Symposium of the Collaborative Research Center 910

Theory and applications of random Poincaré maps

Nils Berglund

Institut Denis Poisson, CNRS UMR 7013 Université d'Orléans, France

TU Berlin, July 6 2018

Joint works with Manon Baudel (Ecole des Ponts, Paris), Barbara Gentz (Bielefeld), Christian Kuehn (TU Munich) and Damien Landon









Nils Berglund

nils.berglund@univ-orleans.fr

http://www.univ-orleans.fr/mapmo/membres/berglund/

Contents

- 1. (Random) Poincaré maps
- Example 1: interspike interval distributions in the stochastic FitzHugh–Nagumo model [B & Landon, Nonlinearity 2012]
- Example 2: mixed-mode oscillations in the stochastic Koper model [B, Gentz & Kuehn, J. Diff. Eq. 2012, J. Dyn. Diff. Eq. 2015]
- 4. Spectral theory for random Poincaré maps [Baudel & B, SIAM J. Math. Anal. 2017]

1. Deterministic Poincaré maps

ODE $\dot{z} = f(z)$ $z \in \mathbb{R}^n$ Flow: $z_t = \varphi_t(z_0)$ $\Sigma \subset \mathbb{R}^n$: (n-1)-dimensional manifold Poincaré map (or first-return map): $T : \Sigma \to \Sigma$



 $T(z) = \varphi_{\tau}(z)$ where $\tau = \inf\{t > 0 \colon \varphi_t(z) \in \Sigma\}$

1. Deterministic Poincaré maps

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$$T(z) = \varphi_{\tau}(z)$$
 where $\tau = \inf\{t > 0 \colon \varphi_t(z) \in \Sigma\}$

Benefits:

- 1. Dimension reduction: T is an (n-1)-dimensional map
- 2. Stability of periodic orbits: no neutral direction
- 3. Bifurcations of periodic orbits easier to study (period doubling, Hopf, ...)

Question: how about SDEs $dz_t = f(z_t) dt + \sigma g(z_t) dW_t$?

Random Poincaré maps

 $dz_t = f(z_t) dt + \sigma g(z_t) dW_t \quad \Rightarrow \quad \text{Sample path } (Z_t^{z_0}(\omega))_{t \ge 0}$



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 $\Delta z_0 = X_0 \in \Sigma \quad \Rightarrow \quad \inf\{t > 0 \colon Z_t^{X_0} \in \Sigma\} = 0$

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July 6, 2018

Random Poincaré maps

 $dz_t = f(z_t) dt + \sigma g(z_t) dW_t \quad \Rightarrow \quad \text{Sample path } (Z_t^{z_0}(\omega))_{t \ge 0}$



 $\begin{array}{ll} & \fbox{Δ} \quad z_0 = X_0 \in \Sigma \quad \Rightarrow \quad \inf\{t > 0 \colon Z_t^{X_0} \in \Sigma\} = 0 \\ & \text{Solution: } \tau_0 = 0, \ \tau'_{n+1} = \inf\{t > \tau_n \colon Z_t^{X_0} \in \Sigma'\} \\ & \tau_{n+1} = \inf\{t > \tau'_{n+1} \colon Z_t^{X_0} \in \Sigma\} \\ & X_n = Z_{\tau_n}^{X_0} \in \Sigma \quad \Rightarrow \quad (X_n)_{n \ge 0} \text{ is a Markov chain} \quad K(x, A) := \mathbb{P}^x\{X_1 \in A\} \\ & (X_n, \omega) \mapsto X_{n+1} \colon \text{ random Poincaré map} \\ & \text{[J. Weiss, E. Knobloch, 1990], [P. Hitczenko, G. Medvedev, 2009]} \end{array}$

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July 6, 2018

Fredholm theory

 $X_n = Z_{\tau_n}^{X_0} \in \Sigma$

 $(X_n)_{n \ge 0}$ Markov chain, of kernel $K(x, A) = \mathbb{P}\{X_{n+1} \in A | X_n = x\}$

