# Notes 15 : Branching processes

Math 733-734: Theory of Probability

Lecturer: Sebastien Roch

References: [Wil91, Section 0], [Dur10, Section 5.3], [AN72, Section I.1-I.5].

### **1** Branching processes

### **1.1 Definitions**

Recall:

**DEF 15.1** A branching process is an SP of the form:

Let X(i, n), i ≥ 1, n ≥ 1, be an array of iid Z<sub>+</sub>-valued RVs with finite mean
m = E[X(1, 1)] < +∞, and inductively,</li>

$$Z_n = \sum_{1 \le i \le Z_{n-1}} X(i, n)$$

To avoid trivialities we assume  $\mathbb{P}[X(1,1) = i] < 1$  for all  $i \ge 0$ .

**LEM 15.2**  $M_n = m^{-n}Z_n$  is a nonnegative MG.

**Proof:** Use the following lemma (proved in homework):

**LEM 15.3** If  $Y_1 = Y_2$  a.s. on  $B \in \mathcal{F}$  then  $\mathbb{E}[Y_1 | \mathcal{F}] = \mathbb{E}[Y_2 | \mathcal{F}]$  a.s. on B.

Then, on  $\{Z_{n-1} = k\}$ ,

$$\mathbb{E}[Z_n \mid \mathcal{F}_{n-1}] = \mathbb{E}[\sum_{1 \le j \le k} X(j,n) \mid \mathcal{F}_{n-1}] = mk = mZ_{n-1}.$$

This is true for all k.

**COR 15.4** 
$$M_n \to M_\infty < +\infty \text{ a.s. and } \mathbb{E}[M_\infty] \le 1.$$

The martingale convergence theorem in itself tells us little about the limit. Here we derive a more detailed picture of the limiting behavior—starting with extinction.

### 1.2 Extinction

Let  $p_i = \mathbb{P}[X(1,1) = i]$  for all i and for  $s \in [0,1]$ 

$$f(s) = p_0 + p_1 s + p_2 s^2 + \dots = \sum_{i \ge 0} p_i s^i.$$

Similarly,  $f_n(s) = \mathbb{E}[s^{Z_n}]$ . One could hope to compute the generating function of the limit—but this is rarely possible. Instead, we derive some of its properties. In particular, note that

$$\pi \equiv \mathbb{P}[Z_n = 0 \text{ for some } n \ge 0]$$
  
= 
$$\lim_{n \to +\infty} \mathbb{P}[Z_n = 0]$$
  
= 
$$\lim_{n \to +\infty} f_n(0),$$

using the fact that 0 is an absorbing state and monotonicity. Moreover, by the Markov property,  $f_n$  as a natural recursive form:

$$f_n(s) = \mathbb{E}[s^{Z_n}]$$
  
=  $\mathbb{E}[\mathbb{E}[s^{Z_n} | \mathcal{F}_{n-1}]]$   
=  $\mathbb{E}[f(s)^{Z_{n-1}}]$   
=  $f_{n-1}(f(s)) = \cdots = f^{(n)}(s)$ 

So we need to study iterates of f. We will prove:

**THM 15.5 (Extinction)** *The probability of extinction*  $\pi$  *is given by the smallest fixed point of f in* [0, 1]*:* 

- 1. If  $m \leq 1$  then  $\pi = 1$ .
- 2. If m > 1 then  $\pi < 1$ .

We first summarize some properties of f. To avoid uninteresting cases, we assume  $p_0 + p_1 < 1$ .

**LEM 15.6** The function f on [0, 1] satisfies:

- *1.*  $f(0) = p_0, f(1) = 1$
- 2. f is indefinitely differentiable on [0, 1)
- 3. f is strictly convex and increasing

4. 
$$\lim_{s\uparrow 1} f'(s) = m < +\infty$$

**Proof:** See Baby Rudin for the relevant power series facts. 1. is clear by definition. The function f is a power series with radius of convergence  $R \ge 1$ . This implies 2. In particular,

$$f'(s) = \sum_{i \ge 1} i p_i s^{i-1} \ge 0,$$

and

$$f''(s) = \sum_{i \ge 2} i(i-1)p_i s^{i-2} > 0.$$

because we must have  $p_i > 0$  for some i > 1 by assumption. This proves 3. Since  $m < +\infty$ , f'(1) is well defined and f' is continuous on [0, 1].

