

EASC2410 Special Topic 2

Special Topic: Mathematical Modeling of Epidemics: Python Implementation

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Review of Lecture 16:

- Program control - if, for loops
- Numpy Arrays
- Pandas data wrangling
- Regression (curve fitting)

In Lecture 17, we will apply the Python knowledge to model the evolution of epidemics using a set of mathematical equations:

- Mathematical descriptions for infectious disease
- Solving those equations using Python
- Visualize, Analyze and Interpret the results

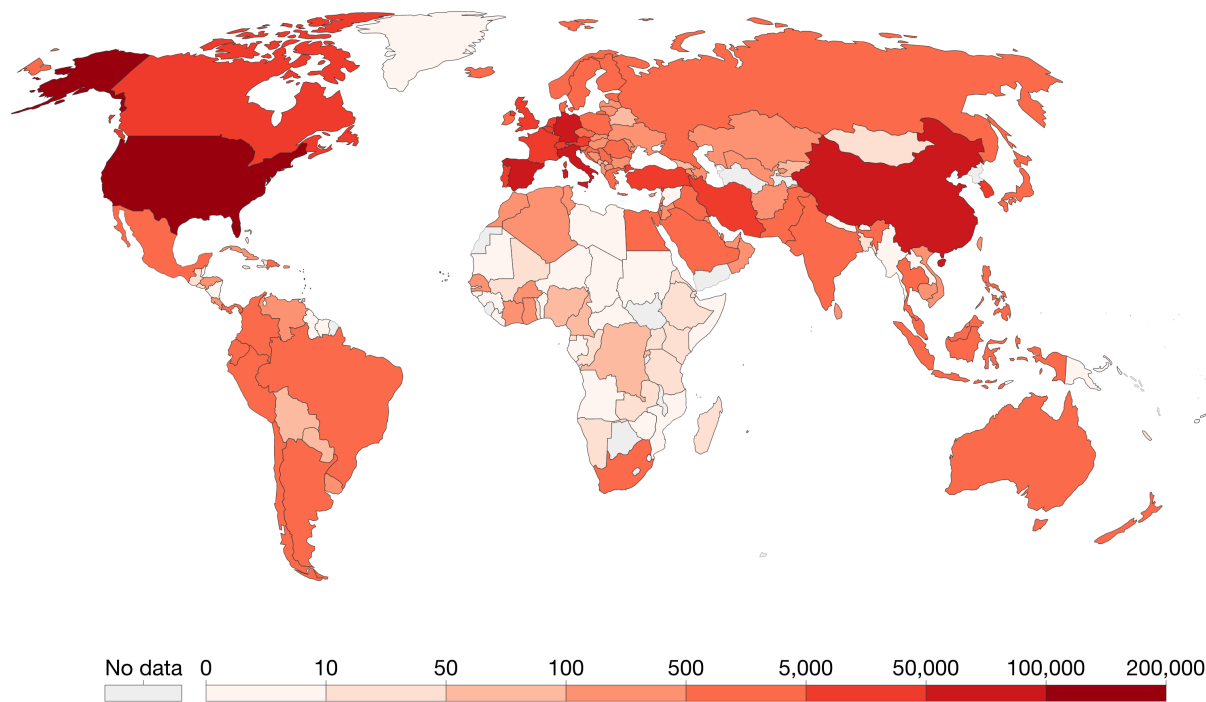
The COVID-19 Pandemic

The COVID-19 outbreak is an unprecedented global public health challenge. In order for governments, organizations and individuals to respond to it effectively, it will be vital that they have easy access to good, clear data and a good understanding of what can and can not be said based on the available data.

Total confirmed COVID-19 cases, Mar 30, 2020

The number of confirmed cases is lower than the number of total cases. The main reason for this is limited testing.

Our World
in Data

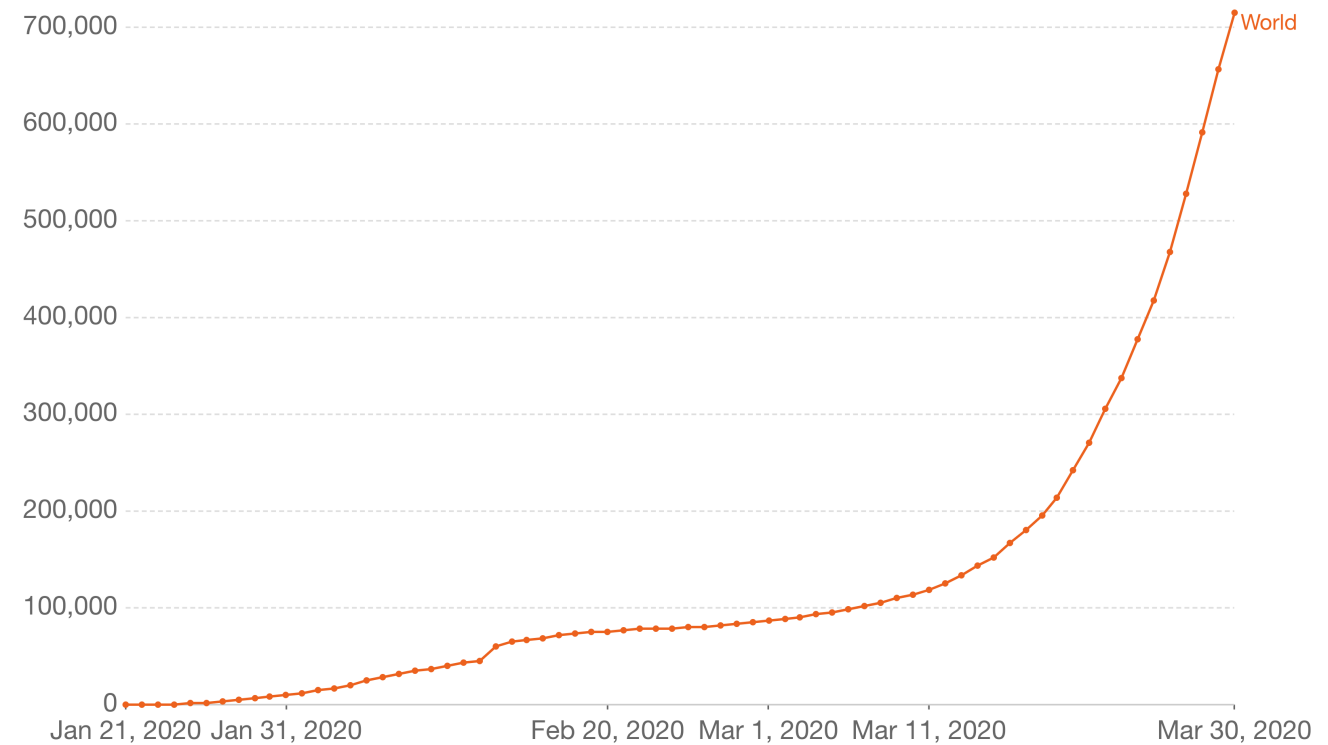


Source: European CDC – Latest Situation Update Worldwide – Last updated 12:45 London time (30th March)
Note: The large increase in the number of cases globally and in China on Feb 13 is the result of a change in reporting methodology.
OurWorldInData.org/coronavirus • CC BY

