# Random Perturbations and Quasi-Stationarity in Stochastic Reaction Networks

Mads Christian Hansen Department of Mathematical Sciences



#### Motivation

• Extinction of some (or all) species is very common in stochastic reaction networks. What is the long-term behavior before extinction?

#### Motivation

- Extinction of some (or all) species is very common in stochastic reaction networks. What is the long-term behavior before extinction?
- The quasi-stationary distribution (QSD) is the likely distribution of the state variable, if the system has been running for a "long" time and is not extinct.

#### Motivation

- Extinction of some (or all) species is very common in stochastic reaction networks. What is the long-term behavior before extinction?
- The quasi-stationary distribution (QSD) is the likely distribution of the state variable, if the system has been running for a "long" time and is not extinct.
- Today, I will focus on the connection with the corresponding deterministic reaction network. In particular, to what extend do we have the following dichotomy, and how are they related?

Deterministic	Stochastic
Attractor	QSD



Consider the logistic network

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S, \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

Modeled with deterministic mass-action, this has an unstable steady state  $x_1^* = 0$  and a stable  $x_2^* = \frac{\alpha_2 - \alpha_1}{\alpha_3}$ .

Consider the logistic network

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S, \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

Modeled with deterministic mass-action, this has an unstable steady state  $x_1^* = 0$  and a stable  $x_2^* = \frac{\alpha_2 - \alpha_1}{\alpha_3}$ .

The corresponding stochastic system on  $\{0\} \sqcup \mathbb{N}$  reaches extinction with probability 1;  $\{0\}$  is a trap; limiting distribution is  $\pi = (1, 0, ..., 0)$ .



Consider the logistic network

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S, \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

Modeled with deterministic mass-action, this has an unstable steady state  $x_1^* = 0$  and a stable  $x_2^* = \frac{\alpha_2 - \alpha_1}{\alpha_3}$ .

The corresponding stochastic system on  $\{0\} \sqcup \mathbb{N}$  reaches extinction with probability 1;  $\{0\}$  is a trap; limiting distribution is  $\pi = (1, 0, \dots, 0)$ . This may, however, take a very long time...





Figure : 
$$X(0) = 1$$
,  $\alpha_1 = 0.05$ ,  $\alpha_2 = 5$ ,  $\alpha_3 = 0.05$ .

Consider the logistic network

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S, \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

Modeled with deterministic mass-action, this has an unstable steady state  $x_1^* = 0$  and a stable  $x_2^* = \frac{\alpha_2 - \alpha_1}{\alpha_3}$ .

The corresponding stochastic system on  $\{0\} \sqcup \mathbb{N}$  reaches extinction with probability 1;  $\{0\}$  is a trap; limiting distribution is  $\pi = (1, 0, ..., 0)$ . This may, however, take a very long time...



## Main Result - In (CRNT-)Layman Terms

Let a reaction network be given. Under the "classical scaling", with  $\varepsilon$  being the inverse of system size, we may consider the family of Markov processes  $\{X_t^{\varepsilon}\}_{\varepsilon>0}$  associated to the network, as a **random** perturbation of the corresponding deterministic system. Under appropriate assumptions the weak\* limit of the quasi-stationary distributions  $\mu_{\varepsilon}$  will have support contained in the union of positive attractors of the deterministic system.



## Main Result - In (CRNT-)Layman Terms

Let a reaction network be given. Under the "classical scaling", with  $\varepsilon$  being the inverse of system size, we may consider the family of Markov processes  $\{X_t^{\varepsilon}\}_{\varepsilon>0}$  associated to the network, as a **random** perturbation of the corresponding deterministic system. Under appropriate assumptions the weak\* limit of the quasi-stationary distributions  $\mu_{\varepsilon}$  will have support contained in the union of positive attractors of the deterministic system.

In particular, for Keizer's paradox,  $\mu_{\varepsilon} \Rightarrow \delta_{x_2^*}$ , where  $x_2^*$  was the only stable fixed point for the deterministic rate equation.

## General Setup of Quasi-Stationarity

Consider a time-homogenous Markov process  $(X_t : t \ge 0)$  evolving in a domain *D* with a set of absorbing states, *A*, constituting a trap.





# General Setup of Quasi-Stationarity

Consider a time-homogenous Markov process  $(X_t: t \ge 0)$  evolving in a domain *D* with a set of absorbing states, *A*, constituting a trap.

