

RECENT TRENDS IN NETWORK SCIENCE

CoCo Seminar

September 7th, 2016

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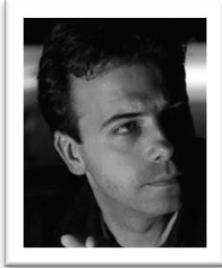
sayama@binghamton.edu

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?



Image: tech.co

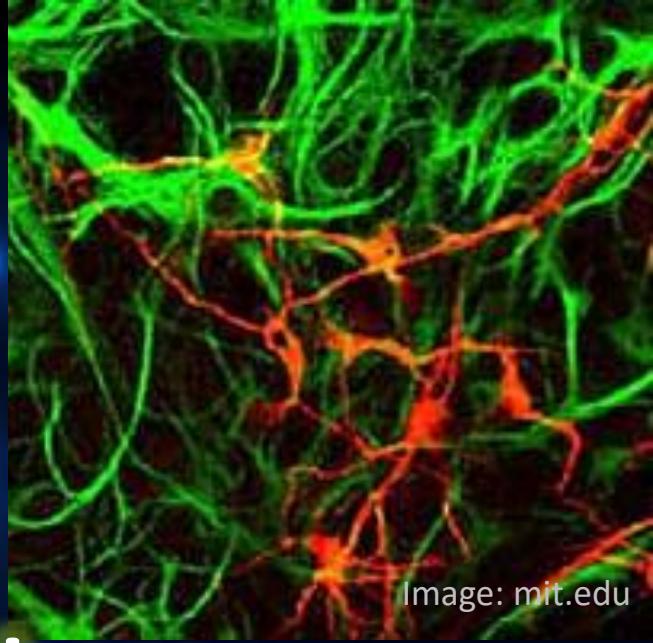


Image: mit.edu

network 6/2011 STAR ALLIANCE Networks everywhere

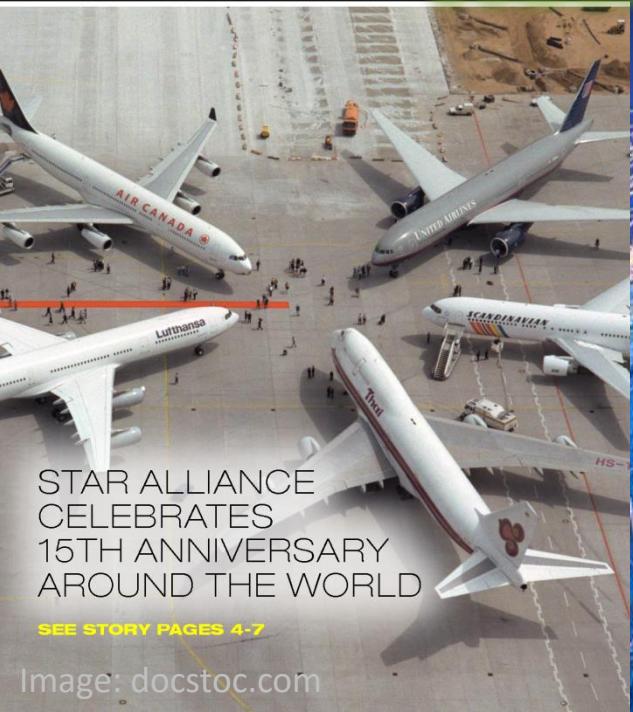


Image: docstoc.com



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

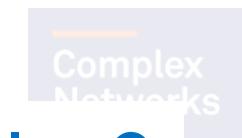
- Conference on Complex Systems

etc...



Seeing trends in conference topics

- International School and Conference on Network Science
 - Summer main conference (NetSci)
 - 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”
- A **What do we see in their session/talk titles?**
- Conference on Complex Systems



etc...



NetSci

The figure is a word cloud visualization representing concepts in network science. The words are arranged in a grid and color-coded by category. The categories include:

- Information**: directed, competition, control, method, diffusion, mobility, quantify, online, theory, risk, world, effect, synchronization.
- Detection**: time, influence, extreme, face, detection, percolation, multiplex, spread, analysis, community, complex, dynamic, transition, temporal, evolution, contagion, epidemic, communication, social, structure, model.
- Percolation**: behavior, spectral, organization, economic, simulation, role, scale, impact, random, pattern, layer, measure, human, disease, graph, phase, group, cascade, local, growth, prediction.
- Analysis**: classification, NetSci, correlation, failure.
- Spread**: small, self, trade, source, structural, algorithm, web, game, power, large, gene, real, optimal, process, computation.
- Community**: measure, human, disease, graph, phase, group, cascade, local, growth, prediction.
- Complex**: process, computation, transition, temporal, evolution, contagion, epidemic, communication, social, structure, model.
- Dynamic**: graph, phase, group, cascade, local, growth, prediction.
- Transition**: multilayer, topology, growth, prediction.
- Temporal**: multilayer, topology, growth, prediction.
- Evolution**: topology, growth, prediction.
- Contagion**: robustness, case, contact, interaction, driven, spatial, node, free.
- Epidemic**: robustness, case, contact, interaction, driven, spatial, node, free.
- Communication**: robustness, case, contact, interaction, driven, spatial, node, free.
- Social**: robustness, case, contact, interaction, driven, spatial, node, free.
- Structure**: robustness, case, contact, interaction, driven, spatial, node, free.
- Model**: robustness, case, contact, interaction, driven, spatial, node, free.



NetSci-X

find behavior individual global spatial

structured different structural identify

challenge mobility distribution

media epidemic detection property

epidemic heterogeneous event

massive control theory order

word evolution application million

local structure hierarchy cascade world

human algorithm number

idea algorithm impact

text data mining

fold temporal dynamic process role

tie large mapping community graph multiple user

link multilayer centrality driver

predict actually complex political

case node knowledge spread urban

indices relationship system friend

citation environment agent method approach state

environment pattern scale

agent routing between model language

formation random

time level opinion multiplex

interaction group hierarchical mobile simulation collective

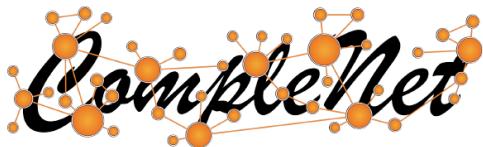
infection

IC²S²

IC2S2
cooperation contact
crowd process collaboration measure individual machine
financial detection market emergence formation
evidence prediction
user data between problem friend media political
comparison public impact learning
space impact
crime digital model graph
share online social analysis
big opinion dynamic temporal
team under learning communication agent
capital choice experimental community behavior
event web media influence evolution
inequality pattern information innovation
success consumption human relationship game peer
complex scale experiment heterogeneous activity
system spread phenomenon facebook
diffusion strategy property mobile method homophily

Sunbelt

Sunbelt
adolescent international market management
between problem friend media political online
formation information analyze personal socio
partner
russia identity migrant
learning
multilevel graph
share theory
ego
actor
global
big
agent
peer activity
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family
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space
progress
status
behavior performance Case
team centrality collaboration evidence
trade strength innovation semantic drug
leader mixed mode decision context alcohol

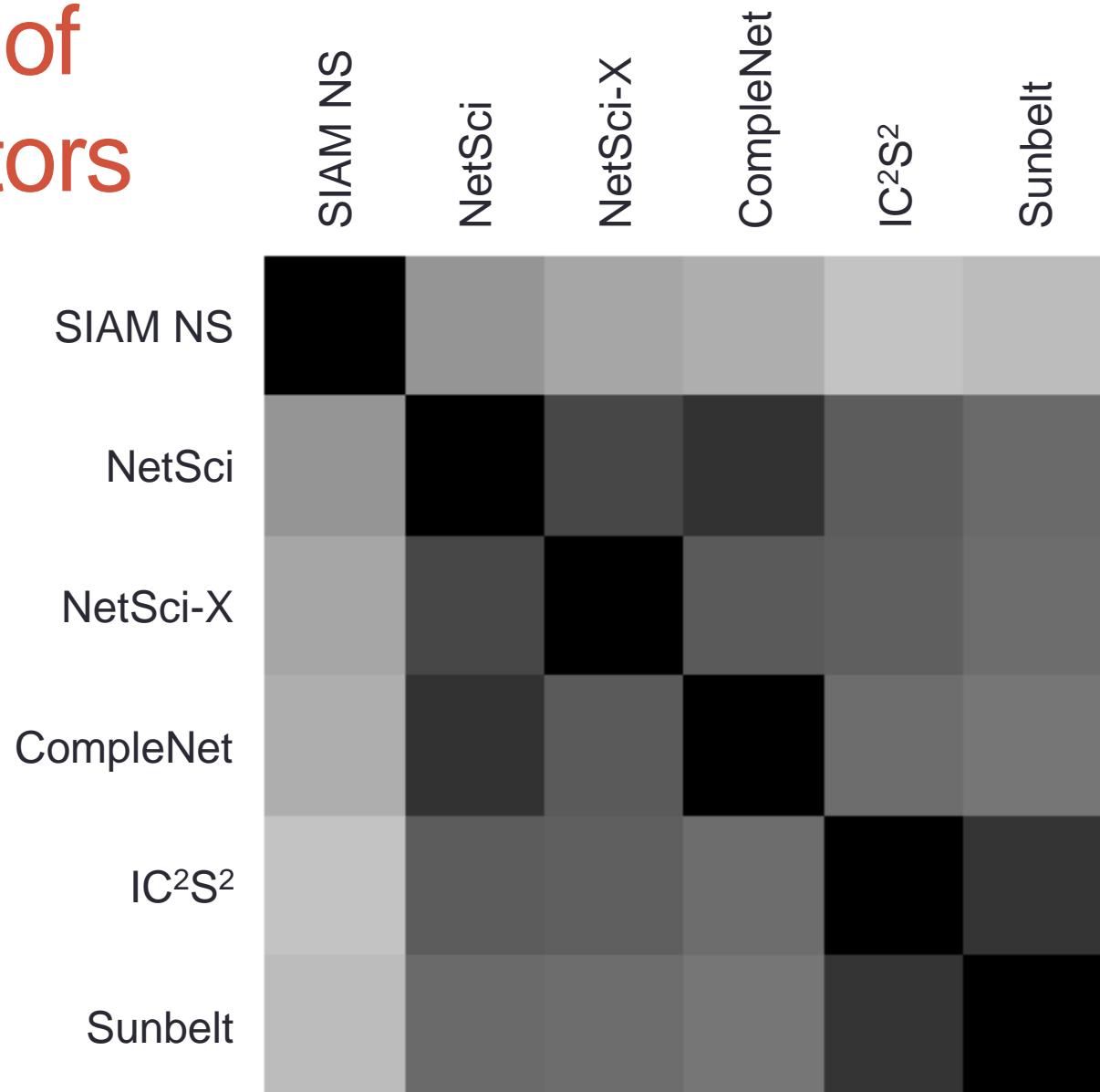


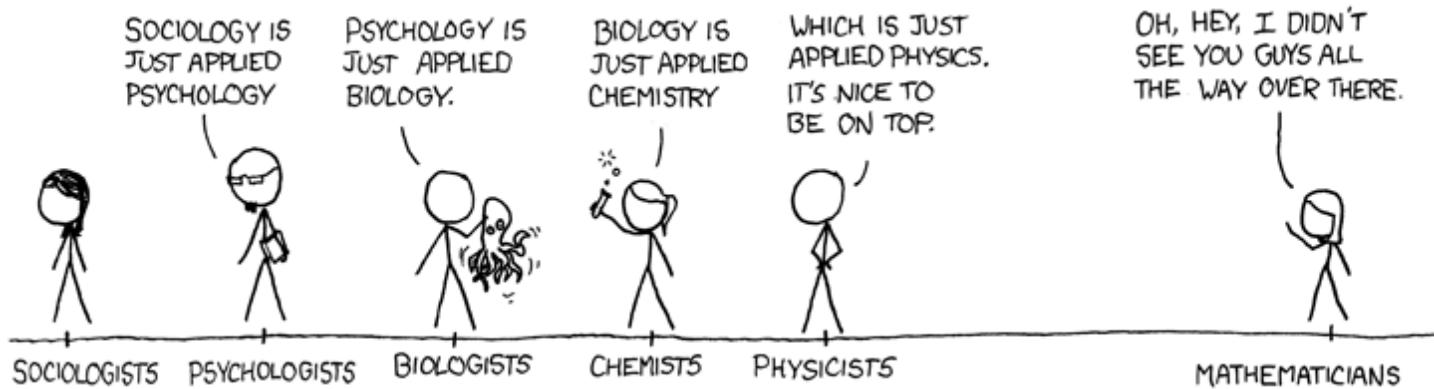
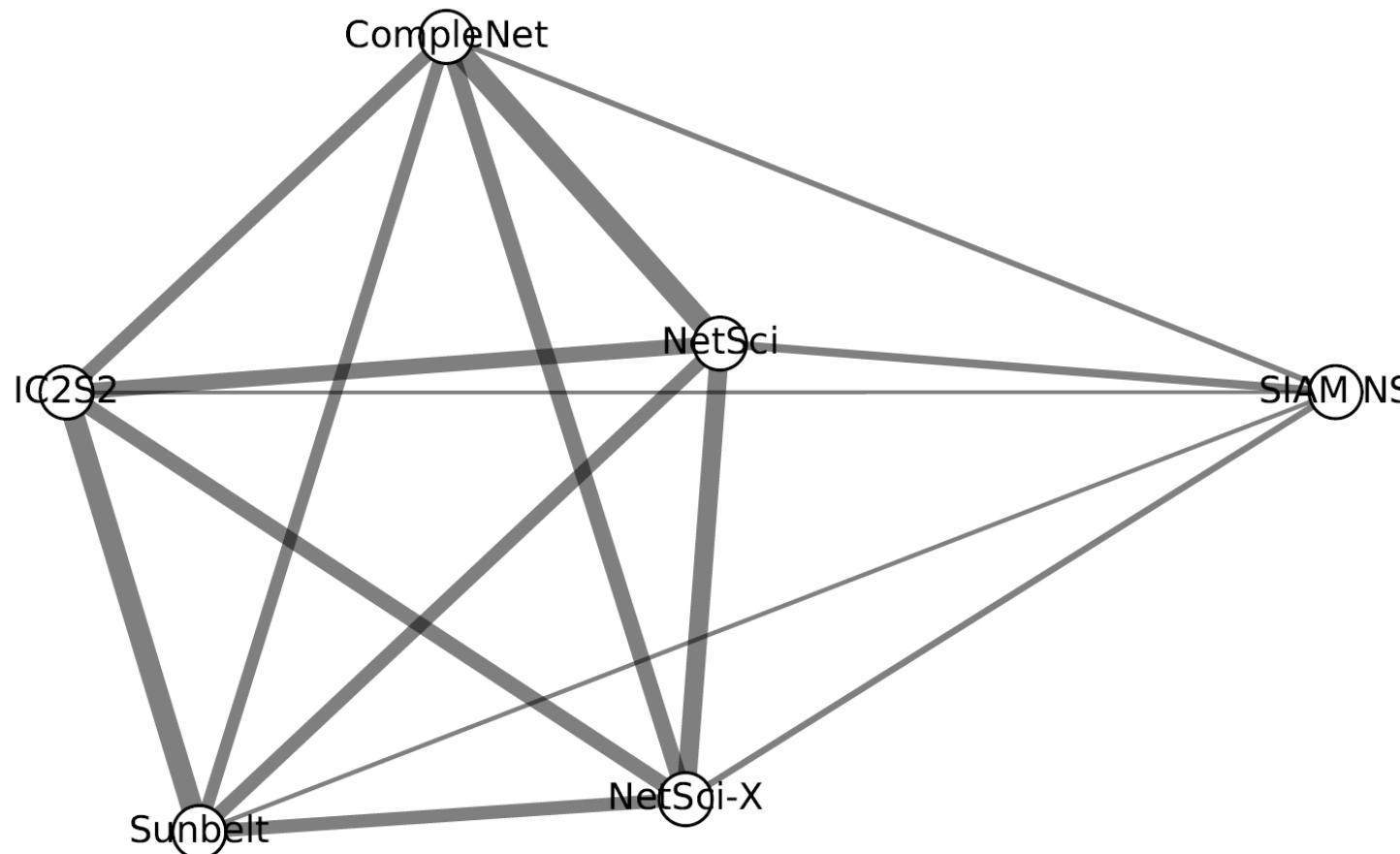
The word cloud illustrates the following categories and their associated terms:

- detection**: robustness, intelligent, connectivity, cascade, narratives, markovian, betweenness, hugos, application, optimization.
- communication**: urban world, collaborative, economic, metric feature.
- social**: organizational, mesoscopic, distributed.
- spread**: synchronization.
- model**: bipartite, problem, random, correlation, function activity.
- dynamic**: temporal.
- analysis**: human, epidemic, theory, risk link peer delay.
- complex**: le, mailing, process, product, finance, mobility, role, making ground.
- effect**: community, spatial, time, centrality, system, global, city, data web.
- community**: core, spatial.
- multiplex**: node, high, graph, algorithm, impact, evolution.
- influence**: degree, large, cooperation, clustering.
- pattern**: heterogeneous, layer modular.
- information**: information, searching.
- evolve**: diffusion, media innovation, interconnected.
- structure**: decision, efficient, hidden online failure, attachment, between.

SIAM Workshop on *Network Science*

Similarity of word vectors





2015

2016

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

SocioPatterns follow us on [twitter](#)

[ABOUT](#) | [GALLERY](#) | [PUBLICATIONS](#) | [NEWS](#) | [PRESS](#) | [DATA](#)

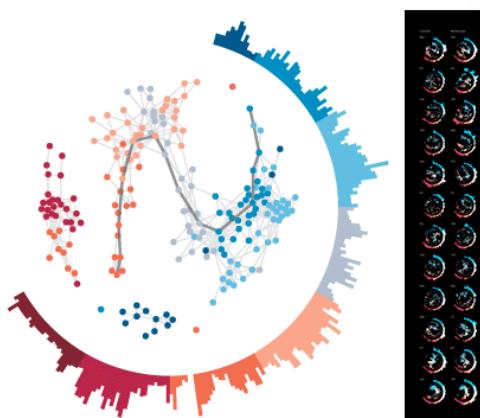
WELCOME

SocioPatterns is an interdisciplinary research collaboration formed in 2008 that adopts a data-driven methodology to study social dynamics and human activity.

Since 2008, we have collected longitudinal data on the physical contacts of individuals in numerous real-world environments, covering across several countries: schools, museums, hospitals, etc. We use this behaviour and to develop agent-based models for the transmission of infectious diseases.

We make most of the collected data freely available to the scientific community.

