL, and Hellinger divergences [13, Section 3]. It is possible to consistently fit an *unnormalised* version of (2) by directly minimising the expected gradient mismatch between the model (2) and the true target density π (observed through samples). This is achieved by generalizing the score matching approach [14] to infinite dimensional parameter spaces. The technique avoids the problem of dealing with the intractable $A(f)$, and reduces the problem to solving a linear system. More importantly, the approach is observed to be relatively robust to increasing dimensions, as opposed to classic kernel density estimation. We will return to the topic of estimation in Section 4, where we develop two efficient approximate empirical estimators. For now, assume access to an $f \in \mathcal{H}$ such that $\nabla f(x) \approx \nabla \log \pi(x)$.

⁴As usual when constructing adaptive MCMC algorithms, we will need to take care when generating proposals based on the history of the Markov chain.

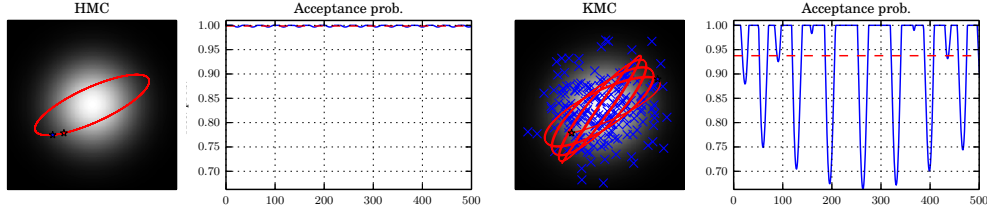


Figure 1: Hamiltonian trajectories on a 2-dimensional standard Gaussian. End points of such trajectories (red stars to blue stars) form the proposal of HMC-like algorithms. **Left:** Plain Hamiltonian trajectories oscillate on a stable orbit, and acceptance probability is close to one. **Right:** Kernel induced trajectories and acceptance probabilities on an estimated energy function.

Kernel Induced Hamiltonian Flow We define a kernel induced Hamiltonian operator $\hat{H}_k := \hat{K} + \hat{U}_k$, where \hat{K} is defined as in (1), and we have replaced the potential energy U with the kernel surrogate $U_k = f$. This induces a kernel induced potential energy operator $\hat{U}_k = \frac{\partial U_k}{\partial p} \frac{\partial}{\partial q}$ and a corresponding kernel Hamiltonian flow. It is clear that the kernel induced potential energy operator results in different trajectories than those induced by the true operator (1). That said, any bias on the resulting Markov chain, in addition to discretisation error from the leap-frog integrator, is naturally corrected for in the Metropolis step. We accept an end-point $\phi_t^{\hat{H}}(p', q)$ of a trajectory starting at (p', q) along the *kernel induced* flow with probability

$$\min \left[1, \exp \left(H \left(\phi_t^{\hat{H}_k}(p', q) \right) - H(p', q) \right) \right], \quad (3)$$

where $H \left(\phi_t^{\hat{H}_k}(p', q) \right)$ denotes evaluation of the *true* Hamiltonian at $\phi_t^{\hat{H}_k}(p', q)$. Any deviations of the kernel induced flow from the true flow results in a decreased acceptance probability (3). We therefore need to control the approximation quality of the kernel induced potential energy to maintain high acceptance probability in practice. See Figure 1 for an illustrative example.

4 Two Efficient Estimators for Infinite Exponential Families in RKHS

We now address the topic of estimating the infinite dimensional exponential family model (2) from data. The original estimator in [13] has large computational costs. This is problematic in the adaptive MCMC context, where the model has to be updated on a regular basis. We propose two efficient approximations, each with its particular strengths and weaknesses. Both the original estimator for (2) and our approximations are based on score matching, see Appendix A.1 for a brief review.

