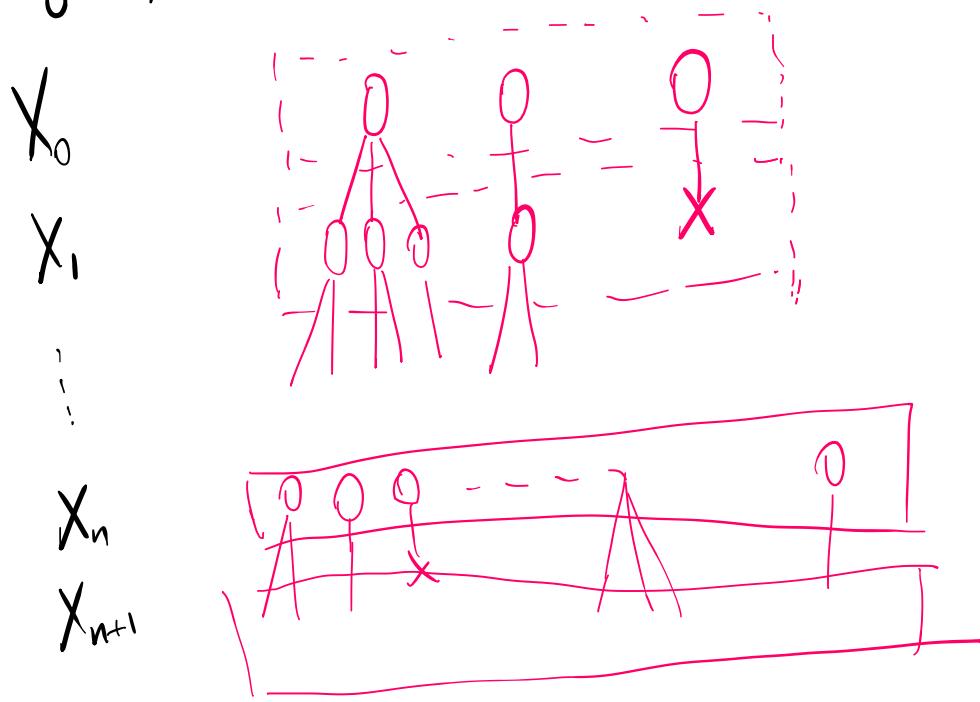


From last lecture:  $L^1, L^P$  convergence of MGRs.

This lecture: more examples.

e.g. Branching process.



Let  $\mu$  be a prob. distr. on  $\{0, 1, 2, \dots\}$

"offspring distribution"!

A branching process  $(X_n)_{n \geq 0}$  is an MC

defined by

$$X_{n+1} = Z_{n,1} + Z_{n,2} + \dots + Z_{n,X_n}$$

where  $Z_{n,i} \stackrel{iid}{\sim} \mu$  for  $i=1, 2, \dots, X_n$   
 (conditionally on  $X_n$ ).

Key question: whether  $(X_n)_{n \geq 0}$  dies out?

Assuming  $\mathbb{E}[X_0] < \infty$  throughout.

$$\begin{aligned}\mathbb{E}[X_{n+1} | \mathcal{F}_n] &= \mathbb{E}[X_{n+1} | X_n] \\ &= \sum_{i=1}^{X_n} \mathbb{E}[Z_{n,i}] = X_n \cdot \underbrace{\mathbb{E}[\mu]}_{=: m}.\end{aligned}$$

So  $Y_n := m^n \cdot X_n$  is an MG.

— When  $m < 1$ ,

$$\mathbb{E}[X_n] = m^n \cdot \mathbb{E}[X_0] \rightarrow 0 \quad (\text{as } n \rightarrow +\infty).$$

$X_n \xrightarrow{L} 0$  (which implies  $X_n \xrightarrow{P} 0$ ).

$X_n$  is integer-valued, this implies a.s. convergence.

— When  $m > 1$ .  $\mu(0) > 0$  (otherwise, impossible to die out)

The process could still die out w.p.  $> 0$   
 (e.g. die out in round 1 w.p.  $\mu(0)^{X_0}$ )

$$\cdot \mathbb{E}[X_n] \rightarrow +\infty.$$

$m=1, \mu(0) > 0$

$(X_n)_{n \geq 1}$  is an MG

$$X_n > 0 \quad \text{So} \quad \mathbb{E}[|X_n|] = \mathbb{E}[X_n] = \mathbb{E}[X_0] < +\infty.$$

$$X_n \xrightarrow{\text{a.s.}} X_\infty \quad \text{for some r.v. } X_\infty.$$

On the other hand,  $(X_n)_{n \geq 0}$  takes only integer values

so  $\exists T < +\infty$  such that after  $n \geq T$ ,  $X_n = X_\infty$ .

