

Parallel Replica algorithm for Langevin dynamics and Adaptive Metadynamics

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- 1 Introduction
 - Metastability in molecular dynamics and the Parallel Replica algorithm
 - Quasi-stationary distribution and Parallel Replica justification
- 2 Langevin process and kinetic Fokker-Planck equation
 - Transition density of the absorbed semigroup
 - Compactness of the absorbed semigroup
- 3 Quasi-stationary distributions and overdamped limit of the Langevin process
 - Existence and long-time convergence
 - Overdamped limit of the QSD
- 4 Metadynamics
 - Description of the algorithm
 - Adaptive Metadynamics

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Motivation

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- The **Underdamped Langevin dynamics** model the evolution of thermostated molecular systems.

Let N particles described by **position** $q_t^i \in \mathbb{R}^3$, and **momentum** $p_t^i \in \mathbb{R}^3$. The process $(X_t = (q_t, p_t))_{t \geq 0} := (q_t^1, \dots, q_t^N, p_t^1, \dots, p_t^N)_{t \geq 0}$ is solution of

$$\begin{cases} dq_t = M^{-1} p_t dt, \\ dp_t = -\nabla V(q_t) dt - \gamma M^{-1} p_t dt + \sqrt{2\gamma\beta^{-1}} dB_t, \end{cases}$$

with $V : \mathbb{R}^{3N} \mapsto \mathbb{R}$ the interaction potential, $\gamma > 0$ the friction parameter, M the mass matrix and $\beta^{-1} = k_B T$.

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Numerical discretization: $(q_{n\Delta t}, p_{n\Delta t}) \sim (\hat{q}_n, \hat{p}_n)$ such that (Velocity-Verlet integrator)

$$(\hat{q}_{n+1}, \hat{p}_{n+1}) = \Phi_{\Delta t}(\hat{q}_n, \hat{p}_n).$$

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$$(\hat{q}_{n+1}, \hat{p}_{n+1}) = \Phi_{\Delta t}(\hat{q}_n, \hat{p}_n).$$

Problem: The sampling of some physical events takes too many iterations! (Typically 10^{-6} s with $\Delta t = 10^{-15}$ s).

An example in dimension 2

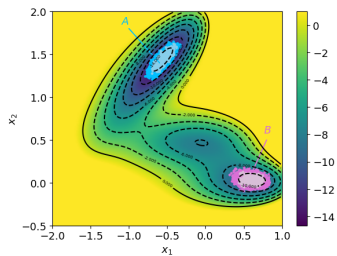


Figure: Sampling in a double well potential. 100 000 iterations

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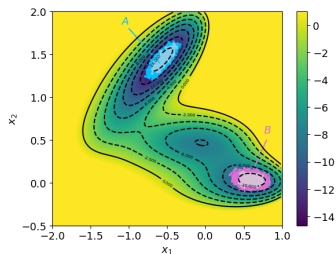


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- Oscillation inside basins of attraction of the potential.
- Transition events take a very long time: metastability because the system needs to overcome an energetic gap.
- Problem in large dimension where metastability correspond to entropic effects (narrow escapes).

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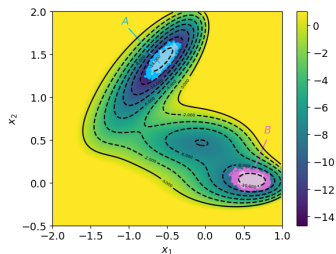


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How to sample **precisely** these transition events?

Parallel Replica algorithm

Conceived by Arthur Voter (Los Alamos National Laboratory) in 1998.

Objective: Parallelize the sampling of the first exit event (first exit time, exit point) from a domain D for the process $(X_t)_{t \geq 0}$.

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Objective: Parallelize the sampling of the first exit event (first exit time, exit point) from a domain D for the process $(X_t)_{t \geq 0}$.

Parallel Replica: Assume that $(X_t)_{t \geq 0}$ stayed in D during τ_c "long enough". Let $\tau_\partial := \inf\{t > \tau_c : X_t \notin D\}$.

