

Asymptotically Optimal Exact Minibatch Metropolis-Hastings

Ruqi Zhang

A. Feder Cooper

Christopher De Sa

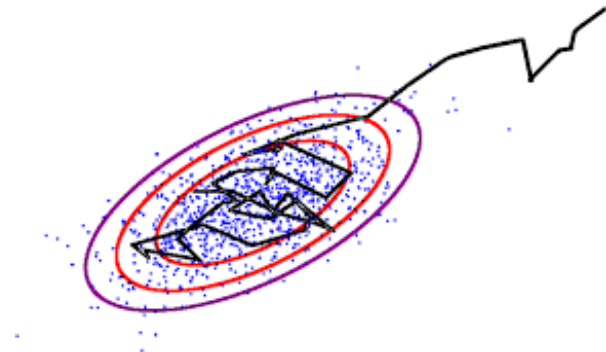
Cornell University

Metropolis-Hasting (MH)

Given: dataset $\{x_i\}_{i=1}^N$ and the prior $p(\theta)$

Goal: sample from the posterior

$$\pi(\theta) \propto \exp\left(-\sum_{i=1}^N U_i(\theta)\right), \text{ where } U_i(\theta) = -\log p(x_i|\theta) - \frac{1}{N} \log p(\theta)$$



Algorithm

- Generate a proposal $\theta' \sim q(\theta'|\theta)$
- Accept it with probability $a(\theta, \theta') = \min\left(1, \exp\left(\sum_{i=1}^N (U_i(\theta) - U_i(\theta'))\right) \cdot \frac{q(\theta|\theta')}{q(\theta'|\theta)}\right)$

Challenge: the accept/reject step is costly when dataset is large!

Minibatch to scale MH

Approximate $a(\theta, \theta')$ based on a minibatch of data

Two classes (whether the posterior is preserved):

Inexact methods

- Pros: **mild** assumptions
- Cons: asymptotic **bias**

[Korattikara et. al.,2014; Bardenet et.al., 2014; Seita et. al.,2017.....]



Which to use?

Exact methods

- Pros: **no** bias
- Cons: **strong** assumptions;
low efficiency

[Maclaurin et.al., 2015; Cornish et.al., 2019; Zhang et.al. 2019]

Is it important to be exact?

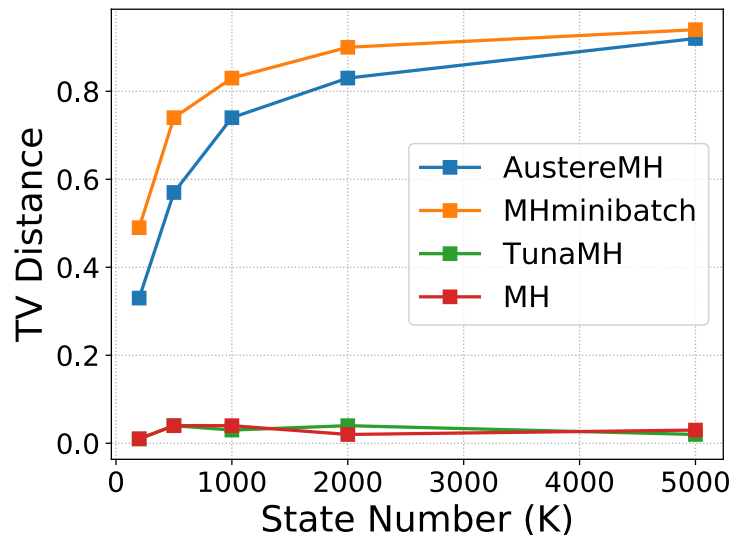
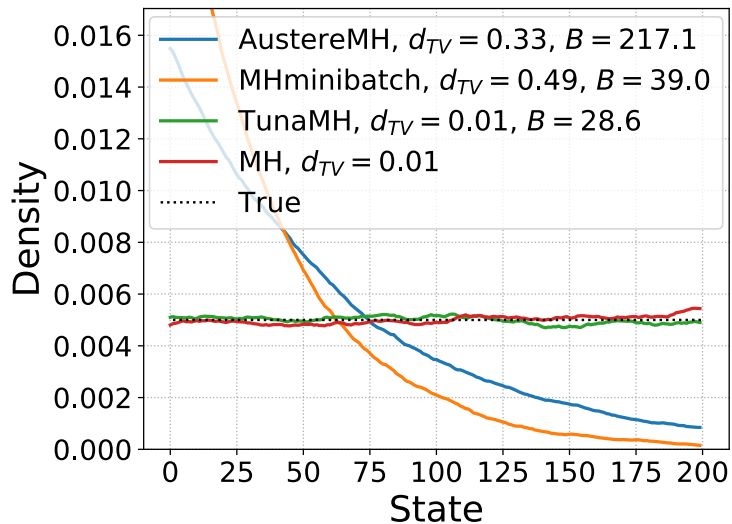
Part I: **Inexact** methods are **unreliable**

