Epidemics

Social Networks Analysis and Graph Algorithms

Prof. Carlos Castillo — https://chato.cl/teach

Sources

- A. L. Barabási (2016). Network Science – Chapter 10

- D. Easley and J. Kleinberg (2010). Networks, Crowds, and Markets — Chapter 21

- URLs cited in the footer of slides

Examples: human epidemics

- Influenza, measles, STIs, …

- Smallpox and other diseases brought by Europeans to America since early 1500s

- The "Black Death" (next slide)

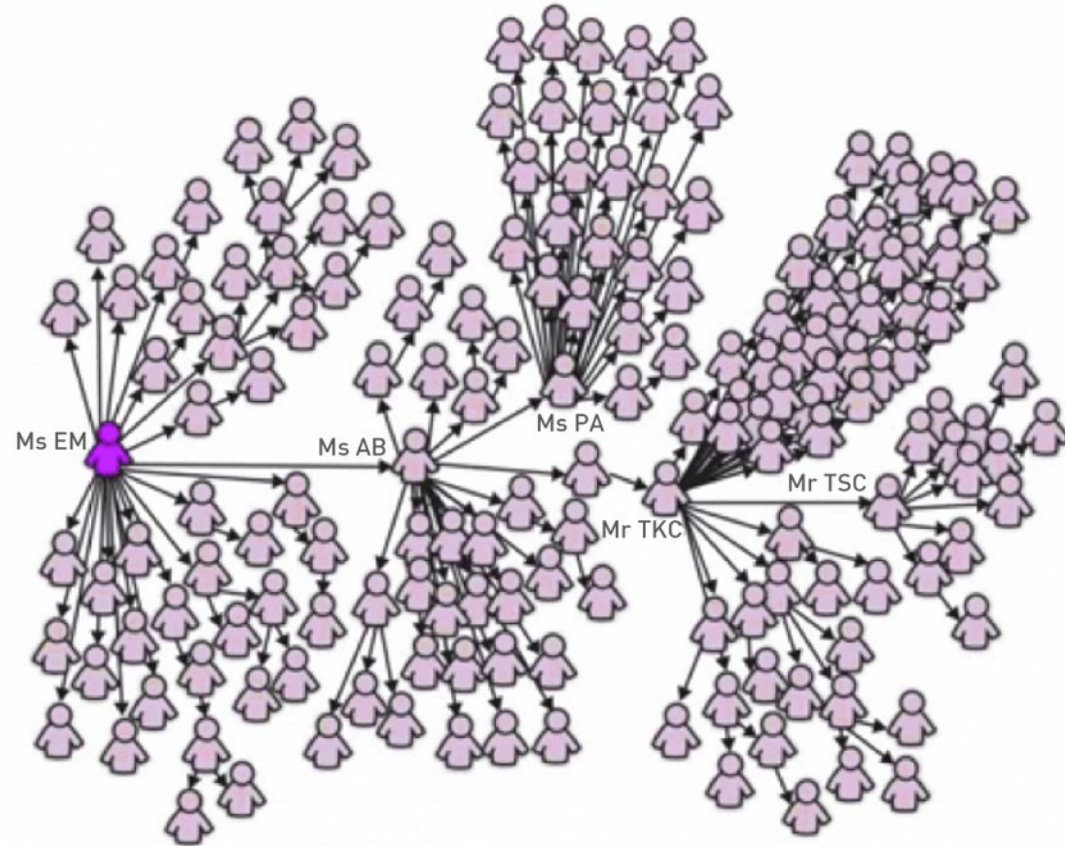**Population Collapse in Mexico**

- 1520 Smallpox (~8 million deaths)
- 1545 Cocoliztli (~12-15 million deaths)
- 1576 Cocoliztli (~2 million deaths)

Y-axis: Population (millions), X-axis: Year

https://en.wikipedia.org/wiki/Cocoliztli_Epidemic_of_1545-1548

The "Black Death"
(Bubonic plague)
1300s

Killed **30%-60%** of the total population of Europe

1346 1347 1348 1349 1350 1351 1352 1353

https://commons.wikimedia.org/wiki/File:1346-1353_spread_of_the_Black_Death_in_Europe_map.svg

SARS Outbreak (2003)

