

Preferential Attachment and Network Evolution

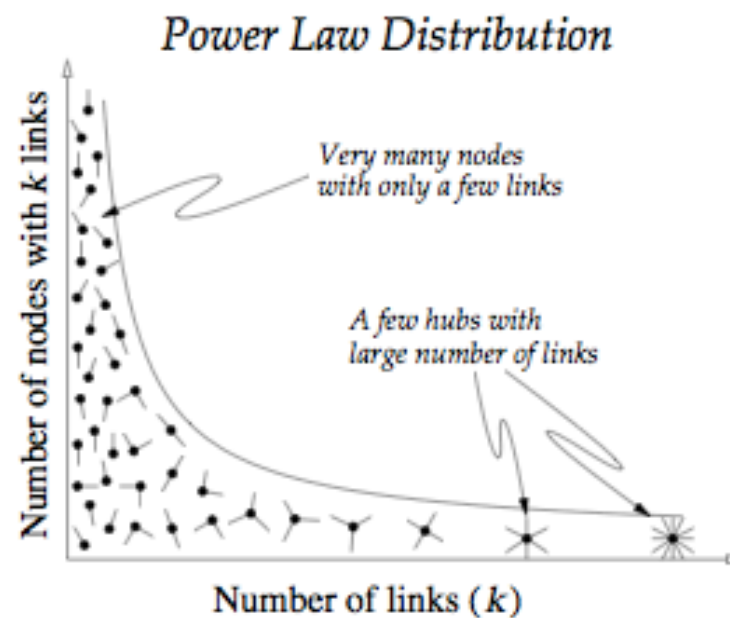
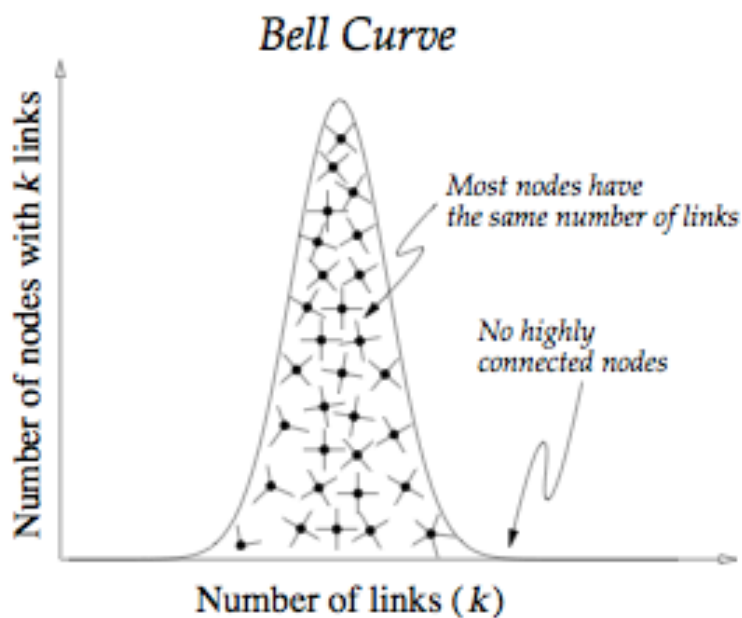
CS224W: Analysis of Networks

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<http://cs224w.stanford.edu>



Exponential vs. Power-Law Tails



Model: G_{np}

?

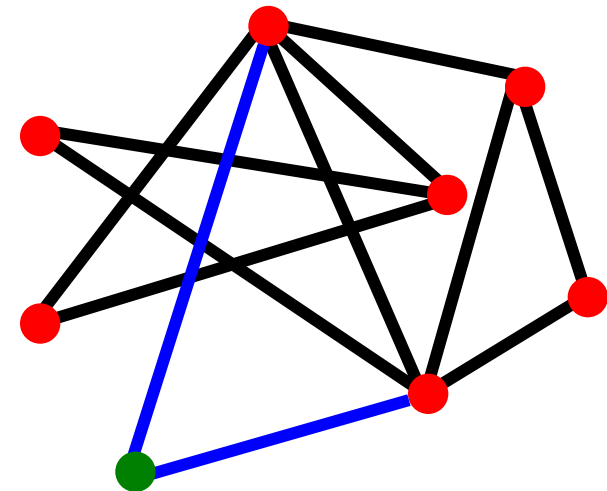
Model: Preferential attachment

■ Preferential attachment:

[de Solla Price '65, Albert-Barabasi '99, Mitzenmacher '03]

- Nodes arrive in order **1,2,...,n**
- At step j , let d_i be the degree of node $i < j$
- A new node j arrives and creates m out-links
- Prob. of j linking to a previous node i is **proportional to degree d_i of node i**

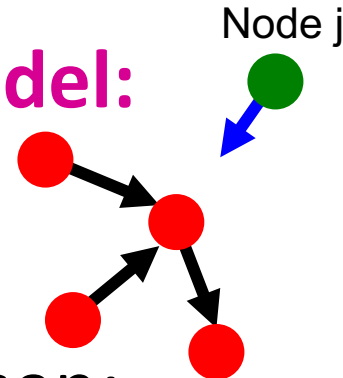
$$P(j \rightarrow i) = \frac{d_i}{\sum_k d_k}$$



The Exact Model

We will analyze the following simple model:

- Nodes arrive in order $1, 2, 3, \dots, n$
- When **node j** is created it makes a **single out-link** to an earlier node i chosen:
 - **1)** With prob. p , j links to i chosen **uniformly at random** (from among all earlier nodes)
 - **2)** With prob. $1 - p$, node j chooses i uniformly at random & links **to a random node l that i points to**
 - **This is same as saying:** With prob. $1 - p$, node j links to node l with prob. proportional to d_l (the in-degree of l)
- **Our graph is directed:** Every node has **out-degree 1**



The Model Gives Power-Laws

- Claim: The described model generates networks where the fraction of nodes with in-degree k scales as:

$$P(d_i = k) \propto k^{-(1+\frac{1}{q})}$$

where $q=1-p$

So we get power-law
degree distribution
with exponent:

$$\alpha = 1 + \frac{1}{1-p}$$

Continuous Approximation

- Consider deterministic and continuous **approximation** to the degree of node i as a function of time t
 - t is the number of nodes that have arrived so far
 - **In-Degree $d_i(t)$** of node i ($i = 1, 2, \dots, n$) is a **continuous quantity** and it **grows deterministically** as a function of time t
- **Plan: Analyze $d_i(t)$ – continuous in-degree** of node i at time t ($t > i$)
 - **Note: Node i arrives to the graph at time i**

Continuous Degree: What We Know

- **Initial condition:**

- $d_i(t) = 0$, when $t = i$ (node i just arrived)

- **Expected change of $d_i(t)$ over time:**

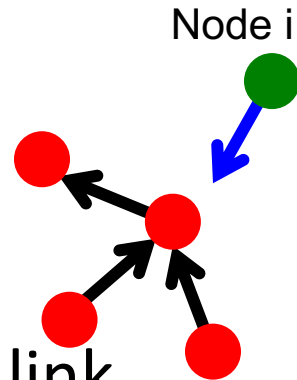
- Node i gains an in-link at step $t + 1$ only if a link from a newly created node $t + 1$ points to it

- **What's the probability of this event?**

- With prob. p node $t + 1$ links randomly:
 - Links to our node i with prob. $1/t$
- With prob. $1 - p$ node $t + 1$ links preferentially:
 - Links to our node i with prob. $d_i(t)/t$

- **Prob. node $t + 1$ links to i is:** $p \frac{1}{t} + (1 - p) \frac{d_i(t)}{t}$

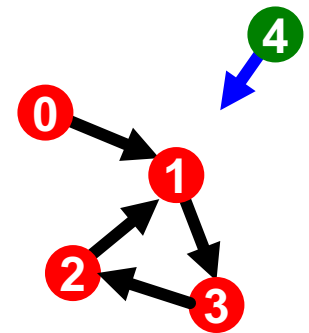
Note: each node creates exactly 1 edge. So after t nodes/steps there are t edges in total.



Continuous Degree

- At $t = 4$ node $i = 4$ comes. It has out-degree of 1 to deterministically share with other nodes:

Node i	$d_i(t)$	$d_i(t+1)$
0	0	$= 0 + p \frac{1}{4} + (1 - p) \frac{0}{4}$
1	2	$= 2 + p \frac{1}{4} + (1 - p) \frac{2}{4}$
2	0	$= 0 + p \frac{1}{4} + (1 - p) \frac{1}{4}$
3	1	$= 1 + p \frac{1}{4} + (1 - p) \frac{1}{4}$
4	/	0



- $d_i(t) - d_i(t - 1) = \frac{dd_i(t)}{dt} = p \frac{1}{t} + (1 - p) \frac{d_i(t)}{t}$
- How does $d_i(t)$ evolve as $t \rightarrow \infty$?

What is the rate of growth of d_i ?

■ Expected change of $d_i(t)$:

$$\underbrace{d_i(t+1) - d_i(t)} = p \frac{1}{t} + (1-p) \frac{d_i(t)}{t}$$

$$\frac{dd_i(t)}{dt} = p \frac{1}{t} + (1-p) \frac{d_i(t)}{t} = \frac{p+q d_i(t)}{t}$$

$$q = (1-p)$$

$$\frac{1}{p+q d_i(t)} dd_i(t) = \frac{1}{t} dt$$

Divide by
 $p + q d_i(t)$

$$\int \frac{1}{p+q d_i(t)} dd_i(t) = \int \frac{1}{t} dt$$

integrate

$$\frac{1}{q} \ln(p + q d_i(t)) = \ln t + c$$

Exponentiate
and let $A = e^c$

$$p + q d_i(t) = e^{qc} t^q \Rightarrow d_i(t) = \frac{1}{q} ((At)^q - p) \quad \mathbf{A=?}$$

What is the constant A?

$$d_i(t) = \frac{1}{q} (At^q - p)$$

What is the value of constant A?

- **We know:** $d_i(i) = 0$
- **So:** $d_i(i) = \frac{1}{q} ((Ai)^q - p) = 0$
- $\Rightarrow A = \frac{p}{i^q}$
- **And so** $\Rightarrow d_i(t) = \frac{p}{q} \left(\left(\frac{t}{i} \right)^q - 1 \right)$

Observation: Old nodes (small i values) have higher in-degrees $d_i(t)$

Degree Distribution

- What is $F(k)$, the fraction of nodes that has degree less than k at time t ?

- How many nodes have degree $< k$?

- $d_i(t) = \frac{p}{q} \left(\left(\frac{t}{i} \right)^q - 1 \right) < k$

- Solve for i and obtain: $i > t \left(\frac{q}{p} k + 1 \right)^{-\frac{1}{q}}$

- There are t nodes total at time t so the fraction $F(k)$ is:

$$F(k) = 1 - \left[\frac{q}{p} k + 1 \right]^{-\frac{1}{q}}$$

Degree Distribution

- What is the fraction of nodes with degree exactly k ?

- Take derivative of $F(k)$:

- $F(k)$ is CDF, so $F'(k)$ is the PDF!

$$F(k) = 1 - \left[\frac{q}{p} k + 1 \right]^{-\frac{1}{q}}$$

$$F'(k) = \frac{1}{q} \left[\frac{q}{p} k + 1 \right]^{-1 - \frac{1}{q}} \Rightarrow \alpha = 1 + \frac{1}{1 - p}$$

q.e.d.

