FU course: Mathematical Strategies for Complex Stochastic Dynamics

Lecture 3

May 07, 2025

Course Information

Tentative plan for grading:

- Solve problems: Each week, I will provide questions/problems. You choose one of them to solve. In total, 8 − 10 questions shall be solved.
- 2 1 short report: I provide 3-4 topics for numerical experiment. Select 1 topic to conduct numerical experiement, and write a short report.
 - length: no requirement. 4-6 pages recommended.
 - problem description and goal
 - method and algorithm
 - details about numerical experiment
- 3 give a 5-10 min presentation.

Two persons can work together.

Last week (1)

• Ito's integration: $\int_0^T f(t)dB_t = \lim_{N \to +\infty} \sum_{n=0}^{N-1} f(t_n)(B_{t_{n+1}} - B_{t_n}).$

$$\mathbb{E}\Big(\int_0^T f(t)dB_t\Big) = 0, \quad \mathbb{E}\Big(\int_0^T f(t)dB_t\Big)^2 = \int_0^T f^2(t)dt. \tag{1}$$
$$(dB_t)^2 = dt, \text{ or } dB_tdB_s = \delta(t-s)dt.$$

Last week (1)

• Ito's integration: $\int_0^T f(t)dB_t = \lim_{N \to +\infty} \sum_{n=0}^{N-1} f(t_n)(B_{t_{n+1}} - B_{t_n}).$

$$\mathbb{E}\Big(\int_0^T f(t)dB_t\Big) = 0, \quad \mathbb{E}\Big(\int_0^T f(t)dB_t\Big)^2 = \int_0^T f^2(t)dt. \tag{1}$$
$$(dB_t)^2 = dt, \text{ or }, dB_tdB_s = \delta(t-s)dt.$$

• SDEs: $dX_t = f(X_t) dt + \sigma(X_t) dB_t$.

$$\mathcal{L}g = f \cdot \nabla g + \frac{1}{2} \sum_{i,j=1}^{d} (\sigma \sigma^{\top})_{ij} \frac{\partial^{2} g}{\partial x_{i} \partial x_{j}}, \quad \mathcal{L}^{\top}g = -\text{div}(fg) + \frac{1}{2} \sum_{i,j=1}^{d} \frac{\partial^{2} ((\sigma \sigma^{\top})_{ij} g)}{\partial x_{i} \partial x_{j}}.$$

Last week (1)

• Ito's integration: $\int_0^T f(t)dB_t = \lim_{N \to +\infty} \sum_{n=0}^{N-1} f(t_n)(B_{t_{n+1}} - B_{t_n}).$

$$\mathbb{E}\Big(\int_0^T f(t)dB_t\Big) = 0, \quad \mathbb{E}\Big(\int_0^T f(t)dB_t\Big)^2 = \int_0^T f^2(t)dt. \tag{1}$$
$$(dB_t)^2 = dt, \text{ or }, dB_tdB_s = \delta(t-s)dt.$$

• SDEs: $dX_t = f(X_t) dt + \sigma(X_t) dB_t$.

$$\mathcal{L} g = \textit{f} \cdot \nabla g + \frac{1}{2} \sum_{i,j=1}^{\textit{d}} (\sigma \sigma^\top)_{ij} \frac{\partial^2 g}{\partial x_i \partial x_j} \,, \quad \mathcal{L}^\top g = -\text{div}(\textit{f} g) + \frac{1}{2} \sum_{i,j=1}^{\textit{d}} \frac{\partial^2 \left((\sigma \sigma^\top)_{ij} g \right)}{\partial x_i \partial x_j} \,.$$

• Ito's lemma: $dg(X_t) = \mathcal{L}g(X_t)dt + \sigma(X_t)g'(X_t)dB_t$.

Last week (2)

• Semigroup: $(T_t g)(x) = \mathbb{E}[g(X(t))|X(0) = x].$

$$T_0 = \mathrm{id}, \quad T_{t+s} = T_t \circ T_s, \quad \mathrm{and} \ \frac{d}{dt} T_t g = \mathcal{L} T_t g.$$
 (2)

Last week (2)

• Semigroup: $(T_t g)(x) = \mathbb{E}[g(X(t))|X(0) = x].$

$$T_0 = \mathrm{id}, \quad T_{t+s} = T_t \circ T_s, \quad \mathrm{and} \ \frac{d}{dt} T_t g = \mathcal{L} T_t g.$$
 (2)

• Fokker-Planck equation $\frac{\partial p}{\partial t} = \mathcal{L}^{\top} p$.

