



Social and Technological Network Data Analytics

Lecture 4: Community Detection and Overlapping Communities

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Communities



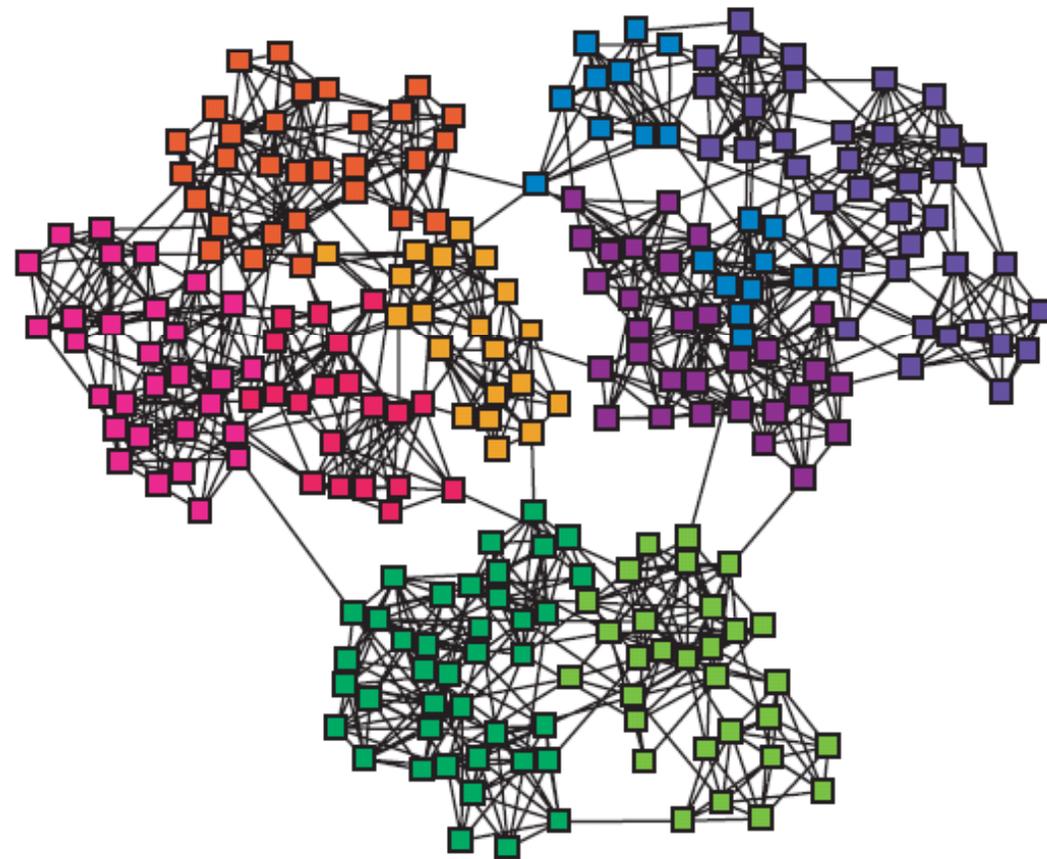
- Weak ties (Lecture 2) seemed to bridge groups of tightly coupled nodes (communities)
- How do we find these communities?

In This Lecture



- We will describe a Community Detection method based on betweenness centrality.
- We will describe the concept of Modularity and Modularity Optimization.
- We will describe methods for overlapping community detection.

What is a Community?



Why do we want to find partitions/communities?

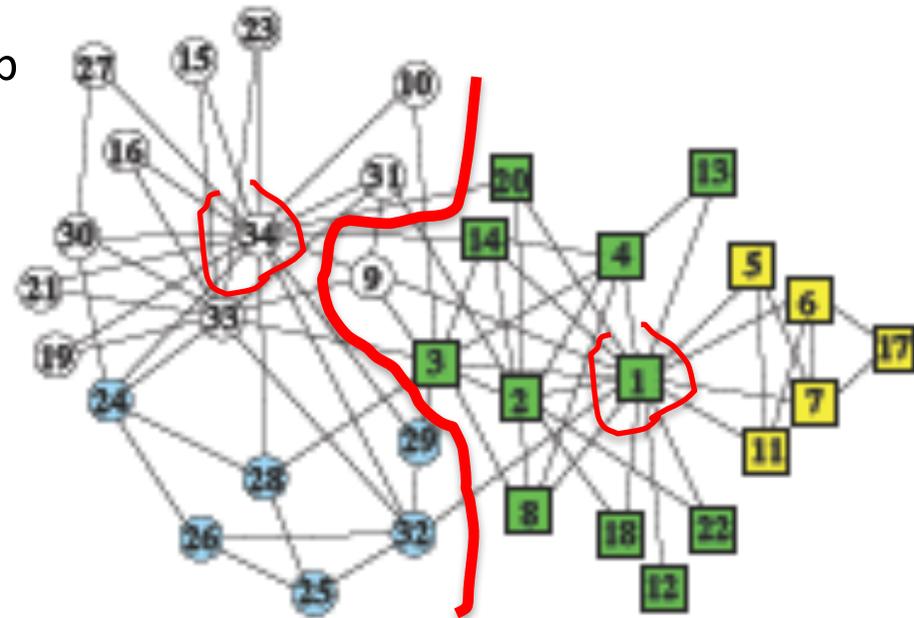
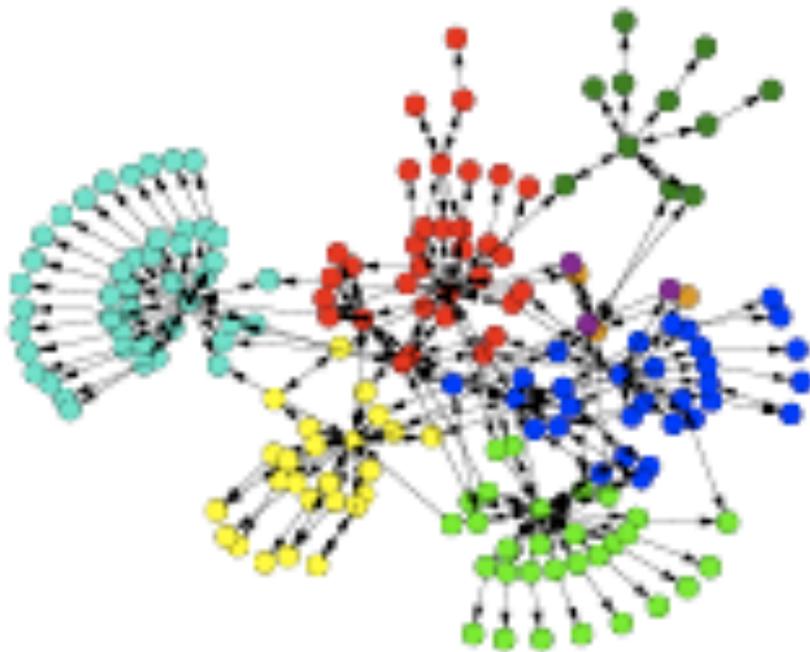


- Clustering online customers with similar interests or geographically near can improve performance
 - Customers with similar interests could be clustered to help recommendation systems
- Clusters in large graphs can be used to create data structures for efficient storage of graph data to handle queries or path searches
- Study the relationship/mediation among nodes
 - Hierarchical organization study



Example

Zachary's Karate club: 34 members of a club over 3 years. Edges: interaction outside the club



