

M1 Info - Systemes Complexes Avances

Cours 5 - Algorithmes de detection de communautés

Girvan-Newman, Louvain, Leiden

Semestre Automne 2022-2023 - Université Côte D'azur

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Communities in complex networks

What is a community?

"Moral" definition

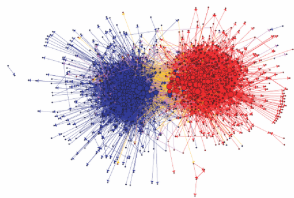
- A group of nodes that share something...
 - ▶ People with a common interest
 - ▶ Web pages with similar content
 - ▶ Proteins realising a common function

Communities in complex networks

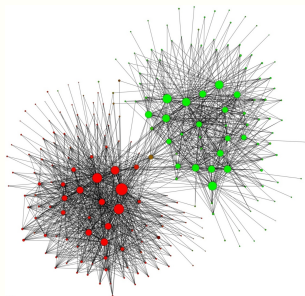
What is a community?

"Moral" definition

- A group of nodes that share something...
 - ▶ People with a common interest
 - ▶ Web pages with similar content
 - ▶ Proteins realising a common function
- ... that makes them be in relationship in the network!



Political blogs in US



Languages in Belgium

Communities in complex networks

What is a community?

Structural definition

- A highly connected group of nodes

Communities in complex networks

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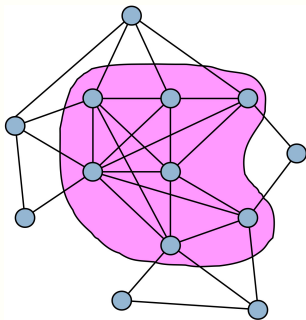
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 - ▶ Density inside the community much higher than global density of the network

Communities in complex networks

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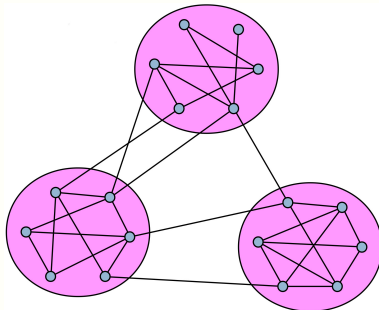
Structural definition

- A highly connected group of nodes
 - ▶ Density inside the community much higher than global density of the network
 - ▶ Only few edges toward the rest of the network



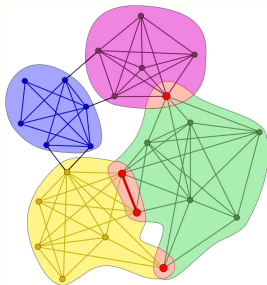
Types of structural communities

- Partition of the nodes into dense parts sparsely connected between them
 - ▶ High density inside communities
 - ▶ Few edges between communities



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 - A node can belong to several communities
 - ▶ more realistic
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A node can belong to several communities

 - ▶ more realistic
 - ▶ problem : how to separate communities ?
- Partition of the links
 - ▶ a link belong to exactly one community
 - ▶ a node can have links in different communities



Partition of the nodes

Various approaches, among them :

- random walks
- spectral methods
- hierarchical clustering
- divisive methods
- Louvain, Leiden

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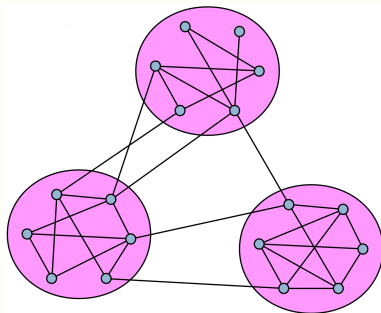
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Divisive approach : Girvan & Newman 2002

The idea :

1. identify inter-community links
2. remove them



How to identify inter-community links?

