

Three Lectures on Networks

Aaron Clauset

 @aaronclauset

Associate Professor of Computer Science

University of Colorado Boulder

External Faculty, Santa Fe Institute

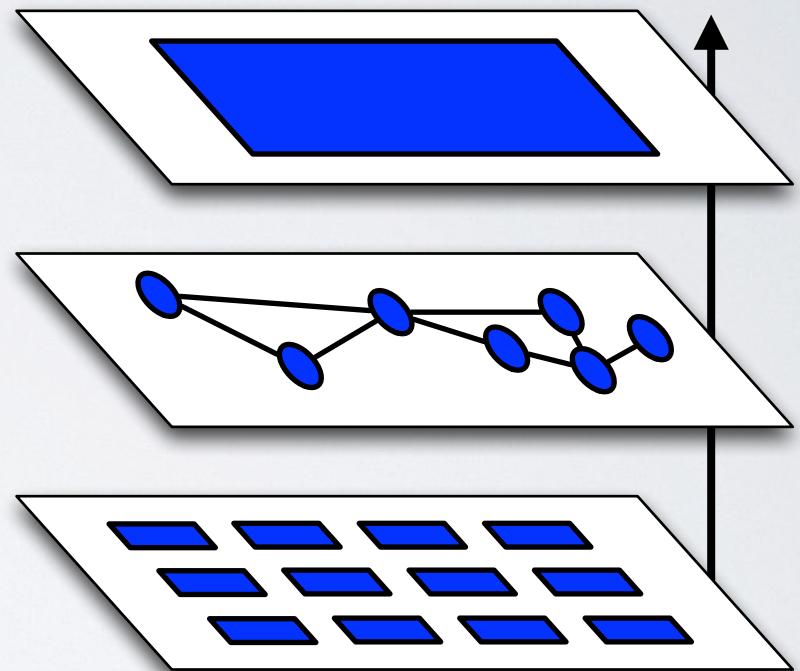
lecture I: what are networks and how do we talk about them?

what are networks?

what are networks?

- an approach
- a representation of complexity
- connect "micro" to "macro"
- *structure above* individuals / components
- *structure below* system / population

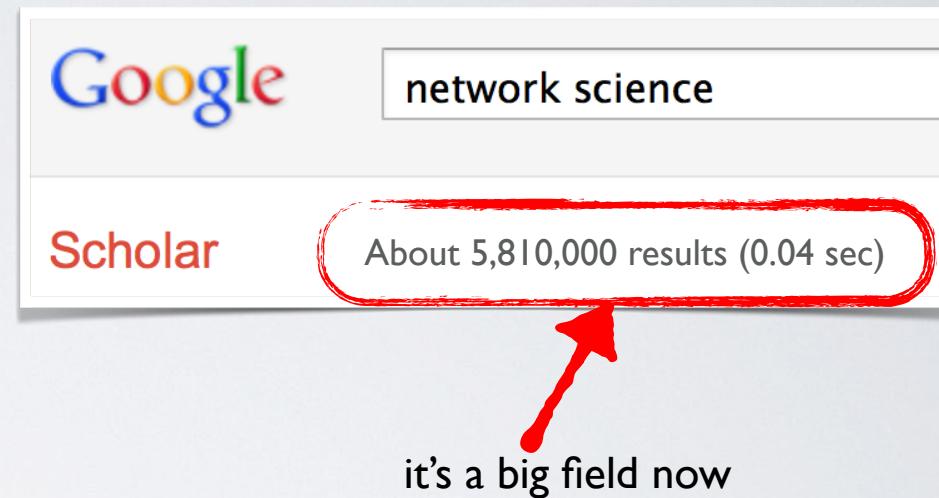
system / population



individuals / components

these lectures

- build intuition
- expose key concepts
- highlight some big questions
- teach a little math
- provide some examples
- give pointers to further study
- prep for other CSSS lectures
- not a substitute for technical coursework



it's a big field now

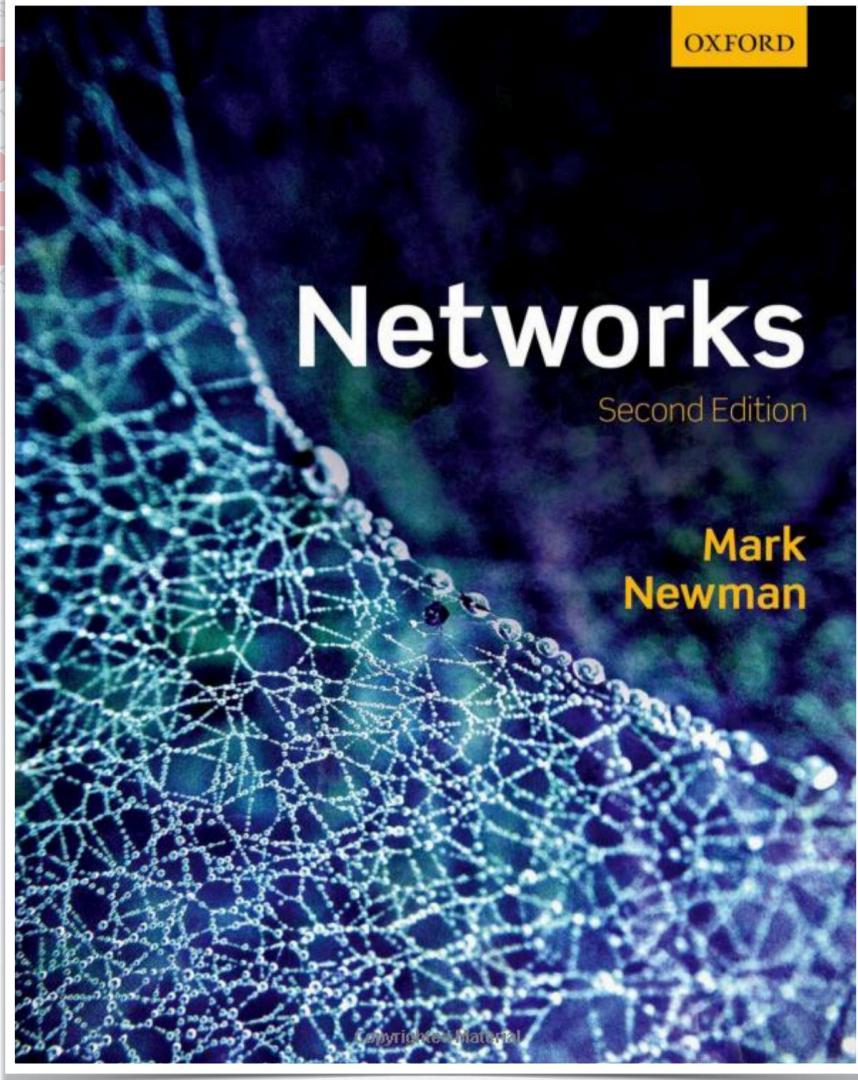


Mark Newman

Professor of Physics
University of Michigan

External Faculty
Santa Fe Institute

<http://www-personal.umich.edu/~mejn/>





University of Colorado **Boulder**

Network Analysis and Modeling

Instructor: Aaron Clauset or Daniel B. Larremore

This graduate-level course will examine modern techniques for analyzing and modeling the structure and dynamics of complex networks. The focus will be on statistical algorithms and methods, and both lectures and assignments will emphasize model interpretability and understanding the processes that generate real data. Applications will be drawn from computational biology and computational social science. No biological or social science training is required. (Note: this is not a scientific computing course, but there will be plenty of computing for science.)

Full lectures notes online (~150 pages in PDF)

<https://aaronclauset.github.io/courses/5352/>



University of Colorado **Boulder**

Biological Networks

Instructor: Aaron Clauset

This undergraduate-level course examines the computational representation and analysis of biological phenomena through the structure and dynamics of networks, from molecules to species. Attention focuses on algorithms for clustering network structures, predicting missing information, modeling flows, regulation, and spreading-process dynamics, examining the evolution of network structure, and developing intuition for how network structure and dynamics relate to biological phenomena.

Full lectures notes online (~150 pages in PDF)

<https://aaronclauset.github.io/courses/3352/>

Software

R

Python

Matlab

★ NetworkX [python]

graph-tool [python, c++]

GraphLab [python, c++]

Standalone editors

UCI-Net

NodeXL

Gephi

Pajek

Network Workbench

Cytoscape

yEd graph editor

Graphviz

Network data sets



Colorado Index of Complex Networks

The screenshot shows a web browser window with the URL [icon.colorado.edu/#!/](http://icon.colorado.edu/#/). The page title is "Index of Complex Networks". There are three main navigation tabs: "NETWORKS" (which is highlighted in blue), "ABOUT", and "SUGGEST".

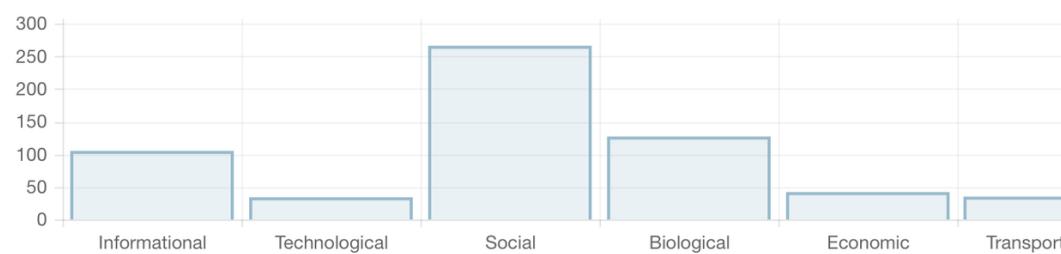
The Colorado Index of Complex Networks (ICON)

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

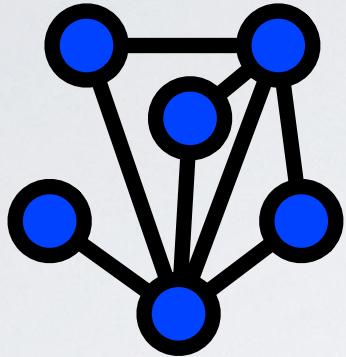
Each network record in the index is annotated with and searchable or browsable by its graph properties, description, size, etc., and many records include links to multiple networks. The contents of ICON are curated by volunteer experts from Prof. Aaron Clauset's research group at the University of Colorado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

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

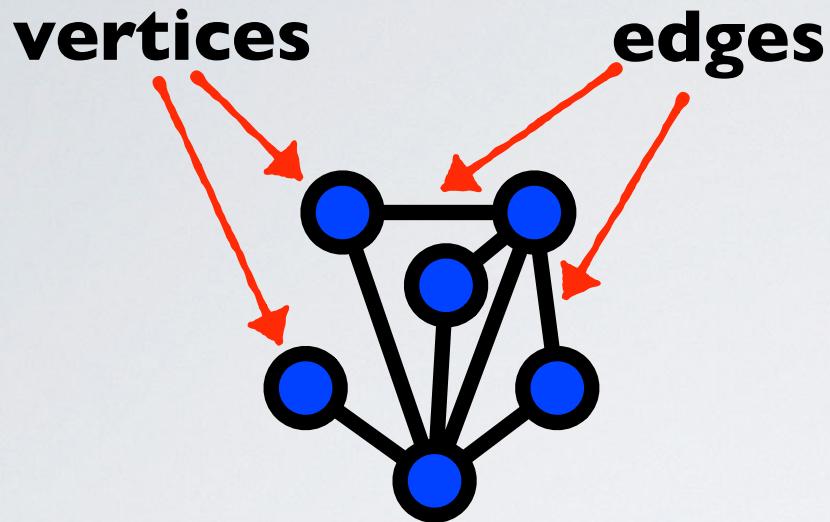
Entries found: 609 Networks found: 4419



1. defining a network
2. describing a network
3. null models and statistical inference for networks



🤔 **the two most fundamental
questions in network science**



what is a vertex?

V distinct objects (vertices / nodes / actors)

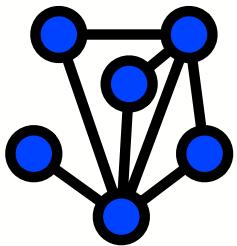
when are two vertices connected?

$$E \subseteq V \times V$$

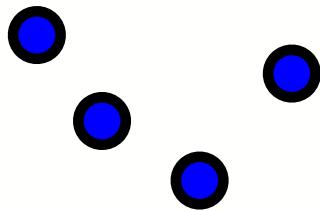
pairwise relations (edges / links / ties)

6 major classes of networks

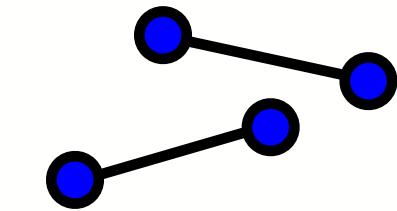
- technological
- information
- transportation
- social
- biological
- economic



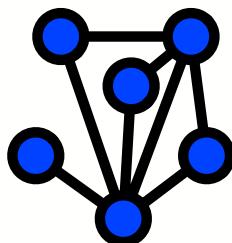
network



vertex



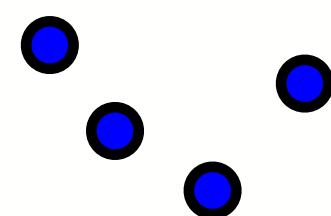
edge



network

Internet(1)

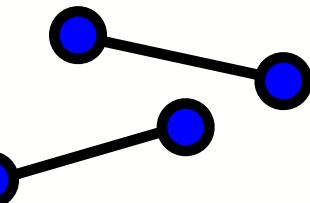
Internet(2)



vertex

computer

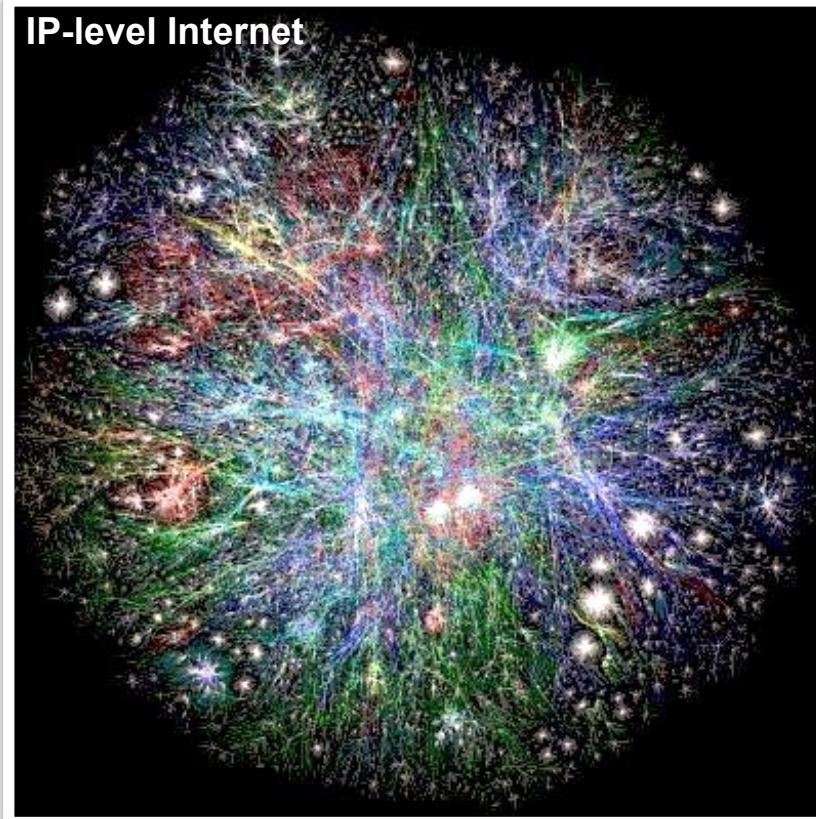
autonomous system (ISP)



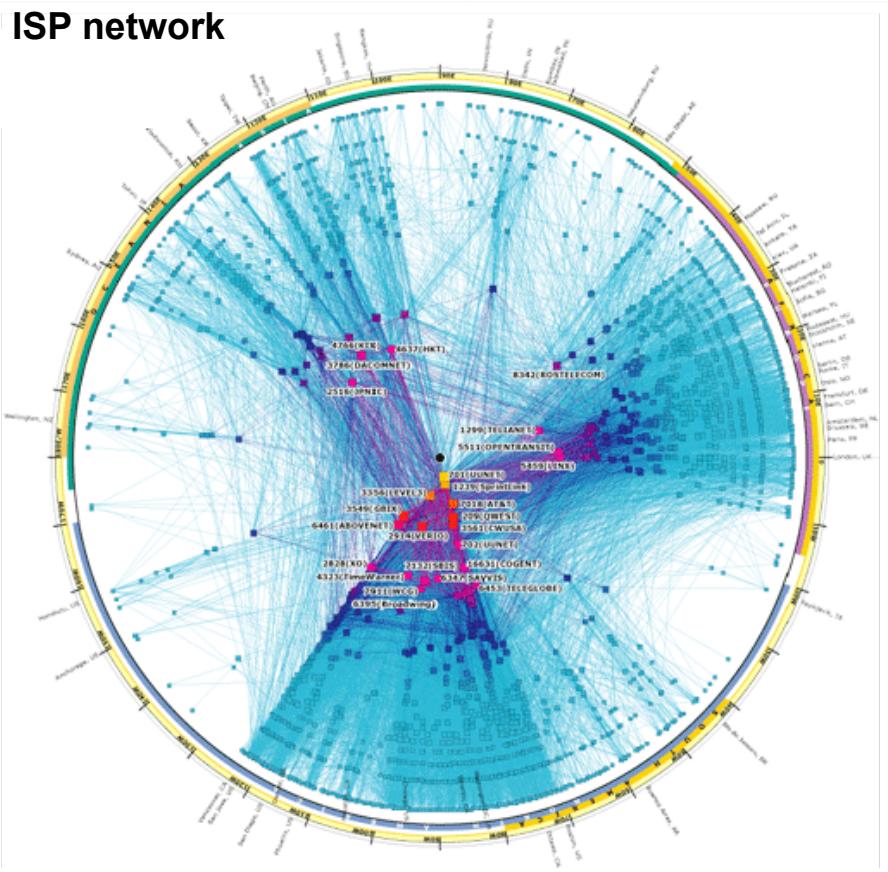
edge

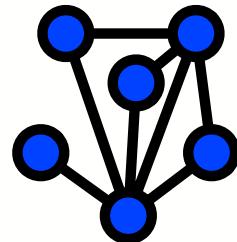
IP network adjacency

BGP connection



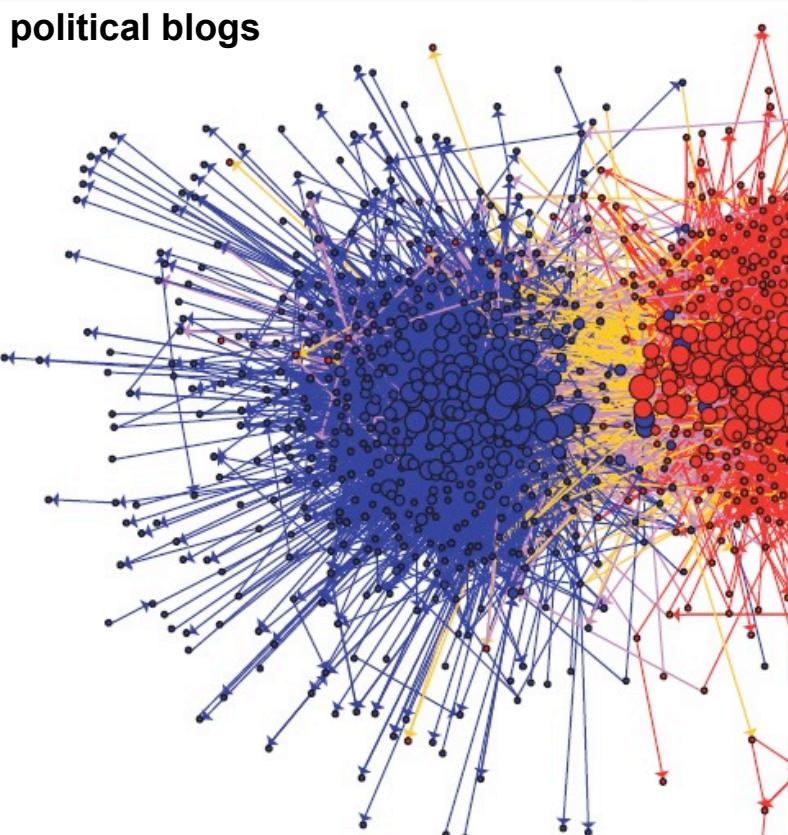
ISP network



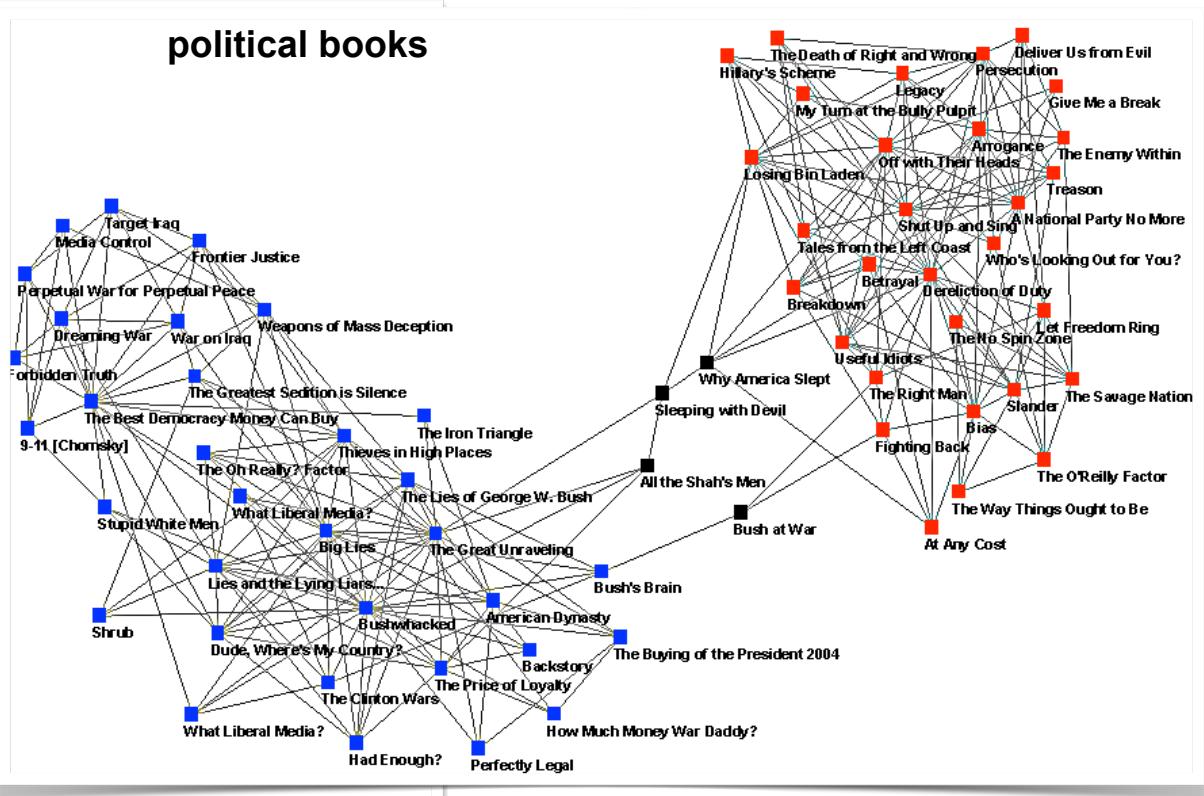


network

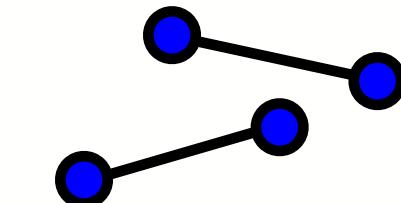
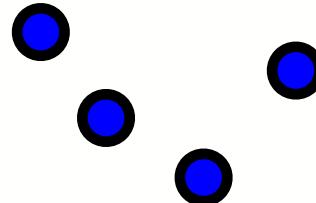
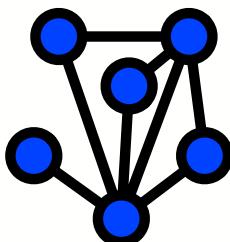
Internet(1)	computer	IP network adjacency
Internet(2)	autonomous system (ISP)	BGP connection
software	function	function call
World Wide Web	web page	hyperlink
documents	article, patent, or legal case	citation