- 1 Initialize N independent replicas $(X_t^1)_{t \geq 0}, \dots, (X_t^N)_{t \geq 0}$ starting from X_{τ_c} and following the same dynamics as $(X_t)_{t \geq 0}$.
- 2 Make the N replicas evolve in D during τ_c (*rejection sampling*).
- 3 Let $\tau_\partial^i = \inf\{t > 0 : X_{t+\tau_c}^i \notin D\}$ and $i^* = \arg \min_{1 \leq i \leq N} \tau_\partial^i$. Define

$$\left(\tau_\partial, X_{\tau_\partial} \right) := \left(N\tau_\partial^{i^*}, X_{\tau_\partial^{i^*}}^{i^*} \right).$$

If justified, the last step would ensure a **speed-up** of N in wall-clock time.

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Definition: Let $\tau_D := \inf\{t > 0 : X_t \notin D\}$. A probability measure ν on D is said to be a **QSD** on D of the process $(X_t)_{t \geq 0}$, if for all $A \subset D$,

$$\frac{\mathbb{P}_\nu(X_t \in A, \tau_D > t)}{\mathbb{P}_\nu(\tau_D > t)} = \nu(A).$$

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First exit event starting from the QSD and justification of ParRep

Assume that $X_0 \stackrel{\mathcal{L}}{=} \text{QSD}$, then, see Collet, Martinez, San Martin (2013),

- τ_∂ follows the exponential law,
- τ_∂ is independent of X_{τ_∂} .

Let (X_0^N, \dots, X_0^N) be i.i.d. according to the QSD and $i^* := \arg \min_{1 \leq i \leq N} \tau_\partial^i$, then

$$(N\tau_\partial^{i^*}, X_{\tau_\partial^{i^*}}^{i^*}) \stackrel{\mathcal{L}}{=} (\tau_\partial, X_{\tau_\partial}).$$

Parallel Replica: Existence of a QSD and long time convergence to the QSD ?

Overdamped case

QSDs have been investigated for the overdamped Langevin dynamics $(\bar{q}_t)_{t \geq 0}$

$$d\bar{q}_t = -\nabla V(\bar{q}_t)dt + \sqrt{2\beta^{-1}}dB_t,$$

on a \mathcal{C}^2 **bounded connected** set \mathcal{O} of \mathbb{R}^d , where $\beta^{-1} = k_B T > 0$, $V \in \mathcal{C}^\infty(\mathbb{R}^d, \mathbb{R}^d)$ (see Gong, Qian and Zhao (1988), Le Bris, Lelièvre, Luskin, Perez (2012)).

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There exists a **unique** QSD $\bar{\mu}$ on \mathcal{O} . Besides, $\bar{\mu}$ satisfies

- 1 (Lebesgue density) $\bar{\mu}(dq) = \bar{\psi}(q)dq$,
- 2 (Spectral interpretation) $\bar{\psi}$ is the unique non-negative, normalized, classical solution in $\mathcal{C}^2(\mathcal{O}) \cap \mathcal{C}^b(\bar{\mathcal{O}})$ of the following eigenvalue problem

$$\begin{cases} \bar{\mathcal{L}}^* \bar{\psi} = -\bar{\lambda} \bar{\psi}, & \text{on } \mathcal{O}, \\ \bar{\psi} = 0, & \text{on } \partial\mathcal{O}, \end{cases}$$

where $\bar{\mathcal{L}}^* = \operatorname{div}(\nabla V \cdot) + \beta^{-1} \Delta$,

- 3 (Convergence) $\exists C > 0, \exists \alpha > 0$ s.t. $\forall t \geq 0, \forall \theta$ probability on \mathcal{O} ,

$$\|\mathbb{P}_\theta(\bar{q}_t \in \cdot | \bar{\tau}_\partial > t) - \bar{\mu}(\cdot)\|_{TV} \leq C e^{-\alpha t},$$

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Question: Extension to the Langevin process on $D := \mathcal{O} \times \mathbb{R}^d$?

