

Lecture 8: Generators as operators and diffusion processes

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Plan for today

- 1. Generators as operators
- 2. Scaling limits and diffusion processes



Generators as operators

Generators as operators

Recall from week 2 that, for a CTMC ($X_t: t \ge 0$) with discrete state space S, we could write an ODE for the distribution at time t:

$$\frac{d}{dt}\langle \pi_t| = \langle \pi_t|G.$$

Furthermore, we also know that, given a function $f:S\to\mathbb{R}$, we can compute its expectation:

$$\mathbb{E}(f(X_t)) = \sum_{x \in S} \pi_t(x) f(x) = \langle \pi_t | f \rangle.$$

Therefore, we can use this to write an ODE to $\mathbb{E}(f(X_t))$:

$$\frac{d}{dt}\mathbb{E}\big[f(X_t)\big] = \frac{d}{dt}\langle \pi_t | f \rangle = \langle \pi_t | G | f \rangle = \mathbb{E}\big[(Gf)(X_t)\big] \ .$$

Generators as operators

We can do the same when $S = \mathbb{R}$, and this motivates the definition of the generator as an (differential) operator acting on functions $f : S \to \mathbb{R}$:

$$G|f\rangle(x)=(Gf)(x)=\sum_{y\neq x}g(x,y)\big[f(y)-f(x)\big].$$

Note that: When we do this, we usually write \mathcal{L} instead of G but I will try to be clear when doing that :)

Example: For **jump processes** with $S = \mathbb{R}$ and rate density r(x, y), the generator is

$$(\mathcal{L}f)(x) = \int_{\mathbb{R}} r(x,y) \big[f(y) - f(x) \big] \, dy.$$

Example: Brownian motion

Let us see what the generator is for the Brownian motion.

Recall that we mentioned yesterday that the transition density solves the **heat** equation:

$$p_t(x,y) = \frac{1}{\sqrt{2\pi\sigma^2 t}} \exp\left(-\frac{(y-x)^2}{2\sigma^2 t}\right), \quad \text{solves} \quad \frac{\partial}{\partial t} p_t(x,y) = \frac{\sigma^2}{2} \frac{\partial^2}{\partial y^2} p_t(x,y)$$

Using this, we obtain, for $f \in C^2(\mathbb{R})$,

$$\frac{d}{dt}\mathbb{E}_{x}\big(f(X_{t})\big) = \int_{\mathbb{R}} \partial_{t} p_{t}(x,y) f(y) dy = \frac{\sigma^{2}}{2} \int_{\mathbb{R}} \partial_{y}^{2} p_{t}(x,y) f(y) dy.$$

Now we integrate by parts:

$$\frac{\sigma^2}{2}\int_{\mathbb{R}}\partial_y^2 p_t(x,y)f(y)dy = \frac{\sigma^2}{2}\int_{\mathbb{R}} p_t(x,y)\partial_y^2 f(y)dy = \mathbb{E}_x((\mathcal{L}f)(X_t)).$$

This means that the generator of BM is

$$(\mathcal{L}f)(x) = \frac{\sigma^2}{2} \Delta f(x) \qquad \Big(\text{ or } \frac{\sigma^2}{2} f''(x) \Big).$$

Brownian motion as scaling limit

An interesting consequence of this is that we can see the Brownian motion as the scaling limit of a jump process:

Proposition:

Let $(X_t : t \ge 0)$ be a jump process on $\mathbb R$ with translation invariant rates r(x,y) = q(y-x) which have

- mean zero $\int_{\mathbb{R}} q(z) z dz = 0$
- finite second moment $\sigma^2 := \int_{\mathbb{R}} q(z) z^2 dz < \infty$.

Then, for all T>0 the rescaled process $(\epsilon X_{t/\epsilon^2}:t\in[0,T])$ converges in distribution to a BM with generator $\mathcal{L}=\frac{1}{2}\sigma^2\Delta$ for all T>0 as $\epsilon\to0$, i.e.

$$(\epsilon X_{t/\epsilon^2}: t \in [0, T]) \longrightarrow (B_t: t \in [0, T]) \text{ as } \epsilon \to 0.$$

Proof. Taylor expansion of the generator for test functions $f \in C^3(\mathbb{R})$, and tightness argument for continuity of paths (requires fixed interval [0, T]).



