

Def. A Brownian motion is a continuous process st.

$$(1) W_0 = 0$$

$$(2) W_t - W_s \sim N(0, t-s), \quad 0 \leq s < t \quad (W_t \sim N(0, t))$$

$$(3) W_t - W_s \text{ is independent of } \mathcal{F}_s, \quad 0 \leq s < t$$

Ex. Find the distribution of  $(W_s, W_t)$  ( $0 < s < t$ )

$W_s$  and  $W_t - W_s$  are independent,  $W_s \sim N(0, s)$ ,  $W_t - W_s \sim N(0, t-s)$

$$\begin{pmatrix} W_s \\ W_t - W_s \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} s & 0 \\ 0 & t-s \end{pmatrix}\right)$$

$$\begin{pmatrix} W_s \\ W_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} W_s \\ W_t - W_s \end{pmatrix}$$

$$W_s \sim N(0, s), \quad W_t \sim N(0, t), \quad \text{Cov}(W_s, W_t) = \mathbb{E}(W_s W_t) - \mathbb{E}W_s \mathbb{E}W_t$$

$$= \mathbb{E}(W_s (W_t - W_s + W_s))$$

$$= \mathbb{E}(W_s (W_t - W_s)) + \mathbb{E}(W_s)^2$$

$$= \mathbb{E}W_s \cdot \mathbb{E}(W_t - W_s) + \text{Var}(W_s) = s$$

$$\Rightarrow \begin{pmatrix} W_s \\ W_t \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} s & s \\ s & t \end{pmatrix}\right).$$

$$\text{For } s > 0, t > 0, \quad \text{Cov}(W_s, W_t) = \mathbb{E}(W_s W_t) = \min\{s, t\} = s \wedge t.$$

Ex.  $X_T = \int_0^T e^{W_t} dt$ ,  $T \geq 0$  ( $X_T^{(w)} = \int_0^T e^{W_t(w)} dt$ )

Compute  $\mathbb{E} X_T$ ,  $\text{Var}(X_T)$ .

Recall: Moment Generating Function,  $Z \sim N(0, 1)$ ,  $M_Z(t) = \mathbb{E} e^{tZ} = e^{\frac{t^2}{2}}$ .

$$\mathbb{E} X_T = \mathbb{E} \left( \int_0^T e^{W_t} dt \right) = \int_0^T \mathbb{E} e^{W_t} dt = \int_0^T \mathbb{E} e^{\sqrt{t} Z} dt = \int_0^T e^{\frac{t}{2}} dt = 2(e^{\frac{T}{2}} - 1).$$

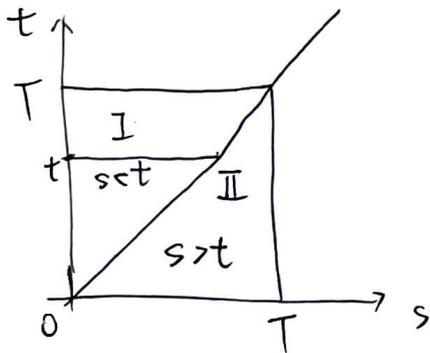
$(W_t \sim N(0, t))$

$$\begin{aligned} \mathbb{E} X_T^2 &= \mathbb{E} \left( \int_0^T e^{W_t} dt \right)^2 = \mathbb{E} \left( \int_0^T e^{W_s} ds \cdot \int_0^T e^{W_t} dt \right) = \mathbb{E} \left( \int_0^T \int_0^T e^{W_s + W_t} ds dt \right) \\ &= \int_0^T \int_0^T \mathbb{E} e^{W_s + W_t} ds dt \end{aligned}$$

$$\mathbb{E}(W_s + W_t) = 0, \quad \text{Var}(W_s + W_t) = \text{Var}(W_s) + \text{Var}(W_t) + 2 \text{Cov}(W_s, W_t) = s + t + 2(st).$$