Total confirmed COVID-19 cases

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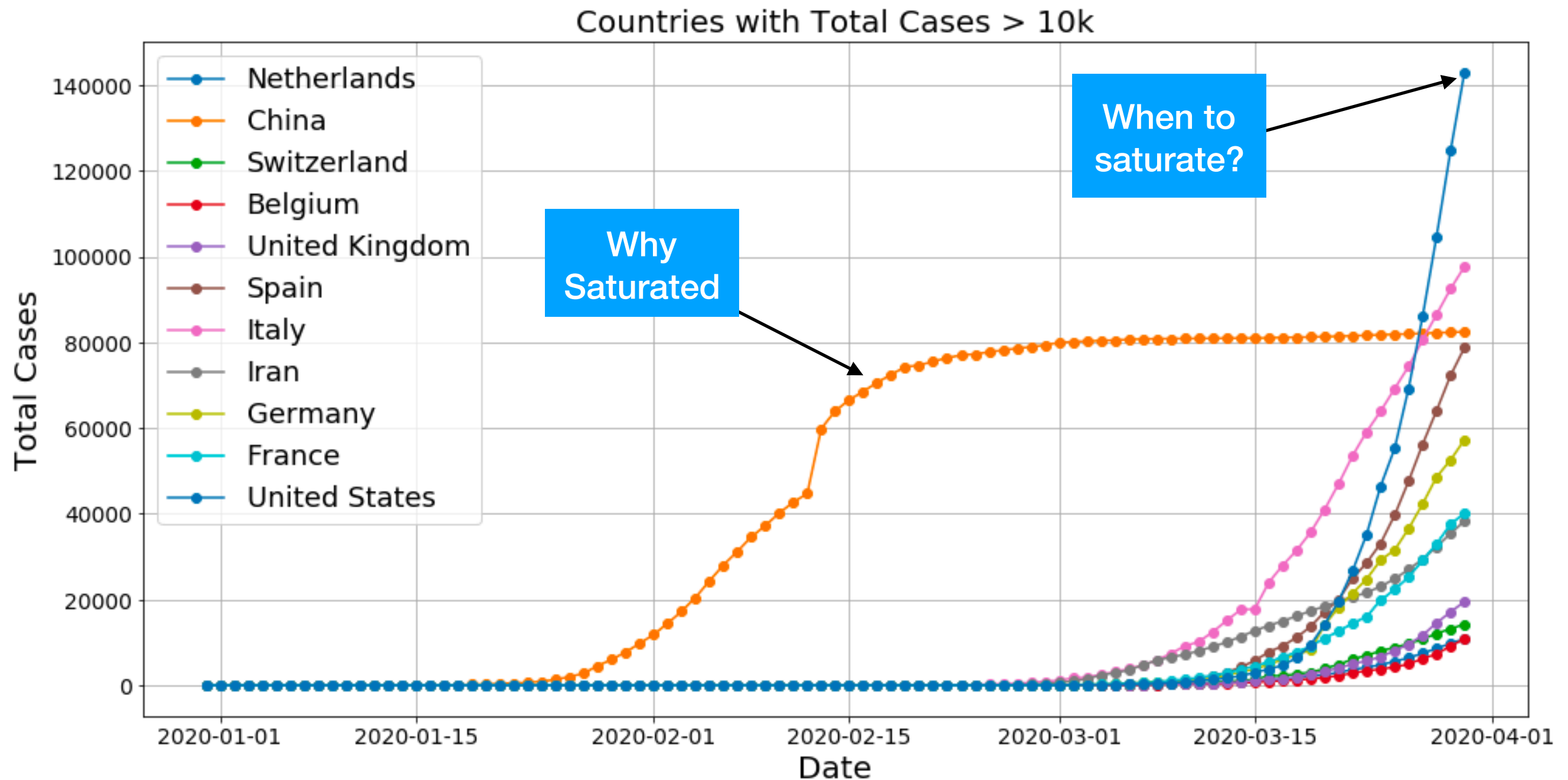


Source: European CDC – Latest Situation Update Worldwide – Last updated 12:45 London time (30th March)
Note: The large increase in the number of cases globally and in China on Feb 13 is the result of a change in reporting methodology.
OurWorldInData.org/coronavirus • CC BY

Data is the key - modeling helps interpret the data (to some extent)

time series with selection criteria

Now let's put the time series of total confirmed cases in the same based on total cases > 10000

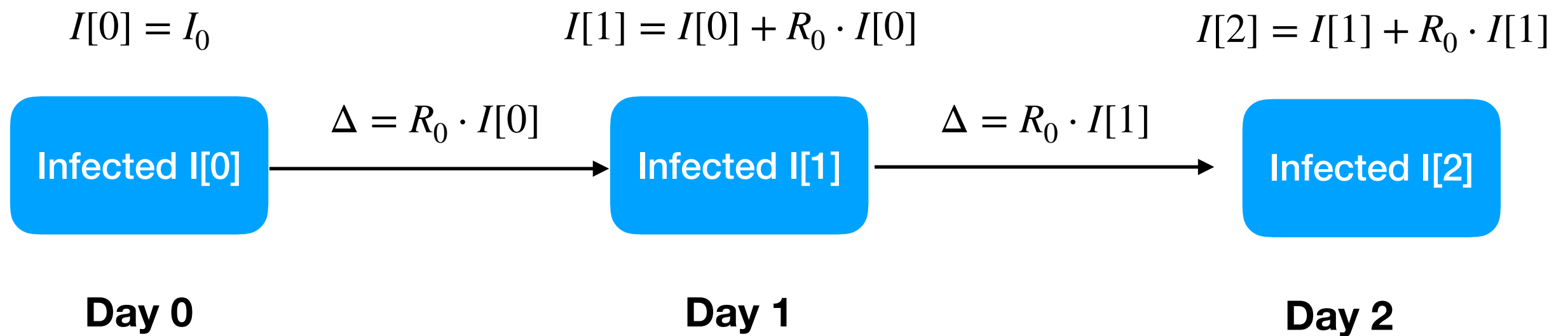


Here I used a linear scale

The Exponential (R_0) Model

Assumptions:

1. Starting from day 0, there was initially $I[0]$ (or I_0) infections;
2. Everyday, one patient infects R_0 persons (the size of the infection grows R_0 times)



So to calculate the number if infections at day $n+1$:

$$I[n + 1] = I[n] + R_0 \cdot I[n] \quad n = 0, 1, 2, \dots$$

of infected on day $n+1$ # of infected on day n

Between day $n+1$ and day n ,
 $R_0 \cdot I[n]$ new infections!

The mathematical form of the Exponential (R_0) Model

$I(t) : \text{Infected}$

$$\dot{I}(t) = R_0 \cdot I(t)$$

- The time rate of change in $I[t]$ is fixed
- The increase is proportional to $I[t]$, i.e., within one day, the new infections caused by the existing patients is $R_0 I[t]$

Time rate of change in $I(t)$

$$\begin{aligned} \dot{I}(t = \text{day } n) &= \frac{I[n+1] - I[n]}{(Day\ n+1) - (Day\ n)} = \frac{I[n+1] - I[n]}{1(day)} \\ &= I[n+1] - I[n] \end{aligned}$$

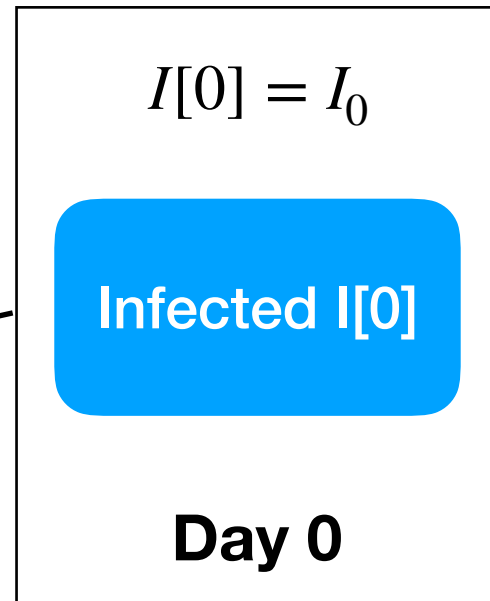
$$I[n+1] - I[n] = R_0 \cdot I[n] \quad n = 0, 1, 2, \dots$$

