

Midterm 2: next week.

— Covering Lectures 6, 7, 8

(may involve some MC as e.g. problem background)

(You're allowed to use any technique).

From last time: MG convergence

Theorem. $(X_n)_{n \geq 0}$ is MG, and $\mathbb{E}[|X_n|] \leq C + \alpha \quad \forall n$

Then there exists an r.v. X_∞

s.t. $P(X_n \rightarrow X_\infty) = 1$.

Question: $\mathbb{E}[X_\infty] \neq \mathbb{E}[X_n]$

(or in general, $\mathbb{E}[|X_n - X_\infty|] \rightarrow 0$).

$$|\mathbb{E}[X_\infty] - \mathbb{E}[X_n]| \leq \mathbb{E}[|X_n - X_\infty|]$$

So L' convergence implies eq. expectation.

Counter-example:

Let $(Z_n)_{n \geq 0}$ be SSRW, and $X_n = Z_{n+1}$.

Let $T := \inf \{t \geq 0 : X_t = 0\}$

Let $Y_n := X_{n \wedge T}$ (stopped MG is MG).

$Y_n \geq 0$, MG.

$$\mathbb{E}[|Y_n|] = \mathbb{E}[Y_n] = 1 < +\infty$$

so $Y_n \rightarrow Y_\infty$ a.s.

(Indeed, the convergence $Y_n \rightarrow 0$ a.s.
immediately shows as $T < +\infty$ w.p. 1).

$$\text{But } \mathbb{E}[Y_0] = \mathbb{E}[Y_\infty] = 0.$$

Need additional assumption.

Recall u.l. $\forall \varepsilon > 0, \exists K$

s.t. $\mathbb{E}[|X_n| \cdot \mathbb{1}_{|X_n| > K}] \leq \varepsilon \quad \forall n \geq 0$

(used e.g. in OST).

Thm $(X_n)_{n \geq 0}$ u.l., $X_n \xrightarrow{\text{a.s.}} X_\infty$ (It's guaranteed that $\mathbb{E}|X_\infty| < +\infty$)
then we have $\mathbb{E}[|X_n - X_\infty|] \rightarrow 0$. by Fatou's lemma.

Proof. $\mathbb{E}[|X_n - X_\infty|]$

$$\leq \mathbb{E}\left[|X_n \cdot \mathbb{1}_{|X_n| \leq K} - X_\infty \cdot \mathbb{1}_{|X_\infty| \leq K}|\right]$$

$$+ \mathbb{E}\left[|X_n| \cdot \mathbb{1}_{|X_n| \geq K}\right] + \mathbb{E}\left[|X_\infty| \cdot \mathbb{1}_{|X_\infty| \geq K}\right].$$

Since $(X_n)_{n \geq 0}$ is u.l.

$\rightarrow 0$ for fixed K
by DCT

and $\mathbb{E}|X_\infty| < +\infty$,

$\forall \varepsilon > 0$ fixed, $\exists K = K_\varepsilon > 0$

s.t. $\mathbb{E}[|X_n| \cdot \mathbb{1}_{|X_n| \geq K}] \leq \varepsilon \quad \forall n$

$$\mathbb{E}[|X_\infty| \cdot \mathbb{1}_{|X_\infty| \geq K}] \leq \varepsilon.$$

For $\varepsilon > 0$, fix it and find $K = K_\varepsilon < \infty$

Let $n \rightarrow \infty$, $\limsup_{n \rightarrow \infty} \mathbb{E}[|X_n - X_\infty|] \leq 2\varepsilon$

Since ε can be arbitrarily small, we have

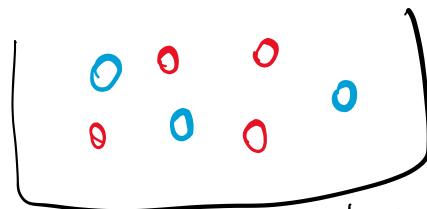
$$\lim_{n \rightarrow \infty} \mathbb{E}[|X_n - X_\infty|] = 0.$$

e.g. $M_n = \sum_{j=1}^n \frac{1}{j} X_j$ where $X_j \stackrel{\text{iid}}{\sim} \begin{cases} 1 & \text{w.p. } \frac{1}{2} \\ -1 & \text{w.p. } \frac{1}{2}. \end{cases}$

$$\mathbb{E}[|M_n|^2] \leq \frac{\pi^2}{6} < \infty \quad \forall n \quad \text{So a.s.}$$

$$M_n \xrightarrow[L]{\text{a.s.}} M_\infty \quad \mathbb{E}[M_\infty] = 0.$$

e.g. Poly's Urn.