FEATURED: INFECTIOUS SOCIOPATTERNS



NEWS

New paper in *Nature Communications*

Index of Complex Networks

[NETWORKS](#) [ABOUT](#) [SUGGEST](#)

The Colorado Index of Complex Networks (ICON)

ICON is a comprehensive index of research-quality network data sets from all domains of network science, including social, web, information, biological, ecological, connectome, transportation, and technological networks.

Each network record in the index is annotated with and searchable or browsable by its graph properties, description, size, etc., and many records include links to multiple networks. The contents of ICON are curated by volunteer experts from Prof. Aaron Clauset's research group at the University of Colorado Boulder.

Click on the [NETWORKS tab](#) above to get started.

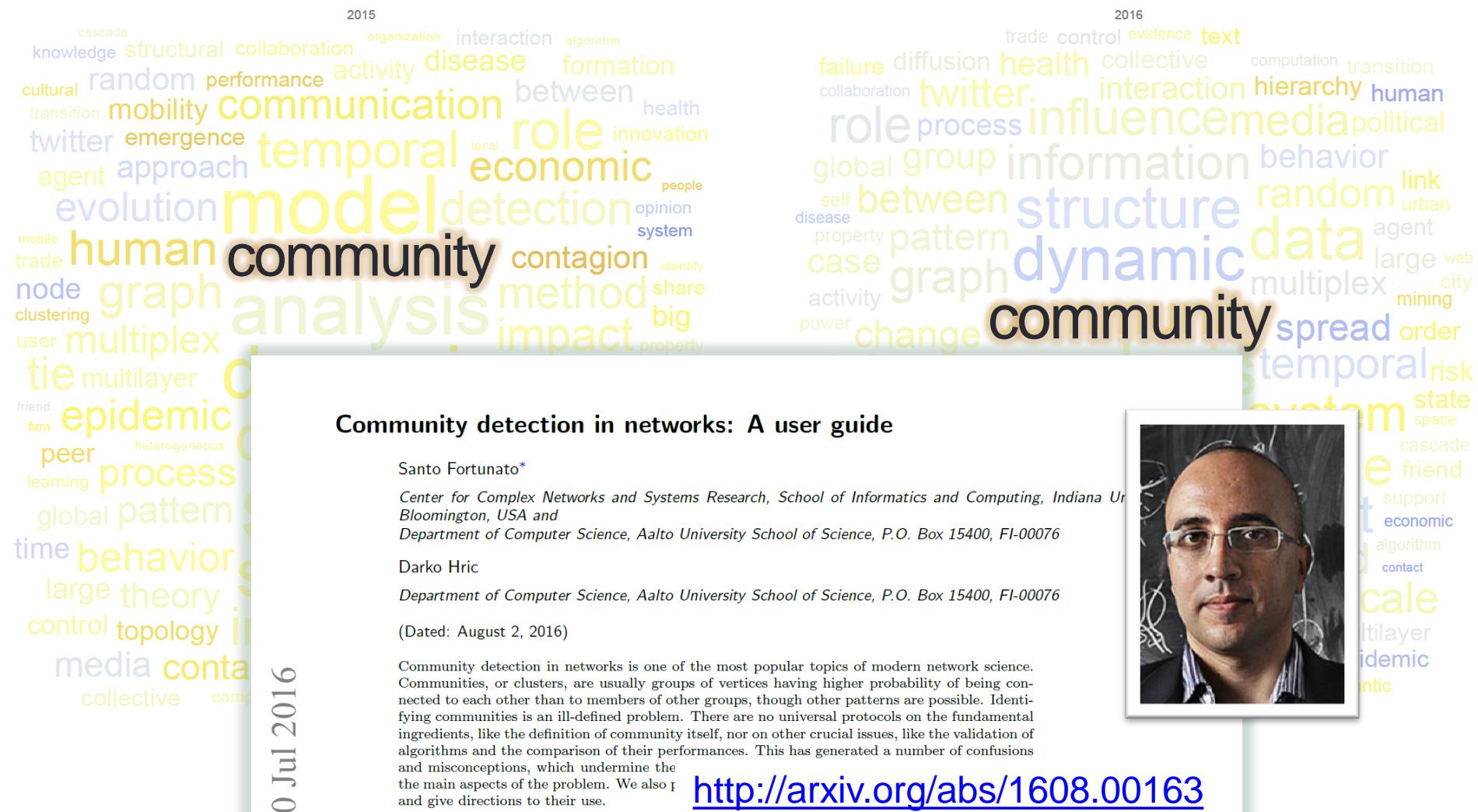
Entries found: 313 Networks found: 3146



<https://icon.colorado.edu/>

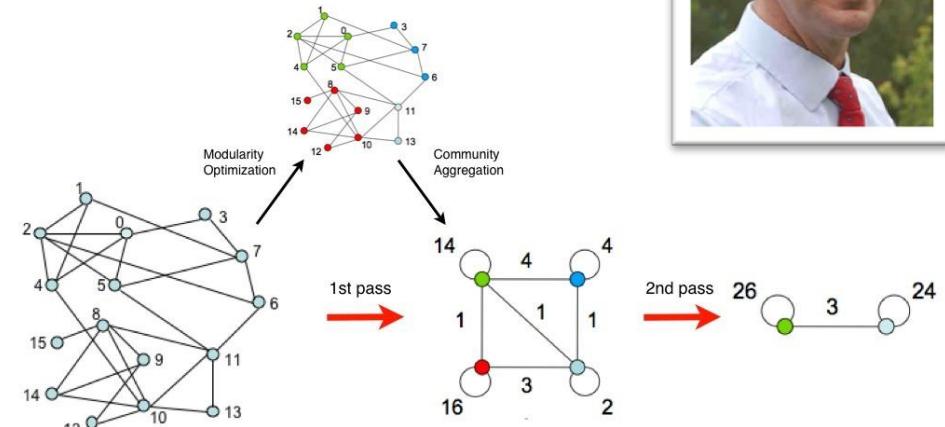
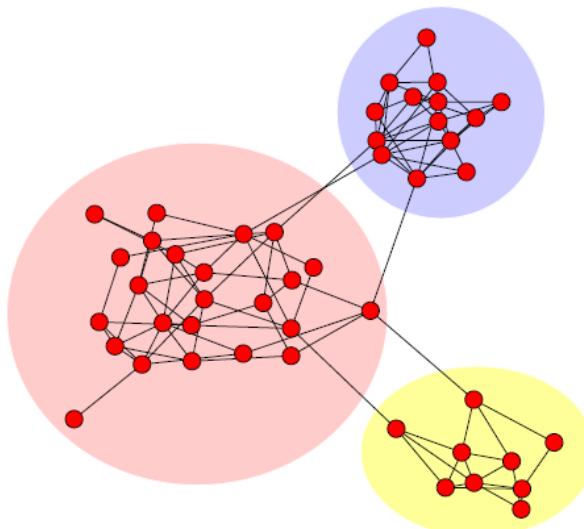
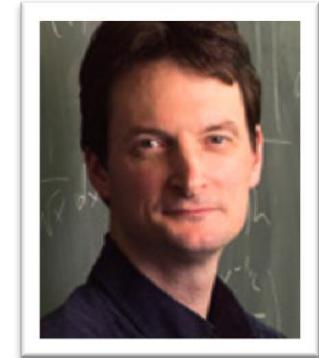
<http://sociopatterns.org/>

Community detection still a big thing



Classic approach: Modularity

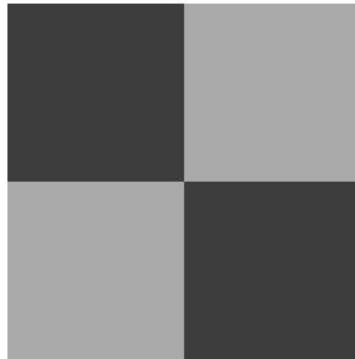
- Newman, M. E. & Girvan, M. (2004) *PRE* 69(2), 026113.
- Blondel, V. D. et al. (2008). *J. Stat. Mech.* 2008(10), P10008.



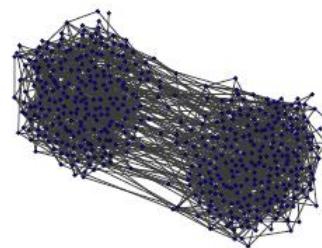
<https://sites.google.com/site/findcommunities/>

Generative approach: Stochastic block models

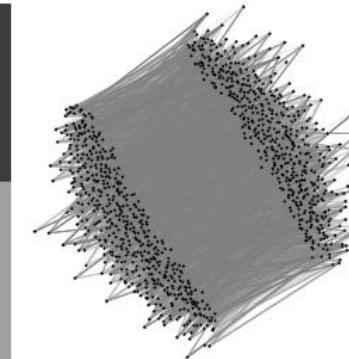
Figure from Fortunato & Hric (2016)
<http://arxiv.org/abs/1608.00163>



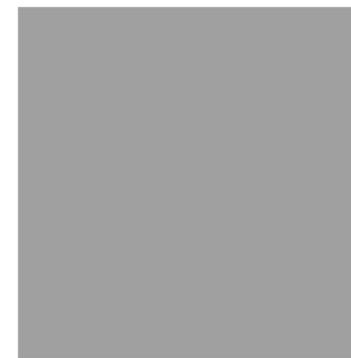
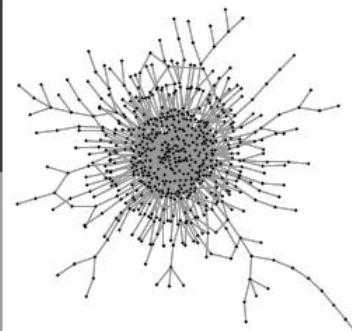
(a) Community structure



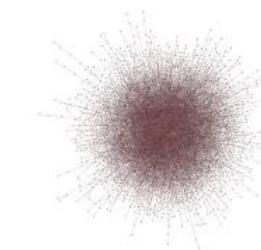
(b) Disassortative structure



(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)

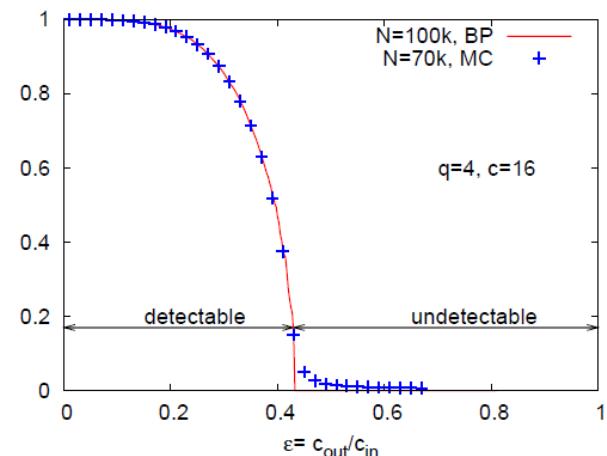
Issues with community detection

- 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



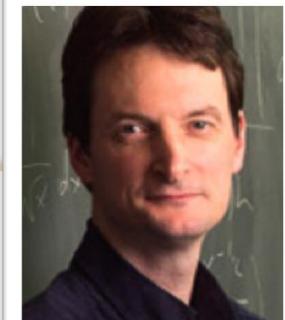
2016 © Clara Granell

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.

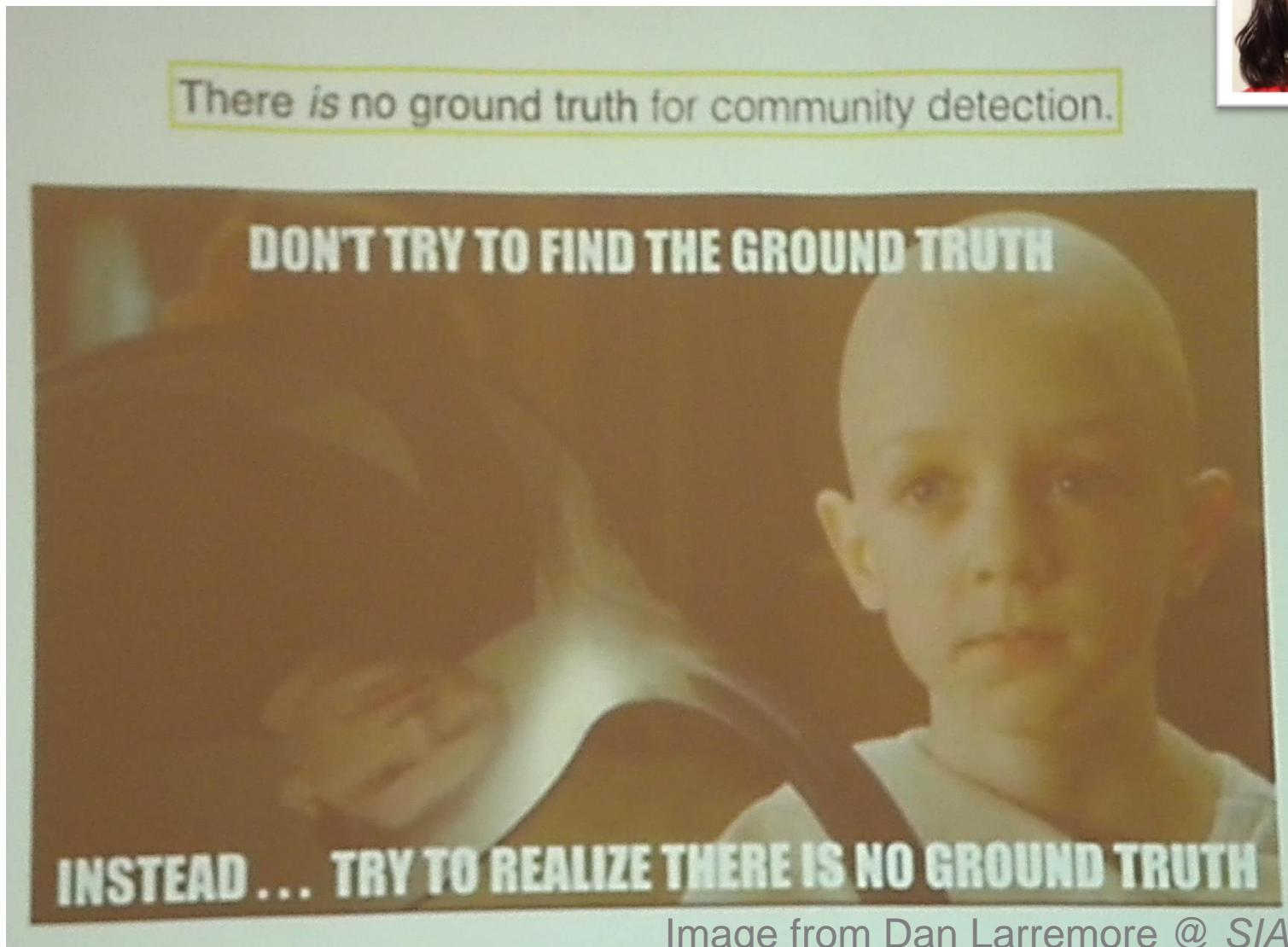
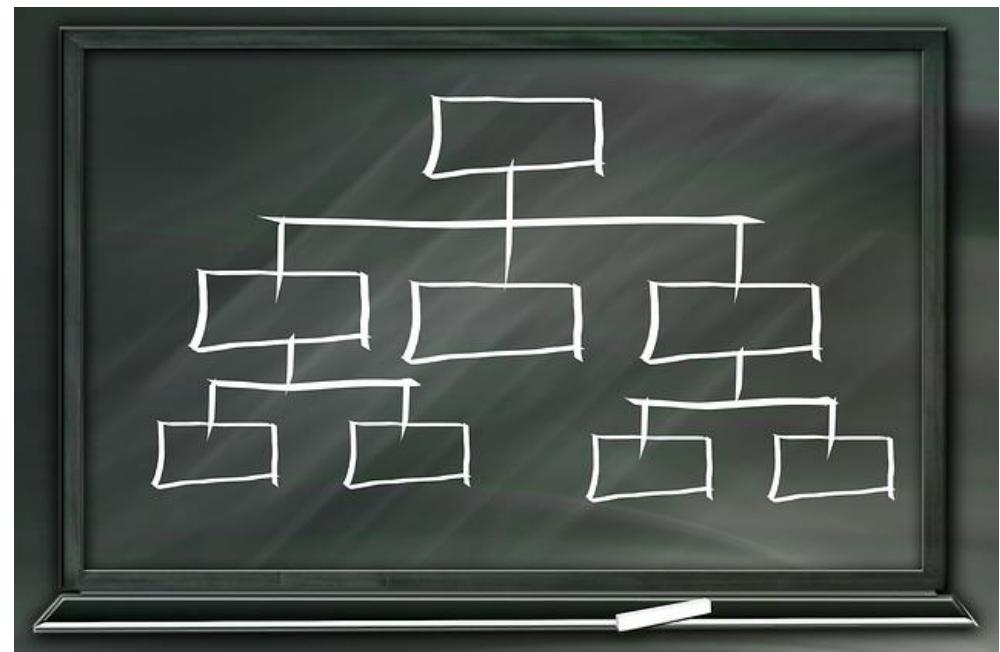