vertex



edge



network

vertex

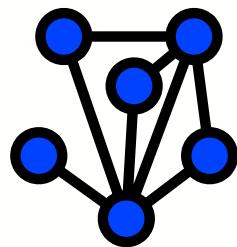
edge

Internet(1)	computer	IP network adjacency
Internet(2)	autonomous system (ISP)	BGP connection
software	function	function call
World Wide Web	web page	hyperlink
documents	article, patent, or legal case	citation
power grid transmission	generating or relay station	transmission line
rail system	rail station	railroad tracks
road network(1)	intersection	pavement
road network(2)	named road	intersection
airport network	airport	non-stop flight

technological

information

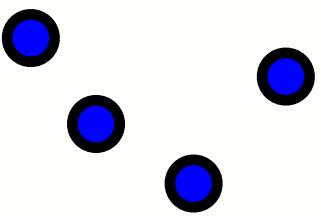
transportation



network

road network(1)

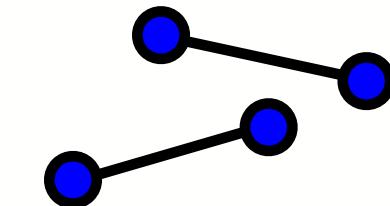
road network(2)



vertex

intersection

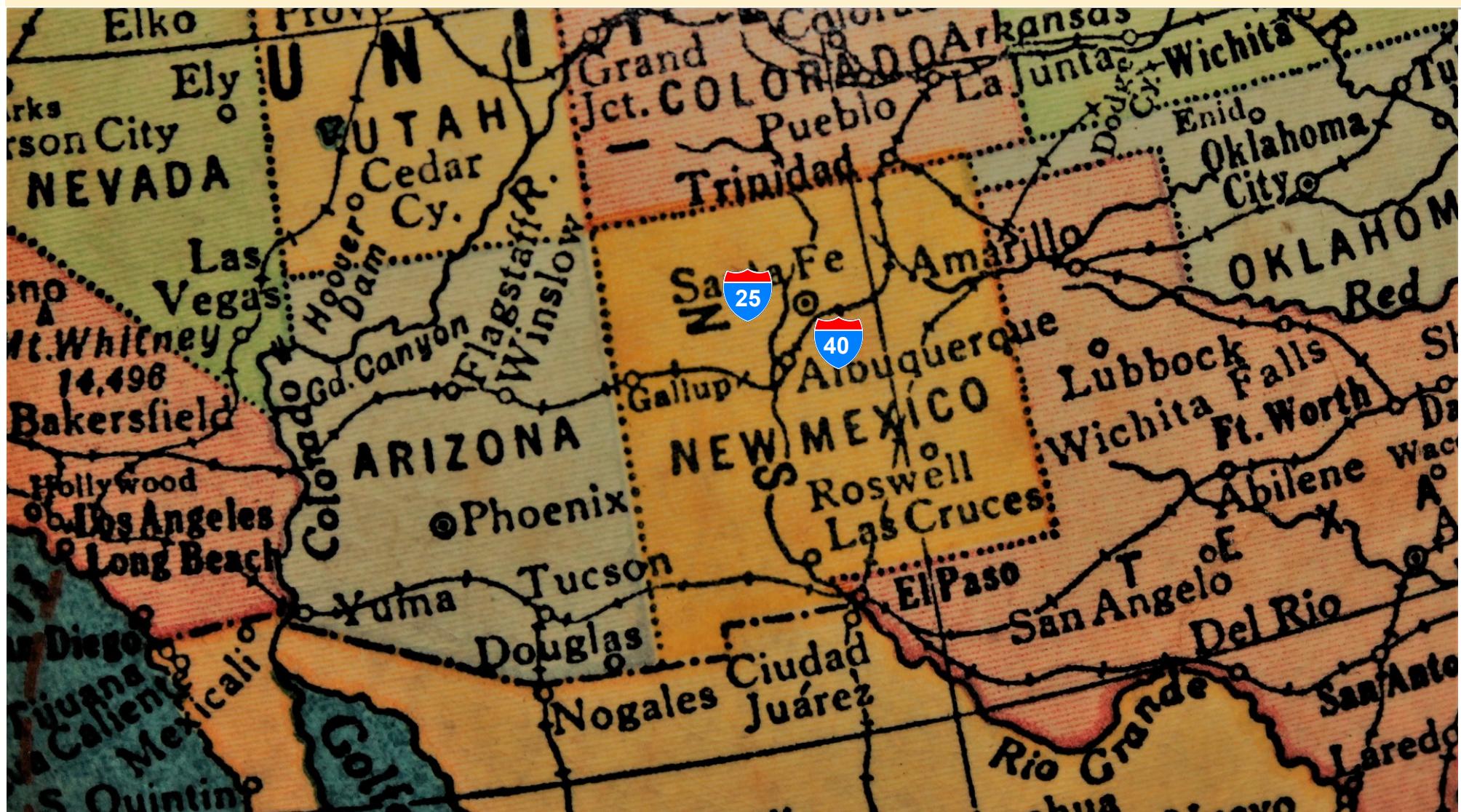
named road

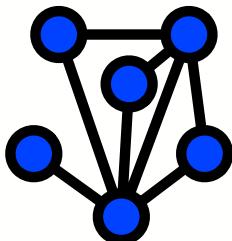


edge

pavement

intersection

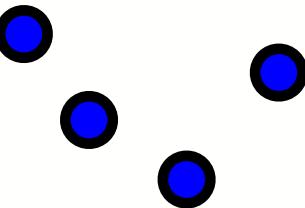




network

road network(1)

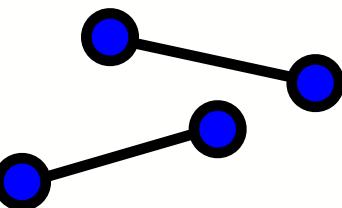
road network(2)



vertex

intersection

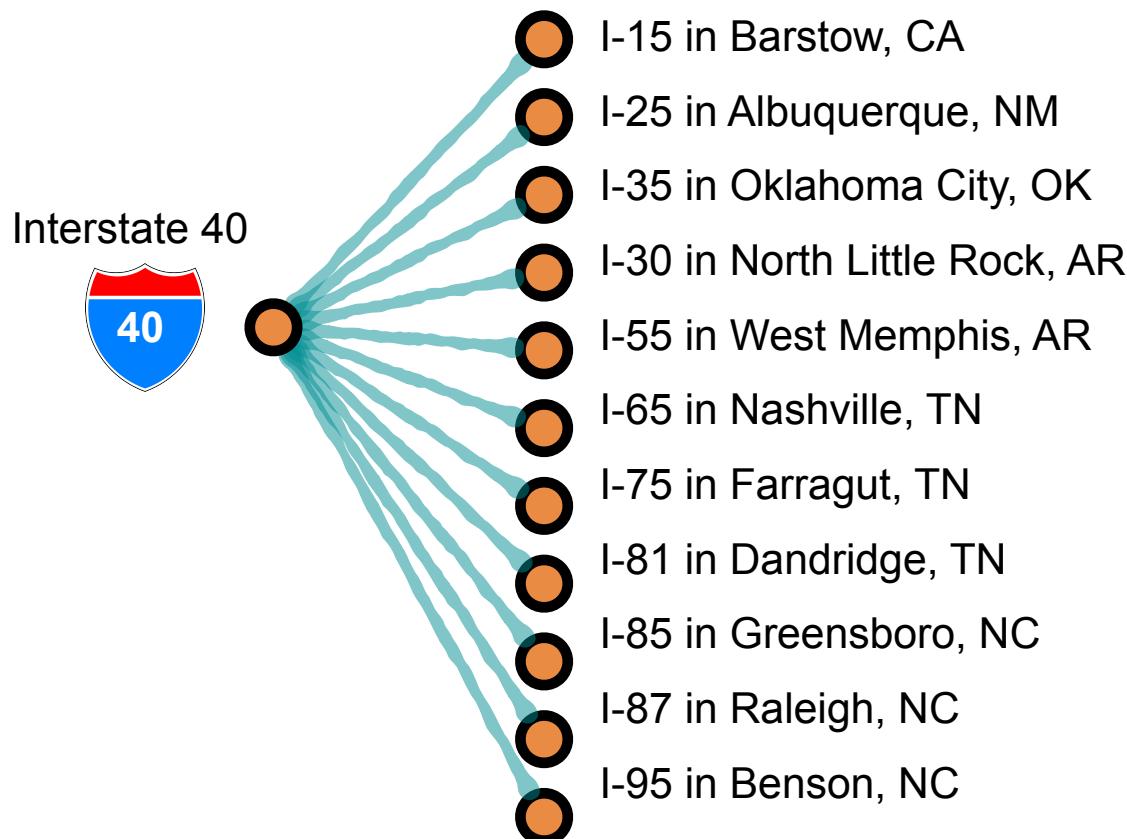
named road

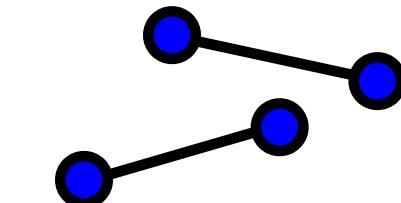
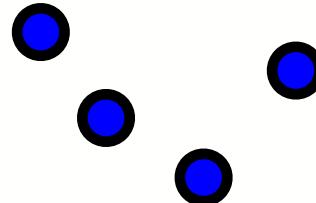
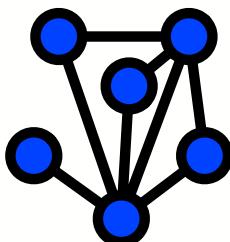


edge

pavement

intersection





network

vertex

edge

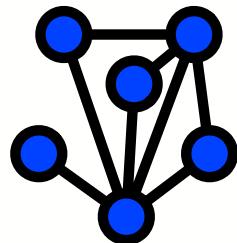
Internet(1)	computer	IP network adjacency
Internet(2)	autonomous system (ISP)	BGP connection
software	function	function call
World Wide Web	web page	hyperlink
documents	article, patent, or legal case	citation
power grid transmission	generating or relay station	transmission line
rail system	rail station	railroad tracks
road network(1)	intersection	pavement
road network(2)	named road	intersection
airport network	airport	non-stop flight
friendship network	person	friendship
sexual network	person	intercourse

technological

information

transportation

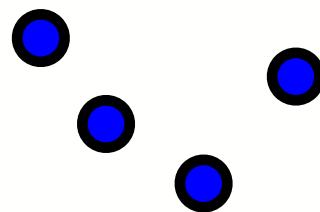
social



network

friendship network

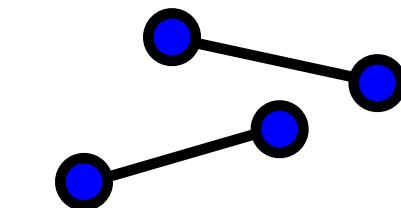
sexual network



vertex

person

person

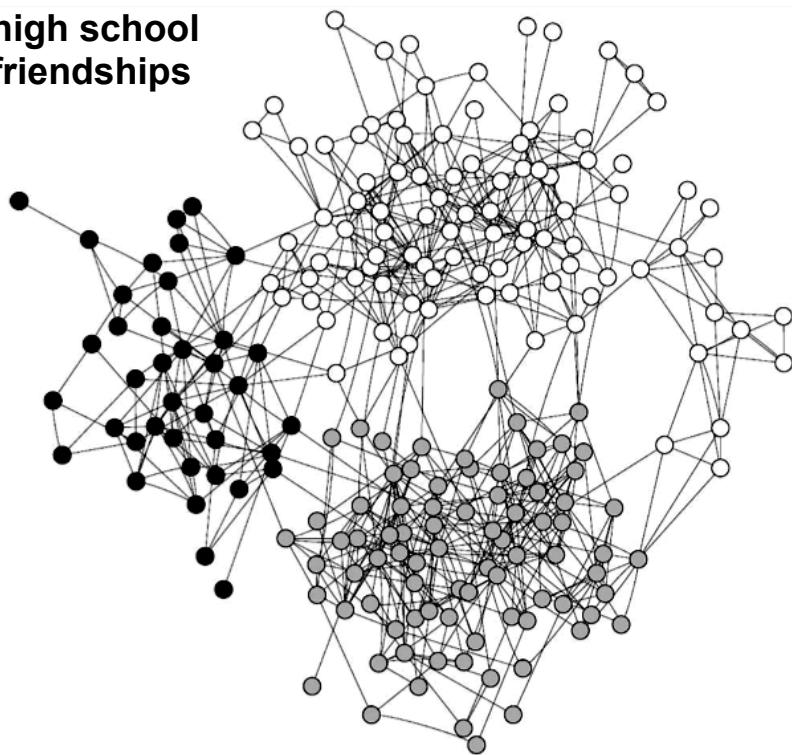


edge

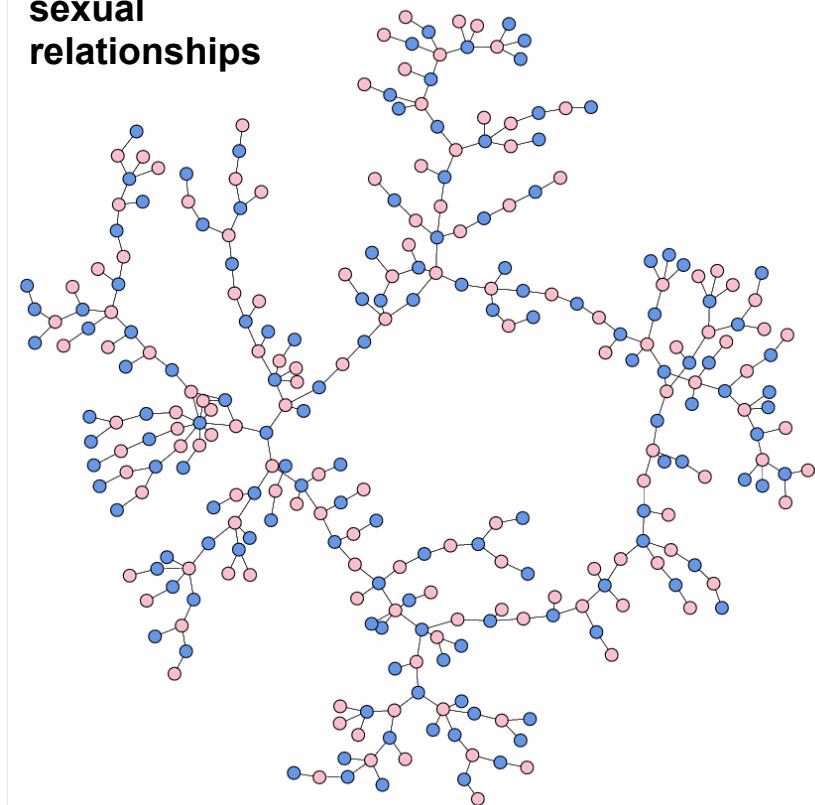
friendship

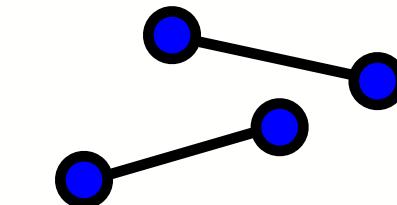
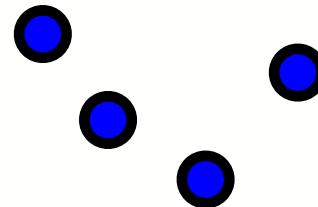
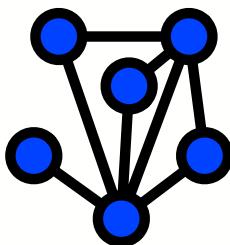
intercourse

**high school
friendships**

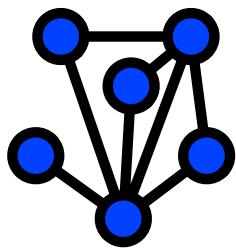


**sexual
relationships**





	network	vertex	edge
technological	Internet(1)	computer	IP network adjacency
	Internet(2)	autonomous system (ISP)	BGP connection
information	software	function	function call
	World Wide Web	web page	hyperlink
documents	documents	article, patent, or legal case	citation
	power grid transmission	generating or relay station	transmission line
transportation	rail system	rail station	railroad tracks
	road network(1)	intersection	pavement
road network(2)	road network(2)	named road	intersection
	airport network	airport	non-stop flight
social	friendship network	person	friendship
	sexual network	person	intercourse
biological	metabolic network	metabolite	metabolic reaction
	gene regulatory network	gene	regulatory effect
	neuronal network	neuron	synapse
	food web	species	predation or resource transfer