Preferential attachment: Good news

- Preferential attachment gives power-law degrees!
- Intuitively reasonable process
- Can tune model parameter p to get the observed exponent
 - On the web, $P[\text{node has degree } d] \sim d^{-2.1}$
 - $2.1 = 1 + 1/(1-p) \rightarrow \underline{p \sim 0.1}$

Preferential Attachment: Bad News

- **Preferential attachment is not so good at predicting network structure**
 - **Age-degree correlation**
 - **Solution:** Node fitness (virtual degree)
 - **Links among high degree nodes:**
 - On the web nodes sometimes avoid linking to each other
- **Further questions:**
 - **What is a reasonable model for how people sample network nodes and link to them?**
 - Short random walks

Many models lead to Power-Laws

- **Copying mechanism** (directed network)
 - Select a node and an edge of this node
 - Attach to the endpoint of this edge
- **Walking on a network** (directed network)
 - The new node connects to a node, then to every first, second, ... neighbor of this node
- **Attaching to edges**
 - Select an edge and attach to both endpoints of this edge
- **Node duplication**
 - Duplicate a node with all its edges
 - Randomly prune edges of new node

Preferential attachment: Reflections

■ Two changes from the G_{np}

- The network grows
- Preferential attachment

■ Do we need both? Yes!

- Add growth to G_{np} (assume $p = 1/n$):

- X_j = degree of node j at the end
- $X_j(u) = 1$ if u links to j , else 0
- $X_j = X_j(j+1) + X_j(j+2) + \dots + X_j(n)$
- $E[X_j(u)] = P[u \text{ links to } j] = 1/(u-1)$
- $E[X_j] = \sum_{j+1}^n \frac{1}{u-1} = \frac{1}{j} + \frac{1}{j+1} + \dots + \frac{1}{n-1} = H_{n-1} - H_j$
- $E[X_j] \approx \log(n-1) - \log(j) = \log((n-1)/j)$ **NOT** $\left(\frac{n}{j}\right)^\alpha$

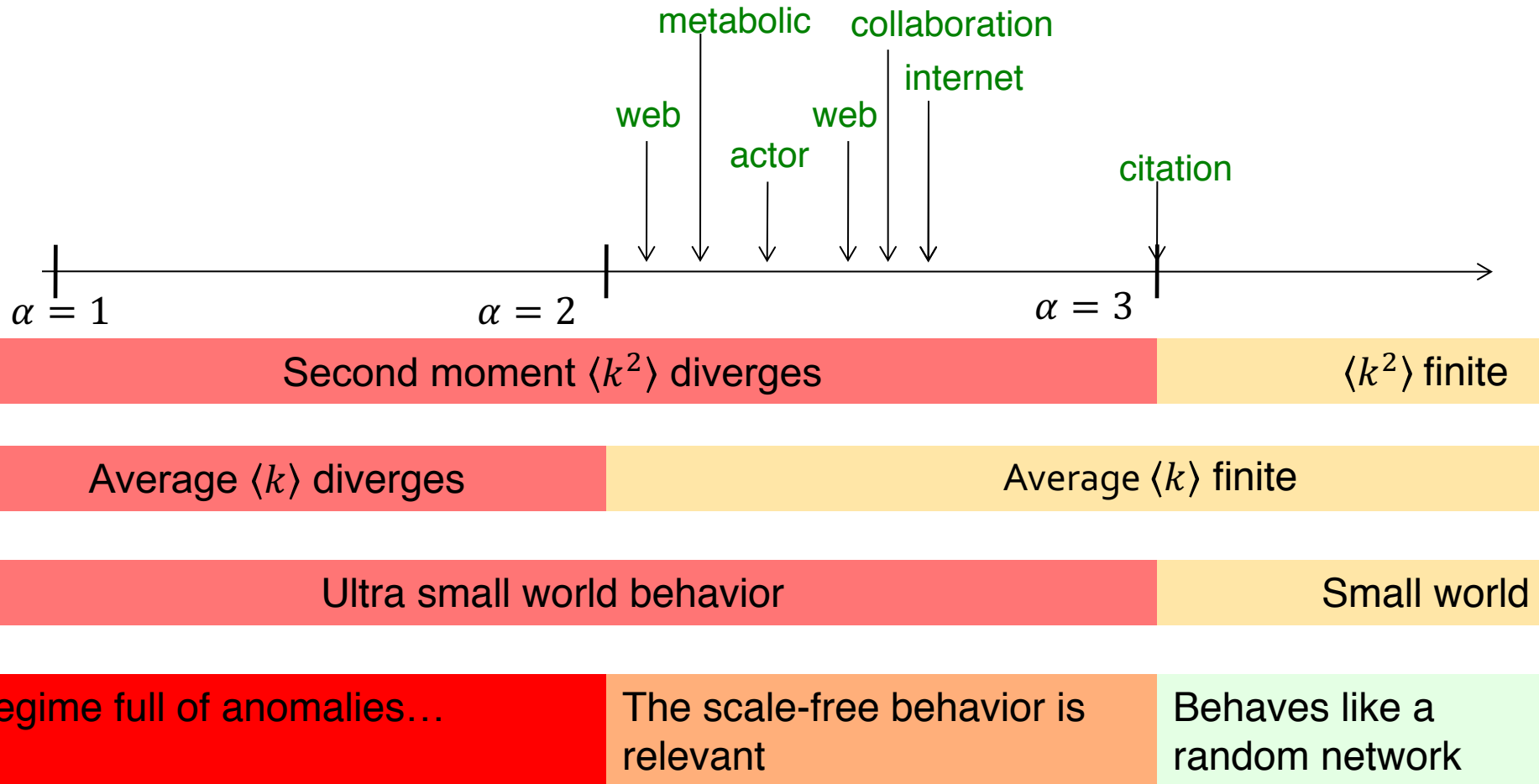
$H_n \dots n$ -th
harmonic
number:
$$= \sum_{k=1}^n \frac{1}{k}$$

Distances in Preferential Attachment

Ultra small world	$\bar{h} = \left\{ \begin{array}{l} \text{const} \\ \frac{\log \log n}{\log(\alpha-1)} \end{array} \right.$	$\alpha = 2$	Size of the biggest hub is of order $O(N)$. Most nodes can be connected within two steps, thus the average path length will be independent of the network size.
		$2 < \alpha < 3$	The average path length increases slower than logarithmically. In G_{np} all nodes have comparable degree, thus most paths will have comparable length. In a scale-free network vast majority of the paths go through the few high degree hubs, reducing the distances between nodes.
Small world	$\bar{h} = \left\{ \begin{array}{l} \frac{\log n}{\log \log n} \\ \log n \end{array} \right.$	$\alpha = 3$	Some models produce $\alpha = 3$. This was first derived by Bollobas et al. for the network diameter in the context of a dynamical model, but it holds for the average path length as well.
		$\alpha > 3$	The second moment of the distribution is finite, thus in many ways the network behaves as a random network. Hence the average path length follows the result that we derived for the random network model earlier.
		Avg. path length	Degree exponent

Summary: Scale-Free Networks

Extra!



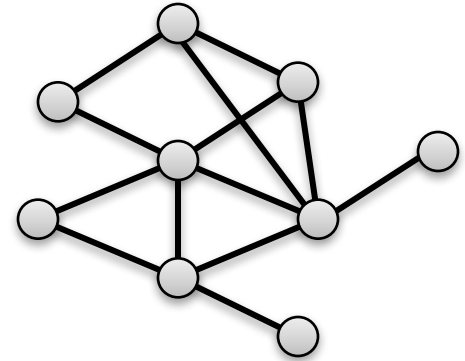
Evolution of Social Networks

Network Evolution: Observation

- Preferential attachment is a model of a growing network
- Can we find a more realistic model?
- What governs network growth & evolution?
 - **P1) Node arrival process:**
 - When nodes enter the network
 - **P2) Edge initiation process:**
 - Each node decides when to initiate an edge
 - **P3) Edge destination process:**
 - The node determines destination of the edge
[Leskovec, Backstrom, Kumar, Tomkins, 2008]

Let's Look at the Data

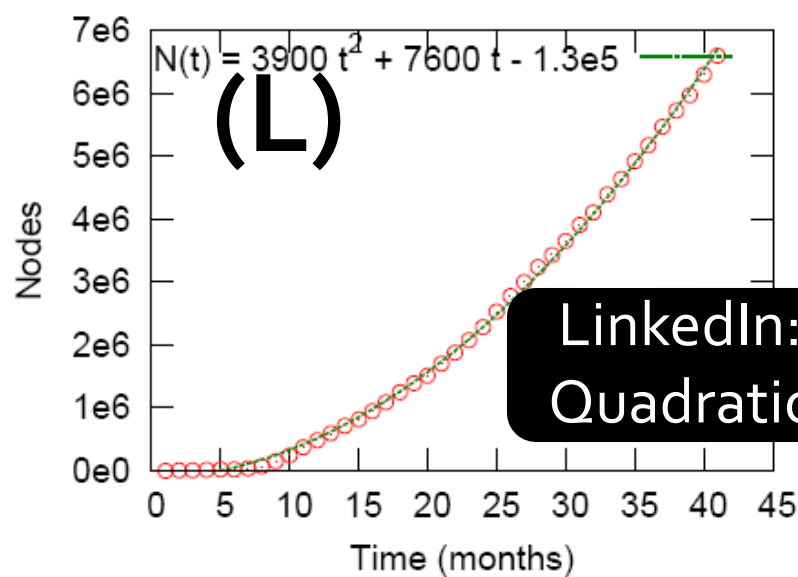
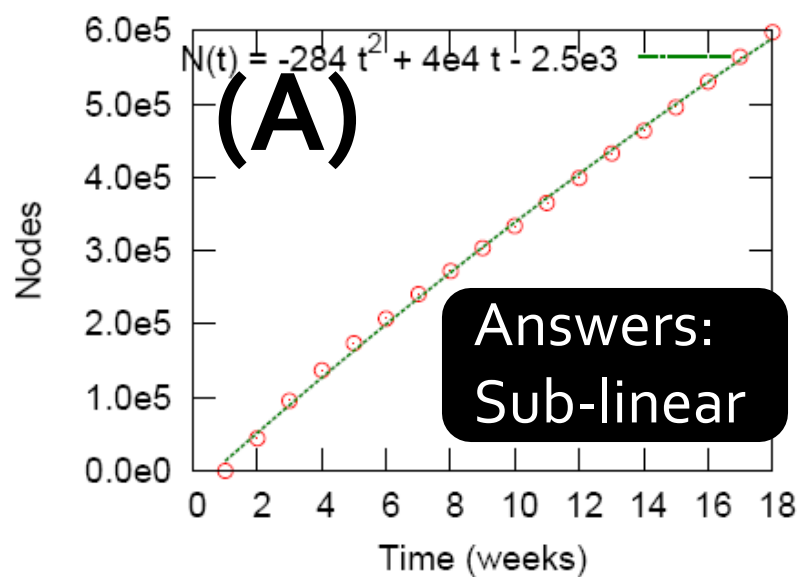
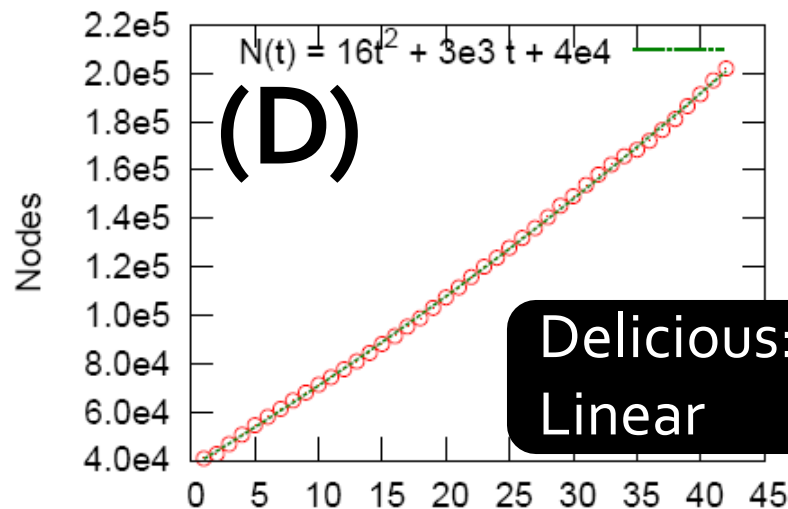
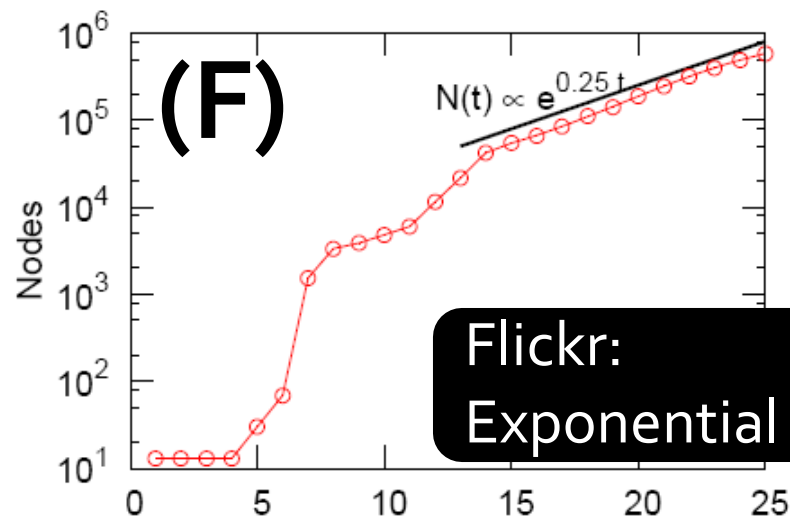
- 4 online social networks with exact **edge arrival sequence**
 - For every edge (u,v) we know exact time of the creation t_{uv}
- Directly observe mechanisms leading to global network properties



