

Large deviation simulations: Equilibrium vs nonequilibrium systems

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Problems

Large deviation problem

$$P(A_n \in B) \approx e^{-nI}$$

Dual problem

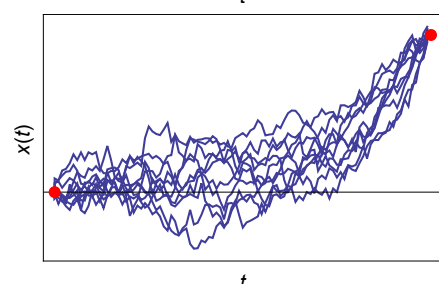
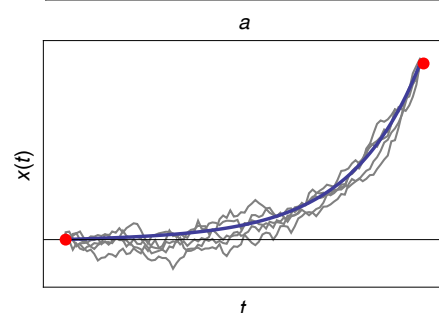
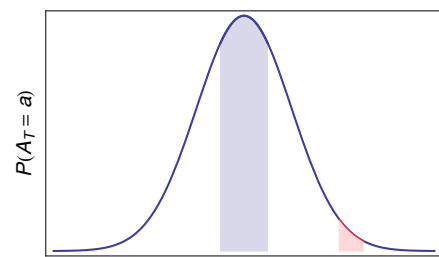
$$E[e^{kA_n}] \approx e^{n\lambda(k)}$$

- Generating function
- Spectral problem (Kac)

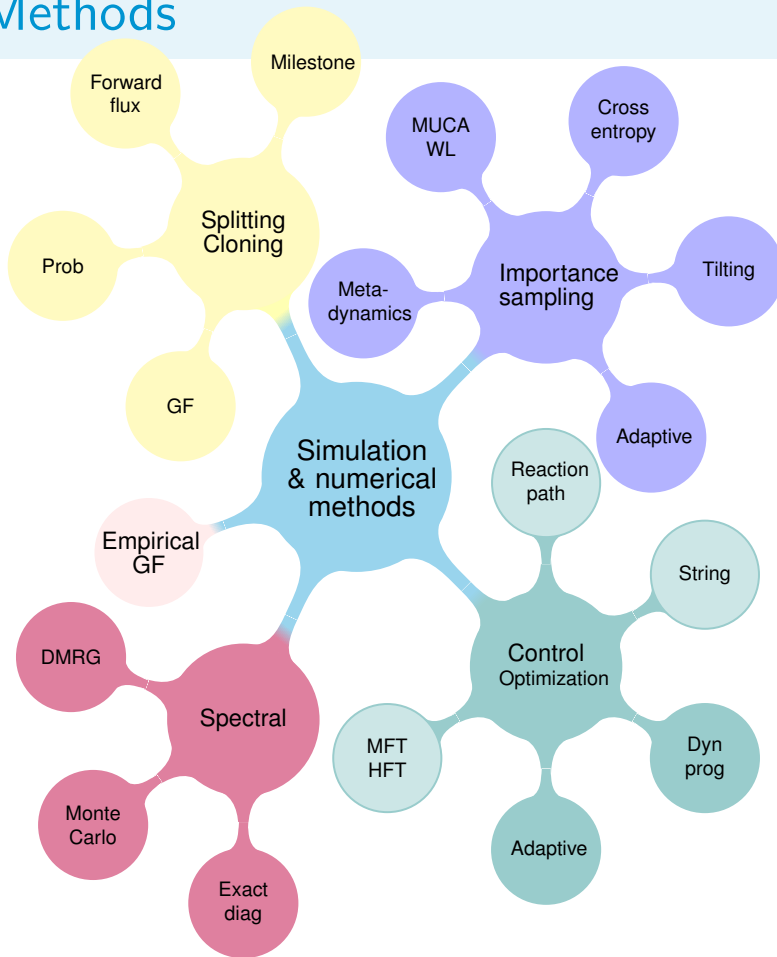
Prediction problem

How is the fluctuation created?

- Reaction or optimal path
- Fluctuation process
- Conditioning



Methods



Questions

- Equilibrium or nonequilibrium method?
- Equilibrium vs nonequilibrium fluctuations
- Nonequilibrium more difficult?

