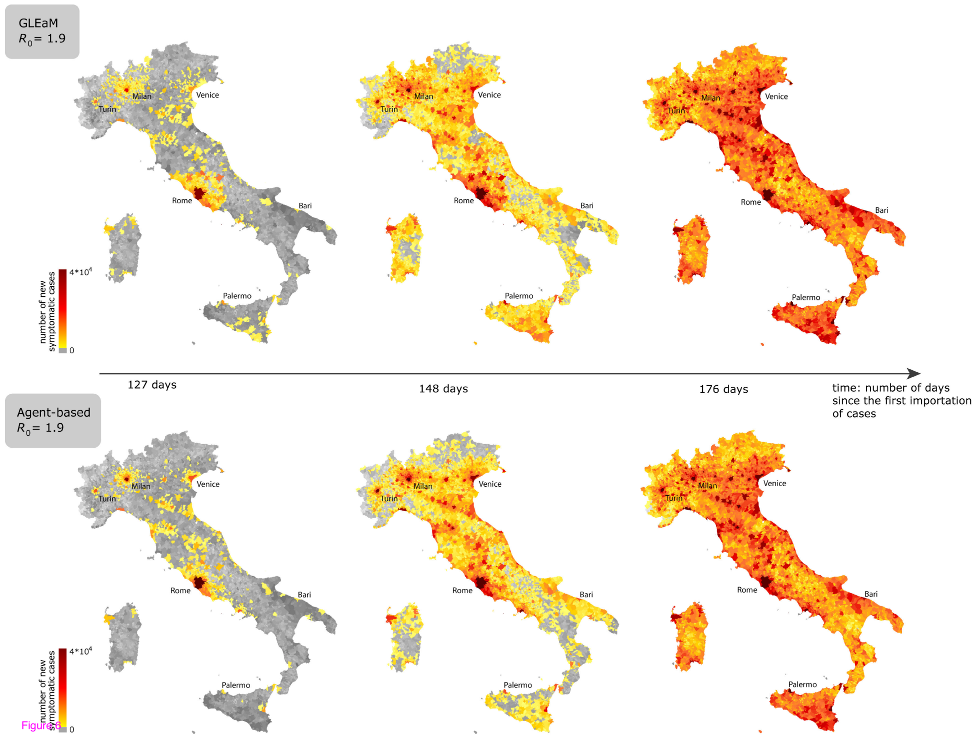
Network Science

Part 2

Spreading processes on networks

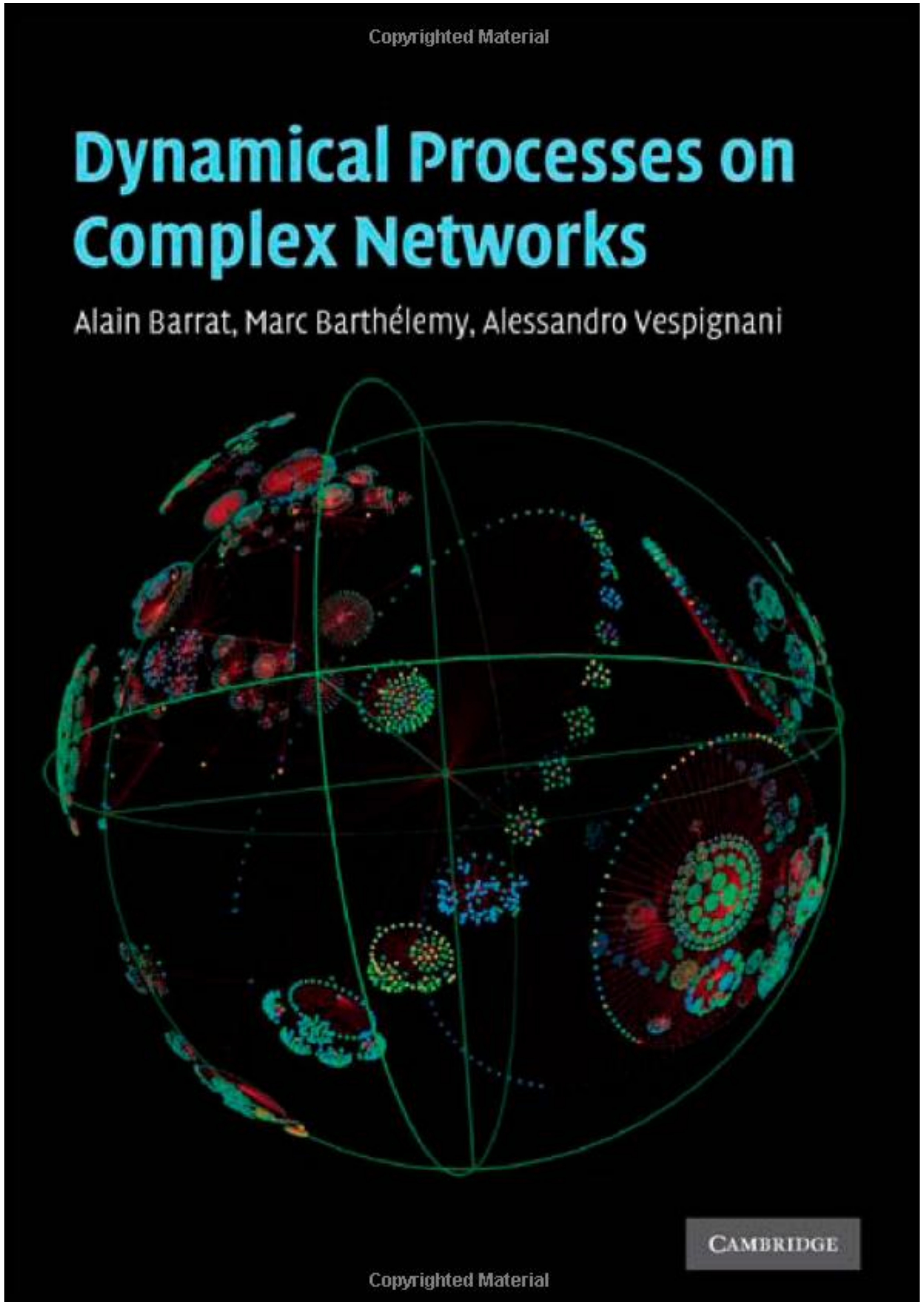


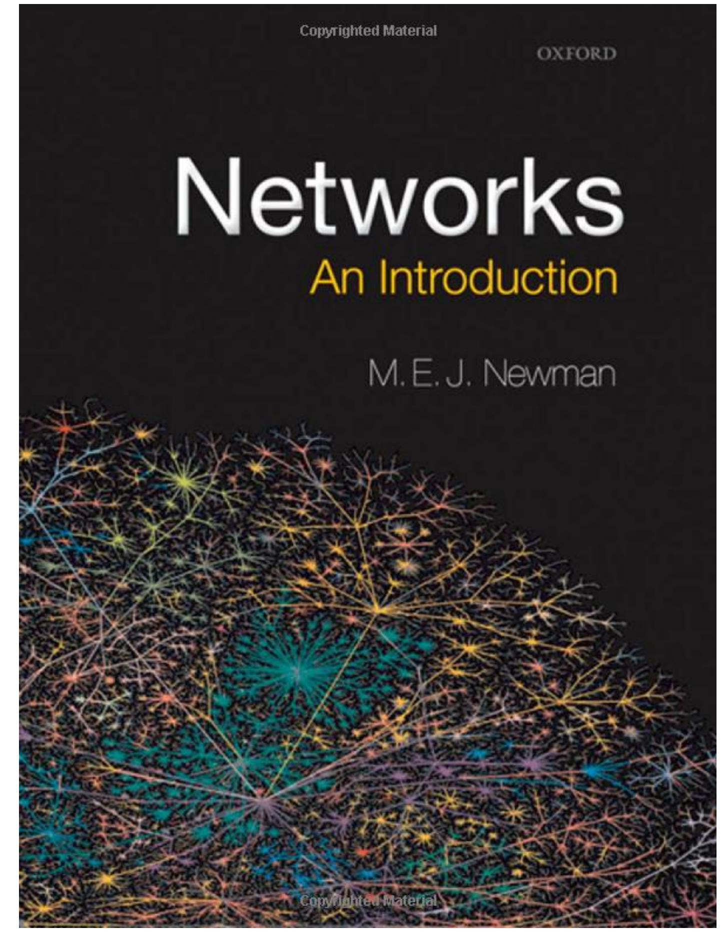
Márton Karsai
Central European University

Todays schedule

1. Real world spreading processes
2. Simple models of epidemic spreading
3. Epidemics spreading on networks
4. Immunisation strategies

Literature





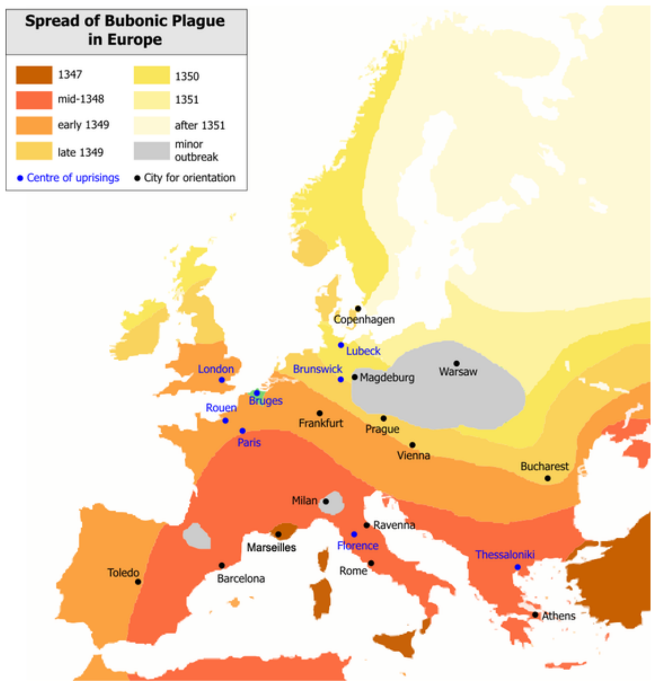
Epidemic processes in complex networks

Romualdo Pastor-Satorras,[1] Claudio Castellano,[2,3] Piet Van Mieghem,[4] and Alessandro Vespignani[5,6]
[1] *Departament de Física i Enginyeria Nuclear, Universitat Politècnica de Catalunya, Campus Nord B4, 08034 Barcelona, Spain*
[2] *Istituto dei Sistemi Complessi (ISC-CNR), via dei Taurini 19, I-00185 Roma, Italy*
[3] *Dipartimento di Fisica, "Sapienza" Università di Roma, P.le A. Moro 2, I-00185 Roma, Italy*
[4] *Delft University of Technology, Delft, The Netherlands*
[5] *Laboratory for the Modeling of Biological and Socio-technical Systems, Northeastern University, Boston MA 02115 USA*
[6] *Institute for Scientific Interchange Foundation, Turin 10133, Italy*

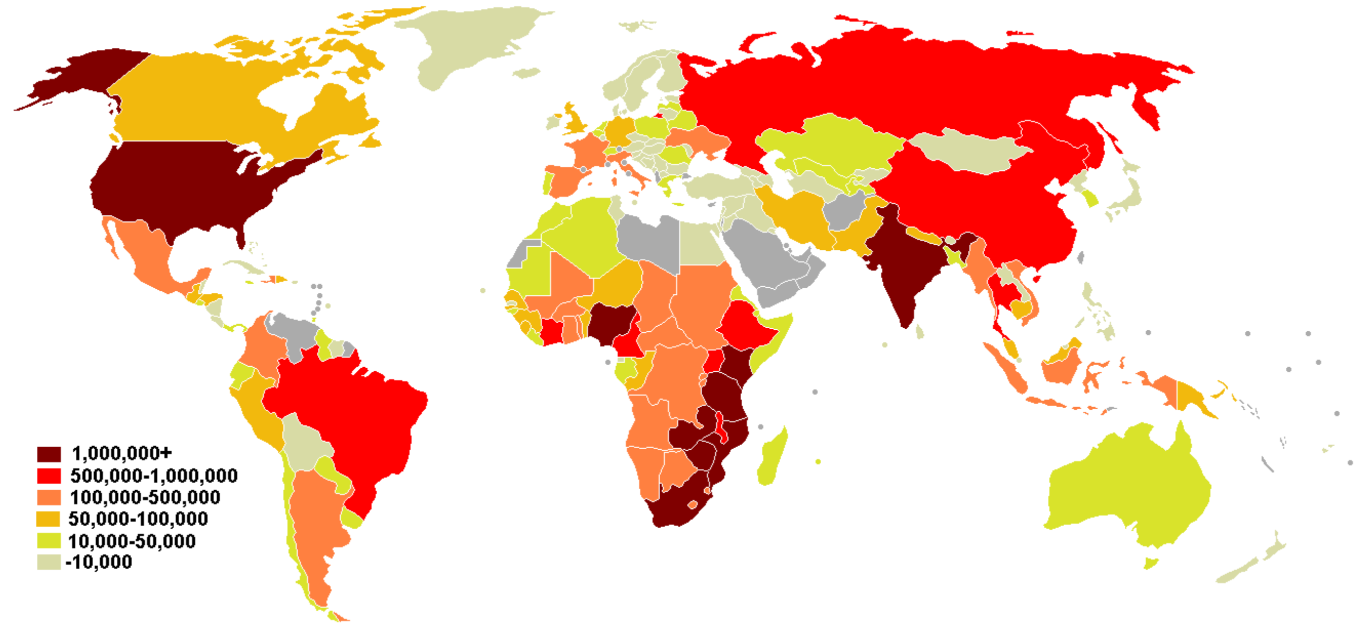
(Dated: March 18, 2014)

