

# Linear response for stochastic dynamics

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# Introduction

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Consider a stochastic dynamics  $(X(t); t \geq 0)$  "at equilibrium", with law  $\mathbb{P}$ .

Introduce a family of "perturbed dynamics"  $(X^\lambda(t); t \geq 0)$ , with law  $\mathbb{P}^\lambda$ . ( $\lambda \in [0, 1]$  is the "strength" of the perturbation. If  $\lambda = 0$ , then  $X^\lambda = X$ . We care about small  $\lambda$ 's. )

Let  $(A(t); t \geq 0)$  be an additive functional. (Observable.)  
Note  $\mathbb{E}[A(t)] = t\mathbb{E}[A(1)]$ .

AIM: Compare  $\frac{1}{T}\mathbb{E}^\lambda[A(T)]$  and  $\mathbb{E}[A(1)]$ .

In particular: express the linear response  $\partial_{\lambda=0} \frac{1}{T}\mathbb{E}^\lambda[A(T)]$  as a correlation or variance or covariance.

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We assume that:  $X$  is reversible.

# Model to start with: diffusions on a torus.

Let  $\mathbb{T}^d = \mathbb{R}^d / \mathbb{Z}^d$  be the  $d$ -dimensional torus.

Let  $(X_x(t); t \geq 0, x \in \mathbb{T}^d)$  be the solution of the sde:

$$dX_x(t) = b(X_x(t))dt + \sigma(X_x(t))dW_t; X_x(0) = x. \quad (1)$$

Here  $(W_t; t \geq 0)$  is a  $\mathbb{T}^d$ -valued Brownian motion defined on some probability space  $(\mathcal{W}, \mathcal{A}, P)$ .

$\sigma = (\sigma(x); x \in \mathbb{T}^d)$  is a smooth field of symmetric non-negative matrices over  $\mathbb{T}^d$ ;  $b = (b(x); x \in \mathbb{T}^d)$  is a smooth vector field.

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The increment  $X_x(t + \Delta t) - X_x(t)$  follows a Gaussian law

$$\mathcal{N}(b(X_x(t))\Delta t; a(X_x(t))\Delta t)$$

independent of the past before time  $t$ . ( $a = \sigma^2$ .)

The stochastic process  $(X_x(t); t \geq 0, x \in \mathbb{T}^d)$  is Markov with generator

$$\mathcal{L}f(x) = \frac{1}{2} \sum_{j,k} a_{j,k}(x) \nabla_j f(x) \nabla_k f(x) + \sum_j b_j(x) \nabla_j f(x).$$

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We assume that

$$a(x) = \sigma(x)^2; b(x) = \frac{1}{2} \operatorname{div}(a(x)); \mathcal{L} = \frac{1}{2} \operatorname{div}(a \nabla).$$

The normalized Lebesgue measure on  $\mathbb{T}^d$ , say  $\pi$ , is a reversible and invariant probability measure.



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**Reversible** means that, for all  $T$ , if  $x = X_x(0)$  has distribution  $\pi$ , then the forward evolution  $(X_x(t); 0 \leq t \leq T)$  and backward evolution  $(X_x(T-t); 0 \leq t \leq T)$  have the same distribution on path space. In particular  $X_x(0)$  and  $X_x(T)$  have the same law.

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The normalized Lebesgue measure on  $\mathbb{T}^d$ , say  $\pi$ , is a reversible and invariant probability measure.

Notation:  $\mathcal{C}(\mathbb{R}_+; \mathbb{T}^d)$  be the set of continuous functions from  $\mathbb{R}_+$  to  $\mathbb{T}^d$ . We use the notation  $\mathbb{P}_x$  to denote the law of  $(X_x(t); t \geq 0)$ . Similarly for  $\mathbb{P}_\pi$  (if  $x$  has distribution  $\pi$ ). So  $\mathbb{P}_\pi$  is a measure on path space. We use the notation  $(X(t); t \geq 0)$  for a continuous path in  $\mathcal{C}(\mathbb{R}_+; \mathbb{T}^d)$ .

