School of Information
University of Michigan

Networks over time

Outline (networks over time)

- dynamic appearance/disappearance of individual nodes and links
  - new links (university email network over time)
  - team assembly (coauthor & collaborator networks)
  - evolution of affiliation network related to social network (online groups, CS conferences)
- evolution of aggregate metrics:
  - densification & shrinking diameters (internet, citation, authorship, patents)
  - models:
    - community structure
    - forest file model

First some thought

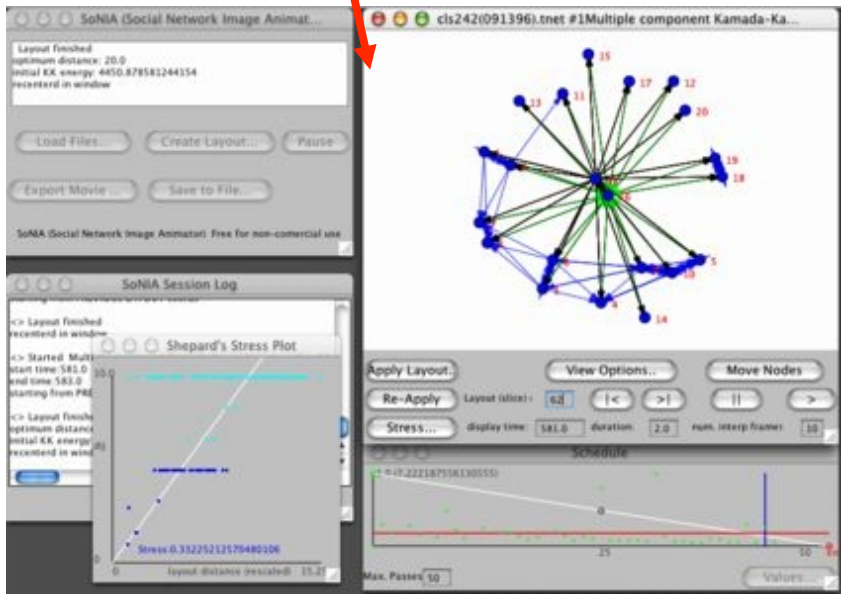
- What events can occur to change a network over time?
- What properties do you expect to remain roughly constant?
- What properties do you expect to change?

Where do you expect new edges to form?

Which edges do you expect to be dropped?

on the software side

- GUESS (range attribute, states, morphs)
- SONIA http://www.stanford.edu/group/sonia/ (visualizing networks over time(



	Effect	Estimate	Standard error
Rate function			
λ_0^X	Rate parameter t_1–t_2	11.74	1.25
λ_1^X	Rate parameter t_2–t_3	9.53	1.07
Objective function			
β_1^X	Density / out-degree	−2.17	0.05
β_2^X	Reciprocity	2.06	0.08
β_3^X	Number of distances 2	−0.80	0.013
β_4^X	Transitive triplets	0.17	0.009
β_5^X	Gender (F) popularity	−0.20	0.08
β_6^X	Gender (F) activity	0.18	0.08
β_7^X	Gender similarity	0.80	0.09
β_8^X	Smoking similarity	0.17	0.05

- SIENA http://stat.gamma.rug.nl/siena.html (includes statistical analysis of factors contributing to tie formation)

Empirical analysis of an evolving social network

- Gueorgi Kossinets & Duncan J. Watts
  - Science, Jan. 6th, 2006

- The data
  - university email logs
  - sender, recipient, timestamp
    - no content
  - 43,553 undergraduate and graduate students, faculty, staff
  - filtered out messages with more than 4 recipients (5% of messages)
  - 14,584,423 messages remaining sent over a period of 355 days (2003-2004 school year)

How does one choose new acquaintances in a social network?

- triadic closure: choose a friend of friend
- homophily: choose someone with similar interests
- proximity: choose someone who is close spatially and with whom you spend a lot of time
- seek novel information and resources
  - connect outside of circle of acquaintances
  - span structural holes between people who don't know each other
- sometimes social ties also dissolve
  - avoid conflicting relationships
  - reason for tie is removed: common interest, activity

weighted ties

$$w_{ij}(t,\tau) = \sqrt{m_{ij} m_{ji}} / \tau$$

- w_{ij} = weight of the tie between individuals i and j
- m = # of messages from i to j in the time period between (t-τ) and t
- "geometric rate" – because rates are multiplied together
  - high if email is reciprocated
  - low if mostly one-way
- τ serves as a relevancy horizon (30 days, 60 days…)
- 60 days chosen as window in study because rate of tie formation stabilizes after 60 days
- sliding window: compare networks day by day (but each day represents an overlapping 60 day window)

cyclic closure & focal closure

shortest path distance between i and j

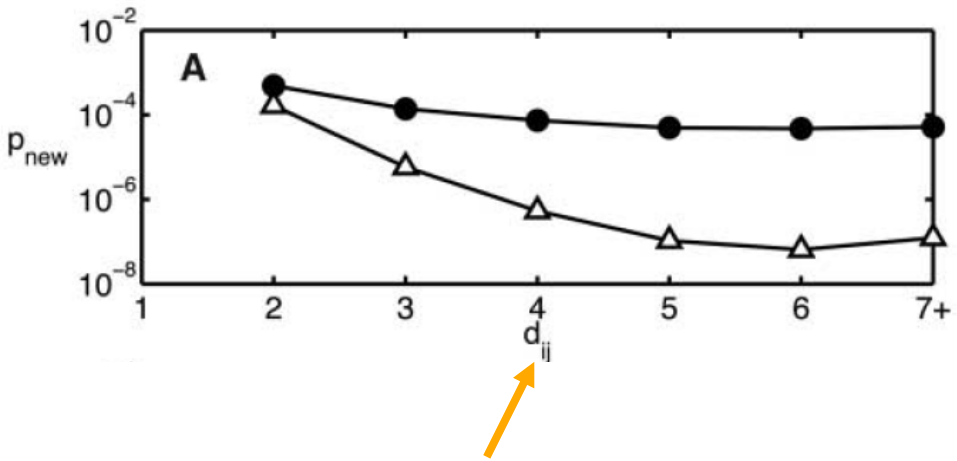
$$P_{new}(d_{ij}, s_{ij}) = \sum_{t=61}^{270} M_{new}(d_{ij}, s_{ij}, t) / \sum_{t=61}^{270} M(d_{ij}, s_{ij}, t)$$

new ties that appeared on day t

ties that were there in the past 60 days

number of common foci, i.e. classes

cyclic closure & focal closure



distance between two people in the email graph

● pairs that attend one or more classes together

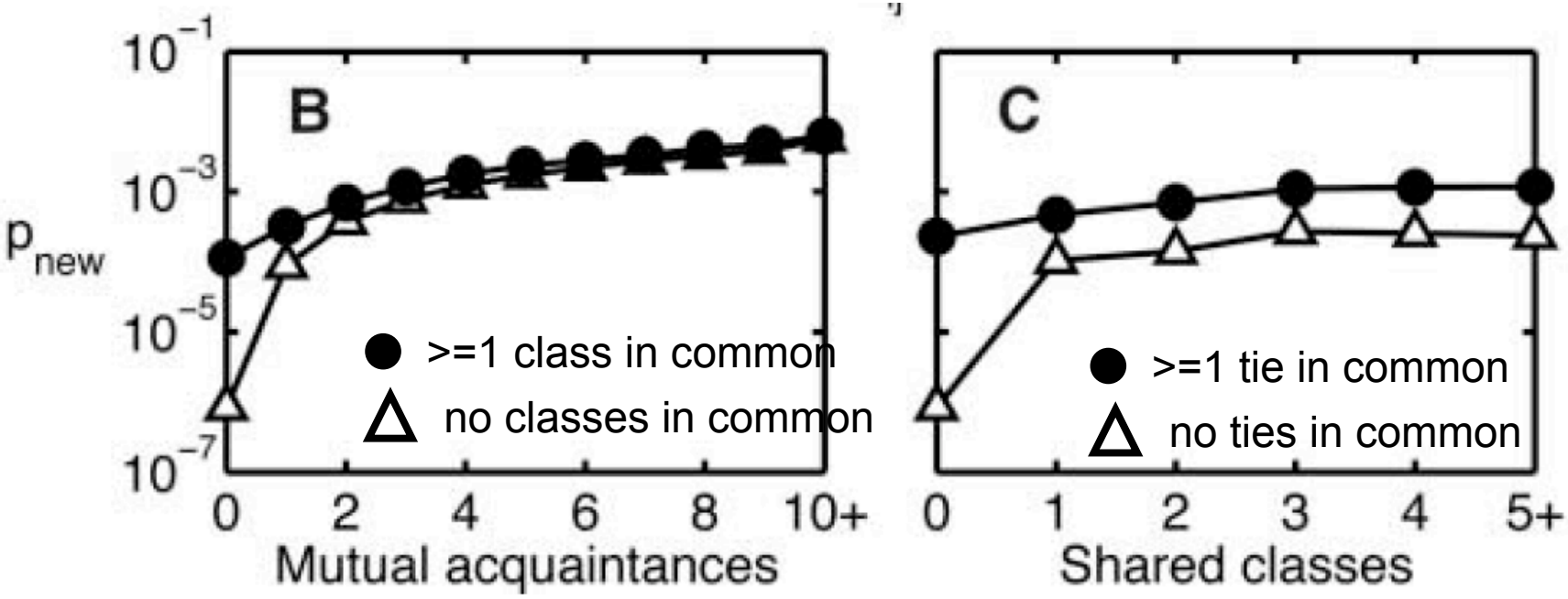
△ do not attend classes together

- Individuals who share at least one class are *three times* more likely to start emailing each other if they have an email contact in common
- If there is no common contact, then the probability of a new tie forming is lower, but ~ 140 times more likely if the individuals share a class than if they don't

Source: Empirical Analysis of an Evolving Social Network; Gueorgi Kossinets and Duncan J. Watts (6 January 2006) Science 311 (5757), 88.