The process is killed when it hits the trap - assume that this happens almost surely,  $\mathbb{P}_x(\tau_A < \infty) = 1$ , where  $\tau_A = \inf\{t \ge 0 : X_t \in A\}$  is the hitting time of A.





# General Setup of Quasi-Stationarity

Consider a time-homogenous Markov process  $(X_t: t \ge 0)$  evolving in a domain *D* with a set of absorbing states, *A*, constituting a trap.

The process is killed when it hits the trap - assume that this happens almost surely,  $\mathbb{P}_x(\tau_A < \infty) = 1$ , where  $\tau_A = \inf\{t \ge 0 : X_t \in A\}$  is the hitting time of A.

We investigate the behavior of the process before being killed.



#### Definition

A probability measure v on  $E = D \setminus A$  is called a **quasi-stationary distribution (QSD)** for the process killed at *A* if for every measurable set  $B \subset E$ 

$$\mathbb{P}_{\mathsf{v}}(X_t \in B \,|\, \mathfrak{r}_A > t) = \mathsf{v}(B), \qquad t \ge 0$$



#### Definition

A probability measure v on  $E = D \setminus A$  is called a **quasi-stationary distribution (QSD)** for the process killed at A if for every measurable set  $B \subset E$ 

$$\mathbb{P}_{\mathbf{v}}(X_t \in B \,|\, \mathbf{\tau}_A > t) = \mathbf{v}(B), \qquad t \ge 0$$

or equivalently, if there exists a probability measure  $\mu$  on E such that

$$\lim_{t\to\infty}\mathbb{P}_{\mu}(X_t\in B\,|\,\tau_A>t)=\nu(B)$$



Let  $D \subseteq \mathbb{R}^d_+$  be the state space of a deterministic reaction network. The solution of the associated ODE yields a semi-flow  $\varphi_t(x)$ .

Let  $D \subseteq \mathbb{R}^d_+$  be the state space of a deterministic reaction network. The solution of the associated ODE yields a semi-flow  $\varphi_t(x)$ .

 $D=D_0\sqcup D_1,$ 

where  $D_0$ ,  $D_1$  are positively  $\varphi$ -invariant and  $D_0$  is a closed and absorbing subset of D,

 $p^{\varepsilon}(t,x,D_1) = 0 \qquad \forall \varepsilon > 0, t > 0, x \in D_0.$ 



Let  $D \subseteq \mathbb{R}^d_+$  be the state space of a deterministic reaction network. The solution of the associated ODE yields a semi-flow  $\varphi_t(x)$ .

 $D=D_0\sqcup D_1,$ 

where  $D_0$ ,  $D_1$  are positively  $\varphi$ -invariant and  $D_0$  is a closed and absorbing subset of D,

$$p^{\varepsilon}(t,x,D_1) = 0 \qquad \forall \varepsilon > 0, t > 0, x \in D_0.$$

#### Definition

A **random perturbation** of a semi-flow  $\phi_t$  is a family of homogeneous Markov processes

$$\{(X_t^{\boldsymbol{\varepsilon}} \colon t \ge 0)\}_{\boldsymbol{\varepsilon} > 0}$$
 on  $D \subseteq \mathbb{R}^d_+$ 

where  $p^{\varepsilon}(t,x,\Gamma)$  satisfy that for any  $\delta > 0, T > 0$  and  $K \subset D_1$  compact,



$$\beta_{\delta,K}(\varepsilon) := \sup_{t \in [0,T]} \sup_{x \in K} p^{\varepsilon} \left( t, x, D \setminus N^{\delta}(\varphi_t(x)) \right) \to 0 \qquad \text{for } \varepsilon \to 0.$$

In reaction networks for  $\varepsilon > 0$  we may embed the stochastic process  $(X_t^{\varepsilon}: t \ge 0)$  on  $\varepsilon \mathbb{N}_0^d$  satisfying the stochastic equation

$$X_t^{\varepsilon} = X_0^{\varepsilon} + \sum_{k \in \mathcal{R}} Y_k \left( \int_0^t \lambda_k^{\varepsilon}(X_s^{\varepsilon}) \, ds \right) \varepsilon \xi_k$$

into  $D \subseteq [0,\infty)^d$  by allowing  $X_0^{\varepsilon}$  to be any point in D and update with the jump rates

$$\lambda_k^{\varepsilon}(x) = \alpha_k \varepsilon^{\|y_k\|_1 - 1} \prod_{i=1}^d \binom{\lfloor x_i/\varepsilon \rfloor}{y_{ki}} y_{ki}!,$$



