

HJP

$X_t \in \Omega$ embedded in $\mathbb{R}^d$ (e.g. $\mathbb{Z}^d$)

R reaction channels with

- rates $\lambda_j(x)$
 - change vectors v_j
- $j = 1 \dots R$.
- $x \in \Omega \Rightarrow x + v_j \in \Omega$

Dynamics:

$$X_{t+\Delta t} | X_t = \begin{cases} X_t + v_j & \text{with prob } \Delta t \lambda_j(X_t) + o(\Delta t) \\ X_t & \text{with prob } 1 - \Delta t \sum_{j=1}^R \lambda_j(X_t) + o(\Delta t) \end{cases} \quad j = 1 \dots R$$

Generator:

$$\begin{aligned} (L\phi)(x) &= \lim_{t \downarrow 0} \frac{1}{t} \mathbb{E}^x [\phi(X_t) - \phi(x)] \\ &= \sum_{j=1}^R \lambda_j(x) [\phi(x + v_j) - \phi(x)] \end{aligned}$$

Since:

$$\mathbb{E}^x \phi(X_t) = \sum_{j=1}^R t \lambda_j(x) \phi(x + v_j) + \left(1 - \sum_{j=1}^R t \lambda_j(x)\right) \phi(x) + o(t)$$

Simulations: rejection free MCMC:

Gillespie / BKL.

$$X_t \rightarrow X_{t+\tau(X_t)} = X_t + \tau_j(X_t) \rightarrow \dots$$

$$\left\{ \begin{array}{ll} \tau(X_t) = \text{exp. with rate } \lambda_0(X_t) = \sum_{j=1}^R \lambda_j(X_t) \\ j(X_t) = \text{drawn from } p_j(X_t) = \frac{\lambda_j(X_t)}{\sum_{k=1}^R \lambda_k(X_t)} \end{array} \right.$$

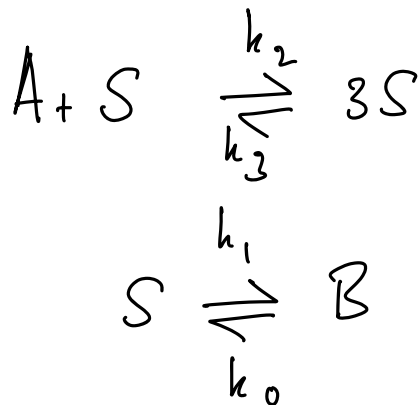
NB. More generally, $X_t \in \mathbb{R}^d$, $z \in \mathbb{R}^p$

$$(L\phi)(x) = \frac{1}{\varepsilon} \int \lambda(x, z) [\phi(x + \varepsilon \tau(z)) - \phi(x)] \mu(dz)$$

some prob. meas.

ex:

1. Schlögl model



$N = \# \text{ mol of species } S$

$\frac{N}{V} = \text{concentration}$

$C_A, C_B = \text{concentrations of } A, B$

$$N \rightarrow N+1 \quad \left\{ \begin{array}{l} k_0 \sqrt{C_B} \\ k_2 C_A \frac{N(N-1)}{V} \end{array} \right. \quad \begin{array}{l} \partial = +1 \\ \partial = +1 \end{array}$$

$$N \rightarrow N-1 \quad \left\{ \begin{array}{l} k_3 \frac{N(N-1)(N-2)}{V^2} \\ k_1 N \end{array} \right. \quad \begin{array}{l} \partial = -1 \\ \partial = -1 \end{array}$$

scaling: $N \gg 1, V \gg 1, \frac{N}{V} = x = O(1)$

$\Rightarrow \varepsilon = 1/V \ll 1$

$$\lambda_+(x) = k_0 + k_1 x(x - \varepsilon) \quad \partial_+ = +1$$

$$\lambda_-(x) = k_1 x + k_3 x(x - \varepsilon)(x - 2\varepsilon) \quad \partial_- = -1$$

2. discrete diffusion:

N_T particles in M boxes.

N_i = # particle in box $i = 1 \dots M$. ($\sum_{i=1}^M N_i = N_T$)

jump right $N_i \rightarrow N_i - 1$ & $N_{i+1} \rightarrow N_{i+1} + 1$ rate $\propto N_i$

jump left $N_i \rightarrow N_i + 1$ & $N_{i-1} \rightarrow N_{i-1} - 1$ rate $\propto N_i$
 $\propto$ -est.

