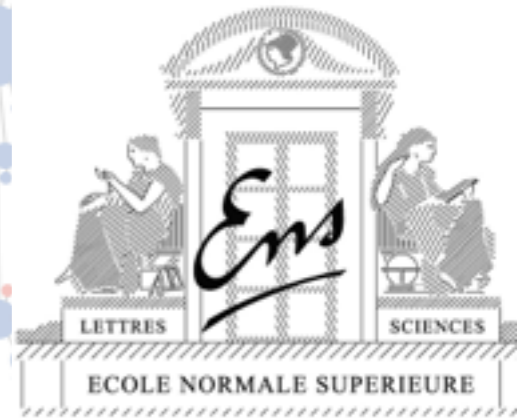
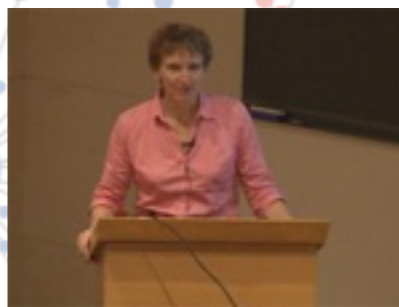




# Homophily and the Emergence of a Glass Ceiling Effect in Social Networks



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# What is the glass ceiling effect?

Federal Glass Ceiling Commission, US Gov, 1994:

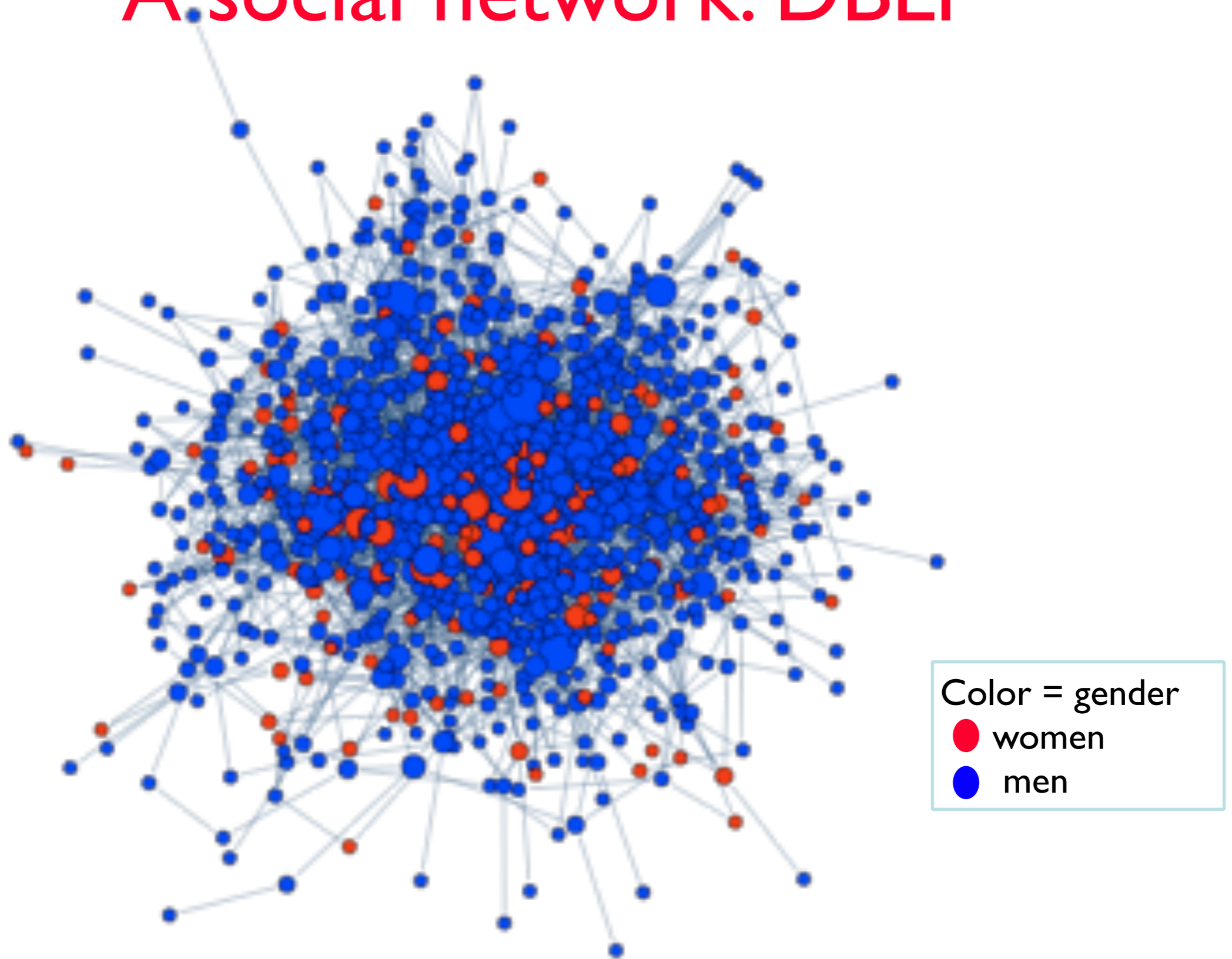
*“the unseen, yet unbreakable barrier that keeps minorities and women from rising to the upper rungs of the corporate ladder, regardless of their qualifications or achievements”*

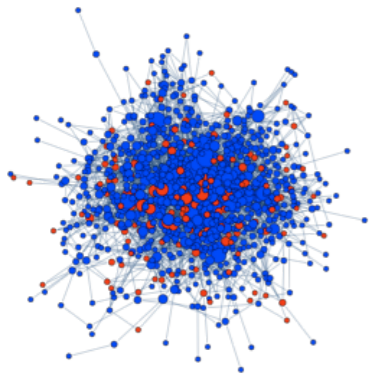
**Merriam-Webster:** *“an unfair system or attitudes that prevents some people (such as women or a certain race) from getting the most powerful jobs”*

## What is our main goal?

Model glass ceiling in a social network, analyze it, compare with empirical data

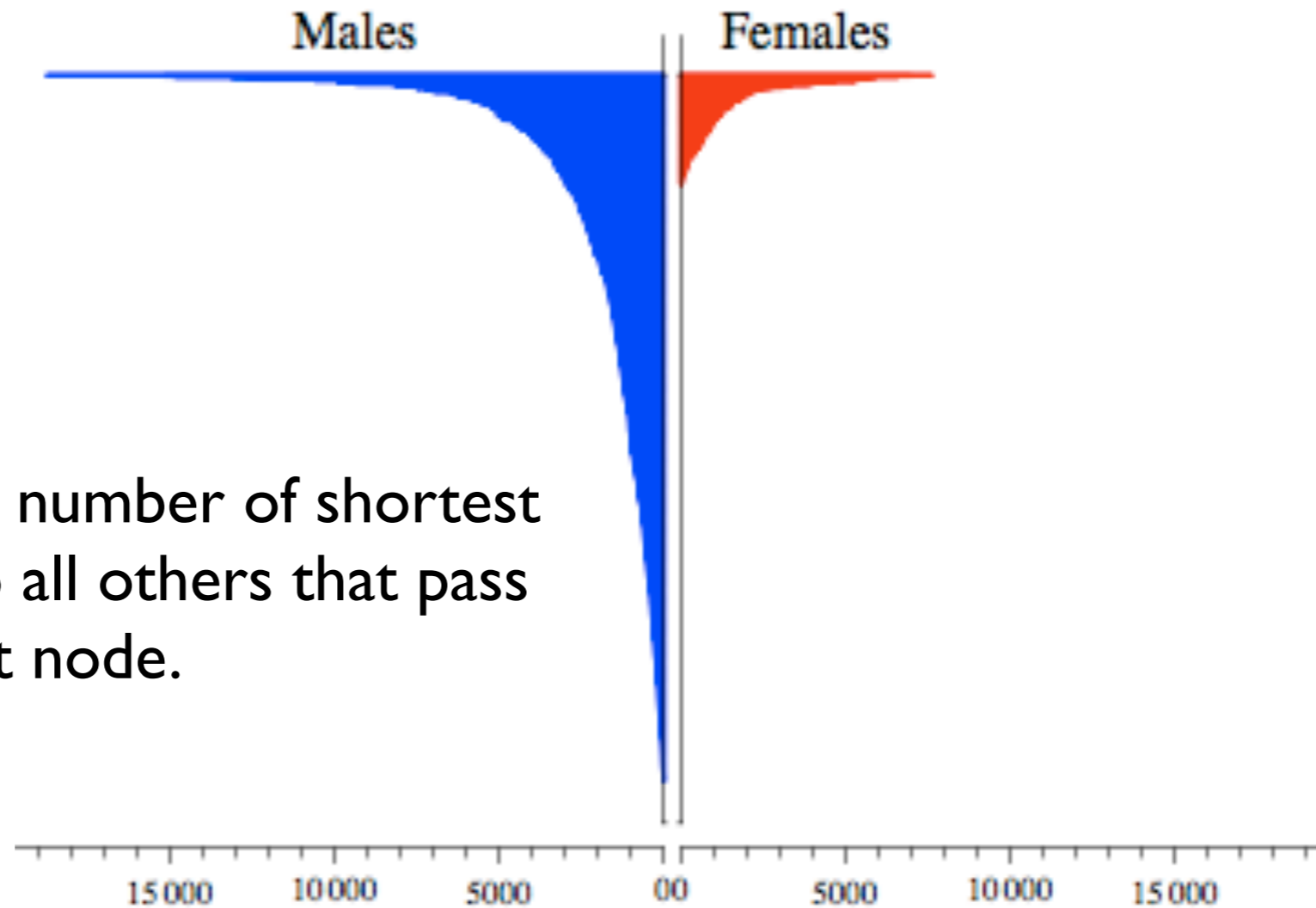
# A social network: DBLP





# Are men and women different?

(from the viewpoint of DBLP)

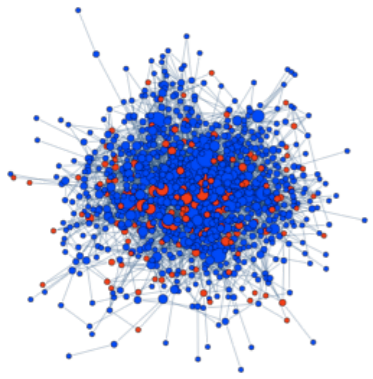


Betweenness centrality = number of shortest paths from all vertices to all others that pass through that node.

