

# Simulating Branching Processes in Python

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## 1. Probability Distributions

$$p_n = \mathbb{P}(Z_{i,t} = n) \quad n = 0, 1, 2, \dots$$

$p_n$  is the probability that case  $i$  infects  $n$  individuals in generation  $t$   
 $Z$  is the number of secondary cases -  $Z_{i,t}$  number of people infected by individual  $i$  in generation  $t$

As an example we will use the **Poisson distribution**, which is a discrete probability distribution

$$Z \sim \text{Poisson}(\lambda)$$

$$\mathbb{P}(Z_{i,t=n}) = \frac{e^{-\lambda} \lambda^n}{n!}$$

Mean =  $\lambda$

Variance =  $\lambda$

Therefore, for our model  $\lambda = R_0$

Probability distributions can be used via `np.random`

To generate random numbers that follow a poisson distribution, we can use:

`np.random.poisson(lam,size)`

`lam` is in our case  $R_0$

`size` is the amount of random numbers generated

The output is an array with the numbers generated

In [1]:

```
#Import numpy
import numpy as np
#Generate random numbers Poisson distribution
print(np.random.poisson(1.5,1))
print(np.random.poisson(1.5,3))
```

```
[0]
[2 1 1]
```

Every time we run the code, we get different random numbers

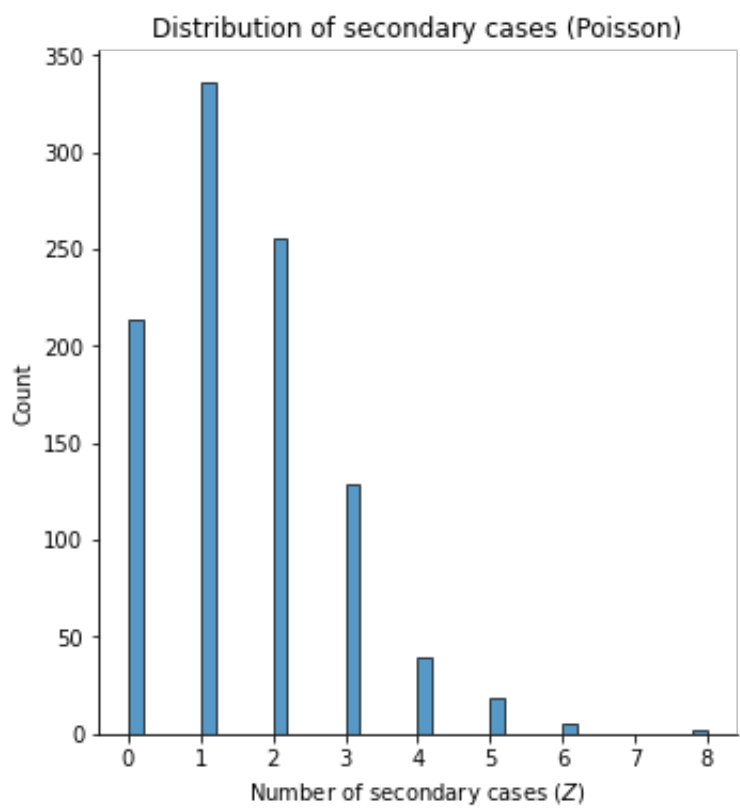
To visualize the output of random number generators, we will use the library `sns.displot`

```
In [2]: #Import matplotlib
import matplotlib.pyplot as plt
#Import seaborn
import seaborn as sns
```

```
In [3]: #Generate random numbers Poisson distribution
Ro = 1.5
size = 1000
random_numbers = np.random.poisson(Ro,size)

#Display numbers
sns.displot(random_numbers)
#sns.displot(random_numbers, kind = "kde")

#Aesthetics of the graph
plt.xlabel("Number of secondary cases ($Z$)")
plt.title("Distribution of secondary cases (Poisson)")
plt.show()
```



