Intro to Social Network Analysis

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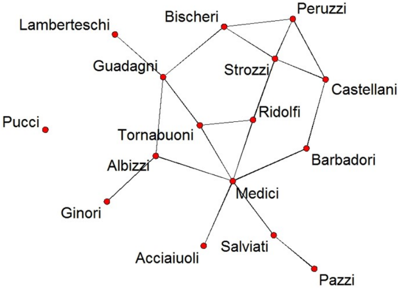
Online Workshop
September 2026

Descriptives



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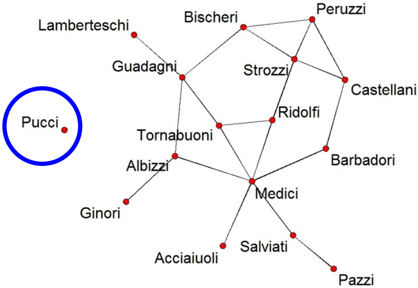
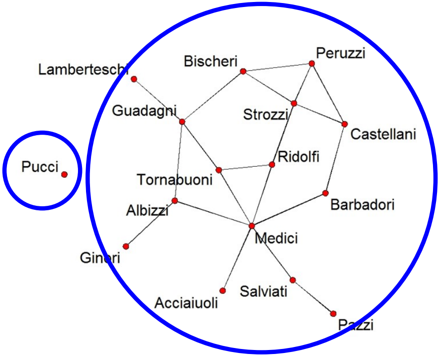


- One isolate

Descriptives



- One isolate
- Two components

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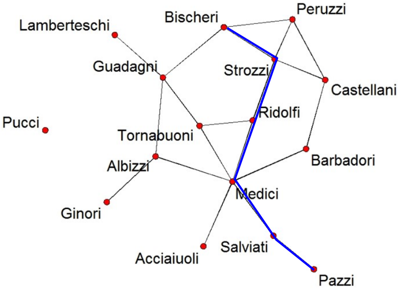

- One isolate
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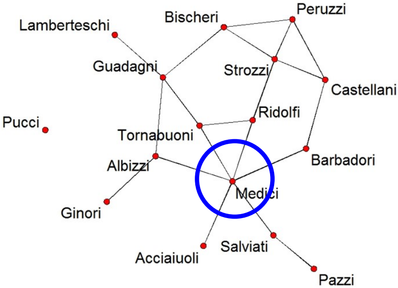
- Diameter is 5

Descriptives



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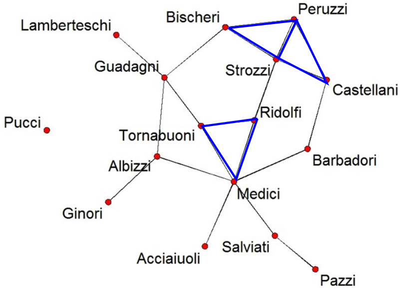
- Two components
- Diameter is 5
- Medici is most popular

Descriptives



- One isolate
- Two components
- Diameter is 5
- Medici is most popular
- Three triads

Degree

For each node, its degree is

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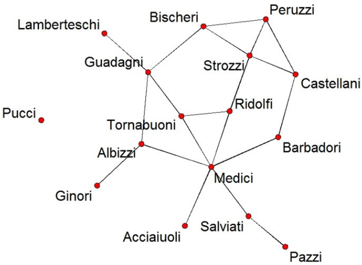

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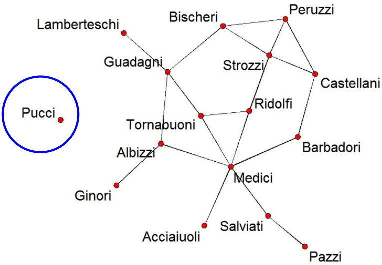

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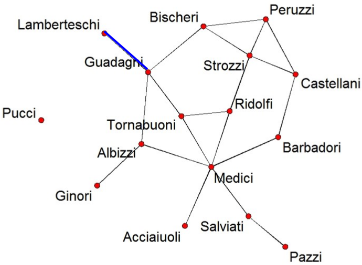

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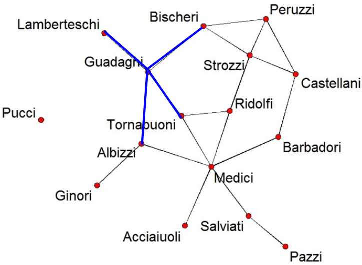

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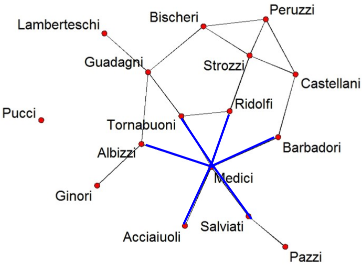
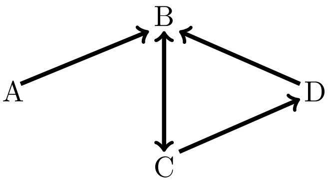


- Pucci has degree 0
- Lamberteschi has degree 1
- Guadagni has degree 4
- Medici has degree 6

Directed Degree

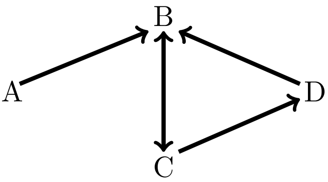
In directed graphs,



Directed Degree

In directed graphs,

- *Indegree* indicates the number of received ties



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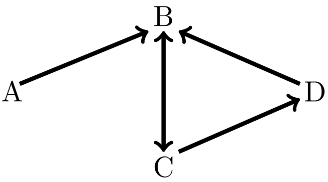

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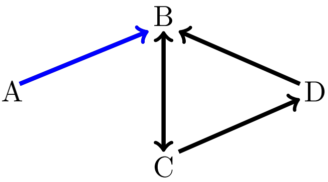

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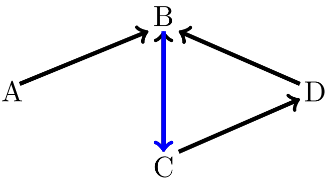

- A has 1 outdegree
- B has 1 outdegree

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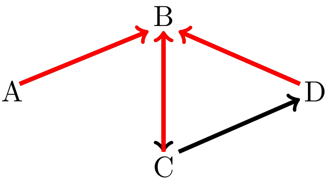

- A has 1 outdegree
- B has 1 outdegree and 3 indegree

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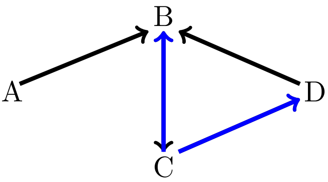

- A has 1 outdegree
- B has 1 outdegree and 3 indegree
- C has 2 outdegree

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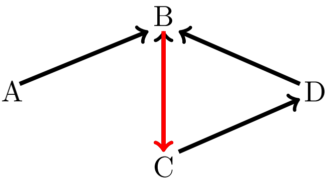

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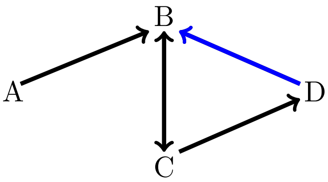

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- C has 2 outdegree and 1 indegree
- D has 1 outdegree