Under appropriate conditions

 $K(x,A) = \int_A k(x,y) \, \mathrm{d} y$



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Markov semigroups:

$$\begin{split} (K\varphi)(x) &= \int_{\Sigma} k(x,y)\varphi(y) \, \mathrm{d}y = \mathbb{E}^{x}[\varphi(X_{1})] \qquad \varphi \in L^{\infty} \\ (\mu K)(y) &= \int_{\Sigma} \mu(x)k(x,y) \, \mathrm{d}x = \mathbb{P}^{\mu}\{X_{1} \in \mathrm{d}y\} \qquad \mu \in L^{1} \end{split}$$

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K is compact operator \Rightarrow Fredholm theory Spectral decomposition: $K\phi_i = \lambda_i\phi_i$ $\pi_i K = \lambda_i\pi_i$ $\langle \pi_i, \phi_j \rangle = \delta_{ij}$ $k(x, y) = \lambda_0\phi_0(x)\pi_0(y) + \lambda_1\phi_1(x)\pi_1(y) + \dots$ Theory and applications of random Poincaré maps July 6, 2018 3/20 (25)



2. Example 1: Stochastic FitzHugh–Nagumo eq.

- $dx_t = \frac{1}{\varepsilon} [x_t x_t^3 + y_t] dt$ neuron membrane potential $dy_t = [a - x_t - by_t] dt$ open ion channels
- ▷ b = 0 for simplicity in this talk, bifurcation parameter $\delta := \frac{3a^2-1}{2}$



 $\begin{array}{l} \varepsilon = 0.1 \\ \delta = 0.02 \end{array}$

2. Example 1: Stochastic FitzHugh–Nagumo eq.

$$dx_t = \frac{1}{\varepsilon} [x_t - x_t^3 + y_t] dt + \frac{\sigma_1}{\sqrt{\varepsilon}} dW_t^{(1)}$$
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$$\triangleright$$
 0 < $\sigma_1, \sigma_2 \ll$ 1, $\sigma = \sqrt{\sigma_1^2 + \sigma_2^2}$



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$$\begin{split} \varepsilon &= 0.1 \\ \delta &= 0.02 \\ \sigma_1 &= \sigma_2 = 0.03 \end{split}$$

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Mixed-mode oscillations (MMOs)



Random Poincaré map



 X_0, X_1, \ldots substochastic Markov chain describing process killed on ∂D Number of small oscillations: $N = \inf\{n \ge 1 \colon X_n \notin \Sigma\}$

Random Poincaré map



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Theorem 1 [B & Landon, Nonlinearity **25**:2303–2335, 2012] *N* is asymptotically geometric: $\lim_{n\to\infty} \mathbb{P}\{N = n + 1 | N > n\} = 1 - \lambda_0$ where $\lambda_0 \in \mathbb{R}_+$: principal eigenvalue of the kernel *K*, $\lambda_0 < 1$ if $\sigma > 0$

Proof: follows from existence of spectral gap

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Histograms of distribution of N (1000 spikes)



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Weak-noise regime

Theorem 2 [B & Landon, Nonlinearity 25:2303–2335, 2012]

Assume ε and $\delta/\sqrt{\varepsilon}$ sufficiently small There exists $\kappa > 0$ s.t. for $\sigma^2 \leq (\varepsilon^{1/4}\delta)^2 / \log(\sqrt{\varepsilon}/\delta)$

Principal eigenvalue:

$$1 - \lambda_0 \leqslant \exp\left\{-\kappa rac{(arepsilon^{1/4} \delta)^2}{\sigma^2}
ight\}$$

Expected number of small oscillations:

$$\mathbb{E}^{\mu_0}[N] \ge C(\mu_0) \exp\left\{\kappa \frac{(\varepsilon^{1/4}\delta)^2}{\sigma^2}\right\}$$

where $C(\mu_0)$ = probability of starting on Σ above separatrix

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Proof: Let $A \subset \Sigma$ have positive Lebesgue measure

$$\lambda_0 \pi_0(A) = \int_{\Sigma} \pi_0(\mathsf{d} x) \mathcal{K}(x, A) \ge \int_{A} \pi_0(\mathsf{d} x) \mathcal{K}(x, A) \quad \Rightarrow \quad \lambda_0 \ge \inf_{x \in A} \mathcal{K}(x, A)$$