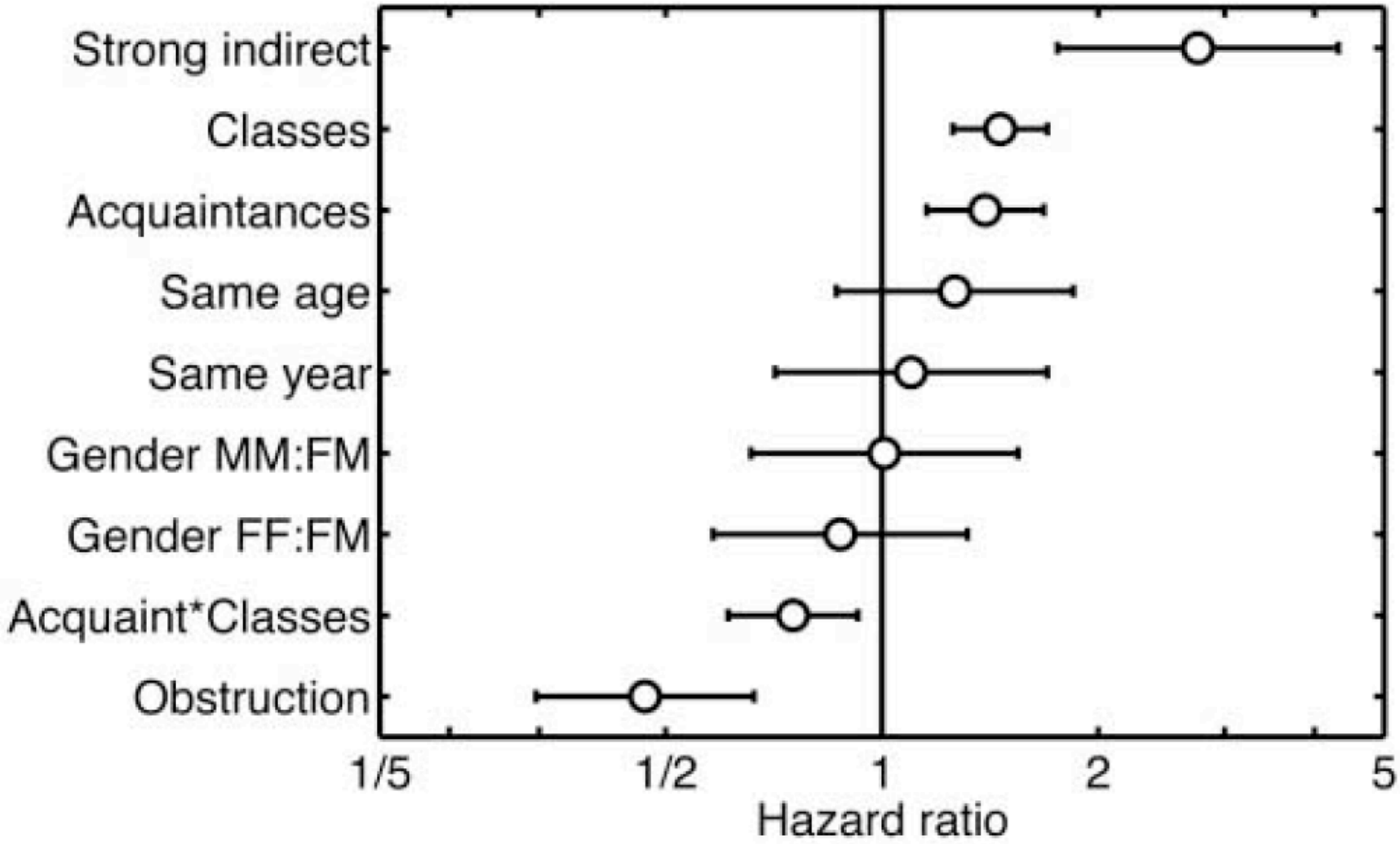
triads vs. # foci

- Having 1 tie or 1 class in common yield equal probability of a tie forming
- probability increases significantly for additional acquaintances, but rises modestly for additional foci



Source: Empirical Analysis of an Evolving Social Network; Gueorgi Kossinets and Duncan J. Watts (6 January 2006) Science 311 (5757), 88.

Multivariate analysis



Source: Empirical Analysis of an Evolving Social Network; Gueorgi Kossinets and Duncan J. Watts (6 January 2006) Science 311 (5757), 88.

the strength of ties

- the stronger the ties, the greater the likelihood of triadic closure
- bridges are on average weaker than other ties
- *but* bridges are more unstable:
  - may get stronger, become part of triads, or disappear

Issues in assembling teams

- Why assemble a team?
  - different ideas
  - different skills
  - different resources

Team Assembly Mechanisms: Determine Collaboration Network Structure and Team Performance
Roger Guimera, Brian Uzzi, Jarrett Spiro, Luıs A. Nunes Amaral; Science, 2005

- What spurs innovation?
  - applying proven innovations from one domain to another

- Is diversity (working with new people) always good?
  - spurs creativity + fresh thinking
  - but
    - conflict
    - miscommunication
    - lack of sense of security of working with close collaborators

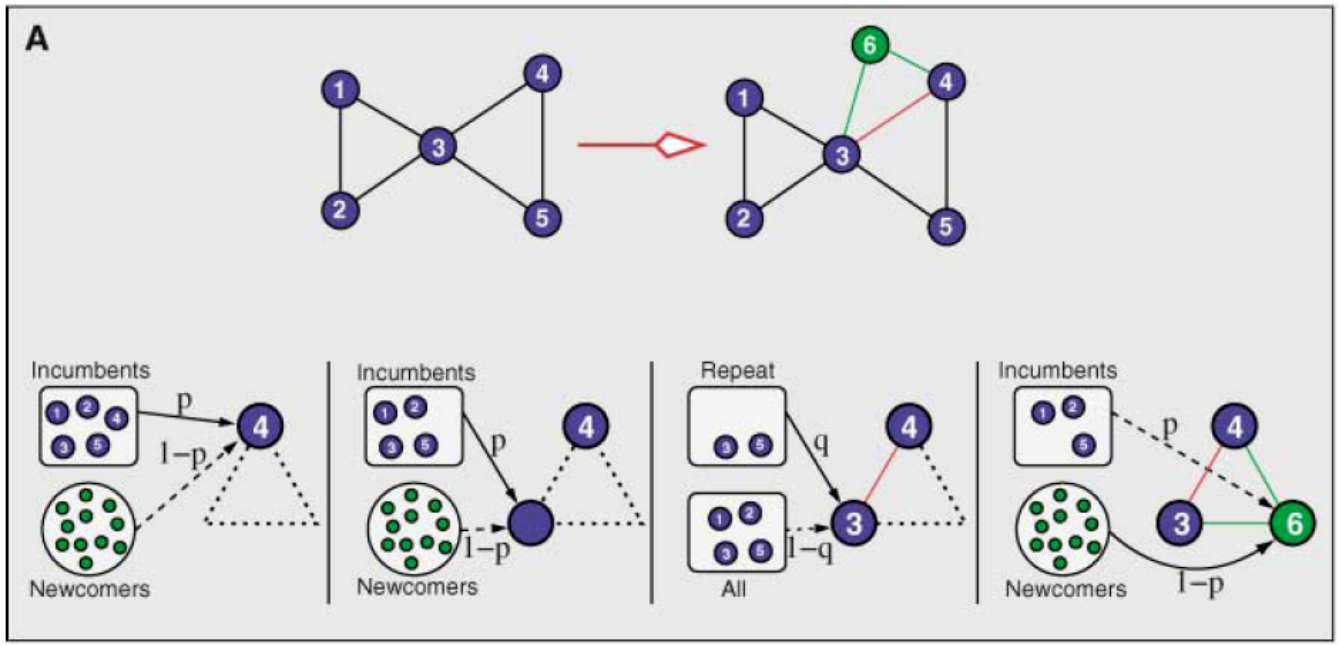
Parameters in team assembly

1. *m*, # of team members
2. *p*, probability of selecting individuals who already belong to the network
3. *q*, propensity of incumbents to select past collaborators

Two phases

- giant component of interconnected collaborators
- isolated clusters

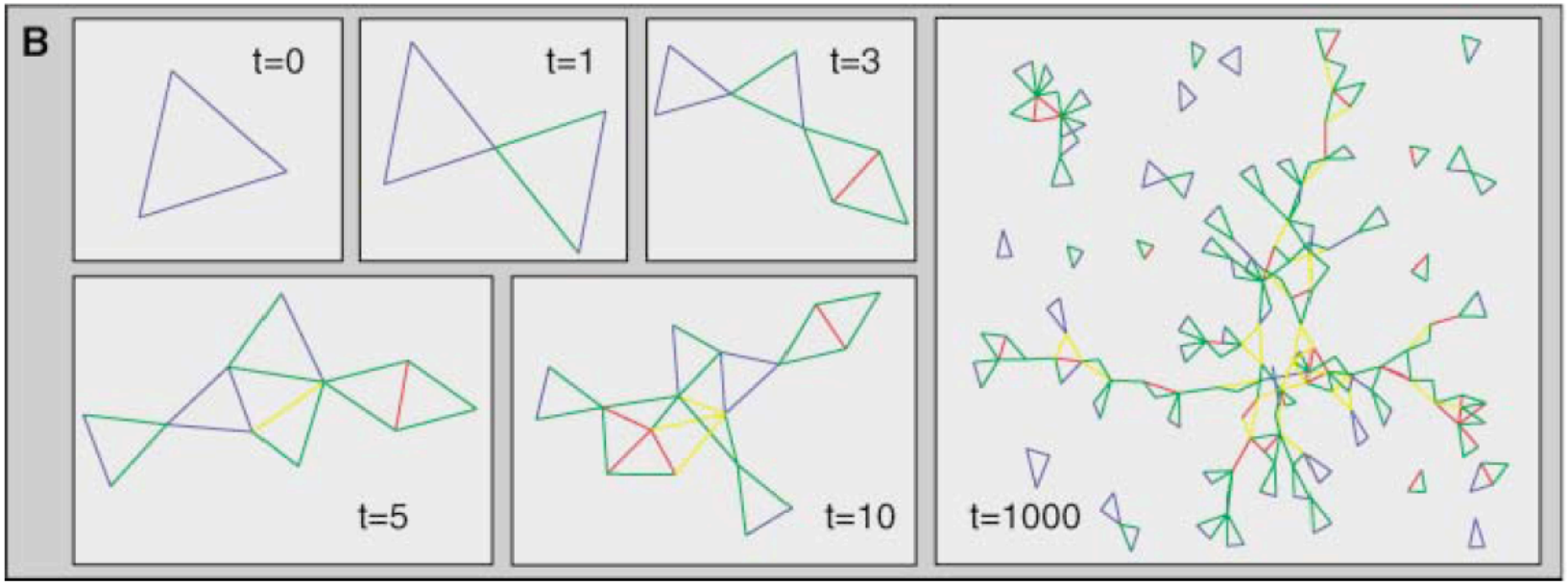
creation of a new team



- incumbents (people who have already collaborated with someone)
- newcomers (people available to participate in new teams)
- pick incumbent with probability p
  - if incumbent, pick past collaborator with probability q

Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

Time evolution of a collaboration network



- newcomer-newcomer collaborations
- newcomer-incumbent collaborations
- new incumbent-incumbent collaborations
- repeat collaborations