WWW: pages and hyperlinks
Identification of clusters can improve page ranking

Remove weak ties

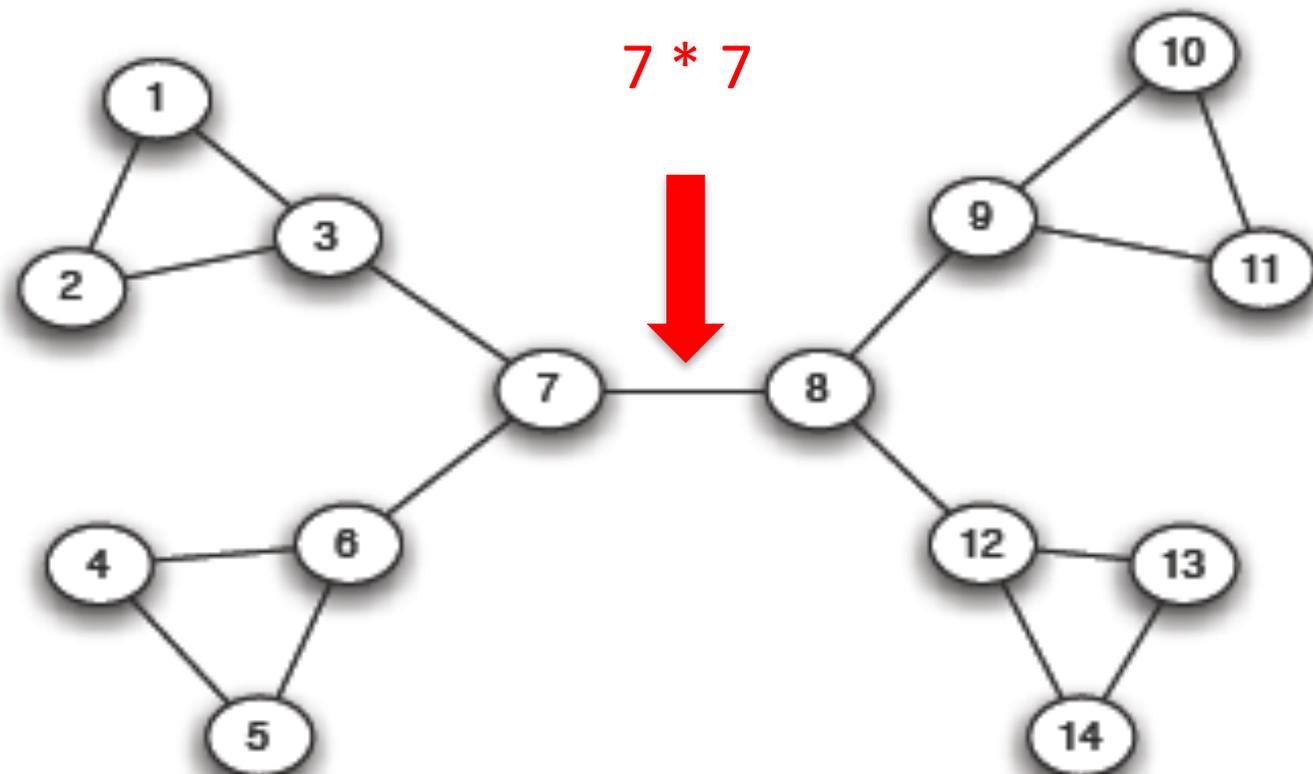


- Local bridges connect weakly interacting parts of the network.
- What if we have many bridges: which do we remove first? Or there might be no bridges.
- Note: **Without those bridges paths between nodes would be longer.**



Edge Betweenness

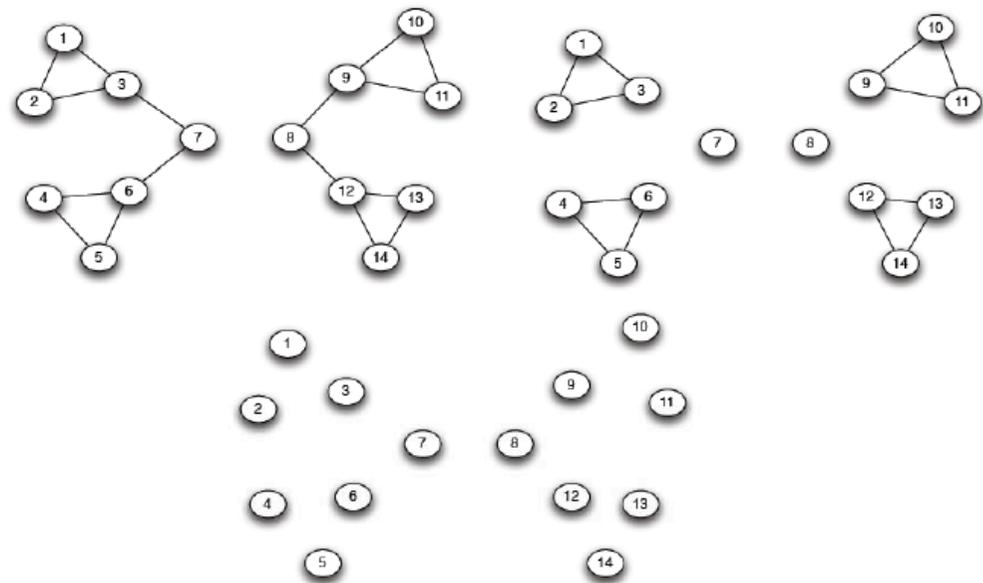
- Edge Betweenness: the number of shortest paths between pairs of nodes that run along the edge.



Algorithm of Girvan-Newmann (PNAS 2002)



- Calculate the betweenness of all edges
- Cut the edge with highest betweenness
- Recalculate edge betweenness



Edge: deletion

When do we stop?



- How do we know when to stop?
- When X communities have been detected?
- When the level of cohesion inside a community has reached Y ?
- There is no prescriptive way for every case
- There are also many other ways of detecting communities.



Modularity

- Perhaps a good measure of when to stop is when for each community the “cohesion” within the community is higher than what would be at random...
- ***$Q = (\text{edges inside the community}) - (\text{expected number of edges inside the community for a random graph with same node degree distribution as the given network})$***



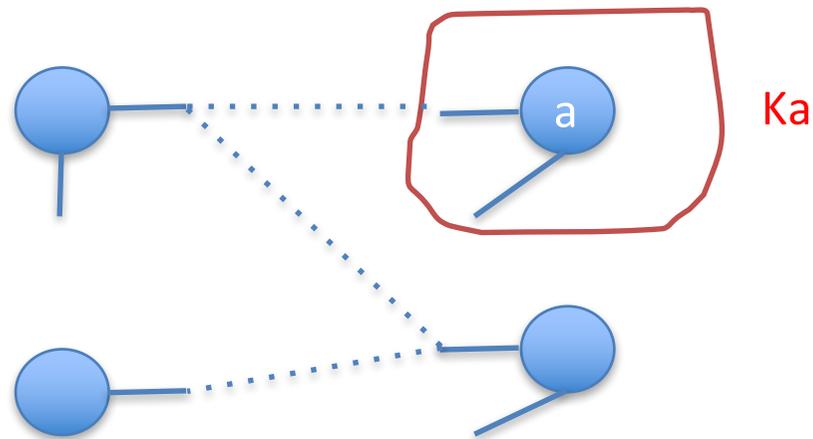
Modularity (2)

- Number of edges **inside** a community:

$$\frac{1}{2} \sum_{a,b} A_{a,b} \delta(c_a, c_b)$$

- Where:
- $A_{a,b}$ is 1 if there is an edge $a \rightarrow b$,
- $\delta(c_a, c_b)$ is the Kronecker Delta (1 if c_a is equal to c_b)

Modularity on a randomized graph calculation



The expected number of edges in the randomized version of the graph where nodes are rewired:

$$\frac{k_a k_b}{2m}$$

m is the number of edges of the graph = $\frac{1}{2} \sum(k_i)$



Modularity (3)

$$Q1 = \frac{1}{2} \sum_{a,b} A_{a,b} \delta(c_a, c_b) - \frac{1}{2} \sum_{a,b} \frac{k_a k_b}{2m} \delta(c_a, c_b)$$

$$Q1 = \frac{1}{2} \sum_{a,b} \left(A_{a,b} - \frac{k_a k_b}{2m} \right) \delta(c_a, c_b)$$

$$Q = \frac{1}{2m} \sum_{a,b} \left(A_{a,b} - \frac{k_a k_b}{2m} \right) \delta(c_a, c_b)$$

Fraction of edges over
all edges m



Modularity (4)

- Modularity ranges from -1 to 1.
 - It is positive if the number of edges inside the group are more than the expected number.
 - Variation from 0 indicate difference with random case.
- Modularity can be used at each round of the Girvan-Newmann algorithm to check if it is time to stop. However the complexity of this is $O(m^2n)$.

Example of Dendrogram

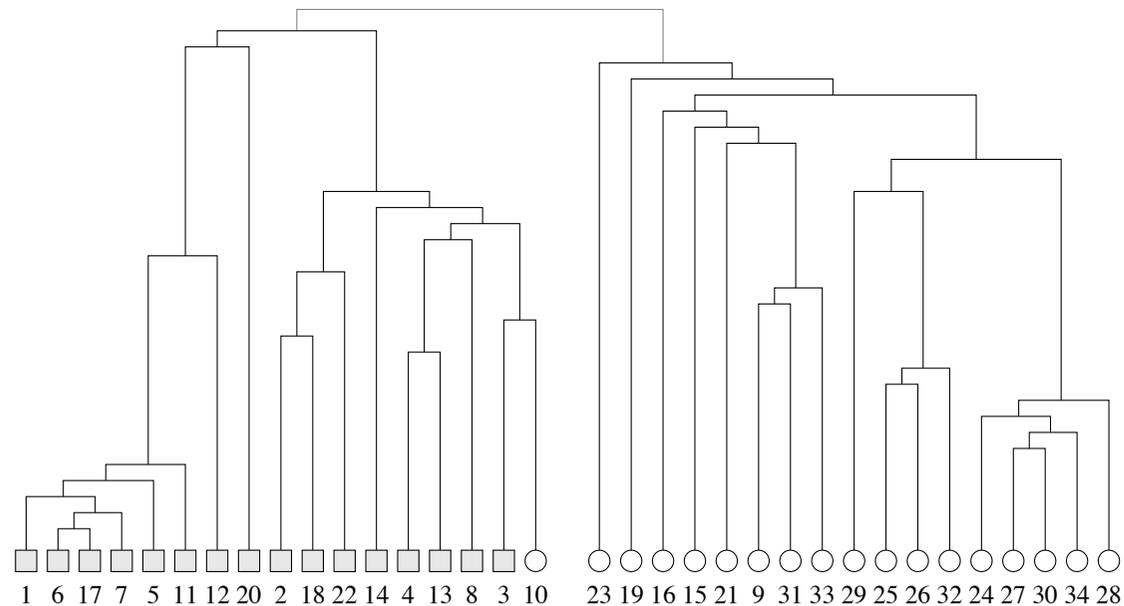


FIG. 2: Dendrogram of the communities found by our algorithm in the “karate club” network of Zachary [5, 17]. The shapes of the vertices represent the two groups into which the club split as the result of an internal dispute.