Let $M_n :=$ Proportion of red balls in the box

add a new ball

For each time, add a new ball
w/ colour $\begin{cases} \text{red} & \text{w.p. } M_n \\ \text{blue} & \text{w.p. } 1 - M_n. \end{cases}$

Easy to verify: $(M_n)_{n \geq 0}$ is MG.

uniformly bold in $[0, 1]$

so $M_n \xrightarrow[L]{\text{a.s.}} M_\infty$.

Further application. OST and MG convergence.

$(X_n)_{n \geq 1}$ is a u.i. MG
T is a stopping time $\mathbb{E}[|X_T|] < +\infty$.
(don't require X_∞ indicates the limiting r.v.)

$$\mathbb{E}[X_T] \neq \mathbb{E}[X_0]. \quad (*)$$

To show (*), consider $(X_{T \wedge n})_{n \geq 0}$ MG
and we have $X_{T \wedge n} \xrightarrow{\text{a.s.}} X_T$.

We can easily verify $(X_{T \wedge n})_{n \geq 0}$ u.i.

$$\mathbb{E}[|X_{T \wedge n}| \mathbf{1}_{|X_{T \wedge n}| \geq K}] \leq \mathbb{E}[|X_n| \mathbf{1}_{|X_n| \geq K}] + \mathbb{E}[|X_T| \mathbf{1}_{|X_T| \geq K}]$$

So we have $\mathbb{E}[X_T] = \mathbb{E}[X_{T \wedge n}]$ (by L^1 converge)

and therefore $\mathbb{E}[X_T] = \mathbb{E}[X_0]$.

How about L^p convergence for $p > 1$?

Tool. $\mathbb{P}\left(\max_{0 \leq t \leq n} |X_t| \geq a\right) \leq \frac{\mathbb{E}[|X_n|^p]}{a^p}$

Darb's L^p max ineq

(Proof similar to L^1 version)

Doob's ineq implies

$$\mathbb{E}\left[\max_{0 \leq t \leq n} |X_t|^p\right] \leq \frac{p}{p-1} \cdot \mathbb{E}[|X_n|^p]$$

for any M.G. $(X_t)_{t \geq 0}$.

(Proof: integrate w.r.t. a and truncation).

From max ineq to L^p convergence.

$$\mathbb{E}\left[\underbrace{|X_n - X_\infty|^p}_{\rightarrow 0 \text{ a.s.}}\right]$$

Need a dominating function.

$$\begin{aligned} |X_n - X_\infty|^p &\leq 2^p(|X_n|^p + |X_\infty|^p) \\ &\leq 2^{p+1}\left(\sup_{n \geq 0} |X_n|^p + |X_\infty|^p\right) \end{aligned}$$

Apply DCT, get L^p convergence.

Conclusion: If $\mathbb{E}[|X_n|^p] \leq C < \infty$ ($p > 1$)

Then $X_n \xrightarrow[L^p]{\text{a.s.}} X_\infty$.

Brownian Motion

Motivation: scaling limit of SRW.

$$X_n = \sum_{i=1}^n \varepsilon_i \quad \text{where } \varepsilon_i = \begin{cases} 1 & \text{w.p. } \frac{1}{2} \\ -1 & \text{w.p. } \frac{1}{2}. \end{cases}$$

- By CLT. $\frac{1}{\sqrt{n}} X_n \xrightarrow{d} N(0, 1).$

- For finitely many $0 \leq t_1 < t_2 < \dots < t_k < +\infty$

$$(X_{[nt_1]}, X_{[nt_2]}, \dots, X_{[nt_k]}).$$

$$\frac{1}{\sqrt{n}} \begin{bmatrix} X_{[nt_1]} \\ X_{[nt_2]} - X_{[nt_1]} \\ \vdots \\ X_{[nt_k]} - X_{[nt_{k-1}]} \end{bmatrix} \xrightarrow{d} N\left(0, \begin{bmatrix} t_1 & & & & 0 \\ t_2 - t_1 & \ddots & & & \\ 0 & \ddots & \ddots & & \\ & \ddots & & t_{k-1} - t_k \end{bmatrix}\right).$$

Hope: $\left(\frac{1}{\sqrt{n}} X_{[nt]}\right)_{0 \leq t \leq T} \xrightarrow{d} \text{something.}$

Defn. $(B_t)_{t \geq 0}$ is a Brownian Motion if.