and so on for millions...

	Network	T	N	E
(F)	FLICKR (03/2003–09/2005)	621	584,207	3,554,130
(D)	DELICIOUS (05/2006–02/2007)	292	203,234	430,707
(A)	ANSWERS (03/2007–06/2007)	121	598,314	1,834,217
(L)	LINKEDIN (05/2003–10/2006)	1294	7,550,955	30,682,028

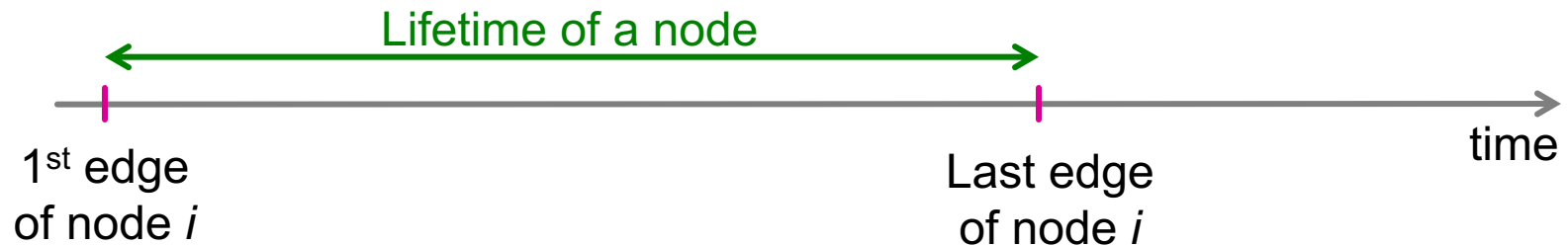
P₁) When are New Nodes Arriving?



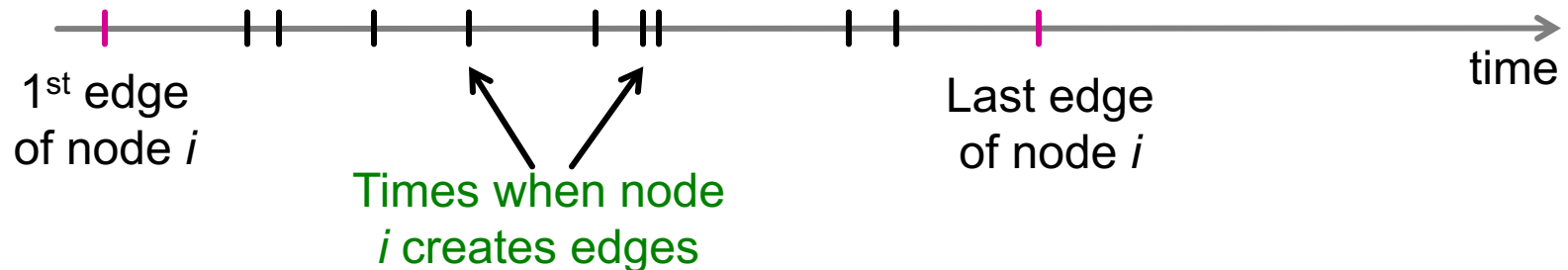
P2) When Do Nodes Create Edges?

■ How long do nodes live?

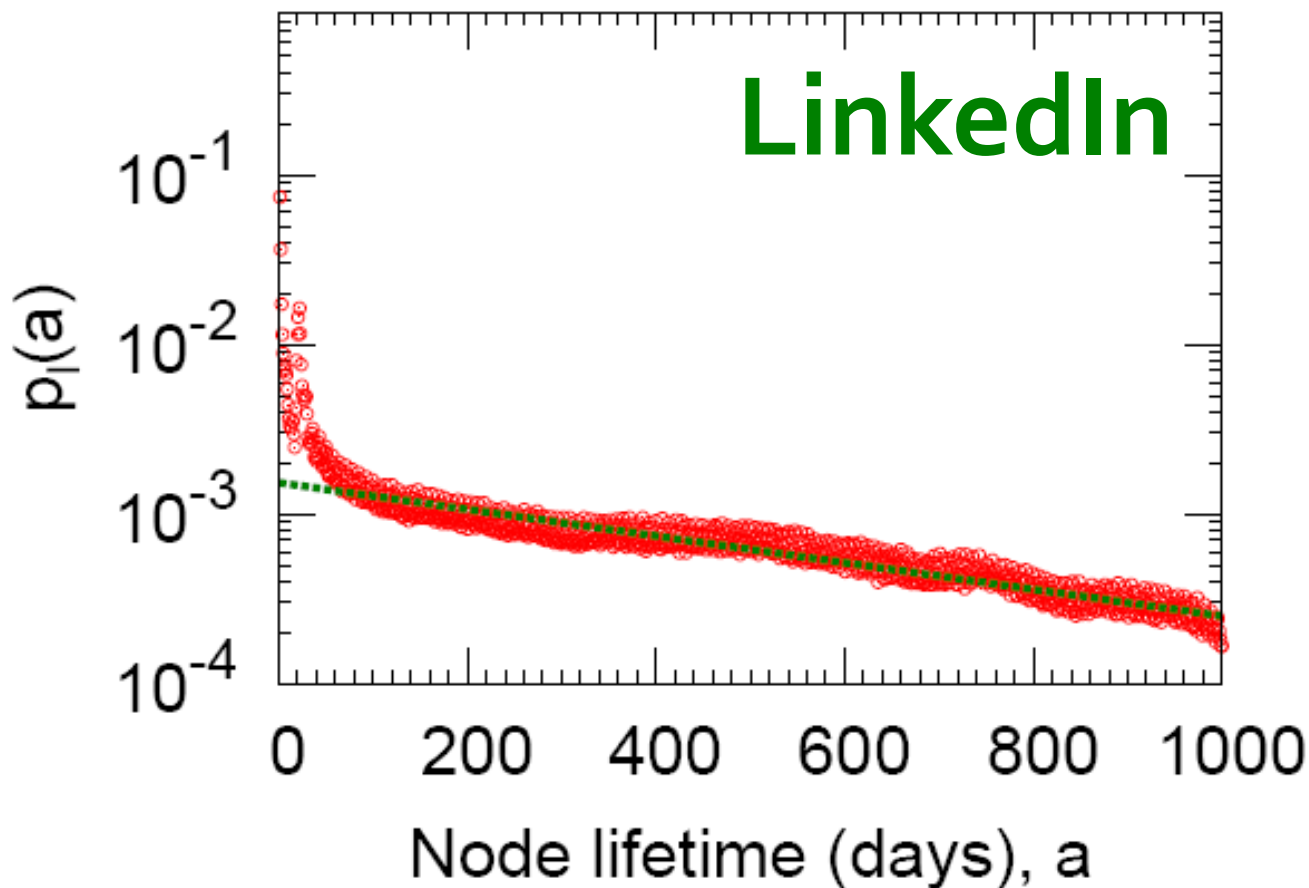
- Node life-time is the time between the 1st and the last edge of a node



■ When do nodes “wake up” to create links?



P2) What is Node Lifetime?



- **Lifetime a :**
Time between
node's first
and last edge

Node lifetime is **exponentially distributed**:

$$p_l(a) = \lambda e^{-\lambda a}$$

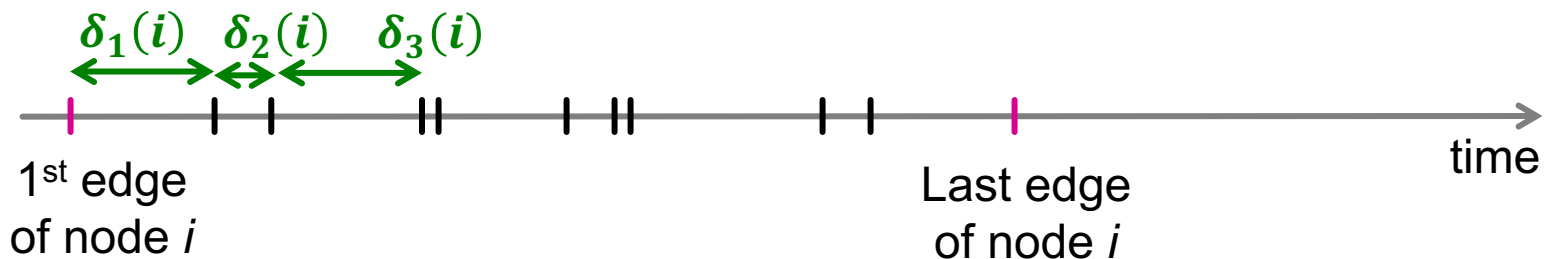
P2) When do Nodes Create Edges?

■ How do nodes “wake up” to create edges?