A Python implementation of the Exponential (R_0) Model

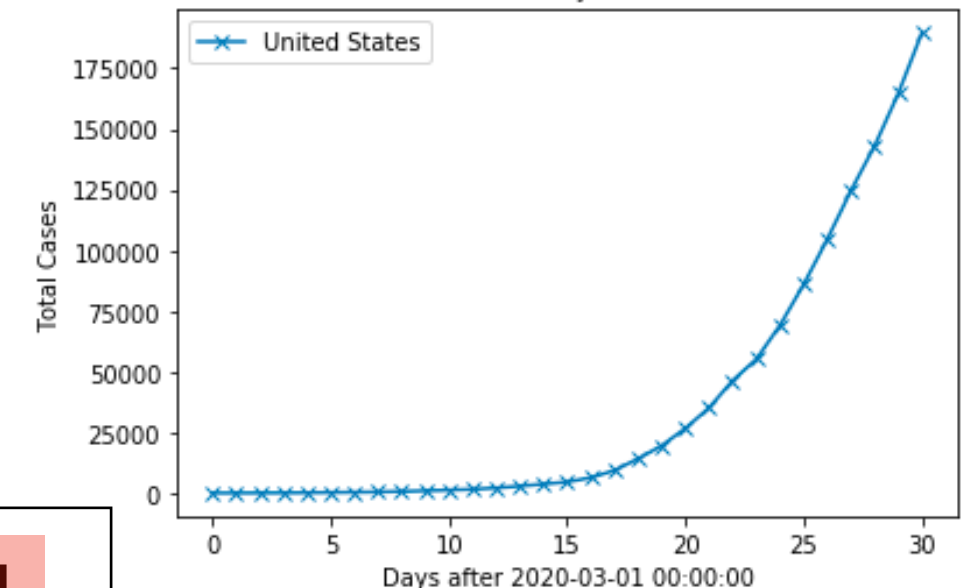
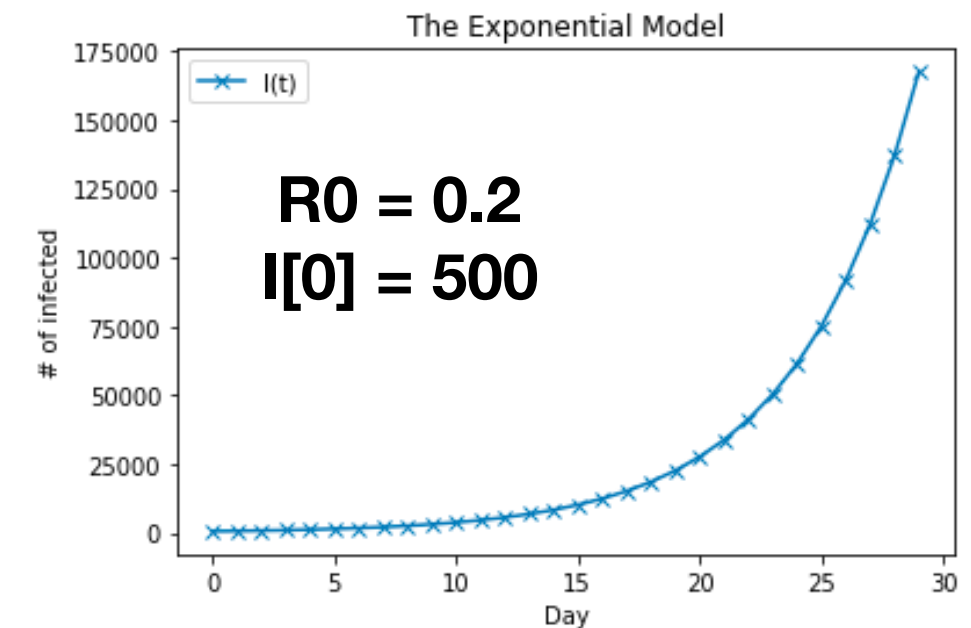
```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 # simulation Time / Day
5 T = 11
6
7 # Base infection rate
8 R0 = 2
9
10 I = np.zeros(T)
11
12 I[0]=1 # on day 0 we had 1 patient
13
14 for n in range(T-1):
15     I[n+1] = I[n] + I[n]*R0
16
17 plt.plot(I, '-x', label='I(t)')
18 plt.xlabel('Day')
19 plt.ylabel('# of infected')
20 plt.title('The Exponential Model')
21 plt.legend()

```



Plotting codes



So to calculate the number if infections at day $n+1$:

$$I[n + 1] = I[n] + R_0 \cdot I[n]$$

$$n = 0, 1, 2, \dots$$

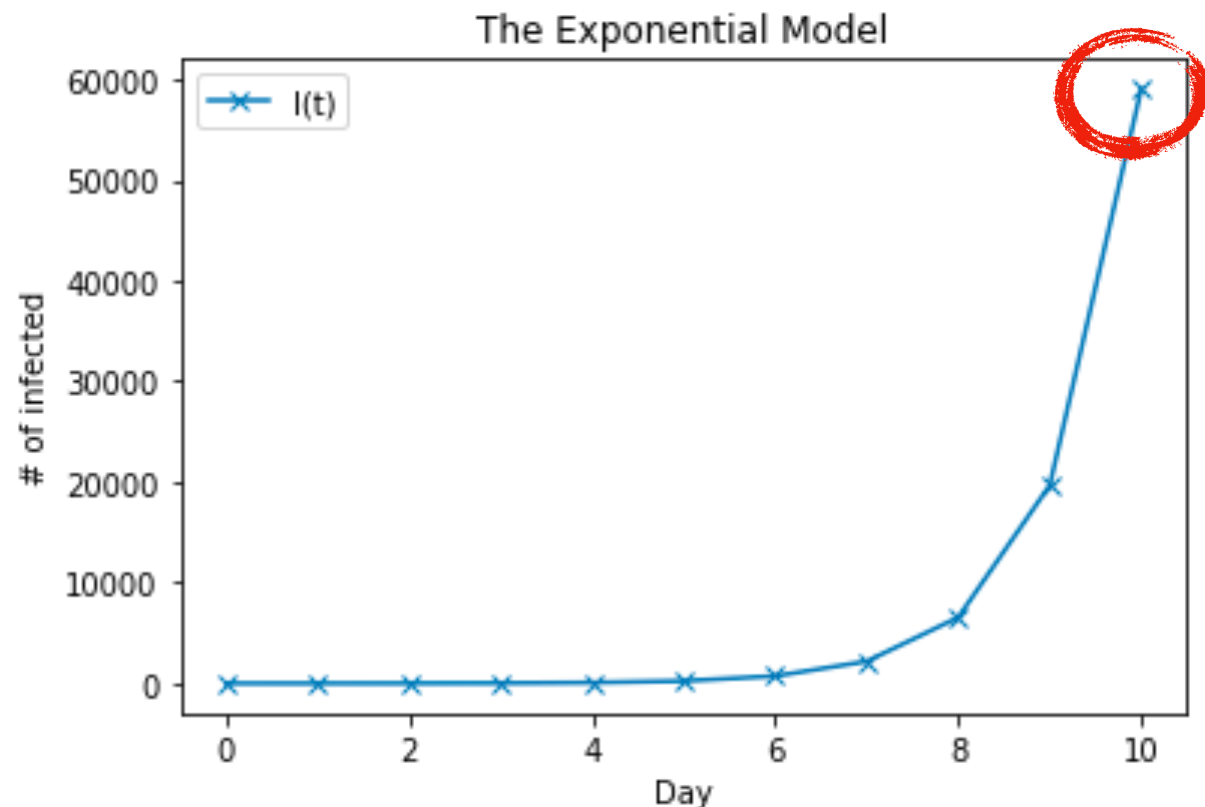
Between day $n+1$ and day n ,
 $R_0 \cdot I[n]$ new infections!

