

From SDE's to SPDE's

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Lecture 1 : Introduction and Motivation

Introduction

- Let $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$ be a filtered probability space satisfying the *usual conditions*:

I) $\mathcal{F}_{t+} := \bigcap_{s > t} \mathcal{F}_s = \mathcal{F}_t, \forall t \geq 0,$

II) \mathcal{F}_0 contains all null sets.

- Consider the following continuous semi-martingale on $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$

$$X_t := X_0 + M_t + V_t,$$

where,

- ★ $\{M_t\}$ continuous, local $\{\mathcal{F}_t\}$ martingale, $M_0 \equiv 0,$
- ★ $\{V_t\}$ continuous $\{\mathcal{F}_t\}$ - adapted process of finite variation, $V_0 \equiv 0.$

- $\{M_t\}$ has a quadratic variation i.e. \exists an unique continuous non-decreasing $\{\mathcal{F}_t\}$ - adapted process denoted by $\{\langle M \rangle_t\}$ s.t. $\{M_t^2 - \langle M \rangle_t\}$ is a continuous, local $\{\mathcal{F}_t\}$ martingale.

- Define,

$$\langle X \rangle_t := \langle M \rangle_t$$

- Let $X_t := (X_t^1, \dots, X_t^d) \in \mathbb{R}^d$ and $X_t^i := X_0^i + M_t^i + V_t^i$, for $i = 1, 2, \dots, d$, then

$$\langle X^i, X^j \rangle_t = \langle M^i, M^j \rangle_t = \frac{1}{4} \{ \langle M^i + M^j \rangle_t - \langle M^i - M^j \rangle_t \}$$

- $\{\langle M^i, M^j \rangle_t\}$ continuous $\{\mathcal{F}_t\}$ - adapted process of finite variation.

- Let $\{h(t, \omega)\}$ be an $\{\mathcal{F}_t\}$ - progressively measurable process satisfying $\int_0^t h^2(s, \omega) d\langle X \rangle_s < \infty, \forall t$ a.s.
- Then the stochastic integral of h w.r.t. $X_t \equiv M_t$ is a continuous local martingale denoted by $\int_0^t h(s) dX_s =: I(h)(t)$ with the following properties :
 - I) $I(h)(0) \equiv 0,$
 - II) $I(\alpha h_1 + \beta h_2)(t) = \alpha I(h_1)(t) + \beta I(h_2)(t),$
 - III) The quadratic variation $\langle I(h) \rangle_t = \int_0^t h^2(s) d\langle X \rangle_s,$
 - IV) When $h(s, \omega) := h(\omega) I_{(u, v]}(s),$ where $h \in \mathcal{F}_u,$ then $I(h)(t) = h(\omega)(X_{t \wedge v} - X_{t \wedge u}).$
 - V) If $\mathbb{E} \int_0^t h^2(s) d\langle X \rangle_s < \infty,$ then

$$\mathbb{E}(I(h)(t))^2 = \mathbb{E} \int_0^t h^2(s) d\langle X \rangle_s.$$

Itô's formula

Theorem (Itô's formula)

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be a C^2 -function

$$f \circ X_t = f \circ X_0 + \int_0^t \partial_i f \circ X_s dX_s^i + \frac{1}{2} \int_0^t \partial_{ij}^2 f \circ X_s d\langle X^i, X^j \rangle_s,$$

where, $(\partial_i f \circ X_s)$, $(\partial_{ij}^2 f \circ X_s)$ are progressively measurable adapted processes and $dX_s^i = dM_s^i + dV_s^i$ and sum is over repeated indices.

- If $X_0 \equiv x = (x^1, \dots, x^d) \in \mathbb{R}^d$, then

$$X_t = x + M_t + V_t = x + Z_t, \quad \text{where } Z_t := M_t + V_t.$$

- Introduce Translation operator τ_z , for $z \in \mathbb{R}^d$

$$\tau_z f(x) := f(x - z).$$

- Therefore, $f(X_t) = f(x + Z_t) = \tau_{-Z_t} f(x)$.

