# IRTG Bielefeld–Seoul Winter School - Stochastic Dynamics Metastable dynamics of Markov processes

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Based on joint works with Manon Baudel, Giacomo Di Gesù, Bastien Fernandez, Barbara Gentz, Damien Landon and Hendrik Weber



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## What is metastabilty?

#### Supercooled water (Source: https://youtu.be/fSPzMva9\_CE)

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#### What is metastabilty?



Particles interacting with a Lennard–Jones potential, coupled to a thermostat (stochastic differential equation, or SDE)

## Contents

- 1. Metastable Markov chains on a finite set
- 2. Continuous-space Markov chains and SDEs
- 3. Example: the FitzHugh-Nagumo equation
- 4. The case of reversible SDEs: The potential-theoretic approach
- 5. The stochastic Allen-Cahn PDE

# 1. Metastable Markov chains on a finite set



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## A simple example



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 $\triangleright \varepsilon = 0$ : P = Id

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- $\triangleright \varepsilon = 0$ : P = Id
- D < ε ≤ ε<sub>max</sub>: irreducible, aperiodic, not reversible
   Stationary distribution:
   Speed of convergence to π<sub>0</sub>?
   Eigenvalues of *P*:

# Main question

How to easily determine leading term of spectral gap  $1 - \lambda_1$ ?

- Linear algebra/analytic methods (singular perturbation theory), e.g. [Schweitzer 68, Hassin & Haviv 92, Avrachenkov & Lasserre 99]
- Probabilistic methods, e.g. [Wentzell 72, Freidlin & Wentzell 70s, Miclo 95, Beltrán & Landim 2010, Cameron & Vanden-Eijnden 2014, Betz & Le Roux 2016, Cameron & Gan 2016]

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Some probabilistic tools:

- $\triangleright$  *W*-graphs
- Lumping of states
- Speeding up time



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- ▷ Speeding up time
- ▷ Here: trace process



## Killed process

 $\mathcal{X}$  finite,  $\{X_n\}_{n \in \mathbb{N}_0}$  irreducible aperiodic M.C., transition matrix  $P, A \subset \mathcal{X}$ 

▷ Process killed upon leaving A:  $P_A(x,y) = P(x,y) \mathbb{1}_{\{x,y \in A\}}$ 

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#### Trace process [Landim, Beltran]

- $\mathcal{X}$  finite,  $\{X_n\}_{n \in \mathbb{N}_0}$  irreducible aperiodic M.C., transition matrix  $P, A \subset \mathcal{X}$ 
  - $\triangleright$  Trace process on A: process monitored only when in A

 $_{A}P(x,y) = \mathbb{P}^{\times}\{X_{\tau_{A}^{+}} = y\}, \quad \tau_{A}^{+} = \inf\{n \ge 1: X_{n} \in A\}$ 

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 ${}_{\mathcal{A}}P(x,y) = \mathbb{P}^{\times}\{X_{\tau_{\mathcal{A}}^+} = y\}, \quad \tau_{\mathcal{A}}^+ = \inf\{n \ge 1: X_n \in \mathcal{A}\}$ 

#### Matrix representation (Schur complement)

$$P = \begin{pmatrix} P_A & P_{AA^c} \\ P_{A^cA} & P_{A^c} \end{pmatrix} \quad \Rightarrow \quad {}_{A}P = P_A + P_{AA^c} [\mathbb{1} - P_{A^c}]^{-1} P_{A^cA}$$

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## Application to the example

## A nice application of the trace process

Recall: the chain in not assumed to be reversible:  $\pi_0(x)P(x,y) \neq \pi_0(y)P(y,x)$  in general

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**Proposition:**  $\forall x, y \in A$ 

 $\pi_0(x)\mathbb{P}^x\{\tau_y^+ < \tau_x^+\} = \pi_0(y)\mathbb{P}^y\{\tau_x^+ < \tau_y^+\}$ 

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- ▷ First proof in non-reversible case: [Betz & Le Roux 2016] Using  $\pi_0(x) = 1/\mathbb{E}^x[\tau_x^+]$
- ▷ Alternative proof using trace process: [Baudel & B 2017] **Remark:**  $\pi_0|_A$  is invariant by  $_AP$

