

SDE

$$X_t^\varepsilon \in \mathbb{R}^n; \mathcal{H}.$$

$$dX_t^\varepsilon = b(t, X_t^\varepsilon) dt + \sqrt{\varepsilon} \sigma(t, X_t^\varepsilon) dW_t \quad X_{t=0}^\varepsilon = x_0$$

det. drift $b \in \mathbb{R}^n$

noise.

$$\sigma \in \mathbb{R}^{n \times n}$$

$W_t =$ Wiener process

Euler-Maruyama

$$\tilde{X}_0 = x_0$$

$$\tilde{X}_{(k+1)\Delta t} = \tilde{X}_{k\Delta t} + b(k\Delta t, \tilde{X}_{k\Delta t}) \Delta t + \sqrt{\varepsilon} \sigma(k\Delta t, \tilde{X}_{k\Delta t}) (W_{(k+1)\Delta t} - W_{k\Delta t})$$

X_t continuous, not diff
Hölder $1/2$

$$\sqrt{\Delta t} \sum_k$$

with: $\sum_k \sim N(0, Id)$
iid.

$$\forall T > 0: \mathbb{E}^{x_0} \left[\sup_{0 \leq k \leq T/\Delta t} |\tilde{X}_{k\Delta t} - X_{k\Delta t}| \right] \xrightarrow{\Delta t \downarrow 0} 0$$

Small noise:

$\Sigma \downarrow 0$

1. LLN

$$\forall T > 0: \quad \mathbb{P}^x \sup_{0 \leq t \leq T} |X_t^\Sigma - X_t| \rightarrow 0 \quad \Sigma \downarrow 0$$

where: $\dot{X}_t = b(X_t)$ $X_{t=0} = x_0$

$$\mathbb{P}^{x_0} \left(\sup_{0 \leq t \leq T} |X_t^\Sigma - X_t| > \varepsilon \right) \rightarrow 0 \quad \Sigma \downarrow 0$$

2. CLT

$$X_t^\Sigma = X_t + \sqrt{\Sigma} \eta_t^\Sigma \Leftrightarrow \eta_t^\Sigma = \frac{X_t^\Sigma - X_t}{\sqrt{\Sigma}}$$

derive η_t for $\lim_{\Sigma \downarrow 0} \eta_t^\Sigma = \eta_t$

linear eq. with coeff dep. on X_t .

3. LDP Given $f: \mathbb{R}^r \rightarrow \mathbb{R}$ & $T > 0$, consider:

$$A_\varepsilon = \mathbb{E}^{x_0} \left[e^{\frac{1}{\varepsilon} f(X_T^\varepsilon)} \right]$$

expect. cond. on $X_{t=0} = x_0$

Use:

$$\tilde{X}_{(k+1)\Delta t} \mid \tilde{X}_{k\Delta t} \sim N \left(\Delta t b(k\Delta t, \tilde{X}_{k\Delta t}), \varepsilon \Delta t \mathcal{D}(k\Delta t, \tilde{X}_{k\Delta t}) \right)$$

$$\mathcal{D}(t, x) = \sigma(t, x) \sigma^T(t, x)$$

$$b(t, x) = b(x), \quad \sigma(t, x) = \text{Id}$$

$$\tilde{A}_\varepsilon = (2\pi \varepsilon \Delta t)^{-K/2} \int dx_1 \dots dx_K \exp \left(\frac{1}{\varepsilon} f(x_{K\Delta t}) \right.$$

$$\left. - \frac{1}{2\varepsilon \Delta t} \sum_{k=1}^{K-1} \left| x_{(k+1)\Delta t} - x_{k\Delta t} - \Delta t b(k\Delta t, x_{k\Delta t}) \right|^2 \right)$$

formally $\downarrow$

$$A_\varepsilon \propto \int_{x_{t=0}=x} \mathcal{D}x_t \exp \left(\frac{1}{\varepsilon} f(x_T) - \frac{1}{2\varepsilon} \int_0^T |\dot{x}_t - b(x_t)|^2 dt \right)$$

$x_{t=0}=x$

path integral.

$\downarrow$
meaning viz Girsanov thm.

