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Graph Mining Techniques for Social Media Analysis

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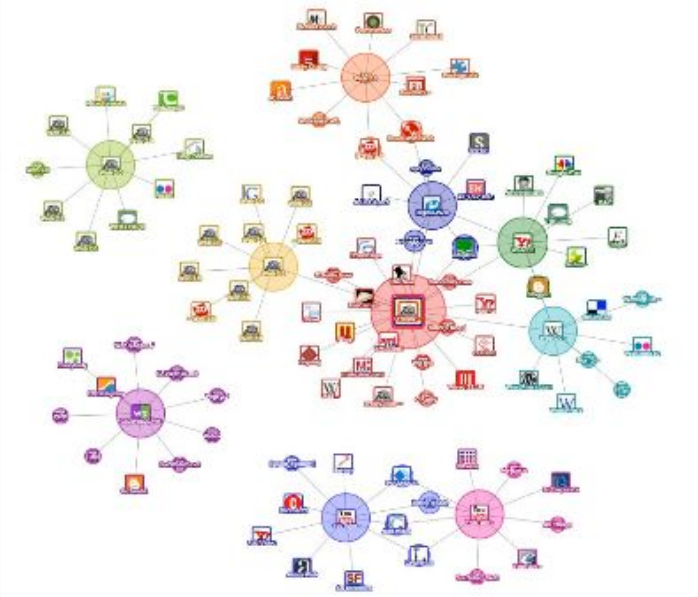
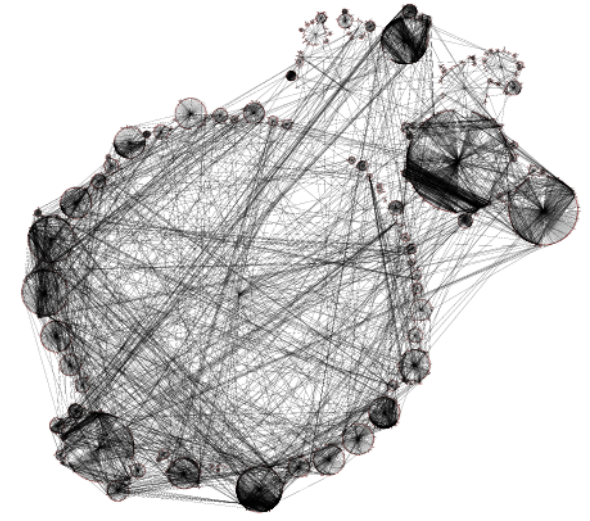
What is graph mining?

- Extracting useful knowledge (patterns, outliers, etc.) from structured data that can be represented as a graph.
- For our purposes, this is usually a social network.`



Facebook graph, via Touchgraph



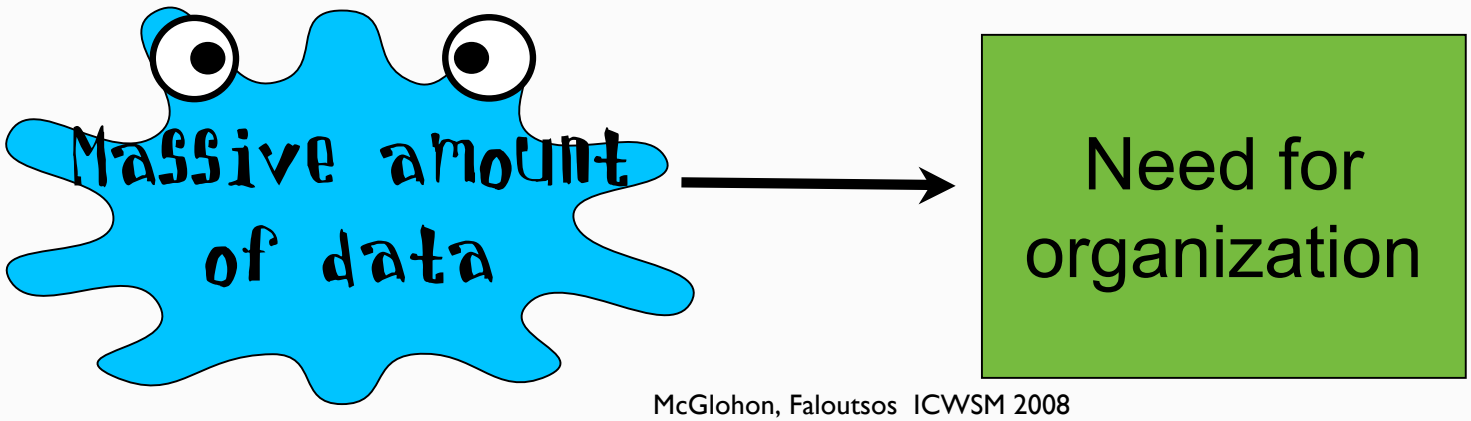
Livejournal, via Lehman and Kottler

What is graph mining?

- Example: Social media host tries to look at certain online groups and predict whether the group will flourish or disband.
- Example: Phone provider looks at cell phone call records to determine whether an account is a result of identity theft.

Why graph mining?

- Thanks to the web and social media, for the first time we have easily accessible network data on a large-scale.
- Understand relationships (links) as well as content (text, images).
- Large amounts of data raise new questions.



Motivating questions

- Q1: How do networks form, evolve, collapse?
- Q2: What tools can we use to study networks?
- Q3: Who are the most influential/central members of a network?
- Q4: How do ideas diffuse through a network?
- Q5: How can we extract communities?
- Q6: What sort of anomaly detection can we perform on networks?

Outline

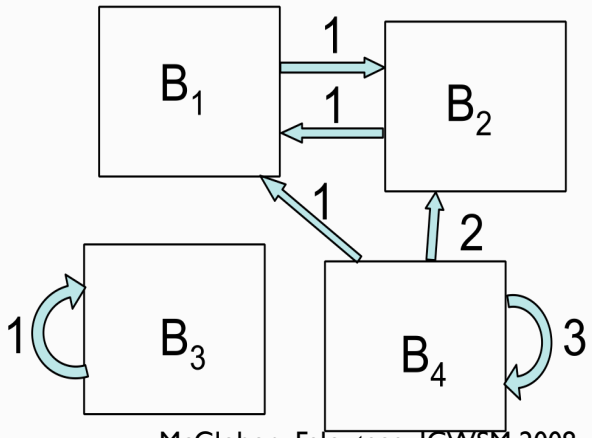
- Part 1: Q1: How do networks form, evolve, collapse?
  - Introduction to networks
  - Patterns, Laws
- Part 2: Q2: What tools can we use to study networks?
  - Q3: Ranking: Who are the most important members of a network?
- Part 3: Case studies
  - Q4: Diffusion: How do ideas diffuse through a network?
  - Q5: How can we extract communities?
  - Q6: What sort of anomaly detection can we perform?

Part 1 Outline

- Introduction to networks and 6 definitions
- Patterns
  - Diameter
  - Degree distribution
  - Connected components
  - Evolution over time

D1: Network

- A network is defined as a graph ***G=(V,E)***
  - ***V*** : set of vertices, or nodes.
  - ***E*** : set of edges.
- Edges may have numerical weights.



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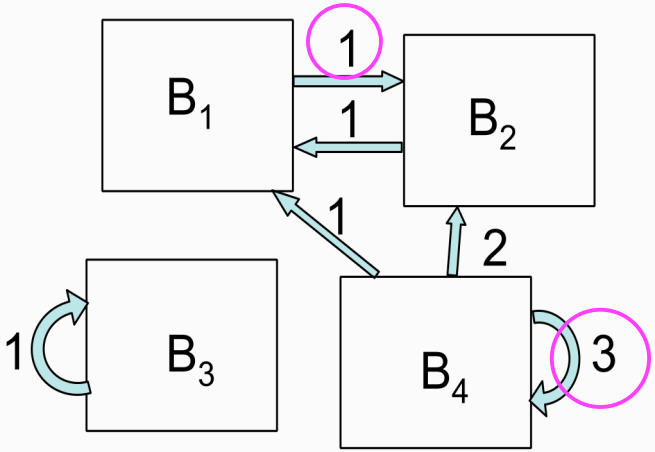
D2: Adjacency matrix

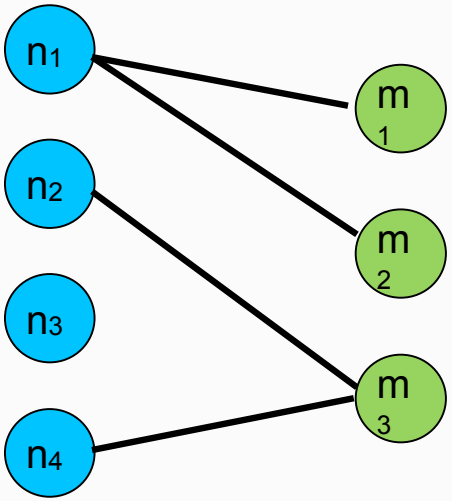
- To represent graphs, use adjacency matrix
- Unweighted graphs: all entries are 0 or 1
- Undirected graphs: matrix is symmetric



from \ *to*	B_1	B_2	B_3	B_4
B_1	0	1	0	0
B_2	1	0	0	0
B_3	0	0	1	0
B_4	1	2	0	3

D3: Bipartite graphs

- In a bipartite graph,
  - 2 sets of vertices
  - edges occur between different sets.
- If graph is undirected, we can represent as a non-square adjacency matrix.



	m_1	m_2	m_3
n_1	1	1	0
n_2	0	0	1
n_3	0	0	0
n_4	0	0	1

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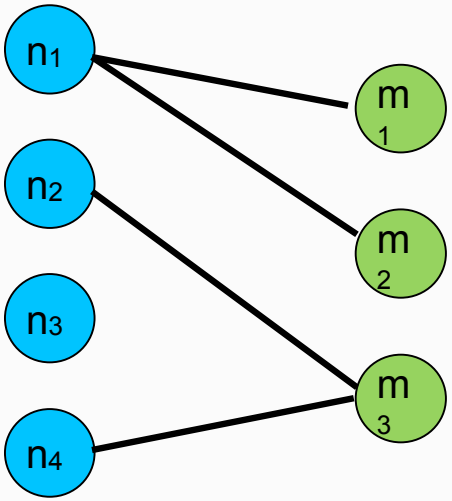
D4: Components

- Component: set of nodes with paths between each.



