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Large-scale structure of complex networks (Part 2)

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(Part 2)

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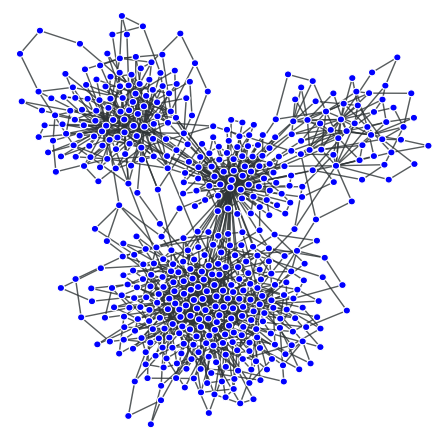
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Hello

Community structure in networks

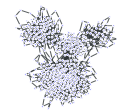


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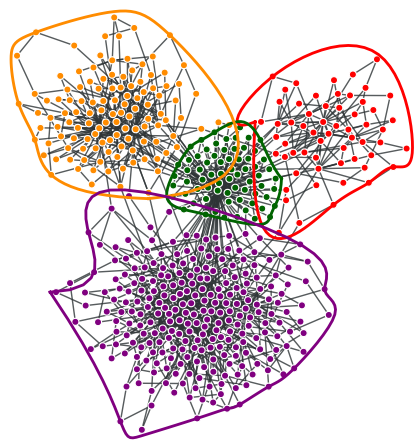
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└ Community structure in networks

Community structure in networks



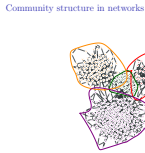
Community structure in networks



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Large-scale structure of complex networks (Part 2)

└ Community structure in networks



Community structure in networks

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Large-scale structure of complex networks (Part 2)

└ Community structure in networks

What are communities?

- **Traditional definition:** Groups of nodes with a high internal link density
- **Modern definition:** Nodes with similar connection probabilities to the rest of the network

What are communities?

- ▶ **Traditional definition:** Groups of nodes with a high internal link density
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Communities in the real-world networks

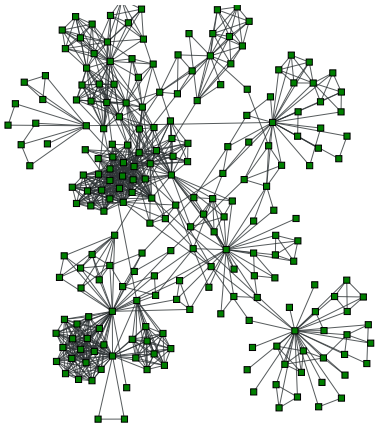
- ▶ **Social networks:**
 - ▶ Friend-circles
 - ▶ Research communities
 - ▶ Co-workers
- ▶ **World Wide Web:**
 - ▶ Pages with similar contents
 - ▶ Webpages under the same domain (e.g. Wikipedia)
- ▶ **Biological networks:**
 - ▶ Proteins with similar roles in protein interaction networks
 - ▶ Chemicals together taking part in chemical reactions in metabolic networks
 - ▶ Communities in neuronal networks

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└ Communities in the real-world networks

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Detecting communities is important!

- ▶ Communities are building blocks of networks
- ▶ Communities allow us to see “the big picture”
- ▶ Functional/Autonomous units
- ▶ Non-trivial effects on the processes on networks

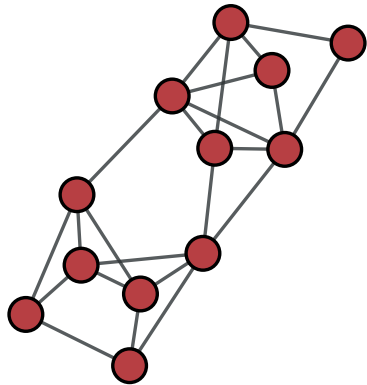
└ Community detection



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Graph partitioning

Problem of dividing a graph in a given number of groups of given sizes such that the number of links between the groups (**cut size**) is minimized



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└ Graph partitioning

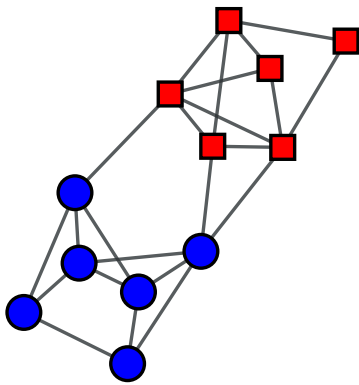
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Large-scale structure of complex networks (Part 2)

└ Graph partitioning

Graph partitioning

Problem of dividing a graph in a given number of groups of given sizes such that the number of links between the groups (**cut size**) is minimized

Partitioning is hard!

- ▶ Graph with n vertices
- ▶ Find two groups with sizes n_1 and n_2 such that the cut size is minimum
- ▶ Number of ways: $\frac{n!}{n_1!n_2!} \approx \frac{2^{n+1}}{\sqrt{n}}$

Heuristics are needed!

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Large-scale structure of complex networks (Part 2)

└ Partitioning is hard!

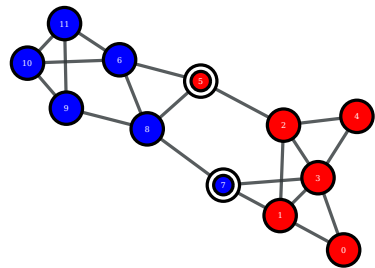
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Kernighan-Lin algorithm

cut size = 4



- Divide the vertices into two groups of the required sizes and calculate the cut size

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm

Kernighan-Lin algorithm

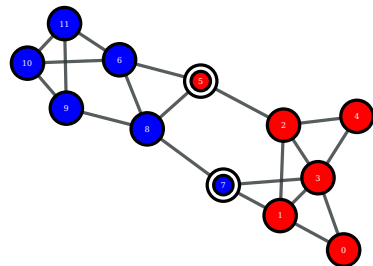
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- Divide the vertices into two groups of the required sizes and calculate the cut size

Kernighan-Lin algorithm

cut size = 4



- ▶ Divide the vertices into two groups of the required sizes and calculate the cut size
- ▶ Find a pair of nodes which when switched, will reduce the cut size most and switch them

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm

Kernighan-Lin algorithm

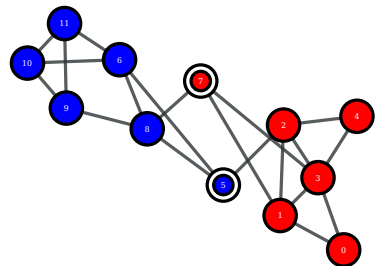
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Kernighan-Lin algorithm

cut size = 2



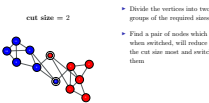
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Large-scale structure of complex networks (Part 2)

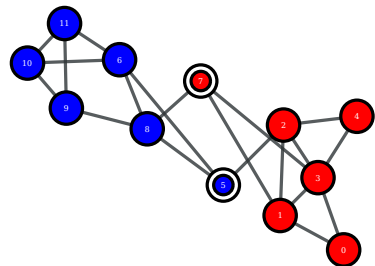
└ Kernighan-Lin algorithm

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Kernighan-Lin algorithm

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- ▶ Divide the vertices into two groups of the required sizes
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- ▶ If no such pair exists, select the pair which least increases the cut size

