

Lecture 3. Ito's formula

— with 3 tables.

- Goal: The "chain rule" for stochastic calculus.

- Fundamental calculus: we apply:

$$\int f(x) dx = \int \frac{d}{dx} F(x) dx = F(x).$$

doesn't make sense!

- Does it work with Ito? $df(B_t) = ? \left(\frac{d B_t}{dt}, f'(B_t) \right) dt$.

- But! BMs has rough paths, nowhere differentiable!

- Instead we look at sum that at least makes sense:

$$df = f'(B_t) dB_t + \frac{1}{2} f''(B_t) (dB_t)^2 + \frac{1}{6} f'''(B_t) (dB_t)^3 + \dots$$

How many terms
do we need?

Difficult part: BM. If we solve the problem for a BM, we can solve it for many other processes.

(Step 1. BM.)

Thm 3.1. (Ito's formula for BM).

Let $f \in C^2(\mathbb{R})$ (cont. twice differentiable) and B_t be a standard BM

For any $t > 0$.

→ an SDE

$$df(B_t) = f'(B_t) dB_t + \frac{1}{2} f''(B_t) dt.$$

Or in integral form,

$$f(B_t) = f(B_0) + \int_0^t f'(B_s) dB_s + \frac{1}{2} \int_0^t f''(B_s) ds$$

→ s.p.

Prf of thm 3.1 w.l.o.g. assume f, f', f'' bdd.

(On top of this we can approximate any fun and pass to the limit)

Take a partition with N equal intervals:

$$f(B_t) - f(0) \stackrel{(*)}{=} \sum_{k=1}^N \underbrace{(f(B_{t_k}) - f(B_{t_{k-1}}))}_{\text{expand.}}$$

By Taylor,

$$f(B_{t_k}) - f(B_{t_{k-1}}) = f'(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}}) + \frac{1}{2} f''(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}})^2$$

Then we can write (*) as

$$f(B_t) - f(0) = \sum_{k=1}^N f'(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}}) + \sum_{k=1}^N \frac{1}{2} f''(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}})^2$$

By the construction of Itô's integral,

$$\sum_{k=1}^N f'(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}}) \xrightarrow{L^2} \int_0^t f'(B_s) dB_s.$$

WTS:

$$\sum_{k=1}^N f''(B_{t_{k-1}})(B_{t_k} - B_{t_{k-1}})^2 \xrightarrow{L^2} \int_0^t f''(B_s) ds.$$

$$\Leftrightarrow \sum_{k=1}^N f''(B_{t_{k-1}}) \left[(B_{t_k} - B_{t_{k-1}})^2 - (t_k - t_{k-1}) \right] \xrightarrow{L^2} 0$$

as continuous trajectories.

Idea: $(dB_t)^2 = dt$

$$\int_0^T (dB_t)^2 = \lim_{N \rightarrow \infty} \sum_{k=1}^N (\Delta B_{t_{k-1}})^2 \xrightarrow{L^2} T = \int_0^T dt$$

$$\mathbb{E} \left[\sum_{k=1}^N (\Delta B_{t_{k-1}})^2 \right] = \sum_{k=1}^N \mathbb{E} [(\Delta B_{t_{k-1}})^2] = \sum_{k=1}^N \Delta t_m = T.$$

Ind.

$$\begin{aligned} \mathbb{E} \left[\left(\sum_{k=1}^N (\Delta B_{t_{k-1}})^2 - T \right)^2 \right] &= \text{Var} \left(\sum_{k=1}^N (\Delta B_{t_{k-1}})^2 - T \right) \\ &= \sum_{k=1}^N \text{Var} \left[(\Delta B_{t_m})^2 \right] \\ &= \sum_{k=1}^N \underbrace{\mathbb{E}[(\Delta B_{t_m})^4]}_{3(\Delta t)^2} - \underbrace{\mathbb{E}[(\Delta B_{t_m})^2]}_{(\Delta t)^2} \\ &= 2 \left(\frac{T}{N} \right)^2 \cdot N = \frac{2T^2}{N} \rightarrow 0. \quad \square. \end{aligned}$$

