

# From random Poincaré maps to stochastic mixed-mode-oscillation patterns

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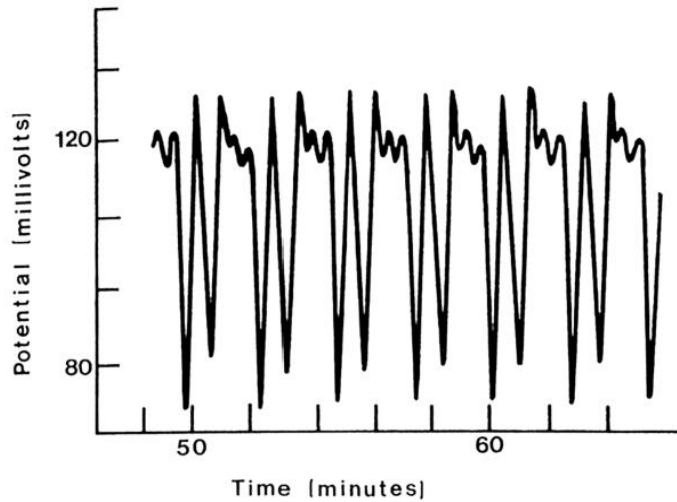
Collaborators:

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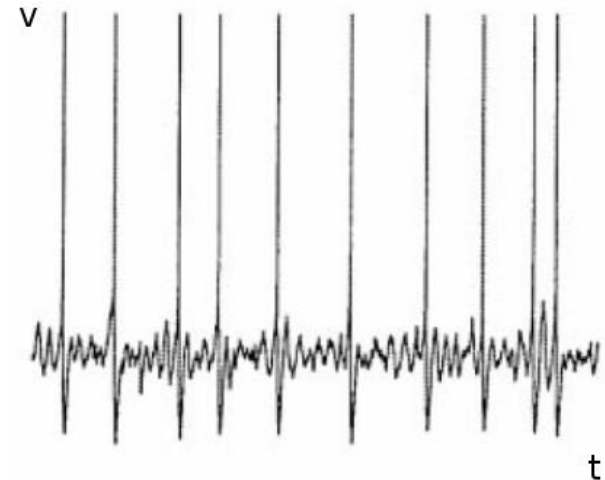
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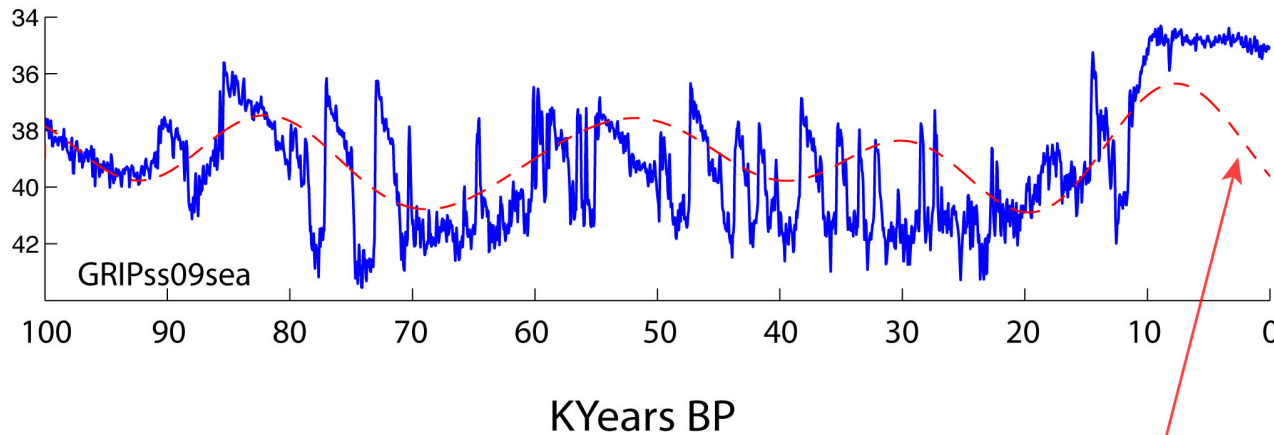
# Mixed-mode oscillations (MMOs)



Belousov-Zhabotinsky reaction [Hudson 79]



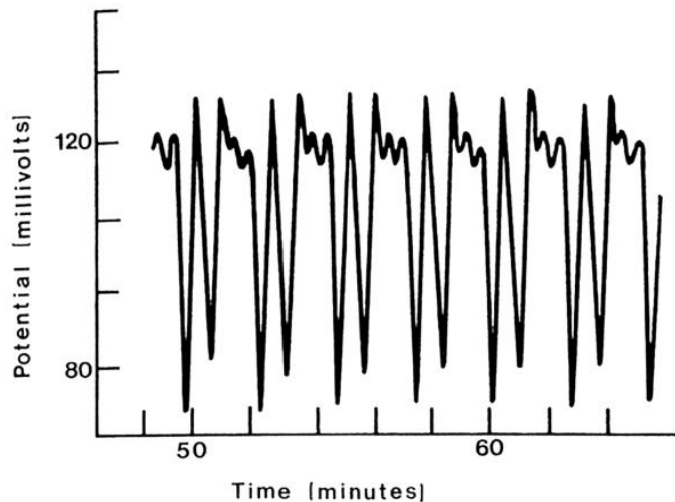
Stellate cells [Dickson 00]



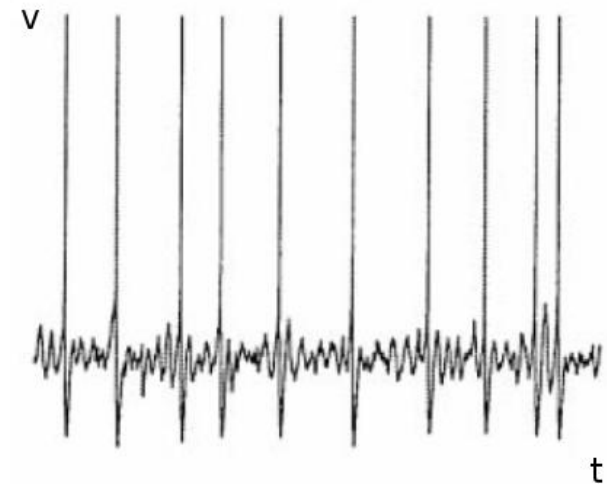
Summer insolation at 65N

Mean temperature based on ice core measurements [Johnson et al 01]

## Mixed-mode oscillations (MMOs)



Belousov-Zhabotinsky reaction [Hudson 79]



Stellate cells [Dickson 00]

- ▷ **Deterministic models** reproducing these oscillations exist and have been abundantly studied

They often involve **singular perturbation theory**

- ▷ We want to understand the effect of **noise** on oscillatory patterns

Noise may also induce oscillations not present in deterministic case

## The deterministic Koper model

$$\varepsilon \dot{x} = f(x, y, z) = y - x^3 + 3x$$

$$\dot{y} = g_1(x, y, z) = kx - 2(y + \lambda) + z$$

$$\dot{z} = g_2(x, y, z) = \rho(\lambda + y - z)$$

▷  $0 < \varepsilon \ll 1$

▷  $k, \lambda, \rho \in \mathbb{R}$ : control parameters

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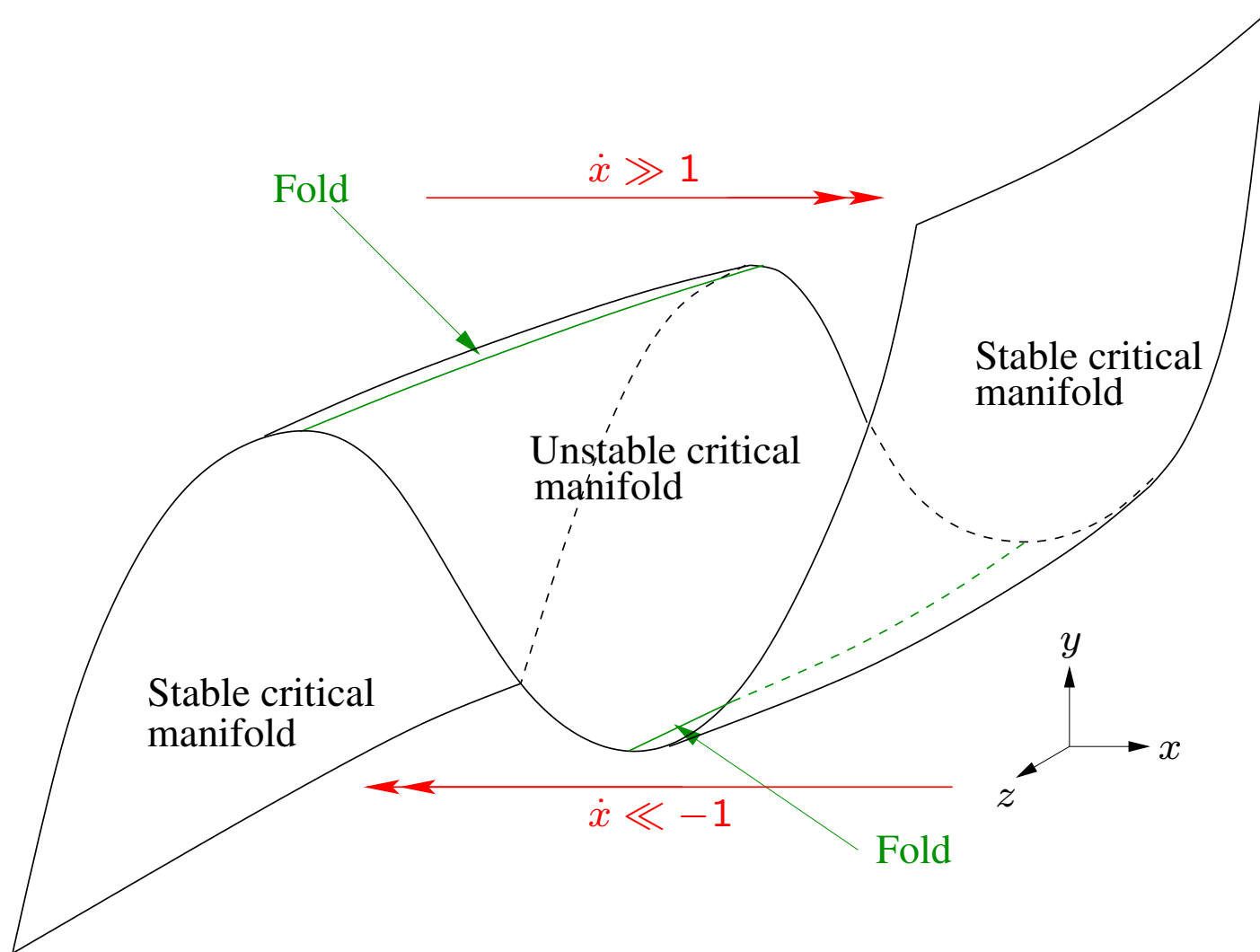
▷  $0 < \varepsilon \ll 1$

▷  $k, \lambda, \rho \in \mathbb{R}$ : control parameters

▷ Critical manifold:  $C_0 = \{f = 0\} = \{y = x^3 - 3x\}$

▷ Folds:  $L = \{f = 0, \partial_x f = 0\} = \{y = x^3 - 3x, x = \pm 1\} = L^+ \cup L^-$

# Critical manifold



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▷  $k, \lambda, \rho \in \mathbb{R}$ : control parameters

▷ Critical manifold:  $C_0 = \{f = 0\} = \{y = x^3 - 3x\}$

▷ Reduced flow on  $C_0$  (Fenichel theory): eliminate  $y$

$$\dot{x} = \frac{kx - 2(x^3 - 3x + \lambda) + z}{3(x^2 - 1)}$$

$$\dot{z} = \rho(\lambda + x^3 - 3x - z)$$

⊗ Generic fold points:  $\dot{x}$  diverges as  $x \rightarrow \pm 1$

⊗ Folded node singularity:  $\dot{x}$  finite,  
(desingularized) system has a node



## Folded node singularity

Normal form [Benoît, Lobry '82, Szmolyan, Wechselberger '01]:

$$\begin{aligned}\epsilon \dot{x} &= y - x^2 \\ \dot{y} &= -(\mu + 1)x - z && (+ \text{ higher-order terms}) \\ \dot{z} &= \frac{\mu}{2}\end{aligned}$$