network

metabolic network

food web

vertex

metabolite

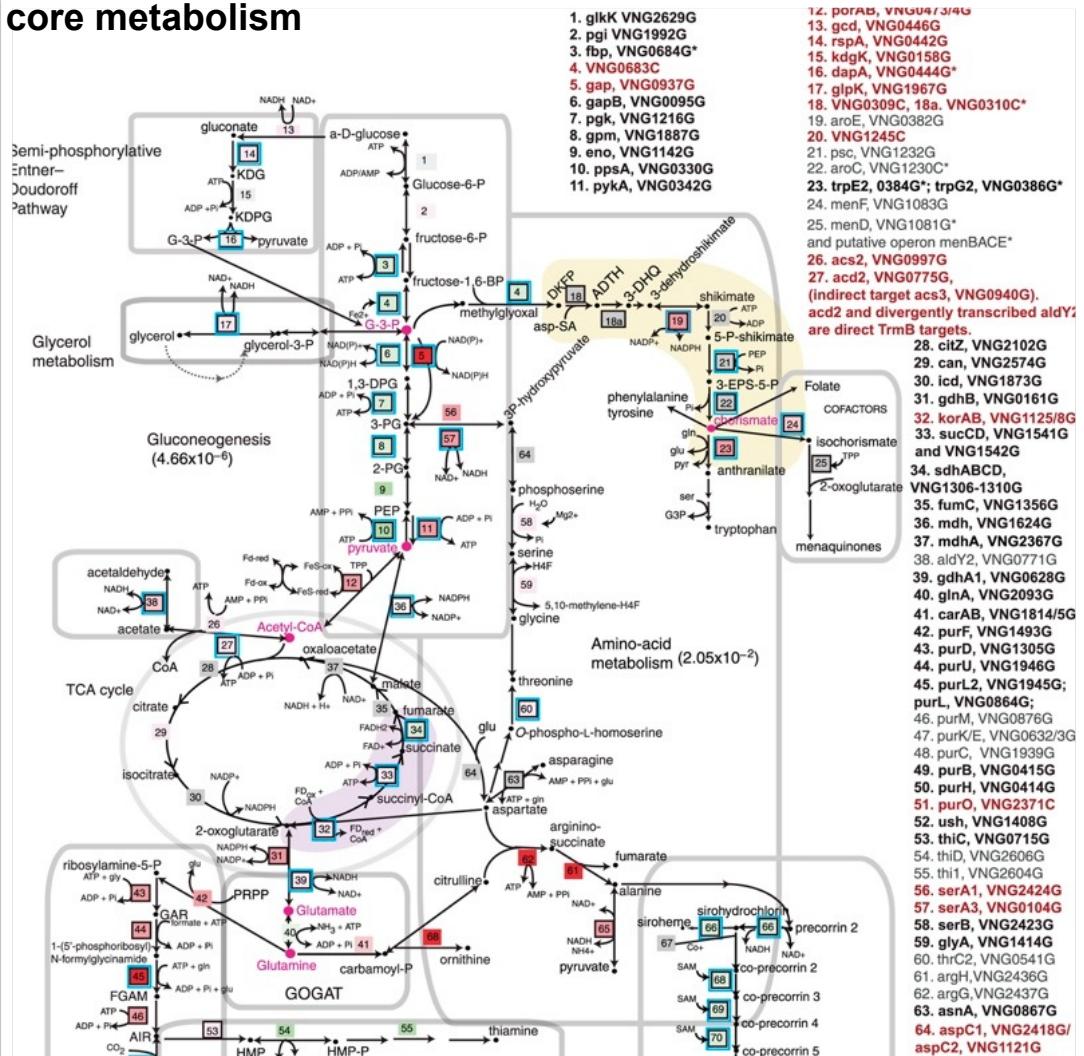
species

edge

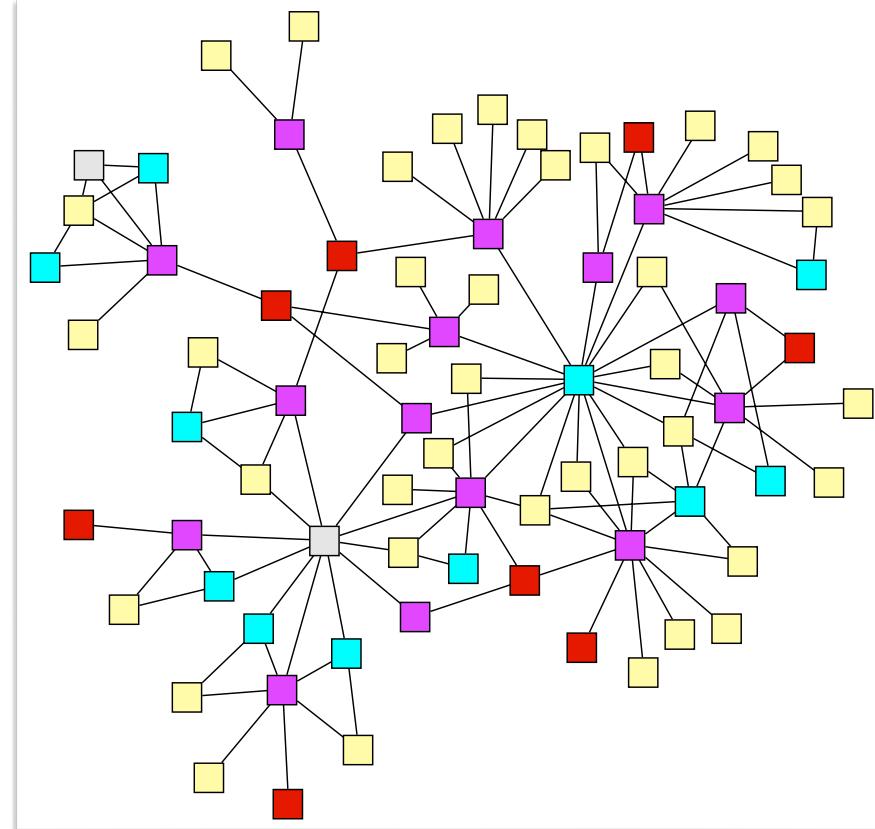
metabolic reaction

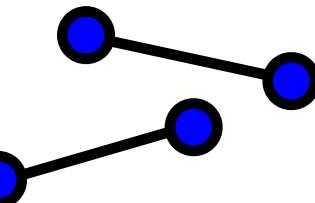
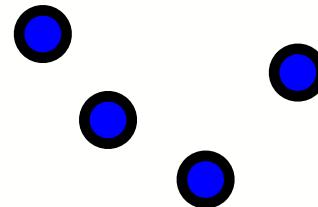
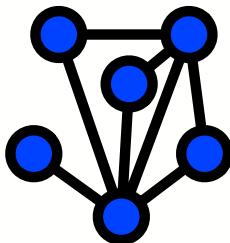
predation or resource transfer

core metabolism

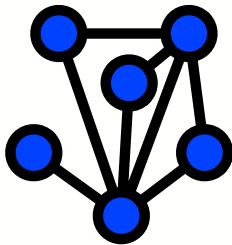


grassland foodweb



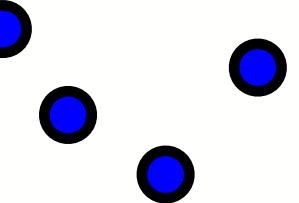


	network	vertex	edge
technological	Internet(1)	computer	IP network adjacency
	Internet(2)	autonomous system (ISP)	BGP connection
information	software	function	function call
	World Wide Web	web page	hyperlink
documents	documents	article, patent, or legal case	citation
	power grid transmission	generating or relay station	transmission line
transportation	rail system	rail station	railroad tracks
	road network(1)	intersection	pavement
road network(2)	road network(2)	named road	intersection
	airport network	airport	non-stop flight
social	friendship network	person	friendship
	sexual network	person	intercourse
biological	metabolic network	metabolite	metabolic reaction
	gene regulatory network	gene	regulatory effect
neuronal network	neuronal network	neuron	synapse
	food web	species	predation or resource transfer
economic	faculty hiring	universities	faculty hiring



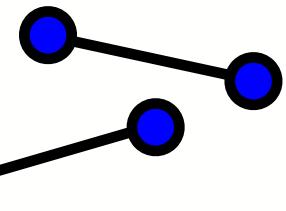
network

faculty hiring



vertex

universities

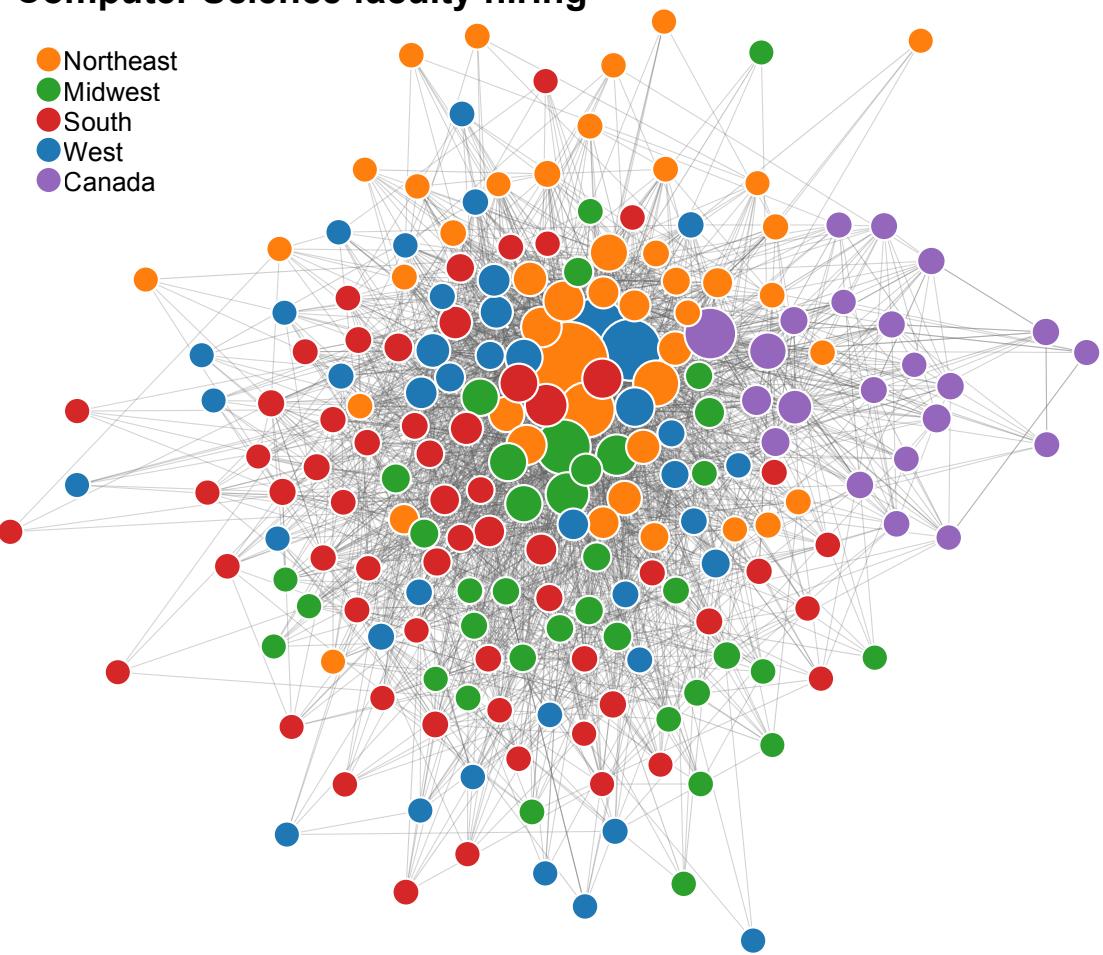


edge

faculty hiring

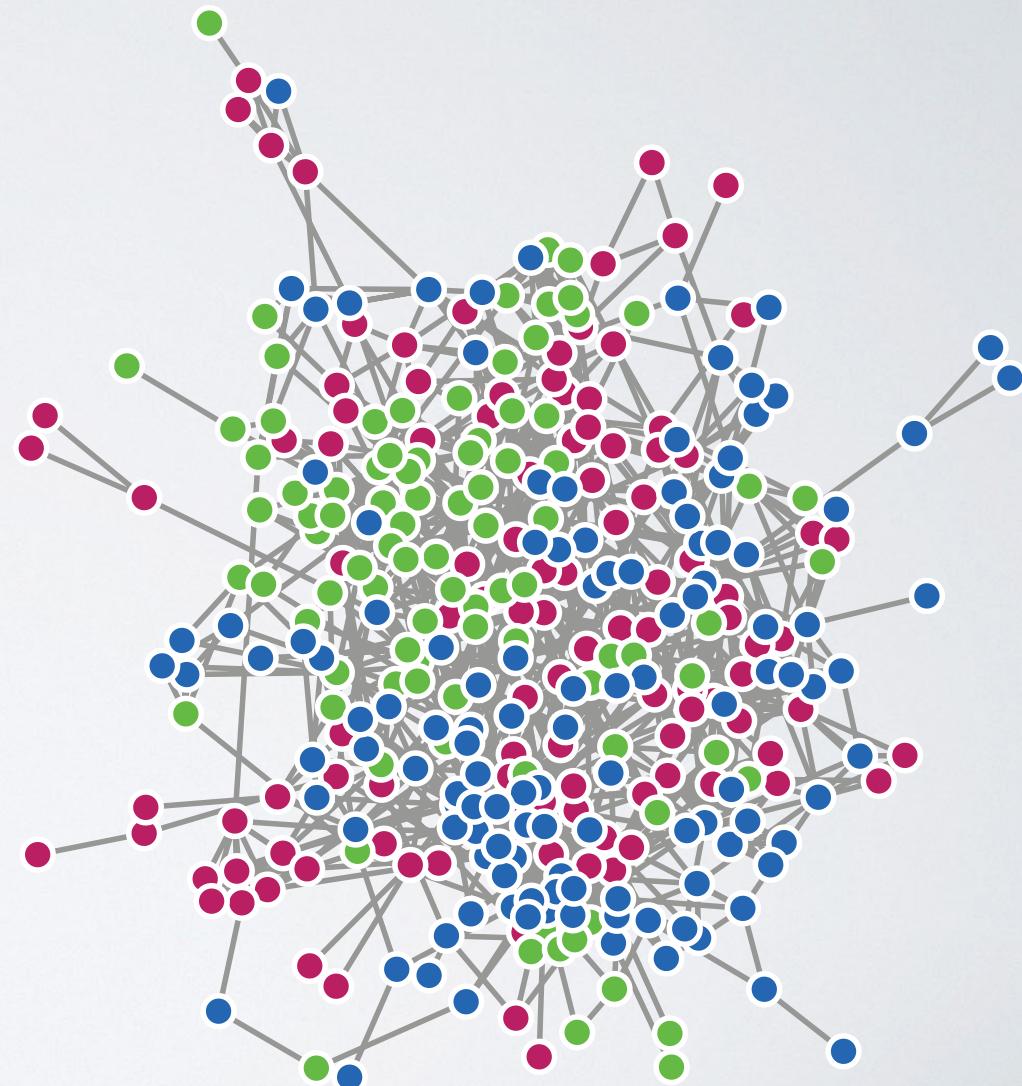
Computer Science faculty hiring

- Northeast
- Midwest
- South
- West
- Canada



analyzing networks

what real networks look like...



analyzing networks

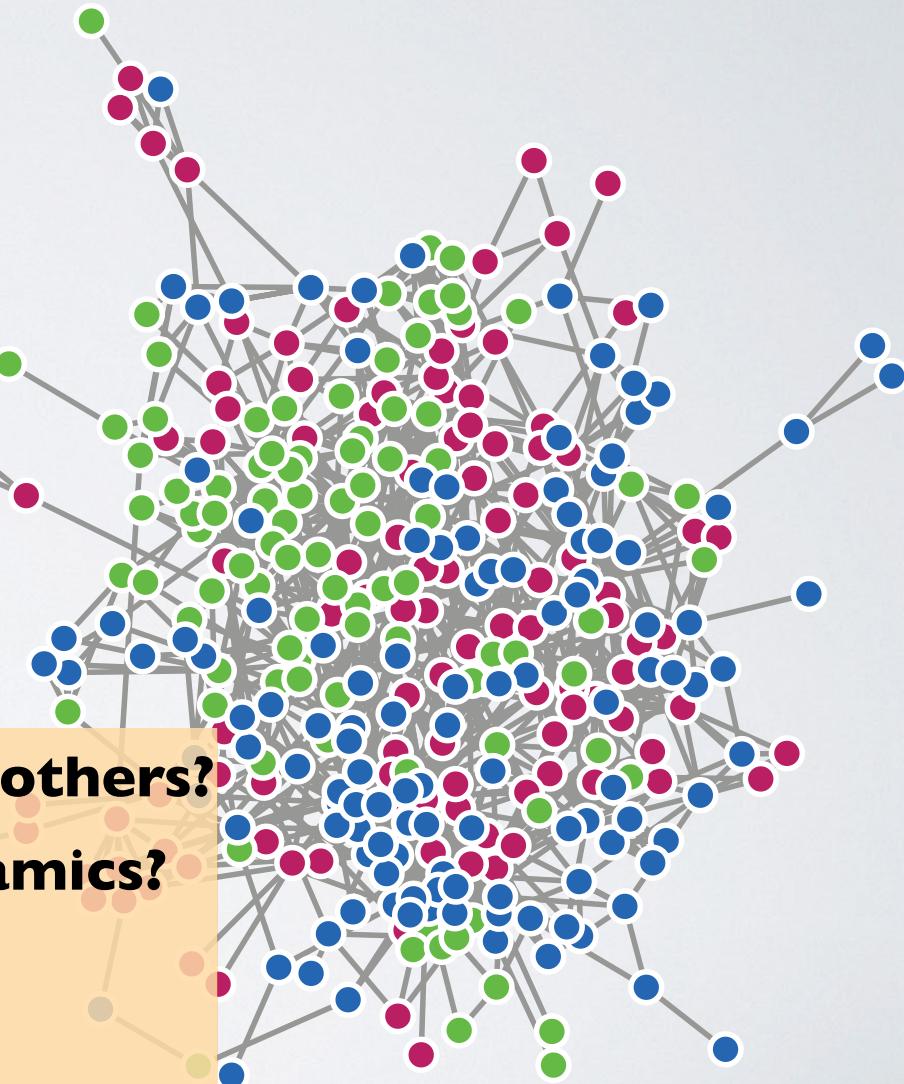
what real networks look like...

questions:

- **how are the edges organized?**
- **how do vertices differ?**
- **does network location matter?**
- **are there underlying patterns?**

what we want to know

- **why do some edges exist, and not others?**
- **how does structure constrain dynamics?**
- **what does structure predict?**
- **how can we tell?**



descriptive questions

process questions

analyzing networks

what we want : understand its structure

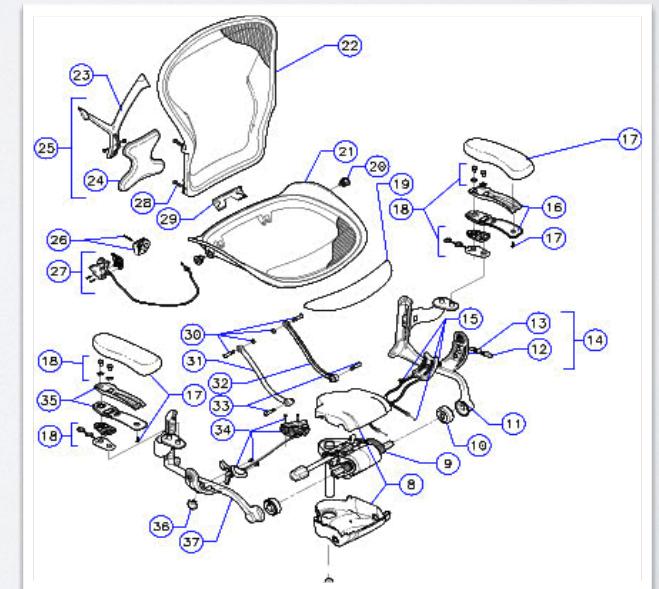
$$f : \text{object} \rightarrow \{\theta_1, \dots, \theta_k\}$$

- **what are the fundamental parts?**
- **how are these parts organized?**
- **where are the degrees of freedom $\vec{\theta}$?**
- **how can we define an abstract class?**
- **structure — dynamics — function?**

what does **local-level structure** look like?

what does **large-scale structure** look like?

how does **structure constrain** function?



analyzing networks

6 major approaches

- I. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)

analyzing networks

6 major approaches

1. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)
2. **simple regressions:** convert network structure into node-level features, and do traditional explanatory modeling

analyzing networks

6 major approaches

1. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)
2. **simple regressions:** convert network structure into node-level features, and do traditional explanatory modeling
3. **null models:** use some kind of random graph to identify non-random patterns as deviations from the null

analyzing networks

6 major approaches

1. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)
2. **simple regressions:** convert network structure into node-level features, and do traditional explanatory modeling
3. **null models:** use some kind of random graph to identify non-random patterns as deviations from the null
4. **mechanisms / simulations:** explain structural or dynamical patterns as caused by specific process

analyzing networks

6 major approaches

1. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)
2. **simple regressions:** convert network structure into node-level features, and do traditional explanatory modeling
3. **null models:** use some kind of random graph to identify non-random patterns as deviations from the null
4. **mechanisms / simulations:** explain structural or dynamical patterns as caused by specific process
5. **predictive models:** fit parametric model of network structure & use it to predict missing or future data (edges, labels, etc.)

