

# Metastability of random processes and solution of resolvent equations

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Small random perturbation of dynamical systems

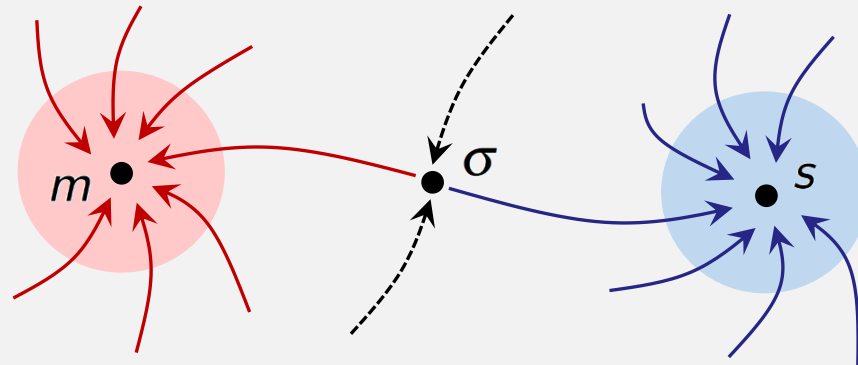
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Metastability and resolvent equations

# Small random perturbation of dynamical systems



- **Dynamical system**  $dx_t = b(x_t)dt$
- Equilibria:  $m, s$  (stable) and  $\sigma$  (unstable, saddle)

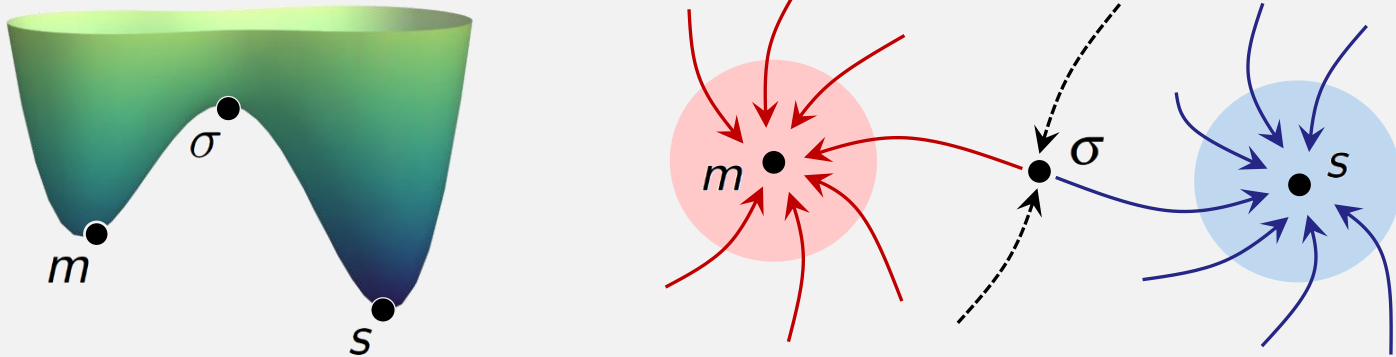
## Small random perturbation of dynamical system (SRPDS)

- **Stochastic** dynamical system

$$dx_t = b(x_t)dt + \sqrt{2\epsilon}dW_t$$

- $\epsilon > 0$ : small parameter (temperature),  $W_t$ : Brownian motion
- Metastability: rare transition from  $m$  to  $s$

# SRPDS: gradient case



- **Dynamical system**  $dx_t = -\nabla U(x_t)dt$
- $U$ : double-well potential (left figure above)

Special case:  $b = -\nabla U$

- **Stochastic** dynamical system

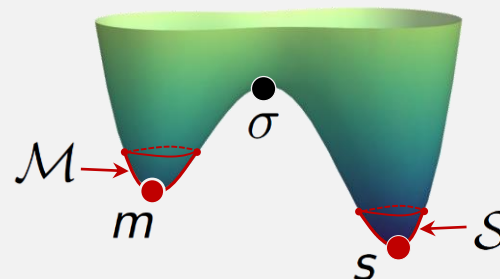
$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$

- $\epsilon > 0$ : small parameter (temperature),  $W_t$ : Brownian motion
- **Metastability**: rare transition from  $m$  to  $s$

# Metastability of SRPDS: mean transition time

**Model:** gradient SRPDS

$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$



**Question:** How long does it take to go from  $m$  to  $s$ ?

- $\tau_{m \rightarrow s}$ : transition time from  $m$  to  $s$
- $\mathbb{E}(\tau_{m \rightarrow s})$ : mean transition time

Large-deviation type estimate (Freidlin-Wentzell, 60s-70s)

$$\log \mathbb{E}(\tau_{m \rightarrow s}) \simeq \frac{U(\sigma) - U(m)}{\epsilon}$$

**Remark.** Sharp estimate is missing:

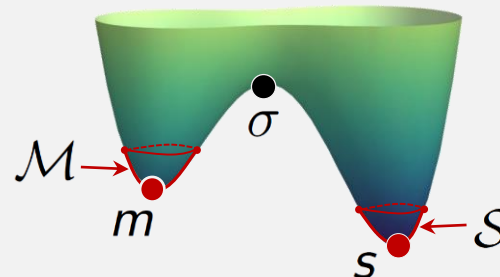
$$\mathbb{E}(\tau_{m \rightarrow s}) \simeq c_\epsilon e^{\frac{U(\sigma) - U(m)}{\epsilon}}$$

where  $c_\epsilon$  can be any sub-exponential term (e.g.  $\epsilon^k$  or  $e^{1/\sqrt{\epsilon}}$ )

# Metastability of SRPDS: mean transition time

**Model:** gradient SRPDS

$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$



**Question:** How long does it take to go from  $m$  to  $s$ ?

- $\tau_{m \rightarrow S}$ : transition time from  $m$  to  $S$
- $\mathbb{E}(\tau_{m \rightarrow S})$ : mean transition time

Eyring-Kramers formula (Bovier et. al., 2004)

$$\mathbb{E}(\tau_{m \rightarrow S}) \simeq \frac{-\mu_\sigma}{2\pi} \sqrt{\frac{\det(\nabla^2 U)(m)}{-\det(\nabla^2 U)(\sigma)}} e^{\frac{U(\sigma) - U(m)}{\epsilon}}$$

