

last time

Definition 6.24. A semi-martingale is a process of the form $X = X_0 + B + M$ where:

- ▷ X_0 is \mathcal{F}_0 -measurable (typically X_0 is constant).
- ▷ B is an adapted process with finite first variation. (total variation)
- ▷ M is a martingale.

Definition 6.25. An Itô-process is a semi-martingale $X = X_0 + B + M$, where:

- ▷ $B_t = \int_0^t b_s ds$, with $\int_0^t |b_s| ds < \infty$ (Riemann Int)
- ▷ $M_t = \int_0^t \sigma_s dW_s$, with $\int_0^t |\sigma_s|^2 ds < \infty$ (Itô int)

Remark 6.26. Short hand notation for Itô processes: $dX_t = b_t dt + \sigma_t dW_t$.

Remark 6.27. Expressing $X = X_0 + B + M$ (or $dX = b dt + \sigma dW$) is called the *semi-martingale decomposition* or the *Itô decomposition* of X .

Theorem 6.28 (Itô formula). If $f \in C^{1,2}$, then

$$df(t, X_t) = \underbrace{\partial_t f(t, X_t)}_{\text{wavy}} \underbrace{dt}_{\text{circle}} + \underbrace{\partial_x f(t, X_t)}_{\text{wavy}} \underbrace{dX_t}_{\text{circle}} + \underbrace{\frac{1}{2} \partial_x^2 f(t, X_t)}_{\text{red}} \underbrace{d[X, X]_t}_{\text{wavy}}$$

Remark 6.29. This is the main tool we will use going forward. We will return and study it thoroughly after understanding all the notions involved.

→ More today

Proposition 6.30. If $X = X_0 + \underbrace{B}_B + \underline{M}$, then $[X, X] = \underline{[M, M]}$.

(M, B are both cts)

Note: $dM = dM' \vee dW$ then $M_t = \cancel{M}_0^{\rightarrow 0} + \int_0^t \underbrace{\sigma_s}_{\sigma_s} dW_s$

Know $[M, M]_t = \int_0^t \sigma_s^2 ds$

$(\Leftrightarrow) d[M, M]_t = \sigma_t^2 dt$ (short hand notation.)

$$\text{Alt Notation: } d[M, M]_t = dM_t dM_t$$

↳ Intuition:



$$\begin{aligned}
 [X, X]_T &= \lim_{\|P\| \rightarrow 0} \sum (\Delta_i X)^2 && (\Delta_i X = X_{t_{i+1}} - X_{t_i}) \\
 &= \lim_{\|P\| \rightarrow 0} \sum (\Delta_i B + \Delta_i M)^2
 \end{aligned}$$

$$\begin{aligned}
 &= \lim_{\|P\| \rightarrow 0} \left[\underbrace{(\Delta_i B)^2}_{\substack{\text{IOU.} \\ \|P\| \rightarrow 0}} + \underbrace{(\Delta_i M)^2}_{\substack{\|P\| \rightarrow 0 \\ [M, M]_T}} + \underbrace{2(\Delta_i B)(\Delta_i M)}_{\substack{\text{IOU} \\ \|P\| \rightarrow 0}} \right] \\
 &\quad \downarrow \quad \quad \quad \downarrow \quad \quad \quad \searrow \\
 &0 \quad \quad \quad [M, M]_T \quad \quad \quad 0
 \end{aligned}$$

① Complete $\lim_{\|P\| \rightarrow 0} \sum (\Delta_i B)^2 \leq \lim_{\|P\| \rightarrow 0} \left(\underbrace{\max_i |\Delta_i B|}_{\text{green}} \underbrace{\sum |\Delta_i B|}_{\text{red}} \right)$

$$\lim_{\|P\| \rightarrow 0} \max_i |B_{t_{i+1}} - B_{t_i}| = 0$$

($\because B$ is cts).