$\varepsilon \downarrow 0$: Laplace method:

$$\lim_{\varepsilon \rightarrow 0} \varepsilon \log A_\varepsilon = - \inf_{\substack{x_t \\ x_0 \text{ fixed.}}} \left[\frac{1}{2} \int_0^T |\dot{x}_t - b(x_t)|^2 dt - f(x_T) \right]$$

$$L(x_t, \dot{x}_t) = \frac{1}{2} |\dot{x}_t - b(x_t)|^2$$

1st order
opt. cond.:

E.L.:

$$\begin{cases} (\dot{x}_t - b(x_t))^\circ = - \nabla b(x_t)^\top (\dot{x}_t - b(x_t)) \\ x_0 = 0 \\ \dot{x}_T - b(x_T) = \nabla f(x_T) \end{cases}$$

define: $\theta_t = \dot{x}_t - b(x_t)$

$$\begin{cases} \dot{x}_t = b(x_t) + \theta_t = \partial_x H(x_t, \theta_t) & x_0 = 0 \\ \dot{\theta}_t = -\nabla b^T(x_t) \theta_t = -\partial_{\theta} H(x_t, \theta_t) & \theta_T = \nabla f(x_T) \end{cases}$$

$$\lim_{\varepsilon \downarrow 0} \varepsilon \log A_{\varepsilon} = -\frac{1}{2} \int_0^T |\theta_t^*|^2 dt + f(x_T^*)$$

control problem

θ^* = opt. noise

Hamiltonian formulation:

$$\begin{cases} H(x, \theta) = \sup_{\gamma} (\gamma \cdot \theta - L(x, \gamma)) & \text{Convex in } \theta \\ L(x, \gamma) = \sup_{\theta} [\gamma \cdot \theta - H(x, \theta)] & \text{Convex in } \gamma \end{cases}$$

$$\lim_{\varepsilon \downarrow 0} \varepsilon \log A_{\varepsilon} = - \inf_x \sup_{\gamma} \left[\int_0^T [\dot{x}_t \cdot \theta_t - H(x_t, \theta_t)] dt - f(x_T) \right]$$

Similarity:

$$\lim_{\varepsilon \downarrow 0} \varepsilon \log \mathbb{P}^{x_0}(X_T^\varepsilon \in B) = -\frac{1}{2} \int_0^T |\dot{\theta}_t^*|^2 dt$$

$$\begin{cases} \dot{x}_t^* = \partial_{\theta} H(x_t^*, \theta_t^*) & x_0^* = x_0 \\ \dot{\theta}_t^* = -\partial_x H(x_t^*, \theta_t^*) & x_1^* = b^* \in B \end{cases}$$

etc.

ex:

$$dX_t^\varepsilon = -X_t^\varepsilon dt + \sqrt{\varepsilon} dW_t, \quad X_{t=0}^\varepsilon = 0$$

$$A_\varepsilon = \mathbb{E}^{X_0=0} \exp\left(\frac{\lambda}{\varepsilon} X_T^\varepsilon\right)$$

$$X_t = \sqrt{\varepsilon} \int_0^t e^{-t+s} dW_s \stackrel{d}{=} \sqrt{\frac{\varepsilon}{2}} (1 - e^{-t})^{1/2} \xi$$

$$\xi \sim N(0, 1)$$

$$A_\varepsilon = \exp\left(\frac{\lambda^2}{4\varepsilon} (1 - e^{-T})\right)$$

$$\begin{cases} \dot{X}_t = -X_t + \vartheta_t & X_{t=0} = 0 \\ \dot{\vartheta}_t = \vartheta_t & \vartheta_{t=T} = \lambda \end{cases}$$

$$\Rightarrow \vartheta_t^* = \lambda e^{t-T}$$

$$X_t^* = \int_0^t e^{-t+s} \vartheta_s^* ds = \lambda \int_0^t e^{-t+2s-T} ds$$

$$X_t^* = \frac{\lambda}{2} e^{-T} (e^t - e^{-t})$$

$t-T \rightarrow t$

$$\begin{cases} \vartheta_t^* = \lambda e^t \\ X_t^* = \frac{\lambda}{2} [e^t - e^{-t-2T}] \xrightarrow{T \downarrow \infty} \frac{\lambda}{2} e^t \end{cases}$$

$$\lim_{\lambda \downarrow 0} \lambda \log A_\lambda = - \frac{1}{2} \int_0^T |\dot{\theta}_t^*|^2 dt + \lambda x_T^*$$

$$= - \frac{\lambda^2}{2} \int_0^T e^{2t-2T} dt + \frac{\lambda^2}{2} e^{-T} (e^T \cdot e^{-T})$$

$$= - \frac{\lambda^2}{2} (1 - e^{-2T}) + \frac{\lambda^2}{2} (1 - e^{-2T})$$

$$= + \frac{\lambda^2}{4} (1 - e^{-2T})$$

SDE.