### COR 15.7 (Fixed points) We have:

- 1. If m > 1 then f has a unique fixed point  $\pi_0 \in [0, 1)$
- 2. If  $m \le 1$  then f(t) > t for  $t \in [0, 1)$  (Let  $\pi_0 = 1$  in that case.)

**Proof:** Since f'(1) = m > 1, there is  $\delta > 0$  s.t.  $f(1 - \delta) < 1 - \delta$ . On the other hand  $f(0) \ge 0$  so by continuity of f there must be a fixed point in  $[0, 1 - \delta)$ . Moreover, by strict convexity, if r is a fixed point then f(s) < s for  $s \in (r, 1)$ , proving uniqueness.

The second part follows by strict convexity and monotonicity.

#### COR 15.8 (Dynamics) We have:

- 1. If  $t \in [0, \pi_0)$ , then  $f^{(n)}(t) \uparrow \pi_0$
- 2. If  $t \in (\pi_0, 1)$  then  $f^{(n)}(t) \downarrow \pi_0$

**Proof:** We only prove 1. The argument for 2. is similar. By monotonicity, for  $t \in [0, \pi_0)$ , we have  $t < f(t) < f(\pi_0) = \pi_0$ . Iterating

$$t < f^{(1)}(t) < \dots < f^{(n)}(t) < f^{(n)}(\pi_0) = \pi_0.$$

So  $f^{(n)}(t) \uparrow L \leq \pi_0$ . By continuity of f we can take the limit inside of

$$f^{(n)}(t) = f(f^{(n-1)}(t)),$$

to get L = f(L). So by definition of  $\pi_0$  we must have  $L = \pi_0$ .

Theorem 15.5 follows.

### 1.3 Discussion

The previous theorem "essentially" settles the subcritical and critical cases. For the supercritical case, however, it remains to understand when  $M_{\infty} = 0$ . When  $M_{\infty} \equiv 0$  for instance, our convergence theorem provides less precise information. Note that convergence of expectations would help exclude that case since that would imply  $\mathbb{E}[M_{\infty}] = 1$ . But this requires some conditions. For instance, note that when  $m \leq 1$ 

$$1 = \mathbb{E}[M_n] \not\rightarrow \mathbb{E}[M_\infty] = 0.$$

In other words, the Martingale Convergence Theorem does not hold in  $L^1$  under the same conditions.

More generally, one could conjecture that  $M_{\infty} = 0$  exactly when we have extinction. We will see conditions under which this is true next time.

## 2 Martingales in $\mathcal{L}^2$

### 2.1 Preliminaries

**DEF 15.9** For  $1 \le p < +\infty$ , we say that  $X \in \mathcal{L}^p$  if

$$||X||_p = \mathbb{E}[|X^p|]^{1/p} < +\infty.$$

By Jensen's inequality, for  $1 \le p \le r < +\infty$  we have  $\|X\|_p \le \|X\|_r$  if  $X \in \mathcal{L}^r$ .

**Proof:** For  $n \ge 0$ , let

$$X_n = (|X| \wedge n)^p.$$

Take  $c(x) = x^{r/p}$  on  $(0, +\infty)$  which is convex. Then

$$(\mathbb{E}[X_n])^{r/p} \le \mathbb{E}[(X_n)^{r/p}] = \mathbb{E}[(|X| \land n)^r] \le \mathbb{E}[|X|^r].$$

Take  $n \to \infty$  and use (MON).