Image from Dan Larremore @ SIAM NS16

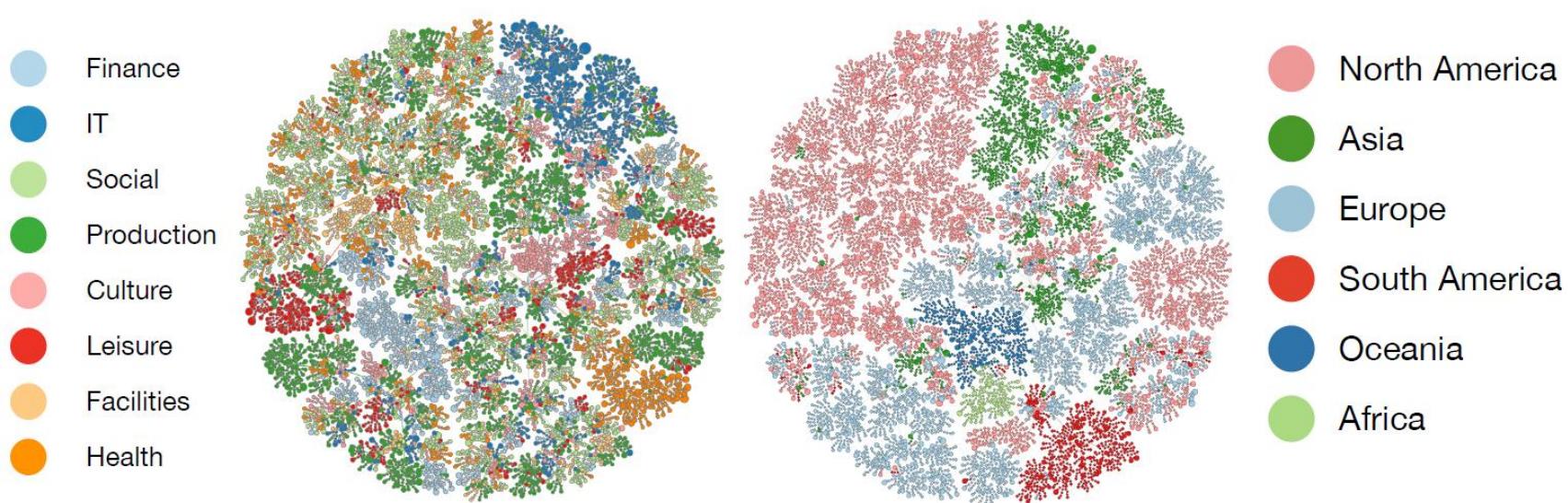
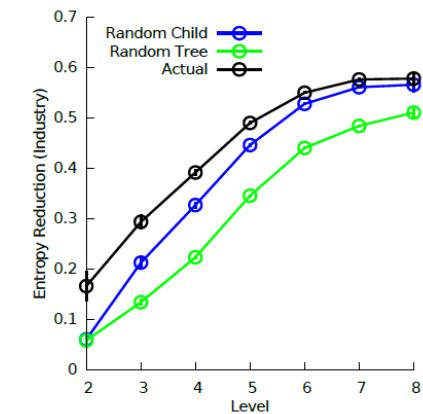
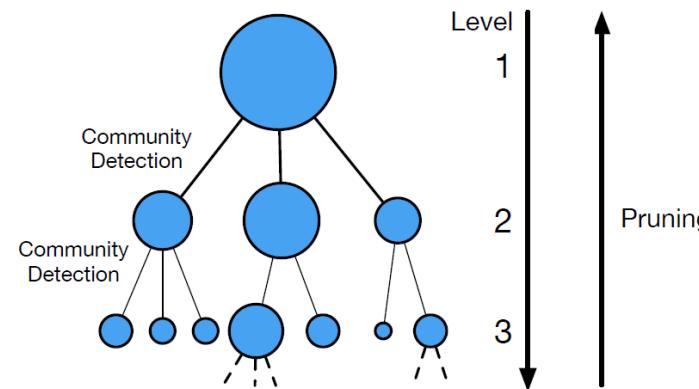
How to find multiscale patterns

- Hierarchical approach
 - Modularity methods
 - Stochastic block models



Hierarchical modularity optimization

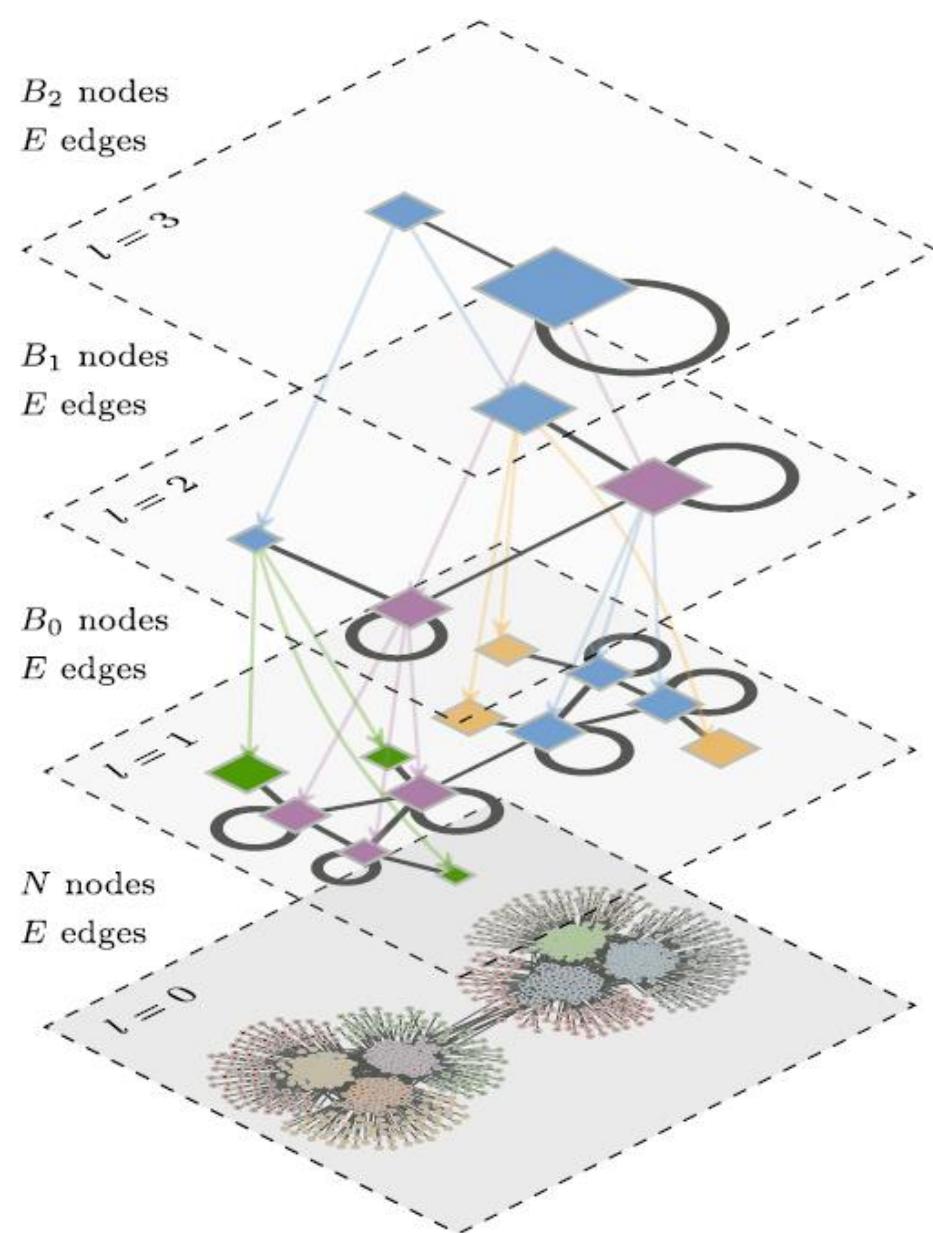
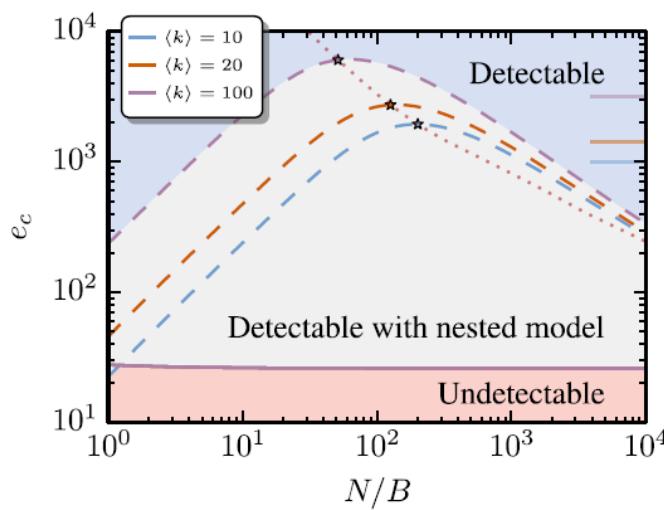
- Ahn, Y. Y., NetSci 2016 HONS (http://bit.ly/netsci_LFN)
 - LinkedIn Economic Graph Challenge



Nested stochastic block models

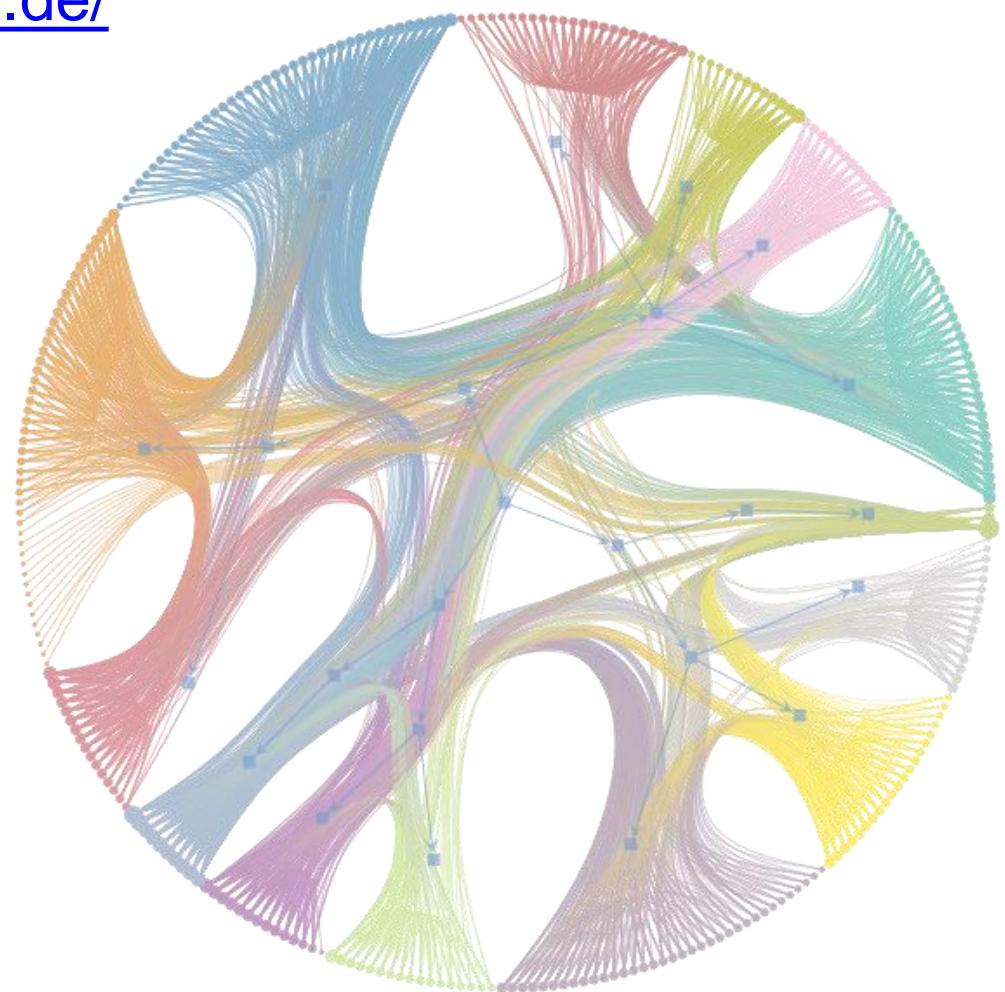
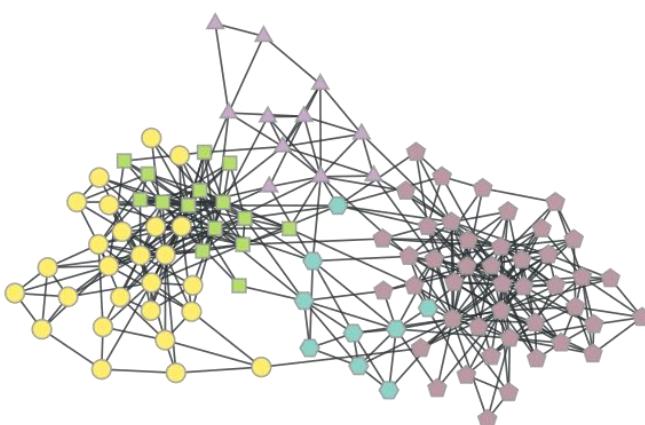


- Peixoto, T. P.
(2014) *PRX*
4(1), 011047.



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)



The screenshot shows the homepage of the FlashX website. The header features the word "FlashX" in a large, green, sans-serif font. Below the header is a navigation bar with links for "HOME", "QUICK START", "DOCS", "BLOG", and a search icon. The main visual is a large, abstract graphic of a binary matrix (0s and 1s) with a complex network of colored nodes (yellow, green, purple) forming a graph structure. A green rectangular overlay on the left side of the graphic contains the text "FlashGraph". At the bottom of the page, there is a brief description: "FlashX is a collection of big data analytics tools." To the right of this text is a green button with the text "Download Now" and a small cloud icon.

FlashX is a collection of big data analytics tools.

FlashX performs data analytics in the form of graphs and matrices and utilize solid-state drives (SSDs) to scale to large datasets in a single machine. It has three main components: FlashGraph is a general-purpose graph analysis framework that allows users to write graph algorithms to analyze billion-node graphs in a single machine; FlashMatrix is a matrix computation engine with a small set of generalized matrix operations to express varieties of data mining and machine learning algorithms; FlashR is an extended R programming framework to process datasets at a scale of terabytes in parallel. All code is released under [Apache License v2](#) and is stored at the [Github](#) repository.

Download Now

2.

HIGHER-ORDER MODELS

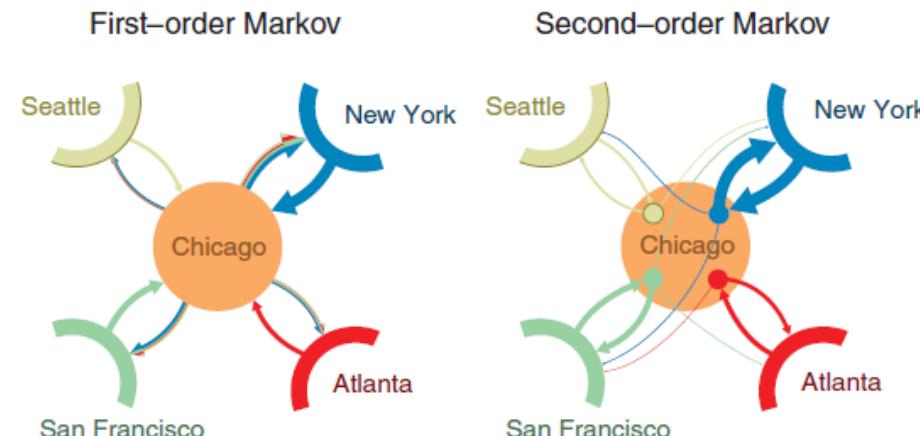
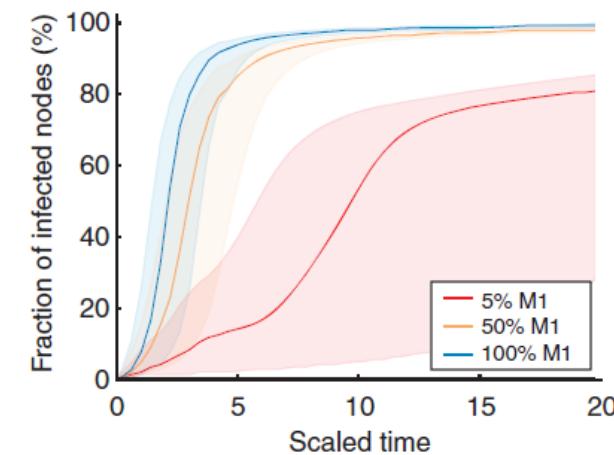
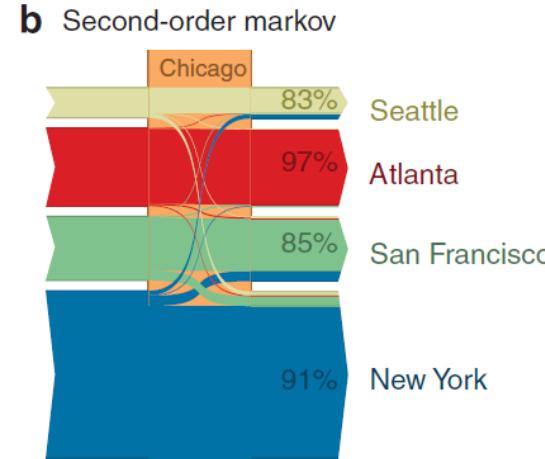
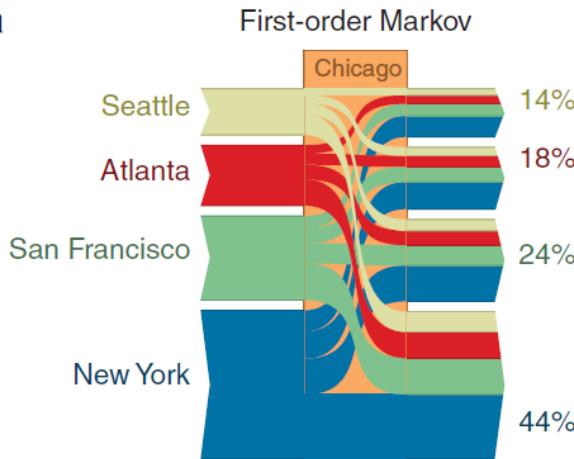
Higher-order models of networks

- 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

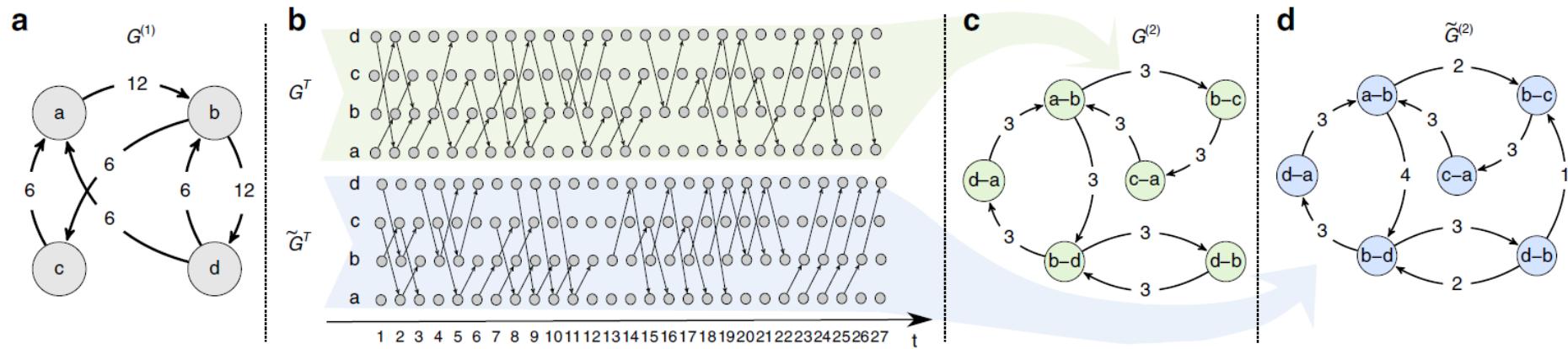
- Rosvall, M. et al. (2014) *Nature Comm.* 5, 4630.