DBLP - top coauthorship network

# Are men and women different?

(from the viewpoint of DBLP)

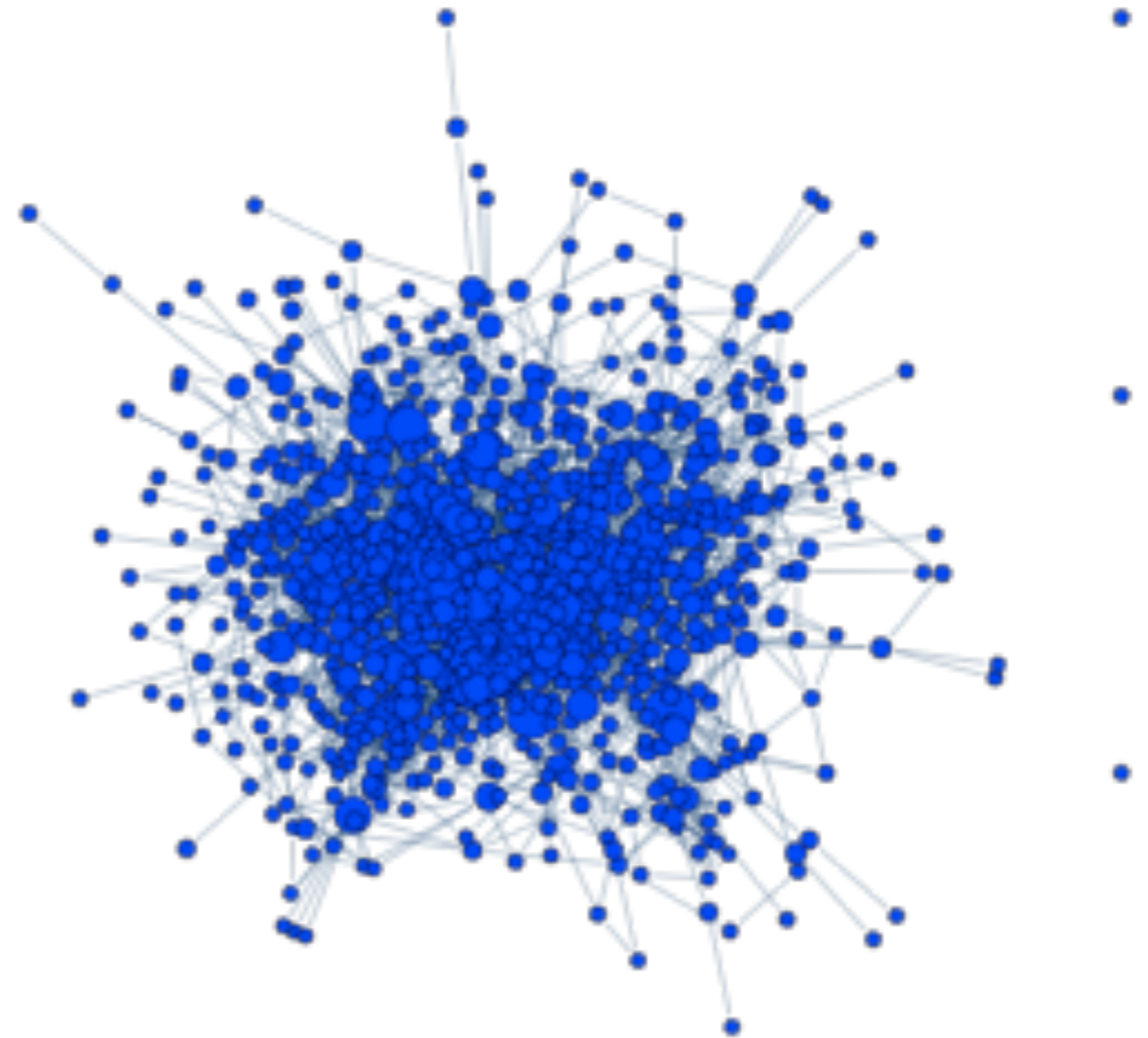


**Induced subgraphs**

Female network

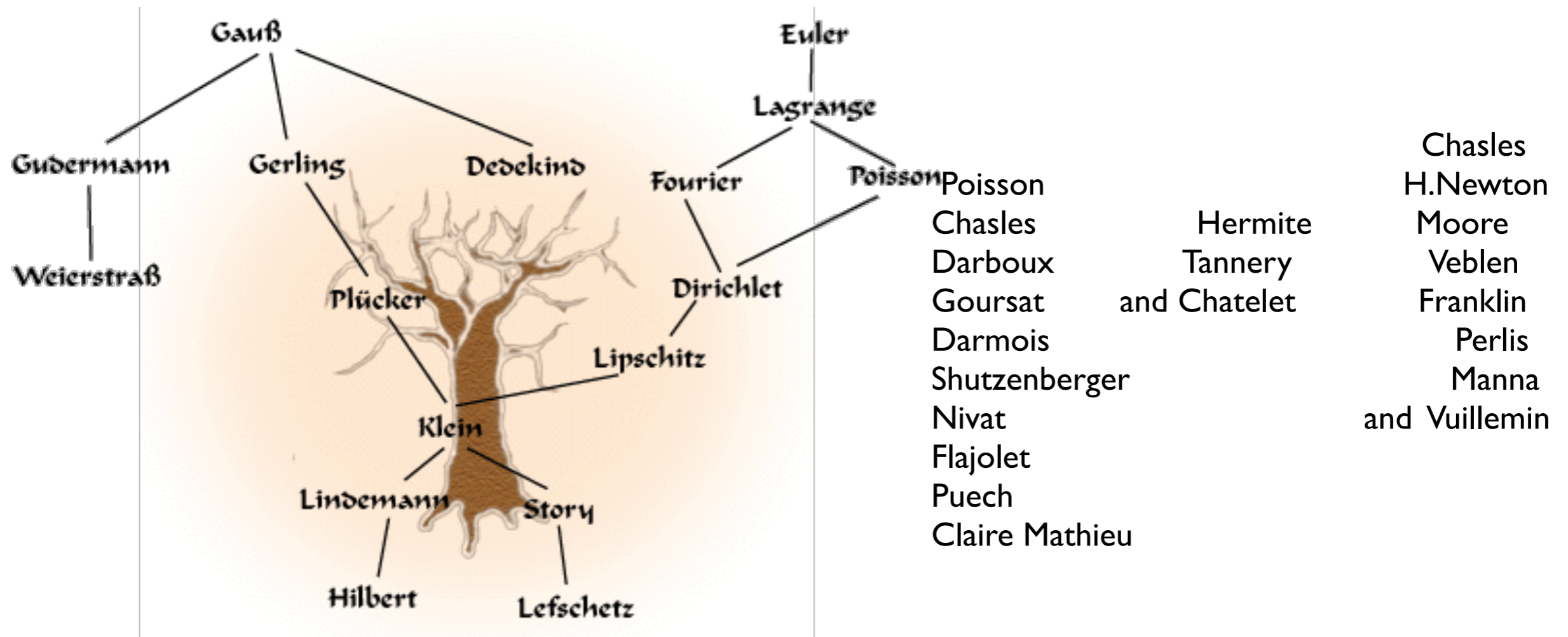


Male network



DBLP - top coauthorship network

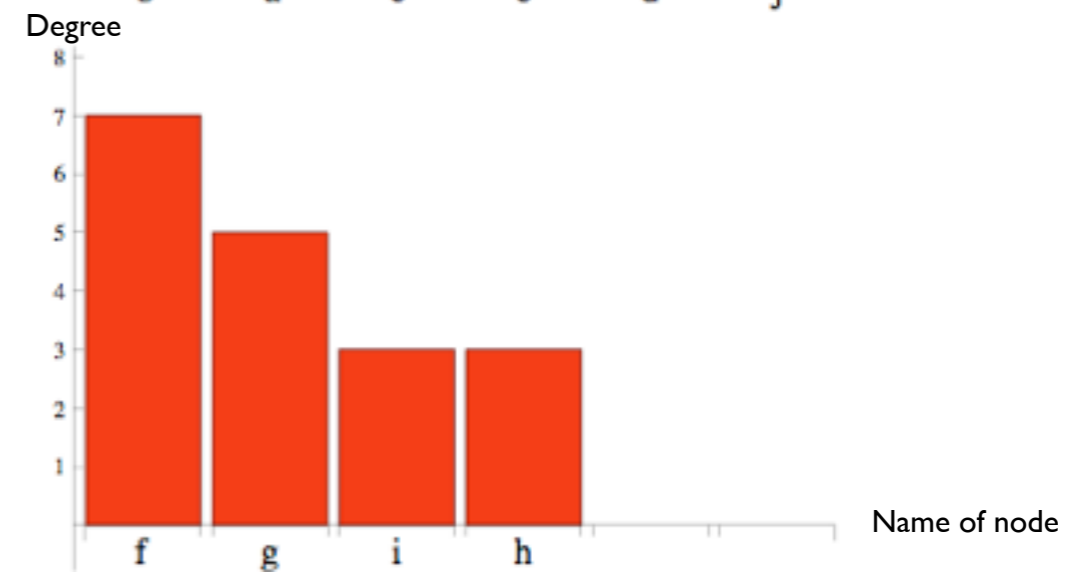
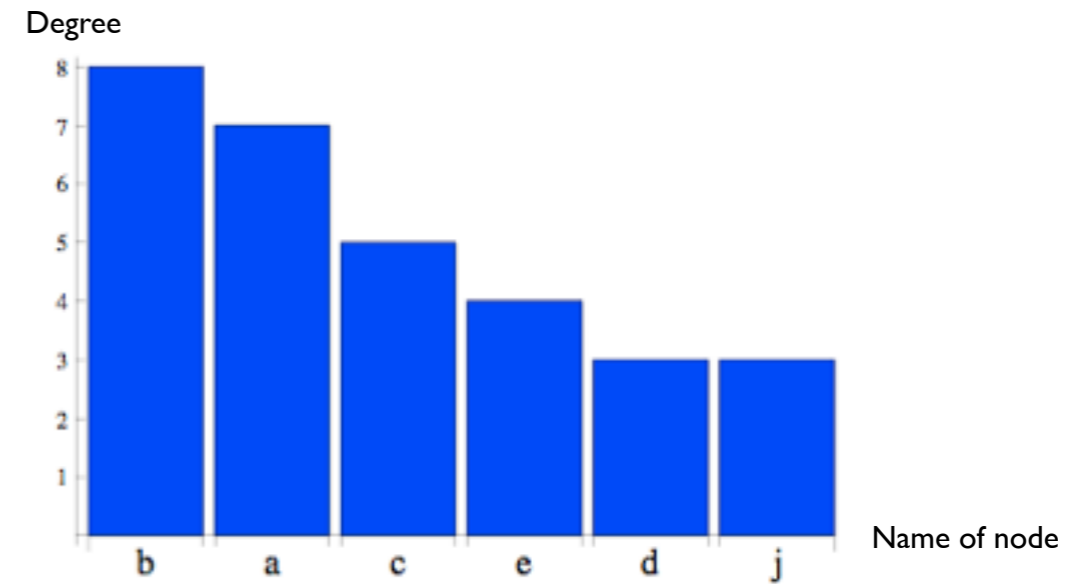
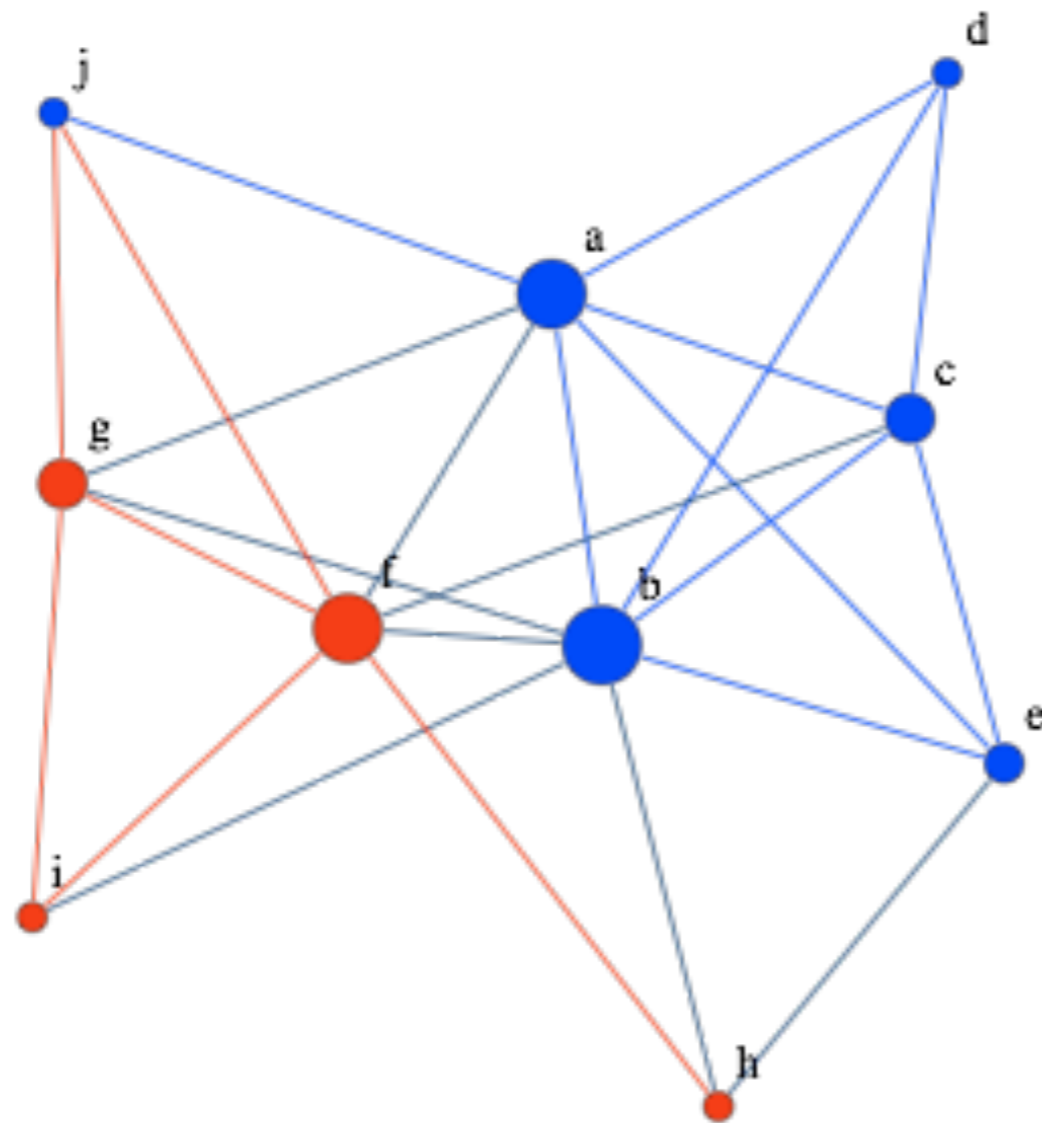
# Another social network: Student-Mentor (advisor) graph in academia



- people: nodes
