
NASDE 08.11.2024



$$p \in [0, \infty)$$

$$L^p(\text{Pred}(\mathbb{F}); \text{HS}(\mathbb{R}^m, \mathbb{R}^d)) \\ = \left\{ X: [0, \mathbb{P}] \times \Omega \rightarrow \mathbb{R}^{d \times m} \text{ is } \mathbb{F}\text{-predictable} \right.$$

and

$$\left. \int_0^{\mathbb{P}} \mathbb{E} \left[\|X_s\|_{\text{HS}}^p \right] ds < \infty \right\}$$

We define $\int_0^{\mathbb{P}} X_s dW_s$ for

$$p=2$$

- First, we define for simple predictable processes:

$Y: [0, \mathbb{P}] \times \Omega \rightarrow \mathbb{R}^{d \times m}$ is simple if

- $\exists n \in \mathbb{N}, 0 \leq t_1 < t_2 \dots < t_n \leq \mathbb{P}$ and
- $H_k: \Omega \rightarrow \mathbb{R}^{d \times m}$ is \mathbb{F}_{t_k} -meas.

(1)

$\forall k \in \{1, \dots, n-1\}$ s.t.

(2)

$$Y_t = \sum_{k=1}^{n-1} H_k \cdot \mathbb{1}_{(t_k, t_{k+1}]}(t) \\ \downarrow \begin{array}{l} \mathbb{F}_{t_k}\text{-meas.} \\ \text{left-cont.} \end{array} \quad \forall t \in [0, \mathbb{P}]$$

$$t \in [0, t_1] \quad Y_t = 0$$

$$t \in (t_1, t_2] \quad Y_t = H_1 \text{ is } \mathbb{F}_{t_1}\text{-meas}$$

$$t \in (t_2, t_3]: \quad Y_t = H_2, \dots \text{ is } \mathbb{F}_{t_2}\text{-meas}$$

$\Rightarrow Y$ is \mathbb{F} -adapted + left-cont

$\Rightarrow Y$ is \mathbb{F} -predictable.

Assume that $Y \in L^2(\text{Pred}(\mathbb{F}), \text{HS})$:

$$\int_0^{\mathbb{P}} \mathbb{E} \left[\|Y_s\|_{\text{HS}}^2 \right] ds < \infty$$

$$\sum_{k=1}^{n-1} \int_{t_k}^{t_{k+1}} \mathbb{E}[\|Y_s\|_{HS}^2] ds \quad (3)$$

$\parallel H_k$

$$\approx \sum_{k=1}^{n-1} \underbrace{(t_{k+1} - t_k)}_{>0} \cdot \mathbb{E}[\|H_k\|_{HS}^2] < \infty$$

$$\Leftrightarrow \mathbb{E}[\|H_k\|_{HS}^2] < \infty \quad \forall k=1, \dots, n-1$$

$$H_k \in L^2(P; HS)$$

If $W: [0, P] \times \Omega \rightarrow \mathbb{R}^m$ BM, we define

$$I_{0, P}^W(Y) := \sum_{k=1}^{n-1} H_k \cdot (W_{t_{k+1}} - W_{t_k})$$

$(\int_0^P Y_s dW_s)$

$$\mathbb{P} \quad 0 \leq a \leq b \leq P; \quad (4)$$

$$I_{-a, b}^W(Y) := \sum_{k=1}^{n-1} H_k \cdot (W_{\min(t_{k+1}, b)} - W_{\min(t_k, a)})$$

Theorem: Let

$$V = \{ \psi \text{ simple}, \psi \in L^2(\text{Pred}, HS) \}$$

Then

$$I_{-a, b}^W : V \rightarrow L^2(P, \mathbb{R}^d)$$

is a well-defined linear operator and for $\psi \in V$ we have

$$(i) \|I_{-a, b}^W(\psi)\|_{L^2(P, \mathbb{R}^d)} = \|\psi\|_{L^2(\text{Pred}, HS)}$$

It's isometry

$$(ii) \quad \|\mathbb{I}_{a,b}^W(Y)\|_{L^2} \leq \|Y\|_{L^2}$$

$\Rightarrow \mathbb{I}_{a,b}^W$ is bounded

$$\mathbb{I}_{a,b}^W : V \rightarrow L^2(\mathbb{P}, \mathbb{R}^d)$$

One shows that V is dense in

$$L^2(\text{Pred}(\mathbb{F}), \text{HS}) \Rightarrow$$

We can cont. extend it to

$$\mathbb{I}_{a,b}^W : L^2(\text{Pred}(\mathbb{F}), \text{HS}) \rightarrow L^2(\mathbb{P}, \mathbb{R}^d)$$

$$\int_a^b Y_s dW_s$$

⑤

Main properties of the stochastic integral: ⑥

If $0 \leq a \leq b \leq T$:

① $\left(\int_a^t X_s dW_s \right)_{t \in [a, b]}$ is

$(\mathbb{F}_t)_{t \in [a, b]}$ -adapted.

