

Network Analysis in Complex Environment

Analysis of weighted networks

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IMFM Ljubljana, IAM UP Koper

Spinaker Summer School
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Outline

Analysis of
weighted
networks

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Introduction

Networks

Properties

Statistics

Connectivity

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subnetworks

References

- 1 Introduction
- 2 Networks
- 3 Properties
- 4 Statistics
- 5 Connectivity
- 6 Important subnetworks
- 7 References



PROGRAM SPINAKER

Vladimir Batagelj: vladimir.batagelj@fmf.uni-lj.si

Last version of slides (July 10, 2023, 14:51): [Wnets.pdf](#)

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Timetable

Fri	7^{th}	14:00 – 15:30
Fri	7^{th}	15:45 – 17:15
Mon	10^{th}	15:45 – 17:15
Tue	11^{th}	11:30 – 13:00
Wed	12^{th}	15:45 – 17:15
Thu	13^{th}	14:00 – 15:30

<http://vladowiki.fmf.uni-lj.si/doku.php?id=vlado:ed:ss:krakow><https://github.com/bavla/wNets><http://mrvar.fdv.uni-lj.si/pajek/>

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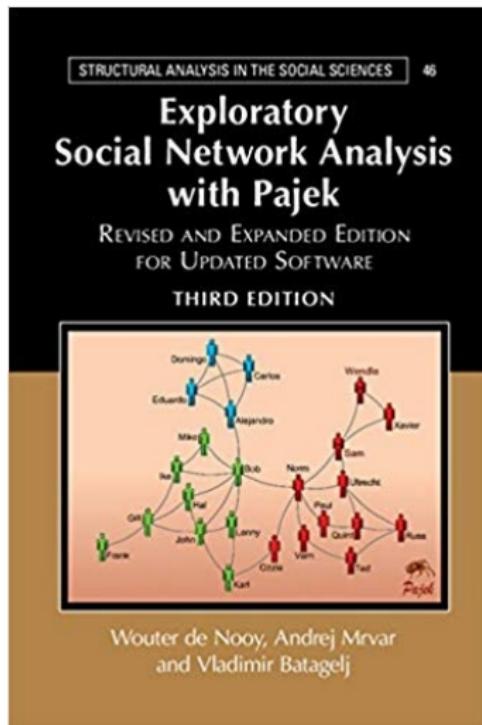
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An introduction to social network analysis with **Pajek** is available in the book **ESNA 3** (de Nooy, Mrvar, Batagelj, CUP 2005, 2011, 2018).

ESNA in Japanese was published by Tokyo Denki University Press in 2010; and in Chinese by Beijing World Publishing in November 2012.

Pajek – program for analysis and visualization of large networks is freely available, for noncommercial use, at its web site.

<http://mrvar.fdv.uni-lj.si/pajek/>

Understanding large networks

Analysis of weighted networks

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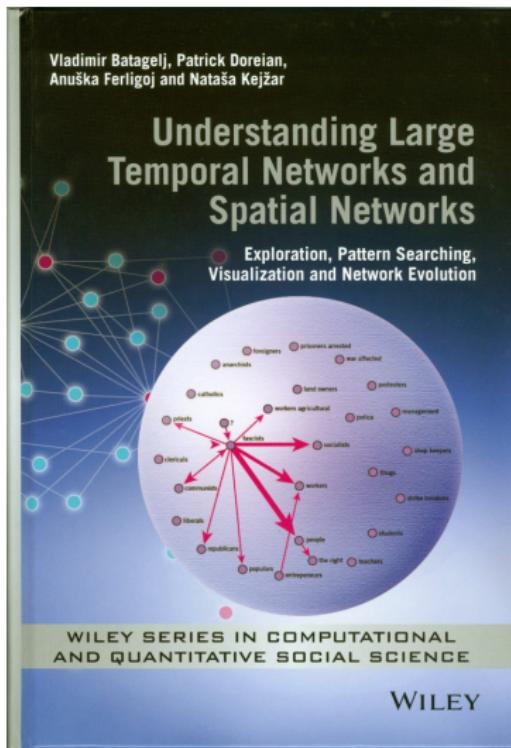
Networks

Properties

$$\mathfrak{S}_1 = \mathbb{A}^2 = \mathbb{A}^2 - \infty$$

... subnetworks

References



This course is closely related to chapters 2 and 3 in the book:

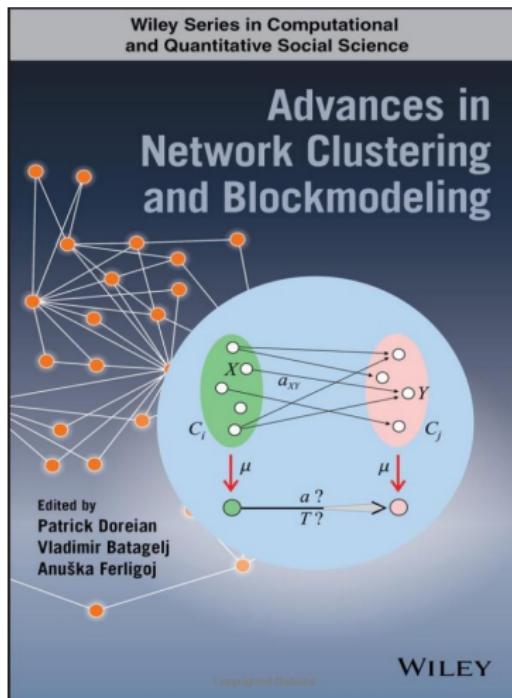
Vladimir Batagelj, Patrick Doreian, Anuška Ferligoj and Nataša Kejžar: Understanding Large Temporal Networks and Spatial Networks: Exploration, Pattern Searching, Visualization and Network Evolution. Wiley Series in Computational and Quantitative Social Science. **Wiley**, October 2014.

Advances in Network Clustering and Blockmodeling

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An overview of the network clustering and blockmodeling is available in the book:

Patrick Doreian, Vladimir Batagelj, Anuška Ferligoj (Eds.): Advances in Network Clustering and Blockmodeling. Wiley Series in Computational and Quantitative Social Science. Wiley, 2020.

Networks

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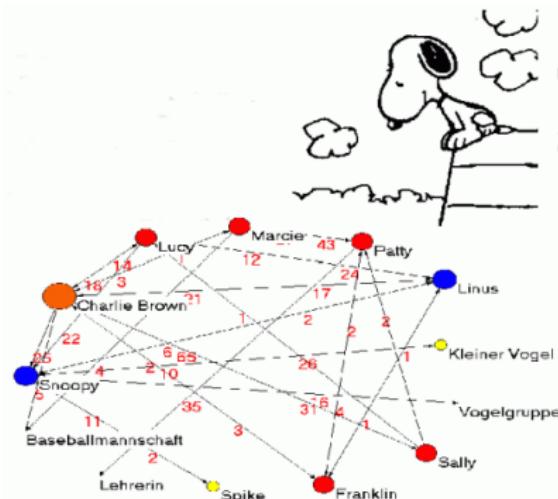
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Alexandra Schuler/ Marion Laging-Glaser:
Analyse von Snoopy Comics

A **network** is based on two sets – set of **nodes** (vertices), that represent the selected **units**, and set of **links** (lines), that represent **ties** between units. They determine a **graph**. A link can be **directed** – an **arc**, or **undirected** – an **edge**.

Additional data about nodes or links can be known – their **properties** (attributes). For example: name/label, type, value, ...

Network = Graph + Data

The data can be measured or computed.

Networks / Formally

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A **network** $\mathbf{N} = (\mathcal{V}, \mathcal{L}, \mathcal{P}, \mathcal{W})$ consists of:

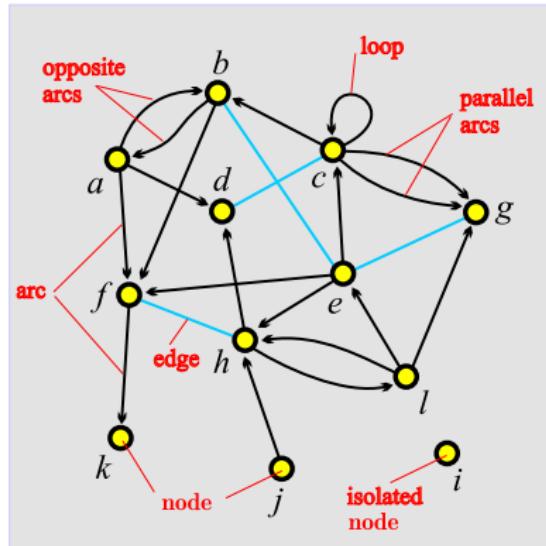
- a **graph** $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, where \mathcal{V} is the set of nodes, \mathcal{A} is the set of arcs, \mathcal{E} is the set of edges, and $\mathcal{L} = \mathcal{E} \cup \mathcal{A}$ is the set of links.
 $n = |\mathcal{V}|$, $m = |\mathcal{L}|$
- \mathcal{P} **node value functions** / properties: $p: \mathcal{V} \rightarrow A$
- \mathcal{W} **link value functions** / weights: $w: \mathcal{L} \rightarrow B$

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unit, actor – node, vertex
tie, line – link, edge, arc

arc = directed link, (a, d)
a is the *initial* node,
d is the *terminal* node.

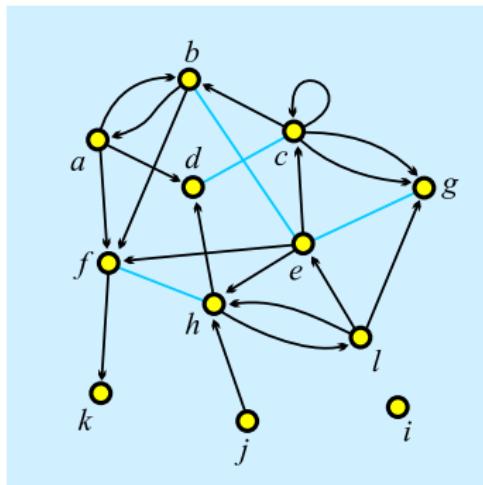
edge = undirected link,
 $(c: d)$
c and d are *end* nodes.

Graph / Sets – NET

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$$\begin{aligned}\mathcal{V} &= \{a, b, c, d, e, f, g, h, i, j, k, l\} \\ \mathcal{A} &= \{(a, b), (a, d), (a, f), (b, a), \\ &\quad (b, f), (c, b), (c, c), (c, g)_1, \\ &\quad (c, g)_2, (e, c), (e, f), (e, h), \\ &\quad (f, k), (h, d), (h, l), (j, h), \\ &\quad (l, e), (l, g), (l, h)\} \\ \mathcal{E} &= \{(b: e), (c: d), (e: g), (f: h)\} \\ \mathbf{G} &= (\mathcal{V}, \mathcal{A}, \mathcal{E}) \\ \mathcal{L} &= \mathcal{A} \cup \mathcal{E}\end{aligned}$$

$\mathcal{A} = \emptyset$ – *undirected* graph; $\mathcal{E} = \emptyset$ – *directed* graph.

Pajek: local: `GraphSet`; `TinaSet`;

WWW: `GraphSet / net`; `TinaSet / net`, picture `picture`.

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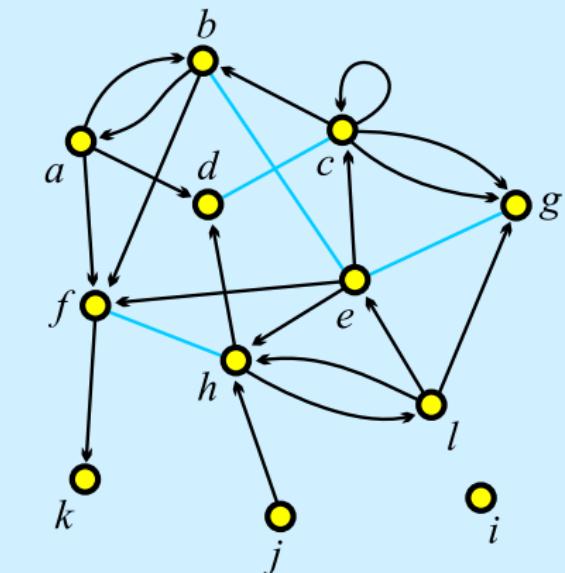
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*Vertices	12
1 "a"	0.1020 0.3226
2 "b"	0.2860 0.0876
3 "c"	0.5322 0.2304
4 "d"	0.3259 0.3917
5 "e"	0.5543 0.4770
6 "f"	0.1552 0.6406
7 "g"	0.8293 0.3249
8 "h"	0.4479 0.6866
9 "i"	0.8204 0.8203
10 "j"	0.4789 0.9055
11 "k"	0.1175 0.9032
12 "l"	0.7095 0.6475

*Arcs	
1	2
2	1
1	4
1	6
2	6
3	2
3	3
3	7
3	7
5	3
5	6
5	8
6	11
8	4
10	8
12	5
12	7
8	12
12	8

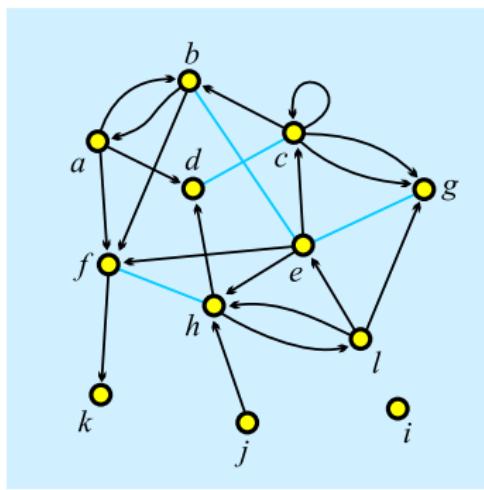
*Edges	
2	5
3	4
5	7
6	8

Graph / Matrix – MAT

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	a	b	c	d	e	f	g	h	i	j	k	l
a	0	1	0	1	0	1	0	0	0	0	0	0
b	1	0	0	0	1	1	0	0	0	0	0	0
c	0	1	1	1	0	0	2	0	0	0	0	0
d	0	0	1	0	0	0	0	0	0	0	0	0
e	0	1	1	0	0	1	1	1	0	0	0	0
f	0	0	0	0	0	0	1	0	0	1	0	0
g	0	0	0	0	1	0	0	0	0	0	0	0
h	0	0	0	1	0	1	0	0	0	0	1	0
i	0	0	0	0	0	0	0	0	0	0	0	0
j	0	0	0	0	0	0	0	1	0	0	0	0
k	0	0	0	0	0	0	0	0	0	0	0	0
l	0	0	0	0	1	0	1	1	0	0	0	0

Pajek: local: [GraphMat](#); [TinaMat](#), picture [picture](#);
WWW: [GraphMat / net](#); [TinaMat / net](#), [paj](#).

Graph G is *simple* if in the corresponding matrix all entries are 0 or 1.

Graph / Matrix – MAT

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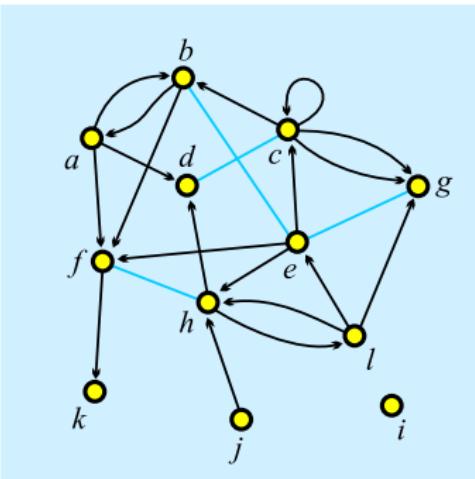
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*Vertices	12
1 "a"	0.1020
2 "b"	0.2860
3 "c"	0.5322
4 "d"	0.3259
5 "e"	0.5543
6 "f"	0.1552
7 "g"	0.8293
8 "h"	0.4479
9 "i"	0.8204
10 "j"	0.4789
11 "k"	0.1175
12 "l"	0.7095

*Matrix	0 1 0 1 0 1 0 0 0 0 0 0
0 1 0 0 0 1 1 0 0 0 0 0 0	1 0 0 0 0 1 1 0 0 0 0 0 0
0 1 1 1 0 0 2 0 0 0 0 0 0	0 1 1 1 0 0 1 1 1 0 0 0 0
0 0 1 0 0 0 0 0 0 0 0 0 0	0 0 1 0 0 0 0 0 0 0 0 0 0
0 1 1 0 0 1 1 1 0 0 0 0 0	0 0 0 0 0 0 0 1 0 0 0 1 0
0 0 0 0 0 0 0 0 1 0 0 0 0	0 0 0 0 1 0 0 0 0 0 0 0 0
0 0 0 0 1 0 0 0 0 0 0 0 0	0 0 0 0 0 1 0 0 0 0 0 0 0
0 0 0 0 0 1 0 0 0 0 0 0 0	0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0 0 0 0 1 0 0 0 0 0 0	0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0 0 0 0 0 1 0 0 0 0 0	0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 1 0 1 1 0 0 0 0	0 0 0 0 0 1 0 1 1 0 0 0 0

Node Properties / CLU, VEC, PER

All three types of files have the same structure:

*vertices n

n is the number of nodes

v_1

node 1 has value v_1

...

v_n

CLUstering – partition of nodes – *nominal* or *ordinal* data about nodes

$v_i \in \mathbb{N}$: node i belongs to the cluster/group v_i ;

VEctor – *numeric* data about nodes

$v_i \in \mathbb{R}$: the property has value v_i on node i ;

PERmutation – *ordering* of nodes

$v_i \in \mathbb{N}$: node i is at the v_i -th position.