Corol 3.2: $f(t, x) \in C^{1,2}([0, \infty) \times \mathbb{R})$, Let $Y_t = f(t, B_t)$, then

$$dY_t = (f_t + \frac{1}{2} f_{xx}) dt + f_x dB_t$$

Remark: $(dB_t)^2$ is computed according to the following table:

	dt	dB_t
dt	0	0
dB_t	0	dt

$\left(\text{Drop terms smaller than } dt. \right)$

Why can we do this? Well, let $p > 0$.

$$\int_0^T (dt)^p = \lim_{N \rightarrow \infty} \sum_{k=1}^N (\Delta t)^p$$

$$= \lim_{N \rightarrow \infty} N \cdot \left(\frac{I}{N}\right)^p$$

$$\xrightarrow{N \rightarrow \infty} 0 \quad \text{if } p > 1.$$

• choose ansatz,

• Apply Itô
• Integrate

Some examples w.r.t. BM: Solve Itô integrals

E.x. 3.2 $I = \int_0^t B_s dB_s$ (Exercise 2.2)

Let $f(t, x) = \frac{1}{2} x^2$ (why? from calculus).

$$Y_t := f(t, B_t) = \frac{1}{2} B_t^2, \quad Y_0 = 0$$

By Itô:

$$dY_t = B_t dB_t + \frac{1}{2} dt$$

$$\begin{aligned} \frac{1}{2} B_t^2 &= Y_t = Y_0 + \int_0^t B_s dB_s + \int_0^t \frac{1}{2} ds \\ &= \int_0^t B_s dB_s + \frac{1}{2} t \end{aligned}$$

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

$$\underline{\text{Ex. 3.3}} \quad I = \int_0^t s dB_s. \quad (\underline{\text{Exercise 2.4}})$$

Let $f(t, x) = t x$. (why?)

$$Y_t := t B_t, \quad Y_0 = 0$$

$$dY_t = B_t dt + t dB_t + 0 \cdot (dB_t)^2$$

$$t B_t = \int_0^t B_s ds + \int_0^t s dB_s$$

$$\Rightarrow \int_0^t s dB_s = t B_t - \underbrace{\int_0^t B_s ds}_{\downarrow} \quad \begin{matrix} \text{what's this guy?} \\ \text{r.v.} \end{matrix}$$

Matches integration by parts.

Remark. $\int_0^t s dB_s \sim N(0, \frac{1}{3} t^3)$. (by exercise).

$\int_0^t B_s ds$ is also Gaussian.

$$E \left[\int_0^t B_s ds \right] = \int_0^t E[B_s] ds = 0$$

$$\begin{aligned} \text{Var} \left[\int_0^t B_s ds \right] &= E \left[\left(\int_0^t B_s ds \right)^2 \right] \\ &= E \left[\int_0^t \int_0^t B_s \cdot B_u ds du \right]. \end{aligned}$$

$$= \int_0^t \int_s^t E[B_s B_u] ds du$$

$$= \int_0^t \int_s^t \min(s, u) ds du.$$

$$= \int_0^t \left(\int_0^u s ds + \int_u^t u ds \right) du$$

$$= \frac{1}{3} t^3.$$

$$\int_0^t B_s ds \sim N(0, \frac{1}{3} t^3)$$

Exercise 1. $\int_0^t B_s^2 dB_s.$

(Step 2 1d Itô process).

• Thm 3.4 Let X_t be an Itô process with

$$dX_t = \mu_t dt + \sigma_t dB_t,$$

Let $f(t, x) \in C^{1,2}([0, \infty), \mathbb{R})$, Define $Y_t = f(t, X_t)$.

Then.

$$\begin{aligned} dY_t &= \underbrace{f_t(t, X_t) dt}_{\text{drift}} + \underbrace{f_x(t, X_t) dX_t + \frac{1}{2} f_{xx}(t, X_t) (dX_t)^2}_{\text{diffusion}} \\ &= f_t dt + f_x (\mu_t dt + \sigma_t dB_t) + \frac{1}{2} f_{xx} (\mu_t dt + \sigma_t dB_t)^2 \\ &\quad \xrightarrow{\text{plug in } dX_t} = (f_t + f_x \mu_t + \frac{1}{2} f_{xx} \sigma_t^2) dt + f_x \sigma_t dB_t. \end{aligned}$$

E.X. 3.5 · (Financial models).

i) $dX = \mu dt + \sigma dB_t$. (Bachelier, 1900)

"normal model". e.g. In 2020 oil price.

ii) $dX = \mu X dt + \sigma X dB_t$. (Geometric BM. Black-Scholes-Merton, 1973)

"lognormal". modern approach.

iii) $dX = \beta X dt + \sigma d\beta_t$. (Ornstein-Uhlenbeck).

