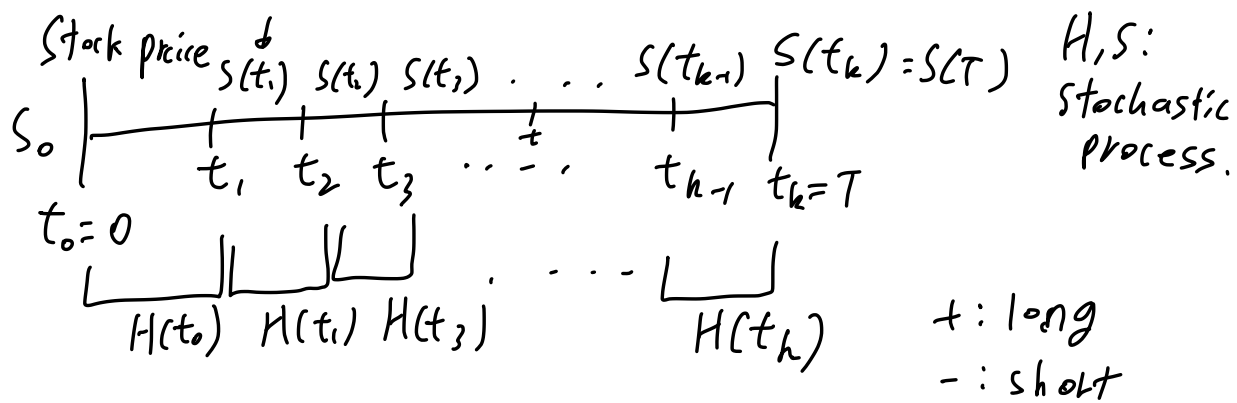


1. Stochastic Integration



$$\begin{aligned} \text{total gain} &= H(t_0)(S(t_1) - S(t_0)) + H(t_1)(S(t_2) - S(t_1)) \\ &\quad + \dots + H(t_{k-1})(S(t_k) - S(t_{k-1})) \\ &= \sum_{n=0}^{k-1} H(t_n)(S(t_{n+1}) - S(t_n)) \leftarrow \text{random variable} \\ &\quad \text{Sum of random variable} \end{aligned}$$

$$\lim_{|t_{i+1} - t_i| \rightarrow 0}$$

$$\Rightarrow \text{total gain} = \int_0^T H(t) dS(t) \leftarrow \text{h.v.}$$

Stochastic integration

$$G_t = \int_0^t H(u) dS(u) \quad (0 \leq t \leq T).$$

Stochastic process

In particular

$$X_t = x + \int_0^t \underbrace{b_u}_{\text{Stochastic process}} du + \int_0^t \underbrace{\sigma_u}_{\text{B.M.}} dW_u$$

is called a Itô process. The relation

$$X_t = x + \int_0^t \underbrace{b_u(X_u)}_{\text{function}} du + \int_0^t \underbrace{\sigma_u(X_u)}_{\text{function}} dW_u$$

is called a SDE (stochastic differential eq.)

$$\begin{cases} dX_t = b_t(r_t)dt + \sigma_t(X_t) \underline{dW}_t \\ X_0 = x \end{cases}$$

If σ_u deterministic process i.e. $\sigma_u(\omega) = \sigma_u$,

$$\int_0^t \sigma_u \underline{dB}_u \sim N(0, \mathbb{E}[(\int_0^t \sigma_u \underline{dB}_u)^2]) \quad \forall t.$$

$\lim_{n \rightarrow \infty} \sum_{i=1}^n \sigma_{t_i} \Delta B_{t_i} \sim N$ σ_u deterministic $\int_0^t \sigma_u \underline{dM}_u$ (M : martingale) is a martingale.

2. Quadratic Variation.

Let M be a martingale.

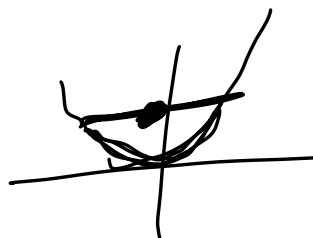
Q: Is M^2 a martingale?

A: Not always.

Jensen's inequality:

$$\mathbb{E}[M_t^2 | \mathcal{F}_s] \geq (\underbrace{\mathbb{E}[M_t | \mathcal{F}_s]}_{M_s})^2 = M_s^2$$

M^2 'bigger' than martingale.



Def Quadratic variation of a martingale M is the unique increasing stochastic process $\langle M \rangle$ such that $M^2 - \langle M \rangle$ is a martingale.

M^2 'bigger' than martingale.

How much bigger?

If M^2 martingale.

$$M_{t+dt} = M_t + dM_t$$

$$(M_t + dM_t)^2 \approx M_t^2$$

$$\underbrace{(M_t + dM_t)^2 - M_t^2}_{\approx 0} = \underbrace{2M_t dM_t}_{\approx 0} + \underbrace{(dM_t)^2}_{\text{This much bigger.}}$$

$$\underbrace{\langle M \rangle_t = \int_0^t (dM_u)^2 = \lim \sum (M_{t_{i+1}} - M_{t_i})^2}$$

$$\underbrace{d\langle M \rangle_t = (dM_t)^2}$$

If σ process

Def More generally if X is a semimartingale,

it can be written as $X_t = \underbrace{A_t}_{\text{f.}} + \underbrace{M_t}_{\text{mg.}}$

$$\langle X \rangle_t := \langle M \rangle_t$$

Examples. B : B.M.

