Emergent Groups: Detecting an Emergent Subgroup

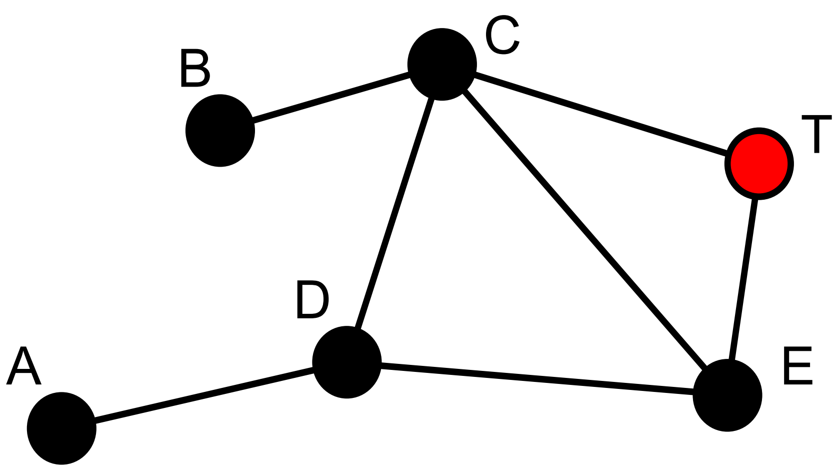
-Clumpiness

-Regions

-Subgroups

Transitivity

- Proportion of triples with 3 ties as a proportion of triples with 2 or more ties
  - Aka the clustering coefficient



cc = 2/6 = 33%

{C,T,E} is a transitive triple, but {B,C,D} is not. {A,D,T} is not counted at all.

Network Regions

Network Regions

- Large “contiguous” areas
- Areas that contain cohesive subgroups
- We will cover:
  - Components
  - K-Cores

Graph Terminology

- A graph G(V,E) consists of a set of nodes V and a set of lines E. Each line $e \in E$ consists of a pair of nodes (u,v)
- A graph G' is a subgraph of a graph G if every line in E(G') is in E(G), and every node in V(G') is in V(G).
- The subgraph S induced by a set of nodes consists of those nodes together with <u>all</u> ties among them

Components

- A subgraph S of a graph G is a component if S is maximal and connected
  - Connected means that every node can reach every other by some path (no matter how long)

Components in Digraphs

- If G is a digraph, then
  - S is a weak component if it is a component of the underlying (undirected) graph
    - i.e., we allow semi-paths rather than require true directed paths
  - S is a strong component if for all u,v in S, there is a path from u to v

Notes on Components

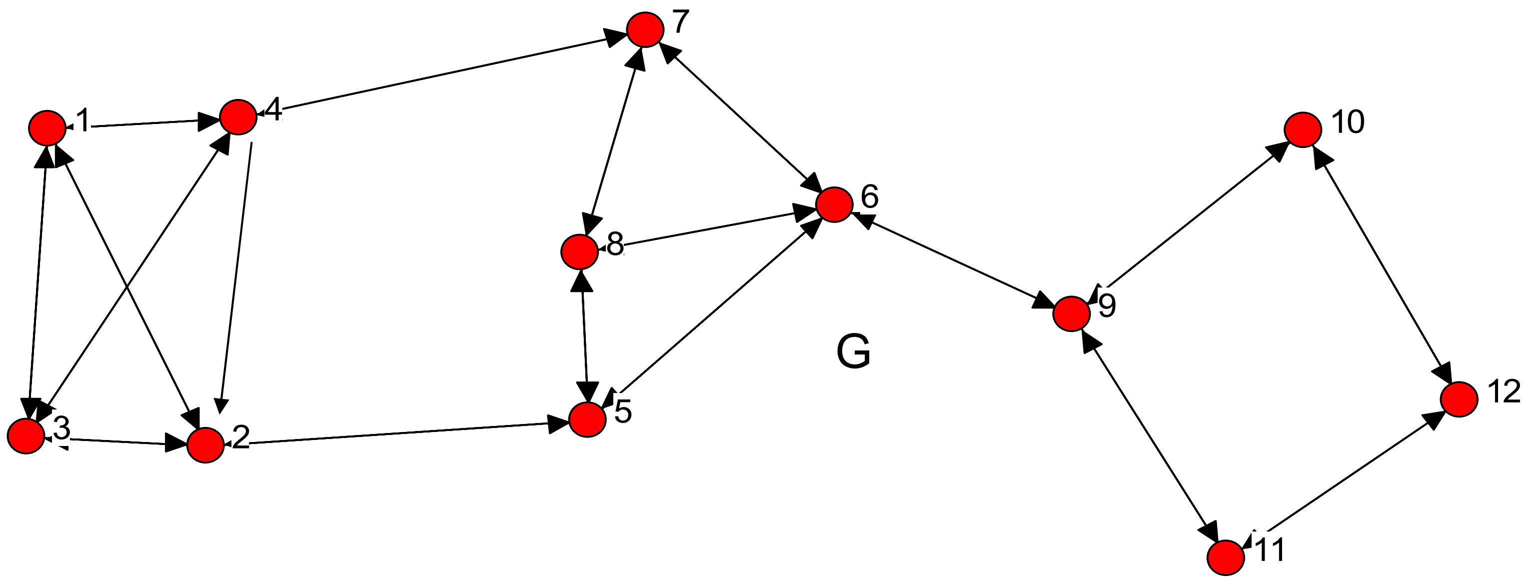
- Isolates are (very small) components
- Finding components is often first step in analysis of large graphs
  - Often analyze each component separately, or discard very small components
  - Many network measures require a connected graph, so they don't work on graphs with multiple components

Alpha Operator

- Let α(S1,S2) be the number of ties from members of set S1 to members of the set S2
- $\alpha(u,S)$ is number of ties node *u* has with members of set S
- $\alpha(S) = \alpha(S,V-S)$ is number of ties from members of set S to members of V-S (i.e., all other nodes)

K-Core

- A subgraph S is a k-core if for all u $\in$ S, α(u,S) >= k, and S is maximal



  – S=G is 1-core & 2-core; S = {1..8} is 3-core
  – There is no 4-core or higher

K-Core Notes

- Finds areas within which cohesive subgroups may be found
- Identifies fault lines across which cohesive subgroups do not span
- In large datasets, you can successively examine the 1-cores, the 2-cores, etc.
  - Progressively narrowing to core of network

Cohesive Subgroups

Cohesive Subgroups

- Initially conceived of as formalizations of fundamental sociological concepts
  - Primary groups
  - Emergent groups
- Now typically thought of in terms of a technique for identifying groups within networks

Canonical Hypothesis

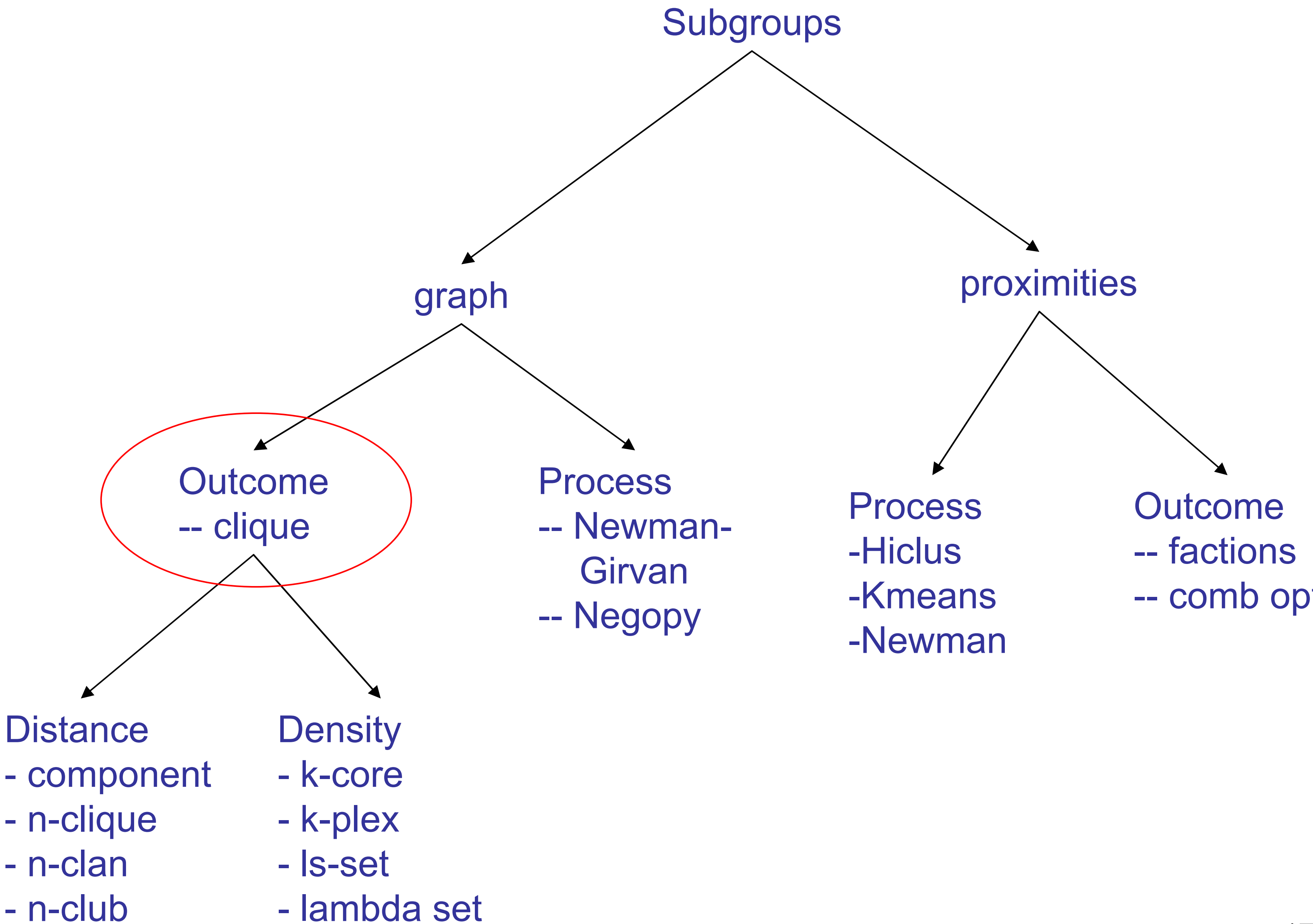
- Members of group will have similar outcomes
  - Ideas, attitudes, illnesses, behaviors
- Due to interpersonal transmission
  - transference
  - Influence / persuasion
  - Co-construction of beliefs & practices
    - As in communities of practice
- So group membership is independent var used to predict commonality of attitudes, beliefs, etc.