- Betweenness centrality of links

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

▶ $\sigma_{st} = \#$ shortest paths from s to t

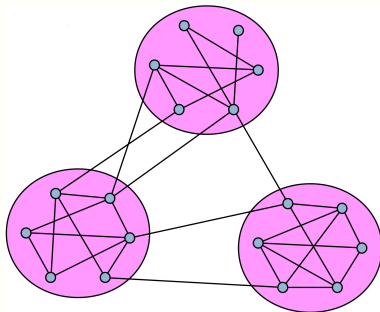
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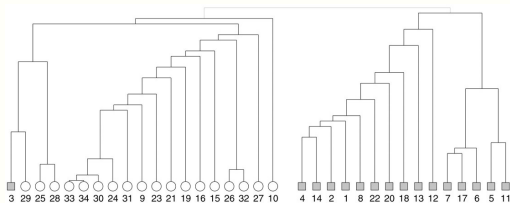
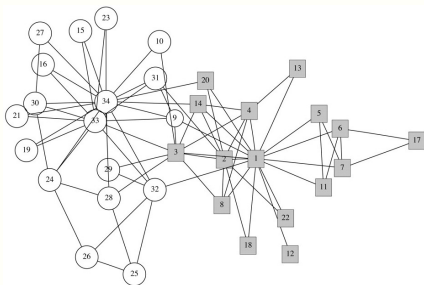
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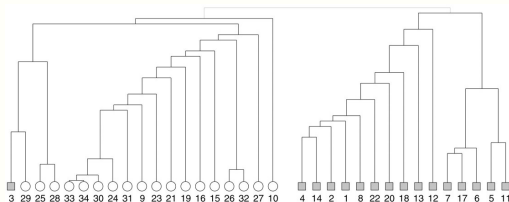
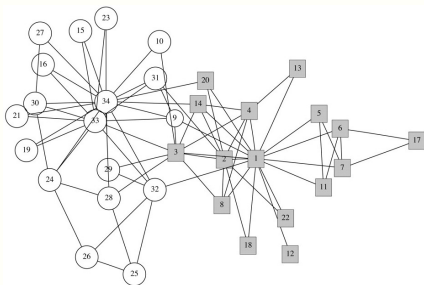
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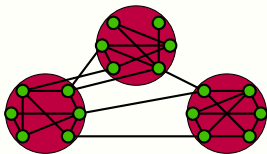


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- Complexity
 - ▶ betweenness for all links : $O(nm)$
 - ▶ connected components : $O(m)$
 - ▶ m iterations
 - ▶ Overall : $O(nm^2)$

The Louvain algorithm

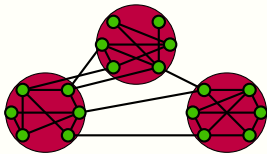
- Idea : optimize a quality function for node partitions



- ▶ **modularity** : maximize($\#edges\ inside - \#edges\ outside$)
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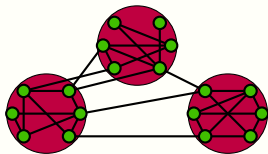
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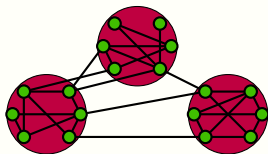
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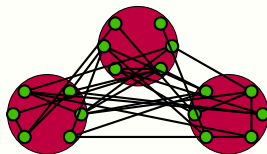


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- Problem... the best partition is a single community !!!
- Correction : compare to a randomized version of the network

