

Relation between PDE and Brown motion:

- ▶ As a simple application of Itô's formula and Doob's optional sampling theorem, we give a probabilistic representation of the solution of  $\Delta u = 0$  on a bounded set  $D$  with Dirichlet boundary condition.

[Theorem 13.2] (Kakutani's theorem) Let  $D \subset \mathbb{R}^d$  be a bounded open set and let  $u \in C^2(D) \cap C(\bar{D})$  satisfy

$$\begin{cases} \Delta u(x) \equiv \sum_{i=1}^d \frac{\partial^2 u}{\partial x_i^2} = 0, & x \in D \\ u(x) = f(x), & x \in \partial D, \end{cases}$$

with  $f \in C(\partial D)$ . For simplicity, we assume that  $u$  can be extended to  $D^c$  such that  $u \in C_b^2(\mathbb{R}^d)$ .

$\implies$

$\implies$  We have

$$u(x) = E_x[f(B_\sigma)], \quad x \in D,$$

where  $E_x$  denotes the expectation for the  $d$ -dimensional Brown motion  $(B_t)$  starting at  $x$  and  $\sigma$  is the first hitting time to the boundary  $\partial D$ :

$$\sigma := \inf\{t > 0; B_t \in \partial D\}$$

(As before, we set  $\sigma = \infty$ , if the set  $\{\dots\}$  inside of  $\inf$  is  $\emptyset$ .)  
Actually,  $\sigma < \infty$  a.s. holds. In particular, the solution of the above Dirichlet problem is unique.  $\square$

- ▶ Later, Theorem 13.2 will be extended from  $\Delta$  to more general elliptic differential operators by means of stochastic differential equations.

[Proof of Theorem 13.2] • First, we show  $\sigma < \infty$  a.s.

☺ Since  $D$  is bounded,  $\exists R > 0$  s.t.  $D \subset B(x, R)$ , which is a closed ball with center  $x$  and radius  $R > 0$ . Therefore,

$$\begin{aligned} P_x(\sigma = \infty) &\leq P_x(\sigma_{\partial B(x,R)} = \infty) \leq P_x(\sigma_{\partial B(x,R)} > t) \quad (\forall t > 0) \\ &\leq P_0(B_t \in B(0, R)) = \int_{B(0,R)} \frac{1}{(2\pi t)^{d/2}} e^{-\frac{|x|^2}{2t}} dx \xrightarrow{t \rightarrow \infty} 0 \quad \square \end{aligned}$$

• Since we assume  $u \in C_b^2(\mathbb{R}^d)$ , one can apply Itô's formula to  $u(B_t)$  and obtain, in the form of stochastic differential:

$$du(B_t) = \frac{\partial u}{\partial x_i}(B_t) dB_t^i + \frac{1}{2} \frac{\partial^2 u}{\partial x_i \partial x_j}(B_t) dB_t^i dB_t^j.$$

However, recalling  $dB_t^i dB_t^j = \delta^{ij} dt$  and writing in integrated form, we obtain

$$u(B_t) = u(x) + \sum_{i=1}^d \int_0^t \frac{\partial u}{\partial x_i}(B_s) dB_s^i + \frac{1}{2} \int_0^t \Delta u(B_s) ds.$$

In particular,  $u(B_{t \wedge \sigma})$  is a bounded martingale.  
(filtration  $(\mathcal{F}_t)$  is the same as that for  $(\mathcal{F}_t)$ -Brown motion  $B$ )



- boundedness follows from  $u \in C_b^2(\mathbb{R}^d)$  (or  $u$  is bounded on  $\bar{D}$ )
- Denote the stochastic integral in the RHS of  $u(B_t)$  by  $M_t$ . Then,  $M$  is a martingale. However, since  $\sigma$  is a Markov time, by Doob's optional sampling theorem,  $M_{t \wedge \sigma}$  is a martingale.
- Denote the last term in the RHS of  $u(B_t)$  by  $A_t$ . Then, since  $\Delta u(B_s) = 0, s < \sigma$ , we see  $A_{t \wedge \sigma} = 0$ . □