after a time τ of inactivity, individuals are removed from the network

Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

BMI data

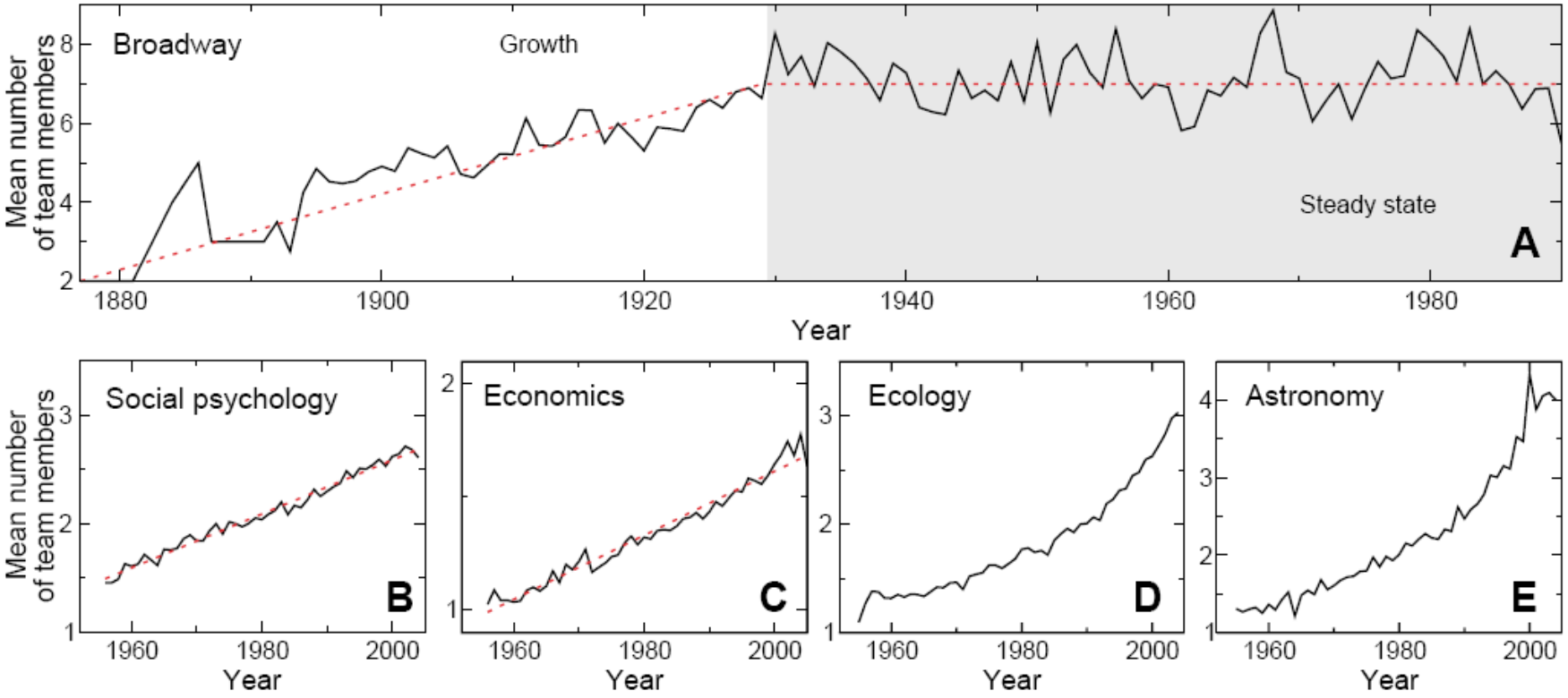
- Broadway musical industry
  - 2258 productions
  - from 1877 to 1990
  - musical shows performed at least once on Broadway
  - team: composers, writers, choreographers, directors, producers but *not* actors
  - Team size increases from 1877-1929
    - the musical as an art form is still evolving
  - After 1929 team composition stabilizes to include 7 people:
    - choreographer, composer, director, librettist, lyricist, producer

Collaboration networks

- 4 fields (with the top journals in each field)
  - social psychology (7)
  - economics (9)
  - ecology (10)
  - astronomy (4)

- impact factor of each journal
  - ratio between citations and recent citable items published
    - **A**= total cites in 1992
    - **B**= 1992 cites to articles published in 1990-91 (this is a subset of A)
    - **C**= number of articles published in 1990-91
    - **D**= B/C = 1992 impact factor

size of teams grows over time

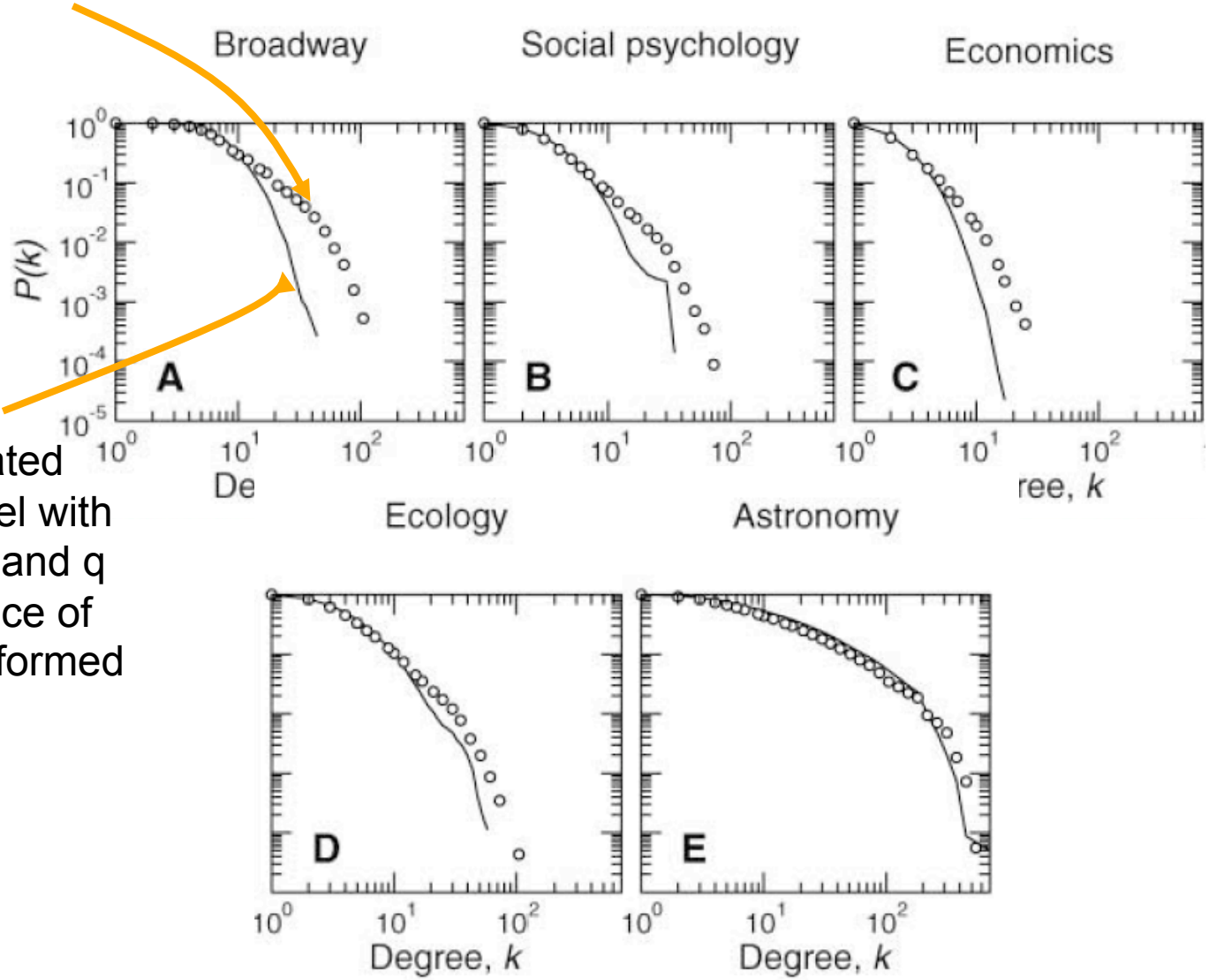


Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

degree distributions

data

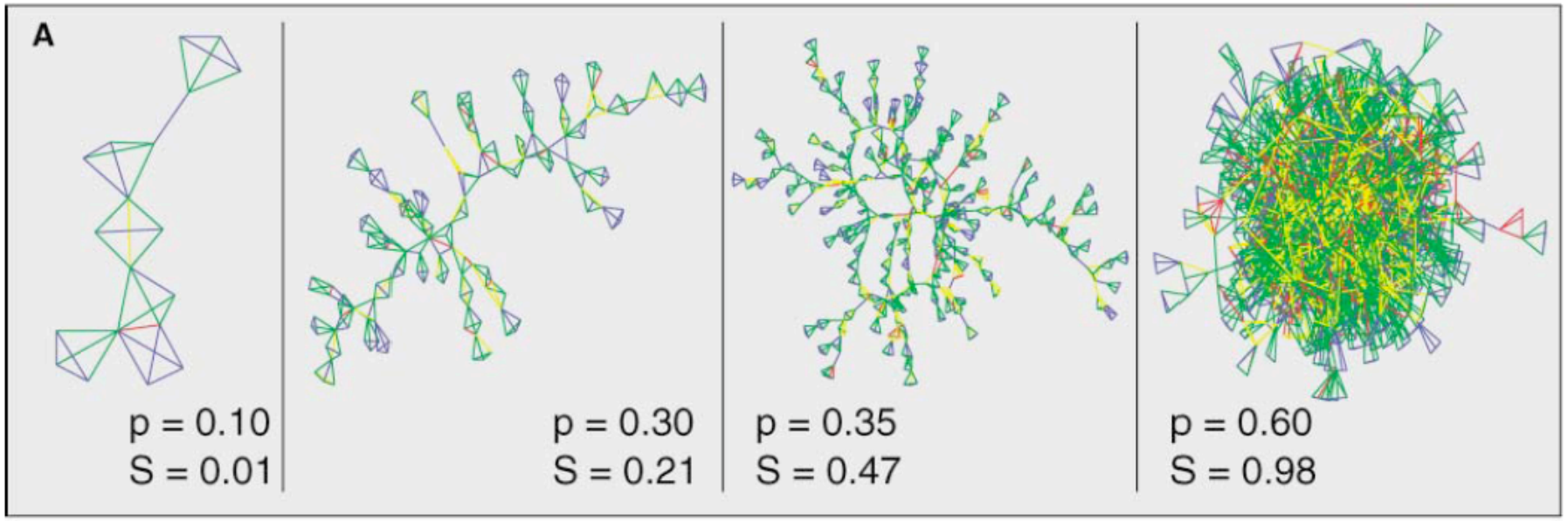
data generated from a model with the same p and q and sequence of team sizes formed



Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

Predictions for the size of the giant component

- higher p means already published individuals are co-authoring – linking the network together and increasing the giant component

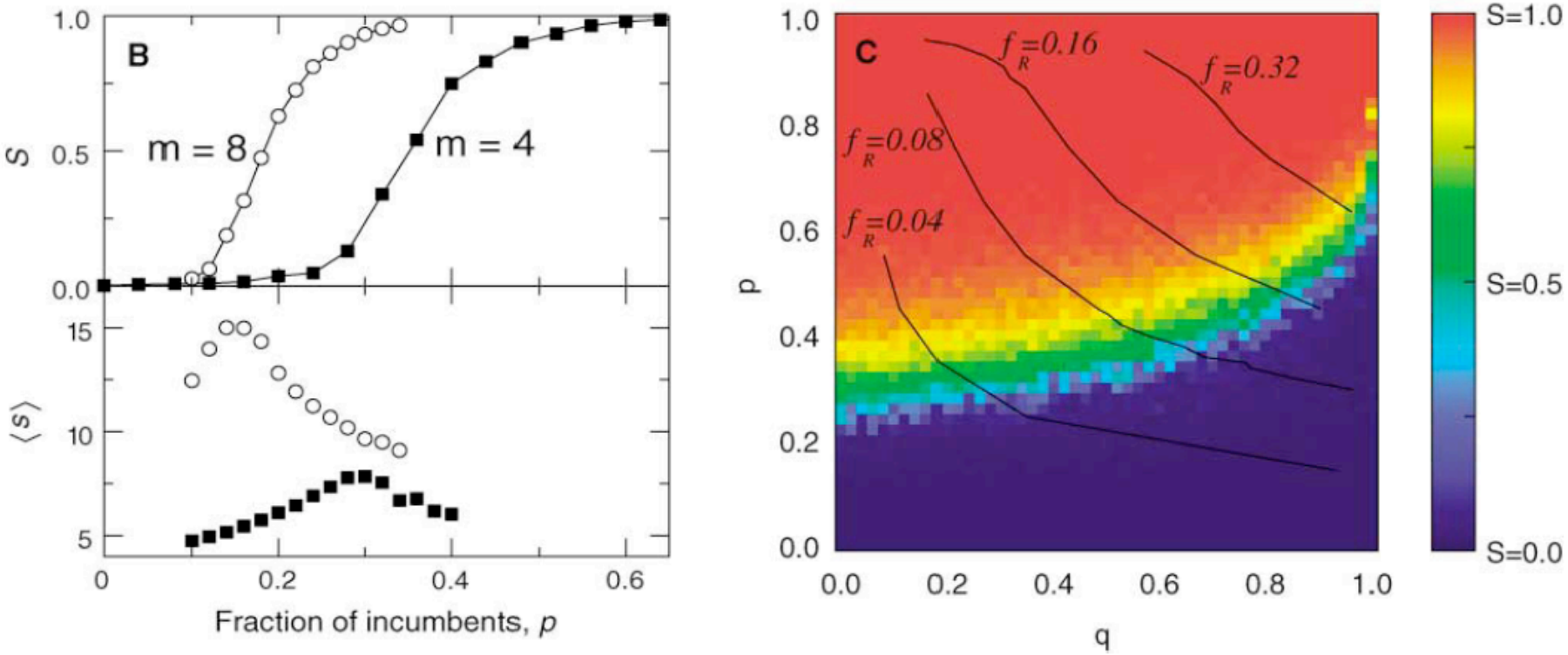


S = fraction of network occupied by the giant component

Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

Predictions for the size of the giant component (cont'd)

