

Epidemics on Networks

Mathematical epidemiology

Dr. Alejandro Lage
Cuba



Facultad de Física, UH

CENTER OF COMPLEX SYSTEMS

University of Havana, Cuba

**Stat-mech and
Systems Biology**

Dr. Roberto Mulet.

**Granular, Active
Matter and Sensors**

Dr. Ernesto Altshuler.

**Big Data and
Population mobility**

Dr. Alejandro Lage



EPIDEMICS ON NETWORKS

What you get

- Compartmental (SIR) models
- Complex networks.
- Simulations in python
- Probability theory/Statistical mechanics.
- Reconstruction of epidemics.

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- Basic calculus
- Probability theory
- Basic programming
- Statistical mechanics and/or combinatorial optimization

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Who cares?

- Working on epidemics
- Working on inference
- Working on networks
- Working on optimization

WHO ARE YOU

Field of Research

- 4 Complex Networks
- 4 Industrial engineering
- 2 Epidemics

2. Why are you taking this class?



Answered: 10 Skipped: 0

I had no other option	0%	0
I am interested in complex networks	60%	6
I am interested in epidemics	20%	2
I am interested in simulations	30%	3
I am interested in inference problems	30%	3
Somebody advice me to go	30%	3
Other (please specify)		0

WHO ARE YOU

Field of Research

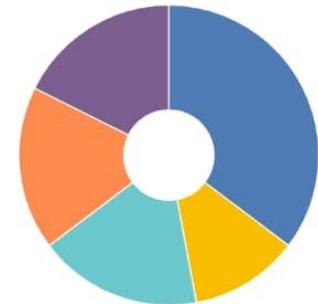
- 4 Complex Networks
- 4 Industrial engineering
- 2 Epidemics

1. What's your education level?



Bachelor, undergraduate	40%	4
Graduated, master student	40%	4
Graduated, PhD student	20%	2
PhD researcher	0%	0

2. Why are you taking this class?



Answered: 10 Skipped: 0

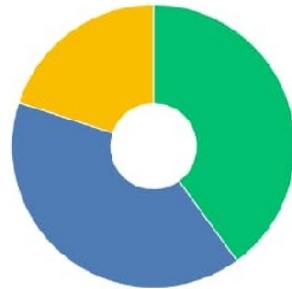
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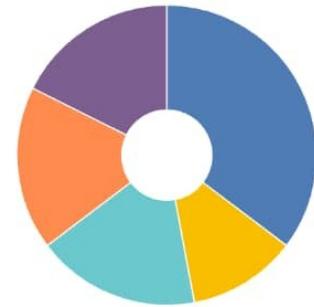
6. Your current level in Python is?



1. What's your education level?

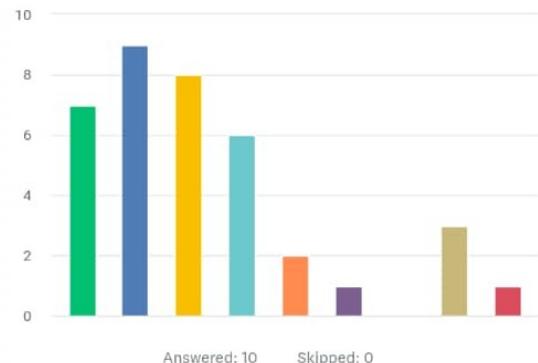


2. Why are you taking this class?



WHO ARE YOU

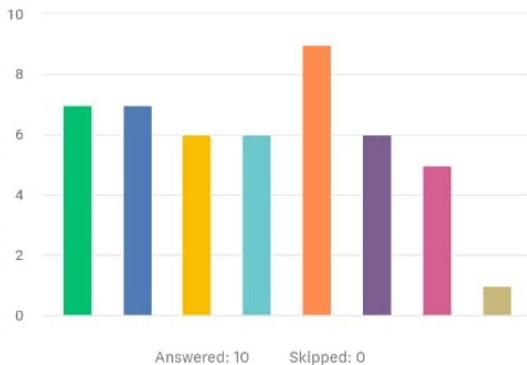
4. Which of the following courses have you passed?



Calculus or mathematical analysis	70%	7
Linear algebra	90%	9
Probability theory	80%	8
Statistics	60%	6
Differential equations	20%	2
Complex systems	10%	1
Tai chi	0%	0
Networks or graph theory	30%	3
Statistical mechanics	10%	1

WHO ARE YOU

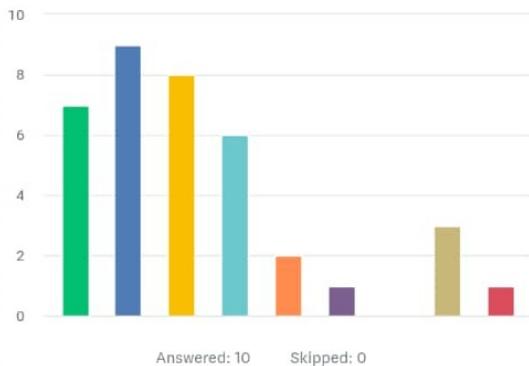
9. Which of the following concepts in probability are known to you?