Diffusion processes

Diffusion processes

We can now define a general class of Markov processes.

Definition

A diffusion process with drift $a(x,t) \in \mathbb{R}$ and diffusion $\sigma(x,t) > 0$ is a real-valued process with continuous paths and generator

$$(\mathcal{L}f)(x) = a(x,t) f'(x) + \frac{1}{2}\sigma^2(x,t) f''(x).$$

Examples.

- The Ornstein-Uhlenbeck process is a diffusion process with generator

$$(\mathcal{L}f)(x) = -\alpha x f'(x) + \frac{1}{2}\sigma^2 f''(x) , \quad \alpha, \sigma^2 > 0.$$

It has a Gaussian stationary distribution $\mathcal{N}(0, \sigma^2/(2\alpha))$. If the initial distribution π_0 is Gaussian, this is a **Gaussian process**.

- **Brownian bridge** is a Gaussian diffusion with $X_0 = 0$ and generator

$$(\mathcal{L}f)(x) = -\frac{x}{1-t}f'(x) + \frac{1}{2}f''(x).$$

Time evolution of diffusion processes

Generators are defined on functions f of the state space. However, they are very useful, as they tell us a lot about the evolution of the underlying probability distributions.

Recall that the generator is given by

$$(\mathcal{L}f)(x) = a(x,t) f'(x) + \frac{1}{2}\sigma^2(x,t) f''(x).$$

Time evolution of the mean:

Use
$$\frac{d}{dt}\mathbb{E}[f(X_t)] = \mathbb{E}[(\mathcal{L}f)(x_t)]$$
 with $f(x) = x$ to obtain

$$\frac{d}{dt}\mathbb{E}[X_t] = \mathbb{E}[a(X_t, t)]$$

Time evolution of diffusion processes

Time evolution of the transition density:

With $X_0 = x$ we have for $p_t(x, y)$

$$\int_{\mathbb{R}} \frac{\partial}{\partial t} p_t(x, y) f(y) dy = \frac{d}{dt} \mathbb{E}[f(X_t)] = \int_{\mathbb{R}} p_t(x, y) \mathcal{L}f(y) dy \quad \text{for any } f.$$

As before, we can use integration by parts to get the Fokker-Planck equation:

$$\int_{-\frac{1}{2}} \frac{\partial^{2}}{\partial t} p_{t}(x,y) = -\frac{\partial}{\partial y} \left(a(y,t) p_{t}(x,y) \right) + \frac{1}{2} \frac{\partial^{2}}{\partial y^{2}} \left(\sigma^{2}(y,t) p_{t}(x,y) \right).$$

$$\int_{-\frac{1}{2}} \frac{\partial^{2}}{\partial t} p_{t}(x,y) \left(a(y,t) p_{t}(x,y) \right) + \frac{1}{2} \frac{\partial^{2}}{\partial y^{2}} \left(\sigma^{2}(y,t) p_{t}(x,y) \right).$$

Time evolution of diffusion processes

Finally, we can also look at stationary distributions for time-independent $a(y) \in \mathbb{R}$ and $\sigma^2(y) > 0$.

A stationary distribution p^* satisfies $\frac{\partial p^*}{\partial t} = 0$ and so we have

$$\frac{d}{dy}(a(y)p^*(y)) = \frac{1}{2}\frac{d^2}{dy^2}(\sigma^2(y)p^*(y)).$$

With this, we can solve for a stationary density (modulo normalisation fixing $p^*(0)$)

$$p^*(x) = p^*(0) \exp\Big(\int_0^x \frac{2a(y) - (\sigma^2)'(y)}{\sigma^2(y)} dy\Big).$$

Note the need for computing a normalisation constant here - connection to MCMC