Big Data Course

Syllabus & Outline

16 Oct 2019

CRI Paris

THE TEACHERS

Administrative information	
UE	0AR0AU23 Big Data
UE referent contact	Marc Santolini Loic Saint Roch
Course name	Big Data
Teacher(s)	Liubov Tupikina, Anirudh Krishnakumar, Marc Santolini, Loic Saint Roch, Felix Schoeller
ECTS credits	4
Schedule	12 sessions of 3 hours
Semester	S1

Referent teachers:
Academic: marc.santolini@cri-paris.org
Company: loic@nunchi.studio

Objectives / Evaluation

Course objectives	• Theoretical foundations of big data management and network science • Analysis and visualisation of real-world network data • Contributing to the development of digital tools (a semantic database & an app) to diagnose, assess, monitor, analyse and improve mental health • Personal research projects related to data mining, analysis of a real-world network, and data for mental health
Key concepts	Network science; Data science; Data visualisation; Big data; Mental Health; Digital tools; Data collection platforms; Ontologies
Examples of work that you will ask during your course	Lectures, hands-on coding sessions, personal research projects.
Evaluation process	**Network part (evaluation 11 Dec):** • Project presentation with notebooks on github / OSF (40%) • Raising issues / make pull requests on at least one other student project on Github (10%) • Editing or creating a Wikipedia article about Network Science (20%) • Presenting what was edited in a reverse classroom presentation (20%) • Attendance to the classes (10%) **Data Efforts in mental health (evaluation 22 Jan)**: • Project documentation and presentations (40%) • Individual/Group research project (50%) • Attendance of the classes (10%)

RESOURCES

https://github.com/Big-data-course-CRI

Resources (see Github)

<table>
<tr>
<td>Bibliography / Course Material</td>
<td>

Introductory material on networks:

- Introductory **interactive textbook** by A-L Barabasi: http://networksciencebook.com/
  - Chapter 2 for network metrics
  - Chapter 9 for community detection
- An introduction to **network visualisation:**
  - **BASIC**
    - **Gephi**: http://www.martingrandjean.ch/gephi-introduction/
  - **INTERMEDIATE**
    - **Cytoscape**: https://github.com/cytoscape/cytoscape-tutorials/wiki
  - **ADVANCED**
    - **R**: https://kateto.net/network-visualization
    - **Python**: https://www.analyticsvidhya.com/blog/2018/04/introduction-to-graph-theory-network-analysis-python-codes/
    - **Cytoscape.js**: https://blog.js.cytoscape.org/2016/05/24/getting-started/
    - **D3.js**: https://www.d3-graph-gallery.com/network

Network databases

- **Index of Complex Networks (ICON):** https://icon.colorado.edu/ 5,000+ networks
- **Network repository:** http://networkrepository.com/ offers a lot of visualisation tools already in the website
- **On Github**:
  - Deezer Social Networks, Facebook Page-Page Networks, Wikipedia Article Networks: https://github.com/benedekrozemberczki/datasets
  - A Repository of Benchmark Graph Datasets for Graph Classification (31 Graph Datasets In Total https://github.com/shiruipan/graph_datasets
  - Repository of Network repositories: https://github.com/ComplexNetTSP/ComplexNetWiki/wiki/Networks-datasets
- **Your own!!** Any dataset with two columns can be a network after all... Why not try with your favorite data?

</td>
</tr>
</table>

Resources (see Github)

<table>
<tr>
<td>Bibliography / Course Material</td>
<td>

For visualisations

- **Gephi** https://gephi.org/ for simple graph visualisation
  - Introduction to Gephi: http://www.martingrandjean.ch/gephi-introduction/
- **Cytoscape** https://cytoscape.org/ for more fine grained visualisation.
  - Introduction to cytoscape https://github.com/cytoscape/cytoscape-tutorials/wiki
- **D3.js** for interactive visualisations: https://www.d3-graph-gallery.com/network
- **Cytoscape.js** for other interactive visualisations: http://js.cytoscape.org/
- **R** by following the (amazing) guide from https://kateto.net/network-visualization
- **A paper and a pen**. Sometimes it's all that it takes: https://benfry.com/exd09/.

For analysis

- **R** https://www.rstudio.com/ with the library **iGraph** (some intro here: https://kateto.net/networks-r-igraph)
- **Python** https://www.python.org/ with the **networkx** library (https://networkx.github.io/)

Other resources

- Exploring complex systems (not just networks): http://www.complexity-explorables.org/
- About collective phenomena and emergence: https://youtu.be/16W7c0mb-rE

Papers about network science:

- https://drive.google.com/drive/u/1/folders/1RXXtMR1DMaWSm22lyqxwSDx_H07kREIt

</td>
</tr>
</table>

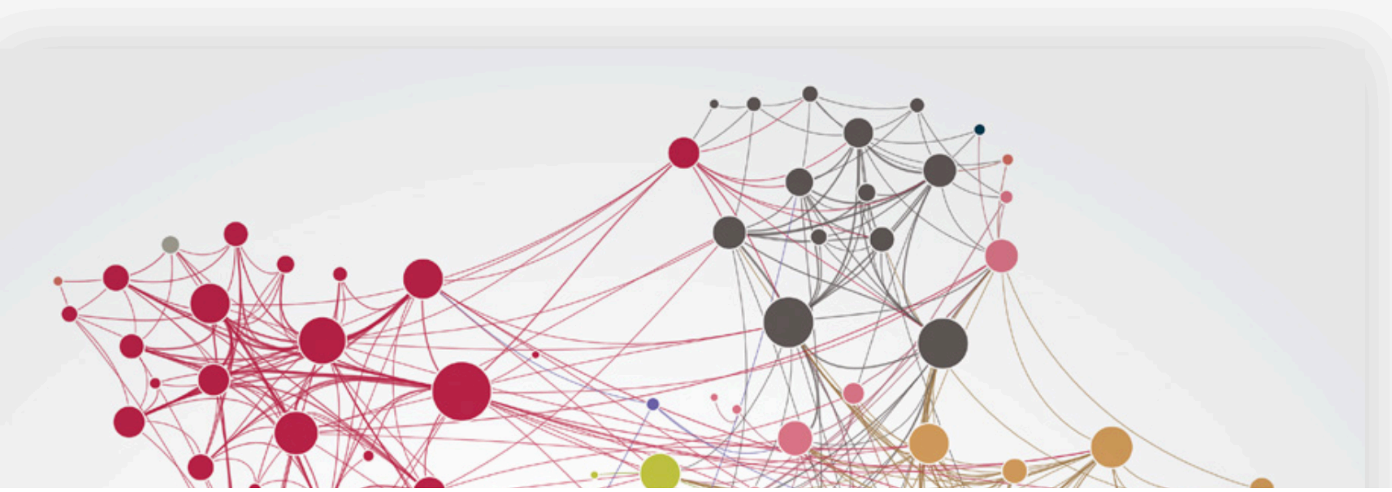
Resource highlight

Network Science

by Albert-László Barabási

Start Reading

English Русский Magyar 日本語

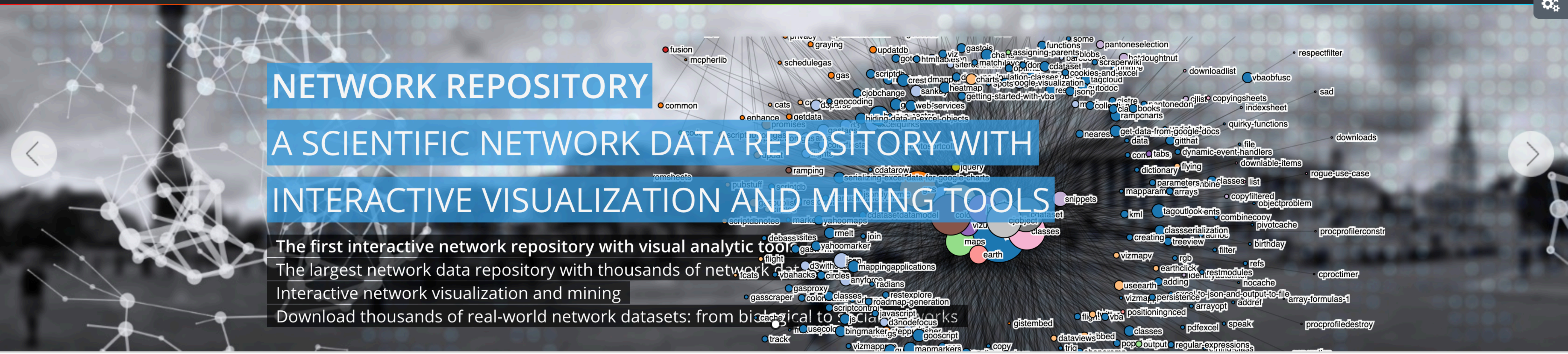


The power of network science,
the beauty of network visualization.

Network Science, a textbook for network science, is

Resource highlight

REPOSITORY ANALYTICS ABOUT CONTRIBUTE Graph search



Network Repository. An **Interactive** *Scientific* Network Data Repository.

THE FIRST SCIENTIFIC NETWORK DATA REPOSITORY WITH INTERACTIVE VISUAL ANALYTICS.

NEW **GraphVis**: interactive visual graph mining and machine learning

The first interactive data and network data repository with real-time visual analytics. Network repository is not only the first interactive repository, but also the *largest network repository* with thousands of donations in 30+ domains (from biological to social network data). This large comprehensive collection of network graph data is useful for making significant research findings as well as benchmark network data sets for a wide variety of applications and domains (e.g., network science, bioinformatics, machine learning, data mining, physics, and social science) and includes relational, attributed, heterogeneous, streaming, spatial, and time series network data as well as non-relational machine learning data. All graph data sets are easily downloaded into a standard consistent format. We also have built a multi-level interactive graph analytics engine that allows users to visualize the structure of the network data as well as macro-level graph data statistics as well as important micro-level network properties of the nodes and edges.

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

GET NETWORK DATA | COMPARE GRAPH DATA | VISUALIZE NETWORKS

Resources (see Github)

Bibliography / Course Material	**Big Data & Mental Health:** **Linked Semantic Mental health Database:** • https://github.com/ChildMindInstitute/mhdb/wiki **MindLogger Data Collection Platform & App:** • https://mindlogger.org/ **Healthy Brain Network Data Collection Project:** • https://healthybrainnetwork.org/ • http://fcon_1000.projects.nitrc.org/indi/cmi_healthy_brain_network/index.html **News, Tutorials, Explorations and Data Adventures of a mental health lab:** • https://matter.childmind.org/blog **Follow a Scientist - Projects and Papers :** • https://www.binarybottle.com/projects.html • https://www.binarybottle.com/papers.html

Skills

Skills badges	When new knowledge merges with experiences and projects, students increase skills. This year, we start to offer skill badges, independently of the internal evaluation of each course. From your point of view, what are the nodal skills that students should target, regarding the field your course opens up? To obtain each skill badge, they will have to offer a project-based proof. This proof definitely can come from the Master program, and also from extra-curriculum action (internship, personal activity, CRI project).
Knowledge skills	Network theory, Mathematical models, Dynamic processes, Algorithms, Data analysis, Data visualisation, Infrastructure, Big data and digital tools in mental health
Operational skills	Network mining, Network analysis, Network visualisation, Data curation
Reflective skills	Conducting a personal/group research project on network data and mental health, Editing a wikipedia article, Open science with OSF, Collaborative Open Science, Open Source
Cooperative skills	Collaboration for personal and group projects, raise issues on github projects from other students, peer-evaluation, joint scientific presentations, peer-to-peer learning

Outline

Planning		
N°	**Type (CM/TP/TD) & hourly rate**	Describe here the content of each session. (1. means first part of the course, 2. the second part, ~1h20 each)
1	16 October (3 hours) - Marc, Liubov, Anirudh, Felix	**Introduction to Networks and Big Data Efforts** 1. **Introduction** to the network part of the course "Why network science?" with presentation of **topics** covered 2. Introduction to the big data part, with a focus on big data for mental health and presentation of **topics** covered
2	23 October (3 hours) - Marc, Liubov	**Networks - basics of network analysis and visualisation** Network metrics and data analysis & create teams for personal projects 1. Theory (network construction, centralities, statistical significance, networkx, other packages) 2. Hands-on session working on a dataframe, creating a network, making some statistical analysis, network visualisation
3	6 Nov (3 hours) - Loic	**Big Data - Infrastructure of big data 1** • Introduction to data engineering, what is the day-to-day jobs and what skills are needed
4	13 Nov (3 hours) - Loic	**Big Data - Infrastructure of big data 2**

Network

Big data

need to revise dates

Planning		
5	20 Nov (3 hours) - Marc, Liubov, Raphael	**Networks - mobility, web-based data** 1. Hands-on Liuba mobility / geographically embedded networks 2. Hands-on How to get data from Youtube/Twitter/etc APIs for data analysis (Raphael Tackx)
6	27 Nov (3 hours) - Marc, Liubov	**Networks - spreading processes** 1. Dynamics on and of networks, temporal networks, information spreading (eg spread of fake news, softwares) 2. Hands-on (data analysis session, sociopatterns etc.)
7	4 Dec (3 hours) - Marc, Liubov	**Networks - dynamics of networks** 1. Theory on networks with attributes: multilayer,multiplex, simplicial, etc. 2. hands-on description of a multilayer network (eg global trade)
8	11 Dec (3 hours) - Marc, Liubov	**Networks EVALUATION** Project presentation (visualisation and descriptive analysis of network data) & reverse classroom (presentation of an advanced topic / paper related to big data / network science and edition of a wikipedia page)

Network

Planning		
9	18 Dec (3 hours) - Anirudh, Felix	**Dynamic Digital Drivers in Mental Health Open Science** Deep dive into the digital tools (MindLogger data collection platform & linked mental health database) to be applied for the final individual/group project(s) 1. Theory (raison d'etre, rationale, significance, challenges behind developing the digital tools for mental health) 2. Hands-on session working with the digital tools Students select topics and teams for personal/group projects and winter exam announcement
10	8 Jan (3 hours) - Anirudh, Felix	**Data Efforts in Mental Health** 1. Assignment presentations and peer-evaluation (each group will provide 3 strong and 3 weak points, and review another group's project) 2. Project review with course tutors and determination of next steps & deliverables
11	15 Jan (3 hours) - Anirudh, Felix	**Individual/Group Mental Health Research Project** 1. Work session - group work continues. 2. Project documentation review
12	22 Jan (3 hours) - Anirudh, Felix	**Individual/Group Mental Health Research Project** Final presentations and discussion

Big data & mental health

BIG DATA COURSE

1. INTRODUCTION TO **NETWORK SCIENCE**

Marc Santolini & Liubov Tupikina
16 Oct 2019
CRI Paris

marc.santolini@cri-paris.org
liubov.tupikina@cri-paris.org

video: Kim Albrecht

NETWORK TEACHERS

Marc Santolini (CRI)
Biological & social networks
R, Gephi, Cytoscape

Liubov Tupikina (Bell Labs)
Mathematics, spreading
python, drawing networks :)

Raphael Tackx (CRI)
Computer Science
Python, community detection, APIs

Today's goal

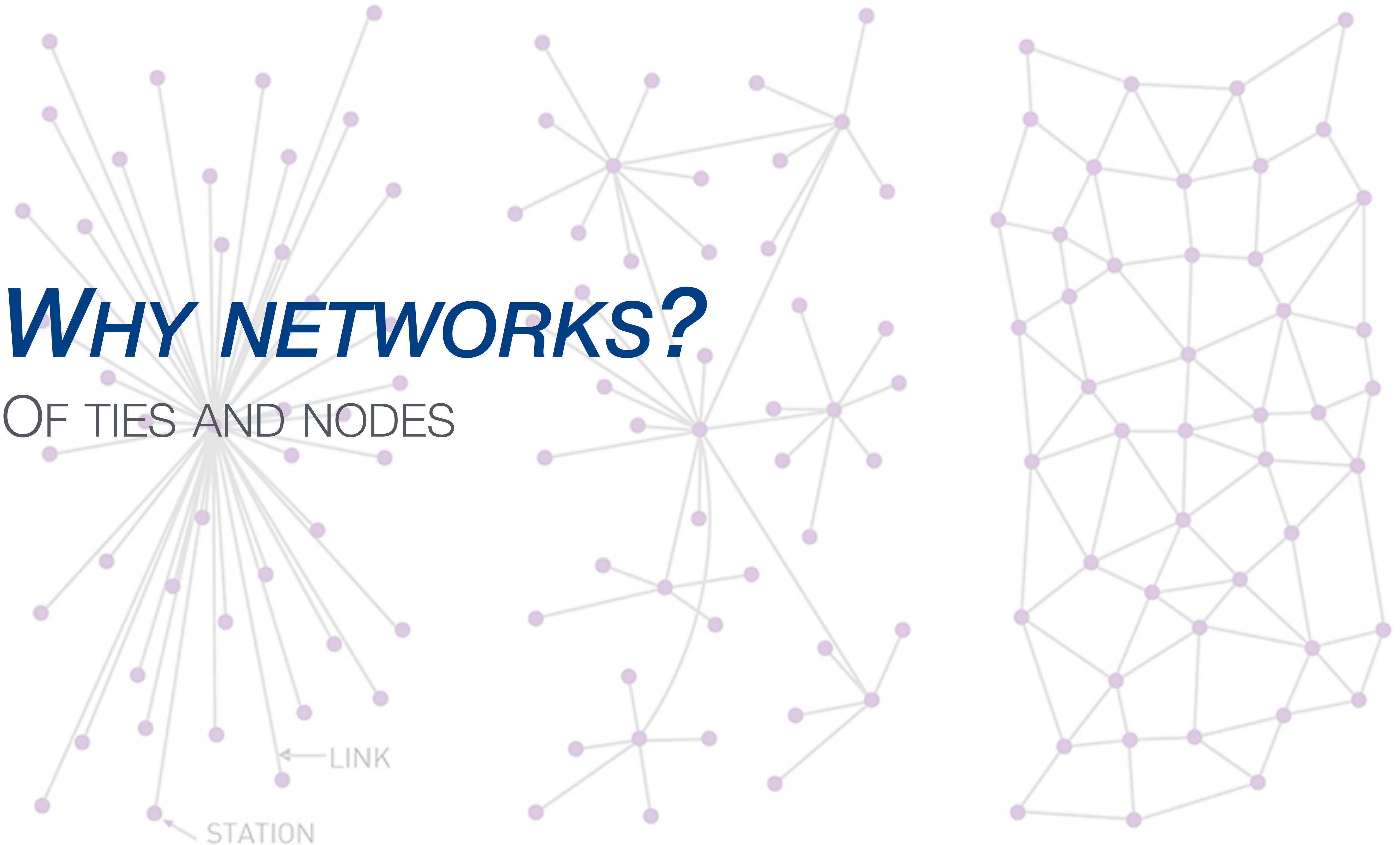
1. Present the field of network science

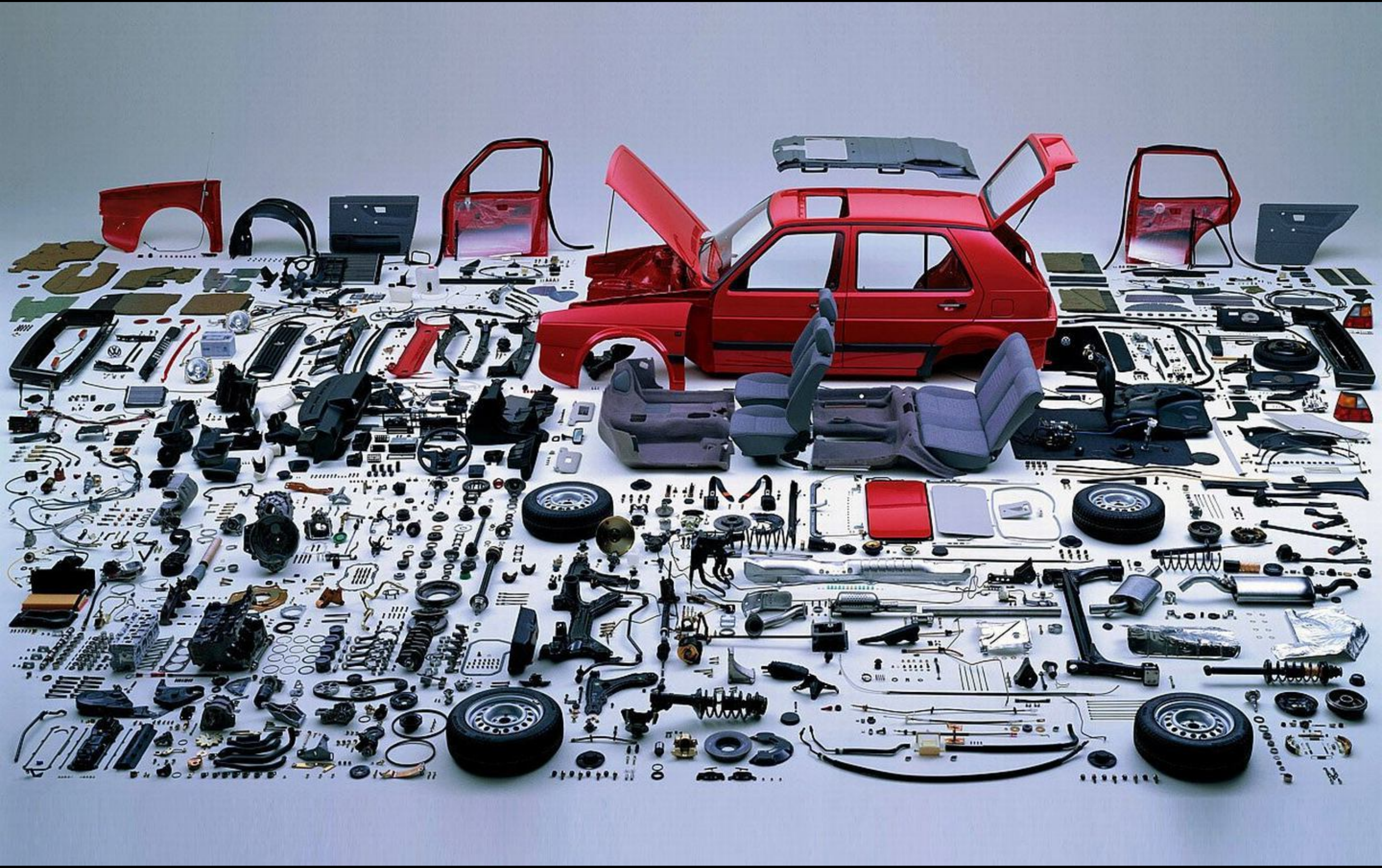
2. Build intuition!

