

① LECTURE 1

Themes of PTI (probability you've seen?)

LOGISTICS

- (1) TAs: Debsurya, Pe, Yate, Zhan
- (2) Survey form on Canvas
- (3) OH survey: this week
- (4) HW 1: next week (Prob. Th. I review)

- Measure theory: (Kolmogorov 1933)
cf. Borel's random chord paradox (1889)
clarifies fuzzy notions of "random", "uniformly random", etc.
- Limit theorems: sequences of r.v. (S_n) "converge" (LLN, random series) or sequences of $P[A_n]$ (CLT, LDP).
- Independence: (= product measures) fundamental assumption leading to all main limit theorems (though can be loosened)
- Key example: sums of iid: $X_i \stackrel{iid}{\sim} P$, $S_n = \sum_{i=1}^n X_i$.

This class: generalizations of sum-of-iid model, sampling of more advanced topics.

- $X_i = \begin{cases} +1 & \text{w.p. } 1/2 \\ -1 & \text{w.p. } 1/2 \end{cases} \rightarrow (S_n)$ describes random walk on \mathbb{Z}



Q: Random walk on graph G ?

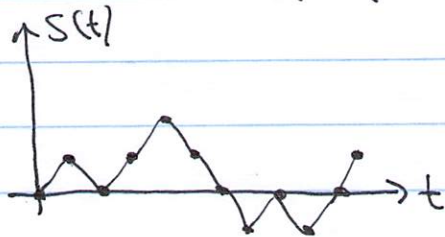
\rightarrow Markov chains.



- X_i = winnings from bet of \$1.
Adaptive strategy: bet depending on history $(S_0, S_1, \dots, S_{n-1})$
 \rightarrow Martingales.
Surprisingly related: analysis of $f(X_1, \dots, X_n)$ beyond summation.

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• Can view $(S_0, S_1, \dots, S_n, \dots)$ as $S: \mathbb{Z}_{\geq 0} \rightarrow \mathbb{R}$



interpolate \rightarrow random function.

"Zoom out" appropriately \rightarrow "converge" to Brownian motion
... for any (nice) ~~map~~ P (Donsker: "dynamical CLT")

Tools for random functions $\mathbb{R} \rightarrow \mathbb{R} =$ stochastic calculus.
(R_k : functions $\mathbb{R}^d \rightarrow \mathbb{R}$, manifold $\rightarrow \mathbb{R} =$ random fields.)

Review of Prob Th I ideas:

R_k : Truncation argument to upgrade to $\mathbb{E}|X_i| < \infty$.

① (Weak) LLN: If $\mathbb{E}X_i^2 < \infty$, $\frac{1}{n}S_n \xrightarrow{P} \mathbb{E}X_1 =: \mu$.
i.e., $\forall \varepsilon > 0$, $P\left[\left|\frac{1}{n}S_n - \mu\right| > \varepsilon\right] \rightarrow 0$.

$$\begin{aligned}
 \text{Pf: } &= P\left[\left|\frac{1}{n}\sum_{i=1}^n (X_i - \mu)\right| > \varepsilon\right] \\
 &\leq \frac{1}{\varepsilon^2} \text{Var}\left[\frac{1}{n}\sum_{i=1}^n (X_i - \mu)\right] \quad (\text{Chebyshev}) \\
 &= O\left(\frac{1}{n}\right) \rightarrow 0.
 \end{aligned}$$

"Strong" version: $\frac{1}{n}S_n \xrightarrow{\text{a.s.}} \mu$, i.e. $P\left[\lim_{n \rightarrow \infty} \frac{1}{n}S_n = \mu\right] = 1$.
Fundamentally different: weak about $\text{Law}(S_n)$, strong about $\text{Law}((S_n))$.
Main tool: Borel-Cantelli.

③

② Characteristic functions : $\phi_X(t) := \mathbb{E} \exp(itX)$

Rk: If X has density $f(x)$, $= \int_{-\infty}^{\infty} \exp(itx) f(x) dx$
 = Fourier transform of f .

Main properties:

- Law $(X) = \text{Law}(Y) \iff \phi_X = \phi_Y$ "conv. in distribution"
- $\phi_{X_n}(t) \rightarrow \phi_Y(t) \forall t \in \mathbb{R} \implies X_n \implies Y$
 (Clearer: Law $(X_n) \xrightarrow{\text{weak}} \text{Law}(Y)$, i.e.
 $\mathbb{E} f(X_n) \rightarrow \mathbb{E} f(Y) \forall$ bdd, cts. f .) Continuity Thm.
- X and Y independent $\implies \phi_{X+Y} = \phi_X \phi_Y$
 (Fourier transform effect on convolution (translation).)

Point: computational tool for conv. in distribution.

Ex: Alternative approach to weak LLN:

$$\begin{aligned} \phi_{\frac{1}{n}S_n}(t) &= \phi_{\frac{1}{n}X_1 + \dots + \frac{1}{n}X_n}(t) \\ &= \phi_{\frac{1}{n}X_1}(t) \dots \phi_{\frac{1}{n}X_n}(t) \\ &= \phi_{\frac{1}{n}X_1}(t)^n \\ &= \left(\mathbb{E} \exp(it \frac{X_1}{n}) \right)^n \end{aligned}$$

$$= \left(1 + \frac{it \mathbb{E} X_1}{n} + o\left(\frac{1}{n^2}\right) \right)^n \rightarrow \exp(it\mu) = \phi_{\mu}(t)$$

deterministic.

Def: dist. fn.
 $F_X(t) := \mathbb{P}[X \leq t]$

$X_n \implies Y$ iff
 $F_{X_n}(t) \rightarrow F_Y(t)$
 when F_Y cts. at t .

④
③ Ljapunov Proof of CLT:

Statement: if (X_i) iid, $\mathbb{E}X_i = \mu$, ~~$\text{Var} X_i = \sigma^2$~~ $\mathbb{E}|X_i|^3 < \infty$
 $\frac{1}{\sqrt{n}} \sum_{i=1}^n (X_i - \mu) \implies \mathcal{N}(0, \sigma^2)$.

↳ can remove with small modification.

Pf: WLOG $\mu = 0$ (some steps) so LHS = $\frac{1}{\sqrt{n}} S_n$.

$$\begin{aligned} \phi_{\frac{1}{\sqrt{n}} S_n}(t) &= \dots = \phi_{\frac{1}{\sqrt{n}} X_1}(t)^n \\ &= \left(\mathbb{E} \exp\left(it \frac{X_1}{\sqrt{n}}\right) \right)^n = \left(1 + \frac{it}{\sqrt{n}} \mathbb{E}X_1 + \frac{\frac{1}{2} t^2}{2n} \mathbb{E}X_1^2 + \mathcal{O}\left(\frac{1}{n^{3/2}}\right) \right)^n \\ &\rightarrow \exp\left(-\frac{\sigma^2 t^2}{2}\right) = \phi_{\mathcal{N}(0, \sigma^2)}(t). \end{aligned}$$

Easy proof, but rather magical/mysterious — not a probabilistic explanation of why CLT holds.

Next week: more "hands-on" proof technique (Lindeberg exchange method) \rightarrow ways to handle X_i non-iid and to get quantitative versions of weak convergence, i.e.

$$\left| \mathbb{E} f\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n (X_i - \mu)\right) - \mathbb{E} f(g) \right| \leq ???$$

$g \sim \mathcal{N}(0, \sigma^2)$