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Langevin process

Let $F \in C^\infty(\mathbb{R}^d, \mathbb{R}^d)$, $\gamma \in \mathbb{R}$, $\sigma > 0$. Consider the **Langevin process** $(X_t = (q_t, p_t))_{t \geq 0}$ on \mathbb{R}^{2d}

$$\begin{cases} dq_t = p_t dt, \\ dp_t = F(q_t) dt - \gamma p_t dt + \sigma dB_t. \end{cases}$$

The **infinitesimal generator** \mathcal{L} of $(q_t, p_t)_{t \geq 0}$ on \mathbb{R}^{2d} (kinetic Fokker-Planck operator) is given by

$$\mathcal{L} = p \cdot \nabla_q + F(q) \cdot \nabla_p - \gamma p \cdot \nabla_p + \frac{\sigma^2}{2} \Delta_p.$$

Differences between the study of $(\bar{q}_t)_{t \geq 0}$ in \mathcal{O} and $(q_t, p_t)_{t \geq 0}$ in $D = \mathcal{O} \times \mathbb{R}^d$:

- \mathcal{L} is only **hypoelliptic** on \mathbb{R}^{2d} but not elliptic,
- \mathcal{O} is **bounded** but $D = \mathcal{O} \times \mathbb{R}^d$ is not.

Boundary of D

Partition of ∂D :

- $\Gamma^+ := \{(q, p) \in \partial \mathcal{O} \times \mathbb{R}^d : \langle p, n(q) \rangle > 0\}$ (*exiting velocities*),
- $\Gamma^- := \{(q, p) \in \partial \mathcal{O} \times \mathbb{R}^d : \langle p, n(q) \rangle < 0\}$ (*entering velocities*),
- $\Gamma^0 := \{(q, p) \in \partial \mathcal{O} \times \mathbb{R}^d : \langle p, n(q) \rangle = 0\}$ (*tangential velocities*),

where $n(q)$ is the unitary outward normal vector to \mathcal{O} at $q \in \partial \mathcal{O}$.

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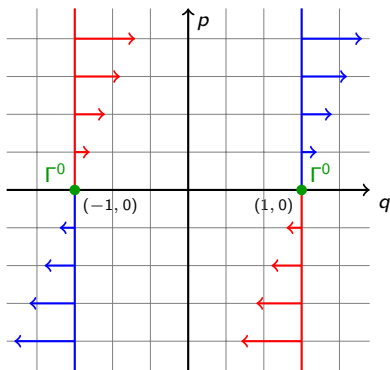


Figure: Boundary of $D = (-1, 1) \times \mathbb{R}$

1. Transition density

Theorem (Transition density)

There exists a smooth function

$$(t, x, y) \mapsto p_t^D(x, y) \in C^\infty(\mathbb{R}_+^* \times D \times D) \times C(\mathbb{R}_+^* \times \bar{D} \times \bar{D})$$

such that for all $t > 0$, $x \in \bar{D}$ and $f \in L^\infty(D)$,

$$P_t^D f(x) := \mathbb{E}_x [\mathbf{1}_{\tau_\partial > t} f(X_t)] = \int_D p_t^D(x, y) f(y) dy,$$

where $\tau_\partial = \inf\{t > 0 : X_t \notin D\}$.

Besides,

- $\forall t > 0, x \in D, \partial_t p_t^D(x, y) = \mathcal{L}_x p_t^D(x, y) = \mathcal{L}_y^* p_t^D(x, y),$
- $p_t^D(x, y) = 0$ if $x \in \Gamma^+ \cup \Gamma^0$ or $y \in \Gamma^- \cup \Gamma^0,$
- $p_t^D(x, y) > 0$ if $x \notin \Gamma^+ \cup \Gamma^0$ and $y \notin \Gamma^- \cup \Gamma^0.$

1. Transition density

For any $\alpha \in (0, 1]$, let $(\widehat{X}_t^{(\alpha)} = (\widehat{q}_t^{(\alpha)}, \widehat{p}_t^{(\alpha)}))_{t \geq 0}$ be the solution on \mathbb{R}^{2d} of

$$\begin{cases} d\widehat{q}_t^{(\alpha)} = \widehat{p}_t^{(\alpha)} dt, \\ d\widehat{p}_t^{(\alpha)} = -\gamma \widehat{p}_t^{(\alpha)} dt + \frac{\sigma}{\sqrt{\alpha}} dB_t. \end{cases}$$

Let $\widehat{p}_t^{(\alpha)}(x, y)$ be its transition density.

