

Community Structure in Networks

CS224W: Social and Information Network Analysis

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<http://cs224w.stanford.edu>



How the Class Fits Together

Observations

Small diameter,
Edge clustering

Patterns of signed
edge creation

Viral Marketing, Blogosphere,
Memetracking

Scale-Free

Densification power law,
Shrinking diameters

Strength of weak ties,
Core-periphery

Models

Erdős-Renyi model,
Small-world model

Structural balance,
Theory of status

Independent cascade model,
Game theoretic model

Preferential attachment,
Copying model

Microscopic model of
evolving networks

Kronecker Graphs

Algorithms

Decentralized search

Models for predicting
edge signs

Influence maximization,
Outbreak detection, LIM

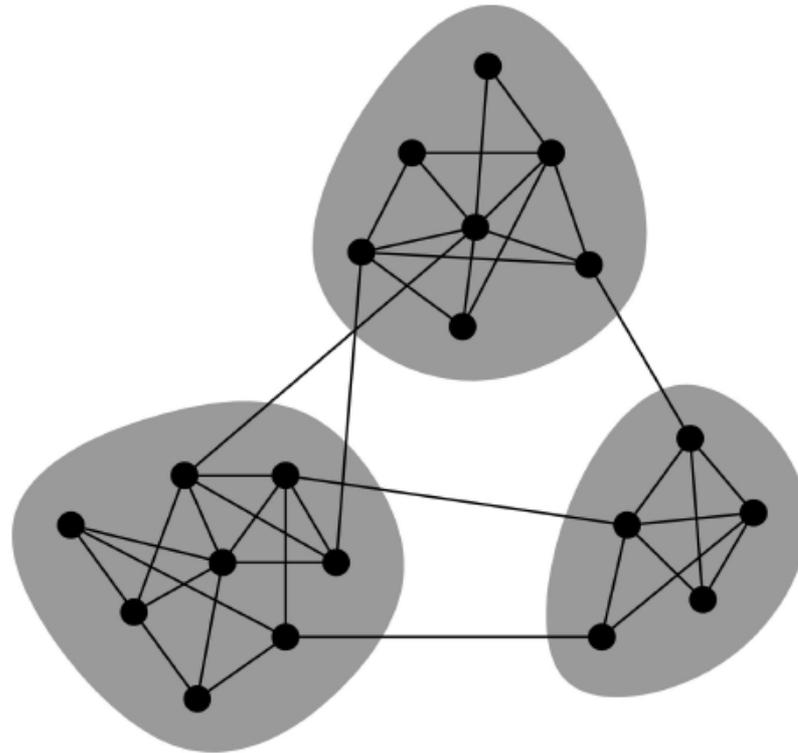
PageRank, Hubs and
authorities

Link prediction,
Supervised random walks

Community detection:
Girvan-Newman, Modularity

Networks & Communities

- We often think of networks “looking” like this:



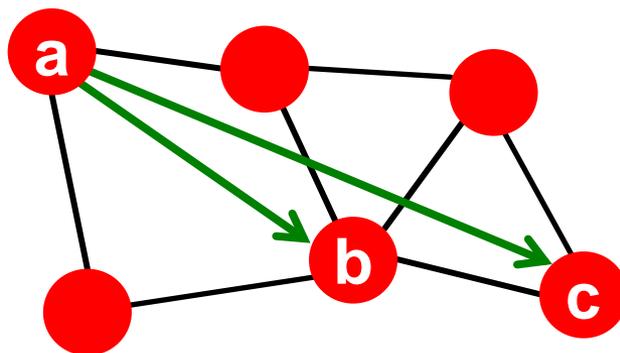
- What lead to such conceptual picture?

Networks: Flow of Information

- **How information flows through the network?**
 - What structurally distinct roles do nodes play?
 - What roles do different **links** (**short** vs. **long**) play?
- **How people find out about new jobs?**
 - Mark Granovetter, part of his PhD in 1960s
 - People find the information through personal contacts
- **But:** Contacts were often **acquaintances** rather than close friends
 - **This is surprising:** One would expect your friends to help you out more than casual acquaintances
- **Why is it that acquaintances are most helpful?**

Granovetter's Answer

- **Two perspectives on friendships:**
 - **Structural:** Friendships span different parts of the network
 - **Interpersonal:** Friendship between two people is either **strong** or **weak**
- **Structural role: Triadic Closure**

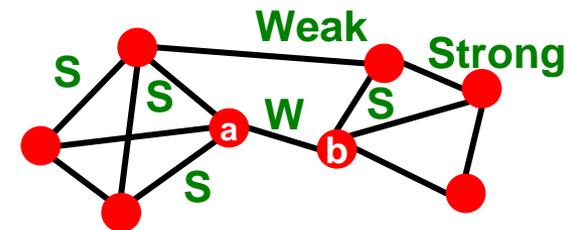


Which edge is more likely a-b or a-c?

If two people in a network have a friend in common, then there is an increased likelihood they will become friends themselves.

Granovetter's Explanation

- Granovetter makes a connection between social and structural role of an edge
- **First point: Structure**
 - Structurally embedded edges are also socially strong
 - Long-range edges spanning different parts of the network are socially weak
- **Second point: Information**
 - Long-range edges allow you to gather information from different parts of the network and get a job
 - Structurally embedded edges are heavily redundant in terms of information access

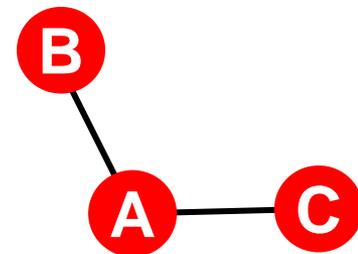


Triadic Closure

- Triadic closure == High **clustering coefficient**

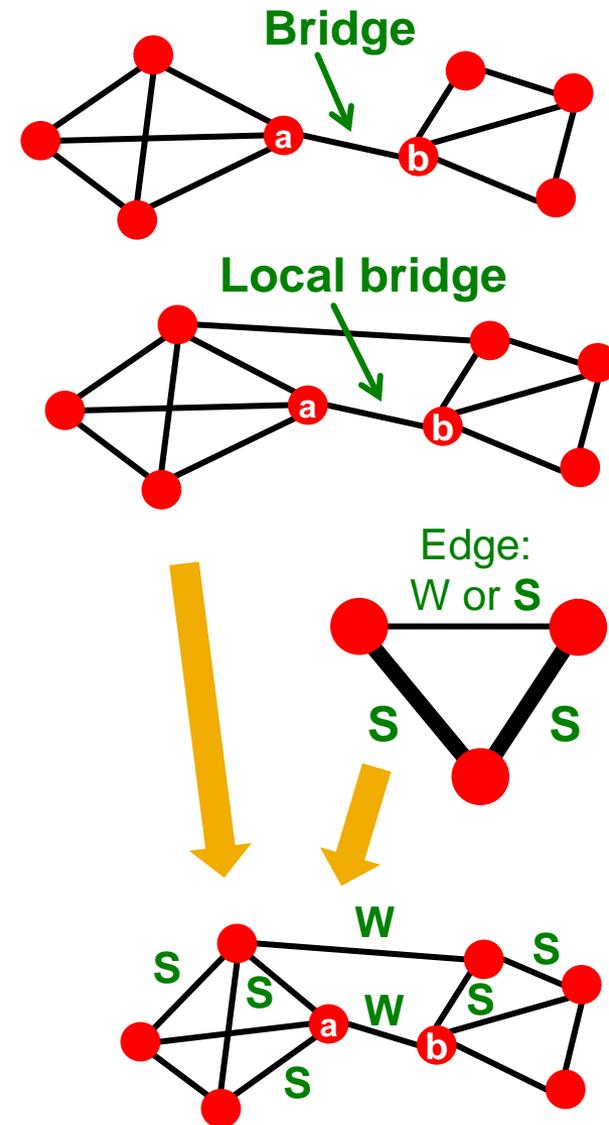
Reasons for triadic closure:

- If ***B*** and ***C*** have a friend ***A*** in common, then:
 - ***B*** is more likely to meet ***C***
 - (since they both spend time with ***A***)
 - ***B*** and ***C*** trust each other
 - (since they have a friend in common)
 - ***A*** has **incentive** to bring ***B*** and ***C*** together
 - (as it is hard for ***A*** to maintain two disjoint relationships)
- **Empirical study by Bearman and Moody:**
 - Teenage girls with low clustering coefficient are more likely to contemplate suicide



Granovetter's Explanation

- Define: Bridge edge
 - If removed, it disconnects the graph
- Define: Local bridge
 - Edge of **Span** > 2
(**Span** of an edge is the distance of the edge endpoints if the edge is deleted. **Local bridges with long span are like real bridges**)
- Define: Two types of edges:
 - **Strong** (friend), **Weak** (acquaintance)
- Define: Strong triadic closure:
 - Two strong ties imply a third edge
- **Fact:** If strong triadic closure is satisfied then **local bridges are weak ties!**

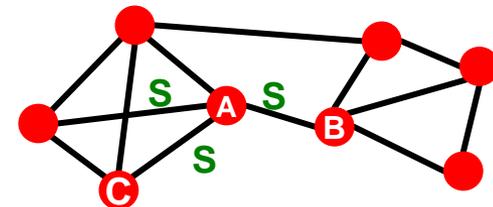
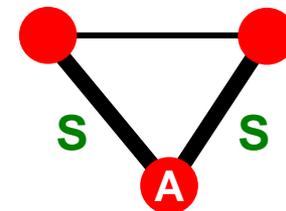


Local Bridges and Weak ties

- **Claim:** If node A satisfies **Strong Triadic Closure** and is involved in at least **two strong ties**, then any **local bridge** adjacent to A must be a **weak tie**.

- **Proof by contradiction:**

- Assume A satisfies **Strong Triadic Closure** and has **2 strong ties**
- Let $A - B$ be **local bridge** and a **strong tie**
- Then $B - C$ must exist because of **Strong Triadic Closure**
- But then $A - B$ is **not a bridge!**
(since $B-C$ must be connected due to Strong Triadic Closure property)



Tie strength in real data

- **For many years the Granovetter's theory was not tested**
- But, today we have large who-talks-to-whom graphs:
 - Email, Messenger, Cell phones, Facebook
- **Onnela et al. 2007:**
 - Cell-phone network of 20% of country's population
 - **Edge strength: # phone calls**

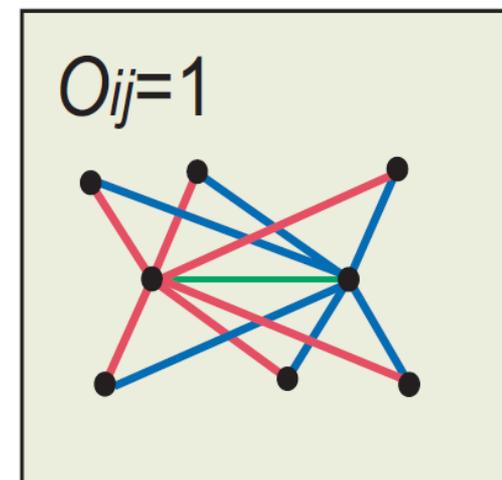
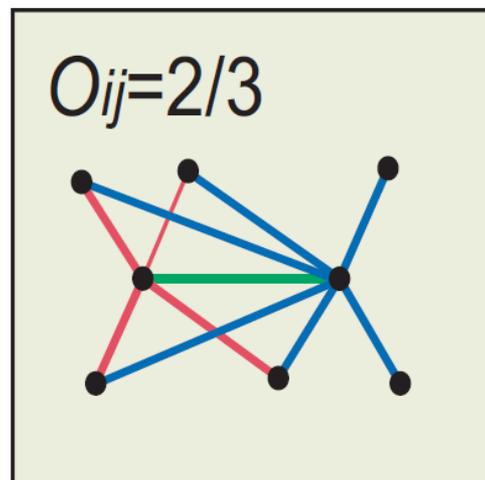
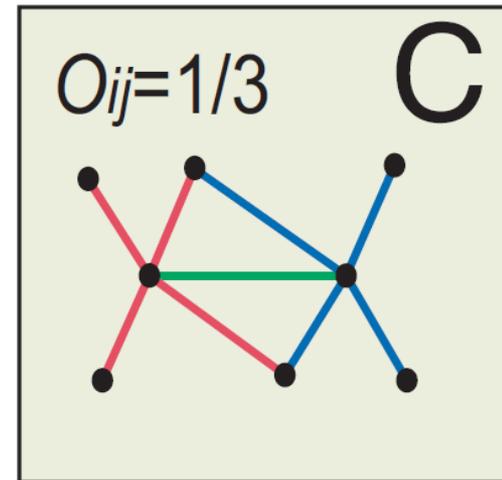
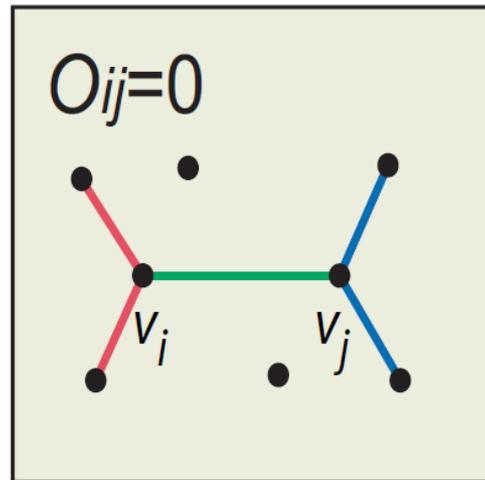
Neighborhood Overlap

- **Edge overlap:**

$$O_{ij} = \frac{N(i) \cap N(j)}{N(i) \cup N(j)}$$

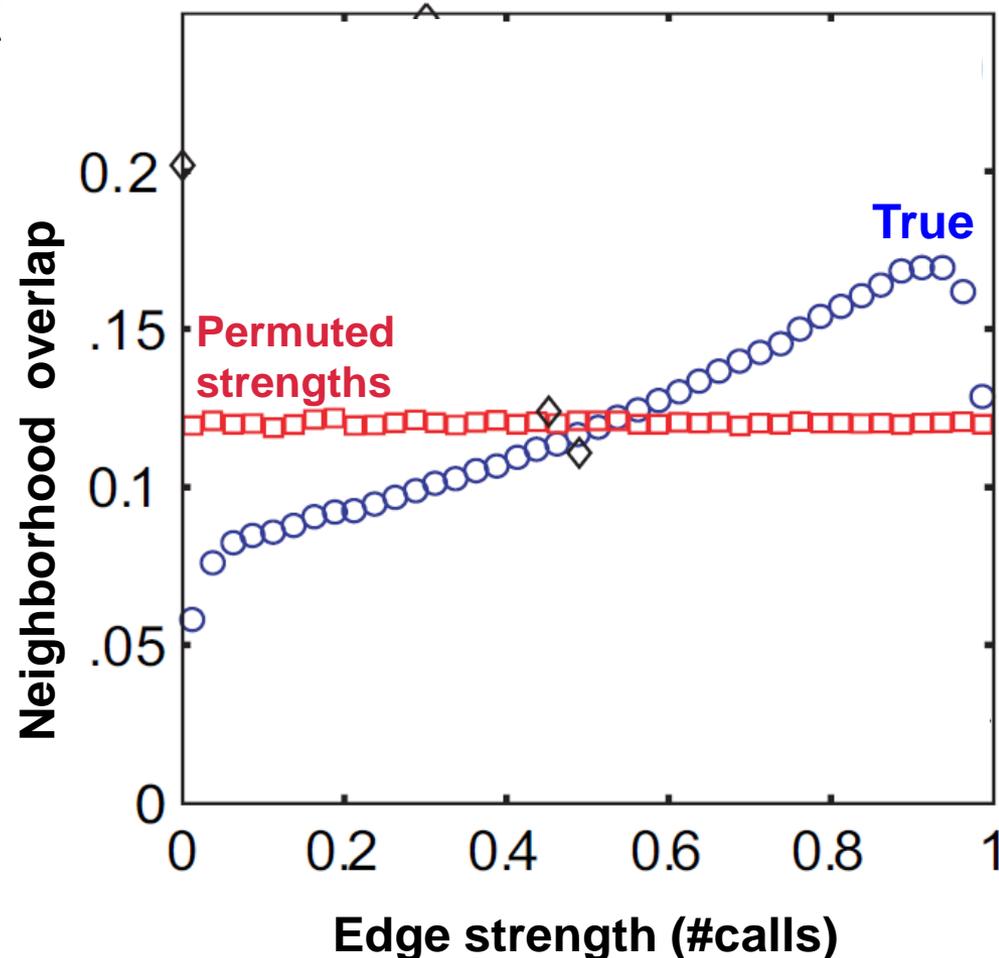
- $N(i)$... a set of neighbors of node i

