

Stochastic Differential Equations

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Definition*: 1-dimensional Ito process

- * Let B_t be a 1-dimensional Brownian motion on (Ω, \mathcal{F}, P) .
An Ito process is a stochastic process X_t of the form

$$X_t = X_0 + \int_0^t u(s, \omega) ds + \int_0^t v(s, \omega) dB_s$$

where $v \in \mathcal{W}_{\mathcal{H}}$, so that

$$P \left[\int_0^t v(s, \omega)^2 ds < \infty \text{ for all } t \geq 0 \right] = 1$$

and u is \mathcal{H}_t - adapted and

$$P \left[\int_0^t |u(s, \omega)| ds < \infty \text{ for all } t \geq 0 \right] = 1$$

Theorem: 1-dimensional Ito formula

* Let X_t be an Ito process given by $dX_t = udt + vdB_t$. Let $g(t, x) \in C^2([0, \infty) \times \mathbb{R})$. Then, $Y_t = g(t, X_t)$ is again an Ito process, and

$$dY_t = \frac{\partial g}{\partial t}(t, X_t)dt + \frac{\partial g}{\partial x}(t, X_t)dX_t + \frac{1}{2} \frac{\partial^2 g}{\partial x^2}(t, X_t) \cdot (dX_t)^2$$

where $(dX_t)^2 = (dX_t) \cdot (dX_t)$ is computed according to the rules

$$dt \cdot dt = dt \cdot dB_t = dB_t \cdot dt = 0, \quad dB_t \cdot dB_t = dt$$

Theorem 5.2.1

Let $T > 0$ and $b : [0, T] \times \mathbb{R}^n \rightarrow \mathbb{R}^n$, $\sigma : [0, T] \times \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$ be measurable functions satisfying

$$|b(t, x)| + |\sigma(t, x)| \leq C(1 + |x|); \quad x \in \mathbb{R}^n, t \in [0, T] \quad (5.2.1)$$

for some constant C , where $|\sigma|^2 = \sum |\sigma_{ij}|^2$ and such that

$$|b(t, x) - b(t, y)| + |\sigma(t, x) - \sigma(t, y)| \leq D|x - y|; \quad x, y \in \mathbb{R}^n, t \in [0, T]. \quad (5.2.2)$$

for some constant D . Let Z be a random variable which is independent of the σ -algebra $\mathcal{F}_\infty^{(m)}$ generated by $B_s, s \geq 0$ and such that

$$E[|Z|^2] < \infty.$$

Then, the stochastic differential equation

$$dX_t = b(t, X_t)dt + \sigma(t, X_t)dB_t, 0 \leq t \leq T, X_0 = Z. \quad (5.2.3)$$

has a unique t -continuous solution $X_t(\omega)$ with the following property:

Theorem 5.2.1 Continued

$X_t(\omega)$ is adapted to the filtration \mathcal{F}_t^Z generated by Z and $B_s(\cdot); s \leq t$ and

$$E \left[\int_0^T |X_t|^2 dt \right] < \infty.$$

- * Conditions (5.2.1) and (5.2.2) are natural in view of the following two simple examples from DDE.

Remark (a)

* The equation

$$\frac{dX_t}{dt} = X_t^2, X_0 = 1$$

has a unique solution

$$X_t = \frac{1}{1-t}; 0 \leq t < 1.$$

Remark (b)

* The equation

$$\frac{dX_t}{dt} = 3X_t^{2/3}; X_0 = 0 \quad (5.2.7)$$

has more than one solution. In fact, for any $a > 0$ the function

$$X_t = \begin{cases} 0 & \text{for } t \leq a \\ (t - a)^3 & \text{for } t > a \end{cases}$$

solves (5.2.7).

Proof of Theorem 5.2.1

- * The uniqueness follows from the Ito isometry and the Lipschitz property.
- * For all $\omega \in \Omega$, let

$$X_1(t, \omega) = X_t(\omega) \quad \text{and} \quad X_2(t, \omega) = \hat{X}_t(\omega)$$

with the initial values of

$$X_1(0, \omega) = Z(\omega) \quad \text{and} \quad X_2(0, \omega) = \hat{Z}_t(\omega)$$

Uniqueness Proof of Theorem 5.2.1

Let $a(s, \omega) = b(s, X_s) - b(s, \hat{X}_s)$ and $\gamma(s, \omega) = \sigma(s, X_s) - \sigma(s, \hat{X}_s)$

Then,

$$\begin{aligned} E[|X_t - \hat{X}_t|^2] &= E\left[\left(Z - \hat{Z} + \int_0^t a ds + \int_0^t \gamma dB_s\right)^2\right] \\ &\leq 3E[|Z - \hat{Z}|^2] + 3E\left[\left(\int_0^t a ds\right)^2\right] + 3E\left[\left(\int_0^t \gamma dB_s\right)^2\right] \\ &\leq 3E[|Z - \hat{Z}|^2] + 3tE\left[\int_0^t a^2 ds\right] + 3E\left[\int_0^t \gamma^2 ds\right] \\ &\leq 3E[|Z - \hat{Z}|^2] + 3(1+t)D^2 \int_0^t E[|X_s - \hat{X}_s|^2] ds. \end{aligned}$$

Uniqueness Proof Continued

* So the function

$$v(t) = E[|X_t - \hat{X}_t|^2]; 0 \leq t \leq T$$

satisfies

$$v(t) \leq F + A \int_0^t v(s) ds,$$

where $F = 3E[|Z - \hat{Z}|^2]$ and $A = 3(1+T)D^2$.

