Random Dynamical Systems

Theory and applications of random Poincaré maps

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Joint works with Manon Baudel (Orléans), Barbara Gentz (Bielefeld), Christian Kuehn (Munich) and Damien Landon









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

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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 $dz_t = f(z_t) dt + \sigma g(z_t) dW_t$?

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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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Random Poincaré maps

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

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Application: 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 $\delta := \frac{3a^2-1}{2}$

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▷ b = 0 for simplicity in this talk, bifurcation parameter $\delta := \frac{3a^2-1}{2}$ ▷ $W_t^{(1)}, W_t^{(2)}$: independent Wiener processes

 \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 $\partial \mathcal{D}$ Number of small oscillations: $N = \inf\{n \ge 1 \colon X_n \notin \Sigma\}$

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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)



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}
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▷ 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: Construct $A \subset \Sigma$ such that K(x, A) exponentially close to 1 for all $x \in A$, $\lambda_0 \pi_0(A) = \int_{\Sigma} \pi_0(dx) K(x, A) \ge \int_A \pi_0(dx) K(x, A) \Rightarrow \lambda_0 \ge \inf_{x \in A} K(x, A)$

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Linear approximation around separatrix provides good description for dynamics with stronger noise

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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 $\mathbb{P}\{N = 1\} \simeq 1$ Interspike interval \simeq constant

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$$\sigma_1 = \sigma_2:$$

$$\mathbb{P}\{N = 1\} \simeq \Phi\left(-\frac{(\pi\varepsilon)^{1/4}(\delta - \sigma^2/\varepsilon)}{\sigma}\right)$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-y^2/2} \, \mathrm{d}y$$

see also

[Muratov & Vanden Eijnden '08]



 $X_n = Z_{\tau_n}^{X_0} \in \Sigma$ (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 $K(x, A) = \int_A k(x, y) \, dy$



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Markov semigroups:

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

K is compact operator \Rightarrow Fredholm theory

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

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

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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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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Assumption 5: Metastable hierarchy $\exists \theta > 0 \text{ s.t. } \forall 2 \leq k \leq N$ $\min_{\substack{\ell < k}} H(k, \ell) \leq \min_{\substack{i \leq k \\ j \neq i}} H(i, j) - \theta$ $H(4, \{1, 2, 3\})$

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

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

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.

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

 $\mathring{\pi}_0^{k+1}: \text{ QSD on } B_{k+1} \text{ and } \mathbb{P}^{\mathring{\pi}_0^{k+1}}\{\tau^+_{\mathcal{M}_k} < \tau^+_{B_{k+1}}\} \simeq \mathrm{e}^{-H(k+1,\{1,\ldots,k\})/\sigma^2}$

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

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

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

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Outlook

- ▷ In progress: cases without metastable hierarchy (eigenvalue crossings)
- ▷ In progress: applications (Hawkes, Lotka–Volterra, Morris–Lecar, ...)
- In progress: numerical algorithms (based on QSDs, adaptive multilevel splitting)

References:

- 1. N. B. & Damien Landon, *Mixed-mode oscillations and interspike interval statistics* in the stochastic FitzHugh–Nagumo model, Nonlinearity **25**, 2303-2335 (2012)
- Manon Baudel & N.B., Spectral theory for random Poincaré maps, SIAM J. Math. Analysis 49, 4319–4375 (2017)

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- In progress: numerical algorithms (based on QSDs, adaptive multilevel splitting)
- ▷ Related: exit through an unstable periodic orbit [3.]
- ▷ Related: MMOs in fast-slow systems with folded node singularity [4.]
- Open: asymptotics beyond large deviations

References:

- 1. N. B. & Damien Landon, *Mixed-mode oscillations and interspike interval statistics* in the stochastic FitzHugh–Nagumo model, Nonlinearity **25**, 2303-2335 (2012)
- Manon Baudel & N.B., Spectral theory for random Poincaré maps, SIAM J. Math. Analysis 49, 4319–4375 (2017)
- 3. N.B. & Barbara Gentz, On the noise-induced passage through an unstable periodic orbit II: General case, SIAM J. Math. Analysis **46**, 310-352 (2014)
- N. B., Barbara Gentz & Christian Kuehn, From random Poincaré maps to stochastic mixed-mode-oscillation patterns, J. Dynam. Diff. Eq. 27, 83-136 (2015)

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]





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

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Theory and applications of random Poincaré maps

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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: ${\cal K}^u(x,{\sf d} y)\simeq {\cal K}^0(x,{\sf d} y)={\mathbb P}^x\{X_{ au_A^+}\in{\sf d} y\}$ Trace process 2nd approximation: $\mathcal{K}^0(x, \mathrm{d} y) \simeq \mathcal{K}^*(x, \mathrm{d} y) = \sum \mathbb{1}_{\{x \in \mathcal{B}_i\}} \mathbb{P}^{\check{\pi}^i_0} \{X_{\tau^+_*} \in \mathrm{d} y\}$ **Lemma**: Though *K* not reversible \forall disjoint $A_1, A_2 \subset \Sigma$ ➡ Back $\int_{A_1} \pi_0(x) \mathbb{P}^x \{ \tau_{A_2}^+ < \tau_{A_1}^+ \} \, \mathrm{d}x = \int_{A_2} \pi_0(x) \mathbb{P}^x \{ \tau_{A_1}^+ < \tau_{A_2}^+ \} \, \mathrm{d}x$