

Lecture 20: (Chap. 7, cont.)

We now begin with the discussion of stochastic differential equations.
The next theorem provides a basic result.

Theorem: (Picard's iterative method)

Assume that $b(\cdot): \mathbb{R}^d \rightarrow \mathbb{R}^d$, and $\sigma(\cdot): \mathbb{R}^d \rightarrow M_{d \times n}$ satisfy the Lipschitz condition

$$(7.3) \quad |b(y) - b(z)| + |\sigma(y) - \sigma(z)| \leq K|y - z|, \text{ for } y, z \in \mathbb{R}^d.$$

Then for any $(\Omega, \mathcal{G}, (\mathcal{G}_t)_{t \geq 0}, \mathbb{P})$ and $B_t, t \geq 0$, as on p. 122, and any $x \in \mathbb{R}^d$, there exists an essentially unique continuous (\mathcal{G}_t) -adapted

$$(7.4) \quad X_t = x + \int_0^t b(X_s) ds + \int_0^t \sigma(X_s) \cdot dB_s.$$

Proof:

— uniqueness:

Consider X, Y two solutions. For $M > |x|$, we define

$$(7.5) \quad T = \inf\{u \geq 0; |X_u| \text{ or } |Y_u| \geq M\},$$

so that P-a.s., for all $t \geq 0$,

$$X_{t \wedge T} - Y_{t \wedge T} = \int_0^{t \wedge T} (b(X_u) - b(Y_u)) du + \int_0^{t \wedge T} (\sigma(X_u) - \sigma(Y_u)) \cdot dB_u.$$

As a result we see that for $t_0 > 0$:

$$E \left[\sup_{t \leq t_0} |X_{t \wedge T} - Y_{t \wedge T}|^2 \right] \leq 2 E \left[\sup_{t \leq t_0} \left| \int_0^{t \wedge T} (\sigma(X_u) - \sigma(Y_u)) \cdot dB_u \right|^2 \right] \\ + 2 t_0 E \left[\int_0^{t_0 \wedge T} |b(X_u) - b(Y_u)|^2 du \right].$$

Using Doob's inequality (4.76), with $p=2$, for each component of the \mathbb{R}^d -valued stochastic integral we find that

$$(7.6) \quad E \left[\sup_{t \leq t_0} |X_{t \wedge T} - Y_{t \wedge T}|^2 \right] \leq 8 E \left[\left| \int_0^{t_0 \wedge T} (\sigma(X_u) - \sigma(Y_u)) \cdot dB_u \right|^2 \right] \\ + 2 t_0 E \left[\int_0^{t_0 \wedge T} |b(X_u) - b(Y_u)|^2 du \right].$$

On the other hand one has:

$$\begin{aligned}
 (7.7) \quad E\left[\left|\int_0^{t_0 \wedge T} (\sigma(X_u) - \sigma(Y_u)) \cdot dB_u\right|^2\right] &= \sum_{i=1}^d E\left[\left(\sum_{j=1}^n \int_0^{t_0 \wedge T} (\sigma_{ij}(X_u) - \sigma_{ij}(Y_u)) dB_u^j\right)^2\right] \\
 &= \sum_{i=1}^d E\left[\sum_{1 \leq j, k \leq n} \int_0^{t_0 \wedge T} (\sigma_{ij}(X_u) - \sigma_{ij}(Y_u)) dB_u^j \int_0^{t_0 \wedge T} (\sigma_{ik}(X_u) - \sigma_{ik}(Y_u)) dB_u^k\right] \\
 \stackrel{(5.90)}{=} \sum_{i=1}^d \sum_{1 \leq j, k \leq n} E\left[\int_0^{t_0 \wedge T} (\sigma_{ij}(X_u) - \sigma_{ij}(Y_u)) (\sigma_{ik}(X_u) - \sigma_{ik}(Y_u)) d\langle B^j, B^k \rangle_u\right] \\
 &= \sum_{i=1}^d \sum_{j=1}^n E\left[\int_0^{t_0 \wedge T} (\sigma_{ij}(X_u) - \sigma_{ij}(Y_u))^2 du\right] \\
 &= E\left[\int_0^{t_0 \wedge T} |\sigma(X_u) - \sigma(Y_u)|^2 du\right].
 \end{aligned}$$

Inserting (7.7) in the right-hand side of (7.6), and taking (7.3) into account we find that for any $t_0 \geq 0$:

$$(7.8) \quad E\left[\sup_{\Delta \leq t_0} |X_{\Delta \wedge T} - Y_{\Delta \wedge T}|^2\right] \leq (8K^2 + 2t_0 K^2) \int_0^{t_0} E[|X_{u \wedge T} - Y_{u \wedge T}|^2] du$$

The next result will be helpful.

