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## Large-scale structure of complex networks (Part 2)

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(Part 2)

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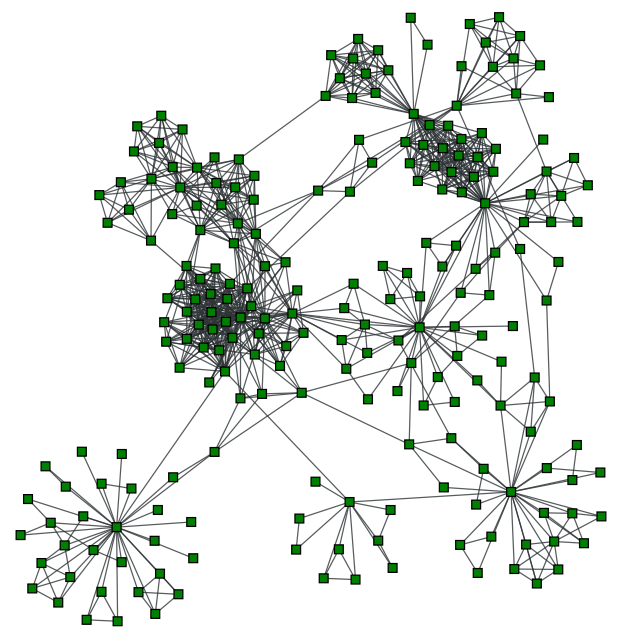
# Large-scale structure of complex networks (Part 2)

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Hello

# Community structure in networks



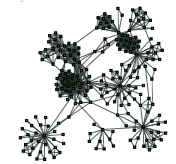
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## Large-scale structure of complex networks (Part 2)

└ Community structure in networks

Network of coauthorships in a university department

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 network:**
  - 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 neuronal networks

## └ Community detection

**Detecting communities is important!**

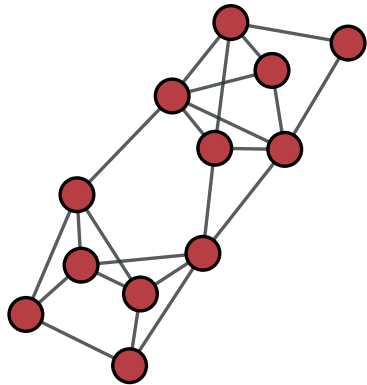
- ▶ Communities are building blocks of networks
- ▶ Communities allow us to see “the big picture”
- ▶ Functional/Autonomous units
- ▶ Non-trivial effects on the processes on networks

**Detecting communities is important!**

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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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## Large-scale structure of complex networks (Part 2)

└ Graph partitioning

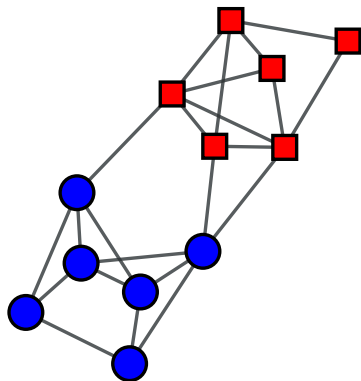
Graph partitioning

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# Graph partitioning

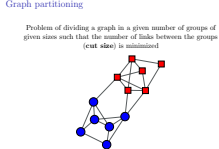
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## Large-scale structure of complex networks (Part 2)

└ Graph partitioning



# 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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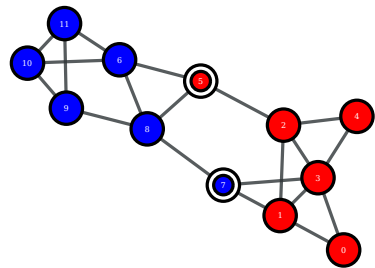
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# Kernighan-Lin algorithm

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

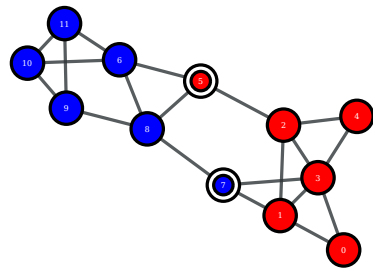
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# Kernighan-Lin algorithm

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

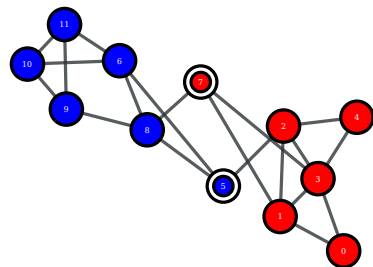
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# Kernighan-Lin algorithm

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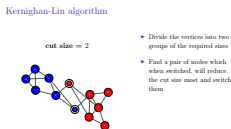


