RECENT TRENDS IN NETWORK SCIENCE

CoCo Seminar

September 7th, 2016

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New to network science?

Google “**SSIE641X**” to learn more

Recent trends in network science?

Temporal Networks


Cattuto, C. et al. (2010) *PLOS ONE*, *5*(7), e11596.
Holme, P., & Saramäki, J. (2012) *Phys. Rep.* 519(3), 97-125.

Multilayer Networks


Kivelä, M. et al. (2014) *J. Complex Netw.* 2(3), 203-271.
Boccaletti, S. et al. (2014) *Phys. Rep. 544*(1), 1-122.

What else?

Networks everywhere


Image: tech.co

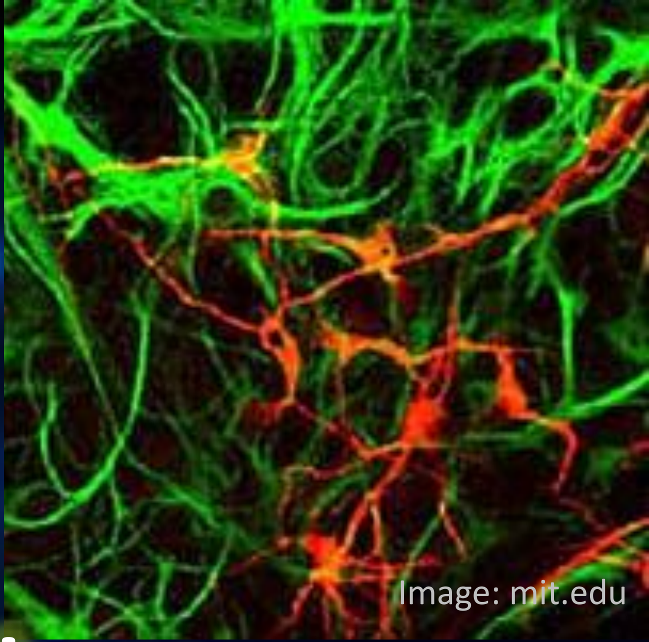
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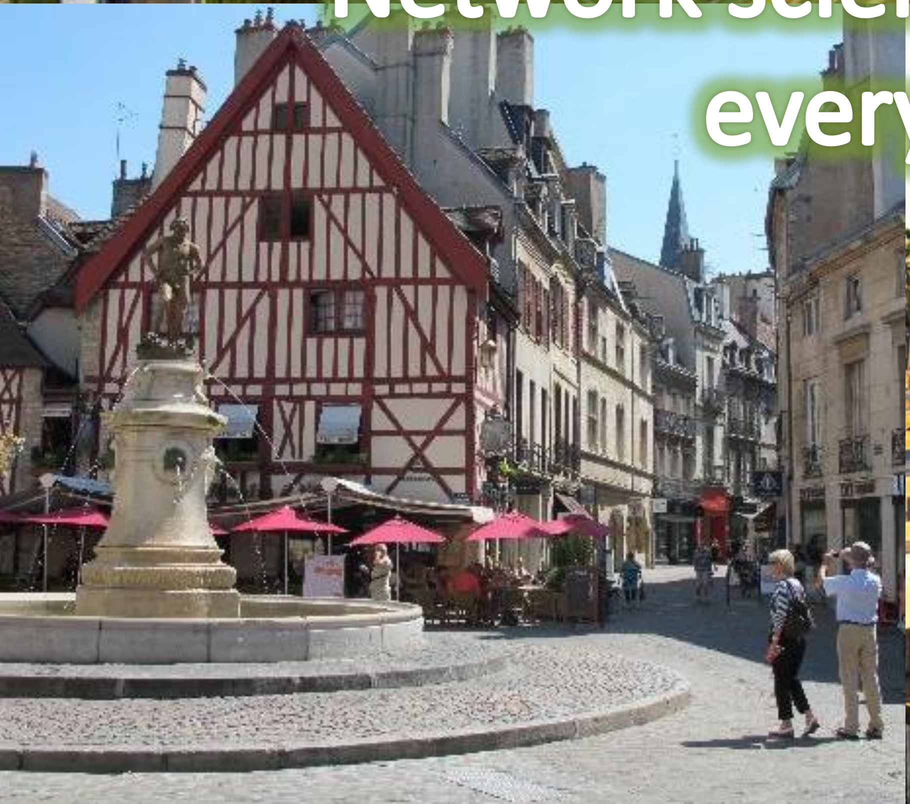
Image: docstoc.com


Image: blog.willis.com

Network science conferences everywhere



OVERVIEW OF NETWORK SCIENCE CONFERENCES

List of network science conferences

- International School and Conference on Network Science
  - Summer main conference (NetSci)
  - Winter regional conference (NetSci-X)
- Conference on Complex Networks
- International Workshop on Complex Networks and Their Applications
- SIAM Workshop on Network Science
- Sunbelt Conference of the INSNA
- International Conference on Computational Social Science
- StatPhys Satellite Conference "Complex Networks"
- ACM Conference on Online Social Networks
- Conference on Complex Systems

etc…

Seeing trends in conference topics

- International School and Conference on Network Science
  - Summer main conference (NetSci)
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- Conference on Complex Networks
- International Workshop on Complex Networks and Their Applications
- SIAM Workshop on Network Science
- Sunbelt Conference of the INSNA
- International Conference on Computational Social Science
- StatPhys Satellite Conference “Complex Networks”
- A
- Conference on Complex Systems

etc…

What do we see in their session/talk titles?


NetSci
directed
competition
control
time
influence
classification
correlation
information
extreme
method
face
detection
behavior
organization
mobility
diffusion
spectral
approach
quantify
theory
percolation
economic
simulation
online
role
world
effect
multiplex
scale
impact
synchronization
random
relation
small
analysis
city
spread
pattern
layer
source
community
measure
structural
human
algorithm
complex
disease
large
power
gene
process
graph
phase
real
group
optimal
computation
dynamic
cascade
transition
multilayer
local
temporal
growth
link
evolution
topology
prediction
robustness
data
contagion
epidemic
contact
case
social
communication
interaction
driven
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brain
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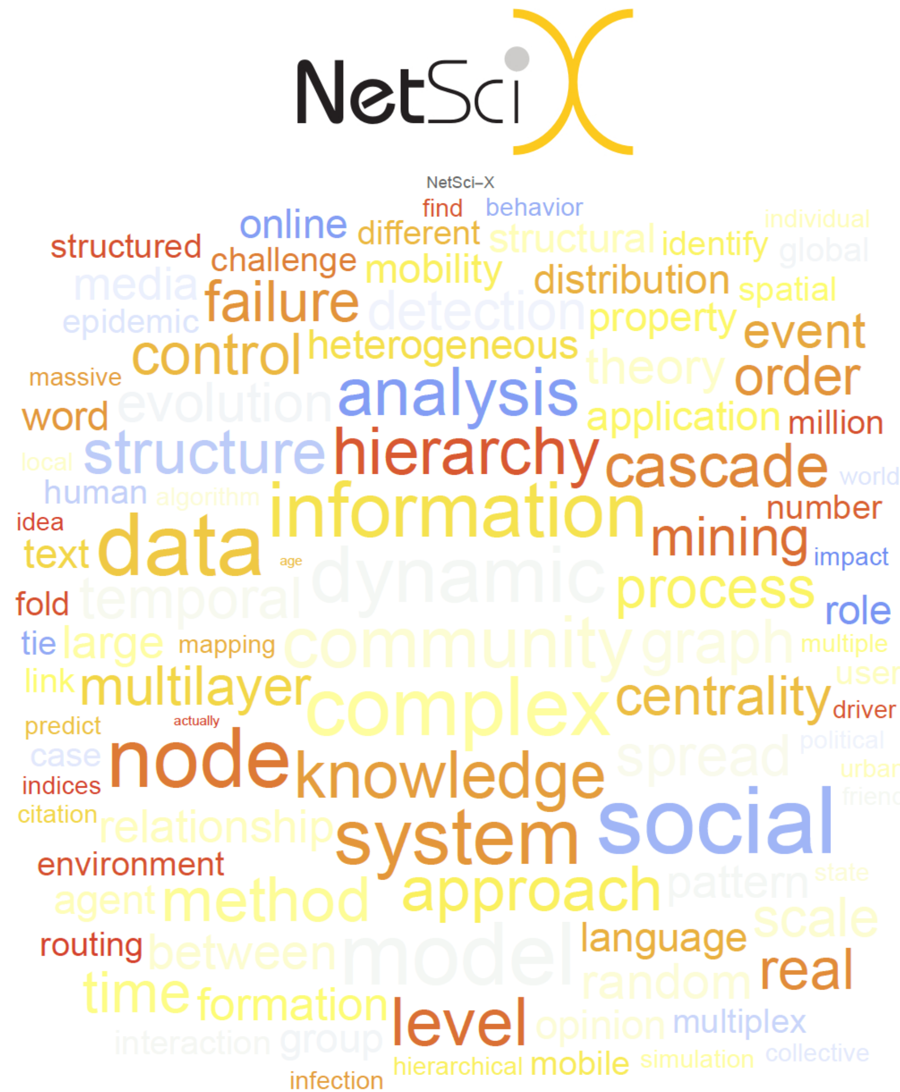
model
free
topological
modular
system
property
bipartite
application
functional
motif


NetSci–X
find
behavior
online
individual
structured
different
structural
identify
global
challenge
mobility
media
distribution
failure
spatial
epidemic
detection
property
event
control
heterogeneous
massive
theory
order
analysis
word
evolution
application
million
hierarchy
local
structure
cascade
world
human
algorithm
number
idea
information
mining
text
data
impact
age
dynamic
process
fold
temporal
role
tie
large
mapping
community
graph
multiple
link
user
multilayer
complex
centrality
driver
predict
actually
case
node
spread
political
indices
knowledge
urban
friend
citation
relationship
system
social
environment
state
agent
method
approach
pattern
scale
routing
between
model
language
random
real
time
formation
level
opinion
multiplex
interaction
group
hierarchical
mobile
simulation
collective
infection

IC2S2

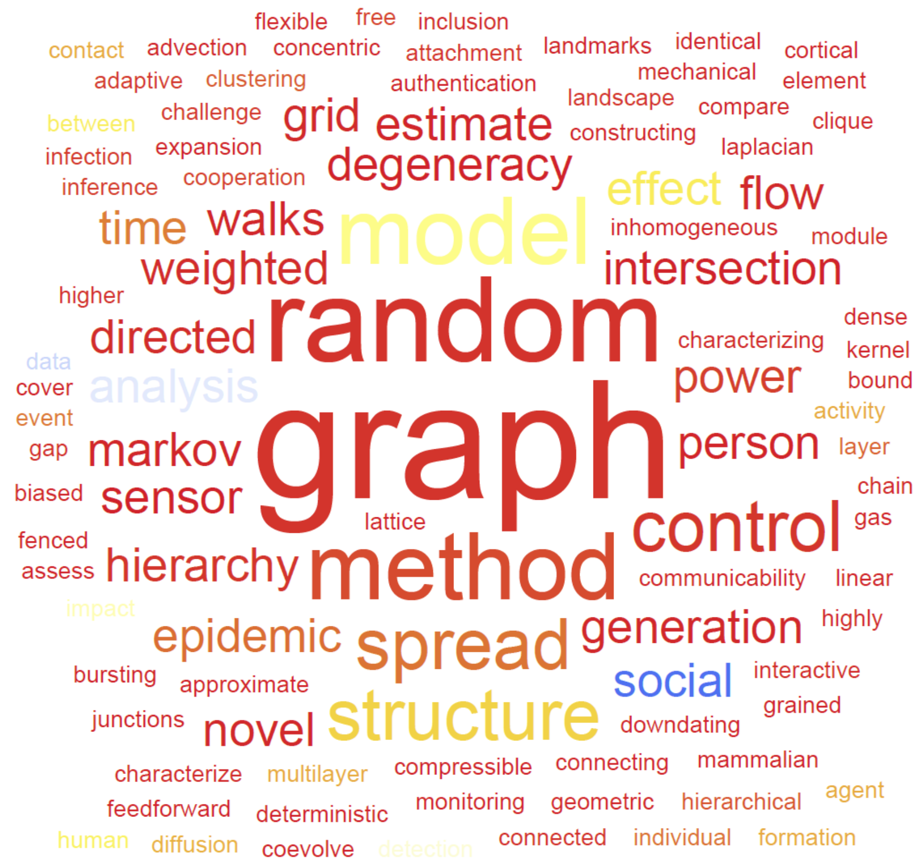
Sunbelt

CompleNet

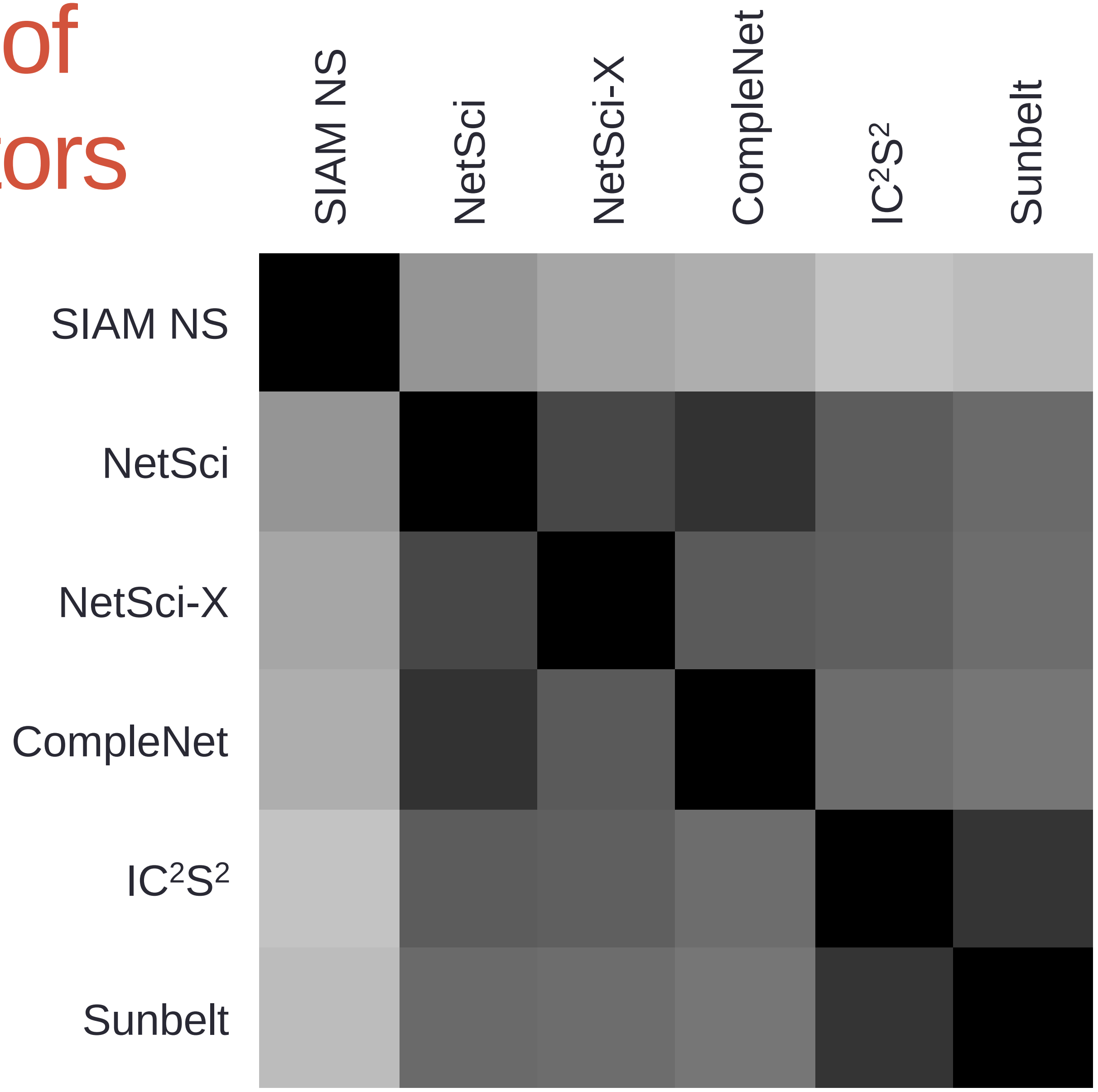
SIAM Workshop on Network Science

CompleNet

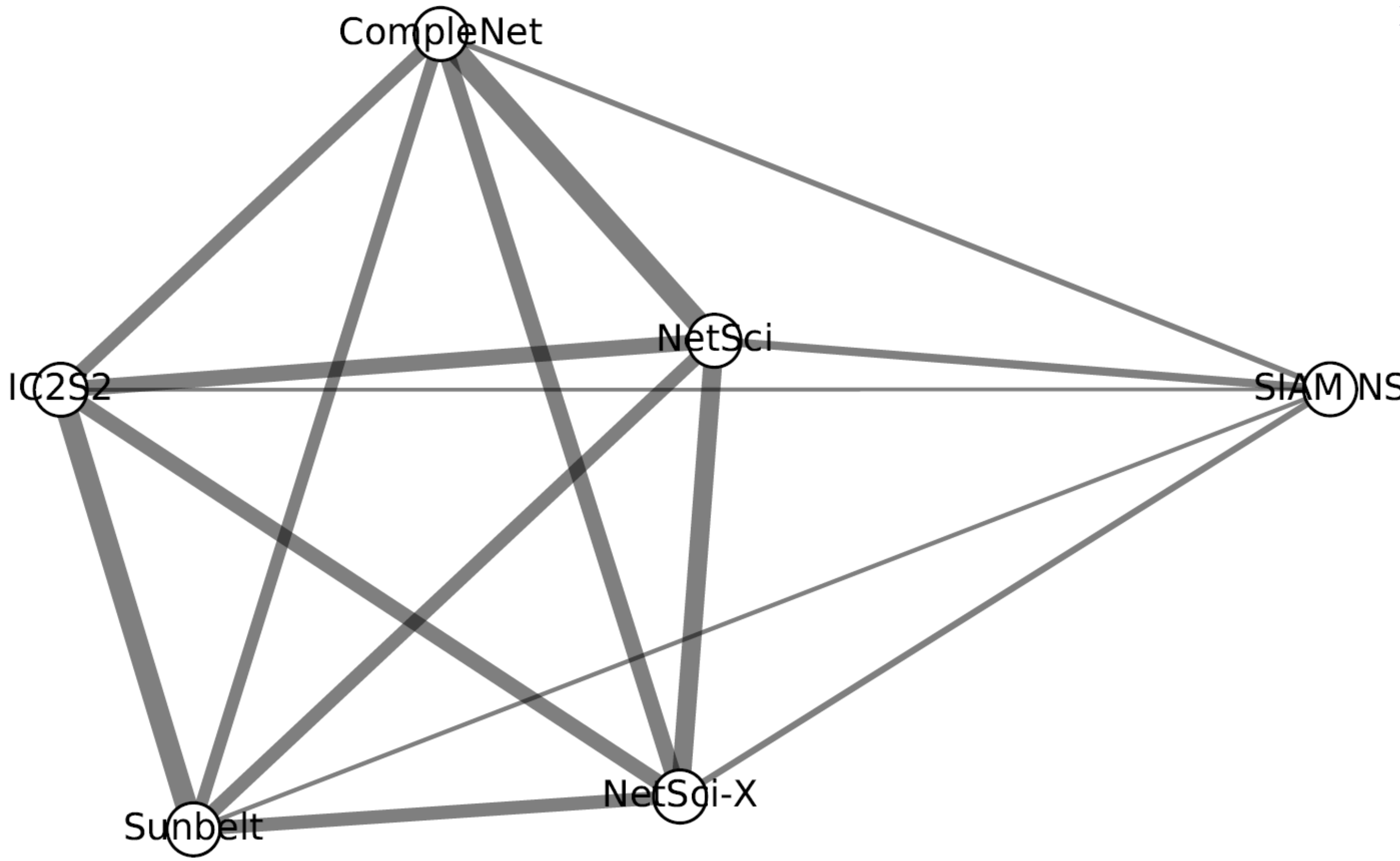
SIAM NS

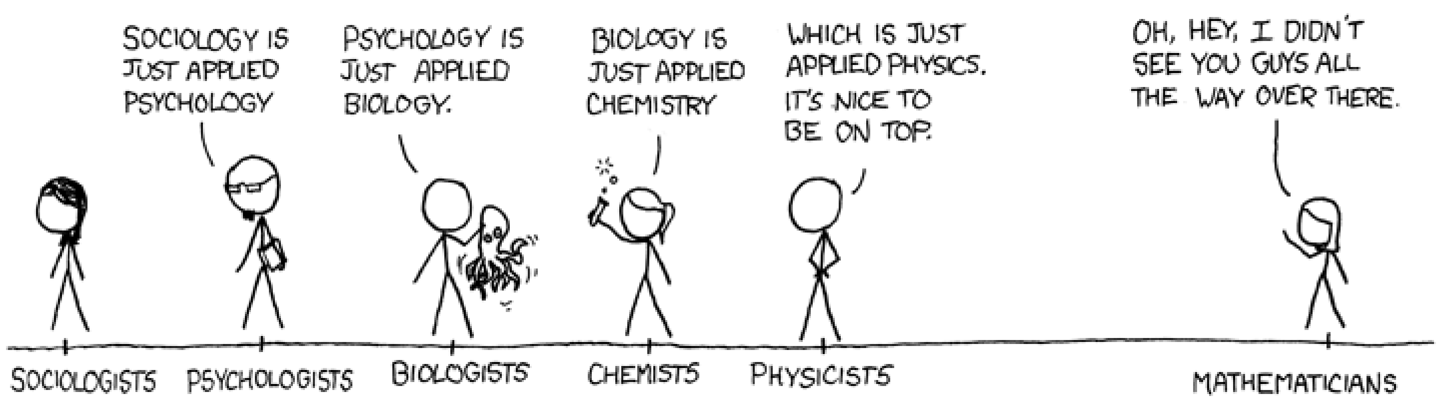


Similarity of word vectors

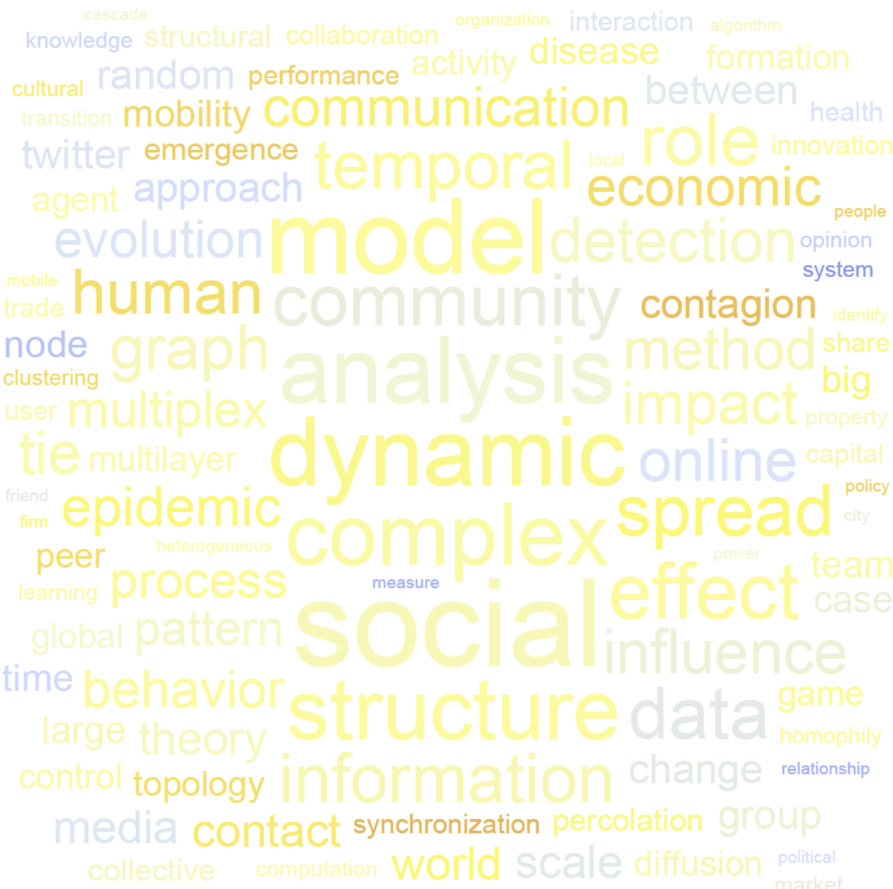


xkcd.com/435/


CompleNet
NetSci
IC2S2
SIAM NS
Sunbelt
NetSci-X


SOCIOLOGY IS JUST APPLIED PSYCHOLOGY
PSYCHOLOGY IS JUST APPLIED BIOLOGY.
BIOLOGY IS JUST APPLIED CHEMISTRY
WHICH IS JUST APPLIED PHYSICS. IT'S NICE TO BE ON TOP.
OH, HEY, I DIDN'T SEE YOU GUYS ALL THE WAY OVER THERE.
SOCIOLOGISTS
PSYCHOLOGISTS
BIOLOGISTS
CHEMISTS
PHYSICISTS
MATHEMATICIANS