2. Simulating discrete-time branching processes

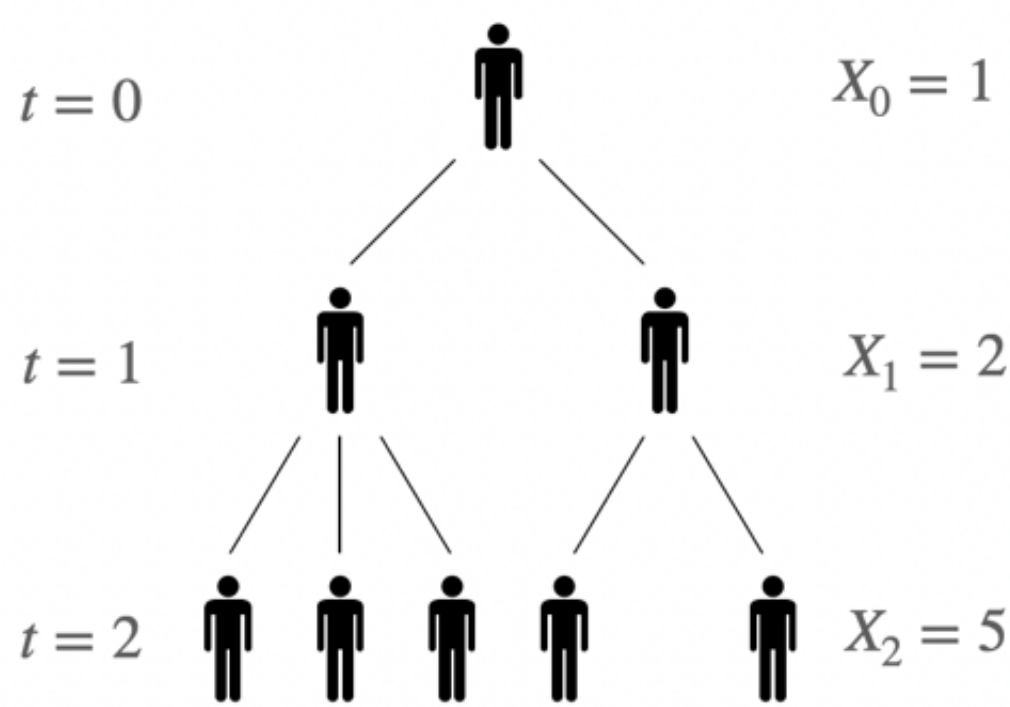


Figure 1

To computationally model this process we will use an array:

	$X_0$	$X_1$	$X_2$	$X_3$	$X_4$
Simulation 1					
Simulation 2					
Simulation 3					
• • •			• • •		
Simulation 100					

Figure 2

```
In [4]: #Initial parameters
number_simulations = 100
number_generations = 5
R0 = 1.5

#Initialize information array
array_info = np.zeros((number_simulations, number_generations))
#Verify the shape of the array
# output --> (rows,columns)
print(np.shape(array_info))
```

(100, 5)

```
In [5]: #Fill the array
#Loop that goes over each simulation
for i in range(number_simulations):

    #X_0 = 1 for all simulations
    number_info = 1
    array_info[i,0] = number_info

    #Loop that goes over each generation
    #Starts in 1, because X_0 is already filled
    for j in range(1,number_generations):

        #Z for every individual in X_t-1
        number_secondary_cases = np.random.poisson(R0,number_info)
        #Sum of secondary cases in t to obtain Xt
        number_info = np.sum(number_secondary_cases)
        #Fill the array element
        array_info[i,j]=number_info
```

The amount of secondary cases caused by each individual ( $Z$ ) is drawn from the same probability distribution, in this example we use the Poisson distribution

