

A Kramers' type law for the collision time of two self-interacting diffusion processes and of their related particle approximation

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Problem: Establishing a Kramers' type for the small viscosity/zero-noise limit of the first collision time:

$$C(\sigma) = \inf\{t \geq 0 : X_t = Y_t\},$$

and related collision location $X_{C(\sigma)}$ between two independent self-stabilizing diffusion processes:

$$X_t = x + \sigma B_t - \int_0^t \left\{ \nabla V(X_s) + \alpha(X_s - \mathbb{E}[X_s]) \right\} ds, \quad t \geq 0,$$

$$Y_t = y + \sigma \tilde{B}_t - \int_0^t \left\{ \nabla V(Y_s) + \alpha(Y_s - \mathbb{E}[Y_s]) \right\} ds, \quad t \geq 0,$$

whenever $(B_t)_{t \geq 0}$ and $(\tilde{B}_t)_{t \geq 0}$ are two independent \mathbb{R}^d -Brownian motions and the potential V admits two possible attractors and each diffusion is driven towards one of these particular attractors.

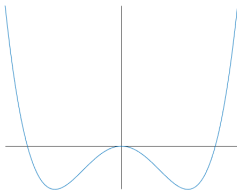
Analog problem for the related particle systems:

$$X_t^{i,N} = x + \sigma B_t^i - \int_0^t \left\{ \nabla V(X_s^{i,N}) + \alpha(X_s^i - \frac{1}{N} \sum_{j=1}^N X_s^{j,N}) \right\} ds, \quad t \geq 0,$$

$$Y_t^{i,N} = y + \sigma \tilde{B}_t^i - \int_0^t \left\{ \nabla V(Y_s^{i,N}) + \alpha(Y_s^i - \frac{1}{N} \sum_{j=1}^N Y_s^{j,N}) \right\} ds, \quad t \geq 0.$$

Prototypical case

Double wells landscape: $d = 1$, $V(x) = \frac{x^4}{4} - \frac{x^2}{2}$.



At the zero-noise limit $\sigma = 0$, $X_t \rightarrow \phi_t(x)$ and $Y_t \rightarrow \phi_t(y)$ for

$$\phi_t(z) = z - \int_0^t \phi_s(z)^3 - \phi_s(z) ds, t \geq 0.$$

Assuming further $x < -1$ and $1 < y$, then collisions between the two self-stabilizing diffusions are due to the (join) effort of the Brownian motions.

As the noise vanishes the collision time is expected to follow a Kramers' type law of the form:

$$\frac{\sigma^2}{2} \log(C(\sigma)) \xrightarrow{\mathbb{P}} H$$

and the collision location $X_{C(\sigma)}$ should persists in some region in the space or be ∞ .

Assumptions

(A) – (i) V admits two distinct minima located in λ_1 and λ_2 .

(A) – (ii) The starting points x and y lie in a respective basin of attraction $\mathcal{G}(\lambda_1)$ and $\mathcal{G}(\lambda_2)$ of the wells of V and, for $\phi_t(z) = z - \int_0^t \nabla V(\phi_s(z)) ds$, the gradient flow related to V , it holds

$$2\epsilon_0 := \inf_{t \geq 0} (|\phi_t(x) - \phi_t(y)|) > 0.$$

(A) – (iii) $V : \mathbb{R}^d \rightarrow \mathbb{R}$ is of class \mathcal{C}^2 , locally Lipschitz, convex at infinity (namely $\inf_{|x| \geq R'} \nabla^2 V(x)$ is positive definite for some $R' > 0$) and is such that ∇V grows at a $2n$ -polynomial rate on \mathbb{R}^d :

$$\sup_{x \in \mathbb{R}^d} \{(1 + |x|^{2n})^{-1} |\nabla V(x)|\} < \infty.$$

(A) – (iv) Synchronization condition: $\alpha I_d + \nabla^2 V$ is definite positive on \mathbb{R}^d .

Freidlin-Wentzell's exit time problem [FW98]

Perturbed dynamical systems:

$$z_t^\sigma = z_0 + \sigma \mathcal{W}_t - \int_0^t \nabla U(z_s^\sigma) ds, t \geq 0.$$