3. Get to know you better: google form

WHY NETWORKS?

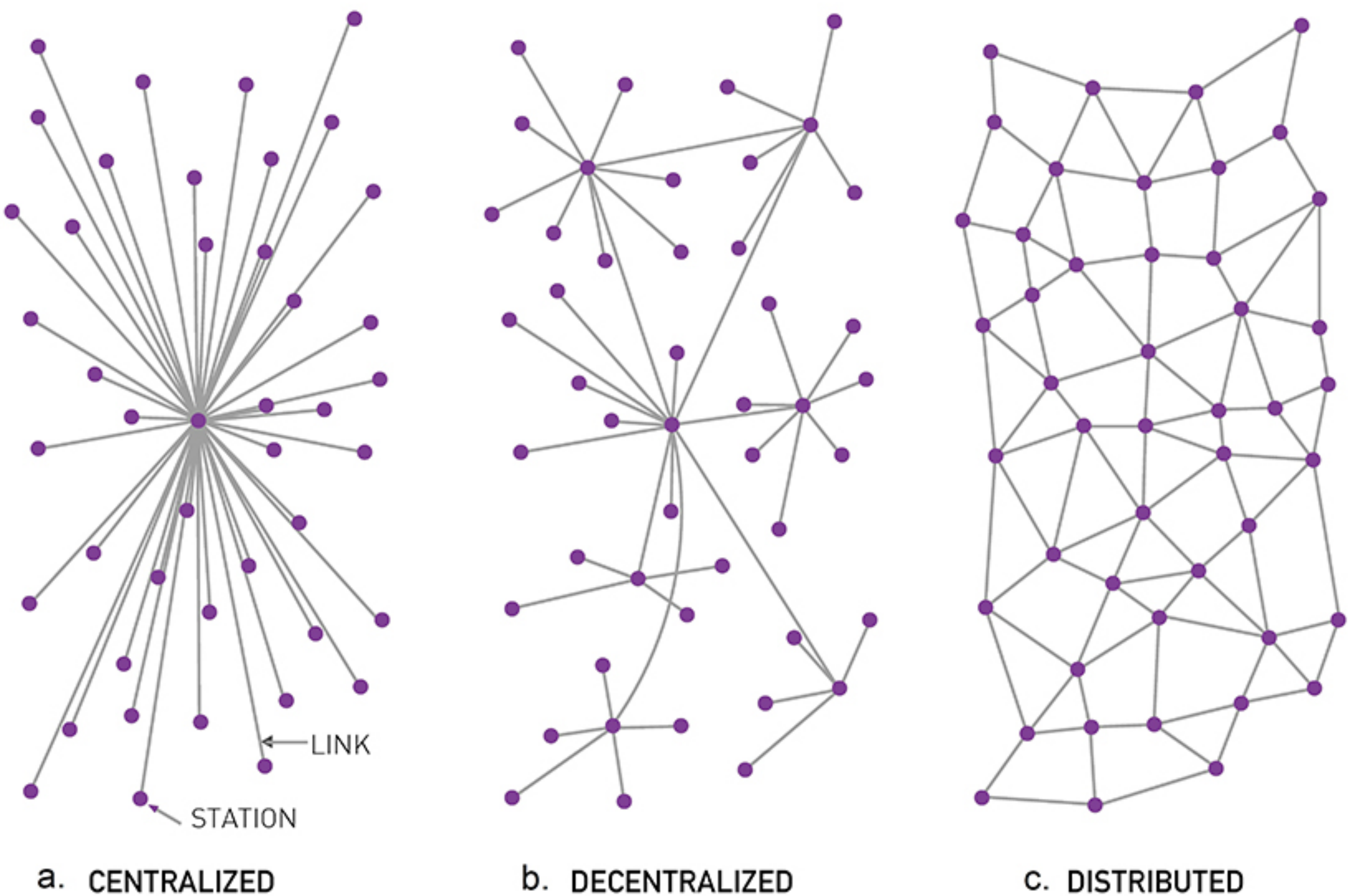
OF TIES AND NODES





interactions matter!

Paul Baran 1964: structure matters



a holistic, multi-level approach

The NEW ENGLAND JOURNAL of MEDICINE

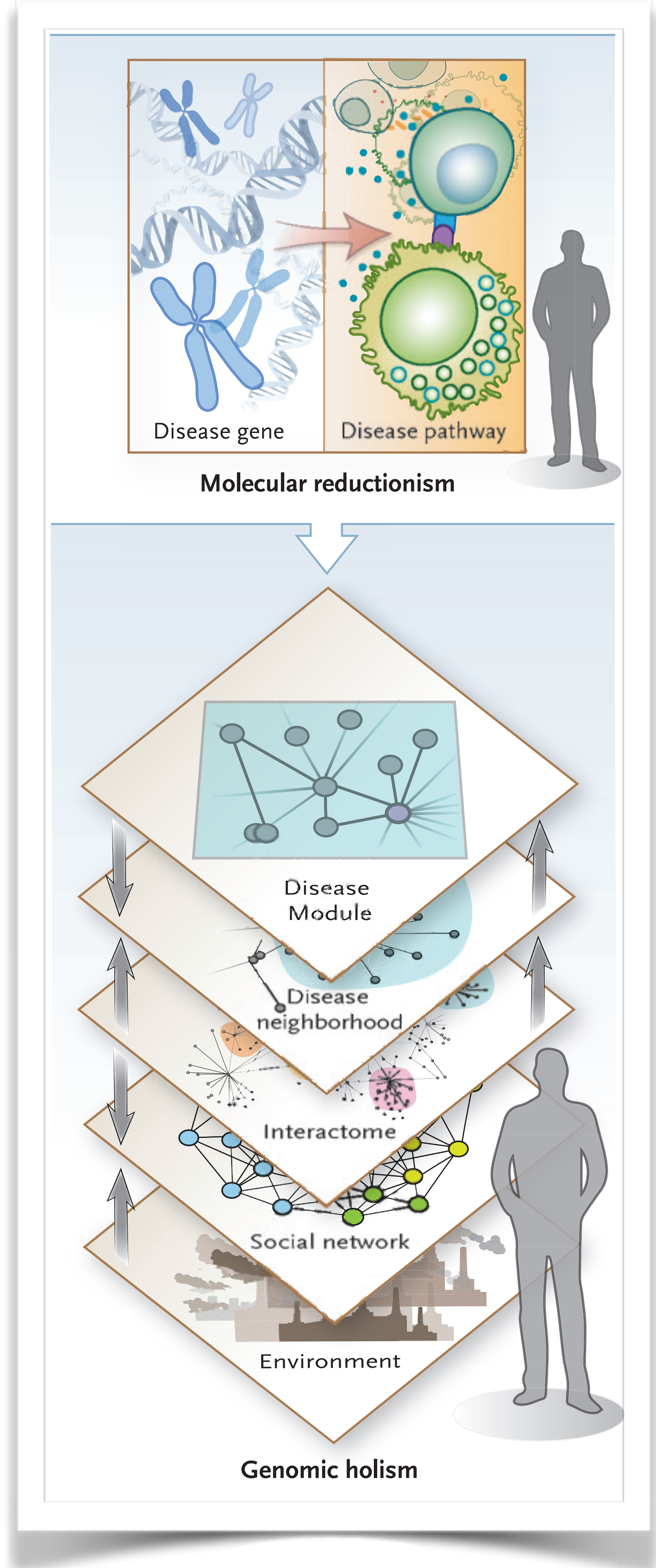
MEDICINE AND SOCIETY

Debra Malina, Ph.D., *Editor*

Putting the Patient Back Together — Social Medicine, Network Medicine, and the Limits of Reductionism

Jeremy A. Greene, M.D., Ph.D., and Joseph Loscalzo, M.D., Ph.D.

N ENGL J MED 377;25 NEJM.ORG DECEMBER 21, 2017

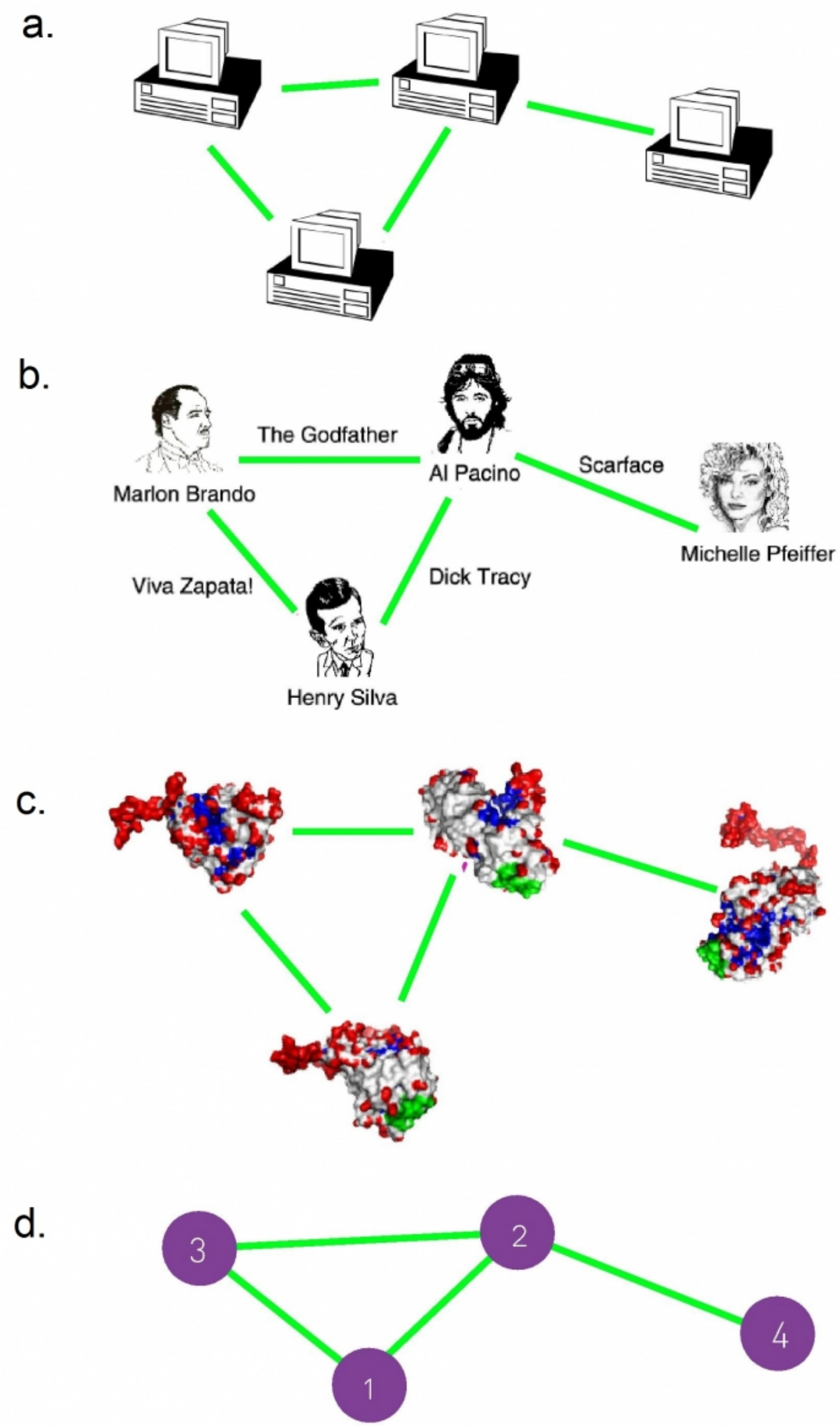


What is a network?

Describing the wiring diagram

$$A_{ij} = \begin{matrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}$$

$$A_{ij} = \begin{matrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}$$

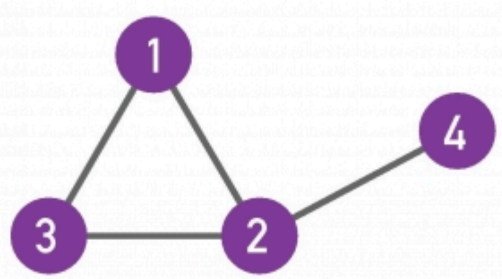

a.
b.
The Godfather
Marlon Brando
Al Pacino
Scarface
Michelle Pfeiffer
Viva Zapata!
Dick Tracy
Henry Silva
c.
d.
3
2
1
4

Representation of networks

a. **Adjacency matrix**

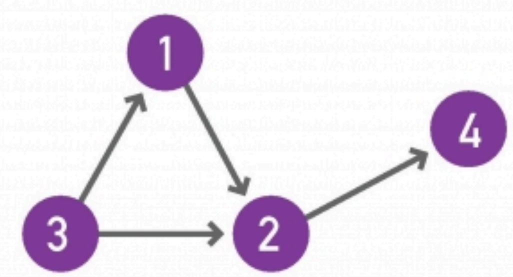
$$A_{ij} = \begin{matrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \\ A_{41} & A_{42} & A_{43} & A_{44} \end{matrix}$$

b. **Undirected network**



$$A_{ij} = \begin{matrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}$$

c. **Directed network**



$$A_{ij} = \begin{matrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}$$

REPRESENTATION OF NETWORKS

Typical format of network data:

Node attributes

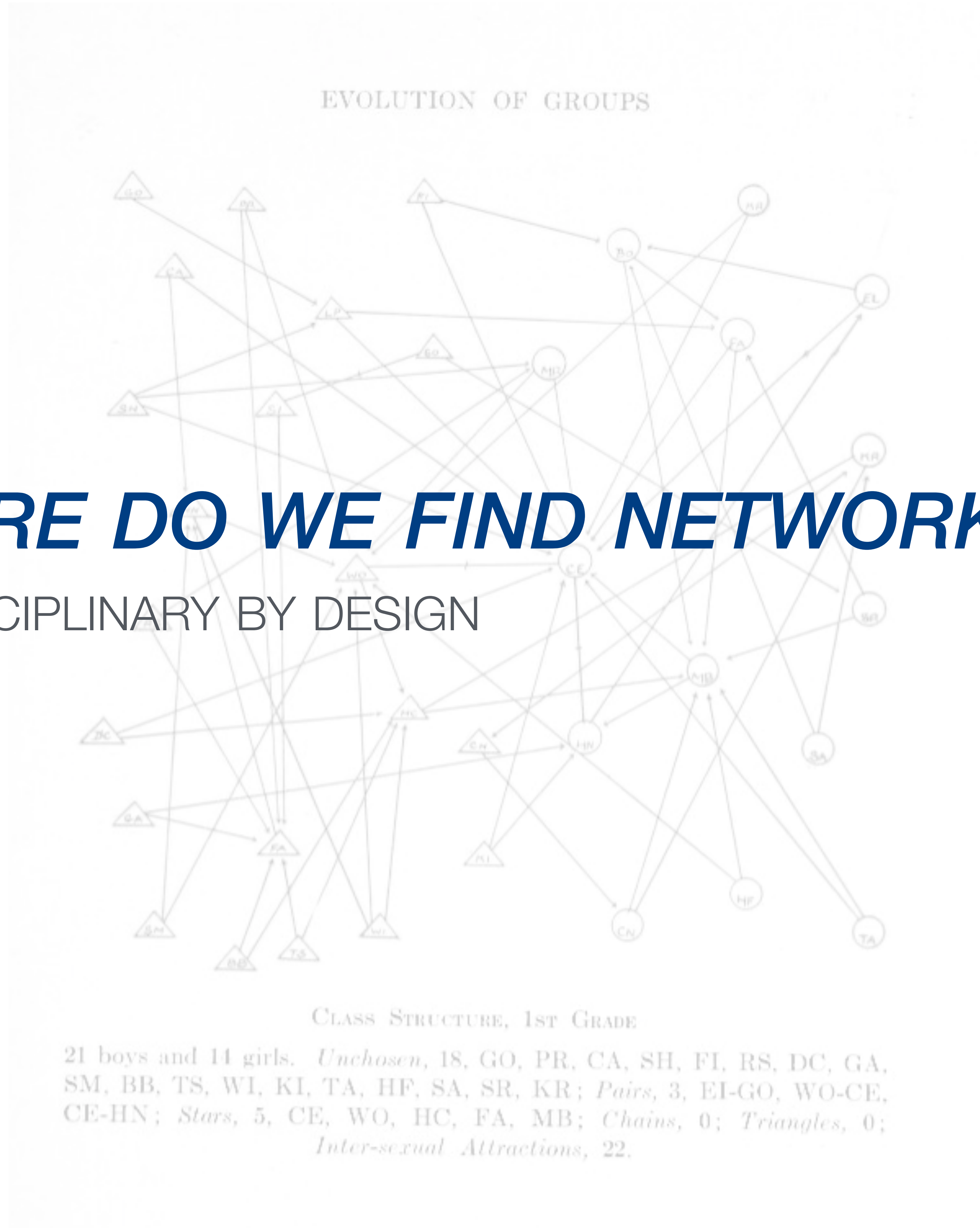
	A	B
1	Id	Label
2	376088951	name1
3	17647430	name2
4	32416061	name3
5	550180187	name4
6	28110685	name5
7	14845783	name7
8	63293	name8
9	22606966	name9
10	193763394	name10
11	191004748	name11
12	61502712	name13
13	2230301	name16
14	17870064	name17
15	123516974	name18
16	10161492	name19
17	16856080	name20
18	94154580	name21
19	20059362	name22
20	20646457	name23
21	109562464	name24

Edge attributes

	A	B	C	D
1	Source	Target	Type	Weight
2	376088951	17647430	Directed	1
3	376088951	32416061	Directed	1
4	376088951	550180187	Directed	2
5	376088951	28110685	Directed	3
6	376088951	870137221	Directed	3
7	550180187	376088951	Directed	2
8	550180187	17870064	Directed	2
9	550180187	320140078	Directed	1
10	550180187	4308031	Directed	1
11	550180187	34881762	Directed	1
12	550180187	17150632	Directed	2
13	550180187	34621309	Directed	3
14	550180187	57601933	Directed	3
15	550180187	277980462	Directed	2
16	550180187	133671478	Directed	3
17	550180187	65947781	Directed	3
18	28110685	376088951	Directed	3
19	28110685	14845783	Directed	1
20	28110685	63293	Directed	2
21	28110685	109562464	Directed	3
22	28110685	320140078	Directed	1

WHERE DO WE FIND NETWORKS?

