

### Cohesion & Cohesive Subgroups

Wednesday Afternoon

Cohesion, generally, deals with issues connectedness. However, within that concept of connectedness, there are multiple approaches to cohesion, and multiple ways in which social network analysts posit connectedness. Under this heading, we study “cohesive subgroups” (finding regions of the network in which actors are more connected to each other than they are to those outside that region), “whole network cohesion” (measures that describe the cohesion of the entire network), and “dyadic cohesion” (measures that quantify the connectedness of pairs of actors within the network).

#### **Objectives:**

After this section, you should be able to:

- Describe the concept of cohesion from a social network perspective
- Differentiate between distance and density based measures of cohesion
- Name at least two measures of dyadic cohesion
- Name at least three measures of whole network cohesion
- Identify the different approaches to identifying cohesive subgroups
- Recognize core-periphery and centralized network structures
- Use UCINET to:
  - Create a geodesic distance matrix
  - Calculate density and fragmentation
  - Run hierarchical clustering on a geodesic matrix
  - Assess core-periphery structures in a network
  - Identify cliques, n-cliques, and k-plexes in a network
- Use NetDraw to:
  - Visualize cohesion measures from a network
  - Calculate and visualize k-cores
  - Run Newman-Girvan to identify cohesive subgroups

Slide 2

Why do we care?

- How do you think network structure interacts with the morale of the group?
- Consider an organization that has one subset that forms a tight group and a second subset who are generally attached to only one or a few of the “insiders.” What might be some of the implications of this structure?

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Slide 3

**Cohesion**

- Cohesion manifests in multiple ways
  - Dyadic & Whole Network Cohesion
    - This measures the degree of connectedness between actors and in the network as a whole
  - Cohesive Subgroups
    - Finding regions (subsets) of the network that are more connected to each other than to the rest of the network

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Slide 4

Dyadic & Whole Network Cohesion

- Dyadic cohesion refers to pairwise social closeness
  - How close two actors are to each other
- Whole network measures can be
  - Averages of dyadic cohesion
  - Measures not easily related to dyadic ones

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### Dyadic Cohesion

- Adjacency
  - Strength of tie
- Reachability
  - A path exists or does not (usually as  $1/d_{ij}$ )
- Distance
  - Length of shortest path between two nodes
- Multiplexity
  - Number of ties of different relations linking two nodes
- Number of paths linking two nodes
  - Vertex independent number is Point Connectivity
  - Edge independent number is Maximum Flow

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**Measures of Whole  
Network Cohesion**

- Density & Average degree
- Average Distance and Diameter
- Number of components
- Fragmentation
- Distance-weighted Fragmentation
- Centralization

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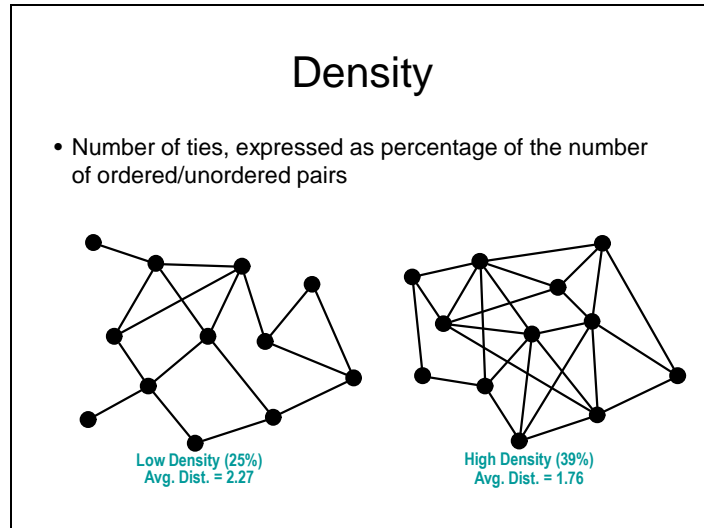
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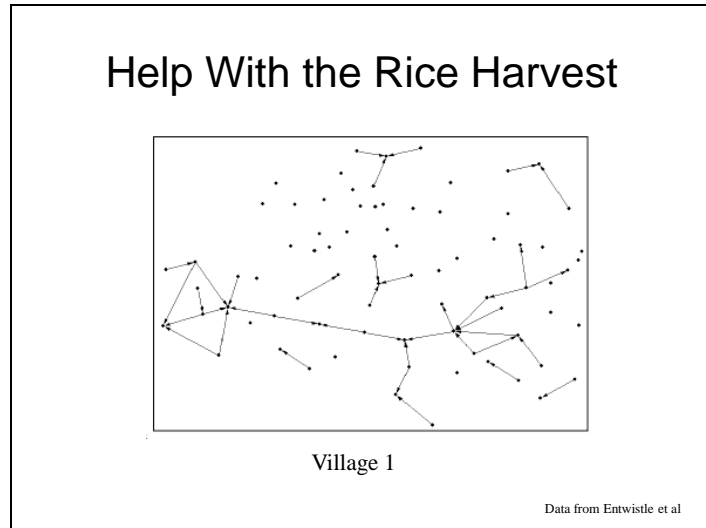
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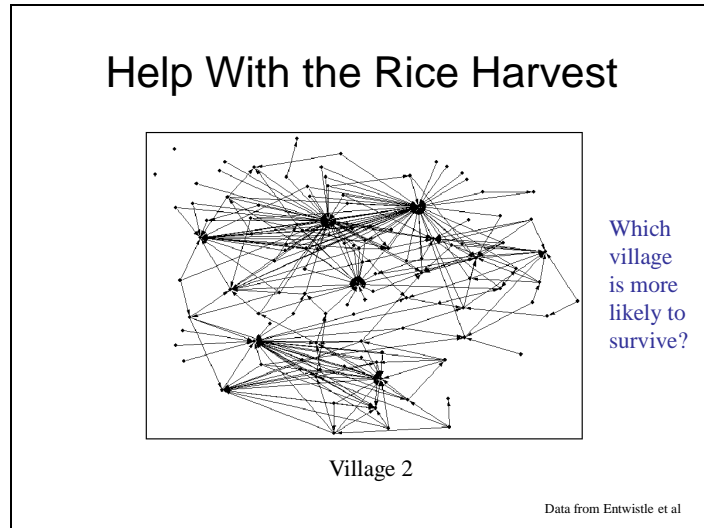
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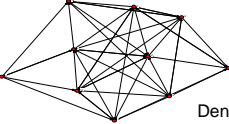
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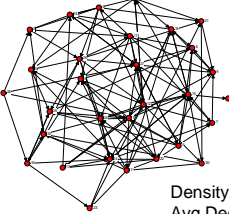
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### Average Degree