$$\mathcal{D}_i^R = (0 \dots -1 \quad +1 \dots 0)$$

$\quad \quad \quad i \quad \quad i+1$

$$\mathcal{D}_i^L = (0 \dots +1 \quad -1 \dots 0)$$

$\quad \quad \quad i-1 \quad \quad i$

periodic

$$\Delta = 1/\varepsilon$$

scaling:

$$N_T \gg 1$$

$$N_i \gg 1$$

$$\frac{N_i}{N} = x_i = O(1)$$

$$\Rightarrow \varepsilon = 1/N \ll 1 \quad \& \quad (\mathcal{L}f)(x) = \frac{\alpha}{\varepsilon} \sum_{i=1}^M \left(x_i [f(x + \varepsilon \mathcal{D}_i^R) - f(x)] + x_i [f(x + \varepsilon \mathcal{D}_i^L) - f(x)] \right)$$

Rescaled generator

$$(L^\varepsilon \phi)(x) = \sum_{j=1}^R \frac{1}{\varepsilon} \lambda_j^\varepsilon(x) [\phi(x + \varepsilon \nu_j) - \phi(x)].$$

$$\text{with: } \lambda_j^\varepsilon(x) = \lambda_j(x) + \varepsilon \tilde{\lambda}_j(x) + O(\varepsilon^2).$$

BKE

$$\mathbb{E}^x F(X_t^\varepsilon) = u^\varepsilon(T, t, x).$$

$$\partial_t u^\varepsilon + L^\varepsilon u^\varepsilon = 0$$

"

$$u^\varepsilon(T, x) = F(x)$$

$$\partial_t u^\varepsilon(t, x) + \frac{1}{\varepsilon} \sum_{j=1}^R \lambda_j^\varepsilon(x) [u^\varepsilon(t, x + \varepsilon \nu_j) - u^\varepsilon(t, x)] = 0$$

NB

forward KE: $p(t, x)$ = PROB that $X_t = x$ @ time t

$$\partial_t p(t, x) = \sum_{j=1}^R [\lambda_j(x - \nu_j) p(t, x - \nu_j) - \lambda_j(x) p(t, x)]$$

LLN

$$u^\varepsilon \rightarrow u$$
$$\varepsilon \downarrow 0$$

$$\partial_t u(t, x) + \sum_{j=1}^R \lambda_j(x) \partial_j \cdot \nabla u(t, x) = 0$$

since: $\frac{1}{\varepsilon} [u(t, x + \varepsilon \partial_j) - u(t, x)] = \partial_j \cdot \nabla u(t, x) + O(\varepsilon)$

BKE for ODE:

$$\dot{X}_t = \sum_{j=1}^R \lambda_j(X_t) \partial_j$$

Law of mass action

CLT

... linear SDE with coeff dep.
on X_t , $\lambda(x)$, $\tilde{\lambda}(x)$

LDP

$$\mathbb{E}^x \left[e^{\frac{1}{\varepsilon} f(X_t^\varepsilon)} \right] = u^\varepsilon(T-t, x).$$

$$\partial_t u^\varepsilon(t, x) + \frac{1}{\varepsilon} \sum_{j=1}^R \lambda_j^\varepsilon(x) [u^\varepsilon(t, x + \varepsilon \partial_j) - u^\varepsilon(t, x)]$$

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

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

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

$$\frac{1}{\varepsilon} \partial_t \sigma^\varepsilon(t, x) e^{\frac{1}{\varepsilon} \sigma^\varepsilon(t, x)}$$

$$+ \frac{1}{\varepsilon} \sum_{j=1}^R \lambda_j^\varepsilon(x) \left[e^{\frac{1}{\varepsilon} \sigma^\varepsilon(t, x + \varepsilon \partial_j)} - e^{\frac{1}{\varepsilon} \sigma^\varepsilon(t, x)} \right] = 0$$

$$\Leftrightarrow \partial_t \sigma^\varepsilon(t, x) + \sum_{j=1}^R \lambda_j^\varepsilon(x) \left[e^{\frac{1}{\varepsilon} [\sigma^\varepsilon(t, x + \varepsilon \partial_j) - \sigma^\varepsilon(t, x)]} - 1 \right] = 0$$

$\varepsilon \downarrow 0$

$$\sigma^2 \rightarrow \sigma$$

$$\sigma \downarrow 0$$

$$\partial_t \sigma(t, x) + \underbrace{\sum_{j=1}^R \lambda_j(x) [\partial_j \sigma(t, x) - 1]}_{H(x, \nabla \sigma)} = 0$$

$$H(x, \nabla \sigma)$$

HJB E

$$\begin{cases} \dot{x}_t = \partial_\theta H(x_t, \theta_t) = \sum_{j=1}^R \lambda_j(x_t) \partial_j e^{\nabla_j \cdot \theta_t} \\ \dot{\theta}_t = -\partial_x H(x_t, \theta_t) = -\sum_{j=1}^R \nabla \lambda_j(x_t) [e^{\nabla_j \cdot \theta_t} - 1] \end{cases}$$

$$\theta_t = 0 \rightarrow \underline{\underline{LN}}$$

$$\dot{x}_t = \partial_\theta H(x_t, \theta_t = 0)$$

! H Not quadratic & quadratic approx of H $\neq$ CLT.