$$dX_t^\varepsilon = b(X_t^\varepsilon) dt + \sqrt{\varepsilon} dw_t$$

Ito calc: 2 key formula:

$$1) d\phi(t, X_t^\varepsilon) = \left[\partial_t \phi(t, X_t^\varepsilon) + b(X_t^\varepsilon) \cdot \nabla \phi(t, X_t^\varepsilon) + \frac{1}{2} \Delta \phi(t, X_t^\varepsilon) \right] dt + \sqrt{\varepsilon} \nabla \phi(t, X_t^\varepsilon) \cdot dw_t.$$

Ito formula

$$= [\partial_t \phi + (L\phi)] dt + \sqrt{\varepsilon} \nabla \phi \cdot dw_t$$

$$(Lf)(x) = b(x) \cdot \nabla f(x) + \frac{1}{2} \Delta f(x)$$

$$= \lim_{t \downarrow 0} \frac{1}{t} \mathbb{E}^x [f(X_t^\varepsilon) - f(x)].$$

generator.

$$2) \mathbb{E} \int_0^T \nabla \phi(t, X_t^\varepsilon) \cdot dw_t = 0$$

$$\mathbb{E} \left| \int_0^T \nabla \phi(t, X_t^\varepsilon) \cdot dw_t \right|^2 = \int_0^T \mathbb{E} |\nabla \phi(t, X_t^\varepsilon)|^2 dt.$$

Ito identity.

Backward Kolmogorov eq.

$$\partial_t u(t, x) + (L u)(t, x) = 0$$

$$u(T, x) = \bar{F}(x).$$

$$\Rightarrow u(0, x) = \mathbb{E}^x \bar{F}(X_T^\varepsilon)$$

Proof:

$$du(t, X_t^\varepsilon) = \underbrace{\left(\partial_t u(t, X_t^\varepsilon) + (L u)(t, X_t^\varepsilon) \right)}_{=0} dt + \sqrt{\varepsilon} \nabla u(t, X_t^\varepsilon) dW_t$$

$$\begin{aligned} \bar{F}(X_T^\varepsilon) &= \int_0^T \sqrt{\varepsilon} \nabla u(t, X_t^\varepsilon) dW_t \\ &= u(T, X_T^\varepsilon) - u(0, X_0^\varepsilon) + \sqrt{\varepsilon} \int_0^T \nabla u(t, X_t^\varepsilon) dW_t \end{aligned}$$

$\mathbb{E}^x$

$$\mathbb{E}^x \bar{F}(X_T^\varepsilon) = \mathbb{E}^x u(0, X_0^\varepsilon) = u(0, x).$$

scaling things

$$\partial_t u^\varepsilon(t, x) + b(x) \cdot \nabla u^\varepsilon(t, x) + \frac{\varepsilon}{2} \Delta u^\varepsilon(t, x) = 0.$$

$$u^\varepsilon(t=T, x) = e^{\frac{1}{\varepsilon} f(x)}$$

$$\text{let } u^\varepsilon(t, x) = e^{\frac{1}{\varepsilon} v^\varepsilon(t, x)}$$

$$\frac{1}{\varepsilon} \partial_t v^\varepsilon + \frac{1}{\varepsilon} b \cdot \nabla v^\varepsilon + \frac{1}{2} \Delta v^\varepsilon + \frac{1}{2\varepsilon} |\nabla v^\varepsilon|^2 = 0$$

$$v^\varepsilon(t=T, x) = f(x).$$

↓

$v^\varepsilon \rightarrow v$
 $\nabla v^\varepsilon \rightarrow \nabla v$

$$\partial_t v + b \cdot \nabla v + \frac{1}{2} |\nabla v|^2 = 0.$$

$$v(t=T, x) = f(x)$$

$H(x, \nabla v)$

HJE

$$v(0, x) = \lim_{\varepsilon \downarrow 0} v^\varepsilon(0, x) = \lim_{\varepsilon \downarrow 0} \varepsilon \log u^\varepsilon(0, x) = \lim_{\varepsilon \downarrow 0} \varepsilon \log e^{\frac{1}{\varepsilon} f(x_t)}$$

$$\text{let. } \begin{cases} \dot{x}_t = b(x_t) + \theta_t \\ \dot{\theta}_t = -(\nabla b)^T(x_t) \end{cases}$$

$$x_{t=0} = 0$$

$$\theta_{t=T} = \nabla f(x_{t=T})$$

$\Downarrow$

$$\Rightarrow \theta_t = \nabla \sigma(t, x_t)$$

$$1) \quad \theta_t = \nabla \sigma(t, x_t)$$

$$\theta_T = \nabla f(x_{t=T}) = \nabla \sigma(T, x_T)$$

$$\partial_t \sigma(bx) + b(bx) \cdot \nabla \sigma(bx) + \frac{1}{2} |\nabla \sigma(bx)|^2 = 0$$

