

Stochastic Integral

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Goal Define $\int_0^t X(s) dB_s$

If G_s was C^1 then we would write

$$\begin{aligned}\int_0^t X(s) dG_s &= \int_0^t X(s) G'(s) ds \\ &= \lim_{n \rightarrow \infty} \sum_{i=1}^n X\left(\frac{i}{n}\right) \left(G\left(\frac{i}{n}\right) - G\left(\frac{i-1}{n}\right)\right)\end{aligned}$$

But Brownian motion is not differentiable and

$$\begin{aligned}\sum_{i=1}^n |B_{i/n} - B_{(i-1)/n}| \\ = \frac{1}{\sqrt{n}} \cdot \sum_{i=1}^n |B_i - B_{i-1}| \rightarrow \infty.\end{aligned}$$

so we need to define things carefully.

X_t is a submartingale / supermartingale if $\forall t' > t > 0$,

$$\mathbb{E}[X_{t'} | \mathcal{F}_t] \geq X_t \quad \text{resp.} \quad \mathbb{E}[X_{t'} | \mathcal{F}_t] \leq X_t.$$

If ψ is convex, X_t is a martingale then $\psi(X_t)$ is a submartingale.

If T is a stopping time with $0 \leq T \leq t$ then

$$\mathbb{E}X_0 \leq \mathbb{E}X_T \leq \mathbb{E}X_t.$$

Dob's Inequality If X_t is a submartingale and $\bar{X}_t = \max_{0 \leq s \leq t} X_s^+$ where $a^+ = \max\{0, a\}$

then $\forall \lambda \geq 0$

$$\lambda \mathbb{P}[\bar{X}_t \geq \lambda] \leq \mathbb{E}X_t \mathbb{I}(\bar{X}_t \geq \lambda) \leq \mathbb{E}X_t^+ \mathbb{I}(\bar{X}_t \geq \lambda)$$

LHS follows since if $T = \epsilon \wedge \inf\{s \leq \epsilon : X_s \geq \lambda\}$ then

$$\mathbb{E}[X_\epsilon | \mathcal{F}_T] \geq X_T \geq M \text{ on } \{\bar{X}_\epsilon \geq \lambda\}.$$

Doob's Maximal Inequality

If X_n is a (sub)martingale then

$$\mathbb{E}[\bar{X}_\epsilon^2] \leq 4 \mathbb{E}[(X_\epsilon^+)^2]$$

Proof:

$$\begin{aligned} \mathbb{E}[(\bar{X}_\epsilon \wedge M)^2] &= \int 2\lambda \mathbb{P}[\bar{X}_\epsilon \wedge M \geq \lambda] d\lambda \\ &\leq \int 2\lambda \left(\lambda^{-1} \mathbb{E}[X_\epsilon^+ I(\bar{X}_\epsilon \wedge M \geq \lambda)] \right) d\lambda \\ &= \mathbb{E}\left[2X_\epsilon^+ \int_0^{\bar{X}_\epsilon \wedge M} 1 \cdot d\lambda \right] \text{ Fubini} \\ &= 2 \mathbb{E}[X_\epsilon^+ (\bar{X}_\epsilon \wedge M)] \\ &\leq 2 \sqrt{\mathbb{E}[(X_\epsilon^+)^2] \mathbb{E}[(\bar{X}_\epsilon \wedge M)^2]} \\ &\quad \text{Cauchy Schwarz} \end{aligned}$$

\Rightarrow for all M ,

$$\mathbb{E}[(\bar{X}_\epsilon \wedge M)^2] \leq 4 \mathbb{E}[(X_\epsilon^+)^2]$$

If Y_t is a martingale and $X_t = |Y_t|$ then

$$\mathbb{E}\left[\left(\max_{0 \leq s \leq \epsilon} |Y_s|\right)^2\right] \leq 4 \mathbb{E}|Y_\epsilon|^2.$$

Quadratic Variation

Let $t_i^n = i2^{-n}$ and

$$\text{let } \langle X \rangle_\epsilon = \lim_n \sum_{i=1}^{t_2^n} (B_{t_i^n} - B_{t_{i-1}^n})^2.$$

Lemma: The limit exists and

$$\langle X \rangle_t = t \text{ a.s.}$$

Proof:

$$\text{Let } D_\varepsilon = \left\{ \max_{0 \leq m \leq n} \sum_{i=1}^m (B_{t_i^n} - B_{t_{i-1}^n})^2 - \frac{m}{2^n} > \varepsilon \right\}$$

$$P[D_\varepsilon] \leq 2^n \exp(-c 2^n)$$

So by Borel-Cantelli, limit exists almost surely for all dyadic points.