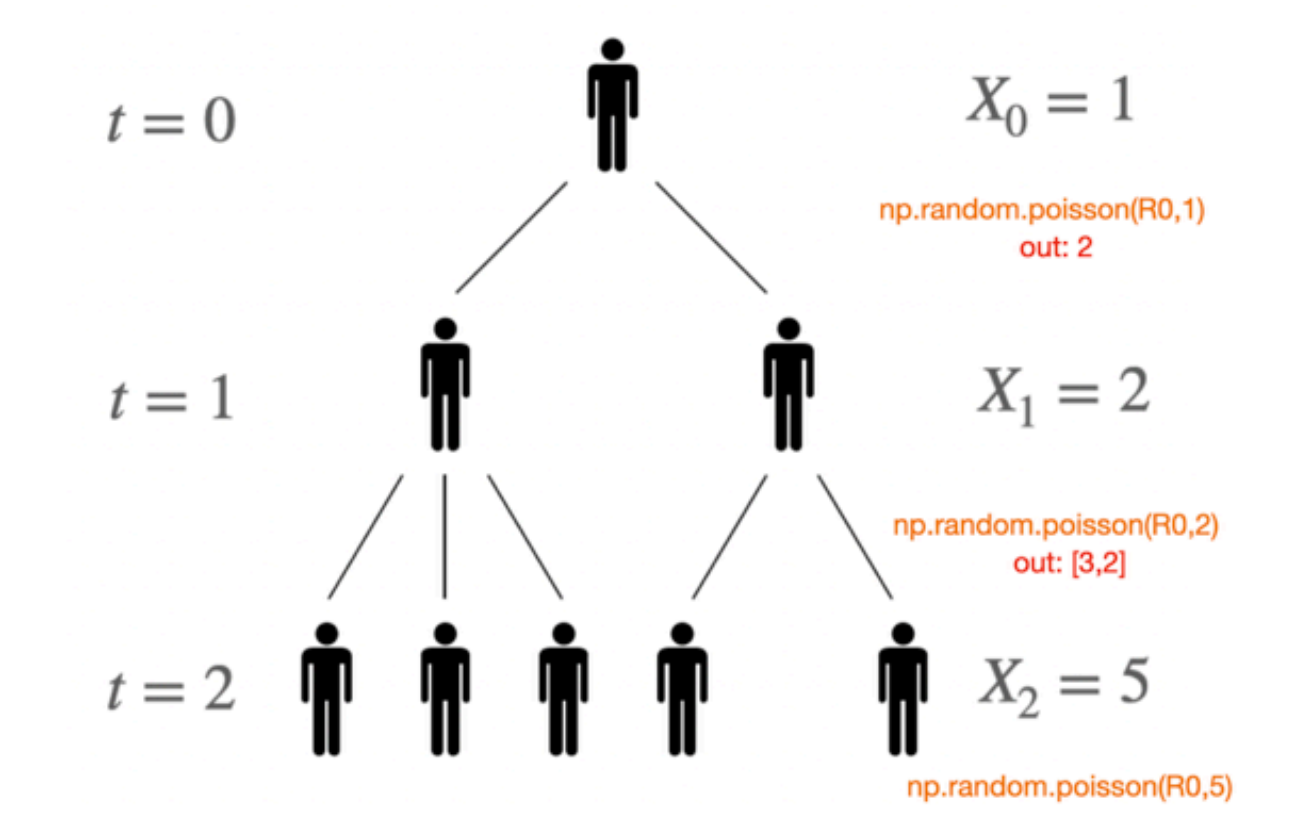
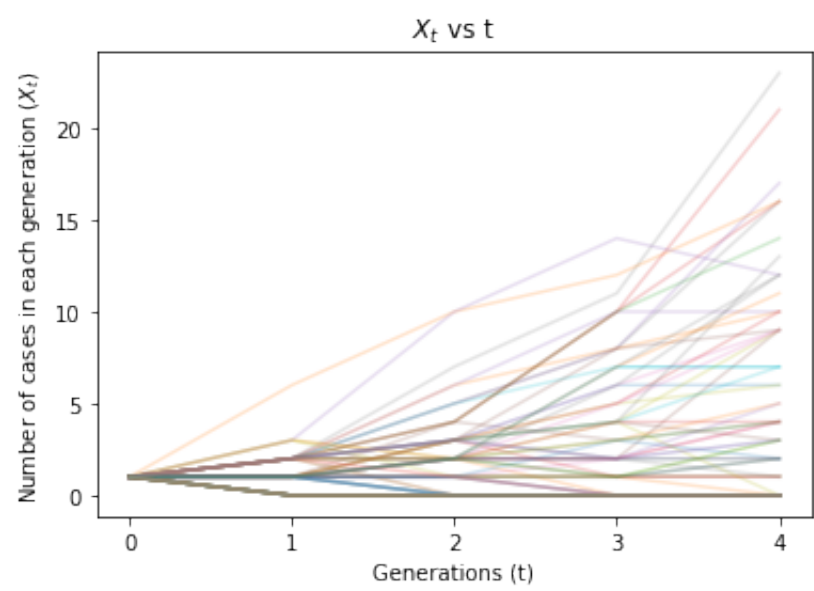