As $\sigma \rightarrow 0$: $z_t^\sigma \rightarrow \Psi_t(z_0)$ solution to

$$\Psi_t(z_0) = z_0 - \int_0^t \nabla U(\Psi_s(z_0)) ds, t \geq 0.$$

Large deviation principle: For any finite arbitrary time horizon T , and for any $\delta > 0$,

$$\begin{aligned} & \lim_{\sigma \rightarrow 0} \frac{\sigma^2}{2} \log \mathbb{P} \left\{ \sup_{t \in [0; T]} |z_t^\sigma - \Psi_t(z_0)| > \delta \right\} \\ &= - \inf_{\Phi} \left\{ I_T(\Phi) : \Phi \in C^1([0, T]; \mathbb{R}^d), \Phi(0) = x_0 \text{ and } \max_{0 \leq t \leq T} |\Phi(t) - \Psi_t(x_0)| > \delta \right\}, \end{aligned}$$

the action functional I_T being given by

$$I_T(\Phi) := \int_0^T \left| \frac{d\Phi}{dt} + \nabla U(\Phi(t)) \right|^2 dt.$$

Definition

Let \mathcal{G} be a subset of \mathbb{R}^d and let ∇U be a Lipschitz vector field on \mathbb{R}^d . We say that the domain \mathcal{G} is stable by ∇U if the orbit $\{\Psi_t(z_0); t \in \mathbb{R}_+\}$ is included in \mathcal{G} for all $z_0 \in \mathcal{G}$.

Exit-time estimate:

Theorem

Let \mathcal{G} be an open bounded set of \mathbb{R}^d , stable by ∇U , where U of class \mathcal{C}^2 and convex. Assume also that for all $x_0 \in \partial\mathcal{G}$, $\Psi_t(x_0)$ converges to a unique point a_0 at large time. Then, for any z_0 in \mathcal{G} , and

$$\tau_{\mathcal{G}}(\sigma) = \inf\{t \geq 0 : z_t^\sigma \notin \mathcal{G}\},$$

we have:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H} - \delta) \right] < \tau_{\mathcal{G}}(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H} + \delta) \right] \right\} = 1. \quad (1)$$

The value \underline{H} representing the main cost of exiting \mathcal{G} is given by

$$\underline{H} = \inf_{z \in \partial\mathcal{G}} \inf_{T > 0} \inf_{\Phi} \{I_{T,z}(\Phi)\} = \inf_{x \in \partial\mathcal{G}} (U(x) - U(a_0))$$

Additionally:

(i) For all z_0 in \mathcal{G} , $\lim_{\sigma \rightarrow 0} \frac{\sigma^2}{2} \log \left(\mathbb{E} \{ \tau_{\mathcal{G}}(\sigma) \} \right) = \underline{H}$;

(ii) Exit location: If $\inf_{x \in \partial\mathcal{G}} (U(x) - U(a_0))$ is achieved in a unique point z_* in $\partial\mathcal{G}$, then, for all $\delta > 0$, $z_0 \in \mathcal{G}$,

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |z_{\tau_{\mathcal{G}}(\sigma)}^\sigma - z_*| < \delta \right\} = 1.$$

A very short over-view on self-stabilizing diffusion processes

- Benachour, Roynette, Talay and Vallois [BRTV98]: Existence of an invariant distribution for the one dimensional model:

$$X_t = X_0 + B_t - \frac{1}{2} \int_0^t \int \beta(X_s - y) \mu_s(dy) ds, \mu_t = \text{Law}(X_t), t \geq 0$$

with $\beta : \mathbb{R} \rightarrow \mathbb{R}$ odd, increasing and satisfying

$$|\beta(x) - \beta(y)| \leq C|x - y|(1 + |x|^r + |y|^r), \text{ for some } r \in \mathbb{N} \setminus \{0\},$$

$$(\beta(x) - \beta(y)) \geq \alpha_1(x - y) + \alpha_2, \alpha > 0, \text{ for all } x \geq y.$$

- Hermann, Imkeller and Peithmann [HIP08]: Long time behaviour of

$$X_t = y + \sigma B_t - \int_0^t \left\{ U(X_s) + \int \Phi(X_s - y) \mu_s(dy) \right\} ds, \mu_t = \text{Law}(X_t), t \geq 0,$$

with U and Φ relatively smooth and (globally) convex functions. The authors further established a Kramers' type law in the case $V = \nabla U$ and $\Phi = \nabla b$, the exit cost being given by

$$\underline{H} = \inf_{z \in \partial G} \inf_{T, \Psi} \frac{1}{2} \int_0^T |\Psi_t(z) - V(\Psi_t(z)) - \Phi(x - z^*)|^2 ds = \inf_{z \in \partial G} (U(z) + b(z - z_*) - U(z_*)).$$

- Tugaut 2007-2021: Kramers' type law in the case of a double wells landscape and other globally non-convex situation (e.g. [T21] for the case of the granular media equation).

