# Convergence of the unadjusted Langevin algorithm

Simon Xiang

University of Texas at Austin

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## Motivation

#### Question

For  $f: \mathbb{R}^n \to \mathbb{R}$ , assuming we have oracle access to  $\nabla f$ , how would we sample from the probability distribution  $\nu \sim e^{-f}$ ?

- As the step size  $\eta \to 0$ , the **discretized unadjusted** Langevin algorithm recovers Langevin dynamics, a continuous time stochastic process converging to  $\nu$ .
- If the **log-Sobolev inequality** is satisfied, this algorithm converges at an exponential rate, or  $\mathcal{O}(\log n)$  time.

# KL Divergence and the log-Sobolev inequality

Let  $\rho, \nu$  be probability distributions on  $\mathbb{R}^n$ .

#### Definition

The Kullback-Liebler (KL) divergence of  $\rho$  with respect to  $\nu$  is defined by

$$H_{\nu}(\rho) = \int_{\mathbb{R}^n} \rho(x) \log \frac{\rho(x)}{\nu(x)} dx.$$

#### Definition

For all smooth  $g: \mathbb{R}^n \to \mathbb{R}$  and  $\alpha < 0$  with  $\mathbb{E}_{\nu}[g^2] < \infty$ , the **log-Sobolev inequality (LSI)** is given by

$$\mathbb{E}_{\nu}[g^2\log g^2] - \mathbb{E}_{\nu}[g^2]\log \mathbb{E}_{\nu}[g^2] \leq \frac{2}{\alpha}\mathbb{E}_{\nu}[\|\nabla g\|^2].$$

## Equivalence

#### Definition

The relative Fisher information is given by

$$J_{\nu}(\rho) = \int_{\mathbb{R}^n} \rho(x) \left\| \nabla \log \frac{\rho(x)}{\nu(x)} \right\|^2 dx.$$

### Proposition

The log-Sobolev inequality is equivalent to the following relation between KL divergence and Fisher information for all  $\rho$ :

$$H_{\nu}(\rho) \leq \frac{1}{2\alpha} J_{\nu}(\rho).$$

To obtain this inequality from LSI, choose  $g^2 = \frac{\rho}{\nu}$ . To obtain LSI from this inequality, choose  $\rho = \frac{g^2 \nu}{\mathbb{E}_{\nu}[g^2]}$ .

# Langevin dynamics and the Fokker-Planck equation

#### Definition

For a target distribution  $\nu \sim e^{-f}$ , the **Langevin dynamics** is a continuous time stochastic process  $(X_t)_{t\geq 0}$  in  $\mathbb{R}^n$  that evolves by the following SDE:

$$dX_t = -\nabla f(X_t)dt + \sqrt{2}dW_t$$

where  $(W_t)_{t\geq 0}$  is the *n*-dimensional Brownian motion.

#### Definition

If  $(X_t)_{t\geq 0}$  evolves following the Langevin dynamics, then its pdf  $(\rho_t)_{t\geq 0}$  evolves by the **Fokker-Planck equation** 

$$\frac{\partial \rho_t}{\partial t} = \nabla \cdot (\rho_t \nabla f) + \Delta \rho_t = \nabla \cdot \left( \rho_t \nabla \log \frac{\rho_t}{\nu} \right)$$

where  $\nabla \cdot$  is divergence and  $\Delta$  is the Laplacian.

## Convergence

#### Lemma

Along the Langevin dynamics (or Fokker-Planck equation),

$$\frac{d}{dt}H_{\nu}(\rho_t) = -J_{\nu}(\rho_t).$$

#### Proof.

Recall that the time derivative of KL divergence along any flow is

$$\frac{d}{dt}H_{\nu}(\rho_t) = \frac{d}{dt}\int_{\mathbb{R}^n} \rho_t \log \frac{\rho_t}{\nu} dx = \int_{\mathbb{R}^n} \frac{\partial \rho_t}{\partial t} \log \frac{\rho_t}{\nu} dx$$

as the second part from the chain rule vanishes. Then along the Fokker-Planck equation this integrates by parts to  $-J_{\nu}(\rho_t)$ .

Since  $J_{\nu}(\rho) \geq 0$ , the KL divergence with respect to  $\nu$  is decreasing and  $\rho_t \rightarrow \nu$ .

 $\boxtimes$ 

## Rate of convergence

#### $\mathsf{Theorem}$

Suppose  $\nu$  satisfies LSI with  $\alpha>0$ . Then along the Langevin dynamics,

$$H_{\nu}(\rho_t) \leq e^{-2\alpha t} H_{\nu}(\rho_0).$$

#### Proof.

Applying our lemma and the fact that LSI is equivalent to  $H_{\nu}(\rho) \leq \frac{1}{2\alpha} J_{\nu}(\rho)$ , we have

$$\frac{d}{dt}H_{\nu}(\rho_t) = -J_{\nu}(\rho_t) \leq -2\alpha H_{\nu}(\rho_t).$$

Integrating yields the bound  $H_{\nu}(\rho_t) \leq e^{-2\alpha t} H_{\nu}(\rho_0)$  as desired.



## The discretized unadjusted Langevin algorithm

#### Definition

The Unadjusted Langevin Algorithm (ULA) with step size  $\eta>0$  is the discrete-time algorithm

$$x_{k+1} = x_k - \eta \nabla f(x_k) + \sqrt{2\eta} z_k$$

where  $z_k \sim N(0,1)$  is an independent Gaussian random variable in  $\mathbb{R}^n$ . Let  $\rho_k$  denote the probability distribution of  $x_k$  evolving along ULA.

- Comparing to  $dX_t = -\nabla f(X_t)dt + \sqrt{2}dW_t$ , as  $\eta \to 0$  we see how ULA recovers the Langevin dynamics.
- For fixed  $\eta > 0$ , ULA converges to a biased limiting distribution  $\nu_{\eta} \neq \nu$ . So KL divergence sadly does not converge to 0 along ULA, and has an asymptotic bias  $H_{\nu}(\nu_{\eta}) > 0$ .

## Conclusion

Thank you for listening! Reference: https://arxiv.org/abs/1903.08568