- increasing q can slow the growth of the giant component – co-authoring with previous collaborators does not create new edges (f_R = fraction of repeat incumbent-incumbent links)



Source: Team Assembly Mechanisms Determine Collaboration Network Structure and Team Performance; Roger Guimerà, Brian Uzzi, Jarrett Spiro, and Luís A. Nunes Amaral (29 April 2005) Science 308 (5722), 697.

network statistics

Field	teams	individuals	p	q	f_R	S (size of giant component)
BMI	2258	4113	0.52	0.77	0.16	0.70
social psychology	16,526	23,029	0.56	0.78	0.22	0.67
economics	14,870	23,236	0.57	0.73	0.22	0.54
ecology	26,888	38,609	0.59	0.76	0.23	0.75
astronomy	30,552	30,192	0.76	0.82	0.39	0.98

what stands out?

what is similar across the networks?

main findings

- all networks except astronomy close to the “tipping” point where giant component emerges
  - sparse and stringy networks
- giant component takes up more than 50% of nodes in each network
- impact factor (how good the journal is where the work was published)
  - p positively correlated
    - going with experienced members is good
  - q negatively correlated
    - new combinations more fruitful

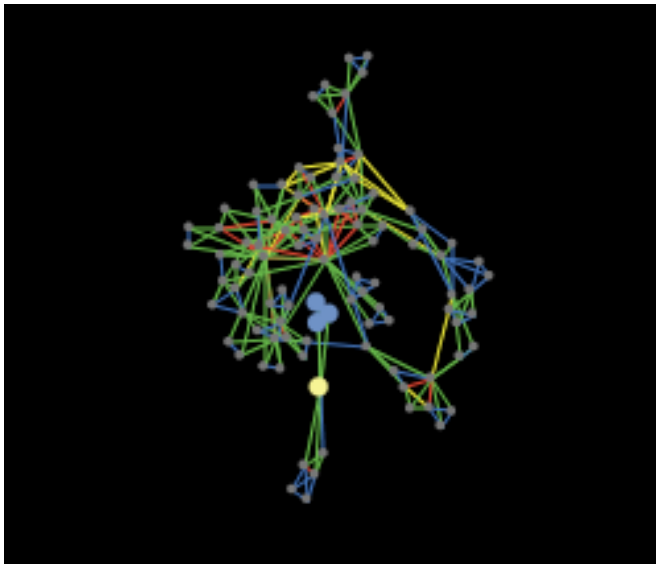
  } ecology, economics, social psychology

  - S for individual journals positively correlated
    - more isolated clusters in lower-impact journals

  } ecology, social psychology

team assembly lab

- In NetLogo demo library:
  - what happens as you increase the probability of choosing a newcomer?
  - what happens as you increase the probability of a repeat collaboration between same two nodes?



http://ccl.northwestern.edu/netlogo/models/TeamAssembly

Group Formation in Large Social Networks: Membership, Growth, and Evolution

- Backstrom, Huttenlocher, Kleinberg, Lan @ KDD 2006

- data:
  - LiveJournal
  - DBLP

the more friends you have in a group, the more likely you are to join

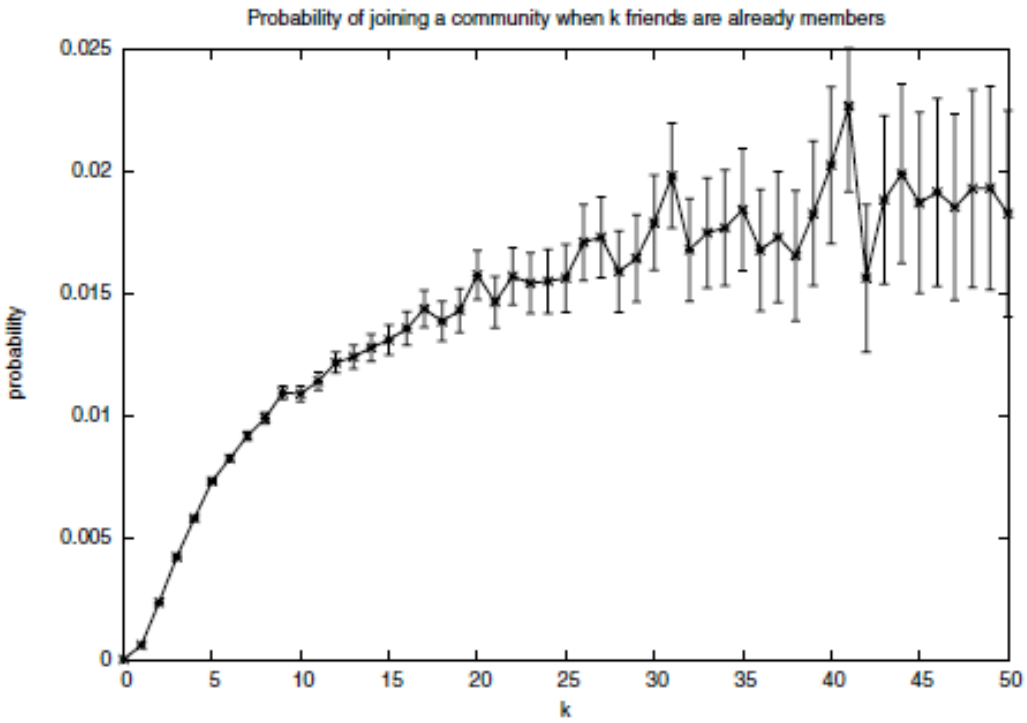


Figure 1: The probability p of joining a LiveJournal community as a function of the number of friends k already in the community. Error bars represent two standard errors.

Source: Backstrom, L., D. Huttenlocher, J. Kleinberg, and Et. Group formation in large social networks: Membership, growth, and evolution.

if it's a "group" of friends that have joined...

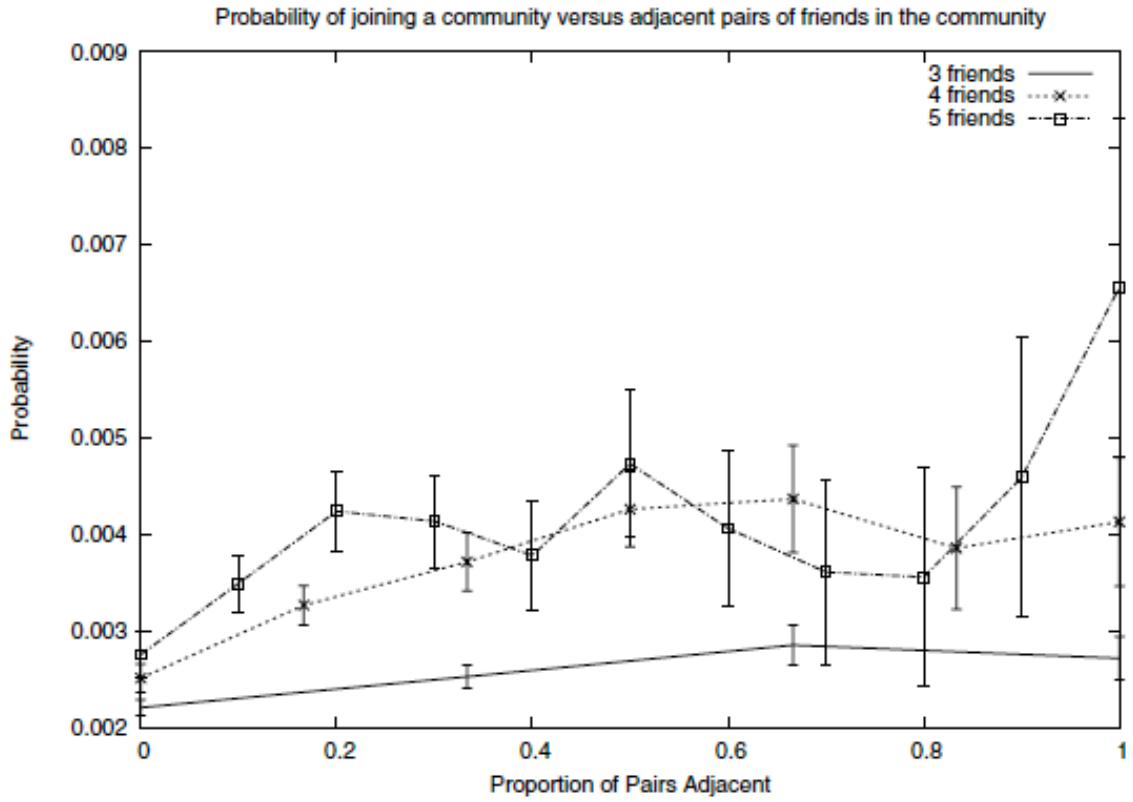


Figure 4: The probability of joining a LiveJournal community as a function of the internal connectedness of friends already in the community. Error bars represent two standard errors.

Source: Backstrom, L., D. Huttenlocher, J. Kleinberg, and Et. Group formation in large social networks: Membership, growth, and evolution.

but community growth is slower if entirely cliquish...