Lemma: (Gronwall's lemma)

Let f be a non-negative integrable function on $[0, t]$ such that for some $a, b \geq 0$, and all $0 \leq u \leq t$:

$$f(u) \leq a + b \int_0^u f(s) ds,$$

then

$$(7.9) \quad f(u) \leq a e^{bu}, \quad \text{for all } 0 \leq u \leq t.$$

Proof:

Iterating the inequality satisfied by f , we see that for $0 \leq u \leq t$,

$$\begin{aligned}
 f(u) &\leq a + b \int_0^u f(s) ds \leq a + bau + b^2 \int_0^u ds_1 \int_0^{s_1} f(s_2) ds_2 \leq \dots \\
 &\leq a + bau + \frac{1}{2} b^2 a u^2 + \dots + \frac{1}{n!} b^n a u^n + b^{n+1} \int_0^u ds_1 \int_0^{s_1} ds_2 \dots \int_0^{s_{n-1}} f(s_n) ds_n \\
 &\leq a e^{bu} + b^{n+1} \int_0^u \frac{(u-s)^n}{n!} f(s) ds \leq a e^{bu} + b^{n+1} \frac{u^n}{n!} \int_0^u f(s) ds.
 \end{aligned}$$

Letting $n \rightarrow \infty$, we find (7.9). \square

We will now apply the above lemma with the choice

$f(u) = E \left[\sup_{\Delta \leq u} |X_{\Delta \wedge T} - Y_{\Delta \wedge T}|^2 \right] (\geq E[|X_{u \wedge T} - Y_{u \wedge T}|^2])$, $0 \leq u \leq t$, $t > 0$,
 $a = 0$, $b = K^2(8+2t)$, and find that (with t some positive number)

$$(7.10) \quad f(u) = 0, \text{ for } 0 \leq u \leq t.$$

Letting M in (7.5) tend to infinity, and then $t \rightarrow \infty$,

$$(7.11) \quad \text{P.a.s., } X_u = Y_u, \text{ for all } u \geq 0,$$

(such a statement is called a strong uniqueness result).

Existence:

We iteratively define for $m \geq 0$, $t \geq 0$,

$$(7.12) \quad \left\{ \begin{array}{l} X_t^0 \equiv x, \\ X_t^1 = x + \int_0^t b(X_s^0) ds + \int_0^t \sigma(X_s^0) dB_s \\ \vdots \\ X_t^{m+1} = x + \int_0^t b(X_s^m) ds + \int_0^t \sigma(X_s^m) dB_s \end{array} \right.$$

Then for $m \geq 1$:

$$(7.13) \quad X_t^{m+1} - X_t^m = \int_0^t (b(X_s^m) - b(X_s^{m+1})) ds + \int_0^t (\sigma(X_s^m) - \sigma(X_s^{m+1})) dB_s, \text{ for } t \geq 0,$$

If we now pick $M > |x|$, and define

$$T_M = \inf \{ u \geq 0; |X_u^m| \text{ or } |X_u^{m+1}| \geq M \},$$

the same calculation as for (7.8) yields that for $0 \leq t_0 \leq t$

$$(7.14) \quad E \left[\sup_{\Delta \leq t_0 \wedge T_M} |X_{\Delta}^{m+1} - X_{\Delta}^m|^2 \right] \leq (8+2t) K^2 \int_0^{t_0} E[|X_{u \wedge T_M}^m - X_{u \wedge T_M}^{m-1}|^2] du.$$

Now $\sup_{\Delta \leq t} |X_{\Delta}^0| = |x|$, $\sup_{\Delta \leq t} |X_{\Delta}^1| \in L^2(P)$, by (7.12).