- **Overlap = 0**
when an edge is a **local bridge**

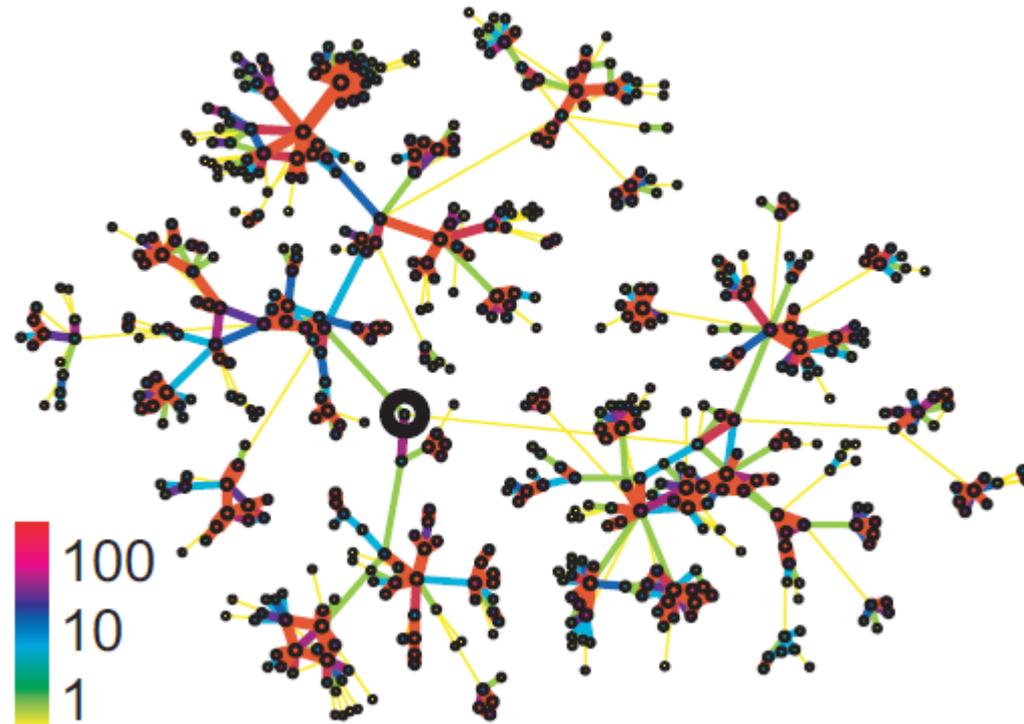


Phones: Edge Overlap vs. Strength

- Cell-phone network
- **Observation:**
 - Highly used links have high overlap!
- **Legend:**
 - **True:** The data
 - **Permuted strengths:** Keep the network structure but randomly reassign edge strengths

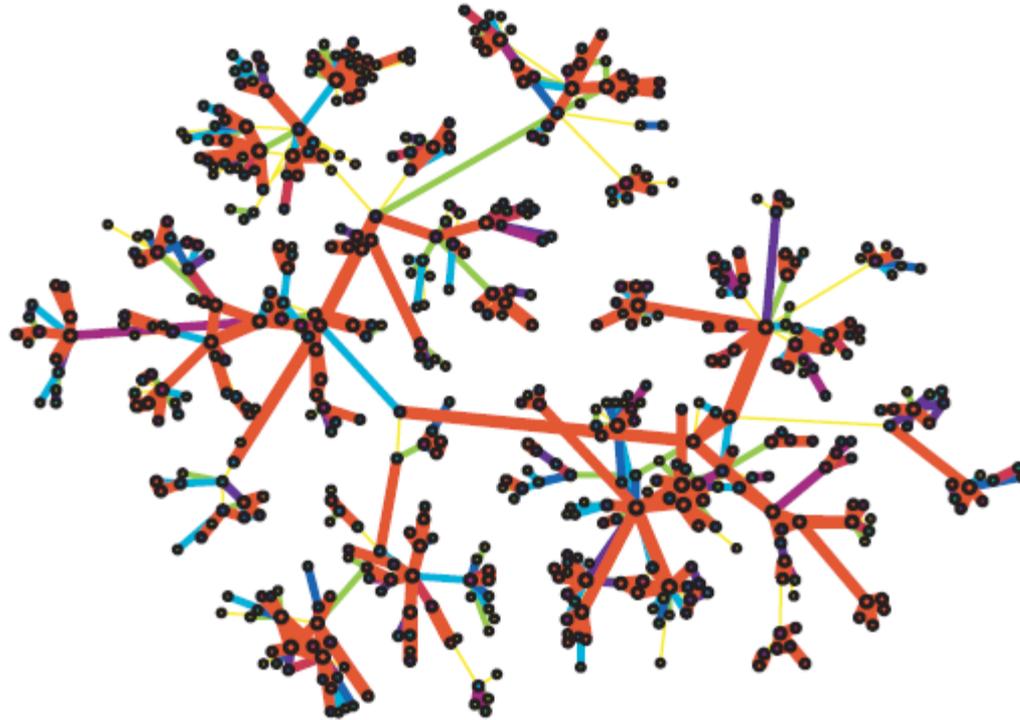


Real Network, Real Tie Strengths



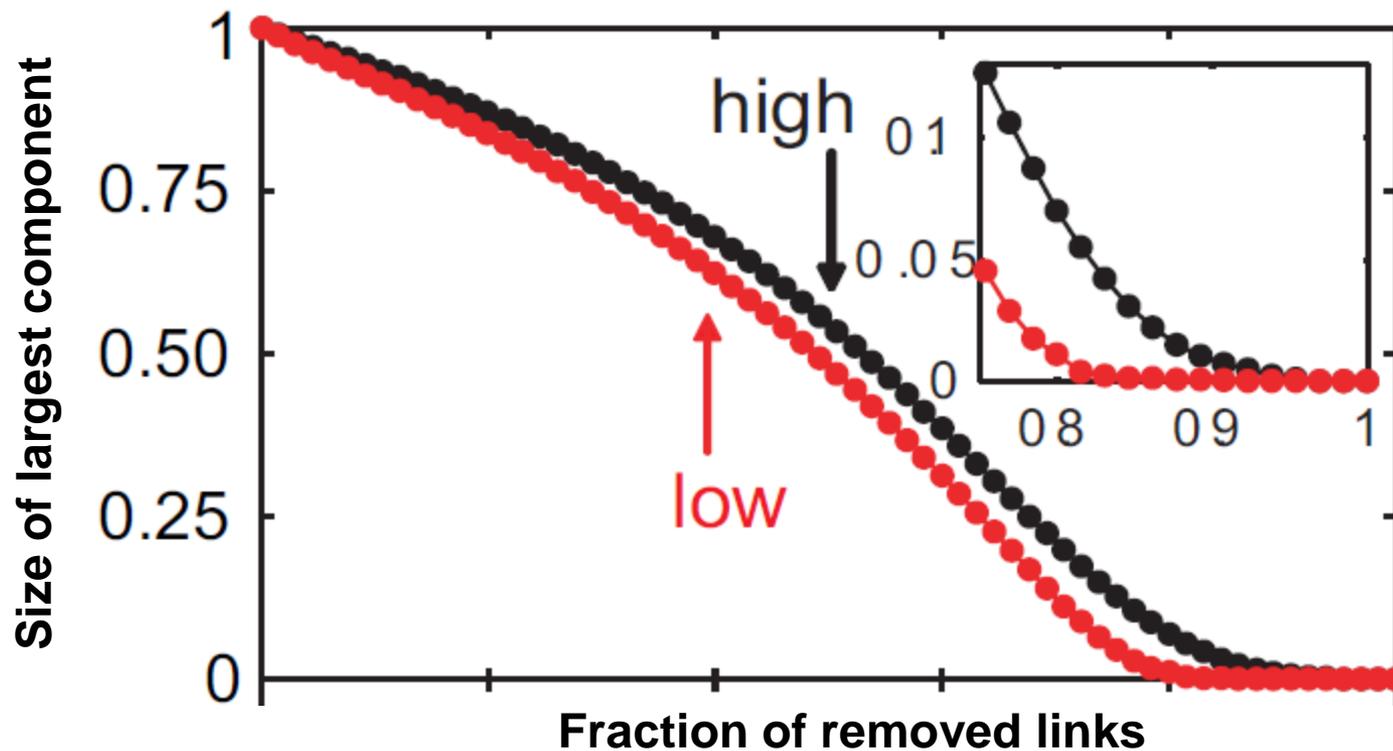
- **Real edge strengths in mobile call graph**
 - Strong ties are more embedded (have higher overlap)

Real Net, Permuted Tie Strengths



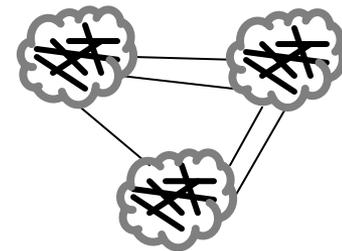
- Same network, same set of edge strengths but now **strengths are randomly shuffled**

Link Removal by Strength



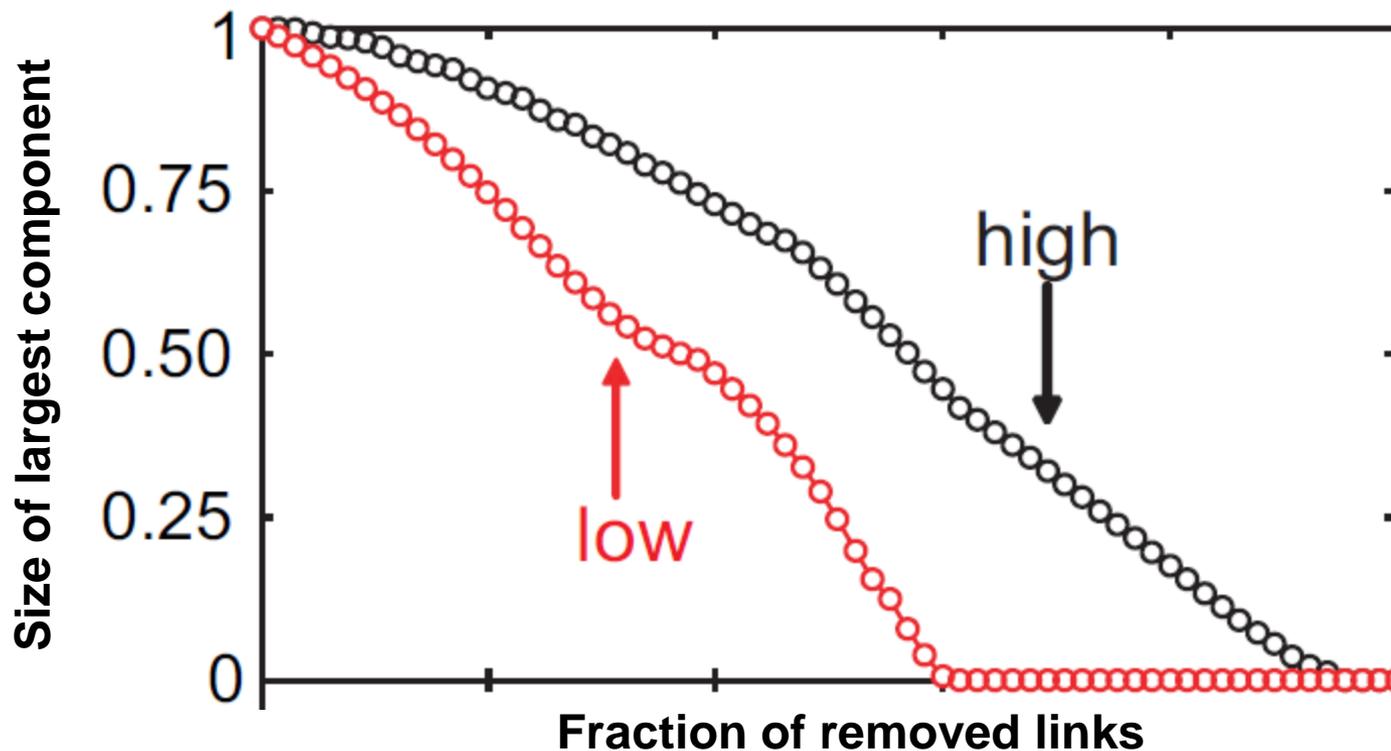
Low
disconnects
the network
sooner

- Removing links by **strength (#calls)**
 - Low to high
 - High to low



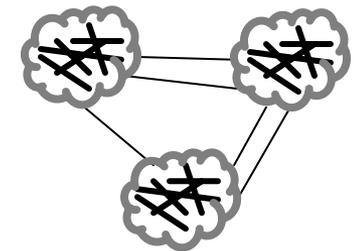
Conceptual picture
of network structure

Link Removal by Overlap



Low
disconnects
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sooner

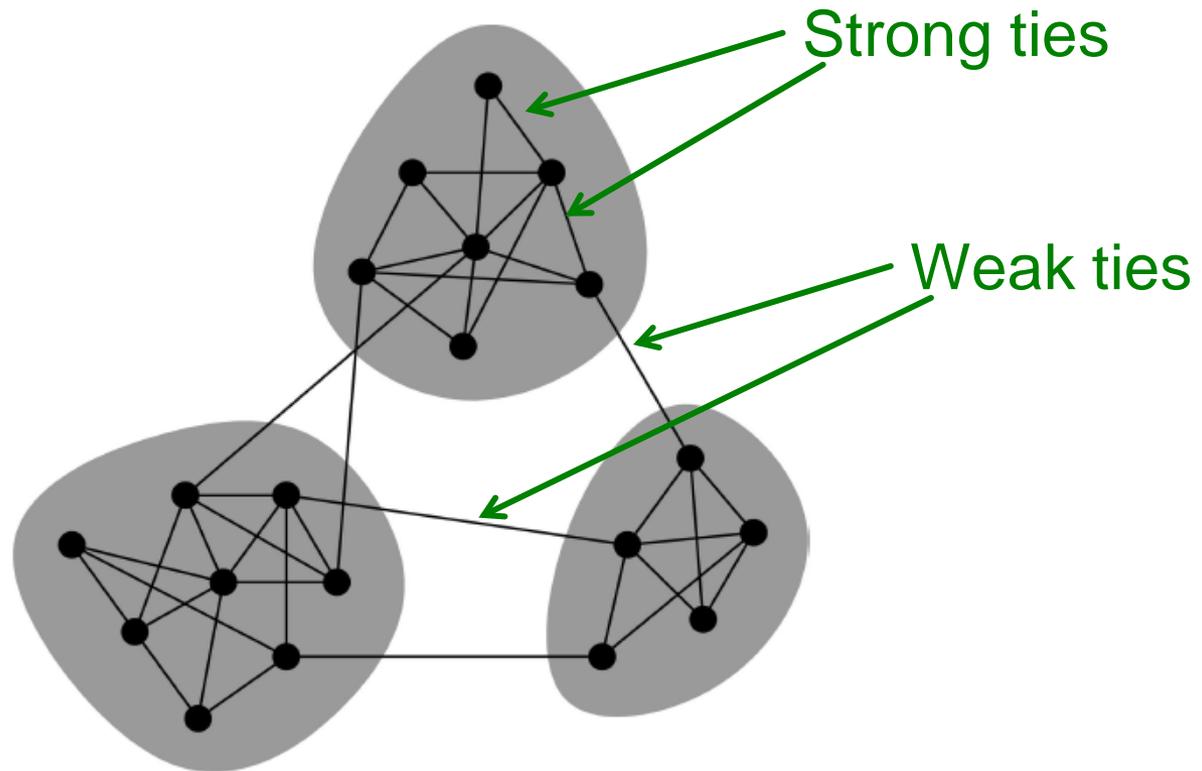
- Removing links based on **overlap**
 - Low to high
 - High to low