 \Rightarrow construct A such that K(x, A) exponentially close to 1 for all $x \in A$

Dynamics near the separatrix

Change of variables:

- ▷ Translate to Hopf bif. point
- Scale space and time
- ▷ Straighten nullcline $\dot{x} = 0$

 \Rightarrow variables (ξ, z) where nullcline: $\{z = \frac{1}{2}\}$

$$d\xi_t = \left(\frac{1}{2} - z_t - \frac{\sqrt{\varepsilon}}{3}\xi_t^3\right) dt$$
$$dz_t = \left(\mu + 2\xi_t z_t + \frac{2\sqrt{\varepsilon}}{3}\xi_t^4\right) dt$$



where

$$\mu = \frac{\delta}{\sqrt{\varepsilon}}$$

Dynamics near the separatrix

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 $d\xi_t = \left(\frac{1}{2} - z_t - \frac{\sqrt{\varepsilon}}{3}\xi_t^3\right) dt + \tilde{\sigma}_1 dW_t^{(1)}$

$$dz_t = \left(\tilde{\mu} + 2\xi_t z_t + \frac{2\sqrt{\varepsilon}}{3}\xi_t^4\right) dt - 2\tilde{\sigma}_1\xi_t dW_t^{(1)} + \tilde{\sigma}_2 dW_t^{(2)}$$

where

$$\tilde{\mu} = \frac{\delta}{\sqrt{\varepsilon}} - \tilde{\sigma}_1^2 \qquad \tilde{\sigma}_1 = -\sqrt{3} \frac{\sigma_1}{\varepsilon^{3/4}} \qquad \tilde{\sigma}_2 = \sqrt{3} \frac{\sigma_2}{\varepsilon^{3/4}}$$

Upward drift dominates if $\tilde{\mu}^2 \gg \tilde{\sigma}_1^2 + \tilde{\sigma}_2^2 \Rightarrow (\varepsilon^{1/4}\delta)^2 \gg \sigma_1^2 + \sigma_2^2$ Rotation around *P*: use that $2z e^{-2z-2\xi^2+1}$ is constant for $\tilde{\mu} = \varepsilon = 0$ Take $A = \{z > \tilde{\mu}^{1-\gamma}\}$ with $0 < \gamma < \frac{1}{4}$

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July 6, 2018

From below to above threshold

Linear approximation:

$$dz_t^0 = \left(\tilde{\mu} + tz_t^0\right) dt - \tilde{\sigma}_1 t \, dW_t^{(1)} + \tilde{\sigma}_2 \, dW_t^{(2)}$$

$$\Rightarrow \quad \mathbb{P}\{\text{no small osc}\} \simeq \Phi\left(-\pi^{1/4} \frac{\tilde{\mu}}{\sqrt{\tilde{\sigma}_1^2 + \tilde{\sigma}_2^2}}\right) \qquad \Phi(x) = \int_{-\infty}^x \frac{e^{-y^2/2}}{\sqrt{2\pi}} \, dy$$

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*:
$$\mathbb{P}$$
{no small osc}
+: $1/\mathbb{E}[N]$
o: $1 - \lambda_0$
curve: $x \mapsto \Phi(\pi^{1/4}x)$

$$x = -rac{ ilde{\mu}}{\sqrt{ ilde{\sigma}_1^2 + ilde{\sigma}_2^2}} = -rac{arepsilon^{1/4} (\delta - \sigma_1^2/arepsilon)}{\sqrt{\sigma_1^2 + \sigma_2^2}}$$

Summary: Parameter regimes



Regime I: rare isolated spikes Theorem 2 applies ($\delta \ll \varepsilon^{1/2}$) Interspike interval \simeq exponential **Regime II:** clusters of spikes # interspike osc asympt geometric

