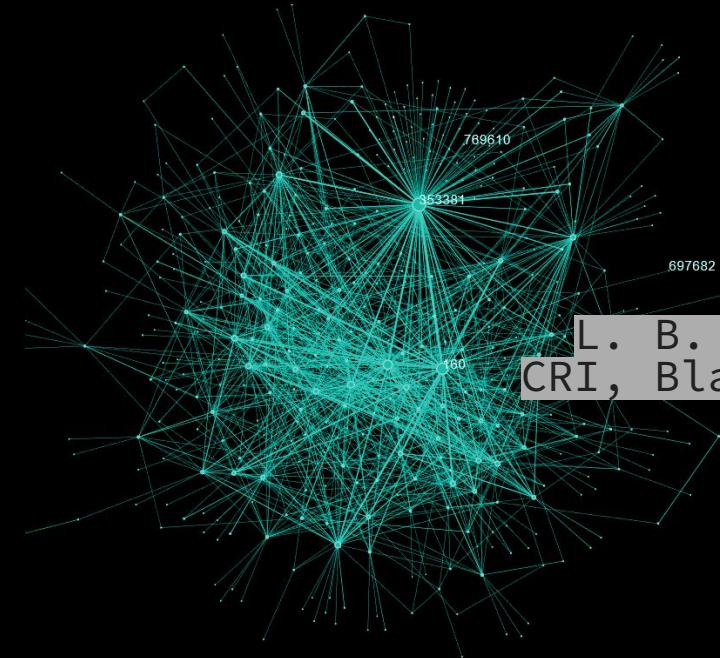


Network modeling of epidemics: SIS, SIR



L. B. Tupikina, Paris, France
CRI, Blabs, City Interactions lab

@aliyubov

IMTECH, India



Who am I?

Researcher at CRI Paris France, Bell
Labs, mathematics, physics, computer
science

City Interaction lab,
CorrelAid Paris



Transport in networks

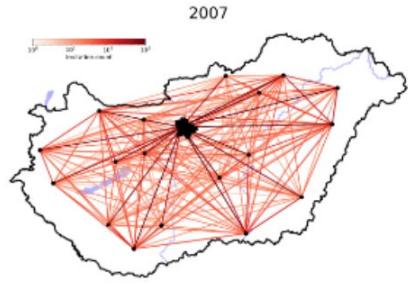
City evolution in time

Citizen science

Innovations in science

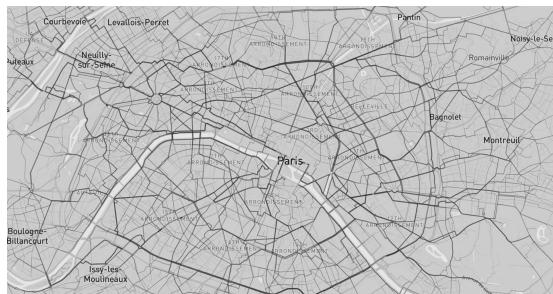
Random walks on networks

Networks and cities

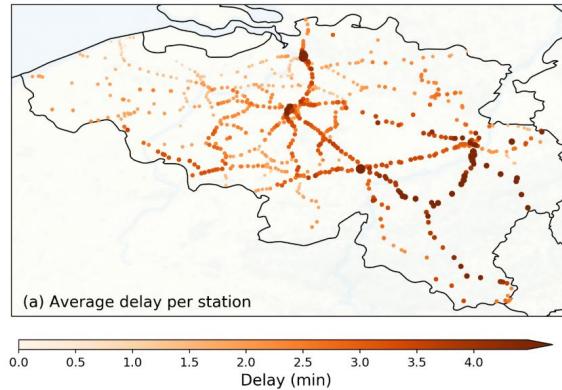


Expanding road network

[Y. Asgari, J. Bara, E. Bokanyi, P. Bouman, G. Burgio, F. Franeck, M. Mazzamurro, L. Tupikina "The effect of infrastructure on social connectivity" (CSS 2022)]

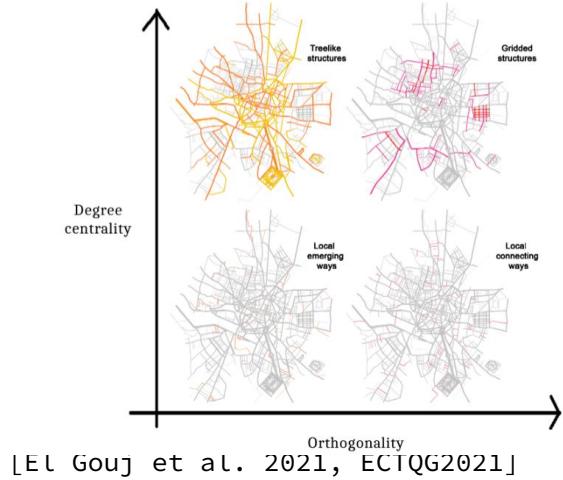


Paris bicycle network and open street map transport API analysis
With correiaid.org and correiaid Paris

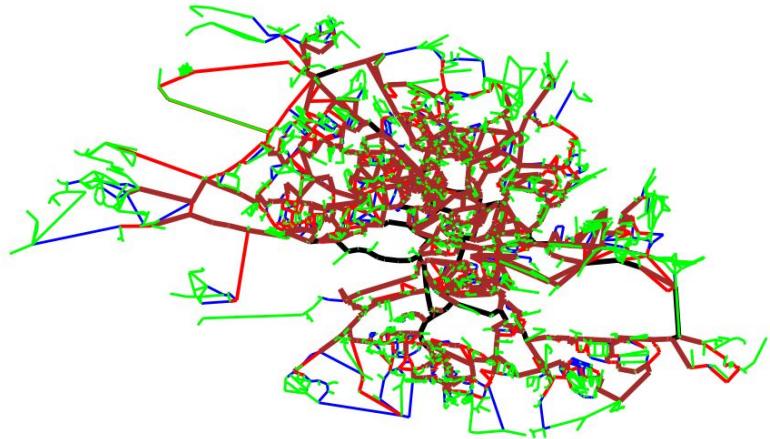


[Dekker, A. N. Medvedev, J. Rombouts, G. Siudem, L. Tupikina, "Modelling railway delay propagation as diffusion-like spreading", EPJ 2022]