In reaction networks for  $\varepsilon > 0$  we may embed the stochastic process  $(X_t^{\varepsilon}: t \ge 0)$  on  $\varepsilon \mathbb{N}_0^d$  satisfying the stochastic equation

$$X_t^{\varepsilon} = X_0^{\varepsilon} + \sum_{k \in \mathcal{R}} Y_k \left( \int_0^t \lambda_k^{\varepsilon}(X_s^{\varepsilon}) \, ds \right) \varepsilon \xi_k$$

into  $D \subseteq [0,\infty)^d$  by allowing  $X_0^{\varepsilon}$  to be any point in D and update with the jump rates

$$\lambda_k^{\varepsilon}(x) = \alpha_k \varepsilon^{\|y_k\|_1 - 1} \prod_{i=1}^d \binom{\lfloor x_i / \varepsilon \rfloor}{y_{ki}} y_{ki}!,$$

In other words, we consider the **classical scaling** (fluid limit, thermodynamic limit...). Kurtz allows us to view these processes as random perturbations of the corresponding deterministic system.

Given a reaction network, we may for each  $\varepsilon > 0$  automatically split the state space for  $(X_t^{\varepsilon}: t \ge 0)$  into the disjoint union  $E^{\varepsilon} \sqcup A^{\varepsilon}$ .



Given a reaction network, we may for each  $\varepsilon > 0$  automatically split the state space for  $(X_t^{\varepsilon}: t \ge 0)$  into the disjoint union  $E^{\varepsilon} \sqcup A^{\varepsilon}$ .

#### Lemma

The state space can be written  $D = D_0 \sqcup D_1 \subseteq [0,\infty)^d$  where

- (i)  $D_0 = \lim_{\epsilon \to 0} A^{\epsilon}$  is a closed subset of D;
- (ii)  $D_1 = \lim_{\epsilon \to 0} E^{\epsilon}$  is an open subset of D;
- (iii)  $D_0$  and  $D_1$  are positively  $\varphi$ -invariant;
- (iv)  $D_0$  is absorbing for the random perturbations,

$$p^{\varepsilon}(t,x,D_1)=0 \qquad \forall \varepsilon > 0, t > 0, x \in D_0.$$



Given a reaction network, we may for each  $\varepsilon > 0$  automatically split the state space for  $(X_t^{\varepsilon}: t \ge 0)$  into the disjoint union  $E^{\varepsilon} \sqcup A^{\varepsilon}$ .

#### Lemma

The state space can be written  $D = D_0 \sqcup D_1 \subseteq [0,\infty)^d$  where

- (i)  $D_0 = \lim_{\epsilon \to 0} A^{\epsilon}$  is a closed subset of D;
- (ii)  $D_1 = \lim_{\epsilon \to 0} E^{\epsilon}$  is an open subset of D;
- (iii)  $D_0$  and  $D_1$  are positively  $\varphi$ -invariant;
- (iv)  $D_0$  is absorbing for the random perturbations,

$$p^{\varepsilon}(t,x,D_1) = 0 \qquad \forall \varepsilon > 0, t > 0, x \in D_0.$$

We assume that for each  $\varepsilon > 0$  there exists at least one QSD  $\mu_{\varepsilon}$  and, for simplicity, that  $E^{\varepsilon}$  is irreducible.



## Assuming a Positive Attractor

From a modeling point of view, the applicability of the QSD depends on the expected time to extinction. This scales exponentially in system size  $\epsilon$ .

#### Proposition

Assume that the flow  $\{\varphi_t\}$  admits an attractor  $K \subset D_1$ . Then, starting according to the QSD,  $\mu_{\varepsilon}$ , the probability of being absorbed by time t > 0 is  $O(\varepsilon e^{-\gamma/\varepsilon})$  while the mean time to extinction is  $O(\varepsilon e^{c/\varepsilon})$ , where  $\gamma, c > 0$ .



