Advanced Human Machine Interaction
Interaction Data Analysis

Social Network Analysis

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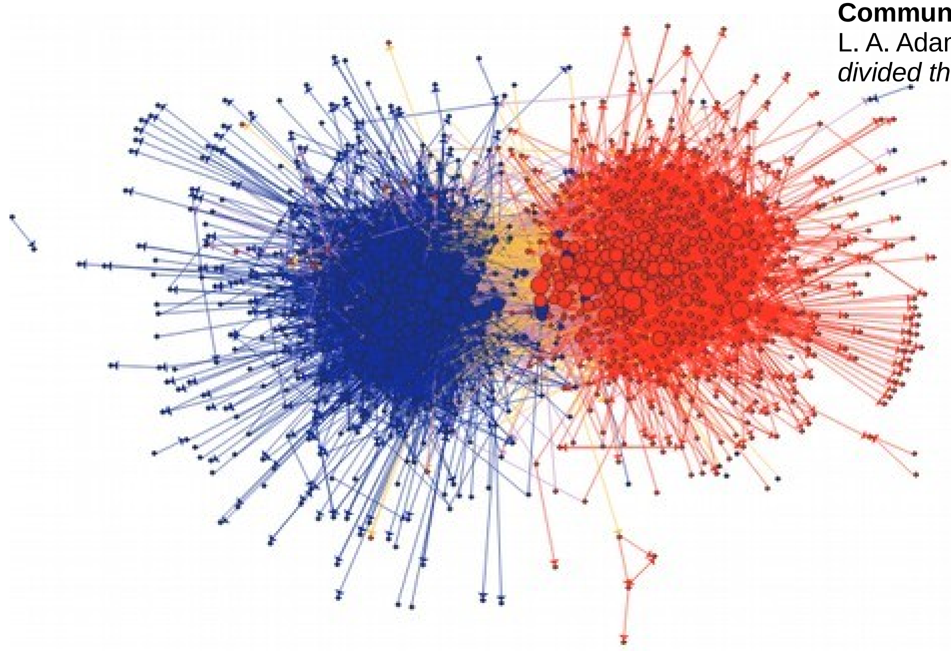
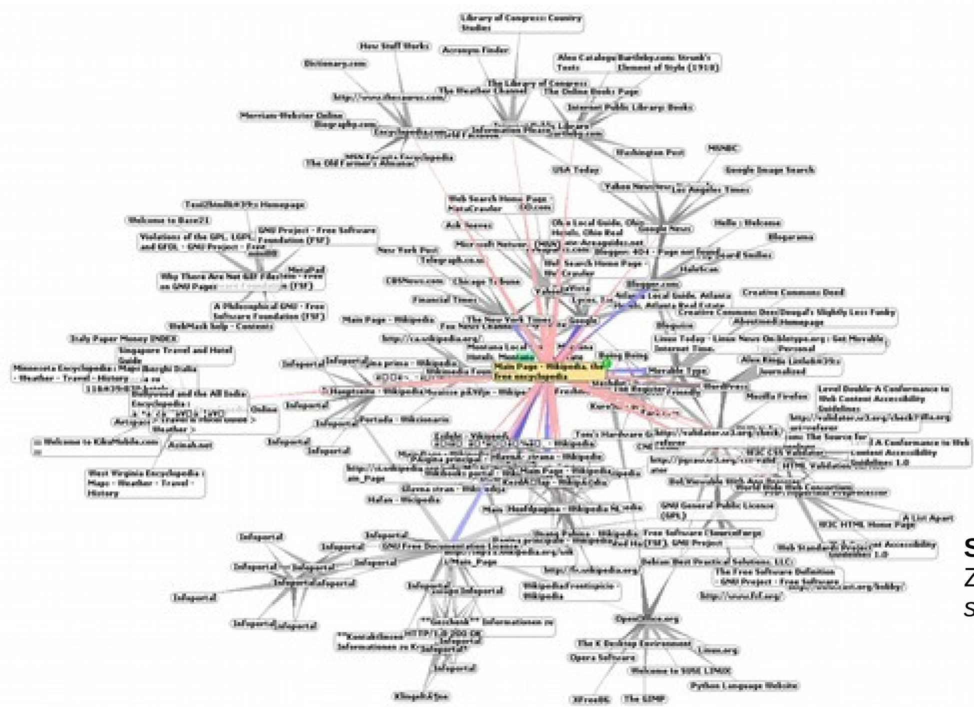
Scope: interactions in social networks

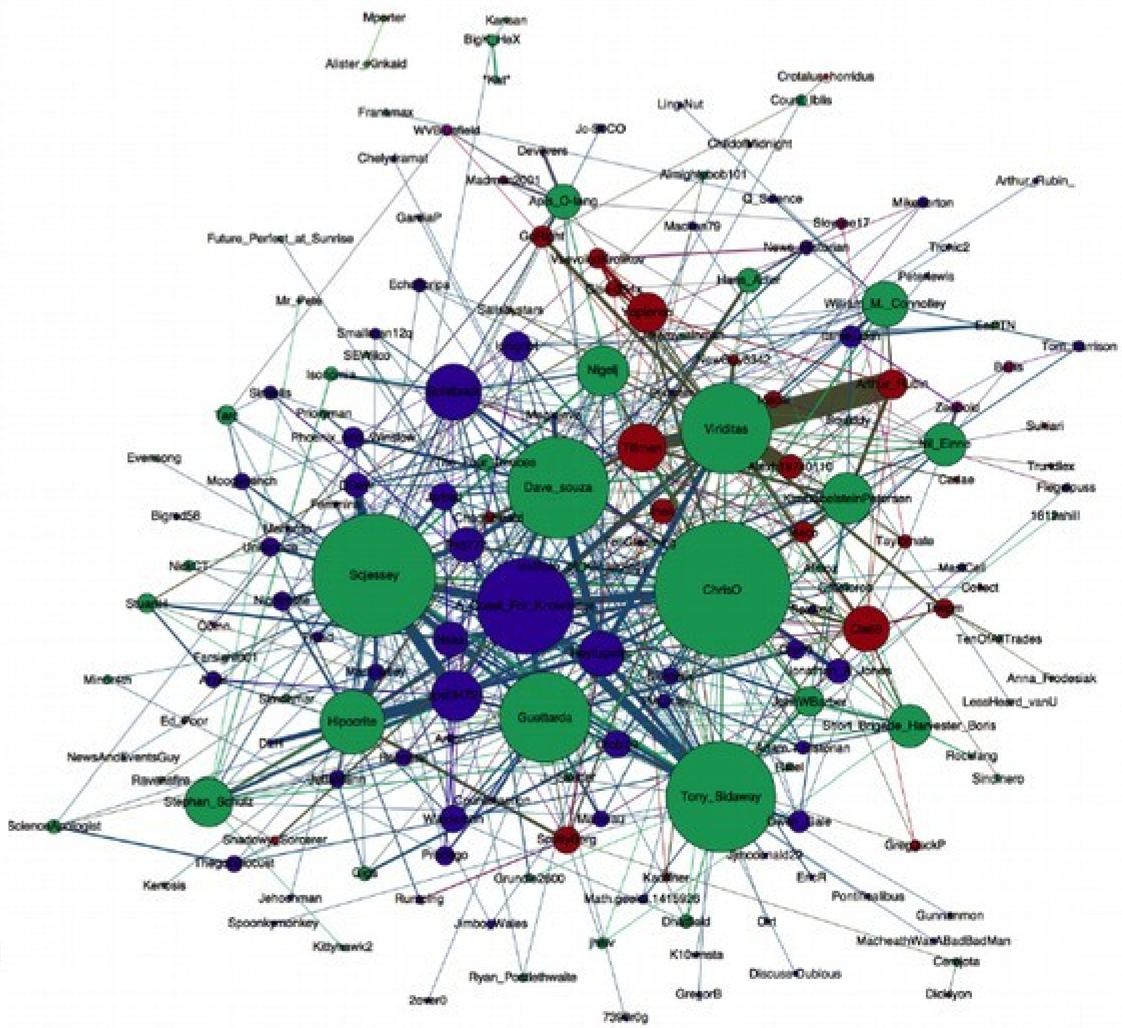
- **Interactions** in social networks:
  - Messages, actions (Friend, Like, …), …
  - Dynamic network
- Interactions in **social** networks:
  - Human-to-human mediated interaction, bots
  - Open world
- Interactions in social **networks**: graph representation

Examples



Community structure of political US blogs.
L. A. Adamic and N. Glance, "*The political blogosphere and the 2004 U.S. election: divided they blog*", In Proceedings of Link discovery (LinkKDD '05), ACM, pp. 36-43, 2005.