Typology of Subgroups

	Process	Outcome
Network / Graph theory	Newman-Girvan	Clique, n-clique, n-clan, n-club, k-plex, ls-set, lambda-set, k-core, component
Proximities / Clustering	Johnson’s Hierarchical clustering; k-means; MDS	Factions, combinatorial optimization

Types of Approaches

- Subgroups
  - graph
    - Outcome
      -- clique
      - Distance
        - component
        - n-clique
        - n-clan
        - n-club
      - Density
        - k-core
        - k-plex
        - ls-set
        - lambda set
    - Process
      -- Newman-Girvan
      -- Negopy
  - proximities
    - Process
      -Hiclus
      -Kmeans
    - Outcome
      -- factions
      -- comb opt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- n-clique
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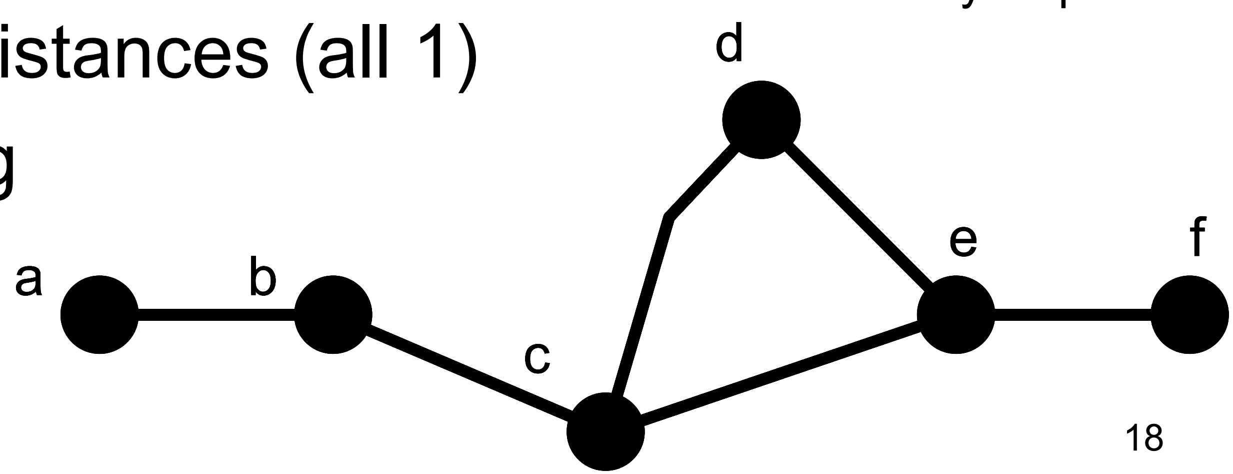
- lambda set

Cliques

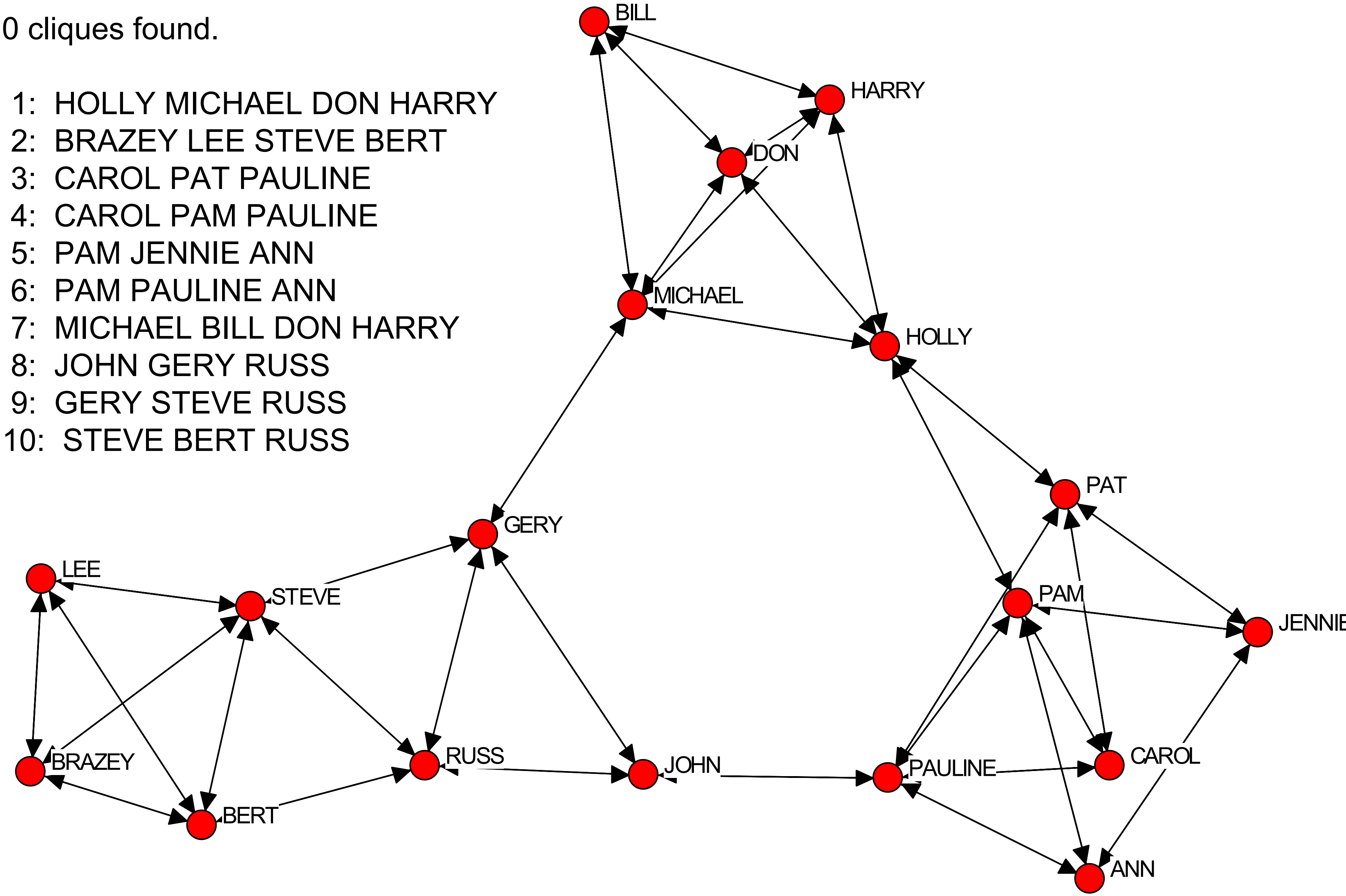
- Definition
  - Maximal, complete subgraph
  - Set S s.t. for all u,v in S, (u,v) in E
- Properties
  - Maximum density (1.0)
  - Minimum distances (all 1)
  - overlapping
  - Strict

{c,d,e} is the only clique



10 cliques found.

1: HOLLY MICHAEL DON HARRY
2: BRAZEY LEE STEVE BERT
3: CAROL PAT PAULINE
4: CAROL PAM PAULINE
5: PAM JENNIE ANN
6: PAM PAULINE ANN
7: MICHAEL BILL DON HARRY
8: JOHN GERY RUSS
9: GERY STEVE RUSS
10: STEVE BERT RUSS

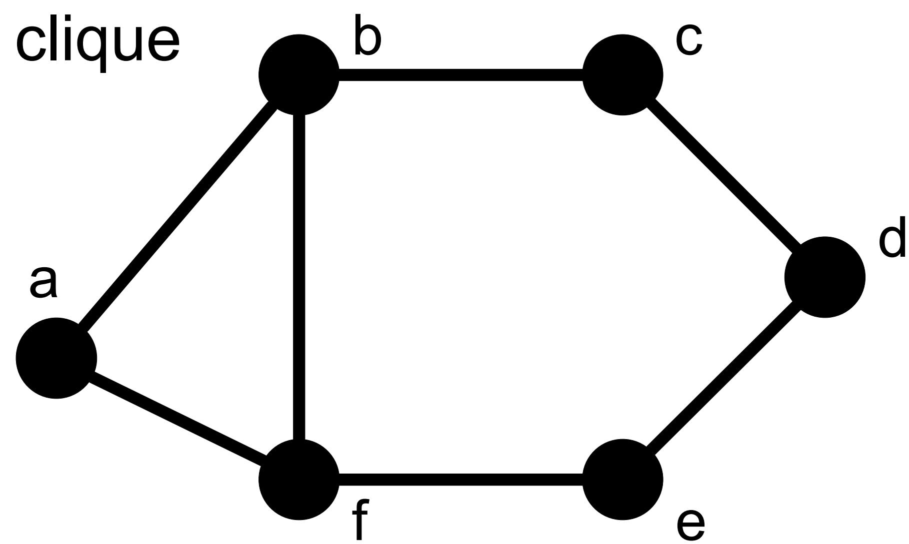


Types of Relaxations

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

N-cliques

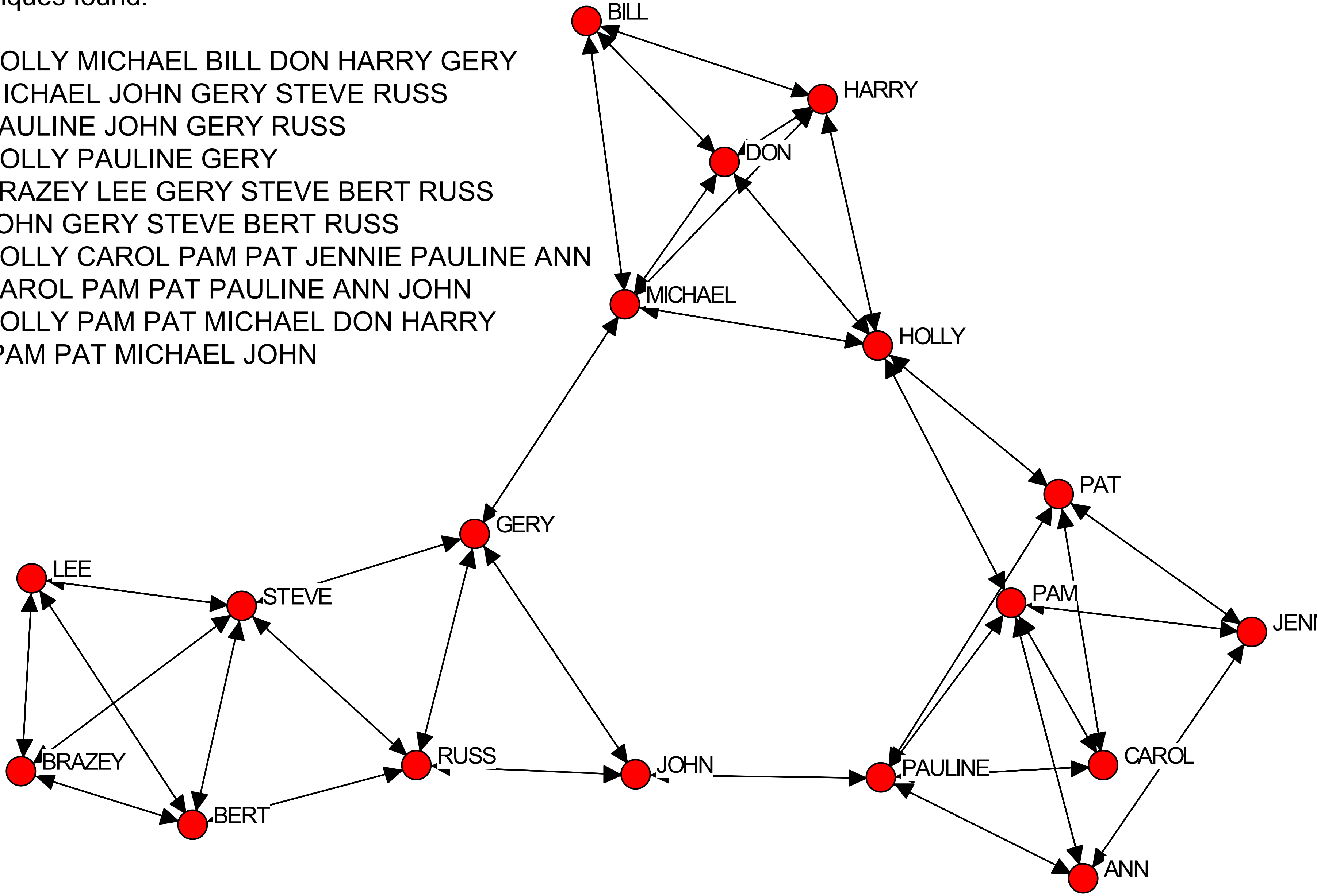
- Definition
  - Maximal subset s.t. for all *u,v* in S, d(*u,v*) <= n
  - Distance among members less than specified maximum
  - When n = 1, we have a clique
- Properties
  - Relaxes notion of clique
    - Avg distance can be greater than 1



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

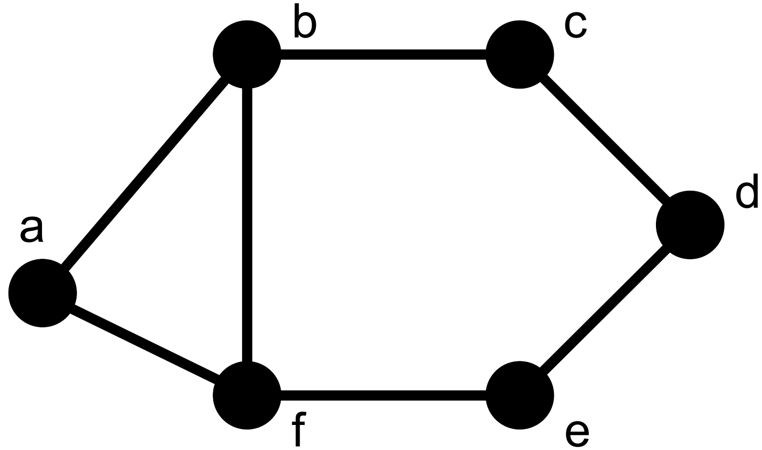
10 2-cliques found.