 $\sigma = (\delta \varepsilon)^{1/2}$: geom(1/2) **Regime III:** repeated spikes

 $\mathbb{P}\{N=1\}\simeq 1$

 $\sigma_1 = \sigma_2$: $\mathbb{P}\{N=1\} \simeq \Phi\left(-\frac{(\pi\varepsilon)^{1/4}(\delta-\sigma^2/\varepsilon)}{\sigma}\right)$ $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-y^2/2} \,\mathrm{d}y$

see also

July 6, 2018

[Muratov & Vanden Eijnden '08]



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Interspike interval \simeq constant

3. Example 2: The Koper model

 $\varepsilon \, \mathrm{d}x_t = [y_t - x_t^3 + 3x_t] \, \mathrm{d}t \qquad + \sqrt{\varepsilon} \sigma F(x_t, y_t, z_t) \, \mathrm{d}W_t$ $\mathrm{d}y_t = [kx_t - 2(y_t + \lambda) + z_t] \, \mathrm{d}t + \sigma' G_1(x_t, y_t, z_t) \, \mathrm{d}W_t$ $\mathrm{d}z_t = [\rho(\lambda + y_t - z_t)] \, \mathrm{d}t \qquad + \sigma' G_2(x_t, y_t, z_t) \, \mathrm{d}W_t$



Folded-node singularity at P^* induces mixed-mode oscillations [Benoît, Lobry '82, Szmolyan, Wechselberger '01, ...] Poincaré map $\Pi : \Sigma \to \Sigma$ is almost 1*d* due to contraction in *x*-direction

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July 6, 2018











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Size of fluctuations



Transition	Δx	Δy	Δz
$\Sigma_2 ightarrow \Sigma_3$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_3 ightarrow \Sigma_4$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_4 o \Sigma_4'$	$\frac{\sigma}{\varepsilon^{1/6}} + \frac{\sigma'}{\varepsilon^{1/3}}$		$\sigma \sqrt{\varepsilon {\log \varepsilon} } + \sigma'$
$\Sigma_4' ightarrow \Sigma_5$		$\sigma\sqrt{\varepsilon} + \sigma'\varepsilon^{1/6}$	$\sigma\sqrt{\varepsilon} + \sigma'\varepsilon^{1/6}$
$\Sigma_5 ightarrow \Sigma_6$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_6 ightarrow \Sigma_1$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_1\to \Sigma_1'$		$(\sigma + \sigma') \varepsilon^{1/4}$	σ'
$\Sigma_1' o \Sigma_1''$ if $z = \mathcal{O}(\sqrt{\mu})$		$(\sigma + \sigma')(\varepsilon/\mu)^{1/4}$	$\sigma'(arepsilon/\mu)^{1/4}$
$\Sigma_1'' o \Sigma_2$		$(\sigma + \sigma') \varepsilon^{1/4}$	$\sigma' \varepsilon^{1/4}$

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July 6, 2018

Main results

[B, Gentz, Kuehn, JDE 2012 & J Dynam Diff Eq 2015]



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Theorem 3: early escape

$$\begin{split} &P_0 \in \Sigma_1 \text{ in sector with } k > 1/\sqrt{\mu} \Rightarrow \text{first hitting of } \Sigma_2 \text{ at } P_2 \text{ s.t.} \\ &\mathbb{P}^{P_0}\{z_2 \geqslant z\} \leqslant C |\log(\sigma + \sigma')|^{\gamma} e^{-\kappa z^2/(\varepsilon \mu |\log(\sigma + \sigma')|)} \end{split}$$

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- \triangleright Saturation effect occurs at $k_{
 m c} \simeq \sqrt{|\log(\sigma + \sigma')|/\mu|}$
- ▷ For $k > k_c$, behaviour indep. of k and $\Delta z \leq O(\sqrt{\varepsilon \mu |\log(\sigma + \sigma')|})$