4.1 Infinite Exponential Families Lite

The original estimator of f in (2) takes a dual form in a RKHS sub-space spanned by $nd + 1$ kernel derivatives, [13, Thm. 4]. The update of the proposal at the iteration t of MCMC requires inversion of a $(td + 1) \times (td + 1)$ matrix. This is clearly prohibitive if we are to run even a moderately large number of iterations of a Markov chain. Following [12], we take a simple approach to avoid prohibitive computational costs in t : we form a proposal using a random sub-sample of a fixed size n from the Markov chain history, $\mathbf{z} := \{z_i\}_{i=1}^n \subseteq \{x_i\}_{i=1}^t$. In order to reduce excessive computational costs arising when d is large, we develop an approximation to the full dual solution in [13] by expressing the solution in terms of $\text{span}(\{k(z_i, \cdot)\}_{i=1}^n)$, which covers the support of the true density by construction, and grows with increasing n . That is, we assume that the log unnormalised density of the model in (2) takes the dual form

$$f(x) = \sum_{i=1}^n \alpha_i k(z_i, x), \quad (4)$$

where $\alpha \in \mathbb{R}^n$ are real valued parameters that are obtained by minimising the empirical score matching objective (see (9) in Appendix A.1). This representation is of a form similar to [20, Section 4.1], the main differences being that the basis functions are chosen randomly, the basis set grows with n , and we will require an additional regularizing term. The estimator is summarised in the following proposition, which is proved in Appendix A.2.

Proposition 1. Given a set of samples $\mathbf{z} = \{z_i\}_{i=1}^n$ and assuming $f(x) = \sum_{i=1}^n \alpha_i k(z_i, x)$ for the Gaussian kernel of the form $k(x, y) = \exp(-\sigma^{-1}\|x - y\|_2^2)$, and $\lambda > 0$, the unique minimiser of the $\lambda\|f\|_{\mathcal{H}}^2$ -regularised empirical score matching objective (9) is given by

$$\hat{\alpha}_\lambda = -\frac{\sigma}{2}(C + \lambda I)^{-1}b, \quad (5)$$

where $b \in \mathbb{R}^n$ and $C \in \mathbb{R}^{n \times n}$ with

$$b = \sum_{\ell=1}^d \left(\frac{2}{\sigma} (K s_\ell + D_{s_\ell} K \mathbf{1} - 2D_{x_\ell} K x_\ell) - K \mathbf{1} \right) \text{ and } C = \sum_{\ell=1}^d [D_{x_\ell} K - K D_{x_\ell}] [K D_{x_\ell} - D_{x_\ell} K],$$

with entry-wise products $s_\ell := x_\ell \odot x_\ell$ and $D_x := \text{diag}(x)$.

The estimator has a cost of $\mathcal{O}(n^3 + dn^2)$ in computation (both for computing C, b , and for inverting C) and $\mathcal{O}(n^2)$ storage for a fixed random chain history sub-sample size n . This can be further reduced to *linear* computation and storage via low-rank approximations to the kernel matrix and conjugate gradient methods, which are derived in Appendix A.2.

Gradients of the estimated log-density are given as $\nabla f(x) = \sum_{i=1}^n \alpha_i \nabla k(x, x_i)$, i.e. they simply require to evaluate gradients of the kernel function. Evaluation and storage of $\nabla f(\cdot)$ both cost $\mathcal{O}(dn)$, which interestingly is independent of the target π , and only depends on the sub-sample \mathbf{z} .

4.2 Exponential Families in Finite Feature Spaces

Instead of fitting an infinite-dimensional model on a subset of the available data, the second estimator is based on fitting a finite dimensional approximation using *all* available data $\{x_i\}_{i=1}^t$, in *primal* form. As we will see, updating the estimator when a new data point arrives can be done online.

Define an m -dimensional approximate⁵ feature space $\mathcal{H}_m = \mathbb{R}^m$, and denote by $\phi_x \in \mathcal{H}_m$ the embedding of a point $x \in \mathcal{X} = \mathbb{R}^d$ into $\mathcal{H}_m = \mathbb{R}^m$. Assume that the embedding approximates the kernel function as a finite rank expansion $k(x, y) \approx \phi_x^\top \phi_y$. The log unnormalised density of the infinite model (2) can be approximated in this feature space as

$$f(x) = \langle \theta, \phi_x \rangle_{\mathcal{H}_m} = \theta^\top \phi_x \quad (6)$$

In order to fit $\theta \in \mathbb{R}^m$, we again minimise the score matching objective in (9) in Appendix A.1.