Social Sybil detection / false identities.
Z. Yamak, J. Saunier, L. Vercouter, "*Automatic detection of multiple account deception in social media*", in proceedings of Web Intelligence, pp. 219-231, 2017.

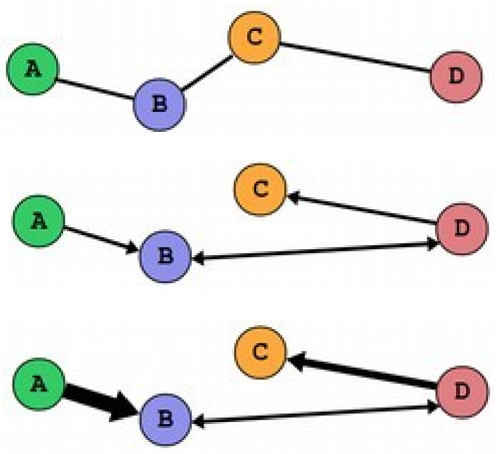
Process

1) Dataset collection

- Anonymization and processing

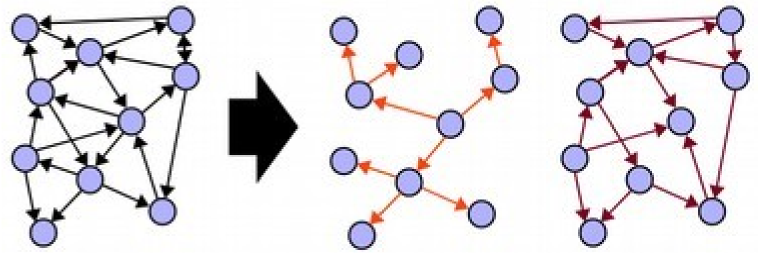
2) Graph construction

- Nodes (vertices)? Links (edges)?
- Directed or undirected graph ?
- Weighted graph ?



3) Filtering

- Node/edge removing
- Network decomposition



4) Community detection

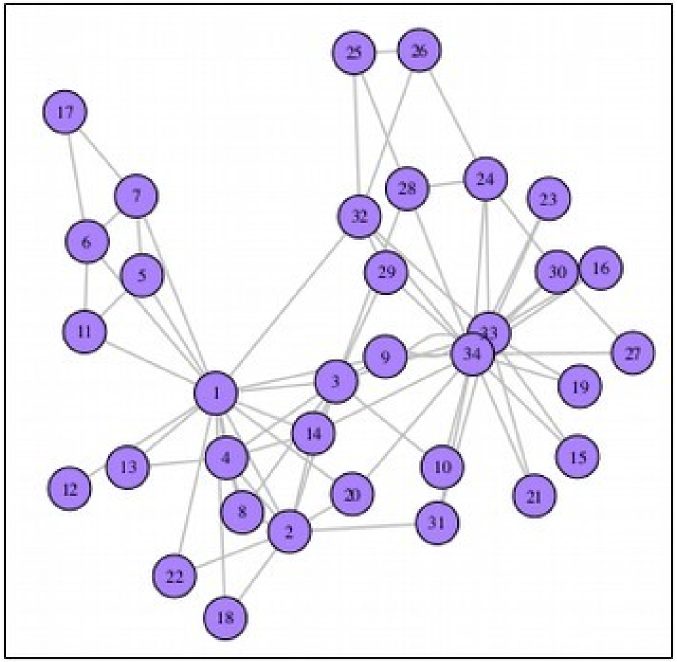
- Objective function?

Graph: definition

A graph G can be represented with:

$$G(V, E, \Psi, \nu, \omega)$$

- V is the set of nodes (vertices);
- E is the set of edges (links);
- Ψ is an incidence function $\Psi: E \rightarrow V \times V$;
- ν is the node-labelling function;
- ω is the edge-labelling function;



Zachary's Karate Club Network
W. W. Zachary, "*An information flow model for conflict and fission in small groups*", Journal of Anthropological Research 33, pp. 452-473 (1977).

Graph construction

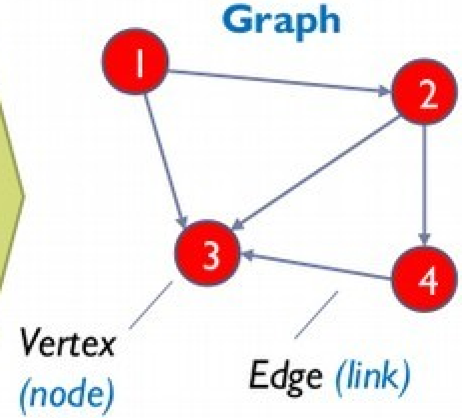
Graph construction

Can we study their interactions as a network?

Communication

Anne: Jim, tell the Murrays they're invited
Jim: Mary, you and your dad should come for dinner!
Jim: Mr. Murray, you should both come for dinner
Anne: Mary, did Jim tell you about the dinner? You must come.
John: Mary, are you hungry?
…

Graph



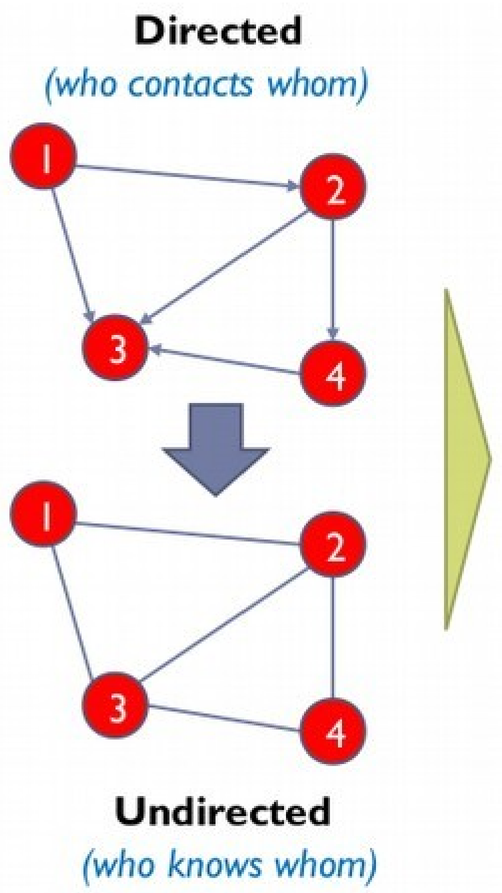
Adjacency matrix

Vertex	1	2	3	4
1	-	1	1	0
2	0	-	1	1
3	0	0	-	0
4	0	0	1	-

Edge list

Vertex	Vertex
1	2
1	3
2	3
2	4
3	4

Directed *versus* undirected graphs



Edge list remains the same

Vertex	Vertex
1	2
1	3
2	3
2	4
3	4

But interpretation is different now

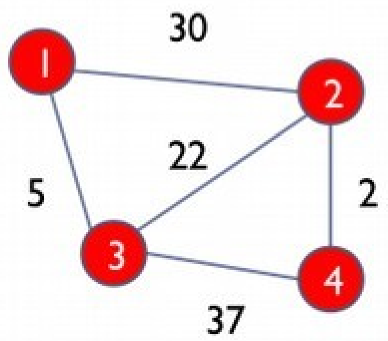
Adjacency matrix becomes symmetric

Vertex	1	2	3	4
1	-	1	1	0
2	1	-	1	1
3	1	1	-	1
4	0	1	1	-

Quizz

- When are edge lists different between directed graphs and undirected graphs?