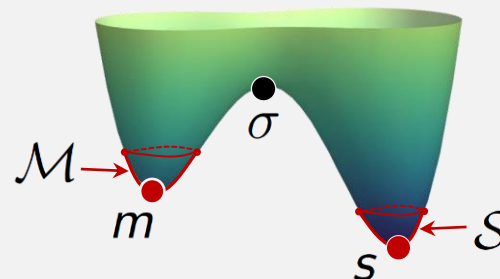
- $\mu_\sigma$ : unique negative e.v. of  $(\nabla^2 U)(\sigma)$
- The **self-adjointness** of associated generator  $\mathcal{L}_\epsilon$  is crucially used:

$$\mathcal{L}_\epsilon f = -\nabla U \cdot \nabla f + \epsilon \Delta f$$

# Metastability of SRPDS: spectral gap

**Model:** gradient SRPDS

$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$



Eyring-Kramers formula (Bovier et. al., 2004)

$$\mathbb{E}(\tau_{m \rightarrow S}) \simeq \frac{-\mu_\sigma}{2\pi} \sqrt{\frac{\det(\nabla^2 U)(m)}{-\det(\nabla^2 U)(\sigma)}} e^{\frac{U(\sigma) - U(m)}{\epsilon}}$$

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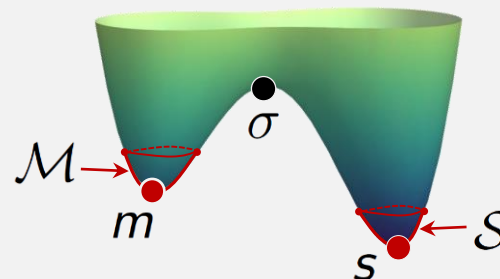
$$\mathcal{L}_\epsilon f = -\nabla U \cdot \nabla f + \epsilon \Delta f$$

- $\lambda_\epsilon$ : smallest non-zero eigenvalue of  $-\mathcal{L}_\epsilon$  (spectral gap)
- $\lambda_\epsilon \simeq \mathbb{E}(\tau_{m \rightarrow S})^{-1}$  (exponentially small)

# Metastability of SRPDS: distributions

**Model:** gradient SRPDS

$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$



**Question:**  $x_0 \in \mathcal{M} \rightarrow$  Estimate of  $\mathbb{P}(x_t \in \mathcal{M})$  and  $\mathbb{P}(x_t \in \mathcal{S})$

**Observation:** something will happen around  $\theta_\epsilon = e^{\frac{U(\sigma) - U(m)}{\epsilon}}$

Landim-Lee-Seo, forthcoming

- $t_\epsilon \ll \theta_\epsilon \rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}) \simeq 1$
- $t_\epsilon = t\theta_\epsilon \rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}) \simeq p(t)$  and  $\mathbb{P}(x_{t_\epsilon} \in \mathcal{S}) \simeq 1 - p(t)$
- $t_\epsilon \gg \theta_\epsilon \rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{S}) \simeq 1$

**Remark.**  $p(t)$  can be computed explicitly

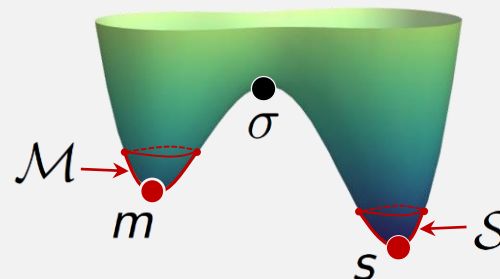


# Connection to parabolic equations

**Model:** gradient SRPDS

$$dx_t = -\nabla U(x_t)dt + \sqrt{2\epsilon}dW_t$$

with generator  $\mathcal{L}_\epsilon = -\nabla U \cdot \nabla + \epsilon\Delta$



**Parabolic equation:** for continuous and bounded  $g$ ,

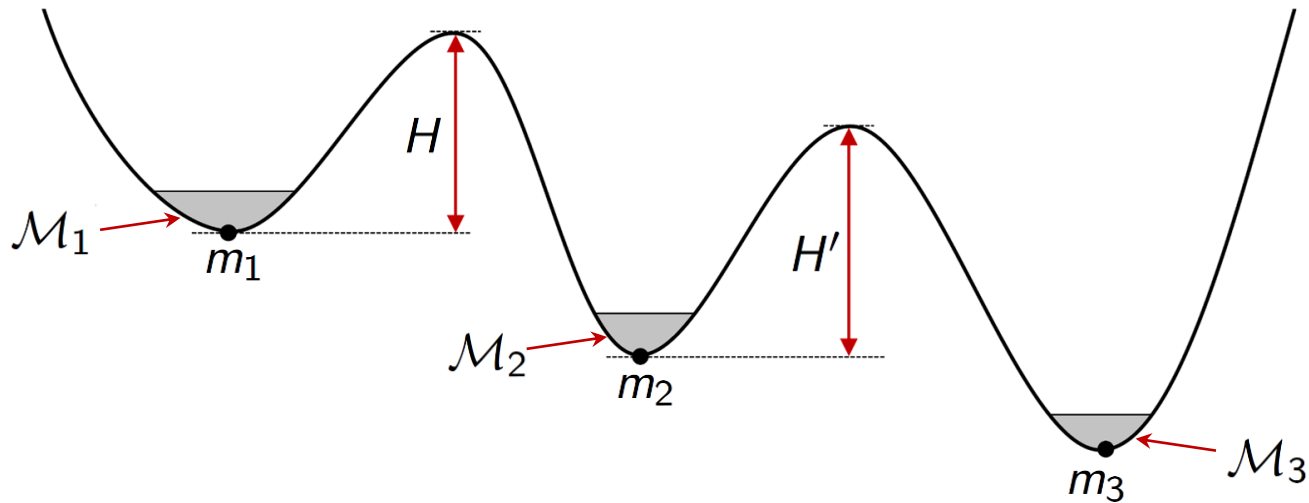
$$\begin{cases} u_t = \mathcal{L}_\epsilon u & \text{for } (t, x) \in (0, \infty) \times \mathbb{R}^d \\ u(0, x) = g(x) & \text{for } x \in \mathbb{R}^d \end{cases}$$

**Probabilistic expression:**  $u(t, x) = \mathbb{E}[g(x_t) | x_0 = x]$

Landim-Lee-Seo, forthcoming

$$x \in \mathcal{M} \rightarrow u(t_\epsilon, x) \simeq \begin{cases} g(m) & \text{if } t_\epsilon \ll \theta_\epsilon \\ p(t)g(m) + 1 - p(t)g(s) & \text{if } t_\epsilon = t\theta_\epsilon \\ g(s) & \text{if } t_\epsilon \gg \theta_\epsilon \end{cases}$$