- Average number of links per person
- Is same as  $\text{density} \times (n-1)$ , where  $n$  is size of network
  - Density is just normalized avg degree
  - Often more intuitive than density
- Which network has the higher density?



Density 0.47  
Avg Deg 4



Density 0.14  
Avg Deg 4

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**Average Distance**

- Average geodesic distance between all pairs of nodes

avg. dist. = 1.9

avg. dist. = 2.4

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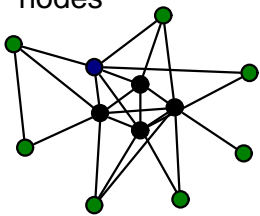
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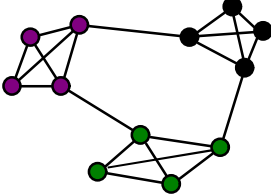
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**Diameter**

- The diameter of the network is simply the maximum distance between any two nodes



Diameter = 3



Diameter = 3

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### Fragmentation Measures

- Component ratio
- F measure of fragmentation
- Distance-weighted fragmentation  $^DF$

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**F Measure of Fragmentation**

- Proportion of pairs of nodes that are unreachable from each other

$$F = 1 - \frac{\sum_{i \neq j} r_{ij}}{n(n-1)}$$

$r_{ij} = 1$  if node  $i$  can reach node  $j$  by a path of any length  
 $r_{ij} = 0$  otherwise

- If all nodes reachable from all others (i.e., one component), then  $F = 0$
- If graph is all isolates, then  $F = 1$

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Computation Formula for F Measure

- No ties across components, and all reachable within components, hence can express in terms of size of components

$$F = 1 - \frac{\sum_k s_k(s_k - 1)}{n(n - 1)}$$

$s_k$  = size of  $k^{\text{th}}$  component

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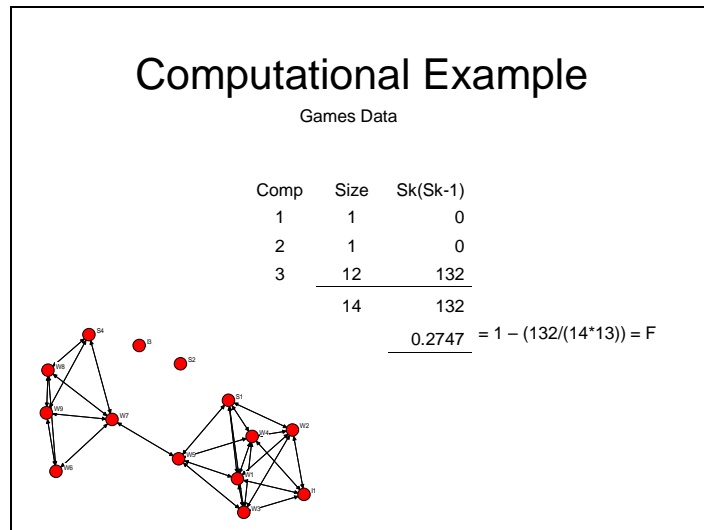
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**Distance-Weighted Fragmentation**

- Use average of the reciprocal of distance
  - letting  $1/\infty = 0$

$${}^D F = 1 - \frac{\sum_{i \neq j} \frac{1}{d_{ij}}}{n(n-1)}$$

- Bounds
  - lower bound of 0 when every pair is adjacent to every other (entire network is a clique, a “Complete” graph)
  - upper bound of 1 when graph is all isolates

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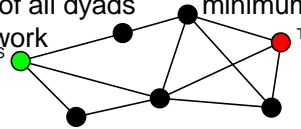
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### Connectivity

- Line connectivity  $\lambda$  is the minimum number of lines that must be removed to disconnect two nodes from each other (the minimum of all dyads is the network measure)
- Point connectivity  $\kappa$  is minimum number of nodes that must be removed to disconnect two nodes from each other (the minimum of all dyads is the network measure)



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### Part II: Subgroups – A Typology

	Found by algorithm based on	Found by finding sets with properties of
Network / Graph theory	<i>Graph-theoretic data driven algorithms</i> Newman-Girvan	<i>Formal definitions of sociological groups (mathematical ethnography)</i> Clique, n-clique, n-clan, n-club, k-plex, ls-set, lambda-set, k-core, component
Proximities / Clustering	<i>Multivariate clustering analysis methods</i> Johnson's Hierarchical clustering; k-means; MDS	<i>Formal definitions of abstract clusters</i> Combinatorial optimization

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Groups defined based algorithm using graph theoretic properties

