

# Stochastic Optimal Control & Applications.

Note Title

## §2: Stochastic Integration.

Let's go back to Example 1.1 above, and consider the places where we waved our hands most frantically... To get (3), we derived an approximation:

$$V(X_{t+\delta t}, t+\delta t) - V(X_t, t) \approx \sigma \frac{\partial V}{\partial x} \delta B_t + \left( (1-u_t) \frac{\partial V}{\partial x} + \frac{\partial V}{\partial t} \right) \delta t + \frac{1}{2} \sigma^2 \frac{\partial^2 V}{\partial x^2} (\delta B)^2 + \text{h.o.t.}$$

and used this to obtain a representation for the average change in  $V$ , but how could we improve this?

Consider breaking  $[0, T]$  into  $0, \delta t, 2\delta t, \dots, N\delta t = T$ ,

then:

$$V(X_T, T) - V(X_0, 0) = \sum_{n=1}^{\infty} \left[ V(X_{i\delta t}, i\delta t) - V(X_{(i-1)\delta t}, (i-1)\delta t) \right]$$

and we can try to sum the RHS similarly. Let

$$\phi_t(\omega) = (1-u_t(\omega)) \frac{\partial V}{\partial x}(X_t^u(\omega), t) + \frac{\partial V}{\partial t}(X_t^u(\omega), t),$$

and observe that  $X_t^u$  is a continuous function with probability 1, so if (eg.)  $\frac{\partial V}{\partial x}, \frac{\partial V}{\partial t}$  are continuous

and  $t \mapsto u_t(\omega)$  is measurable with probability 1, then  $\int_0^T \phi_t dt$  exists a.s. and we should expect

$$\sum \phi(i\delta t) \delta t \rightarrow \int_0^T \phi_t dt.$$

The harder question is what happens to the other

terms:  $\sum_{i=1}^N \frac{\partial V}{\partial x}(x_{i\delta t}, i\delta t) \delta B_{i\delta t}, \sum_{i=1}^N \frac{\partial^2 V}{\partial x^2} (\delta B_{i\delta t})^2$

Or more generally  $\sum_{i=1}^N \phi_{i\delta t} \delta B_{i\delta t}, \sum_{i=1}^N \psi_{i\delta t} (\delta B_{i\delta t})^2$   
for some (nice!) stochastic processes  $\phi_t(\omega), \psi_t(\omega)$ .

A major issue is the following - suppose we want to compute  $\int_0^T B_t dB_t$ , a natural approximation is:

$$Y^1 := \sum_{i=0}^{N-1} B_{i\delta t} (B_{(i+1)\delta t} - B_{i\delta t}), \text{ and by indep. increments, } \mathbb{E} Y^1 = 0.$$

But an alternative approximation is

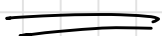
$$Y^2 := \sum_{i=0}^{N-1} B_{(i+1)\delta t} (B_{(i+1)\delta t} - B_{i\delta t}),$$

$$\text{and } \mathbb{E} Y^2 = \mathbb{E} (Y^2 - Y^1) = \sum \mathbb{E} (B_{(i+1)\delta t} - B_{i\delta t})^2 = \sum \delta t = T !$$

But both  $B_{i\delta t}$  and  $B_{(i+1)\delta t}$  look like  $B_t$  as  $\delta t \rightarrow 0$ .

This suggests (in contrast to the Riemann integral) we need to choose our endpoints carefully. For the Ito integral, we will always take sums of the form  $Y^1$ , and it will

be important that the integrand is adapted  
(i.e.  $\phi_t$  is  $\mathcal{F}_t$ -measurable).



Setting: We work on a filtered probability space  $(\Omega, \mathcal{F}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$  (s.t.  $\mathcal{F}_t$  satisfies the usual conditions) on which there exists a B.M.  $B_t$ .

Our set of potential integrands is:

$\mathcal{U}([0, T])$  which contains  $f(t, \omega)$ ,  $f: [0, \infty) \times \Omega \rightarrow \mathbb{R}$

(i)  $f(t, \omega)$  is progressively measurable:

$\forall s \in [0, T], (t, \omega) \mapsto f(t, \omega)$  is

$\mathcal{B}([0, s]) \times \mathcal{F}_s$ -measurable

(this implies  $f(t, \omega)$  is  $\mathcal{F}_t$ -adapted, and is implied by  $\mathcal{F}_t$ -adapted, r-cts or l-cts...)

(ii)  $\mathbb{E} \left[ \int_0^T f(t, \omega)^2 dt \right] < \infty$ .