analyzing networks

6 major approaches

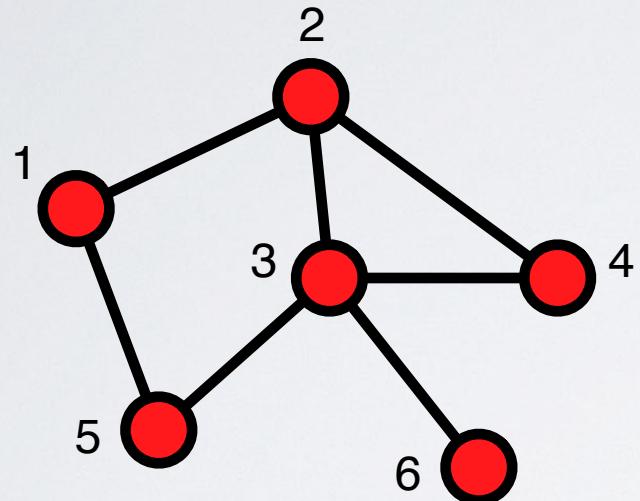
- ★ 1. **exploratory data analysis:** count & compare all the things (degree distributions, centrality scores, community detection, etc.)
- ★ 2. **simple regressions:** convert network structure into node-level features, and do traditional explanatory modeling
- ★ 3. **null models:** use some kind of random graph to identify non-random patterns as deviations from the null
- 4. **mechanisms / simulations:** explain structural or dynamical patterns as caused by specific process
- ★ 5. **predictive models:** fit parametric model of network structure & use it to predict missing or future data (edges, labels, etc.)
- 6. **network experiments:** manipulate structure and measure node-level or graph-level behavior as function of changes

representing networks

4 representations

- ridiculogram nice pictures, best for small networks
 - ★ adjacency matrix mathematically convenient & useful mental model
 - ★ adjacency list efficient computation
 - edge list efficient storage

a simple network

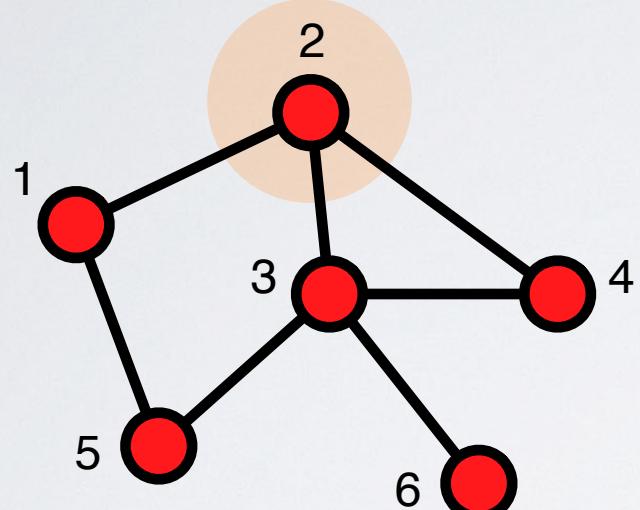


undirected

unweighted

no self-loops

a *simple* network



undirected

unweighted

no self-loops

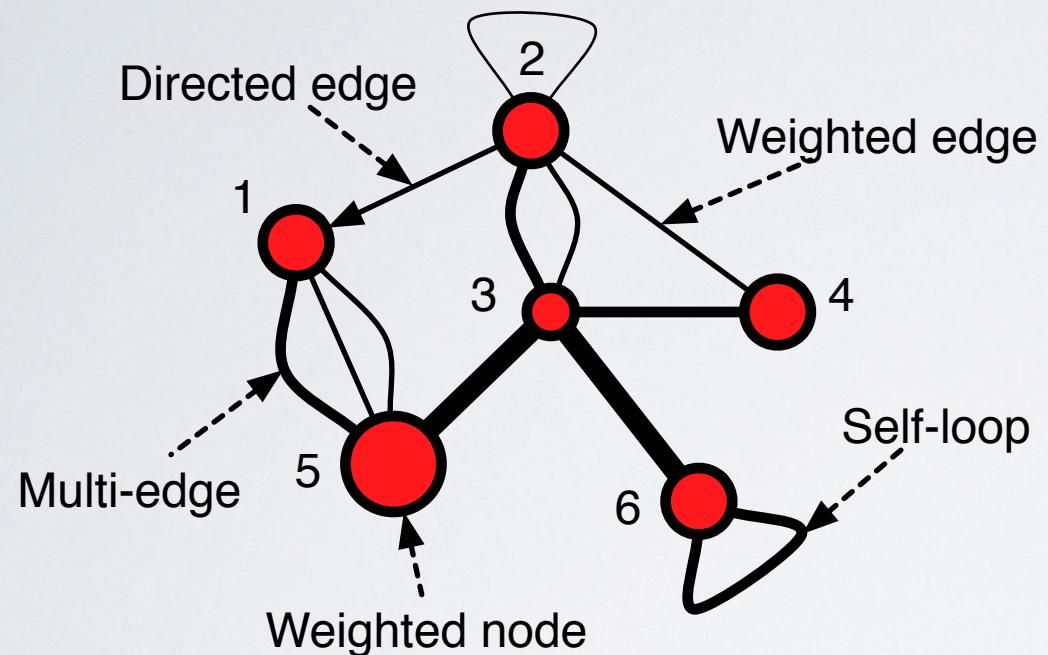
adjacency matrix

A	1	2	3	4	5	6
1	0	1	0	0	1	0
2	1	0	1	1	0	0
3	0	1	0	1	1	1
4	0	1	1	0	0	0
5	1	0	1	0	0	0
6	0	0	1	0	0	0

adjacency list

A
$1 \rightarrow \{2, 5\}$
$2 \rightarrow \{1, 3, 4\}$
$3 \rightarrow \{2, 4, 5, 6\}$
$4 \rightarrow \{2, 3\}$
$5 \rightarrow \{1, 3\}$
$6 \rightarrow \{3\}$

beyond simple graphs

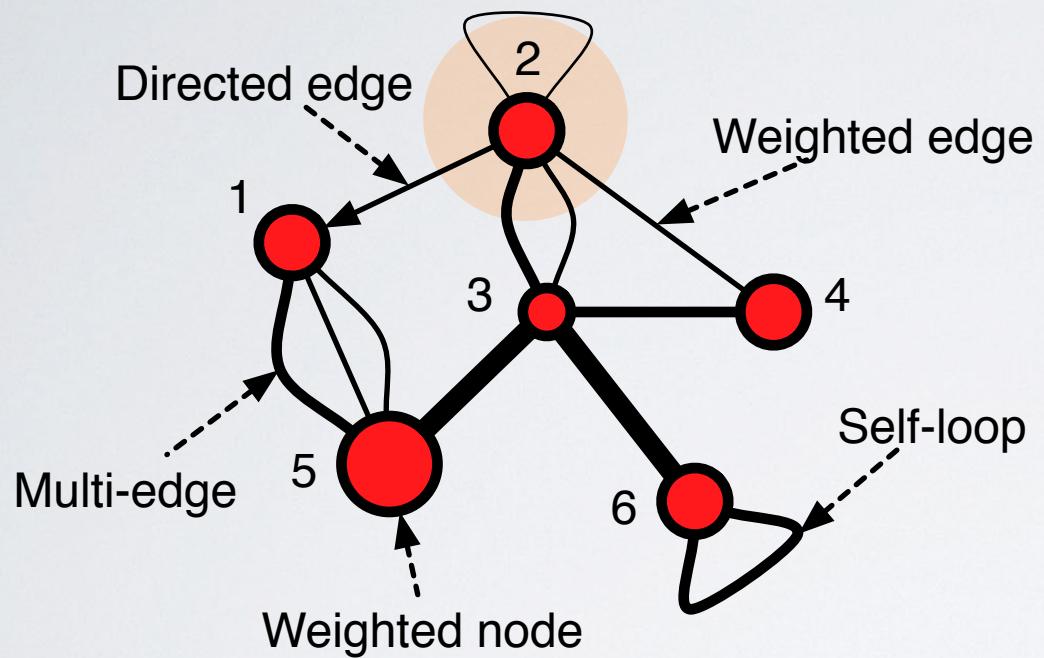


undirected

unweighted

no self loops

beyond simple graphs



adjacency matrix

A	1	2	3	4	5	6
1	0	0	0	0	{1, 1, 2}	0
2	1	$\frac{1}{2}$	{2, 1}	1	0	0
3	0	{2, 1}	0	2	4	4
4	0	1	2	0	0	0
5	{1, 1, 2}	0	4	0	0	0
6	0	0	4	0	0	2

adjacency list

A
1 $\rightarrow \{(5, 1), (5, 1), (5, 2)\}$
2 $\rightarrow \{(1, 1), (2, \frac{1}{2}), (3, 2), (3, 1), (4, 1)\}$
3 $\rightarrow \{(2, 2), (2, 1), (4, 2), (5, 4), (6, 4)\}$
4 $\rightarrow \{(2, 1), (3, 2)\}$
5 $\rightarrow \{(1, 1), (1, 1), (1, 2), (3, 4)\}$
6 $\rightarrow \{(3, 4), (6, 2)\}$

beyond simple graphs

attributes of

edges	nodes	network
{ unweighted		
{ weighted		
{ signed		
{ undirected		
{ directed		
multigraph		
timestamps		

beyond simple graphs

attributes of

edges	nodes	network
unweighted	metadata / attributes	
weighted	locations / coordinates	
signed	state variables	
undirected		
directed		
multigraph		
timestamps		

beyond simple graphs

attributes of

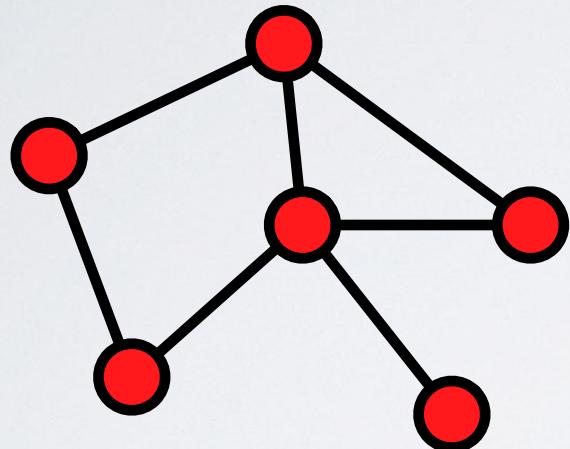
edges	nodes	network
unweighted	metadata / attributes	{ sparse
weighted	locations / coordinates	{ dense
signed	state variables	{ bipartite
{ undirected		{ projection
{ directed		{ connected
multigraph		{ disconnected
timestamps		acyclic
		temporal
		multiplex
		hypergraph

describing networks

aka, summarizing a network's structure

$$f : G \rightarrow \underbrace{\{x_1, \dots, x_k\}}_{\text{summary statistics}}$$

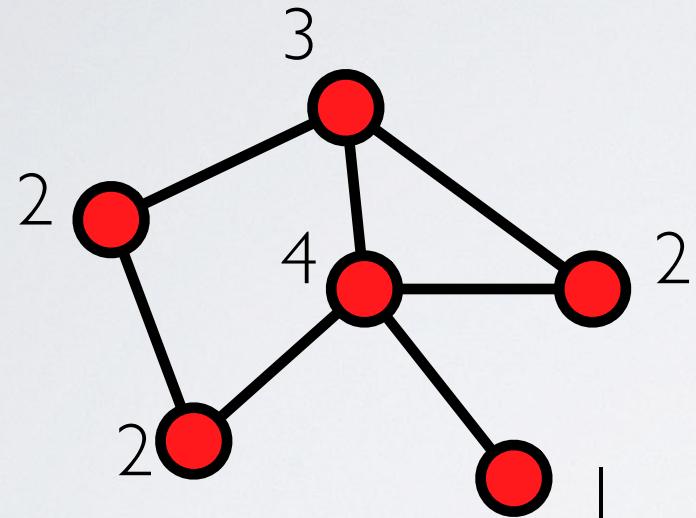
describing networks



degree:

the first order description
of a network

describing networks

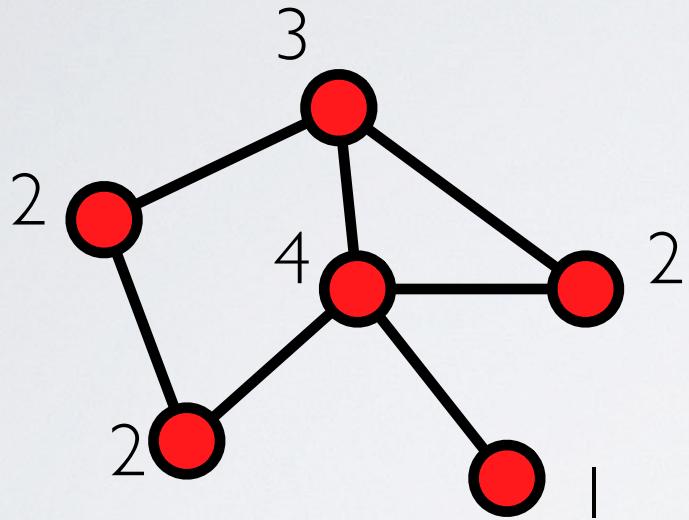


degree:

number of connections k

$$k_i = \sum_j A_{ij}$$

describing networks



number of edges

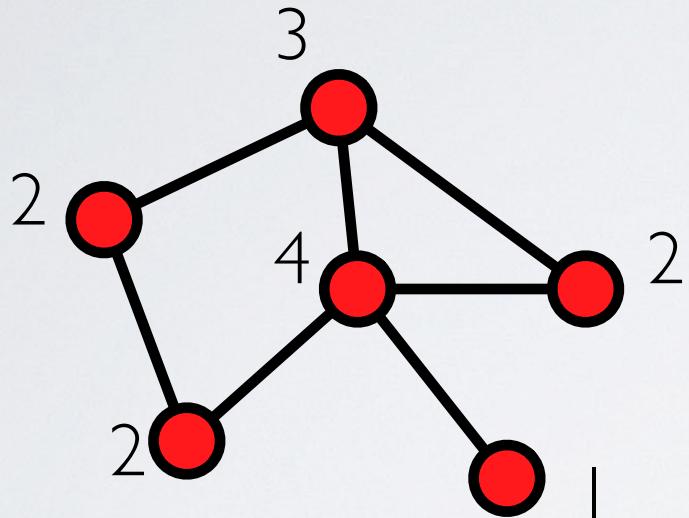
$$m = \frac{1}{2} \sum_{i=1}^n k_i = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n A_{ij} = \frac{1}{2} \sum_{j=1}^n \sum_{i=1}^n A_{ji}$$

degree:

number of connections k

$$k_i = \sum_j A_{ij}$$

describing networks



degree:

number of connections k

$$k_i = \sum_j A_{ij}$$

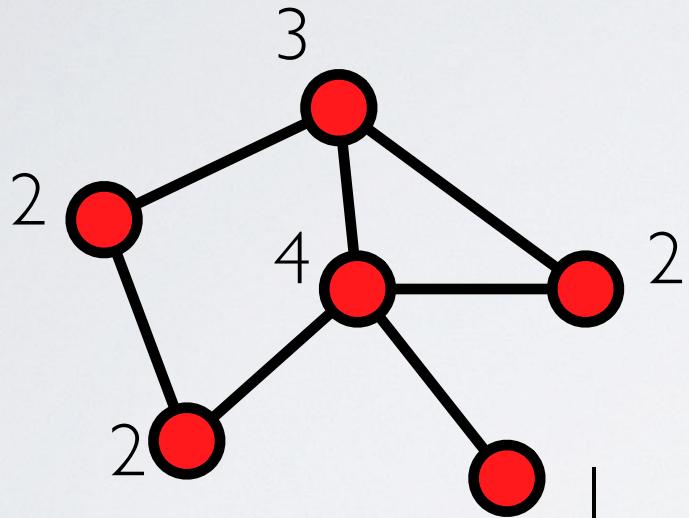
number of edges

$$m = \frac{1}{2} \sum_{i=1}^n k_i = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n A_{ij} = \frac{1}{2} \sum_{j=1}^n \sum_{i=1}^n A_{ji}$$

mean degree

$$\langle k \rangle = \frac{1}{n} \sum_{i=1}^n k_i = \frac{2m}{n}$$

describing networks



degree:

number of connections k

$$k_i = \sum_j A_{ij}$$

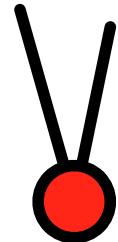
degree sequence $\{1, 2, 2, 2, 3, 4\}$

degree distribution $\Pr(k) = \left[\left(1, \frac{1}{6}\right), \left(2, \frac{3}{6}\right), \left(3, \frac{1}{6}\right), \left(4, \frac{1}{6}\right) \right]$

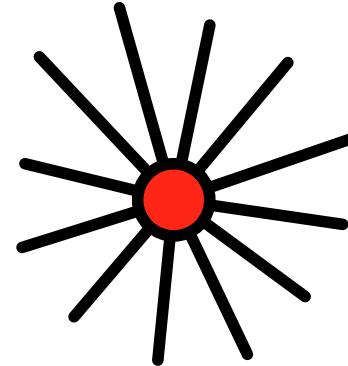
node degrees



Aaron Clauset
@aaronclauset
Tweets Following Followers
1,567 **99** **6,031**



"low" degree



"high" degree



SELENA GOMEZ 'BACK TO YOU'
FEATURED ON THE SEASON 2 SOUNDTRACK FOR
13 REASONS WHY ► NETFLIX
Follow

Selena Gomez 
@selenagomez
Tweets Following Followers
4,375 **1,204** **56.9M**

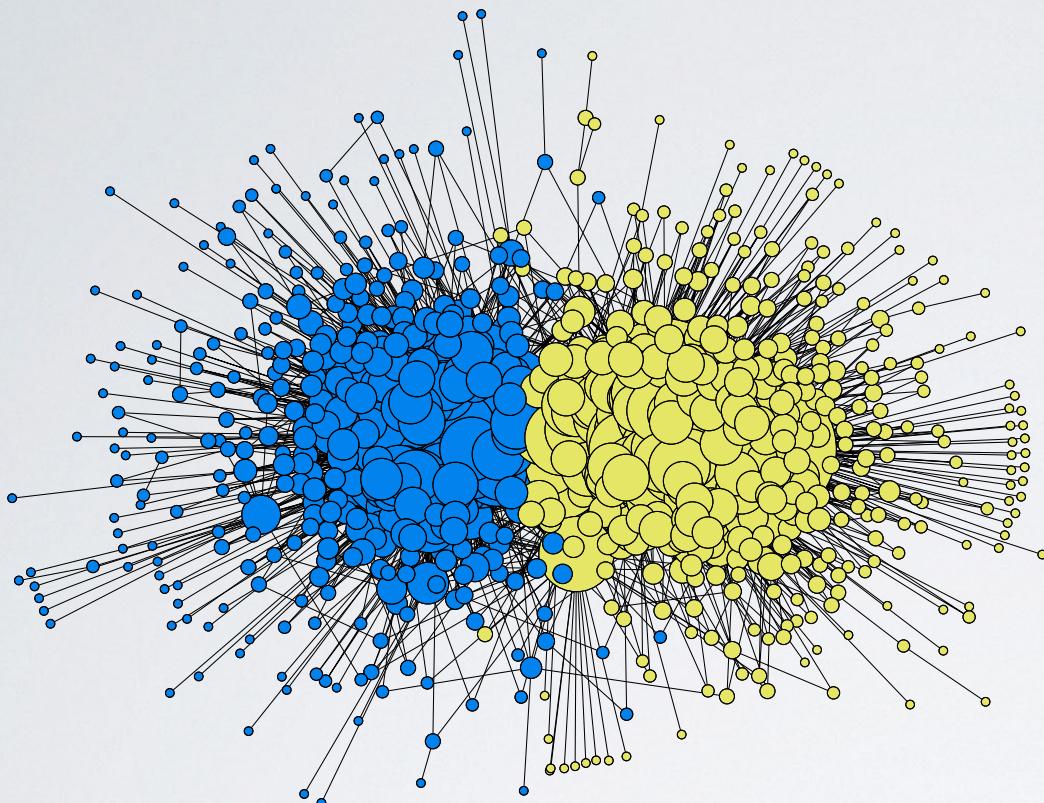
node degrees :

what impact does having fewer or more connections have?

more information? more exposure to disease? more robust connectivity? more influence? less bandwidth? etc.

* scare quotes because 'low' and 'high' are relative terms

degree distributions

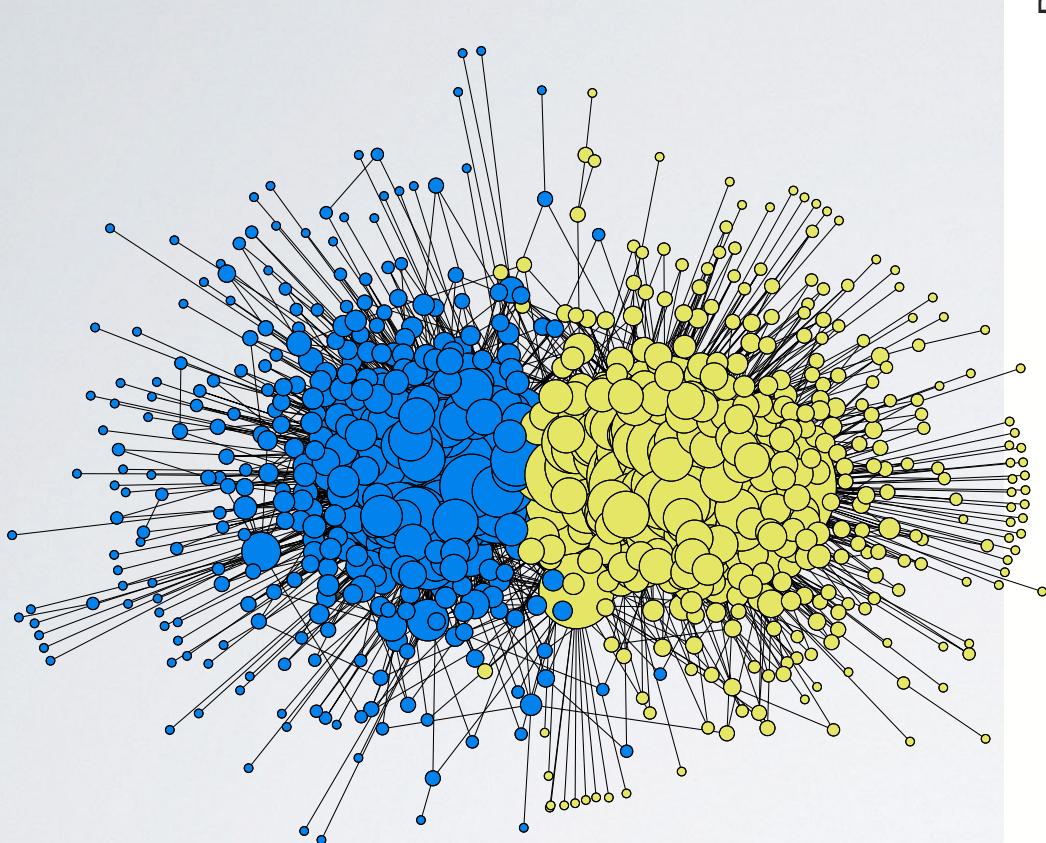


political blogs (2004)

k	1	2	3	4	5	6	7	8	9
$\Pr(k)$	0.271	0.072	0.052	0.034	0.026	0.033	0.020	0.017	0.011