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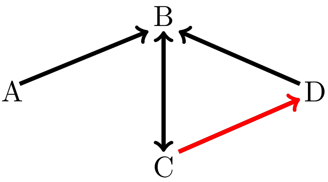

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- D has 1 outdegree and 1 indegree

Betweenness Centrality

Proportion of shortest paths that the given node lies on

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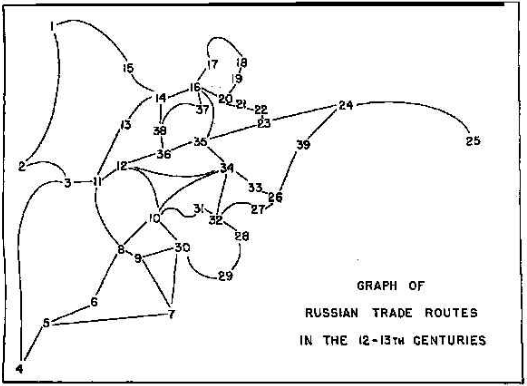
Figure 2. *Graph of Russian trade routes in the 12th - 13th centuries.*



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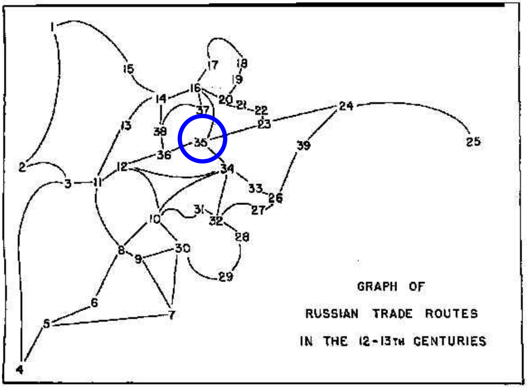

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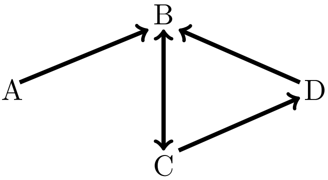
Closeness Centrality – Alternate Measure

How far is each node from the other nodes in the graph



- $C^2(v) = \frac{\sum \frac{1}{d(v,i)}}{|V|-1}$
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  - A = inf

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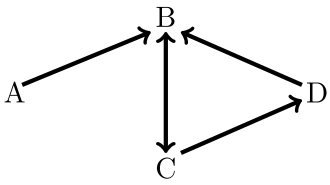

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- B's Distance to
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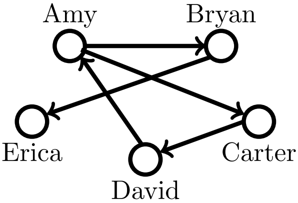
- B's Closeness Centrality $= \frac{\frac{1}{inf} + \frac{1}{1} + \frac{1}{2}}{3} = \frac{1}{2}$

Page Rank and Eigenvector Centrality

Page Rank



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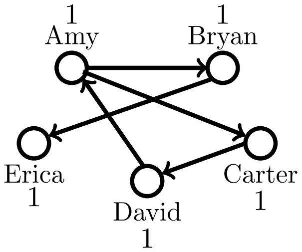

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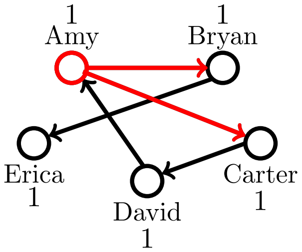

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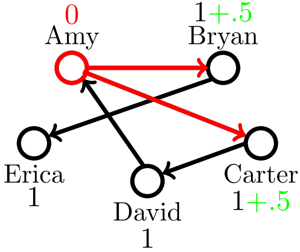

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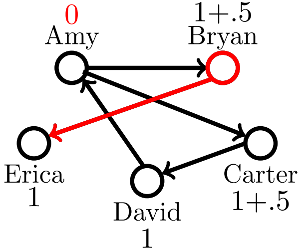

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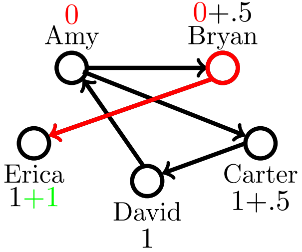

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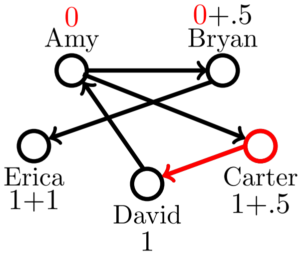

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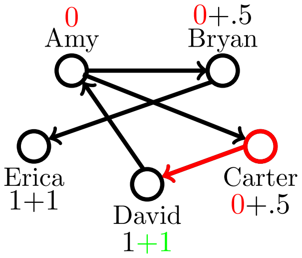

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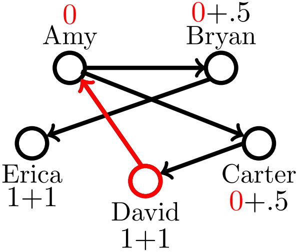

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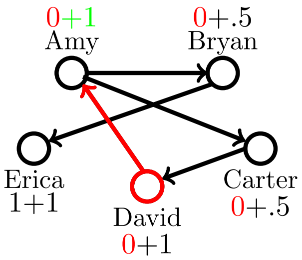

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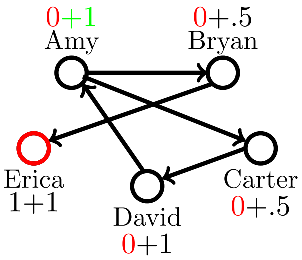

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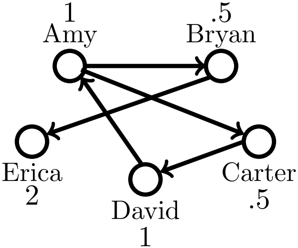

Other Centrality Measures

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- Two-mode centrality measures (Everett and Borgatti 2005)

Graph Level Indices

Density

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- Number of ties, expressed as a percentage of the number of possible ties

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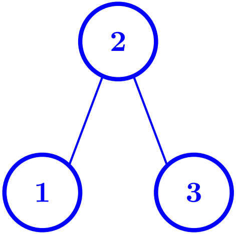

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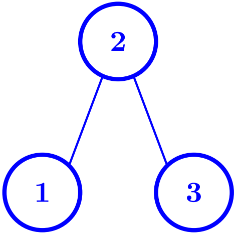
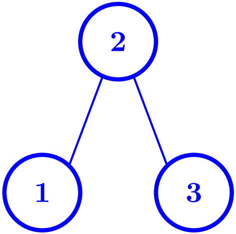


$$= \frac{\frac{2}{3(3-1)}}{2} = \frac{4}{6}$$

Mean Degree

The mean degree, $\bar{d}$, of all nodes in the graph is



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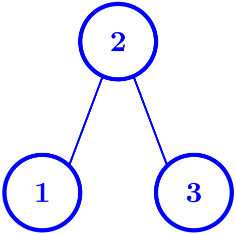
$$\bar{d}(n) = \frac{\sum_{i=1}^{N} d(n_i)}{N} = \frac{2E}{N}$$



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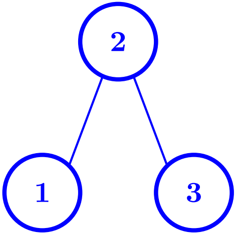
$$= \frac{1+2+1}{3} = \frac{4}{3}$$



Size, Density, and Mean Degree

If we hold the mean degree constant, but vary size, what happens to density?