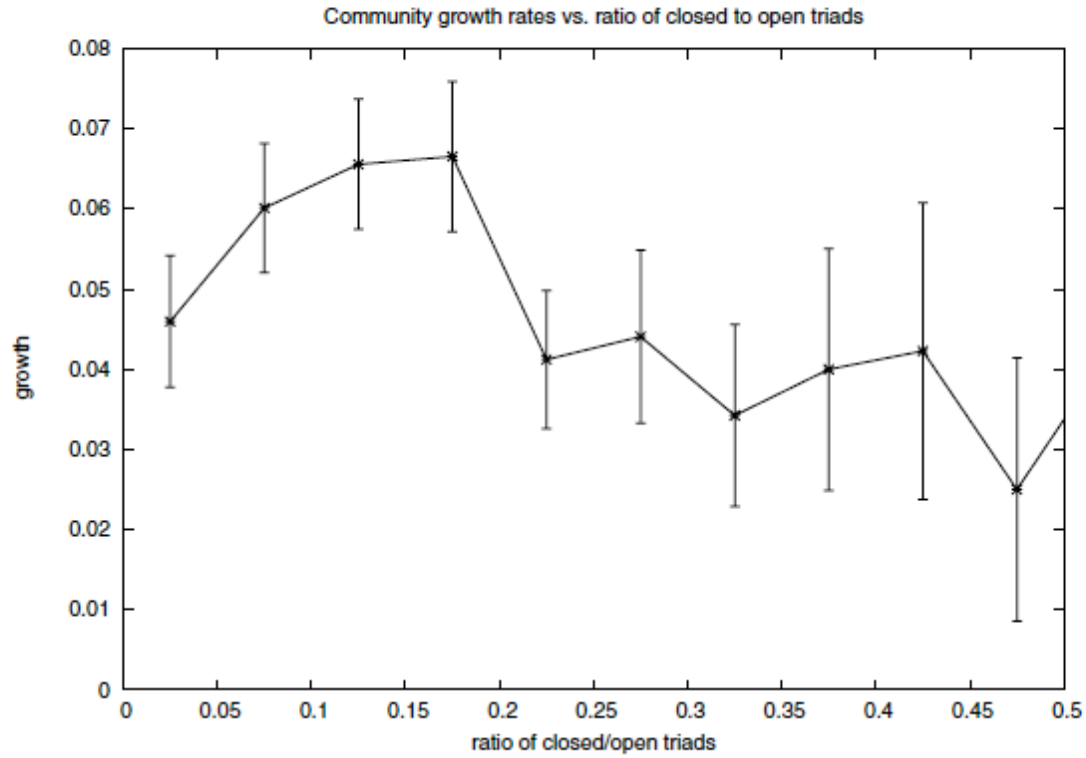


Figure 6: The rate of community growth as a function of the ratio of closed to open triads: having a large density of closed triads (triangles) is negatively related to growth. Error bars represent two standard errors.

Source: Backstrom, L., D. Huttenlocher, J. Kleinberg, and Et. Group formation in large social networks: Membership, growth, and evolution.

group formation & social networks (summary)

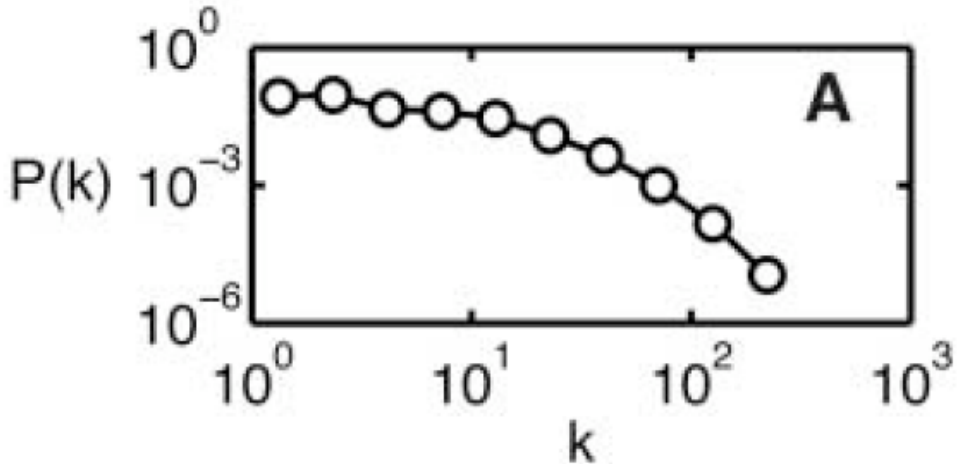
- if your friends join, so will you
- if your friends who join know one another, you're even more likely to join
- cliquish communities grow more slowly

evolution of aggregate network metrics

- as individual nodes and edges come and go, how do aggregate features change?
  - degree distribution?
  - clustering coefficient?
  - average shortest path?

university email network:

- properties such as degree distribution, average shortest path, and size of giant component have seasonal variation (summer break, start of semester, etc.)
  - appropriate smoothing window (τ) needed
- clustering coefficient, shape of degree distribution constant
  - *but* rank of individuals changes over time



Source: Empirical Analysis of an Evolving Social Network; Gueorgi Kossinets and Duncan J. Watts (6 January 2006) Science 311 (5757), 88.

an empirical puzzle of network evolution: Graph Densification

- Densification Power Law

$$E(t) \propto N(t)^a$$

- Densification exponent: $1 \leq a \leq 2$:
  - a=1: linear growth – constant out-degree (assumed in the literature so far)
  - a=2: quadratic growth – clique

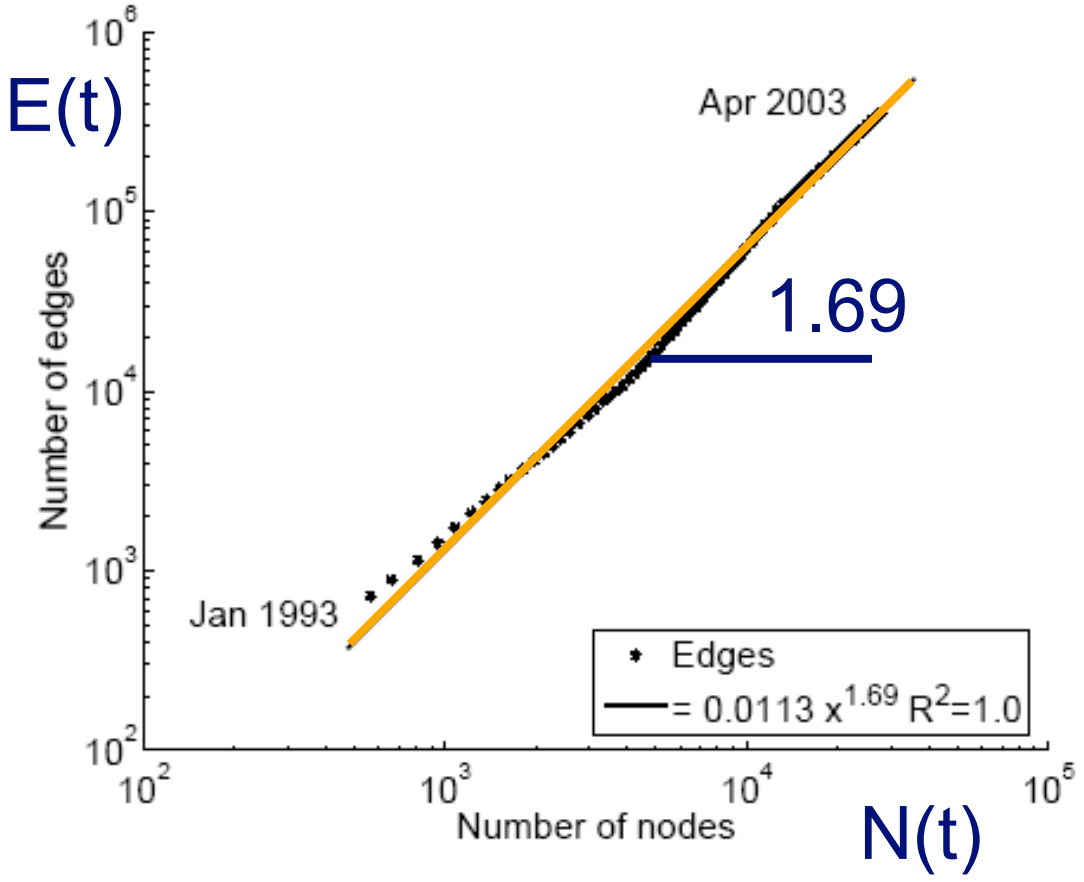
- Let's see the real graphs!

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Densification – Physics Citations

- Citations among physics papers
- 1992:
  - 1,293 papers, 2,717 citations
- 2003:
  - 29,555 papers, 352,807 citations
- For each month *M*, create a graph of all citations up to month *M*

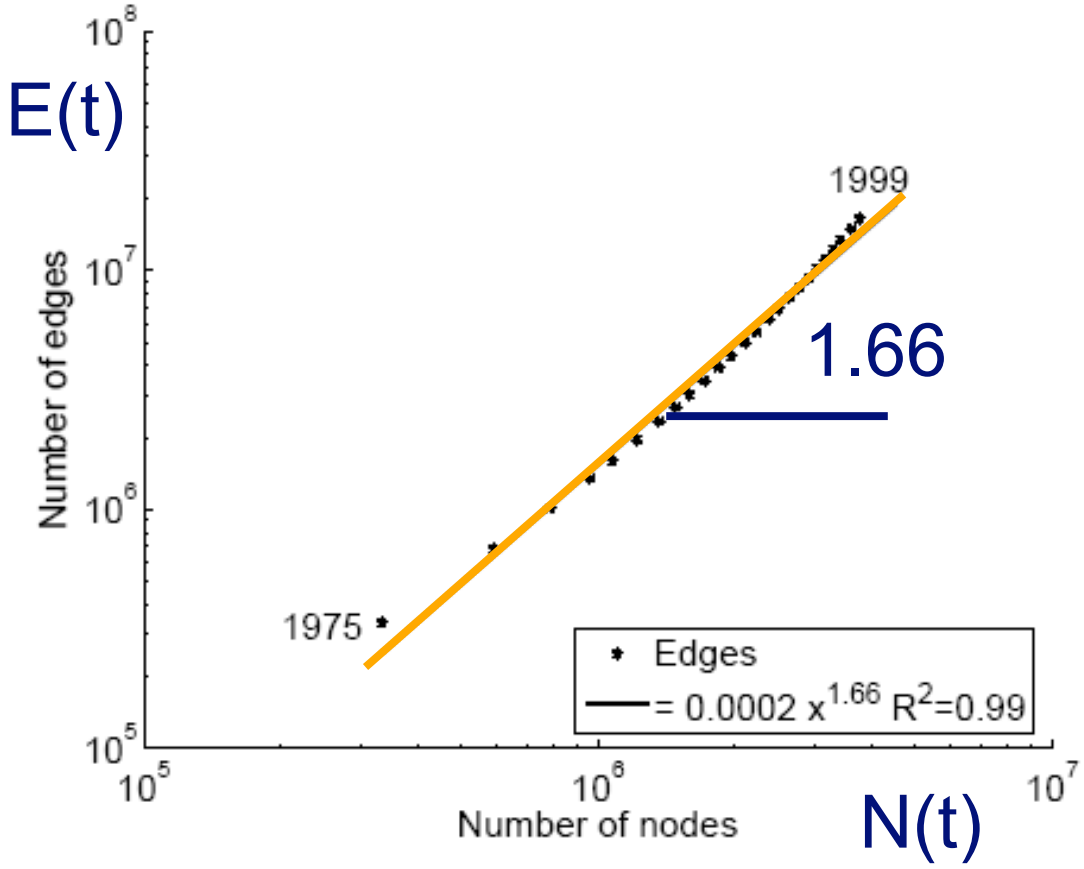


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Densification – Patent Citations

- Citations among patents granted
- 1975
  - 334,000 nodes
  - 676,000 edges
- 1999
  - 2.9 million nodes
  - 16.5 million edges
- Each year is a datapoint