Answered: 10 Skipped: 0

Events	70%	7
Random variables	70%	7
Density distribution	60%	6
Cumulative distribution	60%	6
Mean and variance	90%	9
Conditional probability	60%	6
Likelihood	50%	5
Entropy of a distribution	10%	1

4. Which of the following courses have you passed?

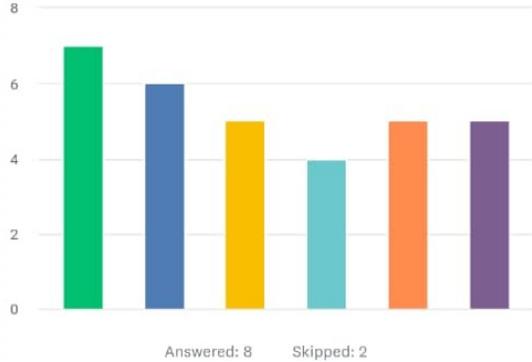


Answered: 10 Skipped: 0

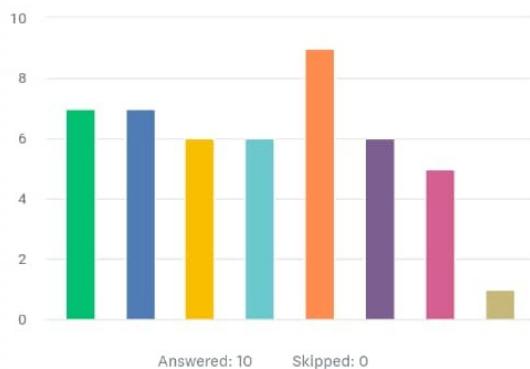
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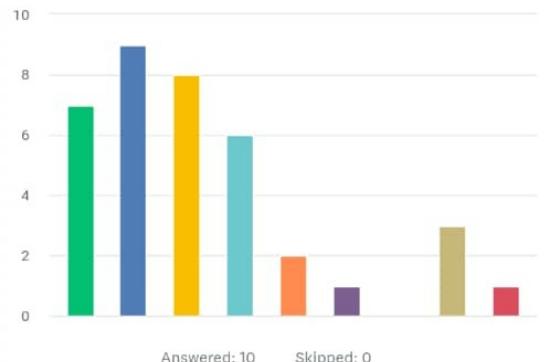
10. Which of the following concepts in graph theory are known to you?



9. Which of the following concepts in probability are known to you?



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EPIDEMICS ON NETWORKS

1. Mathematical epidemiology, origins, early results. The compartmental model family.
2. The mean field description of SIR models. Short and long time limits in SIR.
3. Monte Carlo simulations of epidemics. Gillespie algorithm.
4. Monte Carlo simulations Practical Python Class.
5. Complex networks. Main results. Types and properties. Famous networks. Benchmarks.
6. Playing with networks in Python. Networkx. Plotting. Nice plotting.
7. Master equation of epidemics on networks. The mean field solution and pair based solution.
8. Simulating epidemics on networks. Python libraries.
9. Inference and belief propagation.
10. The zero patient problem. The contamination source detection problem.
11. The infectious backbone as a cascade process.
12. The effect of contact tracing.

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MATHEMATICAL EPIDEMIOLOGY

1. Mathematical epidemiology, origins, early results. The compartmental model family.
2. The mean field description of SIR models. Short and long time limits in SIR.

REVIEWS OF MODERN PHYSICS

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Epidemic processes in complex networks

Romualdo Pastor-Satorras, Claudio Castellano, Piet Van Mieghem, and Alessandro Vespignani
Rev. Mod. Phys. **87**, 925 – Published 31 August 2015

Fred Brauer
Carlos Castillo-Chavez

Mathematical Models
in Population Biology
and Epidemiology

MASTER EQUATION

Stochastic processes:

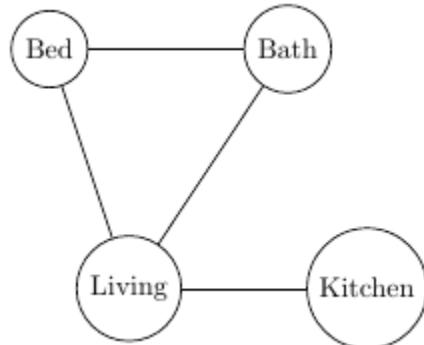
- Set of states
- Transition rates
- Distribution over states

$$\frac{d}{dt}P_i(t) = \sum_j W_{ji}P_j(t) - \sum_j W_{ij}P_i(t),$$

Conservation of mass \rightarrow probability

$$\frac{d}{dt} \int_V \rho dV + \oint_S \rho \mathbf{v} \cdot d\mathbf{S} = 0$$

Classical example: Random walk in a graph



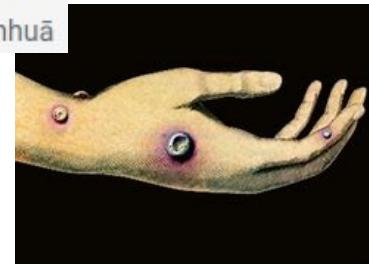
SMALLPOX IN XVIII CENTURY

1760-1766 Daniel Bernoulli at Royal Academy of Science
Effects of smallpox on life expectancy.



天花

Tiānhuā



SMALLPOX IN XVIII CENTURY

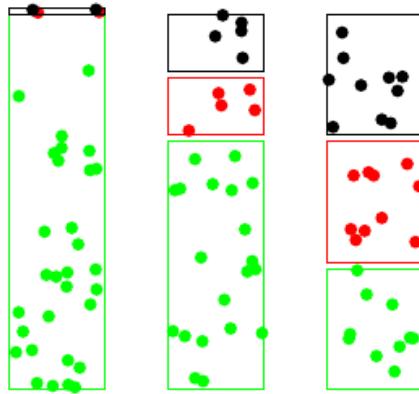
1760-1766 Daniel Bernoulli at Royal Academy of Science
Effects of smallpox on life expectancy.