- edge: advisor-advisee, mentor-mentee

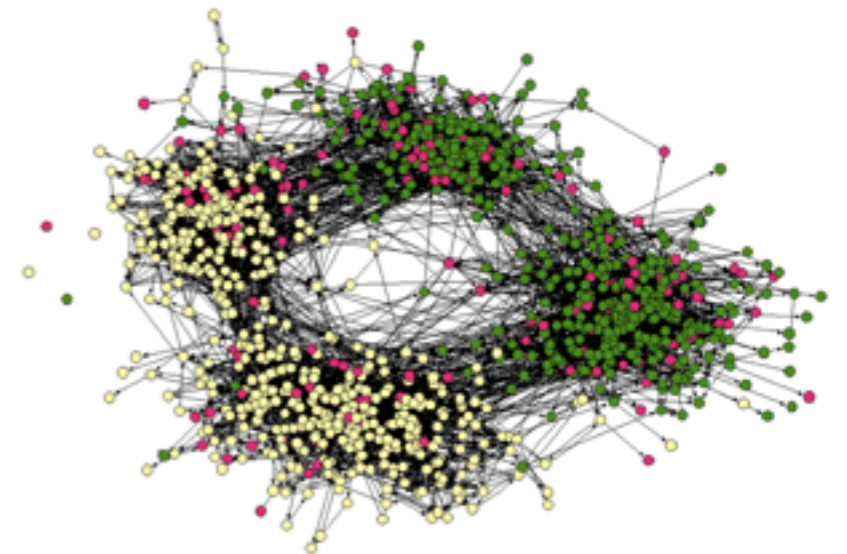
From DBLP, extract gender and Student-Mentor graph

# “Most powerful”, “upper rungs”: high degree



# Social concepts used for the model

- “rich get richer” - preferential attachment
- homophily - tendency of individuals to associate and bond with similar individuals.
- minority





## Rich Get Richer Lyrics

"Rich Get Richer" was written by Jerry A. Lang.