$$\begin{array}{c} \downarrow \|P\| \rightarrow 0 \\ V \quad B \\ [0, T] \\ \text{(Def Var } B) < \infty. \end{array}$$

$$\textcircled{2} \quad \lim_{\|P\| \rightarrow 0} \sum (\Delta_i B) (\Delta_i M) \stackrel{\text{Cauchy-Schwarz}}{\leq} \lim_{\|P\| \rightarrow 0} \left(\sum |\Delta_i B|^2 \right)^{1/2} \left(\sum |\Delta_i M|^2 \right)^{1/2}$$

$$\left(\underbrace{\sum x_i y_i}_{\|x \cdot y\|} \leq \underbrace{\left(\sum x_i^2 \right)^{1/2}}_{\|x\|} \underbrace{\left(\sum y_i^2 \right)^{1/2}}_{\|y\|} \right)$$

$$\begin{array}{c}
 \downarrow \\
 0 \\
 \underbrace{\hspace{10em}} \\
 0
 \end{array}
 \quad
 \begin{array}{c}
 \downarrow \|P\| \rightarrow 0 \\
 [M, M]
 \end{array}$$

Proposition 6.31 (Uniqueness). *The Itô decomposition is unique. That is, if $\underline{X} = \underline{X}_0 + \underline{B} + \underline{M} = \underline{Y}_0 + \underline{C} + \underline{N}$, with:*

▷ $\underline{B}, \underline{C}$ bounded variation, $B_0 = C_0 = 0$

▷ $\underline{M}, \underline{N}$ martingale, $M_0 = N_0 = 0$.

Then $X_0 = Y_0$, $B = C$ and $M = N$.

Check: ① At $t=0$, $M_0 = N_0 = 0$, $B_0 = C_0 = 0$
 $\Rightarrow X_0 = Y_0$.

② Knows $B + M = C + N$

$$\Rightarrow B - C = \underbrace{N - M}$$

Finke ist vor
(B.V.)

↓
Mg.

$$\begin{aligned} \text{Know} \quad E (N_t - M_t)^2 &= E [N - M, N - M]_t \\ &= E [B - C, B - C]_t = 0 \end{aligned}$$

$$\Rightarrow N = M \quad \& \quad B = C$$

Corollary 6.32. Let $dX_t = \overbrace{b_t dt} + \sigma_t dW_t$ with $\mathbf{E} \int_0^t b_s ds < \infty$ and $\mathbf{E} \int_0^t \sigma_s^2 ds < \infty$. Then X is a martingale if and only if $b = 0$.

(If X was a mg, then

$$\begin{aligned}
 X_t &= X_0 + \overset{\text{BV}}{\underbrace{0}} + \underbrace{(X_t - X_0)}_{\text{Mg}} \\
 &= X_0 + \int_0^t b_s ds + \int_0^t \sigma_s dW_s
 \end{aligned}$$

Uniqueness $\Rightarrow \int_0^t b_s ds = 0 \quad \forall t$ & $X_t = X_0 + \int_0^t \sigma_s dW_s \quad (\Rightarrow b=0)$

Definition 6.33. If $dX = b dt + \sigma dW$ define $\int_0^T D_t dX_t = \int_0^T D_t b_t dt + \int_0^T D_t \sigma_t dW_t$.

Remark 6.34. Note $\int_0^T D_t b_t dt$ is a Riemann integral, and $\int_0^T D_t \sigma_t dW_t$ is a Itô integral.

6.6. Itô's formula.

Remark 6.35. If f and X are differentiable, then

$$df(t, X_t) = \partial_t f(t, X_t) dt + \partial_x f(t, X_t) dX_t$$

Chain Rule: $f = f(t, x)$ diff.

Want $x = x(t)$ some diff fun.

What is $\frac{d}{dt} \left[f(t, x(t)) \right] \stackrel{\text{Chain Rule}}{=} \partial_t f(t, x(t)) + \partial_x f(t, x(t)) \frac{dx}{dt}$

$$u(t) \longrightarrow X_t.$$

$$Y_t = f(t, X_t) \longrightarrow \text{same process}$$

$$dY_t = \left(\frac{d}{dt} f(t, X_t) \right) dt$$

$$= \frac{\partial}{\partial t} f(t, X_t) dt + \frac{\partial}{\partial X_t} f(t, X_t) \frac{dX_t}{dt} dt$$

$$d(f(t, X_t)) = \underbrace{\frac{\partial f}{\partial t}(t, X_t)}_{\text{red underline}} dt + \underbrace{\frac{\partial f}{\partial X_t}(t, X_t)}_{\text{red wavy underline}} dX_t$$

ONLY WORKS IF X is a diff fn of t .

All (non-constant) M_j 's are NOT diff fns of t .