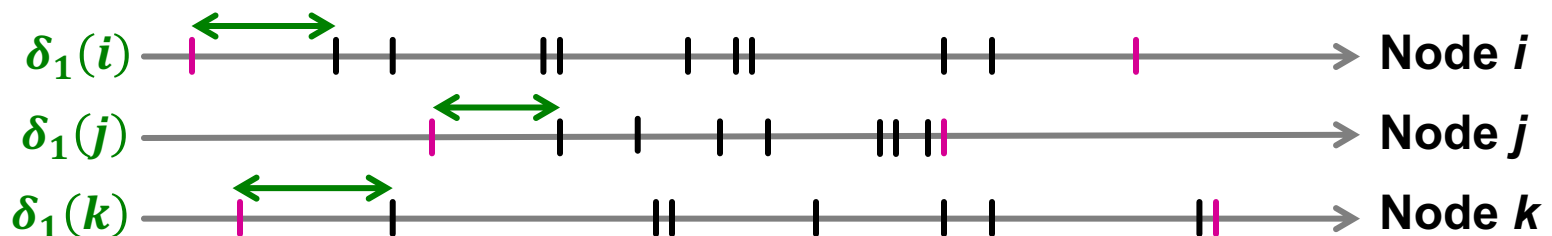
- **Edge gap $\delta_d(i)$** : time between d^{th} and $d + 1^{st}$ edge of node i :

- Let $t_d(i)$ be the creation time of d -th edge of node i

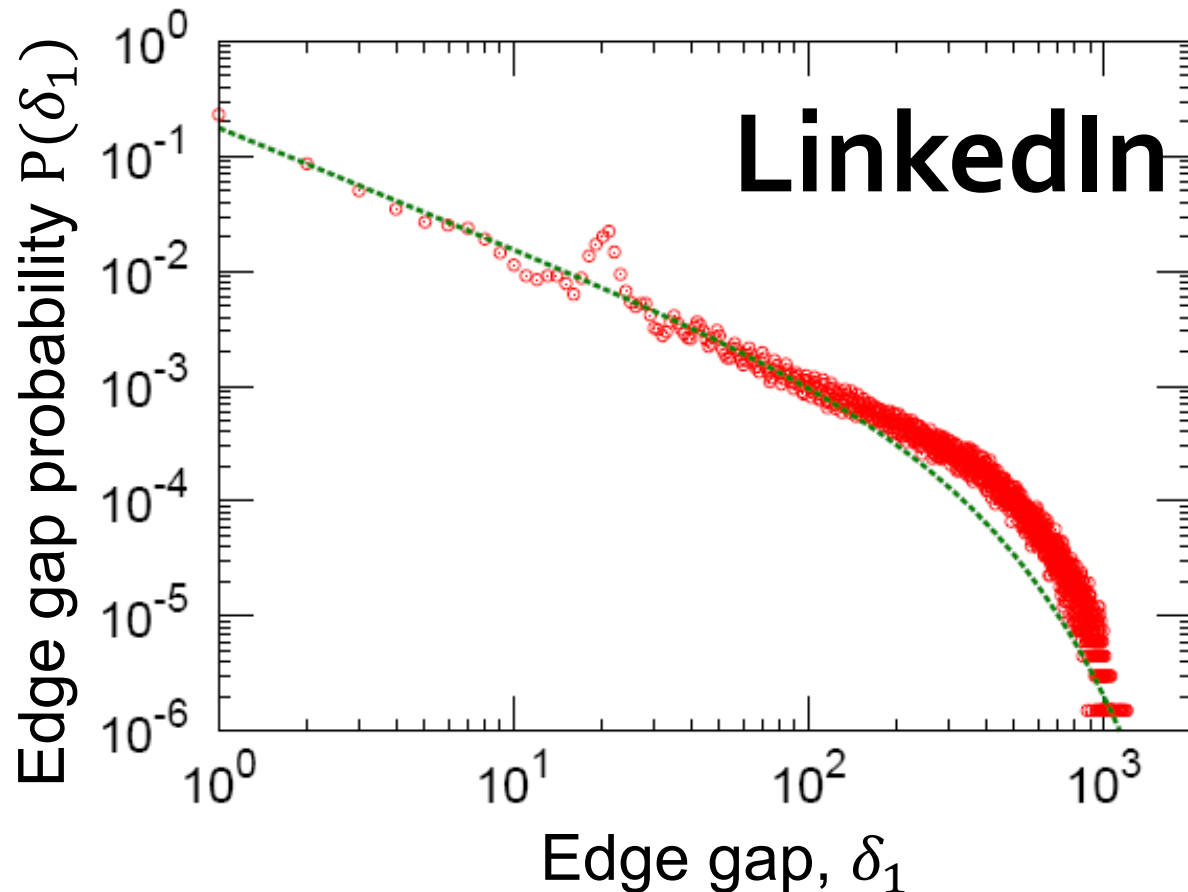
- $\delta_d(i) = t_{d+1}(i) - t_d(i)$



- δ_d is a distribution (histogram) of $\delta_d(i)$ over all nodes i



P2) When do Nodes Create Edges?



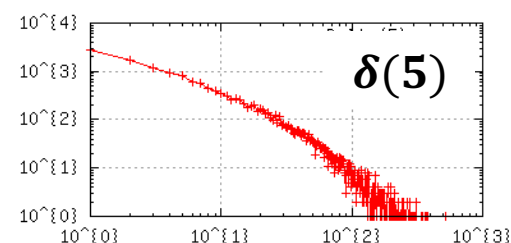
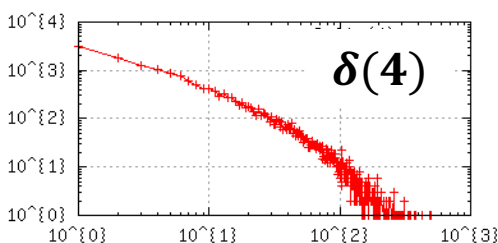
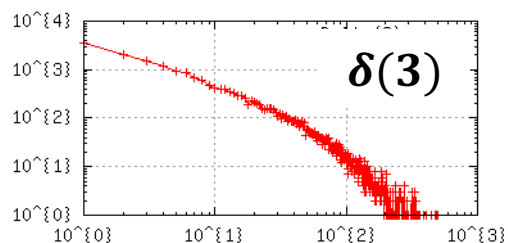
Edge gap δ_d : inter-arrival time between d^{th} and $d + 1^{st}$ edge is distributed by a power-law with exponential cut-off

For every d we make a separate histogram

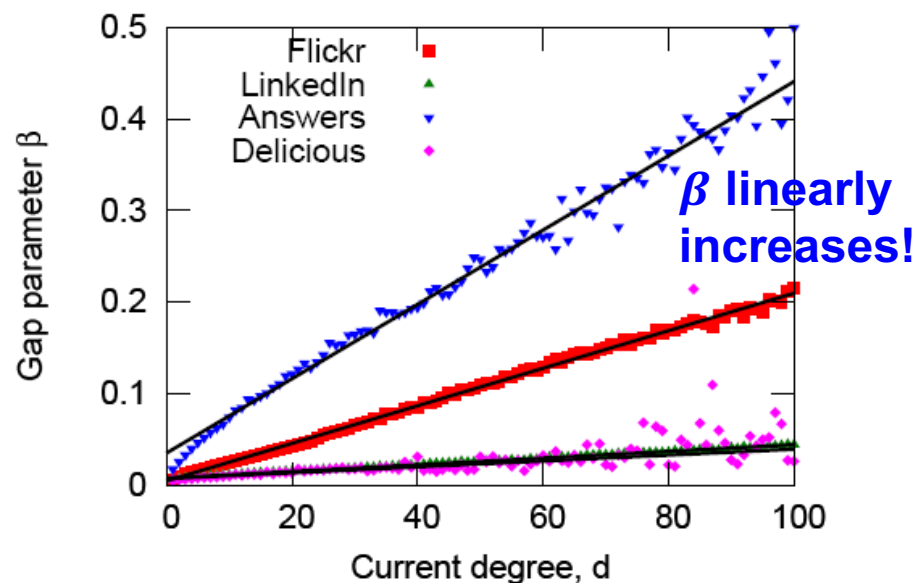
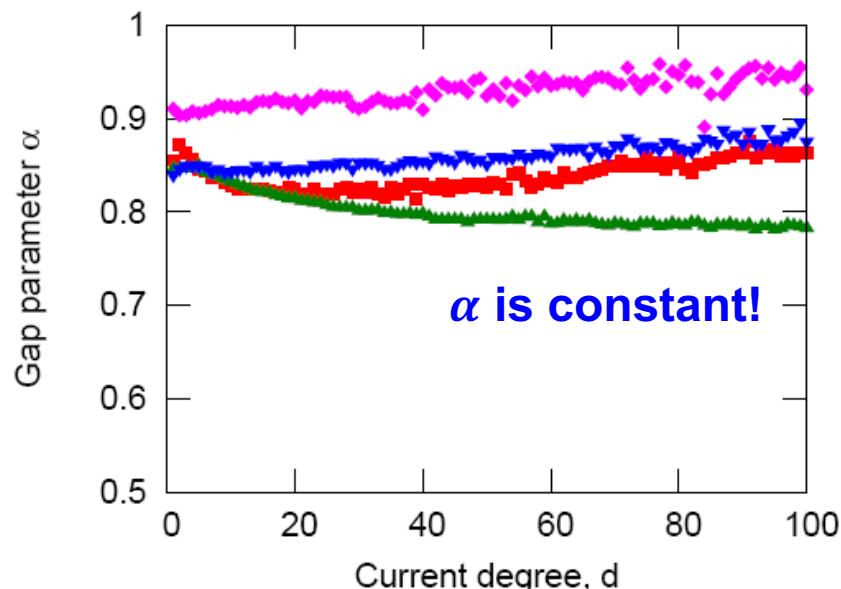
$$p_g(\delta_1) \propto \delta_1^{-\alpha} e^{-\beta \delta_1}$$

P2) How do α and β evolve with d ?

- How do α and β change as a function of d ?