You might have more than me,  
I'm not so blind I can't see,  
The rich getting richer, who says that it has to be?  
Money talks, money screams,  
Middle class lies, American dreams,  
The rich get richer, the poor get poorer,  
Who says it has to be.

# Model glass ceiling in a social network: Biased Preferential Attachment (BPA) - $G(n, r, \rho)$

1. New node (student) arrives. **Minority** parameter:

- **Red** with probability  $r < 1/2$
- **Blue** with probability  $1 - r$

2. Selects a neighbor (advisor)  
by preferential attachment

$$\frac{\delta_t(v)}{\sum_{i \in V(t)} \delta_t(i)}$$

3. Checks neighbor's color. **Homophily** effect:

Same color: accept

Different color: accept with probability  $\rho$ ,  
otherwise go to step 2.

# of (red, blue) nodes with degree at least  $k$ :  $\text{top}_k(\mathbf{R}), \text{top}_k(\mathbf{B})$

- **Tail glass ceiling:**  $G(n)$  exhibits **tail glass ceiling effect** for the red nodes if:

$$\lim_{G \rightarrow \infty} \frac{\text{top}_k(\mathbf{R})}{\text{top}_k(\mathbf{B})} \rightarrow 0$$

while  $k=k(n)$  is s.t.

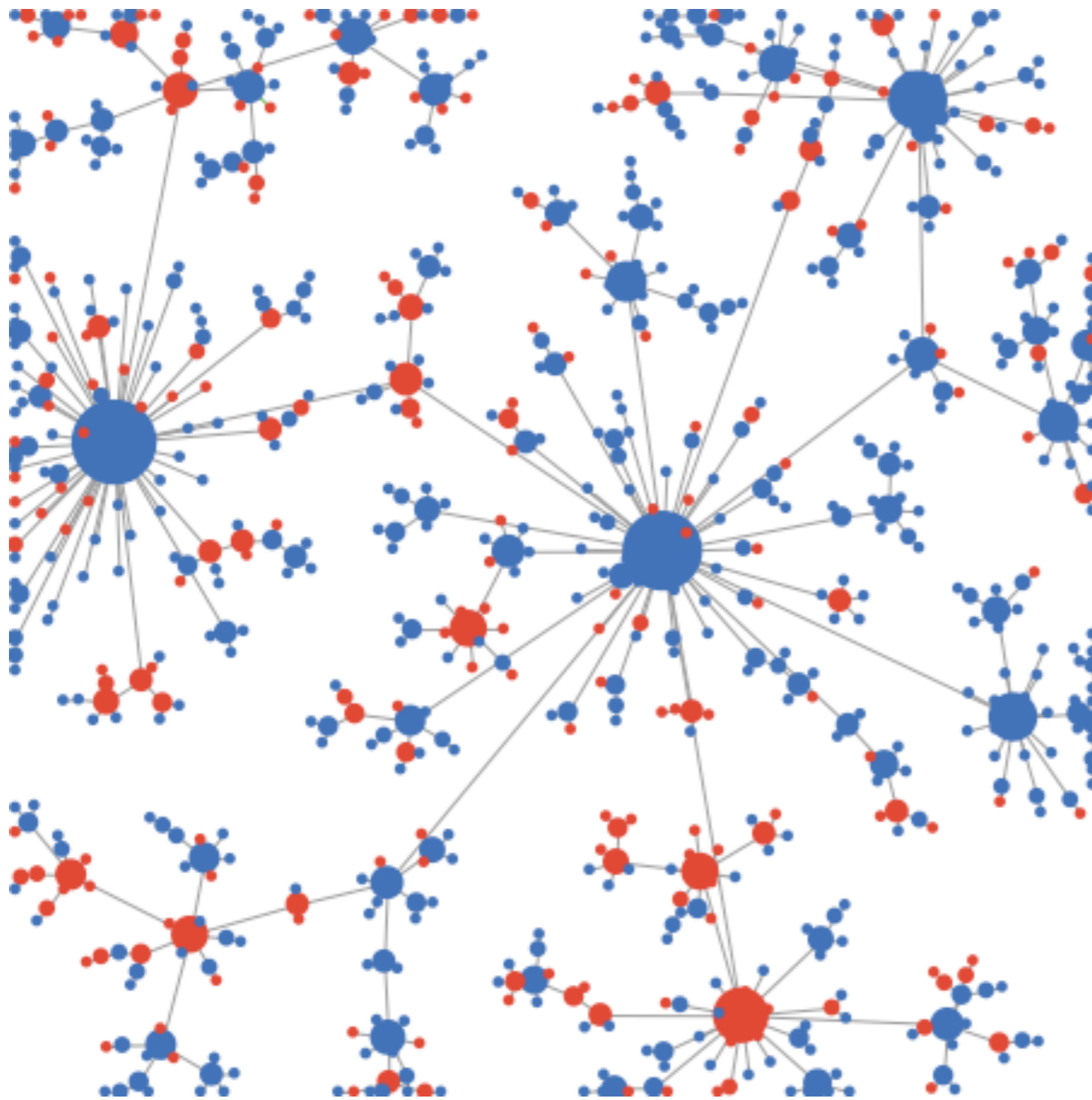
$$\text{top}_k(\mathbf{B}) \rightarrow \infty$$

- **Moment glass ceiling:** ratio of expected square degree of red vs. of blue vertices

# Main Theorem

- If  $0 < r < \frac{1}{2}$  and  $0 < \rho < 1$  then: **glass ceiling**
- If  $r = \frac{1}{2}$  (no minority) or  $\rho = 1$  (no homophily) then:  
**no glass ceiling**
- If new vertex selects advisor uniformly (no preferential attachment) then: **no moment glass ceiling.**

I.e.: three assumptions  $\rightarrow$  glass ceiling ,  
any two assumptions  $\rightarrow$  no glass ceiling



Proving  
the  
glass  
ceiling  
effect

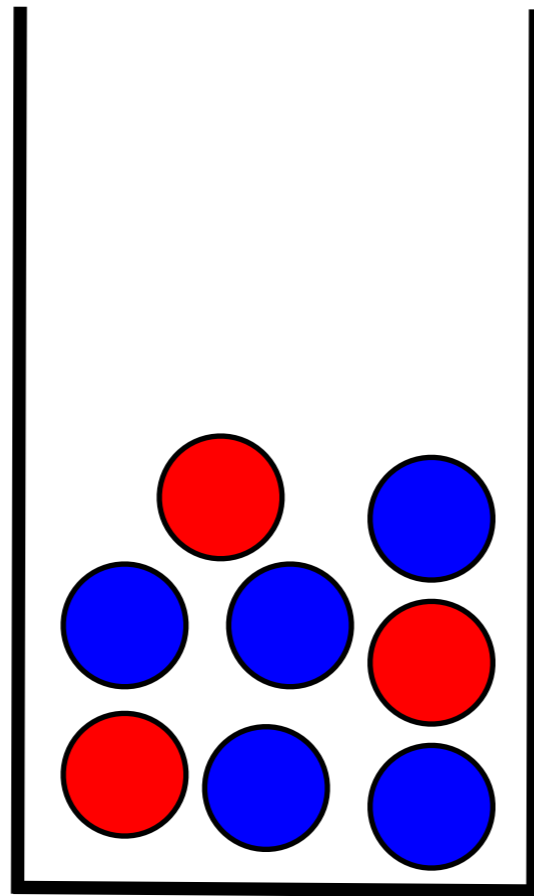
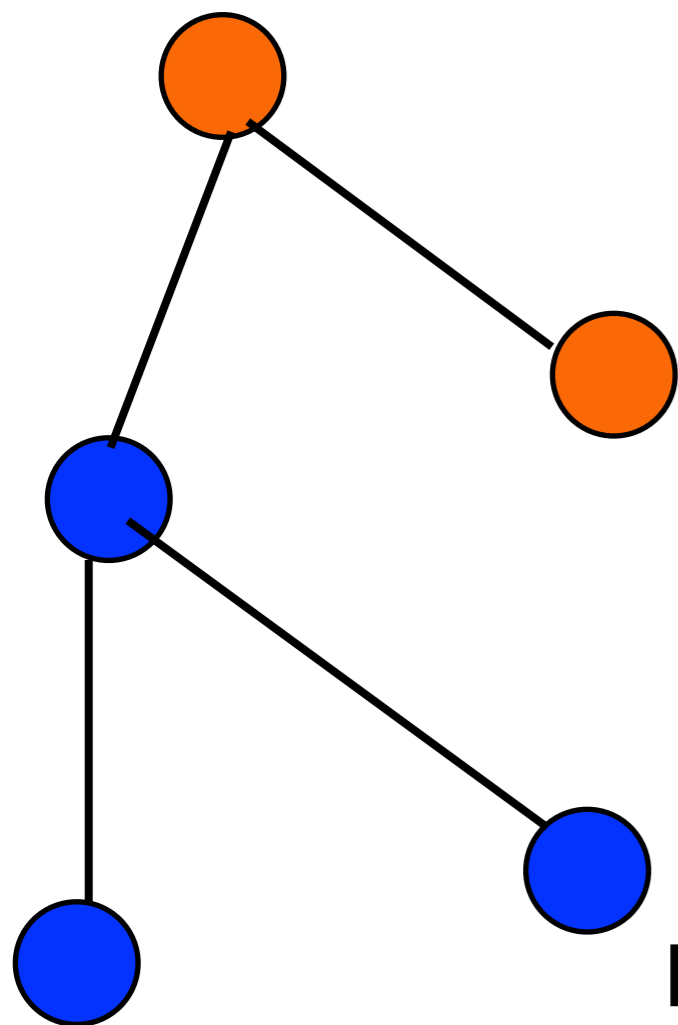
$$r=30, \rho=0.71$$

