

MARKOV PROCESSES

Let $\{X_t\}$ be a homogeneous (time invariant) Markov process. Define the evolution operator

$$P_t f(x) = E[f(X_t) | X_0 = x] \quad \leftarrow \text{semigroup}$$

If the strong limit

$$\mathcal{L}f = \lim_{\Delta t \rightarrow 0} \frac{(P_{\Delta t} f) - f}{\Delta t}$$

exists, we call \mathcal{L} the infinitesimal

generator of the Markov process.

It fully characterizes it.

At least formally, if \mathcal{L} does not depend on time (homogeneous), we write:

$$P_t = \exp[\mathcal{L}t]$$

Consider the evolution of an observable

$$u(x, t) = \mathbb{E}[u(x_t) \mid X_0 = x]$$

↑
abuse notation

⇒

$$\frac{\partial u}{\partial t} = \mathcal{L}u, \quad u(x, 0) = u_0(x)$$

Backward Kolmogorov equation

Now consider the evolution of a state, more precisely, a probability measure μ of initial conditions in phase space. For simplicity, assume that this measure can be related to a probability distribution function $g(y, t)$:

$$\mu_t = \int g(y, t) dy$$

which mathematicians call the law of the Markov process.

The time evolution of $S(y, t)$ is governed by the Fokker-Planck equation

$$\frac{\partial S}{\partial t} = \mathcal{L}^* S$$

Forward Kolmogorov eq.

where \mathcal{L}^* is the L^2 -adjoint of the generator

$$\int (\mathcal{L}f) h \, dx = \int f (\mathcal{L}^* h) \, dx$$

expectation of f if initial conditions are distributed according to h

$\mathcal{L}^* h$ is the time-evolved probability distribution

A Markov process is ergodic if the generator \mathcal{L} has only constants in its null space.

An ergodic Markov process has an invariant measure or invariant density

$$\mu_{eq}(dx) = \rho_{eq}(x) dx$$

$$\mathcal{L}^* \rho_{eq} = 0$$

which is unique since \mathcal{L} is ergodic

Time averages of trajectories equal phase space averages w.r.t ρ_{eq} (ergodic)

1) Recall Hamiltonian dynamics:

$$\partial_t S = - \underbrace{iL}_L S$$

Louville operator

$$(iL)^* = -iL^* = +iL$$

$$\Rightarrow \partial_t f = iL f = \dot{z} \frac{\partial f}{\partial z}$$

2) For jump Markov processes on a finite state space, \mathcal{L} is just the matrix of transition probabilities

$$\mathcal{L}_{ij} = w_{i \rightarrow j}, \quad \mathcal{L}_{ii} = - \sum_j w_{i \rightarrow j}$$

Note that

$$\mathcal{L} \cdot \mathbf{1} = 0$$

vector of ones in null space

and $\mathcal{L}^* \pi = 0 \Rightarrow$

$$\forall i : \mathcal{L}_{ji} \pi_j = w_{ji} \pi_j = 0$$

$$\Rightarrow w_{ji} \pi_j + \pi_i = \pi_i$$

Discrete time Markov chain $\left\{ \begin{array}{l} P_{ij} \pi_j = \pi_i \\ \text{where } P_{ii} = 1 - \sum_j w_{ij} \end{array} \right.$

③ Stochastic Differential equation:

$$\dot{x} = \underset{\substack{\uparrow \\ \text{drift}}}{h(x)} + \underset{\substack{\uparrow \\ \text{diffusion}}}{g(x)} W(t)$$

The FPE is the forward Kolmogorov

$$\frac{\partial P}{\partial t} = \mathcal{L}^* P = - \frac{\partial}{\partial x} \cdot (h P) + \frac{1}{2} \frac{\partial^2}{\partial x^2} \cdot (g g^* P)$$

$$\Rightarrow \mathcal{L}^* = - \frac{\partial}{\partial x} \cdot h + \frac{1}{2} \frac{\partial^2}{\partial x^2} \cdot (g g^*)$$

How do we take the adjoint of this to get the generator \mathcal{L} ?

Here is a quick-and-dirty way:

Adjoint of a gradient is negative divergence:

$$\left(\frac{\partial}{\partial x}\right)^* = -\frac{\partial}{\partial x} \quad (\text{think integration by parts})$$

$$\frac{\partial}{\partial x} \cdot \frac{\partial}{\partial x} = \left(\frac{\partial^2}{\partial x^2}\right)^* = \left(\frac{\partial^2}{\partial x^2}\right) \quad (\text{Laplacian is self adjoint})$$

\Rightarrow

$$\mathcal{L} = \underbrace{h \cdot \frac{\partial}{\partial x} + \frac{1}{2} (\sigma \sigma^*)}_{\frac{\partial^2}{\partial x^2}}$$

This is Ito's formula for the drift in $f(x(t))$