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Network communities

Social Network Analysis. MAgOLEGO course.

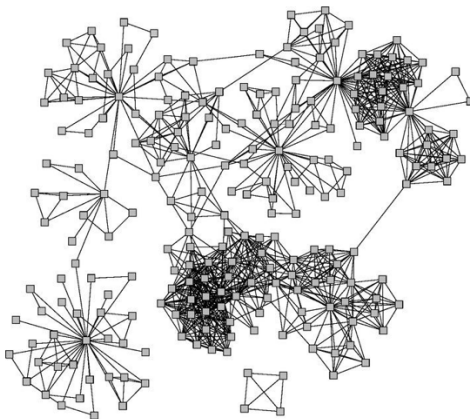
Lecture 5

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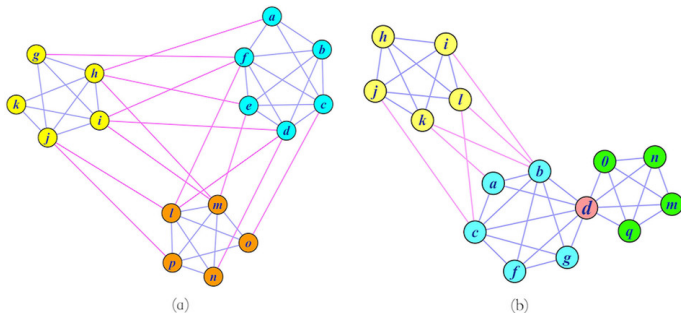


Connected and undirected graphs

What makes a community (cohesive subgroup):

- Mutuality of ties. Everyone in the group has ties (edges) to one another
- Compactness. Closeness or reachability of group members in small number of steps, not necessarily adjacency
- Density of edges. High frequency of ties within the group
- Separation. Higher frequency of ties among group members compared to non-members

Wasserman and Faust



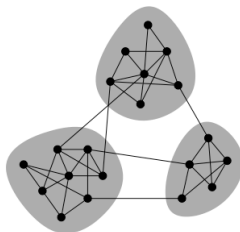
Community types:

- Non-overlapping
- Overlapping

image from W. Liu , 2014

Definition

Network communities are groups of vertices such that vertices inside the group connected with many more edges than between groups.



- Will consider non-overlapping communities, each node assigned only to one community

- Graph $G(V, E)$, $n = |V|$, $m = |E|$
- Community - set of nodes S
 n_s -number of nodes in S , m_s - number of edges in S
- Graph density

$$\rho = \frac{m}{n(n-1)/2}$$

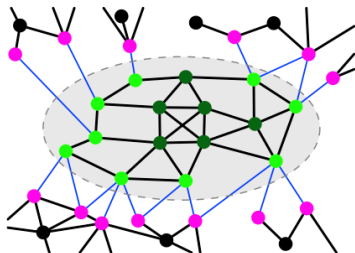
- community internal density

$$\delta_{int}(C) = \frac{m_s}{n_s(n_s-1)/2}$$

- external edges density

$$\delta_{ext}(C) = \frac{m_{ext}}{n_c(n - n_c)}$$

- community (cluster): $\delta_{int} > \rho$, $\delta_{ext} < \rho$



Graph cut is a partition of the vertices of a graph $G(E, V)$ into two disjoint subsets: $V = V_1 + V_2$

$$Q = \text{cut}(V_1, V_2) = \sum_{i \in V_1, j \in V_2} e_{ij}$$

image from Fortunato 2016

- Compare fraction of edges within the cluster to expected fraction in random graph with identical degree sequence

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

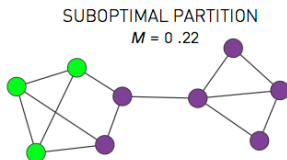
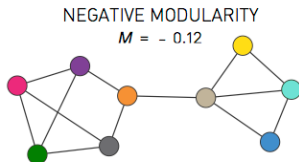
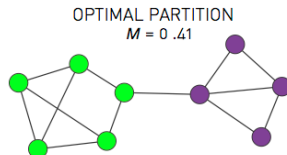
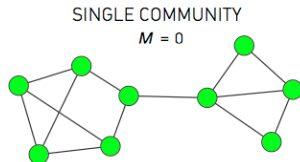
- Modularity score

