

Convergence to equilibrium for rough differential equations

Samy Tindel

Purdue University

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Joint work with Aurélien Deya (Nancy) and Fabien Panloup (Angers)

Outline

- 1 Setting and main result
- 2 Convergence to equilibrium for diffusion processes
 - Poincaré inequality
 - Coupling method
- 3 Elements of proof

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Definition of fBm

Definition 1.

A 1-d fBm is a continuous process $X = \{X_t; t \in \mathbb{R}\}$ such that $X_0 = 0$ and for $H \in (0, 1)$:

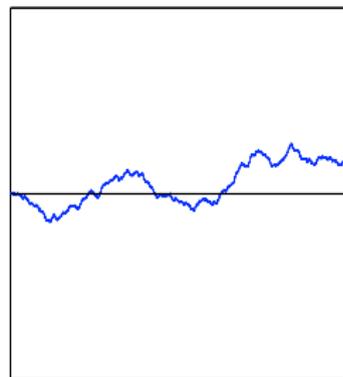
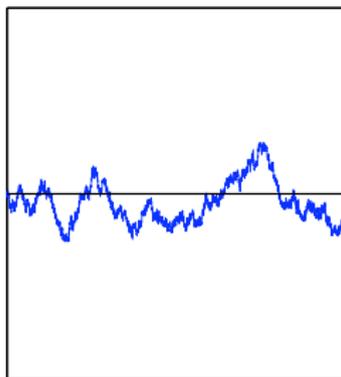
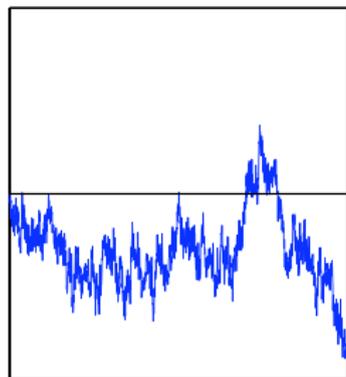
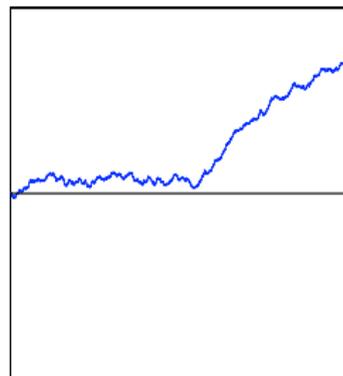
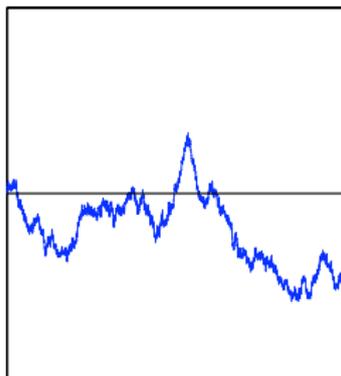
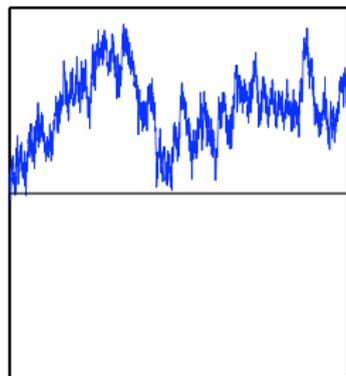
- X is a centered Gaussian process
- $\mathbf{E}[X_t X_s] = \frac{1}{2}(|s|^{2H} + |t|^{2H} - |t - s|^{2H})$

d -dimensional fBm: $X = (X^1, \dots, X^d)$, with X^i independent 1-d fBm

Variance of increments:

$$\mathbf{E}[|\delta X_{st}^j|^2] \equiv \mathbf{E}[|X_t^j - X_s^j|^2] = |t - s|^{2H}$$

Examples of fBm paths



$H = 0.35$

$H = 0.5$

$H = 0.7$

System under consideration

Equation:

$$dY_t = b(Y_t)dt + \sigma(Y_t) dX_t, \quad t \geq 0 \quad (1)$$

Coefficients:

- $x \in \mathbb{R}^d \mapsto \sigma(x) \in \mathbb{R}^{d \times d}$ smooth enough
- $\sigma = (\sigma_1, \dots, \sigma_d) \in \mathbb{R}^{d \times d}$ invertible
- $\sigma^{-1}(x)$ bounded uniformly in x
- $X = (X^1, \dots, X^d)$ is a d -dimensional fBm, with $H > \frac{1}{3}$

