

§. Stochastic Integration

4.2 Quadratic Variation

Def. 4.2.1. Let M be a stochastic process. Then

$$[M, M]_T(\omega) := \lim_{\|\Pi\| \rightarrow 0} \sum_{i=0}^{n-1} (\Delta M_i(\omega))^2$$

where $\Delta M_i := M_{t_{i+1}} - M_{t_i}$ and $\Pi = \{0 = t_0 < t_1 < \dots < t_n = T\}$

for Brownian motion W , $[W, W]_t = t$

Lemma. 4.2.1 $M_t = W_t^2 - t$ is a martingale

proof: • Adapted: M_t is \mathcal{F}_t -measurable because W_t is \mathcal{F}_t -measurable and M_t is a function of W_t and t .

• Martingale property: check $E[M_t | \mathcal{F}_s] = M_s \quad \forall t > s$

$$\begin{aligned} E[M_t | \mathcal{F}_s] &= E[W_t^2 - t | \mathcal{F}_s] \\ &= E[(W_t - W_s + W_s)^2 - t | \mathcal{F}_s] \\ &= E[(W_t - W_s)^2 + 2(W_t - W_s)W_s + W_s^2 - t | \mathcal{F}_s] \\ &= E[\underbrace{(W_t - W_s)^2}_{\text{ind. of } \mathcal{F}_s} | \mathcal{F}_s] + E[2(W_t - W_s) \cdot \underbrace{W_s}_{\mathcal{F}_s\text{-measurable}} | \mathcal{F}_s] \\ &\quad + E[\underbrace{W_s^2}_{\mathcal{F}_s\text{-measurable}} | \mathcal{F}_s] - E[t | \mathcal{F}_s] \\ &= E[(W_t - W_s)^2] + 2W_s E[W_t - W_s] \\ &\quad + W_s^2 - t \\ &= t - s + W_s^2 - t \\ &= W_s^2 - s \\ &= M_s \end{aligned}$$

Theorem 4.2.1 Let M be a martingale w.r.t. a filtration $(\mathcal{F}_t)_{t \geq 0}$

Then for all $t \geq 0$, $E[M_t^2] < \infty \Leftrightarrow E[[M, M]_t] < \infty$

In this case, $(M_t^2 - [M, M]_t)_{t \geq 0}$ is a martingale w.r.t. the same filtration, and $E[M_t^2] - E[M_0^2] = E[[M, M]_t]$

Example: $M = W$ is a martingale $\Rightarrow (W_t^2 - t)_{t \geq 0}$ is a martingale

Theorem 4.2.2. If M is a martingale and A_t is a continuous adapted increasing stochastic process s.t. $A_0 = 0$ and

$(M_t^2 - A_t)_{t \geq 0}$ is a martingale, then

$$A_t = [M, M]_t \quad (\text{proof is omitted})$$

Example: $M = W$, $A_t = t$

A_t is continuous, adapted, \mathcal{F}_0 -measurable, increasing, and $A_0 = 0$

$M_t^2 - A_t = W_t^2 - t$ is a martingale $\Rightarrow A_t = [W, W]_t$

Remark:

▷ intuition for first variation and quadratic variation:

divide the interval $[0, T]$ into $T/(\delta t)$ intervals of size δt .

if X has finite first variation, then on each subinterval

$(k\delta t, (k+1)\delta t)$ the increment of X should be of order δt .

Similarly, X has finite quadratic variation \Rightarrow increment

▷ If a continuous process has finite first variation, $\propto \sqrt{\delta t}$
its quadratic variation will necessarily be zero.

If a continuous process has finite and non-zero quadratic variation, its first variation will necessarily be infinite

4.3. Construction of Itô integral.

Let W be a standard BM, $(\mathcal{F}_t)_{t \geq 0}$ be the Brownian filtration and D be an adapted process.

Let $(\Delta_t)_{t \geq 0}$ be our position in S at time t , that is

invest $\Delta_t S_t$ at time t and the value of portfolio

time $t+1$ is $\Delta_t \cdot S_{t+1}$ however, almost any continuous martingale S will not have finite first variation, thus we need the Itô integral

$$\Rightarrow P_{n1} = \sum_{i=0}^{n-1} \Delta_i (S_{i+1} - S_i) \xrightarrow{n \rightarrow \infty} \int \Delta_t \cdot dS_t$$