	Group by defined Algorithm	Group by defined Characteristics
Network/ Graph Theory	Newman-Girvan	<b>Distance:</b> Component, Clique, n-clique, n-clan, n-club  <b>Density:</b> Clique, k-core, k-plex, ls-set, lambda set
Proximity /Distance	Hierarchical Clustering MDS K-Means	Factions (Core/Periphery)  (Combinatorial Optimization)

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**Groups w/specified characteristics,  
based on Graph Theoretic Measures**

	Group by defined Algorithm	Group by defined Characteristics
Network/ Graph Theory	Newman-Girvan	<b>Distance:</b> Component, Clique, n-clique, n-clan, n-club  <b>Density:</b> Clique, k-core, k-plex, <i>ls-set</i> , <i>lambda set</i>
Proximity /Distance	Hierarchical Clustering MDS K-Means	Factions (Core/Periphery)  (Combinatorial Optimization)

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Defined by graph-theoretic characteristics of resultant sets

- Most Common
  - Components
  - Clique (n-clique)
  - k-Plex
  - k-Core
  
- More advanced variations
  - n-clans
  - n-clubs
  - *Lambda sets*
  - *LS Sets*

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## Components

- Maximally **connected** subgraph
  - In digraph there are strong and weak components:
    - **Strong components** mean everyone can reach everyone else, even when considering the one-way streets in the network
    - **Weak components** means, if we ignore the directionality of the ties, everyone is reachable by everyone else

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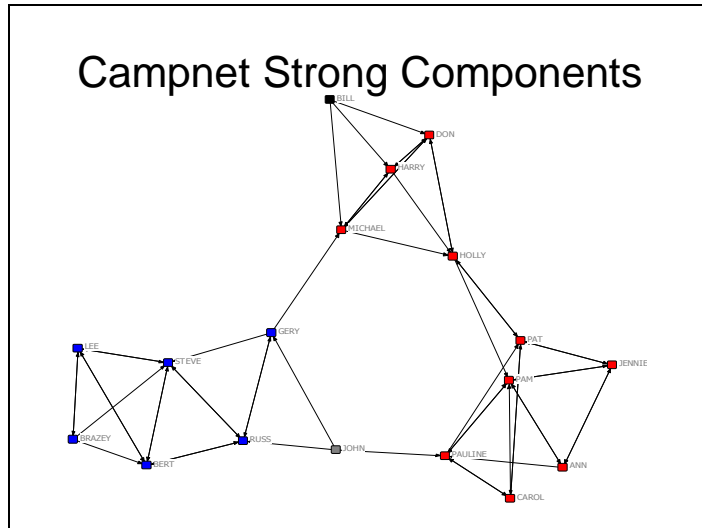
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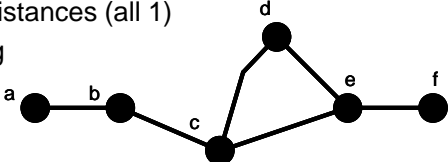
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### Cliques

- Definition
  - Maximal, complete subgraph
  - Set  $S$  s.t. for all  $u, v$  in  $S$ ,  $(u, v)$  in  $E$
- Properties
  - Maximum density (1.0)
  - Minimum distances (all 1)
  - overlapping
  - Strict

$\{c, d, e\}$  is the only clique



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graph LR; a --- b; b --- c; c --- e; e --- f; c --- d; d --- e;
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### Subgraphs

- Set of nodes
  - Is just a set of nodes
- A subgraph
  - Is set of nodes together with ties among them
- An induced subgraph
  - Subgraph defined by a set of nodes
  - Like pulling the nodes and ties out of the original graph

Subgraph induced by {a,b,c,f,e}

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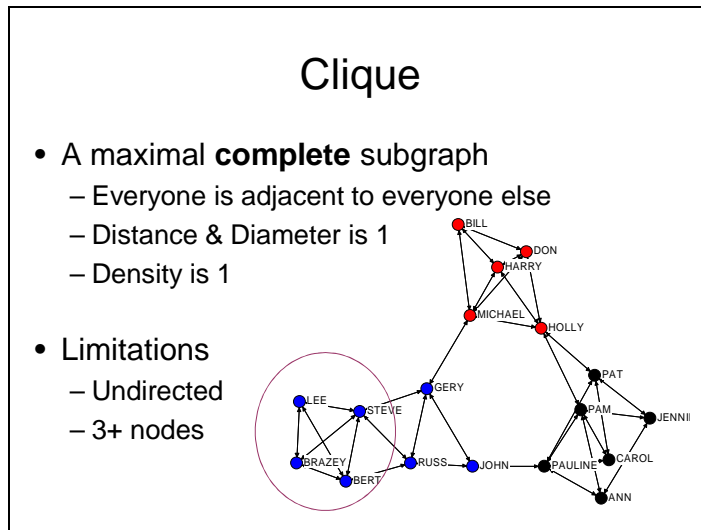
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### Problems with Cliques

- Can be too many or too few
- If too many:
  - Can put minimum on size
  - Can look at overlap
- If too few, relax requirements in terms of
  - Distance:
    - n-cliques, n-clans, n-clubs
    - This may also bring DOWN the number of cliques
  - Density
    - k-cores, k-plexes, ls-sets, lambda sets

