Graph and Network Analysis

Clique

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Web Science Doctoral Summer School 2011

UCD DUBLIN

sfi Science Foundation Ireland

DERI

NUI Galway OÉ Gaillimh

Tutorial Overview

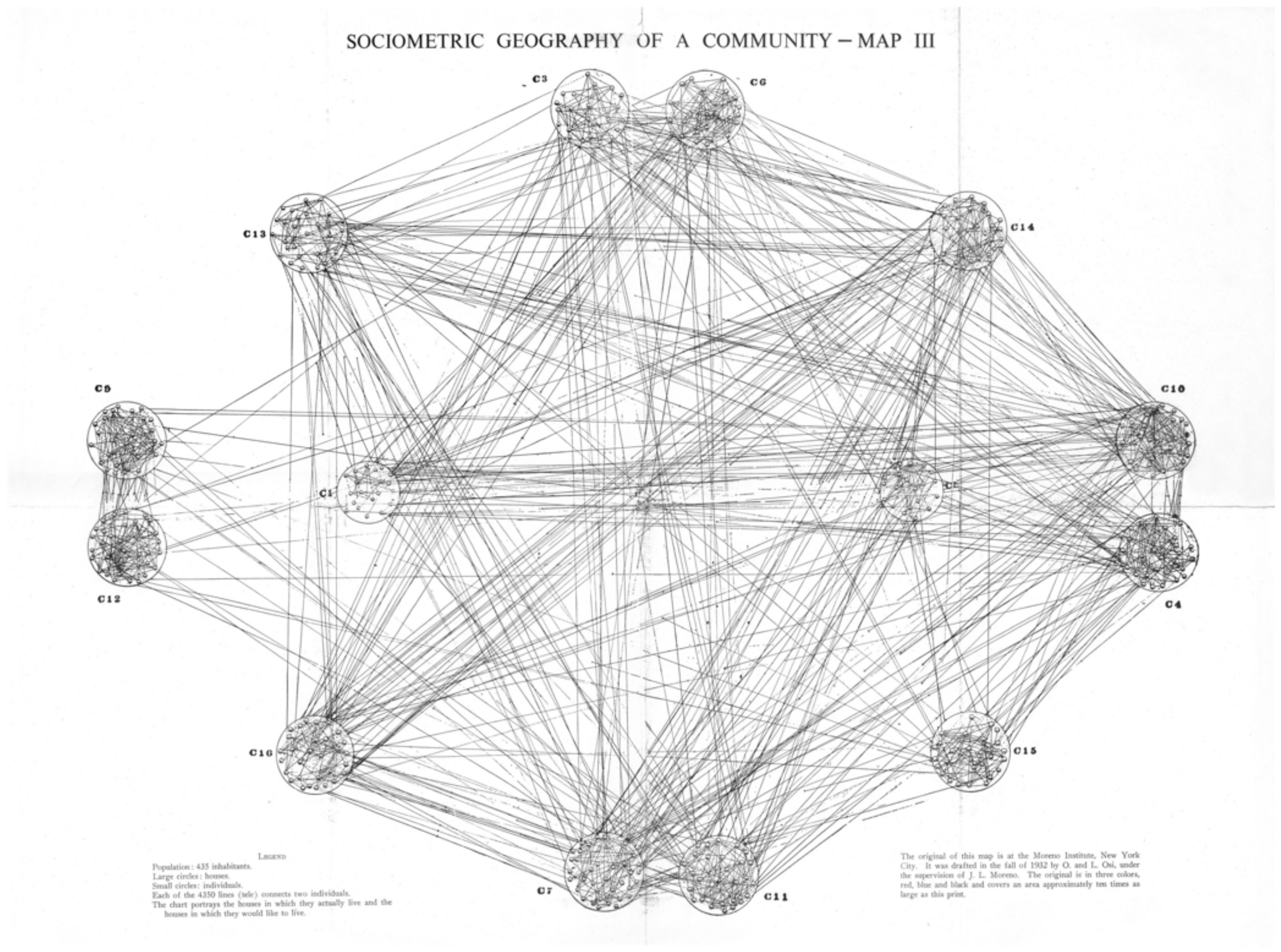
- Practical Network Analysis
  - Basic concepts
  - Network types and structural properties
  - Identifying central nodes in a network
- Communities in Networks
  - Clustering and graph partitioning
  - Finding communities in static networks
  - Finding communities in dynamic networks
- Applications of Network Analysis