Then  $\phi \in \mathcal{U}([0, T])$  is simple if

$$\phi(t, \omega) = \sum_{j \geq 0} e_j(\omega) \mathbb{1}_{\{[t_j, t_{j+1})\}}(t),$$

some  $0 \leq t_0 < t_1 < \dots < t_j \leq T$ . So adapted implies  $e_j(\omega)$  is  $\mathcal{F}_{t_j}$ -measurable. Write  $\phi \in \mathcal{S}([0, T])$ .

For  $\phi \in \mathcal{S}([0, T])$ , we define the Itô integral by:

$$\int_0^T \phi(t, \omega) dB_t = \sum_{j \geq 0} e_j(\omega) (B_{t_{j+1}} - B_{t_j}).$$

## Theorem (Itô Isometry)

For  $\phi \in \mathcal{S}([0, T])$  bounded,

$$\mathbb{E} \left[ \left( \int_0^T \phi(t, \omega) dB_t \right)^2 \right] = \mathbb{E} \left[ \int_0^T \phi(t, \omega)^2 dt \right]$$

Proof Set  $\Delta B_j = B_{t_{j+1}} - B_{t_j}$ . Then

$$\mathbb{E} [e_i e_j \Delta B_i \Delta B_j] = \begin{cases} 0 & i \neq j \\ \mathbb{E} [e_i^2] (t_{i+1} - t_i) & i = j \end{cases}$$

since  $\Delta B_j$  indep of  $e_i, e_j, \Delta B_i$  if  $j > i$ .

$$\begin{aligned} \text{So } \mathbb{E} \left[ \left( \int_0^T \phi_s dB_s \right)^2 \right] &= \sum_{i,j} \mathbb{E} [e_i e_j \Delta B_i \Delta B_j] \\ &= \sum_{j \geq 0} \mathbb{E} [e_i^2] (t_{i+1} - t_i) \\ &= \mathbb{E} \left[ \int_0^T \phi_t^2 dt \right] \quad \square \end{aligned}$$

Now we show  $\phi \in \mathcal{U}([0, T])$  can be approximated by simple functions in  $\mathcal{S}([0, T])$ .

① If  $t \mapsto \phi(t, \omega)$  is continuous for each  $\omega \in \Omega$ , and  $\phi$  bounded, then  $\phi_n = \phi(t_i) \mathbb{1}_{\{[t_i, t_{i+1})\}}(t)$

$$\begin{aligned} &\longrightarrow \phi(t) \text{ pointwise,} \\ \text{so } \mathbb{E} \left[ \int_0^T (\phi_n - \phi)^2 dt \right] &\longrightarrow 0. \end{aligned}$$

② If  $\phi_t$  bounded, there exists a continuous function

$\rho_n(t)$  such that  $\rho_n(t) = 0$  if  $t \notin (-1/n, 0)$ ,  
 and  $\int_{-\infty}^{\infty} \rho_n(t) dt = 1$ .

Then  $g_n(t, \omega) = \int_0^t \rho_n(s-t) \phi(s, \omega) ds$

is continuous and bounded, and (non-trivial ...!) in  $\mathcal{U}([0, T])$ , and (non-trivial)

$$\int_0^T (g_n(s, \omega) - \phi(s, \omega))^2 \rightarrow 0 \text{ for each } \omega \in \Omega.$$

[Again... here is the hand-waving]

So also in  $\mathbb{E}$ .

③ Finally if  $\phi_+$  unbounded, since  $\mathbb{E} \int_0^T \phi_+^2 dt < \infty$ ,  

$$\mathbb{E} \left[ \int_0^T (\phi_+ - ((\phi_+ \wedge n) \vee (-n)))^2 dt \right] \rightarrow 0$$
  
 as  $n \rightarrow \infty$ .

So, given  $\phi \in \mathcal{U}([0, T])$ , we can find  $\phi_n \in \mathcal{S}([0, T])$   
 such that  $\mathbb{E} \left[ \int_0^T |\phi_n - \phi|^2 dt \right] \rightarrow 0$ .

But  $\int_0^T \phi_n(t) dB_t \in L^2(\mathbb{P})$  for all  $n \in \mathbb{N}$ . But it follows  
 that  $\left\| \int \phi_n dB_t - \int \phi_m dB_t \right\|_2^2 = \mathbb{E} \left( \int_0^T (\phi_m - \phi_n)^2 dt \right)$   
 $\rightarrow 0$

ie.  $\int \phi_n dB_t$  are a Cauchy sequence in  $L^2(\mathbb{P})$ ,  
 which is a complete space  $\Rightarrow \exists!$  Limit!