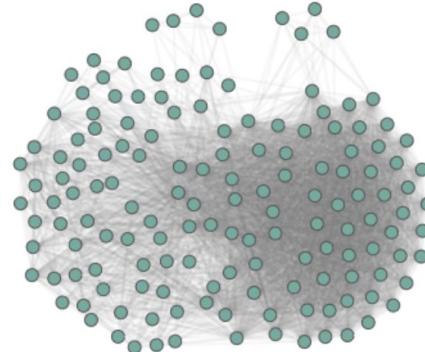
Networks and cities



[Tupikina, Nemotolahi et al. 2022, CityVis2022]



[Jacquet, Tupikina, 2021, GSI 2021]



[Tupikina, Haklay et al. CS und.rev. 2021, ECSA 2022]

City networks and trees

What are good indices for greenness of our streets?

https://github.com/Liyubov/open_tree_data_analysis

Project with Sorbonne, Sony labs (Rome, Paris)

Workshop CityVis2022



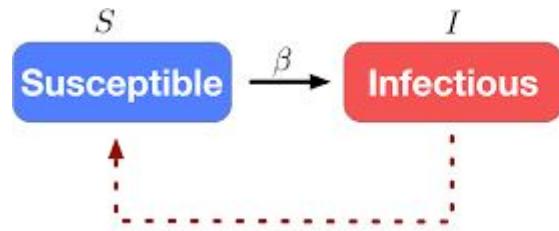
Epidemics spreading

1. Epidemics spreading model
2. **Global and local network** measures to facilitate spreading
3. **Showcase:** spreading in small graphs

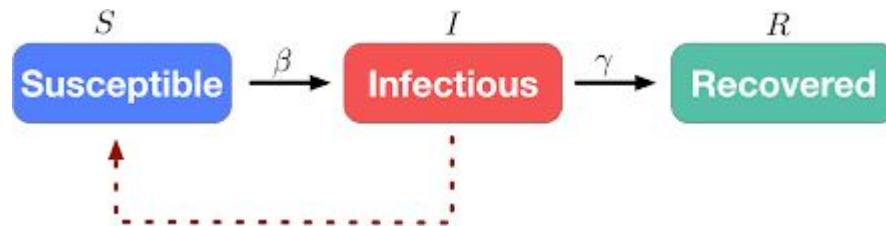


[The Flu Epidemic, 1918 – Vermont Historical Society](#)

1. Epidemics spreading model



1. Epidemics spreading models: SI, SIR, ...



1. Epidemics spreading model

SIR model

Was proposed by Kermack–McKendrick 1927

Is usually formulated as a differential equation system.

$$\frac{ds}{dt} = -\beta si$$

$$\frac{di}{dt} = \beta si - vi$$

$$\frac{dr}{dt} = vi$$

$$\Omega = r(\infty) = 1 - \exp[-R_0 \Omega]$$

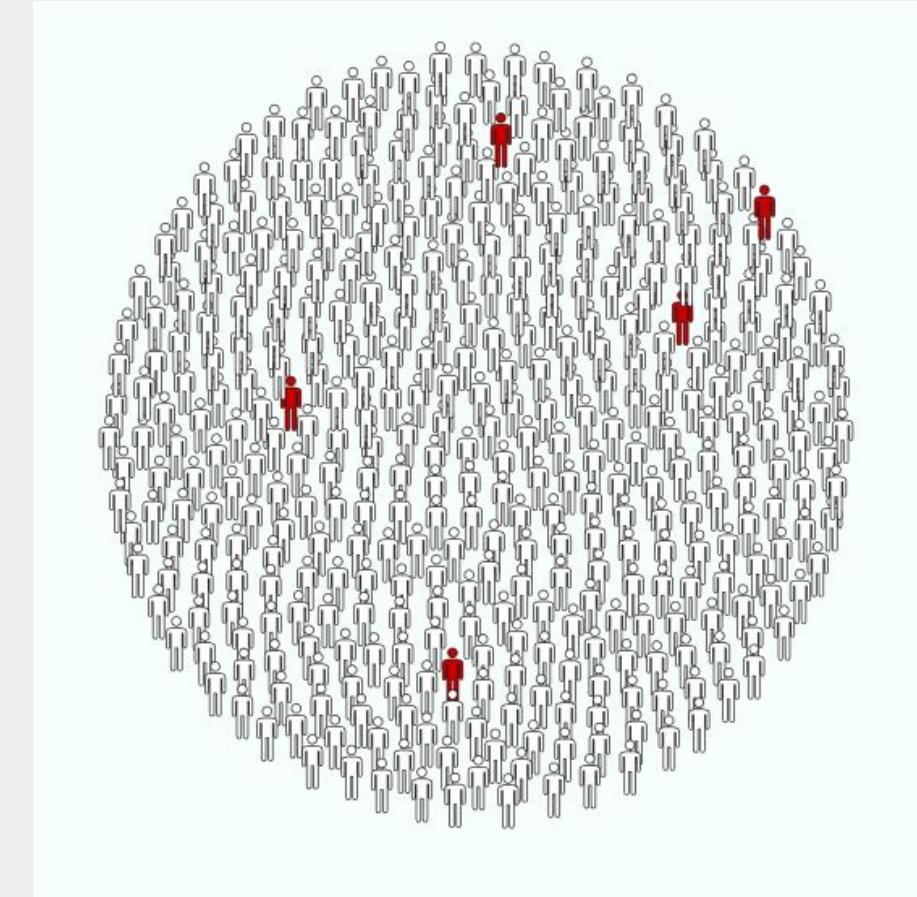
$$\text{where } R_0 = \beta/v$$

$\Omega > 0$ if and only if $R_0 > 1$

The epidemic
threshold

SIR model simulations

Susceptible individuals (S) can be infected by coming in contact with other infected (I) individuals. Once infected they can transmit the disease until they recover (R) and become immune. After some time immunity wanes and individuals become susceptible again:



SIR model

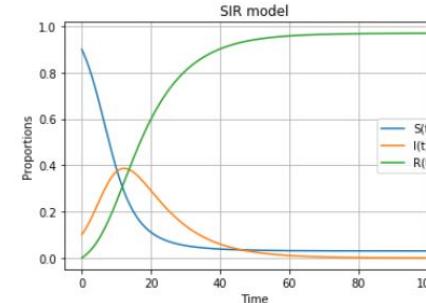
of epidemics spreading.