Weighted edges



Weights could be:

- *Frequency of interaction in period of observation*
- *Number of items exchanged in period*
- *Individual perceptions of strength of relationship*
- *Costs in communication or exchange, e.g. distance*
- *Combinations of these*

Edge list: add column of weights

Vertex	Vertex	Weight
1	2	30
1	3	5
2	3	22
2	4	2
3	4	37

Adjacency matrix: add weights instead of 1

Vertex	1	2	3	4
1	-	30	5	0
2	30	-	22	2
3	5	22	-	37
4	0	2	37	-

Quizz

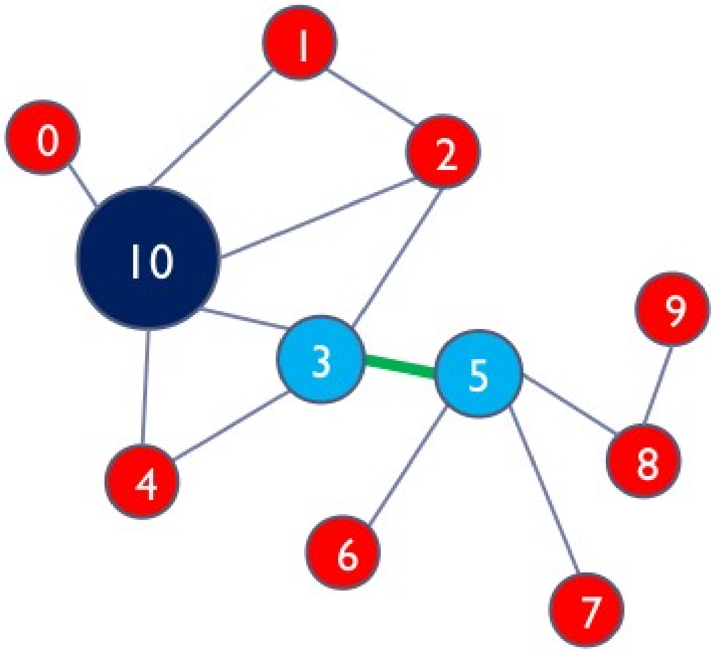
Construct the interaction graph of these messages

Auteur	Message	Interaction	Thème
1	hello @2 viens sur mon site : http :url	ME	Autre
1	hello @3 viens sur mon site : http :url	ME	Autre
1	hello @4 viens sur mon site : http :url	ME	Autre
6	un cinéma @5 ?	ME	Cinéma
5	@6 : quel film ? #Film, #Film1 ou photo_Film_2 ?	RE	Cinéma
5	allons au cinéma @4 ! @6 vient aussi	ME	Cinéma
4	@5 : ok	RE	Autre
4	super #Film, à la prochaine @6	ME	Cinéma
5	RT @4 : super #Film, à la prochaine @6	RT, ME	Cinéma
6	RT @4 : super #Film, à la prochaine @6	RT, ME	Cinéma
5	la bande-annonce de photo_Film_2 :) ! #Film2 dès demain !		Cinéma
4	RT @5 : la bande-annonce de photo_Film_2 :) ! #Film2 dès demain !	RT	Cinéma
4	au fait, @8, tu devrais aller voir #Film	ME	Cinéma
5	le théâtre c'est bien aussi		Théâtre
4	RT @5 : le théâtre c'est bien aussi	RT	Théâtre
7	RT @5 : le théâtre c'est bien aussi	RT	Théâtre
8	RT @5 : le théâtre c'est bien aussi	RT	Théâtre
6	@7 : cinéma :-) theââââatre :-(	RE	Cinéma
7	viens @8, allons au théâtre	ME	Théâtre

Identification of Key-users Roles in Social Networks

Identifying key users

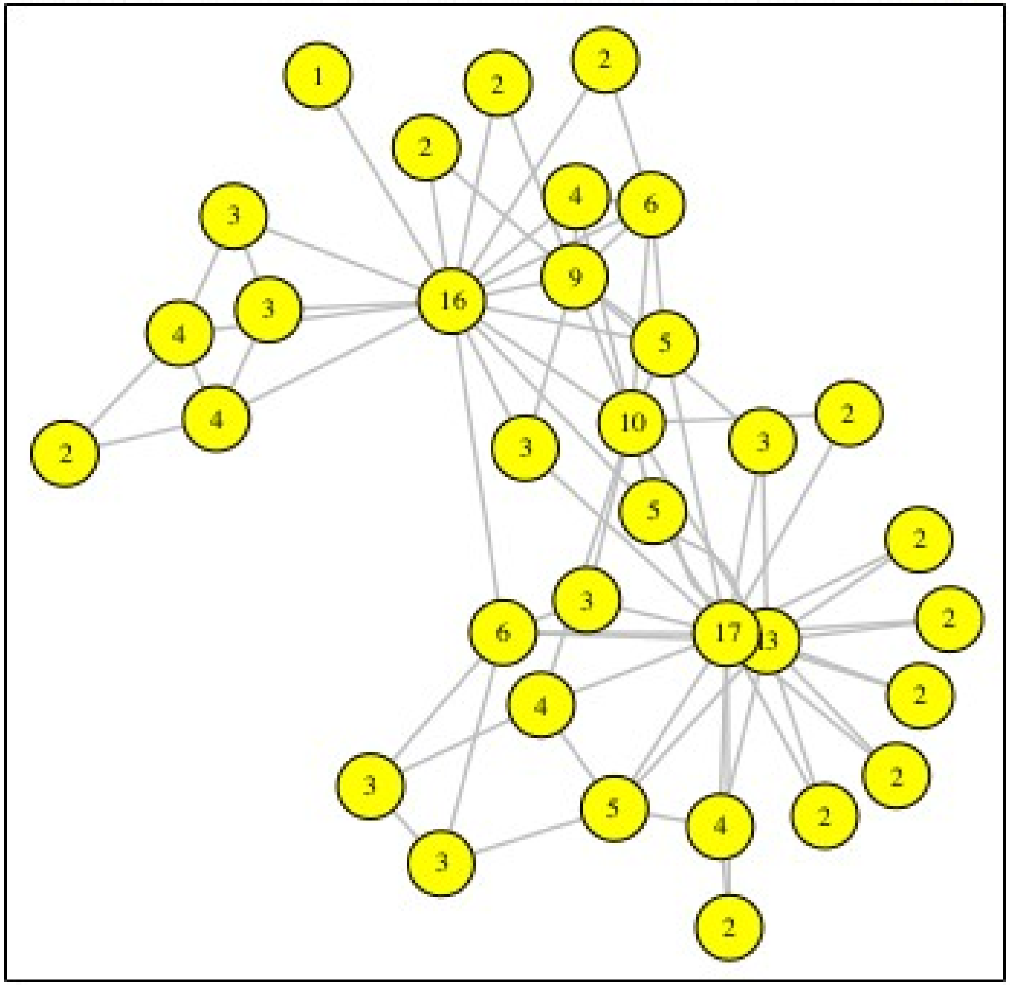
- In the network on the right, node 10 is the most central according to centrality
- But nodes 3 and 5 together reach more nodes with paths of length 2
- Moreover, the tie between them is critical; if removed, the network will break into two isolated sub-networks
- Other things being equal, nodes 3 and 5 seems more 'important' than 10