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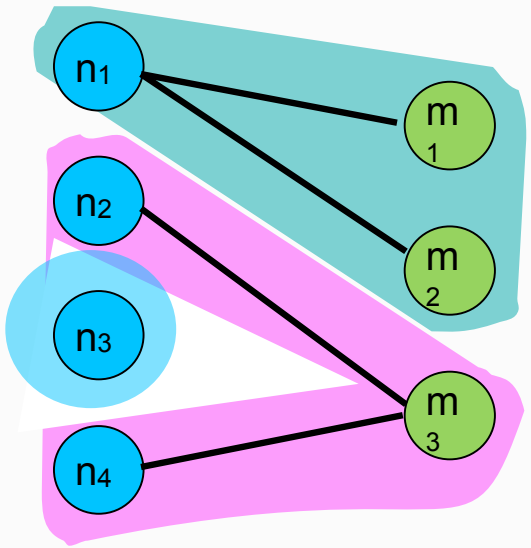
D4: Components

- Component: set of nodes with paths between each.
- We will see later that often real graphs form a giant connected component.



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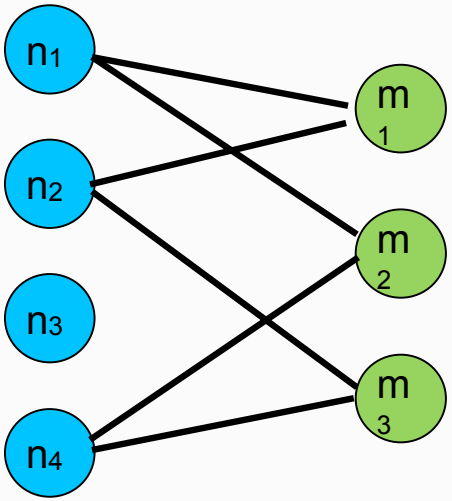
D5: Diameter

- Diameter of a graph is the “longest shortest path”.



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D5: Diameter

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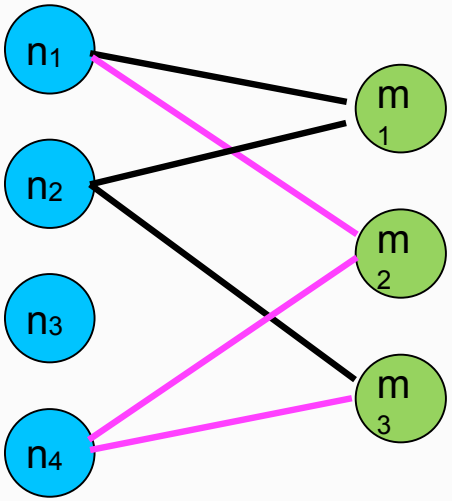

diameter=3

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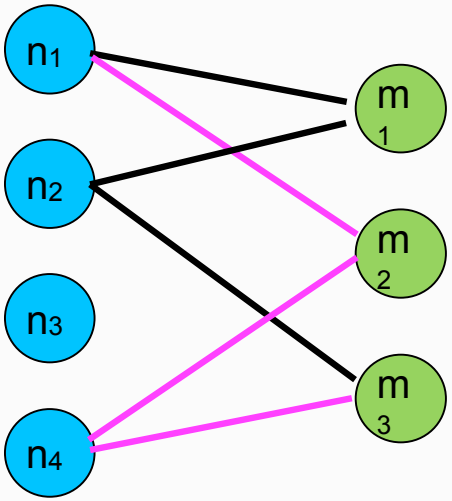
D5: Diameter

- Diameter of a graph is the "longest shortest path".
- We can estimate this by sampling.
- Effective diameter is the distance at which 90% of nodes can be reached.



diameter=3

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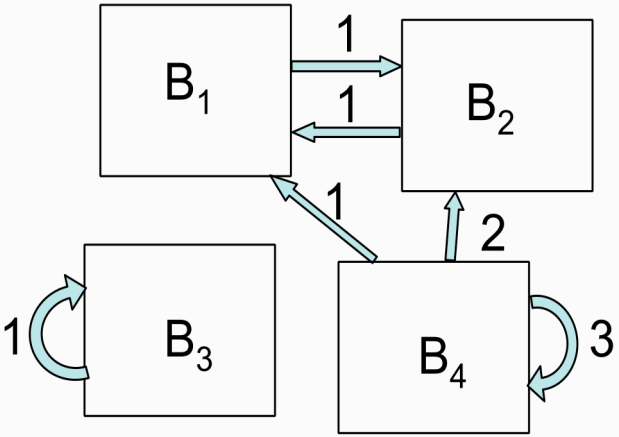
D6: Degree distribution

- We can find the degree of any node by summing entries in the (unweighted) adjacency matrix.



from \ to	B_1	B_2	B_3	B_4	out-degree
B_1	0	1	0	0	1
B_2	1	0	0	0	1
B_3	0	0	1	0	1
B_4	1	1	0	1	3
in-degree	2	2	1	1	

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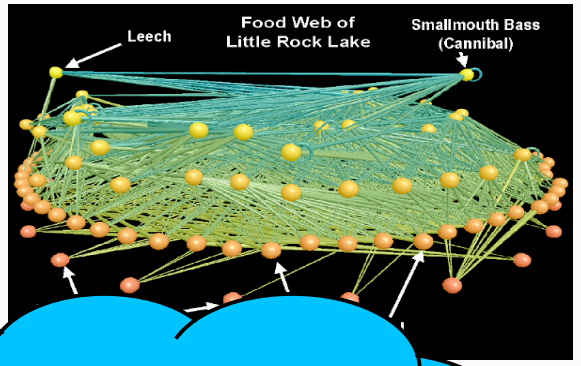
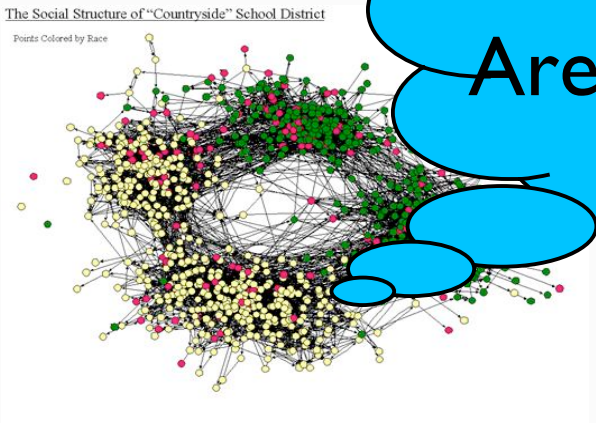
Some graphs

Internet Map [lumeta

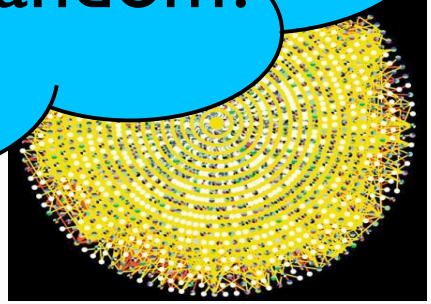


1]

Research question:
Are real graphs random?
(no)



Friendship Network [Moody '01]



Protein Interactions
[genomebiology.com]

Part 1 Outline

- Introduction to networks
- Patterns
  - Diameter
  - Degree distribution
  - Connected components
  - Evolution over time

Small-world effect

- Graphs usually display small diameter.
- First demonstrated by Travers & Milgram in 1960.
  - Most of the time, distance was around 6.
- Similarly, real graphs we see have small diameter…