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm

Kernighan-Lin algorithm

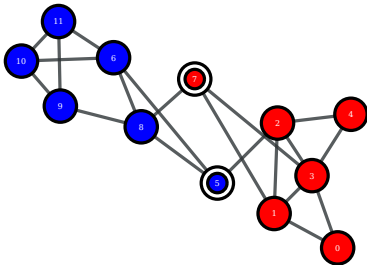
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- ▶ Continue this such that the already switched pair is not switched again

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm

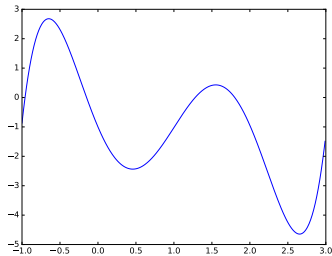
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Kernighan-Lin algorithm



- ▶ Go through all the states and select the one with the least cut size
- ▶ Start with this state and repeat the whole procedure
- ▶ Continue till the cut size no longer becomes smaller
- ▶ Starting with many random initial conditions is better

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm

Group sizes remain constant

Kernighan-Lin algorithm



- Go through all the states and select the one with the least cut size
- Start with this state and repeat the whole procedure
- Continue till the cut size no longer becomes smaller
- Starting with many random initial conditions is better

Spectral partitioning

- ▶ Faster algorithm than Kernighan-Lin
- ▶ Uses properties of the graph Laplacian
- ▶ More complex to implement than Kernighan-Lin

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└ Spectral partitioning

Spectral partitioning

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Spectral partitioning

Cut size:

$$R = \frac{1}{2} \sum_{\substack{i,j \text{ in} \\ \text{different} \\ \text{groups}}} A_{ij}$$

Define

$$s_i = \begin{cases} +1 & \text{if vertex } i \text{ belongs to group 1} \\ -1 & \text{if vertex } i \text{ belongs to group 2} \end{cases}$$

Then

$$\frac{1}{2}(1 - s_i s_j) = \begin{cases} 1 & \text{if } i \text{ and } j \text{ are in different groups,} \\ 0 & \text{if } i \text{ and } j \text{ are in the same group} \end{cases}$$

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└ Spectral partitioning

Spectral partitioning

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Spectral partitioning

$$R = \frac{1}{4} \sum_{ij} A_{ij} (1 - s_i s_j)$$

First term,

$$\sum_{ij} A_{ij} = \sum_i k_i = \sum_i k_i s_i^2 = \sum_{ij} k_i \delta_{ij} s_i s_j$$

$$R = \frac{1}{4} \sum_{ij} (k_i \delta_{ij} - A_{ij}) s_i s_j = \frac{1}{4} \sum_{ij} L_{ij} s_i s_j$$

$$R = \frac{1}{4} \mathbf{s}^T \mathbf{L} \mathbf{s}$$

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Large-scale structure of complex networks (Part 2)

└ Spectral partitioning

L is so imp that we have a name for it! Laplacian

·
s is a columnvector

·
L: structure, s: division

·
find s that minimizes R

·
Problem is hard, s takes only integer values

·

Spectral partitioning

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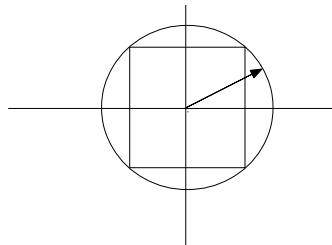
$$R = \frac{1}{4} \mathbf{s}^T \mathbf{L} \mathbf{s}$$

Relaxation method

Two constraints:

- ▶ s_i can be only ± 1
- ▶ $\sum_i s_i = n_1 - n_2 \Rightarrow \mathbf{1}^T \mathbf{s} = n_1 - n_2$

Relax the first constraint



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Large-scale structure of complex networks (Part 2)

└ Relaxation method

hypercube

.

continuous s, differentiate

Relaxation method

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▶ s_i can be only ± 1
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Relax the first constraint



Spectral partitioning

Minimization with constraints \Rightarrow Lagrange multipliers

$$\frac{\partial}{\partial s_i} \left[\sum_{jk} L_{jk} s_j s_k + \lambda \left(n - \sum_j s_j^2 \right) + 2\mu \left((n_1 - n_2) - \sum_j s_j \right) \right] = 0$$

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Large-scale structure of complex networks (Part 2)

└ Spectral partitioning

Spectral partitioning

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$$\frac{\partial}{\partial s_i} \left[\sum_{jk} L_{jk} s_j s_k + \lambda \left(n - \sum_j s_j^2 \right) + 2\mu \left((n_1 - n_2) - \sum_j s_j \right) \right] = 0$$

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$$\sum_j L_{ij} s_j = \lambda s_i + \mu$$

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Large-scale structure of complex networks (Part 2)

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$$\sum_j L_{ij} s_j = \lambda s_i + \mu$$

$$\mathbf{L}\mathbf{s} = \lambda\mathbf{s} + \mu\mathbf{1} = \lambda \left(\mathbf{s} + \frac{\mu}{\lambda}\mathbf{1} \right)$$

$$\mathbf{L} \left(\mathbf{s} + \frac{\mu}{\lambda}\mathbf{1} \right) = \lambda \left(\mathbf{s} + \frac{\mu}{\lambda}\mathbf{1} \right)$$

$\mathbf{1}$ is an eigenvector of the Laplacian with eigenvalue 0

$$\mathbf{L}\mathbf{x} = \lambda\mathbf{x}$$

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Large-scale structure of complex networks (Part 2)

└ Spectral partitioning

Spectral partitioning

Minimization with constraints \Rightarrow Lagrange multipliers

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$$\mathbf{L}\mathbf{x} = \lambda\mathbf{x}$$

Spectral partitioning

\mathbf{x} is an eigenvector of the Laplacian with eigenvalue λ

Which eigenvector to choose?

\mathbf{x} cannot be the eigenvector $\mathbf{1} = \begin{pmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{pmatrix}$

$$\mathbf{1}^T \mathbf{x} = \mathbf{1} \left(\mathbf{s} + \frac{\mu}{\lambda} \mathbf{1} \right) = (n_1 - n_2) + \frac{\mu}{\lambda} n = 0$$

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└ Spectral partitioning

\mathbf{x} is orthogonal to $\mathbf{1}$

.

\mathbf{x} is eigenvector but not $\mathbf{1}$

Spectral partitioning

\mathbf{x} is an eigenvector of the Laplacian with eigenvalue λ

Which eigenvector to choose?

\mathbf{x} cannot be the eigenvector $\mathbf{1} = \begin{pmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{pmatrix}$

$$\mathbf{1}^T \mathbf{x} = \mathbf{1} \left(\mathbf{s} + \frac{\mu}{\lambda} \mathbf{1} \right) = (n_1 - n_2) + \frac{\mu}{\lambda} n = 0$$

Which eigenvector to choose?

$$R = \frac{1}{4} \mathbf{s}^T \mathbf{L} \mathbf{s} = \frac{1}{4} \mathbf{x}^T \mathbf{x} = \frac{n_1 n_2}{n} \lambda$$

Choose the eigenvector with smallest possible eigenvalue!