* By the Gronwall inequality, we conclude that

$$v(t) \leq F \exp(At).$$

* Assume that $Z = \hat{Z}$. Then, $F = 0$ and so $v(t) = 0$ for all $t \geq 0$.

The Last Step for Uniqueness

* Hence we obtain

$$P\left[\left|X_t - \hat{X}_t\right| = 0 \forall t \in \mathbf{Q} \cap [0, T]\right] = 1,$$

where \mathbf{Q} denotes the rational numbers.

* By continuity of $t \rightarrow |X_t - \hat{X}_t|$, it follows that

$$P\left[\left|X_1(t, \omega) - X_2(t, \omega)\right| = 0 \forall t \in [0, T]\right] = 1.$$

Existence Proof

* Define $Y_t^{(0)} = X_0$ and $Y_t^{(k)} = Y_t^{(k)}(\omega)$ inductively by

$$Y_t^{(k+1)} = X_0 + \int_0^t b(s, Y_s^{(k)}) ds + \int_0^t \sigma(s, Y_s^{(k)}) dB_s. \quad (5.2.12)$$

* A similar computation as for the uniqueness proof gives

$$E[|Y_t^{(k+1)} - Y_t^{(k)}|^2] \leq (1+T)3D^2 \int_0^t E[|Y_s^{(k+1)} - Y_s^{(k)}|^2] ds \quad \text{for } k \geq 1, t \leq T$$

and

$$E[|Y_t^{(1)} - Y_t^{(0)}|^2] \leq 2C^2 t^2 (1 + E[|X_0|^2]) + 2C^2 t (1 + E[|X_0|^2]) \leq A_1 t,$$

where A_1 only depends on C, T and $E[|X_0|^2]$.

* By induction, we obtain

$$E[|Y_t^{(k+1)} - Y_t^{(k)}|^2] \leq \frac{A_2^{k+1} t^{k+1}}{(k+1)!}; \quad k \geq 0, t \in [0, T]$$

where A_2 only depends on C, D, T and $E[|X_0|^2]$.

Existence Proof Continued

* Let λ denote Lebesgue measure on $[0, T]$ and $m > n \geq 0$.

* Then, we obtain

$$\begin{aligned} \|Y_t^{(m)} - Y_t^{(n)}\|_{L^2(\lambda \times P)} &= \left\| \sum_{k=n}^{m-1} [Y_t^{(k+1)} - Y_t^{(k)}] \right\|_{L^2(\lambda \times P)} \\ &\leq \sum_{k=n}^{m-1} \| [Y_t^{(k+1)} - Y_t^{(k)}] \|_{L^2(\lambda \times P)} = \sum_{k=n}^{m-1} \left(E \left[\int_0^T |Y_t^{(k+1)} - Y_t^{(k)}|^2 dt \right] \right)^{1/2} \\ &\leq \sum_{k=n}^{m-1} \left(\int_0^T \frac{A_2^{k+1} t^{k+1}}{(k+1)!} dt \right)^{1/2} = \sum_{k=n}^{m-1} \left(\frac{A_2^{k+1} T^{k+2}}{(k+2)!} \right)^{1/2} \rightarrow 0 \quad \text{as } m, n \rightarrow \infty. \end{aligned}$$

* Thus, $\{Y_t^{(n)}\}_{n=0}^{\infty}$ is a Cauchy sequence in $L^2(\lambda \times P)$.

Existence Proof Continued

- * Define the limit in $L^2(\lambda \times P)$ by $X_t := \lim_{n \rightarrow \infty} Y_t^{(n)}$.
- * We claim that X_t satisfies (5.2.3).
- * For all n and all $t \in [0, T]$, we have

$$Y_t^{(n+1)} = X_0 + \int_0^t b(s, Y_s^{(n)}) ds + \int_0^t \sigma(s, Y_s^{(n)}) dB_s.$$

- * As $n \rightarrow \infty$, in $L^2(P)$, by the Holder inequality,

$$\int_0^t b(s, Y_s^{(n)}) ds \rightarrow \int_0^t b(s, X_s) ds$$

and by the Ito isometry

$$\int_0^t \sigma(s, Y_s^{(n)}) dB_s \rightarrow \int_0^t \sigma(s, X_s) dB_s.$$

The Last Step in Existence Proof

- * It remains to show that X_t can be chosen to be continuous.
- * By Theorem 3.2.5, there exists a continuous \tilde{X}_t that for almost all ω satisfies:

$$\begin{aligned}\tilde{X}_t &= X_0 + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dB_s \\ &= X_0 + \int_0^t b(s, \tilde{X}_s) ds + \int_0^t \sigma(s, \tilde{X}_s) dB_s\end{aligned}$$

