A era da complexidade

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Universidade de São Paulo

Francisco Rodrigues

2001: **Física** - IFSC

2004: **Mestrado em Física Computacional** - IFSC

2007: **Doutorado em Física Computacional** - IFSC

2010: Professor – ICMC

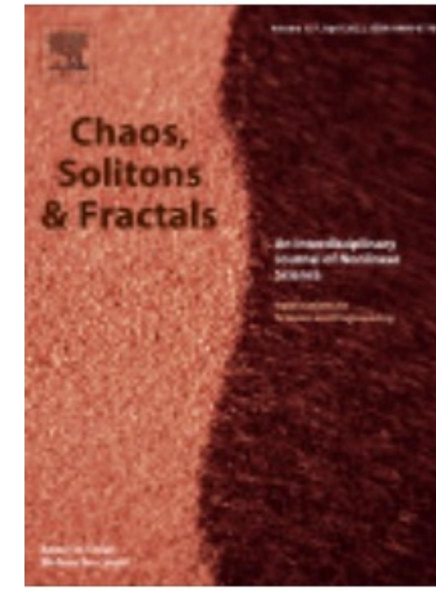
2018: Leverhulme Professor: University of Warwick

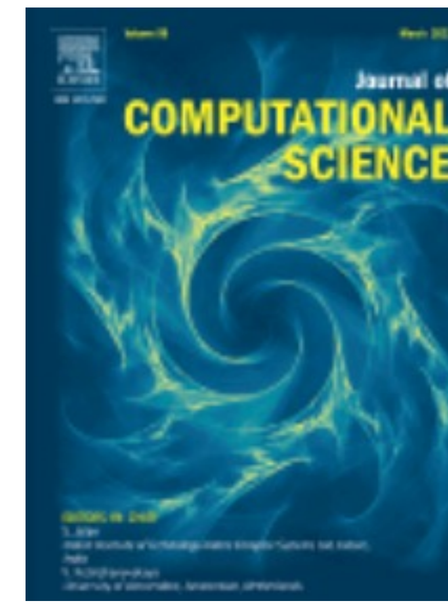
Grupo de Sistemas Complexos:

- 3 pós-doutores
- 9 alunos de doutorado
- 4 alunos de mestrado
- 2 alunos de iniciação científica

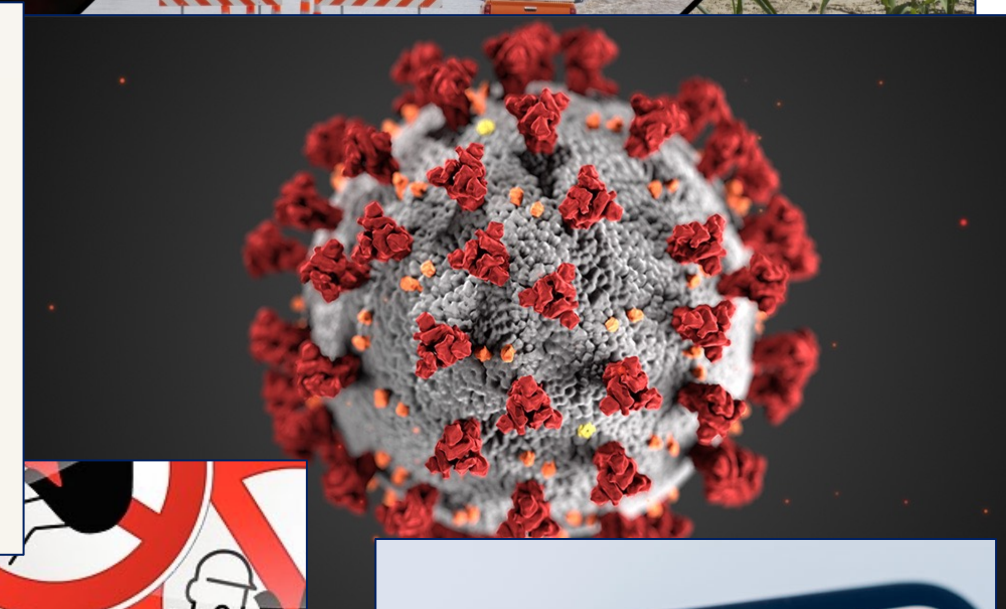
Editor:

- Chaos, Solitons and Fractals (Elsevier)
- Europhysics Letters (EPL)
- Journal of Physics: Complexity (IOP)
- Journal of Computational Science (Elsevier)





The Biggest Global Issues Facing Mankind



Complex system

A complex system is made of many connected elements presenting emergent properties, like collective behavior, universality and adaptation.

The whole is more than the sum of its parts.

Complex system

https://www.youtube.com/watch?v=4BdjxYUdJS8&ab_channel=NationalGeographic

Complex system

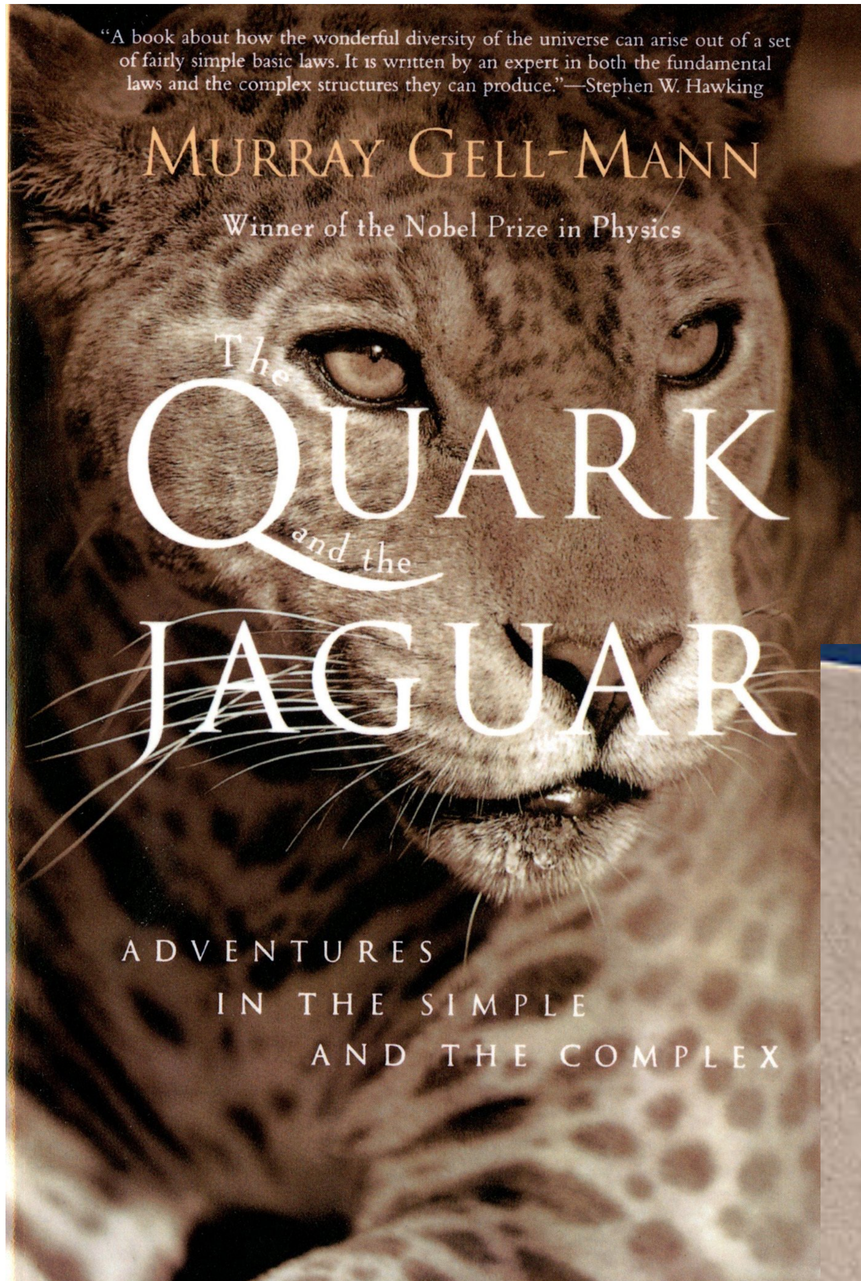
https://www.youtube.com/watch?v=0dskCpuxqtI&feature=emb_logo

Complex system

https://www.youtube.com/watch?v=KnPiP9PkLAs&ab_channel=konzeptunddialog

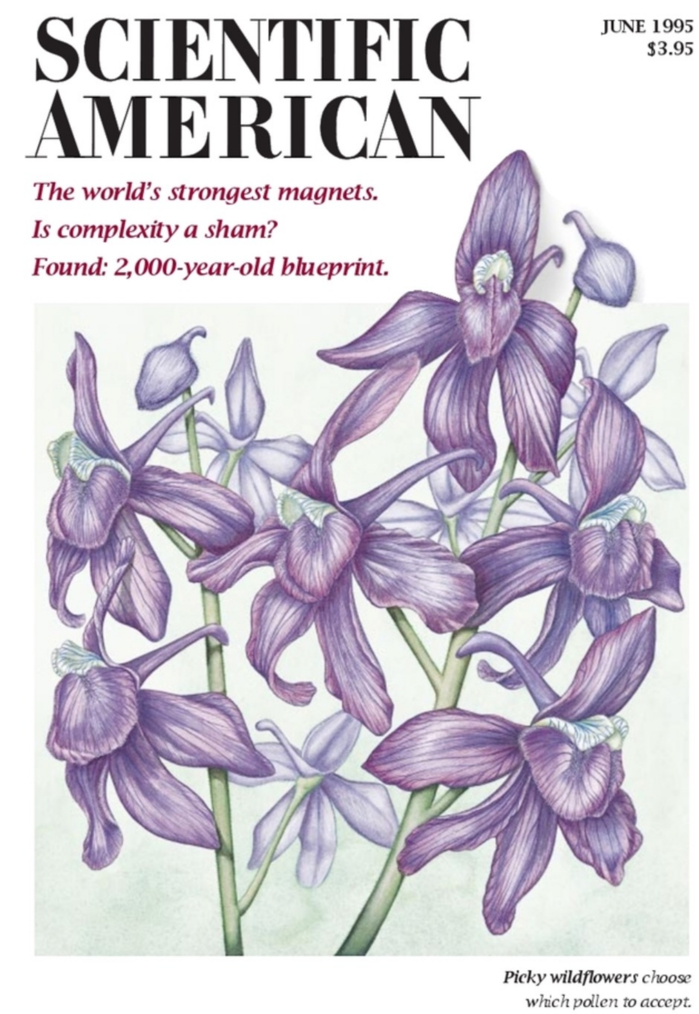
Complex system

História...



Murray Gell-Mann

1984



1995: A complexidade é uma farsa?

História...

A era das redes

Collective dynamics of 'small-world' networks

Duncan J. Watts* **& Steven H. Strogatz**

Department of Theoretical and Applied Mechanics, Kimball Hall, Cornell University, Ithaca, New York 14853, USA

Nature, 1998

Emergence of Scaling in Random Networks

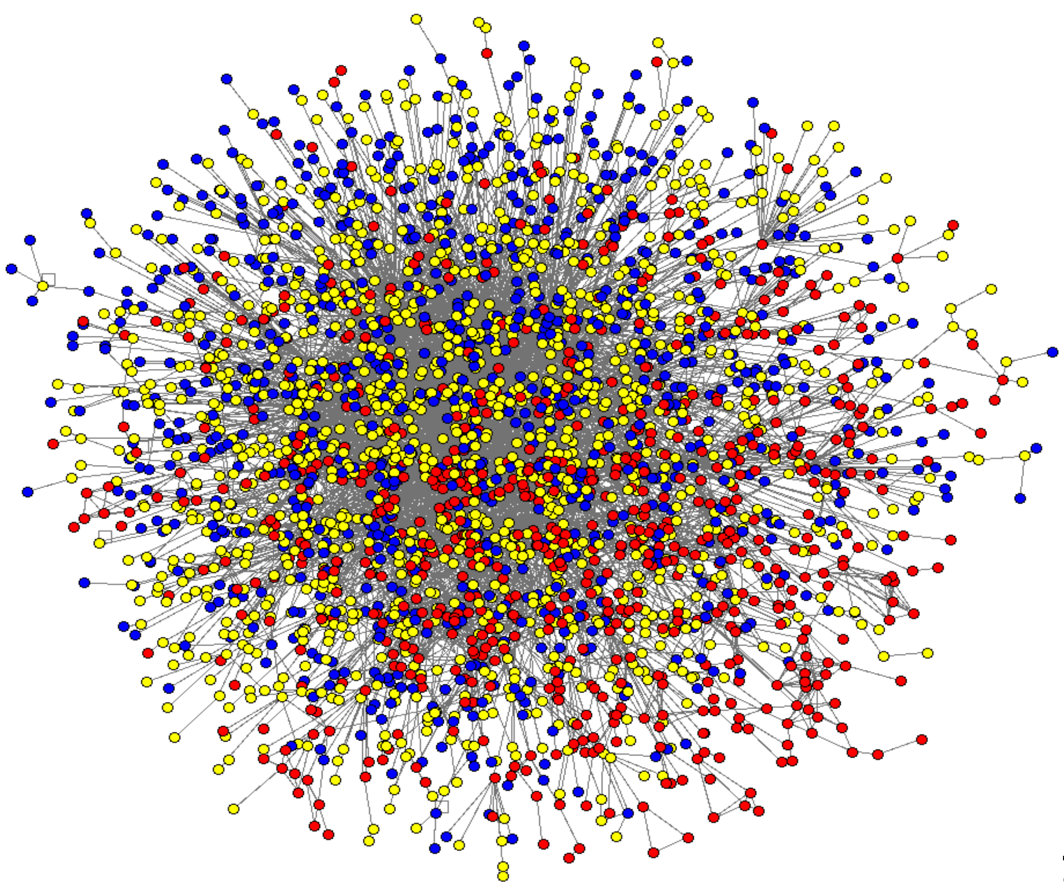
Albert-László Barabási* and Réka Albert

Systems as diverse as genetic networks or the World Wide Web are best described as networks with complex topology. A common property of many large networks is that the vertex connectivities follow a scale-free power-law distribution. This feature was found to be a consequence of two generic mechanisms: (i) networks expand continuously by the addition of new vertices, and (ii) new vertices attach preferentially to sites that are already well connected. A model based on these two ingredients reproduces the observed stationary scale-free distributions, which indicates that the development of large networks is governed by robust self-organizing phenomena that go beyond the particulars of the individual systems.

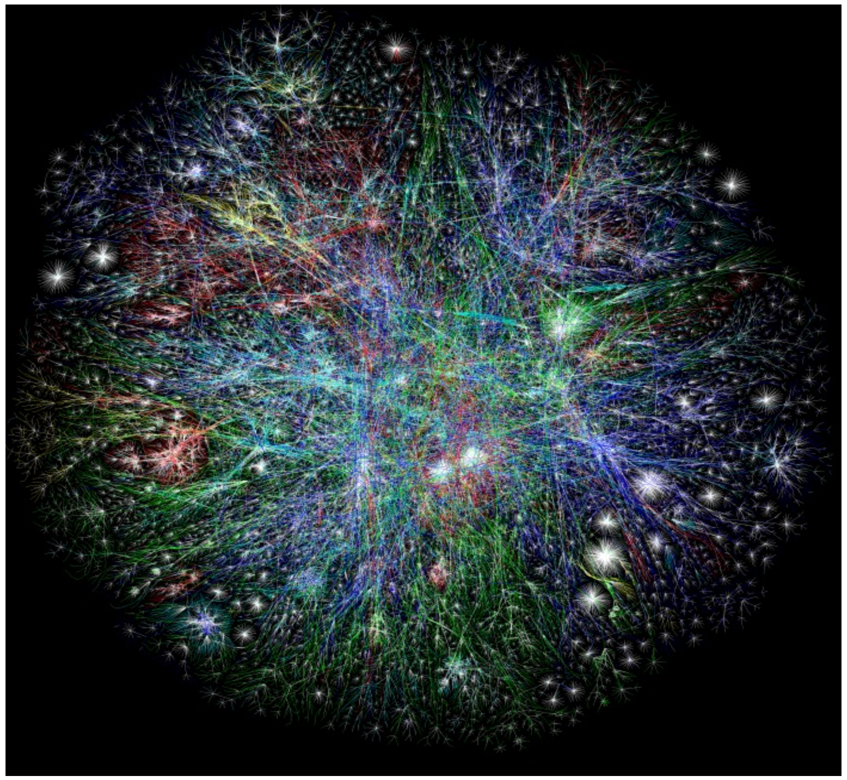
Science, 1999

"Behind each system studied in complexity there is an intricate wiring diagram, or a **network**, that defines the interactions between the component."

Complex networks



twork Science, A. L. Barabási.



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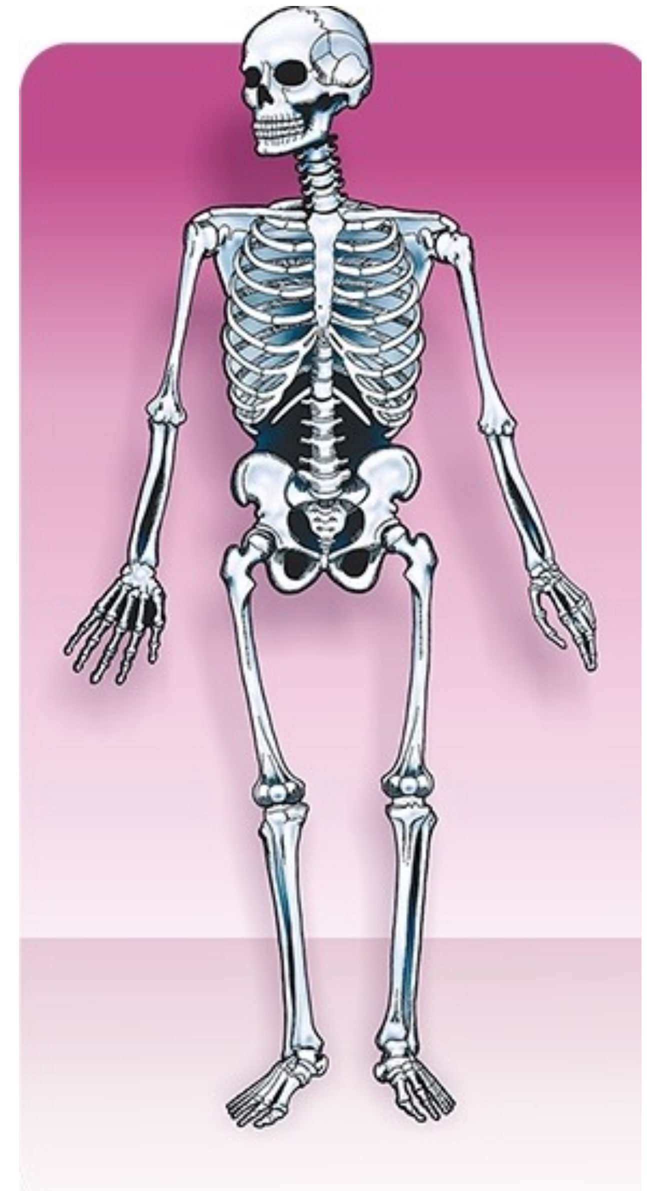
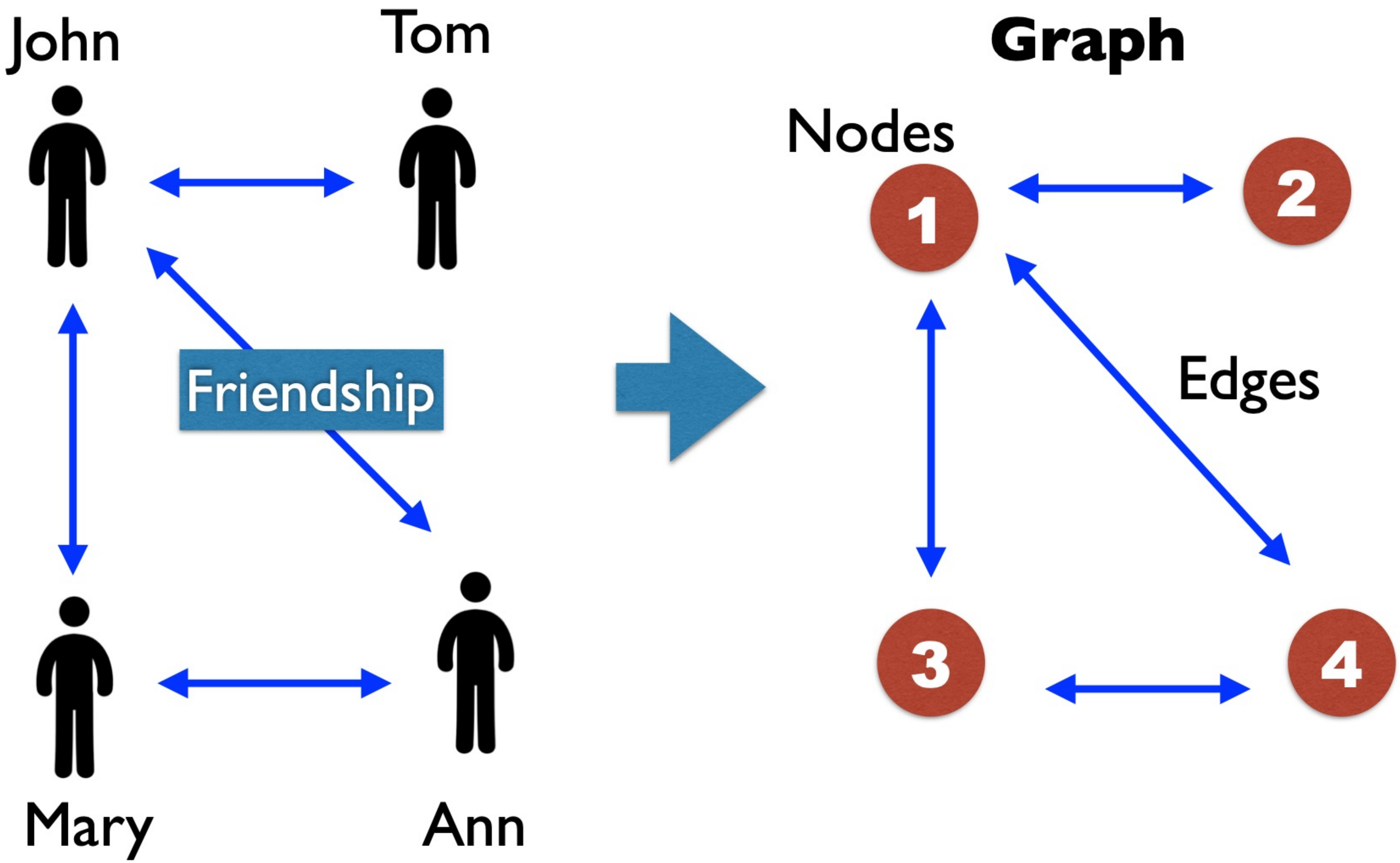
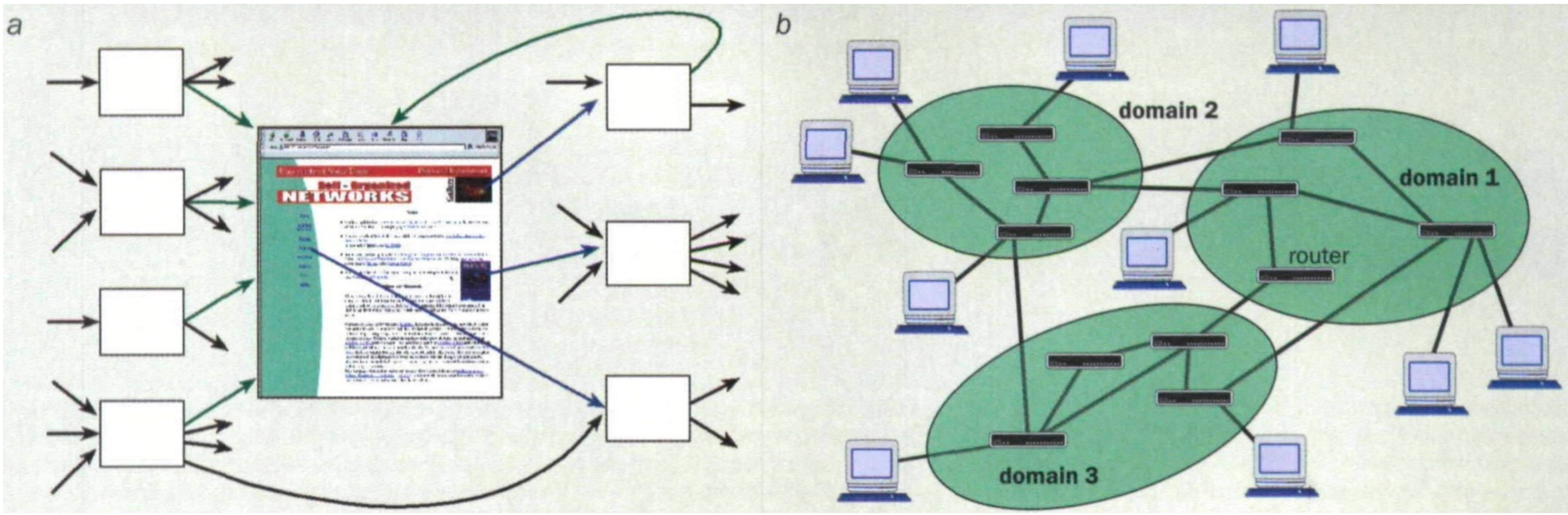


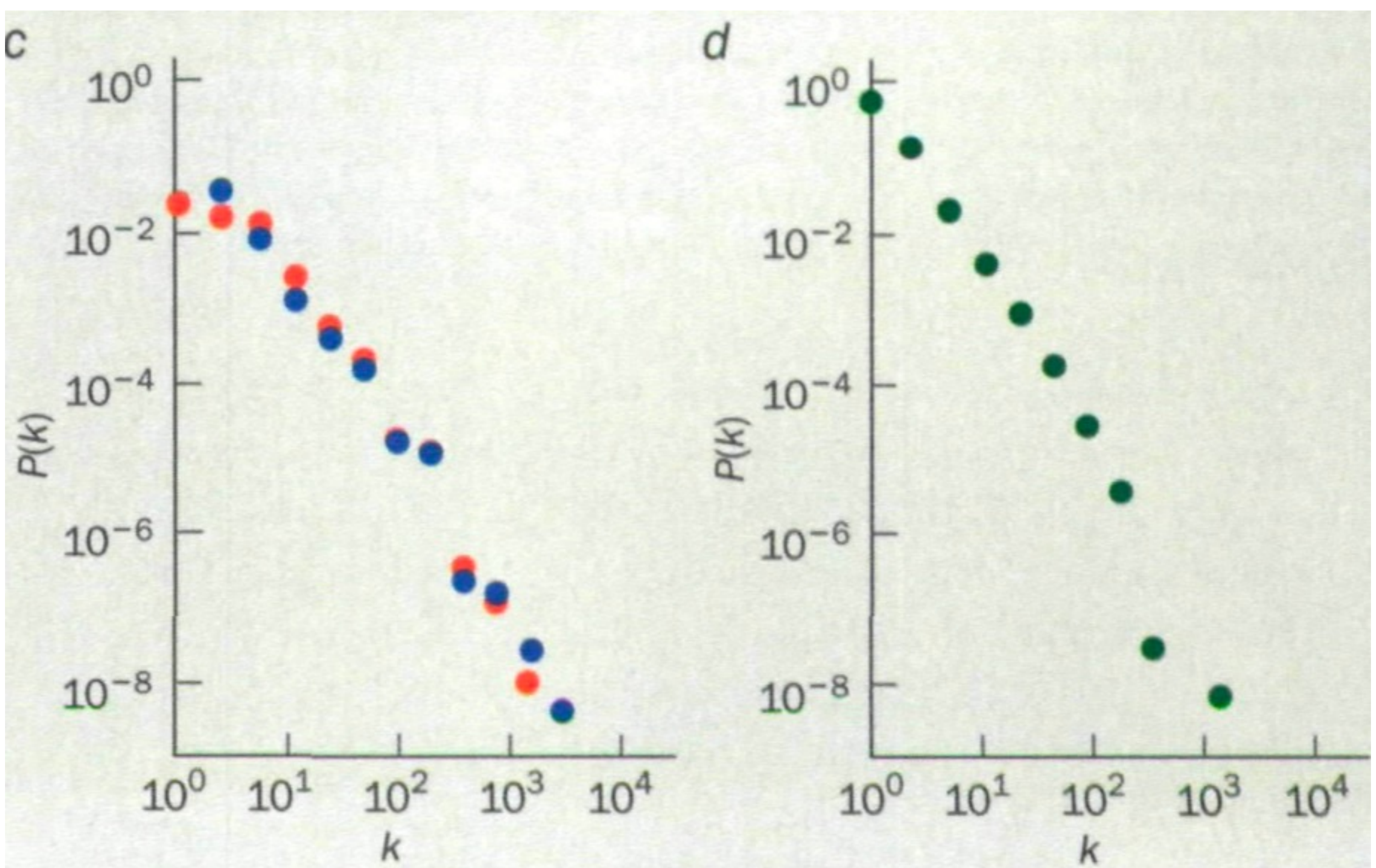
Networks represent the structure of complex systems.

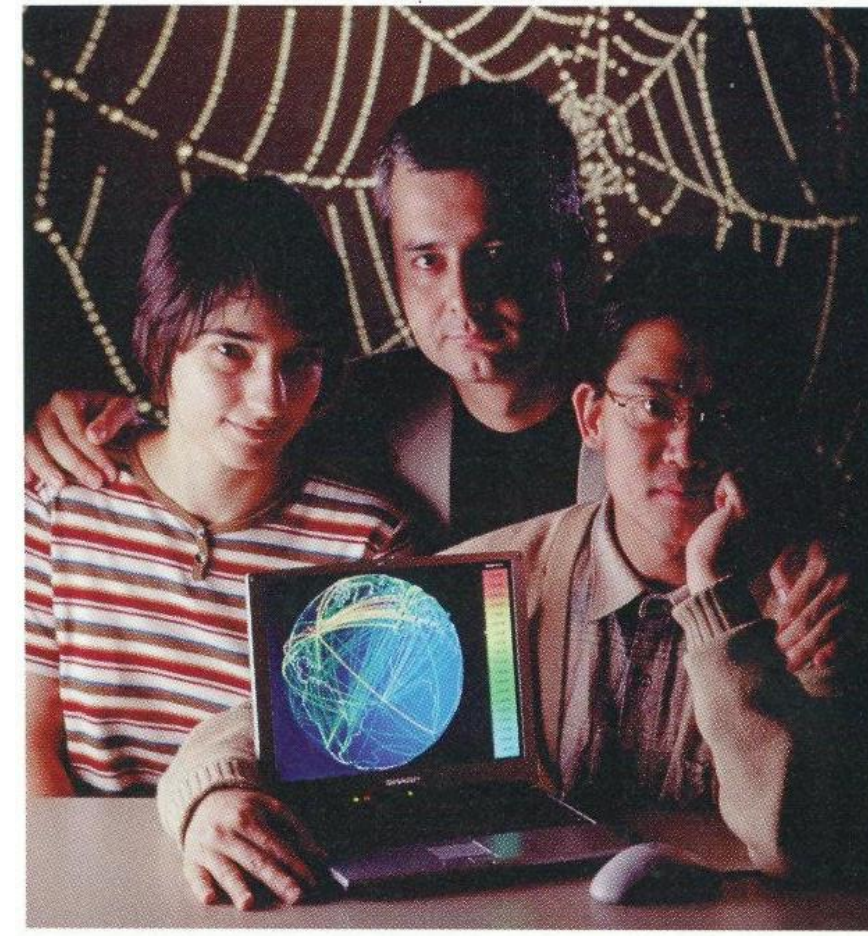
What is a network?



Complex networks

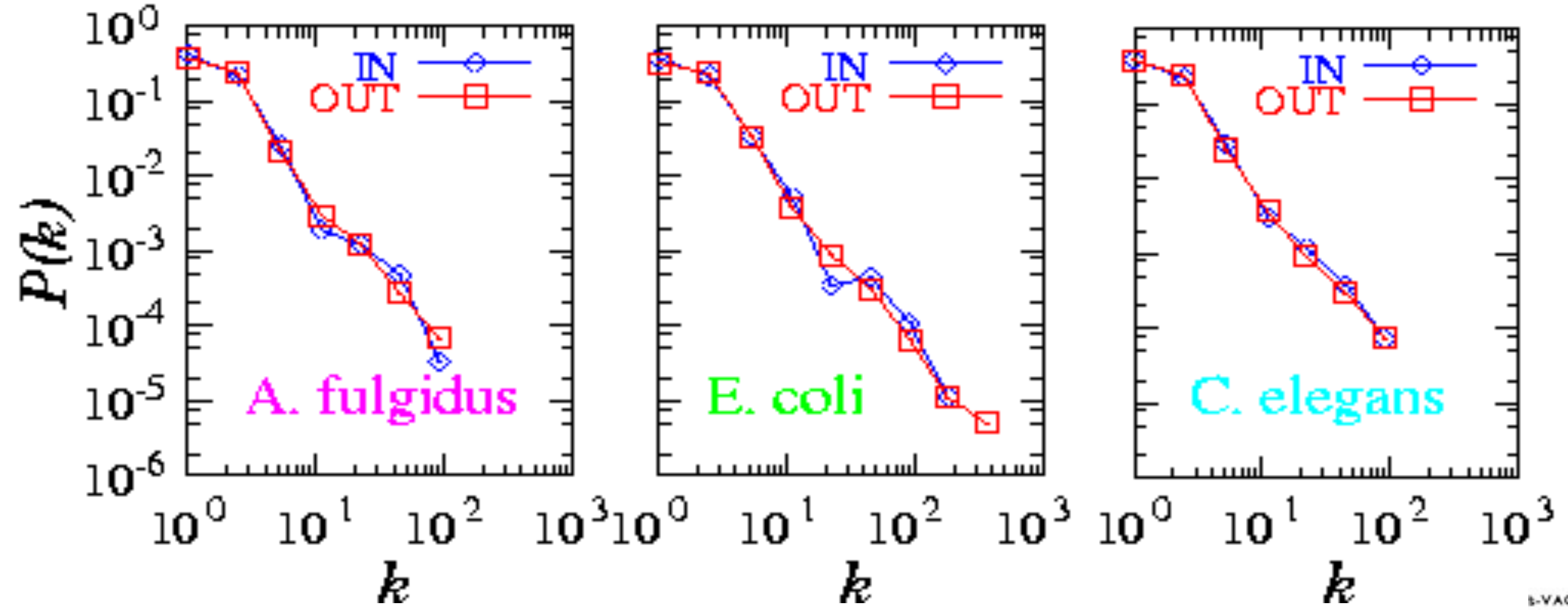




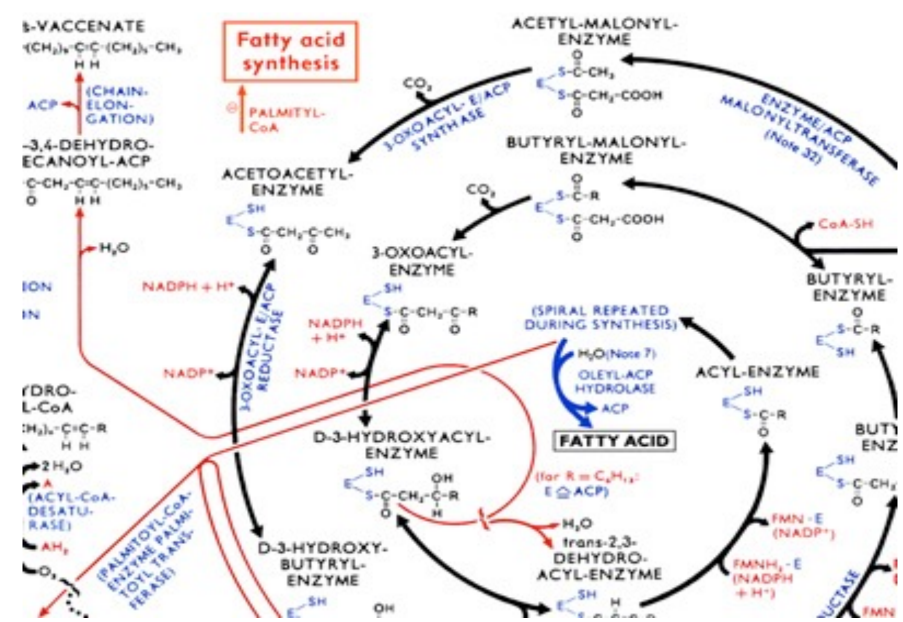


Complex networks

Metabolic networks



"Organisms from all three domains of life are **scale-free** networks!"



*H. Jeong et al., Nature, **407** 651 (2000)*

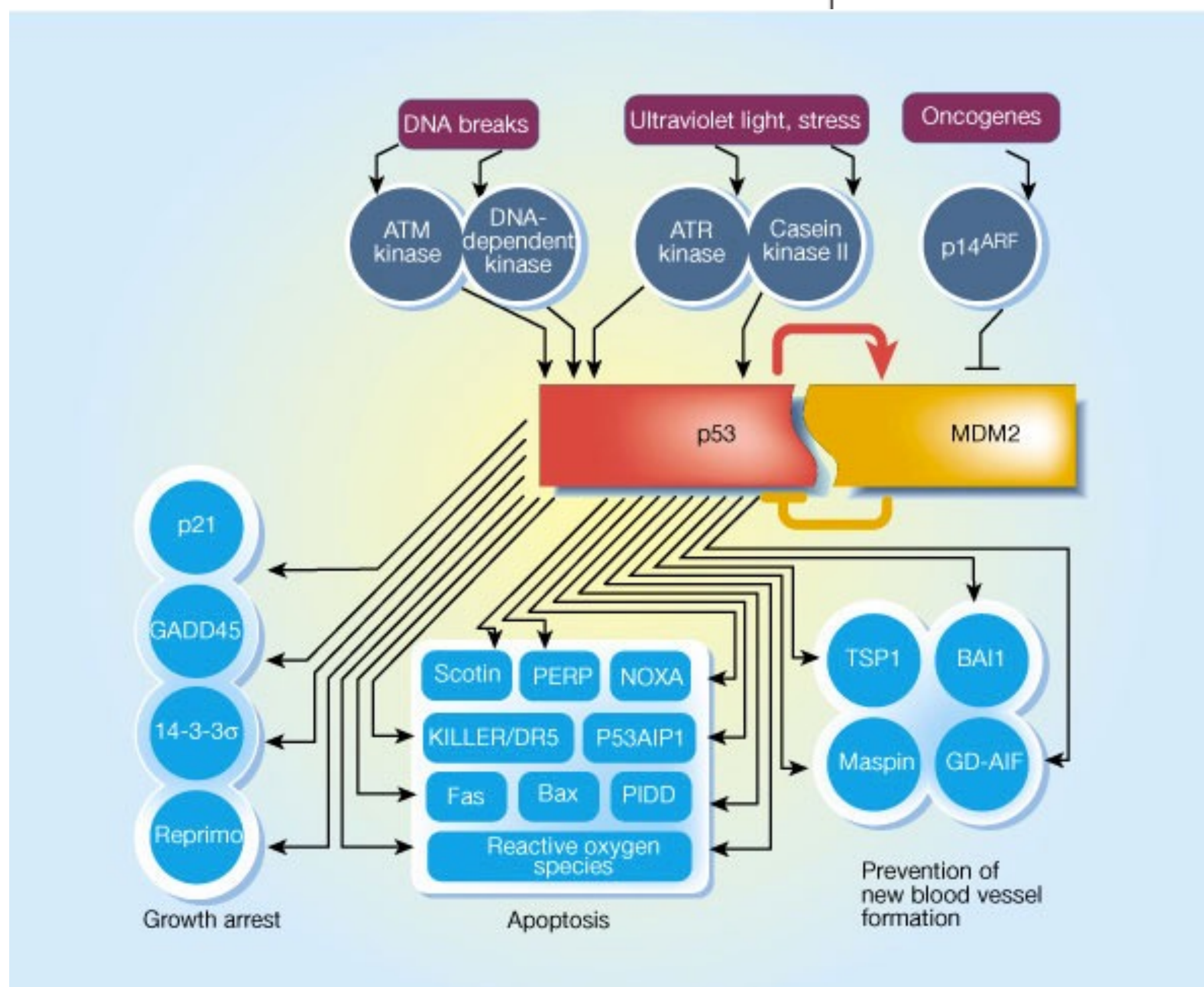
Complex networks

news and views feature

Surfing the p53 network

Bert Vogelstein, David Lane and Arnold J. Levine

The p53 tumour-suppressor gene integrates numerous signals that control cell life and death. As when a highly connected node in the Internet breaks down, the disruption of p53 has severe consequences.



Bert Vogelstein, David Lane & Arnold J. Levine, Nature **408**, 2000

Complex networks

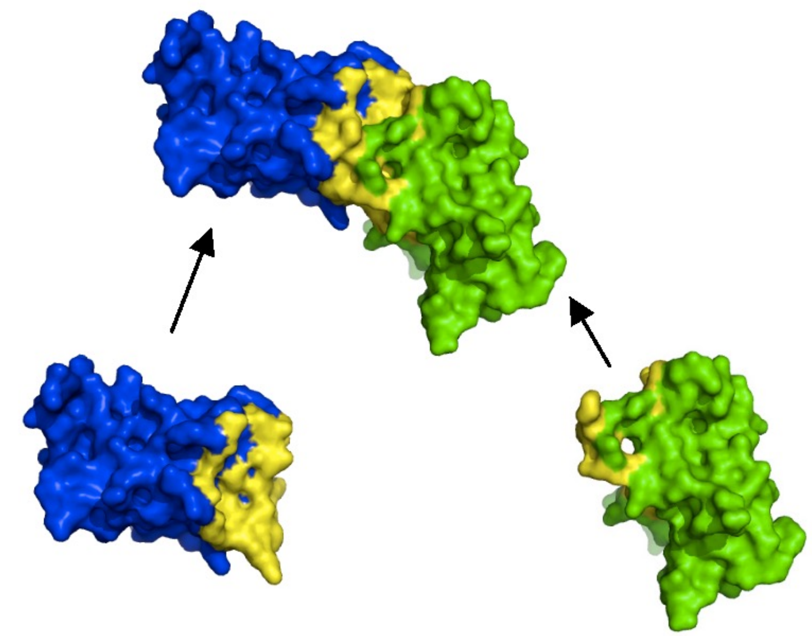
nature
International journal of science

Brief Communication | Published: 03 May 2001

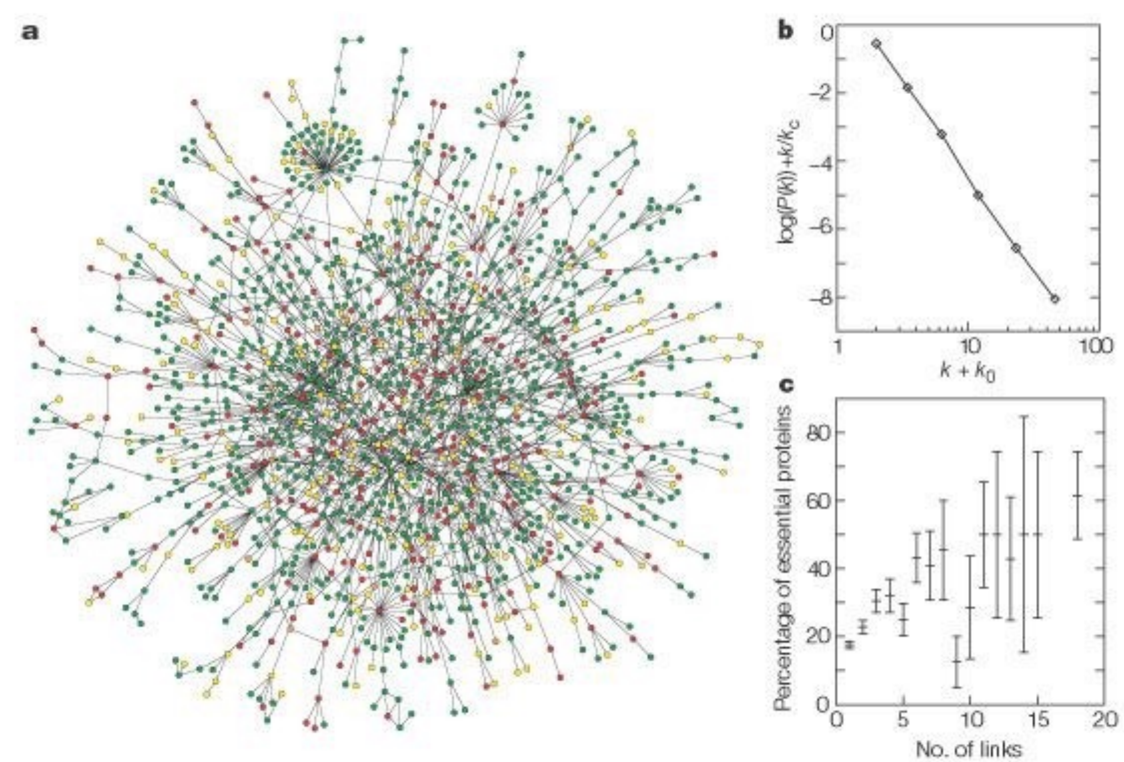
Lethality and centrality in protein networks

H. Jeong, S. P. Mason, A.-L. Barabási & Z. N. Oltvai

Nature **411**, 41–42 (2001) | Download Citation



The most highly connected proteins in the cell are the most important for its survival.