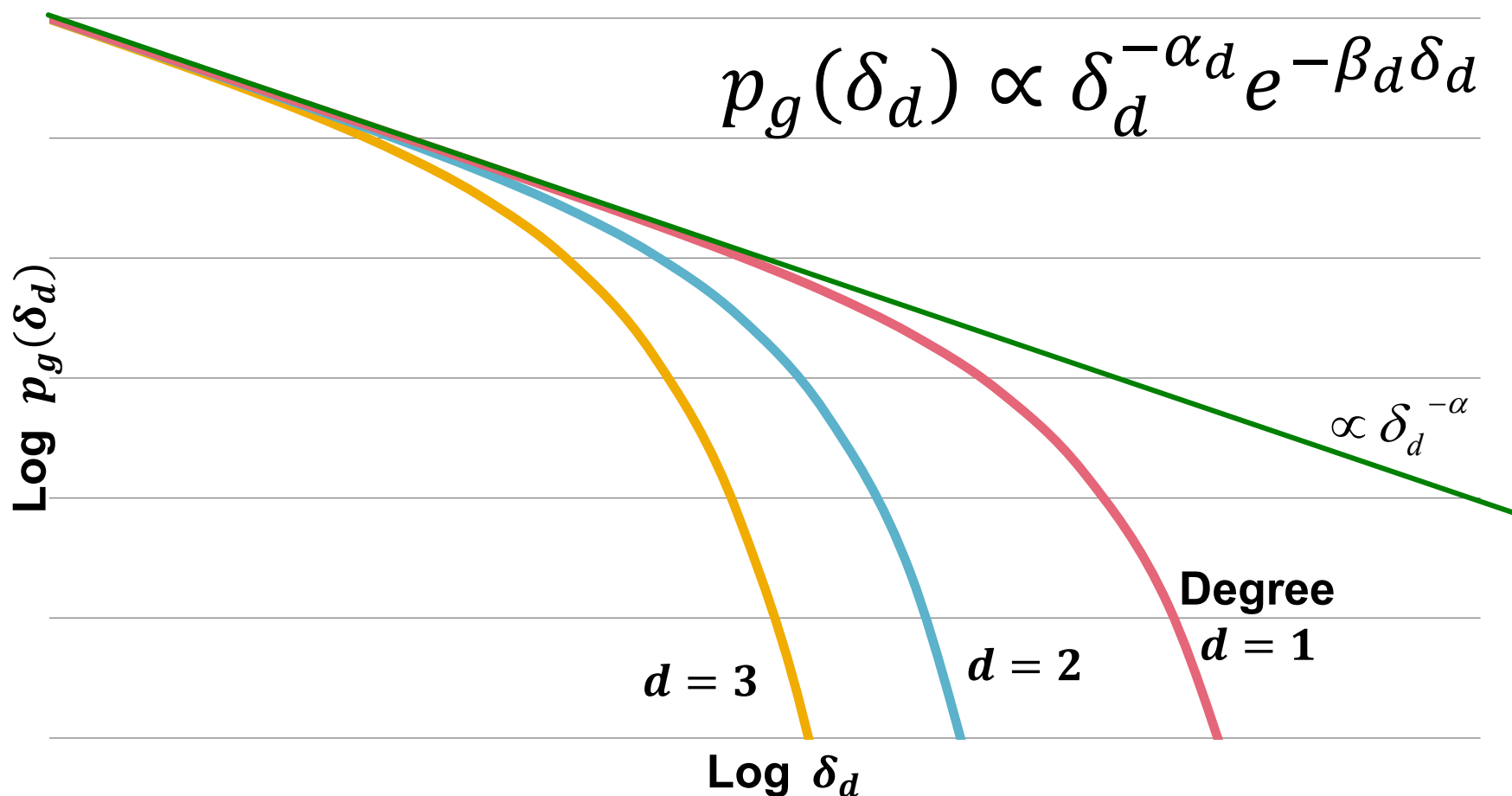


To each plot of δ_d fit: $p_g(\delta_d) \propto \delta_d^{-\alpha_d} e^{-\beta_d \delta_d}$



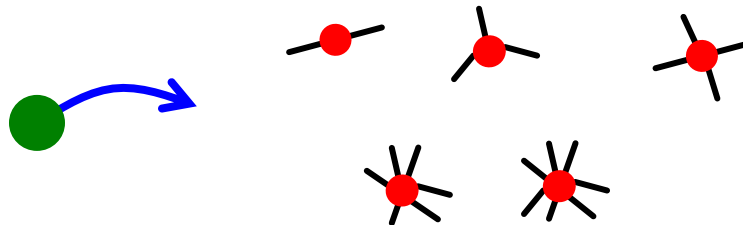
P2) Evolution of Edge Gaps

- α const., β linear in d . What does this mean?
- Gaps get smaller with d !

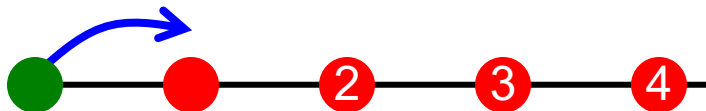


P3) How to Select Destination?

- Source node i wakes up and creates an edge
- How does i select a target node j ?
 - What is the degree of the target j ?
 - Does preferential attachment really hold?

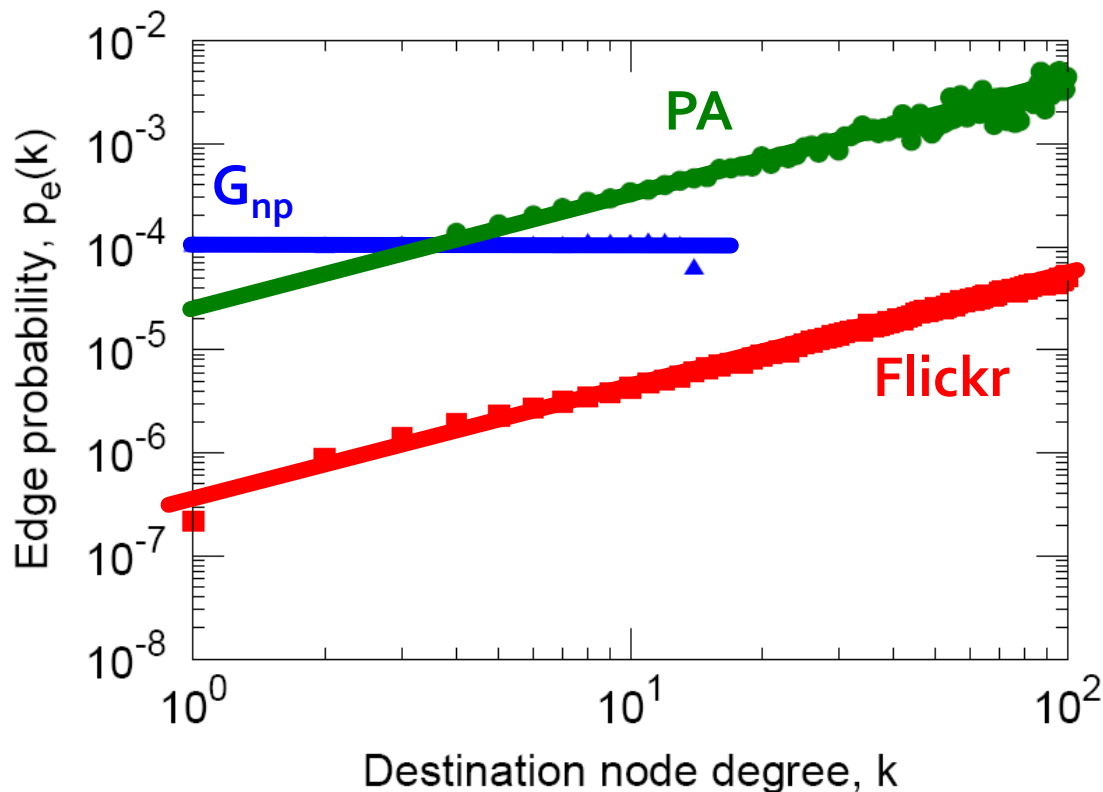


- How many hops away is the target j ?
 - Are edges attaching locally?



Edge Attachment Degree Bias

- Are edges more likely to connect to higher degree nodes? YES!

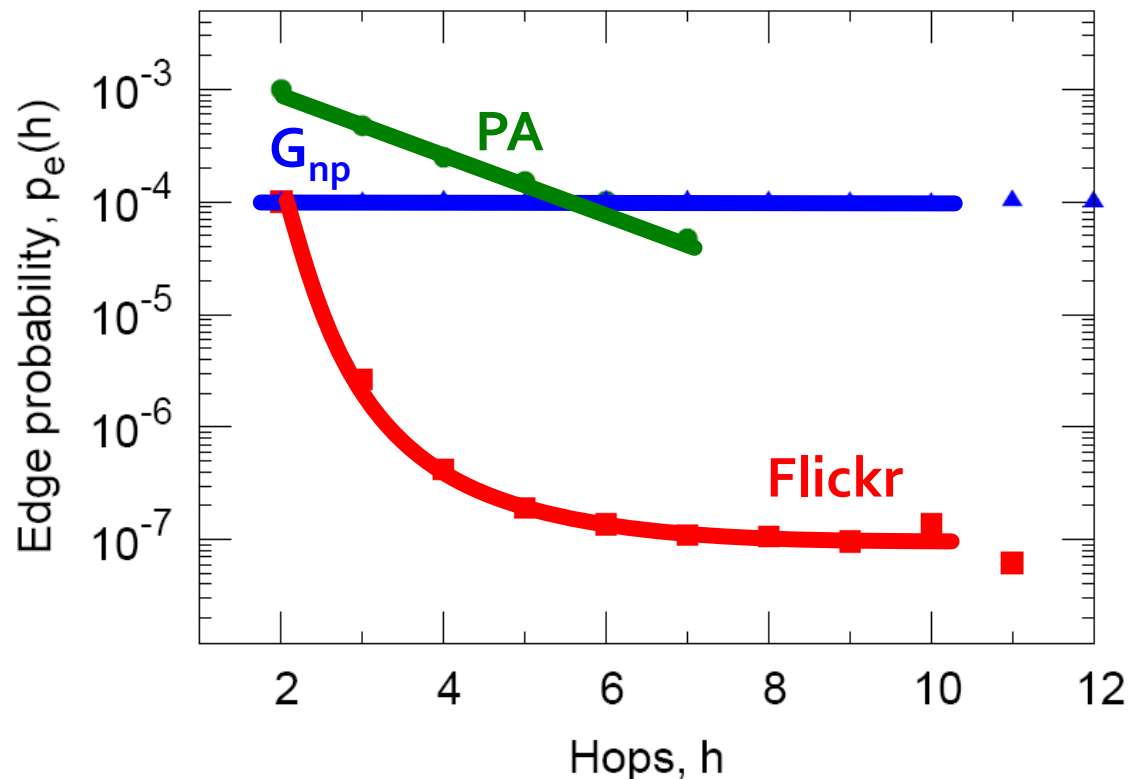


$$p_e(k) \propto k^\tau$$

Network	τ
G_{np}	0
PA	1
Flickr	1
Delicious	1
Answers	0.9
LinkedIn	0.6

How “far” is the Target Node?

- Just before the edge (u, w) is placed how many hops are between u and w ?



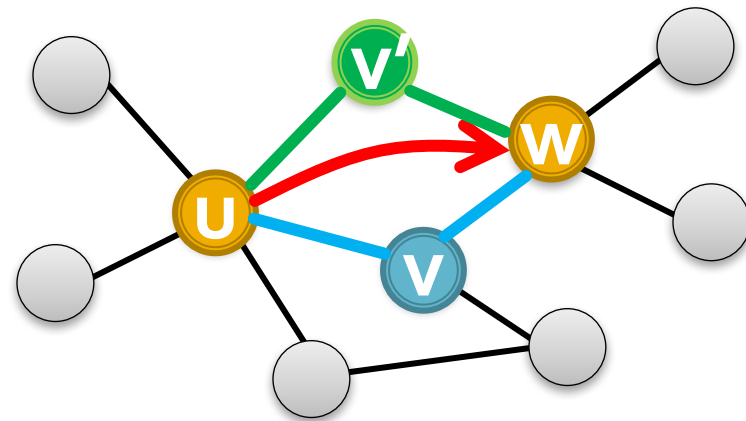
Fraction of triad closing edges

Network	% Δ
Flickr	66%
Delicious	28%
Answers	23%
LinkedIn	50%

Real edges are local!
Most of them close triangles!

How to Close the Triangles?

- Focus only on triad-closing edges
- New triad-closing edge (u,w) appears next
- 2 step walk model:
 - u is about to create an edge
 1. u chooses neighbor v
 2. v chooses neighbor w and u connects to w
- One can use different strategies for choosing v and w : **Random-Random works well. Why?**
 - More common friends (more paths) helps
 - High-degree nodes are more likely to be hit



Triad Closing Strategies

Extra!