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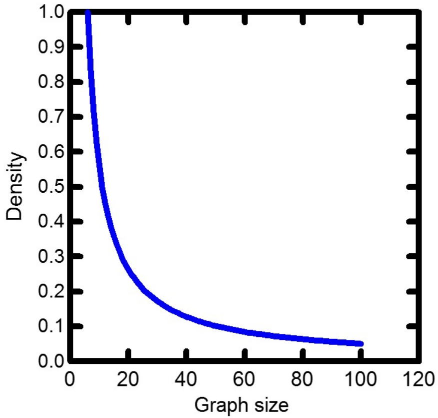

Centralization

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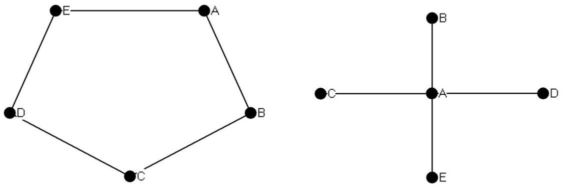
- Most centralized structure is usually a star network



Dyad Census

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Mutual (M)

Dyad Census

Mutual (M)

Assymetric (A)

Dyad Census

Mutual (M)

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Null (N)

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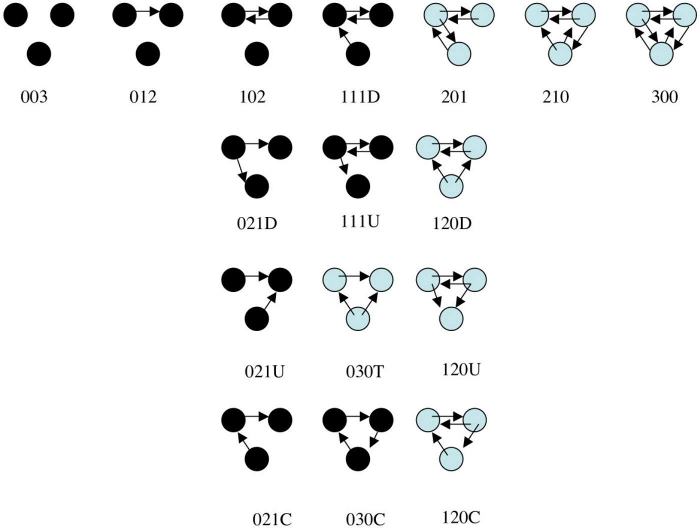
- Dyadic non-null: the proportion of non-null dyads that are reciprocal $\frac{M}{M+A}$
- Edgewise: $\frac{2*M}{2*M+A}$

Triad Census



Holland and Leinhardt 1974

Triad Census

16 different triad types

One row per network

Triad Census

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One row per network

i,j cell is the number
of triad type j
in network i

Triad Census

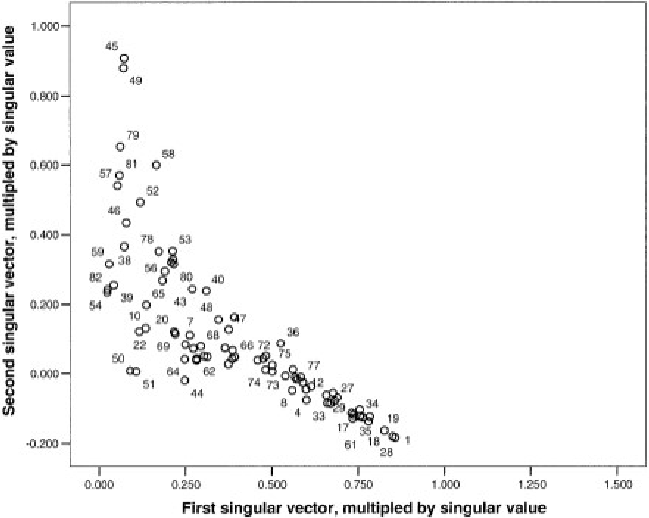
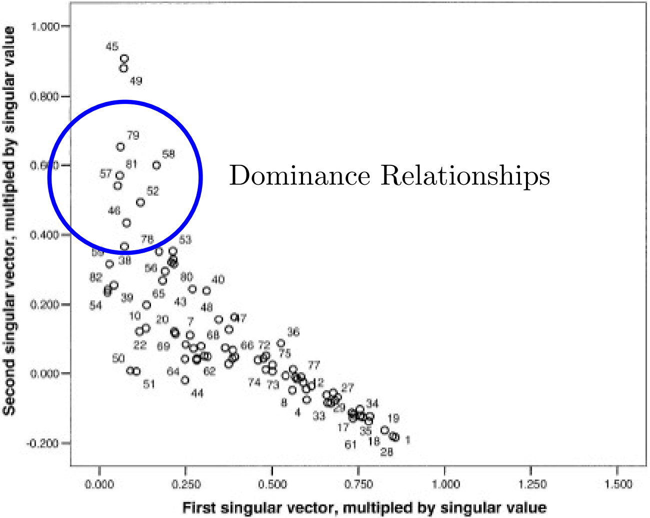


FIGURE 2. Singular value decomposition of triad census array, first two left singular vectors, multiplied by singular values, $N = 82$ networks.

Faust 2007

Triad Census



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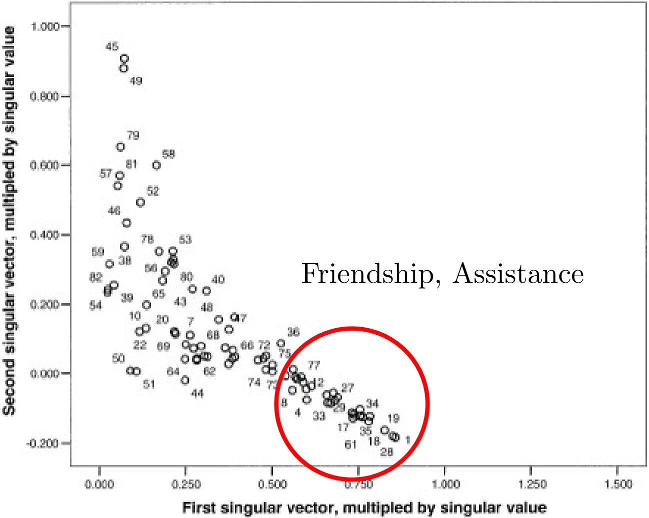

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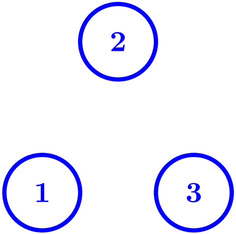

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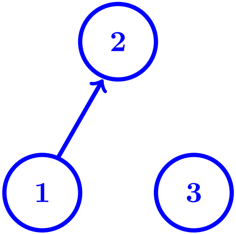