Conceptual picture
of network structure

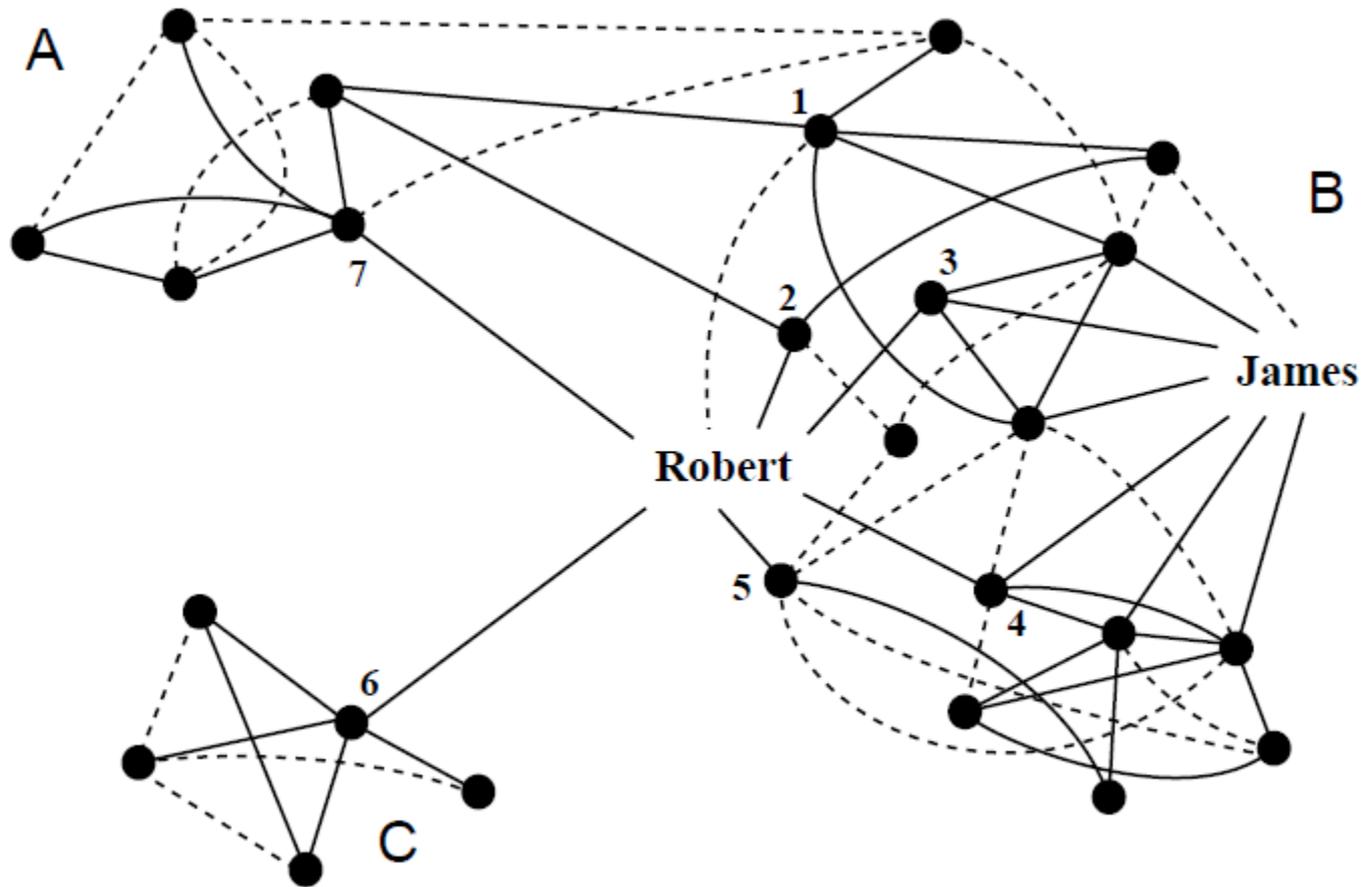
Conceptual Picture of Networks

- Granovetter's theory leads to the following conceptual picture of networks



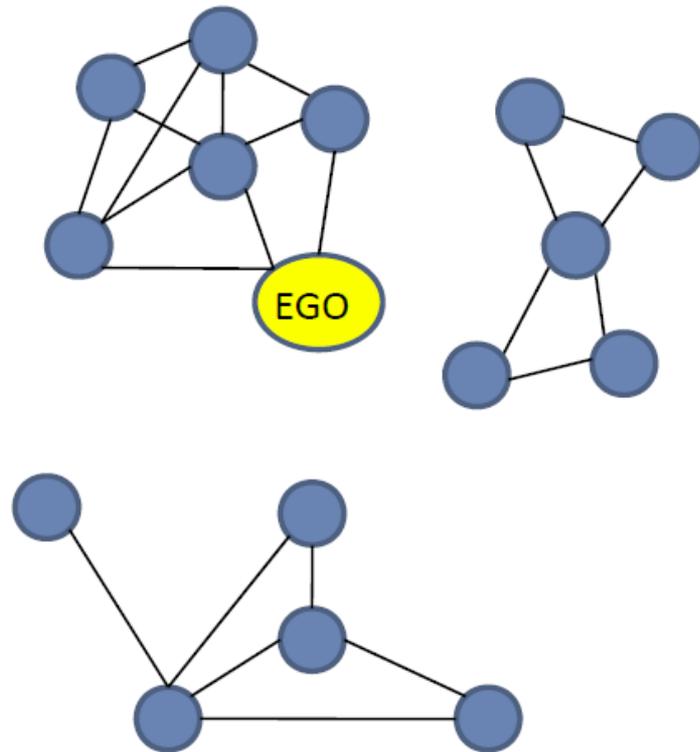
Small Detour:
Structural Holes

Small Detour: Structural Holes

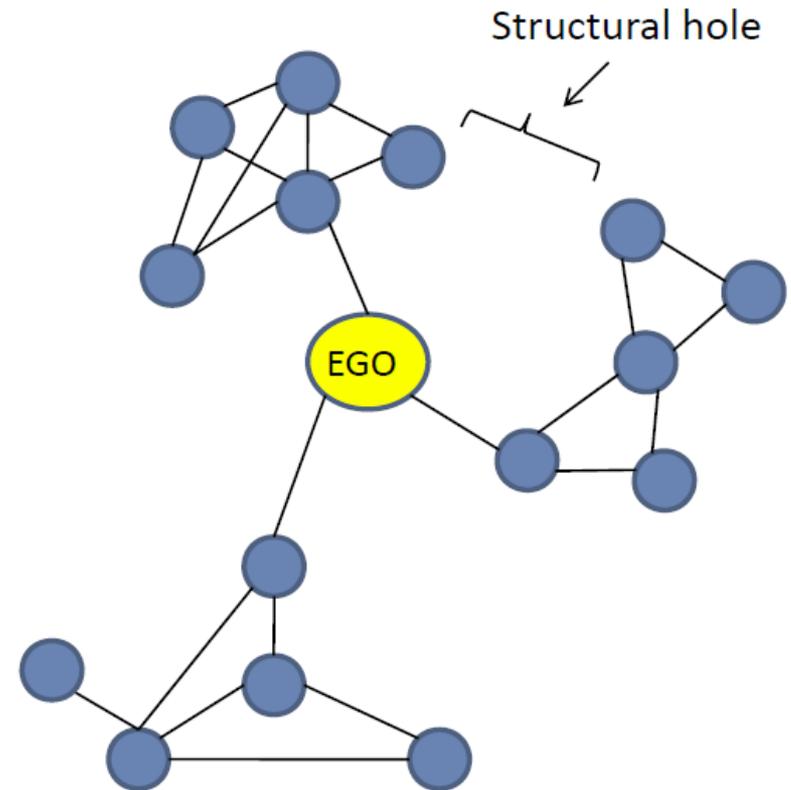


Who is better off Robert or James?

Structural Holes



Few structural holes

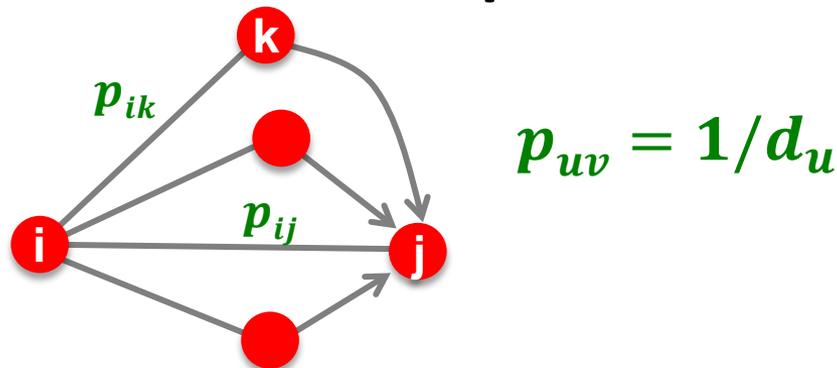


Many structural holes

Structural Holes provide ego with access to novel information, power, freedom

Structural Holes: Network Constraint

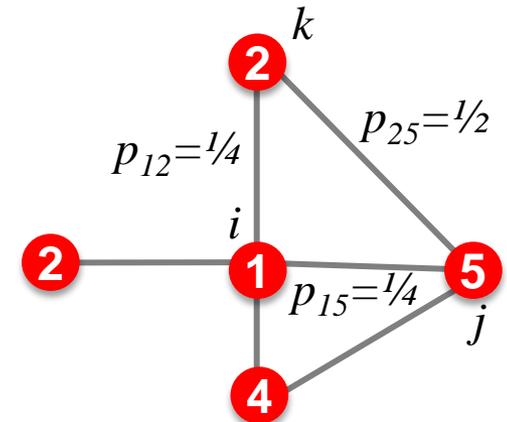
- The “network constraint” measure [Burt]:
 - To what extent are person’s contacts redundant



- **Low**: disconnected contacts
- **High**: contacts that are close or strongly tied

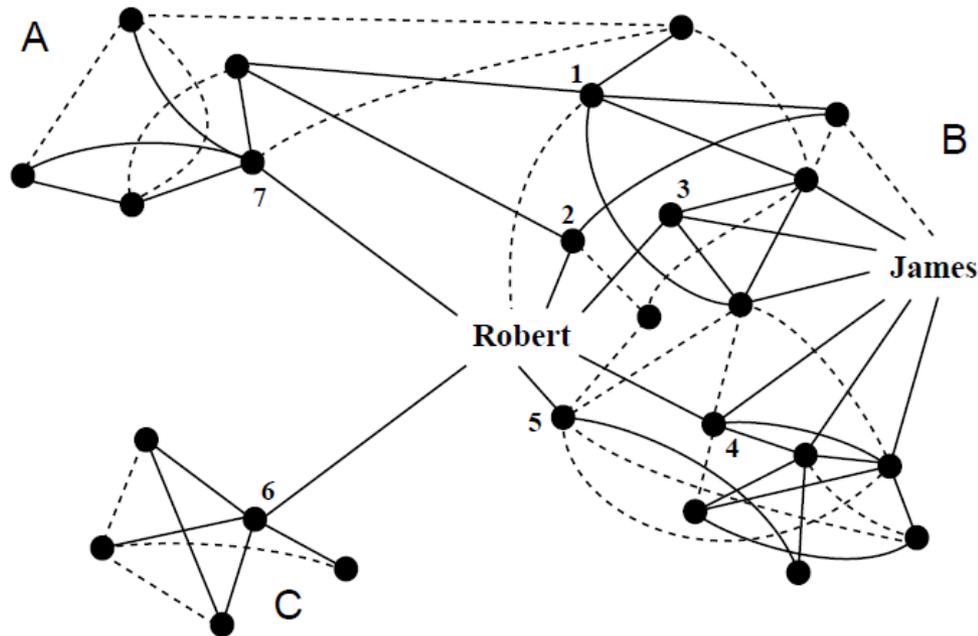
$$c_i = \sum_j c_{ij} = \sum_j \left[p_{ij} + \sum_k (p_{ik} p_{kj}) \right]^2$$

p_{uv} ... prop. of u 's “energy” invested in relationship with v



	p_{uv}				
	1	2	3	4	5
1	.00	.25	.25	.25	.25
2	.50	.00	.00	.00	.50
3	1.0	.00	.00	.00	.00
4	.50	.00	.00	.00	.50
5	.33	.33	.00	.33	.00

Example: Robert vs. James



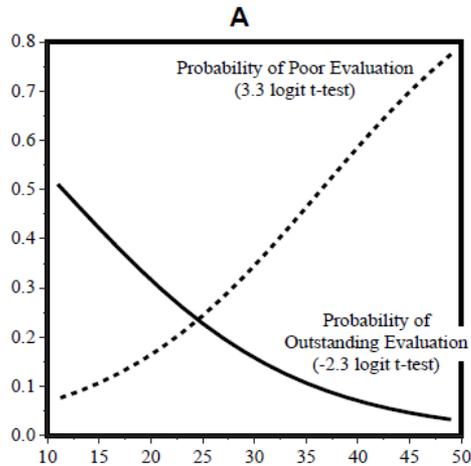
- **Constraint:** To what extent are person's contacts redundant
 - **Low:** disconnected contacts
 - **High:** contacts that are close or strongly tied

- **Network constraint:**

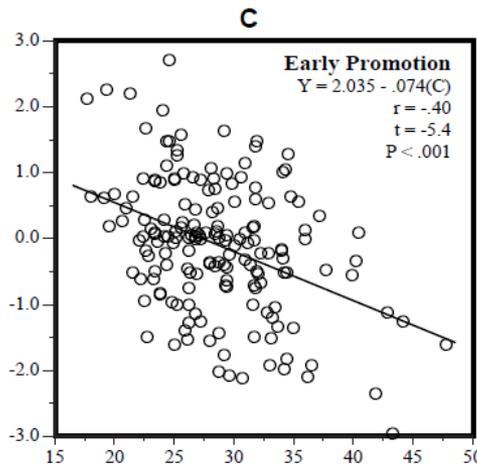
- James: $c_J = 0.309$

- Robert: $c_R = 0.148$

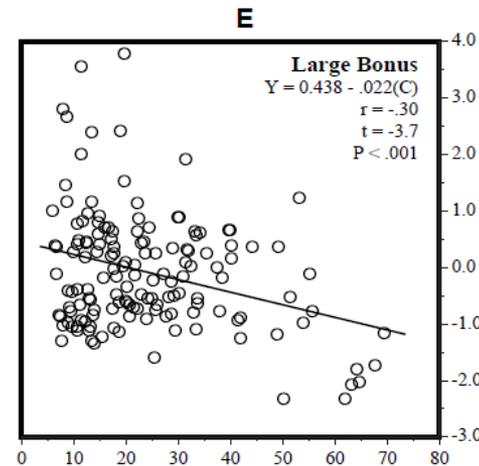
Spanning Holes Matters



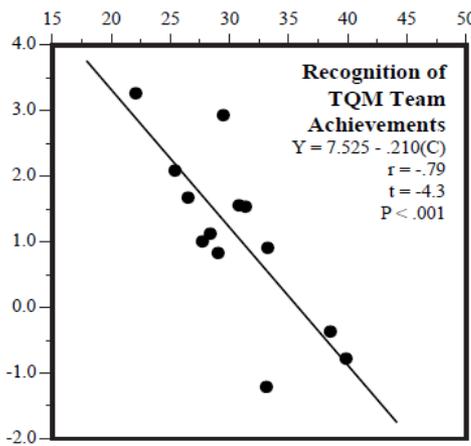
Network Constraint
 many ——— Structural Holes ——— few
 (manager C above, mean C in team below)