- $$\partial_i f(X_t) = \partial_i f(x + Z_t) = \tau_{-Z_t}(\partial_i f)(x) = \partial_i(\tau_{-Z_t} f)(x).$$

- Similarly,

$$\partial_{ij}^2 f(X_t) = \partial_{ij}^2(\tau_{-Z_t} f)(x).$$

- Hence, we can rewrite the Itô's formula

$$\begin{aligned} \tau_{-Z_t} f(x) &= f(x) + \int_0^t \partial_i(\tau_{-Z_s} f)(x) dZ_s^i \\ &\quad + \frac{1}{2} \int_0^t \partial_{ij}^2(\tau_{-Z_s} f)(x) d\langle Z^i, Z^j \rangle_s \\ \Rightarrow \tau_{-Z_t} f &= f + \int_0^t \partial_i(\tau_{-Z_s} f) dZ_s^i \\ &\quad + \frac{1}{2} \int_0^t \partial_{ij}^2(\tau_{-Z_s} f) d\langle Z^i, Z^j \rangle_s. \end{aligned}$$

- The above equation can be written as an equation in a suitable space of functions H .

- Interesting case, when H is a Hilbert space having the property that $\tau_Z f \in H$, whenever $f \in H$.

Stochastic Differential Equations

$$dX_t = \bar{\sigma}(X_t) \cdot dB_t + \bar{b}(X_t) dt,$$

$$X_0 = x.$$

$$X_t = x + \int_0^t \bar{\sigma}(X_s) \cdot dB_s + \int_0^t \bar{b}(X_s) ds.$$

- $x \in \mathbb{R}^d$, $\bar{\sigma} = (\bar{\sigma}_{ij}) : \mathbb{R}^d \rightarrow \mathbb{R}^{d^2}$, $\bar{b} : \mathbb{R}^d \rightarrow \mathbb{R}^d$ and the coefficients $(\bar{\sigma}_{ij}(X_s))$, $(\bar{b}_i(X_s))$ are jointly measurable adapted processes. $(B_t) = (B_t^1, \dots, B_t^d)$ and $X_t = (X_t^1, \dots, X_t^d)$ are \mathcal{F}_t -adapted.

Theorem

If $\bar{\sigma}$, \bar{b} are Lipschitz continuous, i.e. \exists a constant $k \in \mathbb{R}$

$$|\bar{\sigma}_{ij}(x) - \bar{\sigma}_{ij}(y)| + |\bar{b}_i(x) - \bar{b}_i(y)| \leq k |x - y|,$$

then the above SDE has an unique global strong solution $\{X_t^x\}_{t \geq 0}$.

- Remark

I) Global Lipschitz \Rightarrow solution exists $\forall t, t \geq 0$.

II) Local Lipschitz $\Rightarrow \exists \eta$ and $0 < \eta < \infty$ s.t. $\{X_t\}_{0 \leq t < \eta}$.

III) Strong solution $\Leftrightarrow X_t \in \mathcal{F}_t^B := \sigma\{B_s, s \leq t\}$.

IV) The solution has strong Markov property.

- Let C_b^∞ denotes the space of C^∞ functions with uniformly bounded derivative.

Theorem

Suppose $\bar{\sigma}_{ij}, \bar{b}_i \in C_b^\infty(\mathbb{R}^d)$. Then almost surely, the map $x \rightarrow X_t^x(\omega)$ is a C^∞ - diffeomorphism for every $t \geq 0$.

- Remark

$\bar{\sigma}_{ij}, \bar{b}_i \in C_b^\infty(\mathbb{R}^d)$, they are Lipschitz continuous and global strong solution exists.

- For $\phi \in C^\infty(\mathbb{R}^d)$, let us define

$$\bar{L}^* \phi(x) := \frac{1}{2} \sum_{ij} \partial_{ij}^2 ((\bar{\sigma} \bar{\sigma}^t)_{ij}(x) \phi(x)) - \sum_i \partial_i (\bar{b}_i(x) \phi(x)).$$

- The **transition probability** function

$$P(t, x, A) := P(X_t^x \in A).$$

- Then $P(t, x, A)$ satisfies the '**forward equation**'

$$\begin{aligned} \frac{\partial P}{\partial t}(t, x, \cdot) &= \bar{L}^* P(t, x, \cdot), \\ P(0, x, \cdot) &= \delta_x. \end{aligned}$$

This means,

$$\langle f, P(t, x, \cdot) \rangle = f(x) + \int_0^t \langle \bar{L} f, P(s, x, \cdot) \rangle ds$$

- Note that, $\mathbb{E}f(X_t^x) := \langle f, P(t, x, \cdot) \rangle$, $\langle f, \mu \rangle := \int f(x) \mu(dx)$ and

$$\bar{L} f(x) := \frac{1}{2} \sum_{ij} (\bar{\sigma} \bar{\sigma}^t)_{ij}(x) \partial_{ij}^2 f(x) + \sum_i \bar{b}_i(x) \partial_i f(x).$$