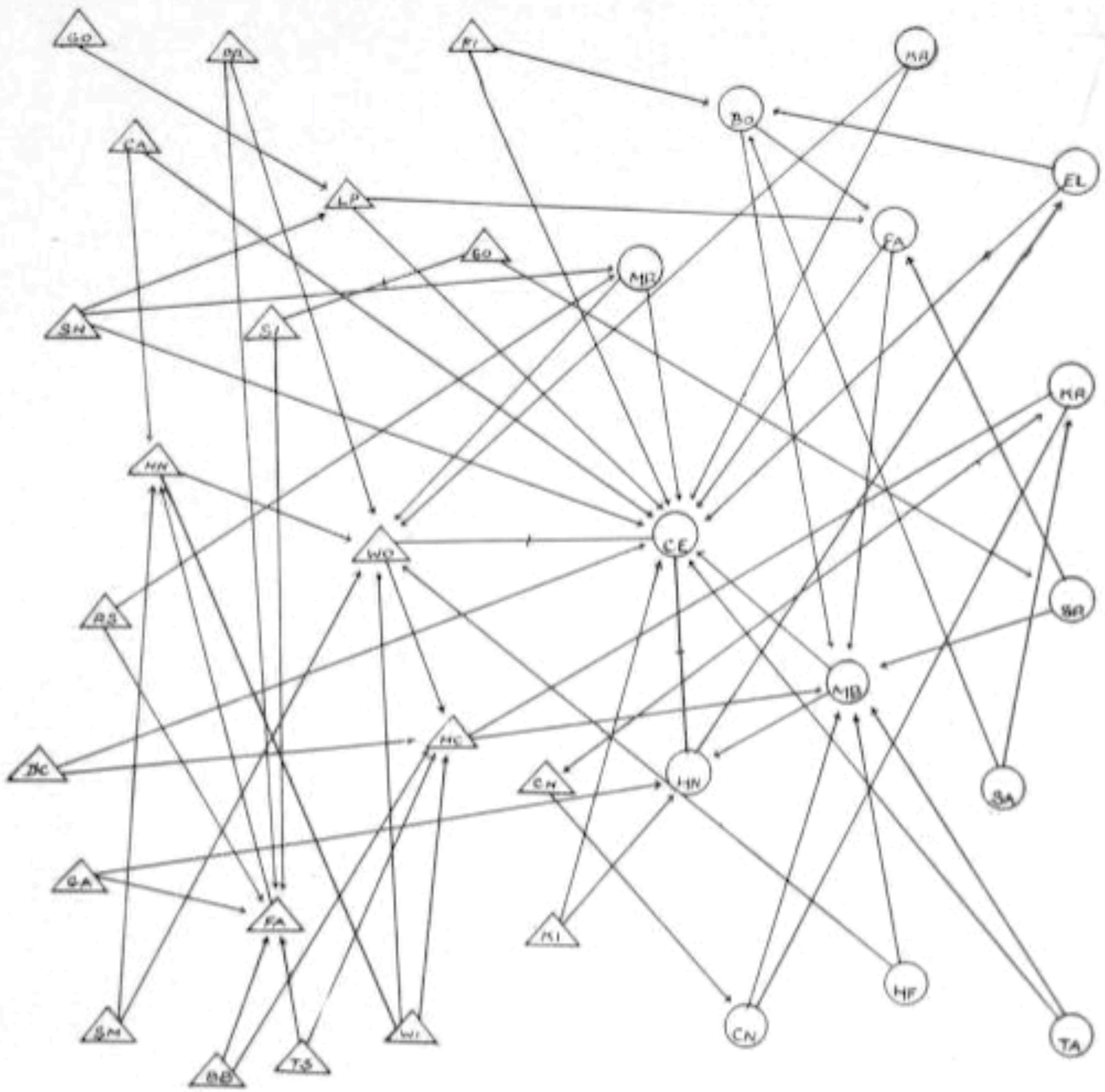
INTERDISCIPLINARY BY DESIGN



neurosciences

Camillo Golgi 1875
"diffuse nervous network"

Santiago Ramon y Cajal 1887
“cable theory”



Class Structure, 1st Grade

21 boys and 14 girls. *Unchosen*, 18, GO, PR, CA, SH, FI, RS, DC, GA, SM, BB, TS, WI, KI, TA, HF, SA, SR, KR; *Pairs*, 3, EI-GO, WO-CE, CE-HN; *Stars*, 5, CE, WO, HC, FA, MB; *Chains*, 0; *Triangles*, 0; *Inter-sexual Attractions*, 22.

social sciences

Moreno sociogram 1934

Transportation networks: Tolstoi 1930

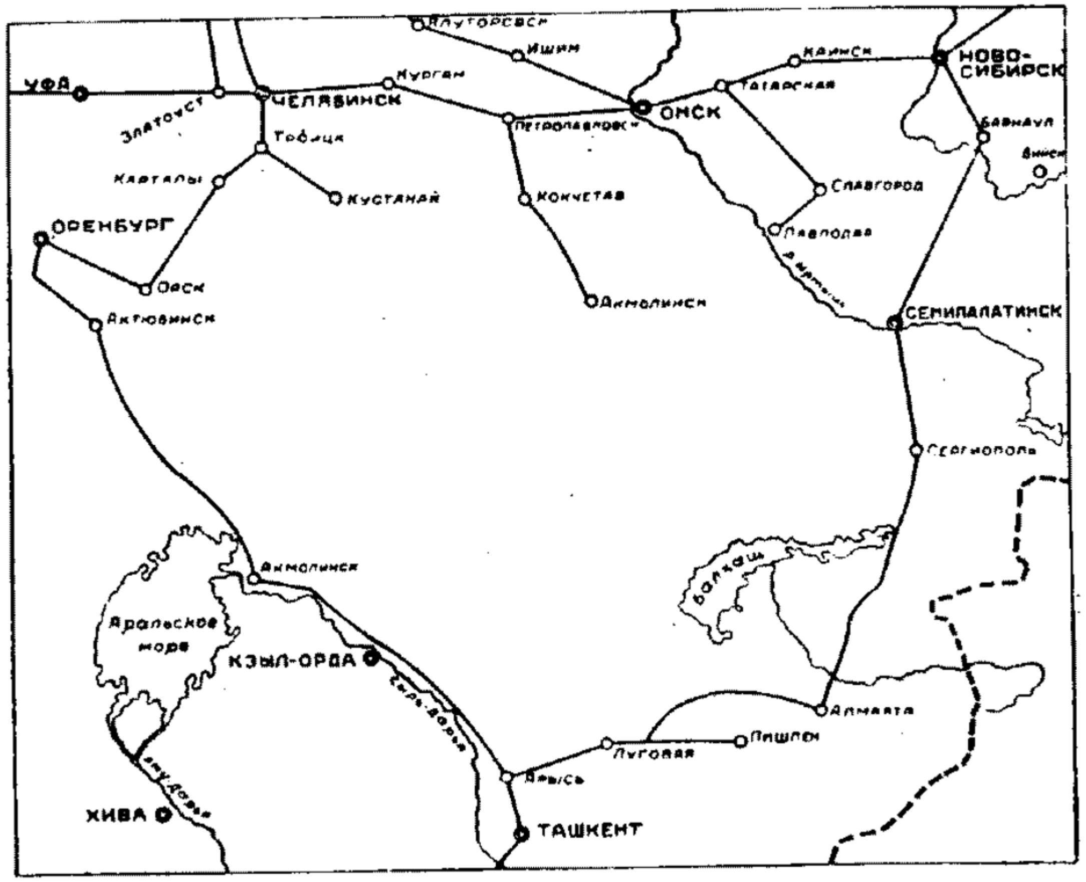


Figure 1
Figure from Tolstoĭ [1930] to illustrate a negative cycle.

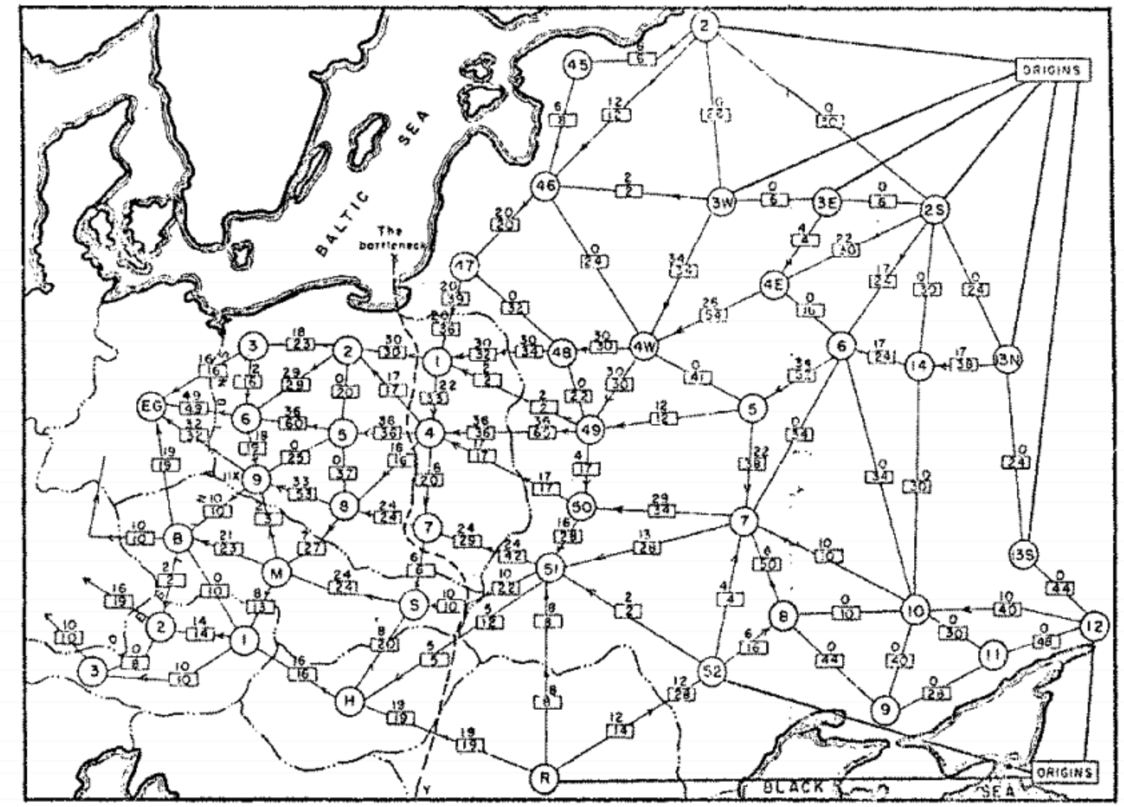
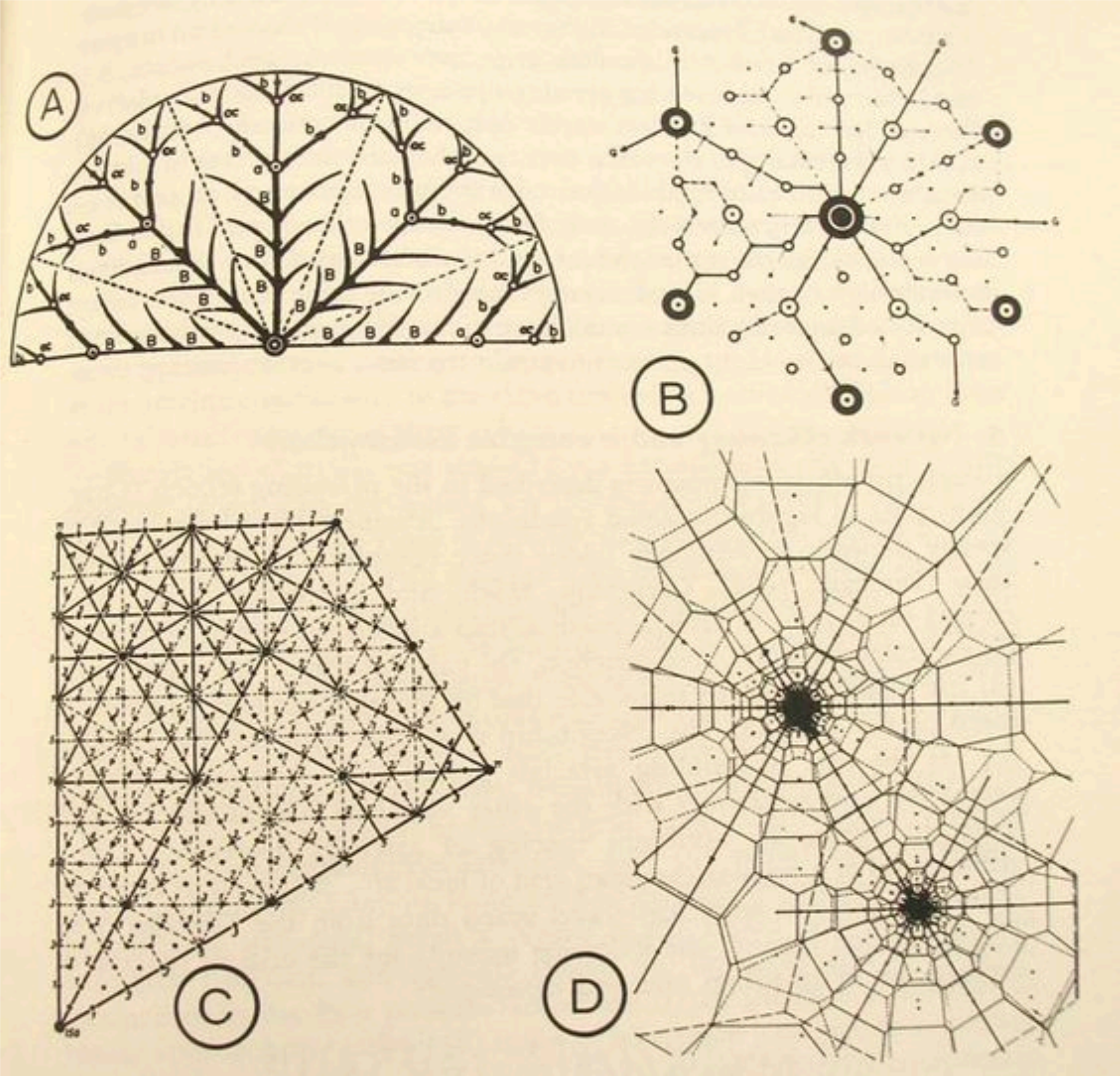
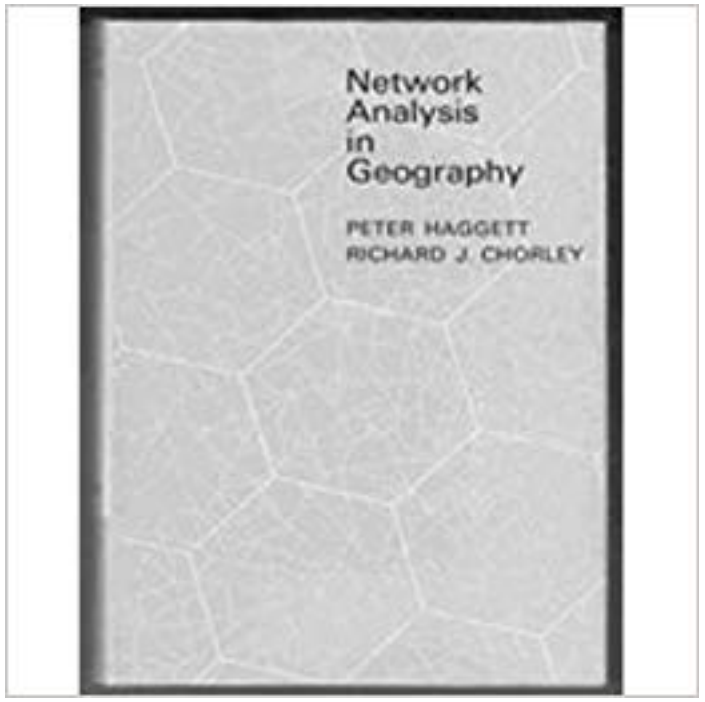


Figure 2
From Harris and Ross [1955]: Schematic diagram of the railway network of the Western Soviet Union and Eastern European countries, with a maximum flow of value 163,000 tons from Russia to Eastern Europe, and a cut of capacity 163,000 tons indicated as "The bottleneck".

geographical networks





Network Analysis in Geography, 1969, Haggett & Chorley

Transport networks for theoretical settlements (A) Kohl, 1850 (B) Christaller, 1933 (C) Losch, 1954 (D) Isard, 1960.

information flow in social networks

Granovetter 1973
"Strength of weak ties"

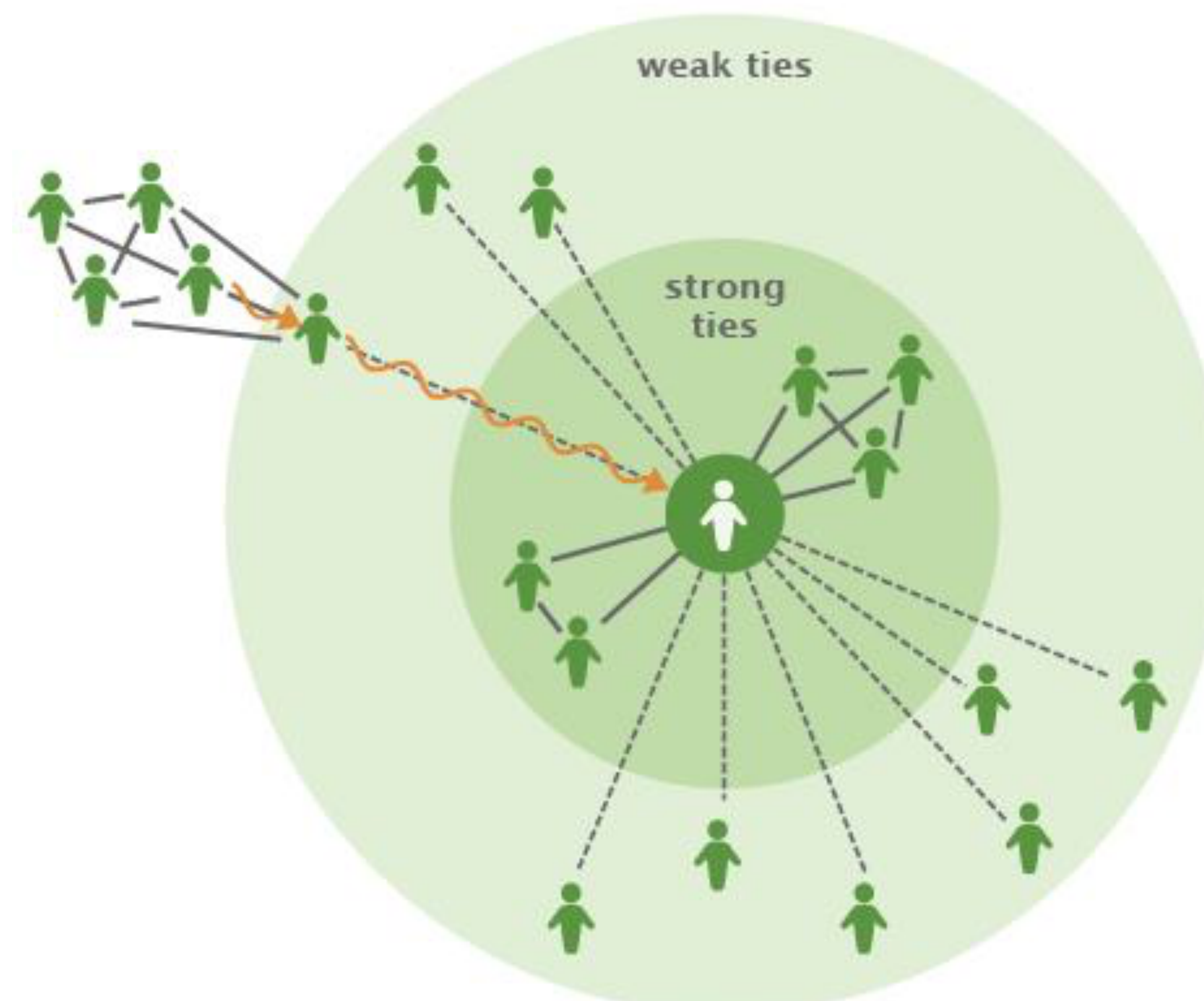
The Strength of Weak Ties[1]

Mark S. Granovetter
Johns Hopkins University

Analysis of social networks is suggested as a tool for linking micro and macro levels of sociological theory. The procedure is illustrated by elaboration of the macro implications of one aspect of small-scale interaction: the strength of dyadic ties. It is argued that the degree of overlap of two individuals' friendship networks varies directly with the strength of their tie to one another. The impact of this principle on diffusion of influence and information, mobility opportunity, and community organization is explored. Stress is laid on the cohesive power of weak ties. Most network models deal, implicitly, with strong ties, thus confining their applicability to small, well-defined groups. Emphasis on weak ties lends itself to discussion of relations *between* groups and to analysis of segments of social structure not easily defined in terms of primary groups.