**a**

Higher-order temporal network analysis

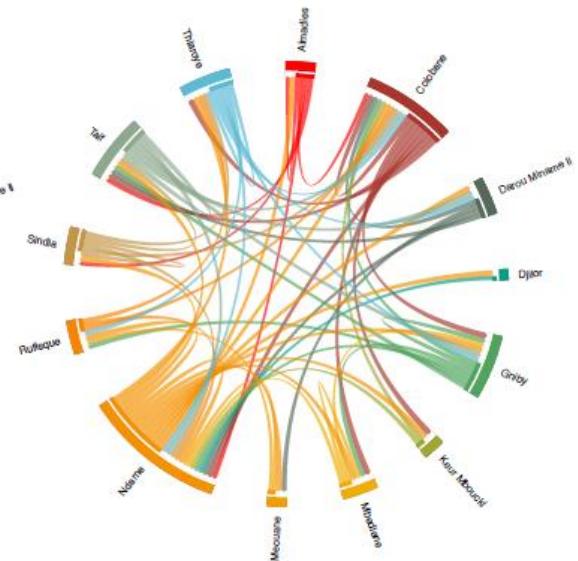
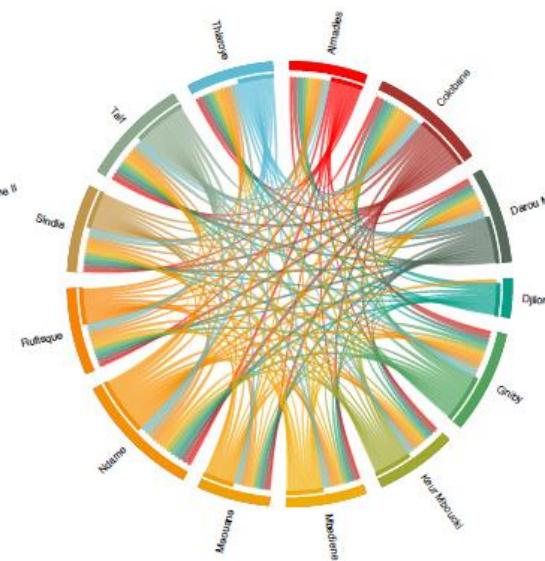
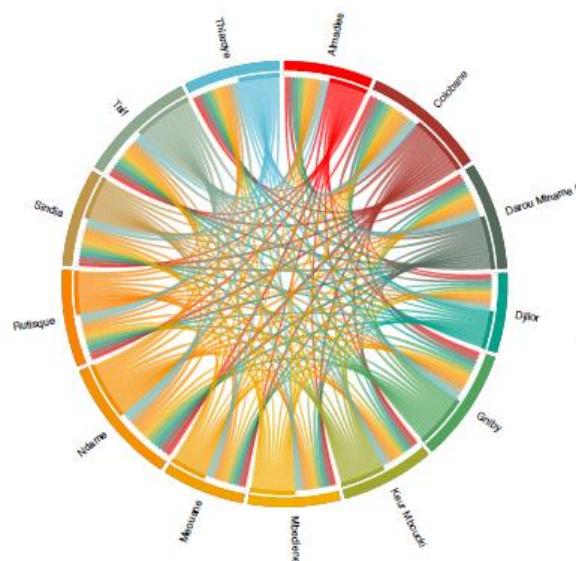
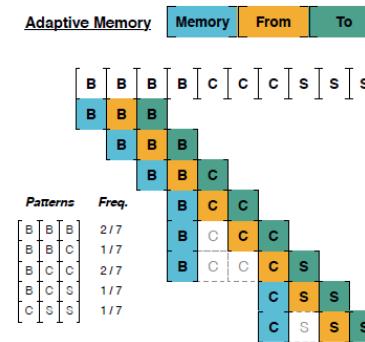
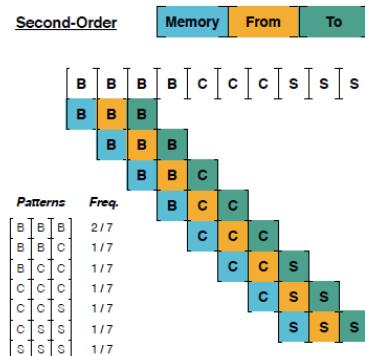
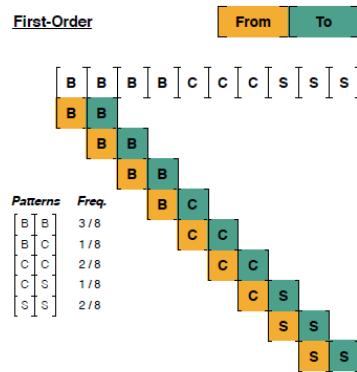


- Scholtes, I. et al. (2014) *Nature Comm.* 5, 5024.
- Scholtes, I. et al. (2016) *EPJ-B*, 89(3), 1-15.



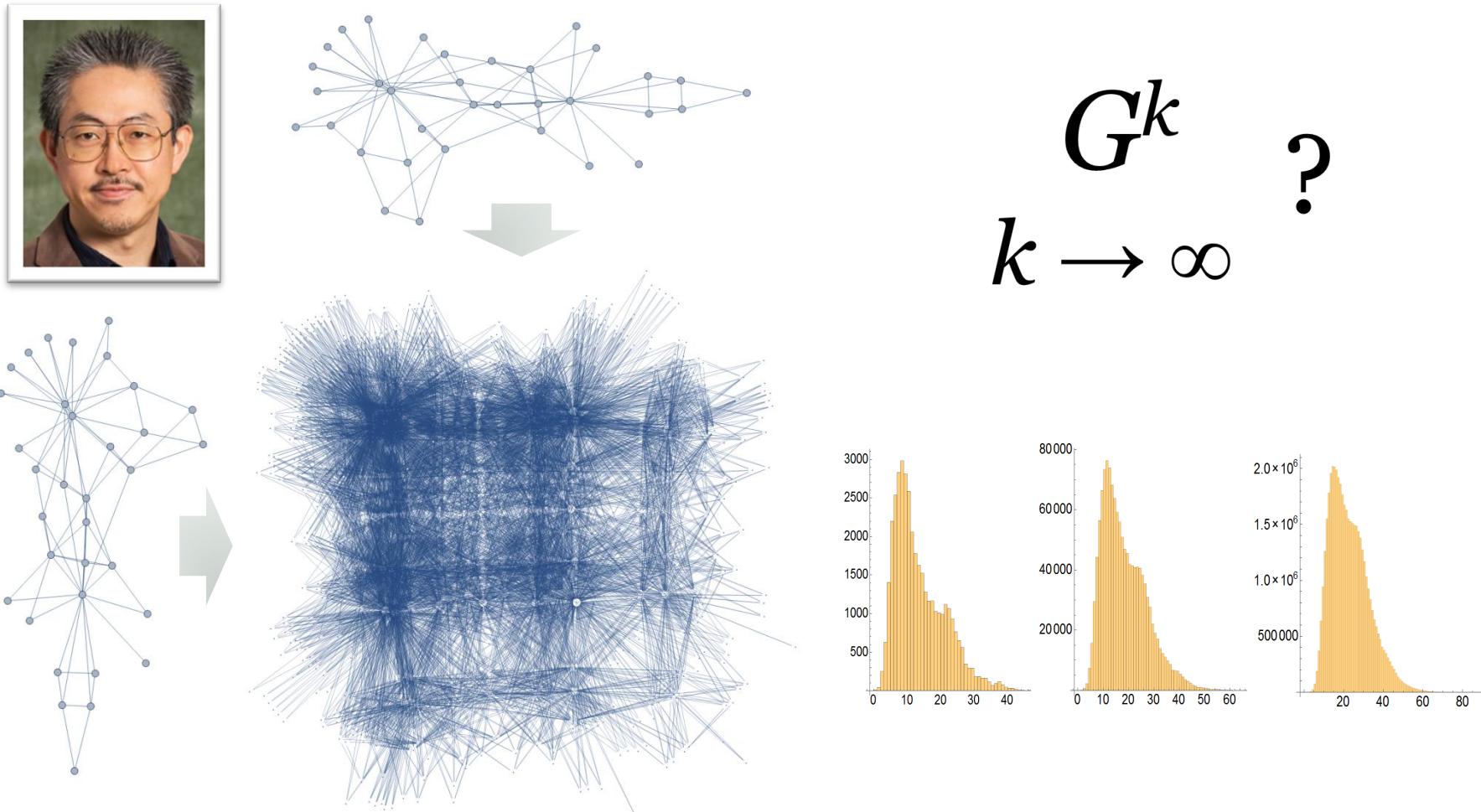
Non-Markovian movements with adaptive memory

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



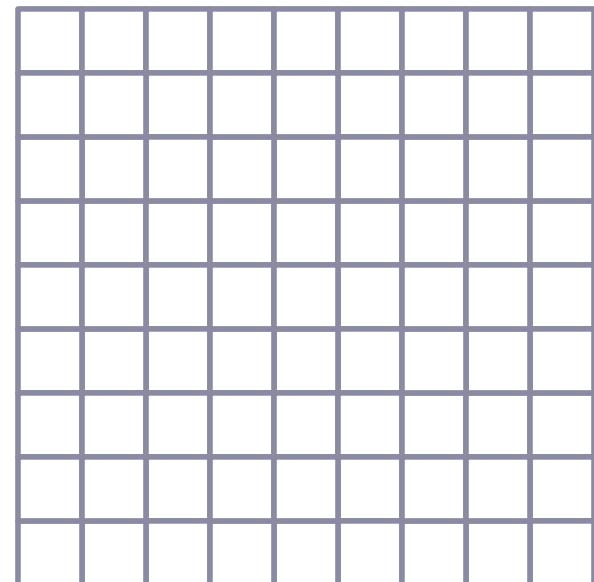
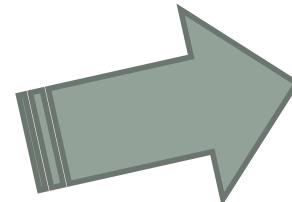
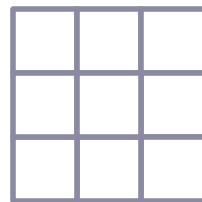
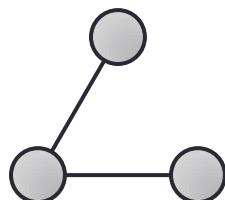
Graph product multilayer networks

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



“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

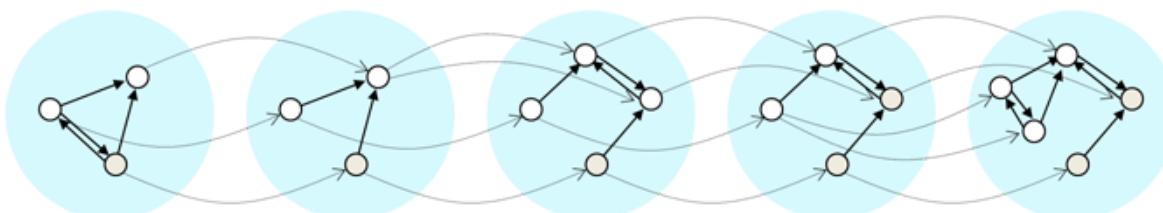
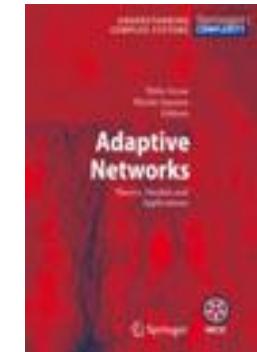


3.

INTERACTION BETWEEN DYNAMICS ON AND OF NETWORKS (COEVOLUTION)

Adaptive networks

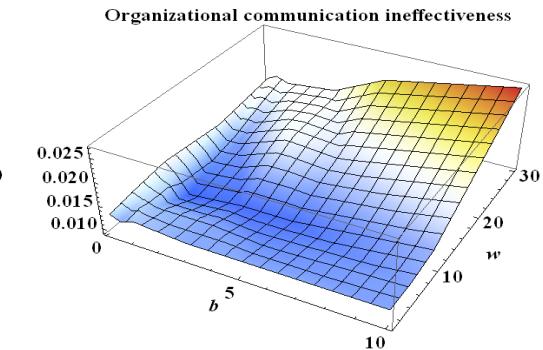
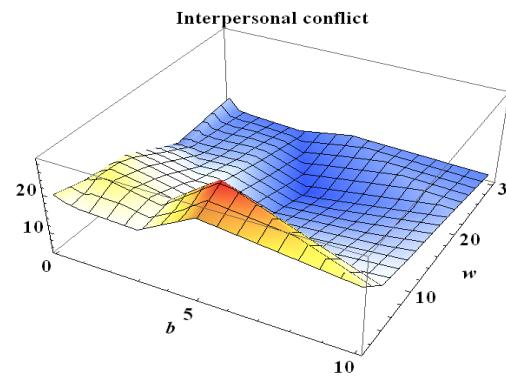
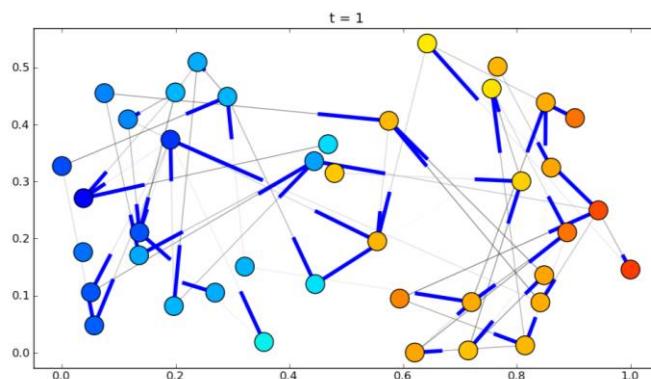
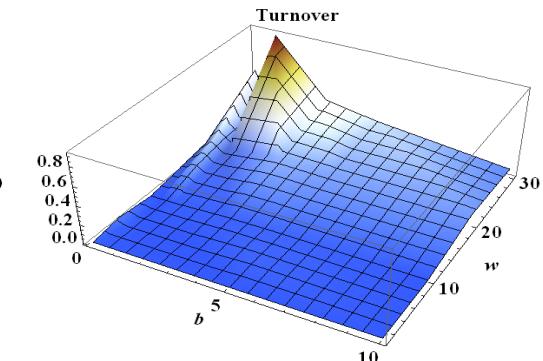
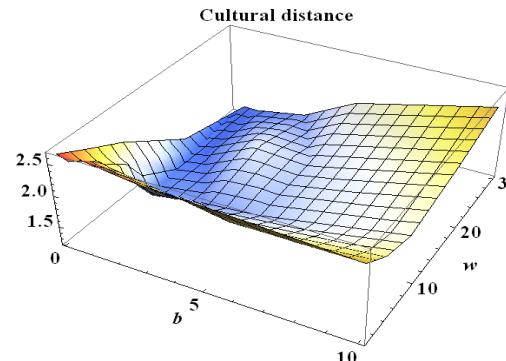
- Complex networks whose states and topologies co-evolve, often over similar time scales
 - Node states adaptively change according to link states
 - Link states (weights, connections) adaptively change according to node states
 - Sayama, H. et al. (2013) *Comput. Math. Appl.* 65(10), 1645-1664.



T. Gross

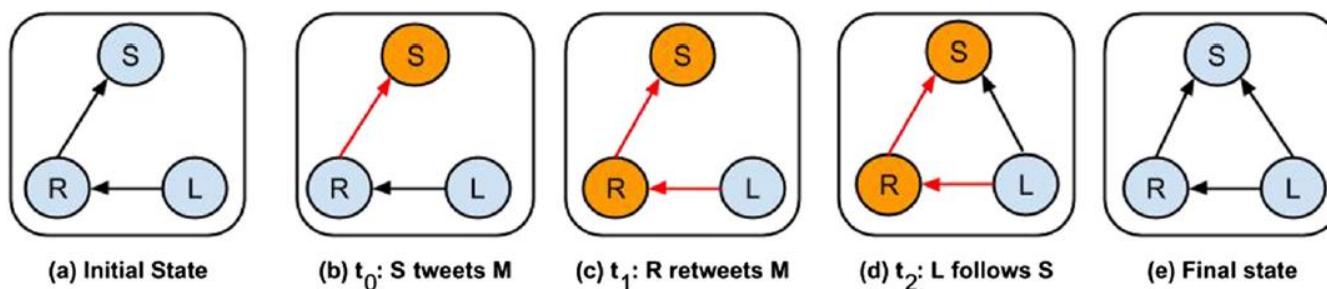
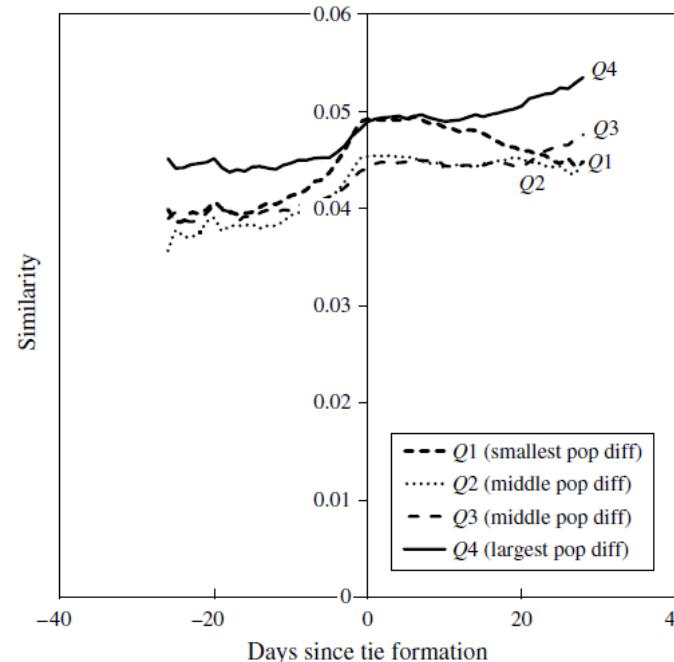
Cultural integration in merging firms