(Degree) Centrality
is the number of links that lead into and out of a node

Degree centrality

Degree Centrality for Zachary's Karate Club Network (Zachary, 1977)



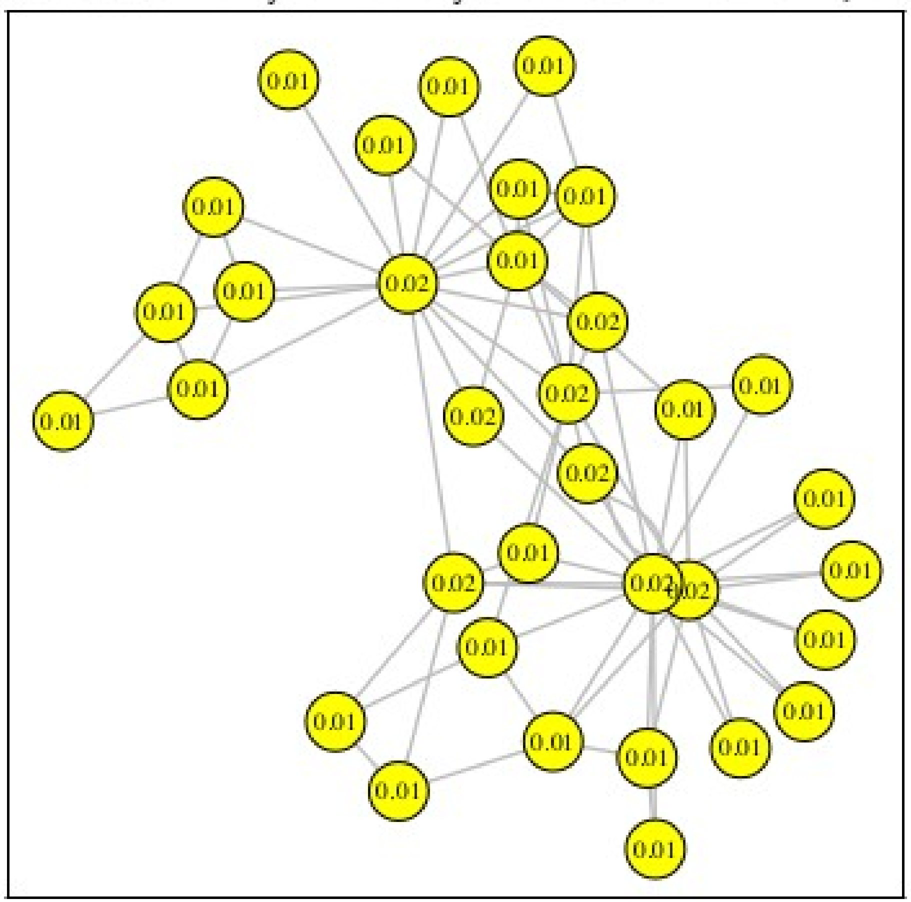
- A node (**in-**) or (**out-**)**degree** is the number of (weighted) links that lead into or out of the node
- In an undirected graph: $d_{in} = d_{out}$
- Often used as measure of a node connectedness and hence of influence and/or popularity
- Useful for assessing which nodes are central in terms of information spread and influence upon others in their immediate 'neighborhood'

Shortest paths and closeness

- **Shortest paths:**
  - A *path* between 2 nodes is a sequence of non-repeating edges connecting those 2 nodes
  - The *shortest path* between 2 nodes is the path that connects those 2 nodes with the shortest number of edges (also called the distance between the nodes).

    NB: Shortest paths are desirable when speed of communication or exchange is desired.

Closeness Centrality for Zachary's Karate Club Network (Zachary, 1977)

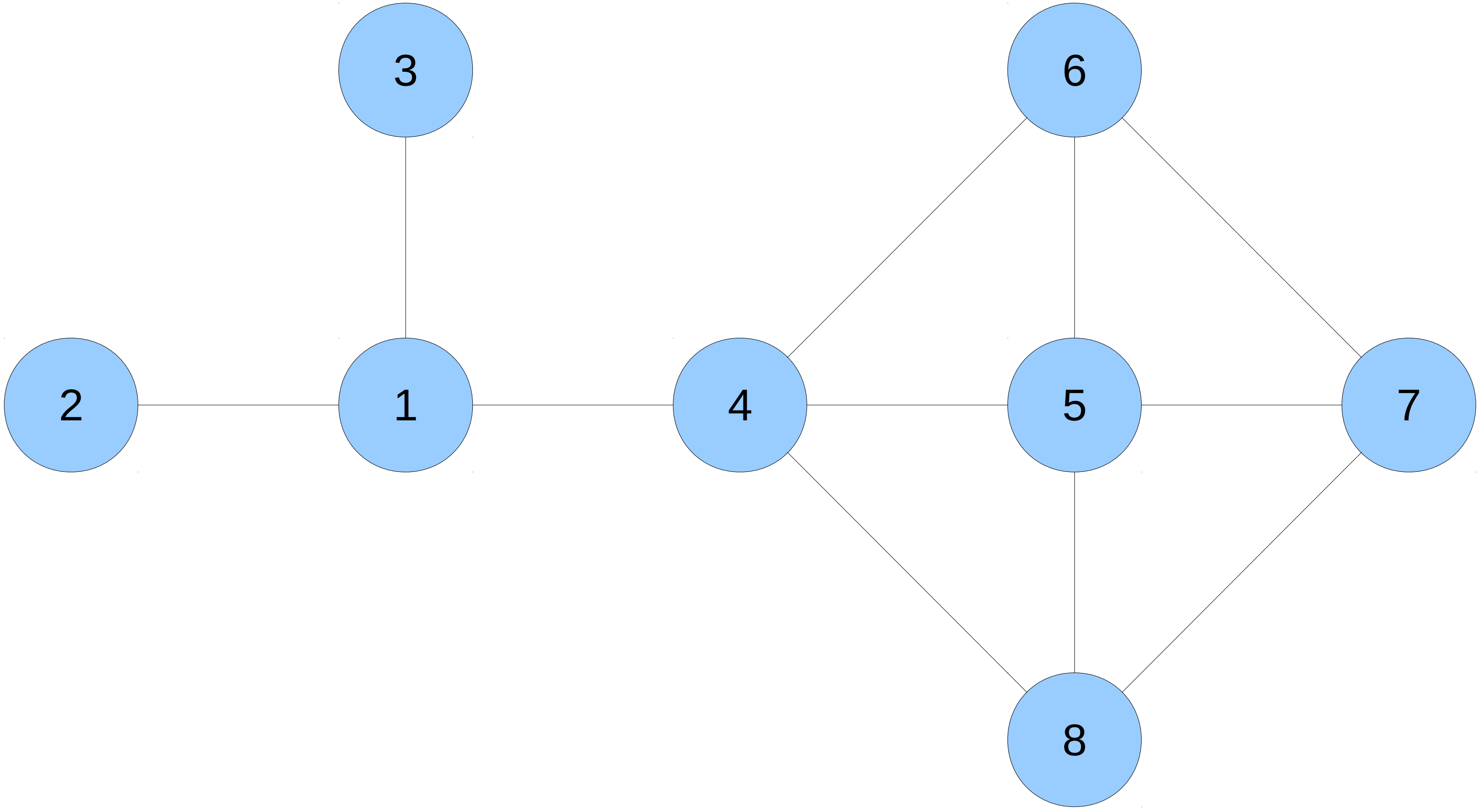


- **Closeness centrality**:
  - Average length of the shortest path between a node and all other nodes in the graph. The more central a node is, the closer it is to all other nodes.
  - It is a measure of the speed with which information can reach other nodes from a given starting node.

