

Integration & differentiation w.r.t B.M.

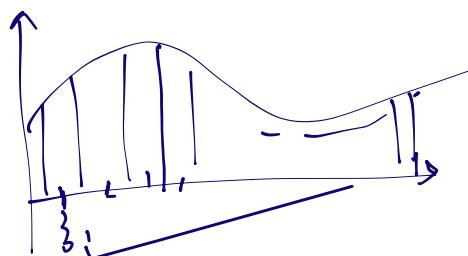
Goal: to make sense of $\int_0^t Y_s dB_s$
 Y_s "nice".

B_s ; gambling game
 Y_s : the gambling strategy with $[S - S + \Delta S]$.

Require Y_t
 Y_t is determined by $(B_s)_{s \leq t}$ (i.e. F_t)

$$\rightarrow \mathbb{E}[|Y_t|^2] < \infty \quad (\text{H}) \rightarrow \int_0^t \mathbb{E}[Y_s^2] ds < \infty.$$

Recall: Riemann integral.

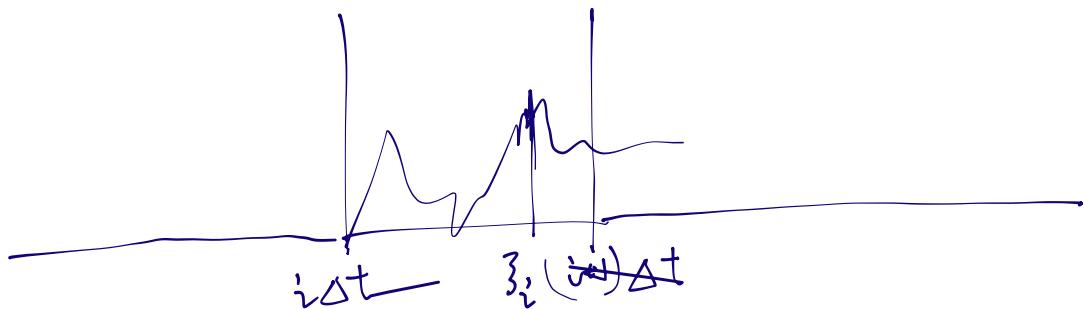


$$\int_a^b f(t) dt$$

$$= \lim_{\Delta t \rightarrow 0} \sum_{i=0}^{n-1} f(z_i) \cdot \Delta t$$

Want to define

$$\int_0^T Y_s dB_s \stackrel{?}{=} \lim_{\Delta t \rightarrow 0} \sum_{i=0}^{t/\Delta t} (B_{(i+1)\Delta t} - B_{i\Delta t}) \cdot Y_{(i+\frac{1}{2})\Delta t}.$$



e.g. $\int_0^T B_s dB_s \stackrel{?}{=} \lim_{\Delta t \rightarrow 0} \sum_{i=0}^{t/\Delta t} (B_{(i+1)\Delta t} - B_{i\Delta t}) \cdot B_{(i+\frac{1}{2})\Delta t}$

$$\sum_{i=0}^{t/\Delta t} (B_{(i+1)\Delta t} - B_{i\Delta t}) \cdot B_{(i+\frac{1}{2})\Delta t} = \sum_{i=0}^{t/\Delta t} (B_{(i+1)\Delta t} - B_{i\Delta t}) \cdot (B_{(i+\frac{1}{2})\Delta t} - B_{i\Delta t}) + \sum_{i=0}^{t/\Delta t} (B_{(i+1)\Delta t} - B_{i\Delta t}) \cdot B_{i\Delta t}.$$

Zero-mean.

→ in Riemann Integral.