$$W_s + W_t \sim N(0, s + t + 2(st)).$$

$$\mathbb{E} X_T^2 = \int_0^T \int_0^T \mathbb{E} e^{\sqrt{s+t+2(st)} Z} ds dt = \int_0^T \int_0^T e^{\frac{s}{2} + \frac{t}{2} + st} ds dt$$



$$= \iint_{\text{I}} e^{\frac{3}{2}s + \frac{1}{2}t} ds dt + \iint_{\text{II}} e^{\frac{1}{2}s + \frac{3}{2}t} ds dt$$

$$= 2 \iint_{\text{I}} e^{\frac{3}{2}s + \frac{1}{2}t} ds dt = 2 \int_0^T \int_0^t e^{\frac{3}{2}s + \frac{1}{2}t} ds dt$$

$$\mathbb{E}X_T^2 = 2 \int_0^T e^{\frac{t}{2}} \int_0^t e^{\frac{3}{2}s} ds dt = 2 \int_0^T e^{\frac{t}{2}} \cdot \frac{2}{3} (e^{\frac{3}{2}t} - 1) dt = \frac{2}{3} e^{2T} - \frac{8}{3} e^{\frac{T}{2}} + 2.$$

$$\text{Var}(X_T) = \mathbb{E}X_T^2 - (\mathbb{E}X_T)^2 = \frac{2}{3} e^{2T} - 4e^T + \frac{16}{3} e^{\frac{T}{2}} - 2.$$

• Continuous time (C) BM  $W_t$

Discrete time (D) SRW  $S_n = \xi_1 + \dots + \xi_n$ ,  $\xi_i$  i.i.d.  $\mathbb{P}(\xi_i = 1) = \mathbb{P}(\xi_i = -1) = \frac{1}{2}$ .

• Quadratic Variation

(C)  $X_t$  is a continuous adapted process,

$$[X, X]_T = \lim_{\|P\| \rightarrow 0} \sum_{k=0}^{n-1} (X_{t_{k+1}} - X_{t_k})^2, \quad 0 = t_0 < t_1 < \dots < t_n = T.$$

$$[W, W]_T = T.$$

(D)  $X_n$  is an adapted process

$$[X, X]_N = \sum_{k=0}^{N-1} (X_{k+1} - X_k)^2.$$

$$[S, S]_n = \sum_{k=0}^{n-1} (S_{k+1} - S_k)^2 = \sum_{k=0}^{n-1} (\xi_{k+1})^2 = \sum_{k=0}^{n-1} 1 = n.$$

(C) If  $M_t$  is a continuous MRT, then

$M_t^2 - [M, M]_t$  is also a continuous MRT.

(D) If  $M_n$  is a ~~continuous~~ MRT, then

$M_n^2 - [M, M]_n$  is also a continuous MRT.

pf. (1)  $M_n^2 - \sum_{k=0}^{n-1} (M_{k+1} - M_k)^2$  is  $\mathcal{F}_n$ -measurable.

$$(2) \mathbb{E}_n (M_{n+1}^2 - [M, M]_{n+1}) = \mathbb{E}_n (M_{n+1}^2 - \sum_{k=0}^n (M_{k+1} - M_k)^2)$$

$$= \mathbb{E}_n (M_{n+1}^2 - \underbrace{\sum_{k=0}^{n-1} (M_{k+1} - M_k)^2}_{=[M, M]_n} - (M_{n+1} - M_n)^2)$$

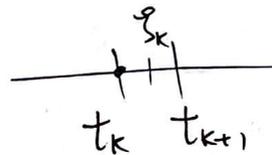
$$= \mathbb{E}_n (M_{n+1}^2 - (M_{n+1} - M_n)^2) - [M, M]_n$$

$$\stackrel{5}{=} \mathbb{E}_n (2M_{n+1}M_n - M_n^2) = 2M_n \mathbb{E}_n M_{n+1} - M_n^2 = 2M_n^2 - M_n^2 = M_n^2$$

• Itô Integral

(C)  $D_t$  is an adapted process

$$I_T = \int_0^T D_t dW_t = \lim_{\|P\| \rightarrow 0} \left[ \sum_{k=0}^{n-1} D_{t_k} (W_{t_{k+1}} - W_{t_k}) + D_{t_n} (W_T - W_{t_n}) \right], T \in (t_n, t_{n+1})$$



$I_t$  is a martingale.