ex: 1. Schlögl:

$$\lambda_+^\varepsilon(x) = k_0 + k_1 x(x - \varepsilon) \quad \vartheta^+ = +1$$

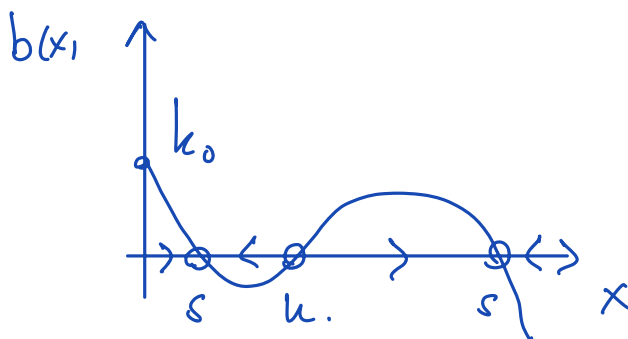
$$\lambda_-^\varepsilon(x) = k_1 x + k_3 x(x - \varepsilon)(x - 2\varepsilon) \quad \vartheta^- = -1$$

$$H(x, \vartheta) = (k_0 + k_1 x^2)(e^\vartheta - 1) + (k_1 x + k_3 x^3)(e^{-\vartheta} - 1)$$

$$\begin{cases} \dot{x}_t = (k_0 + k_1 x_t^2) e^{\vartheta_t} - (k_1 x_t + k_3 x_t^3) e^{-\vartheta_t} \\ \dot{\vartheta}_t = 2k_1 x_t^2 (e^{\vartheta_t} - 1) + (k_1 + 3k_3 x_t^2)(e^{-\vartheta_t} - 1) \end{cases}$$

@ $\vartheta_t = 0$

$$\dot{x}_t = k_0 + k_1 x_t^2 - \overbrace{k_1 x_t + k_3 x_t^3}^{= b(x_t)}$$



12w of mes, 2ehra

2. discrete diffusion:

$$\begin{aligned} H(x, \theta) &= \alpha \sum_{j=1}^M \left[x_j^i (e^{\theta_{j+1}^i - \theta_j^i} - 1) \right. \\ &\quad \left. + x_j^i (e^{\theta_{j-1}^i - \theta_j^i} - 1) \right] \\ &= \alpha \sum_{j=1}^M x_j^i [e^{\theta_{j+1}^i - \theta_j^i} + e^{\theta_{j-1}^i - \theta_j^i} - 2] \end{aligned}$$

$$\dot{x}_t^i = \frac{\partial H}{\partial \theta_i^i} = 2\alpha \left[x_t^{i-1} e^{\theta_t^i - \theta_t^{i-1}} - x_t^i e^{\theta_t^{i+1} - \theta_t^i} \right. \\ \left. + x_t^{i+1} e^{\theta_t^i - \theta_t^{i+1}} - x_t^i e^{\theta_t^{i-1} - \theta_t^i} \right]$$

$$\dot{\theta}_t^i = -\frac{\partial H}{\partial x_i^i} = -\alpha (e^{\theta_{i+1}^i - \theta_i^i} + e^{\theta_{i-1}^i - \theta_i^i} - 2)$$

LLN: $\dot{x}_t^i = 2\alpha [x_t^{i+1} + x_t^{i-1} - 2x_t^i]$

discrete diff eq.

NB

continuous limit

$$\theta_j = \theta(j\Delta s) \rightarrow \theta(s)$$

$$e^{\frac{\theta_{j-1} - \theta_j}{-1}} = e^{-h \partial_s \theta + \frac{h^2}{2} \partial_s^2 \theta + \dots} - 1$$

$$= -h \partial_s \theta + \frac{h^2}{2} (\partial_s^2 \theta + |\partial_s \theta|^2) + \dots$$

$$e^{\theta_{j+1} - \theta_j} = e^{+h \partial_s \theta + \frac{h^2}{2} \partial_s^2 \theta + \dots}$$

$$= h \partial_s \theta + \frac{h^2}{2} (\partial_s^2 \theta + |\partial_s \theta|^2)$$

$$\sim H(x, \theta) = 2\alpha \int_0^1 ds \, x(s) [\partial_s^2 \theta + |\partial_s \theta|^2].$$

$$\left\{ \begin{array}{l} \partial_t x(s) = \frac{\delta H}{\delta \theta(s)} = 2\alpha \partial_s^2 x_t(s) - 2\alpha \partial_s (x_t(s) \partial_s \theta_t(s)) \\ \partial_t \theta(s) = -\frac{\delta H}{\delta x(s)} = -2\alpha [\partial_s^2 \theta_t(s) + |\partial_s \theta_t(s)|^2] \end{array} \right.$$