Science
24 July 2009 | $10
Complex Systems
and Networks
AAAS
March 23, 2021 | vol. 118 | no. 12
PNAS
Proceedings of the National Academy of Sciences of the United States of America
www.pnas.org
Visualizing biochemical
networks
Ocean warming and Yangtze River flooding
Global effects of tropical volcanic eruptions
Revised timing of Neanderthal disappearance
Host–parasite dynamics in the tropical Andes
20 July 2006
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
nature
ECOLOGICAL
COMPLEXITY
UNTANGLED
The architecture of ecosystem fragility
NEANDERTHAL DNA
New enthusiasm for
old bones
PARTING CONTINENTS
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NON-MENDELIAN
GENETICS
RNA implicated in
paramutation in maize
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A 3D wiring
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Primate brain cortical
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OCTOBER 2015 VOL 11 NO 10
www.nature.com/naturephysics
Ten years of Nature Physics
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How to get around
PARTICLE PHYSICS
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NITROGEN-VACANCY CENTRES
Single-spin manipulation
JNeurosci
THE JOURNAL OF NEUROSCIENCE
SOCIETY for NEUROSCIENCE
The international journal of science / 7 November 2019
nature
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NETWORK
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A web of multidisciplinary
research and discovery
EXPLORE
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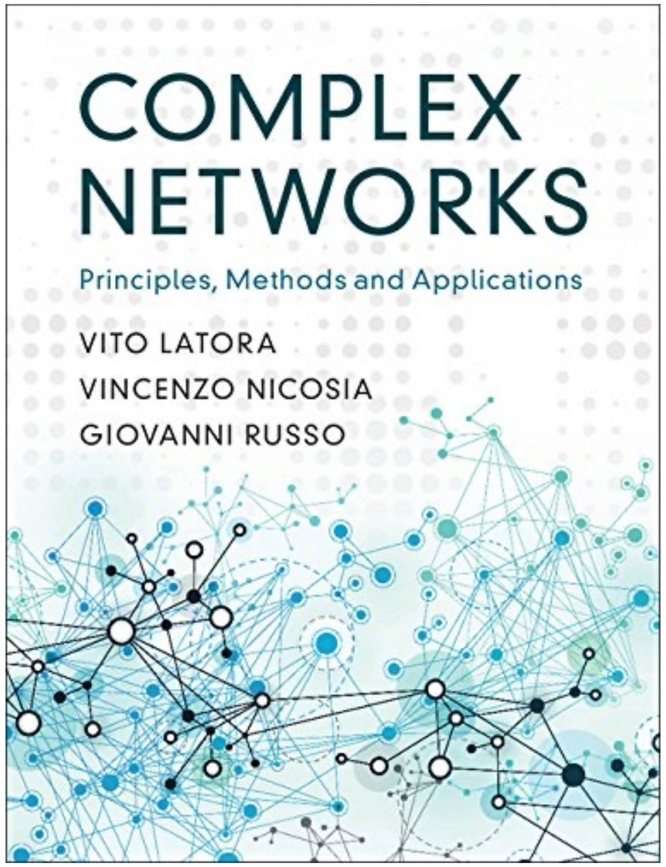
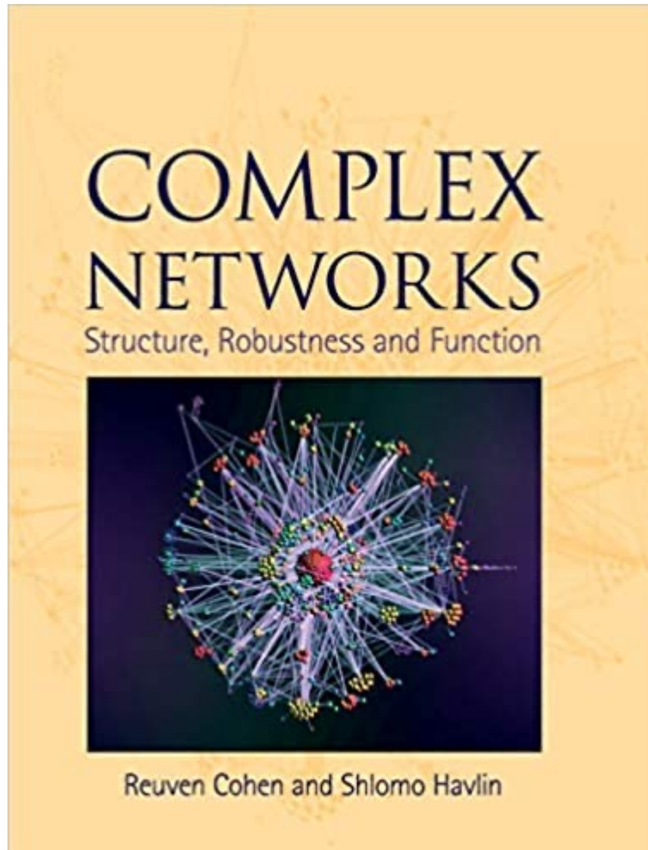

COMPLEX
NETWORKS
Principles, Methods and Applications
VITO LATORA
VINCENZO NICOSIA
GIOVANNI RUSSO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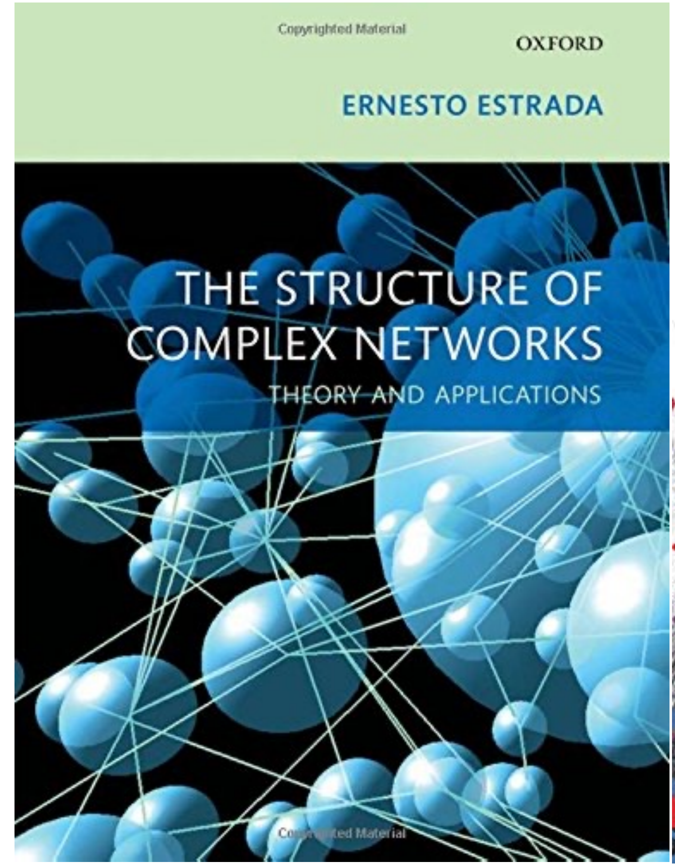
Structure, Robustness and Function
Reuven Cohen and Shlomo Havlin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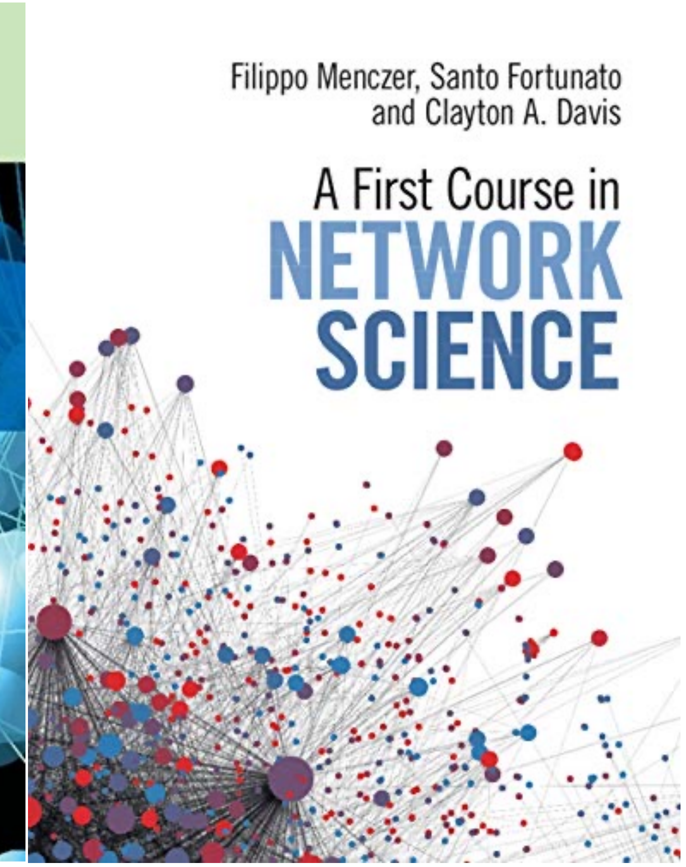
THEORY AND APPLICATIONS


Filippo Menczer, Santo Fortunato
and Clayton A. Davis
A First Course in
NETWORK
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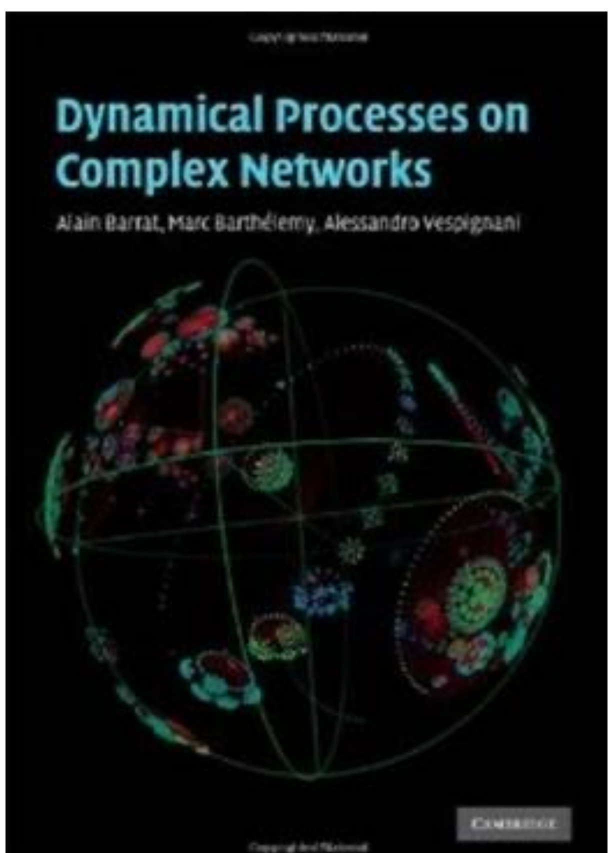
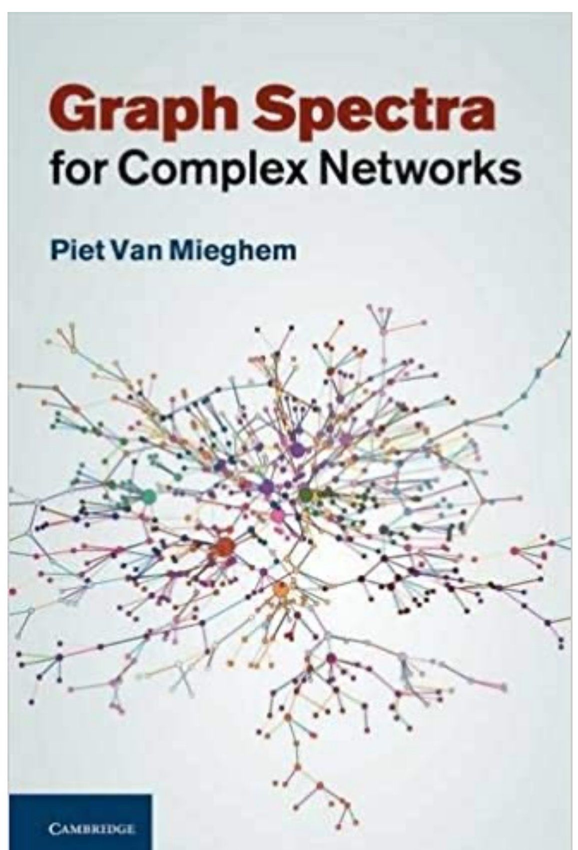
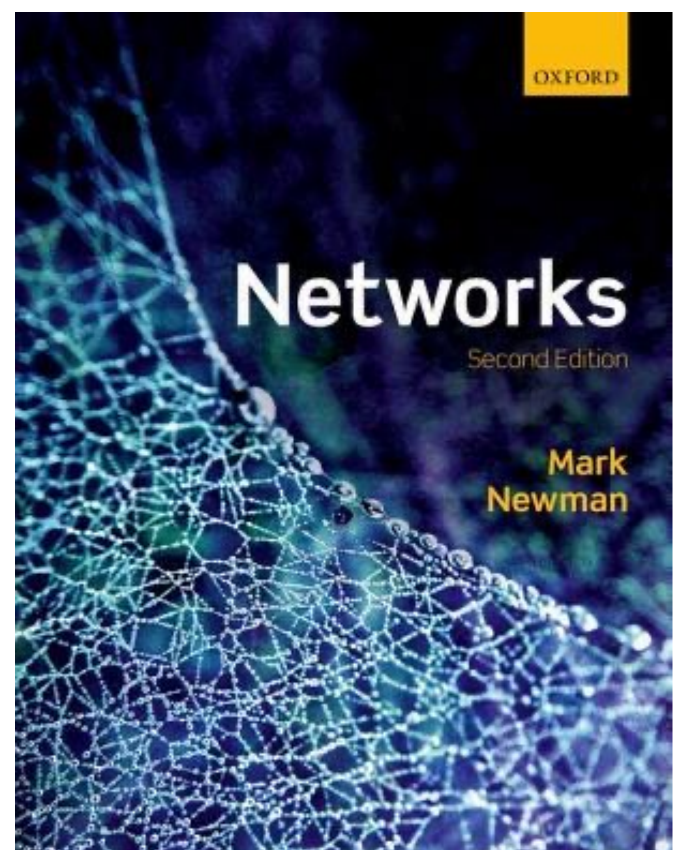

Dynamical Processes on
Complex Networks
Alain Barrat, Marc Barthélemy, Alessandro Vespignani


Graph Spectra
for Complex Networks
Piet Van Mieghem
CAMBRIDGE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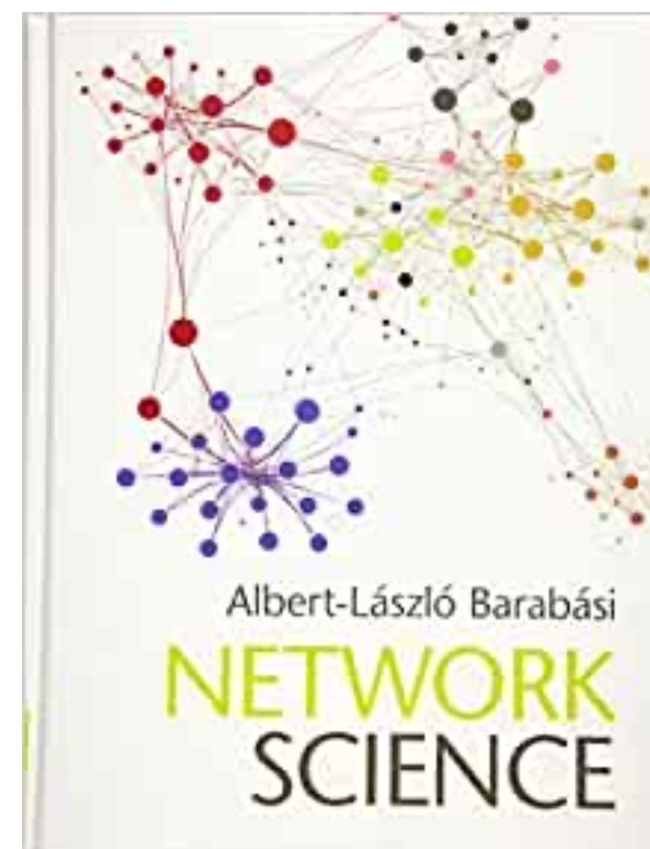

Albert-László Barabási
NETWORK
SCIENCE

Stephen Hawking

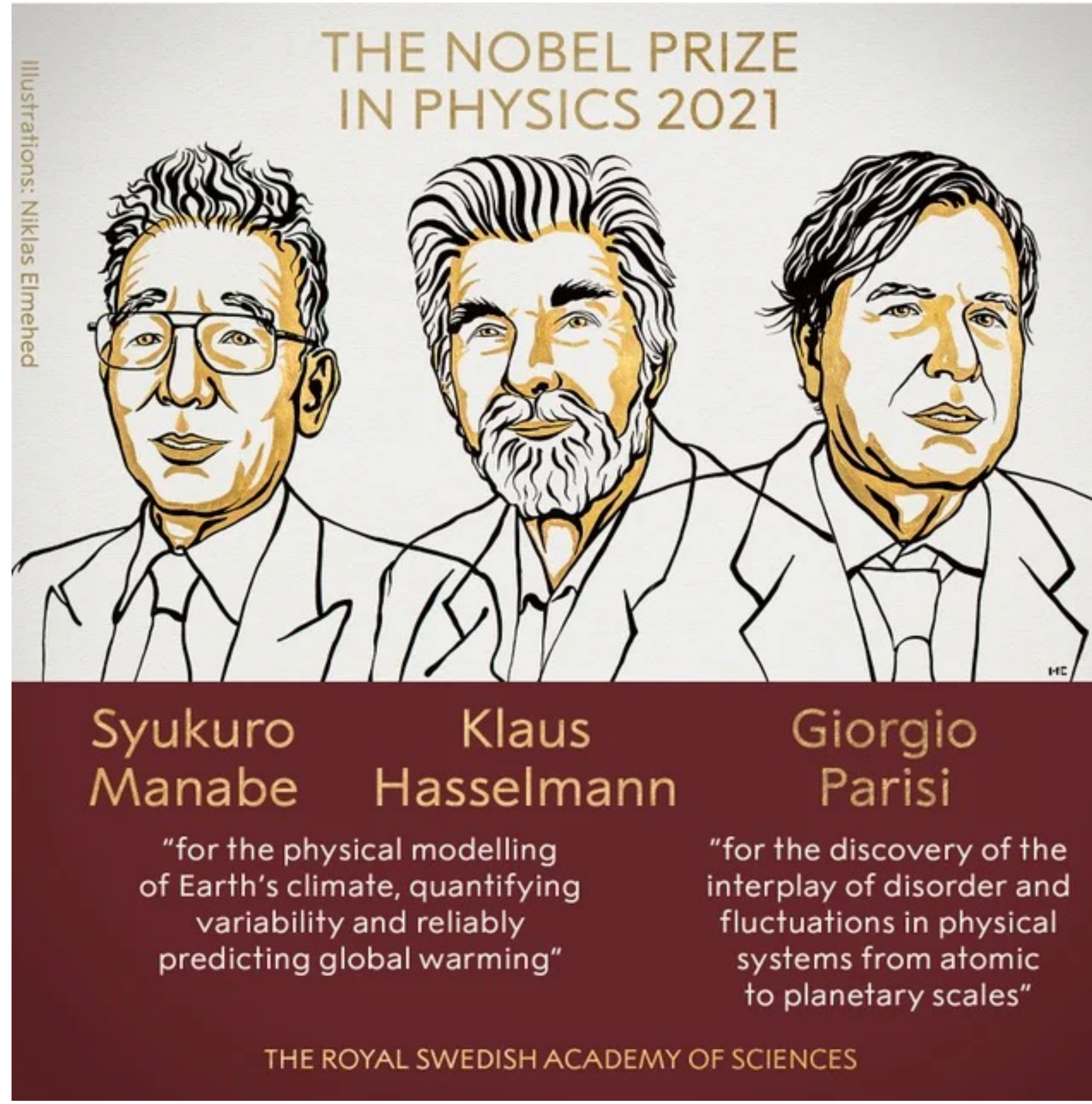
"I think the next century will be the century of complexity."

January 23, 2000, San Jose Mercury News

The Nobel Prize in Physics 2021

"for groundbreaking contributions to our understanding of complex systems"

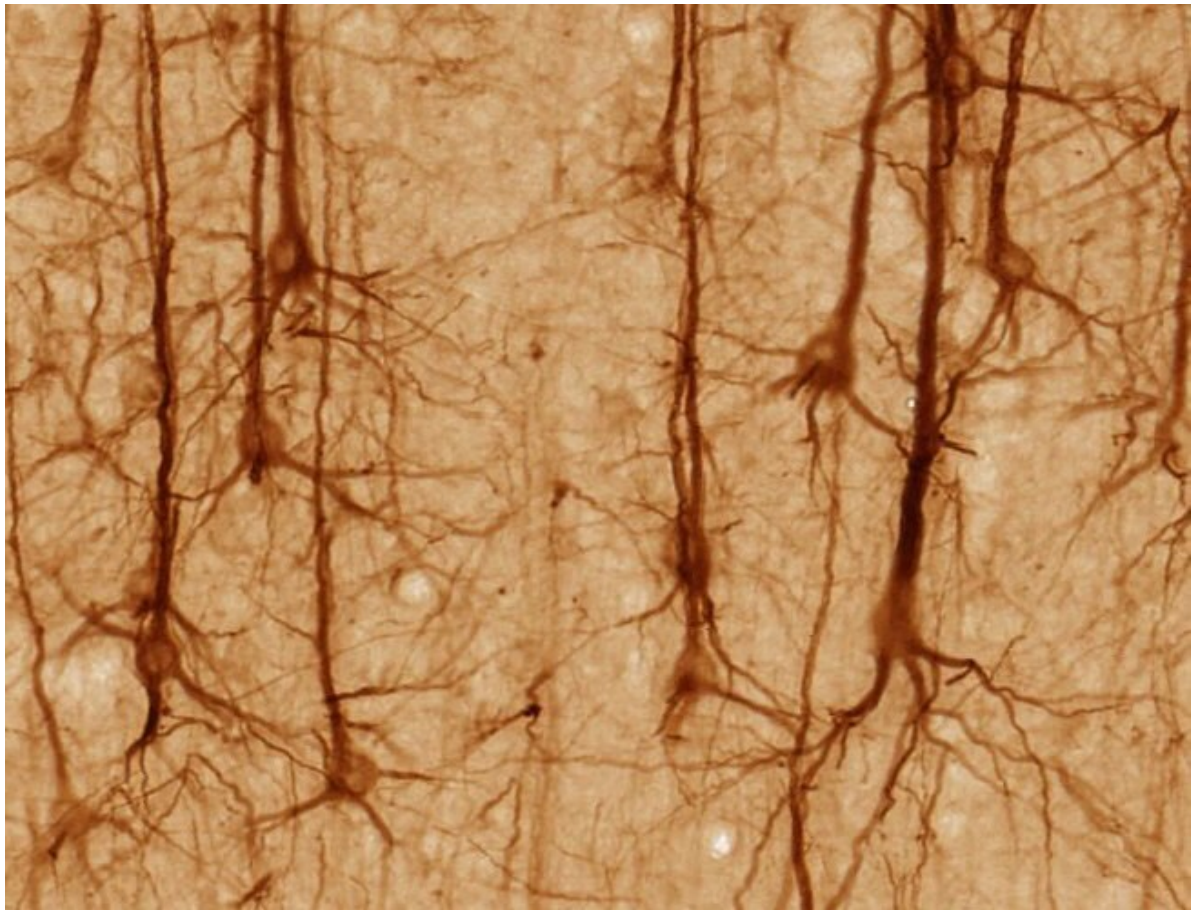
This year's Nobel Prize in Physics is awarded with one half jointly to Syukuro Manabe, Klaus Hasselmann and the other half to Giorgio Parisi. They have laid the foundation of our knowledge of the Earth's climate and how humanity influences it, as well as revolutionized the theory of disordered materials and random processes.

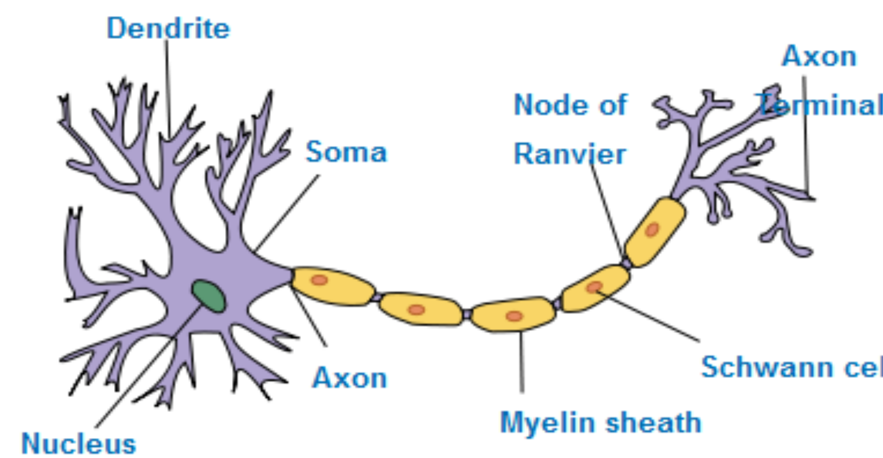


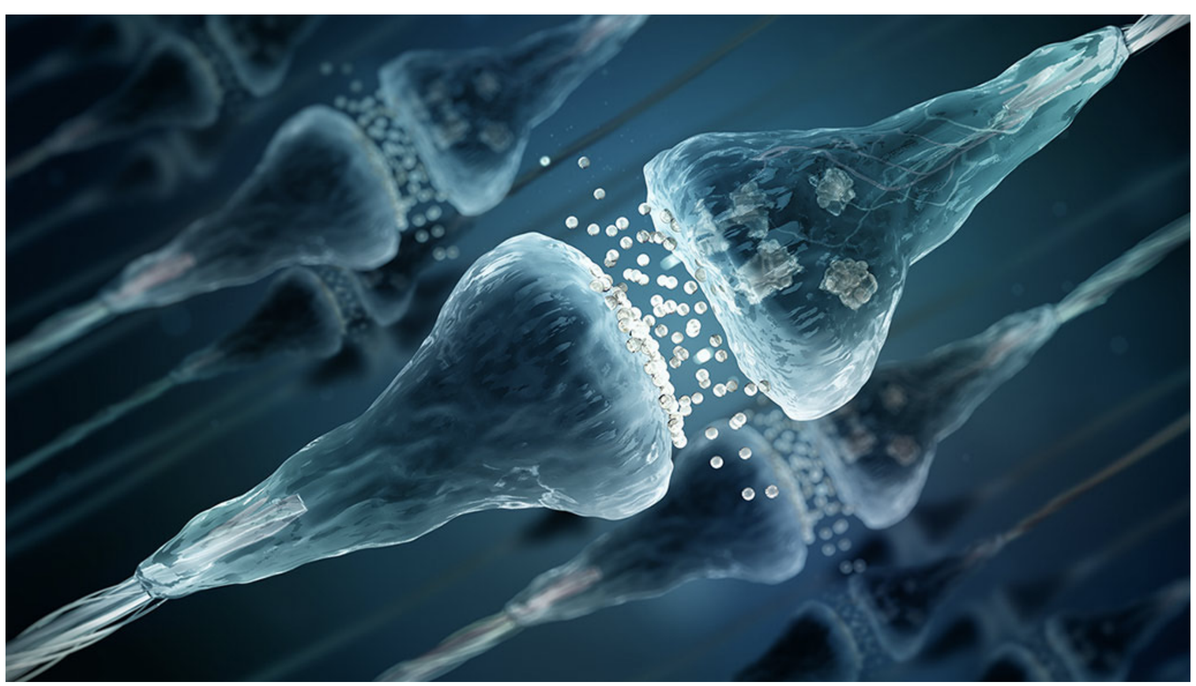
https://www.nobelprize.org/prizes/physics/2021/press-release

Examples of complex systems

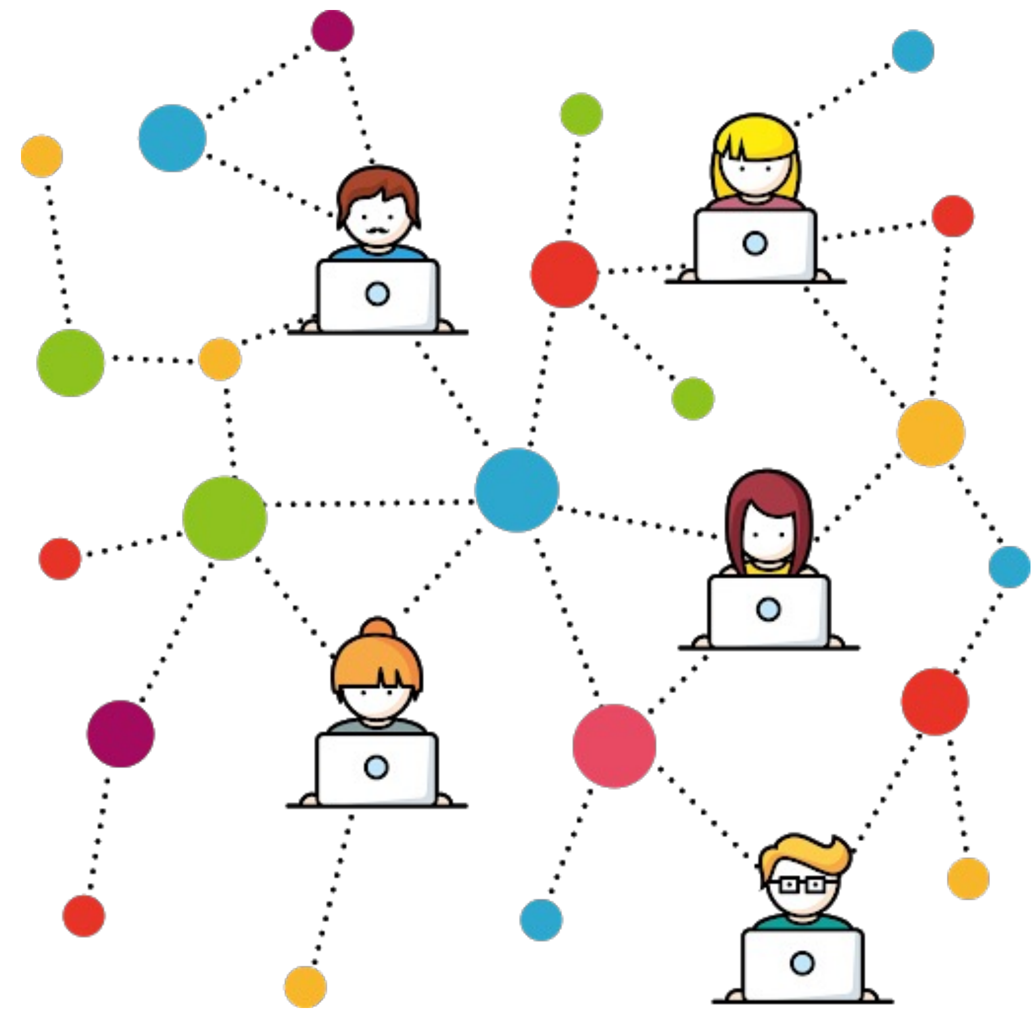
Brain



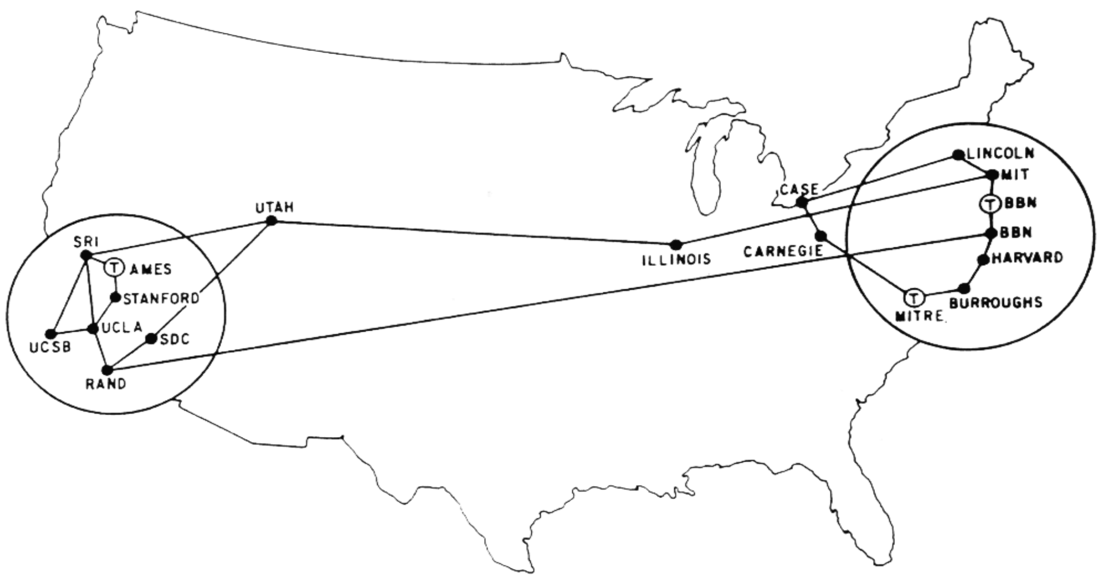

Dendrite
Axon
Node of
Terminal
Soma
Ranvier
Axon
Schwann cell
Myelin sheath
Nucleus



Society



Internet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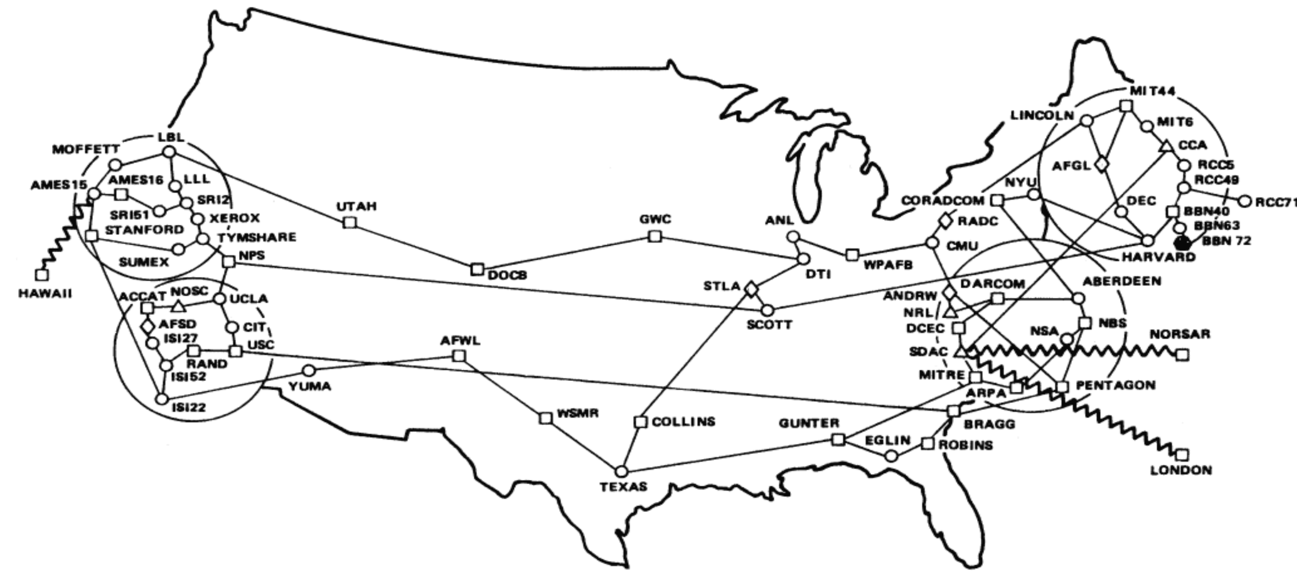
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UTAH
DOCB
GWC
ANL
DTI
WPAFB
STLA
SCOTT
AFWL
WSMR
COLLINS
TEXAS
GUNTER
EGLIN
ROBINS
BRAGG
ARPA
MITRE
SDAC
DCEC
NRL
ANDRW
DARCOM
CMU
RADC
CORADCOM
NYU
LINCOLN
MIT44
MIT6
CCA
AFGL
RCC5
RCC49
RCC71
DEC
BBN40
BBN63
BBN 72
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ABERDEEN
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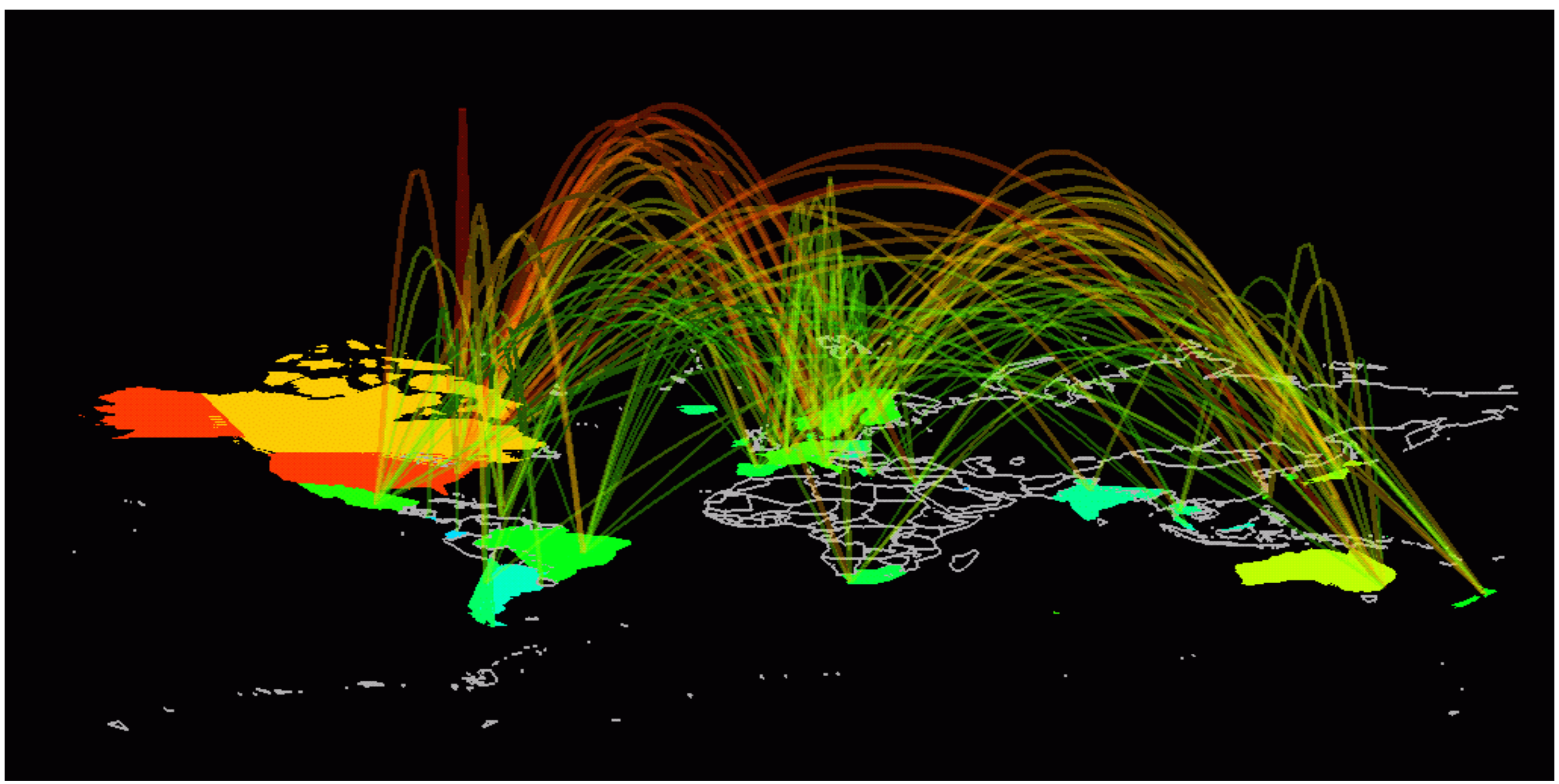
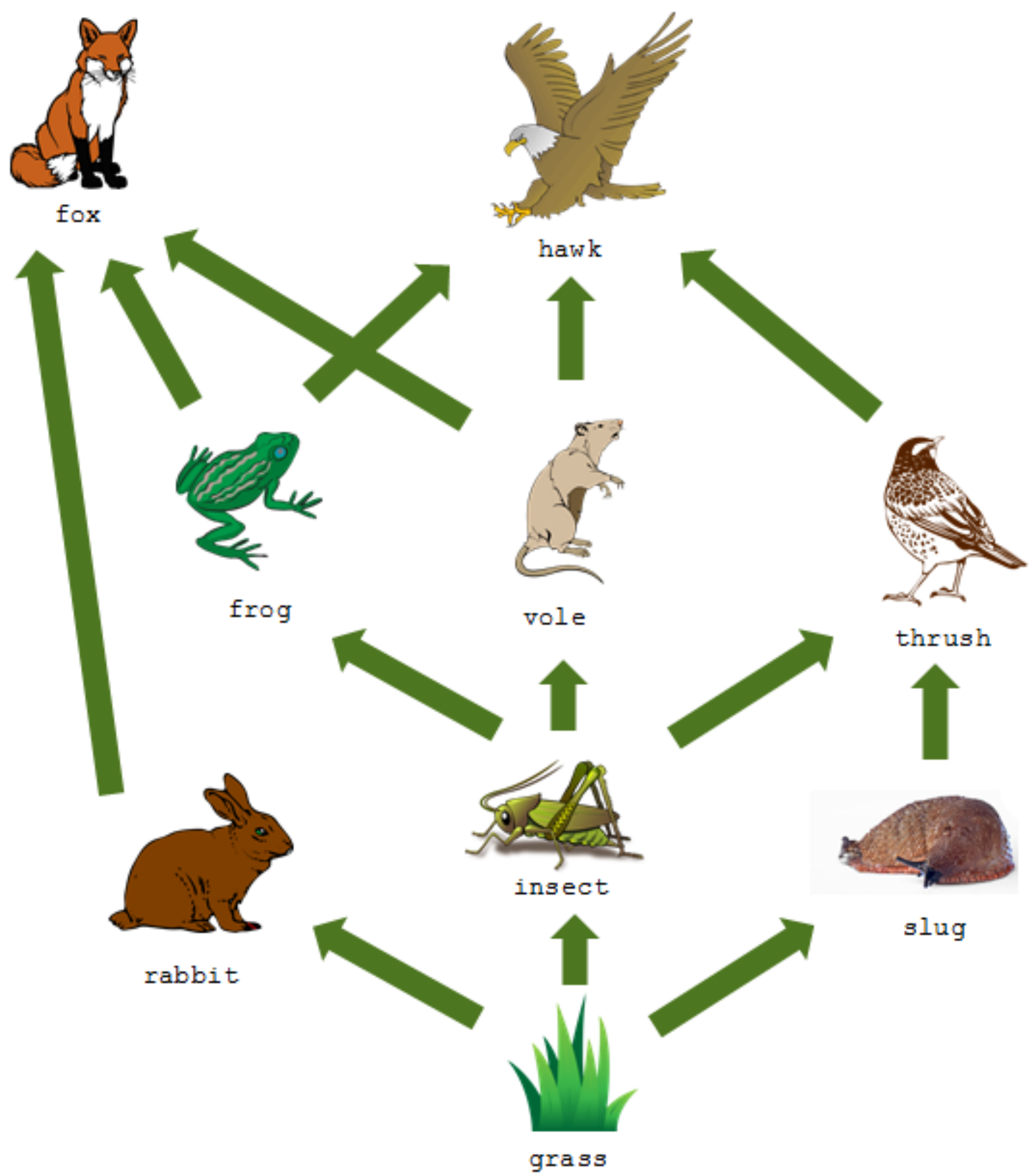
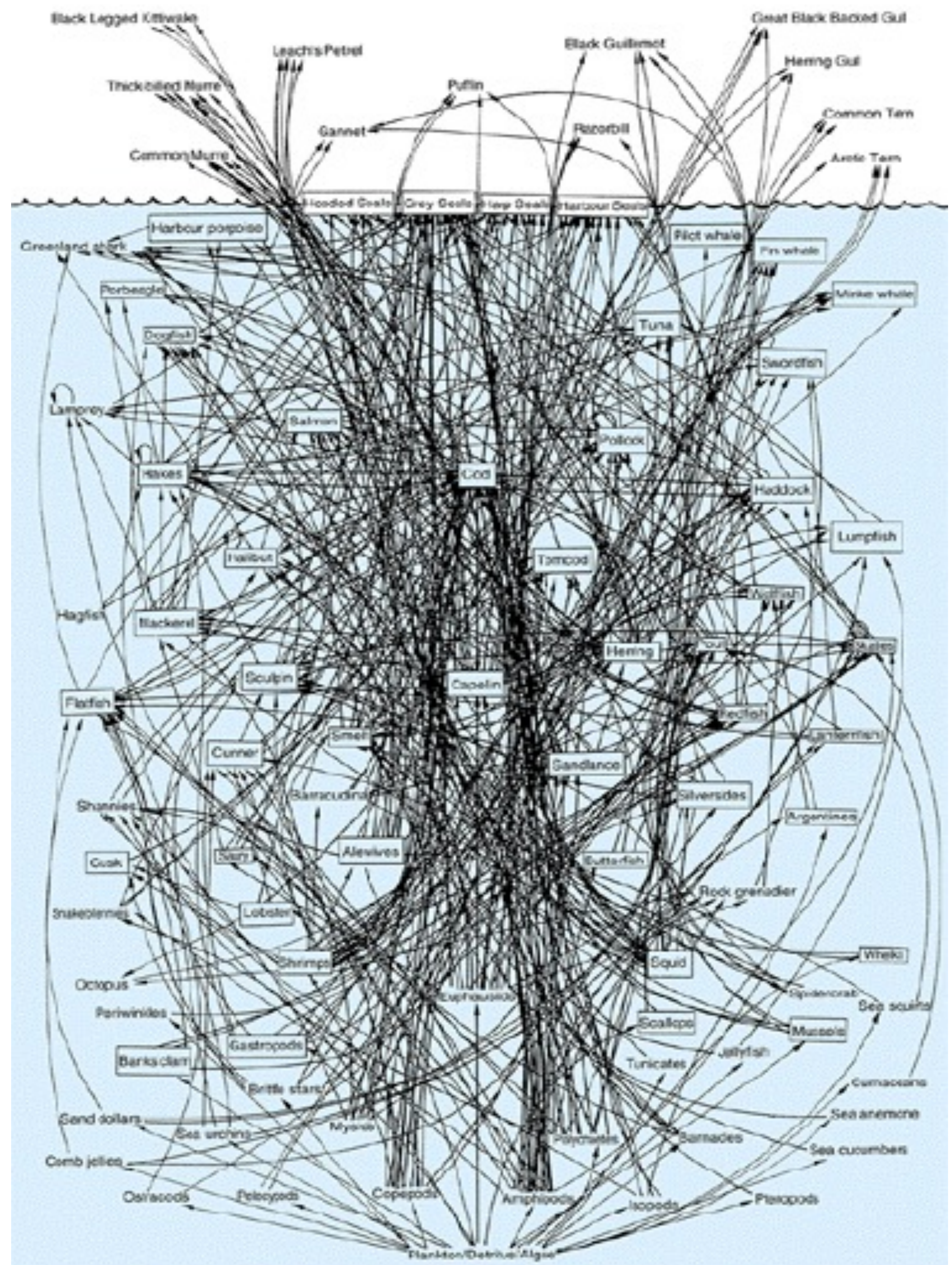