2015


cascade
knowledge
structural
collaboration
organization
interaction
algorithm
cultural
random
performance
activity
disease
formation
transition
mobility
communication
between
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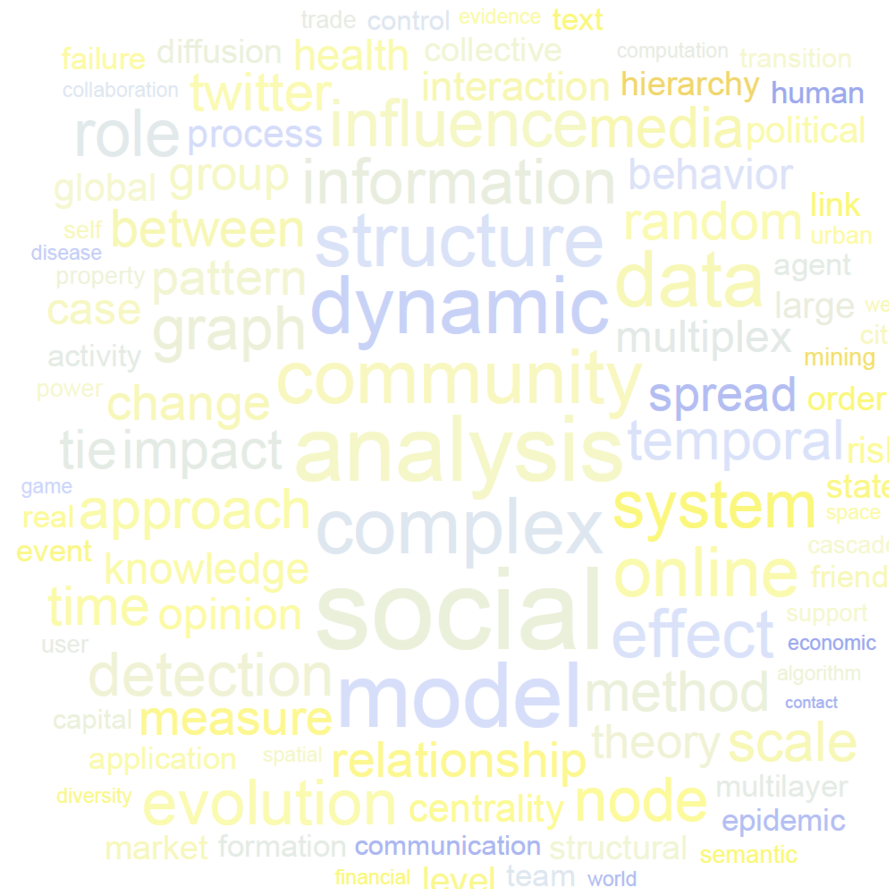
twitter
emergence
temporal
local
role
innovation
agent
approach
economic
people
evolution
model
detection
opinion
system
mobile
human
trade
community
contagion
identify
node
graph
method
share
clustering
analysis
big
user
multiplex
impact
property
tie
multilayer
dynamic
online
capital
friend
epidemic
policy
firm
complex
spread
city
peer
heterogeneous
power
team
learning
process
measure
effect
case
global
pattern
social
influence
time
behavior
game
large
theory
structure
data
homophily
control
topology
relationship
information
change
media
contact
synchronization
percolation
group
collective
computation
world
scale
diffusion
political
market

2016


trade
control
evidence
text
failure
diffusion
health
collective
computation
transition
collaboration
twitter
interaction
hierarchy
human
role
process
influence
media
political
global
group
information
behavior
self
between
random
link
disease
structure
urban
property
pattern
data
agent
case
dynamic
large
web
activity
graph
multiplex
city
mining
power
change
community
spread
order
tie
impact
analysis
temporal
risk
game
state
real
approach
complex
system
space
event
cascade
knowledge
online
friend
time
opinion
social
support
user
effect
economic
detection
algorithm
method
contact
capital
measure
model
theory
scale
application
spatial
relationship
diversity
evolution
centrality
node
multilayer
epidemic
market
formation
communication
structural
semantic
financial
level
team
world


2016
trade control evidence text
failure diffusion health collective computation transition
collaboration twitter interaction hierarchy human
role process influence media political
global group information behavior
self between structure random link urban
disease property pattern data agent
case dynamic large web
graph multiplex city
activity mining
power change community spread order
tie impact analysis temporal risk
game
real approach complex system state space
event cascade
knowledge online friend
time opinion social effect support
user economic
detection model method algorithm
contact
capital measure theory scale
application spatial relationship multilayer
diversity evolution centrality node epidemic
market formation communication structural semantic
financial level team world

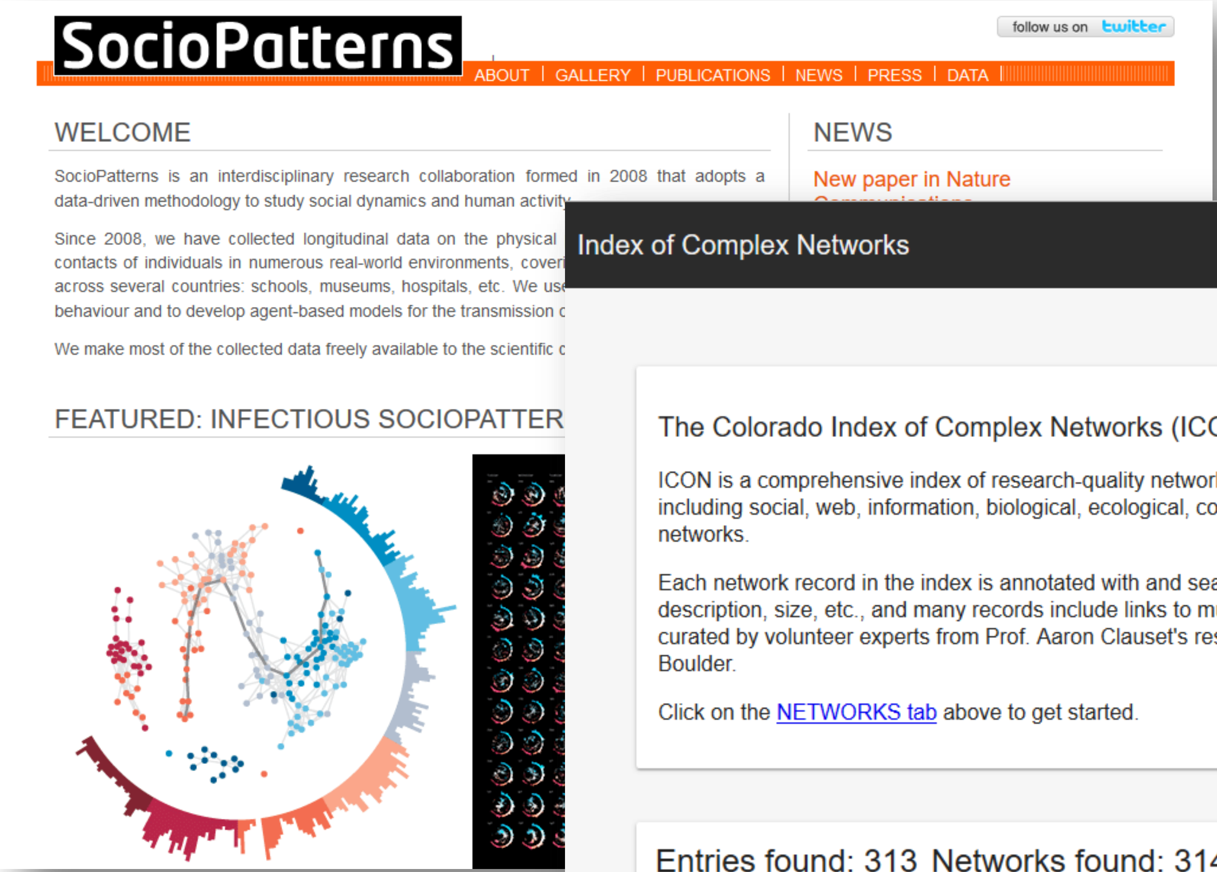
Topics

1. Community detection and multiscale structures
2. Higher-order models
3. Interaction between dynamics *on* and *of* networks (coevolution)
4. Network resilience and failure
5. Applications I: Neuro and brain science
6. Applications II: Finance and marketing
7. Network science and education

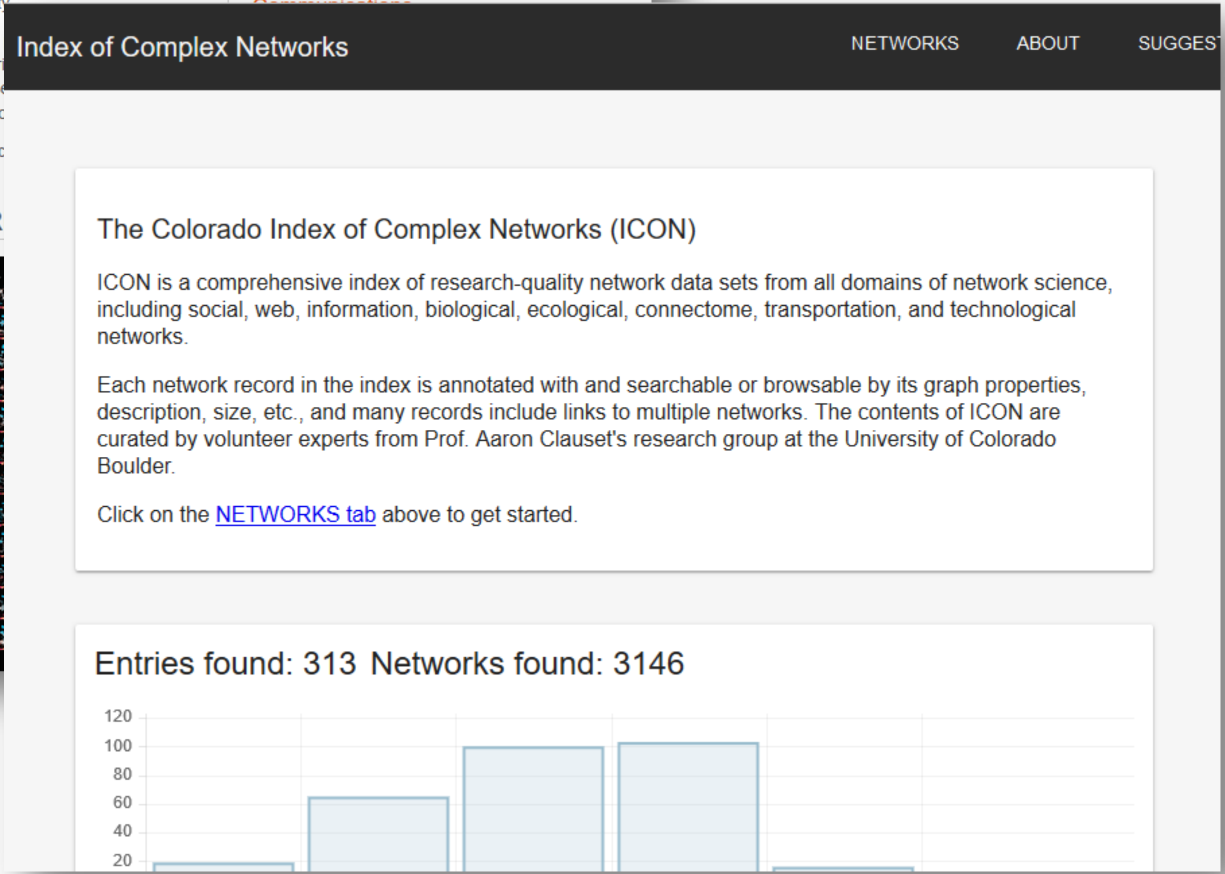
Warning: I am not an expert for most of these topics

1.
COMMUNITY DETECTION AND MULTISCALE STRUCTURES

More and more data sets

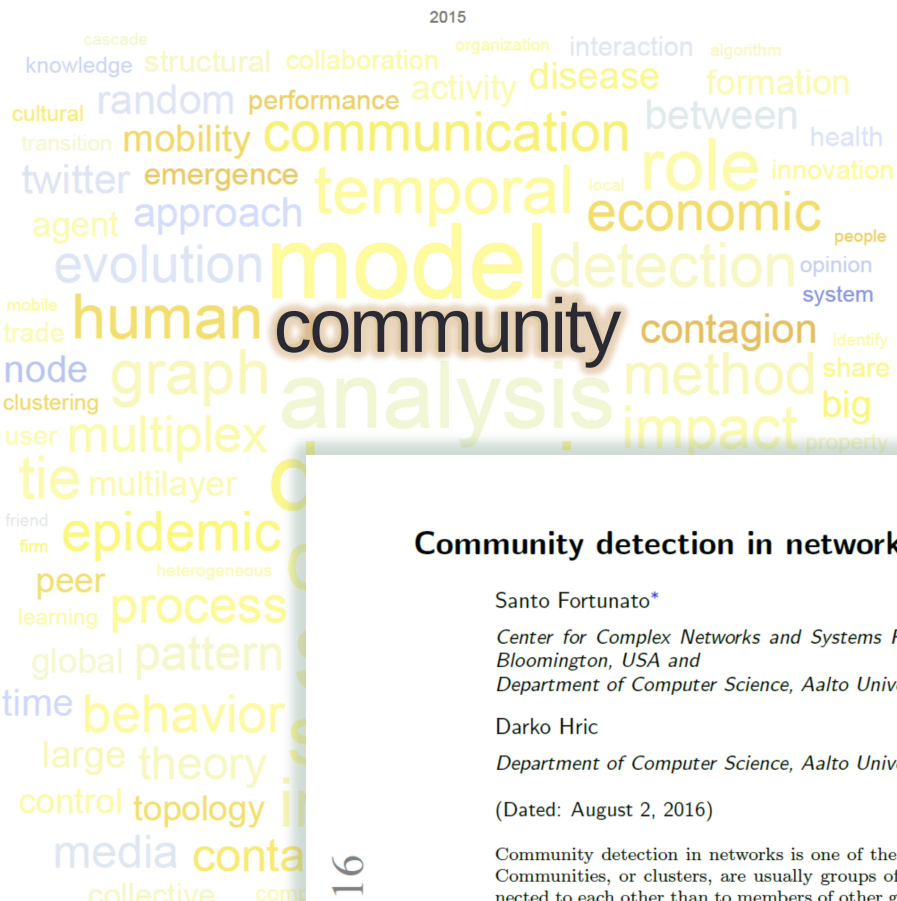


http://sociopatterns.org/



https://icon.colorado.edu/

Community detection still a big thing



Community detection in networks: A user guide

Santo Fortunato*

Center for Complex Networks and Systems Research, School of Informatics and Computing, Indiana Ur
Bloomington, USA and
Department of Computer Science, Aalto University School of Science, P.O. Box 15400, FI-00076

Darko Hric

Department of Computer Science, Aalto University School of Science, P.O. Box 15400, FI-00076

(Dated: August 2, 2016)

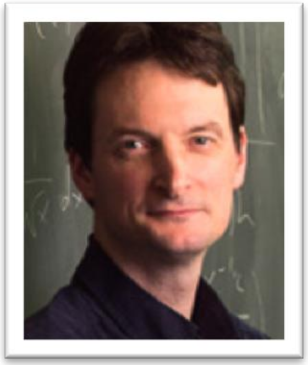
Community detection in networks is one of the most popular topics of modern network science. Communities, or clusters, are usually groups of vertices having higher probability of being connected to each other than to members of other groups, though other patterns are possible. Identifying communities is an ill-defined problem. There are no universal protocols on the fundamental ingredients, like the definition of community itself, nor on other crucial issues, like the validation of algorithms and the comparison of their performances. This has generated a number of confusions and misconceptions, which undermine the
the main aspects of the problem. We also p
and give directions to their use.

30 Jul 2016

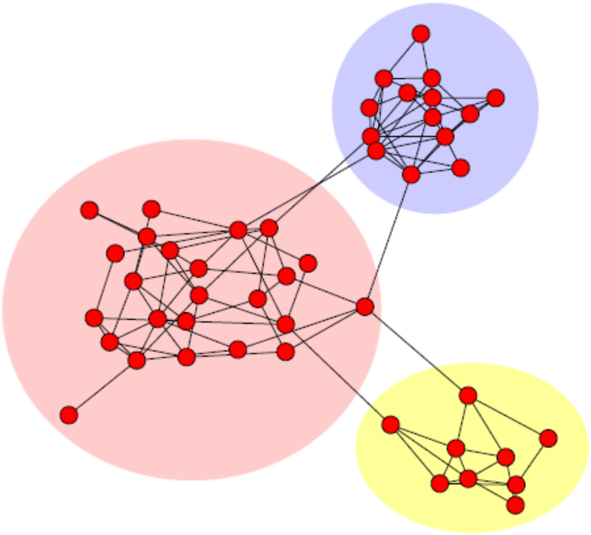
http://arxiv.org/abs/1608.00163

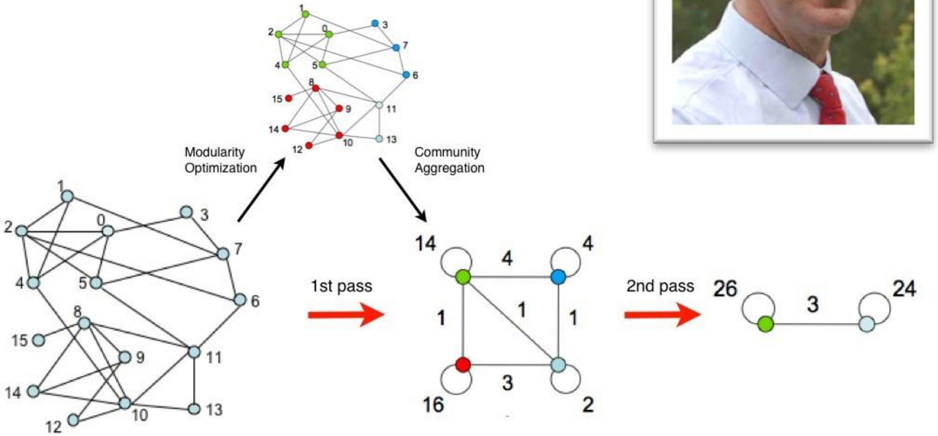
Classic approach: Modularity

- Newman, M. E. & Girvan, M. (2004) *PRE 69*(2), 026113.



- Blondel, V. D. et al. (2008). *J. Stat. Mech. 2008*(10), P10008.