$$(i) \mathbb{E}[\underbrace{B_t^2 - t}_{\text{martingale}} | \mathcal{F}_s]$$

$$= \mathbb{E}[\underbrace{(B_t - B_s + B_s)^2 - t}_{\text{martingale}} | \mathcal{F}_s]$$

$$= \mathbb{E}[\underbrace{(B_t - B_s)^2}_{\text{martingale}} | \mathcal{F}_s] + 2\mathbb{E}[\underbrace{(B_t - B_s)B_s}_{\text{martingale}} | \mathcal{F}_s]$$

$$B_t - B_s \sim N(0, t-s) \quad \mathbb{E}[\underbrace{B_s^2}_{\text{measurable}} | \mathcal{F}_s] - t. \quad \approx 2!$$

$$= (t-s) + 2 \cdot 0 + \underbrace{B_s^2}_{\text{measurable}} - t = \underbrace{B_s^2 - s}_{\text{martingale}}$$

$\Rightarrow B_t^2 - t$: martingale.

$$\boxed{\langle B \rangle_t = t.}$$

$$\lim \sum (B_{t_{i+1}} - B_{t_i})^2 = t.$$

$$(ii) \quad X_t = \int_0^t b_u du + \underbrace{\int_0^t \sigma_u dB_u}_{\text{Martingale.}}$$

$$\langle X \rangle = \langle \int_0^t \sigma_u dB_u \rangle$$

$$d\langle M \rangle = (dM)^2$$

$$\begin{aligned} (\sigma_t dB_t)^2 &= \sigma_t^2 \underbrace{(dB_t)^2}_{dt} \\ &= \sigma_t^2 d\langle B \rangle_t \\ &= \sigma_t^2 dt. \end{aligned}$$

$$\langle X \rangle_t = \int_0^t \sigma_u^2 du.$$

Def The quadratic covariation of two martingales M, N is the unique process $\langle M, N \rangle$ such that $MN - \langle M, N \rangle$ is a martingale.

$$\text{If } X = A_1 + M_1, Y = A_2 + M_2 \\ \langle X, Y \rangle = \langle M_1, M_2 \rangle$$

As before,

$$d\langle X, Y \rangle_t = dX_t dY_t$$

$$\langle X, Y \rangle_t = \lim \sum (X_{t_{i+1}} - X_{t_i})(Y_{t_{i+1}} - Y_{t_i}).$$

Examples

$$(i) \quad t = 0 + \underbrace{0}_{\text{martingale}}, \quad B_t = 0 + \underbrace{B_t}_{\text{martingale part.}}$$

$$\Rightarrow \langle t, B_t \rangle = \langle 0, B_t \rangle = 0$$

i.e. $dt \perp dB_t = 0$

$$(ii) \quad dX_t = \underbrace{\sigma_1(t) dt + \sigma_1(t) dB_t}_{dY_t}$$
$$dY_t = \sigma_1(t) dt + \sigma_2(t) dB_t$$
$$dX_t dY_t = \sigma_1(t) \sigma_2(t) (dB_t)^2$$

$\stackrel{=}{=} d\langle B \rangle_t = dt$

$$= \sigma_1(t) \sigma_2(t) dt.$$

$$\therefore \langle X, Y \rangle_t = \int_0^t \sigma_1(u) \sigma_2(u) du.$$

Itô isometry,

M : martingale,

$$\underbrace{\mathbb{E} \left[\left(\int_0^t \sigma_u dM_u \right)^2 \right]}_{\text{Var} \left(\int_0^t \sigma_u dM_u \right)} = \underbrace{\mathbb{E} \left[\int_0^t \sigma_u^2 d\langle M \rangle_u \right]}$$

$$\int_0^t \sigma_u dB_u \sim N \left(0, \mathbb{E} \left[\int_0^t \sigma_u^2 dB_u \right] \right)$$

3. Itô Formula.

Recall

$$f(t, x) = f(0, 0) + \int \frac{\partial f}{\partial t}(t, x) dt + \int \frac{\partial f}{\partial x}(t, x) dx.$$

$$\therefore e. \quad df(t, x) = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial x} dx$$

: Taylor expansion (up to first order).

$$\begin{aligned} f(t+dt, x+dx) &= f(t, x) + \underbrace{\frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial x} dx}_{1^{st} \text{ order}} + \underbrace{\frac{1}{2} \frac{\partial^2 f}{\partial t^2} (dt)^2 + \frac{\partial^2 f}{\partial t \partial x} dt dx + \frac{1}{2} \frac{\partial^2 f}{\partial x^2} (dx)^2}_{2^{nd} \text{ order}} \end{aligned}$$

$$\begin{aligned} (dt)^2 &= 0, \quad dt dx, \quad \dots \\ (dx_t)^2 &= d\langle X \rangle_t \neq 0. \end{aligned}$$

Similarly.

$$df(t, X_t) = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial x} dX_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2} d\langle X \rangle_t$$

$$\begin{aligned} f(t, X_t) &= \int_0^t \frac{\partial f}{\partial t}(u, X_u) du + \int_0^t \frac{\partial f}{\partial x}(u, X_u) dX_u \\ &\quad + \frac{1}{2} \int_0^t \frac{\partial^2 f}{\partial x^2}(u, X_u) d\langle X \rangle_u. \end{aligned}$$

$$df(X_t, Y_t)$$

$$\begin{aligned} &= \frac{\partial f}{\partial x} dX_t + \frac{\partial f}{\partial y} dY_t + \frac{1}{2} \frac{\partial^2 f}{\partial x^2} d\langle X \rangle_t \\ &\quad + \frac{\partial^2 f}{\partial x \partial y} d\langle X, Y \rangle_t + \frac{1}{2} \frac{\partial^2 f}{\partial y^2} d\langle Y \rangle_t. \end{aligned}$$