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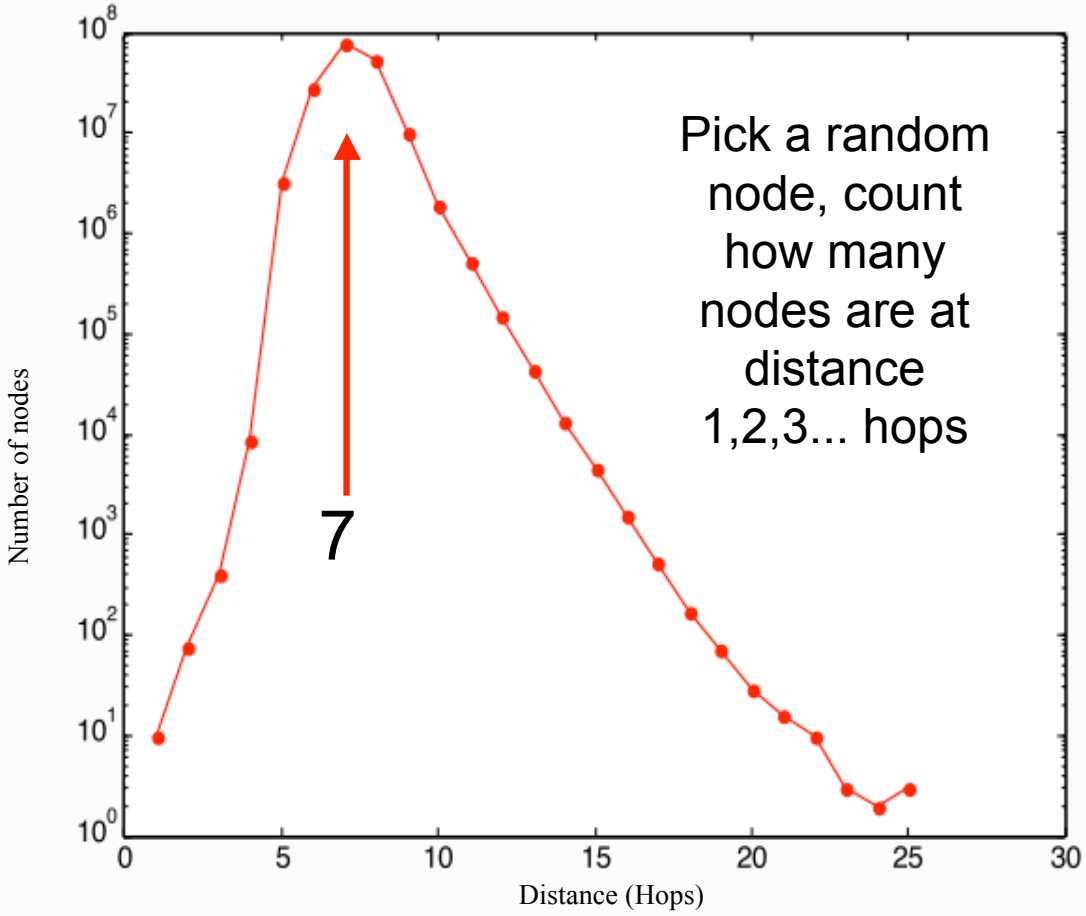
[Leskovec & Horvitz 07]

- Distribution of shortest path lengths
- Microsoft Messenger network
  - 180 million people
  - 1.3 billion edges
  - Edge if two people exchanged at least one message in one month period



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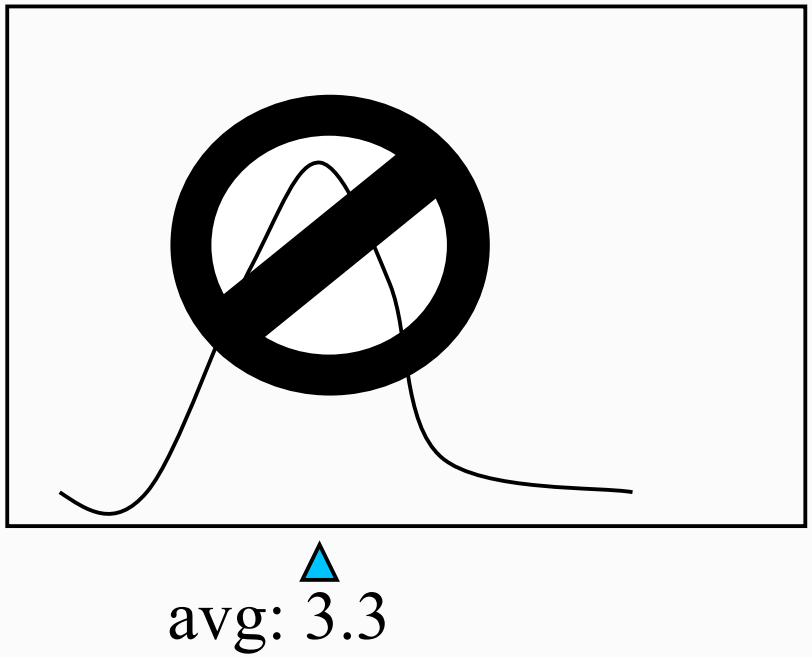
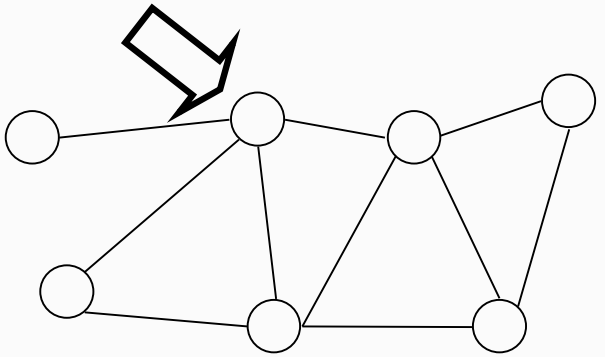
Degree distribution

Count vs. degree



- Suppose average degree is 3.3
- If we pick a node at random, can we guess its degree?
- In real graph, “mode” is 1!



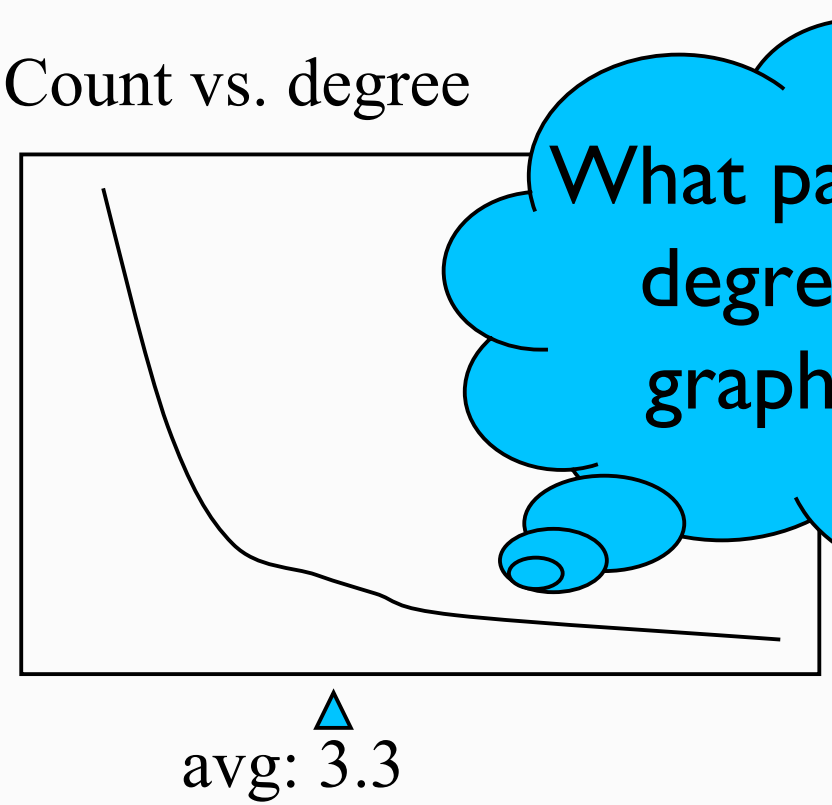
Degree distribution

- Suppose average degree is 3.3

ick a node at
can we
degree?

aph, "mode" is 1!

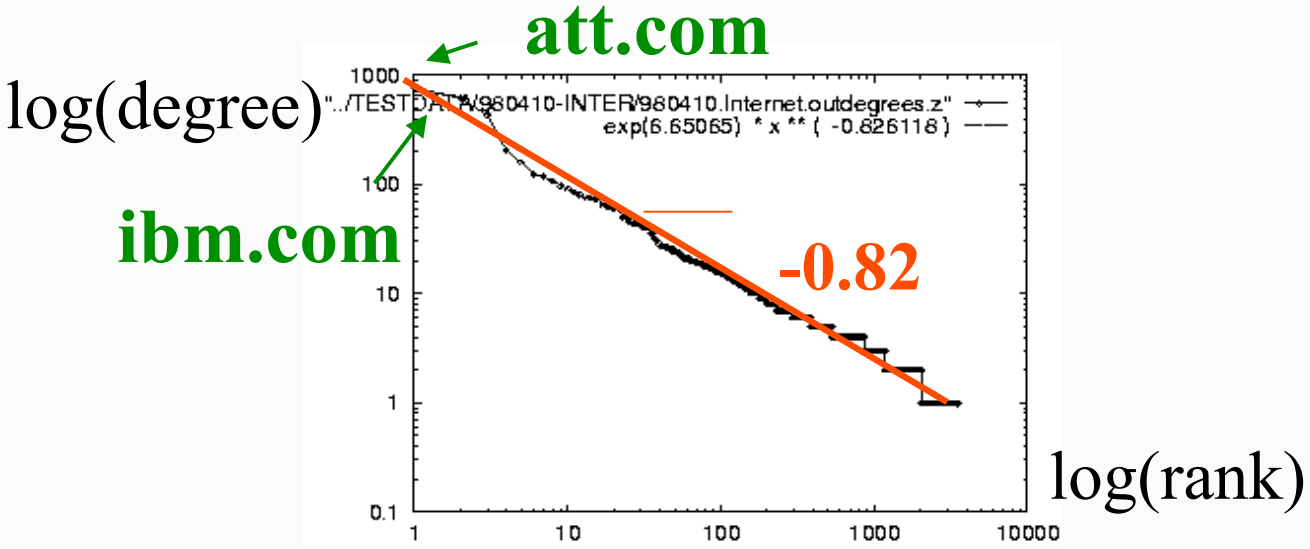
herefore, mean is "meaningless".