Hence, for  $\phi \in \mathcal{U}([0, T])$ , we can define the Itô integral  
 as the limit of the Itô integrals of approximating  
 simple functions.

Then also:

Corollary (Itô Isometry):

$$\mathbb{E} \left[ \left( \int_0^T \phi_t dB_t \right)^2 \right] = \mathbb{E} \left[ \int_0^T \phi_t^2 dt \right] \quad \forall \phi \in \mathcal{U}([0, T]).$$

Example: Assume (as usual)  $B_0 = 0$ . Then:

$$\int_0^t B_s dB_s = \frac{1}{2} B_t^2 - \frac{1}{2} t.$$

Proof: Take  $\phi_n(t) := \sum B_{t_j} \mathbb{1}_{\{[t_j, t_{j+1})\}}(t)$

$$\begin{aligned} \text{then} \quad \mathbb{E} \left[ \int_0^T (\phi_n(t) - B_t)^2 dt \right] &= \mathbb{E} \left[ \sum \int_{t_j}^{t_{j+1}} (B_{t_j} - B_s)^2 ds \right] \\ &= \sum \int_{t_j}^{t_{j+1}} (s - t_j) ds = \frac{1}{2} \sum (t_{j+1} - t_j)^2 \rightarrow 0. \end{aligned}$$

$$\begin{aligned} \int_0^T \phi_n(t) dB_t &= \sum B_{t_j} (B_{t_{j+1}} - B_{t_j}) \\ &= \frac{1}{2} \sum \left[ B_{t_{j+1}}^2 - B_{t_j}^2 - (B_{t_{j+1}} - B_{t_j})^2 \right] \\ &= \frac{1}{2} \left[ B_{t_N}^2 - B_{t_{N-1}}^2 + B_{t_{N-1}}^2 - B_{t_{N-2}}^2 + \dots - B_0^2 \right] \\ &\quad - \frac{1}{2} \sum (B_{t_{j+1}} - B_{t_j})^2 \end{aligned}$$

But  $\sum (B_{t_{j+1}} - B_{t_j})^2 \rightarrow T$  in  $L^2(\mathbb{P})$ ,

$$\text{So } \int_0^T B_t dB_t = \frac{1}{2} (B_T^2 - T) \quad !$$

Properties of the stochastic / Itô Integral:

$$(i) \int_s^T f_t dB_t = \int_s^u f_t dB_t + \int_u^T f_t dB_t \quad (s \leq u \leq T)$$

(ii) Linear  $\left(\int (\alpha f + \beta g) dB_t = \alpha \int f dB_t + \beta \int g dB_t, \alpha, \beta \in \mathbb{R}\right)$ .

(iii)  $\int_0^T f dB_t$  is  $\mathcal{F}_T$ -measurable

$X_t$  a version of  $Y_t$   
if  $P(X_t = Y_t) = 1 \forall t$ .

(iv) There exists a continuous version of  $t \mapsto \int_0^t f_s dB_s$  which is a martingale. (In future, we will work with this version).

More generally, a stochastic integral or an Ito process is a stochastic process  $X_t$  such that:

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

where  $v$  is progressively meas. &  $P\left(\int_0^t v(s, \omega)^2 ds < \infty \forall t \geq 0\right) = 1$ .

We will often write this as

$$dX_t = u_t dt + v_t dB_t.$$

So  $\int_0^T B_t dB_t = \frac{1}{2}(B_T^2 - T)$  is equivalently

$$d\left(\frac{1}{2} B_t^2\right) = \frac{1}{2} dt + B_t dB_t.$$

Theorem (Ito's formula). Let  $X_t$  be an Ito process,

$$dX_t = u_t dt + v_t dB_t$$

Let  $g(t, x) \in C^2([0, \infty) \times \mathbb{R})$ . Then

$$Y_t = g(X_t, t)$$

is again an Ito process, and

$$dY_t = \left( \frac{\partial g}{\partial t}(t, X_t) + u_t \frac{\partial g}{\partial x}(t, X_t) + \frac{1}{2} v_t^2 \frac{\partial^2 g}{\partial x^2}(t, X_t) \right) dt + v_t \frac{\partial g}{\partial x}(t, X_t) dB_t.$$

which can also be thought of as:

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

where  $(dX_t)^2$  is computed by  $dt \cdot dt = dt \cdot dB_t = dB_t \cdot dt = 0$ ,  
 $dB_t \cdot dB_t = dt$ .