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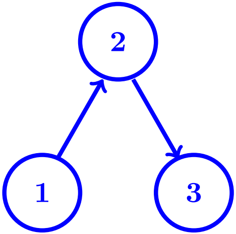

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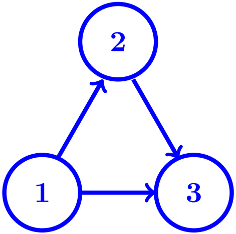

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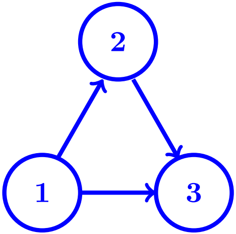
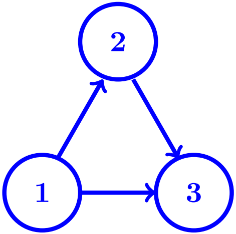


- Usually calculated as the fraction of completed two-paths

Transitivity



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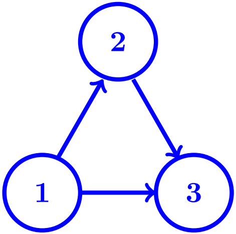
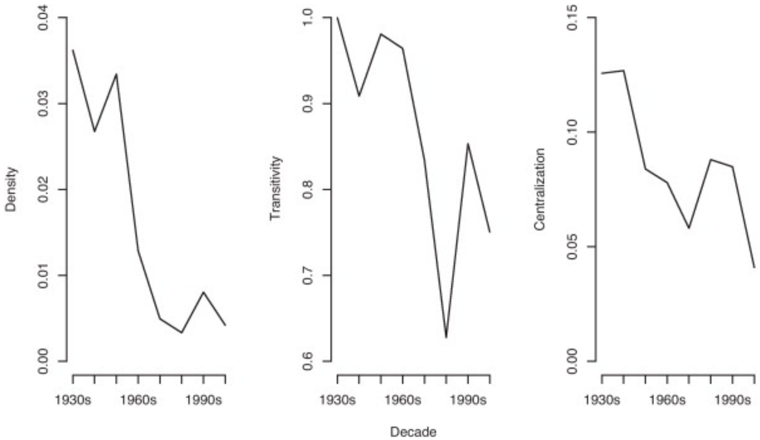


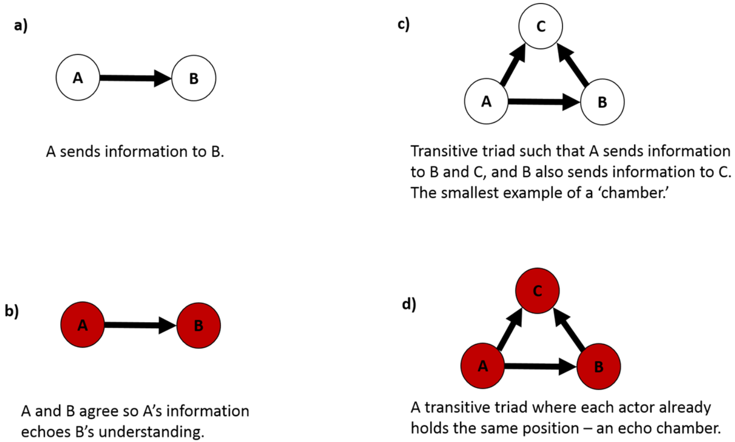
- Usually calculated as the fraction of completed two-paths
- Related to Grannovetter's 'forbidden triad' (1983)
- Can be directed or undirected

Example



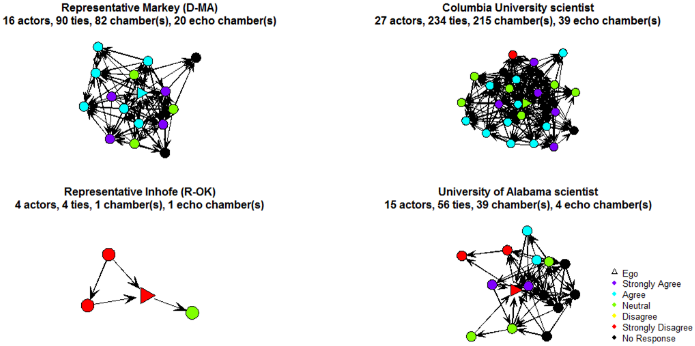
Janet Box-Steffensmeier and Dino Christenson
"The evolution and formation of amicus curiae networks"
Social Networks 2012

Example



Jasny et al 2015

Example



Jasny et al 2015

Example

Jasny et al 2015

Code Time

- Section 3-4.7

Forbidden Triad or Structural Hole?

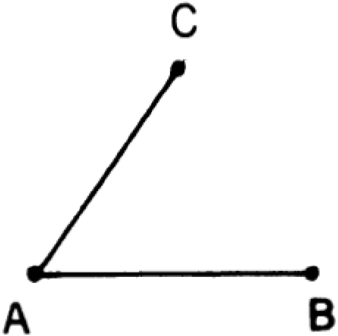


FIG. 1.—Forbidden triad

Forbidden Triad or Structural Hole?

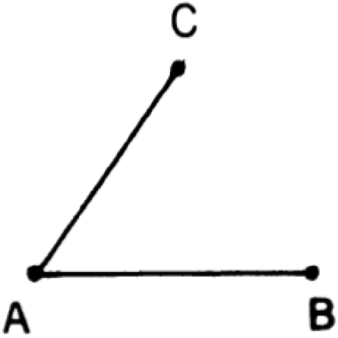
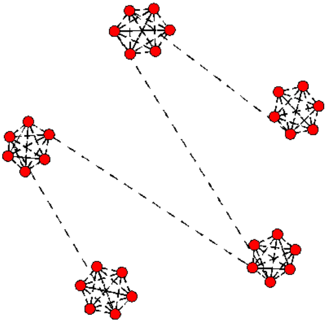


FIG. 1.—Forbidden triad

- Granovetter, Mark S. 1973. "The Strength of Weak Ties"

Forbidden Triad or Structural Hole?



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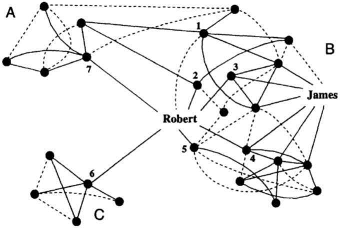

- Burt, Ronald S. 2004. "Structural Holes: The Social Structure of Competition"

Extensions

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- Properties of nodes, edges, or even networks

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- Extension based on edge attributes: Structural Balance

Brokerage

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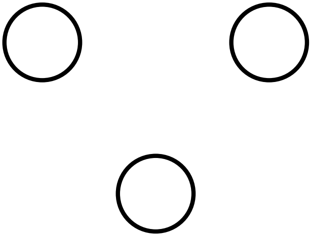
- Brokers play a crucial role in knitting together diverse groups of people, organizations, parties
- Brokers can gain a lot – early access to information, prestige
- But can also be distrusted by everyone

Brokerage: Formal Concept

In a network N with edges E,



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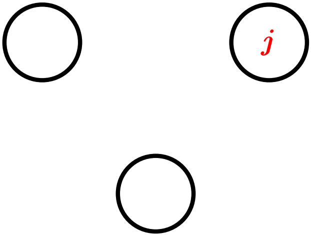