A fundamental weakness of current sociological theory is that it does not relate micro-level interactions to macro-level patterns in any convincing way. Large-scale statistical, as well as qualitative, studies offer a good deal of insight into such macro phenomena as social mobility, community organization, and political structure. At the micro level, a large and increasing body of data and theory offers useful and illuminating ideas about what transpires within the confines of the small group. But how interaction in small groups aggregates to form large-scale patterns eludes us in most cases.

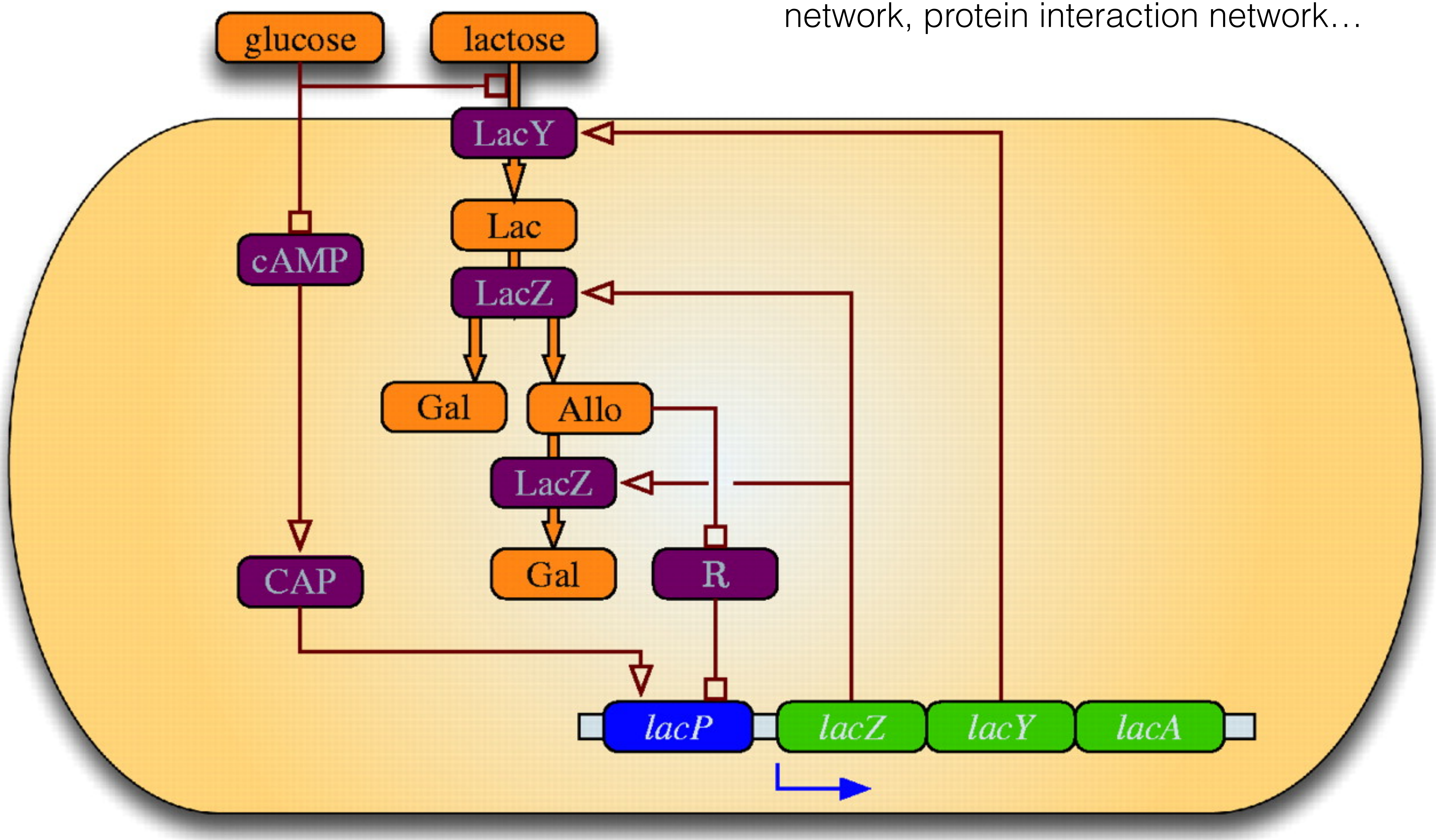
I will argue, in this paper, that the analysis of processes in interpersonal networks provides the most fruitful micro-macro bridge. In one way or another, it is through these networks that small-scale interaction becomes



Monod & Jacob 1961

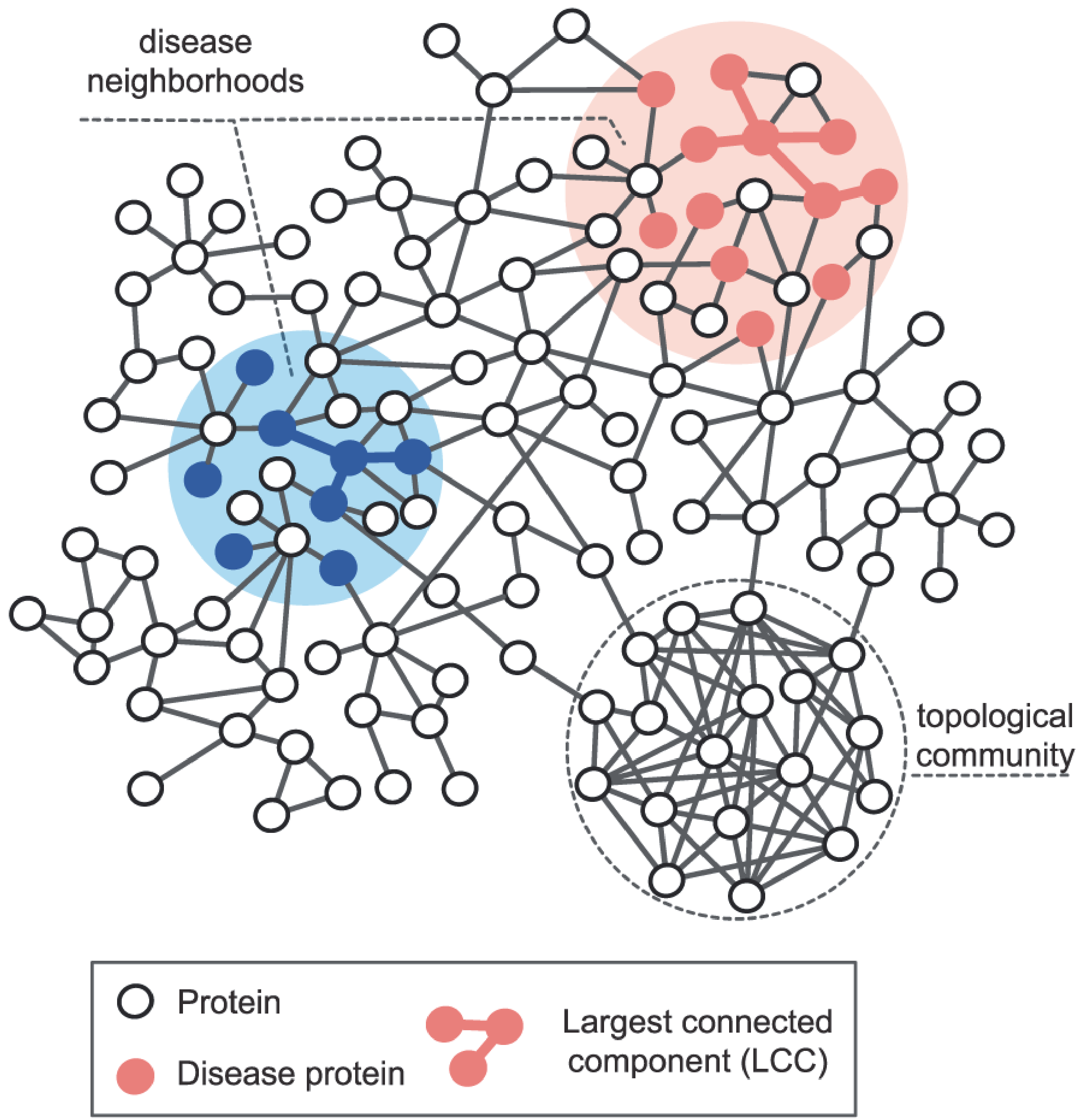
biological networks

Gene regulatory networks, metabolic network, protein interaction network…



network medicine

"disease modules" identification, drug target prediction, drug repurposing..



cognitive networks

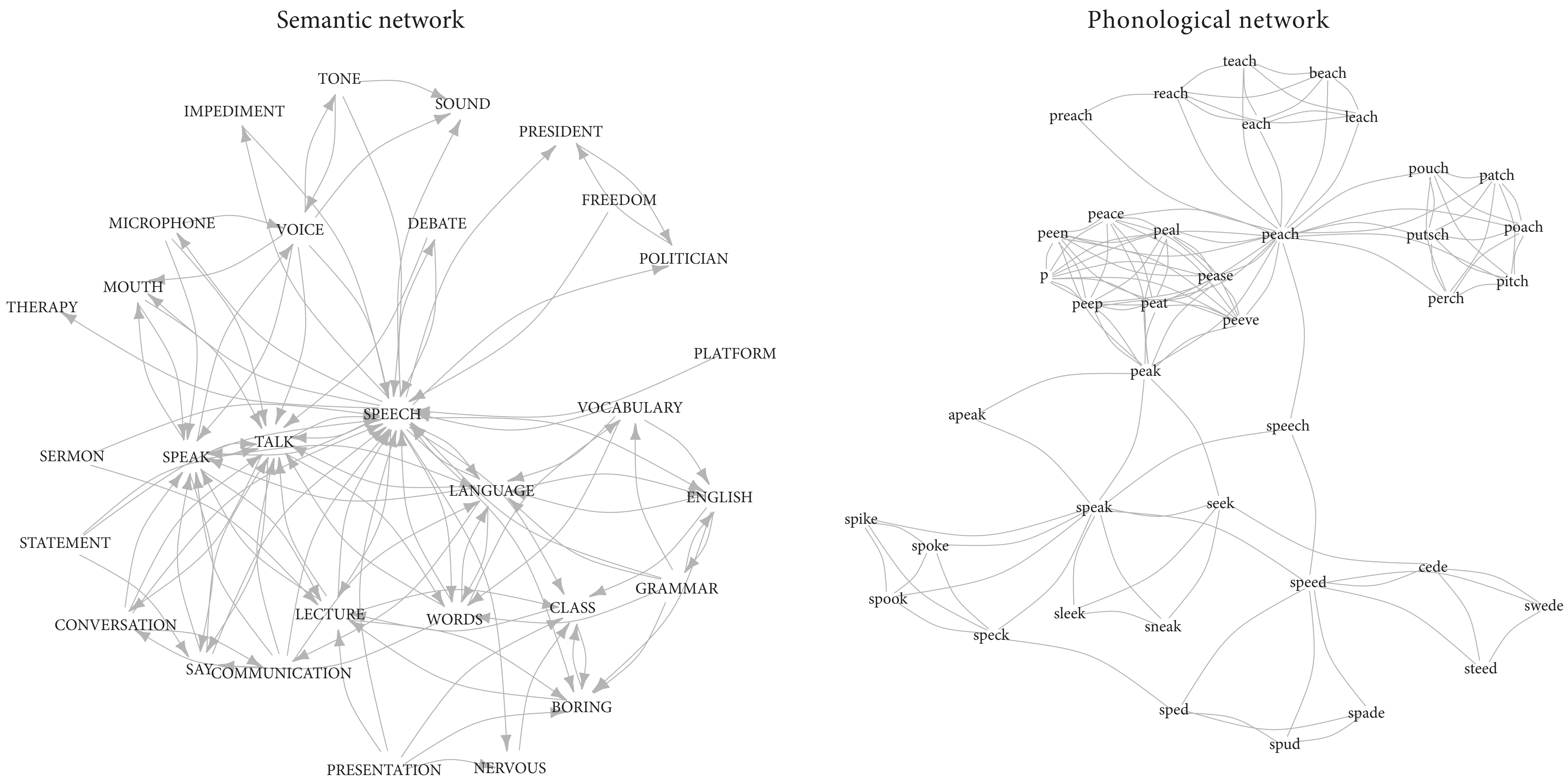


FIGURE 1: Examples of cognitive networks. Semantic network of free associations to the word *speech* (Left) and phonological network of words that sound similar to the word *speech* (Right).

Siew et al, Complexity 2019

THE RISE OF NETWORKS

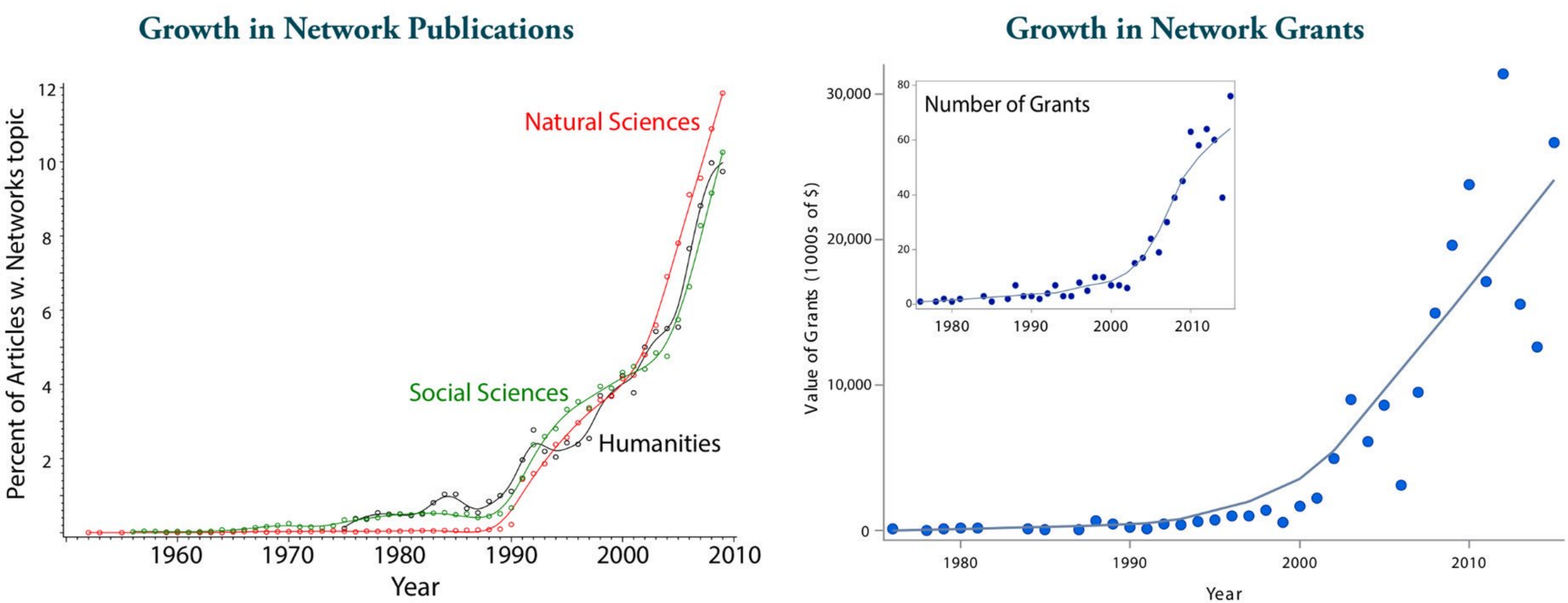
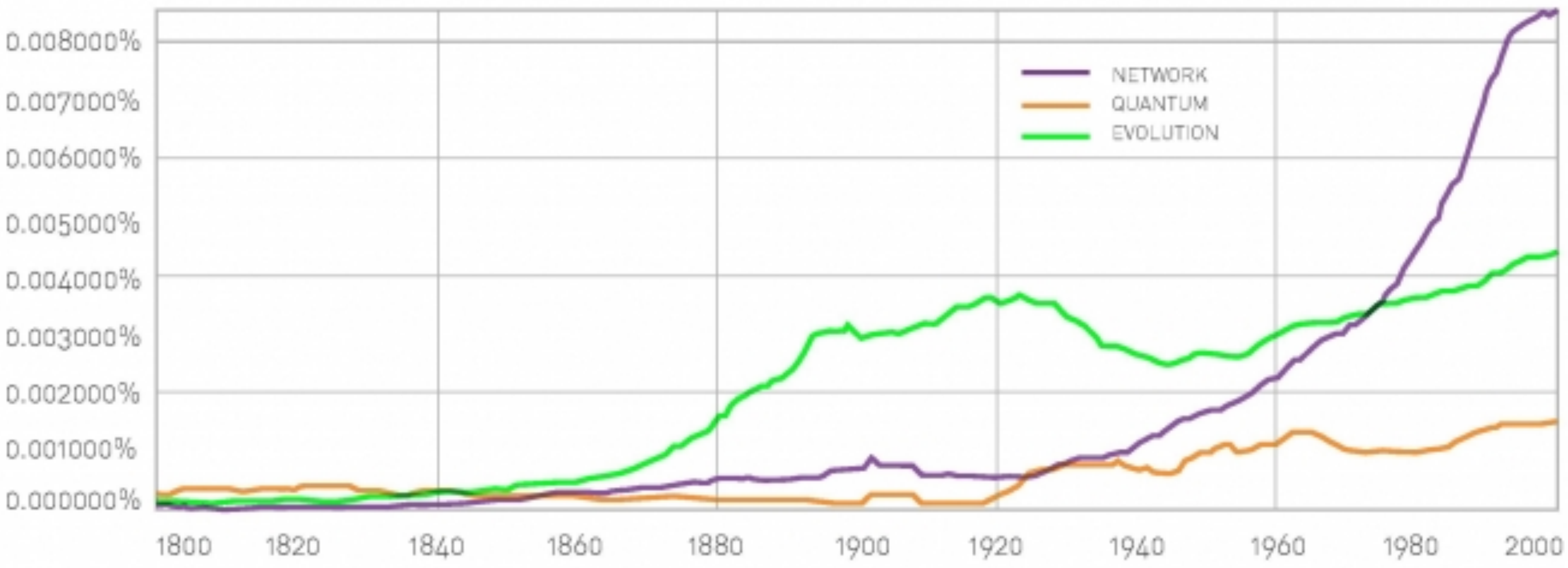


Figure 1. Publications of network studies and NSF grants with "network analysis" has increased dramatically from 1950 to 2016. *(Credit: James Moody, Duke University)*