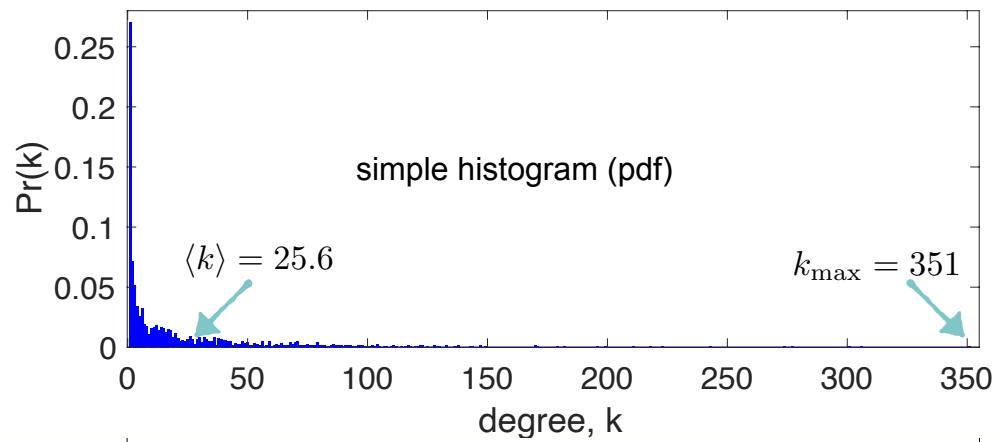
$$\begin{aligned}n &= 1490 \\m &= 19090 \\\langle k \rangle &= 25.6\end{aligned}$$

degree distributions



simple pdf:

$$\Pr(K = k) \text{ vs. } k$$

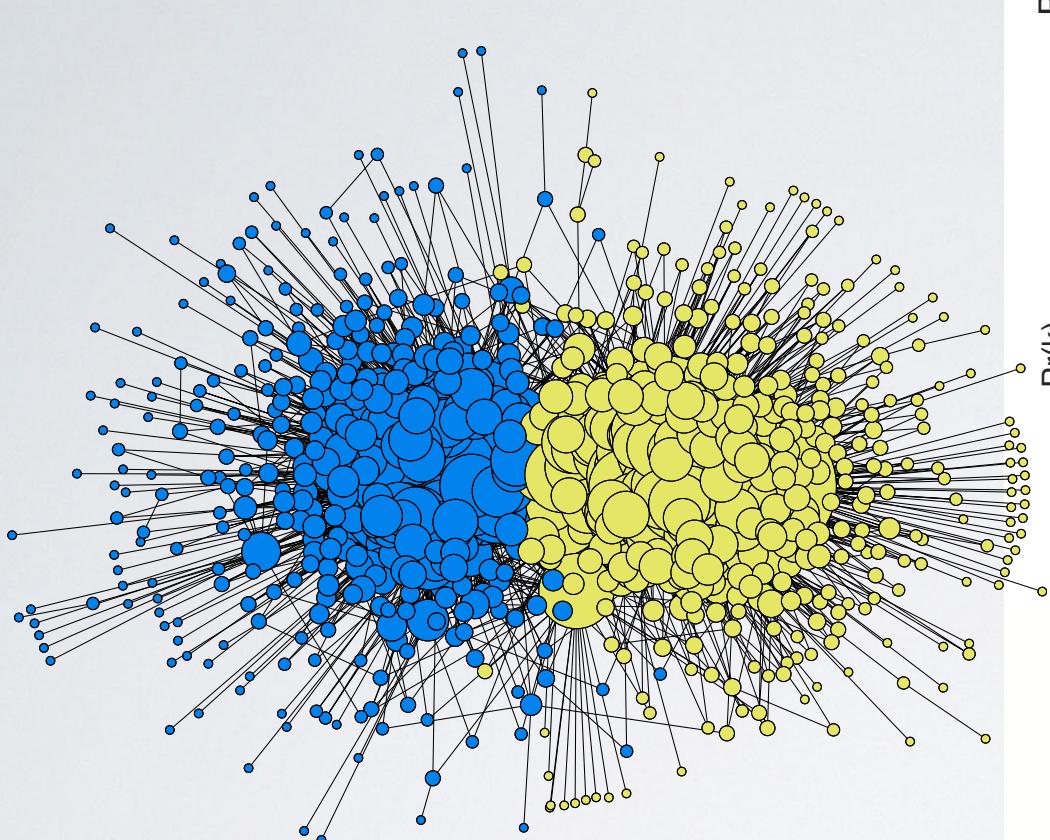


semilog y pdf

loglog pdf

loglog ccdf

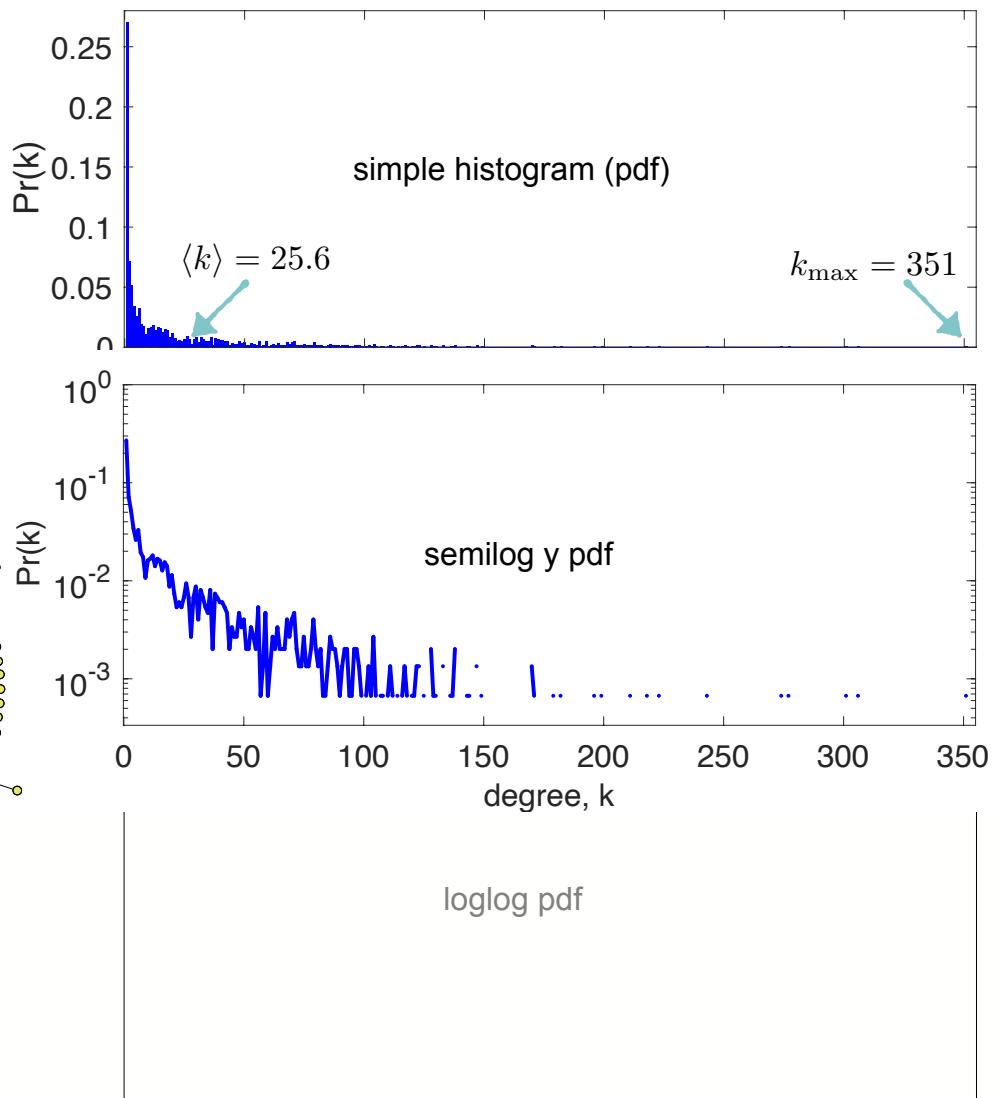
degree distributions



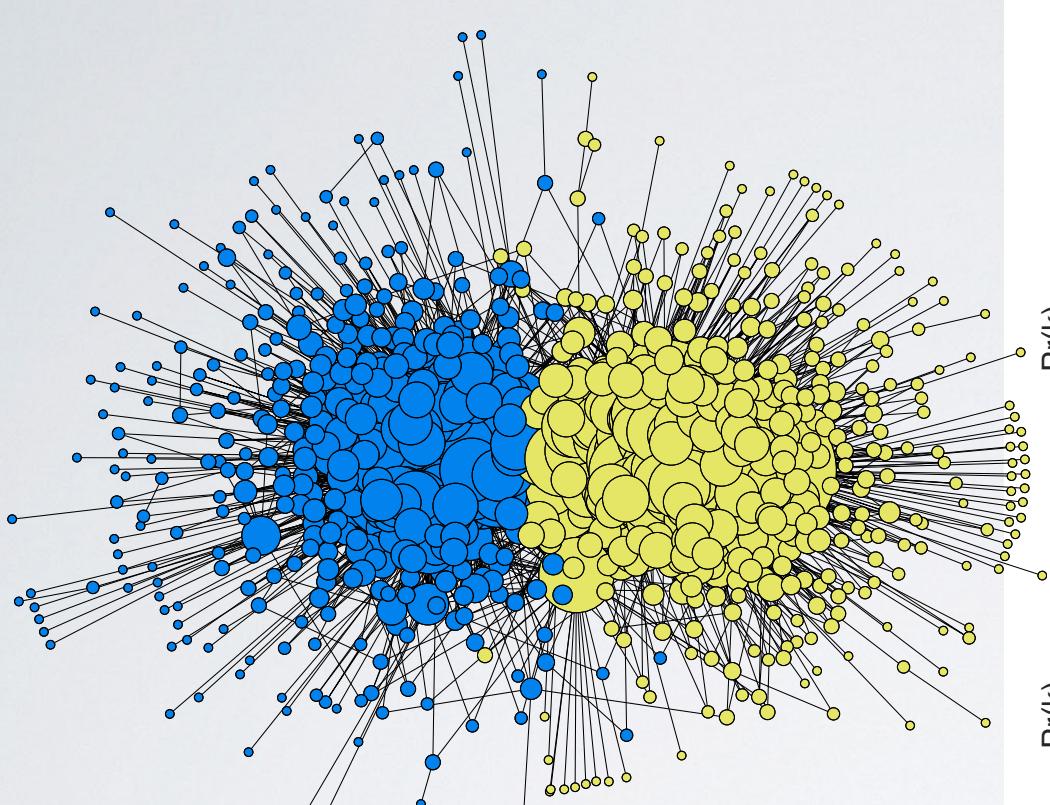
political blogs (2004)

simple pdf:

$\log_{10} \Pr(K = k)$ vs. k



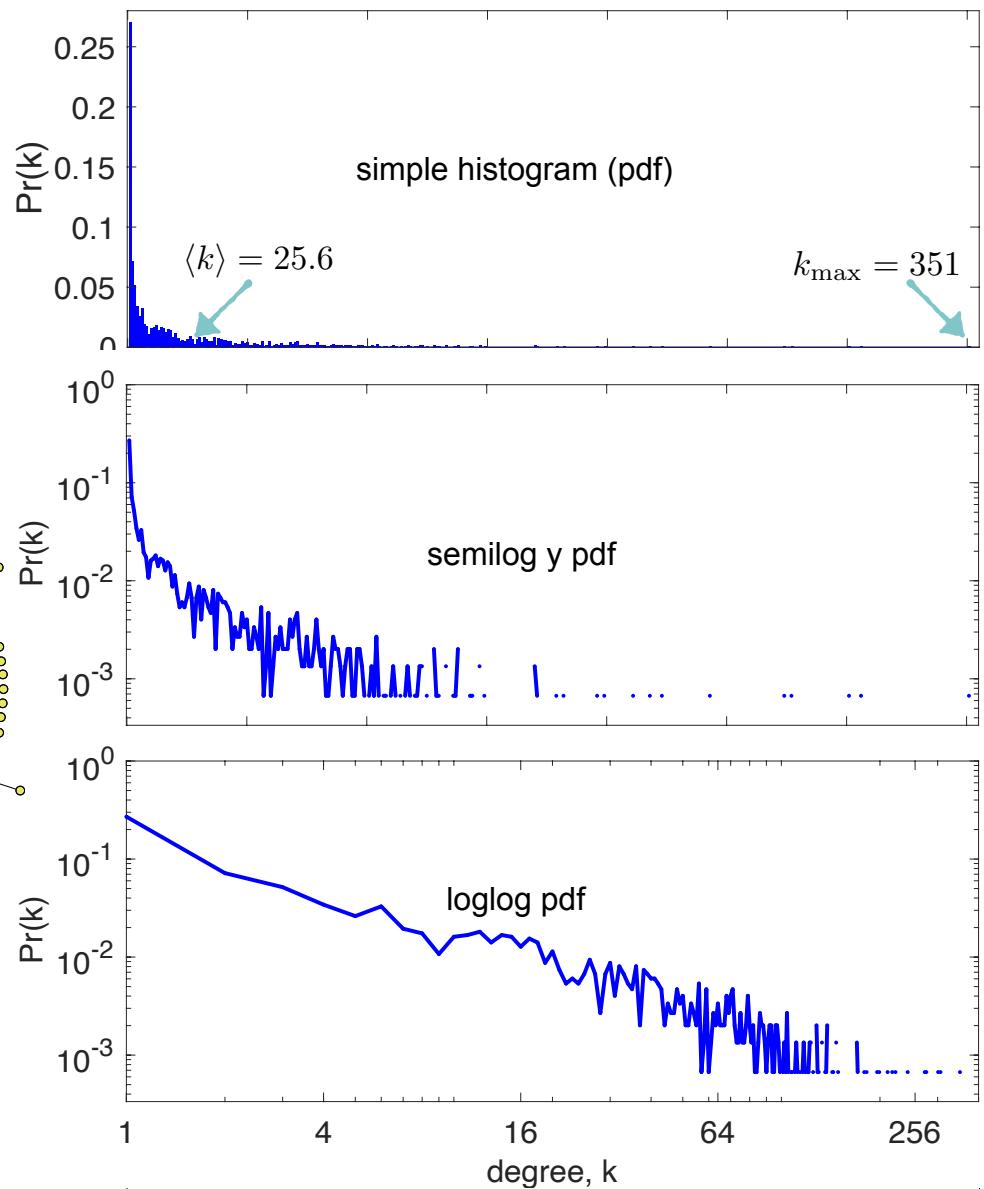
degree distributions



political blogs (2004)

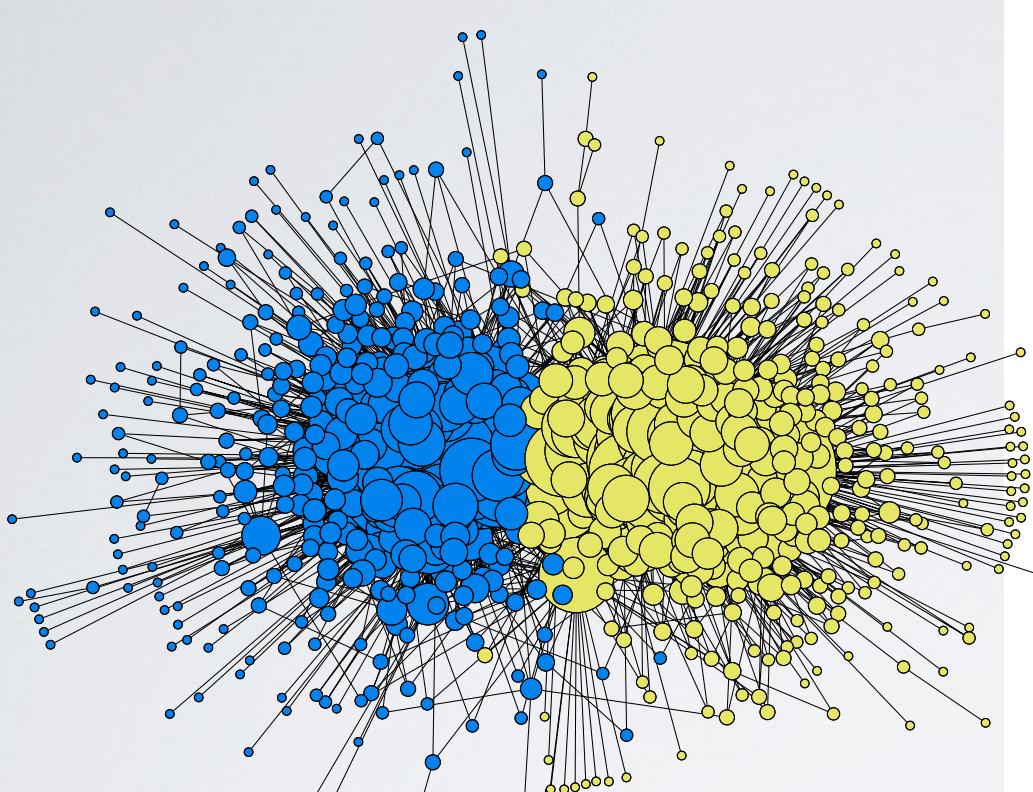
simple pdf:

$\log_{10} \Pr(K = k)$ vs. $\log_{10} k$



loglog ccdf

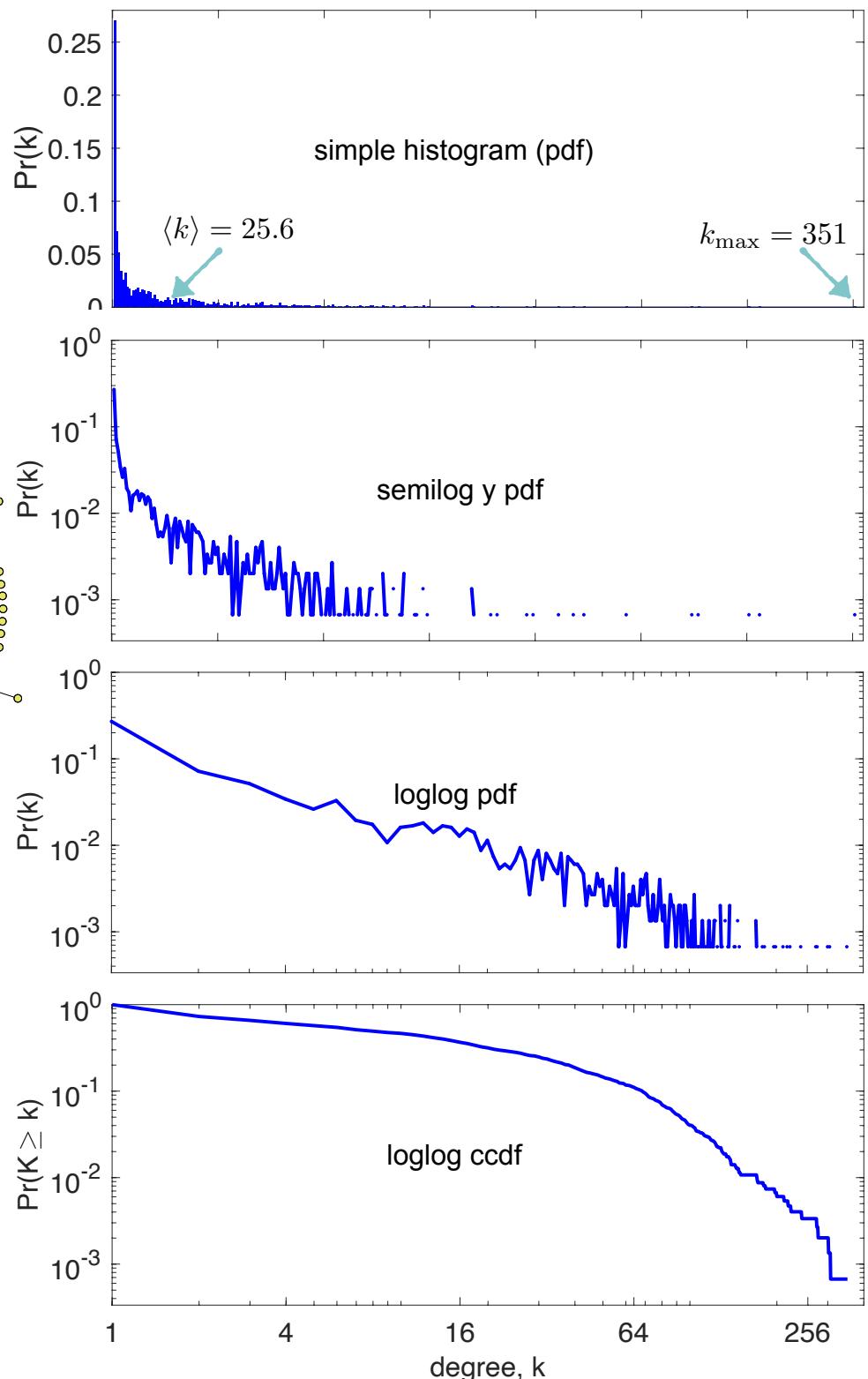
degree distributions



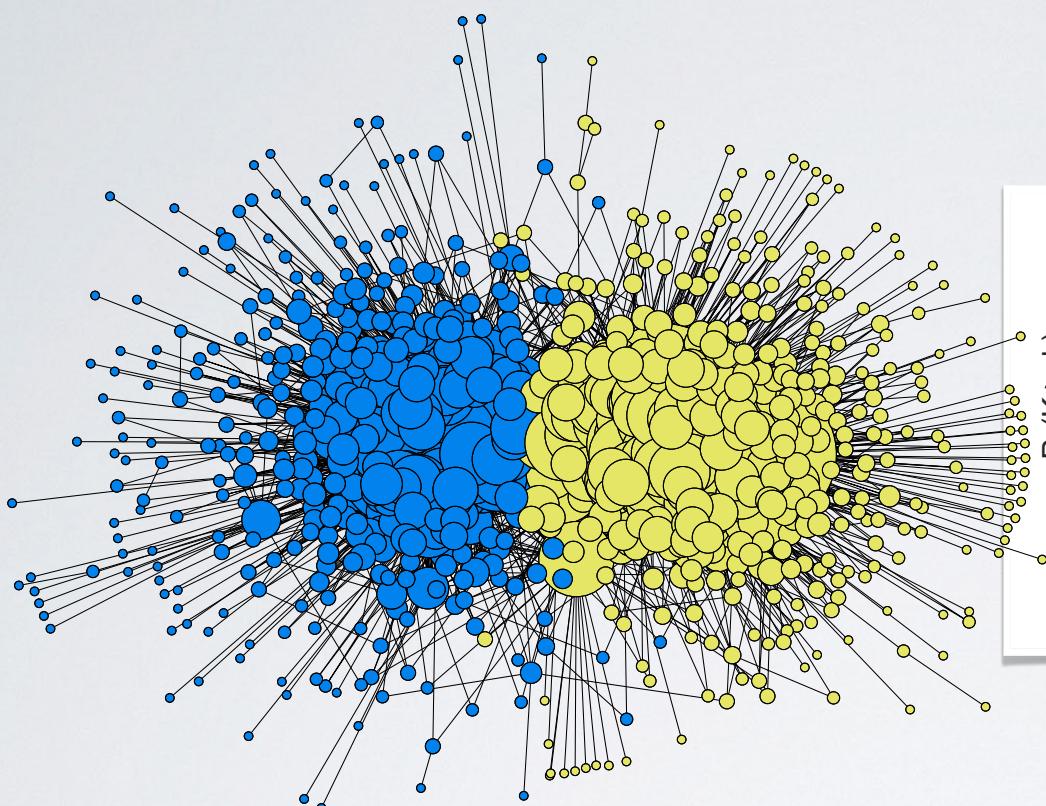
political blogs (2004)