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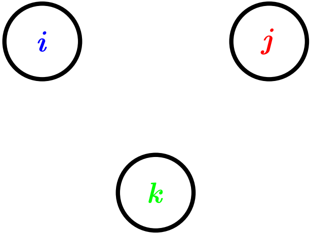

Brokerage: Formal Concept

In a network N with edges E,
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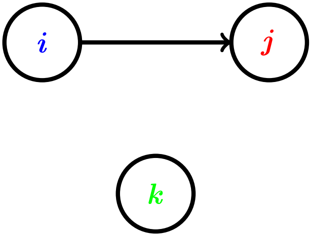
if $e_{ij} \in E$



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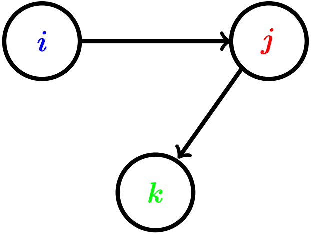

Brokerage: Formal Concept

In a network N with edges E,
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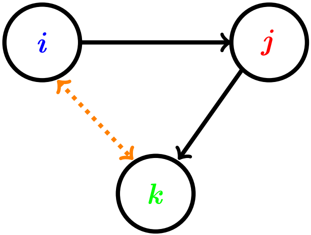

Brokerage: Formal Concept

Gould and Fernandez (1989, 1994)

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- formalized the concept

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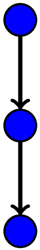
Brokerage: Formal Concept

Gould and Fernandez (1989, 1994)

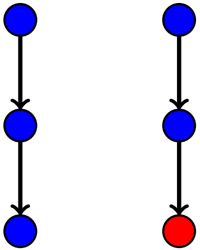
- formalized the concept
- added a vertex attribute component
- compared empirical brokerage counts to counts from random graphs conditioned on the number of edges

Brokerage



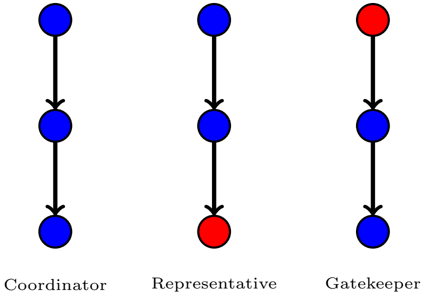
Coordinator

Brokerage

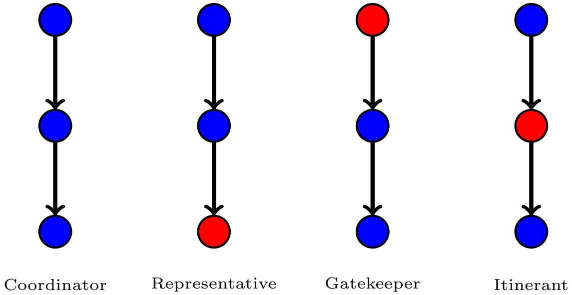


Coordinator Representative

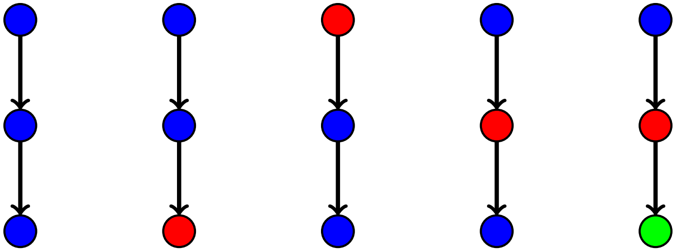
Brokerage



Brokerage



Brokerage



Coordinator Representative Gatekeeper Itinerant Liaison

Gould and Fernandez' Findings

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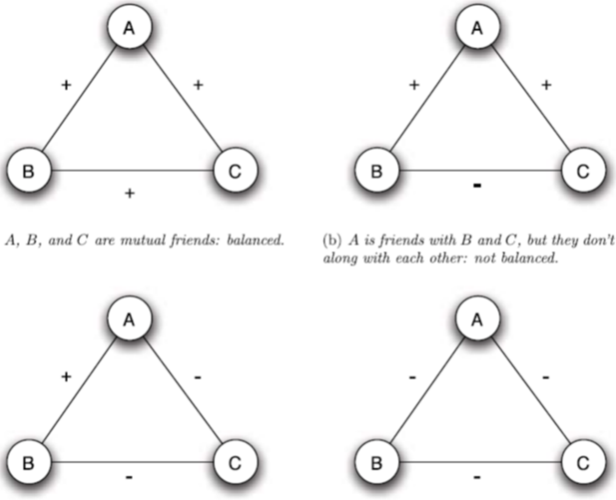
- non-governmental organizations were found to have more influence when they held any type of brokerage position
- governmental organizations gained influence only when they held "outsider" brokerage roles in itinerant and liaison chains

Structural Balance



(a) *A, B, and C are mutual friends: balanced.*

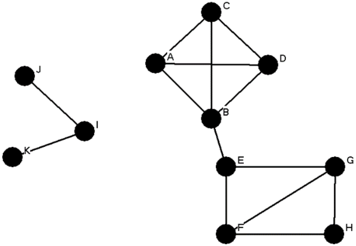
(b) *A is friends with B and C, but they don't get along with each other: not balanced.*

(c) *A and B are friends with C as a mutual enemy: balanced.*

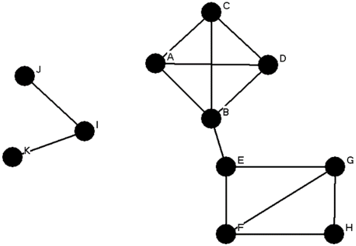
(d) *A, B, and C are mutual enemies: not balanced.*

Cartwright and Harary 1956

Subgroups

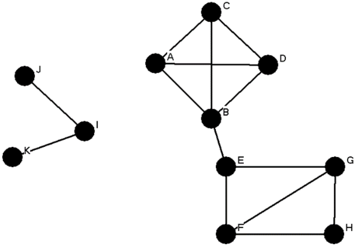


Subgroups



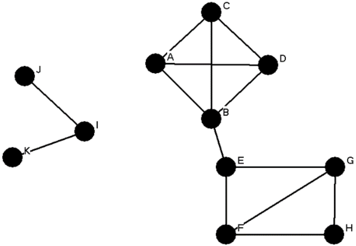
- Component: A maximal connected subgraph

Subgroups



- Component: A maximal connected subgraph
- A subgraph is *maximal* with respect to some property if it has the property, but loses it with the addition of more nodes or edges

Cliques



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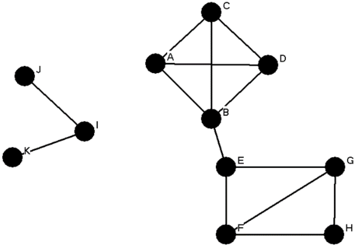

- A maximally complete subgraph of 3 or more

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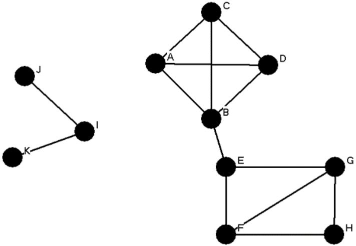