of infected on day $n+1$

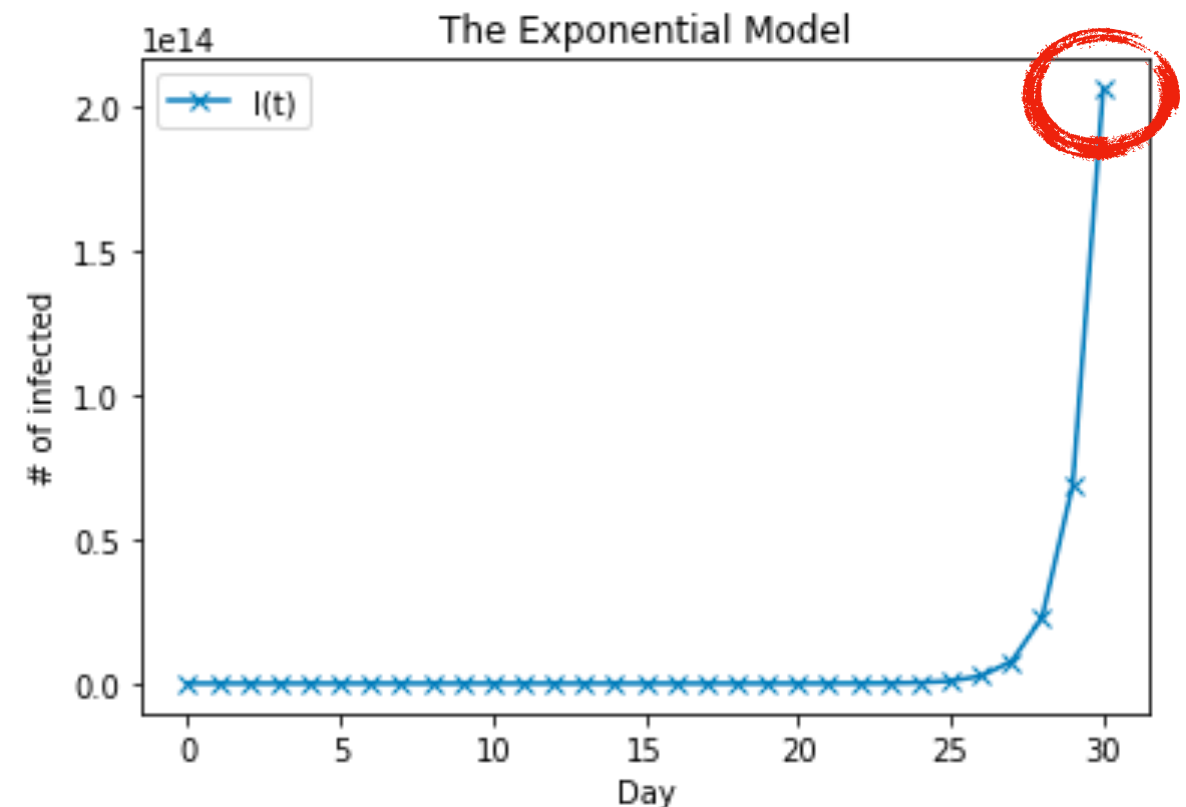
of infected on day n

The problem of the Exponential (R_0) Model

```
# simulation Time / Day  
T = 11  
  
# Base infection rate  
R0 = 2
```



```
# simulation Time / Day  
T = 31  
  
# Base infection rate  
R0 = 2
```



- Starting from day 0, 1 infection
- At day 11, 60k infections
- At day 31, 10^{14} infections (more than the whole population of the world!)

What's the problem here?

The S-I model

Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Starting from day 0, there was initially $I[0]$ infections;
3. Everyday, new infection is through contact rate $\lambda \cdot I \cdot S$
4. New infections are removed from S

λ : contact rate



	Suspectible	Infected	Newly Infected
Day n	$S[n]$	$I[n]$	$\lambda \cdot I[n] \cdot S[n]$
Day n+1	$S[n] - \lambda \cdot I[n]S[n]$	$I[n] + \lambda \cdot I[n]S[n]$	

of susceptible on day n+1, $S[n+1]$

of infected on day n+1, $I[n+1]$

The S-I model

Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Starting from day 0, there was initially $I[0]$ infections;
3. Everyday, new infection is through contact rate $\lambda \cdot I \cdot S$
4. New infections are removed from S

λ : contact rate



So to calculate the number if infections at day $n+1$:

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n]$$

Removed
from $S[n]$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n]$$

$n = 0, 1, 2, \dots$

of infected on day $n+1$

of infected on day n

Between day $n+1$ and day n ,
 $\lambda \cdot I[n]$ new infections!

Added to $I[n]$

A Python implementation of the S-I Model

```
1 # population
2 N = 1e7
3 # simulation Time / Day
4 T = 70
5 # susceptible ratio
6 s = np.zeros([T])
7 # infective ratio
8 i = np.zeros([T])
9 # contact rate
10 lamda = 0.5
11
12 # initial infective people
13 i[0] = 5 / N
14 s[0] = 1
15
16 for t in range(T-1):
17     s[t + 1] = s[t] - i[t] * lamda * s[t]
18     i[t + 1] = i[t] + i[t] * lamda * s[t]
19
20 plt.plot(i*N,label='infected')
21 plt.plot(s*N,label='susceptible')
22 plt.xlabel('Day')
23 plt.ylabel('# of cases')
24 plt.title('The S-I Model')
25 plt.legend()
```

Plotting codes

Initialization

- Setting N, T and lamda
- Setting I and S at day 0

N: total # of population (susceptible)
T: total days of model simulation
lamda = contact rate