- $u(a)$ the probability for an individual of being alive and susceptible (uninfected) at age a
- $w(a)$ the probability for an individual of being alive and immune at age a
- $d(a)$ is the probability of being dead at age a , but since probabilities add up to 1, and there are only three possible states, $d(a) = 1 - u(a) - w(a)$.



$$\begin{aligned}\frac{du}{da} &= -(\lambda + \mu(a))u(a) \\ \frac{dw}{da} &= \lambda(1 - c)\mu(a)u(a) - \mu(a)w(a)\end{aligned}$$

SMALLPOX IN XIII CENTURY



Compartments contains people of a certain category

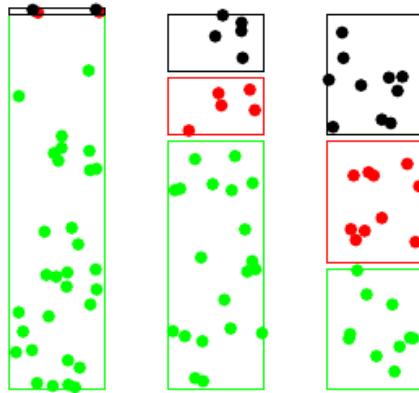
Compartments are:

- Susceptible
- Immune
- Dead

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SMALLPOX IN XIII CENTURY

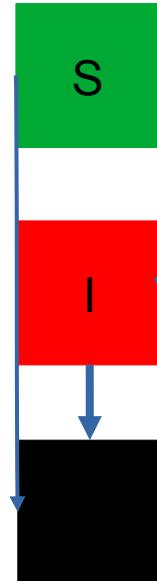


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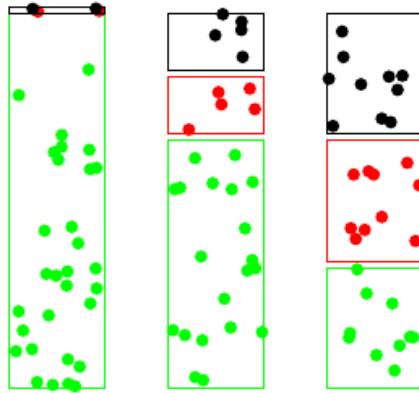
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- $\mu(a)$ the rate of death of all causes except smallpox, for an individual of age a
- β is the **force of infection**: the rate at which susceptible individual get infected
- $c = 1 - s$ the fraction of individuals infected that dies of smallpox.



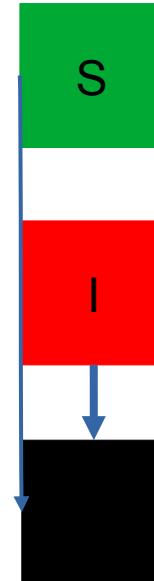
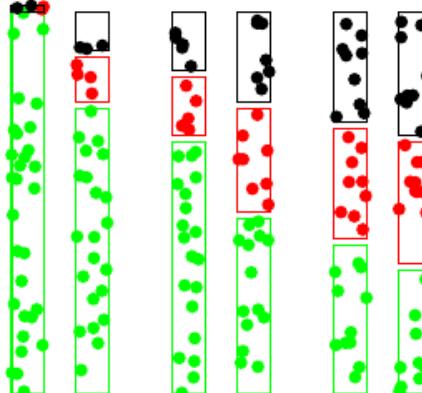
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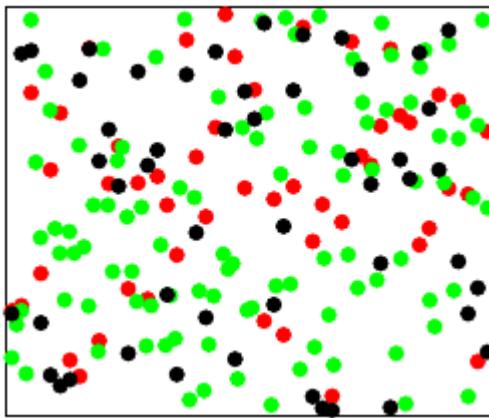
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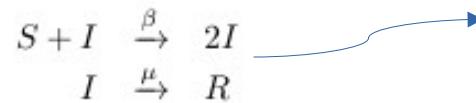
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COMPARTMENTAL MODELS

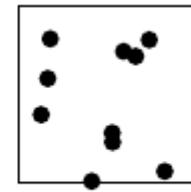
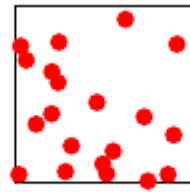
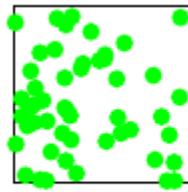
A gas of persons



Catalytic reactions



- Stochastic process
- Monte Carlo simulation
- Gillespie Alrogirthm



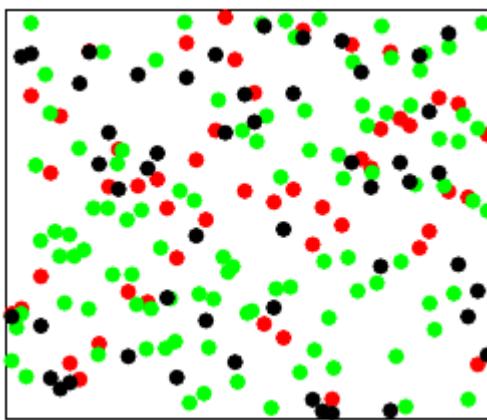
Compartment S

Compartment I

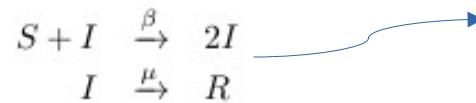
Compartment R

COMPARTMENTAL MODELS

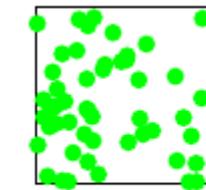
A gas of persons



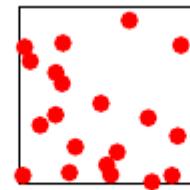
Catalytic reactions



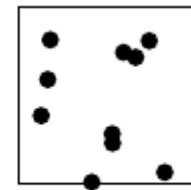
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Compartment S