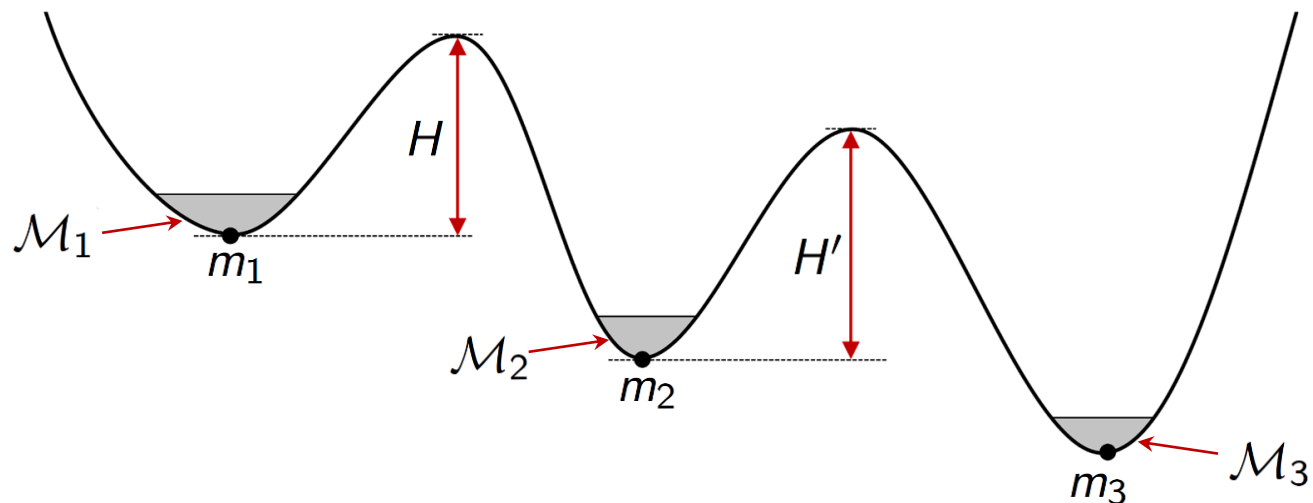
# Difficulty in complex potential



**(Case 1)**  $H < H'$ : two-scales  $\theta_\epsilon = e^{H/\epsilon}$  and  $\sigma_\epsilon = e^{H'/\epsilon}$

- $t_\epsilon \ll \theta_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq 1$
- $t_\epsilon = t\theta_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq p(t)$  and  $\mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_2) \simeq 1 - p(t)$
- $\theta_\epsilon \ll t_\epsilon \ll \sigma_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_2) \simeq 1$
- $t_\epsilon = t\sigma_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_2) \simeq q(t)$  and  $\mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_3) \simeq 1 - q(t)$
- $t_\epsilon \gg \sigma_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_3) \simeq 1$

# Difficulty in complex potential



**(Case 2)**  $H = H'$ : complex behavior at scale  $\theta_\epsilon = e^{H/\epsilon}$

- $t_\epsilon \ll \theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq 1$
- $t_\epsilon = t\theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_i) \simeq p_i(t)$  for  $i = 1, 2, 3$
- $t_\epsilon \gg \theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_3) \simeq 1$

# Discussion on general SRPDS

Same questions for the **general** SRPDS

$$dx_t = b(x_t)dt + \sqrt{2\epsilon}dW_t$$

are widely open because of the following difficulties:

- 1 Complexity of the **invariant measure**
- 2 Generator is **not** self-adjoint

## Remarks on invariant measure:

- Gradient model ( $b = -\nabla U$ ) has **Gibbs invariant measure**  $e^{-U(x)/\epsilon}$
- Friedlin-Wentzell decomposition:  $b = -\nabla U + \ell$  with  $\nabla U \cdot \ell \equiv 0$
- Gibbs invariant measure if and only if  $\nabla \cdot \ell \equiv 0$
- Without condition  $\nabla \cdot \ell \equiv 0$ , invariant measure is highly complex;  
Bouchet-Reygner, 2016

# Discussion on general SRPDS

Same questions for the **general** SRPDS

$$dx_t = b(x_t)dt + \sqrt{2\epsilon}dW_t$$

are widely open because of the following difficulties:

- ① Complexity of the **invariant measure**
  - ② Generator is **not** self-adjoint
- Friedlin-Wentzell decomposition:  $b = -\nabla U + \ell$  with  $\nabla U \cdot \ell \equiv 0$
  - Gibbs invariant measure if and only if  $\nabla \cdot \ell \equiv 0$

## Metastability under Gibbs invariant measure

- Eyring-Kramers formula: Lee-Seo, 2022
- Spectral gap: Le Peutrec-Michel, 2021
- Distributions: Landim-Lee-See, forthcoming

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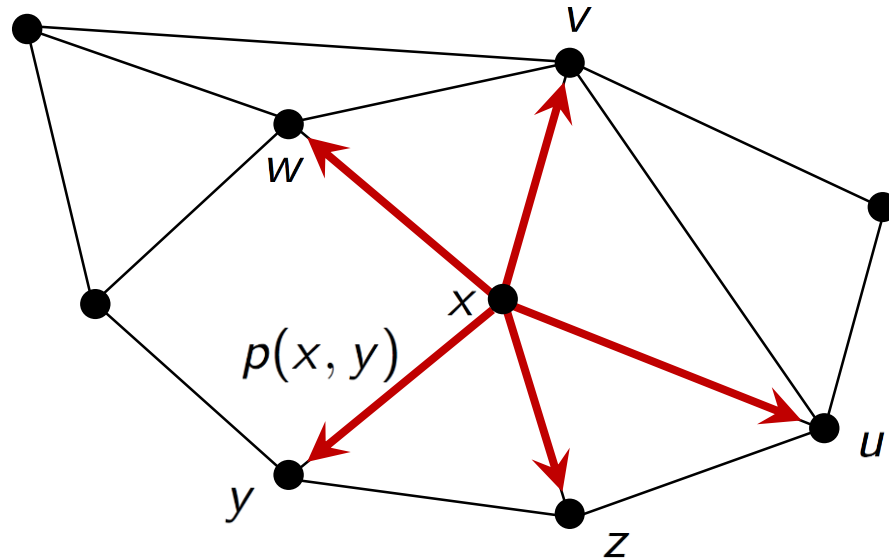
Metastability and resolvent equations