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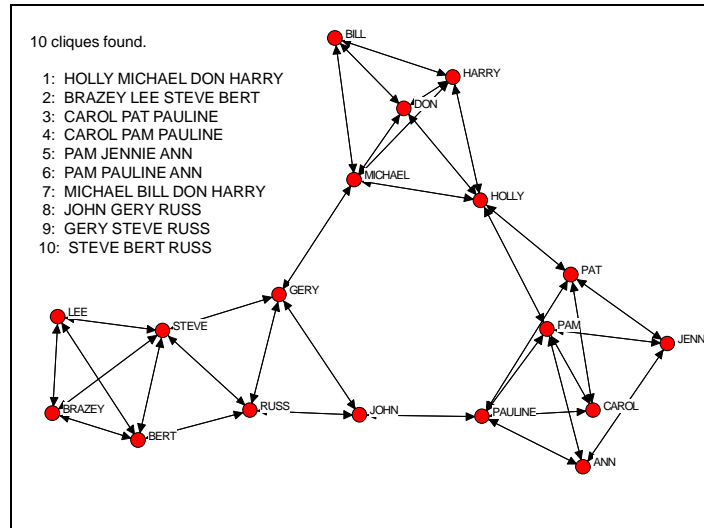
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## Slide 31



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### Types of Relaxations

- Distance (length of paths)
  - N-clique, n-clan, n-club
- Density (number of ties)
  - K-plex, k-core, component, *Is-set*, *lambda set*,

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Too Few, RELAX (Don't Do It)  
Distance Requirement

- n-Clique
  - Maximal subset with all nodes within n steps of each other
    - Path can include nodes not in n-Clique
    - A Clique is a 1-Clique (we don't count self-loops)

Is this a 2-Clique?  
NO!  
What about now?

But so is this!!!

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**N-cliques**

- Definition
  - Maximal subset s.t. for all  $u, v$  in  $S$ ,  $d(u, v) \leq n$
  - Distance among members less than specified maximum
  - When  $n = 1$ , we have a clique
- Properties
  - Relaxes notion of clique
    - Avg distance can be greater than 1

Is {a,b,c,f,e} a 2-clique?  
yes

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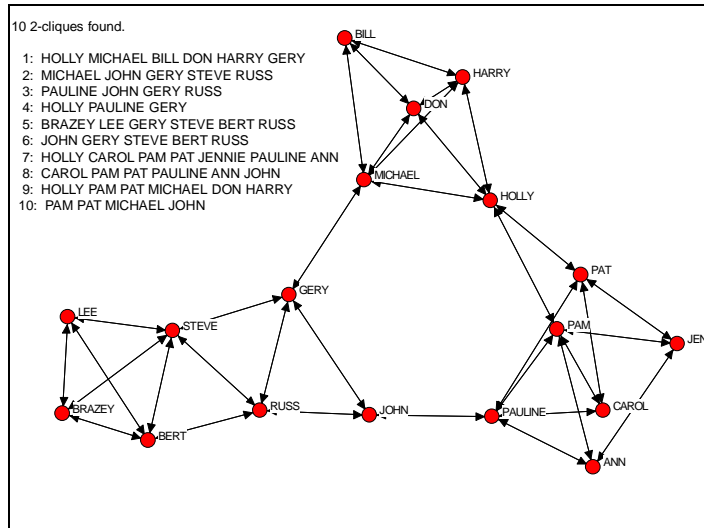
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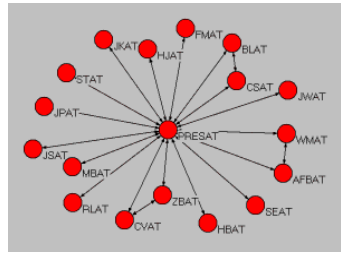
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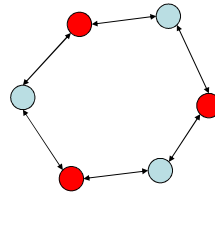
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Some are counter-intuitive  
(And not necessarily cohesive)



This is a 2-Clique



Red Nodes form a  
2-Clique, so do Blues

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So, we can force more cohesion

- n-Clan is an n-Clique whose diameter in the subgraph induced from the nodes in the n-Clique is  $\leq n$ 
  - Don't allow paths to go outside subset

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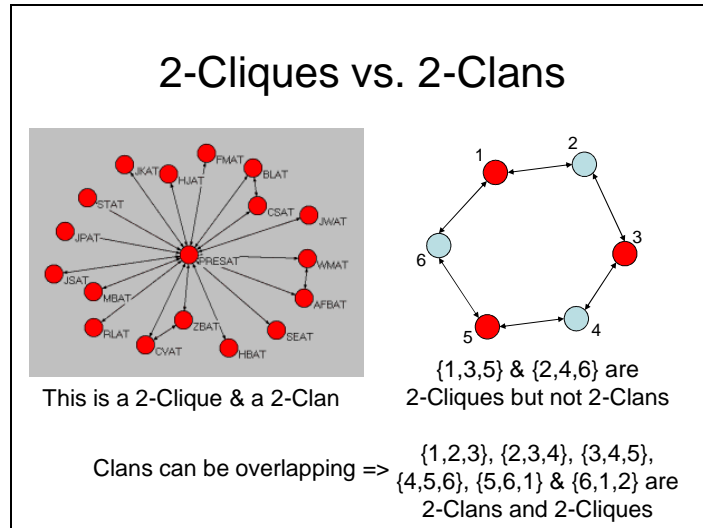
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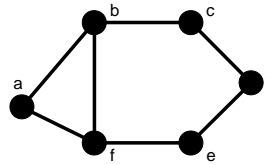
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**But, n-Clans have issues, too**

- The n-Clique requirement is restrictive, so there are few found in the data
- Is {a,b,c,f} a 2-Clan?
- How many 2-Clans are there in this graph?