- February 21st: Chinese doctor who have been several treating "atypical pneumonia" cases check-ins into hotel in Hong Kong
  - Hospitalized on Feb 22nd
  - Died on March 4th
- March 1st: "Ms. E. M." returns to Singapore after visiting Hong Kong
  - Graph depicts 144 out of the first 206 SARS patients in Singapore
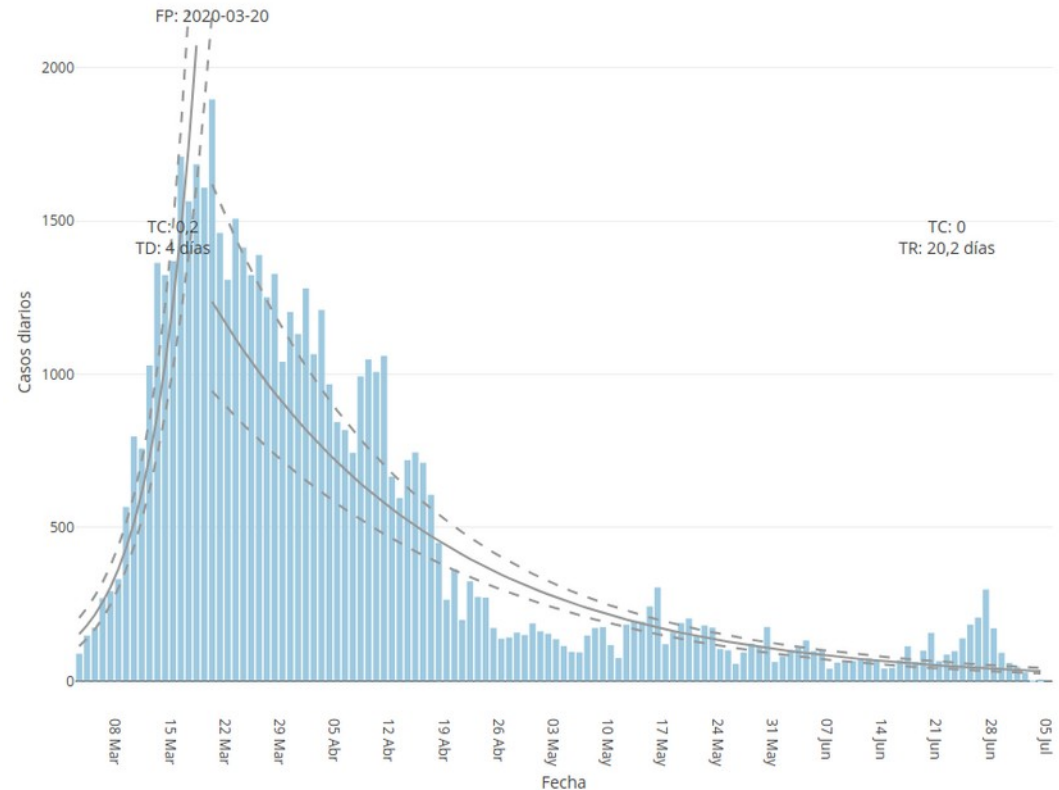 - Ms. E. M. lived, various of her family members died

https://en.wikipedia.org/wiki/Timeline_of_the_SARS_outbreak

COVID-19
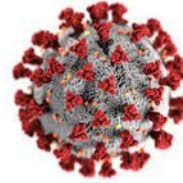
Why this curve?

How can one make
this kind of forecast?

COVID-19 cases in Catalonia as of July 2020 - https://cnecovid.isciii.es/covid19/#ccaa

Diffusion of ideas vs diseases

- Adopting a new idea, behavior, fashion, product, taste, may also spread from person to person: "social contagion"

- There is a certain agency of the receiver

- In diffusion of diseases, we assume there is no agency: each contagion is random

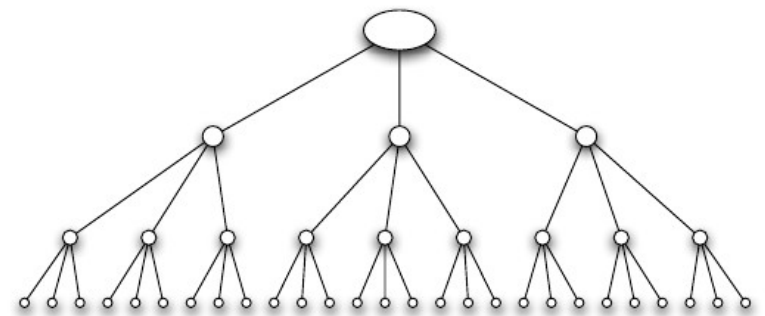# Simple model: branching process

Modeling epidemics

- There are many factors:

  - Contagiousness

  - Length of infectious period,

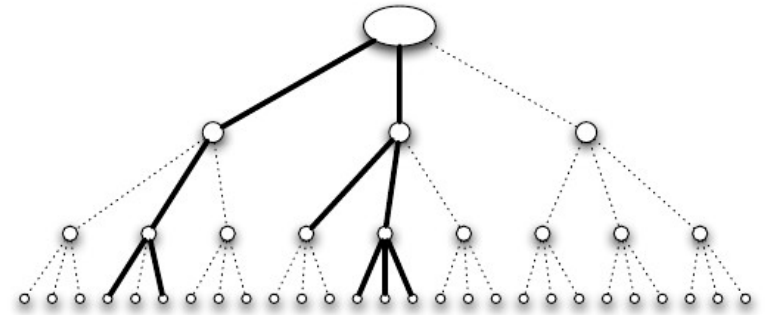 - Severity

  - ...