# **Good domains**

Α

#### **Definition:** For $A \subset \mathcal{X}$ , let

$$p_{in}(A) = \inf_{x \in A^c} \mathbb{P}^x \{ X_1 \in A \}$$
$$p_{out}(A) = \sup_{x \in A} \mathbb{P}^x \{ X_1 \in A^c \}$$
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$$A \text{ is a good domain if } \lim_{\varepsilon \to 0} \frac{p_{out}(A)}{p_{in}(A)} = 0$$

#### Example:



# Main idea

For a good domain A,

$$P = \begin{pmatrix} P_A & P_{AA^c} \\ P_{A^cA} & P_{A^c} \end{pmatrix}$$
 is well-approximated by  $\widehat{P} = \begin{pmatrix} AP & 0 \\ P_{A^cA} & P_{A^c} \end{pmatrix}$ 

## Main idea

For a good domain A,  $P = \begin{pmatrix} P_A & P_{AA^c} \\ P_{A^cA} & P_{A^c} \end{pmatrix}$ is well-approximated by  $\widehat{P} = \begin{pmatrix} A^P & 0 \\ P_{A^cA} & P_{A^c} \end{pmatrix}$ Norm:  $\|Q\| = \sup_{\|\varphi\|_{\infty}=1} \|Q\varphi\|_{\infty} = \sup_{\|\mu\|_{1}=1} \|\muQ\|_{1} = \sup_{x \in \mathcal{X}} \sum_{y \in \mathcal{X}} |Q(x, y)|$ Lemma:  $\|P - \widehat{P}\| = 2p_{\text{out}}(A)$ 

#### Main idea

Fact from spectral theory (using complex analysis, Riesz projector):  $\hat{\lambda}$  simple eigenvalue of  $\hat{P}$  at distance  $> \|P - \hat{P}\|$  from remaining spectrum  $\Rightarrow P$  has unique eigenvalue at distance  $\mathcal{O}(\|P - \hat{P}\|)$  from  $\hat{\lambda}$ 

**Consequence:** If 
$$A^c = \{x\}$$
 then  $p_{in}(A) = 1 - P(x, x) = 1 - \hat{\lambda}$   
 $\Rightarrow 1 - \lambda = 1 - \hat{\lambda} + \mathcal{O}(p_{out}(A)) = (1 - \hat{\lambda}) \Big[ 1 + \mathcal{O}\Big(\frac{p_{out}(A)}{p_{in}(A)} \Big) \Big]$ 

**Example:**  $\hat{\lambda}_2 = 1 - \varepsilon$  perturbs to  $\lambda_2 = 1 - \varepsilon + \mathcal{O}(\varepsilon^2)$ The argument does not suffice to compare spectra of  $P_A$  and  $_AP$ 

$$\widehat{P} = \begin{pmatrix} 1 - \varepsilon^3 - \varepsilon^4 & \varepsilon^3 + \varepsilon^4 & 0 \\ \varepsilon^3 & 1 - \varepsilon^3 & 0 \\ 0 & \varepsilon & 1 - \varepsilon \end{pmatrix}$$

 $u \in \mathbb{C} \implies \mathbb{E}^{\times}[e^{u\tau_A^+}]$  exists for

$$|e^{-u}| > 1 - p_{in}(A)$$
 (\*)

Follows from  $\mathbb{P}^{y}{\tau_{A}^{+} > n} \leq (1 - p_{in}(A))^{n} \quad \forall y \in A^{c}$ 

 $u \in \mathbb{C} \implies \mathbb{E}^{\times}[e^{u\tau_{A}^{+}}] \text{ exists for } |e^{-u}| > 1 - p_{in}(A) \quad (\star)$ Follows from  $\mathbb{P}^{y}\{\tau_{A}^{+} > n\} \leq (1 - p_{in}(A))^{n} \quad \forall y \in A^{c}$ **Proposition** [Feynman–Kac type relation] Under (\star), ((D )) ((\lambda)) = -u\_{in}(A) = -u\_{in}(A)

$$\begin{cases} (P\phi)(x) = e^{-u} \phi(x) & x \in A^c \\ \phi(x) = \overline{\phi}(x) & x \in A \end{cases}$$

admits unique solution  $\phi(x) = \mathbb{E}^{x} [e^{u\tau_{A}} \overline{\phi}(X_{\tau_{A}})], \tau_{A} = \inf\{n \ge 0: X_{n} \in A\}$ 