Eigenvalues of the Laplacian are non-negative and smallest is always 0

$\mathbf{v}_1 = \mathbf{1}$ is ruled out already. So choose \mathbf{v}_2 with the smallest positive eigenvalue

└ Spectral partitioning

Which eigenvector to choose?
 $R = \frac{1}{4} \mathbf{s}^T \mathbf{L} \mathbf{s} = \frac{1}{4} \mathbf{x}^T \mathbf{x} = \frac{n_1 n_2}{n} \lambda$
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Eigenvalues of the Laplacian are non-negative and smallest is always 0
 $\mathbf{v}_1 = \mathbf{1}$ is ruled out already. So choose \mathbf{v}_2 with the smallest positive eigenvalue

Spectral partitioning

$$\mathbf{s} = x + \frac{n_1 - n_2}{n} \mathbf{1}$$

OR

$$s_i = x_i + \frac{n_1 - n_2}{n}$$

But s_i can be only ± 1

Thus, we want \mathbf{x} to be as close as possible to \mathbf{s}

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Large-scale structure of complex networks (Part 2)

└ Spectral partitioning

Spectral partitioning

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But s_i can be only ± 1

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Spectral partitioning

Maximize:

$$\mathbf{s}^T \left(\mathbf{x} + \frac{n_1 - n_2}{n} \mathbf{1} \right) = \sum_i s_i \left(x_i + \frac{n_1 - n_2}{n} \right)$$

Equivalently, maximize:

$$\sum_i s_i x_i$$

Simply put the n_1 vertices with most positive elements in group 1 and the rest ones in group 2

Group assignments are arbitrary

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Large-scale structure of complex networks (Part 2)

└ Spectral partitioning

Choose the assignment with the smaller cut size

Spectral partitioning

Maximize:

$$\mathbf{s}^T \left(\mathbf{x} + \frac{n_1 - n_2}{n} \mathbf{1} \right) = \sum_i s_i \left(x_i + \frac{n_1 - n_2}{n} \right)$$

Equivalently, maximize:

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Simply put the n_1 vertices with most positive elements in group 1 and the rest ones in group 2

Group assignments are arbitrary

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- Spectral partitioning

- Calculate v_2 of the Laplacian
- Put vertices corresponding to largest n_1 elements in group 1 and others in group 2. Calculate the cut size
- Put vertices corresponding to smallest n_1 elements in group 1 and others in group 2. Calculate the cut size
- Choose the division with the smallest cut size among the two

└ Community detection is harder!

- ▀ **Graph partitioning**
 - well defined
 - Number of groups is fixed
 - Sizes of the groups are fixed
 - Divide even if no good division exists
- ▀ **Community detection**
 - ill-defined
 - Number of groups depends on the structure of the network
 - Sizes of the groups depend on the structure of the network
 - Discover natural fault lines

► Graph partitioning

- well defined
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Many definitions.. many algorithms!

- ▶ Girvan-Newman algorithm
- ▶ Kernighan-Lin-Newman algorithm
- ▶ Spectral decomposition
- ▶ Clique-percolation
- ▶ Random walk methods
- ▶ Statistical inference
- ▶ Label propagation
- ▶ Hierarchical clustering

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Large-scale structure of complex networks (Part 2)

└ Many definitions.. many algorithms!

I can go on.. These algorithms use different definitions/views of communities

- ▶ Girvan-Newman algorithm
- ▶ Kernighan-Lin-Newman algorithm
- ▶ Spectral decomposition
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- └ Broad classification

- ## Broad classification
- ▶ **Agglomerative algorithms:**
 - ▶ Hierarchical clustering
 - ▶ Louvain method
 - ▶ CNM algorithm
 - ▶ **Divisive algorithms:**
 - ▶ Girvan-Newman algorithm
 - ▶ Radicchi algorithm
 - ▶ **Assignment algorithms:**
 - ▶ Label propagation
 - ▶ Spectral partitioning
 - ▶ Kernighan-Lin-Newman algorithm

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Large-scale structure of complex networks (Part 2)

└ “The” simplest community detection problem

- Bisecting a graph with n nodes
- Group sizes are not fixed
- Minimum cut size?
 - Trivial partition
 - Needs ad hoc specification of sizes

- ▶ Bisecting a graph with n nodes
- ▶ Group sizes are not fixed
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Empty group

“The” simplest community detection problem

- ▶ Bisecting a graph with n nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?
 - ▶ Trivial partition
 - ▶ Needs ad hoc specification of sizes

A different measure of the quality of division is required..

Large-scale structure of complex networks (Part 2)

- └ “The” simplest community detection problem

Different measure

- ▶ Bisecting a graph with n nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?
 - Trivial partition
 - Needs ad hoc specification of sizes

A different measure of the quality of division is required..

Quantification of community structure

- Fewer than expected edges between the groups

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- └ Quantification of community structure

few edges = expected edges = not a good division

- Fewer than expected edges between the groups

Quantification of community structure

- ▶ Fewer than expected edges between the groups
- ▶ Equivalently, more than expected edges inside the groups

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└ Quantification of community structure

Remember assortativity

- Fewer than expected edges between the groups
- Equivalently, more than expected edges inside the groups

Quantification of community structure

- ▶ Fewer than expected edges between the groups
- ▶ Equivalently, more than expected edges inside the groups
- ▶ Assortativity mixing and modularity

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└ Quantification of community structure

Divide network using modularity

- Fewer than expected edges between the groups
- Equivalently, more than expected edges inside the groups
- Assortativity mixing and modularity

Quantification of community structure

- ▶ Fewer than expected edges between the groups
- ▶ Equivalently, more than expected edges inside the groups
- ▶ Assortativity mixing and modularity
- ▶ Look for divisions with high modularity

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Large-scale structure of complex networks (Part 2)

└ Quantification of community structure

Heuristics are needed

- Fewer than expected edges between the groups
- Equivalently, more than expected edges inside the groups
- Assortativity mixing and modularity
- Look for divisions with high modularity

Modularity

How to find the division which maximizes the modularity?

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- ▶ Check the value of Q for all possible divisions and choose the best one

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- ▶ Consider, $N = 100$, $n_1 = n_2 = 50$

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How to find the division which maximizes the modularity?

- ▶ Check the value of Q for all possible divisions and choose the best one
- ▶ Consider, $N = 100$, $n_1 = n_2 = 50$
- ▶ Total possible divisions = ${}^{100}C_{50} > 10^{29}$

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Large-scale structure of complex networks (Part 2)

└ Modularity

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Kernighan-Lin-Newman algorithm

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin-Newman algorithm

Variation of KL algorithm

- Sizes of the groups are not fixed
- No swapping

Kernighan-Lin-Newman algorithm

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Large-scale structure of complex networks (Part 2)

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Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin-Newman algorithm

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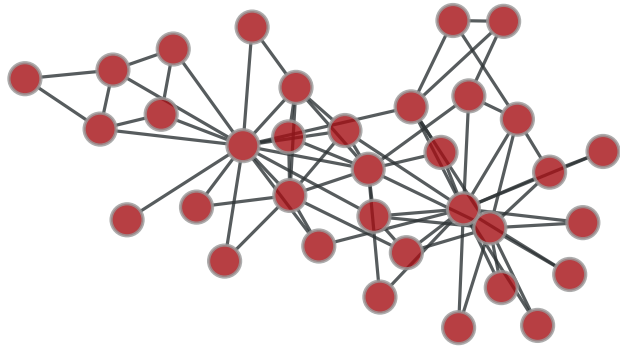
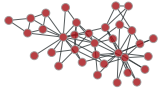
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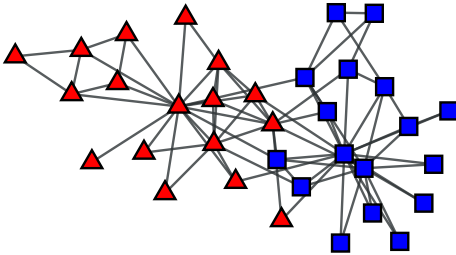
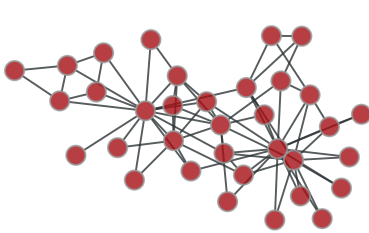
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Large-scale structure of complex networks (Part 2)



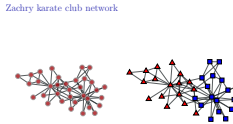
Does somebody know this network?