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### Loosening the restriction

- n-Clubs are, effectively, n-Clans that do not have the n-Clique requirement, or...
  - A maximal subset  $S$  such that the graph induced by the nodes  $S$  has a diameter  $\leq n$
  - Now  $\{a,b,c,f\}$  is a 2-Club, so is  $\{a,b,e,f\}$
- Properties:
  - Painful (impossible) to compute
  - More plentiful than n-Clans
  - Overlapping

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### Loosen the density restriction

- n-Cliques, n-Clans, and n-Clubs all start from the definition of Cliques and relax the distance requirement (all distances = 1) in varying ways
- But, Cliques also have maximum density ( $d = 1$ ), and we can relax that definition instead...
- But for this, we must define the alpha operator,  $\alpha$ , such that  $\alpha(u,G)$  is the number of lines from node  $u$  to nodes in graph  $G$

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### Relaxing the Density Requirement

- k-Plex
  - A clique where members don't have to be connected to everyone else, just all but  $k$  members, or...
  - a [maximal] subset  $S$  s.t. for all  $u$  in  $S$ ,  $\alpha(u,S) \geq |S| - k$ , where  $|S|$  is size of set  $S$ 
    - All subsets of k-plexes are k-plexes (if non-maximal)
    - Get distance for free based on  $S$ ,  $k$ .
      - If  $k < (|S|+2)/2$  then diameter  $\leq 2$
    - Numerous & Overlapping
    - May be more intuitive than distance-based measures
    - A Clique is a 1-plex (We assume it not tied to itself)

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**K-Plex**

Is {a,b,d,e} a 2-plex?  
Is {a,b,c,d,e} a 2-plex?  
Is {a,b,d} a 2-plex?

Is the graph as a whole a 2-plex?  
Is it a 3-plex?

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### k-Core

- Sort of opposite approach from k-plex
  - Because the size of the group is not taken into account, k-cores are more directly about specifying how many ties MUST be present independent of how many nodes are in the core, whereas the k-plex is about how many may be missing.
- A k-Core is maximal subgraph within which all nodes have ties to at least k other nodes
  - All nodes in a components are at least 1-Cores
  - Each nodes is assigned a “core” which is the largest k-core to which it belongs (and it therefore also belongs to all lower cores that exist)
  - K-cores are hierarchical and form a partition
  - However, they may be disconnected

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**Another definition**

- A k-core is a maximal subgraph such that for all  $u$  in  $S$ ,  $\alpha(u, S) \geq k$

- All nodes are 2-core (and 1-core)  
Red nodes are 3-core.
- Great for analyzing large networks

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### Factions

- Computationally arrange nodes into mutually exclusive groups such that some predefined criteria is optimized
  - For example, make groups that maximize density of internal ties and minimize density of external ties

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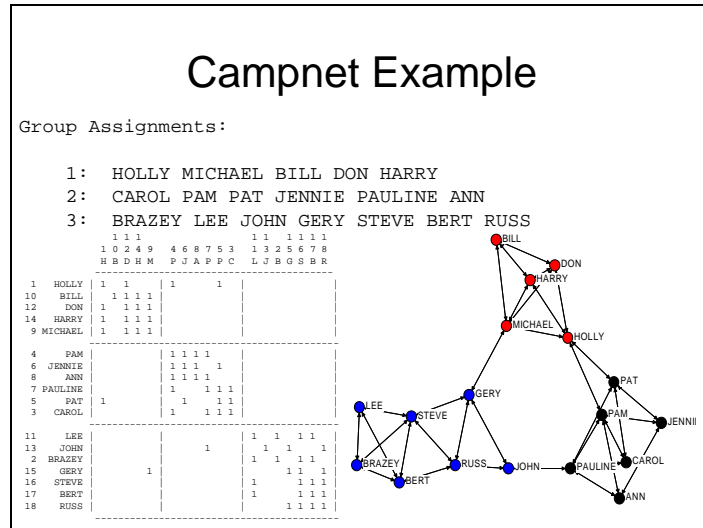
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### Core-Periphery Models

- A core periphery structure has a single cohesive subgroup with a set of other nodes, loosely connected to the core
- Core members interact with (lots of) other core members
- Peripheral members interact with (a few) core members

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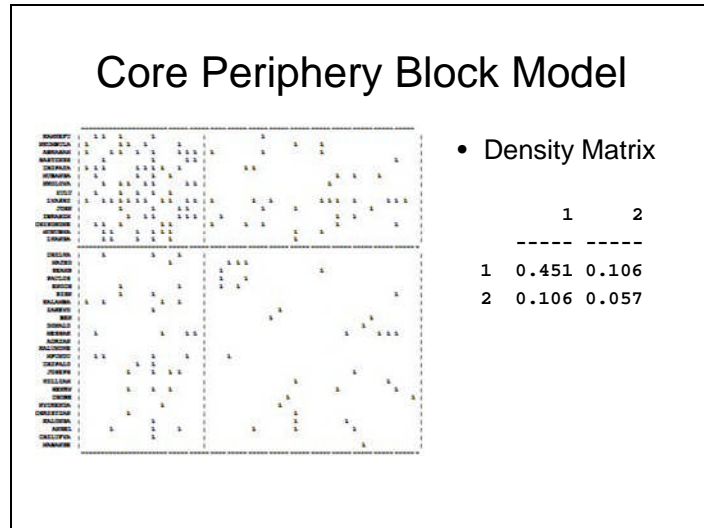
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### Finding Core/Periphery Structures

- Two ways to deal with it...
  - One is a special case of factions, which maximizes density of core-to-core relations and minimizes all others (categorical)
  - Another is a continuous model that calculates a “coreness” which is how much this node looks like a core node (continuous).