Ito-Doelkin

Theorem (Itô's formula, Theorem 6.28). If $f \in C^{1,2}$, then

$$df(t, X_t) = \underbrace{\partial_t f(t, X_t)}_{\text{blue}} dt + \underbrace{\partial_x f(t, X_t)}_{\text{red}} dX_t + \underbrace{\frac{1}{2} \partial_x^2 f(t, X_t) d[X, X]_t}_{\text{green}}$$

Remark 6.36. If $dX_t = b_t dt + \sigma_t dW_t$ then

~~$$df(t, X_t) = \left(\partial_t f(t, X_t) + b_t + \frac{1}{2} \sigma_t^2 \right) dt + \partial_x f(t, X_t) \sigma_t dW_t.$$~~

$f \in C^{1,2}$

$$\rightarrow f = f(t, x)$$

① f is diff in t

② f is twice diff in x .

$Y_t = f(t, X_t) \leftarrow$ new process.

$$Q: dY_t = ?$$

$$\text{Note } dX = b dt + \sigma dW$$

$$df(t, X_t) = \frac{\partial f}{\partial t}(t, X_t) dt + \frac{\partial f}{\partial X}(t, X_t) dX + \frac{1}{2} \frac{\partial^2 f}{\partial X^2}(t, X_t) d[X, X]$$

$$= \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial X} (b dt + \sigma dW) + \frac{1}{2} \frac{\partial^2 f}{\partial X^2} \sigma^2 dt$$

$$= \left(\frac{\partial f}{\partial t} + \frac{\partial f}{\partial X} \cdot b + \frac{1}{2} \frac{\partial^2 f}{\partial X^2} \sigma^2 \right) dt + \frac{\partial f}{\partial X} \sigma dW$$

Intuition behind Itô's formula?

Simple case : $f(t, x) = f(x)$ (indep of t).

$$X_t = W_t.$$

$$\text{Itô: } d f(x_t) = d f(W_t) = f'(W_t) dt + \frac{1}{2} f''(W_t) dt$$

Will show





$$f(w_T) - f(w_0) = \sum \Delta_i f(w) = \sum f(w_{t_{i+1}}) - f(w_{t_i})$$

Taylor Exp
=

$$\underbrace{\sum f'(w_{t_i})(w_{t_{i+1}} - w_{t_i})}_{(1)} + \frac{1}{2} \underbrace{\sum f''(w_{t_i})(w_{t_{i+1}} - w_{t_i})^2}_{(2) + \text{small terms.}}$$

→ 0

$$\lim_{\|P\| \rightarrow 0} \textcircled{1} = \lim_{\|P\| \rightarrow 0} \sum f(W_{t_i}) \Delta_i W \longrightarrow \int_0^T f(W_t) dW_t$$

$$\lim_{\|P\| \rightarrow 0} \textcircled{2} = \lim_{\|P\| \rightarrow 0} \frac{1}{2} \sum f''(W_{t_i}) (\Delta_i W)^2$$

$$= \lim_{\|P\| \rightarrow 0} \frac{1}{2} \sum f''(W_{t_i}) \underbrace{(t_{i+1} - t_i)}$$

$$\xrightarrow{\|P\| \rightarrow 0} \frac{1}{2} \int_0^T f''(W_t) dt$$

$$+ \lim_{\|P\| \rightarrow 0} \frac{1}{2} \sum f''(w_{t_i}) \cdot \underbrace{\left((\Delta_i W)^2 - (t_{i+1} - t_i) \right)}$$

NTS $\rightarrow 0$

Note : $(\Delta_i W)^2 - (t_{i+1} - t_i) \sim \underbrace{\left(N(0, t_{i+1} - t_i)^2 - (t_{i+1} - t_i) \right)}$

① Mean 0.

② Variance $2 \underbrace{(t_{i+1} - t_i)}^2$

Guess: $\frac{1}{2} \sum f''(W_{t_i}) \left(\underbrace{(\Delta_i W)^2 - (t_{i+1} - t_i)} \right)$

mean 0 & variance $\sum \underbrace{f''(W_{t_i})^2}_{\text{variance}} \cdot 2(t_{i+1} - t_i)^2$

$\xrightarrow{|P| \rightarrow 0} 0$

Example 6.37. Find the quadratic variation of W_t^2 .

Q: What is QV of W_t

What is QV of t

What is QV of t^2

W_t ? \rightarrow t ✓

t ? \rightarrow t^2 ✓

W_t^2

\rightarrow guess W_t^2

Hopelessly Wrong!!