Spreading processes

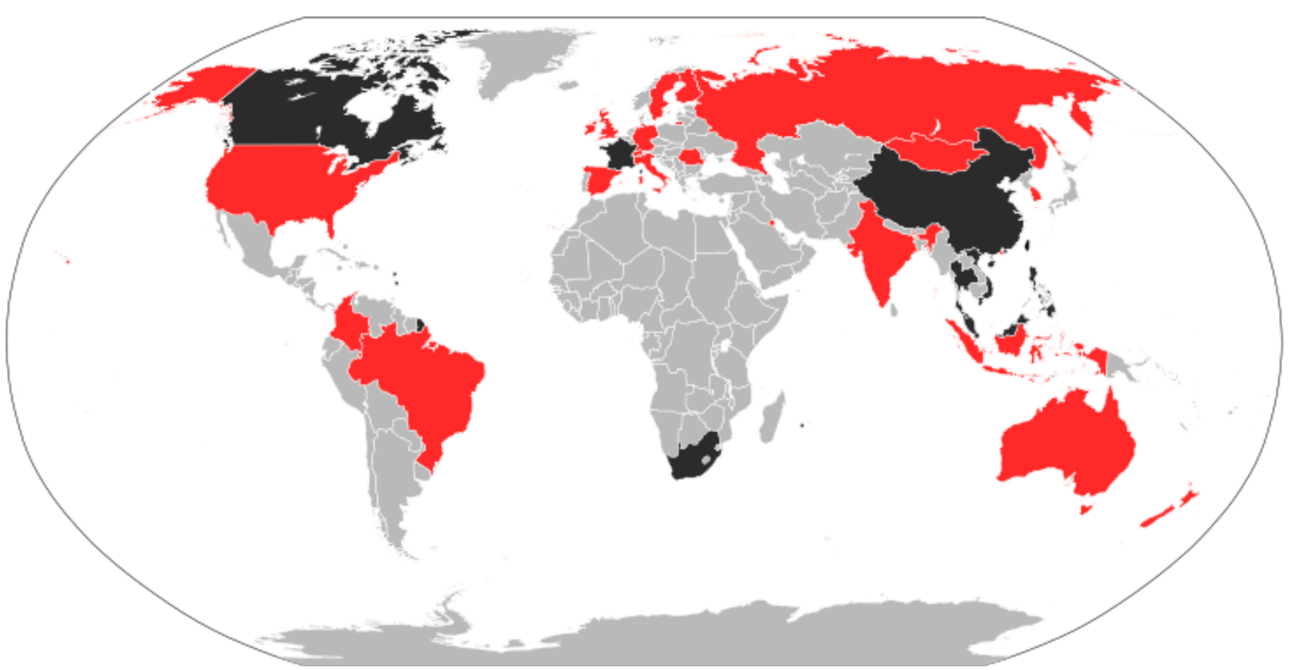
Biological epidemic spreading



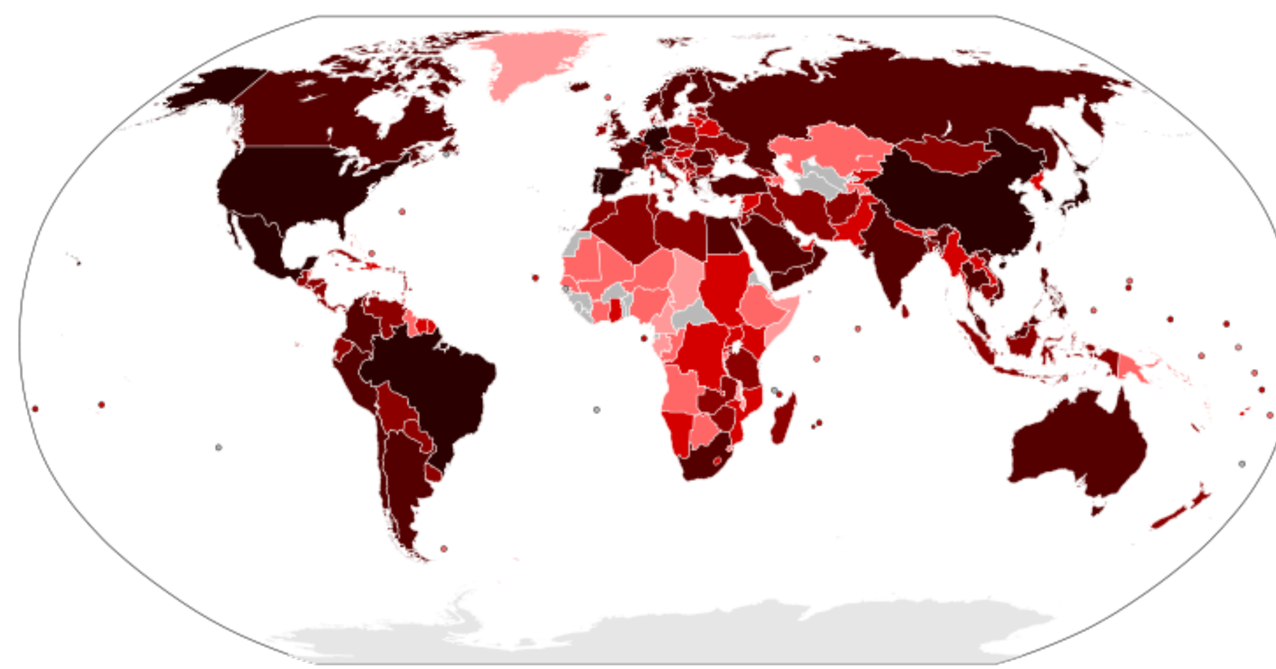
The great plague (14th century)



HIV (2008)



SARS (2008)

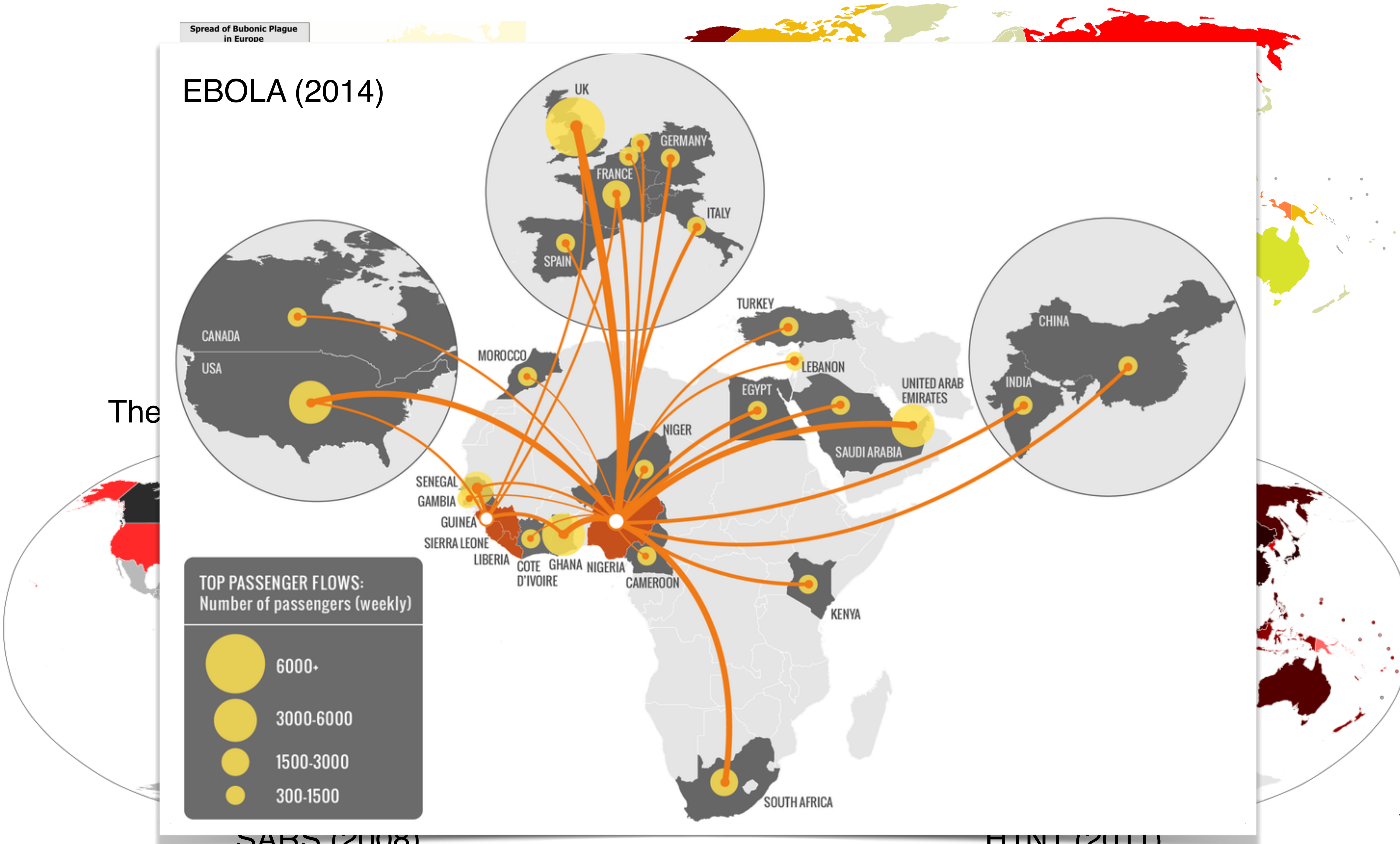


H1N1 (2011)

Wikipedia

Spreading processes

Biological epidemic spreading



The

SARS (2008)

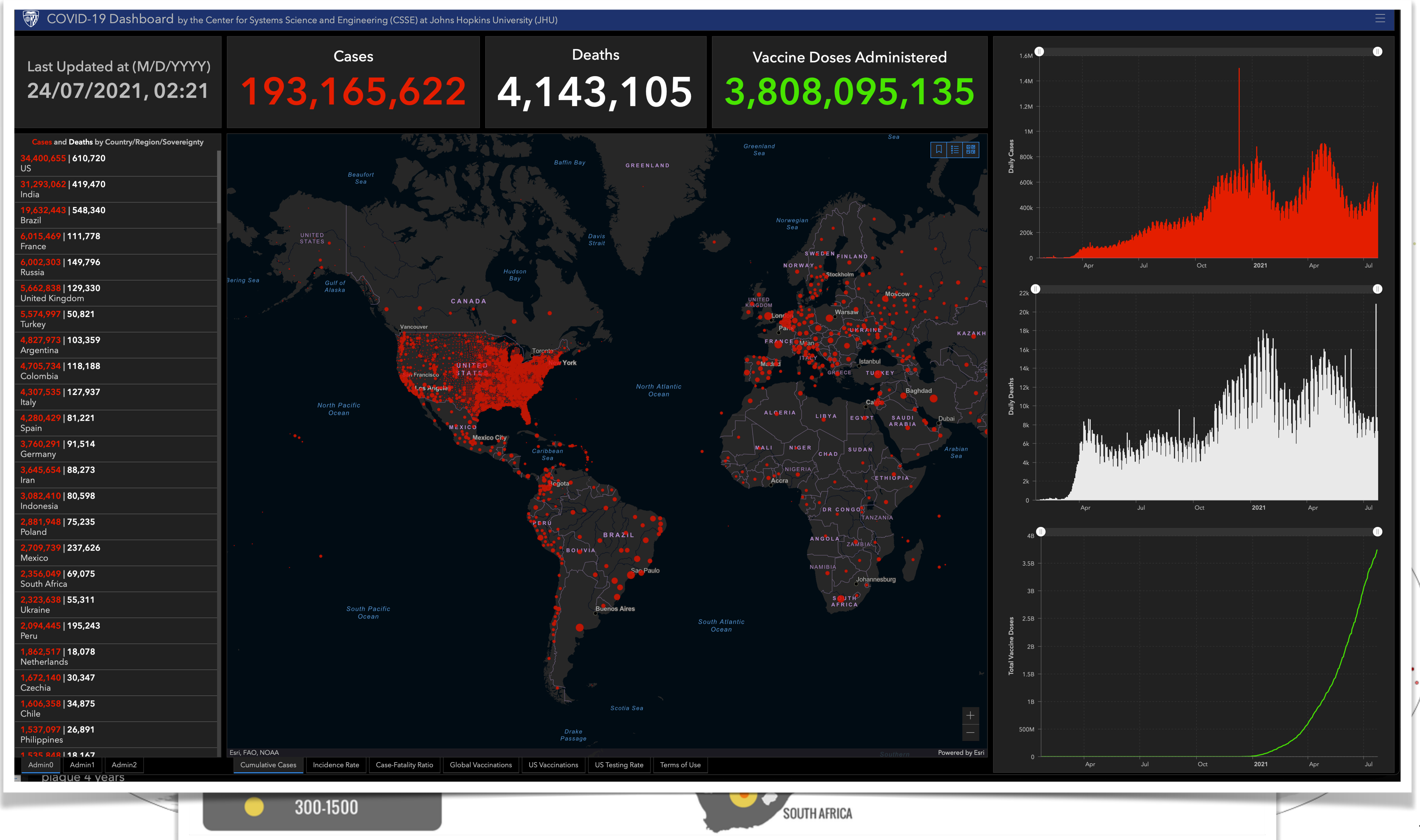
H1N1 (2011)

Wikipedia

Spreading processes

Biological epidemic spreading

SARS Cov-2 (2020/21)