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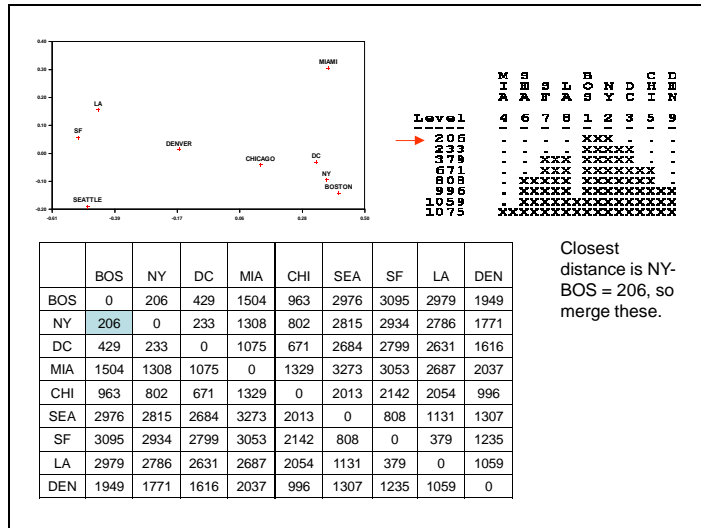
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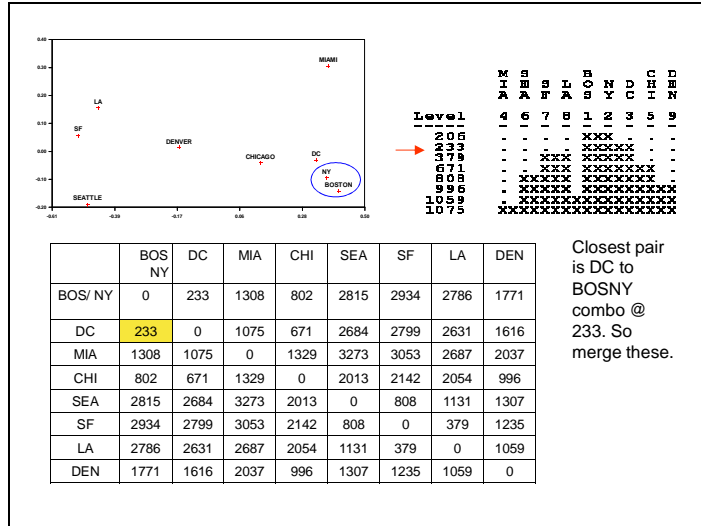
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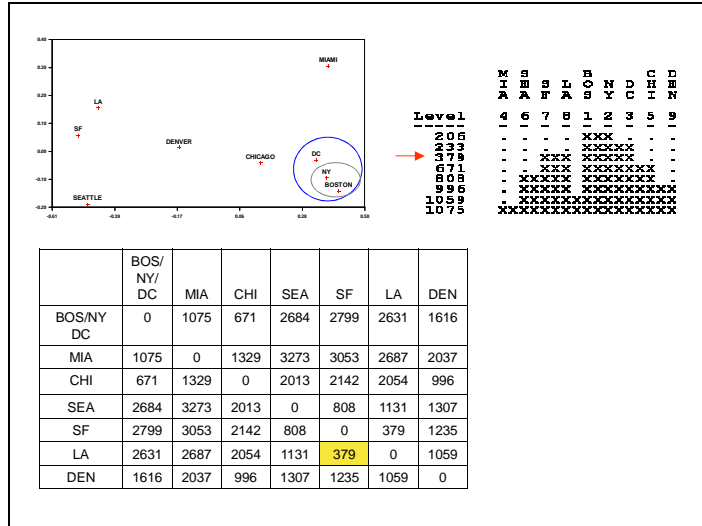
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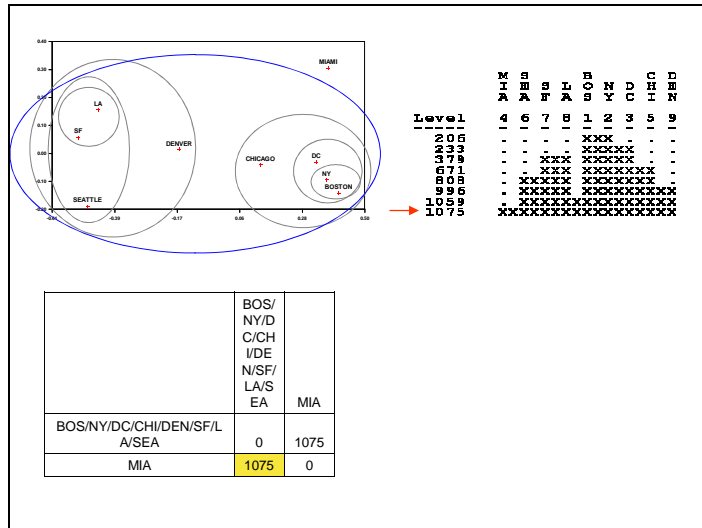
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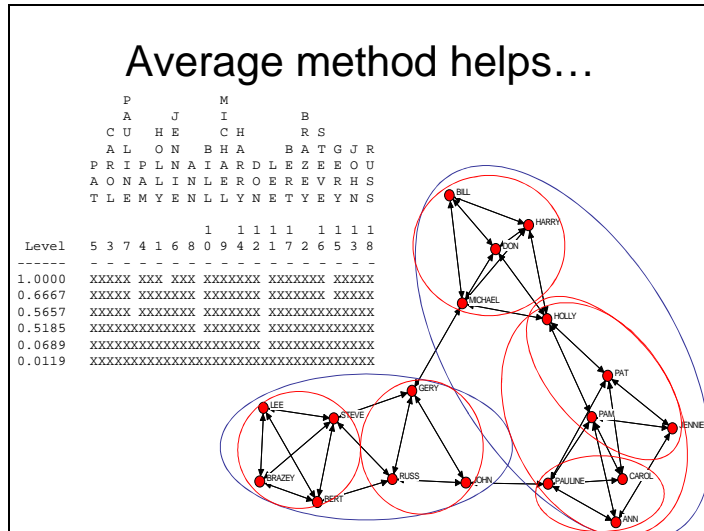
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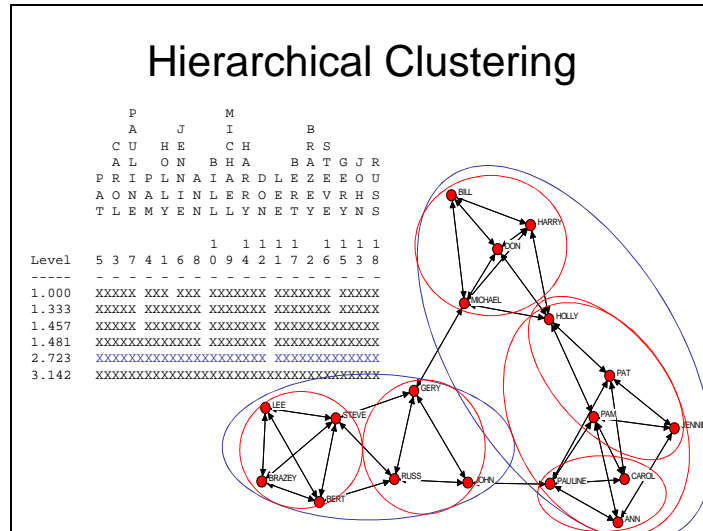
### Applying HiClus to Network Data

