

Stochastic PDEs.

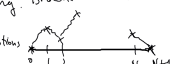
1st part: Week 1: White noise
Gaussian measures
Heat eq, Additive
stochastic PDEs.
Stochastic integrals
Multiplication SDEs

2nd part: Week 5 to 8
- prop. of solutions
to mult. stoch. heat eq
x C.V. of discrete models
* Approximation of SDEs.
2 -> pm only.

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Weijun Xu
Cyril Labbe

Motivating example.

chain of N oscillators $X_1(t), \dots, X_N(t)$
with nearest neighbors interaction
random ext. forcing: Brown motion
 $B_i, i=1 \dots N$
indep. Brown Motions



$$dX_i(t) = (X_{i+1}(t) - X_i(t))dt + (X_i(t) - X_{i-1}(t))dt + dB_i(t)$$

$$= \Delta X_i(t)dt + dB_i(t)$$

Q: What happens when $N \rightarrow \infty$?

-> Need a rescaling: $\mu(t, x) = \frac{1}{\sqrt{N}} X_{[xN]}(tN)$

$$d_\epsilon u(t, x) = \sum_{k \geq 0} \frac{1}{\sqrt{N}} d_\epsilon X_{[xN]}(tN) \chi_k \in [0, 1]$$

$$\tilde{\chi}_x(t, x) \approx \frac{1}{\sqrt{N}} \Delta X_{[xN]}(tN)$$

$$d_\epsilon u(t, x) = \sum_x u(t, x) + N \sum_x d_\epsilon B_{[xN]}(tN)$$

Behaviour of $N^{\frac{1}{2}} d_\epsilon B_{[xN]}(tN)$

Scaling prop. of BM $(\frac{1}{N} B_\epsilon(tN), t \geq 0)$

$$\stackrel{BM}{=} (W(t), t \geq 0) \text{ BM}$$

$$\rightarrow \left(\frac{1}{N} d_\epsilon B_\epsilon(tN), t \geq 0 \right) \stackrel{BM}{=} (d_\epsilon W_\epsilon(t), t \geq 0)$$

$$\text{So } N^{\frac{1}{2}} d_\epsilon B_{[xN]}(tN) \stackrel{BM}{=} (\sqrt{N} d_\epsilon W_{[xN]}(t), t \geq 0)$$

Take $\varphi, \psi \in C_c^\infty((0, \infty) \times (0, 1))$

$$\mathbb{E} \left[\langle \varphi, \sqrt{N} d_\epsilon W_{[xN]} \rangle \langle \psi, \sqrt{N} d_\epsilon W_{[yN]} \rangle \right]$$

$$= \mathbb{E} \left[\sum_{i=0}^N \sum_{j=0}^N \int_{t=0}^{\infty} \int_{s=0}^{\infty} \varphi(x, t) \psi(y, s) N d_\epsilon W_{[xN]} d_\epsilon W_{[yN]} \right]$$

$$\approx \sum_{i=0}^N \sum_{j=0}^N \int_{t=0}^{\infty} \int_{s=0}^{\infty} \varphi\left(\frac{i}{N}, t\right) \psi\left(\frac{j}{N}, s\right) N d_\epsilon W_i(t) d_\epsilon W_j(s)$$

$$\approx \sum_{i=0}^N \sum_{j=0}^N \int_{t=0}^{\infty} \int_{s=0}^{\infty} \varphi\left(\frac{i}{N}, t\right) \psi\left(\frac{j}{N}, s\right) \frac{N}{N} \mathbb{E} [d_\epsilon W_i(t) d_\epsilon W_j(s)]$$

$$\approx \frac{1}{N} \int_{t=0}^{\infty} \int_{s=0}^{\infty} \varphi\left(\frac{i}{N}, t\right) \psi\left(\frac{j}{N}, s\right) dt ds \approx \langle \varphi, \psi \rangle$$