4. Spectral theory of random Poincaré maps

 $X_n = Z_{\tau_n}^{X_0} \in \Sigma$ $(X_n)_{n \ge 0} \text{ Markov chain, of kernel}$ $K(x, A) = \mathbb{P}\{X_{n+1} \in A | X_n = x\}$ Under appropriate conditions $K(x, A) = \int_A k(x, y) \, dy$



Markov semigroups:

$$(K\varphi)(x) = \int_{\Sigma} k(x, y)\varphi(y) \, dy = \mathbb{E}^{x}[\varphi(X_{1})] \qquad \varphi \in L^{\infty}$$
$$(\mu K)(y) = \int_{\Sigma} \mu(x)k(x, y) \, dx = \mathbb{P}^{\mu}\{X_{1} \in dy\} \qquad \mu \in L^{1}$$

K is compact operator \Rightarrow Fredholm theory

Spectral decomposition: $K\phi_i = \lambda_i\phi_i$ $\pi_i K = \lambda_i\pi_i$ $\langle \pi_i, \phi_j \rangle = \delta_{ij}$ $k \ (x, y) = \lambda_0\phi_0(x)\pi_0(y) + \lambda_1\phi_1(x)\pi_1(y) + \dots$

Theory and applications of random Poincaré maps

July 6, 2018

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Theory and applications of random Poincaré maps

July 6, 2018

 $\mathrm{d} z_t = f(z_t) \, \mathrm{d} t + \sigma g(z_t) \, \mathrm{d} W_t$

Assumption 1: Domain

 $f \in \mathcal{C}^2(\mathcal{D}_0, \mathbb{R}^{d+1}), \mathcal{D} \subset \mathcal{D}_0$ positively invariant under deterministic flow

 $z_t \in \mathcal{D}_0 \subset \mathbb{R}^{d+1}$

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Assumption 2: Deterministic α - and ω -limit sets $N \ge 2$ asymptotically stable periodic orbits $\Gamma_1, \ldots, \Gamma_N$ in \mathcal{D} Other limit sets are unstable points or orbits, no heteroclinic connections

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Assumption 3: Ellipticity $g \in C^1(\mathcal{D}_0, \mathbb{R}^{(d+1) \times k})$ $0 < c_- \|\xi\|^2 \leq \langle \xi, g(z)g(z)^{\mathsf{T}}\xi \rangle \leq c_+ \|\xi\|^2 \qquad \forall z \in \mathcal{D} \ \forall \xi \in \mathbb{R}^{d+1} \setminus \{0\}$

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Assumption 3: Ellipticity $g \in C^1(\mathcal{D}_0, \mathbb{R}^{(d+1) \times k})$ $0 < c_- \|\xi\|^2 \leq \langle \xi, g(z)g(z)^\mathsf{T}\xi \rangle \leq c_+ \|\xi\|^2 \quad \forall z \in \mathcal{D} \ \forall \xi \in \mathbb{R}^{d+1} \setminus \{0\}$ Assumption 4: Confinement $\exists \text{ Lyapunov function } V \in C^2(\mathcal{D}_0, \mathbb{R}_+), \ \|V(z)\| \to \infty \text{ as } z \to \partial \mathcal{D}_0$ $(\mathcal{L}V)(z) \leq -cV + d\mathbb{1}_{z \in \mathcal{D}}, \quad c > 0, \ d \geq 0$ Theory and applications of random Poincaré maps $\int u|y| 6, 2018$ 17/20 (25)

Freidlin–Wentzell theory: Rate function: $I_{[0,T]}(\gamma) = \frac{1}{2} \int_0^T (\dot{\gamma}_s - f(\gamma_s))^T [gg^T(\gamma_s)]^{-1} (\dot{\gamma}_s - f(\gamma_s)) ds$ Large-deviation principle: $\mathbb{P}\{(z_t)_{0 \le t \le T} \in \Lambda\} \simeq e^{-\inf_{\gamma \in \Lambda} I_{[0,T]}(\gamma)/\sigma^2}$

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Quasipotential between periodic orbits: $H(i,j) = \inf_{T>0} \inf_{\gamma:\Gamma_i \to \Gamma_j} I_{[0,T]}(\gamma)$