# Analyze it: Proof outline

1.  $\sum_{v \text{ red}} \text{degree}(v) / \#(\text{red nodes})$  : **fast convergence in expectation**
2.  $\sum_{v \text{ red}} \text{degree}(v) / \#(\text{red nodes})$  : **fast convergence with high probability**
3. **Distribution** of degrees of red nodes and of degrees of blue nodes

$$\sum_{v \text{ red}} \text{degree}(v) / \#(\text{red nodes})$$

# From graph to urn



Ball = half-edge,  
color = color of endpoint

Generate new ball, red or blue  
 $(r, 1-r)$

Pick existing ball uniformly from  
urn

Same color - add a copy

Different color -

with probability  $\rho$  add a copy  
with probability  $1-\rho$  retry

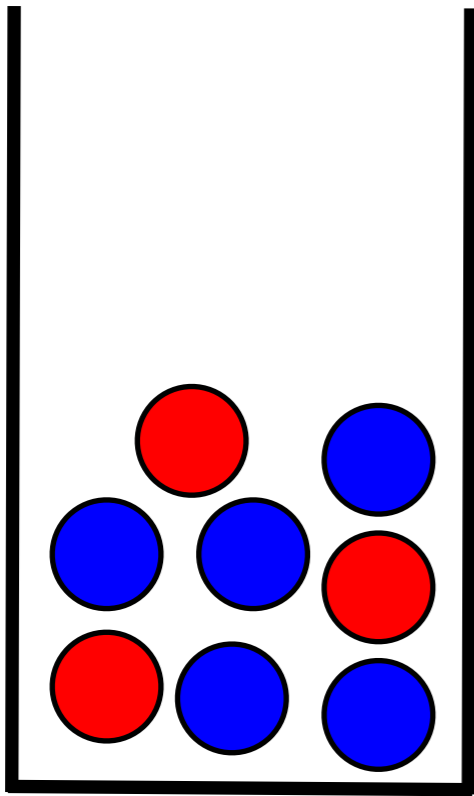
$$\sum_{v \text{ red}} \text{degree}(v) \sim \#(\text{red balls})$$

$$\#(\text{red nodes}) \sim rt$$

$$\#(\text{balls}) \sim 2t$$

Analyze  $\frac{\#(\text{red balls})}{\#(\text{balls})}$

# step 1 - expected fraction of red balls (1/3)



Generate new ball, red or blue  
( $r, 1-r$ )

Pick existing ball uniformly from  
urn

Same color - add a copy

Different color -

with probability  $\rho$  add a copy

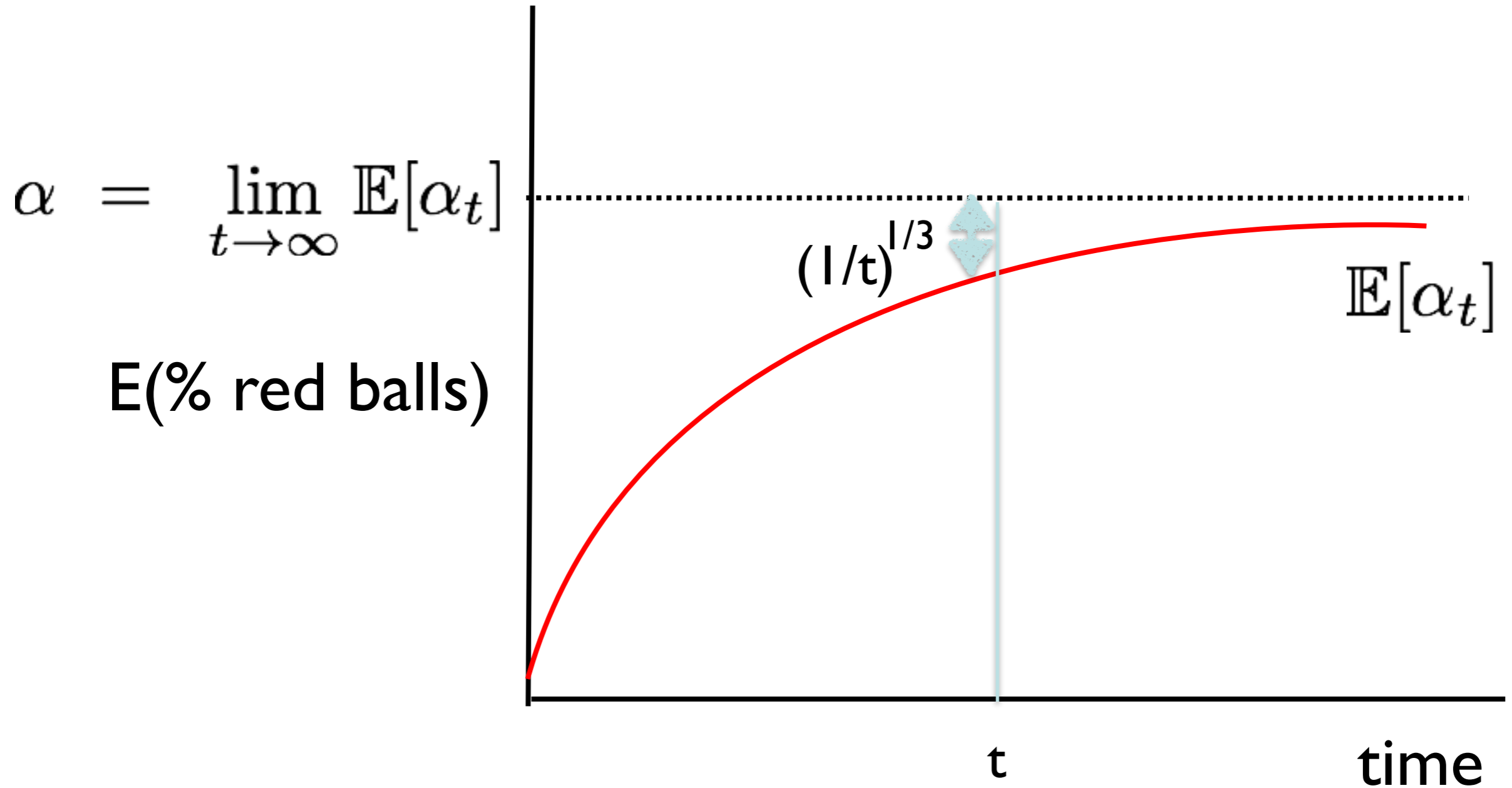
with probability  $1-\rho$  retry

Let  $X_t = \#(\text{red balls})$

$$\text{Let } \alpha_t = \#(\text{red balls}) / \#(\text{balls})$$
$$X_{t+1} - X_t = \begin{cases} 2 & \text{w.p. } \frac{r\alpha_t}{1-(1-\alpha_t)(1-\rho)} \\ 0 & \text{w.p. } \frac{(1-r)(1-\alpha_t)}{(1-\alpha_t)(1-\rho)} \\ 1 & \text{otherwise} \end{cases}$$
$$\implies \mathbb{E}(\alpha_{t+1} | \alpha_t)$$



# Rate of convergence of expectation (3/3)



## step 2 - High probability convergence (1/3)

**Martingale def'n:**  $B_i$  is a martingale if  
 $\mathbb{E}(B_{i+1} | \text{history up to time } t) = B_i$

**Doob martingale:** If  $N_i$  = number of new red balls at time  $i$  then

$B_i = \mathbb{E}(N_0 + \dots + N_t | N_0, \dots, N_i)$  is a martingale.

