

## MCMC, part III

From before: Aim is to "sample" (or, e.g., compute integrals) w.r.t. some target measure  $\pi$  on  $S$ .

$\Rightarrow$  Create a Markov chain  $\{X_n\}_{n \geq 0}$ , or process  $\{X_t\}_{t \geq 0}$ , with  $\pi$  as stationary distribution.

Q: How to analyse convergence?

From before: Let  $K$  be the kernel associated w.  $\{X_n\}_{n \geq 0}$

$$P(X_{n+1} \in A | X_n = x) = K(x, A)$$

$$K^n(x, A) = \int K^{n-1}(y, A) K(x, dy), \quad n \geq 2$$

Set for  $k \in \mathbb{N}$ ,  $x \in S$

$$d_k(x) = \sup_{A \in \mathcal{P}(S)} |P_x(X_k \in A) - \pi(A)|$$

$$=: \|K^k(x, \cdot) - \pi\|_{TV}$$

Uniform ergodicity:

$$K^n(x, A) \geq \varepsilon \nu(A), \quad \text{for all } x \in S, A \in \mathcal{P}(S), \\ \text{some } \varepsilon \in (0, 1) \text{ and } \nu \in \mathcal{P}(S).$$

Exponential/geometric ergodicity:  $\exists 0 < \gamma < 1$  and

$$h: S \rightarrow \mathbb{R} \text{ s.t. } d_k(x) \leq h(x) g^k.$$

Other common quantities:

Mixing time: (here, w.r.t. TV):

$$\tau(\epsilon) := \min \{n: \forall x \in S, \|K^n(x, \cdot) - \pi\|_{TV} \leq \epsilon\}$$

(can replace TV with other "distances", e.g. relative entropy).

Spectral gap: Smallest eigenvalue of

$$I - \frac{1}{2}(K + K^*)$$

If  $K$  reversible w.r.t.  $\pi$ , then  $K$  self-adjoint  
 $\Rightarrow$  smallest eigenvalue of  $I - K$ .

AGT: difference between two largest eigenvalues (in abs. value):  $1 - \max_x |\lambda_x|$ .

Large spectral gap  $\Rightarrow$  faster convergence.

Now, consider  $\pi$  on the form

$$\pi(dx) \propto e^{-U(x)} dx, \text{ some } U.$$

Optimization:  $\min_{x \in X} U(x)$ . Can be "solved"  
 by samples from  $\pi$ .

Common choice: Langevin SDE

$$dX_t = -\nabla U(X_t) dt + \sqrt{2} dB_t, \{B_t\} \text{ d-dim. BM.}$$

[Exercise: Show that  $\pi$  is invariant for  $\{X_t\}$ ].

One way to analyse convergence properties: via functional analytical methods.

For now:  $\{X_t\}$  generic Markov process on  $\mathbb{R}^d$ ,  
with transition function/kernel:  $P(t, \cdot, \cdot)$  ( $P_t(\cdot, \cdot)$ )

Take  $f \in C_0^2(\mathbb{R}^d)$  and define

$$(*) (*) \quad (P_t f)(x) := \mathbb{E}[f(X_t) | X_0 = x] = \int f(y) P(t, x, dy)$$

Note: Linear operator,  $(P_0 f)(x) = f(x)$ ,  $P_0 = \text{Id. } \mathbb{R}^d$

Moreover:

$$\begin{aligned} (P_{t+s} f)(x) &= \int_{\mathbb{R}^d} f(y) P(t+s, x, dy) \\ &= \int_{\mathbb{R}^d} \underbrace{\int_{\mathbb{R}^d} f(y) P(s, z, dy)}_{(P_s f)(z)} P(t, x, dz) \\ &= \int_{\mathbb{R}^d} (P_s f)(z) P(t, x, dz) = (P_t \circ P_s)(f)(x) \end{aligned}$$

$\therefore P_{t+s} = P_t \circ P_s$ , i.e.  $(*) (*)$  defines a Markov semigroup.