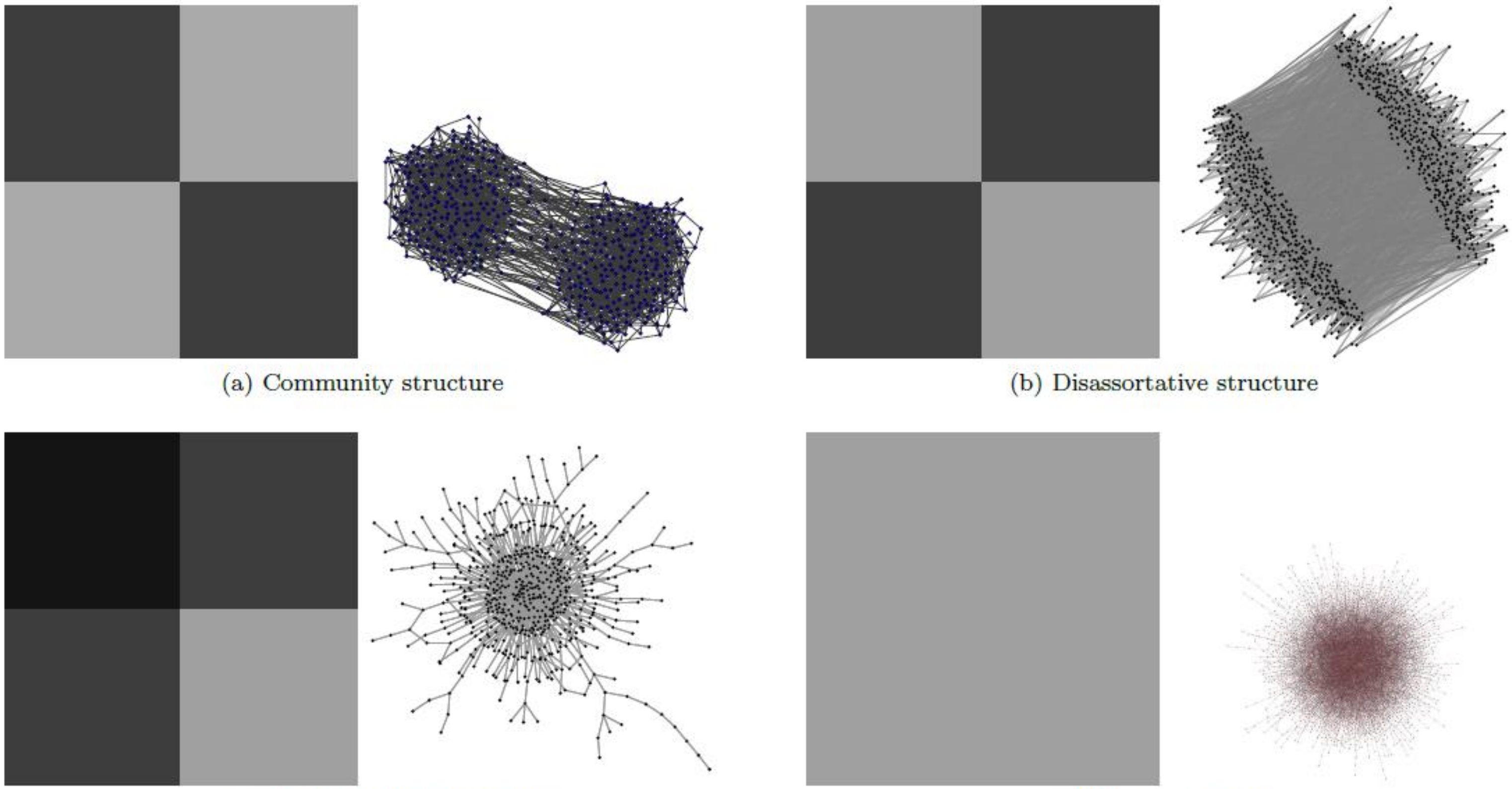




https://sites.google.com/site/findcommunities/

Generative approach: Stochastic block models

Figure from Fortunato & Hric (2016)
http://arxiv.org/abs/1608.00163



(a) Community structure
(b) Disassortative structure
(c) Core-periphery structure
(d) Random graph

- Non-degree-corrected (Holland, P. W. et al. (1983) *Soc. Netw. 5*(2), 109-137)
- Degree-corrected (Karrer, B. & Newman, M. E. (2011) *PRE 83*(1), 016107)

Issues with community detection

- Modularity maximization doesn't always give you the "right" results
- Detectability is limited; community detection doesn't work well for very large networks in general

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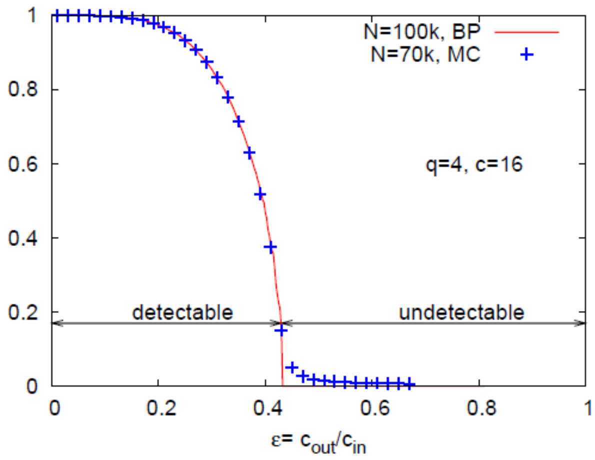
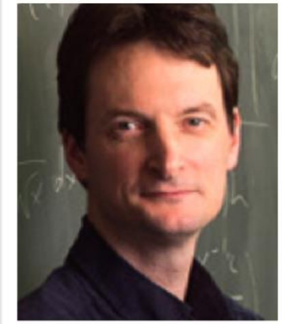
Decelle, A. et al. (2011) *PRL* 107, 065701.
Nadakuditi, R. R. & Newman, M. E. (2012) *PRL 108*, 188701.
Ghasemian, A. et al. (2016) *PRX 6*(3), 031005.



Newman never holds back



https://arxiv.org/abs/1606.02319

Community detection in networks: Modularity optimization and maximum likelihood are equivalent

M. E. J. Newman
Department of Physics and Center for the Study of Complex Systems, University of Michigan, Ann Arbor, MI 48109

We demonstrate an exact equivalence between two widely used methods of community detection in networks, the method of modularity maximization in its generalized form which incorporates a resolution parameter controlling the size of the communities discovered, and the method of maximum likelihood applied to the special case of the stochastic block model known as the planted partition model, in which all communities in a network are assumed to have statistically similar properties. Among other things, this equivalence provides a mathematically principled derivation of the modularity function, clarifies the conditions and assumptions of its use, and gives an explicit formula for the optimal value of the resolution parameter.

I. INTRODUCTION

Community detection, sometimes called network clustering, is the division of the nodes of an observed network into groups such that connections are dense within groups but sparser between them [1–3]. Not all networks support such divisions, but many do, and the existence of good divisions is often taken as a hint of underlying semantic structure or possible mechanisms of network formation, making community detection a useful tool for interpreting network data.

The development of methods or algorithms to perform community detection on empirical networks has been a popular pursuit among researchers in physics, mathe-

maximization.

A. Modularity maximization

Modularity maximization is perhaps the most widely used method for community detection for networks. It operates by defining a benefit function, called the modularity, that measures the quality of divisions of a network into communities. One optimizes this benefit function over possible divisions of the network of interest to find the one that gives the highest score, taking this to be the definitive division of the network. Since the number of possible divisions of a network is exponentially large, we

Shift of mindset

Peel, L. et al. (2016) *arXiv:1608.05878*.

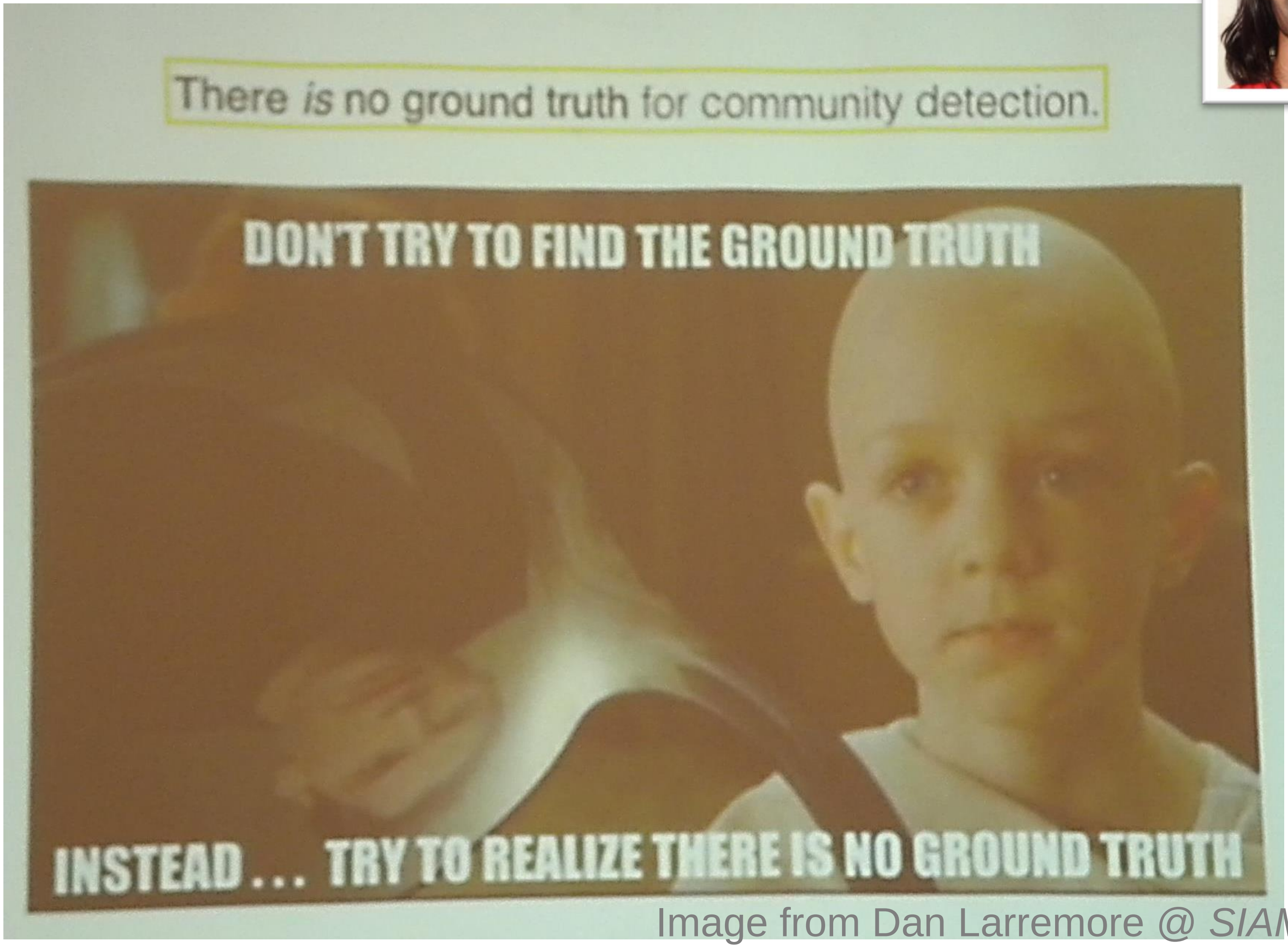
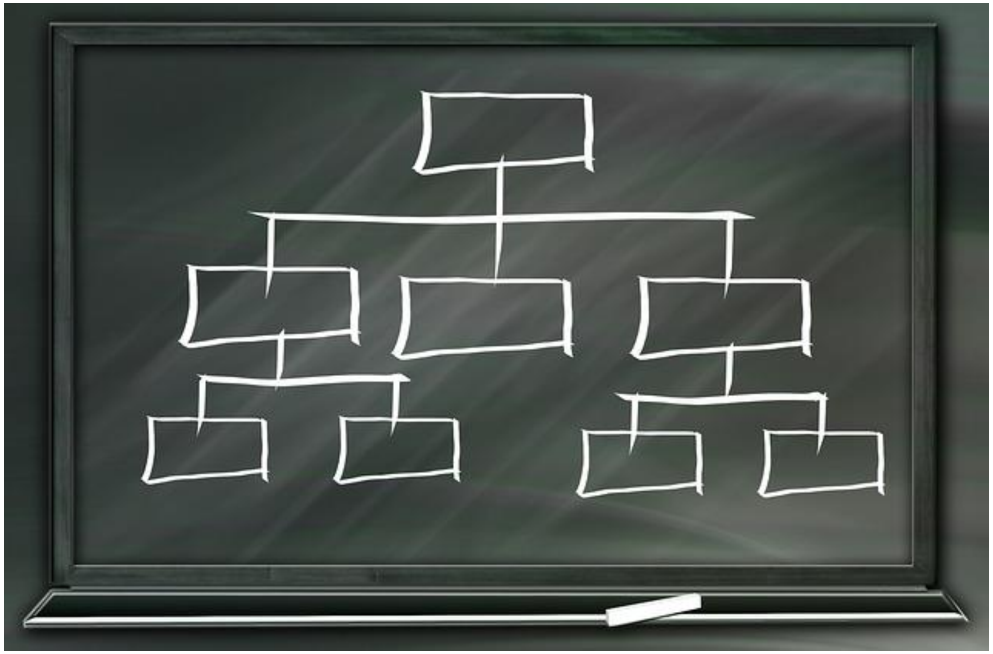


Image from Dan Larremore @ *SIAM NS16*

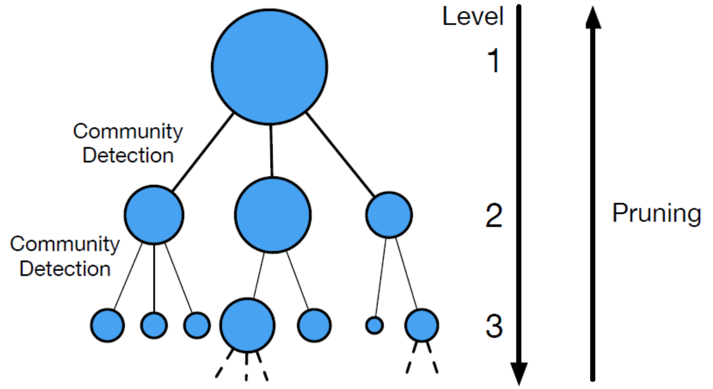
How to find multiscale patterns

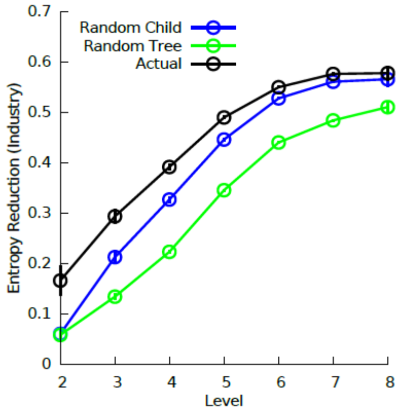
- Hierarchical approach
  - Modularity methods
  - Stochastic block models

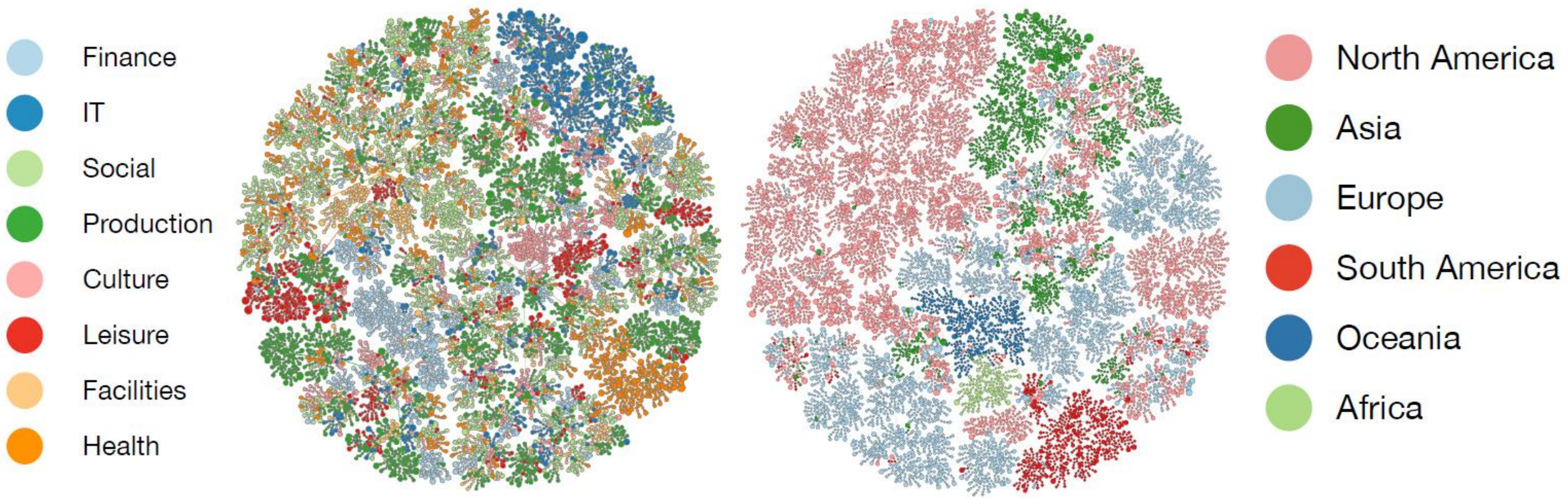


Hierarchical modularity optimization

- Ahn, Y. Y., NetSci 2016 HONS (http://bit.ly/netsci_LFN)
  - LinkedIn Economic Graph Challenge

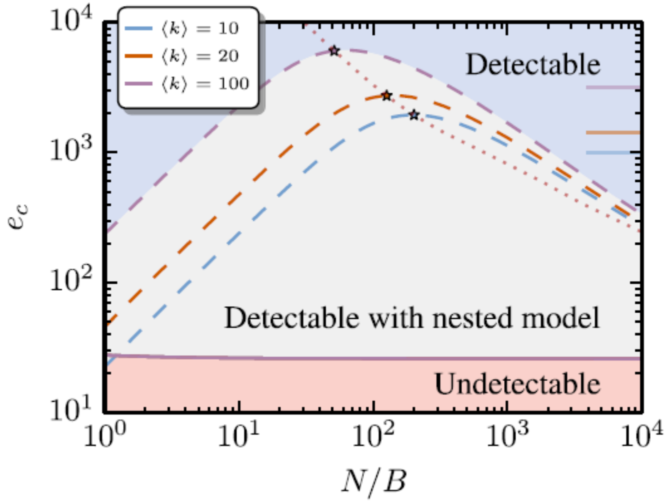


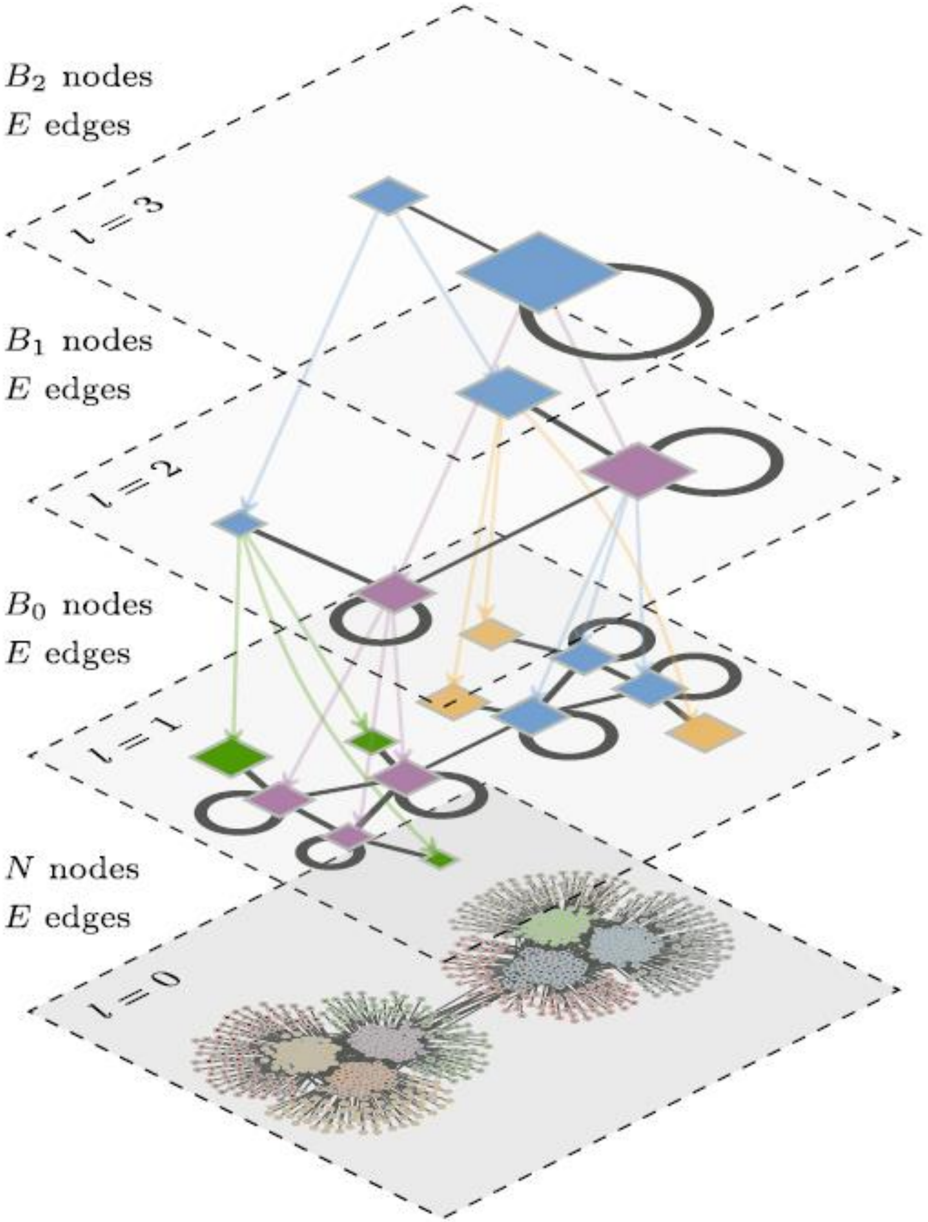




Nested stochastic block models

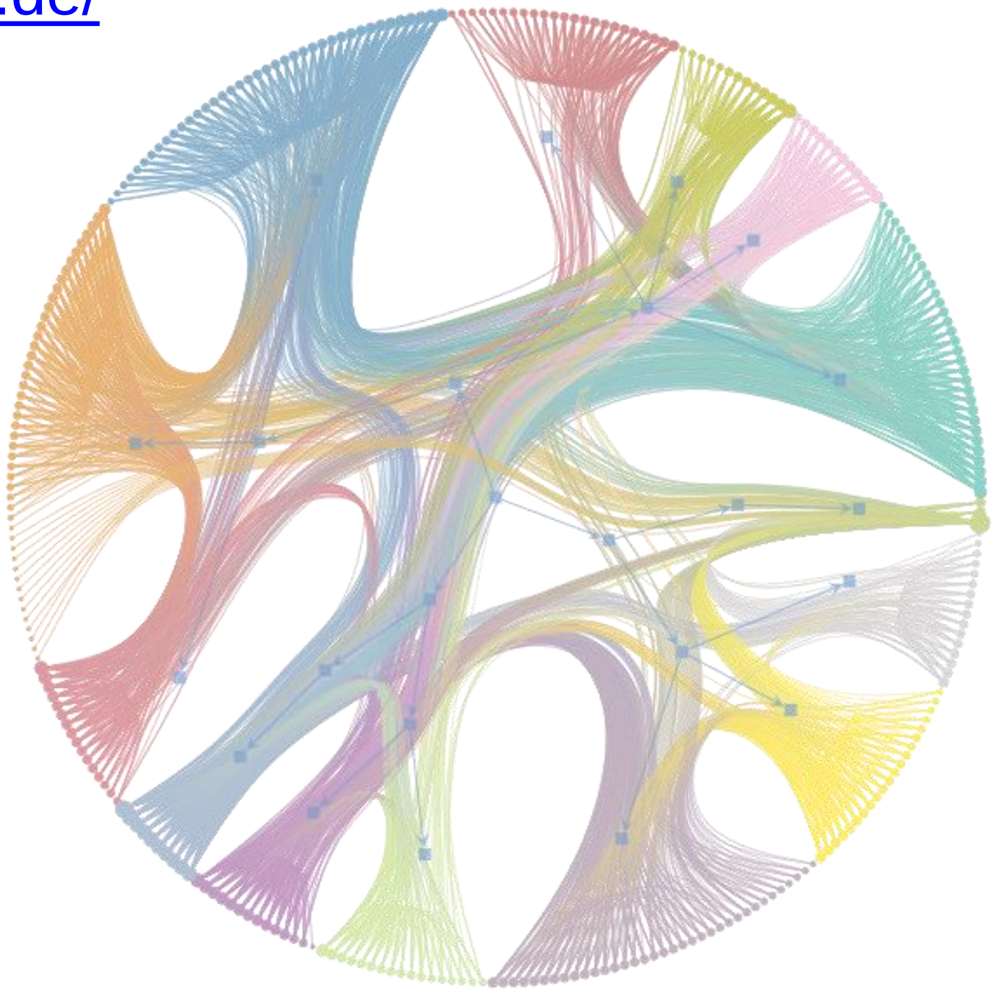
- Peixoto, T. P. (2014) *PRX* 4(1), 011047.