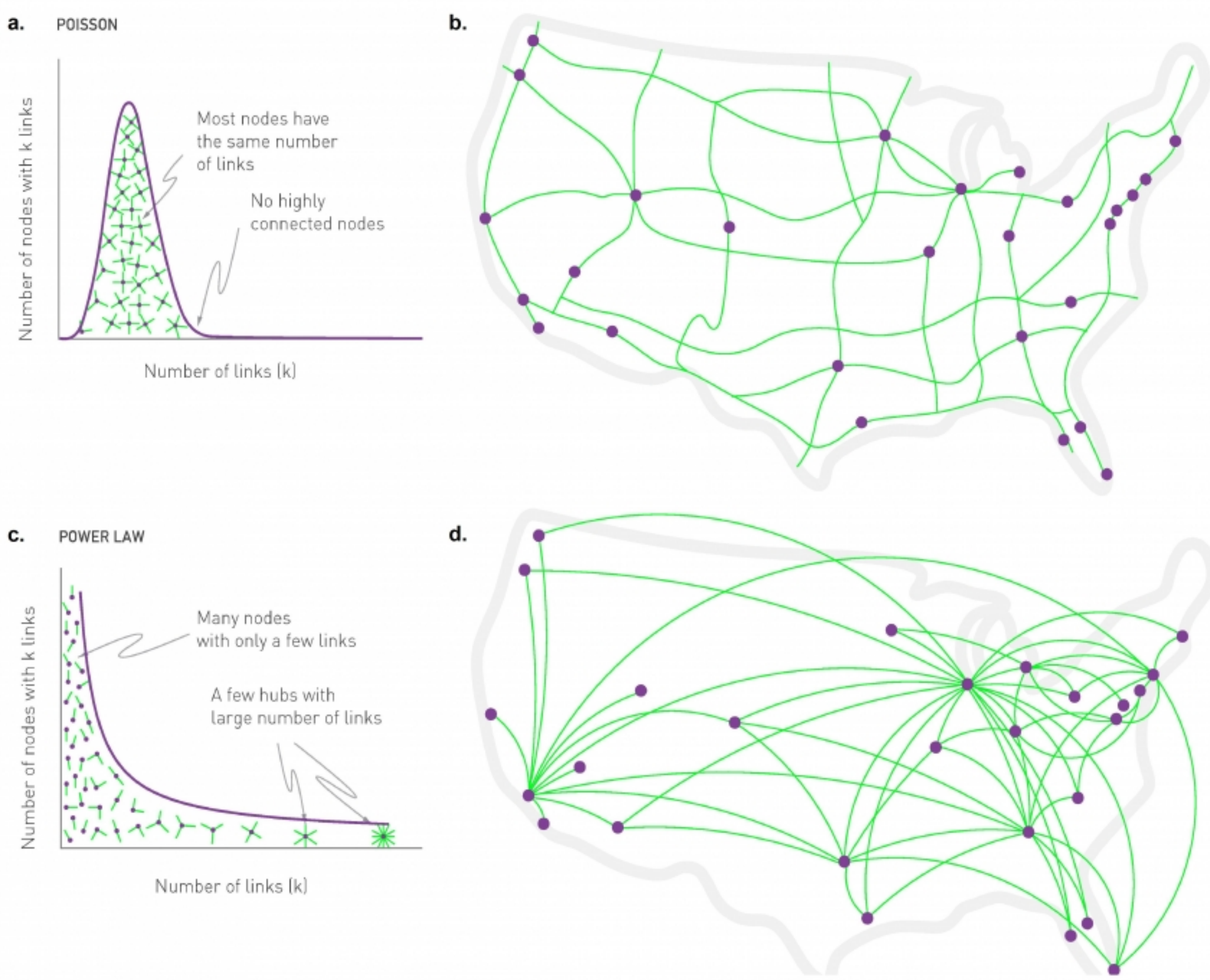
The rise of networks



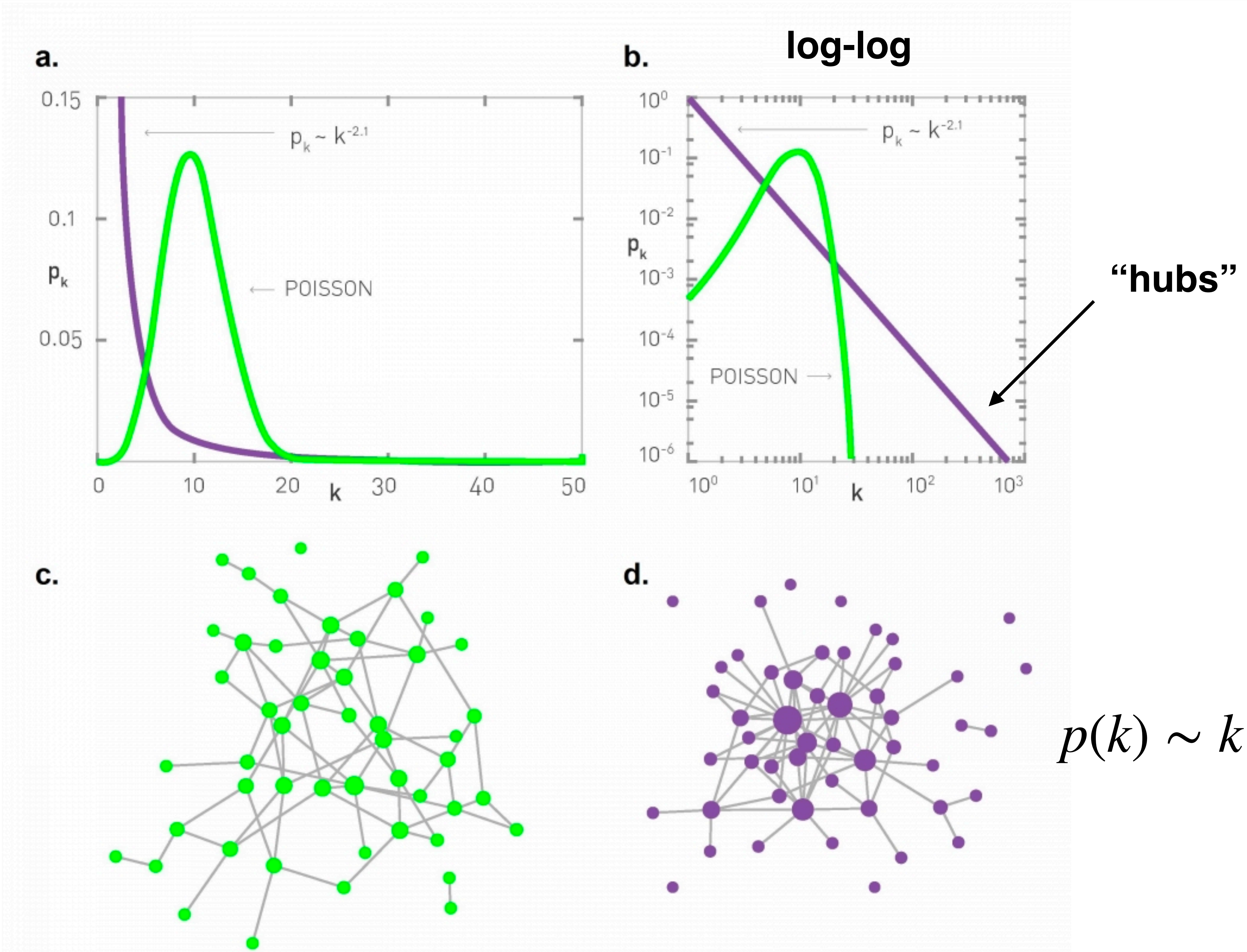
HUBS, COMMUNITIES

REAL-WORLD NETWORK ARE NOT RANDOM

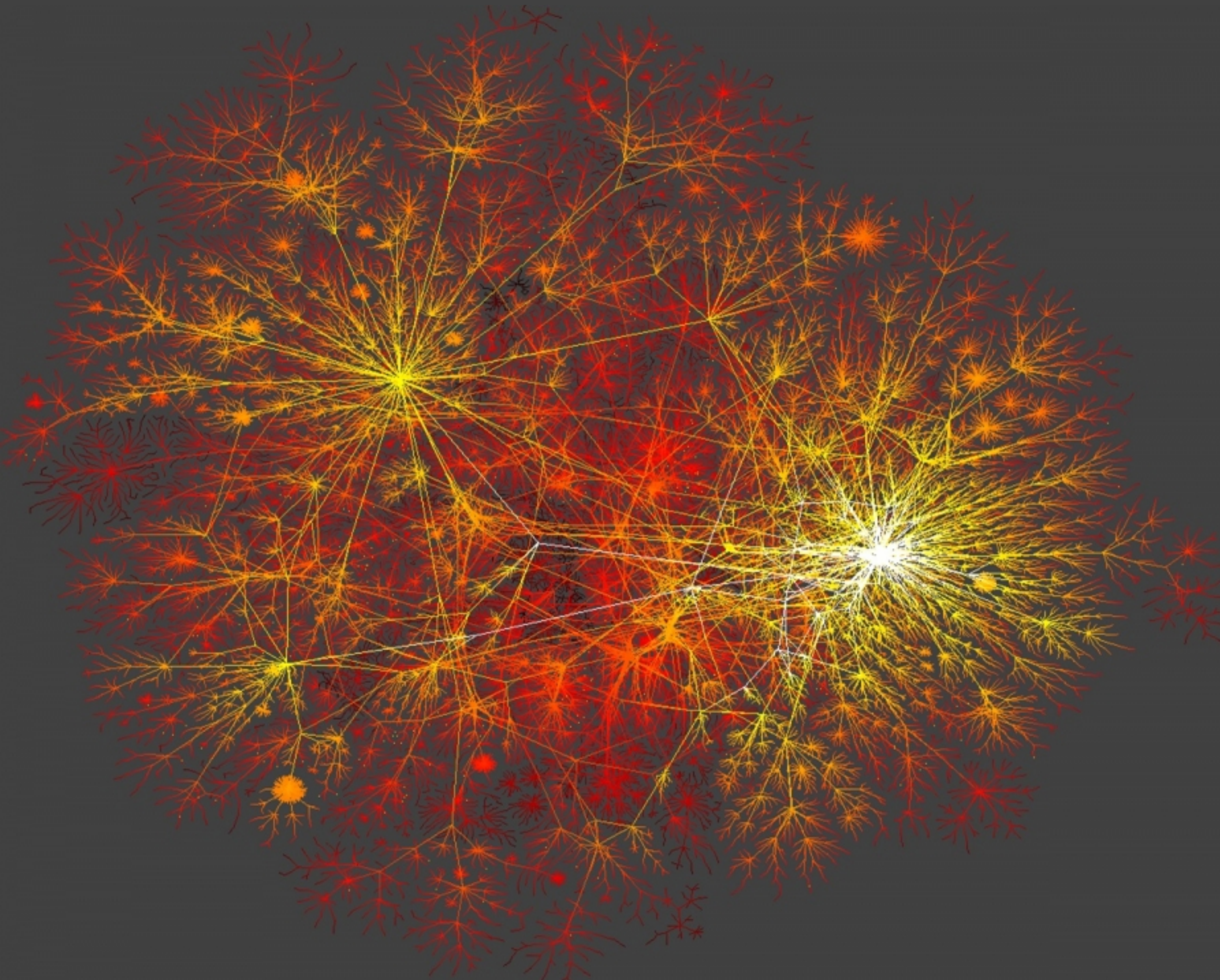
SCALE-FREE NETWORKS



HUBS

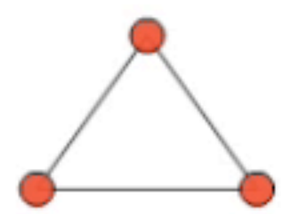


$$p(k) \sim k^{-\gamma}$$

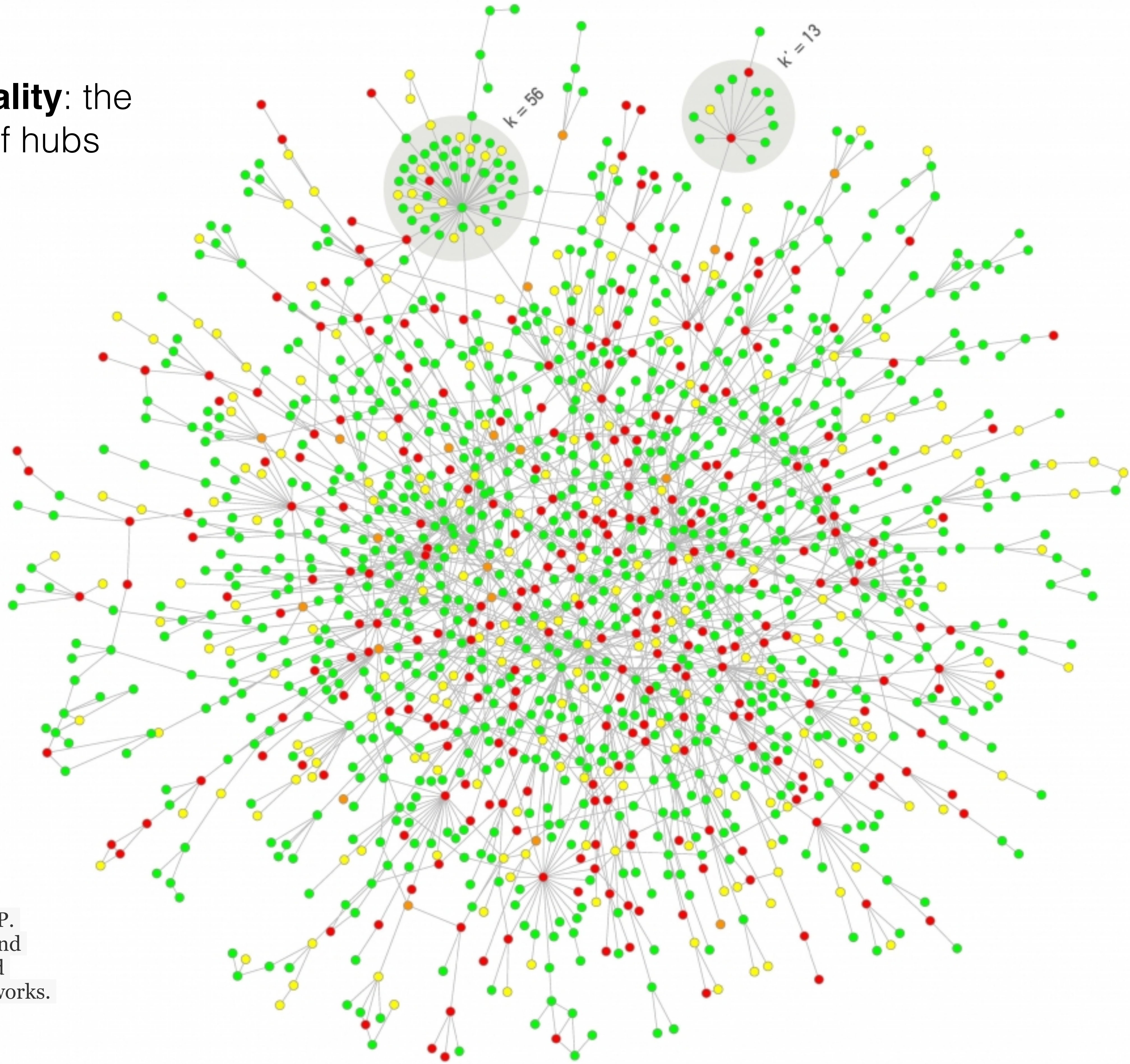


Barabasi-Albert model 1999

Preferential attachement

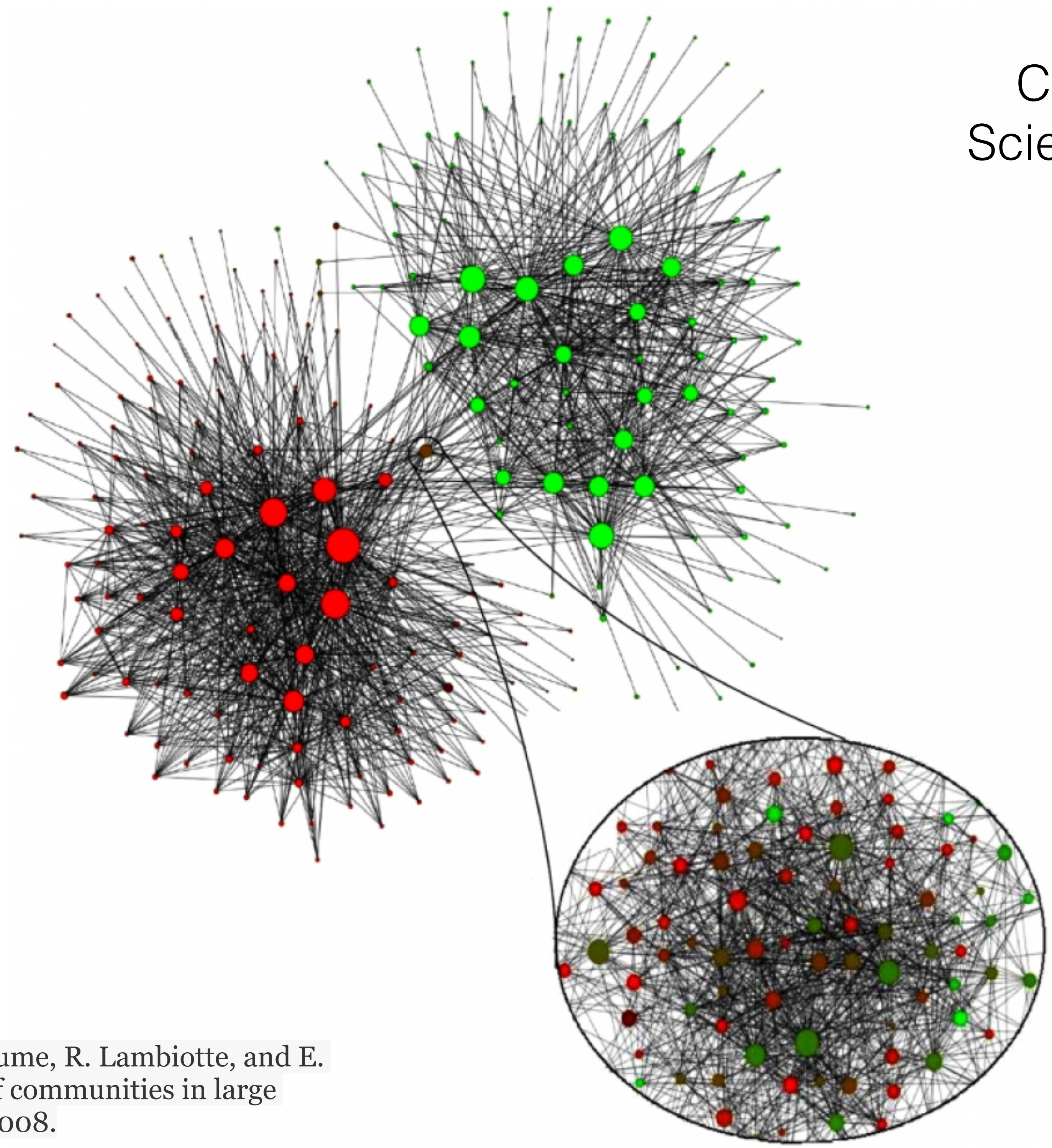


centrality-lethality: the importance of hubs



H. Jeong, B. Tombor, S. P. Mason, A.-L. Barabási, and Z.N. Oltvai. Lethality and centrality in protein networks. Nature 411: 41-42, 2001.