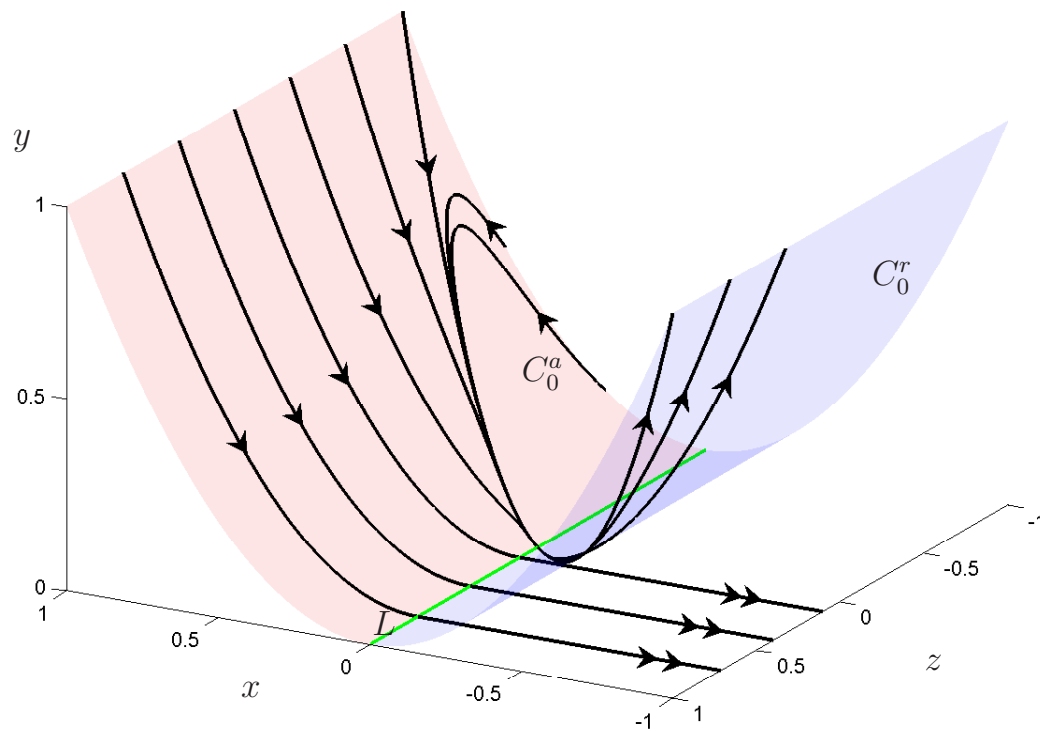
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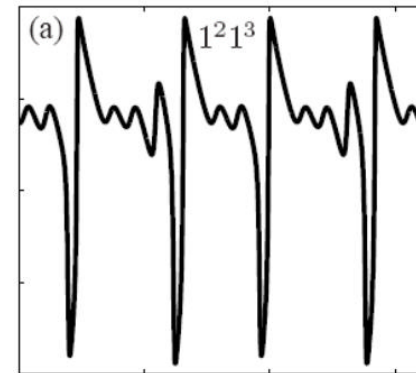
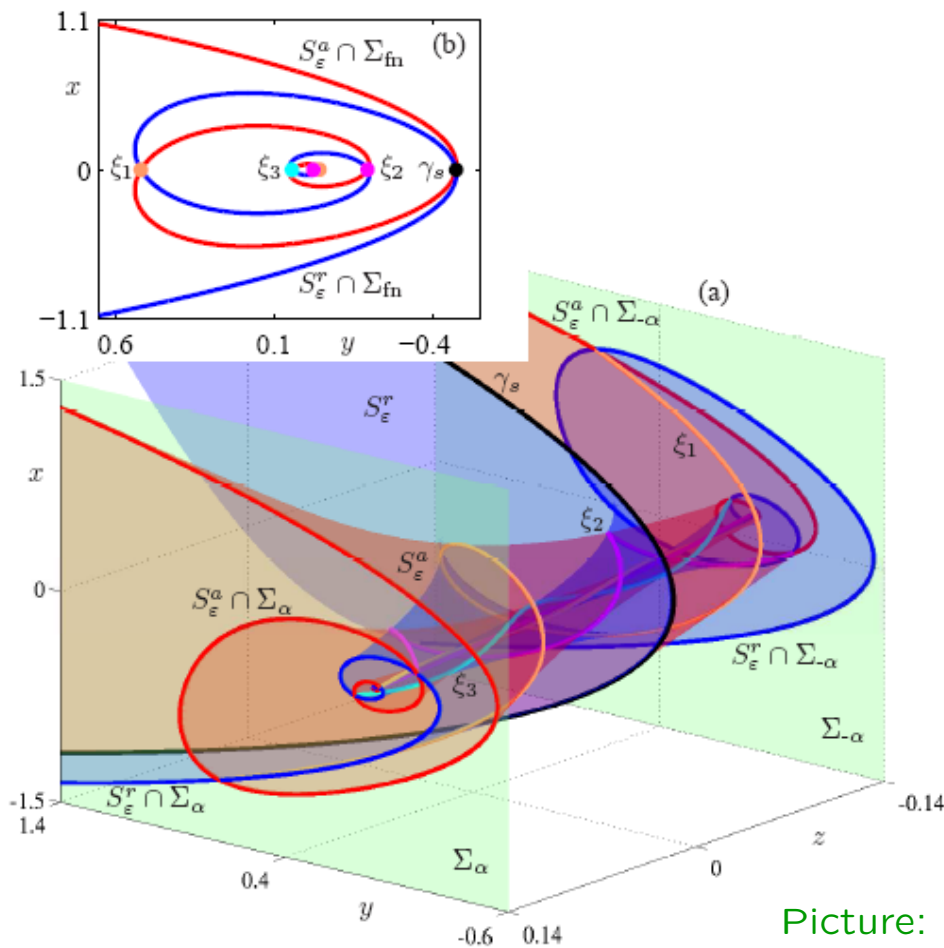


## Folded node singularity

**Theorem** [Benoît, Lobry '82, Szmolyan, Wechselberger '01]:

For  $2k + 1 < \mu^{-1} < 2k + 3$ , the system admits  $k$  canard solutions

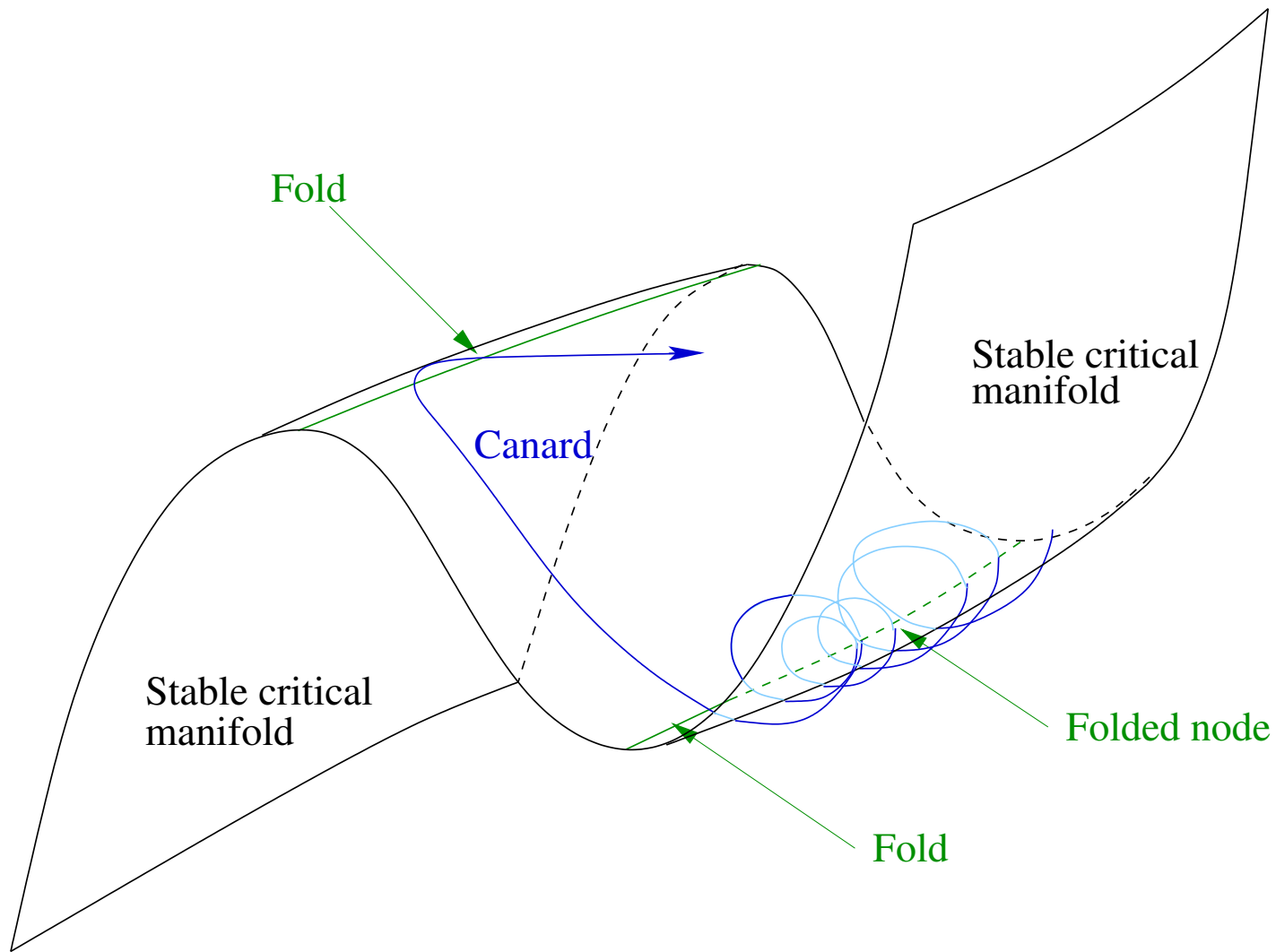
The  $j^{\text{th}}$  canard makes  $(2j + 1)/2$  oscillations



Mixed-mode oscillations (MMOs)

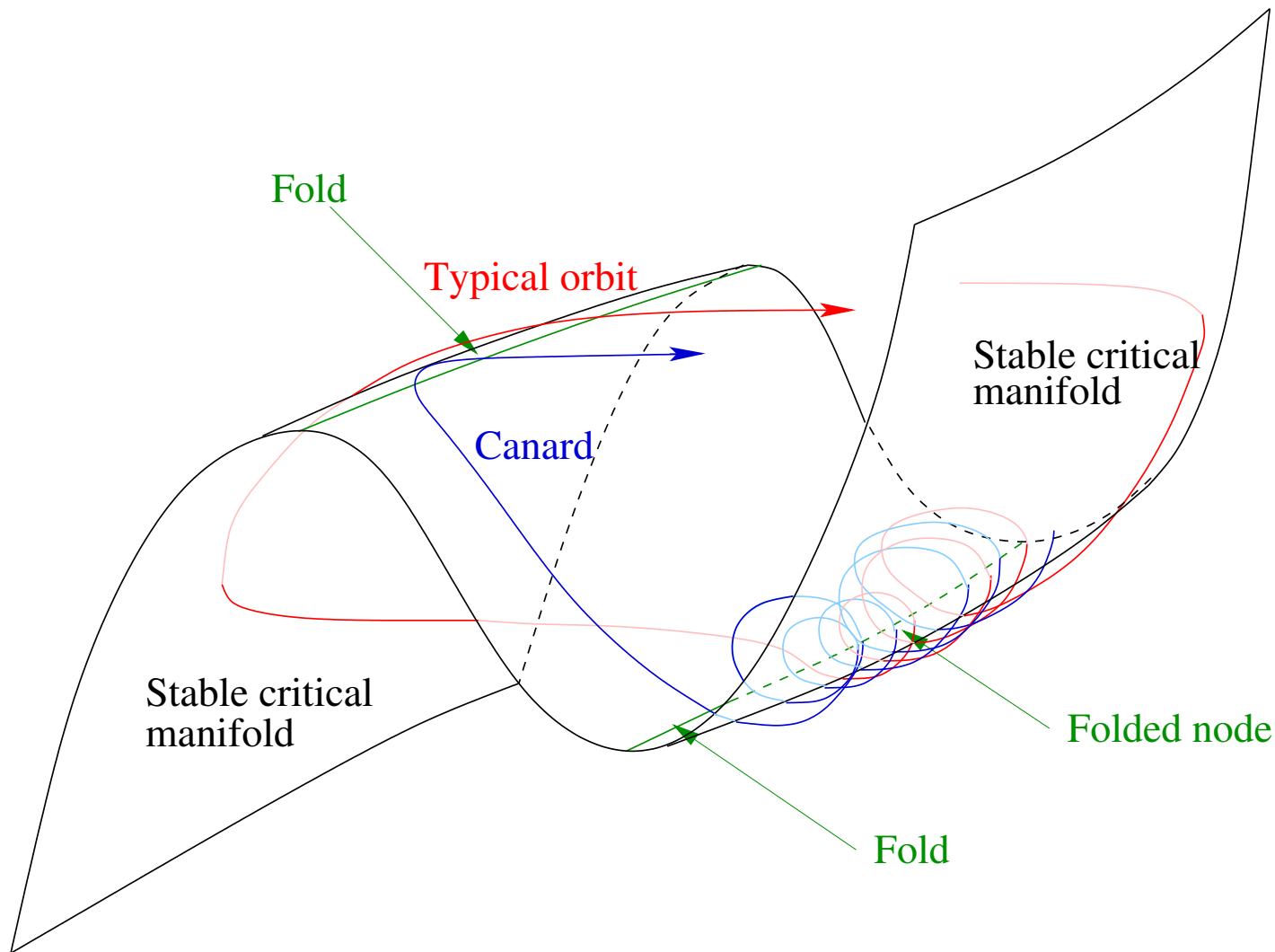
Picture: Mathieu Desroches

# Global dynamics



▷ Canard orbits track unstable manifold (for some time)