Power law degree distribution

- Measure with rank exponent R
- [SIGCOMM99]

internet domains



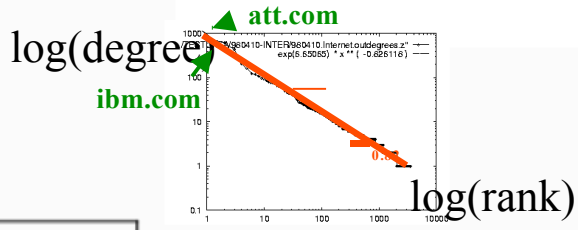
Power laws - discussion

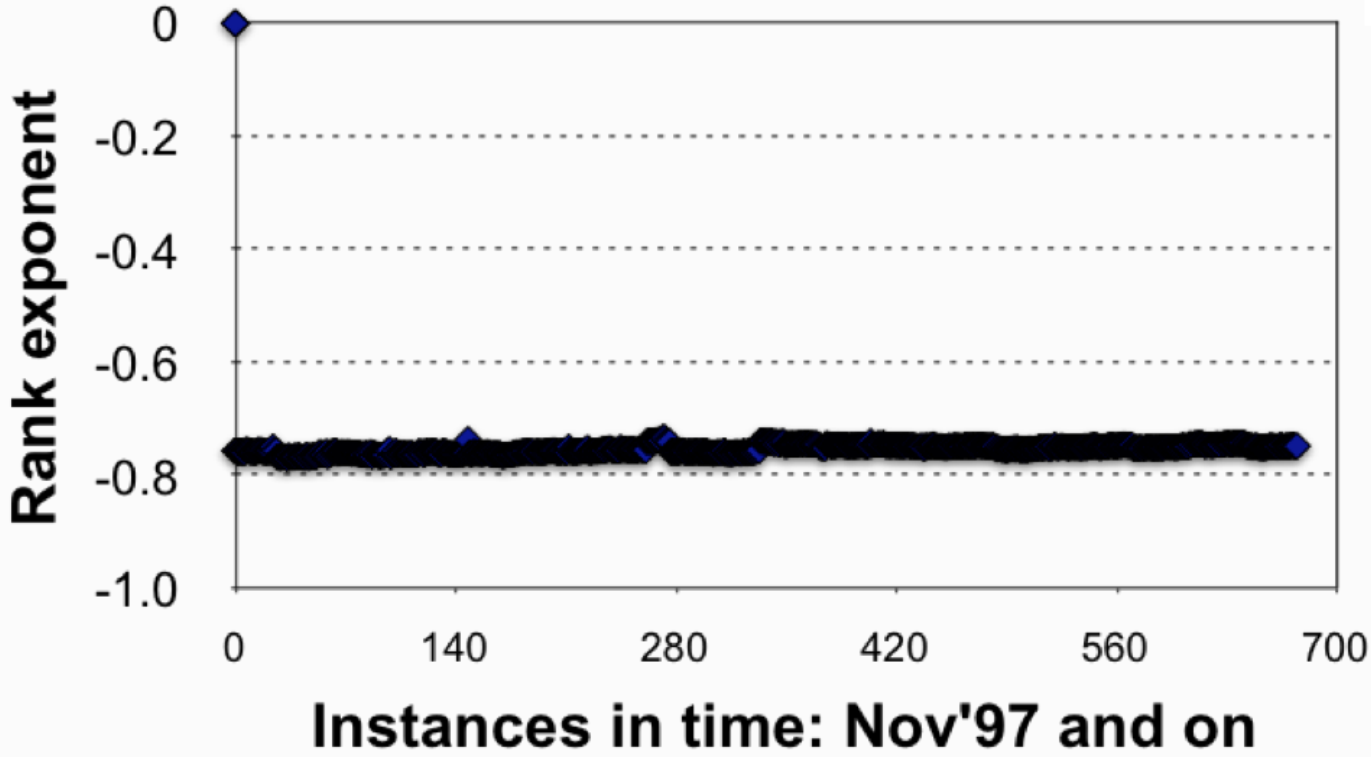
- Do they hold, over time?
- Do they hold on other graphs/domains?

Power laws - discussion

- Do they hold, over time?
  - Yes! for multiple years [Siganos+]
- Do they hold on other graphs/domains?
  - Yes!
  - Web sites and links [Tomkins+], [Barabasi+]
  - Peer-to-peer graphs (gnutella-style)
  - Who-trusts-whom (epinions.com)

Time Evolution: rank *R*



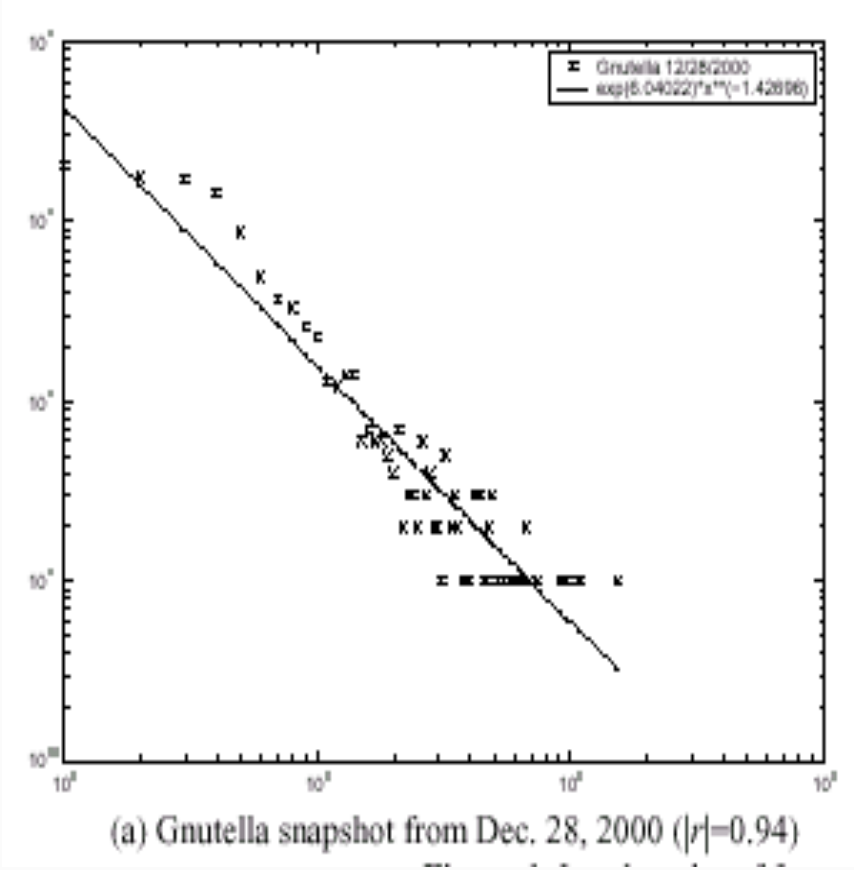


Domain level

- The rank exponent has not changed! [Siganos+]

The Peer-to-Peer Topology

count



(a) Gnutella snapshot from Dec. 28, 2000 ($|r|$=0.94)