$$C(x) = \frac{N}{\sum_{y} d(y, x)}$$

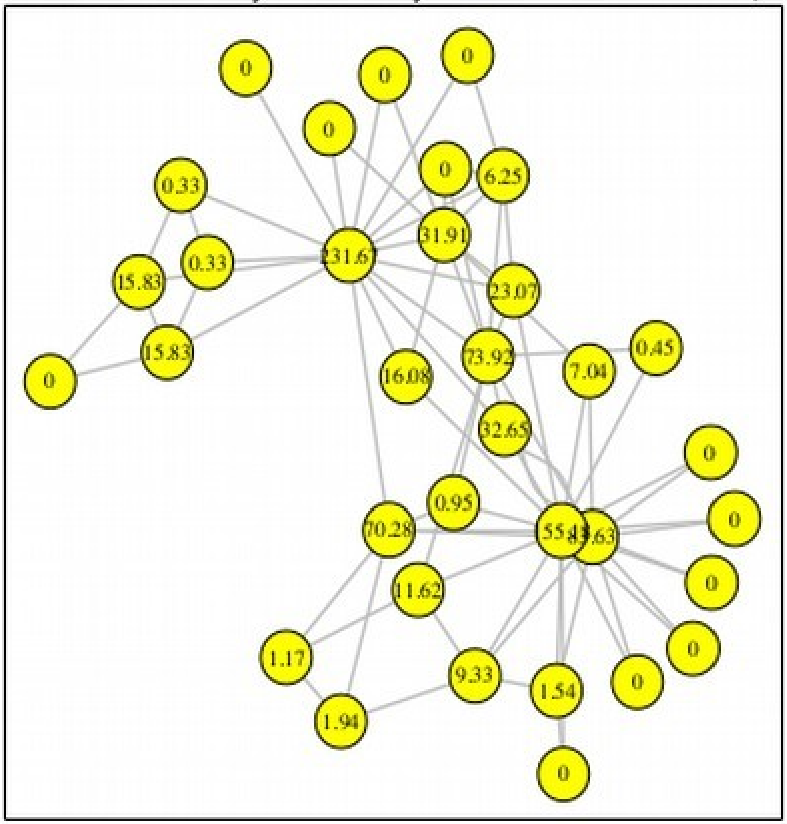
Quizz

Identify the key-users according to degree centrality and closeness



Betweenness centrality

Betweenness Centrality for Zachary's Karate Club Network (Zachary, 1977)



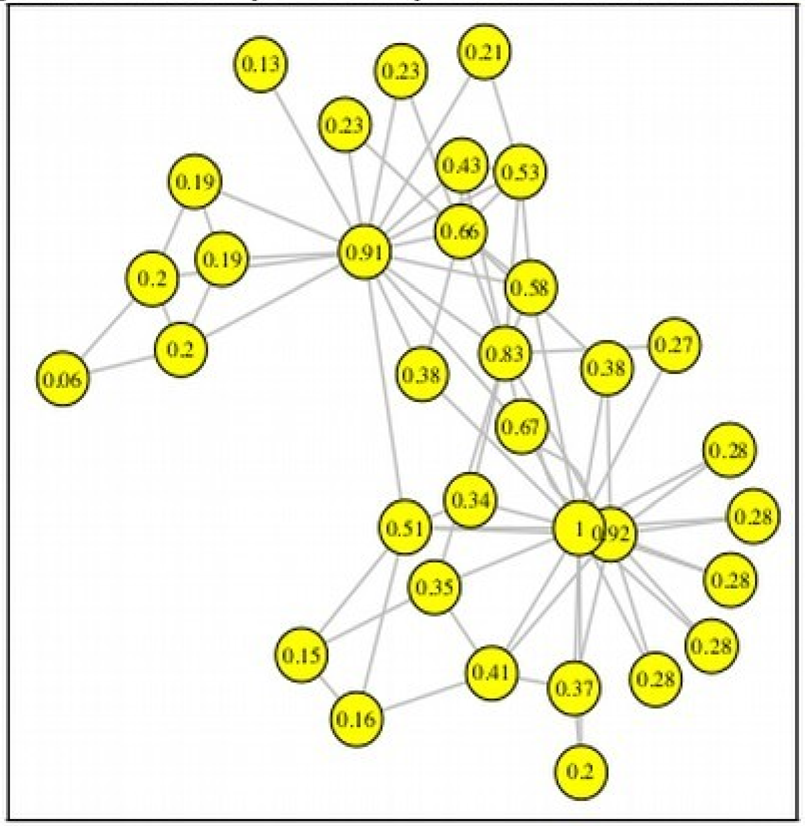
- **Betweenness**:
  - Number of times a node acts as a bridge along the shortest path between 2 nodes
  - Shows which nodes are:
    - more likely to be in communication paths between other nodes
    - breaking points of a network

$$C_B(v) = \frac{\sum_{s \neq v \neq t \in V} \sigma_{st}(v)}{\sigma_{st}}$$

1) For each pair of nodes, compute the shortest paths between them;
2) For each pair of nodes, determine the fraction of shortest paths that pass through this very node (here, node/vertex v);
3) Sum these fractions over all pairs of nodes.

Eigenvector centralities (or eigencentralities)

Eigenvector Centrality for Zachary's Karate Club Network (Zachary, 1977)



- **Eigenvector centrality**:
  - Eigencentrality is a measure of the influence of a node in a network; a node with a high eigencentrality is connected to other nodes with high eigenvector centrality
  - This is similar to how Google ranks web pages: links from highly linked-to pages count more (pagerank)
  - Useful in determining who is connected to the most connected nodes