Methods covered

- Spectral
- Optimization
- Importance sampling

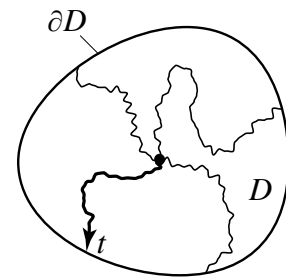
Low-noise large deviations

- Process:

$$dX_t^\varepsilon = F(X_t^\varepsilon)dt + \sqrt{\varepsilon} dW_t, \quad X_0 \in O$$

- Transition rare event:

$$P(X_T^\varepsilon \in B | X_0 \in O) \approx e^{-V/\varepsilon}, \quad \varepsilon \rightarrow 0$$



Freidlin-Wentzell-Graham

$$V = \inf_{x \in B} \underbrace{V(x)}_{\text{quasi-potential}} = \inf_{x \in B} \inf_{x_0 \in O, x_t = x} \underbrace{\frac{1}{2} \int_0^t (\dot{x}_s - F(x_s))^2 ds}_{\text{FW action, Lagrangian } J[x]}$$

- Deterministic control problem
- Optimal path $\{x_t^*\}$
- $V(x)$ solves Hamilton-Jacobi-Bellman equation (1st order)

Low-noise large deviations (cont'd)

Fluctuation created by optimal path

Conditioning

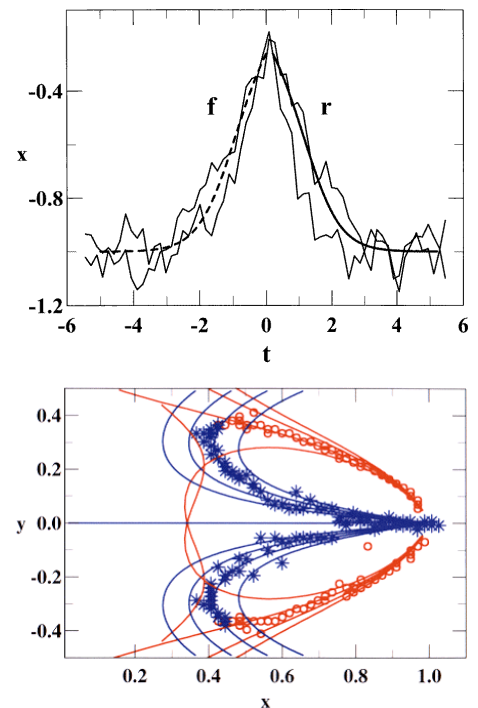
- $P[x] \approx e^{-J[x]/\varepsilon} \max$
- $P[x|\text{escape event}]$ concentrates on optimal path

Equilibrium

- Optimal path = relaxation path^R
- $V(x) = J[x_{\text{relax}}^R]$

Nonequilibrium

- Optimal path \neq relaxation path^R
- Current loops
- Transversal decomposition [Graham 80's]



[Luchinsky et al 1997]

Applications

SDEs

$$dX_t = F(X_t)dt + \sqrt{\varepsilon} \text{ noise}$$

- Escape, transition paths, escape time
[Onsager-Machlup 1953] [Freidlin-Wentzell 70s] [Graham 80-90s] ...
- Experiments [Luchinsky and McClintock 90s]
- Metastability [Olivieri-Vares 2005]

SPDEs

$$d\rho(x, t) = F[\rho]dt + \sqrt{\varepsilon} \text{ noise}$$

- Heat equation [Faris, Jona-Lasinio 1982]
- Ginzburg equation [Graham 1990s]
- Reaction-diffusion [Vanden-Eijnden 2000s]
- 2D fluid equations [Laurie-Bouchet 2014]
- MFT/HFT [Bertini et al 2000s]

Long-time large deviations

- Process:

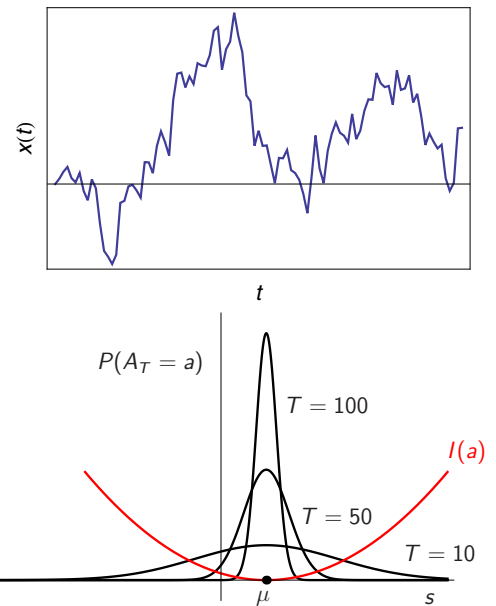
$$dX_t = F(X_t)dt + \sigma dW_t$$

- Observable:

$$A_T = \frac{1}{T} \int_0^T f(X_t) dt + \frac{1}{T} \int_0^T g(X_t) \circ dX_t$$