Proof:

**Corollary** [Reduction to eigenvalue problem on A] Under (\*),  $P\phi = e^{-u}\phi$  in  $\mathcal{X} \iff {}_{A}P^{u}\phi = e^{-u}\phi$  in A where  ${}_{A}P^{u}(x, y) = \mathbb{E}^{x} \left[ e^{u(\tau_{A}^{+}-1)} \mathbb{1}_{\{X_{\tau_{a}^{+}}=y\}} \right]$  is such that  ${}_{A}P^{0} = {}_{A}P$ 

**Proof of**  $\Rightarrow$ :

#### Proposition

$$\|_{A}P^{u} - {}_{A}P^{0}\| \leq \frac{|1 - e^{-u}|\sup_{x \in A} \mathbb{E}^{\times}[\tau_{A}^{+} - 1]}{1 - |1 - e^{-u}|\sup_{x \in A^{c}} \mathbb{E}^{\times}[\tau_{A}^{+}]} \leq \frac{|1 - e^{-u}|p_{\mathsf{out}}(A)}{p_{\mathsf{in}}(A) - |1 - e^{-u}|}$$

#### Main result – nondegenerate case

Algorithm in nondegenerate case:

- ▷ Assume  $\exists x \in \mathcal{X}$  such that  $1 P(x, x) \gg 1 P(y, y) \forall y \neq x$
- $\triangleright \text{ Take } A = \mathcal{X} \setminus \{x\} \text{ (A is a good set)}$
- ▷ Then 1 P has ev  $1 \lambda = P(x, x) [1 + O(p_{in}(A)/p_{out}(A))] \in \mathbb{R}$
- $\triangleright$  Compute  $_AP$  and start again with P replaced by  $_AP$

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- $\triangleright$  Compute  $_{A}P$  and start again with P replaced by  $_{A}P$

#### Theorem [Baudel & B, 2017]

- ▷ Non-degenerate case:  $\exists A_1 \subset A_2 \subset \cdots \subset A_n = \mathcal{X}$  s.t.  $\#(A_{k+1} \setminus A_k) = 1$ , each  $A_k$  good set for  $_{A_{k+1}}P$ Renumber states s.t.  $A_k = \{1, \ldots, k\}$ . Then
- $\triangleright \ \lambda_0 = 1, \ \lambda_k = 1 \mathbb{P}^{k+1} \{ \tau_{A_k}^+ < \tau_{k+1}^+ \} \Big[ 1 + \mathcal{O}\Big( \frac{p_{\mathsf{out}}(A_k|A_{k+1})}{p_{\mathsf{in}}(A_k|A_{k+1})} \Big) \Big] \quad \in \mathbb{R}$

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- $\triangleright \ \lambda_0 = 1, \ \lambda_k = 1 \mathbb{P}^{k+1} \big\{ \tau_{A_k}^+ < \tau_{k+1}^+ \big\} \Big[ 1 + \mathcal{O}\Big( \frac{p_{\mathsf{out}}(A_k|A_{k+1})}{p_{\mathsf{in}}(A_k|A_{k+1})} \Big) \Big] \quad \in \mathbb{R}$
- $\triangleright \quad k\text{th right eigenvector } \phi_k \text{ close to } \mathbb{P}^{\times} \{ \tau_{k+1} < \tau_{A_k} \}$
- ▷ kth left eigenvector  $\pi_k$  close to quasistationary distribution (QSD) of  $P_{A_k}$  (left eigenvect of  $P_{A_k}$  for Perron–Frobenius principal eigenval)

## Algorithm in degenerate case



# Algorithm in degenerate case



Degenerate part, leading order:



Effective trace process:



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**Eigenvalues:** 

 $1 = \varepsilon$  $1 - 2\varepsilon$ 

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