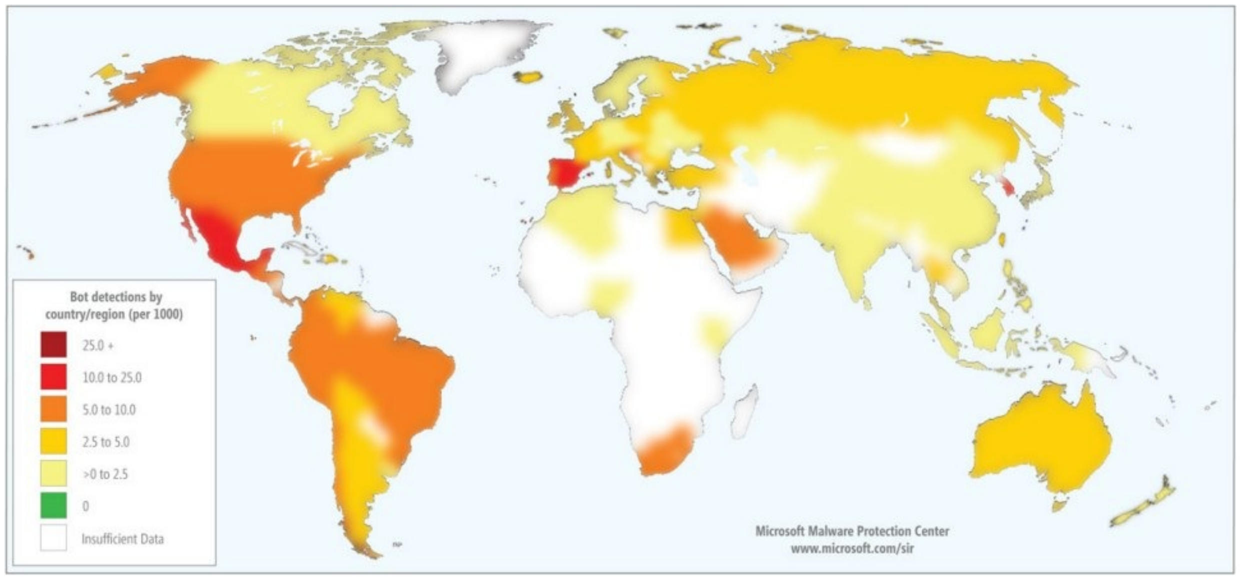
SARS (2008)

H1N1 (2011)

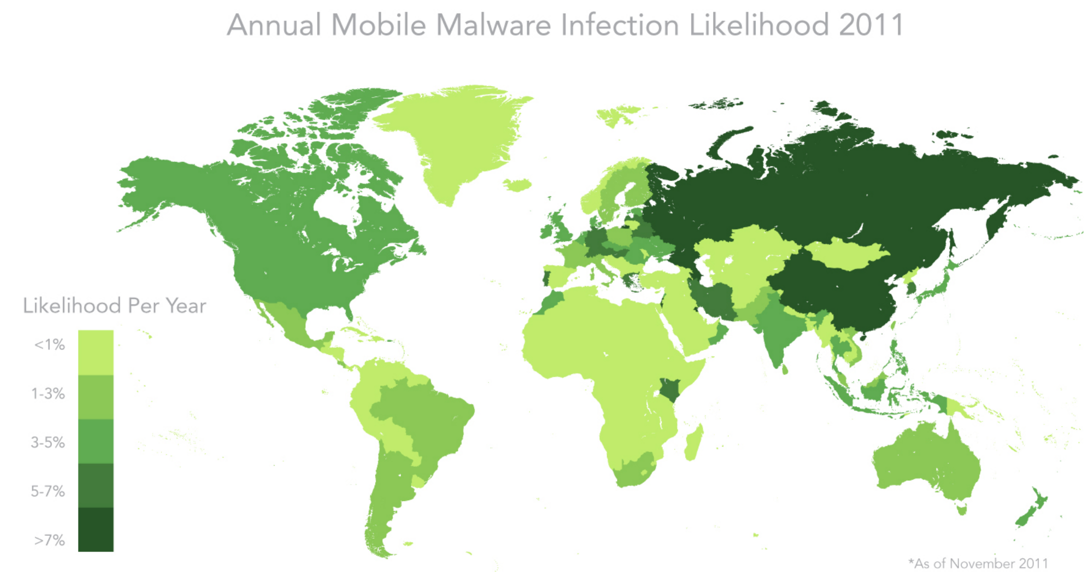
Wikipedia

Spreading processes

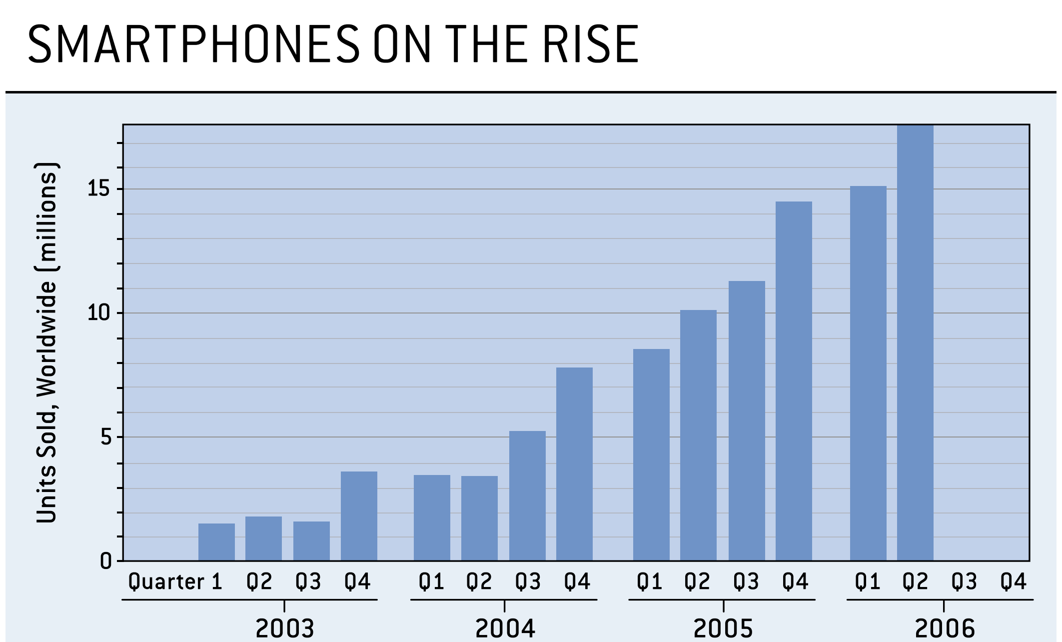
Malware spreading

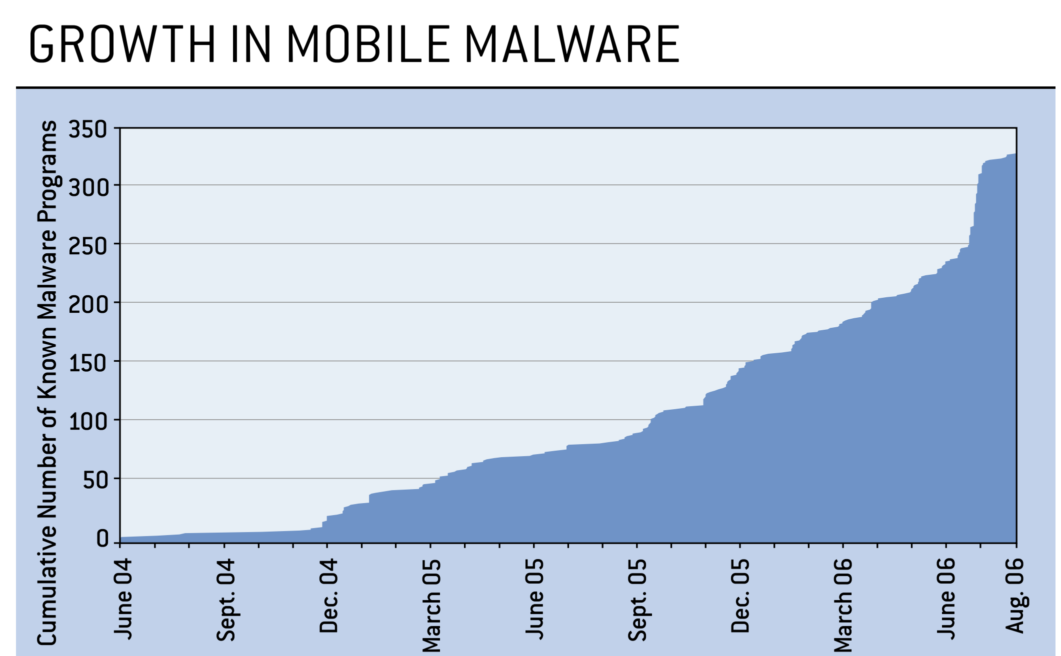


Botnet infections (2010)



Mobile malware (2011)

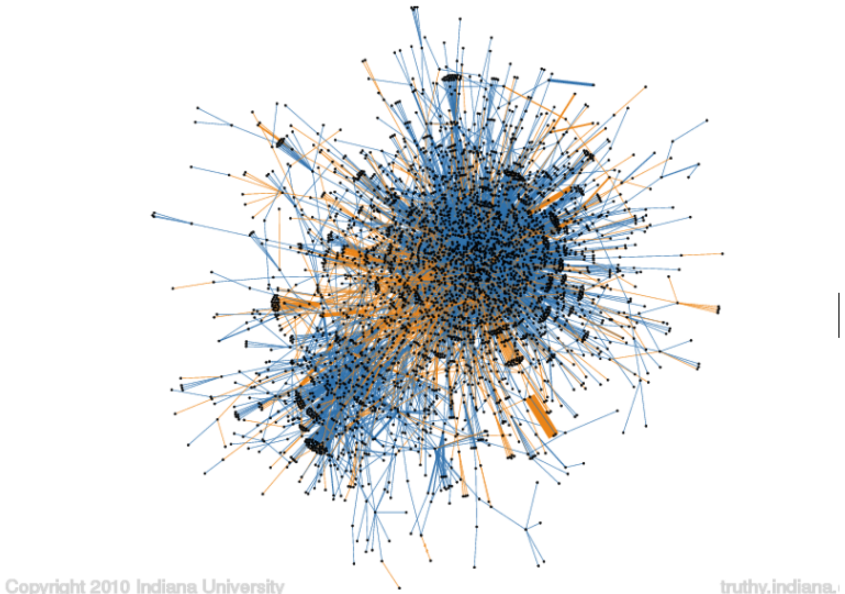




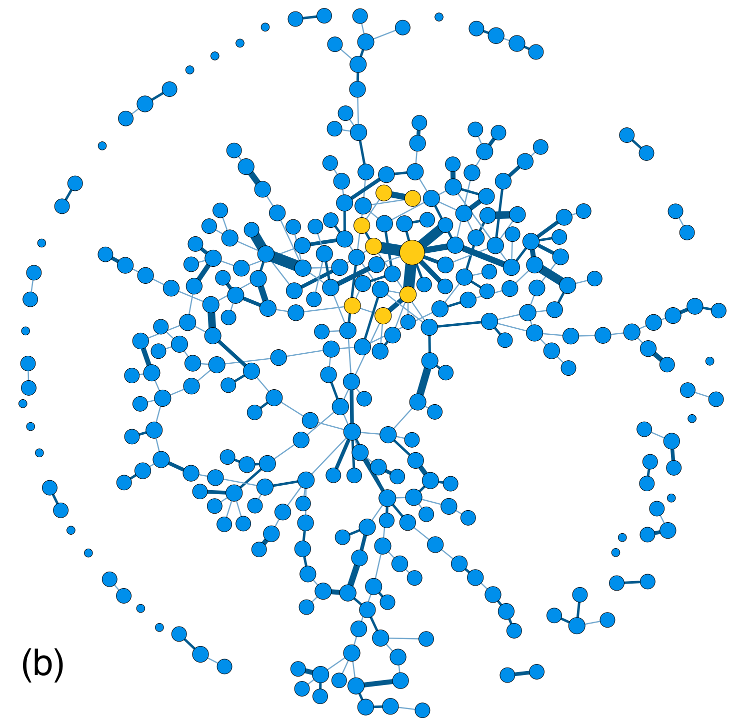
Hypponen M. *Scientific American* Nov. 70-77 (2006).

