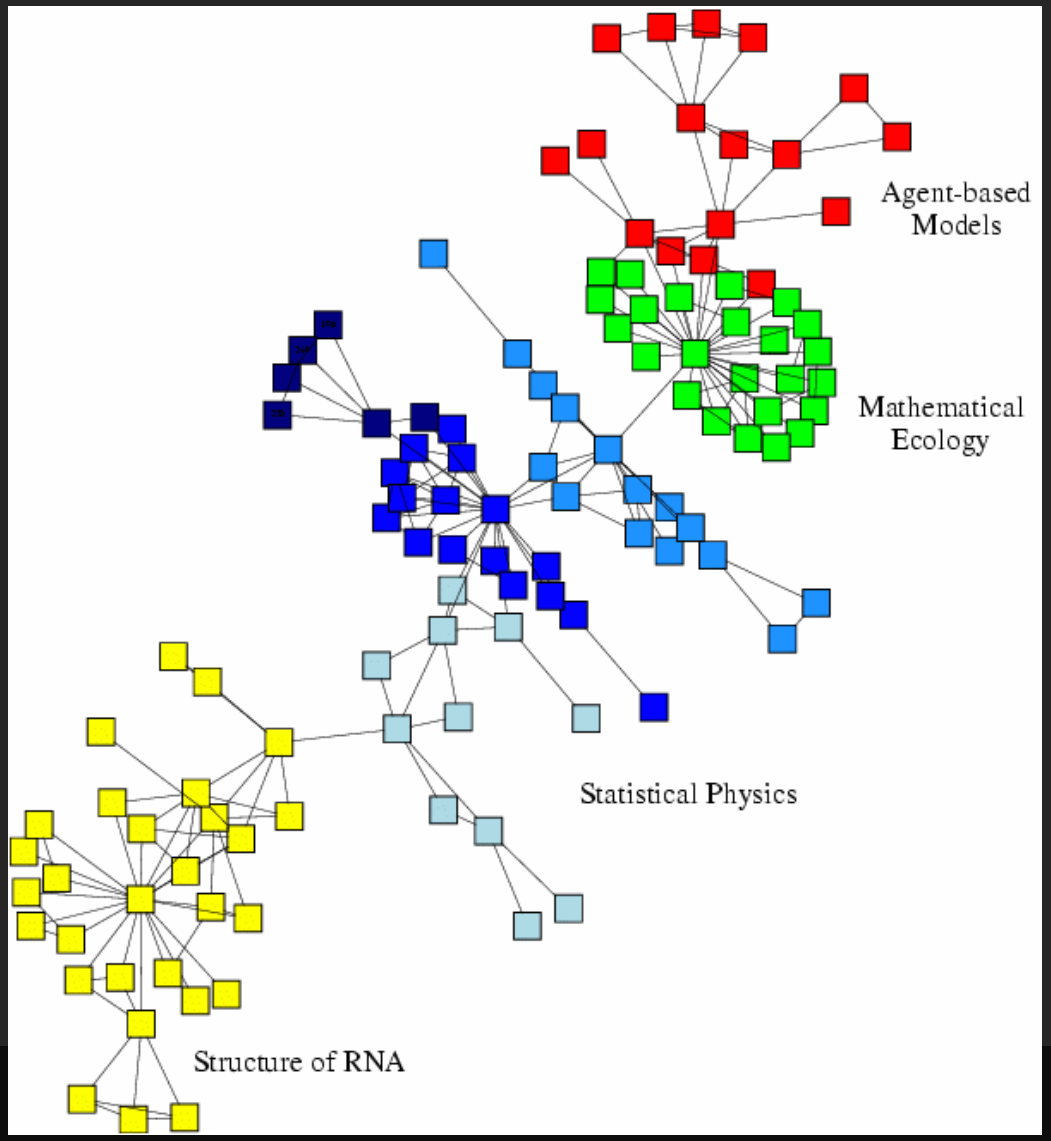
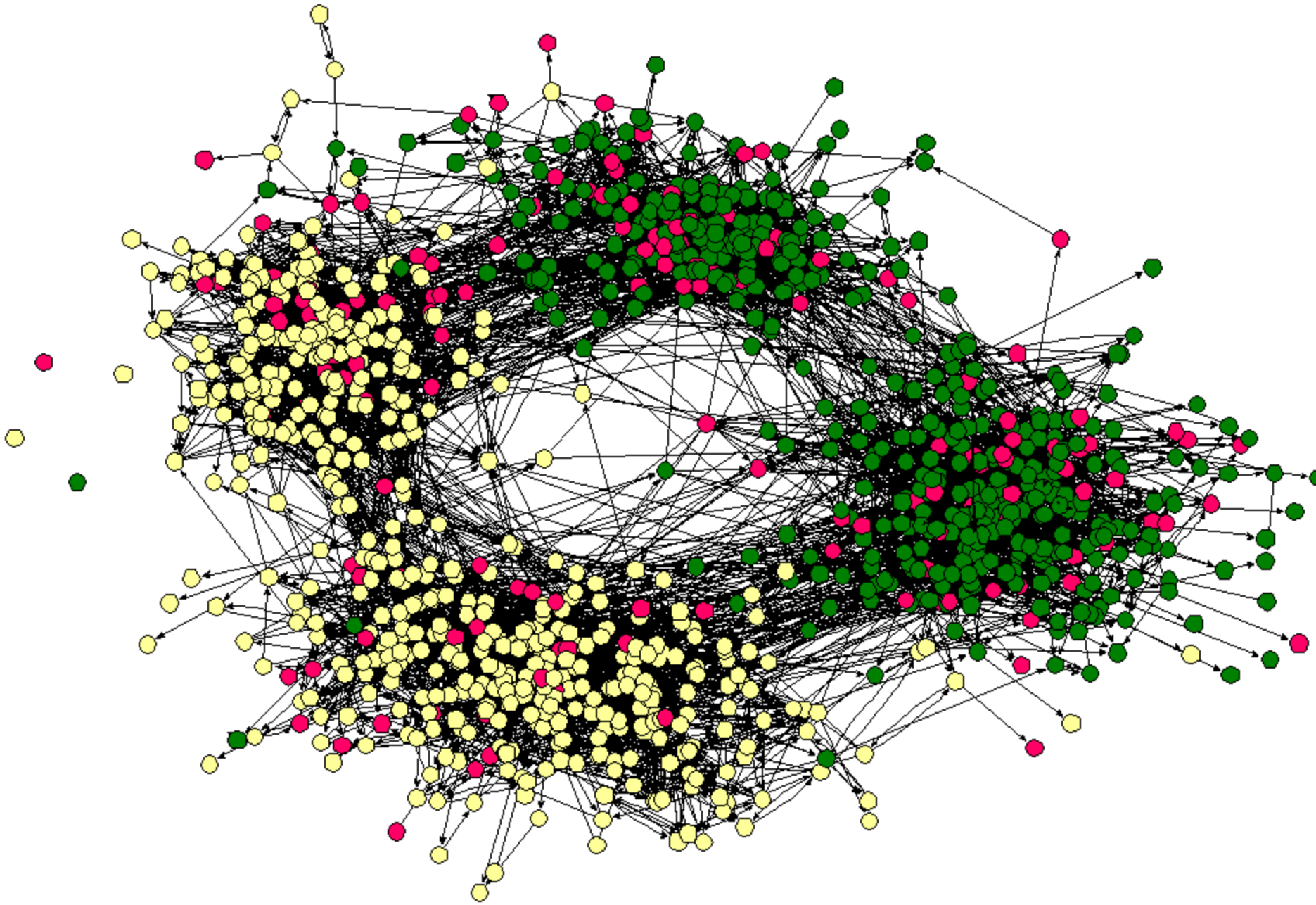
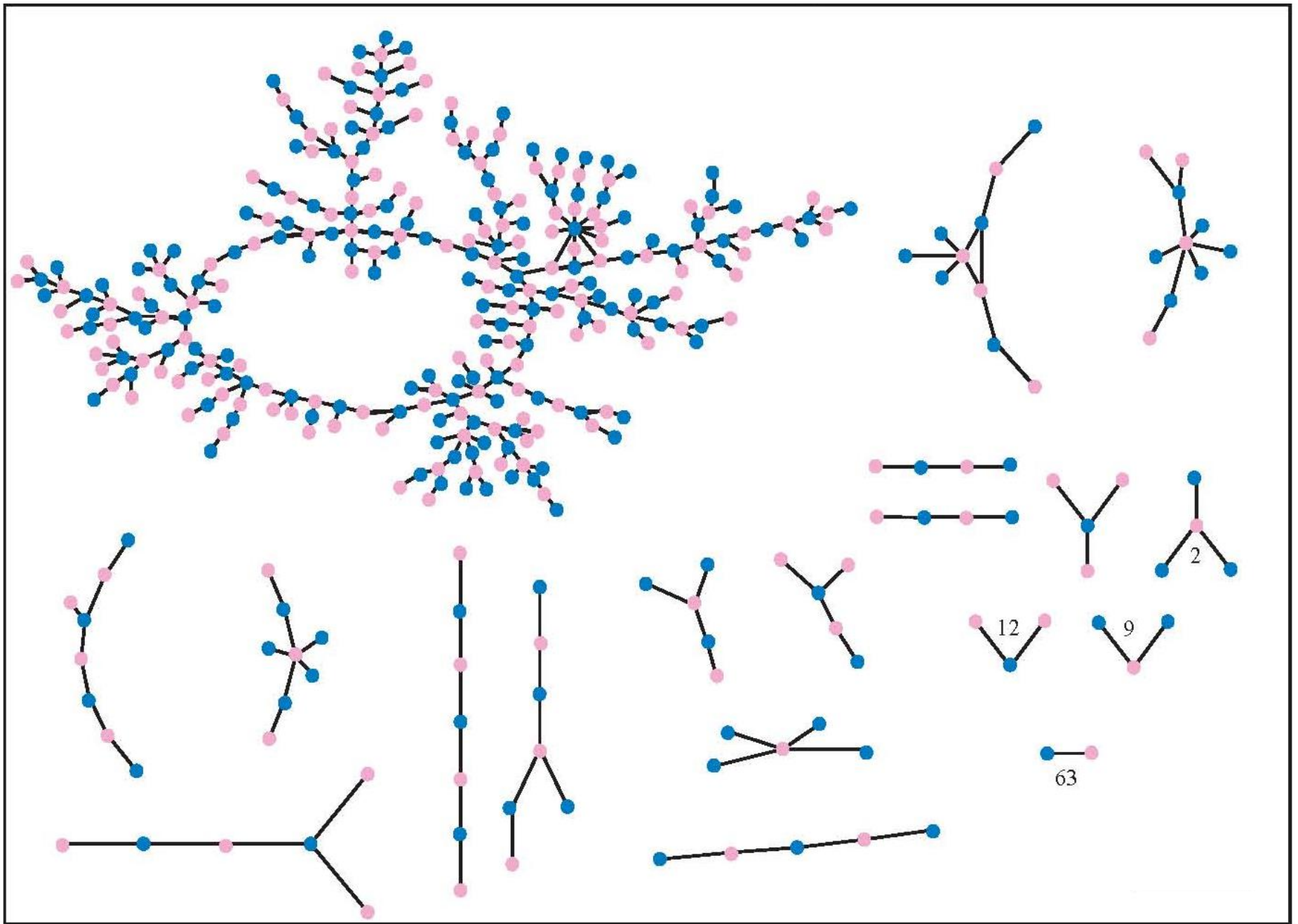
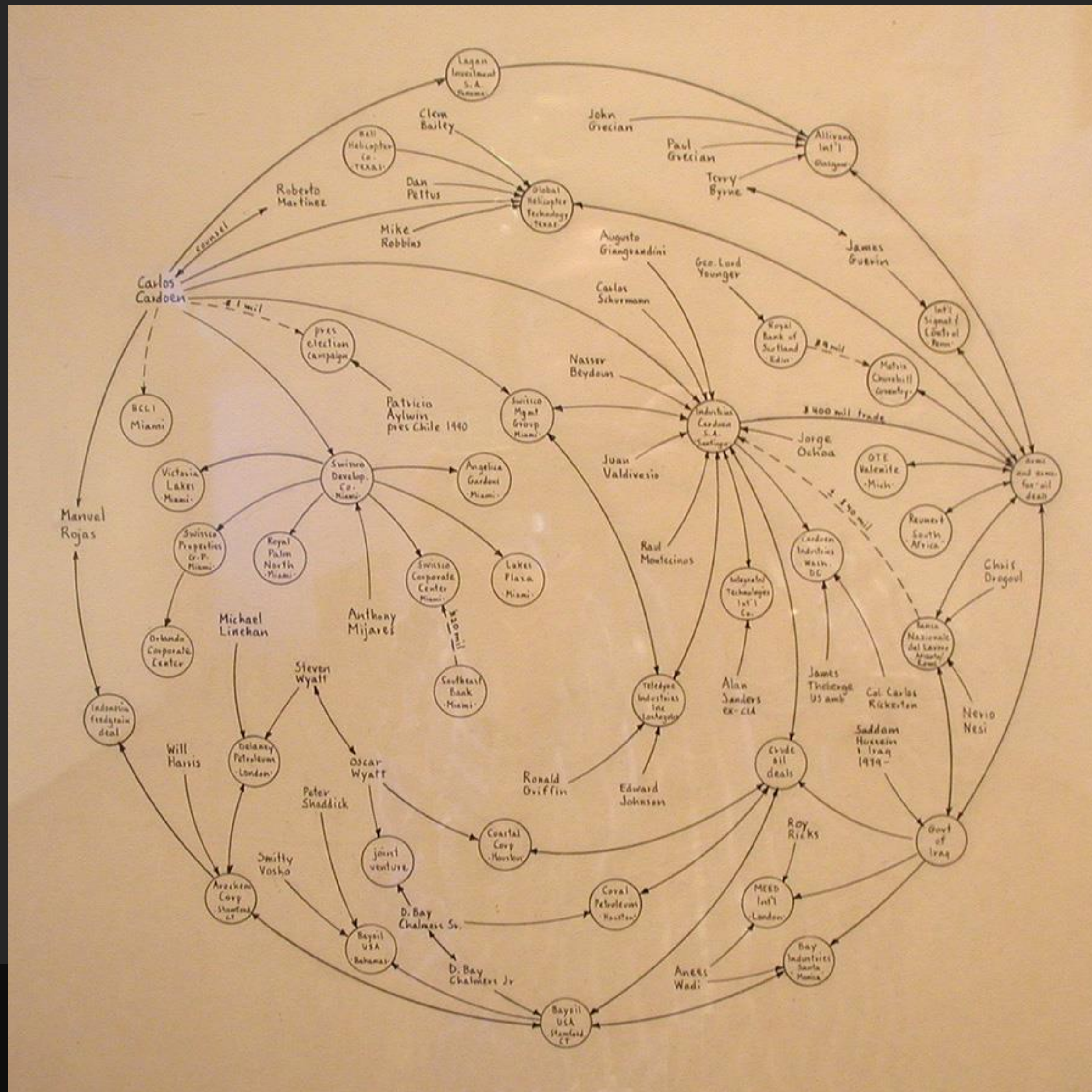
Social Network Analysis