Theorem: we prove that the stationary distribution of **any inexact** method can be arbitrarily **far** from the posterior (in terms of **TV distance** and **KL divergence**)

Takeaway

- **Any inexact** minibatch MH can be arbitrarily **wrong**
- We should use **exact** methods

Random Walk Example



- The stationary distributions of inexact methods (AustereMH and MHminibatch) **diverge** significantly from the true distribution
- Divergence can be arbitrarily **large**

So we should use **exact** methods for
correctness guarantee
But...existing methods are
restrictive and **inefficient**

Part II: Our **exact** method: **TunaMH**



- **Mild** assumptions on the posterior
(**local** bounds on the energy: $|U_i(\theta) - U_i(\theta')| \leq c_i M(\theta, \theta')$)
- Convergence rate **guarantee**: at most a constant factor slower than standard (i.e. full-batch) MH
- A **tunable** trade-off between scalability (batch size) and efficiency (convergence rate)

Our exact method: TunaMH



Algorithm 2 TunaMH

given: hyperparameter χ \longrightarrow A dial for convergence rate and batch size trade-off
loop

propose $\theta' \sim q(\cdot|\theta)$ and **compute** $M(\theta, \theta')$ \longrightarrow generate a proposal

▷ Form **minibatch** \mathcal{I}

sample $B \sim \text{Poisson}(\chi C^2 M^2(\theta, \theta') + CM(\theta, \theta'))$ \longrightarrow sample batch size B

initialize minibatch indices $\mathcal{I} \leftarrow \emptyset$ (an initially empty multiset)

for $b \in \{1, \dots, B\}$ **do**

sample i_b such that $\mathbf{P}(i_b = i) = c_i/C$, for $i = 1 \dots N$

with probability $\frac{\chi c_{i_b} CM^2(\theta, \theta') + \frac{1}{2}(U_{i_b}(\theta') - U_{i_b}(\theta) + c_{i_b} M(\theta, \theta'))}{\chi c_{i_b} CM^2(\theta, \theta') + c_{i_b} M(\theta, \theta')}$ **add** i_b to \mathcal{I}

} select data to the minibatch

end for

▷ Accept/reject step based on **minibatch** \mathcal{I}

compute MH ratio $r \leftarrow \exp\left(2\sum_{i \in \mathcal{I}} \text{artanh}\left(\frac{U_i(\theta) - U_i(\theta')}{c_i M(\theta, \theta')(1 + 2\chi CM(\theta, \theta'))}\right)\right) \cdot \frac{q(\theta'|\theta)}{q(\theta|\theta')}$

with probability $\min(1, r)$, set $\theta \leftarrow \theta'$

end loop

Compute acceptance rate based on the minibatch

Is it possible to develop a
better exact method?