Can study properties of  $\{X_t\}$  by studying  $\{P_t\}_{t \geq 0}$

Invariance:  $\mu \in \mathcal{P}(\mathbb{R}^d)$  is an invariant measure for  $\{P_t\}_{t \geq 0}$ .

if for every bounded, meas.  $f: \mathbb{R}^d \rightarrow \mathbb{R}$ ,  
and every  $t \geq 0$ ,

$$\int (P_t f) d\mu = \int f d\mu. \quad \int P_t f(x) dx = \int f dx$$

The associated (infinitesimal) generator,  $\mathcal{L}$ , is defined

by

$$\mathcal{L}f = \lim_{t \downarrow 0} \frac{P_t f - f}{t} \quad (*)$$

for  $f \in \mathcal{D}(\mathcal{L})$ : the set of functions in, e.g.,  $L^2(\mu)$ , for which (\*) is well-defined.

[General theory: Hille-Yosida theory, e.g. Ethier & Kurtz]

\* Classification: Formula given in class requires additional assumptions.

Instead, we can use that of  $\mu$  is invariant, then for  $f \in L^1(\mu)$

$\int \mathcal{L}f d\mu = 0$ . Conversely, for any class of function  $\mathcal{F}$  dense in  $L^1(\mu)$

if  $\int \mathcal{L}f d\mu = 0, \forall f \in \mathcal{F}$ , then  $\mu$  is invariant for  $P = \{P_t\}_{t \geq 0}$ .

Formally:  $P_t = e^{t\mathcal{L}}$

Define  $u(x,t) = (P_t f)(x)$  some observable  $f$ .

$$\begin{aligned} \frac{\partial}{\partial t} u(x,t) &= \frac{\partial}{\partial t} \left[ (P_t f)(x) \right] = \frac{\partial}{\partial t} \left[ e^{tL} f(x) \right] \\ &= L \left( e^{tL} f \right)(x) = L u(x,t) \\ &\quad (P_t f)(x) = u(x,t) \end{aligned}$$

Backward Kolmogorov eq : 
$$\begin{cases} \frac{\partial}{\partial t} u(x,t) = L u(x,t) \\ u(x,0) = f(x) \end{cases}$$

Generates evolution of expectation of an observable  $f$ .

Adjoint semigroup:  $P_t$  acts on functions.

Can define an adjoint operator,  $P_t^*$ , that acts on measures:

$$A \in \mathcal{B}(\mathbb{R}^d), \mu \in \mathcal{P}(\mathbb{R}^d)$$

$$\begin{aligned} (P_t^* \mu)(A) &= \int_{\mathbb{R}^d} \mathbb{P}(X_t \in A | X_0 = x) \mu(dx) \\ &= \int_{\mathbb{R}^d} P(t, x, A) d\mu(x) \end{aligned}$$

$(P_t^* \mu)$ : a probability measure. Formally adjoint of

$P_t$  in an  $L^2$ -sense:

$$\int_{\mathbb{R}^d} (P_t f)(x) d\mu(x) = \int_{\mathbb{R}^d} f d(P_t^* \mu)(x)$$

Let  $L^*$  be the formal adjoint of  $L$  in an  $L^2$ -sense:

$$\int_{\mathbb{R}^d} (L f) h \, d\mu(x) = \int f (L^* h) \, d\mu(x)$$

Can write  $P_t^* = e^{tL^*}$

If  $\{X_t\}$  is a Markov process w. generator  $L$ ,  $X_0 \sim \mu$ ,

Then  $\mu_t = P_t^* \mu$  is the law of  $X_t$ .

Arguments similar to derivation of Backward Kolmogorov:

if  $\mu_t, \mu$  have densities  $\rho_t, \rho$  w.r.t. Lebesgue,

$$\text{Then } \begin{cases} \frac{\partial}{\partial t} \rho_t(x) = L^* \rho_t(x) \\ \rho_0(x) = \rho(x) \end{cases}$$

Forward  
Kolmogorov eq.