Modularity Optimization



- Why not optimize modularity directly?
- Finding the configuration with maximum modularity in a graph is an NP complete problem.
- However there are good approximation algorithms.

(Greedy) Fast Modularity



- Start with a network of n communities of 1 node
- Merge the communities that lead to largest increase in Q (calculated over the whole graph)
- Repeat previous step until one community remains
- Cross cut the dendrogram where Q is maximum.
- This runs in $O((m + n)n)$.

- A further optimization runs in $O(m d \log n)$ [d depth of dendrogram].
- Most networks are sparse so $m \sim n$ and $d \sim \log n$

Application to Amazon Recommendations



- Network of products.
- A link between product a and product b if b was frequently purchased by buyers of a.
- 200000 nodes and 2M edges.
- Max when 1684 communities
- Mean size of 243 products

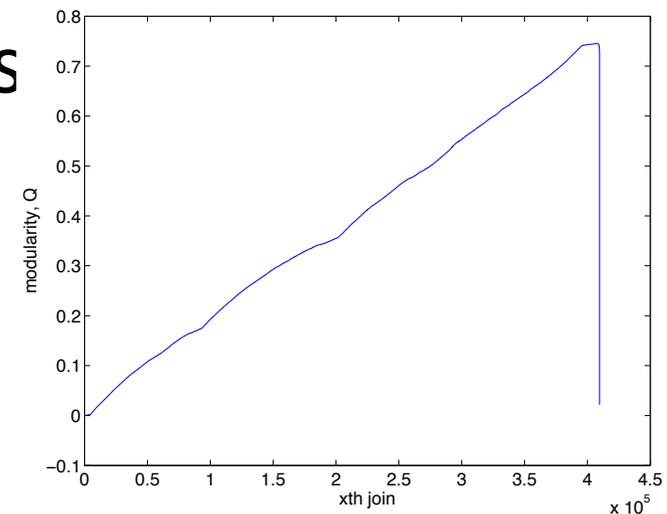


FIG. 1: The modularity Q over the course of the algorithm (the x axis shows the number of joins). Its maximum value is $Q = 0.745$, where the partition consists of 1684 communities.

Amazon: Top Communities (87% of nodes)



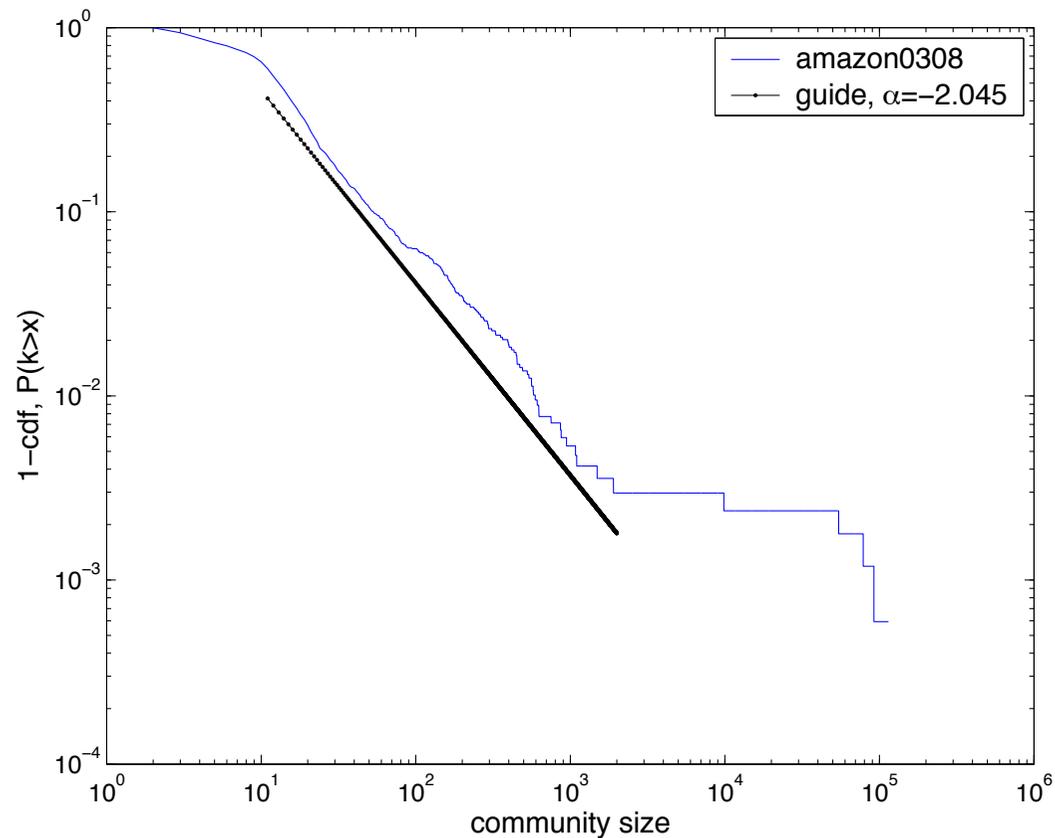
Rank	Size	Description
1	114538	General interest: politics; art/literature; general fiction; human nature; technical books; how things, people, computers, societies work, etc.
2	92276	The arts: videos, books, DVDs about the creative and performing arts
3	78661	Hobbies and interests I: self-help; self-education; popular science fiction, popular fantasy; leisure; etc.
4	54582	Hobbies and interests II: adventure books; video games/comics; some sports; some humor; some classic fiction; some western religious material; etc.
5	9872	classical music and related items
6	1904	children's videos, movies, music and books
7	1493	church/religious music; African-descent cultural books; homoerotic imagery
8	1101	pop horror; mystery/adventure fiction
9	1083	jazz; orchestral music; easy listening
10	947	engineering; practical fashion

TABLE I: The 10 largest communities in the Amazon.com network, which account for 87% of the vertices in the network.

Amazon: Community Size Distribution



- A power law distribution of community size
- (more on power laws in later lectures)



Limitations of Modularity



- Modularity is not a perfect measure
 - Plus the algorithm described has a complexity of N^2 and does not work well with large networks
- Problems for modules with a number of internal links of the order of $\sqrt{2L}$ or smaller.
- Intuition: modularity depends on links of a community to the “outside”, ie the rest of the network.

Louvain Method



- Faster method with complexity $O(L)$
- Step I:
 - Initially, all nodes assigned to a different community.
 - For each node i consider neighbours (j) and evaluate gain in modularity of community if i moves to j 's community.
 - Move node i to j 's community which has the largest positive gain.
 - Do this for all nodes. Stop when no improvement can be achieved.

Louvain (Step 2)

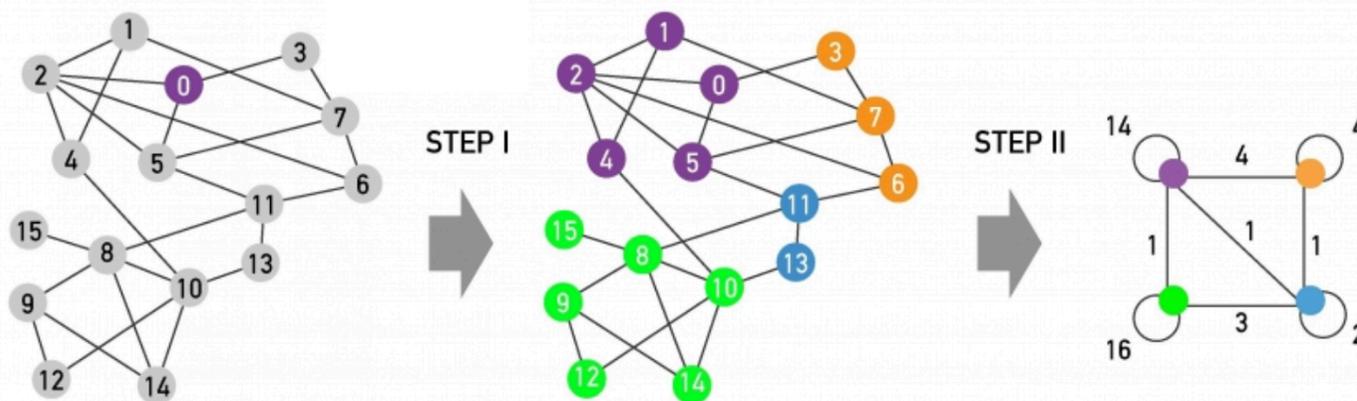


- Step II:
 - Construct a new network whose nodes are the communities identified during Step I.
 - The weight of the link between two nodes is the sum of the weight of the links between the nodes in the corresponding communities. Links between nodes of the same community lead to weighted self-loops.
- Repeat Step I and Step II on this network.
- The passes are repeated until there are no more changes and maximum modularity is attained.