Kramers' type law for the first collision time of two self-stabilizing diffusions

Strategy: Given the multi-dimensional self-stabilizing diffusions:

$$X_t = x + \sigma B_t - \int_0^t \left\{ \nabla V(X_s) + \alpha(X_s - \mathbb{E}[X_s]) \right\} ds, \quad t \geq 0,$$

$$Y_t = y + \sigma \tilde{B}_t - \int_0^t \left\{ \nabla V(Y_s) + \alpha(Y_s - \mathbb{E}[Y_s]) \right\} ds, \quad t \geq 0,$$

introduce the ϵ -approximation:

$$C_\epsilon(\sigma) = \inf \{ t \geq 0 : |X_t - Y_t| \leq 2\epsilon \}, \quad \epsilon < \epsilon_0,$$

reformulate this time in terms of an exit time

$$\begin{aligned} C_\epsilon(\sigma) &= \inf_{\lambda \in \mathbb{R}^d} \beta_{\lambda, \epsilon}(\sigma), \\ \beta_{\lambda, \epsilon}(\sigma) &:= \inf \{ t \geq 0 : X_t \in B(\lambda, \epsilon), Y_t \in B(\lambda, \epsilon) \} \\ &= \inf \left\{ t \geq 0 : X_t \notin (\mathbb{R}^d \setminus B(\lambda, \epsilon)), Y_t \notin (\mathbb{R}^d \setminus B(\lambda, \epsilon)) \right\}, \end{aligned}$$

and apply a particular coupling between (X_t, Y_t) and linearized version:

$$x_t^\sigma = x + \sigma B_t - \int_0^t \left\{ \nabla V(x_s^\sigma) + \alpha(x_s^\sigma - \lambda_1) \right\} ds, \quad t \geq 0,$$

$$y_t^\sigma = y + \sigma \tilde{B}_t - \int_0^t \left\{ \nabla V(y_s^\sigma) + \alpha(y_s^\sigma - \lambda_2) \right\} ds, \quad t \geq 0.$$

Preliminaries: First collision time of two stochastic gradient flows

Models:

$$x_t^\sigma = x_0 + \sigma B_t - \int_0^t \nabla \Psi_1(x_s^\sigma) ds, t \geq 0,$$

and

$$y_t^\sigma = y_0 + \sigma \tilde{B}_t - \int_0^t \nabla \Psi_2(y_s^\sigma) ds, t \geq 0.$$

Assumptions:

- Ψ_1 and Ψ_2 are of class \mathcal{C}^2 , strictly convex and admits λ_1 and λ_2 as their respective minimizers.
 - $\inf_{t \geq 0} |\phi_t^1(x) - \phi_t^2(y)| > 2\epsilon_0$ for $\phi_t^i(z) = z - \int_0^t \nabla \Psi_i(\phi_s^i(z)) ds, t \geq 0, i = 1, 2.$
- ϵ approximation of the first collision time:

$$c_\epsilon(\sigma) := \inf \{t \geq 0 : |x_t^\sigma - y_t^\sigma| \leq 2\epsilon\}, \epsilon > 0.$$

Strategy: For $\epsilon < \epsilon_0$,

$$c_\epsilon(\sigma) = \inf_{\lambda} \beta_{\lambda, \epsilon}(\sigma),$$

$$\begin{aligned} \beta_{\lambda, \rho}(\sigma) &= \inf \{t \geq 0 : (x_t^\sigma, y_t^\sigma) \in B(\lambda, \rho) \times B(\lambda, \rho)\} \\ &= \inf \{t \geq 0 : (x_t^\sigma, y_t^\sigma) \notin (\mathbb{R}^d \setminus B(\lambda, \rho)) \times (\mathbb{R}^d \setminus B(\lambda, \rho))\} \end{aligned}$$

and approximate $\beta_{\lambda, \rho}(\sigma)$ by $\hat{\beta}_{\lambda, \rho}(\sigma)$ where $\hat{\beta}_{\lambda, \rho}(\sigma)$ is the first entering time of $D^1(\lambda, \rho) \times D^2(\lambda, \rho)$ for

$$D^i(\lambda, \rho) := \{\phi_t^{i,+}(z) : t \geq 0, z \in B(\lambda, \rho)\}, \quad \phi_t^{i,+}(z) = z + \int_0^t \nabla \Psi_i(\phi_s^{i,+}(z)) ds, t \geq 0.$$

Note:

- Whenever λ is too close to one of the two infimum, say $|\lambda - \lambda_1| = \tilde{\epsilon}$ with $\tilde{\epsilon} < \rho$, then, $B(\lambda, \rho)$ is an attractive set for $\phi^{1,+}$ and so $\mathcal{D}_{\lambda,\rho}^1 = \mathbb{R}^d$. If $\tilde{\epsilon}$ is (strictly) smaller than ϵ_0 , this reduces $\widehat{\beta}_{\lambda,\rho}(\sigma)$ to the first exit-time from $\mathcal{D}_{\lambda,\rho}^2$.
- In the opposite case, $\min_{i=1,2}(|\lambda - \lambda_i|) > \rho$, $(\mathbb{R}^d \setminus \mathcal{D}_{\lambda,\rho}^1) \times (\mathbb{R}^d \setminus \mathcal{D}_{\lambda,\rho}^2)$ is stable by $(-\nabla\Psi^1, -\nabla\Psi^2)$.
- The cases $|\lambda - \lambda_i| = \rho$ are singular and require a rescaling.
- Outside these "degenerated" cases, the exit-costs of $\mathbb{R}^d \setminus \mathcal{D}_{\lambda,\rho}^i$ and of $\mathbb{R}^d \setminus B(\lambda, \rho)$ are the same:

$$\inf_{x \in \partial B(\lambda, \rho)} (\Psi_i(x) - \Psi_i(\lambda_i)) = \inf_{x \in \partial \mathcal{D}_{\lambda,\rho}^i} (\Psi_i(x) - \Psi_i(\lambda_i)), \quad i = 1, 2.$$

Last approximation: For $\epsilon < \epsilon_0$, $0 < \rho < 1$,

$$\widehat{\beta}_{\lambda,\epsilon}^\rho(\sigma) := \inf \{t \geq 0 : (x_t^\sigma, y_t^\sigma) \in \mathcal{O}_{\lambda,\epsilon,\rho}\} \quad (2)$$

where the domain $\mathcal{O}_{\lambda,\epsilon,\rho}$ is given by

$$\mathcal{O}_{\lambda,\epsilon,\rho} := \begin{cases} \partial \mathcal{D}^1(\lambda, \rho\epsilon) \times \partial \mathcal{D}^2(\lambda, \epsilon) & \text{if } |\lambda - \lambda_1| = \epsilon, \\ \partial \mathcal{D}^1(\lambda, \epsilon) \times \partial \mathcal{D}^2(\lambda, \rho\epsilon) & \text{if } |\lambda - \lambda_2| = \epsilon, \\ \partial \mathcal{D}^1(\lambda, \epsilon) \times \partial \mathcal{D}^2(\lambda, \epsilon) & \text{otherwise.} \end{cases}$$

Applying classical Kramers' type law:

Lemma

For any λ in \mathbb{R}^d and for any $\delta > 0$,

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (H_\epsilon^\rho(\lambda) - \delta) \right] < \widehat{\beta}_{\lambda, \epsilon}^\rho(\sigma) < \exp \left[\frac{2}{\sigma^2} (H_\epsilon^\rho(\lambda) + \delta) \right] \right\} = 1,$$

for

$$H_\epsilon^\rho(\lambda) = \begin{cases} \inf_{x \in \partial B(\lambda; \rho \epsilon)} (\Psi_1(x) - \Psi_1(\lambda_1)) + \inf_{y \in \partial B(\lambda; \epsilon)} (\Psi_2(y) - \Psi_2(\lambda_2)) & \text{if } |\lambda - \lambda_1| = \epsilon, \\ \inf_{x \in \partial B(\lambda; \epsilon)} (\Psi_1(x) - \Psi_1(\lambda_1)) + \inf_{y \in \partial B(\lambda; \rho \epsilon)} (\Psi_2(y) - \Psi_2(\lambda_2)) & \text{if } |\lambda - \lambda_2| = \epsilon, \\ \inf_{x \in B(\lambda; \epsilon)} (\Psi_1(x) - \Psi_1(\lambda_1)) + \inf_{y \in B(\lambda; \epsilon)} (\Psi_2(y) - \Psi_2(\lambda_2)) & \text{otherwise.} \end{cases}$$

Moreover, we have: for any $\delta > 0$,

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \min \left(\text{dist} \left(x_{\widehat{\beta}_{\lambda, \epsilon}^\rho(\sigma)}^\sigma, B(\lambda, \rho) \right), \text{dist} \left(y_{\widehat{\beta}_{\lambda, \epsilon}^\rho(\sigma)}^\sigma, B(\lambda; \rho) \right) \right) \leq \delta \right\} = 1.$$

for $\text{dist}(x, B(\lambda; \rho)) := \inf_{z \in B(\lambda; \rho)} |x - z|$.