When collecting the network data consider to provide as much properties as possible.

Example: Wolfe Monkey Data

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inter.net	inter.net	sex.clu	age.vec	rank.per
*Vertices 20		*vertices 20	*vertices 20	*vertices 20
1 "m01"	1 6 5	1	15	1
2 "m02"	1 7 9	1	10	2
3 "m03"	1 8 7	1	10	3
4 "m04"	1 9 4	1	8	4
5 "m05"	1 10 3	1	7	5
6 "f06"	1 11 3	2	15	10
7 "f07"	1 12 7	2	5	11
8 "f08"	1 13 3	2	11	6
9 "f09"	1 14 2	2	8	12
10 "f10"	1 15 5	2	9	9
11 "f11"	1 16 1	2	16	7
12 "f12"	1 17 4	2	10	8
13 "f13"	1 18 1	2	14	18
14 "f14"	2 3 5	2	5	19
15 "f15"	2 4 1	2	7	20
16 "f16"	2 5 3	2	11	13
17 "f17"	2 6 1	2	7	14
18 "f18"	2 7 4	2	5	15
19 "f19"	2 8 2	2	15	16
20 "f20"	2 9 6	2	4	17
*Edges				
1 2 2	2 11 5			
1 3 10	2 12 4			
1 4 4	2 13 3			
- - -	2 14 2			
	...			

Important note: 0 is not allowed as node number.

Pajek's Project File / PAJ

All types of data can be combined into a single file – Pajek's **project** file *file.paj*.

The easiest way to do this is:

- read all data files in Pajek,
- compute some additional data,
- delete (dispose) some data,
- save all as a project file with
File/Pajek Project File/Save.

Next time you can restore everything with a single
File/Pajek Project File/Read.

Wolfe network as a (**Pajek's project file**).

Sources of networks

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Indexes and repositories

- ICON - The Colorado Index of Complex Networks
- Netzschleuder
- Network Data Repository
- Kaggle
- UCI Network Data Repository
- KONECT - Koblenz Network Collection
- Bayesys
- Stanford Large Network Dataset Collection
- Pajek datasets
-

Representations of properties

Properties of nodes \mathcal{P} and links \mathcal{W} can be measured in different scales: numerical, ordinal and nominal. They can be *input* as data or *computed* from the network.

In **Pajek** numerical properties of nodes are represented by *vectors*, nominal properties by *partitions* or as *labels* of nodes. Numerical property can be displayed as *size* (width and height) of node (figure), as its *coordinate*; and a nominal property as *color* or *shape* of the figure, or as a node's *label* (content, size and color).

We can assign in **Pajek** numerical values to links. They can be displayed as *value*, *thickness* or *grey level*. Nominal values can be assigned as *label*, *color* or *line pattern* (see **Pajek manual**, section **4.3**).

Some related operations

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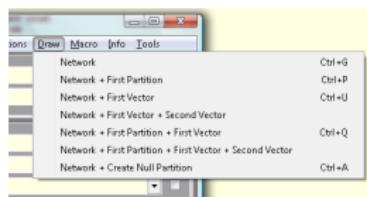
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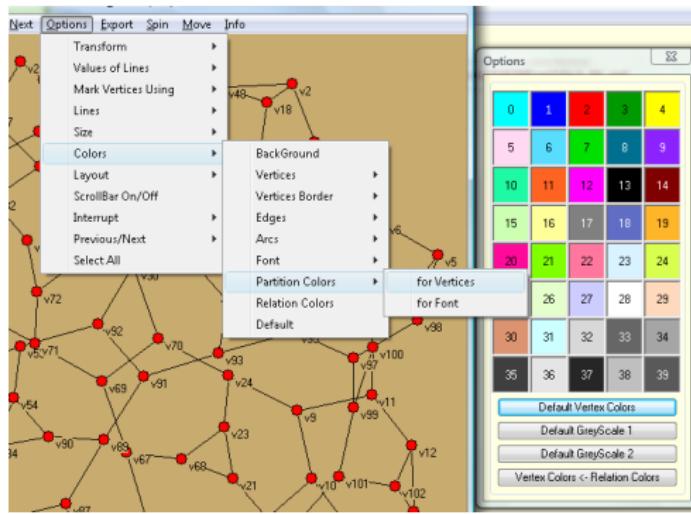
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Operations/Network+Vector/Transform/Put
Network/Create Vector/Get Coordinate
[Draw] Options
[Draw] Layout/Energy/Kamada-Kawai/Free
[Draw] Export/2D/EPS-PS



"Countryside" school district

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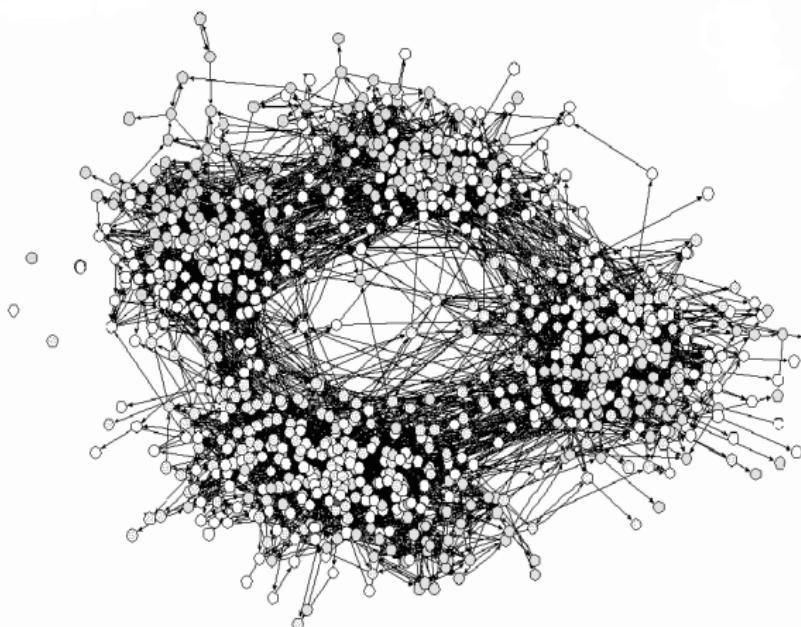
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James Moody (2001) AJS Vol 107, 3,679–716, friendship relation

Only small or sparse networks can be displayed readable.

On large networks graph drawing algorithms can reveal their overall structure.

Can we explain the obtained structure?

Visualization:
initial network exploration,
reporting results,
story telling.

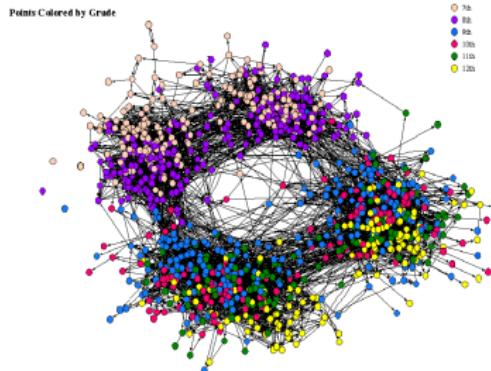
Display of properties – school (Moody)

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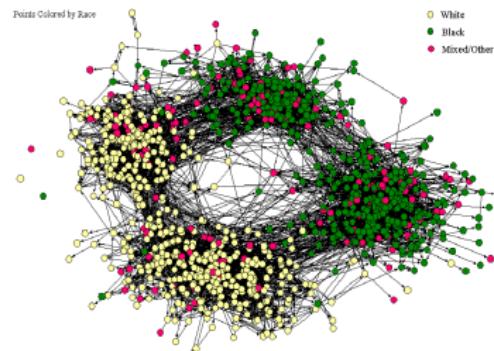
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The Social Structure of "Countryside" School District



The Social Structure of "Countryside" School District



Besides the graph, we need data to understand the network!

A display of World Trade 1999 network

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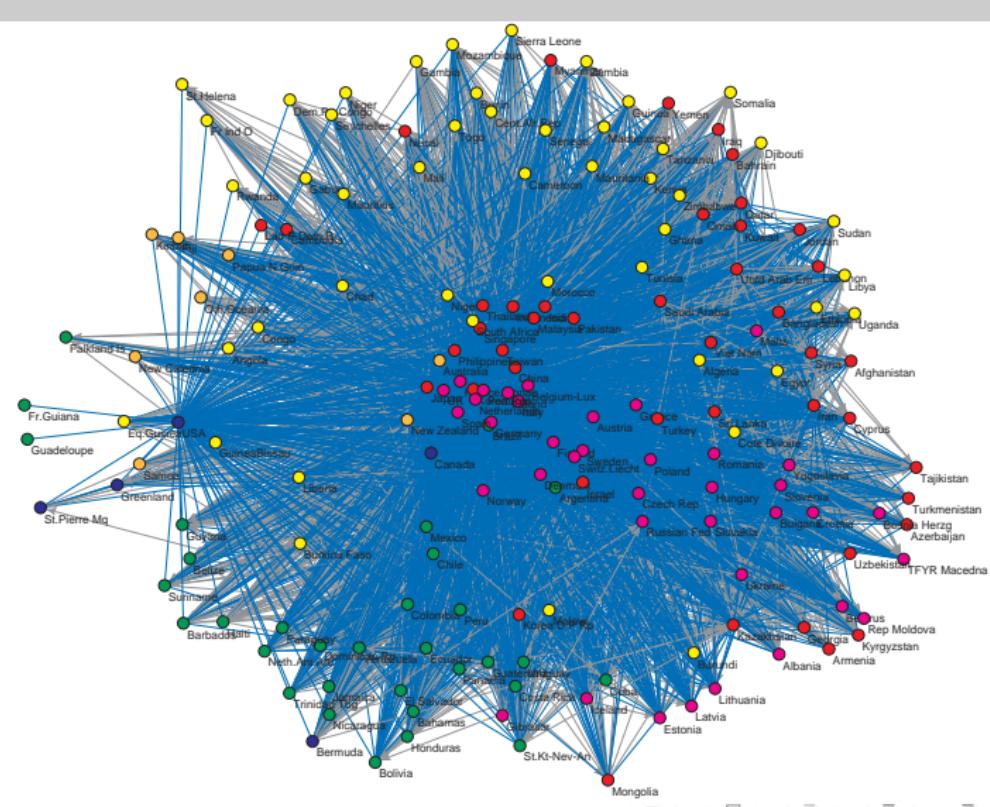
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Matrix display of World Trade 1999 network

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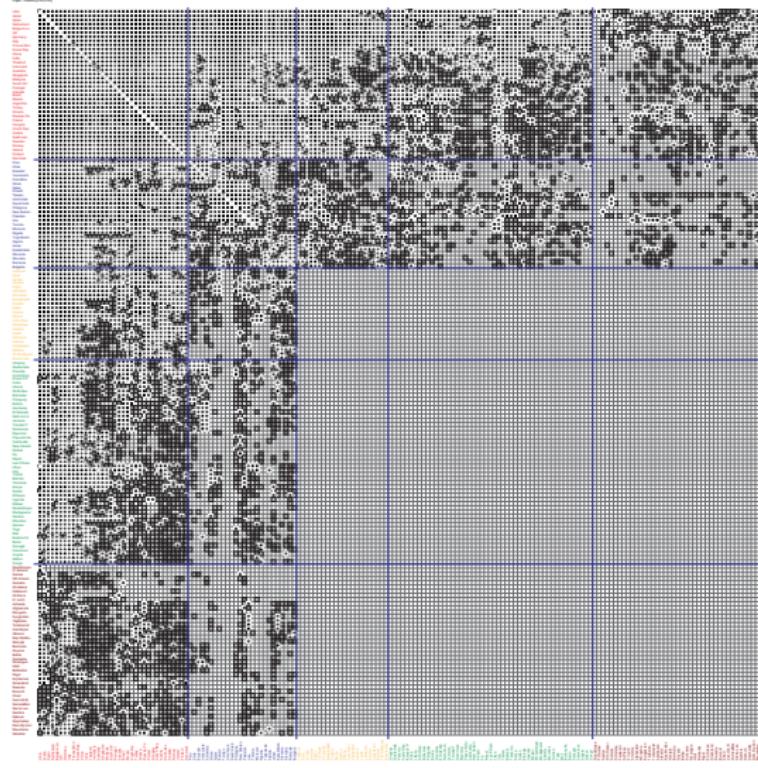
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World trade 1999 clustering

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Feenstra, RC, Lipsey, RE, Deng, H, Ma, AC, Mo, H: **World Trade Flows: 1962-2000; info → weights in 1000 USD.**

```
read World Trade 1999 Pajek project file
button Info network
Network/Info/Line values
Network/Create new network/Transform/Line values/Ln
Network/Create Vector/Centrality/Weighted degree/All
Vector/Make permutation
Permutation/Mirror permutation
File/Network/Export as matrix/EPS/Using permutation

Cluster/Create complete cluster
Operations/Network+cluster/Dissimilarity*/Network based/
    d5 [1]
manually reorder and close hierarchy
Hierarchy/Make partition
Hierarchy/Make permutation
select ln network as the First
File/Network/Export as matrix/EPS/Using
    permutation+partition
```

Types of networks

Besides ordinary (directed, undirected, mixed) networks some extended types of networks are also used:

- ***2-mode networks***, bipartite (valued) graphs – networks between two disjoint sets of nodes $\mathbf{N} = ((\mathcal{U}, \mathcal{V}), \mathcal{L}, \mathcal{P}, \mathcal{W})$
- ***multi-relational networks*** $\mathbf{N} = (\mathcal{V}, (\mathcal{L}_1, \mathcal{L}_2, \dots, \mathcal{L}_k), \mathcal{P}, \mathcal{W})$
- ***temporal networks***, dynamic graphs – networks changing over time $\mathbf{N}_T = (\mathcal{V}, \mathcal{L}, \mathcal{P}, \mathcal{W}, T)$
- specialized networks: representation of genealogies as ***p-graphs***; ***Petri's nets***, ...

The network (input) file formats should provide means to express all these types of networks. All interesting data should be recorded (respecting privacy).

Pictures in SVG: **66 days**.