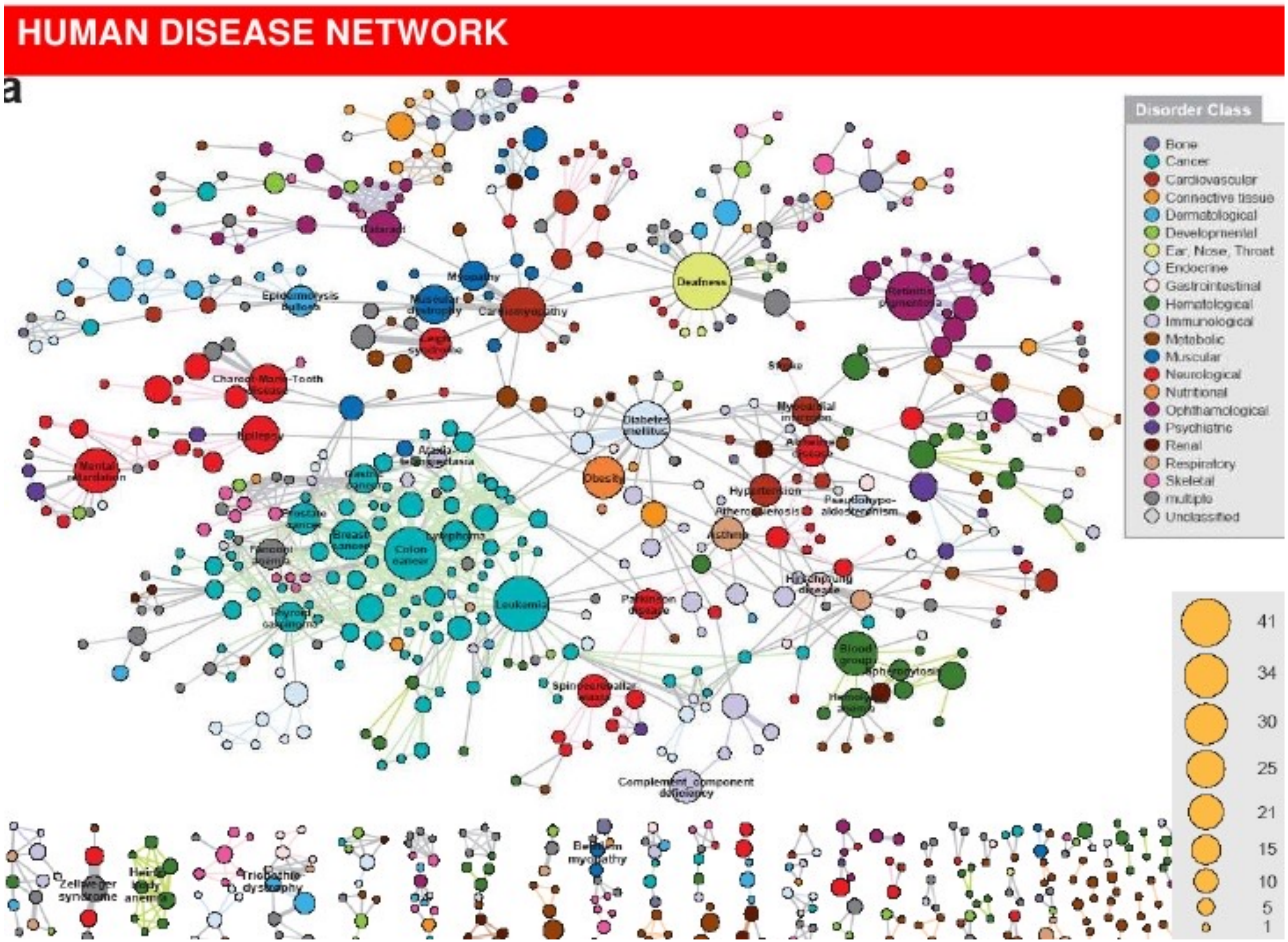
Food webs





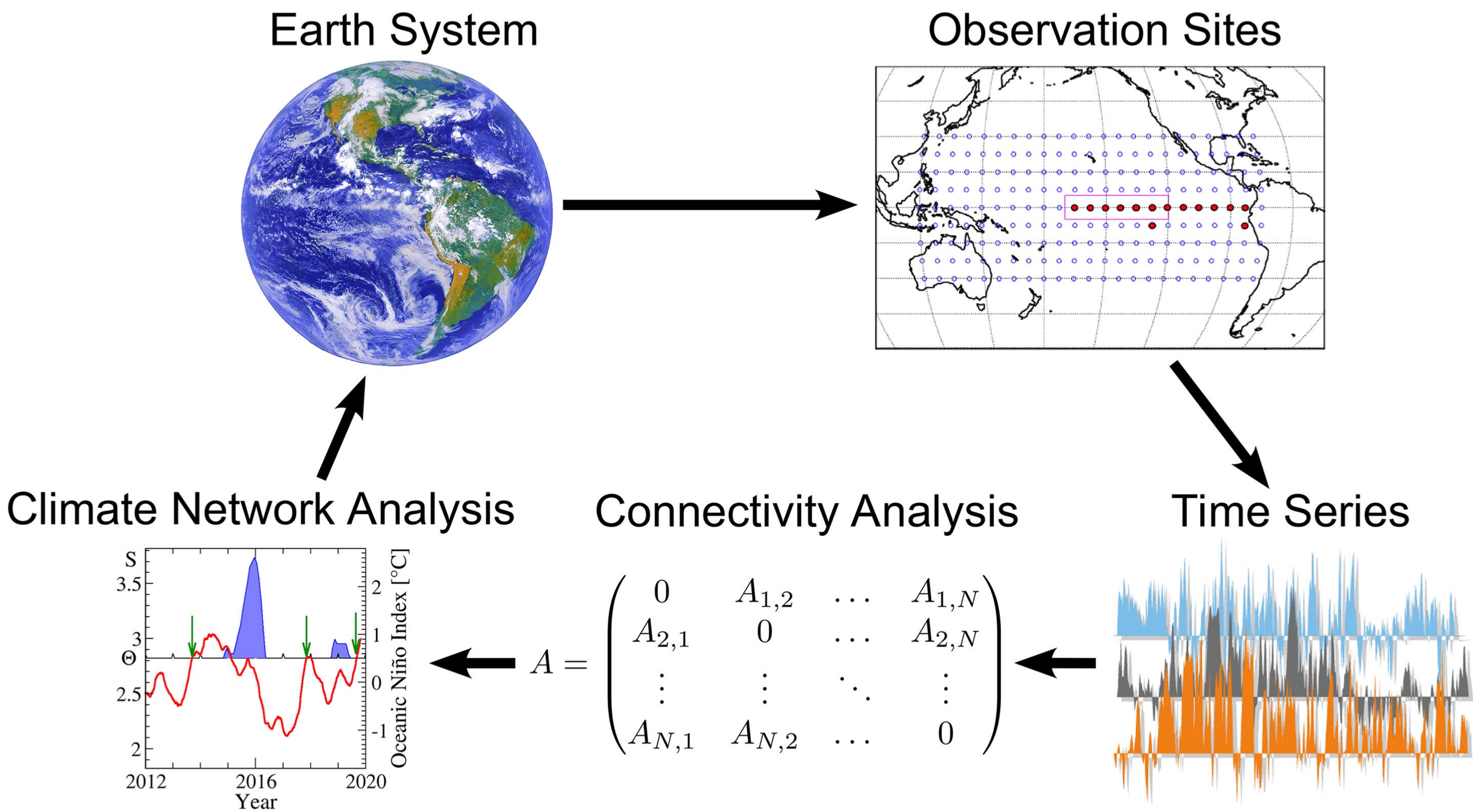
A simplified food web for the Northwest Atlantic

Human disease network



Barabási, Networks Science, Cambridge Un. Press

Climate networks

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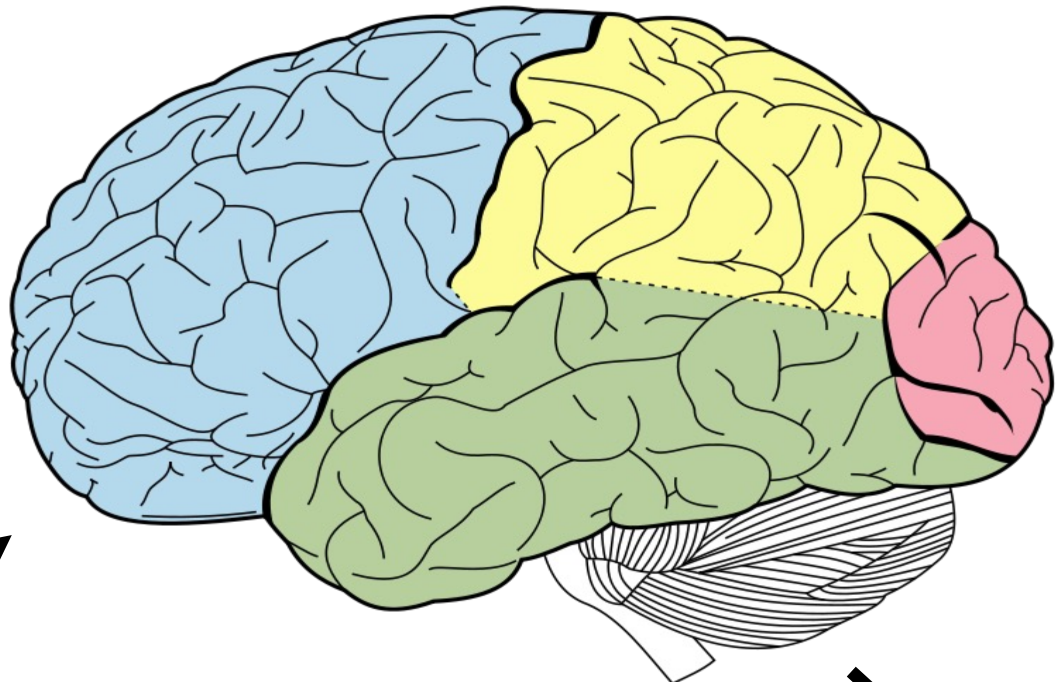
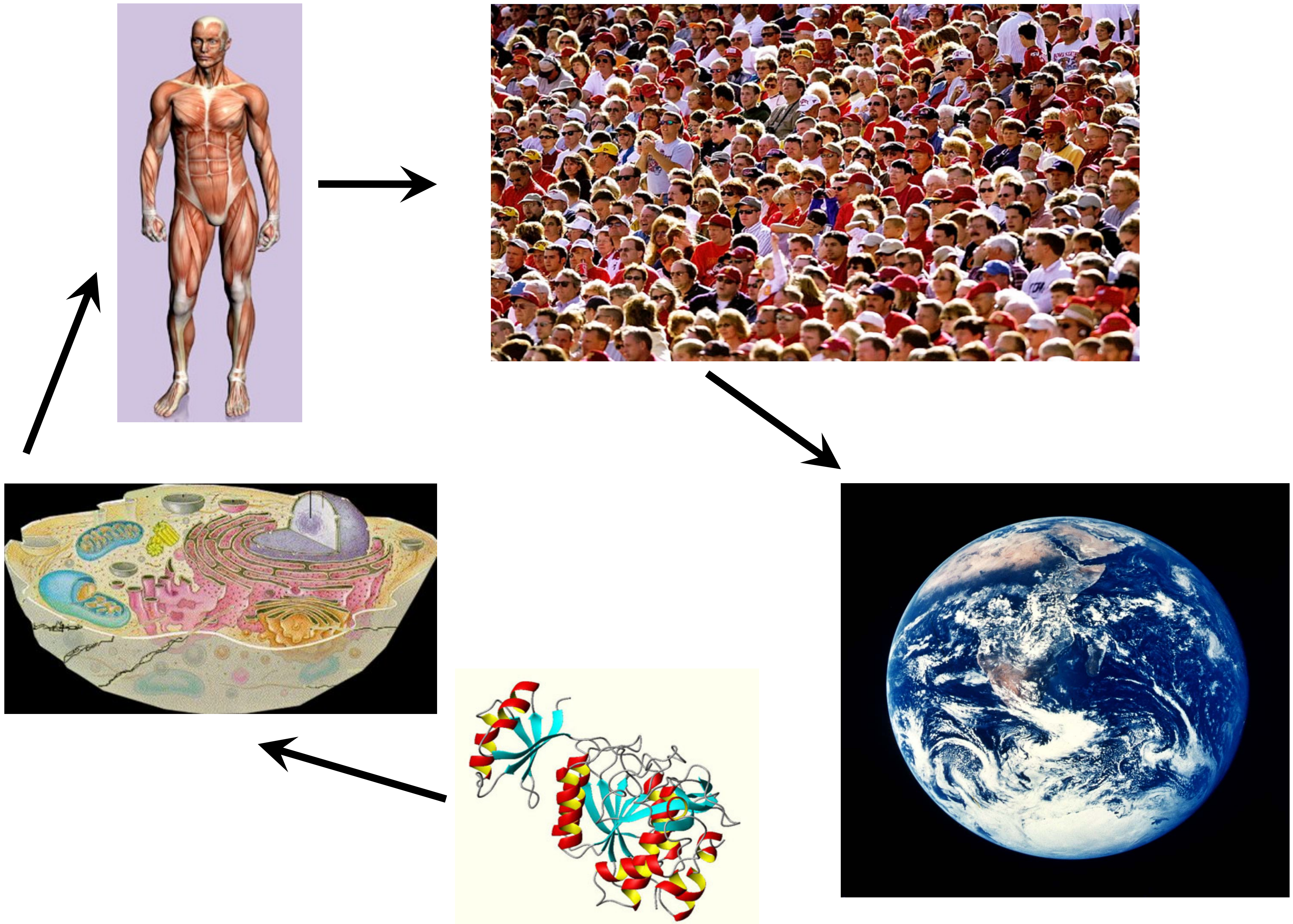
Emergence

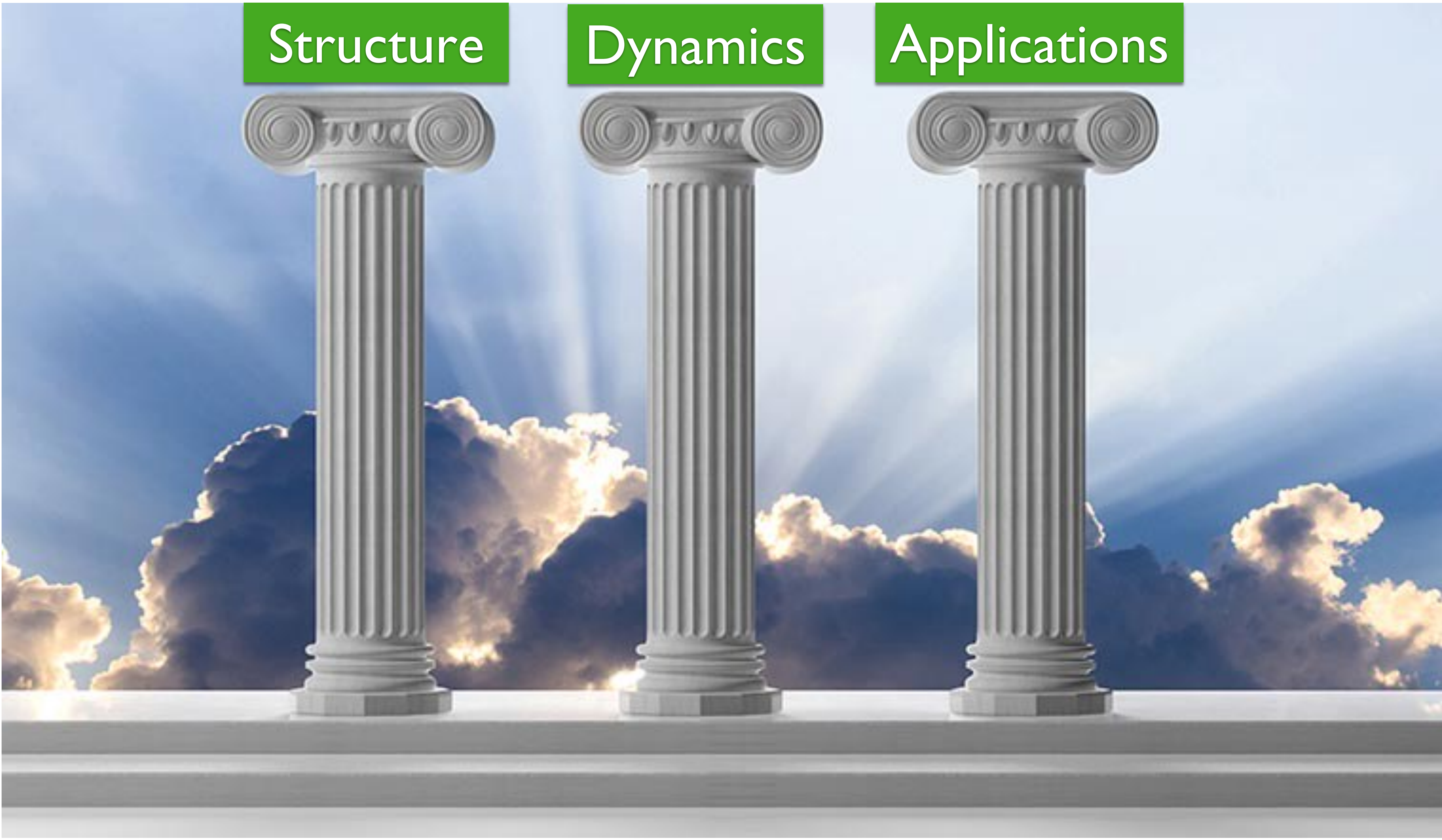


Hierarchy

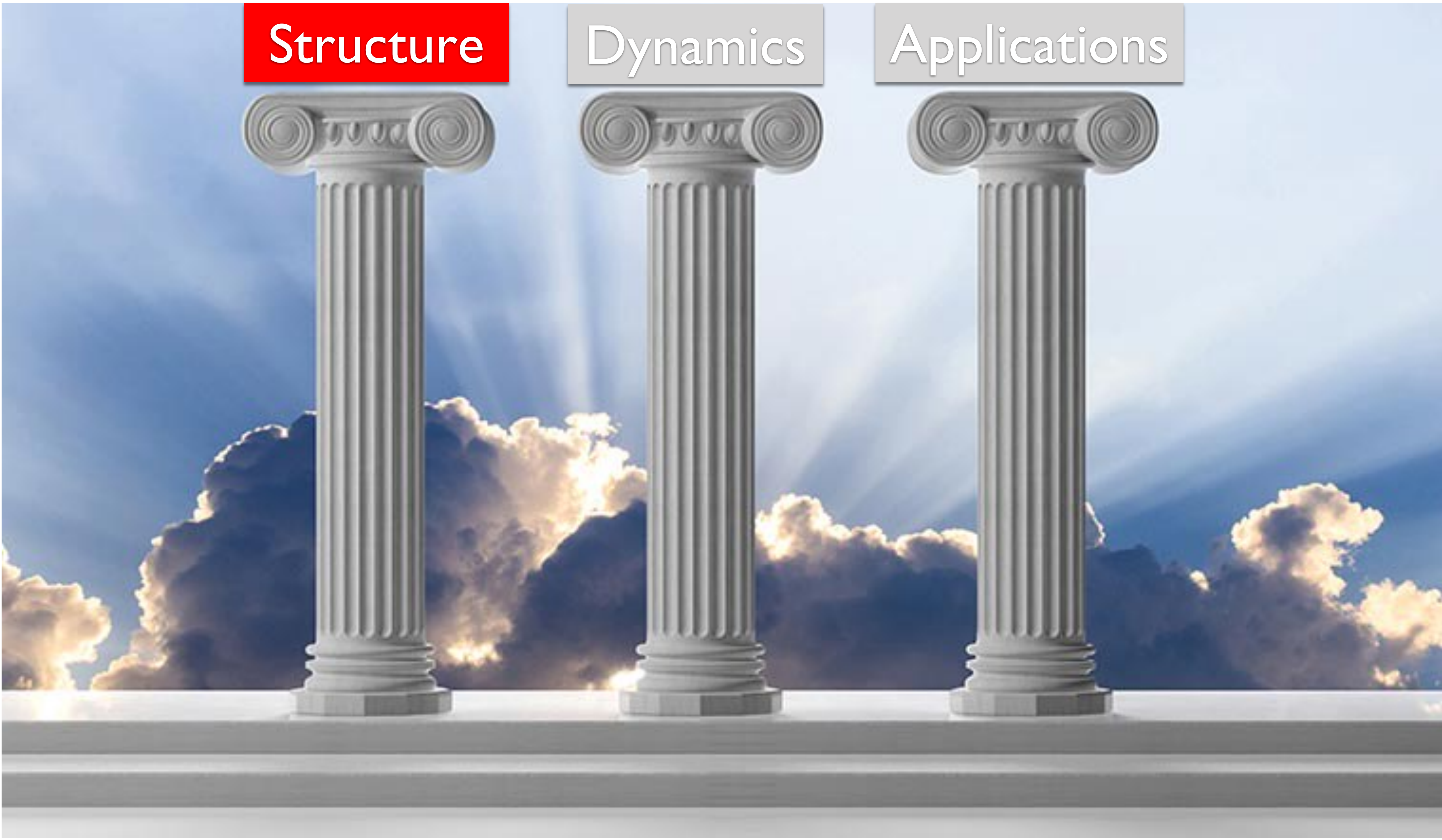


How do we study complex systems?

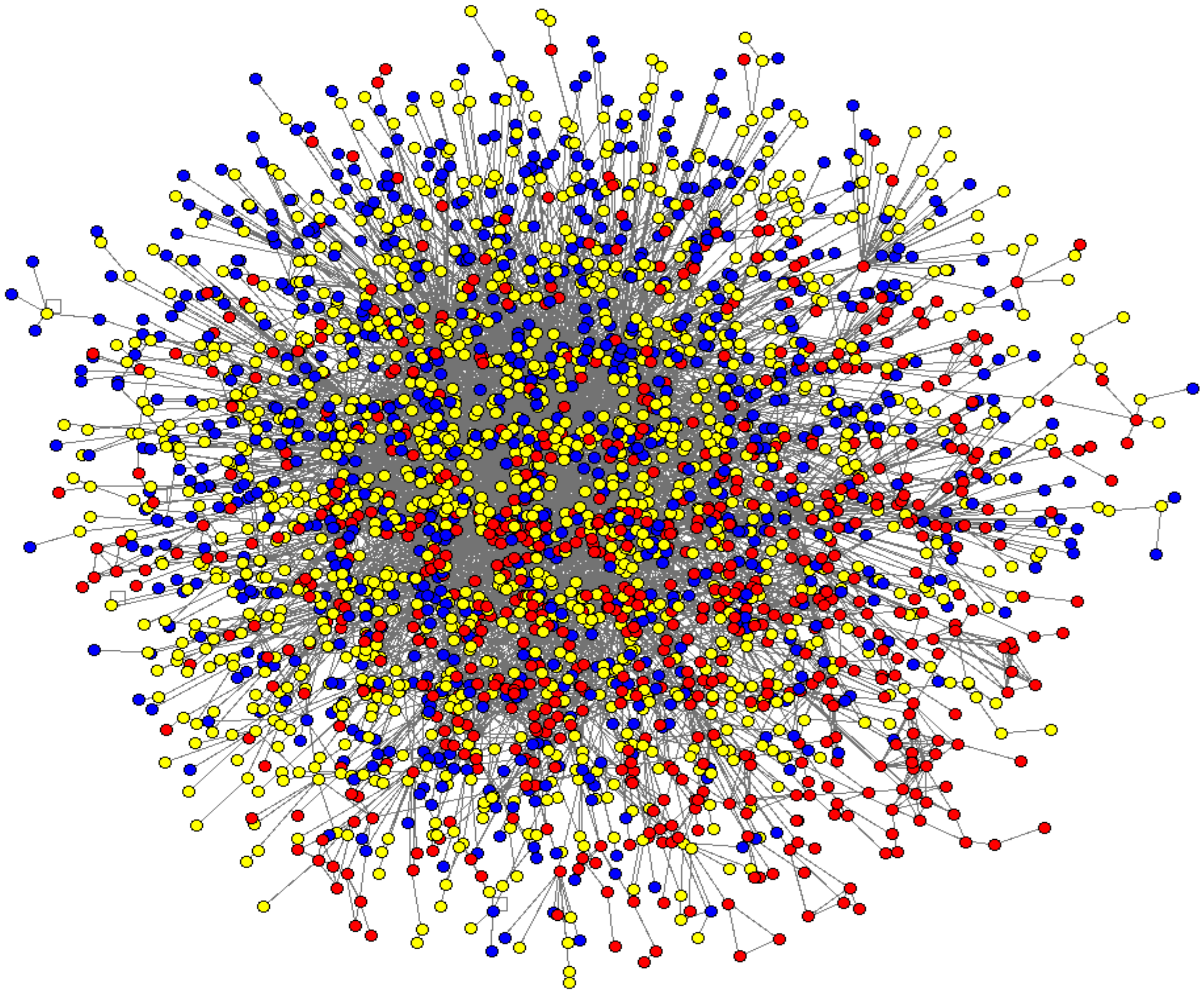
Complex Systems



Complex Systems



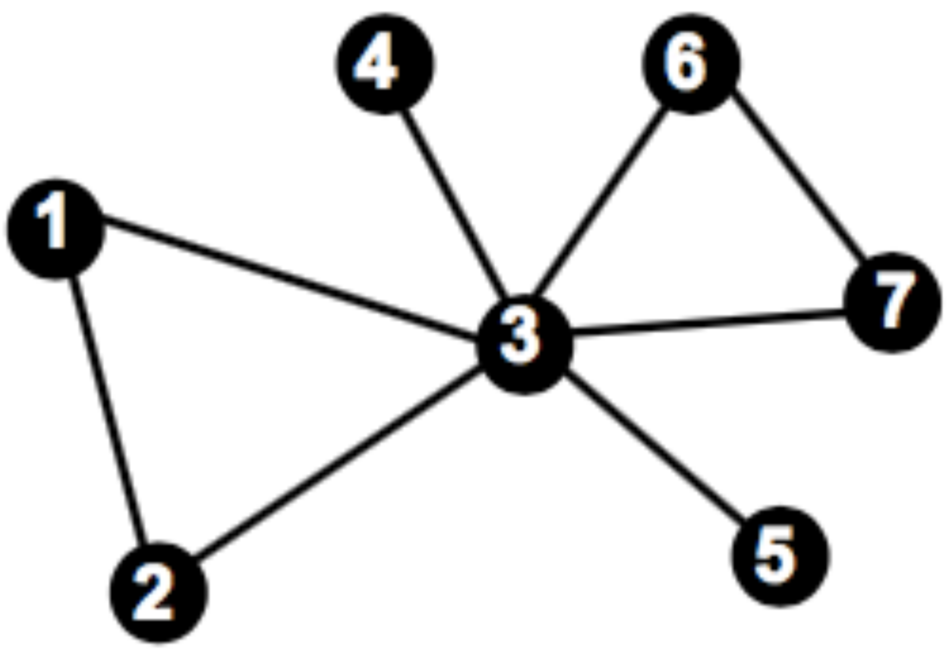
Network structure



$$\longrightarrow \quad \mathbf{x} = [x_1, x_2, \ldots]$$

Adjacency matrix

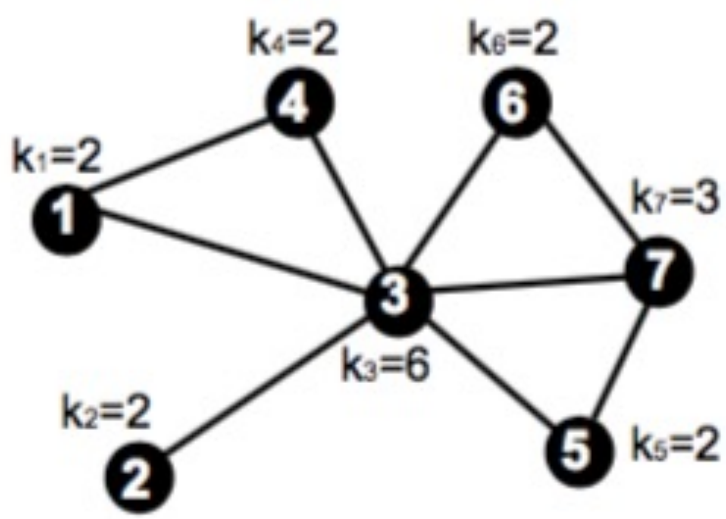
$$A_{ij} = \begin{cases} 1 & \text{if there is a connection between i and j} \\ 0 & \text{otherwise.} \end{cases}$$

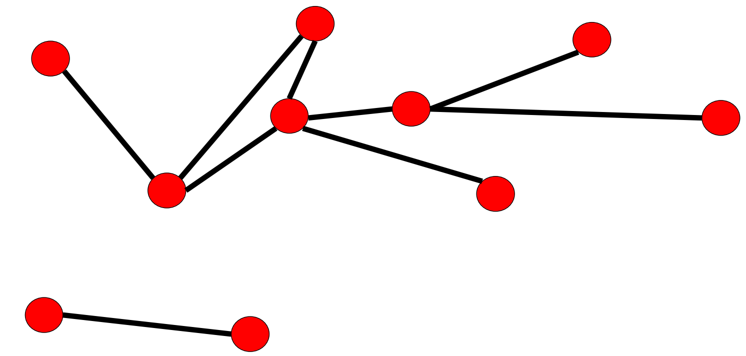


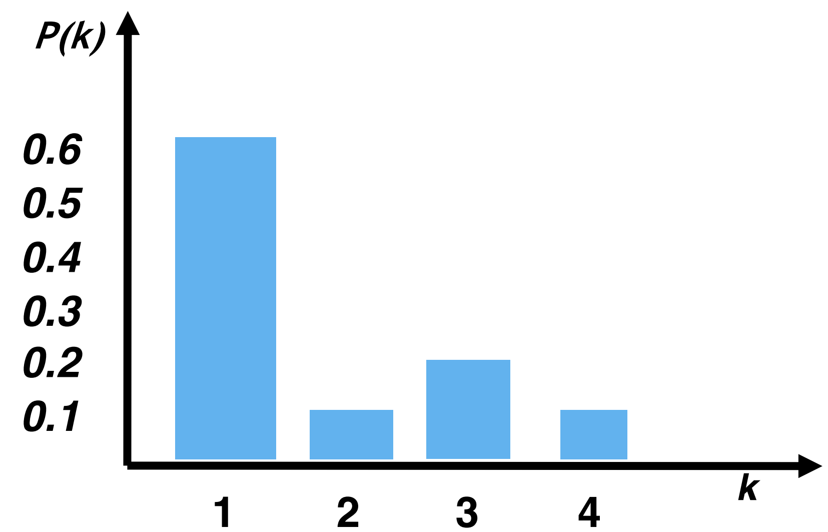
$$A = \begin{array}{c c} & \begin{array}{ccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \end{array} & \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$

Degree distribution

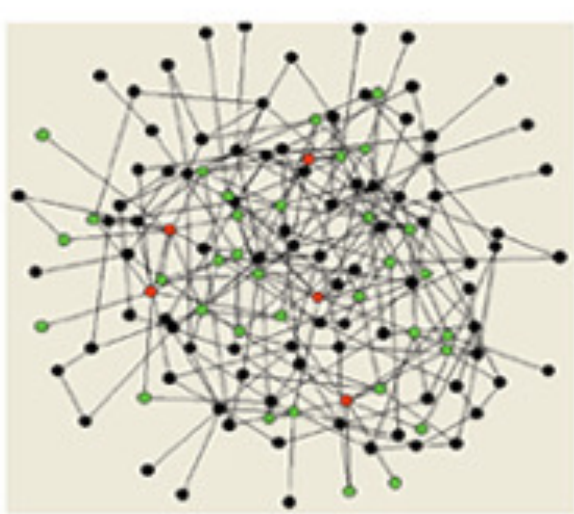
P(k) : probability that a node has degree k

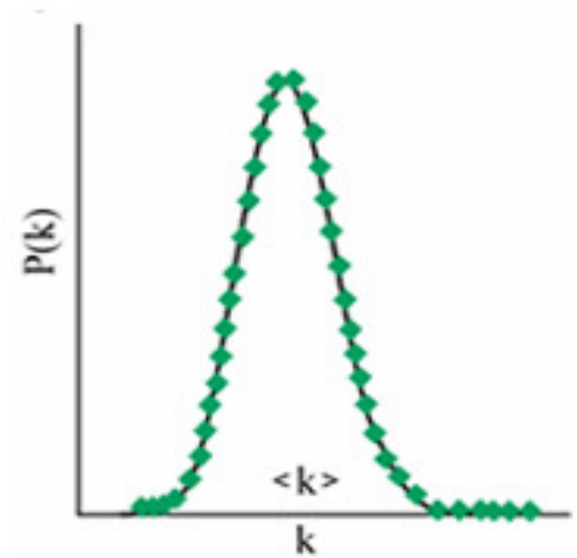




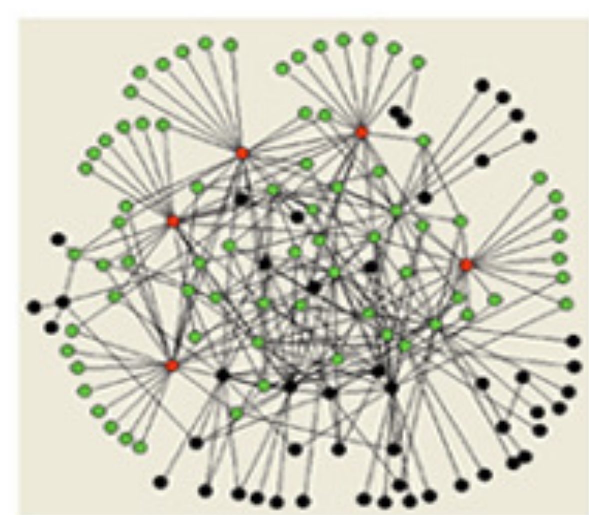


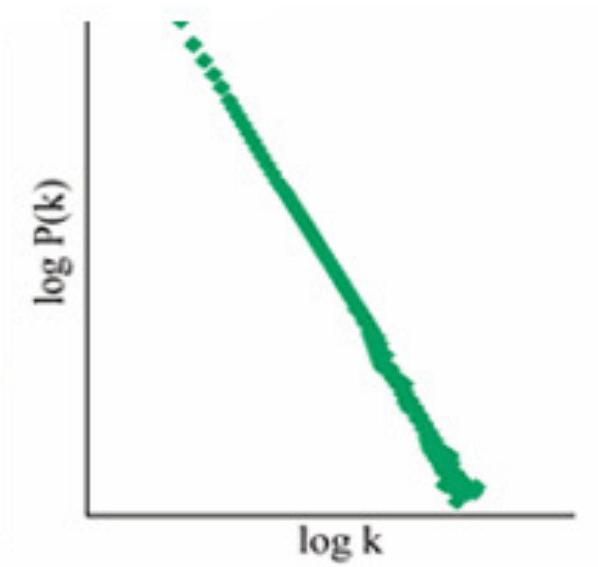
Random networks



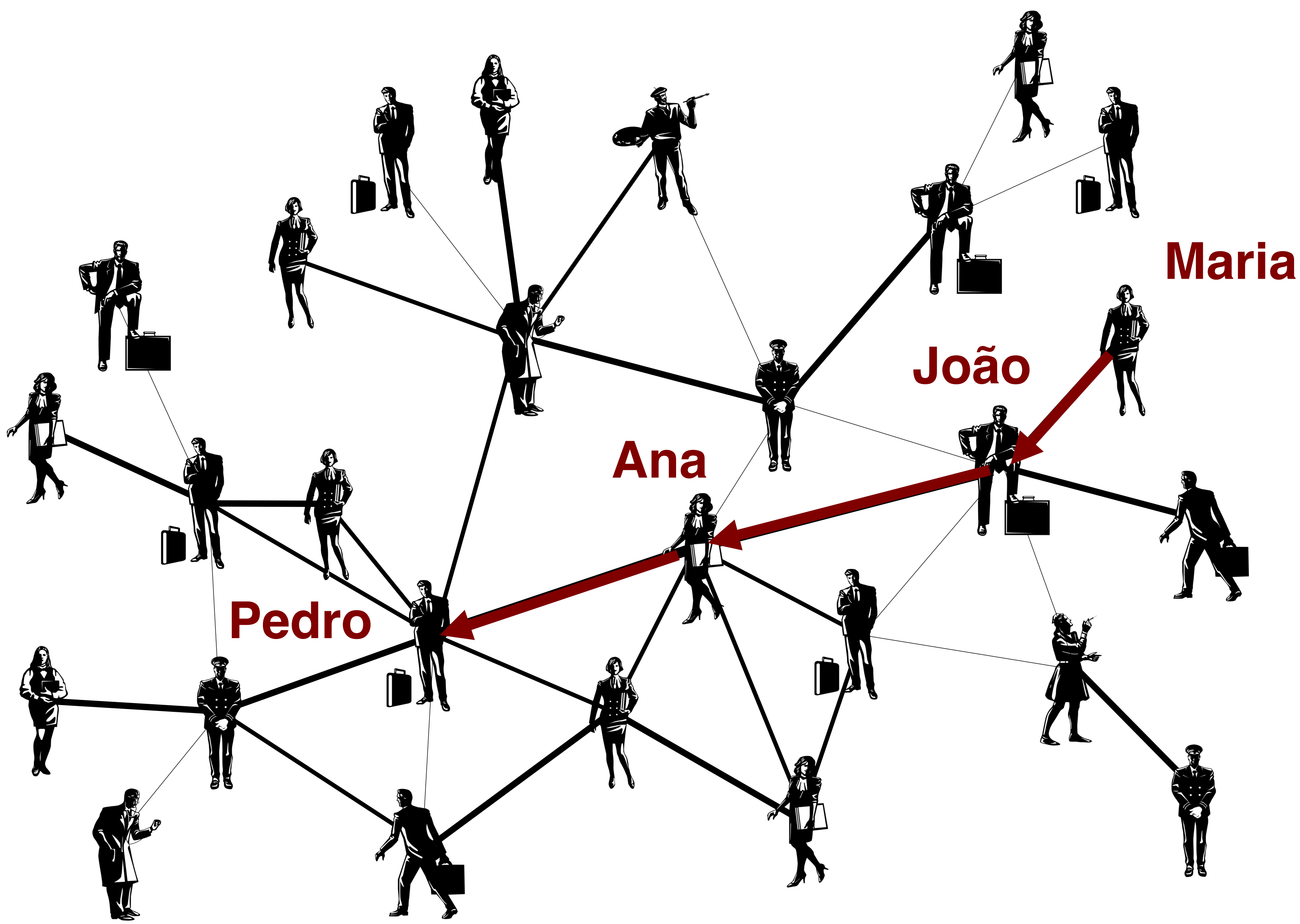


Scale-free networks





Distance

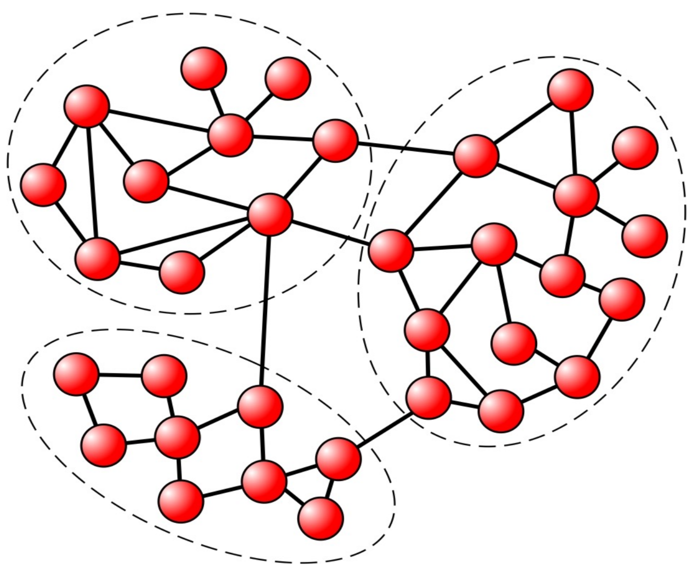


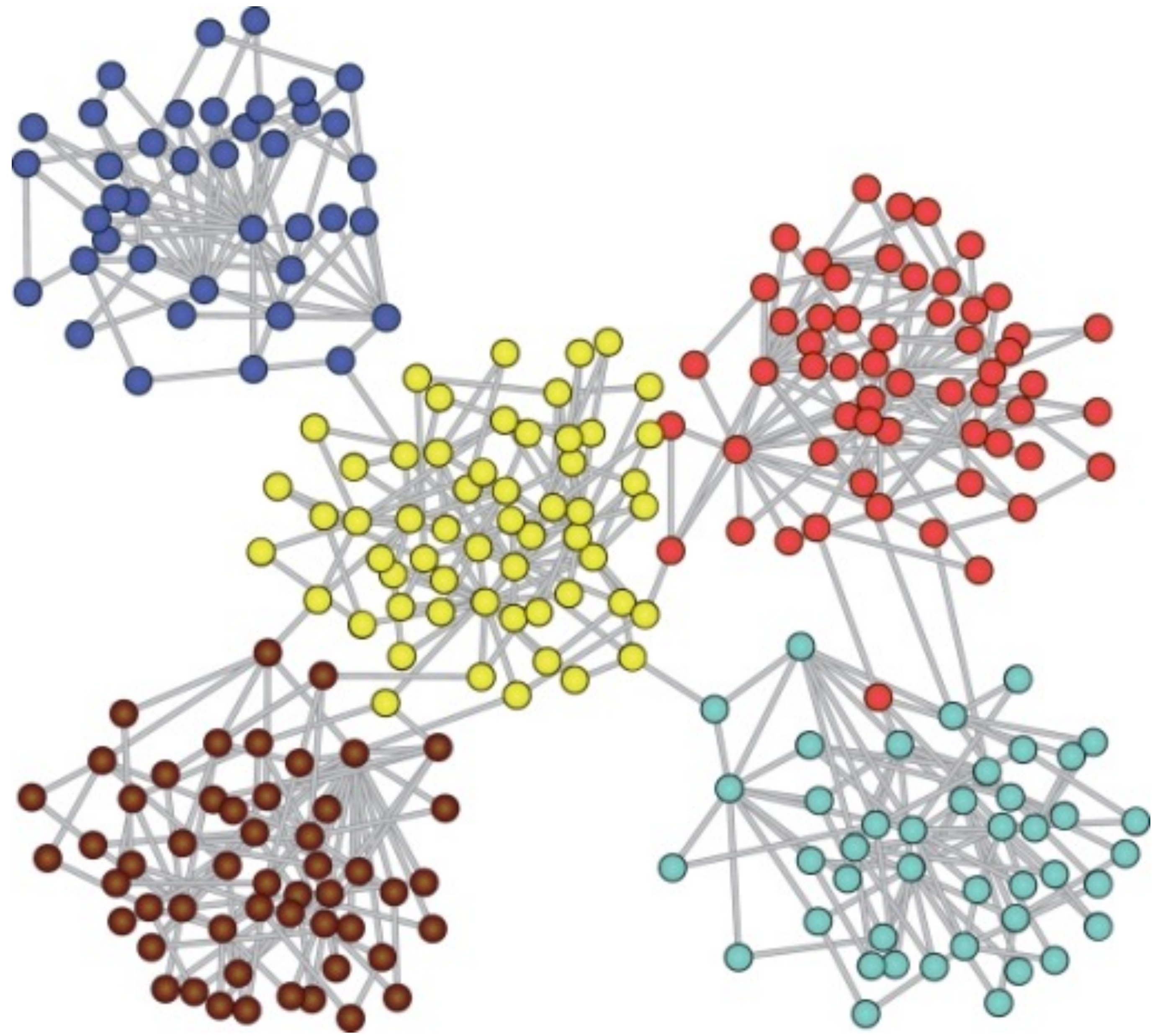
Distance = 3

Sociedade:
Six degrees
S. Milgram 1967

WWW:
19 degrees
Albert et al. 1999

Community structure



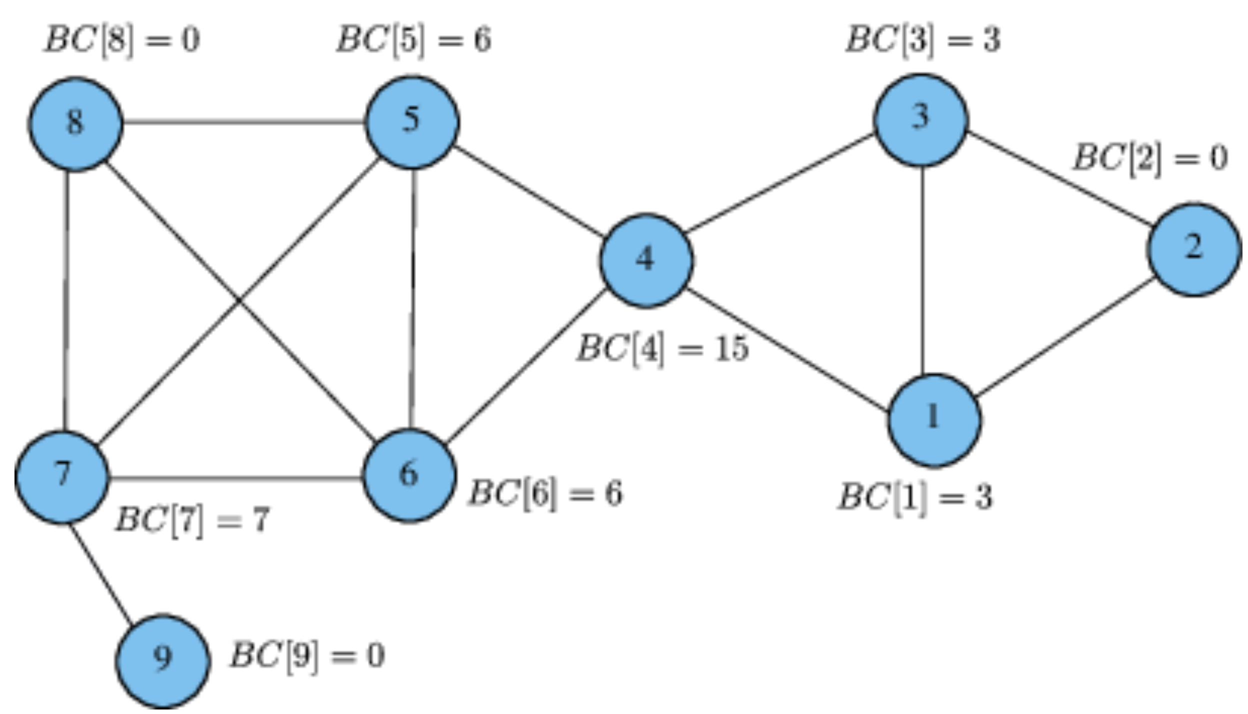


$$Q = \frac{1}{2L} \sum_{i=1}^{N} \sum_{j=1}^{N} (A_{ij} - P_{ij}) \, \delta_{g_i, g_j}$$