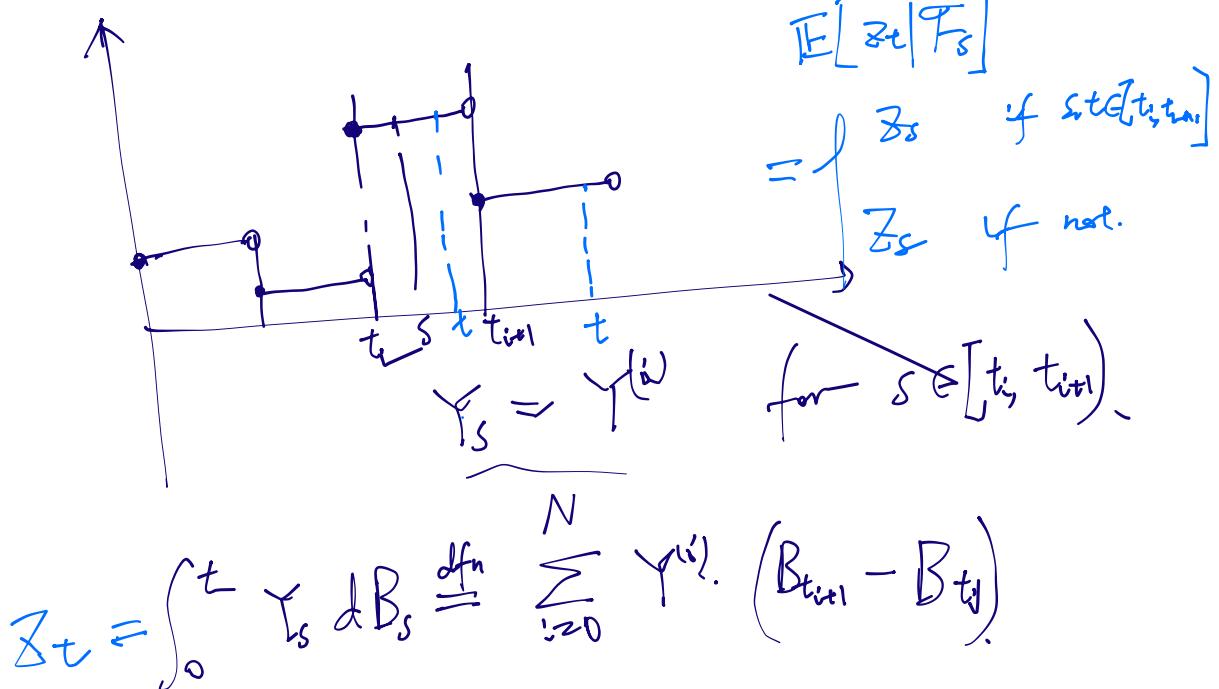
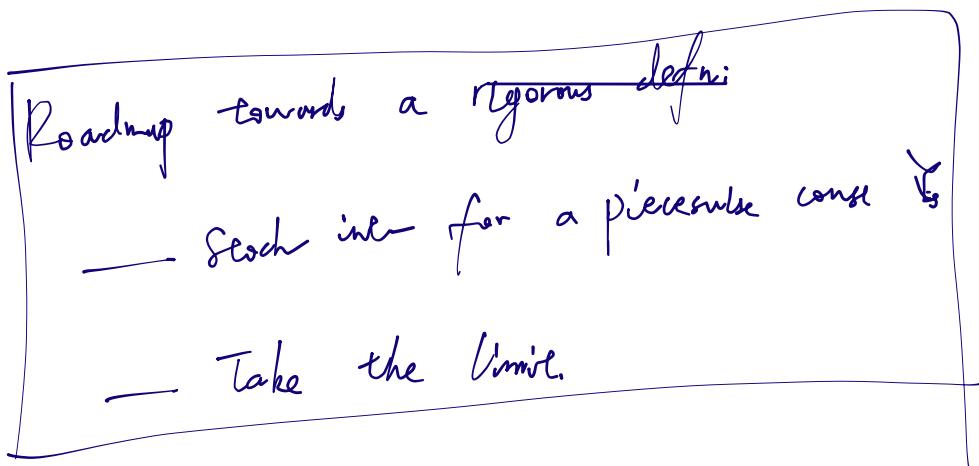
For stochastic integration.
each term s.t. $\mathbb{E}[---] = \frac{\Delta t}{2}$.