NB:

Another derivation:

$$dX_t^i = b(X_t^i) dt + \frac{1}{N} \sum_{j=1}^N c(X_t^i, X_t^j) dt + \sqrt{2D} dW_t^i.$$

$$\rho_N(t, x) = \frac{1}{N} \sum_{i=1}^N \delta(x - X_t^i)$$

empirical measure

$$\begin{aligned} d\rho_N(t, x) &= -\frac{1}{N} \sum_{i=1}^N \nabla \delta(x - X_t^i) \cdot dX_t^i \\ &\quad + \frac{D}{N} \sum_{i=1}^N \Delta \delta(x - X_t^i) dt \end{aligned}$$

$$\begin{aligned} &= -\frac{1}{N} \sum_{i=1}^N \nabla \delta(x - X_t^i) \cdot \left(b(X_t^i) + \frac{1}{N} \sum_{j=1}^N c(X_t^i, X_t^j) \right) dt \\ &\quad + \frac{D}{N} \sum_{i=1}^N \Delta \delta(x - X_t^i) dt \\ &\quad - \frac{\sqrt{2D}}{N} \sum_{i=1}^N \nabla \delta(x - X_t^i) \cdot dW_t^i \end{aligned}$$

$$\begin{aligned} d\rho_N(t, x) &= -\nabla \cdot \left[\left(b(x) + \int c(x, y) \rho_N(t, y) dy \right) \rho_N(t, x) \right] dt \\ &\quad + D \Delta \rho_N(t, x) dt \\ &\quad - \sqrt{2D} \sum_{i=1}^N \nabla \delta(x - X_t^i) \cdot dW_t^i. \end{aligned}$$

$$\lim_{t \downarrow 0} \frac{1}{t} \mathbb{E}^{\rho_N^0} \left(\Phi[\rho_N(t)] - \Phi[\rho_N^0] \right)$$

$$= - \int \nabla \cdot \left[\left(b(x) + \int c(x, \gamma) \rho_N^0(\gamma) d\gamma \right) \rho_N^0(x) \right] \frac{\delta \Phi}{\delta \rho_N^0(x)} dx$$

$$+ \int \mathbb{D} \Delta \rho_N^0 \frac{\delta \Phi}{\delta \rho_N^0(x)}$$

$$+ \underbrace{\frac{\Theta}{N^2} \sum_{i,j=1}^N \int \nabla_x \delta(x - x_0^i) \cdot \nabla_\gamma \delta(\gamma - x_0^j) \frac{\delta^2 \Phi}{\delta \rho_N^0(x) \delta \rho_N^0(\gamma)} dx d\gamma}_{//}$$

$$\frac{\Theta}{N} \sum_{i=1}^N \int \nabla_x \delta(x - x_0^i) \cdot \nabla_\gamma \delta(\gamma - x_0^i) \frac{\delta^2 \Phi}{\delta \rho_N^0(x) \delta \rho_N^0(\gamma)} dx d\gamma$$

$$= \frac{\Theta}{N} \int \rho_N^0(x) \delta(x - \gamma) \nabla_x \cdot \nabla_\gamma \frac{\delta^2 \Phi}{\delta \rho_N^0(x) \delta \rho_N^0(\gamma)} dx d\gamma.$$

$$\Rightarrow H(p, \theta) = \int \nabla \theta(x) \cdot \left(b(x) + \int c(x, y) p(y) dy \right) p(x) dx \\ + \mathcal{D} \int \Delta \theta(x) p(x) dx + \mathcal{D} \int |\nabla \theta|^2 p(x) dx$$

$$\partial_t p_t(x) = \frac{\delta H}{\delta \theta(x)} = - \nabla \cdot \left[\left(b(x) + \int c(x, y) p_t(y) dy \right) p_t(x) \right] \\ + \mathcal{D} \Delta p_t(x) - 2 \nabla \cdot (p_t(x) \nabla \theta_t(x))$$

$$\partial_t \theta_t(x) = - \frac{\delta H}{\delta p(x)} = - b(x) \cdot \nabla \theta_t(x) - \int c(y, x) \nabla \theta_t(y) p_t(y) dy \\ - \mathcal{D} \Delta \theta_t(x) - \mathcal{D} |\nabla \theta_t(x)|^2$$