Figure 3

```
In [6]: #Plot results (X_t vs t)
#Plot every simulation
for i in range(number_simulations):
    plt.plot(range(number_generations),array_info[i,:],alpha=0.2)

#Aesthetics of the graph
plt.title("$X_t$ vs t")
plt.xlabel("Generations (t)")
plt.ylabel("Number of cases in each generation ($X_t$)")
plt.xticks([0,1,2,3,4],["0","1","2","3","4"])
plt.show()
```



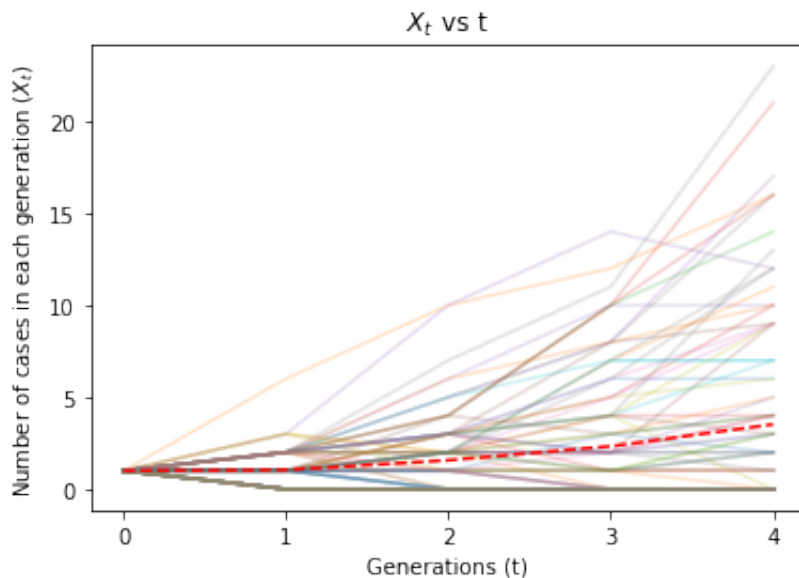
To calculate the mean of  $X_t$  for all generations, we will use `np.mean(array,axis)`  
`array` is the array for which we want to calculate the mean  
`axis=0` calculates the mean by columns  
`axis=1` calculates the mean by rows

```
In [7]: #Calculate the average
mean_info = np.mean(array_info,axis=0)

#Plot results ( $X_t$  vs  $t$ )
#Plot every simulation
for i in range(number_simulations):
    plt.plot(range(number_generations),array_info[i,:],alpha=0.2)

#Plot mean
plt.plot(range(number_generations),mean_info,"r--")

#Aesthetics of the graphs
plt.title("$X_t$ vs  $t$ ")
plt.xlabel("Generations ( $t$ )")
plt.ylabel("Number of cases in each generation ( $X_t$ )")
plt.xticks([0,1,2,3,4],["0","1","2","3","4"])
plt.show()
```



### 3. Calculate the extinction probability with simulations

We want to know how many of the total amount of simulations have no individuals infected in  $t_{final}$ , which in this case is  $t = 4$

```
In [8]: #We use the information contained in the array
#We check how many of the 100 simulations have  $X_4 = 0$ 

#Count how many simulations become extinct in  $t_{final}$ 
Amount_simu_extincted = 0

#Loop over each simulation
for i in range(number_simulations):
    #Take info of last generation
    last_generation = array_info[i,-1]

    #Check if it is equal to zero
    if last_generation == 0:
        Amount_simu_extincted = Amount_simu_extincted + 1

print(Amount_simu_extincted)

#Probability of extinction
prob_extinction = Amount_simu_extincted/number_simulations
print(prob_extinction)

#Probability of outbreak
prob_outbreak = 1 - prob_extinction
print(prob_outbreak)
```

```
53
0.53
0.47
```

For the case of  $Z \sim \text{Poisson}(R_0)$ , with  $R_0 = 1.5$ , the probability of extinction is  $q$ . Therefore, the probability of outbreak is  $1 - q$ . For 100 simulations.