COMMUNITIES

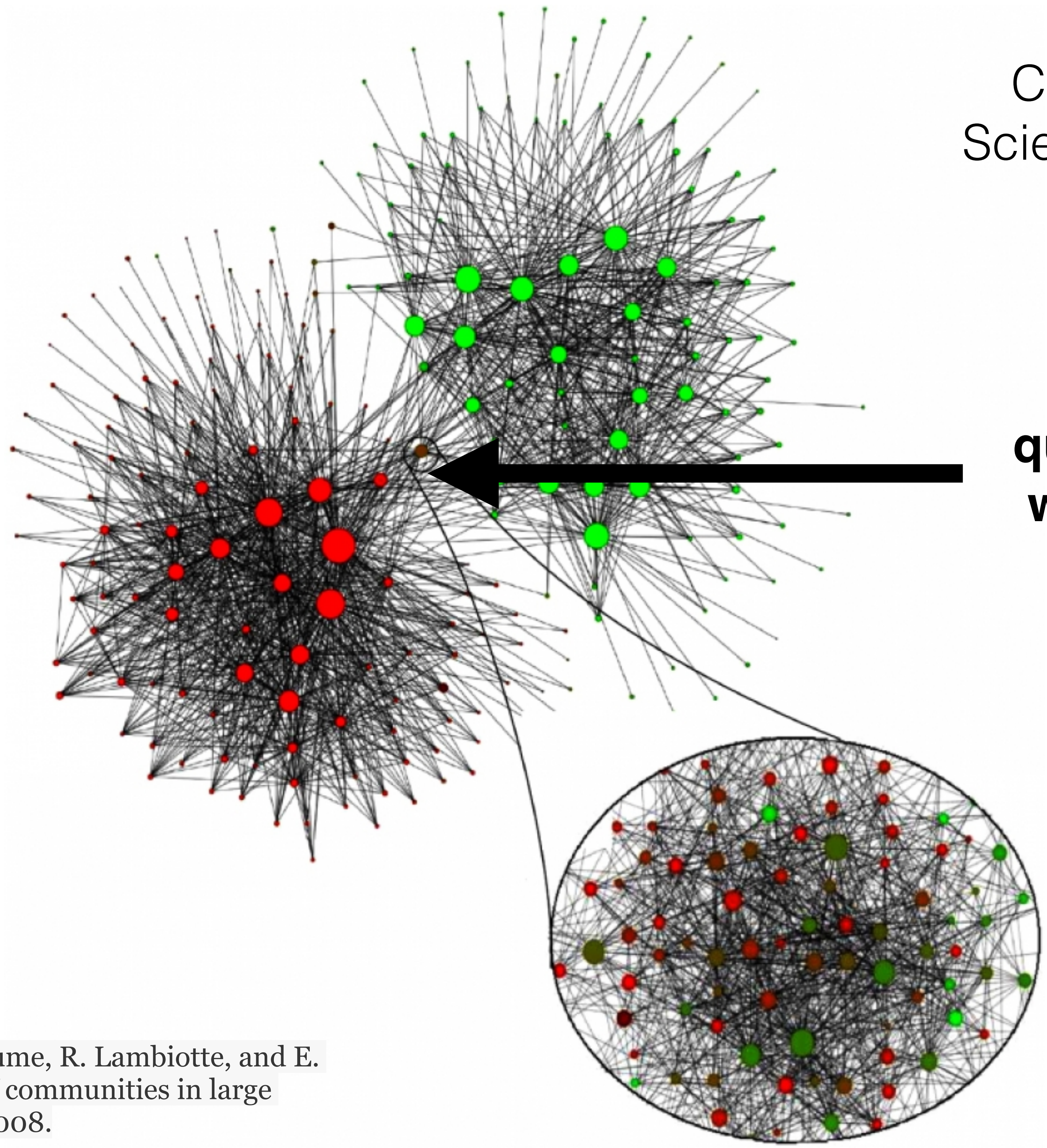


Chapter 9, Network Science Book, Barabasi

V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre. Fast unfolding of communities in large networks. J. Stat. Mech., 2008.

COMMUNITIES

Chapter 9, Network Science Book, Barabasi



question: is it a hub?
why is it important?

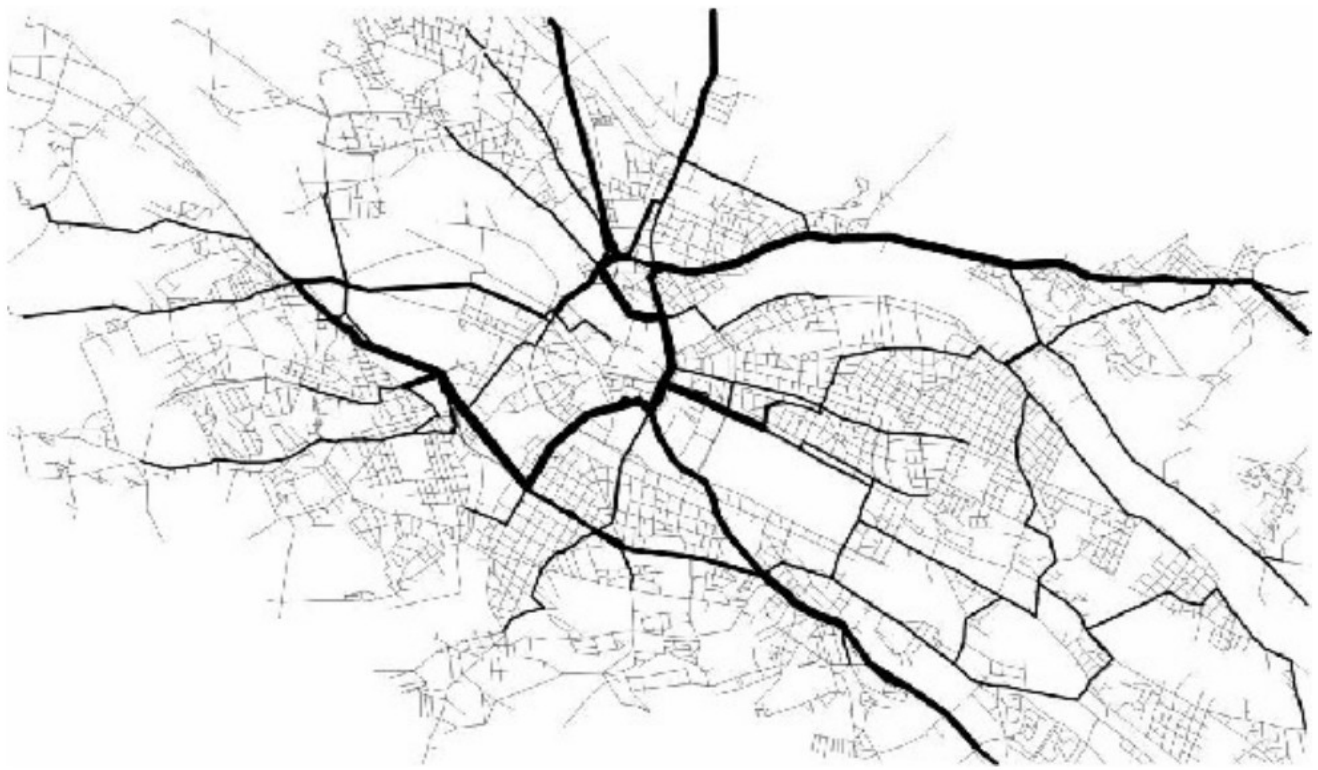
V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre. Fast unfolding of communities in large networks. J. Stat. Mech., 2008.

SPATIAL NETWORKS

PHYSICAL NETWORKS

M.Barthelemy, “Spatial networks”, Phys.Rep.2011

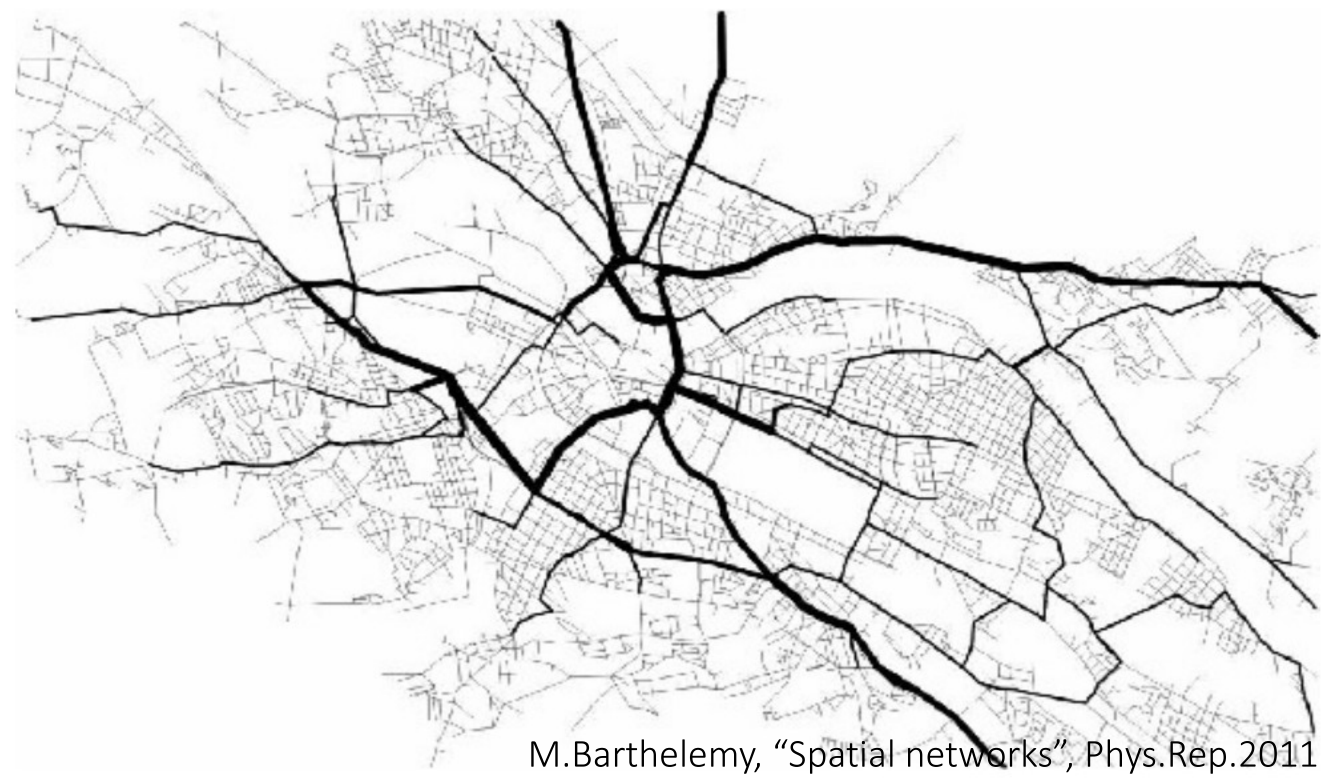
Networks embedded in space



M.Barthelemy,
“Spatial networks”, Phys.Rep.2011

Networks spatially embedded*

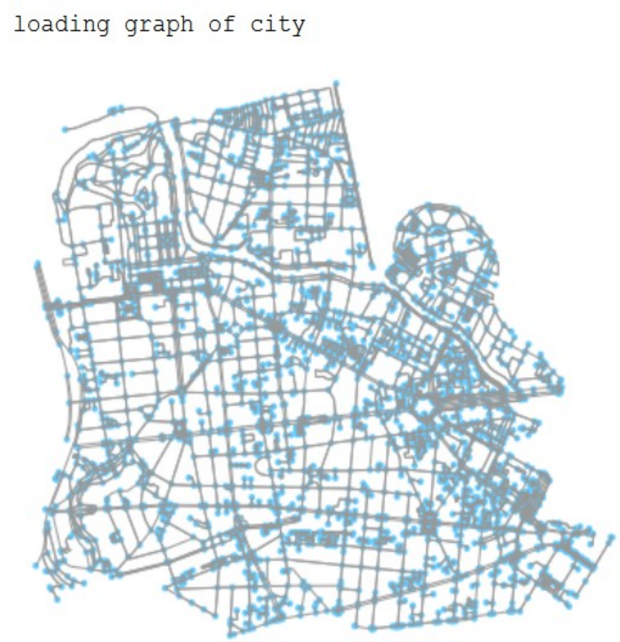
Questions: what are properties of networks spatially

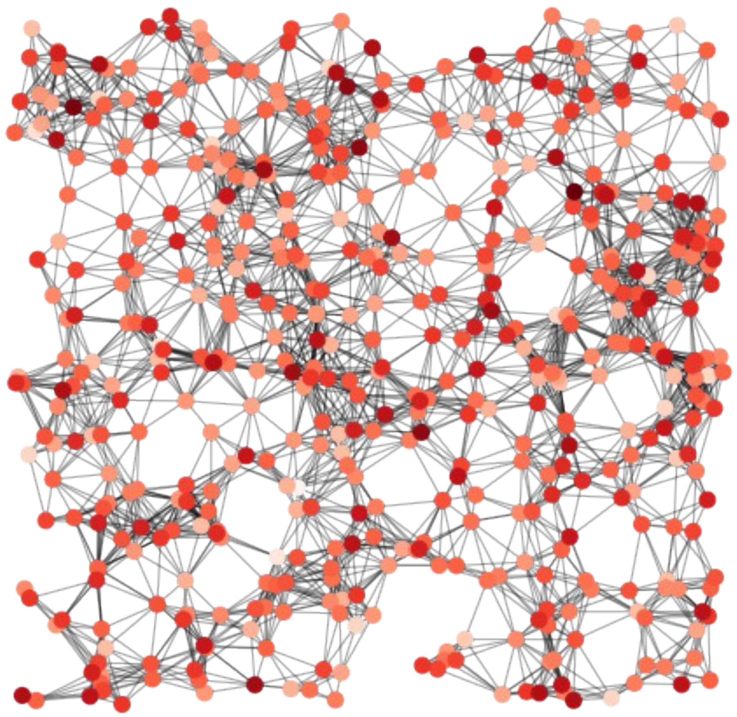


M.Barthelemy, “Spatial networks”, Phys.Rep.2011

*embedding of a network – assigning spatial coordinates to nodes/edges

Networks spatially embedded*
Questions: what are properties of networks spatially



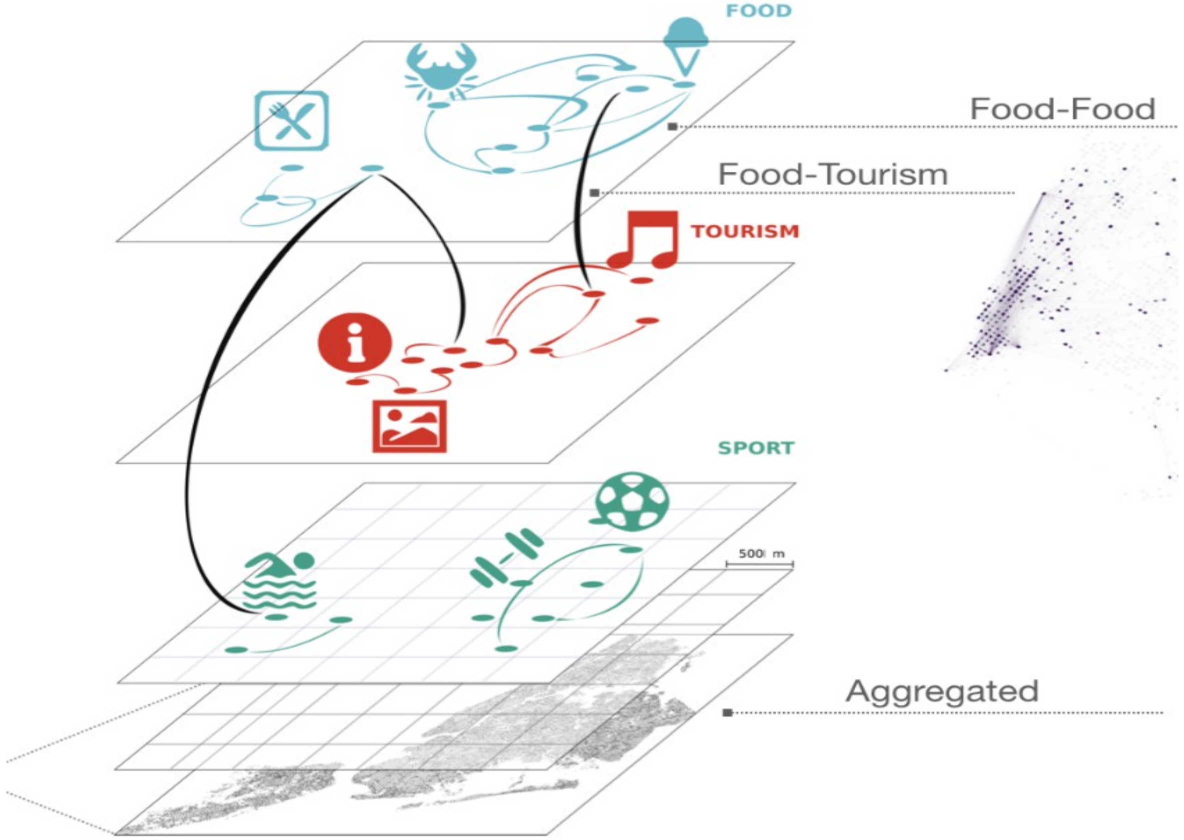


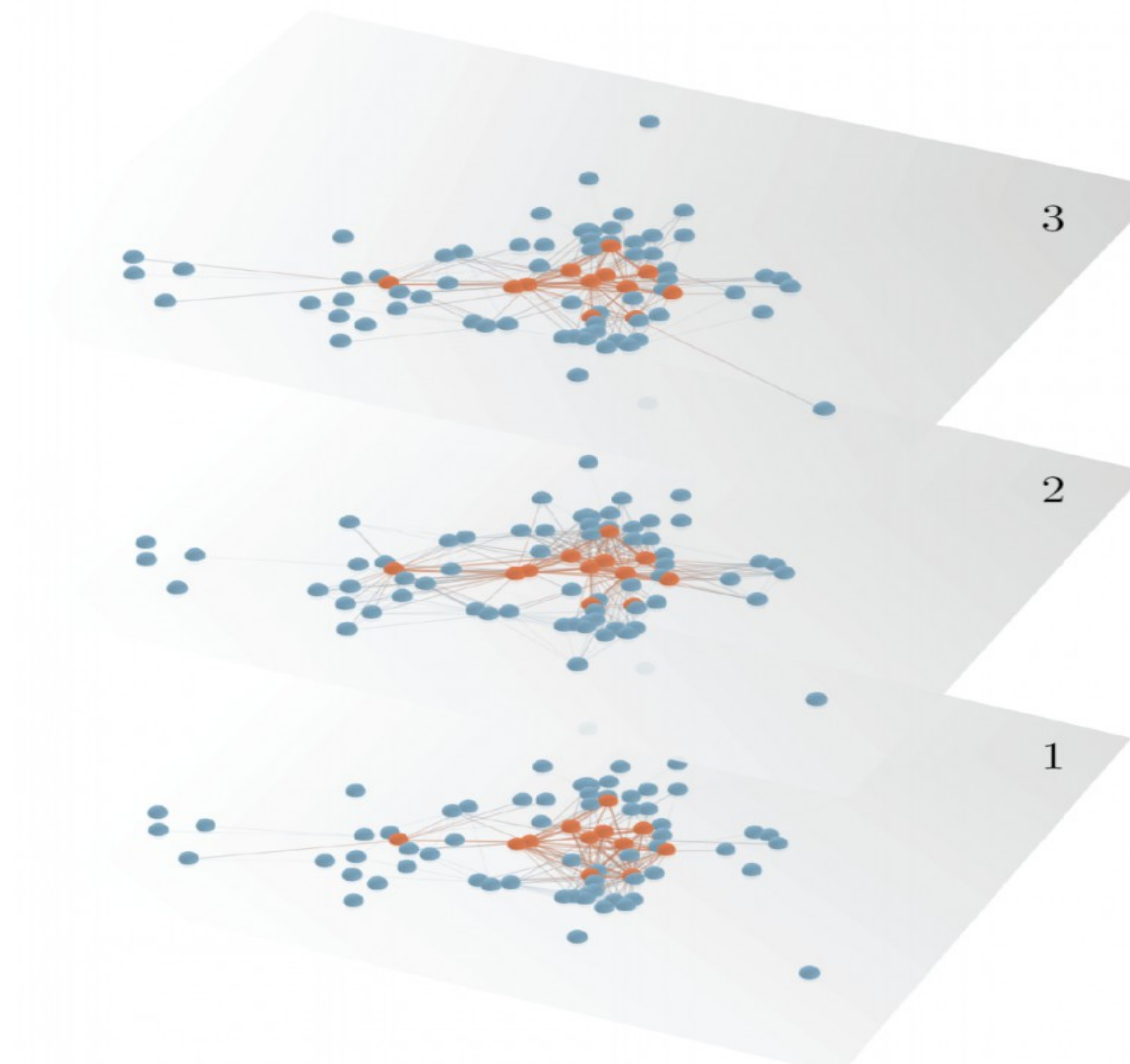
Train network

Geometric graphs

*embedding of a network – assigning spatial coordinates to nodes/edges

Geography of social networks





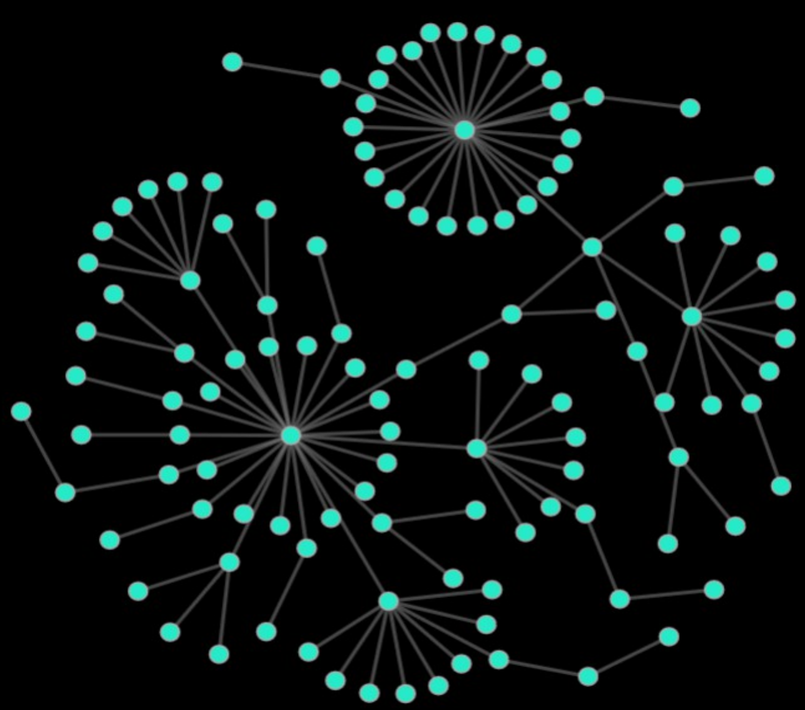
Data source:
Foursquare - Location-Based Social Networking