Susceptible
at day n

New infections
removed at day n

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n]$$

Infected
at day n

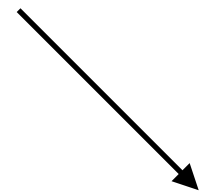
New infections
Added at day n

The mathematical form of the S-I Model

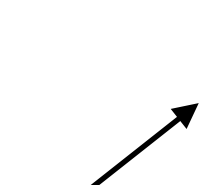
$S(t) : \textit{Susceptible}$

$I(t) : \textit{Infected}$

Time rate of change in $S(t)$


$$\dot{S}(t) = -\lambda \cdot S(t) \cdot I(t)$$

Time rate of change in $I(t)$


$$\dot{I}(t) = \lambda \cdot S(t) \cdot I(t)$$


$$I[n + 1] - I[n] = \lambda \cdot S[n] \cdot I[n] \quad n = 0, 1, 2, \dots$$

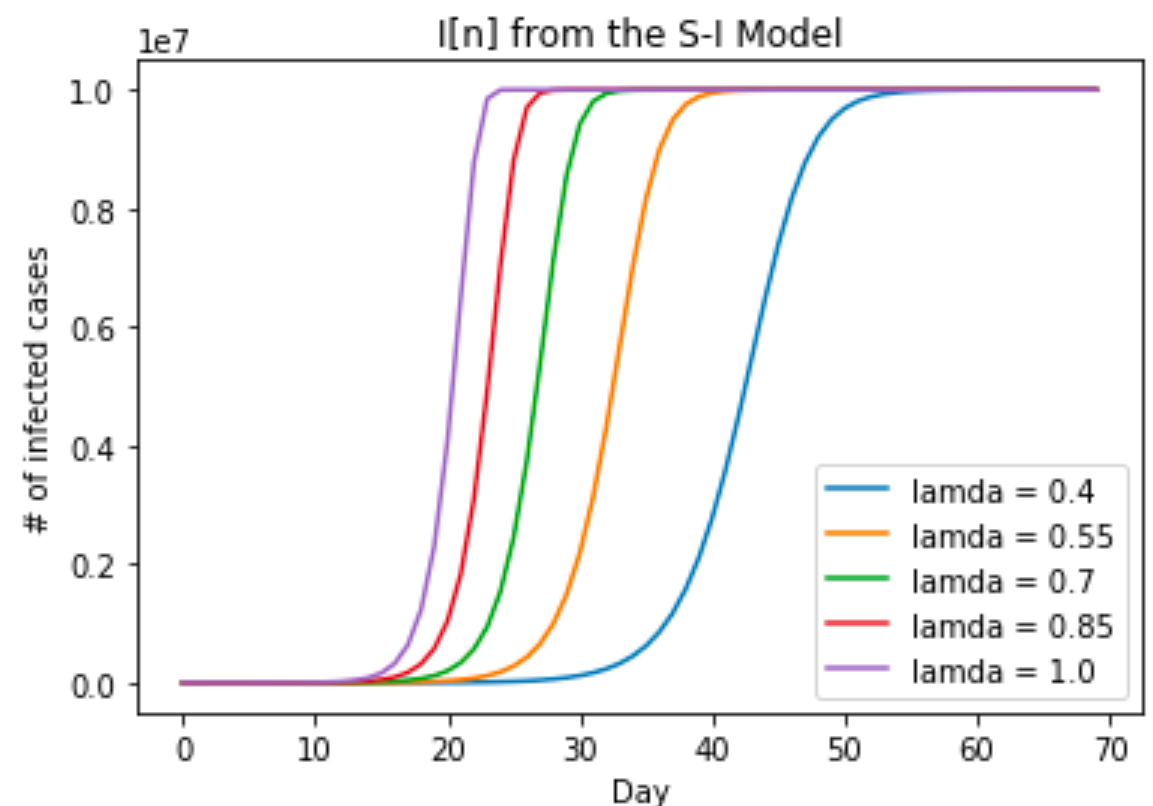
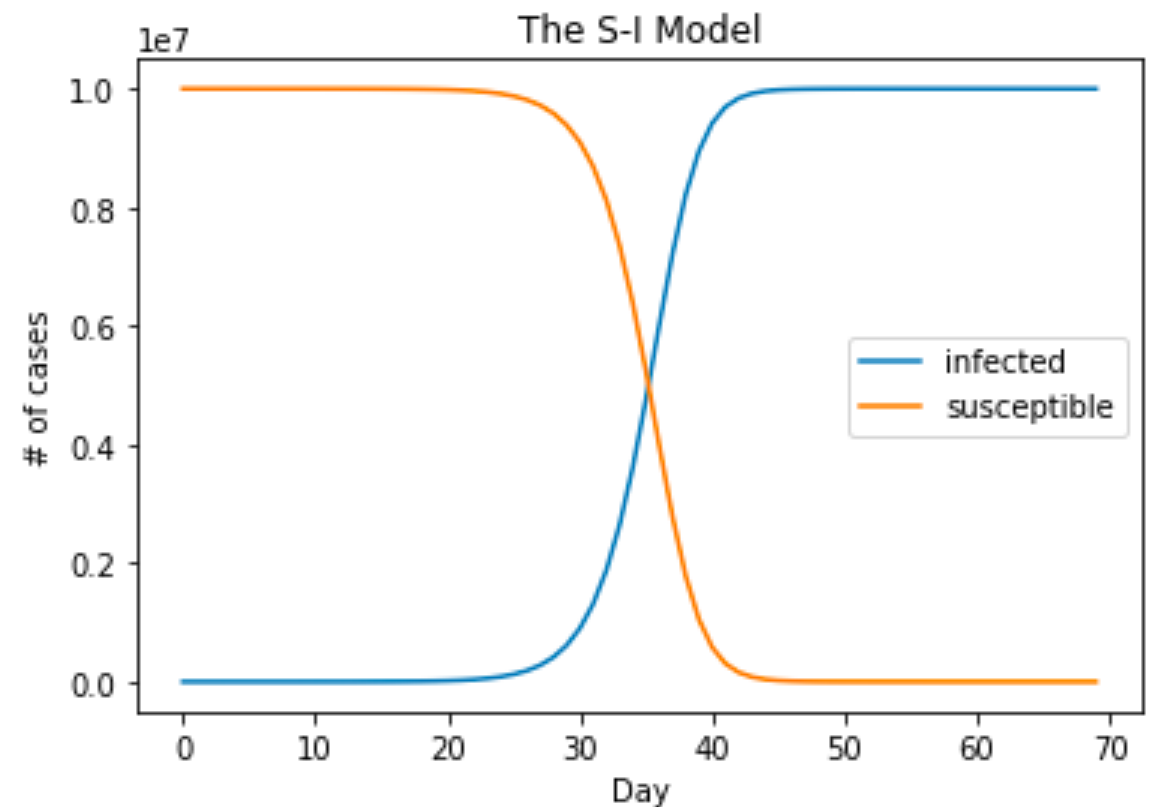
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7 # infective ratio
8 i = np.zeros([T])
9 # contact rate
10 lamda = 0.5
11
12 # initial infective people
13 i[0] = 5 / N
14 s[0] = 1
15
16 for t in range(T-1):
17     s[t + 1] = s[t] - i[t] * lamda * s[t]
18     i[t + 1] = i[t] + i[t] * lamda * s[t]
19
20 plt.plot(i*N,label='infected')
21 plt.plot(s*N,label='susceptible')
22 plt.xlabel('Day')
23 plt.ylabel('# of cases')
24 plt.title('The S-I Model')
25 plt.legend()
```

Plotting codes

- Starting from day 0, 1 infection
- Lamda determines the rate of infection

What's the problem here?



The S-I-S model (no immunity)

Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Everyday, new infection is through contact rate $\lambda \cdot I \cdot S$
3. New infections are removed from S (added to I)
4. New cured is $\gamma \cdot I$, they are added back to S (no immunity)

λ : **contact rate**

γ : **cure rate**



	Suspectible (S)	Infected (I)	Newly Infected	Cured
Day n	$S[n]$	$I[n]$	$\lambda \cdot I[n] \cdot S[n]$	$\gamma \cdot I[n]$

Day n+1

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n] + \gamma \cdot I[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma \cdot I[n]$$

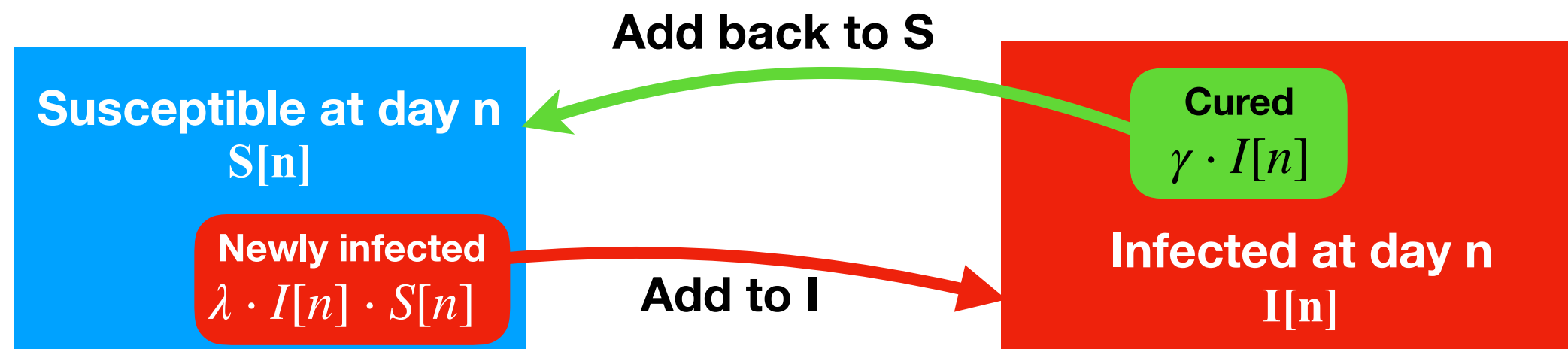
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3. New infections are removed from S (added to I)
4. New cured is $\gamma \cdot I$, they are added back to S (no immunity)

λ : **contact rate**

γ : **cure rate**



$n = 0, 1, 2, \dots$

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n] + \gamma I[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma I[n]$$

Annotations for the equations:

- $I[n + 1]$: # of infected on day n+1
- $I[n]$: # of infected on day n
- $\lambda \cdot I[n] \cdot S[n]$: Between day n+1 and day n, new infections through contact
- $\gamma I[n]$: # of cured on day n
- $\gamma I[n]$ (in the S equation): Add back to $S[n]$

A Python implementation of the S-I-S Model

```
1 # susceptible ratio
2 s = np.zeros([T])
3 # infective ratio
4 i = np.zeros([T])
5
6 # contact rate
7 lamda = 1.0
8 # recover rate
9 gamma = 0.3
10
11 # initial infective people
12 i[0] = 45.0 / N
13 s[0] = 1.0
```

Initialization

- Setting N, T
lamda,
gamma
- Setting I and S
at day 0

N: total # of population (susceptible)
T: total days of model simulation
lamda = contact rate
gamma = recover rate

```
14
15 for t in range(T-1): # step through day 0 to day T-1
16
17     s[t + 1] = s[t] - i[t] * lamda * s[t] + gamma*i[t]
18     i[t + 1] = i[t] + i[t] * lamda * s[t] - gamma*i[t]
```