Sum $\xrightarrow{LLN} \frac{t}{2}$.

Criterion for choosing the midpoint:

make $\left(\int_0^t Y_s dB_s \right)_{t \geq 0}$ a martingale

Need to choose $z_i = i \cdot \Delta t$ (left endpoint)



Easy to verify } martingale

$$\int_0^t (aY_s + bY'_s) dB_s = a \int_0^t Y_s dB_s + b \int_0^t Y'_s dB_s.$$

(Itô isometry) $\mathbb{E}[Z_t^2] = \int_0^t \mathbb{E}[Y_s^2] ds. \quad (\star)$

Verify (\star) .

$$\int_0^t \mathbb{E}[Y_s^2] ds = \sum_i \mathbb{E}[(Y^{(i)})^2] (t_{i+1} - t_i)$$

$$Z_t^2 = \sum_i (Y^{(i)})^2 \cdot (B_{t_{i+1}} - B_{t_i})^2 + \text{cross terms.}$$

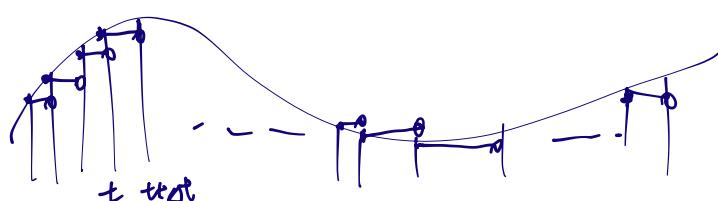
$\mathbb{E}[\cdot] = \sum_i \mathbb{E}[(Y^{(i)})^2] \cdot (t_{i+1} - t_i).$

\hookrightarrow cross term for $i < k$

$$\mathbb{E} [(Y^{(i)}) \cdot Y^{(k)} \cdot (B_{t_{i+1}} - B_{t_i}) \cdot (B_{t_{k+1}} - B_{t_k})]$$

determined by F_{t_k} . endp of F_{t_k} .

$(Y_s)_{s \geq 0}$ cts, adapted to $(F_s)_{s \geq 0}$.



$(Y_s^{(n)})_{s \geq 0}$.

$$\tilde{Z}_t^{(n)} := \int_0^t \tilde{Y}_s^{(n)} dB_s.$$

$$\tilde{Z}_t^{(n)} - \tilde{Z}_t^{(m)} = \int_0^t (\tilde{Y}_s^{(n)} - \tilde{Y}_s^{(m)}) dB_s$$

$$\mathbb{E} [\tilde{Z}_t^{(n)} - \tilde{Z}_t^{(m)}]^2 = \int_0^t \mathbb{E} [(\tilde{Y}_s^{(n)} - \tilde{Y}_s^{(m)})]^2 ds \rightarrow 0.$$

if $n, m \rightarrow \infty$.

$$\tilde{Z}_t^{(n)} \xrightarrow{\mathbb{P}} \tilde{Z}_t.$$

MG

try to verify \tilde{Z}_t satisfies

linearity

Itô isometry

"Notation":

$$F = \int f ds \Leftrightarrow dF = f ds.$$

$$Z_t = \int_0^t X_s ds + \int_0^t Y_s dB_s \quad (\dagger)$$

$$dZ_t = X_t dt + Y_t dB_t$$

It's formula.