Multi-relational temporal network – KEDS/WEIS

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```
% Recoded by WEISmonths, Sun Nov 28 21:57:00 2004
% from http://www.ku.edu/~keds/data.dir/balk.html
*vertices 325
1 "AFG" [1-*]
2 "AFR" [1-*]
3 "ALB" [1-*]
4 "ALBMED" [1-*]
5 "ALG" [1-*]

318 "YUGGOV" [1-*]
319 "YUGMAC" [1-*]
320 "YUGMED" [1-*]
321 "YUGMTN" [1-*]
322 "YUGSER" [1-*]
323 "ZAI" [1-*]
324 "ZAM" [1-*]
325 "ZIM" [1-*]

*arcs :0 "**** ABANDONED"
*arcs :10 "YIELD"
*arcs :11 "SURRENDER"
*arcs :12 "RETREAT"
...
*arcs :223 "MIL ENGAGEMENT"
*arcs :224 "RIOT"
*arcs :225 "ASSASSINATE TORTURE"
*arcs
224: 314 153 1 [4] 890402 YUG KSV 224 (RIOT) RIOT-TORN
212: 314 83 1 [4] 890404 YUG ETHALB 212 (ARREST PERSON) ALB ETHNI
224: 3 83 1 [4] 890407 ALB ETHALB 224 (RIOT) RIOTS
123: 83 153 1 [4] 890408 ETHALB KSV 123 (INVESTIGATE) PROBING

42: 105 63 1 [175] 030731 GER CYP 042 (ENDORSE) GAVE SUPPORT
212: 295 35 1 [175] 030731 UNWCT BOSSER 212 (ARREST PERSON) SENTENCED
43: 306 87 1 [175] 030731 VAT EUR 043 (RALLY) RALLIED
13: 295 35 1 [175] 030731 UNWCT BOSSER 013 (RETRACT) CLEARED
121: 295 22 1 [175] 030731 UNWCT BAL 121 (CRITICIZE) CHARGES
122: 246 295 1 [175] 030731 SER UNWCT 122 (DENIGRATE) TESTIFIED
121: 35 295 1 [175] 030731 BOSSER UNWCT 121 (CRITICIZE) ACCUSED
```

Kansas Event Data System *KEDS*



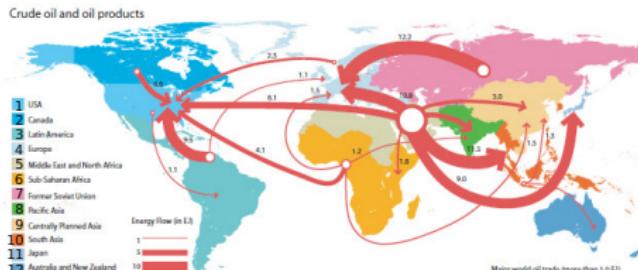
Task1: Example Oil trade

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Let's describe in Pajek format the network in picture wNet21.jpeg.
First we number the nodes (vertices)



Then we prepare the NET file oilTrade.net. Two arcs are without value - we guess it from the arc's thickness.

We read the network in Pajek and draw it Draw/Network. Manually move the nodes to the "right" places. Set thickness on [Draw]Options/Lines/Different widths. Set the size of links [Draw]Options/Size/Of lines [1] and the size of arrows [Draw]Options/Size/Of arrows [3]. Export the picture. Save the network with picture coordinates File/Network/Save [oilTradeXY.net].

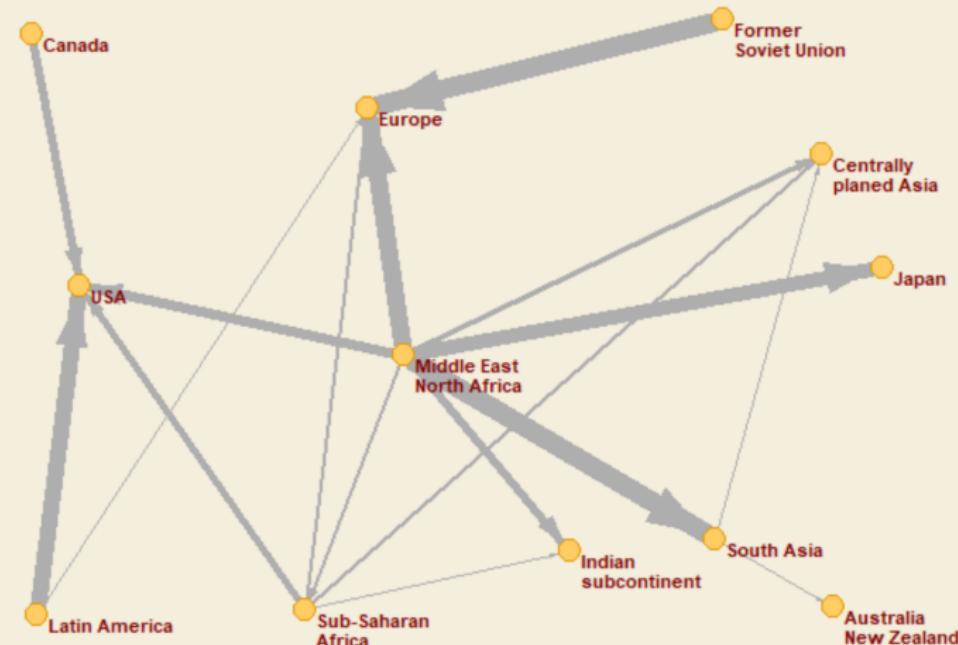
```
% Oil trade (more than 1 EJ)
% Pajek format by Vladimir Batagelj
% Spinaker summer school, Krakow 2023
*vertices 12
1 "USA"
2 "Canada"
3 "Latin America"
4 "Europe"
5 "Middle East\nNorth Africa"
6 "Sub-Saharan\nAfrica"
7 "Former\nSoviet Union"
8 "Indian\nsubcontinent"
9 "Centrally\nplanned Asia"
10 "South Asia"
11 "Japan"
12 "Australia\nNew Zealand"
*arcs
1 3 1.1
2 1 4.6
3 1 9.5
3 4 1.1
5 1 6.1
5 4 10.8
5 6 1.8
5 8 5.0
5 9 3.0
5 10 11.5
5 11 9.0
6 4 1.5
6 1 4.1
6 9 1.5
6 8 1.2
7 4 12.2
10 9 1.3
10 12 1.0
```

Task 1

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Important nodes and links in network

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To identify important / interesting elements (nodes, links) in a network we often try to express our intuition about important / interesting elements using an appropriate measure (index, weight) following the scheme

*larger is the measured value of an element,
more important / interesting is this element*

Too often, in the analysis of networks, researchers uncritically pick some measures from the literature. For a formal approach see **Roberts**.

The (importance) measure can be obtained as input data – an **observed** property, or computed from the network description – a **structural** property.

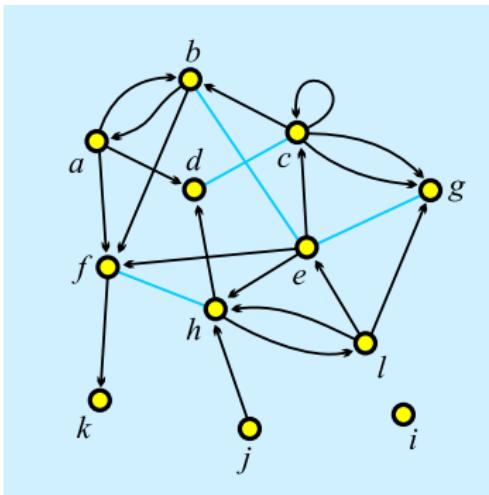
An interesting question is studying associations among structural and observed properties. Can an observed property be explained with some structural property/ies?

Degrees

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degree of node v , $\deg(v)$ = number of links with v as an endnode;

indegree of node v , $\text{indeg}(v)$ = number of links with v as a terminal node (endnode is both initial and terminal);

outdegree of node v , $\text{outdeg}(v)$ = number of links with v as an initial node.

initial node $v \Leftrightarrow \text{indeg}(v) = 0$

terminal node $v \Leftrightarrow \text{outdeg}(v) = 0$

$$n = 12, m = 23, \text{indeg}(e) = 3, \text{outdeg}(e) = 5, \deg(e) = 6$$

$$\sum_{v \in \mathcal{V}} \text{indeg}(v) = \sum_{v \in \mathcal{V}} \text{outdeg}(v) = |\mathcal{A}| + 2|\mathcal{E}| - |\mathcal{E}_0|, \sum_{v \in \mathcal{V}} \deg(v) = 2|\mathcal{L}| - |\mathcal{L}_0|$$

Node indices

The most important distinction between different node *indices* is based on the view/decision of whether the network is considered directed or undirected.

Closeness, betweenness, clustering, eigen-vector, ...

Weighted degree, indegree and outdegree

$$\text{wdeg}(v) = \sum_{e \in \text{star}(v)} w(e),$$

$$\text{windeg}(v) = \sum_{e \in \text{instar}(v)} w(e) \quad \text{and} \quad \text{woutdeg}(v) = \sum_{e \in \text{outstar}(v)} w(e)$$

Hubs and authorities

To each node v of a network $\mathbf{N} = (\mathcal{V}, \mathcal{L})$ we assign two values: quality of its content (*authority*) x_v and quality of its references (*hub*) y_v .

A good authority is selected by good hubs; and good hub points to good authorities (see [Kleinberg](#)).

$$x_v = \sum_{u:(u,v) \in \mathcal{L}} y_u \quad \text{and} \quad y_v = \sum_{u:(v,u) \in \mathcal{L}} x_u$$

Let \mathbf{W} be a matrix of network \mathbf{N} and \mathbf{x} and \mathbf{y} authority and hub vectors. Then we can write these two relations as $\mathbf{x} = \mathbf{W}^T \mathbf{y}$ and $\mathbf{y} = \mathbf{W} \mathbf{x}$.

We start with $\mathbf{y} = [1, 1, \dots, 1]$ and then compute new vectors \mathbf{x} and \mathbf{y} . After each step we normalize both vectors. We repeat this until they stabilize.

We can show that this procedure converges. The limit vector \mathbf{x}^* is the principal eigen vector of matrix $\mathbf{W}^T \mathbf{W}$; and \mathbf{y}^* of matrix $\mathbf{W} \mathbf{W}^T$.

... Hubs and authorities: football

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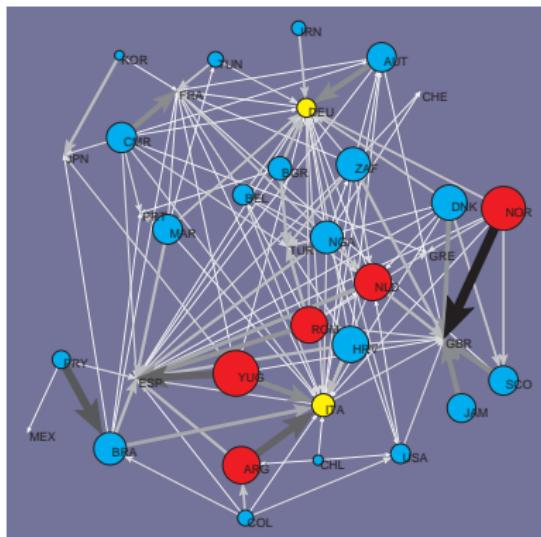
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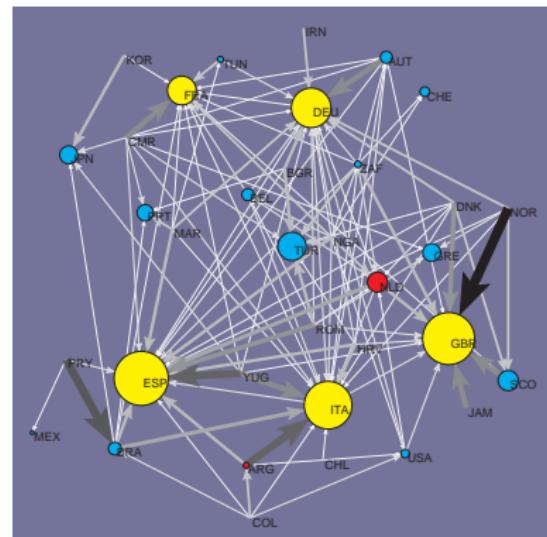
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Exporters (hubs)



Importers (authorities)

Example: Krebs, [Krempl](#). World Cup 1998 in Paris, 22 national teams. A player from first country is playing in the second country.

Important links – Weighted networks

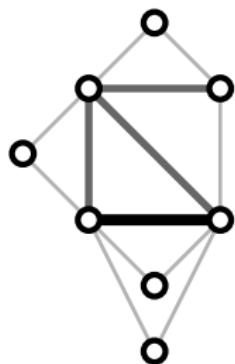
A very important characteristic of weight is its nature – should it be considered a *similarity* (larger is the link weight more similar are its end-nodes) or a *dissimilarity* (larger is the link weight more different are its end-nodes; weight for links with equal end-nodes is usually 0)?

Structural weights are computed based on network structure. For example

$$w(e(u, v)) = \deg(u) \cdot \deg(v)$$

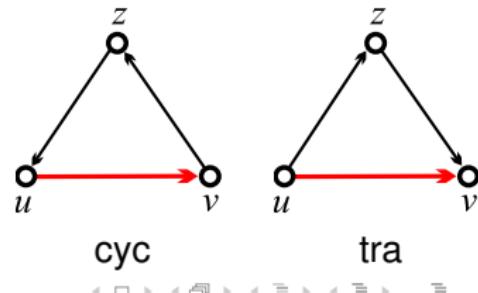
More substantial weights exist.

Triangular network



Let \mathbf{G} be a simple undirected graph. A *triangular network* $\mathbf{N}_T(\mathbf{G}) = (\mathcal{V}, \mathcal{E}_T, w)$ determined by \mathbf{G} is a subgraph $\mathbf{G}_T = (\mathcal{V}, \mathcal{E}_T)$ of \mathbf{G} whose set of edges \mathcal{E}_T consists of all triangular edges of $\mathcal{E}(\mathbf{G})$. For $e \in \mathcal{E}_T$ the weight $w(e)$ equals to the number of different triangles in \mathbf{G} to which e belongs. Triangular networks can be used to efficiently identify dense clique-like parts of a graph. If an edge e belongs to a k -clique in \mathbf{G} then $w(e) \geq k - 2$.

If a graph \mathbf{G} is mixed we replace edges with pairs of opposite arcs. Let $\mathbf{G} = (\mathcal{V}, \mathcal{A})$ be a simple directed graph without loops. For a selected arc $(u, v) \in \mathcal{A}$ there are only two different types of directed triangles: **cyclic** and **transitive**.



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To a simple (no parallel arcs) two-mode **network** $\mathbf{N} = (\mathcal{I}, \mathcal{J}, \mathcal{A}, w)$; where \mathcal{I} and \mathcal{J} are sets of **nodes**, \mathcal{A} is a set of **arcs** linking \mathcal{I} and \mathcal{J} , and $w : \mathcal{A} \rightarrow \mathbb{R}$ (or some other semiring) is a **weight**; we can assign a **network matrix** $\mathbf{W} = [w_{i,j}]$ with elements: $w_{i,j} = w(i,j)$ for $(i,j) \in \mathcal{A}$ and $w_{i,j} = 0$ otherwise.

Given a pair of compatible networks $\mathbf{N}_A = (\mathcal{I}, \mathcal{K}, \mathcal{A}_A, w_A)$ and $\mathbf{N}_B = (\mathcal{K}, \mathcal{J}, \mathcal{A}_B, w_B)$ with corresponding matrices $\mathbf{A}_{\mathcal{I} \times \mathcal{K}}$ and $\mathbf{B}_{\mathcal{K} \times \mathcal{J}}$ we call a **product of networks** \mathbf{N}_A and \mathbf{N}_B a network $\mathbf{N}_C = (\mathcal{I}, \mathcal{J}, \mathcal{A}_C, w_C)$, where $\mathcal{A}_C = \{(i,j) : i \in \mathcal{I}, j \in \mathcal{J}, c_{i,j} \neq 0\}$ and $w_C(i,j) = c_{i,j}$ for $(i,j) \in \mathcal{A}_C$. The product matrix $\mathbf{C} = [c_{i,j}]_{\mathcal{I} \times \mathcal{J}} = \mathbf{A} * \mathbf{B}$ is defined in the standard way

$$c_{i,j} = \sum_{k \in \mathcal{K}} a_{i,k} \cdot b_{k,j}$$

In the case when $\mathcal{I} = \mathcal{K} = \mathcal{J}$ we are dealing with ordinary one-mode networks (with square matrices).

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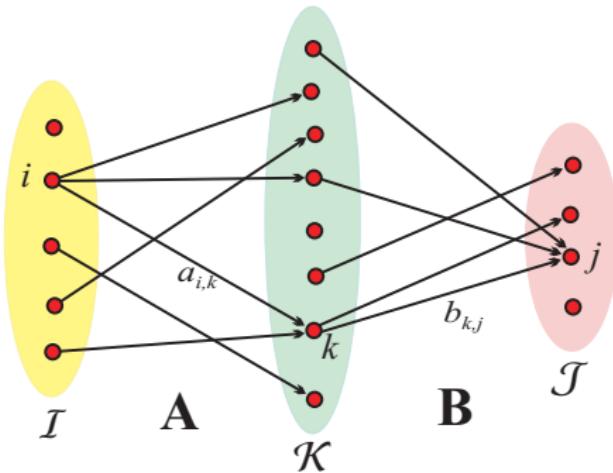
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$$c_{i,j} = \sum_{k \in N_A(i) \cap N_B^-(j)} a_{i,k} \cdot b_{k,j}$$

If all weights in networks \mathbf{N}_A and \mathbf{N}_B are equal to 1 the value of $c_{i,j}$ counts the number of ways we can go from $i \in \mathcal{I}$ to $j \in \mathcal{J}$ passing through \mathcal{K} , $c_{i,j} = |N_A(i) \cap N_B^-(j)|$.

Multiplication of networks

The standard matrix multiplication has the complexity $O(|\mathcal{I}| \cdot |\mathcal{K}| \cdot |\mathcal{J}|)$ – it is too slow to be used for large networks. For sparse large networks we can multiply much faster considering only nonzero elements.