# Markov process: discrete time

## Discrete time Markov chain on finite set

$X_1, X_2, \dots$  is called a **Markov chain** with jump probability  $p(x, y)$  if it jumps from  $x$  to  $y$  with probability  $p(x, y)$ :

$$\mathbb{P}(X_{t+1} = y | X_t = x) = p(x, y)$$



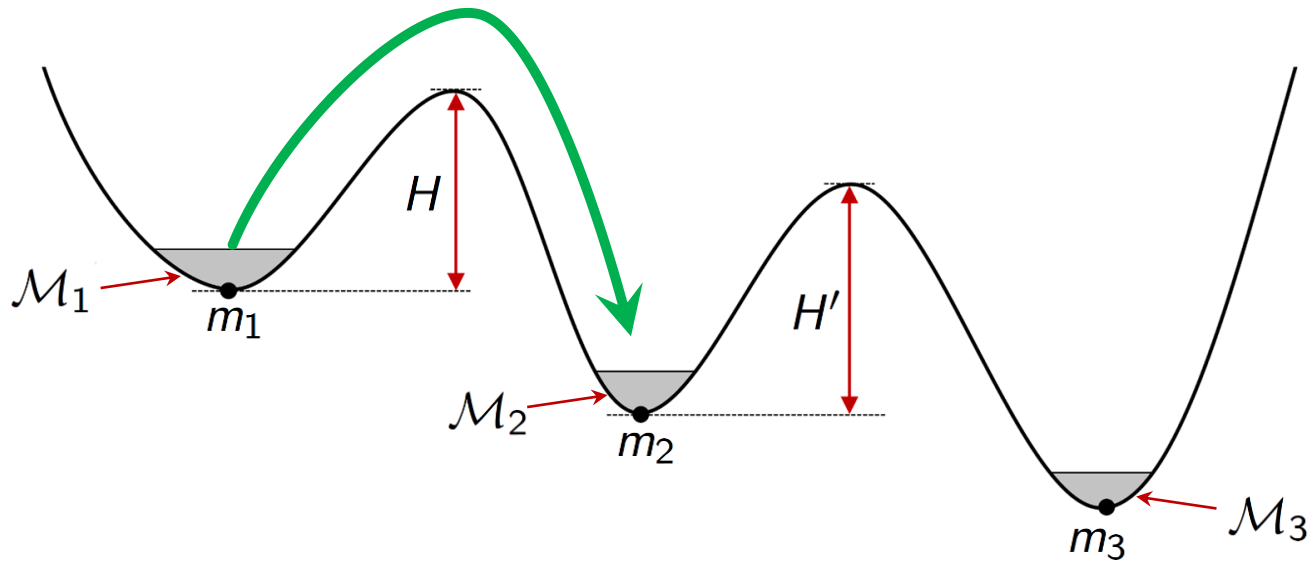
$$p(x, y) + p(x, z) + p(x, w) + p(x, u) + p(x, v) = 1$$

# Markov process: discrete time

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Jump from  $\mathcal{M}_1$  to  $\mathcal{M}_2$  after waiting a **random** amount of time



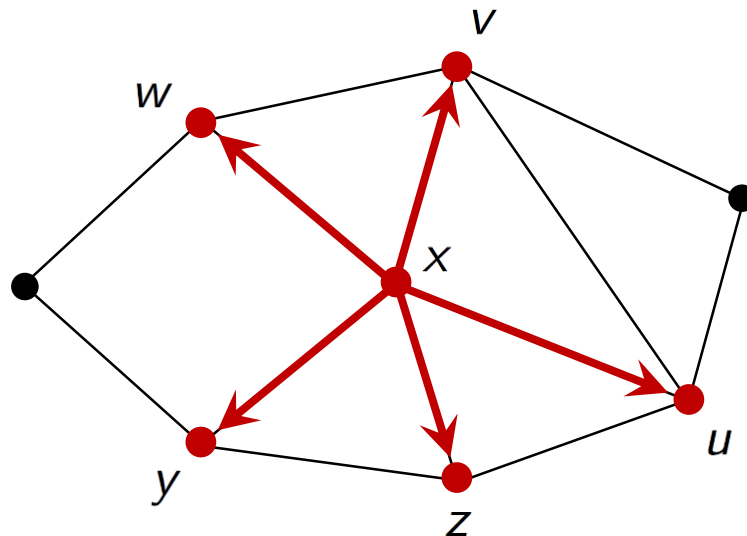
# Markov process: continuous time

## Continuous time Markov process on finite set

$(X_t)_{t \geq 0}$  is called a **Markov process** with **jump rate**  $r(x, y)$  if

- 1 the process at  $x$  waits for random time of mean  $\frac{1}{\sum_u r(x, u)}$
- 2 and then jumps to  $y$  with probability  $\frac{r(x, y)}{\sum_u r(x, u)}$

- By increasing  $r(\cdot, \cdot)$ , not only jump probability is increased but also the **jump occurs more quickly**



# Markov process: continuous time

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- ② and then jumps to  $y$  with probability  $\frac{r(x, y)}{\sum_u r(x, u)}$

- By increasing  $r(\cdot, \cdot)$ , not only jump probability is increased but also the **jump occurs more quickly**
- Associated generator  $L$ :

$$(Lf)(x) = \sum_u r(x, u)(f(u) - f(x))$$

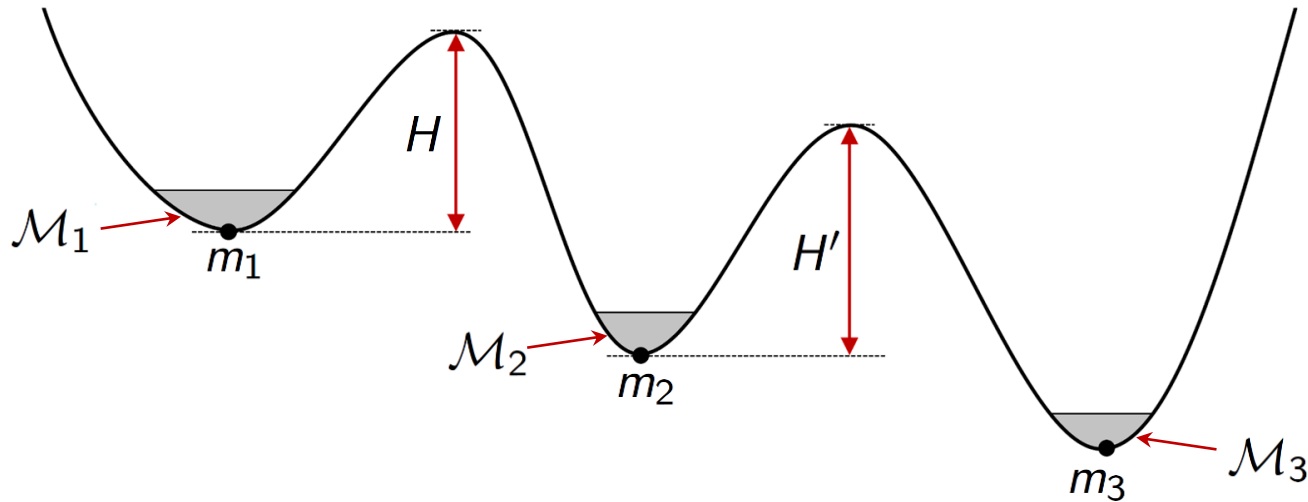
- The generator  $L$  contains all the essential information