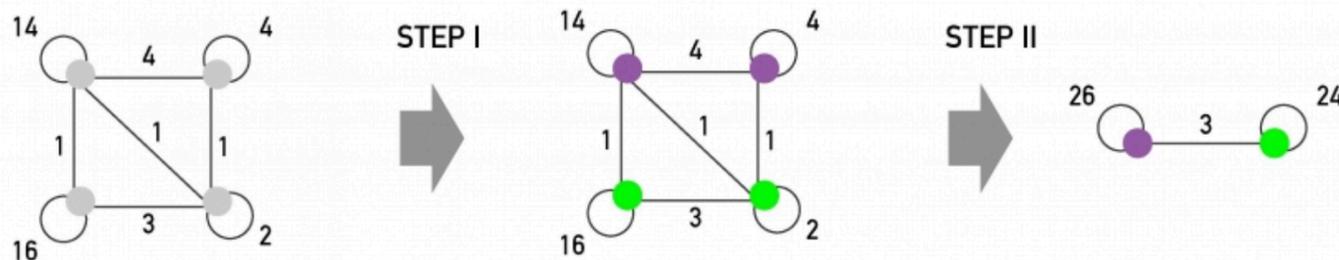


Example

1ST PASS



2ND PASS



Efficiency



- Faster than other algorithms
- Complexity is linear on typical and sparse data.
 - Possible gains in modularity are easy to compute and number of communities decreases drastically after a few steps.

Performance and Modularity results for various networks and approaches



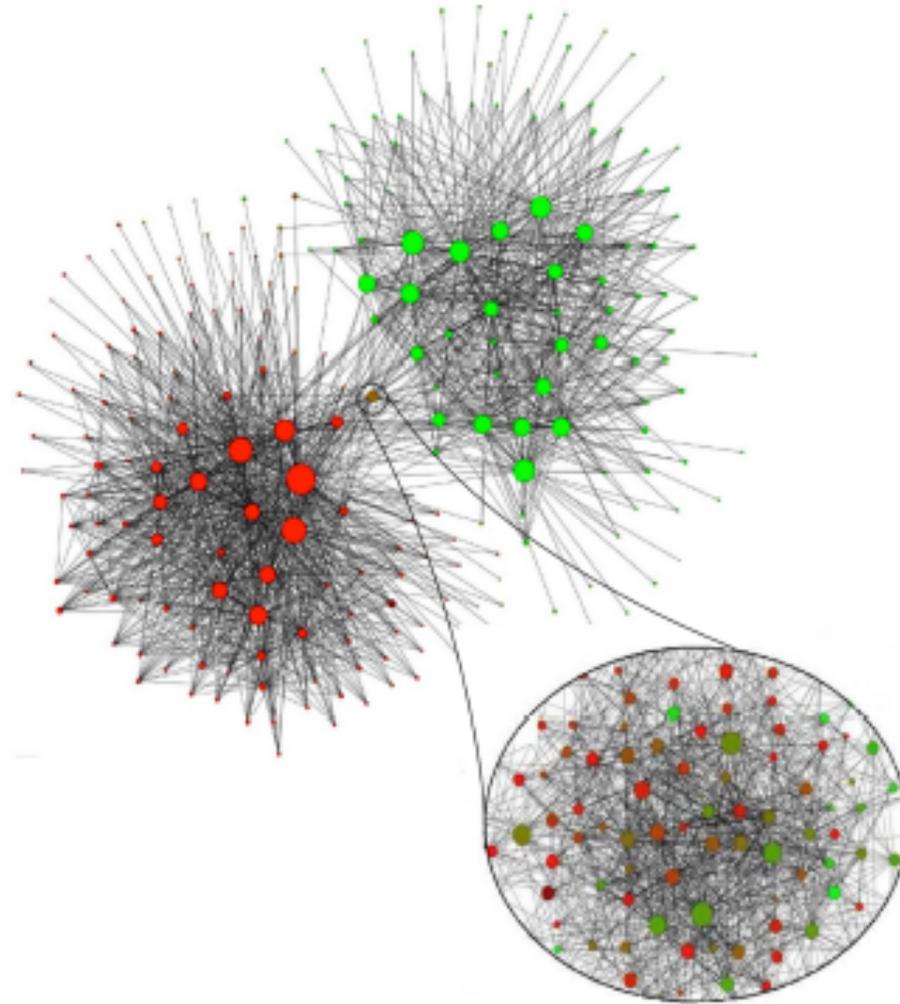
	Karate	Arxiv	Internet	Web nd.edu	Phone	Web uk-2005	Web WebBase 2001
Nodes/links	34/77	9k/24k	70k/351k	325k/1M	2.6M/6.3M	39M/783M	118M/1B
CNM	.38/0s	.772/3.6s	.692/799s	.927/5034s	-/-	-/-	-/-
PL	.42/0s	.757/3.3s	.729/575s	.895/6666s	-/-	-/-	-/-
WT	.42/0s	.761/0.7s	.667/62s	.898/248s	.56/464s	-/-	-/-
Our algorithm	.42/0s	.813/0s	.781/1s	.935/3s	.769/134s	.979/738s	.984/152mn

Louvain over a telecom network in Belgium



The colours are different languages spoken by people. The intermediate node is one with a lot of language mixing.

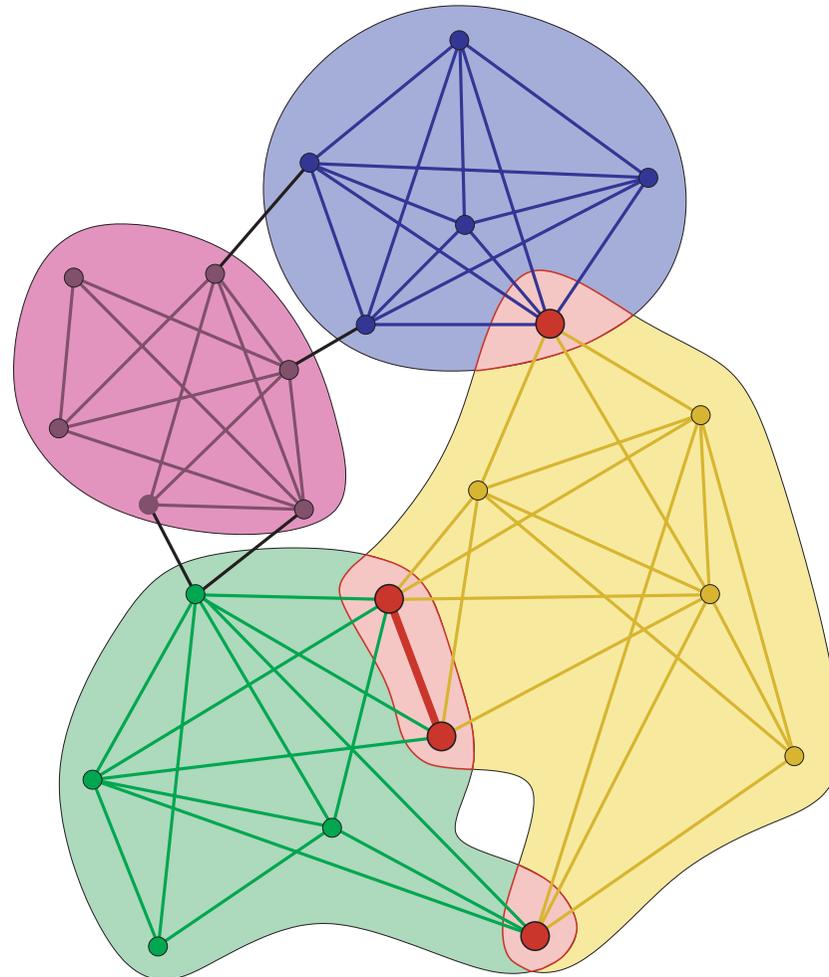
Edges are calls. Each of these communities are more than 100 people.