Centrality

Betweenness centrality

$$B_i = \sum_{(a,b)} \frac{\eta(a,i,b)}{\eta(a,b)},$$



Network measures

Advances in Physics,
Vol. 56, No. 1, February 2007, 167–242

Taylor & Francis
Taylor & Francis Group

Characterization of complex networks: A survey of measurements

L. DA F. COSTA*, F. A. RODRIGUES,
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Caixa Postal 369, 13560-970, São Carlos, SP, Brazil

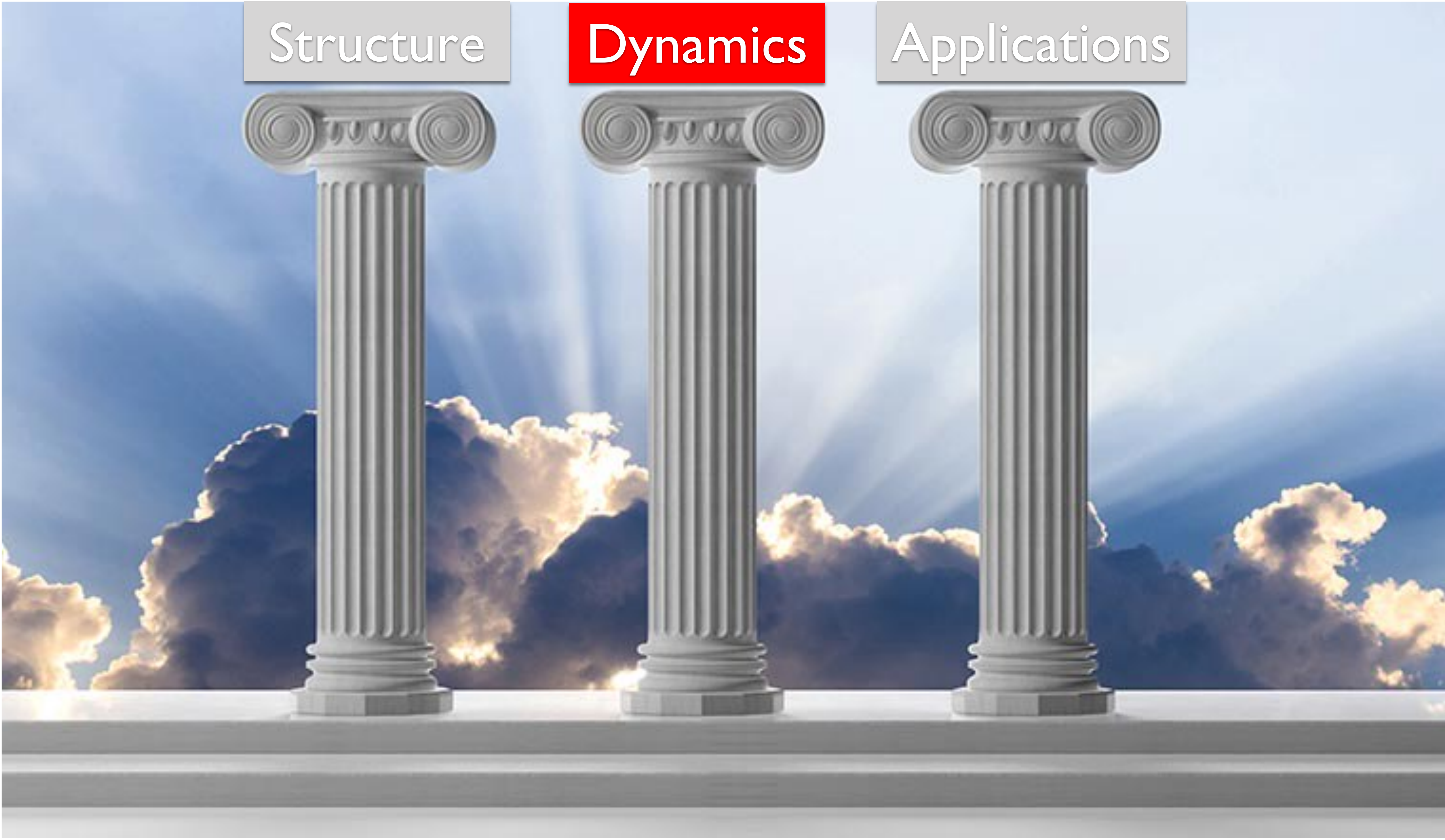
(*Received 21 August 2006; in final form 4 December 2006*)

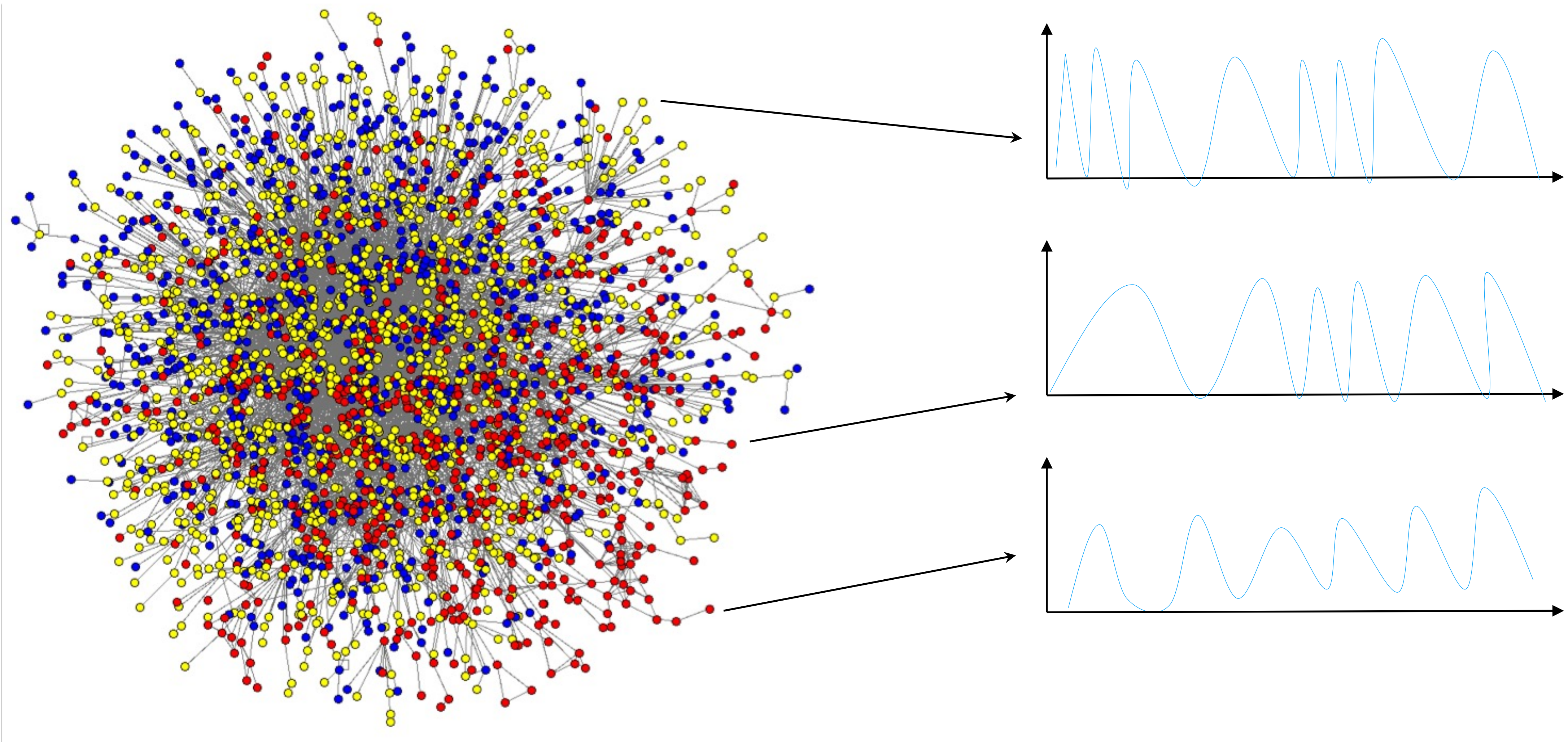
Each complex network (or class of networks) presents specific topological features which characterize its connectivity and highly influence the dynamics of processes executed on the network. The analysis, discrimination, and synthesis of complex networks therefore rely on the use of measurements capable of expressing the most relevant topological features. This article presents a survey of such measurements. It includes general considerations about complex network characterization, a brief review of the principal models, and the presentation of the main existing measurements. Important related issues covered in this work comprise the representation of the evolution of complex networks in terms of trajectories in several measurement spaces, the analysis of the correlations between some of the most traditional measurements, perturbation analysis, as well as the use of multivariate statistics for feature selection and network classification. Depending on the network and the analysis task one has in mind, a specific set of features may be chosen. It is hoped that the present survey will help the proper application and interpretation of measurements.

Measurement	Symbol
Mean geodesic distance	ℓ
Global efficiency	E
Harmonic mean distance	h
Vulnerability	V
Network clustering coefficient	C and $\widetilde{C}$
Weighted clustering coefficient	C^w
Cyclic coefficient	Θ
Maximum degree	$k_{\max}$
Mean degree of the neighbors	$k_{\mathrm{nn}}(k)$
Degree-degree correlation coefficient	r
Assortativity coefficient	$\widetilde{\mathbb{Q}}, \mathbb{Q}$
Bipartivity degree	b and β
Degree Distribution entropy	$H(i)$
Average search information	$\mathcal{S}$
Access information	$\mathcal{A}_i$
Hide information	$\mathcal{H}_i$
Target entropy	$\mathcal{T}$
Road entropy	$\mathcal{R}$
Betweenness centrality	B_i
Central point dominance	CPD
lth moment	M_l
Modularity	Q
Participation coefficient	P_i
z-score	z_i
Significance profile	SP_i
Subgraph centrality	SC
Hierarchical clustering coefficient	C_{rs}
Convergence ratio	$cv_d(i)$
Divergence ratio	$dv_d(i)$
Edge reciprocity	ϱ and ρ
Matching index of edge (i, j)	μ_{ij}

Costa, Rodrigues, Travieso, Villas Boas. Advances in Physics 2007

Complex Systems

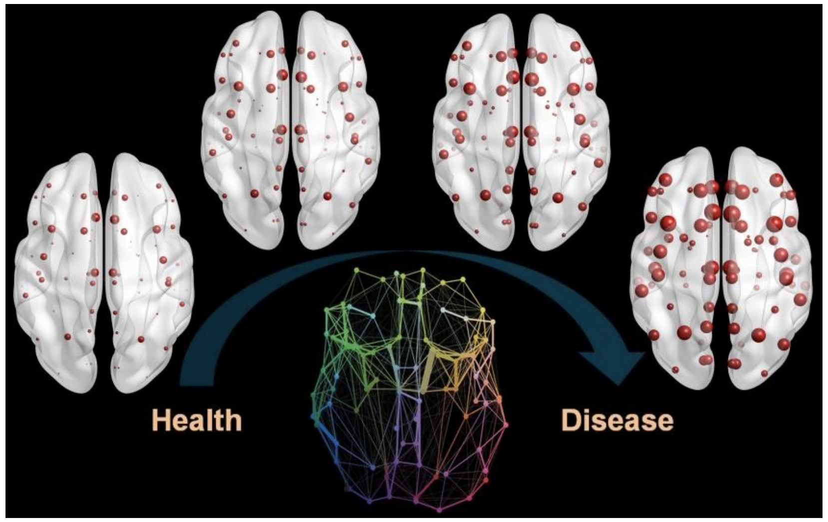


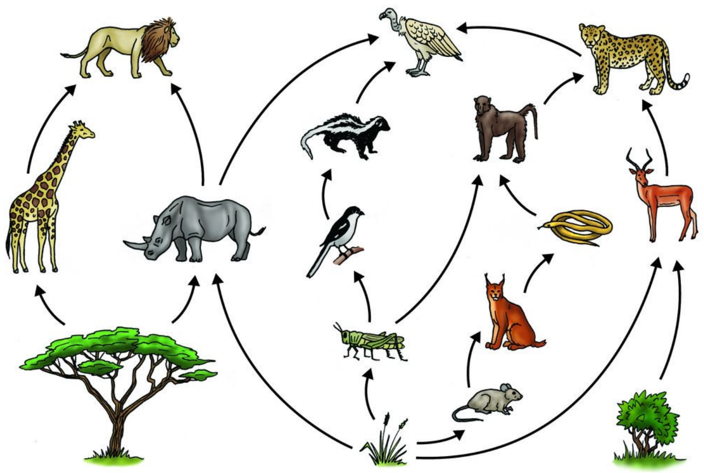


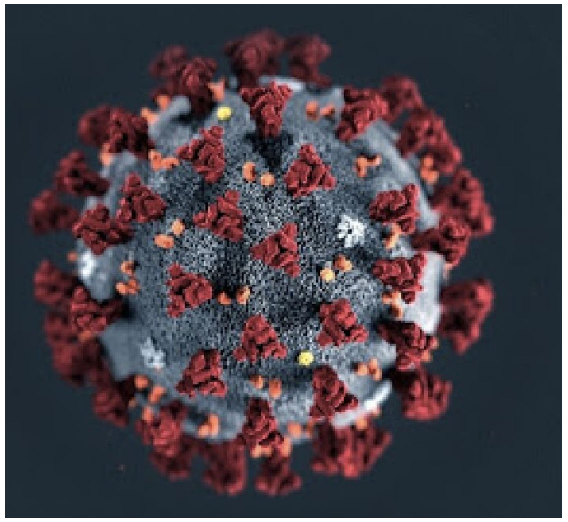
$$\frac{d\phi_i}{dt} = F(\phi_i) + \sum_j A_{ij} G(\phi_i, \phi_j)$$

Dynamical processes in networks

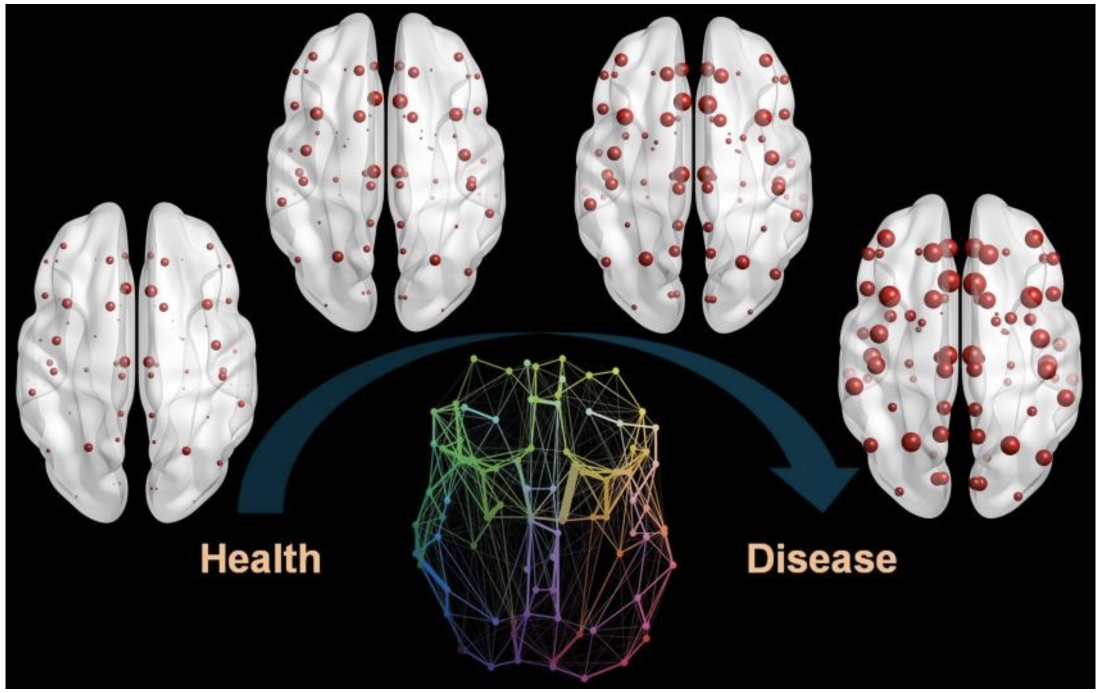
- Synchronization
- Epidemics Spreading
- Rumor Spreading
- Cascade failures
- Cooperation
- Opinion dynamics
- …

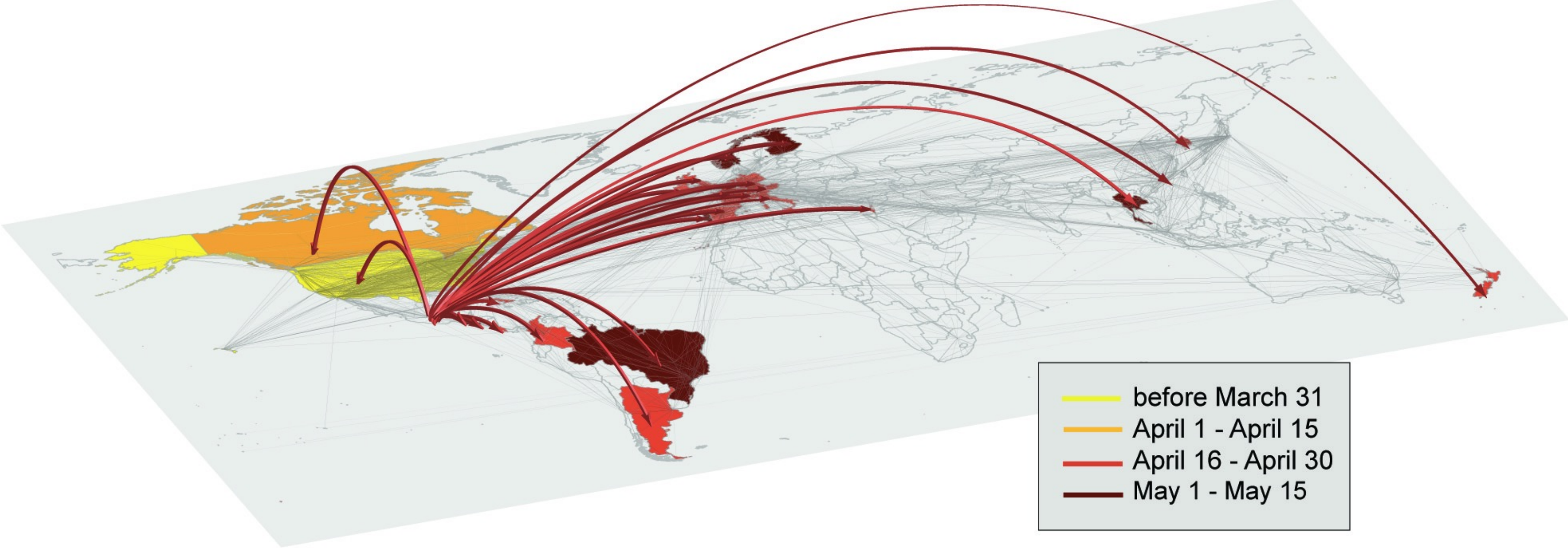






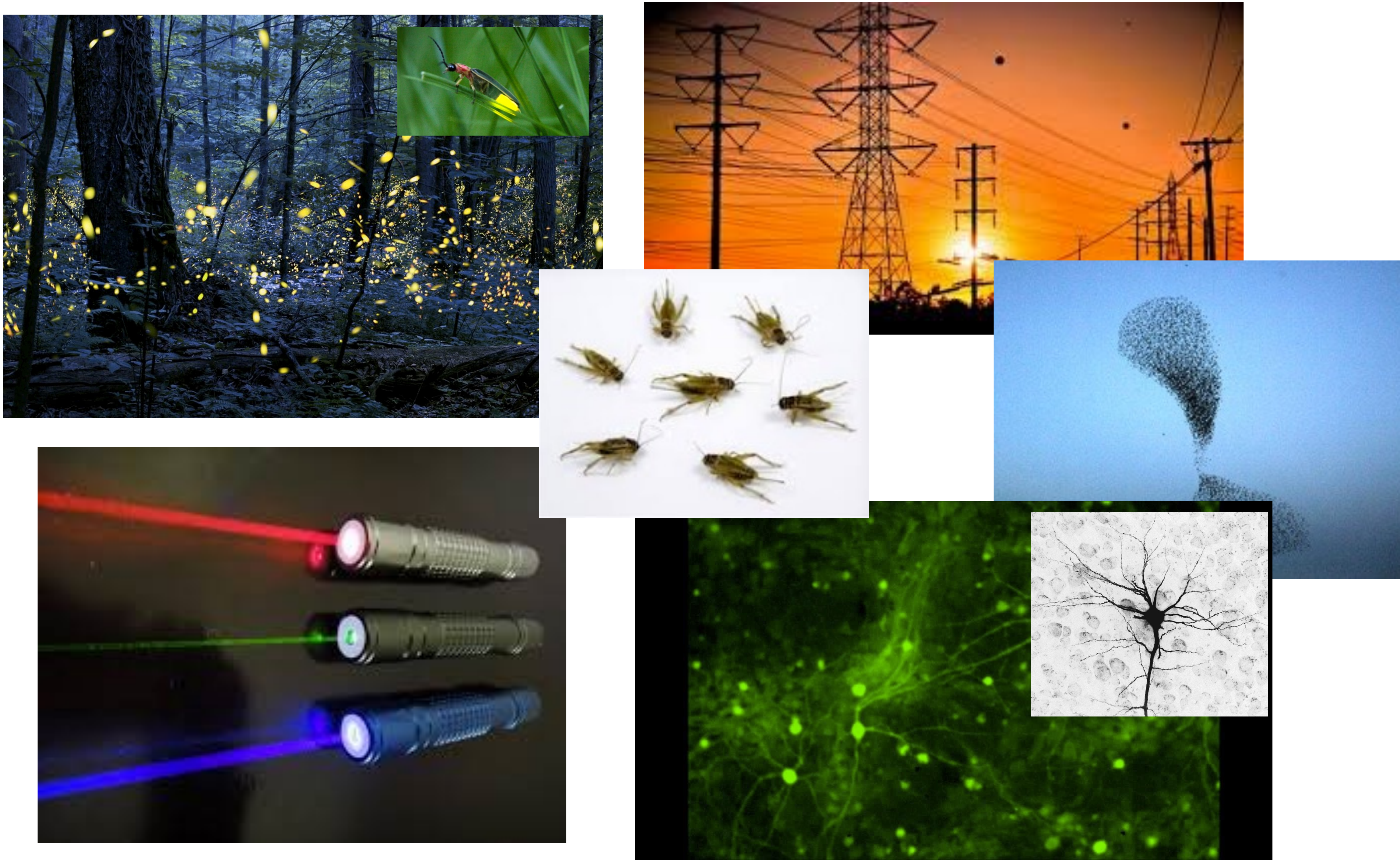
Structure X Dynamics





We can control dynamical processes by changing the network structure.

Synchronization



Synchronization

https://www.youtube.com/watch?v=W1TMZASCR-I&ab_channel=AlirezaBahraminasab

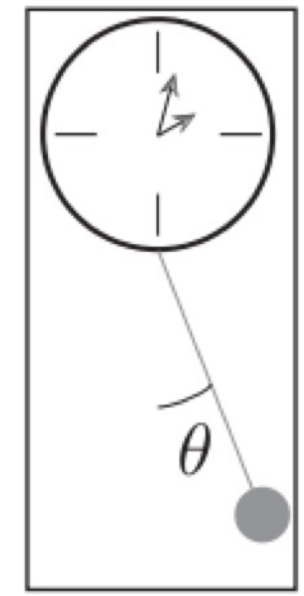
Kuramoto model

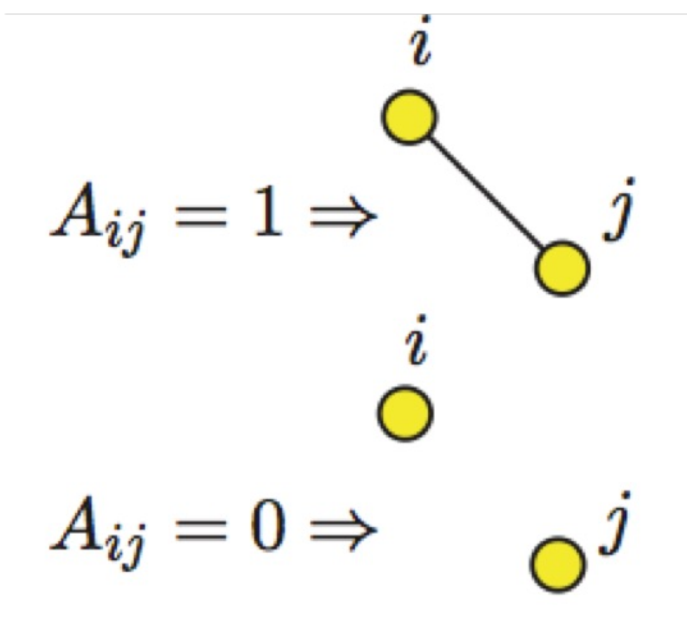
Coupling

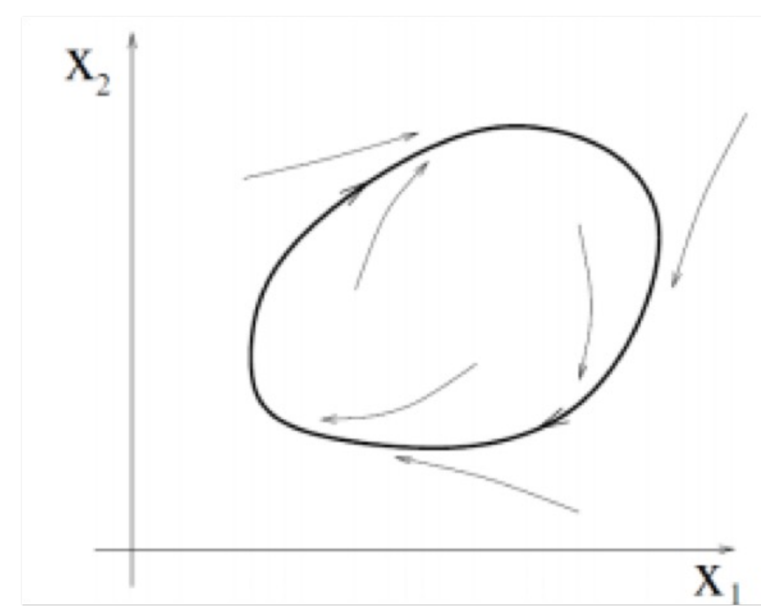
$$\frac{d\theta_i(t)}{dt} = \omega_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

Natural frequency

Phase







Ichinomiya, T,. Phys. Rev. E, (2004)

Kuramoto model

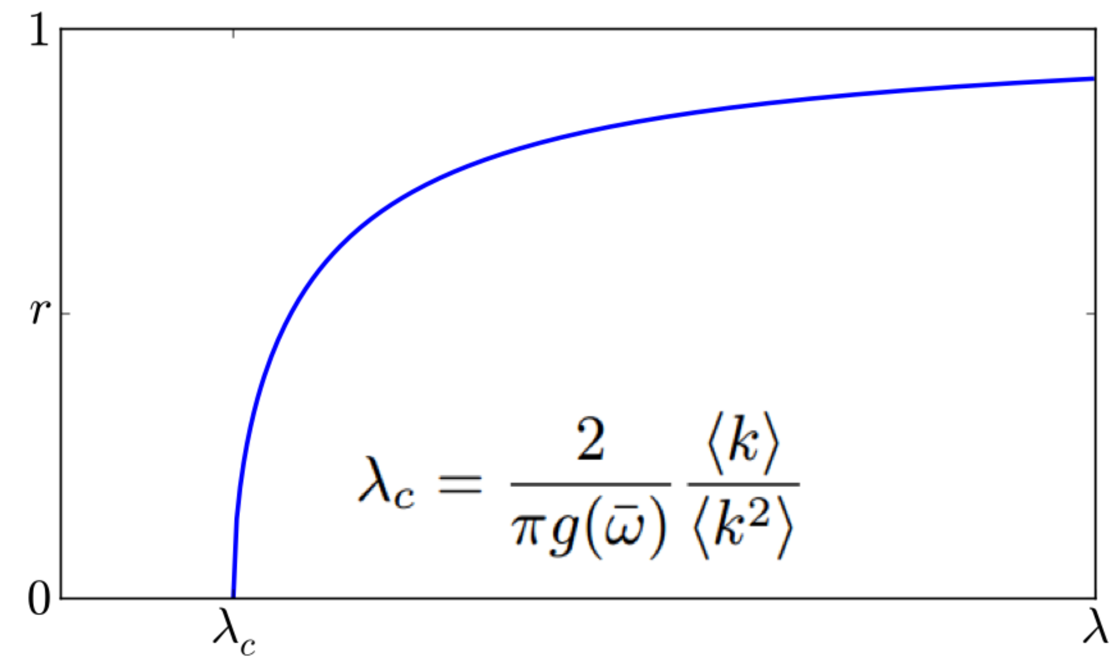
$$\frac{d\theta_i(t)}{dt} = \omega_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

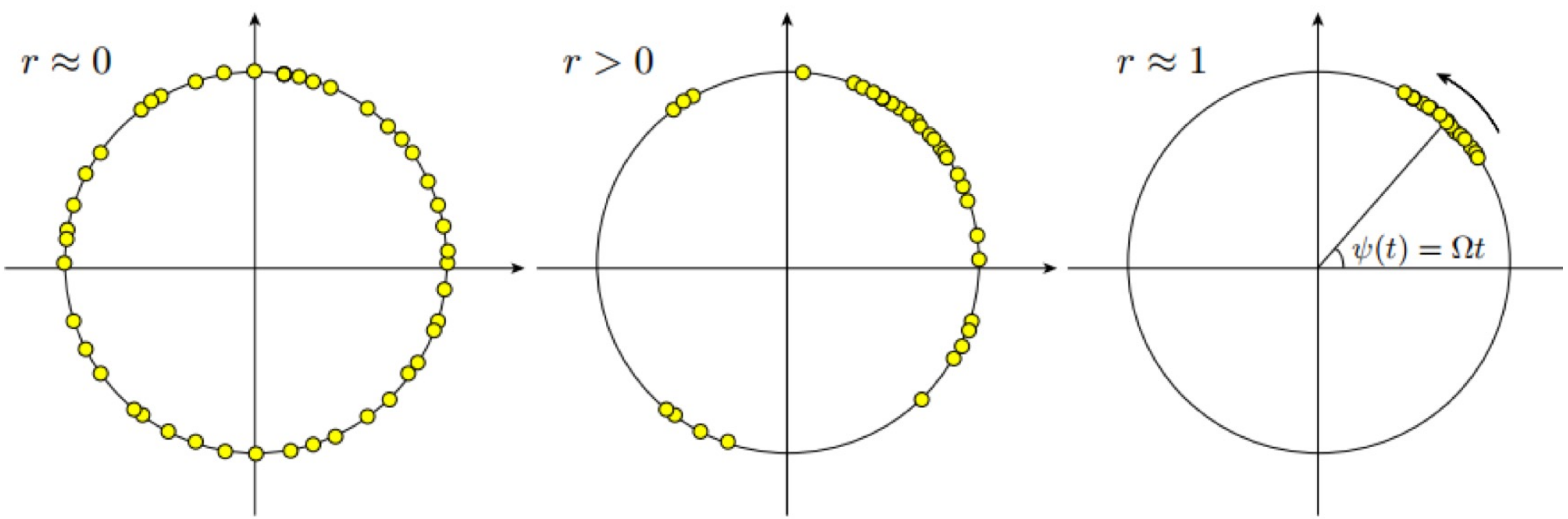
Order parameter

$$re^{i\psi(t)} = \frac{\sum_i r_i}{\sum_i k_i}$$

$$r_i e^{i\phi_i(t)} = \sum_{j=1}^{N} A_{ij} e^{i\theta_j}$$

Continuous phase transition

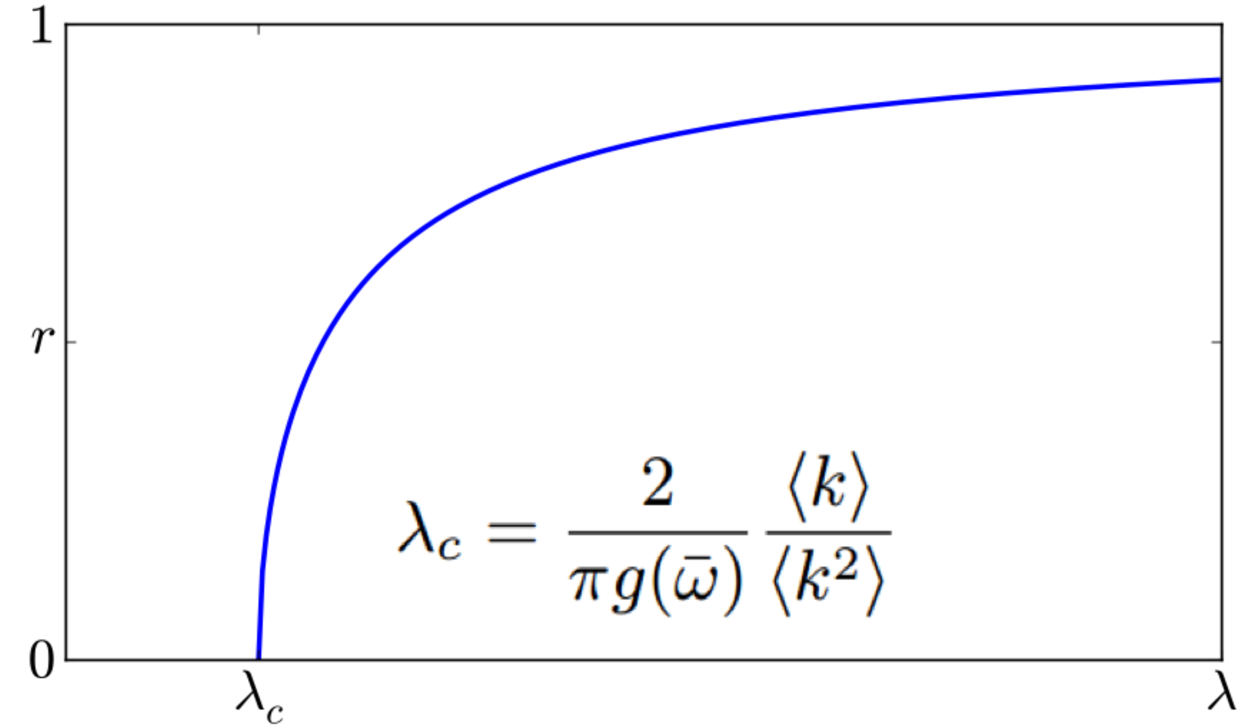


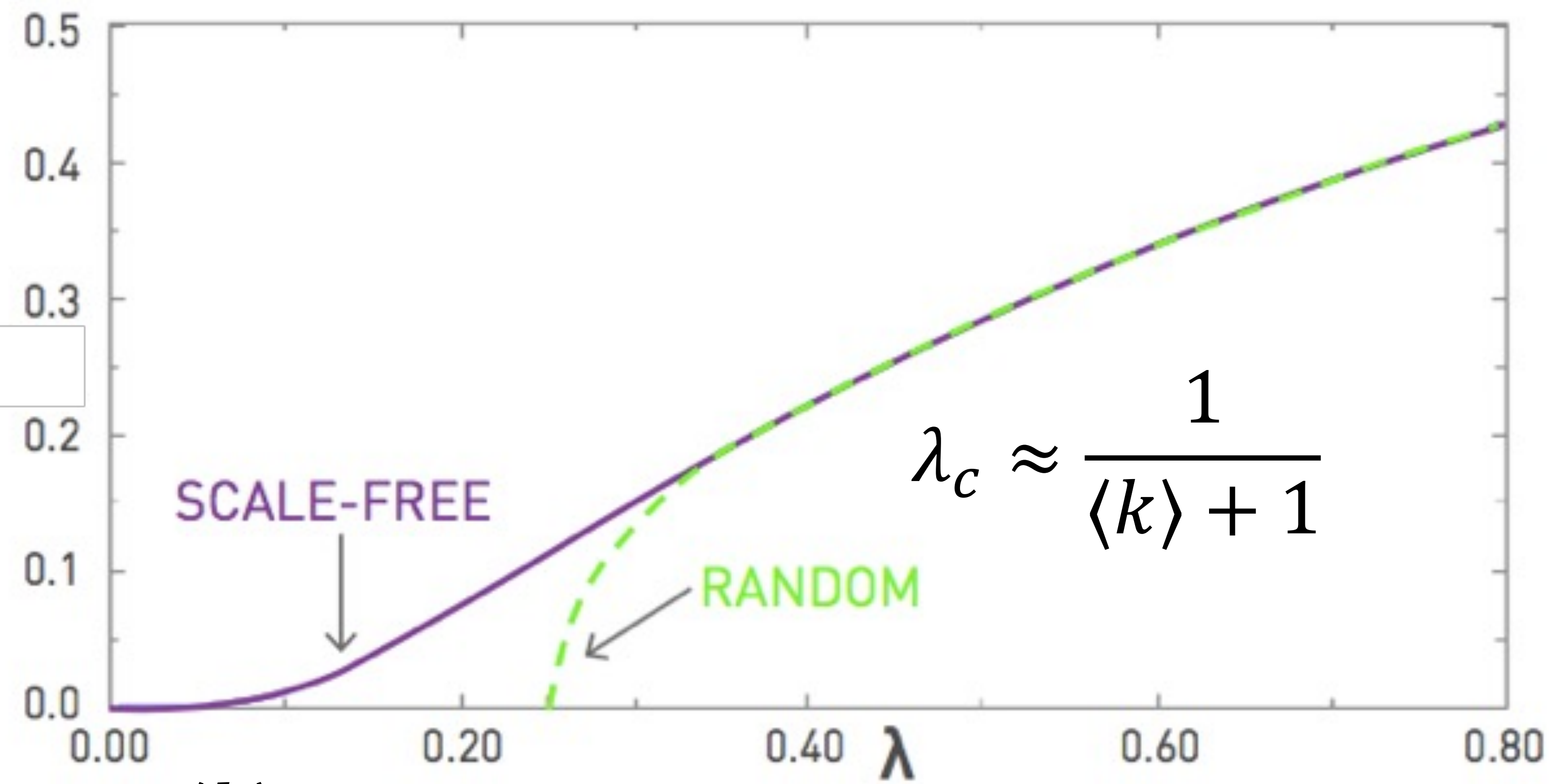


Ichinomiya, T,. Phys. Rev. E, (2004)