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



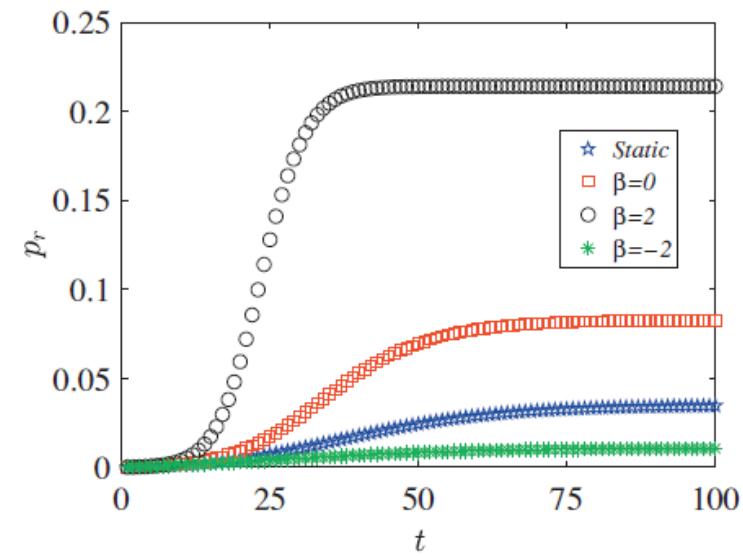
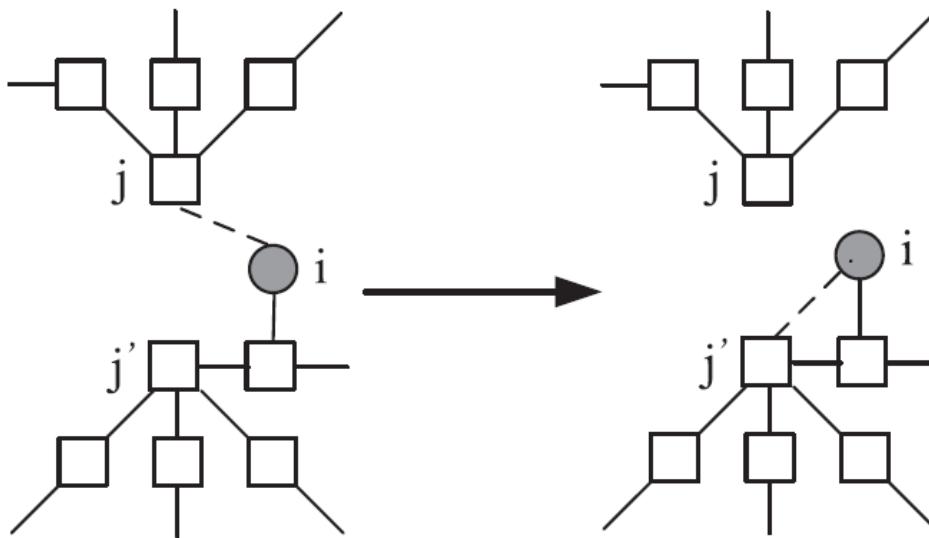
Coevolutionary dynamics on OSNs

- 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]



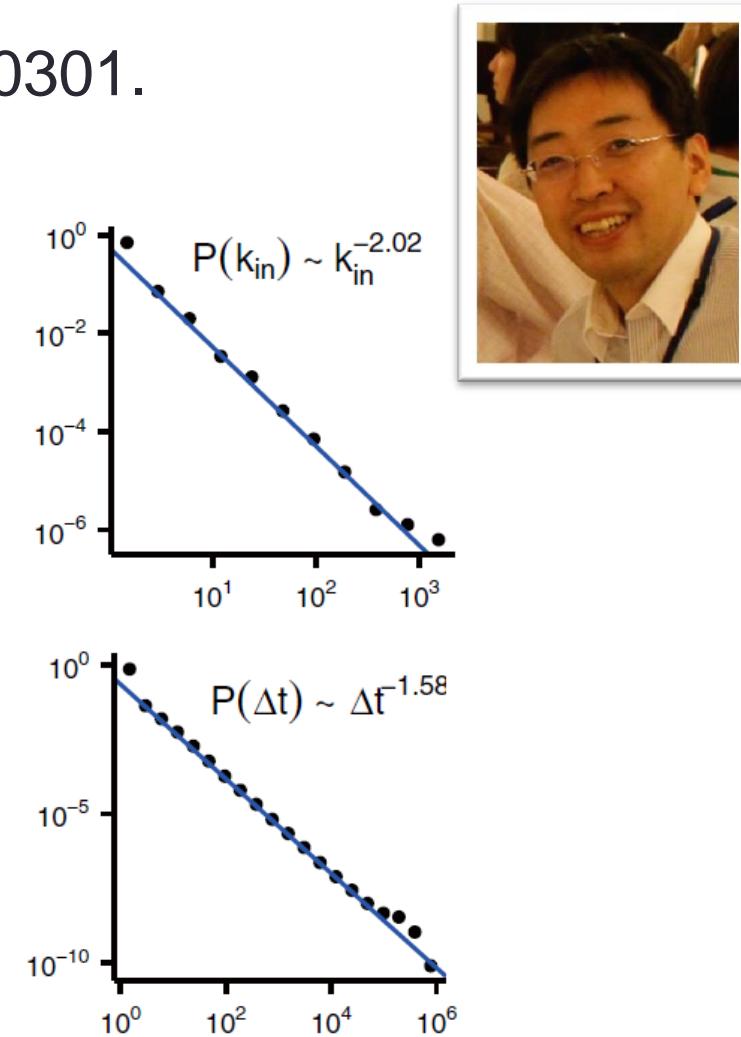
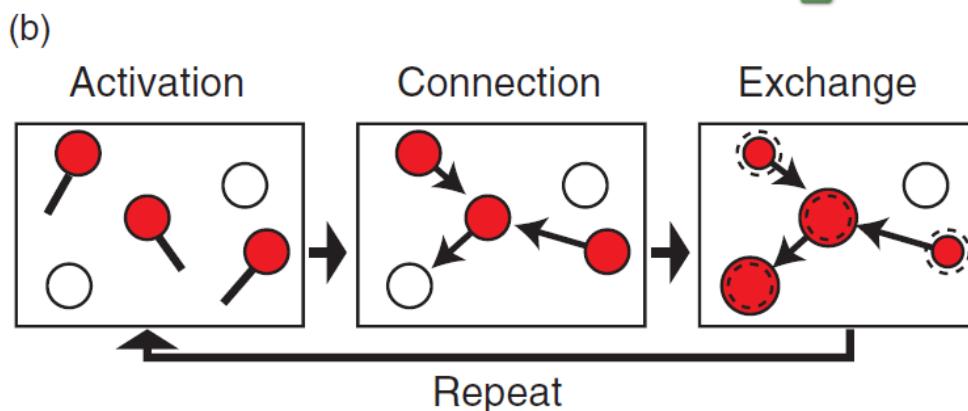
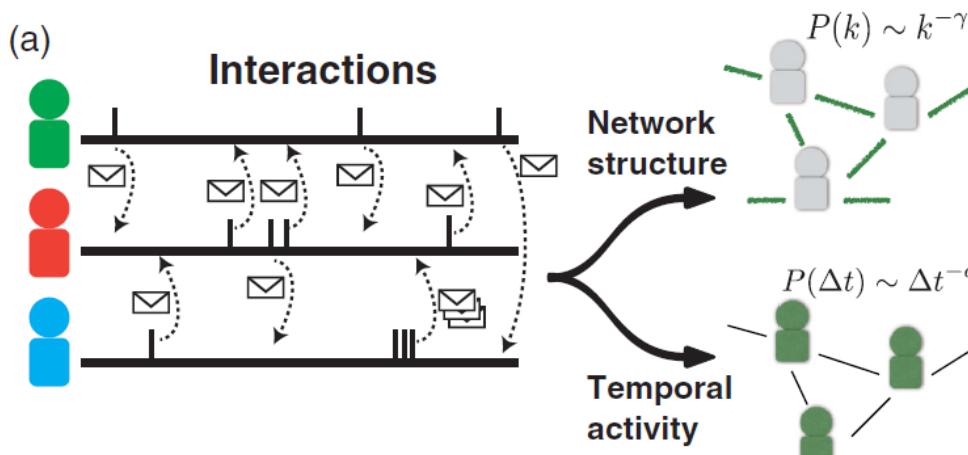
Fast information spreading by adaptive local link rewiring

- 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.

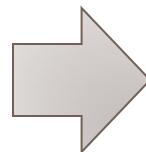
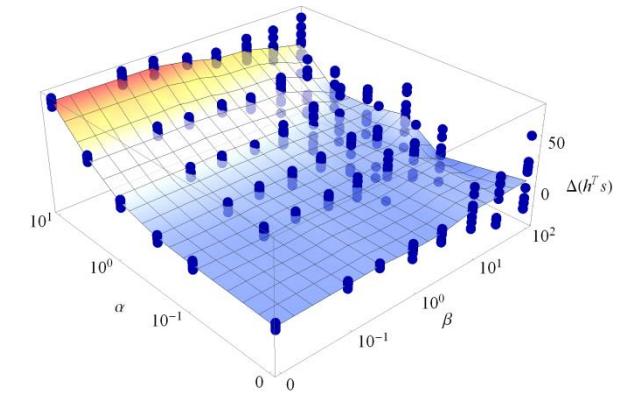


Social diffusion and global drift

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



$$\frac{ds_i}{dt} = c(\langle s_j \rangle_j^i - s_i)$$
$$\frac{d(h^T s)}{dt} \neq 0$$



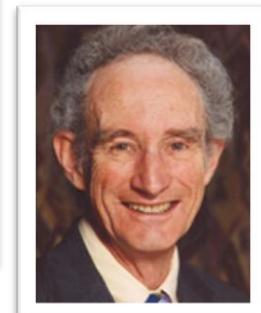
4.

NETWORK RESILIENCE AND FAILURE

Network resilience: A classic problem

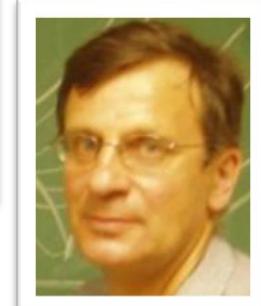
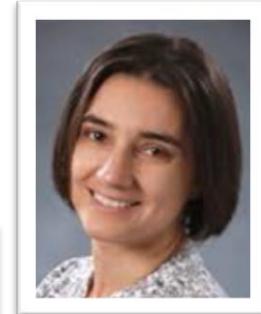
Dynamical stability:

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



Topological connectivity:

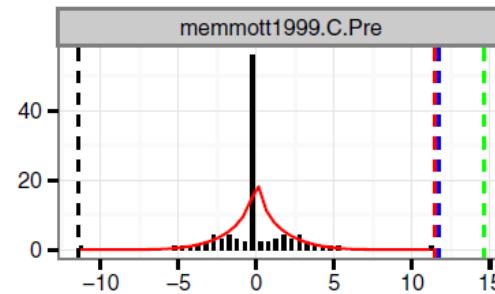
- Albert, R. et al. (2000) *Nature* 406, 378-382.
- Tanizawa, T. et al. (2005) *PRE* 71(4), 047101.
- Buldyrev, S. V. et al. (2010) *Nature* 464, 1025-1028.



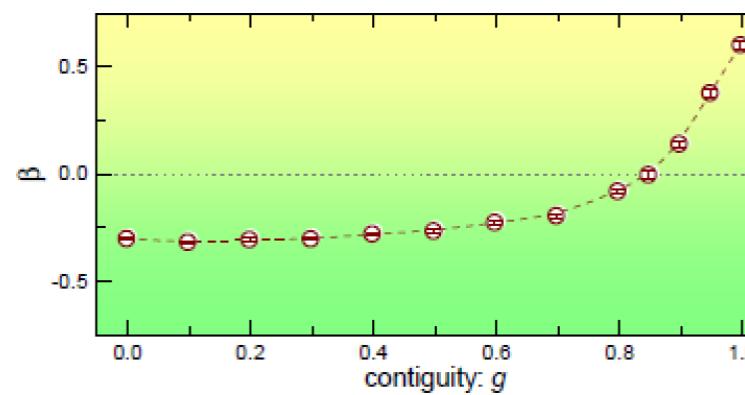
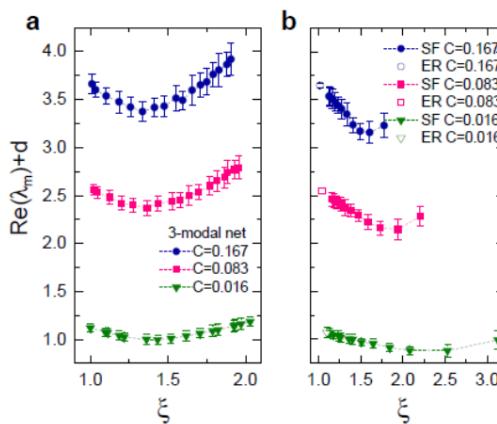
Heterogeneity of networks and stability

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

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

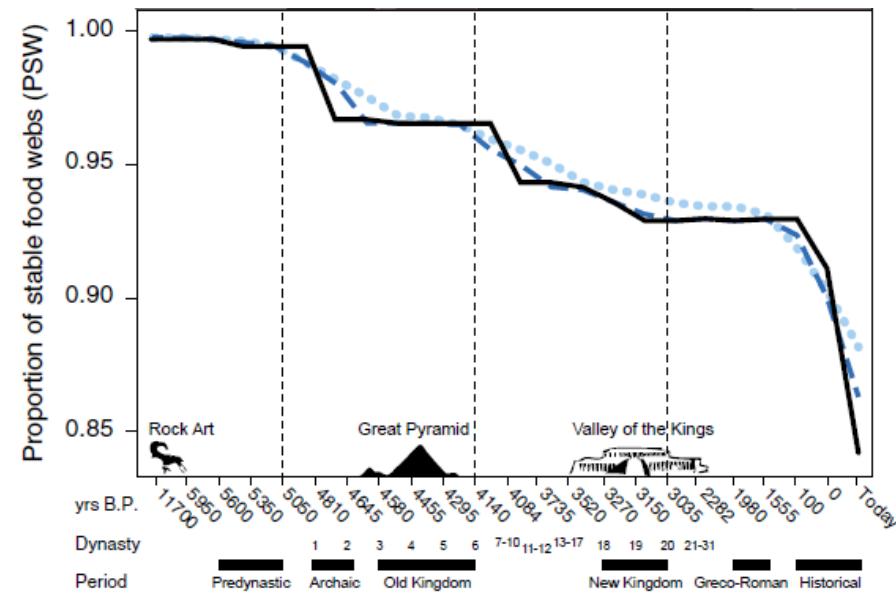
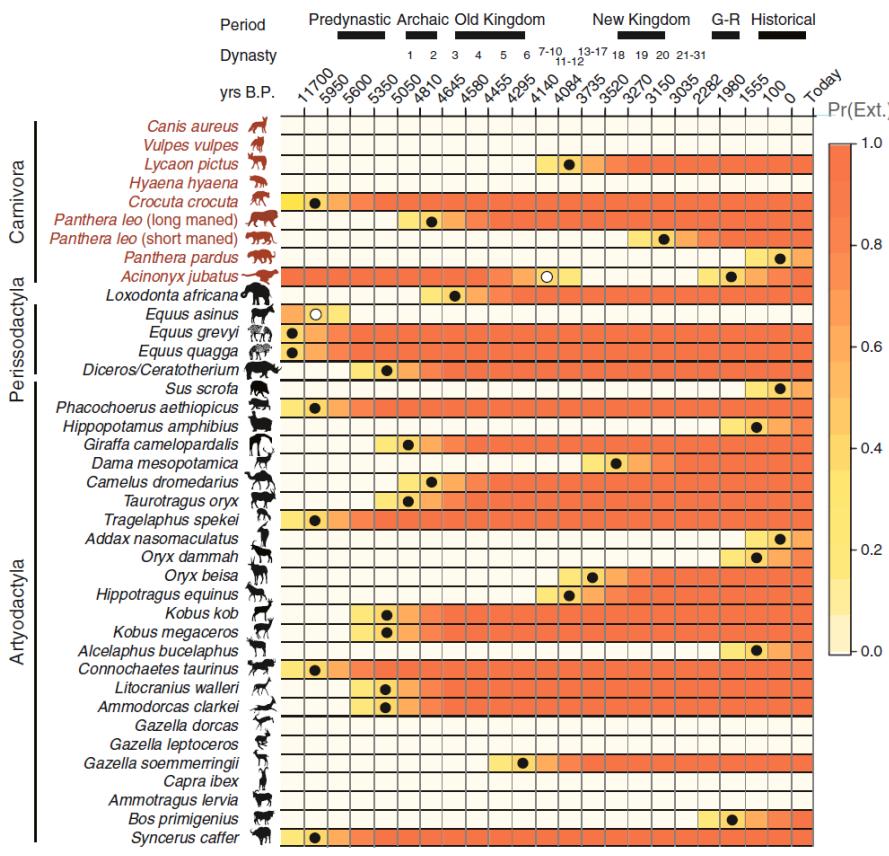


- Yan, G. et al. (2014) arXiv:1409.4137.