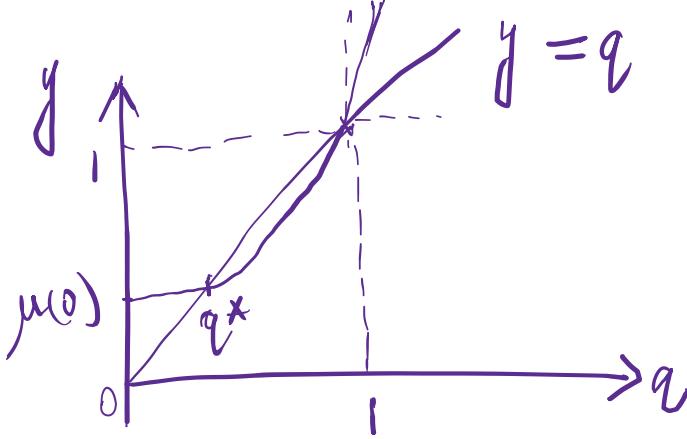
$$\text{So } X_n \rightarrow 0 \quad \text{a.s.}$$

Extinction prob. in super-critical case ( $m > 1$ ).

$$P(\text{Extinction} \mid X_0 = k) = P(\text{Extinction} \mid X_0 = 1)^k.$$

$$q = P(\text{Extinction} \mid X_0 = 1).$$

$$q = \sum_{k \geq 0} \mu(k) \cdot q^k, \quad \text{generating func of } \mu.$$



Generating func is  
(strictly) convex,  
intersects w/  $y=q$  twice  
at  $q=q^*$  and  $q=1$ .

When  $m > 1$ ,  $P(X_n \rightarrow +\infty) > 0$ ,  
and extinction prob. =  $q^*$ .

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e.g. Doob's MG.

$X$  : a random variable  $\mathbb{E}[X] < +\infty$ .

$$\mathcal{F}_1 \subseteq \mathcal{F}_2 \subseteq \mathcal{F}_3 \subseteq \dots \subseteq \mathcal{F}_n \subseteq \dots$$

"flow of information".

$$M_n := \mathbb{E}[X | \mathcal{F}_n]$$

Claim:  $(M_n)_{n \geq 0}$  is an MG.

$$\begin{aligned} \mathbb{E}[M_{n+1} | \mathcal{F}_n] &= \mathbb{E}[\mathbb{E}[X | \mathcal{F}_{n+1}] | \mathcal{F}_n] = \mathbb{E}[X | \mathcal{F}_n] \\ &= M_n. \end{aligned}$$

Uniform integrability.

$$\begin{aligned}
 & \mathbb{E}[M_n \cdot 1_{|M_n| \geq K}] \\
 &= \mathbb{E}\left[\left|\mathbb{E}(X | \mathcal{F}_n)\right| \cdot 1_{|M_n| \geq K}\right] \\
 &\leq \mathbb{E}\left[|X| \cdot 1_{\max_{1 \leq i \leq n} |M_i| \geq K}\right]. \quad \text{uniformly in } n \in \mathbb{N}.
 \end{aligned}$$

By Doob's maximal ineq.

$$\mathbb{P}\left(\max_{1 \leq i \leq n} |M_i| \geq K\right) \leq \frac{\mathbb{E}|M_n|}{K} \leq \frac{\mathbb{E}|X|}{K} \rightarrow 0.$$

$|X|$  as a dominating function, by DCT,

$$\mathbb{E}\left[|X| \cdot 1_{\max_{1 \leq i \leq n} |M_i| \geq K}\right] \rightarrow 0 \quad \text{So u.i.}$$

Consequently

$$X_n \xrightarrow[\mathcal{L}]{\text{a.s.}} X_\infty.$$

(Indeed,  $\mathcal{F}_\infty = \bigcup_{n=1}^{\infty} \mathcal{F}_n$ , "Info of the whole seq")

we have  $X_\infty = \mathbb{E}[X | \mathcal{F}_\infty]$

If  $X$  is determined by the seq, then  $X_\infty = X$ .

Application: posterior consistency.

$$\theta \sim \pi(\text{prior})$$

$$X_1, \dots, X_n | \theta \stackrel{iid}{\sim} P_\theta$$

$$\pi(\theta | X_1, \dots, X_n) = \frac{\pi(\theta) \cdot P_\theta(X_1) P_\theta(X_2) \cdots P_\theta(X_n)}{\int \pi(\theta') P_{\theta'}(X_1) \cdots P_{\theta'}(X_n) d\theta'}$$

Question : estimate  $g(\theta)$

$$\hat{g}_n = \mathbb{E}[g(\theta) | X_1, \dots, X_n] \xrightarrow{?} g(\theta)$$

Let  $X = g(\theta)$ ,  $F_n = (X_1, X_2, \dots, X_n)$

$(\hat{g}_n)_{n>0}$  is Doob's MG.

$$\hat{g}_n \xrightarrow[L]{\text{a.s.}} \hat{g}_\infty$$

(in Bayesian literature,  $\hat{g}_\infty = g(\theta)$   
under mild conditions).