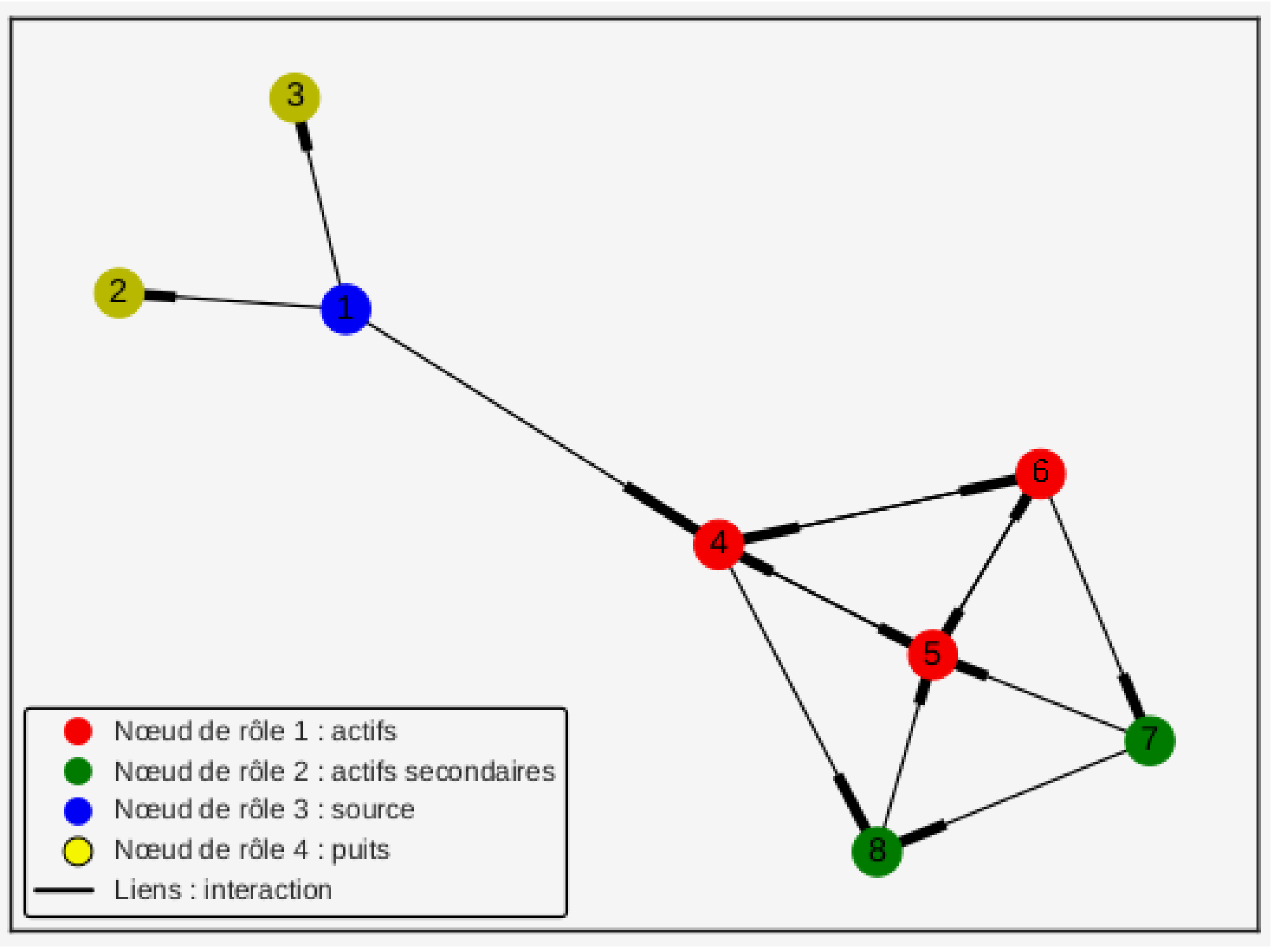
Interpretations

Centrality measure	Interpretation in social networks
▸ Degree	How many people can this person reach directly?
▸ Betweenness	How likely is this person to be the most direct route between two people in the network?
▸ Closeness	How fast can this person reach everyone in the network?
▸ Eigenvector	How well is this person connected to other well-connected people?
▸ Degree	In network of music collaborations: how many people has this person collaborated with?
▸ Betweenness	In network of spies: who is the spy though whom most of the confidential information is likely to flow?
▸ Closeness	In network of sexual relations: how fast will an STD spread from this person to the rest of the network?
▸ Eigenvector	In network of paper citations: who is the author that is most cited by other well-cited authors?

RolX [Henderson et al., 2012]

- Topological measures (degrees, centralities, …)
- Selection of characteristics
- Non-negative factorization to extract characteristic roles

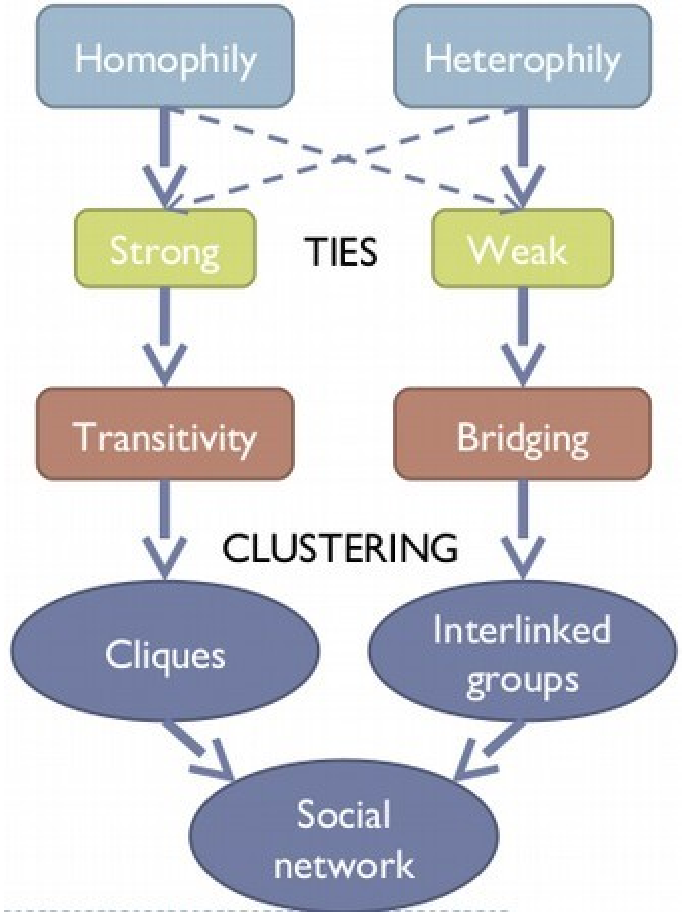
NB: the number of roles must be fixed



Groups of users in Social Networks
Community Detection

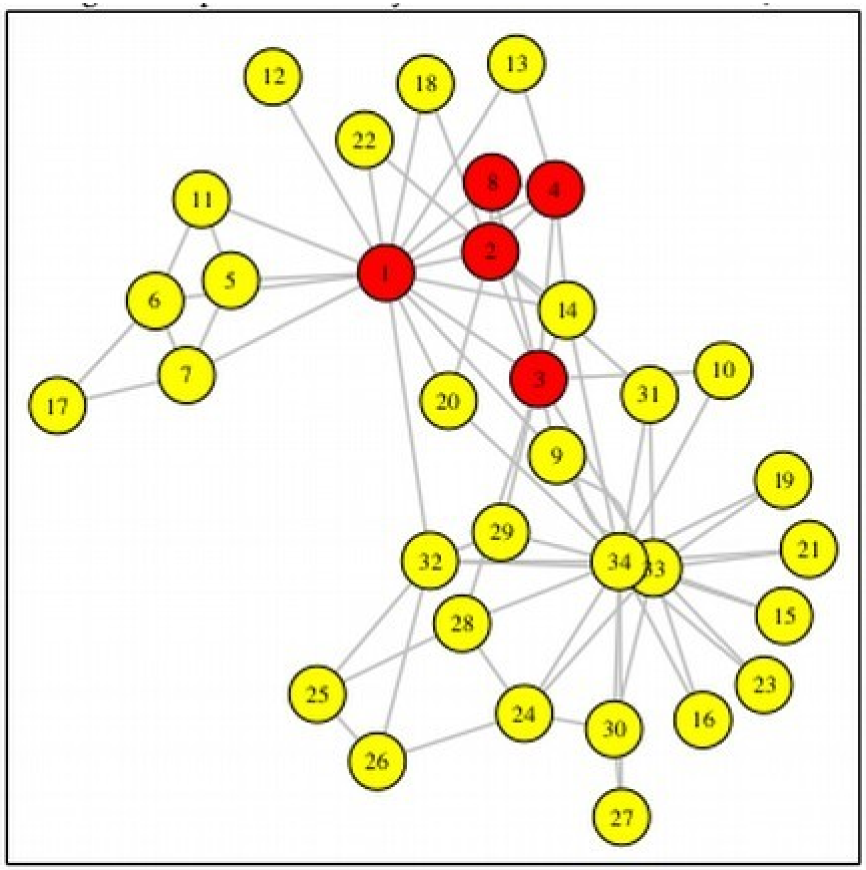
Homophily, transitivity, and bridging

- **Homophily** is the tendency to relate to people with similar characteristics (status, beliefs, etc.)
  - It leads to the formation of homogeneous groups (clusters) where relations are easier
  - Homophilous ties can be strong or weak
- **Transitivity** in SNA is a property of ties: if there is a tie between A and B and one between B and C, then in a transitive network A and C will also be connected
  - Strong ties are more often transitive than weak ties; transitivity is a hint of strong ties (but not a necessary or sufficient condition)
  - Transitivity and homophily together lead to the formation of cliques (fully connected clusters)
- **Bridges** are nodes and edges that connect across groups
  - Facilitate inter-group communication, increase social cohesion, and help stimulating innovation
  - They are usually weak ties, but not every weak tie is a bridge

