

Lecture 16:

Galton - Watson Process

1°

The motivation comes from Galton's statistical investigation of the extinction of family names. This model is the simplest possible model for a population evolving in time. It's based on the assumption that the individuals give birth to a number of children independent of each other and all with the same distribution.

①. We start the process with a single individual which is the 0th generation of the population.

②. This individual gives birth to a random number $X \in \mathbb{N}$ of children with $\mathbb{P}(X=0) > 0$ and $\mu := \mathbb{E}[X] < \infty$.

These are the 1st generation of the population.

③. For r -th individual in the n -th generation, it gives birth to children, the number of which,

$X_{r,n}$, has the same distribution with X , and independent of all the other individuals in the generation.

Suppose we are given a doubly infinite sequence

$$\{X_{r,n} : r \in \mathbb{N} \setminus \{0\}, n \in \mathbb{N}\}$$

of i.i.d. random variables, each with the same distribution with X :

$$\mathbb{P}(X_{r,n} = k) = \mathbb{P}(X = k).$$

Let Z_n denote the size of the n -th generation.

$$\text{Then } \begin{cases} Z_{n+1} = X_{1,n} + X_{2,n} + \cdots + X_{Z_n,n}, & \forall n \geq 0. \\ Z_0 = 1. \end{cases}$$

Q: Is $\{Z_n\}_{n \in \mathbb{N}}$ a Markov chain?

$$\begin{aligned} \text{A: } & \mathbb{P}(Z_{n+1} = z_{n+1} \mid (Z_i)_{i \in [0, n]} = (z_i)_{i \in [0, n]}) \\ & = \mathbb{P}(Z_{n+1} = z_{n+1} \mid Z_n = z_n). \end{aligned}$$

Q: What's the expected value of Z_n ?

A: By Tower Rule, $\forall n \in \mathbb{N}$.

$$\begin{aligned} & E[Z_{n+1}] \\ &= E[E[Z_{n+1} | Z_n]] \\ &= E[E[\sum_{r=1}^{Z_n} X_{r,n} | Z_n]] \\ &= \sum_{j=1}^{\infty} E[\sum_{r=1}^j X_{r,n} | Z_n = j] \cdot P(Z_n = j) \\ &= \sum_{j=1}^{\infty} E[\sum_{r=1}^j X_{r,n}] \cdot P(Z_n = j) \\ &= \sum_{j=1}^{\infty} \left(\sum_{r=1}^j E[X_{r,n}] \right) \cdot P(Z_n = j) \\ &= \sum_{j=1}^{\infty} j \cdot \mu \cdot P(Z_n = j) \\ &= \mu \cdot E[Z_n]. \end{aligned}$$

Thus, $E[Z_n] = \mu^n E[Z_0]$

$$= \mu^n \xrightarrow{n \rightarrow \infty} \begin{cases} \infty, & \text{if } \mu > 1; \\ 1, & \text{if } \mu = 1; \\ 0, & \text{if } \mu < 1. \end{cases}$$

Remark 16.1. We've essentially proved the Wald's Identity.

Theorem 16.1. (Wald's Identity)

Suppose $\{X_n\}_{n \in \mathcal{N}}$ is a sequence of real-valued i.i.d. random variables, and N is a nonnegative integer-valued random variable that is independent of the sequence $\{X_n\}_{n \in \mathcal{N}}$. Suppose both have finite expectations, then $\mathbb{E}[X_1 + X_2 + \dots + X_N] = \mathbb{E}[N] \mathbb{E}[X_1]$.

Q: How to compute $\mathbb{P}(\text{Survival}) = ?$

A: Notice that Survival means survival in each generation, i.e., $\forall n \in \mathcal{N}$, $Z_n \neq 0$. So,

$$\{\text{Survival}\} = \bigcap_{n=0}^{\infty} \{Z_n \neq 0\}, \text{ and}$$

$$\{\text{Extinction}\} = \{\text{Survival}\}^c$$

$$= \bigcup_{n=0}^{\infty} \{Z_n \neq 0\}^c = \bigcup_{n=0}^{\infty} \{Z_n = 0\}.$$

Notice that $\{Z_n = 0\} \subseteq \{Z_{n+1} = 0\}$, $\forall n \in \mathcal{N}$.