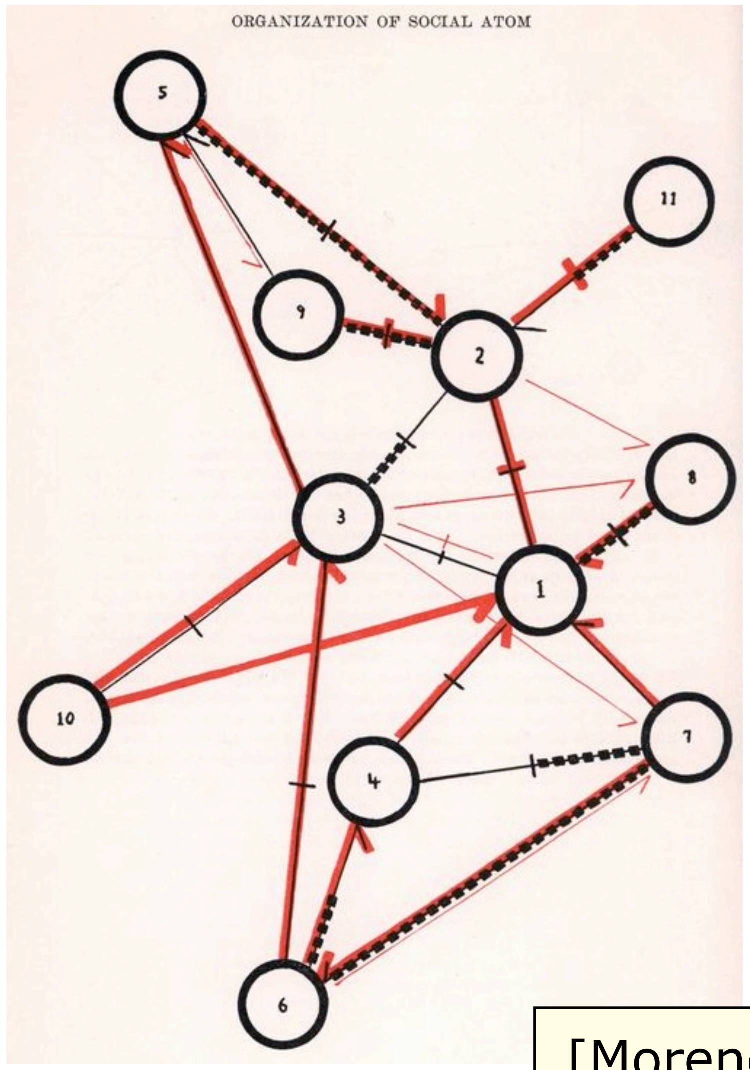
Tutorial Resources

- **NetworkX**: Python software for network analysis (v1.5)
  http://networkx.lanl.gov
- Python 2.6.x / 2.7.x
  http://www.python.org
- **Gephi**: Java interactive visualisation platform and toolkit.
  http://gephi.org
- Slides, full resource list, sample networks, sample code snippets online here:
  http://mlg.ucd.ie/summer

Introduction

- Social network analysis - an old field, rediscovered...





[Moreno,1934]

Introduction

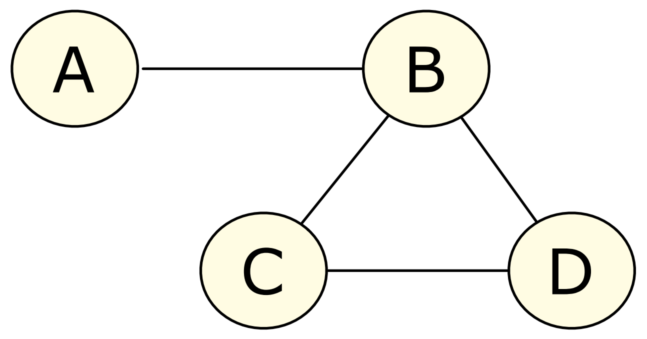
- We now have the computational resources to perform network analysis on large-scale data...

facebook
FROM FACEBOOK
December 2010

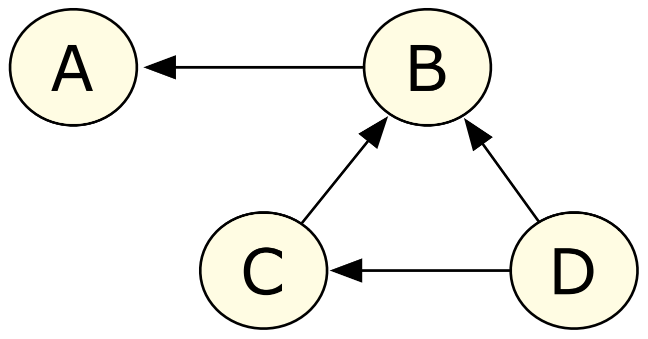
http://www.facebook.com/note.php?note_id=469716398919

Basic Concepts

- Graph: a way of representing the relationships among a collection of objects.
- Consists of a set of objects, called nodes, with certain pairs of these objects connected by links called edges.