Therefore, we obtain

$$u(x) \underset{\forall t > 0}{=} E_x[u(B_{t \wedge \sigma})] \xrightarrow{t \rightarrow \infty} E_x[u(B_\sigma)] = E_x[f(B_\sigma)].$$

Indeed,

- the 1st identity follows from the martingale property shown above,
- the limit as  $t \rightarrow \infty$  is shown by Lebesgue's convergence theorem noting that  $\sigma < \infty$  a.s. and  $u$  is bounded.
- The last equality follows from  $B_\sigma \in \partial D$  and  $u = f$  on  $\partial D$ . In fact, " $B_\sigma \in \partial D$ " is shown noting that, by the definition of  $\sigma$ ,  $\exists t_n \downarrow \sigma$  s.t.  $B_{t_n} \in \partial D$  and  $\partial D$  is a closed set.

This concludes the proof of Theorem 13.2. □

## §14 Stochastic differential equations

- ▶ For a given time-dependent vector field  $b = b(t, x)$  on  $\mathbb{R}^d$ , one can consider an ordinary differential equation (ODE) for  $X_t \in \mathbb{R}^d$ :

$$\dot{X}_t \left( = \frac{dX_t}{dt} \right) = b(t, X_t).$$

- ▶ The stochastic differential equation (SDE) is formally a randomization of ODE:

$$\dot{X}_t = b(t, X_t) + \alpha(t, X_t) \dot{B}_t.$$

- ▶  $\dot{B}_t$  actually does not exist, but formally it is given by  $\dot{B}_t = \lim_{h \downarrow 0} \frac{1}{h} (B_{t+h} - B_t)$  so that, by the independence of increments,  $\dot{B}_t$  is considered to be independent for different  $t$ .
- ▶ In other words, we consider the system with an external noise which is created independently for each  $t$ .
- ▶  $\alpha = \alpha(t, x)$  describes the strength of noise at  $(t, x)$ .

- ▶ More precisely, let **continuous** functions

$\alpha : [0, \infty) \times \mathbb{R}^d \rightarrow \mathbb{R}^{d \times N}$  denoted by

$$\alpha = \alpha(t, x) \equiv (\alpha_k^i(t, x))_{1 \leq i \leq d, 1 \leq k \leq N},$$

$b : [0, \infty) \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  denoted by

$$b = b(t, x) \equiv (b^i(t, x))_{1 \leq i \leq d}$$

and

$B_t = (B_t^k)_{1 \leq k \leq N}$ :  $N$ -dimensional  $(\mathcal{F}_t)$ -Brownian motion defined on a probability space  $(\Omega, \mathcal{F}, P)$

be given.

- ▶ We denote  $\mathbb{R}^{d \times N} = \{d \times N \text{ real matrices}\}$ .

- Then, **stochastic differential equation (SDE)** is the following formal equation for  $X_t = (X_t^i)_{1 \leq i \leq d} \in \mathbb{R}^d$ , written in terms of stochastic differentials

$$dX_t = \alpha(t, X_t) dB_t + b(t, X_t) dt \quad (1)$$

or written componentwisely

$$dX_t^i = \sum_{k=1}^N \alpha_k^i(t, X_t) dB_t^k + b^i(t, X_t) dt, \quad 1 \leq i \leq d.$$

- We call  $\alpha$  the **diffusion coefficient** and  $b$  the **drift coefficient**.