To define the perturbed process, let us consider a smooth vector field  $\mathcal{V}$  defined on  $\mathbb{T}^d$  and a real parameter  $\lambda > 0$  and let  $(X_x^\lambda(t); t \geq 0, x \in \mathbb{T}^d)$  be the solution of the stochastic differential equation:

$$X_x^\lambda(0) = x,$$

$$dX_x^\lambda(t) = b(X_x^\lambda(t))dt + \lambda \sigma(X_x^\lambda(t))\mathcal{V}(X_x^\lambda(t))dt + \sigma(X_x^\lambda(t))dW_t. \quad (2)$$

Then  $(X_x^\lambda(t); t \geq 0, x \in \mathbb{T}^d)$  is Markov with generator

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Notation: as before  $\mathbb{P}_x^\lambda$  is the law of  $(X_x^\lambda(t); t \geq 0)$  on path space. Also  $\mathbb{P}_\pi^\lambda$  when we are at equilibrium.

# Additive functionals (observables)

We may consider

**symmetric additive functionals** e.g.  $A(t) = \int_0^t f(X(s)) ds$ ,  
 $f : \mathbb{T}^d \rightarrow \mathbb{R}$ ,

or

**anti-symmetric additive functionals** e.g. let  $(Z(t); t \geq 0)$  be the lift of  $(X(t); t \geq 0)$  to  $\mathbb{R}^d$ . More generally

$$A(t) = \int_0^t g(X(s)) \circ dX(s),$$

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The words **symmetric vs anti-symmetric** refer to symmetry vs anti-symmetry with respect to time reversal.

Anti-symmetric additive functionals correspond to **currents** in physics.

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$$A(t) = \int_0^t g(X(s)) \circ dX(s),$$

$g : \mathbb{T}^d \rightarrow \mathbb{R}^d$  a vector field.

Observe that all anti-symmetric additive functionals have zero mean: for all  $t$ ,  $\mathbb{E}_\pi[\int_0^t g(X(s)) \circ dX(s)] = 0$ .

# Additive functionals

For diffusion processes (as in Equation (1)), symmetric and anti-symmetric additive functionals are related by

$$\int_0^t g(X_x(s)) \circ dX_x(s) = m_t + \frac{1}{2} \int_0^t \operatorname{div}(ag)(X_x(s)) ds,$$

where  $m$  is the **martingale**

$$m_t = \int_0^t (\sigma g)(X_x(s)) \cdot dW_s$$

under  $P$ .

Martingales are always easy to deal with. Results about anti-symmetric additive functionals transfer to symmetric additive functionals easily with the formula above. But ...



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observe we only get symmetric additive functionals where  $f$  is of the form

$$f = \operatorname{div}(ag).$$

Such  $f$ 's form the  $H_{-1}$  space.

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In the rest of the talk we focus on  
anti-symmetric additive functionals.

# Linear response with a fixed time horizon

Fix a time horizon  $T$ .

On the space of trajectories  $\mathcal{C}([0, T]; \mathbb{T}^d)$ , the two measures  $\mathbb{P}_\pi$  and  $\mathbb{P}_\pi^\lambda$  are equivalent and the Radon-Nikodym derivative is given by the **Girsanov weight**:

$$E[F(X_x^\lambda([0, T]))] = E[F(X_x([0, T]))e^{\lambda B(T) - \frac{\lambda^2}{2} \langle B \rangle (T)}],$$

where

$$B(t) = \int_0^t \mathcal{V}(X_x(s)) \cdot dW_s; \quad \langle B \rangle (T) = \int_0^T |\mathcal{V}(X_x(s))|^2 ds.$$

So

$$\partial_{\lambda=0} \frac{1}{T} \mathbb{E}_\pi^\lambda[A(T)] = \frac{1}{T} \mathbb{E}_\pi[A(T)B(T)].$$

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Indeed a covariance.

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$$\partial_{\lambda=0} \frac{1}{T} \mathbb{E}_\pi^\lambda[A(T)] = \frac{1}{T} \mathbb{E}_\pi[A(T)B(T)].$$

Note at this point, we do not need the anti-symmetry of  $A$ . Not even the fact that we are at equilibrium.