# Markov process: continuous time

## Continuous time Markov process on finite set

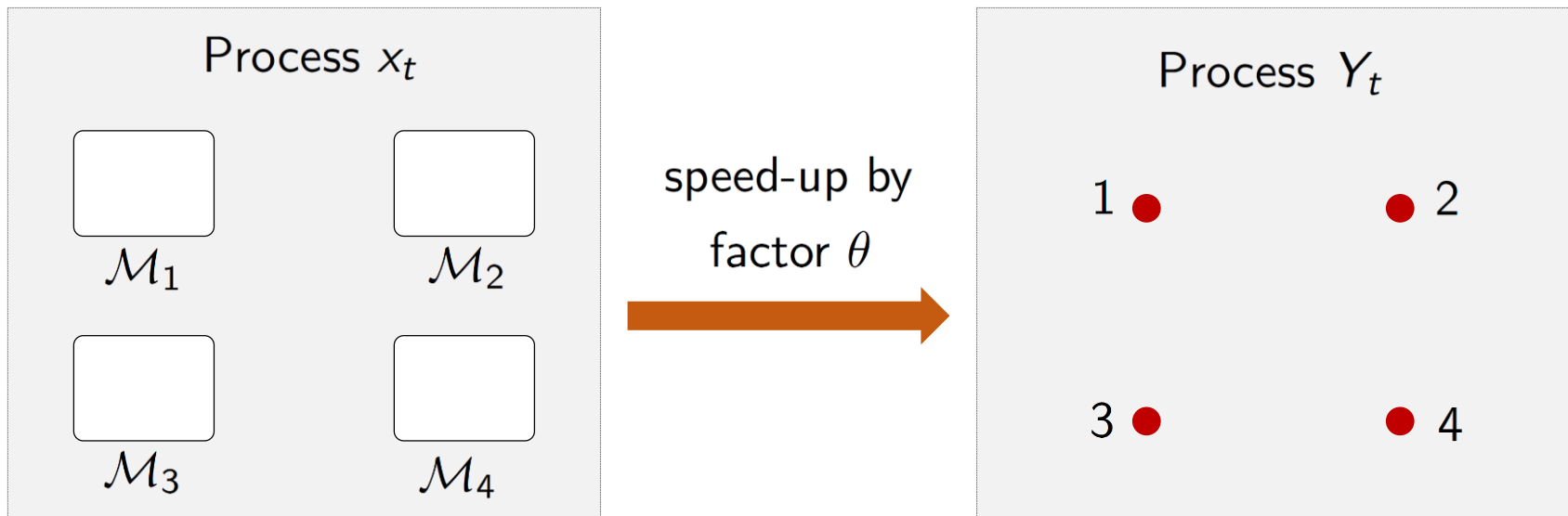
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Metastable behavior of  $x_t$  is described by a MP on  $\{1, 2, 3\}$

# Description of metastable behavior



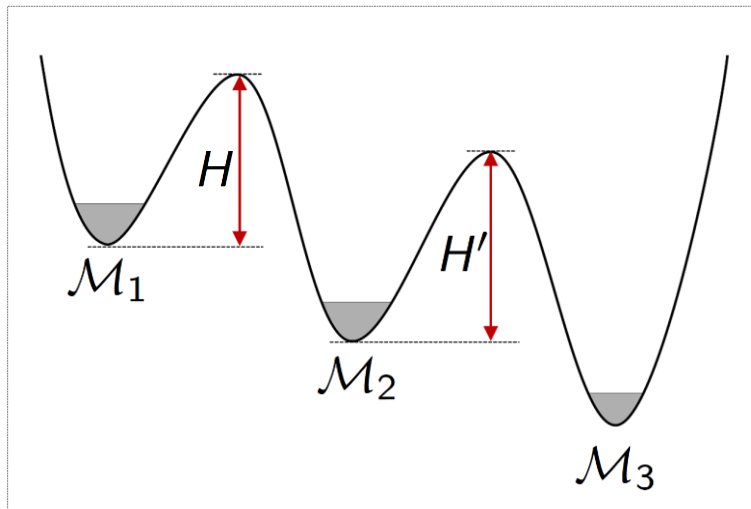
- $x_t$ : metastable process
- $Y_t$ : continuous time Markov process on  $\{1, 2, 3, 4\}$

## Description of metastable behavior

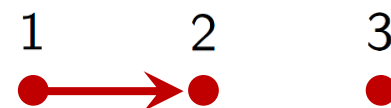
Metastable behavior of  $x_t$  is described by MP  $Y_t$  at time scale  $\theta$ :