Lemma 4.3.1 let $\Pi = \{0 = t_0 < t_1 < \dots < t_n\}$ be an increasing sequence of times and assume that D is constant on $[t_i, t_{i+1}) \forall i$ (i.e. the asset is only traded at time t_0, \dots, t_n)

$$\text{let } I_T^\Pi = \sum_{i=0}^{n-1} D_{t_i} \Delta W_i + D_{t_n} (W_T - W_{t_n}) \text{ if } T \in [t_n, t_{n+1})$$

$$\text{where } \Delta W_i = W_{t_{i+1}} - W_{t_i}$$

denote the cumulative earnings up to time T , then

$$E[(I_T^\Pi)^2] = E\left[\sum_{i=0}^{n-1} D_{t_i}^2 (t_{i+1} - t_i) + D_{t_n}^2 (T - t_n)\right] \text{ if } T \in [t_n, t_{n+1})$$

Moreover, I^Π is a martingale and.

$$[I^\Pi, I^\Pi]_T = \sum_{i=0}^{n-1} D_{t_i}^2 (t_{i+1} - t_i) + D_{t_n}^2 (T - t_n) \text{ if } T \in [t_n, t_{n+1})$$

Theorem 4.3.1 If $\int_0^T D_t^2 dt < \infty$, then as $\|\Pi\| \rightarrow 0$, the process

I^Π converge to a cost process I given by

$$I_T := \lim_{\|\Pi\| \rightarrow 0} I_T^\Pi = \int_0^T D_t dW_t$$

Note that D should be adapted, and is sampled at the left endpoint of the time interval, i.e. terms in the sum are $D_{t_i}(W_{t_{i+1}} - W_{t_i})$

This is called the Itô integral of D w.r.t. W .

If further, $E[\int_0^T D_t^2 dt] < \infty$, then the process I is a martingale and the quadratic variation $[I, I]$ satisfies $[I, I]_T = \int_0^T D_t^2 dt$ almost surely. Besides, $E[\int_0^T D_t dW_t] = 0$

Property 4.3.1 (linearity)

If D^1, D^2 are two adapted process, $\lambda \in \mathbb{R}$, then

$$\int_0^T (D_t^1 + \lambda D_t^2) dW_t = \int_0^T D_t^1 dW_t + \lambda \int_0^T D_t^2 dW_t$$

Itô Isometry

If $E[\int_0^T D_t^2 dt] < \infty$, then

$$E[(\int_0^T D_t dW_t)^2] = E[\int_0^T D_t^2 dt]$$

Example: $D_t = 1$, then

$$E[(\int_0^T D_t dW_t)^2] = E[\int_0^T 1^2 dt]$$

$\underbrace{\hspace{10em}}_{W_T - W_0} \qquad \underbrace{\hspace{10em}}_T$

$$\Rightarrow E[W_T^2] = T$$

Remark:

positivity is not preserved by Itô integrals. Namely, if $D^1 \leq D^2$, there is no reason to expect $\int_0^T D_t^1 dW_t \leq \int_0^T D_t^2 dW_t$.

Def (GBM). We define Geometric Brownian Motion S as

$$dS_t = \beta S_t dW_t + \alpha S_t dt, \quad \beta, \alpha \in \mathbb{R}$$

\Rightarrow stochastic differential equation (SDE)

$$\int_0^T 1 dS_t = \int_0^T \beta S_t dW_t + \int_0^T \alpha S_t dt$$

$$\Rightarrow S_T - S_0 = \int_0^T \beta S_t dW_t + \int_0^T \alpha S_t dt$$

4.4. Itô formula

Goal: Compute $\int_0^T W_t dW_t = ?$

Def 4.4.1 Let b, σ be adapted process. Then a process X defined as

$$X_T = X_0 + \int_0^T b_t dt + \int_0^T \sigma_t dW_t \quad X_0 \in \mathbb{R}$$

Riemann integral Itô integral

is called an Itô process if X_0 is deterministic (not random)

and for all $T \geq 0$ $E[\int_0^T \sigma_t^2 dt] < \infty$ and $\int_0^T |b_t| dt < \infty$

Remark:

the equation above is equivalent to

$$dX_t = b_t dt + \sigma_t dW_t$$

property 4.4.1 The quadratic variation of X is

$$[X, X]_T = \int_0^T \sigma_t^2 dt$$

Def 4.4.2. Process X which can be decomposed as $X = A + M$
(semi-MG)

where M is a martingale and A has finite variation
are called semi-martingale. (first)

▷ M is called the martingale part of X

▷ A is called the finite variation part of X

prop 4.4.2 The semi-MG decomposition is unique, that is

if $X = A_1 + M_1 = A_2 + M_2^{(*)}$, then

$$A_1 = A_2, M_1 = M_2$$

(where A_1, A_2 are finite variation processes, M_1, M_2 are martingales)

proof: by (*) we have

$$\underbrace{A_1 - A_2}_{\text{finite variation}} = \underbrace{M_1 - M_2}_{\text{MG}} := M$$

thus M is a MG with finite variation $\Rightarrow [M, M]_T = 0$

$$\stackrel{A.2.1}{\Rightarrow} E[M_t^2] = E[[M, M]_T] = 0$$

$(M^2 - [M, M])_t$
is a M.G.)