\downarrow
 ζ_0

"mean reversion". e.g. Vasicek model.

Solution to ii) with Ito:

$$\text{Let } Y_t = \log(X_t).$$

$$dY_t = \frac{1}{X_t} dX_t + \frac{1}{2} \left(-\frac{1}{X_t^2} \right) (dX_t)^2$$

$$= \mu dt + \sigma dB_t + \left(-\frac{1}{2} \sigma^2 dt \right)$$

$$= (\mu - \frac{1}{2} \sigma^2) dt + \sigma dB_t$$

$$Y_t = Y_0 + \int_0^t (\mu - \frac{1}{2} \sigma^2) ds + \int_0^t \sigma dB_s$$

$$= \log(X_0) + (\mu - \frac{1}{2} \sigma^2)t + \sigma B_t$$

$$X_t = \exp(Y_t) = X_0 \exp \{ (\mu - \frac{1}{2} \sigma^2)t + \sigma B_t \}.$$

Exercise = solve iii)

E.X. 3.6. Calculate $\mathbb{E}[e^{\alpha W_t}]$, $\alpha \in \mathbb{R}$.

• By prob., $X \sim \text{lognormal}(\mu, \sigma^2)$, $\mathbb{E}[X] = e^{\mu + \frac{1}{2}\sigma^2}$

$$\Rightarrow \mathbb{E}[e^{\alpha W_t}] = \exp(\mu + \frac{1}{2}\alpha^2 t) = e^{\frac{1}{2}\alpha^2 t}.$$

• By Itô, Let $Y = e^{\alpha W_t}$, $Y_0 = 1$

$$dY = \alpha e^{\alpha W_t} dW_t + \frac{1}{2} \alpha^2 e^{\alpha W_t} dt$$

$$= \alpha Y dW_t + \frac{1}{2} \alpha^2 Y dt$$

$$Y_t = Y_0 + \frac{1}{2} \alpha^2 \int_0^t Y_s ds + \alpha \int_0^t Y_s dW_s$$

$$M_t := \mathbb{E}[Y_t] = Y_0 + \frac{1}{2} \alpha^2 \int_0^t \mathbb{E}[Y_s] ds + 0$$

$$dM_t = \frac{1}{2} \alpha^2 M_t, \quad M_0 = Y_0 = 1$$

$$M_t = M_0 \exp\left(\frac{1}{2}\alpha^2 t\right) = \exp\left(\frac{1}{2}\alpha^2 t\right).$$

Exercise: Calculate $\mathbb{E}[X_t]$ where X_t is a GBM. ($\mathbb{E}[X_t] = X_0 e^{\mu t}$).

(Step 3, n-dim Itô).

Recall: $A = [a_{ij}]$, $B = [b_{ij}]$, $m \times n$ matrices. We define their

Frobenius product:

$$\langle A, B \rangle = \sum_{ij} a_{ij} b_{ij} = \text{Tr}(AB^\top)$$

Thm 3.7 Let $f(t, x) \in C^{1,2}$, we write

$$f_x = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix}, \quad f_{xx} = \left[\frac{\partial^2 f}{\partial x_i \partial x_j} \right]$$

Let X_t be an n -dim Itô process, i.e.

$$dX = \mu dt + \sigma dB_t$$

$\overset{n \times 1}{\uparrow} \quad \overset{n \times 1}{\uparrow} \quad \overset{n \times d}{\uparrow} \quad \overset{d \times 1, \text{ ind!}}{\uparrow}$

Let $Y_t = f(t, X_t)$,

$$dY_t = f_t + \sum_{i=1}^n \frac{\partial f}{\partial x_i} dX_i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j} dX_i dX_j$$

$$= (f_t + \underbrace{\langle \mu, f_x \rangle + \frac{1}{2} \langle \sigma \sigma^T, f_{xx} \rangle}_{\text{at } (t, X_t)} dt + \langle f_x, \sigma dB \rangle).$$

check!

