

## II. Wiener process & Martingale

Def: Symmetric Random Walk (초기값 0에서 시작하는 무작위 걸음)

→ We repeatedly toss a fair coin (prob. =  $\frac{1}{2}$ )

Let  $X_j = \begin{cases} 1 & \text{if Head} \\ -1 & \text{if Tail} \end{cases}$  and \*  $E[X_j] = 0, \text{Var}(X_j) = 1$

define  $M_0 = 0, M_k = \sum_{j=1}^k X_j, k = 1, 2, \dots$

The process  $M_k, k = 1, 2, \dots$  is a symmetric random walk.

\* Properties of Symmetric Random Walk

→ ① If we choose nonnegative integers  $0 = k_0 < k_1 < \dots < k_m$ , the random variables  $M_{k_1} - M_{k_0}, M_{k_2} - M_{k_1}, \dots, M_{k_m} - M_{k_{m-1}}$  are independent.

② Each of these random variables  $M_{k_{i+1}} - M_{k_i}$  is called an increment of the random walk.

$$\textcircled{3} E[M_{k_{i+1}} - M_{k_i}] = E\left[\sum_{j=k_i+1}^{k_{i+1}} X_j\right] = \sum_{j=k_i+1}^{k_{i+1}} E[X_j] = 0$$

$$\textcircled{4} \text{Var}(M_{k_{i+1}} - M_{k_i}) = \sum_{j=k_i+1}^{k_{i+1}} \text{Var}(X_j) = \sum_{j=k_i+1}^{k_{i+1}} 1 = k_{i+1} - k_i$$

⑤ For  $k < l$ ,

$$\begin{aligned} E[M_l | \mathcal{F}_k] &= E[(M_l - M_k) + M_k | \mathcal{F}_k] \\ &= E[M_l - M_k | \mathcal{F}_k] + E[M_k | \mathcal{F}_k] \\ &\stackrel{\text{independent}}{=} E[M_l - M_k] + M_k \\ &= M_k \quad \therefore \text{martingale} \end{aligned}$$

⑥ Quadratic Variation

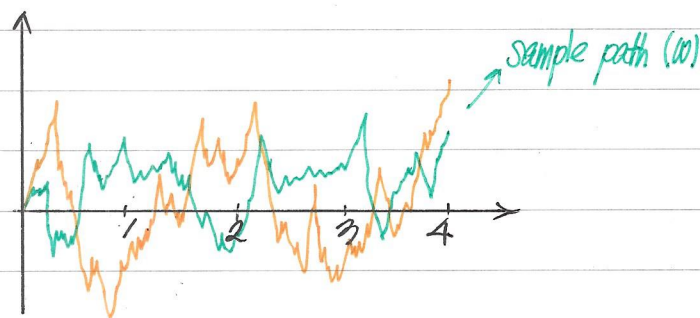
$$[M, M]_k = \sum_{j=1}^k (M_j - M_{j-1})^2 = \sum_{j=1}^k X_j^2 = k$$

Def: Scaled Symmetric Random Walk.

$$\rightarrow W^{(n)}(t) = \frac{1}{\sqrt{n}} M_{nt} \quad \left( \sim N(0, t) \text{ as } n \rightarrow \infty \right)$$

Ex:  $W^{(100)}$  up to  $t=4$

→ this was generated by 400 coin tosses with a step up or down of size  $\frac{1}{10}$  on each coin toss.