$\Rightarrow M_t^2 \geq 0$ thus $M_t = 0$, that is $A_1 = A_2$
 $M_1 = M_2$

Prop 4.4.3 Let X be an Itô process, then

X is a MG $\Leftrightarrow b_t = 0 \quad \forall t \geq 0$ (i.e. $X_T = X_0 + \int_0^T \sigma_t dW_t$)

proof: If $b_t = 0 \quad \forall t \geq 0 \Rightarrow X$ is a M.G.

Suppose X is a M.G. Define

$$A_T := \int_0^T b_t dt = \underbrace{X_T - X_0}_{\text{M.G.}} - \underbrace{\int_0^T \sigma_t dW_t}_{\text{M.G.}}$$

$\Rightarrow A$ is a martingale. (also a semi-M.G.)

$$A = \underbrace{A + 0}_{\uparrow} = 0 + A \quad \text{thus } A = 0 \Leftrightarrow b_t = 0$$

Def 4.4.3. We define the integral of D w.r.t. X by

$$\int_0^T D_t dX_t := \int_0^T D_t b_t dt + \int_0^T D_t \sigma_t dW_t$$

where $dX_t = b_t dt + \sigma_t dW_t$

[Given an adapted process D , we interpret X as the price of an asset, and D as our position in it, which can be positive or negative.)

Theorem 4.4 (Itô formula)

Recall that

if $f: \mathbb{R} \rightarrow \mathbb{R}$ is continuously differentiable

$$f(y) - f(x) = \int_x^y \frac{\partial f}{\partial x}(z) dz$$

If $f: [0, \infty) \times \mathbb{R} \rightarrow \mathbb{R}$ is such that

$t \mapsto f(t, x)$ is cont. differentiable $\forall x \in \mathbb{R}$ $\partial_t f(t, x)$ exists

$x \mapsto f(t, x)$ is twice cont. differentiable.

$\forall t \in \mathbb{R}$. $\partial_x f(t, x)$, $\partial_x^2 f(t, x)$ exist

and if X is an Itô process, then

$$f(T, X_T) - f(0, X_0) = \int_0^T \partial_t f(t, X_t) dt + \int_0^T \partial_x f(t, X_t) dX_t + \underbrace{\frac{1}{2} \int_0^T \partial_x^2 f(t, X_t) d[X, X]_t}_{\text{Itô correction term}}$$

Remark:

- ▷ $\partial_t f(t, X_t)$ stands for taking derivative of $f(t, X_t)$ w.r.t. t and then substitute X_t , Similar for $\partial_x f(t, X_t)$, $\partial_x^2 f(t, X_t)$
- ▷ The Itô formula is simply a version of the chain rule for Stochastic processes.

Stochastic form:

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

Substitute (the Itô process) $\begin{cases} dX_t = b_t dt + \sigma_t dW_t \\ d[X, X]_t = \sigma_t^2 dt \end{cases}$ we have

$$\begin{aligned} \Rightarrow df(t, X_t) &= \partial_t f(t, X_t) dt + \partial_x f(t, X_t) [b_t dt + \sigma_t dW_t] \\ &\quad + \frac{1}{2} \partial_x^2 f(t, X_t) \cdot \sigma_t^2 dt \\ &= [\partial_t f(t, X_t) + \partial_x f(t, X_t) \cdot b_t + \frac{1}{2} \partial_x^2 f(t, X_t) \sigma_t^2] dt \\ &\quad + \partial_x f(t, X_t) \cdot \sigma_t dW_t \end{aligned}$$

if the term before dt is zero, $f(t, X_t)$ is a martingale.