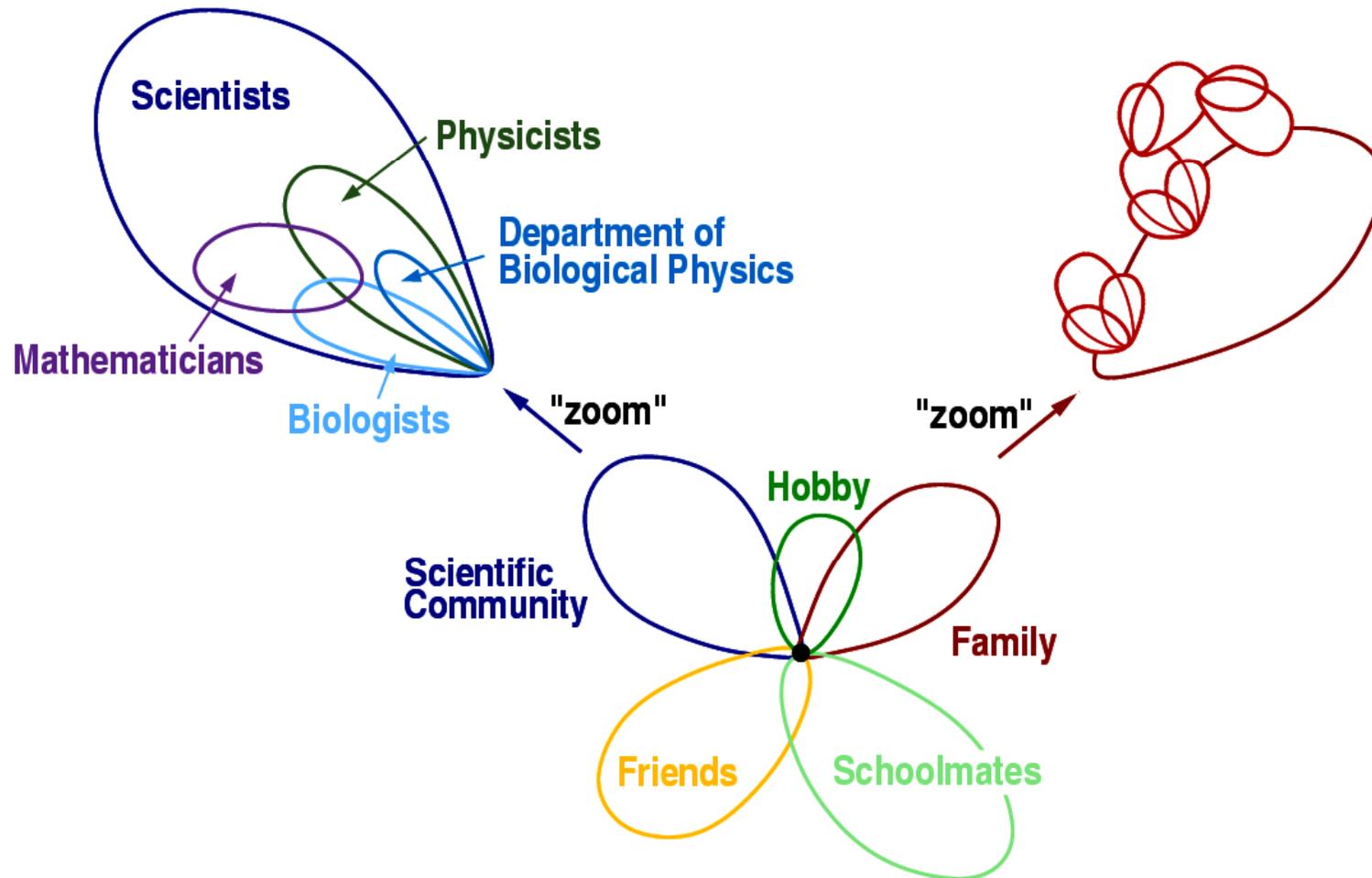
Overlapping Communities



- Community membership could overlap: a node could be part of more than 1 community.



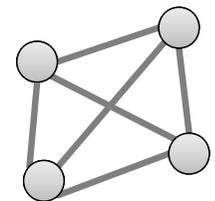
Nodes can belong to more than 1 social circle!



Clique Percolation Method: the idea (Palla 2005)



- Two nodes belong to the same community if they can be connected through adjacent k -cliques.
- A k -clique is a fully connected graph of k nodes.
- K -cliques are adjacent if they have $k-1$ overlapping nodes.
- K -clique community: nodes which can be reached through a sequence of adjacent k -cliques.



4-clique

Clique Percolation Method: The algorithm

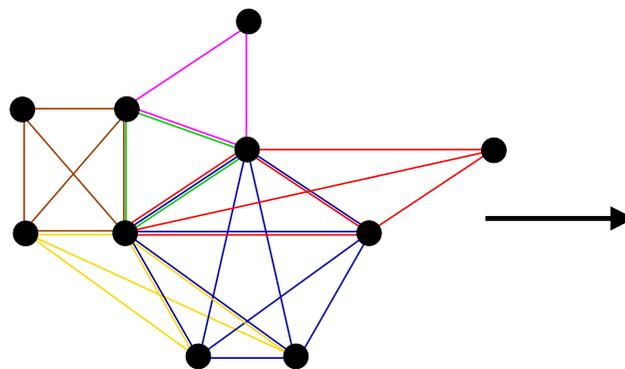


- Find the maximal cliques
 - A maximal clique is a clique that cannot be extended by including one more adjacent vertex
 - This is complex but real networks are relatively sparse.
- Build clique overlap matrix
 - Each clique is an entry
 - Connect two cliques if they overlap in at least $k-1$ nodes
- Communities:
 - Connected components of the clique overlap matrix



Example

Maximal cliques



	Blue	Red	Green	Magenta	Yellow	Brown
Blue	5	3	2	1	3	1
Red	3	4	2	1	1	1
Green	2	2	3	2	1	2
Magenta	1	1	2	3	0	1
Yellow	3	1	1	0	4	2
Brown	1	1	2	1	2	4

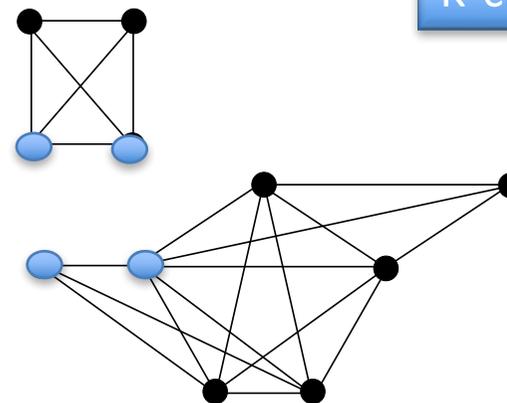
Overlap Matrix:
elements are n. of
overlapping
nodes

k=4

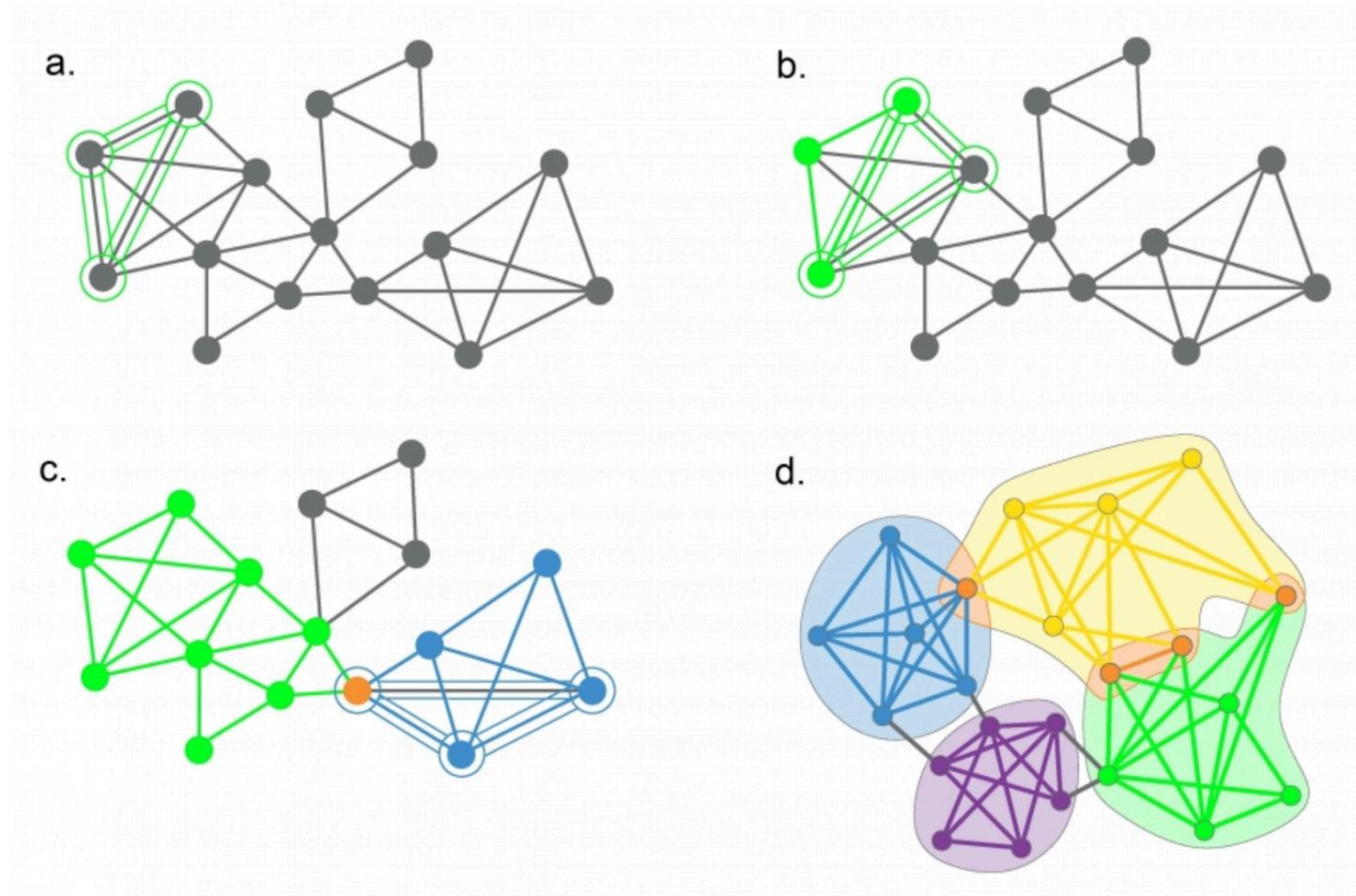
Erase elements
less than 4 on
diagonal and less
than 3 elsewhere

	Blue	Red	Green	Magenta	Yellow	Brown
Blue	1	1	0	0	1	0
Red	1	1	0	0	0	0
Green	0	0	0	0	0	0
Magenta	0	0	0	0	0	0
Yellow	1	0	0	0	1	0
Brown	0	0	0	0	0	1