complementary cdf:

$$\Pr(K \geq k) = \sum_{j=k}^n \Pr(K = j)$$



degree distributions

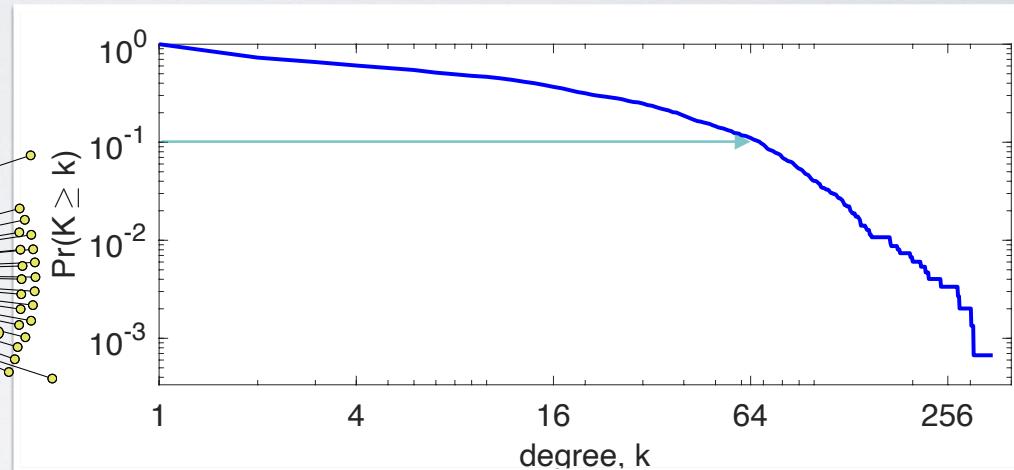


political blogs (2004)

$$n = 1490$$

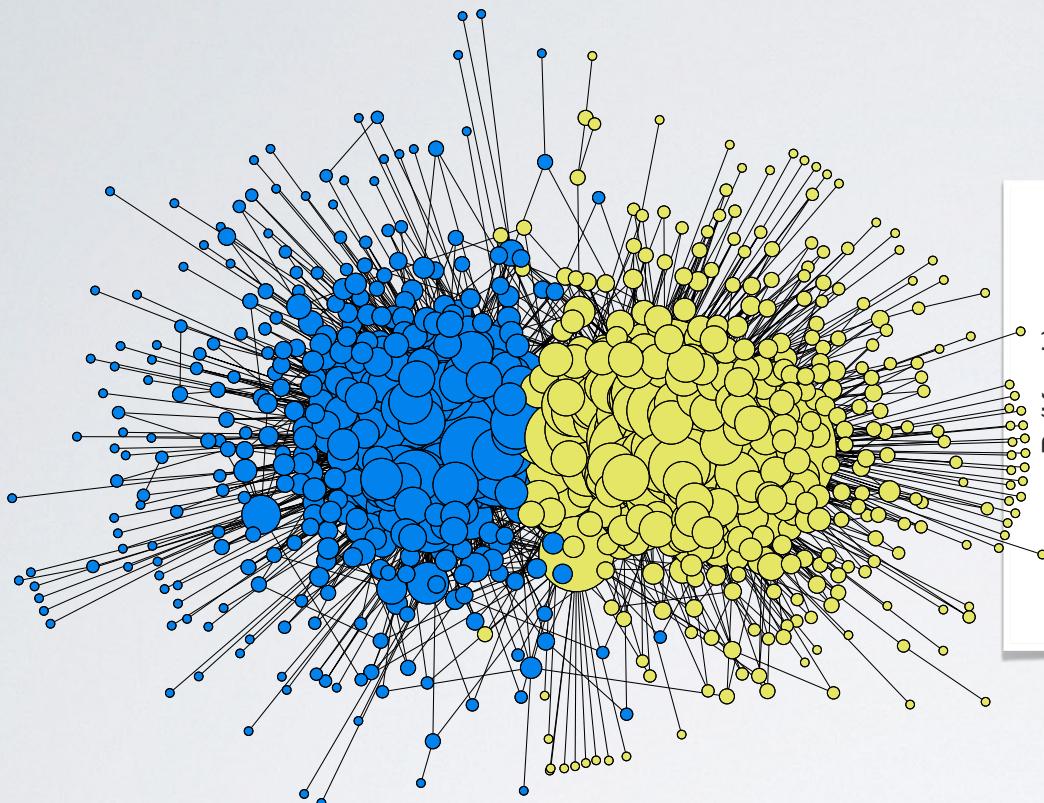
$$m = 19090$$

$$\langle k \rangle = 25.6$$



- 90% (1349) have $k \leq 67$ connecting to 53% of all m

degree distributions

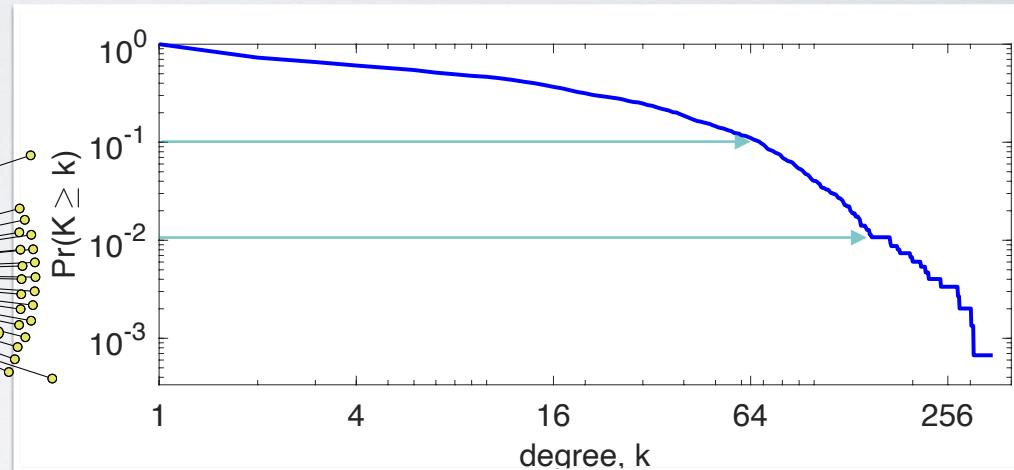


political blogs (2004)

$$n = 1490$$

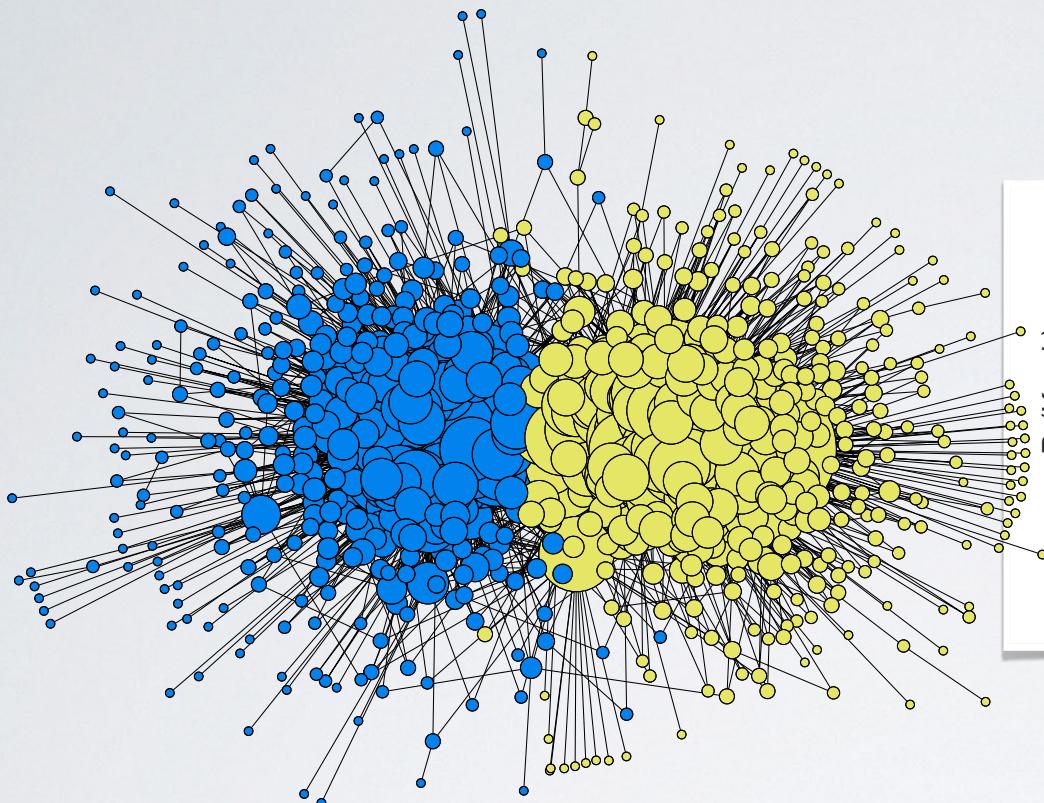
$$m = 19090$$

$$\langle k \rangle = 25.6$$



- 90% (1349) have $k \leq 67$
connecting to 53% of all m
- only 1% (14) have $k > 169$
connecting to 10% of all m

degree distributions

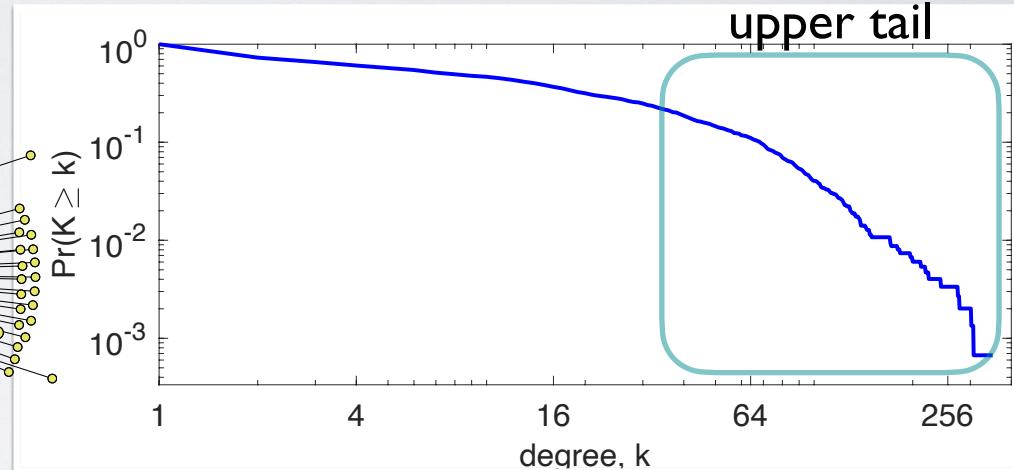


political blogs (2004)

$$n = 1490$$

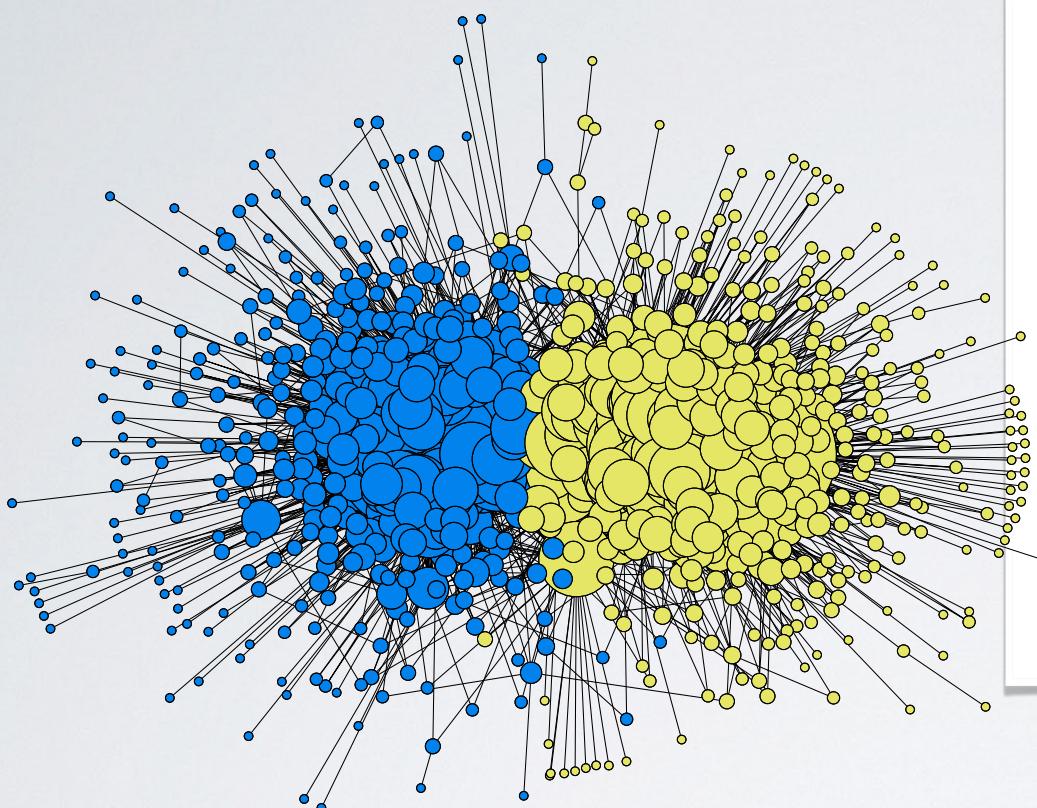
$$m = 19090$$

$$\langle k \rangle = 25.6$$



- 90% (1349) have $k \leq 67$
connecting to 53% of all m
- only 1% (14) have $k > 169$
connecting to 10% of all m

degree distributions

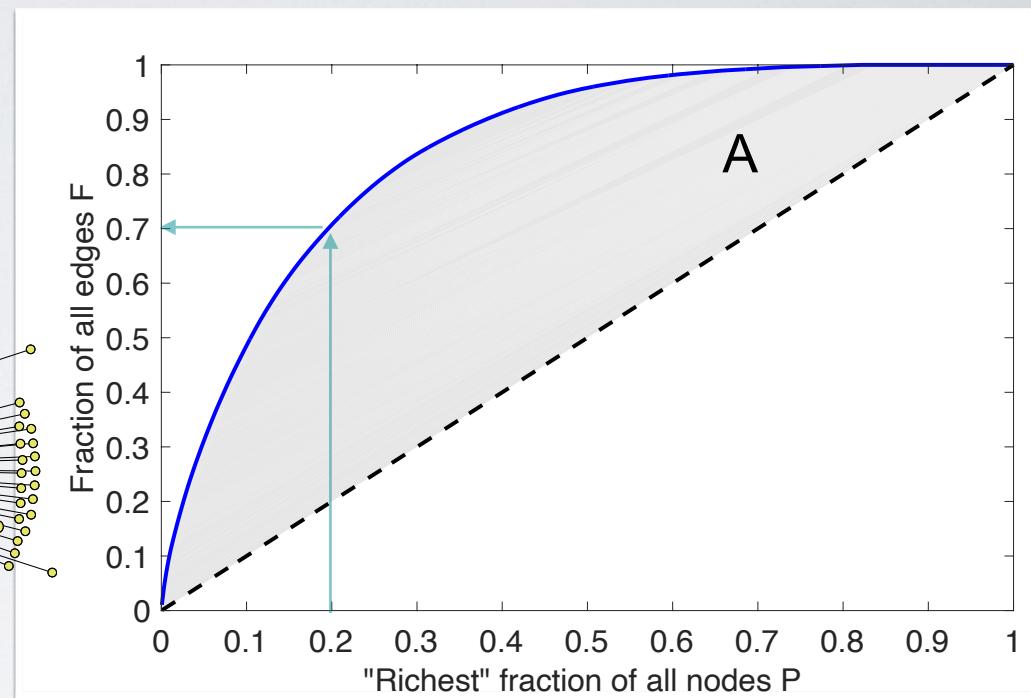


political blogs (2004)

$$n = 1490$$

$$m = 19090$$

$$\langle k \rangle = 25.6$$



Lorenz curve

- fraction of all edges F held by "richest" fraction of all nodes P
- Gini coefficient: $G = 2A$
 $= 0.69$

exploring degree distributions

the complementary CDF:

$$\Pr(K \geq k) = 1 - \Pr(K < k)$$

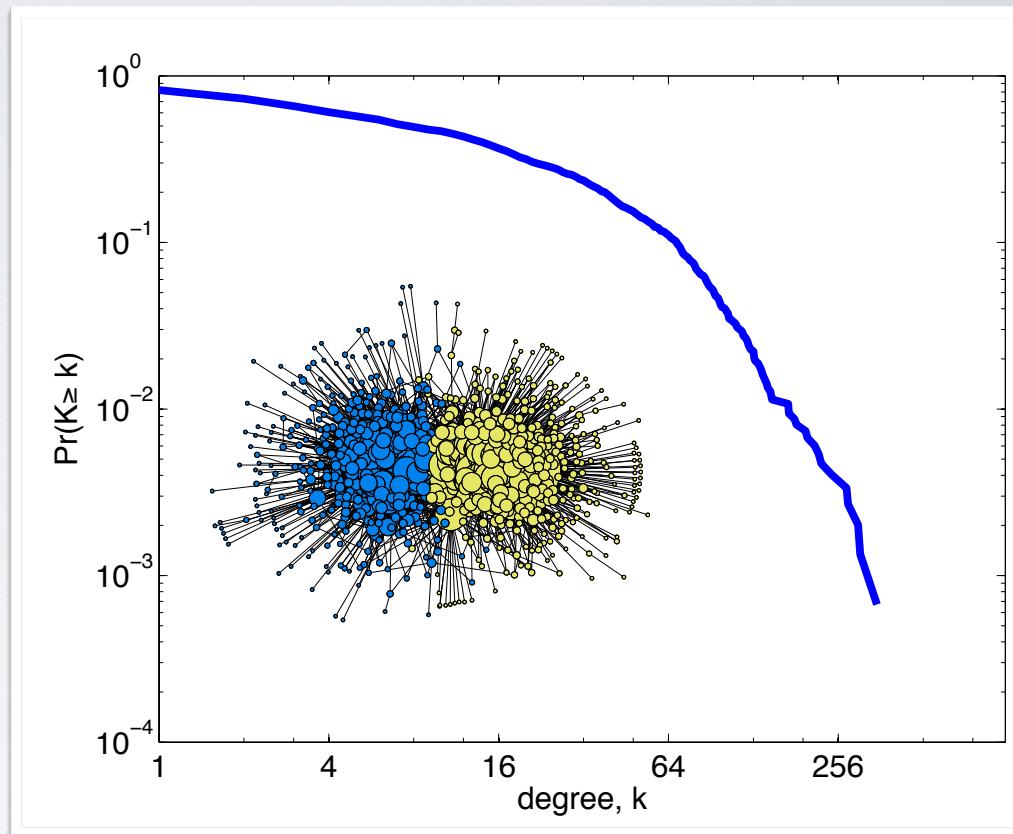
- fraction with degree $K \geq k$
- monotonic
- smoother than PDF
- better reveals curvature

"loglog" plots:

- good for high variance quantities

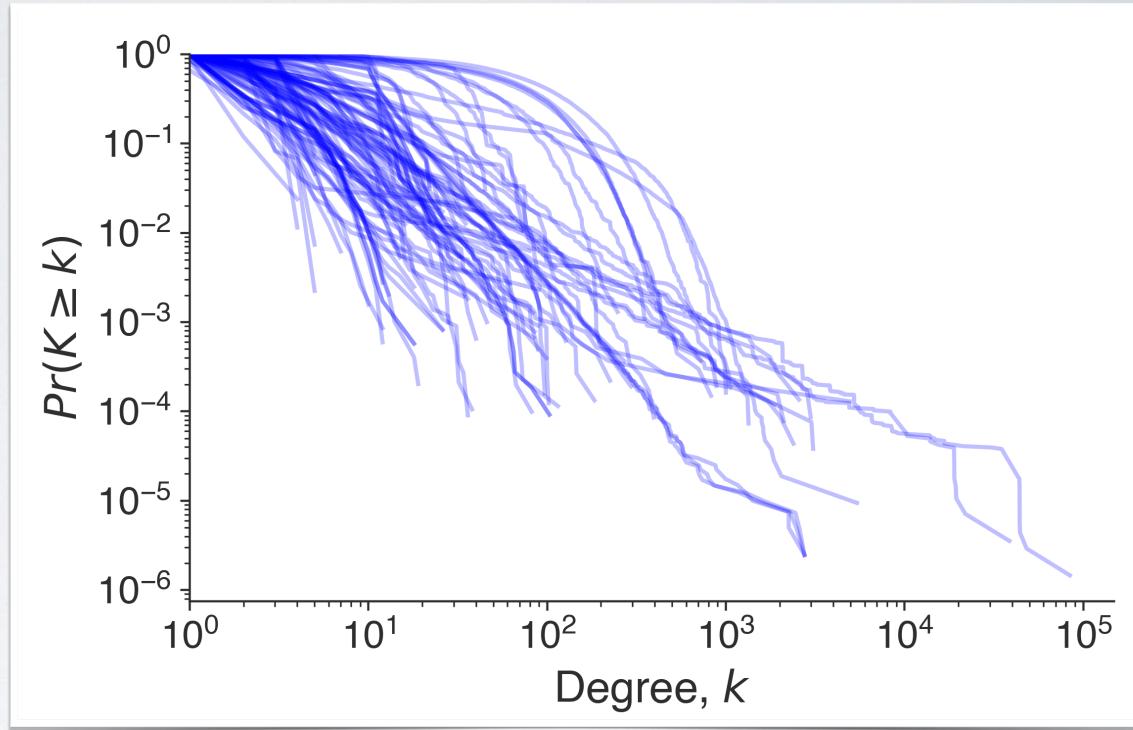
Lorenz curves & Gini:

- captures level of inequality



exploring degree distributions

- nearly all real networks exhibit a ***heavy-tailed degree distribution***
- ***very few*** networks exhibit convincing power-law degree distributions
- ***some*** distributions exhibit power-law tails
- power laws are cool!
but knowing one from garbage
requires statistics*
- ***does the specific distributional form matter?***
think carefully about whether it does (it may not).