Zachry karate club network



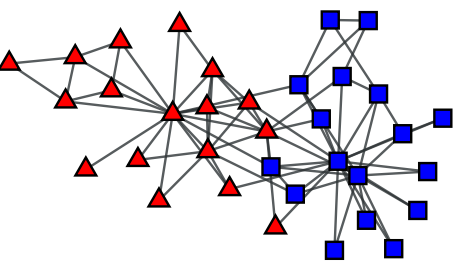
2018-01-06 Large-scale structure of complex networks (Part 2)

└ Zachry karate club network



Application to Zachry karate club

Actual division



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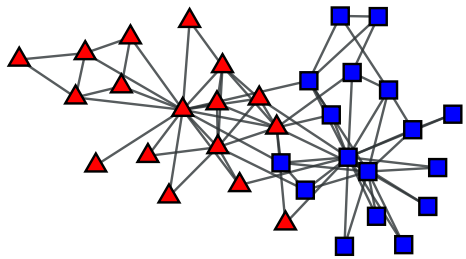
Large-scale structure of complex networks (Part 2)

└ Application to Zachry karate club

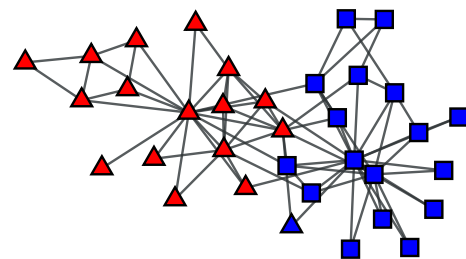


Application to Zachry karate club

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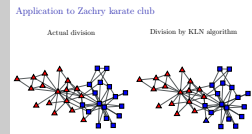
Division by KLN algorithm



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Large-scale structure of complex networks (Part 2)

└ Application to Zachry karate club



Spectral modularity maximization

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) = \frac{1}{2m} \sum_{ij} B_{ij} \delta(c_i, c_j)$$

Note that:

$$\sum_j B_j = \sum_j A_{ij} - \frac{k_i}{2m} \sum_j k_j = k_i - \frac{k_i}{2m} 2m = 0$$

└ Spectral modularity maximization

spectral partitioning: cut size

·
analogous algorithm exists

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$$s_i = \begin{cases} +1 & \text{if vertex } i \text{ belongs to group 1} \\ -1 & \text{if vertex } i \text{ belongs to group 2} \end{cases}$$

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Large-scale structure of complex networks (Part 2)

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Large-scale structure of complex networks (Part 2)

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- Relaxation method
- Numbers of elements with values +1 and -1 are not fixed
 - Only constraint: $\mathbf{s}^T \mathbf{s} = \sum_i s_i^2 = n$

$$\frac{\partial}{\partial s_i} \left[\sum_{j,k} B_{jk} s_j s_k + \beta \left(n - \sum_j s_j^2 \right) \right] = 0$$

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$$\mathbf{B} \mathbf{s} = \beta \mathbf{s}$$



Large-scale structure of complex networks (Part 2)

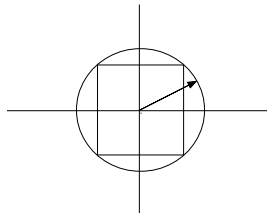
└ Spectral modularity maximization

\mathbf{s} is eigenvector of modularity matrix

Spectral modularity maximization

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Spectral modularity maximization

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Thus, choose \mathbf{s} to be the eigenvector \mathbf{u}_1 corresponding to the largest eigenvalue of the modularity matrix

Maximize:

$$\mathbf{s}^T \mathbf{u}_1 = \sum_i s_i u_{1i}$$

Maximum is achieved when each term is non-negative \Rightarrow Use signs of u_{1i} !

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Large-scale structure of complex networks (Part 2)

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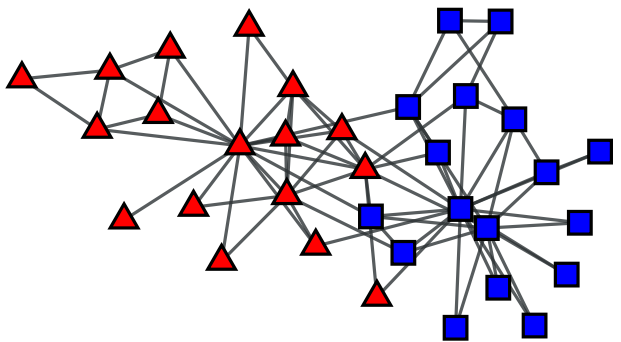
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└ Spectral modularity maximization

- ▶ Calculate the modularity matrix
- ▶ Calculate its eigenvector corresponding to the largest eigenvalue
- ▶ Assign nodes to communities based on the signs of elements

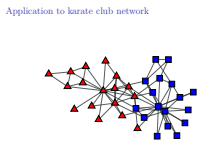
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Application to karate club network

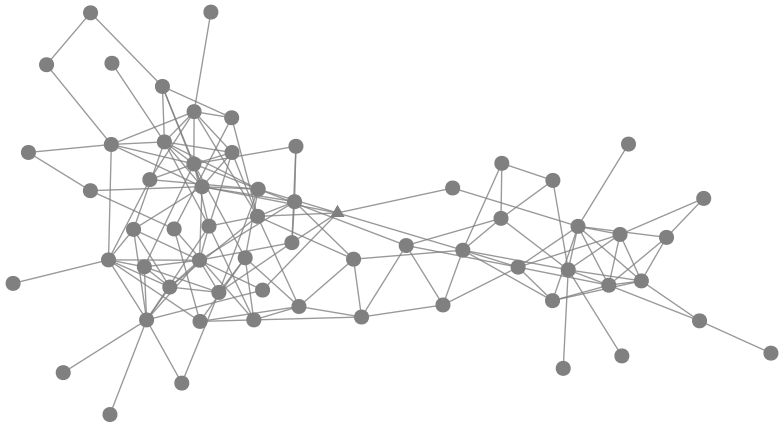


2018-01-06 Large-scale structure of complex networks (Part 2)

└ Application to karate club network



Bottlenose dolphins



1

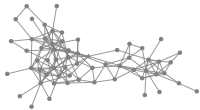
¹Lusseau D, Schneider K, Boisseau OJ, Haase P, Slooten E, Dawson SM
(2003) Behav Ecol Sociobiol 54:396405

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Large-scale structure of complex networks (Part 2)