Kuramoto model

$$\frac{d\theta_i(t)}{dt} = \omega_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

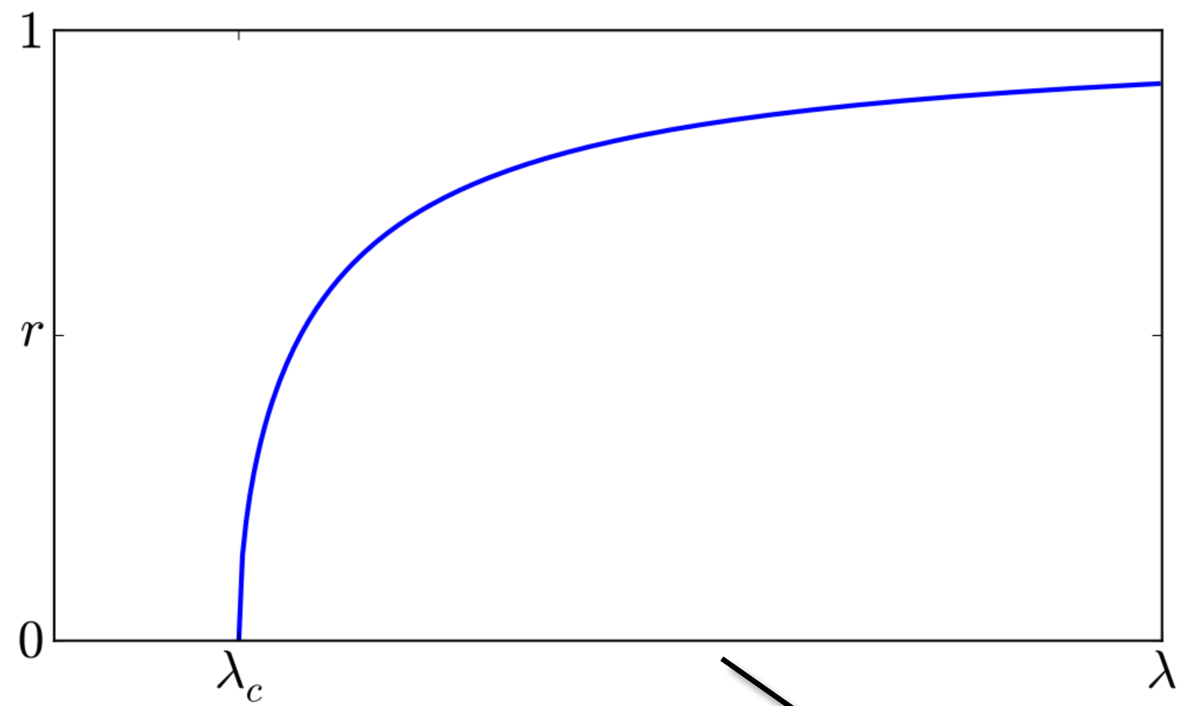




$$\lambda_c \approx \frac{\langle k \rangle}{\langle k^2 \rangle} \approx 0$$

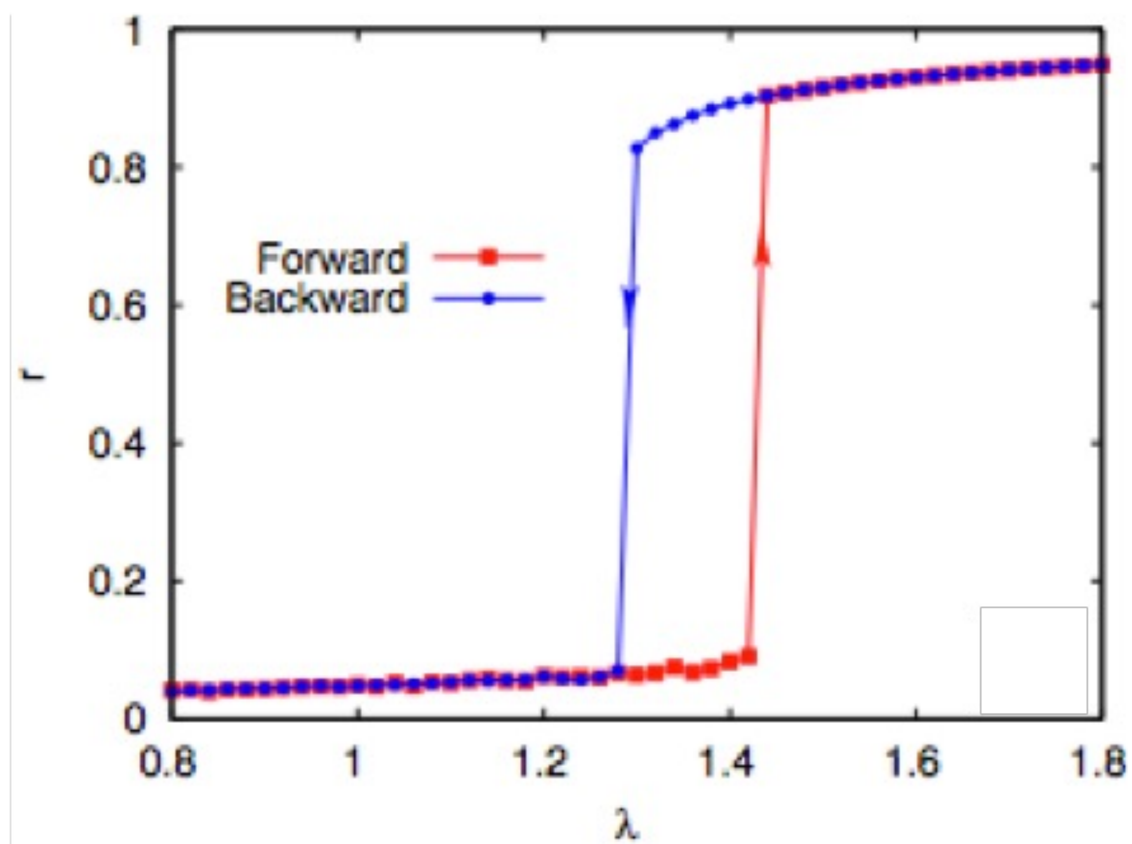
Explosive synchronization

Continuous phase transition



$$\frac{d\theta_i(t)}{dt} = \omega_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

First-order phase transition



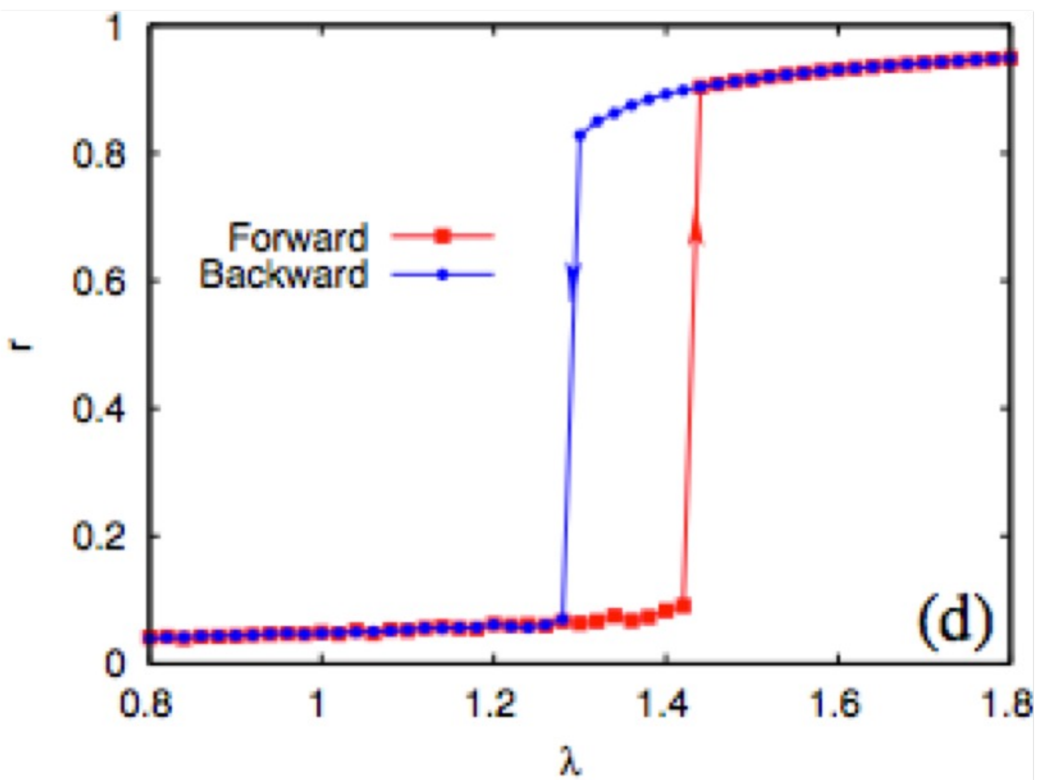
$$\frac{d\theta_i(t)}{dt} = k_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

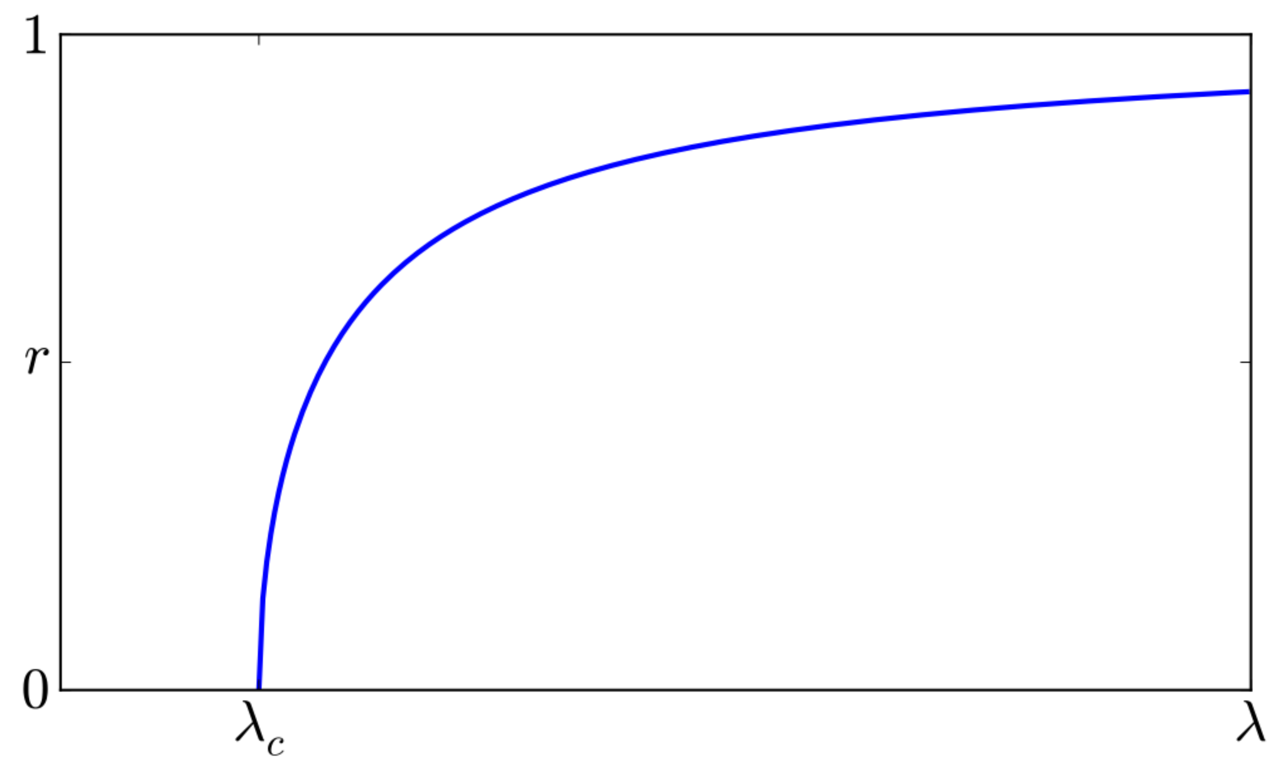
Explosive synchronization

$$\frac{d\theta_i(t)}{dt} = \omega_i + \lambda \sum_{i=1}^{N} A_{ij} \sin\left[\theta_j(t) - \theta_i(t)\right]$$

$$\omega_i = k_i$$

$$\lambda_c = \frac{2}{\pi \langle k \rangle P(\langle k \rangle)} \neq \lambda_c = \frac{2}{\pi g(\bar{\omega})} \frac{\langle k \rangle}{\langle k^2 \rangle}$$



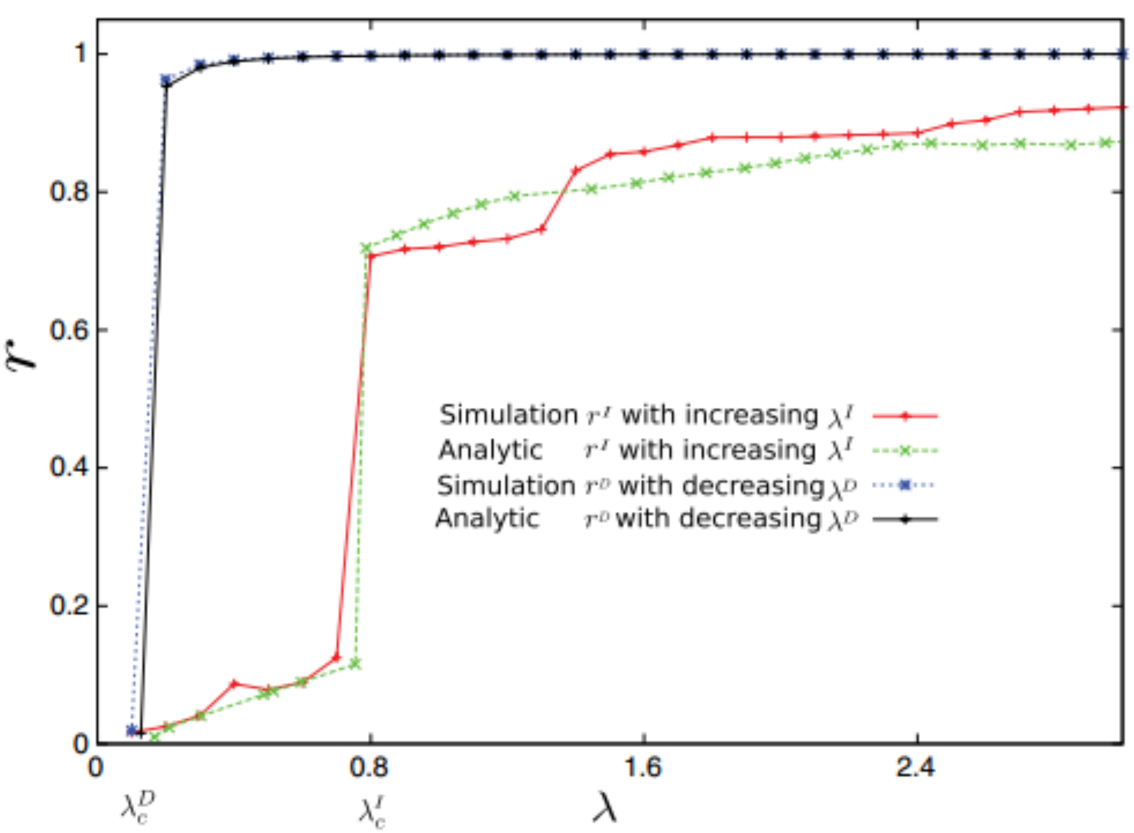


Peron and Rodrigues, PRE, 2012

Second-order Kuramoto model

$$\frac{d^2\theta_i}{dt^2} = -\alpha\frac{d\theta_i}{dt} + \Omega_i + \sum_{j=1}^{N}\lambda_{ij}A_{ij}\sin(\theta_j - \theta_i)$$

$$\Omega_i = D(k_i - \langle k \rangle)$$



PRL 110, 218701 (2013) PHYSICAL REVIEW LETTERS week ending 24 MAY 2013

Cluster Explosive Synchronization in Complex Networks

Peng Ji,[1,2,*] Thomas K. DM. Peron,[3,†] Peter J. Menck,[1,2] Francisco A. Rodrigues,[4,‡] and Jürgen Kurths[1,2,5]

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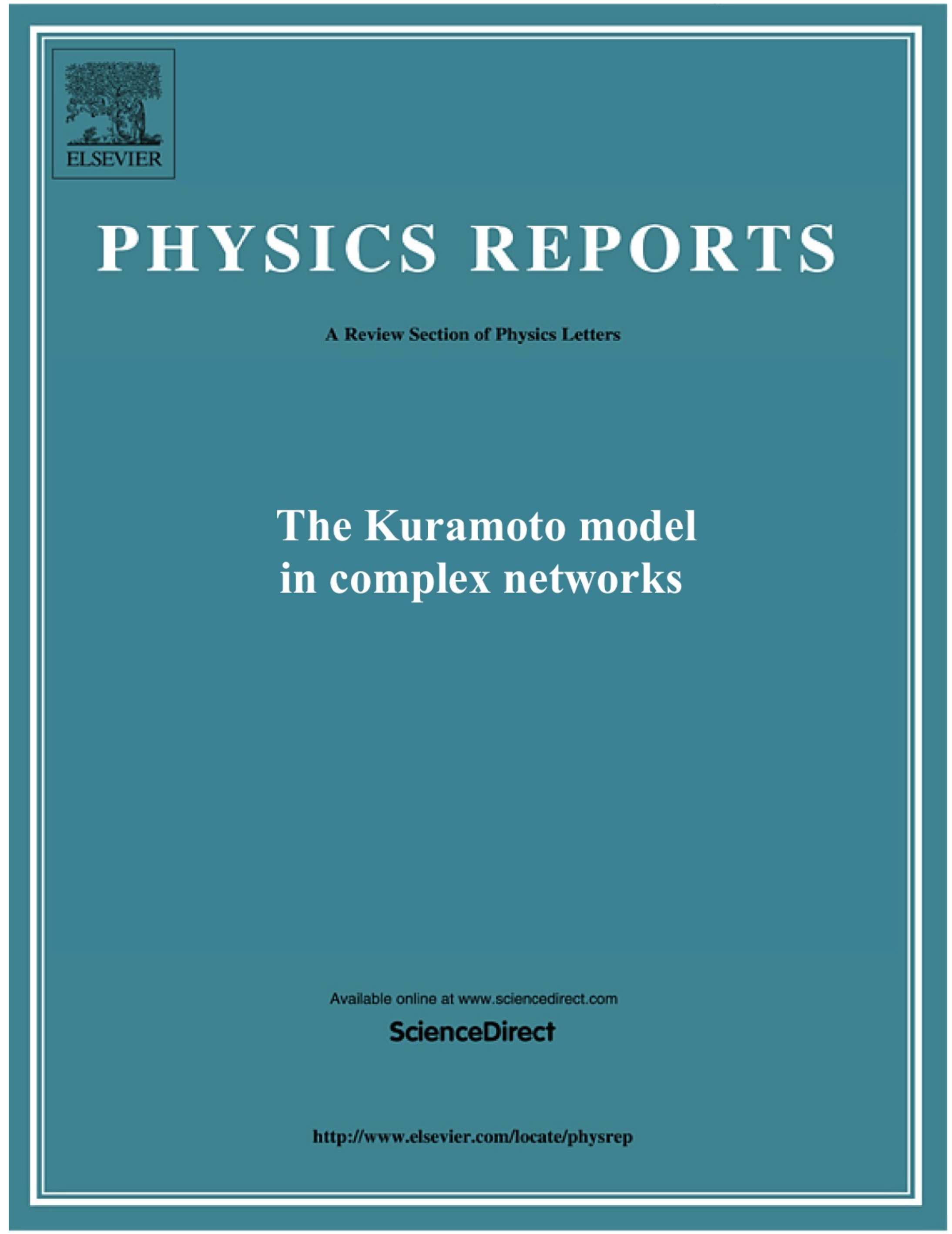
(Received 22 January 2013; revised manuscript received 29 April 2013; published 23 May 2013)

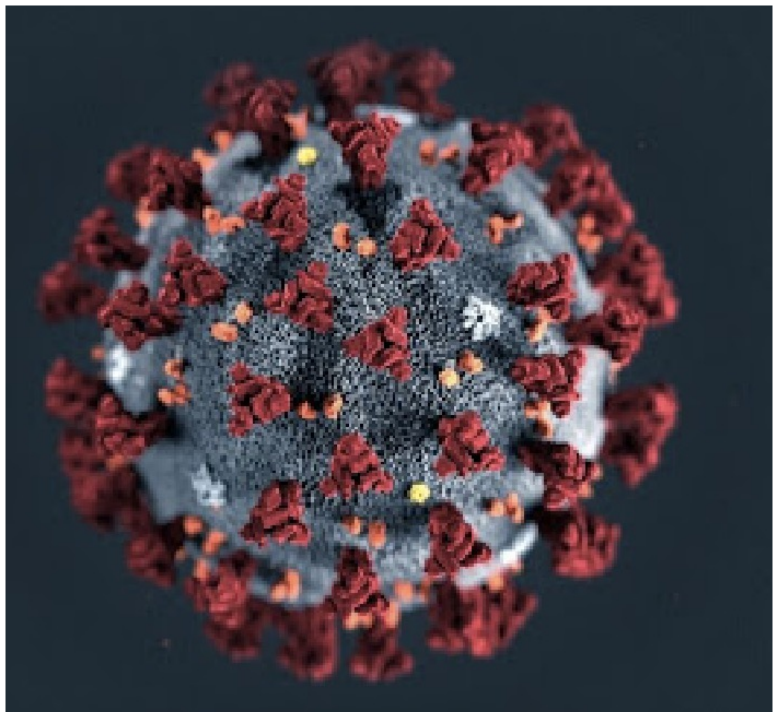
The emergence of explosive synchronization has been reported as an abrupt transition in complex networks of first-order Kuramoto oscillators. In this Letter we demonstrate that the nodes in a second-order Kuramoto model perform a cascade of transitions toward a synchronous macroscopic state, which is a novel phenomenon that we call cluster explosive synchronization. We provide a rigorous analytical treatment using a mean-field analysis in uncorrelated networks. Our findings are in good agreement with numerical simulations and fundamentally deepen the understanding of microscopic mechanisms toward synchronization.

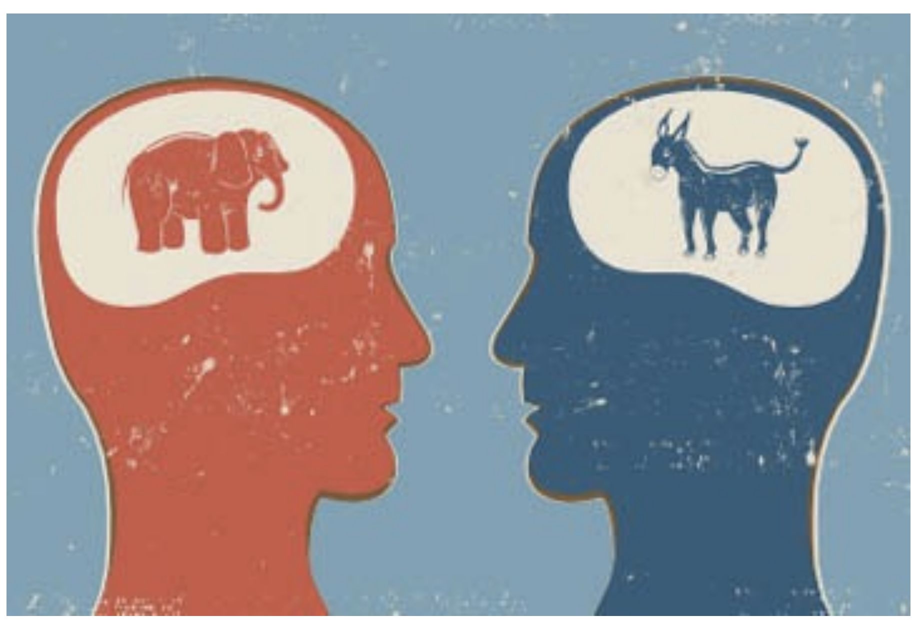
DOI: 10.1103/PhysRevLett.110.218701 PACS numbers: 89.75.Hc, 05.45.Xt, 89.75.Kd



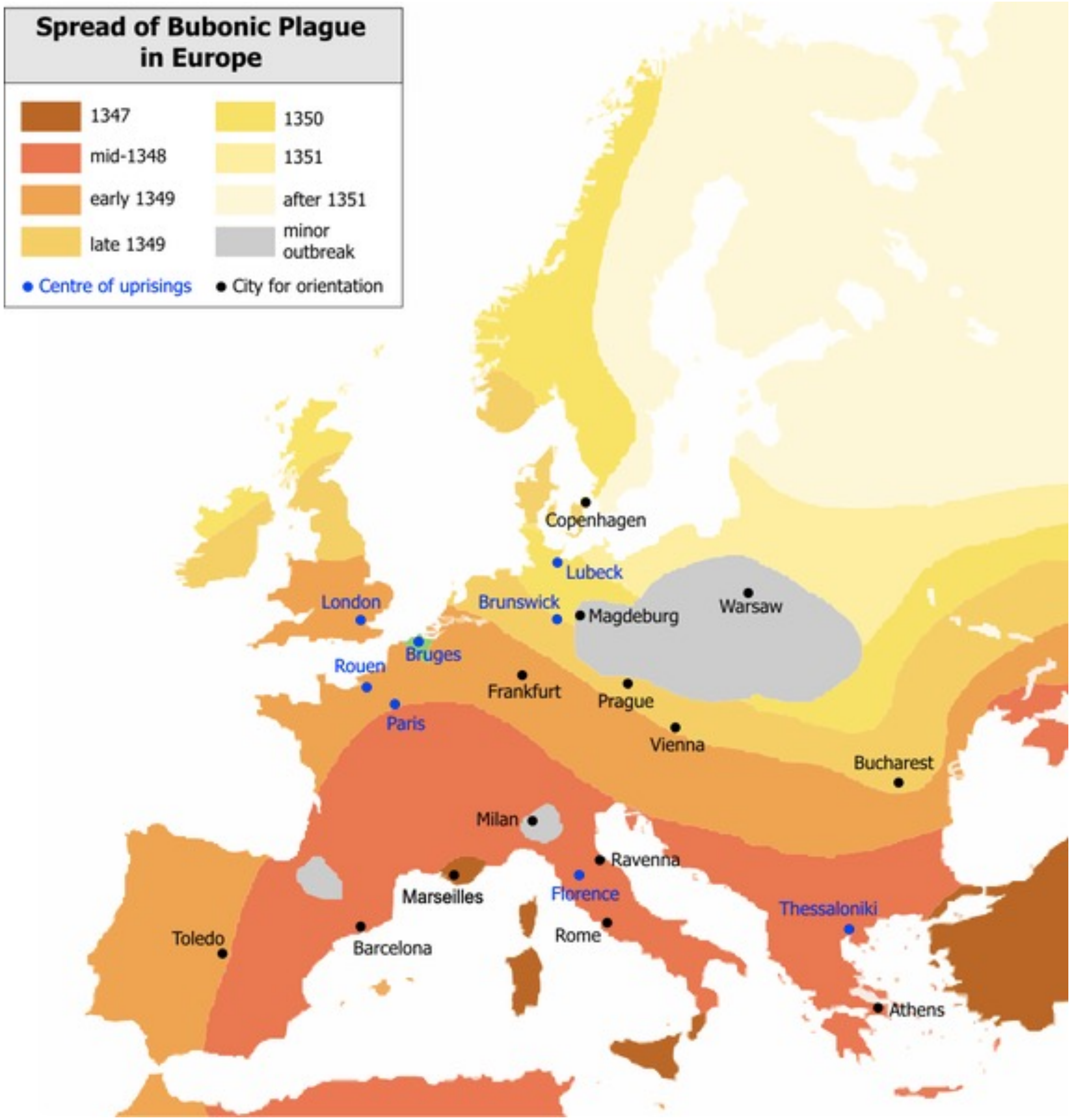
Francisco A. Rodrigues, Thomas K.DM. Peron, Peng Ji, Jürgen Kurths
The Kuramoto model in complex networks
Physics Reports*, V. 610, Pages 1–98, (2016).*

Spreading





Bubonic Plague



H1N1

2009 flu pandemic

Spreading depends on the network structure!

How to study epidemic processes?

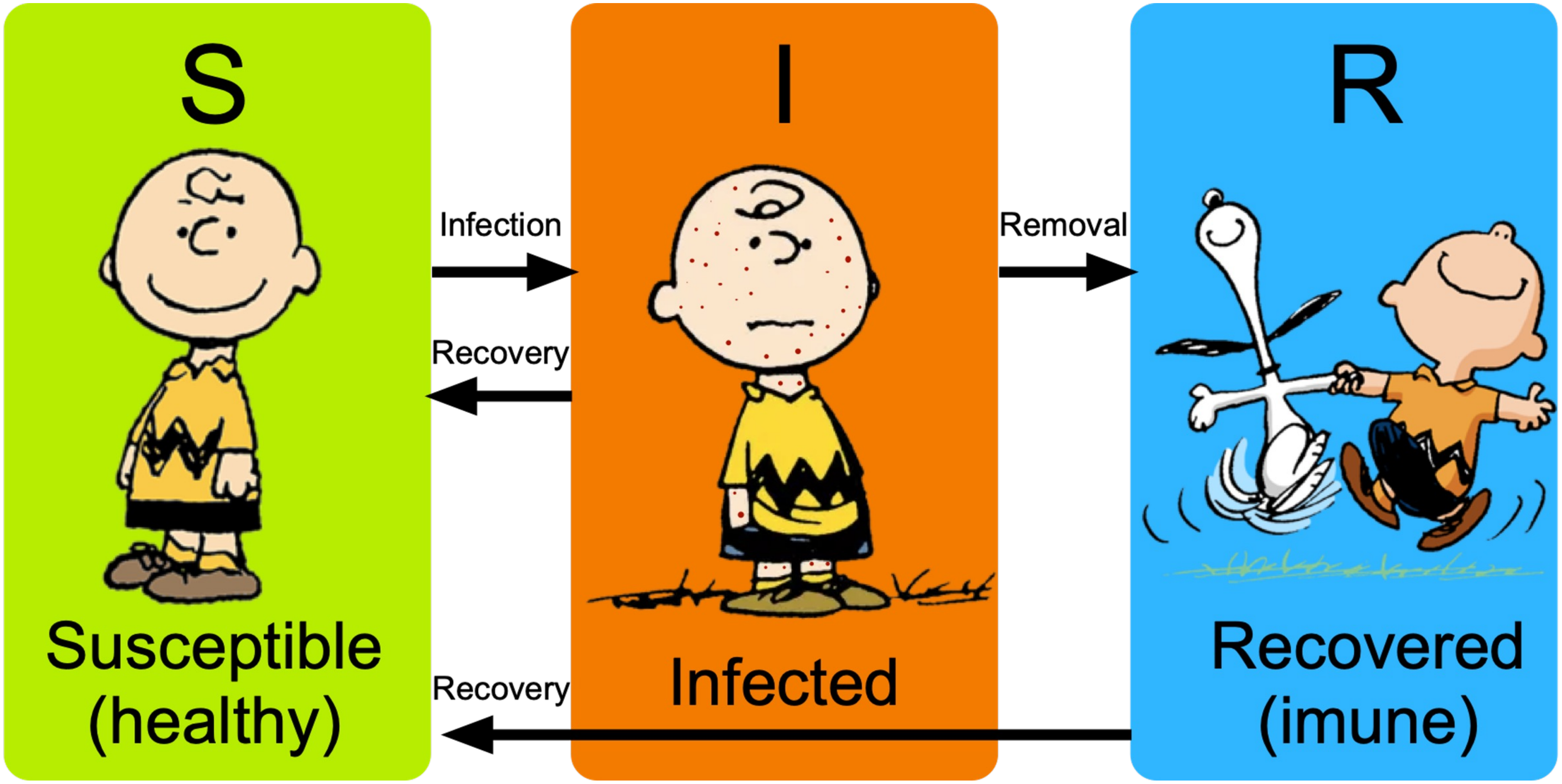
Theoretical:

- Mathematical models
- Agent-based models

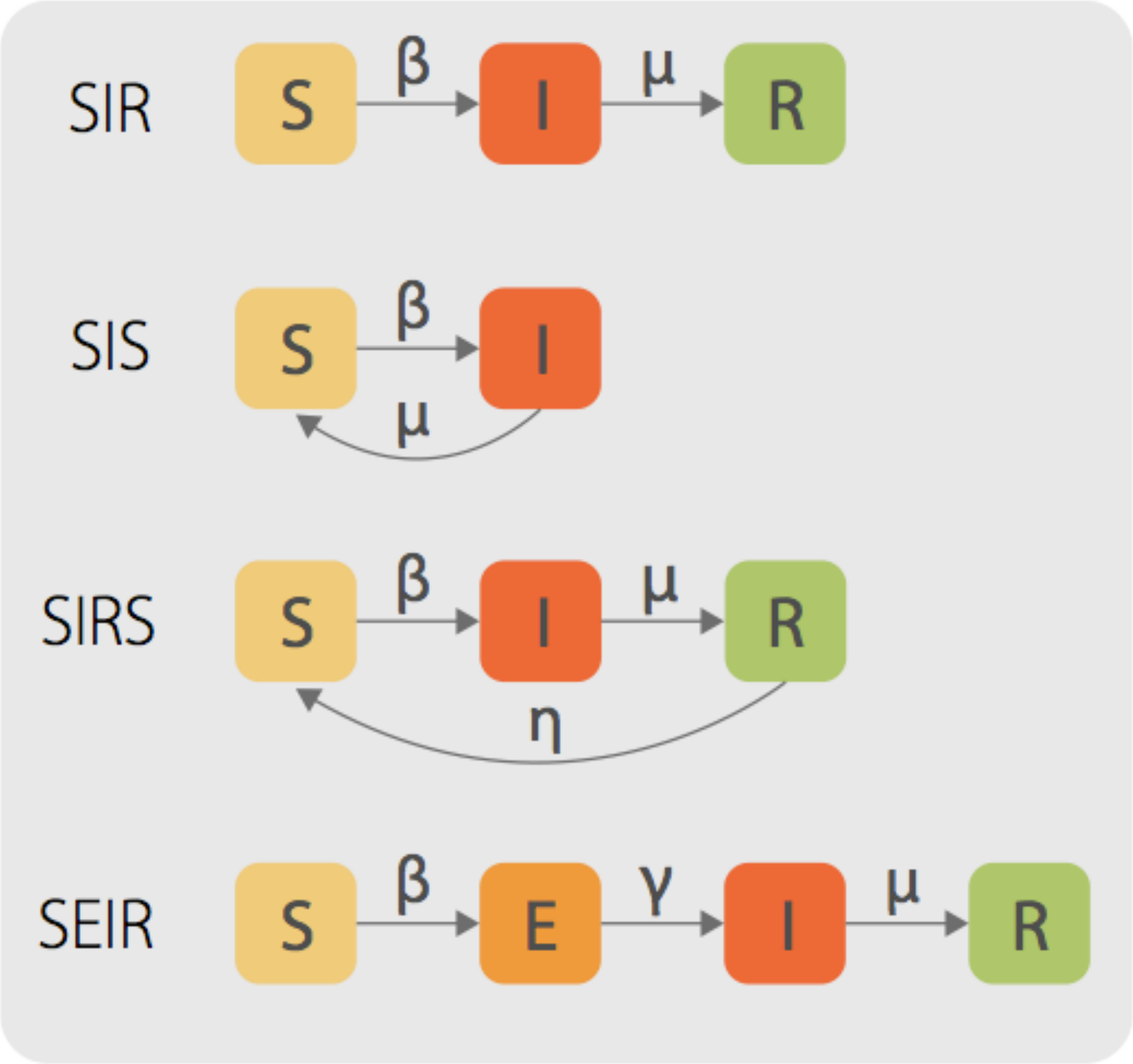
Data Driven:

- Mathematical Models
- Time series forecasting (ML, Statistics)

Epidemic Spreading models

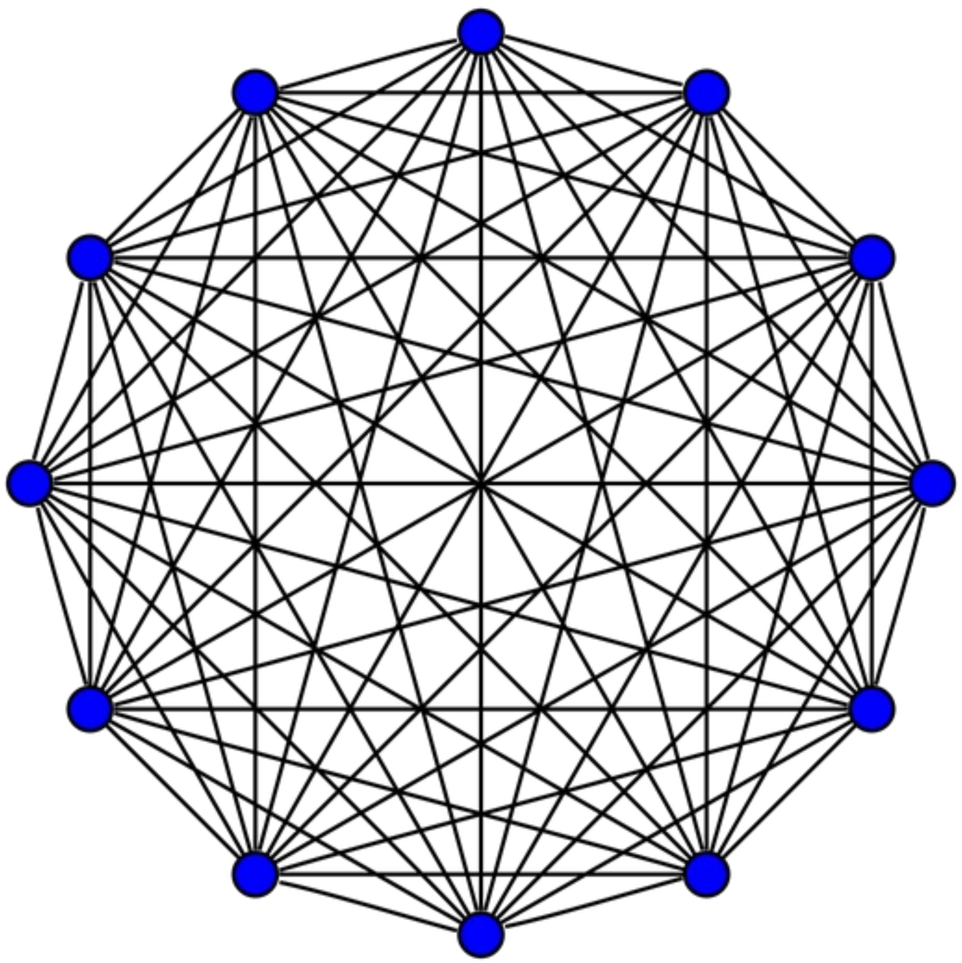


Epidemic Spreading models



Pastor-Satorras et al. Reviews of Modern Physics 2014

Epidemic Spreading models



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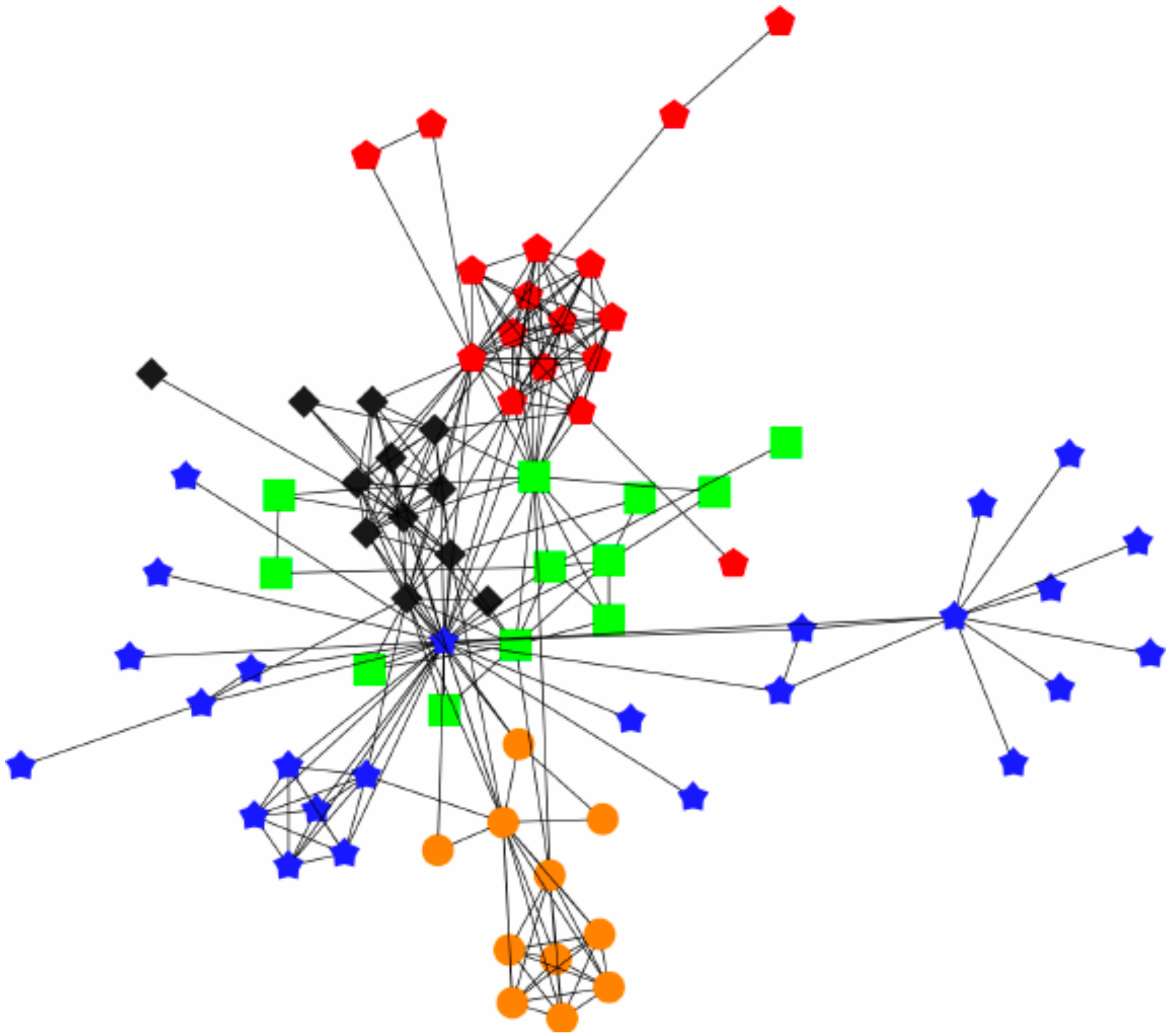
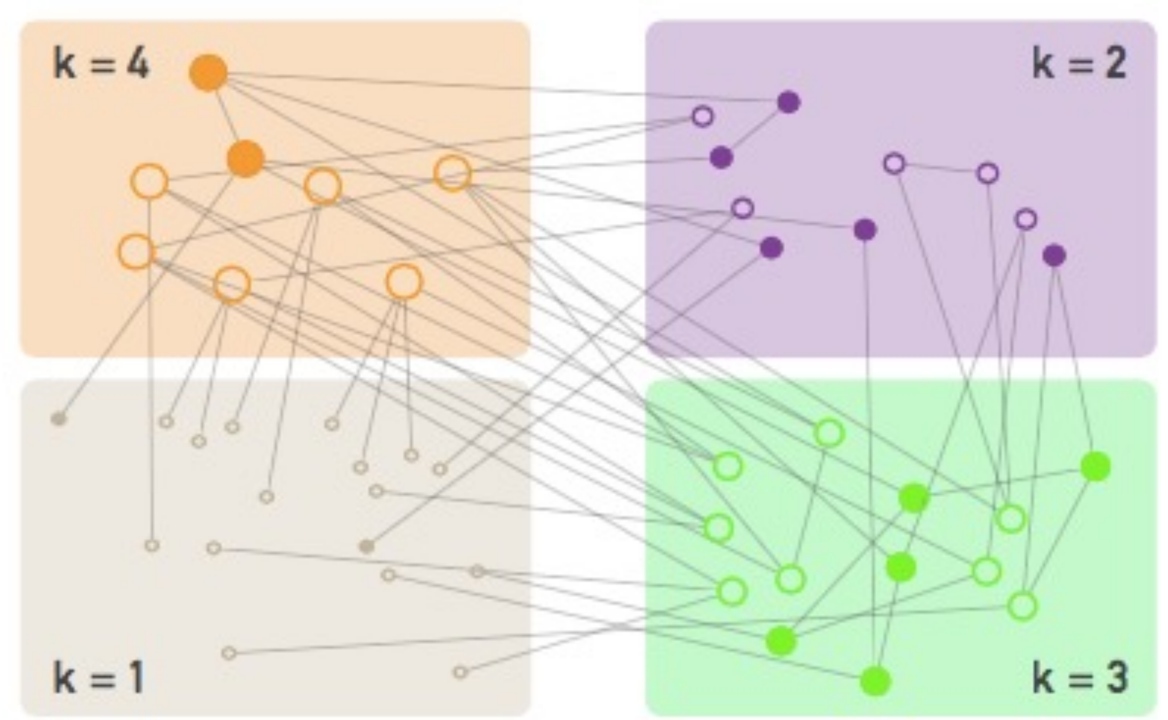


- A. G. McKendrick and W. O. Kermack (1927): deterministic model.