Theorem (Gaussian upper-bound)

For any $\alpha \in (0, 1)$, $T > 0$, there exists $C > 0$ such that for all $t \in (0, T]$, for all $x, y \in D$,

$$p_t^D(x, y) \leq C \widehat{p}_t^{(\alpha)}(x, y).$$

This result is inspired from work on the parametrix method by Konakov, Menozzi, Molchanov (2010). One can show that $\widehat{p}_t^{(\alpha)} \in L^\infty(D \times D) \cap L^1(D \times D)$ (thus in any $L^p(D \times D)$ for $p \geq 1$).

2. Compactness

Compactness of the semigroup

For any $p \in [1, +\infty]$ and $t > 0$, the operator P_t^D is compact from $C^b(\overline{D})$ to $C^b(\overline{D})$.

Proof:

- $\widehat{p}_t^{(\alpha)} \in L^2(D \times D) \Rightarrow P_t^D$ is a Hilbert-Schmidt integral operator, hence compact in $L^2(D)$.
- Propagate to $C^b(\overline{D})$ using the Gaussian upper-bound.

Reference: Lelievre, R., Reygner - *Journal of Evolution Equations* (2022).

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Krein-Rutman theorem

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Theorem (QSD existence/uniqueness and convergence properties)

There exists a unique QSD μ on $D = \mathcal{O} \times \mathbb{R}^d$ for the Langevin process $(X_t)_{t \geq 0}$. Besides, μ satisfies:

- 1 $\mu(dx) = \psi(x)dx$ on D ,
- 2 ψ is the unique, normalized, non-negative classical solution in $\mathcal{C}^2(D) \cap \mathcal{C}^b(D \cup \Gamma^-)$ of the following eigenvalue problem

$$\begin{cases} \mathcal{L}^* \psi(x) = -\lambda \psi(x), & x \in D \\ \psi(x) = 0, & x \in \Gamma^- \end{cases}$$

- 3 There exists $\alpha > 0$ such that for all θ probability on D , there exists $C_\theta > 0$ and for all $t \geq 0$,

$$\|P_\theta(X_t \in \cdot | \tau_\partial > t) - \mu(\cdot)\|_{TV} \leq C_\theta e^{-\alpha t}.$$

Langevin exit point

Overdamped Langevin exit point

If $\bar{q}_0 \sim \bar{\mu}(dq) = \bar{\psi}(q)dq$ (QSD), then

$$\bar{q}_{\bar{\tau}_\partial} \sim \frac{\beta^{-1}}{\lambda} |\partial_n \bar{\psi}(q)| \sigma_{\partial\mathcal{O}}(dq),$$

where $\sigma_{\partial\mathcal{O}}$ is the surface measure on $\partial\mathcal{O}$.

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Proof: Integration by parts on

$$\int_{\mathcal{O}} \mathbb{E}_q [f(\bar{q}_{\bar{\tau}_\partial})] \bar{\psi}(q) dq,$$

using that $\mathcal{L}^* \bar{\psi} = -\lambda \bar{\psi}$ (see Le Bris, Lelievre, Luskin, Perez (2010)).

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Langevin exit point

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$$(q_{\tau_\partial}, p_{\tau_\partial}) \sim \frac{1}{\lambda} |p \cdot n(q)| \psi(q, p) \sigma_{\partial\mathcal{O}}(dq) dp,$$

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Reference: Lelievre, R., Reygner - *Stochastic Process and its Applications* (2022)

Overdamped limit

Consider here $\gamma > 0$ and $\sigma = \sqrt{2\gamma\beta^{-1}}$. Let $(X_t^{(\gamma)} = (q_t^{(\gamma)}, p_t^{(\gamma)}))_{t \geq 0}$ be the Langevin process

$$\begin{cases} dq_t^{(\gamma)} = p_t^{(\gamma)} dt, \\ dp_t^{(\gamma)} = F(q_t^{(\gamma)}) dt - \gamma p_t^{(\gamma)} dt + \sqrt{2\gamma\beta^{-1}} dB_t. \end{cases}$$