**DEF 15.10** We say that  $X_n$  converges to  $X_\infty$  in  $\mathcal{L}^p$  if  $||X_n - X_\infty||_p \to 0$ . By the previous result, convergence on  $\mathcal{L}^r$  implies convergence in  $\mathcal{L}^p$  for  $r \ge p \ge 1$ . (Moreover, by Chebyshev's inequality, convergence in  $\mathcal{L}^p$  implies convergence in probability.)

**LEM 15.11** Assume  $X_n, X_\infty \in \mathcal{L}^1$ . Then

$$||X_n - X_\infty||_1 \to 0,$$

implies

$$\mathbb{E}[X_n] \to \mathbb{E}[X_\infty]$$

**Proof:** Note that

$$|\mathbb{E}[X_n] - \mathbb{E}[X_\infty]| \le \mathbb{E}|X_n - X_\infty| \to 0.$$

**DEF 15.12** We say that  $\{X_n\}_n$  is bounded in  $\mathcal{L}^p$  if

$$\sup_{n} \|X_n\|_p < +\infty.$$

## **2.2** $\mathcal{L}^2$ convergence

**THM 15.13** Let  $\{M_n\}$  be a MG with  $M_n \in \mathcal{L}^2$ . Then  $\{M_n\}$  is bounded in  $\mathcal{L}^2$  if and only if

$$\sum_{k\geq 1} \mathbb{E}[(M_k - M_{k-1})^2] < +\infty.$$

When this is the case,  $M_n$  converges a.s. and in  $\mathcal{L}^2$ . (In particular, it converges in  $\mathcal{L}^1$ .)

#### **Proof:**

**LEM 15.14 (Orthogonality of increments)** Let  $\{M_n\}$  be a MG with  $M_n \in \mathcal{L}^2$ . Let  $s \leq t \leq u \leq v$ . Then,

$$\langle M_t - M_s, M_v - M_u \rangle = 0.$$

**Proof:** Use  $M_u = \mathbb{E}[M_v | \mathcal{F}_u]$ ,  $M_t - M_s \in \mathcal{F}_u$  and apply the  $\mathcal{L}^2$  characterization of conditional expectations.

That implies

$$\mathbb{E}[M_n^2] = \mathbb{E}[M_0^2] + \sum_{1 \le i \le n} \mathbb{E}[(M_i - M_{i-1})^2],$$

proving the first claim.

By monotonicity of norms, M is bounded in  $\mathcal{L}^2$  implies  $\{M_n\}$  is bounded in  $\mathcal{L}^1$  which, in turn, implies M converges a.s. Then using (FATOU) in

$$\mathbb{E}[(M_{n+k} - M_n)^2] = \sum_{n+1 \le i \le n+k} \mathbb{E}[(M_i - M_{i-1})^2],$$

gives

$$\mathbb{E}[(M_{\infty} - M_n)^2] \le \sum_{n+1 \le i} \mathbb{E}[(M_i - M_{i-1})^2].$$

The RHS goes to 0 which proves the second claim.

### **3** Back to branching processes

**THM 15.15** Let Z be a branching process with  $Z_0 = 1$ ,  $m = \mathbb{E}[X(1,1)] > 1$ and  $\sigma^2 = \operatorname{Var}[X(1,1)] < +\infty$ . Then,  $M_n = m^{-n}Z_n$  converges in  $L^2$ , and in particular,  $\mathbb{E}[M_{\infty}] = 1$ .

**Proof:** We bound  $\mathbb{E}[M_n^2]$  by computing it explicitly by induction. From the orthogonality of increments

$$\mathbb{E}[M_n^2] = \mathbb{E}[M_{n-1}^2] + \mathbb{E}[(M_n - M_{n-1})^2].$$

On  $\{Z_{n-1} = k\}$ 

$$\mathbb{E}[(M_n - M_{n-1})^2 | \mathcal{F}_{n-1}] = m^{-2n} \mathbb{E}[(Z_n - mZ_{n-1})^2 | \mathcal{F}_{n-1}]$$
  
=  $m^{-2n} \mathbb{E}[(\sum_{i=1}^k X(i,n) - mk)^2 | \mathcal{F}_{n-1}]$   
=  $m^{-2n} k \sigma^2$   
=  $m^{-2n} Z_{n-1} \sigma^2$ .