(Fokker-Planck).

Invariance: If  $\mu$  invariant for  $P = \{P_t\}_{t \geq 0}$ ,

Then  $P_t^* \mu = \mu$ ;  $\Rightarrow$  stationary Fokker-Planck:

$$\boxed{L^* \rho(x) = 0}$$

Carre' du champ operator: Take  $f, g \in \mathcal{D}(L)$

$$\text{Define: } \Gamma(f, g) = \frac{1}{2} [L(fg) - fLg - gLf]$$

Notation:  $\mathcal{P}(f) = \mathcal{P}(f, f)$

Example: If  $L = \Delta$  [ $\Omega$ : What process?]

$$\text{Then } P(f, g) = \nabla f \cdot \nabla g$$

Dirichlet form:  $\mathcal{E}(f, g) = \int P(f, g) d\mu$

Notation:  $\mathcal{E}(f) = \mathcal{E}(f, f)$ .

Def  $\mu$  satisfies a Poincaré inequality (PI) w. constant  $C_{PI} > 0$  if, for all suitably regular  $f$ ,

$$\left( \text{Var}_\mu(f) \leq C_{PI} \mathcal{E}(f) \right)$$
$$\int (f - \int f d\mu)^2 d\mu$$

Remark: An alternative def. of the spectral gap  $\lambda^*$  is:

$$\lambda^* = \min_f \left\{ \frac{\mathcal{E}(f)}{\text{Var}_\mu(f)} : \text{Var}_\mu(f) \neq 0 \right\}.$$

From (PI):  $\lambda^* \geq \frac{1}{C_{PI}}$ . Actually, for any non-zero

eigenvalue  $\lambda$  of  $-\mathcal{L}$ ,  $\lambda \geq \frac{1}{C_{PI}}$ .

Back to Langevin diffusion:

$$(*) \quad dX_t = -\nabla U(X_t) dt + \sqrt{2} dB_t$$

Here,  $\mathcal{L}f = -\nabla u \cdot \nabla f + \Delta f$

Adjoint:  $\mathcal{L}^*f = \nabla \cdot (f \nabla u) + \Delta f$  [Exercise: Derive this]

=> Forward Kolmogorov:

$$\frac{\partial_t \mathbb{E}_x f_t = \nabla_x \cdot (\mathbb{E}_x \nabla_x u) + \Delta_x \mathbb{E}_x f_t$$

Exercise: Using the different characterisations of invariance, show  $\pi \propto e^{-u}$  is invariant for  $\{X_t\}$ .

Suppose  $\pi$  satisfies a PI, with constant  $C$ .

Consider  $\chi^2$ -divergence of  $\pi_t = \text{Law}(X_t)$ , w.r.t.  $\pi$ ,

$$\chi^2(\pi_t | \pi) = \int \left( \frac{d\pi_t}{d\pi} - 1 \right)^2 d\pi$$

Ans: Use (PI) to get an upper bound on  $\chi^2(\pi_t | \pi)$ .

For this  $\mathcal{L}$  [Exercise: Check this]

$$\mathcal{E}(f) = \mathbb{E}_\pi \left[ u \nabla f \right]^2$$

$$\frac{\partial}{\partial t} \chi^2(\pi_t | \pi) = \frac{\partial}{\partial t} \int \left( \frac{d\pi_t}{d\pi} - 1 \right)^2 d\pi = \frac{\partial}{\partial t} \int \left( \frac{d\pi_t}{d\pi} \right)^2 d\pi$$

$$= \frac{\partial}{\partial t} \int \left( P_t \frac{d\pi_0}{d\pi} \right)^2 d\pi$$

\*1 Correction: Use the def. of  $P_t$  and conditional expectation



$$= 2 \int \left( P_t \frac{d\pi_0}{dt} \right) \cdot \frac{\partial}{\partial t} \left( P_t \frac{d\pi_0}{dt} \right) dt$$

