

§ Chapter 2. Brownian Motion

Def 1.2.4: A stochastic process $X = (X_t)_{t \geq 0}$ is a collection of random variables $\{X_t : 0 \leq t < \infty\}$

We think about X as a function

$$X: \Omega \times [0, \infty) \rightarrow \mathbb{R}$$

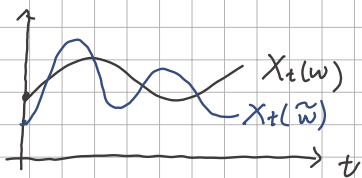
$$X: \omega \times t \rightarrow X_t(\omega)$$

In particular,

• for fixed t : $\omega \mapsto X_t(\omega)$ is a r.v.

i.e. \mathcal{F} -measurable $\{\omega \in \Omega : X_t(\omega) \leq c\} \in \mathcal{F} \quad \forall c \in \mathbb{R}$

• for fixed ω $t \mapsto X_t(\omega)$ is called the sample path / trajectory of X

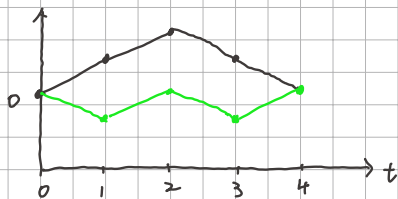


A process X is called continuous if its sample paths are continuous, i.e. $\lim_{s \rightarrow t} X_s(\omega) = X_t(\omega)$

Def. 2.1. (Symmetric Random Walks) Take r.v. ξ_1, ξ_2, \dots iid

$P(\xi_1 = 1) = P(\xi_1 = -1) = \frac{1}{2}$. Define $\xi_0 = 0$. $S_k = \sum_{n=1}^k \xi_n \quad \forall k \in \mathbb{N}$

e.g.



S_t (with adjacent integers)
= linear interpolation of S_k

3. observations:

- S has independent increments

for all $0 = k_0 < k_1 < k_2 < \dots < k_m$ $m \in \mathbb{N}$ integers

$(S_{k_1} - S_{k_0}), (S_{k_2} - S_{k_1}), \dots, (S_{k_m} - S_{k_{m-1}})$

are independent

observe that
$$S_{k_{i+1}} - S_{k_i} = \sum_{n=1}^{k_{i+1}} \zeta_n - \sum_{n=1}^{k_i} \zeta_n$$

$$= \sum_{n=k_i+1}^{k_{i+1}} \zeta_n$$
non-overlapping r.v.

$$E[S_{k_{i+1}} - S_{k_i}] = E\left[\sum_{n=k_i+1}^{k_{i+1}} \zeta_n\right] = \sum_{n=k_i+1}^{k_{i+1}} E[\zeta_n] = 0$$

$$\text{Var}[S_{k_{i+1}} - S_{k_i}] = \text{Var}\left[\sum_{n=k_i+1}^{k_{i+1}} \zeta_n\right] = \sum_{n=k_i+1}^{k_{i+1}} \text{Var}[\zeta_n] = k_{i+1} - k_i$$

$$(\text{Var}[\zeta_n] = E[\zeta_n^2] - E[\zeta_n]^2 = \frac{1}{2} [1^2 + (-1)^2] - 0^2 = 1)$$

$$\Rightarrow \text{Var}(S_k) = \text{Var}(S_k - S_0) = k - 0 = k$$

$$E[S_k] = E[S_k - S_0] = 0$$

rescale S so that it takes a random step at shorter and shorter time intervals.

Def. 2.2. (scaled symmetric random walks)

For $\epsilon > 0$ $S_t^\epsilon := \sqrt{\epsilon} S_{\frac{t}{\epsilon}}$ random walk at time $\frac{t}{\epsilon}$

if $\frac{t}{\epsilon} \in \mathbb{N}$ the def 2.1 tells us that

$$E[S_t^\epsilon] = E[\sqrt{\epsilon} S_{\frac{t}{\epsilon}}] = \sqrt{\epsilon} E[S_{\frac{t}{\epsilon}}] = \sqrt{\epsilon} \cdot 0 = 0$$

$$\text{Var}[S_t^\varepsilon] = \text{Var}(\sqrt{\varepsilon} \cdot S_{t/\varepsilon}) = \varepsilon \cdot \text{Var}(S_{t/\varepsilon}) = \varepsilon \cdot t/\varepsilon = t$$

From CLT, one can show that (proof omitted)

Theorem 2.1: For $t \geq 0$, the distribution of S_t^ε converges to a normal distribution with mean 0 and variance t for $\varepsilon \rightarrow 0$.

Def 2.2.1:

(Brownian motion).