1. $B_0 = 0$

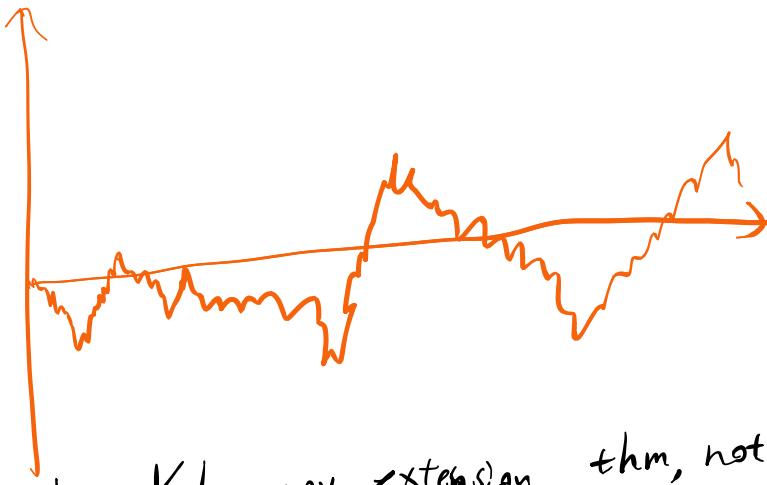
2. For any t_1, \dots, t_k , $(B_{t_1}, B_{t_2}, \dots, B_{t_k})$ jointly normal.

3. Independent increments.

For $t > s$, $B_t - B_s \sim N(0, t-s)$, independent from $(B_r)_{0 \leq r < s}$.

4. $t \mapsto B_t$ is a continuous function w.p. 1.

Intuitively: Within infinitesimal time interval $[t, t+\Delta t]$, make an indep inc $\sim N(0, \Delta t)$.



(Existence: by Kolmogorov extension thm, not covered.)

Fact. $(B_t)_{t \geq 0}$ is a martingale.

cts-time martingales: $(X_t)_{t \geq 0}$

- $\mathbb{E}[|X_t|] < +\infty$

- $\mathbb{E}[X_t | \mathcal{F}_s] (= \mathbb{E}[X_t | (X_r)_{0 \leq r \leq s}]) = X_s$.

Stopping time T :

the event $\{T \leq t\}$ determined by $(X_s)_{0 \leq s \leq t}$.

e.g. hitting time of a set.

e.g. $T_1 \wedge T_2$, $T_1 \wedge T_2$, where T_1 and T_2 are stopping times.

OST in continuous time $(X_t)_{t \geq 0}$ is MG

T is a stopping time

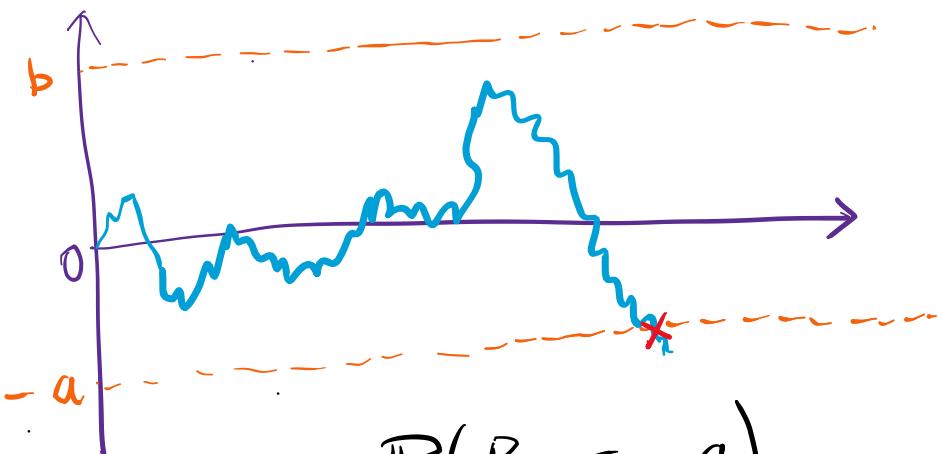
$$\left\{ \begin{array}{l} \mathbb{E}[|X_T|] < +\infty \\ \lim_{t \rightarrow +\infty} \mathbb{E}[|X_t| \cdot \mathbf{1}_{\{T>t\}}] = 0 \end{array} \right.$$

Then $\mathbb{E}[X_T] = \mathbb{E}[X_0]$.