```
19
20 plt.plot(i*N,label='infected')
21 plt.plot(s*N,label='susceptible')
22 plt.xlabel('Day')
23 plt.ylabel('# of cases')
24 plt.title('The S-I-S Model')
25 plt.legend()
```

Plotting codes

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n] + \gamma I[n]$$
$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma I[n]$$

Infected
at day n

Newly infected
at day n

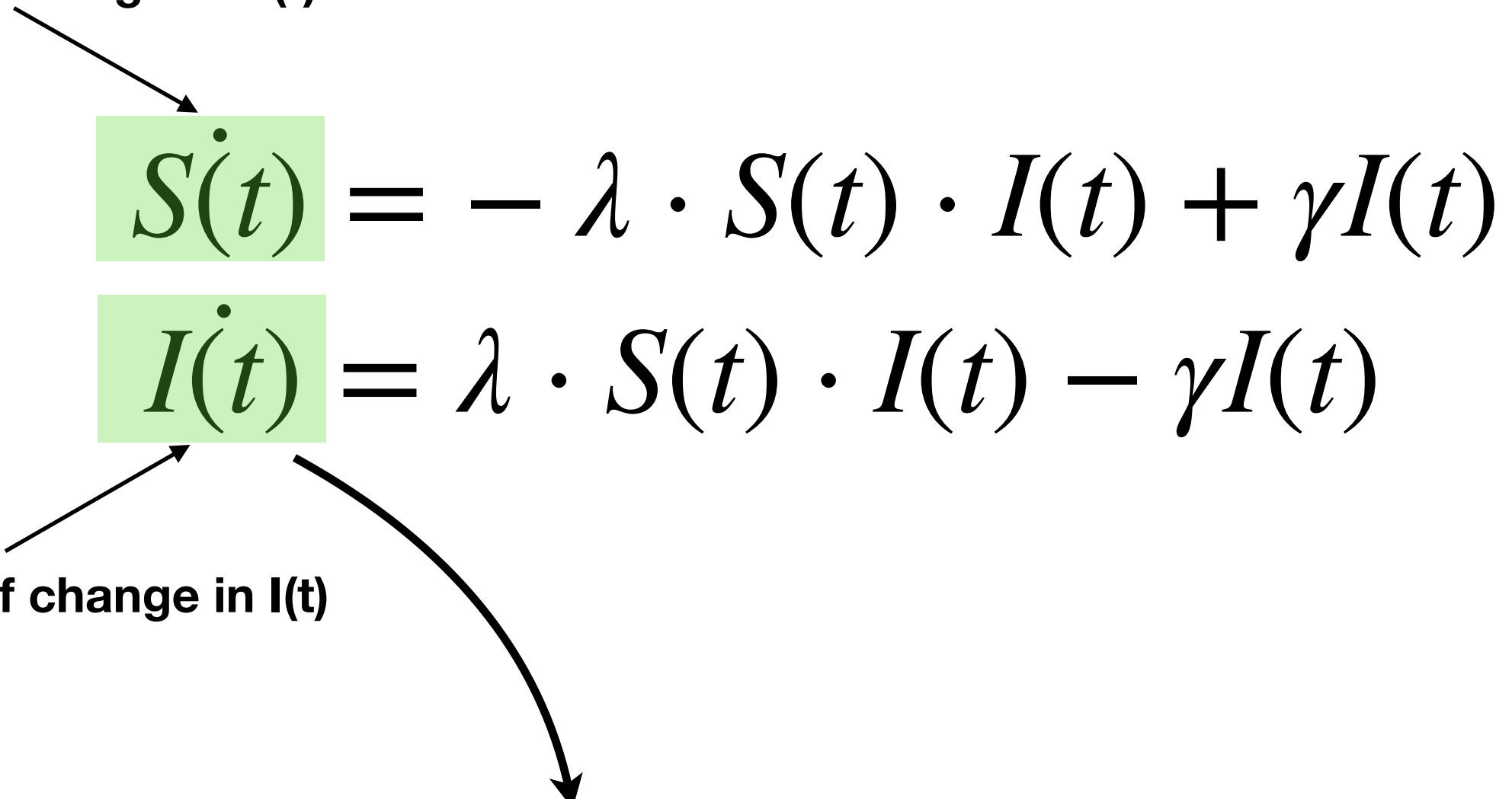
Recovered
at day n

The mathematical form of the S-I-S Model

$S(t)$: *Susceptible*

$I(t)$: *Infected*

Time rate of change in S(t)


$$\dot{S}(t) = -\lambda \cdot S(t) \cdot I(t) + \gamma I(t)$$

$$\dot{I}(t) = \lambda \cdot S(t) \cdot I(t) - \gamma I(t)$$

Time rate of change in I(t)

$$I[n + 1] - I[n] = \lambda \cdot S[n] \cdot I[n] - \gamma \cdot I[n]$$

$$n = 0, 1, 2, \dots$$

A Python implementation of the S-I-S Model

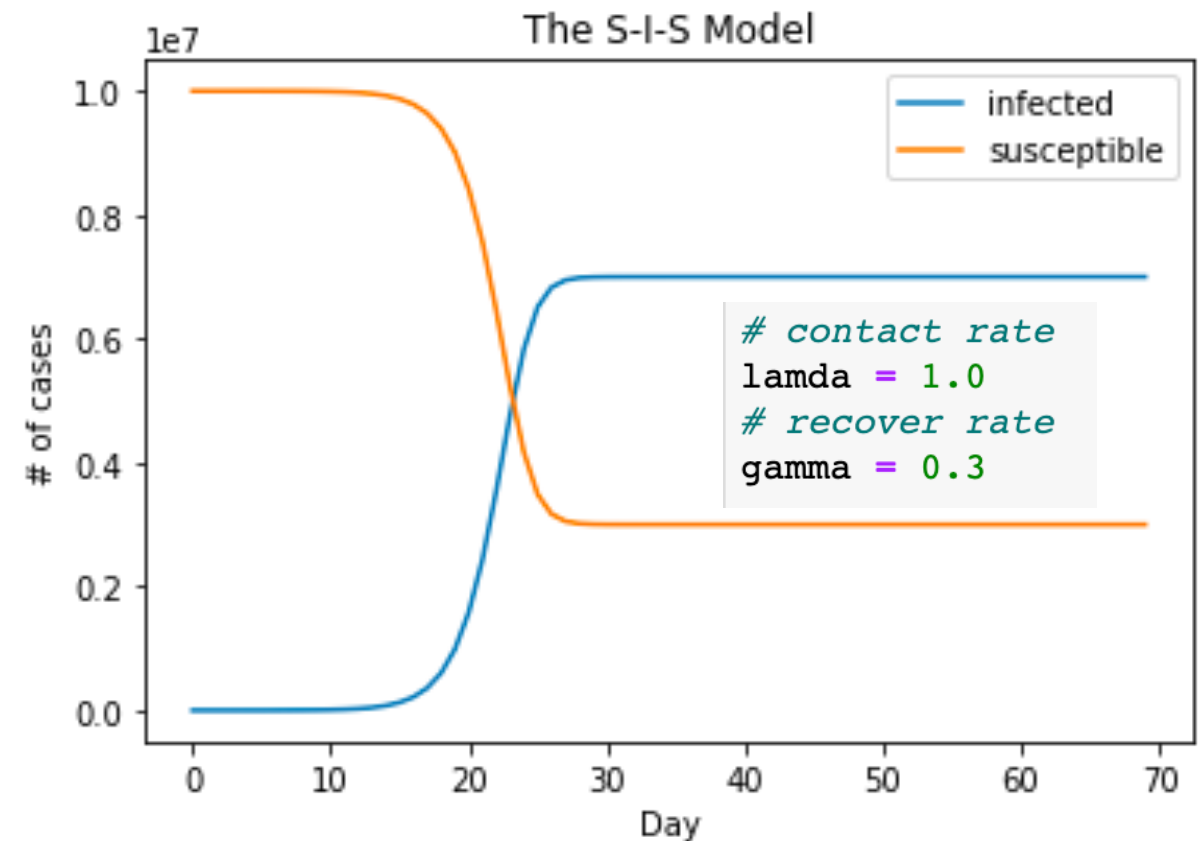
```