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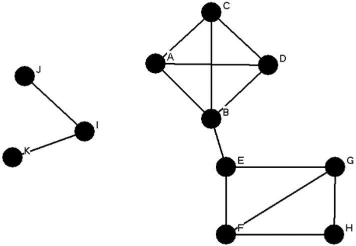

- A maximally complete subgraph of 3 or more
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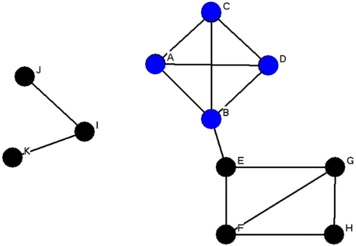

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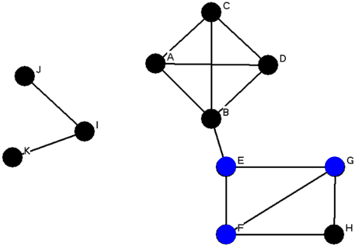

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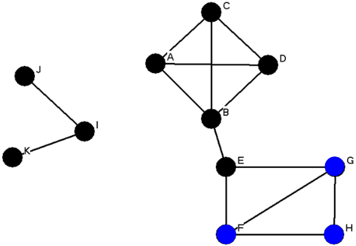

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Limitations of Cliques

- A very strict definition
- Often networks contain many small overlapping cliques
- Cliques have no internal structure

Relaxations of Cliques

Subgroups based on reachability or diameter

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- n-clan: an n-clique in which the geodesic distance between all nodes in the subgraph is no greater than n **for paths within the subgraph**
- n-club: a maximal subgraph of diameter n

Relaxations of Cliques

Subgroups based on nodal degree

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Relaxations of Cliques

Subgroups based on nodal degree

- k-plex: a subgrah of g nodes in whcich each node is adjacent to no fewer than $g - k$ ndoes in the subgraph
- k-core: a subgraph in which each node is adjacent to at least k other nodes in the subgroup

What to do with these subgroup definitions?

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- characterize the overall structure of the network

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- characterize the overall structure of the network
- analyze the pattern of co-membership in cliques, etc.

K-Core Example

RESEARCH ARTICLE

The Critical Periphery in the Growth of Social Protests

Pablo Barberá[1]*, Ning Wang[2], Richard Bonneau[3,4], John T. Jost[1,5,6], Jonathan Nagler[6], Joshua Tucker[6], Sandra González-Bailón[7]*

1 Center for Data Science, New York University, New York, New York, 10003, United States of America, **2** Mathematical Institute and Oxford Internet Institute, University of Oxford, Oxford, OX26GG, United Kingdom, **3** Center for Genomics and System Biology, New York University, New York, New York, 10003, United States of America, **4** Simons Center for Data Analysis, Simons Foundation, New York, New York, 10010, United States of America, **5** Department of Psychology, New York University, New York, New York, 10003, United States of America, **6** Department of Politics, New York University, New York, New York, 10012, United States of America, **7** Annenberg School for Communication, University of Pennsylvania, Philadelphia, Pennsylvania, 19104, United States of America

* pablo.barbera@nyu.edu (PB); sgonzalezbailon@asc.upenn.edu (SGB)

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K-Core Example

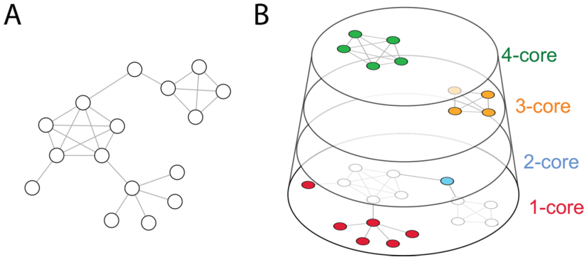

Fig 2. Schematic representation of the *k*-core decomposition for a random network with N = 16 vertices and E = 24 edges. This technique recursively prunes the network to remove nodes with the lowest degree. The coreness of a vertex is *k* if it belongs to the *k*-core but not to the (*k*+1)-core.

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K-Core Example

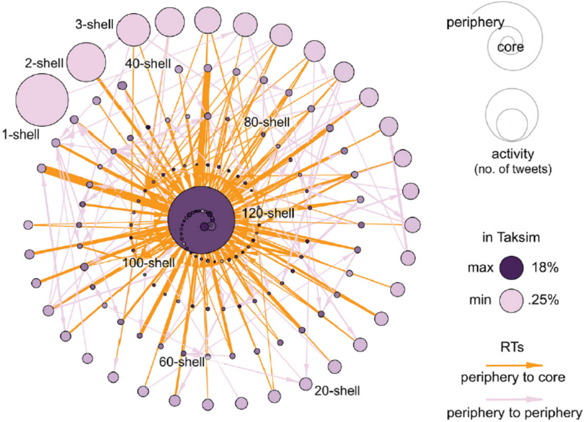

Fig 3. *K*-core decomposition of the network of retweets that emerged during the 2013 Taksim Gezi Park protests in Turkey (see S1 Text). Participants have been grouped in their corresponding *k*-shells, here represented by nodes. Lower *k*-shells contain participants at the periphery of the network; higher *k*-shells contain core participants. Node size is proportional to aggregated activity, measured as total number of protest messages (not just retweets). Arcs indicate retweeting activity, and their width is proportional to normalized strength (arcs with lower strength have been filtered to improve the visualization of the network). The darkness of nodes is proportional to the percentage of participants who reported being in the Taksim Gezi Park (the geographical epicenter of the protests), as indicated by the geographic information attached to their tweets. Most of these participants are at the core of the network where most RTs are also sourced from, thus allowing information to flow from the core to the periphery.

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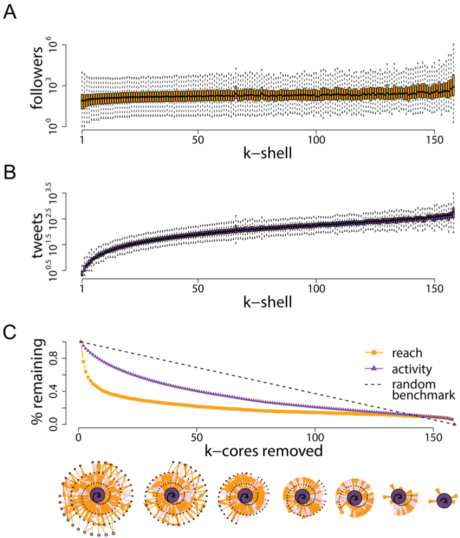
K-Core Example



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Block Models

Block Models

- Attribute Based

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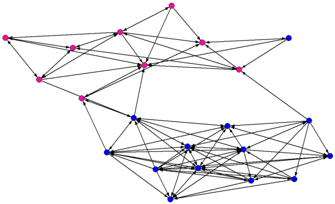