Undirected Graph



Directed Graph

- Two nodes are neighbours if they are connected by an edge.
- Degree of a node is the number of edges ending at that node.
- For a directed graph, the in-degree and out-degree of a node refer to numbers of edges incoming to or outgoing from the node.

NetworkX - Creating Graphs

```
>>> import networkx
```

Import library

```
>>> g = networkx.Graph()
```

Create new undirected graph

```
>>> g.add_node("John")
>>> g.add_node("Maria")
>>> g.add_node("Alex")
>>> g.add_edge("John", "Alex")
>>> g.add_edge("Maria", "Alex")
```

Add new nodes with unique IDs.

Add new edges referencing associated node IDs.

```
>>> print g.number_of_nodes()
3
>>> print g.number_of_edges()
2
>>> print g.nodes()
['John', 'Alex', 'Maria']
>>> print g.edges()
[('John', 'Alex'), ('Alex', 'Maria')]
```

Print details of our newly-created graph.

```
>>> print g.degree("John")
1
>>> print g.degree()
{'John': 1, 'Alex': 2, 'Maria': 1}
```

Calculate degree of specific node, or map of degree for all nodes.

NetworkX - Directed Graphs

```
>>> g = networkx.DiGraph()
```

Create new directed graph

```
>>> g.add_edges_from([("A","B"), ("C","A")])
```

Edges can be added in batches.

```
>>> print g.in_degree(with_labels=True)
{'A': 1, 'C': 0, 'B': 1}
>>> print g.out_degree(with_labels=True)
{'A': 1, 'C': 1, 'B': 0}
```

Nodes can be added to the graph "on the fly".

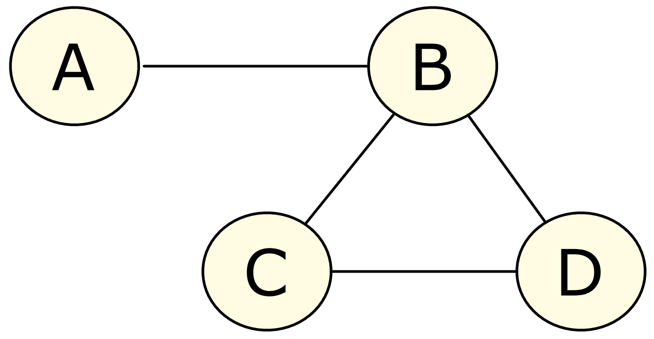
```
>>> print g.neighbors("A")
['B']
>>> print g.neighbors("B")
[]
```

```
>>> ug = g.to_undirected()
>>> print ug.neighbors("B")
['A']
```

Convert to an undirected graph

NetworkX - Loading Existing Graphs

- Library includes support for reading/writing graphs in a variety of file formats.



Edge List Format

```
a b
b c
b d
c d
```

Node pairs, one edge per line.

```
>>> g = networkx.read_edgelist("test.edges")
>>> print g.edges()
[('a', 'b'), ('c', 'b'), ('c', 'd'), ('b', 'd')]
```