Thus, $\mathbb{P}(\text{Extinction}) = \lim_{n \rightarrow \infty} \mathbb{P}(Z_n = 0)$.

2°. Definition 16.1. (Generating Functions).

① We define the probability generating function

G_X of a nonnegative integer-valued random variable

X as the map $G_X: [0, 1] \longrightarrow [0, 1]$, where

$$G_X(\theta) := \mathbb{E}[\theta^X] = \sum_{k=0}^{\infty} \theta^k \mathbb{P}(X=k)$$

$$= \mathbb{P}(X=0) + \theta \mathbb{P}(X=1) + \theta^2 \mathbb{P}(X=2) + \dots$$

② We define the moment generating function M_X

of a nonnegative integer-valued random variable X

as the map $M_X: (-r, r) \longrightarrow \mathbb{R}$, where

$$M_X(t) := \mathbb{E}[e^{tX}] = \sum_{k=0}^{\infty} e^{tk} \mathbb{P}(X=k)$$

$$= 1 + t \mathbb{E}[X] + \frac{t^2}{2!} \mathbb{E}[X^2] + \dots + \frac{t^n \mathbb{E}[X^n]}{n!} + \dots$$

and $r > 0$ such that the expectation exists on $(-r, r)$.

Remark 16.2. (Properties of the generating functions).

$$\textcircled{1} G_X(0) = P(X=0), \quad G_X(1) = \sum_{k=0}^{\infty} P(X=k) = 1,$$

$$G'_X(\theta) = \left(\sum_{k=0}^{\infty} \theta^k P(X=k) \right)' = \sum_{k=0}^{\infty} (k \theta^{k-1} P(X=k))' = \sum_{k=1}^{\infty} k \cdot \theta^{k-1} P(X=k) \\ = E[X \cdot \theta^{X-1}].$$

In particular, $G'_X(1) = E[X]$.

$$\frac{d^n}{d\theta^n} G_X(\theta) = \sum_{k=n}^{\infty} \frac{k!}{(k-n)!} \theta^{k-n} P(X=k), \quad \forall n \in \mathcal{N}.$$

$$\textcircled{2} M_X(0) = 1,$$

$$\frac{d^n}{dt^n} M_X(t) = \sum_{k=0}^{\infty} k^n \cdot e^{tk} P(X=k) = E[X^n \cdot e^{tX}], \quad \forall n \in \mathcal{N}.$$

$$\frac{d^n}{dt^n} M_X(0) = E[X^n], \quad \forall n \in \mathcal{N}.$$

Remark 16.3. To know the distribution of a random variable X , it is equivalent to find its probability generating function.

Pf. " \Rightarrow ". Trivial from the definition of G_X .

" \Leftarrow ". From the above formula, we know, $\forall n \in \mathcal{N}$,

$$P(X=n) = \frac{1}{n!} \frac{d^n}{dz^n} G_X(0).$$

3°.

Let us come back to the Galton-Watson model.

$$\text{Define } f_n(\theta) = \mathbb{E}[\theta^{Z_n}], \quad \forall n \geq 1.$$

$$\text{Then } f_1(\theta) = \mathbb{E}[\theta^{Z_1}] = \mathbb{E}[\theta^{X_{1,0}}] = \mathbb{E}[\theta^X], \text{ and}$$

$$f_{n+1}(\theta) = \mathbb{E}[\theta^{Z_{n+1}}] = \mathbb{E}[\mathbb{E}[\theta^{Z_{n+1}} | Z_n]], \quad \forall n \geq 1.$$

$$\text{For each } k \in \mathcal{N}, \quad \mathbb{E}[\theta^{Z_{n+1}} | Z_n = k]$$

$$= \mathbb{E}[\theta^{X_{1,n} + \dots + X_{k,n}} | Z_n = k]$$

$$= \mathbb{E}[\theta^{X_{1,n}} \dots \theta^{X_{k,n}} | Z_n = k]$$

$$= \mathbb{E}[\theta^{X_{1,n}} \dots \theta^{X_{k,n}}]$$

$$= \mathbb{E}[\theta^{X_{1,n}}] \dots \mathbb{E}[\theta^{X_{k,n}}]$$

$$= [f_1(\theta)]^k.$$

why?