$$Q = \sum_u \left(\frac{m_u}{m} - \left(\frac{k_u}{2m} \right)^2 \right)$$

m_u - number of internal edges in a community u ,

k_u - sum of node degrees within a community

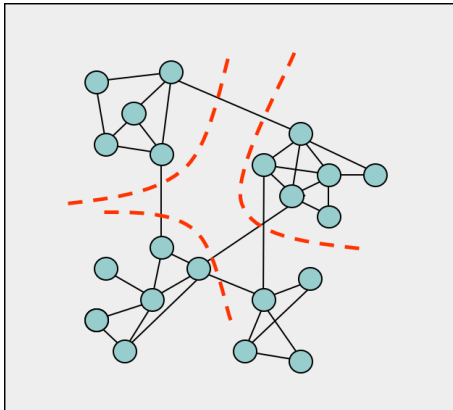
- Modularity score range $Q \in [-1/2, 1)$, single community $Q = 0$

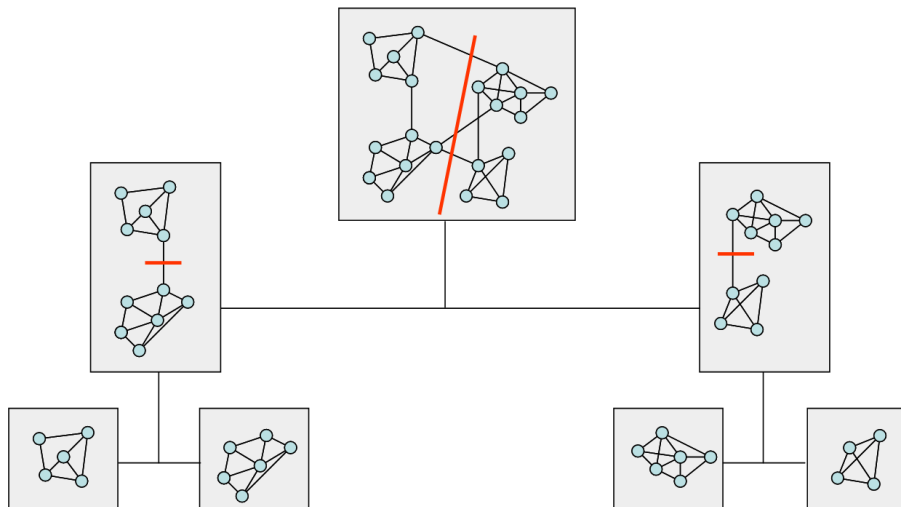


- The higher the modularity score - the better are communities

image from A.L. Barabasi 2016

- Combinatorial optimization problem:
 - optimization criterion (density, graph cut, modularity score)
 - optimization method
- Exact solution NP-hard
(bi-partition: $n = n_1 + n_2$, $n!/(n_1!n_2!)$ combinations)
- Solved by greedy, approximate algorithms or heuristics
- Recursive top-down 2-way partition, multiway partition

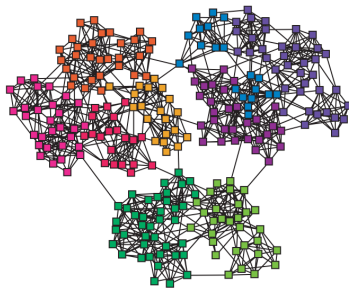




Focus on edges that connect communities.

Edge betweenness - number of shortest paths $\sigma_{st}(e)$ going through edge e

$$C_B(e) = \sum_{s \neq t} \frac{\sigma_{st}(e)}{\sigma_{st}}$$



Newman-Girvan, 2004

Algorithm: Edge Betweenness

Input: graph $G(V,E)$

Output: Dendrogram/communities

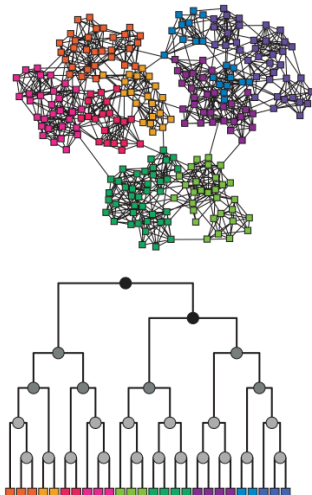
repeat

 For all $e \in E$ compute edge betweenness $C_B(e)$;
 remove edge e_i with largest $C_B(e_i)$;