Proposition 2. Given a set of samples $\mathbf{x} = \{x_i\}_{i=1}^t$ and assuming $f(x) = \theta^\top \phi_x$ for a finite dimensional feature embedding $x \mapsto \phi_x \in \mathbb{R}^m$, and $\lambda > 0$, the unique minimiser of the $\lambda\|\theta\|_2^2$ -regularised empirical score matching objective (9) is given by

$$\hat{\theta}_\lambda := (C + \lambda I)^{-1}b, \quad (7)$$

where

$$b := -\frac{1}{n} \sum_{i=1}^t \sum_{\ell=1}^d \ddot{\phi}_{x_i}^\ell \in \mathbb{R}^m, \quad C := \frac{1}{n} \sum_{i=1}^t \sum_{\ell=1}^d \dot{\phi}_{x_i}^\ell \left(\dot{\phi}_{x_i}^\ell \right)^\top \in \mathbb{R}^{m \times m},$$

with $\dot{\phi}_x^\ell := \frac{\partial}{\partial x_\ell} \phi_x$ and $\ddot{\phi}_x^\ell := \frac{\partial^2}{\partial x_\ell^2} \phi_x$.

An example feature embedding based on random Fourier features [17] and a standard Gaussian kernel is $\phi_x = \sqrt{\frac{2}{m}} [\cos(\omega_1^\top x + u_1), \dots, \cos(\omega_m^\top x + u_m)]$, with $\omega_i \sim \mathcal{N}(\omega)$ and $u_i \sim \text{Uniform}[0, 2\pi]$. The estimator has a one-off cost of $\mathcal{O}(tm^2 + m^3)$ computation and $\mathcal{O}(m^2)$ storage. However, given that we have computed a solution based on the Markov chain history $\{x_i\}_{i=1}^t$, it is straightforward to update C, b , and the solution $\hat{\theta}_\lambda$ online, after a new point x_{t+1} arrives. This is achieved by storing running averages and performing low-rank updates of matrix inversions, and costs $\mathcal{O}(m^2)$ computation and storage, *independent* of t . Further details are given in Appendix A.3.

Gradients of the estimated log-density are written $\nabla f(x) = [\nabla \phi_x]^\top \hat{\theta}$, i.e., they require the evaluation of the gradient of the feature space embedding. Both the evaluation and storage of $\nabla f(\cdot)$ cost $\mathcal{O}(m)$, which is again independent of π and the Markov chain history.

Algorithm 1 Kamiltonian Monte Carlo – Pseudo-code

Input: Target (estimator) π , adaptation schedule a_t , HMC parameters,
Size of basis m or sub-sample size n .

At iteration $t + 1$, current state x_t , history $\{x_i\}_{i=1}^t$, perform (1-4) with probability a_t

KMC lite:

KMC finite:

- | | |
|---|---|
| 1. Update sub-sample $\mathbf{z} \subseteq \{x_i\}_{i=1}^t$ | 1. Update to C, b from Prop. 2 |
| 2. Re-compute C, b from Prop. 1 | 2. Perform rank- d update to C^{-1} |
| 3. Solve $\hat{\alpha}_\lambda = -\frac{\sigma}{2}(C + \lambda I)^{-1}b$ | 3. Update $\hat{\theta}_\lambda = (C + \lambda I)^{-1}b$ |
| 4. $\nabla f(x) \leftarrow \sum_{i=1}^n \alpha_i \nabla k(x, z_i)$ | 4. $\nabla f(x) \leftarrow [\nabla \phi_x]^\top \hat{\theta}$ |
| 5. Propose (p', x^*) with kernel induced Hamiltonian flow, using $\nabla_x U = \nabla_x f$ | |
| 6. Perform Metropolis step using π , $x_{t+1} \leftarrow x^*$ w.p. (3) and $x_{t+1} \leftarrow x_t$ otherwise | |
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5 Kamiltonian Monte Carlo

Constructing a kernel induced Hamiltonian flow as in Section 3 from the gradients of the infinite dimensional exponential family model (2), and approximate estimators (4),(6), we arrive at a gradient free, adaptive MCMC algorithm: *Kamiltonian Monte Carlo*, see Algorithm 1. KMC overcomes random-walk behaviour of competing state-of-the-art samplers KAMH and AMH.

