

3.3 Brownian Motion

- $W^{(n)}(t) = \frac{1}{\sqrt{n}} M_{nt}$
- When $n \rightarrow \infty \Rightarrow$ Brownian motion

Def. 3.3.1

- Let (Ω, \mathcal{F}, P) be a probability space
- For each $\omega \in \Omega$, there is a cont. function $W(t), t \geq 0, W(0) = 0$ and that depends on ω .
- $W(t), t \geq 0$, is a Brownian motion if for all $0 = t_0 < t_1 < \dots < t_m$ the 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 is normally distributed with

$$E[W(t_{i+1}) - W(t_i)] = 0,$$
$$\text{Var}[W(t_{i+1}) - W(t_i)] = t_{i+1} - t_i$$

Distribution of Brownian Motion

- $W(t_1), W(t_2), \dots, W(t_m)$ are jointly normally distributed.

1. $E[W(t_i)] = \mathbf{0}$

2. For $0 \leq s < t$, $\mathit{cov}[W(s), W(t)] = s$.

$$\begin{aligned} E[W(s), W(t)] &= E[W(s)(W(t) - W(s)) + W^2(s)] \\ &= E[W(s)]E[(W(t) - W(s))] + E[W^2(s)] \\ &= 0 + \mathit{Var}[W(s)] = s. \end{aligned}$$

Covariance Matrix

- the covariance matrix for Brownian motion (i.e., for the m -dimensional random vector $(W(t_1), W(t_2), \dots, W(t_m))$) is

$$\begin{bmatrix} E[W^2(t_1)] & E[W(t_1)W(t_2)] & \cdots & E[W(t_1)W(t_m)] \\ E[W(t_2)W(t_1)] & E[W^2(t_2)] & \cdots & E[W(t_2)W(t_m)] \\ \vdots & \vdots & \ddots & \vdots \\ E[W(t_m)W(t_1)] & E[W(t_m)W(t_2)] & \cdots & E[W^2(t_m)] \end{bmatrix} = \begin{bmatrix} t_1 & t_1 & \cdots & t_1 \\ t_1 & t_2 & \cdots & t_2 \\ \vdots & \vdots & \ddots & \vdots \\ t_1 & t_2 & \cdots & t_m \end{bmatrix}$$

Prepare for m.g.f

- Recall the MGF of 1-dim normal r.v. $X \sim N(0, t)$

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2t}}, \varphi(u) = e^{\frac{1}{2}tu^2}$$

For Brownian motion

$$\begin{aligned} & u_m W(t_m) + u_{m-1} W(t_{m-1}) + \cdots + u_1 W(t_1) \\ &= u_m (W(t_m) - W(t_{m-1})) + (u_{m-1} + u_m) (W(t_{m-1}) - W(t_{m-2})) \\ &+ \cdots + (u_1 + u_2 + \cdots + u_m) W(t_1) \end{aligned}$$

moment-generating function

$$\begin{aligned} & \varphi(u_1, u_2, \dots, u_m) \\ &= E \exp\{u_m W(t_m) + u_{m-1} W(t_{m-1}) + \dots + u_1 W(t_1)\} \\ &= E \exp\{u_m (W(t_m) - W(t_{m-1})) + (u_{m-1} + u_m) (W(t_{m-1}) - W(t_{m-2})) \\ &+ \dots + (u_1 + u_2 + \dots + u_m) W(t_1)\} \\ &= E \exp\{u_m (W(t_m) - W(t_{m-1})) \\ &* E \exp\{(u_{m-1} + u_m) (W(t_{m-1}) - W(t_{m-2}))\} \\ &* E \exp\{(u_1 + u_2 + \dots + u_m) W(t_1)\} \\ &= \exp\left\{\frac{1}{2} (u_m)^2 (t_m - t_{m-1})\right\} * \exp\left\{\frac{1}{2} (u_{m-1} + u_m)^2 (t_{m-1} - t_{m-2})\right\} * \dots \\ &* \exp\left\{\frac{1}{2} (u_1 + u_2 + \dots + u_m)^2 (t_1)\right\} \end{aligned}$$

Alternative characterizations of Brownian motion

- Let (Ω, \mathcal{F}, P) be a probability space
- For each $\omega \in \Omega$, there is a cont. function $W(t), t \geq 0, W(0) = 0$ and that depends on ω . The following three properties are equivalent.