Let $(\bar{q}_t)_{t \geq 0}$ be the overdamped Langevin process

$$d\bar{q}_t = F(\bar{q}_t) dt + \sqrt{2\beta^{-1}} dB_t.$$

Assume that F is globally Lipschitz, then for $T > 0$,

$$\text{Law}((q_{\gamma t}^{(\gamma)})_{t \in [0, T]}) \xrightarrow{\gamma \rightarrow \infty} \text{Law}((\bar{q}_t)_{t \in [0, T]}).$$

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Question: Overdamped limit of the Langevin QSD ?

Overdamped limit

Overdamped limit of the Langevin QSD

Let $\mu^{(\gamma)}$ be the Langevin QSD on D and $\bar{\mu}$ be the overdamped Langevin QSD on \mathcal{O} , then

$$\mu^{(\gamma)}(dqdp) \xrightarrow{\gamma \rightarrow \infty} \bar{\mu}(dq) \frac{e^{-\beta \frac{|p|^2}{2}}}{(2\pi\beta^{-1})^{d/2}} dp.$$

Besides,

$$\lambda^{(\gamma)} \underset{\gamma \rightarrow \infty}{\sim} \frac{\bar{\lambda}}{\gamma}.$$

Reference: R. - *Electronic Journal of Probability* (2022).

Overdamped limit

Overdamped limit of the Langevin QSD

Let $\mu^{(\gamma)}$ be the Langevin QSD on D and $\bar{\mu}$ be the overdamped Langevin QSD on \mathcal{O} , then

$$\mu^{(\gamma)}(dqdp) \xrightarrow{\gamma \rightarrow \infty} \bar{\mu}(dq) \frac{e^{-\beta \frac{|p|^2}{2}}}{(2\pi\beta^{-1})^{d/2}} dp.$$

Besides,

$$\lambda(\gamma) \underset{\gamma \rightarrow \infty}{\sim} \frac{\bar{\lambda}}{\gamma}.$$

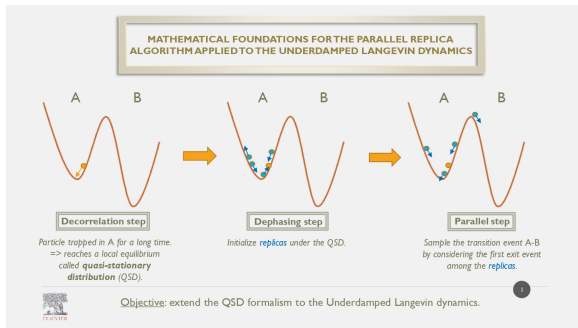
Reference: R. - *Electronic Journal of Probability* (2022).

Stationary overdamped limit

Let $\mu_{\infty}^{(\gamma)}$ be the Langevin stationary distribution and $\bar{\mu}_{\infty}$ be the overdamped Langevin stationary distribution, then there exists $C > 0$ such that for all $\gamma \geq 2$,

$$\mathcal{W}\left(\mu_{\infty}^{(\gamma)}, \bar{\mu}_{\infty} \otimes \mathcal{L}(Z)\right) \leq C \frac{\sqrt{\log(\gamma)}}{\gamma}.$$

Reference: Monmarché, R. - *Electronic Communications in Probability* (2022)



R. , Lelièvre and Reygner - Mathematical foundations for the Parallel Replica algorithm applied to the underdamped Langevin dynamics - *MRS Communications*, 2022.

