# Rare Event Simulation for Molecular Dynamics 

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Joint work with :

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## Introduction

The aim of Molecular Dynamics computations is to evaluate macroscopic quantities from models at the microscopic scale.
(i) thermodynamics quantities: stress, heat capacity, free energy (average of some observable wrt an equilibrium measure);
(ii) dynamical quantities: diffusion coefficients, viscosity, transition rates (average over trajectories at equilibrium).
$\Rightarrow$ Many applications in various fields: biology, physics, chemistry, materials science, etc. But Molecular dynamics computations consume today a lot of CPU time.

## Introduction

- A molecular dynamics model $\Leftrightarrow$ a potential $V$.
- A configuration $x=\left(x_{1}, \ldots, x_{n}\right) \Rightarrow$ an energy $V\left(x_{1}, \ldots, x_{n}\right)$.
- Consider the over-damped Langevin (or gradient) dynamics

$$
d X_{t}=-\nabla V\left(X_{t}\right) d t+\sqrt{2 \beta^{-1}} d W_{t}
$$

where $\beta=1 /\left(k_{B} T\right)$.

- Equilibrium Boltzmann-Gibbs measure

$$
d \mu=Z^{-1} \exp (-\beta V(x)) d x
$$

where $Z=\int_{\mathbb{R}^{n}} \exp (-\beta V(x)) d x$ is the partition function.

## Introduction

Difficulty: In practice, $X_{t}$ is a metastable process, so that the convergence to equilibrium is very slow.
$\Rightarrow \mathrm{A} 2 \mathrm{~d}$ schematic picture: $X_{t}^{1}$ is a slow variable of the system.



## Reactive Trajectories

Let $A$ and $B$ denote two metastable (recurrent) regions in $\mathbb{R}^{d}$.


- Reactive trajectory: piece of equilibrium trajectory that leaves $A$ and goes to $B$ without going back to $A$ in the meantime.
- Problem: one may wait a long time before the trajectory eventually reaches $B$.


## Reaction Coordinate

- Reaction coordinate: Smooth one-dimensional function

$$
\xi: \mathbb{R}^{d} \rightarrow \mathbb{R}
$$

with $|\nabla \xi| \neq 0$, and there exist $\xi_{\text {min }}<\xi_{\text {max }}$ such that

$$
A \subset\left\{x \in \mathbb{R}^{d}, \xi(x)<\xi_{\min }\right\} \text { and } B \subset\left\{x \in \mathbb{R}^{d}, \xi(x)>\xi_{\max }\right\}
$$

- Examples: $\xi(x)=\left\|x-x_{A}\right\|$ or $\xi(x)=\left|x^{1}-x_{A}^{1}\right|$.
- Remark: Reaction coordinate in Molecular Dynamics $\Leftrightarrow$ Importance function in Rare Events literature.


## Reaction Coordinate



- Example: $\xi(x)=\left\|x-x_{A}\right\|$, where $x_{A}$ is a configuration in $A$.
- The level sets $\{\xi(x)=c\}$ are then Euclidean hyperspheres.
- Importance Splitting [Kahn and Haris, 1951]: clone the trajectories approaching $B$ (wrt $\xi$ ), kill the other ones.
- Question: what is the best choice for $\xi$ ?


## Committor Function

For the estimation of transition probabilities, it is well known that the optimal reaction coordinate is the committor function

$$
q(x) \triangleq \mathbb{P}\left(\tau_{B}(x)<\tau_{A}(x)\right)=\mathbb{P}\left(X_{t}^{x} \text { reaches } B \text { before } A\right)
$$

solution of the following PDE

$$
\left\{\begin{array}{l}
-\nabla V \cdot \nabla q+\beta^{-1} \Delta q=0 \text { in } \mathbb{R}^{d} \backslash(\bar{A} \cup \bar{B}), \\
q=0 \text { on } \partial A \text { and } q=1 \text { on } \partial B .
\end{array}\right.
$$