- Structure of contacts in a population

Simple model: branching process

(a) *The contact network for a branching process*

- Each person interacts with other k people

- Each interaction ends in infection with probability β

Example: k=3

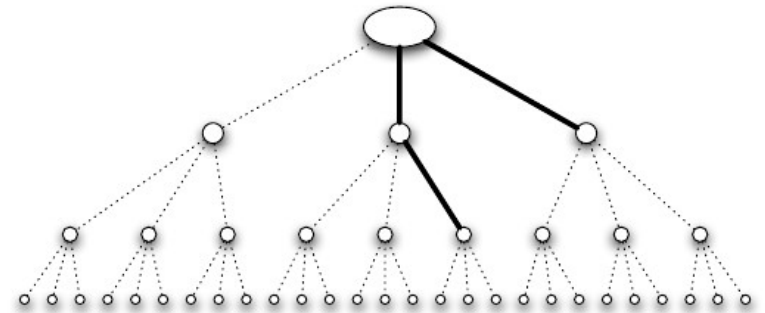(b) *With high contagion probability, the infection spreads widely*

(c) *With low contagion probability, the infection is likely to die out quickly*

Transmission rate or "Basic reproductive number" R_0

- Each person interacts with other k people
- Each interaction ends in infection with probability β

- What is the expected number of cases caused by a single individual, R_0?

- What do you think happens if $R_0 < 1$?

- What do you think happens if $R_0 > 1$?

Disease	Transmission	R_0
Measles	Airborne	12-18
Pertussis	Airborne droplet	12-17
Diptheria	Saliva	6-7
Smallpox	Social contact	5-7
Polio	Fecal-oral route	5-7
Rubella	Airborne droplet	5-7
Mumps	Airborne droplet	4-7
HIV/AIDS	Sexual contact	2-5
SARS	Airborne droplet	2-5
Influenza (1918 strain)	Airborne droplet	2-3

Changing $R_0 = \beta k$

- **Sanitary practices** (to reduce what?)

- **Quarantine** (to reduce what?)

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Changing $R_0 = \beta k$

- **Sanitary practices** reduce β

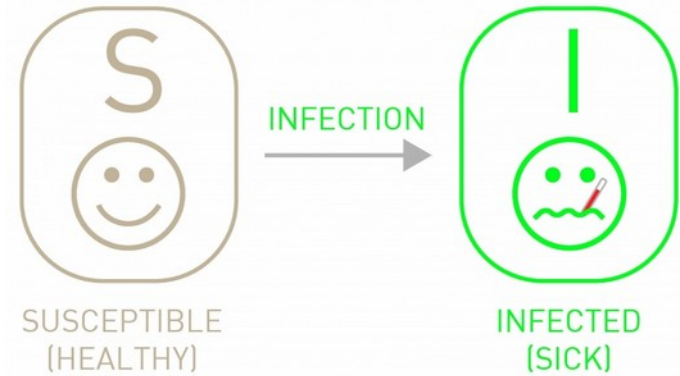- **Quarantine** reduces k

The SI model
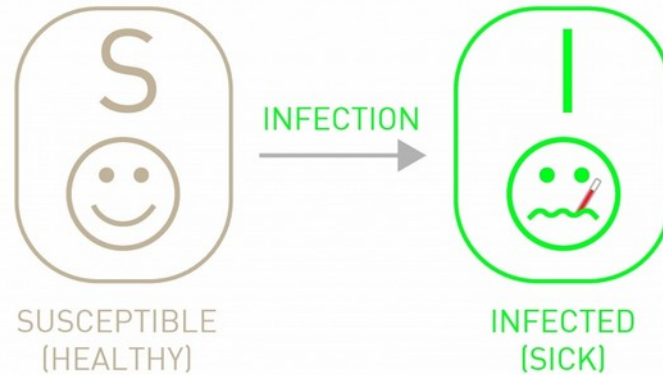
The SI model

- ## Susceptible:

  - The node can catch the disease

- ## Infected:

  - The node has the disease and can spread it

  - It will stay sick forever

Notation

- Number of susceptible S(t)

  – Fraction of susceptible s(t) = S(t) / N

- Number of infected I(t)

  – Fraction of infected i(t) = I(t) / N

- s(t) + i(t) = 1

How many susceptible neighbors a node has?

$$\langle k \rangle \frac{S(t)}{N} = \langle k \rangle \, s(t)$$

How many new infections are produced?