We now see from (7.14), with $m=1$, letting $M \rightarrow \infty$, that

$\sup_{\Delta \leq t} |X_{\Delta}^2| \in L^2(P)$, and repeating the argument that

$$(7.15) \quad \sup_{\Delta \leq t} |X_{\Delta}^m| \in L^2(P), \text{ for any } m \geq 0, \text{ and } t \geq 0.$$

Coming back to (7.14) we can thus let $M \rightarrow \infty$ and find that for $0 \leq t_0 \leq t$:

$$(7.16) \ E \left[\sup_{\Delta \leq t_0} |X_{\Delta}^{m+1} - X_{\Delta}^m|^2 \right] \leq K^2(8+2t) \int_0^{t_0} E[|X_u^m - X_u^{m-1}|^2] du$$

and iterating

$$\leq \{K^2(8+2t)\}^m \int_0^{t_0} dt_1 \int_0^{t_1} dt_2 \dots \int_0^{t_{m-1}} dt_m E[|X_{t_m}^1 - X_{t_m}^0|^2].$$

With (7.12) we also have:

$$(7.17) \ E[|X_{t_m}^1 - X_{t_m}^0|^2] \leq 2|b(x)|^2 t_m^2 + 2E[|\sigma(x) \cdot B_{t_m}|^2] \\ \leq K'(x, t) t_m, \text{ for } 0 \leq t_m \leq t.$$

Hence we (7.16) we obtain that

$$(7.18) \ E \left[\sup_{\Delta \leq t} |X_{\Delta}^{m+1} - X_{\Delta}^m|^2 \right] \leq K'(x, t) \frac{(8K^2 + 2tK^2)^m}{(m+1)!} t^{m+1}, \text{ for } t > 0, m \geq 0.$$

We have thus proved that for $t > 0$,

$$(7.19) \ \sum_{m \geq 0} E \left[\sup_{\Delta \leq t} |X_{\Delta}^{m+1} - X_{\Delta}^m|^2 \right]^{1/2} < \infty.$$

As a consequence P.-a.s., X^m converges uniformly on bounded time intervals to X^{∞} , which can be chosen

(\mathcal{G}_t) -adapted continuous, (see for instance (4.75)), and

$$(7.20) \ E \left[\sup_{\Delta \leq t} |X_{\Delta}^{\infty} - X_{\Delta}^m|^2 \right]^{1/2} \stackrel{\text{Fubini}}{\leq} \liminf_{P \rightarrow \infty} E \left[\sup_{\Delta \leq t} |X_{\Delta}^P - X_{\Delta}^m|^2 \right]^{1/2} \leq$$

$$\sum_{k=m}^{\infty} E \left[\sup_{\Delta \leq t} |X_{\Delta}^{k+1} - X_{\Delta}^k|^2 \right]^{1/2} \xrightarrow{m \rightarrow \infty} 0, \text{ for } t > 0.$$

Hence we see that for $t > 0$, P.-a.s.

$$X_t^{m+1} = x + \int_0^t b(X_u^m) du + \int_0^t \sigma(X_u^m) dB_u$$

$$\downarrow^{L^2} \quad \downarrow^{L^2} \quad \downarrow^{L^2}$$

$$X_t^{\infty} = x + \int_0^t b(X_u^{\infty}) du + \int_0^t \sigma(X_u^{\infty}) dB_u,$$

and in view of the continuity of X^{∞} , we see that P.-a.s.

$$(7.21) \ X_t^{\infty} = x + \int_0^t b(X_u^{\infty}) du + \int_0^t \sigma(X_u^{\infty}) dB_u, \text{ for } u \geq 0.$$

Hence X^{∞} is a solution of (7.4). □

Remark:

From the definition of the X^m in (7.12), and the fact that

P.a.s., X_t^m converges uniformly to X_t^∞ on compact time intervals, we see that for each $t \geq 0$:

(7.22) $\mathcal{F}_t^{X^\infty} = \text{def}$ the smallest σ -algebra containing all negligible sets of \mathcal{G} and making X_s^∞ measurable for $s \leq t \in \mathcal{F}_t^{B_0}$, (defined analogously, with B_0 in place of X_0^∞).