- Large deviation principle (LDP):

$$P(A_T = a) \approx e^{-T I(a)}, \quad T \rightarrow \infty$$



Examples

- Occupation time, empirical density
- Current, mean speed, activity
- Work, heat, entropy production (stochastic thermo)

Dual problem

Scaled cumulant function

$$\lambda(k) = \lim_{T \rightarrow \infty} \frac{1}{T} \ln E[e^{TkA_T}]$$

Gärtner-Ellis Theorem

$\lambda(k)$ differentiable, then

- 1 LDP for A_T
- 2 $I(a) = \sup_k \{ka - \lambda(k)\}$

Feynman-Kac-Perron-Frobenius

$$\mathcal{L}_k r_k = \lambda(k) r_k$$

- Tilted (twisted) operator: \mathcal{L}_k
- Dominant eigenvalue: $\lambda(k)$
- Dominant eigenfunction: r_k

Jump processes

$$\mathcal{L}_k = W e^{kg} - \lambda + kf$$

Diffusions

$$\mathcal{L}_k = F \cdot (\nabla + kg) + \frac{D}{2} (\nabla + kg)^2 + kf$$

Spectral problem

Equilibrium

- X_t reversible, g gradient, f arbitrary
- \mathcal{L}_k non-Hermitian but conjugated to Hermitian:

$$\mathcal{H}_k = \rho^{1/2} \mathcal{L}_k \rho^{-1/2}, \quad \psi_k^2 = r_k l_k$$

- Real spectrum (quantum problem)

Nonequilibrium

- X_t nonreversible OR g non-gradient, f arbitrary
- \mathcal{L}_k non-Hermitian, not conjugated to Hermitian
- Complex spectrum
- Full spectral problem:

$$\begin{aligned} \mathcal{L}_k r_k &= \lambda(k) r_k & r_k(x) l_k(x) &\xrightarrow{|x| \rightarrow \infty} 0 \\ \mathcal{L}_k^\dagger l_k &= \lambda(k) l_k \end{aligned}$$

Algorithms

Markov chains

- Non-symmetric positive matrices
- Direct diagonalization
- Power method
- DMRG [Gorissen-Vanderzande 2011]

Diffusions

- Equilibrium: (Quantum) spectral methods
- Nonequilibrium: Fourier decomposition, basis functions

Cloning/splitting

- Particle/trajectory simulation
- Yields SCGF
- No eigenvector

Other approach: Optimization and control

$$A_T = \tilde{A}(\rho_T, J_T) = \int f(x) \underbrace{\rho_T(x)}_{\text{dist.}} dx + \int g(x) \underbrace{J_T(x)}_{\text{current}} dx$$

Drift optimization

$$I(a) = \inf_{u: E_u[A_T]=a} \frac{1}{2\sigma^2} \int (u(x) - F(x))^2 \rho_{\text{inv}}^u(x) dx$$

- Requires stationary distribution ρ_{inv}^u

Stochastic optimal control

$$I(a) = \lim_{T \rightarrow \infty} \inf_{u: A_T^u \rightarrow a} \frac{1}{2\sigma^2 T} \int_0^T (u(X_t^u) - F(X_t^u))^2 dt$$

- Controlled process: X_t^u
- Constrained control (dual for SCGF is unconstrained)
- Solves Hamilton-Jacobi-Bellman equation (2nd order)

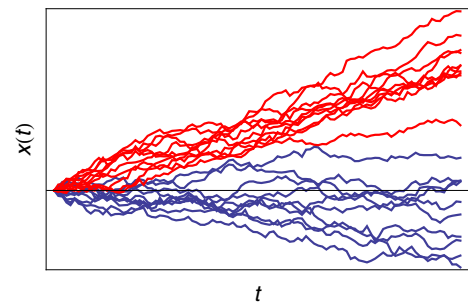
Fluctuation process

Optimal control process

$$d\hat{X}_t = F_k(\hat{X}_t)dt + \sigma dW_t$$

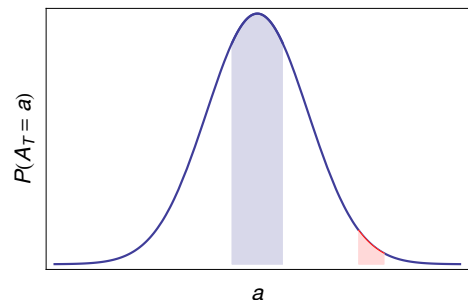
- Optimal drift:

$$F_k(x) = F(x) + D(kg + \nabla \ln r_k), \quad I'(a) = k$$



Conditioning

$$\underbrace{X_t | A_T = a}_{\text{conditioned microcanonical}} \xrightarrow{T \rightarrow \infty} \underbrace{\hat{X}_t}_{\text{driven canonical}}$$



- Effective process creating the fluctuation
- Process generalization of optimal path