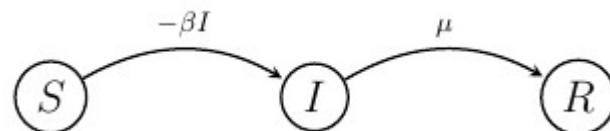
Compartment I



Compartment R

Compartmental model:

- Mean field approximation
- Well mixed
- No spatial correlations



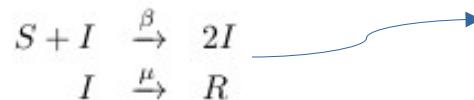
COMPARTMENTAL MODELS

$$\frac{dS}{dt} = -\beta SI$$

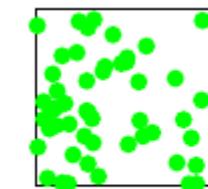
$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dR}{dt} = \mu I$$

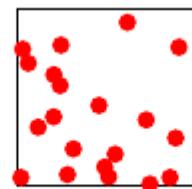
Catalytic reactions



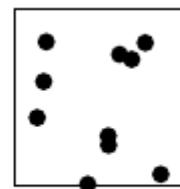
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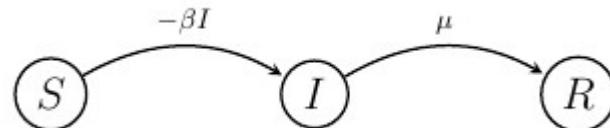
Compartment I



Compartment R

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- Well mixed
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Kermack, W.O. and A.G. McKendrick (1932) Contributions to the mathematical theory of epidemics, part. II, *Proc. Roy. Soc. London*, **138**:55-83.

COMPARTMENTAL MODELS

Probabilities

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dR}{dt} = \mu I$$

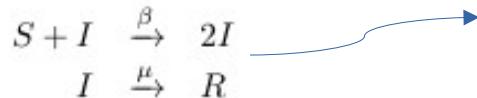
Extensive

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

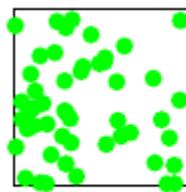
$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

$$\frac{dR}{dt} = \gamma I,$$

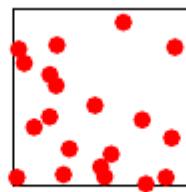
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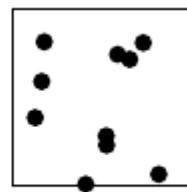
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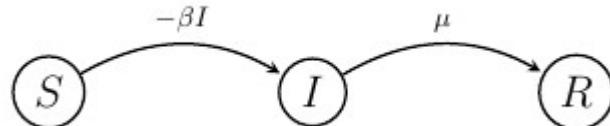
Compartment S



Compartment I



Compartment R



TECHNICAL TERMS

Technical terms

EARLY EPIDEMICS

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta S(t)I(t) - \mu I(t),$$

$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dI}{dt} = \lambda I(t), \quad \text{where } \lambda = \beta - \mu.$$

$$\frac{dR}{dt} = \mu I$$

$$I(t) = I(0) \exp(\lambda t).$$

Basic reproduction number

$$R_0 = \beta\tau = \beta/\mu$$

$$\tau = 1/\mu$$

Attention,
exponentials



LARGE TIME LIMIT

$$\frac{dS}{dt} = -\beta SI \quad S'(t) + I'(t) = -\mu I(t) \quad 1 - S_\infty = \mu \int_0^\infty I(t) dt$$

$$\frac{dI}{dt} = \beta SI - \mu I \quad \frac{d \log S(t)}{dt} = -\beta I(t)$$

$$\frac{dR}{dt} = \mu I \quad \log(S_\infty/S_0) = -\beta \int_0^\infty I(t) dt$$

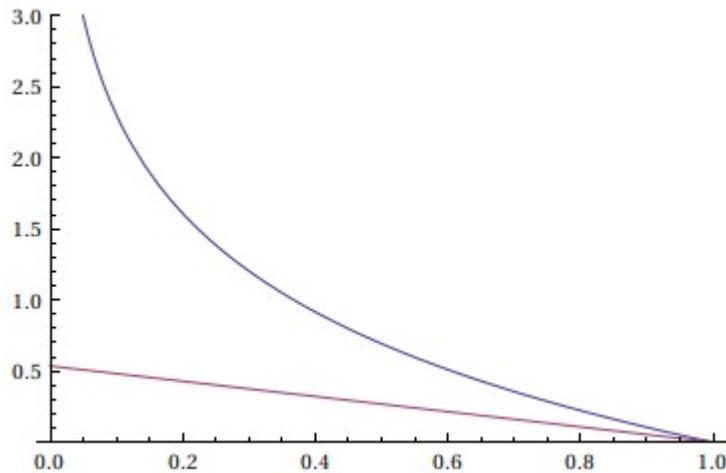
$$\log(S_0/S_\infty) = \frac{\beta}{\mu}(1 - S_\infty) \quad 1 - I_\infty \text{ or } 1 - \frac{I_\infty}{N}$$

is called the *attack rate*

$$= R_0(1 - S_\infty)$$

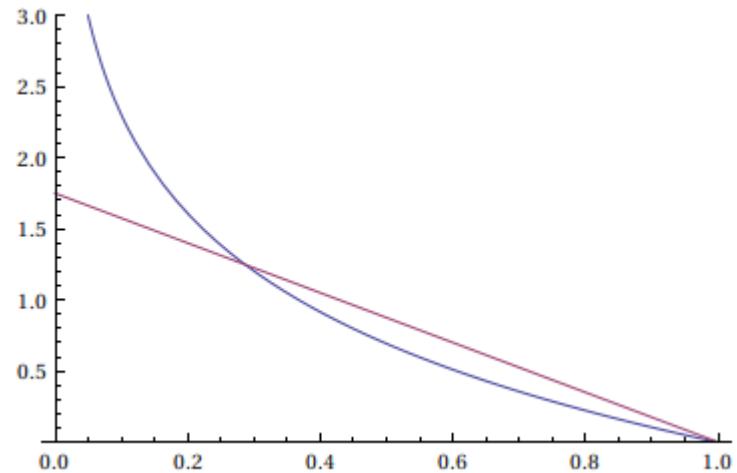
LARGE TIME LIMIT

$$\begin{aligned}\frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \mu I \\ \frac{dR}{dt} &= \mu I\end{aligned}$$