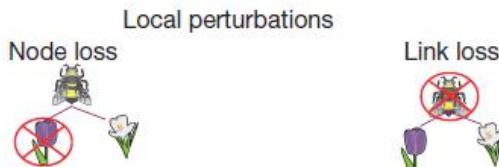
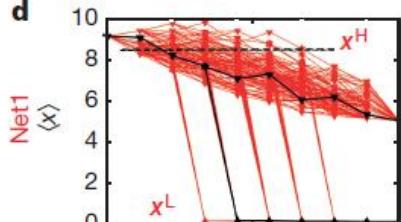
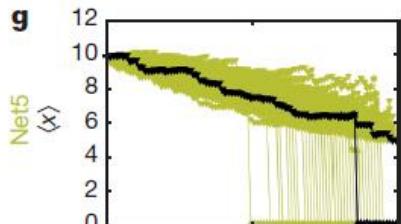
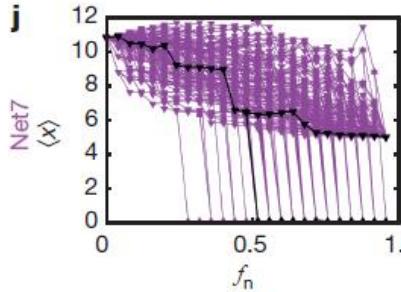
Ecological collapse captured & modeled

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

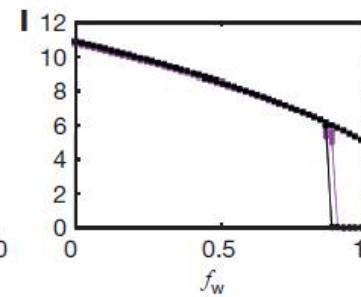
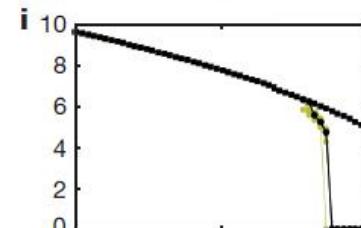
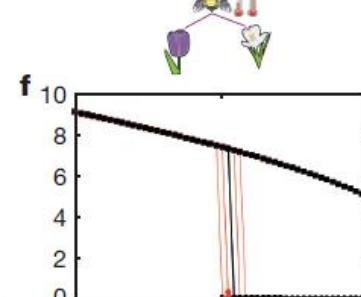
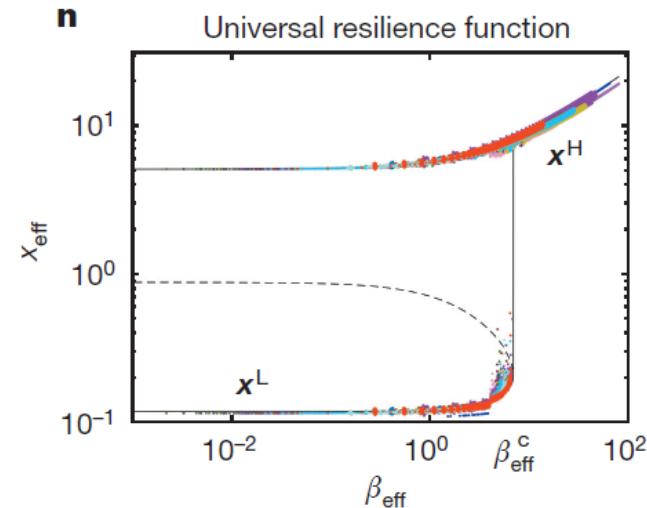


Universal patterns of collapse

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

c**d****g****j**

Global perturbations
Weight loss

**n**

<https://www.youtube.com/watch?v=xZ3OmIbtaMU>

Math behind universal patterns

- Original dynamical network:

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

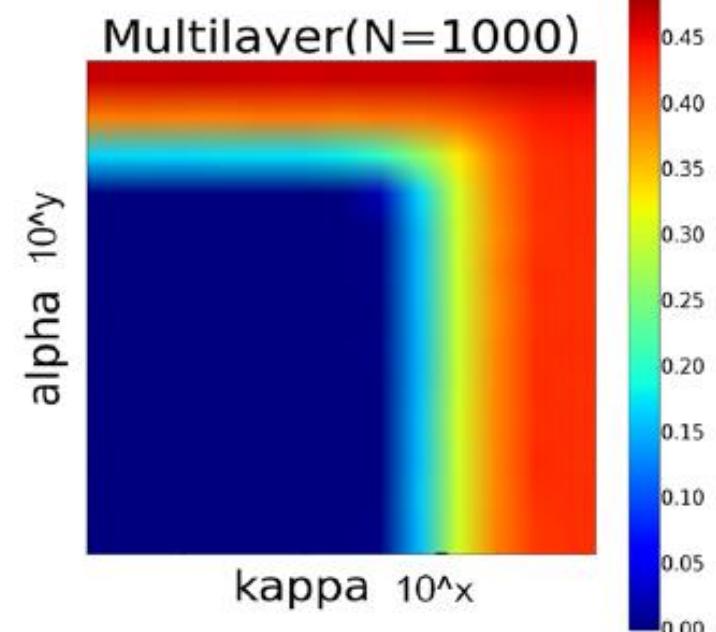
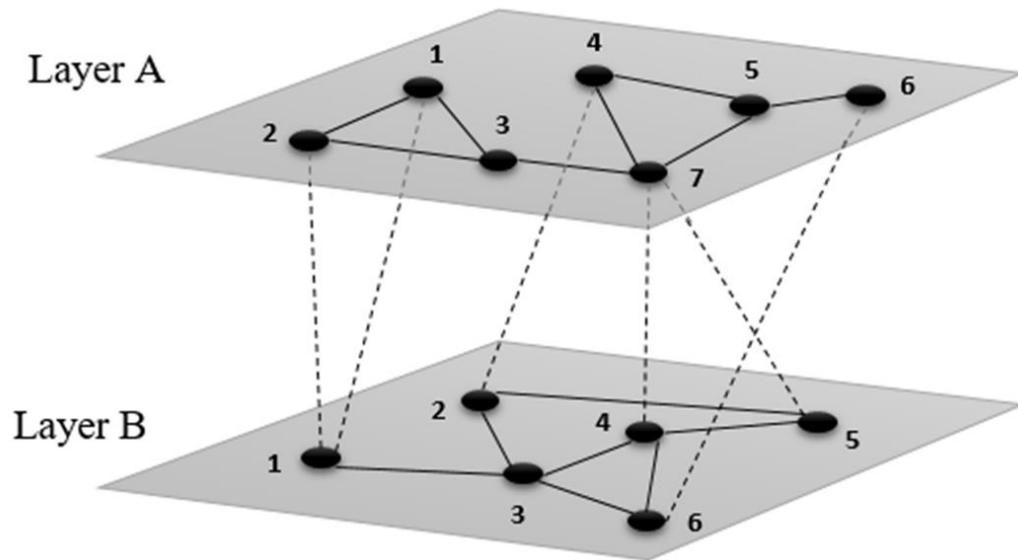
- Reduced to 1-D dynamical equation

$$\frac{dx_{\text{eff}}}{dt} = F(x_{\text{eff}}) + \beta_{\text{eff}} G(x_{\text{eff}}, x_{\text{eff}})$$

$$x_{\text{eff}} = \frac{\mathbf{1}^\top A \mathbf{x}}{\mathbf{1}^\top A \mathbf{1}} = \frac{\langle s^{\text{out}} x \rangle}{\langle s \rangle} \quad \beta_{\text{eff}} = \frac{\mathbf{1}^\top A \mathbf{s}^{\text{in}}}{\mathbf{1}^\top A \mathbf{1}} = \frac{\langle s^{\text{out}} s^{\text{in}} \rangle}{\langle s \rangle}$$

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)

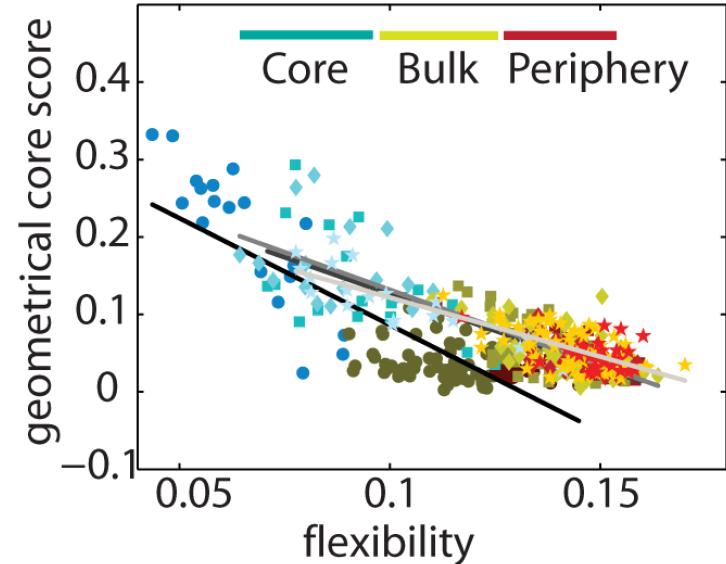
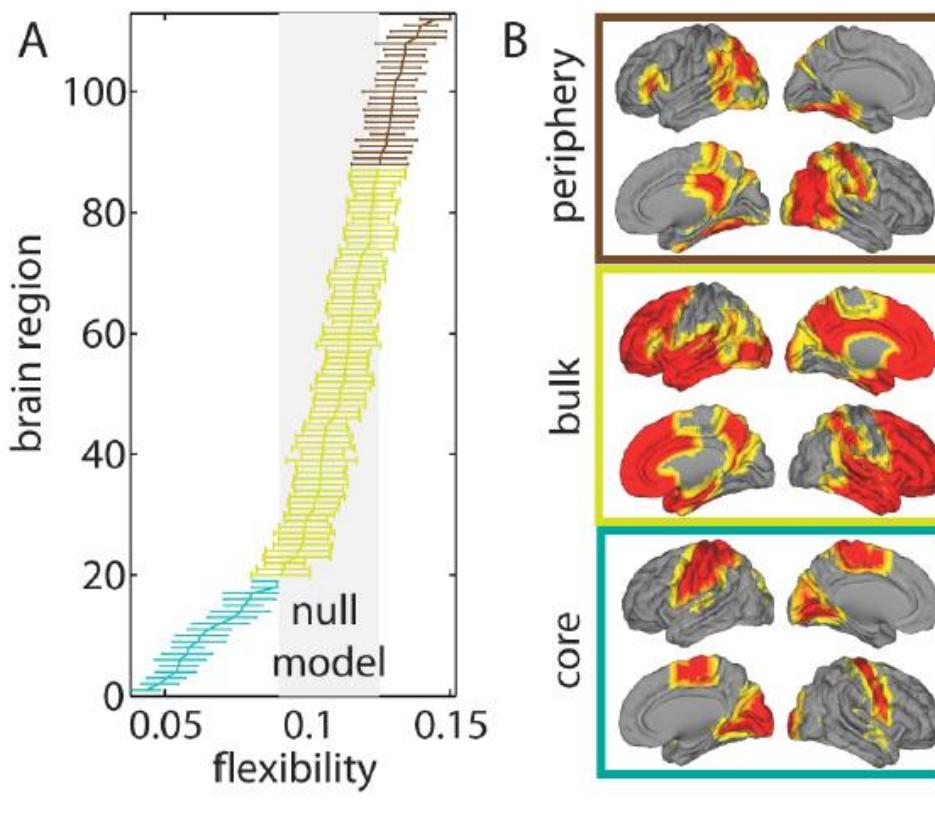
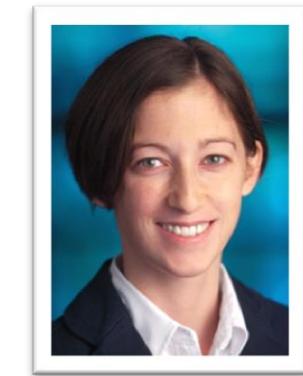


17:30-18:00: Closing Remarks and Discussion

NetSci 2016 Brain Networks satellite program

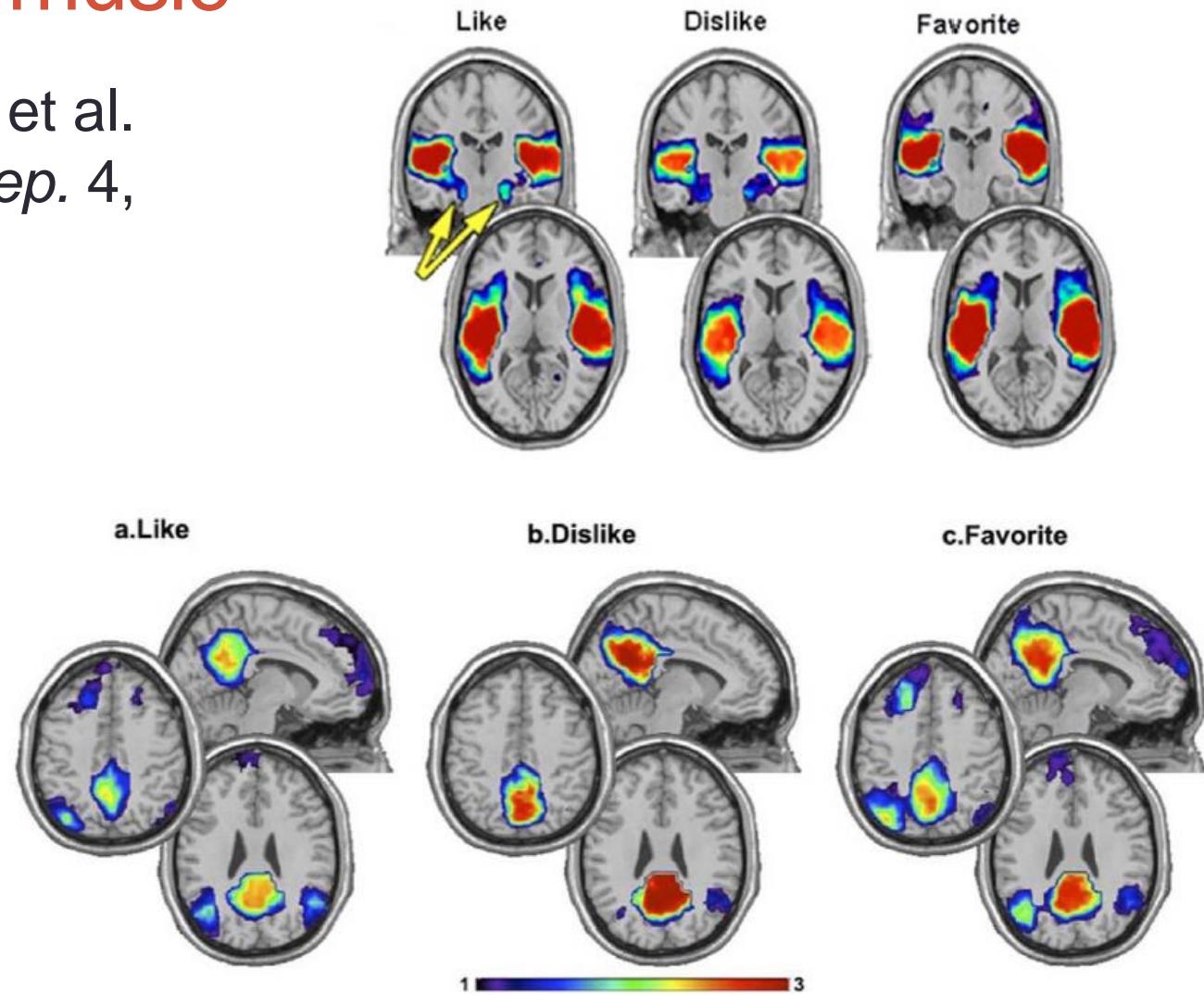
Temporal core-periphery structure of functional brain networks during learning

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



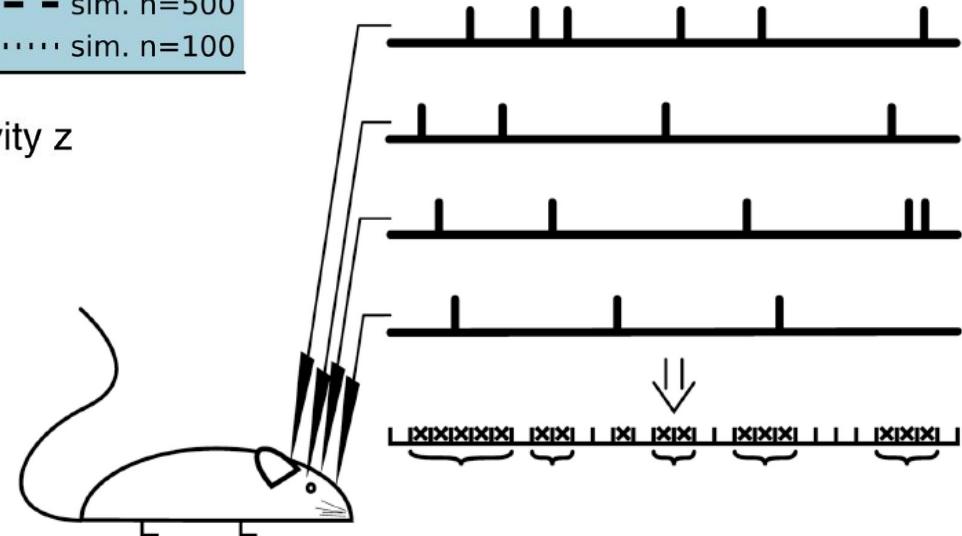
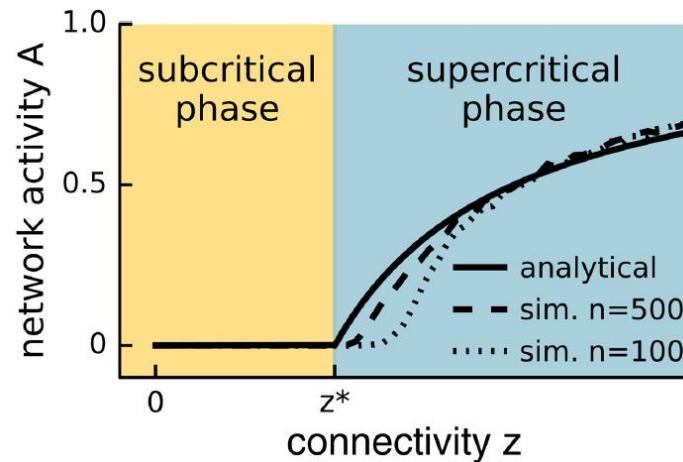
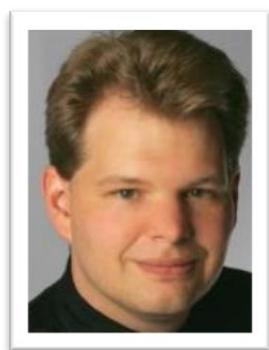
Functional brain connectivity while listening to music

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



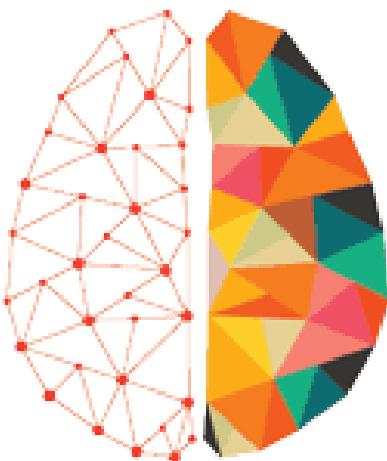
“Critical brain” hypothesis

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



New journal coming up

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



NET WORK
NEURO
SCIENCE

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6. APPLICATIONS II: FINANCE AND MARKETING