Computational Efficiency, Geometric Ergodicity, and Burn-in KMC finite using (6) allows for online updates using the *full* Markov chain history and therefore is a more elegant solution than sub-sampling. However, due to the parametric nature of this approximate model, the tails of the estimator are not guaranteed to decay. For example, the random Fourier features embedding described below Proposition 2 contains periodic cosine functions and therefore oscillates in the tails of (6), resulting in a reduced acceptance probability. As we will demonstrate in the experiments, this problem does not appear when KMC finite is initialised in high-density regions, and after burn-in. In situations where this information about the target density is unknown, and during burn-in, we suggest to use the lite estimator (5), whose gradients decay outside of the training data. Consequently, in the tails or before burn-in completion, KMC lite is guaranteed to fall back to a random walk, and smoothly transitions to HMC-like proposals as the MCMC chain grows. This is formalised in the following result, which comes at the expense of increased computational costs and having to sub-sample the chain history. We give intuition below, see Appendix A.4 for the detailed proof.

Proposition 3. Assume $d = 1$, $\pi(x)$ is log-concave in the tails, regularity conditions of [21, Thm 2.2] (implying π -irreducibility and smallness of compact sets), MCMC adaptation stops after a fixed time, and a fixed number L of ϵ -leapfrog steps. If $\nabla f(x) \nearrow 0$ as $x \rightarrow \infty$ and $\nabla f(x) \searrow 0$ as $x \rightarrow -\infty$, and $\exists M : \forall x : \|\nabla f(x)\|_2 \leq M$, then KMC lite is geometrically ergodic from π -almost any starting point.

Proof Sketch Define $c(x^{(0)}) := \epsilon^2 \sum_{i=0}^{L-1} \nabla f(x^{(i\epsilon)})/2$ and $d(x^{(0)}) := \epsilon(\nabla f(x^{(0)}) + \nabla f(x^{(Le)}))/2 + \epsilon \sum_{i=1}^{L-1} \nabla f(x^{(i\epsilon)})$, where $x^{(i\epsilon)}$ is the i -th point of the leapfrog integration from $x = x^{(0)}$. At x_t , the marginal KMC proposal on position space looks like $x^*(p') = x_t + c(x_t) + N\epsilon p'$ where wlog. $p' \sim \mathcal{N}(0, I)$. This is accepted with probability $\text{acc}(x_t, x^*(p')) = \min\left(1, \frac{\pi(x^*(p'))}{\pi(x_t)} \exp\left(-\frac{1}{2}[p'd(x_t) + d(x_t)^2]\right)\right)$. From the distribution of p' , we have $c(x_t) \xrightarrow{P} 0$ as $\|x_t\|_2 \rightarrow \infty$, and similarly for $d(x_t)$. So for large x_t , we have $x^* \approx x_t + L\epsilon p'$ and $\text{acc}(x_t, x^*) \approx \min(1, \pi(x^*)/\pi(x_t))$, meaning in the tails the chain will behave as a Random Walk Metropolis. Consequently, KMC lite is geometrically ergodic whenever the Random Walk Metropolis is. Generalisations to $d \geq 2$ require an additional curvature condition of [21] but are out of the scope of this paper.

Vanishing adaptation MCMC algorithms that use the history of the Markov chain for constructing proposals might not be asymptotically correct. We follow [12, Sec. 4.2] and the idea of “vanishing adaptation” [11], to avoid such biases. Let $\{a_t\}_{t=0}^\infty$ be a schedule of decaying probabilities such that $\lim_{t \rightarrow \infty} a_t = 0$ and $\sum_{t=0}^\infty a_t = \infty$. We update the density gradient estimate according to that schedule in Algorithm 1. Intuitively, adaptation becomes less likely as the MCMC chain is pro-

⁵We deliberately don’t state the form of the approximation yet, but will give details later.