$$\log(S_0/S_\infty) = \frac{\beta}{\mu}(1 - S_\infty)$$

$$= R_0(1 - S_\infty)$$



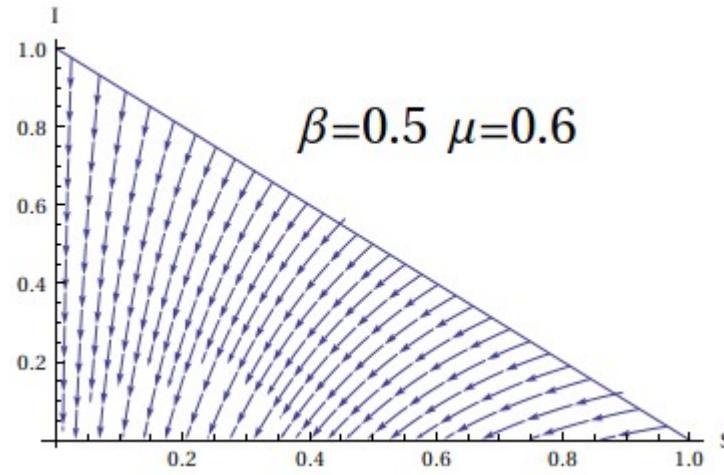
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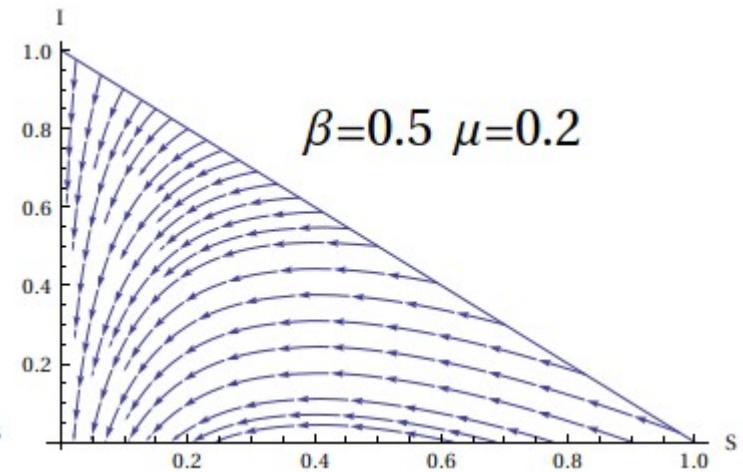
$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dR}{dt} = \mu I$$

$$I(t) + S(t) - \frac{\mu}{\beta} \log S(t) = 1 - \frac{\mu}{\beta} \log S_0$$



$\beta=0.5 \ \mu=0.6$



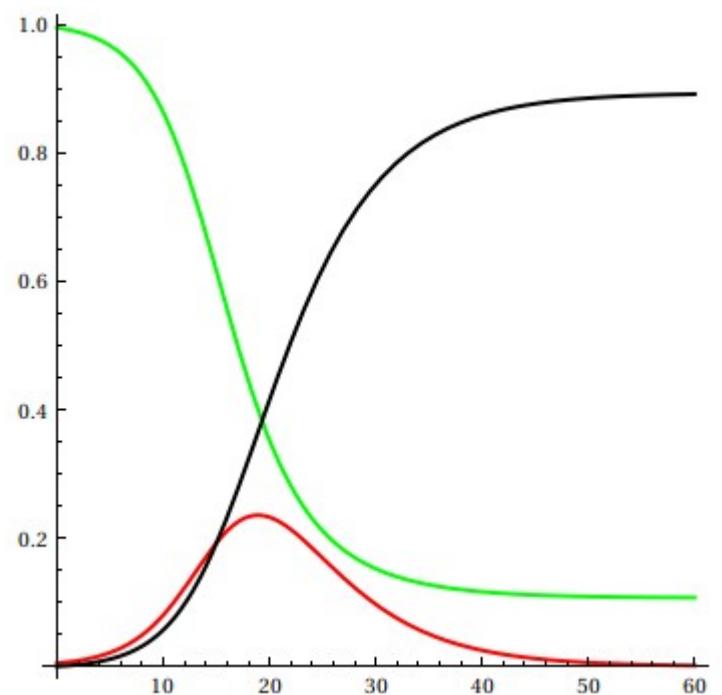
$\beta=0.5 \ \mu=0.2$

FINITE TIME INTEGRATION

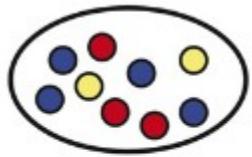
$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \mu I$$

$$\frac{dR}{dt} = \mu I$$



BEYOND SIR



**Homogeneous
mixing**

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

$$\frac{dR}{dt} = \gamma I,$$

Space

SIR

Time

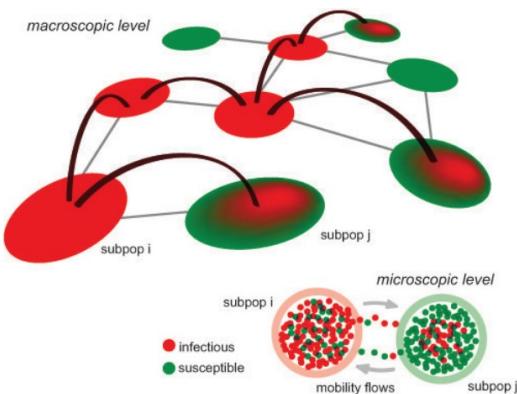
Compartments

Geographic patches:

- Countries, Cities, provinces, municipalities
- Mobility patterns
- Household, workplace, schools, commuters

Age patches:

- Seasonality
- Virus mutation
- Non pharmocological measu



SIR

Space

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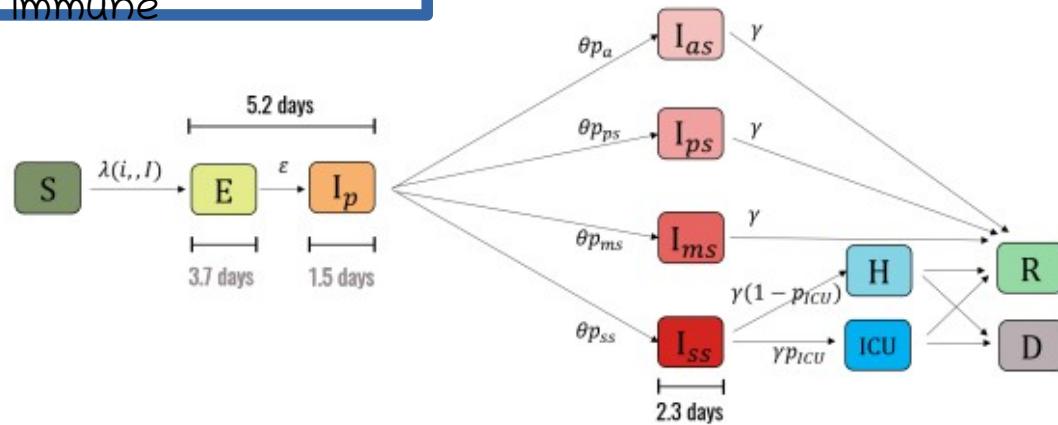
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Compartments

- Exposed
- Symptomatic vs Asymptomatic
- Quarantained
- Immune

Time



SIR

Space

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- Virus mutation
- Non pharmocolical measures

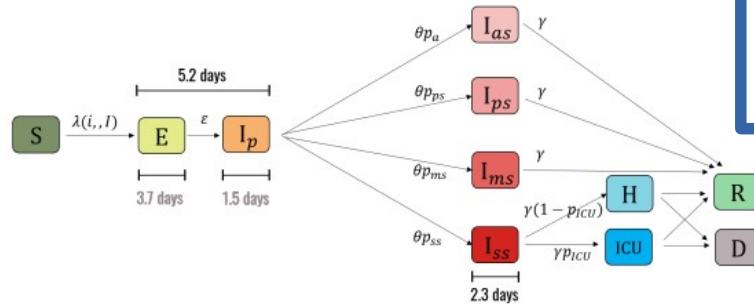
Compartments

- Exposed
- Symptomatic vs Asymptomatic
- Quarantined
- Immune

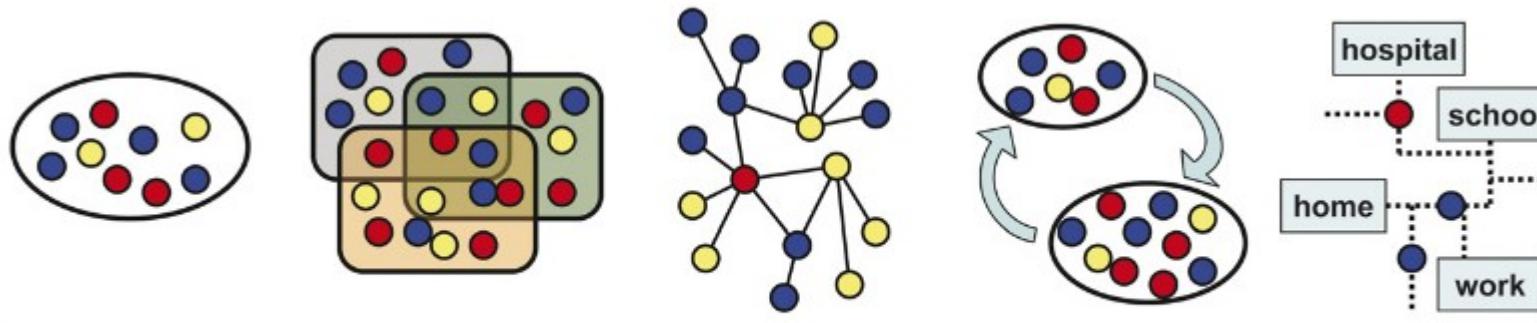
Time

Parameters in time:

- Seasonality
- Virus mutation
- Non pharmocolical measures
- Vaccination



MODELING EPIDEMICS



Homogeneous
mixing

Social structure

Contact network
models

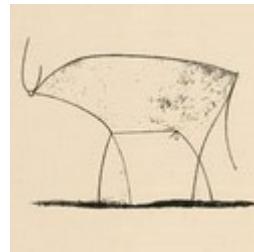
Multi-scale
models

Agent Based
models

MODELING EPIDEMICS

Simple

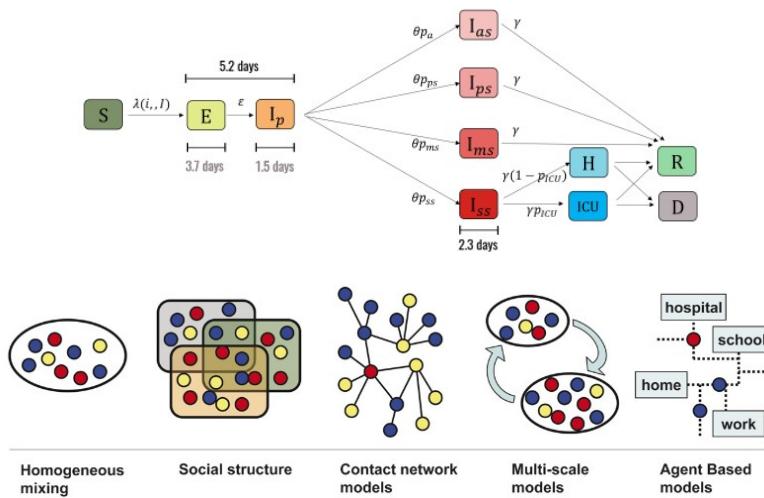
Un-specific



$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

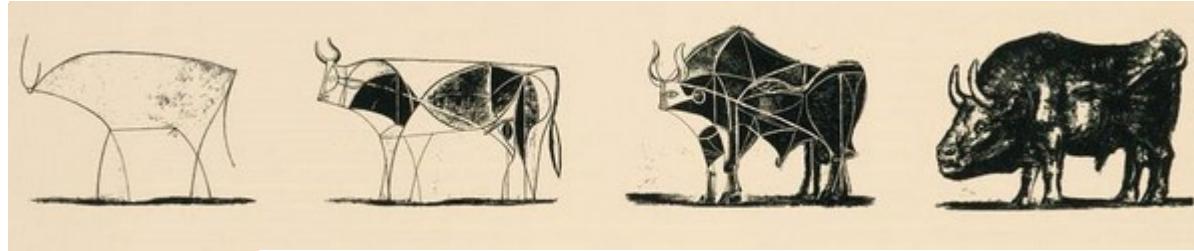
$$\frac{dR}{dt} = \gamma I,$$



MODELING EPIDEMICS

Simple

Un-specific

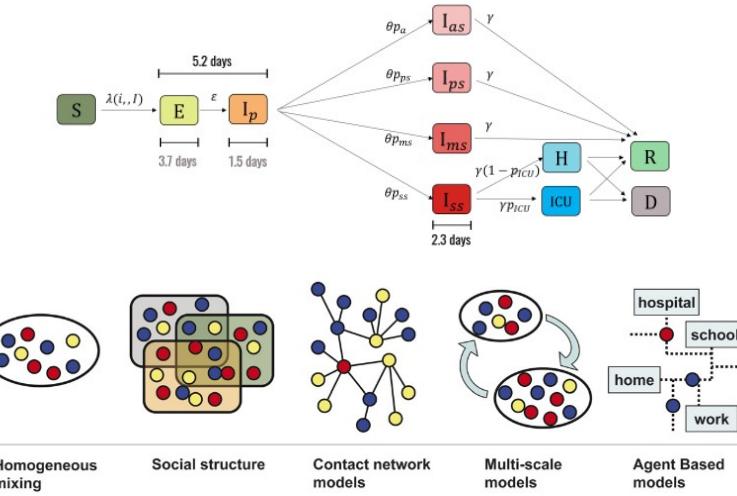


Complex
Specific

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

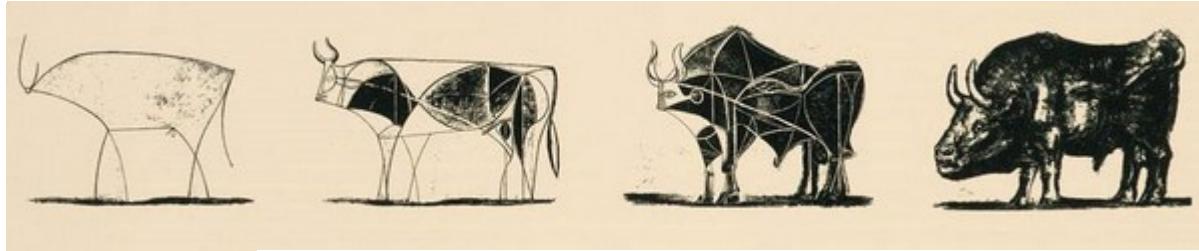
$$\frac{dR}{dt} = \gamma I,$$



MODELING EPIDEMICS

Simple

Un-especific



Complex

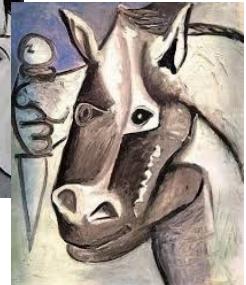
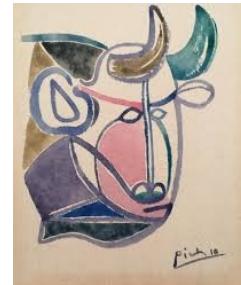
Specific

Hard to fit

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

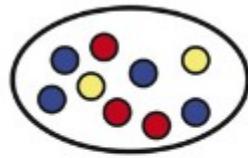
$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