Agent-based
Models
Mathematical
Ecology
Statistical Physics
Structure of RNA

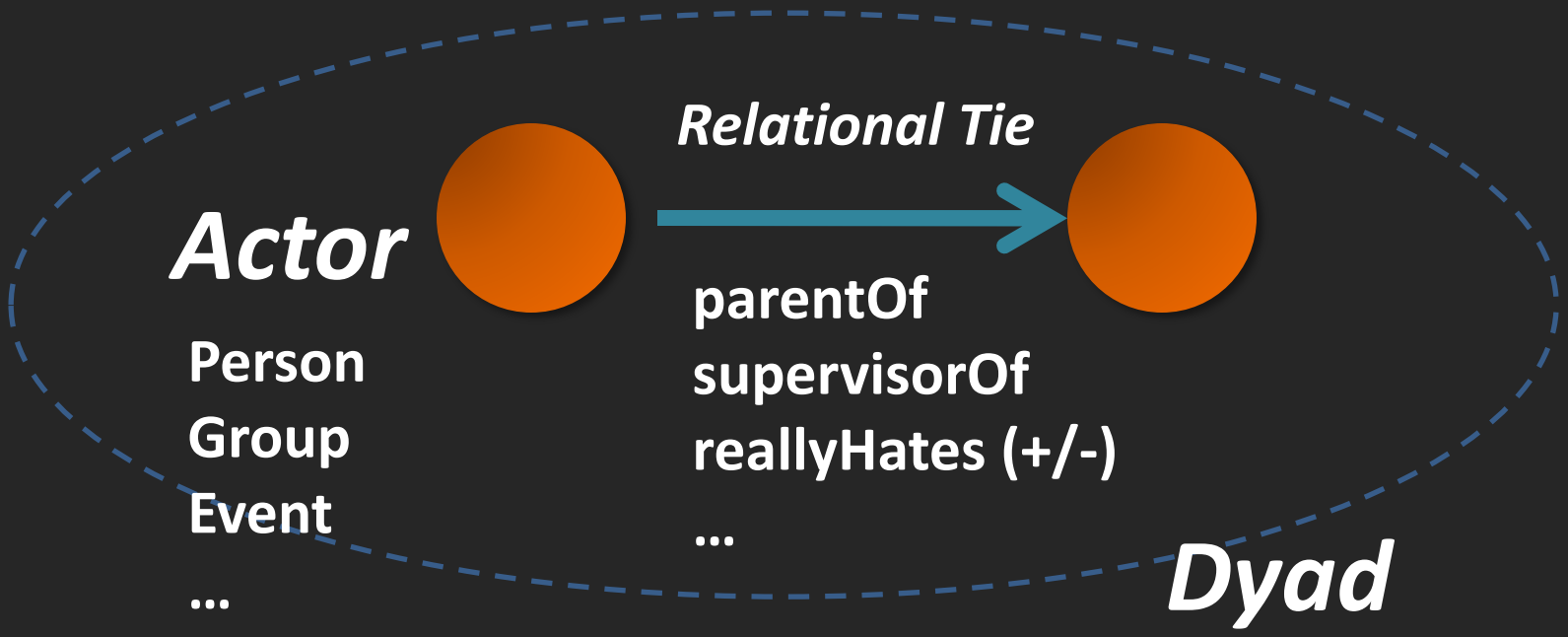



2
12
9
63



Lagan Investment S.A.
Clem Bailey
Bell Helicopter Co. Texas
John Grecian
Paul Grecian
Terry Byrne
Alliavant Int'l
Roberto Martinez
counsel
Dan Pettus
Mike Robbins
Global Helicopter Technology Texas
Augusto Giangrandini
Geo. Lord Younger
James Guerin
Carlos Cardoen
Carlos Schurmann
Int'l Signal & Control
Royal Bank of Scotland Edin
Matrix Churchill Coventry
pres election campaign
Nasser Beydoun
BCCI Miami
Patricio Aylwin pres Chile 1990
Swissco Mgmt Group Miami
Industrias Cardoen S.A. Santiago
$ 400 mil trade
Jorge Ochoa
Juan Valdivesio
GTE Valenite Mich
arms and arms-for-oil deals
Swissco Develop. Co. Miami
Victoria Lakes Miami
Angelica Gardens Miami
Reumech South Africa
Manuel Rojas
Swissco Properties G.P. Miami
Royal Palm North Miami
Swissco Corporate Center Miami
Lakes Plaza Miami
Raul Montecinos
Cardoen Industries Wash. DC
Integrated Technologies Int'l Co.
Chris Drogoul
Michael Linehan
Anthony Mijares
Orlando Corporate Center
Banca Nazionale del Lavoro Atlanta/Rome
Steven Wyatt
Southeast Bank Miami
Teledyne Industries Inc
Alan Sanders ex-CIA
James Theberge US amb
Col. Carlos Rickerton
Nevio Nesi
Indonesia feedgrain deal
Will Harris
Delaney Petroleum London
Oscar Wyatt
Saddam Hussein & Iraq 1979-
Crude oil deals
Ronald Griffin
Edward Johnson
Peter Shaddick
Roy Ricks
Govt of Iraq
Smitty Vosko
joint venture
Coastal Corp Houston
Arochem Corp Stamford CT
D. Bay Chalmers Sr.
Coral Petroleum Houston
MEED Int'l London
Bayoil USA Bahamas
D. Bay Chalmers Jr
Anees Wadi
Bay Industries Santa Monica
Bayoil USA Stamford CT

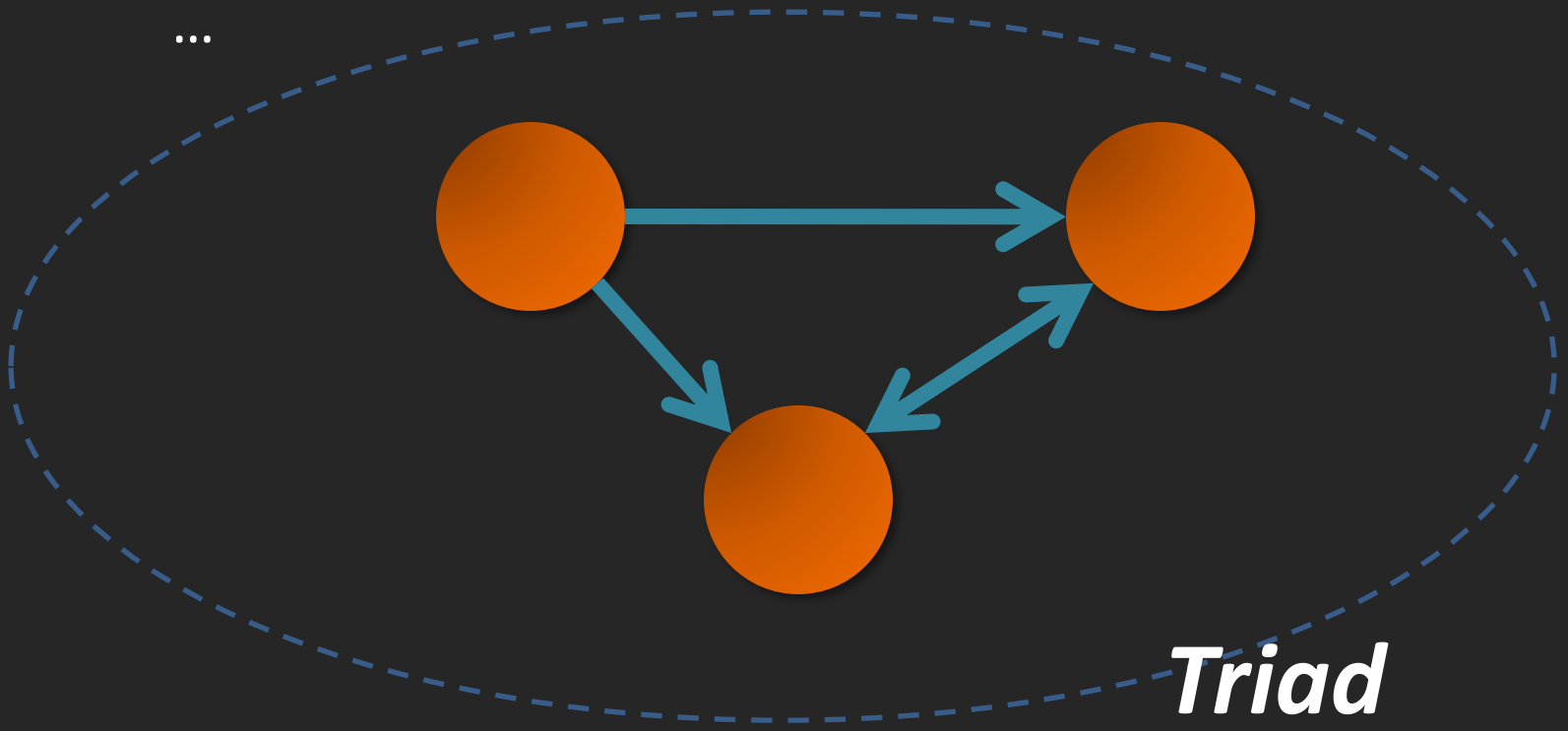
Vocabulary Lesson



Relation: **collection of ties of a specific type (every parentOf tie)**

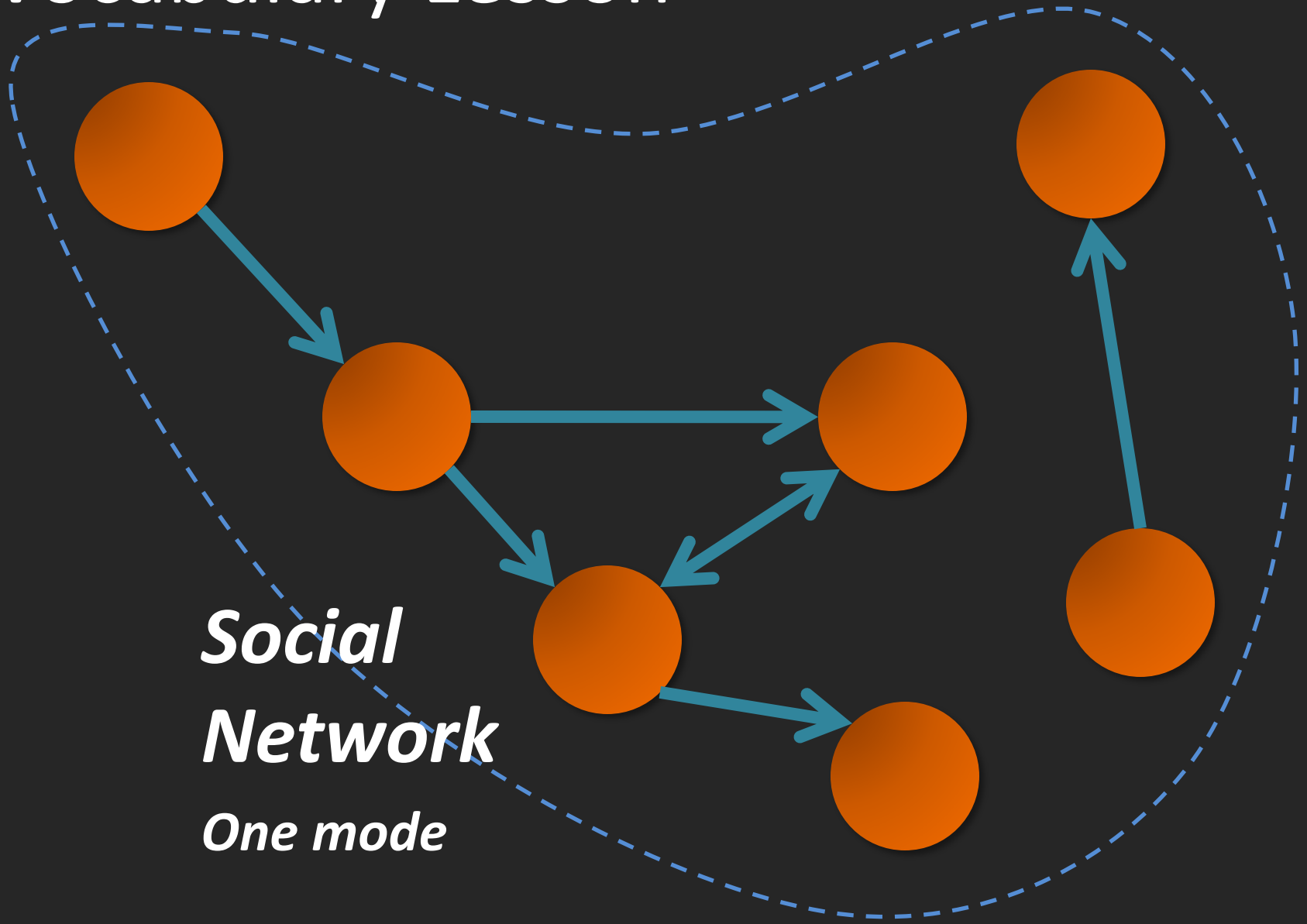
Vocabulary Lesson

If A likes B and B likes C then A likes C (transitivity)
If A likes B and C likes B then A likes C
…