Network model:
Multilayer structure

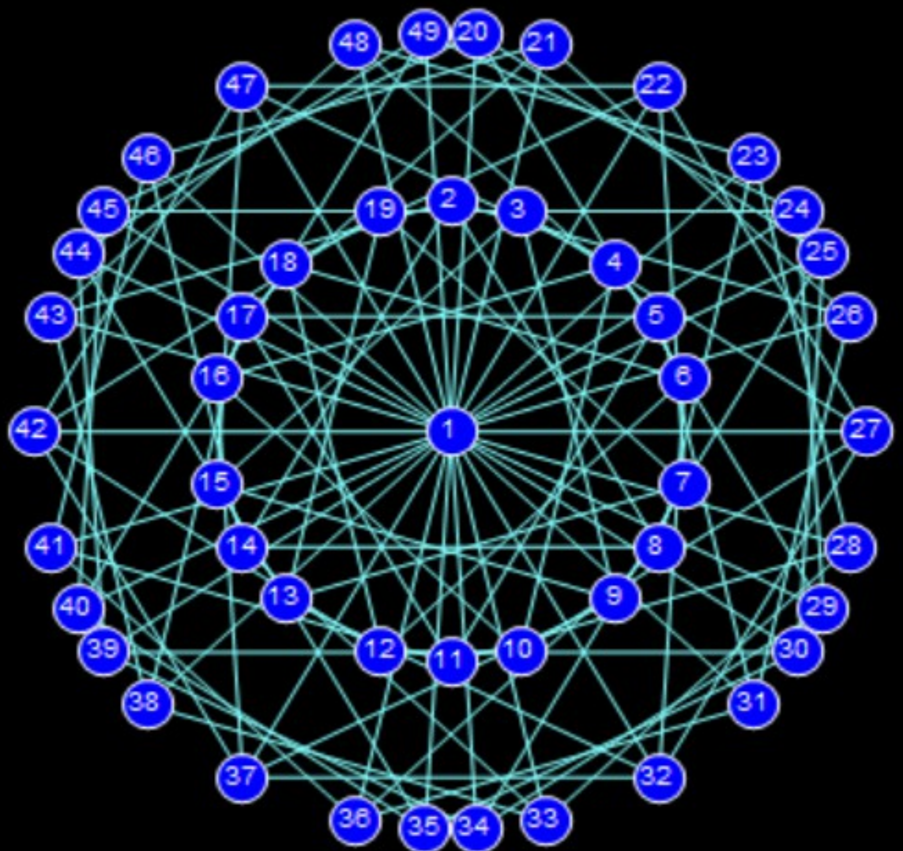
M.Domenico et al. “Disentangling activity-aware human flows reveals the hidden functional organization of urban systems”

Different types of networks

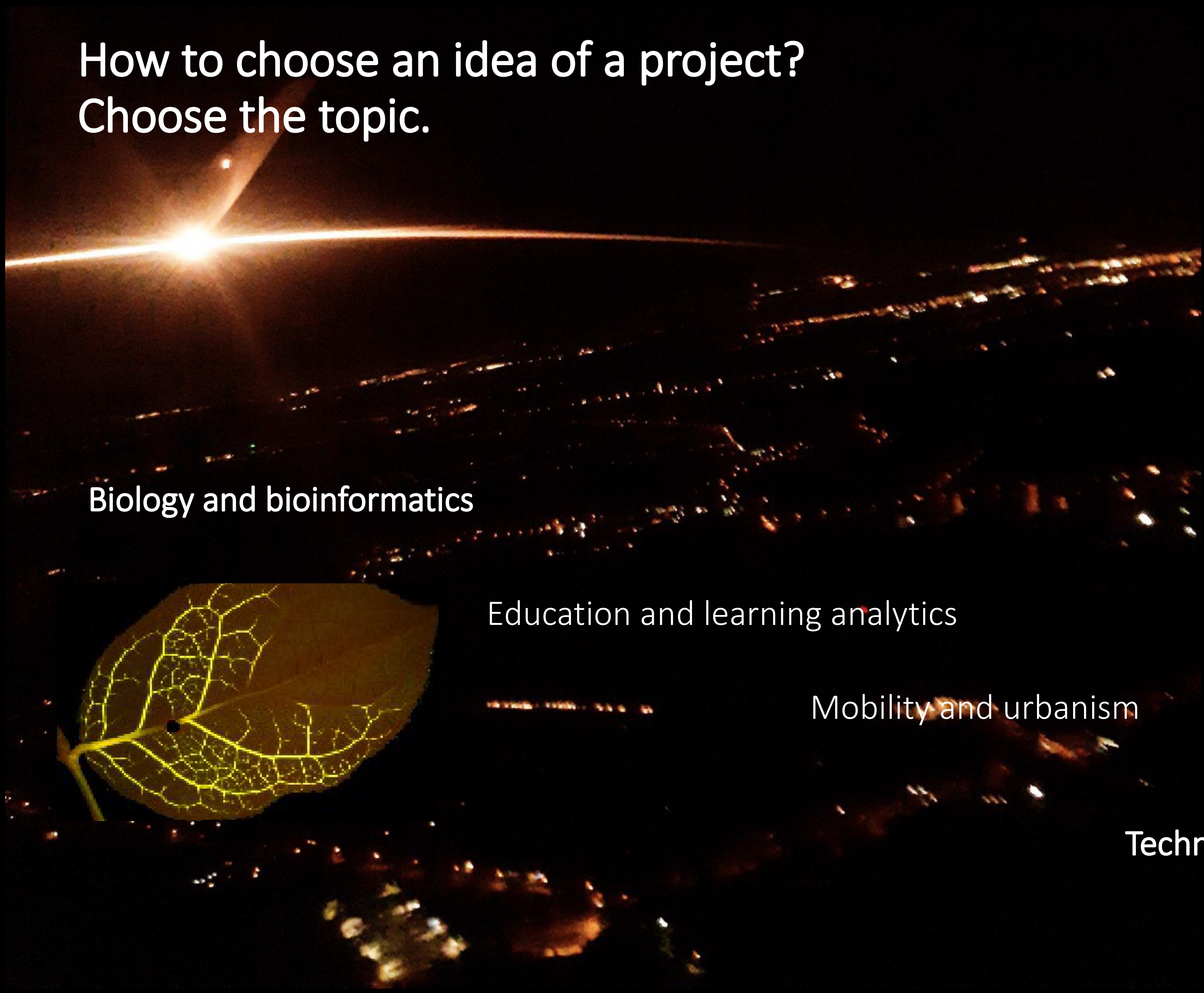
Tree graph
is a graph in which any two vertices are connected by exactly one path.



Cycles in networks



How to choose an idea of a project?
Choose the topic.

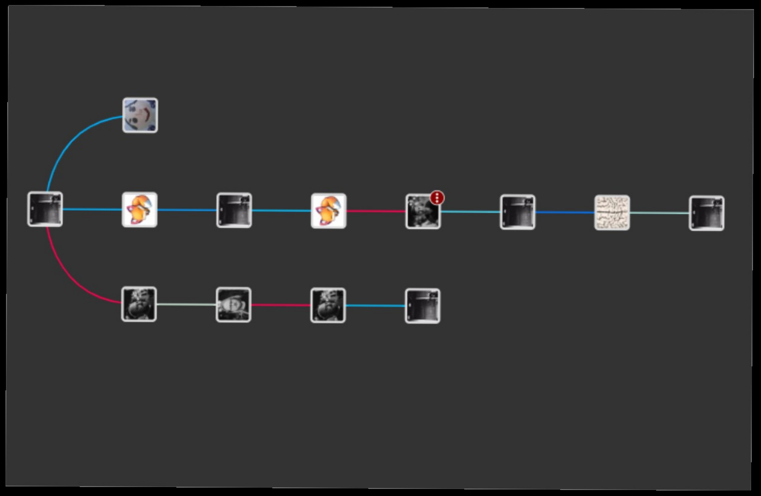


Biology and bioinformatics

Education and learning analytics

Mobility and urbanism

Social networks analysis



Technology and AI

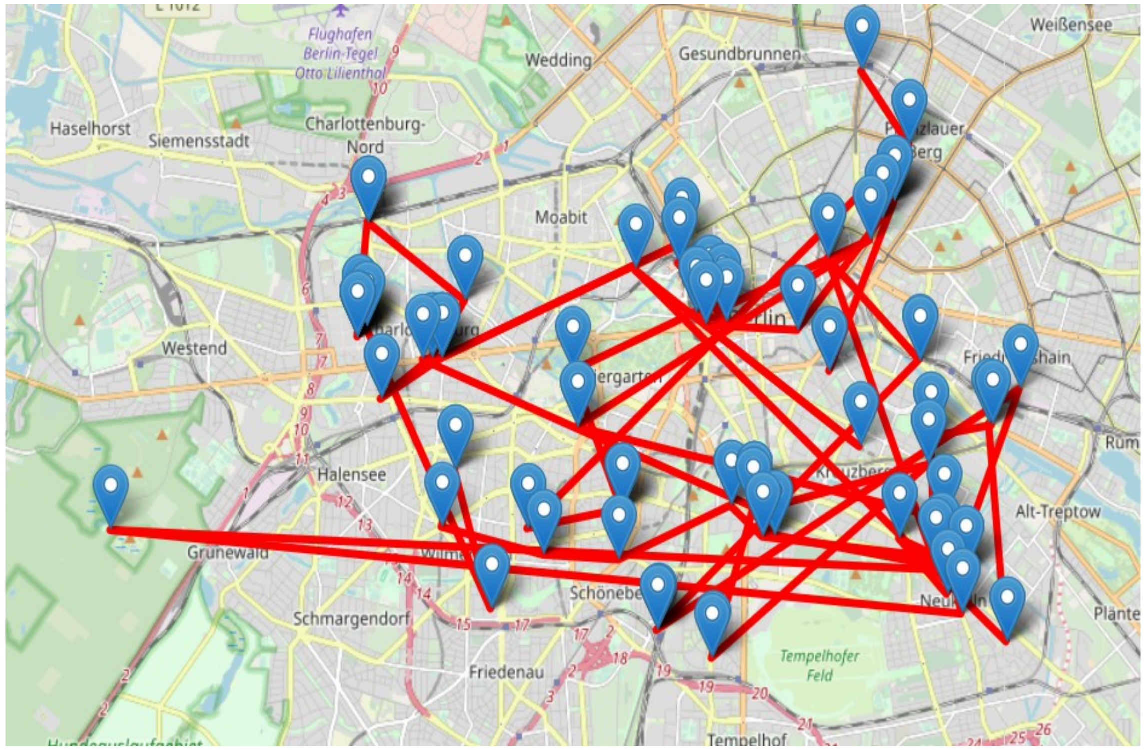
Networks geographically embedded

A. Transportation networks:
1. Representations
2. Airline networks
3. Bus, subway, railway, and commuters, Cargo-ship

B. Infrastructure networks:
1. Road and street networks
2. Power grids and water distribution networks, the Internet
3. Geography in social networks

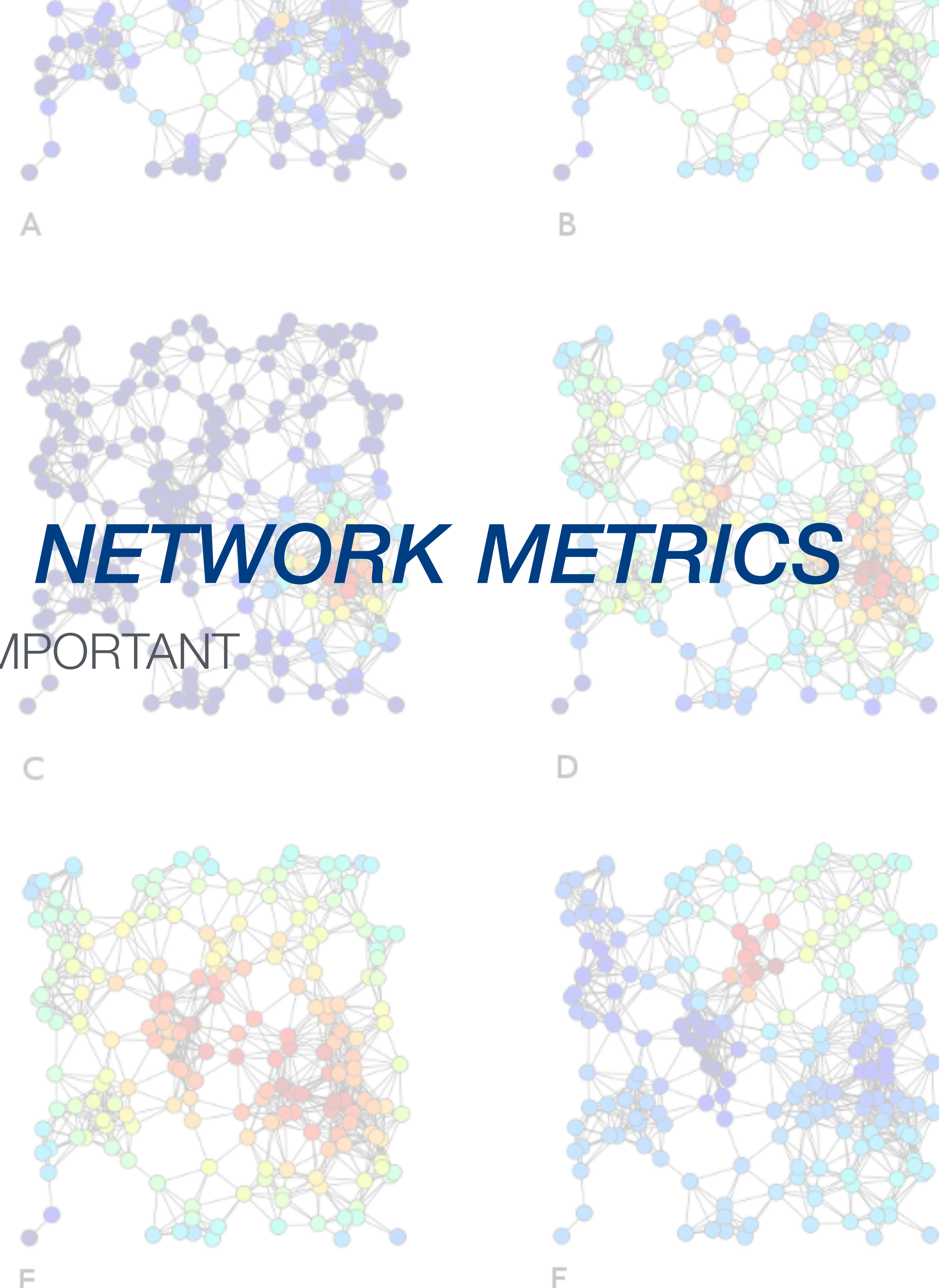
C. Origin-destination matrix and mobility networks:
1. Importance of human mobility
2. Distribution of the trip duration and length
3. The gravity law

D. Neural networks



Next week: *network metrics*

Revealing what's important



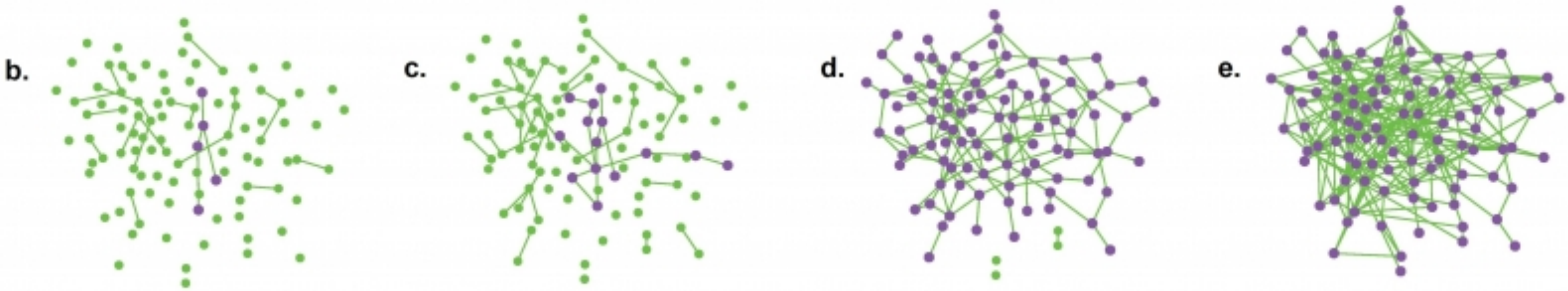
many metrics…

TABLE 2: Definitions of network science terms and variables.