## 4. Calculate the extinction probability with numerical methods

To obtain the extinction probability  $q$ , we have to solve the equation  $q = f(q)$ .

$f(s)$  is the probability generating function, which is specific to each probability distribution.

$$f(s) = \sum_{n=0}^{\infty} p_n s^n$$

It is not possible to find an analytical solution of  $q = f(q)$  for every distribution, therefore we need to use numerical methods

The first step to solve  $q = f(q)$  is to graph  $y = q$  and  $y = f(q)$ . The point(s) where these graphs intersect each other will give us a first approximation of the solution(s) of  $q = f(q)$ .

For example, for the case of the Poisson distribution (as it was calculated in the homework)

$$f(s) = e^{\lambda(s-1)}$$

Therefore,

$$q = f(q) \rightarrow q = e^{\lambda(q-1)}$$

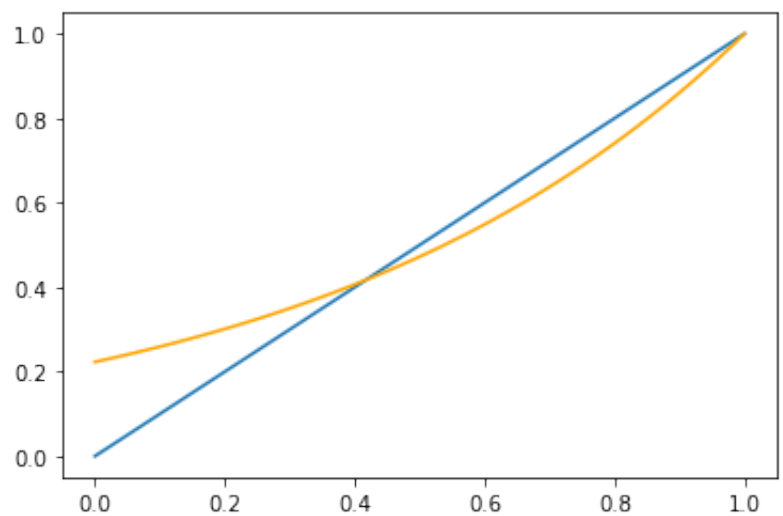
So we need to graph  $y = q$  and  $y = e^{\lambda(q-1)}$

```
In [9]: #Define functions
#y=q
def func1(x):
    ans = x
    return ans

#y=f(q)
def func2(Ro,x):
    ans = np.exp(Ro*(x-1))
    return ans

#Define function parameters
#q range (0,1) because q is a prob.extinction
q=np.linspace(0,1)
#Ro
Ro=1.5

#Graph functions
plt.plot(q,func1(q))
plt.plot(q,func2(Ro,q),color="orange")
plt.show()
```



If you spot typos or other mistakes,  
please create an issue in the following GitHub repository: <https://github.com/MA-Ramirez>

At first glance, we can see that there are 2 solutions  $q \sim 1$  and  $q \sim 0.4$

To have more accurate solutions  $q=f(q)$ , we will use `fsolve` from `scipy.optimize`. This function is based on the Newton-Raphson method.

## Newton-Raphson Method

Root-finding algorithm which produces successively better approximations to the roots (or zeroes)  $f(x) = 0$  of a function  $y = f(x)$ .