Lemma

The same Kramers' type law holds for

$$\beta_{\lambda, \epsilon}^{\rho}(\sigma) = \begin{cases} \inf \{t \geq 0 : (x_t^{\sigma}, y_t^{\sigma}) \in \partial B(\lambda, \rho\epsilon) \times \partial B(\lambda, \epsilon)\} & \text{if } |\lambda - \lambda_1| = \epsilon, \\ \inf \{t \geq 0 : (x_t^{\sigma}, y_t^{\sigma}) \in \partial B(\lambda, \epsilon) \times \partial B(\lambda, \rho\epsilon)\} & \text{if } |\lambda - \lambda_2| = \epsilon, \\ \inf \{t \geq 0 : (x_t^{\sigma}, y_t^{\sigma}) \in \partial B(\lambda, \epsilon) \times \partial B(\lambda, \epsilon)\} & \text{otherwise.} \end{cases}$$

Asymptotic $\rho \rightarrow 1$:

Lemma

For any $\lambda \in \mathbb{R}^d$, and for any $\delta > 0$:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (H_{\epsilon}(\lambda) - \delta) \right] < \beta_{\lambda, \epsilon}(\sigma) < \exp \left[\frac{2}{\sigma^2} (H_{\epsilon}(\lambda) + \delta) \right] \right\} = 1.$$

for

$$H_{\epsilon}(\lambda) = \inf_{x \in \partial B(\lambda, \epsilon)} (\Psi_1(x) - \Psi_1(\lambda_1)) + \inf_{y \in \partial B(\lambda, \epsilon)} (\Psi_2(y) - \Psi_2(\lambda_2)).$$

Moreover,

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \min \left(\text{dist} \left(x_{\beta_{\lambda, \epsilon}^{\rho}(\sigma)}^{\sigma}, B(\lambda, \rho) \right), \text{dist} \left(y_{\beta_{\lambda, \epsilon}^{\rho}(\sigma)}^{\sigma}, B(\lambda, \rho) \right) \right) \leq \delta \right\} = 1.$$

Kramers' type laws for $c_\epsilon(\sigma) = \inf_\lambda \beta_{\lambda, \epsilon}(\sigma)$

Theorem

For any $\delta > 0$:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_\epsilon - \delta) \right] < c_\epsilon(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_\epsilon + \delta) \right] \right\} = 1,$$

where

$$\underline{H}_\epsilon = \inf_{\lambda \in \mathbb{R}^d} H_\epsilon(\lambda).$$

In addition, for \mathcal{H}_ϵ the set of all minimizers λ_ϵ of $\lambda \mapsto H_\epsilon(\lambda)$, and for ϵ small enough:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \inf_{\lambda_\epsilon \in \mathcal{H}_\epsilon} \max \left(|x_{c_\epsilon(\sigma)}^\sigma - \lambda_\epsilon|, |y_{c_\epsilon(\sigma)}^\sigma - \lambda_\epsilon| \right) \leq \delta \right\} = 1.$$

Note: The exit-cost \underline{H}_ϵ can be achieved in more than one points. Nevertheless,

$$\forall \lambda \in \mathbb{R}^d, \lim_{\epsilon \rightarrow 0} H_\epsilon(\lambda) = H_0(\lambda) := (\Psi_1(\lambda) - \Psi_1(\lambda_1)) + (\Psi_2(\lambda) - \Psi_2(\lambda_2))$$

and

$$\lim_{\sigma \rightarrow 0} \underline{H}_\epsilon = \underline{H}_0.$$

Corollary

For λ_0 the minimizer of $\lambda \mapsto H_0(\lambda) = (\Psi_1(\lambda) - \Psi_1(\lambda_1)) + (\Psi_2(\lambda) - \Psi_2(\lambda_2))$, and $\underline{H}_0 := H_0(\lambda_0)$, we have: for any $\delta > 0$:

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 - \delta) \right] < c_\epsilon(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 + \delta) \right] \right\} = 1$$

and

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \max \left(|x_{c_\epsilon(\sigma)}^\sigma - \lambda_0|, |y_{c_\epsilon(\sigma)}^\sigma - \lambda_0| \right) \leq \delta \right\} = 1.$$

Kramers' type law for the first collision time of two self-stabilizing diffusions

Under the assumptions (A) – (i) to (A) – (iv), [HIP08]: the dynamics $(X_t)_{t \geq 0}$ and $(Y_t)_{t \geq 0}$ are wellposed (in the pathwise sense) and

$$\sup_{t \geq 0} \mathbb{E}[|X_t|^p + |Y_t|^p] < \infty, \forall p \in \mathbb{Z}.$$

Moreover [T21]: Given $\kappa > 0$, there exists a finite (non-random) time T_κ and a critical threshold σ_κ such that

$$\max_{\sigma \leq \sigma_\kappa, t \geq T_\kappa} \mathbb{E}[|X_t - \lambda_1|^2] + \mathbb{E}[|Y_t - \lambda_2|^2] \leq \kappa.$$

Corollary (Coupling estimate)