Thus,

$$f_{n+1}(\theta) = \mathbb{E}[\mathbb{E}[\theta^{Z_{n+1}} | Z_n]] = \mathbb{E}[[f_1(\theta)]^{Z_n}] = f_n(f_1(\theta)), \quad \forall n \geq 1.$$

$$\text{By induction, } f_{n+1}(\theta) = \underbrace{f_1 \circ f_1 \circ \dots \circ f_1}_{\text{"n+1" times}}(\theta) = f_1(f_n(\theta)), \quad \forall n \geq 1.$$

$$\text{Assume that } s = \lim_{n \rightarrow \infty} f_n(\theta) \text{ exists.}$$

Since f_1 is continuous, taking limits at both sides gives

$$s = \lim_{n \rightarrow \infty} f_{n+1}(0) = f_1(\lim_{n \rightarrow \infty} f_n(0)) = f_1(s).$$

That is, s is a fixed point of the function f_1 .

On the other hand, $f_n(0) = \mathbb{P}(Z_n = 0)$. Therefore,

$$\mathbb{P}(\text{Extinction}) = \lim_{n \rightarrow \infty} \mathbb{P}(Z_n = 0) = \lim_{n \rightarrow \infty} f_n(0) = s.$$

This is to say, $\mathbb{P}(\text{Extinction})$ is a fixed point of f_1 .

Notice

$$(f_1)'(\theta) = \sum_{k=1}^{\infty} k \cdot \theta^{k-1} \mathbb{P}(X=k) \geq 0, \quad \forall \theta \in [0,1].$$

and

$$(f_1)''(\theta) = \sum_{k=2}^{\infty} k(k-1) \cdot \theta^{k-2} \mathbb{P}(X=k) \geq 0, \quad \forall \theta \in [0,1].$$

Thus, f_1 is increasing and convex on $[0,1]$.

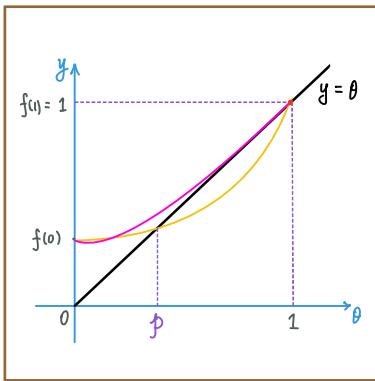
Combining Remark 16.2 and our assumptions on μ

and $\mathbb{P}(X=0)$, one has $f_1(0) = \mathbb{P}(X=0) > 0$,

$f_1(1) = 1$, and $f_1'(1) = \mathbb{E}[X] = \mu < \infty$.

why?

Therefore, there are at most 2 fixed points.



Case I: $\mu = f'(1) \leq 1$.

In this case, $f(1) = 1$ is the unique fixed point on $[0, 1]$.

Then $\mathbb{P}[\text{Extinction}] = 1$.

Case II: $\mu = f'(1) > 1$.

In this case, there will be two fixed points on $[0, 1]$, say p and 1 , where $0 < p < 1$.

Since f is increasing and $p > 0$, $p = f(p) \geq f(0)$.

Moreover, $p = f_n(p) \geq f_n(0)$, $\forall n \geq 1$.

Taking limits at both sides yields

$$p \geq \lim_{n \rightarrow \infty} f_n(0) = \mathbb{P}(\text{Extinction}).$$

Because $\mathbb{P}(\text{Extinction})$ is a fixed point of f , that does not exceed p , we have

$$\mathbb{P}(\text{Extinction}) = p < 1.$$

Theorem 16.2. If $E[X] > 1$, then the extinction probability is the unique root of the equation $p = f_1(p)$ that lies in $(0, 1)$.

If $E[X] \leq 1$, then the extinction probability is 1.

This is the end of this lecture !