$$\mathbb{P}(x_{\theta t} \in \mathcal{M}_i) \simeq \mathbb{P}(Y_t = i)$$

# Concluding remarks



Markov process  $Y_t$

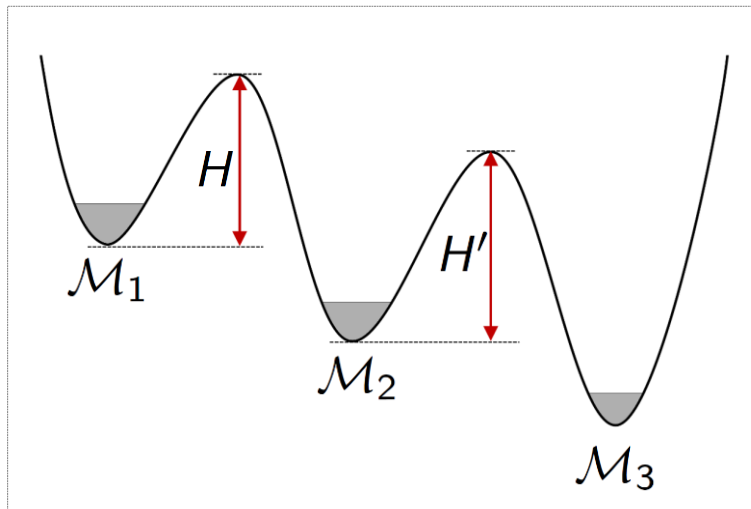


$$p(t) = \mathbb{P}(Y_t = 1)$$

**(Case 1)**  $H < H'$ : two-scales  $\theta_\epsilon = e^{H/\epsilon}$  and  $\sigma_\epsilon = e^{H'/\epsilon}$

- $t_\epsilon \ll \theta_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq 1$
- $t_\epsilon = t\theta_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq p(t)$  and  $\mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_2) \simeq 1 - p(t)$
- $\theta_\epsilon \ll t_\epsilon \ll \sigma_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_2) \simeq 1$

# Concluding remarks



Scale  $\sigma_\epsilon$

Markov process  $Y_t$

$\{1, 2\}$

3

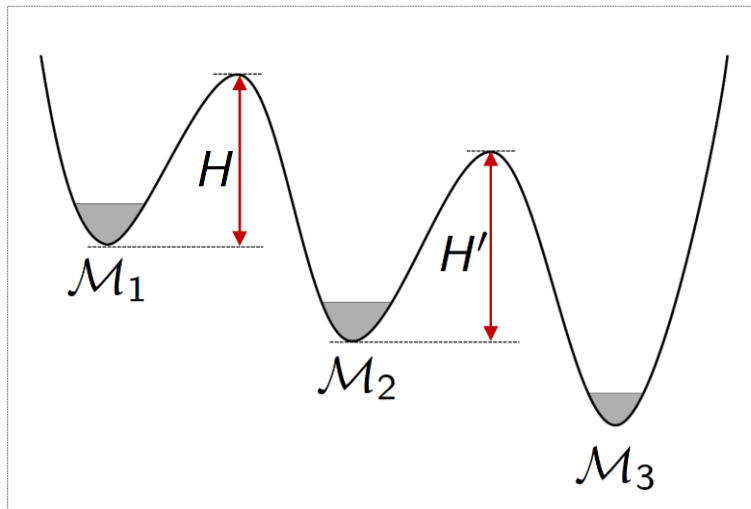


$q(t) = \mathbb{P}(Y_t = \{1, 2\})$

**(Case 1)**  $H < H'$ : two-scales  $\theta_\epsilon = e^{H/\epsilon}$  and  $\sigma_\epsilon = e^{H'/\epsilon}$

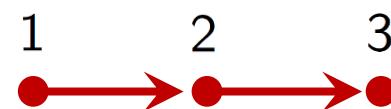
- $t_\epsilon \ll \theta_\epsilon \implies \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq 1$
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# Concluding remarks



Scale  $\theta_\epsilon$

Markov process  $Y_t$



$$p_i(t) = \mathbb{P}(Y_t = i)$$

**(Case 2)**  $H = H'$ : complex behavior at scale  $\theta_\epsilon = e^{H/\epsilon}$

- $t_\epsilon \ll \theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_1) \simeq 1$
- $t_\epsilon = t\theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_i) \simeq p_i(t)$  for  $i = 1, 2, 3$
- $t_\epsilon \gg \theta_\epsilon \Rightarrow \mathbb{P}(x_{t_\epsilon} \in \mathcal{M}_3) \simeq 1$

**Remark.** Jump rate of  $Y_t$  can be inferred from Eyring-Kramers formula

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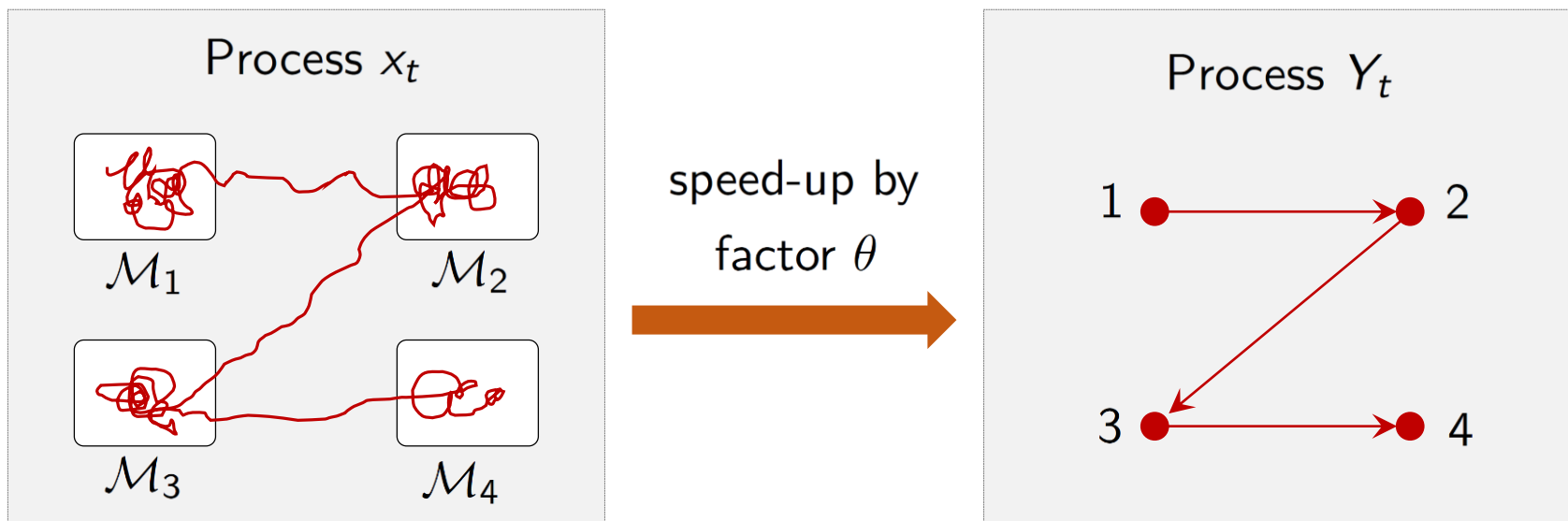
Markov process description of metastability

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Metastability and resolvent equations