Mathematically, the SDE (1) is defined in an integrated form:

[Definition 14.1]  $X = (X_t)_{t \geq 0}$  is called a solution of the SDE (1) starting at  $x \in \mathbb{R}^d$ , if  $X$  is an  $(\mathcal{F}_t)$ -adapted and measurable (as a map  $X : [0, \infty) \times \Omega \rightarrow \mathbb{R}^d$ )  $\mathbb{R}^d$ -valued continuous stochastic process defined on  $(\Omega, \mathcal{F}, P)$  and satisfies

1. For  $\forall i, k$ ,  $\alpha_k^i(t, X_t) \in \mathcal{L}^2(\mathcal{F}_t)$ ,  $b^i(t, X_t) \in L_{loc}^1([0, \infty))$  a.s. (i.e.  $\int_0^T |b^i(t, X_t)| dt < \infty, \forall T \geq 0$  a.s.) and
2. the following stochastic integral equation is satisfied:

$$X_t = x + \int_0^t \alpha(s, X_s) dB_s + \int_0^t b(s, X_s) ds \quad (2)$$

or componentwisely,

$$X_t^i = x^i + \sum_{k=1}^N \int_0^t \alpha_k^i(s, X_s) dB_s^k + \int_0^t b^i(s, X_s) ds, \quad 1 \leq i \leq d.$$

Especially,  $(\mathcal{F}_t^B)$ -adapted solution is called a strong solution.



[Remark] • By the condition 1, each term in the RHS of (2) has meaning. • Strong solution is a solution.

- ▶ In the theory of ODEs, the simplest condition to guarantee the existence and uniqueness of a solution is the **Lipschitz condition** for the coefficients.
- ▶ Similar theorem holds also for the SDEs, which is a stochastic version of Cauchy's theorem.
- ▶ Euclidean norms of  $\alpha \in \mathbb{R}^{d \times N}$  and  $b \in \mathbb{R}^d$  are defined by

$$\|\alpha\| := \sqrt{\sum_{i=1}^d \sum_{k=1}^N (\alpha_k^i)^2}, \quad |b| = \sqrt{\sum_{i=1}^d (b^i)^2}.$$

[Theorem 14.1] Assume that the coefficients  $\alpha, b$  are continuous in  $(t, x)$  and (globally) Lipschitz continuous in  $x$ , i.e. for  $\forall T > 0$ , there exists  $K = K_T > 0$  such that

$$\|\alpha(t, x) - \alpha(t, y)\| + |b(t, x) - b(t, y)| \leq K|x - y|$$

for  $\forall t \in [0, T], \forall x, y \in \mathbb{R}^d$ . Then, for each starting point  $x$ , a strong solution  $X = (X_t^i)$  of (1) exists and the solution is unique. i.e. If two solutions  $X, X' (\in \mathcal{L}_T^2)$  with the same starting point exist, then  $P(X_t = X'_t, \forall t \geq 0) = 1$  holds. We call such uniqueness the pathwise uniqueness.  $\square$

- ▶ The Lipschitz condition and the continuity of the coefficients imply the linear growth condition (which is non-explosion condition for the solution):

$$\|\alpha(t, x)\| + |b(t, x)| \leq K'(1 + |x|), \quad t \in [0, T], x \in \mathbb{R}^d,$$

with some  $K' = K'_T$ .

[Proof of Theorem 14.1]

[Step 1] Construction of strong solution:

• It is enough to consider for  $t \in [0, T]$  for every fixed  $T > 0$ . We apply **Picard's successive approximation**. Namely, we set  $X_t^{(1)} = x$  for  $n = 1$  and then, if  $X_t^{(n-1)}$  is determined, we define  $X_t^{(n)}$ ,  $n \geq 2$  by

$$X_t^{(n)} = x + \int_0^t \alpha(s, X_s^{(n-1)}) dB_s + \int_0^t b(s, X_s^{(n-1)}) ds. \quad (3)$$