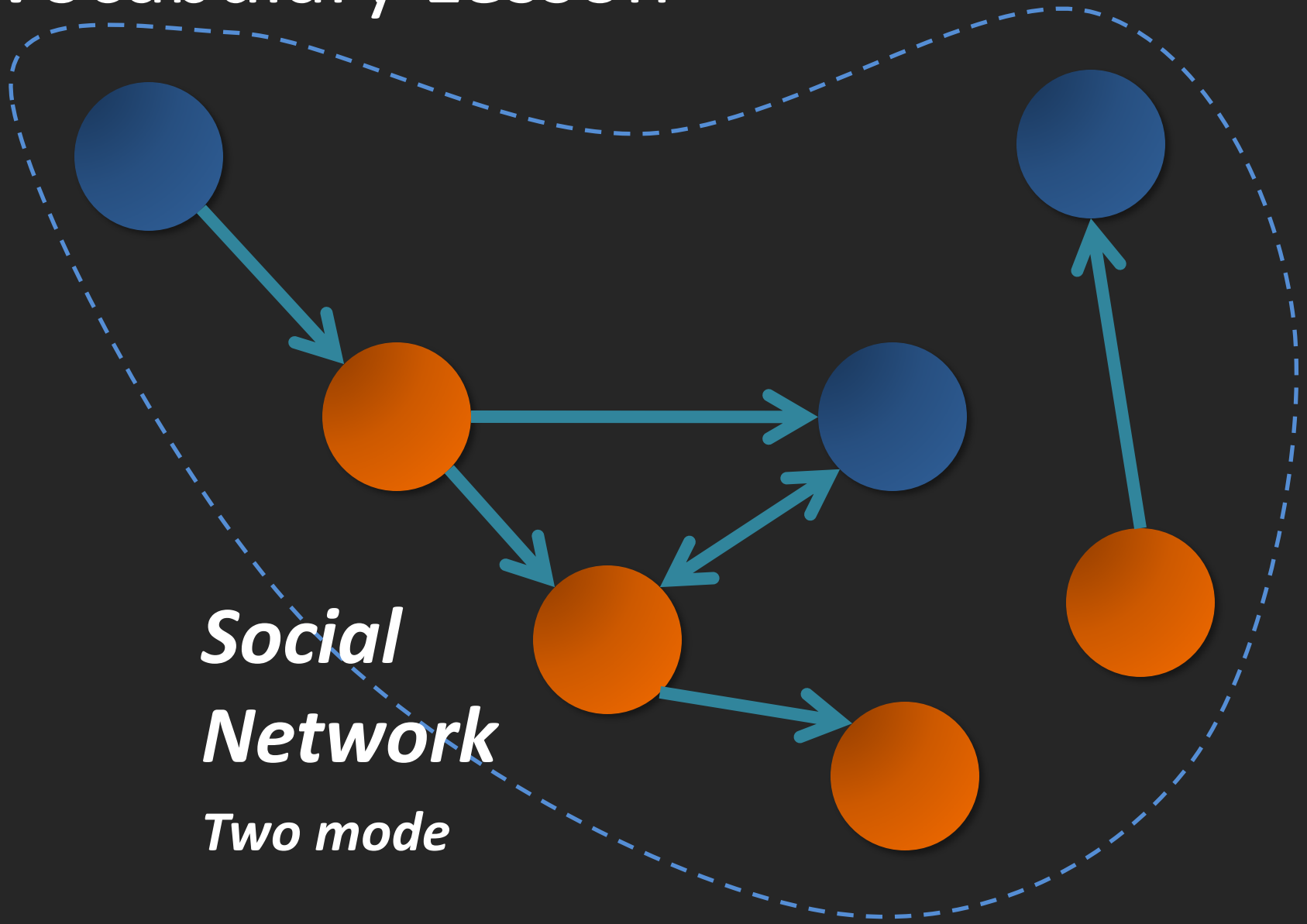


Triad

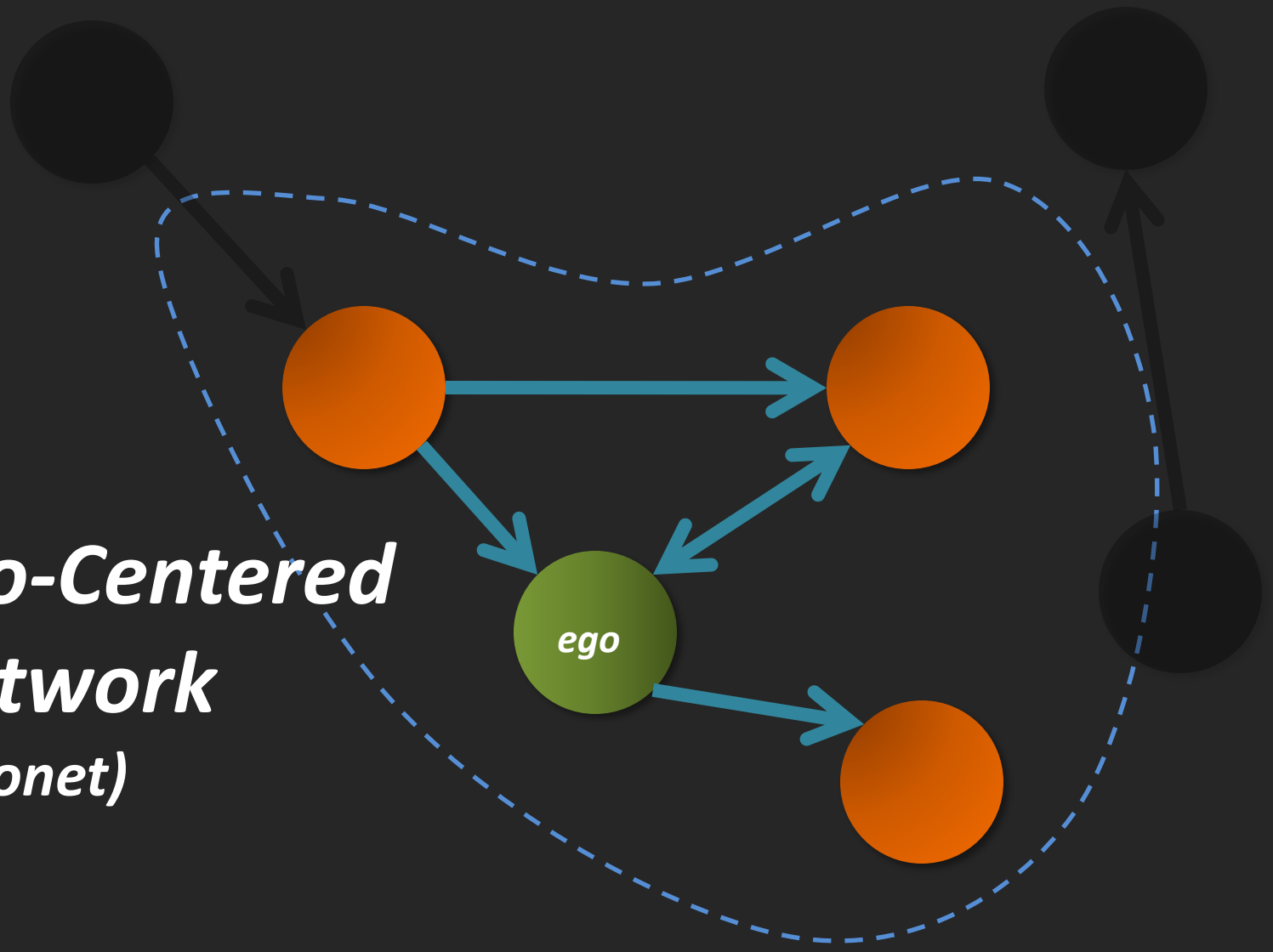
Vocabulary Lesson



Vocabulary Lesson



Vocabulary Lesson



Ego-Centered Network

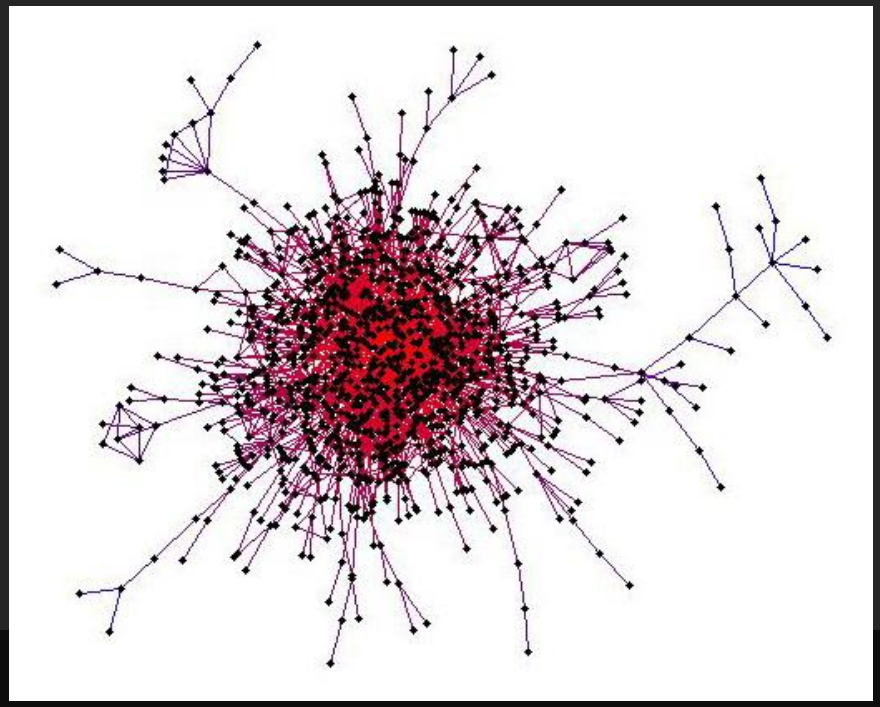
(egonet)

Describing Networks

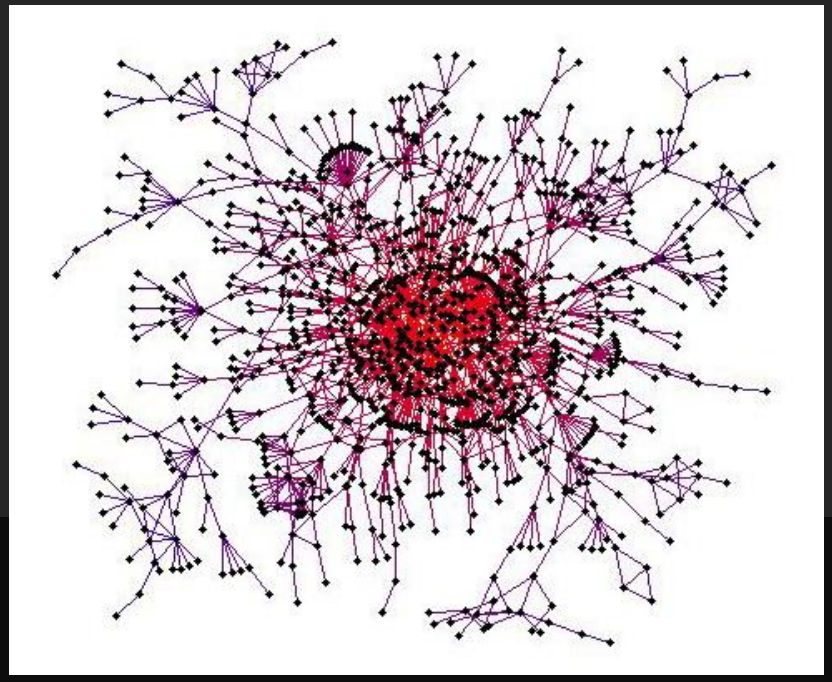
- Graph theoretic
  - Nodes/edges, what you'd expect
- Sociometric
  - Sociomatrix (2D matrix representation)
  - Sociogram (the adjacency matrix)
- Algebraic
  - $n_i \rightarrow n_j$
  - Also what you'd expect
- Basically complimentary

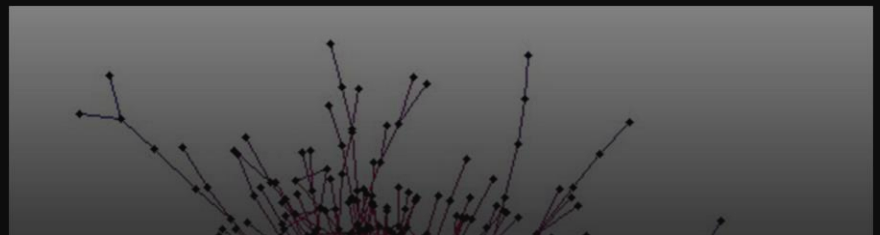
Describing Networks

MIT



Stanford





Describing Networks

- *Geodesic*
  - shortest_path(n,m)
- *Diameter*
  - max(geodesic(n,m)) n,m actors in graph
- *Density*
  - Number of existing edges / All possible edges
- *Degree distribution*

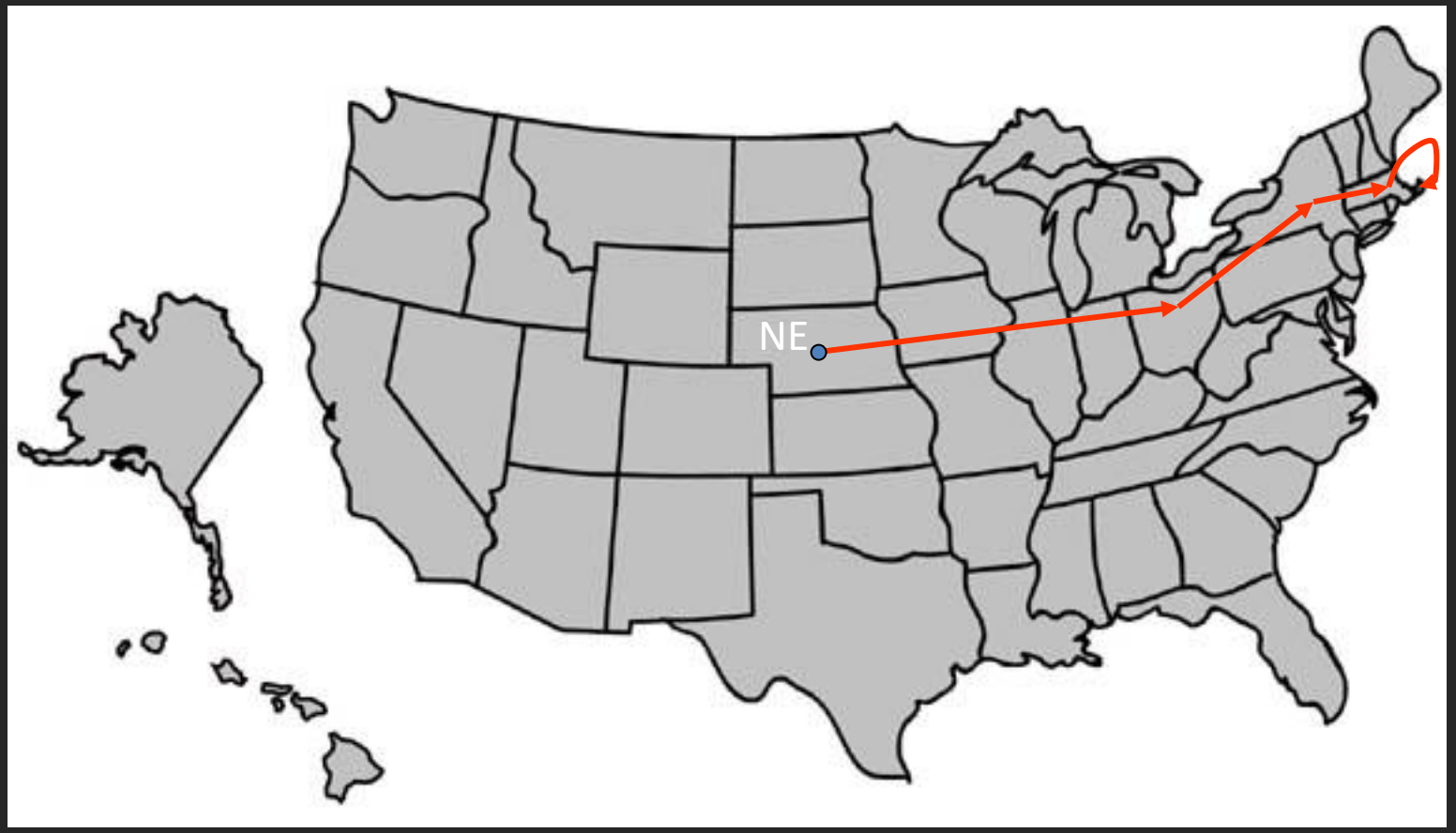
Types of Networks/Models

- A few quick examples
  - Erdős–Rényi
    - *G(n,M)*: randomly draw *M* edges between *n* nodes
    - Does not really model the real world
      - Average connectivity on nodes conserved

Types of Networks/Models

- A few quick examples
  - Erdős–Rényi
  - Small World
    - Watts-Strogatz
    - Kleinberg lattice model

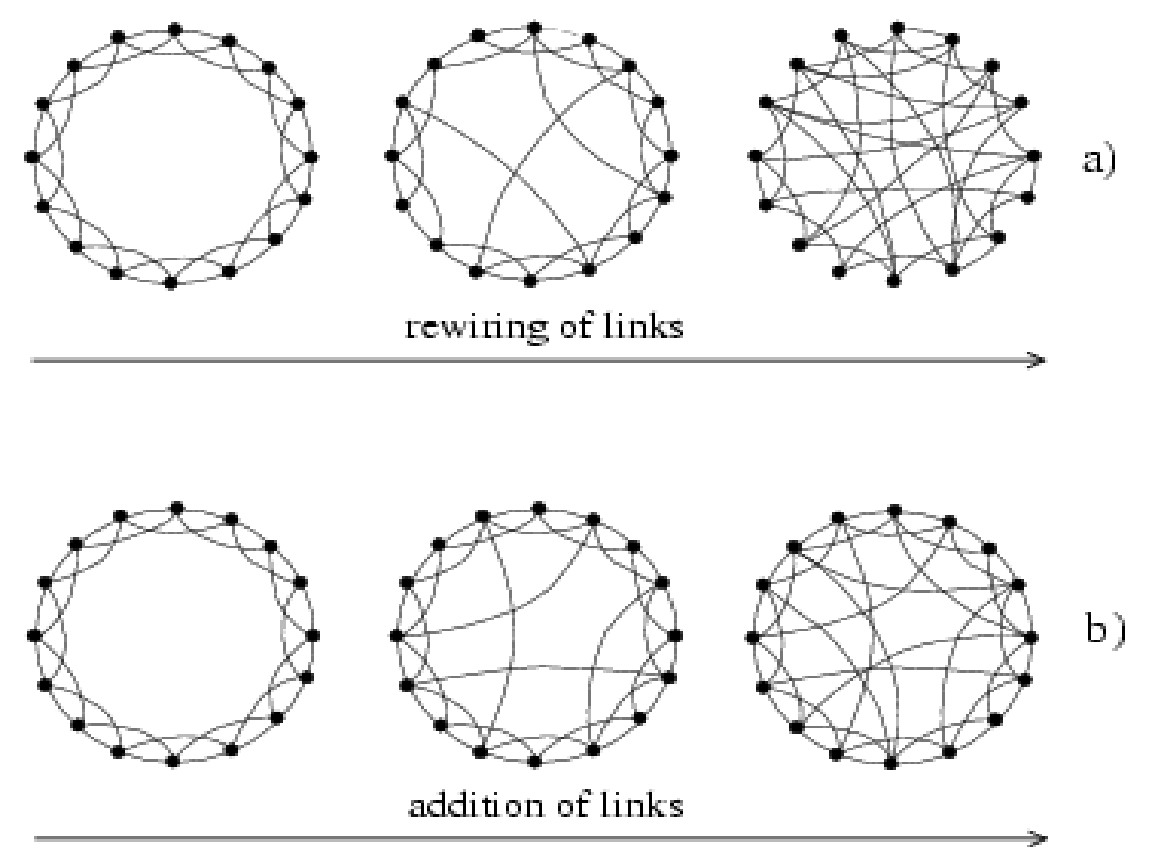
Small world experiments then



Milgram's experiment (1960's):

Given a target individual and a particular property, pass the message to a person you correspond with who is "closest" to the target.