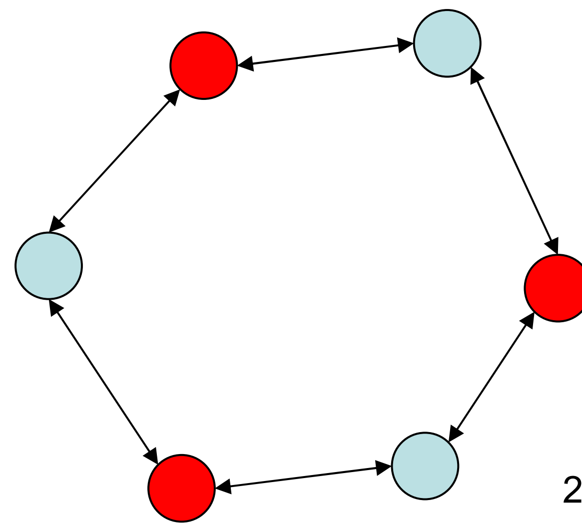
1: HOLLY MICHAEL BILL DON HARRY GERY
2: MICHAEL JOHN GERY STEVE RUSS
3: PAULINE JOHN GERY RUSS
4: HOLLY PAULINE GERY
5: BRAZEY LEE GERY STEVE BERT RUSS
6: JOHN GERY STEVE BERT RUSS
7: HOLLY CAROL PAM PAT JENNIE PAULINE ANN
8: CAROL PAM PAT PAULINE ANN JOHN
9: HOLLY PAM PAT MICHAEL DON HARRY
10: PAM PAT MICHAEL JOHN



Issues with N-Cliques

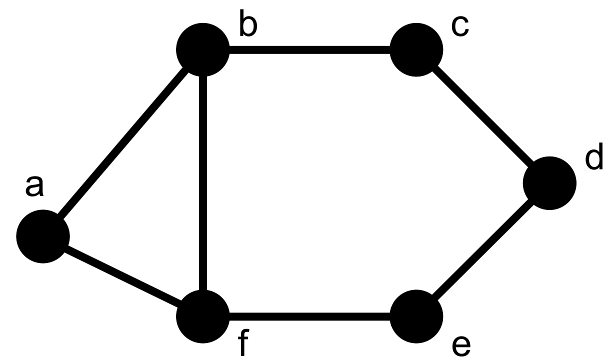
- Overlapping
  - {a,b,c,f,e} and {b,c,d,f,e} are both 2-cliques
- Membership criterion satisfiable through non-members
- Even 2-cliques can be fairly non-cohesive
  - Red nodes belong to same 2-clique but none are adjacent

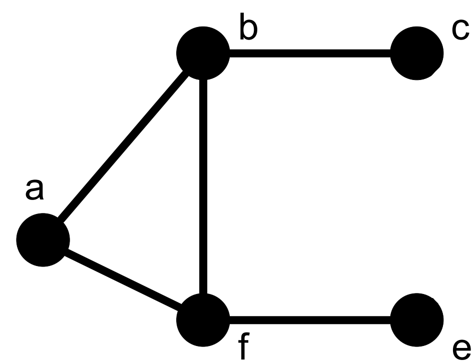




Subgraphs

- 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

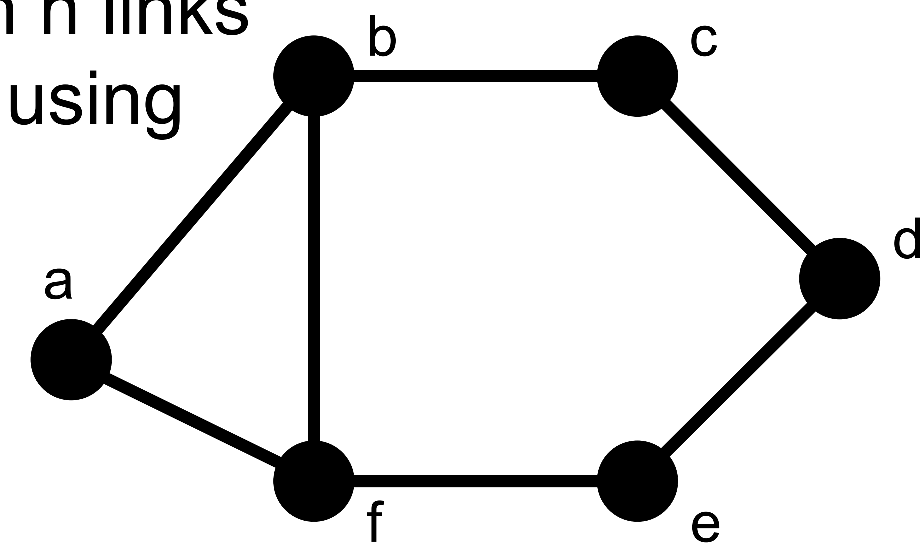




Subgraph induced by {a,b,c,f,e}

N-Clan

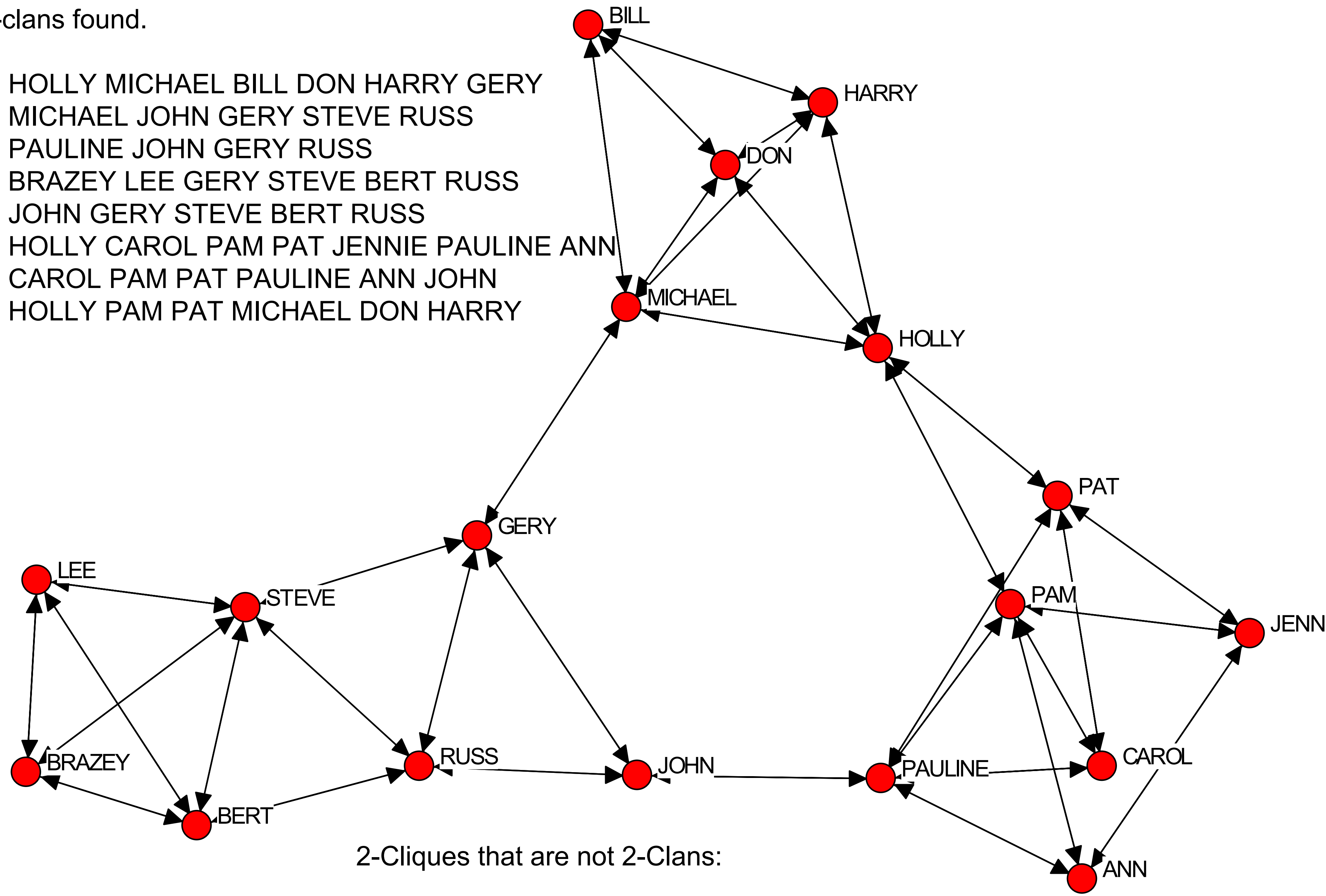
- Definition
  - An n-clique S whose diameter in the subgraph induced by S is <= n
  - Members of set within n links of each other without using outsiders
- Properties
  - More cohesive than n-cliques



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

8 2-clans found.

1: HOLLY MICHAEL BILL DON HARRY GERY
2: MICHAEL JOHN GERY STEVE RUSS
3: PAULINE JOHN GERY RUSS
5: BRAZEY LEE GERY STEVE BERT RUSS
6: JOHN GERY STEVE BERT RUSS
7: HOLLY CAROL PAM PAT JENNIE PAULINE ANN
8: CAROL PAM PAT PAULINE ANN JOHN
9: HOLLY PAM PAT MICHAEL DON HARRY

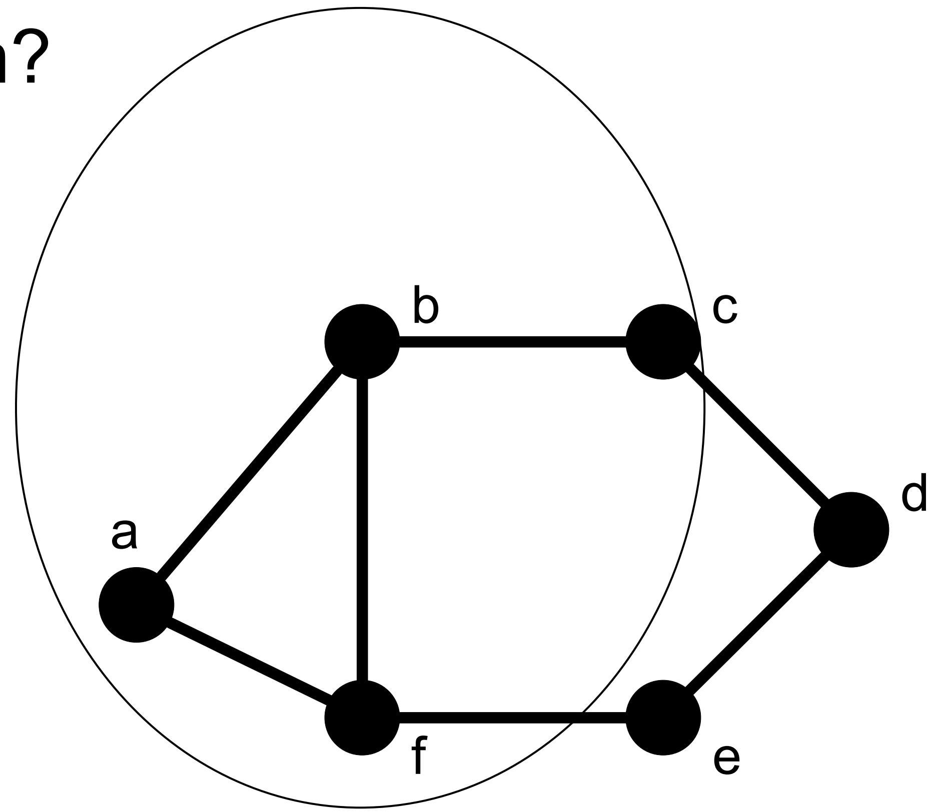


2-Cliques that are not 2-Clans:

4: HOLLY PAULINE GERY
10: PAM PAT MICHAEL JOHN

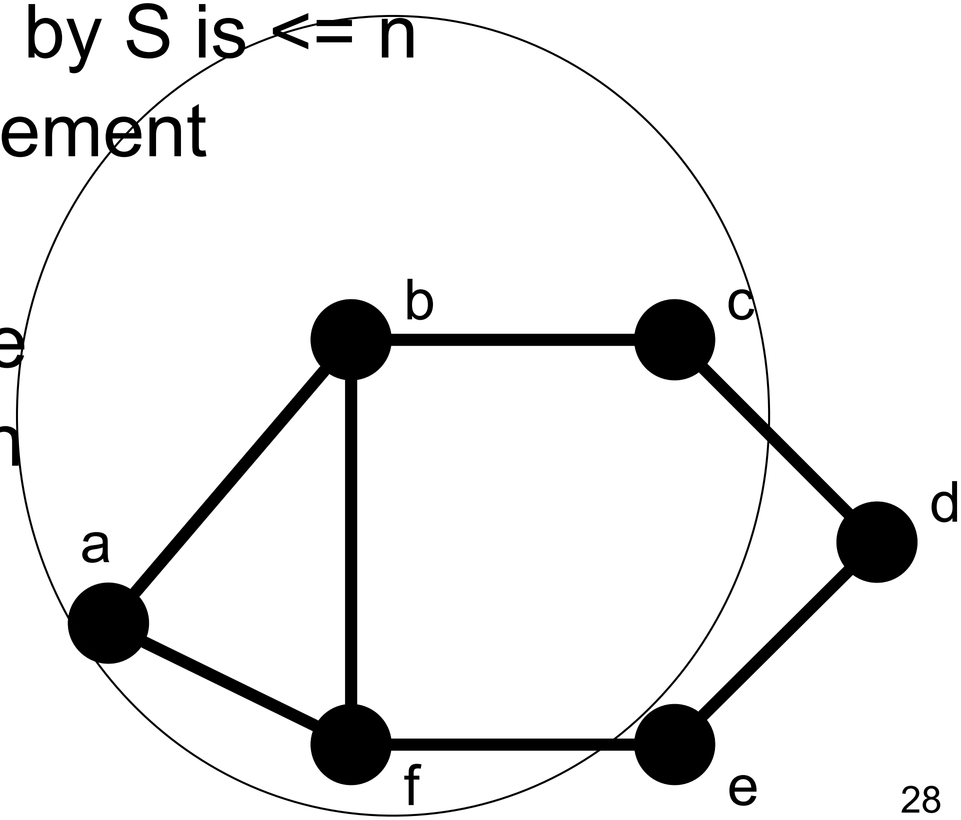
N-Clan Issues

- n-clique membership a bother
  - Is {a,b,c,f} a 2-clan?
  - List all 2-clans
- few found in data
- overlapping

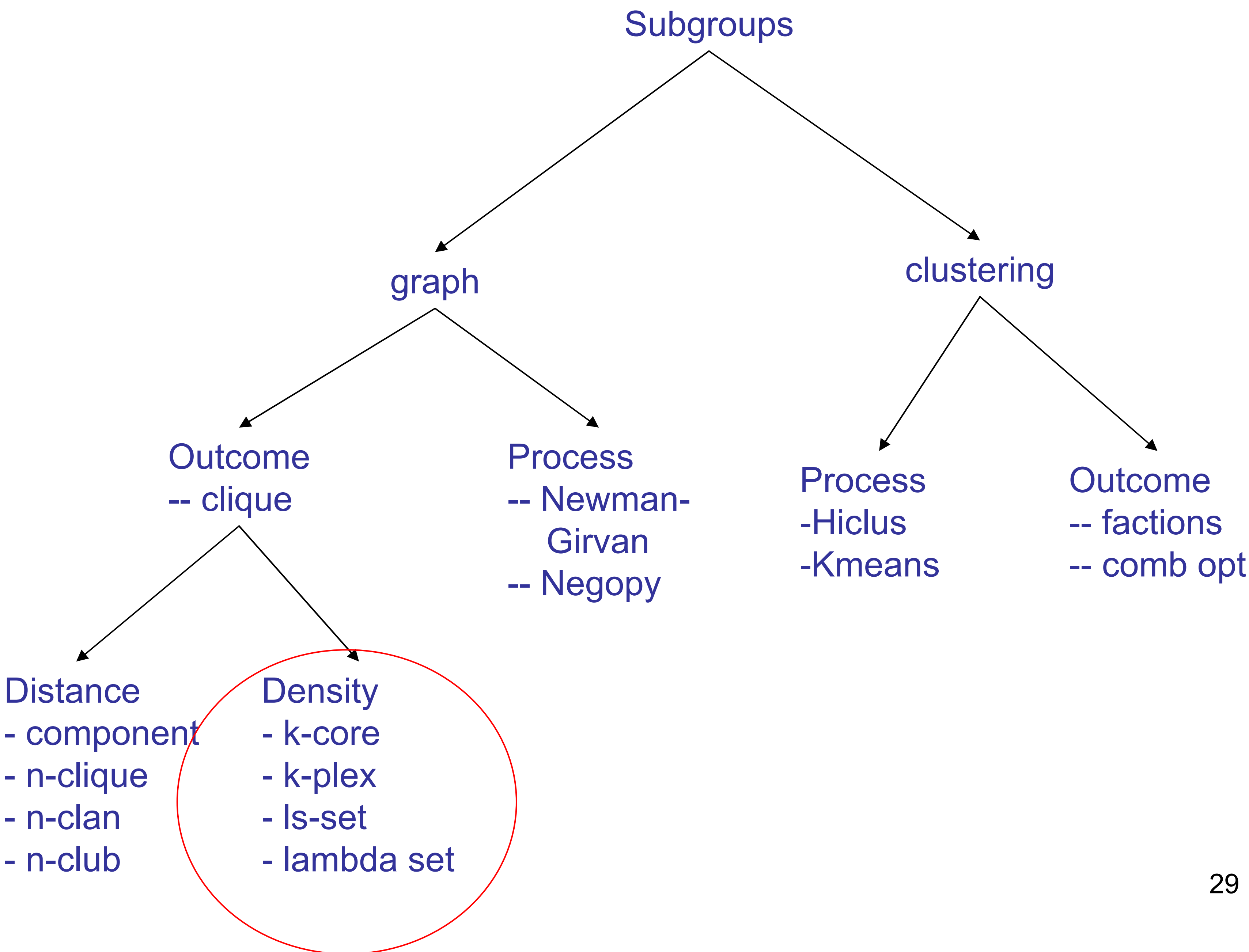


N-Club

- Definition
  - A maximal subset S whose diameter in the subgraph induced by S is <= n
  - No n-clique requirement
- Properties
  - Painful to compute
  - More plentiful than n-clans
  - overlapping



Is {a,b,c,f} a 2-club?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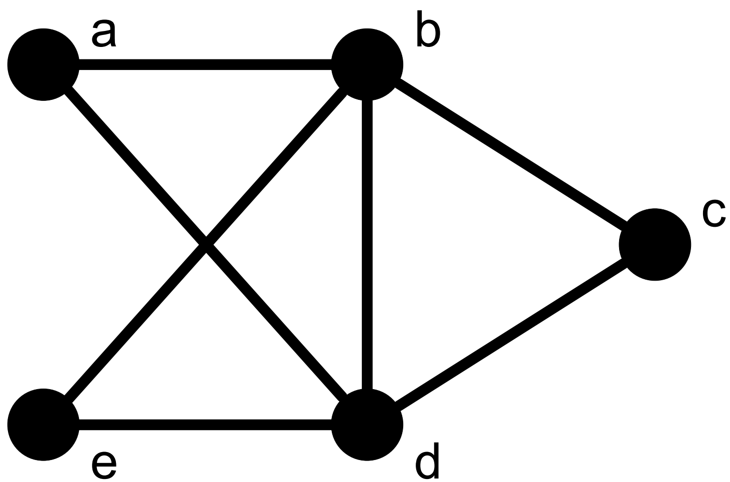
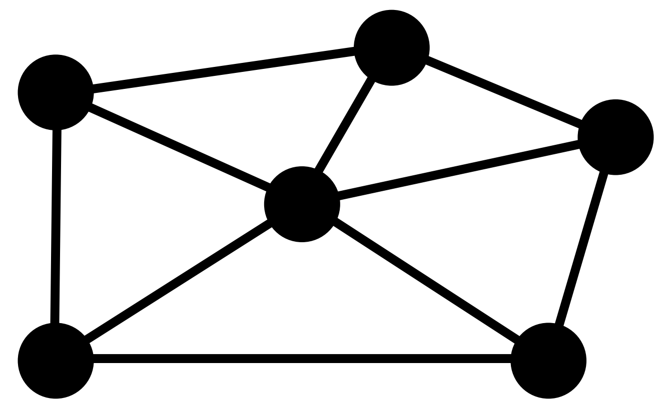
K-Plexes

- Definition
  - A k-plex is a [maximal] subset S s.t. for all *u* in S, $\alpha(u,S) >= |S|-k$, where $|S|$ is size of set S
- Properties
  - Subsets of k-plexes are k-plexes
  - Limited diameter (i.e., get distance as freebie)
    - If $k < (|S|+2)/2$ then diameter <= 2
  - Very numerous & overlapping
  - Sometimes better match to intuition than distance relaxations

K-Plex



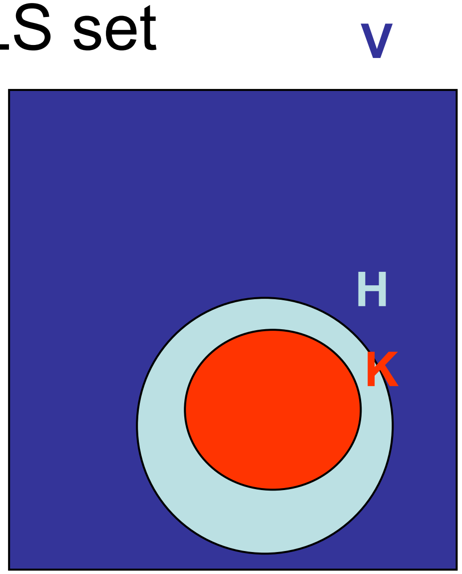
Is {a,b,d,e} a 2-plex?
Is {a,b,c,d,e} a 2-plex?
Is {a,b,d} a 2-plex?



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

LS-Sets

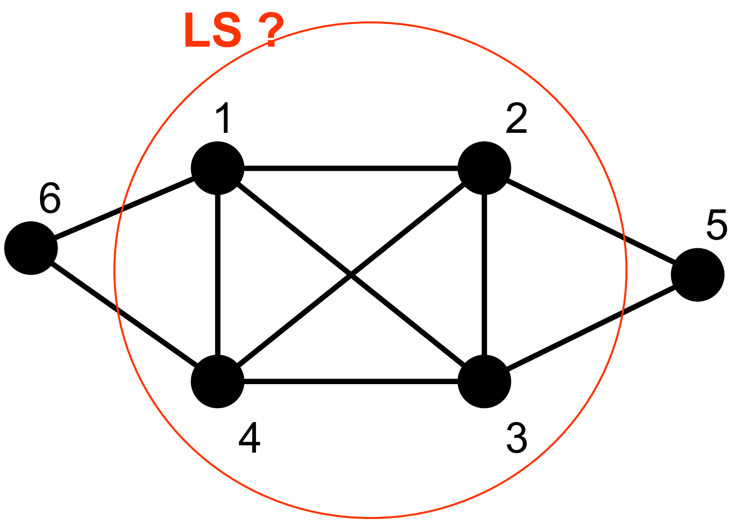
- Definition
  - Given a graph G(V,E), let H be a subset of V, and let K be <u>any</u> proper subset of H
  - H is **LS** if α(K,H-K) > α(K,V-H) for all K
    - All subsets of the LS set are more connected to other LS members than outsiders of LS set