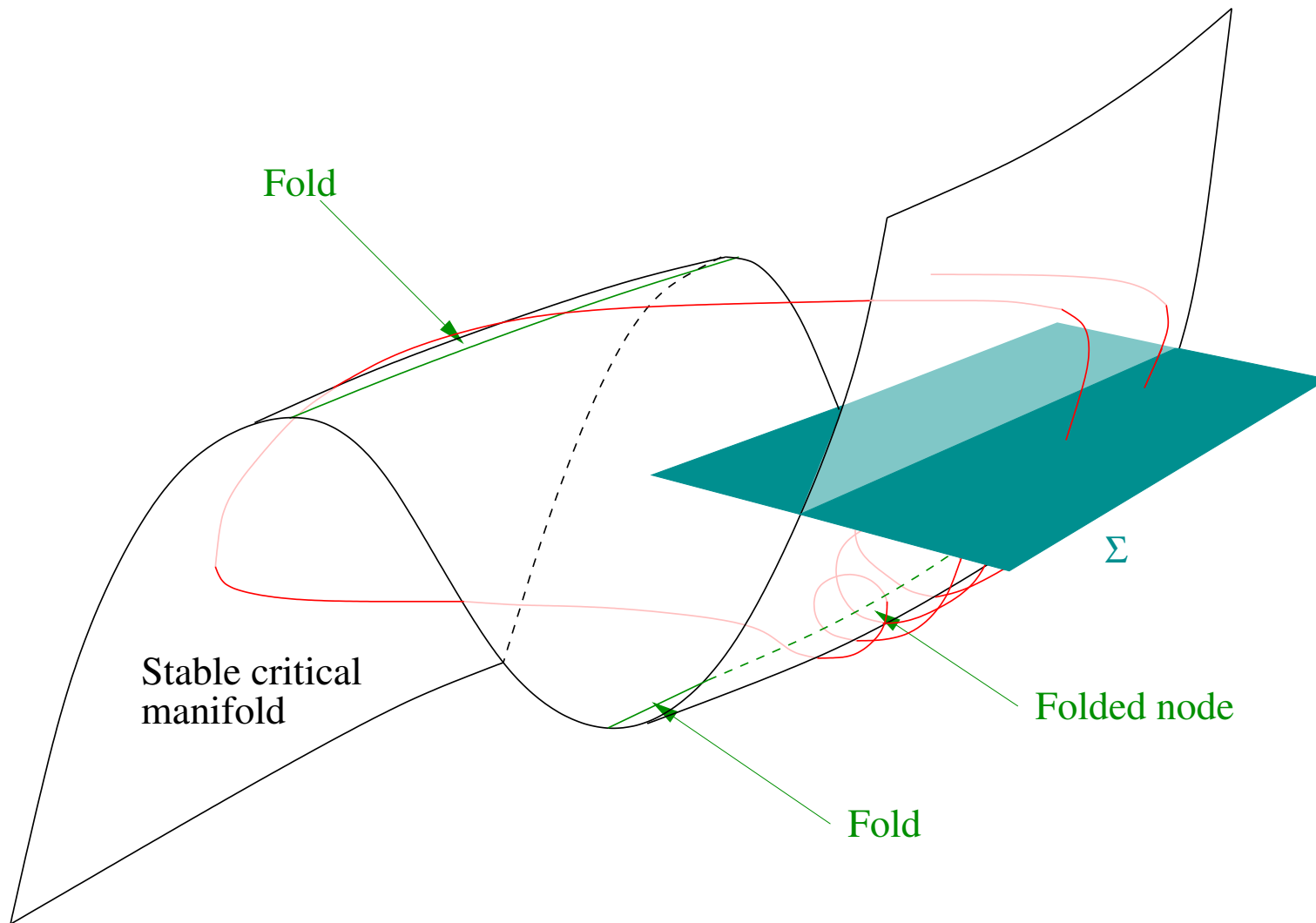
# Global dynamics



- ▷ Canard orbits track unstable manifold (for some time)
- ▷ Typical orbits may jump earlier to stable manifold

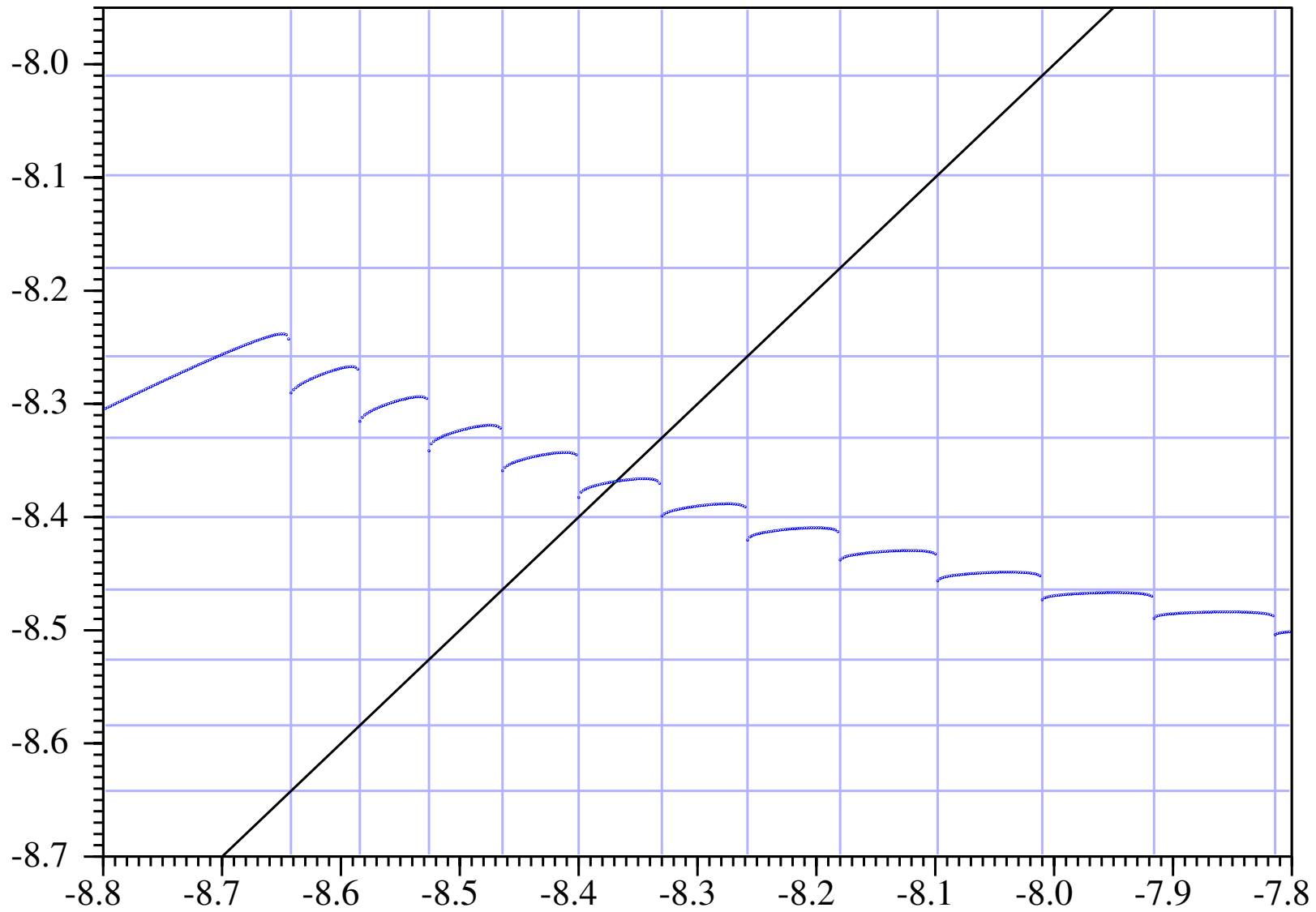
# Poincaré map

c.f. e.g. [Guckenheimer, Chaos, 2008]



- ▷ Poincaré map  $\Pi : \Sigma \rightarrow \Sigma$ , invertible, 2-dimensional
- ▷ Due to contraction along  $C_0$ , close to 1d, non-invertible map

## Poincaré map $z_n \mapsto z_{n+1}$



$$k = -10, \lambda = -7.35, \rho = 0.7, \varepsilon = 0.01$$

## The stochastic Koper model

$$dx_t = \frac{1}{\varepsilon} f(x_t, y_t, z_t) dt + \frac{\sigma}{\sqrt{\varepsilon}} F(x_t, y_t, z_t) dW_t$$

$$dy_t = g_1(x_t, y_t, z_t) dt + \sigma' G_1(x_t, y_t, z_t) dW_t$$

$$dz_t = g_2(x_t, y_t, z_t) dt + \sigma' G_2(x_t, y_t, z_t) dW_t$$

- ▷  $W_t$ :  $k$ -dimensional Brownian motion
- ▷  $\sigma, \sigma'$ : small parameters (may depend on  $\varepsilon$ )

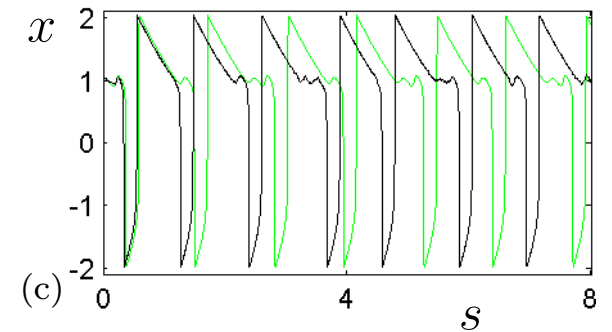
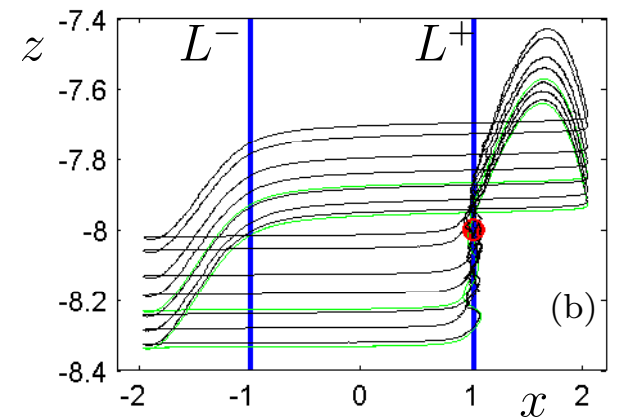
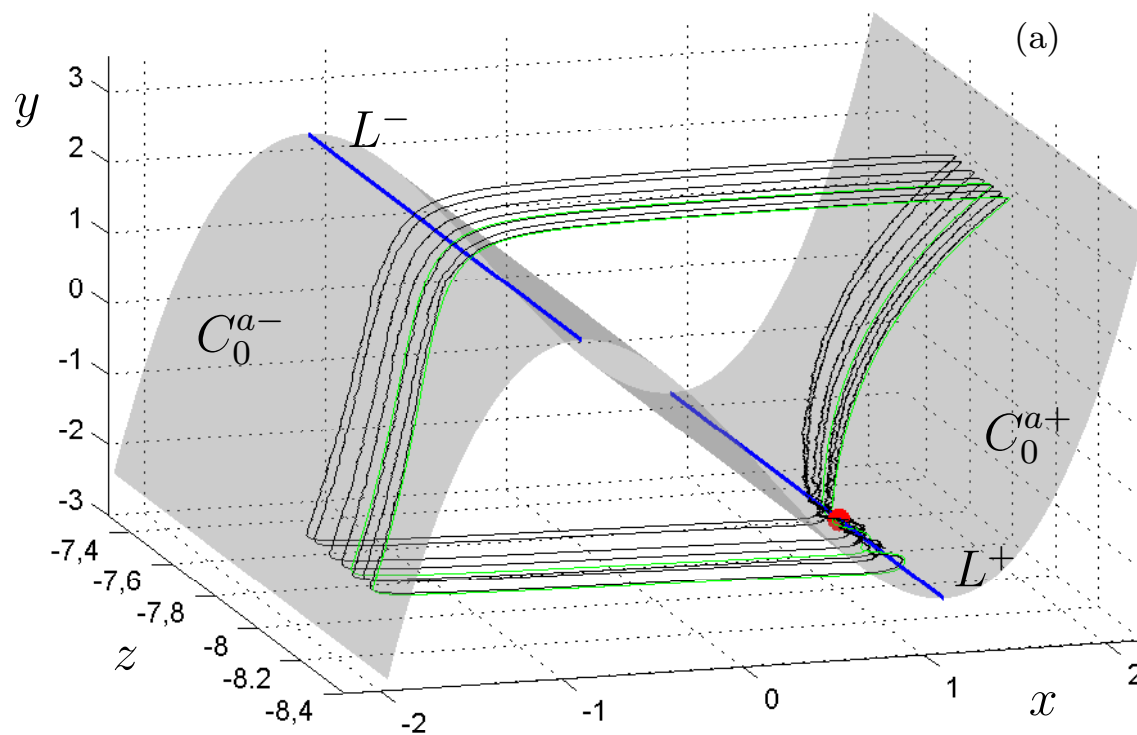