Make your own simulations of susceptible individuals count and on a network or in population

<https://www.complexity-explorables.org/>

<https://github.com/Big-data-course-CRI/materials big data cri 2019/blob/master/resources%20Python/spreading on networks.ipynb>

```
solution=scipy.integrate.odeint(SIR_model,[S0,I0,R0],t,args=(beta,gamma))  
solution=numpy.array(solution)
```



$$\frac{ds}{dt} = -\beta si$$

$$\frac{di}{dt} = \beta si - vi$$

$$\frac{dr}{dt} = vi$$

$$\Omega = r(\infty) = 1 - \exp[-R_0 \Omega]$$

where $R_0 = \beta/v$

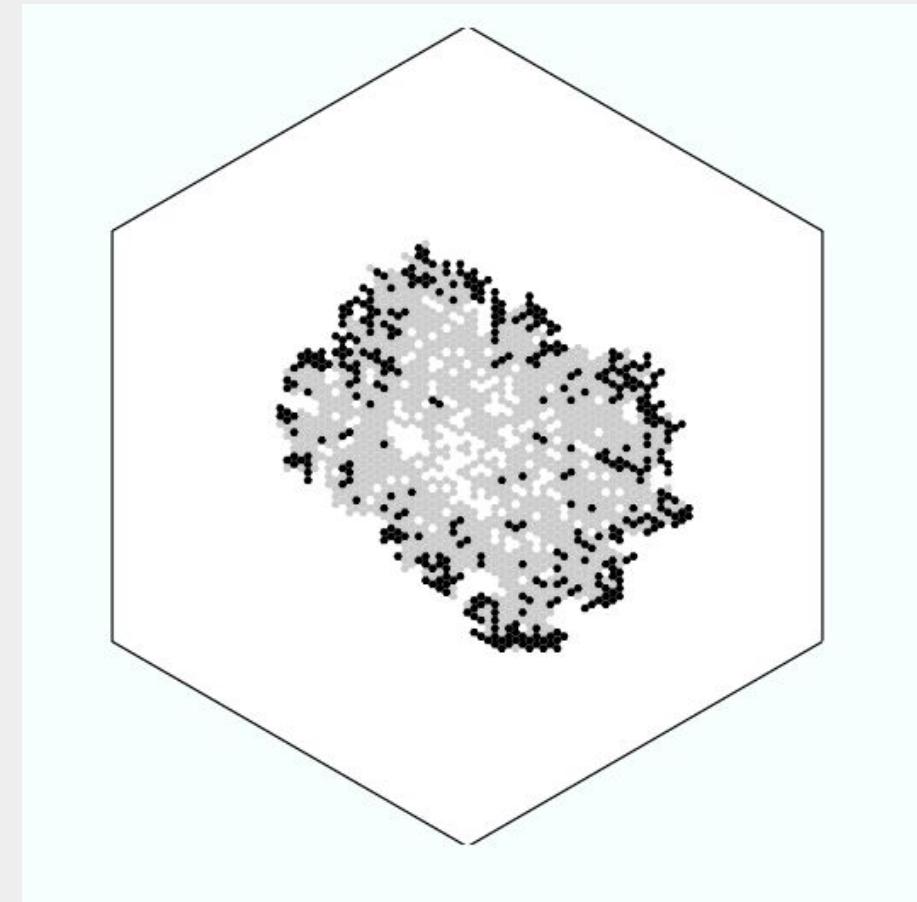
$\Omega > 0$ if and only if $R_0 > 1$

The epidemic threshold

SIR model

of epidemics spreading with
spatial parameter

<https://www.complexity-explorables.org/slides/critical-hexsirsize/>

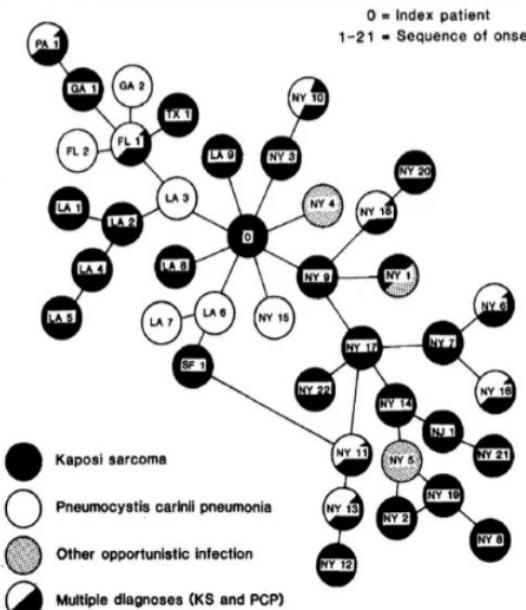


Epidemics spreading

1. Epidemics spreading model
2. **Global and local network** measures to facilitate spreading in networks
3. Spreading in small graphs

Epidemics spreading on networks

Auerbach et al. “Cluster of cases of immune deficiency syndrome” 1984

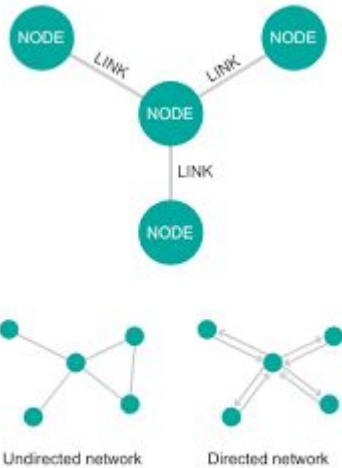


City LA - Los Angeles, NY - New York City, SF - San Francisco

State FL - Florida, GA - Georgia, NJ - New Jersey, PA - Pennsylvania,
TX - Texas

Epidemics spreading on networks

Brief introduction into networks:

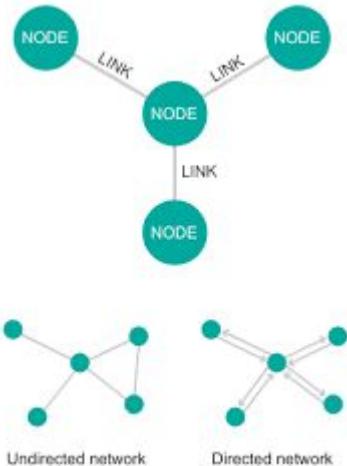


Epidemics spreading on networks

Brief introduction into networks:

$G = (\text{nodes } N, \text{ links } E)$

Directed, undirected network types, matrix notation



	A	B	C	D	E
A	0	1	1	1	1
B	1	0	1	1	1
C	1	1	0	1	1
D	1	1	1	0	1
E	1	1	1	1	0

	A	B	C	D	E
A	0	1	1	1	1
B	1	0	0	0	0
C	1	0	0	0	0
D	1	0	0	0	0
E	1	0	0	0	0

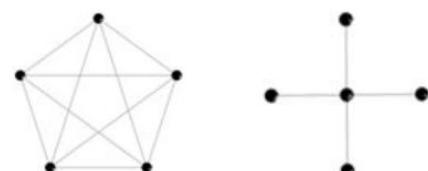
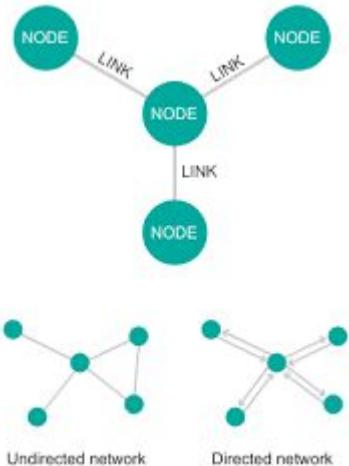
Epidemics spreading on networks

Brief introduction into networks:

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Local network measures: degree, betweenness



	A	B	C	D	E
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D	1	0	0	0	0
E	1	0	0	0	0

Epidemics spreading on networks

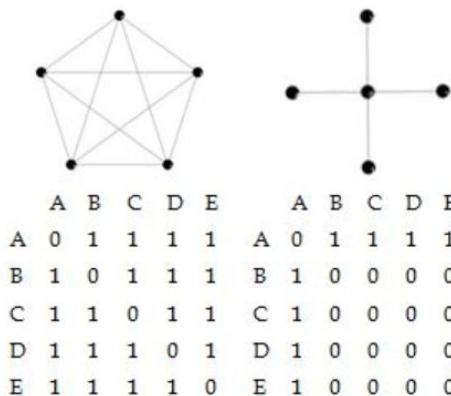
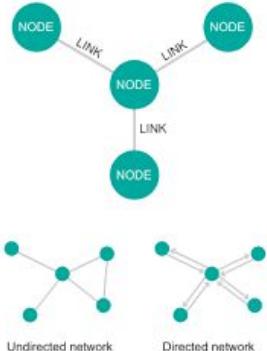
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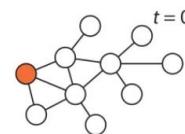
Global network measures: average local measures...



Epidemics spreading on networks

“Time evolution of predictability of epidemics on networks”

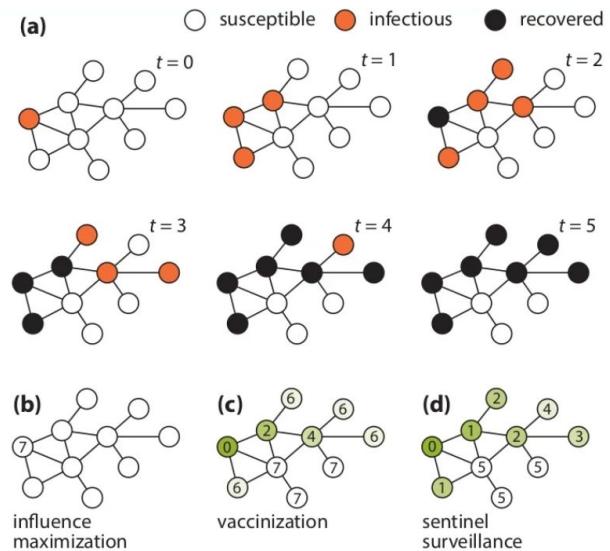
P.Holme et al. PRE, 2014



Epidemics spreading on networks

“Time evolution of predictability of epidemics on networks”

P.Holme et al. PRE, 2014



Local measures for spreading

Different ways to define node importance and local measures

Petter Holme, Three faces of node importance in network epidemiology: Exact results for small graphs, arxiv: 1708.06456.

Global measures for spreading

Assortativity was originally defined by Newman in 2002.

Networks with low and high assortativity help spreading
[Boccaletti, Barabasi, Christakis, Holme].

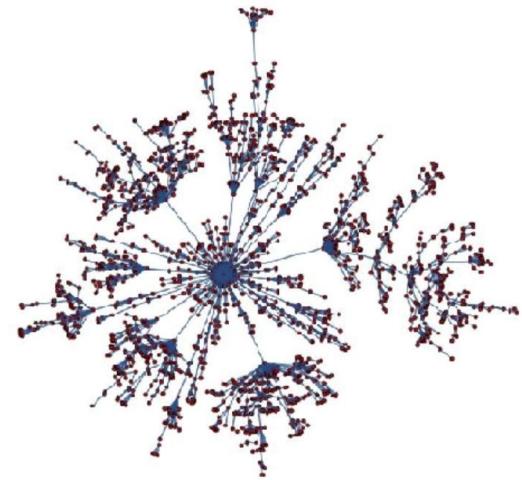
Assortativity is expressed as a scalar value, ρ , in the range $-1 \leq \rho \leq 1$. Degree assortativity is identified as ρ_D . A network is said to be assortative when high degree nodes are, on average, connected to other nodes with high degree and low degree nodes are, on average, connected to other nodes with low degree.