- First we show by induction that  $X^{(n)} \in \mathcal{L}_T^2$  and  $X_t^{(n)}$  is  $(\mathcal{F}_t^B)$ -adapted. (Once this is shown, we see that the stochastic integral in (3) is well-defined.)
  - Indeed, this is obvious for  $n = 1$ .
  - If this is shown for  $n - 1$ , since  $\alpha$  is of linear growth, by  $X^{(n-1)} \in \mathcal{L}_T^2$ , we see  $\alpha(s, X_s^{(n-1)}) \in \mathcal{L}_T^2$  so that the stochastic integral in (3) is well-defined and  $\in \mathcal{L}_T^2$  is obtained by Itô isometry.
  - For the drift term, one can show it belongs to  $\mathcal{L}_T^2$ .
  - Thus, we observe  $X^{(n)} \in \mathcal{L}_T^2$ .
  - The  $(\mathcal{F}_t^B)$ -adaptedness of  $X_t^{(n)}$  follows by considering the stochastic integral under the filtration  $(\mathcal{F}_t^B)$ .

- To show the convergence of  $X^{(n)}$ , for  $\forall n \geq 3, t \in [0, T]$ ,

$$\begin{aligned}
& E \left[ \sup_{0 \leq r \leq t} |X_r^{(n)} - X_r^{(n-1)}|^2 \right] \\
& \leq 2E \left[ \sup_{0 \leq r \leq t} \left| \int_0^r \{ \alpha(s, X_s^{(n-1)}) - \alpha(s, X_s^{(n-2)}) \} dB_s \right|^2 \right] \\
& \quad + 2E \left[ \sup_{0 \leq r \leq t} \left| \int_0^r \{ b(s, X_s^{(n-1)}) - b(s, X_s^{(n-2)}) \} ds \right|^2 \right] \\
& \leq 8E \left[ \int_0^t \|\alpha(s, X_s^{(n-1)}) - \alpha(s, X_s^{(n-2)})\|^2 ds \right] \\
& \quad + 2tE \left[ \int_0^t |b(s, X_s^{(n-1)}) - b(s, X_s^{(n-2)})|^2 ds \right] \\
& \leq C_1 \int_0^t E \left[ |X_s^{(n-1)} - X_s^{(n-2)}|^2 \right] ds \leq C_1 \int_0^t E \left[ \sup_{0 \leq r \leq s} |X_r^{(n-1)} - X_r^{(n-2)}|^2 \right] ds,
\end{aligned}$$

where  $C_1 = (8 + 2T)K_T^2$ . For the 1st inequality, we first compute  $X_r^{(n)} - X_r^{(n-1)}$  by (3) and then use  $(a + b)^2 \leq 2(a^2 + b^2)$ ,  $a, b \in \mathbb{R}$ . For the 2nd, we apply Doob's inequality, Itô isometry and Schwarz's inequality. For the 3rd, we use the Lipschitz continuity of  $\alpha, b$ .

- We have shown for  $\forall n \geq 3, t \in [0, T]$ :

$$E \left[ \sup_{0 \leq r \leq t} |X_r^{(n)} - X_r^{(n-1)}|^2 \right] \leq C_1 \int_0^t E \left[ \sup_{0 \leq r \leq s} |X_r^{(n-1)} - X_r^{(n-2)}|^2 \right] ds$$

From this estimate and by induction, we obtain

$$E \left[ \sup_{0 \leq r \leq t} |X_r^{(n)} - X_r^{(n-1)}|^2 \right] \leq C_2 \frac{(C_1 t)^{n-2}}{(n-2)!}, \quad \forall t \in [0, T], \forall n \geq 2 \quad (4)$$

where  $C_2 := E \left[ \sup_{0 \leq t \leq T} |X_t^{(2)} - X_t^{(1)}|^2 \right] < \infty$ . (This can be easily checked.) Thus, by using Schwarz's inequality, we have

$$\begin{aligned} E \left[ \sum_{n=2}^{\infty} \sup_{0 \leq t \leq T} |X_t^{(n)} - X_t^{(n-1)}| \right] &= \sum_{n=2}^{\infty} E \left[ \sup_{0 \leq t \leq T} |X_t^{(n)} - X_t^{(n-1)}| \right] \\ &\leq \sum_{n=2}^{\infty} E \left[ \sup_{0 \leq t \leq T} |X_t^{(n)} - X_t^{(n-1)}|^2 \right]^{\frac{1}{2}} \leq \sum_{n=2}^{\infty} a_n < \infty, \end{aligned}$$

where  $a_n := \sqrt{C_2 \frac{(C_1 T)^{n-2}}{(n-2)!}}$ . Note that the last series converges, since  $\frac{a_{n+1}}{a_n} = \sqrt{\frac{CT}{n-1}} \rightarrow 0$ .