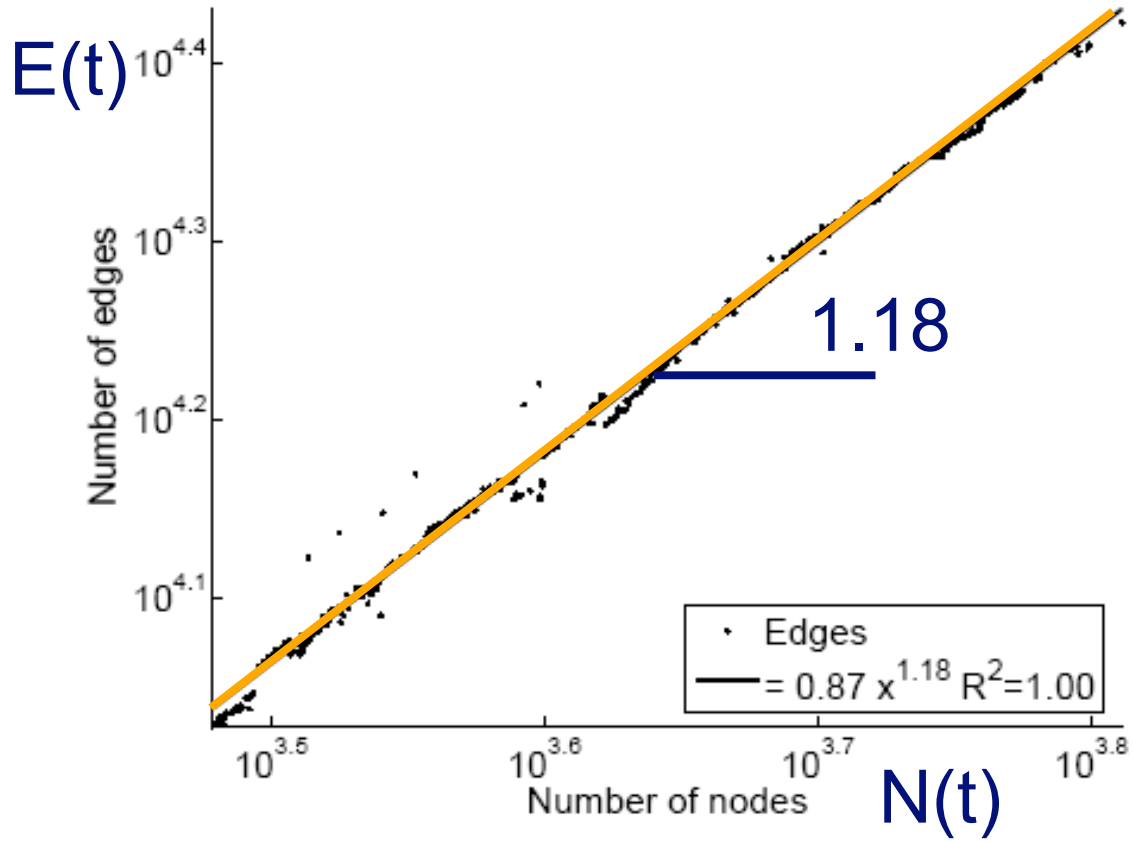


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Densification – Autonomous Systems

- Graph of Internet
- 1997
  - 3,000 nodes
  - 10,000 edges
- 2000
  - 6,000 nodes
  - 26,000 edges
- One graph per day

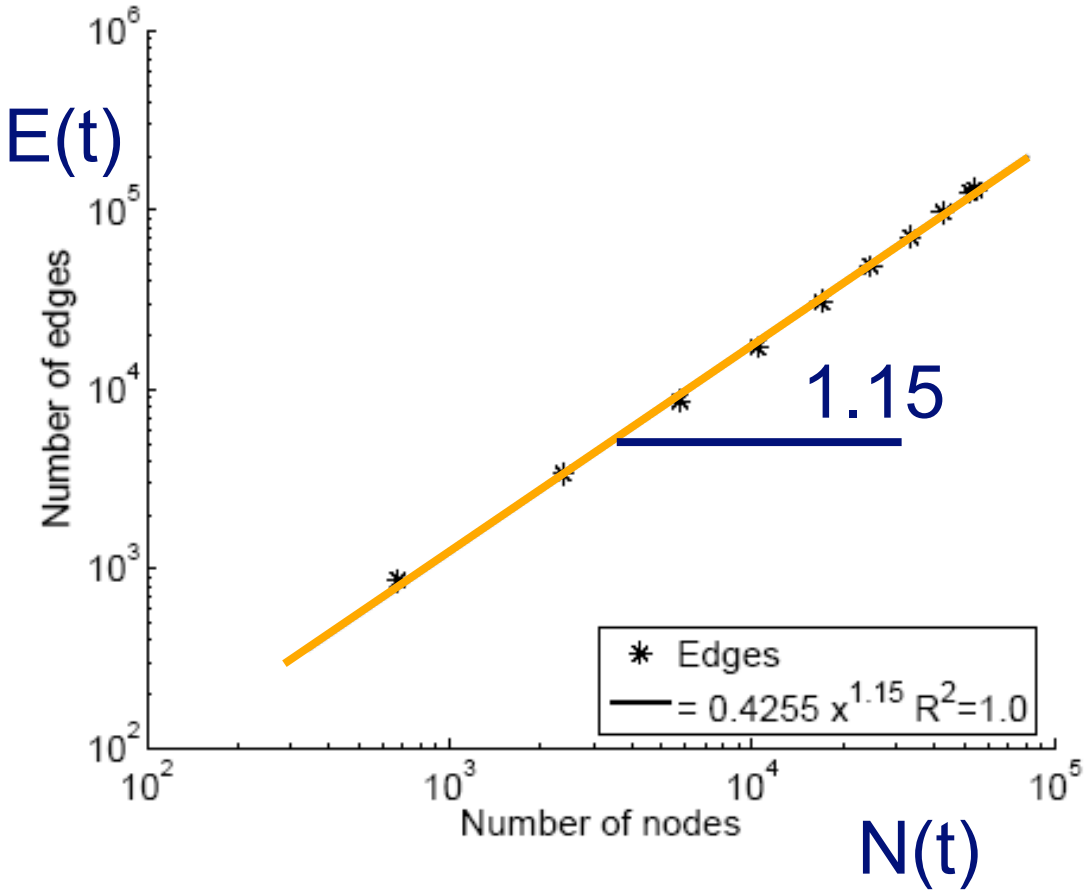


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Densification – Affiliation Network

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



slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Graph Densification – Summary

- The traditional constant out-degree assumption does not hold
- Instead:

$$E(t) \propto N(t)^a$$

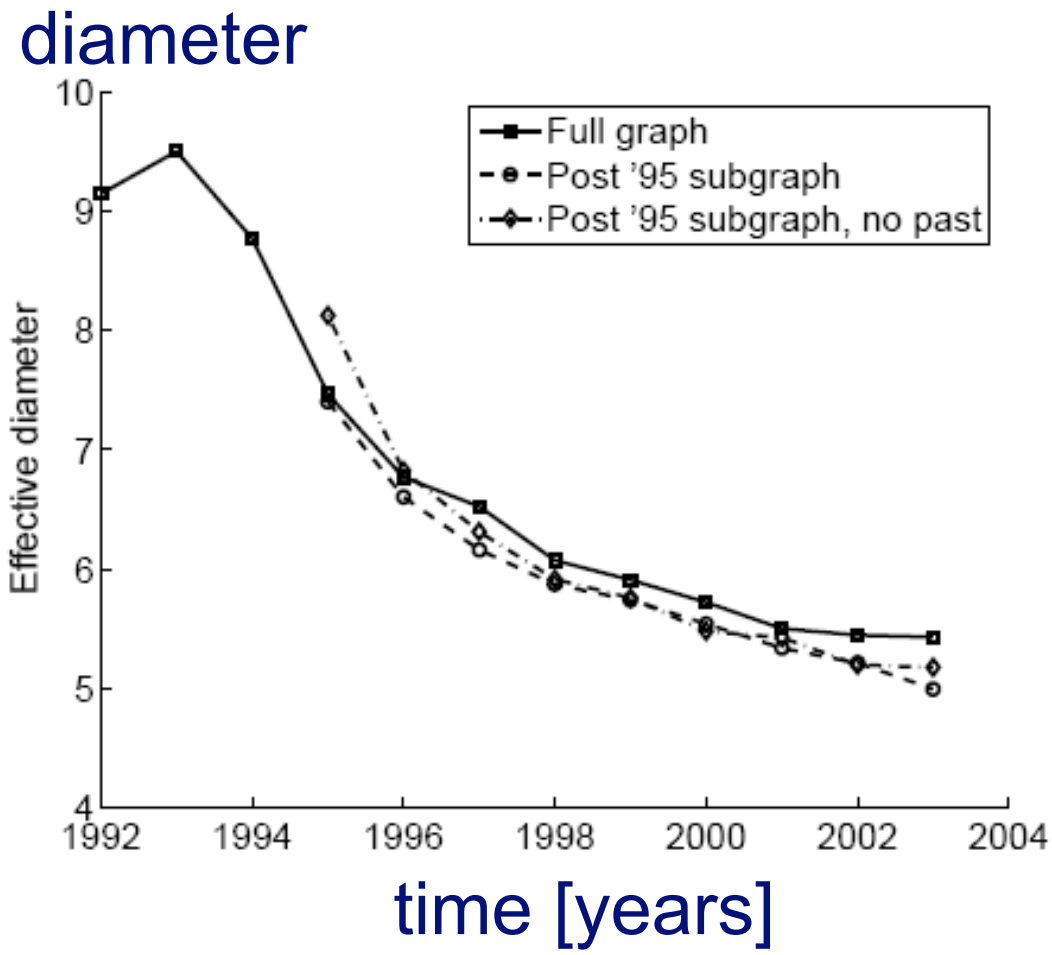
- the number of edges grows faster than the number of nodes – average degree is increasing

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Diameter – ArXiv citation graph

- Citations among physics papers
- 1992 –2003
- One graph per year

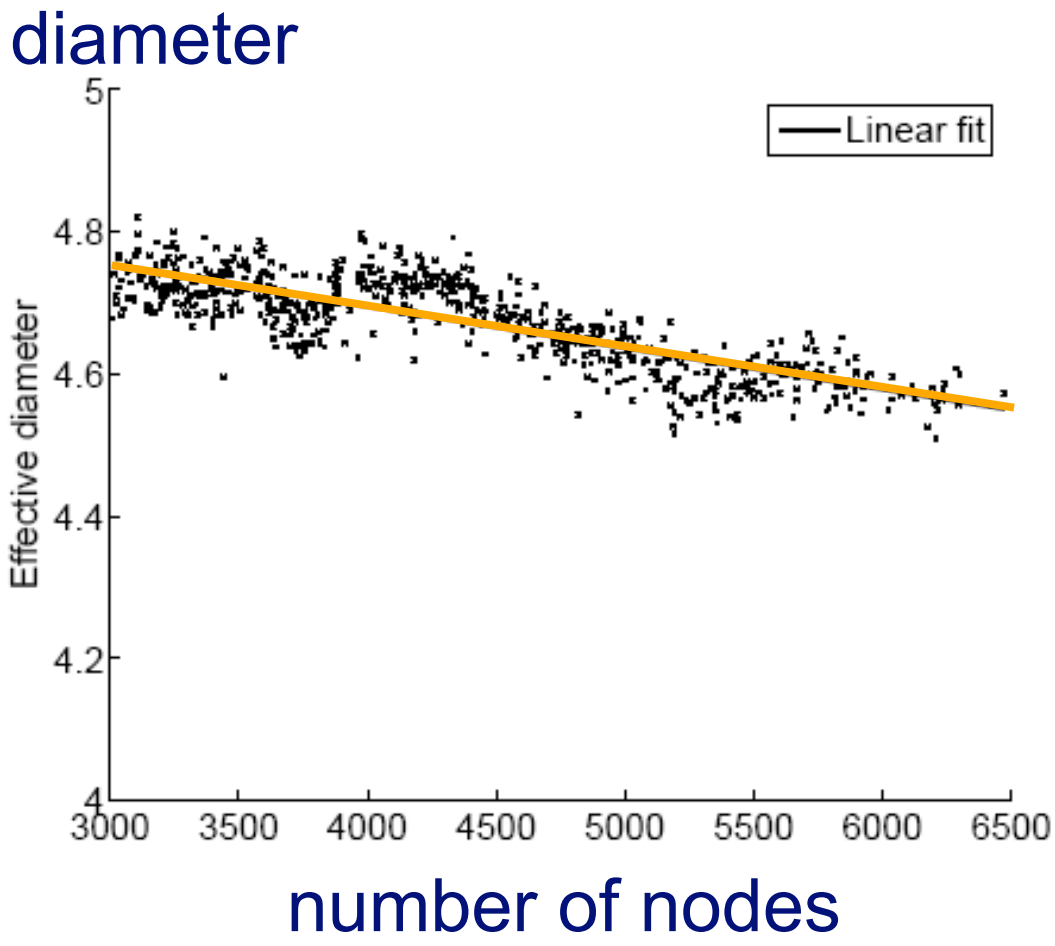


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Diameter – "Autonomous Systems"