Steps:

1. Start with an initial guess  $x_1$  which is reasonably close to the root.
2. Take the tangent line to  $y = f(x)$  at  $x_1$ .
3. Given that the slope of the tangent line is  $m = f'(x_1)$ , we can use the **formula of the tangent line** to calculate the x-intercept of the tangent line i.e.  $x_2$ .  $x_2$  is a better approximation to the root than  $x_1$ . (See [Figure 4](#))
4. Use  $x_2$  to perform steps 2 and 3.
5. Repeat steps 2,3 and 4 repeatedly to obtain an accurate approximation to the root. (See [Figure 5](#))

### Formula of the tangent line

We can write the equation of the tangent line, given that we have two points in the line  $(x_a, y_a)$  and  $(x_b, y_b)$

$$m = f'(x_a) = \frac{\Delta Y}{\Delta X} = \frac{y_b - y_a}{x_b - x_a}$$

In this case, we have  $(x_b, y_b) = (x_2, 0)$  and  $(x_a, y_a) = (x_1, f(x_1))$ . Therefore,

$$m = f'(x_1) = \frac{\Delta Y}{\Delta X} = \frac{0 - f(x_1)}{x_2 - x_1}$$

$$f'(x_1) = \frac{-f(x_1)}{x_2 - x_1}$$

### Calculation $x_2$

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)}$$

### Generalization | Newton-Raphson method

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$