In particular, we have shown that

$$\sum_{n=2}^{\infty} \sup_{0 \leq t \leq T} |X_t^{(n)} - X_t^{(n-1)}| < \infty \quad \text{a.s.}$$

This implies that  $X_t^{(n)}$  is a Cauchy sequence in the space  $(C([0, T], \mathbb{R}^d), \|\cdot\|_{\infty})$  a.s. so that it converges uniformly on  $[0, T]$  a.s. Set the limit  $X_t$ . Then, it is a strong solution of the SDE(1). Indeed,

- The limit  $X_t$  is  $(\mathcal{F}_t^B)$ -adapted, since  $X_t^{(n)}$  are  $(\mathcal{F}_t^B)$ -adapted.
- By the estimate (4),  $X_t^{(n)}$  is a Cauchy sequence also in the space  $\mathbb{L}_T^2 = L^2([0, T] \times \Omega)$  so that  $X^{(n)} \rightarrow X$  in  $\mathcal{L}_T^2$ . Thus, by the Lipschitz continuity of  $\alpha$  and Itô isometry, we have

$$\int_0^t \alpha_k^i(s, X_s^{(n-1)}) dB_s^k \longrightarrow \int_0^t \alpha_k^i(s, X_s) dB_s^k \quad \text{in } \mathcal{M}_{c,T}^2,$$

where  $\mathcal{M}_{c,T}^2$  equips the inner product  $E[\langle \cdot, \cdot \rangle_T]$ . In particular, this convergence holds in  $L^2(\Omega)$  for any fixed  $t \in [0, T]$ .



- On the other hand, for the drift term, since  $X_s^{(n-1)} \rightarrow X_s$  uniformly in  $s \in [0, t]$  (a.s.), we have

$$\int_0^t b^i(s, X_s^{(n-1)}) ds \longrightarrow \int_0^t b^i(s, X_s) ds \quad \text{a.s.}$$

- Thus, letting  $n \rightarrow \infty$  (along a subsequence) in (3), we see that (2) holds for  $\forall t \in [0, T]$  (a.s.) However, since the both sides are continuous in  $t$ , we obtain

$$P((2) \text{ holds for } \forall t \in [0, T]) = 1,$$

which shows that  $X_t$  is a desired strong solution.

**[Step 2] Uniqueness of the solution:** Assume that we have two solutions  $X, X' \in \mathcal{L}_T^2$ . Then, as above, we obtain

$$E[|X_t - X'_t|^2] \leq C_1 \int_0^t E[|X_s - X'_s|^2] ds, \quad t \in [0, T].$$

Thus, by **Gronwall's lemma** stated below, we have

$E[|X_t - X'_t|^2] = 0$ . Recalling the continuity of  $X, X'$  in  $t$ , we finally obtain  $P(X_t = X'_t \text{ for } \forall t \geq 0) = 1$ . □

We recall Gronwall's lemma which is introduced and used in the usual course of ODEs.

[Lemma 14.2] Assume  $u(t) \geq 0$  is a continuous function on  $[0, T]$  and satisfies with  $\exists C_1, C_2 \geq 0$  that

$$u(t) \leq C_1 + C_2 \int_0^t u(s) ds, \quad t \in [0, T].$$

Then, we have  $u(t) \leq C_1 e^{C_2 t}, t \in [0, T]$ . □