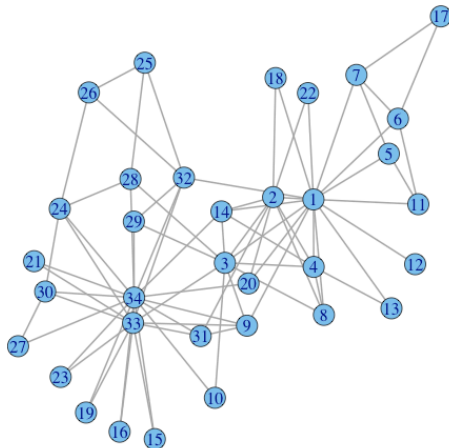
until *edges left*;

If bi-partition, then stop when graph splits in two components
(check for connectedness)

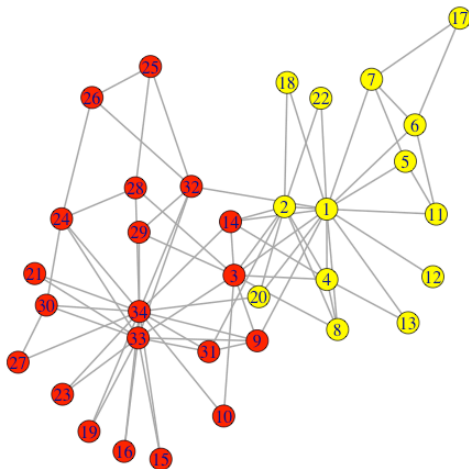
Hierarchical algorithm, dendrogram



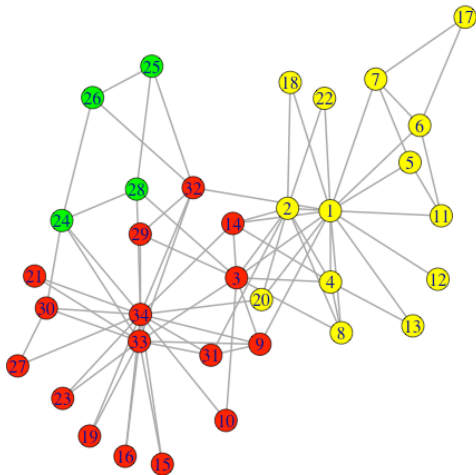
Zachary karate club

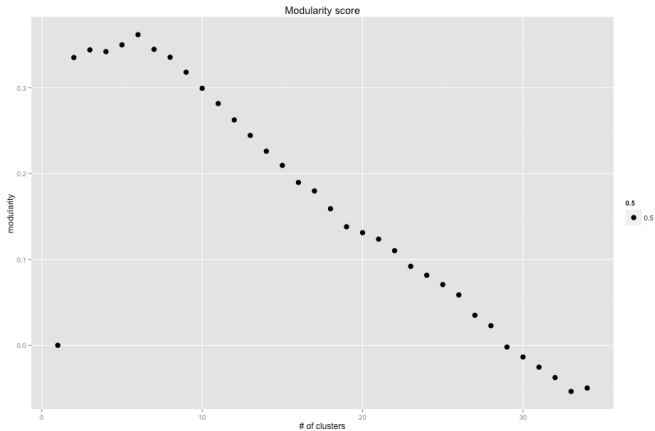


Zachary karate club



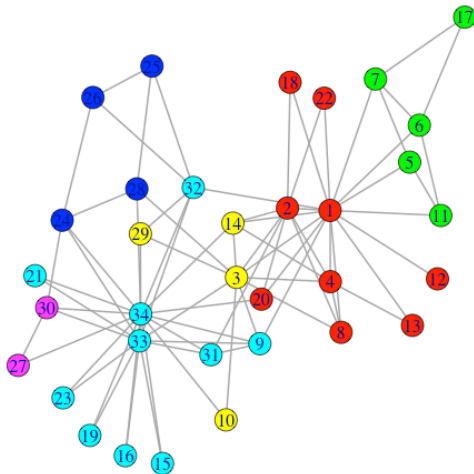
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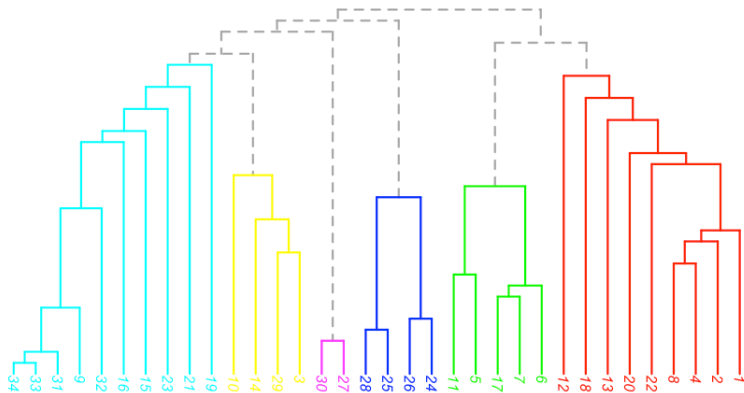