“Assortativity in Complex Networks” Rogier Noldus and Piet Van Mieghem 2014

Global measures for spreading

Hubs and spreading

$$p(k) \sim k^{-\gamma}$$

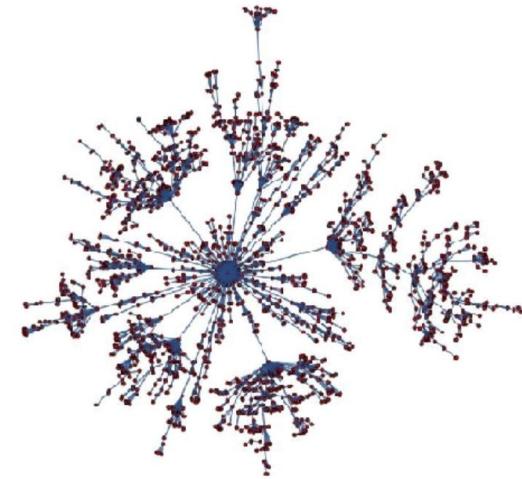


Global measures for spreading

Hubs and spreading

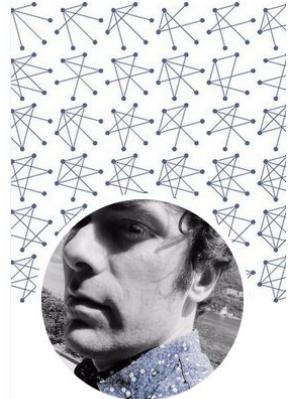
$$p(k) \sim k^{-\gamma}$$

The hubs are also responsible for effective spreading of material on network. In an analysis of disease spreading or information flow, hubs are referred to as super-spreaders.



Epidemics spreading

1. Epidemics spreading model
2. **Global and local network** measures to facilitate spreading
3. Spreading in **small graphs**
(work in collaboration with P.Holme)

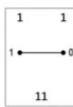


Petter Holme

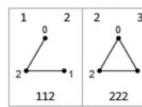
Epidemics spreading

Main idea: In cases of small graphs or limited populations (New Zealand case) it is possible to model and understand all the details about spreading **time** of epidemics population, **extinction, node importance**

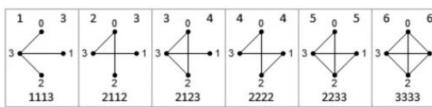
Connected graphs with 2 nodes



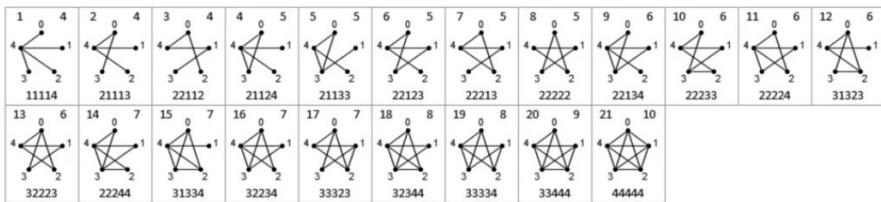
Connected graphs with 3 nodes



Connected graphs with 4 nodes



Connected graphs with 5 nodes



Epidemics spreading



OPEN ACCESS

PAPER

Epidemic extinction in networks: insights from the 12 110 smallest graphs

RECEIVED

12 August 2018

REVISED

28 October 2018

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12 November 2018

PUBLISHED

DD MM 2018

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¹ Institute of Innovative Research, Tokyo Institute of Technology, Nagatsuta-cho 4259, Midori-ku, Yokohama, Kanagawa, 226-8503, Japan

² Laboratoire de Physique de la Matière Condensée (UMR 7643), CNRS—Ecole Polytechnique, F-91128 Palaiseau, France

E-mail: holme@cns.pi.titech.ac.jp

Keywords: network epidemiology, complex networks, small graphs

Abstract

We investigate the expected time to extinction in the susceptible-infectious-susceptible model of disease spreading. Rather than using stochastic simulations, or asymptotic calculations in network models, we solve the extinction time exactly for all connected graphs with three to eight vertices. This

Epidemics spreading: simple setup

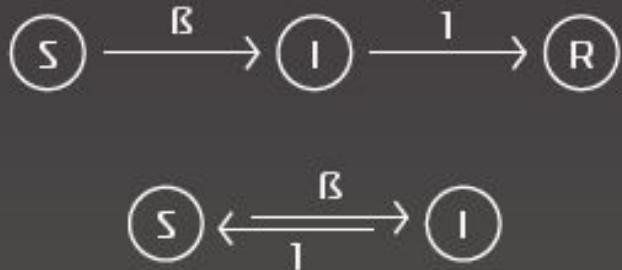


The standard, Markovian, SIR and SIS models.

Outbreaks start at one, random vertex.

Diseases spread on connected graphs of N vertices and M edges.

Epidemics spreading: simple setup



The standard, Markovian, SIR and SIS models.

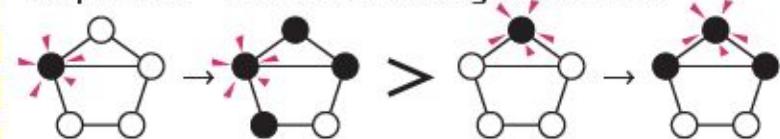
Outbreaks start at one, random vertex.

Diseases spread on connected graphs of N vertices and M edges.