Watts-Strogatz Ring Lattice Rewiring

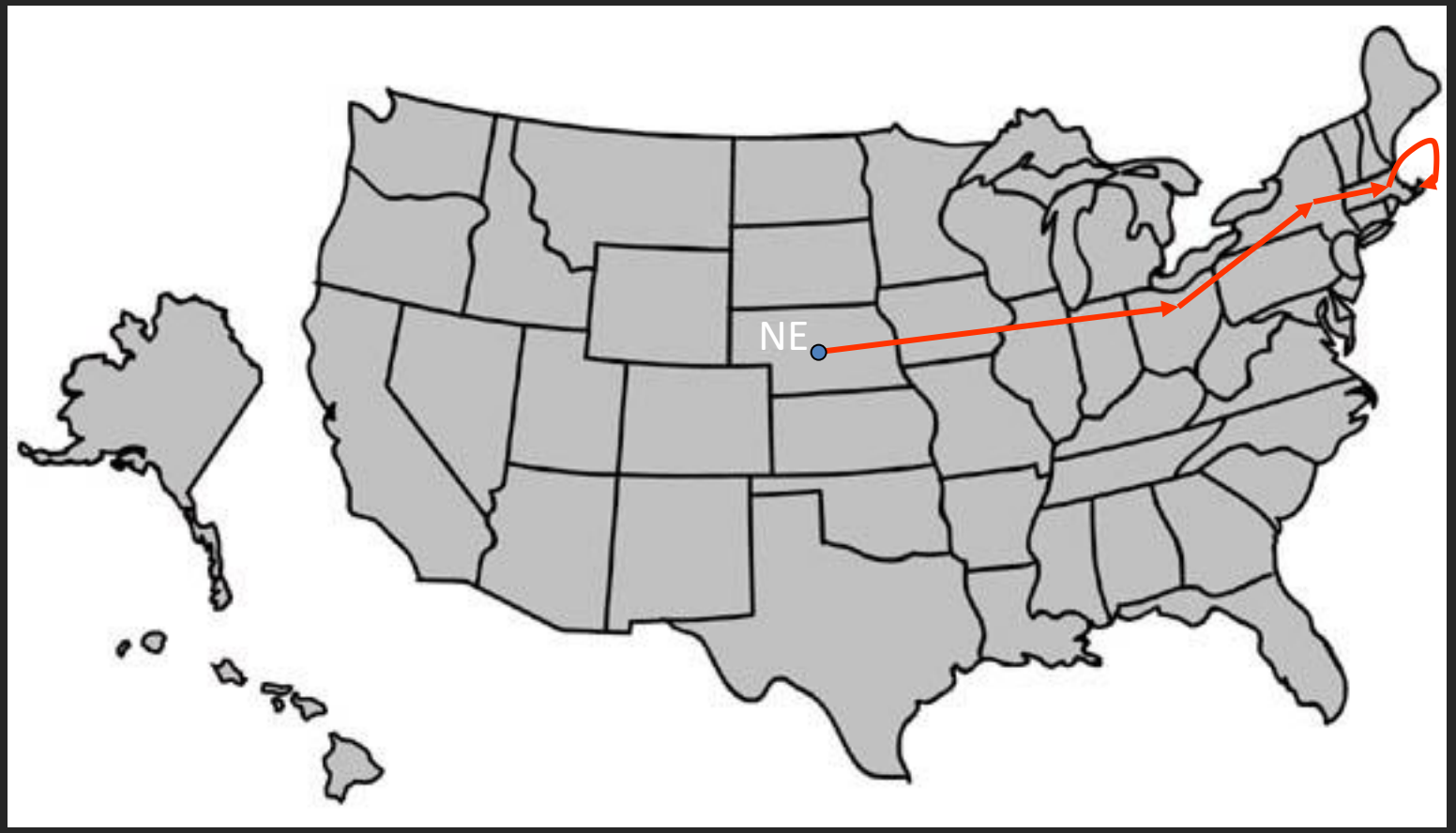


Select a fraction p of edges
Reposition on of their endpoints

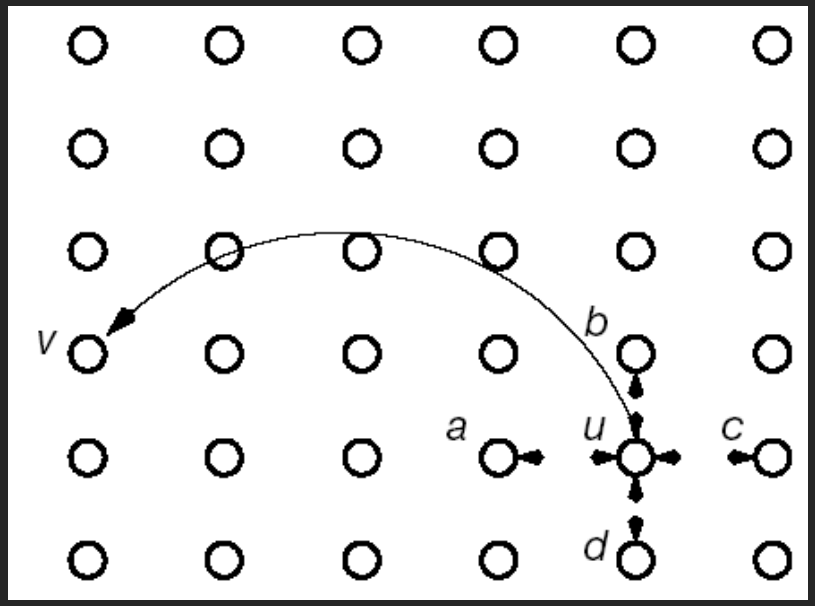
Add a fraction p of additional edges leaving underlying lattice intact

- As in many network generating algorithms
  - Disallow self-edges
  - Disallow multiple edges

Geographical search



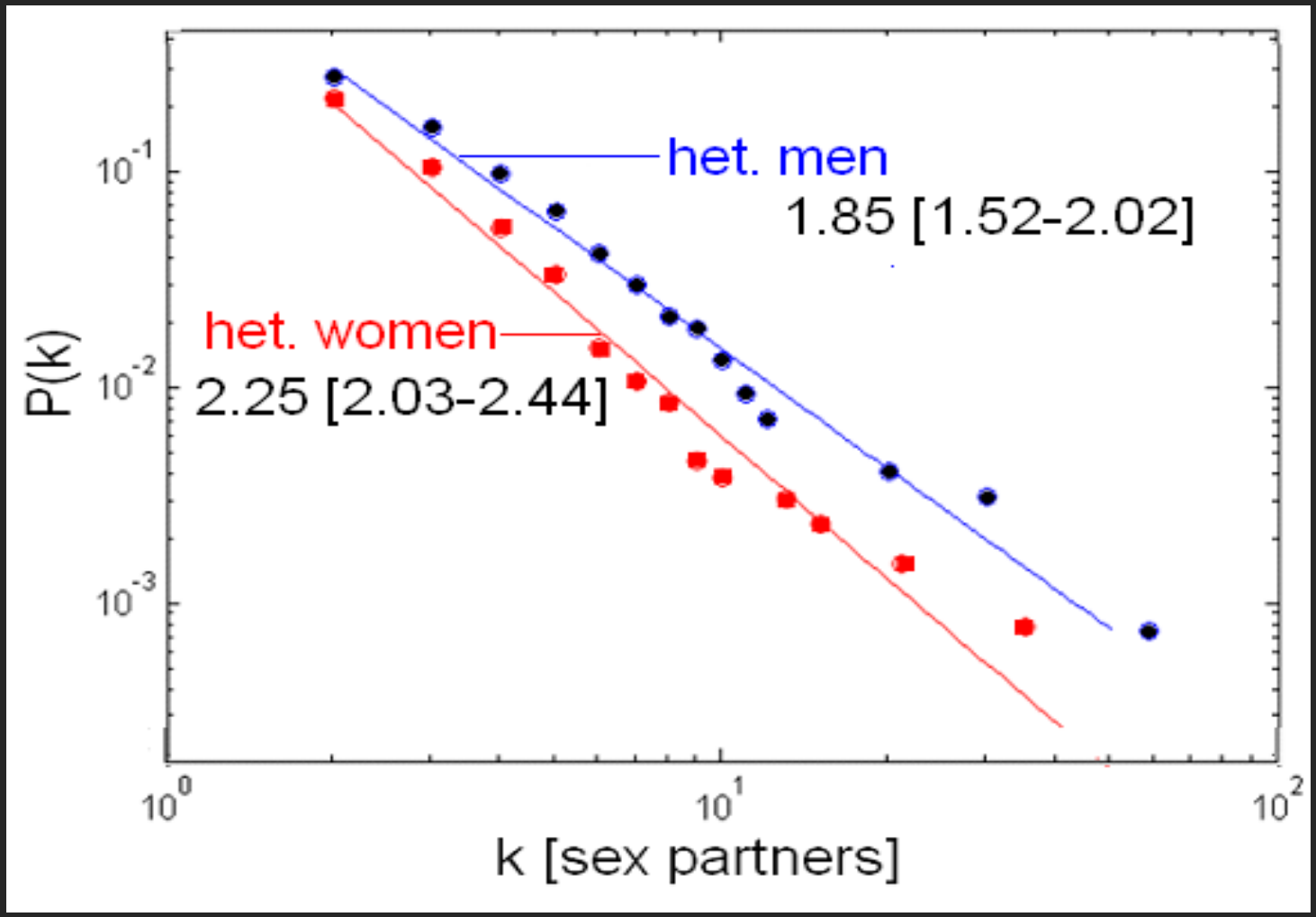
Kleinberg Lattice Model



nodes are placed on a lattice and connect to nearest neighbors

additional links placed with $p_{uv} \sim d_{uv}^{-r}$

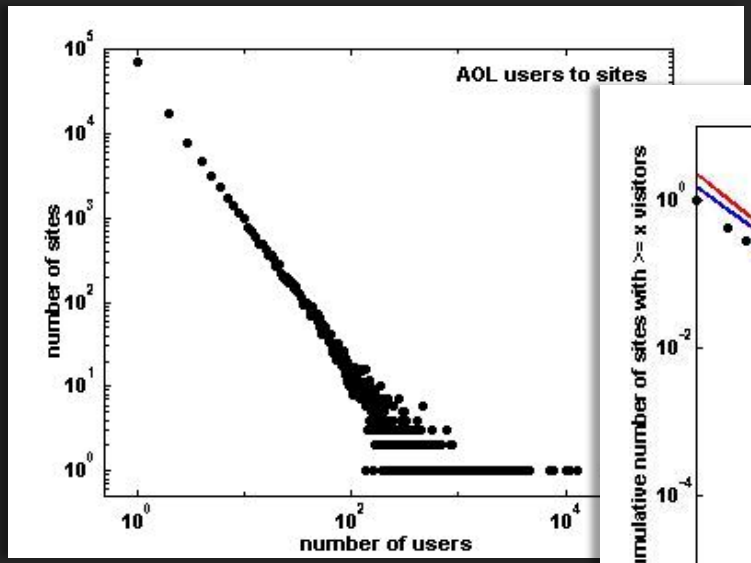
Kleinberg, 'The Small World Phenomenon, An Algorithmic Perspective' (Nature 2000)


het. men
1.85 [1.52-2.02]
het. women
2.25 [2.03-2.44]
P(k)
10^{-1}
10^{-2}
10^{-3}
10^{0}
10^{1}
10^{2}
k [sex partners]

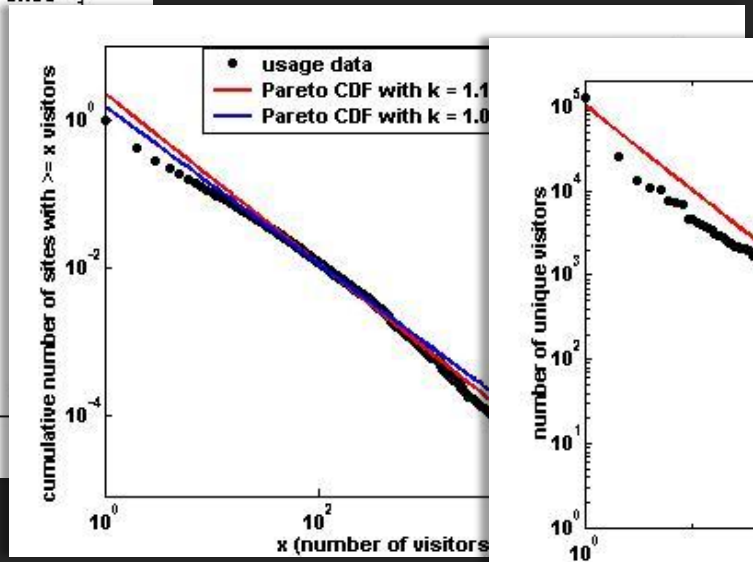
A little more on degree distribution

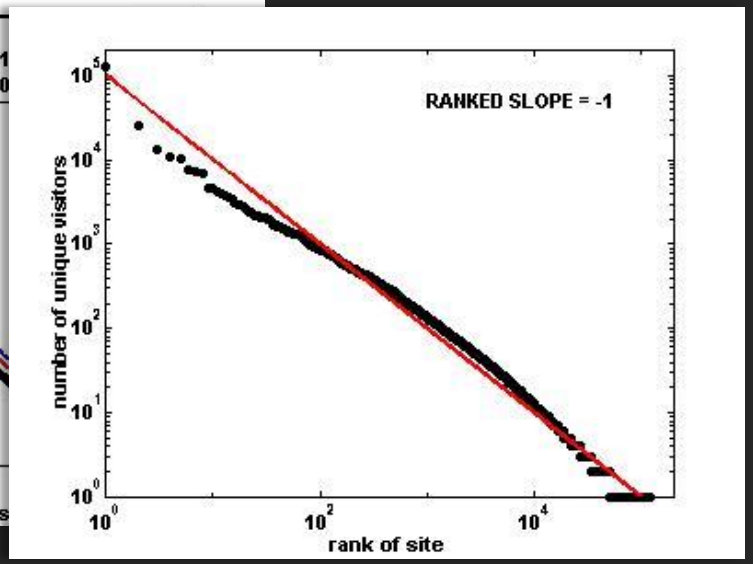
- Power-laws, zipf, etc.