Resolution of the equation:

- Thanks to rough paths methods
↪ Limit of Wong-Zakai approximations

Illustration of ergodic behavior

Equation with damping: $dY_t = -\lambda Y_t dt + dX_t$

Simulation: For 2 values of the parameter λ

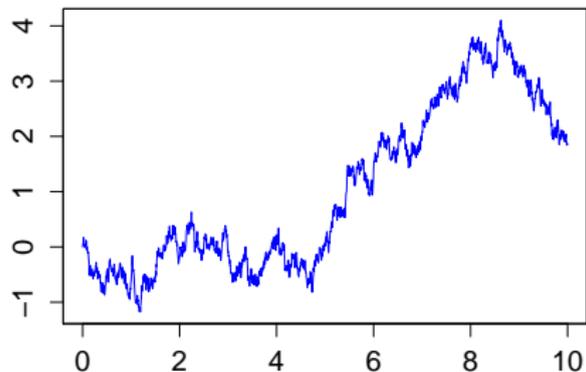


Figure: $H = 0.7$, $d = 1$, $\lambda = 0.1$

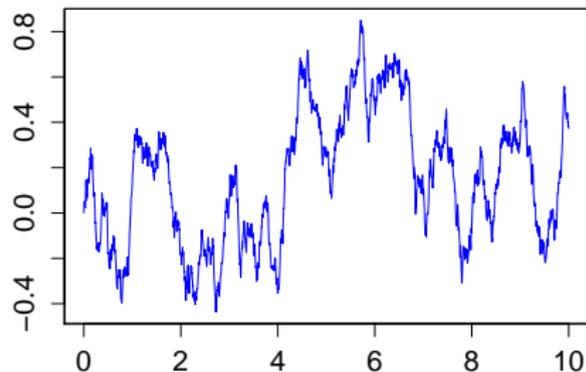
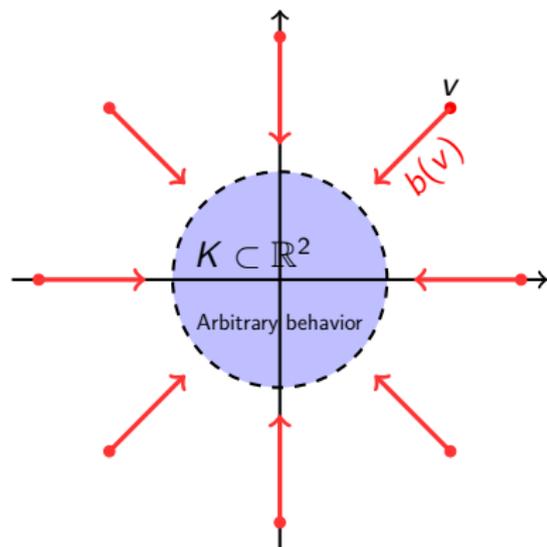


Figure: $H = 0.7$, $d = 1$, $\lambda = 3$

Coercivity assumption for b

Hypothesis: for every $v \in \mathbb{R}^d$, one has

$$\langle v, b(v) \rangle \leq C_1 - C_2 \|v\|^2$$



Interpretation of the hypothesis:
Outside of a compact $K \subset \mathbb{R}^d$,
 $b(v) \simeq -\lambda v$ with $\lambda > 0$

Ergodic results for equation (1)

Brownian case: If X is a Brownian motion and b coercive

- Exponential convergence of $\mathcal{L}(X_t)$ to invariant measure μ
- Markov methods are crucial
- See e.g. Khashminskii, Bakry-Gentil-Ledoux

Fractional Brownian case: If X is a fBm and b coercive

- Markov methods not available
- Existence and uniqueness of invariant measure μ , when $H > \frac{1}{3}$
↔ Series of papers by Hairer et al.
- Rate of convergence to μ :
 - ▶ When $\sigma \equiv \text{Id}$: Hairer
 - ▶ When $H > \frac{1}{2}$ and further restrictions on σ : Fontbona–Panloup

Main result (loose formulation)

Theorem 2.