## 2D Example [Metzner, Schütte and Vanden-Eijnden (2006)]

$$
\begin{aligned}
V(x, y)= & 3 \mathrm{e}^{-x^{2}-\left(y-\frac{1}{3}\right)^{2}}-3 \mathrm{e}^{-x^{2}-\left(y-\frac{5}{3}\right)^{2}}-5 \mathrm{e}^{-(x-1)^{2}-y^{2}} \\
& -5 \mathrm{e}^{-(x+1)^{2}-y^{2}}+0.2 x^{4}+0.2\left(y-\frac{1}{3}\right)^{4} .
\end{aligned}
$$



## 2D Example [Metzner, Schïte and Vanden-Eijnden (2006)]



- Level Sets of the Committor Function $q$ for $\beta=1.67$.
- Difficulty: in general, finding these level sets is too hard...
$\Rightarrow$ Use another reaction coordinate, e.g. $\xi(x)=\left\|x-x_{A}\right\|$.


## Algorithm



## Algorithm



## Algorithm



## Algorithm



## Algorithm



## Algorithm



## Algorithm



## Algorithm



## Algorithm

- Stopping Rule: iterate until step $k_{\text {max }}$ when all the paths reach $\left\{\xi(x)=\xi_{\max }\right\}$, keep only those which reach $B$ (proportion $r$ ).
- Estimation: The probability

$$
\hat{p}=r\left(1-\frac{1}{N}\right)^{k_{\max }}
$$

is the "probability of observing a reactive trajectory".

- Remark: The algorithm can be seen as a kind of adaptive Forward Flux Sampling [Allen, Valeriani, Ten Wolde, 2009]. It is also related to the Interface Sampling Method [Bolhuis, van Erp, Moroni 2003] and the Milestoning Method [Elber, Faradjian 2004].


## 2D Example



- 2 Deep Minima: $H_{ \pm}=( \pm 1,0) \Rightarrow A \& B=\mathcal{B}\left(H_{ \pm}, 0.05\right)$.
- 1 Shallow Minimum: $M=(0,1.5)$.
- 3 Saddle Points: $U_{ \pm}=( \pm 0.6,1.1)$ and $L=(0,-0.4)$.
- 2 Channels $\Rightarrow 2$ scenarii, depending on the temperature.


## A Few Reactive Trajectories



- Subsamplings of the generated trajectories.
- Reaction coordinate: $\xi(x)=\left\|x-x_{A}\right\|$.
- $\beta=1.67$ (high temperature): shallow is shallow.
- $\beta=6.67$ (low temperature): shallow becomes deep...


## Flux of Reactive Trajectories




- The color indicates the norm of the flux.
- Reaction coordinate: $\xi(x)=\left\|x-x_{A}\right\|$.
- $\beta=1.67$ : the lower channel is preferred (entropic effect).
- $\beta=6.67$ : the upper channel is preferred (lower energy barrier).


## Density of Reactive Paths: : $\xi(x)=\left\|x-x_{A}\right\|$

## Density for beta $=1.67$



Density for beta $=6.67$


## Density of Reactive Paths: : $\xi(x)=\left|x^{1}-x_{A}^{1}\right|$

## Density for beta $=1.67$

Density for beta $=6.67$



## 1D Example: $V(x)=x^{4}-2 x^{2}$.



- Metastable States: $A=(-1.1 ;-0.9)$ and $B=(0.9 ; 1.1)$.
- Reaction Coordinate: $\xi(x)=x$.
- Application: distribution of the duration of the reactive paths.


## 1D Example



## Framework



- Recall:

$$
d X_{t}=-V^{\prime}\left(X_{t}\right) d t+\sqrt{2 k_{B} T} d W_{t}
$$

- Assumption: $V$ is an even double well potential, $V^{\prime \prime}(0)=-1$.
- Metastable States: $A$ and $B$.
- Question: knowing $T_{a}<T_{-a}$, what is the law of $T_{-a \rightarrow a}$ ?