Spreading processes

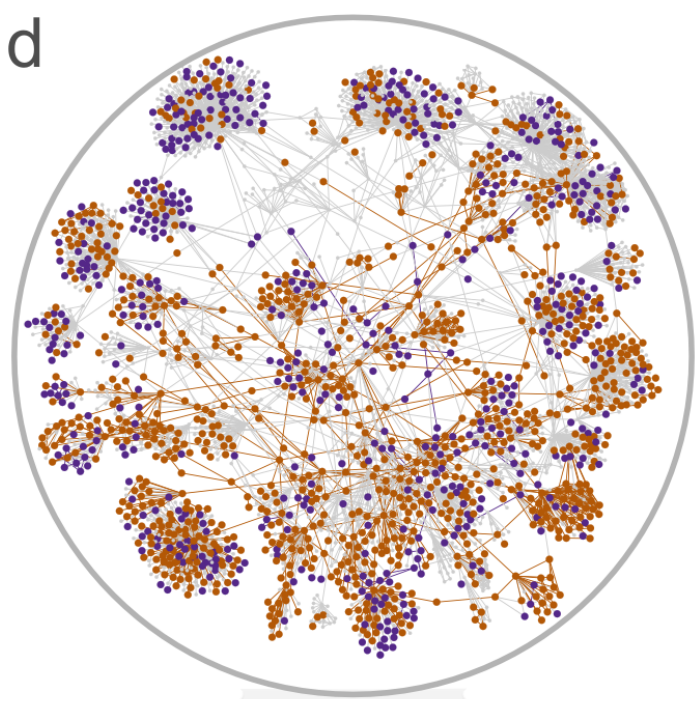
Social contagion



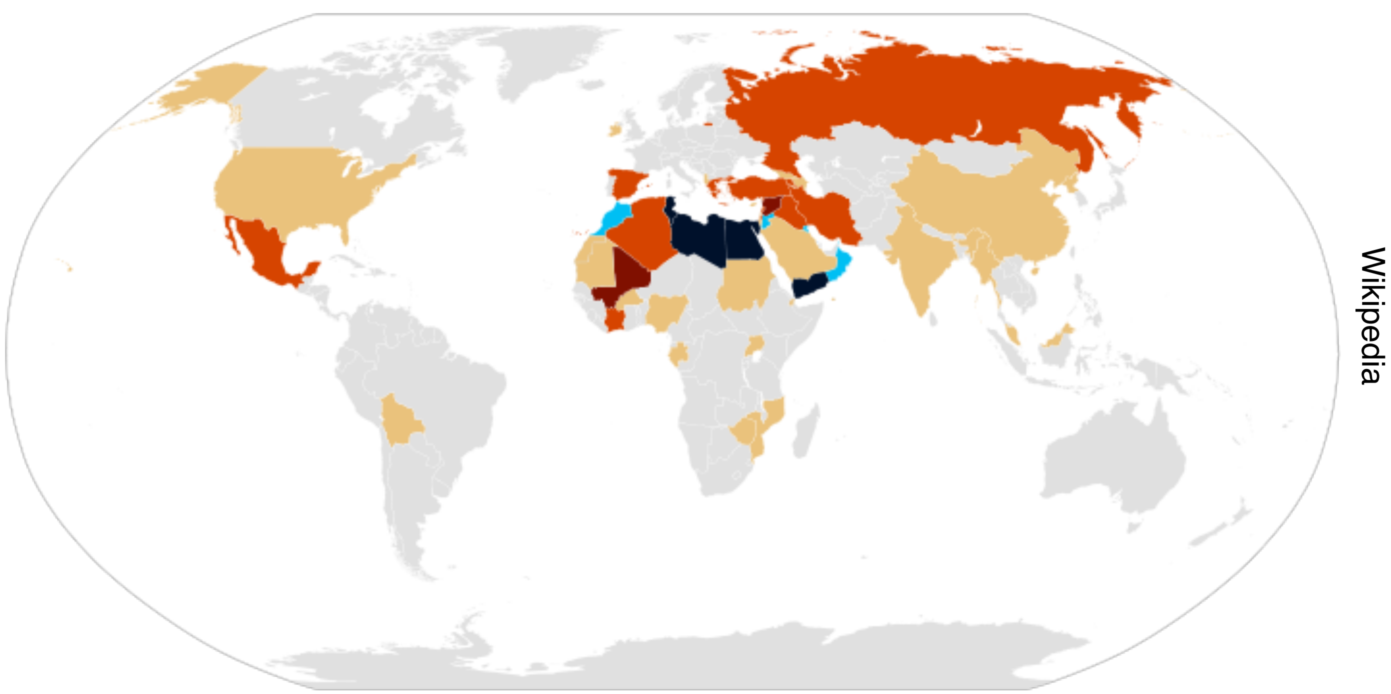
Information spreading



Rumour spreading
Karsai et.al. (2014)



Adoption spreading (Skype)
Karsai et.al. (2014)



Protest diffusion (Arabian spring)

Spreading processes

Why?

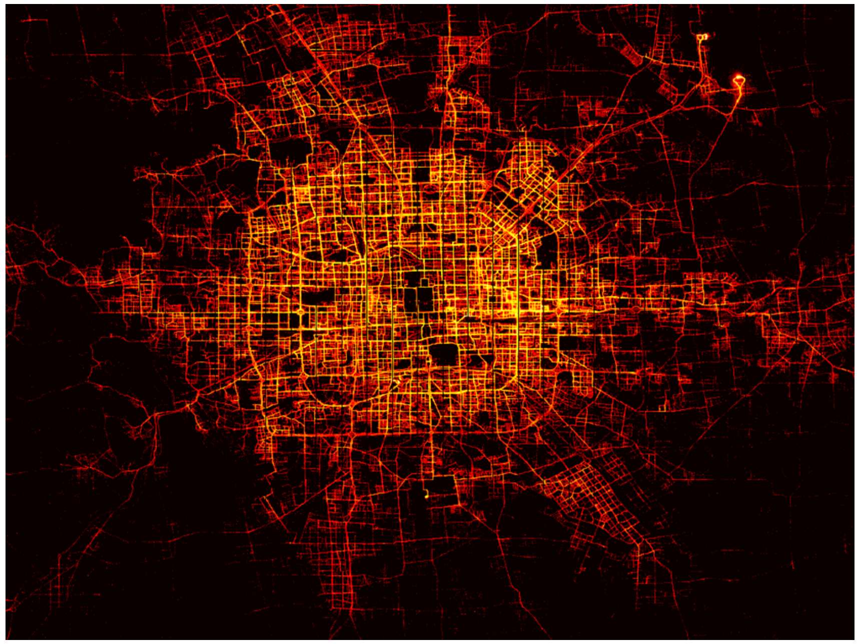
- High population density
- Interconnected and mixing population
- Dynamical mobility patterns

Why on networks?

- Spreading can happen only through interactions between agents
  - Geographic vicinity
  - Physical connection
  - Social interaction
  - etc.
- Network structure critically influence the dynamics of spreading processes

PPD blog, Jooseery (2011)

Freese (2009)



Unknown

Why modelling?

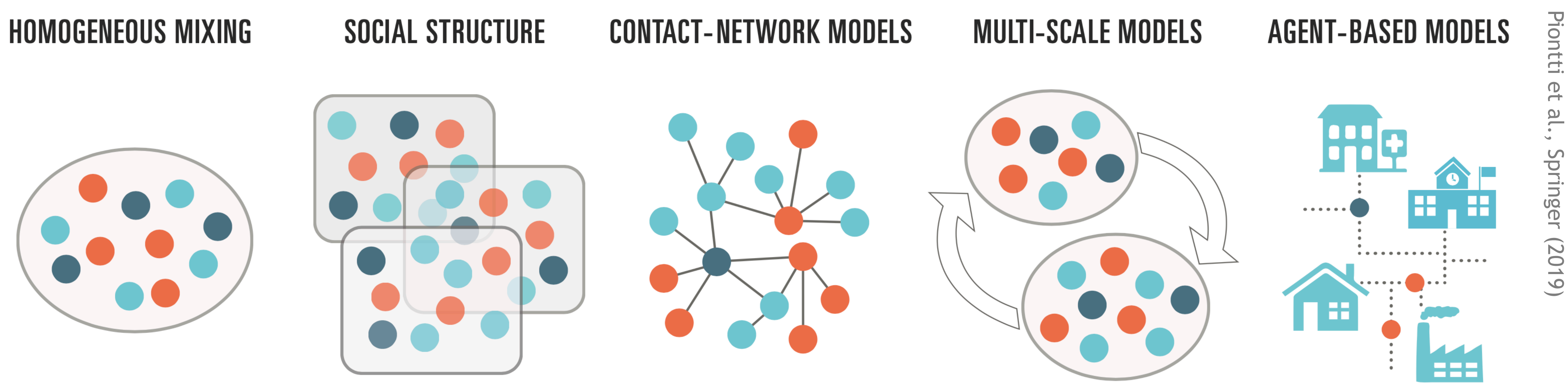
Predictions

- They are important for the design of effective interventions
  - Transmission reduced intervention
  - Contact reducing interventions
  - Vaccination strategies

Types of predictions

- ‘What if’ analysis
  - Prototypical values for spreading parameters
  - To understand effects of time of interpretation of specific policies
  - To consider different scenarios of the epidemic outcome
- Real-time predictions
  - Based on several assumptions coming from earlier observations
  - Calibrate the model by as many key parameters as possible to observed during the epidemic outbreak
  - Match as less parameters from historical data as possible

Complexity of epidemics models



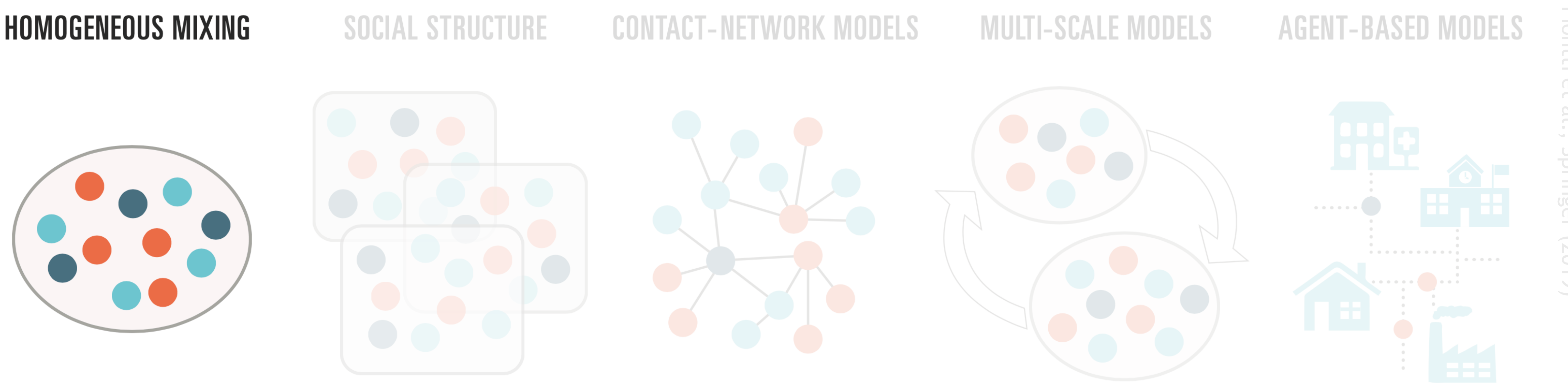
Computationally enabled

Simple

Realistic

Mathematically enabled

Complexity of epidemics models



Computationally enabled

Simple ⇄ **Realistic**

Mathematically enabled

Simple models

of

epidemic spreading

Spreading processes

Model assumptions of spreading processes

- Constant set of interacting agents
- Nodes are partitioned into distinct compartments based on their actual states
- States are defined by the distinct mutually exclusive stages of the epidemics:

Susceptible (S)
(Healthy)

Mi jin Lee's cartoons, (after P. Holme)

Spreading processes

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Mi jin Lee's cartoons, (after P. Holme)

Spreading processes

Model assumptions of spreading processes

- Constant set of interacting agents
- Nodes are partitioned into distinct compartments based on their actual states
- States are defined by the distinct mutually exclusive stages of the epidemics:

$$S+I+R=N$$

Susceptible (S)
(Healthy)

Infected (I)
(Sick)

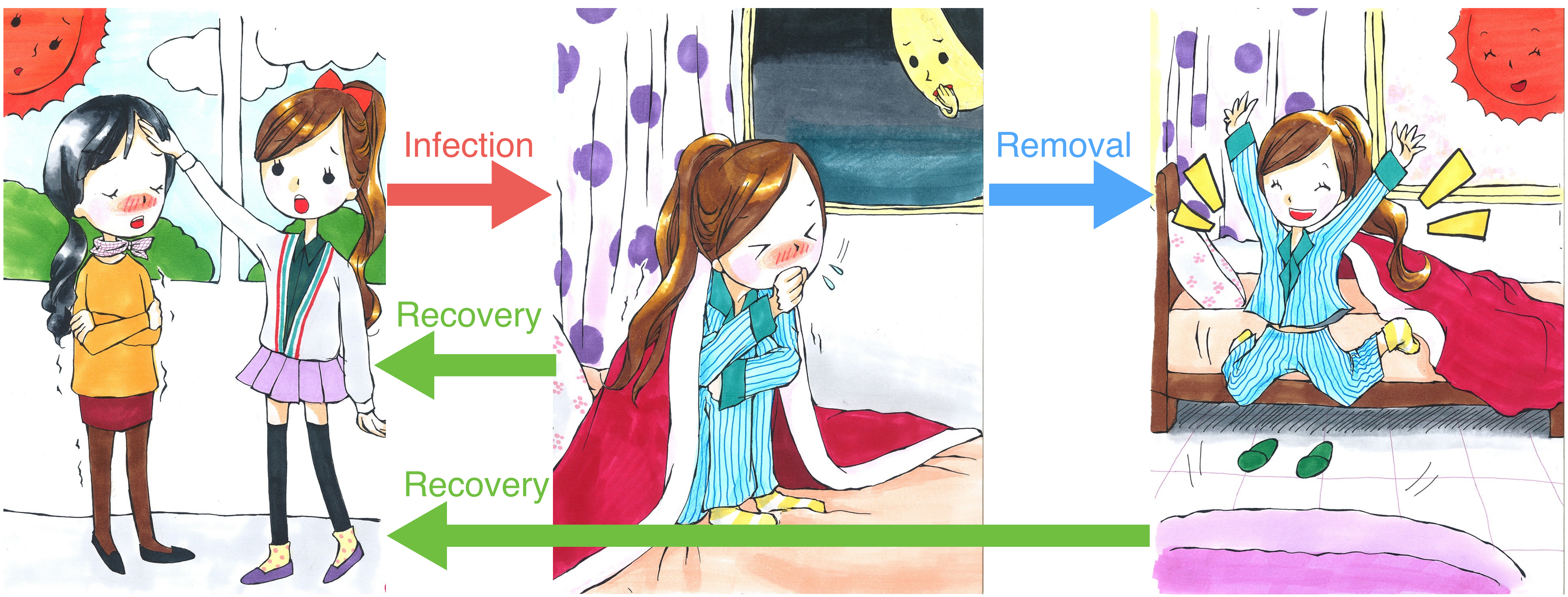
Recovered (R)
(Removed, dead)

Mi jin Lee's cartoons, (after P. Holme)

Spreading processes

Simple spreading phenomena

- Lack of decision to become infected
- State change depends on the absolute number of stimuli coming from neighbours
- Examples: epidemic spreading, biological contagion, information spreading, etc.