For

$$\begin{aligned}x_t^\sigma &= x_1 + \sigma B_t - \int_0^t \{\nabla V(x_s^\sigma) + \nabla F(x_s^\sigma - \lambda_1)\} ds, \\y_t^\sigma &= x_2 + \sigma \tilde{B}_t - \int_0^t \{\nabla V(y_s^\sigma) + \nabla F(y_s^\sigma - \lambda_2)\} ds,\end{aligned}$$

and any $\kappa > 0$, there exists $T_\kappa, \sigma_\kappa > 0$ such that

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \max_{t \geq T_\kappa} |X_t - x_t^\sigma|^2 + |Y_t - y_t^\sigma|^2 \geq \kappa \right\} = 0.$$

From the Kramers' type law for $(x_t^\sigma, y_t^\sigma)_{t \geq 0}$ to the Kramers' law for $(X_t, Y_t)_{t \geq 0}$:

Proposition

Define

$$\hat{\tau}_{\lambda, \epsilon}(\sigma) := \inf \left\{ t \geq 0 : (X_t, Y_t) \in \mathbb{B}(\lambda; \epsilon)^2 \right\},$$

the first time the nonlinear diffusion $(X_t, Y_t)_{t \geq 0}$ enters in the domain $B(\lambda; \epsilon) \times B(\lambda; \epsilon)$. Then, for any $\lambda \in \mathbb{R}^d$, for any $\delta > 0$, we have

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (H_\epsilon(\lambda) - \delta) \right] < \hat{\tau}_{\lambda, \epsilon}(\sigma) < \exp \left[\frac{2}{\sigma^2} (H_\epsilon(\lambda) + \delta) \right] \right\} = 1, \quad (3)$$

where

$$H_\epsilon(\lambda) = \inf_{x \in \partial B(\lambda, \epsilon)} (V(x) + F(x - \lambda_1) - V(\lambda_1)) + \inf_{y \in \partial B(\lambda, \epsilon)} (V(y) + F(y - \lambda_2) - V(\lambda_2)).$$

Theorem

Given $\epsilon > 0$, let $\lambda(\epsilon)$ be an arbitrary minimizer of H_ϵ . Then, for any $\delta > 0$, we have

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (H_\epsilon(\lambda(\epsilon)) - \delta) \right] < C_\epsilon(\sigma) < \exp \left[\frac{2}{\sigma^2} (H_\epsilon(\lambda(\epsilon)) + \delta) \right] \right\} = 1.$$

In addition, for \mathcal{H}_ϵ the set of all minimizers λ_ϵ of $\lambda \mapsto H_\epsilon(\lambda)$, and for ϵ small enough:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \inf_{\lambda_\epsilon \in \mathcal{H}_\epsilon} \max \left(|X_{C_\epsilon(\sigma)} - \lambda_\epsilon|, |Y_{C_\epsilon(\sigma)} - \lambda_\epsilon| \right) \leq \delta \right\} = 1.$$

Corollary

For any $\delta > 0$, we have

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 - \delta) \right] < C_\epsilon(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 + \delta) \right] \right\} = 1.$$

where

$$\underline{H}_0 = \min H_0(\lambda), \quad H_0(\lambda) = \lim_{\epsilon \rightarrow 0} H_\epsilon(\lambda) = (V(\lambda) + F(\lambda - \lambda_1) - V(\lambda_1))$$

Moreover, for

$$\lambda_0 = \operatorname{argmin}_\lambda H_0(\lambda) = \left(\nabla V + \alpha I_d \right)^{-1} (\alpha(\lambda_1 + \lambda_2)/2),$$

it holds

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \{ |X_{C_\epsilon(\sigma)} - \lambda_0| \leq \delta \} = 1 = \lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \{ |Y_{C_\epsilon(\sigma)} - \lambda_0| \leq \delta \}.$$

Example: In the prototypical case: $V(x) = \frac{x^4}{4} - \frac{x^2}{2}$,

$$\operatorname{argmin} \underline{H}_0 = \alpha + \frac{1}{2}, \quad \operatorname{argmin} H_\epsilon \in \left\{ \alpha + \frac{1}{2}, 4\epsilon^4 - 2\epsilon^2 + \alpha(2\epsilon \pm 1)^2 + \frac{1}{2} \right\}.$$

Collision time for the particle systems

Zero-noise limit of

$$C_\epsilon(\sigma)^N = \inf_{1 \leq i \leq N} \inf \left\{ t \geq 0 : |X_t^{i,N} - Y_t^{i,N}| \leq \epsilon \right\}$$

where

$$X_t^{i,N} = x + \sigma B_t^i - \int_0^t \left\{ \nabla V(X_s^{i,N}) + \alpha(X_s^{i,N} - \frac{1}{N} \sum_{j=1}^N X_s^{j,N}) \right\} ds, \quad t \geq 0,$$

$$Y_t^{i,N} = y + \sigma \tilde{B}_t^i - \int_0^t \left\{ \nabla V(Y_s^{i,N}) + \alpha(Y_s^{i,N} - \frac{1}{N} \sum_{j=1}^N Y_s^{j,N}) \right\} ds, \quad t \geq 0,$$

for $(B_t^1)_{t \geq 0}, \dots, (B_t^N)_{t \geq 0}$, and $(\tilde{B}_t^1)_{t \geq 0}, \dots, (\tilde{B}_t^N)_{t \geq 0}$, two families of independent Brownian motions.