Let

- $H > \frac{1}{3}$, equation $dY_t = b(Y_t)dt + \sigma(Y_t) dX_t$
- Y unique solution with initial condition μ_0
- μ unique invariant measure

Then for all $\varepsilon > 0$ we have:

$$\|\mathcal{L}(Y_t^{\mu_0}) - \mu\|_{\text{tv}} \leq c_\varepsilon t^{-(\frac{1}{8}-\varepsilon)}$$

Remark:

- Subexponential (non optimal) rate of convergence
- This might be due to the correlation of increments for X

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Poincaré and convergence to equilibrium

Theorem 3.

Let X be a diffusion process. We assume:

- μ is a symmetrizing measure, with Dirichlet form \mathcal{E}
- Poincaré inequality: $\text{Var}_\mu(f) \leq \alpha \mathcal{E}(f)$

Then the following inequality is satisfied:

$$\text{Var}_\mu(P_t f) \leq \exp\left(-\frac{2t}{\alpha}\right) \text{Var}_\mu(f)$$

Comments on the Poincaré approach

Remarks:

- 1 Theorem 3 asserts that

$$X_t \xrightarrow{(d)} \mu, \quad \text{exponentially fast}$$

- 2 The proof relies on identity $\partial_t P_t = LP_t$
 \hookrightarrow Hard to generalize to a non Markovian context
- 3 One proves Poincaré with Lyapunov type techniques
 \hookrightarrow Coercivity enters into the picture

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A general coupling result

Proposition 4.

Consider:

- Two processes $\{Z_t; t \geq 0\}$ and $\{Z'_t; t \geq 0\}$
- A coupling (\hat{Z}, \hat{Z}') of (Z, Z')

We set

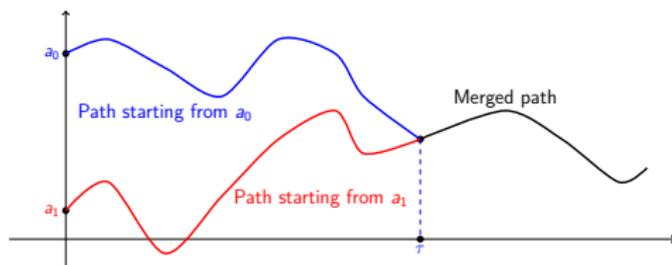
$$\tau = \inf \left\{ t \geq 0; \hat{Z}_u = \hat{Z}'_u \text{ for all } u \geq t \right\}$$

Then we have:

$$\|\mathcal{L}(Z_t) - \mathcal{L}(Z'_t)\|_{\text{tv}} \leq 2\mathbf{P}(\tau > t)$$

Comments on the coupling method

- 1 Proposition 4 is general, does not assume a Markov setting
↪ can be generalized (unlike Poincaré)
- 2 In a Markovian setting
↪ Merging of paths as soon as they touch