* data from 100 networks from 4 scientific domains

[Newman, Contemporary Physics 46, 323-351 \(2005\)](#)

[Clauset et al. SIAM Review 51, 661–703 \(2009\)](#)

[Broido & Clauset, Nat. Comm. 10 \(2019\)](#)

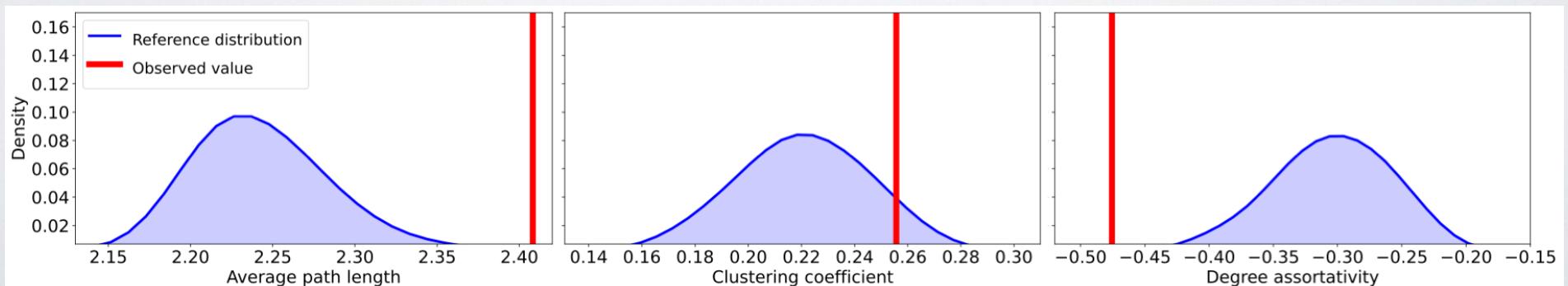
exploring degree distributions

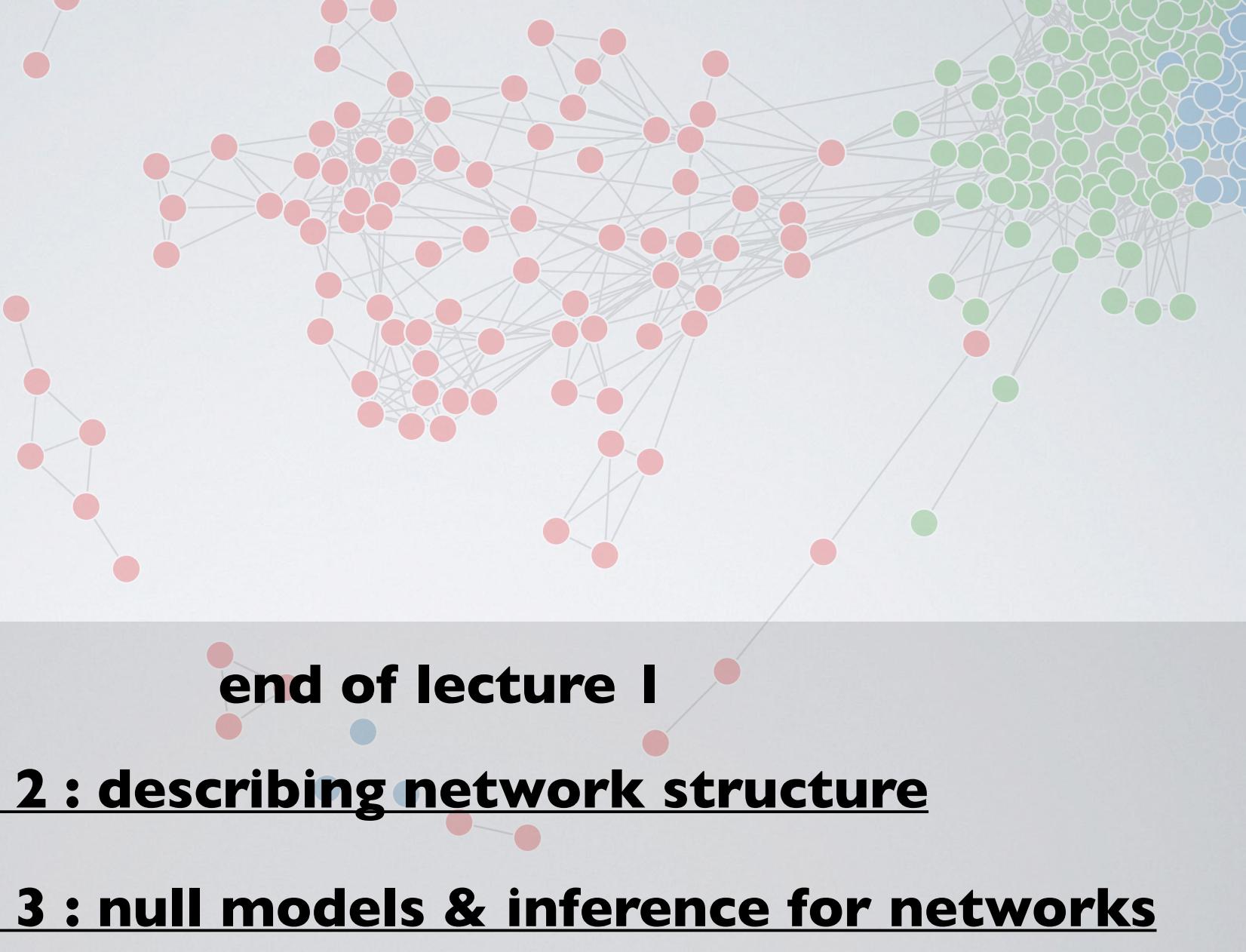
degree structure is the first-order description of network structure

- drives interesting phenomena ("friendship paradox", spreading dynamics, etc.)
- explains many other network patterns (various centralities, disassortativity, etc.)

how can we tell if degrees explain a pattern?

- the **configuration model** : random graphs with specified (empirical) degree sequence (use Python package from Dutta)
- assess whether a node-level or network-level measure is big, typical, or small — it's a *null model*

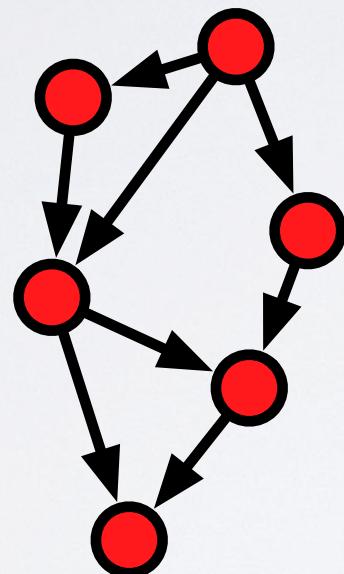




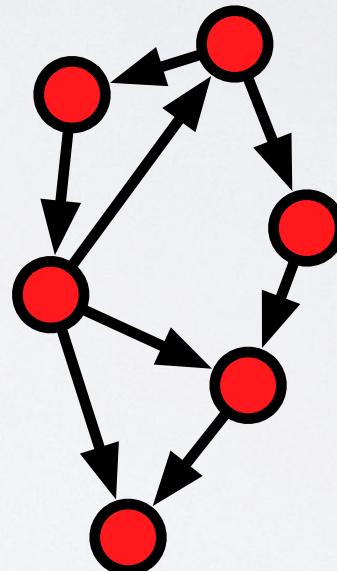
directed networks

$$A_{ij} \neq A_{ji}$$

citation networks
foodwebs*
epidemiological
others?



directed acyclic graph

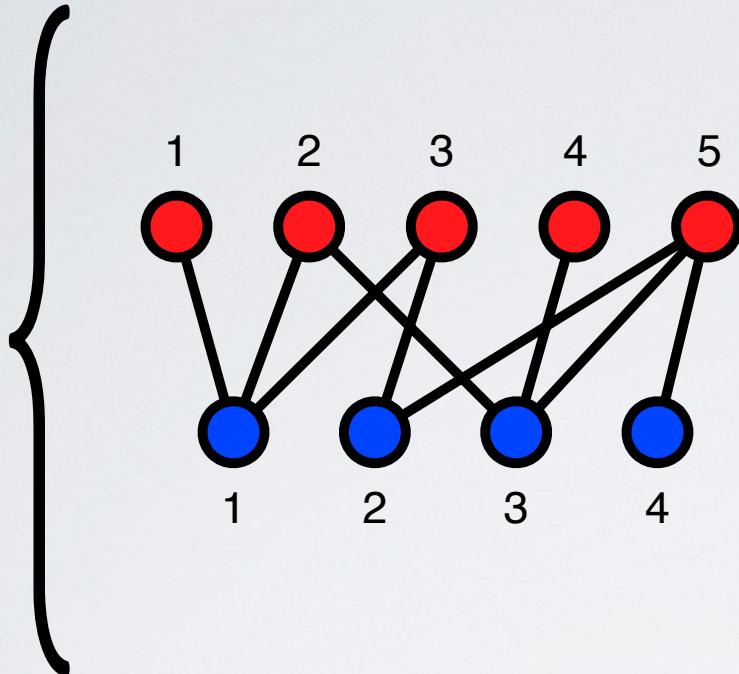


directed graph

WWW
friendship?
flows of goods,
information
economic exchange
dominance
neuronal
transcription
time travelers

bipartite networks

**bipartite
network**



no within-type edges

authors & papers

actors & movies/scenes

musicians & albums

people & online groups

people & corporate boards

people & locations (checkins)

metabolites & reactions

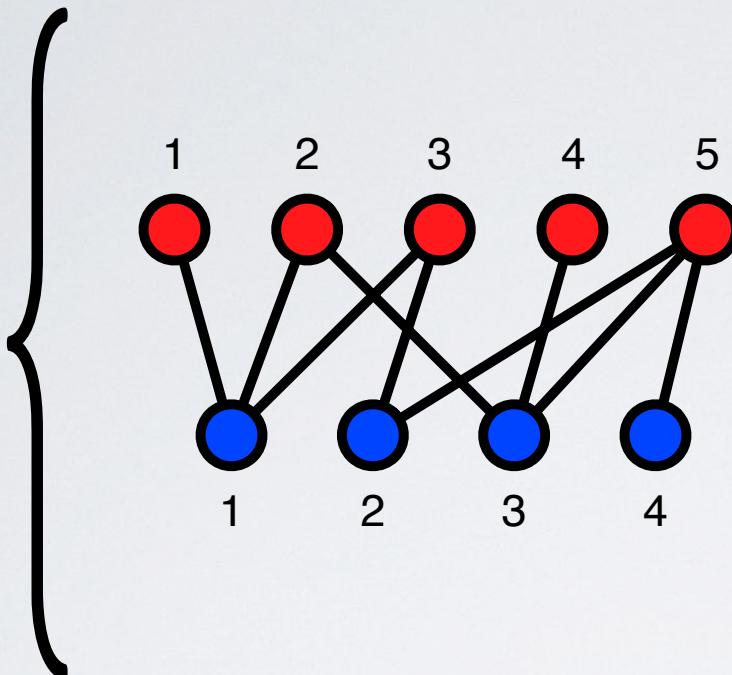
genes & substrings

words & documents

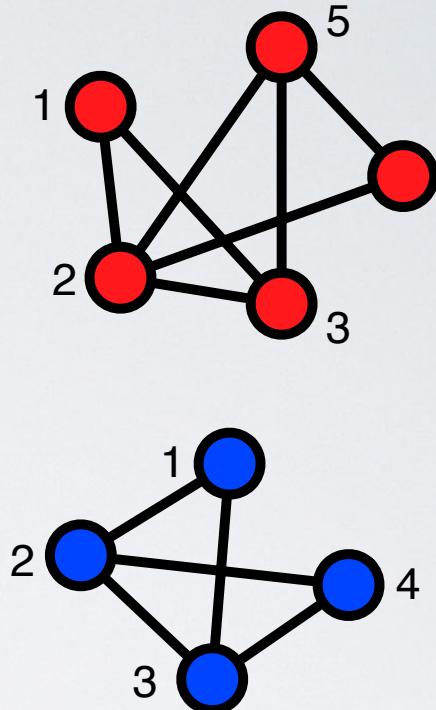
plants & pollinators

bipartite networks

bipartite network



no within-type edges



one type only

one-mode projections

authors & papers

people & locations (checkins)

actors & movies/scenes

metabolites & reactions

musicians & albums

genes & substrings

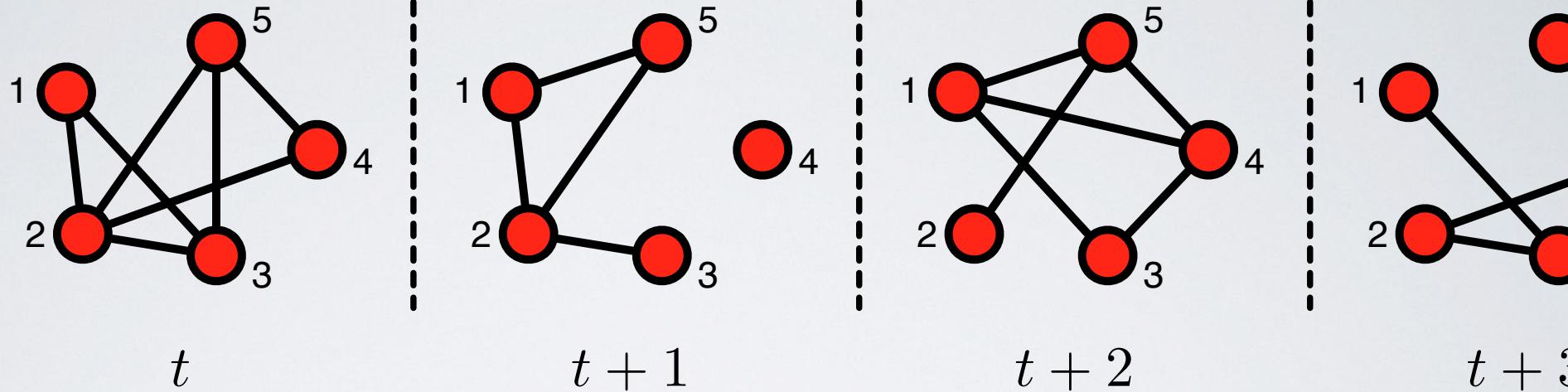
people & online groups

words & documents

people & corporate boards

plants & pollinators

temporal networks



any network over time

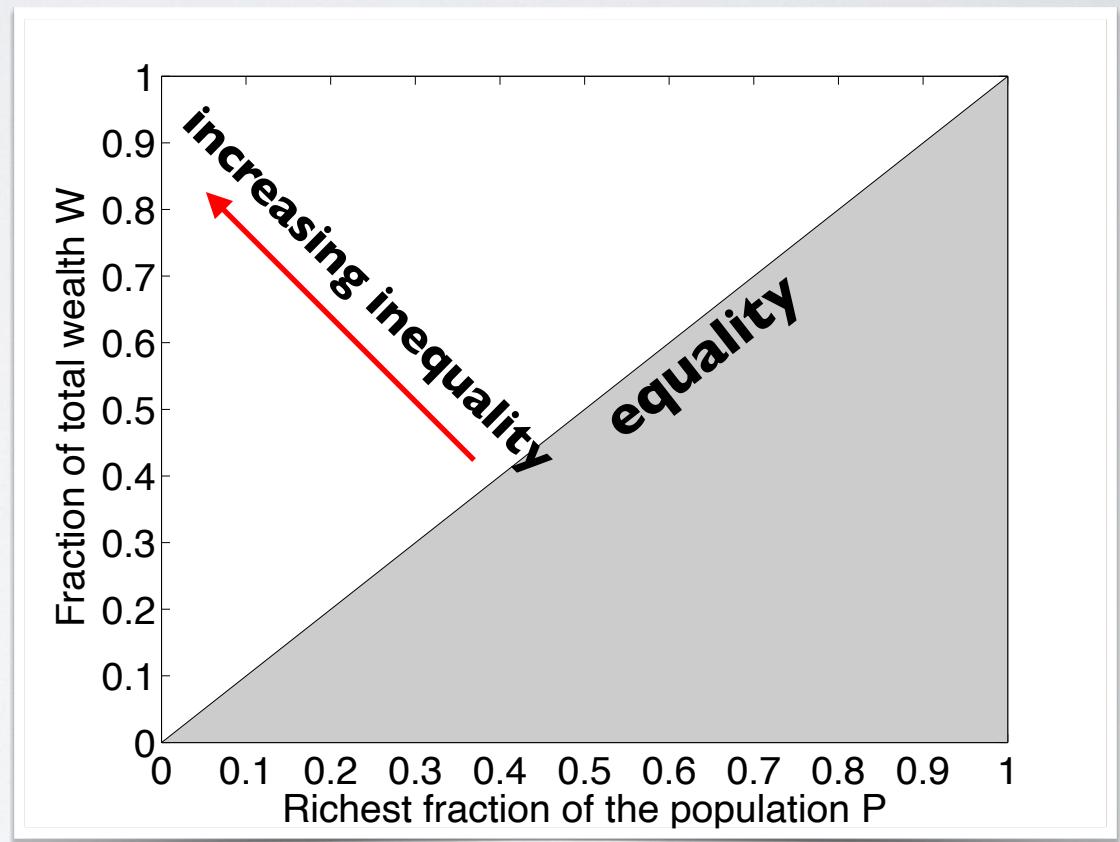
discrete time (snapshots), edges (i, j, t)

continuous time, edges $(i, j, t_s, \Delta t)$

degree distributions

degree "wealth"

what fraction of total wealth W
is owned by richest fraction P



Lorenz curve

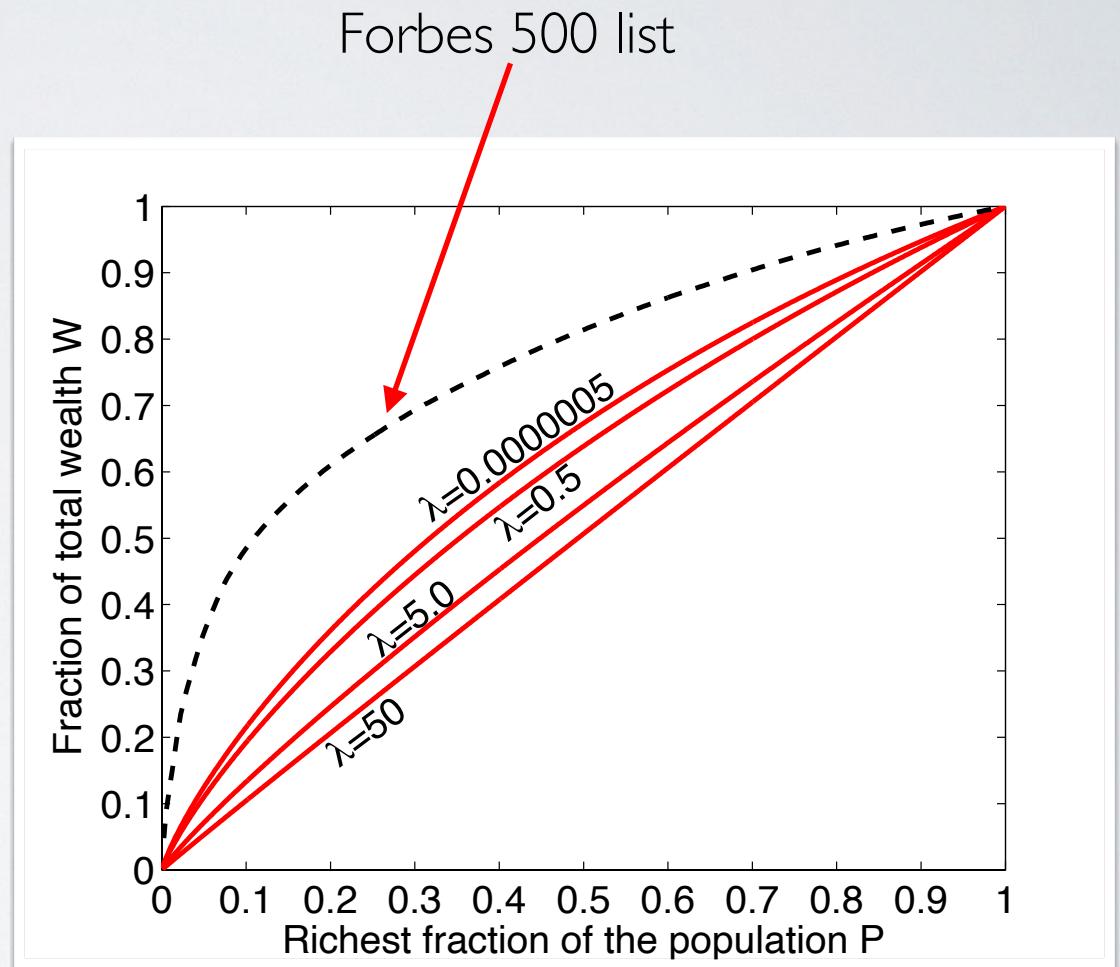
degree distributions

degree "wealth"