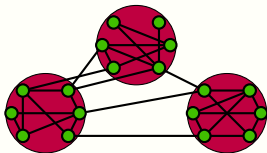


original network

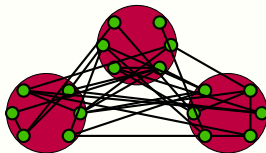


configuration model

Modularity



original network



configuration model

- Proportion of edges inside communities

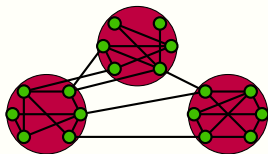
A the adjacency matrix of G

k_i the degree of node i

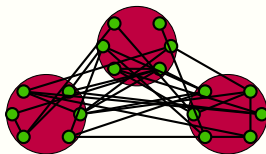
c_i the community of node i

δ is the Kronecker symbol : $\delta(c_i, c_j) = 1$ iff $c_i = c_j$

Modularity



original network



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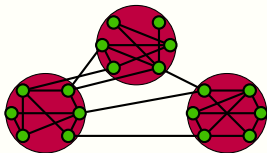
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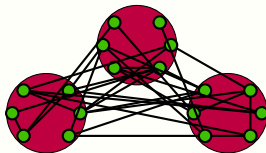
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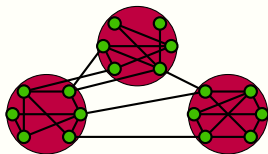
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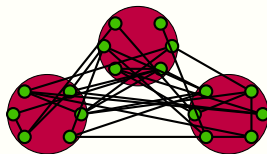
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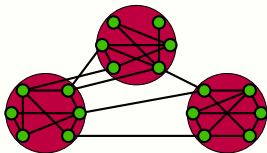
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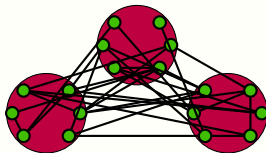
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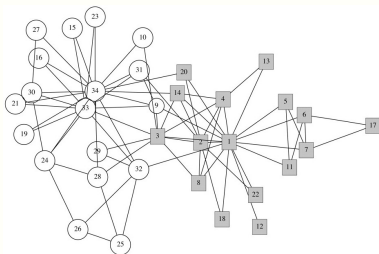
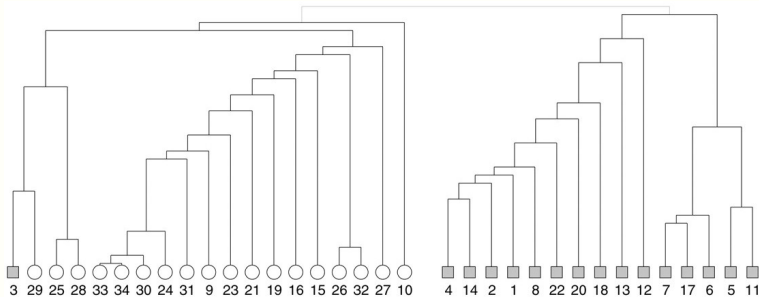
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▶ **NP-hard** to maximize modularity

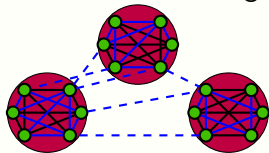
Utility of modularity

- Come back to the dendrogram produced by Girvan-Newman



Other quality functions

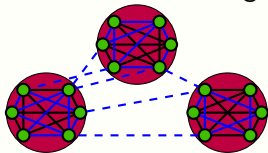
- Distance to cluster graphs



▶ $\text{dist-cluster}(\mathcal{P}) = \# \text{missing edges inside} + \# \text{edges outside}$

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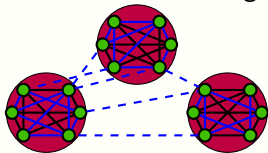
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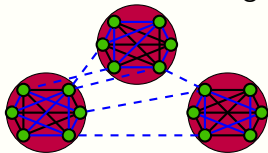
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 - ▶ $\text{CPM}(\mathcal{P}) = \sum_c [e_c - \gamma \binom{n_c}{2}]$
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 γ is a chosen constant ≤ 1

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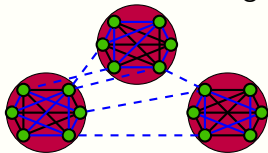
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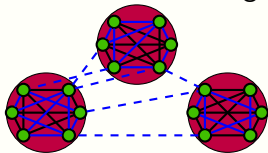
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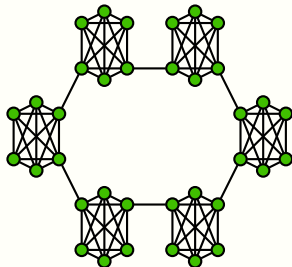
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Is modularity a good quality function ?

- Resolution issue : tends to make too large communities

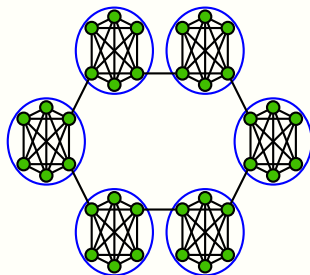
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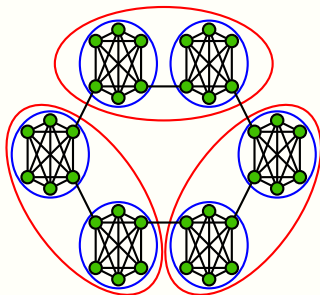
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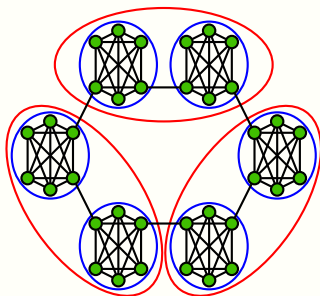


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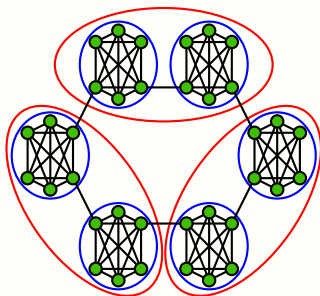
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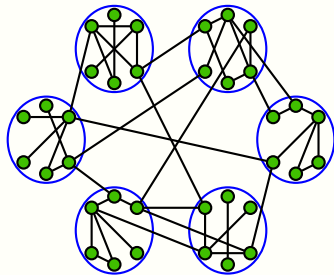
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- ▶ Which one is "morally" the best community partition ?
- ▶ Which one has higher modularity ?