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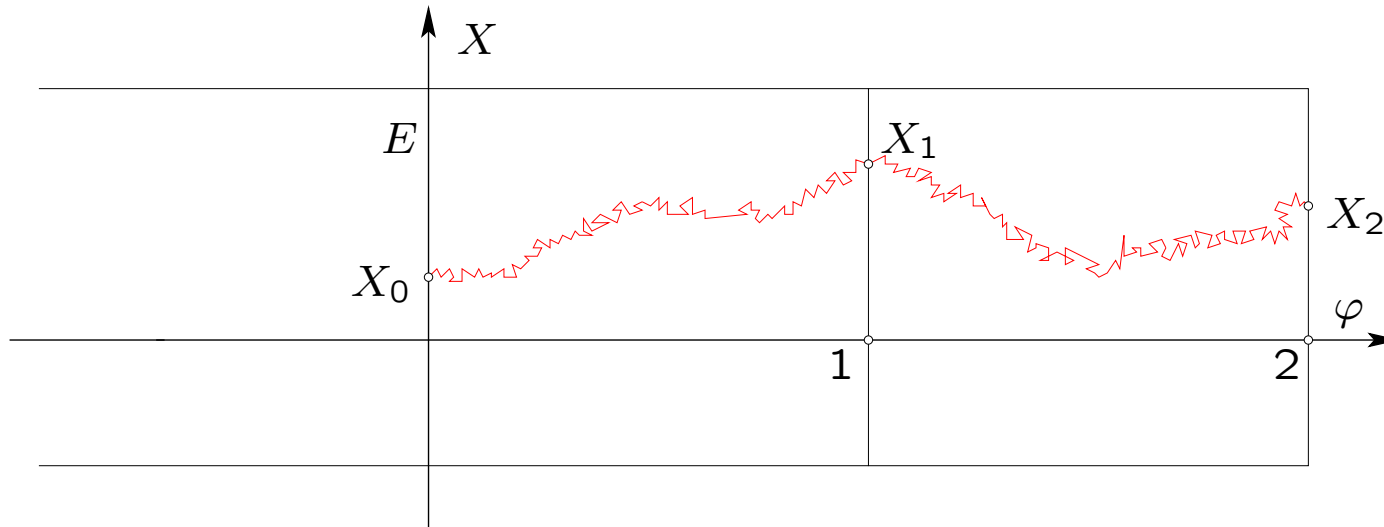
## Random Poincaré map

In appropriate coordinates

$$\begin{aligned} d\varphi_t &= \hat{f}(\varphi_t, X_t) dt + \hat{\sigma} \hat{F}(\varphi_t, X_t) dW_t & \varphi &\in \mathbb{R} \\ dX_t &= \hat{g}(\varphi_t, X_t) dt + \hat{\sigma} \hat{G}(\varphi_t, X_t) dW_t & X &\in E \subset \Sigma \end{aligned}$$

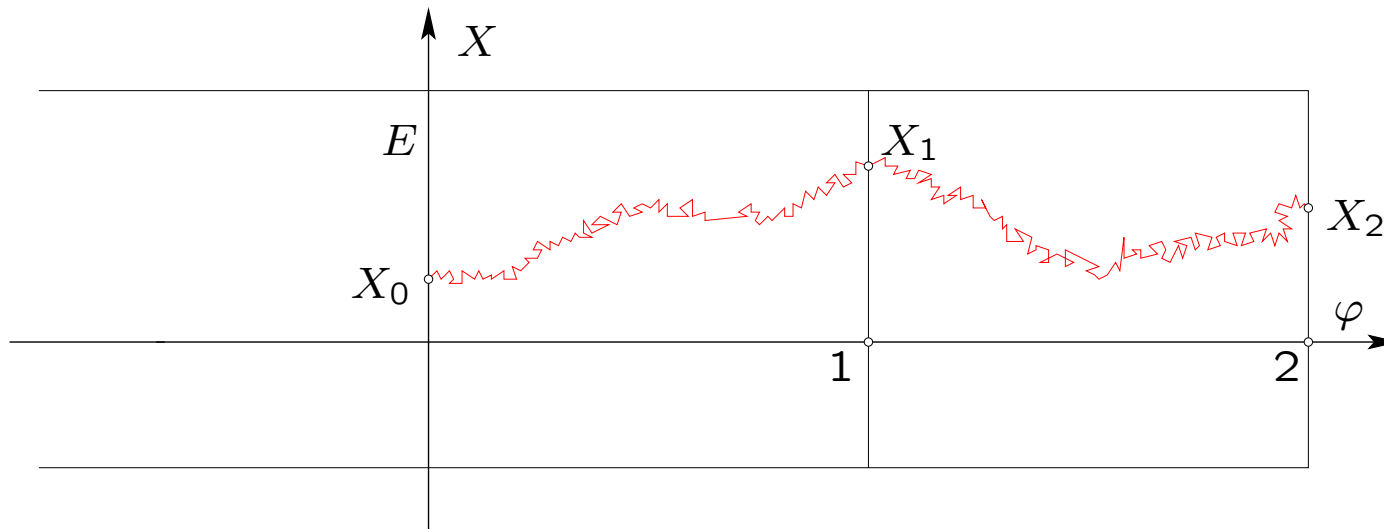
- ▷ all functions periodic in  $\varphi$  (say period 1)
- ▷  $\hat{f} \geq c > 0$  and  $\hat{\sigma}$  small  $\Rightarrow \varphi_t$  likely to increase
- ▷ process may be killed when  $X$  leaves  $E$

## Random Poincaré map



▷  $X_0, X_1, \dots$  form (substochastic) Markov chain

## Random Poincaré map

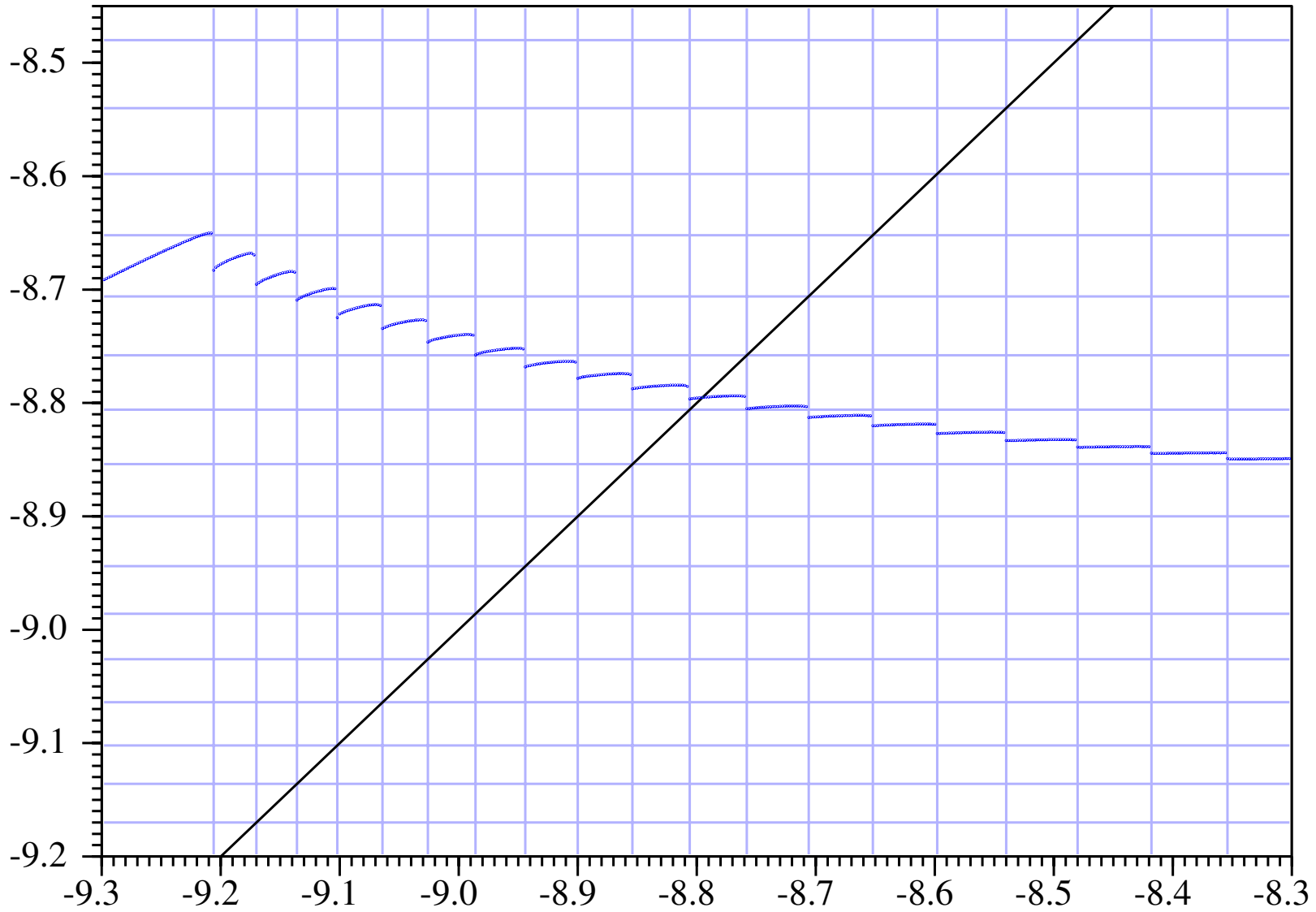


- ▷  $X_0, X_1, \dots$  form (substochastic) Markov chain
- ▷  $\tau$ : first-exit time of  $Z_t = (\varphi_t, X_t)$  from  $\mathcal{D} = (-M, 1) \times E$
- ▷  $\mu_Z(A) = \mathbb{P}^Z\{Z_\tau \in A\}$ : harmonic measure (wrt generator  $\mathcal{L}$ )
- ▷ [Ben Arous, Kusuoka, Stroock '84]: under hypoellipticity cond,  $\mu_Z$  admits (smooth) density  $h(Z, Y)$  wrt Lebesgue on  $\partial\mathcal{D}$
- ▷ For  $B \subset E$  Borel set

$$\mathbb{P}^{X_0}\{X_1 \in B\} = K(X_0, B) := \int_B K(X_0, dy)$$

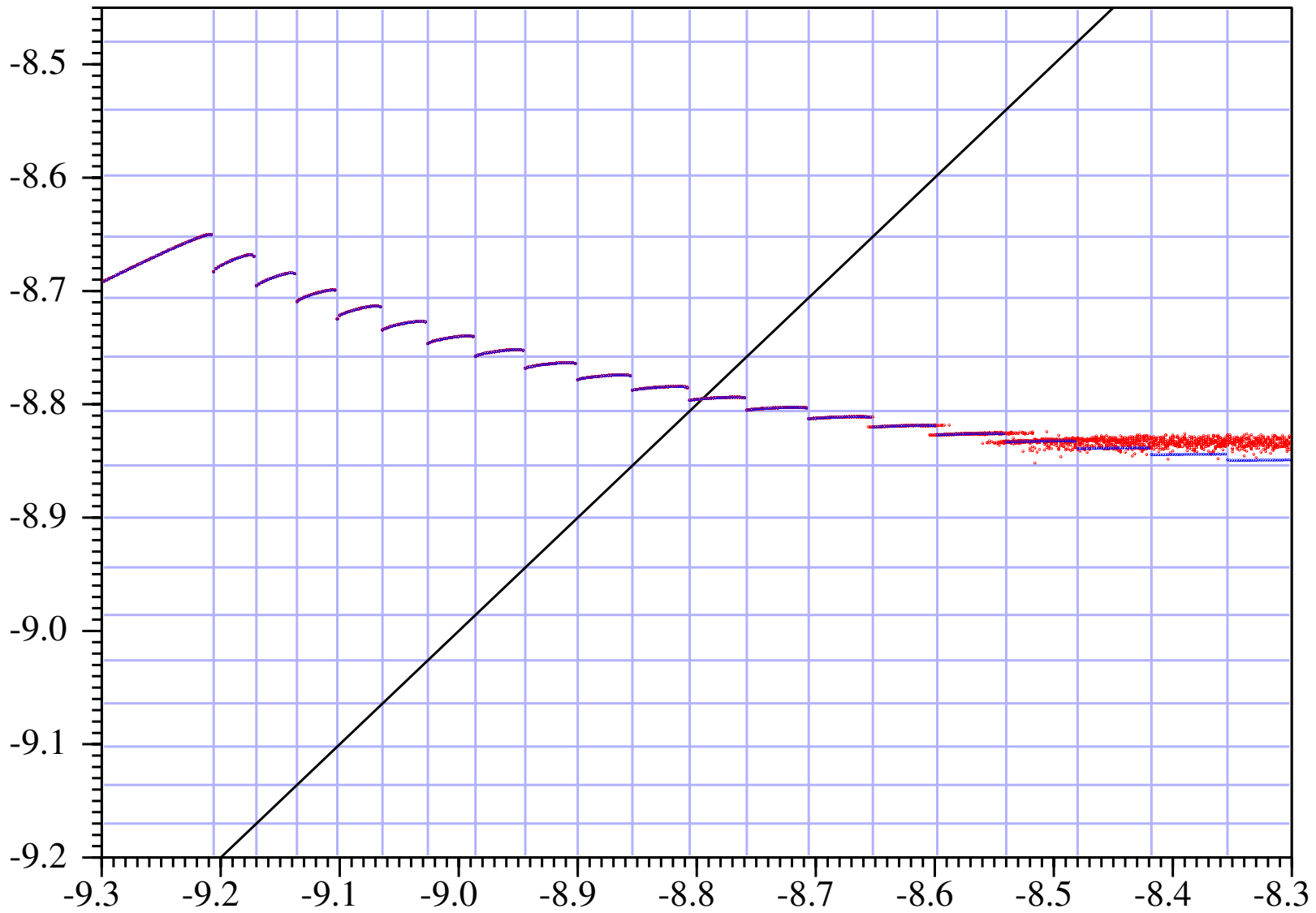
where  $K(x, dy) = h((0, x), (1, y)) dy =: k(x, y) dy$