$$\frac{dR}{dt} = \gamma I,$$

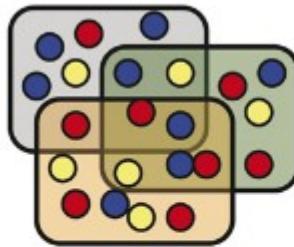


EPIDEMICS ON NETWORKS

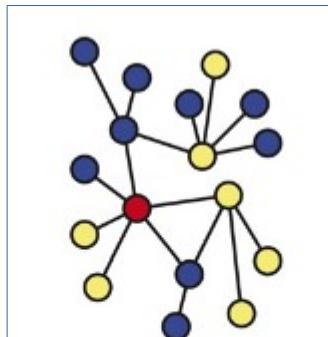
Nc



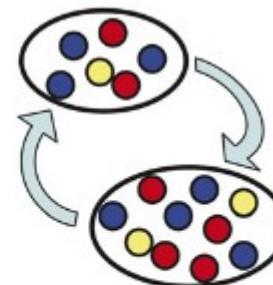
Homogeneous
mixing



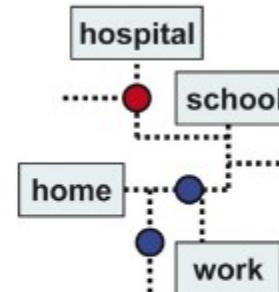
Social structure



Contact network
models



Multi-scale
models



Agent Based
models

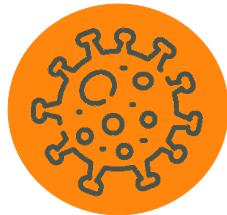
NEXT CLASS

Introduction to graphs and networks

Graph metrics

Graphs for benchmarking

Representing graphs on Python

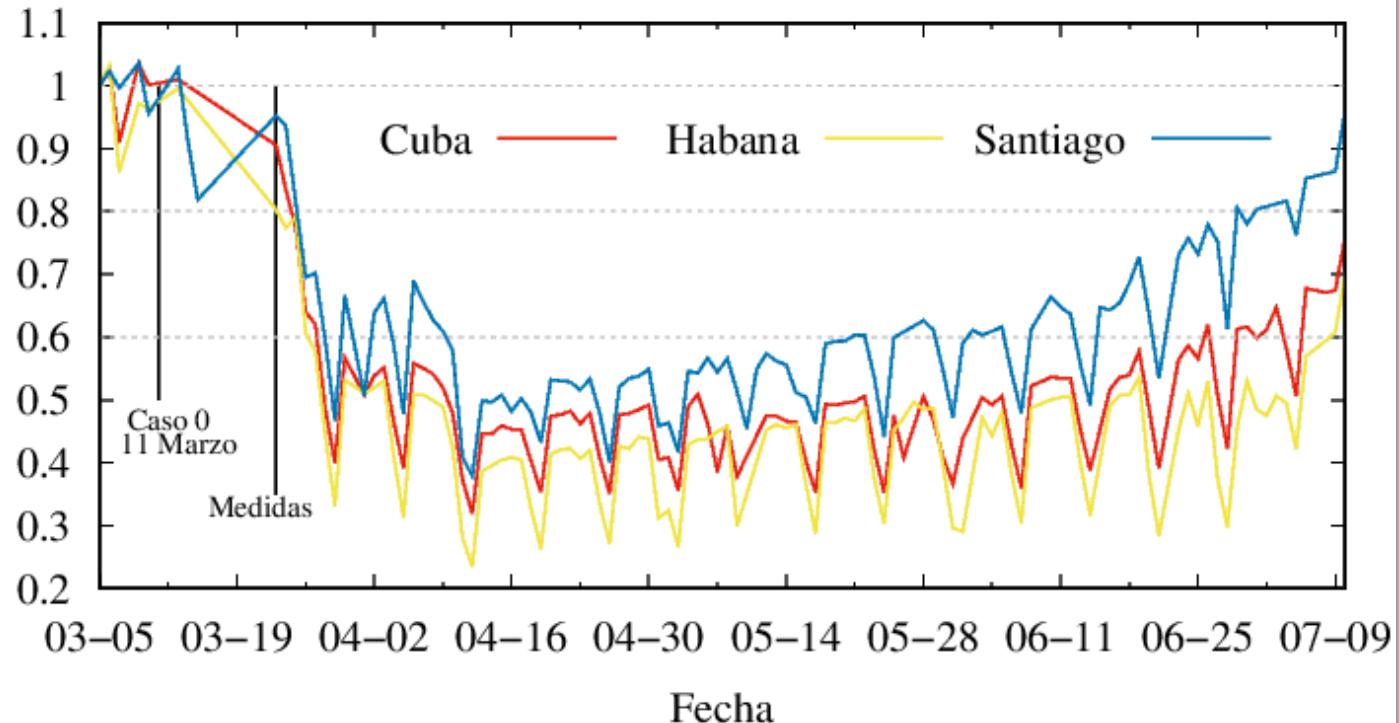


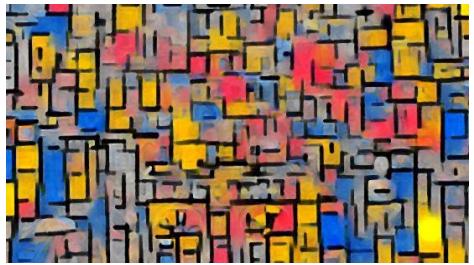
MOVILIDAD Y COVID

COVID 2020

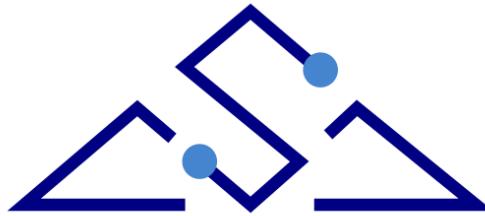
- Primer caso 11 de marzo
- Cierre de escuelas, 23 de marzo
- Cierre transporte, 3 de abril

Movilidad relativa a Marzo





你好



CENTRO DE **SISTEMAS
COMPLEJOS**

Facultad de Física
Universidad de La Habana

WHY SHOULD YOU CARE?

Recent epidemics:

Covid, SARS, HIV, Ebola

Each epidemic is different. And you have one opportunity.

You can not do experiments with epidemics.

Epidemics is part of a more general set of problems, like the spread of information, the expansion of memes, computer viruses. Stochastics processes running on networks.

A field that is changing: big data, cellphones, social networks, allow for new descriptions of the phenomena.