- BETTER:  
Compute geodesic distances first, then cluster the distance matrix
- Or cluster the structural equivalence matrix

Geodesic Distances

	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	8
H	B	C	P	P	J	P	A	M	B	L	D	J	H	G	S	B	R	
1 HOLLY	0	4	2	1	1	2	2	2	1	2	4	1	3	1	2	3	4	3
2 BRAZEY	4	0	5	5	5	6	4	5	3	4	1	4	3	4	2	1	1	2
3 CAROL	2	5	0	1	1	2	1	2	3	4	5	3	2	3	3	4	4	3
4 PAM	1	5	1	0	2	1	1	1	2	3	5	2	2	2	3	4	4	3
5 PAT	1	5	1	2	0	1	1	2	2	3	5	2	2	2	3	4	4	3
6 JENNIE	2	6	2	1	1	0	2	1	3	4	6	3	3	3	4	5	5	4
7 PAULINE	2	4	1	1	1	2	0	1	3	4	4	3	1	3	2	3	3	2
8 ANN	2	5	2	1	2	1	1	0	3	4	5	3	2	3	3	4	4	3
9 MICHAEL	1	3	3	2	2	3	3	3	0	1	3	1	2	1	1	2	3	2
10 BILL	2	4	4	3	3	4	4	4	1	0	4	1	3	1	2	3	4	3
11 LEE	4	1	5	5	5	6	4	5	3	4	0	4	3	4	2	1	1	2
12 DON	1	4	3	2	2	3	3	3	1	1	4	0	3	1	2	3	4	3
13 JOHN	3	3	2	2	2	3	1	2	2	3	3	3	0	3	1	2	2	1
14 HARRY	1	4	3	2	2	3	3	3	1	1	4	1	3	0	2	3	4	3
15 GERY	2	2	3	3	3	4	2	3	1	2	2	2	1	2	0	1	2	1
16 STEVE	3	1	4	4	4	5	3	4	2	3	1	3	2	3	1	0	1	1
17 BERT	4	1	4	4	4	5	3	4	3	4	1	4	2	4	2	1	0	1
18 RUSS	3	2	3	3	3	4	2	3	2	3	2	3	1	3	1	1	1	0

Slide 67



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## Finding Cohesive Subgroups

- With UCINET
  - Network | Subgroups |
    - Cliques
    - n-Cliques
    - Factions
  - Network | Regions |
    - K-cores
    - Components
  - Networks | Core/Periphery
- With NetDraw
  - Analysis | Subgroups | Newman-Girvan
  - Analysis | K-cores
  - Analysis | Subgroups | Factions

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### **Cohesion Lab**

For this lab we will use four datasets:

#### **CAMPNET:**

This is a dichotomous adjacency matrix of 18 participants in a qualitative methods class. Ties are directed and represent that the ego indicated that the nominated alter was one of the three people with which s/he spent the most time during the seminar.

#### **KAPTAL:**

This is a stacked dataset containing four dichotomous matrices. There are two adjacency matrices each for social ties (indicating the pair had social interaction) and instrumental ties (indicating the pair had work-related interaction). The two pairs of matrices represent two different points in time. The names of the datasets encode the type of tie in the sixth letter, and the time period in the seventh. Thus, the dataset KAPFTS1 is social ties at time 1 and KAPFTI2 is instrumental ties at time 2, etc.

#### **ZACKAR & ZACHATTR:**

ZACKAR is another stacked dataset, containing a dichotomous adjacency matrix, ZACHE, which represents the simple presence or absence of ties between members of a Karate Club, and ZACHC, which contains valued data counting the number of interactions between actors. ZACHATTR is a rectangular matrix with three columns of attributes for each of the actors from the ZACKAR datasets.

#### **PV504:**

This is a symmetric, valued dataset. It has data for 504 actors that are employees of a consulting organization, with values representing the number of days on which each pair worked together on projects.

**EXERCISES:**

- 1) Cohesion using UCINET with **CAMPNET**
  - a. Calculate the following measures of cohesion using Network | Cohesion
    - Density
    - Distance
    - Maximum Flow
  - b) Distance produces a matrix. Using this matrix, how would you determine the network diameter?
  - c) Using your Netdraw visualization, verify a couple entries in the distance, point connectivity, and maximum flow matrices produced.