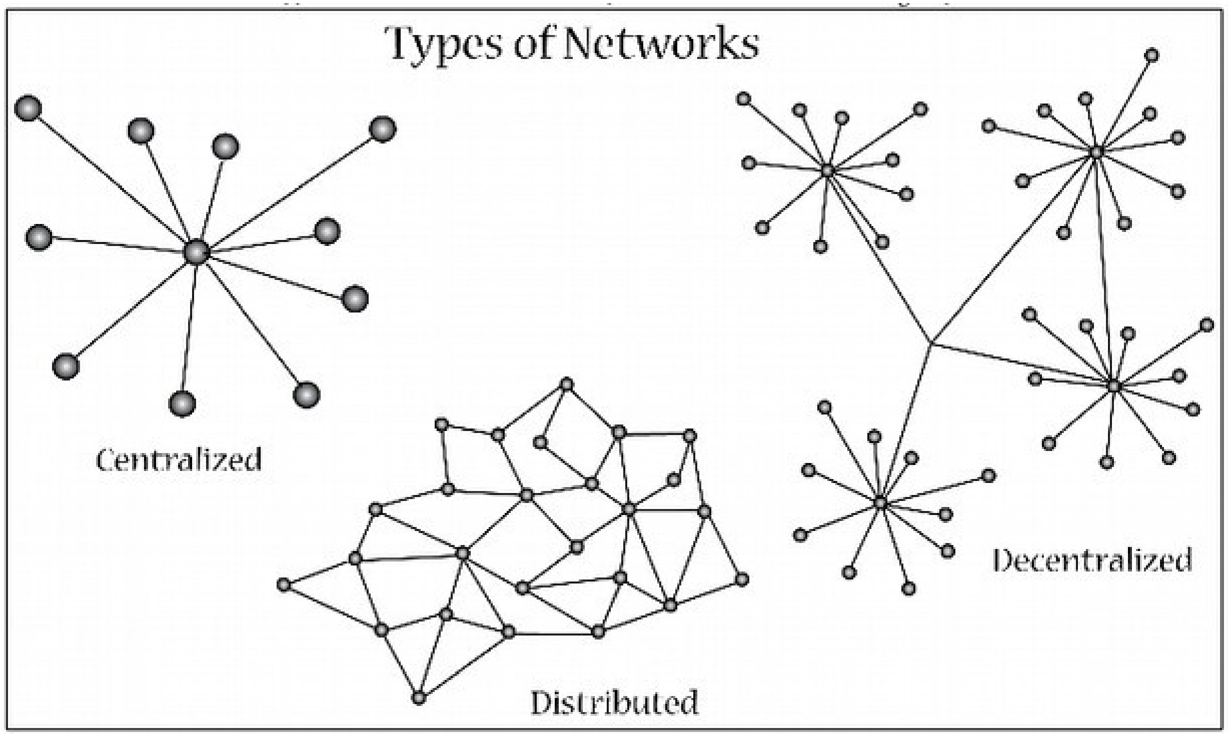


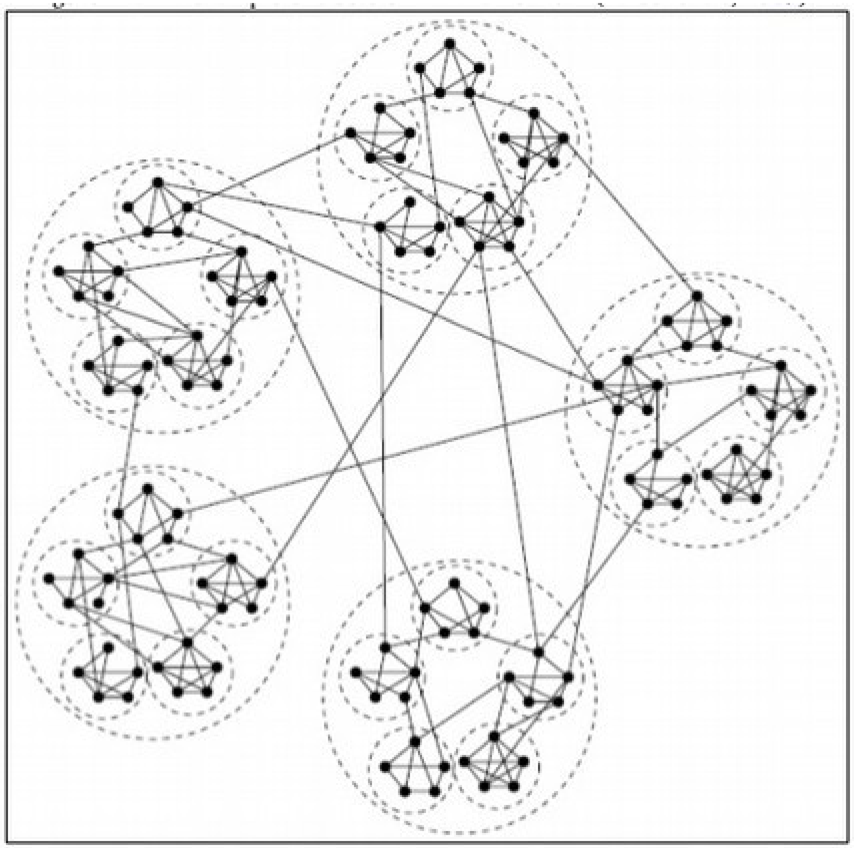
Strong homophily: cliques of users

A **clique** is a subset of nodes in a network such that every two nodes in the subset are connected by a tie. A **k-clique** is a clique of degree k.