Epidemic spreading in heterogeneous networks

Degree-based mean field: SIS model

$$\frac{di_k}{dt} = \beta(1-i_k)k\Theta_k(t) - \mu i_k$$



v

$$\Theta_k = \frac{\sum_{k'} k' p_{k'} i_{k'}}{\langle k \rangle} = \Theta$$

the fraction of infected neighbors of a susceptible node k

Keeping only the first order terms:

$$\frac{di_k}{dt} = \beta k\Theta - \mu i_k$$

Multiplying the equation with (k–1)pk/〈k〉 and summing over k

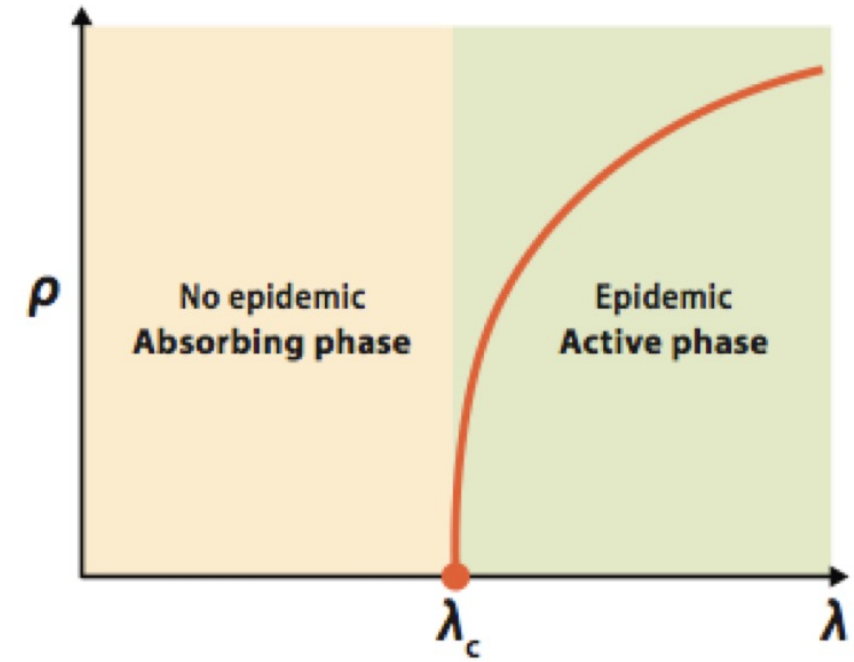
$$\frac{d\Theta}{dt} = \left(\beta\frac{\langle k^2\rangle}{\langle k\rangle} - \mu\right)\Theta \longrightarrow \boxed{\Theta(t) = Ce^{t/\tau};} \quad \boxed{\tau = \frac{\langle k\rangle}{\beta\langle k^2\rangle - \langle k\rangle\mu}}$$

characteristic time

Epidemic spreading in heterogeneous networks

Degree-based mean field: SIS model

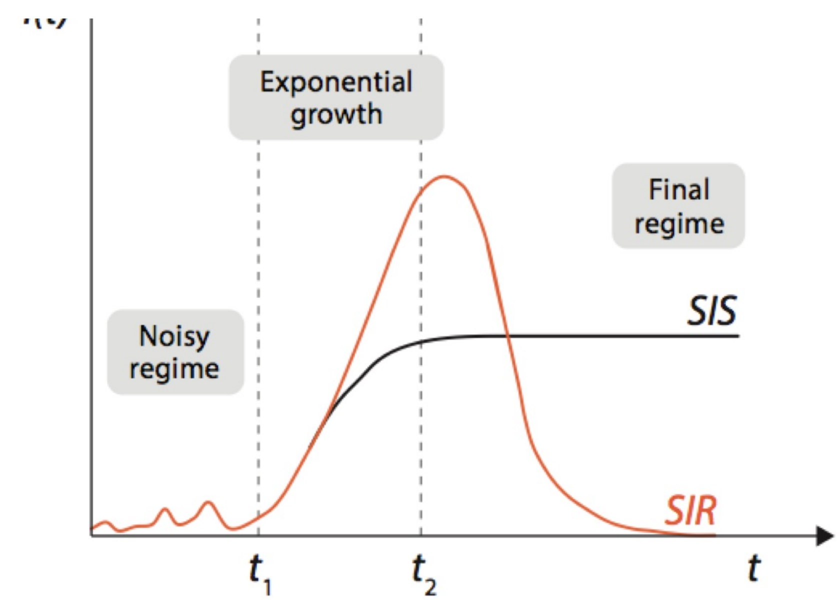
$$\Theta(t) = Ce^{t/\tau}; \quad \tau = \frac{\langle k \rangle}{\beta\langle k^2 \rangle - \langle k \rangle \mu}$$



A global outbreak is possible if $\tau > 0$, which yields the condition for a global outbreak as

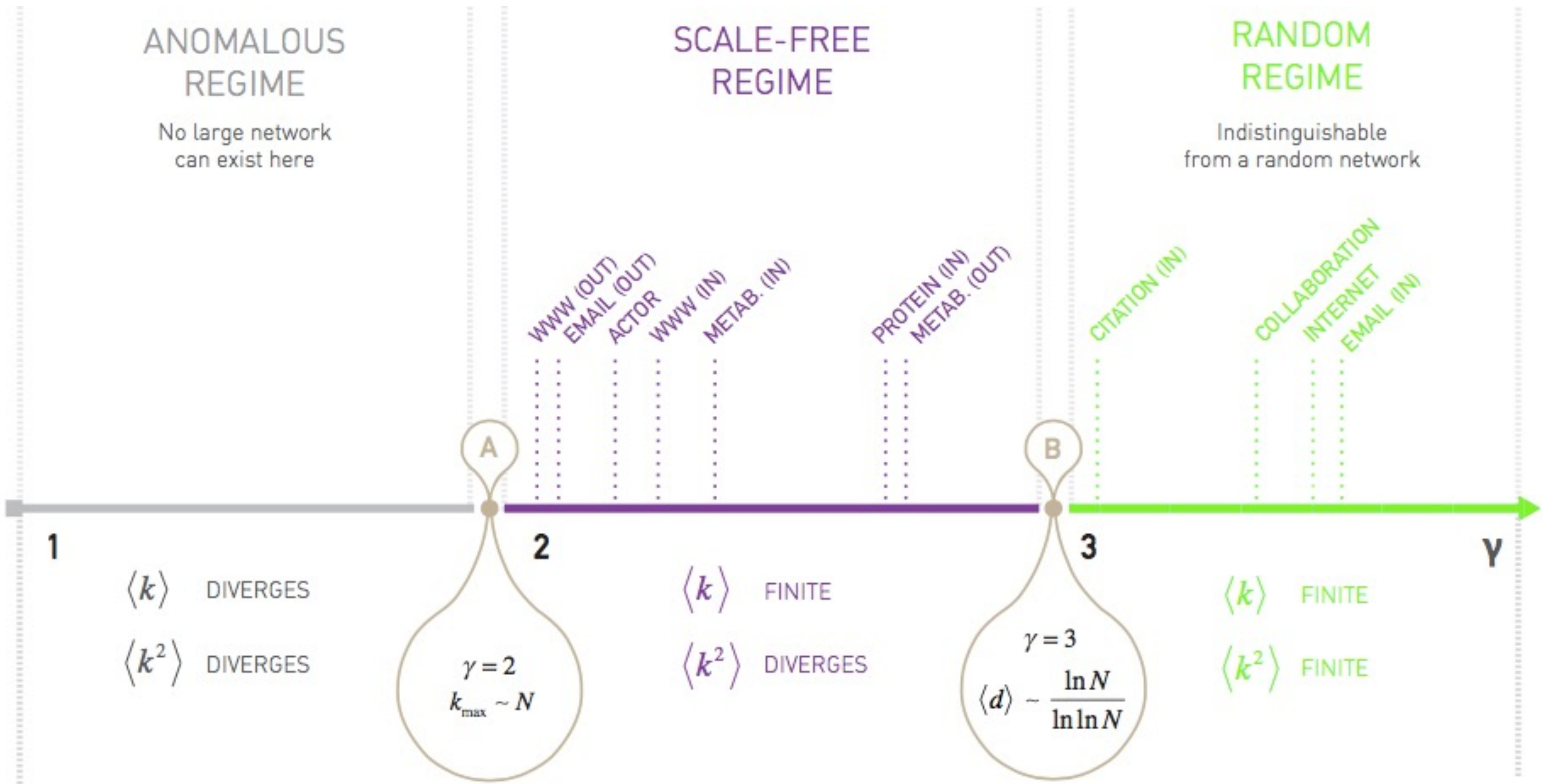
$$\lambda = \frac{\beta}{\mu} > \frac{\langle k \rangle}{\langle k^2 \rangle}$$

$$\boxed{\lambda_c = \frac{\langle k \rangle}{\langle k^2 \rangle}.}$$



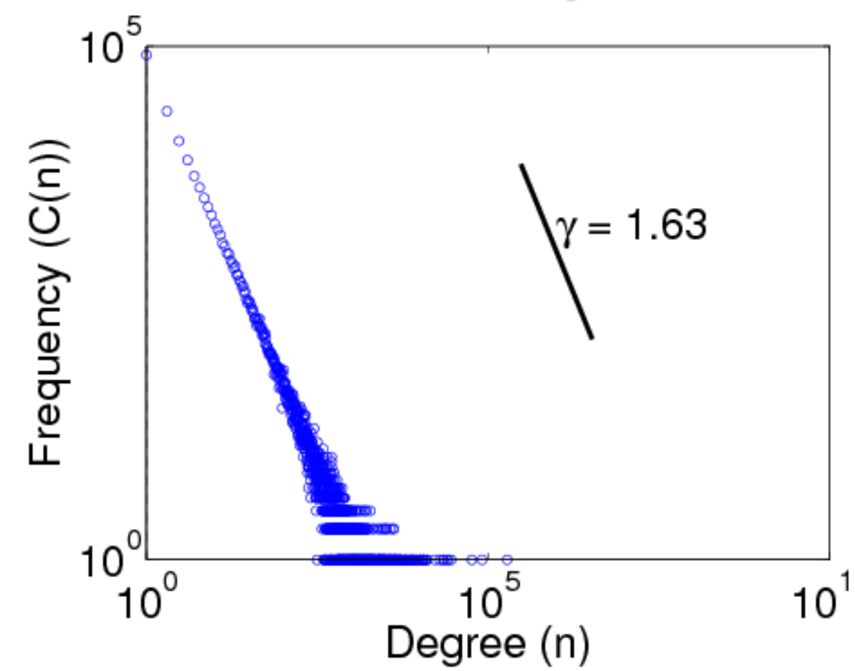
Satorras and Vespignani, PRL, 2001

Scale-free networks

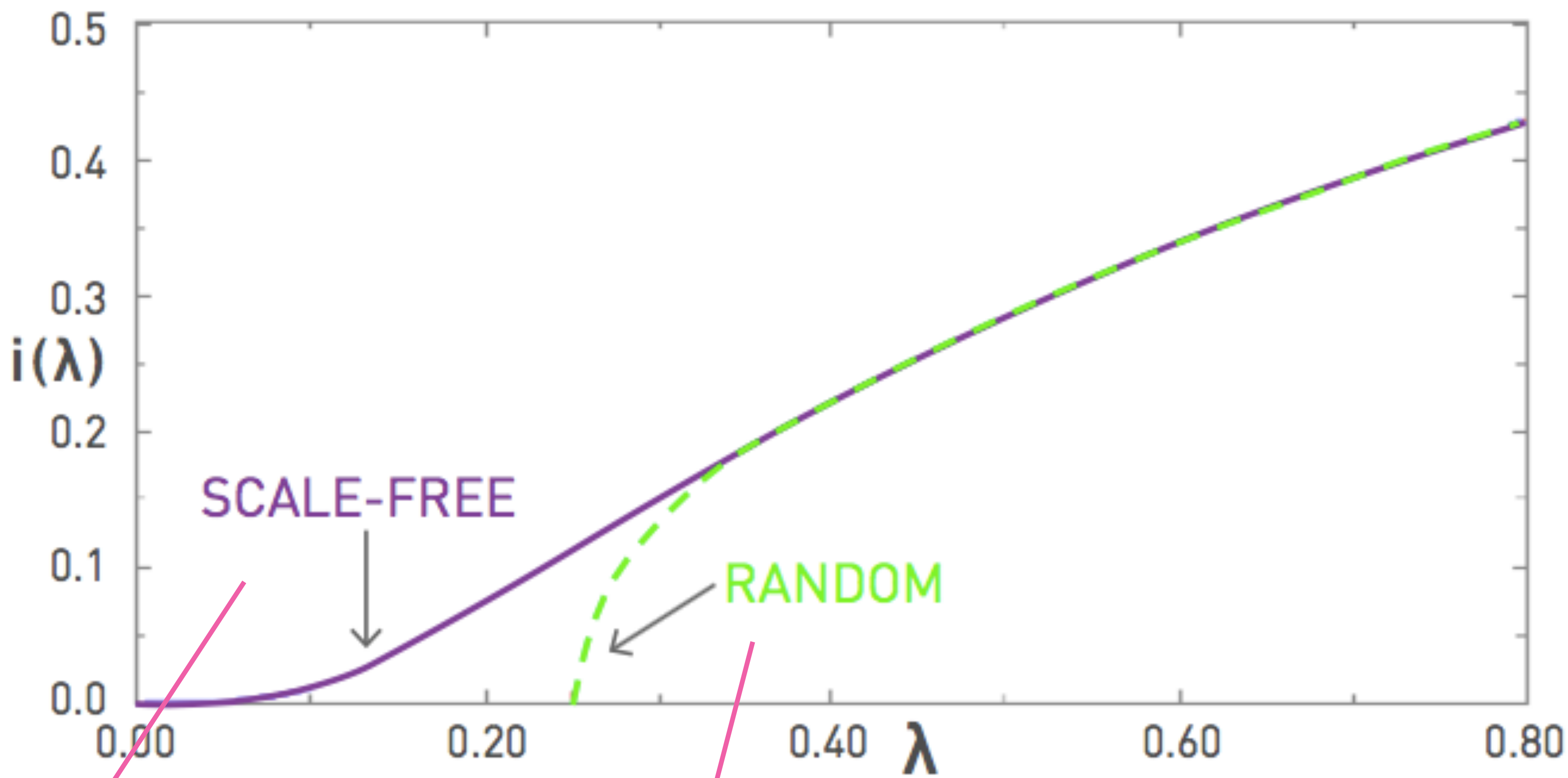


$$P(k) \sim k^{-\gamma}$$

$$\boxed{\lambda_c = \frac{\langle k \rangle}{\langle k^2 \rangle}}$$



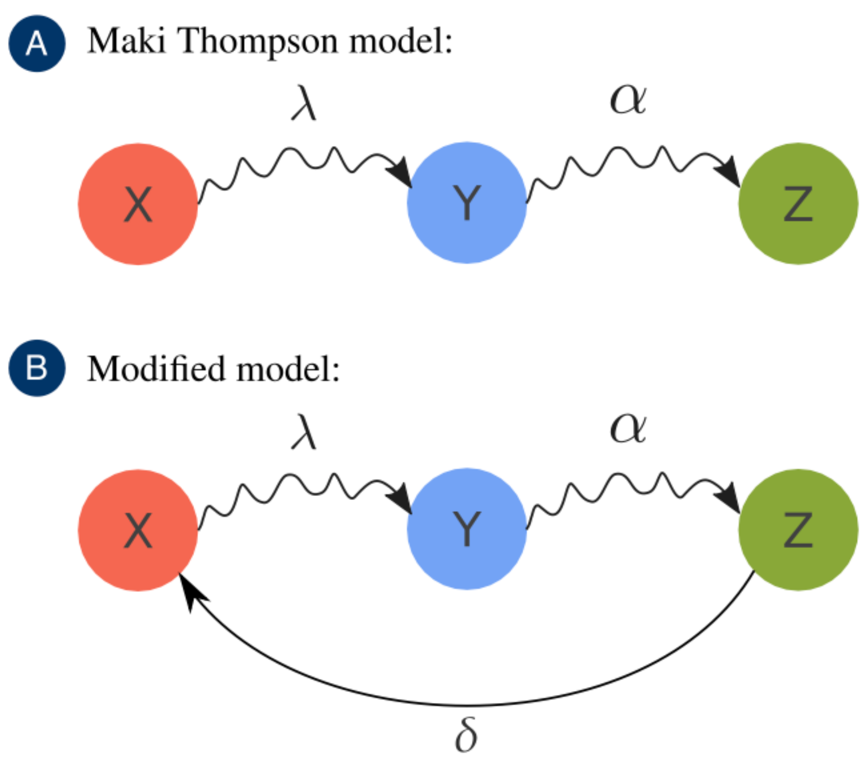
Epidemic spreading in heterogeneous networks



$$\lambda_c = \frac{\langle k \rangle}{\langle k^2 \rangle} \sim \mathbf{0} \qquad \lambda_c = \frac{1}{\langle k \rangle + 1}$$

A. L. Barabási, Network Science, Cambridge, 2015.

Rumor spreading



$$(0,1,0)_i + (1,0,0)_j \xrightarrow{\lambda} (0,1,0)_i + (0,1,0)_j,$$
$$(0,1,0)_i + (0,1,0)_j \xrightarrow{\alpha} (0,1,0)_i + (0,0,1)_j,$$
$$(0,1,0)_i + (0,0,1)_j \xrightarrow{\alpha} (0,0,1)_i + (0,0,1)_j,$$
$$(0,0,1)_i \xrightarrow{\delta} (1,0,0)_i.$$

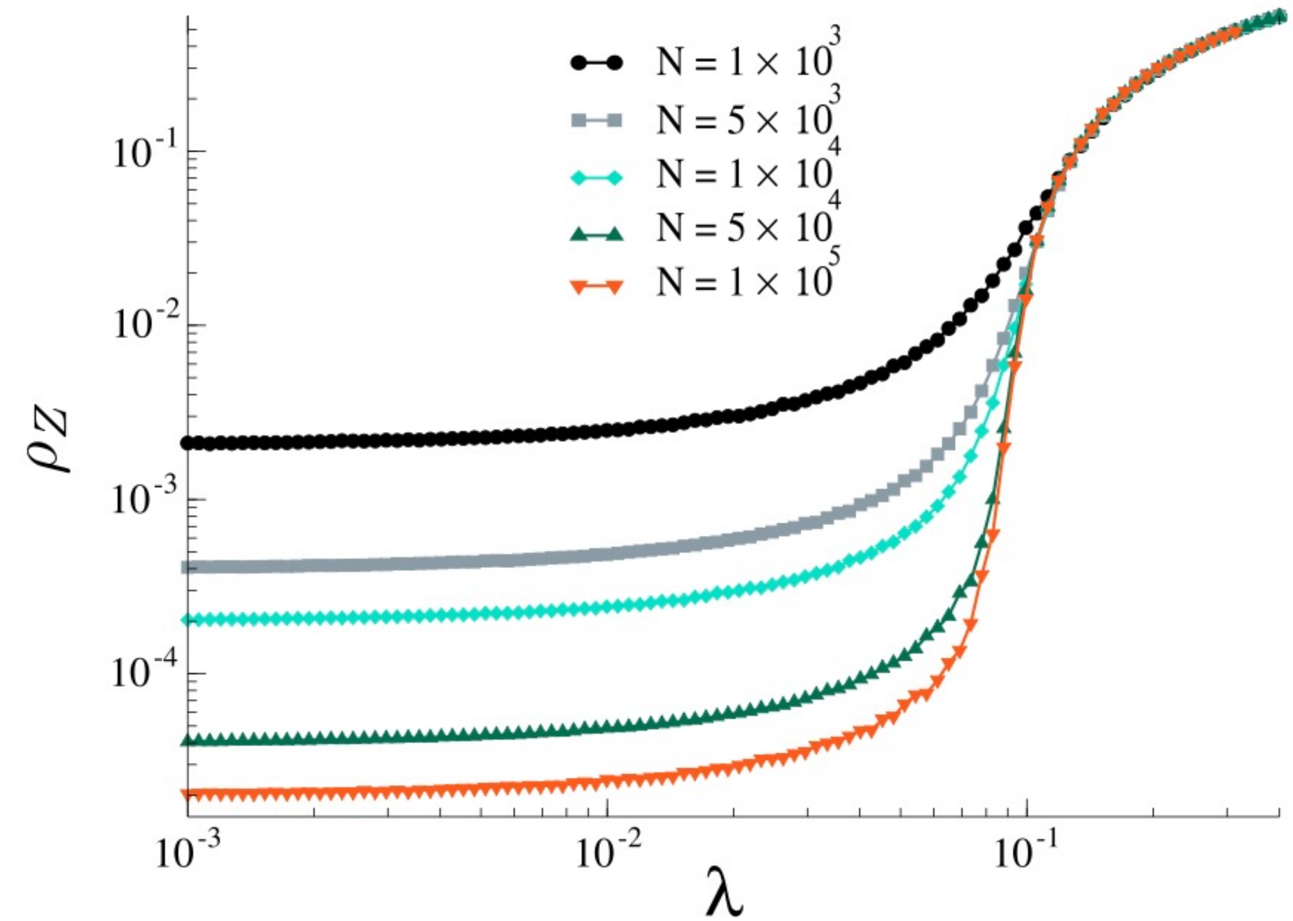
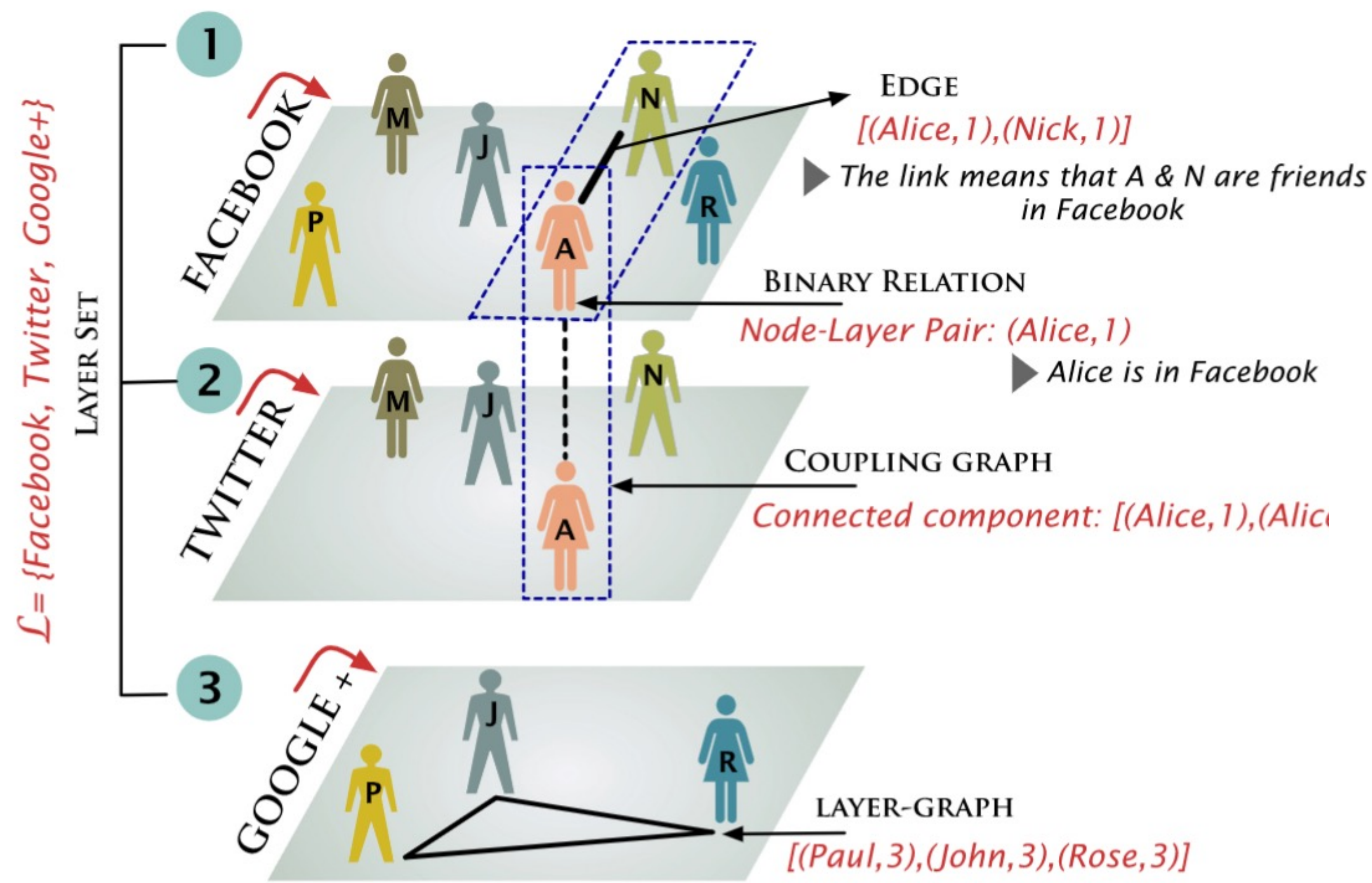


Fig. 2 Phase diagram for the standard MT model. Results for $\alpha = 1$ and different sizes on a random regular networks with $\langle k \rangle_k = 10$.

Arruda et al. Nature Communications, 2022.

Multilayer networks

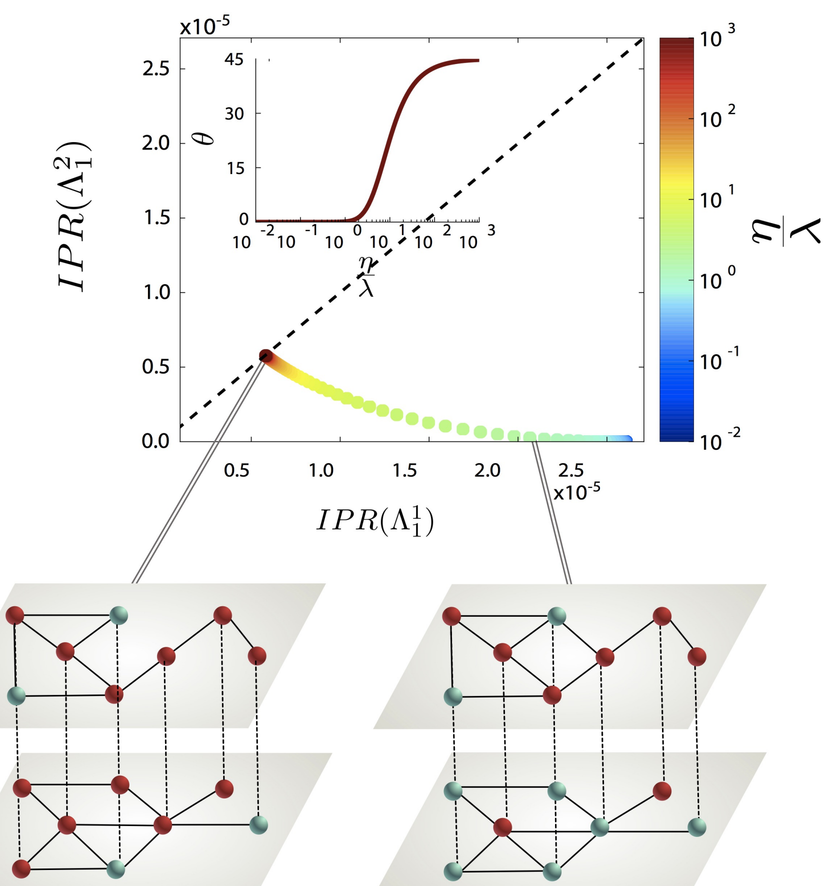


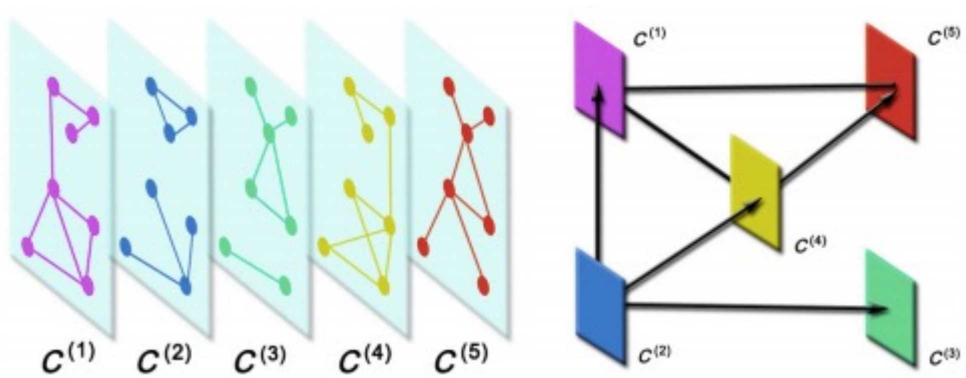
SET OF SOCIAL ACTORS: *n= {Alice, John, Mary, Nick, Paul, Rose}*

Alice	John	Mary	Nick	Paul	Rose
A	J	M	N	P	R

$$\boxed{\frac{dX_{\beta\tilde{\delta}}}{dt} = -\mu X_{\beta\tilde{\delta}} + (1 - X_{\beta\tilde{\delta}})\lambda \mathcal{R}^{\alpha\tilde{\gamma}}_{\beta\tilde{\delta}}(\lambda, \eta) X_{\alpha\tilde{\gamma}}}$$

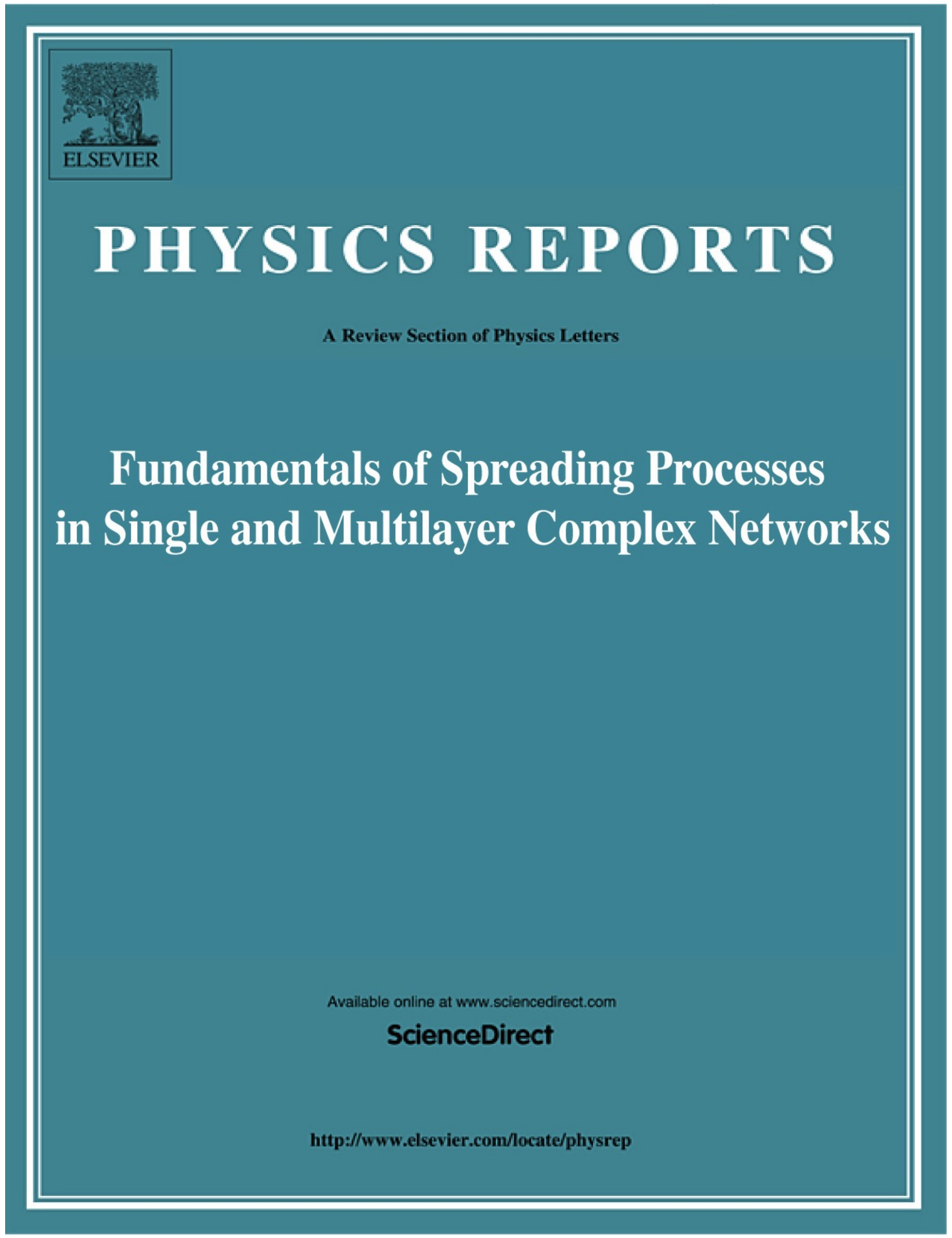
$$\mathrm{IPR}(\Lambda) \equiv (f_{\beta\tilde{\delta}}(\Lambda))^4 U^{\beta\tilde{\delta}}$$





$$M^{\alpha\tilde{\delta}}_{\beta\tilde{\gamma}} = \sum_{\tilde{h},\tilde{k}=1}^{m} C^{\alpha}_{\beta}(\tilde{h}\,\tilde{k}) E^{\tilde{\delta}}_{\tilde{\gamma}}(\tilde{h}\,\tilde{k})$$

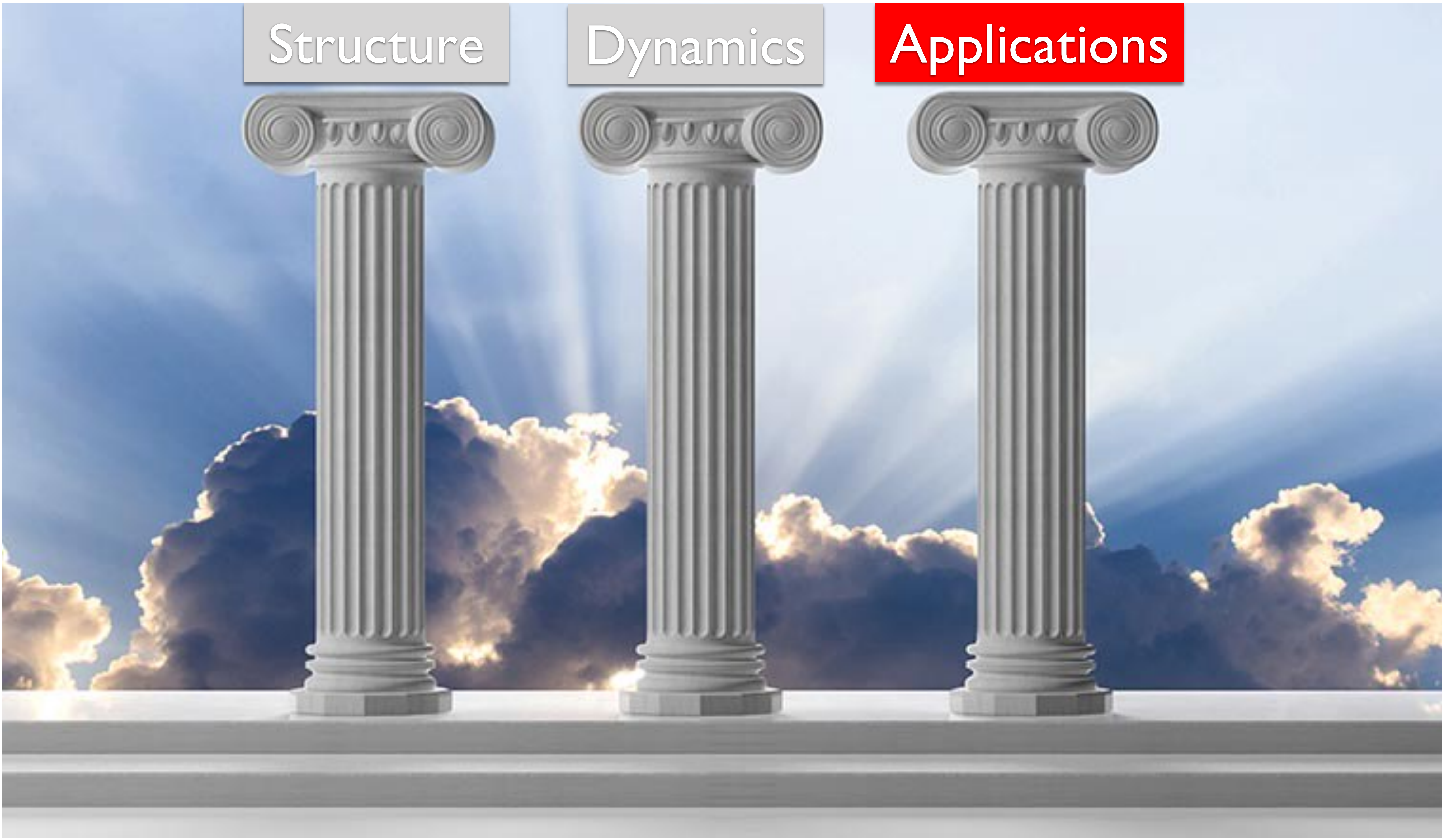
Arruda et al., Physical Review X, 2017



1. Mean-field
2. Markov chain
3. Quenched-MF (QMF)
4. Pair approximation
5. Individual based MF
6. Message passing
7. ...