Block Models

- Attribute Based

```
                         Boys                   Girls
          1 2 4 5 5 7 8 9 9 0 1 2 6   3 4 3 6 7 8 0 1 2
          1 2 1 1 5 1 1 1 9 1 1 1 1   1 4 3 6 7 8 2 2 2
        -------------------------------------------------
  1  1 |     1 1 1   1           1 |     1   1         |
  2  2 |       1 1 1     1   1   1 |                   |
 14 14 | 1 1   1 1 1 1   1   1 1 1 |                   |
 15 15 | 1   1   1   1   1   1   1 |                   |
  5  5 | 1 1 1       1   1       1 |     1             |
 17 17 | 1 1   1 1   1 1 1   1   1 |                   |
 18 18 | 1     1 1           1     |                   |
 19 19 |     1 1         1       1 |                   |
  9  9 |     1 1                 1 |                   |
 10 10 |                           |       1 1       1 |
 11 11 |   1   1     1             |                   |
 12 12 |   1 1       1 1     1   1 |                 1 |
 16 16 |     1 1         1         |                   |
        -------------------------------------------------
 13 13 |                           |   1         1 1 1 |
  4  4 | 1                         | 1       1   1 1   |
  3  3 |                           |       1 1         |
  6  6 |                   1       |                   |
  7  7 |                           |     1             |
  8  8 |                           |       1 1   1     |
 20 20 |                           | 1 1   1 1 1   1 1 |
 21 21 |                           | 1 1     1         |
 22 22 |                           | 1     1 1   1     |
        -------------------------------------------------
```

Boys

Girls

Block Models

- Attribute Based
- Relation Based

Block Models

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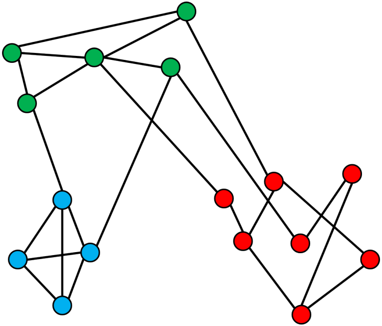

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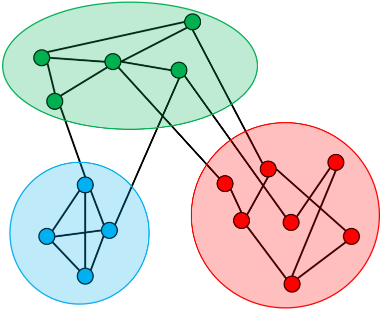

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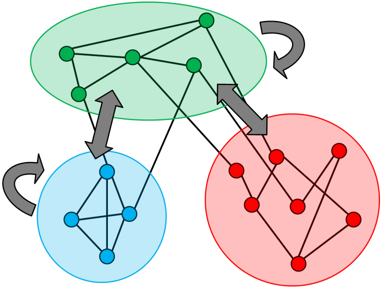

Block Models

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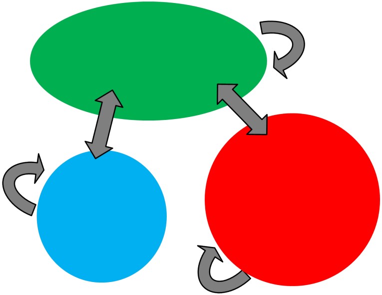

Block Models

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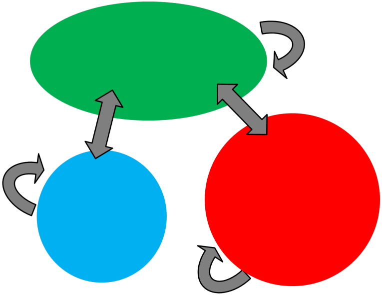
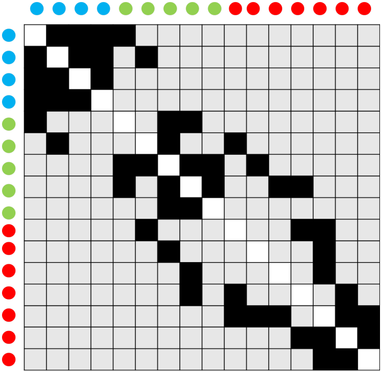
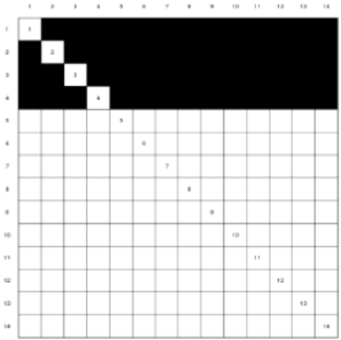
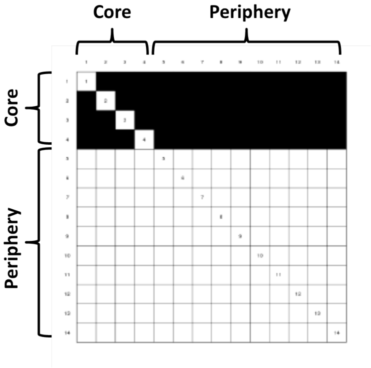




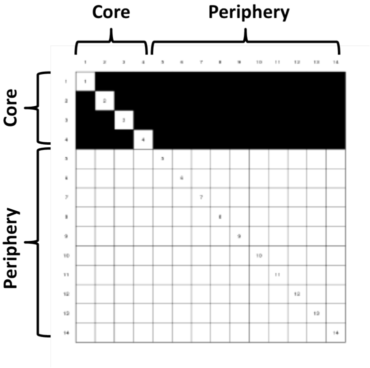
Core-Periphery Models

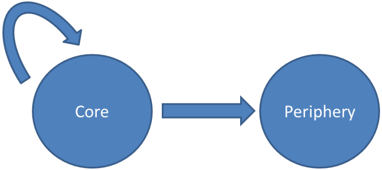


Core-Periphery Models



Core-Periphery Models

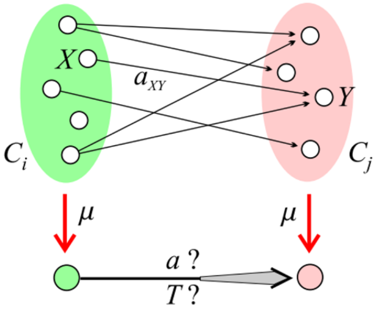




Even more blockmodeling

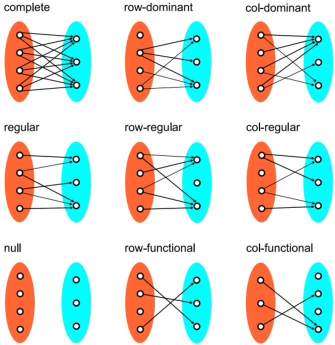
Generalized Blockmodeling

A *blockmodel* consists of structures obtained by identifying all units from the same cluster of the clustering **C**. For an exact definition of a blockmodel we have to be precise also about which blocks produce an arc in the *reduced graph* and which do not, and of what *type*. Some types of connections are presented in the figure on the next slide. The reduced graph can be represented by relational matrix, called also *image matrix*.