1  # susceptible ratio
2  s = np.zeros([T])
3  # infective ratio
4  i = np.zeros([T])
5
6  # contact rate
7  lamda = 1.0
8  # recover rate
9  gamma = 0.3
10
11 # initial infective people
12 i[0] = 45.0 / N
13 s[0] = 1.0
14
15 for t in range(T-1): # step through day 0 to day T-1
16
17     s[t + 1] = s[t] - i[t] * lamda * s[t] + gamma*i[t]
18     i[t + 1] = i[t] + i[t] * lamda * s[t] - gamma*i[t]
19
20 plt.plot(i*N,label='infected')
21 plt.plot(s*N,label='susceptible')
22 plt.xlabel('Day')
23 plt.ylabel('# of cases')
24 plt.title('The S-I-S Model')
25 plt.legend()

```

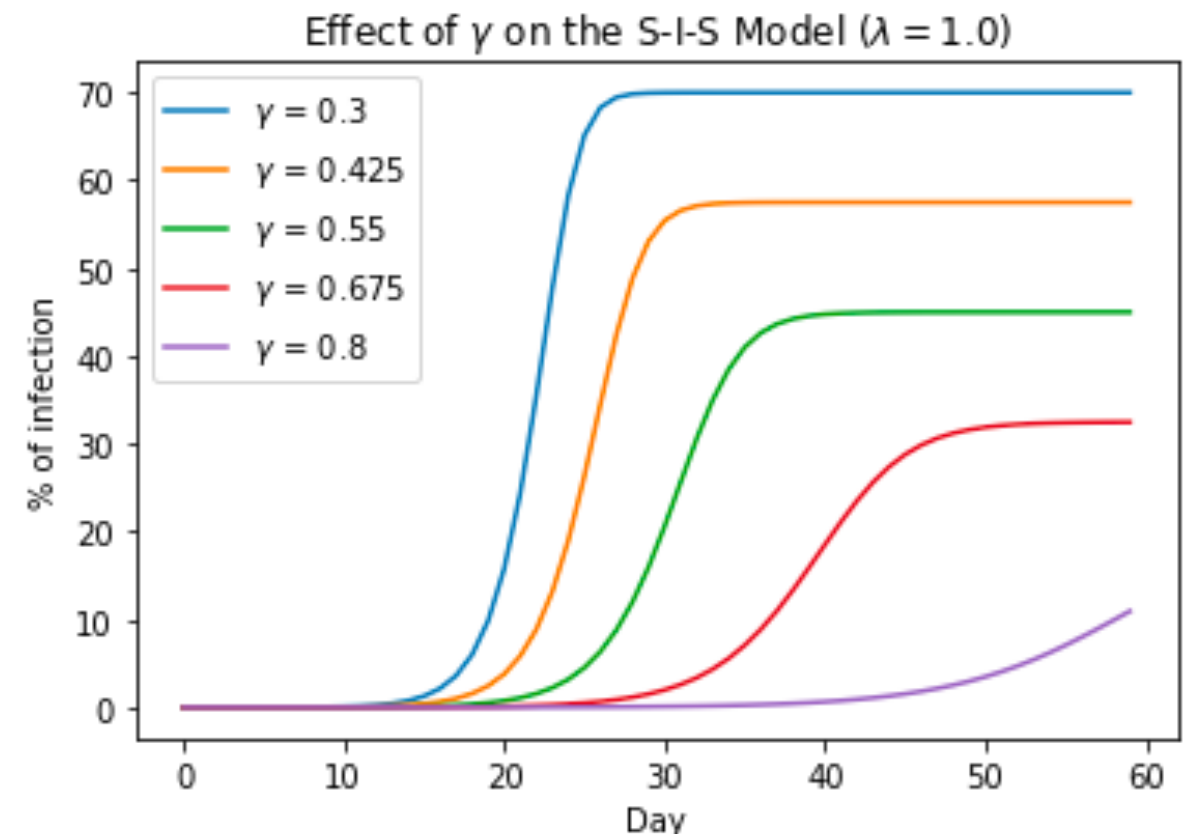
Initialization

- Setting N, T
lamda,
gamma
- Setting I and S
at day 0



- Starting from day 0, 1 infection
- Lamda determines the rate of infection
- Gamma determines the rate of cure

What's the problem here?



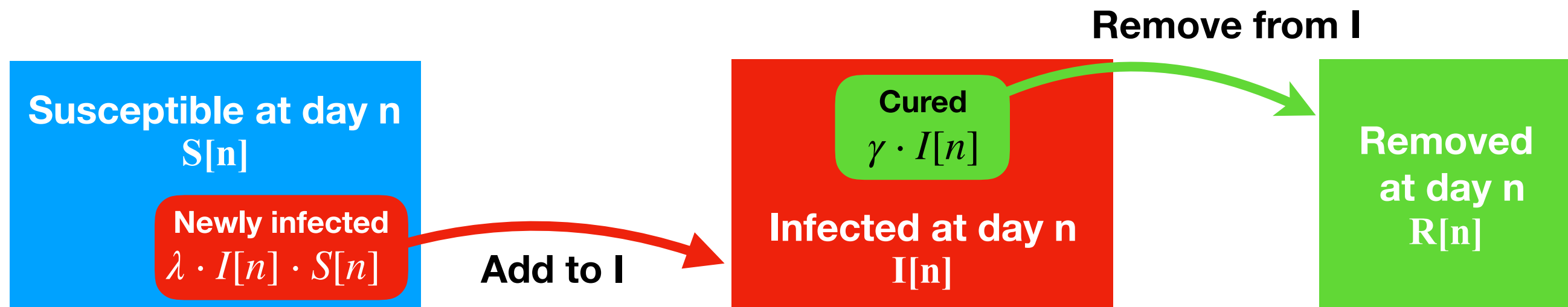
The S-I-R model (immunity)

Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Everyday, new infection is through contact rate $\lambda \cdot I \cdot S$
3. New infections are removed from S (added to I)
4. New cured is $\gamma \cdot I$, they are removed from I (immunity)

λ : **contact rate**

γ : **cure rate**



	Suspectible (S)	Infected (I)	Removed (R)	Newly Infected	Cured (immuned)
Day n	$S[n]$	$I[n]$	$R[n]$	$\lambda \cdot I[n] \cdot S[n]$	$\gamma \cdot I[n]$

Day n+1

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma \cdot I[n]$$

$$R[n + 1] = R[n] + \gamma \cdot I[n]$$

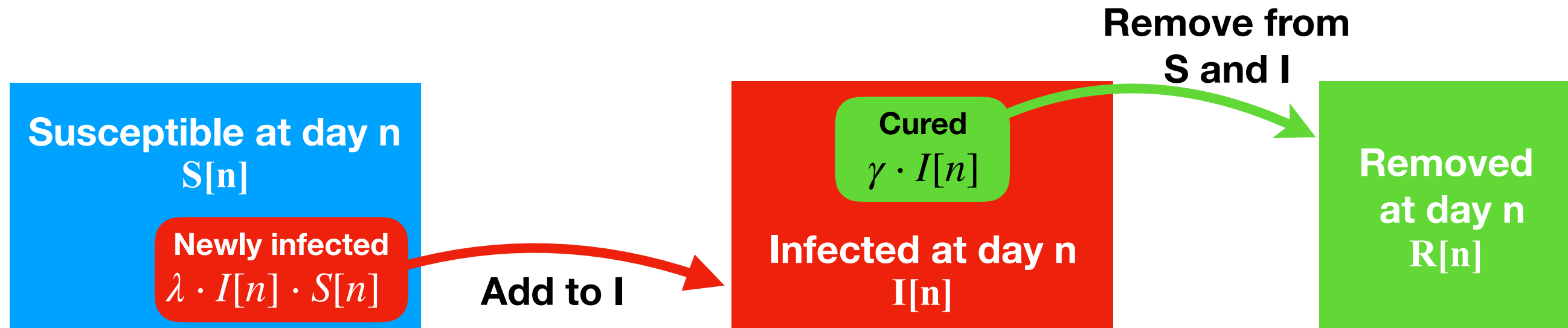
The S-I-R model (immunity)

Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Everyday, new infection is through contact rate $\lambda \cdot I \cdot S$
3. New infections are removed from S (added to I)
4. New cured is $\gamma \cdot I$, they are removed from I (immunity)

λ : contact rate

γ : cure rate



$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma I[n]$$

$$R[n + 1] = R[n] + \gamma I[n]$$

of recovered on day n

Between day n+1 and day n,
new infections through contact

The mathematical form of the S-I-R Model

$S(t)$: *Susceptible*

$I(t)$: *Infected*

$R(t)$: *Removed*

Time rate of
change in S(t)

$$\dot{S}(t) = - \overset{\text{Contact}}{\lambda \cdot S(t) \cdot I(t)}$$

Time rate of
change in I(t)

$$\dot{I}(t) = \underset{\text{Contact}}{\lambda \cdot S(t) \cdot I(t)} - \underset{\text{Removed}}{\gamma I(t)}$$

Time rate of
change in R(t)

$$\dot{R}(t) = \underset{\text{Removed}}{\gamma I(t)}$$

A Python implementation of the S-I-R Model

```
1 N = 1e7 + 10 + 5
2 # simulation Time / Day
3 T = 170
4 # susceptible ratio
5 s = np.zeros([T])
6 # infective ratio
7 i = np.zeros([T])
8 # remove ratio
9 r = np.zeros([T])
10
11 # contact rate
12 lamda = 0.2586
13 # recover rate
14 gamma = 0.0821
15
16 # initial infective people
17 i[0] = 10.0 / N
18 s[0] = 1e7 / N
```

```
19 for t in range(T-1):
20     i[t + 1] = i[t] + i[t] * lamda * s[t] - gamma*i[t]
21     s[t + 1] = s[t] - lamda * s[t] * i[t]
22     r[t + 1] = r[t] + gamma*i[t]
```