Distribution of users among web sites



CDF of users to sites





Sites ranked by popularity

A little more on degree distribution

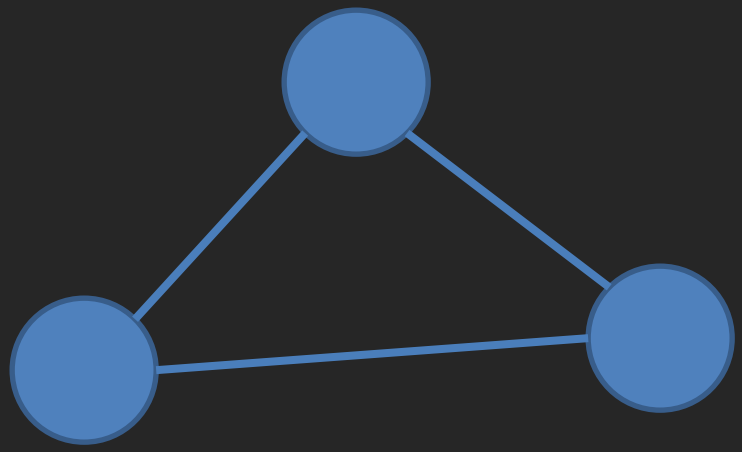
- Pareto/Power-law
  - Pareto: CDF $P[X > x] \sim x^{-k}$
  - Power-law: PDF $P[X = x] \sim x^{-(k+1)} = x^{-a}$
  - Some recent debate (Aaron Clauset)
    - http://arxiv.org/abs/0706.1062
- Zipf
  - Frequency versus rank $y \sim r^{-b}$ (small b)
- More info:
  - Zipf, Power-laws, and Pareto – a ranking tutorial (http://www.hpl.hp.com/research/idl/papers/ranking/ranking.html)

Types of Networks/Models

- A few quick examples
  - Erdős–Rényi
  - Small World
    - Watts-Strogatz
    - Kleinberg lattice model
  - Preferential Attachment
    - Generally attributed to Barabási & Albert

Basic BA-model

- Very simple algorithm to implement
  - start with an initial set of m_0 fully connected nodes
    - e.g. $m_0 = 3$



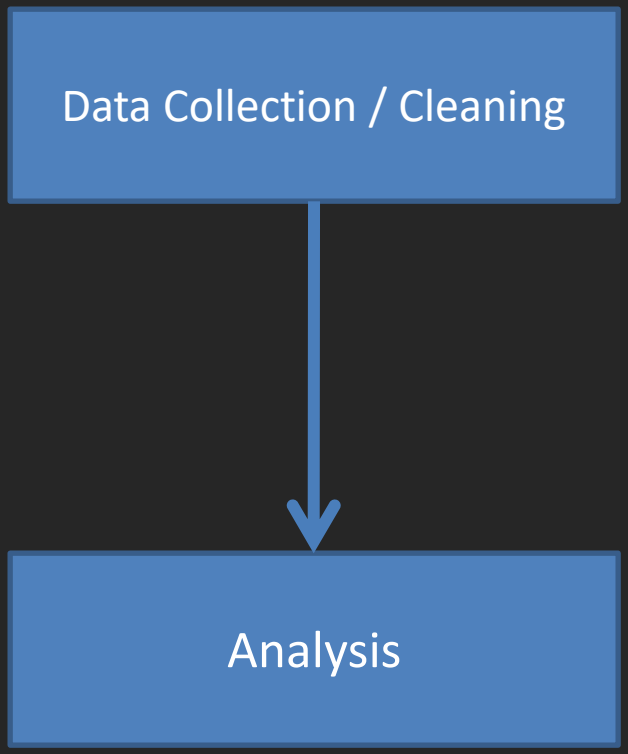
  - now add new vertices one by one, each one with exactly m edges
  - each new edge connects to an existing vertex in proportion to the number of edges that vertex already has → ***preferential attachment***

Properties of the BA graph

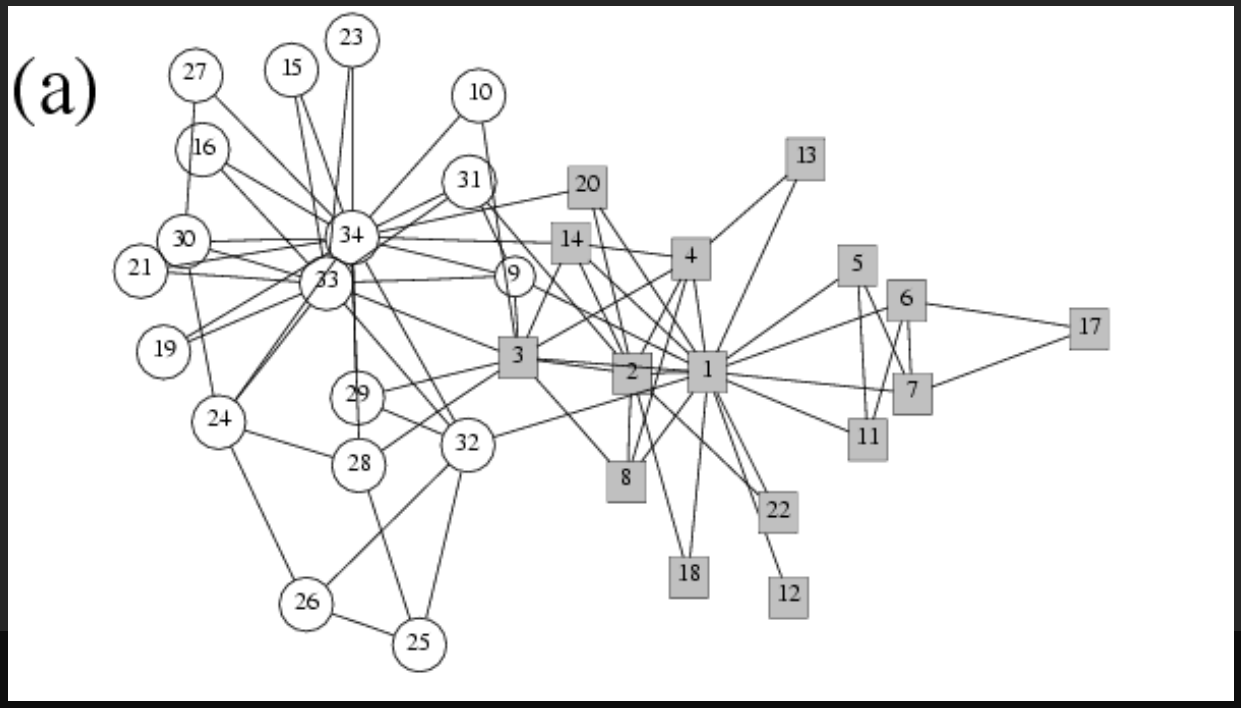
- The distribution is scale free with exponent $\alpha = 3$
  $P(k) = 2\ m^2/k^3$
- The graph is connected
  - Every new vertex is born with a link or several links (depending on whether m = 1 or m > 1)
  - It then connects to an ‘older’ vertex, which itself connected to another vertex when it was introduced
  - And we started from a connected core
- The older are richer
  - Nodes accumulate links as time goes on, which gives older nodes an advantage since newer nodes are going to attach preferentially – and older nodes have a higher degree to tempt them with than some new kid on the block

Common Tasks

- Measuring “importance”
  - Centrality, prestige
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
  - Motifs, Isomorphisms, etc.
- Visualization/Privacy/etc.


Data Collection / Cleaning
Analysis

Past


(a)
23
27
15
10
16
31
20
13
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34
14
4
5
21
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17
19
3
2
1
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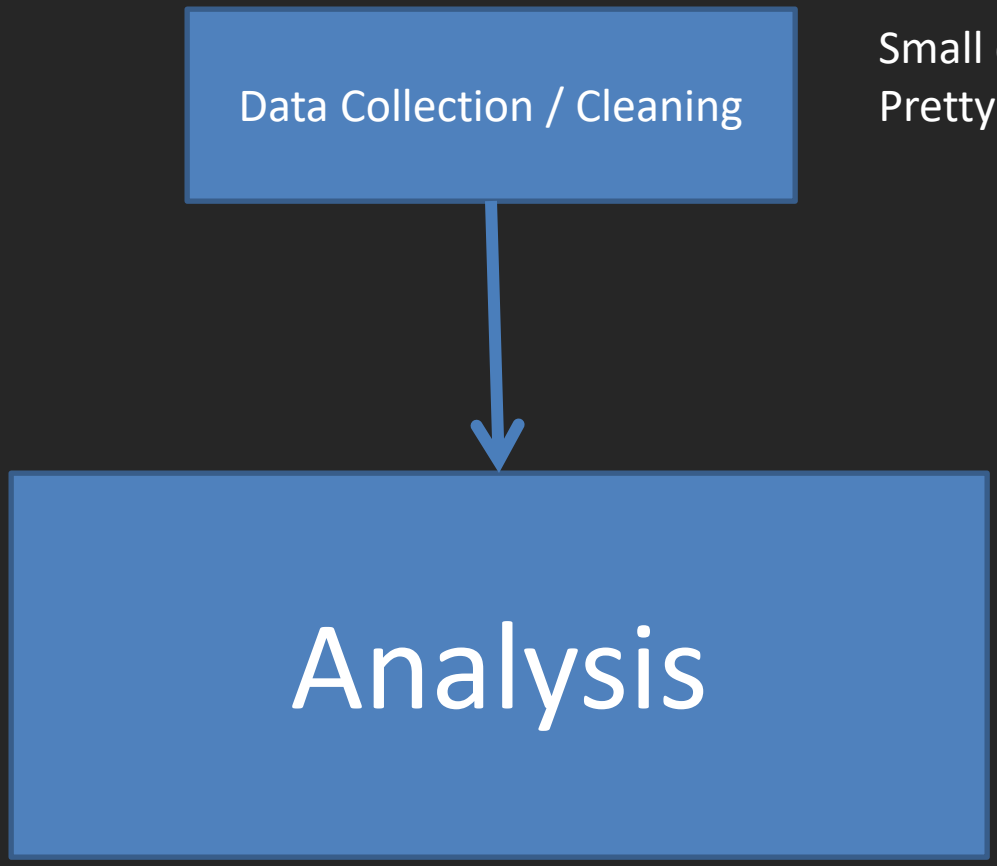
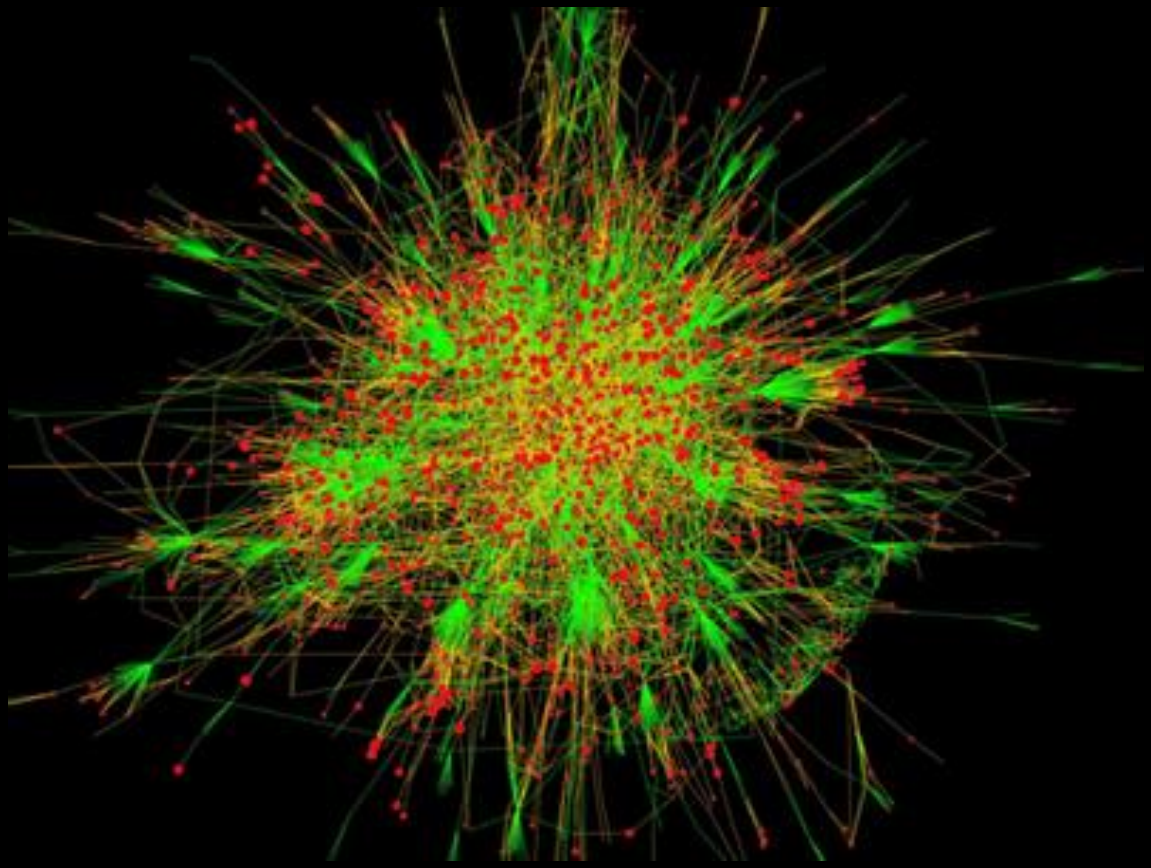
26
25

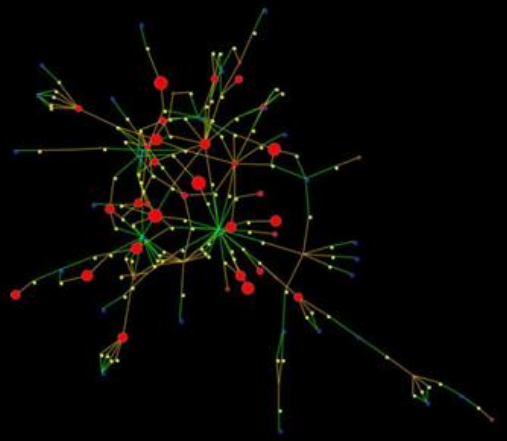


Small datasets
Pretty explicit connections

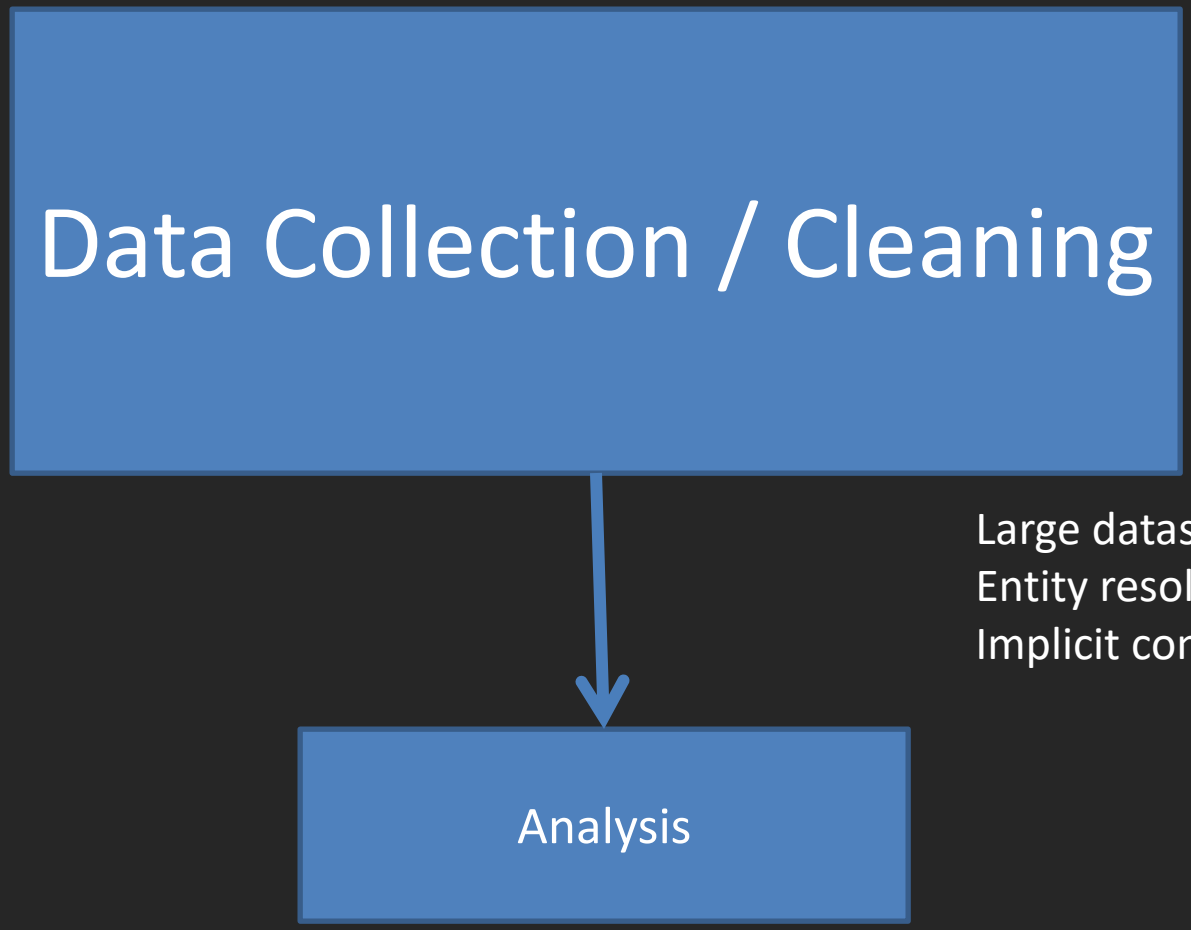
Understand the properties

Past





Present


Data Collection / Cleaning
Large datasets
Entity resolution
Implicit connections
Analysis
Understand the properties