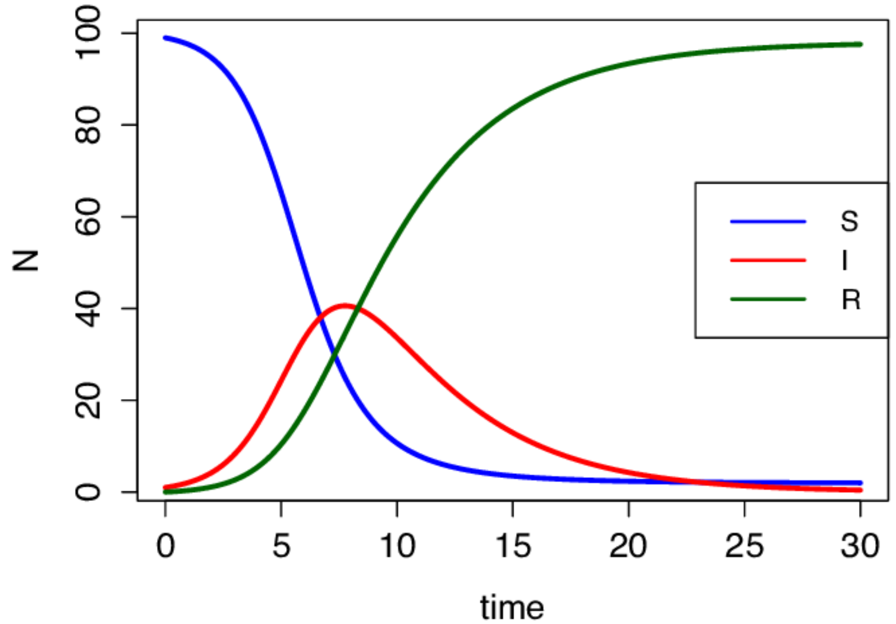
Mi jin Lee's cartoons, (after P. Holme)

Susceptible (S)
(Healthy)

Infected (I)
(Sick)

Recovered (R)
(Removed, dead)

Susceptible-Infected-Recovered (SIR) model



Basic reproduction number: $R_0 = \frac{\beta}{\mu}$

Average number new infections an infected node produces in a unit time

Infection

β

Removal

μ

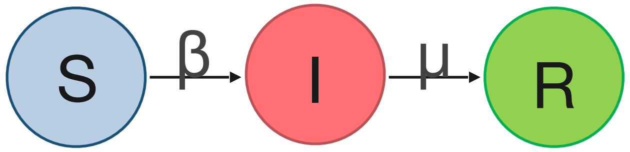
Mi jin Lee's cartoons, (after P. Holme)

Susceptible (S)
(Healthy)

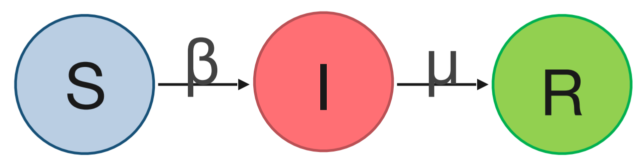
Infected (I)
(Sick)

Recovered (R)
(Removed, dead)

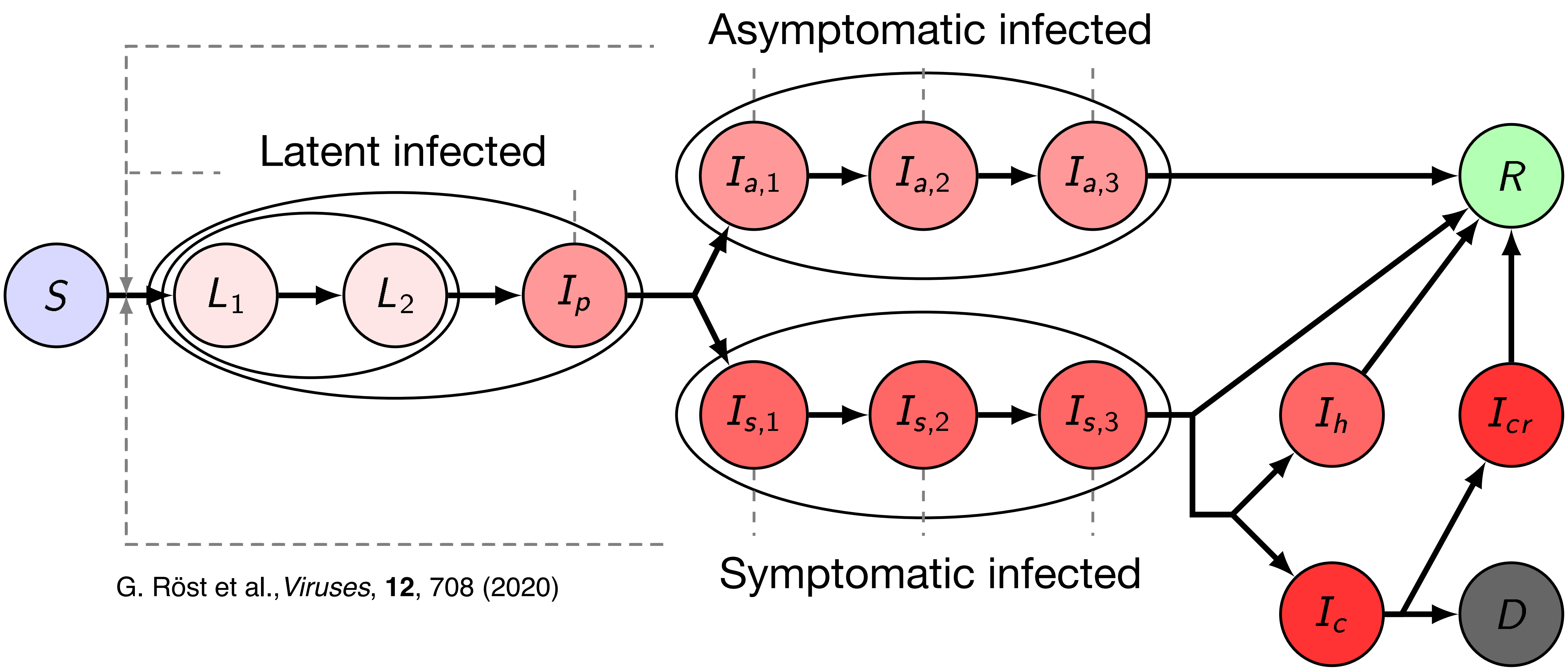
SIR transmission scheme



SIR transmission scheme

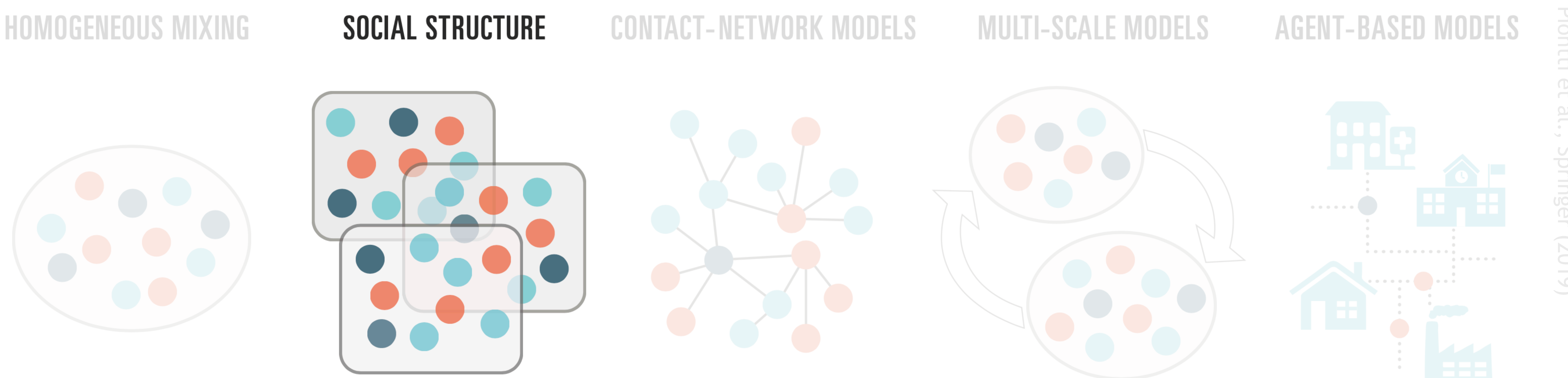


COVID-19 transmission scheme



G. Röst et al., *Viruses*, **12**, 708 (2020)

Complexity of epidemics models



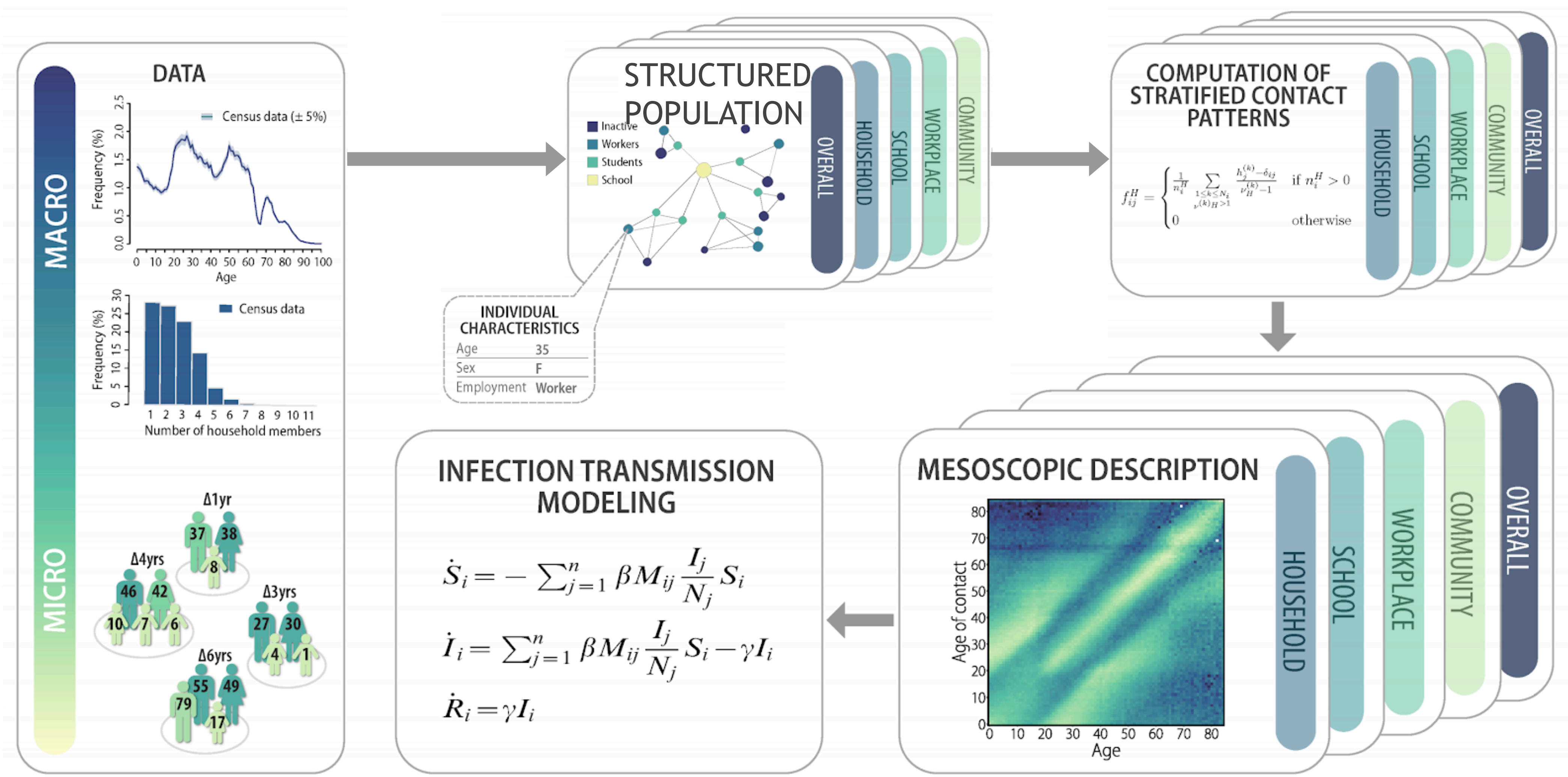
Computationally enabled

Simple

Realistic

Mathematically enabled

Epidemics models with stratified populations

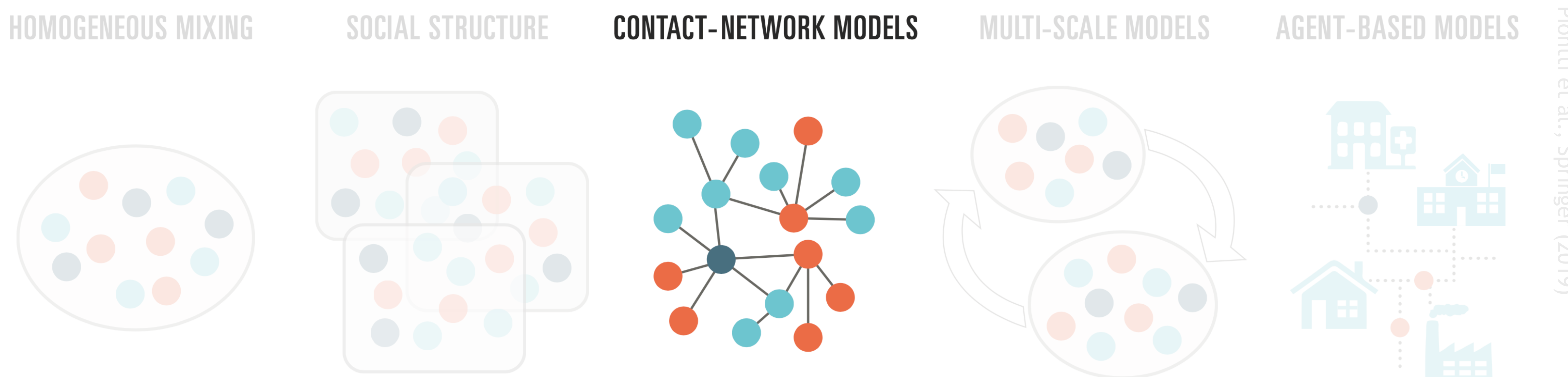


Age-contact matrix reconstruction for Hungary

M. Karsai, J. Koltai, O. Vásárhelyi, G. Röst
Hungary in masks/“MASZK” in Hungary
Corvinus Journal of Sociology and Social Policy
11, 2, 139-146 (2020)

J. Koltai, O. Vásárhelyi, G. Röst, M. Karsai
Monitoring behavioural responses during pandemic via reconstructed contact matrices from online and representative surveys
e-print: arxiv:2102.09021