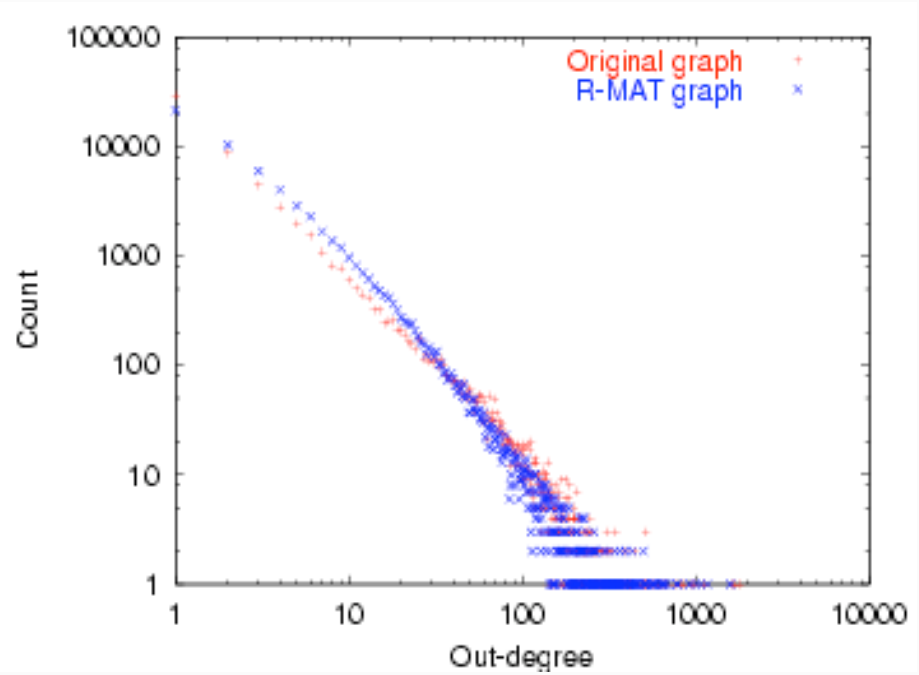
[Jovanovic+]

degree

- Number of immediate peers (= degree), follows a power-law

epinions.com

count



(out) degree

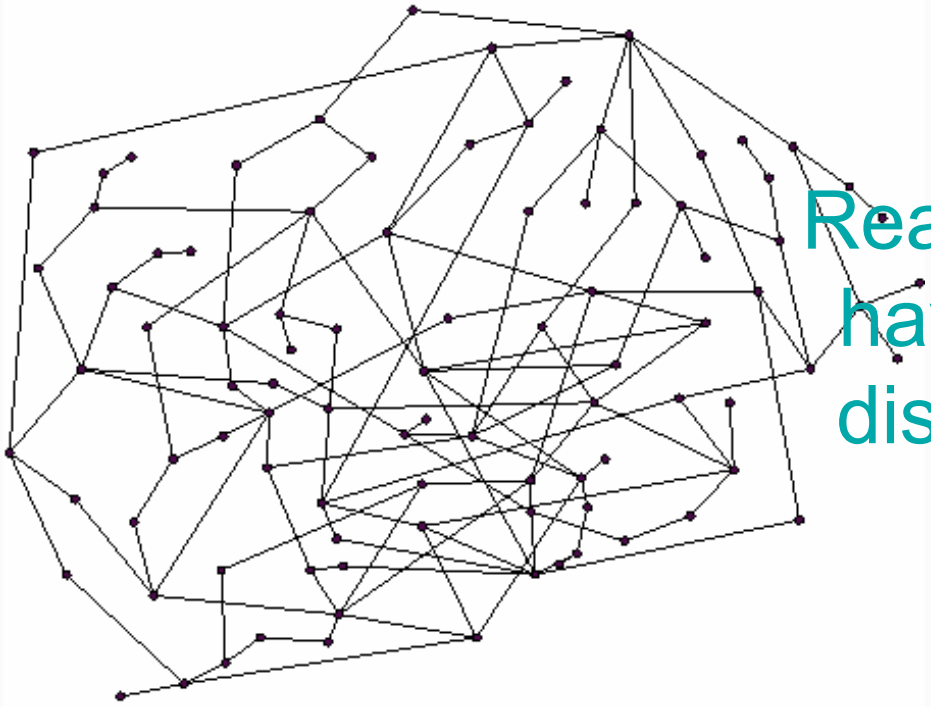
- who-trusts-whom [Richardson + Domingos, KDD 2001]

Part 1 Outline

- Introduction to networks
- Patterns
  - Diameter: “small world effect”
  - Degree distribution: power law
  - Connected components
  - Evolution over time

Components

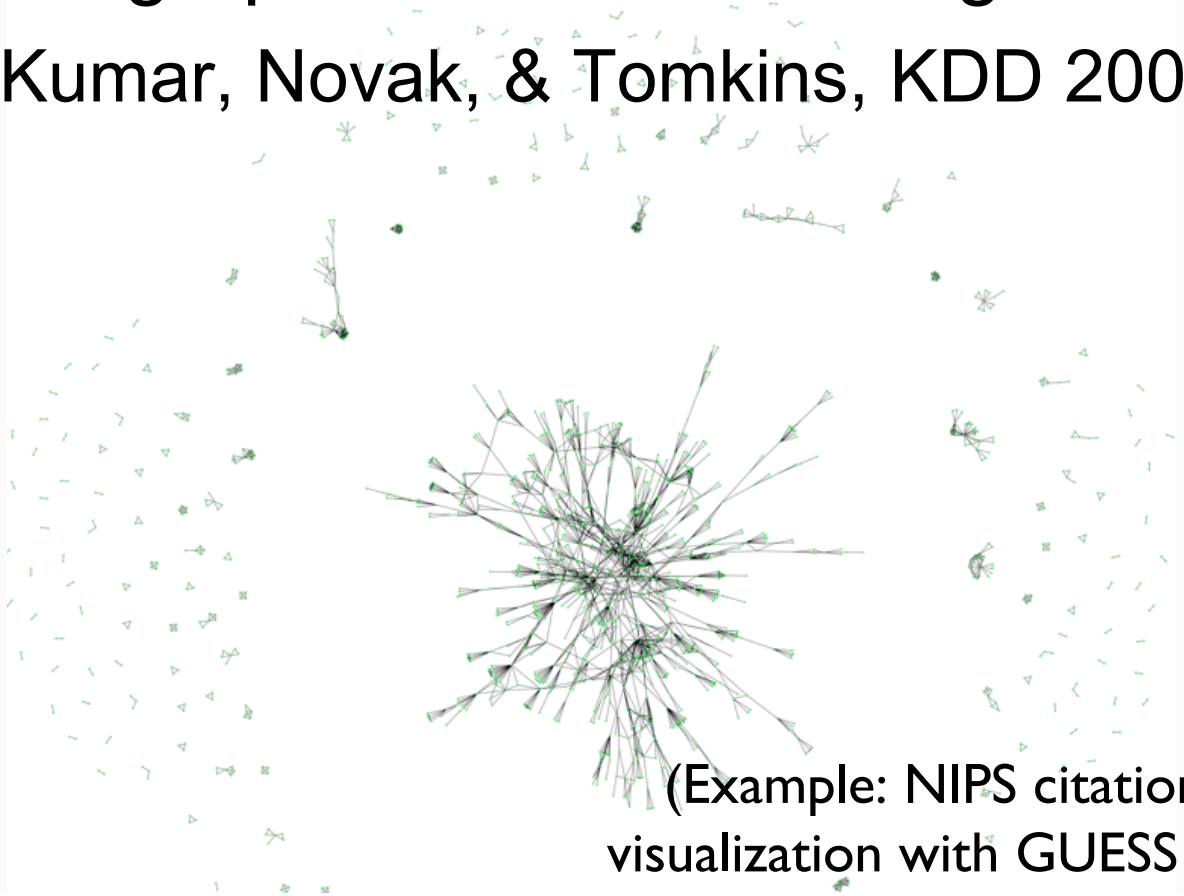
- Basic graph generator, Erdos-Renyi
  - For *n* vertices, connect any two IID with probability *p*.
- Many provable properties, including emergence of a giant connected component.



Real graphs do not have E-R degree distribution, but...

Giant connected component

- Nearly all real networks have a giant connected component (GCC) emerge!
- Often SM graphs have “middle region”
  - See [Kumar, Novak, & Tomkins, KDD 2006]



(Example: NIPS citation graph, visualization with GUESS [Adar 06]

Part 1 Outline

- Introduction to networks
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  - Connected components: giant CC
  - Evolution over time

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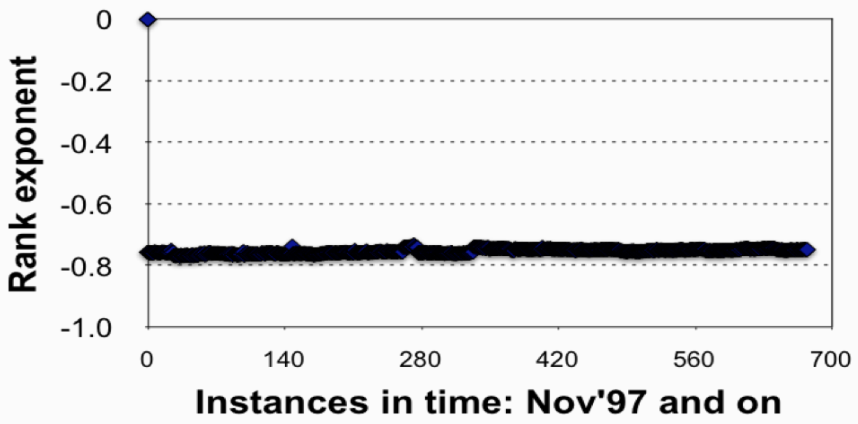
Motivating questions

- How do graphs evolve?
- Degree-exponent seems constant - any other consistent patterns?



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Evolution of diameter?

- Prior analysis, on power-law-like graphs, hints diameter slowly increasing with time.

  diameter ~ O(log(N)) or

  diameter ~ O(log(log(N)))

- Slowly increasing with network size
- What is happening, in reality?