Sketch Proof: By approximation if necessary, we can assume  $f$  and all its derivatives are bounded. Applying Taylor's theorem, we get:

$$\begin{aligned} g(t, X_t) - g(0, X_0) &= \sum_j \frac{\partial g}{\partial t} \Delta t_j + \sum_j \frac{\partial g}{\partial x} \Delta X_j + \frac{1}{2} \sum_j \frac{\partial^2 g}{\partial t^2} (\Delta t_j)^2 \\ &\quad + \sum_j \frac{\partial^2 g}{\partial x \partial t} (\Delta t_j)(\Delta X_j) + \frac{1}{2} \sum_j \frac{\partial^2 g}{\partial x^2} (\Delta X_j)^2 \\ &\quad + \sum_j R_j, \end{aligned}$$

where all partial derivatives are evaluated at  $(t_j, X_j)$ , and  $R_j = o((\Delta t)^2 + (\Delta X_j)^2)$ . Since the functions are assumed bounded, we get

$$\sum_j \frac{\partial g}{\partial t} \Delta t_j \rightarrow \int_0^T \frac{\partial g}{\partial t} dt, \quad \sum_j \frac{\partial g}{\partial x} \Delta X_j \rightarrow \int_0^T \frac{\partial g}{\partial x}(s, X_s) dX_s$$

If also  $u, v$  are simple:

$$\begin{aligned} \sum_j \frac{\partial^2 g}{\partial x^2} (\Delta X_j)^2 &= \sum_j \frac{\partial^2 g}{\partial x^2} u_j^2 (\Delta t_j)^2 + 2 \sum_j \frac{\partial^2 g}{\partial x^2} u_j v_j (\Delta t_j)(\Delta B_j) \\ &\quad + \sum_j \frac{\partial^2 g}{\partial x^2} v_j^2 (\Delta B_j)^2, \end{aligned}$$

and e.g.

$$\begin{aligned} &\mathbb{E} \left[ \left( \sum_j \frac{\partial^2 g}{\partial x^2} u_i v_j (\Delta t_i) (\Delta B_j) \right)^2 \right] \\ &= \sum_j \mathbb{E} \left[ \left( \frac{\partial^2 g}{\partial x^2} u_i v_j \right)^2 \right] (\Delta t_i)^3 \rightarrow 0 \end{aligned}$$

as  $(\Delta t) \rightarrow 0$



So the term we need to analyse is the last one.

Claim:  $\sum_j \frac{\partial^2 g}{\partial x^2} v_j^2 (\Delta B_j)^2 \rightarrow \int_0^t v_s^2 \frac{\partial^2 g}{\partial x^2} ds$   
 in  $L^2(\mathbb{P})$ .

Writing  $a_t = v_t \frac{\partial^2 g}{\partial x^2}$ , then:

$$\begin{aligned} & \mathbb{E} \left[ \left( \sum_j a_j (\Delta B_j)^2 - \sum_j a_j \Delta t_j \right)^2 \right] \\ &= \sum_{i,j} \mathbb{E} \left[ a_i a_j \left( (\Delta B_i)^2 - \Delta t_i \right) \left( (\Delta B_j)^2 - \Delta t_j \right) \right] \end{aligned}$$

But for  $i \neq j$ , the terms vanish, and we get:

$$\begin{aligned} \sum_j \mathbb{E} \left[ a_j^2 \left( (\Delta B_j)^2 - \Delta t_j \right)^2 \right] &= \sum_j \mathbb{E} [a_j^2] \cdot \underbrace{\mathbb{E} [\dots]}_{= 2(\Delta t)^2} \\ &\rightarrow 0 \quad \text{as } \Delta t \rightarrow 0. \end{aligned}$$

Martingale Representation Theorem:

Let  $B_t$  be a BM, and  $\mathcal{F}_t^B$  its natural filtration, and suppose  $M_t$  an  $\mathcal{F}_t^{(B)}$ -martingale, and  $M_t \in L^2(\mathbb{P})$  for all  $t \geq 0$ . Then there exists  $g(s, \omega)$  such that:

$$M_t(\omega) = \mathbb{E}[M_0] + \int_0^t g(s, \omega) dB_s \quad \text{a.s. } \forall t \geq 0.$$

(Sketch proof)

Can show linear span of  $\exp \left\{ \int_0^T h_t dB_t - \frac{1}{2} \int_0^T h_t^2 dt \right\}$ ,  
 $h \in L^2([0, T])$  (deterministic), is dense in  $L^2(\mathcal{F}_T^B, \mathbb{P})$ .