└ Bottlenose dolphins

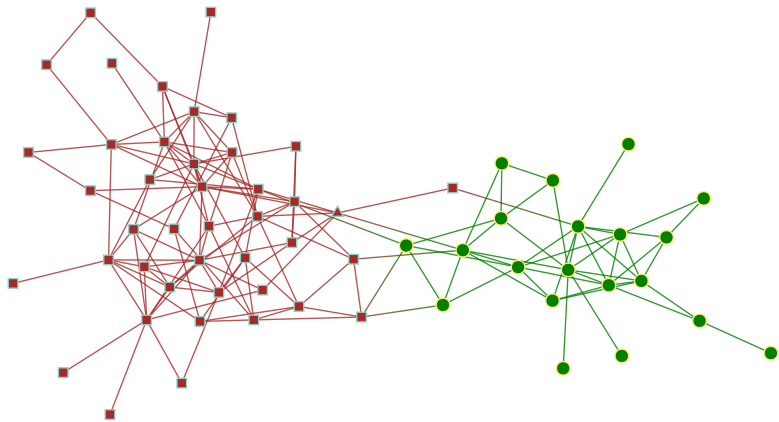
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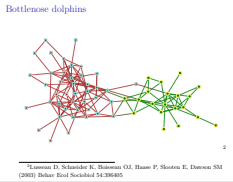


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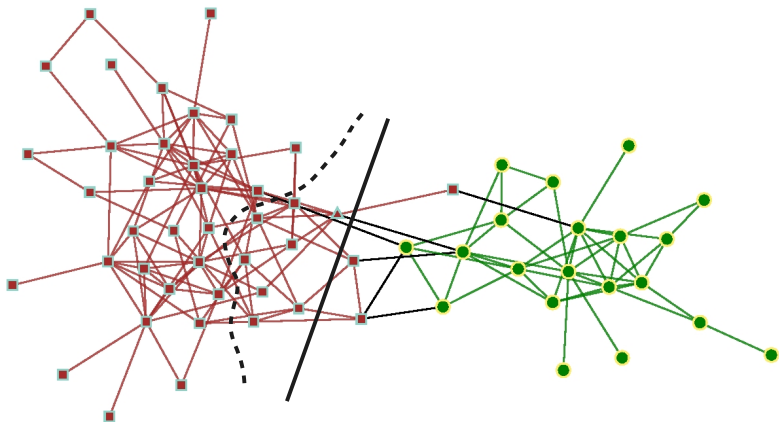
Large-scale structure of complex networks (Part 2)

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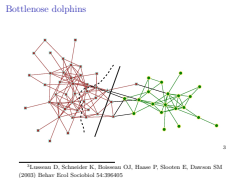
3

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Newman-Girvan algorithm

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Large-scale structure of complex networks (Part 2)

- └ Newman-Girvan algorithm

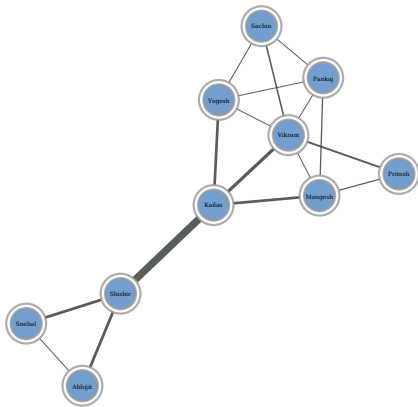
Let's have a look at the edge betweenness

- ▶ Look for edges between the communities
- ▶ Edge betweenness

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Edge betweenness

- ▶ Path between two nodes
- ▶ Shortest path between two nodes
- ▶ Number of shortest paths that go through a given edge



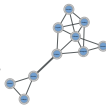
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Large-scale structure of complex networks (Part 2)

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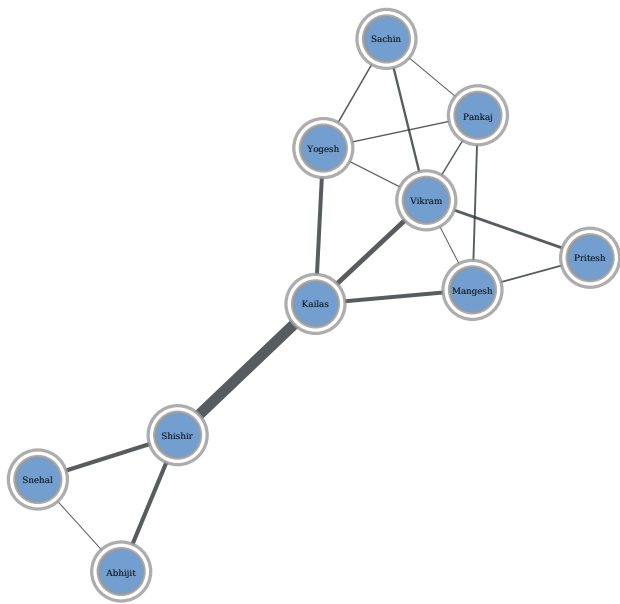


The algorithm

- ▶ Calculate betweenness for all edges
- ▶ Remove the edge with the highest betweenness
- ▶ Recalculate betweenness for all edges
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Girvan-Newman algorithm

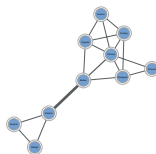


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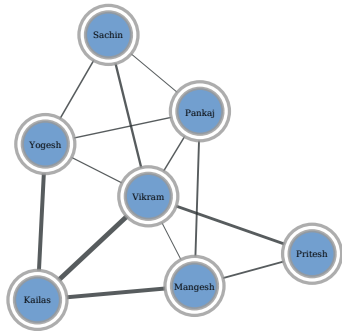
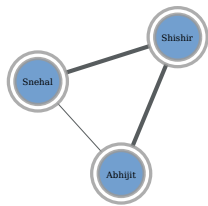
Large-scale structure of complex networks (Part 2)

└ Girvan-Newman algorithm

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Girvan-Newman algorithm

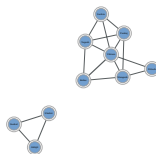


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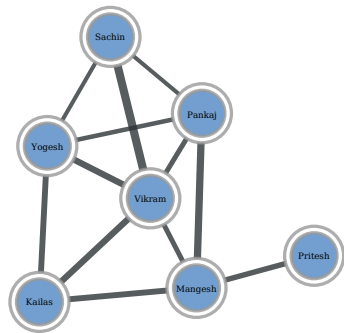
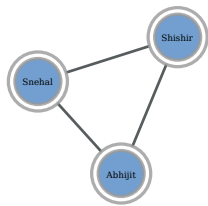
Large-scale structure of complex networks (Part 2)

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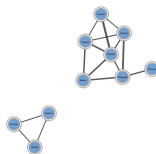


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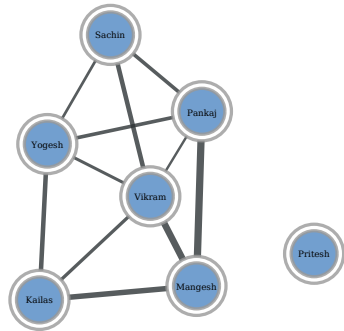
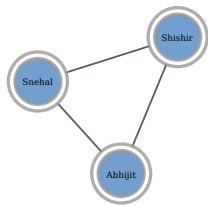
Large-scale structure of complex networks (Part 2)

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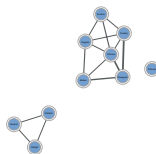


