

## Chapter 6: Branching Processes:

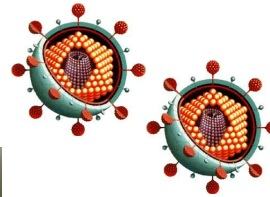
### The Theory of Reproduction



Royalty



DNA



Viruses



Aphids



Although the early development of Probability Theory was motivated by problems in gambling, probabilists soon realised that, if they were to continue as a breed, they must also study



Reproduction is a complicated business, but considerable insights into population growth can be gained from simplified models. The **Branching Process** is a simple but elegant model of population growth. It is also called the **Galton-Watson Process**, because some of the early theoretical results about the process derive from a correspondence between Sir Francis Galton and the Reverend Henry William Watson in 1873. Francis Galton was a cousin of Charles Darwin. In later life, he developed some less elegant ideas about reproduction — namely eugenics, or selective breeding of humans. Luckily he is better remembered for branching processes.

## 6.1 Branching Processes

Consider some sort of *population* consisting of reproducing individuals.

**Examples:** living things (animals, plants, bacteria, royal families);  
diseases; computer viruses;  
rumours, gossip, lies (one lie always leads to another!)

*Start conditions:*

*Each individual:*

*How many offspring?*

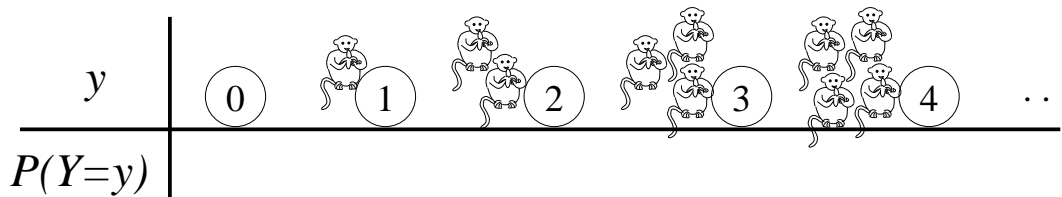
*Each offspring:*

*and so on...*

### Assumptions

- 1.
- 2.

### Family size distribution, $Y$



*Definition:* A **branching process** is defined as follows.

- Single individual at time  $n = 0$ .
- Every individual lives exactly one unit of time, then produces  $Y$  offspring, and dies.
- The number of offspring,  $Y$ , takes values  $0, 1, 2, \dots$ , and the probability of producing  $k$  offspring is
- All individuals reproduce independently. Individuals  $1, 2, \dots, n$  have family sizes  $Y_1, Y_2, \dots, Y_n$ , where
- Let  $Z_n$  be the
- Then the branching process is

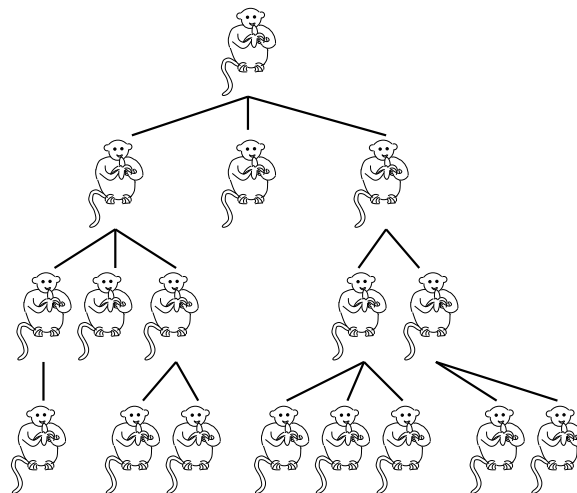
*Definition:* The **state** of the branching process at time  $n$  is

**Note:** When we want to say that two random variables  $X$  and  $Y$  have the same distribution, we write:

For example:

**Note:** The definition of the branching process is easily generalized to start with more than one individual at time  $n = 0$ .