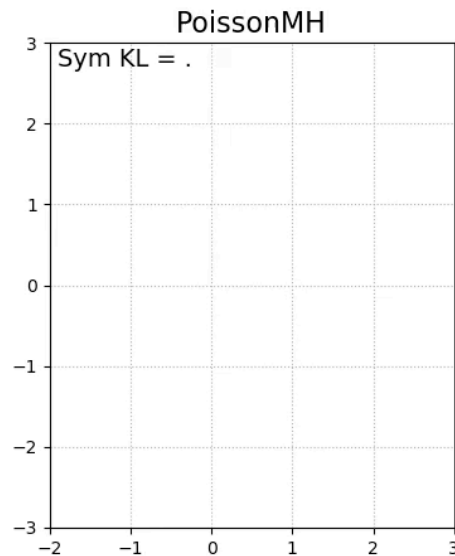
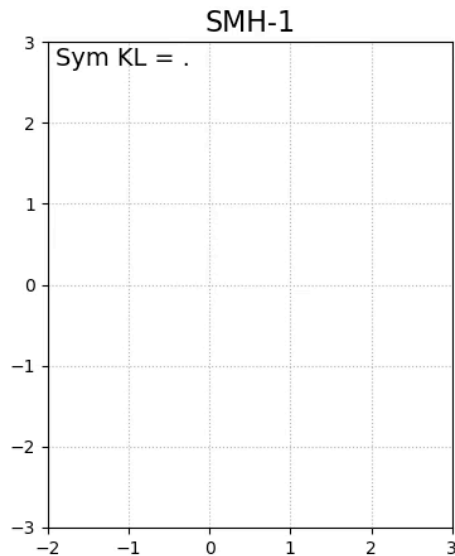
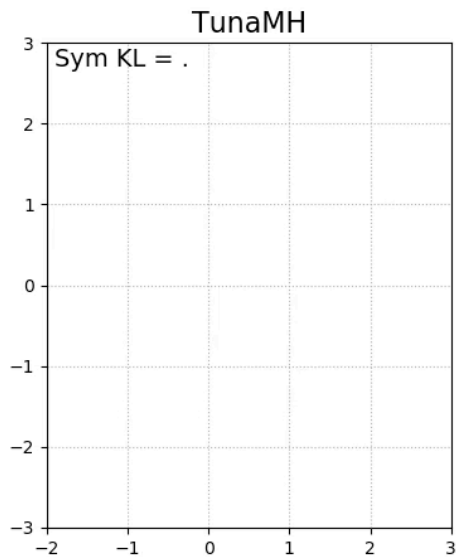
Part III: How **efficient** can an **exact** minibatch MH be?

Theorem: given a target convergence rate, we prove a **lower** bound on the required batch size for **any exact** minibatch MH