Influence
Impermeability
Infection
Influence
Impermeability
Infection

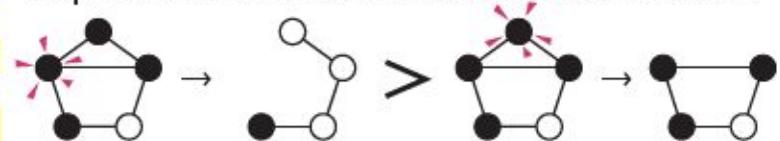
Influence maximization:

Important = able to start large outbreak.



Vaccination:

Important = reduce outbreaks much if deleted.

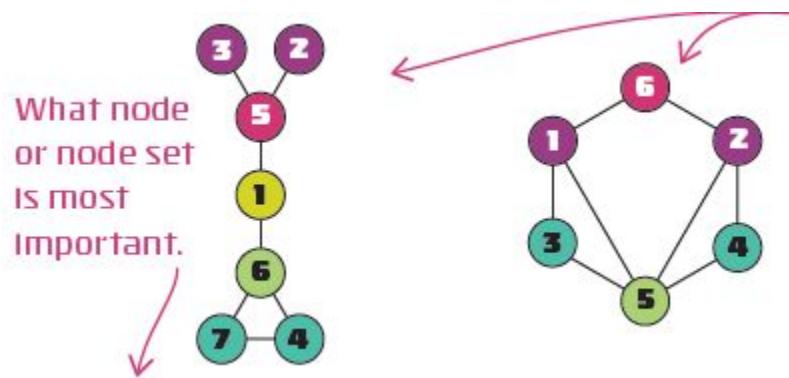


Sentinel surveillance:

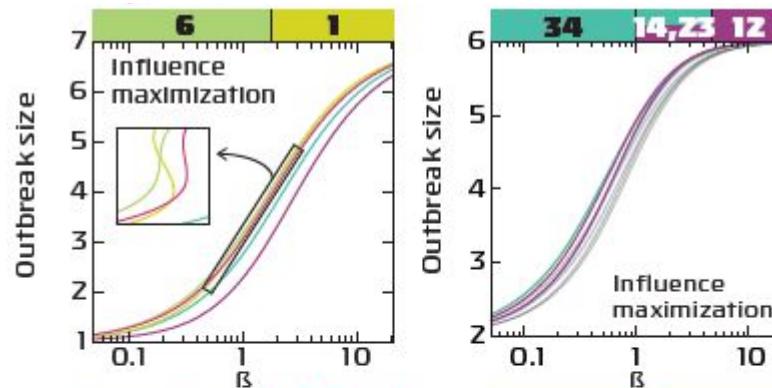
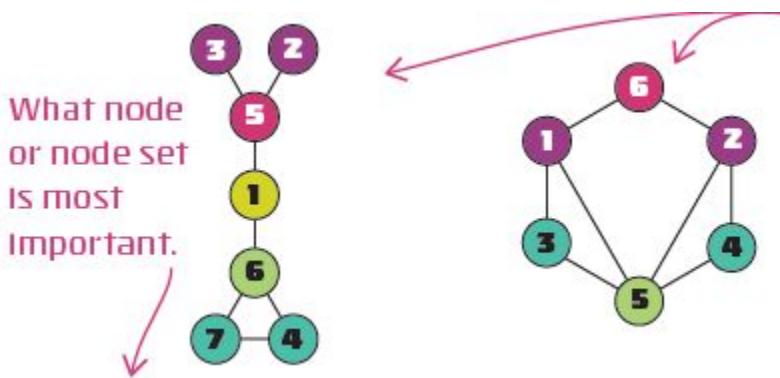
Important = getting infected reliably and early.



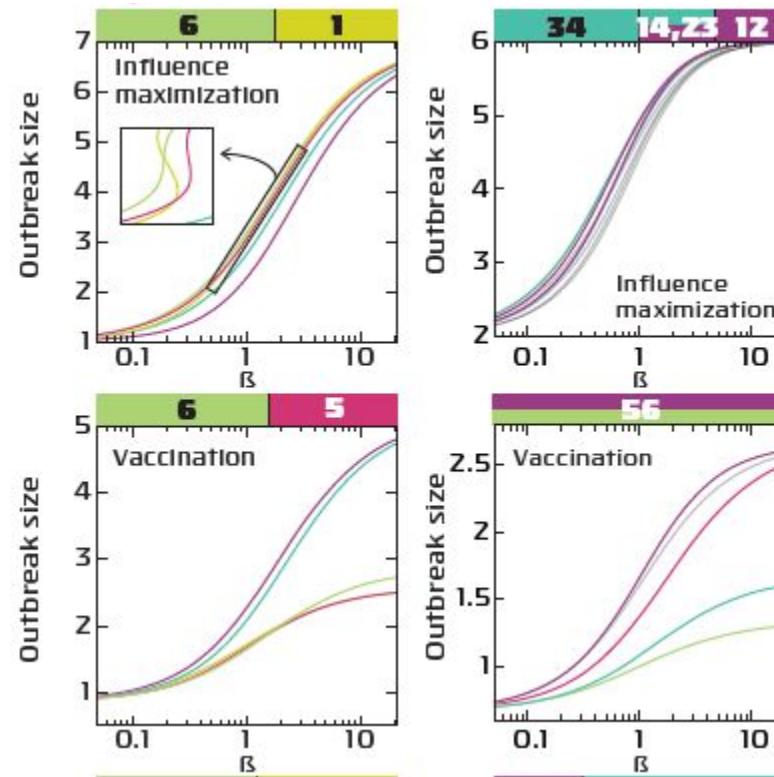
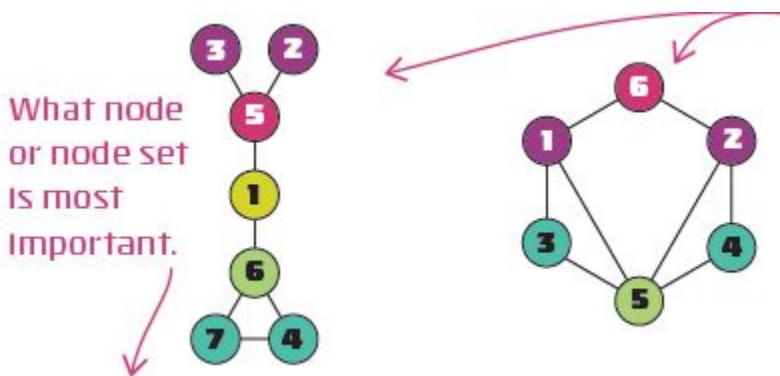
Epidemics spreading: simple setup