(D)  $D_n$  is an adapted process

$$I_N = \sum_{k=0}^{N-1} D_k \Delta S_k = \sum_{k=0}^{N-1} D_k (S_{k+1} - S_k)$$

$I_n$  is a martingale.

pf. (1)  $I_n$  is adapted ✓

$$\begin{aligned} (2) \mathbb{E}_n I_{n+1} &= \mathbb{E}_n \left( \sum_{k=0}^n D_k (S_{k+1} - S_k) \right) = \mathbb{E}_n \left( \underbrace{\sum_{k=0}^{n-1} D_k (S_{k+1} - S_k)}_{I_n} + D_n (S_{n+1} - S_n) \right) \\ &= I_n + \mathbb{E}_n (D_n (S_{n+1} - S_n)) = I_n + D_n \underbrace{\mathbb{E}_n (S_{n+1} - S_n)}_{=0} = I_n. \end{aligned}$$

$$(C) \quad I_T = \int_0^T D_t dW_t$$

$$[I, I]_T = \int_0^T D_t^2 dt \quad \left( = \int_0^T D_t^2 \underbrace{(dW_t)^2}_{dt} \right)$$

$$(D) \quad I_N = \sum_{k=0}^{N-1} D_k (S_{k+1} - S_k)$$

$$\begin{aligned} [I, I]_N &= \sum_{k=0}^{N-1} (I_{k+1} - I_k)^2 = \sum_{k=0}^{N-1} D_k^2 (S_{k+1} - S_k)^2 = \sum_{k=0}^{N-1} D_k^2 (\Delta S_{k+1})^2 \\ &= \sum_{k=0}^{N-1} D_k^2 \left( \sum_{k=0}^{N-1} D_k^2 ((k+1) - k) \right) \end{aligned}$$

Def. A semi-martingale is a process of the form  $X_t = X_0 + B_t + M_t$ , where

1) Typically  $X_0$  is a constant.

2)  $B_t$  is an adapted process with finite first variation (BV bounded variation)

$$\begin{aligned} ([B, B]_T) &\stackrel{\text{def}}{=} \sum_{k=0}^{n-1} (B_{t_{k+1}} - B_{t_k})^2 = \lim_{\|P\| \rightarrow 0} \sum_{k=0}^{n-1} (B_{t_{k+1}} - B_{t_k})^2 = \lim_{\|P\| \rightarrow 0} \sum_{k=0}^{n-1} |B_{t_{k+1}} - B_{t_k}| \cdot \underbrace{|B_{t_{k+1}} - B_{t_k}|}_{\max |\Delta B_{t_k}|} \\ &\leq \lim_{\|P\| \rightarrow 0} \underbrace{\sum_{k=0}^{n-1} |B_{t_{k+1}} - B_{t_k}|}_{V_{[0, T]}(B) < \infty} \cdot \underbrace{\max |\Delta B_{t_k}|}_{\downarrow 0} = 0 \end{aligned}$$

$\|P\| = \max_{0 \leq k \leq n-1} |B_{t_{k+1}} - B_{t_k}|$   
 $\|P\| \rightarrow 0 \Rightarrow \max_k |\Delta B_{t_k}| \rightarrow 0$

3)  $M_t$  is a martingale.

Def. An Itô process  $X$  is a semi-martingale, where

$$X_t = X_0 + \int_0^t b_s ds + \int_0^t \sigma_s dW_s, \quad \mathbb{E} \int_0^t |b_s| ds < \infty, \quad \mathbb{E} \int_0^t |\sigma_s|^2 ds < \infty$$

Equivalently,  $dX_t = b_t dt + \sigma_t dW_t$ .