Guess limiting eq⁰

$$\partial_t u = \partial_x^2 u + \xi + F(u)$$

ξ : Gaussian, covariance

$$E[\langle \xi, \varphi \rangle \langle \xi, \psi \rangle] = \langle \varphi, \psi \rangle_{L^2(\mathbb{R}^d)}$$

Today, def of ξ white noise

def: The white noise is a linear map ξ from $L^2(\mathbb{R}^d, dx)$ into $L^2(\Omega, \mathcal{F}, \mathbb{P})$ such that: $\forall f \in L^2(\mathbb{R}^d, dx)$

$$\xi(f) = \langle \xi, f \rangle \sim \mathcal{N}(0, \|f\|_{L^2}^2)$$

Prop: (i) Isometry from $L^2(\mathbb{R}^d, dx)$ into $L^2(\Omega)$ preserves the inner product:

$$(i) \forall A \in \mathcal{B}(\mathbb{R}^d), \xi(A) = \xi(\mathbb{1}_A)$$

Here, if $(A_n)_{n \geq 1}$ seq of disjoint Borel sets then

$$\xi\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_n \xi(A_n)$$

Proof (i) Isometry \checkmark
Inner product: $f, g \in L^2(\mathbb{R}^d)$

$$\xi(f+g) = \xi(f) + \xi(g)$$

$$E[\xi(f+g)^2] = \|f+g\|_{L^2}^2 = \|f\|_{L^2}^2 + \|g\|_{L^2}^2$$

$$E[(\xi(f) + \xi(g))^2] = E[\xi(f)^2] + E[\xi(g)^2]$$

$$E[\xi(f)\xi(g)] = \langle f, g \rangle_{L^2} \checkmark$$

(i) $(A_n)_{n \geq 1}$ disjoint sets of \mathbb{R}^d

$$E\left[\left(\sum_n \xi(A_n)\right)^2\right] = \sum_n E[\xi(A_n)^2] = \sum_n \text{Leb}(A_n)$$

if $\text{Leb}\left(\bigcup_{n=1}^{\infty} A_n\right) < \infty$.

$$E\left[\left(\sum_n \xi(A_n)\right)^2\right] < \infty$$

By linearity, we know $\xi\left(\bigcup_n A_n\right) = \sum_n \xi(A_n)$

Pass to the limit on $E\left[\left(\sum_n \xi(A_n)\right)^2\right]$

as $N \rightarrow \infty$ D.

References:

- * Introduction to SPDEs, Martin Hairer
- * Stochastic PDEs, Walsh 1984.
- * Stochastic eq in infinite dimension, Da Prato - Zabczyk.

There are 2 view points for considering random processes:

1) A collection of random variables $X_t, t \in \mathcal{T}$

$$\forall t \in \mathcal{T} \quad X_t: (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$$

Endowed with the Kolmogorov's σ -algebra, i.e. smallest σ -algebra st $\forall n \geq 1, \forall t_1, \dots, t_n \in \mathcal{T}$

$$(X_{t_1}, \dots, X_{t_n}): \Omega \rightarrow \mathbb{R}^n$$

is measurable.

→ Finite-dimensional marginals are sufficient to characterize completely the law of a random process w.r.t. Kolmogorov's σ -alg.

$$\mathcal{G} = \left\{ (X_{t_1}, \dots, X_{t_n})^{-1}(A) : n \geq 1, t_1, \dots, t_n \in \mathcal{T}, A \in \mathcal{B}(\mathbb{R}^n) \right\}$$

stable under intersection.

So, if μ and ν are 2 laws of random processes then $\mathcal{M} = \{A \in \mathcal{G}, \mu(A) = \nu(A)\}$

if $\mathcal{M} \supset \mathcal{G}$ then $\mathcal{M} \supset \sigma(\mathcal{G})$.

2) Random process as a law on a space of functions of $t \in \mathcal{T}$.