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Quasipotential between periodic orbits: $H(i,j) = \inf_{T>0} \inf_{\gamma:\Gamma_i \to \Gamma_j} I_{[0,T]}(\gamma)$



Freidlin–Wentzell theory: Rate function: $I_{[0,T]}(\gamma) = \frac{1}{2} \int_0^T (\dot{\gamma}_s - f(\gamma_s))^T [gg^T(\gamma_s)]^{-1} (\dot{\gamma}_s - f(\gamma_s)) ds$ Large-deviation principle: $\mathbb{P}\{(z_t)_{0 \leq t \leq T} \in \Lambda\} \simeq e^{-\inf_{\gamma \in \Lambda} I_{[0,T]}(\gamma)/\sigma^2}$

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Remark: Using Doob's *h*-transform, one may replace Assumption 4 by Assumption 4': Confinement

 $\exists heta' > 0$ such that $\min_i H(i, \partial D) \geqslant \max_{\substack{i \neq j}} H(i, j) + heta'$

Main results [Baudel & B, SIAM J. Math. Anal. **49**:4319–4375, 2017] $B_k \subset \Sigma$: nbh of $\Gamma_k \cap \Sigma$, $\mathcal{M}_k = \bigcup_{j \leq k} B_k$, τ_A, τ_A^+ 1st-passage/return time to A**Theorem 1**: Eigenvalues

The *N* largest eigenvalues of *K* are real and positive. $\exists \theta_k, c > 0$ s.t.

$$\begin{split} \lambda_0 &= 1\\ \lambda_k &= 1 - \mathbb{P}^{\mathring{\pi}_0^{k+1}} \{ \tau_{\mathcal{M}_k}^+ < \tau_{\mathcal{B}_{k+1}}^+ \} [1 + \mathcal{O}(\mathrm{e}^{-\theta_k/\sigma^2})] & 1 \leqslant k \leqslant N-1\\ |\lambda_k| &< 1 - \frac{c}{\log(\sigma^{-1})} =: \rho & k \geqslant N \end{split}$$

 $\mathring{\pi}_{0}^{k+1}: \text{ QSD on } B_{k+1} \text{ and } \mathbb{P}^{\mathring{\pi}_{0}^{k+1}}\{\tau_{\mathcal{M}_{k}}^{+} < \tau_{B_{k+1}}^{+}\} \simeq e^{-H(k+1,\{1,\ldots,k\})/\sigma^{2}}$

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$$\begin{split} &\mathring{\pi}_{0}^{k+1} \colon \text{QSD on } B_{k+1} \text{ and } \mathbb{P}^{\mathring{\pi}_{0}^{k+1}} \{ \tau_{\mathcal{M}_{k}}^{+} < \tau_{B_{k+1}}^{+} \} \simeq e^{-H(k+1,\{1,\dots,k\})/\sigma^{2}} \\ & \text{Theorem 2} \colon \text{Eigenfunctions} \\ & \phi_{0}(x) = 1 \qquad \phi_{k}(x) = \mathbb{P}^{x} \{ \tau_{B_{k+1}} < \tau_{\mathcal{M}_{k}} \} [1 + \mathcal{O}(e^{-\bar{\theta}/\sigma^{2}})] + \mathcal{O}(e^{-\bar{\theta}_{k}/\sigma^{2}}) \\ & \pi_{k}(B_{k+1}) = 1 - \mathcal{O}(e^{-\kappa/\sigma^{2}}) \qquad \pi_{k}(B_{j}) = \mathcal{O}(e^{-\bar{\theta}/\sigma^{2}}) \qquad 0 \leqslant k < j < N \\ & k^{n}(x, y) = \pi_{0}(y) + \sum_{i=1}^{N-1} \lambda_{i}^{n} \phi_{i}(x) \pi_{i}(y) + \mathcal{O}(\rho^{n}) \qquad n \gg \log(\rho^{-1}) \qquad \text{``Proofs} \end{split}$$