A Brownian motion w is a continuous stochastic process such that
(BM)

- ① w has independent increments
 - ② for $s < t$, $w_t - w_s \sim N(0, \sigma^2(t-s))$
- } show these properties to verify a process as BM

(Standard BM)

A standard BM is a BM for which $w_0 = 0$ and $\sigma^2 = 1$

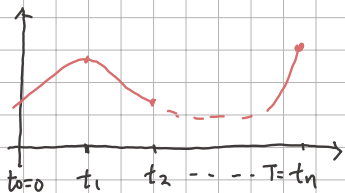
Quick Recall:

- stochastic process $\{X_t : 0 \leq t < \infty\}$
- trajectory / sample $t \mapsto X_t(w)$ for fixed $w \in \Omega$
- X is called continuous if each trajectory is continuous
- X has stationary increments, if $\forall n \geq 0$, the distribution of $X_{t+n} - X_t$ does not depend on t (but n)

2.3. First-order variation

For now: functions $f: [0, T] \rightarrow \mathbb{R}$

We take any partition $\Pi = \{t_0, t_1, \dots, t_n\}$ of $[0, T]$: $0 = t_0 < t_1 < \dots < t_n = T$
 $n \in \mathbb{N}$



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

Now take $\Pi = \{0, \frac{1}{n}, \frac{2}{n}, \dots, T\}$ $n \in \mathbb{N}$

if f is continuously differentiable, there exist $t_k^* \in [t_k, t_{k+1}]$
 with $f(t_{k+1}) - f(t_k) = f'(t_k^*)(t_{k+1} - t_k)$, thus

$$\sum_{j=0}^{n-1} |f(t_{j+1}) - f(t_j)| = \sum_{j=0}^{n-1} |f'(t_j^*)| (t_{j+1} - t_j), \text{ and}$$

$$FV_T(f) = \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f'(t_j^*)| (t_{j+1} - t_j) = \int_0^T |f'(t)| dt$$

Prop 2.3.1: If w is a standard BM, then

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[\sum_{k=0}^{n-1} |W_{\frac{k+1}{n}} - W_{\frac{k}{n}}| \right] = \infty$$

\Rightarrow BM has first-order variation ∞ almost surely

2.4 The quadratic variation of BM

Def 2.4.1 $f: [0, T] \rightarrow \mathbb{R}$, the quadratic variation of f up to time T is

$$[f, f]_T := \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f(t_{j+1}) - f(t_j)|^2 \quad \Pi = \{t_0, \dots, t_n\}$$

$$0 = t_0 < \dots < t_n = T$$

Theorem. If f is continuously differentiable, then $[f, f]_T = 0$

Proof: According to the Mean-Value theorem.

$$\begin{aligned} \sum_{k=0}^{n-1} [f(t_{k+1}) - f(t_k)]^2 &= \sum_{k=0}^{n-1} [f'(t_k^*) (t_{k+1} - t_k)]^2 \\ &\leq \max_{0 \leq t \leq T} \{ [f'(t)]^2 \} \cdot \sum_{k=0}^{n-1} (t_{k+1} - t_k)^2 \\ &= \max_{0 \leq t \leq T} \{ [f'(t)]^2 \} \cdot \sum_{k=0}^{n-1} \frac{T^2}{n^2} \\ &= \max_{0 \leq t \leq T} \{ [f'(t)]^2 \} \frac{T^2}{n} \xrightarrow{n \rightarrow \infty} 0 \end{aligned}$$

Remark:

$$\sum_{k=0}^{n-1} (t_{k+1} - t_k)^2 \rightarrow 0 \iff dt \cdot dt = 0$$

Theorem 2.4.2. Let w be standard BM. Then $[w, w]_t = t \quad \forall t \geq 0$
a.s.

$$\lim_{\|\pi\| \rightarrow 0} \underbrace{\sum_{j=0}^{n-1} |W_{t_{j+1}} - W_{t_j}|^2}_{\text{r.v.}}$$

a random variable

Remark:

▷ the paths of Brownian motion cannot be differentiated w.r.t. time

▷ If we use BM to model the price of a stock, we do not want the path of BM to be differentiable. The existence of a derivative would permit one to see whether the price is rising or falling.

D. We also have $\text{Var}[W(T)] = T$. but it's computed by averaging over all possible paths. The quadratic variation is computed along a single path, and we get the same answer regardless of the path.

Proof.

we have $t_{k+1} - t_k = \frac{T}{n}$

$$\begin{aligned} \sum_{k=0}^{n-1} [W(t_{k+1}) - W(t_k)]^2 &= T \cdot \frac{1}{n} \sum_{k=0}^{n-1} \left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{T/n}} \right]^2 \\ &= T \cdot \frac{1}{n} \sum_{k=0}^{n-1} \left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \right]^2 \end{aligned}$$

For each k , the random variable

$$\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \sim N(0, 1)$$

thus, the r.v. $\left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \right]^2$ are i.i.d. having the same mean value of 1 ($E[X^2] = \text{Var}(X) + E[X]^2$)

by Law of Large Numbers.

$$\frac{1}{n} \sum_{k=0}^{n-1} \left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \right]^2 \rightarrow E \left(\left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \right]^2 \right) = 1$$

thus

$$\sum_{k=0}^{n-1} [W(t_{k+1}) - W(t_k)]^2 = T \cdot \frac{1}{n} \sum_{k=0}^{n-1} \left[\frac{W(t_{k+1}) - W(t_k)}{\sqrt{t_{k+1} - t_k}} \right]^2 \rightarrow T$$

the equation is equivalent to $dW(t) dW(t) = dt$

Additional Theorems

$$\langle 1 \rangle \quad \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} |W(t_{k+1}) - W(t_k)| (t_{k+1} - t_k) = 0$$

we record this fact by writing $dW(t) dt = 0$

$$\langle 2 \rangle \quad \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} |W(t_{k+1}) - W(t_k)|^3 = 0$$

we record this fact by writing $(dW(t))^3 = 0$