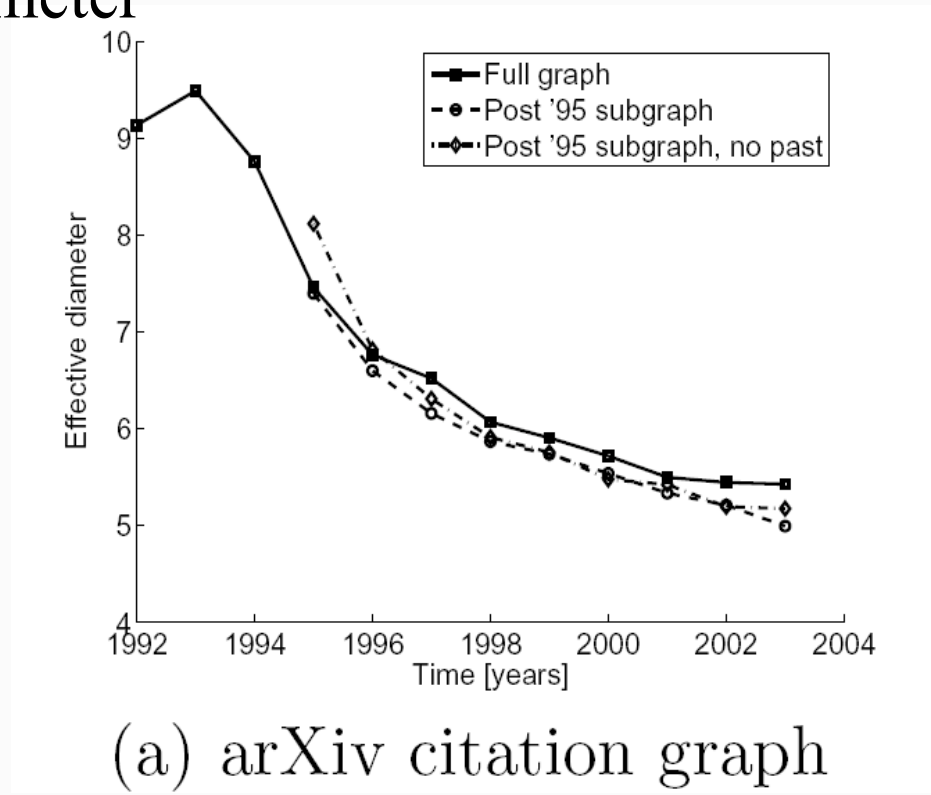
Diameter shrinks, toward a constant value!

Shrinking diameter

[Leskovec, Faloutsos, Kleinberg KDD 2005]

- Citations among physics papers
- 11yrs; @ 2003:
  - 29,555 papers
  - 352,807 citations
- For each month *M*, create a graph of all citations up to month *M*

diameter



(a) arXiv citation graph

time

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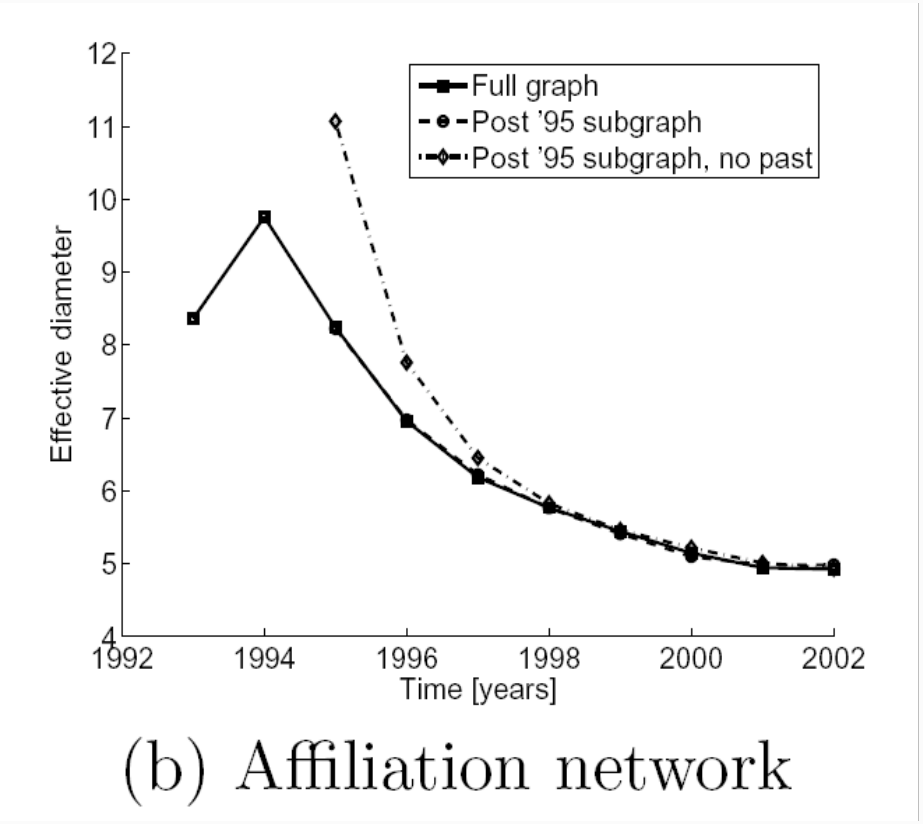
Shrinking diameter

- Authors & publications
- 1992
  - 318 nodes
  - 272 edges
- 2002
  - 60,000 nodes
- 20,000 authors
- 38,000 papers
  - 133,000 edges



(b) Affiliation network

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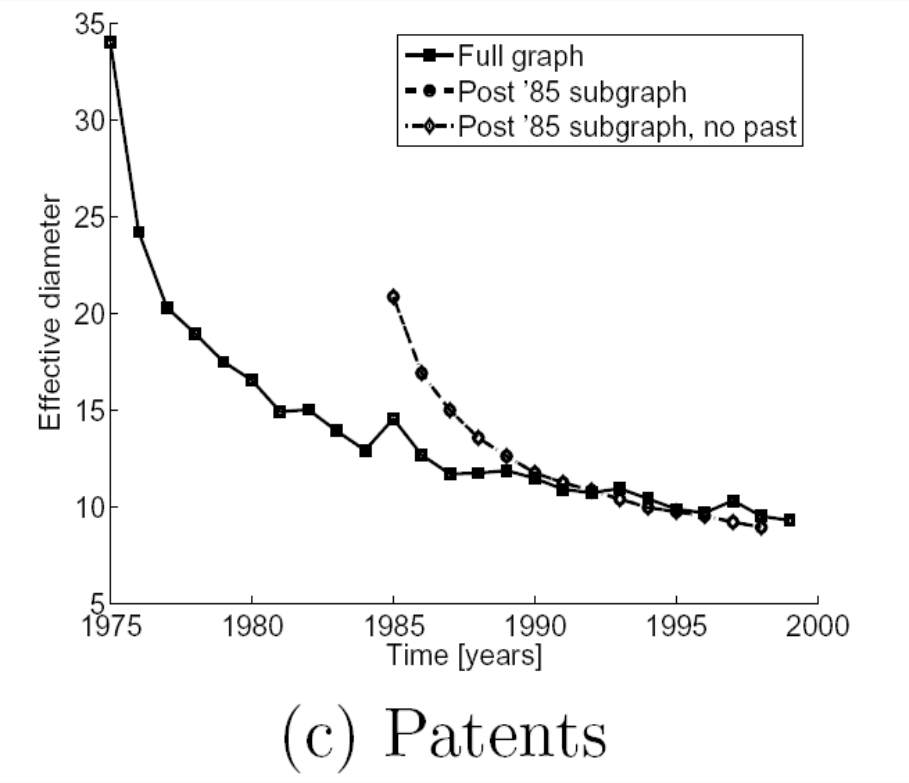
Shrinking diameter

- Patents & citations
- 1975
  - 334,000 nodes
  - 676,000 edges
- 1999
  - 2.9 million nodes
  - 16.5 million edges
- Each year is a datapoint



(c) Patents

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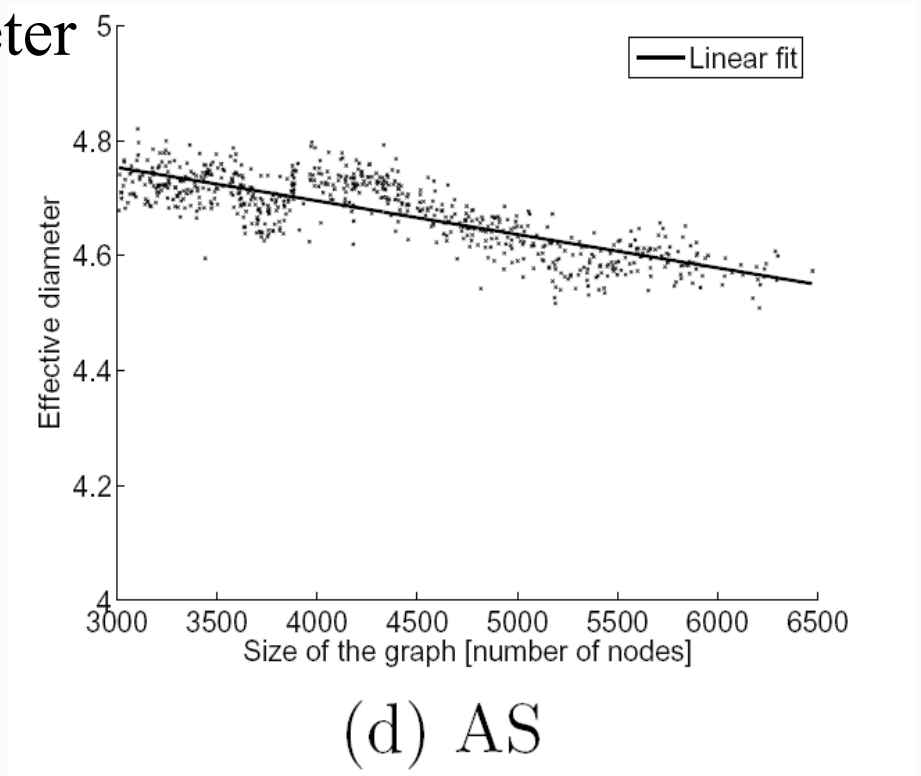
Shrinking diameter

- Autonomous systems
- 1997
  - 3,000 nodes
  - 10,000 edges
- 2000
  - 6,000 nodes
  - 26,000 edges
- One graph per day

diameter



(d) AS

N

Temporal evolution

- N(t) nodes; E(t) edges at time t
- Suppose that

$$N(t+1) = 2 * N(t)$$

- What is your guess for

$$E(t+1) =? 2 * E(t)$$

Temporal evolution

- N(t) nodes; E(t) edges at time t
- Suppose that

$$N(t+1) = 2 * N(t)$$

- What is your guess for

$$E(t+1) =? 2 * E(t)$$

- Edges over-double!

