

LDP for SPDEs: a Martingale Approach

Sergey V. Lototsky
Department of Mathematics
University of Southern California

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SPDEs: Setting

$(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$, $u = u(t, x)$, $0 \leq t \leq T$, $x \in G$,

G is d -dimensional (can be \mathbb{R}^d);

$\{h_k, k \geq 1\}$ — CONS in $L_2(G)$,

w_k — independent Wiener processes; **Itô Integral**.

$$du = (Au + f)dt + \sum_{k \geq 1} (M_k u + g_k)dw_k(t), \quad u(0, x) = u_0(x).$$

• **Additive noise:** $M_k = 0$ for all k .

• **Multiplicative noise:** otherwise.

• **Space-time white noise:**

$$dW(t, x) = \sum_{k \geq 1} h_k(x)dw_k(t).$$

$$M_k u = h_k M u,$$

$$g_k(t, x) = h_k(x)g(t, x):$$

$$du = (Au + f)dt + (Mu + g)dW(t, x).$$

• **colored in space, white in time noise:**

$$dW_Q(t, x) = \sum_{k \geq 1} q_k h_k(x)dw_k(t), \quad \lim_{k \rightarrow \infty} q_k = 0.$$

• **Solution** — **Strong in every sense of the word:**

$$(u, \varphi)(t) = (u_0, \varphi) + \int_0^t (Au + f, \varphi)(s)ds \\ + \sum_{k \geq 1} \int_0^t (M_k u + g_k, \varphi)(s)dw_k(s).$$

Examples

- **Linear second-order equation**

$$du = (a_{ij}D_iD_ju + b_iD_i + cu + f)dt + (\sigma_{ik}D_iu + \nu_ku + g_k)dw_k.$$

$$D_i = \partial/\partial x_i,$$

$a, b, c, \sigma, \nu, f, g$ can be functions of t, x, ω .

- **Reaction-diffusion equation**

$$du = (au_{xx} + f(u))dt + g(u)dW(t, x), \quad x \in \mathbb{R}.$$

$$f = 0, \quad g(u) = \sqrt{u} \text{ — super-Brownian motion.}$$

$$f = 0, \quad g(u) = \sqrt{u(1-u)} \text{ — Fleming-Viot model.}$$

$$f(u) = u(1-u), \quad g = 1 \text{ — KPP-Fisher.}$$

- **Deterministic XYZ equation + “noise” = stochastic XYZ equation.**

Additive space-time white noise is often the first choice.

SPDEs: Problems

Forward problems

- Existence, uniqueness, regularity of the solution

Inverse problems

- Statistical inference

Here, space-time white noise is more difficult.

Fun problems

- Averaging and homogenization
- Invariant measures
- Large deviations

Here, space-time white noise can help.

Example

Time-only noise is easier than space-time.

Time only: $du = \Delta u dt + u dw(t);$

$$u(t, x) = \left(\frac{1}{(4\pi t)^{d/2}} \int_{\mathbb{R}^d} e^{-|x-y|^2/(4t)} u_0(y) dy \right) e^{w(t) - (t/2)}.$$

Compare this with

Space-time: $du = \Delta u dt + u dW(t, x);$

- no closed-form solution;
- u Holder $< 1/2$ in space;
- u Holder $< 1/4$ in time;
- **only if $d = 1$.**

A Different Example

Time-only noise is harder than space-time.

$$du = u_{xxx}dt + \sqrt{\varepsilon} u dW(t, x), \quad t \in (0, T), \quad x \in (0, 1):$$

Have LDP:

$$J(\psi) = \frac{1}{2} \int_0^T \int_0^1 \left(\frac{\psi_t(t, x) - \psi_{xxx}(t, x)}{\psi(t, x)} \right)^2 dx dt$$

Ioffe (1991), Sowers (1992),

Chenal and Millet (1997), Cardon-Weber (1999)

Compare this with

$$du = u_{xxx}dt + \sqrt{\varepsilon} u dw(t).$$

$$u(t, x) = u_{heat}(t, x) e^{\sqrt{\varepsilon} w(t) - (\varepsilon t/2)}.$$

Do we have an LDP here?