Here ξ is a process indexed by \mathbb{L}

Existence of the white noise:

- Kolmogorov's extension th ✓
- More explicit: take $(e_n)_{n \geq 1}$ orthonormal basis of $L^2(\mathbb{R}^d, dx)$, take $(Z_n)_{n \geq 1}$ iid $\mathcal{N}(0,1)$ on $(\Omega, \mathcal{F}, \mathbb{P})$.

$$\text{Set } \langle \xi, f \rangle = \sum_{n \geq 1} \langle e_n, f \rangle Z_n$$

Easy to check that ξ is a white noise. Informally $\xi = \sum_{n \geq 1} Z_n \cdot e_n$

Examples: $d=1$ ($\xi = \mathbb{1}_{[0, \infty)}$, $t \geq 0$) is a Brownian Motion.
 $d=2$ ($\xi = \mathbb{1}_{[0, \infty) \times [0, \infty)}$, $x > 0, y > 0$) Brownian sheet.

SPDEs we will be interested in the case where $L^2((0, \infty) \times \mathbb{R}^d, dt \otimes dx)$

ξ white noise on time space $L^2((0, \infty) \times \mathbb{R}^d)$: will be called space-time white noise.

Take $(e_n)_{n \geq 1}$ orthonormal basis $L^2(\mathbb{R}^d, dx)$

$$W_t^n := \xi(\mathbb{1}_{[0, t]} \otimes e_n), \quad n \geq 1$$

$(W_t^n, n \geq 1)$ is a seq of indep BM.

Prop: $\forall f \in L^2(\mathbb{R}^d)$, $W_t(f) = \sum_{n \geq 1} \langle e_n, f \rangle W_t^n$ is a well-defined r.v.

$$\mathbb{E}[W_t(f) W_s(g)] = t \wedge s \langle f, g \rangle$$

Proof (1) $\sum_{n=1}^N W_n^n \langle f, e_n \rangle$
 $E \left[\left(\sum_{n=1}^N W_n^n \langle f, e_n \rangle \right)^2 \right] = \sum_{n=1}^N E \langle f, e_n \rangle^2$

Since $f \in L^2$, this is a Cauchy
 Seq. in $L^2(\Omega, \mathcal{F}, \mathbb{P})$.

(2) $E [W_t(f) \cdot W_t(g)] = E \left[\sum_{n,m} W_n^t W_m^t \langle f, e_n \rangle \langle g, e_m \rangle \right]$
 $= \sum_n E \langle f, e_n \rangle \langle g, e_n \rangle$
 $= E \langle f, g \rangle_t$

$W_t(f) = \sum_{n=1}^{\infty} W_n^t \langle f, e_n \rangle$
 We would like to write $W_t = \sum_{n=1}^{\infty} W_n^t e_n \dots$
 $\rightarrow (W_t, t \geq 0)$ cylindrical Wiener
 process.

Want to learn more info about the
 regularity of Ξ (or W_t).

White noise on $L^2(\mathbb{R}^d, dx)$, $(e_n)_{n \geq 1}$ basis

$\mathcal{H}^\alpha = \left\{ f \in \mathcal{S}'(\mathbb{R}^d) : \sum_{n \geq 1} |\langle f, e_n \rangle|^2 n^{2\alpha} < \infty \right\}$
 $\alpha \in \mathbb{R}$ Sobolev space.

$\mathcal{H}^0 = L^2(\mathbb{R}^d)$; \mathcal{H}^α more regular $\alpha > 0$
 less regular $\alpha < 0$.

Prop * Ξ admits a modification which
 is almost surely in \mathcal{H}^α , $\alpha > 1/2$.
 * $\mathbb{P}(\Xi \in L^2) = 0$.

Proof: $\lambda > 0$, $E \left[e^{-\lambda \sum_{n=1}^N \Xi(e_n)^2} \right] = e^{-\lambda \frac{N}{2}}$

then $N \rightarrow \infty$
 $\mathbb{P} \left(\sum_{n=1}^N \Xi(e_n)^2 < \infty \right) = 0$

L^2 -norm of Ξ is ∞ a.s.