Weak and Strong Solutions

- * Strong solution: The version B_t of Brownian motion is given in advance and the solution X_t constructed from it is $\mathcal{F}_t^{(Z)}$ adapted.
- * Weak solution: if we are given only the functions $b(t, x)$ and $\sigma(t, x)$, and ask for a pair of processes $((\tilde{X}_t, \tilde{B}_t), \mathcal{H}_t)$ on a probability space (Ω, \mathcal{H}, P) such that (5.2.3) holds, then the solution \tilde{X}_t is called a weak solution.
- * A strong solution is a weak solution
- * But the reverse is not true.
- * “Weak uniqueness” means that any two solutions are identical in law.

Lemma 5.3.1

- * If b and σ satisfy the conditions of Theorem 5.2.1, then we have

A solution (weak or strong) of (5.2.3) is weakly unique.

- * Sketch of Proof: Let

$$\left(\left(\tilde{X}_t, \tilde{B}_t \right), \tilde{\mathcal{H}}_t \right) \quad \text{and} \quad \left(\left(\hat{X}_t, \hat{B}_t \right), \hat{\mathcal{H}}_t \right)$$

be two weak solutions. Let

$$X_t \quad \text{and} \quad Y_t$$

be strong solutions constructed from \tilde{B}_t and \hat{B}_t .

- * The same uniqueness argument applies to show that

$$X_t = \tilde{X}_t \quad \text{and} \quad Y_t = \hat{X}_t \quad \text{for all } t \text{ a.s.}$$

Sketch of Proof Continued

- * It suffices to show that

$$X_t \quad \text{and} \quad Y_t$$

are identical in law.

- * We can show this by induction that if

$$X_t^{(k)} \quad \text{and} \quad Y_t^{(k)}$$

are the process in the Picard iteration defined by (5.2.12) with Brownian motions \tilde{B}_t and \hat{B}_t , then

$$\left(X_t^{(k)}, \tilde{B}_t \right) \quad \text{and} \quad \left(Y_t^{(k)}, \hat{B}_t \right)$$

have the same law for all k .

The Tanaka equation

- * Consider the 1-dimensional stochastic differential equation

$$dX_t = \text{sign}(X_t)dB_t; \quad X_0 = 0, \quad (5.3.1)$$

where

$$\text{sign}(x) = \begin{cases} +1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}.$$

- * The Tanaka equation does not have a strong solution.
- * Proof: Let \hat{B}_t be a Brownian motion generating the filtration and define

$$Y_t = \int_0^t \text{sign}(\hat{B}_s) d\hat{B}_s.$$

Proof Continued

- * By The Tanaka formula, we have

$$Y_t = |\hat{B}_t| - |\hat{B}_0| - \hat{L}_t(\omega)$$

where $\hat{L}_t(\omega)$ is the local time for $\hat{B}_t(\omega)$ at 0.

- * It follows that Y_t is measurable w.r.t the σ -algebra \mathcal{G}_t generated by $|\hat{B}_s(\cdot)|; s \leq t$ which is strictly contained in $\widehat{\mathcal{F}}_t$.
- * Hence, the σ -algebra \mathcal{N}_t generated by $|Y_s(\cdot)|; s \leq t$ is also strictly contained in $\widehat{\mathcal{F}}_t$.

Theorem 8.4.2

* An Ito process

$$dY_t = v dB_t; \quad Y_0 = 0 \quad \text{with } v(t, \omega) \in \mathcal{V}_{\mathcal{H}}^{n \times m}$$

coincides (in law) with n-dimensional Brownian motion if and only if

$$vv^T(t, \omega) = I_n \quad \text{for a.a. } (t, \omega) \text{ w.r.t. } dt \times dP$$

where I_n is the n-dimensional identity matrix.

Proof Continued

- * Suppose that X_t is a strong solution.
- * Then, by Theorem 8.4.2, it is a Brownian motion w.r.t. P .
- * Let \mathcal{M}_t be the σ -algebra generated by $|X_s(\cdot)|; s \leq t$.
- * Rewrite (5.3.1) as

$$dB_t = \text{sign}(X_t)dX_t.$$

- * This contradicts that X_t is a strong solution because:
 - * Let $\hat{B}_t = X_t, Y_t = B_t$ in this argument.
 - * Then, \mathcal{F}_t is strictly contained in \mathcal{M}_t .

Weak Solution

- * Choose X_t to be any Brownian motion \hat{B}_t .
- * Define \tilde{B}_t by:

$$d\tilde{B}_t = \text{sign}(X_t) dX_t.$$

- * Then,

$$dX_t = \text{sign}(X_t) d\tilde{B}_t.$$