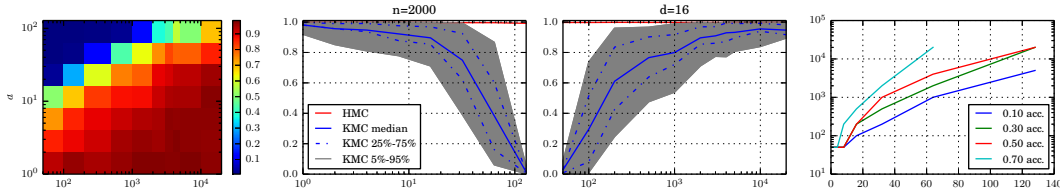


Figure 2: Acceptance probability of kernel induced Hamiltonian flow in high dimensions. **Left:** As a function of $n = m$ (x-axis) and d (y-axis). **Middle:** Slices through left plot with error bars for a fixed $n = m$ and as a function in d (left), and for a fixed d as a function of $n = m$ (right). **Right:** Number of data $n = m$ needed to reach given acceptance probabilities as a function of d .

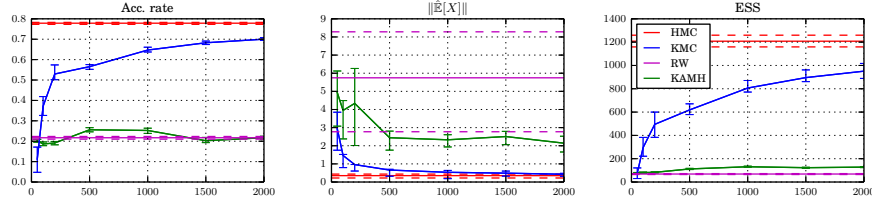


Figure 3: Results for 8-dimensional synthetic Banana. As the number of seen data increases, KMC performs close to HMC – outperforming KAMH and RW. 80% error bars over 30 runs.

gressing, but never fully stops while sharing asymptotic convergence with adaptation that stops at a fixed point, [22, Theorem 1]. Note that Proposition 3 is a stronger statement about the convergence rate.

6 Experiments

We start by quantifying performance of KMC finite on synthetic targets. We emphasise that these results can be reproduced with the lite version.

KMC finite: Stability of trajectories in high dimensions In order to quantify efficiency in growing dimensions, we study average acceptance probabilities purely over trajectories from the origin along the kernel induced Hamiltonian flow (no MCMC yet) on a standard Gaussian target. Figure 2 shows the average acceptance over 100 independent trials as a function of the number of data and of basis functions, which are set to be equal $n = m$, and of dimension d . In dimensions up to $d \approx 100$, we are able to obtain acceptance probabilities comparable to plain HMC with the finite estimator fitted in a few seconds on a laptop computer.

KMC finite: HMC-like mixing on a synthetic example We now show that KMC is able to match performance of HMC as it sees more data. We compare KMC, HMC, an isotropic random walk (RW), and KAMH on the 8-dimensional nonlinear banana-shaped target from [12, 10]. To only quantify mixing, both KMC and KAMH use the same set of fixed burn-in samples. We quantify performance on estimating the target’s mean, which is exactly 0. We tune the scaling of KAMH and RW to achieve 23% acceptance. We set HMC parameters to achieve 80% acceptance and then use the same parameters for KMC. We run all samplers for 2000+200 iterations from a random start point (chosen from burn-in samples), discard the burn-in and compute average acceptance rate, the norm of the empirical mean $\|\mathbb{E}[x]\|$, and average effective sample size (ESS) across dimensions. For KAMH and KMC, we repeat the experiment for an increasing number of burn-in samples and basis functions $m = n$. Figure 3 shows the results as a function of $m = n$. KMC clearly outperforms RW and KAMH, and eventually achieves performance close to HMC as $n = m$ grows.