But if  $F = \exp \left\{ \int_0^T h_s dB_s - \frac{1}{2} \int_0^T h_s^2 ds \right\}$

$$\Rightarrow F = Y_T, \quad Y_t = \exp \left\{ \int_0^t h_s dB_s - \frac{1}{2} \int_0^t h_s^2 ds \right\}$$

$$\begin{aligned} \text{Itô} \Rightarrow dY_t &= Y_t h_t dB_t + \frac{1}{2} Y_t h_t^2 dt \\ &\quad - \frac{1}{2} Y_t h_t^2 dt \\ &= Y_t h_t dB_t, \end{aligned}$$

So can approximate a dense set of  $F \in L^2(P)$  by martingales. Use Itô isometry to extend from dense set to all  $F$ .

Finally, given  $M$ , using  $F = M_T$ , we get

$$\begin{aligned} M_t &= \mathbb{E}[M_T | \mathcal{F}_t] = \mathbb{E} \left[ \mathbb{E}[M_T] + \int_0^T \phi_s dB_s \mid \mathcal{F}_t \right] \\ &= M_0 + \int_0^t \phi_s dB_s + \mathbb{E} \left[ \int_t^T \phi_s dB_s \mid \mathcal{F}_t \right] \\ &= M_0 + \int_0^t \phi_s dB_s, \end{aligned}$$

$$\text{So } M_t = M_0 + \int_0^t \phi_s dB_s. \quad \square$$

### §3. Stochastic Differential Equations:

An SDE is an equation of the form:

$$dX_t = b(t, X_t) dt + \sigma(t, X_t) dB_t, \quad X_0 \text{ given.}$$

Theorem: Fix  $T > 0$ , sse  $b(\cdot, \cdot) : [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$ ,

$\sigma(\cdot, \cdot) : [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$  measurable s.t

$$|b(t, x)| + |\sigma(t, x)| \leq C(1 + |x|)$$

and  $|b(t, x) - b(t, y)| + |\sigma(t, x) - \sigma(t, y)| \leq D|x - y|$

for some constants,  $C, D$ . Let  $Z$  be an r.v.

independent of  $\mathcal{F}_\infty^B$ ,  $\mathbb{E}|z|^2 < \infty$ .

Then the SDE 
$$\begin{cases} dX_t = b(t, X_t) dt + \sigma(t, X_t) dB_t \\ 0 \leq t \leq T, X_0 = Z \end{cases}$$

has a unique  $t$ -continuous solution  $X_t(\omega)$  adapted to  $\mathcal{F}_t^Z$ , gen by  $Z, B$ , and

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

Note that the bounded & Lipschitz conditions are

natural: •)  $dX_t = X_t^2 dt \Rightarrow X_t = \frac{1}{1-t}$ , explodes...

•)  $dX_t = 3X_t^{2/3} dt$ ,  $X_0 = 0$  has solutions:

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

for any  $a > 0$ .

Proof

(Uniqueness:) Let  $X^1, X^2$  be solutions:  $:= a_s$

$$\mathbb{E} |X_T^1 - X_T^2|^2 = \mathbb{E} \left[ \left( \int_0^T [b(s, X_s^1) - b(s, X_s^2)] ds + \int_0^T (\underbrace{\sigma(s, X_s^1) - \sigma(s, X_s^2)}_{:= \gamma_s}) dB_s \right)^2 \right]$$

$$\leq 2 \mathbb{E} \left[ \left( \int_0^T a_s ds \right)^2 \right] + 2 \mathbb{E} \left[ \left( \int_0^T \gamma_s dB_s \right)^2 \right]$$

$$\leq 2T \mathbb{E} \left[ \int_0^T a_s^2 ds \right] + 2 \mathbb{E} \left[ \int_0^T \gamma_s^2 ds \right]$$

$$\leq 2(T+1)D^2 \mathbb{E} \left[ \int_0^T |X_s^1 - X_s^2|^2 ds \right]$$

$$\leq 2(T+1)D^2 \int_0^T \mathbb{E} \left[ |X_s^1 - X_s^2|^2 \right] ds.$$

ie. if  $v(s) = \mathbb{E} |X_s^1 - X_s^2|^2$ ,

$$v(t) \leq C \int_0^t v(s) ds,$$

and by Gronwall's inequality:  $v(t) = 0 \quad \forall t \geq 0$ .

Path continuity  $\Rightarrow X^1 = X^2$  for all  $t \in [0, T]$  a.s..