\* Properties of Scaled Symmetric Random Walk.

$$\rightarrow \textcircled{1} E[W^{(n)}(t) - W^{(n)}(s)] = 0$$

$$\textcircled{2} \text{Var}(W^{(n)}(t) - W^{(n)}(s)) = \frac{1}{n} (nt - ns) = t - s$$

$$\textcircled{3} E[W^{(n)}(t) | \mathcal{F}_s] = W^{(n)}(s)$$

$$\begin{aligned} \textcircled{4} [W^{(n)}, W^{(n)}](t) &= \sum_{j=1}^{nt} \left[ W^{(n)}\left(\frac{j}{n}\right) - W^{(n)}\left(\frac{j-1}{n}\right) \right]^2 \\ &= \sum_{j=1}^{nt} \frac{1}{n} X_j^2 \\ &= \frac{1}{n} \times nt \\ &= t \end{aligned}$$

# THM. Central Limit Theorem.

Fix  $t \geq 0$ . As  $n \rightarrow \infty$ , the distribution of the scaled random walk  $W^{(n)}(t)$  evaluated at time  $t$  converges to the normal distribution with mean zero and variance  $t$ .

$\Rightarrow W^{(n)}(t) \sim N(0, t)$  as  $n \rightarrow \infty$

pf) \* ~~the~~ mgf ~~of~~ ~~the~~ distribution of ~~test~~.

$$\varphi^{(n)}(u) = \mathbb{E}[e^{u W^{(n)}(t)}]$$

$$= \mathbb{E}[e^{u \cdot \frac{1}{\sqrt{n}} M_{nt}}]$$

$$= \mathbb{E}[e^{u \cdot \frac{1}{\sqrt{n}} \sum_{j=1}^{nt} X_j}]$$

$$= \mathbb{E}[\prod_{j=1}^{nt} e^{\frac{u}{\sqrt{n}} X_j}]$$

$$= \prod_{j=1}^{nt} \mathbb{E}[e^{\frac{u}{\sqrt{n}} X_j}]$$

*If  $X, Y$  independent,  $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$*

$$= \prod_{j=1}^{nt} \left( e^{\frac{u}{\sqrt{n}} \times \frac{1}{2}} + e^{-\frac{u}{\sqrt{n}} \times \frac{1}{2}} \right)$$

$$= \left( \frac{1}{2} e^{\frac{u}{\sqrt{n}}} + \frac{1}{2} e^{-\frac{u}{\sqrt{n}}} \right)^{nt}$$

$$\ln \varphi^{(n)}(u) = nt \cdot \ln \left( \frac{1}{2} e^{\frac{u}{\sqrt{n}}} + \frac{1}{2} e^{-\frac{u}{\sqrt{n}}} \right)$$

(Let  $x = \frac{1}{\sqrt{n}} \rightarrow 0$  as  $n \rightarrow \infty$ )

$$= t \cdot \frac{\ln \left( \frac{1}{2} e^{ux} + \frac{1}{2} e^{-ux} \right)}{x^2}$$

$$\xrightarrow{\text{L'Hospital}} t \cdot \frac{\frac{u}{2} e^{ux} - \frac{u}{2} e^{-ux}}{2x \cdot \left( \frac{1}{2} e^{ux} + \frac{1}{2} e^{-ux} \right)}$$

$$= \frac{t}{\frac{1}{2} e^{ux} + \frac{1}{2} e^{-ux}} \cdot \frac{\frac{u}{2} e^{ux} - \frac{u}{2} e^{-ux}}{2x}$$

$$\Rightarrow t \cdot \frac{\frac{u^2}{2} e^{ux} + \frac{u^2}{2} e^{-ux}}{2} \Rightarrow \frac{u^2 t}{2}$$

Note that if  $X \sim N(\mu, \sigma^2)$ , mgf of  $X = e^{u\mu + \frac{1}{2}\sigma^2 u^2}$

$\therefore X \sim N(0, t) \Rightarrow$  mgf of  $X = e^{\frac{1}{2} u^2 t}$

$$\lim_{n \rightarrow \infty} \varphi^{(n)}(u) = e^{\frac{1}{2} u^2 t}$$

$\therefore W^{(n)}(t) \sim N(0, t)$  as  $n \rightarrow \infty$

cf,  $\equiv$  : there exists (exists)

## Def: Brownian Motion

Limit of the scaled random walk  $W^{(n)}(t)$ .