Temporal evolution

- Growth of edges obeys power law with:

$$E(t) \sim N(t)^a \quad \text{for all } t$$

where $1<a<2$

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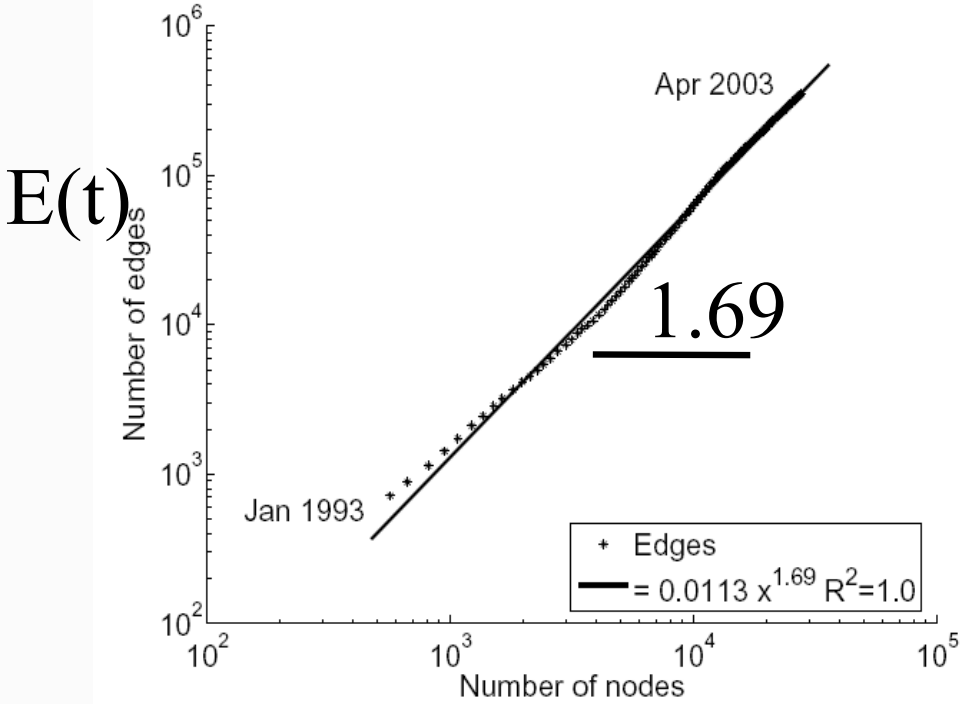
Densification Power Law

ArXiv: Physics papers and their citations



E(t)

(a) arXiv

N(t)

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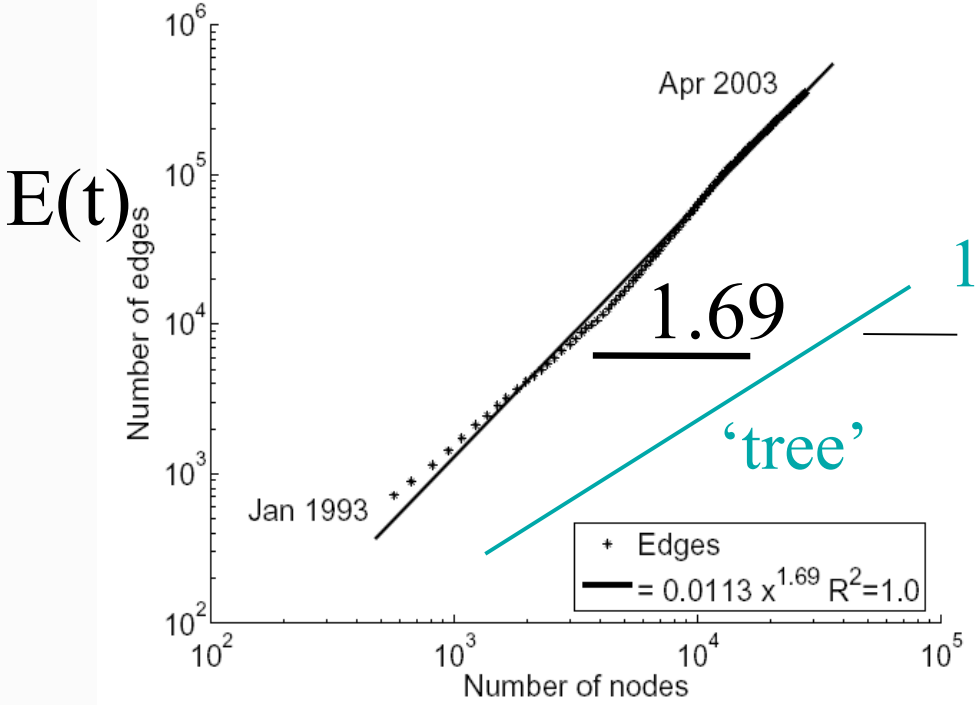
Densification Power Law

ArXiv: Physics papers and their citations



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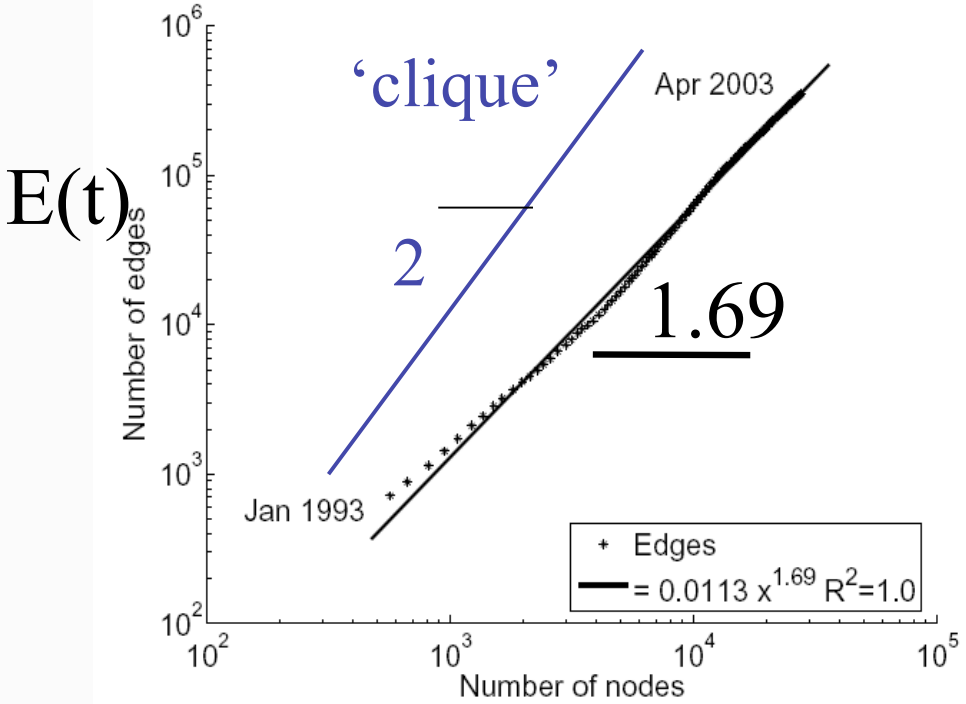
Densification Power Law

ArXiv: Physics papers and their citations



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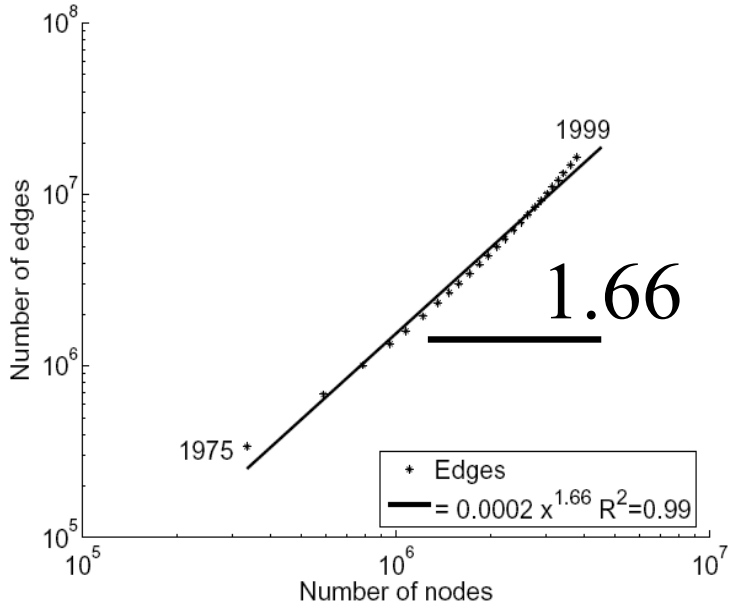
Densification Power Law