KMC lite: Pseudo-Marginal MCMC for GP Classification on real world data Following [12, Section 5.1], we next apply KMC to sample the marginal posterior over hyper-parameters of a Gaussian Process Classification (GPC) model on the UCI Glass dataset [23]. Note that HMC is *unavailable* for this problem, due to the intractability of the marginal data likelihood given the hyper-parameters. Our experimental protocol mostly follows [12, Section 5.1], but uses only 1200+5000 MCMC iterations. We compare convergence in terms of all mixed moments of order up to 3 to a set of benchmark samples (MMD [24], lower is better). KMC randomly uses between 1 and

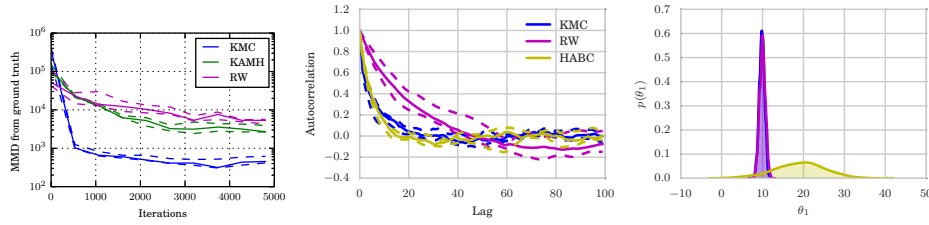


Figure 4: **Left:** Results for 9-dimensional marginal posterior over length scales of a GPC model applied to the UCI Glass dataset. The plots shows convergence of all mixed moments up to order 3 to a previously generated heavily thinned benchmark sample used as ground truth (lower MMD is better). **Middle/right:** ABC-MCMC auto-correlation and marginal θ_1 posterior for a 10-dimensional skew normal likelihood. While KMC mixes as well as HABC, it does not suffer from a significant bias (overlaps with RW) and requires fewer simulations per proposal.

10 leapfrog steps of a size chosen uniformly in $[0.01, 0.1]$, a standard Gaussian momentum, and a cross-validation tuned kernel width (tuned after burn-in), achieving 45% acceptance. We did not extensively tune the HMC parameters of KMC as the current settings were sufficient. Both KMC and KAMH use 1000 samples from the chain history. Figure 4 (left) shows that KMC clearly outperforms both RW and the earlier state-of-the-art KAMH. These results are backed by the average ESS (not plotted), which is around 800 for KMC and is around 90 and 60 for KAMH and RW respectively. All samplers took roughly 1h of computing time as most time is spent on estimating the marginal likelihood, which is in line with [12, Sec. 5.1].

KMC lite: Reduced simulations and no additional bias in ABC We now apply KMC in the context of Approximate Bayesian Computation (ABC), which often is employed when the data likelihood is intractable but can be simulated from, see e.g. [6]. ABC-MCMC [5], targets an approximate posterior, by constructing an unbiased Monte Carlo estimator of the approximate likelihood. As each such evaluation requires expensive simulations from the likelihood, the goal of all ABC methods is to reduce the number of such simulations. [8] recently proposed Hamiltonian ABC: combining the synthetic likelihood approach [25], with gradients based on stochastic finite differences. We remark that this requires to simulate from the likelihood in *every* leapfrog step, and that the additional bias from Gaussian likelihood approximation can be problematic. In contrast, KMC does not require simulations to construct a proposal but rather ‘invests’ simulations into an accept/reject step (3) that ensures convergence to the *original* ABC target. On a 10-dimensional skew-normal distribution $p(y|\theta) = 2\mathcal{N}(\theta, I)\Phi(\langle\alpha, y\rangle)$ with $\theta = \alpha = 1 \cdot 10$, Figure 4 (right) compares performance of RW, HABC (sticky random numbers and SPAS, [8, Sec. 4.3, 4.4]), and KMC. KMC mixes as well as HABC – without suffering from a significant bias, and at a factor of $L = 50$ reduced number of simulations per proposal.

7 Discussion

We have introduced KMC, a kernel-based gradient free adaptive MCMC algorithm that mimics HMC’s behaviour via estimating target gradients in a RKHS. In experiments, KMC outperforms random walk based sampling methods in up to moderately high dimensions ($d \leq 100$), including the recent kernel-based KAMH [12]. KMC is in particular useful when gradients of the target density are unavailable, such as PM-MCMC or ABC-MCMC, as HMC is not an option there. We have proposed two efficient empirical estimators with orthogonal strengths and weaknesses and given experimental evidence of the robustness of both.

Future work includes establishing theoretical consistency and uniform convergence rates for the empirical estimators, and a thorough experimental study in the ABC-MCMC context where we see KMC’s biggest potential. We will publish our code to reproduce all experimental results.

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