Exercise: Show that the st. of  $\mathcal{L}$

$$= 2 \int \left( P_t \frac{d\pi_0}{dt} \right) \mathcal{L} \left( P_t \frac{d\pi_0}{dt} \right) dt$$

Now, take  $f = \left( P_t \frac{d\pi_0}{dt} \right) = \left( \frac{d\pi_t}{dt} \right)$

Then above is then

(\*) Addition: For reversible processes (symmetric semigroups),  $\mathcal{E}(fg) = -\int f \mathcal{L}g d\mu$

$$\frac{\partial}{\partial t} \chi^2(\pi_t | \pi) = -2 \mathcal{E} \left( \frac{d\pi_t}{dt} \right)$$

Moreover, note:

$$\text{Var}_{\pi} \left( \frac{d\pi_t}{dt} \right) = \int \left( \frac{d\pi_t}{dt} - \int \left( \frac{d\pi_t}{dt} \right) d\pi \right)^2 d\pi$$

$$= \int \left( \frac{d\pi_t}{dt} - 1 \right)^2 d\pi = \chi^2(\pi_t | \pi)$$

The PI for  $\pi$  then states

$$\chi^2(\pi_t | \pi) \leq C \mathcal{E} \left( \frac{d\pi_t}{dt} \right)$$

$$\Rightarrow \frac{\partial}{\partial t} \chi^2(\pi_t | \pi) = -2 \mathcal{E} \left( \frac{d\pi_t}{dt} \right) \leq -\frac{2}{C} \chi^2(\pi_t | \pi)$$

Grönwall's:  $0 \leq \chi^2(\pi_t | \pi) \leq \chi^2(\pi_0 | \pi) e^{\int_0^t (-\frac{2}{C}) ds} = \chi^2(\pi_0 | \pi) e^{-\frac{2t}{C}}$

$$0 \leq \chi^2(\pi_t | \pi) \leq \chi^2(\pi_0 | \pi) e^{-\frac{2t}{C}}$$

$$\therefore \chi^2(\pi_t | \pi) \rightarrow 0 \text{ as } t \rightarrow \infty.$$

Requires that  $\pi \propto e^{-U}$  satisfies a PI.

Requires assumptions on  $U$ .

Ex: If  $\text{Hess}(U) \geq \lambda I$ , some  $\lambda$ , then  $\pi$  satisfies a PI with  $C = \frac{1}{\lambda}$ .

Implementation-wise:  $dX_t = -\nabla U(X_t) dt + \sqrt{2} dB_t$ .

Vanilla-implementation: EM-scheme

$$X_{k+1} = X_k - \gamma_k \nabla U(X_k) + \sqrt{2\gamma_k} Z_{k+1}$$

$\{Z_k\}$ : iid  $N(0,1)$ ,  $\{\gamma_k\}$ : step-size sequence.

$\gamma_k \equiv \gamma$ :  $\{X_k\}$  is irreducible, pos. recurrent  $\Rightarrow$  unique invariant dist  $\pi_\gamma$ .

However:  $\pi_\gamma \neq \pi$ .

$\Rightarrow$  Metropolis-adjusted Langevin (MALA):

Add a accept-reject step to remove bias:

$\gamma$  - Propose  $Y_{k+1} \sim X_k - \gamma \nabla U(X_k) + \sqrt{2\gamma} Z_{k+1}$

• Acceptance ratio:  $\alpha_r(x, y) = \min \left\{ 1, \frac{\pi(y) r_r(y, x)}{\pi(x) r_r(x, y)} \right\}$

where  $r_r(x, y) \propto e^{-\|y-x - r \nabla U(x)\|^2} \cdot \frac{1}{4r}$

• Accept according to  $\alpha_r(X_n, Y_n)$

$\Rightarrow$  Markov chain w. correct invariant dist.  $\pi$ .

• Ethier & Kurtz

• Bakry - Gentil - Ledoux (14)