`igraph:modularity()`

best: clusters = 6, modularity = 0.345



Zachary karate club



`igraph:dendPlot()`

V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, 2008 "The Louvain method"

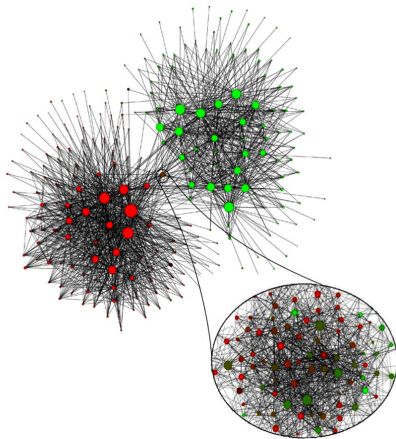
- Heuristic method for greedy modularity optimization
- Find partitions with high modularity
- Multi-level (multi-resolution) hierarchical scheme
- Scalable

Modularity:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j) = \sum_u \left(\frac{m_u}{m} - \left(\frac{k_u}{2m} \right)^2 \right)$$

V. Blondel et.al., 2008

Multi-resolution scalable method



2 mln mobile phone network

V. Blondel et.al., 2008

Input: Graph $G(V,E)$

Output: Communities

Assign every node to its own community;

repeat

repeat

 For every node evaluate modularity gain from removing node from its community and placing it in the community of its neighbor;

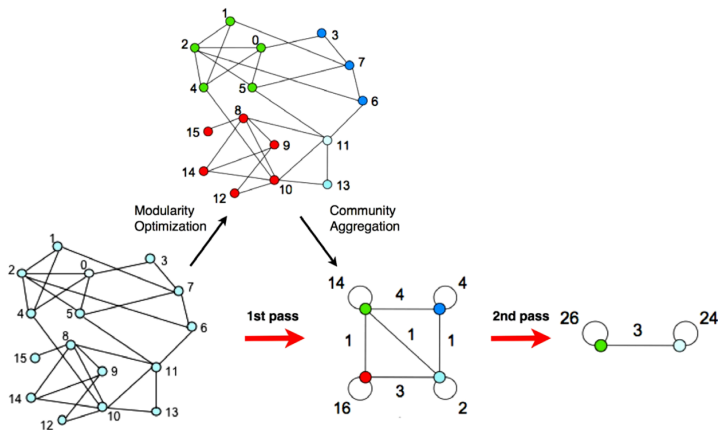
 Place node in the community maximizing modularity gain;

until *no more improvement (local max of modularity);*

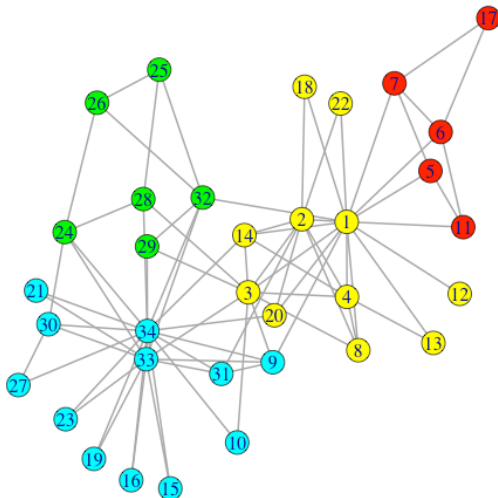
 Nodes from communities merged into "super nodes" ;