what fraction of total wealth W
is owned by richest fraction P

$$\Pr(k) \propto e^{-\lambda k}$$

exponential distribution



Lorenz curve

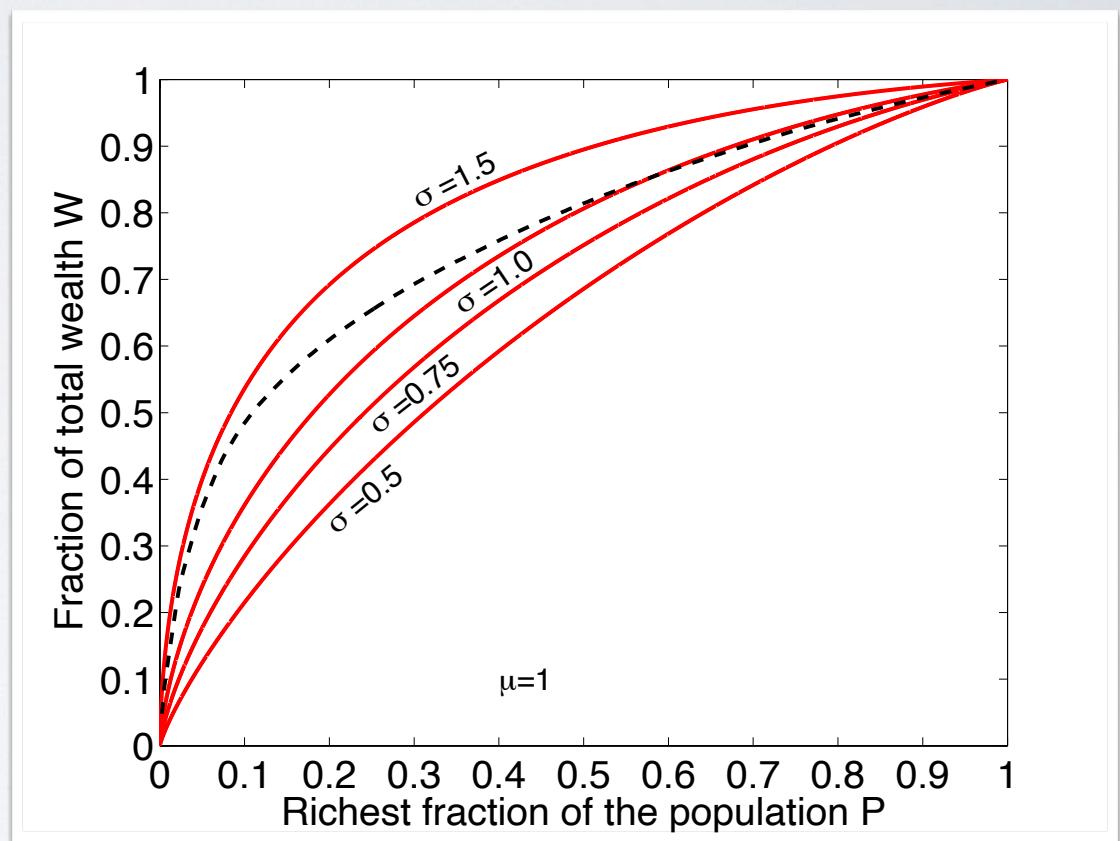
degree distributions

degree "wealth"

what fraction of total wealth W
is owned by richest fraction P

$$\Pr(k) \propto \frac{1}{k} e^{-\left(\frac{\ln k - \mu}{\sigma \sqrt{2}}\right)^2}$$

log-normal distribution



Lorenz curve

degree distributions

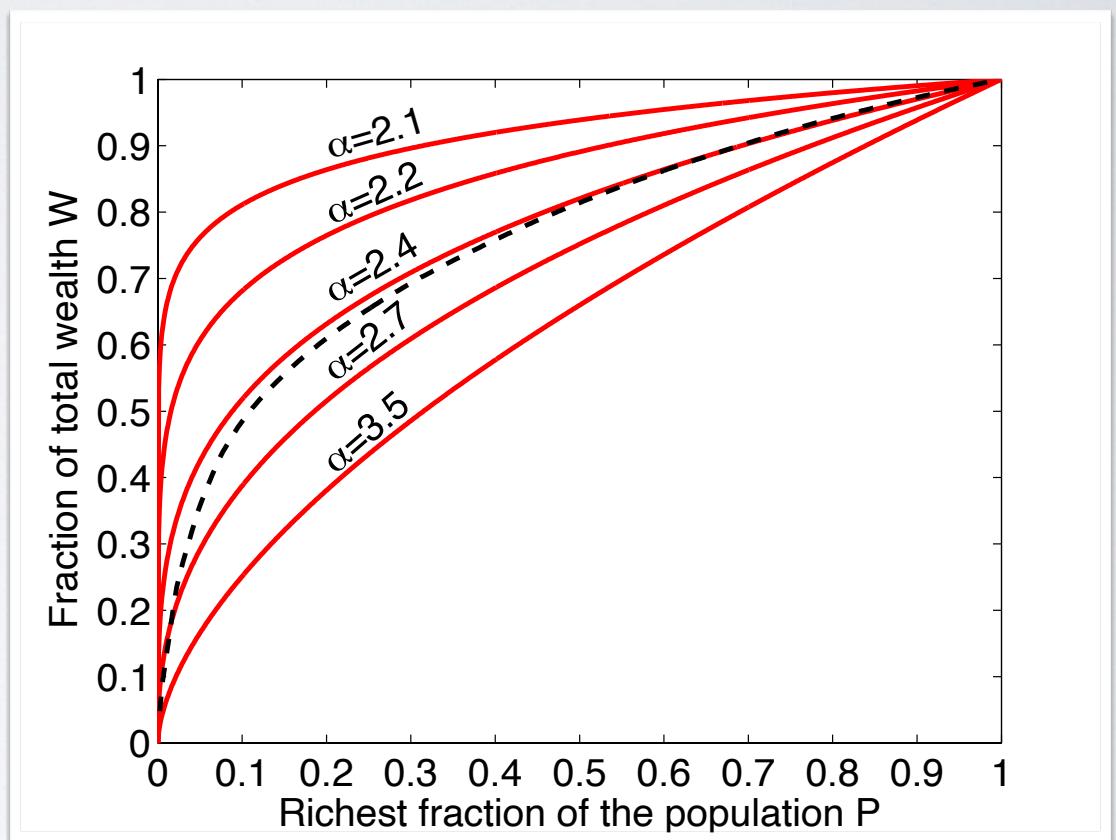
degree "wealth"

what fraction of total wealth W
is owned by richest fraction P

$$\Pr(k) \propto k^{-\alpha}$$

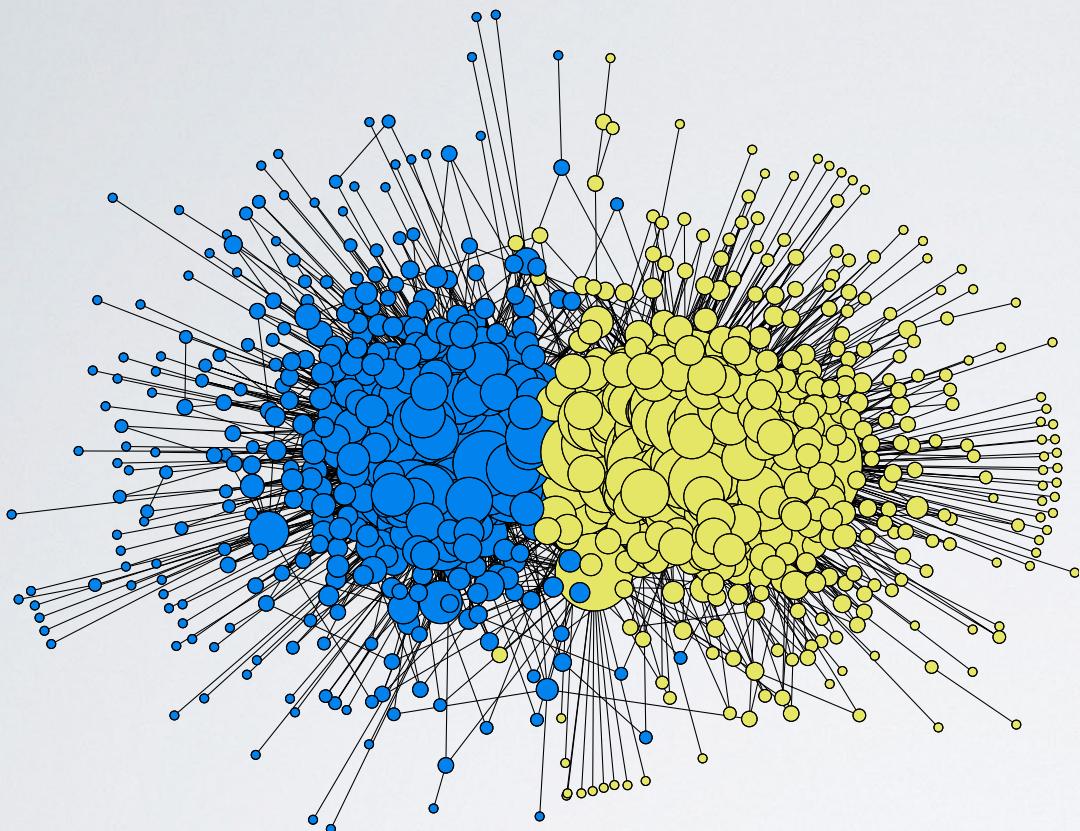
power-law distribution

80/20 rule

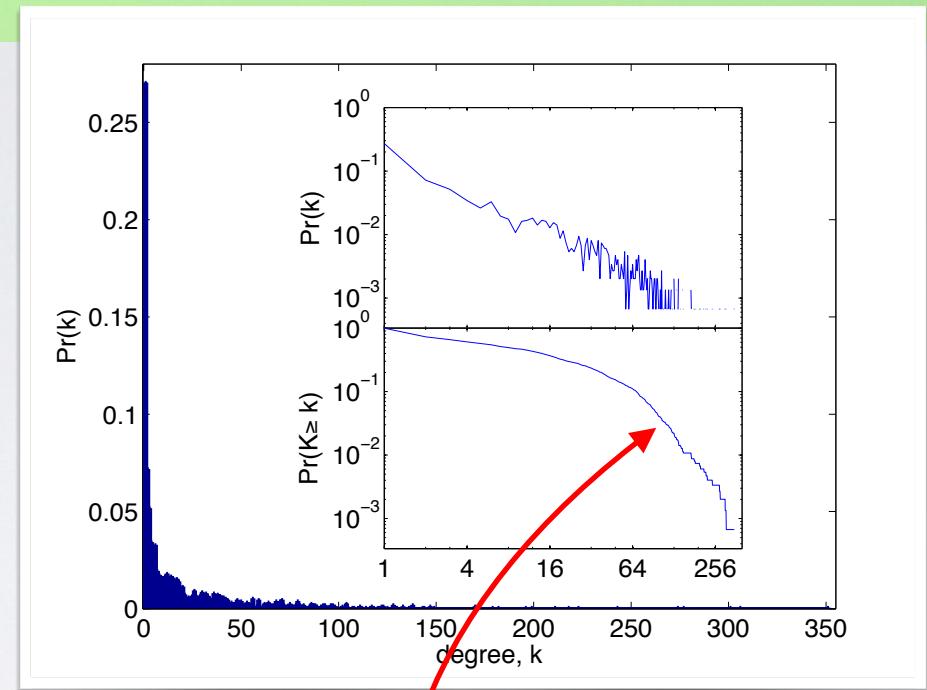


Lorenz curve

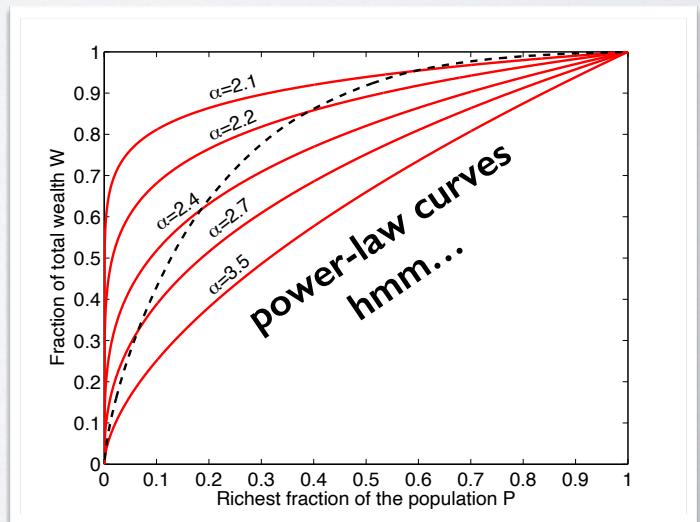
degree distributions



political blogs*



is this a power law?



power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- let's do some math
- (a nice warm up for other things, later)

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- normalization (probability density function)

$$1 = \int_{k_{\min}}^{\infty} \Pr(k) dk \quad \rightarrow \quad \text{pdf}$$

- complementary cumulative distribution function

$$P(k) = \int_k^{\infty} \Pr(y) dy \quad \rightarrow \quad \text{ccdf}$$

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- normalization (probability density function)*

$$1 = \int_{k_{\min}}^{\infty} \Pr(k) dk \rightarrow \Pr(k) = \frac{\alpha - 1}{k_{\min}} \left(\frac{k}{k_{\min}} \right)^{-\alpha} \quad \text{pdf}$$

- complementary cumulative distribution function

$$P(k) = \int_k^{\infty} \Pr(y) dy \rightarrow P(k) = \left(\frac{k}{k_{\min}} \right)^{-\alpha+1} \quad \text{ccdf}$$

- power laws have unusual properties, imply unusual underlying mechanisms

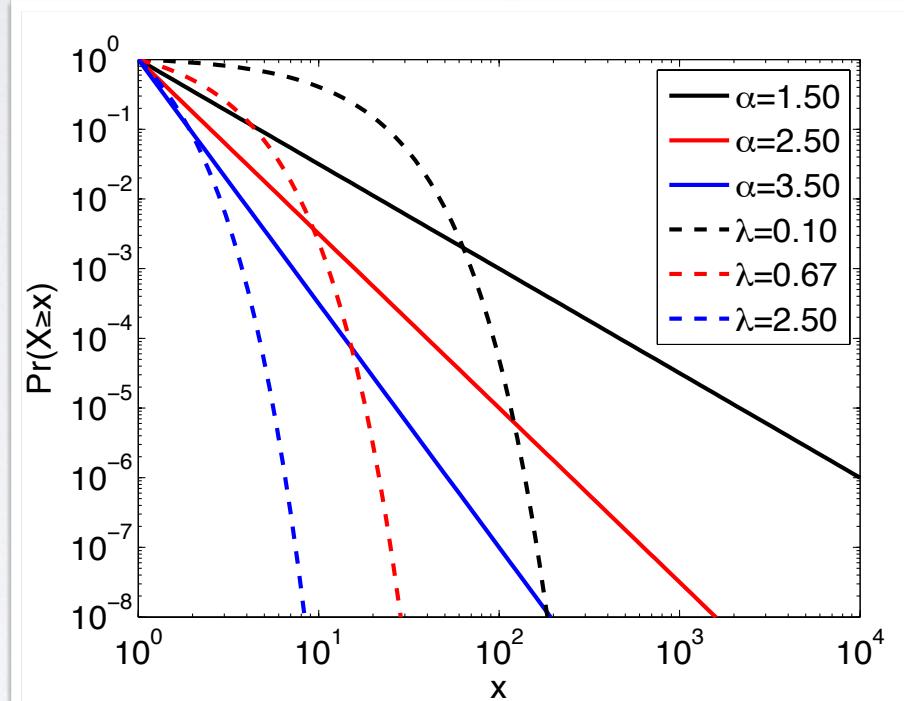
* the math here is easier for the continuous variables, but qualitatively similar results hold for discrete variables. also, yes, vertex degree is discrete not continuous.

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for} \quad k \geq k_{\min}$$

- high-variance

$$\langle k^m \rangle = \int_{k_{\min}}^{\infty} k^m \Pr(k) dk$$



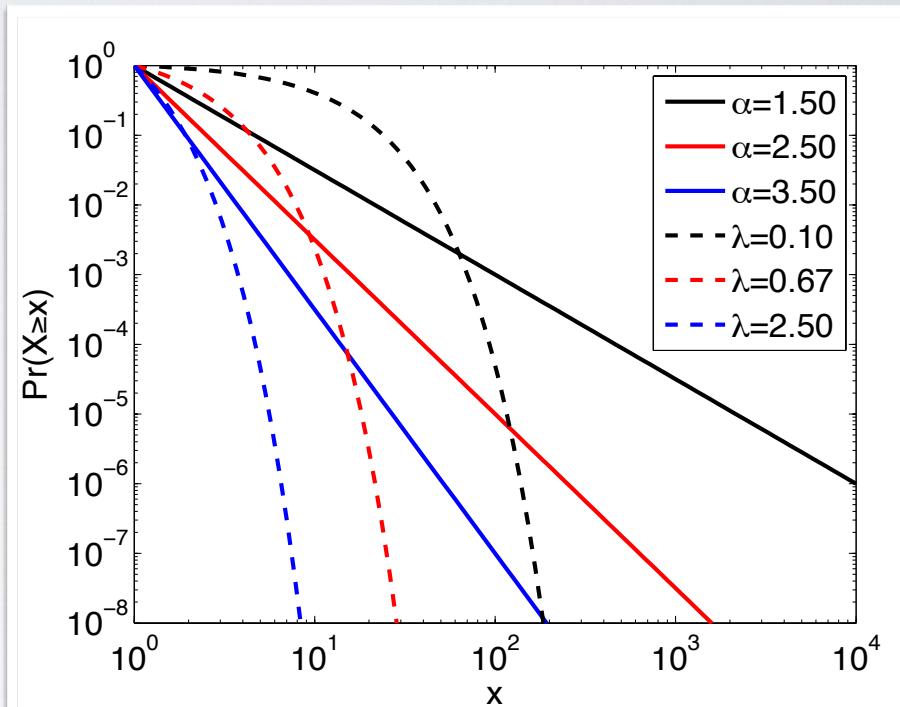
power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- high-variance

$$\begin{aligned}\langle k^m \rangle &= \int_{k_{\min}}^{\infty} k^m \Pr(k) dk \\ &= k_{\min}^m \left(\frac{\alpha - 1}{\alpha - 1 - m} \right)\end{aligned}$$

- **infinite mean** $1 < \alpha < 2$
- **infinite variance** $2 < \alpha < 3$
- much, much heavier tails than exponential, normal, etc.
- heavier than log-normal (asymptotically)



power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- "scale invariance" (aka "scale free")

$$\Pr(c k) = (\alpha - 1) k_{\min}^{\alpha-1} (c k)^{-\alpha}$$

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- "scale invariance" (aka "scale free")

$$\begin{aligned}\Pr(c k) &= (\alpha - 1) k_{\min}^{\alpha-1} (c k)^{-\alpha} \\ &= c^{-\alpha} [(\alpha - 1) k_{\min}^{\alpha-1} k^{-\alpha}] \\ &\propto \Pr(k)\end{aligned}$$

- power law is *only distribution* with this property
- implies no natural "scale" of distribution
- implies signature form: straight line on log-log plot

$$\ln \Pr(k) = \ln C - \alpha \ln k$$

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- exotic mechanisms
 - preferential attachment [Yule 1925, Simon 1955, Price 1976, etc.]
 - combinations of exponentials [Miller 1957, Reed & Hughes 2002]
 - phase transitions [many]
 - self-organized criticality (SOC) [Bak et al. 1988]
 - highly optimized tolerance (HOT) [Carlson and Doyle, 1999]
 - fragmentation [many]
 - multiplicative random walks (with lower limit) [many]
 - many, many others

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- how do you know? statistics.
- estimating α from data $\{k_i\}$ via maximum likelihood

$$\ln \mathcal{L}(\{k_i\} | \theta) = \ln \prod_{i=1}^n \Pr(k_i | \theta)$$

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- how do you know? statistics.
- estimating α from data $\{k_i\}$ via maximum likelihood

$$\ln \mathcal{L}(\{k_i\} | \theta) = \ln \prod_{i=1}^n \Pr(k_i | \theta)$$

- for the power-law distribution (log-likelihood)

$$\ln \mathcal{L}(\{k_i\} | \alpha, k_{\min}) = n \ln \left(\frac{\alpha - 1}{k_{\min}} \right) - \alpha \sum_{i=1}^n \ln \left(\frac{k_i}{k_{\min}} \right)$$

- solving $\partial \mathcal{L} / \partial \alpha = 0$, yields MLE

$$\hat{\alpha} = 1 + n \sqrt[n]{\sum_{i=1}^n \ln \left(\frac{k_i}{k_{\min}} \right)}$$

with standard error

$$\hat{\sigma} = \frac{\hat{\alpha} - 1}{\sqrt{n}} + O(1/n)$$

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- how do you know? statistics.
- estimating α from data $\{k_i\}$ via maximum likelihood

$$\ln \mathcal{L}(\{k_i\} | \theta) = \ln \prod_{i=1}^n \Pr(k_i | \theta)$$

- for the power-law distribution (log-likelihood)

$$\ln \mathcal{L}(\{k_i\} | \alpha, k_{\min}) = n \ln \left(\frac{\alpha - 1}{k_{\min}} \right) - \alpha \sum_{i=1}^n \ln \left(\frac{k_i}{k_{\min}} \right)$$

- solving $\partial \mathcal{L} / \partial \alpha = 0$, yields MLE with standard error

$$\hat{\alpha} = 1 + n \sqrt[n]{\sum_{i=1}^n \ln \left(\frac{k_i}{\bar{k}_{\min}} \right)}$$

$$\hat{\sigma} = \frac{\hat{\alpha} - 1}{\sqrt{n}} + O(1/n)$$

umm... we don't know this value

power-law distributions

$$\Pr(k) = C k^{-\alpha} \quad \text{for } k \geq k_{\min}$$

- we can choose k_{\min} smartly [see SIAM Review **51**; code is here *]
- but how do we know if the model is good? fitting is easy

moral: always check your model's goodness-of-fit

- ways to do this:
 1. compute a p -value relative to a *reasonable* null model
 2. compare your model against *reasonable* alternatives
 3. compare synthetic data drawn from your model with your empirical data
 4. use your model to predict something *reasonable*