Louvain algorithm

- **Given a partition**, make a pass through all the vertices :
 - ▶ consider each vertex x once in an arbitrary order
 - ▶ move x to the community that gives the largest increase in modularity

$G (n=30,m=46)$

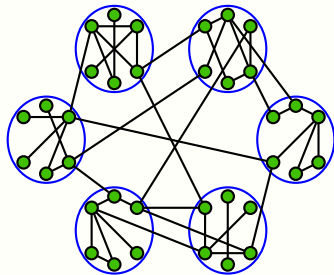


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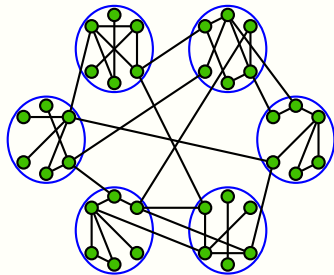


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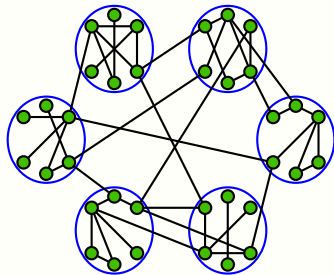
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Decompose the move :

- ▶ place x alone in its own community
- ▶ consider moving x to each neighbouring community

G ($n=30,m=46$)



Louvain algorithm

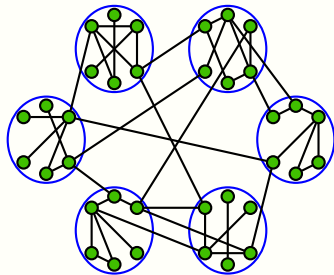
- **Given a partition**, make a pass through all the vertices :
 - ▶ consider each vertex x once in an arbitrary order
 - ▶ move x to the community that gives the largest increase in modularity (eventually isolated in its own community)

Obs. : non-neighbouring community is never the best

Decompose the move :

- ▶ place x alone in its own community
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$$\Delta Q(C, i) = \left[\frac{e_C + k_{i,C}}{2m} - \left(\frac{a_C + k_i}{2m} \right)^2 \right] - \left[\frac{e_C}{2m} - \left(\frac{a_C}{2m} \right)^2 - \left(\frac{k_i}{2m} \right)^2 \right]$$

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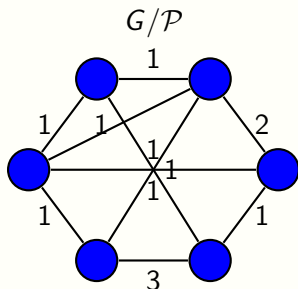
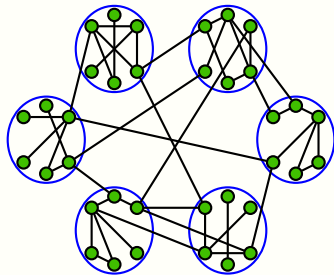
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```
1 augmented ← true;
2 while augmented do
3    $\mathcal{P}_0 \leftarrow \{\{x\} \mid x \in V(G)\}$ ;  $\mathcal{P} \leftarrow \mathcal{P}_0$ ;  $Q \leftarrow 0$ ;
4   while augmented do
5     augmented ← faux;
6     for i de 1 a n do
7        $Q_{ori} \leftarrow Q$ ;
8       i moves to  $c_{iso} = \{i\}$ ;  $Q \leftarrow Q - \Delta Q_{out}(i)$ ;
9        $Q_{max} \leftarrow Q$ ;  $c_{max} \leftarrow c_{iso}$ ;
10      for  $c \in \mathcal{P}$  do
11        if  $Q + \Delta Q_{in}(c) > Q_{max}$  then
12           $Q_{max} \leftarrow Q + \Delta Q_{in}(i, c)$ ;
13           $c_{max} \leftarrow c$ ;
14        end
15      end
16      If  $Q_{max} = Q_{ori}$  then  $c_{max} \leftarrow c_{ori}$  else augmented ← true;
17      i moves to  $c_{max}$ ;  $Q \leftarrow Q_{max}$ ;
18    end
19  end
20  If  $\mathcal{P} \neq \mathcal{P}_0$  then augmented ← true;  $G \leftarrow G/\mathcal{P}$ ;
21 end
22 return  $\{Expand(P) \mid P \in \mathcal{P}\}$ ;
```

Leiden algorithm

Two improvements over Louvain

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 - ▶ At the next step start from the partition defined by the whole communities