$B_0$  = Expected number of red balls at time  $t$

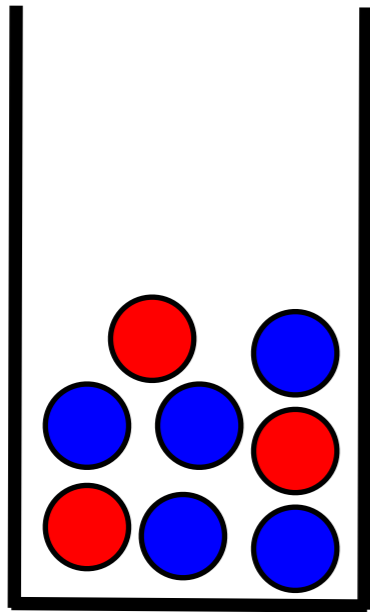
$B_t$  = Actual number of red balls at time  $t$

**Azuma's inequality:** Martingale  $B_i$  and bounded change  $|B_i - B_{i-1}|$  implies tail exponential decay

**Application to our problem:**  $|B_i - B_{i-1}|$  is  $O(\sqrt{t/i})$

$$\mathbb{P}(|B_t - B_0| \geq x) < 2e^{-\frac{x^2}{2 \sum_i c_i^2}}$$

## step 2 - High probability convergence (2/3)



Generate new ball, red or blue

$(r, 1-r)$

Pick existing ball uniformly from urn

Same color - add a copy

Different color -

with probability  $\rho$  add a copy

with probability  $1-\rho$  retry

**Application to our problem:**  $|B(i)-B(i-1)|$  is  $O(\sqrt{t/i})$ .

To compute  $|B(i)-B(i-1)|$ : analyze  $z(i)$  = expected number of additional red balls at times  $[i,t]$  given that there is one additional red ball at time  $i$

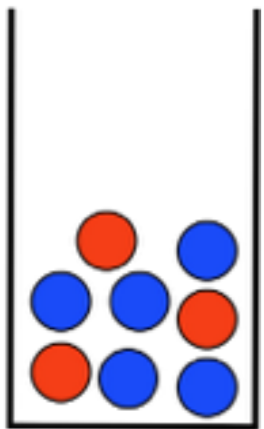
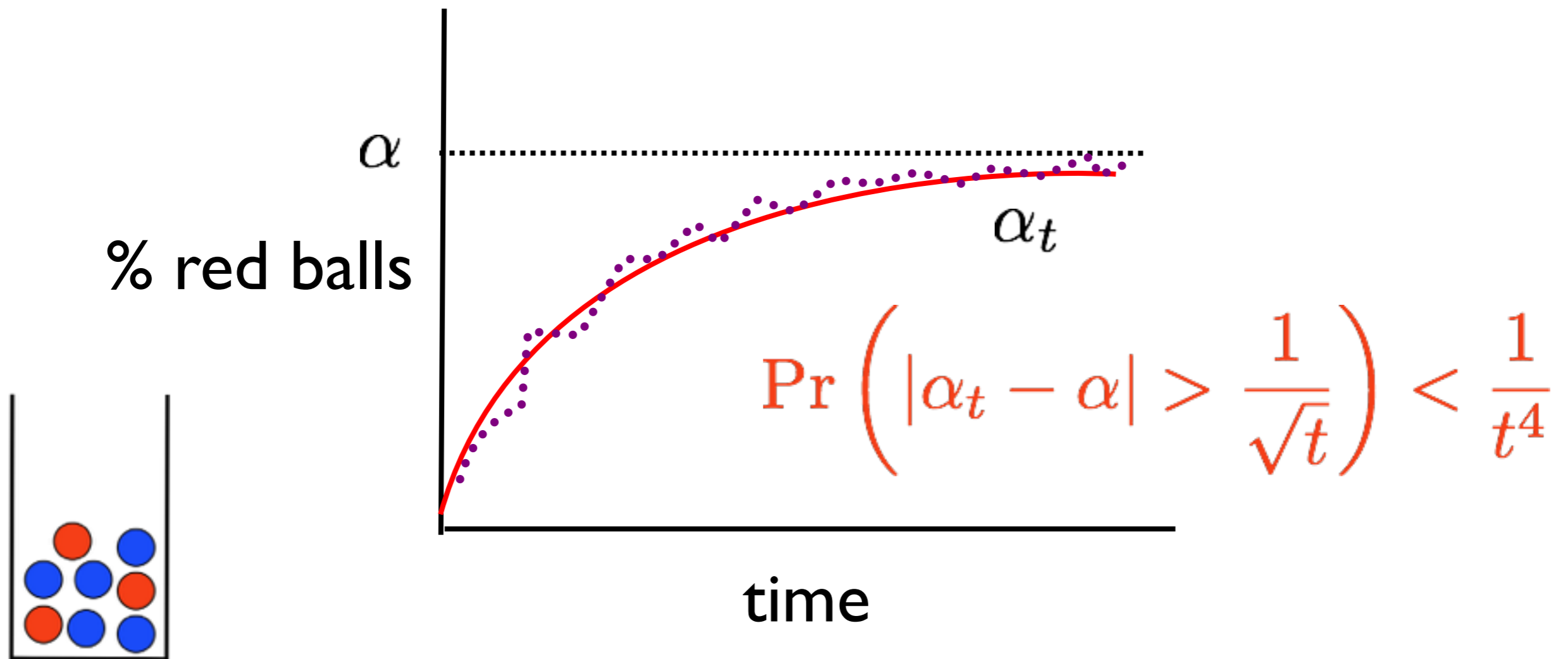
Note: each additional red ball creates an **independent** effect on the color of its descendants (copies of the ball)

$$z_i = 1 + \frac{\gamma}{2(i+1)} z_{i+1} + \frac{\gamma}{2(i+2)} z_{i+2} + \cdots + \frac{\gamma}{2t} z_t$$

# step 2- high probability convergence (3/3)

$$\alpha_t = \frac{R(t)}{2t}$$

$$\alpha = \lim_{t \rightarrow \infty} \mathbb{E}[\alpha_t]$$



# step 3- Degree distribution (1/3)

extend analysis of degree distribution of preferential attachment graph:

**red node** with degree  $k$  at time  $t$

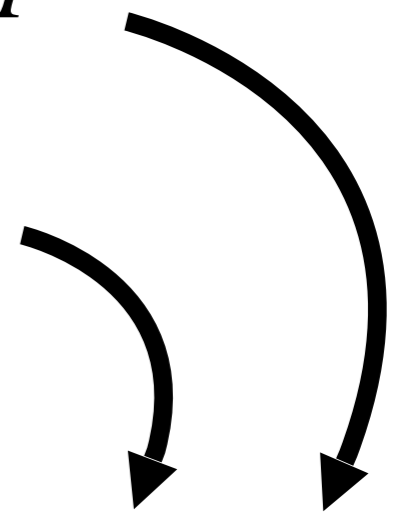
$(m_{k,t}(R) = \#(\text{red nodes of degree } k \text{ at time } t))$

comes from

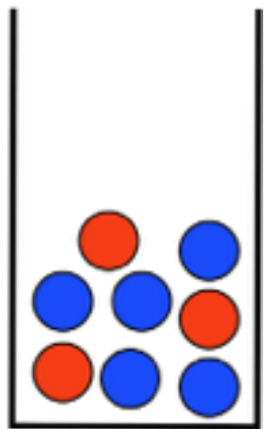
**red node** with degree  $k$  at time  $t-1$

or

**red node** with degree  $k-1$  at  $t-1$



**Homophily,  $r$ ,  $k$  and % of red nodes play a role**



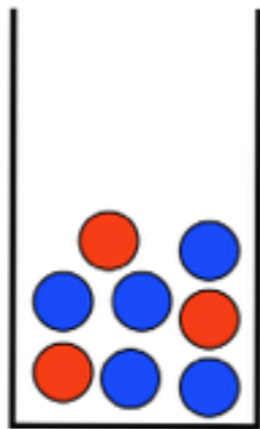
$$\mathbb{E}(m_{k,t}(R)|\text{history}) = \dots m_{k,t-1}(R) \dots m_{k-1,t-1}(R) \dots$$

## step 3- Degree distribution (2/3)

The expected degree distribution of both the blue nodes and the red nodes follows a power law with **different** parameters:

$$M_k(\mathbf{R}) \propto k^{-\beta(\mathbf{R})}$$

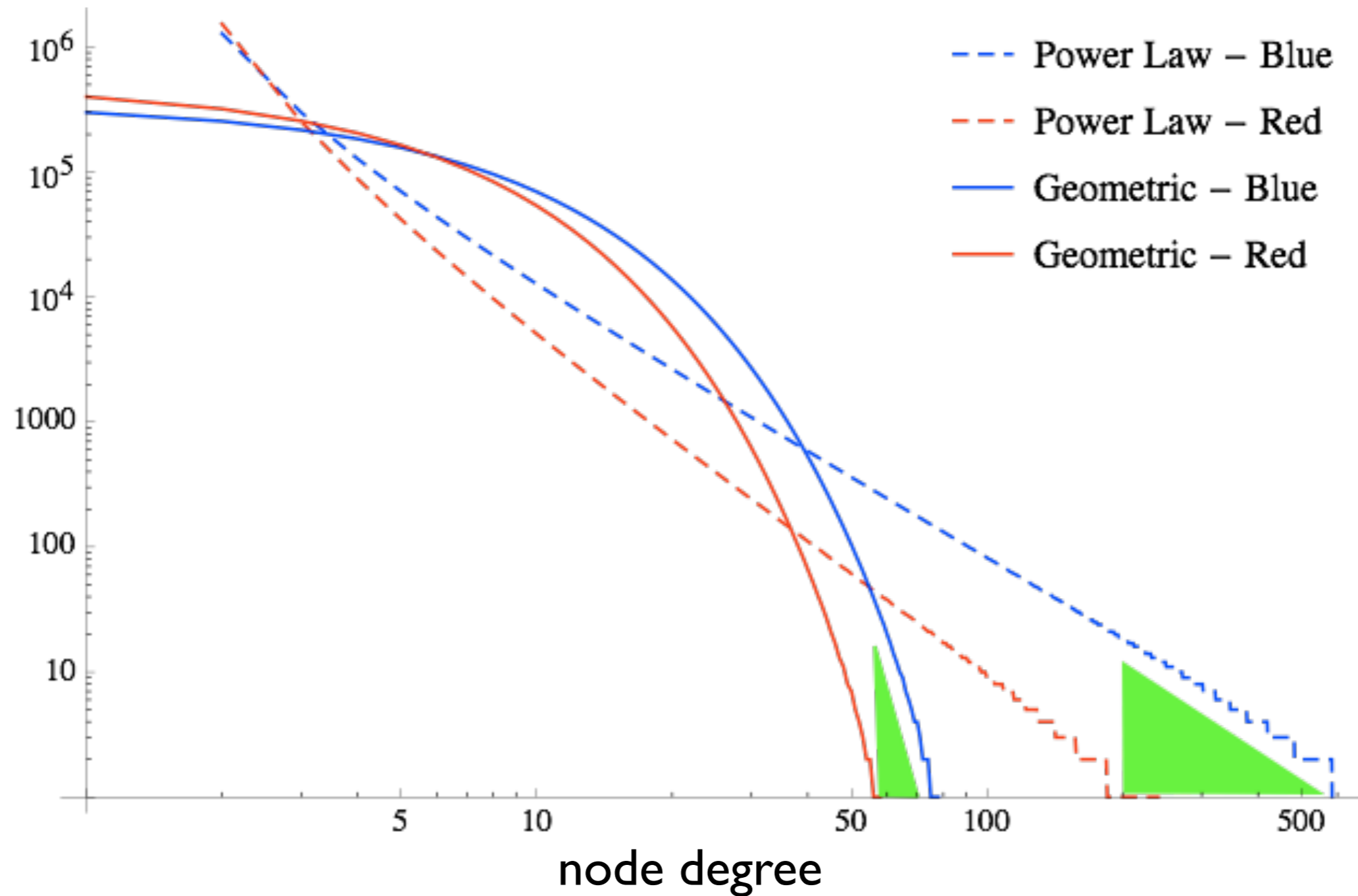
$$M_k(\mathbf{B}) \propto k^{-\beta(\mathbf{B})}$$