Theory and applications of random Poincaré maps

July 6, 2018

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$$|\lambda_{k}| < 1 - \frac{c}{\log(\sigma^{-1})} =: \rho \qquad k \geq N$$

Theorem 3: Expected hitting times $\mathbb{E}^{x}[\tau_{\mathcal{M}_{k}}] = [1 - \lambda_{k}]^{-1}[1 + \mathcal{O}(e^{-\kappa/\sigma^{2}})] \quad \forall x \in B_{k+1}, \ 1 \leq k \leq N-1$

Outlook

- ▷ In progress: cases without metastable hierarchy (eigenvalue crossings)
- Open: asymptotics beyond large deviations

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- 5. _____, From random Poincaré maps to stochastic mixed-mode-oscillation patterns, J. Dynam. Diff. Eq. 27, 83–136 (2015)
- Manon Baudel & N.B., Spectral theory for random Poincaré maps, SIAM J. Math. Analysis 49, 4319–4375 (2017)

Theory and applications of random Poincaré maps

July 6, 2018

Proof of asymptotically geometric distribution

Theorem 1 [B & Landon, Nonlinearity 25:2303–2335, 2012] N is asymptotically geometric: $\lim_{n \to \infty} \mathbb{P}\{N = n + 1 | N > n\} = 1 - \lambda_0$

where $\lambda_0 \in (0,1)$ if $\sigma > 0$ is principal eigenvalue of the kernel K

Proof:

Markov chain on Σ , kernel K with density k [Ben Arous, Kusuoka, Stroock '84]

$$\begin{split} & \succ \ \lambda_0 \leqslant \sup_{x \in \Sigma} K(x, \Sigma) < 1 \text{ by ellipticity } (k \text{ bounded below}) \\ & \triangleright \ \mathbb{P}^{\mu_0} \{ N > n \} = \mathbb{P}^{\mu_0} \{ X_n \in \Sigma \} = \int_{\Sigma} \mu_0(\mathrm{d}x) K^n(x, \Sigma) \\ & = \int_{\Sigma} \mu_0(\mathrm{d}x) \lambda_0^n \phi_0(x) [1 + \mathcal{O}((|\lambda_1|/\lambda_0)^n)] \\ & = \lambda_0^n \langle \mu_0, \phi_0 \rangle [1 + \mathcal{O}((|\lambda_1|/\lambda_0)^n)] \\ & \triangleright \ \mathbb{P}^{\mu_0} \{ N = n + 1 \} = \int_{\Sigma} \int_{\Sigma} \mu_0(\mathrm{d}x) K^n(x, \mathrm{d}y) [1 - K(y, \Sigma)] \\ & = \lambda_0^n (1 - \lambda_0) \langle \mu_0, \phi_0 \rangle [1 + \mathcal{O}((|\lambda_1|/\lambda_0)^n)] \end{split}$$

Existence of spectral gap follows from positivity condition [Birkhoff '57]



Estimating noise-induced fluctuations



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July 6, 2018

Estimating noise-induced fluctuations

 $\zeta_t = (x_t, y_t, z_t) - (x_t^{\mathsf{det}}, y_t^{\mathsf{det}}, z_t^{\mathsf{det}})$

$$d\zeta_{t} = \frac{1}{\varepsilon} A(t)\zeta_{t} dt + \frac{\sigma}{\sqrt{\varepsilon}} \mathcal{F}(\zeta_{t}, t) dW_{t} + \frac{1}{\varepsilon} \underbrace{b(\zeta_{t}, t)}_{=\mathcal{O}(||\zeta_{t}||^{2})} dt$$
$$\zeta_{t} = \frac{\sigma}{\sqrt{\varepsilon}} \int_{0}^{t} U(t, s) \mathcal{F}(\zeta_{s}, s) dW_{s} + \frac{1}{\varepsilon} \int_{0}^{t} U(t, s) b(\zeta_{s}, s) ds$$

where U(t,s) principal solution of $\varepsilon \dot{\zeta} = A(t)\zeta$.