Where there is money

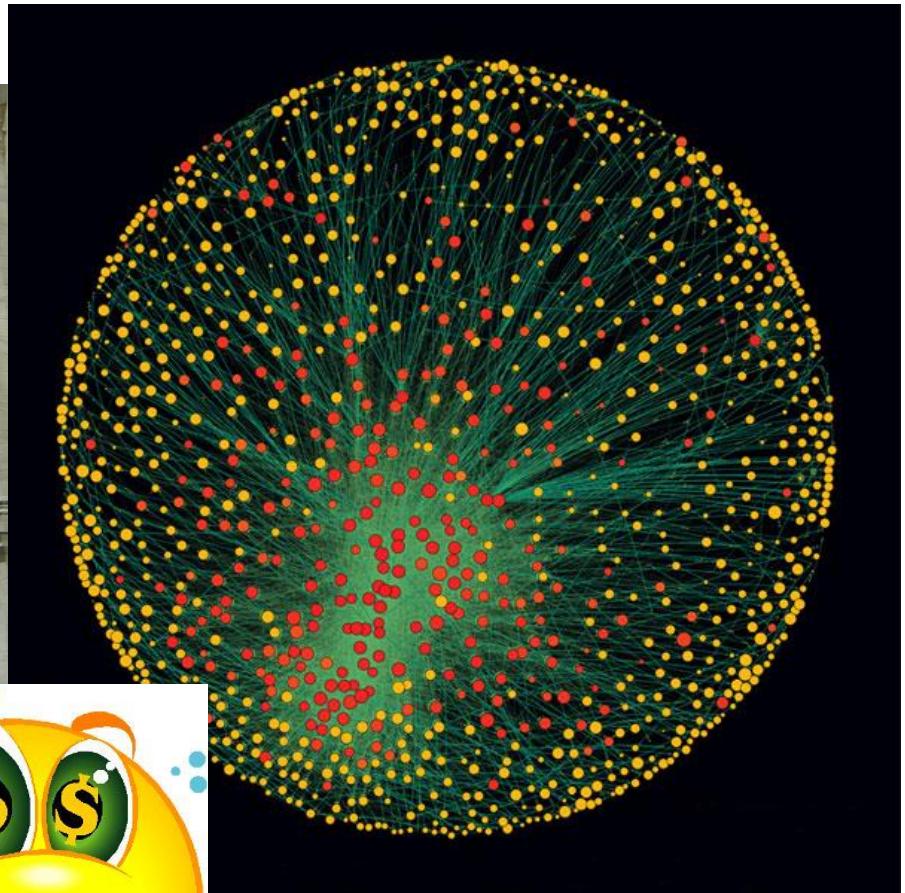
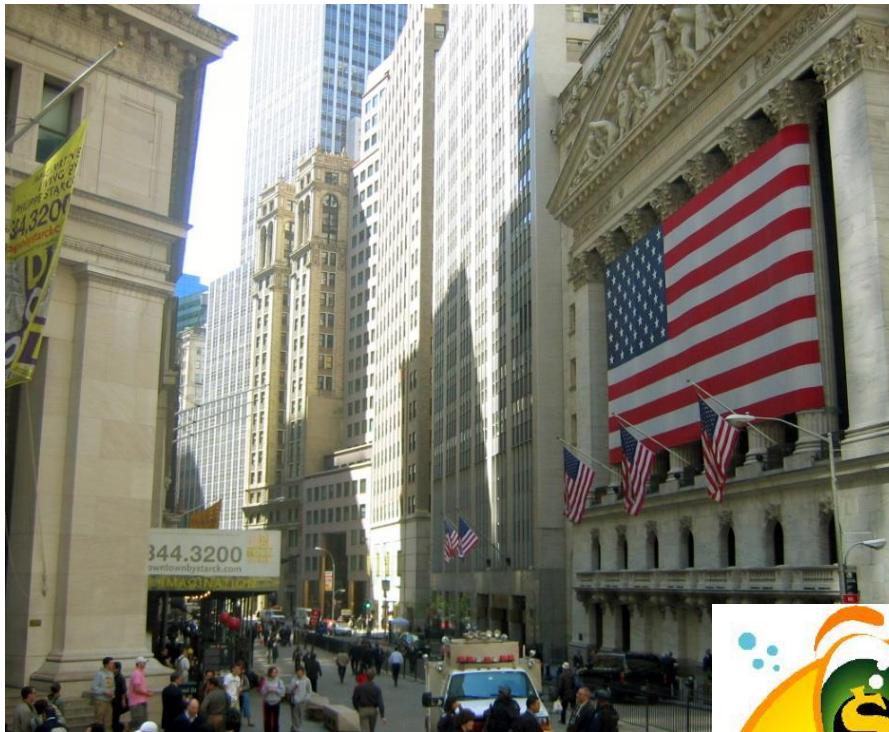
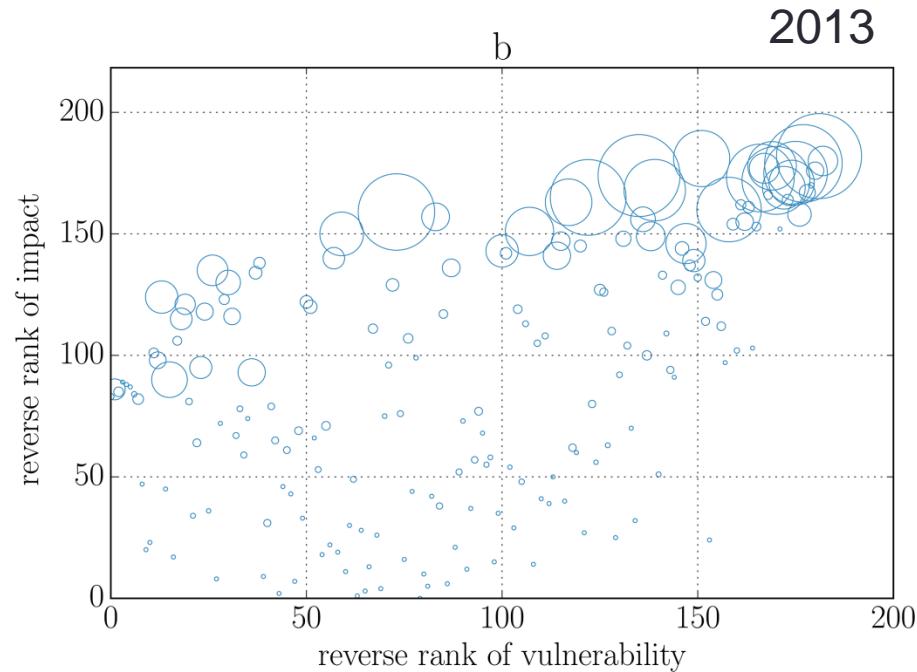
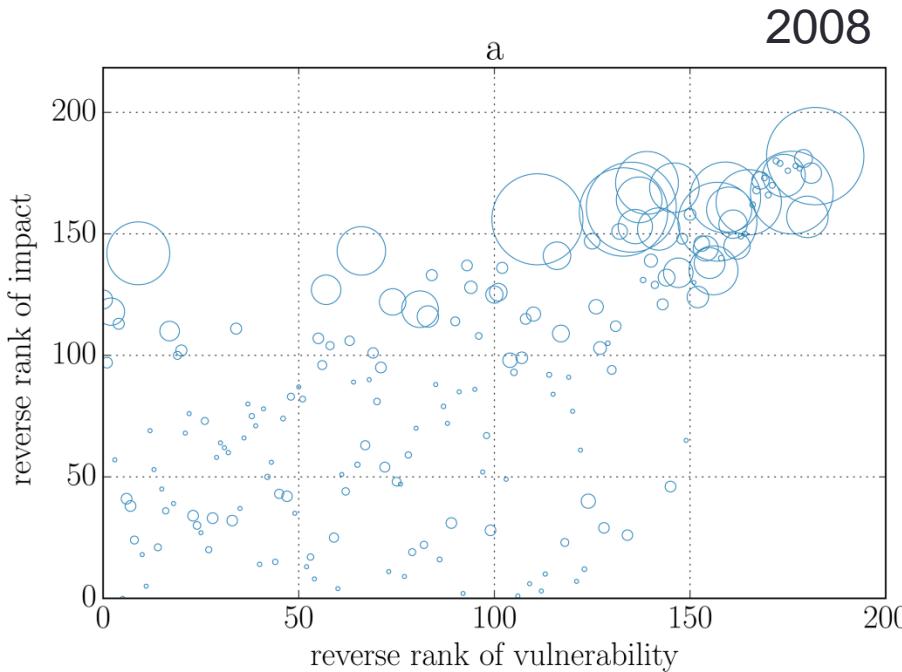


Image from: Vitali, S. et al. (2011)
PLOS ONE 6(10), e25995.

Generalization of “DebtRank”: Micro-level model of financial network dynamics

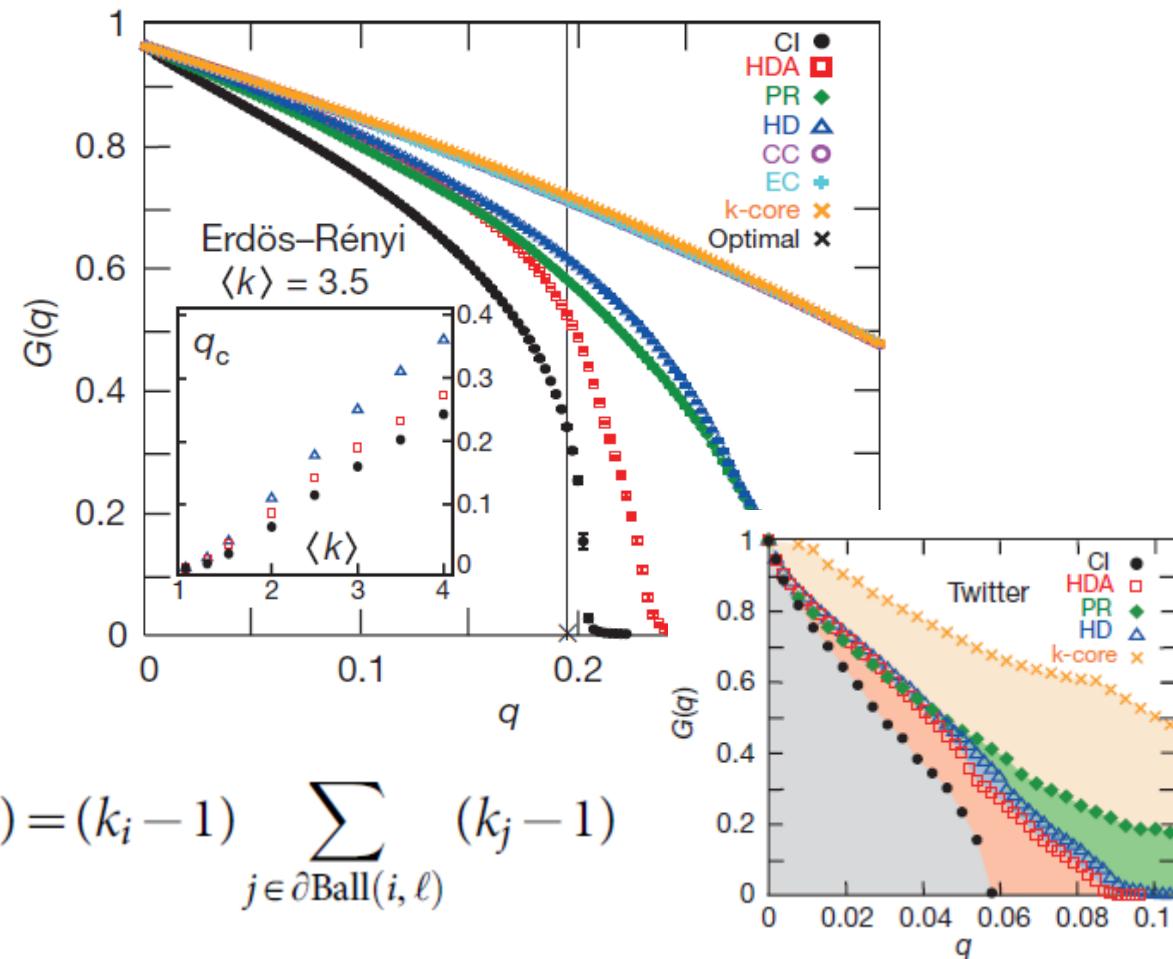
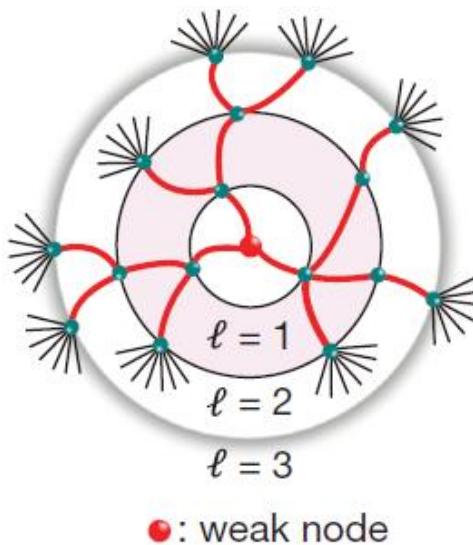


- Bardoscia, M. et al. (2015). *PLOS ONE* 10(6), e0130406.

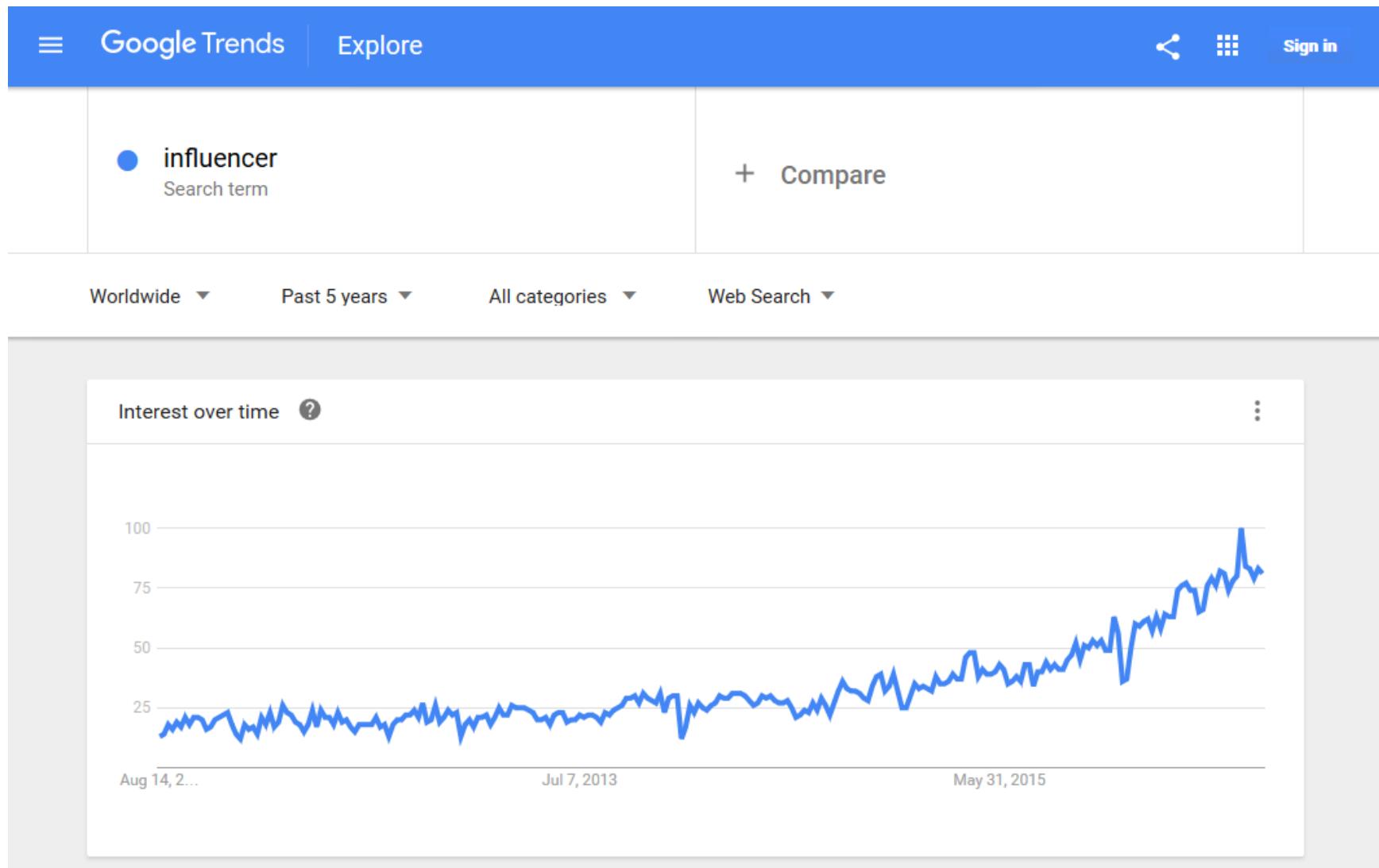


Influencer set optimization

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



“Influencer” business growing

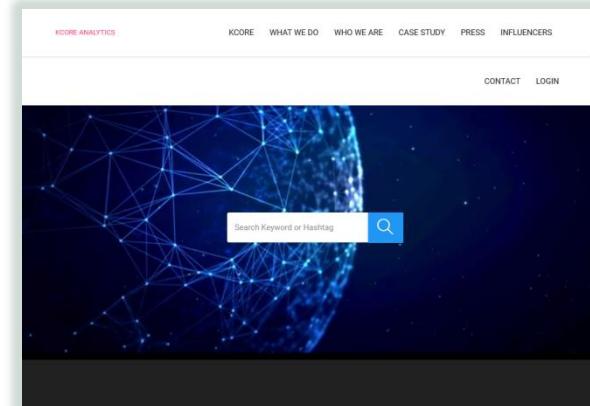


Kcore Analytics

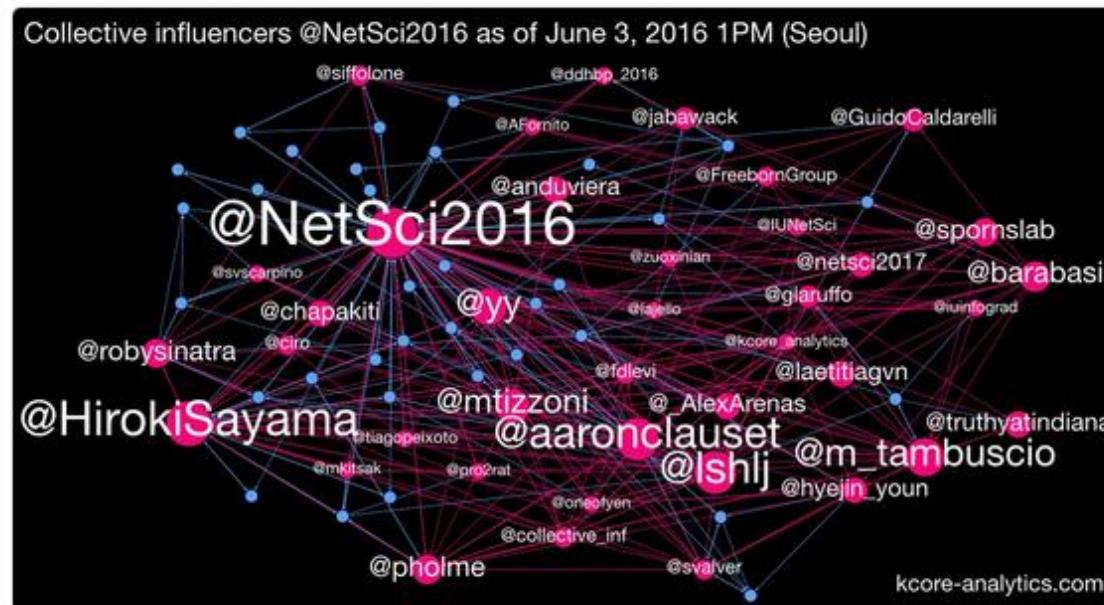
- <http://www.kcore-analytics.com/>



Hernan Makse
@kcore_analytics



Kcore Award to @HirokiSayama Top Influencer at @NetSci2016 according to kcore-analytics.com search engine!