For all $0 = t_0 < t_1 < \dots < t_m$

(1) the 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 is normally distributed with

$$E[W(t_{i+1}) - W(t_i)] = 0,$$
$$\text{Var}[W(t_{i+1}) - W(t_i)] = t_{i+1} - t_i$$

Alternative characterizations of Brownian motion

(2) The random variables $\mathbf{W}(t_1), \mathbf{W}(t_2), \dots, \mathbf{W}(t_m)$ are jointly normally distributed with means equal to zero and covariance matrix.

$$\begin{bmatrix} t_1 & t_1 & \cdots & t_1 \\ t_1 & t_2 & \cdots & t_2 \\ \vdots & \vdots & & \vdots \\ t_1 & t_2 & \cdots & t_m \end{bmatrix}$$

(3) The random variables $\mathbf{W}(t_1), \mathbf{W}(t_2), \dots, \mathbf{W}(t_m)$ have the joint moment-generating function

$$\exp\left\{\frac{1}{2}(u_m)^2(t_m - t_{m-1})\right\} * \exp\left\{\frac{1}{2}(u_{m-1} + u_m)^2(t_{m-1} - t_{m-2})\right\} \\ * \cdots * \exp\left\{\frac{1}{2}(u_1 + u_2 + \cdots + u_m)^2(t_1)\right\}$$

Filtration for Brownian Motion

- Def. 3.3.3

Let (Ω, \mathcal{F}, P) be a prob. space defined on a Brownian motion $W(t), t \geq 0$.

A filtration for the Brownian motion is a collection of σ – *algebras* $\mathcal{F}(t), t \geq 0$, satisfying:

(1) (Information accumulates)

For $0 \leq s < t$, $\mathcal{F}(s) \subseteq \mathcal{F}(t)$

(2) (Adaptivity)

For each $t \geq 0$, $W(t)$ is $\mathcal{F}(t)$ *msb*.

(3) (Independence of future increments)

For $0 \leq t < u$, the increment $W(u) - W(t)$ is indep. of $\mathcal{F}(t)$

Def. Adaptivity

- Let $\Delta(t)$, $t \geq 0$, be a stochastic process. We say that $\Delta(t)$ is adapted to the filtration $\mathcal{F}(t)$ if for each $t \geq 0$ the random variable $\Delta(t)$ is $\mathcal{F}(t)$ -measurable.

Martingale Property for Brownian Motion

- Theorem 3.3.4.

Brownian motion is a martingale.

proof:

Let $0 \leq s \leq t$ be given. Then

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

3.4 Quadratic Variation

- First-Order Variation

Choose a partition $\Pi = \{t_0, t_1, \dots, t_n\}$ of $[0, T]$

which is a set of times $0 = t_0 < t_1 < \dots < t_n = T$

The maximum step size of the partition:

$$\|\Pi\| = \max_{j=0, \dots, n-1} (t_{j+1} - t_j)$$

Then we define first-order variation:

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

Mean Value Theorem

- Let $f'(t)$ is defined everywhere

$\forall t_j, t_{j+1} \exists t_j^* \in [t_j, t_{j+1}]$ s.t.