# When $T \rightarrow +\infty$

We first need to understand the  $T \rightarrow +\infty$  limit in the formula:

$$\partial_{\lambda=0} \frac{1}{T} \mathbb{E}_{\pi}^{\lambda} [A(T)] = \frac{1}{T} \mathbb{E}_{\pi} [A(T)B(T)].$$

**Central limit Theorem:**

Assume  $A(t) = \int_0^t g(X(s)) \circ dX(s)$  with  $\int g^2 d\pi < \infty$  i.e.  $\mathbb{E}_{\pi} [A(1)^2] < \infty$ . When  $T$  tends to  $+\infty$ , then the law of the vector  $\frac{1}{\sqrt{T}}(A(T), B(T))$  under  $\mathbb{P}_{\pi}$  converges to a Gaussian law with a certain covariance  $\mathcal{S}$  and

$$\frac{1}{T} \mathbb{E}_{\pi} [A(T)B(T)] \rightarrow \mathcal{S}.$$

The CLT only holds in this form if  $\pi$  is ergodic. Otherwise we get a mixture of Gaussian laws but the existence of  $\mathcal{S}$  still holds.

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Can we exchange the two limits?

$$\limsup_{T \rightarrow +\infty} \left| \frac{1}{\lambda T} \mathbb{E}_{\pi}^{\lambda}[A(T)] - \mathcal{S} \right| \xrightarrow{\lambda \rightarrow 0} 0?$$

*J. Lebowitz, H. Rost '94.*

The limit in the scaling  $\lambda^2 T = 1$  still exists:

$$\begin{aligned}\frac{1}{\lambda T} \mathbb{E}_\pi^\lambda[A(T)] &= \frac{1}{\lambda T} \mathbb{E}_\pi[A(T) e^{\lambda B(T) - \frac{\lambda^2}{2} \langle B \rangle(T)}] \\ &= \mathbb{E}_\pi \left[ \frac{1}{\sqrt{T}} A(T) e^{\frac{1}{\sqrt{T}} B(T) - \frac{1}{2T} \langle B \rangle(T)} \right] \\ &\rightarrow E[\bar{A} e^{\bar{B} - \frac{1}{2} E[\bar{B}^2]}] = E[\bar{A} \bar{B}] = \mathcal{S},\end{aligned}$$

where  $(\bar{A}, \bar{B})$  is the Gaussian vector given by the C.L.T. with covariance  $E[\bar{A} \bar{B}] = \mathcal{S}$ .

Once again the CLT only holds when  $\pi$  is ergodic. Otherwise we have a mixture of Gaussian laws and the conclusion still holds.



$$T = +\infty?$$

Conclusions so far:

Linear response holds for fixed times.

Linear response holds for larger times in the Lebowitz-Rost scaling for observables that satisfy the CLT.

What about infinite times?

# Reversible diffusions in a random environment

On  $\mathbb{R}^d$ .

$$dZ_x(t) = b^\omega(Z_x(t))dt + \sigma^\omega(Z_x(t))dW_t; Z_x(0) = x. \quad (3)$$

$$a^\omega(x) = \sigma^\omega(x)^2; b^\omega(x) = \frac{1}{2} \operatorname{div}(a^\omega(x)); \mathcal{L}^\omega = \frac{1}{2} \operatorname{div}(a^\omega \nabla).$$

Now the coefficients  $(\sigma^\omega(x); x \in \mathbb{R}^d)$  are random i.e. depend on some  $\omega \in \Omega$  with law  $\mathbb{Q}$  on  $\Omega$ .

We assume:  $\mathbb{Q}$  is stationary and ergodic (w.r.t. translations in  $\mathbb{R}^d$ ).

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Perturbation

$$dZ_x^\lambda(t) = b^\omega(Z_x^\lambda(t))dt + \lambda \sigma^\omega(Z_x^\lambda(t)) \mathcal{V}^\omega(Z_x^\lambda(t))dt + \sigma^\omega(Z_x^\lambda(t))dW_t. \quad (4)$$

$$\mathcal{V}^\omega(x) = \sigma^\omega(x) \cdot e_1.$$

(Constant force in direction  $e_1$ .)