K-cliques



Example

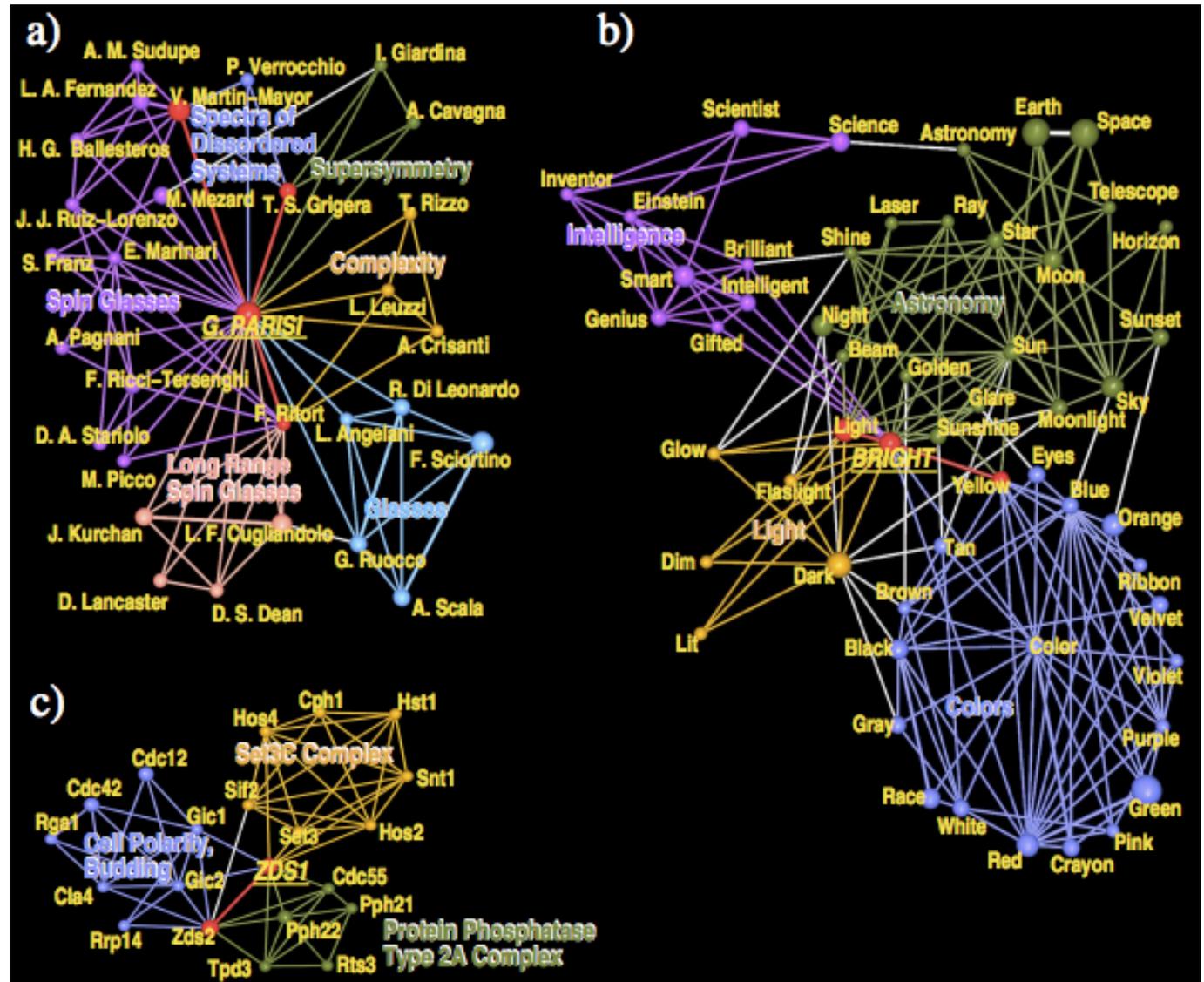


Application

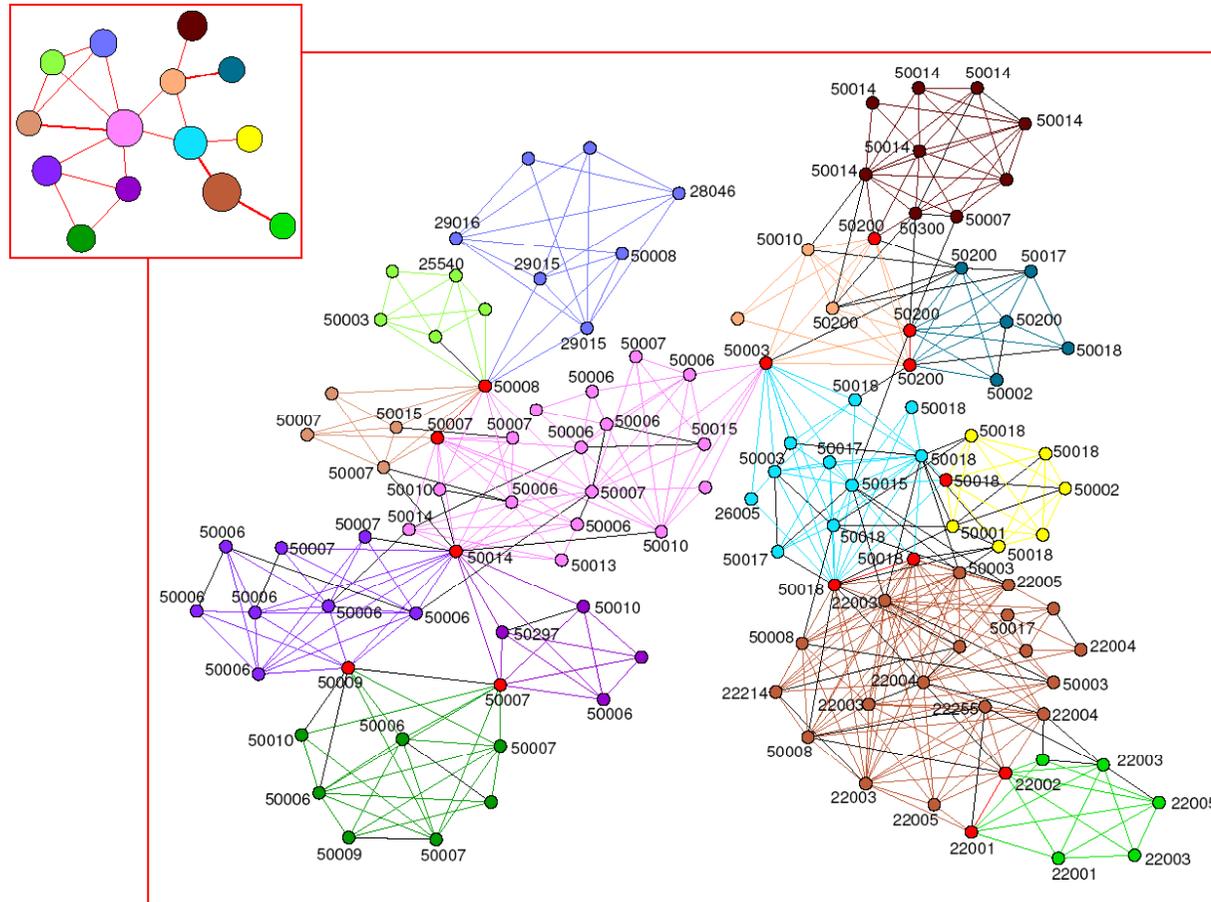


Overlapping networks:

- 1) Parisi's coauthorship networks
- 2) Networks of "bright" in the word association network
- 3) Protein to protein interaction network