Epidemics spreading: simple setup

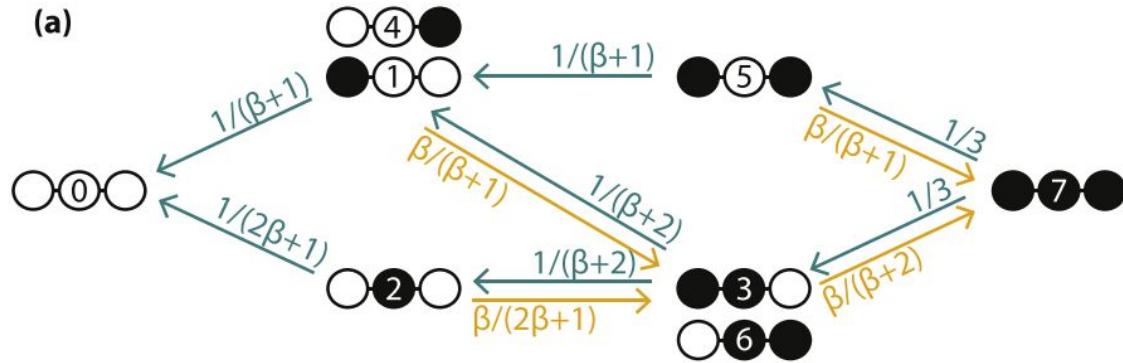


Epidemics spreading: simple setup

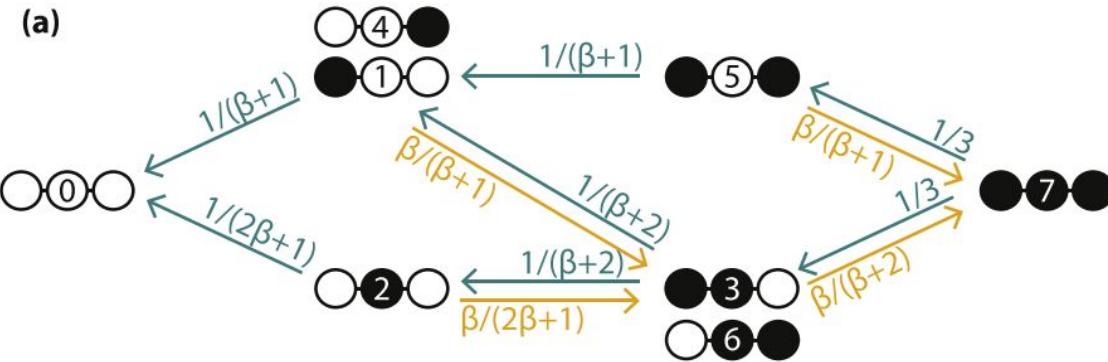


Epidemics spreading

(a)



Epidemics spreading: idea of Markovian models



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PAPER

Epidemic extinction in networks: insights from the 12 110 smallest graphs

Petter Holme¹ and Liubov Tupikina²

¹ Institute of Innovative Research, Tokyo Institute of Technology, Nagatsuta-cho 4259, Midori-ku, Yokohama, Kanagawa, 226-8503, Japan

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E-mail: holme@cns.pi.titech.ac.jp

Keywords: network epidemiology, complex networks, small graphs

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Abstract

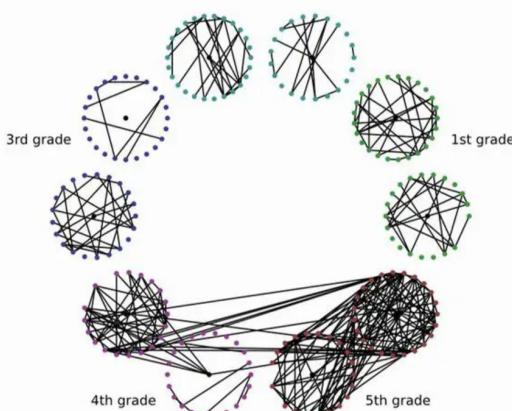
We investigate the expected time to extinction in the susceptible-infectious-susceptible model of disease spreading. Rather than using stochastic simulations, or asymptotic calculations in network models, we solve the extinction time exactly for all connected graphs with three to eight vertices. This

Epidemics spreading

1. Epidemics spreading model
2. **Global and local network** measures to facilitate spreading
3. **Showcase:** spreading in small graphs
4. Other resources