Since t is monotone and dyadic points are dense

$$\lim_n \sum_{i=1}^{[t 2^n]} (B_{t_i^n} - B_{t_{i-1}^n})^2 \rightarrow t \text{ a.s.}$$

Note that $d\langle X \rangle_t = dt$.

We will define the Ito integral

$$\int_0^t X(s) dB_s$$

first when $X(s) = f(B_s)$ where $f: \mathbb{R} \rightarrow \mathbb{R}$ is a C^1 function. Let $t_i^n = i 2^{-n}$. Define

$$\int_0^t f(B_s) dB_s := \sum_{i=1}^{[t 2^n]} f(B_{t_i^n}) (B_{t_{i+1}^n} - B_{t_i^n}) = I_t^n$$

• First assume that $\|f\|_\infty, \|f'\| \leq k$.

Then for $n > m$, set $A_i^{n,m} = f(B_{t_i^n})$, $D_i^{n,m} = f(B_{t_i^m})$:

$$E(I_t^n - I_t^m)^2 = E\left(\sum (A_i - D_i)(B_{t_{i+1}^n} - B_{t_i^n})\right)^2$$

$$= \sum_i \mathbb{E} (A_i - D_i)^2 (B_{t_{i+1}} - B_{t_i})^2$$

$$+ \sum_{i,j} \underbrace{\mathbb{E} (A_i - D_i)(A_j - D_j)(B_{t_{i+1}} - B_{t_i})(B_{t_{j+1}} - B_{t_j})}_{=0 \quad (\#1)}$$

$$= \sum_i \mathbb{E} \left[(A_i - D_i)^2 \mathbb{E} \left((B_{t_{i+1}} - B_{t_i})^2 \mid \mathcal{F}_{t_i} \right) \right]$$

$$= \sum_i \mathbb{E} \left[(A_i - D_i)^2 \cdot 2^{-n} \right]$$

$$\leq K^2 t \mathbb{E} \max_i (B_{t_i} - B_{t_{i-2^{m-n}}})^2$$

$$\leq K^2 t C \cdot 2^{-m/3}$$

Since

$$(\#1) = \mathbb{E} \left[(A_i - D_i)(A_j - D_j)(B_{t_{i+1}} - B_{t_i}) \underbrace{\mathbb{E} [B_{t_{j+1}} - B_{t_j} \mid \mathcal{F}_{t_j}]}_{=0} \right]$$

$$= 0$$

So $I_t^n \xrightarrow{a.s.} I_t$ so the limit exists.

To reduce to the case of general $f \in C^1$, take $T_M = \inf \{t : |B_t| = M\}$, define

$I \in \mathcal{I}_{T_M}$ up to time T_M , then let $M \rightarrow \infty$.

$$\text{So } \int_0^t f(B_s) dB_s := I_t.$$

• Properties of Stochastic Integral

Martingale: If $I_t = \int_0^t f(B_s) dB_s$ then

I_t is a martingale.

Proof: Let $0 < t < t'$ Then

$$\begin{aligned} \mathbb{E}[I_{t'} | \mathcal{F}_t] &= \mathbb{E}\left[\lim_n \sum_{i=0}^{t'2^n-1} f(B_{t_i^n}) (B_{t_{i+1}^n} - B_{t_i^n}) \mid \mathcal{F}_t\right] \\ &= \lim_n \sum_{i=0}^{t'2^n-1} f(B_{t_i^n}) (B_{t_{i+1}^n} - B_{t_i^n}) \\ &\quad + \lim_n \sum_{i=t2^n}^{t'2^n-1} \mathbb{E}\left[f(B_{t_i^n}) (B_{t_{i+1}^n} - B_{t_i^n}) \mid \mathcal{F}_t\right] \\ &= 0. \\ &= I_t. \end{aligned}$$

Continuity: By above estimator

$$\mathbb{E}[(I_t^n - I_t^{n+1})^2] \leq C 2^{-nr/3}$$

$$\text{so } \mathbb{E} \max_t (I_t^n - I_t^{n+1})^2 \leq 4C 2^{-nr/3}$$

Since I_t^n are continuous martingales,

I_t^n converges uniformly to I_t a.s.