Last week (2)

• Semigroup: $(T_t g)(x) = \mathbb{E}[g(X(t))|X(0) = x].$

$$T_0 = \mathrm{id}, \quad T_{t+s} = T_t \circ T_s, \quad \mathrm{and} \ \frac{d}{dt} T_t g = \mathcal{L} T_t g.$$
 (2)

- Fokker-Planck equation $\frac{\partial p}{\partial t} = \mathcal{L}^{\top} p$.
- Brownian motion: $dX_l = dB_l$, $\mathcal{L} = \mathcal{L}^{\top} = \frac{1}{2}\Delta$, heat equation.

Density under ODE

Consider the ODE

$$\frac{dx(t)}{dt} = f(x(t), t), \quad t \in [0, T], \tag{3}$$

where the prob. density of x(0) is $p_0(x)$. Let p(x,t) be the density of x(t) at $t \in [0, T]$.

Density under ODE

Consider the ODE

$$\frac{dx(t)}{dt} = f(x(t), t), \quad t \in [0, T], \tag{3}$$

where the prob. density of x(0) is $p_0(x)$. Let p(x,t) be the density of x(t) at $t \in [0, T]$.

Lemma

The density p satisfies the continuity equation

$$\frac{\partial p}{\partial t} + div(fp) = 0, \quad \forall \ t \in (0, T]
p(x, 0) = p_0.$$
(4)

Density under ODE

Consider the ODE

$$\frac{dx(t)}{dt} = f(x(t), t), \quad t \in [0, T], \tag{3}$$

where the prob. density of x(0) is $p_0(x)$. Let p(x,t) be the density of x(t) at $t \in [0, T]$.

Lemma

The density p satisfies the continuity equation

$$\frac{\partial p}{\partial t} + div(fp) = 0, \quad \forall \ t \in (0, T]
p(x, 0) = p_0.$$
(4)

Remark

With $\mathcal{L}_t g = f \cdot \nabla g$, $\mathcal{L}_t^{\top} g = -\text{div}(fg)$, we can write (4) as $\frac{\partial p}{\partial t} = \mathcal{L}_t^{\top} p$.

Invariant distribution and ergodicity

Invariant distribution

Assume the probability density $X_0 = x$ is $\pi(x)$. Then the probability density of X_t satisfies the Fokker-Planck equation

$$\frac{\partial p}{\partial t} = \mathcal{L}^{\top} p, \quad t > 0,
p(x,0) = \pi(x).$$
(5)

Invariant distribution

Assume the probability density $X_0 = x$ is $\pi(x)$. Then the probability density of X_t satisfies the Fokker-Planck equation

$$\frac{\partial p}{\partial t} = \mathcal{L}^{\top} p, \quad t > 0,
p(x,0) = \pi(x).$$
(5)

Definition

 π is an invariant density, if $p(\cdot, t) = \pi$ for all $t \ge 0$.

Invariant distribution

Assume the probability density $X_0 = x$ is $\pi(x)$. Then the probability density of X_t satisfies the Fokker-Planck equation

$$\frac{\partial p}{\partial t} = \mathcal{L}^{\top} p, \quad t > 0,
p(x,0) = \pi(x).$$
(5)

Definition

 π is an invariant density, if $p(\cdot, t) = \pi$ for all $t \ge 0$.

Therefore, π is (smooth) invariant density if and only if

$$\mathcal{L}^{\top}\pi = \mathbf{0}. \tag{6}$$

In many cases, the process X_t approaches equilibrium as $t \to +\infty$.

In many cases, the process X_t approaches equilibrium as $t \to +\infty$.

Definition

 X_t is **ergodic** with respect to an invariant density π , if p(x,t) converges to π as $t \to +\infty$ starting from any density p(x,0) at time t=0.