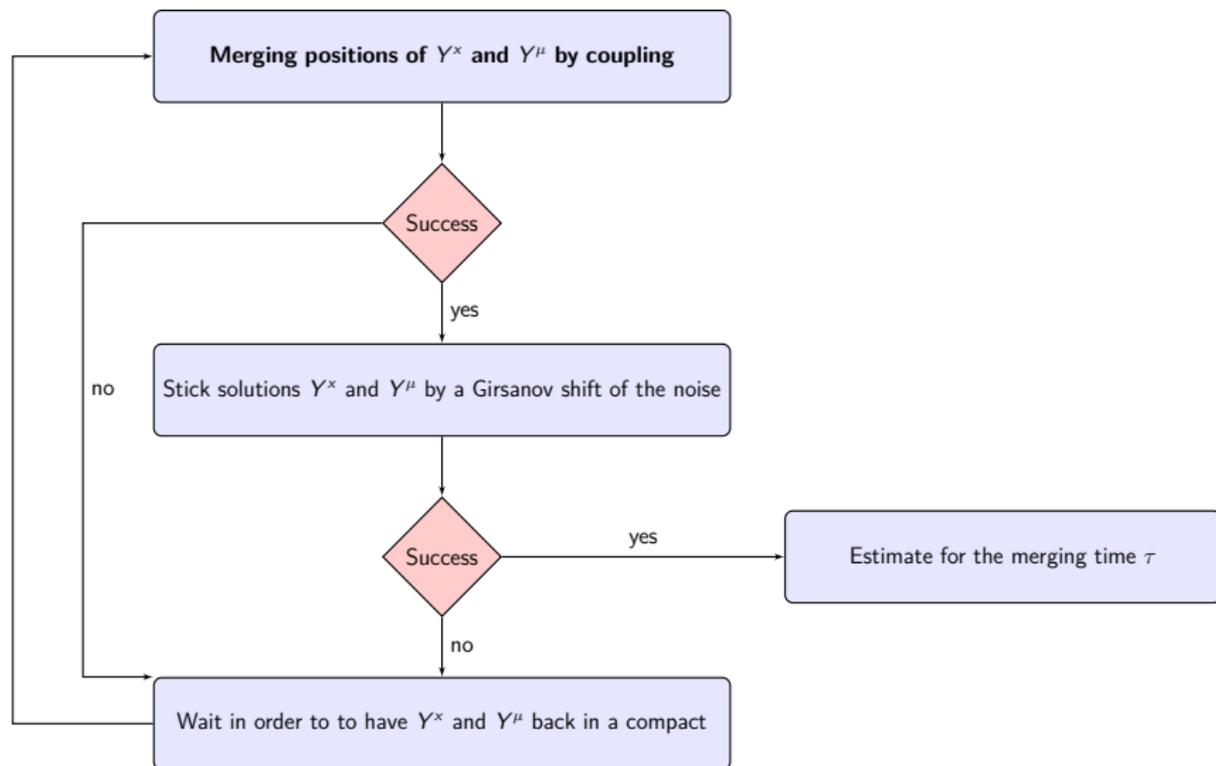


- 3 In our case
↪ We have to merge both Y, Y' and the noise

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Algorithmic view of the coupling



Merging positions (1)

Simplified setting:

We start at $t = 0$, and consider $d = 1$

Effective coupling: We wish to consider y^0, y^1 and h such that

- We have

$$\begin{cases} dy_t^0 = b(y_t^0) dt + \sigma(y_t^0) dX_t \\ dy_t^1 = b(y_t^1) dt + \sigma(y_t^1) dX_t + h_t dt \end{cases}$$

- Merging condition: $y_0^0 = a_0$, $y_0^1 = a_1$ and $y_1^0 = y_1^1$

Computation of the merging probability:

Through Girsanov's transform involving the shift h

Merging positions (2)

Generalization of the problem:

We wish to consider a family $\{y^\xi, h^\xi; \xi \in [0, 1]\}$ such that

- We have

$$dy_t^\xi = b(y_t^\xi) dt + \sigma(y_t^\xi) dX_t + h_t^\xi dt$$

- Merging condition:

$$y_0^\xi = a_0 + \xi(a_1 - a_0), \quad y_1^0 = y_1^1, \quad h^0 \equiv 0$$

Remark:

Here y has to be considered as a function of 2 variables t and ξ

Merging positions (3)

Solution of the problem: Consider a system with **tangent** process

$$\begin{cases} dy_t^\xi = \left[b(y_t^\xi) - \int_0^\xi d\eta j_t^\eta \right] dt + \sigma(y_t^\xi) dX_t \\ dj_t^\xi = b'(y_t^\xi) j_t^\xi dt + \sigma'(y_t^\xi) j_t^\xi dX_t \end{cases}$$

and initial condition $y_0^\xi = a_0 + \xi(a_1 - a_0)$, $j_0^\xi = a_1 - a_0$

Heuristics: A simple integrating factor argument shows that

$$\partial_\xi y_t^\xi = j_t^\xi(1 - t), \quad \text{and thus} \quad \partial_\xi y_1^\xi = 0$$

Hence y^ξ solves the merging problem

Merging positions (4)

Rough system under consideration: for $t, \xi \in [0, 1]$

$$\begin{cases} dy_t^\xi = \left[b(y_t^\xi) - \int_0^\xi d\eta j_t^\eta \right] dt + \sigma(y_t^\xi) dX_t \\ dj_t^\xi = b'(y_t^\xi) j_t^\xi dt + \sigma'(y_t^\xi) j_t^\xi dX_t \end{cases}$$

Then y_1^ξ does not depend on ξ !

Difficulties related to the system:

- 1 $t \mapsto y_t$ is function-valued
- 2 Unbounded coefficients, thus local solution only
- 3 Conditioning \implies additional drift term with singularities
- 4 Evaluation of probability related to Girsanov's transform