(for every infected, iterate through its susceptible neighbors, infect with probability β)

$$i(t) \, \underbrace{\langle k \rangle \, s(t)} \beta$$

infected   susceptible neighbors   infection probability
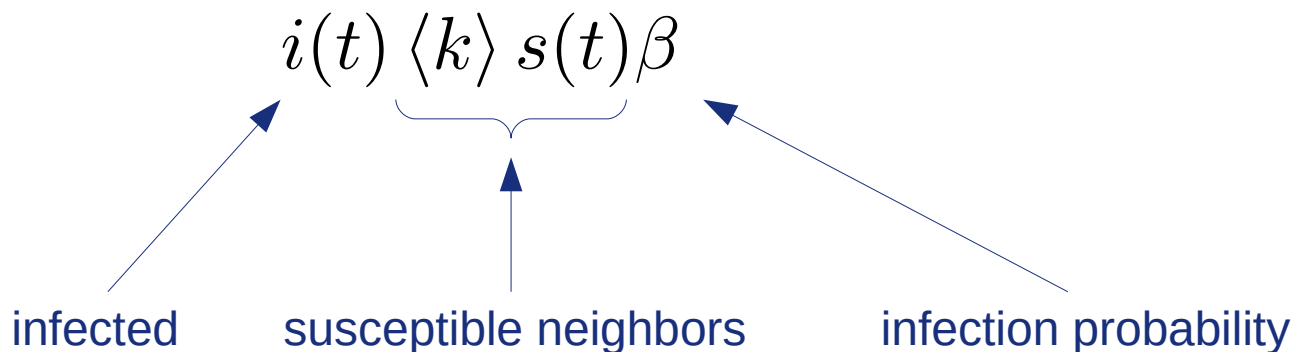
Prove that $i(t) = \dfrac{i_0 e^{\beta \langle k \rangle t}}{1 - i_0 + i_0 e^{\beta \langle k \rangle t}}$

Begin from: $\dfrac{di(t)}{dt} = i(t) \langle k \rangle (1 - i(t)) \beta$

First, place all terms with $i(t)$ on the left side

Second, use $\dfrac{1}{x \cdot (1 - x)} = \dfrac{1}{x} + \dfrac{1}{1 - x}$

Third, integrate from $t = 0$ to t and denote by $i_0 = i(t = 0)$

$$\int \frac{1}{x} dx = \log x + C \qquad \int \frac{1}{1 - x} dx = -\log(1 - x) + C$$

Behavior in the limit $t \to \infty$

- What is the limit of when $t \to \infty$?

$$i(t) = \frac{i_0 e^{\beta \langle k \rangle t}}{1 - i_0 + i_0 e^{\beta \langle k \rangle t}}$$
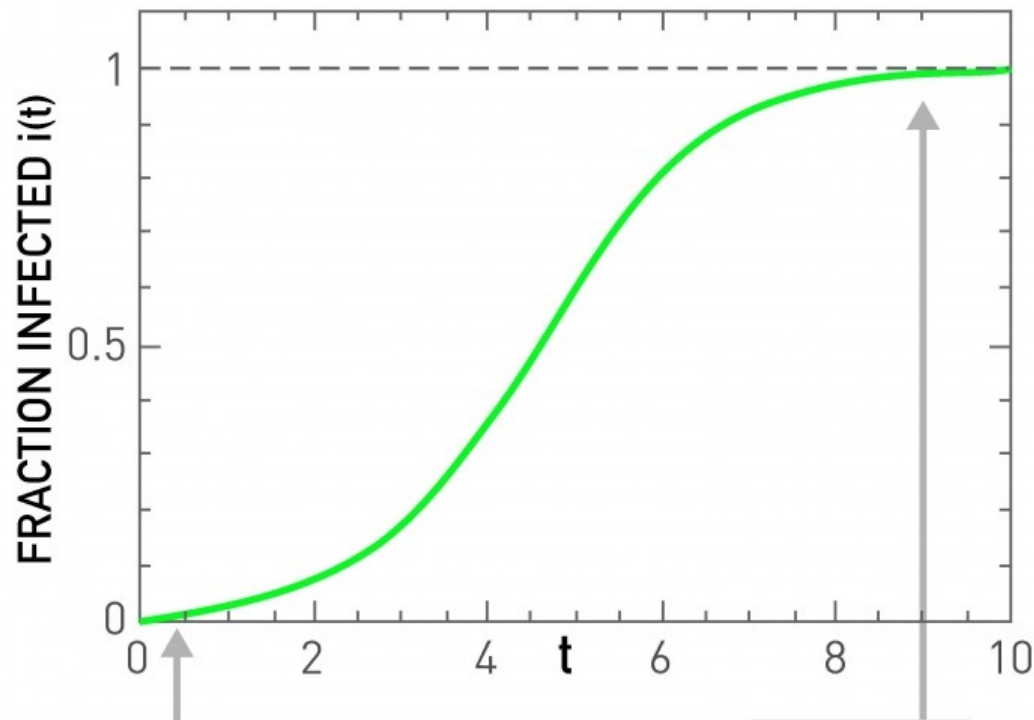
- Hint: similar to