- $X_t = X_0 + B_t + M_t$  — semi-martingale.

$$\underline{[X, X]_t = [M, M]_t}$$

- Itô formula

$f = f(t, x) : [0, \infty) \times \mathbb{R} \rightarrow \mathbb{R}$ ,  $f \in C^{1,2}$  ( $\partial_t f$ ,  $\partial_x f$ ,  $\partial_x^2 f$  are continuous)

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

$$f(t, X_t) = f(0, X_0) + \int_0^t \partial_t f(s, X_s) ds + \int_0^t \partial_x f(s, X_s) dX_s + \frac{1}{2} \int_0^t \partial_x^2 f(s, X_s) d[X, X]_s.$$

Suppose  $X$  is an Itô process

$$X_t = X_0 + \underbrace{\int_0^t b_s ds}_{B_t} + \underbrace{\int_0^t \sigma_s dW_s}_{M_t}$$

$$\underline{dX_t = b_t dt + \sigma_t dW_t}, \quad [X, X]_t = [M, M]_t = \int_0^t \sigma_s^2 ds, \quad \underline{d[X, X]_t = \sigma_t^2 dt}$$

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

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

Ex. What is  $\int_0^t W_s dW_s$ ?

$$X_t = W_t^2 - t \quad (X \text{ is a martingale})$$

$$f(t, x) = x^2 - t, \quad \partial_t f(t, x) = -1, \quad \partial_x f(t, x) = 2x, \quad \partial_x^2 f(t, x) = 2.$$

$$X_t = f(t, W_t)$$

$$dX_t = \partial_t f(t, W_t) dt + \partial_x f(t, W_t) dW_t + \frac{1}{2} \partial_x^2 f(t, W_t) dt$$

$$= \cancel{-dt} + 2W_t dW_t + \cancel{\frac{1}{2} \cdot 2 dt} = 2W_t dW_t$$

$$X_t - X_0 = 2 \int_0^t W_s dW_s \Rightarrow \int_0^t W_s dW_s = \frac{1}{2} X_t = \frac{1}{2} (W_t^2 - t).$$

Ex.  $M_t = e^{\lambda W_t - \frac{1}{2} \lambda^2 t}$  (From HW2,  $M$  is a MRT). Find  $dM_t$ .

$$f(t, x) = e^{\lambda x - \frac{1}{2} \lambda^2 t}, \quad \partial_t f(t, x) = -\frac{1}{2} \lambda^2 f(t, x), \quad \partial_x f(t, x) = \lambda f(t, x), \quad \partial_x^2 f(t, x) = \lambda^2 f(t, x).$$

$$dM_t = df(t, W_t) = \partial_t f(t, W_t) dt + \partial_x f(t, W_t) dW_t + \frac{1}{2} \partial_x^2 f(t, W_t) dt$$

$$= \cancel{-\frac{1}{2} \lambda^2 M_t dt} + \lambda M_t dW_t + \cancel{\frac{1}{2} \lambda^2 M_t dt} = \lambda M_t dW_t.$$

• If  $f(t, W_t)$  is a MRT, then  $df(t, W_t)$  has no  $dt$  term.

$$f(t, W_t) = f(0, 0) + \int_0^t (\dots) dW_s.$$

Ex.  $X_t = e^{W_t}$ , Find  $[X, X]_t$ .

$$f(t, x) = e^x, \quad \partial_t f(t, x) = 0, \quad \partial_x f(t, x) = \partial_x^2 f(t, x) = e^x.$$

$$X_t = f(t, W_t).$$

$$\begin{aligned} dX_t &= df(t, W_t) = \partial_t f(t, W_t) dt + \partial_x f(t, W_t) dW_t + \frac{1}{2} \partial_x^2 f(t, W_t) dt \\ &= 0 + \frac{1}{2} e^{W_t} dt + e^{W_t} dW_t. \end{aligned}$$

$$X_t = X_0 + \underbrace{\frac{1}{2} \int_0^t e^{W_s} ds}_{B_t} + \underbrace{\int_0^t e^{W_s} dW_s}_{M_t}.$$

$$[X, X]_t = [M, M]_t = \int_0^t e^{2W_s} ds.$$