- 2) Fragmentation using UCINET and **KAPTAIL**

Using the **KAPFTS1** dataset (you may have to unpack **KAPTAIL** if you have not already done so), calculate its fragmentation under Network | Centrality using both measures in the options portion of the dialog box and compare the results. Why did they generate different results? Which one is more useful for this network? When would you choose to use one or the other?

- 3) Hierarchical Clustering using UCINET with **ZACKAR**
  - a. This section uses the ZACHE dataset (you may have to unpack **ZACKAR** to create **ZACHE**) and the **ZACHATTR** attribute dataset. Check to make sure you have both, and let one of the facilitators know if you do not.
  - b. Now, run SINGLE\_LINK method Hierarchical Clustering (Tools|Cluster|Hierarchical) on the **ZACHE** adjacency matrix (specifying the appropriate kind of data). What does the output tell you? Why did you get this result?

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- c. Now re-run using the AVERAGE method on the same data. Why did you get a different result? Which one is more useful in identifying cohesive subgroups from these data?
  - d. Now, create the geodesic distance matrix from these data (Network|Cohesion|Distance) and run that matrix through Hierarchical clustering with the **appropriate parameters**, using both the AVERAGE and SINGLE\_LINK methods. How did your results (and parameters) vary from using the adjacency matrix?
- 4) Newman-Girvan using NetDraw with **ZACKAR**
- a. Open the **ZACKAR** stacked dataset in NetDraw. It should open to displaying the relation **ZACHE** but if not, make sure it does.
  - b. Now, open the attribute file, **ZACHATTR**, using the folder with the A next to it. (It should display a spreadsheet with four columns. Just close that window.)
  - c. Run the Newman-Girvan analysis (Analysis|Subgroups|Newman-Girvan) specifying a minimum of 2 and a maximum of 40 clusters desired. It should automatically color your nodes so that there are nodes are one of two colors. What it has done behind the scenes is color based on the ngPart\_2 partition (a partition with 2 colors). Click on the color palette icon and pull down on the drop down list to select ngPart\_3 to see how it partitions it next. And then ngPart\_4. How useful are these partitions?
  - d. Using the color palette, go back to the ngPart\_2 partition. Now, click on the shape palette icon, and select "Club" from the list. This will shape the nodes according to which club the members went to after the split. How well did the N-G algorithm predict the affiliation of the club members?
- 5) Factions using Netdraw with **ZACKAR**

Now run Analysis|Subgroups|Factions selecting 2 for the desired number of groups. This time, instead of using the color palette, use

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- the “Nodes” tab in the control area on the right hand side of the screen and scroll down to the last attribute, which should be called “Factions 2” and then click the “Color” checkbox. How does factions compare with the Newman-Girvan algorithm in terms of predicting the affiliations? How could you display both the Newman-Girvan results and the Factions result at the same time?
- 6) Factions using UCINET with **KAPTAIL**
- If you have not already done so, in UCINET, unpack the **KAPTAIL** dataset to make **KAPFTI1**, **KAPFTI2**, **KAPFTS1**, **KAPFTS2**. These are “instrumental” and “social” ties at time 1 & 2 from a tailor shop in Zambia. The instrumental ties are asymmetric, and the social ties are undirected. We will be using the social ties at time 1 (**KAPFTS1**) for this analysis.
  - Run Network|Subgroups|Factions on **KAPFTS1** and specify two factions. Review the results. How well do you think the two factions describe the subgroup structure of the network? Run it a couple more times, increasing the number of factions. How do the results change? Why? How would you interpret those changes?
- 7) Core-Periphery using UCINET with **KAPTAIL**
- Run Network|Core/Periphery on **KAPFTS1** and **KAPFTS2**. How do the results differ? Which time might you expect that there was a successful strike in the Tailor Shop and why?
- 8) Cliques using UCINET and NetDraw with **KAPTAIL**
- In UCINET run Network|Subgroups|Cliques on **KAPFTS2** with the a minimum size of 3. How many cliques do you get? How useful is this?
  - Let’s visualize the data. Open **KAPFTS2** in NetDraw. Does this help us identify clique structures?
  - What about if we open **CliqueOverlap** (which is an actor-by-actor matrix in which each cell holds the number of different cliques

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that this pair of actors is in together that was created when we ran Cliques in UCINET). Start increasing the filter at the bottom of the “Rels” tab on the control panel on the right side of the screen up from 1 using the “+” button. Does this indicate there is a significant or minimal overlap of cliques in this structure?

- d. Now open **CliqueSets** in Netdraw and set the filter value back down to 0 and redraw the picture. This is a two-mode network where lines indicate actors (typically red circles with names) belong to a specific clique (typically blue squares with numbers). What does this picture convey about the structure of the network?
  - e. Try deleting the pendants (nodes with only one line, in this case, they would be people who are members of only one clique) by pressing the button labeled **Pen** on the icon bar in NetDraw, and the isolates (those with no lines, in this case not members of any clique) using the **Iso** button. How much did that affect the meaning of the visualization for you?
- 9) n-Cliques using UCINET and NetDraw with **KAPTAL**

Now, run Network|Subgroups|n-Cliques on **KAPFTS1** specifying  $n = 2$ , and minimum size of 4. How many 3-cliques did you get? Open **nClqSets** in NetDraw and compare that picture with the one from the previous step. What is the difference between these two pictures?

10) K-CORES using NetDraw with **PV504**

- a. Open **PV504** in NetDraw. Increase the filtering to only show relations of more than 3 (days together on a projects), turn off labels (using the script L button), and redraw the network.
- b. Now run Analysis|K-Cores. It will automatically color the nodes according to their k-Core. Select the Nodes tab, and pull down to the \*K-core attribute, and use the “s” button to step through the k-cores from 1 to 10. What does this tell you about the network?