Theorem (Birkhoff ergodic theorem)

Assume X_t is ergodic with respect to the invariant density π . Let $g: \mathbb{R}^d \to \mathbb{R}$ be a measuable function such that $\int_{\mathbb{R}^d} |g(x)| \pi(x) dx < \infty$. Then, with probability one, we have

$$\lim_{T\to+\infty}\frac{1}{T}\int_0^T g(X_t)dt=\int_{\mathbb{R}^d}g(x)\pi(x)dx. \tag{7}$$

Theorem (Birkhoff ergodic theorem)

Assume X_t is ergodic with respect to the invariant density π . Let $g: \mathbb{R}^d \to \mathbb{R}$ be a measuable function such that $\int_{\mathbb{R}^d} |g(x)| \pi(x) dx < \infty$. Then, with probability one, we have

$$\lim_{T\to+\infty}\frac{1}{T}\int_0^T g(X_t)dt=\int_{\mathbb{R}^d}g(x)\pi(x)dx. \tag{7}$$

Remark

Theorem above allows to compute the mean $\int_{\mathbb{R}^d} f(x)\pi(x)dx$ by simulating SDEs.

Euler-Maruyama scheme

SDE:

$$dX_t = f(X_t)dt + \sigma(X_t)dB_t$$
 (8)

Discretized scheme

$$x_{n+1} = x_n + f(x_n)h + \sqrt{h}\sigma(x_n)\eta_n, \quad n = 0, 1, 2, \cdots.$$
 (9)

Estimator:

$$\int_{\mathbb{R}^d} g(x)\pi(x)dx \approx \frac{1}{N}\sum_{n=1}^N g(x_n)$$
 (10)

Euler-Maruyama scheme

Algorithm Euler-Maruyama scheme

- 1: n = 0, $h = \frac{T}{N}$.
- 2: while $n < \hat{N}$ do
- 3: generate $\eta_n \sim \mathcal{N}(0, 1)$.
- 4: $x_{n+1} = x_n + f(x_n)h + \sqrt{h}\sigma(x_n)\eta_n.$
- 5: $n \leftarrow n + 1$.
- 6: end while

Euler-Maruyama scheme

Algorithm Euler-Maruyama scheme

- 1: n = 0, $h = \frac{T}{N}$.
- 2: while n < N do
- 3: generate $\eta_n \sim \mathcal{N}(0, 1)$.
- 4: $x_{n+1} = x_n + f(x_n)h + \sqrt{h}\sigma(x_n)\eta_n.$
- 5: $n \leftarrow n + 1$.
- 6: end while

In 1D, given x_n , we have

$$X_{n+1} \sim \mathcal{N}(X_n + f(X_n)h, \sigma(X_n)^2h).$$

Connections between SDEs and PDEs

Feynman-Kac

Given $g, h : \mathbb{R}^d \to \mathbb{R}$. Let us define

$$u(x,t) = \mathbb{E}\Big[e^{-\int_t^T h(X_s)ds}g(X_T)\Big|X_t = x\Big], \quad x \in \mathbb{R}^d, \quad t \in [0,T].$$
 (11)

Feynman-Kac

Given $g, h : \mathbb{R}^d \to \mathbb{R}$. Let us define

$$u(x,t) = \mathbb{E}\Big[e^{-\int_t^T h(X_s)ds}g(X_T)\Big|X_t = x\Big], \quad x \in \mathbb{R}^d, \quad t \in [0,T].$$
 (11)

Proposition

The function u in (11) solves the PDE

$$\frac{\partial u}{\partial t} + \mathcal{L}u = h, \quad 0 \le t < T,
 u(x, T) = g, \quad t = T$$
(12)

Feynman-Kac

Given $g, h : \mathbb{R}^d \to \mathbb{R}$. Let us define

$$u(x,t) = \mathbb{E}\left[e^{-\int_t^T h(X_s)ds}g(X_T)\middle|X_t = x\right], \quad x \in \mathbb{R}^d, \quad t \in [0,T]. \tag{11}$$

Proposition

The function u in (11) solves the PDE

$$\frac{\partial u}{\partial t} + \mathcal{L}u = h, \quad 0 \le t < T,$$

$$u(x, T) = g, \quad t = T$$
(12)

Proof.