- Graph of Internet
- One graph per day
- 1997 – 2000



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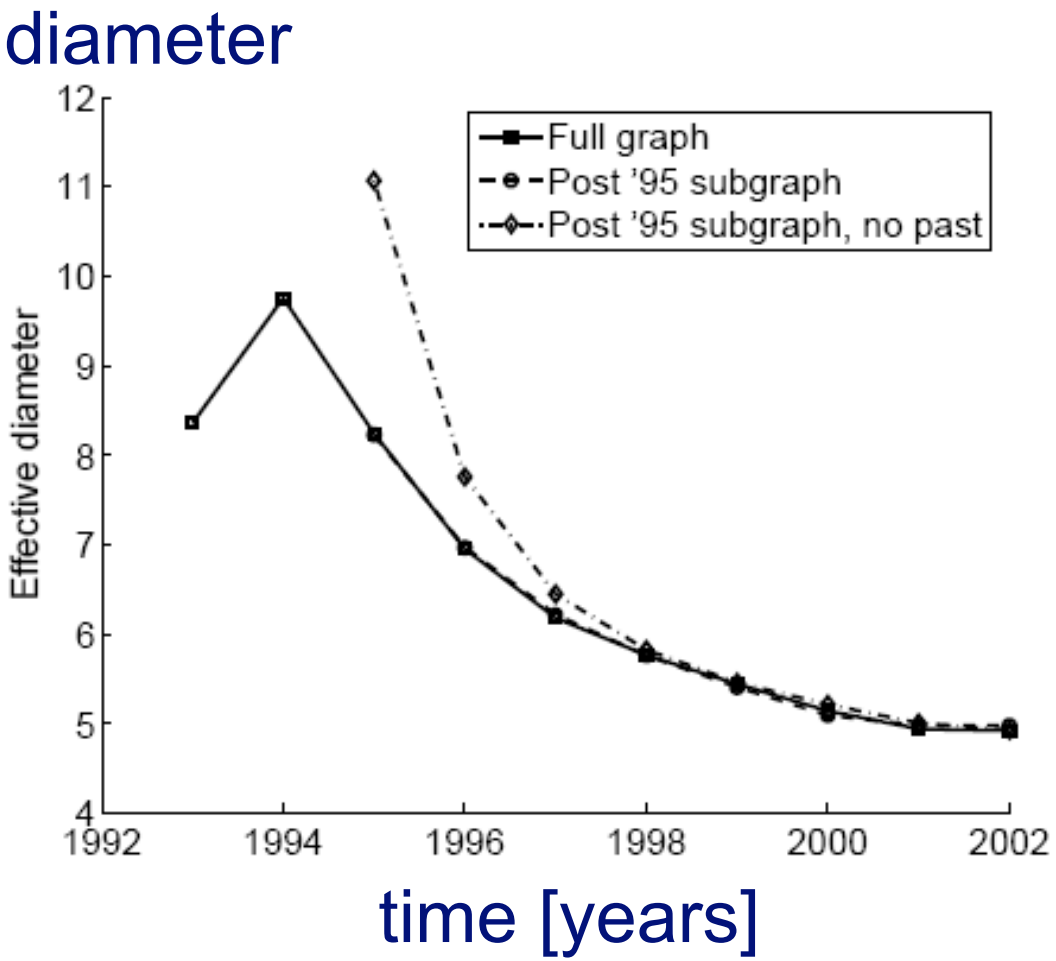
Source: *Leskovec et al. KDD 2005*

Diameter – "Affiliation Network"

- Graph of collaborations in physics – authors linked to papers
- 10 years of data

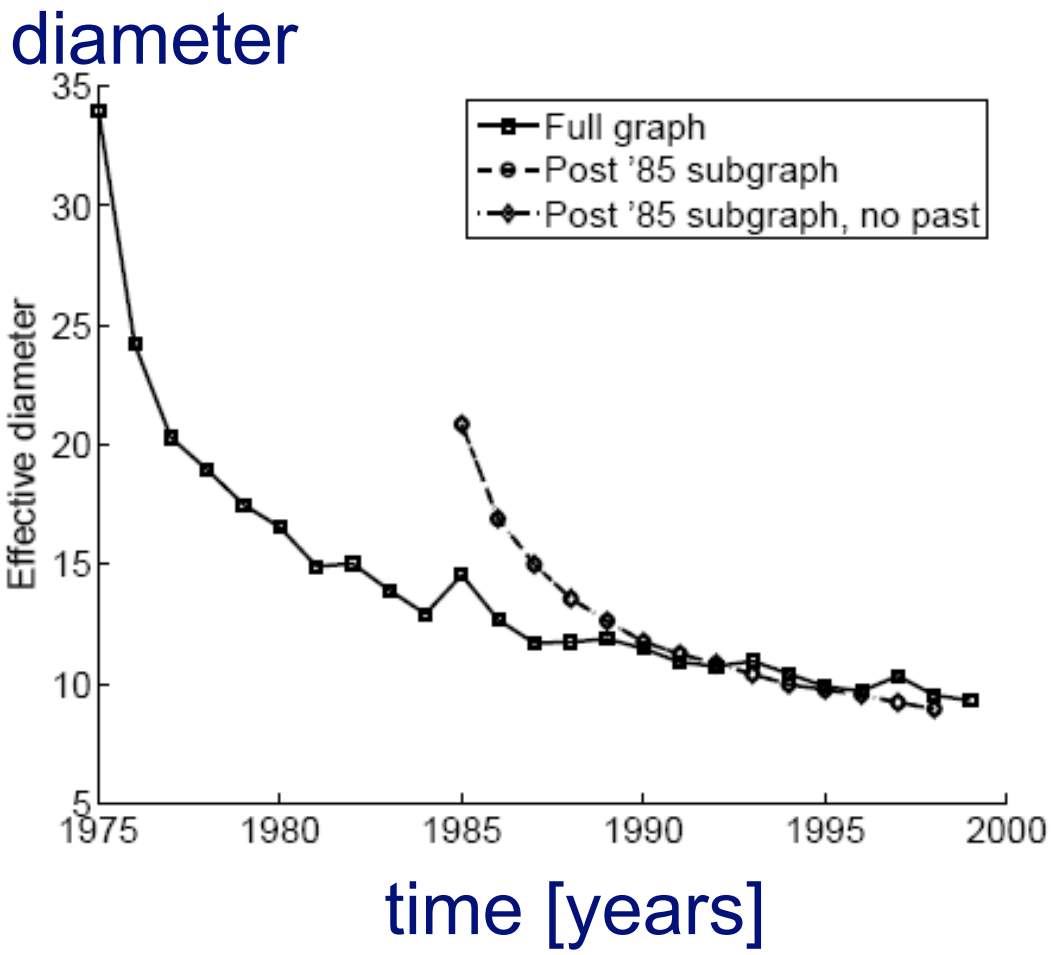


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Diameter – "Patents"

- Patent citation network
- 25 years of data



slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Densification – Possible Explanation

- Existing graph generation models do not capture the Densification Power Law and Shrinking diameters
- Can we find a simple model of local behavior, which naturally leads to observed phenomena?

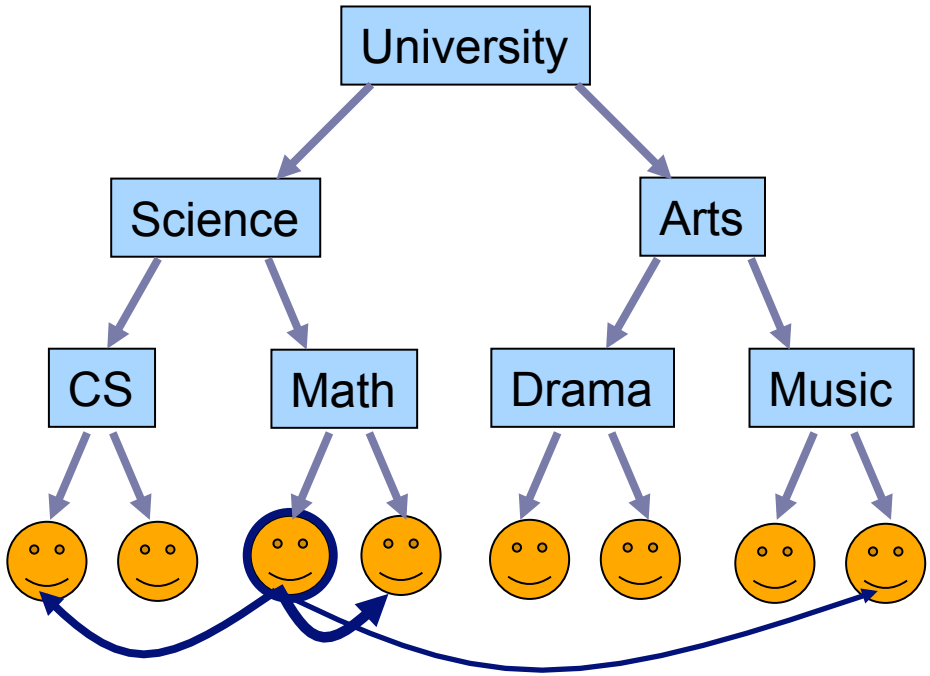
- Yes! We present 2 models:
  - Community Guided Attachment – obeys Densification
  - Forest Fire model – obeys Densification, Shrinking diameter (and Power Law degree distribution)

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Community structure

- Let's assume the community structure
- One expects many within-group friendships and fewer cross-group ones
- How hard is it to cross communities?