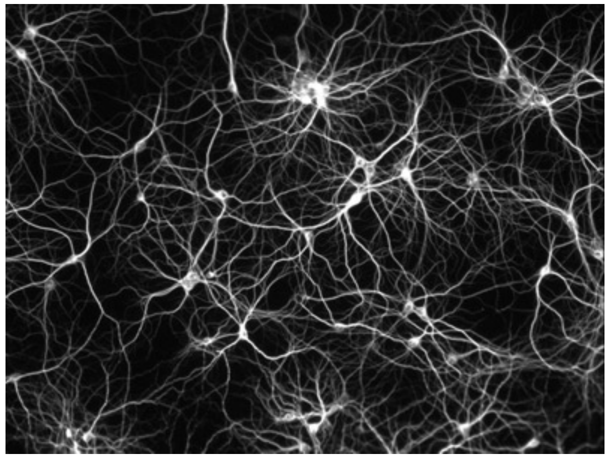
Guilherme F. de Arruda, Francisco A. Rodrigues, and Yamir Moreno
Fundamentals of spreading processes in single and multilayer complex networks
Physics Reports*, Volume 756, Pages 1-60 (2018).*

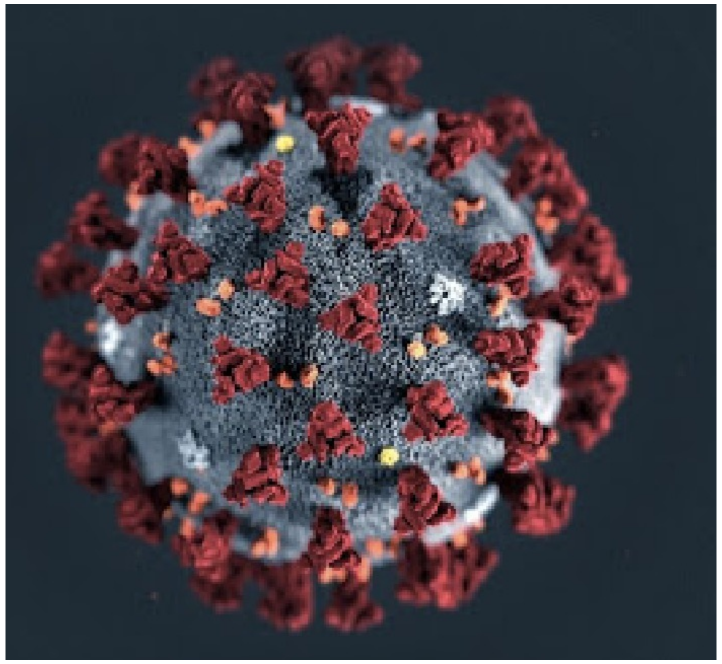
Complex Systems

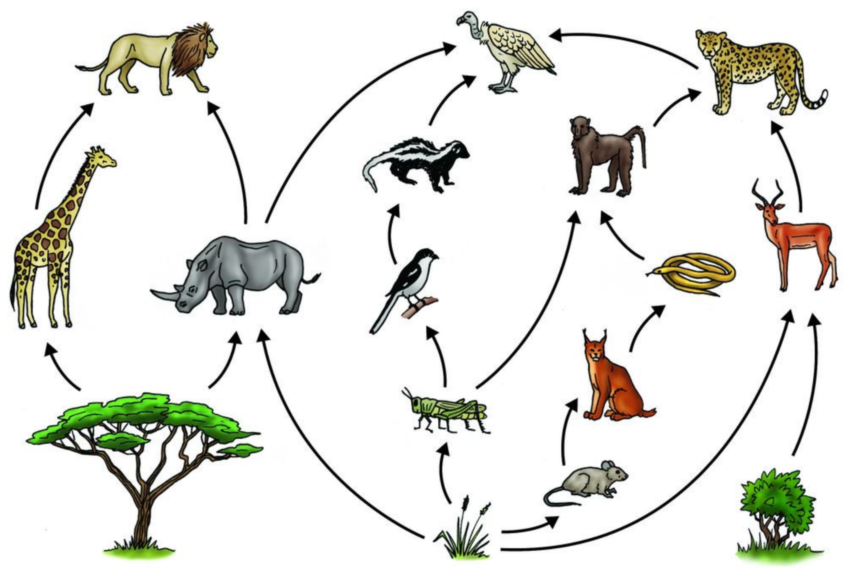


Applications

- Physics
- Biology
- Medicine
- Engineering
- Ecology
- Climate
- Financial Market
- Sociology
- Computer Science
- Neuroscience
- …

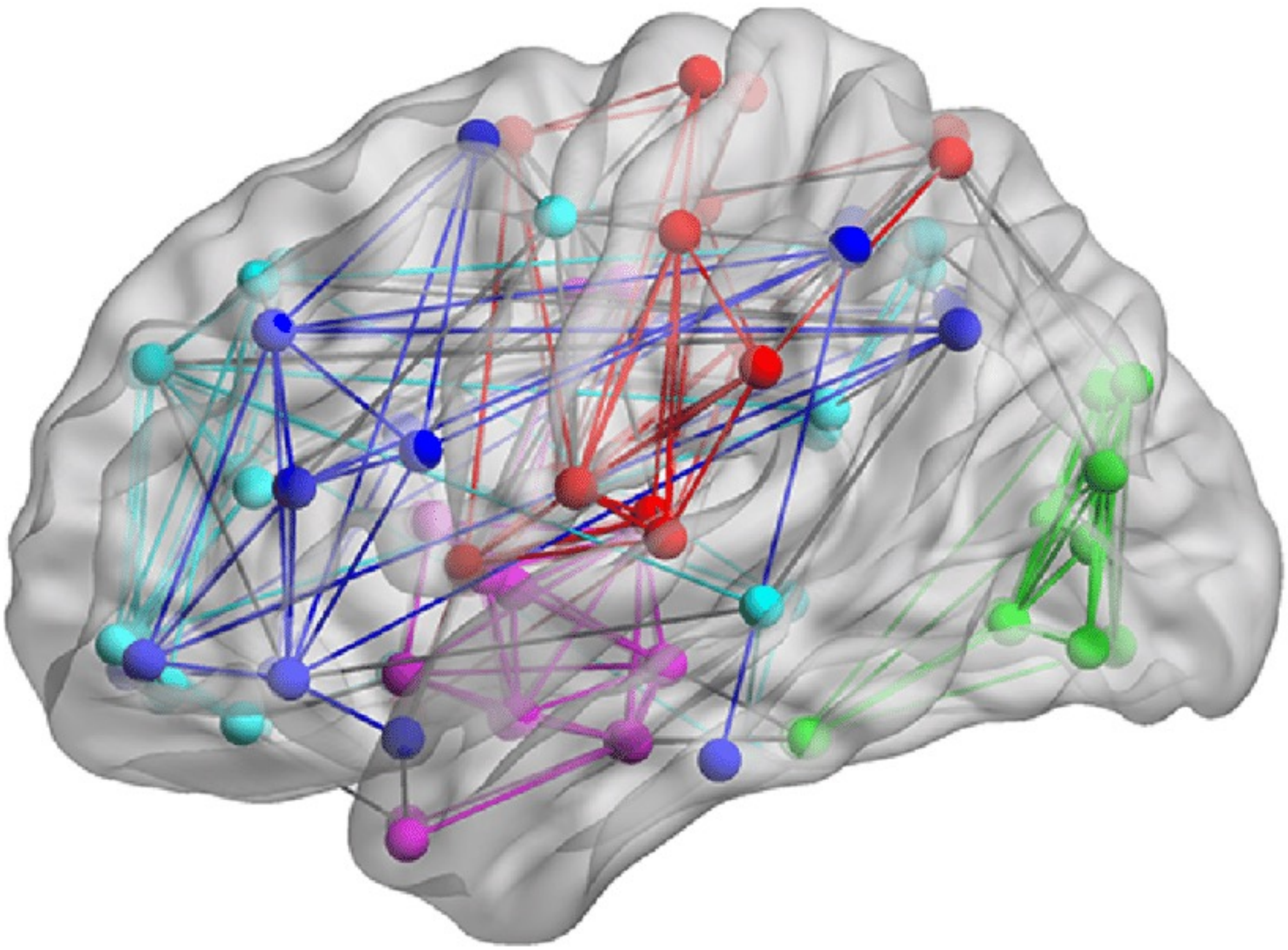




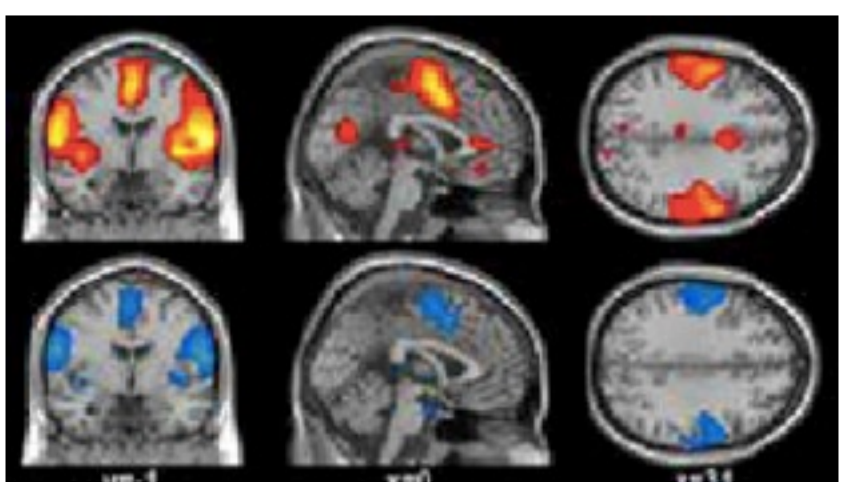


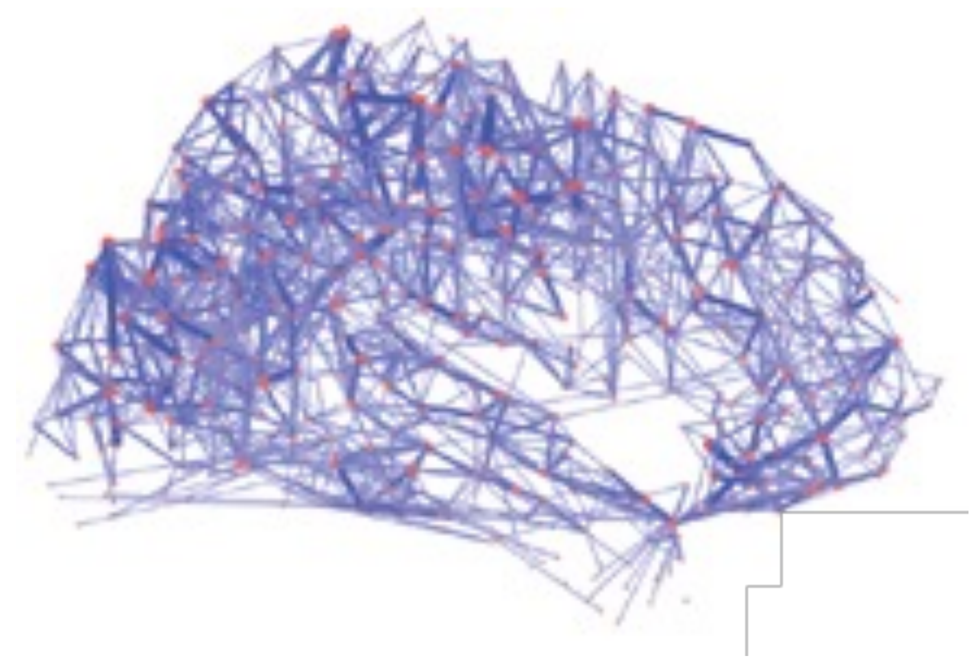
http://www.visualcomplexity.com

Brain networks



Diagnosis of mental disorders





Machine Learning

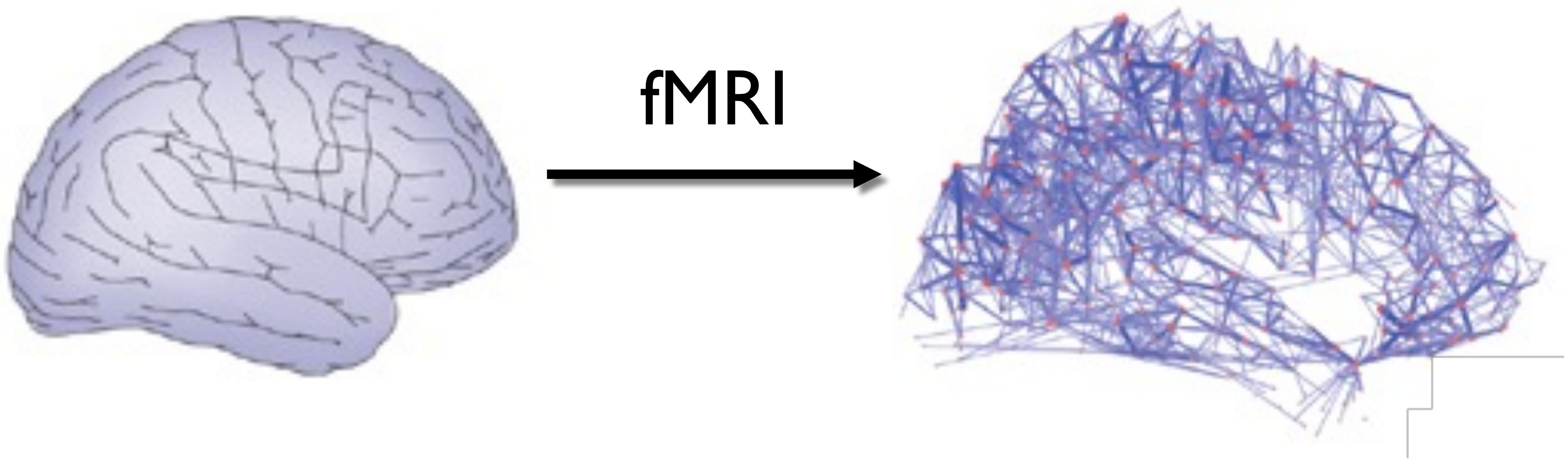
YES NO

Child-onset schizophrenia

Child-onset schizophrenia
(or pediatric schizophrenia) is a type of mental disorder characterized by degeneration of thinking, motor, and emotional processes in children and adolescents under the age of 18.

Challenge: Early diagnosis.

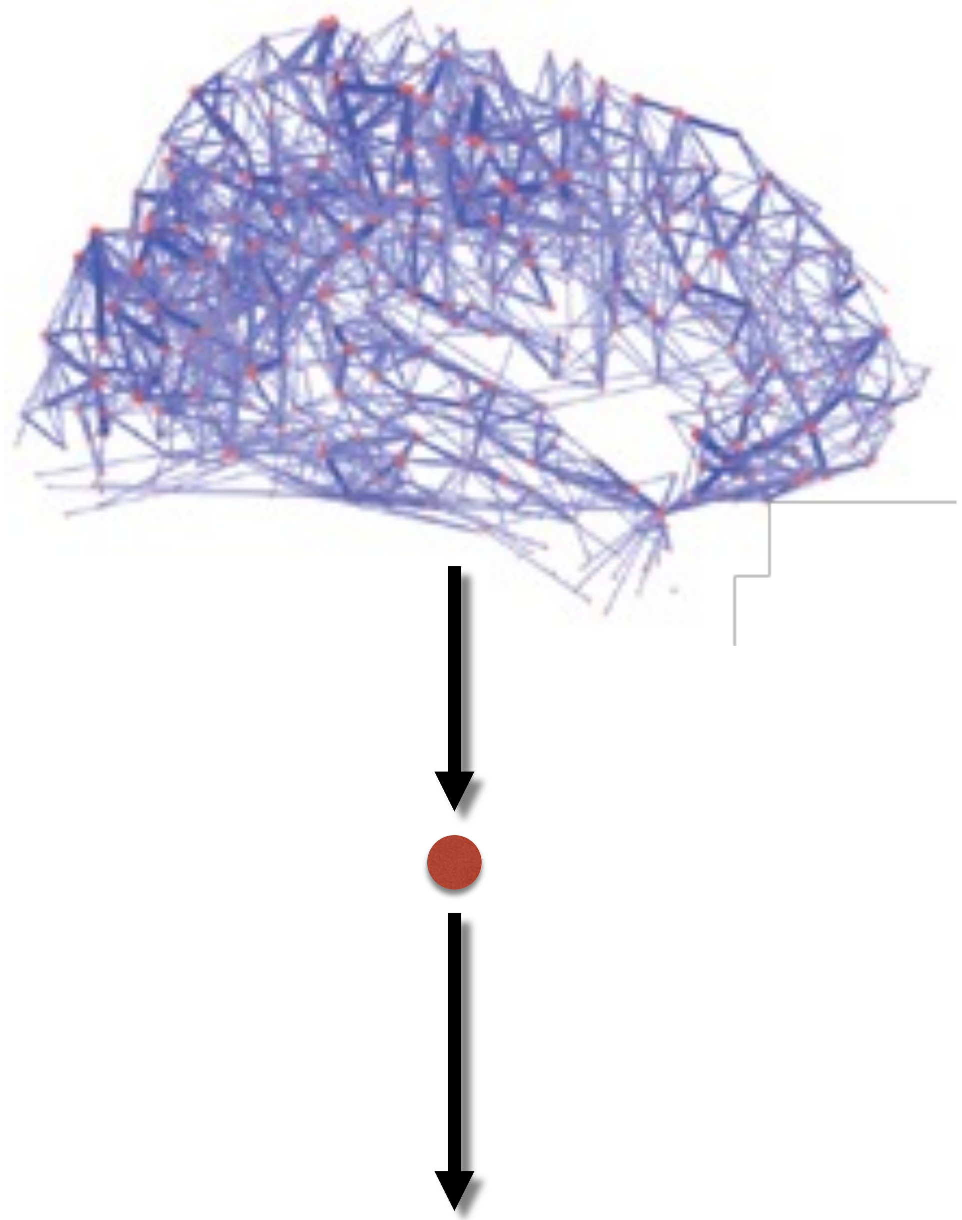
Child-onset schizophrenia



Data: Healthy subjects (n = 20, mean age 19.7 years; 11 male)
adolescent participants with childhood-onset schizophrenia
(n = 19, mean age 18.7 years; 9 male).
The subjects were scanned using a General Electric Signa MRI scanner
operating at 1.5 Tesla.
Only the right hemisphere (140 regions).

Arruda et al. Clinical Neurophysiology, 2013

Child-onset schizophrenia



$V_i = [M1, M2, M3, \ldots, M54]$

54 measures calculated for each node.

Arruda et al. Clinical Neurophysiology, 2013

Child-onset schizophrenia

Table 1: Feature ranking of network measures calculated by using symmetrical uncertainty (U) and chi-squared test ($\mathcal{X}^2$). The features are ordered according to the symmetrical uncertainty.

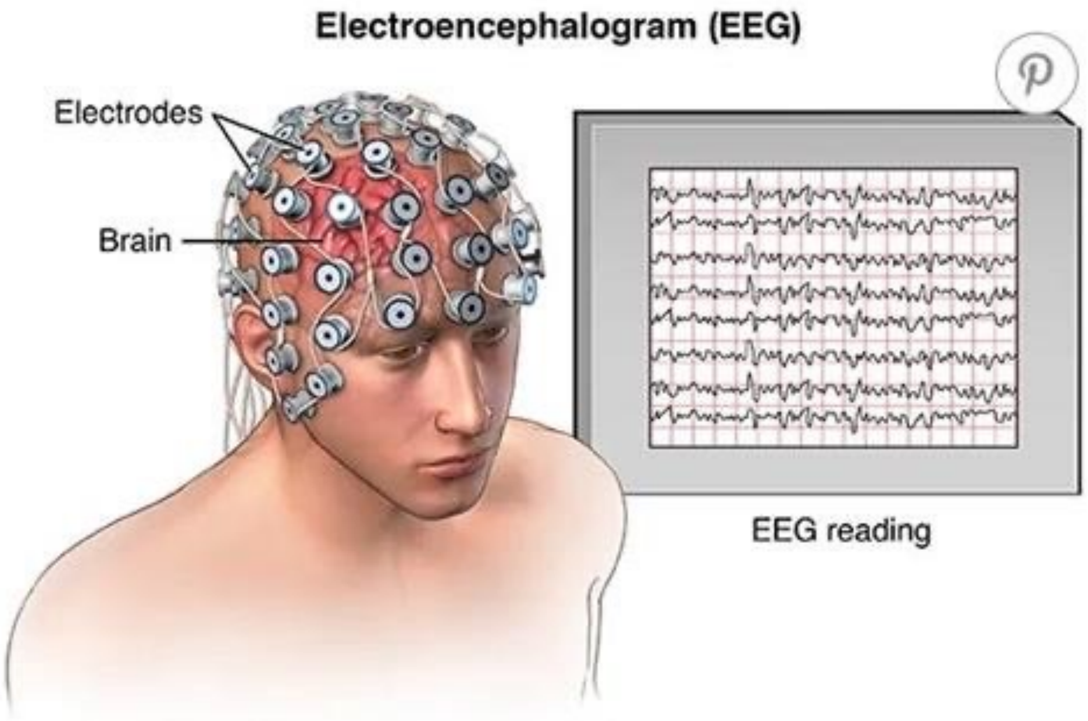
$U(C, A)$	$\mathcal{X}^2$	Feature
0.326	15.55	Variance of the closeness centrality
0.289	10.13	First moment of K-core
0.263	12.88	Modularity
0.258	12.74	Variance of the accessibility

Table 2: Percentage of correct classification of networks obtained from healthy and schizophrenic subjects considering 4 or 54 measures. PC is the positive class, H. indicates the healthy class and S., schizophrenic subjects.

	Naive Bayes		Bayesian network		C4.5 Decision tree	
	54 meas.	4 meas.	54 meas.	4 meas.	54 meas.	4 meas.
Accuracy	0.74	0.76	0.71	0.78	0.45	0.71
Precision (PC: H.)	0.68	0.73	0.70	0.76	0.46	0.68
Specificity: Recall (PC: H.)	0.90	0.84	0.74	0.84	0.58	0.79
F-Measure (PC: H.)	0.77	0.78	0.72	0.80	0.51	0.73
Precision (PC: S.)	0.85	0.81	0.72	0.82	0.43	0.75
Sensitivity: Recall (PC: S.)	0.58	0.68	0.68	0.74	0.32	0.63
F-Measure (PC: S.)	0.69	0.74	0.70	0.78	0.36	0.69

Arruda et al. Clinical Neurophysiology, 2013

Alzheimer's disease and schizophrenia



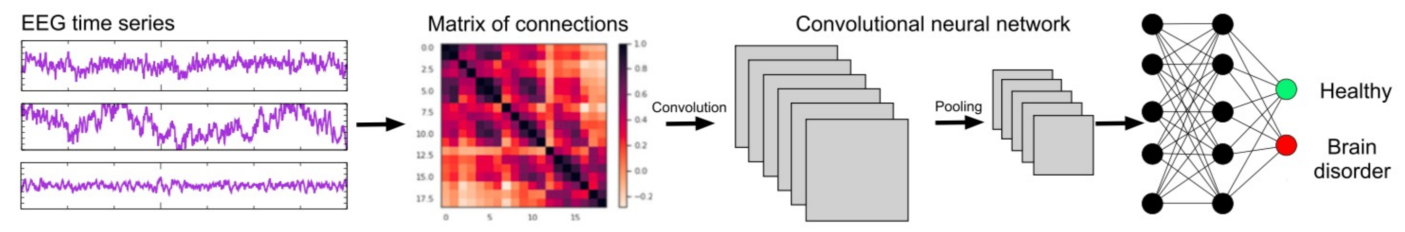


Figure 1. Illustration of the method for automatic diagnosis of mental disorders based on EEG time series. Time series are collected and the correlation between electrodes are calculated yielding the matrices of connections, which encompass the functional connectivity between brain regions. Finally, the CNN is adjusted to enable the automatic classification of individuals.

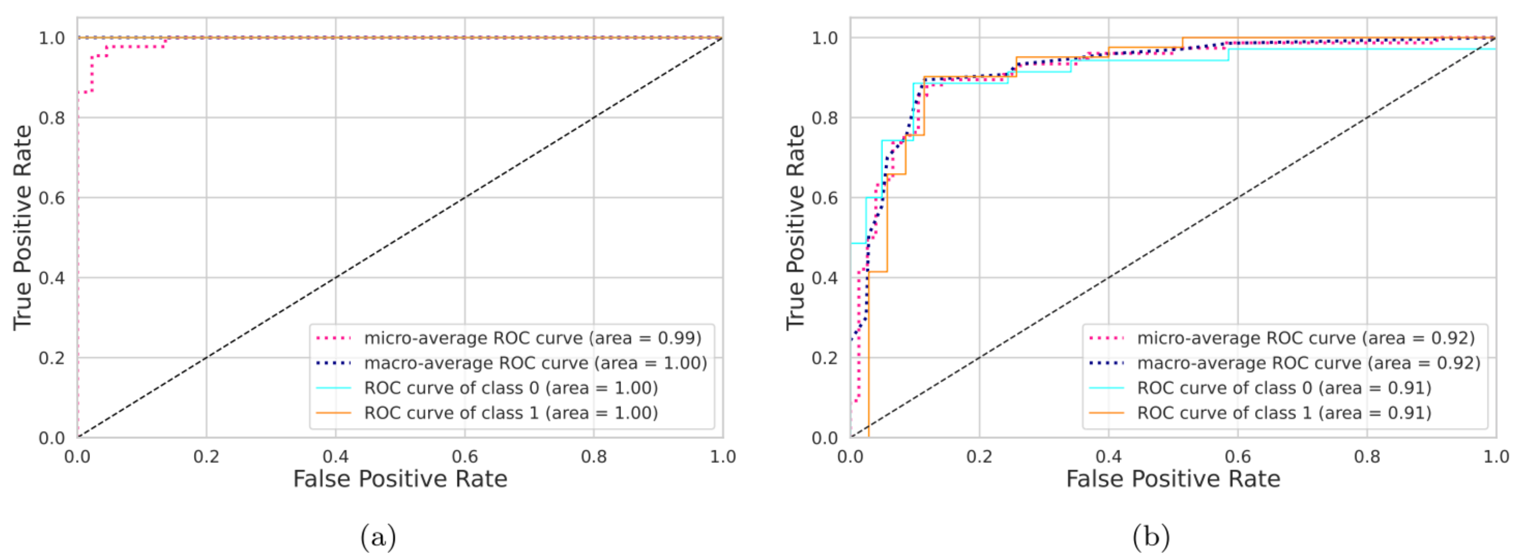


Figure 4. ROC curve obtained from the $\mathrm{CNN}_{\mathrm{tuned}}$ model. The matrices of connections are constructed by (a) Pearson's correlation for AD disease and (b) Granger causality for individuals diagnosed with SZ.

Alves et al., Journal of Physics: Complexity, (2022).

Diagnosis of mental disorder

Attention Deficit Hyperactivity Disorder

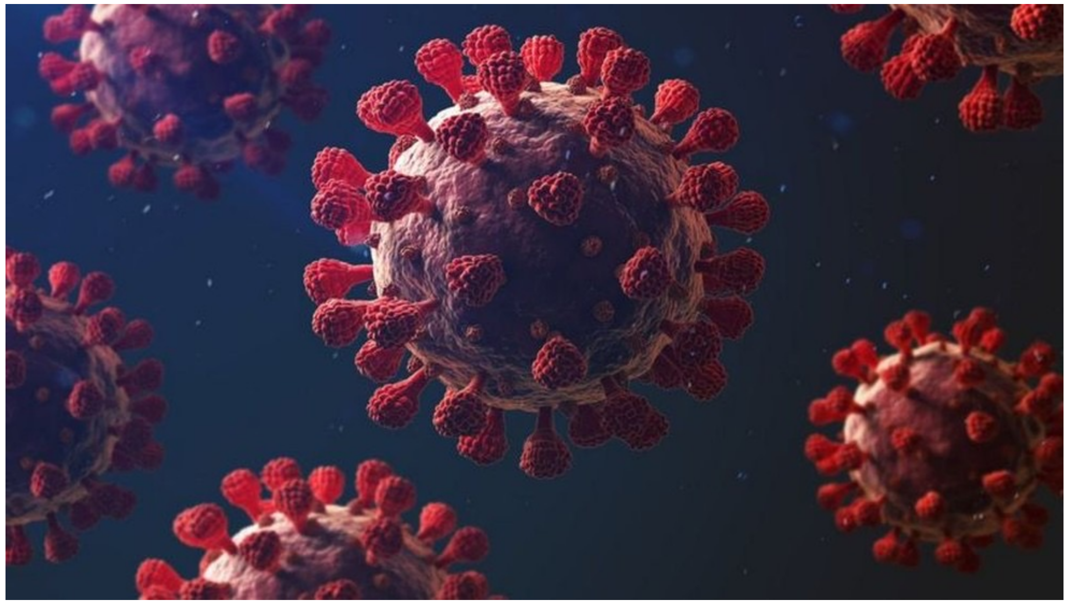
Classifier	Accuracy	AUC
Knn	0.58	0.53
Naive Bayes	0.63	0.50
Decision Trees	0.63	0.51
Neural Networks	**0.65**	**0.50**

Autism spectrum disorders

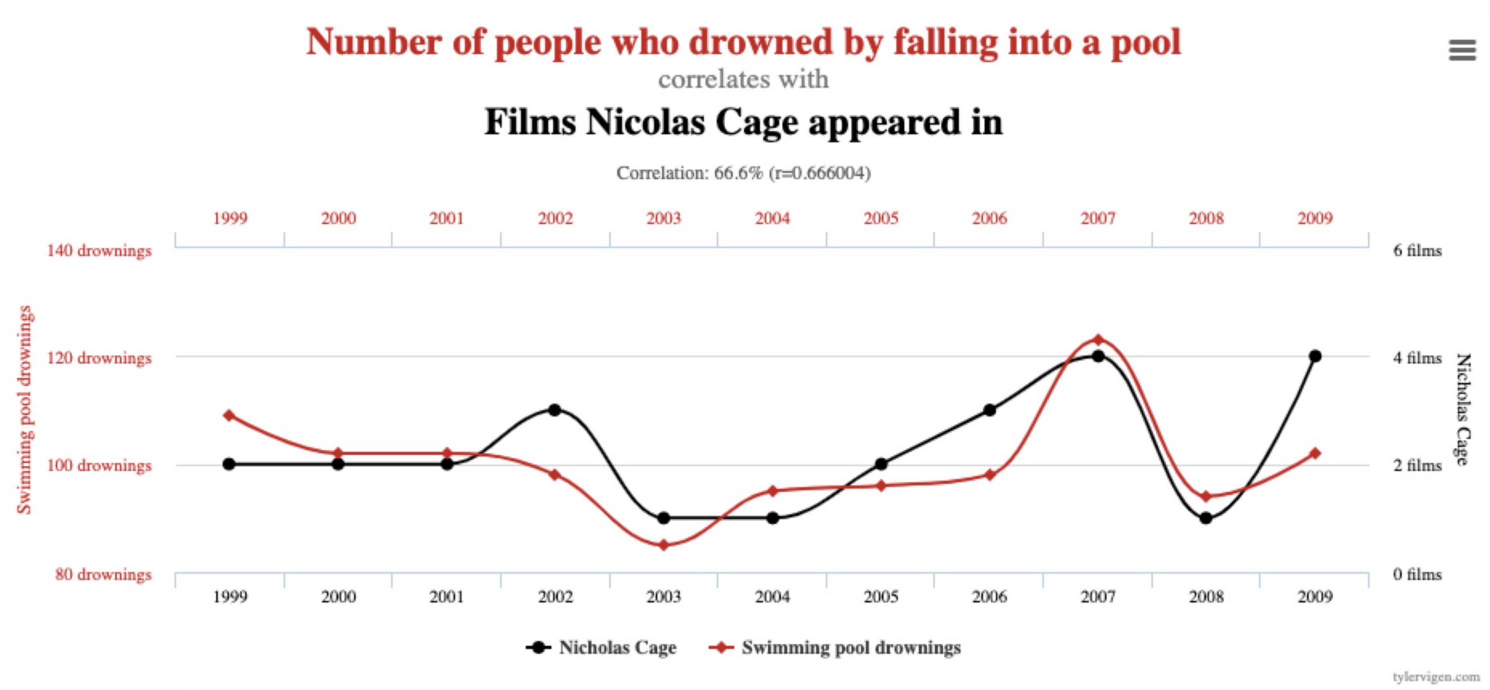
Classifier	Accuracy	AUC
Knn	0.57	0.44
Naive Bayes	0.58	0.54
Decision Trees	**0.67**	**0.62**
Neural Networks	0.63	0.52

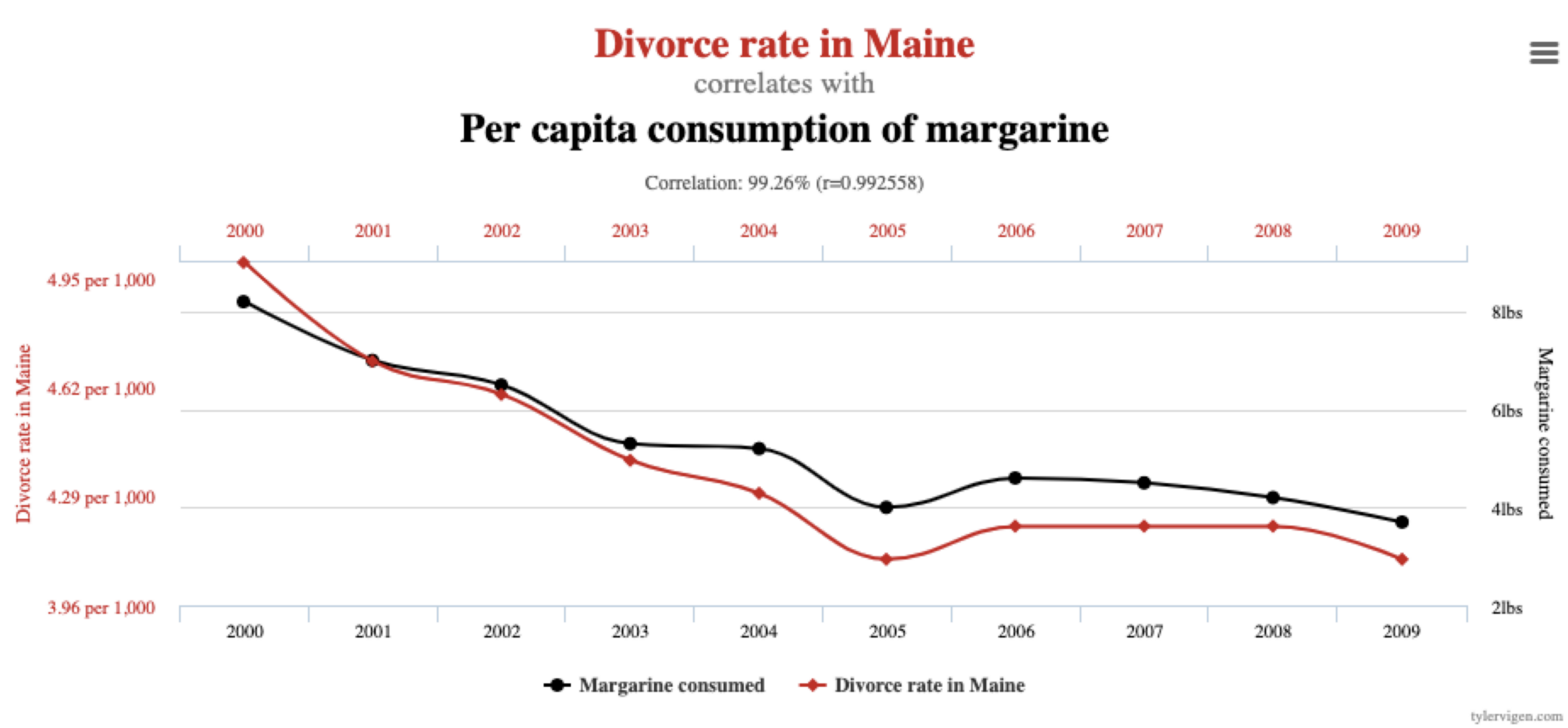
Disorders

Epidemic outbreaks



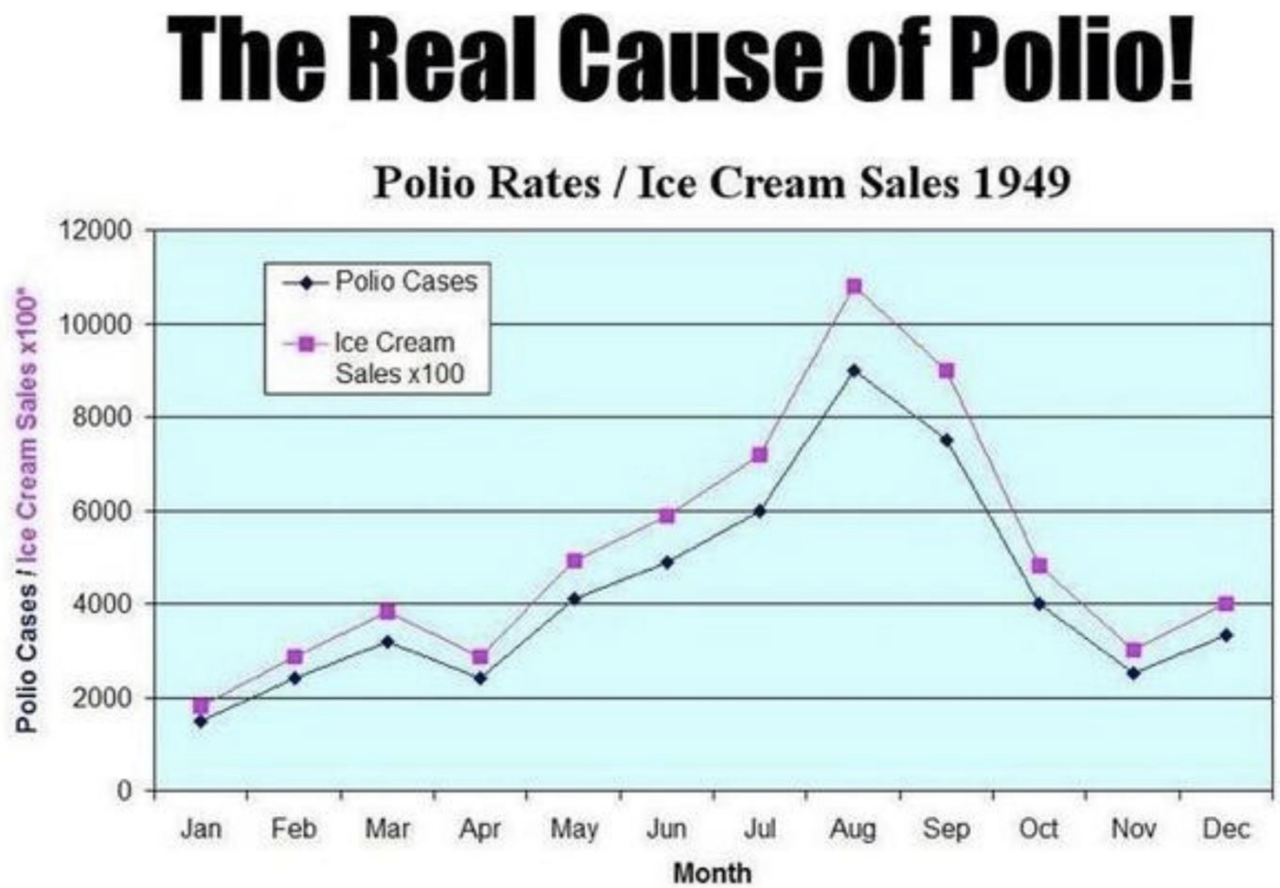
Correlation versus Causation



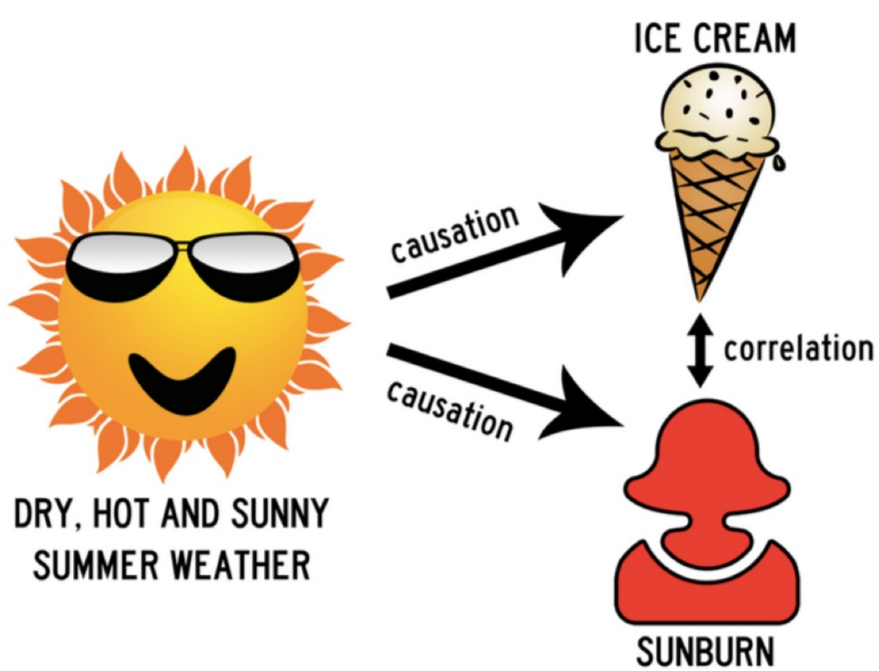


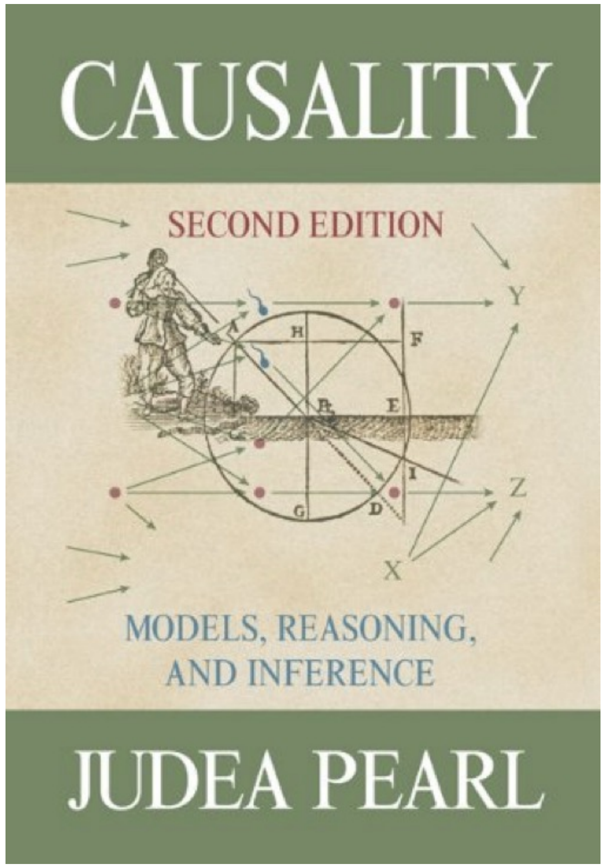
https://www.tylervigen.com/spurious-correlations

Causal inference



In the 1940s Polio example, public health experts recommended that people stop eating ice cream as part of an "anti-polio diet".





Causal inference and epidemiology

Epidemiology

- Epidemiology: study of how and why diseases (& health) spread.
- Two public health goals:
  - forecasting disease prevalence to anticipate outbreaks and allocate resources
  - understanding disease drivers to develop effective preventative interventions.

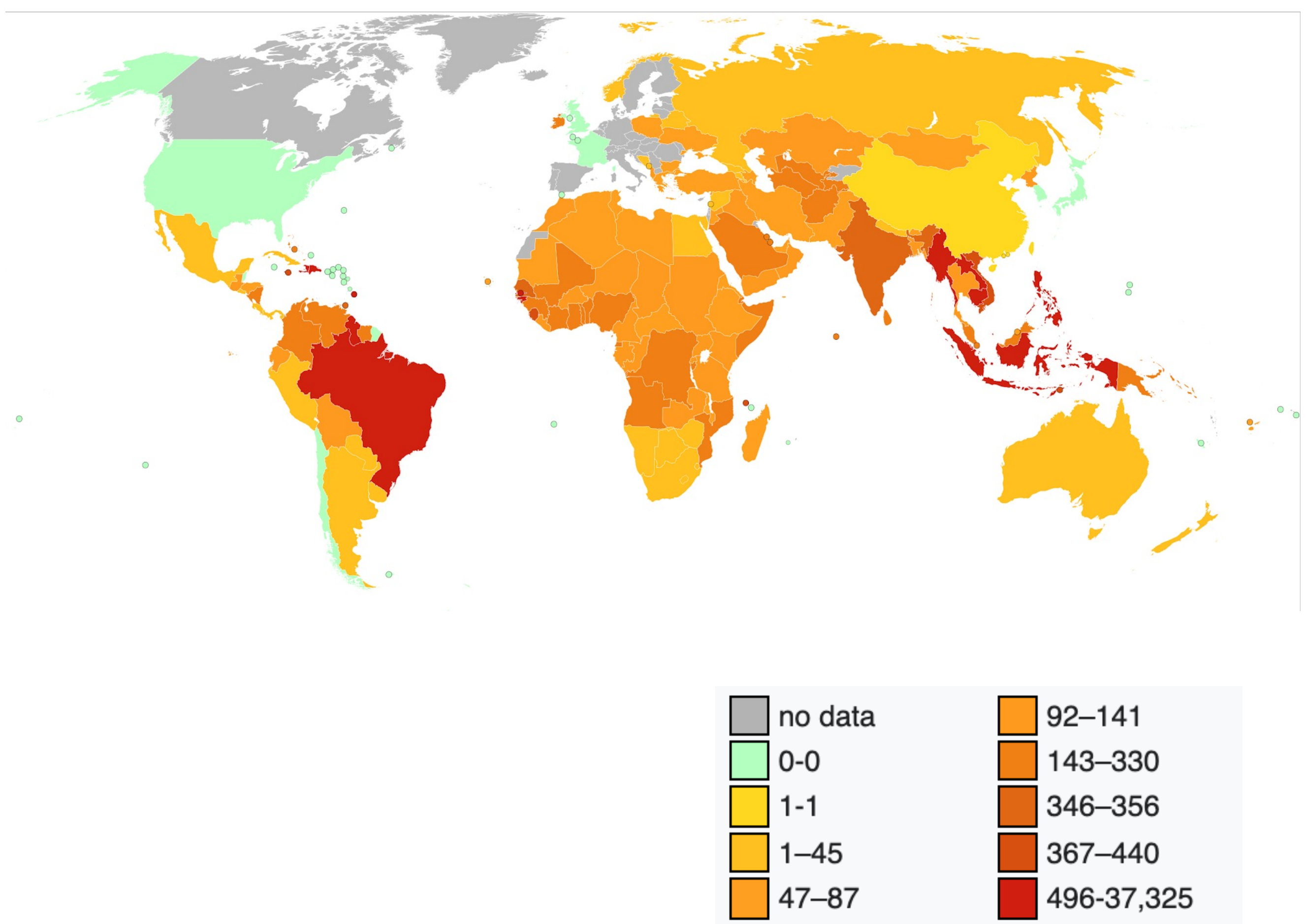
Causal machine learning

- Machine learning: fit function from patterns in data without explicit encoding of rules.
- High predictive accuracy, especially in modern big data world.
- But: criticized for lack of generalizability, transparency, and fairness.
- Can causal machine learning help?
  - Encodes causal assumptions about the world
  - Robust to domain shifts

Dengue is a serious public health concern

- Half of the world's population is at risk of dengue infection
- Brazil's economic burden of dengue in 2013 was 300 million USD
- Climate change is expected to increase incidence of dengue and other vector-borne diseases around the world
- Given the lack of vaccine and specific treatments, primary preventative measures are vector control and disease surveillance

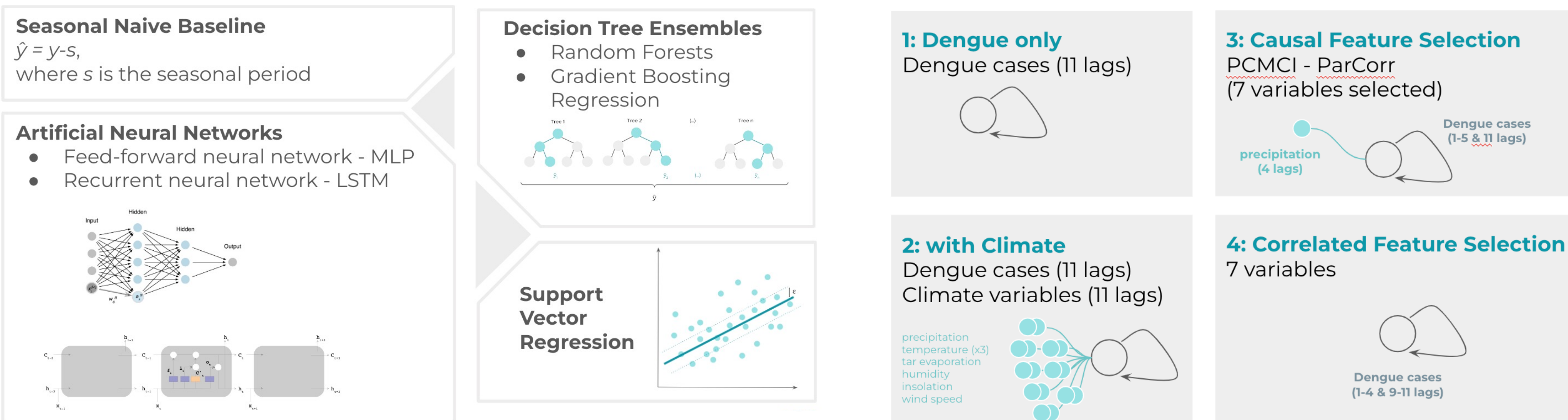
Disability-adjusted life years for dengue fever per million inhabitants in 2012.