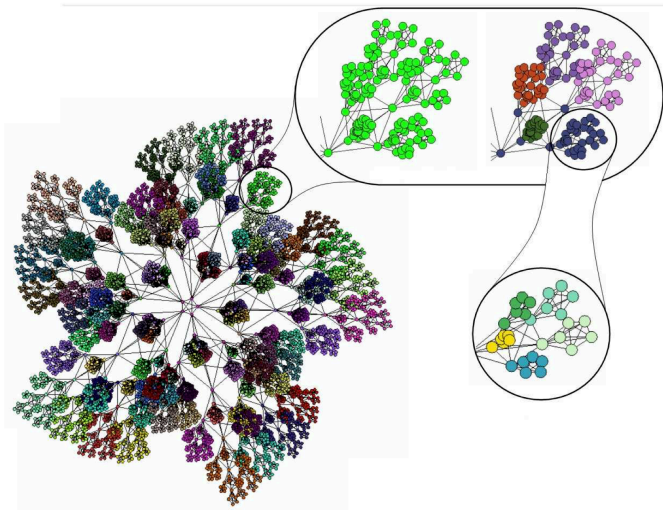
 Weight on the links added up

until *no more changes (max modularity):*



clusters = 4, modularity = 0.445





Author	Ref.	Label	Order
Eckmann & Moses	(Eckmann and Moses, 2002)	EM	$O(m\langle k^2 \rangle)$
Zhou & Lipowsky	(Zhou and Lipowsky, 2004)	ZL	$O(n^3)$
Latapy & Pons	(Latapy and Pons, 2005)	LP	$O(n^3)$
Clauset et al.	(Clauset <i>et al.</i> , 2004)	NF	$O(n \log^2 n)$
Newman & Girvan	(Newman and Girvan, 2004)	NG	$O(nm^2)$
Girvan & Newman	(Girvan and Newman, 2002)	GN	$O(n^2m)$
Guimerà et al.	(Guimerà and Amaral, 2005; Guimerà <i>et al.</i> , 2004)	SA	parameter dependent
Duch & Arenas	(Duch and Arenas, 2005)	DA	$O(n^2 \log n)$
Fortunato et al.	(Fortunato <i>et al.</i> , 2004)	FLM	$O(m^3n)$
Radicchi et al.	(Radicchi <i>et al.</i> , 2004)	RCCLP	$O(m^4/n^2)$
Donetti & Muñoz	(Donetti and Muñoz, 2004, 2005)	DM/DMN	$O(n^3)$
Bagrow & Boltt	(Bagrow and Boltt, 2005)	BB	$O(n^3)$
Capocci et al.	(Capocci <i>et al.</i> , 2005)	CSCC	$O(n^2)$
Wu & Huberman	(Wu and Huberman, 2004)	WH	$O(n + m)$
Palla et al.	(Palla <i>et al.</i> , 2005)	PK	$O(\exp(n))$
Reichardt & Bornholdt	(Reichardt and Bornholdt, 2004)	RB	parameter dependent

Author	Ref.	Label	Order
Girvan & Newman	(Girvan and Newman, 2002; Newman and Girvan, 2004)	GN	$O(nm^2)$
Clauset et al.	(Clauset <i>et al.</i> , 2004)	Clauset et al.	$O(n \log^2 n)$
Blondel et al.	(Blondel <i>et al.</i> , 2008)	Blondel et al.	$O(m)$
Guimerà et al.	(Guimerà and Amaral, 2005; Guimerà <i>et al.</i> , 2004)	Sim. Ann.	parameter dependent
Radicchi et al.	(Radicchi <i>et al.</i> , 2004)	Radicchi et al.	$O(m^4/n^2)$
Palla et al.	(Palla <i>et al.</i> , 2005)	Cfinder	$O(\exp(n))$
Van Dongen	(Dongen, 2000a)	MCL	$O(nk^2)$, $k < n$ parameter
Rosvall & Bergstrom	(Rosvall and Bergstrom, 2007)	Infomod	parameter dependent
Rosvall & Bergstrom	(Rosvall and Bergstrom, 2008)	Infomap	$O(m)$
Donetti & Muñoz	(Donetti and Muñoz, 2004, 2005)	DM	$O(n^3)$
Newman & Leicht	(Newman and Leicht, 2007)	EM	parameter dependent
Ronhovde & Nussinov	(Ronhovde and Nussinov, 2009)	RN	$O(m^\beta \log n)$, $\beta \sim 1.3$

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- V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech. P10008 (2008).