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. For each  $\omega \in \Omega$ , Suppose  $\equiv$  a continuous function  $W(t)$  of  $t \geq 0$  that satisfies  $W(0) = 0$  and depends on  $\omega$ . Then,  $W(t), t \geq 0$ , is a Brownian Motion if for all  $0 = t_0 < t_1 < \dots < t_m$  increments  $W(t_1) - W(t_0), W(t_2) - W(t_1), \dots, W(t_m) - W(t_{m-1})$  are independent and each of these increments is normally distributed with  $\mathbb{E}[W(t_{j+1}) - W(t_j)] = 0$ ,  $\text{Var}(W(t_{j+1}) - W(t_j)) = t_{j+1} - t_j$

$$W(t_{j+1}) - W(t_j) \sim N(0, t_{j+1} - t_j)$$

Wiener process.

$W(t) \sim N(0, t)$  with independent increment

$$W(0) = 0$$

$$\mathbb{E}[W(t)] = 0$$

$$\text{Var}(W(t) - W(s)) = t - s \quad (t \geq s)$$

$$(t_1, t_2) \cap (s_1, s_2) = \emptyset \Rightarrow W(t_2) - W(t_1)$$

is independent

$$\text{Cov}(W(t), W(s)) = s \wedge t (= \min(s, t))$$



## Def: Quadratic Variation

THM.

Let  $f(t)$  be a function defined for  $0 \leq t \leq T$ . The quadratic variation of  $f(t)$  up to time  $T$  is

$$[f, f](T) = \lim_{\|\pi\| \rightarrow 0} \sum_{j=0}^{n-1} [f(t_{j+1}) - f(t_j)]^2$$

where  $\pi = \{t_0, \dots, t_n\}$  and  $0 = t_0 < t_1 < \dots < t_n = T$

$$\|\pi\| = \max_j |t_{j+1} - t_j|$$

$[W, W](T) = T, \forall T \geq 0$  (fixed  $T$ )

$$\sum_{j=0}^{n-1} |W(t_{j+1}) - W(t_j)|^2 = T \text{ on } [0, T]$$

pf: Let  $Q_\pi = \sum_{j=0}^{n-1} (W(t_{j+1}) - W(t_j))^2$

$$E[(W(t_{j+1}) - W(t_j))^2]$$

$$= \text{Var}(W(t_{j+1}) - W(t_j)) = t_{j+1} - t_j$$

$$\therefore E[Q_\pi] = E\left[\sum_{j=0}^{n-1} (W(t_{j+1}) - W(t_j))^2\right]$$

$$= \sum_{j=0}^{n-1} E[(W(t_{j+1}) - W(t_j))^2]$$

$$= \sum_{j=0}^{n-1} (t_{j+1} - t_j)$$

$$= T$$

## Remarks

Let  $f \in C_{[0, T]}$

Lemma:  $E[W(t)^4] = 3t^2$

$$QV(f) = \lim_{\|\pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f(t_{j+1}) - f(t_j)|^2$$

$$= \lim_{\|\pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f(t_j^*)|^2 |t_{j+1} - t_j|^2 \quad (\because \text{Mean Value Thm})$$

$$\leq \lim_{\|\pi\| \rightarrow 0} \sum_{j=0}^{n-1} \|\pi\| \cdot |f(t_j^*)|^2 |t_{j+1} - t_j|$$

$$= \lim_{\|\pi\| \rightarrow 0} \|\pi\| \cdot \int_0^T |f(t)|^2 dt = 0$$

$$\therefore QV(f) = 0$$

cf:  $E[X] = m, \text{Var}(X) = 0 \Rightarrow X = m$

$$\begin{aligned} & \text{Var}((W(t_{j+1}) - W(t_j))^2) \\ &= E[(W(t_{j+1}) - W(t_j))^4 - E[(W(t_{j+1}) - W(t_j))^2]^2] \\ &= E[(W(t_{j+1}) - W(t_j))^4 - 2(t_{j+1} - t_j)(W(t_{j+1}) - W(t_j))^2 + (t_{j+1} - t_j)^2] \\ &= E[(W(t_{j+1}) - W(t_j))^4] - 2(t_{j+1} - t_j)E[(W(t_{j+1}) - W(t_j))^2] + (t_{j+1} - t_j)^2 \end{aligned}$$