■ Improvement in log-likelihood over baseline:

- **Baseline:** Pick a random node 2 hops away

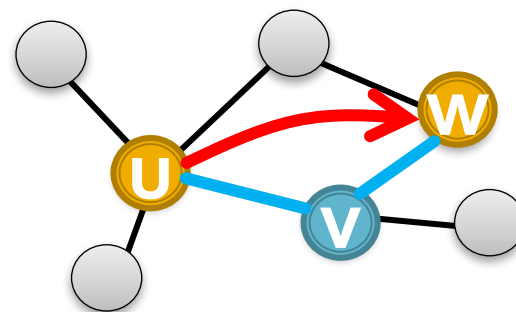
Strategy to select v (1st node)

Select w (2nd node)

FLICKR	random	deg ^{0.2}	com	last ^{-0.4}	comlast ^{-0.4}
random	13.6	13.9	14.3	16.1	15.7
deg ^{0.1}	13.5	14.2	13.7	16.0	15.6
last ^{0.2}	14.7	15.6	15.0	17.2	16.9
com	11.2	11.6	11.9	13.9	13.4
comlast ^{0.1}	11.0	11.4	11.7	13.6	13.2

Strategies to pick a neighbor:

- **random:** uniformly at random
- **deg:** proportional to its degree
- **com:** prop. to the number of common friends
- **last:** prop. to time since last activity
- **comlast:** prop. to **com*****last**



Summary of the Model

■ The model of network evolution

Process	Model
P1) Node arrival	<ul style="list-style-type: none">• Node arrival function is given
P2) Edge initiation	<ul style="list-style-type: none">• Node lifetime is exponential• Edge gaps get smaller as the degree increases
P3) Edge destination	Pick edge destination using random-random

Analysis of the Model

- **Theorem:** Exponential node lifetimes and power-law with exponential cutoff edge gaps lead to power-law degree distributions
- **Comments:**
 - The proof is based on a combination of exponentials
 - Interesting as temporal behavior predicts a structural network property

Evolving the Networks

- Given the model one can take an existing network and continue its evolution
- Compare true and predicted (based on the theorem) degree exponent:

	FLICKR	DELICIOUS	ANSWERS	LINKEDIN
λ	0.0092	0.0052	0.019	0.0018
α	0.84	0.92	0.85	0.78
β	0.0020	0.00032	0.0038	0.00036
true	1.73	2.38	1.90	2.11
predicted	1.74	2.30	1.75	2.08

degree exponent

Macroscopic Evolution of Networks

Macroscopic Evolution

- **How do networks evolve at the macro level?**
 - What are global phenomena of network growth?
- **Questions:**
 - What is the relation between the number of nodes $n(t)$ and number of edges $e(t)$ over time t ?
 - How does diameter change as the network grows?
 - How does degree distribution evolve as the network grows?

Network Evolution

- $N(t)$... nodes at time t

- $E(t)$... edges at time t

- Suppose that

$$N(t + 1) = 2 \cdot N(t)$$

- Q: what is:

$$E(t + 1) = ? \quad \text{Is it } 2 \cdot E(t)?$$

- A: More than doubled!

- But obeying the **Densification Power Law**

Q1) Network Evolution

- What is the relation between the number of nodes and the edges over time?

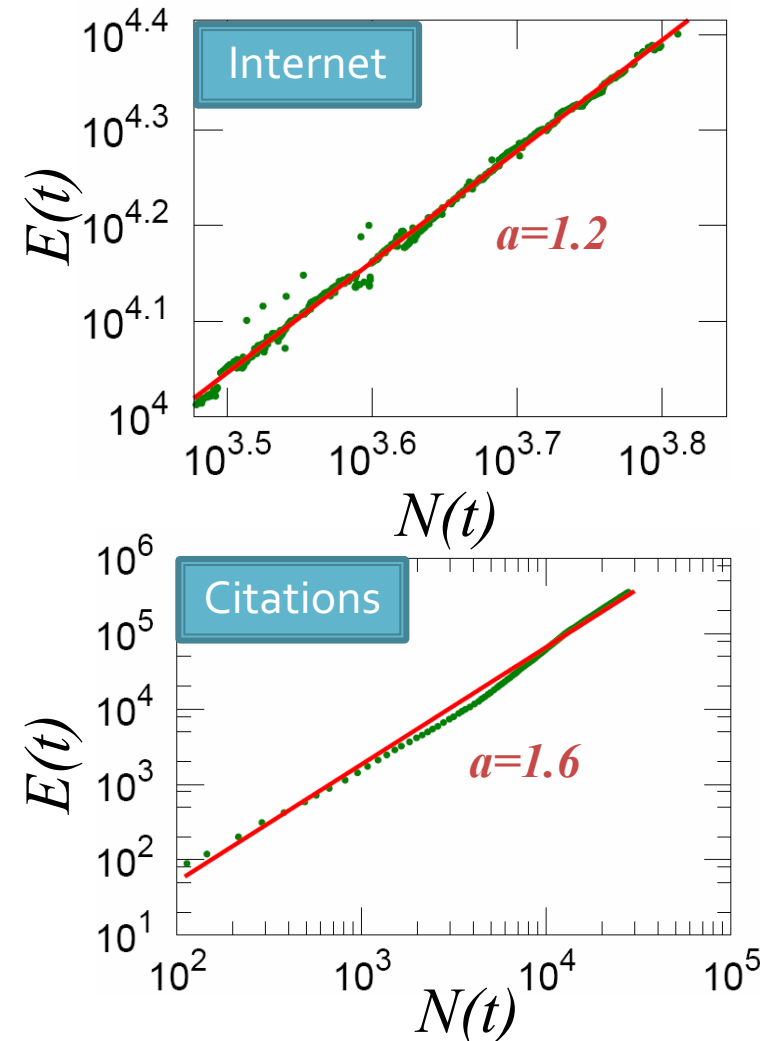
- ~~■ First guess: constant average degree over time~~

- Networks are **denser** over time

- **Densification Power Law:**

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

a ... densification exponent ($1 \leq a \leq 2$)



Densification Power Law

■ Densification Power Law

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

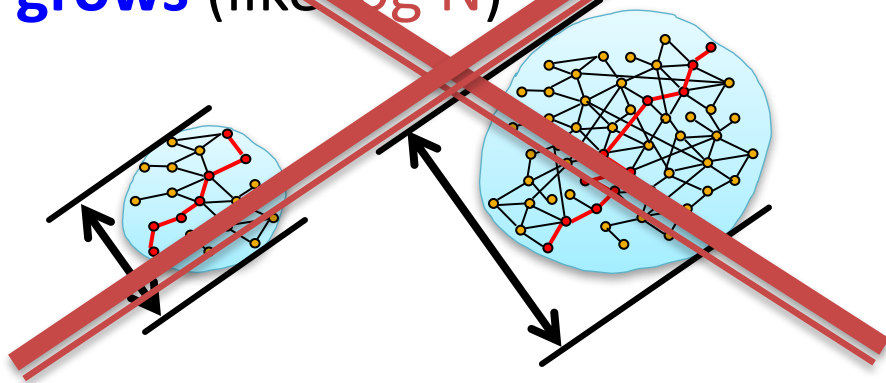
$$E(t) \propto N(t)^a \quad \text{or equivalently} \quad \frac{\log(E(t))}{\log(N(t))} = \text{const}$$

a ... densification exponent: $1 \leq a \leq 2$:

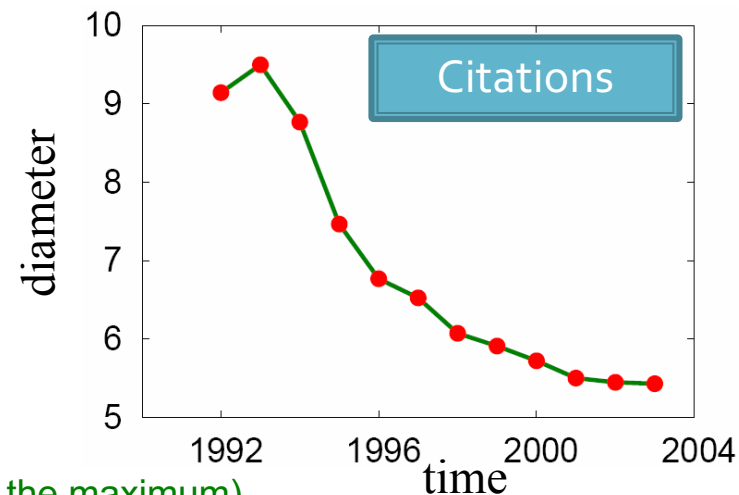
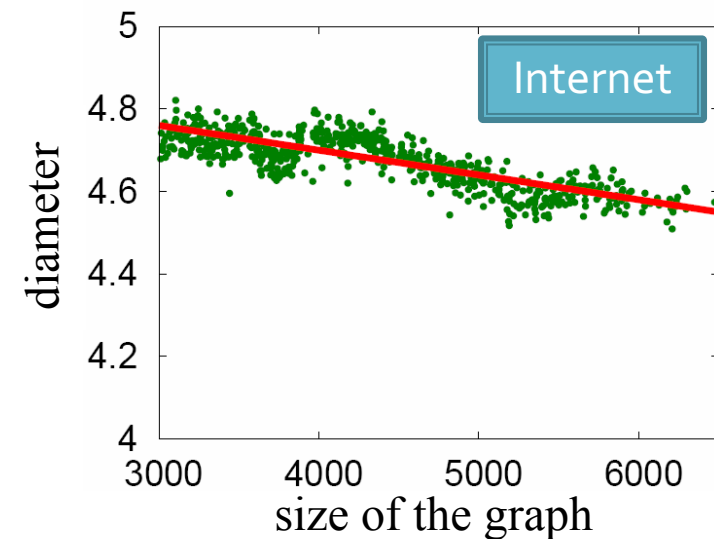
- **a=1: linear growth** – constant out-degree (traditionally assumed)
- **a=2: quadratic growth** – fully connected graph

Q1) Network Evolution

- Prior models and intuition say that the network **diameter slowly grows** (like $\log N$)



- **Diameter shrinks over time**
 - As the network grows the distances between the nodes slowly **decrease**