Itô's Formula (1)

If f is C^2 then

$$f(B_t) - f(B_0) = \underbrace{\int_0^t f'(B_s) dB_s}_{\text{Martingale}} + \frac{1}{2} \underbrace{\int_0^t f''(B_s) ds}_{\text{Bounded Variation}}$$

By Taylor Series if $f \in C^2$

$$f(x+z) = f(x) + f'(x)z + \frac{1}{2} f''(y)z^2$$

for some $y \in [x, x+z]$. Hence

$$f(B_t) - f(B_0) = \sum_{i=0}^{2^n t-1} f(B_{t_i^n}) - f(B_{t_{i+1}^n})$$

$$\begin{aligned}
 f(B_t) - f(B_0) &= \sum_{i=0}^{2^n t - 1} f(B_{t_{i+1}^n}) - f(B_{t_i^n}) \\
 &= \sum_{i=0}^{2^n t - 1} f(B_{t_i^n}) (B_{t_{i+1}^n} - B_{t_i^n}) \rightarrow \int_0^t f'(B_s) dB_s \\
 &\quad + \sum_{i=0}^{2^n t - 1} f(B_{y_i^n}) \cdot (B_{t_{i+1}^n} - B_{t_i^n})^2
 \end{aligned}$$

where $y_i^n \in [t_i^n, t_{i+1}^n]$

Claim: If $\mu_n \rightarrow \mu$ weakly on $[0, t]$
and $f_n \rightarrow f$ uniformly then

$$\int f_n d\mu_n \rightarrow \int f d\mu.$$

Proof: Write X_n R.V. with $\text{Law} \frac{\mu_n}{\mu[0, t]}$
 $X_n \xrightarrow{d} X.$

$$\int f_n d\mu_n = \mathbb{E}[f_n(X_n)]$$

$$|\int f_n - f d\mu_n| \leq \|f - f_n\|_\infty \mu_n[0, t] \rightarrow 0.$$

$$|\int f d\mu_n - \int f d\mu| = |\mathbb{E} f(X_n) - \mathbb{E} f(X)| \rightarrow 0.$$

So writing $f_n(t_i^n) = f(B_{y_i^n})$, $f_n \rightarrow f$ uniformly

$$\text{So } \sum_{i=0}^{2^n t - 1} f(B_{y_i^n}) (B_{t_{i+1}^n} - B_{t_i^n})^2 \rightarrow \int_0^t f(B_s) ds.$$

General Stochastic Integral.

Definition: $X(t)$ is adapted (w.r.t \mathcal{F}_t) if $\forall t$,
 $X(t)$ is \mathcal{F}_t measurable.

Then $\int_0^t f(B_s) dB_s$ is adapted.

Definition: X_t is progressively measurable if
for all t , $X: \Omega \times [0, t]$

is $\mathcal{F}_t \otimes \mathcal{B}[0, t]$ measurable.

(Right continuous + Adapted) \Rightarrow Progressively measurable

\Rightarrow Adapted

Stochastic Integral for a step function

$$H_t = \sum H_i \mathbb{I}(t_i \leq t < t_{i+1})$$

where $\mathbb{E}(H_i^2) < \infty$.

Write $\|H\|_2^2 = \int \mathbb{E} H_t^2 dt$ and

$$\langle H, H' \rangle = \int \mathbb{E} H_t H'_t dt.$$

Then

$$I_t^H = \int_0^t H_s dB_s := \sum_i H_i (B_{t_{i+1} \wedge t} - B_{t_i \wedge t}).$$

With this definition I_t^H is a martingale and

$$\|I_t^H\|^2 := \mathbb{E}[(I_t^H)^2], \quad \langle I_t^H, I_t^{H'} \rangle = \mathbb{E}[I_t^H I_t^{H'}].$$

then

$$\begin{aligned} \|I_t^H\|^2 &= \mathbb{E} \sum_{i,j} H_i (B_{t_{i+1}} - B_{t_i}) H_j (B_{t_{j+1}} - B_{t_j}) \\ &= \mathbb{E} \sum_i H_i^2 (B_{t_{i+1}} - B_{t_i})^2 \\ &= \sum \mathbb{E} H_i^2 (t_{i+1} - t_i) = \int \mathbb{E} H_t^2 dt \\ &= \|H\|^2 \end{aligned}$$

So $H_t \mapsto I_t^H$ is an isometry.

Thus for a general progressively measurable H , if we can find

step functions $\|H_n - H\| \rightarrow 0$ then

$\|I^{H_n} - I^H\| \rightarrow 0$ for some limit I^H .