Socio patterns

Or how people interact in classrooms



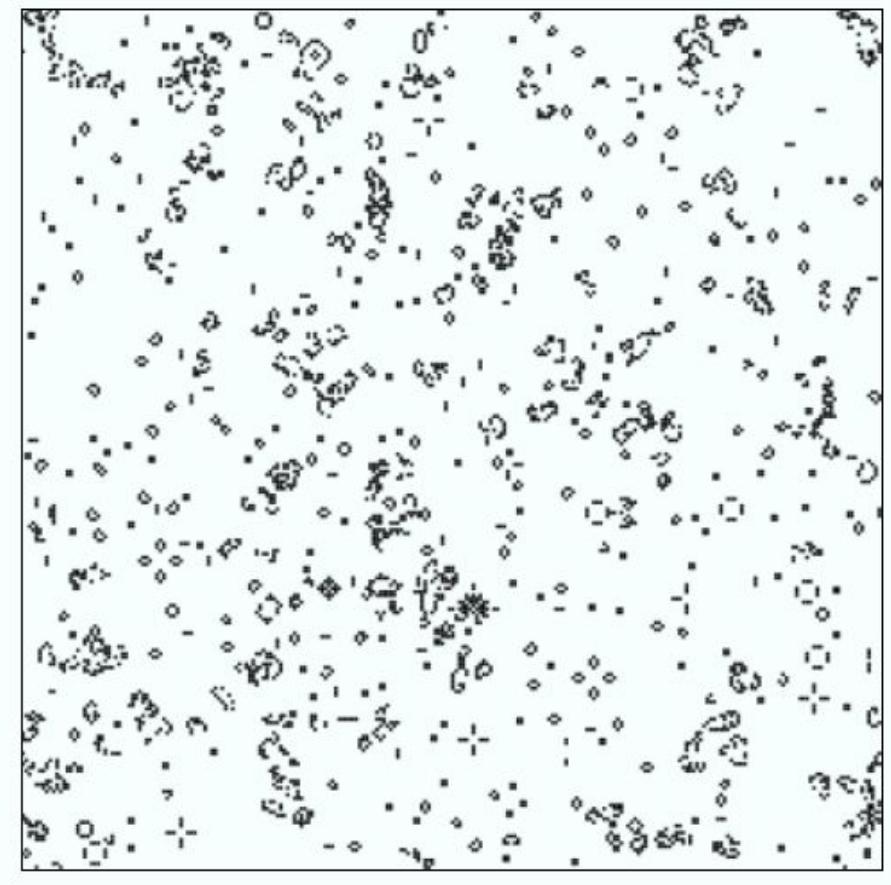
https://vimeo.com/31490438?embedded=true&source=vimeo_logo&owner=5516521

<http://www.sociopatterns.org/>

Conway game of life model

An attempt to describe life from deterministic point of view of cellular automata

<https://mathworld.wolfram.com/GameofLife.html>



COVID19 models predictions

of epidemics spreading with
spatial parameter

V. Colizza et al. 2021, Vespigniani
et al. 2021

Read only peer-review research

<https://www.youtube.com/watch?v=gxAaO2rsdls>

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Article | Published: 21 December 2020

Underdetection of cases of COVID-19 in France threatens epidemic control

Giulia Pullano, Laura Di Domenico, Chiara E. Sabbatini, Eugenio Valdano, Clément Turbelin, Marion Debin, Caroline Guerrisi, Charly Kengne-Kuetche, Cécile Souty, Thomas Hanslik, Thierry Blanchon, Pierre-Yves Boëlle, Julie Figoni, Sophie Vaux, Christine Campèse, Sibylle Bernard-Stoecklin & Vittoria Colizza✉

Nature 590, 134–139 (2021) | [Cite this article](#)

38k Accesses | 82 Citations | 422 Altmetric | [Metrics](#)

Network resources

<http://networkrepository.com/networks.php>

<http://networksciencebook.com/chapter/3#advanced-b>



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Check out **GraphVis**: the interactive visual network mining and machine learning tool.

GET NETWORK DATA

COMPARE GRAPH DATA

VISUALIZE NETWORKS

Network resources

<http://networkrepository.com/networks.php>

<http://networksciencebook.com/chapter/3#advanced-b>

Spatial Networks

Marc Barthélémy*

Institut de Physique Théorique, CEA, IPHT CNRS, URA 2306 F-91191 Gif-sur-Yvette France and
Centre d'Analyse et de Mathématique Sociales (CAMS), UMR 8557 CNRS-EHESS
Ecole des Hautes Etudes en Sciences Sociales, 54 bd. Raspail, F-75270 Paris Cedex 06, France.

Complex systems are very often organized under the form of networks where nodes and edges are embedded in space. Transportation and mobility networks, Internet, mobile phone networks, power grids, social and contact networks, neural networks, are all examples where space is relevant and where topology alone does not contain all the information. Characterizing and understanding the structure and the evolution of spatial networks is thus crucial for many different fields ranging from urbanism to epidemiology. An important consequence of space on networks is that there is a cost associated to the length of edges which in turn has dramatic effects on the topological structure of these networks. We will expose thoroughly the current state of our understanding of how the spatial constraints affect the structure and properties of these networks. We will review the most recent empirical observations and the most important models of spatial networks. We will also discuss various processes which take place on these spatial networks, such as phase transitions, random walks, synchronization, navigation, resilience, and disease spread.

Contents

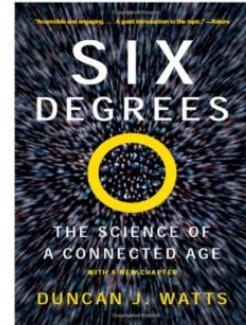
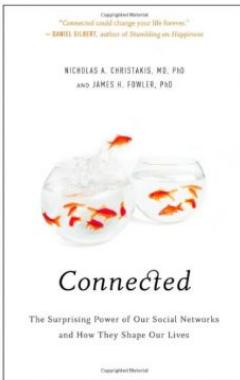
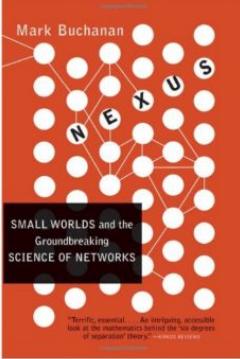
I. Networks and space	2	1. Erdos-Renyi graph	39
A. Introduction	2	2. Planar Erdos-Renyi graph	39
B. Quantitative geography and networks	2	3. The hidden variable model for spatial networks	40
C. What this review is (not) about	2	4. The Waxman model	41
II. Characterizing spatial networks	3	C. Spatial small worlds	41
A. Generalities on planar networks	3	1. The Watts-Strogatz model	41
1. Spatial and planar networks	3	2. Spatial generalizations	42
2. Classical results for planar networks	3	D. Spatial growth models	43
3. Voronoi tessellation	4	1. Generalities	43
		2. Preferential attachment and distance selection	43
		3. Growth and local optimization	46
		E. Optimal networks	49

How Everything Is Connected to
Everything Else and What It Means for
Business, Science, and Everyday Life

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Albert-László Barabási
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