

(4.17)

By Levy's reflection principle, for $u > 0$ and $a \leq u$

$$P(M_T > u, B_T \leq a) = P(B_T > 2u - a) \quad (1)$$

We can partition $\{B_T \leq a\}$ as

$$\{B_T \leq a\} = \{M_T \leq u, B_T \leq a\} \cup \{M_T > u, B_T \leq a\}$$

Let $F(u, a) :=$ joint cdf of M_T, B_T

$$F(u, a) = P(M_T \leq u, B_T \leq a) = P(B_T \leq a) - P(M_T > u, B_T \leq a).$$

Using (1) we have $F(u, a) = P(B_T \leq a) - P(B_T > 2u - a) =$

$$= P(B_T \leq a) - (1 - P(B_T \leq 2u - a)) = \text{Since } B_T \sim N(0, T)$$

If we scale for variance we have

since $\phi_T(x) = \frac{1}{\sqrt{2\pi T}} e^{-\frac{x^2}{2T}}$
 if we define $z = \frac{B_T}{\sqrt{T}}$
 we see $z \sim N(0,1)$

$$F(m,a) = \Phi\left(\frac{a}{\sqrt{T}}\right) - (1 - \Phi\left(\frac{2m-a}{\sqrt{T}}\right)) = \Phi\left(\frac{a}{\sqrt{T}}\right) + \Phi\left(\frac{2m-a}{\sqrt{T}}\right)$$

To obtain the joint pdf we have to derive on both m and a

so $f(m,a) = \frac{\partial F(m,a)}{\partial m \partial a}$ ~~scribbles~~

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After many calculations, we realized it's easier to just derive the original expression $P(B_T > 2m-a)$.

Let $\phi_T(x) = \frac{1}{\sqrt{2\pi T}} e^{-\frac{x^2}{2T}}$
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~~scribbles~~ $\frac{\partial F(m,a)}{\partial m \partial a} = \frac{\partial P(B_T > 2m-a)}{\partial a} = \frac{\partial}{\partial a} \int_{2m-a}^{\infty} \phi_T(x) dx =$

$= \phi_T(2m-a)$

$\frac{\partial F(m,a)}{\partial m \partial a} = \frac{\partial [\phi_T(2m-a)]}{\partial m} = \frac{2(2m-a)}{T} \phi_T(2m-a) =$

$= \frac{2(2m-a)}{T} \cdot \phi_T(2m-a) = \frac{2(2m-a)}{T} \cdot \frac{1}{\sqrt{2\pi T}} e^{-\frac{x^2}{2T}} =$

$= \frac{2(2m-a)}{T^{3/2} \sqrt{2\pi}} e^{-\frac{(2m-a)^2}{2T}}$

as we wanted to prove

Gen AI was used to help for the rigor of the proof, and to write the first draft of the code in the last numerical project

- 5.1. **Stopped martingales are martingales.** Let $(M_n, n = 0, 1, 2, \dots)$ be a martingale in discrete time for the filtration $(\mathcal{F}_n, n \geq 0)$. Let τ be a stopping time for the same filtration. Use the martingale transform with the process

$$X_n(\omega) = \begin{cases} +1 & \text{if } n < \tau(\omega), \\ 0 & \text{if } n \geq \tau(\omega) \end{cases}$$

to show that the stopped martingale $(M_{\tau \wedge n}, n \geq 0)$ is a martingale.

define $M_n^\tau = M_0 + \sum_{k=1}^n X_{k-1} (M_k - M_{k-1})$

M is a martingale, X_n is bounded and predictable

So M_n^τ is a martingale

So the stopping process $M_{\tau \wedge n}$ is a martingale

- 5.3. **Convergence in L^2 implies convergence of first and second moments.** Let $(X_n, n \geq 0)$ be a sequence of random variables that converge to X in $L^2(\Omega, \mathcal{F}, P)$.

- (a) Show that $E[X_n^2]$ converges to $E[X^2]$.

Hint: Write $X = (X - X_n) + X_n$. The Cauchy-Schwarz inequality might be useful.

- (b) Show that $E[X_n]$ converges to $E[X]$.

Hint: Write $|E[X_n] - E[X]|$ and use Jensen's inequality twice.