[Chetrite HT, PRL 2013, AHP 2015, JSTAT 2015]

Equilibrium vs nonequilibrium

$$A_T = \tilde{A}(\rho_T, J_T) = \int f(x) \underbrace{\rho_T(x)}_{\text{dist.}} dx + \int g(x) \underbrace{J_T(x)}_{\text{current}} dx$$

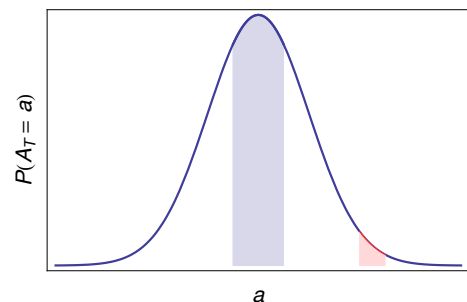
X_t	g	\hat{X}_t
Reversible	0	Reversible Same spectrum Rayleigh-Ritz variational principle
	Gradient	Reversible Rayleigh-Ritz variational principle
	Non-gradient	Non-reversible
Non-reversible	0	Non-reversible Donsker-Varadhan principle
	Other	Non-reversible

- Process closest to X_t that creates fluctuation
- Distance: $\|u - F\|_{\rho_{\text{inv}}^u}$ or $\frac{1}{T} S(P_{\hat{X}} \| P_X)$

Simulations: Importance sampling

- $P(A_T = a) \approx e^{-TI(a)}$
- Direct sampling:

$$\text{sample size} = L \sim e^T$$



Importance sampling

- Change process: $X_t \rightarrow \hat{X}_t$
- Make $A_T = a$ typical
- Change of measure:

$$P(A_T = a) = E_X[\mathbb{1}_a(A_T)] = E_{\hat{X}} \left[\frac{dP_X}{dP_{\hat{X}}} \mathbb{1}_a(A_T) \right]$$

- Estimator:

$$\hat{P}_L(a) = \frac{1}{L} \sum_{j=1}^L \mathbb{1}_a(A_T^{(j)}) R$$

Efficiency

Zero-variance process

- Conditioned process: $X_t | A_T = a$
- Estimator variance:

$$\text{var}_{\hat{X}}(\hat{P}_L) = \frac{E_{\hat{X}}[R^2 \mathbb{1}_a(A_T)] - p^2}{L} = 0$$

Effective process

- Not zero variance
- Asymptotic optimality:

$$\lim_{T \rightarrow \infty} -\frac{1}{T} \ln E_{\hat{X}}[R^2 \mathbb{1}_a(A_T)] = 2I(a)$$

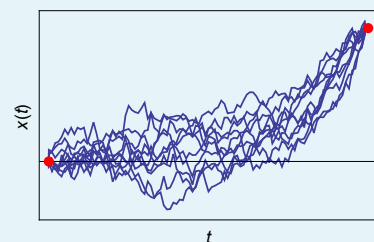
- Variance goes to 0 with largest rate
- Exponential tilting:

$$P_{\text{driven}}[x] \approx P_k[x] = \frac{e^{TkA_T[x]} P[x]}{E[e^{TkA_T}]}$$

Connections

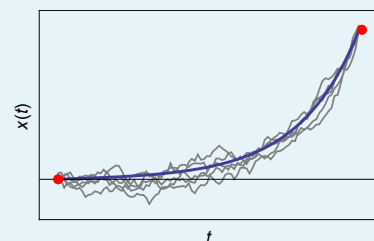
$\sigma > 0$

- Stochastic optimal control
- Quadratic cost function (log RND)
- Nonlinear HJB equation (2nd order)
- Similar to cross-entropy minimization



$\sigma \rightarrow 0$

- Deterministic optimal control
- Quadratic cost function (log RND)
- Nonlinear HJB (1st order, viscosity)



Optimal controller

Dyn programming

\hat{X}_t

Value function

HJB equations

LD functions

↔ Exponential tilting

Conclusions

LD \equiv control/optimization \equiv spectral
Type of fluctuations determines class of control designs

Equilibrium fluctuations

Reversible control
Hermitian spectral problem

Nonequilibrium fluctuations

Non-reversible control
Non-hermitian spectral problem

Future work

- Adapt methods from quantum mechanics
- Methods for non-hermitian operators
- HJB-based methods
- Adaptive control methods
- Error bars
- Benchmarking

References



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Introduction to large deviations: Theory, applications, simulations
2011 Oldenburg School Lecture Notes, [arxiv:1106.4146](#)



[R. Chetrite, H. Touchette](#)

Variational and optimal control representations
of conditioned and driven processes
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[J. Bucklew](#)

Introduction to Rare Event Simulation
[Springer, 2004](#)



[More pointers at](#)

www.physics.sun.ac.za/~htouchette/ldt