## **Branching Process**



## 6.2 Questions about the Branching Process

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When we have a situation that can be modelled by a branching process, there are several questions we might want to answer.

### If the branching process is just beginning, what will happen in the future?

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1. What can we find out about the distribution of  $Z_n$  (the population size at generation  $n$ )?
  - can we find the mean and variance of  $Z_n$ ?  
— *yes, using the probability generating function of family size,  $Y$ ;*
  - can we find the whole distribution of  $Z_n$ ?  
— *for special cases of the family size distribution  $Y$ , we can find the PGF of  $Z_n$  explicitly;*
  - can we find the probability that the population has become extinct by generation  $n$ ,  
?  
— *for special cases where we can find the PGF of  $Z_n$  (as above).*
2. What can we find out about eventual extinction?
  - can we find the probability of eventual extinction,  
?  
—
  - can we find general conditions for eventual extinction?  
—
  - if eventual extinction is definite, can we find the distribution of the time to extinction?  
—

**Example:** Modelling cancerous growths. Will a colony of cancerous cells become extinct before it is sufficiently large to overgrow the surrounding tissue?

## If the branching process is already in progress, what happened in the past?

1. How long has the process been running?
  - *how many generations do we have to go back to get to the single common ancestor?*
2. What has been the distribution of family size over the generations?
3. What is the total number of individuals (over all generations) up to the present day?

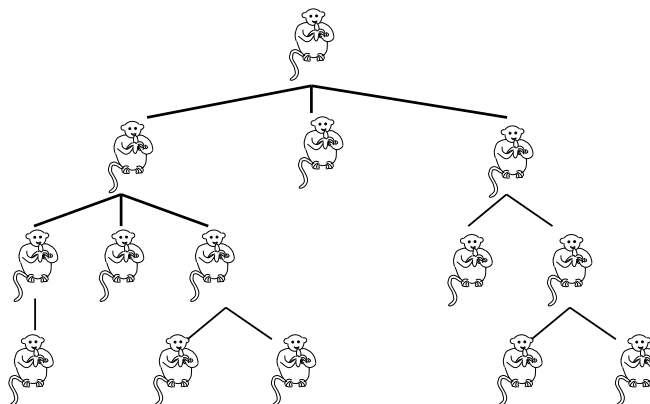
**Example:** It is believed that all humans are descended from a single female ancestor, who lived in Africa. How long ago?

What has been the mean family size over that period?



## 6.3 Analysing the Branching Process

**Key Observation:**



## $Z_n$ as a randomly stopped sum

Most of the interesting properties of the branching process centre on the distribution of  $Z_n$  (the population size at time  $n$ ). Using the Key Observation from overleaf, we can find an expression for the probability generating function of  $Z_n$ .

Consider the following.

•

•

•

•

**Note:** 1.

2.

## Probability Generating Function of $Z_n$

Let  $G_Y(s) = \mathbb{E}(s^Y)$  be the probability generating function of  $Y$ .  
(Recall that  $Y$  is the

Now  $Z_n$  is a randomly stopped sum: it is the sum of  $Y_1, Y_2, \dots$ , stopped by the random variable  $Z_{n-1}$ . So we can use Theorem 4.6 (Chapter 4) to express the PGF of  $Z_n$  directly in terms of the PGFs of  $Y$  and  $Z_{n-1}$ .

By Theorem 4.6, if  $Z_n = Y_1 + Y_2 + \dots + Y_{Z_{n-1}}$ , and  $Z_{n-1}$  is itself random, then the PGF of  $Z_n$  is given by:

For ease of notation, we can write:

Note that  
so we can also write:

Thus,

**Note:**

1.

2.

3.

We are trying to find the PGF of  $Z_n$ , the population size at time  $n$ .

So far, we have:  $G_n(s) = G_{n-1}(G(s)). \quad (\star)$

But by the same argument,

Substituting in  $(\star)$ ,

By the same reasoning, we will obtain:

and so on, until we finally get:

We have therefore proved the following Theorem.