Anticipated exit cost: The potential related to each family of particles

$$\Upsilon_N(\mathbf{x}^N) = \sum_{i=1}^N V(x_i) + \frac{\alpha}{2N} \sum_{i,j=1}^N |x_i - x_j|^2, \quad \mathbf{x}^N = (x_1, \dots, x_N) \in \mathbb{R}^{Nd},$$

and the exit-cost is given by

$$\begin{aligned} & \lim_{\epsilon \rightarrow 0} \inf_{\lambda \in \mathbb{R}^{dN}} \inf_{\mathbf{x}^N \in \partial B^N(\lambda, \epsilon)} \Upsilon_N(\mathbf{x}^N) - \Upsilon_N(\lambda_1, \dots, \lambda_1) \\ & + \lim_{\epsilon \rightarrow 0} \inf_{\lambda \in \mathbb{R}^{dN}} \inf_{\mathbf{y}^N \in \partial B^N(\lambda, \epsilon)} \Upsilon_N(\mathbf{y}^N) - \Upsilon_N(\lambda_2, \dots, \lambda_2), \end{aligned}$$

for

$$B^N(\lambda, \epsilon) = \left\{ \mathbf{x}^N = (x_1, \cdot, x_N) \in \mathbb{R}^{dN} ; \forall i, x_i \notin \mathbb{B}(\lambda, \epsilon) \right\}.$$

- As long as (A) hold the particle systems and their "linear" analog:

$$x_t^{i,\sigma} = x_1 + \sigma B_t^i - \int_0^t \nabla V(x_s^{i,\sigma}) ds - \int_0^t \nabla F(x_s^{i,\sigma} - \lambda_1) ds,$$

$$y_t^{i,\sigma} = x_2 + \sigma \tilde{B}_t^i - \int_0^t \nabla V(y_s^{i,\sigma}) ds - \int_0^t \nabla F(y_s^{i,\sigma} - \lambda_2) ds.$$

are well-posed in the pathwise sense. Moreover, for all $1 \leq i \leq N$, T finite and $1 \leq p < \infty$

$$\max_{t \in [0, T]} \mathbb{E}[|X_t^{i,N}|^p + |Y_t^{i,N}|^p] < \infty.$$

- Propagation of chaos: For $(X_t^1)_{t \geq 0}, \dots, (X_t^N)_{t \geq 0}$ and $(Y_t^1)_{t \geq 0}, \dots, (Y_t^N)_{t \geq 0}$, N -copies of $(X_t)_{t \geq 0}$ and $(Y_t)_{t \geq 0}$ driven respectively by $(B_t^1)_{t \geq 0}, \dots, (B_t^N)_{t \geq 0}$ and $(\tilde{B}_t^1)_{t \geq 0}, \dots, (\tilde{B}_t^N)_{t \geq 0}$,

$$\mathbb{E}[\max_{0 \leq t \leq T} |X_t^{i,N} - X_t^i|^p + \max_{0 \leq t \leq T} |Y_t^{i,N} - Y_t^i|^2] \leq \frac{C(\sigma, T)}{N}.$$

Non-uniform propagation of chaos \Rightarrow We cannot rely on the Kramers' law established in the mean-field limit situation to deal with the particle case.

\Rightarrow **Start over and apply a strategy analog to the mean-field case.** Namely: Establish the Kramers' type law from a coupling between the particle systems and their linear analogs.

Lemma

For any $\kappa > 0$ and for all $N > 0$ large enough, there exists a finite (deterministic) time $0 \leq T_\kappa$, uniform with respect to σ , such that $\bar{X}_t^N = \frac{1}{N} \sum_{j=1}^N X_t^{j,N}$ and $\bar{Y}_t^N = \frac{1}{N} \sum_{j=1}^N Y_t^{j,N}$, it holds

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \max_{t \in [T_\kappa, \exp[\frac{2}{\sigma^2}(H_0(\lambda_0)+2)]]} \left(\|\bar{X}_t^N - \lambda_1\| + \|\bar{Y}_t^N - \lambda_2\| \right) \leq 2\kappa \right\} = 1.$$

Proposition

For any $\xi > 0$, there exists a finite time T_κ such that

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left(\sup_{T_\kappa \leq t \leq \exp[\frac{2}{\sigma^2}(H_0(\lambda_0)+2)]} \left\{ \|\bar{X}_t^{i,N} - x_t^{i,\sigma}\| + \|\bar{Y}_t^{i,N} - y_t^{i,\sigma}\| \right\} \geq \xi \right) = 0,$$

and

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left(\sup_{T_\kappa \leq t \leq \exp[\frac{2}{\sigma^2}(H_0(\lambda_0)+2)]} \|\bar{Y}_t^{i,N} - y_t^{i,\sigma}\| \geq \xi \right) = 0,$$

provided that κ and σ are small enough while N is large enough.