# Assuming a Positive Attractor

From a modeling point of view, the applicability of the QSD depends on the expected time to extinction. This scales exponentially in system size  $\epsilon$ .

#### Proposition

Assume that the flow  $\{\varphi_t\}$  admits an attractor  $K \subset D_1$ . Then, starting according to the QSD,  $\mu_{\varepsilon}$ , the probability of being absorbed by time t > 0 is  $O(\varepsilon e^{-\gamma/\varepsilon})$  while the mean time to extinction is  $O(\varepsilon e^{c/\varepsilon})$ , where  $\gamma, c > 0$ .

#### Proposition

Suppose the flow  $\{\varphi_t\}$  admits an attractor  $K \subset D_1$ . Then the set of limit points of  $\{\mu_{\varepsilon}\}$  for the weak<sup>\*</sup> topology is a subset of the set of invariant measures for the flow  $\{\varphi_t\}$ .



#### Metastability

We assume  $\mu_\epsilon$  converges weakly to a Borel probability measure  $\mu$  for  $\epsilon\to 0.$  By the Poincaré recurrence theorem, one may conclude

$$supp \mu \subseteq BC(\varphi) := \overline{\{x \in D \colon x \in \omega(x)\}}.$$

Our main result aims to refine this statement.



#### Metastability

We assume  $\mu_\epsilon$  converges weakly to a Borel probability measure  $\mu$  for  $\epsilon\to 0.$  By the Poincaré recurrence theorem, one may conclude

$$supp \mu \subseteq BC(\varphi) := \overline{\{x \in D \colon x \in \omega(x)\}}.$$

Our main result aims to refine this statement. Based on a sample path large deviations result, one may obtain the preliminary proposition

#### Proposition

Suppose the flow  $\{\varphi_t\}$  admits an attractor  $K \subset D_1$ . Then there exists a neighborhood  $V_0$  of  $D_0$  such that  $\mu(V_0) = 0$ .



#### Metastability

We assume  $\mu_{\epsilon}$  converges weakly to a Borel probability measure  $\mu$  for  $\epsilon \rightarrow 0$ . By the Poincaré recurrence theorem, one may conclude

$$supp \mu \subseteq BC(\varphi) := \overline{\{x \in D \colon x \in \omega(x)\}}.$$

Our main result aims to refine this statement. Based on a sample path large deviations result, one may obtain the preliminary proposition

#### Proposition

Suppose the flow  $\{\varphi_t\}$  admits an attractor  $K \subset D_1$ . Then there exists a neighborhood  $V_0$  of  $D_0$  such that  $\mu(V_0) = 0$ .

We also have a complimentary statement excluding metastability

#### Proposition

Assume that  $D_0$  is a global attractor. Then  $\mu$  is supported by  $D_0$ .



To refine these results further, we introduce some terminology. Assume that the flow allows a global attractor given by

$$G = \bigcap_{t \ge 0} \varphi_t(D). \tag{1}$$



To refine these results further, we introduce some terminology. Assume that the flow allows a global attractor given by

$$G = \bigcap_{t \ge 0} \varphi_t(D). \tag{1}$$

#### Definition

A **Morse decomposition** of the dynamics of  $\varphi_t$  is a collection of non-empty  $\varphi$ -invariant pairwise disjoint compact sets  $\{M_1, \ldots, M_m\}$ , called Morse sets, such that

- M<sub>i</sub> is isolated,
- for every x ∈ G\U<sup>m</sup><sub>i=1</sub>M<sub>i</sub>, there exists i > j such that ω(x) ⊆ M<sub>i</sub> and α(x) ⊆ M<sub>j</sub>.

To refine these results further, we introduce some terminology. Assume that the flow allows a global attractor given by

$$G = \bigcap_{t \ge 0} \varphi_t(D). \tag{1}$$

#### Definition

A **Morse decomposition** of the dynamics of  $\varphi_t$  is a collection of non-empty  $\varphi$ -invariant pairwise disjoint compact sets  $\{M_1, \ldots, M_m\}$ , called Morse sets, such that

- M<sub>i</sub> is isolated,
- for every x ∈ G\U<sup>m</sup><sub>i=1</sub>M<sub>i</sub>, there exists i > j such that ω(x) ⊆ M<sub>i</sub> and α(x) ⊆ M<sub>j</sub>.