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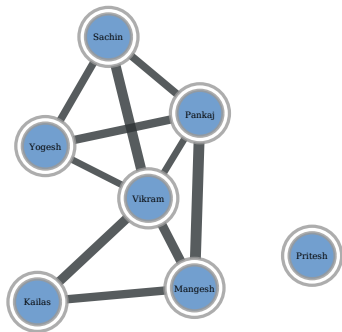
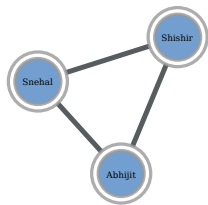
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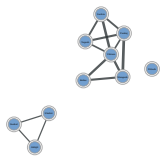


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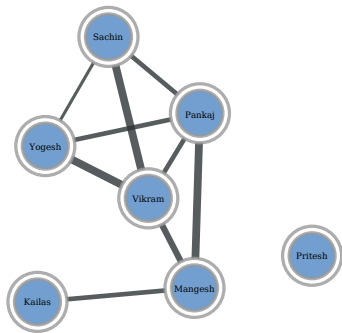
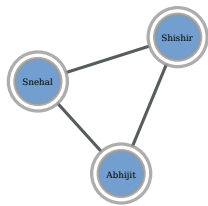
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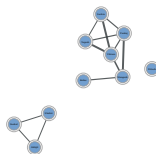


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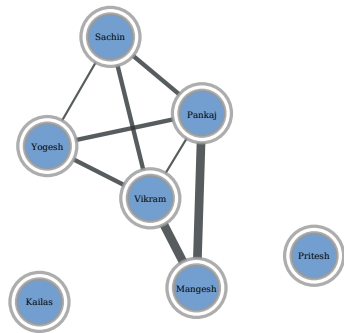
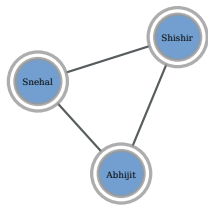
Large-scale structure of complex networks (Part 2)

└ Girvan-Newman algorithm

Girvan-Newman algorithm



Girvan-Newman algorithm

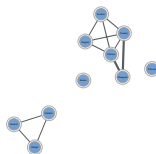


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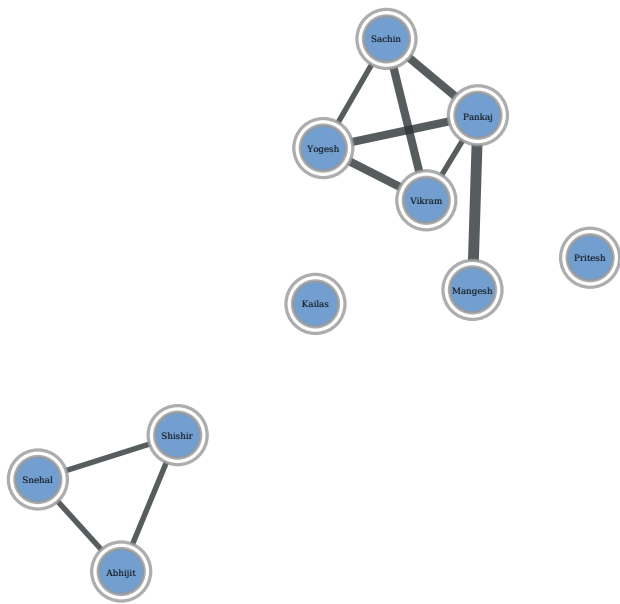
Large-scale structure of complex networks (Part 2)

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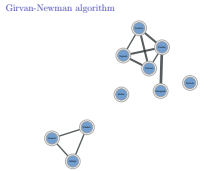
Girvan-Newman algorithm



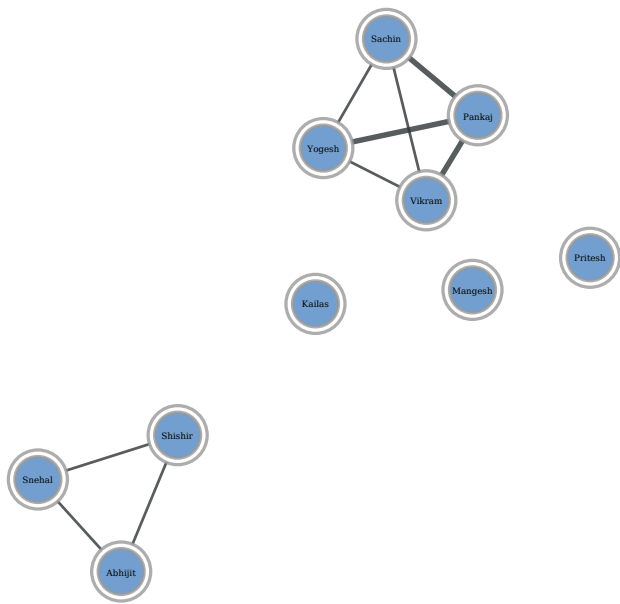
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Large-scale structure of complex networks (Part 2)

└ Girvan-Newman algorithm



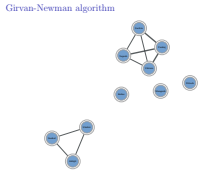
Girvan-Newman algorithm



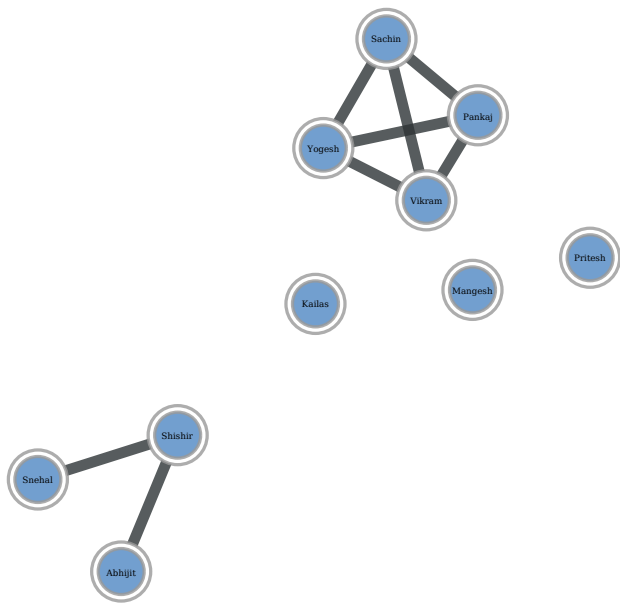
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Large-scale structure of complex networks (Part 2)