Complexity of epidemics models



Simple

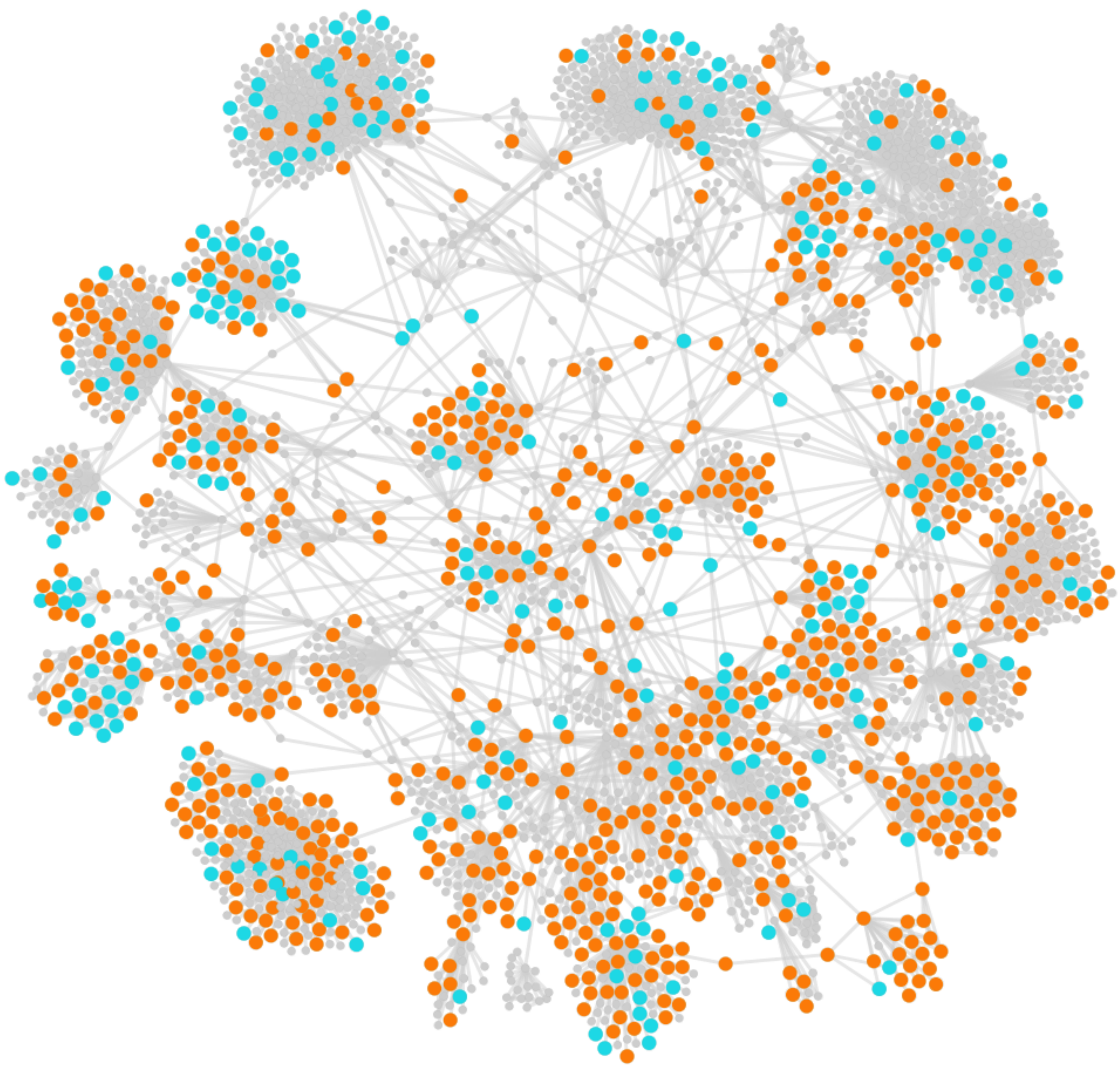
Computationally enabled →

← Mathematically enabled

Realistic

Spreading on social networks

- **Nodes**: individuals
- **Links**: social ties (potentially transmitting information/disease between people)



Scale-free structure (hubs)

+

Small-world structure (short paths)

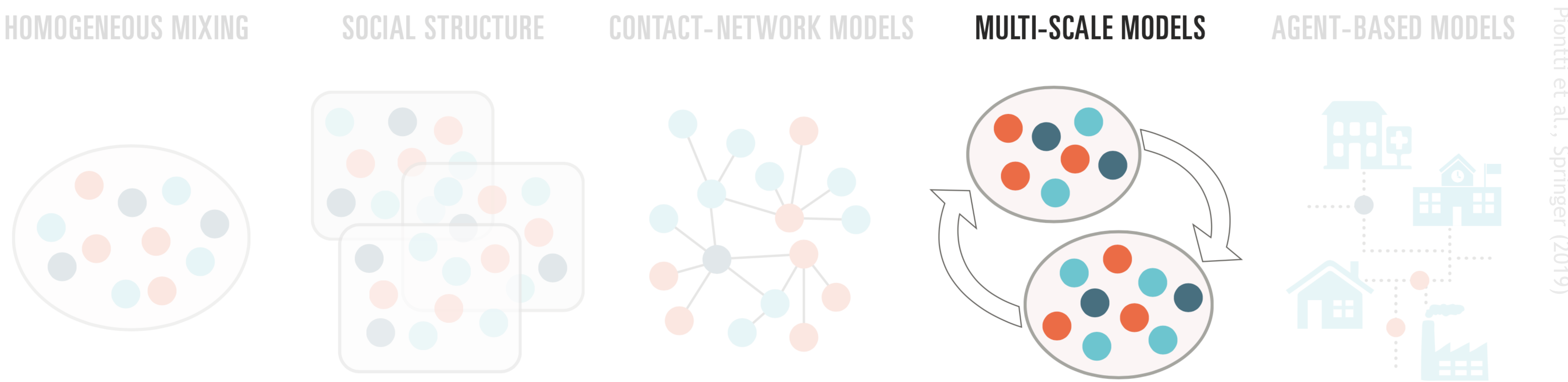
=

Vulnerable against spreading processes

Difficult to observe fully a social structure:

- Limitation due to collection methods (offline or digital)
- Limitation due to privacy
- Changing in time on various time-scales

Complexity of epidemics models



Computationally enabled

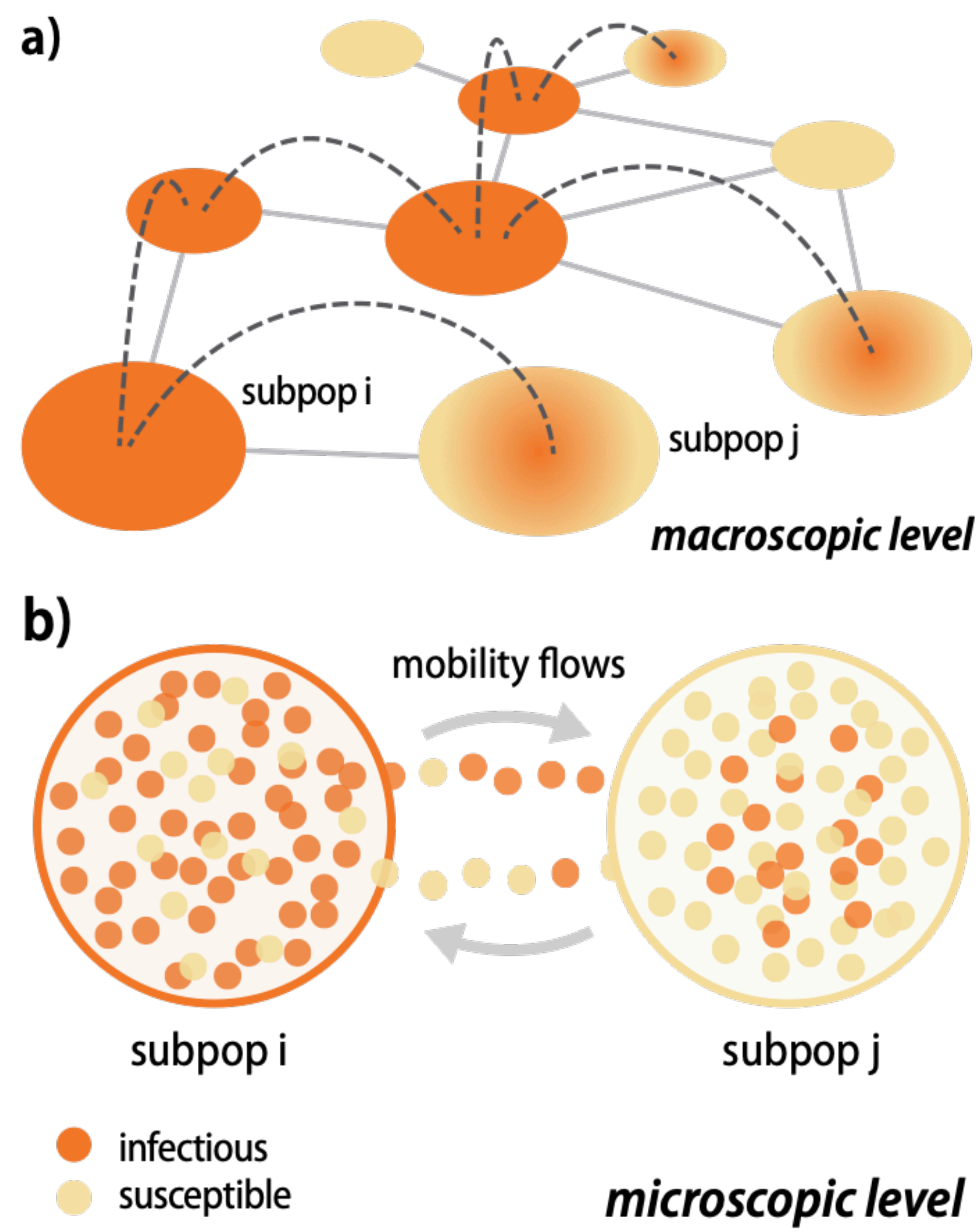
Simple

Realistic

Mathematically enabled

Metapopulation models of epidemic spreading

- **Nodes:** cities with given population size
  - **Data:** census
- **Links:** commuting/flight/train connections between cities weighted by the number of commuters/travellers
  - **Data:** census, IATA data, mobile phone data,...



MoBS Laboratory (Samay/Vespignani)

- **Reaction:** people mix homogeneously inside populations possible transmitting a disease among them

  SIR model: $S \xrightarrow{\beta} I \xrightarrow{\mu} R$

  $\mathcal{I}_0$ - set of initially infected agents:

  $R_0 = \beta/\mu$ - basic reproduction number

- **Diffusion:** Agents (possibly infected) move to neighbouring populations according to link weights w_{ij} and a mobility scaling fact p_m

Real-time predictions

- **Population layers**
  - Mixing and local commuting
  - Global mobility and travels
- **Epidemic layers**
  - Meta-population modelling
  - Identify the spreading scheme
- **Identify other effects**
  - Seasonality
  - Structure of societies
    - age structure, families, etc.
- **Identify and estimate key parameters**
- **Run data-driven model simulations** with the estimated parameters
- **Make predictions**
- **Verify predictions agains the data**

Tizzoni *et al. BMC Medicine* 2012, **10**:165
http://www.biomedcentral.com/1741-7015/10/165

BMC Medicine

RESEARCH ARTICLE Open Access

Real-time numerical forecast of global epidemic spreading: case study of 2009 A/H1N1pdm

Michele Tizzoni[1], Paolo Bajardi[1,2], Chiara Poletto[1,3], José J Ramasco[4], Duygu Balcan[1], Bruno Gonçalves[5], Nicola Perra[6], Vittoria Colizza[3,7,8] and Alessandro Vespignani[6,8,9*]

BMC Medicine

BioMed Central

Research article Open Access

Seasonal transmission potential and activity peaks of the new influenza A(H1N1): a Monte Carlo likelihood analysis based on human mobility

Duygu Balcan[†1,2], Hao Hu[†1,2,3], Bruno Goncalves[†1,2], Paolo Bajardi[†4,5], Chiara Poletto[†4], Jose J Ramasco[4], Daniela Paolotti[4], Nicola Perra[1,6,7], Michele Tizzoni[4,8], Wouter Van den Broeck[4], Vittoria Colizza[4] and Alessandro Vespignani*[1,2,4]

PNAS

Multiscale mobility networks and the spatial spreading of infectious diseases

Duygu Balcan[a,b], Vittoria Colizza[c], Bruno Gonçalves[a,b], Hao Hu[d], José J. Ramasco[b], and Alessandro Vespignani[a,b,c,1]