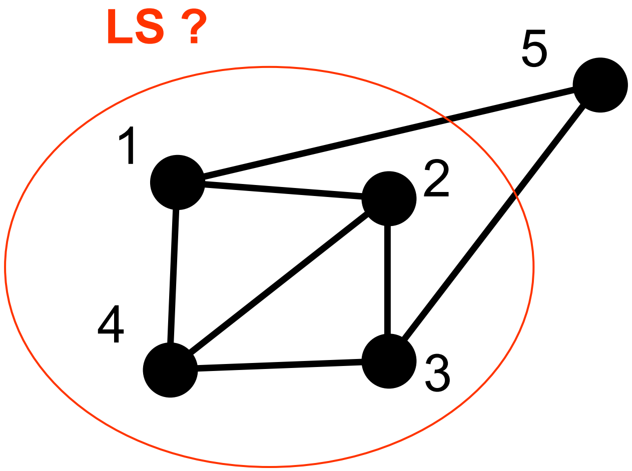


or…

  - H is **LS** if α(K) > α(H)
    - Subsets better off joining LS set
    - This one's usually easier to compute

LS-Sets

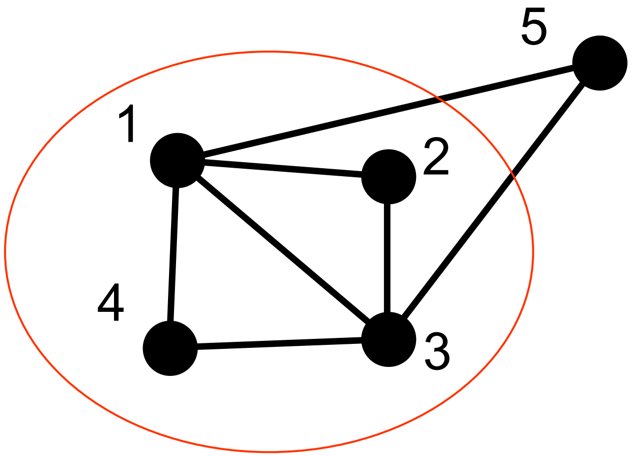




- H is LS if $\alpha(K,H-K) > \alpha(K,V-H)$
  - Use when K is large

or …

- H is LS if $\alpha(K) > \alpha(H)$
  - Use when K is small



LS-Sets

- Properties – very cohesive
  - Wholly nested or disjoint: no partial overlaps
  - More ties within than between (doesn’t just consider density inside density)
  - Contain no minimum weight cutsets (lie on either side of “fault lines”)
  - Multiple edge-independent paths within
    - High edge-connectivity

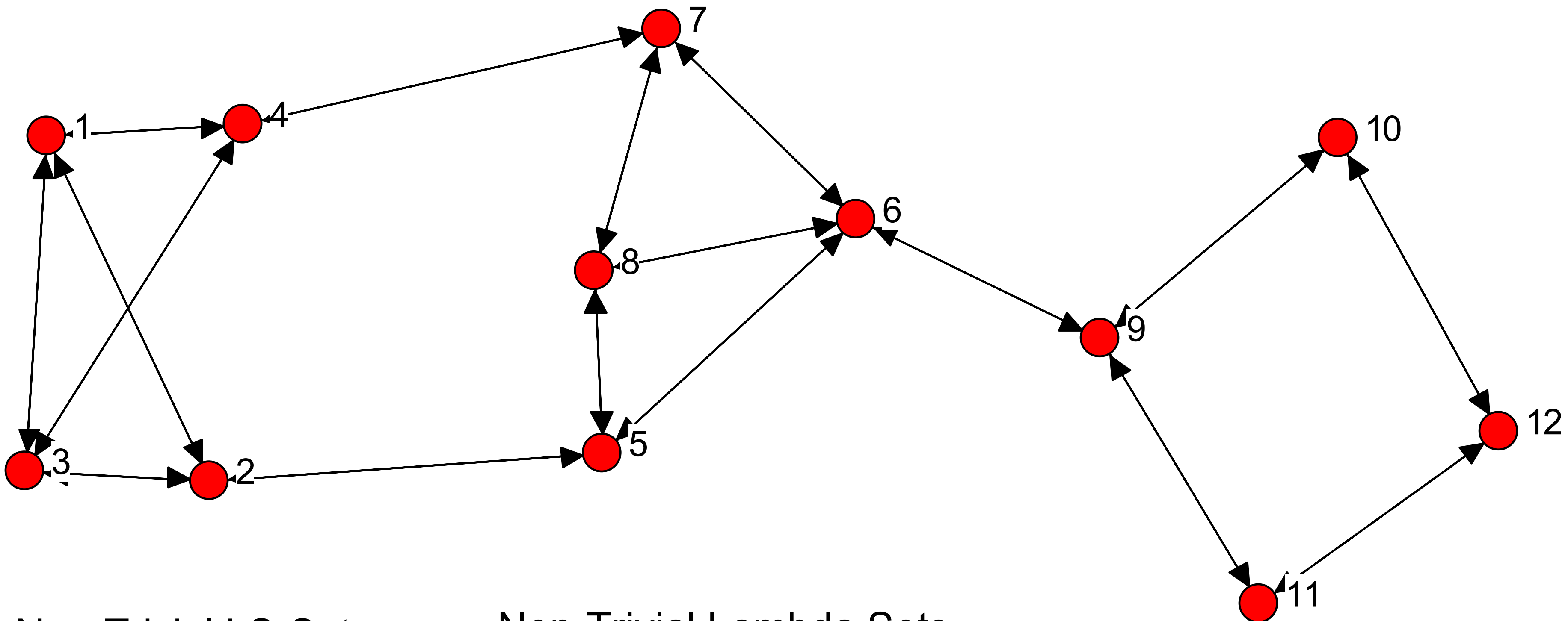
Lambda Operator

- Let $\lambda(u,v)$ be the number of edge-independent paths from node u to node v
- $\lambda(u,v)$ is also the minimum number of ties that must be removed from the network in order to disconnect u and v

Lambda Sets

- Definition
  - A set of nodes S is a lambda set if for all *a,b,c* in S and *d* not in S, $\lambda(a,b) > \lambda(c,d)$
    - More independent paths to other group members than to outsiders
- Properties
  - Robust
    - very difficult to disconnect even with intelligent attack
  - Mutually exclusive or wholly inclusive
    - No partially overlapping groups
  - Pure – like n-clubs, defined on a single attribute

Lambda Sets



<u>Non-Trivial LS-Sets</u>

{1,2,3,4}

{1,2,3,4,5,6,7,8}

{9,10,11,12}

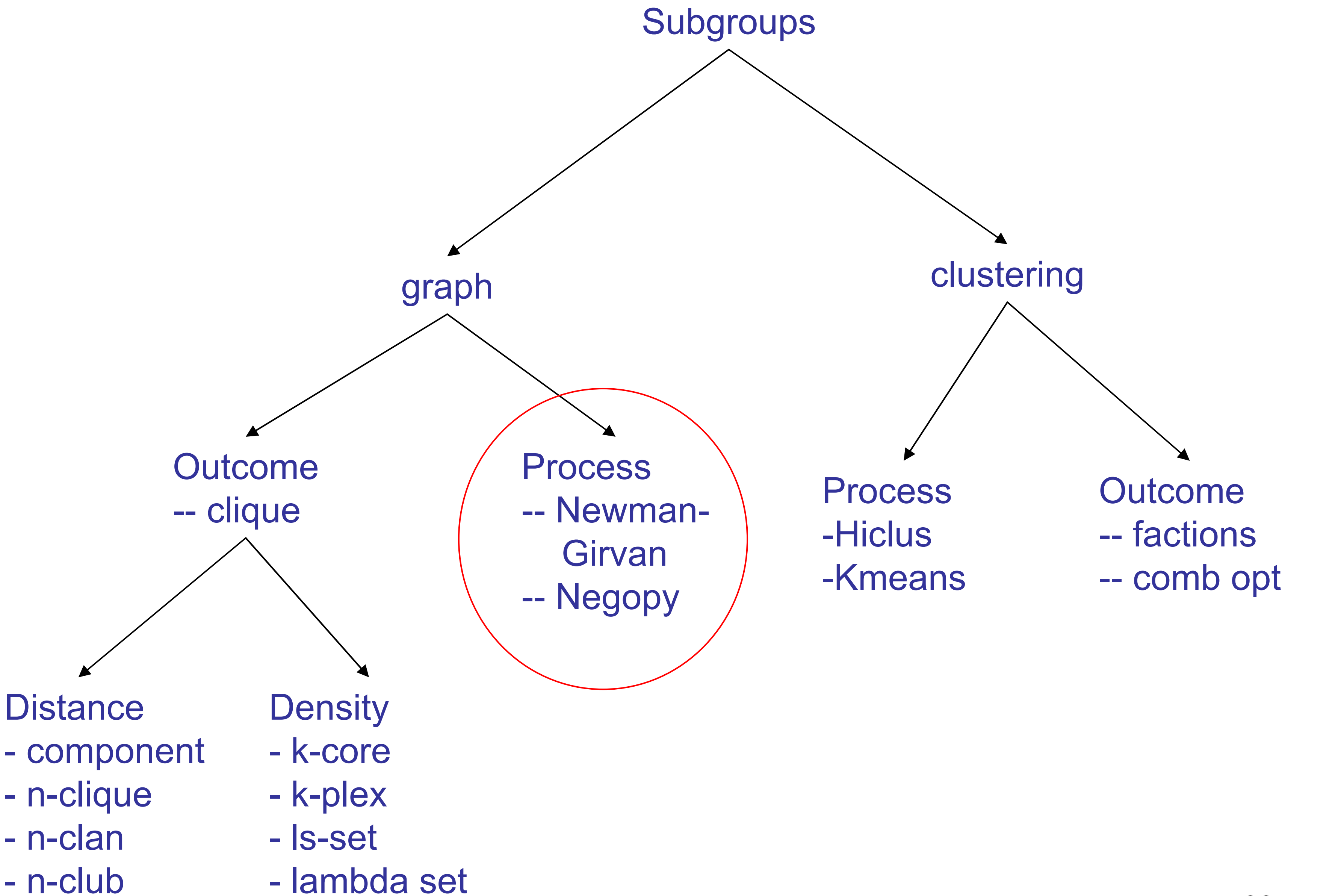
<u>Non-Trivial Lambda Sets</u>

{1,2,3,4}

{1,2,3,4,5,6,7,8}

{9,10,11,12}

{5,6,7,8}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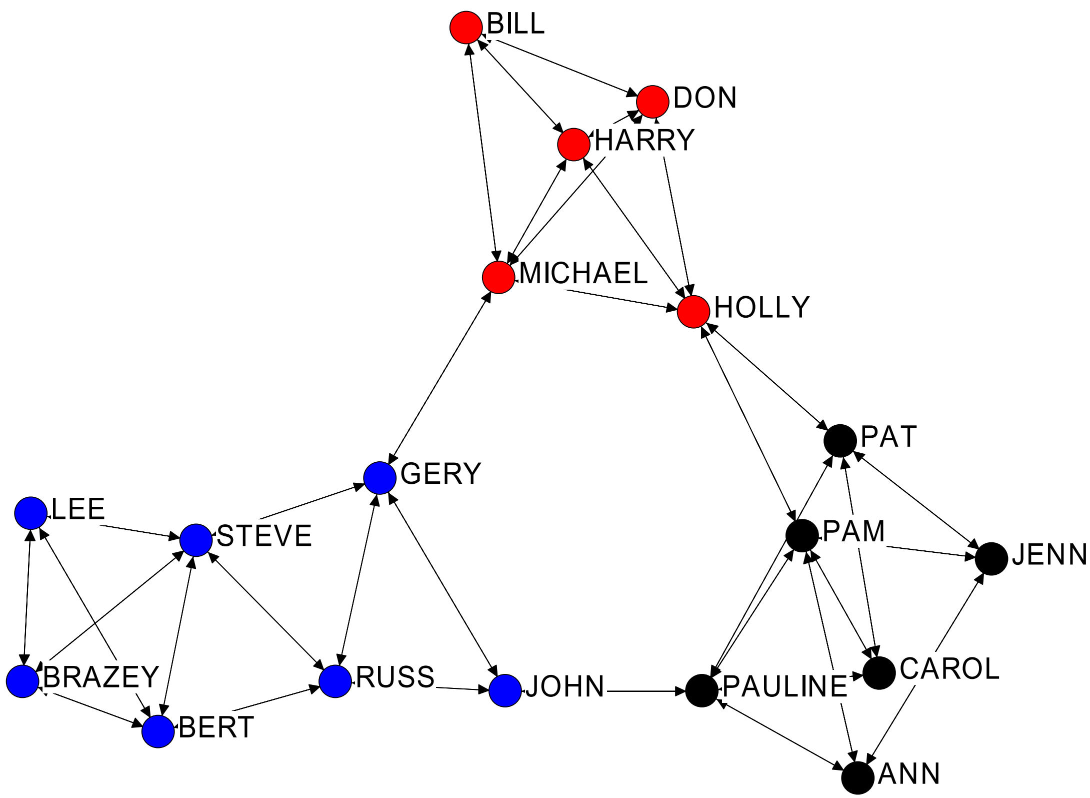
Newman-Girvan