└ Girvan-Newman algorithm



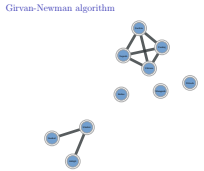
Girvan-Newman algorithm



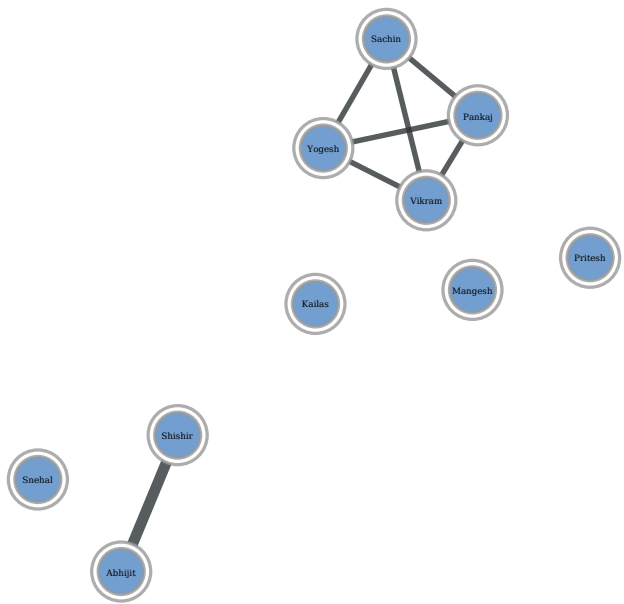
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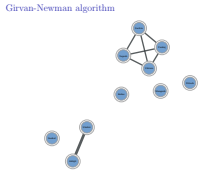
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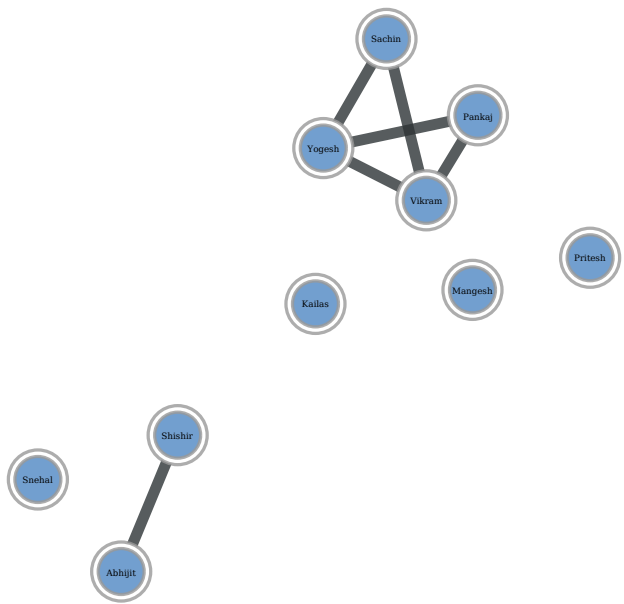
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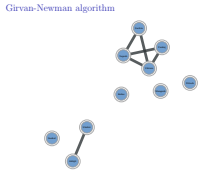
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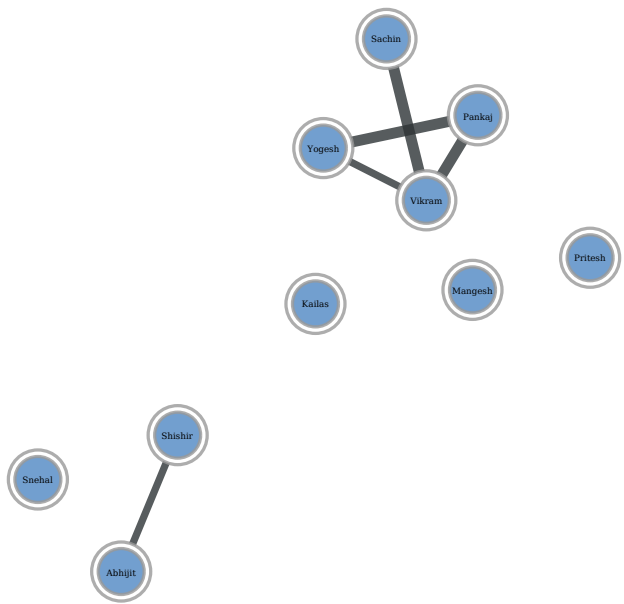
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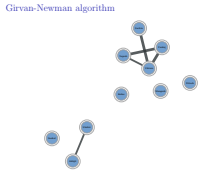
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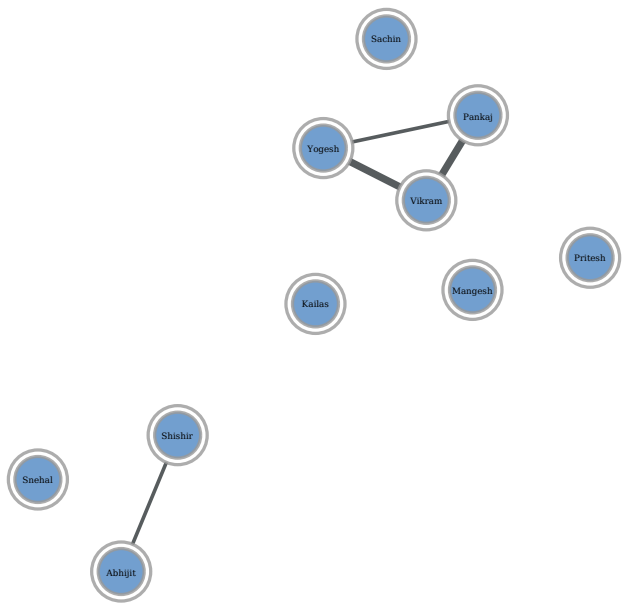
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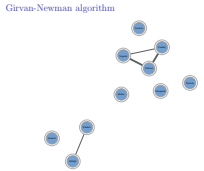
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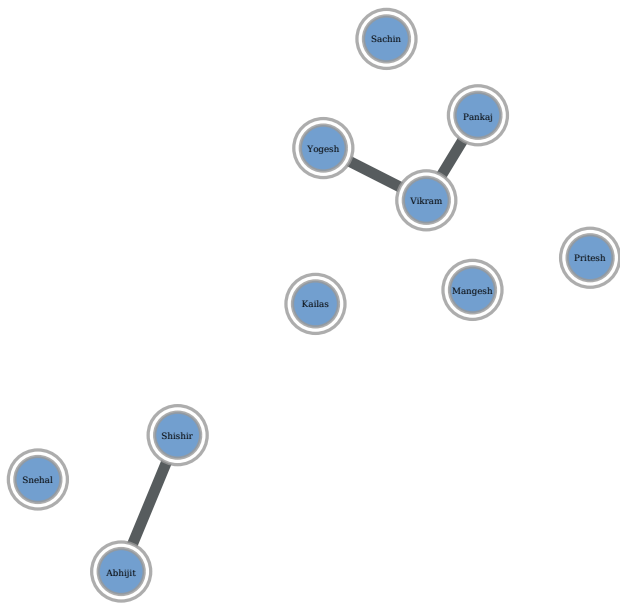
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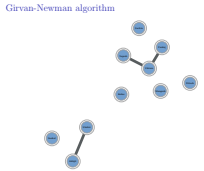
Girvan-Newman algorithm



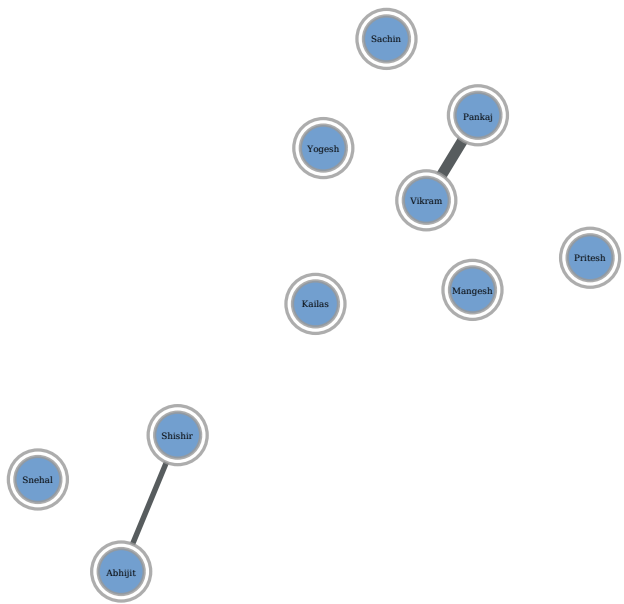
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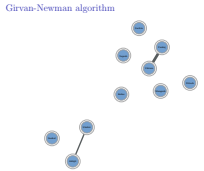
Girvan-Newman algorithm