The C.L.T. holds for the process  $(Z_x(t); t \geq 0)$ :

$$u \cdot \Sigma v = \lim_{T \rightarrow +\infty} \frac{1}{T} (E[u \cdot Z_x(T) v \cdot Z_x(T)] - E[u \cdot Z_x(T)] E[v \cdot Z_x(T)]).$$

$\Sigma$  is the asymptotic covariance matrix of  $Z$ .

$$\ell(\lambda) = \lim_{T \rightarrow +\infty} \frac{1}{T} Z_x^\lambda(T)$$

(Does the limit exist?)

$$\partial_{\lambda=0} \ell(\lambda) = \Sigma e_1.$$

Einstein relation.

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C.L.T. was proved in the 80's (Kipnis-Varadhan, DeMasi-Ferrari-Goldstein-Wick ...). Since  $\mathbb{Q}$  is ergodic,  $\Sigma$  is deterministic.

# Einstein relation

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Einstein relation.

The existence of the speed  $\ell(\lambda)$  is non trivial (Off-equilibrium problem.) and not known in general.

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Einstein relation.

This model is infinite dimensional. Very non-hyperbolic.

We establish the Einstein relation

$$\partial_{\lambda=0} \ell(\lambda) = \Sigma e_1 .$$

under two extra assumptions:

- $\sigma^\omega$  is **uniformly elliptic** (bounded from below and above),
- $\sigma^\omega$  has **finite range of correlation** (values of  $\sigma^\omega(x)$  and  $\sigma^\omega(y)$  are independent when  $d(x, y) \geq R$  for some fixed  $R$ ).

(Ref Gantert-Mathieu-Piatnitski 2012.)



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The existence of the speed  $\ell(\lambda)$  was obtained by Shen in 2003.

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Key step of the proof is: show the perturbed diffusion reaches equilibrium by time  $T = 1/\lambda^2$ ; then compare with LR scaling.

# Einstein relation: results

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Key step of the proof is: show the perturbed diffusion reaches equilibrium by time  $T = 1/\lambda^2$ ; then compare with LR scaling.

This is an example where, the smallest the perturbation, the largest the equilibrium time. See later for a more elementary finite dimensional example.

# Continuity of the variance

Let

$$u \cdot \Sigma(\lambda) v = \lim_{T \rightarrow +\infty} \frac{1}{T} (E[u \cdot Z_x^\lambda(T) v \cdot Z_x^\lambda(T)] - E[u \cdot Z_x^\lambda(T)] E[v \cdot Z_x^\lambda(T)]),$$

be the asymptotic covariance of the perturbed diffusion  $Z^\lambda$ .

We also establish the Continuity of variance:

$$\lim_{\lambda \rightarrow 0} \Sigma(\lambda) = \Sigma.$$

(Ref: Mathieu-Piatnitski 2018.)

The continuity of variance is stronger than linear response.

# Continuity of the variance

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We also establish the Continuity of variance:

$$\lim_{\lambda \rightarrow 0} \Sigma(\lambda) = \Sigma.$$

(Ref: Mathieu-Piatnitski 2018.)

The continuity of variance is stronger than linear response.

Many questions (and few results) to extend to time-dependent perturbations.

# Diffusions on a torus

Back to diffusions on a torus:

$$dX_x(t) = b(X_x(t))dt + \sigma(X_x(t))dW_t; X_x(0) = x.$$

$$dX_x^\lambda(t) = b(X_x^\lambda(t))dt + \lambda\sigma(X_x^\lambda(t))\mathcal{V}(X_x^\lambda(t))dt + \sigma(X_x^\lambda(t))dW_t.$$

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Questions (in increasing order of difficulty)

1. **Continuity of 'steady state'**: is  $\frac{1}{T}\mathbb{E}_\pi^\lambda[A(T)]$  uniformly close to  $\frac{1}{T}\mathbb{E}_\pi[A(T)] = \mathbb{E}_\pi[A(1)]$ ?
2. **Linear response**: compute  $\partial_{\lambda=0}\frac{1}{T}\mathbb{E}_\pi^\lambda[A(T)]$  for large  $T$ ?
3. **Continuity of variance**: what can we say about the variance of  $A(T)$  under  $\mathbb{P}_\pi^\lambda$  as  $T \rightarrow +\infty$  and for small  $\lambda$ ?

