Large-scale structure of complex networks (Part 2)

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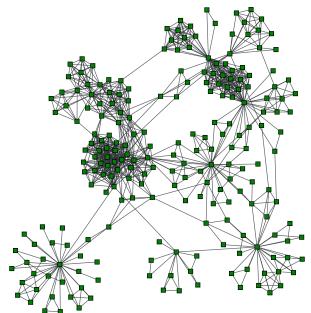
Suehal M. Shekotkor

Caste for modifieg and simulation.

S.P. Pane University, Pane

Hello

Community structure in networks





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Community structure in networks

Network of coauthorships in a university department

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

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Community structure in networks

Community structure in networks

What are communities?

 Traditional definition: Groups of nodes with a high internal link density
 Modern definition: Nodes with similar connection

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 the real-world networks

Communities in the real-world networks

Social networks:

Friend-circles
 Research communities

➤ World Wide Web:

➤ Pages with similar contents

Webpages under the same domain (e.g. Wikipedia)
 Biological network:

Proteins with similar robes in protein interaction networks
 Chemicals together taking part in chemical reactions in metabolic networks
 Communities in neuronal networks

- Commission is intuiting protection

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



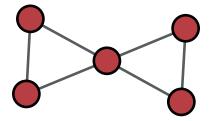
-Community detection

Detecting communities is important!

- · Non-trivial effects on the processes on networks

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 is minimized



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-Graph partitioning

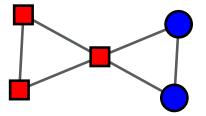
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Graph partitioning

Problem of dividing a graph in a given number of groups of given sizes such that the number of links between the groups is



Number of ways: al = 2n+1 / 2l

Partitioning is hard!

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

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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

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-Community detection is harder!

Community detection is harder!

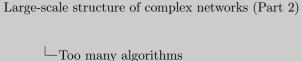
· Graph partitioning

- well defined Number of groups is fixed
- · Sizes of the groups are fixed Divide even if no rood division exists
- ► Community detection

- · Number of groups depends on the structure of the network
- · Discover natural fault lines

Too many algorithms

- ► Girvan-Newman algorithm
- ► Modularity maximization
- ► Spectral decomposition
- ► Clique-percolation
- ▶ Radom walk methods
- ► Statistical inference
- ► Label propagation
- ► Hierarchical clustering



 Modularity maximization ▶ Spectral decomposition

· Clique-percolation

Too many algorithms

► Radom walk method

 Statistical inference ► Label propagation

Hierarchical clustering

I can go on

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"The" simplest community detection problem

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





Minimum cut size?

"The" simplest community detection problem

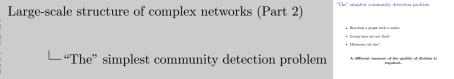
Empty group

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"The" simplest community detection problem

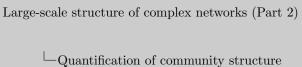
- ightharpoonup Bisecting a graph with n nodes
- ► Group sizes are not fixed
- ▶ Minimum cut size?

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



Different measure

▶ Fewer than expected edges between the groups

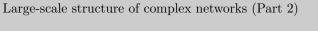


Quantification of community structure

• Fewer than expected edges between the groups

few edges = expected edges = not a good division

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



└─Quantification of community structure

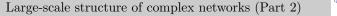
Quantification of community structure

Fewer than expected edges between the groups

Equivalently, more than expected edges inside the group

Remember assortativity

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



—Quantification of community structure

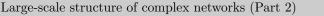
Quantification of community structure

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➤ Assortativity mixing and modularity

Divide network using modularity

- ▶ 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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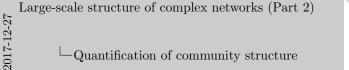
Quantification of community structure

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- er than expected edges between the groups
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- Assortativity mixing and modul
- Look for divisions with h

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 maximization is hard



-Quantification of community structure

Quantification of community structure

Heuristic algorithms for modularity maximization

► Agglomerative algorithms:

- ► Hierarchical clustering
- ▶ Louvain method
- ► CNM algorithm

▶ Divisive algorithms:

- ▶ Girvan-Newman algorithm
- ▶ Radichhi algorithm

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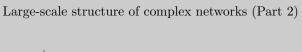
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Heuristic algorithms for modularity maximization

- Hierarchical clustering
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 CNM algorithm
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Newman-Girvan algorithm

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



▶ Look for edges between the communities

Newman-Girvan algorithm

► Edge betweenness

└─Newman-Girvan algorithm

Let's have a look at the edge betweenness