```
for k in K do
    for (i,j) in N_A^-(k) × N_B(k) do
        if ∃ c_{i,j} then c_{i,j} := c_{i,j} + a_{i,k} · b_{k,j}
        else new c_{i,j} := a_{i,k} · b_{k,j}
```

Networks/Multiply Networks

In general the multiplication of large sparse networks is a 'dangerous' operation since the result can 'explode' – it is not sparse.

Multiplication of networks

From the network multiplication algorithm we see that each intermediate node $k \in \mathcal{K}$ adds to a product network a complete two-mode subgraph $K_{N_A^-(k), N_B(k)}$ (or, in the case $\mathcal{I} = \mathcal{J}$, a complete subgraph $K_{N(k)}$). If both degrees $\deg_A(k) = |N_A^-(k)|$ and $\deg_B(k) = |N_B(k)|$ are large then already the computation of this complete subgraph has a quadratic (time and space) complexity – the result 'explodes'.

If at least one of the sparse networks \mathbf{N}_A and \mathbf{N}_B has small maximal degree on \mathcal{K} then also the resulting product network \mathbf{N}_C is sparse.

If for the sparse networks \mathbf{N}_A and \mathbf{N}_B there are in \mathcal{K} only few nodes with large degree and no one among them with large degree in both networks then also the resulting product network \mathbf{N}_C is sparse.

Projections of two-mode networks

Often we transform a two-mode network $\mathbf{N} = (\mathcal{U}, \mathcal{V}, \mathcal{E}, w)$ into an ordinary (one-mode) network $\mathbf{N}_1 = (\mathcal{U}, \mathcal{E}_1, w_1)$ or/and

$\mathbf{N}_2 = (\mathcal{V}, \mathcal{E}_2, w_2)$, where \mathcal{E}_1 and w_1 are determined by the matrix $\mathbf{W}^{(1)} = \mathbf{W}\mathbf{W}^T$,

$$w_{uv}^{(1)} = \sum_{z \in \mathcal{V}} w_{uz} \cdot w_{zv}^T = \sum_{z \in \mathcal{V}} w_{uz} \cdot w_{vz}.$$

Evidently $w_{uv}^{(1)} = w_{vu}^{(1)}$. There is an edge $(u : v) \in \mathcal{E}_1$ in \mathbf{N}_1 iff $N(u) \cap N(v) \neq \emptyset$. Its weight is $w_1(u, v) = w_{uv}^{(1)}$.

The network \mathbf{N}_2 is determined in a similar way by the matrix $\mathbf{W}^{(2)} = \mathbf{W}^T\mathbf{W}$.

The networks \mathbf{N}_1 and \mathbf{N}_2 are analyzed using standard methods.

Network/2-Mode Network/2-Mode to 1-Mode/Rows

Derived networks

WA – works \times authors – authorship network

WK – works \times keywords

Ci – works \times works – citation network

AK = **WA**^T * **WK** – authors \times keywords

Co = **WA**^T * **WA** – coauthorship

ACi = **WA**^T * **Ci** * **WA** – citations between authors

co_{ij} = the number of works that authors i and j wrote together

It holds: $co_{ij} = co_{ji}$. Using the weights co_{ij} we can determine the Salton's cosine similarity or Ochiai coefficient between authors i and j as

$$S(i, j) = \cos(i, j) = \frac{co_{ij}}{\sqrt{co_{ii}co_{jj}}}$$

Properties of Salton index

The Salton index has the following properties

- ① $S(i, j) \in [-1, 1]$
- ② $S(i, j) = S(j, i)$
- ③ $S(i, i) = 1$
- ④ $wa_{pi} \in \mathbb{R}_0^+ \Rightarrow S(u, t) \in [0, 1]$
- ⑤ $S(\alpha i, \beta j) = S(i, j), \quad \alpha, \beta > 0$
- ⑥ $S(\alpha i, i) = 1, \quad \alpha > 0$

Normalizations

In networks obtained from large two-mode networks, there are often huge differences in weights. Therefore it is not interesting to compare the nodes according to the raw data – the nodes with large weights will prevail. First, we have to *normalize* the network to make the weights comparable.

There exist several ways how to do this. Some of them are presented in the following. They can be used also on other weighted networks. Often a given weighted network is essentially a projection of a two-mode network; sometimes without loops. Assume that the network is described with a square matrix \mathbf{C} .

Let us denote the row sum $R(u) = \sum_{v \in V} c[u, v]$, which is the total of weights from node u to other nodes. Let $C(v) = \sum_{u \in V} c[u, v]$ denote the column sum for the node v . If the network is a projection of a two-mode network we set $R(u) = C(u) = c[u, u]$.

... Normalizations

Markov (also known as stochastic, affinity, output, row) normalization: For $R(u) > 0$

$$c_M[u, v] = \frac{c[u, v]}{R(u)}$$

If $R(u) = 0$ also $c_M[u, v] = 0$.

Jaccard-like normalization:

$$c_J[u, v] = \frac{c[u, v]}{R(u) + R(v) - c[u, v]}$$

Salton-like normalization:

$$c_S[u, v] = \frac{c[u, v]}{\sqrt{R(u) \cdot R(v)}}$$

... Normalizations

Balassa or activity normalization: Let $T = \sum_{u,v} c[u, v]$ be the total sum of weights in the network.

$$A[u, v] = \frac{c[u, v] \cdot T}{R(u) \cdot C(v)}$$

If $A[u, v] > 1$ the measured weight is larger than expected.

$$c_B[u, v] = \log_2 A[u, v] \quad \text{for } A[u, v] > 0$$

... Normalizations

$$c_{\min}[u, v] = \frac{c[u, v]}{\min(R(u), R(v))} \quad c_{\max}[u, v] = \frac{c_{uv}}{\max(c_{uu}, c_{vv})}$$

$$c_{\min\text{Dir}}[u, v] = \begin{cases} \frac{c[u, v]}{R(u)} & R(u) \leq R(v) \\ 0 & \text{otherwise} \end{cases}$$

$$c_{\max\text{Dir}}[u, v] = \begin{cases} \frac{c[u, v]}{R(v)} & R(u) \leq R(v) \\ 0 & \text{otherwise} \end{cases}$$

After a selected normalization the important parts of the network are obtained by link-cuts or islands approaches.

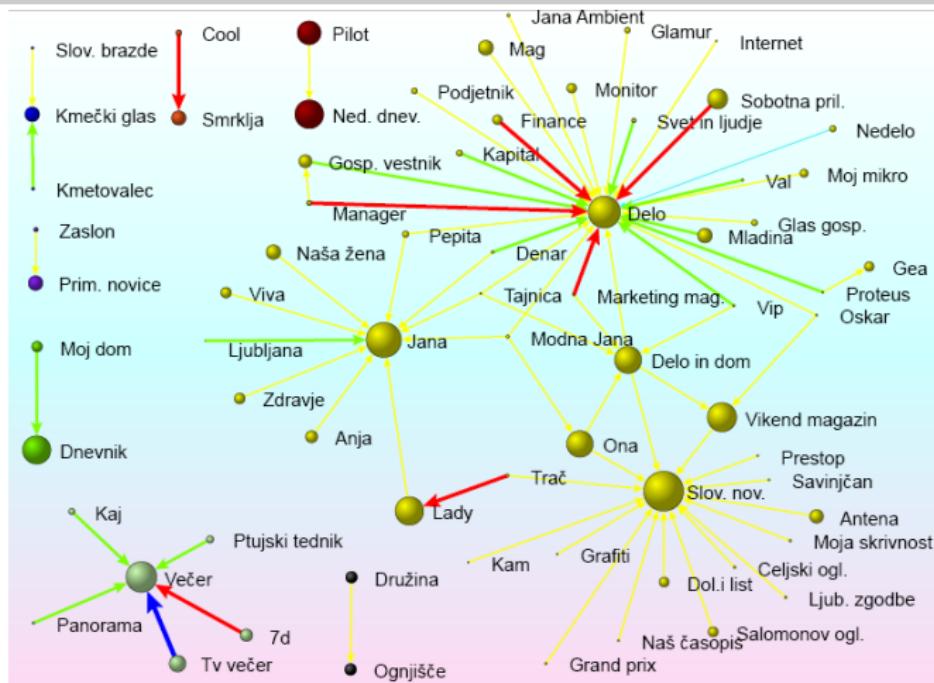
Reuters Terror News: **GeoDeg**, **MaxDir**, **MinDir**. Slovenian journals.

minDir of Slovenian journals 2000

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Over 100000 people were asked in the years 1999 and 2000 about the journals they read.
They mentioned 124 different journals. (source Cati)

Normalized co-authorship network

Let \mathbf{N} be the normalized version $\forall p \in W : \sum_{i \in A} n_{pi} \in \{0, 1\}$ obtained from \mathbf{WA} by $n_{pi} = wa_{pi} / \max(1, \text{outdeg}_{\mathbf{WA}}(p))$, or by some other rule determining the author's contribution – the *fractional* approach. Then the *normalized co-authorship network* is

$$\mathbf{Cn} = \mathbf{N}^T \cdot \mathbf{N}$$

$cn_{ij} =$ the total contribution of ‘collaboration’ of authors i and j to works.

It holds $cn_{ij} = cn_{ji}$ and $\sum_{i \in A} \sum_{j \in A} n_{pi} n_{pj} = 1$.

The total contribution of a complete subgraph corresponding to the authors of a work p is 1.

$$\sum_{i \in A} \sum_{j \in A} cn_{ij} = |W|$$

Normalized strict co-authorship network

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Newman defined a *strict normalization* \mathbf{N}' obtained from \mathbf{WA} by $n'_{pi} = wa_{pi} / \max(1, \text{outdeg}_{\mathbf{WA}}(p) - 1)$. Then the *normalized strict co-authorship network* is

$$\mathbf{Cn}' = \mathbf{N}'^T \cdot \mathbf{N}'$$

The diagonal (loops) of the so-obtained network \mathbf{Cn}' is set to 0.

The network \mathbf{Cn}' doesn't consider the contribution of single-author works.

Size of network

The size of a network/graph is expressed by two numbers:
number of nodes $n = |\mathcal{V}|$ and number of links $m = |\mathcal{L}|$.

In a *simple undirected* graph (no parallel edges, no loops)
 $m \leq \frac{1}{2}n(n - 1)$; and in a *simple directed* graph (no parallel arcs)
 $m \leq n^2$.

Small networks (some tens of nodes) – can be represented by a picture and analyzed by many algorithms (**UCINET**, **NetMiner**).

Also, *middle size* networks (some hundreds of nodes) can still be represented by a picture (!?), but some analytical procedures can't be used.

Till 1990 most networks were small – they were collected by researchers using surveys, observations, archival records, ... The advances in IT allowed to create networks from the data already available in the computer(s). *Large* networks became reality. Large networks are too big to be displayed in detail; special

Large networks

Large network – several thousands or millions of nodes. Can be stored in the computer's memory – otherwise **huge** network. 64-bit computers!

Jure Leskovec: SNAP – Stanford Large Network Dataset Collection

• Social networks

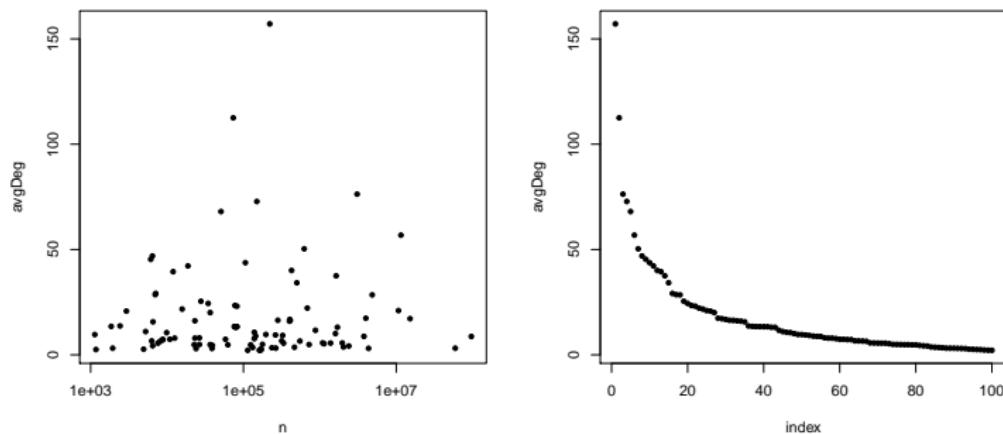
Name	Type	Nodes	Edges	Description
ego-Facebook	Undirected	4,039	88,234	Social circles from Facebook (anonymized)
ego-Gplus	Directed	107,614	13,673,453	Social circles from Google+
ego-Twitter	Directed	81,306	1,768,149	Social circles from Twitter
soc-Epinions1	Directed	75,879	508,837	Who-trusts-whom network of Epinions.com
soc-LiveJournal1	Directed	4,847,571	68,993,773	LiveJournal online social network
soc-Pokec	Directed	1,632,803	30,622,564	Pokec online social network
soc-Slashdot0811	Directed	77,360	905,468	Slashdot social network from November 2008
soc-Slashdot0922	Directed	82,168	948,464	Slashdot social network from February 2009
wiki-Vote	Directed	7,115	103,689	Wikipedia who-votes-on-whom network

• Networks with ground-truth communities

Name	Type	Nodes	Edges	Communities	Description
com-LiveJournal	Undirected, Communities	3,997,962	34,681,189	287,512	LiveJournal online social network
com-Friendster	Undirected, Communities	65,608,366	1,806,067,135	957,154	Friendster online social network
com-Orkut	Undirected, Communities	3,072,441	117,185,083	6,288,363	Orkut online social network

Dunbar's number

Average degrees of the SNAP and Konect networks



Average degree $\bar{d} = \frac{1}{n} \sum_{v \in V} \deg(v) = \frac{2m}{n}$. Most real-life large networks are **sparse** – the number of nodes and links are of the same order. This property is also known as a **Dunbar's number**.

The basic idea is that if each node has to spend for each link a certain amount of "energy" to maintain the links to selected other nodes then since it has a limited "energy" at its disposal, the number of links should be limited. In human networks, Dunbar's number is between 100 and 150.

Complexity of algorithms

Let us look to time complexities of some typical algorithms:

	T(n)	1.000	10.000	100.000	1.000.000	10.000.000
LinAlg	$O(n)$	0.00 s	0.015 s	0.17 s	2.22 s	22.2 s
LogAlg	$O(n \log n)$	0.00 s	0.06 s	0.98 s	14.4 s	2.8 m
SqrtAlg	$O(n\sqrt{n})$	0.01 s	0.32 s	10.0 s	5.27 m	2.78 h
SqrAlg	$O(n^2)$	0.07 s	7.50 s	12.5 m	20.8 h	86.8 d
CubAlg	$O(n^3)$	0.10 s	1.67 m	1.16 d	3.17 y	3.17 ky

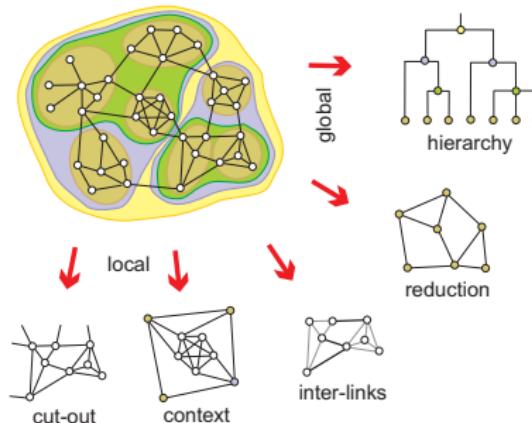
For the interactive use on large graphs already quadratic algorithms, $O(n^2)$, are too slow.

Approaches to large networks

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In the analysis of a *large* network (several thousands or millions of nodes, the network can be stored in computer memory) we can't display it in its totality; also there are only a few algorithms available.

To analyze a large network we can use a statistical approach or we can identify smaller (sub) networks that can be analyzed further using more sophisticated methods.

Measured properties – Input data

- numeric → **vector**
- ordinal → **permutation**
- nominal → **clustering** (partition)

Computed properties

global: number of nodes, edges/arcs, components; maximum core number, ...

local: degrees, cores, indices (betweenness, hubs, authorities, ...)

inspections: partition, vector, values of lines, ...

Associations between computed (structural) data and input (measured) data.

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The global computed properties are reported by **Pajek**'s commands or can be seen using the **Info** option. In *repetitive* commands they are stored in vectors.

The local properties are computed by **Pajek**'s commands and stored in vectors or partitions. To get information about their distribution use the **Info** option.

As an example, let us look at **The Edinburgh Associative Thesaurus** network. The EAT is a network of word associations collected from subjects (students). The weight on the arcs is the count of word associations.

File/Network/Read EATnewSR.net
Info/Network/General

It has 23219 nodes and 325593 arcs (564 loops); number of links with value=1 is 227459; and Average Degree = 28.045 .

... Statistics

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To identify the nodes with the largest degree:

Network/Create vector/Centrality/Degree/All
button Info/Vector +10

The largest degrees have the nodes:

	vertex	deg	label
1	12720	1108	ME
2	12459	1074	MAN
3	8878	878	GOOD
4	18122	875	SEX
5	13793	803	NO
6	13181	799	MONEY
7	23136	732	YES
8	15080	723	PEOPLE
9	13948	720	NOTHING
10	22973	716	WORK

What about indegree and outdegree?

Distribution of weights

Network/Info/Line values

... weighted indegrees

To identify the words selected by the largest number of respondents we look to their weighted indegrees

Network/Create vector/Centrality/Weighted degree/In
button Info/Vector +20

The result is:

	wideg	word		wideg	word	
1	4387	MONEY		11	2019	TREE
2	3299	WATER		12	1988	GOOD
3	2918	FOOD		13	1972	HOUSE
4	2515	ME		14	1896	BIRD
5	2435	MAN		15	1891	UP
6	2434	CAR		16	1881	CHURCH
7	2224	SEA		17	1802	TIME
8	2154	SEX		18	1795	FIRE
9	2100	HORSE		19	1762	SHIP
10	2073	DOG		20	1722	MUSIC

Big picture of EAT at Ars Electronica 2004

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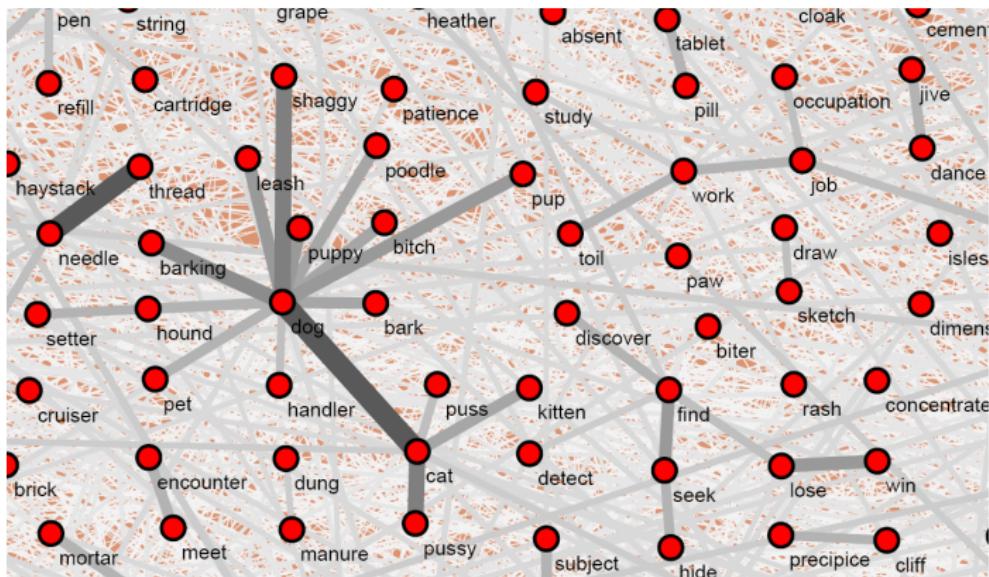
Part of the big picture of EAT

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The glasses in this case are based on ordering the edges in increasing order of their values and drawing them in this order – stronger edges cover the weaker ones. The picture emphasizes the strongest substructures; the remaining elements form a background.



Statistics with **Pajek** and R

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Pajek supports interaction with statistical program R and the use of other external programs as tools (menu Tools).

In **Pajek** we determine the degrees of nodes and submit them to R

Network/Create Vector/Centrality/Degree/All
Tools/R/Send to R/Current Vector

In R we determine their distribution and plot it