QV of W :

$$\text{Let } X_t = W_t.$$

$$\text{Let } f(t, x) = x^2$$

$$\text{Then } W_t^2 = f(t, W_t).$$

$$\text{By Ito: } d(W_t^2) = \frac{\partial}{\partial t} f(t, X_t) dt + \frac{\partial}{\partial x} f(t, X_t) dX_t + \frac{1}{2} \frac{\partial^2}{\partial x^2} f(t, X_t) \underbrace{d[X, X]}.$$

k

$$\textcircled{1} \partial_{tt} f = 0$$

$$\textcircled{2} \partial_x f = 2x$$

$$\textcircled{3} \partial_x^2 f = 2$$

$$\textcircled{4} d[X, X] = dt.$$

$$= 0 + 2X_t dX_t$$

$$+ \frac{1}{2} \cdot 2 \cdot dt$$

$$= 2W_t dW_t + dt$$

$$\Rightarrow d(W_t^2) = 2W_t dW_t + \underline{\underline{dt}}$$

$$\Rightarrow d [W^2, W^2]_t = 4 W_t^2 dt + 0$$

$$\Rightarrow [W, W]_T = \int_0^T 4 W_t^2 dt$$

Example 6.38. Find $\int_0^t W_s dW_s$.

← Itô's Lemma.

Example 6.39. Let $M_t = \underline{W}_t$, and $N_t = \underline{W}_t^2 - t$.

▷ We know M, N are martingales.

▷ Is MN a martingale?

Is $W_t (W_t^2 - t)$ a mg?

\Leftrightarrow Is $W_t^3 - W_t t$ a mg?

Option 1: Find $E_S (W_t^3 - W_t t)$

by using $W_t = W_t - W_c + W_c$
& ind lemma

Option 2: Ito's formula:

$$Y_t = f(t, W_t), \quad \text{where } f(t, x) = x^3 - at.$$

Compute $dY = \overset{It\ddot{o}}{=} = (\underline{\quad})dt + (\underline{\quad})dW$

Y is a mg if and only if the dt term vanishes.

$$\textcircled{1} \partial_t f = -1$$

$$\textcircled{2} \partial_x f = 3x^2 - t$$

$$\textcircled{3} \partial_x^2 f = 6x$$

$$\textcircled{4} d[W, W]_t = dt$$

$$dY = d f(t, \underbrace{W}_t)$$

$$= \partial_t f dt + \partial_x f dW + \frac{1}{2} \partial_x^2 f dt$$

$$= -W_t dt + (3W_t^2 - t) dW + \frac{1}{2} \cdot 6W_t dt$$

(Replace α with W_t in \rightarrow)

$$= \underbrace{2W_t}_{\neq 0} dt + (3W_t^2 - t) dW$$

$\rightarrow f(t, W_t)$ is NOT a mg.

Example 6.40. Let $X_t = t \sin(W_t)$. Is $X_t^2 - [X, X]_t$ a martingale?

Guess: IDK (X ~~is~~ ^{need} not be a mg).

Ito: $f(t, x) = t \sin x$

$$\partial_t f = \sin x$$

$$\partial_x f = t \cos x$$

$$\partial_x^2 f = -t \sin x$$

$$dX_t = \partial_t f dt + \partial_x f dW + \frac{1}{2} \partial_x^2 f dt$$

$$= \sin(W_t) dt + t \cos W_t dW$$

$$- \frac{1}{2} t \sin(W_t) dt$$

$$= \left(\underbrace{\left(1 - \frac{t}{2}\right) \sin W_t}_{\text{red wavy underline}} \right) dt + t \cos W_t dW.$$

$$\Rightarrow d[X, X]_t = \underbrace{t^2 \cos^2(W_t)}_{\text{red wavy underline}} dt$$

NT & Check $X^2 - [X, X]$ is a mg.

$$Y = \underline{X^2} - [X, X] \Rightarrow dY = 2X dX + \frac{1}{2} \cdot 2 \cdot d[X, X] - d[X, X]$$

$$= 2X dX$$

$$= 2X \left(\left(1 - \frac{t}{2}\right) \sin W_t \right) dt$$

$$+ 2X t \cos W_t dW$$

$\rightarrow \neq 0$

$\Rightarrow X^2 - [X, X]$ is not a mgf!