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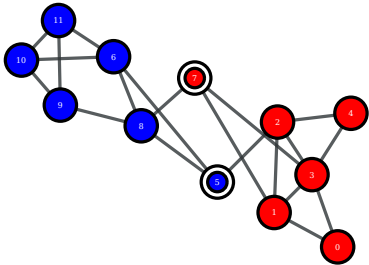
## Large-scale structure of complex networks (Part 2)

└ Kernighan-Lin algorithm



# Kernighan-Lin algorithm

cut size = 2



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

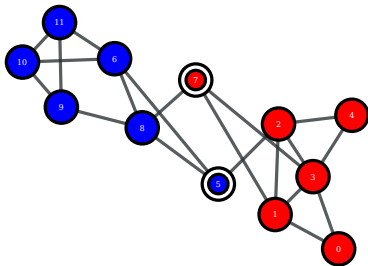
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# Kernighan-Lin algorithm

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- ▶ Divide the vertices into two groups of the required sizes
- ▶ Find a pair of nodes which when switched, will reduce the cut size most and switch them
- ▶ If no such pair exists, select the pair which least increases the cut size
- ▶ 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

Kernighan-Lin algorithm

cut size = 2



- ▶ Divide the vertices into two groups of the required sizes
- ▶ Find a pair of nodes which when switched, will reduce the cut size most and switch them
- ▶ If no such pair exists, select the pair which least increases the cut size
- ▶ Continue this such that the already switched pair is not switched again

# 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

- ▶ 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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## Large-scale structure of complex networks (Part 2)

### └ Spectral partitioning

Spectral partitioning

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## Large-scale structure of complex networks (Part 2)

└ 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
- ▀ Number of groups is fixed
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▀ **Community detection**

- ▀ ill-defined
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- ▀ Sizes of the groups depend on the structure of the network
- ▀ Discover natural fault lines



# 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
- ▶ Clique-percolation
- ▶ Random walk methods
- ▶ Statistical inference
- ▶ Label propagation
- ▶ Hierarchical clustering

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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

- ▶ Bisecting a graph with  $n$  nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?

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## Large-scale structure of complex networks (Part 2)

└ “The” simplest community detection problem

Empty group

- ▶ Bisecting a graph with  $n$  nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?

# “The” simplest community detection problem

- ▶ Bisecting a graph with  $n$  nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?

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

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## Large-scale structure of complex networks (Part 2)

└ “The” simplest community detection problem

“The” simplest community detection problem

- ▶ Bisecting a graph with  $n$  nodes
- ▶ Group sizes are not fixed
- ▶ Minimum cut size?

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

Different measure

# Quantification of community structure

- Fewer than expected edges between the groups

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## Large-scale structure of complex networks (Part 2)

### └ 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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## Large-scale structure of complex networks (Part 2)

### └ Quantification of community structure

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

Remember assortativity

# 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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## Large-scale structure of complex networks (Part 2)

### └ 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
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- ▶ Look for divisions with high modularity



# Quantification of community structure

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## Large-scale structure of complex networks (Part 2)

### └ 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
- ▶ Modularity maximization is hard

- ▶ Fewer than expected edges between the groups
- ▶ Equivalently, more than expected edges inside the groups
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- ▶ Look for divisions with high modularity
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# Newman-Girvan algorithm

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## Large-scale structure of complex networks (Part 2)

### └ Newman-Girvan algorithm

Newman-Girvan algorithm

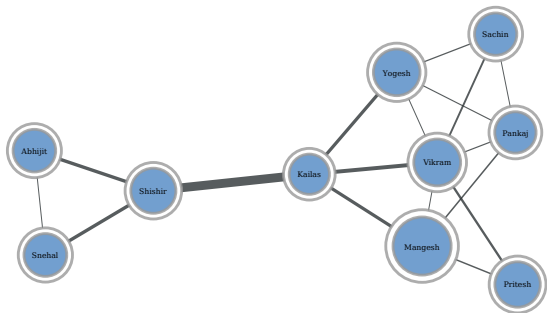
- Look for edges between the communities
- Edge betweenness

Let's have a look at the edge betweenness

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

# 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)

└ Edge betweenness

Edge betweenness

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

The diagram shows a small network graph with 8 nodes and 10 edges. The nodes are arranged in a roughly circular pattern. The edges are represented by lines connecting the nodes. The graph is used to illustrate the concept of edge betweenness, which is the number of shortest paths between two nodes that pass through a given edge.

# The algorithm

- ▶ Calculate betweenness for all edges
- ▶ Remove the edge with the highest betweenness
- ▶ Recalculate betweenness for all edges
- ▶ Repeat

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