$$f(t) = \frac{e^t}{1 + e^t}$$

Infected as a function of time (SI)

$$i(t) = \frac{i_0 e^{\beta \langle k \rangle t}}{1 - i_0 + i_0 e^{\beta \langle k \rangle t}}$$

Characteristic time
(to infect $1/e \simeq 36\%$ of people):

$$\tau = \frac{1}{\beta \langle k \rangle}$$
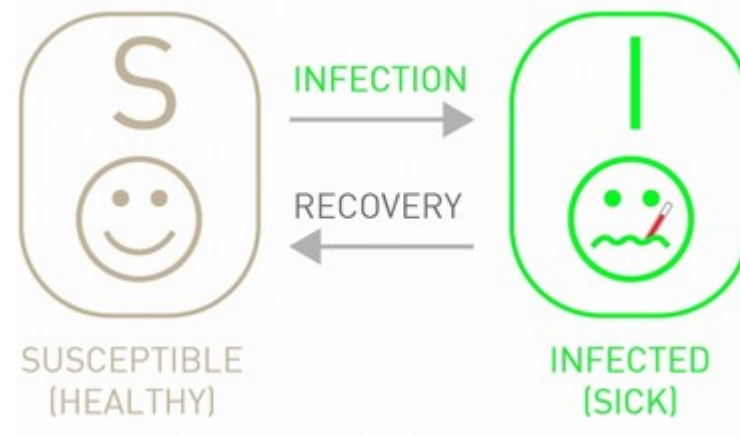

exponential regime

If i is small,

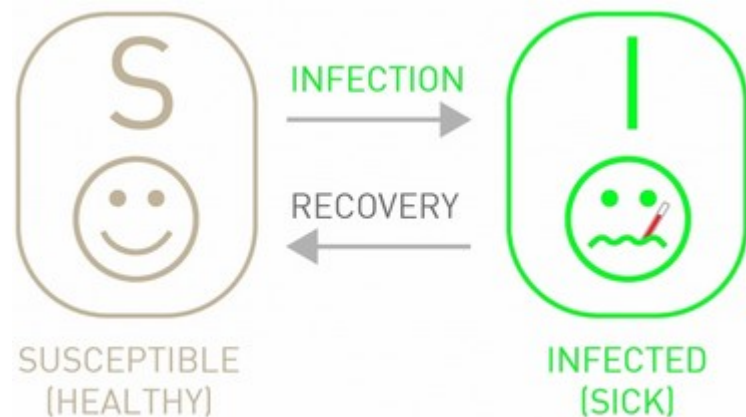$$i \approx i_0 e^{\beta \langle k \rangle t}$$

saturation regime

If $i \to 1$,

$$\frac{di}{dt} \to 0$$

The SIS model

The SIS model

- **Susceptible:**

  – The node can catch the disease

- **Infected:**

  – The node has the disease and can spread it

  – After some time, it recovers … but it becomes susceptible again

Infection dynamics

$$\frac{di(t)}{dt} = \beta \langle k \rangle i(t)(1 - i(t)) - \mu i(t)$$

- μ is the recovery rate, i.e., the probability of becoming susceptible again in an unit of time

$$i(t) = \left(1 - \frac{\mu}{\beta \langle k \rangle} \right) \frac{C e^{(\beta \langle k \rangle - \mu)t}}{1 + C e^{(\beta \langle k \rangle - \mu)t}}$$