$$\frac{f(t_{j+1}) - f(t_j)}{t_{j+1} - t_j} = f'(t_j^*)$$

Mean Value Theorem

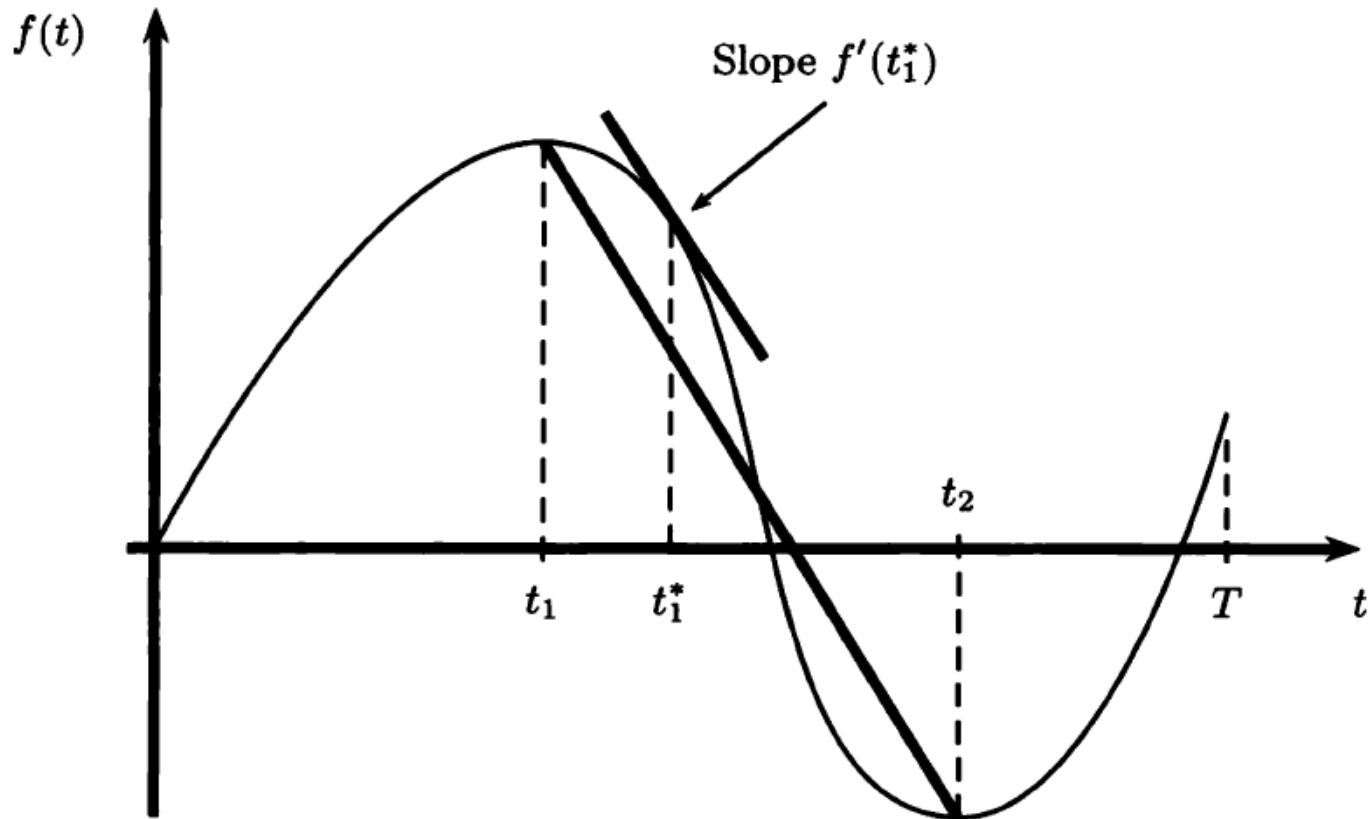


Fig. 3.4.2. Mean Value Theorem.

Mean Value Theorem

$$\frac{f(t_{j+1}) - f(t_j)}{t_{j+1} - t_j} = f'(t_j^*) \Rightarrow f(t_{j+1}) - f(t_j) = f'(t_j^*)(t_{j+1} - t_j)$$

$$\begin{aligned} \Rightarrow FV_T(f) &= \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f(t_{j+1}) - f(t_j)| \\ &= \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} |f'(t_j^*)|(t_{j+1} - t_j) \quad (\text{Riemann sum}) \\ &= \int_0^T |f'(t_j^*)| dt \end{aligned}$$

Quadratic Variation

- Definition 3.4.1.
- Let $f(t)$ be a function defined for $0 \leq t \leq T$.

The quadratic variation of f up to time T is

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

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

Quadratic Variation

- Remark 3.4.2.
- Suppose the function f has a continuous derivative. By mean value theorem

$$\begin{aligned} \sum_{j=0}^{n-1} [f(t_{j+1}) - f(t_j)]^2 &= \sum_{j=0}^{n-1} [f'(t_j^*)]^2 (t_{j+1} - t_j)^2 \\ &\leq \|\Pi\|^2 \sum_{j=0}^{n-1} [f'(t_j^*)]^2 (t_{j+1} - t_j) \end{aligned}$$

Quadratic Variation

and thus

$$\begin{aligned} [f, f](T) &\leq \lim_{\|\Pi\| \rightarrow 0} [\|\Pi\| * \sum_{j=0}^{n-1} [f'(t_j^*)]^2 (t_{j+1} - t_j)] \\ &= \lim_{\|\Pi\| \rightarrow 0} \|\Pi\| * \lim_{\|\Pi\| \rightarrow 0} \sum_{j=0}^{n-1} [f'(t_j^*)]^2 (t_{j+1} - t_j) \\ &= \lim_{\|\Pi\| \rightarrow 0} \|\Pi\| * \int_0^T [f'(t)]^2 dt = 0 \end{aligned}$$

In the last step of this argument, we use the fact that $f'(t)$ is **continuous** to ensure that $\int_0^T [f'(t)]^2 dt$ is **finite**.