Doreian, Batagelj, and Ferligoj *Generalized Blockmodeling*, 2005

Even more blockmodeling



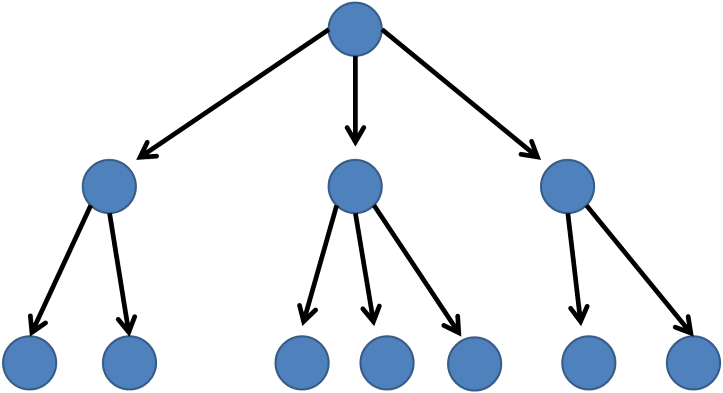
null	nul	all 0 *
complete	com	all 1 *
regular	reg	1-covered rows and columns
row-regular	rre	each row is 1-covered
col-regular	cre	each column is 1 -covered
row-dominant	rdo	∃ all 1 row *
col-dominant	cdo	∃ all 1 column *
row-functional	rfn	∃! one 1 in each row
col-functional	cfn	∃! one 1 in each column
non-null	one	∃ at least one 1

* except this may be diagonal

Doreian, Batagelj, and Ferligoj *Generalized Blockmodeling*, 2005

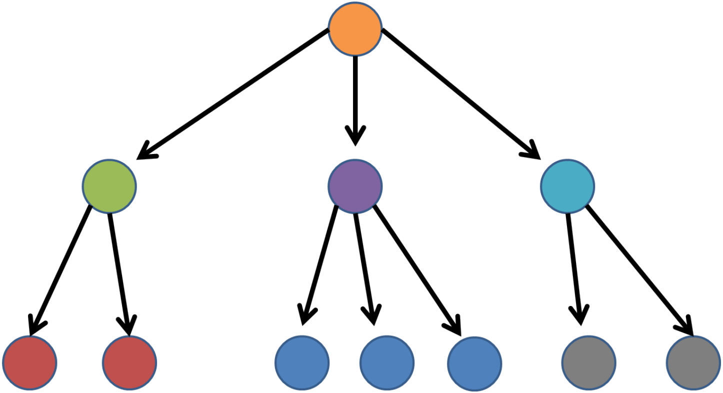
Structural Equivalence

Structural Equivalence



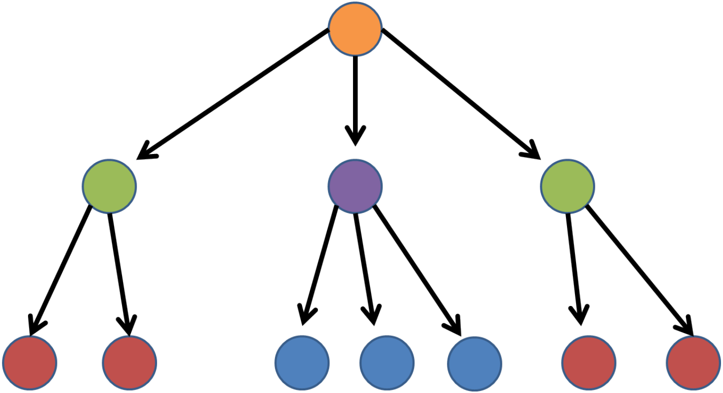
Sailer 1978

Structural Equivalence



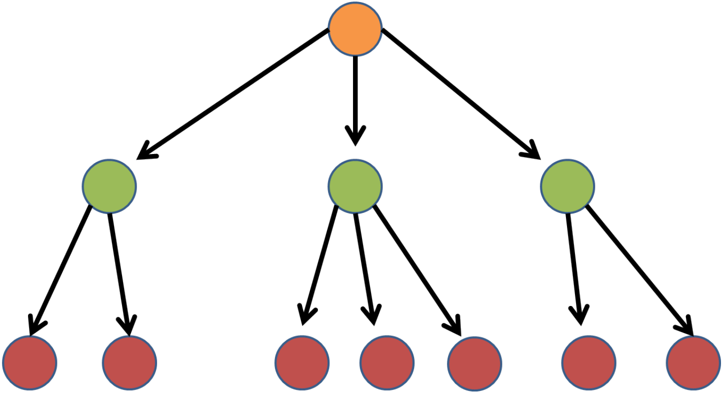
Sailer 1978

Automorphic Equivalence



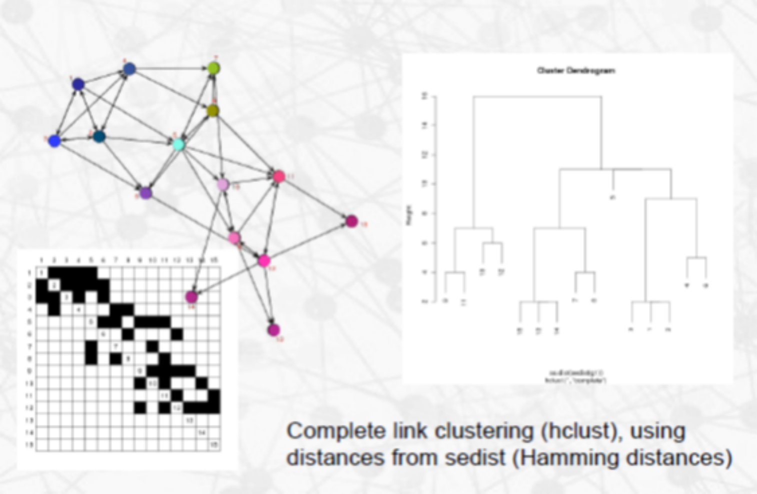
Sailer 1978

Regular Equivalence

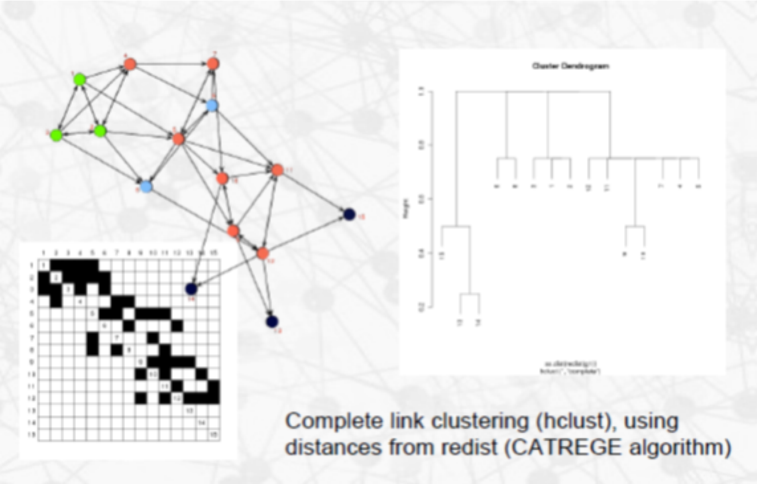


Sailer 1978

Structural Equivalence Example



Regular Equivalence Example



Everett and Borgatti 1994

Community Structure

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- M.E.J. Newman “Modularity and community structure in networks” *Proc Natl Acad Sci* 2006

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