## Poincaré map $z_n \mapsto z_{n+1}$



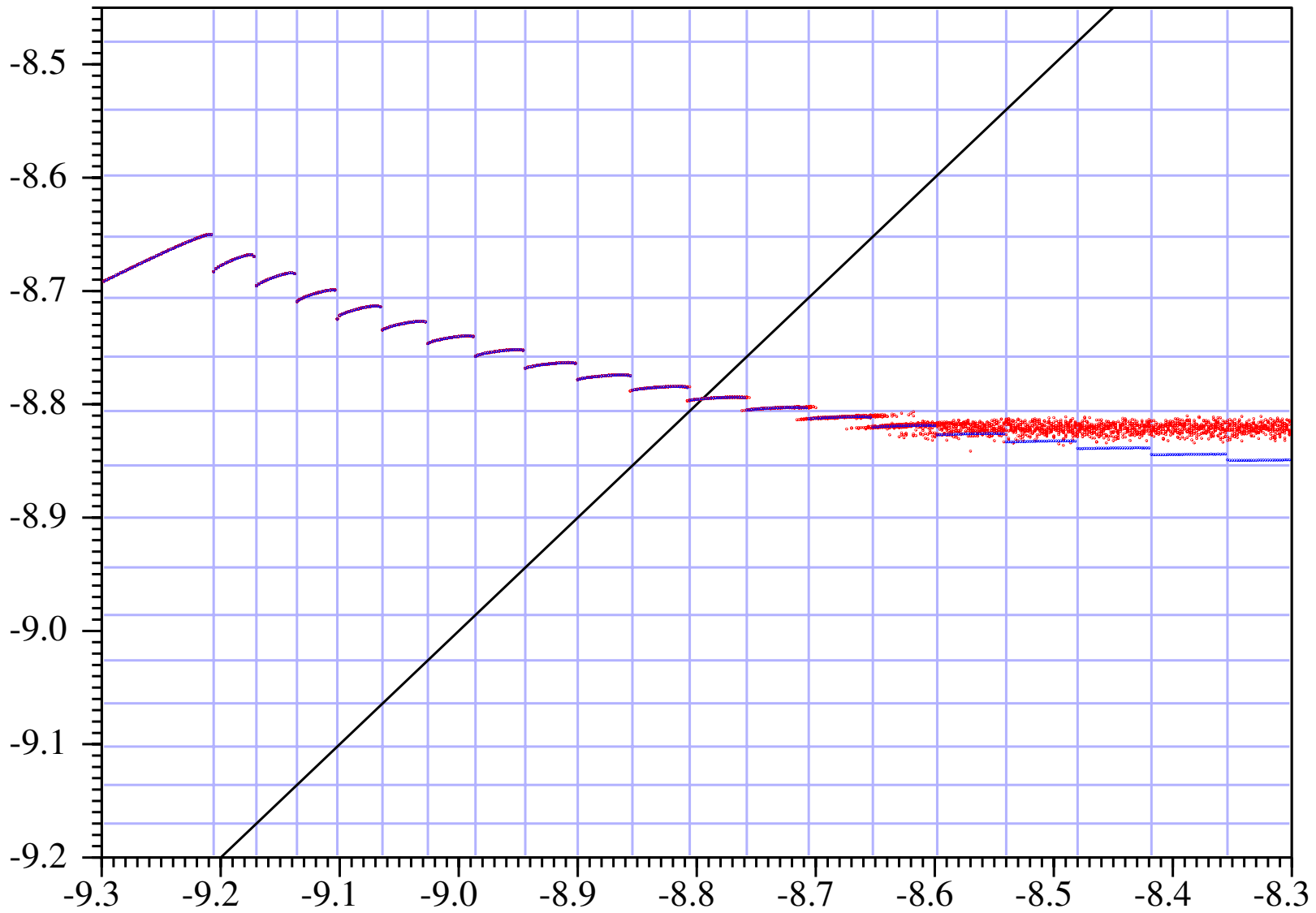
$$k = -10, \lambda = -7.6, \rho = 0.7, \varepsilon = 0.01, \sigma = \sigma' = 0$$

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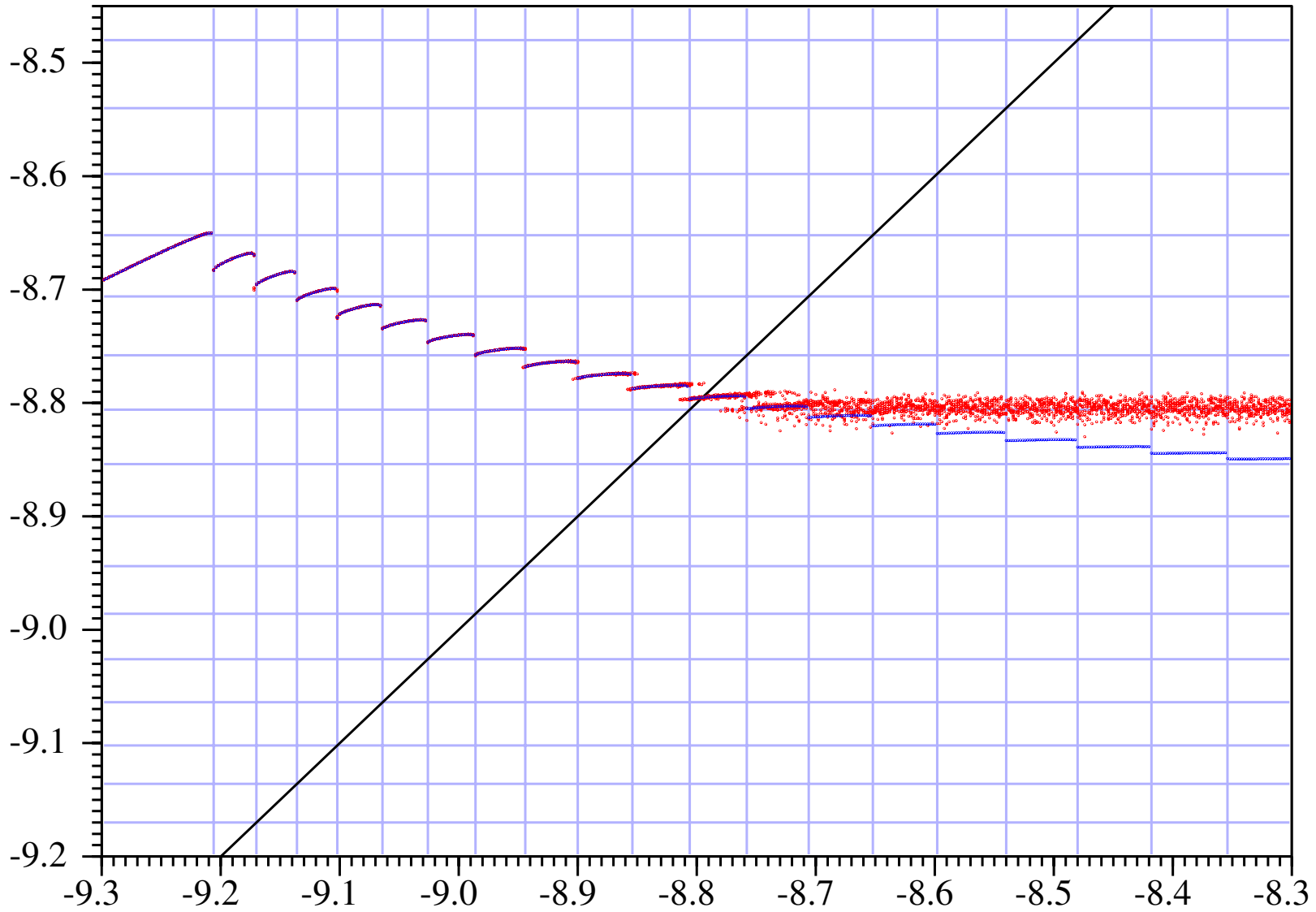
$$k = -10, \lambda = -7.6, \rho = 0.7, \varepsilon = 0.01, \sigma = \sigma' = 2 \cdot 10^{-7}$$

## Poincaré map $z_n \mapsto z_{n+1}$



$$k = -10, \lambda = -7.6, \rho = 0.7, \varepsilon = 0.01, \sigma = \sigma' = 2 \cdot 10^{-6}$$

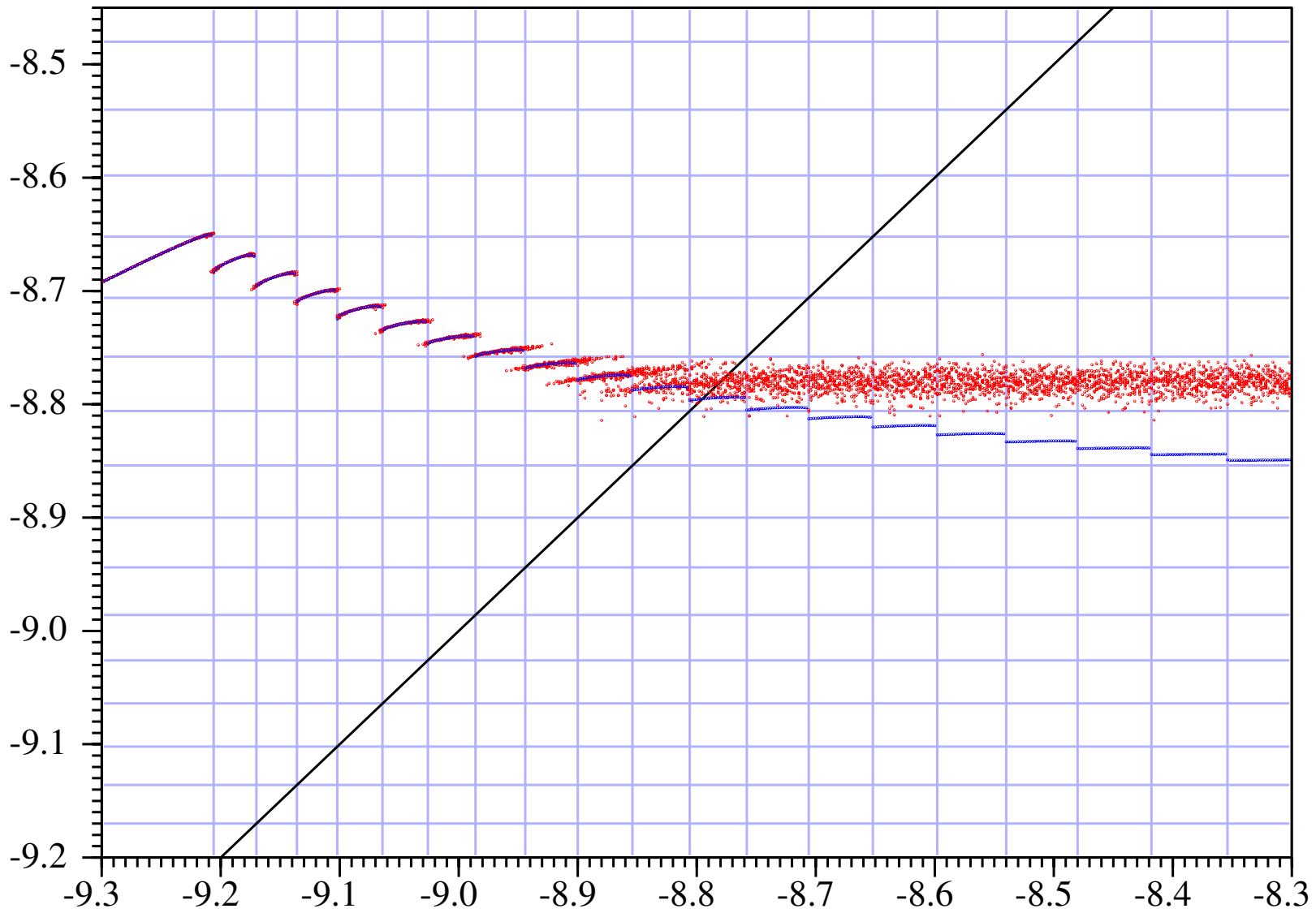
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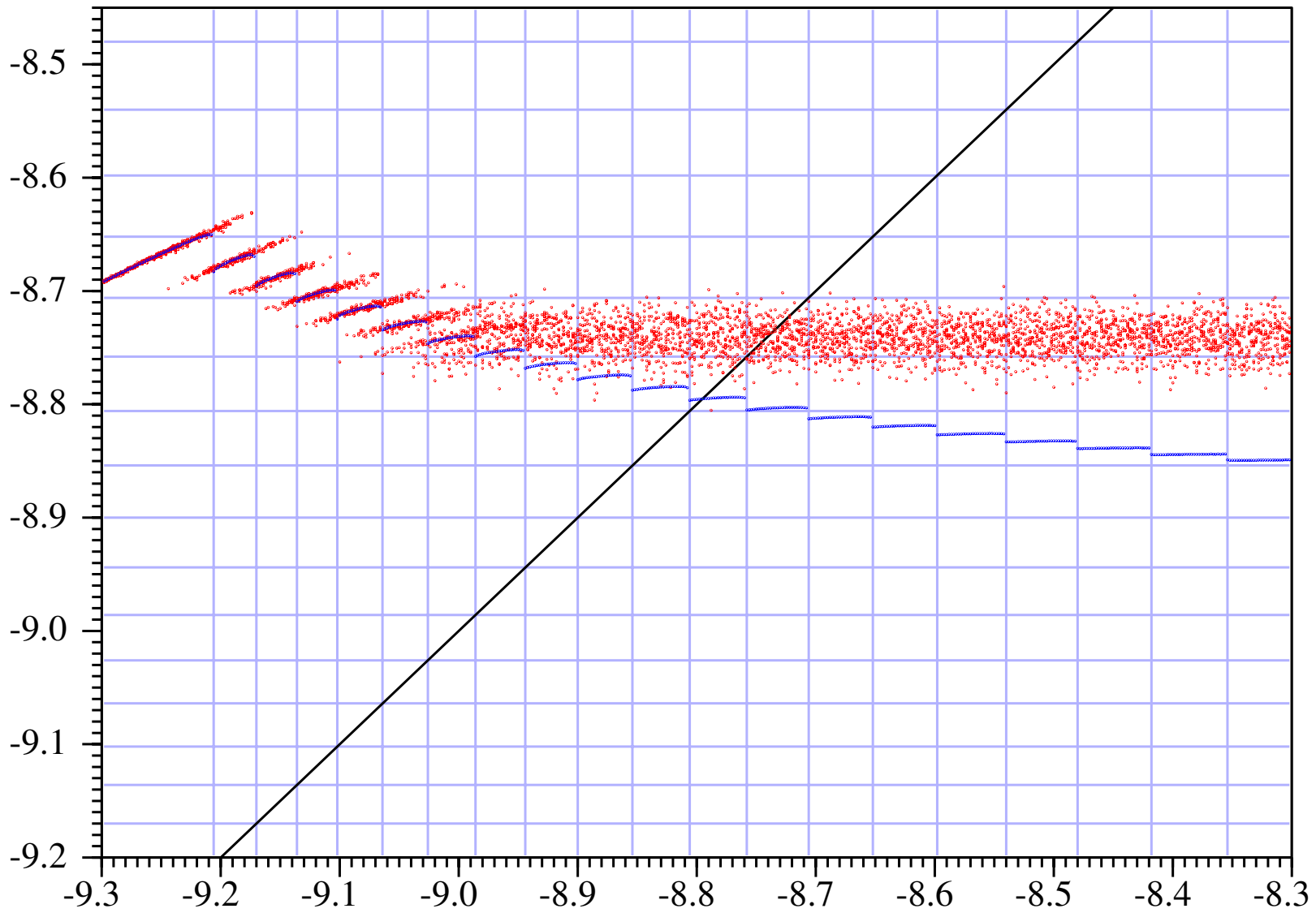