Application: Phone Call Network



Community Detection and Weak Ties

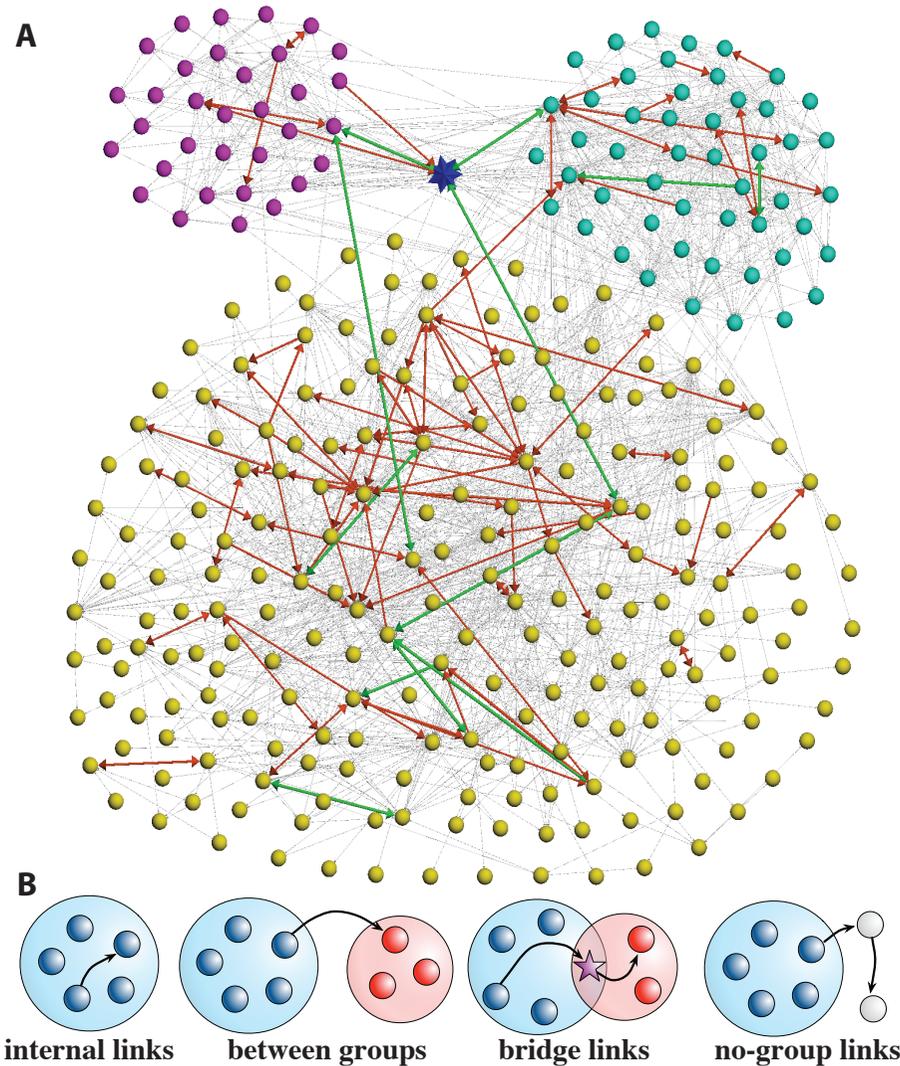


- Twitter was analyzed trying to identify if the static network of followers gives information about the dynamics of retweeting and mentioning.
- Dataset: follower network (undirected), 2M users, and network of tweets, mention and retweets for 1 month.
- Some community detection methods are used to find clusters in the follower network.

Sample



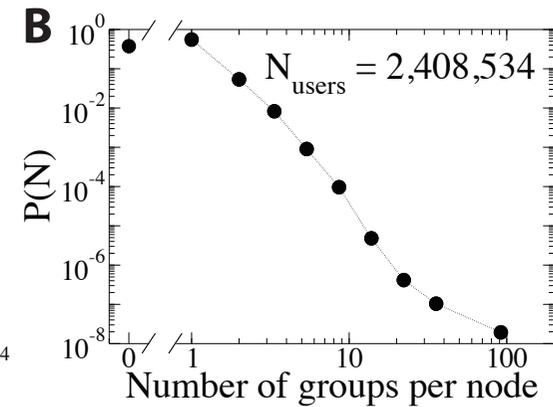
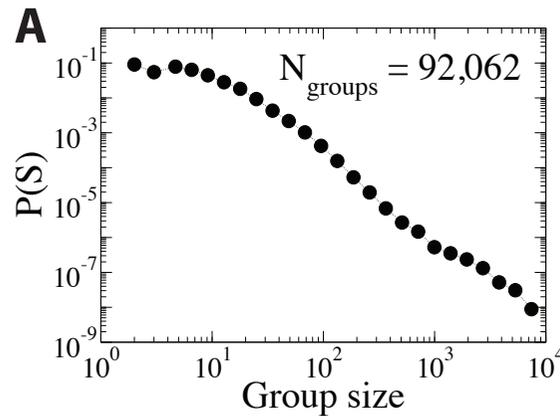
- Gray: followers
- Red: mentions
- Green: retweet
- 3 groups, one user between groups.



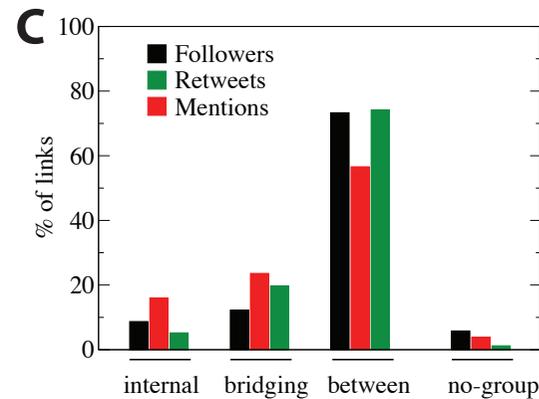
Some statistics



92,000 groups
Largest group: 10,000 users
37% users: no group



Mentions are double the followers in
internal and bridging



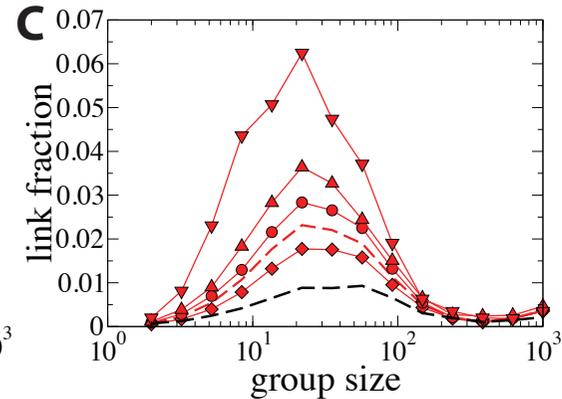
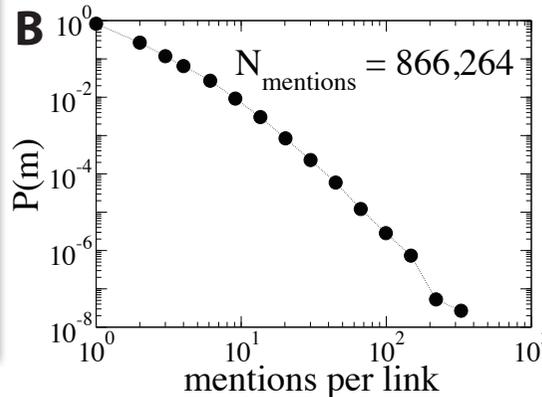
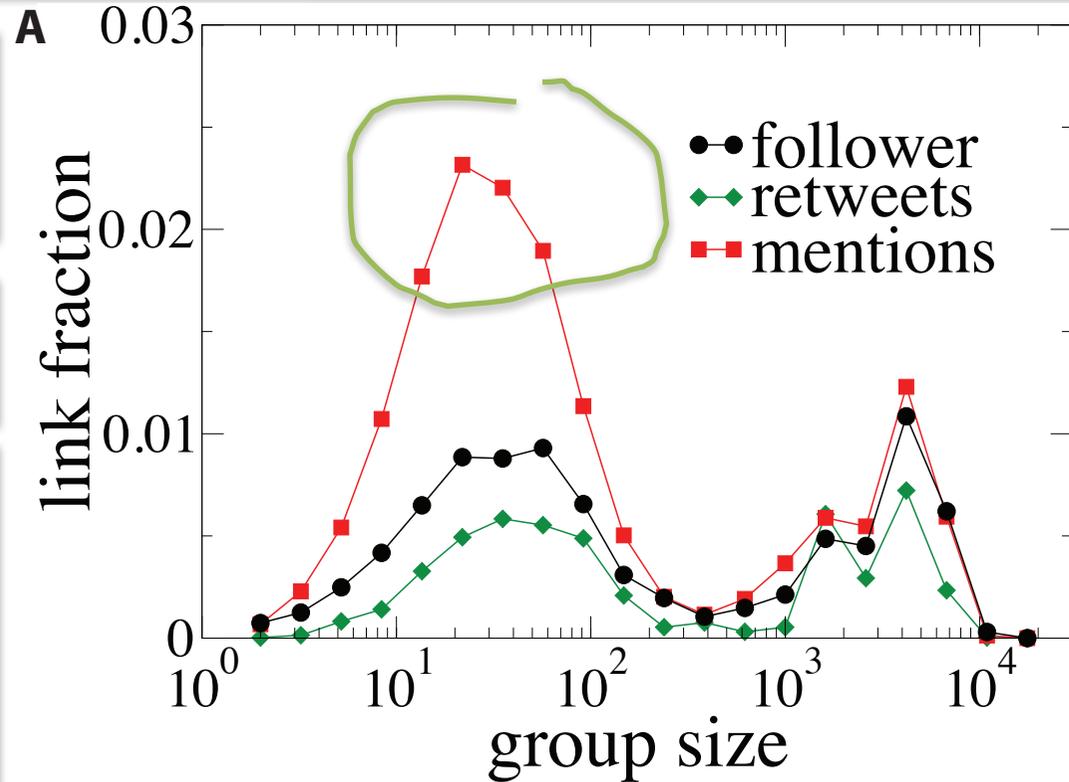
Internal Links



Internal mentions are more than follower links with groups around 100.

The distribution of mentions over links is quite wide

C: The dashed curves are the total for the follower network (black) and for the links with mentions (red). Others (from bottom to top): fractions of links with: 1 non-reciprocated mentions (diamonds), 3 mentions (circles), 6 mentions (triangle up) and more than 6 reciprocated mentions (triangle down).