- C is a constant that depends on i_0
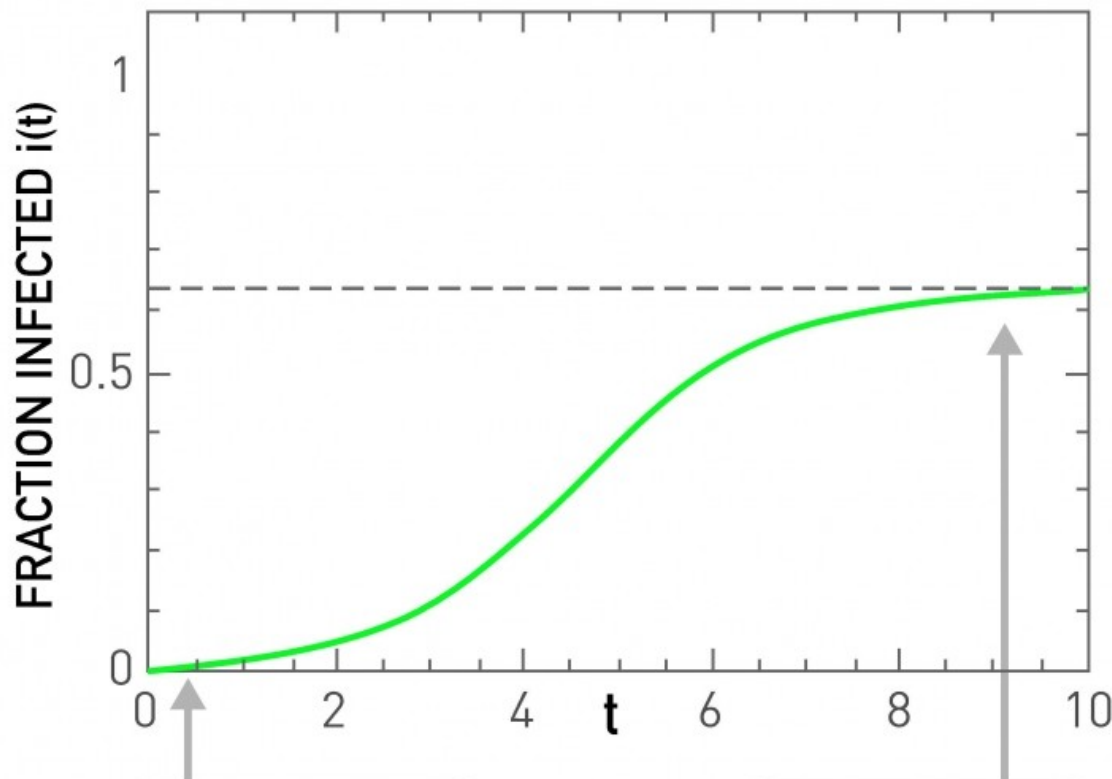
Behavior in the limit $t \rightarrow \infty$

- What is the limit of $i(t) = \left(1 - \dfrac{\mu}{\beta \langle k \rangle} \right) \dfrac{Ce^{(\beta \langle k \rangle - \mu)t}}{1 + Ce^{(\beta \langle k \rangle - \mu)t}}$
  when $t \rightarrow \infty$?

- Hint: similar to $\quad f(t) = \alpha \dfrac{e^t}{1 + e^t}$

Infected as a function of time (SIS)

$$i(t) = \left(1 - \frac{\mu}{\beta \langle k \rangle}\right) \frac{Ce^{(\beta\langle k \rangle - \mu)t}}{1 + Ce^{(\beta\langle k \rangle - \mu)t}}$$

This is in the case $\mu < \beta \langle k \rangle$

FRACTION INFECTED i(t)

exponential outbreak

If i is small,

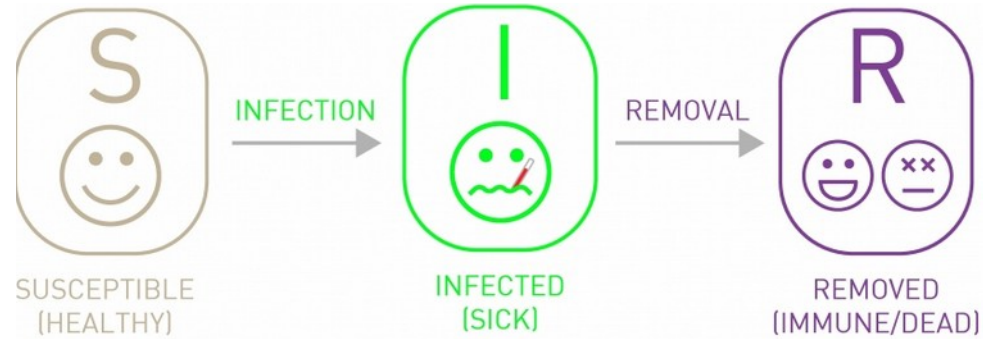$i \approx i_0 e^{(\beta\langle k \rangle t - \mu)t}$