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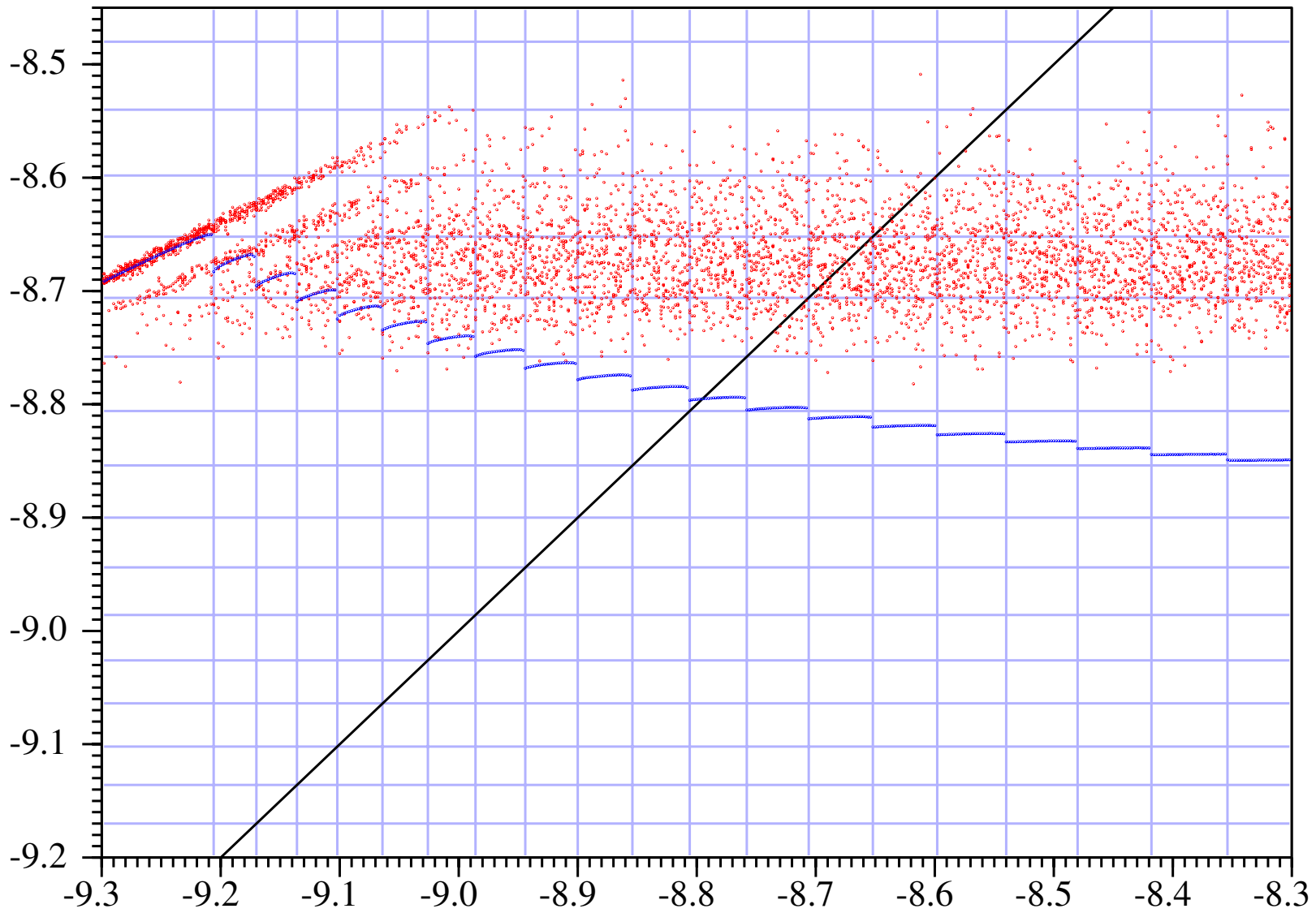
$$k = -10, \lambda = -7.6, \rho = 0.7, \varepsilon = 0.01, \sigma = \sigma' = 2 \cdot 10^{-4}$$

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# Poincaré map $z_n \mapsto z_{n+1}$



$$k = -10, \lambda = -7.6, \rho = 0.7, \varepsilon = 0.01, \sigma = \sigma' = 10^{-2}$$

## Random Poincaré map

### Observations:

- ▷ Size of fluctuations depends on noise intensity  
and canard number  $k$ : high order canards are more sensitive
- ▷ Saturation effect: constant distribution of  $z_{n+1}$  for  $k > k_c(\sigma, \sigma')$
- ▷ Consequence: if  $k_c < k_{\text{det}}^*$ , number of SAOs increases

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- ▷ Consequence: if  $k_C < k_{\text{det}}^*$ , number of SAOs increases

### Questions:

- ▷ Prove saturation effect
- ▷ How does  $k_C$  depend on  $\sigma, \sigma'$ ?
- ▷ How does size of fluctuations depend on  $\sigma, \sigma'$   
and canard number  $k$ ?
- ▷ In particular, size of fluctuations for  $k > k_C$ ?

## Size of noise-induced fluctuations

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

$$d\zeta_t = \frac{1}{\varepsilon} A(t) \zeta_t dt + \frac{\sigma}{\sqrt{\varepsilon}} \mathcal{F}(\zeta_t, t) dW_t + \frac{1}{\varepsilon} \underbrace{b(\zeta_t, t)}_{=\mathcal{O}(\|\zeta_t\|^2)} dt$$

$$\zeta_t = \frac{\sigma}{\sqrt{\varepsilon}} \int_0^t U(t, s) \mathcal{F}(\zeta_s, s) dW_s + \frac{1}{\varepsilon} \int_0^t U(t, s) b(\zeta_s, s) ds$$

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

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**Lemma** (Bernstein-type estimate):

$$\mathbb{P} \left\{ \sup_{0 \leq s \leq t} \left\| \int_0^s \mathcal{G}(\zeta_u, u) dW_u \right\| > h \right\} \leq 2n \exp \left\{ -\frac{h^2}{2V(t)} \right\}$$

where  $\int_0^s \mathcal{G}(\zeta_u, u) \mathcal{G}(\zeta_u, u)^T du \leq V(s)$  and  $n = 3$

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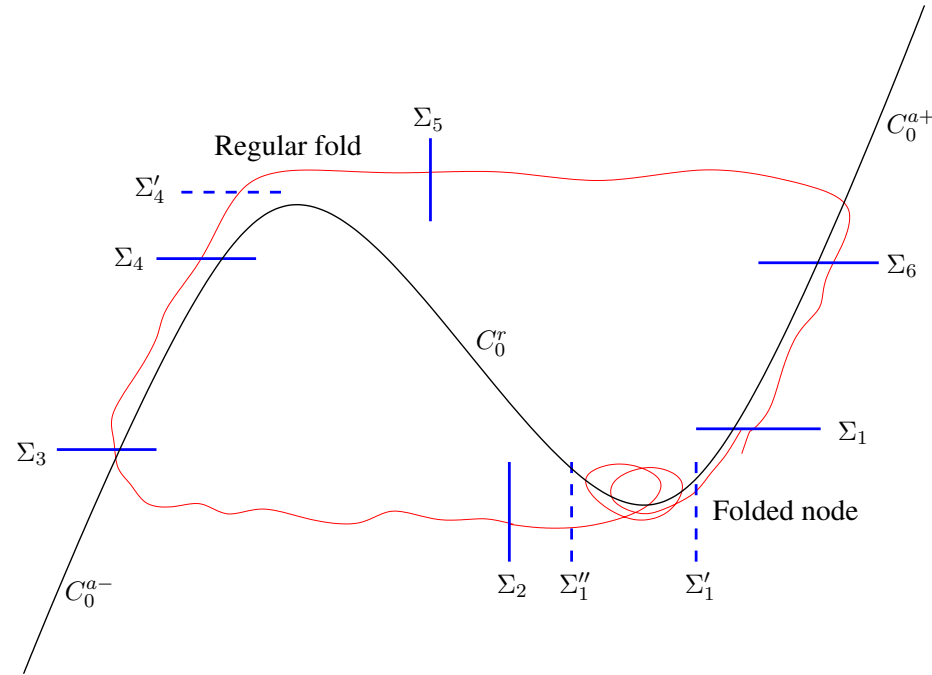
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**Remark:** more precise results using ODE for covariance matrix of

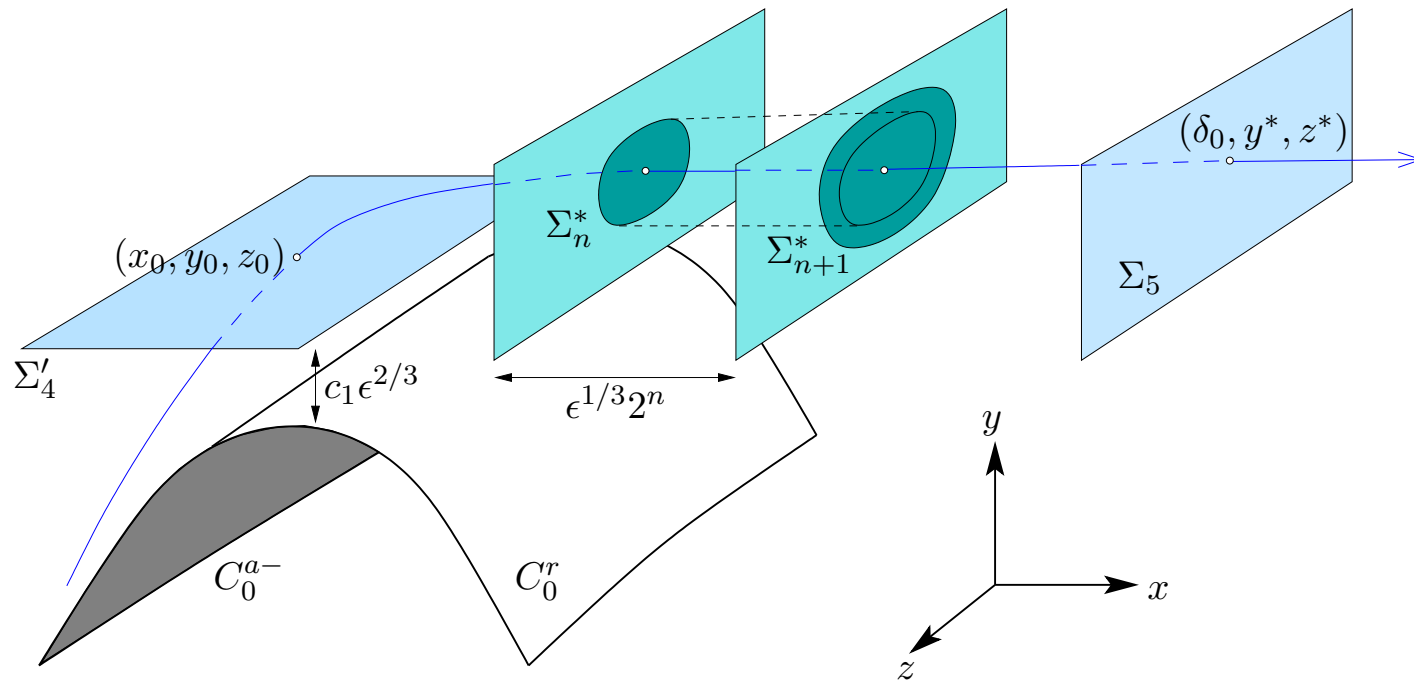
$$\zeta_t^0 = \frac{\sigma}{\sqrt{\varepsilon}} \int_0^t U(t, s) \mathcal{F}(0, s) dW_s$$