Spatial Effects of Time-Only Noise

$$du(t, x) = a u_{xx} dt + \sigma u_x dw(t), \quad x \in \mathbb{R}.$$

$$\hat{u}(t, y) = \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} u(t, x) e^{-ixy} dx, \quad i = \sqrt{-1}.$$

$$d\hat{u}(t, y) = -ay^2 \hat{u}(t, y) dt - i\sigma y \hat{u}(t, y) dw(t)$$

$$\hat{u}(t, y) = \hat{u}(0, y) e^{-\left(a - (\sigma^2/2)\right)y^2 t - iy\sigma w(t)}.$$

Parabolicity condition: $\sigma^2 < 2a$

Connection with physics: stochastic transport equation; $a - (\sigma^2/2)$ is the effective viscosity.

Proving LDP

$(\Omega, \mathcal{F}, \mathbb{P})$, a probability space.

(X, ρ) , a metric space.

$(\xi_\varepsilon, \varepsilon > 0)$, a family of X -valued random elements.

$\exists \psi^\circ \in X : \lim_{\varepsilon \rightarrow 0} \mathbb{P}(\rho(\xi_\varepsilon, \psi^\circ) > \delta) = 0, \delta > 0.$

$G \subset X, \psi^\circ \notin G.$

Goal—LDP:

$$\mathbb{P}(\xi_\varepsilon \in G) \asymp e^{-\varepsilon^{-1} \inf_{\psi \in G} J(\psi)}.$$

Need

Exponential Tightness:

$\forall \psi \in X \exists K, \text{ compact in } X :$

$$\limsup_{\varepsilon \rightarrow 0} \varepsilon \ln \mathbb{P}(\xi_\varepsilon \notin K) < -C.$$

AND

Local LDP:

$$\lim_{\delta \rightarrow 0} \lim_{\varepsilon \rightarrow 0} \varepsilon \ln \mathbb{P}(\rho(\xi_\varepsilon, \psi) < \delta) = -J(\psi).$$

Local LDP, Upper Bound

- **Stochastic exponential:**

Find $H = H(\lambda, \psi) : X_1 \times X_2 \rightarrow \mathbb{R}$ so that X_1, X_2 are sufficiently large subsets of X , $\sup_{\lambda} H(\lambda, \psi) = H(\lambda^*, \psi)$, $\lambda^* = \lambda(\psi)$, and

$$\mathbb{E} e^{\varepsilon^{-1} H(\lambda, \xi_{\varepsilon})} = 1, \quad \lambda \in X_1.$$

- **Upper bound:**

$$1 \geq \mathbb{E} \left(\mathbf{1}_{\rho(\xi_{\varepsilon}, \psi) < \delta} e^{\varepsilon^{-1} H(\lambda, \xi_{\varepsilon})} \right) \gtrsim e^{\varepsilon^{-1} H(\lambda, \psi)} \mathbb{P}(\rho(\xi_{\varepsilon}, \psi) < \delta);$$

$$\lim_{\delta \rightarrow 0} \limsup_{\varepsilon \rightarrow 0} \varepsilon \ln \mathbb{P}(\rho(\xi_{\varepsilon}, \psi) < \delta) \leq - \sup_{\lambda} H(\lambda, \psi).$$

Reasonable guess: $J(\psi) = \sup_{\lambda} H(\lambda, \psi) = H(\lambda^*, \psi)$.

Local LDP, Lower Bound

- **Change of measure:**

$$d\tilde{\mathbb{P}} = e^{\varepsilon^{-1}H(\lambda^*, \xi_\varepsilon)} d\mathbb{P}$$

- **Shift of the limit:**

$$\lim_{\varepsilon \rightarrow 0} \tilde{\mathbb{P}}(\rho(\xi_\varepsilon, \psi) < \delta) = 1, \quad \delta > 0.$$