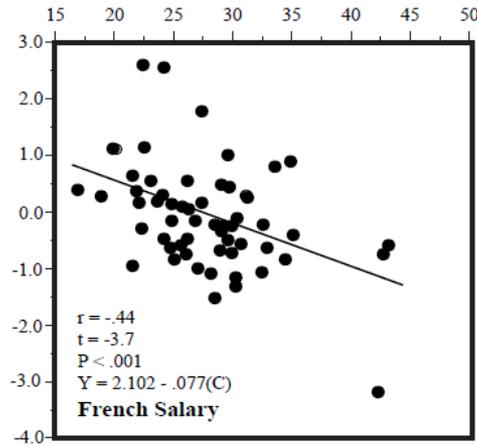
Network Constraint
 many ——— Structural Holes ——— few
 (C for manager's network)



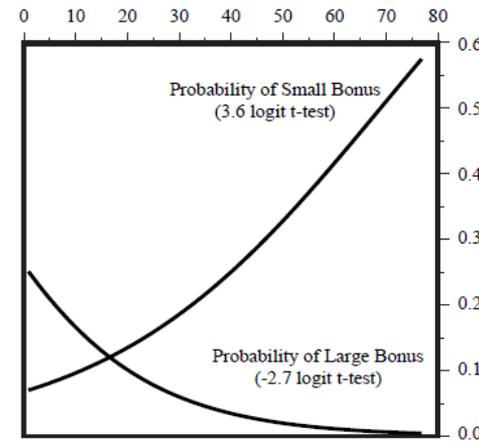
Network Constraint
 many ——— Structural Holes ——— few
 (C for officer's network)



B



D

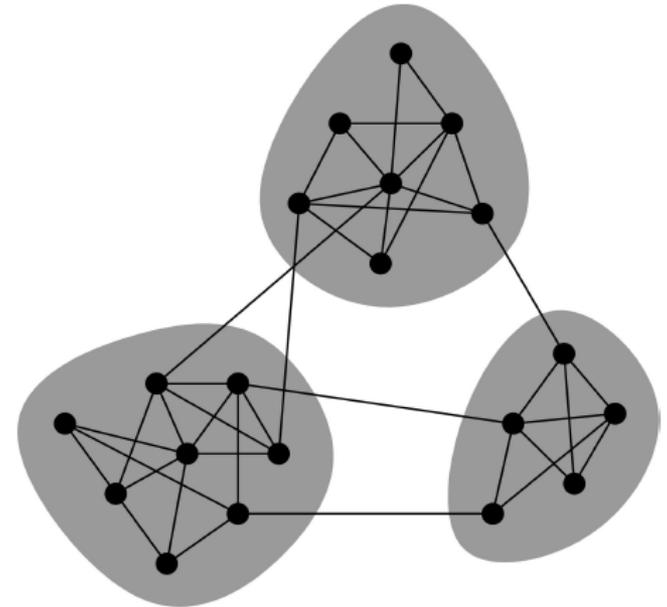


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Network Communities

Network Communities

- Granovetter's theory suggest that networks are composed of **tightly connected sets of nodes**

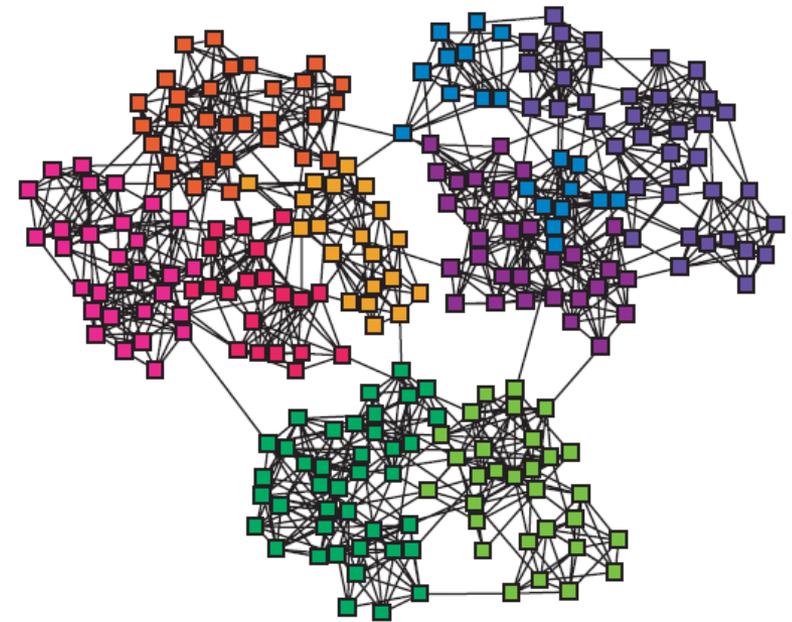


Communities, clusters, groups, modules

- **Network communities:**
 - Sets of nodes with **lots** of connections **inside** and **few** to **outside** (the rest of the network)

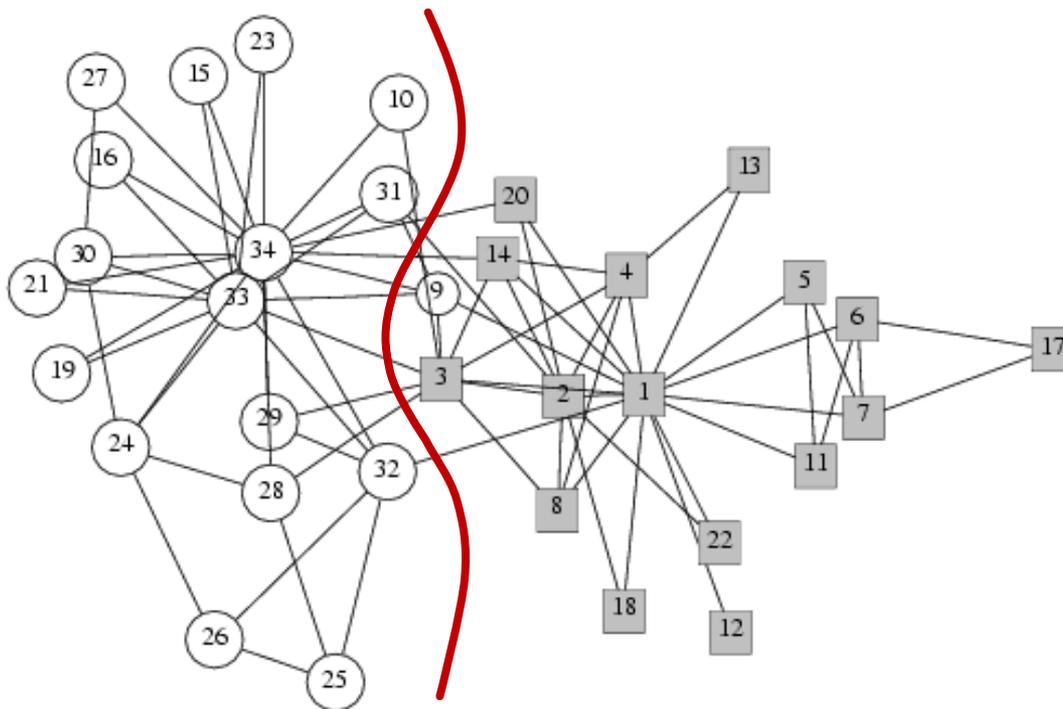
Finding Network Communities

- How to automatically find such densely connected groups of nodes?
- Ideally such automatically detected clusters would then correspond to real groups
- For example:



Communities, clusters,
groups, modules

Social Network Data

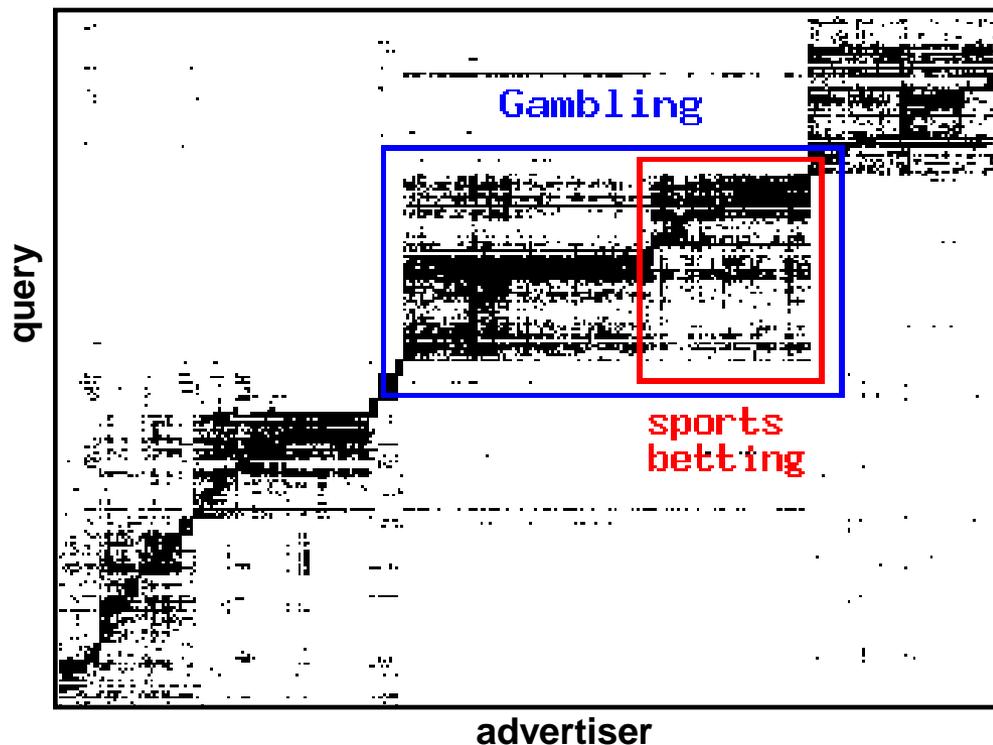


- **Zachary's Karate club network:**

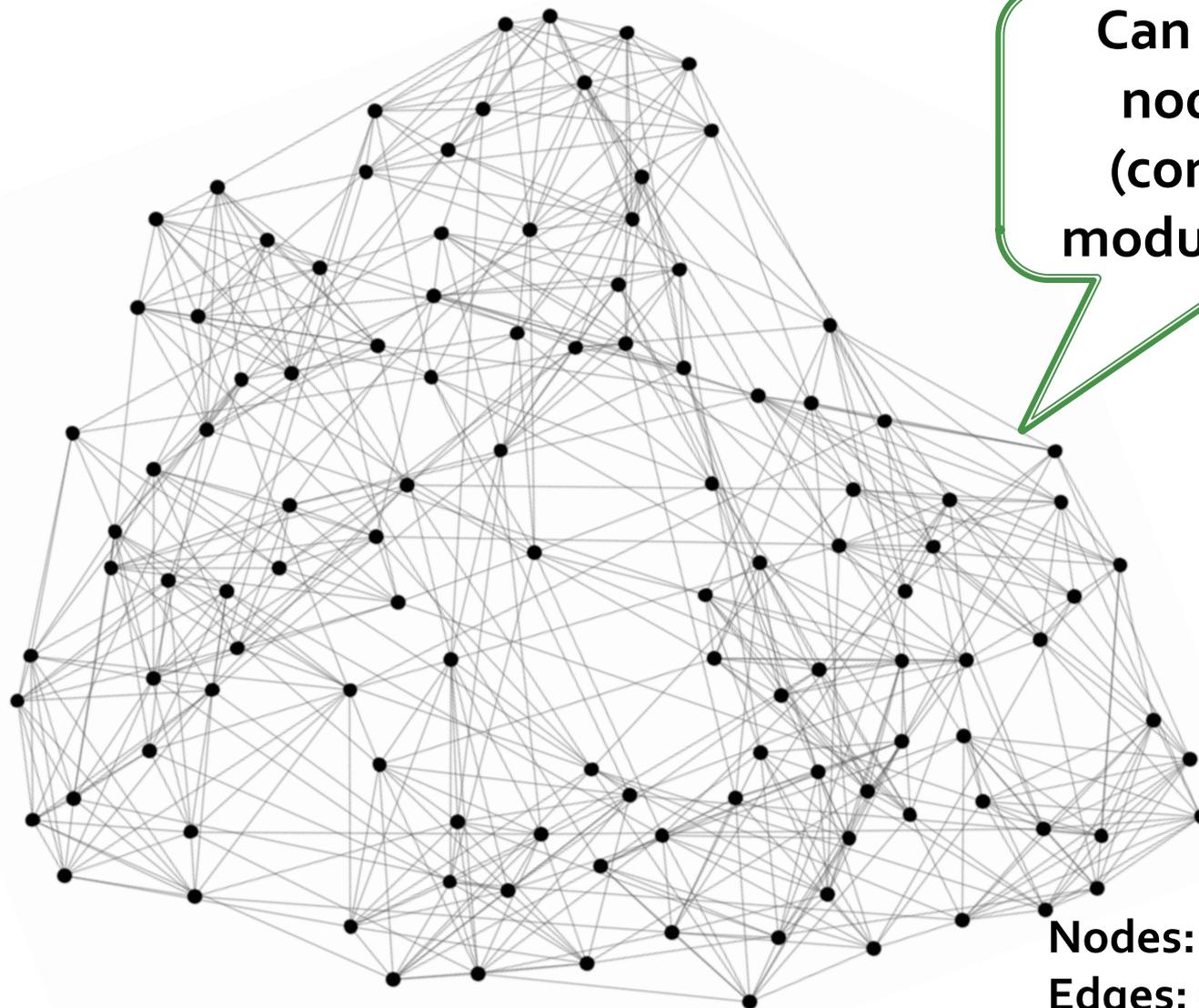
- Observe social ties and rivalries in a university karate club
- During his observation, conflicts led the group to split
- Split could be explained by a minimum cut in the network

Micro-Markets in Sponsored Search

Find micro-markets by partitioning the “query x advertiser” graph:



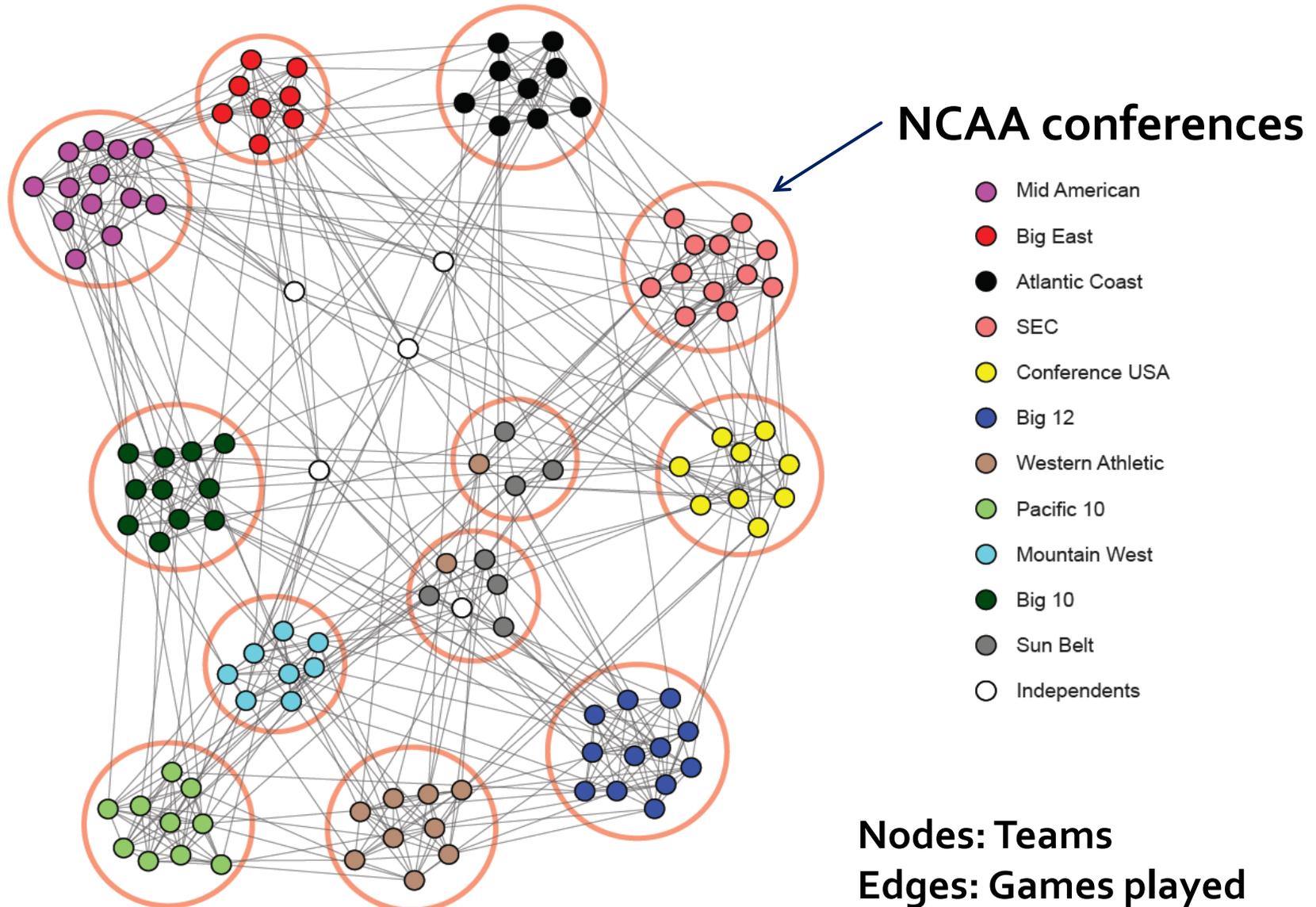
NCAA Football Network



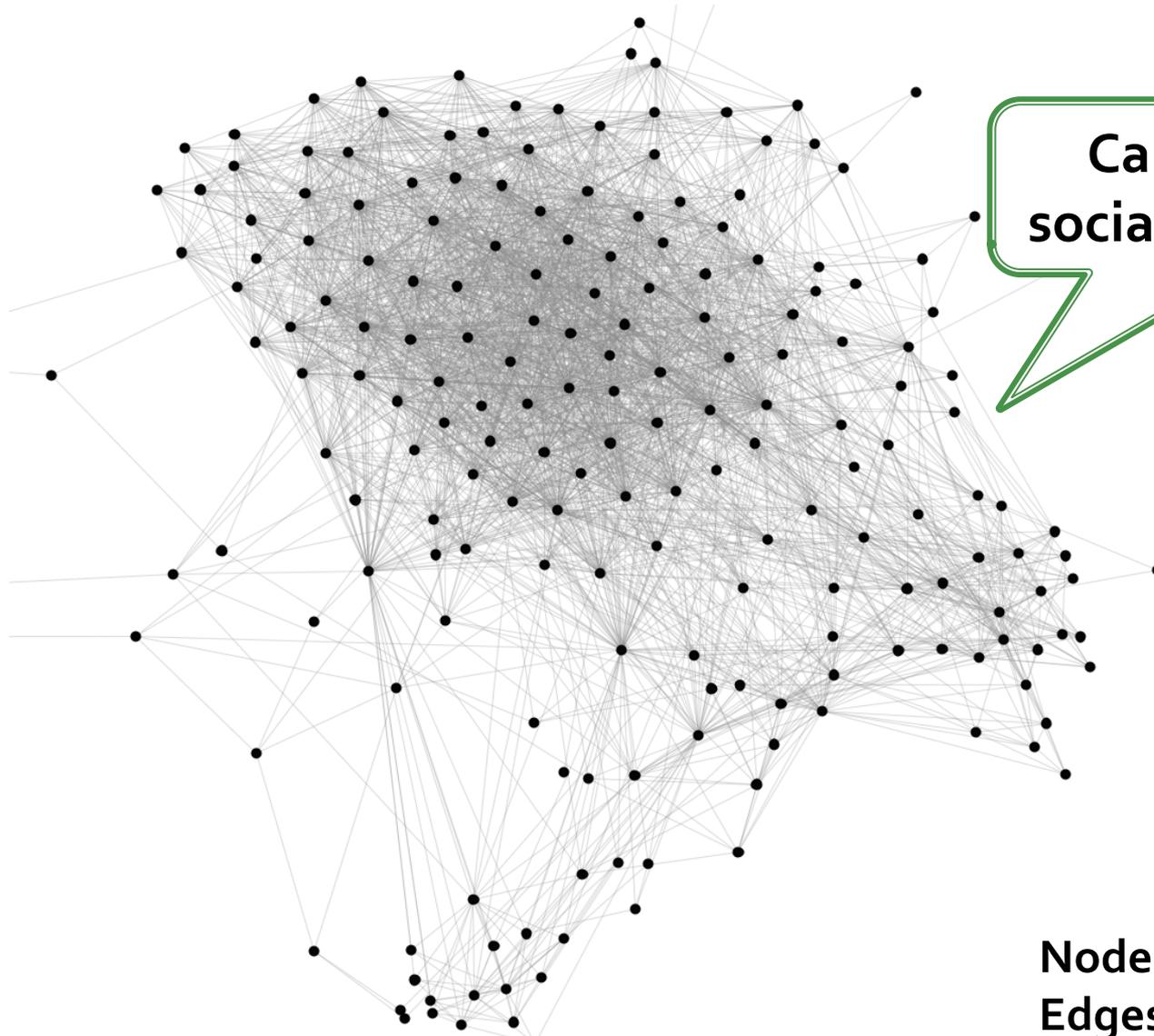
Can we identify
node groups?
(communities,
modules, clusters)

Nodes: Teams
Edges: Games played

NCAA Football Network



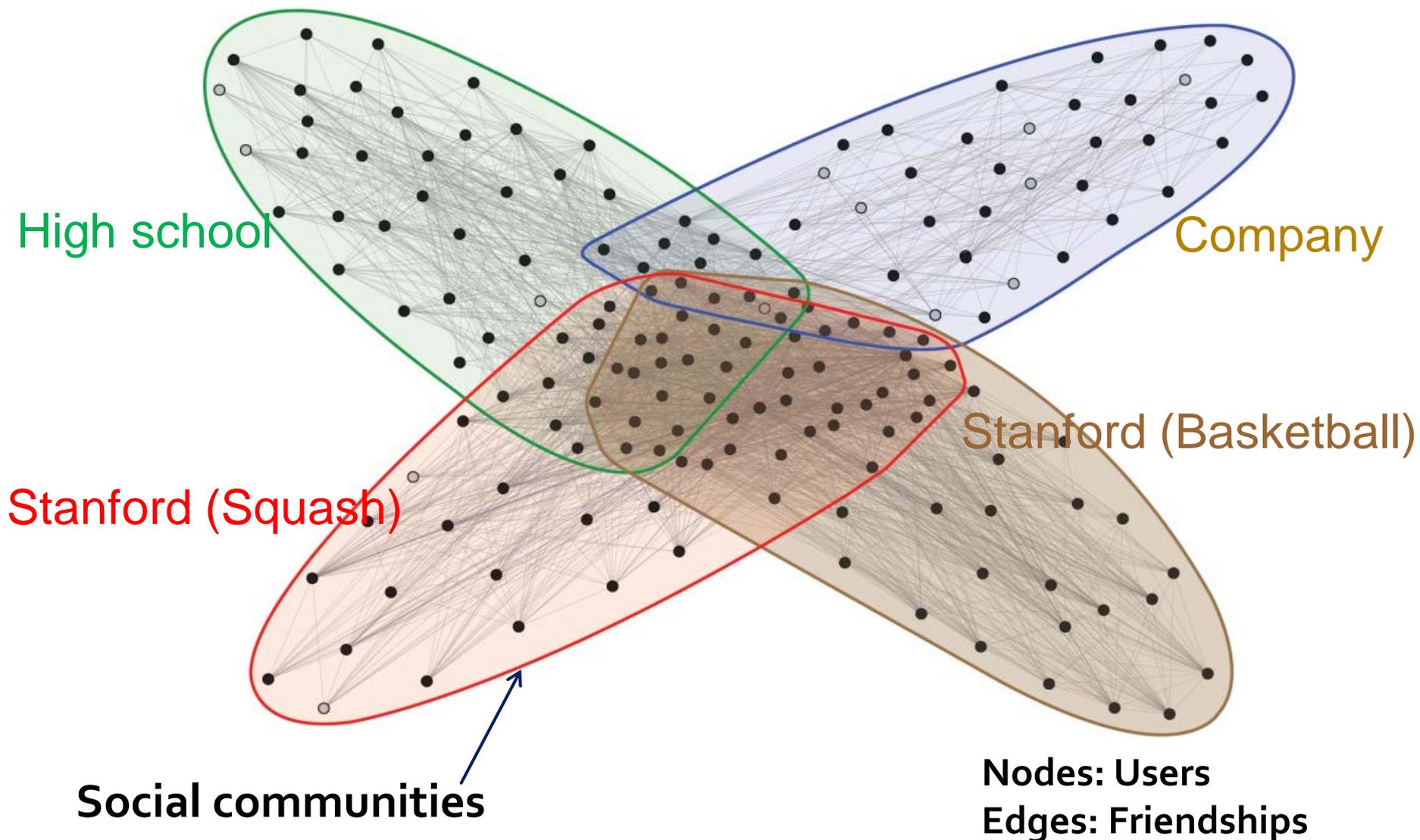
Facebook Ego-network



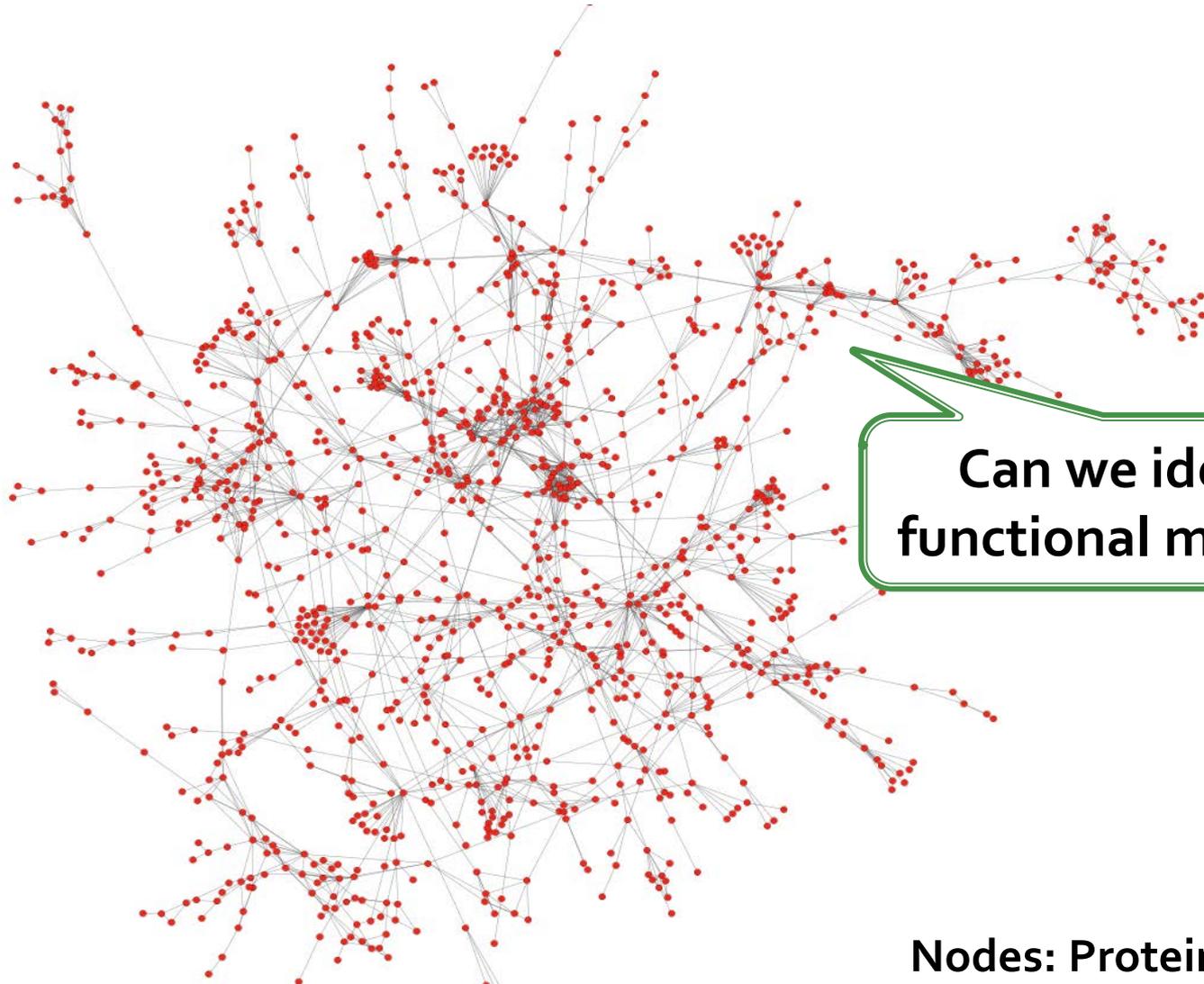
Can we identify
social communities?