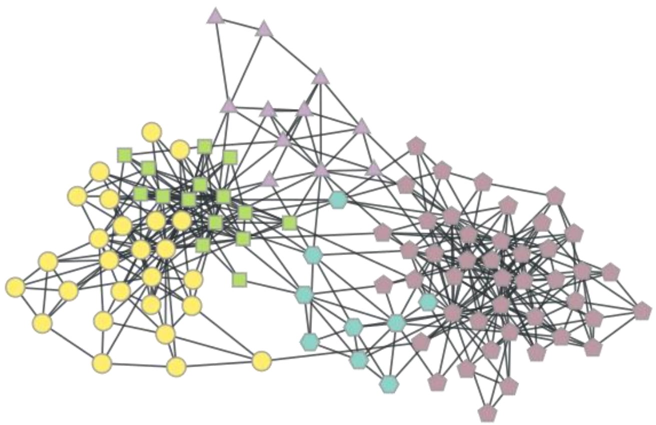




Tiago Peixoto's "graph-tool"

- https://graph-tool.skewed.de/
- Python module for fast graph analysis and visualization (including hierarchical stochastic block models)





Other tools: FlashX

- Zheng, D. et al. (2016) http://arxiv.org/abs/1602.01421
- http://flashx.io (API for R available)

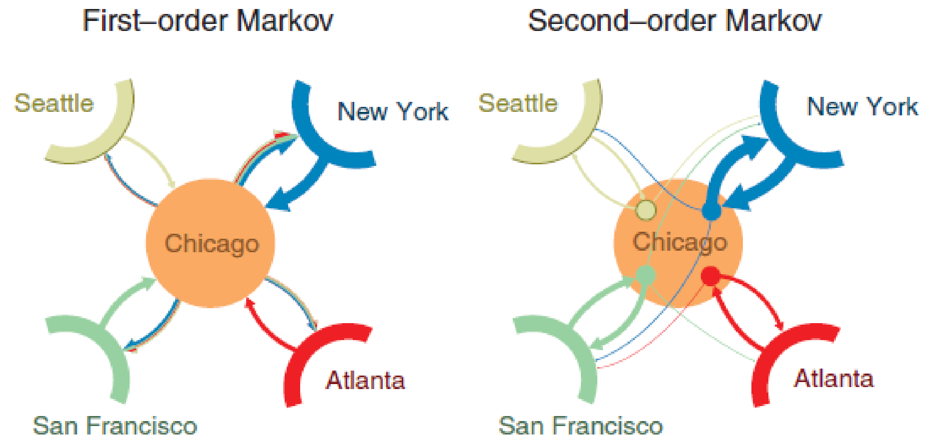
2.
HIGHER-ORDER MODELS

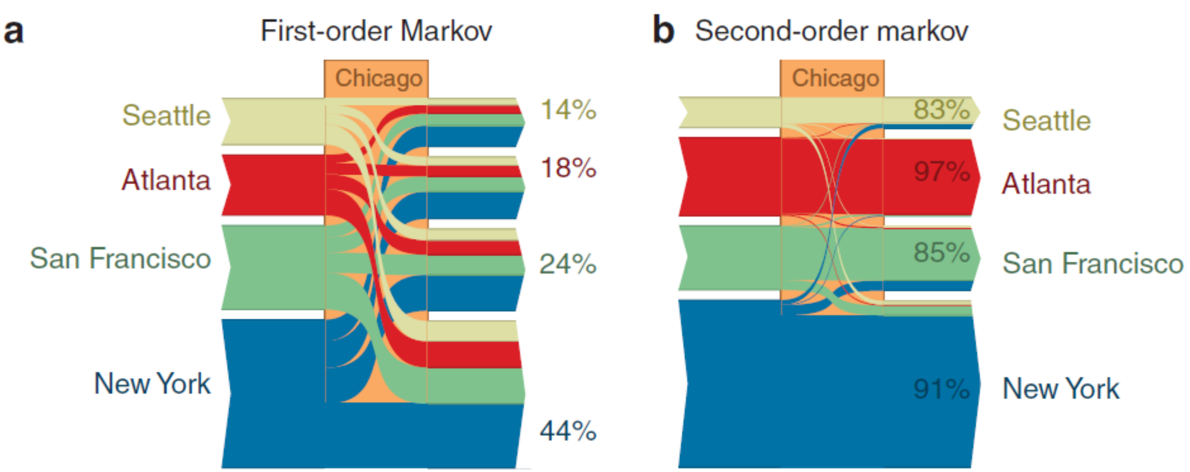
Higher-order models of networks

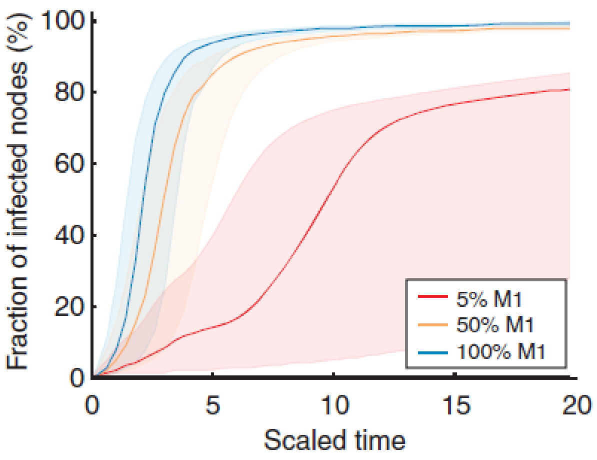
- Typical network models describe N-node systems in $N \times N$ matrices (adjacency, Laplacian, transition, etc.)
- What are absent in such representations?
- Can we capture any “higher-order” structure/dynamics?

Higher-order Markov processes

- Rosvall, M. et al. (2014) *Nature Comm.* 5, 4630.

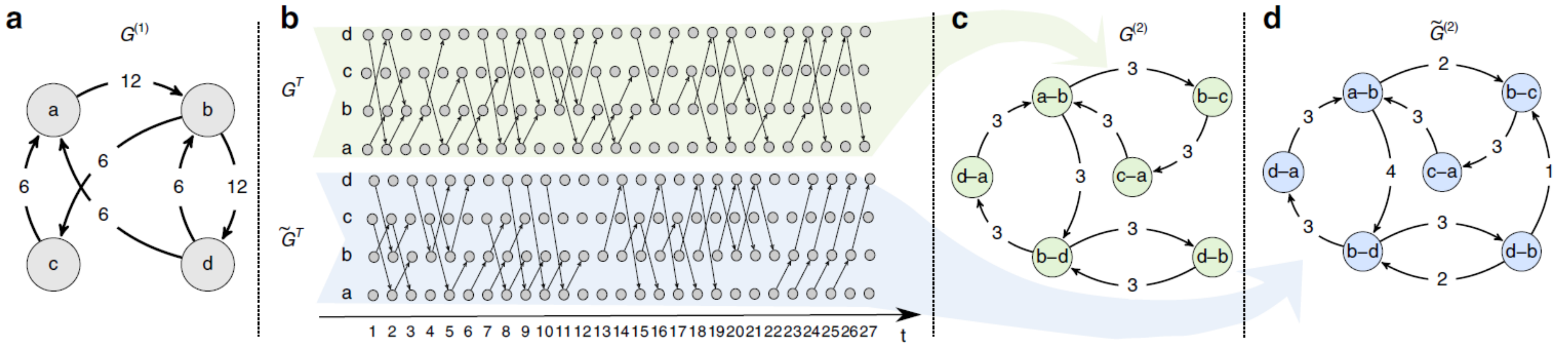






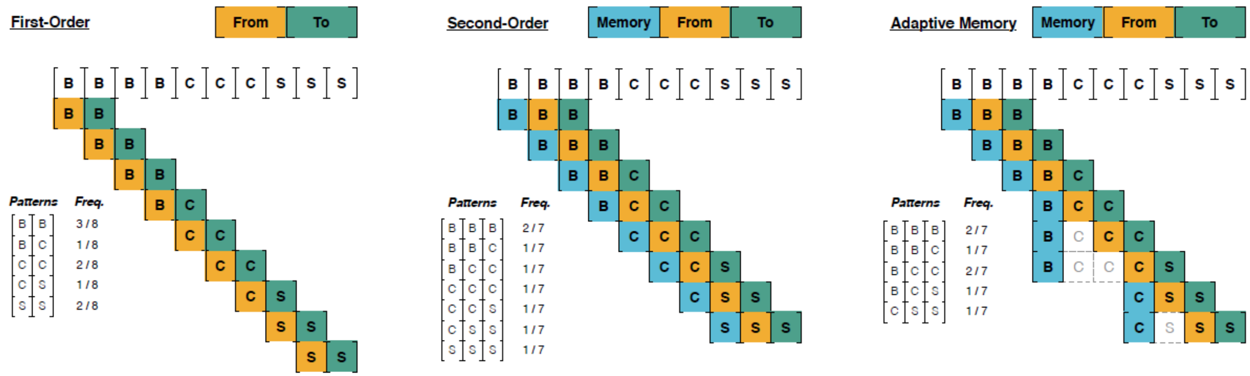
Higher-order temporal network analysis

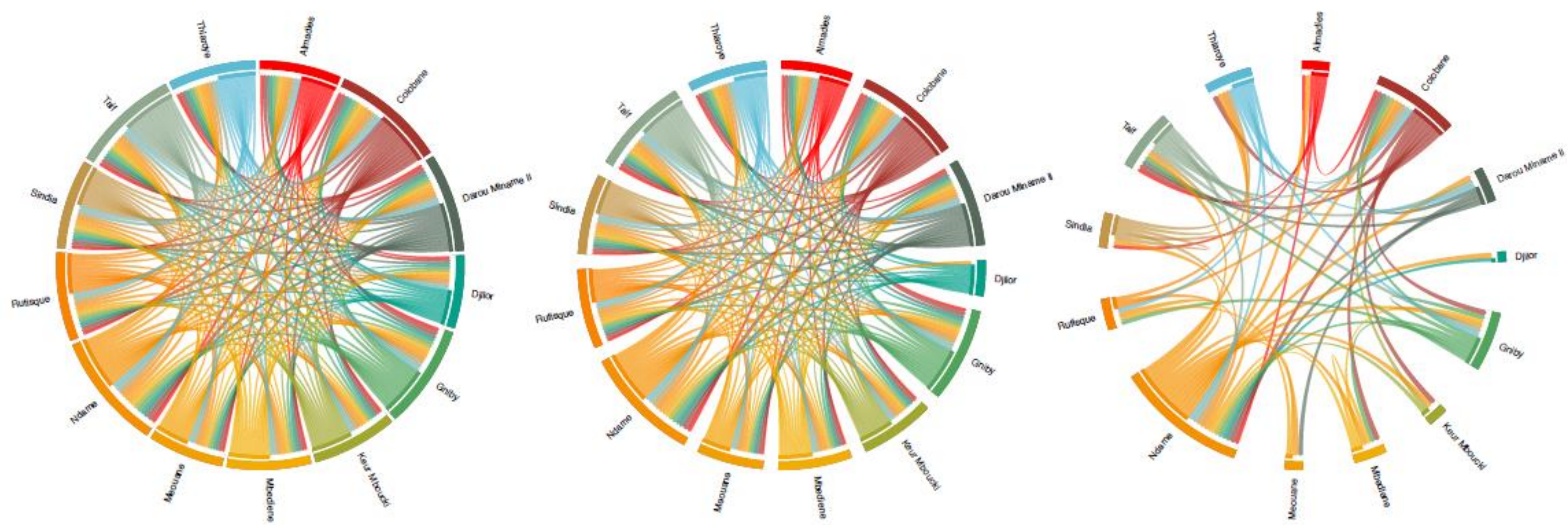
- Scholtes, I. et al. (2014) *Nature Comm.* 5, 5024.
- Scholtes, I. et al. (2016) *EPJ-B*, *89*(3), 1-15.



Non-Markovian movements with adaptive memory

De Domenico, M. et al. (2016) http://arxiv.org/abs/1603.05903
(recently published in *J. R. Soc. Interface 13*(121), 2016.0203.



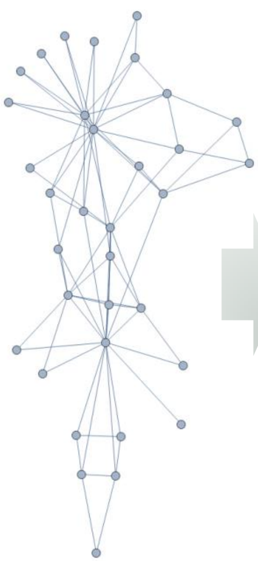


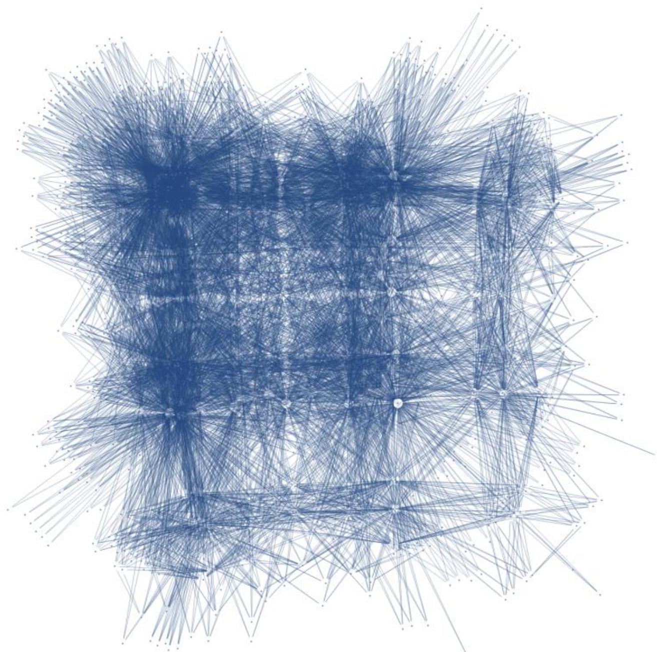
(a) First-Order (b) Second-Order (c) Adaptive Memory

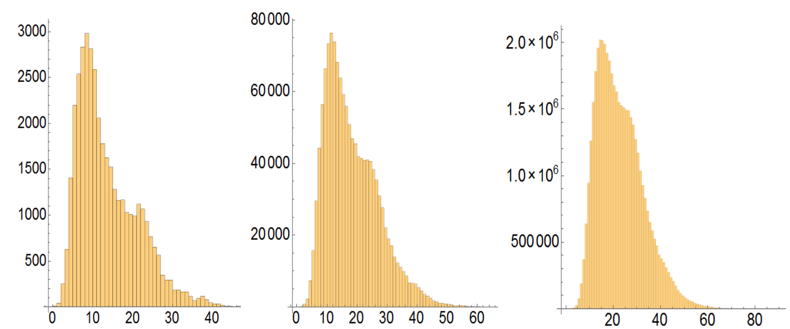
Graph product multilayer networks

- Sayama, NetSci 2016 HONS (http://bit.ly/2bjp9RB)

$$G^k$$
$$k \to \infty$$
?

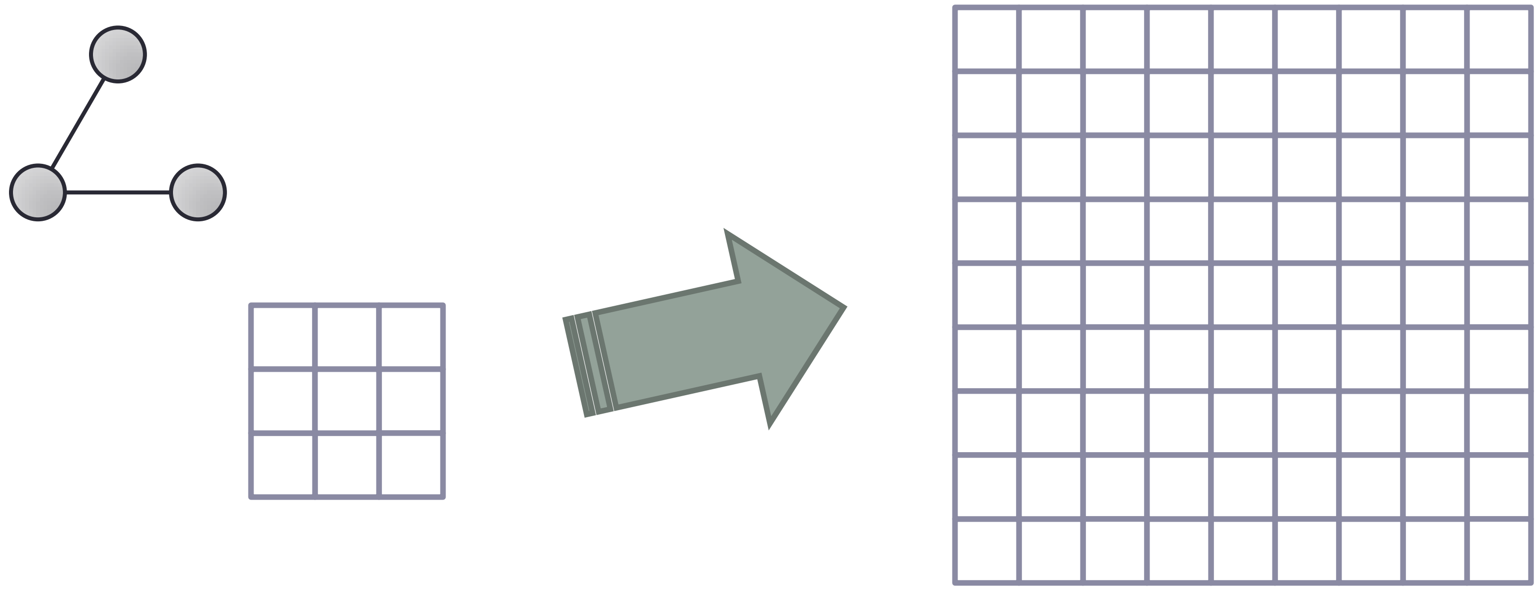






"Higher order": Unexplored territory

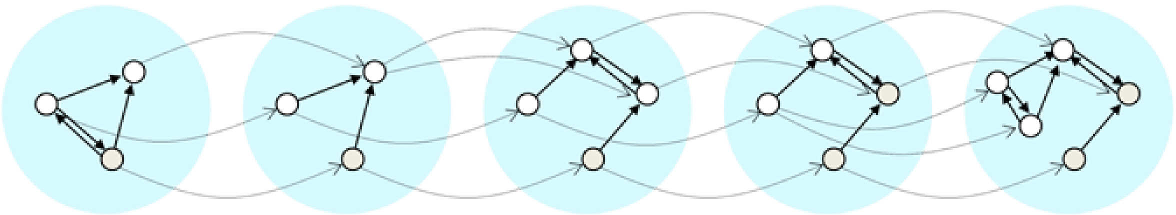
- "Higher order" can embrace any modeling/analysis effort to study $N^k \times N^k$ properties of a network ($k > 1$)
- The field is still unexplored and wide open



3.
INTERACTION BETWEEN DYNAMICS *ON* AND *OF* NETWORKS (COEVOLUTION)

Adaptive networks

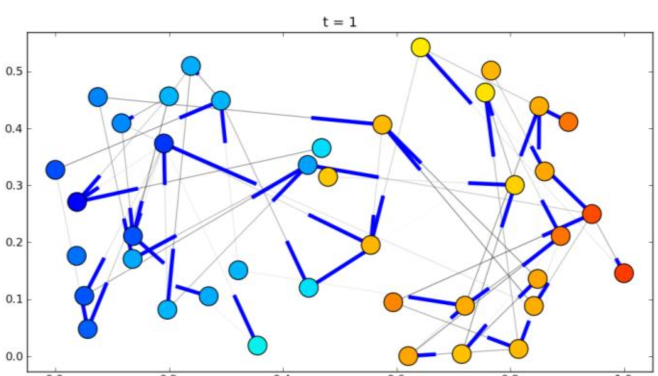
- Complex networks whose states and topologies co-evolve, often over similar time scales
  - Node states adaptively change according to link states
  - Link states (weights, connections) adaptively change according to node states
  - Sayama, H. et al. (2013) *Comput. Math. Appl. 65*(10), 1645-1664.