- **Lower bound:**

$$\mathbb{P}(\rho(\xi_\varepsilon, \psi) < \delta) = \tilde{\mathbb{E}}\left(\mathbf{1}_{\rho(\xi_\varepsilon, \psi) < \delta} e^{-\varepsilon^{-1}H(\lambda^*, \xi_\varepsilon)}\right)$$

$$\gtrsim e^{-\varepsilon^{-1}H(\lambda^*, \psi)} \tilde{\mathbb{P}}(\rho(\xi_\varepsilon, \psi) < \delta);$$

$$\lim_{\delta \rightarrow 0} \liminf_{\varepsilon \rightarrow 0} \varepsilon \ln \mathbb{P}(\rho(\xi_\varepsilon, \psi) < \delta) \geq -J(\psi).$$

Reference (SODEs): Liptser–Puhalskii (1992)

Example 1. $X = \mathcal{C}(0, T)$, $\xi_\varepsilon = \sqrt{\varepsilon} w(t)$, $\psi(0) = 0$.

$$H(\lambda, \psi) = \int_0^T \lambda(t) \psi'(t) dt - \frac{1}{2} \int_0^T \lambda^2(t) dt.$$

$$\lambda^* = \psi' = \frac{d\psi}{dt}, \quad J(\psi) = \frac{1}{2} \int_0^T |\psi'(t)|^2 dt.$$

Change of measure is Girsanov's Theorem

Example 2. $X = \mathcal{C}((0, T) \times \mathbb{R})$, $\xi_\varepsilon = u_\varepsilon(t, x)$,

$$du_\varepsilon = (u_\varepsilon)_{xx} dt + \sqrt{\varepsilon} u_\varepsilon dW(t, x).$$

$$H(\lambda, \psi) = \int_0^T \int_{\mathbb{R}} \lambda(t, x) (\psi_t(t, x) - \psi_{xx}(t, x)) dx dt - \frac{1}{2} \int_0^T \int_{\mathbb{R}} \psi^2(t, x) \lambda^2(t, x) dx dt.$$

$$\lambda^*(t, x) = \frac{\psi_t(t, x) - \psi_{xx}(t, x)}{\psi^2(t, x)},$$

$$J(\psi) = \frac{1}{2} \int_0^T \int_{\mathbb{R}} \left(\frac{\psi_t(t, x) - \psi_{xx}(t, x)}{\psi(t, x)} \right)^2 dx dt.$$

Example 3. $X = \mathcal{C}((0, T) \times \mathbb{R})$, $\xi_\varepsilon = u_\varepsilon(t, x)$,

$$du_\varepsilon = (u_\varepsilon)_{xx} dt + \sqrt{\varepsilon} (u_\varepsilon)_x dw(t).$$

$$H(\lambda, \psi) = \int_0^T \int_{\mathbb{R}} \lambda(t, x) (\psi_t(t, x) - \psi_{xx}(t, x)) dx dt \\ - \frac{1}{2} \int_0^T \left(\int_{\mathbb{R}} \psi_x(t, x) \lambda(t, x) dx \right)^2 dt.$$

If $\psi_t(t, x) - \psi_{xx}(t, x) = f(t)\psi_x(t, x)$, then

$$\lambda^*(t, x) = \lambda^*(t) = \frac{f(t)}{\int_{\mathbb{R}} \psi_x(t, x) dx},$$

AND

$$J(\psi) = \frac{1}{2} \int_0^T f^2(t) dt;$$

otherwise, $J(\psi) = +\infty$.

In general, consider

$$du_\varepsilon(t, x) = \mathbf{A}u_\varepsilon(t, x)dt + \sqrt{\varepsilon} \sum_{k \geq 1} \mathbf{M}_k u_\varepsilon(t, x)dw_k(t).$$

(Expected) Theorem

If $\psi_t(t, x) - \mathbf{A}\psi(t, x) = \sum_{k \geq 1} f_k(t)\mathbf{M}_k\psi(t, x)$, then

$$J(\psi) = \frac{1}{2} \inf \sum_{k \geq 1} \int_0^T f_k^2(t)dt.$$

Otherwise, $J(\psi) = +\infty$.

$$\lambda^* : \int_{\mathbb{R}} \lambda^*(t, x)\mathbf{M}_k\psi(t, x)dx = f_k(t).$$

Conclusion

LDP for SPDEs:

Easy answers, hard proofs.

What about **Huge Deviations?**