$$= 3(t_{j+1} - t_j)^2 - (t_{j+1} - t_j)^2$$

$$= 2(t_{j+1} - t_j)^2$$

$$\therefore \text{Var}(Q_\pi) = \text{Var}\left(\sum_{j=0}^{n-1} (W(t_{j+1}) - W(t_j))^2\right)$$

$$= \sum_{j=0}^{n-1} \text{Var}((W(t_{j+1}) - W(t_j))^2)$$

$$= \sum_{j=0}^{n-1} 2(t_{j+1} - t_j)^2$$

$$\leq 2 \cdot \|\pi\| \cdot \sum_{j=0}^{n-1} (t_{j+1} - t_j)$$

$$= 2T \cdot \|\pi\| \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\therefore \begin{cases} \lim_{n \rightarrow \infty} E[Q_\pi] = T \\ \lim_{n \rightarrow \infty} \text{Var}(Q_\pi) = 0 \end{cases}$$

$$\therefore [W, W](T) = \lim_{\|\pi\| \rightarrow 0} Q_\pi = E[Q_\pi] = T$$

cf:  $d[W, W] = dW dW$

Remark.

$$\begin{aligned} \hookrightarrow E[(W(t_{j+1}) - W(t_j))^2] &= t_{j+1} - t_j \\ \text{Var}[(W(t_{j+1}) - W(t_j))^2] &= 2(t_{j+1} - t_j)^2 \ll 1 \rightarrow 0 \\ \therefore \underbrace{(W(t_{j+1}) - W(t_j))^2}_{\Delta W \Delta W} &\approx \underbrace{t_{j+1} - t_j}_{\Delta t} \end{aligned}$$

$$\Rightarrow dWdW = dt$$

$$\hookrightarrow \lim_{\| \pi \| \rightarrow 0} \sum_{j=0}^{n-1} (W(t_{j+1}) - W(t_j))(t_{j+1} - t_j) = 0$$

$$\begin{aligned} \text{pf) } \sum_{j=0}^{n-1} |W(t_{j+1}) - W(t_j)|(t_{j+1} - t_j) &= \sum_{j=0}^{n-1} |W(t_{j+1}) - W(t_j)| \cdot (t_{j+1} - t_j) \\ &\leq \max_j |W(t_{j+1}) - W(t_j)| \cdot \sum_{j=0}^{n-1} (t_{j+1} - t_j) \\ &= T \cdot \max_j |W(t_{j+1}) - W(t_j)| \rightarrow 0 \text{ as } \| \pi \| \rightarrow 0. \\ &\quad (\because W(t) \text{ is continuous}) \end{aligned}$$

$$\Rightarrow dWdt = 0$$

$$\hookrightarrow \lim_{\| \pi \| \rightarrow 0} \sum_{j=0}^{n-1} (t_{j+1} - t_j)^2 = 0$$

$$\begin{aligned} \text{pf) } \sum_{j=0}^{n-1} (t_{j+1} - t_j)^2 &\leq \| \pi \| \cdot \sum_{j=0}^{n-1} (t_{j+1} - t_j) \\ &= \| \pi \| \cdot T \rightarrow 0 \text{ as } \| \pi \| \rightarrow 0. \end{aligned}$$

$$\Rightarrow dt dt = 0$$

cf) General properties of Expectation.