Transition	$\Delta x$	$\Delta y$	$\Delta z$
$\Sigma_2 \rightarrow \Sigma_3$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_3 \rightarrow \Sigma_4$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_4 \rightarrow \Sigma_4'$	$\frac{\sigma}{\varepsilon^{1/6}} + \frac{\sigma'}{\varepsilon^{1/3}}$		$\sigma\sqrt{\varepsilon \log \varepsilon } + \sigma'$
$\Sigma_4' \rightarrow \Sigma_5$		$\sigma\sqrt{\varepsilon} + \sigma'\varepsilon^{1/6}$	$\sigma\sqrt{\varepsilon} + \sigma'\varepsilon^{1/6}$
$\Sigma_5 \rightarrow \Sigma_6$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_6 \rightarrow \Sigma_1$	$\sigma + \sigma'$		$\sigma\sqrt{\varepsilon} + \sigma'$
$\Sigma_1 \rightarrow \Sigma_1'$		$(\sigma + \sigma')\varepsilon^{1/4}$	$\sigma'$
$\Sigma_1' \rightarrow \Sigma_1''$ if $z = \mathcal{O}(\sqrt{\mu})$		$(\sigma + \sigma')(\varepsilon/\mu)^{1/4}$	$\sigma'(\varepsilon/\mu)^{1/4}$
$\Sigma_1'' \rightarrow \Sigma_2$		$(\sigma + \sigma')\varepsilon^{1/4}$	$\sigma'\varepsilon^{1/4}$

## Example: Analysis near the regular fold



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

$$\mathbb{P} \left\{ \|(y_{\tau_{\Sigma_5}}, z_{\tau_{\Sigma_5}}) - (y^*, z^*)\| > h_1 \right\} \\ \leq \frac{C|\log \epsilon|}{\epsilon} \left( \exp \left\{ -\frac{\kappa h_1^2}{\sigma^2 \epsilon + (\sigma')^2 \epsilon^{1/3}} \right\} + \exp \left\{ -\frac{\kappa \epsilon}{\sigma^2 + (\sigma')^2 \epsilon} \right\} \right)$$

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

## The global return map

**Theorem** [B, Gentz, Kuehn, 2013]

$$P_2 = (x_2^*, y_2^*, z_2^*) \in \Sigma_2$$

$(x_1^*, y_1^*, z_1^*)$  deterministic first-hitting point of  $\Sigma_1$

$(x_1, y_1^*, z_1)$  stochastic first-hitting point of  $\Sigma_1$

$$\begin{aligned} & \mathbb{P}^{P_2} \left\{ |x_1 - x_1^*| > h \text{ or } |z_1 - z_1^*| > h_1 \right\} \\ & \leq \frac{C|\log \varepsilon|}{\varepsilon} \left( \exp \left\{ -\frac{\kappa h^2}{\sigma^2 + (\sigma')^2} \right\} + \exp \left\{ -\frac{\kappa h_1^2}{\sigma^2 \varepsilon |\log \varepsilon| + (\sigma')^2} \right\} \right. \\ & \quad \left. + \exp \left\{ -\frac{\kappa \varepsilon}{\sigma^2 + (\sigma')^2 \varepsilon^{-1/3}} \right\} \right) \end{aligned}$$

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▷ Useful for  $\sigma \ll \sqrt{\varepsilon}$ ,  $\sigma' \ll \varepsilon^{2/3}$

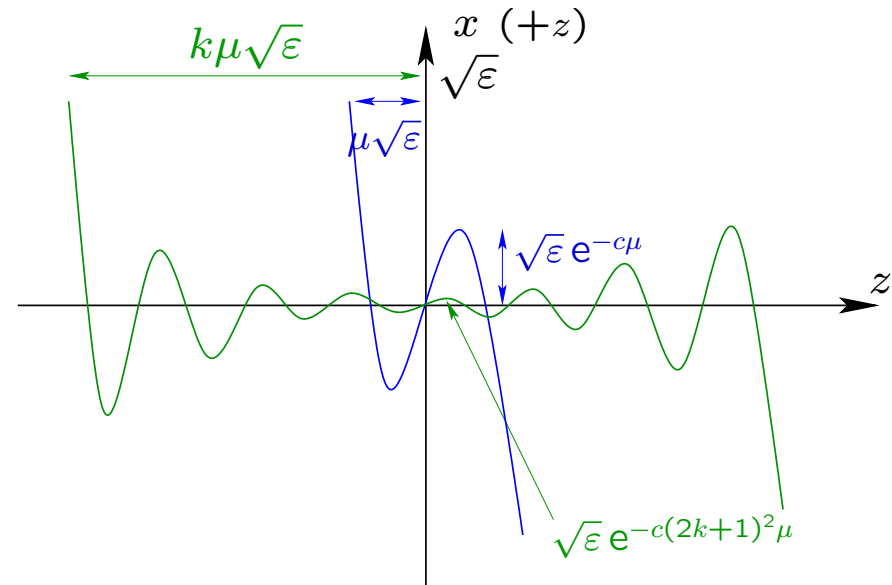
▷  $\Delta x \asymp \sigma + \sigma'$

▷  $\Delta z \asymp \sigma \sqrt{\varepsilon |\log \varepsilon|} + \sigma'$

## Local analysis near the folded node [B, Gentz, Kuehn, JDE 2012]

### Thm 1: (Canard spacing)

For  $z = 0$ , the  $k^{\text{th}}$  canard lies at dist.  $\sqrt{\varepsilon} e^{-c(2k+1)^2 \mu}$  from primary canard



## Local analysis near the folded node [B, Gentz, Kuehn, JDE 2012]

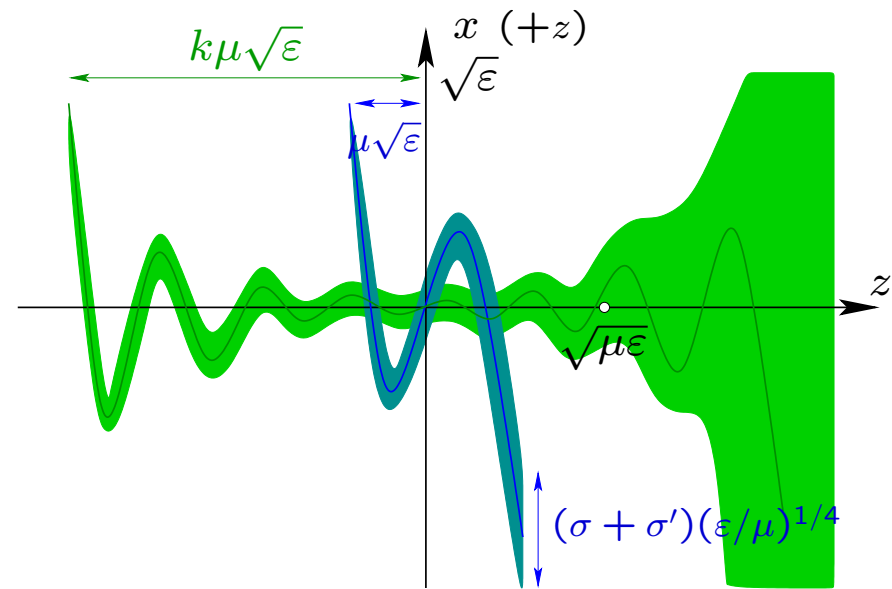
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### Thm 2: Size of fluctuations

$(\sigma + \sigma')(\varepsilon/\mu)^{1/4}$  up to  $z = \sqrt{\varepsilon\mu}$

$(\sigma + \sigma')(\varepsilon/\mu)^{1/4} e^{z^2/(\varepsilon\mu)}$  for  $z \geq \sqrt{\varepsilon\mu}$



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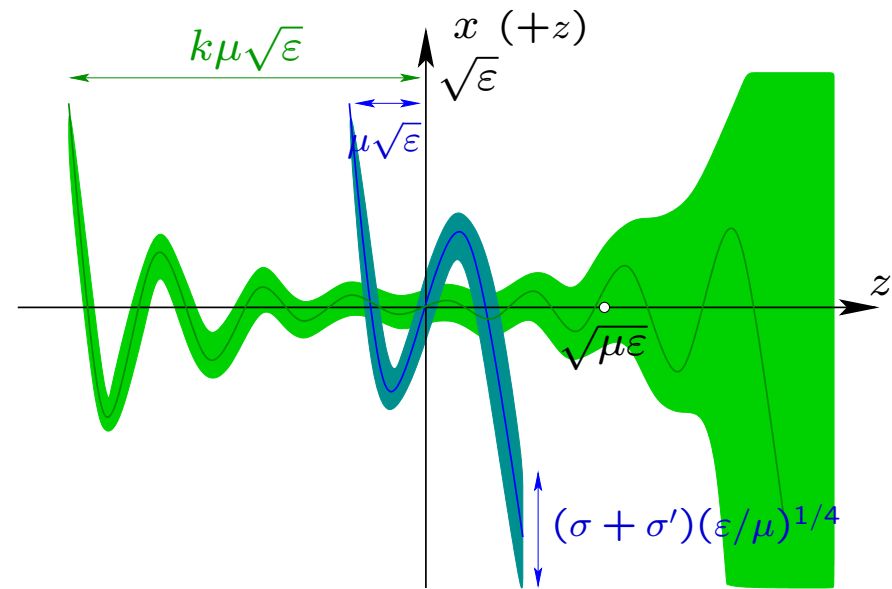
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### Thm 3: (Early escape)

Prob. to stay near det. solution

$\leq C|\log(\sigma + \sigma')|^\gamma e^{-\kappa z^2/(\varepsilon\mu|\log(\sigma + \sigma')|)}$



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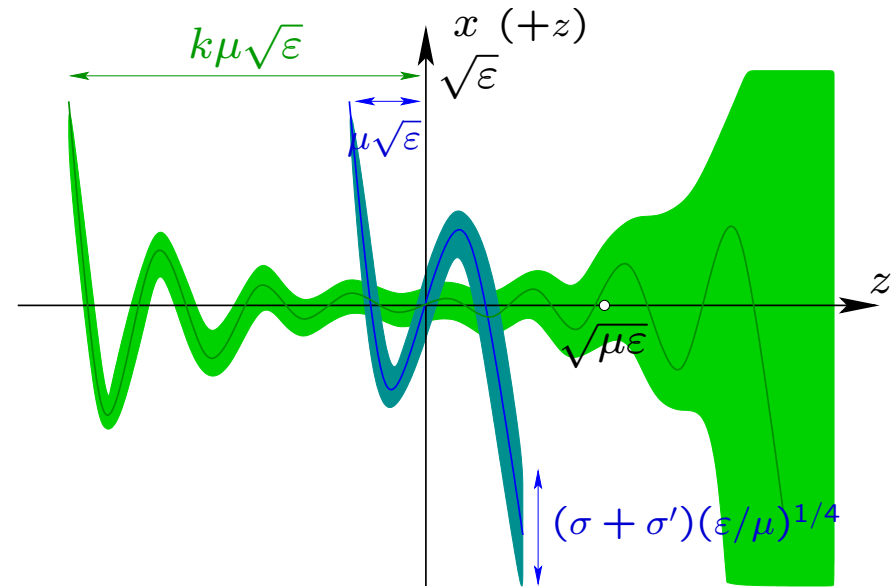
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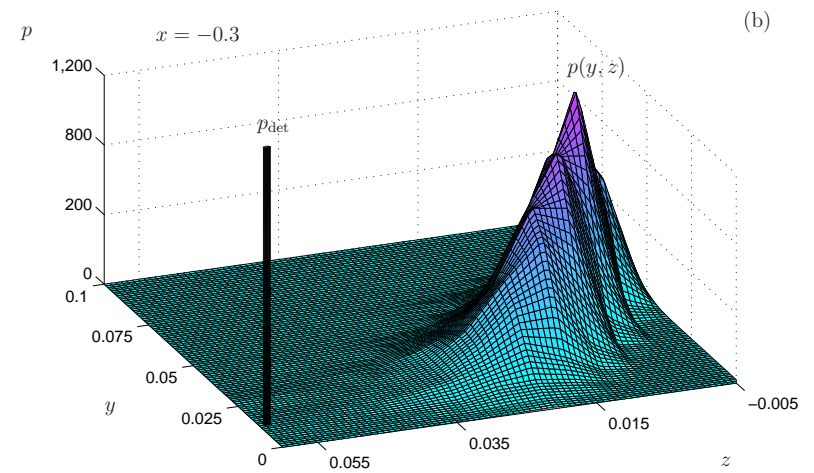
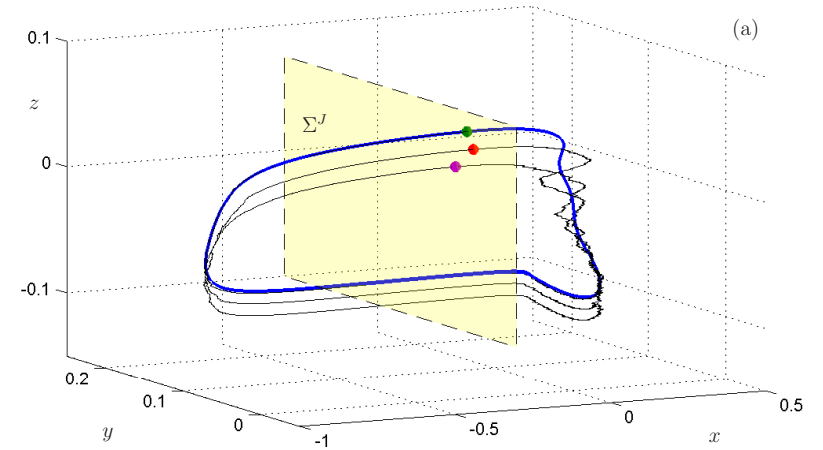
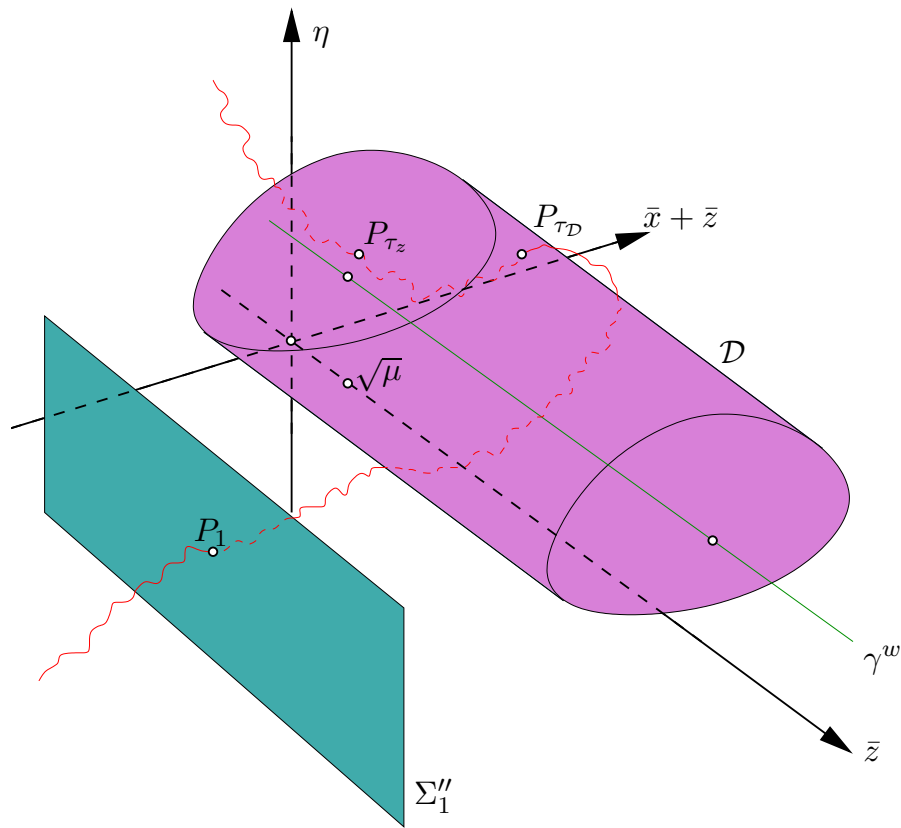