Due to (7.22), X_t^∞ is called a strong solution of (7.4), (intuitively X_t^∞ is a function of the noise B_0).

The above theorem shows that for any $(\Omega, \mathcal{G}, (\mathcal{G}_t)_{t \geq 0}, \mathbb{P})$, $(B_t)_{t \geq 0}$, we have a strong solution of (7.4), which is strongly unique, cf. (7.11). \square

We will now see that solutions of stochastic differential equations (SDE's) can be used to represent solutions of certain partial differential equations (PDE's).

We begin with a result that will also be helpful in the subsequent discussion of martingale problems.

Proposition:

Assume that $b(\cdot): \mathbb{R}^d \rightarrow \mathbb{R}^d$, $\sigma(\cdot): \mathbb{R}^d \rightarrow M_{d \times n}$ are measurable locally bounded functions, $x \in \mathbb{R}^d$, and in some $(\Omega, \mathcal{G}, (\mathcal{G}_t)_{t \geq 0}, \mathbb{P})$ endowed with an n -dimensional (\mathcal{G}_t) -Brownian motion $(B_t)_{t \geq 0}$, a continuous adapted \mathbb{R}^d -valued, $(X_t)_{t \geq 0}$, satisfies P.a.s., for $t \geq 0$:

$$(7.23) X_t = x + \int_0^t b(X_s) ds + \int_0^t \sigma(X_s) \cdot dB_s,$$

then for any $f \in C^2(\mathbb{R}^d, \mathbb{R})$,

(7.24) $M_t^f \stackrel{\text{def}}{=}} f(X_t) - f(X_0) - \int_0^t L f(X_s) ds$, $t \geq 0$, is a continuous local martingale where we used the notation

$$(7.25) L f(y) = \frac{1}{2} \sum_{1 \leq i, j \leq d} a_{ij}(y) \partial_{ij}^2 f(y) + \sum_{1 \leq i \leq d} b_i(y) \partial_i f(y), \quad a(y) = \sigma(y) \sigma(y)^T, \quad \text{for } y \in \mathbb{R}^d.$$

$\in M_{d \times d}$

Proof:

We apply Ito's formula and find that P. a. s., for $t \geq 0$:

$$(7.26) \quad f(X_t) = f(X_0) + \sum_{i=1}^d \int_0^t \partial_i f(X_s) dX_s^i + \frac{1}{2} \sum_{i,j=1}^d \int_0^t \partial_{ij}^2 f(X_s) d\langle X^i, X^j \rangle_s.$$

Note that from (5.90) and (7.23) follows

$$(7.27) \quad \langle X^i, X^j \rangle_t = \left\langle \sum_{k=1}^m \int_0^t \sigma_{i,k}(X_u) dB_u^k, \sum_{l=1}^m \int_0^t \sigma_{j,l}(X_u) dB_u^l \right\rangle \\ = \sum_{k=1}^m \int_0^t \sigma_{i,k}(X_u) \sigma_{j,k}(X_u) du = \int_0^t a_{ij}(X_u) du.$$

Hence coming back to (7.26), we find that P. a. s., for $t \geq 0$,

$$(7.28) \quad f(X_t) = f(X_0) + \sum_{i=1}^d \int_0^t \partial_i f(X_s) b_i(X_s) ds + \sum_{i=1}^d \sum_{k=1}^m \int_0^t \partial_i f(X_s) \sigma_{i,k}(X_s) dB_s^k \\ + \frac{1}{2} \sum_{i,j=1}^d \int_0^t a_{ij}(X_s) \partial_{ij}^2 f(X_s) ds \\ = f(X_0) + \int_0^t Lf(X_s) ds + \int_0^t \nabla f(X_s) \cdot \underbrace{\sigma(X_s)}_{\substack{\uparrow \\ \text{scalar product}}} \cdot \underbrace{dB_s}_{\substack{\uparrow \\ \text{d-vector}}}.$$

The claim (7.24) now follows. □