**Theorem 6.3:** Let  $G(s) = \mathbb{E}(s^Y) = \sum_{y=0}^{\infty} p_y s^y$  be the PGF of the family size distribution,  $Y$ . Let  $Z_0 = 1$  (start from a single individual at time 0), and let  $Z_n$  be the population size at time  $n$  ( $n = 0, 1, 2, \dots$ ). Let  $G_n(s)$  be the PGF of the random variable  $Z_n$ . Then

$$G_n(s) = \underbrace{G\left(G\left(\dots G(s)\dots\right)\right)}_{n \text{ times}}. \quad \square$$

**Note:**  $G_n(s) = \underbrace{G\left(G\left(\dots G(s)\dots\right)\right)}_{n \text{ times}}$  is called the

We have therefore found an expression for the PGF of the population size at generation  $n$ , although there is no guarantee that it is possible to write it down or manipulate it very easily for large  $n$ . For example, if  $Y$  has a Poisson( $\lambda$ ) distribution, then  $G(s) = e^{\lambda(s-1)}$ , and already by generation  $n = 3$  we have the following fearsome expression for  $G_3(s)$ :

$$G_3(s) = e^{\lambda\left(e^{\lambda\left(e^{\lambda(s-1)}-1\right)}-1\right)}. \quad (\text{Or something like that!})$$

However, in some circumstances we can find quite reasonable closed-form expressions for  $G_n(s)$ , notably when  $Y$  has a Geometric distribution. In addition, for any distribution of  $Y$  we can use the expression  $G_n(s) = G_{n-1}(G(s))$  to derive properties such as the mean and variance of  $Z_n$ , and the probability of eventual extinction ( $\mathbb{P}(Z_n = 0)$  for some  $n$ ).

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## 6.4 What does the distribution of $Z_n$ look like?

Before deriving the mean and the variance of  $Z_n$ , it is helpful to get some intuitive idea of how the branching process behaves. For example, it seems reasonable to calculate the mean,  $\mathbb{E}(Z_n)$ , to find out what we expect the population size to be in  $n$  generations time, but why are we interested in  $\text{Var}(Z_n)$ ?

The answer is that  $Z_n$  usually has a “boom-or-bust” distribution: either the population will take off (boom), and the population size grows quickly, or the population will fail altogether (bust). In fact, if the population fails, it is likely to do so very quickly, within the first few generations. This explains why we are

interested in  $\text{Var}(Z_n)$ . A huge variance will alert us to the fact that the process does not cluster closely around its mean values. In fact, the mean might be almost useless as a measure of what to expect from the process.

### **Simulation 1: $Y \sim \text{Geometric}(p = 0.3)$**

The following table shows the results from 10 simulations of a branching process, where the family size distribution is  $Y \sim \text{Geometric}(p = 0.3)$ .

Simulation	$Z_0$	$Z_1$	$Z_2$	$Z_3$	$Z_4$	$Z_5$	$Z_6$	$Z_7$	$Z_8$	$Z_9$	$Z_{10}$
1	1	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0	0
3	1	4	19	42	81	181	433	964	2276	5383	12428
4	1	3	3	5	3	15	29	86	207	435	952
5	1	0	0	0	0	0	0	0	0	0	0
6	1	1	0	0	0	0	0	0	0	0	0
7	1	2	8	26	68	162	360	845	2039	4746	10941
8	1	1	0	0	0	0	0	0	0	0	0
9	1	1	0	0	0	0	0	0	0	0	0
10	1	1	4	13	18	39	104	294	690	1566	3534

Often, the population is extinct by generation 10. However, when it is not extinct, it can take enormous values (12428, 10941, ...).