Theorem

Let $\lambda_0(\epsilon)$ be a minimizer of H_ϵ . Then, for any $\delta > 0$ and for N large enough:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_\epsilon - \delta) \right] < \mathcal{C}_{\epsilon, N}(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_\epsilon + \delta) \right] \right\} = 1.$$

Moreover, the collision persists near the minimizers of H_ϵ in the sense: for \mathcal{H}_ϵ the set of all minimizers λ_ϵ of $\lambda \mapsto H_\epsilon(\lambda)$, and for ϵ small enough:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \inf_{\lambda_\epsilon \in \mathcal{H}_\epsilon} \max \left(|X_{C_\epsilon^N(\sigma)}^{i, N} - \lambda_\epsilon|, |Y_{C_\epsilon^N(\sigma)}^{i, N} - \lambda_\epsilon| \right) \leq \delta \right\} = 1.$$

Corollary

For any $\delta > 0$, we have, for N large enough:

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 - \delta) \right] < \mathcal{C}_{\epsilon, N}(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 + \delta) \right] \right\} = 1.$$

Moreover, for any $1 \leq i \leq N$,

$$\lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |X_{C_{\epsilon, N}(\sigma)}^{i, N} - \lambda_0| \leq \delta \right\} = 1 = \lim_{\epsilon \rightarrow 0} \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |Y_{C_{\epsilon, N}(\sigma)}^{i, N} - \lambda_0| \leq \delta \right\}.$$

Note on the one-dimensional case

In this situation, one can deal more directly with the true collision times:

$$C(\sigma) = \inf \{t \geq 0 : X_t = Y_t\}, \quad C_N(\sigma) = \inf_{1 \leq i \leq N} \inf \left\{ t \geq 0 : X_t^{i,N} = Y_t^{i,N} \right\}.$$

Theorem

For any $\delta > 0$:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 - \delta) \right] < C(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 + \delta) \right] \right\} = 1.$$

Moreover, for λ_0 the minimizer of H_0 ,

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |X_{C(\sigma)} - \lambda_0| \leq \delta \right\} = 1 = \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |Y_{C(\sigma)} - \lambda_0| \leq \delta \right\}.$$

Theorem

For any $\delta > 0$, and N sufficiently large:

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 - \delta) \right] < C_N(\sigma) < \exp \left[\frac{2}{\sigma^2} (\underline{H}_0 + \delta) \right] \right\} = 1,$$

and, for all $1 \leq i \leq N$

$$\lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |X_{C_N(\sigma)}^{i,N} - \lambda_0| \leq \delta \right\} = 1 = \lim_{\sigma \rightarrow 0} \mathbb{P} \left\{ |Y_{C_N(\sigma)}^{i,N} - \lambda_0| \leq \delta \right\}.$$

Generalizations

- Random initial conditions: As long as (x_0^σ, y_0^σ) or (X_0, Y_0) are a.s. bounded, at a $2\epsilon_0$ -distance from each others, and the law of X_0 and Y_0 have full support on different basin of attraction of V , our main results still hold true.
- Regular multi-wells confining potential. For instance if V admits m wells located at $\lambda_1, \dots, \lambda_m$ then, again, the Kramers' law for $C_\epsilon(\sigma)$, $C_{\epsilon, N}(\sigma)$, $C(\sigma)$ and $C_N(\sigma)$ hold and the collision λ_0 is located at

$$\left(\sum_{l=1}^m \nabla \Psi_l \right)^{-1} \left(\alpha \sum_{l'=1}^m \lambda_{l'} \right), \quad \Psi_l(x) = V(x) + \frac{\alpha}{2} \|x - \lambda_l\|^2.$$

- Further self-stabilizing forces: Provided that F is a smooth function such that $F(x) = G(\|x\|)$ where $G : \mathbb{R} \rightarrow \mathbb{R}$ is a even polynomial function G , with a degree larger than 2, satisfying $G(0) = 0$ (i.e. framework of [HT10, T20]) then the self-stabilizing force derive can be extended into more general kernel

$$\int F(x - y) \mu(dy).$$

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