Approximation

Progressively measurable

↓

Bounded & P.M.

(A)

↓

Bounded continuous & P.M.

(B)

↓

Bounded Simple Function P.M.

(C)

For (A) set $H_t^n = H_t I(|H_t| \leq n)$

then $\|H_t^n\|_\infty \leq n$ and $\|H^n - H\| \rightarrow 0$.

For (B) set

$$H_t^n = n \int_{t-\frac{1}{n}}^t H_s ds$$

then H^n has cts paths and

$H_t^n(t, \omega) \rightarrow H(t, \omega)$ t -almost everywhere
for all ω so

$$\|H^n - H\| \rightarrow 0.$$

For (C) take

$$H_t^n = \sum H_{t_i^n} I(t_{i-1}^n \leq t < t_i^n).$$

Do these definitions coincide?

- Yes since they are both the limit of the same simple functions.
-

What about replacing B_t with something else?

$\int X_s dM_s$.

If M_t is an L^2 martingale define

$$\langle M \rangle_{t,n} := \sum_i (M_{\epsilon_{i+1}, t} - M_{\epsilon_i, t})^2.$$

We will show that

$$\langle M \rangle_t := \lim_n \langle M \rangle_{t,n} \text{ exists.}$$

and that

$$M_t^2 - \langle M \rangle_t \text{ is a martingale.}$$

If M_t is a martingale and $i \leq j \leq n$ then

$$\mathbb{E}[(M_{t_n} - M_{t_j})^2 | \mathcal{F}_{t_i}]$$

$$= \mathbb{E}[M_{t_n}^2 - 2M_{t_n}M_{t_j} + M_{t_j}^2 | \mathcal{F}_{t_i}]$$

$$= \mathbb{E}[M_{t_n}^2 - 2M_{t_j} \mathbb{E}[M_{t_n} | \mathcal{F}_{t_j}] + M_{t_j}^2 | \mathcal{F}_{t_i}]$$

$$= \mathbb{E}[M_{t_n}^2 - M_{t_j}^2 | \mathcal{F}_{t_i}].$$

Claim: If $\|M\|_\infty \leq K$ then

$$\mathbb{E}[\langle M \rangle_t^2] \leq 6K^4.$$

Proof:

$$\begin{aligned} & \mathbb{E} \left(\sum_{i < j} (M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 (M_{\epsilon_{j+1}} - M_{\epsilon_j})^2 \right) \\ &= \sum_i \mathbb{E} \left[(M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 \mathbb{E} \left(\sum_j (M_{\epsilon_{j+1}} - M_{\epsilon_j})^2 \mid \mathcal{S}_{\epsilon_{i+1}} \right) \right] \\ &= \sum_i \mathbb{E} \left[(M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 \mathbb{E} (M_t^2 - M_{\epsilon_{i+1}}^2 \mid \mathcal{S}_{\epsilon_{i+1}}) \right] \\ &\leq K^2 \sum_i \mathbb{E} (M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 \leq K^2 \mathbb{E} \sum_i M_{\epsilon_{i+1}}^2 - M_{\epsilon_i}^2 \\ &\leq K^4 \end{aligned}$$

$$\begin{aligned} \mathbb{E} \sum_i (M_{\epsilon_{i+1}} - M_{\epsilon_i})^4 &\leq 4K^2 \mathbb{E} \sum_i (M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 \\ &\leq 4K^4 \end{aligned}$$

$$\begin{aligned} \mathbb{E}[\langle M \rangle_t^2] &= \sum_i \mathbb{E} (M_{\epsilon_{i+1}} - M_{\epsilon_i})^4 \\ &\quad + 2 \sum_{i < j} (M_{\epsilon_{i+1}} - M_{\epsilon_i})^2 (M_{\epsilon_{j+1}} - M_{\epsilon_j})^2 \\ &\leq 6K^4. \end{aligned}$$

Claim: $M_t^2 - \langle M \rangle_{t,n}$ is a martingale.