- 1 Introduction
 - Metastability in molecular dynamics and the Parallel Replica algorithm
 - Quasi-stationary distribution and Parallel Replica justification

- 2 Langevin process and kinetic Fokker-Planck equation
 - Transition density of the absorbed semigroup
 - Compactness of the absorbed semigroup

- 3 Quasi-stationary distributions and overdamped limit of the Langevin process
 - Existence and long-time convergence
 - Overdamped limit of the QSD

- 4 Metadynamics
 - Description of the algorithm
 - Adaptative Metadynamics

Metadynamics for the Mueller potential

Consider the two-dimensional overdamped Langevin dynamics

$$dX_t = -\nabla V(X_t)dt + \sqrt{2k_B T}dB_t,$$

where V is the Mueller potential defined by:

$$V(x_1, x_2) = \sum_{i=1}^4 K_i e^{a_i(x_1 - \beta_i)^2 + b_i(x_1 - \beta_i)(x_2 - \gamma_i) + c_i(x_2 - \gamma_i)^2}.$$

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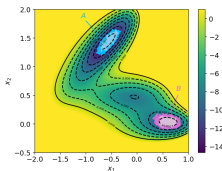


Figure: Sampling in the Mueller potential. 100 000 iterations

We want to sample a transition path between A and B using Metadynamics.

Metadynamics

Definition: A collective variable $s : \mathbb{R}^2 \mapsto \mathbb{R}$ captures the low-dimensional information of the system. A good collective variable takes different values in relevant *metastable states* and *transition states*.

Equilibrium distribution:

$$X_\infty \sim \mu(x) = \frac{e^{-V(x)/k_B T}}{\alpha}.$$

Latent equilibrium distribution:

$$s(X_\infty) \sim p(s) = \int_{\mathbb{R}^2} \mu(x) \delta_{s(x)=s}(\mathrm{d}x).$$

Free energy:

$$F(s) = -k_B T \log(p(s)).$$

Assuming one has an estimate $B \approx -F$. If we perturb the potential into $\tilde{V}(x) = V(x) + B(s(x))$.

$$\begin{aligned} s(\tilde{X}_\infty) \sim \tilde{p}(s) &\propto \int_{\mathbb{R}^2} \delta_{s(x)=s}(\mathrm{d}x) e^{-(V(x)+B(s(x)))/k_B T} \\ &= e^{-B(s)/k_B T} \int_{\mathbb{R}^2} \delta_{s(x)=s}(\mathrm{d}x) e^{-V(x)/k_B T} \\ &= e^{-B(s)/k_B T} e^{-F(s)/k_B T} \approx 1. \end{aligned}$$

As a result,

$$s(\tilde{X}_\infty) \sim \text{Uniform}$$

Problem: We need a free energy estimate first ...

Metadynamics

Build an approximation of F iteratively:

$$B_{t+1}(s) = B_t(s) + w e^{-\frac{(s_t - s)^2}{2\sigma^2}}.$$

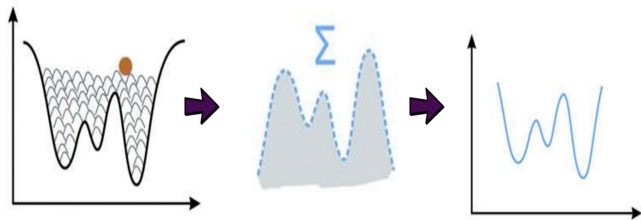
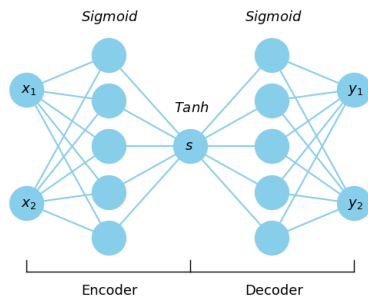


Figure: Metadynamics

Generates uniform samples on the path $A \leftrightarrow B$.

Autoencoder

Train the sampled data on an **autoencoder** to obtain the collective variable.



$$Loss = \|x - y\|^2.$$

Metadynamics trajectories

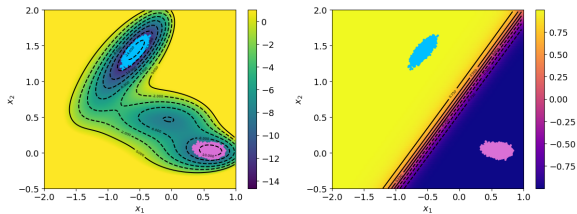


Figure: 50 000 Metadynamics iterations with autoencoder trained on the database of A and B