Same calculations
 $E \left[e^{-\lambda \sum_{n=1}^N \Xi(e_n)^2 n^{-2\alpha}} \right] = e^{-\lambda \sum_{n=1}^N n^{-2\alpha}}$

Pass to the limit $N \rightarrow \infty$, $\alpha > 1/2$

So: Pass to the limit $\lambda \rightarrow 0$.

$\mathbb{P} \left(\sum_{n=1}^{\infty} \Xi(e_n)^2 n^{-2\alpha} < \infty \right) = 1$.

On an event $\tilde{\Omega} = \left\{ \omega : \sum_{n=1}^{\infty} \Xi(e_n)^2 n^{-2\alpha} < \infty \right\}$

of probn 1, we can define
 $\tilde{\Xi} := \begin{cases} \sum_{n=1}^{\infty} \Xi(e_n) e_n & \text{on } \tilde{\Omega} \\ 0 & \text{on } \tilde{\Omega}^c \end{cases}$

Almost surely, $\|\tilde{\Xi}\|_{\mathcal{H}^\alpha} < \infty$.

$\sum_{n=1}^{\infty} n^{-2\alpha} < \infty$. The structure behind
 is that the embedding of $L^2 \hookrightarrow \mathcal{H}^\alpha$ is
 Hilbert-Schmidt.

Cef: ξ can be viewed as a random element of a space of distributions.
 We get the 2nd viewpoint, we get into the topic of Gaussian measures.

Def (Gaussian Measure). Let \mathcal{B} be a Banach space, separable. Then μ is a Gauss. meas. on \mathcal{B} if $\exists \{f \in \mathcal{B}^*\}$ (space of continuous linear maps on \mathcal{B}) the pushforward of μ through f is Gaussian. \otimes if μ is a probab. measure on \mathcal{B} , and

In our setting, the white noise can be seen as a Gaussian measure on $\mathcal{H}^{-\alpha}$.
 Then $\mathcal{B}^* = \mathcal{H}^{\alpha}$.

$\forall f \in \mathcal{H}^{\alpha}$, $f^* \mu$ is a Gaussian measure on \mathbb{R} , variance $f^* \mu$ is $\|f\|_{\mathcal{H}^{\alpha}}^2$.

Th (Cameron-Martin Theorem).

Let $h \in \mathcal{H}^{\alpha}$. $T_h: \mathcal{H}^{-\alpha} \rightarrow \mathcal{H}^{-\alpha}$
 $f \mapsto f+h$

$\mu \sim T_h^* \mu$ iff $h \in L^2(\mathbb{R}^{\mathbb{N}})$.

Proof:

* Let $h \in L^2$. Then $f = \sum_{i=1}^{\infty} f_i e_i$

where $f_i = \langle f, e_i \rangle$
 $(\sum_{i=1}^{\infty} f_i^2)^{1/2}$

Then, $f^* \mu \sim \mathcal{N}(0, \|f\|_{L^2}^2 = 1)$

want to see $f^* T_h^* \mu \sim \mathcal{N}(\langle f, h \rangle, \|f\|_{L^2}^2 = 1)$

$d_{TV}(\mu, T_h^* \mu) = 1$
 $\geq d_{TV}(f^* \mu, f^* T_h^* \mu)$



* if $h \in L^2$, $f^* \mu$ law of

$\langle f, h \rangle \sim \mathcal{N}(0, \|h\|_{L^2}^2)$

$e^{\langle f, h \rangle}$ is integrable against μ .

$e^{\langle f, h \rangle} = -\frac{1}{2} \|h\|_{L^2}^2$
 Radon-Nikodym derivative $d\mu = d\mu_h$

Compute $\hat{\mu}_h$ and $T_h^* \mu$.