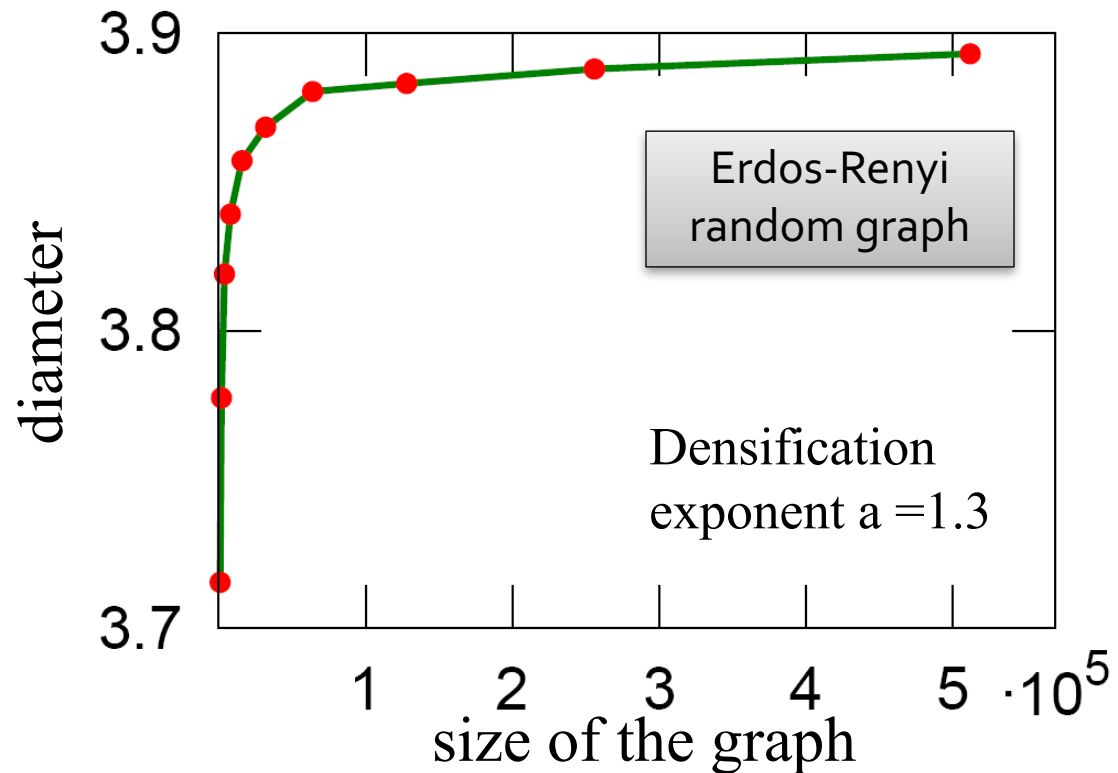
How do we compute diameter in practice?

-- Long paths: Take 90th-percentile or average path length (not the maximum)

-- Disconnected components: Take only largest component or average only over connected pairs of nodes

Diameter of a Densifying G_{np}

Is shrinking diameter just a consequence of densification?



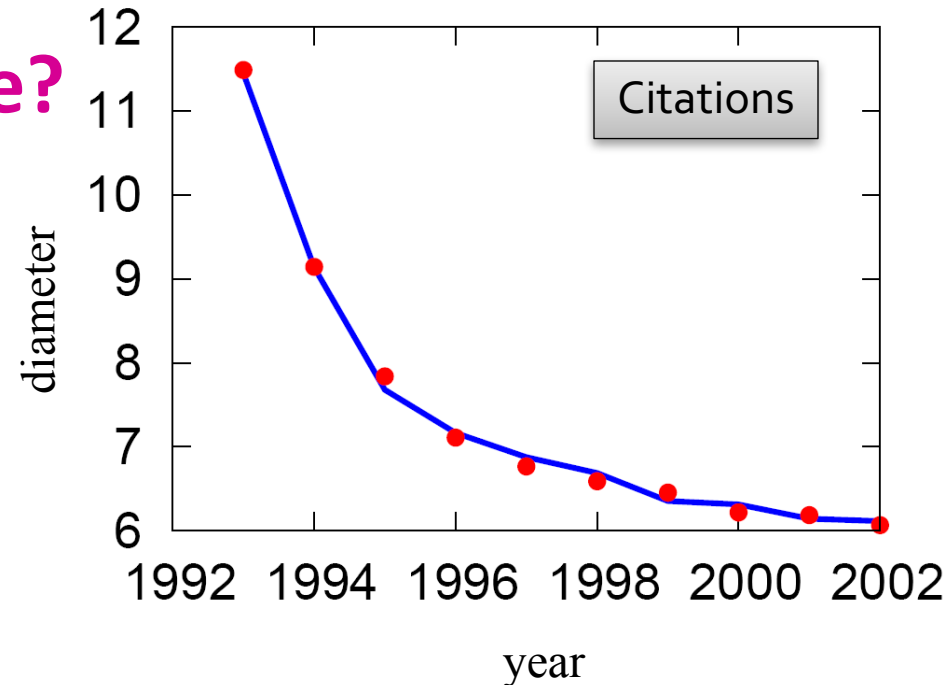
Densifying random graph has increasing diameter
 \Rightarrow There is more to shrinking diameter than just densification!

Diameter of a Rewired Network

Is it the degree sequence?

Compare diameter of a:

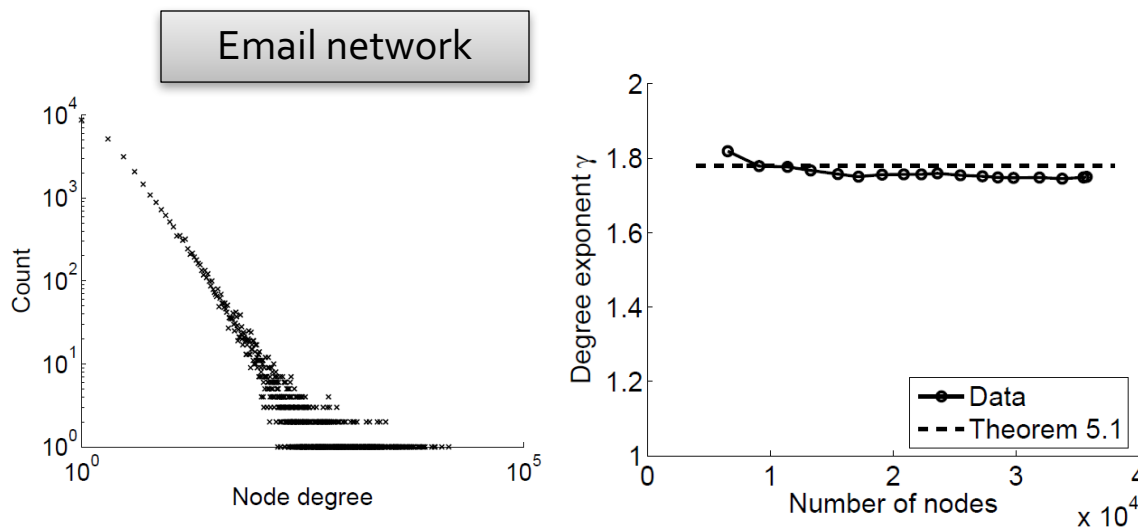
- Real network (**red**)
- Random network with the same degree distribution (**blue**)



**Densification + degree sequence
gives shrinking diameter**

Connecting Degrees & Densification

- How does degree distribution evolve to allow for densification?
- **Option 1)** Degree exponent γ_t is constant:
 - **Fact 1:** If $\gamma_t = \gamma \in [1, 2]$, then: $\alpha = 2/\gamma$



A consequence of what we learned in the Power law lecture:

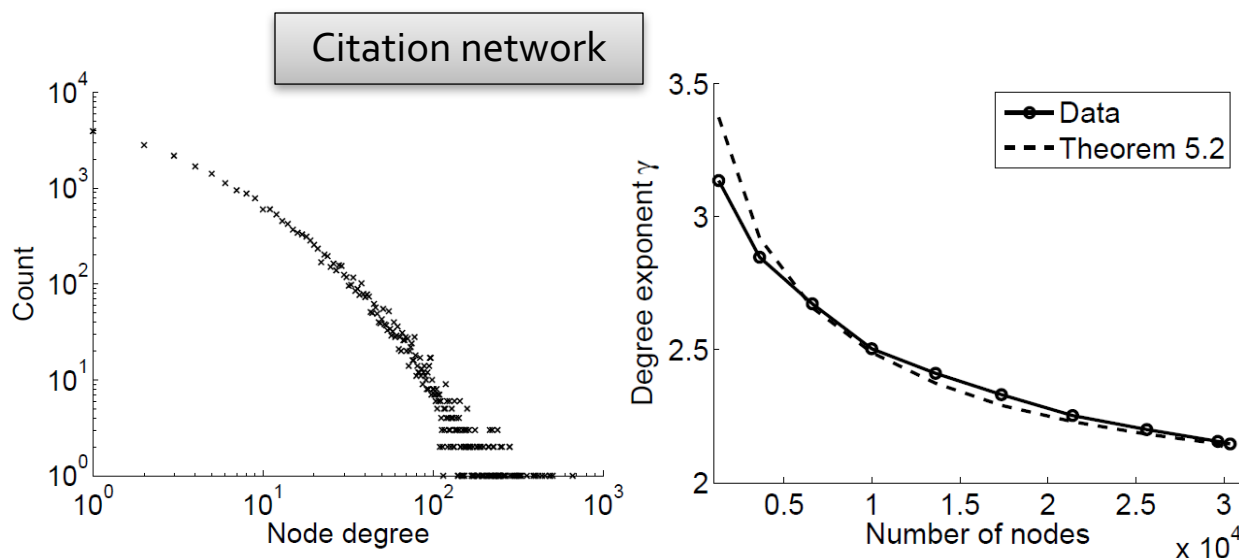
- Power-laws with exponents < 2 have infinite expectations.
- So, by maintaining constant degree exponent α the average degree grows.

Connecting Degrees & Densification

- How does degree distribution evolve to allow for densification?
- **Option 2)** γ_t evolves with graph size n :

■ **Fact 2:** If $\gamma_t = \frac{4n_t^{x-1}-1}{2n_t^{x-1}-1}$, then: $a = x$

Notice: $\gamma_t \rightarrow 2$
as $n_t \rightarrow \infty$



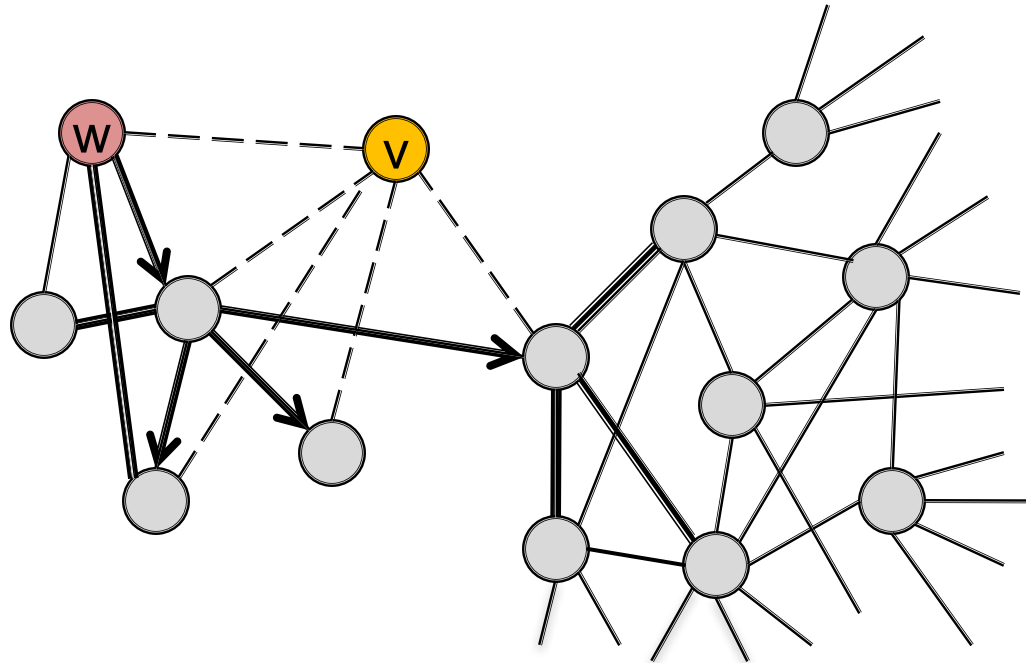
Remember, the expected degree in a power law is:

$$E[X] = \frac{\gamma_t - 1}{\gamma_t - 2} x_m$$

So γ_t has to decay as a function of graph size n_t for the avg. degree to go up.