Lemma (Bernstein-type estimate):

$$\mathbb{P}\left\{\sup_{0\leqslant s\leqslant t}\left\|\int_{0}^{s}\mathcal{G}(\zeta_{u},u)\,\mathrm{d}W_{u}\right\|>h\right\}\leqslant 2n\exp\left\{-\frac{h^{2}}{2V(t)}\right\}$$

where $\int_0 \mathcal{G}(\zeta_u, u) \mathcal{G}(\zeta_u, u)' \, du \leq V(s)$ a.s. and n = 3 space dimension

Remark: more precise results using ODE for covariance matrix of

$$\zeta_t^0 = \frac{\sigma}{\sqrt{\varepsilon}} \int_0^t U(t,s) \mathcal{F}(0,s) \,\mathrm{d} W_s$$

Theory and applications of random Poincaré maps

July 6, 2018



Example: analysis near the regular fold



Proposition: For
$$h_1 = \mathcal{O}(\varepsilon^{2/3})$$

$$\mathbb{P}\left\{ \| (y_{\tau_{\Sigma_{\mathbf{5}}}}, z_{\tau_{\Sigma_{\mathbf{5}}}}) - (y^*, z^*) \| > h_1 \right\}$$

$$\leq C \| \log \varepsilon \| \left(\exp\left\{ -\frac{\kappa h_1^2}{\sigma^2 \varepsilon + (\sigma')^2 \varepsilon^{1/3}} \right\} + \exp\left\{ -\frac{\kappa \varepsilon}{\sigma^2 + (\sigma')^2 \varepsilon} \right\} \right)$$

Useful if $\sigma, \sigma' \ll \sqrt{\varepsilon}$

Theory and applications of random Poincaré maps

July 6, 2018

➡ Back

Feynman–Kac-type relation: For $|e^{-u}| > \sup_{x \in A^c} \mathbb{P}^x \{X_1 \in A^c\}$

 $\begin{cases} (K\psi)(x) = e^{-u} \psi(x) & x \in A^c \\ \psi(x) = \phi(x) & x \in A \end{cases} \qquad \Leftrightarrow \qquad \psi(x) = \mathbb{E}^x [e^{u\tau_A} \phi(X_{\tau_A})] \end{cases}$

To estimate (λ_k, ϕ_k) choose $A = \mathcal{M}_{k+1} = \bigcup_{j=1}^{k+1} B_j$

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To estimate (λ_k, ϕ_k) choose $A = \mathcal{M}_{k+1} = \bigcup_{i=1}^{k+1} B_i$ Restricted kernel: $\mathcal{K}^{u}(x, dy) = \mathbb{E}^{\times}[e^{u(\tau_{A}^{+}-1)} \mathbb{1}_{\{X_{x^{+}} \in dy\}}]$ $(K\phi)(x) = e^{-u}\phi(x) \quad \forall x \in \Sigma \qquad \Leftrightarrow \qquad (K^u\phi)(x) = e^{-u}\phi(x) \quad \forall x \in A$ 1st approximation: $K^u(x, dy) \simeq K^0(x, dy) = \mathbb{P}^x \{X_{\tau_A^+} \in dy\}$ Trace process 2nd approximation: $\mathcal{K}^0(x, \mathrm{d}y) \simeq \mathcal{K}^*(x, \mathrm{d}y) = \sum_{i=1}^{N+1} \mathbb{1}_{\{x \in B_i\}} \mathbb{P}^{\hat{\pi}_0^i} \{X_{\tau^+_*} \in \mathrm{d}y\}$ **Lemma**: Though *K* not reversible \forall disjoint $A_1, A_2 \subset \Sigma$ $\int_{A_1} \pi_0(x) \mathbb{P}^x \{ \tau_{A_2}^+ < \tau_{A_1}^+ \} \, \mathrm{d}x = \int_{A_2} \pi_0(x) \mathbb{P}^x \{ \tau_{A_1}^+ < \tau_{A_2}^+ \} \, \mathrm{d}x$