Types of networks



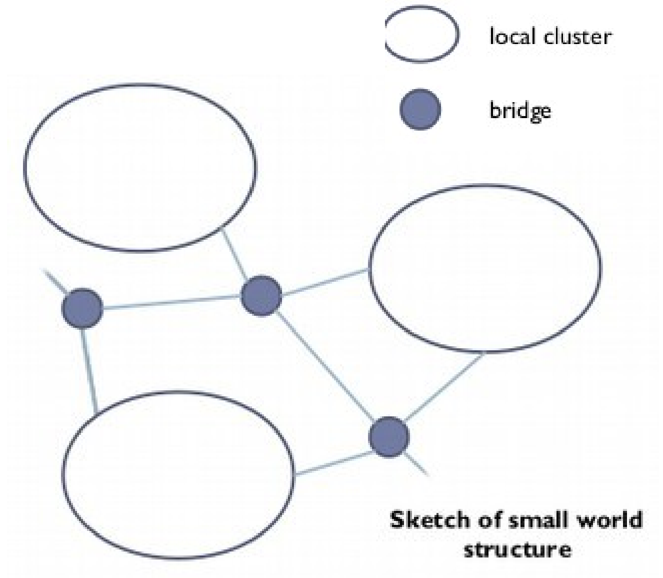


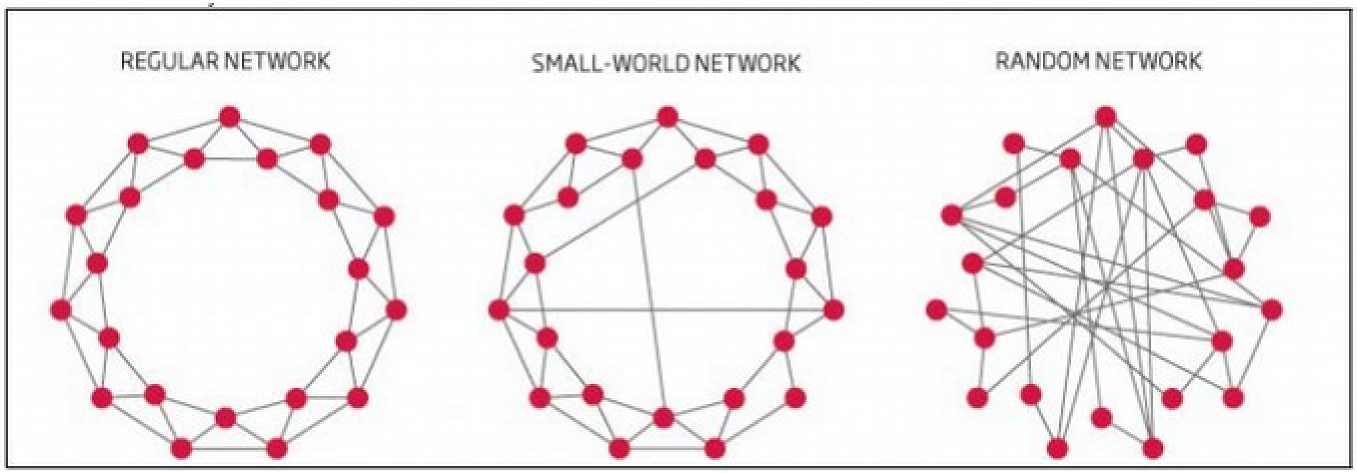
Small words: communities in SN

•A **small world** is a network that looks almost random but exhibits a significantly high clustering coefficient (nodes tend to cluster locally) and a relatively short average path length (nodes can be reached in a few steps)

•It is a very common structure in social networks because of transitivity in strong social ties and the ability of weak ties to reach across clusters

•Such a network has many clusters but also many bridges between clusters that help shorten the average distance between nodes





Community detection algorithms

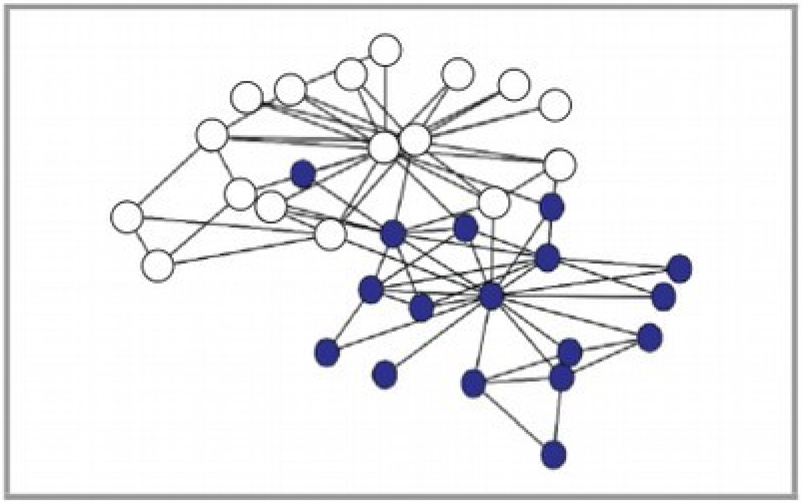


Fig. 1. Detected communities (Clauset&Newman aglorithm).

FastGreedy
Clauset, A., Newman, M. E., and Moore, C. : "*Finding community structure in very large networks",* Physical review E, 70(6), 2004.

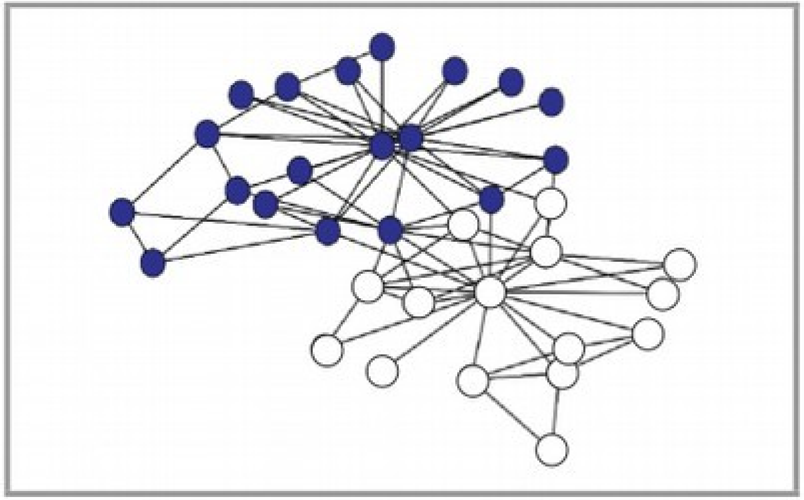


Fig. 2. Detected communities (MLC aglorithm).

Markov CLustering for graphs (MCL)
Van Dongen, S. M., *"Graph clustering by flow simulation*", PhD thesis, 2000.

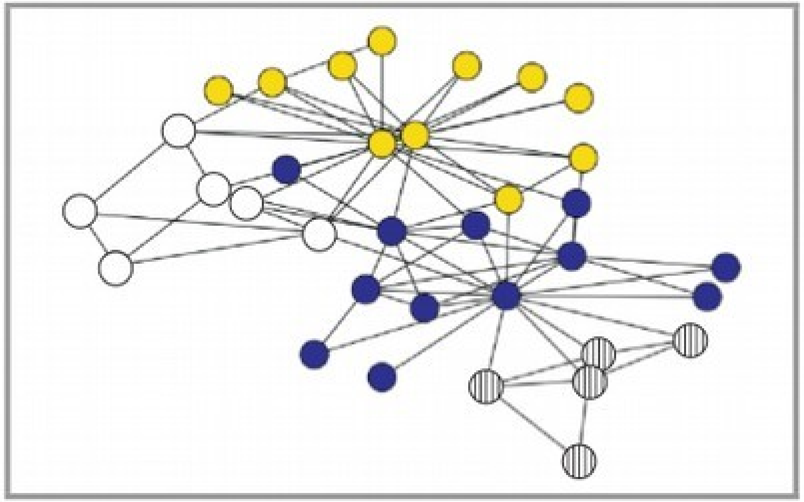


Fig. 3. Detected communities (Blondel aglorithm).

Blondel/Louvain
Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E., "*Fast unfolding of communities in large networks*", Journal of statistical mechanics : theory and experiment, volume 10, 2008.

Topological measures of communities

G=(V, E) with n=|V| nodes and m=|E| edges

A community S have n_S=|S| nodes, m_S internal edges, c_S external edges

- **Internal density**: ratio between the actual number of edges over the maximum number of edges.

$$d_{directed}(S) = \frac{2m_s}{n_s(n_s-1)} \qquad d_{undirected}(S) = \frac{m_s}{n_s(n_s-1)}$$

- **Triad participation ratio**: number of nodes belonging to a triad in the community.

$$TPR(S) = \frac{\left|\{u : u \in S, \{(v,w) : v,w \in S, (u,v) \in E, (u,w) \in E, (v,w) \in E\} \neq \emptyset\}\right|}{n_s}$$

- **Conductance**: proportion of edges that are directed to other communities.

$$C(S) = \frac{c_s}{2m_s + c_s}$$

- **Modularity**: number of internal edges to the groups, compared with a graph model with random edges

$$M(S) = \frac{1}{4}(m_s - E(m_s))$$