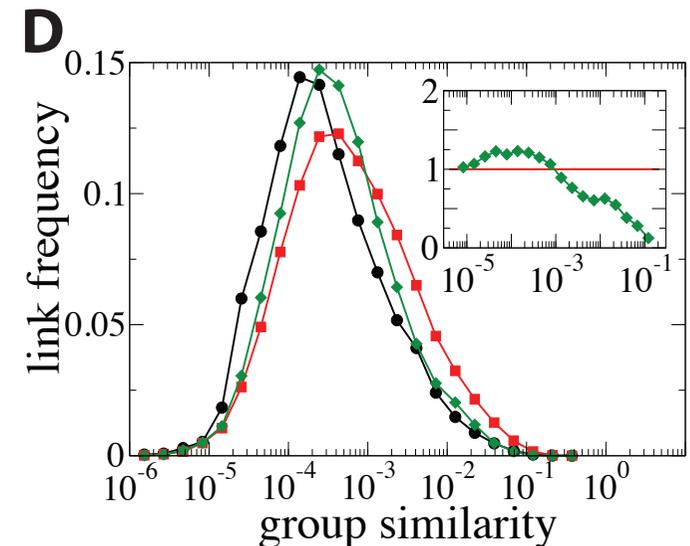
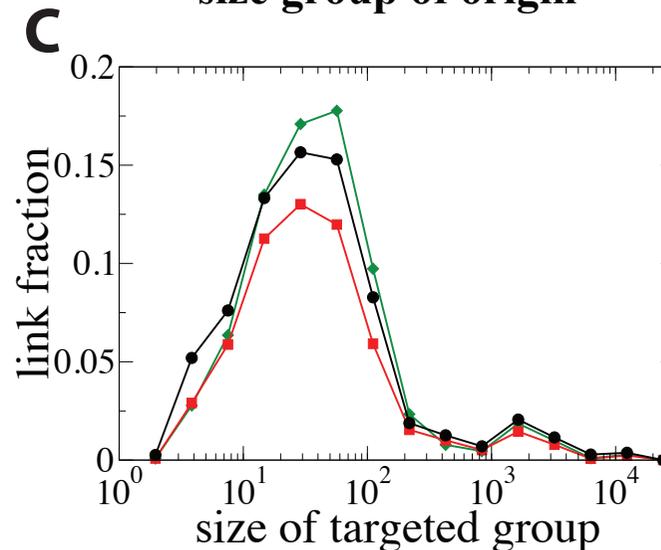
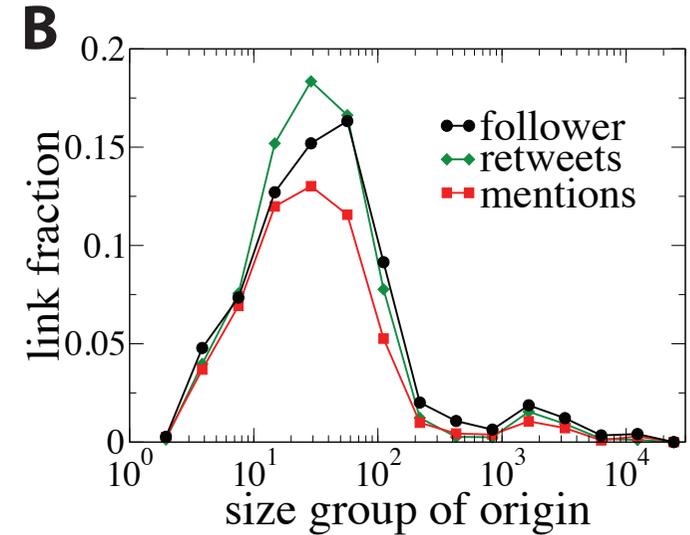
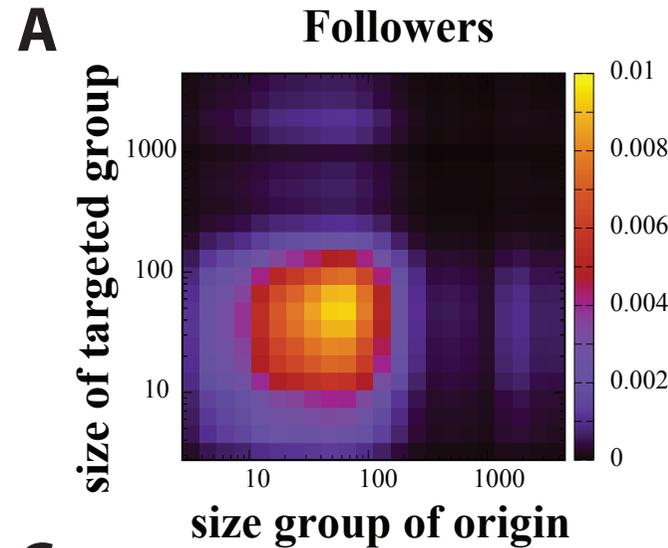
Links between groups



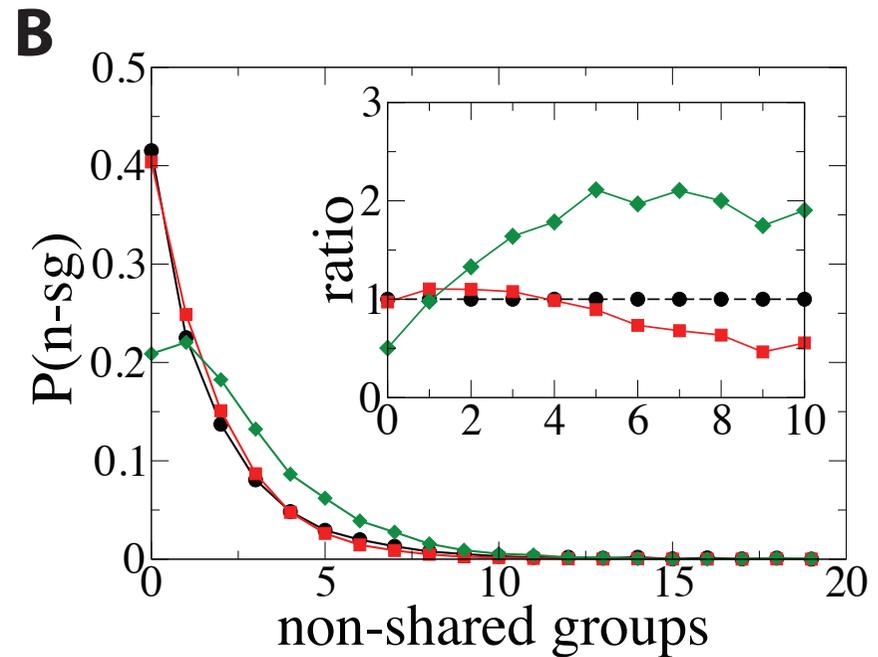
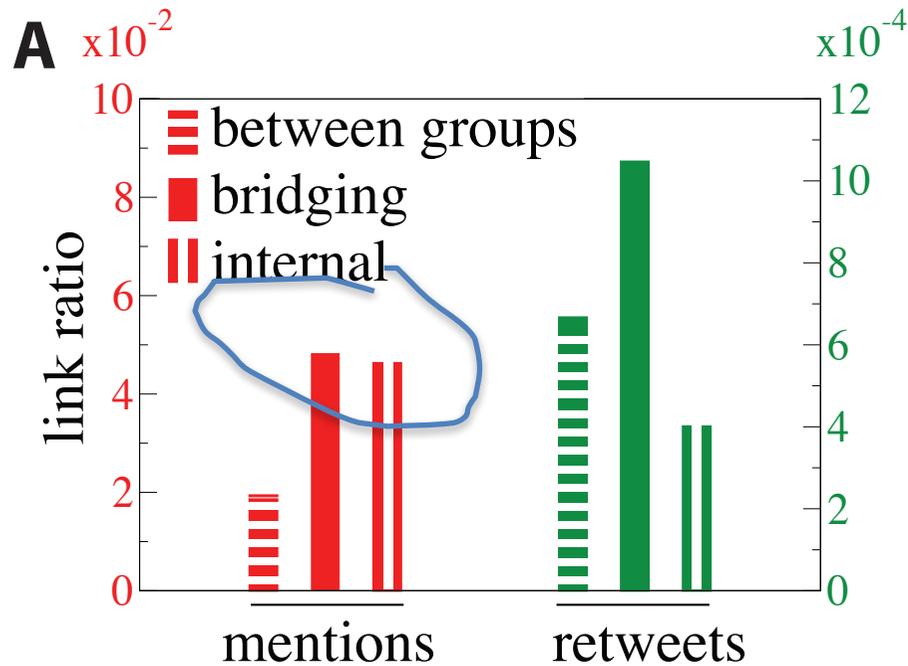
Occur between groups of <200 nodes

$$sim(A, B) = \frac{|\cap linksAandB|}{|\cup linksAandB|}$$

Retweets seem to occur more between groups than within! Weak ties!!!!
Retweets also seem to happen **between** less similar groups!



Bridge Links



Retweets on a bridge increase with the number of groups assigned to the bridging nodes



Discussion on findings

- There seems to be a correlation with the role of weak ties and the clustering done on the followers network
- Weak ties seem to be carrier of information (retweets) while internal group links seem to be more about mentions and communication

Summary



- We have discussed modularity based community detection as well as overlapping community detection.
- Many methods exist...
- We have shown cluster and weak ties analysis on an online social network dataset.

References



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