Source: WHO Disease Burden Estimates,

Forecasting dengue in Brazilian cities

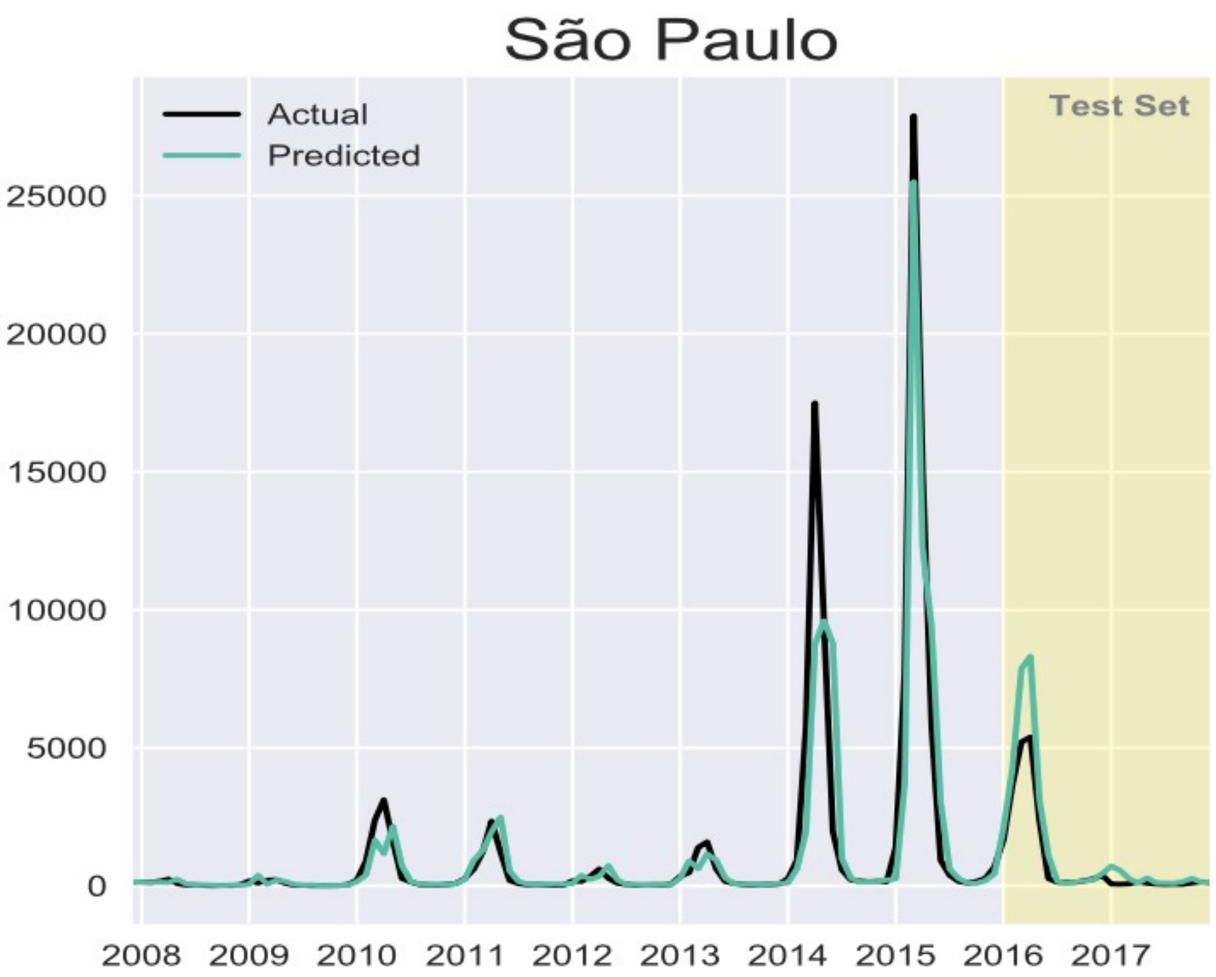
Compare machine learning algorithms & feature selection methods

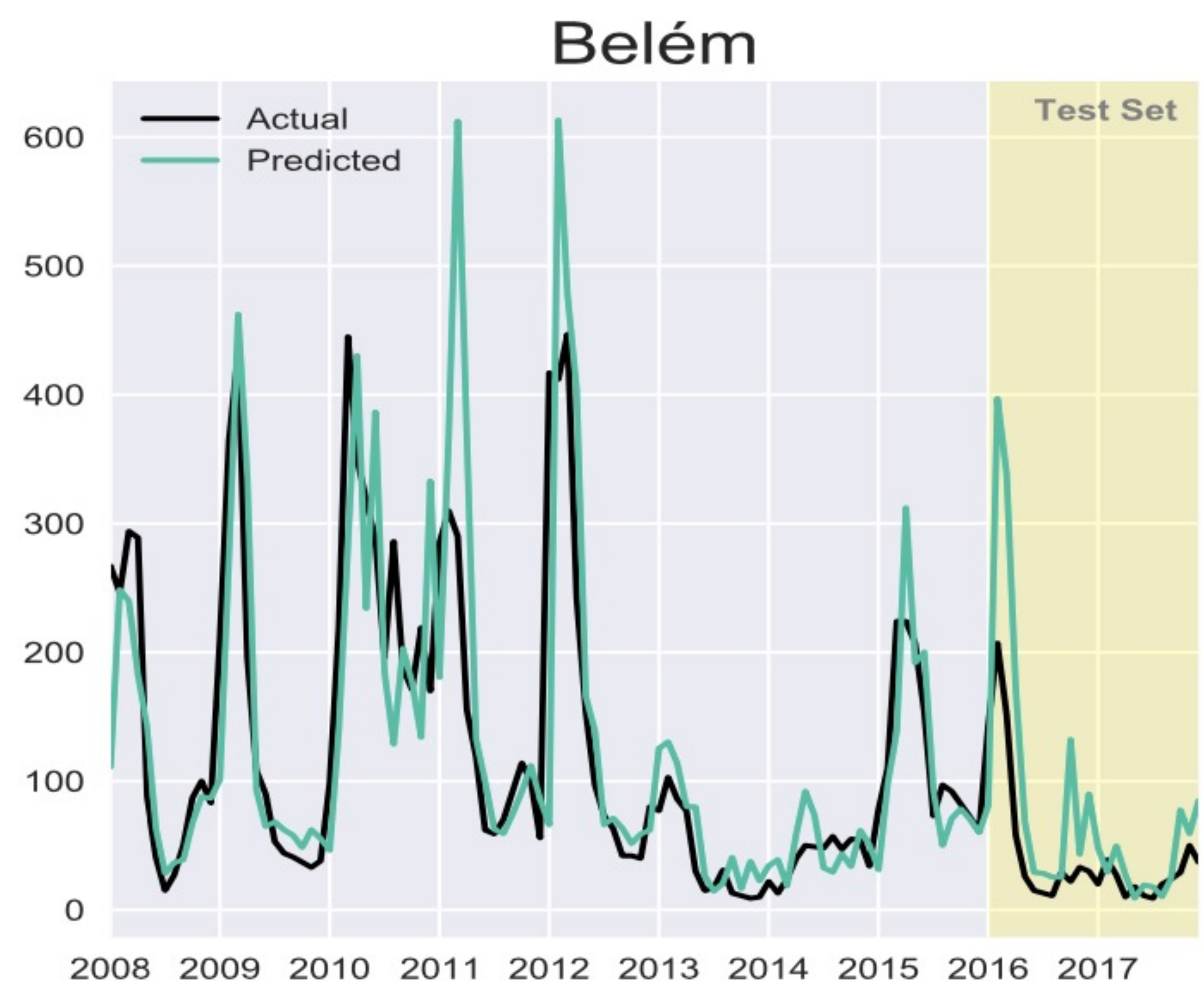


Which model is optimal for individual cities vs for all cities in Brazil? Does causal feature selection improve predictions? Or is there a predictive cost of more causally informed models?

Roster, Connaughton and Rodrigues, American Journal of Epidemiology, (2022).

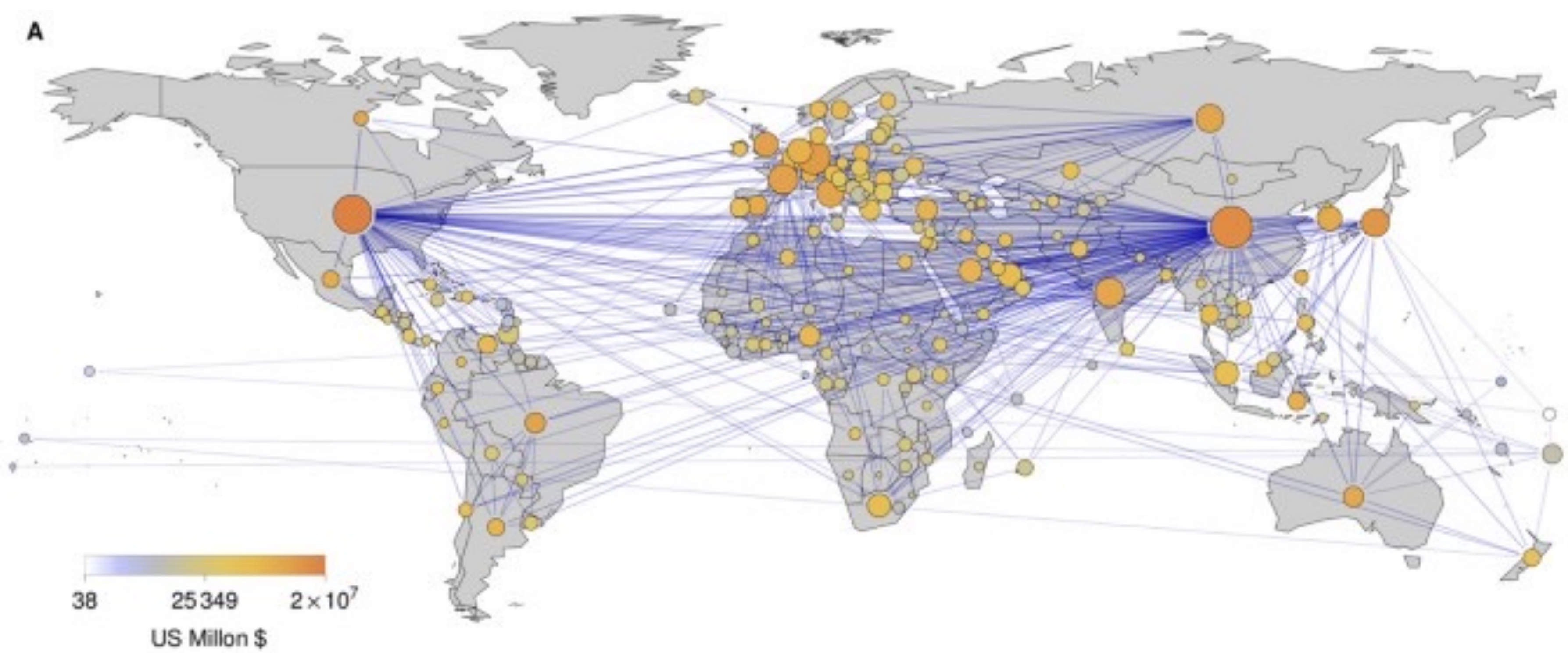
Forecasting dengue in Brazilian cities



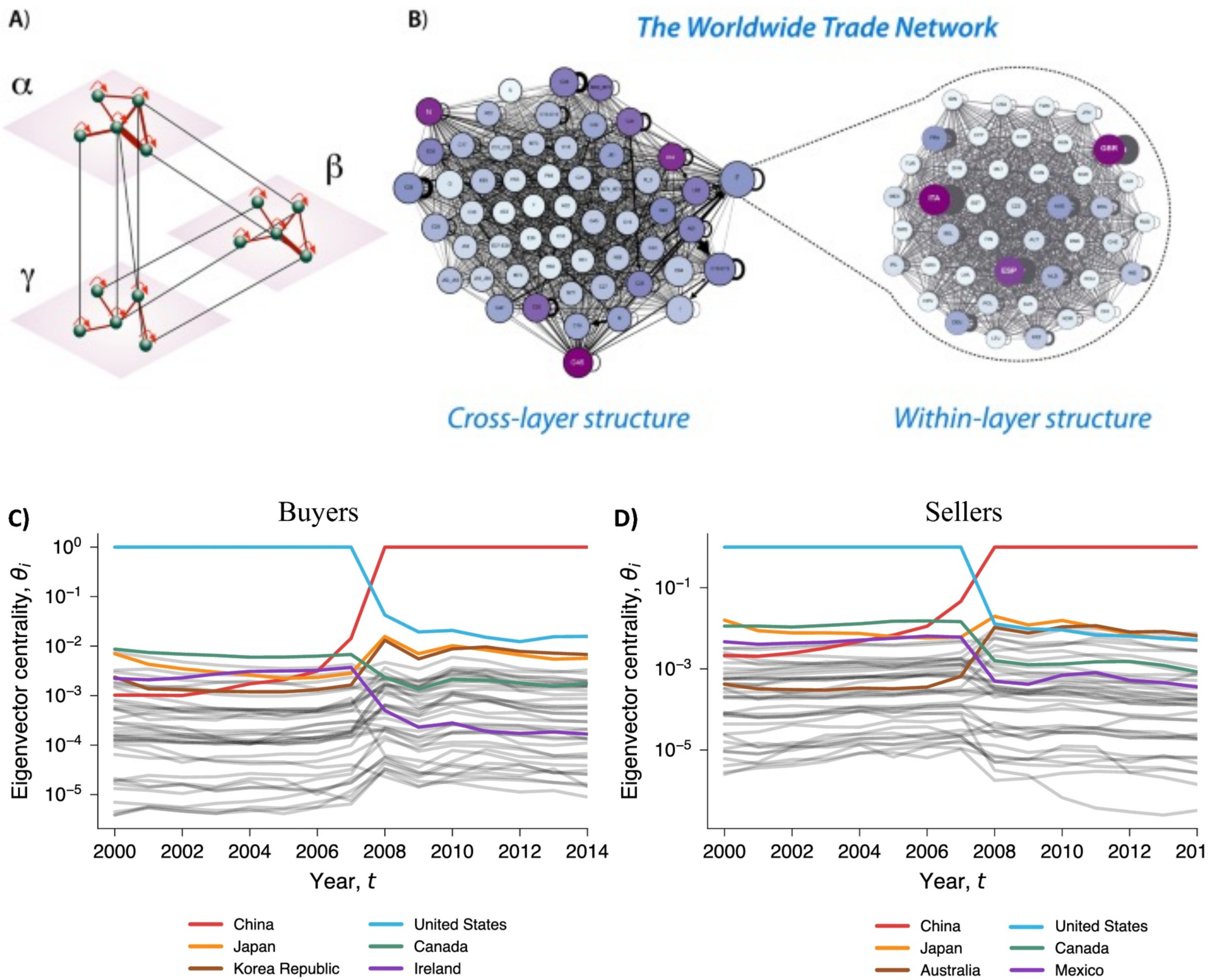


Roster, Connaughton and Rodrigues, American Journal of Epidemiology, (2022).

Economic networks



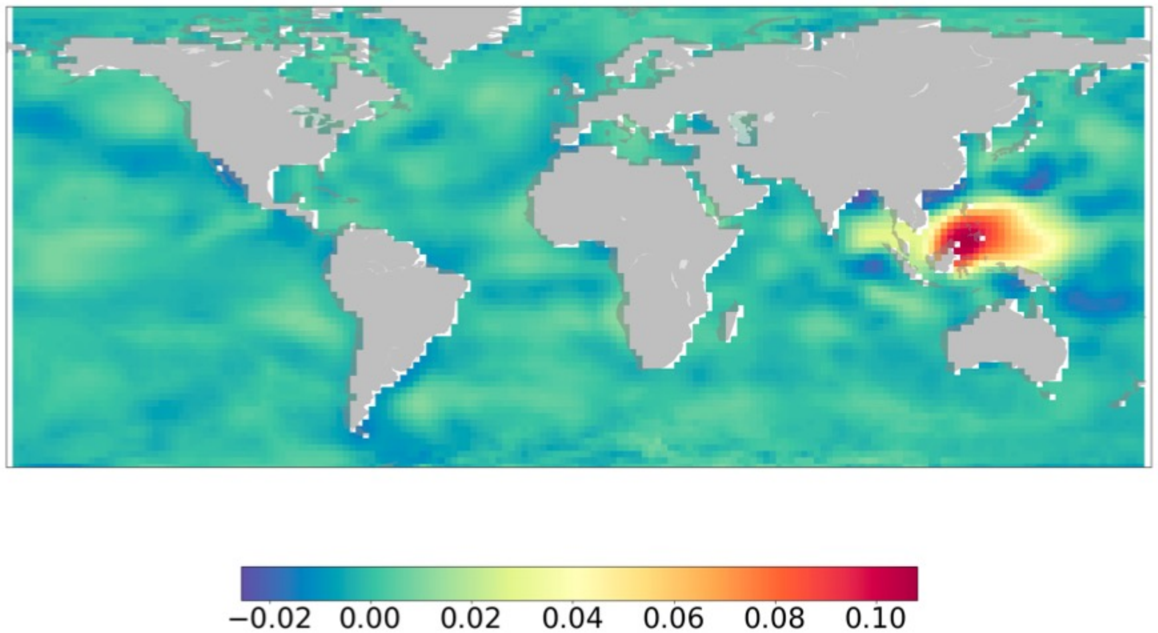
Worldwide trade multi-layer network

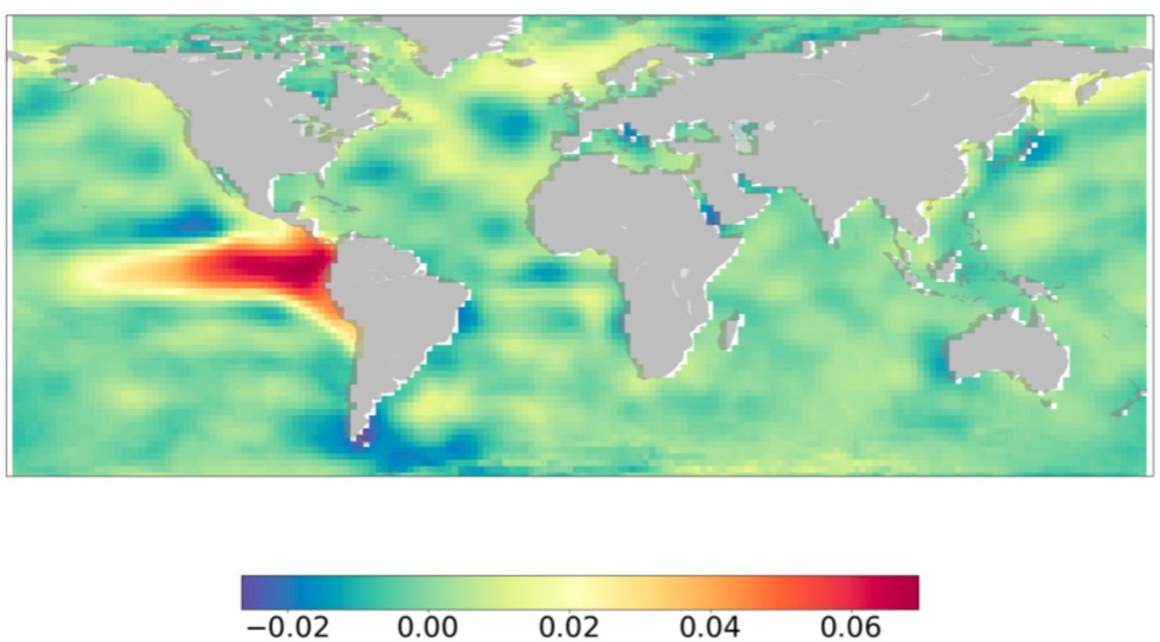


Alves et al., Scientific Reports, 2022.

Climate networks

Discovering causal factors of drought in Ethiopia





Noorbakhsh et al. Climate Informatics, 2020.

Complex systems

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Marco A. R. Mello, Gabriel M. Felix, Rafael B. P. Pinheiro, Renata L. Muylaert, Cullen Geiselman, Sharlene E. Santana, Marco Tschapka, Nastaran Lotfi, Francisco A. Rodrigues & Richard D. Stevens

Nature Ecology & Evolution **3**, 1525–1532 (2019) | Cite this article

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T. K. Dal'Maso Peron[1] and F. A. Rodrigues[2]

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Europhysics Letters, Volume 96, Number 4

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Francisco A. Rodrigues,*[a] Luciano da Fontoura Costa[b] and André Luiz Barbieri[b]

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RESEARCH ARTICLE

Clustering algorithms: A comparative approach

Mayra Z. Rodriguez, Cesar H. Comin, Dalcimar Casanova, Odemir M. Bruno, Diego R. Amancio, Luciano da F. Costa, Francisco A. Rodrigues

Segmentation of large images based on super-pixels and community detection in graphs

Author(s): Oscar A.C. Linares[1]; Glenda Michele Botelho[2]; Francisco Aparecido Rodrigues[1]; João Batista Neto[1]

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Source: Volume 11, Issue 12, December 2017, p. 1219 – 1228

DOI: 10.1049/iet-ipr.2016.0072, Print ISSN 1751-9659, Online ISSN 1751-9667

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Advances in Physics
Vol. 60, No. 3, May–June 2011, 329–412

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REVIEW ARTICLE

Analyzing and modeling real-world phenomena with complex networks: a survey of applications

Luciano da Fontoura Costa[a,b]*, Osvaldo N. Oliveira Jr.[a], Gonzalo Travieso[a], Francisco Aparecido Rodrigues[c], Paulino Ribeiro Villas Boas[a], Lucas Antiqueira[a], Matheus Palhares Viana[a] and Luis Enrique Correa Rocha[d]

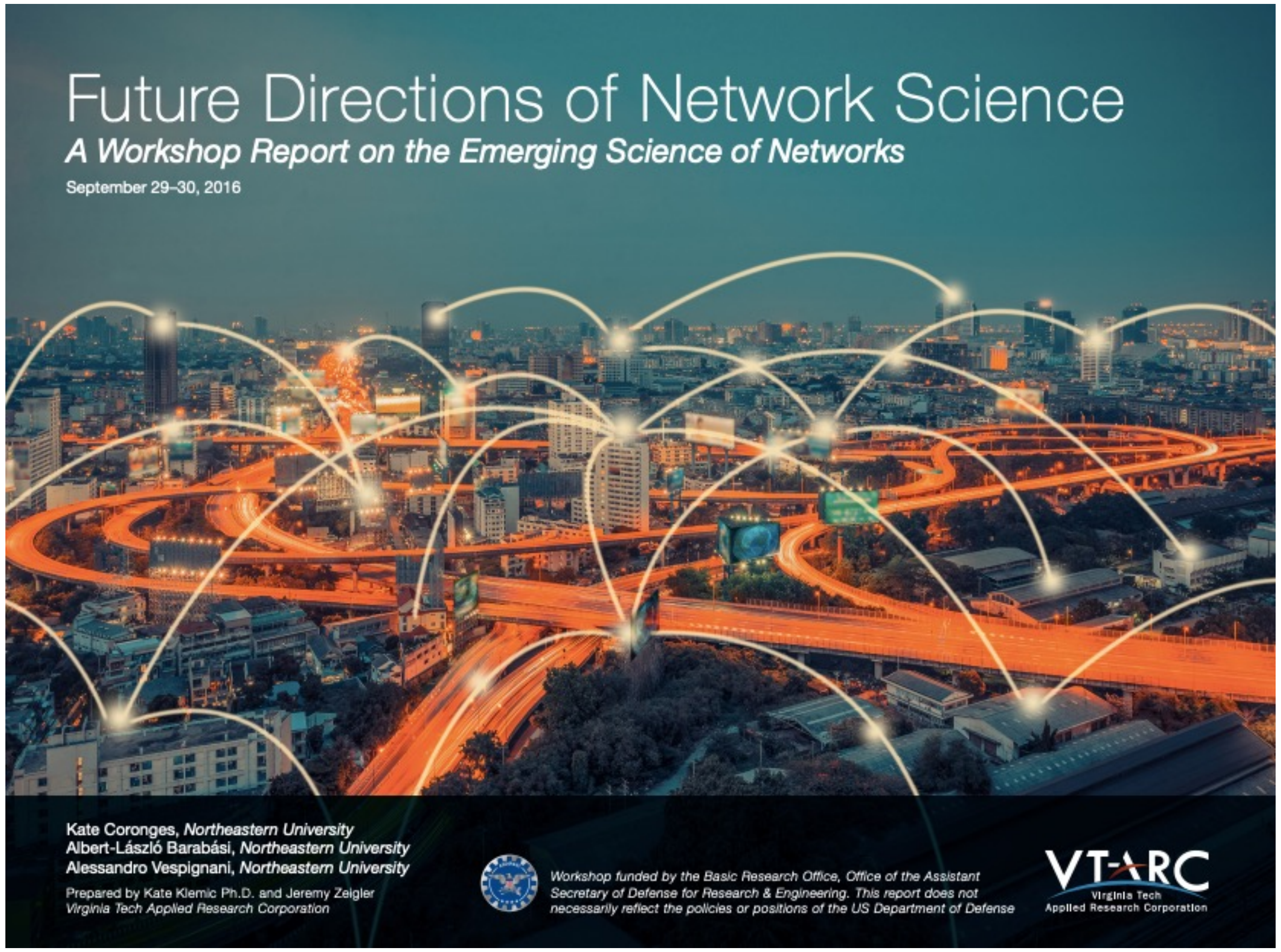
[a]*Instituto de Física de São Carlos, Universidade de São Paulo, PO Box 369, 13560-970, São Carlos, São Paulo, Brazil;* [b]*National Institute of Science and Technology for Complex Systems, Brazil;* [c]*Instituto de Ciêcias Matemáticas e de Computação, Universidade de São Paulo, PO Box 668, 13560-970, São Carlos, São Paulo Brazil;* [d]*Department of Physics, Umeå University, 90187 Umeå, Sweden*

(*Received 2 November 2009; final version received 9 March 2011*)

The success of new scientific areas can be assessed by their potential in contributing to new theoretical approaches and in applications to real-world problems. Complex networks have fared extremely well in both of these aspects, with their sound theoretical basis being developed over the years and with a variety of applications. In this survey, we analyze the applications of complex networks to real-world problems and data, with emphasis in representation, analysis and modeling. A diversity of phenomena are surveyed, which may be classified into no less than 11 areas, providing a clear indication of the impact of the field of complex networks.

PACS: 89.75.Fb Structures and organization in complex systems; 02.10.Ox Combinatorics; graph theory; 89.75. He Networks and genealogical trees; 89.75.Da Systems obeying scaling laws; 89.75.Kd Patterns

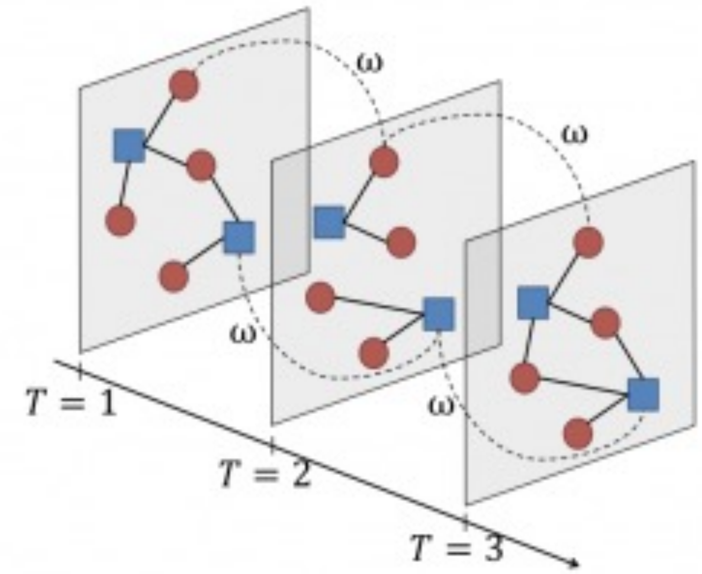
Challenges

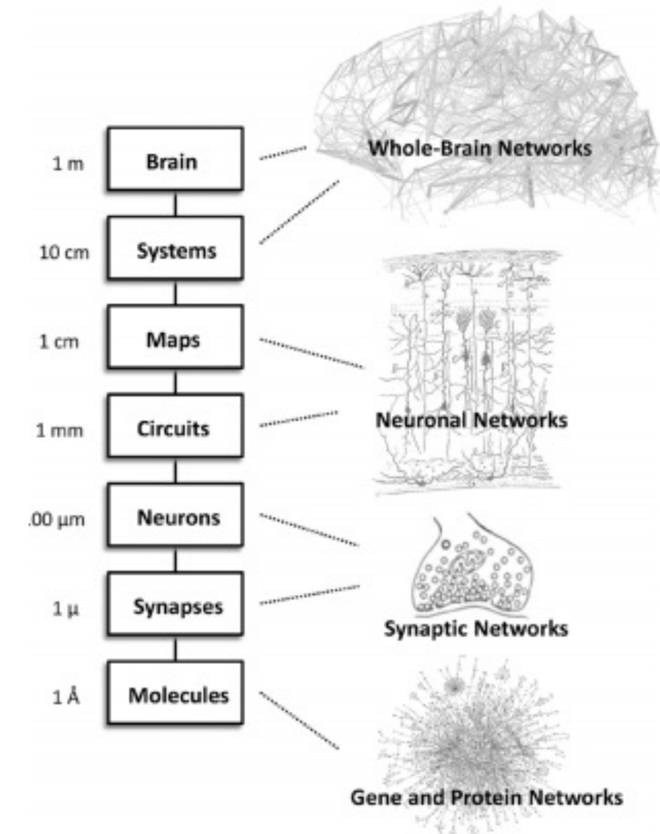


"With roots in physical, information, and social sciences, network science provides a formal set of methods, tools, and theories to describe, prescribe, and predict dynamics and behavior of complex systems."

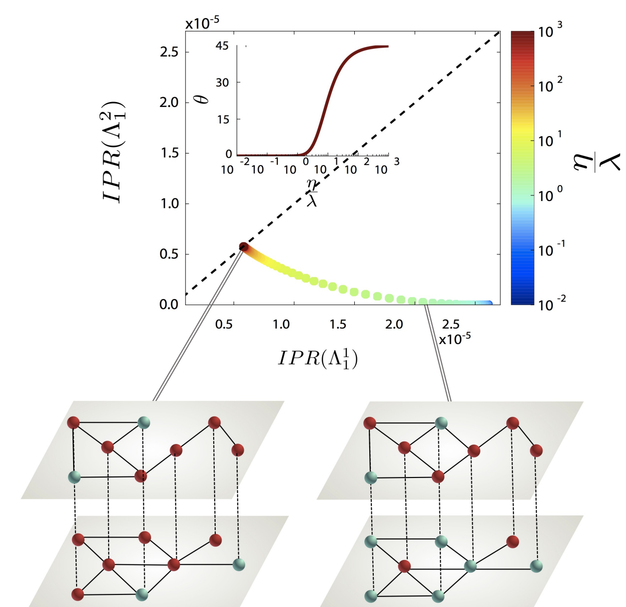
https://basicresearch.defense.gov/Portals/61/Documents/future-directions/Network_Sciences.pdf

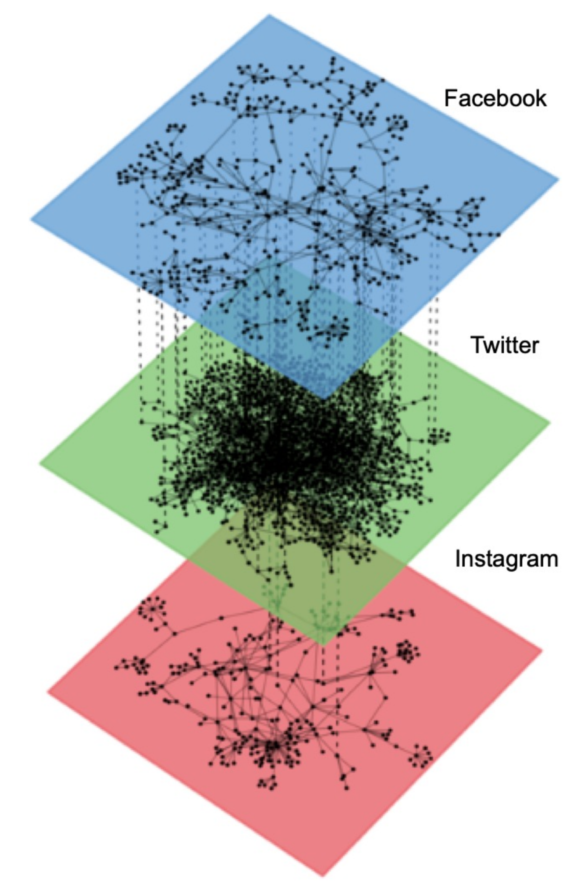
Challenges





- Temporal networks
- Multilayer networks
- Networks with noise
- Heterogeneous dynamics
- Interaction between dynamical processes
- Hierarchical structure
- Applications: genetics, biology, neuroscience, engineering.





Arruda et al., Physical Review X, 2017

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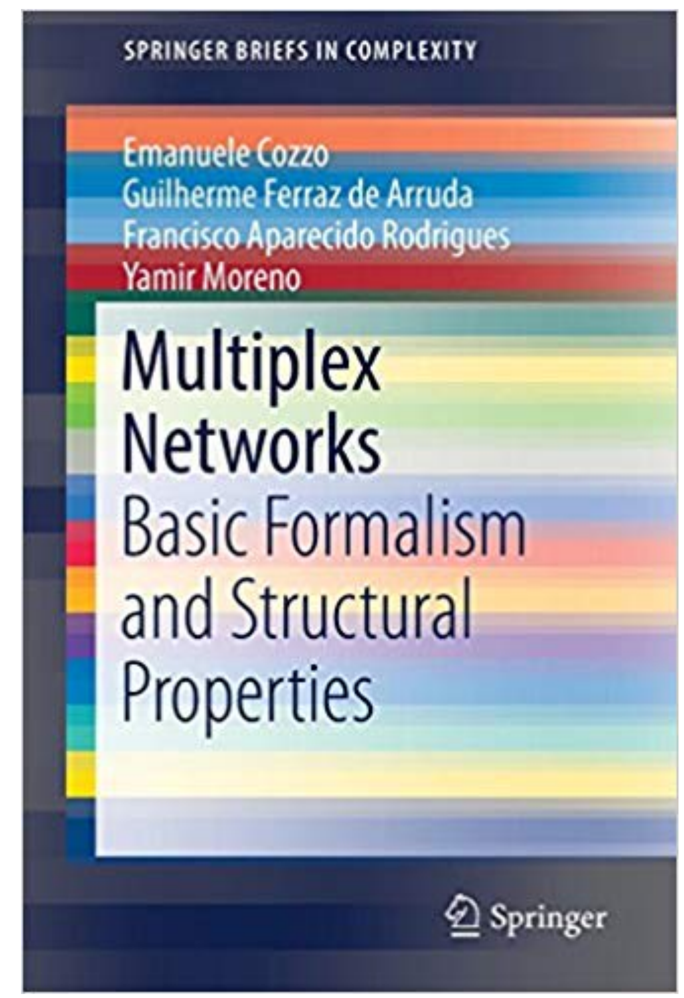
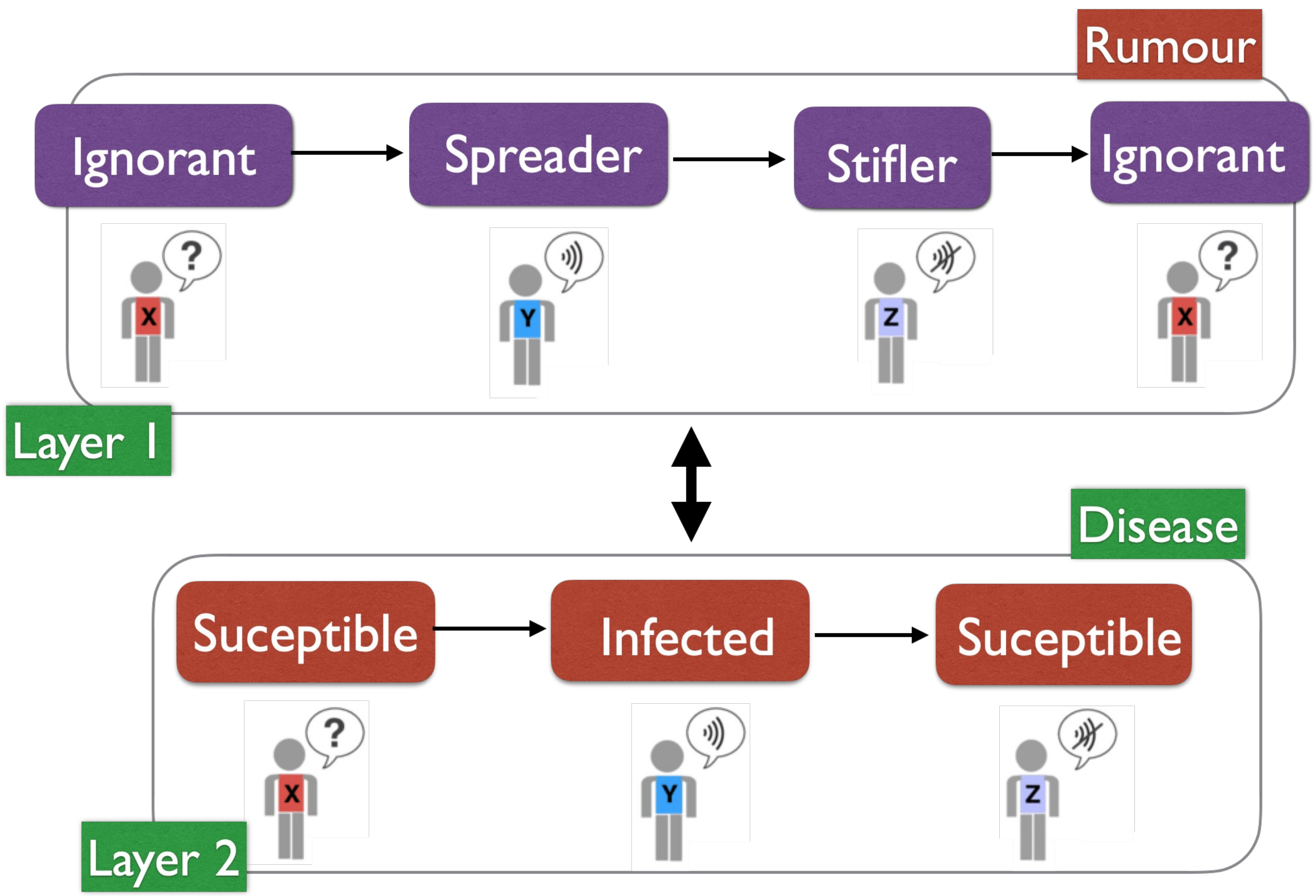
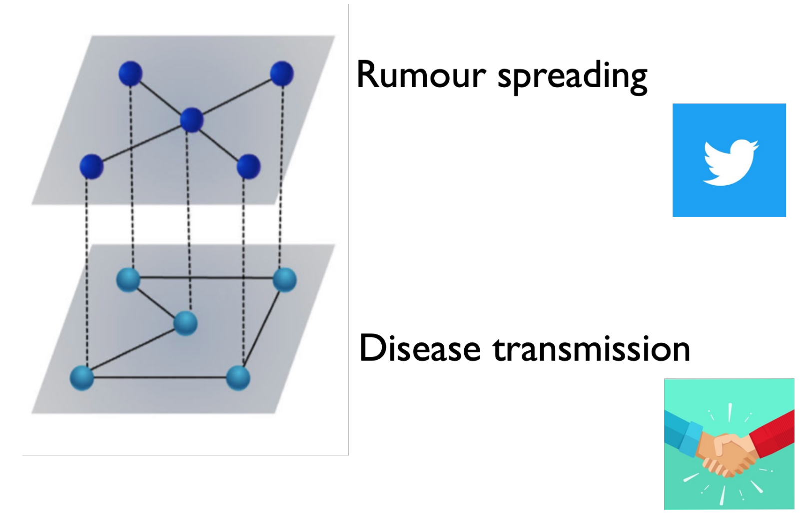
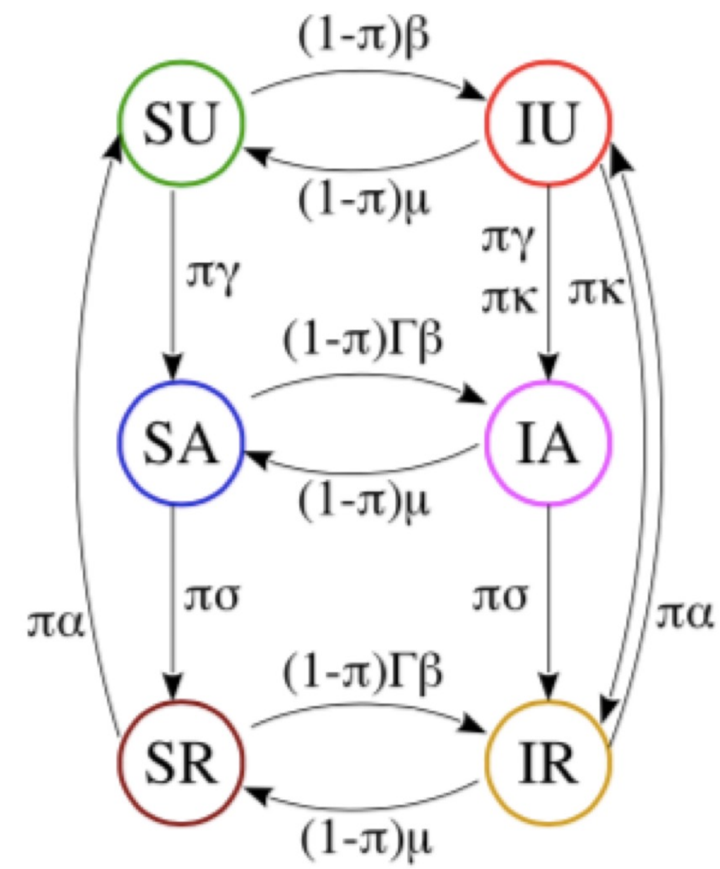
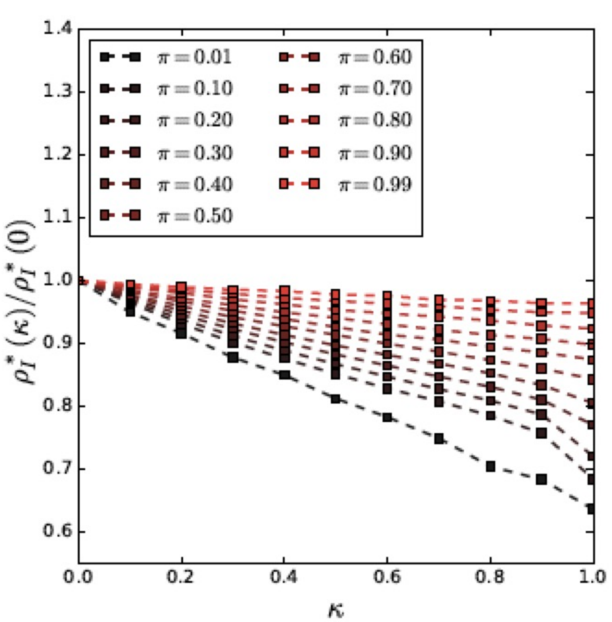


Multilayer networks

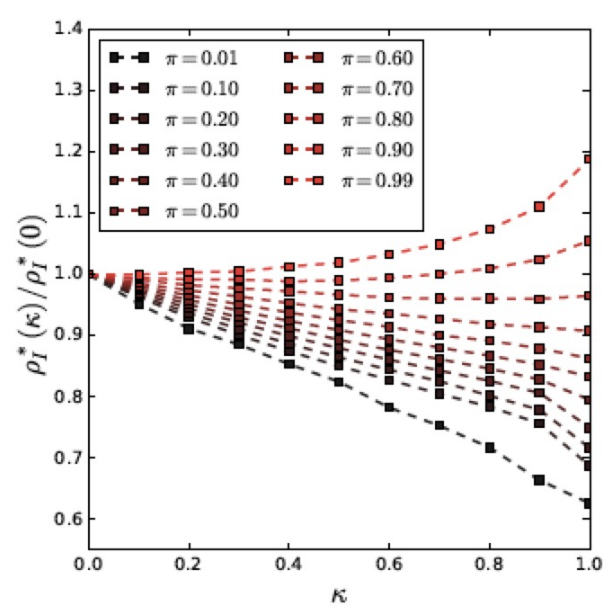








(a)Baseline model



(b)Modified model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Why STDs are on the rise in America

Ventura et al., Physical Review E, 2019