Nodes: Users
Edges: Friendships

Facebook Ego-network



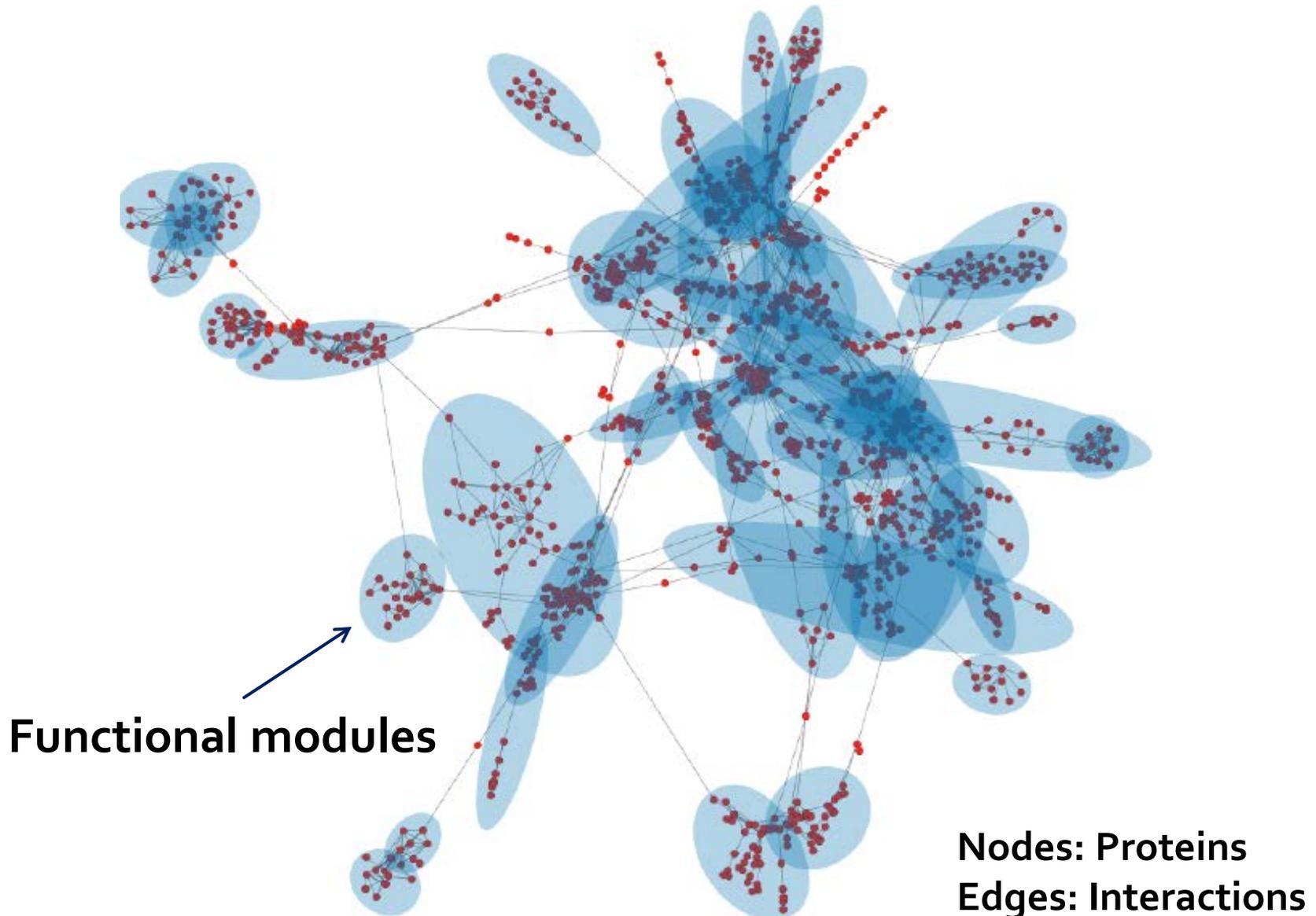
Protein-Protein Interactions



Can we identify functional modules?

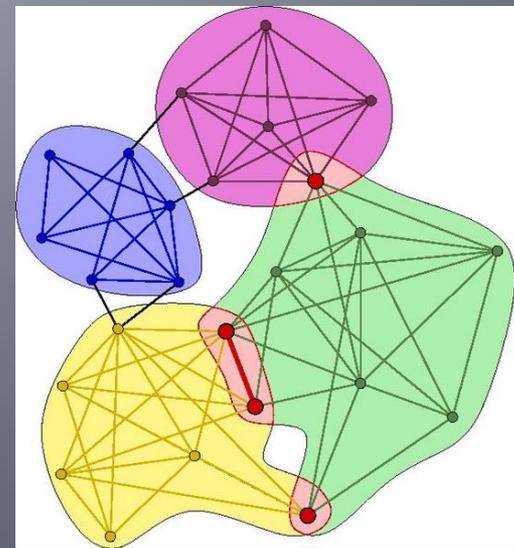
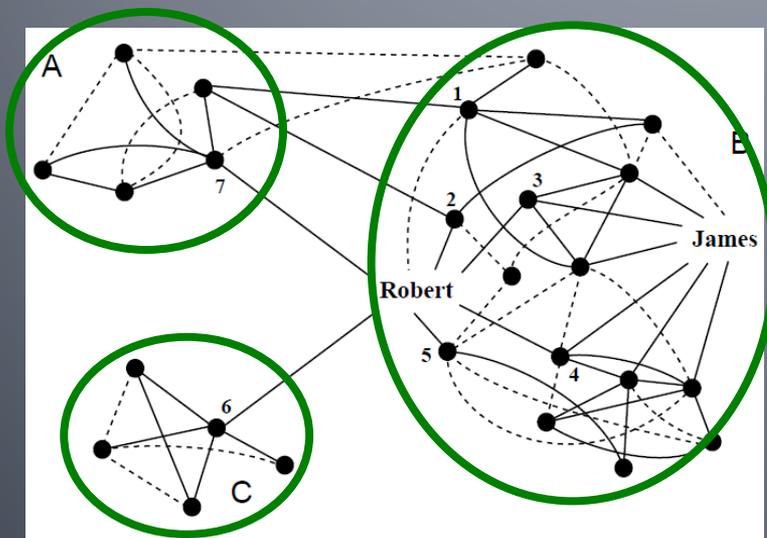
Nodes: Proteins
Edges: Interactions

Protein-Protein Interactions



Community Detection

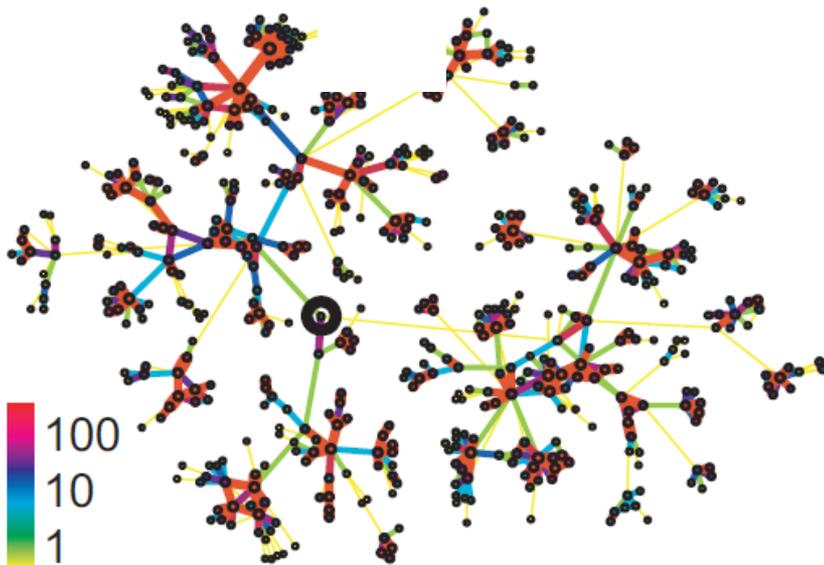
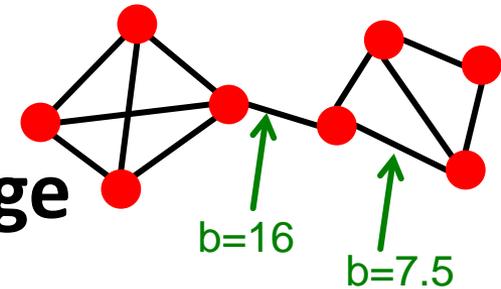
How to find communities?



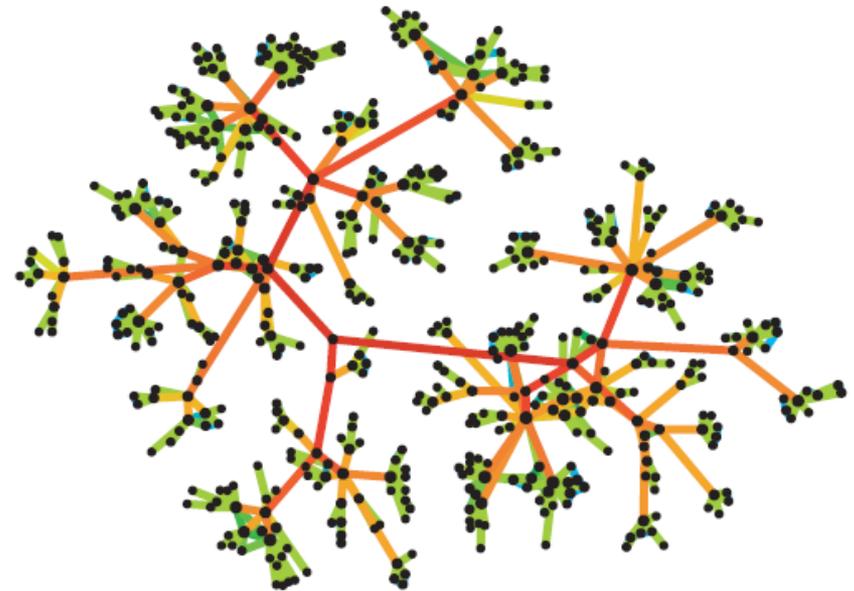
We will work with **undirected** (unweighted) networks

Method 1: Strength of Weak Ties

- **Edge betweenness:** Number of shortest paths passing over the edge
- **Intuition:**



Edge strengths (call volume)
in a real network

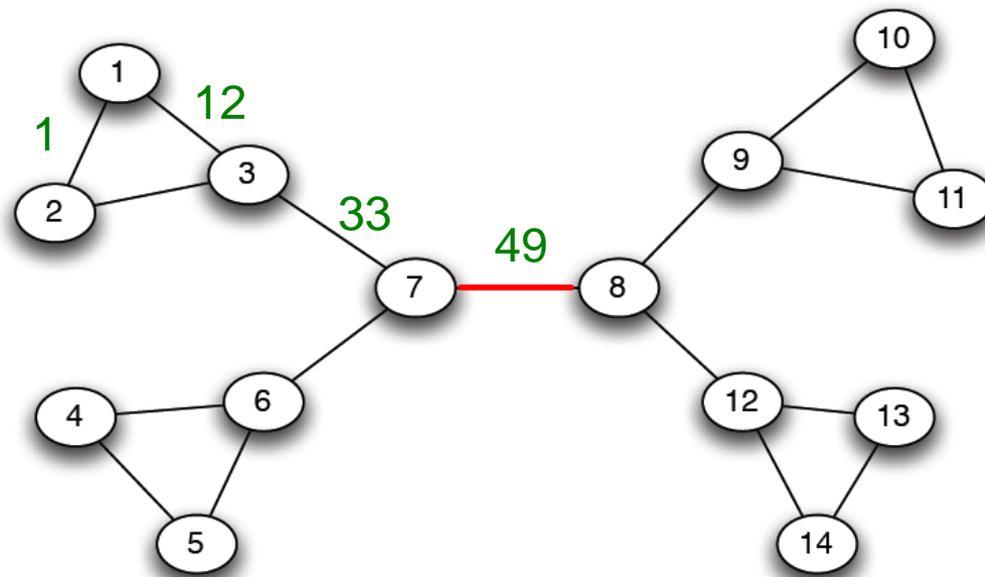


Edge betweenness
in a real network

Method 1: Girvan-Newman

- Divisive hierarchical clustering based on the notion of edge **betweenness**:
 - **Number of shortest paths passing through the edge**
- **Girvan-Newman Algorithm**:
 - Undirected unweighted networks
 - **Repeat until no edges are left**:
 - Calculate betweenness of edges
 - Remove edges with highest betweenness
 - Connected components are communities
 - Gives a hierarchical decomposition of the network

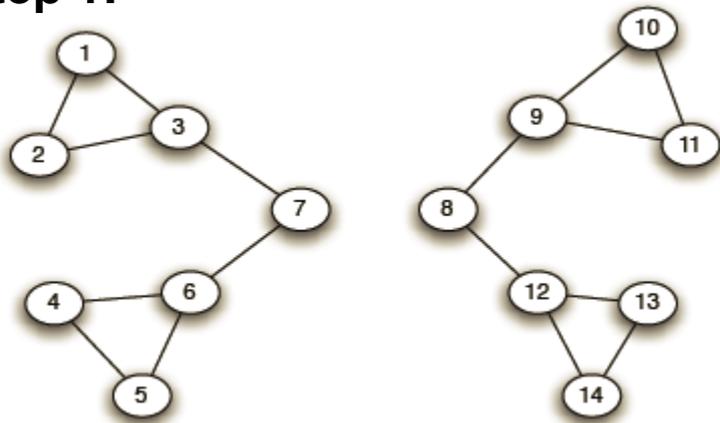
Girvan-Newman: Example



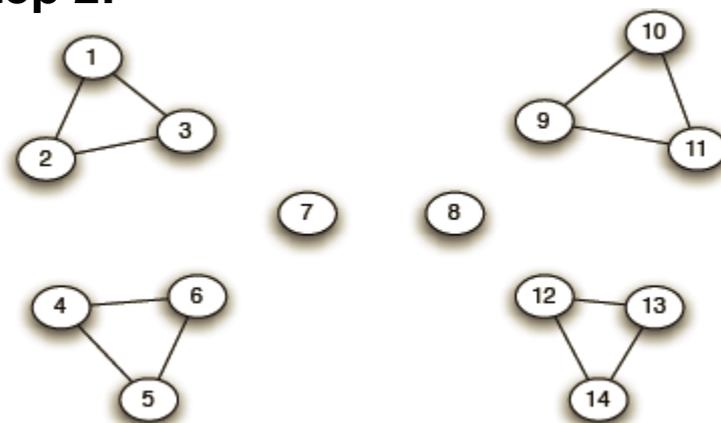
Need to re-compute
betweenness at
every step

Girvan-Newman: Example

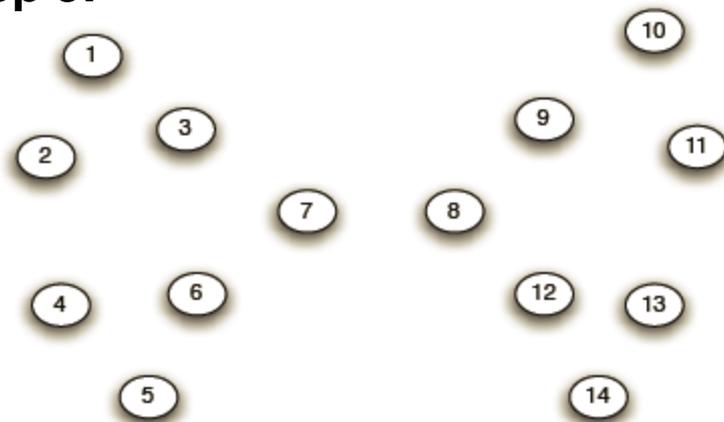
Step 1:



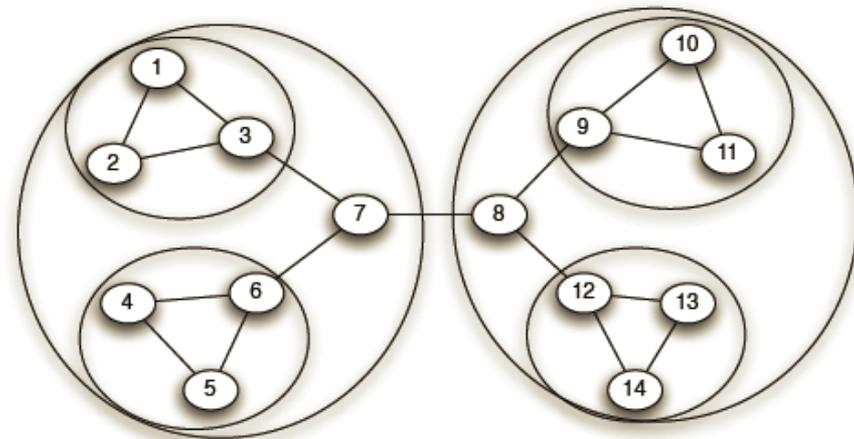
Step 2:



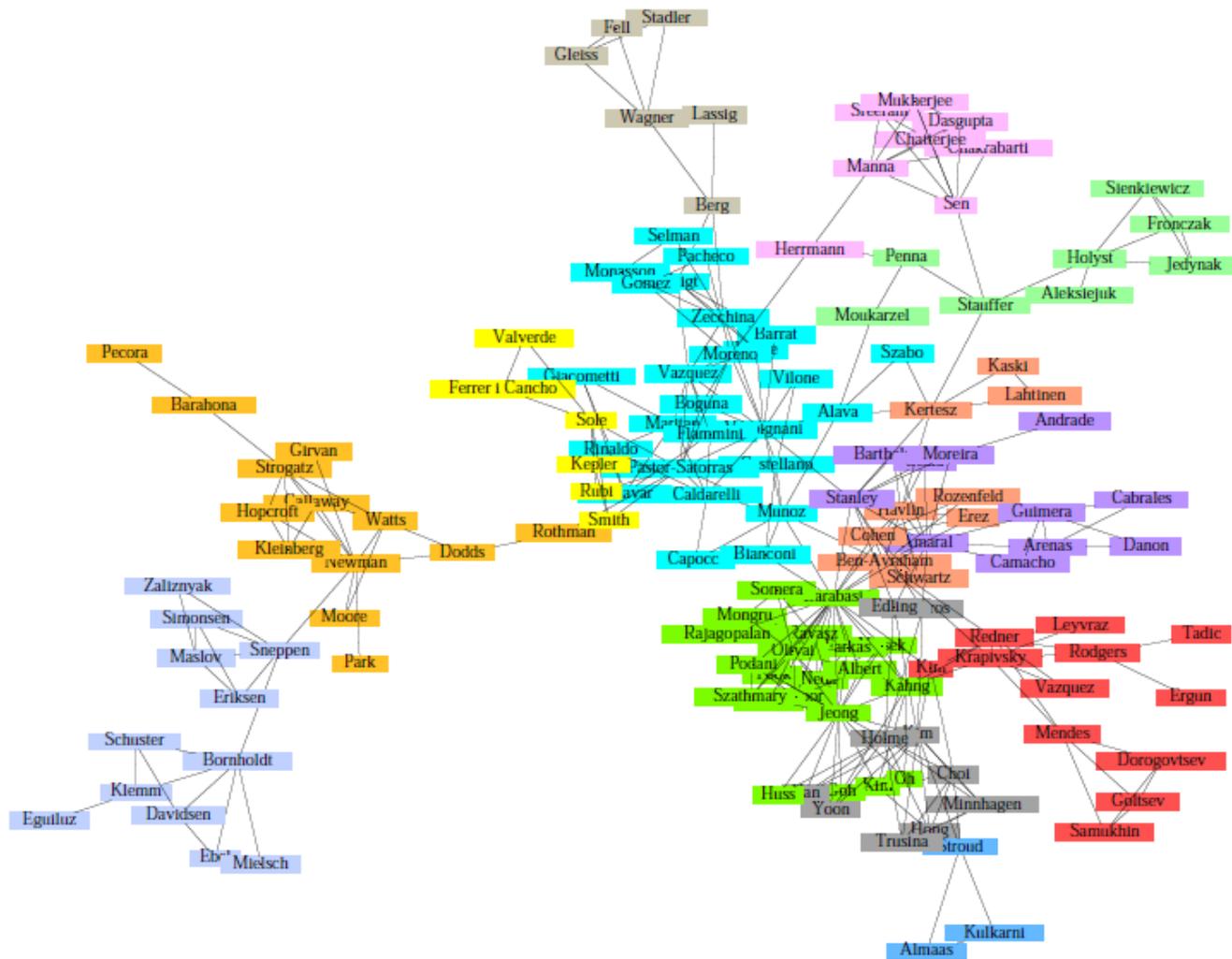
Step 3:



Hierarchical network decomposition:



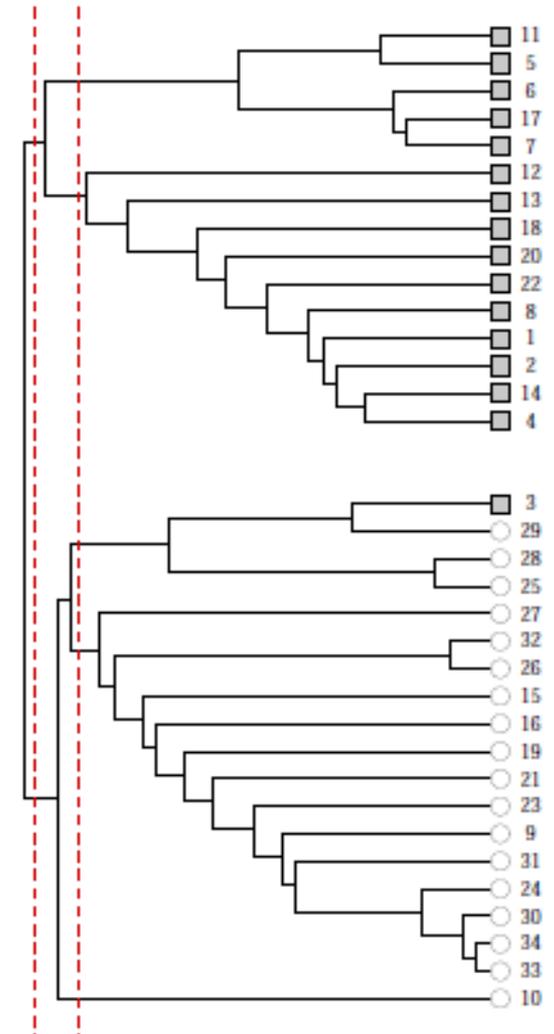
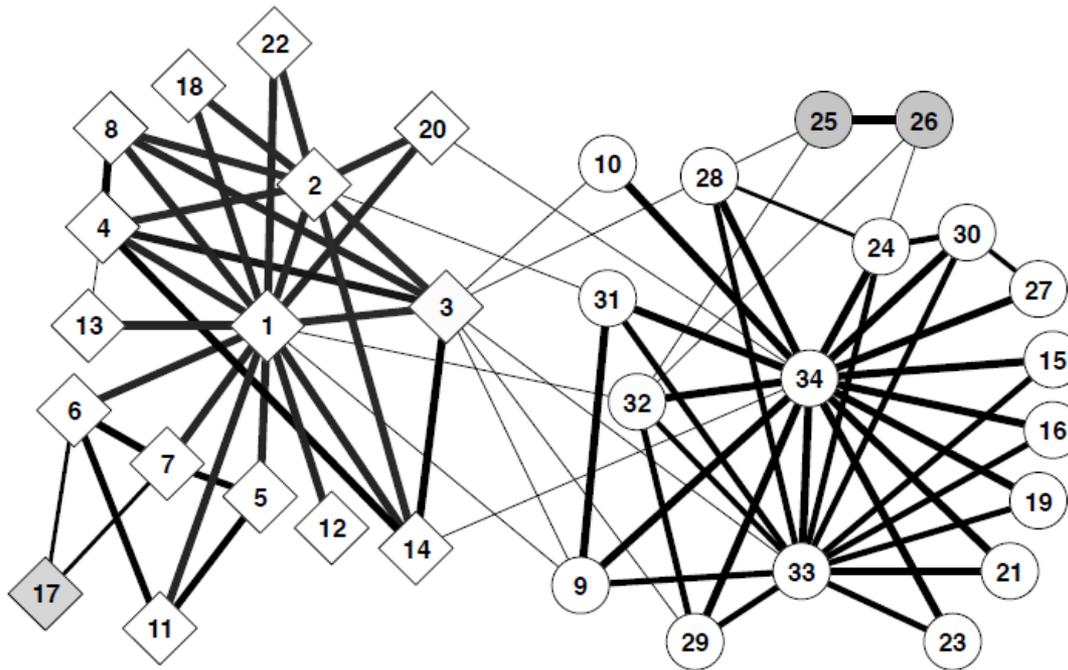
Girvan-Newman: Results



Communities in physics collaborations

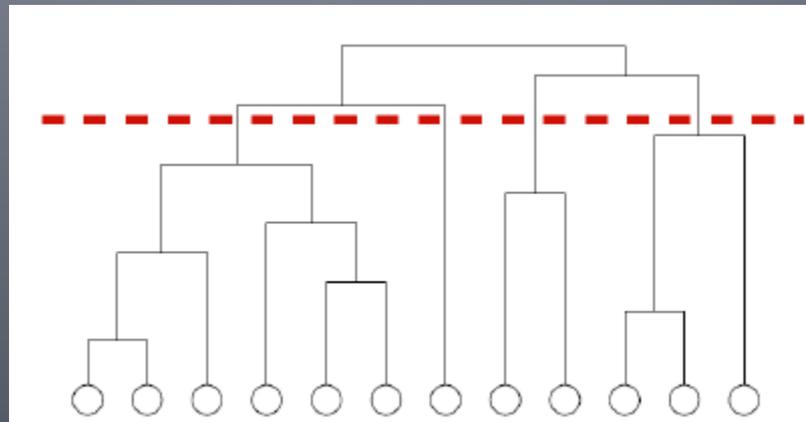
Girvan-Newman: Results

- **Zachary's Karate club:**
Hierarchical decomposition



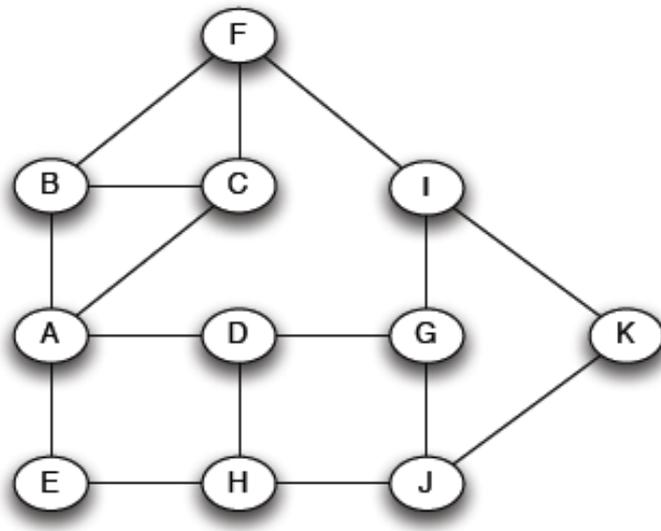
We need to resolve 2 questions

1. How to compute betweenness?
2. How to select the number of clusters?

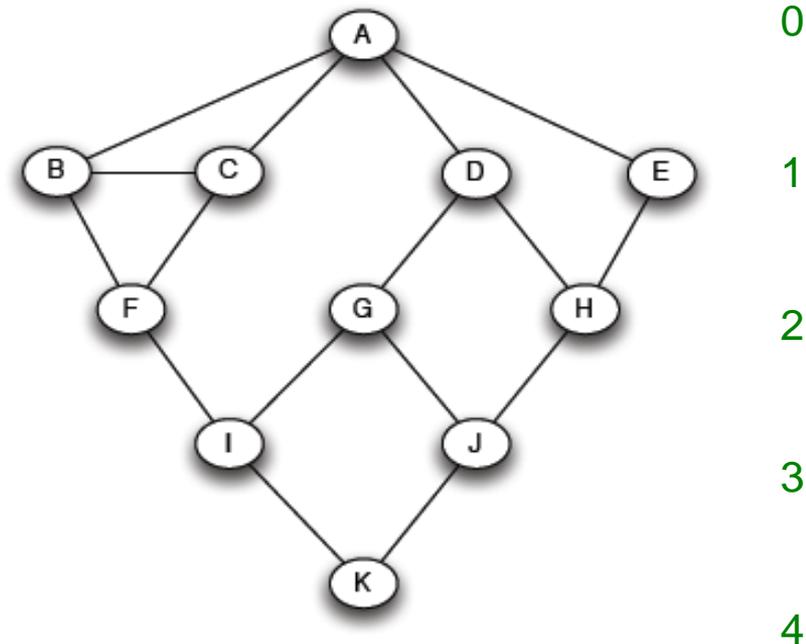


How to Compute Betweenness?

- Want to compute betweenness of paths starting at node *A*

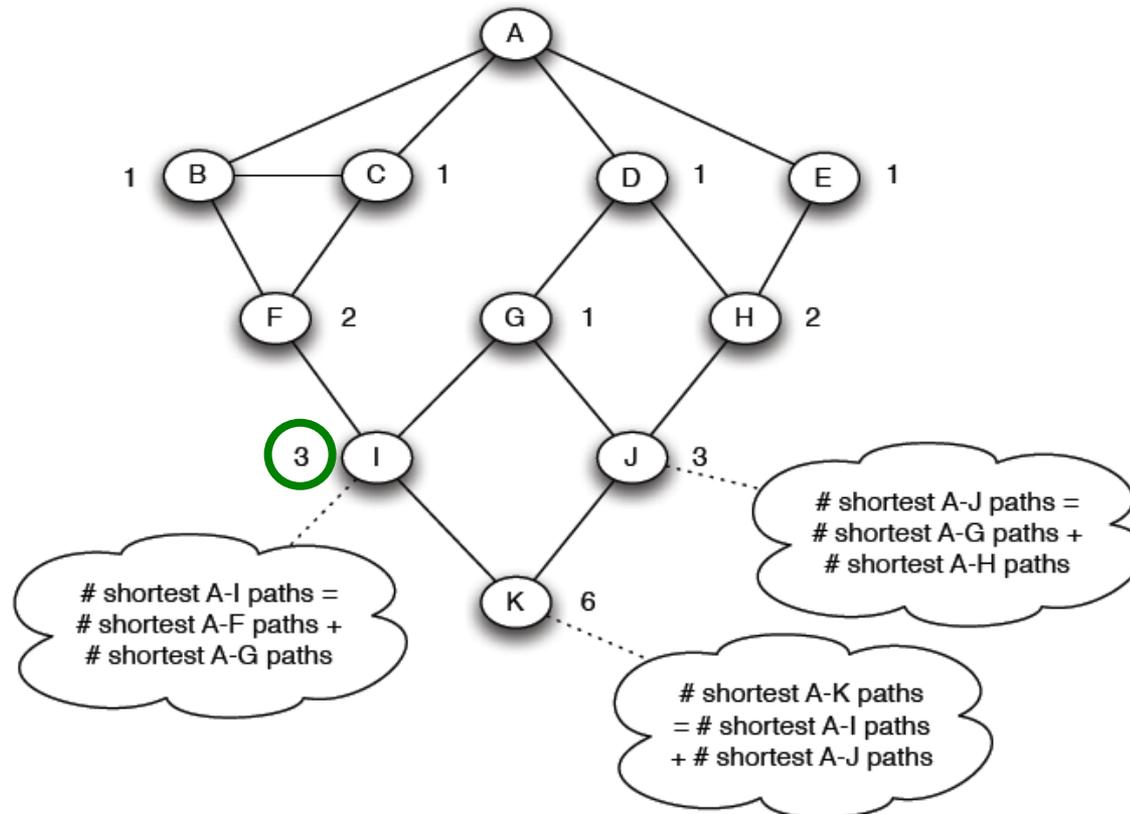


- Breath first search starting from *A*:



How to Compute Betweenness?

- Count the number of shortest paths from **A** to all other nodes of the network:



How to Compute Betweenness?