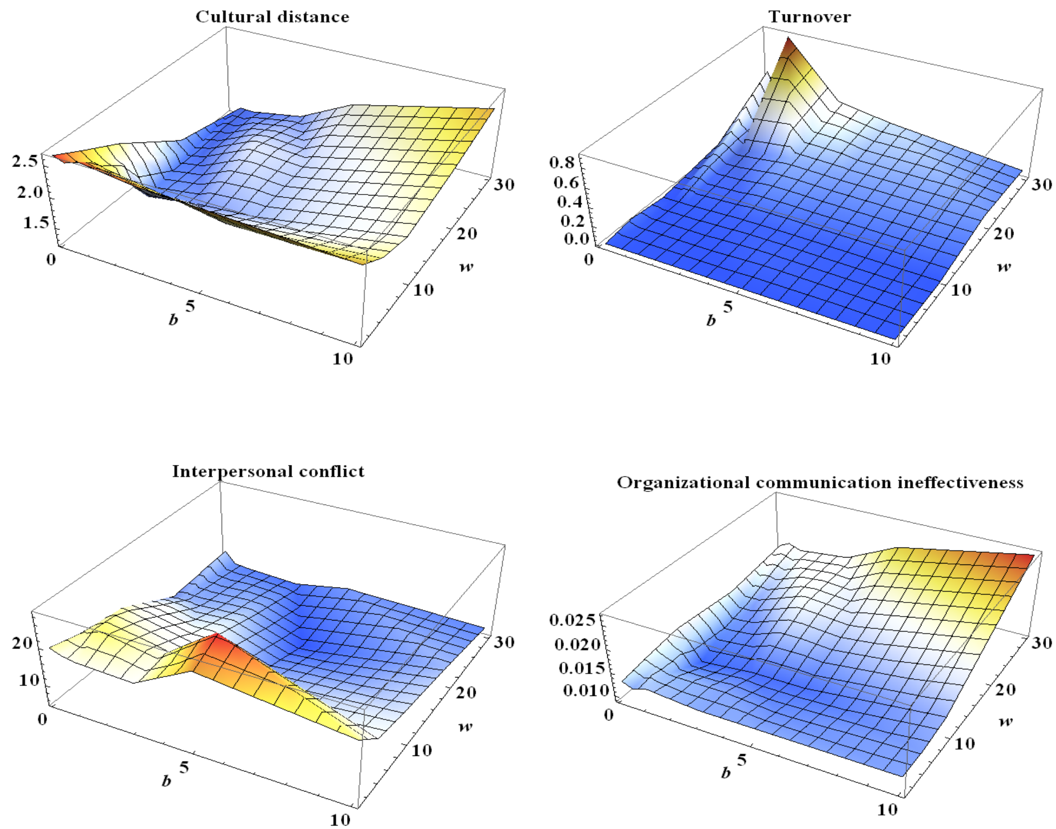


T. Gross

Cultural integration in merging firms

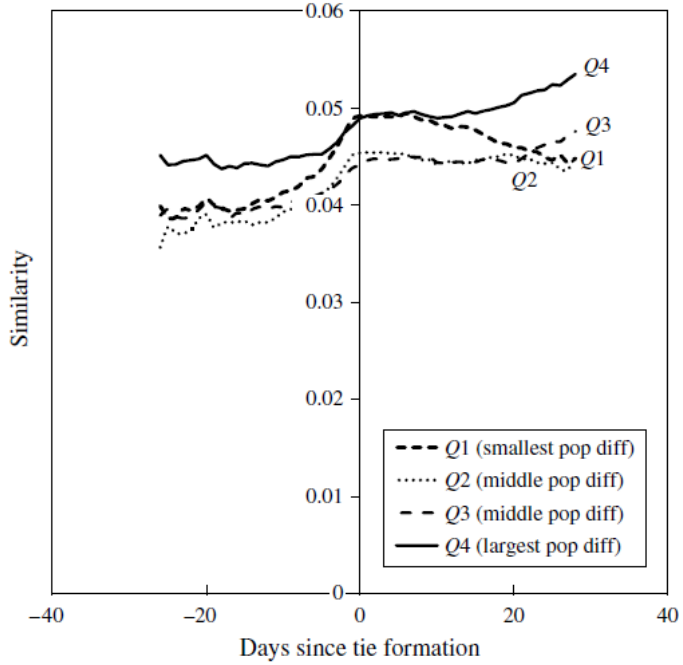
- Yamanoi, J. & Sayama, H. (2013) *CMOT 19*(4), 516-537.

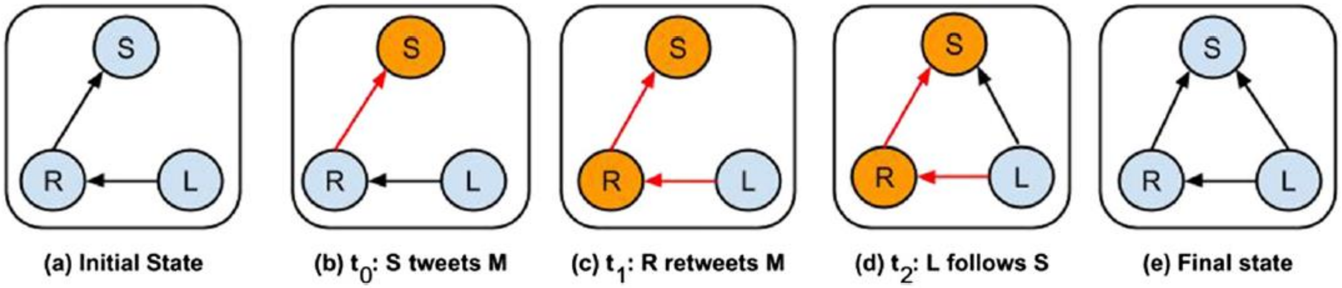




Coevolutionary dynamics on OSNs

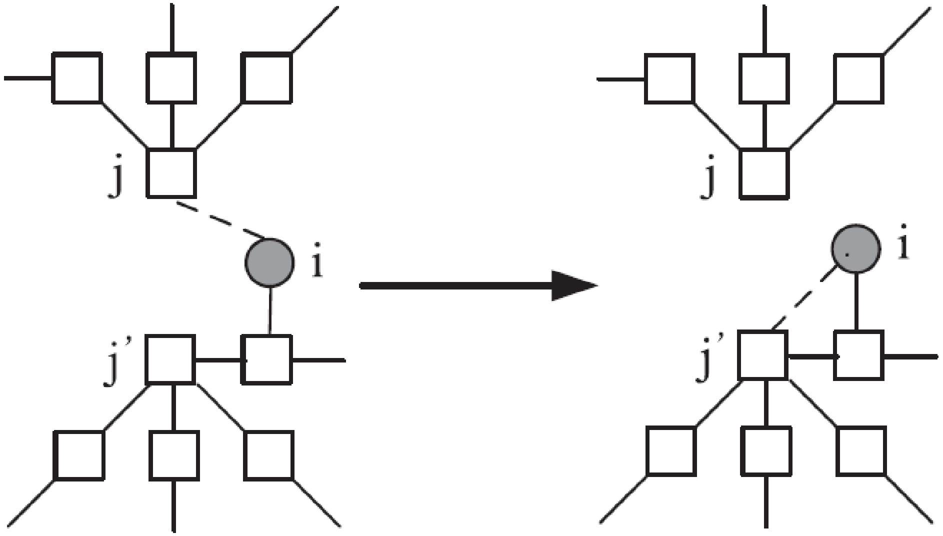
- Zeng, X. & Wei, L. (2013) *Info. Sys. Research* 24(1), 71-87. [about Flickr]
- Antoniades, D. & Dovrolis, C. (2015) *Comput. Soc. Netw.* 2(1), 1. [about Twitter]

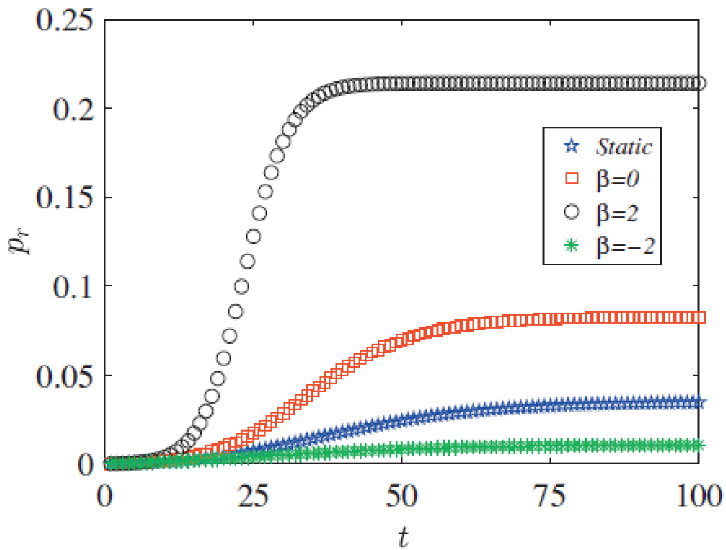




Fast information spreading by adaptive local link rewiring

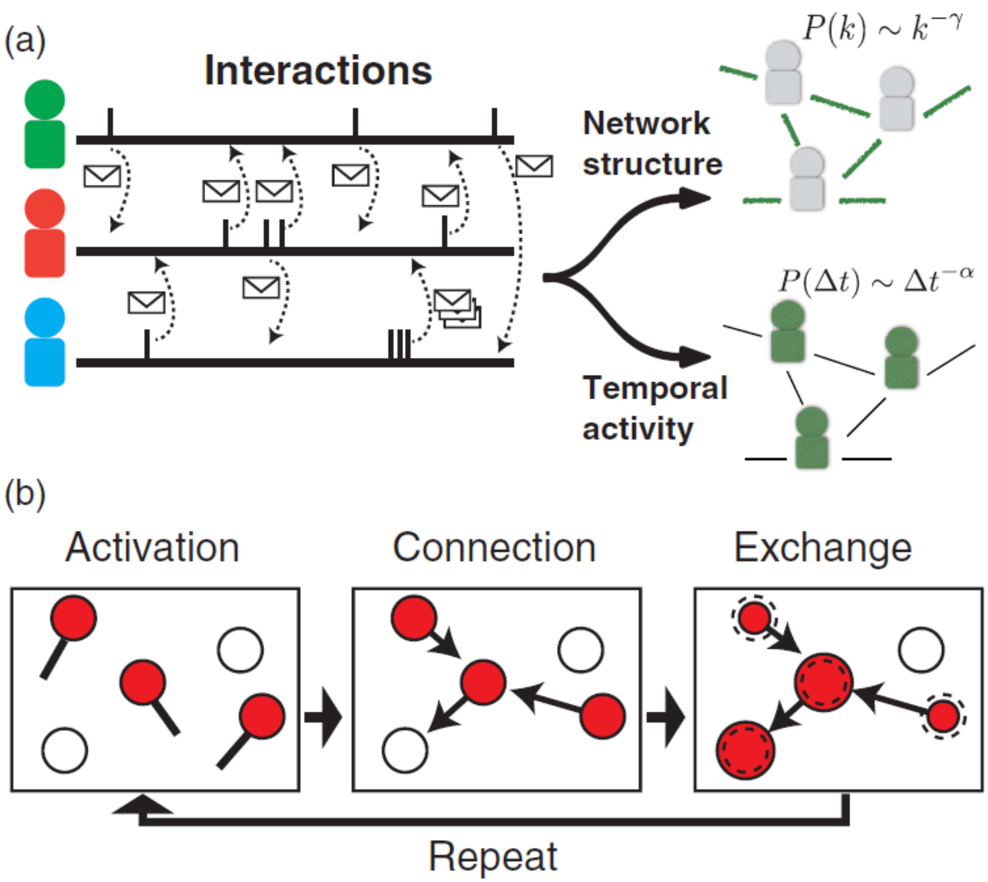
- Liu, C. & Zhang, Z. K. (2014) *CNSNS* 19(4), 896-904.

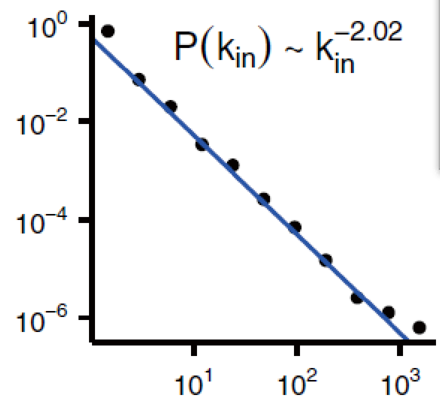


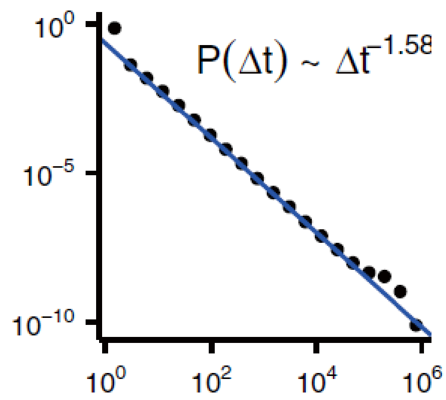


Adaptive network dynamics producing structural and temporal heterogeneities

- Aoki, T. et al. (2016) *PRE* 93(4), 040301.





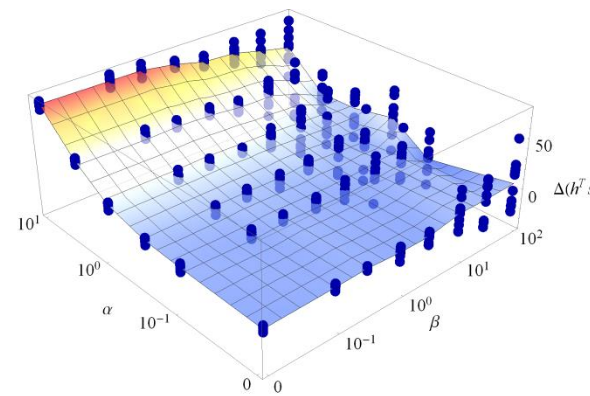


Social diffusion and global drift

- Sayama, H. & Sinatra, R. (2015) *PRE* 91(3), 032809.

$$\frac{ds_i}{dt} = c\left(\langle s_j \rangle_j^i - s_i\right)$$

$$\frac{d(h^T s)}{dt} \neq 0$$



4.
NETWORK RESILIENCE AND FAILURE

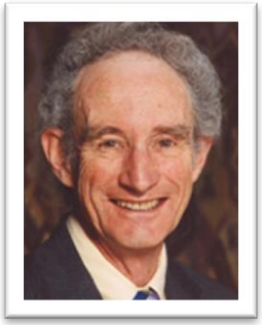
Network resilience: A classic problem

Dynamical stability:

- Gardner, M. R. & Ashby, W. R. (1970) *Nature* 228, 784.
- May, R. M. (1972) *Nature* 238, 413-414.

Topological connectivity:

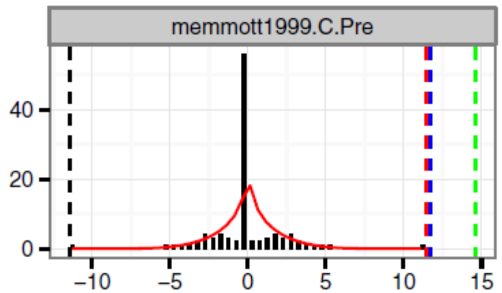
- Albert, R. et al. (2000) *Nature* 406, 378-382.
- Tanizawa, T. et al. (2005) *PRE* 71(4), 047101.
- Buldyrev, S. V. et al. (2010) *Nature* 464, 1025-1028.

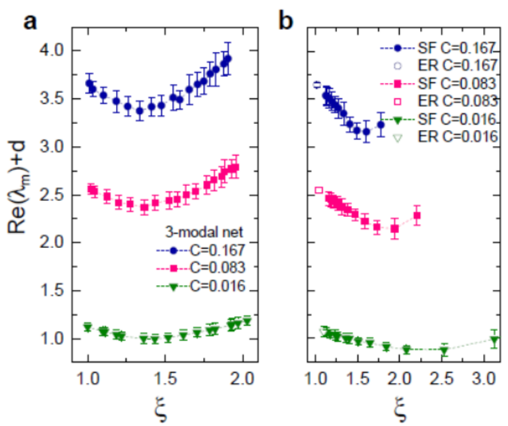

Heterogeneity of networks and stability

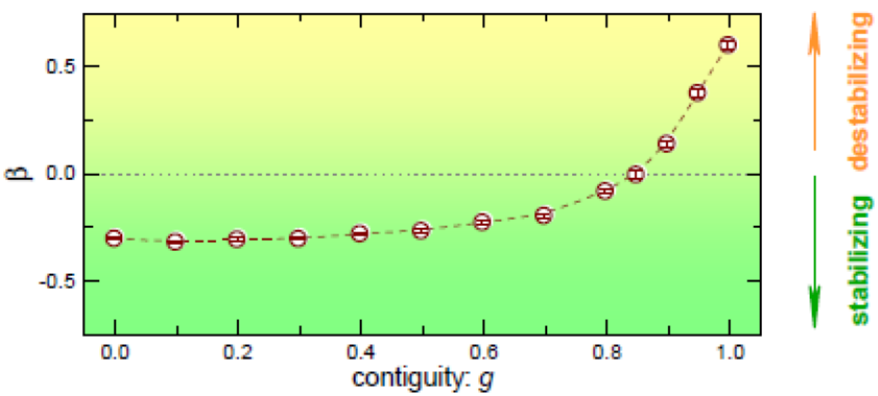
- Feng, W. & Takemoto, K. (2014) *Sci. Rep.* 4, 5912.

$$\lambda_1^2 \approx \sqrt{H_k - \frac{L}{2} + \frac{C_4}{2} - \frac{L^2}{s} + \frac{2L}{s}}$$



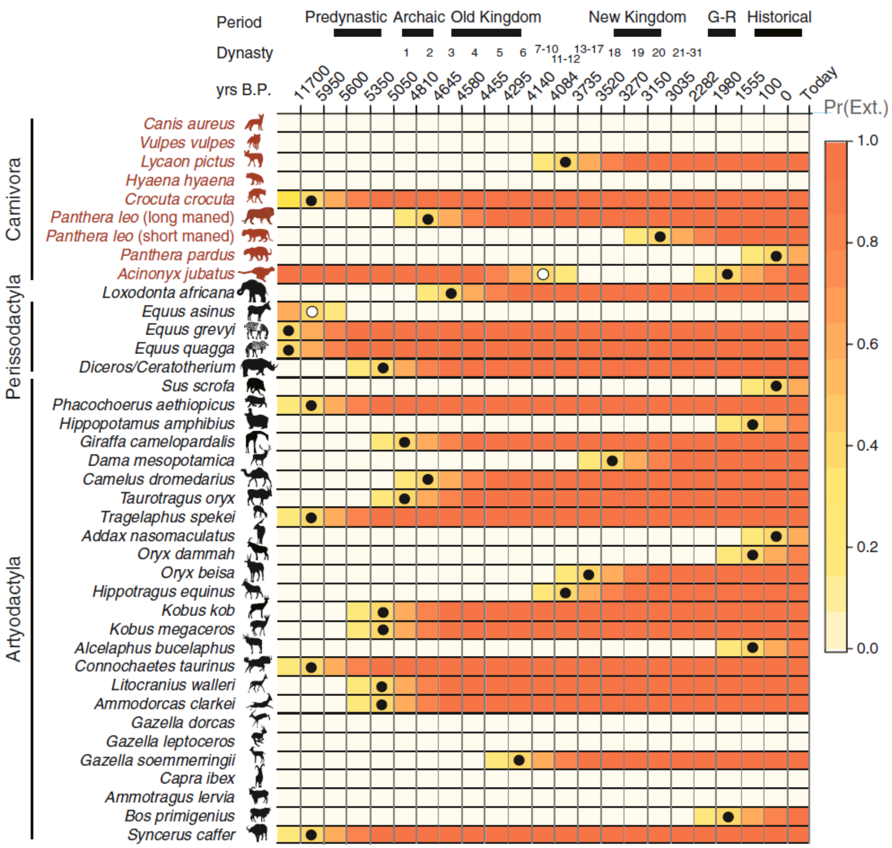
- Yan, G. et al. (2014) arXiv:1409.4137.