Hence

$$\mathbb{E}[M_n^2] = \mathbb{E}[M_{n-1}^2] + m^{-n-1}\sigma^2.$$

Since  $\mathbb{E}[M_0^2] = 1$ ,

$$\mathbb{E}[M_n^2] = 1 + \sigma^2 \sum_{i=2}^{n+1} m^{-i},$$

which is uniformly bounded when m > 1. So  $M_n$  converges in  $L^2$ . Finally by (FATOU)

$$\mathbb{E}|M_{\infty}| \le \sup \|M_n\|_1 \le \sup \|M_n\|_2 < +\infty$$

and

$$|\mathbb{E}[M_n] - \mathbb{E}[M_\infty]| \le ||M_n - M_\infty||_1 \le ||M_n - M_\infty||_2,$$

implies the convergence of expectations.

In a homework problem, we will show that under the assumptions of the previous theorem

$$\{M_{\infty} = 0\} = \{Z_n = 0, \text{ for some } n\},\$$

and

$$\mathbb{P}[M_{\infty}=0]=\pi,$$

the probability of extinction.

### EX 15.16 (Geometric Offspring) Assume

$$0$$

Then

$$f(s)=\frac{p}{1-sq},\;\pi=\min\{\frac{p}{q},1\}.$$

• Case  $m \neq 1$ . If G is a 2 × 2 matrix, denote

$$G(s) = \frac{G_{11}s + G_{12}}{G_{21}s + G_{22}}$$

Then G(H(s)) = (GH)(s). By diagonalization,

$$\begin{pmatrix} 0 & p \\ -q & 1 \end{pmatrix}^n = (q-p)^{-1} \begin{pmatrix} 1 & p \\ 1 & q \end{pmatrix} \begin{pmatrix} p^n & 0 \\ 0 & q^n \end{pmatrix} \begin{pmatrix} q & -p \\ -1 & 1 \end{pmatrix}$$

(the columns of the first matrix on the RHS are the right eigenvectors) leading to

$$f_n(s) = \frac{pm^n(1-s) + qs - p}{qm^n(1-s) + qs - p}$$

In particular, when m < 1 we have  $\pi = \lim f_n(0) = 1$ . On the other hand, if m > 1, we have by (DOM) for  $\lambda \ge 0$ 

$$\mathbb{E}[\exp(-\lambda M_{\infty})] = \lim_{n} f_{n}(\exp(-\lambda/m^{n}))$$
$$= \frac{p\lambda + q - p}{q\lambda + q - p}$$
$$= \pi + (1 - \pi)\frac{(1 - \pi)}{\lambda + (1 - \pi)}$$

The first term corresponds to a point mass at 0 and the second term corresponds to an exponential with mean  $1/(1 - \pi)$ .

• Case m = 1. By induction

$$f_n(s) = \frac{n - (n - 1)s}{n + 1 - ns},$$

so that

$$\mathbb{P}[Z_n > 0] = 1 - f_n(0) = \frac{1}{n+1},$$

and

$$\mathbb{E}[e^{-\lambda Z_n/n} \mid Z_n > 0] = \frac{f_n(e^{-\lambda/n}) - f_n(0)}{1 - f_n(0)} \to \frac{1}{1 + \lambda},$$

which is the Laplace transform of an eponential mean 1. This is consistent with  $\mathbb{E}[Z_n] = 1$ .

## References

- [AN72] Krishna B. Athreya and Peter E. Ney. *Branching processes*. Springer-Verlag, New York, 1972.
- [Dur10] Rick Durrett. *Probability: theory and examples*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press, Cambridge, 2010.
- [Wil91] David Williams. *Probability with martingales*. Cambridge Mathematical Textbooks. Cambridge University Press, Cambridge, 1991.