Application: gambler's ruin in continuous space.

$(B_t : t \geq 0)$ BM. (for $a, b > 0$).

$$T := \inf \{ t \geq 0 : B_t = -a \text{ or } B_t = b \}$$



Interested in $P(B_T = -a)$.

Solution: OST.

Note that $(B_t)_{t \geq 0}$ is a MG

$$|B_t \mathbf{1}_{t \leq T}| \leq \max\{a, b\}$$

"Bounded up to time T ".

$$0 = \mathbb{E}[B_0] = \mathbb{E}[B_T]$$

$$= -a \cdot P(B_T = -a) + b \cdot P(B_T = b)$$

So we get $P(B_T = -a) = \frac{b}{a+b}$.

Remark: requires $P(T < +\infty) = 1$ $P(B_t \in [-a, b]) \rightarrow 0$
 can be shown by From SRW and MC theory

To large
deterministic time

Starting from any $x \in [-a, b]$,

$$P(\text{escape } [-a, b] \text{ within } T_0) > c$$



$$P(T \geq kT_0) \leq (1-c)^k.$$

How about $\mathbb{E}[T]$?

$$\text{Define: } M_t := B_t^2 - t.$$

$$\mathbb{E}[M_t | \mathcal{F}_s] = \mathbb{E}\left[\left(B_s + (B_t - B_s)\right)^2 \middle| \mathcal{F}_s\right] - t$$

$$= B_s^2 + (t-s) - t = B_s^2 - s = M_s$$

$$\mathbb{E}[|M_t| \mathbf{1}_{T \geq t}] \leq \mathbb{E}\left[\left(\max(a, b)^2 + T\right) \mathbf{1}_{T \geq t}\right]$$

T has exponentially decaying tail

$$\Rightarrow \mathbb{E}[M_t | T > t] \rightarrow 0.$$

So by OST, we have

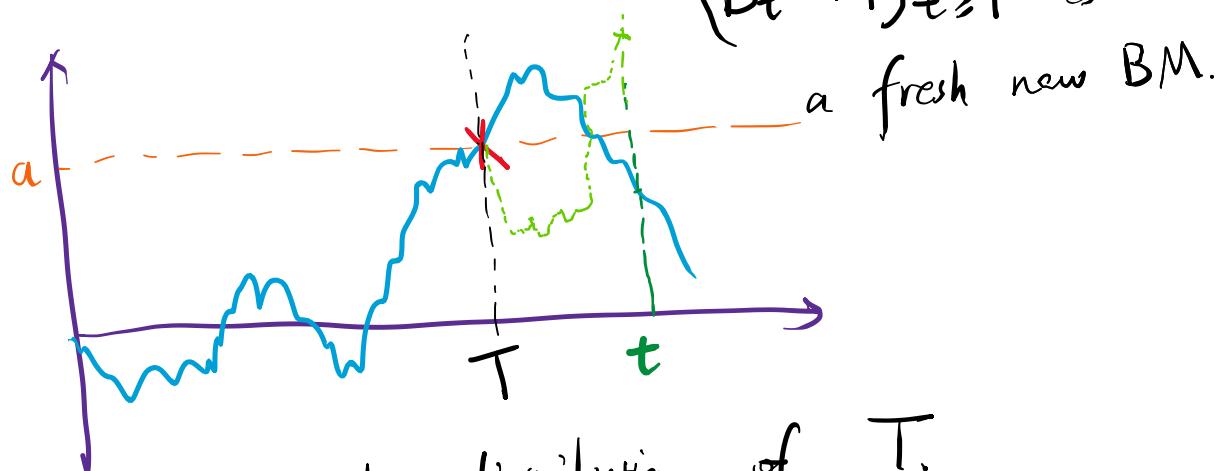
$$0 = \mathbb{E}[M_0] = \mathbb{E}[M_T] = \mathbb{E}[B_T^2] - \mathbb{E}[T]$$

$$\text{So } \mathbb{E}[T] = \mathbb{E}[B_T^2] = \frac{b a^2}{a+b} + \frac{ab^2}{a+b} = ab.$$

Reflection principle.

$(B_t)_{t \geq 0}$ BM,

$$T := \inf \{t : B_t \geq a\} \quad \text{for some } a > 0.$$



Can we get the distribution of T .