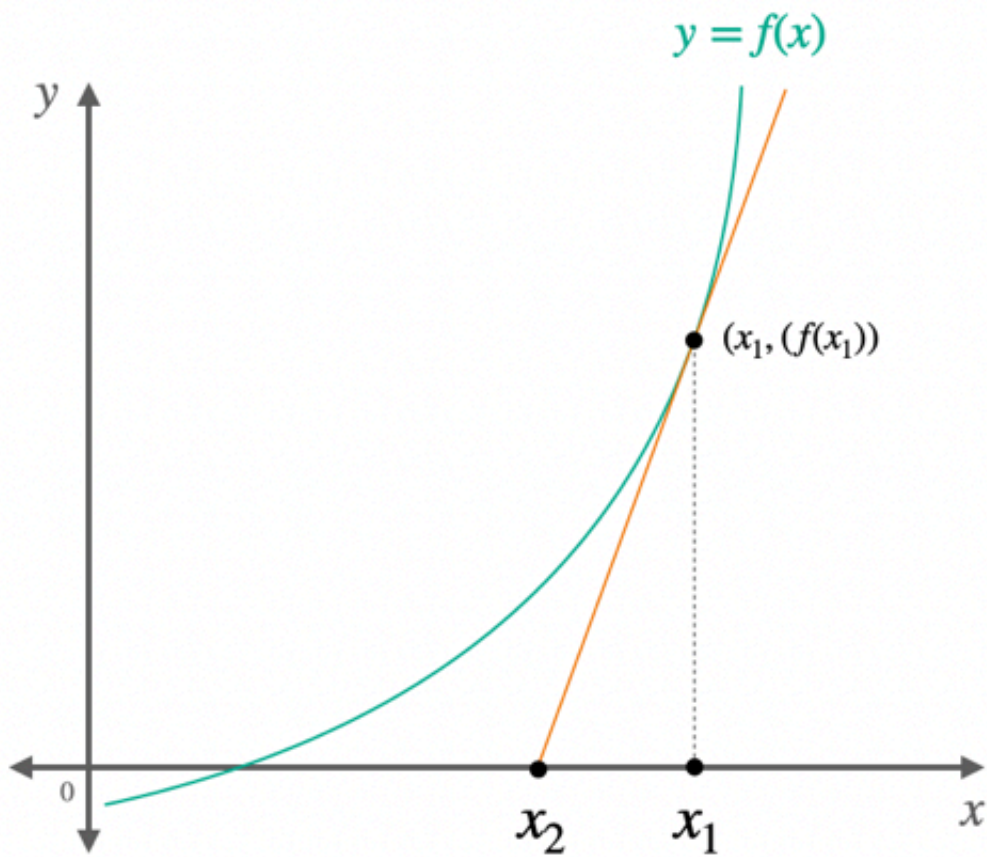
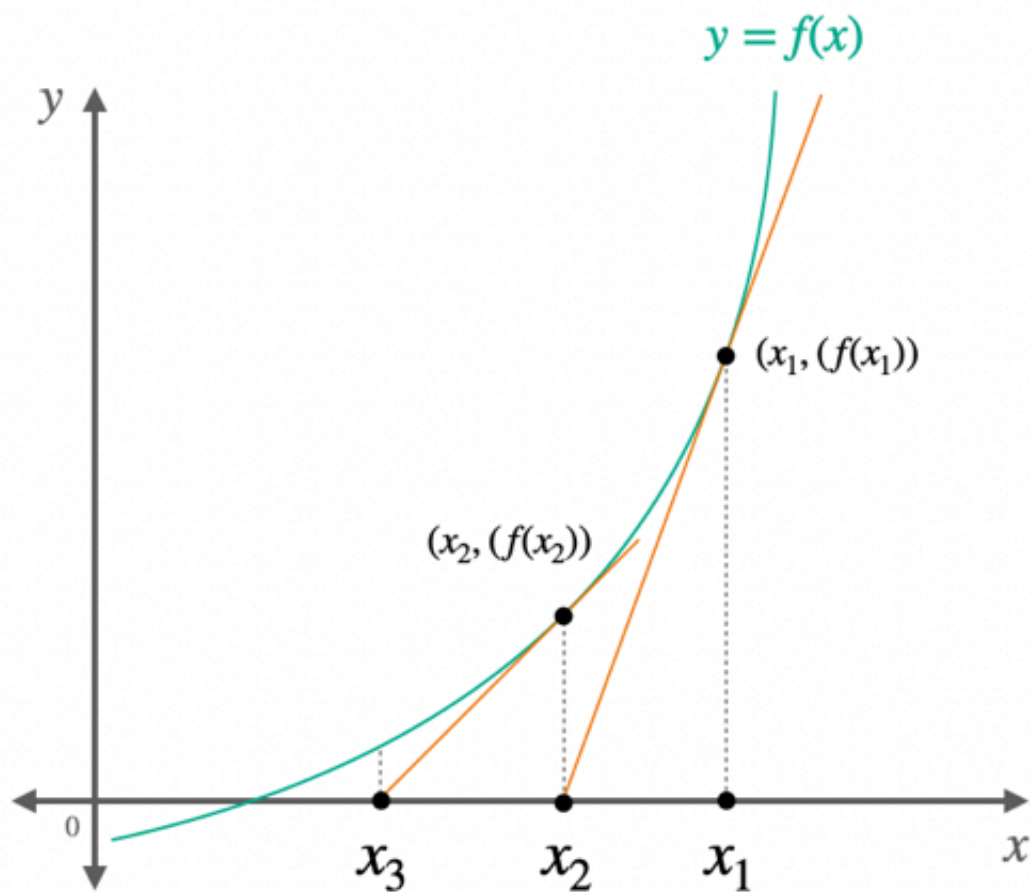


Figure 4



Figure

5

## Solve $q = f(q)$

To solve  $q = f(q)$  we will find the roots of  $0 = f(q) - q$ .

For this we will use `fsolve` from `scipy.optimize`, such that `fsolve(func, x1)` `func` in our case is  $f(q) - q$

`x1` is the initial guess of the root (obtained from the graphs)

The output is the solution of solving  $f(q) = q$  for  $q$ . This is the probability of extinction  $q$ .

```
In [10]: from scipy.optimize import fsolve

#define the function f(q)-q
def func3(x):
    Ro=1.5
    ans1 = x
    ans2 = np.exp(Ro*(x-1))
    ans = ans2-ans1
    return ans

#Initial guess obtained from the graph
x1=0.4

#Use fsolve to obtain the solution
solution = fsolve(func3,x1)
print(solution)

#Initial guess obtained from the graph
x1=1

#Use fsolve to obtain the solution
solution = fsolve(func3,x1)
print(solution)
```

```
[0.41718836]
[1.]
```

The extinction probability is  $q = 0.41718836 \rightarrow 41.7\%$  and  $q = 1$  for a Poisson distribution and  $R_0 = 1.5$