- $\hookrightarrow$  ①  $E[aX + bY | \mathcal{G}] = aE[X | \mathcal{G}] + bE[Y | \mathcal{G}]$
- ②  $E[E[X | \mathcal{G}]] = E[X]$  Law of iterated expectation.
- ③  $E[XY | \mathcal{G}] = XE[Y | \mathcal{G}]$  if  $X$  is  $\mathcal{G}$ -measurable
- ④  $E[X | \mathcal{G}] = E[X]$  if  $X$  is independent of  $\mathcal{G}$
- ⑤  $E[E[X | \mathcal{G}] | \mathcal{H}] = E[X | \mathcal{H}]$  if  $\mathcal{H} \subset \mathcal{G}$

cf) convex

$\hookrightarrow$  A function  $f: \mathbb{R} \rightarrow \mathbb{R}$  is convex if for any  $x, y \in \mathbb{R}$  &  $\lambda \in [0, 1]$ ,  
 $f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y)$   
 Ex)  $\lambda = \frac{1}{2} \Rightarrow f\left(\frac{x+y}{2}\right) \leq \frac{f(x)+f(y)}{2}$

cf) Jensen's Inequality

$\hookrightarrow f: \mathbb{R} \rightarrow \mathbb{R}$ , convex

$X$ : integrable random variable.

$f(X)$  is also integrable.

Then,  $f(E[X | \mathcal{G}]) \leq E[f(X) | \mathcal{G}]$ ,  $\forall \mathcal{G} \subset \mathcal{F}$   
 $f(E[X]) \leq E[f(X)]$



## Def, Filtration

↳ A sequence of  $\sigma$ -fields  $\mathcal{F}_1, \mathcal{F}_2, \dots$  s.t.  $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$  is called a filtration

## Def, adapted

↳ We say that a sequence of random variables  $X_1, X_2, \dots$  is "adapted" to a filtration  $\mathcal{F}_1, \mathcal{F}_2, \dots$  if  $X_n$  is  $\mathcal{F}_n$ -measurable for each  $n=1, 2, \dots$

## Def, Martingale

↳ A sequence  $X_1, X_2, \dots$  of random variables is called a martingale with respect to a filtration  $\mathcal{F}_1, \mathcal{F}_2, \dots$  if

- ①  $X_n$  is integrable for all  $n$ .  $E[|X_n|] < \infty$
- ②  $X_1, X_2, \dots$  is adapted to  $\mathcal{F}_1, \mathcal{F}_2, \dots$
- ③ " $E[X_{n+1} | \mathcal{F}_n] = X_n$ " for all  $n$ .

$$\hookrightarrow E[E[X_{n+1} | \mathcal{F}_n]] = E[X_n]$$

$$\therefore E[X_{n+1}] = E[X_n] \Rightarrow \text{fair game.}$$

For  $k < l$ ,

$$E[X_l | \mathcal{F}_k] = X_k \Rightarrow \text{martingale}$$

## Ex> Brownian Motion is martingale

$$\begin{aligned} \hookrightarrow p.f. E[W(t) | \mathcal{F}(s)] \\ &= E[W(t) - W(s) + W(s) | \mathcal{F}(s)] \\ &= E[W(t) - W(s) | \mathcal{F}(s)] + E[W(s) | \mathcal{F}(s)] \\ &= E[W(t) - W(s)] + W(s) \\ &= W(s) \end{aligned}$$

## Def, supermartingale / submartingale

↳ A sequence  $X_1, \dots, X_n$  is a supermartingale / submartingale with respect to a filtration  $\mathcal{F}_1, \mathcal{F}_2, \dots$  if

- ①  $X_n$  is integrable for all  $n$ .
- ②  $X_1, X_2, \dots$  is adapted to  $\mathcal{F}_1, \mathcal{F}_2, \dots$

$$\textcircled{1} E[X_{n+1} | \mathcal{F}_n] \begin{cases} \leq X_n & \text{supermartingale} \\ \geq X_n & \text{submartingale} \end{cases}$$

supermartingale

$$E[X_{n+1}] \leq E[X_n]$$

unfavourable

submartingale

$$E[X_{n+1}] \geq E[X_n]$$

favourable