U.S. Patents, citing each other

E(t)



(b) Patents

N(t)

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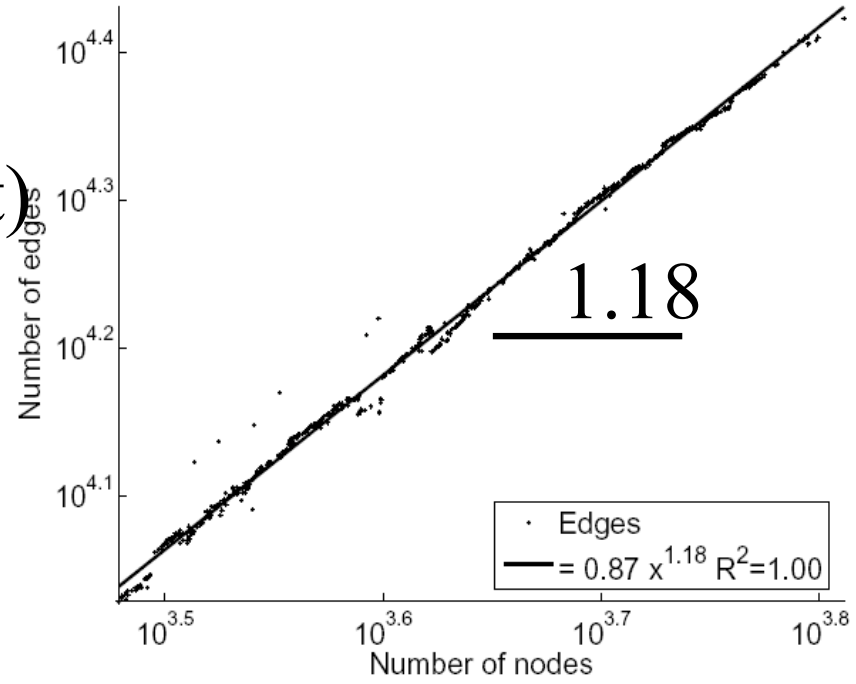
Densification Power Law

Autonomous Systems

E(t)



(c) Autonomous Systems

N(t)

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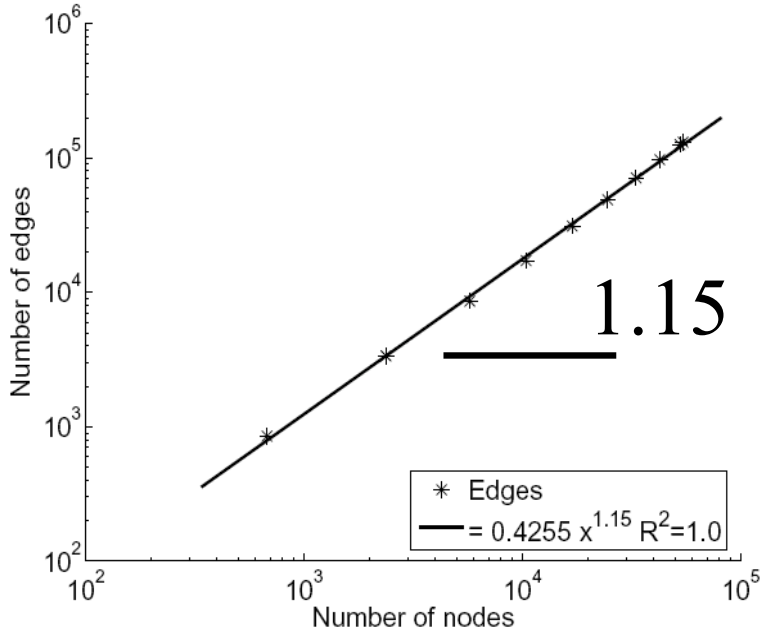
Densification Power Law

ArXiv: authors & papers

E(t)



(d) Affiliation network

N(t)

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- Introduction to networks
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  - Diameter: "small world effect"
  - Degree distribution: power law
  - Connected components: giant CC
  - Evolution over time: Shrinking diameter, Densification power law

Another big question

- Q: How can we generate realistic networks?

Another big question

- Q: How can we generate realistic networks?
- A: Answering this question fully would require another tutorial. ☺
- Some models are preferential attachment (Barabasi et. al.), copying model (Kleinberg et. al.), “winners don’t take all” (Pennock et. al.), Kronecker multiplication (Leskovec et. al.).

Bibliography: Part 1

- Power Laws and patterns
  - Albert, R. & Barabasi, A. (2002), 'Statistical mechanics of complex networks', *Reviews of Modern Physics* **74**, 47.
  - Barabasi, A. L. & Albert, R. (1999), 'Emergence of scaling in random networks', *Science* **286**(5439), 509--512.
  - Domingos, P. & Richardson, M. (2001), Mining the network value of customers, *in* 'KDD '01: Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining', ACM Press, New York, NY, USA, pp. 57--66.
  - Faloutsos, M.; Faloutsos, P. & Faloutsos, C. (1999), 'On Power-law Relationships of the Internet Topology', *SIGCOMM*, 251-262.

Bibliography: Part 1

- Jovanovic, M. A. (2001), 'Modeling Large-scale Peer-to-Peer Networks and a Case Study of Gnutella ', Master's thesis, University of Cincinatti.
- Kossinets, G. & Watts, D. J. (2006), 'Empirical Analysis of an Evolving Social Network', *Science* **311**(5757), 88--90.
- Kumar, R.; Novak, J.; Raghavan, P. & Tomkins, A. (2004), 'Structure and evolution of blogspace', *Commun. ACM* **47**(12), 35--39.
- Kumar, R.; Novak, J.; Raghavan, P. & Tomkins, A. (2003), On the bursty evolution of blogspace, *in* 'WWW '03: Proceedings of the 12th international conference on World Wide Web', ACM Press, New York, NY, USA, pp. 568--576.
- Kumar, R.; Novak, J. & Tomkins, A. (2006), Structure and evolution of online social networks, *in* 'KDD '06: Proceedings of the 12th ACM SIGKDD International Conference on Knowedge Discover and Data Mining', pp. 611--617

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Bibliography: Part 1

- Leland, W.; Taqqu, M.; Willinger, W. & Wilson, D. (1994), 'On the Self-Similar Nature of Ethernet Traffic', *IEEE Transactions on Networking* **2**(1), 1-15.
- Leskovec, J.; Kleinberg, J. & Faloutsos, C. (2005), Graphs over time: densification laws, shrinking diameters and possible explanations, *in* 'KDD '05.
- Milgram, S. (1967), 'The small-world problem', *Psychology Today* **2**, 60--67.
- Newman, M. E. J. (2005), 'Power laws, Pareto distributions and Zipf's law', *Contemporary Physics* **46**, 323.
- Siganos, G.; Faloutsos, M.; Faloutsos, P. & Faloutsos, C. (2003), 'Power laws and the AS-level internet topology.', *IEEE/ACM Trans. Netw.* **11**(4), 514-524.
- Zipf, G. (1949), *Human Behavior and Principle of Least Effort: An Introduction to Human Ecology*, Addison Wesley, Cambridge, Massachusetts.

Bibliography: Part 1

- Models
  - Barabasi, A. (2005), 'The origin of bursts and heavy tails in human dynamics', *Nature* **435**, 207.
  - Erdos, P. & Renyi, A. (1960), 'On the evolution of random graphs', *Publ. Math. Inst. Hungary. Acad. Sci.* **5**, 17-61.
  - Granovetter, M. (1978), 'Threshold Models of Collective Behavior', *Am. Journal of Sociology* **83**(6), 1420--1443.
  - Leskovec, J.; Faloutsos, C. Scalable modeling of real graphs using Kronecker Multiplication. ICML 2007.
  - Vazquez, A.; Oliveira, J. G.; Dezso, Z.; Goh, K. I.; Kondor, I. & Barabasi, A. L. (2006), 'Modeling bursts and heavy tails in human dynamics', *Physical Review E* **73**, 036127.
  - Watts, D. J. & Strogatz, S. H. (1998), 'Collective dynamics of 'small-world' networks.', *Nature* **393**(6684), 440--442.

Bibliography: Part 1

- Visualization example
  - Adar, Eytan, "GUESS: A Language and Interface for Graph Exploration," CHI 2006
  - Katharina Anna Lehmann, Stephan Kottler, Michael Kaufmann. Visualizing Large and Clustered Networks. Graph Drawing 2006
  - Touchgraph: http://www.touchgraph.com/TGFacebookBrowser.html

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