# Negligibility of excursions

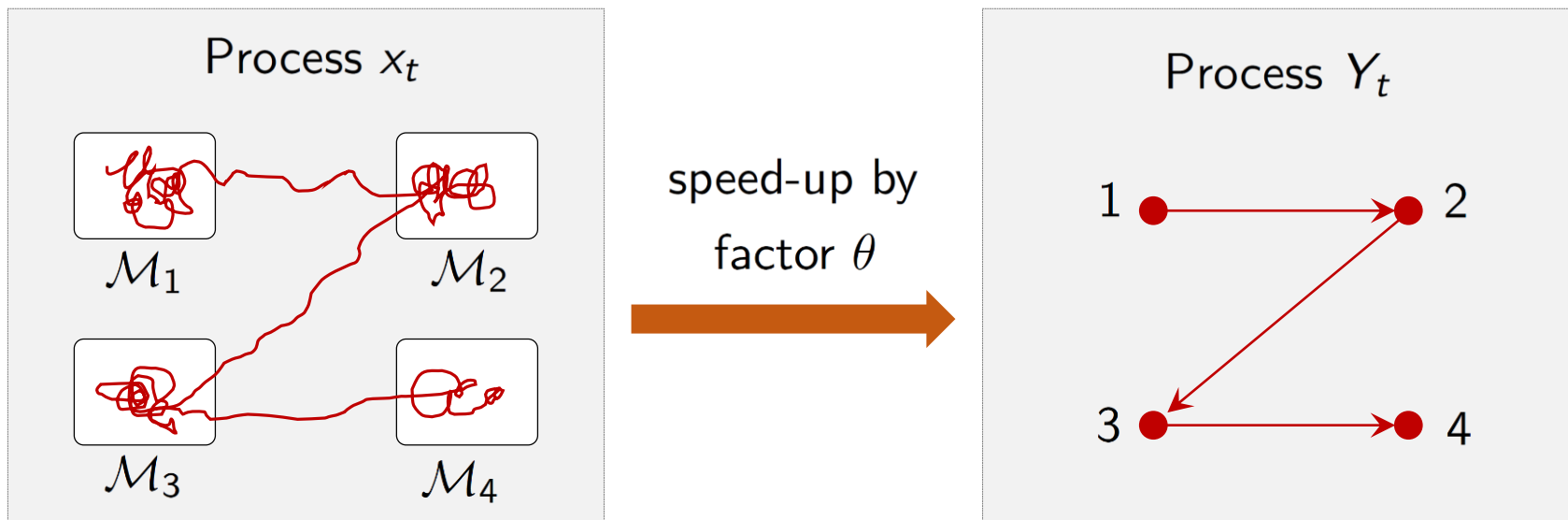


- Condition **(N)**: if the process  $x_t$  starts at a metastable set,

$$\mathbb{E} \left[ \int_0^T \mathbf{1} \left( x_{\theta t} \notin \bigcup \mathcal{M}_i \right) \right] \simeq 0$$

**Meaning:** speeded-up process spends **negligible** amount of time outside of metastable sets

# Description of metastable behavior

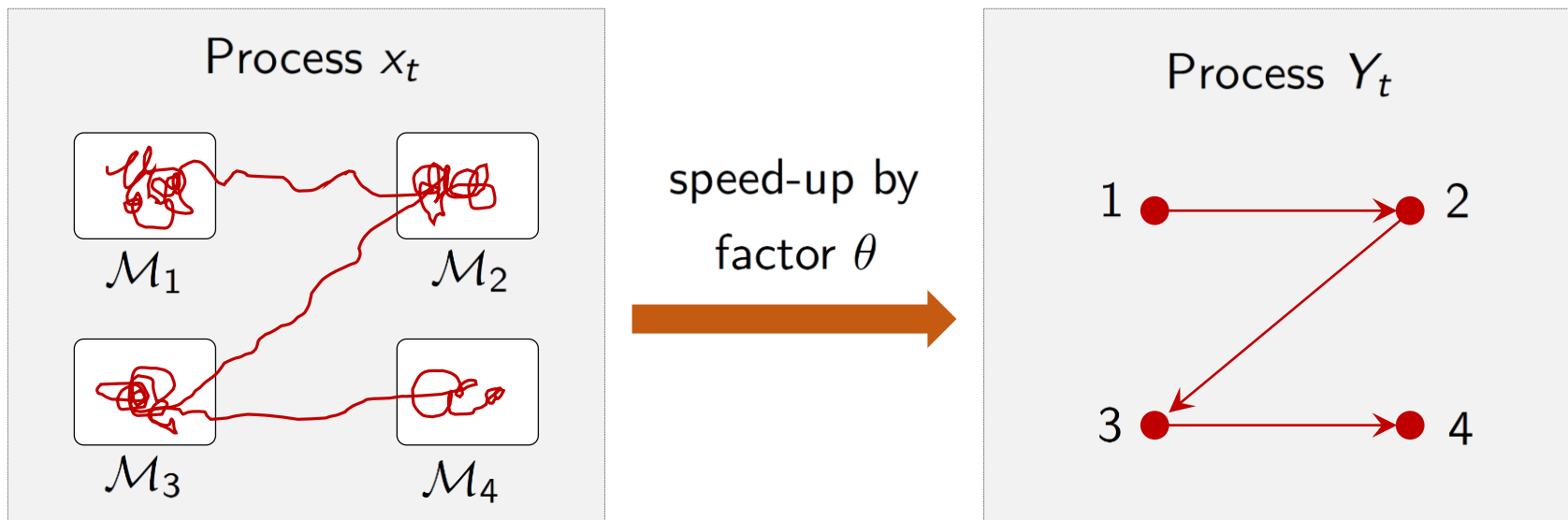


- Condition **(C)**: For all  $t_1 < \dots < t_k$  and  $i_1, \dots, i_k$ ,

$$\mathbb{P}(x_{\theta t_1} \in \mathcal{M}_{i_1}, \dots, x_{\theta t_k} \in \mathcal{M}_{i_k}) \simeq \mathbb{P}(Y_{t_1} = i_1, \dots, Y_{t_k} = i_k)$$

**Meaning:** the MP  $Y_t$  describes metastable behavior of the process  $x_t$  at time scale  $\theta$

# Resolvent equation



- Condition **(R)**: For any  $f : S \rightarrow \mathbb{R}$ , the solution  $F$  of

$$\lambda F(x) - \theta(\mathcal{L}F)(x) = \sum_{i \in S} (\lambda f - Lf)(i) \mathbf{1}_{\mathcal{M}_i}(x)$$

satisfies  $F(x) \simeq f(i)$  on each  $\mathcal{M}_i$

- $S$ : state space of  $Y_t$  (e.g.,  $S = \{1, 2, 3, 4\}$  for example above)
- $\mathcal{L}$ : generator of  $x_t$
- $L$ : generator of  $Y_t$