Proof: Enough to prove that for
 $\epsilon_i \wedge s \leq t \leq \epsilon_{i+1}$ that

$$\begin{aligned} & \mathbb{E} [M_t^2 - \langle M \rangle_{t,n} - (M_s^2 - \langle M \rangle_{s,n}) \mid \mathcal{S}_s] = 0. \\ &= \mathbb{E} [M_t^2 - (M_t - M_{\epsilon_i})^2 - M_s^2 - (M_s - M_{\epsilon_i})^2 \mid \mathcal{S}_s] \\ &= \mathbb{E} [M_{\epsilon_i} (2M_t - M_{\epsilon_i}) - M_{\epsilon_i} (2M_s - M_{\epsilon_i}) \mid \mathcal{S}_s] \\ &= M_{\epsilon_i} \mathbb{E} [2M_t - M_s \mid \mathcal{S}_s] = 0. \end{aligned}$$

Let $m < n$ and

$$J_t = \langle M \rangle_{t,n} - \langle M \rangle_{t,m}$$

$$= (M_t^2 - \langle M \rangle_{t,m}) - (M_t^2 - \langle M \rangle_{t,n})$$

is a martingale since it is

a difference of two martingales.

$$\text{Let } \Delta_m = \sup_j \sup_{s \in (t_j^m, t_{j+1}^m)} |M_s - M_{t_j^m}|$$

$$\text{Then } \mathbb{E} J_t^2 = \mathbb{E} \sum_i (J_{t_{i+1}} - J_{t_i})^2$$

If $t_j^m \leq t_i^n < t_{i+1}^n \leq t_{j+1}^m$ then

$$\begin{aligned} J_{t_{i+1}} - J_{t_i} &= (M_{t_{i+1}^n} - M_{t_i^n})^2 \\ &\quad - ((M_{t_{i+1}^n} - M_{t_j^m})^2 - (M_{t_i^n} - M_{t_j^m})^2) \end{aligned}$$

$$= 2(M_{t_{i+1}^n} - M_{t_i^n})(M_{t_j^m} - M_{t_i^n})$$

$$\text{So } \mathbb{E}(J_{t_{i+1}} - J_{t_i})^2 \leq 4 \mathbb{E}((M_{t_{i+1}^n} - M_{t_i^n})^2 \cdot \Delta_m^2)$$

$$\begin{aligned} \mathbb{E} J_t^2 &\leq 4 \mathbb{E}[\langle M \rangle_{t,n} \cdot \Delta_m^2] \\ &\leq 4 \sqrt{\mathbb{E}[\langle M_{t,n} \rangle^2]} \sqrt{\mathbb{E} \Delta_m^4} \\ &= 4 \sqrt{\delta k^4} \sqrt{\mathbb{E} \Delta_m^4} \rightarrow 0 \text{ as } m \rightarrow \infty \end{aligned}$$

Hence $\langle M \rangle_{t,n} \xrightarrow{L^2} \langle M \rangle_t$.

When M is unbounded we let

$T_k = \inf\{s : |M_s| = k\}$ and set M_k

$$\langle M \rangle_t = \lim_{k \rightarrow \infty} \langle M_{t \wedge T_k} \rangle_t.$$

The quadratic variation process is

continuous, increasing and

$M_t^2 - \langle M \rangle_t$ is a martingale and so

$$\mathbb{E}[M_{t_{i+1}}^2 - M_{t_i}^2 \mid \mathcal{F}_{t_i}] = \mathbb{E}[\langle M \rangle_{t_{i+1}} - \langle M \rangle_{t_i}].$$

Example (Homework)

$$\text{If } M_t = \int_0^t H_s dB_s \text{ then}$$

$$\langle M \rangle_t = \int_0^t H_s ds.$$

General Integrals with respect to
continuous martingales $\int_0^t H_s dM_s$

- H_t P.M. w.r.t. σ -algebra generated by M_t
- For a step function $H = \sum H_i I(t_i \leq t < t_{i+1})$

$$I_t^H = \sum_i H_i (M_{t_{i+1} \wedge t} - M_{t_i \wedge t})$$

which is a martingale so

$$\begin{aligned} \mathbb{E}[I_t^H]^2 &= \sum_i \mathbb{E}[(H_i (M_{t_{i+1}} - M_{t_i}))^2] \\ &= \sum_i \mathbb{E}\left[H_i^2 \mathbb{E}[(M_{t_{i+1}} - M_{t_i})^2 \mid \mathcal{F}_{t_i}]\right] \\ &= \sum_i \mathbb{E}\left[H_i^2 \mathbb{E}[M_{t_{i+1}}^2 - M_{t_i}^2 \mid \mathcal{F}_{t_i}]\right] \\ &= \sum_i \mathbb{E}\left[H_i^2 (\langle M \rangle_{t_{i+1}} - \langle M \rangle_{t_i})\right] \\ &= \mathbb{E}\left[\int_0^t H_s^2 d\langle M \rangle_s\right] \end{aligned}$$

$$\text{If } \|H\|_M^2 = \mathbb{E}\left[\int_0^t H_s^2 d\langle M \rangle_s\right]$$

then $H \mapsto I_t^H$ is an isometry
and we define

$$I_t^H = \lim_n I_t^{H_n}$$

F(t) is Function of Finite variation

$$\text{if } F(t) = F^+(t) - F^-(t) \text{ where}$$

FCV is function of

if $F(t) = F^+(t) - F^-(t)$ where
 $F^\pm(t)$ are increasing.