otherwise not

4.5 Examples

ex 1. write W^2 as a sum of dt and dW_t -integral

use the Itô formula and substitute $f(t, X) = X^2$, $X = W_t$

$$\Rightarrow \partial_t f(t, X) = 0, \quad \partial_x f(t, X) = 2X, \quad \partial_x^2 f(t, X) = 2$$

$$\Rightarrow [W, W]_t = t$$

By Itô formula

$$\begin{aligned} d(W_t^2) &= d(f(t, W_t)) = \overset{\rightarrow 0}{\partial_t f(t, W_t)} dt + \overset{\rightarrow 2W_t}{\partial_x f(t, W_t)} dW_t \\ &\quad + \frac{1}{2} \underbrace{\partial_x^2 f(t, W_t)}_{\rightarrow 2} \underbrace{d[W, W]_t}_t \\ &= 2W_t dW_t + dt \end{aligned}$$

calculating the integral from 0 to T

$$\begin{aligned} W_T^2 - 0 &= \int_0^T 2W_t dW_t + \int_0^T dt = \int_0^T 2W_t dW_t + T \\ \Rightarrow \int_0^T W_t dW_t &= \frac{1}{2} (W_T^2 - T) \end{aligned}$$

Q: calculate $[W^2, W^2]_T$

$$\begin{aligned} [W^2, W^2]_T &= \int_0^T (2W_t)^2 dt = 4 \int_0^T W_t^2 dt \\ &\quad \begin{array}{l} \rightarrow \text{not constant.} \\ \text{a r.v.} \end{array} \end{aligned}$$

ex 2. Let $M_t = W_t$, $N_t = W_t^2 - t$, is M, N a M.G.?

first method is to verify $E[M_t \cdot N_t | \mathcal{F}_s] = M_s \cdot N_s \quad \forall t \geq s$

another method is to use the Itô formula.

$$\text{Note } M_t \cdot N_t = W_t(W_t^2 - t) = W_t^3 - W_t \cdot t$$

$$f(t, X) = X^3 - tx \quad X_t = W_t \quad [X, X]_t = t$$

$$\Rightarrow \partial_x f(t, x) = 3x^2 - t \quad \partial_t f(t, x) = -x \quad \partial_x^2 f(t, x) = 6x$$

$$\begin{aligned} \Rightarrow df(t, x) &= \partial_t f(t, x_t) dt + \partial_x f(t, x_t) dx_t \\ &\quad + \frac{1}{2} \partial_x^2 f(t, x_t) d[x, x]_t \\ &= -x dt + (3x^2 - t) dx_t + 3x dt \\ &= 2x dt + (3x^2 - t) dx_t \\ &= 2W_t dt + (3W_t^2 - t) dW_t \end{aligned}$$

$$M_T N_T = \int_0^T 2W_t dt + \int_0^T (3W_t^2 - t) dW_t$$

Since the finite (first) Variation part is not zero,

$M_T N_T$ is not a martingale.

ex3. Let $X_t = t \sin(W_t)$. Is $X^2 - [X, X]$ a martingale?

$$\text{let } f(t, x) = t \sin(x) \quad \partial_t f = \sin x \quad \partial_x f = t \cos x$$

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

$$\begin{aligned} \Rightarrow dX_t &= \sin W_t dt + t \cos W_t dW_t - \frac{1}{2} t \sin W_t dt \\ &= \left(\sin W_t - \frac{1}{2} t \sin W_t \right) dt + t \cos W_t dW_t \end{aligned}$$

$$(\text{then, } d[X, X] = t^2 \cos^2 W_t dt)$$

$$dX_t^2 = 2X_t dX_t + d[X, X]_t$$

$$\begin{aligned} \Rightarrow d[X^2 - [X, X]] &= 2X_t dX_t \\ &= 2t \sin(W_t) \cdot \left[\sin(W_t) - \frac{1}{2} t \sin(W_t) \right] dt \\ &\quad + 2t^2 \sin(W_t) \cdot \cos(W_t) \cdot dW_t \end{aligned}$$

Since the dt term above is not 0, thus $X^2 - [X, X]$ is not a martingale

4.6.1 Multidimensional Itô

Def 4.6.1 (quadratic covariation)

Let X, Y be two Itô processes. Define

$$[X, Y]_T = \lim_{\|\pi\| \rightarrow 0} \sum_{i=0}^{n-1} (X_{i+1} - X_i)(Y_{i+1} - Y_i)$$

$$\pi = \{0 = t_0 < \dots < t_n = T\}$$

the quadratic covariation

lemma: $\forall a, b \in \mathbb{R} \quad ab = \frac{1}{4}[(a+b)^2 - (a-b)^2]$

$$\Rightarrow \text{let } a = (X_{i+1} - X_i) \quad b = (Y_{i+1} - Y_i)$$

$$\text{thus } [X, Y]_T = \frac{1}{4} [[X+Y, X+Y]_T - [X-Y, X-Y]_T]$$

Prop 4.6.1 (Product Rule) For Itô processes X, Y , we have

$$d(XY) = XdY + YdX + d[X, Y]$$

Prop 4.6.2 If X is an Itô process and A is adapted

process of finite variation, then $[X, A] = 0$

(Note that $[X \pm A, X \pm A] = [X, X]$)