Term/variable	Definition
N	number of nodes, N, in graph
E	number of edges, E, in graph
network density	ratio of the number of edges to the maximum number of possible edges $\frac{2E}{N(N-1)}$
distance, $d(n_i, n_j)$	shortest path between node i and node j $d(n_i, n_j)$ where $n_i, n_j \in N$
average shortest path length, L	average length of shortest path between pairs of nodes $L = \frac{1}{N(N-1)} \cdot \sum_{i \neq j} d\left(n_i, n_j\right)$
diameter, D	largest shortest path between nodes $D = \max_{n_i \in N, n_j \in N} d\left(n_i, n_j\right)$
closeness centrality	inverse of the sum of the length of the shortest paths between node i and all other nodes in the graph $C_i = \frac{1}{\sum_j d\left(n_i, n_j\right)}$
degree, k_i	number of edges attached to node i
average degree, $\langle k \rangle$	average number of edges per node in network $\langle k \rangle = \frac{1}{N} \sum_{n=i}^{N} k_i$
local clustering coefficient, c_i	number of edges between the neighbors of node i divided by the maximum number of edges between those neighbors $c_i = \frac{2\lvert e_{jk} \rvert}{k_i(k_i - 1)}$ where $n_j, n_k \in N_i$, $e_{jk} \in E$
average clustering coefficient, $\langle C \rangle$	average clustering coefficient of nodes in the network $\langle C \rangle = \frac{1}{N} \sum_{n=i}^{N} c_i$
modularity, Q	proportion of edges that fall within subgroups of nodes minus the expected proportion if edges were randomly distributed, range $[-1, 1]$
average efficiency, E_G	measure of how efficiently information is exchanged in the network $E_G = \frac{1}{n(n-1)} \sum_{i \neq j \in N} \frac{1}{d\left(n_i, n_j\right)}$
largest connected component	largest group of nodes in the network that are connected to each other in a single component
degree distribution, $P(k)$	probability distribution of node degrees in the network
γ	power-law exponent for the degree distribution
Small world structure	network with short average path lengths and relatively high clustering coefficient (relative to a random graph with similar density)
scale-free network	network with a degree distribution that is power-law distributed

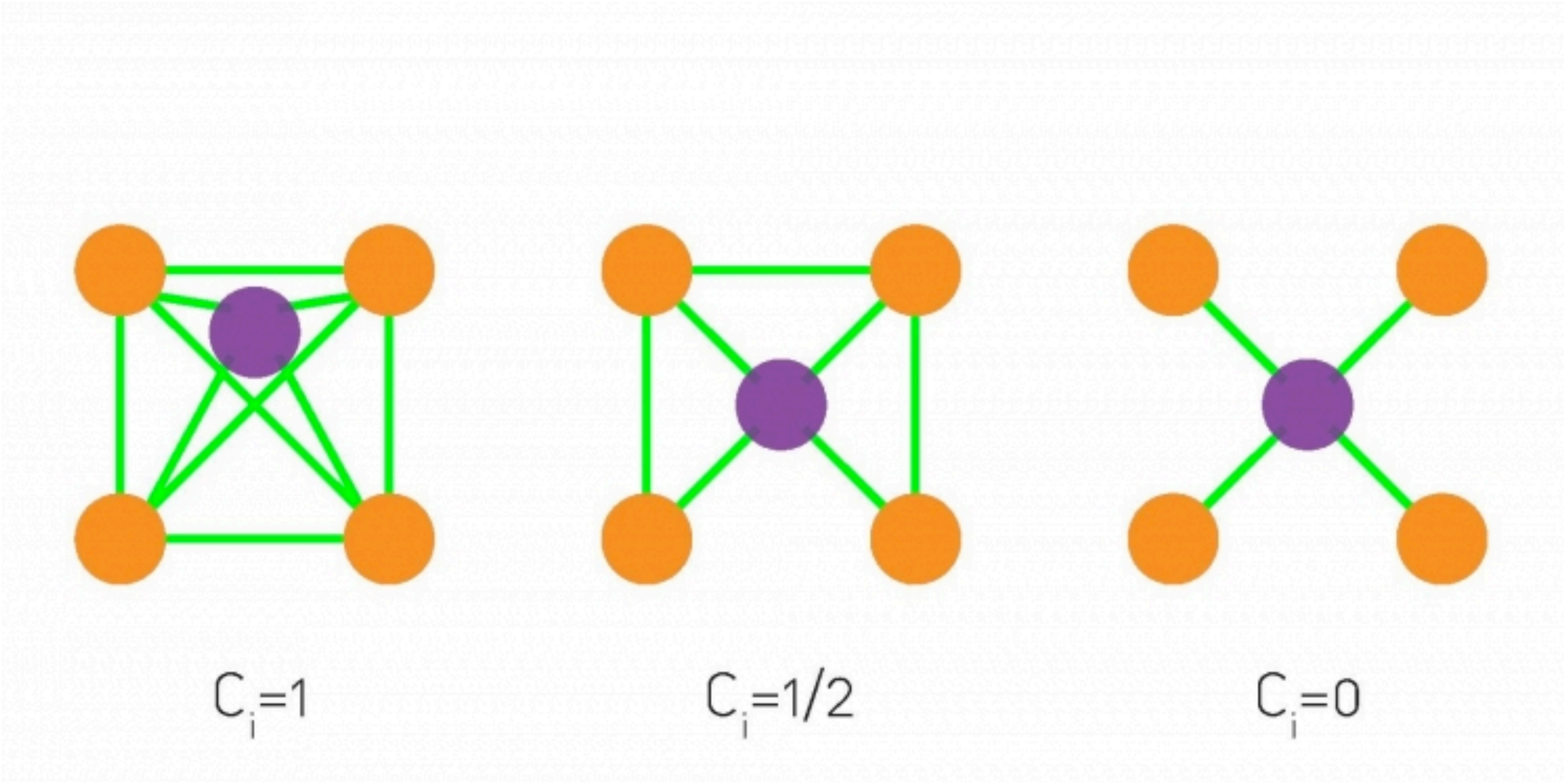
example from Siew et al, Complexity 2019

Density

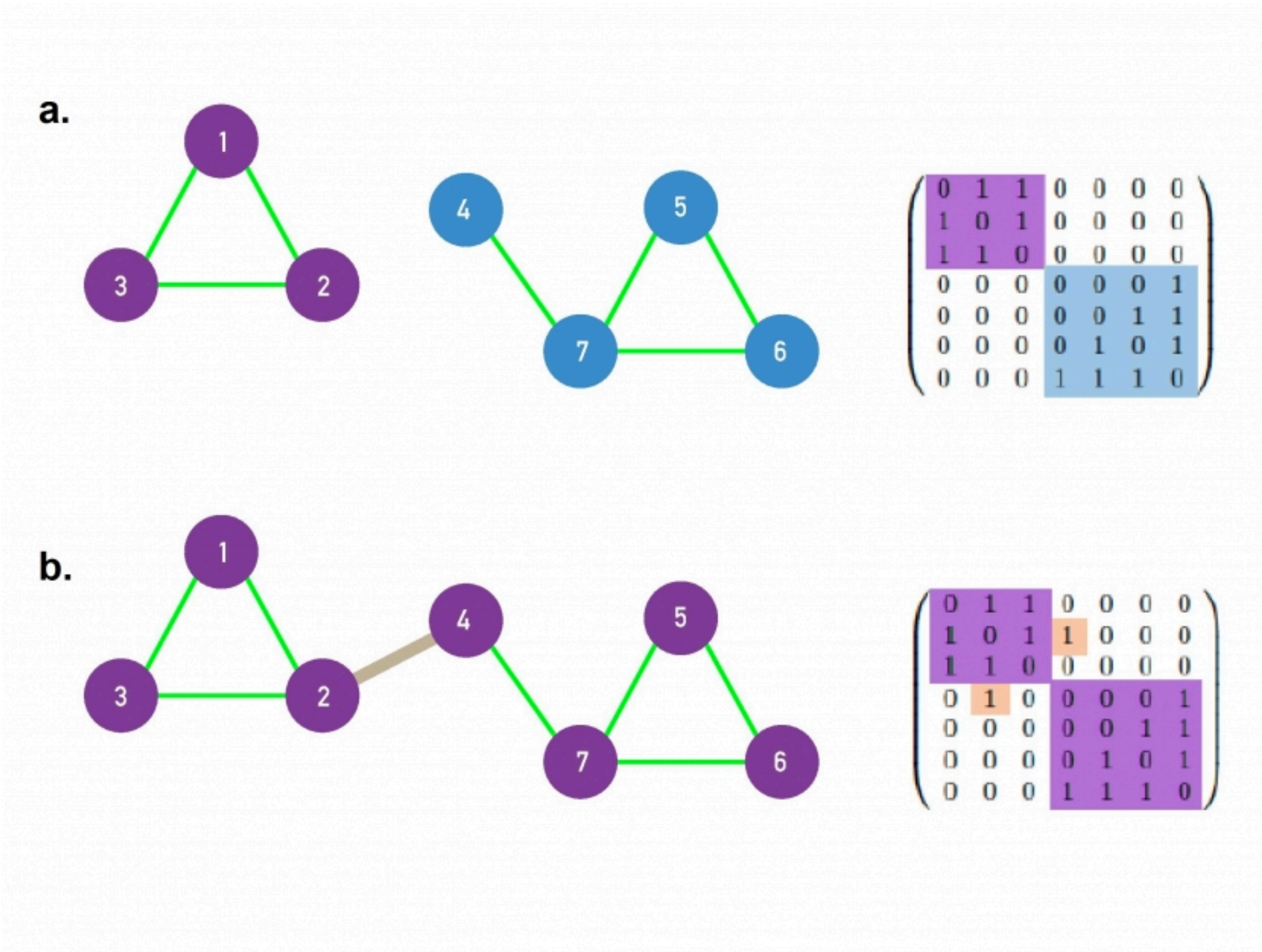


low **high**

CLUSTERING COEFFICIENT



Connected components



Centralities

https://en.wikipedia.org/wiki/Centrality

Betweenness centrality

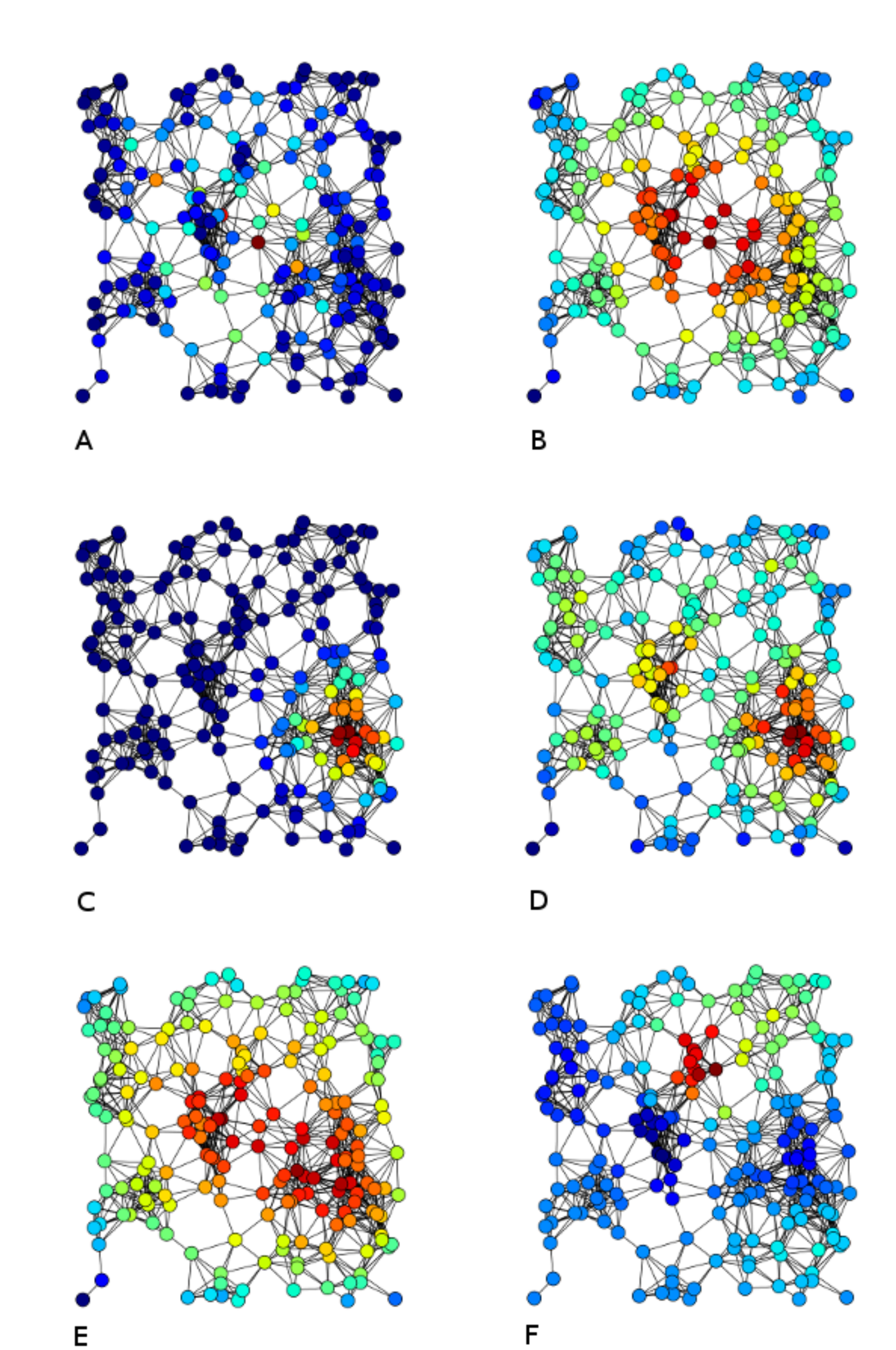
Closeness centrality

Eigenvector centrality

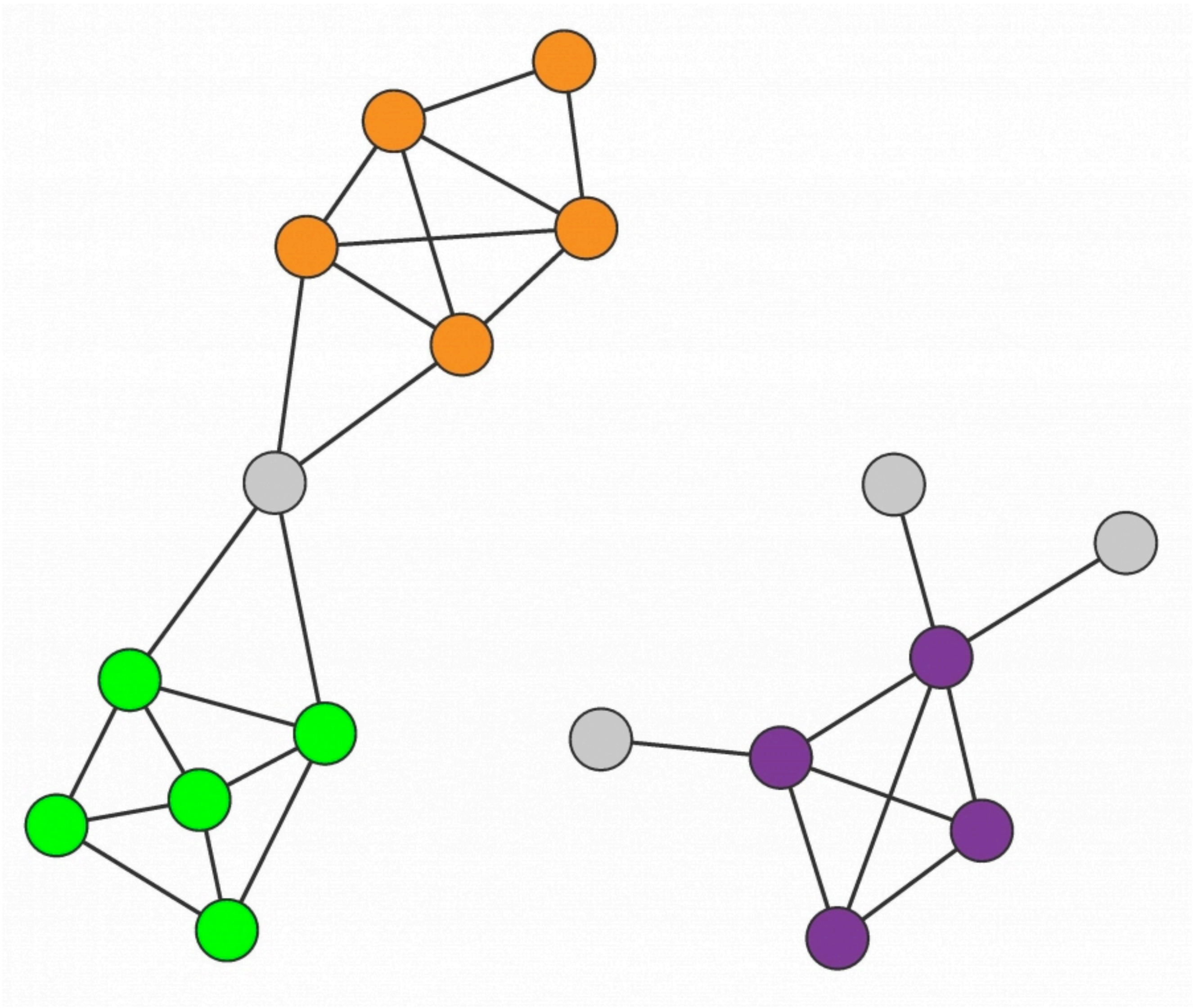
Degree centrality

Harmonic centrality

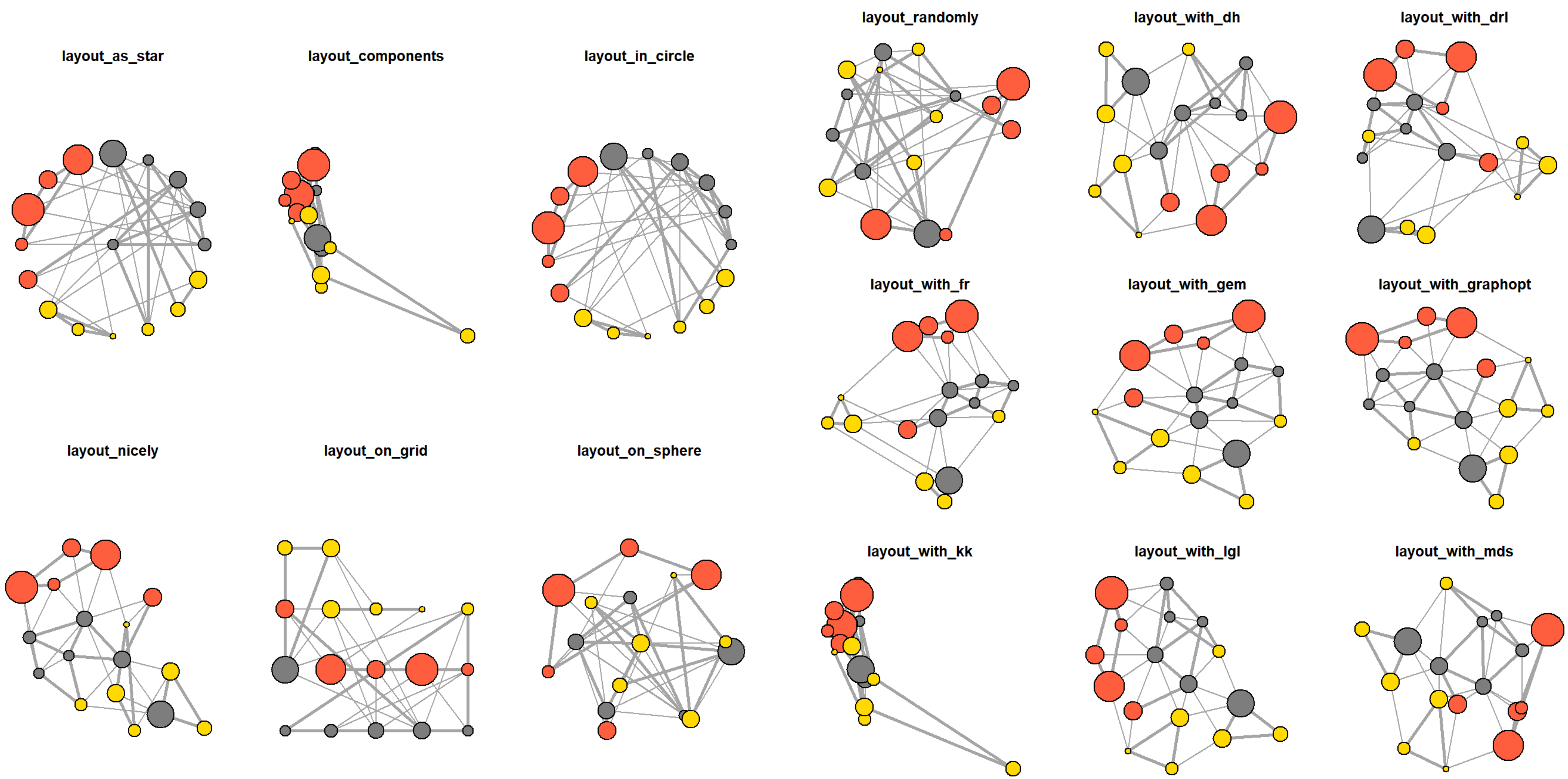
Katz centrality



COMMUNITIES



LAYOUTS


layout_as_star
layout_components
layout_in_circle
layout_randomly
layout_with_dh
layout_with_drl
layout_with_fr
layout_with_gem
layout_with_graphopt
layout_nicely
layout_on_grid
layout_on_sphere
layout_with_kk
layout_with_lgl
layout_with_mds

Going further