endemic state

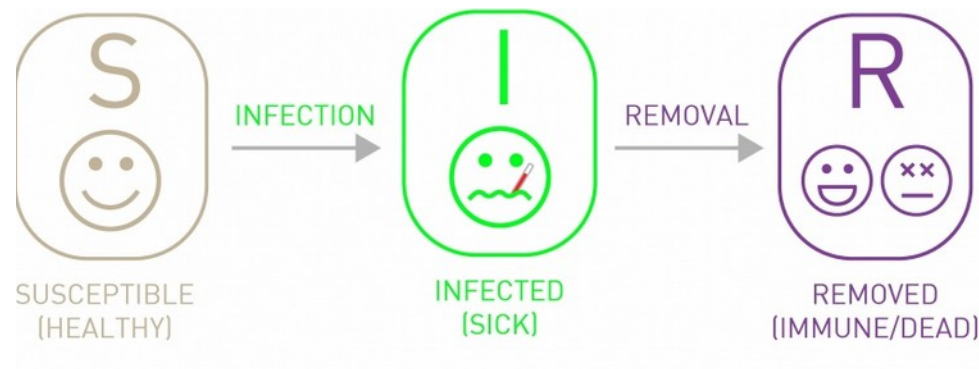$i(\infty) = 1 - \frac{\mu}{\beta\langle k \rangle}$

What happens if $\mu > \beta \langle k \rangle$?

- Remember: $\dfrac{di(t)}{dt} = \beta \langle k \rangle i(t)(1 - i(t)) - \mu i(t)$

The SIR model

The SIR model

SUSCEPTIBLE (HEALTHY) → INFECTION → INFECTED (SICK) → REMOVAL → REMOVED (IMMUNE/DEAD)

- ## Susceptible:

  – The node can catch the disease

- ## Infected:

  – The node has the disease and can spread it

- ## Removed:

  – The node no longer has the disease, and cannot catch it or propagate it again (permanent immunity -or- death)

Infection dynamics in SIR

$$\frac{di(t)}{dt} = \beta \langle k \rangle i(t)(1 - r(t) - i(t)) - \mu i(t)$$

$$\frac{dr(t)}{dt} = \mu i(t)$$

$$\frac{ds(t)}{dt} = -\frac{di(t)}{dt} - \frac{dr(t)}{dt} = -\beta \langle k \rangle i(t)(1 - r(t) - i(t))$$
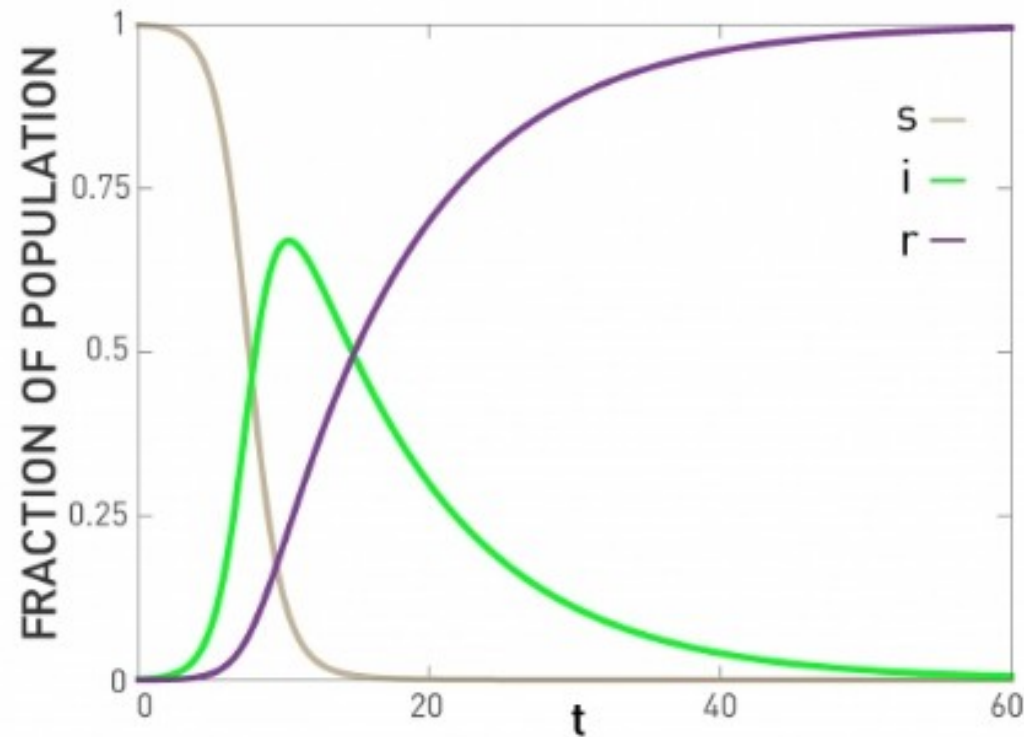
- No closed form solution
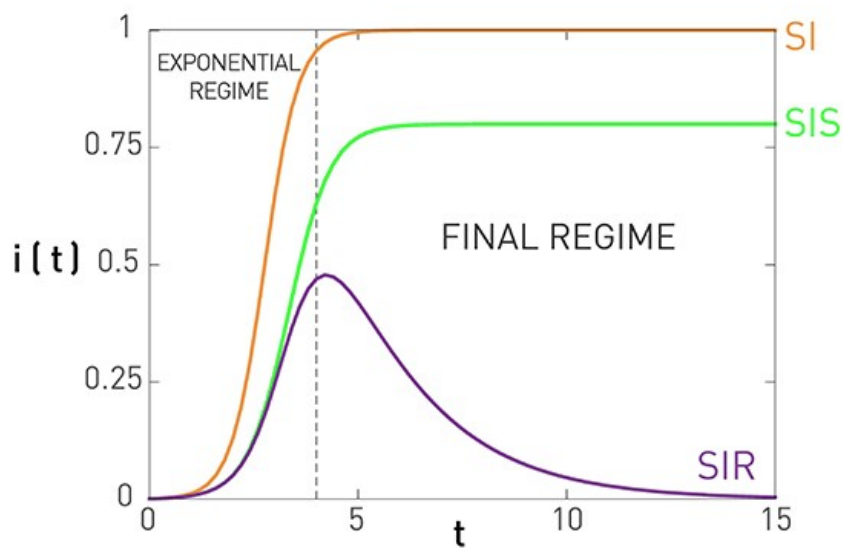
Infection dynamics (SIR)