Prop 4.6.4 If X, Y, Z are Itô processes and $\alpha \in \mathbb{R}$, then

(Bi-linearity) $[X, Y + \alpha Z] = [X, Y] + \alpha [X, Z]$

Prop 4.6.6 Let X, Y be two continuous martingales (e.g. Itô processes) w.r.t. a common filtration $(\mathcal{F}_t)_{t \geq 0}$ such that $E[X_t^2] < \infty$ and $E[Y_t^2] < \infty$, if X, Y are independent, then $[X, Y] = 0$

the converse is not true, for example $X_t = \int_0^t 1_{\{w_s > 0\}} dw_s$

$Y_t = \int_0^t 1_{\{w_s < 0\}} dw_s$, $[X, Y] = 0$ but $X \neq Y$

Theorem 4.6.1 Multidimensional Itô process

Let X^1, X^2, \dots, X^n be Itô processes and $X = (X^1, X^2, \dots, X^n)$

Let $f: [0, +\infty) \times \mathbb{R}^n \rightarrow \mathbb{R}$ $(t, X) \rightarrow f(t, X)$

be C^1 in t ($\partial_t f$ exists)

be C^2 in X^i ($\partial_{X^i} f = \partial_i f$, $\partial_{X^i X^j} f = \partial_i \partial_j f$ exist)

Then

$$f(T, X_T) = f(0, X_0) + \int_0^T \partial_t f(t, X_t) dt + \sum_{i=1}^n \int_0^T \partial_i f(t, X_t) dX_t^i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \int_0^T \partial_i \partial_j f(t, X_t) d[X^i, X^j]_t$$

or

$$df(t, X_t) = \partial_t f(t, X_t) dt + \sum_{i=1}^n \partial_i f(t, X_t) dX_t^i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \partial_i \partial_j f(t, X_t) d[X^i, X^j]_t$$

Remark: we most often use the two dimensions case

$$df(t, X_t, Y_t) = \partial_t f dt + \partial_x f dX_t + \partial_y f dY_t + \frac{1}{2} [\partial_x^2 f d[X, X]_t + 2 \partial_x \partial_y f d[X, Y]_t + \partial_y^2 f d[Y, Y]_t]$$

Prop 4.6.3. Let M, N be Martingales. Then

(1) $M \cdot N - [M, N]$ is a MG

(when $M=N$, $M^2 - [M, M]$ is a MG, which is mentioned before)

(2) If A is adapted process of finite variation such

that $A_0=0$ and $MN - A$ is a MG, then $A = [M, N]$

Example: $M=W$, $N=-W$ $[W, -W]_t = -[W, W]_t = -t$

(Typically, M, N are MG $\nRightarrow M \cdot N$ is MG, eg $M=N=W$)

Prop 4.6.5. let X^1, X^2 be Itô processes, σ^1, σ^2 be adapted processes and $I_t^j = \int_0^t \sigma_s^j dx_s^j \quad j=1,2$.

$$\text{Then } [I^1, I^2]_t = \int_0^t \sigma_s^1 \sigma_s^2 d[X^1, X^2]_s$$

Def 4.6.2. We say that $W = (W^1, W^2, \dots, W^n)$ is a n -dimensional standard BM if

- ① each W^j is a standard BM $\forall j=1, \dots, n$
- ② $\forall i \neq j \quad W^i$ and W^j are independent.

Example.

o for a 2-dimensional sBM $W = (W^1, W^2)$

$$[W^1, W^2]_t = 0 \quad [W^1, W^1]_t = [W^2, W^2]_t = t$$

$$df(W^1, W^2) = \partial_1 f(W^1, W^2) dW^1 + \partial_2 f(W^1, W^2) dW^2 + \frac{1}{2} [\partial_1^2 f(W^1, W^2) dt + \partial_2^2 f(W^1, W^2) dt]$$

Theorem (Lévy)

If $M = (M^1, M^2, \dots, M^d)$ is a continuous martingale such that $M_0 = 0$ and $d[M^i, M^j]_t = 1_{i=j} dt$,

Then M is n -dimensional Brownian motion

Remark:

$$\underbrace{\text{Cov}(X_t, Y_t)}_{\text{a scalar}} \neq \underbrace{[X, Y]_t}_{\text{a random variable}}$$