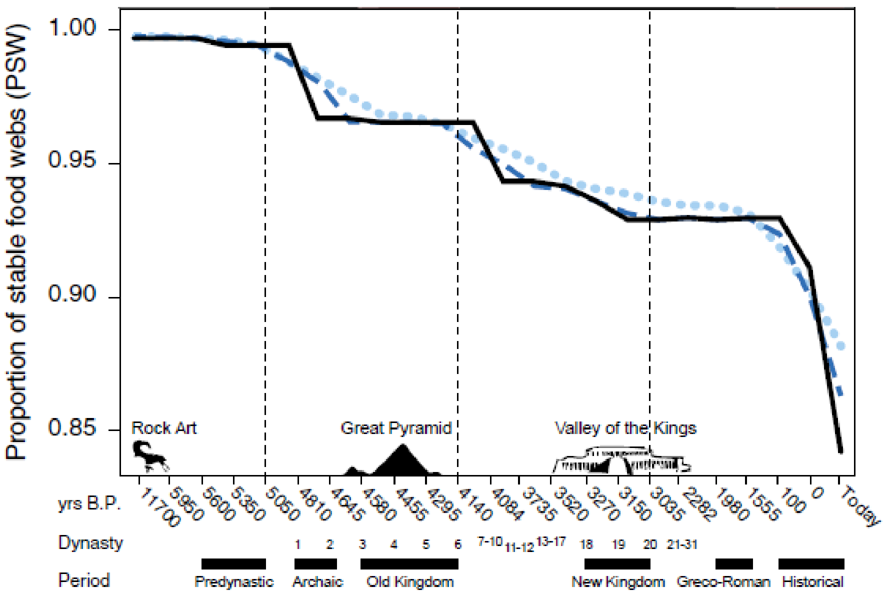




Ecological collapse captured & modeled

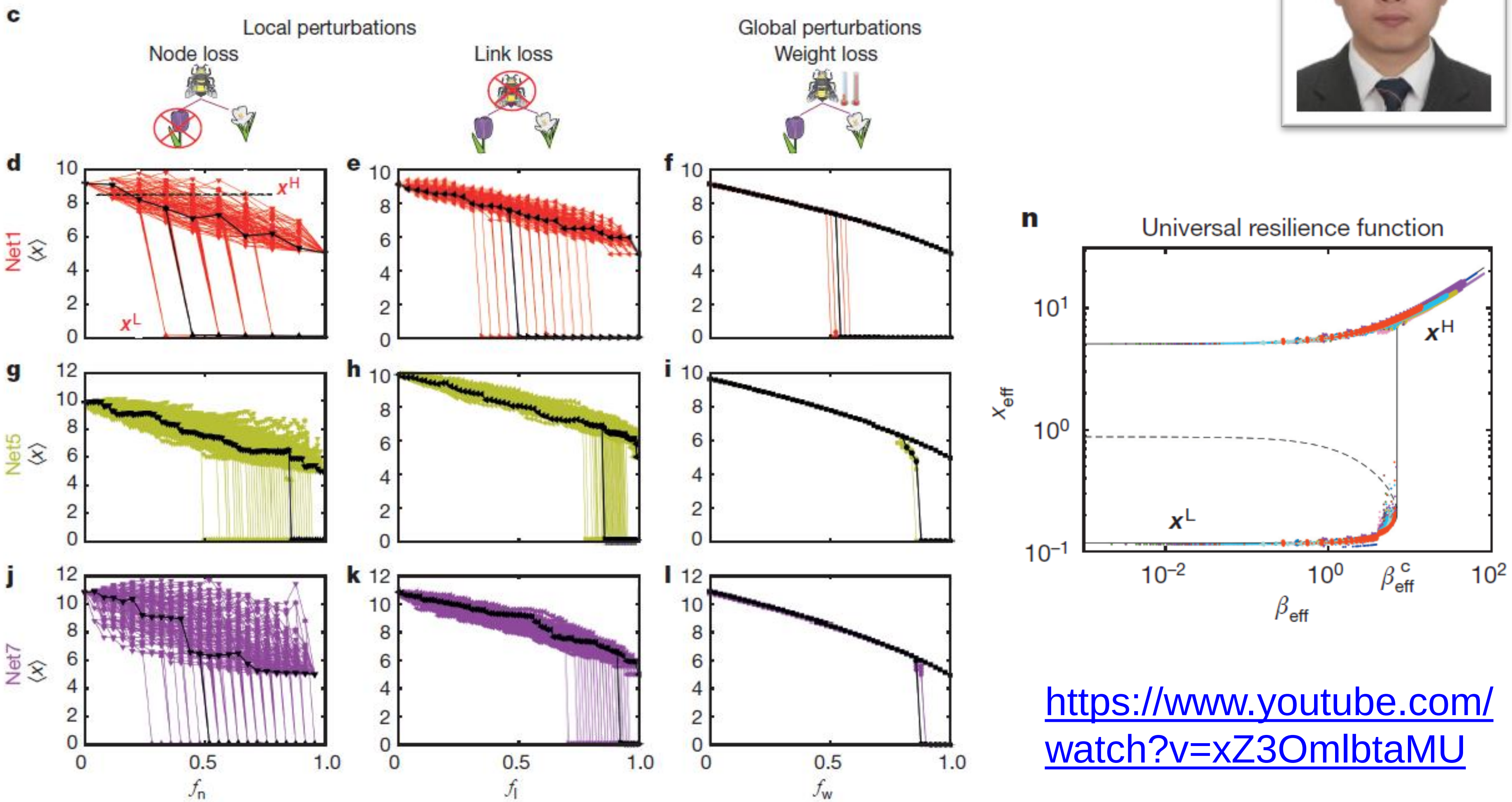
- Yeakel, J. D. et al. (2014) *PNAS* 111(40), 14472-14477.





Universal patterns of collapse

- Gao, J. et al. (2016) *Nature* 530(7590), 307-312.



https://www.youtube.com/watch?v=xZ3OmlbtaMU

Math behind universal patterns

- Original dynamical network:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = F(x_i) + \sum_{j=1}^{N} A_{ij} G(x_i, x_j)$$

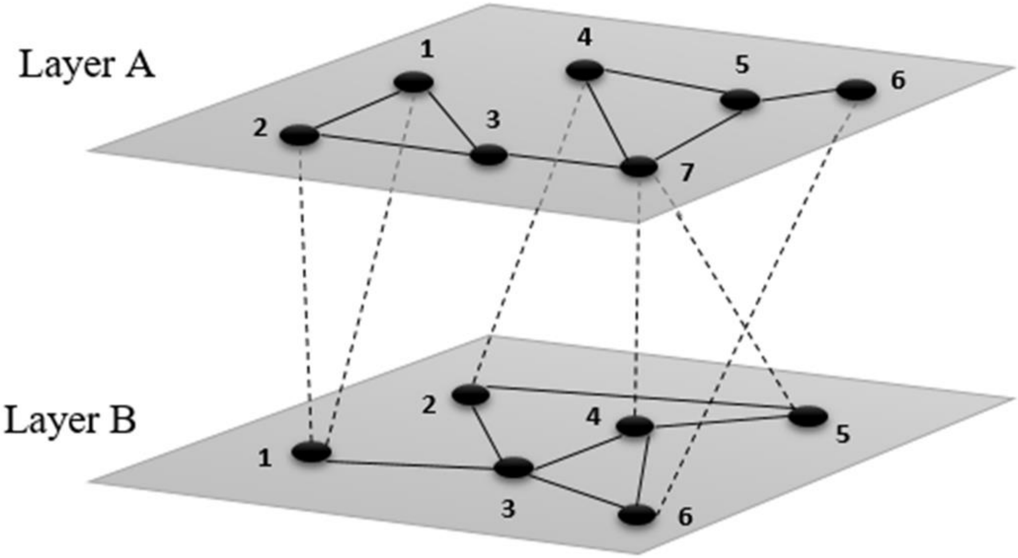
- Reduced to 1-D dynamical equation

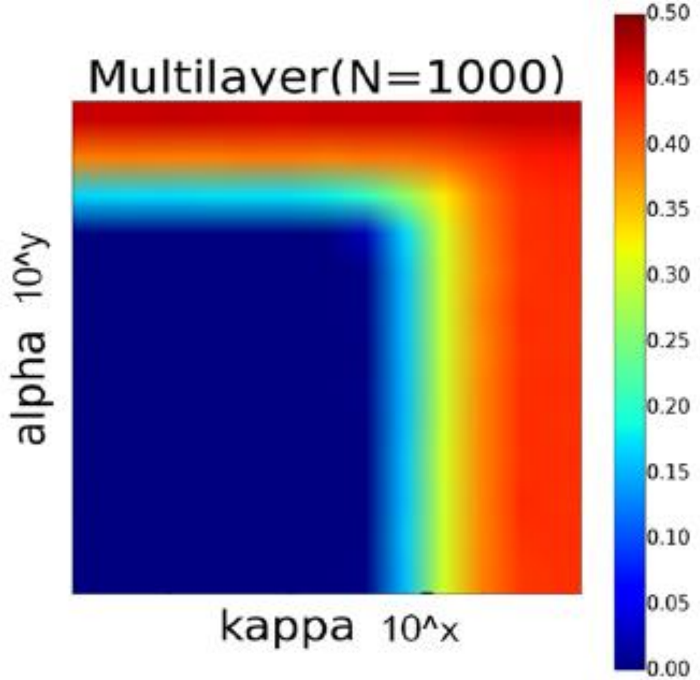
$$\frac{\mathrm{d}x_{\mathrm{eff}}}{\mathrm{d}t} = F(x_{\mathrm{eff}}) + \beta_{\mathrm{eff}} G(x_{\mathrm{eff}}, x_{\mathrm{eff}})$$

$$x_{\mathrm{eff}} = \frac{\boldsymbol{1}^{\top} A \boldsymbol{x}}{\boldsymbol{1}^{\top} A \boldsymbol{1}} = \frac{\langle s^{\mathrm{out}} x \rangle}{\langle s \rangle} \qquad \beta_{\mathrm{eff}} = \frac{\boldsymbol{1}^{\top} A \boldsymbol{s}^{\mathrm{in}}}{\boldsymbol{1}^{\top} A \boldsymbol{1}} = \frac{\langle s^{\mathrm{out}} s^{\mathrm{in}} \rangle}{\langle s \rangle}$$

Stability of multilayer networks

- Kim, H. et al. (2016) CCS 2016 talk (paper soon to be posted on arXiv).





5.
APPLICATIONS I:
NEURO AND BRAIN SCIENCE

Many going into brain science

NETSCI 2016 HOME ABOUT SPEAKERS CONTRIBUTIONS & REGISTRATION PROGRAM ORGANIZERS CONTACT

SESSION I: 31ST MAY MORNING

9:00-9:15: Opening Remarks

9:15-9:45: Graph analysis of functional brain networks: outcome interpretation and statistical issues (F. De Vico Fallani)

9:45-10:15: Segregation and integration in large-scale brain networks (Alex Fornito)

10:15-10:30: EEGNet: Probabilistic inference toolbox for constructing brain network model from EEG data (Hoang Nguyen)

11:00-11:30: The Human Brainnetome Atlas: A New Brain Atlas Based on Connectional Architecture (Tianzi Jiang)

11:30-12:00: Hierarchical organization of functional connectivity in the mouse brain: a complex network approach (Andrea Gabrielli)

12:00-12:30: The local community paradigm theory and its application in brain connectomics (Carlo Cannistraci)

12:30-13:00: A robust network of network model of brain activation predicts the collective influence map of the human brain (Hernan Makse)

SESSION II: 31ST MAY AFTERNOON

14:30-15:00: T.B.A. (Robin W. Wilkins)

15:00-15:30: Effective connectivity in neuronal cultures: from network reconstruction to medicine (Jordi Soriano)

15:30-16:00: Chain-like organization and hierarchy in the human functional brain network (Guido Caldarelli)

16:30-17:00: T.B.A. (Sean L. Simpson)

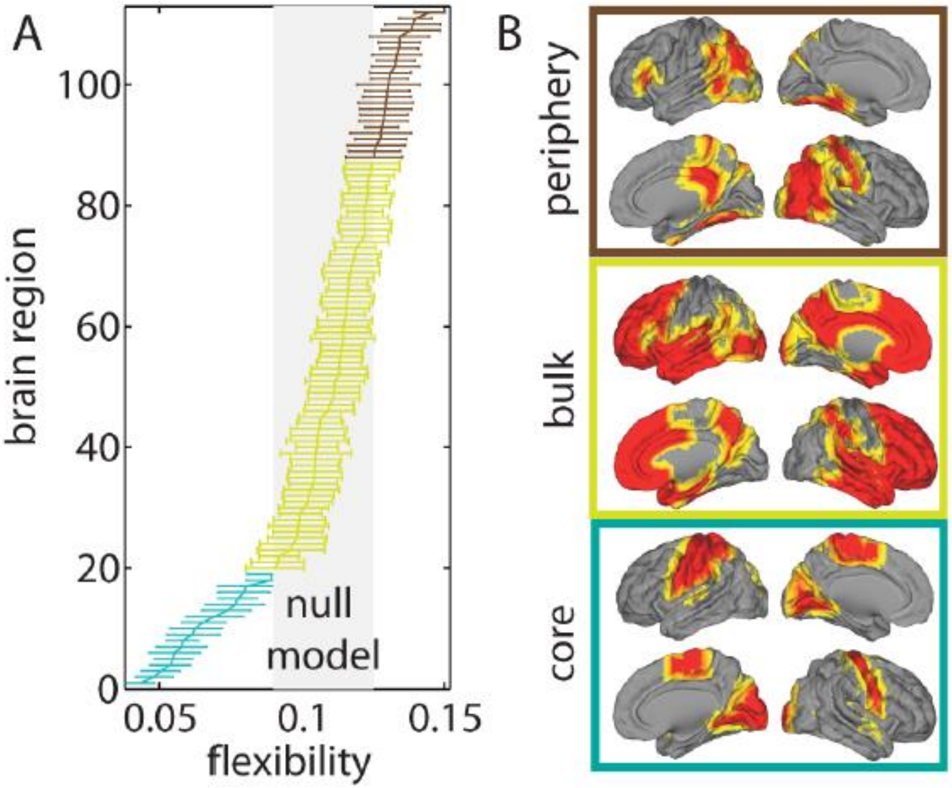
17:00-17:30: Mapping multiplex hubs in human functional brain network (Alex Arenas)

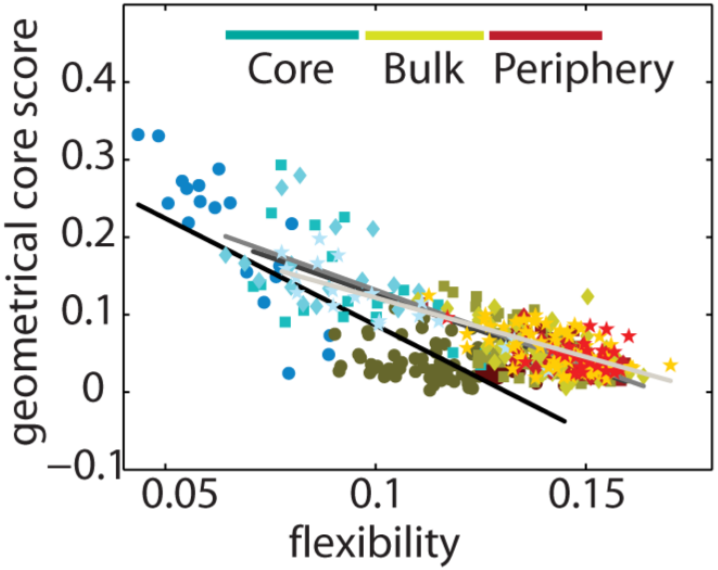
17:30-18:00: Closing Remarks and Discussion

NetSci 2016 Brain Networks satellite program

Temporal core-periphery structure of functional brain networks during learning

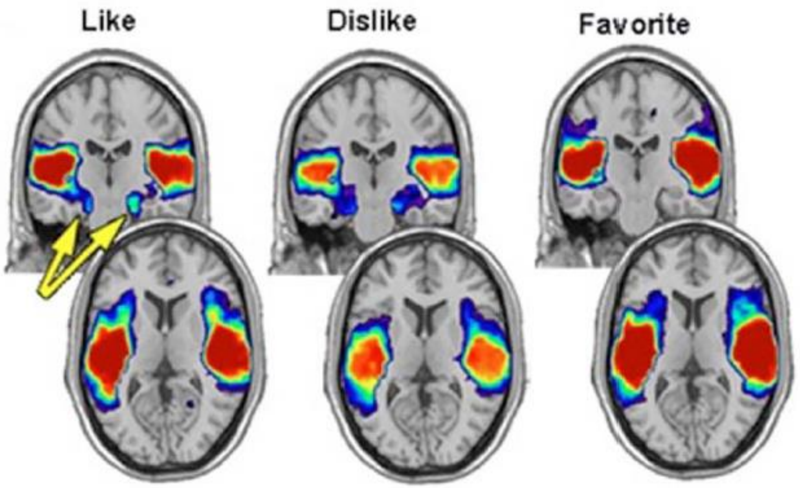
- Bassett, D. S. et al. (2013) *PLoS Comp. Biol.* 9(9), e1003171.

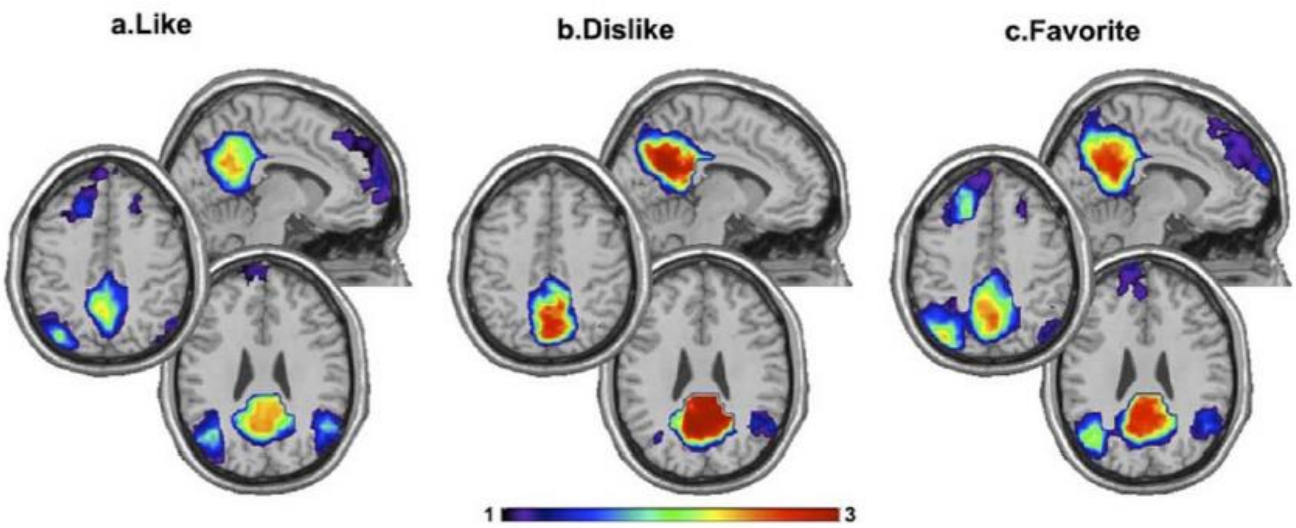




Functional brain connectivity while listening to music

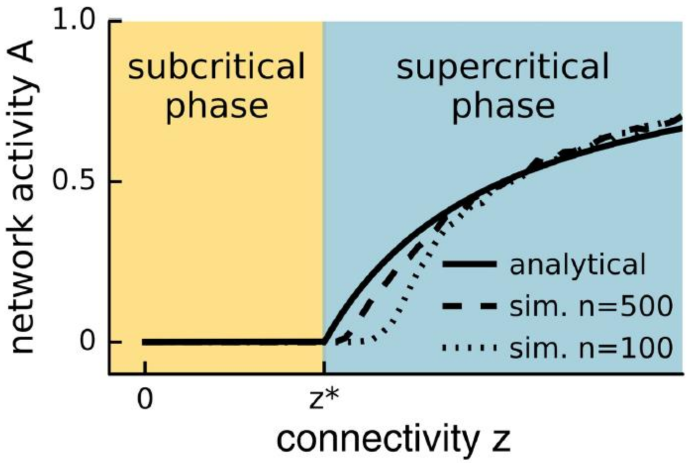
- Wilkins, R. W. et al. (2014). *Sci. Rep.* 4, 6130.

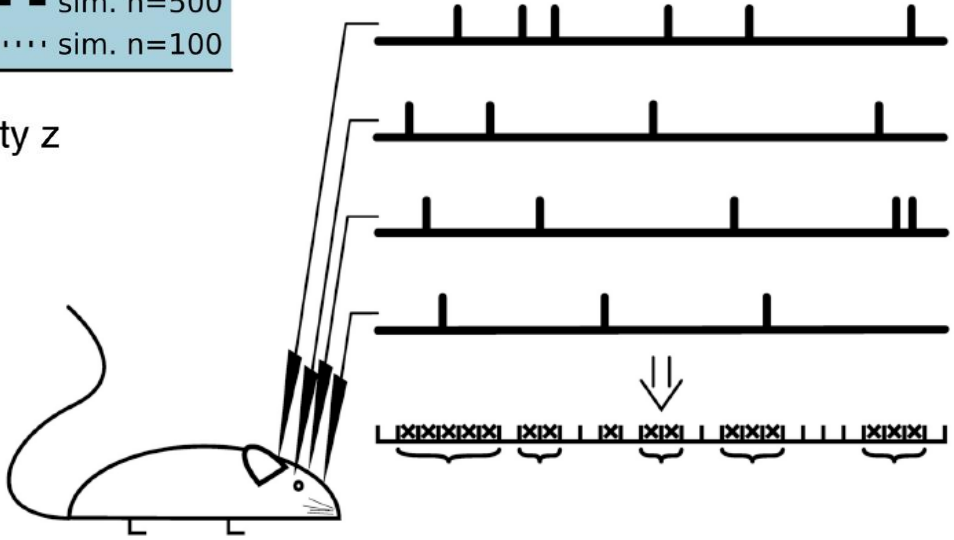




"Critical brain" hypothesis

- Hesse, J. & Gross, T. (2014) *Front. Syst. Neurosci.* 8, 166.