From SDE's to SPDE's

$$\begin{aligned} X_t^x &= x + \int_0^t \bar{\sigma}(X_s^x) \cdot dB_s + \int_0^t \bar{b}(X_s^x) ds \\ &= x + Z_t^x. \end{aligned}$$

Then,

$$\begin{aligned} \tau_{-Z_t^x} f &= f + \int_0^t \partial_i \tau_{-Z_s^x} f dZ_s^i \\ &\quad + \frac{1}{2} \int_0^t \partial_{ij}^2 \tau_{-Z_s^x} f d\langle Z^i, Z^j \rangle_s \end{aligned}$$

- **Remark**

We shall consider the Hilbert spaces H with the property that $\tau_Z f \in H$, whenever $f \in H$. In addition when H is a Hermite-Sobolev space i.e. $H \equiv \mathcal{S}_{-p}$, for $p > \frac{d}{4}$, then $f = \delta_x \in H$. Then $\tau_{-Z_t^x} f = \tau_{-Z_t^x} \delta_x = \delta_{x+Z_t^x}$.

- Therefore,

$$\begin{aligned}dZ_t^x &= \bar{\sigma}(x + Z_t^x) \cdot dB_t + \bar{b}(x + Z_t^x) dt \\ &= \sigma(\delta_{x+Z_t^x}) \cdot dB_t + b(\delta_{x+Z_t^x}) dt,\end{aligned}$$

where, $\sigma_{ij} : H \rightarrow \mathbb{R}$ s.t. $\sigma_{ij}(\delta_x) = \bar{\sigma}_{ij}(x)$.

- For example, if

$$\bar{\sigma} \in H' \Rightarrow \sigma_{ij}(f) = \langle \bar{\sigma}_{ij}, f \rangle, \quad f \in H.$$

Similarly,

$$b_i(f) = \langle \bar{b}_i, f \rangle, \quad f \in H,$$

also satisfies $b_i(\delta_x) = \bar{b}_i(x)$, for $f = \delta_x$.

- Hence, for $f = \delta_x$

$$Y_t := \delta_{x+Z_t} = \delta_{X_t} = \tau_{-Z_t} f.$$

- Then from the earlier Itô's formula

$$Y_t = \delta_x + \int_0^t L(Y_s) ds + \int_0^t A_i(Y_s) dB_s^i,$$

where $(L(Y_s))$, $(A_i(Y_s))$ are jointly measurable, adapted and

$$L(\phi) := \frac{1}{2} \sum_{ij} (\sigma \sigma^t)_{ij}(\phi) \partial_{ij}^2 \phi - \sum_i b_i(\phi) \partial_i \phi,$$

$$A(\phi) := (A_1 \phi, \dots, A_d \phi)$$

$$A_i(\phi) := - \sum_j \sigma_{ji}(\phi) \partial_j \phi$$

- Remark

1)

$$\langle f, L(\delta_x) \rangle = \frac{1}{2} \sum_{ij} (\bar{\sigma} \bar{\sigma}^t)_{ij}(x) \partial_{ij}^2 f(x) + \sum_i \bar{b}_i(x) \partial_i f(x) =: \bar{L}f(x),$$

$$\langle f, A_i(\delta_x) \rangle = \sum_j \bar{\sigma}_{ji}(x) \partial_j f(x) =: \bar{A}_i f(x).$$

II) To arrive at the SPDE we used the imbedding $\mathbb{R}^d \rightarrow H$ given by $x \rightarrow \delta_x$ and consequently $X_t^x \rightarrow \delta_{X_t^x} = \delta_{x+Z_t^x}$.

III) Consider $\bar{\sigma}_{ij}, \bar{b}_i \in C_b^\infty(\mathbb{R}^d)$ and let $f \in \mathcal{S}$ (Schwartz space), then the map $x \rightarrow f \circ X_t^x$ is C^∞ . Thus we get the linear map from $\mathcal{S} \rightarrow C^\infty : f \rightarrow X_t(f) := f \circ X_t$.