(Existence) Define  $Y_t^{(0)} = X_0$ ,

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

$$\text{Then } \mathbb{E} |Y_t^{k+1} - Y_t^k|^2 \leq (1+T)2D^2 \int_0^t \mathbb{E} |Y_s^{k+1} - Y_s^k|^2 ds$$

for  $k \geq 1$  and

$$\mathbb{E} |Y_t^1 - Y_t^0|^2 \leq 4C^2 t^2 (1 + \mathbb{E} |X_0|^2)$$

$$\leq A_1 t$$

By induction on  $k$ , get

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

$$\text{So if } \|r_s\| = \mathbb{E} \left[ \int_0^T r_s^2 ds \right]^{1/2},$$

$$\|Y_t^{(m)} - Y_t^{(n)}\| = \left\| \sum_{k=n}^{m-1} (Y_t^{k+1} - Y_t^k) \right\|$$

$$\begin{aligned}
&\leq \sum_{k=n}^{m-1} \|Y_t^{k+1} - Y_t^k\| \\
&\leq \sum \left( \int_0^T \frac{A_2^{k+1} t^{k+1}}{(k+1)!} dt \right)^{1/2} \\
&= \sum \frac{A_2^{k+1} T^{k+2}}{(k+2)!} \rightarrow 0
\end{aligned}$$

Therefore  $Y_t^n$  a Cauchy sequence & convergent

By Hölder inequality & Itô isometry, integrals

converge, so  $X_t = \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dB_s$

(also,  $X_t$  is  $\mathcal{F}_t^z$ -meas. & can be chosen to be continuous -)

□

Weak + Strong solutions:

Above, we've been given a BM & a filtration.

Such a solution is called a strong solution.

In some circumstances, we may not be able to do this, but, given  $\sigma, b$ , we may be able to construct a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  and

$(B_t, X_t, \mathcal{F}_t)$  such that  $X_t$  solves the SDE.

E.g. Tanaka equation:  $dX_t = \text{sign}(X_t) dB_t$ .

## §4. Diffusions

A (time-homogeneous) Itô diffusion is a solution to the SDE:

$$dX_t = b(X_t) dt + \sigma(X_t) dB_t$$

for  $t \geq s$ ,  $X_s = x$ ,  $X_t \in \mathbb{R}^n$ ,  $b: \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  
 $\sigma: \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$ ,  $B_t$  an  $m$ -dim. B.M., and  
 $\sigma, b$  are Lipschitz.

NB: often:  $X_t = X_t^{s,x}$ ,  $X_t^x = X_t^{0,x}$ .

Now  $\{X_{s+h}^{s,x}\}_{h \geq 0}$  and  $\{X_h^{0,x}\}_{h \geq 0}$  have same  
(Strong) distributions.

Then (Markov Property)  $f$  bounded Borel,  $\mathbb{R}^n \rightarrow \mathbb{R}$ .  
Then, for  $t, h \geq 0$   $E^x [f(X_{t+h}) | \mathcal{F}_t^{(m)}] = E^{X_t^{(x)}} [f(X_h)]$   
where  $\mathcal{F}_t^{(m)}$  is the filtration generated by the driving  
B.M. &  $\tau \in \mathcal{F}_t^{(m)}$ -stopping time.

Let  $\{X_t\}$  be a time-homog. diffusion on  $\mathbb{R}^n$ . Then  
the (infinitesimal) generator  $A$  of  $X_t$  given by

$$Af(x) = \lim_{t \downarrow 0} \frac{E^x [f(X_t)] - f(x)}{t} \quad x \in \mathbb{R}^n$$

The set of functions  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  such that the limit  
exists for all  $x \in \mathbb{R}^n$  is  $\mathcal{D}_A$ .

Lemma: Let  $X_t$  be an Itô process as above, and  $f \in C_0^2(\mathbb{R}^n)$  (twice diff. & compact support), and  $\tau$  a stopping time s.t.  $\mathbb{E}^x[\tau] < \infty$ , then

$$\mathbb{E}^x[f(X_\tau)] = f(x) + \mathbb{E}^x \left[ \int_0^\tau \left( \sum_i b_i(x_s) \frac{\partial f}{\partial x_i}(x_s) + \frac{1}{2} \sum_{i,j} (\sigma \sigma^\top)_{ij} \frac{\partial^2 f}{\partial x_i \partial x_j}(x_s) \right) ds \right]$$

Sketch proof: (in 1-D)

Applying Itô to  $f(X_s)$ , and taking expectations, we get the above formula plus the term:

$$\mathbb{E}^x \left[ \int_0^\tau \sigma(x_s) \frac{\partial f}{\partial x} dB_s \right]$$

By the martingale property, this is 0 if  $\tau$  bounded. In general,

$$\mathbb{E}^x \left[ \left( \int_0^\tau - \int_0^{\tau \wedge k} \sigma(x_s) \frac{\partial f}{\partial x} dB_s \right)^2 \right]$$

$$\leq \mathbb{E}^x \int_{\tau \wedge k}^\tau \sigma(x_s) \frac{\partial^2 f}{\partial x^2} ds$$

$$\leq M \mathbb{E}(\tau - \tau \wedge k) \rightarrow 0$$

as  $k \rightarrow \infty$ .