$\nabla \downarrow$

$$\partial_t \nabla \sigma(bx) + (\nabla b)^T \cdot \nabla \sigma(bx) + b(bx) \cdot \nabla \nabla \sigma + \nabla \sigma \cdot \nabla \nabla \sigma = 0$$

$$\frac{d}{dt} \nabla \sigma(bx_t) = \partial_t \nabla \sigma(bx_t) + b \cdot \nabla \nabla \sigma + \theta_t \cdot \nabla \nabla \sigma$$

$$= -(\nabla b)^T \nabla \sigma(t, x_t) - \nabla \sigma \cdot \nabla \nabla \sigma + \theta_t \cdot \nabla \nabla \sigma$$

$$= 0 \text{ if } \theta_t = \nabla \sigma(t, x_t)$$

$$2) \quad \frac{d}{dt} \sigma(bx_t) = \partial_t \sigma + \dot{x}_t \cdot \nabla \sigma = \partial_t \sigma + b \cdot \nabla \sigma + \theta_t \cdot \nabla \sigma$$

$$= \frac{1}{2} |\theta_t|^2$$

$$\underbrace{\sigma(T, X_T)}_{//} - \underbrace{\sigma(0, X_0)}_{''} = \frac{1}{2} \int_0^T |\theta_t|^2 dt.$$

$$f(X_T) \quad \sigma(0, X_0) = \lim_{\varepsilon \downarrow 0} \varepsilon \log \#^{X_0} \exp\left(\frac{1}{\varepsilon} f(X_T)\right)$$

$\Downarrow$

$$\begin{aligned} \lim_{\varepsilon \downarrow 0} \varepsilon \log \#^{X_0} \exp\left(\frac{1}{\varepsilon} f(X_T^\varepsilon)\right) \\ = f(X_T) - \frac{1}{2} \int_0^T |\theta_t|^2 dt. \end{aligned}$$

as before.

$$\partial_t \sigma + H(x, \nabla \sigma) = 0$$

$$\sigma(T, x) = f(x).$$

$$\begin{cases} \dot{x}_t = \partial_{\theta} H(x_t, \theta_t) \\ \dot{\theta}_t = -\partial_x H(x_t, \theta_t) \end{cases}$$

Girsanov formula:

$$dX_t^\varepsilon = b(X_t^\varepsilon) dt + \sqrt{\varepsilon} dW_t$$

$$dY_t^\varepsilon = \dot{X}_t^* dt + \sqrt{\varepsilon} dW_t$$

$$Y_t^\varepsilon = X_t^* + \sqrt{\varepsilon} W_t.$$

"sol. to

$$\dot{X}_t^* = \partial_x H(X_t^*, \theta_t^*)$$

$$\dot{\theta}_t^* = -\partial_\theta H(X_t^*, \theta_t^*) + BC$$

$$\mathbb{E}^X \left[e^{\frac{1}{\varepsilon} f(X_t^\varepsilon)} \right] = \mathbb{E}^{X_0} \left[e^{\frac{1}{\varepsilon} f(Y_t^\varepsilon)} M_T \right]$$

$$M_T = \exp \left(-\frac{1}{2\varepsilon} \int_0^T |\dot{X}_t^* - b(Y_t^\varepsilon)|^2 dt + \frac{1}{\sqrt{\varepsilon}} \int_0^T (\dot{X}_t^* - b(Y_t^\varepsilon)) \cdot dW_t \right).$$

$$\mathbb{E} M_T = 0.$$

$$M_T = \exp \left(-\frac{1}{2\varepsilon} \int_0^T |\dot{X}_t^* - b(X_t^*)|^2 dt + o(1) \right).$$

$$\begin{aligned}
 \text{cf.} \quad & -\frac{1}{2} |\dot{x} - b|^2 + \frac{1}{2} |\dot{x} - \dot{x}_*|^2 \\
 = & -(\dot{x}_* - b) \dot{x} - \frac{1}{2} |b|^2 + \frac{1}{2} |\dot{x}_*|^2 \\
 & \quad \quad \quad \text{"} \\
 & \quad \quad \quad \dot{x}_* + \sqrt{\varepsilon} \dot{w}
 \end{aligned}$$

$$\begin{aligned}
 = & -|\dot{x}_*|^2 + b \cdot \dot{x}_* - \frac{1}{2} |b|^2 + \frac{1}{2} |\dot{x}_*|^2 \\
 & \quad \quad \quad + \sqrt{\varepsilon} (\dot{x}_* - b) \dot{w}
 \end{aligned}$$

$$= -\frac{1}{2} |\dot{x}_* - b|^2 + \sqrt{\varepsilon} (\dot{x}_* - b) \dot{w}$$