Present

Common Tasks

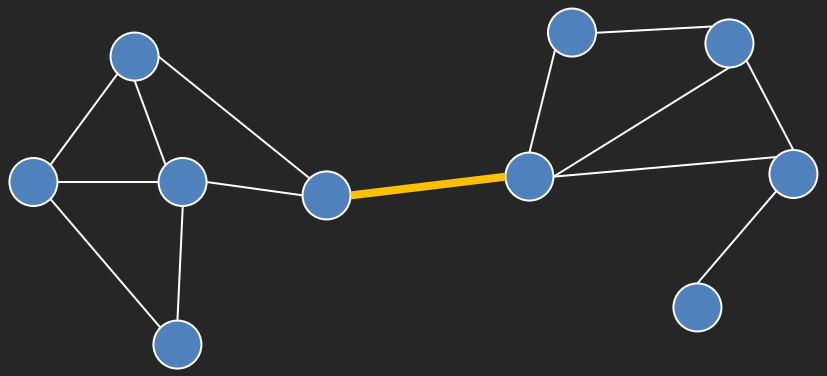
- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
  - Motifs, Isomorphisms, etc.
- Visualization/Privacy/etc.

Centrality Measures

- Degree centrality
  - Edges per node (the more, the more important the node)
- Closeness centrality
  - How close the node is to every other node
- Betweenness centrality
  - How many shortest paths go through the edge node (communication metaphor)
- Information centrality
  - All paths to other nodes weighted by path length
- Bibliometric + Internet style
  - PageRank

Tie Strength

- Strength of Weak Ties (Granovetter)
  - Granovetter: How often did you see the contact that helped you find the job prior to the job search
    - 16.7 % often (at least once a week)
    - 55.6% occasionally (more than once a year but less than twice a week)
    - 27.8% rarely – once a year or less
  - Weak ties will tend to have different *information* than we and our close contacts do



weak ties will tend to have high beweenness and low transitivity

Common Tasks

- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
  - Motifs, Isomorphisms, etc.
- Visualization/Privacy/etc.

Link Prediction

Link Prediction in Social Net Data

- *We know things about structure*
  - *Homophily* = like likes like or bird of a feather flock together or similar people group together
  - *Mutuality*
  - *Triad closure*

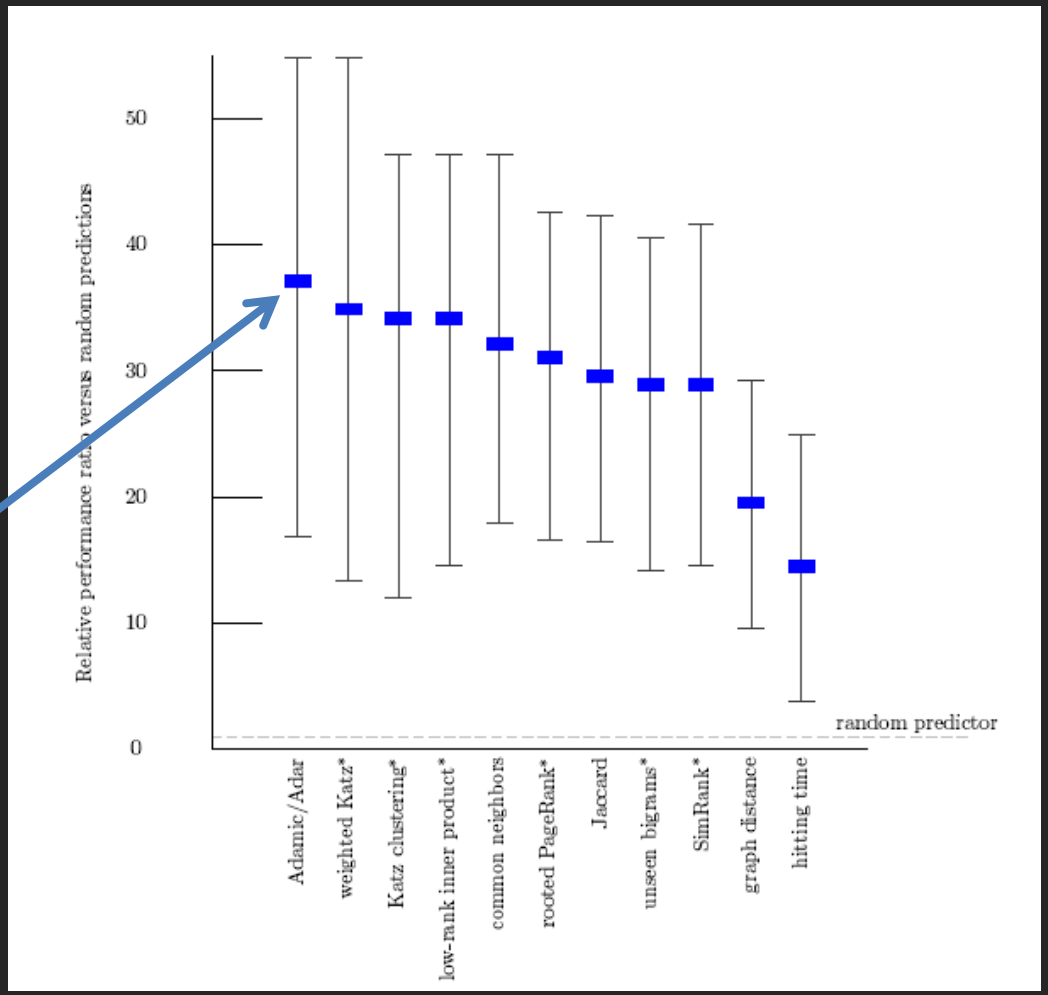
- Various measures that try to use this

Link Prediction

- Simple metrics
  - Only take into account graph properties

$$\sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log |\Gamma(z)|}$$

Γ(x) = neighbors of x
Originally: 1 / log(frequency(z))



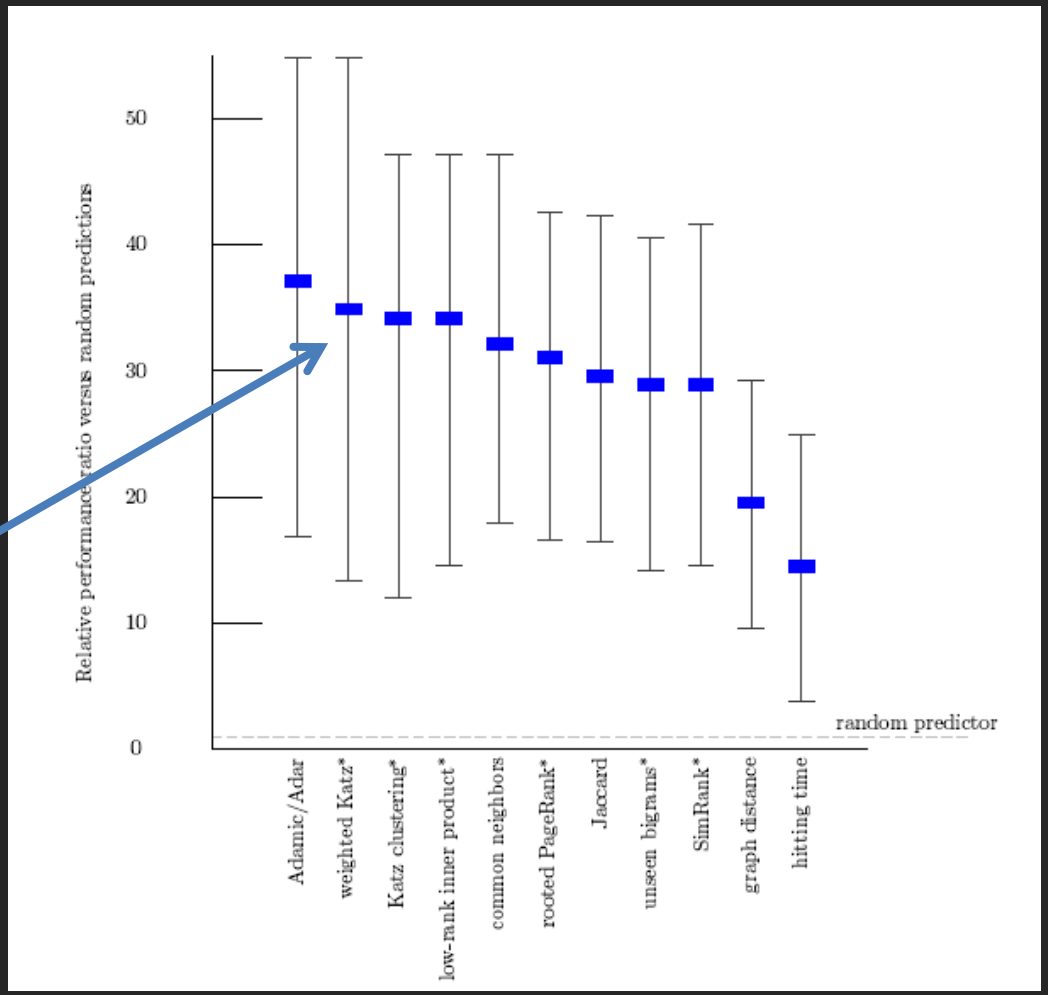
Liben-Nowell, Kleinberg (CIKM'03)

Link Prediction

- Simple metrics
  - Only take into account graph properties

$$\sum_{l=1}^{\infty} \beta^l \mid paths_{x,y}^{<l>} \mid$$

Paths of length *l* (generally 1) from x to y
weighted variant is the number of times the two collaborated



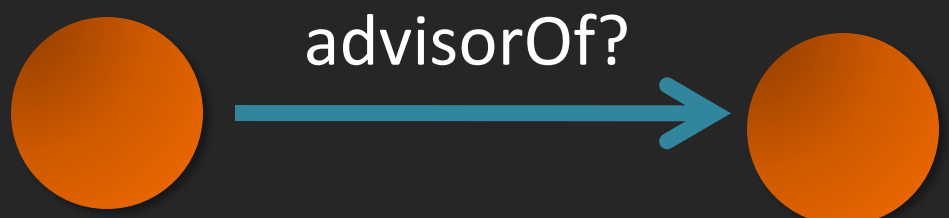
Liben-Nowell, Kleinberg (CIKM'03)

Link Prediction in Relational Data

- *We know things about structure*
  - *Homophily* = like likes like or bird of a feather flock together or similar people group together
  - *Mutuality*
  - *Triad closure*

- Slightly more interesting problem if we have relational data on actors and ties
  - Move beyond structure

Relationship & Link Prediction



Employee /contractor
Salary
Time at company
…

Link/Label Prediction in Relational Data

- Koller and co.
  - Relational Bayesian Networks
  - Relational Markov Networks
    - Structure (subgraph templates/cliques)
      - Similar context
      - Transitivity
- Getoor and co.
  - Relationship Identification for Social Network Discovery
    - Diehl/Namata/Getoor AAAI'07
  - Enron data
    - Traffic statistics and content to find supervisory relationships?
  - Traffic/Text based
  - Not really identification, more like ranking

Common Tasks

- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
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- Visualization/Privacy/etc.

Epidemiological

- Viruses
  - Biological, computational
  - STDs, needle sharing, etc.
  - Mark Handcock at UW
- Blog networks
  - Applying SIR models (Info Diffusion Through Blogspace, Gruhl et al.)
    - Induce transmission graph, cascade models, simulation
  - Link prediction (Tracking Information Epidemics in Blogspace, Adar et al.)
    - Find repeated “likely” infections
  - Outbreak detection (Cost-effective Outbreak Detection in Networks, Leskovec et al.)
    - Submodularity