## An Asymptotic Expansion



Theorem
On the set $\left\{T_{a}<T_{-a}\right\}$, one has

$$
T_{-a \rightarrow a} \underset{T \rightarrow 0}{\sim}-\log \left(k_{B} T\right)+2 \log a-2 H_{a}(0)+G
$$

where $G$ is a standard Gumbel random variable and

$$
H_{a}(s)=\int_{s}^{a} \frac{t+V^{\prime}(t)}{t V^{\prime}(t)} d t
$$

## Sketch of the Proof (1)



Denote $\varepsilon=k_{B} T$, and decompose the reactive path in 3 parts

$$
T_{-a \rightarrow a}=T_{-a \rightarrow-\sqrt{\varepsilon}}+T_{-\sqrt{\varepsilon} \rightarrow+\sqrt{\varepsilon}}+T_{\sqrt{\varepsilon} \rightarrow a}
$$

on the event $\left\{T_{a}<T_{-a}\right\}$.

## Proof (2): Going Down Is Easy



Thanks to Gronwall's Lemma

$$
T_{\sqrt{\varepsilon} \rightarrow a}-t_{\sqrt{\varepsilon} \rightarrow a} \xrightarrow[\varepsilon \rightarrow 0]{\text { a.s. }} 0
$$

with $t_{\sqrt{\varepsilon} \rightarrow a}$ the time for the unnoised process to reach a from $\sqrt{\bar{\varepsilon}}$ :

$$
t_{\sqrt{\varepsilon} \rightarrow a}=-\int_{\sqrt{\varepsilon}}^{a} \frac{1}{V^{\prime}(s)} d s \underset{\varepsilon \rightarrow 0}{\sim} \log \sqrt{\varepsilon}-\log a+H_{a}(0)
$$

## Proof (3): The Climbing Part



Freidlin-Wentzell's theory ensures that

$$
T_{-a \rightarrow-\sqrt{\varepsilon}}-t_{-\sqrt{\varepsilon} \rightarrow-a} \xrightarrow[\varepsilon \rightarrow 0]{\text { a.s. }} 0
$$

and since $V$ is even

$$
t_{-\sqrt{\varepsilon} \rightarrow-a}=-\int_{-\sqrt{\varepsilon}}^{-a} \frac{1}{V^{\prime}(s)} d s=t_{\sqrt{\varepsilon} \rightarrow a}
$$

A reactive path doesn't need more time to go up than to go down!

## Proof (4): The Middle Earth



Things happen "almost" like for a repulsive Ornstein-Uhlenbeck

$$
d X_{t}=X_{t} d t+\sqrt{2 \varepsilon} d W_{t}
$$

On the set $\left\{T_{\sqrt{\varepsilon}}<T_{-\sqrt{\varepsilon}}\right\}$, one can prove that

$$
T_{-\sqrt{\varepsilon} \rightarrow \sqrt{\varepsilon}} \underset{\varepsilon \rightarrow 0}{\sim}-\log (\varepsilon)+G+o_{\varepsilon}(1) .
$$

where $G$ is a standard Gumbel random variable.

## Recall: The Gumbel Distribution



- PDF: $\forall x \in \mathbb{R}, f(x)=e^{-x-e^{-x}}$.
- Extreme Value Theory: if $X_{1}, \ldots, X_{n}$ are i.i.d. $\mathcal{E}(1)$, then

$$
\max \left(X_{1}, \ldots, X_{n}\right)-\log n \underset{n \rightarrow \infty}{\mathcal{L}} G
$$

## Conclusion

A new adaptive multilevel splitting type algorithm with a random number of levels. Other possible applications:

- Estimation of the transition times between metastable states.
- Exploration of the energy landscape without any a priori.

References:

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