- Show $u(x,t) = \mathbb{E}\left[e^{-\int_t^{t'}h(X_s)ds}u(X_{t'},t')\Big|X_t=x\right]$, for $t \leq t' \leq T$.
- Apply Ito's formula to $e^{-\int_t^{t'} h(X_s) ds} u(X_{t'}, t')$.



Exit time

Consider a bounded domain $D \subseteq \mathbb{R}^d$. Define

$$\omega(x) = \mathbb{E}\Big[g(X_{\tau_D}) + \int_0^{\tau_D} h(X_s) ds \Big| X_0 = x\Big], \quad x \in D.$$
 (13)

where

$$\tau_D = \inf\{t \ge 0, X_t \in \partial D\} \tag{14}$$

is the exit time from D.

Exit time

Consider a bounded domain $D \subseteq \mathbb{R}^d$. Define

$$\omega(x) = \mathbb{E}\Big[g(X_{\tau_D}) + \int_0^{\tau_D} h(X_s) ds \Big| X_0 = x\Big], \quad x \in D.$$
 (13)

where

$$\tau_D = \inf\{t \ge 0, X_t \in \partial D\} \tag{14}$$

is the exit time from D.

Proposition

 ω in (13) solves the PDE

$$\mathcal{L}\omega = -h, \quad \text{in } D$$

$$\omega = g, \quad \text{on } \partial D.$$
(15)

Exit time

Consider a bounded domain $D \subseteq \mathbb{R}^d$. Define

$$\omega(x) = \mathbb{E}\Big[g(X_{\tau_D}) + \int_0^{\tau_D} h(X_s) ds \Big| X_0 = x\Big], \quad x \in D.$$
 (13)

where

$$\tau_D = \inf\{t \ge 0, X_t \in \partial D\} \tag{14}$$

is the exit time from D.

Proposition

 ω in (13) solves the PDE

$$\mathcal{L}\omega = -h, \quad \text{in } D$$

$$\omega = g, \quad \text{on } \partial D. \tag{15}$$

Proof.

Apply Ito's formula to the solution to (15) up to time $t = \tau_D$.

Concrete SDEs

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta > 0$ is a constant.

$$dX_t = -\nabla V(X_t) dt + \sqrt{2\beta^{-1}} dB_t, \quad t > 0$$

• $V: \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta > 0$ is a constant.

$$dX_t = -\nabla V(X_t) dt + \sqrt{2\beta^{-1}} dB_t, \quad t > 0$$

Its generator is

$$\mathcal{L} g = -
abla V \cdot
abla g + rac{1}{eta} \Delta g$$
 .

• The adjoint of \mathcal{L} is

$$\mathcal{L}^ op g = \operatorname{\mathsf{div}}(
abla V g) + rac{1}{eta} \Delta g \,.$$

Definition (Boltzmann distribution)

$$\pi(x) = \frac{1}{Z} e^{-\beta V(x)}, \quad x \in \mathbb{R}^d, \tag{16}$$

where $Z = \int_{\mathbb{R}^d} e^{-\beta V(x)} dx$, such that $\int_{\mathbb{R}^d} \pi(x) dx = 1$.

Definition (Boltzmann distribution)

$$\pi(x) = \frac{1}{Z} e^{-\beta V(x)}, \quad x \in \mathbb{R}^d, \tag{16}$$

where $Z = \int_{\mathbb{R}^d} e^{-\beta V(x)} dx$, such that $\int_{\mathbb{R}^d} \pi(x) dx = 1$.

Proposition

The probability density π in (16) is invariant under the Brownian dynamics

$$dX_t = -\nabla V(X_t) dt + \sqrt{2\beta^{-1}} dB_t \,, \quad t>0 \,.$$

Ornstein-Unlenbeck process

When $V(x) = \frac{\kappa |x|^2}{2}$, the Brownian dynamics is

$$dX_t = -\kappa X_t dt + \sqrt{2\beta^{-1}} dB_t, \quad t > 0$$
 (17)

The invariant density is

$$\pi(x) = \frac{1}{Z} e^{-\frac{\beta \kappa |x|^2}{2}}.$$
 (18)

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta, \gamma > 0$ is a constant.

$$dQ_t = P_t dt$$

 $dP_t = -\nabla V(Q_t) dt - \gamma P_t dt + \sqrt{2\gamma\beta^{-1}} dB_t$.