Common Tasks

- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
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  - Blockmodeling, Girvan-Newman
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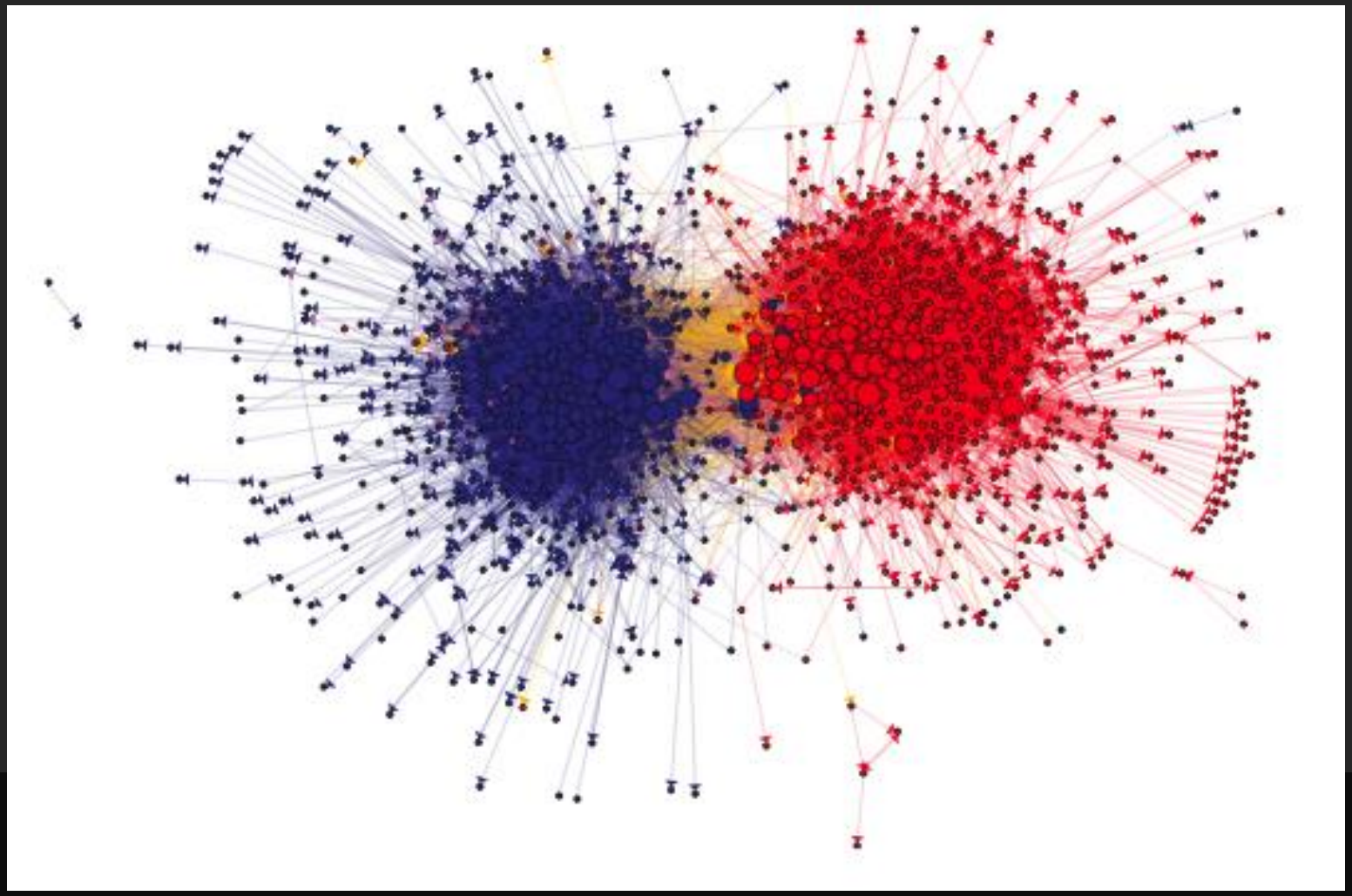
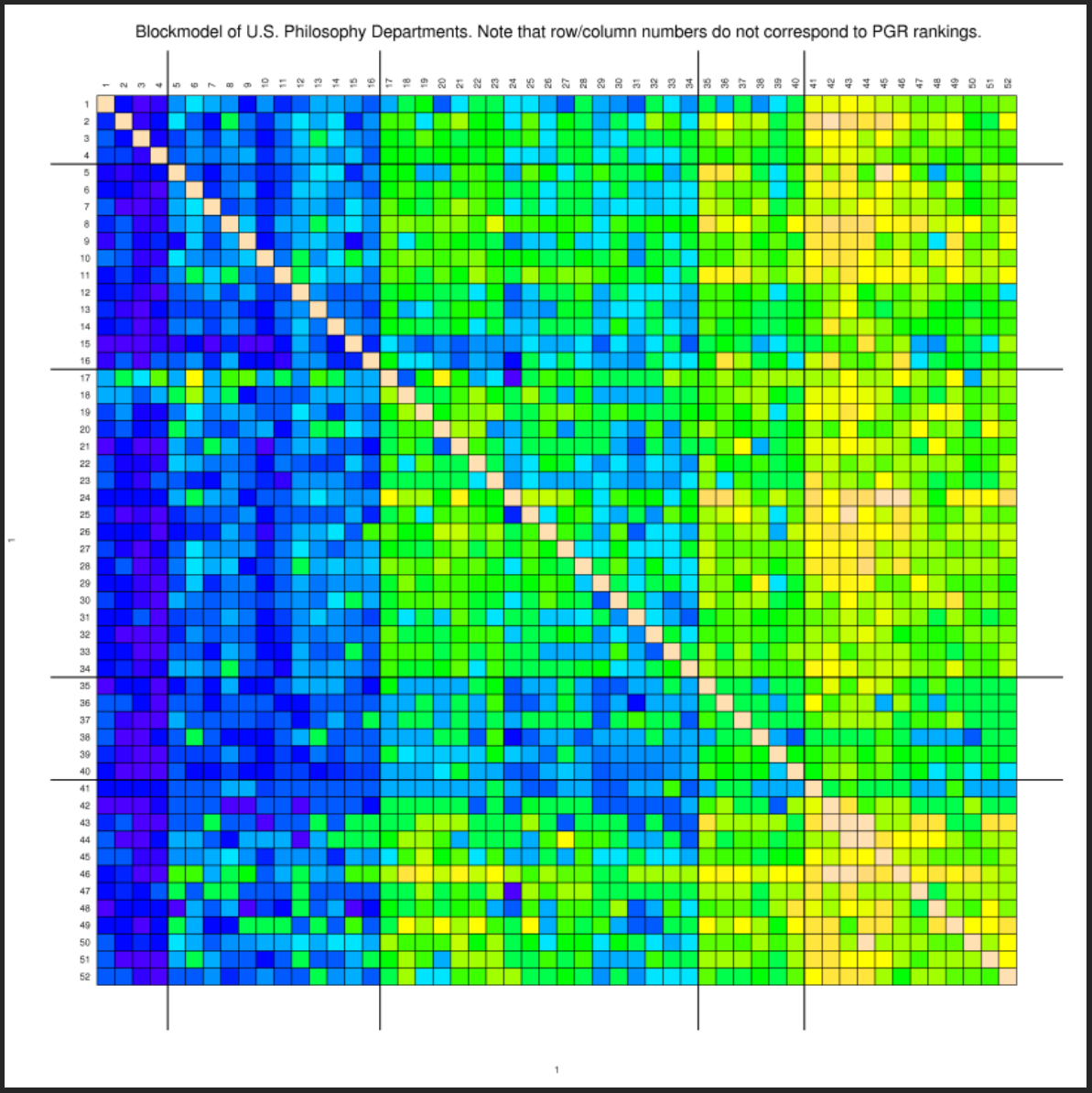
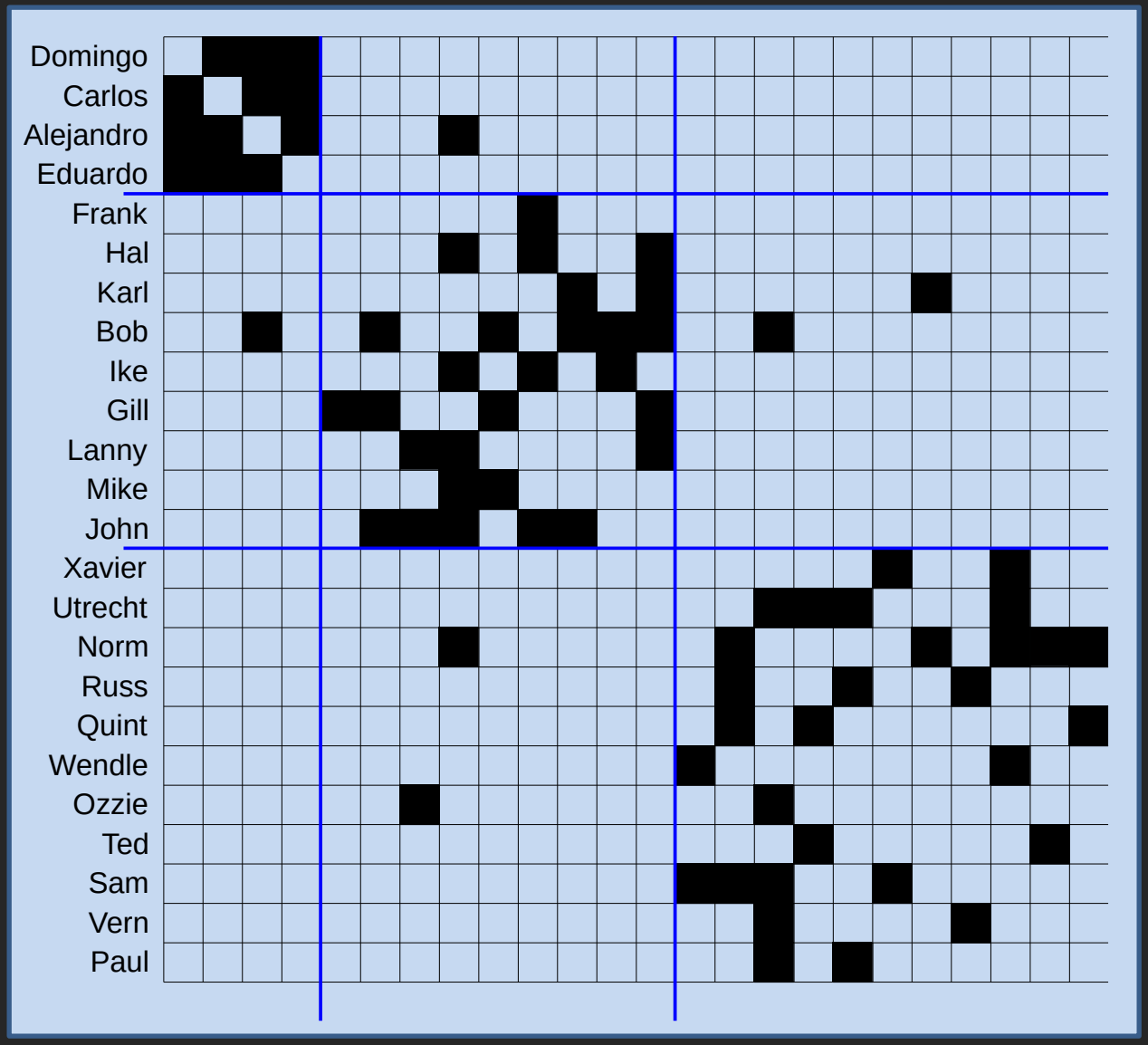



Blockmodel of U.S. Philosophy Departments. Note that row/column numbers do not correspond to PGR rankings.
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52
1
1

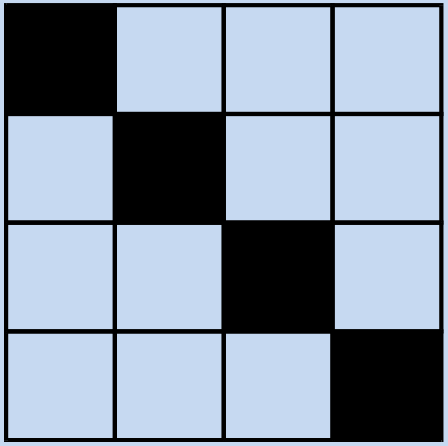

Domingo
Carlos
Alejandro
Eduardo
Frank
Hal
Karl
Bob
Ike
Gill
Lanny
Mike
John
Xavier
Utrecht
Norm
Russ
Quint
Wendle
Ozzie
Ted
Sam
Vern
Paul

Blockmodels

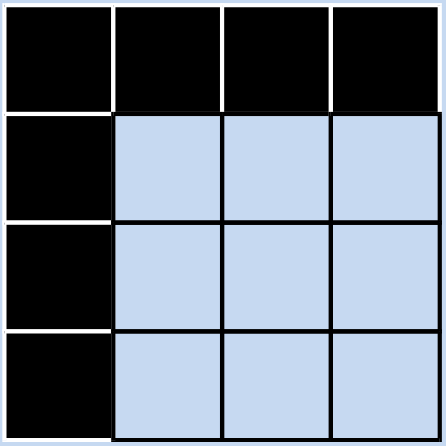
- Actors are portioned into *positions*
  - Rearrange rows/columns
- The sociomatrix is then reduced to a smaller *image*
- Hierarchical clustering
  - Various distance metrics
    - Euclidean, CONvergence of CORrelation (CONCOR)
- Various “fit” metrics

Image matrix

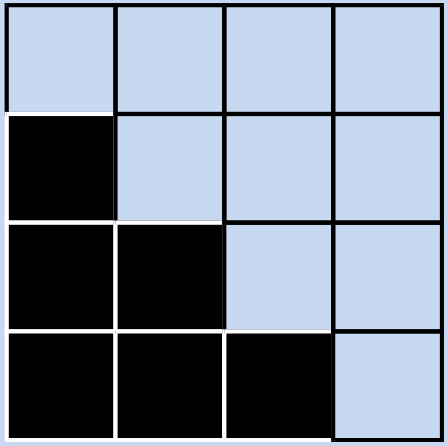
Cohesion

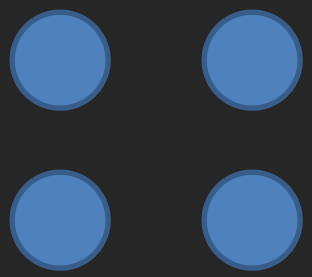


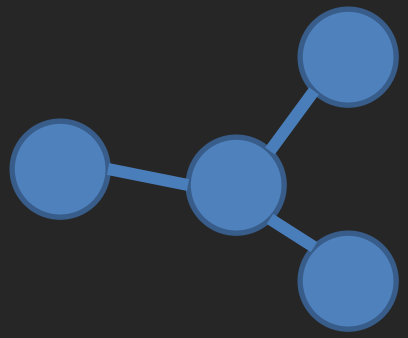
Center-periphery

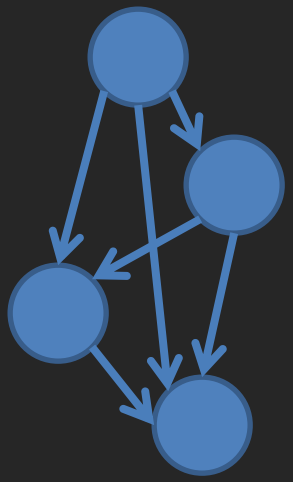


Ranking









Girvan-Newman Algorithm

- Split on shortest paths (“weak ties”)

1. Calculate betweenness on all edges
2. Remove highest betweenness edge
3. Recalculate
4. Goto 1

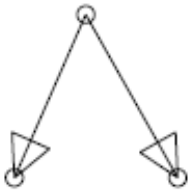
Other solutions

- Min-cut based
- “Voltage” based
- Hierarchical schemes

Common Tasks

- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
  - Motifs, Isomorphisms, etc.
- Visualization/Privacy/etc.

id6



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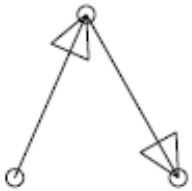

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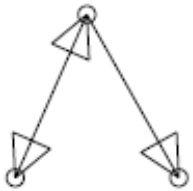

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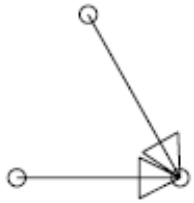

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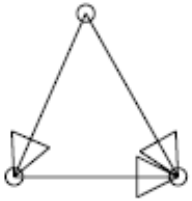

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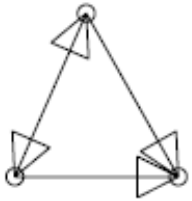

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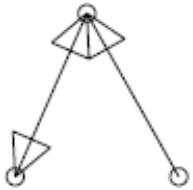

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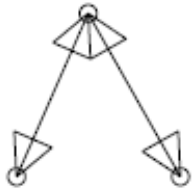

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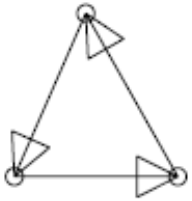

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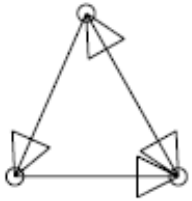

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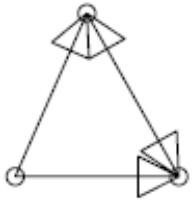

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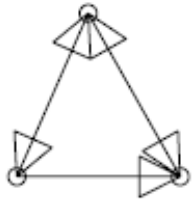

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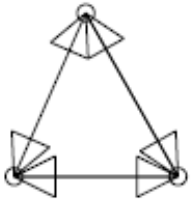