Equivalently:

$$\sup_{\{t_i\}} \sum_i |F(t_i) - F(t_{i-1})| < \infty$$

over all partitions t_i .

Proof: Set $F^+(t) = \sup_{0 \leq t_1 \leq \dots \leq t_n = t} \sum_i (F(t_i) - F(t_{i-1}))^+$

and $F^-(t) = F(t) - F^+(t)$.

Brownian motion is not of finite variation.

For any bounded H_s and Y_s of finite variation we can define

$$\int_0^t H_s dY_s = \int_0^t H_s dY_s^+ - \int_0^t H_s dY_s^-$$

So if $X_t = M_t + Y_t$ then

$$\int_0^t H_s dX_s := \int_0^t H_s dM_s + \int_0^t H_s dY_s$$

We call X_t a semi-martingale.

If $f \in C^2$ then

$$f(X_t) - f(X_0) = \int_0^t f'(B_s) dB_s + \int_0^t \frac{1}{2} f''(B_s) ds$$

martingale finite variation

so $f(X_t)$ is a semi-martingale and we can write Ito's formula as

$$df(X_s) = f'(B_s) dB_s + \frac{1}{2} f''(B_s) ds$$

Ito's Formula for general martingales

If M is a continuous L^2 martingale

$$\begin{aligned} f(M_t, t) - f(M_0, 0) &= \int_0^t f_x(M_s) dM_s \\ &+ \int_0^t f_t(M_s) ds \\ &+ \frac{1}{2} \int_0^t f_{xx}(M_s) ds \end{aligned}$$

Ito's Formula II

Let $f(x, t) \in C^2$ be such that

$$\mathbb{E} \int (f_x(B_s))^2 ds < \infty$$

Then

$$\begin{aligned} f(B_t, t) - f(B_0, 0) &= \int_0^t f_x(B_s, s) dB_s \\ &+ \int_0^t f_t(B_s, s) ds \\ &+ \frac{1}{2} \int_0^t f_{xx}(B_s, s) ds. \end{aligned}$$

Proof:

Write

$$\begin{aligned} f(B_{t_{i+1}}, t_{i+1}) - f(B_{t_i}, t_i) &= f_x(B_{t_i}, t_i)(B_{t_{i+1}} - B_{t_i}) + f_t(B_{t_i}, t_i)(t_{i+1} - t_i) \\ &+ \frac{1}{2} f_{xx}(B_{t_i}, t_i)(B_{t_{i+1}} - B_{t_i})^2 + f_{xt}(B_{t_i}, t_i)(B_{t_{i+1}} - B_{t_i})(t_{i+1} - t_i) \\ &+ \frac{1}{2} f_{tt}(B_{t_i}, t_i)(t_{i+1} - t_i)^2 + \dots \end{aligned}$$

Check that last two terms are negligible.

Multi-dimensional Brownian Motion

• We say B_t is d-dimensional Brownian motion if $B_t = (B_t^{(1)}, \dots, B_t^{(d)})$ is an \mathbb{R}^d valued stochastic process where $B_t^{(i)}$ are independent Brownian motions.

• Properties:

- Gaussian process

- Independent increments

$$\{B_{t_{i+1}} - B_{t_i}\}_{i \geq 0} \sim N(0, (t_{i+1} - t_i) I_d).$$

- Continuous paths.

It is uniquely defined by these properties.

Also - Martingale

- Scaling $B_t \stackrel{d}{=} a^{-1/2} B_{at}$

- Strong Markov Property

• If Q is an orthogonal matrix, $Q Q^T = I_d$.

$$Q B_t \stackrel{d}{=} B_t$$

- check covariances

$$\begin{aligned} \text{Cov}(x^T B_t, y^T B_s) &= \text{Cov}\left(\sum_i x_i B_t^{(i)}, \sum_j y_j B_s^{(j)}\right) \\ &= (t \wedge s) x^T y \end{aligned}$$

$$\begin{aligned} \text{Cov}(x^T Q B_t, y^T Q B_s) \\ &= (t \wedge s) x^T Q Q^T y \\ &= (t \wedge s) x^T y. \end{aligned}$$

Higher Dimensional Ito's Formula

If B_t is d -dimensional B.M.