```
summary(v2)
t <- table(v2)
x<-as.numeric(names(t))
plot(x,t,log='xy',main='degree distribution',
      xlab='deg',ylab='freq')
```

The obtained picture can be saved with File/Save as in selected format (PDF or PS for L^AT_EX; Windows metafile format for inclusion in Word; SVG for WWW).

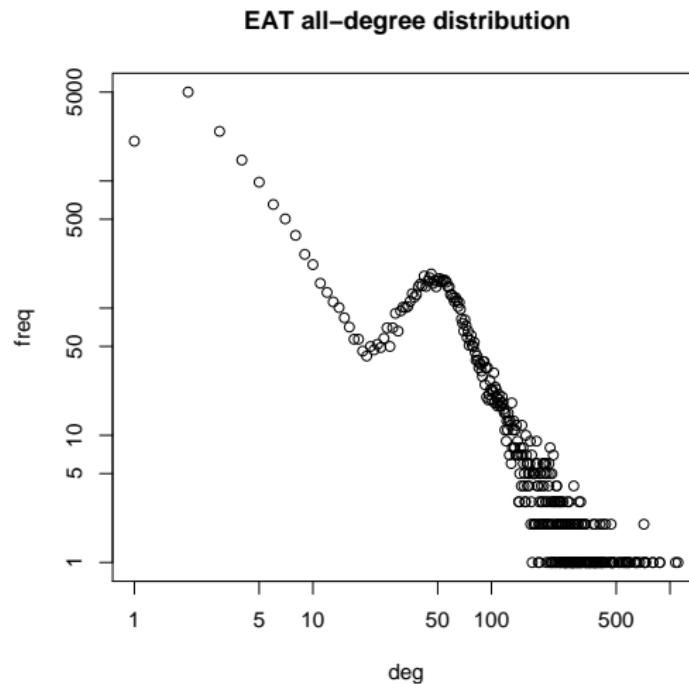
Attention! The nodes of degree 0 make problems with log='xy'.

EAT all-degree distribution

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Erdős and Renyi's random graphs

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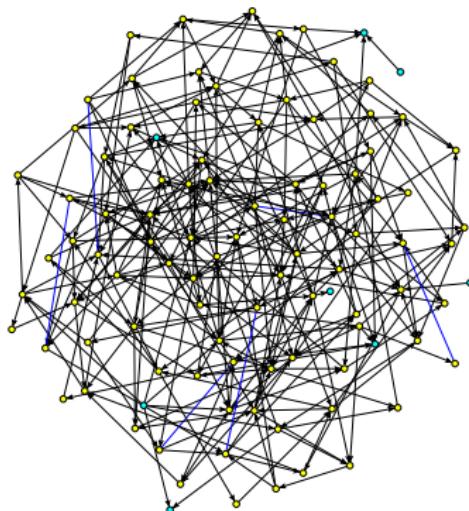
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Erdős and Renyi defined a *random graph* as follows: every possible link is included in a graph with a given probability p .

In **Pajek** instead of probability p a more intuitive average degree is used

$$\overline{\deg} = \frac{1}{n} \sum_{v \in V} \deg(v)$$

Network/Create Random Network/Bernoulli/Poisson/Undirected/General [100] [3]

It holds $p = \frac{m}{m_{\max}}$ and, for simple graphs, also $\overline{\deg} = \frac{2m}{n}$.

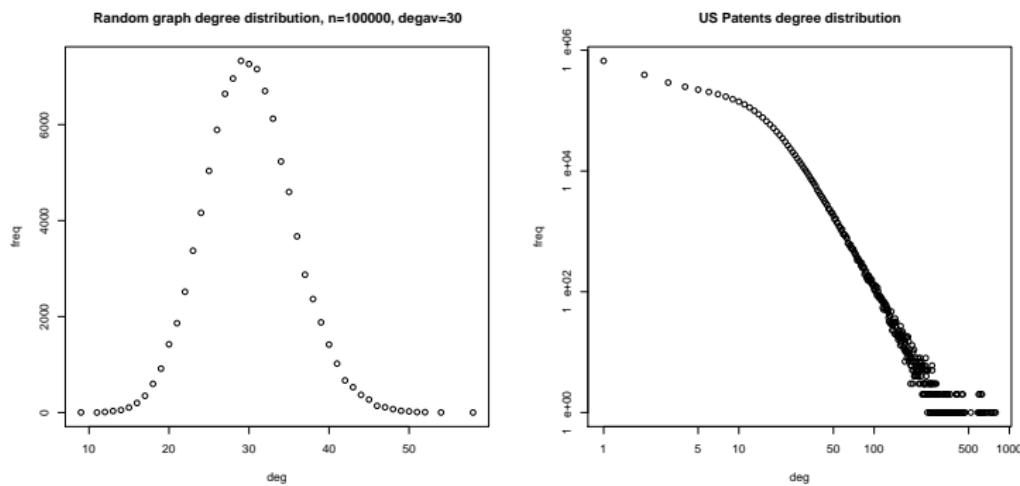
The random graph in the picture has 100 nodes and an average degree 3.

Degree distribution

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Real-life networks are usually not random in the Erdős/Renyi sense. The analysis of their distributions gave a new view about their structure – Watts ([Small worlds](#)), Barabási ([nd/networks](#), [Linked](#)).

in/out-degree distributions

We read in **Pajek** the Centrality citation network `cite.net`. First, we remove loops and multiple links. Then we determine the indegrees and outdegrees and call R from **Pajek** submitting all vectors.

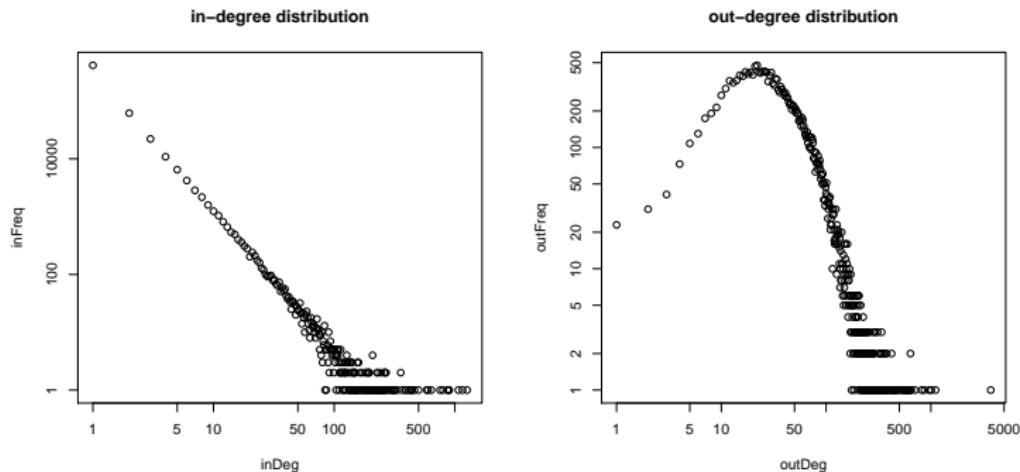
```
#####
# R called from Pajek
The following vectors read:
v1   : Input Degree of N1 (548600)
v2   : Output Degree of N1 (548600)
v3   : All Degree of N1 (548600)
-----
> inTab <- table(v1)
> indeg <- as.integer(names(inTab))
> inDeg <- indeg[indeg>0]
> inFreq <- as.vector(inTab[indeg>0])
> plot(inDeg,inFreq,log='xy',main="in-degree distribution")
> ouTab <- table(v2)
> outdeg <- as.integer(names(ouTab))
> outDeg <- outdeg[outdeg>0]
> outFreq <- as.vector(ouTab[outdeg>0])
> plot(outDeg,outFreq,log='xy',main="out-degree distribution")
```

in/out-degree distributions

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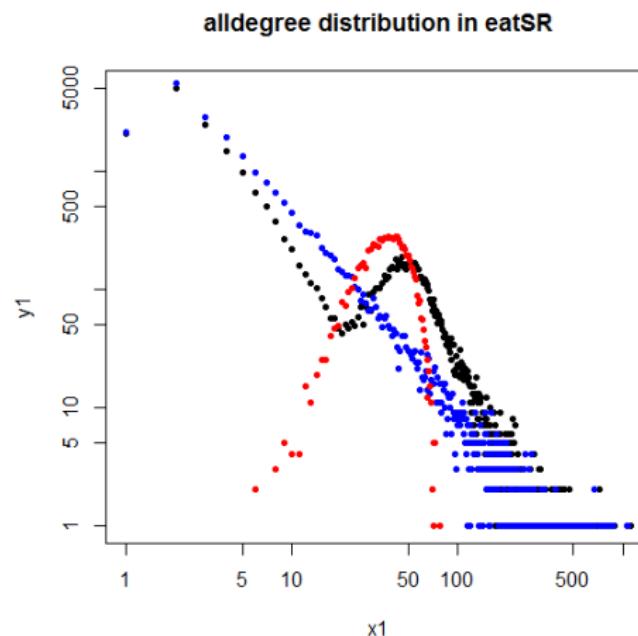
The in-degree distribution is "scale-free"-like – it follows the *power law* $inFreq = k \cdot inDeg^{-\alpha}$. The parameters k and α can be determined using the package of Clauset, Shalizi and Newman. See also Stumpf, et al.: Critical Truths About Power Laws.

EAT all/in/out-degree distributions

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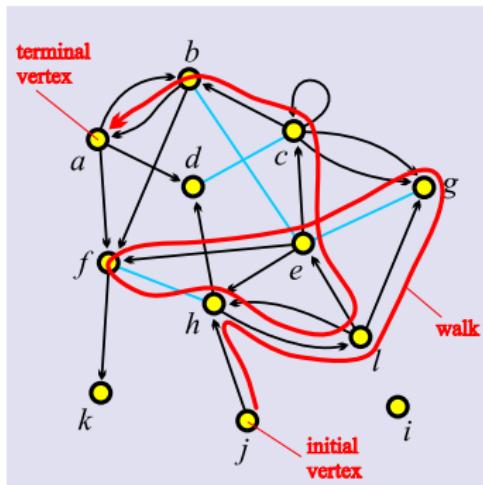
It is important to consider the direction of links!

Walks

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length $|s|$ of the walk s is the number of links it contains.

$$s = (j, h, l, g, e, f, h, l, e, c, b, a)$$
$$|s| = 11$$

A walk is **closed** iff its initial and terminal node coincide.

If we don't consider the direction of the links in the walk we get a **semiwalk** or **chain**.

trail – walk with all links different

path – walk with all nodes different

cycle – closed walk with all internal nodes different

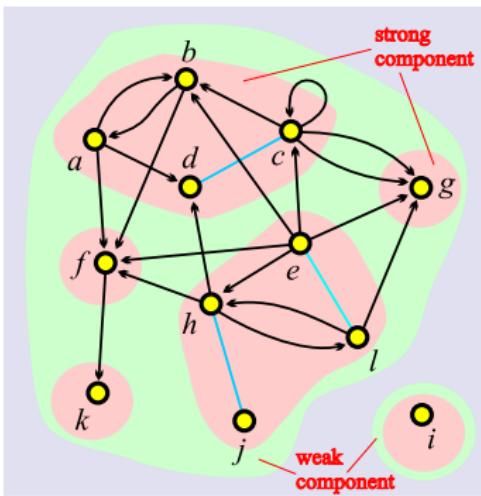
A graph is **acyclic** if it doesn't contain any cycle.

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Node u is *reachable* from node v iff there exists a walk with initial node v and terminal node u .

Node v is *weakly connected* with node u iff there exists a semiwalk with v and u as its end-nodes.

Node v is *strongly connected* with node u iff they are mutually reachable.

Weak and strong connectivity are equivalence relations.

Equivalence classes induce weak/strong *components*.

Network/Create Partition/Components/

Subgraph

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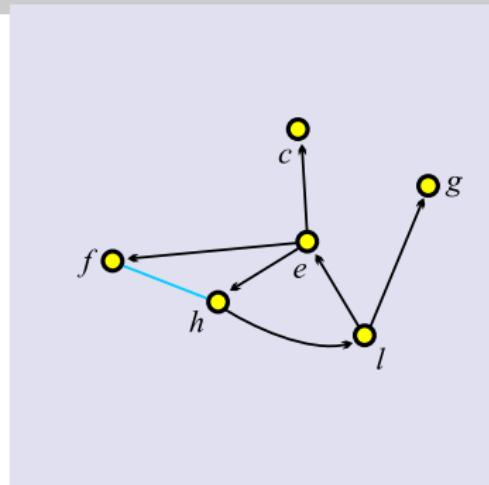
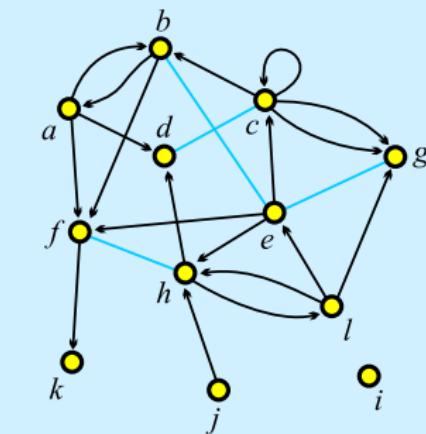
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A **subgraph** $\mathbf{H} = (\mathcal{V}', \mathcal{L}')$ of a given graph $\mathbf{G} = (\mathcal{V}, \mathcal{L})$ is a graph which set of links is a subset of set of links of \mathbf{G} , $\mathcal{L}' \subseteq \mathcal{L}$, its node set is a subset of set of nodes of \mathbf{G} , $\mathcal{V}' \subseteq \mathcal{V}$, and it contains all endnodes of \mathcal{L}' .

A subgraph can be *induced* by a given subset of nodes or links. It is a *spanning* subgraph iff $\mathcal{V}' = \mathcal{V}$.

To obtain a **subnetwork** also the properties/weights have to be restricted to \mathcal{V}' and \mathcal{L}').

Cut-out – induced subgraph: World trade Africa

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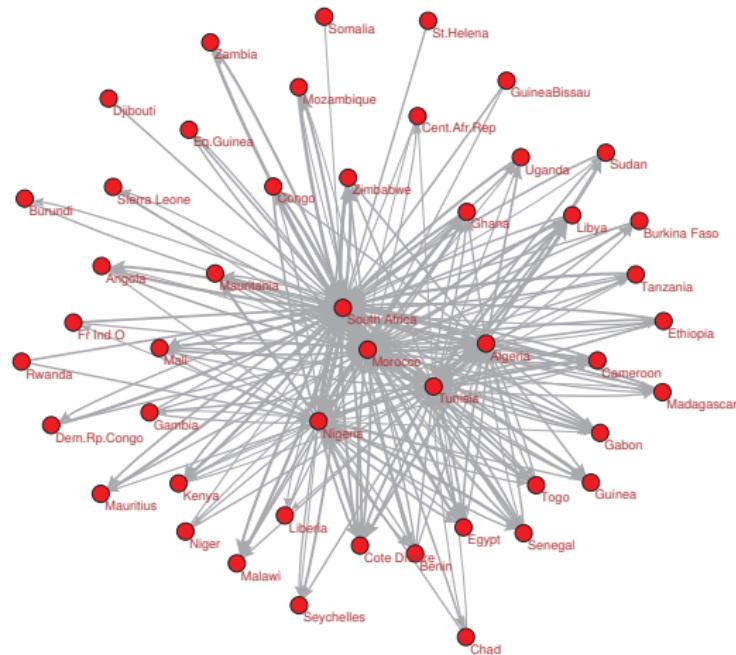
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select Continet 1999 partition as First
Operations/Network+Partition/Extract/Subnetwork [6]

Cut-out: World trade North America : Oceania

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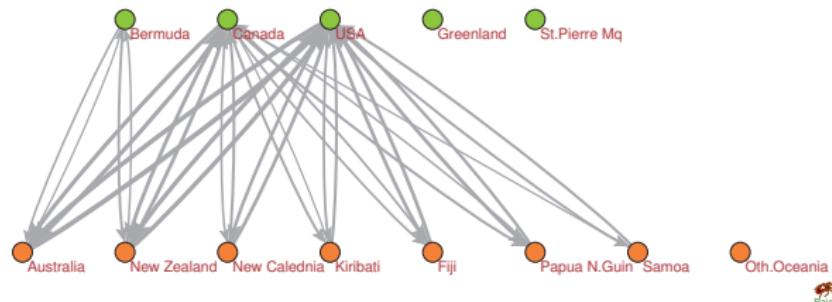
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Operations/Network + Partition/Extract/Subnetwork [2, 7]
Operations/Network + Partition/Transform/Remove lines/
Inside clusters [2, 7]

The nodes can be manually put on a rectangular grid produced by

[Draw] Move/Grid

Cuts

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The standard approach to find interesting groups inside a network is based on properties/weights – they can be *measured* or *computed* from network structure.

The *node-cut* of a network $\mathbf{N} = (\mathcal{V}, \mathcal{L}, p)$, $p : \mathcal{V} \rightarrow \mathbb{R}$, at selected level t is a subnetwork $\mathbf{N}(t) = (\mathcal{V}', \mathcal{L}(\mathcal{V}'), p)$, determined by the set

$$\mathcal{V}' = \{v \in \mathcal{V} : p(v) \geq t\}$$

and $\mathcal{L}(\mathcal{V}')$ is the set of links from \mathcal{L} that have both endnodes in \mathcal{V}' .

The *link-cut* of a network $\mathbf{N} = (\mathcal{V}, \mathcal{L}, w)$, $w : \mathcal{L} \rightarrow \mathbb{R}$, at selected level t is a subnetwork $\mathbf{N}(t) = (\mathcal{V}(\mathcal{L}'), \mathcal{L}', w)$, determined by the set

$$\mathcal{L}' = \{e \in \mathcal{L} : w(e) \geq t\}$$

and $\mathcal{V}(\mathcal{L}')$ is the set of all endnodes of the links from \mathcal{L}' .

Cuts in Pajek

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The threshold value t is determined on the basis of distribution of values of weight w or property p . Usually we are interested in cuts that are not too large, but also not trivial.

Node-cut: p stored in a vector