Takeaway

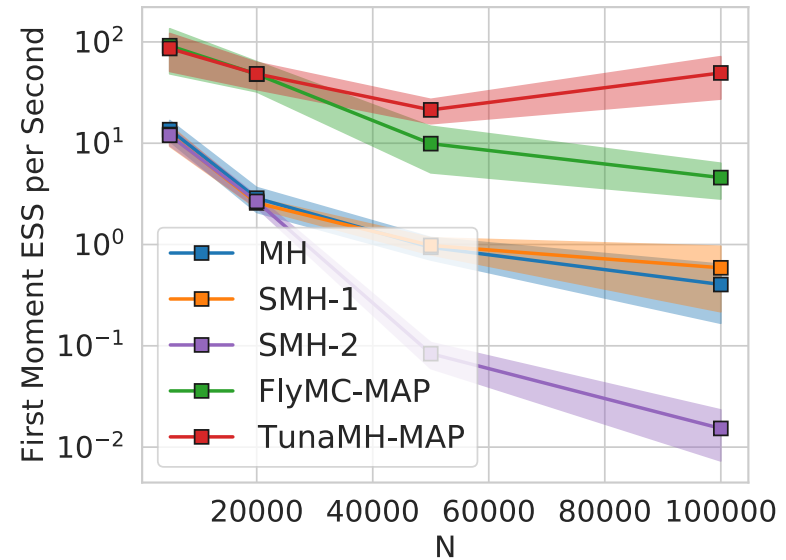
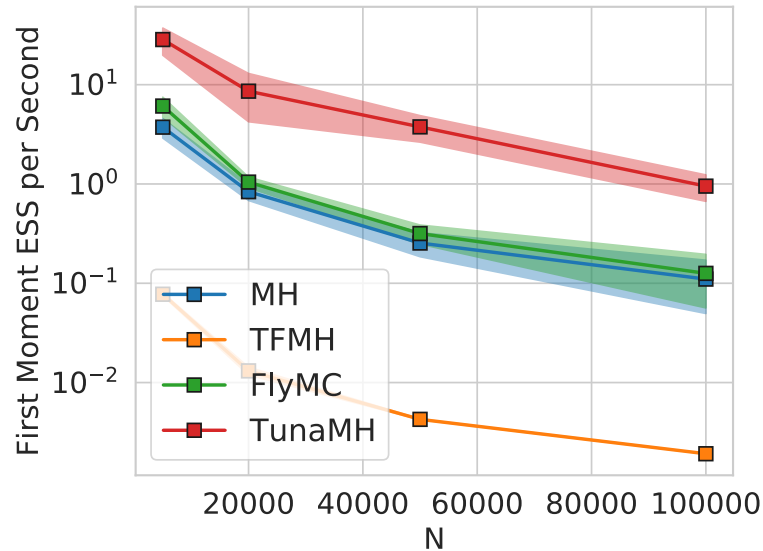
- The **first** theorem to provide a **ceiling** for the performance of exact minibatch MH
- TunaMH is **asymptotically optimal** in the batch size

Gaussian Mixture



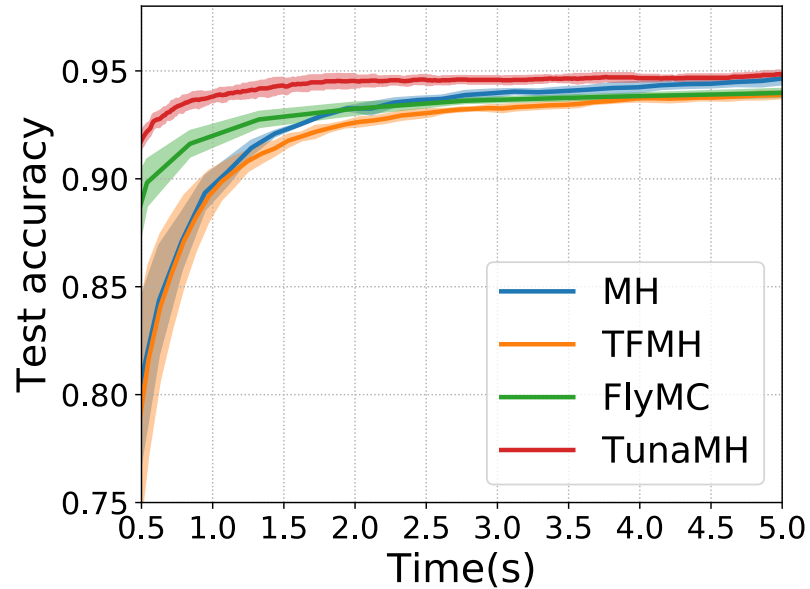
- Compared to SOTA exact methods, TunaMH is the **fastest** to converge

Robust Linear Regression



- TunaMH has the **highest** ESS per second, even compared to methods using MAP/control variates

Logistic Regression on MNIST



- TunaMH has the **highest** test accuracy given time

Summary

- We should use **exact** methods, as **any inexact** minibatch MH can perform arbitrarily **poorly**
- **TunaMH** is an **exact** minibatch MH, with **mild** assumptions and convergence rate **guarantees**
- We provide a **lower** bound on the batch size of **any** exact methods and show TunaMH is **asymptotically optimal**
- **Empirical** demonstration on common tasks

arXiv.org <https://arxiv.org/abs/2006.11677>



<https://github.com/ruqizhang/tunamh>