Corollary:

If  $f \in C_0^2(\mathbb{R}^n)$ ,  $f \in \mathcal{D}_A$  and

$$Af(x) = \sum_i b_i(x) \frac{\partial f}{\partial x_i} + \frac{1}{2} \sum_{i,j} (\sigma \sigma^\top)_{ij}(x) \frac{\partial^2 f}{\partial x_i \partial x_j}.$$

□

## Corollary II: Dynkin's Formula

Let  $f \in C_0^2(\mathbb{R}^n)$ , and  $\tau$  a stopping time s.t.

$\mathbb{E}^x[\tau] < \infty$ . Then:

$$\mathbb{E}^x[f(X_\tau)] = f(x) + \mathbb{E}^x\left[\int_0^\tau Af(X_s) ds\right].$$

## Kolmogorov's Backward Equation:

Let  $f \in C_0^2(\mathbb{R}^n)$ ,  $X_t$  as above. Then

$$u(t, x) := \mathbb{E}^x[f(X_t)]$$

satisfies  $u(t, \cdot) \in \mathcal{D}_A \forall t$ ,

$$\left. \begin{aligned} \frac{\partial u}{\partial t} &= Au & t > 0, x \in \mathbb{R}^n \\ u(0, x) &= f(x) & x \in \mathbb{R}^n. \end{aligned} \right\} \textcircled{\star}$$

Moreover, if  $w \in C^{1,2}(\mathbb{R} \times \mathbb{R}^n)$  a bounded fn satisfying  $\textcircled{\star}$ , then  $w = u$ .

Sketch proof: Fix  $t$ , let  $g(x) = u(t, x)$ . Then:

$$\frac{\mathbb{E}^x[g(X_r)] - g(x)}{r} = \frac{1}{r} \mathbb{E}^x[\mathbb{E}^{X_r}[f(X_t)] - \mathbb{E}^x f(X_t)]$$

$$= \frac{1}{r} \mathbb{E}^x[\mathbb{E}^x[f(X_{t+r}) | \mathcal{F}_r] - \mathbb{E}^x[f(X_t) | \mathcal{F}_r]]$$

$$= \frac{1}{r} \mathbb{E}^x[f(X_{t+r}) - f(X_t)]$$

$$= \frac{u(t+r, x) - u(t, x)}{r} \rightarrow \frac{\partial u}{\partial r} \text{ as } r \downarrow 0$$

But  $Au = \lim_{r \downarrow 0} \frac{\mathbb{E}^x[g(X_r)] - g(x)}{r}$ , so  $Au = \frac{\partial u}{\partial r}$ .



Uniqueness: Apply Dynkin's formula to  $Y_t$  in  $\mathbb{R}^{n+1}$ ,

$$Y_t = (s-t, X_t^{0,x}),$$

which has generator  $\tilde{A}w = -\frac{\partial w}{\partial t} + Aw$ ,

$$\text{so } w(s,x) = \mathbb{E}^{s,x}[w(Y_t)]$$

$$t=s \Rightarrow w(s,x) = \mathbb{E}^{s,x}[f(X_s)]. \quad \square$$

Note that the trick of moving from time-homogeneous diffusions to space-time diffusions similar to above is quite useful!

Similar results---

Feynman-Kac:

$f \in C_0^2(\mathbb{R}^n)$ ,  $q \in C(\mathbb{R}^n)$ ,  $q$  bounded below.

Then  $v(t,x) := \mathbb{E}^x \left[ \exp \left\{ -\int_0^t q(X_s) ds \right\} f(X_t) \right]$

solves  $\frac{\partial v}{\partial t} = Av - qv \quad t > 0, x \in \mathbb{R}^n$

and  $v(0,x) = f(x)$ .