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta, \gamma > 0$ is a constant.

$$egin{aligned} dQ_t = & P_t dt \ dP_t = & -
abla V(Q_t) \, dt - \gamma P_t dt + \sqrt{2\gamma eta^{-1}} \, dB_t \, . \end{aligned}$$

• It corresponds to $dX_t = f(X_t)dt + \sigma(X_t)dB_t$ with $x = (q, p) \in \mathbb{R}^{2d}$, and

$$f(q,p) = (p, -\nabla V(q) - \gamma p)^{\top} \in \mathbb{R}^{2d},$$

$$\sigma = \begin{pmatrix} 0 & 0 \\ 0 & \sqrt{2\gamma\beta^{-1}}I_d \end{pmatrix} \in \mathbb{R}^{2d \times 2d}.$$
(19)

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta, \gamma > 0$ is a constant.

$$egin{aligned} dQ_t = & P_t dt \ dP_t = & -
abla V(Q_t) \, dt - \gamma P_t dt + \sqrt{2\gamma eta^{-1}} \, dB_t \, . \end{aligned}$$

• It corresponds to $dX_t = f(X_t)dt + \sigma(X_t)dB_t$ with $x = (q, p) \in \mathbb{R}^{2d}$, and

$$f(q,p) = (p, -\nabla V(q) - \gamma p)^{\top} \in \mathbb{R}^{2d},$$

$$\sigma = \begin{pmatrix} 0 & 0 \\ 0 & \sqrt{2\gamma\beta^{-1}}I_d \end{pmatrix} \in \mathbb{R}^{2d \times 2d}.$$
(19)

In physics notation:

$$\frac{d^2Q_t}{dt^2} = -\nabla V(Q_t) dt - \gamma \frac{dQ_t}{dt} dt + \sqrt{2\gamma\beta^{-1}} \frac{dB_t}{dt}.$$

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta, \gamma > 0$ is a constant.

$$dQ_t = P_t dt$$

 $dP_t = -\nabla V(Q_t) dt - \gamma P_t dt + \sqrt{2\gamma\beta^{-1}} dB_t$.

The generator is

$$\mathcal{L}g = p \cdot \nabla_q g - \nabla V \cdot \nabla_p g - \gamma p \cdot \nabla_p g + \frac{\gamma}{\beta} \Delta_p g.$$

• $V : \mathbb{R}^d \to \mathbb{R}$ is smooth, and $\beta, \gamma > 0$ is a constant.

$$dQ_t = P_t dt$$

 $dP_t = -\nabla V(Q_t) dt - \gamma P_t dt + \sqrt{2\gamma\beta^{-1}} dB_t$.

The generator is

$$\mathcal{L}g = p \cdot \nabla_q g - \nabla V \cdot \nabla_p g - \gamma p \cdot \nabla_p g + \frac{\gamma}{\beta} \Delta_p g.$$

Its adjoint is

$$egin{aligned} \mathcal{L}^{ op} g &= -\operatorname{div}_q(pg) + \operatorname{div}_p(
abla Vg) + \gamma \operatorname{div}_p(pg) + rac{\gamma}{eta} \Delta_p g \ &= -p \cdot
abla_q g +
abla V \cdot
abla_p g + \gamma \operatorname{div}_p \Big(pg + eta^{-1}
abla_p g \Big) \,. \end{aligned}$$

Definition (Hamiltonian)

Define the Hamiltonian

$$H(q,p) = V(q) + \frac{|p|^2}{2}$$
 (20)

Definition (Hamiltonian)

Define the Hamiltonian

$$H(q,p) = V(q) + \frac{|p|^2}{2}$$
 (20)

Proposition

The probability density $Z_1^{-1} e^{-\beta H}$ is invariant under Langevin dynamics, where $Z_1 = \int_{\mathbb{R}^{2d}} e^{-\beta H} dq dp$.

Questions?