```
Vector/Info [+30] [#20]
Vector/Make Partition/by Intervals/Selected Thresholds [t]
Operations/Network + Partition/Extract Subnetwork [2]
```

Link-cut: weighted network

```
Network/Info/Line values [#20]
Network/Create New Network/Transform/Remove/Lines with Value/
    lower than [t]
Network/Create Partition/Degree/All
Operations/Network + Partition/Extract Subnetwork [1-*]
```

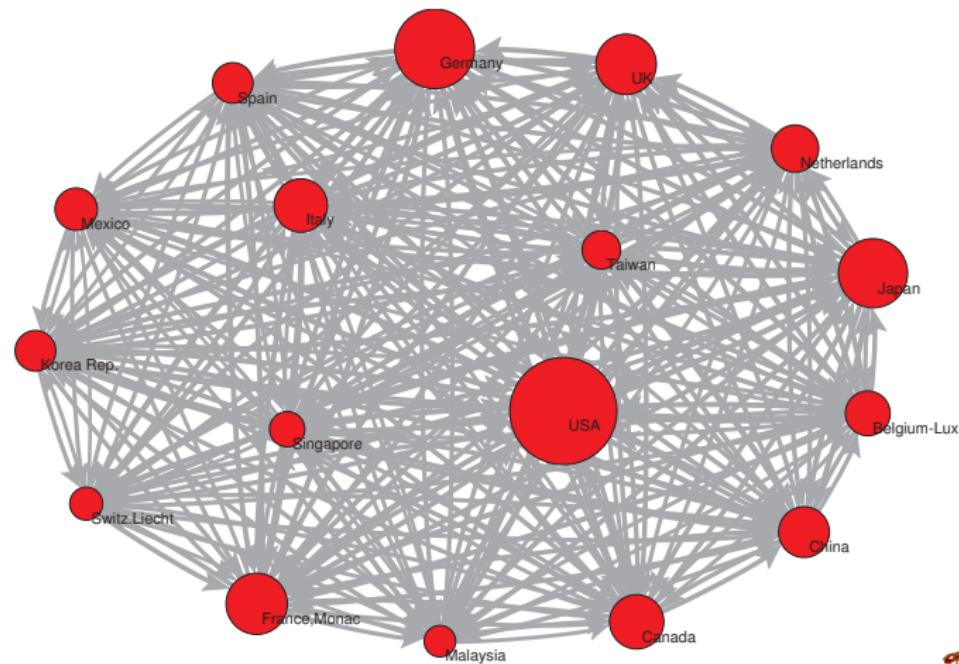
Node-cut: World trade, wdeg=150000

weights devided by 1000

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Link-cut: World trade, wdeg=25000

weights devided by 1000

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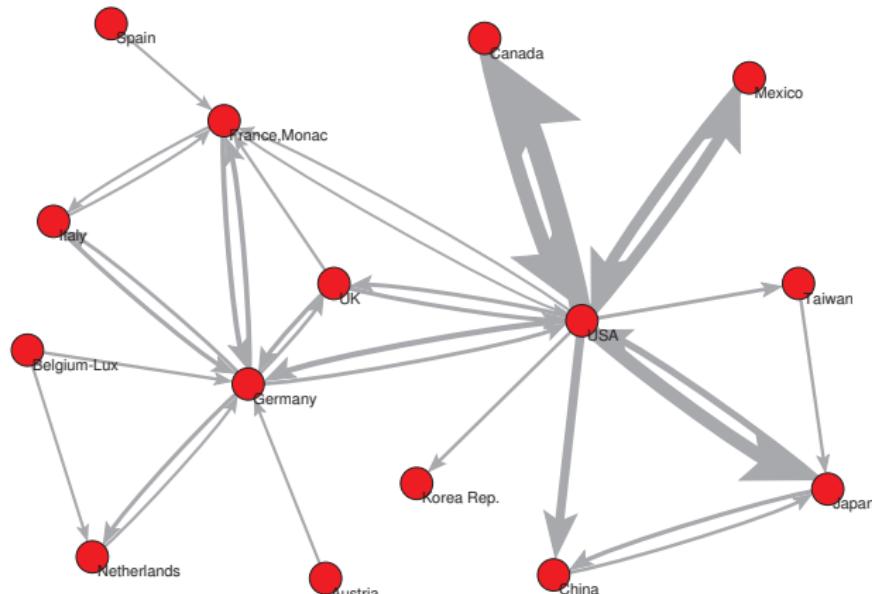
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Skeletons

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Skeletons are subnetworks in which only the most important links are preserved.

In the ***top k-neighbors skeleton*** in each node the k links with the highest weights are preserved.

Network/Create New Network/Transform/Remove/all arcs from each vertex except/ k with highest line values [k]

Let the weight w be a dissimilarity ($w' = 1/w$). The Pathfinder algorithm was proposed in eighties by Schvaneveldt [9] for simplification of weighted networks. It removes from the network all links that do not satisfy the triangle inequality – if for a link a shorter path exists connecting its endnodes then the link is removed. The obtained subnetwork is called the ***Pathfinder skeleton***.

Network/Create New Network/Transform/Line values/Power [-1]
Network/Create New Network/Transform/Reduction/Pathfinder [1]
select the original network as the Second
Networks/Cross-intersection/Second

Nearest neighbor skeleton: World trade

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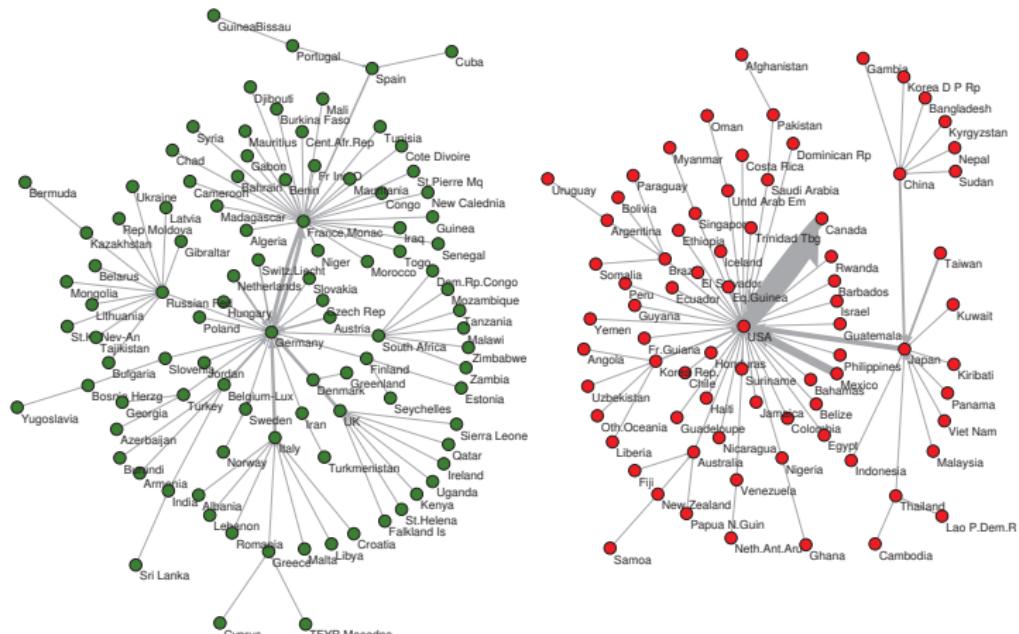
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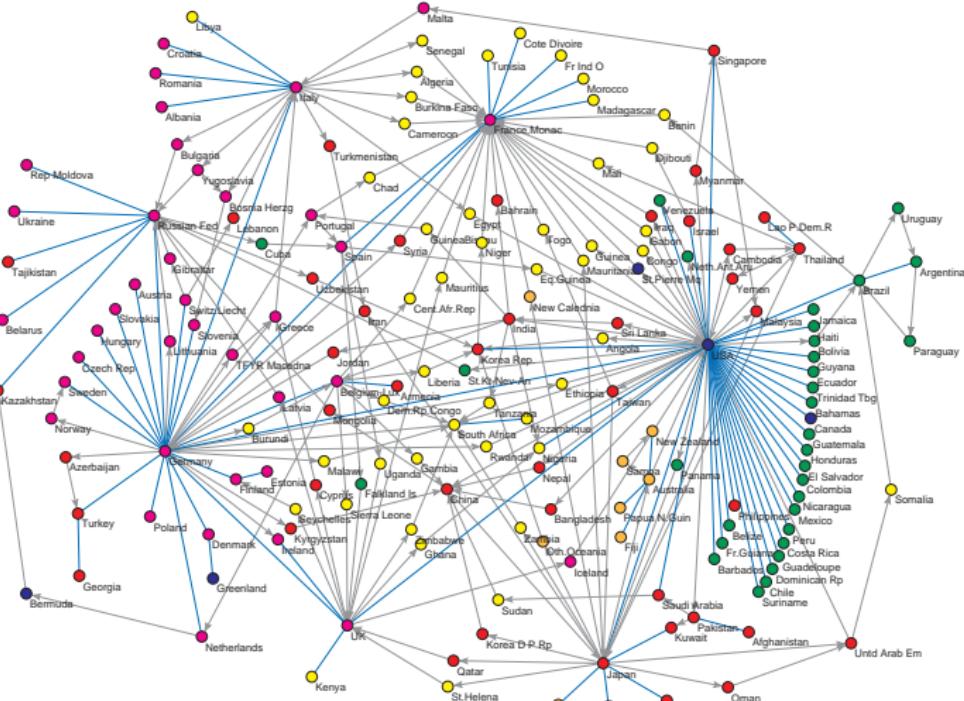


Pathfinder skeleton of World Trade 1999 network

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Simple analysis using cuts

We look at the components of $\mathbf{N}(t)$. Their number and sizes depend on t . Usually there are many small components. Often we consider only components of size at least k and not exceeding K . The components of size smaller than k and not containing important nodes/links are discarded as "noninteresting"; and the components of size larger than K are cut again at some higher level.

The values of thresholds t , k and K are determined by inspecting the distribution of node/link-values and the distribution of component sizes and considering additional knowledge on the nature of network or goals of analysis.

We developed some new and efficiently computable properties/weights.

Citation weights

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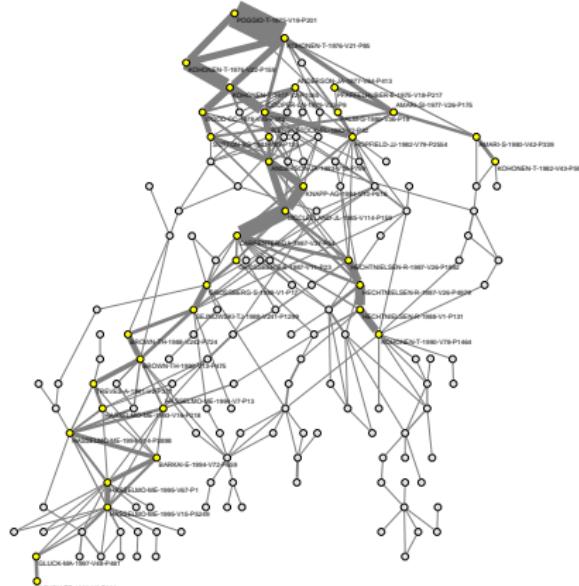
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The citation network analysis started in 1964 with the paper of Garfield et al. In 1989 Hummon and Doreian proposed three indices – weights of arcs that are proportional to the number of different source-sink paths passing through the arc. We developed algorithms to efficiently compute these indices.

Main subnetwork (arc-cut at level 0.007) of the SOM (self-organizing maps) citation network (4470 nodes, 12731 arcs).

See [paper](#).

Islands

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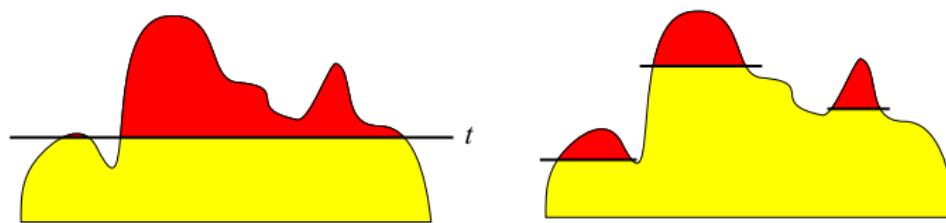
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If we represent a given or computed value of nodes / links as a height of nodes / links and we immerse the network into a water up to selected level we get *islands*. Varying the level we get different islands.



We developed very efficient algorithms to determine the islands hierarchy and to list all the islands of selected sizes.

See [details](#).

... Islands

Islands are very general and efficient approach to determine the 'important' subnetworks in a given network.

We have to express the goals of our analysis with a related property of the nodes or weight of the links. Using this property we determine the islands of an appropriate size (in the interval k to K).

In large networks we can get many islands which we have to inspect individually and interpret their content.

An important property of the islands is that they identify locally important subnetworks on different levels. Therefore they detect also emerging groups.

... Islands

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A set of nodes $C \subseteq \mathcal{V}$ is a *regular node island* in network

$\mathbf{N} = (\mathcal{V}, \mathcal{L}, p)$, $p : \mathcal{V} \rightarrow \mathbb{R}$ iff it induces a connected subgraph and the nodes from the island are 'higher' than the neighboring nodes

$$\max_{u \in N(C)} p(u) < \min_{v \in C} p(v)$$

A set of nodes $C \subseteq \mathcal{V}$ is a *regular link island* in network

$\mathbf{N} = (\mathcal{V}, \mathcal{L}, w)$, $w : \mathcal{L} \rightarrow \mathbb{R}$ iff it induces a connected subgraph and the links inside the island are 'stronger related' among them than with the neighboring nodes – in \mathbf{N} there exists a spanning tree \mathbf{T} over C such that

$$\max_{(u,v) \in \mathcal{L}, u \notin C, v \in C} w(u, v) < \min_{(u,v) \in \mathbf{T}} w(u, v)$$

US patents

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US patents network ([Nber, US Patents](#)) has 3 774 768 nodes and 16 522 438 arcs (1 loop). Without the loop it is acyclic. The weight of an arc is the proportion of paths through the arc from some initial node to some terminal node – Hummon and Doreian's weight. We determined all (2,90)-islands. The corresponding subnetwork has 470 137 nodes, 307472 arcs and for different k : $C_2 = 187\,610$, $C_5 = 8\,859$, $C_{30} = 101$, $C_{50} = 30, \dots$ islands. [Rolex](#)

[1]	0	139793	29670	9288	3966	1827	997	578	362	250
[11]	190	125	104	71	47	37	36	33	21	23
[21]	17	16	8	7	13	10	10	5	5	5
[31]	12	3	7	3	3	3	2	6	6	2
[41]	1	3	4	1	5	2	1	1	1	1
[51]	2	3	3	2	0	0	0	0	0	1
[61]	0	0	0	0	1	0	0	2	0	0
[71]	0	0	1	1	0	0	0	1	0	0
[81]	2	0	0	0	0	1	2	0	0	7

Main path and main island in US Patents

Nber, US Patents; $n = 3774768$, $m = 16522438$

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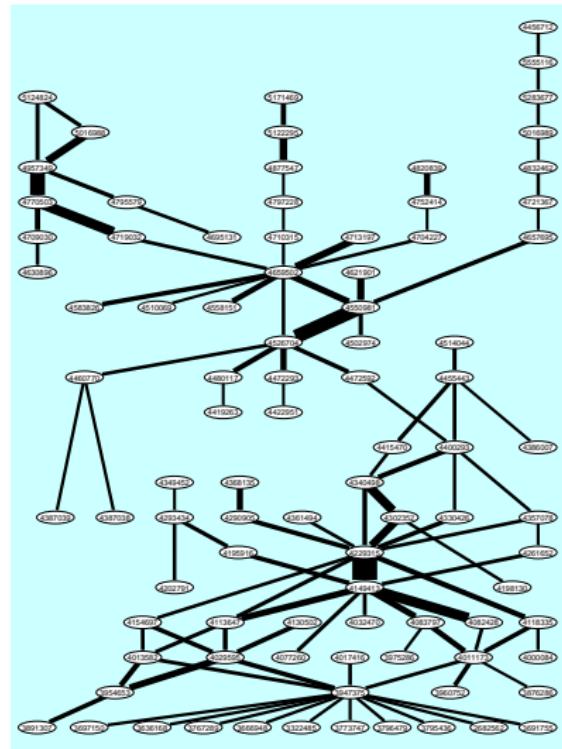
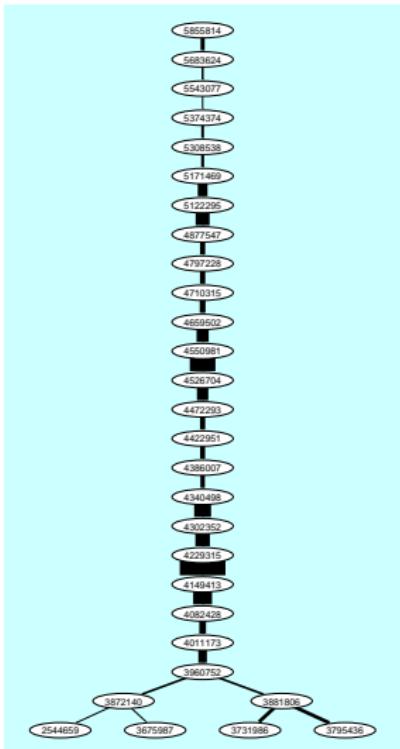
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Main island – Liquid crystal display

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Table 1: Patents on the liquid-crystal display

patent	date	inventor(s) and title
2649599	Mar 13, 1955	Dreyer, Dilettio. High-vacuum sheet and the like and the formation and use thereof.
2602562	Jan 29, 1955	Williams. Electro-optical elements utilizing an organic esterification reaction.
3322485	May 30, 1967	Williams. Electro-optical elements utilizing an organic esterification reaction.
3636168	Jan 18, 1972	Jaschinski. Preparation of polyacrylate aromatic compounds.
3666048	May 30, 1972	Blackmer, et al. Liquid crystal television imaging system.
3673987	Jul 11, 1972	Balano. Liquid crystal compositions and devices.
3691753	Sep 19, 1972	Balano. Liquid crystal compositions and devices.
3697156	Oct 10, 1972	Wysotski. Electro-optic systems in which an electrophoretic-like or dielectric material is dispersed throughout a liquid.
3731986	May 8, 1973	Ferguson. Display devices utilizing liquid crystal light modulation.
3767289	Oct 23, 1973	Shapiro, et al. Class of stable trans-etherane compounds, some displaying nematic mesophases at or near room temperature, others showing a transition up to the isotropic state.
3773447	Nov 20, 1973	Schoeniger. Substituted azo leucine compounds.
3795436	Mar 5, 1974	Baker, et al. Nematicogen material which exhibit the Kerr effect.
3796479	Mar 12, 1974	Bellrich, et al. Electro-optical light-modulation cell utilizing a nematicogen material which exhibits the Kerr effect.