- Successively deleting the tie with the most edge betweenness, and identifying components, then recalculating betweenness
- Yields a hierarchical clustering

Newman-Girvan



Proximities / Clustering and Scaling Methods

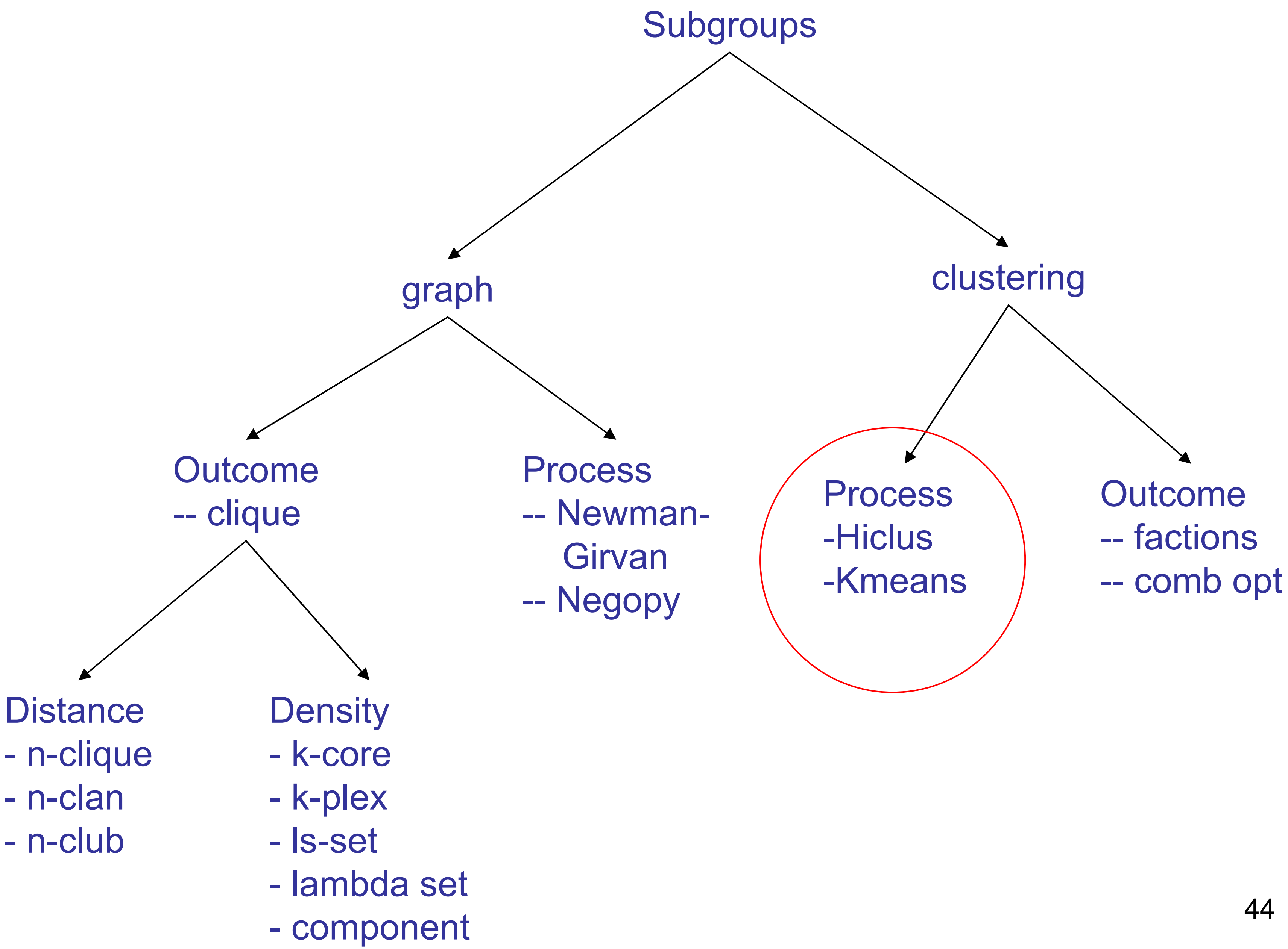
- First compute dyadic cohesion matrix
  - E.g. geodesic distance
- Then cluster or scale
  - Two major kinds of clustering routines
    - Process-defined
    - Outcome-defined
- Typical result is a partition

Partitions

- Partition P is just an assignment of nodes to classes
  - P(i) gives the class of node i
  - Every node assigned to one & only one class
- A partition P is nested in partition M if for all nodes i and j, P(i)=P(j) implies M(i)=M(j)
- Trivial partitions
  - Identity: P(i) = i for all i
  - Complete: P(i) = 1 for all i

Process-Defined Clustering

- Heuristic definitions
  - Multivariate methods
    - Johnson’s hierarchical
    - Wards
    - K-means
  - Graph-theoretic / Network methods
    - Newman-Girvan
- Sometimes specify number of groups a priori, sometimes not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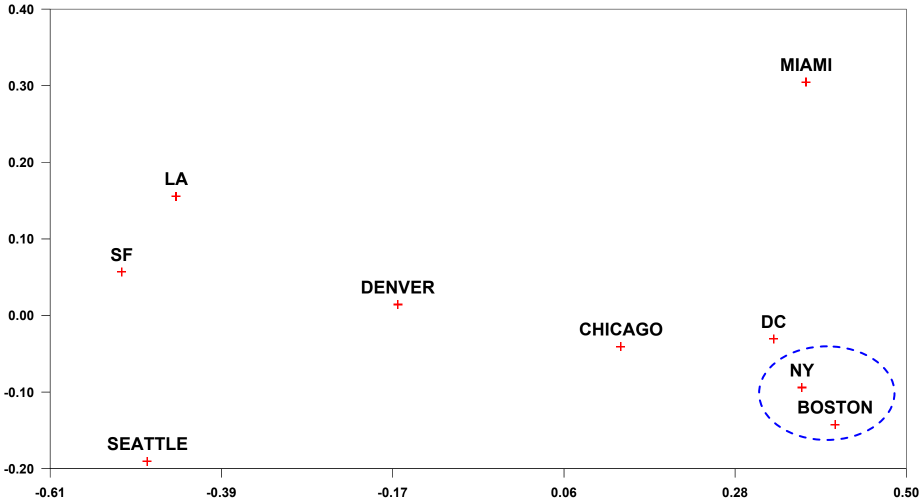
Johnson’s Hierarchical Clustering

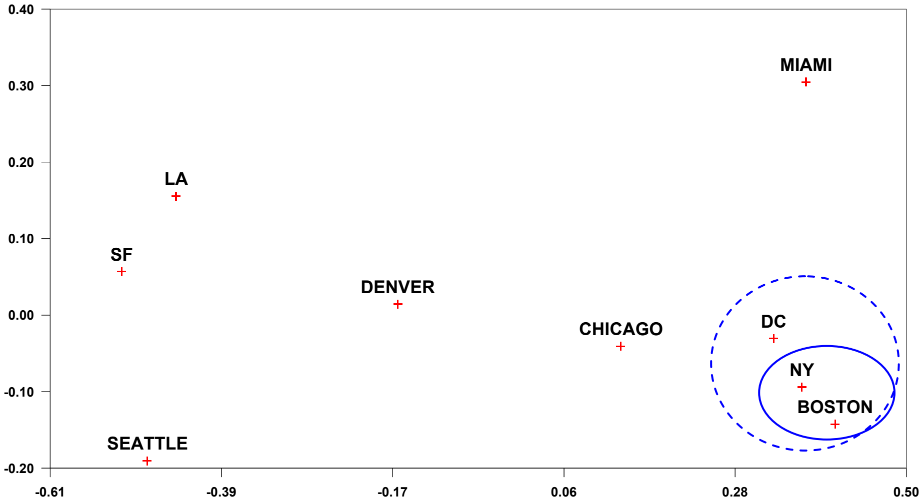
- Output is a set of nested partitions, starting with identity partition and ending with the complete partition
- Different flavors based on how distance from a point to a cluster is defined
  – Single linkage; connectedness; minimum
  – Complete linkage; diameter; maximum
  – Average, median, etc.




```
      M S     B     C D
      I E S L O N D H E
      A A F A S Y C I N

Level 4 6 7 8 1 2 3 5 9
----- - - - - - - - - -
  206 . . . . XXX . . .
  233 . . . . XXXXX . .
  379 . . XXX XXXXX . .
  671 . . XXX XXXXXXX .
  808 . XXXXX XXXXXXX .
  996 . XXXXX XXXXXXXXX
 1059 . XXXXXXXXXXXXXXX
 1075 XXXXXXXXXXXXXXXXX
```

	BOS	NY	DC	MIA	CHI	SEA	SF	LA	DEN
BOS	0	206	429	1504	963	2976	3095	2979	1949
NY	206	0	233	1308	802	2815	2934	2786	1771
DC	429	233	0	1075	671	2684	2799	2631	1616
MIA	1504	1308	1075	0	1329	3273	3053	2687	2037
CHI	963	802	671	1329	0	2013	2142	2054	996
SEA	2976	2815	2684	3273	2013	0	808	1131	1307
SF	3095	2934	2799	3053	2142	808	0	379	1235
LA	2979	2786	2631	2687	2054	1131	379	0	1059
DEN	1949	1771	1616	2037	996	1307	1235	1059	0

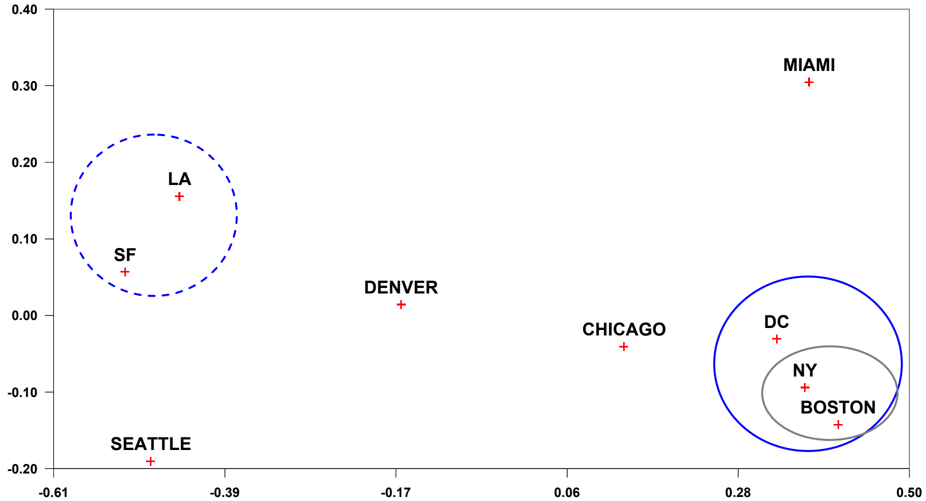
Closest distance is NY-BOS = 206, so merge these.




```
            M S       B     C D
            I E S L   O N D H E
            A A F A   S Y C I N

Level       4 6 7 8   1 2 3 5 9
-----       - - - -   - - - - -
  206       . . . .   XXX . . .
  233       . . . .   XXXXX . .
  379       . . XXX   XXXXX . .
  671       . . XXX   XXXXXXX .
  808       . XXXXX   XXXXXXX .
  996       . XXXXX   XXXXXXXXX
 1059       . XXXXXXXXXXXXXXXXX
 1075       XXXXXXXXXXXXXXXXXXX
```