$f: \mathbb{R}^d \times \mathbb{R} \rightarrow \mathbb{R}$, f is C^2 and

$\int_0^t |\nabla f(B_s, s)|^2 ds < \infty$ then

$$\begin{aligned} f(B_t, t) - f(B_0, 0) &= \sum_{i=1}^d \int_0^t f_{x_i}(B_s, s) dB^{i,i} \\ &+ \int_0^t f_t(B_s, s) ds \\ &+ \sum_{i=1}^d \int_0^t f_{x_i x_i}(B_s, s) ds \\ &= \int_0^t \nabla f(B_s, s) \cdot dB_s \\ &+ \int_0^t f_t(B_s, s) ds \\ &+ \int_0^t \Delta f(B_s, s) ds \end{aligned}$$

Proof: Expand out

$$\begin{aligned} &f(B_{t_{i+1}}, t_{i+1}) - f(B_{t_i}, t_i) \\ &= \sum_i f_{x_i}(B_{t_i}, t_i) (B_{t_{i+1}} - B_{t_i}) \\ &+ f_t(B_{t_i}, t_i) (t_{i+1} - t_i) \\ &+ \frac{1}{2} \sum_i f_{x_i x_i}(B_{t_i}, t_i) (B_{t_{i+1}}^{(i)} - B_{t_i}^{(i)})^2 \\ &+ \frac{1}{2} \sum_{i \neq j} f_{x_i x_j}(B_{t_i}, t_i) (B_{t_{i+1}}^{(i)} - B_{t_i}^{(i)}) (B_{t_{i+1}}^{(j)} - B_{t_i}^{(j)}) \\ &+ \sum_i f_{x_i t}(B_{t_i}, t_i) (B_{t_{i+1}}^{(i)} - B_{t_i}^{(i)}) (t_{i+1} - t_i) + \dots \end{aligned}$$

Recurrence and transience.

For $d \geq 3$ let $\varphi(x) = |x|^{2-d}$

Then $\varphi_{x_i, x_i}(x) = \frac{d^2}{dx_i^2} \left(\sum_i x_i^2 \right)^{1-d/2}$

$$= \frac{d}{dx_i} (1-\frac{d}{2}) 2x_i \left(\sum_i x_i^2 \right)^{-d/2}$$

$$= -\frac{d}{2} (1-\frac{d}{2}) 4x_i^2 \left(\sum_i x_i^2 \right)^{-d/2-1}$$

$$+ (1-\frac{d}{2}) 2 \left(\sum_i x_i^2 \right)^{-d/2}$$

$$\sum_{i=1}^d \varphi_{x_i, x_i} = (1-\frac{d}{2}) |x|^{-d} (-2d + 2d) = 0,$$

so $\Delta \varphi = 0$.

Is $\varphi(B_t)$ a martingale? No. Why?

Well $E[\varphi(B_t)] = E[|B_t|^{2-d}]$

$$= E[|t^{1/2} B_1|^{2-d}]$$

$$= t^{\frac{2-d}{2}} E|B_1|^{2-d}$$

$$E|B_1|^{2-d} = \frac{1}{(2\pi)^{d/2}} \int_{\mathbb{R}^d} |x|^{2-d} \exp(-|x|^2/2) dx$$

$$= C \int_0^\infty r^{d-2} r^{2-d} \exp(-r^2/2) dr$$

$$= C_1$$

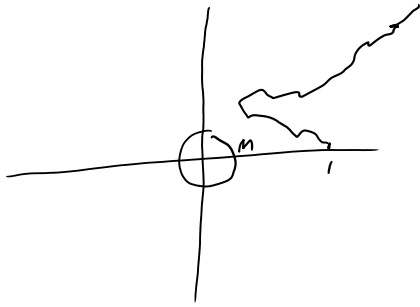
So $E[\varphi(B_t)] \rightarrow 0$.

It is, however, a local martingale.

Defn: X_t is a local martingale if there exists stopping times T_n such that $T_n \uparrow \infty$ a.s. and $X_{t \wedge T_n}$ is a martingale.

Set $B_0 = 1$, $T_M = \inf\{t : |B_t| = M\}$.