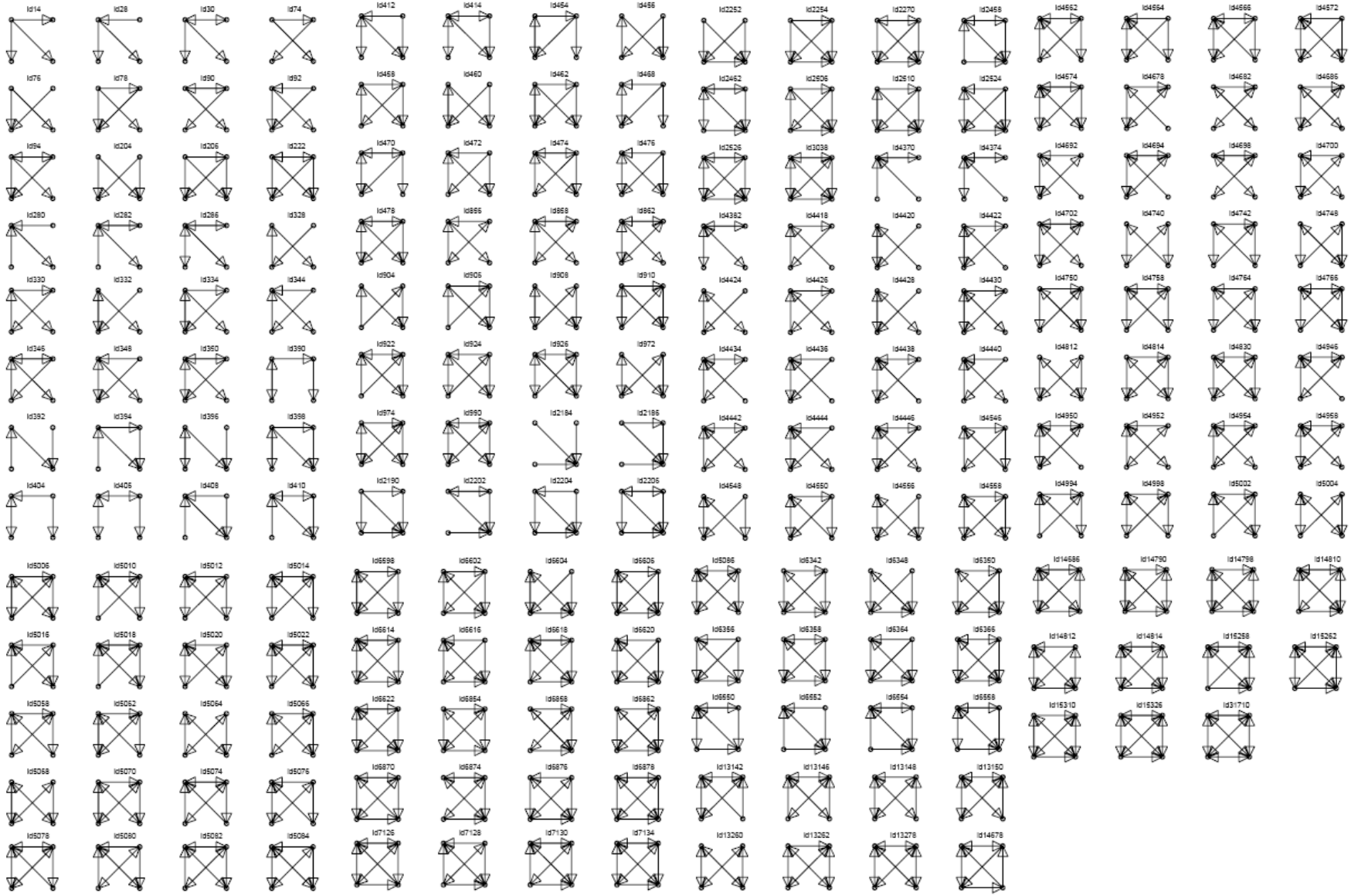
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Id13278
Id14678

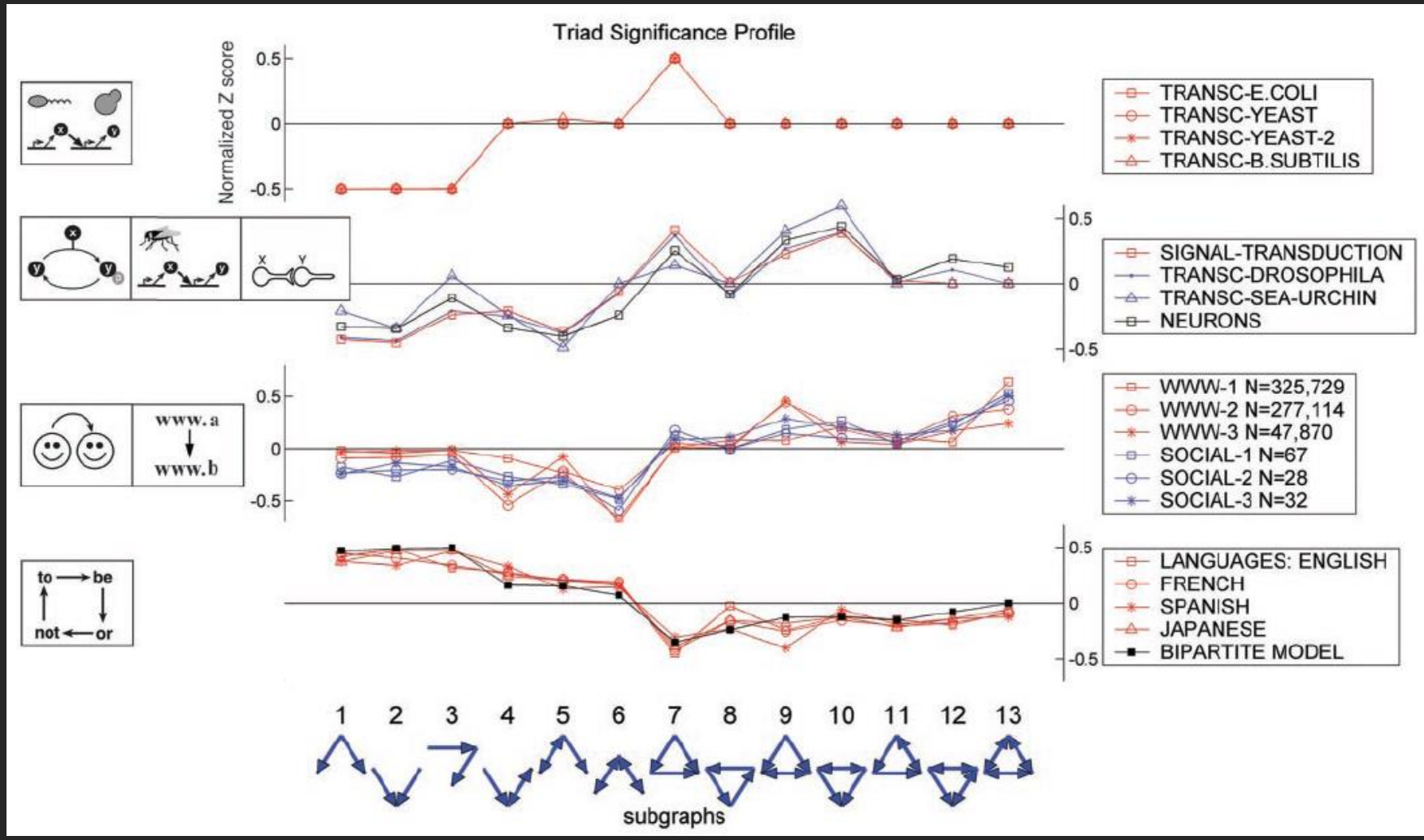
Network motif detection

- How many more motifs of a certain type exist over a random network

- Started in biological networks
  - http://www.weizmann.ac.il/mcb/UriAlon/

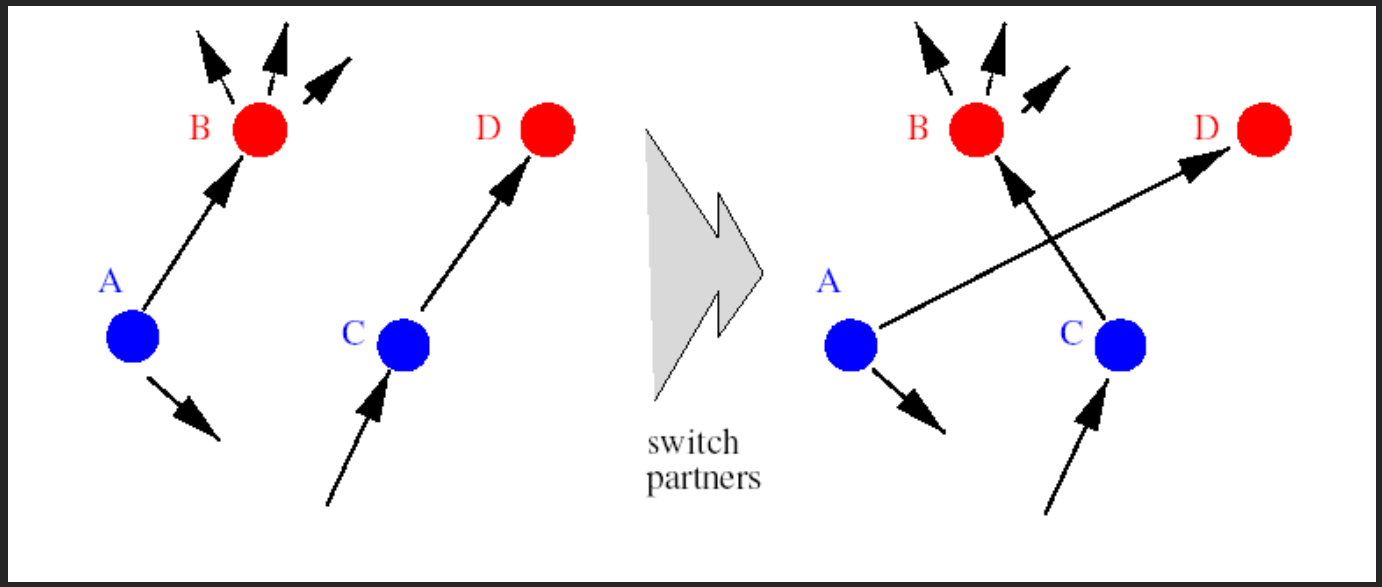
Basic idea

- construct many random graphs with the same number of nodes and edges (same node degree distribution?)
- count the number of motifs in those graphs
- calculate the Z score: the probability that the given number of motifs in the real world network could have occurred by chance

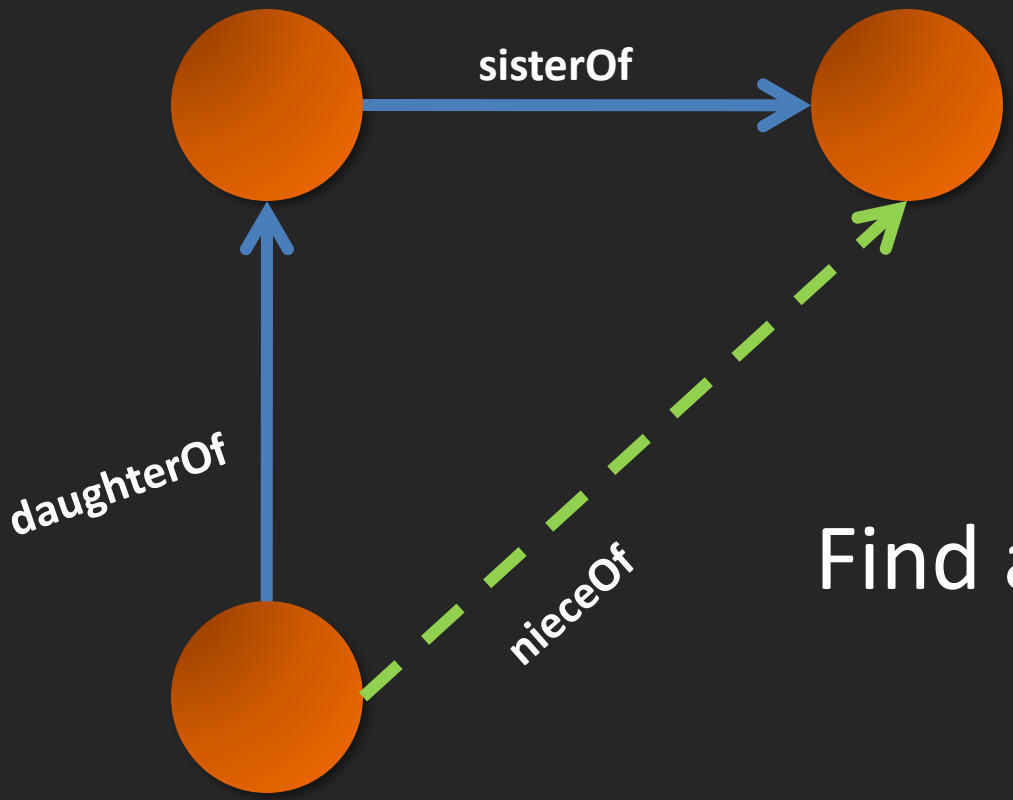

Triad Significance Profile
Normalized Z score
0.5
0
-0.5
TRANSC-E.COLI
TRANSC-YEAST
TRANSC-YEAST-2
TRANSC-B.SUBTILIS
SIGNAL-TRANSDUCTION
TRANSC-DROSOPHILA
TRANSC-SEA-URCHIN
NEURONS
www.a
www.b
WWW-1 N=325,729
WWW-2 N=277,114
WWW-3 N=47,870
SOCIAL-1 N=67
SOCIAL-2 N=28
SOCIAL-3 N=32
to
be
not
or
LANGUAGES: ENGLISH
FRENCH
SPANISH
JAPANESE
BIPARTITE MODEL
1 2 3 4 5 6 7 8 9 10 11 12 13
subgraphs

Generating random graphs

- Many models don’t preserve the desired features
- Have to be careful how we generate



Other Structural Analysis



Find all

Common Tasks

- Measuring “importance”
  - Centrality, prestige (incoming links)
- Link prediction
- Diffusion modeling
  - Epidemiological
- Clustering
  - Blockmodeling, Girvan-Newman
- Structure analysis
  - Motifs, Isomorphisms, etc.
- Visualization/Privacy/etc.

Privacy

- Emerging interest in anonymizing networks
  - Lars Backstrom (WWW'07) demonstrated one of the first attacks
- How to remove labels while preserving graph properties?
  - While ensuring that labels cannot be reapplied

Network attacks

- Terrorist networks
  - How to attack them
  - How they might attack us
- Carley at CMU

Software

- Pajek
  - http://vlado.fmf.uni-lj.si/pub/networks/pajek/
- UCINET
  - http://www.analytictech.com/
- KrackPlot
  - http://www.andrew.cmu.edu/user/krack/krackplot.shtml
- GUESS
  - http://www.graphexploration.org
- Etc.

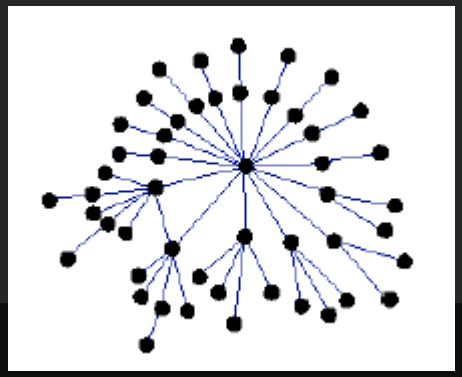
Books/Journals/Conferences

- *Social Networks/Phs. Rev*
- Social Network Analysis (Wasserman + Faust)
- The Development of Social Network Analysis (Freeman)
- Linked (Barabsi)
- Six Degrees (Watts)
- Sunbelt/ICWSM/KDD/CIKM/NIPS

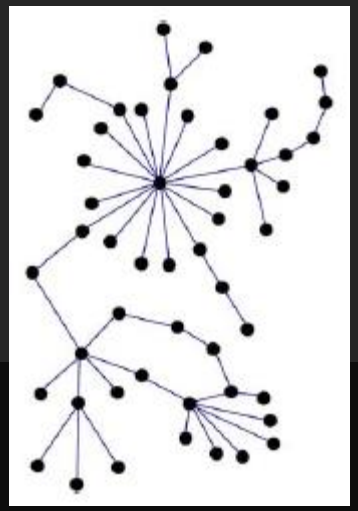
Assortativity

- Social networks are assortative:
  - the gregarious people associate with other gregarious people
  - the loners associate with other loners
- The Internet is disassorative:

Assortative:
hubs connect to hubs



Random



Disassortative:
hubs are in the periphery