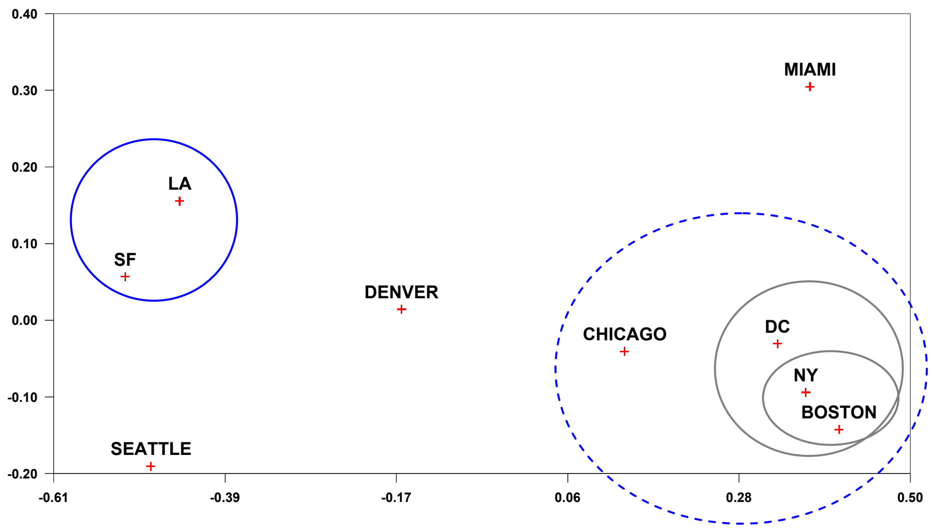
	BOS NY	DC	MIA	CHI	SEA	SF	LA	DEN
BOS/ NY	0	223	1308	802	2815	2934	2786	1771
DC	223	0	1075	671	2684	2799	2631	1616
MIA	1308	1075	0	1329	3273	3053	2687	2037
CHI	802	671	1329	0	2013	2142	2054	996
SEA	2815	2684	3273	2013	0	808	1131	1307
SF	2934	2799	3053	2142	808	0	379	1235
LA	2786	2631	2687	2054	1131	379	0	1059
DEN	1771	1616	2037	996	1307	1235	1059	0

Closest pair is DC to BOSNY combo @ 223. So merge these.



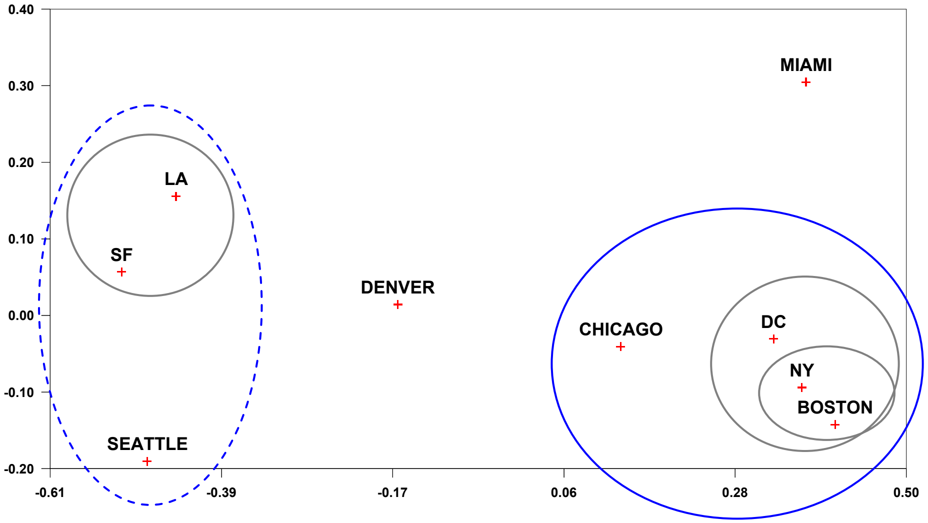

```
          M S       B       C D
          I E S L O N D H E
          A A F A S Y C I N

Level     4 6 7 8 1 2 3 5 9
-----     - - - - - - - - -
  206     . . . . XXX . . .
  233     . . . . XXXXX . .
  379     . . XXX XXXXX . .
  671     . . XXX XXXXXXX .
  808     . XXXXX XXXXXXX .
  996     . XXXXX XXXXXXXXX
 1059     . XXXXXXXXXXXXXXX
 1075     XXXXXXXXXXXXXXXXX
```

	BOS/ NY/ DC	MIA	CHI	SEA	SF	LA	DEN
BOS/NY DC	0	1075	671	2684	2799	2631	1616
MIA	1075	0	1329	3273	3053	2687	2037
CHI	671	1329	0	2013	2142	2054	996
SEA	2684	3273	2013	0	808	1131	1307
SF	2799	3053	2142	808	0	379	1235
LA	2631	2687	2054	1131	379	0	1059
DEN	1616	2037	996	1307	1235	1059	0



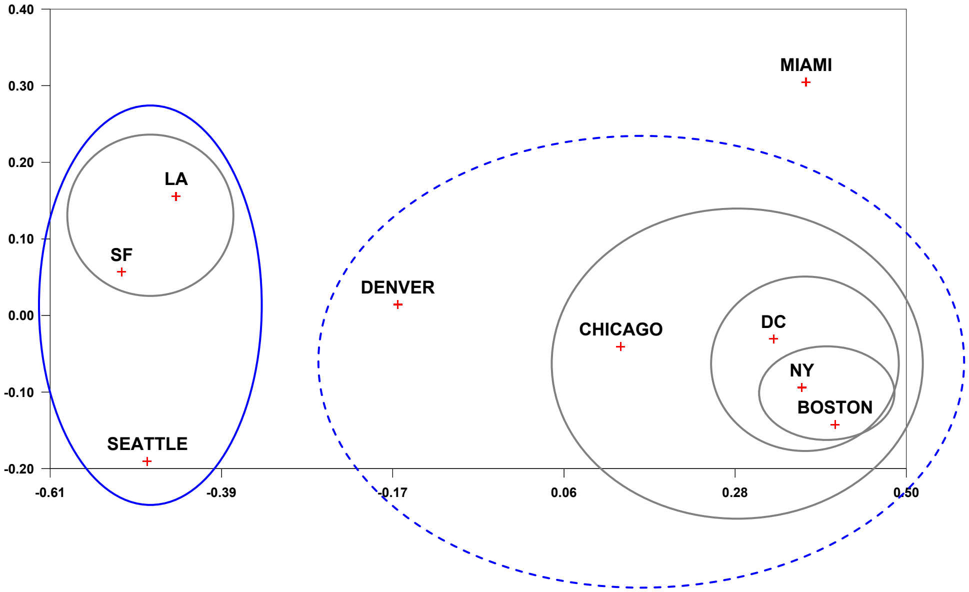

```
           M  S        B        C  D
           I  E  S  L  O  N  D  H  E
           A  A  F  A  S  Y  C  I  N

Level      4  6  7  8  1  2  3  5  9
-----      -  -  -  -  -  -  -  -  -
  206      .  .  .  .  XXXX  .  .  .
  233      .  .  .  .  XXXXXXX  .  .
  379      .  .  XXXX  XXXXXXX  .  .
  671      .  .  XXXX  XXXXXXXXXX  .
  808      .  XXXXXXX  XXXXXXXXXX  .
  996      .  XXXXXXX  XXXXXXXXXXXXX
 1059      .  XXXXXXXXXXXXXXXXXXXXXX
 1075      XXXXXXXXXXXXXXXXXXXXXXXXX
```

	BOS/ NY/DC	MIA	CHI	SEA	SF/LA	DEN
BOS/NY/DC	0	1075	671	2684	2631	1616
MIA	1075	0	1329	3273	2687	2037
CHI	671	1329	0	2013	2054	996
SEA	2684	3273	2013	0	808	1307
SF/LA	2631	2687	2054	808	0	1059
DEN	1616	2037	996	1307	1059	0



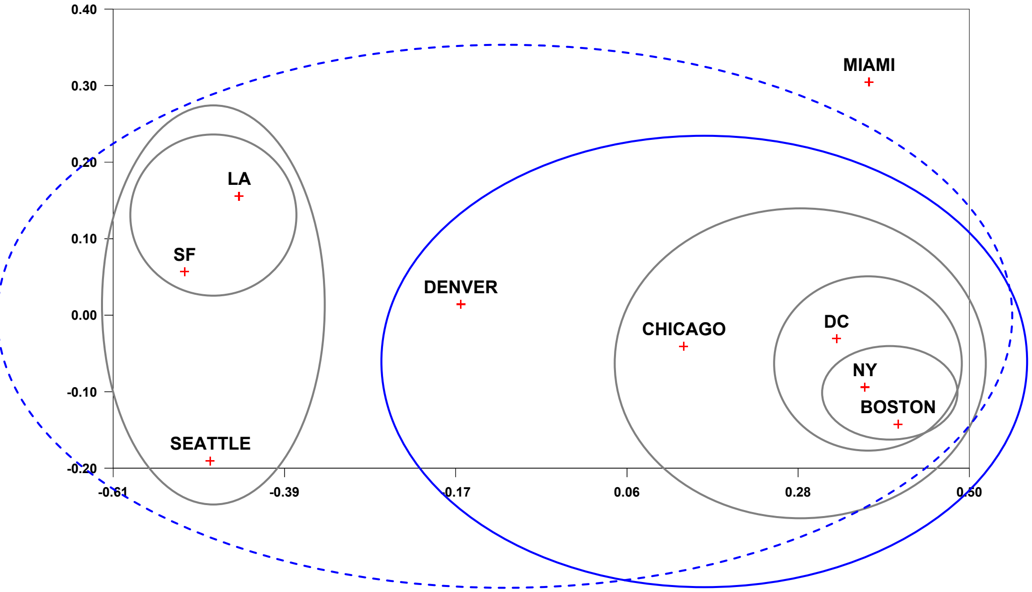

```
          M S     B     C D
          I E S L O N D H E
          A A F A S Y C I N
Level     4 6 7 8 1 2 3 5 9
-----     - - - - - - - - -
  206     . . . . XXX . . .
  233     . . . . XXXXX . .
  379     . . XXX XXXXX . .
  671     . . XXX XXXXXXX .
  808     . XXXXX XXXXXXX .
  996     . XXXXX XXXXXXXXX
 1059     . XXXXXXXXXXXXXXX
 1075     XXXXXXXXXXXXXXXXX
```

	BOS/NY/DC/CHI	MIA	SEA	SF/LA	DEN
BOS/NY/DC/CHI	0	1075	2013	2054	996
MIA	1075	0	3273	2687	2037
SEA	2013	3273	0	808	1307
SF/LA	2054	2687	808	0	1059
DEN	996	2037	1307	1059	0



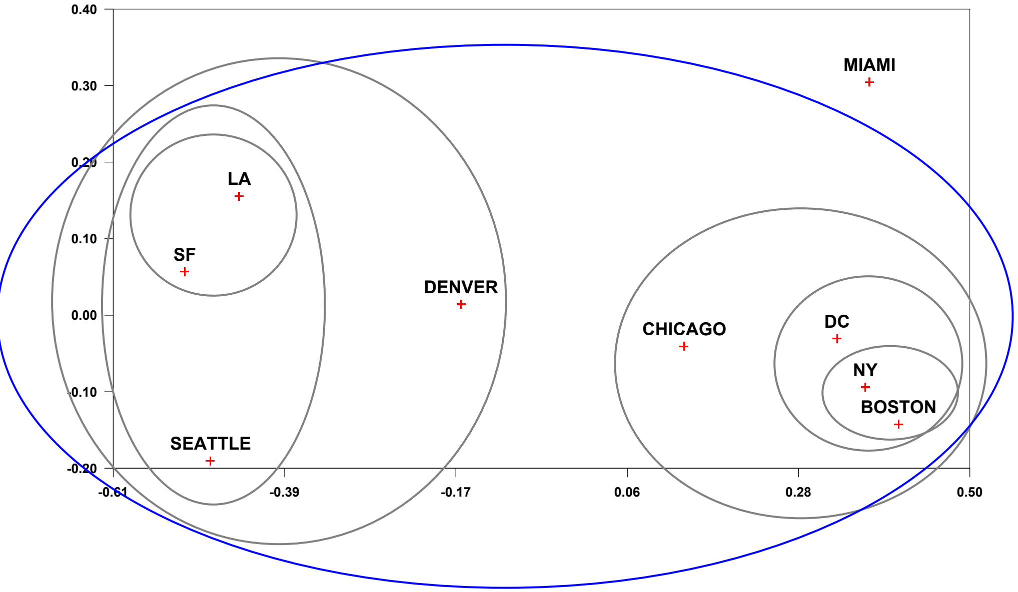

```
          M S       B       C D
          I E S L O N D H E
          A A F A S Y C I N

Level     4 6 7 8 1 2 3 5 9
-----     - - - - - - - - -
  206     . . . . XXX . . .
  233     . . . . XXXXX . .
  379     . . XXX XXXXX . .
  671     . . XXX XXXXXXX .
  808     . XXXXX XXXXXXX .
  996     . XXXXX XXXXXXXXX
 1059     . XXXXXXXXXXXXXXX
 1075     XXXXXXXXXXXXXXXXX
```