### Consequence: Dichotomy

- ▷ Canards with  $k \leq \sqrt{1/\mu}$ :  $\Delta z \asymp \sigma\sqrt{\varepsilon|\log \varepsilon|} + \sigma'$  (assuming  $\varepsilon \leq \mu$ )
- ▷ Canards with  $k > \sqrt{|\log(\sigma + \sigma')|/\mu}$ :  $\Delta z \leq \mathcal{O}\left(\sqrt{\varepsilon\mu|\log(\sigma + \sigma')|}\right)$

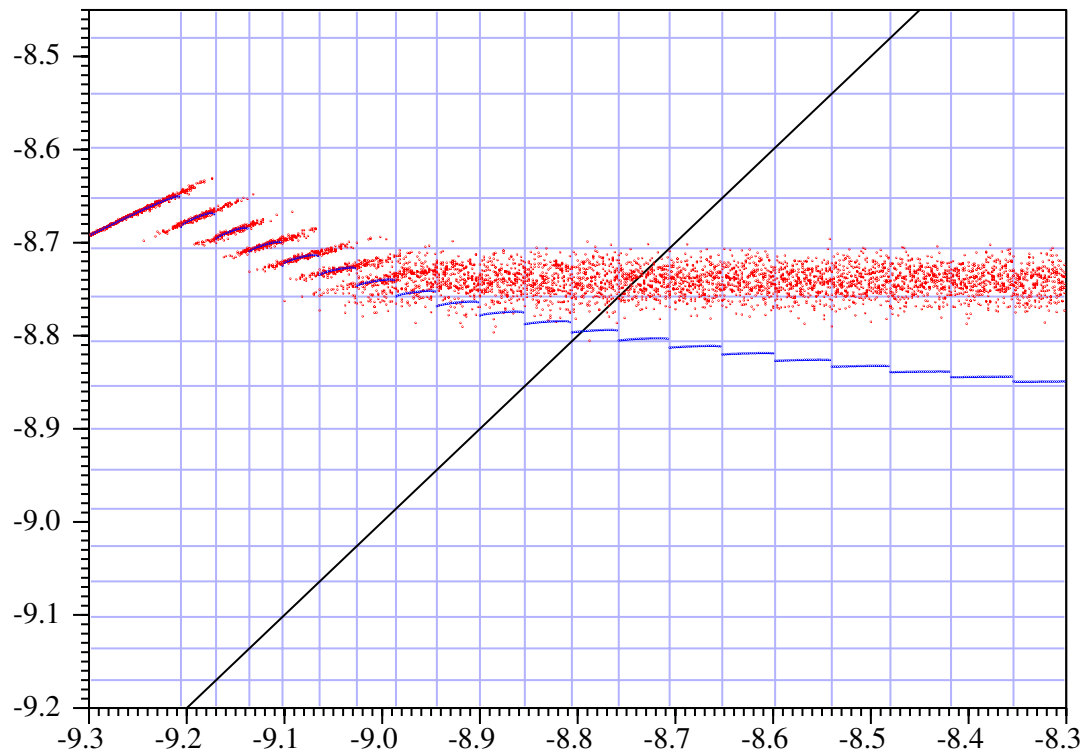


# Local analysis near the folded node: early escapes



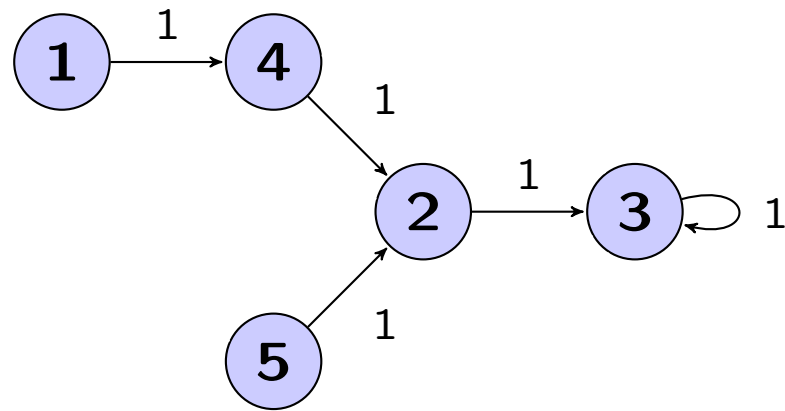
## Summary

- ▷  $\sqrt{1/\mu} < k_c \leq \sqrt{|\log(\sigma + \sigma')|/\mu}$
- ▷ For  $k \leq k_c$ , dispersion  $\Delta z \asymp \sigma \sqrt{\varepsilon |\log \varepsilon|} + \sigma'$
- ▷ For  $k > k_c$ , dispersion  $\Delta z \leq \mathcal{O}\left(\sqrt{\varepsilon \mu |\log(\sigma + \sigma')|}\right)$
- ▷ If the deterministic system has MMO pattern with  $k^*$  SAOs and  $k^* < k_c$  then noise **increases** number of SAOs



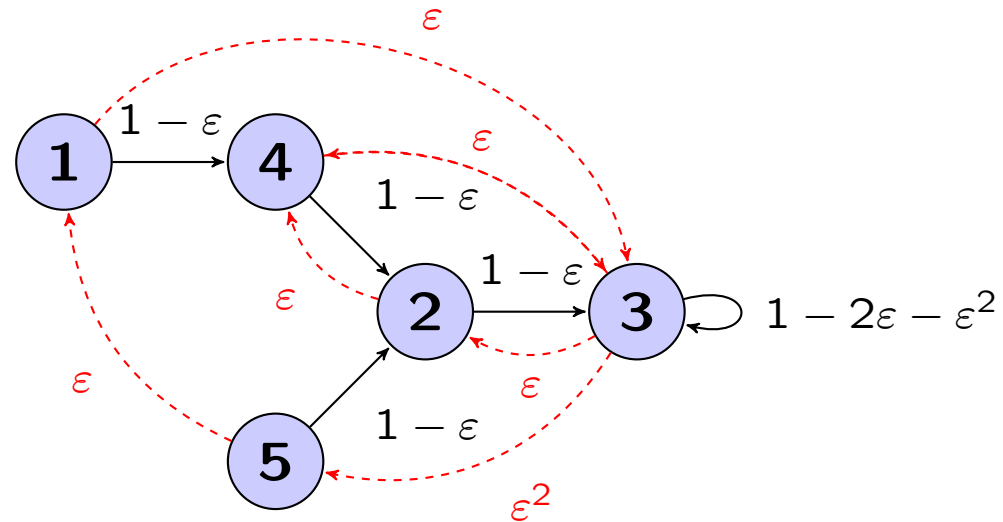
## Further ways to analyse random Poincaré map

- ▷ Theory of singularly perturbed Markov chains



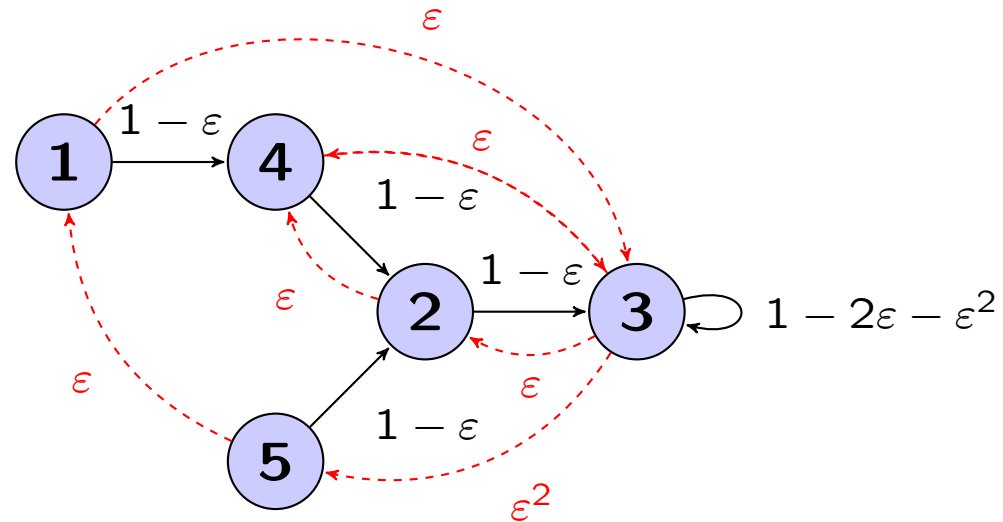
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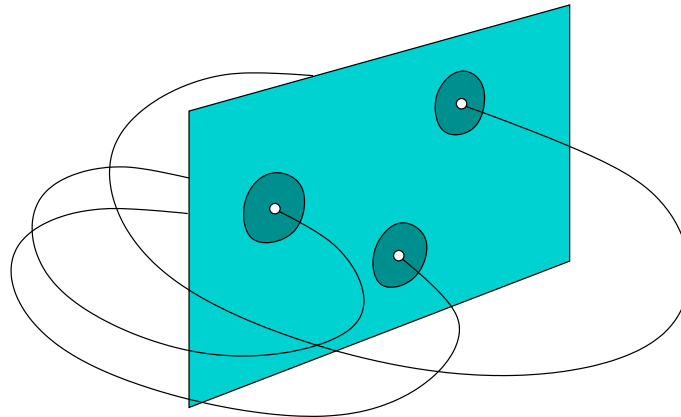


## Further ways to analyse random Poincaré map

- ▷ Theory of singularly perturbed Markov chains



- ▷ For coexisting stable periodic orbits: **Metastable transitions**



## Thanks for your attention – Further reading

N.B. and Barbara Gentz, *Noise-induced phenomena in slow-fast dynamical systems, A sample-paths approach*, Springer, Probability and its Applications (2006)

N.B. and Barbara Gentz, *Stochastic dynamic bifurcations and excitability*, in C. Laing and G. Lord, (Eds.), *Stochastic methods in Neuroscience*, p. 65-93, Oxford University Press (2009)

N.B., *Stochastic dynamical systems in neuroscience*, Oberwolfach Reports **8**:2290–2293 (2011)

N.B., Barbara Gentz and Christian Kuehn, *Hunting French Ducks in a Noisy Environment*, J. Differential Equations **252**:4786–4841 (2012). arXiv:1011.3193

N.B. and Damien Landon, *Mixed-mode oscillations and interspike interval statistics in the stochastic FitzHugh–Nagumo model*, Nonlinearity **25**:2303–2335 (2012). arXiv:1105.1278

N.B. and Barbara Gentz, *On the noise-induced passage through an unstable periodic orbit II: General case*, preprint arXiv:1208.2557