Morse sets contain all limit sets, and no cycles between Morse sets are allowed.



To refine these results further, we introduce some terminology. Assume that the flow allows a global attractor given by

$$G = \bigcap_{t \ge 0} \varphi_t(D). \tag{1}$$

#### Definition

A **Morse decomposition** of the dynamics of  $\varphi_t$  is a collection of non-empty  $\varphi$ -invariant pairwise disjoint compact sets  $\{M_1, \ldots, M_m\}$ , called Morse sets, such that

- M<sub>i</sub> is isolated,
- for every x ∈ G\U<sup>m</sup><sub>i=1</sub>M<sub>i</sub>, there exists i > j such that ω(x) ⊆ M<sub>i</sub> and α(x) ⊆ M<sub>j</sub>.

Morse sets contain all limit sets, and no cycles between Morse sets are allowed. Modulo replacing each  $M_i$  with points one may think of  $\varphi$  as being gradient-like, with the flow moving from lower to higher indexed morse sets.



A Morse decomposition  $\{M_1, \ldots, M_m\}$  is called finer than a Morse decomposition  $\{M'_1, \ldots, M'_{m'}\}$  if for all  $j \in \{1, \ldots, m'\}$  there is  $i \in \{1, \ldots, m\}$  with  $M_i \subset M'_j$ .



A Morse decomposition  $\{M_1, \ldots, M_m\}$  is called finer than a Morse decomposition  $\{M'_1, \ldots, M'_{m'}\}$  if for all  $j \in \{1, \ldots, m'\}$  there is  $i \in \{1, \ldots, m\}$  with  $M_i \subset M'_j$ .

#### Theorem (Main)

Let  $M_1, \ldots, M_m$  be the finest Morse decomposition for  $\varphi_t$  such that  $M_j, \ldots, M_m$  are attractors. If

- $M_i \subset D_0$  or  $M_i \subset D_1$ ,
- $M_i \subset D_1$  for some  $i \geq j$ .

then any weak\*-limit point of  $\{\mu^{\varepsilon}\}_{\varepsilon>0}$  is  $\varphi_t$ -invariant and is supported by the union of attractors in  $D_1$ .



A Morse decomposition  $\{M_1, \ldots, M_m\}$  is called finer than a Morse decomposition  $\{M'_1, \ldots, M'_{m'}\}$  if for all  $j \in \{1, \ldots, m'\}$  there is  $i \in \{1, \ldots, m\}$  with  $M_i \subset M'_j$ .

#### Theorem (Main)

Let  $M_1, \ldots, M_m$  be the finest Morse decomposition for  $\varphi_t$  such that  $M_j, \ldots, M_m$  are attractors. If

- $M_i \subset D_0$  or  $M_i \subset D_1$ ,
- $M_i \subset D_1$  for some  $i \ge j$ .

then any weak\*-limit point of  $\{\mu^{\varepsilon}\}_{\varepsilon>0}$  is  $\varphi_t$ -invariant and is supported by the union of attractors in  $D_1$ .

The proof is based on so called absorption preserving pseudo-orbits, introduced by Schreiber et al. and a large deviations result, generalizing the work of Kifer and Conley.



Returning to network,

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

for each  $\epsilon > 0$  there exists a unique QSD.



Returning to network,

$$\emptyset \xleftarrow{\alpha_1}{\leftarrow} S \xleftarrow{\alpha_2}{\underset{\alpha_3}{\leftarrow}} 2S \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

for each  $\epsilon > 0$  there exists a unique QSD. The state space is

 $D=\{0\}\sqcup (0,\infty).$ 



Returning to network,

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\longrightarrow}} 2S \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

for each  $\epsilon > 0$  there exists a unique QSD. The state space is

$$D = \{0\} \sqcup (0, \infty).$$

The finest Morse decomposition of the dynamics is

$$M_1 = \{0\}, \qquad M_2 = \left\{ rac{lpha_2 - lpha_1}{lpha_3} 
ight\}$$

where  $M_2$  is an attractor.