$$\beta(\mathbf{B}) > \beta(\mathbf{R})$$

# step 3- Degree distribution (3/3)

# of nodes



$$\lim_{G \rightarrow \infty} \frac{\text{top}_k(\mathbf{R})}{\text{top}_k(\mathbf{B})} \rightarrow 0$$

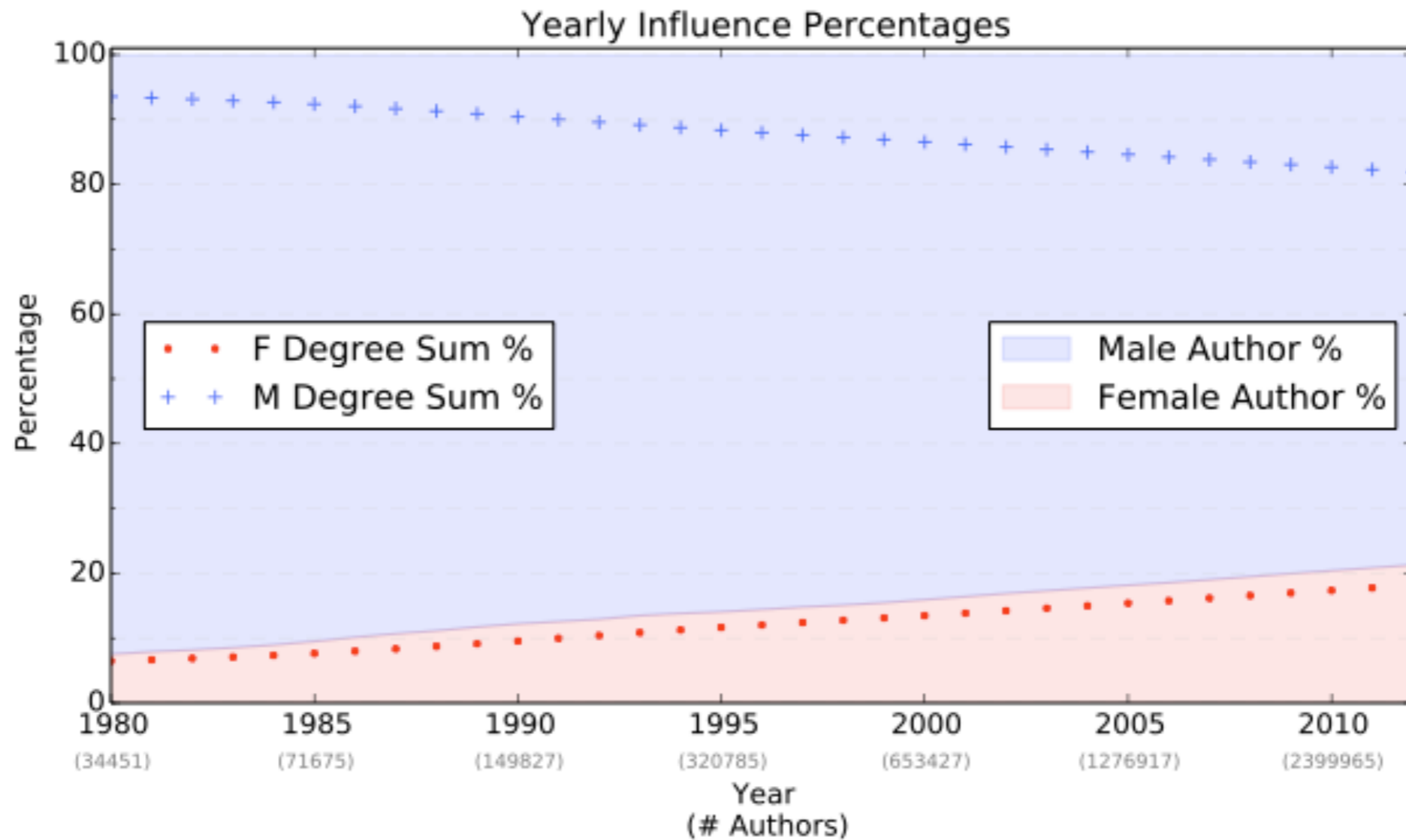
Compare with **empirical** data :