New journal coming up

- Network Neuroscience (MIT Press) http://www.mitpressjournals.org/netn

NETWORK
NEURO
SCIENCE

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6. APPLICATIONS II: FINANCE AND MARKETING

Where there is money

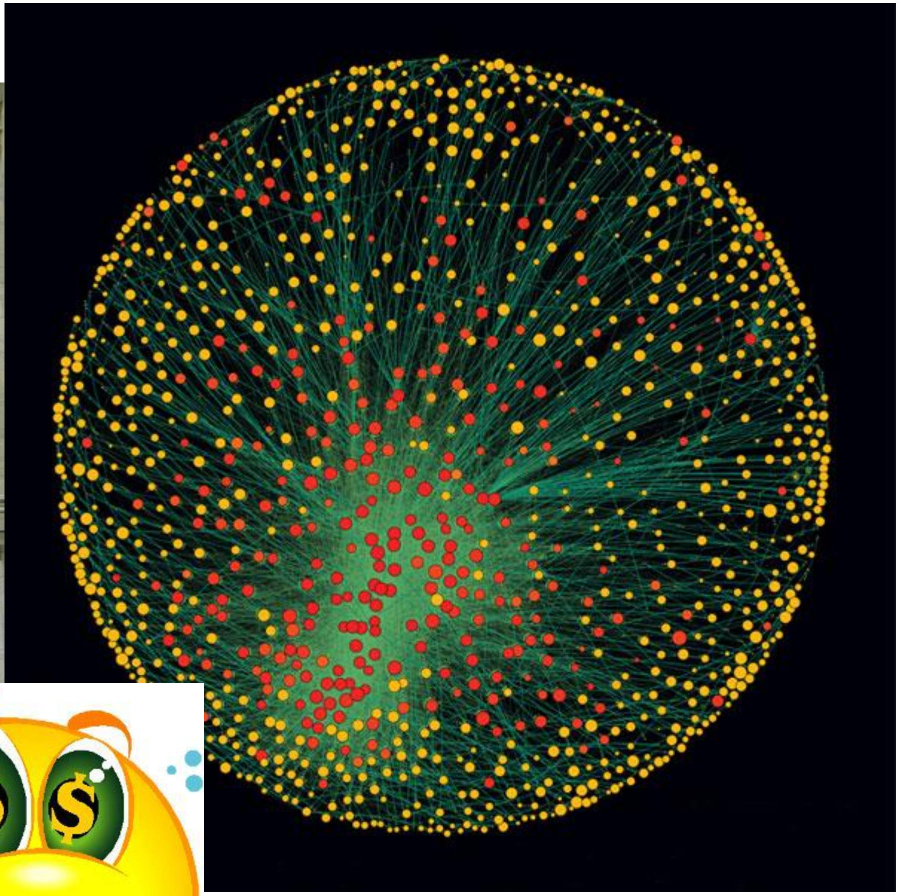
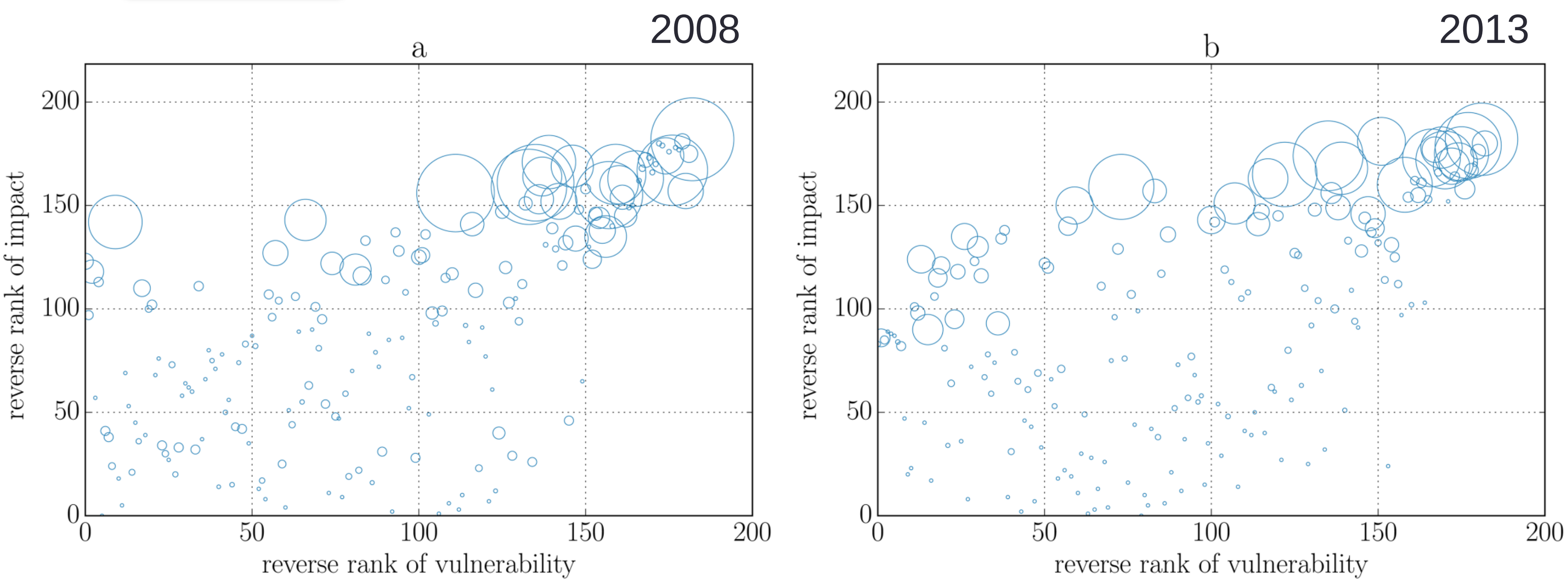


Image from: Vitali, S. et al. (2011) *PLOS ONE 6*(10), e25995.

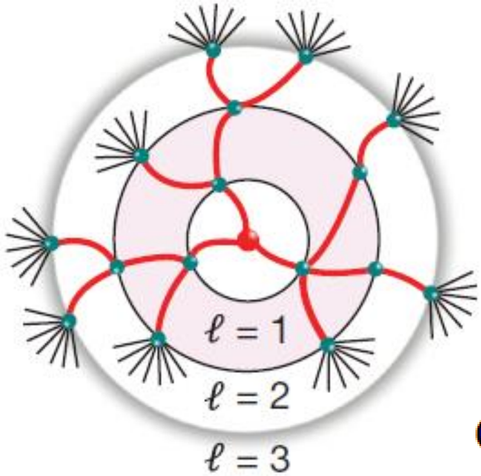
Generalization of "DebtRank": Micro-level model of financial network dynamics

- Bardoscia, M. et al. (2015). *PLOS ONE* 10(6), e0130406.

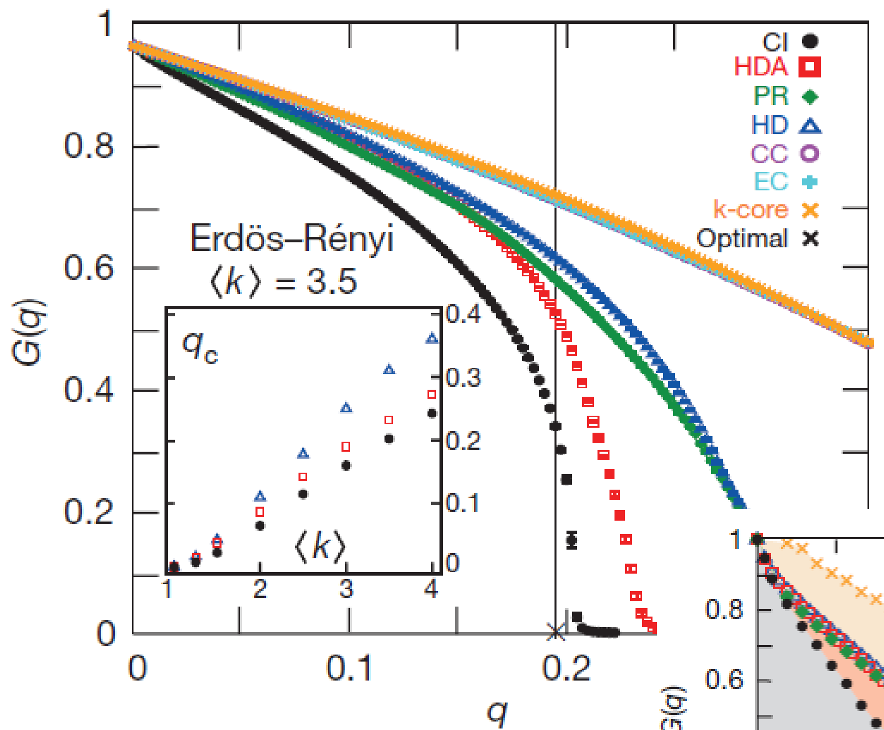


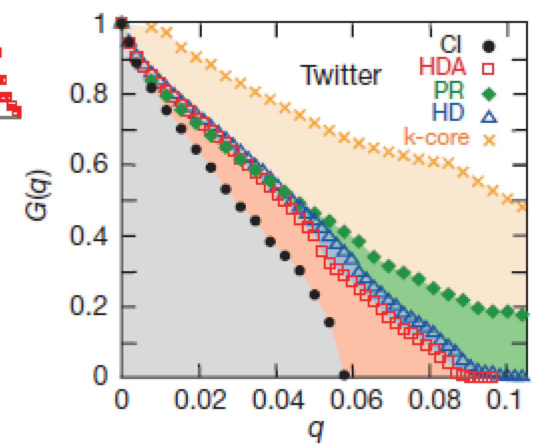
Influencer set optimization

- Morone, F. & Makse, H. A. (2015) *Nature* 524, 65-68.



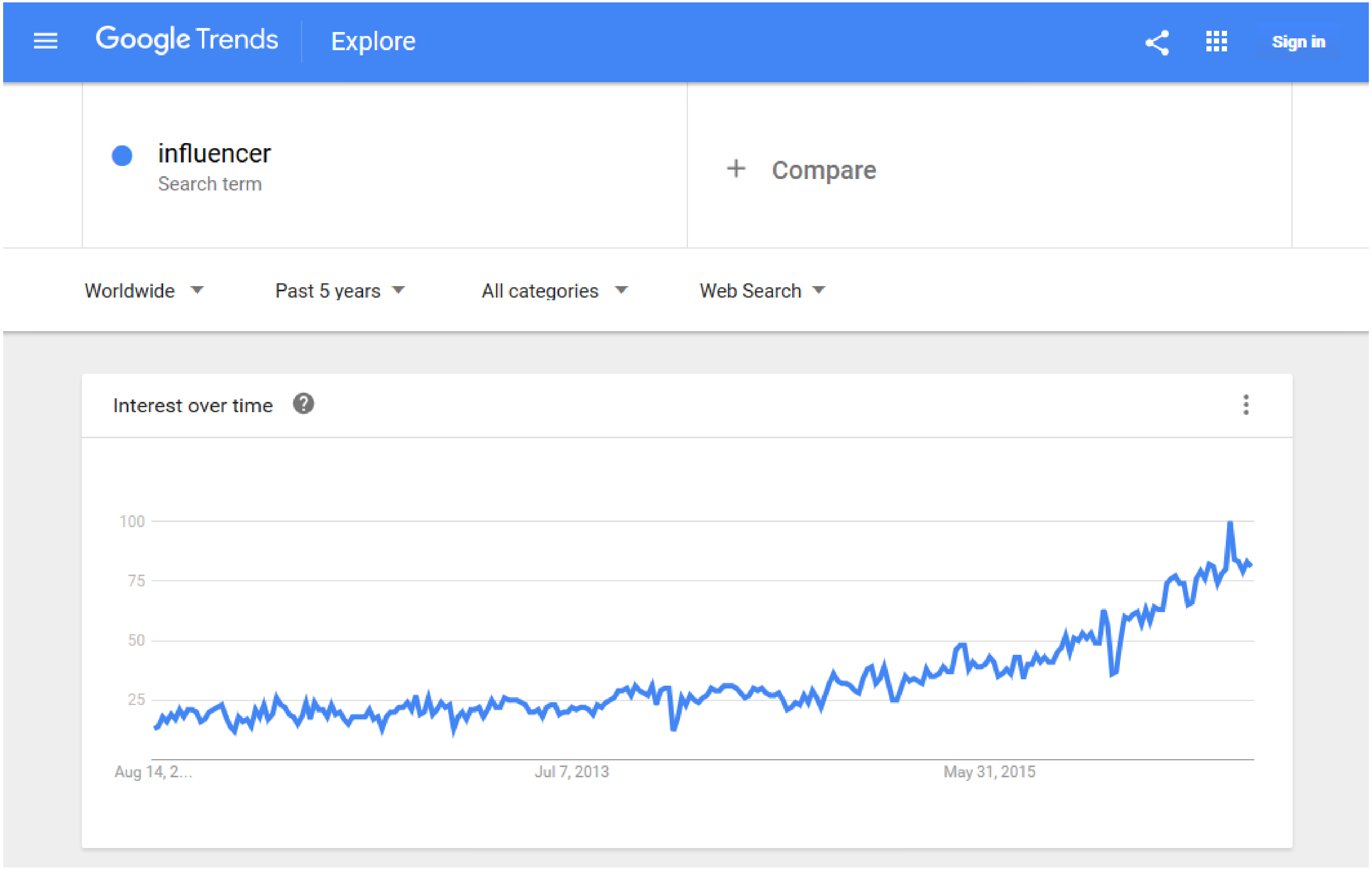
●: weak node





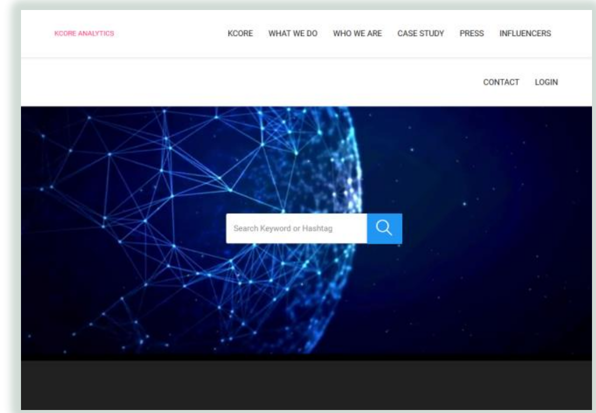
$$\mathrm{CI}_\ell(i) = (k_i - 1) \sum_{j \in \partial \mathrm{Ball}(i,\ell)} (k_j - 1)$$

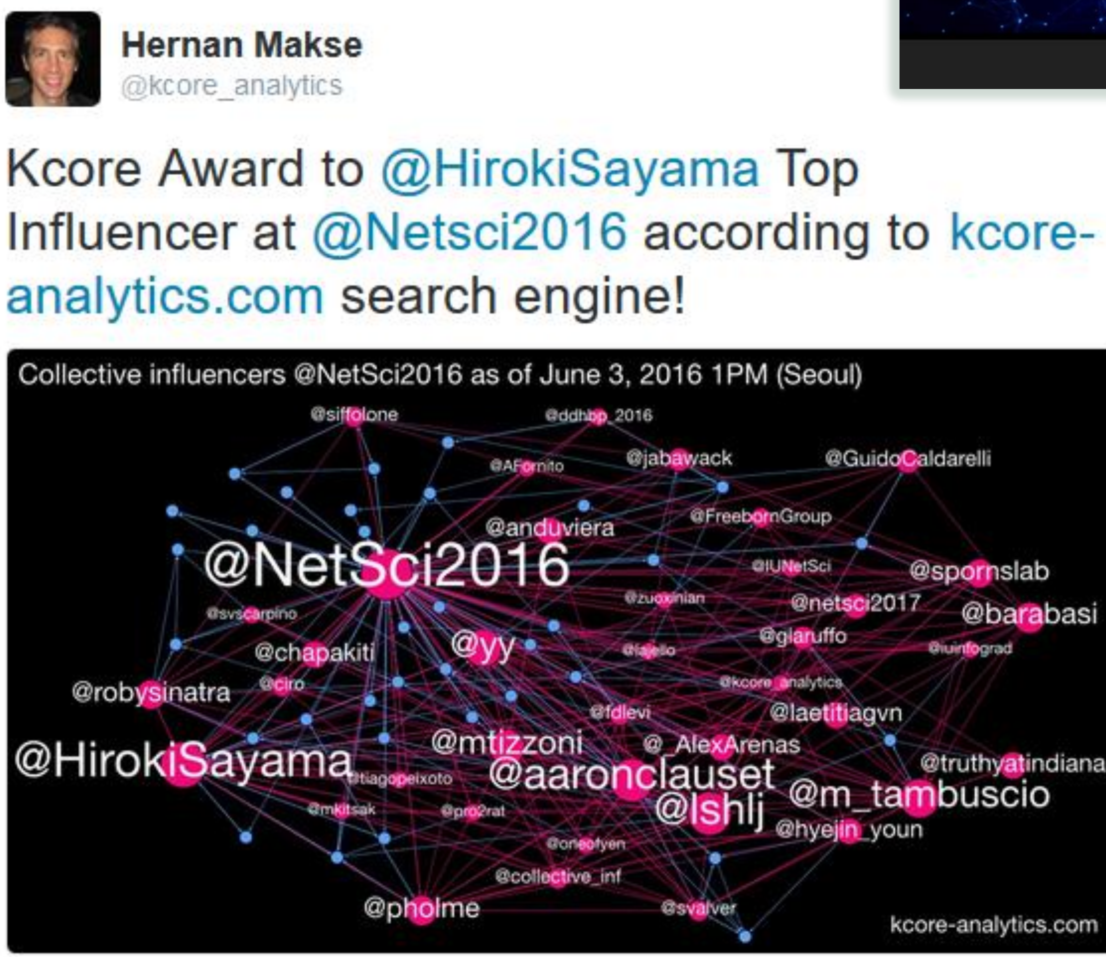
"Influencer" business growing



Kcore Analytics

- http://www.kcore-analytics.com/

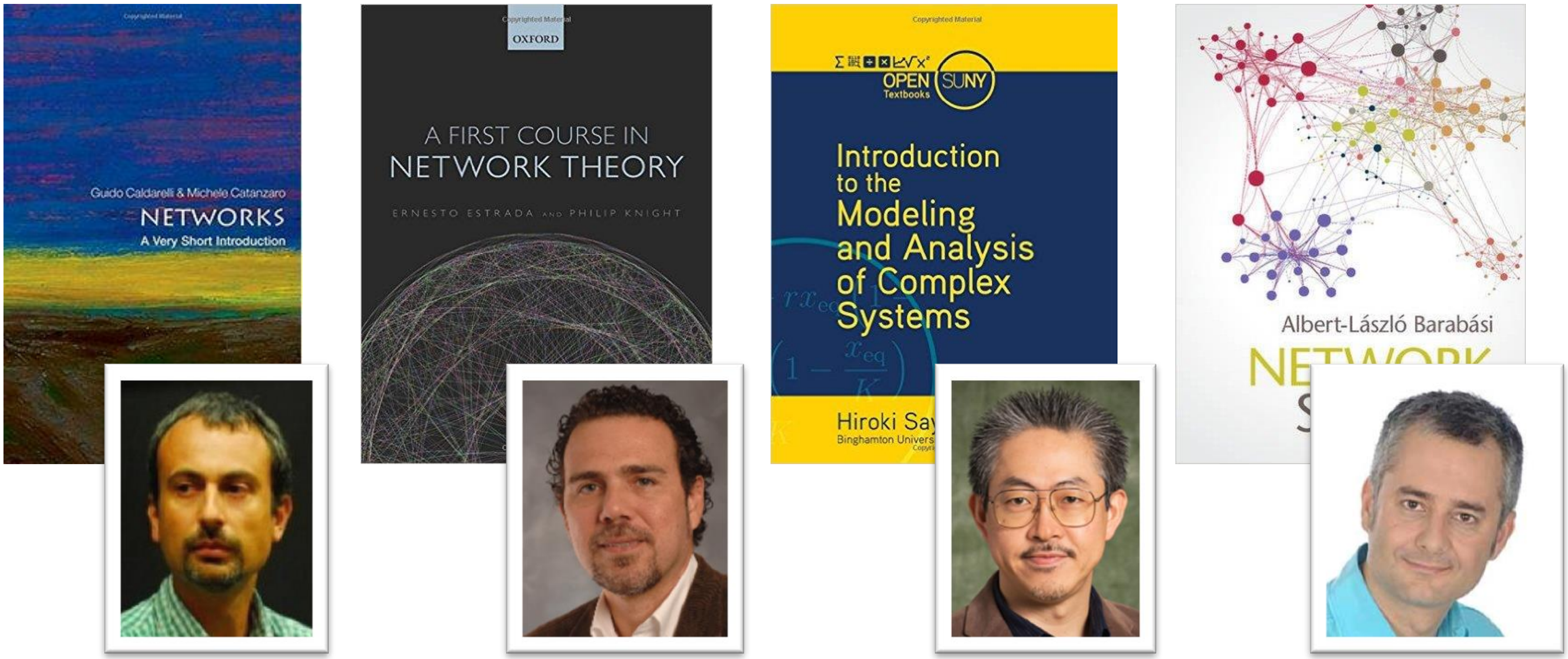




7. NETWORK SCIENCE AND EDUCATION

Network science textbooks

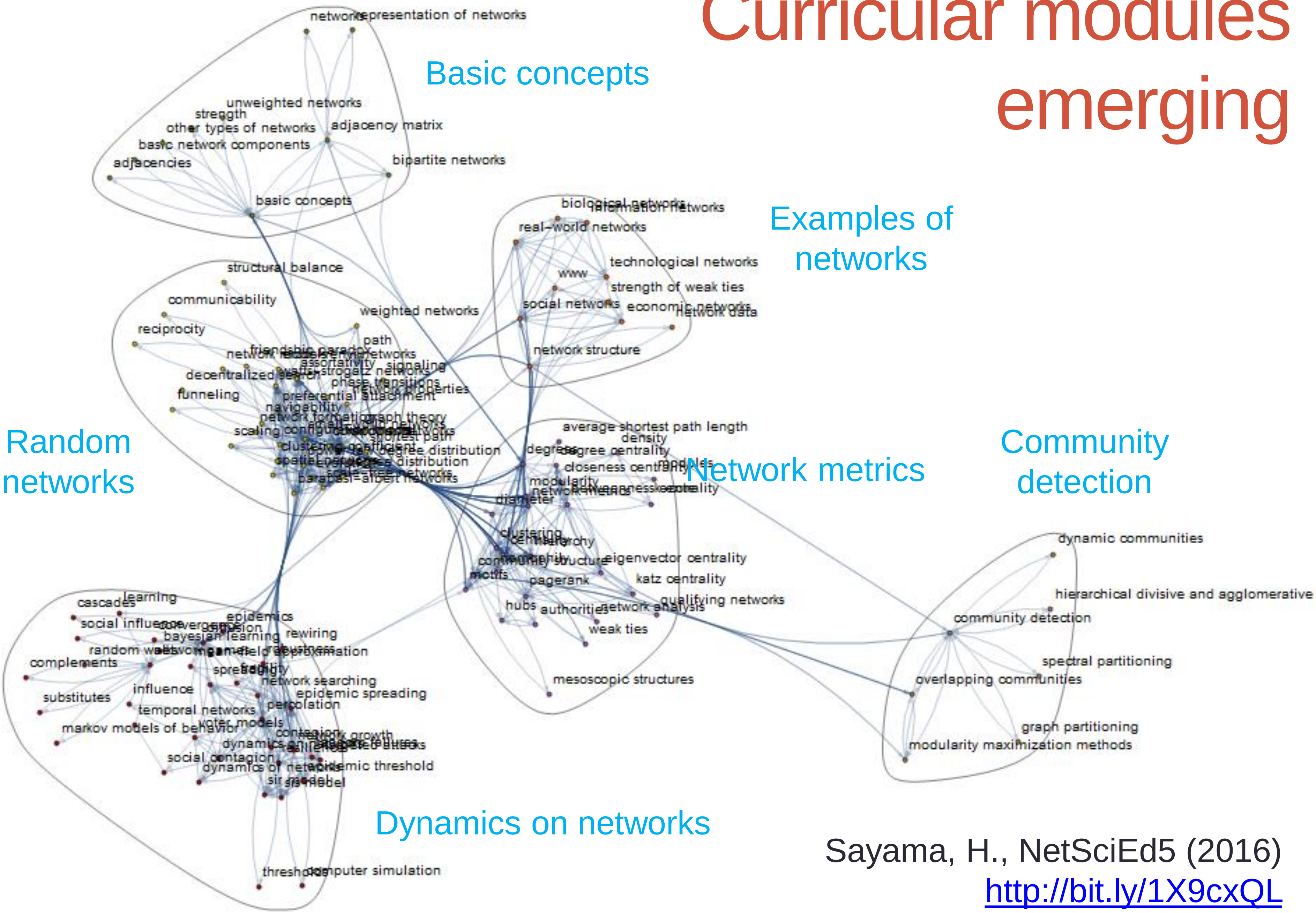
- Caldarelli & Catanzaro (2012); Estrada (2015); Sayama (2015); Barabasi (2016); etc…