- **Ex.** For $\psi \in C_c^\infty$, define $Y_t(\psi) := \int_{\mathbb{R}^d} \psi(x) \delta_{X_t^x} dx$. Then Y_t is the formal adjoint of the map $f \rightarrow X_t^x(f)$ as can be seen from the duality relation–

$$\langle Y_t(\psi), f \rangle = \int_{\mathbb{R}^d} \psi(x) f(X_t^x) dx = \int_{\mathbb{R}^d} \psi(x) (X_t^x(f))(x) dx = \langle \psi, X_t(f) \rangle .$$

- From Itô's formula

$$f \circ X_t^x = f(x) + \int_0^t \bar{L}f(X_s^x) ds + \int_0^t \bar{A}_i f(X_s^x) dB_s^i,$$

$x \rightarrow f \circ X_t^x \in H$. Where $x \rightarrow \bar{L}f(X_s^x)$, $x \rightarrow \bar{A}_i f(X_s^x)$ are C^∞ functions. Then, from the above mentioned adjoint relation we get

$$Y_t(\psi) = \psi + \int_0^t \bar{L}^* Y_s(\psi) ds + \int_0^t \bar{A}_i^* Y_s(\psi) dB_s^i,$$

because

$$\langle \bar{L}f(X_s^x), \psi \rangle = \langle \bar{L}f, Y_s(\psi) \rangle = \langle f, \bar{L}^* Y_s(\psi) \rangle,$$

$$\langle \bar{A}_i f(X_s^x), \psi \rangle = \langle \bar{A}_i f, Y_s(\psi) \rangle = \langle f, \bar{A}_i^* Y_s(\psi) \rangle.$$

- Remark

I) The above computations extend to the case when ψ is a finite signed measure, say $\psi = \mu$; in that case define

$Y_t(\psi) := \int_{\mathbb{R}^d} \delta_{X_t^x} d\mu(x)$. In particular, when $\psi = \delta_x$, then $Y_t(\psi) = \delta_{X_t^x}$. In this case the linear SPDE above coincides with the non-linear SPDE derived earlier for $\delta_{X_t^x}$.

II) Taking expectation on both sides of the above linear SPDE

$$\mathbb{E}(Y_t(\psi)) = \psi + \int_0^t \bar{L}^* \mathbb{E}(Y_s(\psi)) ds.$$

when $\psi = \delta_x$ we get the forward equation satisfied by

$$\mathbb{E}(Y_t(\psi)) = \mathbb{E}(\delta_{X_t^x}) = P(s, x, \cdot).$$

Note that,

$$\langle f, \mathbb{E}(Y_t(\psi)) \rangle = \langle f, \mathbb{E}(\delta_{X_t^x}) \rangle = \mathbb{E} f(X_t^x) = \int f(y) P(s, x, dy).$$

$\mathcal{S}, \mathcal{S}', \mathcal{S}_p$ spaces

- Let $\mathcal{S}(\mathbb{R}^d)$ denotes the space of smooth rapidly decreasing real valued functions on \mathbb{R}^d with the topology given by L. Schwartz, called the Schwartz space

$$\mathcal{S}(\mathbb{R}^d) := \left\{ f \in C^\infty(\mathbb{R}^d) \mid |x^\alpha \partial^\beta f(x)| \rightarrow 0, \text{ as } |x| \rightarrow \infty \right\}.$$

- $|x|$ denotes the Euclidean norm of \mathbb{R}^d .
- If $\beta = (\beta_1, \dots, \beta_d) \in \mathbb{Z}_+^d$, then $|\beta| = \beta_1 + \dots + \beta_d$.
- $\partial^\beta \phi = \partial_1^{\beta_1} \dots \partial_d^{\beta_d} \phi$.
- For $p \in \mathbb{R}$, $\mathcal{S}_p(\mathbb{R}^d) = \text{closure of } \mathcal{S}(\mathbb{R}^d) \text{ w.r.t. } \|\cdot\|_p$.

$$\langle f, g \rangle_p := \sum_{k \in \mathbb{Z}_+^d} (2|k| + d)^{2p} \langle f, h_k \rangle_0 \langle g, h_k \rangle_0, \quad f, g \in \mathcal{S}.$$

$\{h_k\}_{k \in \mathbb{Z}_+^d}$ is an ONB for $\mathcal{L}^2(\mathbb{R}^d, dx)$, called the Hermite functions.

$\langle \cdot, \cdot \rangle_0$ denotes inner product in \mathcal{L}^2 .

- $h_k(x_1, \dots, x_d) := h_{k_1}(x_1) \times \dots \times h_{k_d}(x_d), \forall (x_1, \dots, x_d) \in \mathbb{R}^d$.