For any $t > 0$, want to compute

$$\mathbb{P}(T \leq t).$$

Intuition: after reaching T , two possibilities

$$\left. \begin{array}{l} X_t \geq a \\ X_t < a \end{array} \right\} \xrightarrow{\text{some prob.}} \text{probability} = P(X_t \geq a).$$

Intuitively $P(T \leq t) = 2P(X_t \geq a)$.

Making it rigorous:
By strong Markov property.

$$P(X_t \geq a) = P(T \leq t) \cdot P(B_t \geq a | T \leq t).$$

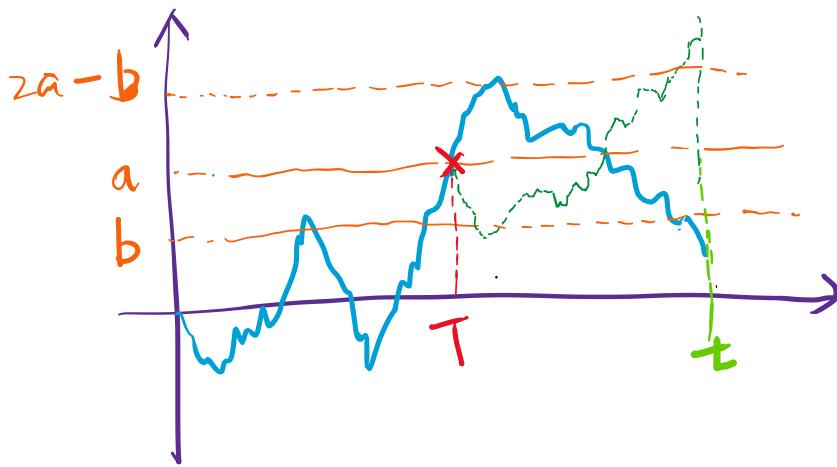
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$$= P(T \leq t) \cdot \underbrace{P(B_t - B_T \geq 0 | T \leq t)}_{\text{Can condition on } (B_s)_{0 \leq s \leq T} \text{ for } T \leq t}.$$

$$\int_a^{+\infty} \frac{1}{\sqrt{2\pi t}} \exp\left(-\frac{z^2}{2t}\right) dz = \frac{1}{2} P(T \leq t).$$

(can get density by taking derivative).

e.g.



T : stopping time

t : deterministic time.

$$P(T \leq t, B_t \leq b) \quad (\text{for } b < a).$$

$$= P(T \leq t) \cdot P(B_t \leq b \mid T \leq t).$$

$$= P(T \leq t) \cdot P(B_t - B_T \leq -(a-b) \mid T \leq t)$$

$$= P(T \leq t) \cdot P(B_t - B_T \geq a-b \mid T \leq t).$$

$$= P(T \leq t, B_t \geq 2a-b).$$

$$= P(B_t \geq 2a-b)$$

$$= \int_{2a-b}^{+\infty} \frac{1}{\sqrt{2\pi t}} \exp\left(-\frac{z^2}{2t}\right) dz.$$

Corollary. $(T_a: \text{hitting time of } a > 0)$

$$P(T_a \leq t) = 2 \cdot P(B_t \geq a)$$

$$\stackrel{\parallel}{=} P\left(\max_{0 \leq s \leq t} B_s \geq a\right) \quad \stackrel{\parallel}{=} P(|B_t| \geq a)$$

$$\text{So } \max_{0 \leq s \leq t} B_s \stackrel{d}{=} |B_t|.$$

Qualitative properties of BM.

Time derivative?

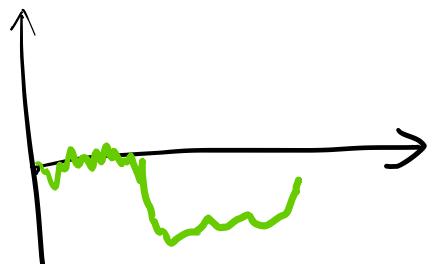
$$\frac{B_{t+\Delta t} - B_t}{\Delta t} \sim N(0, \frac{1}{\Delta t})$$

Easy to show $\forall t, P((B_s)_{s \geq 0} \text{ differentiable at } t) = 0.$

With some efforts, one can show

$$P(\exists t > 0, B \text{ diff at } t) = 0.$$

Fact : $S := \{ t > 0 : B_t = 0 \}$



$\forall \epsilon > 0,$

$S \cap [0, \epsilon]$ is infinite