- (a) given $E[(X_n - X)^2] \rightarrow 0$, prove $E(X_n^2) \rightarrow E(X^2)$

$$\begin{aligned} |E(X_n^2) - E(X^2)| &= |E[(X_n - X)(X_n + X)]| \leq \sqrt{E[(X_n - X)^2]} \sqrt{E[(X_n + X)^2]} \\ &\leq \sqrt{2E(X_n^2) + 2E(X^2)} \sqrt{E[(X_n - X)^2]} \end{aligned}$$

$$E(X_n^2) = E[(X + (X_n - X))^2] \leq 2E(X^2) + 2E[(X_n - X)^2]$$

$$E(X_n^2) \leq 2E(X^2) + 2 \rightarrow 0$$

$$E[(X_n + X)^2] \leq 2[2E(X^2) + 2] + 2E(X^2) = 6E(X^2) + 4$$

have a upper limit

$$\lim_{n \rightarrow \infty} |E(X_n^2) - E(X^2)| = 0 \Rightarrow E(X_n^2) \rightarrow E(X^2)$$

$$(b) |E(X_n) - E(X)| = |E(X_n - X)| \leq E(|X_n - X|) \leq \sqrt{E[(X_n - X)^2]} \rightarrow 0$$

$$\Rightarrow E(X_n) \rightarrow E(X)$$

5.4)

$$(a) (M_t)_{t \geq 0} \quad t_1 \leq t_2 \leq t_3 \leq t_4$$

$$E[(M_{t_2} - M_{t_1})(M_{t_4} - M_{t_3})] =$$

$$E[E[(M_{t_2} - M_{t_1})(M_{t_4} - M_{t_3}) | \mathcal{F}_3]]$$

Applying filtration on \mathcal{F}_3

$$= \text{Now } M_{t_2} \text{ and } M_{t_1} \text{ are } \mathcal{F}_3 \text{ measurable.}$$

$$E[(M_{t_2} - M_{t_1}) \cdot E[(M_{t_4} - M_{t_3}) | \mathcal{F}_3]]$$

$$E[M_{t_4} | \mathcal{F}_3] = M_{t_3}$$

$$E[(M_{t_4} - M_{t_3}) | \mathcal{F}_3] = 0$$

$$\Rightarrow E[(M_{t_2} - M_{t_1}) \cdot 0] = 0$$

(b) B_t be brownian motion

$$X \in L^2_c(T)$$

$$M_t = \int_0^t x_s dB_s \quad t \leq T$$

$$t < t' \\ \int_0^{t'} x_s dB_s = \underbrace{\int_0^t x_s dB_s}_M + \int_t^{t'} x_s dB_s \\ M_{t'} - M_t$$

$$\begin{aligned} E \left[\left(\int_0^t x_s dB_s \right) \int_0^{t'} x_s dB_s \right] \\ = E[M_t^2] + E[M_t(M_{t'} - M_t)] \end{aligned}$$

Now cross term = 0 from above

$$E[M_t^2] = E \left[\left(\int_0^t x_s dB_s \right)^2 \right] = \int_0^t E[x_s^2] ds$$

by ito's symmetry

$$E \left[\left(\int_0^t x_s dB_s \right) \left(\int_0^t x_s dB_s \right) \right] = \int_0^t E[x_s^2] ds$$

5.6) To check $(M_t)_{t \leq T}$ is in $\mathcal{H}_c^2(T)$
 B_t is adapted to paths $e^{\sigma B_t - \frac{1}{2}\sigma^2 t}$
is continuous.

Square Integrable

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

$$E[e^{\theta B_t}] = e^{\frac{1}{2}\theta^2 t} \left\{ \begin{array}{l} \text{M.G.F} \\ \text{of Normal} \end{array} \right\}$$

$$\begin{aligned} E(M_t^2) &= E[e^{2\sigma B_t - \sigma^2 t}] \\ &= e^{-\sigma^2 t} E[e^{2\sigma B_t}] \\ &= e^{-\sigma^2 t} e^{+2\sigma^2 t} \\ &= e^{\sigma^2 t} \end{aligned}$$

$$\int_0^T E(M_t^2) \cdot dt = \int_0^T e^{\sigma^2 t} \cdot dt$$

$$= \frac{e^{\sigma^2 T} - 1}{\sigma^2} < \infty$$

5.7 $M_t = e^{B_t^2} \quad t \leq T.$

$$E(M_t^2) = E(e^{2B_t^2}) \quad B_t \sim N(0, t)$$

$$E(e^{2B_t^2}) = \int_{-\infty}^{\infty} \frac{e^{2x^2} \cdot e^{-\frac{x^2}{2t}}}{\sqrt{2\pi t}} dx$$

For this to be finite we need coeff. of $x^2 < 0$ otherwise it diverges

$$2 - \frac{1}{2t} < 0$$

$$2 < \frac{1}{2t} \quad \{t > 0\}$$

$$\text{Hence } t \leq \frac{1}{4}$$

For $t \leq \frac{1}{4}$

From C.D.F

$$E(M_t^2) = \frac{1}{\sqrt{1-4t}} \left\{ \begin{array}{l} \text{Since the integration} \\ \text{is} = \frac{1}{\sqrt{1-4t}} \end{array} \right.$$

$$\int_0^T \frac{1}{\sqrt{1-4t}} dt$$

$< \infty$

$$T \leq \frac{1}{4}$$

$$\rightarrow \frac{1}{2} (1 - \sqrt{1-4T})$$

$$T \leq \frac{1}{4}$$