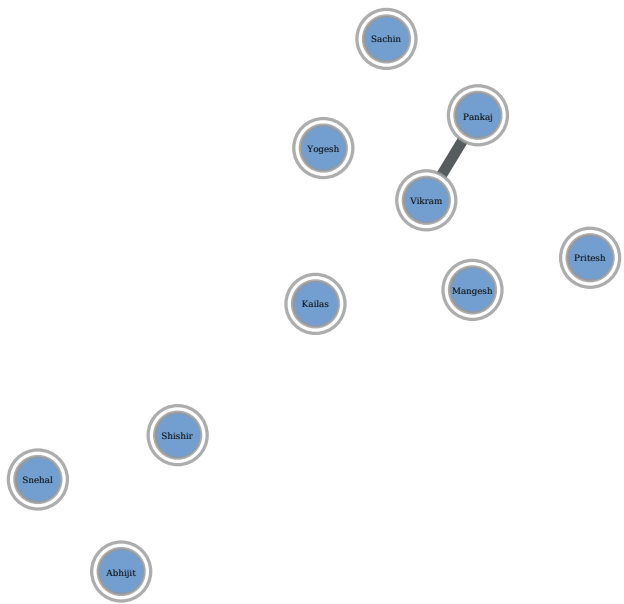
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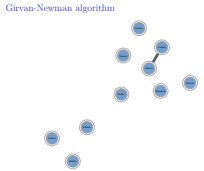
Girvan-Newman algorithm



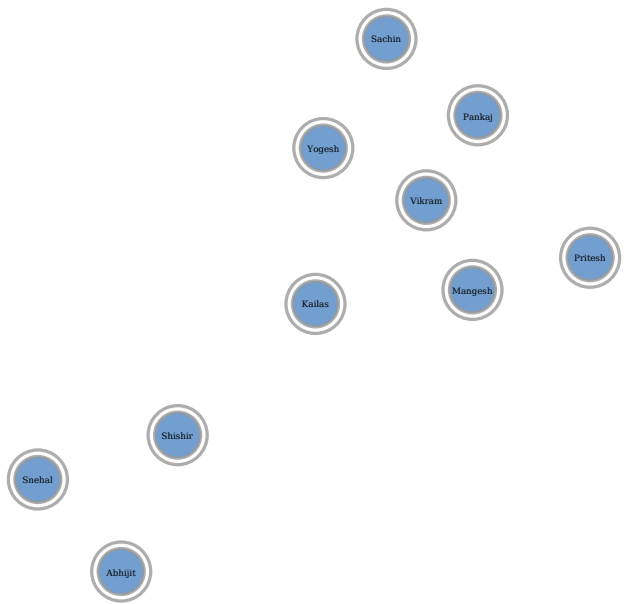
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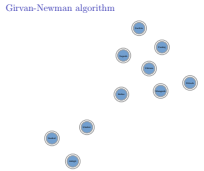
Girvan-Newman algorithm



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Large-scale structure of complex networks (Part 2)

└ Girvan-Newman algorithm



Problems with traditional community detection algorithms

- ▶ Degeneracy
- ▶ Resolution limit
- ▶ Structure vs Noise

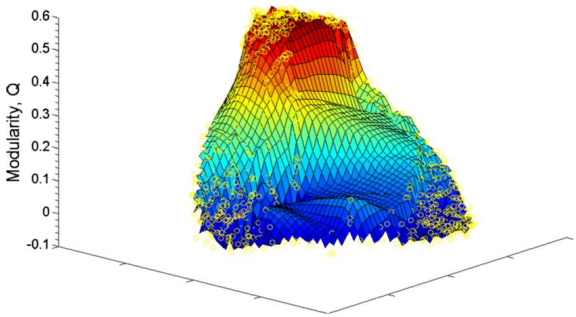
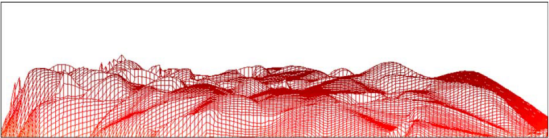
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Large-scale structure of complex networks (Part 2)

└ Problems with traditional community detection algorithms

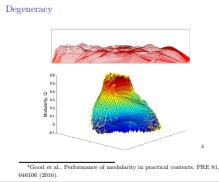
- Problems with traditional community detection algorithms
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 - ▶ Resolution limit
 - ▶ Structure vs Noise

Degeneracy



4

⁴Good et al., Performance of modularity in practical contexts, PRE 81, 046106 (2010).



Resolution limit

- ▶ Maximizing the modularity can fail to resolve small sized modules
- ▶ Modular structures like cliques can be hidden in the larger groups of nodes with higher modularity score
- ▶ Peak of the modularity function may not coincide with divisions that identify such modular structures

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

Contribution of the group s ,

$$Q_s = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, s) \delta(c_j, s) = \frac{e_s}{m} - \left(\frac{d_s}{2m} \right)^2$$

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Large-scale structure of complex networks (Part 2)

Resolution limit

- e_s : Number of links inside module s
-
- d_s : sum of the degrees inside s

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Resolution limit

The group s is a module whenever $Q_s > 0 \Rightarrow \frac{e_s}{m} > \left(\frac{d_s}{2m}\right)^2$

Consider two modules s_1 and s_2 with $e_{s_1 s_2}$ edges between them
The change in modularity if we merge these:

$$\Delta Q_{s_1 s_2} = \frac{e_{s_1 s_2}}{m} - 2 \left(\frac{d_{s_1}}{2m}\right) \left(\frac{d_{s_2}}{2m}\right) > 0$$

whenever:

$$e_{s_1 s_2} > \frac{d_{s_1} d_{s_2}}{2m} \rightarrow 0$$

Thus, modules would be merged even when the number of links $e_{s_1 s_2}$ between them is small! ⁵

⁵Fortunato, Barthelemy, Resolution limit in community detection, PNAS, (2006)

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Large-scale structure of complex networks (Part 2)

Resolution limit

High wavelength light

Resolution limit

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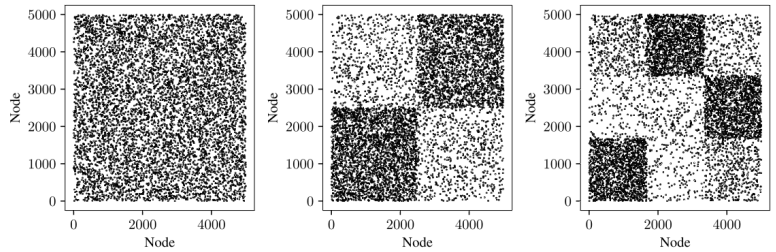
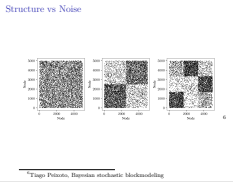
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Structure vs Noise



Conclusions

- ▶ Community structure is a fundamental property of networks
- ▶ Community detection is an ill-defined problem
- ▶ (Too) many algorithms exist
- ▶ Community detection is still an open problem!

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Large-scale structure of complex networks (Part 2)

└─ Conclusions

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