```
24 plt.plot(s*N,label='susceptible')
25 plt.plot(i*N,label='infected')
26 plt.plot(r*N,label='removed')
27 plt.xlabel('Day')
28 plt.ylabel('# of cases')
29 plt.title('The S-I-R Model')
30 plt.legend()
```

Initialization

- Setting N, T
lamda,
gamma
- Setting I and S
at day 0

N: total # of population (susceptible)
T: total days of model simulation
lamda = contact rate
gamma = recover rate

$$S[n + 1] = S[n] - \lambda \cdot I[n] \cdot S[n]$$

$$I[n + 1] = I[n] + \lambda \cdot I[n] \cdot S[n] - \gamma I[n]$$

$$R[n + 1] = R[n] + \gamma I[n]$$

Infected
at day n

Newly infected
at day n

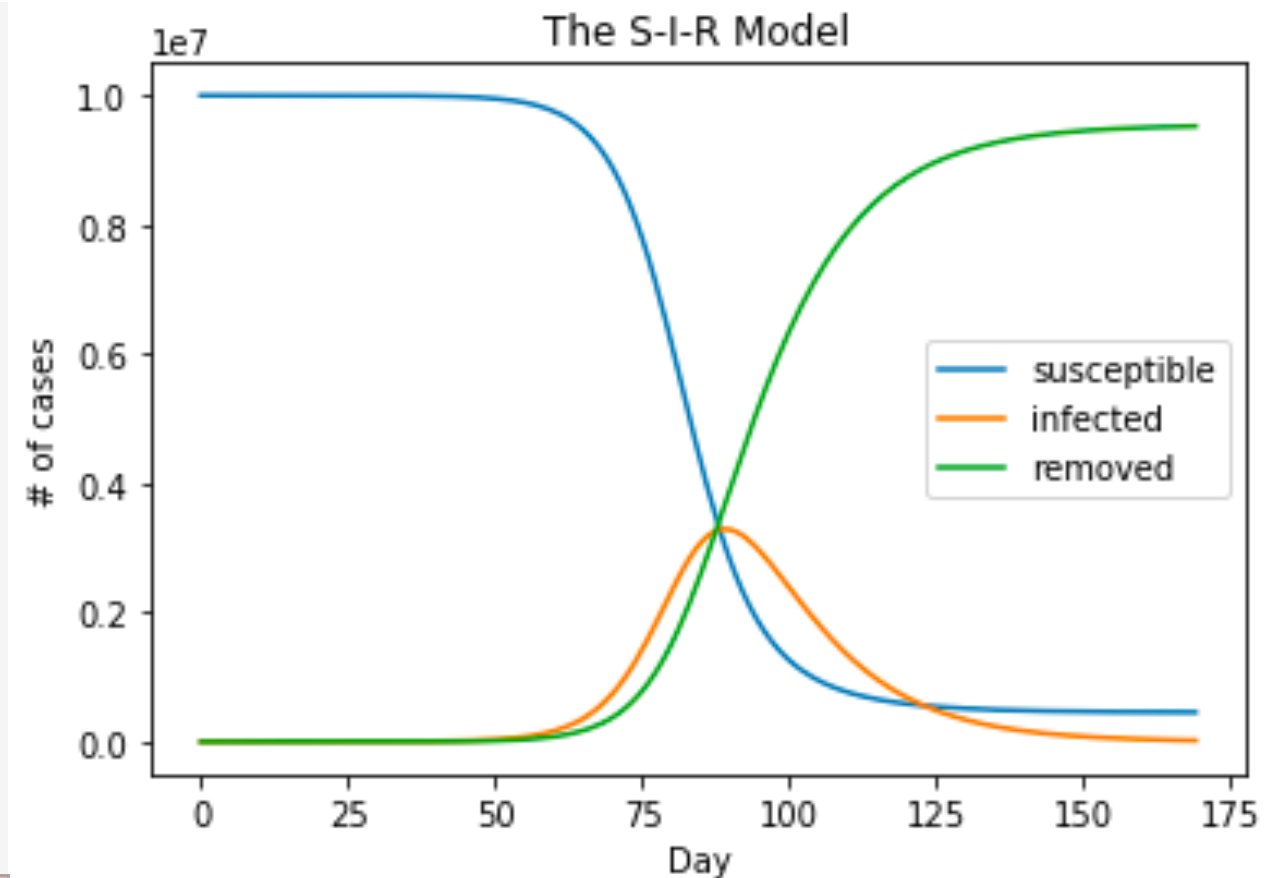
Recovered
at day n

Plotting codes

A Python implementation of the S-I-R Model

```
1 N = 1e7 + 10 + 5
2 # simulation Time / Day
3 T = 170
4 # susceptible ratio
5 s = np.zeros([T])
6 # infective ratio
7 i = np.zeros([T])
8 # remove ratio
9 r = np.zeros([T])
10
11 # contact rate
12 lamda = 0.2586
13 # recover rate
14 gamma = 0.0821
15
16 # initial infective people
17 i[0] = 10.0 / N
18 s[0] = 1e7 / N
19 for t in range(T-1):
20     i[t + 1] = i[t] + i[t] * lamda * s[t] - gamma*i[t]
21     s[t + 1] = s[t] - lamda * s[t] * i[t]
22     r[t + 1] = r[t] + gamma*i[t]
23
24 plt.plot(s*N,label='susceptible')
25 plt.plot(i*N,label='infected')
26 plt.plot(r*N,label='removed')
27 plt.xlabel('Day')
28 plt.ylabel('# of cases')
29 plt.title('The S-I-R Model')
30 plt.legend()
```

From
SARS data



- Starting from day 0, 10 infections within 1M population
- Lamda determines the rate of infection
- Gamma determines the rate of cure
- Here the parameters are from data collected during the SARS
- The pandemic peaks around day 90 and decays after day 150 (~ 5 months)

Plotting codes

Now, what's still missing here?

The S-E-I-R model

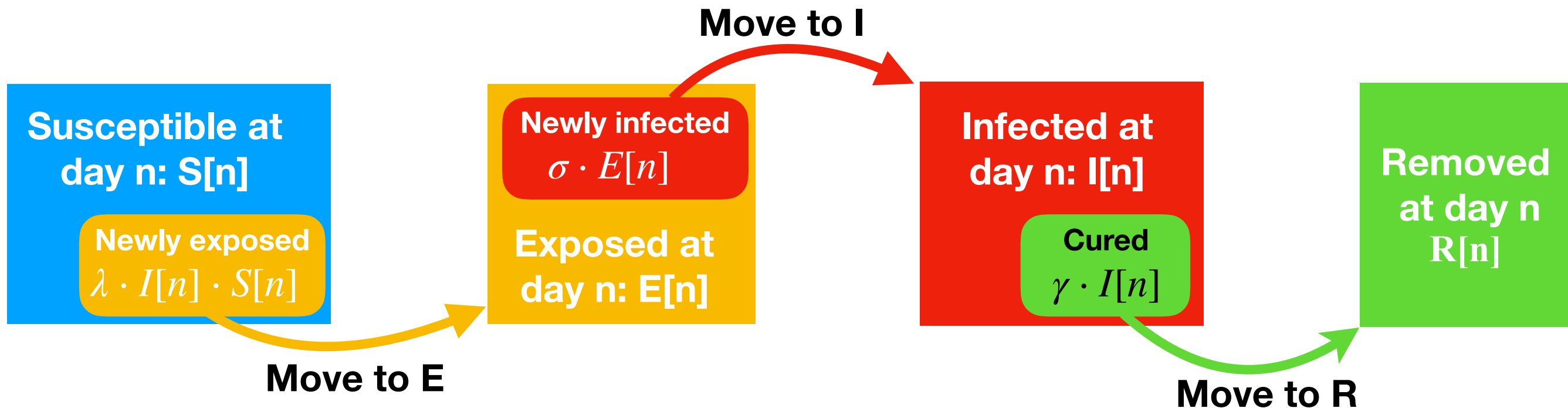
Assumptions:

1. The total population (susceptible) is N_0 , i.e., $S[0] = N_0$
2. Everyday, newly **exposed** is through contact rate $\lambda \cdot I \cdot S$
3. New **infections** are from the exposed population due to incubation $\sigma \cdot E$
4. New **cured** is $\gamma \cdot I$, they are removed from S and I (immunity)

λ : contact rate

σ : incubation

γ : cure rate



	Susceptible (S)	Exposed (E)	Infected (I)	Removed (R)	Newly exposed	Newly infected	Cured (immuned)
Day n	$S[n]$	$E[n]$	$I[n]$	$R[n]$	$\lambda \cdot I[n] \cdot S[n]$	$\sigma \cdot E[n]$	$\gamma \cdot I[n]$

Day $n+1$

$$S[n + 1] =$$

$$E[n + 1] =$$

$$I[n + 1] =$$

$$R[n + 1] =$$

?