# Main results

Landim-Marcondes-Seo, 2021

Under the condition **(N)**, the conditions **(C)** and **(R)** are **equivalent**

- Condition **(C)**: For all  $t_1 < \dots < t_k$  and  $i_1, \dots, i_k$ ,

$$\mathbb{P}(x_{\theta t_1} \in \mathcal{M}_{i_1}, \dots, x_{\theta t_k} \in \mathcal{M}_{i_k}) \simeq \mathbb{P}(Y_{t_1} = i_1, \dots, Y_{t_k} = i_k)$$

- Condition **(R)**: For any  $f : S \rightarrow \mathbb{R}$ , the solution  $F$  of

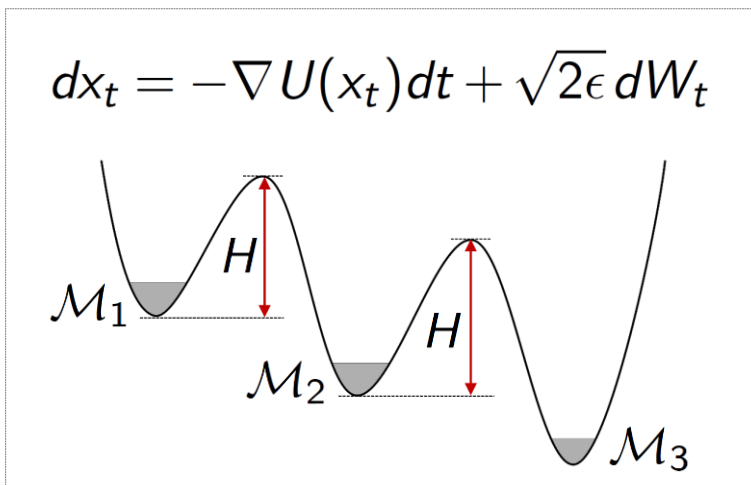
$$\lambda F(x) - \theta(\mathcal{L}F)(x) = \sum_{i \in S} (\lambda f - Lf)(i) \mathbf{1}_{\mathcal{M}_i}(x)$$

satisfies  $F(x) \simeq f(i)$  on each  $\mathcal{M}_i$

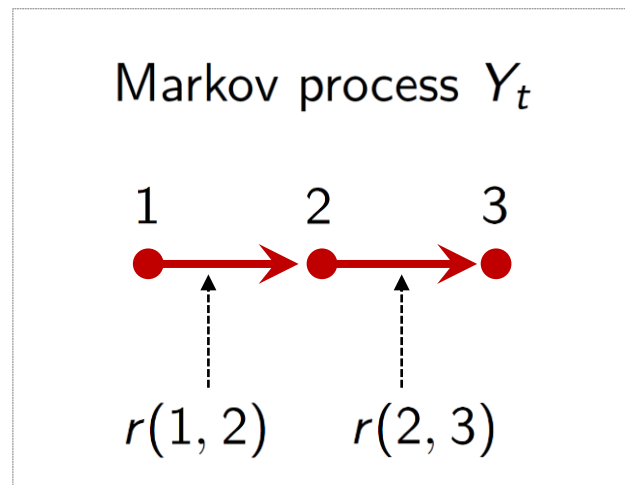
## Remarks.

- 1 Condition **(N)** is a technical one and can be proven independently
- 2 Condition **(R)** implies condition **(N)**

# Application to SRPDS



Scale  $\theta_\epsilon$



- Generator of  $x_t \Rightarrow \mathcal{L}_\epsilon F = -\nabla U \cdot \nabla F + \epsilon \Delta F$
- Generator of  $Y_t \Rightarrow Lf(i) = \sum_j r(i, j)(f(j) - f(i))$
- $Y_t$  describes the metastable behavior of  $x_t$  at scale  $\theta_\epsilon = e^{H/\epsilon}$  iff

Condition **(R)** holds

The solution  $F$  of

$$(\lambda - \theta_\epsilon \mathcal{L}_\epsilon)F(x) = \sum_{i=1}^3 (\lambda f - Lf)(i) \mathbf{1}_{\mathcal{M}_i}(x)$$

satisfies  $\|F(x) - f(i)\|_{L^\infty(\mathcal{M}_i)} \rightarrow 0$  as  $\epsilon \rightarrow 0$

# Flatness of solutions

Condition **(R)**: For any  $f : S \rightarrow \mathbb{R}$ , the solution  $F$  of

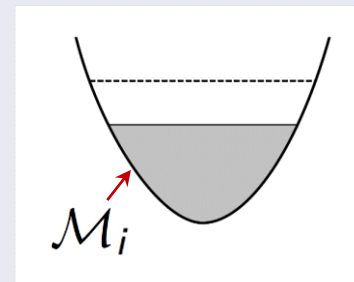
$$\lambda F(x) - \theta(\mathcal{L}F)(x) = \sum_{i \in S} (\lambda f - Lf)(i) \mathbf{1}_{\mathcal{M}_i}(x)$$

satisfies  $F(x) \simeq f(i)$  on each  $\mathcal{M}_i$

## General flatness: Landim-Marcondes-Seo, 2021

There exists  $c(i) \in \mathbb{R}$  such that  $F(x) \simeq c(i)$  on  $\mathcal{M}_i$  if

$$(1.1) \quad \text{mixing time} \ll \text{escape time}$$



- Self-adjoint case: **mixing time** can be replaced with **spectral gap**<sup>-1</sup>
- (1.1) has been verified for SRPDS
- Proving  $c(i) \simeq f(i)$  is model dependent part

# Concluding remarks

① We developed several robust methods to prove  $c(i) \simeq f(i)$

② This method is also applied to

- (Landim-Lee-Seo, forthcoming) SRPDS

$$dx_t = b(x_t) + \sqrt{2\epsilon}W_t \quad (1.2)$$

with [Gibbs invariant measure](#), i.e.  $b = -\nabla U + \ell$  with

$$\nabla U \cdot \ell \equiv \nabla \cdot \ell \equiv 0$$

- (Landim-Marcondes-Seo, 2021) Condensing interacting particle system with weak mixing property

③ We believe that the methodology is robust and can be applied to general SRPDS (1.2) as well

END OF PRESENTATION

徐仁錫