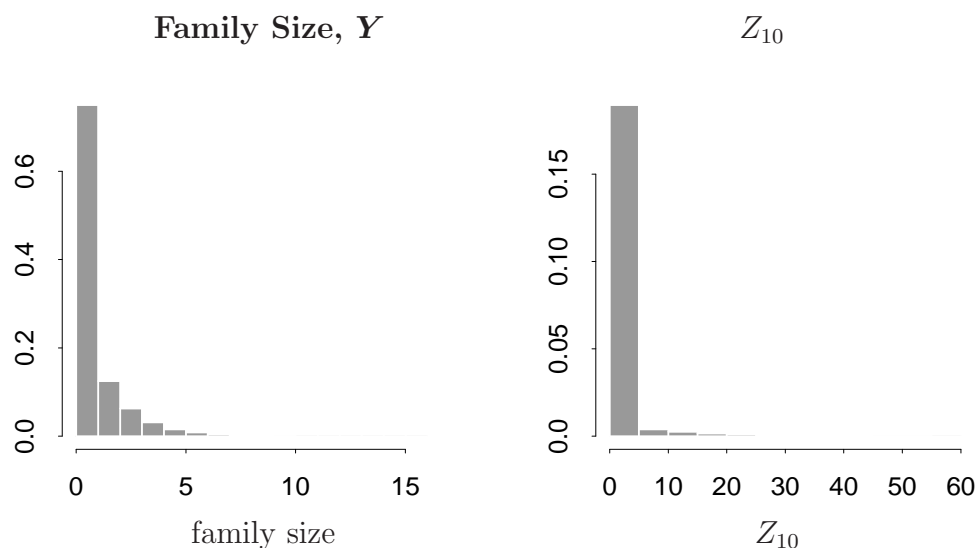
The same simulation was repeated 5000 times to find the empirical distribution of the population size at generation 10 ( $Z_{10}$ ). The figures below show the distribution of family size,  $Y$ , and the distribution of  $Z_{10}$  from the 5000 simulations.



[illegible]

This time, almost all the populations become extinct. We will see later that this value of  $p$  (just) guarantees eventual extinction with probability 1.

The family size distribution,  $Y \sim \text{Geometric}(p = 0.5)$ , and the results for  $Z_{10}$  from 5000 simulations, are shown below. Family sizes are often zero, but families of size 2 and 3 are not uncommon. It seems that this is not enough to save the process from extinction. This time, the maximum population size observed for  $Z_{10}$  from 5000 simulations was only 56, and the mean and variance of  $Z_{10}$  are much smaller than before.



Proportion of samples extinct by generation 10: 0.9108

Summary of  $Z_n$ :

Min	1st Qu	Median	Mean	3rd Qu	Max
0	0	0	0.965	0	56

Mean of  $Z_n$ : 0.965

Variance of  $Z_n$ : 19.497

### What happens for larger values of $p$ ?

It was mentioned above that  $Y \sim \text{Geometric}(p = 0.5)$  just guarantees eventual extinction with probability 1. For  $p > 0.5$ , extinction is also guaranteed, and tends to happen quickly. For example, when  $p = 0.55$ , over 97% of simulated populations are already extinct by generation 10.

## 6.5 Mean and variance of $Z_n$

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The previous section has given us a good idea of the significance and interpretation of  $\mathbb{E}(Z_n)$  and  $\text{Var}(Z_n)$ . We now proceed to calculate them. Both  $\mathbb{E}(Z_n)$  and  $\text{Var}(Z_n)$  can be expressed in terms of

Thus,

**Theorem 6.5:** Let  $\{Z_0, Z_1, Z_2, \dots\}$  be a branching process with  $Z_0 = 1$  (start with a single individual). Let  $Y$  denote the family size distribution, and suppose that  $\mathbb{E}(Y) = \mu$ . Then

**Proof:**

**Examples:** Consider the simulations of Section 6.4.

1. Family size  $Y \sim \text{Geometric}(p = 0.3)$ .

Expected population size by generation  $n = 10$  is:

The theoretical value,

2. Family size  $Y \sim \text{Geometric}(p = 0.5)$ .

### Variance of $Z_n$

**Theorem 6.5:** Let  $\{Z_0, Z_1, Z_2, \dots\}$  be a branching process with  $Z_0 = 1$  (start with a single individual). Let  $Y$  denote the family size distribution, and suppose that  $\mathbb{E}(Y) = \mu$  and  $\text{Var}(Y) = \sigma^2$ . Then

$$\text{Var}(Z_n) = \begin{cases} \sigma^2 n & \text{if } \mu = 1, \\ \sigma^2 \mu^{n-1} \left( \frac{1 - \mu^n}{1 - \mu} \right) & \text{if } \mu \neq 1 \quad (> 1 \text{ or } < 1). \end{cases}$$

### Proof:

Write  $V_n = \text{Var}(Z_n)$ . The proof works by finding a recursive formula for  $V_n$ .

Using the Law of Total Variance for randomly stopped sums from Section 3.4 (page 60),

$$\begin{aligned} Z_n &= \sum_{i=1}^{Z_{n-1}} Y_i \\ \Rightarrow \text{Var}(Z_n) &= \{\mathbb{E}(Y_i)\}^2 \times \text{Var}(Z_{n-1}) + \text{Var}(Y_i) \times \mathbb{E}(Z_{n-1}) \\ \Rightarrow V_n &= \mu^2 V_{n-1} + \sigma^2 \mathbb{E}(Z_{n-1}) \\ \Rightarrow V_n &= \mu^2 V_{n-1} + \sigma^2 \mu^{n-1}, \end{aligned}$$

using  $\mathbb{E}(Z_{n-1}) = \mu^{n-1}$  as above.

Also,

$$V_1 = \text{Var}(Z_1) = \text{Var}(Y) = \sigma^2.$$

**Find  $V_n$  by repeated substitution:**

$$V_1 = \sigma^2$$

$$V_2 = \mu^2 V_1 + \sigma^2 \mu = \mu^2 \sigma^2 + \mu \sigma^2 = \mu \sigma^2 (1 + \mu)$$

$$V_3 = \mu^2 V_2 + \sigma^2 \mu^2 = \mu^2 \sigma^2 (1 + \mu + \mu^2)$$

$$V_4 = \mu^2 V_3 + \sigma^2 \mu^3 = \mu^3 \sigma^2 (1 + \mu + \mu^2 + \mu^3)$$

$\vdots$  etc.

Completing the pattern,

$$\begin{aligned} V_n &= \mu^{n-1} \sigma^2 (1 + \mu + \mu^2 + \dots + \mu^{n-1}) \\ &= \mu^{n-1} \sigma^2 \sum_{r=0}^{n-1} \mu^r \\ &= \mu^{n-1} \sigma^2 \left( \frac{1 - \mu^n}{1 - \mu} \right). \quad \text{Valid for } \mu \neq 1. \\ &\quad \text{(sum of first } n \text{ terms of Geometric series)} \end{aligned}$$

When  $\mu = 1$  :

$$V_n = 1^{n-1} \sigma^2 \underbrace{(1^0 + 1^1 + \dots + 1^{n-1})}_{n \text{ times}} = \sigma^2 n.$$

Hence the result:

$$\text{Var}(Z_n) = \begin{cases} \sigma^2 n & \text{if } \mu = 1, \\ \sigma^2 \mu^{n-1} \left( \frac{1 - \mu^n}{1 - \mu} \right) & \text{if } \mu \neq 1. \end{cases} \quad \square$$


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**Examples:** Again consider the simulations of Section 6.4.

1. Family size  $Y \sim \text{Geometric}(p = 0.3)$ . So  $\mu = \mathbb{E}(Y) = \frac{q}{p} = \frac{0.7}{0.3} = 2.33$ .

2. Family size  $Y \sim \text{Geometric}(p = 0.5)$ . So  $\mu = \mathbb{E}(Y) = \frac{q}{p} = \frac{0.5}{0.5} = 1$ .