Self-similar university community structure

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Fundamental Assumption

- If the cross-community linking probability of nodes at tree-distance *h* is scale-free
- cross-community linking probability:

$$f(h) = c^{-h}$$

where: $c \geq 1$ … the *Difficulty constant*

h … tree-distance

slide by Jure Leskovec

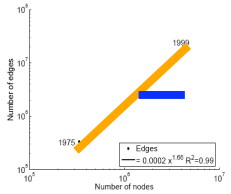
Source: *Leskovec et al. KDD 2005*

Densification Power Law (1)

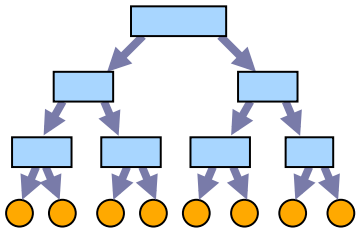
- Theorem: The Community Guided Attachment leads to Densification Power Law with exponent

$$a = 2 - \log_b(c)$$

- a … densification exponent
- b … community structure branching factor
- c … difficulty constant



$$E(t) \propto N(t)^a$$



slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Difficulty Constant

- Theorem:

$$a = 2 - \log_b(c)$$

- Gives any non-integer Densification exponent
- If c = 1: easy to cross communities
  - Then: a=2, quadratic growth of edges – near clique
- If c = b: hard to cross communities
  - Then: a=1, linear growth of edges – constant out-degree

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Room for Improvement

- Community Guided Attachment explains Densification Power Law
- Issues:
  - Requires explicit Community structure
  - Does not obey Shrinking Diameters

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

“Forest Fire” model – Wish List

- Want no explicit Community structure
- Shrinking diameters
- and:
  - “Rich get richer” attachment process, to get heavy-tailed in-degrees
  - “Copying” model, to lead to communities
  - Community Guided Attachment, to produce Densification Power Law

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

“Forest Fire” model – Intuition (1)

- How do authors identify references?
  1. Find first paper and cite it
  2. Follow a few citations, make citations
  3. Continue recursively
  4. From time to time use bibliographic tools (e.g. CiteSeer) and chase back-links

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

“Forest Fire” model – Intuition (2)

- How do people make friends in a new environment?
  1. Find first a person and make friends
  2. Follow a of his friends
  3. Continue recursively
  4. From time to time get introduced to his friends

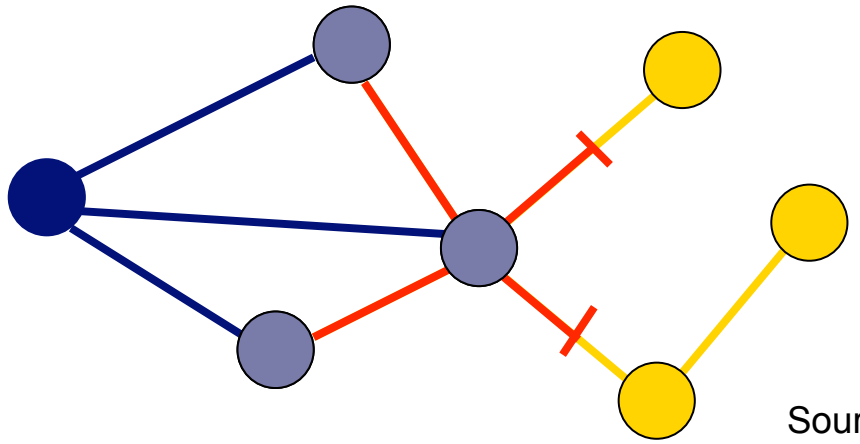
- Forest Fire model imitates exactly this process

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

“Forest Fire” – the Model

- A node arrives
- Randomly chooses an “ambassador”
- Starts burning nodes (with probability *p*) and adds links to burned nodes
- “Fire” spreads recursively

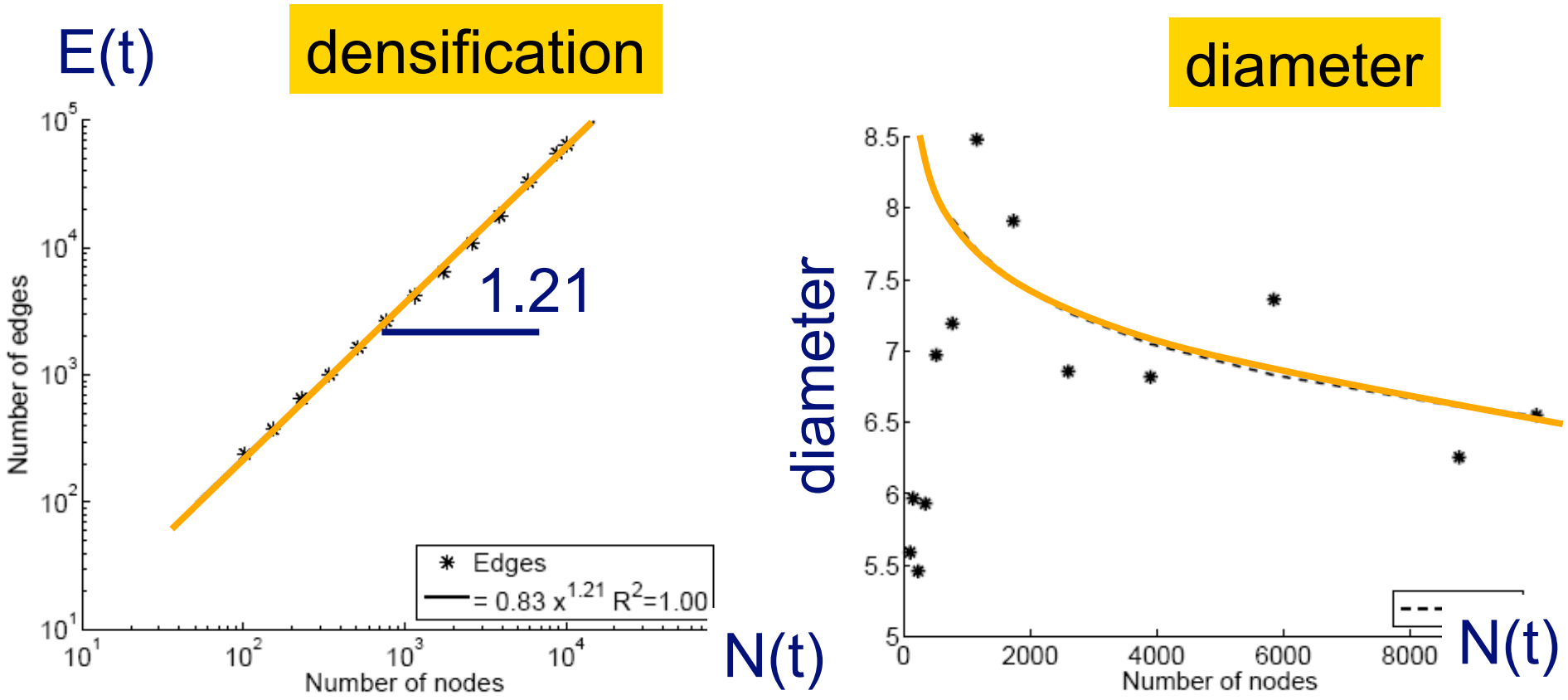


slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Forest Fire in Action (1)

- Forest Fire generates graphs that Densify and have Shrinking Diameter

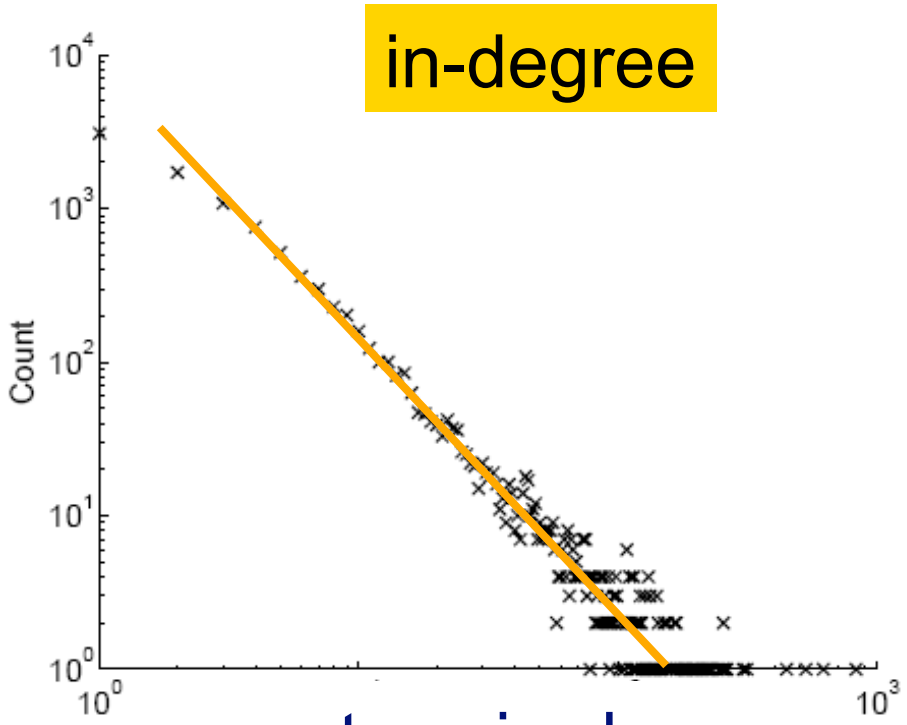


slide by Jure Leskovec

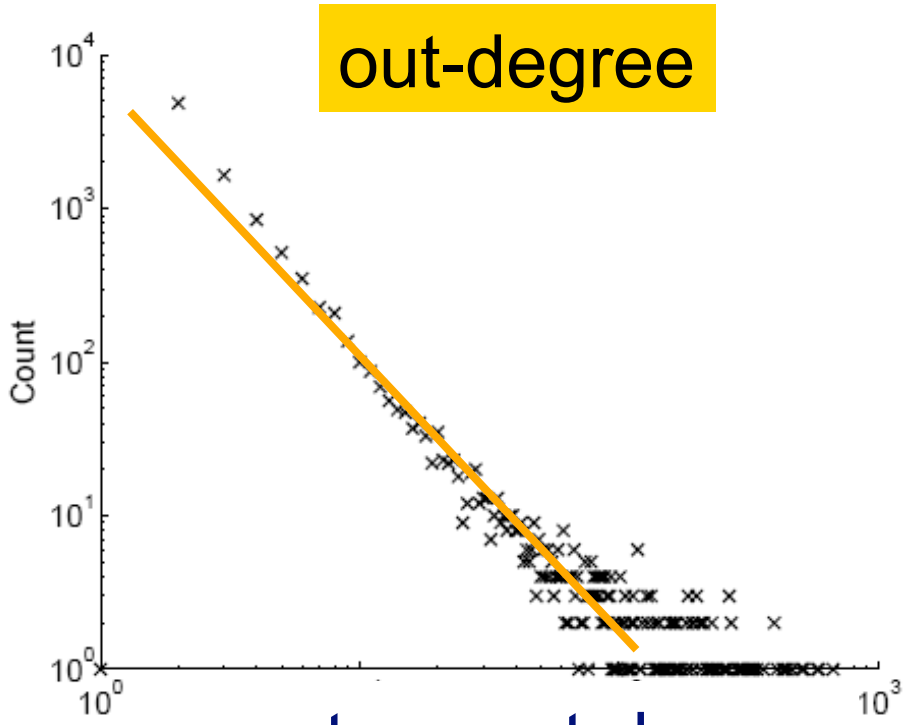
Source: *Leskovec et al. KDD 2005*

Forest Fire in Action (2)

- Forest Fire also generates graphs with heavy-tailed degree distribution



count vs. in-degree



count vs. out-degree

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Forest Fire model – Justification

- Densification Power Law:
  - Similar to Community Guided Attachment
  - The probability of linking decays exponentially with the distance – Densification Power Law
- Power law out-degrees:
  - From time to time we get large fires
- Power law in-degrees:
  - The fire is more likely to burn hubs

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

Forest Fire model – Justification

- Communities:
  - Newcomer copies neighbors' links
- Shrinking diameter

slide by Jure Leskovec

Source: *Leskovec et al. KDD 2005*

wrap up

- networks evolve
- we can sometimes predict where new edges will form
  - e.g. social networks tend to display triadic closure (friends introduce friends to other friends)
- network structure as a whole evolves
  - densification: edges are added at a greater rate than nodes
    - e.g. papers today have longer lists of references