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Below partial answers to 1.



# A degenerate example

On the interval  $[0, 1]$ .

$$dX_x(t) = b(X_x(t))dt + \sigma(X_x(t))dW_t; X_x(0) = x.$$

$$a = \sigma^2; b = \frac{1}{2} \operatorname{div} a.$$

Choose  $a(x) = x^\alpha$  for small positive  $x$  and  $\alpha > 2$  and  $a$  bounded from below elsewhere.

Choose:  $\mathcal{V}(x) = -1$  for small positive  $x$ .

$$dX_x^\lambda(t) = \frac{\alpha}{2}(X_x^\lambda(t))^{\alpha-1}dt - \lambda(X_x^\lambda(t))^{\frac{\alpha}{2}}dt + (X_x^\lambda(t))^{\frac{\alpha}{2}}dW_t.$$

Note  $x^{\frac{\alpha}{2}}$  is larger than  $x^{\alpha-1}$  for small  $x$ .

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Then, for all positive  $\lambda$ , for almost all trajectories,

$$X_x^\lambda(T) \rightarrow 0.$$

For any  $\lambda > 0$ , the steady state is  $\delta_0!$

Recall  $A(t) = \int_0^t g(X(s)) \circ dX(s)$ .

**THEOREM** Choose  $g$  continuous.

$$\mathbb{E}_\pi^\lambda[A(T)] \leq 4\lambda T (\|\mathcal{V}\|_\infty + \frac{2\gamma_2}{\lambda\sqrt{T}}) \|\sigma \cdot g\|_\infty.$$

In particular

$$\limsup_{\lambda \rightarrow 0} \frac{1}{\lambda} \limsup_{T \rightarrow +\infty} \frac{1}{T} |\mathbb{E}_\pi^\lambda[A(T)]| \leq 4\|\mathcal{V}\|_\infty \|\sigma \cdot g\|_\infty.$$

The result says the steady state is always Lipschitz continuous: not as a measure (See example before.) but as a distribution on anti-symmetric additive functionals or, equivalently, on  $H_{-1}$ .

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Proof is based on forward-backward martingale decomposition for  $A$  and concentration inequalities (Large deviations).

Recall

$$dZ_x^\lambda(t) = b^\omega(Z_x^\lambda(t))dt + \lambda \sigma^\omega(Z_x^\lambda(t)) \mathcal{V}^\omega(Z_x^\lambda(t))dt + \sigma^\omega(Z_x^\lambda(t))dW_t.$$

$$\mathcal{V}^\omega(x) = \sigma^\omega(x) \cdot e_1.$$

Coefficients  $(\sigma^\omega(x); x \in \mathbb{R}^d)$  are random stationary.

Let

$$\ell(\lambda) = \lim_{T \rightarrow +\infty} \frac{1}{T} Z_x^\lambda(T)$$

(if it exists.)

Then

$$|\ell(\lambda)| \leq 4\lambda \|\sigma \cdot e_1\|_\infty^2.$$

# Optimistic Lipschitz bounds

Recall  $A(t) = \int_0^t g(X(s)) \circ dX(s)$ .

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The bound also holds for **time-dependent parameters**  $\sigma$  or perturbation  $\mathcal{V}$ .

**THEOREM** Assume  $\mathcal{V}$  depends on time and that

$$\lim_{T \rightarrow +\infty} \sup_x \|\mathcal{V}_T(x)\|_\infty = 0.$$

Then

$$\lim_{T \rightarrow +\infty} \frac{1}{T} \mathbb{E}_\pi^\lambda[A(T)] = 0.$$

Concluding remark:

Martingale techniques always useful for stochastic dynamics:  
Girsanov transforms, CLT's, deviation inequalities ... and flexible  
enough to adapt to time-dependent models.

End of the talk.