3872140	Mar 18, 1974	Khandpur, et al. Liquid crystalline compositions and methods of preparing same.
3876286	Apr 8, 1974	Deutsche, et al. Use of nematic liquid crystalline substances.
3881306	May 6, 1974	Saito. Electro-optical display device.
3901267	Jun 24, 1974	Shapiro, et al. Class of stable trans-etherane compounds of the voltage applied to opposite electrodes for a cholesteric to nematic phase transition.
3947371	Mar 30, 1976	Shapiro. Liquid crystal materials and devices.
3954653	May 4, 1976	Vassallo. Liquid crystal composition having high dielectric constant.
3968752	Jan 1, 1978	Khandpur, et al. Liquid crystal compositions.
3972386	Aug 17, 1978	Ok. Low voltage activated field effect liquid crystals.
4008684	Dec 28, 1978	Bokel, et al. Liquid crystal mixtures for electro-optical display devices.
4011173	Mar 8, 1979	Shapiro. Modified nematic mixtures with positive dielectric anisotropy.
4013582	Mar 22, 1979	Shapiro. Electro-optical liquid crystal compositions and devices incorporating them and electro-optic devices.
4077416	Apr 12, 1979	Izutsu, et al. P -cyanophenyl-4-alkyl-4'-lithophenoxyphenyl compounds and liquid crystal compositions using same.
4029995	Jan 14, 1979	Ross, et al. Novel liquid crystal compounds and electro-optic devices incorporating them.
4033470	Jan 28, 1979	Ishino, et al. Electro-optic device.
4077280	Mar 7, 1979	Shapiro. Electro-optic liquid crystal compositions and liquid crystal materials containing them.
4084248	Apr 4, 1979	Hen. Liquid crystal composition and method.

Table 2: Patents on the liquid-crystal display

patent	date	inventor(s) and title
4085979	Apr 11, 1979	Ole. Nematic liquid crystal compositions.
4115260	Sept 5, 1979	Kondo, et al. Liquid crystal materials.
4118325	Sept 5, 1979	Kondo, et al. Liquid crystal compositions of reduced viscosity.
4120505	Dec 19, 1979	Eldenshak, et al. Liquid crystalline cyclohexane derivatives.
4149412	Apr 17, 1980	Eldenshak, et al. Liquid crystal compositions and liquid crystal devices containing them.
4154407	May 15, 1980	Eldenshak, et al. Liquid crystalline hexadiphenylbenzene.
4195016	Aug 1, 1980	Costes, et al. Liquid crystal compounds.
4195017	Aug 1, 1980	Costes, et al. Liquid crystal compositions.
4202791	Mar 13, 1980	Sato, et al. Nematic liquid crystalline materials.
4229313	Oct 21, 1980	Sato, et al. Liquid crystalline cyclohexane derivatives.
4260055	Apr 18, 1980	Costes, et al. Liquid crystal compositions and liquid crystal devices containing them.
4260057	Apr 18, 1980	Kashe. Ester compounds.
4293514	Sept 6, 1980	Costes, et al. Liquid crystal compounds.
4302325	Nov 24, 1980	Eldenshak, et al. Fluorophenylcyclohexanes, the preparation thereof and their use in electro-optic devices.
4304042	May 18, 1982	Eldenshak, et al. Cyclohexylphenole, their preparation and use in electro-optic and electrooptical display elements.
4304048	Jul 20, 1982	Oman, et al. Liquid crystal compositions.
4349452	Sep 14, 1982	Oman, et al. Cyclohexylphenolcyclohexanes.
4357078	Nov 2, 1982	Carr, et al. Liquid crystal compositions containing an alicyclic compound, a cyclohexane derivative and liquid crystal materials and devices incorporating such compounds.
4361954	Nov 20, 1982	Oman. Anisotropic compounds with negative or positive DC-anisotropy and low polarized anisotropy.
4368125	Jan 11, 1983	Oman. Anisotropic compounds with negative or positive DC-anisotropy and low polarized anisotropy.
4369067	May 31, 1983	Shapiro, et al. Liquid crystal compositions and devices containing them.
4370703	Jun 7, 1983	Fukui, et al. 4 -(Tetra- α -alkylhexyl) benzene acid 4'-cyan-4'-diphenyl ether.
4370709	Jun 7, 1983	Shapiro, et al. Liquid crystal compositions containing cyclohexylphenole and derivatives and electro-optic display elements.
4400025	Aug 23, 1983	Russer, et al. Liquid crystal compositions.
4415470	Nov 15, 1983	Tanaka, et al. Liquid crystal dispersions containing cyclohexylphenole and derivatives and electro-optic display elements.
4439262	Dec 6, 1983	Prasfeld, et al. Liquid crystalline cyclohexane carboxylic derivatives.
4422951	Dec 27, 1983	Lipari, et al. Liquid crystal benzene derivatives.
4455443	June 19, 1984	Takatori, et al. Nematic liquid crystal compositions.
4457131	July 10, 1984	Petrzilka, et al. Liquid crystal compositions.
4460770	Jul 17, 1984	Petrzilka, et al. Liquid crystal anisitors.
4472250	Sep 18, 1984	Sagnotti, et al. High temperature liquid crystal substances of the same.
4472252	Sep 18, 1984	Takatori, et al. Nematic liquid crystal compositions.
4480117	Oct 30, 1984	Takatori, et al. Nematic liquid crystal compositions.
4482070	Nov 21, 1984	Shapiro, et al. Liquid crystal compositions.
4503067	Aug 9, 1985	Shapiro, et al. Cyclohexane derivatives.

Table 3: Patents on the liquid-crystal display

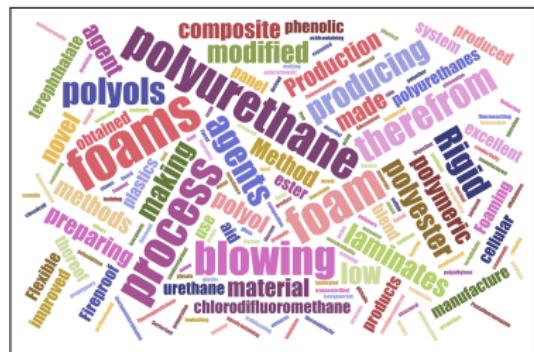
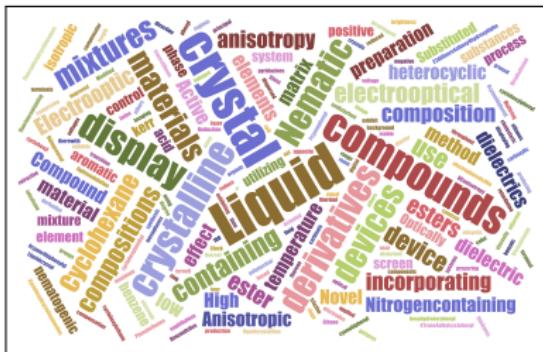
patent	date	inventor(s) and title
4510144	Apr 30, 1985	Grajeda, et al. Liquid crystal compositions.
4526707	Jul 2, 1985	Eldenshak, et al. Fluorophenylcyclohexane.
4550983	Nov 5, 1985	Petrzilka, et al. Liquid crystal compositions.
4551000	Nov 5, 1985	Petrzilka, et al. Novel liquid crystal mixtures.
4582636	Aug 22, 1986	Petrzilka, et al. Novel liquid crystal compositions.
4582637	Aug 22, 1986	Petrzilka, et al. Polyphenol.
4621963	Nov 12, 1986	Petrzilka, et al. Novel liquid crystal mixtures.
4622000	Nov 12, 1986	Petrzilka, et al. Novel liquid crystal compositions.
4675705	Aug 24, 1987	Furukawa, et al. Substituted pyridones.
4695131	Aug 24, 1987	Furukawa, et al. Substituted ethanes and their use in liquid crystal materials and devices.
4704227	Nov 2, 1987	Petrzilka, et al. Novel liquid crystal compositions.
4705030	Nov 24, 1987	Petrzilka, et al. Novel liquid crystal mixtures.
4710155	Dec 1, 1987	Schad, et al. Anisotropic compounds and liquid crystal compositions.
4713197	Dec 15, 1987	Eldenshak, et al. Nitrogen-containing heterocyclic compounds.
4713200	Dec 15, 1987	Wacheler, et al. Cyclhexane derivatives.
4713207	Dec 22, 1987	Eldenshak, et al. Liquid crystal compositions.
4724114	Jan 21, 1988	Eldenshak, et al. Cyclohexylcyclohexane compounds.
4724115	Jan 21, 1988	Eldenshak, et al. Cyclohexylcyclohexane derivatives.
4755739	Jun 3, 1989	Vaneck, et al. 2,2'-difluoro-4-fluoro-4-hydroxydiphenyle and their derivatives, their production process and their use in liquid crystal displays.
4757228	Jan 10, 1989	Goto, et al. Cyclohexane derivative and liquid crystal compositions containing same.
4820639	Apr 11, 1989	Petrzilka, et al. Fluorophenylcyclohexane.
4832462	Mar 22, 1989	Clark, et al. Liquid crystal devices.
4832463	Mar 22, 1989	Clark, et al. Liquid crystal devices.
4957349	Sep 18, 1990	Clerc, et al. Active matrix screen for the color display of television pictures, control systems and process for producing same.
5016949	Mar 21, 1991	Imamura. Liquid crystal display device by a birefringent liquid crystal polymer.
5016950	Mar 21, 1991	Ohta, et al. Liquid crystal element with improved contrast and brightness.
5122295	Jan 16, 1992	Matsuura, et al. Matrix liquid crystal display.
5124914	Jan 22, 1992	Konoi, et al. Liquid crystal display device comprising a retardation compensating layer having a successive principal refractive index gradient in the thickness direction.
5171469	Dec 15, 1992	Hattori, et al. Liquid-crystal matrix display.
5280327	Mar 31, 1993	Wobet, et al. Superpixel liquid-crystal display.
5340770	Aug 6, 1996	Ringer, et al. Nematic liquid-crystal composition.
5355116	Sep 10, 1996	Ishikawa, et al. Liquid crystal display having adjacent pixels with different refractive indices.
5463824	Nov 4, 1997	Sekiguchi, et al. Liquid crystal composition and liquid crystal display elements.
5585514	Dec 1, 1999	Sekiguchi, et al. Liquid crystal composition and liquid crystal display elements.

Word clouds for LCD island and foam island

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Dense groups

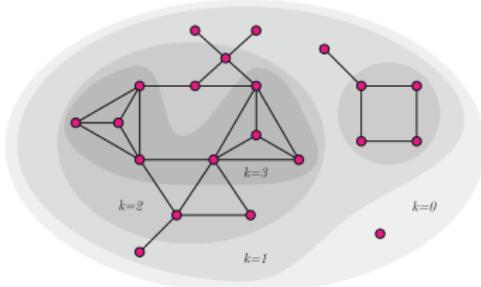