Poisson-Dirichlet:

Suppose  $D$  a domain in  $\mathbb{R}^n$ ,  $\phi \in C(\partial D)$  bounded,

$g \in C(D)$ ,  $\mathbb{E}^x \int_0^{\tau_D} |g(X_t)| dt, \forall x$ ,

$\tau_D = \inf \{ t \geq 0 : X_t \notin D \}$ ,

and  $w \in C^2(D)$  bounded, solving

$$(i) \quad Lw = -g \quad \text{in } D$$

$$(ii) \quad \lim_{t \uparrow \tau_0} w(x_t) = \phi(x_{\tau_0}) \mathbb{1}_{\{\tau_0 < \infty\}} \\ \mathbb{P}^x \text{ a.s. } \forall x,$$

Then

$$w(x) = \mathbb{E}^x \left[ \phi(x_{\tau_0}) \mathbb{1}_{\{\tau_0 < \infty\}} + \int_0^{\tau_0} g(x_t) dt \right]$$

§5. Girsanov's Theorem:

Let  $Y_t \in \mathbb{R}^n$  be an Ito process of form:

$$dY_t = \beta_t dt + \sigma_t dB_t, \quad t \leq T$$

$B_t \in \mathbb{R}^m$ ,  $\beta_t \in \mathbb{R}^n$ ,  $\sigma_t \in \mathbb{R}^{n \times m}$ , such that there exist progressively meas.  $u_t, \alpha_t$  where

$$\sigma_t u_t = \beta_t - \alpha_t.$$

$$\text{Set } M_t = \exp \left\{ - \int_0^t u_s dB_s - \frac{1}{2} \int_0^t u_s^2 ds \right\}$$

If  $M_t$  a martingale

$\frac{d\mathbb{Q}}{d\mathbb{P}} = M_T$  on  $\mathcal{F}_T$ , then  $\mathbb{Q}$  a probability

measure, and under  $\mathbb{Q}$ ,

$$\hat{B}_t := \int_0^t u_s ds + B_t$$

is a Brownian motion, and

$$dY_t = \alpha_t dt + \sigma_t d\hat{B}_t$$

Note:  $\frac{dQ}{dP} = M_T$  on  $\mathcal{F}_T$  means, for

$$A \in \mathcal{F}_T, \quad \mathbb{Q}(A) = \mathbb{E}^P[\mathbb{1}_A \cdot M_T].$$

Sketch Proof: First note that

$$\begin{aligned} dM_t &= -u_t M_t dB_t + \frac{1}{2} u_t^2 M_t dt \\ &\quad - \frac{1}{2} u_t^2 M_t dt \\ &= -u_t M_t dB_t \end{aligned}$$

So  $M_t$  is a  $P$ -martingale, modulo (assumed) integrability conditions, and then  $M_0 = 1 \Rightarrow$

$$\mathbb{Q}(\Omega) = \mathbb{E}^P[1 \cdot M_T] = 1, \text{ other properties of p.m. also follow.}$$

Now, consider  $1-D$ , and

$$\begin{aligned} d(M_t \hat{B}_t) &= M_t d\hat{B}_t + \hat{B}_t dM_t + dM_t d\hat{B}_t \\ &= M_t (dB_t + u_t dt) - \hat{B}_t u_t M_t dB_t \\ &\quad - u_t M_t dt \\ &= (M_t - \hat{B}_t u_t M_t) dB_t. \end{aligned}$$

So, under  $\mathbb{Q}$ ,  $\hat{B}_t$  is a continuous (local-) martingale. Moreover:  $d(\hat{B}_t^2) = 2\hat{B}_t d\hat{B}_t + dt$

$$\begin{aligned} d(M_t \hat{B}_t^2) &= 2M_t \hat{B}_t d\hat{B}_t - M_t dt - u_t M_t \hat{B}_t^2 dB_t \\ &\quad - 2M_t u_t \hat{B}_t dt \end{aligned}$$

$$= 2M_t \hat{B}_t dB_t + 2M_t \hat{B}_t u_t dt + M_t dt - u_t M_t \hat{B}_t^2 dB_t - 2M_t \hat{B}_t u_t dt$$

$$\begin{aligned} \Rightarrow \mathbb{E}^{\mathbb{Q}}[\hat{B}_t^2] &= \mathbb{E}^{\mathbb{P}}[M_t B_t^2] \\ &= \mathbb{E}\left[\int_0^t M_t dt\right] \\ &= \int_0^t \mathbb{E}[M_t] dt = \int_0^t 1 dt = t. \end{aligned}$$

Hence, under  $\mathbb{Q}$ ,  $\hat{B}_t$ ,  $\hat{B}_t^2 - t$  are martingales

$$\Rightarrow \hat{B}_t \text{ a } \mathbb{Q}\text{-BM}$$

$$\begin{aligned} dY_t &= \beta_t dt + \sigma_t dB_t \\ &= \beta_t dt + \sigma_t (d\hat{B}_t - u_t dt) \\ &= (\beta_t - \sigma_t u_t) dt + \sigma_t d\hat{B}_t \\ &= \alpha_t dt + \sigma_t d\hat{B}_t. \end{aligned}$$

□