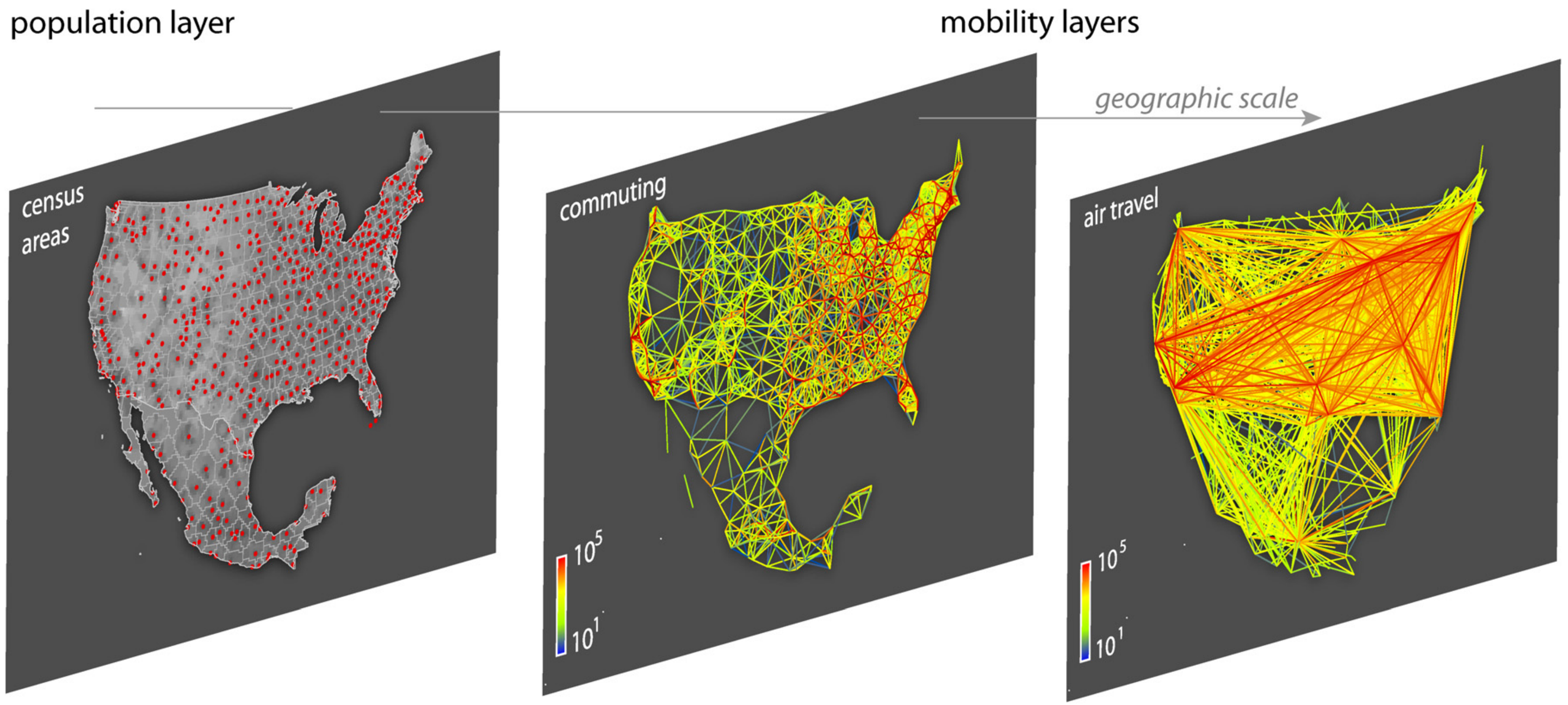
[a]Center for Complex Networks and Systems Research, School of Informatics and Computing, Indiana University, Bloomington, IN 47408; [b]Pervasive Technology Institute, Indiana University, Bloomington, IN 47404; [c]Computational Epidemiology Laboratory, Institute for Scientific Interchange Foundation, 10133 Torino, Italy; and [d]Department of Physics, Indiana University, Bloomington, IN 47406

GLEAMviz The Global Epidemic and Mobility Model

NEWS TEAM PUBLICATIONS PRESS

VISION CHALLENGES APPROACH MODEL SIMULATOR CASE STUDY

Population layers

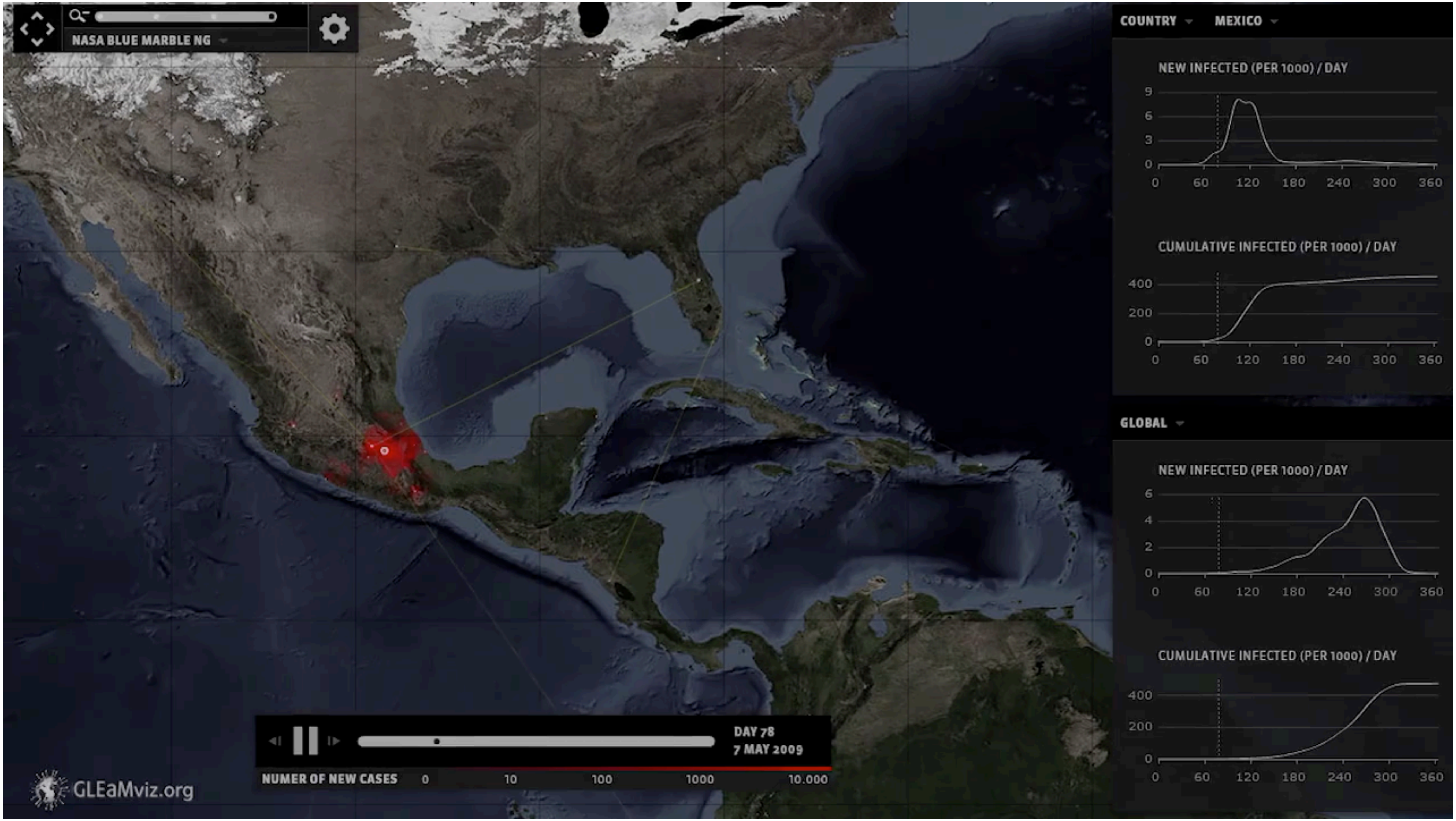


- Geographical resolution of 15º × 15º
- Populations centred around airports
- 3,362 subpopulations in 220 countries worldwide

- Commuting between populations were estimated from national census data (29 countries)
- For the rest of the populations estimated from the gravity law

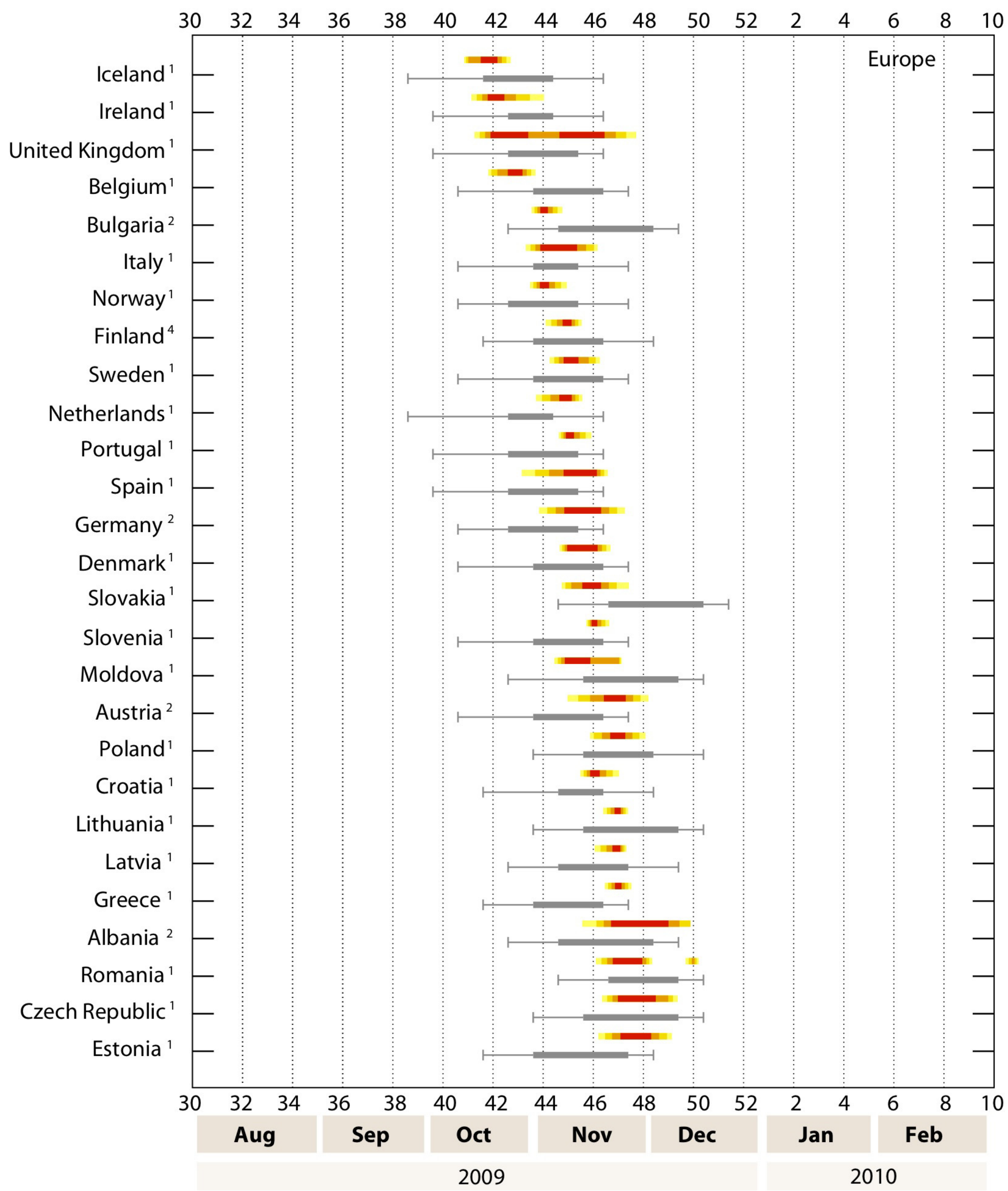
- Air travel network was obtained from a world-wide IATA dataset
- Contains flight connections and number of available seats between airports

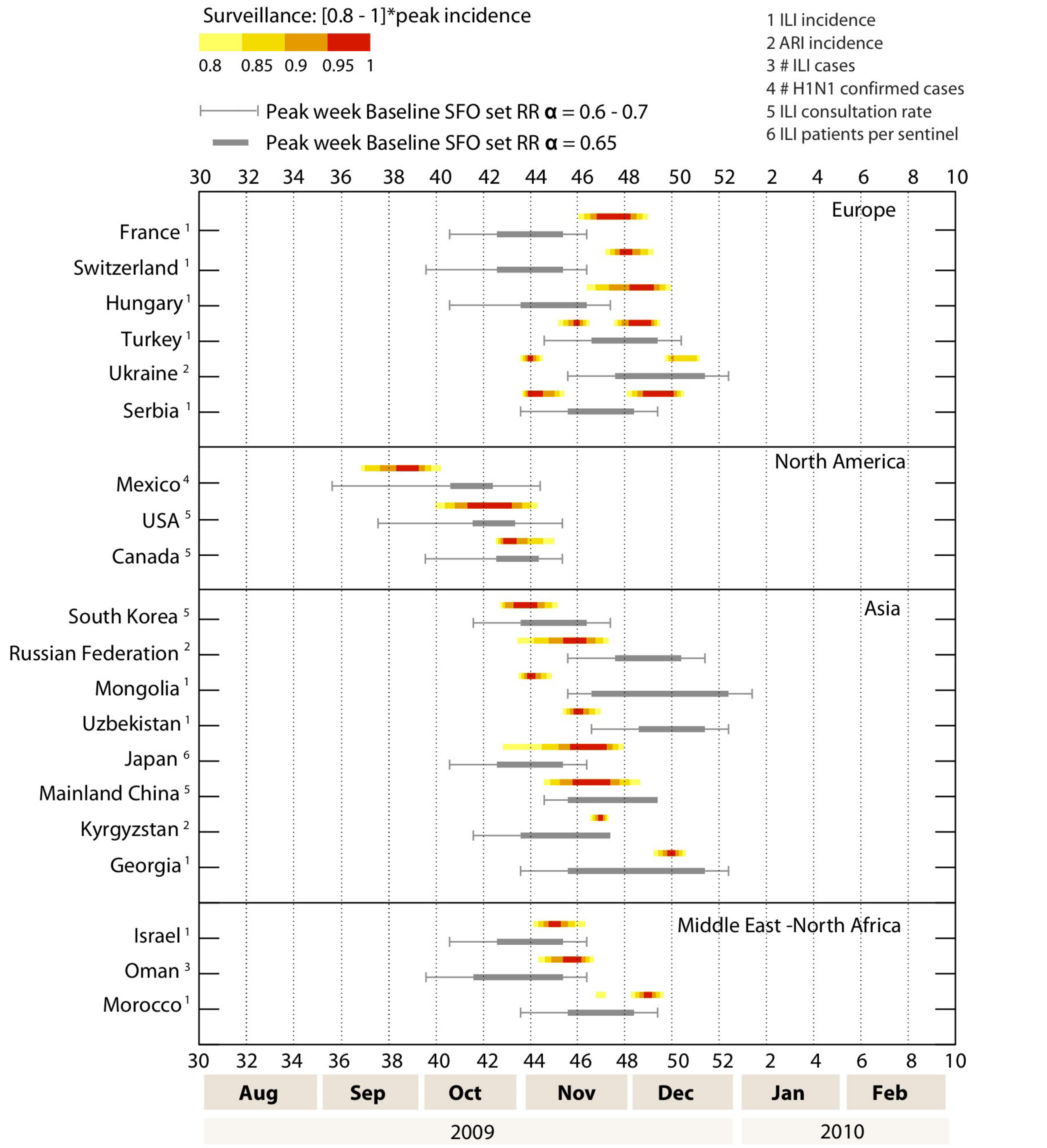
Epidemic simulations for H1N1 epidemic



- Initiate the epidemics from Mexico
- Monte Carlo simulations of thousands of possible infection trees
- Maximum likelihood parameter estimation

Peak times on the northern hemisphere





Immunisation strategies

Immunisation and control

How to control epidemics?