Activities in a part of network usually increase local density (number of nodes and links) in that part of network. Several notions were proposed in attempts to formally describe dense groups in graphs.

Clique of order k is a maximal complete subgraph (isomorphic to K_k), $k \geq 3$.

s-plexes, LS sets, lambda sets, cores, . . .

For all of them, except for cores, it turned out that they are "expensive" to determine.

Cores and generalized cores



The notion of core was introduced by Seidman in 1983. Let $\mathbf{G} = (\mathcal{V}, \mathcal{E})$ be a graph. A subgraph $\mathbf{H} = (W, \mathcal{E}|W)$ induced by the set W is a ***k-core*** or a ***core of order k*** iff $\forall v \in W : \deg_{\mathbf{H}}(v) \geq k$, and \mathbf{H} is a maximal subgraph with this property. The core of maximum order is also called the ***main core***.

The ***core number*** of node v is the highest order of a core that contains this node. The degree $\deg(v)$ can be: in-degree, out-degree, in-degree + out-degree, etc., determining different types of cores.

Properties of cores

From the figure, representing 0, 1, 2 and 3 core, we can see the following properties of cores:

- The cores are nested: $i < j \implies H_j \subseteq H_i$
- Cores are not necessarily connected subgraphs.

An efficient algorithm for determining the cores hierarchy is based on the following property:

If from a given graph $\mathbf{G} = (\mathcal{V}, \mathcal{E})$ we recursively delete all nodes, and edges incident with them, of degree less than k , the remaining graph is the k -core.

Generalized cores

The notion of core can be generalized to networks. Let $\mathbf{N} = (\mathcal{V}, \mathcal{E}, w)$ be a network, where $\mathbf{G} = (\mathcal{V}, \mathcal{E})$ is a graph and $w : \mathcal{E} \rightarrow \mathbb{R}$ is a function assigning values to edges. A *node property function* on \mathbf{N} , or a p -function for short, is a function $p(v, U)$, $v \in \mathcal{V}$, $U \subseteq \mathcal{V}$ with real values. Let $N_U(v) = N(v) \cap U$. Besides degrees and (corrected) clustering coefficient, here are some examples of p -functions:

$$p_S(v, U) = \sum_{u \in N_U(v)} w(v, u), \text{ where } w : \mathcal{E} \rightarrow \mathbb{R}_0^+$$

$$p_M(v, U) = \max_{u \in N_U(v)} w(v, u), \text{ where } w : \mathcal{E} \rightarrow \mathbb{R}$$

$$p_t(v, U) = \frac{|\mathcal{L}(U) \cap \mathcal{L}(K(N^+(v)))|}{|\mathcal{L}(K(N^+(v)))|}$$

$$p_k(v, U) = \text{number of cycles of length } k \text{ through node } v \text{ in } (U, \mathcal{E}|U)$$

The subgraph $\mathbf{H} = (C, \mathcal{E}|C)$ induced by the set $C \subseteq \mathcal{V}$ is a *p -core at level $t \in \mathbb{R}$* iff $\forall v \in C : t \leq p(v, C)$ and C is a maximal such set.

Additional p -functions

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relative density

$$p_\gamma(v, \mathcal{C}) = \frac{\deg(v, \mathcal{C})}{\max_{u \in N(v)} \deg(u)}, \text{ if } \deg(v) > 0; 0, \text{ otherwise}$$

diversity

$$p_\delta(v, \mathcal{C}) = \max_{u \in N^+(v, \mathcal{C})} \deg(u) - \min_{u \in N^+(v, \mathcal{C})} \deg(u)$$

average weight

$$p_a(v, \mathcal{C}) = \frac{1}{|N(v, \mathcal{C})|} \sum_{u \in N(v, \mathcal{C})} w(v, u), \text{ if } N(v, \mathcal{C}) \neq \emptyset; 0, \text{ otherwise}$$

Generalized cores algorithms

The function p is *monotone* iff it has the property

$$C_1 \subset C_2 \Rightarrow \forall v \in \mathcal{V} : (p(v, C_1) \leq p(v, C_2))$$

The degrees and the functions p_S , p_M and p_k are monotone. For a monotone function the p -core at level t can be determined, as in the ordinary case, by successively deleting nodes with value of p lower than t ; and the cores on different levels are nested

$$t_1 < t_2 \Rightarrow \mathbf{H}_{t_2} \subseteq \mathbf{H}_{t_1}$$

The p -function is *local* iff $p(v, U) = p(v, N_U(v))$.

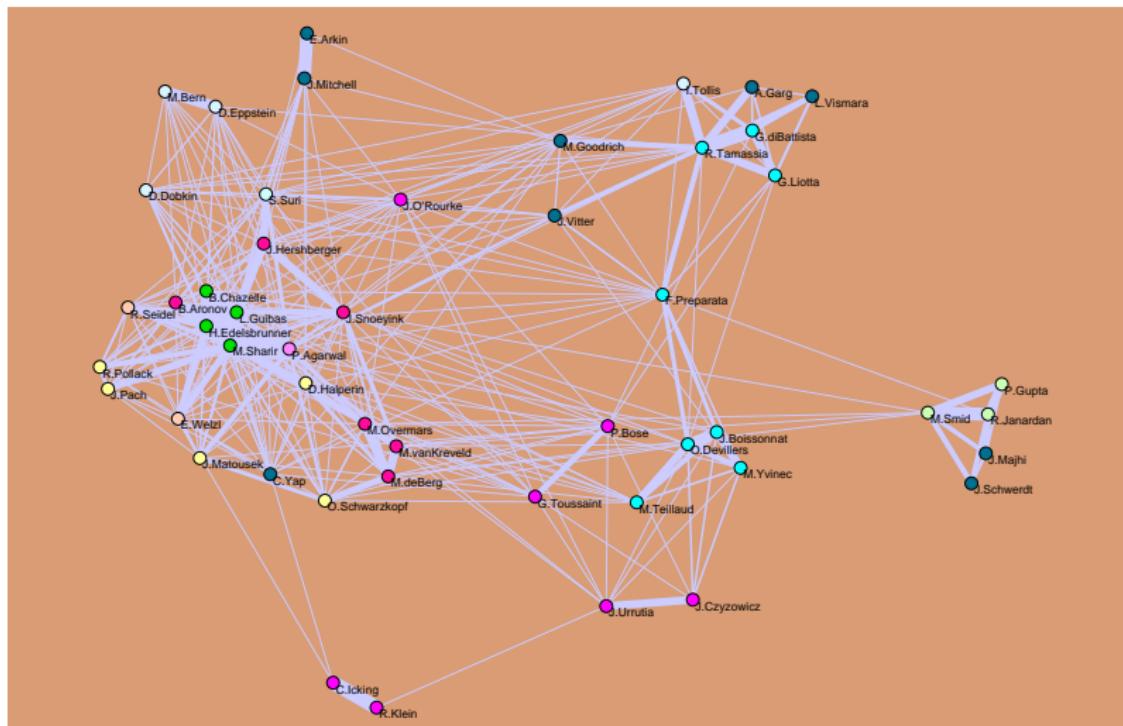
The degrees, p_S and p_M are local; but p_k is **not** local for $k \geq 4$. For a local p -function an $O(m \max(\Delta, \log n))$ algorithm for determining the p -core levels exists, assuming that $p(v, N_C(v))$ can be computed in $O(\deg_C(v))$.

p_S -core at level 46 of Geombib network

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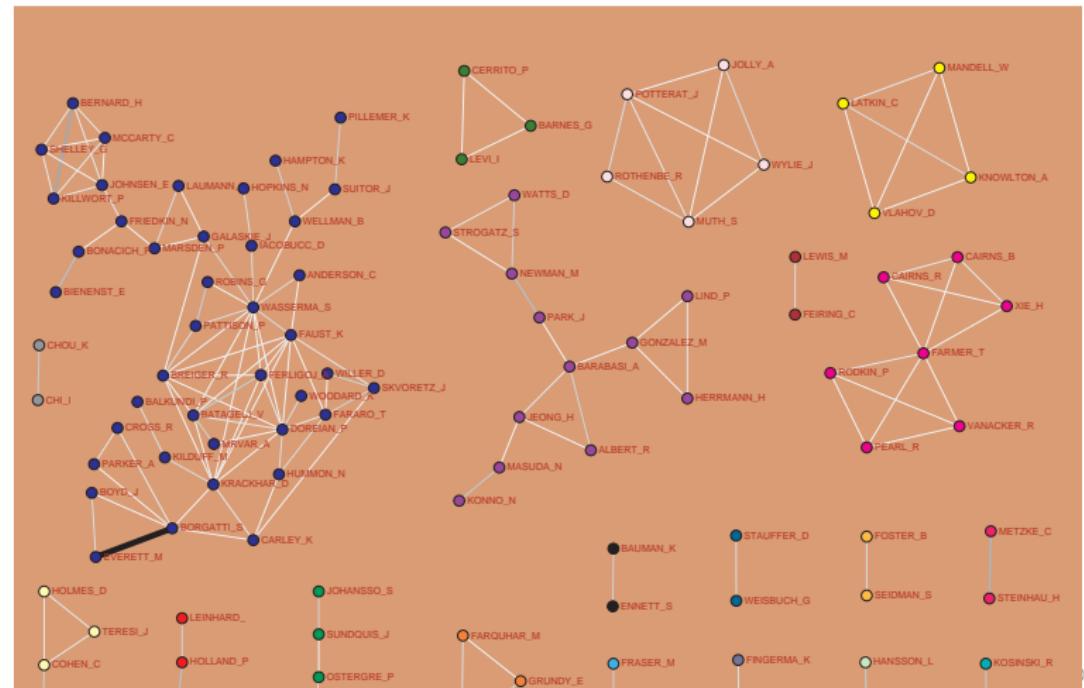


p_S -core at level 0.75 in $C_n(SN5)$

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Clustering and blockmodeling

For clustering the nodes, we use the normalized matrices. When computing the dissimilarity $d[u, v]$ between nodes u and v in a weighted network \mathbf{C} it is important to use the corrected dissimilarities. Here we compare the entry $c[u, t]$ with the entry $c[v, t]$ for t different from u or v , and the entry $c[u, v]$ with the entry $c[v, u]$, and the entry $c[u, u]$ with the entry $c[v, v]$. We selected the *corrected Euclidean distance* (Doreian et al., 2005, p. 181)

$$d_e[u, v] = \sqrt{(c[u, v] - c[v, u])^2 + (c[u, u] - c[v, v])^2 + \sum_{t: t \neq u \wedge t \neq v} (c[u, t] - c[v, t])^2}$$

The US geographical data, 2016

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From the site <https://datausa.io/profile/geo/united-states/> we obtained the data about US states in 2016 for the following variables: crime – homicide deaths, violent – violent crimes, smoking – adult smoking prevalence, drinking – excessive drinking prevalence, diabetes – diabetes prevalence, opioid – opioid overdose death rate, and income – median household income.

In his book *The Stanford GraphBase* D.E. Knuth provided a description of neighboring relation for the contiguous part of USA `contiguous-usa.dat` (without Alaska and Hawaii). Because of missing data we removed also Washington DC.

wiki

USA: Ward clustering (left) and Maximum/Tolerant clustering (right)

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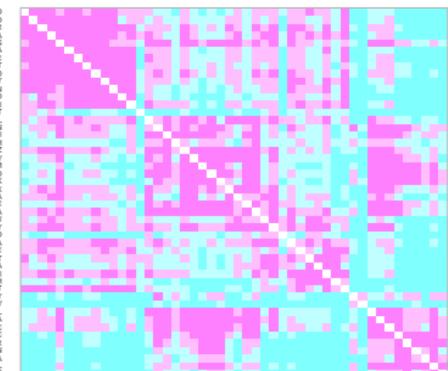
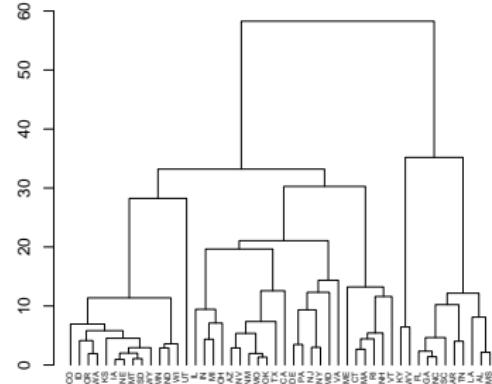
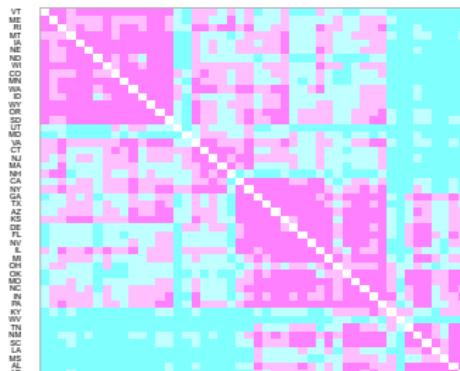
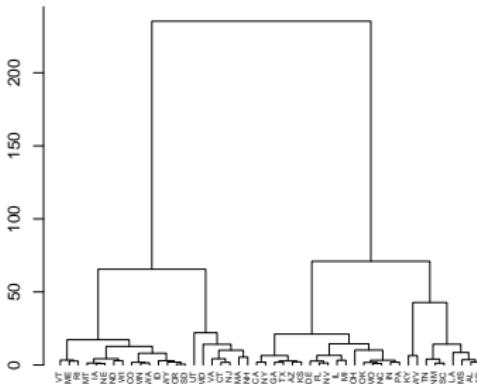
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USA: Ward clustering (left) and Maximum/Tolerant clustering (right)

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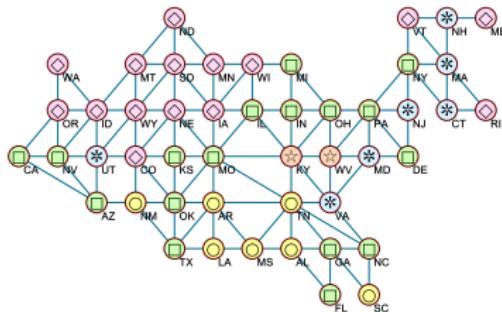
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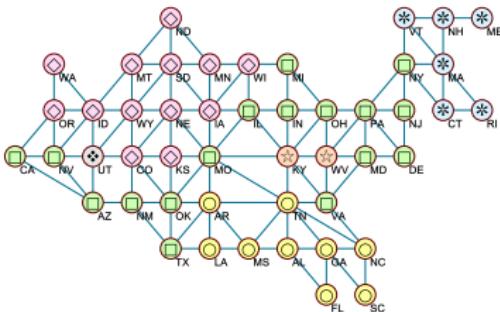
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$$\begin{aligned} C_1 &= \{AL, AR, LA, MS, NM, TN, SC\}, \\ C_2 &= \{AZ, CA, DE, FL, GA, IL, IN, KS, MI, MO, \\ &\quad NC, NV, NY, OH, OK, PA, TX\}, \\ C_3 &= \{CO, IA, ID, ME, MN, MT, ND, NE, OR, \\ &\quad SD, WY, RI, WI, WA, VT\}, \\ C_4 &= \{CT, MA, MD, NH, NJ, UT, VA\}, \\ C_5 &= \{KY, WV\}. \end{aligned}$$


$$\begin{aligned} C_1 &= \{AL, AR, FL, GA, LA, MS, NC, TN, SC\}, \\ C_2 &= \{AZ, CA, DE, IL, IN, MD, MI, MO, NJ, \\ &\quad NM, NV, NY, OH, OK, PA, VA, TX\}, \\ C_3 &= \{CO, IA, ID, KS, MN, MT, ND, NE, OR, \\ &\quad SD, WY, WI, WA\}, \\ C_4 &= \{CT, MA, ME, NH, RI, VT\}, \\ C_5 &= \{KY, WV\}, \\ C_6 &= \{UT\}. \end{aligned}$$

Averages for Maximum/Tolerant clustering

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	<i>crime</i>	<i>violent</i>	<i>smoking</i>	<i>drinking</i>	<i>diabetes</i>	<i>opioid</i>	<i>income</i>
	C_1	8.1667	462.00	0.2140	0.1488	0.1160	10.788
	C_2	5.9701	425.91	0.1804	0.1719	0.1032	15.794
	C_3	2.8385	265.25	0.1765	0.2005	0.0852	7.408
	C_4	2.3833	234.31	0.1660	0.1932	0.0880	26.717
	C_5	4.9000	273.02	0.2645	0.1195	0.1210	33.500
	C_6	1.9000	204.72	0.0970	0.1210	0.0710	16.400
	<i>all</i>	4.9563	354.23	0.1856	0.1748	0.0989	14.700
	C_1	1.3181	0.8278	0.8162	-0.8584	1.1929	-0.4304
	C_2	0.4165	0.5506	-0.1502	-0.0928	0.3026	0.1204
	C_3	-0.8695	-0.6836	-0.2620	0.8523	-0.9584	-0.8024
	C_4	-1.0564	-0.9212	-0.5625	0.6087	-0.7599	1.3223
	C_5	-0.0231	-0.6239	2.2668	-1.8260	1.5416	2.0687
	C_6	-1.2548	-1.1485	-2.5445	-1.7764	-1.9456	0.1871
							0.8767

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