② linearity:

$$\int_a^b [\alpha X_s + \beta Y_s] dW_s = \alpha \int_a^b X_s dW_s + \beta \int_a^b Y_s dW_s$$

③ If $a \leq c \leq b$

$$\int_a^b X_s dW_s = \int_a^c X_s dW_s + \int_c^b X_s dW_s$$

(4) $\mathbb{E} \left[\int_0^t X_s dW_s \right] = 0$

(4)

(5) Martingale property:

$$\mathbb{E} \left[\int_0^t X_s dW_s \mid \mathcal{F}_u \right] = \int_0^u X_s dW_s \quad 0 \leq u \leq t \leq T$$

i.e. $\left(\int_0^t X_s dW_s \right)_{t \in [0, T]}$ is $(\mathcal{F}_t)_{t \in [0, T]}$ martingale

Proof: Idea: Prove for $X \in V$

Simple. Use the density of $V \subset L^2(\text{Pred}(\mathcal{F}), \mathcal{H}_s)$ to extend it to $L^2(\text{Pred}(\mathcal{F}), \mathcal{H}_s)$.

→ We use stochastic integral (8) to define Ito processes

In classical analysis: the fundamental thm of calculus tells us

$x: [0, T] \rightarrow \mathbb{R}$ is in C^1 iff

$\exists y: [0, T] \rightarrow \mathbb{R}$ cont. such that

$$x(t) = x(0) + \int_0^t y(s) ds \quad \forall t \in [0, T]$$

and in this case

$$y = x'$$

In stochastic analysis: An analogue of C^1 is Ito process.

Def-n: An (\mathcal{F}_t) -adapted process

$$X: [0, T] \times \Omega \rightarrow \mathbb{R}^D \text{ with cont.}$$

sample path is called an Ito process if

$$X_t = X_0 + \int_0^t V_s ds + \int_0^t Z_s dW_s$$

for some $V \in L^2$, $Z \in L^{2,0}$
 V -drift, Z -diffusion

Remark on notation: One also writes
 $dX_t = V_t dt + Z_t dW_t, t \in [0, T]$

In classical analysis: We have chain rule: $f \in C^1$, then
 for $x: [0, T] \rightarrow \mathbb{R}$ is also in C^1
 $t \mapsto f(x(t))$ and
 $(f \circ x)'(t) = f'(x(t)) \cdot x'(t)$

or equivalently (10)
 $f(x(t)) = f(x(0)) + \int_0^t f'(x(s)) y(s) ds$
 where

$$x(t) = x(0) + \int_0^t y(s) ds$$

→ The stochastic alternative of the chain rule is Ito formula

Theorem: If $f \in C^2(\mathbb{R}^d, \mathbb{R})$ then

$$f(X_t) = f(X_a) + \int_a^t \nabla f(X_s)^T Y_s ds + \frac{1}{2} \int_a^t \text{trace}(Z_s^T (D^2 f)(X_s) Z_s) ds + \int_a^t \nabla f(X_s)^T Z_s dW_s \quad \text{P-a.s.}$$

i.e. $(f(X_t))_{t \in [0, T]}$ is also an Itô process with drift

$$(\nabla f(X_t))^T Y_t + \frac{1}{2} \text{trace}(Y_t^T (D^2 f)(X_t) Y_t)$$

and diffusion

$$(\nabla f(X_t))^T Y_t \quad t \in [0, T].$$

Remark: Using this you can deduce time dependent version of Itô formula

$$f(t, X_t) = \dots \quad (\text{sheet 4})$$

→ One can also have $f \in C^2(\mathbb{R}^d, \mathbb{R}^n)$

Example: Geometric BM

$$X_t = \xi \cdot \exp\left(\left(\alpha - \frac{\beta^2}{2}\right)t + \beta W_t\right)$$

$\xi, \alpha, \beta \in \mathbb{R}$ are constants

Denote

$$\begin{aligned} X_t &= \left(\alpha - \frac{\beta^2}{2}\right)t + \beta \cdot W_t \\ &= \int_0^t \left(\alpha - \frac{\beta^2}{2}\right) ds + \int_0^t \beta dW_s \\ &= X_0 + \underbrace{\int_0^t \left(\alpha - \frac{\beta^2}{2}\right) ds}_{Y_s} + \underbrace{\int_0^t \beta dW_s}_{Z_s} \end{aligned}$$

X is an Itô process. $f(y) = \xi \cdot e^y$

$$X_t = f(X_t) = f(X_0) + \int_0^t f'(X_s) \cdot \left(\alpha - \frac{\beta^2}{2}\right) ds$$

$Y_0 = \xi$, $t \in [0, T]$

Next time: SDEs, existence uniqueness, examples.

$$+ \frac{1}{2} \int_0^t \beta^2 \cdot f''(X_s) ds + \int_0^t f'(X_s) \beta dW_s \quad (3)$$

$$= f(X_0) + \int_0^t \left[\alpha \cdot e^{X_s} \left(2 - \frac{\beta^2}{2} \right) + \frac{1}{2} \beta^2 \xi \cdot e^{X_s} \right] ds$$

$$+ \int_0^t \xi \cdot e^{X_s} \cdot \beta \cdot dW_s$$

$$= \xi + \int_0^t \xi \cdot e^{X_s} \alpha ds + \int_0^t \xi \cdot e^{X_s} \cdot \beta dW_s$$

$$= \xi + \int_0^t \alpha \cdot \tilde{X}_s ds + \int_0^t \beta \cdot \tilde{X}_s dW_s$$

$$\Rightarrow \tilde{X}_t = \xi + \int_0^t \alpha \tilde{X}_s ds + \int_0^t \beta \tilde{X}_s dW_s$$

\tilde{X} is a sol-n of the stochastic differential eq-n (SDE)

$$dY_t = \alpha Y_t dt + \beta Y_t dW_{t,1}$$