Any connection to real life? -

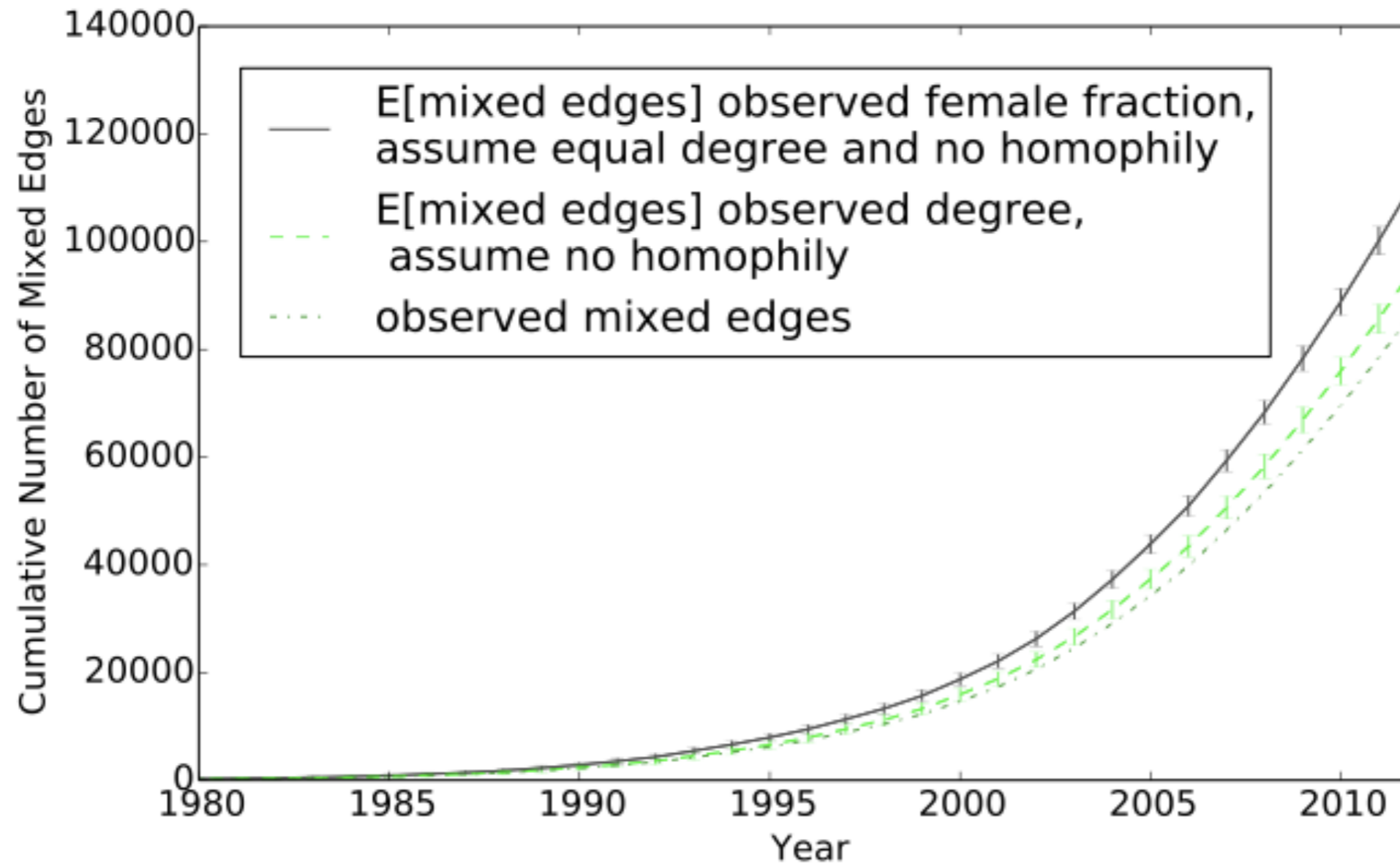
Student-advisor links in DBLP



# Are women a minority in DBLP?



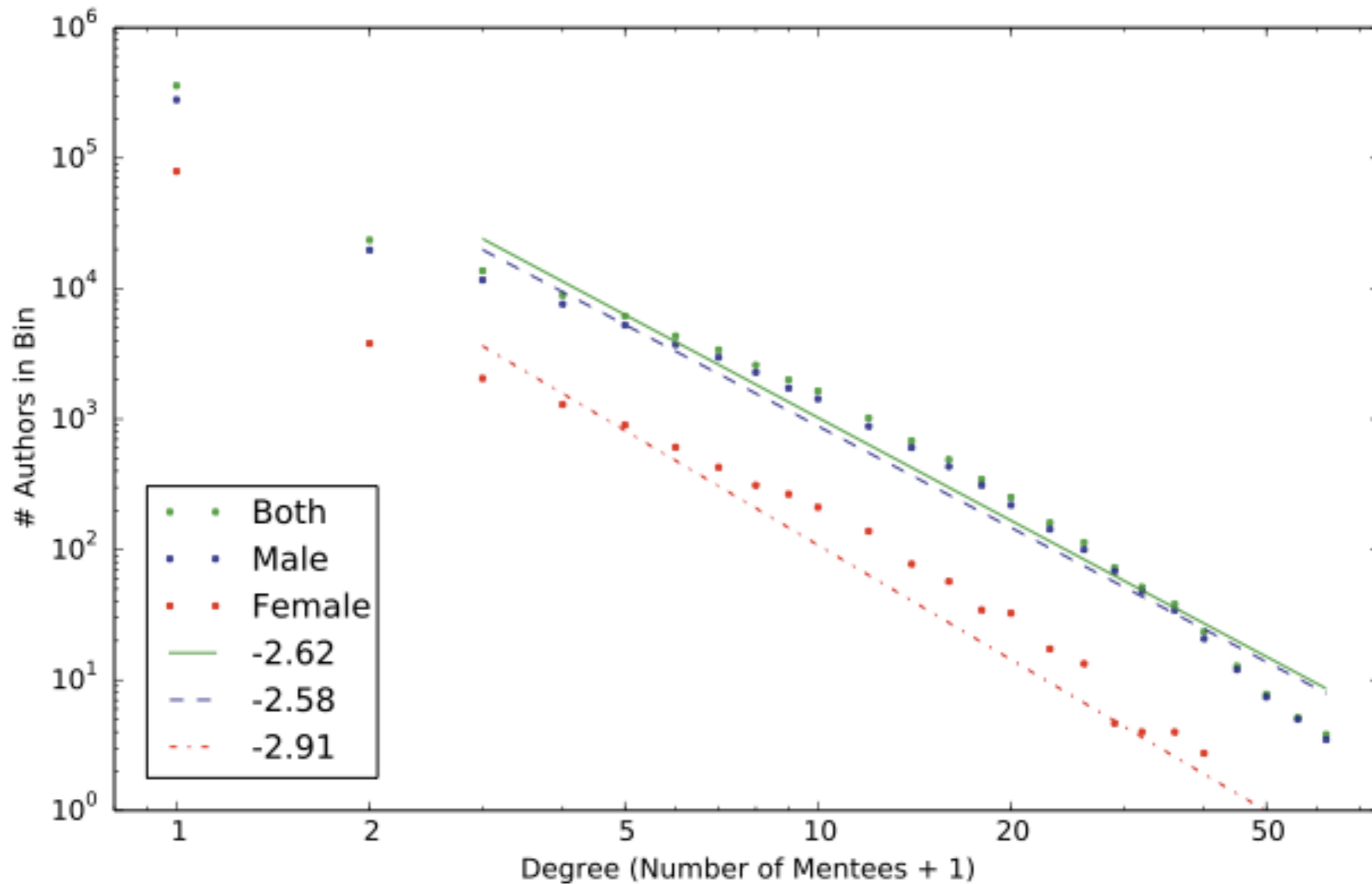
# Is there homophily in DBLP?



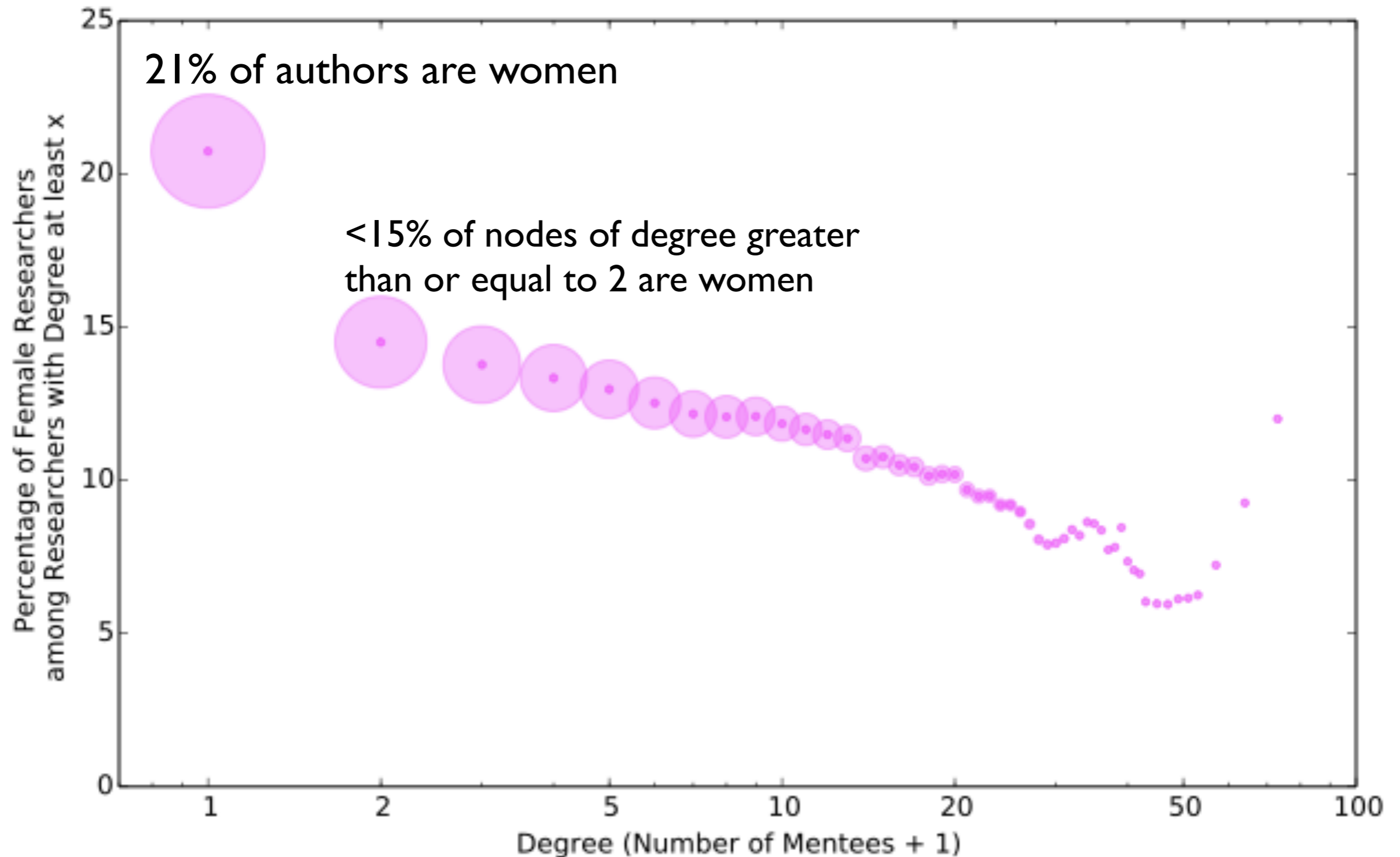
Homophily: unconditional or conditional on total degree

# Is there preferential attachment in DBLP?

## Distribution of degrees



# Is there a glass ceiling in DBLP?



**Q: How does one extract gender from DBLP?**

**A: To assign a gender to the authors in DBLP we looked up their first name in our dictionary. If the probability of the name being female or male was over 90%, then the corresponding gender was assigned to the author.**

**Q: How does one extract the student-advisor network from DBLP?**

**A: A person was only considered as a potential mentor of a mentee if the difference in the number of years between the dates of their first articles exceeded four.**

# Notes

1. no minority?
2. no homophily?
3. no preferential attachment?
4. unequal rate and unequal qualification?
5. “leaky pipeline”?