Motivation: Newton-Leibniz

$$\int_a^b f'(t) dt = f(b) - f(a).$$

Not true for stochastic integral

$$\int_0^t B_s dB_s \neq \underbrace{\frac{1}{2} (B_{t\wedge}^2 - B_0^2)}_{\text{mean } 0}.$$

$$\text{mean } \frac{t}{2}.$$

$$f(B_{\Delta t}) - f(B_0) \quad (\text{if } f \in C^2)$$
$$= f'(B_0) \cdot B_{\Delta t} + \frac{1}{2} f''(B_0) \cdot \underbrace{B_{\Delta t}^2}_{\text{of order } \Delta t} + o(|B_{\Delta t}|^2)$$

$$f(B_{\Delta t}) - f(B_0)$$
$$= \sum_{j=0}^{m-1} f'\left(\frac{B_{j\wedge t}}{n}\right) \cdot \left(\frac{B_{(j+1)\wedge t}}{n} - \frac{B_{j\wedge t}}{n}\right) + \frac{1}{2} \sum_{j=0}^{m-1} f''\left(\frac{B_{j\wedge t}}{n}\right) \left(\frac{B_{(j+1)\wedge t}}{n} - \frac{B_{j\wedge t}}{n}\right)^2$$
$$+ \boxed{\sum_{j=0}^{m-1} o\left(\frac{1}{n}\right)} = o(1).$$

$$\approx \int_0^t f'(B_s) dB_s + ?$$

In general interested in

$$\lim_{n \rightarrow \infty} \sum_{j=0}^m g\left(\frac{B_{j+1}}{n}\right) \cdot \left(\underbrace{\frac{B_{j+1}}{n} - \frac{B_j}{n}}_{= \frac{t}{n} W} \right)^2$$

where $W \sim N(0, 1)$.

e.g. $g = |$

$$\frac{1}{n} \sum_{j=0}^m n \left(\frac{B_{j+1}}{n} - \frac{B_j}{n} \right)^2 \xrightarrow{\text{SLN}} t.$$

Normal guess: $\int_0^t g(B_s) ds$.

Roadmap: - converge g

↓
piecewise const. g

↓
cts processes (includes cts fns)
of BM

Thm. $f \in C^2$

$$f(B_t) - f(B_0) = \int_0^t f'(B_s) dB_s + \frac{1}{2} \int_0^t f''(B_s) ds.$$

$$\text{eg } f(x) = x^2.$$

$$B_t^2 = \int_0^t 2B_s dB_s + t.$$

$$\int_0^t B_s dB_s = \underbrace{\frac{1}{2}B_t^2 - \frac{1}{2}t}_{\text{MG}}$$

(used for
Gaussian noise)

$$\left(f(B_t) - f(B_0) - \frac{1}{2} \int_0^t f''(B_s) ds \right)_{t \geq 0} \text{ is MG.}$$

$$\text{eg. } X_t = e^{B_t}$$

$$X_t - 1 = \int_0^t e^{Bs} dB_s + \frac{1}{2} \int_0^t e^{Bs} ds.$$

$$dX_t = X_t dB_t + \frac{1}{2} X_t dt.$$

$$\text{Extensions. } dZ_t = X_t dt + Y_t dB_t$$

$$df(Z_t) = f'(Z_t) dZ_t + \frac{1}{2} f''(Z_t) Y_t^2 dt$$

$$= f'(Z_t) X_t dt + f'(Z_t) Y_t dB_t + \frac{1}{2} f''(Z_t) Y_t^2 dt$$

$$f(z) - f(z_0) = \sum_{j=0}^m \underbrace{f'(\underline{z}_{\frac{j+1}{n}})}_{-} \left(\underline{z}_{\frac{(j+1)t}{n}} - \underline{z}_{\frac{jt}{n}} \right)$$

$$+ \frac{1}{2} \sum_{j=0}^m f''(\underline{z}_{\frac{jt}{n}}) \cdot \left(\underline{z}_{\frac{(j+1)t}{n}} - \underline{z}_{\frac{jt}{n}} \right)^2.$$

$\in O(1)$.

$$\underline{z}_{\frac{(j+1)t}{n}} - \underline{z}_{\frac{jt}{n}} \approx \underline{x}_{\frac{jt}{n}} \cdot \left(\frac{t}{n} \right) + \underline{y}_{\frac{jt}{n}} \cdot \left(\underline{B}_{\frac{(j+1)t}{n}} - \underline{B}_{\frac{jt}{n}} \right)$$