- Transmission reduced intervention
  - face masks
  - gloves, hand washing
- Contact reducing interventions
  - quarantaines
  - closing schools
  - reduce travels and mobility
- Vaccination: remove nodes from the network
  - Question: who should we vaccinate?

These strategies may reduce the transmission rate if applied for the majority of the population

These strategies make the networks sparser and may increase the critical transmission rate (and they are very expensive)

These strategies suppress the population below the epidemic threshold

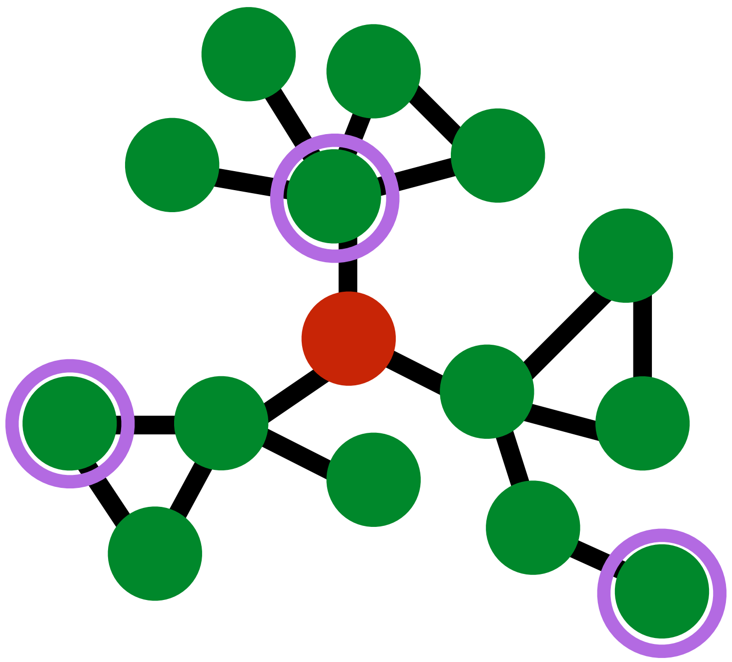
Barrat, Barthelemy, Vespignani book

Immunisation strategies

Random immunisation

- Immunise g fraction of nodes randomly selected from the population
- This strategy does not make difference between nodes of different degrees
- It is rescaling the spreading rate

$$\beta \rightarrow \beta(1-g)$$



- A critical immunised population size can be defined

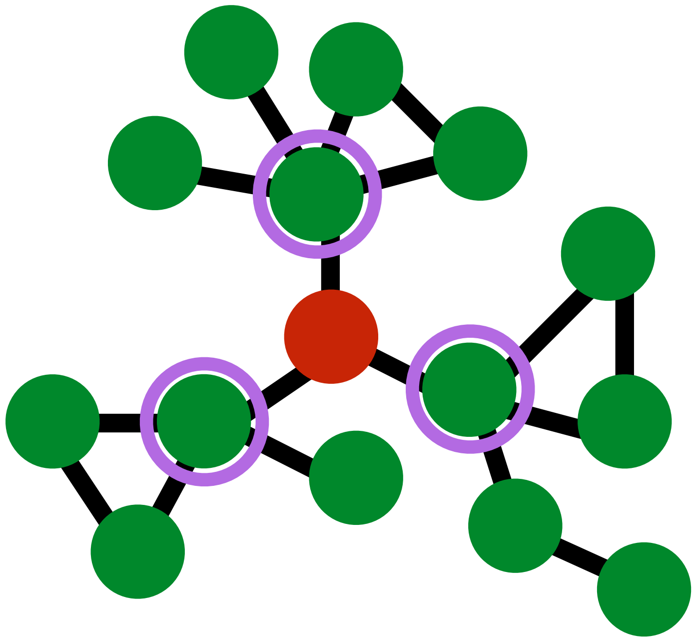
$$\frac{\beta}{\mu}(1-g_c) = \frac{\langle k \rangle}{\langle k^2 \rangle} \quad \text{where} \quad g_c = 1$$

- As $\langle k^2 \rangle \rightarrow \infty$ the threshold still goes $\lambda_c \rightarrow 0$, only the epidemics will be slower
- Random immunisation cannot prevent the outbreak

Barrat, Barthelemy, Vespignani book

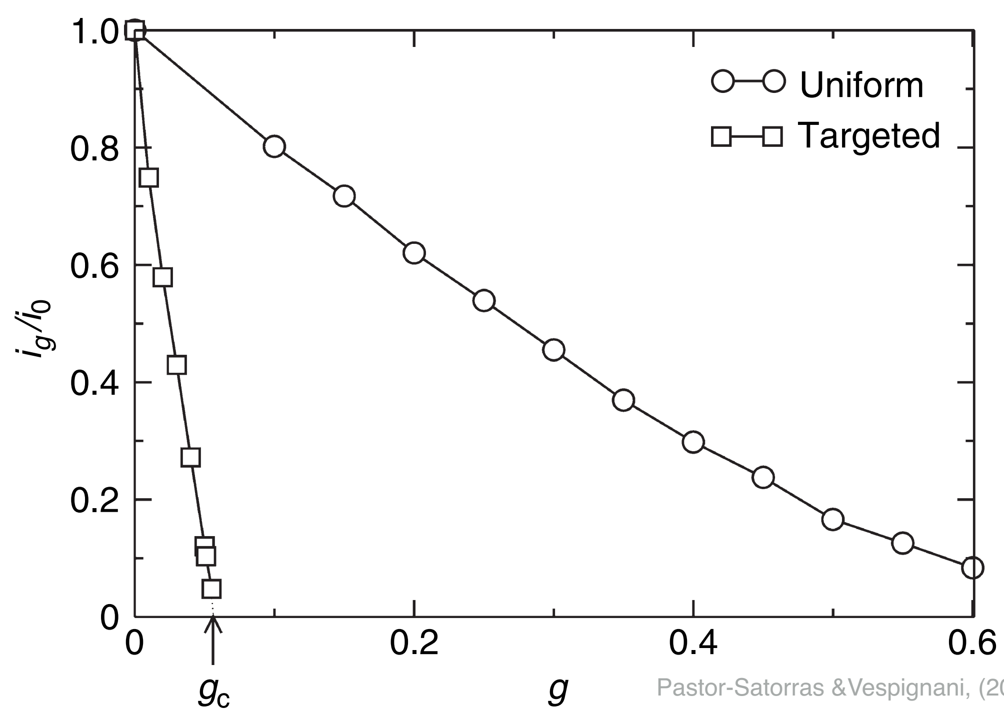
Immunisation strategies with global knowledge

Degree targeted immunisation



- Rank nodes by their degrees and introduce a g fraction with the highest degree
- By removing a g fraction of highest degrees the degree distribution will change - fluctuations of $\langle k^2 \rangle$ will be reduced
- There will be a critical g_c fraction which will stop the epidemics as threshold will became larger than zero

$$\frac{\langle k \rangle_{g_c}}{\langle k^2 \rangle_{g_c}} = \frac{\beta}{\mu}$$



Pastor-Satorras &Vespignani, (2002)

Barrat, Barthelemy, Vespignani book

- $\langle k^n \rangle$: n^{th} moment of the $P_g(k)$ after dilution with g
- The leading term of the critical fraction (for a BA network with $\gamma=3$):

$$g_c \sim \exp(-2\mu/m\beta)$$

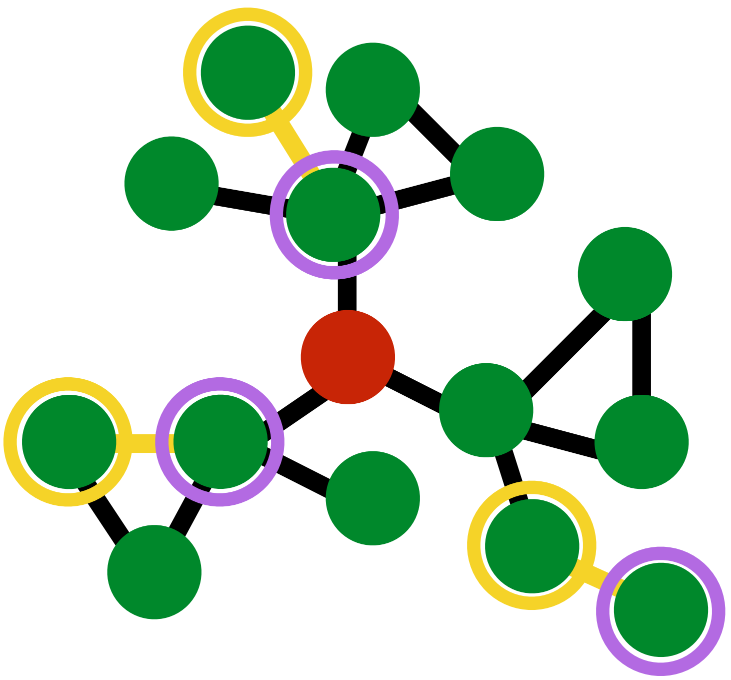
- This is the point where the network becomes "disconnected" regarding the diffusion of epidemics

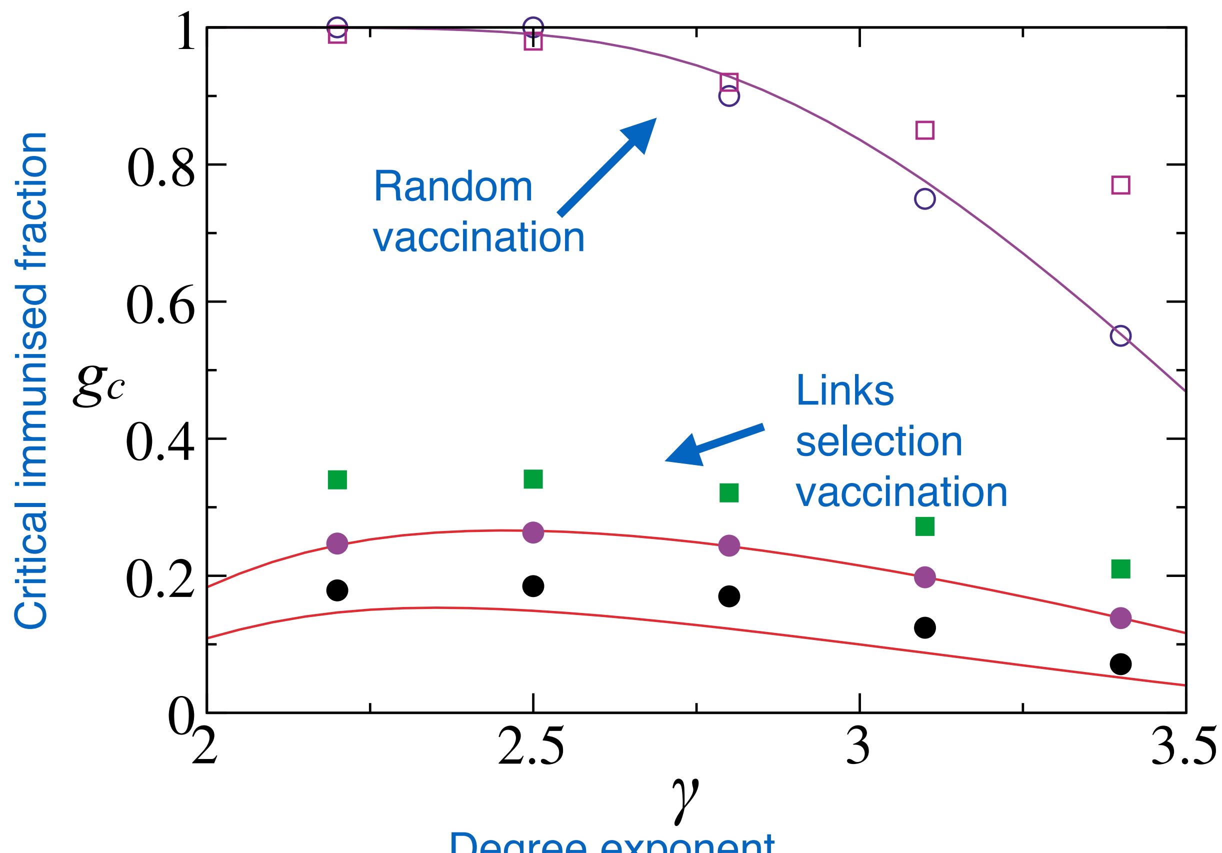
- Problem: these immunisation strategies require complete knowledge about the network (what we usually do not have!)

Immunisation strategies with local knowledge

Acquaintance based strategy

- Exploit degree heterogeneity and that a randomly selected link connects to a large degree node with higher probability
- Method:
  - Select a random node (~P(k))
  - Select a random link of the randomly selected node and immunise (~kP(k))





- Considerably out-performs the random strategy
- It performs worse compared to the targeted strategy
- Does not require global knowledge about the network structure

Barrat, Barthelemy, Vespignani book

R. Cohen et al, Phys. Rev. Lett 91, 247901 (2003)

Thank you
for
your attention!

karsaim@ceu.edu

www.martonkarsai.com