Returning to network,

$$\emptyset \stackrel{\alpha_1}{\leftarrow} S \stackrel{\alpha_2}{\underset{\alpha_3}{\rightleftharpoons}} 2S \qquad \qquad \frac{dx}{dt} = (\alpha_2 - \alpha_1)x - \alpha_3 x^2.$$

for each  $\epsilon > 0$  there exists a unique QSD. The state space is

$$D = \{0\} \sqcup (0, \infty).$$

The finest Morse decomposition of the dynamics is

$$M_1 = \{0\}, \qquad M_2 = \left\{\frac{\alpha_2 - \alpha_1}{\alpha_3}\right\}$$

where  $M_2$  is an attractor. Thus, any weak<sup>\*</sup> limit point of  $\{\mu^{\varepsilon}\}_{\varepsilon>0}$  is supported by  $M_2$ .



Figure : 
$$\varepsilon = 1, 1/2, 1/4, 1/8, 1/16, 1/32, 1/64$$
.

#### A 2D-example



$$\frac{d}{dt}\begin{pmatrix}x_1\\x_2\end{pmatrix} = \begin{pmatrix}\alpha_1x_1^2 - \alpha_2x_1^3 - \alpha_3x_1x_2^2\\\alpha_3x_1x_2^2 + \alpha_4x_2^2 - \alpha_5x_2^3\end{pmatrix}$$

For each  $\epsilon > 0$  there exists a unique QSD.



#### A 2D-example



$$\frac{d}{dt} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \alpha_1 x_1^2 - \alpha_2 x_1^3 - \alpha_3 x_1 x_2^2 \\ \alpha_3 x_1 x_2^2 + \alpha_4 x_2^2 - \alpha_5 x_2^3 \end{pmatrix}$$

For each  $\varepsilon > 0$  there exists a unique QSD. The state space is

$$D = \partial \mathbb{R}^2_+ \sqcup (0, \infty)^2$$



Figure : 
$$\varepsilon = 1/2, 1/4, 1/8, 1/16, 1/32, 1/64$$
.





$$\frac{dx}{dt} = \alpha_1 x - \alpha_2 x^2 + \alpha_3 x^3 - \alpha_4 x^4.$$

For each  $\epsilon > 0$  there exists a unique QSD.





$$\frac{dx}{dt} = \alpha_1 x - \alpha_2 x^2 + \alpha_3 x^3 - \alpha_4 x^4.$$

For each  $\varepsilon > 0$  there exists a unique QSD. The state space is  $D = \{0\} \sqcup (0, \infty).$ 





$$\frac{dx}{dt} = \alpha_1 x - \alpha_2 x^2 + \alpha_3 x^3 - \alpha_4 x^4.$$

For each  $\epsilon > 0$  there exists a unique QSD. The state space is

$$D = \{0\} \sqcup (0, \infty).$$

With parameters  $\alpha_1 = 900, \alpha_2 = 320, \alpha_3 = 33, \alpha_4 = 1$ , the finest Morse decomposition is

$$M_1 = \{0\}, \quad M_2 = \{10\}, \quad M_3 = \{5\}, \quad M_4 = \{18\}$$

with  $M_3, M_4$  being attractors.





$$\frac{dx}{dt} = \alpha_1 x - \alpha_2 x^2 + \alpha_3 x^3 - \alpha_4 x^4.$$

For each  $\epsilon > 0$  there exists a unique QSD. The state space is

$$D = \{0\} \sqcup (0, \infty).$$

With parameters  $\alpha_1 = 900, \alpha_2 = 320, \alpha_3 = 33, \alpha_4 = 1$ , the finest Morse decomposition is

$$M_1 = \{0\}, \quad M_2 = \{10\}, \quad M_3 = \{5\}, \quad M_4 = \{18\}$$

with  $M_3, M_4$  being attractors. Thus

$$supp\mu \subseteq \{5\} \cup \{18\}. \tag{2}$$



#### Figure : $\epsilon = 1/2, 1/4, 1/8, 1/32, 1/64, 1/128, 1/256, 1/512.$

# Future (ongoing) work

- When will there exist a QSD for a given reaction network? (Hard)
- When will the limit converge to a single positive attractor? Which one will it be? (Friedlin-Wentzel theory for absorbing processes?)
- If there are no positive attractors, are all the weak\* limit points supported by *D*<sub>0</sub>?
- Can we determine the rate of convergence to μ (in the total variations norm say)?
- Can we describe the QSDs far away from equilibrium?

# Thanks!

Mads Christian Hansen University of Copenhagen mads@math.ku.dk