In other words :

	dt	dB_i	dB_j
dt	0	0	0
dB_i	0	dt	0
dB_j	0	0	dt

Ex. 3.8 (Important).

Denote the Euclidean norm by $\|\cdot\|$, and let B_t be an n -dim BM starting from $X_0 \in \mathbb{R}^n$. Let $f(x) = \|x\|^2$.

$$f(B_t) = B_1^2(t) + \dots + B_n^2(t).$$

$$f_x(B_t) = 2B_t, \quad f_{xx} = 2I_n$$

$$\begin{aligned} df(B_t) &= (0 + 0 + \frac{1}{2} \langle I_n, 2I_n \rangle) dt + \langle 2B_t, dB_t \rangle \\ &= n dt + \langle 2B_t, dB_t \rangle. \end{aligned}$$

Or, in integral form,

$$\|B_t\|^2 = \|X_0\|^2 + n t + 2 \sum_{i=1}^n \int_0^t B_i(s) dB_i(s).$$

(Step 4. n-dim correlated I_w).

\nwarrow BMs are correlated.

Suppose the components of BMs are not independent, such that for $s < t$,

$$\begin{aligned} \text{Corr}(B_i(t) - B_i(s), B_j(t) - B_j(s)) &= \frac{1}{t-s} E[B_i(t) - B_i(s), B_j(t) - B_j(s)] \\ &= \rho_{ij} \end{aligned}$$

Denote $P = [\rho_{ij}]$ as the correlation matrix.

Thm 3.9. I_w 's lemma still holds, but with $\sigma \sigma^\top$ changed to $\sigma P \sigma^\top$.

i.e. the following table:

	dt	dB_i	dB_j
dt	0	0	0
dB_i	0	dt	$\rho_{ij} dt$
dB_j	0	$\rho_{ij} dt$	dt

Application

Thm 3.10. (Martingale representation thm).

Let M_t be an \mathcal{F}_t^B -martingale such that $M_T \in L^2$. Then there exists a unique \mathcal{F}_t^B -adapted process $\{H_s\}_{s \leq T} \in L^2$

$$M_t = M_0 + \int_0^t H_s dB_s \quad \text{a.s. for all } t.$$

\hookrightarrow deterministic.

Remark: We know "an Ito integral is a m.g." This tells us the converse: "Given a m.g. it can be written as an Ito integral."

Why is this important? \rightarrow application to finance.

$$\phi_t = \phi_0 + \int_0^t H_s dB_s$$

$\underline{\quad}$ $\overline{\quad}$ \hookrightarrow stock price.

Contract value. hedging strategy.

H_t is the amount of stock at the beginning of each infinitesimal period.

How to find H ? e.g. Ito!

In the simple case where $M_t = f(t, B_t)$, by Ito,

$$M_t = M_0 + \int_0^t (f_s + \frac{1}{2} f_{xx}) (s, B_s) ds + \int_0^t f_x (s, B_s) dB_s.$$

\downarrow it has to be that

$$f_s + \frac{1}{2} f_{xx} = 0.$$

and $H_+(w) = \underbrace{f_+(t, B_+)}_{\text{process}}(w).$

\hookrightarrow derivative.

H.E.

e.g. $M_t := B_+^2 - t.$

$$\Rightarrow = \int_0^t 2B_s dB_s.$$

m.g. rep.

$$M_t := \exp(\pi B_+ - \frac{1}{2}\pi^2 t). \rightarrow \text{what's this?}$$

$$\Rightarrow = \pi \int_0^t e^{\pi B_s - \frac{1}{2}\pi^2 s} dB_s. \quad (\text{Wald m.g. / GBM})$$

m.g. rep.

$$= \int_0^t \pi M_s dB_s.$$

Exercise. Find $f(x)$ s.t.

$$M_t = B_+^3 + \int_0^t f(B_s) ds. \quad \text{B a m.g.}$$