Metadynamics trajectories

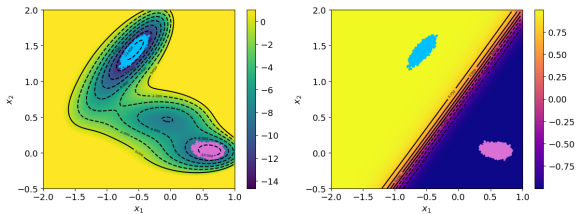


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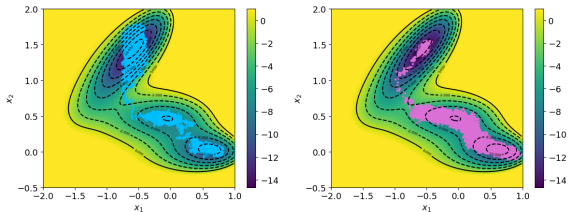


Figure: 25 000 Metadynamics iterations with CV as the orthogonal projection on $[AB]$

Adaptative Metadynamics

Train the autoencoder adaptatively on the previous trajectory after every 1000 Metadynamics iterations.

Adaptive Metadynamics

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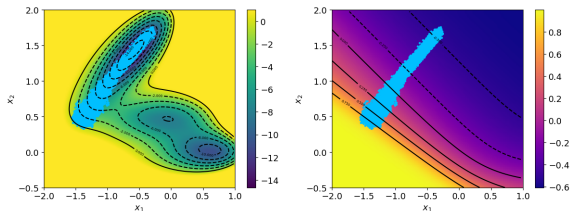


Figure: 40 000 Metadynamics iterations with autoencoder trained iteratively on the trajectory

Adaptative Metadynamics

Impose conditions on the path such that it visits A and B .

Adaptative Metadynamics

Impose conditions on the path such that it visits A and B .

$$Loss = \|x - AE(x)\|^2 + (\|AE(x_A) - x_A\|^2 + \|AE(x_B) - x_B\|^2)/2.$$

The path is defined by:

- (Latent projection) $s_A = s(x_A)$, $s_B = s(x_B)$
- (Discretization) $s_i = s_A + i(s_B - s_A)/N$, ($1 \leq i \leq N$).
- Path is given by $(D(s_i))_{1 \leq i \leq N}$,

where D is the decoder of the autoencoder.

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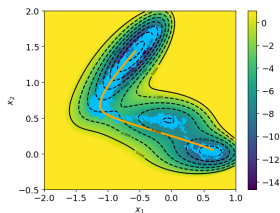


Figure: 38 000 Metadynamics iterations with autoencoder trained iteratively on the trajectory. Path is plotted in orange.

Adaptative Metadynamics

Consider a modified Mueller potential \tilde{V} defined by:

$$\tilde{V}(x) = V(x) + (-100 + \|x - \eta\|^2)e^{-2\|x - \eta\|^2},$$

with $\eta = [-1.7, 0.2]$.

Adaptative Metadynamics

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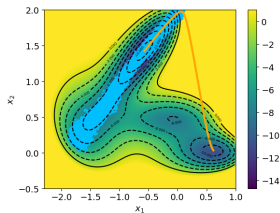


Figure: 100 000 Metadynamics iterations with autoencoder trained iteratively on the trajectory. Path in orange.

Adaptative Metadynamics

Penalize high energy configurations happening in the path.

$$Loss = \|x - y\|^2 + (\|AE(x_A) - x_A\|^2 + \|AE(x_B) - x_B\|^2)/2 + E_{path},$$

where

$$E_{path} = \sum_{i=1}^N \|D(s_{i+1}) - D(s_i)\| (V(D(s_i)) + C),$$

with $C > 0$ such that $V(D(s_i)) + C > 0$.

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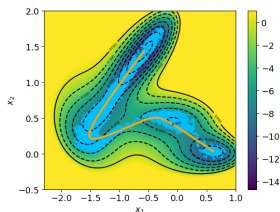


Figure: 100 000 Metadynamics iterations with autoencoder trained iteratively on the trajectory. Path in orange.

Reference: R., Boudier, Goryaeva, Marinica and Maillet - *Journal of Chemical Theory and Computation*, (2022).

Thank you for your attention!