$$\frac{di(t)}{dt} = \beta \langle k \rangle i(t)(1 - r(t) - i(t)) - \mu i(t)$$

$$\frac{dr(t)}{dt} = \mu i(t)$$

$$\frac{ds(t)}{dt} = -\beta \langle k \rangle i(t)(1 - r(t) - i(t))$$

Comparison of $i(t)$

	SI	SIS	SIR
Exponential Regime: Number of infected individuals grows exponentially	$i = \dfrac{i_0 e^{\beta\langle k \rangle t}}{1 - i_0 + i_0 e^{\beta\langle k \rangle t}}$	$i = \left(1 - \dfrac{\mu}{\beta\langle k \rangle}\right)\dfrac{Ce^{(\beta\langle k \rangle - \mu)t}}{1 + Ce^{(\beta\langle k \rangle - \mu)t}}$	No closed solution
Final Regime: Saturation at $t \to = \infty$	$i(\infty) = 1$	$i(\infty) = 1 - \dfrac{\mu}{\beta\langle k \rangle}$	$i(\infty) = 0$
Epidemic Threshold: Disease does not always spread	No threshold	$R_0 = 1$	$R_0 = 1$

Things to remember

- SI, SIS, SIR models

- Which are the states in each process and which are the possible transitions

- Equations for number of nodes in each state

- Regimes under different parameters

- Practice executing by hand and write code if it helps you remember better each process

Practice on your own

Under the **SIS** model,
$$i(t) = \left(1 - \frac{\mu}{\beta \langle k \rangle}\right) \frac{Ce^{(\beta \langle k \rangle - \mu)t}}{1 + Ce^{(\beta \langle k \rangle - \mu)t}}$$

1. When $\mu < \beta \langle k \rangle$ what is the limit of $i(t)$?

2. How is this state called?

3. What happens when $\mu > \beta \langle k \rangle$?

4. What conditions lead to large values of $i(t)$?

Practice on your own (cont.)

- In the **SIRS** epidemic model, there are three possible states for a node: susceptible, infected, and recovered. Susceptible nodes can become infected, infected nodes can become recovered, and *recovered nodes can become susceptible again.*

- During one unit of time, with probability β an infected node can infect one of its contacts, with probability μ, an infected node can recover, and with probability σ, a recovered node can become susceptible again.

- Let s(t) be the fraction of susceptible nodes, i(t) be the fraction of infected nodes, r(t) the fraction of recovered nodes, and <k> the average degree of the graph. Write the equations, simplifying them appropriately, for:

$$1. \frac{di(t)}{dt} \quad 2. \frac{dr(t)}{dt} \quad 3. \frac{ds(t)}{dt}$$

4. Is σ > μ sufficient to say that the recovered will tend to zero in the long run?