- **Compute betweenness by working up the tree:** If there are multiple paths count them fractionally

The algorithm:

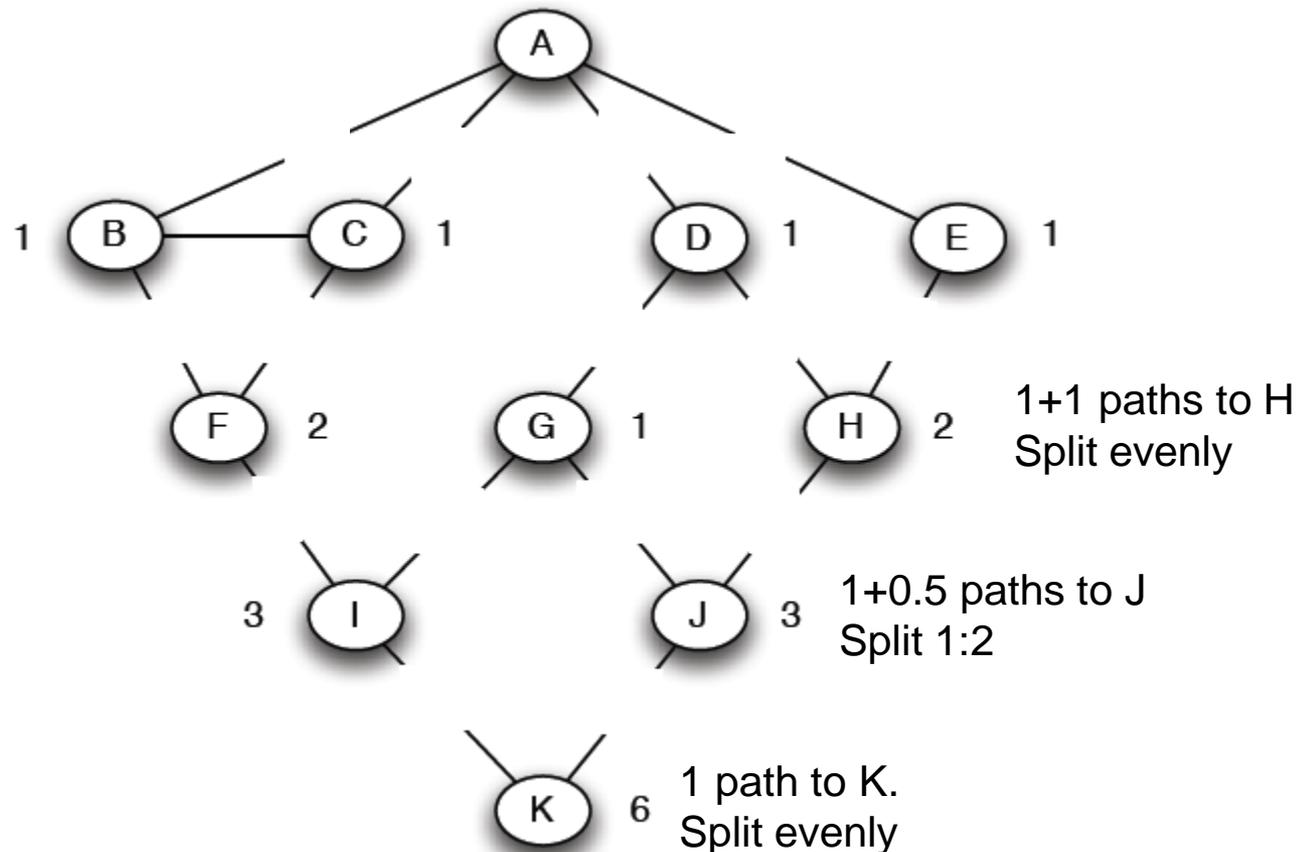
- Add edge flows:

- node flow =

$$1 + \sum \text{child edges}$$

- split the flow up based on the parent value

- Repeat the BFS procedure for each starting node U



How to Compute Betweenness?

- Compute betweenness by working up the tree: If there are multiple paths count them fractionally

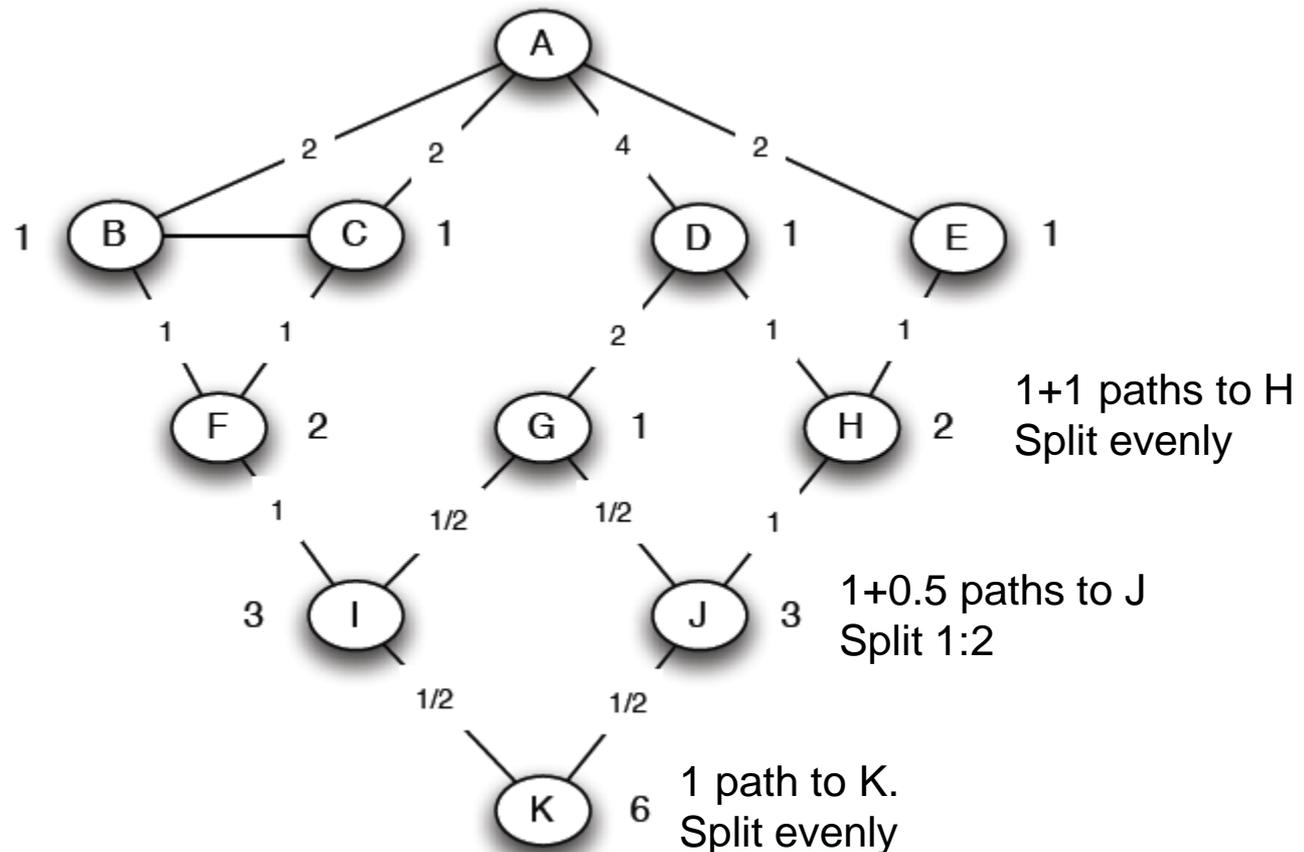
The algorithm:

- Add edge flows:

- node flow = $1 + \sum \text{child edges}$

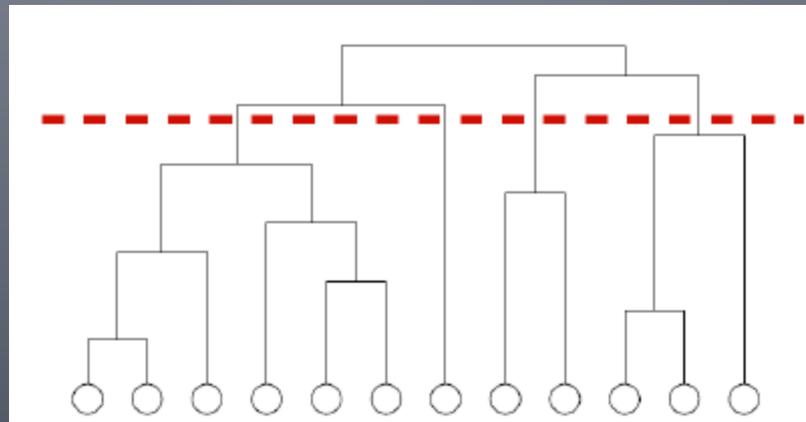
- split the flow up based on the parent value

- Repeat the BFS procedure for each starting node U



We need to resolve 2 questions

1. How to compute betweenness?
2. How to select the number of clusters?



Network Communities

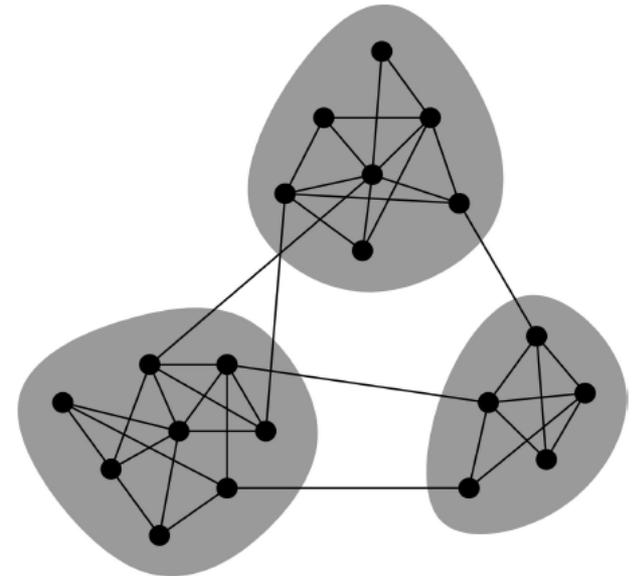
- **Communities:** sets of tightly connected nodes

- Define: **Modularity Q**

- A measure of how well a network is partitioned into communities
- Given a partitioning of the network into groups $s \in \mathcal{S}$:

$$Q \propto \sum_{s \in \mathcal{S}} [\underbrace{(\# \text{ edges within group } s) - (\text{expected } \# \text{ edges within group } s)}]$$

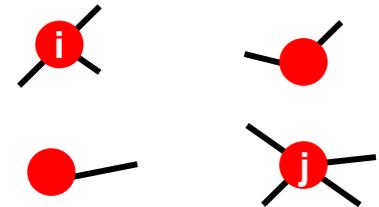
Need a null model!



Null Model: Configuration Model

- Given real G on n nodes and m edges, construct rewired network G'

- Same degree distribution but random connections



- Consider G' as a **multigraph**

- The expected number of edges between nodes

i and j of degrees k_i and k_j equals to: $k_i \cdot \frac{k_j}{2m} = \frac{k_i k_j}{2m}$

- The expected number of edges in (multigraph) G' :

$$\blacksquare = \frac{1}{2} \sum_{i \in N} \sum_{j \in N} \frac{k_i k_j}{2m} = \frac{1}{2} \cdot \frac{1}{2m} \sum_{i \in N} k_i \left(\sum_{j \in N} k_j \right) =$$

$$\blacksquare = \frac{1}{4m} 2m \cdot 2m = m$$

Note:

$$\sum_{u \in N} k_u = 2m$$

Modularity

- **Modularity of partitioning S of graph G :**

- $Q \propto \sum_{s \in S} [(\# \text{ edges within group } s) - (\text{expected } \# \text{ edges within group } s)]$

- $Q(G, S) = \frac{1}{2m} \sum_{s \in S} \sum_{i \in s} \sum_{j \in s} \left(A_{ij} - \frac{k_i k_j}{2m} \right)$

Normalizing const.: $-1 < Q < 1$

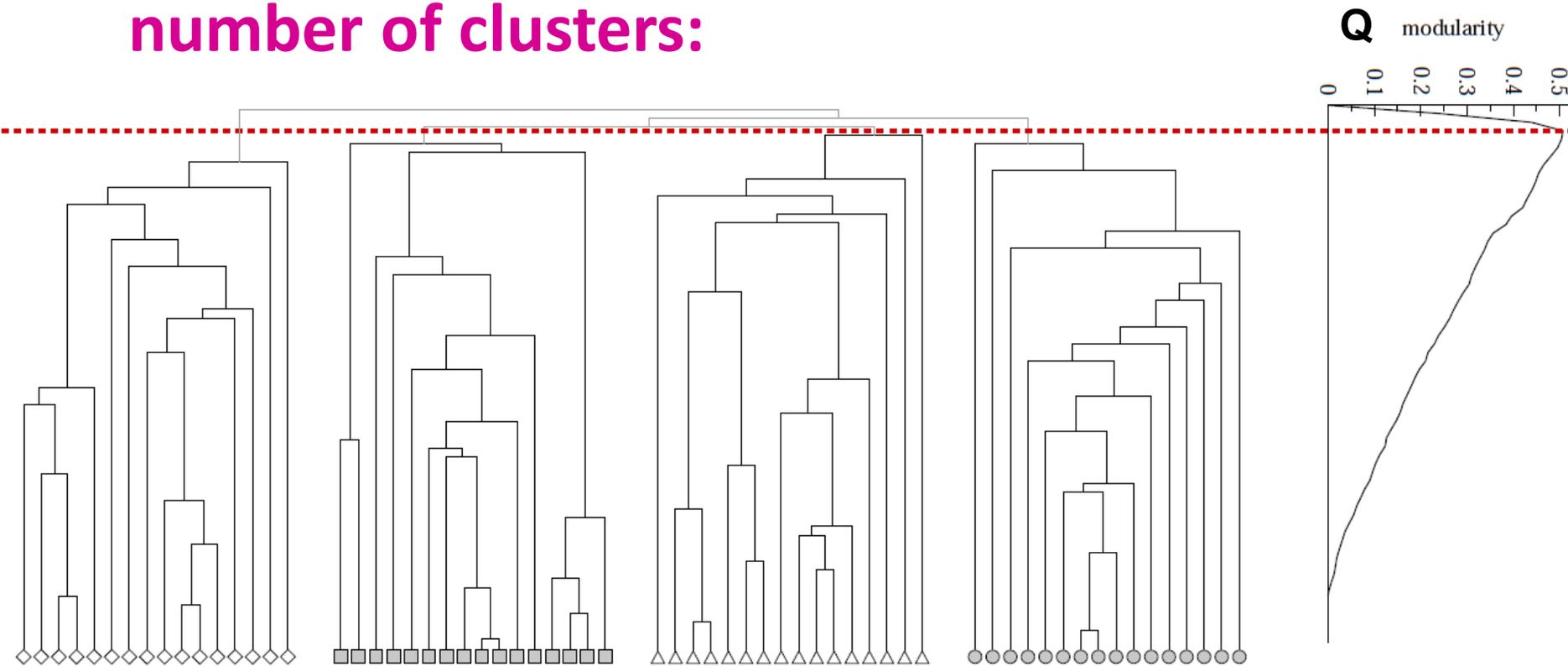
$A_{ij} = 1$ if $i \rightarrow j$,
0 else

- **Modularity values take range $[-1, 1]$**

- It is positive if the number of edges within groups exceeds the expected number
- **$0.3-0.7 < Q$** means significant community structure

Modularity: Number of clusters

- Modularity is useful for selecting the number of clusters:



Next time: Why not optimize Modularity directly?