For $M < 1$,



$\mathcal{U}(B_{t \wedge T_n})$ is a martingale.

$$\mathbb{E} \mathcal{U}(B_{t \wedge T_n}) = \mathbb{E}[\mathcal{U}(B_0)] = 1$$

$$\lim_{t \rightarrow \infty} \mathbb{E} \mathcal{U}(B_{t \wedge T_n}) = M^{2-d} \mathbb{P}[T_n < \infty]$$

$$\text{so } \mathbb{P}[T_n < \infty] = M^{d-2} \text{ for } M < 1.$$

Hence $\mathbb{P}[\exists t: B_t = 0] = 0$, B_t is transient.

Furthermore $\mathcal{U}(B_t)$ is a local martingale w.r.t. T_n^{-1} .

What about $d=2$

Set $\mathcal{U}(x) = \log |x|$, $\Delta(\mathcal{U}) = 0$.

If $|B_0| = x > 0$, if B_t were recurrent then for some M , $|B_t|$ hits 0 before M with positive probability $p > 0$.

Set $T_n = \inf \{t: |B_t| \in \{\frac{1}{n}, M\}\}$.

Then $\mathcal{U}(B_{t \wedge T_n})$ is a martingale and

$$\begin{aligned} \log x &= \mathcal{U}(B_0) \\ &= \mathbb{E} \mathcal{U}(B_{t \wedge T_n}) \\ &\rightarrow \mathbb{E} \mathcal{U}(B_{T_n}) \\ &= (-\log n) \mathbb{P}[B_{T_n} = \frac{1}{n}] + \mathbb{P}[B_{T_n} = M] (\log M) \\ &\leq -p \log n + (1-p) \log M \\ &\rightarrow -\infty \end{aligned}$$

as $n \rightarrow \infty$.

Hence not recurrent.

Now let $T = \inf \{t : |B_t| \in \{\frac{x}{2}, 2x\}\}$.

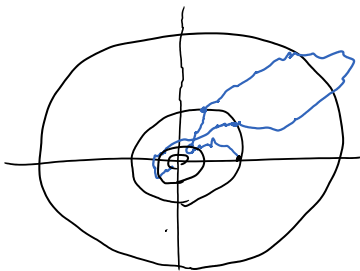
Then $\mathcal{L}(B_{t \wedge T})$ is a martingale and

$$E \mathcal{L}(B_T) = E(B_0) = \log x$$

$$= P\left[|B_T| = \frac{x}{2}\right](\log x - \log 2)$$

$$+ P\left[|B_T| = 2x\right](\log x + \log 2)$$

$$\text{so } P\left[|B_T| = 2x\right] = P\left[|B_T| = \frac{x}{2}\right]$$



Random walk on
 $\{x : x = 2^k\}$.

Let's apply Ito's formula to

$$f(x) = |x|.$$

$$\text{Then } f_{x_i}(x) = \frac{x_i}{|x|}$$

$$f_{x_i x_i}(x) = \frac{1}{|x|} - \frac{x_i^2}{|x|^3}$$

$$\text{so } |\nabla f(x)|^2 = \sum_i \frac{x_i^2}{|x|^2} = 1.$$

$$\Delta f(x) = -(d-1)/|x|$$

$$\nabla f(B_{t_i}) \cdot (B_{t_{i+1}} - B_{t_i}) \stackrel{d}{=} N(0, 2^{-n})$$

independent of \mathcal{F}_{t_i} .

Consider

$$\sum_{i=0}^{2^n} \nabla f(B_{t_i}) \cdot (B_{t_{i+1}} - B_{t_i})$$

$$\sum_{i=0}^{n-1} \nabla F(B_{t_i}) \cdot (B_{t_{i+1}} - B_{t_i})$$

$$\stackrel{d}{=} \sum_{i=0}^{n-1} (B_{t_{i+1}} - B_{t_i}) \rightarrow \text{Brownian motion}$$

So if $Y_t = |B_t|$ then

$$Y_t - Y_0 = \underbrace{\int_0^t \sum_{i=1}^d f_{x_i}(B_s) dB_s^{(i)}}_{\text{Brownian motion}} - \frac{d-1}{2} \int_0^t Y_s^{-1} ds$$

A solution to the stochastic differential equation (SDE)

$$dY_s = dB_s - \frac{d-1}{2} Y_s^{-1} ds$$

called a Bessel Process of order d .

We will see later that Brownian motion, conditioned to be non-negative, has the law of a Bessel-3.