Network science courses

1. http://barabasi.com/book/network-science
2. http://bingweb.binghamton.edu/~sayama/SSIE641/
3. http://faculty.nps.edu/rgera/MA4404.html
4. http://hornacek.coa.edu/dave/Teaching/Networks.11/
5. http://mae.engr.ucdavis.edu/dsouza/mae298
6. http://networksatharvard.com/
7. http://ocw.mit.edu/courses/economics/14-15j-networks-fall-2009/
8. http://ocw.mit.edu/courses/media-arts-and-sciences/mas-961-networks-complexity-and-its-applications-spring-2011/
9. http://perso.ens-lyon.fr/marton.karsai/Marton_Karsai/complexnet.html
10. https://cns.ceu.edu/node/31544
11. https://cns.ceu.edu/node/31545
12. https://cns.ceu.edu/node/38501
13. https://courses.cit.cornell.edu/info2040_2015fa/
14. https://iu.instructure.com/courses/1491418/assignments/syllabus
15. https://sites.google.com/a/yale.edu/462-562-graphs-and-networks/
16. https://www0.maths.ox.ac.uk/courses/course/28833/synopsis
17. https://www.coursera.org/course/sna
18. https://www.sg.ethz.ch/media/medialibrary/2014/11/syllabus-cn15.pdf
19. http://tuvalu.santafe.edu/~aaronc/courses/5352/
20. http://web.stanford.edu/class/cs224w/handouts.html
21. http://web.stanford.edu/~jugander/mse334/
22. http://www2.warwick.ac.uk/fac/cross_fac/complexity/study/msc_and_phd/co901/
23. http://www.ait-budapest.com/structure-and-dynamics-of-complex-networks
24. http://www.cabdyn.ox.ac.uk/Network%20Courses/SNA_Handbook%202013-14.pdf
25. http://www.cc.gatech.edu/~dovrolis/Courses/NetSci/
26. http://www.columbia.edu/itc/sociology/watts/w3233/
27. http://www.cse.unr.edu/~mgunes/cs765/
28. http://www-personal.umich.edu/~mejn/courses/2015/cscs535/index.html
29. http://www.stanford.edu/~jacksonm/291syllabus.pdf
30. http://www.uvm.edu/~pdodds/teaching/courses/2016-01UVM-303/

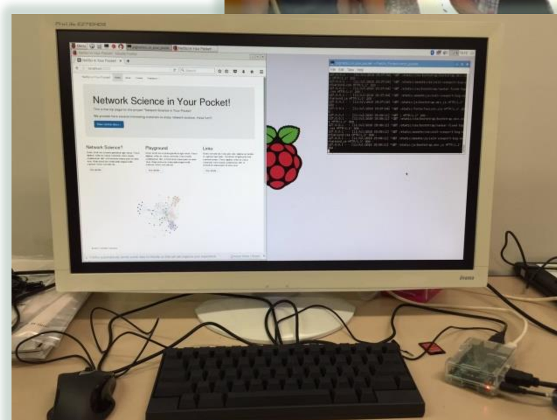
Curricular modules emerging



Sayama, H., NetSciEd5 (2016)
http://bit.ly/1X9cxQL

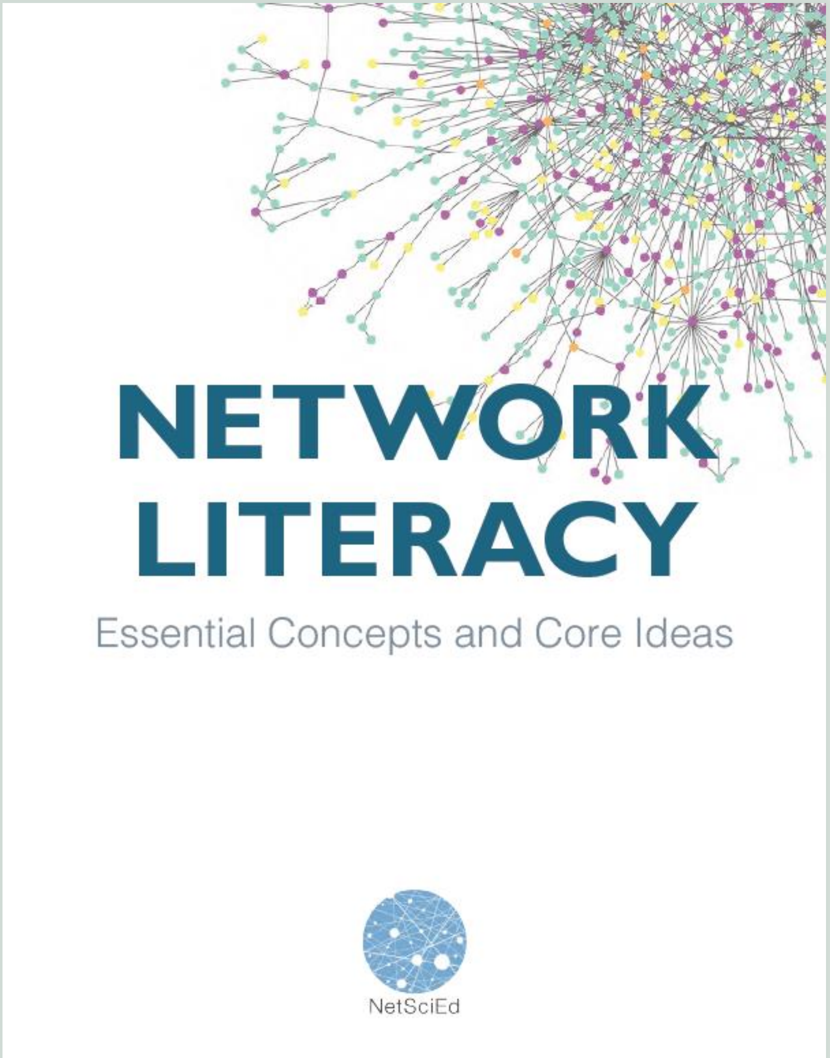
Educational outreach

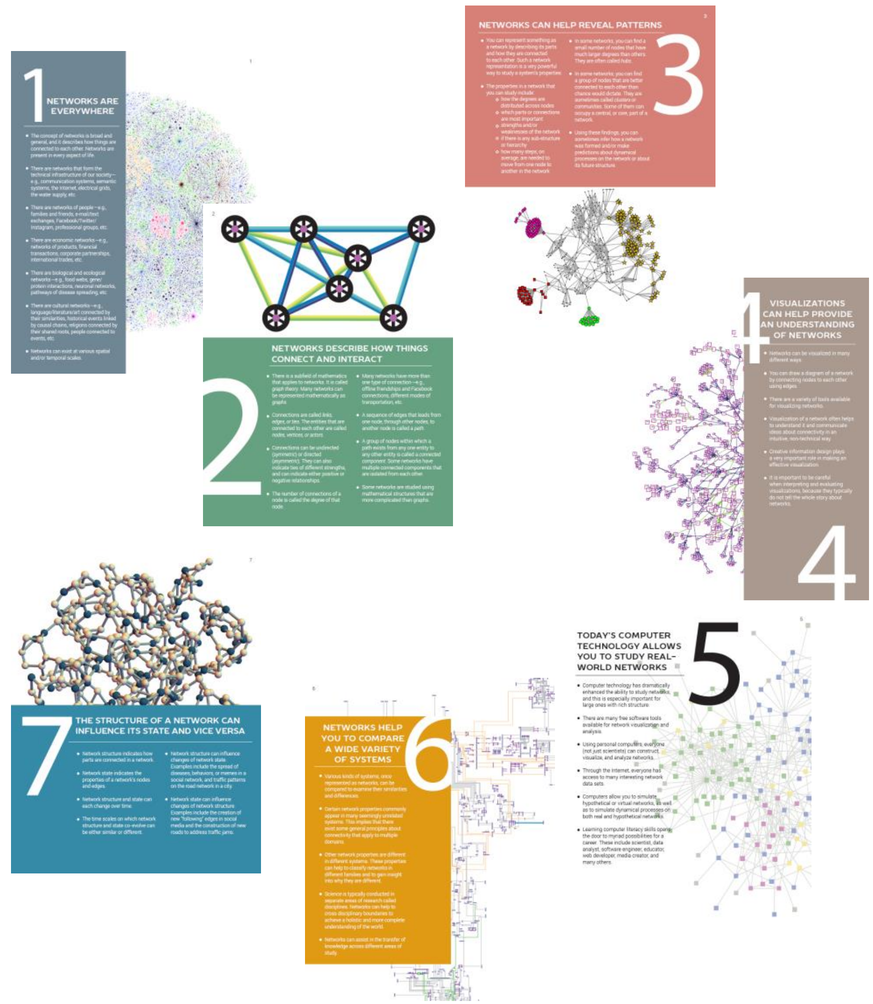
- University of Oxford
  - http://youtu.be/9dcdjcyA-8E
    http://arxiv.org/abs/1302.6567
- Universidad Carlos III de Madrid
  - http://arxiv.org/abs/1403.3618
- NetSci High
  - http://tinyurl.com/netscihigh
  - http://arxiv.org/abs/1412.3125
- NetSciEd
  - http://tinyurl.com/netscied
- NetSci in Your Pocket
  - By Toshi Tanizawa



"Network Literacy: Essential Concepts and Core Ideas"

Sayama, H. et al. (2015) *J. Complex Netw. cnv028.*

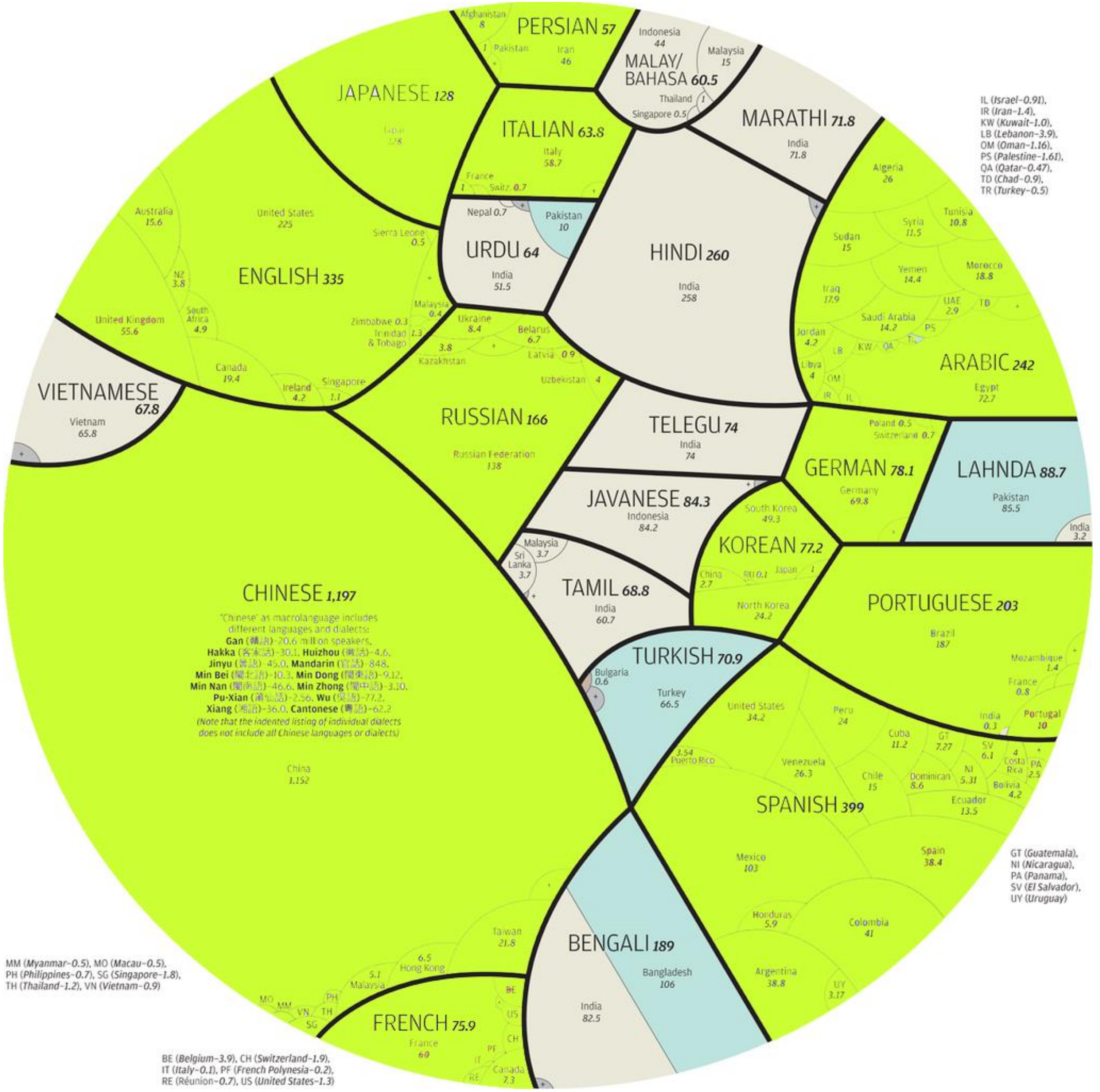




http://tinyurl.com/networkliteracy

International spread

- Now available in *seventeen* different languages!
  - All translated by volunteers



CONCLUDING REMARKS

Seeing a bunch of cool papers, now what?

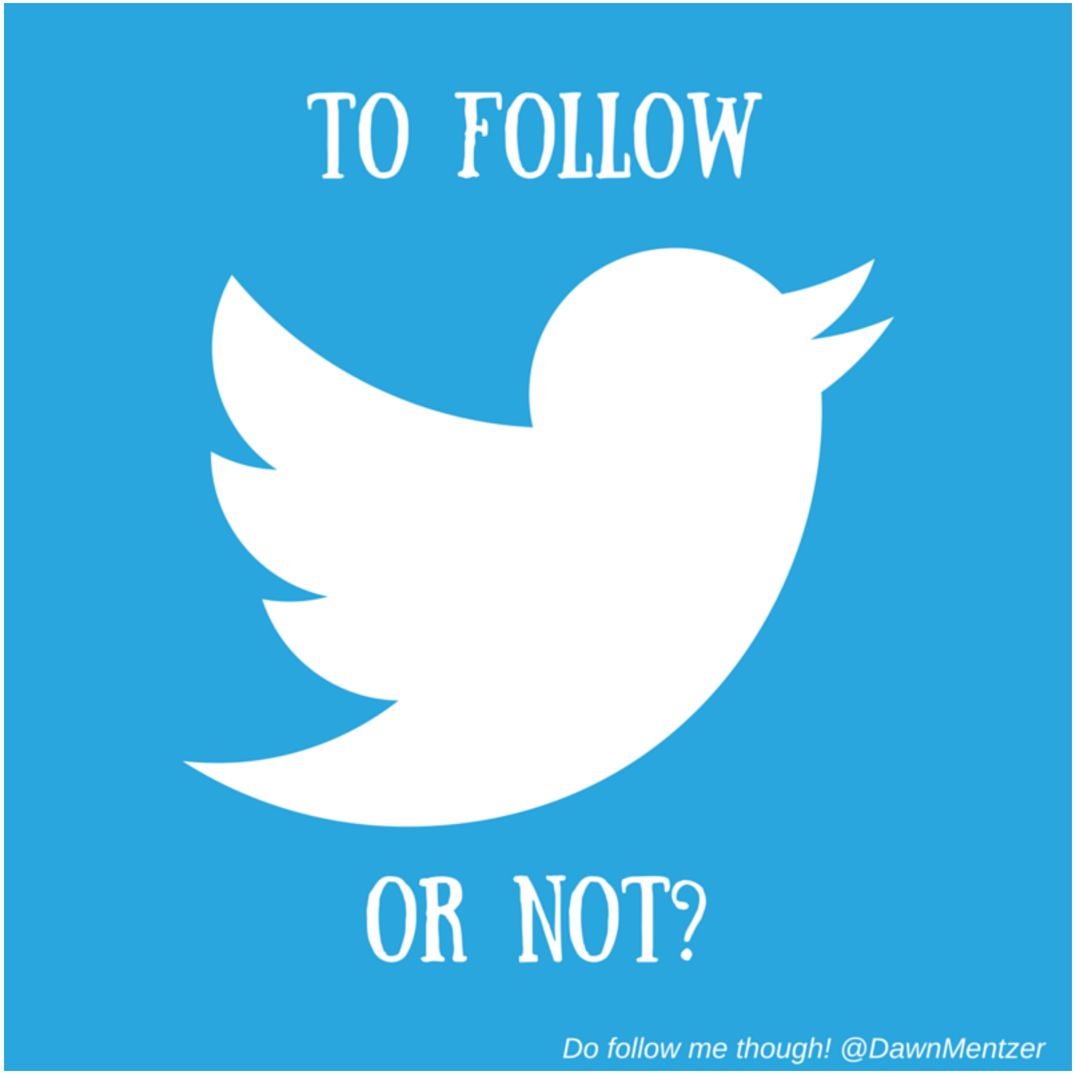
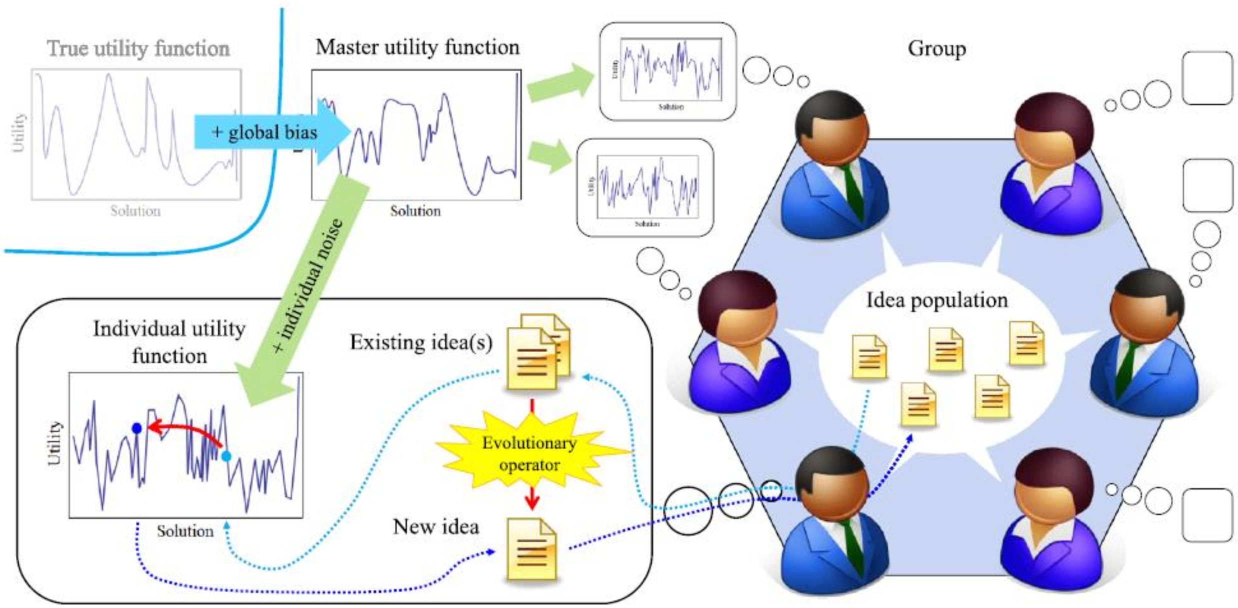
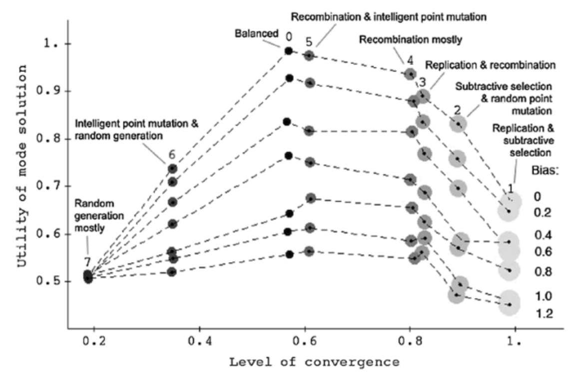


Image by @DawnMentzer

Exploration, exploitation, scientific progress

- Trends are the results of researchers' collective attention
- Following trends → exploitation (i.e., local search)





Sayama, H., & Dionne, S. D. (2015) *Artificial life 21*:379-393.

- **Scientific progress relies on healthy balance between exploration and exploitation**

Concluding haiku

A trend is something

That you should create yourself,

Not just to follow

https://youtu.be/xbNJq90t0Wk

Thank You

And special thanks to my collaborators, mentors, students & funding agencies

@hirokisayama