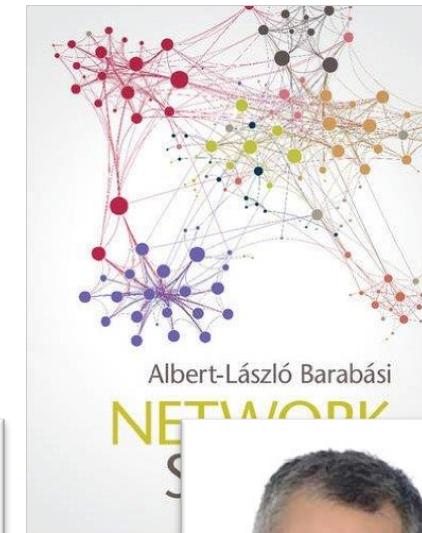
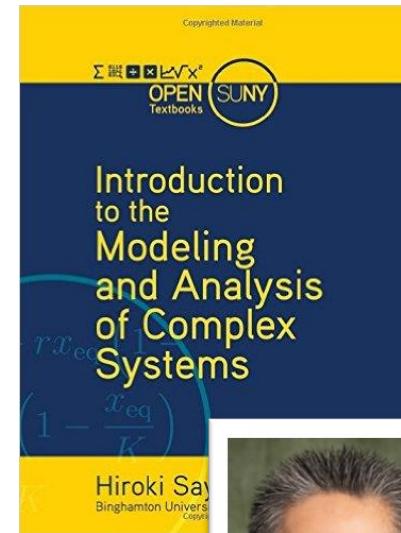
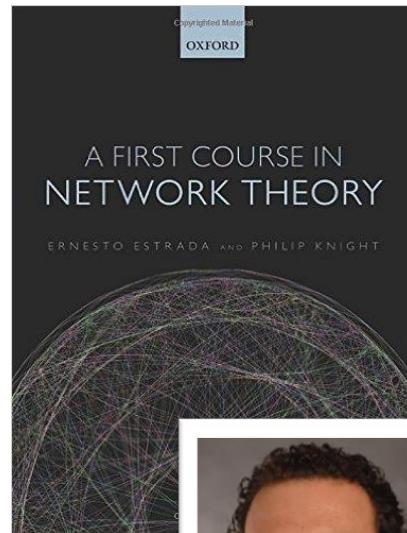
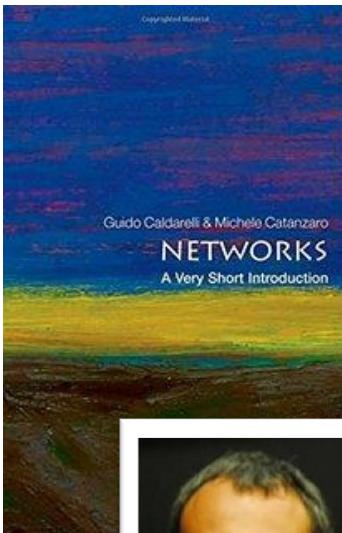


7.

NETWORK SCIENCE AND EDUCATION

Network science textbooks

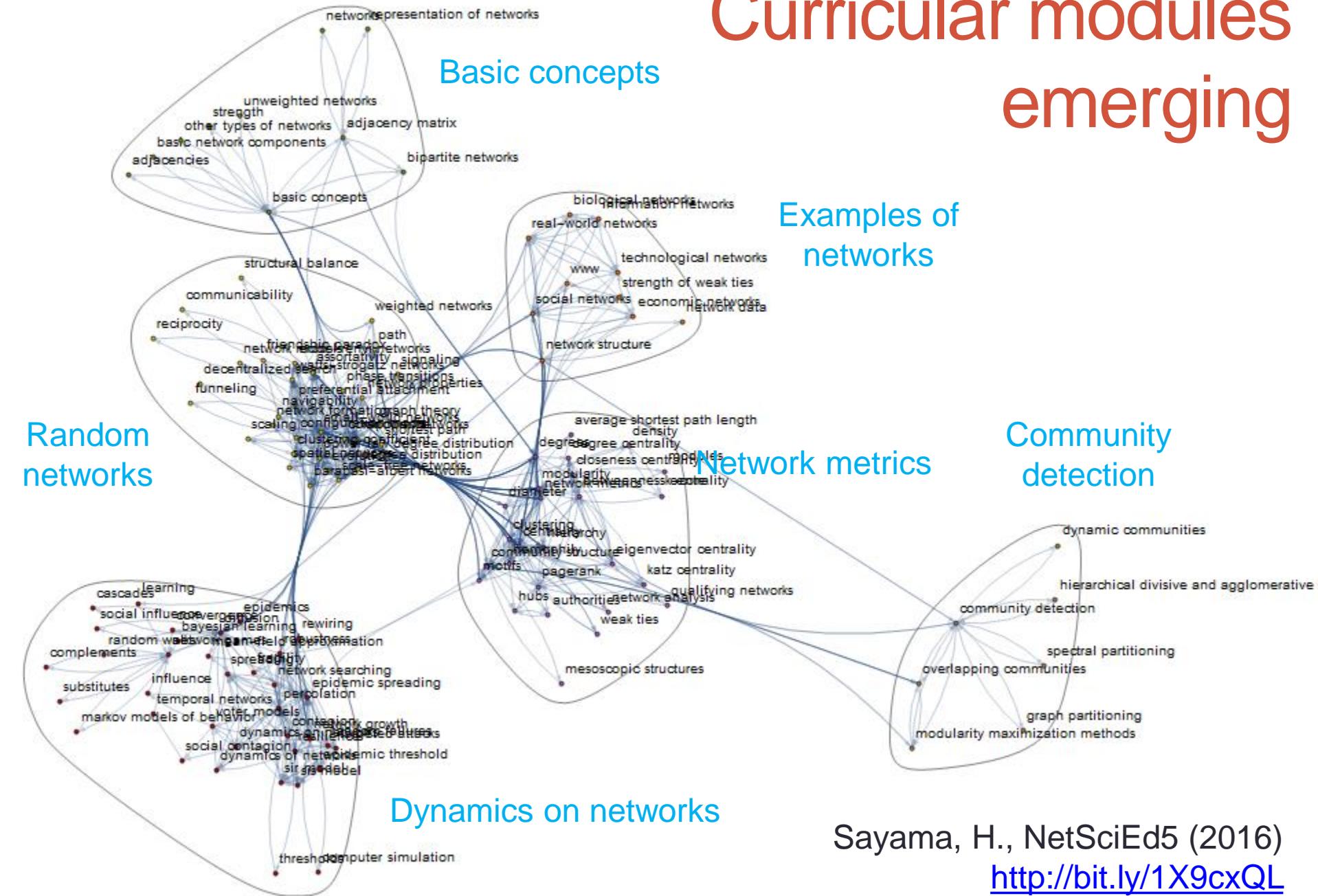
- Caldarelli & Catanzaro (2012); Estrada (2015); Sayama (2015); Barabasi (2016); etc...



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/~aarond/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/>

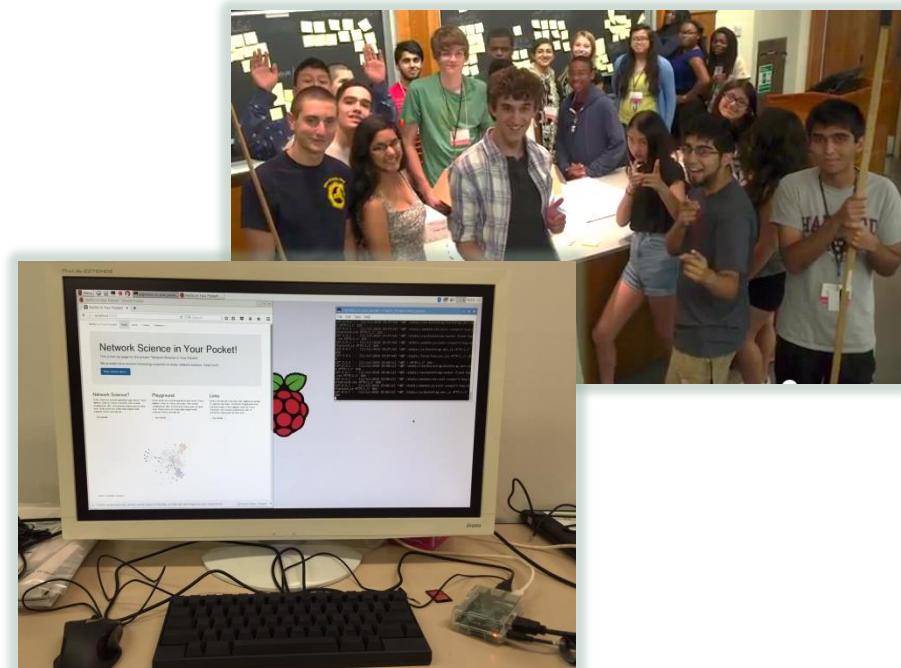
Network science courses

Curricular modules emerging



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.

NETWORK LITERACY

Essential Concepts and Core Ideas

NetSciEd

1 NETWORKS ARE EVERYWHERE

- The concept of networks is broad and general, and it describes how things are connected to one another. Networks are present in every aspect of life.
- There are networks that form the backbone of society, such as communication systems, transportation systems, social networks, and the entire supply chain.
- There are networks of people – families and friends, at work, in school, in organizations, professional groups, etc.
- There are economic networks – e.g., transportation, corporate partnerships, international trade, and so on.
- There are biological and ecological networks – e.g., food webs, gene regulatory networks, neural networks, patterns of disease spreading, etc.
- There are linguistic networks – language/lexicon/artist connected by their use, or people connected by their interests, people connected by their events, etc.
- Networks can exist at various spatial and temporal scales.

2 NETWORKS DESCRIBE HOW THINGS CONNECT AND INTERACT

- There are many ways to represent your system as a network. A network can be represented mathematically as a graph.
- Connections are called links, edges, or arcs. The vertices that are connected by a link are called nodes, mode, vertices, or actors.
- Connections can be directed (one way) or undirected (two ways). They can also have weights or values that indicate levels of different strengths, intensities, or potential positive or negative relationships.
- The number of connections of a node is called the degree of that node.

3 NETWORKS CAN HELP REVEAL PATTERNS

- In tree networks, you can find a single path between any two nodes that are much larger degrees apart. This is called a shortest path.
- In small networks, you can find a group of nodes that all interact with each other. This is called a cluster or community.
- The properties of a network that provide these patterns include:
 - the size of the degree distribution
 - which parts or communities are more densely connected
 - strength and direction of connections
 - if there is any self-similarity
 - how many nodes are in a cluster
 - how many connections are between clusters
- Using these findings, you can predict future behavior, make informed decisions about current conditions, or avoid potential problems in the future.

4 VISUALIZATIONS CAN HELP PROVIDE AN UNDERSTANDING OF NETWORKS

- Networks can be visualized in many ways.
- You can draw a diagram of a network by connecting nodes to each other.
- There are a variety of tools available for creating networks:
 - Small tools help you quickly get started and communicate ideas.
 - Large tools help you analyze complex networks.
- Create informative design projects that help others learn about networks in an effective and meaningful way.
- It is important to understand and evaluate network visualizations, because they typically do not tell the whole story about networks.

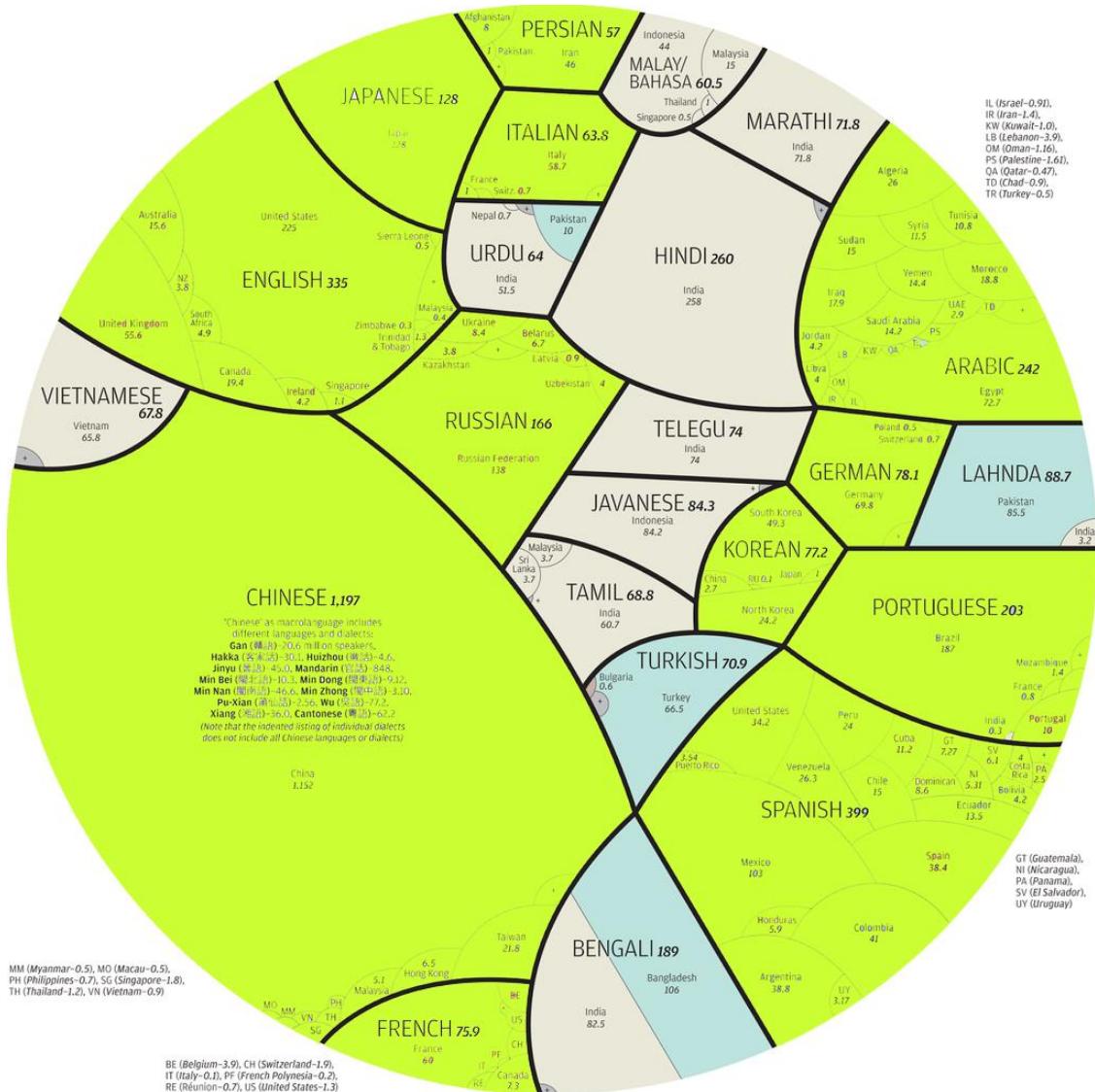
5 TODAY'S COMPUTER TECHNOLOGY ALLOWS YOU TO STUDY REAL-WORLD NETWORKS

- Computer technology has dramatically enhanced the ability to study networks, especially large ones with rich structures.
- There are many free software tools available for creating, visualizing, and analyzing networks.
- Cloud-based computing makes it easier for anyone to access and analyze network data.
- Through the internet, anyone has access to many interesting network data sets.
- Companies allow you to simulate hypothetical or real networks. We can test our ideas without having to build both real and hypothetical networks.
- Networks are used as a means to share knowledge across different areas of study.

<http://tinyurl.com/networkliteracy>

International spread

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



CONCLUDING REMARKS

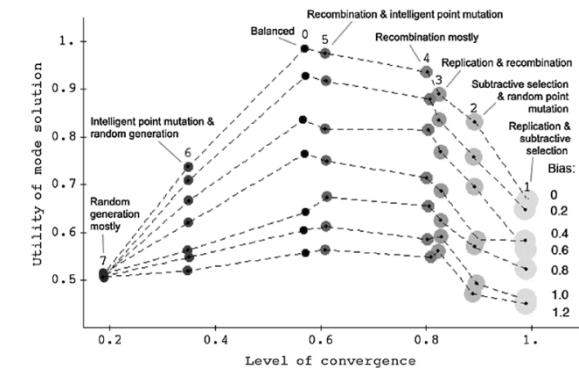
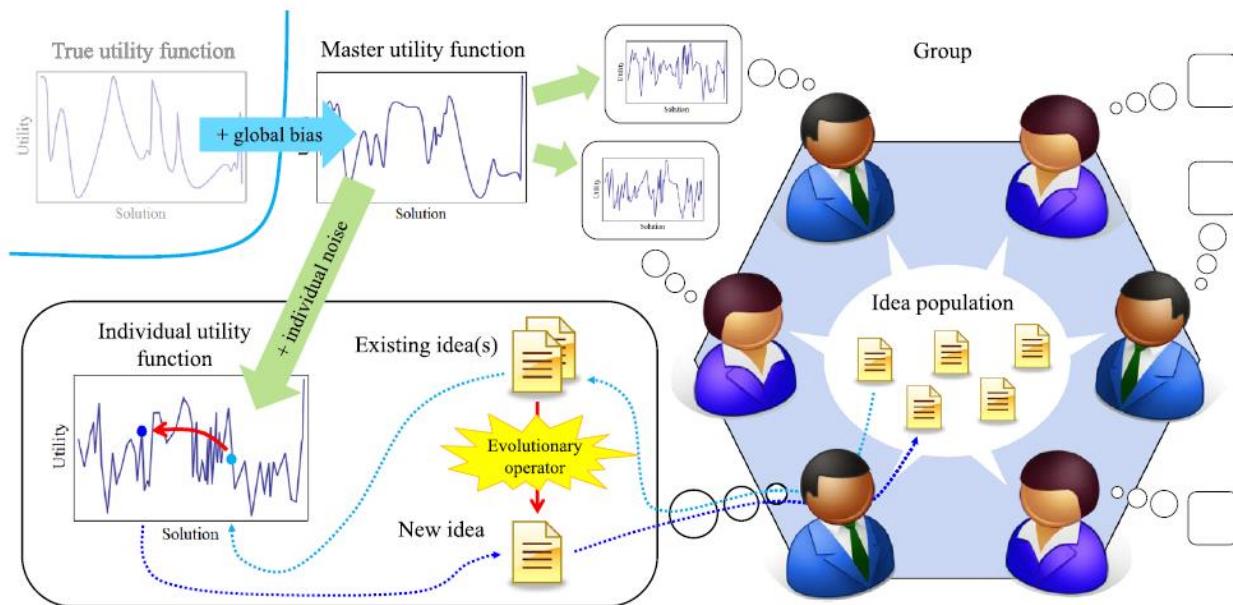
Seeing a bunch of cool papers, now what?



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



KEVIN WINTER VIA GETTY IMAGES

**STAY WEIRD.
STAY DIFFERENT.**

And when it's your
turn to stand on
this stage, pass the
message along.
-Graham Moore

Thank You

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

A collage of various academic and research-related terms and names, including "binghamton", "research", "university", "networks", "systems", "adaptive", "institute", and "sayama".

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