Forest Fire Model

- Want to model graphs that densify and have shrinking diameters
- Intuition:
 - How do we meet friends at a party?
 - How do we identify references when writing papers?



Forest Fire Model

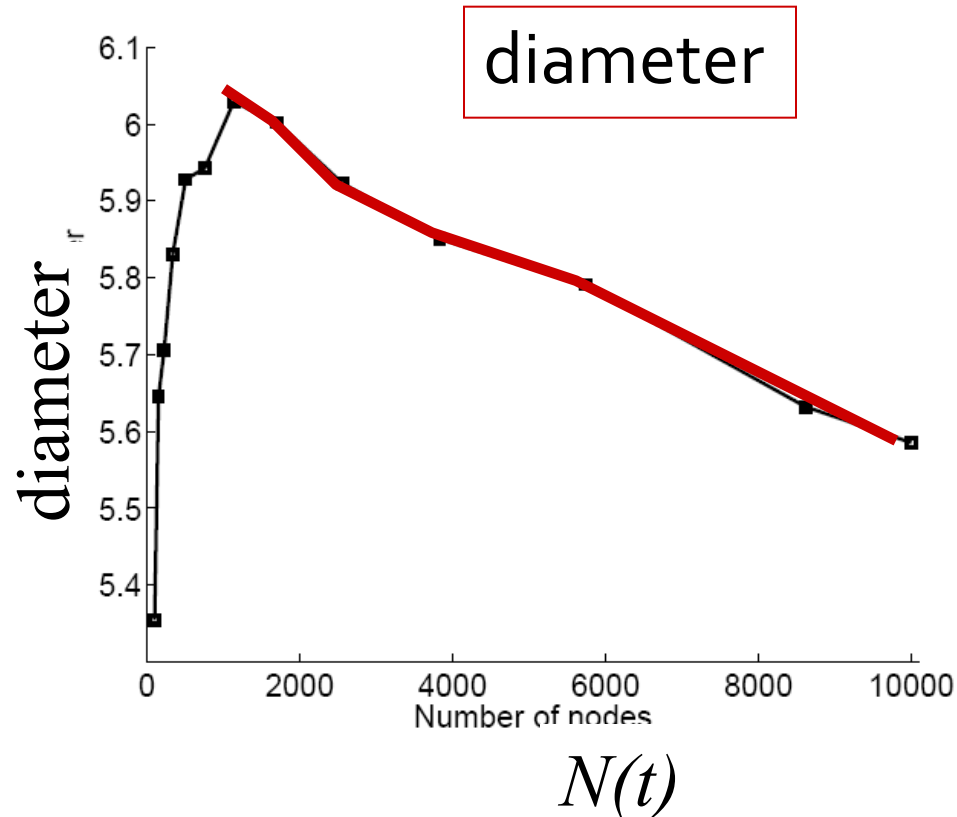
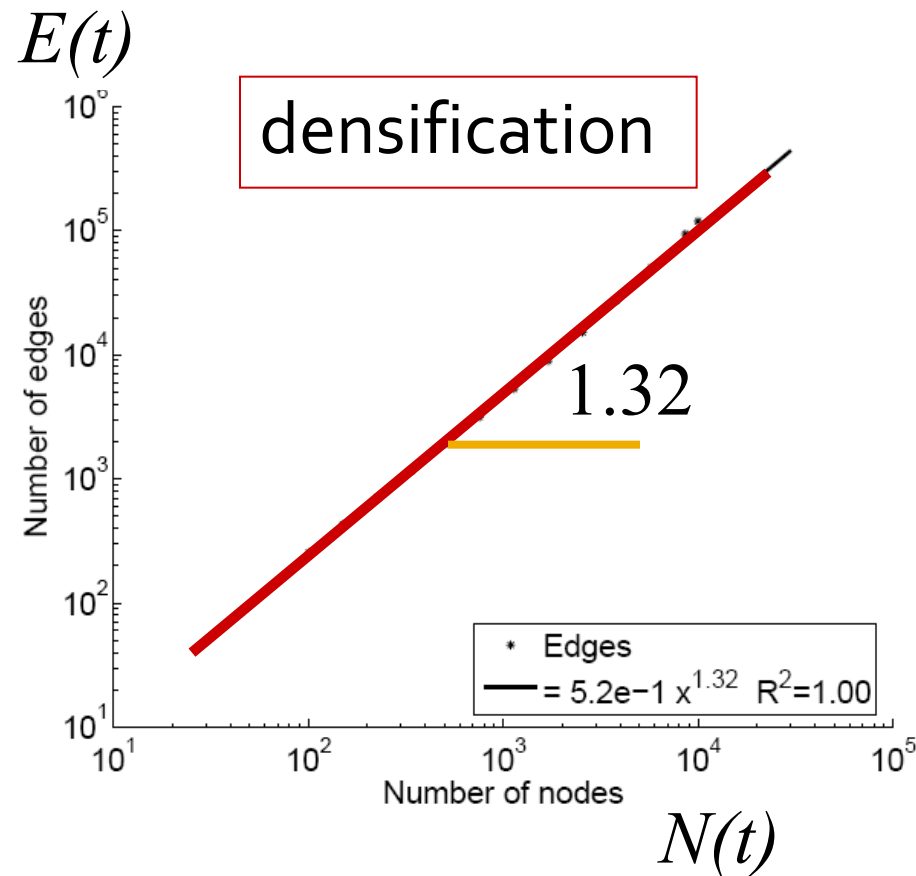
- **The Forest Fire model has 2 parameters:**
 - p ... forward burning probability
 - r ... backward burning probability
- **The model: Directed Graph**
 - Each turn a new node v arrives
 - Uniformly at random chooses an “ambassador” w
 - Flip 2 geometric coins (based on p and r) to determine the number of **in-** and **out-links** of w to follow
 - “Fire” spreads recursively until it dies
 - New node v links to all burned nodes

Geometric distribution:

$$\Pr(X = k) = (1 - p)^{k-1} p$$

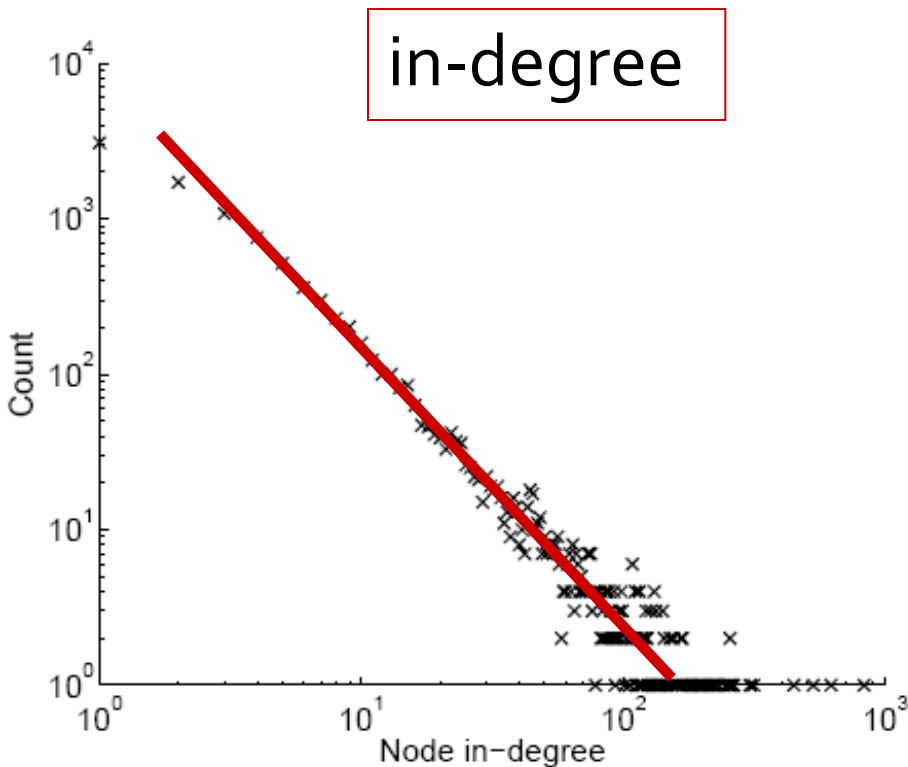
Forest Fire Model

- Forest Fire generates graphs that **densify** and have **shrinking diameter**

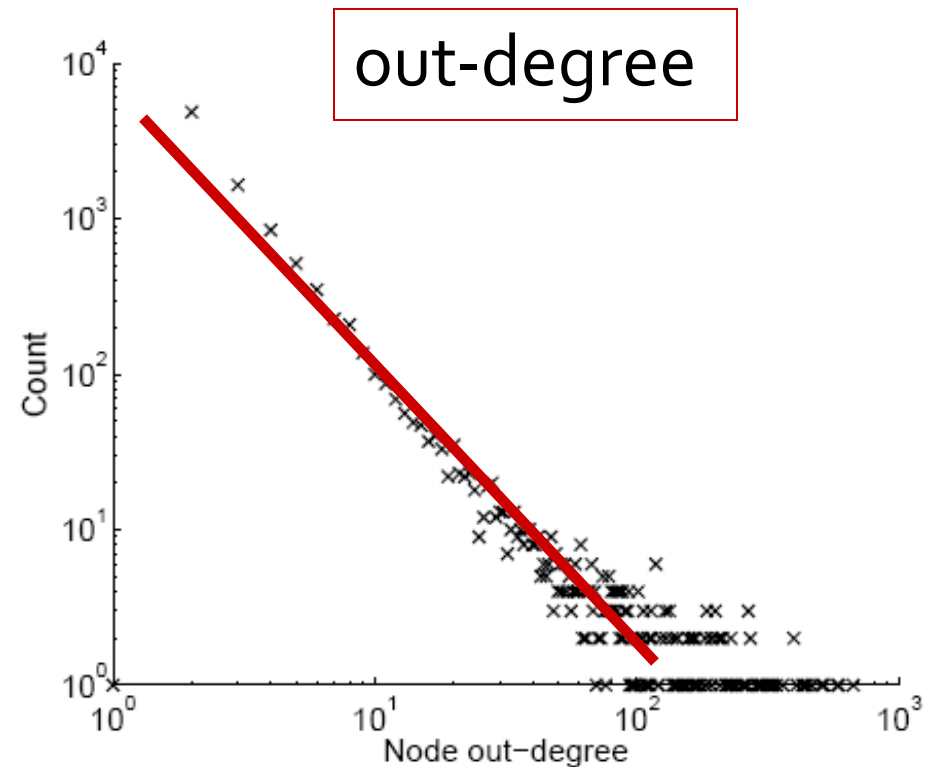


Forest Fire Model

- Forest Fire also generates graphs with **power-law degree distribution**



log count vs. log in-degree



log count vs. log out-degree

Forest Fire: Phase Transition

- Fix backward probability r and vary forward burning prob. p
- Notice a sharp transition between sparse and clique-like graphs
- The “sweet spot” is very narrow