	BOS/NY/DC/CHI	MIA	SF/LA/SEA	DEN
BOS/NY/DC/CHI	0	1075	2013	996
MIA	1075	0	2687	2037
SF/LA/SEA	2054	2687	0	1059
DEN	996	2037	1059	0




```
         M S       B       C D
         I E S L O N D H E
         A A F A S Y C I N

Level    4 6 7 8 1 2 3 5 9
-----    - - - - - - - - -
  206    . . . . XXX . . .
  233    . . . . XXXXX . .
  379    . . XXX XXXXX . .
  671    . . XXX XXXXXXX .
  808    . XXXXX XXXXXXX .
  996    . XXXXX XXXXXXXXX
 1059    . XXXXXXXXXXXXXXX
 1075    XXXXXXXXXXXXXXXXX
```

	BOS/NY/DC/CHI/DEN	MIA	SF/LA/SEA
BOS/NY/DC/CHI/DEN	0	1075	1059
MIA	1075	0	2687
SF/LA/SEA	1059	2687	0




```
       M S     B     C D
       I E S L O N D H E
       A A F A S Y C I N

Level  4 6 7 8 1 2 3 5 9
-----  - - - - - - - - -
  206  . . . . XXX . . .
  233  . . . . XXXXX . .
  379  . . XXX XXXXX . .
  671  . . XXX XXXXXXX .
  808  . XXXXX XXXXXXX .
  996  . XXXXX XXXXXXXXX
 1059  . XXXXXXXXXXXXXXX
 1075  XXXXXXXXXXXXXXXXX
```

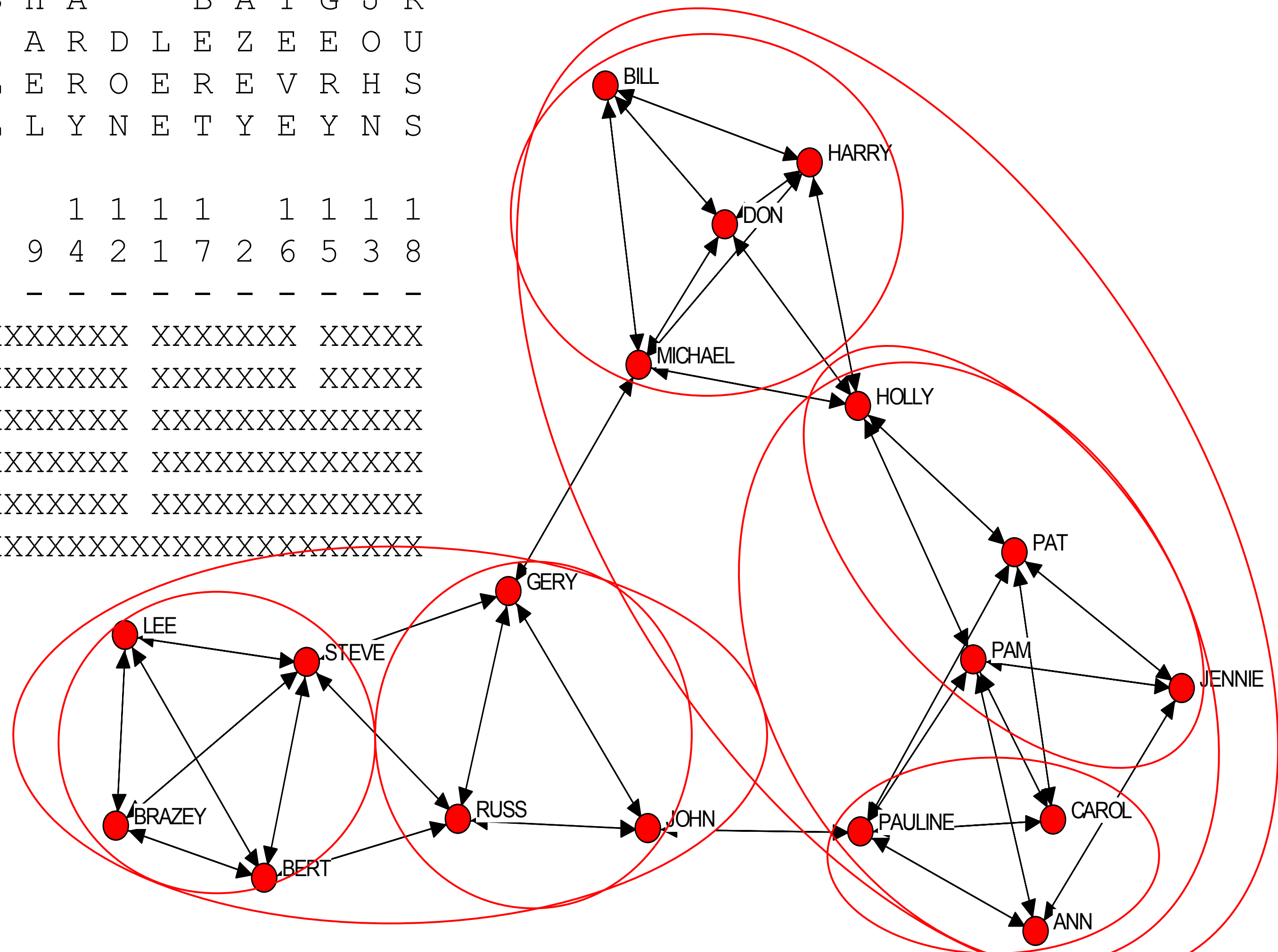
	BOS/NY/DC/CHI/DEN/SF/LA/SEA	MIA
BOS/NY/DC/CHI/DEN/SF/LA/SEA	0	1075
MIA	1075	0

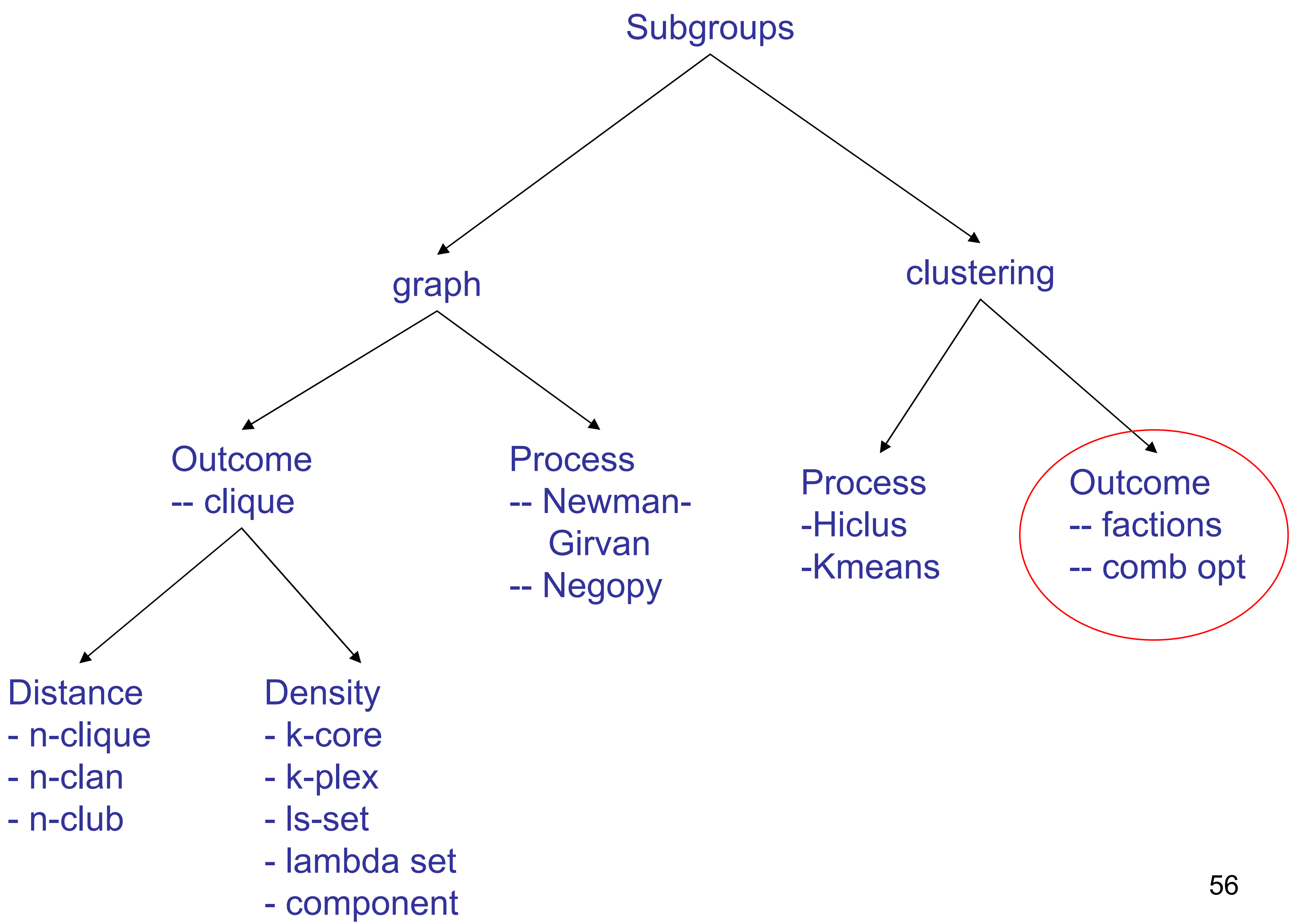
Geodesic Distances

		1 H	2 B	3 C	4 P	5 P	6 J	7 P	8 A	9 M	10 B	11 L	12 D	13 J	14 H	15 G	16 S	17 B	18 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

Hierarchical Clustering

```
            P           M
            A     J     I         B
          C U   H E     C H       R S
          A L   O N   B H A     B A T G J R
        P R I P L N A I A R D L E Z E E O U
        A O N A L I N L E R O E R E V R H S
        T L E M Y E N L L Y N E T Y E Y N S

                      1   1 1 1 1   1 1 1 1
Level   5 3 7 4 1 6 8 0 9 4 2 1 7 2 6 5 3 8
-----   - - - - - - - - - - - - - - - - - -
1.000   XXXXX XXX XXX XXXXXXX XXXXXXX XXXXX
1.333   XXXXX XXXXXXX XXXXXXX XXXXXXX XXXXX
1.457   XXXXX XXXXXXX XXXXXXX XXXXXXXXXXXXX
1.481   XXXXXXXXXXXXX XXXXXXX XXXXXXXXXXXXX
2.723   XXXXXXXXXXXXXXXXXXXXX XXXXXXXXXXXXX
3.142   XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```




Subgroups
graph
clustering
Outcome
-- clique
Process
-- Newman-
Girvan
-- Negopy
Process
-Hiclus
-Kmeans
Outcome
-- factions
-- comb opt
Distance
- n-clique
- n-clan
- n-club
Density
- k-core
- k-plex
- ls-set
- lambda set
- component

Factions

- Outcome-Defined Clustering
- Input is proximity matrix X
  - Could be similarities or distances
- Assign items to clusters such that
  - For similarities, maximize similarities within cluster while minimizing similarities between clusters
  - For distances, minimize distance within cluster while maximizing distances between clusters
- Optimize explicit fitness function
  - Correlation with idealized image matrix
- Typically choose # of groups *a priori*

Factions

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