Adjacency List Format

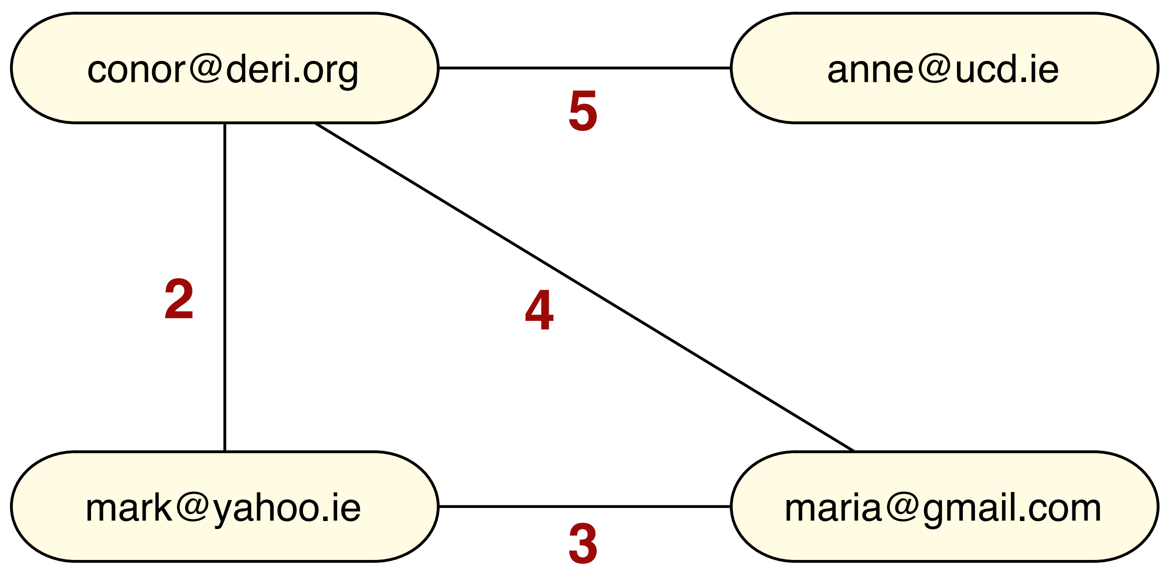
```
a b
b c d
c d
```

First label in line is the source node. Further labels in the line are considered target nodes.

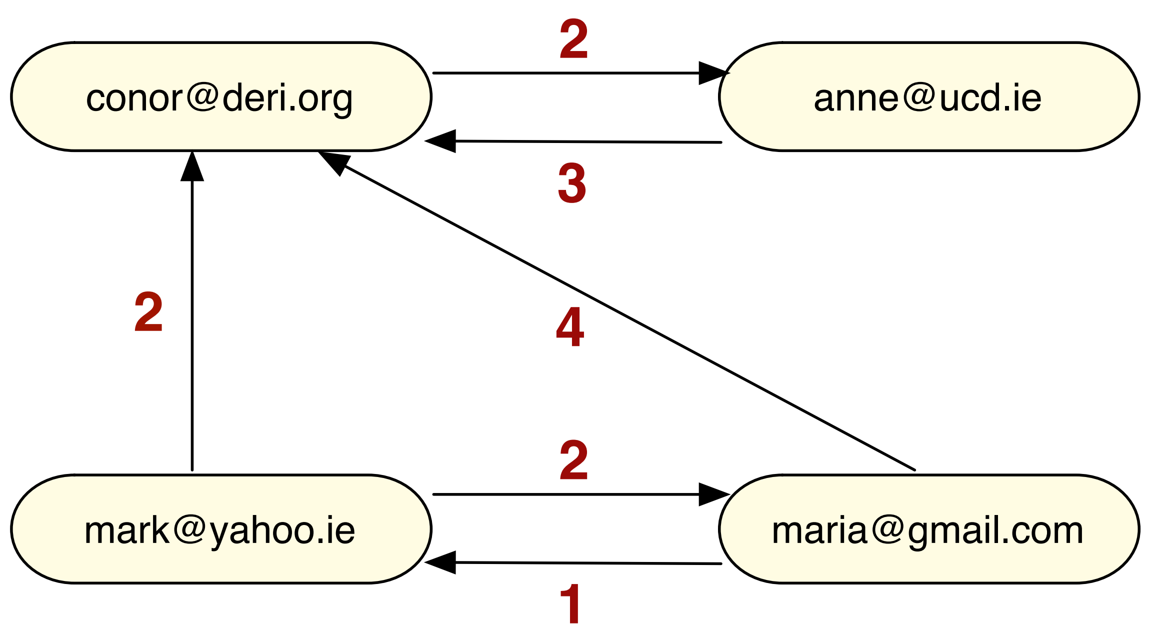
```
>>> g = networkx.read_adjlist("test_adj.txt")
>>> print edges()
[('a', 'b'), ('c', 'b'), ('c', 'd'), ('b', 'd')]
```

Weighted Graphs

- Weighted graph: numeric value is associated with each edge.
- Edge weights may represent a concept such as similarity, distance, or connection cost.



Undirected weighted graph



Directed weighted graph

NetworkX - Weighted Graphs

```
g = networkx.Graph()
```

```
g.add_edge("conor@deri.org", "anne@ucd.ie", weight=5)
g.add_edge("conor@deri.org", "mark@yahoo.ie", weight=2)
g.add_edge("conor@deri.org", "maria@gmail.com", weight=4)
g.add_edge("mark@yahoo.ie", "maria@gmail.com", weight=3)
```

Add weighted edges to graph.

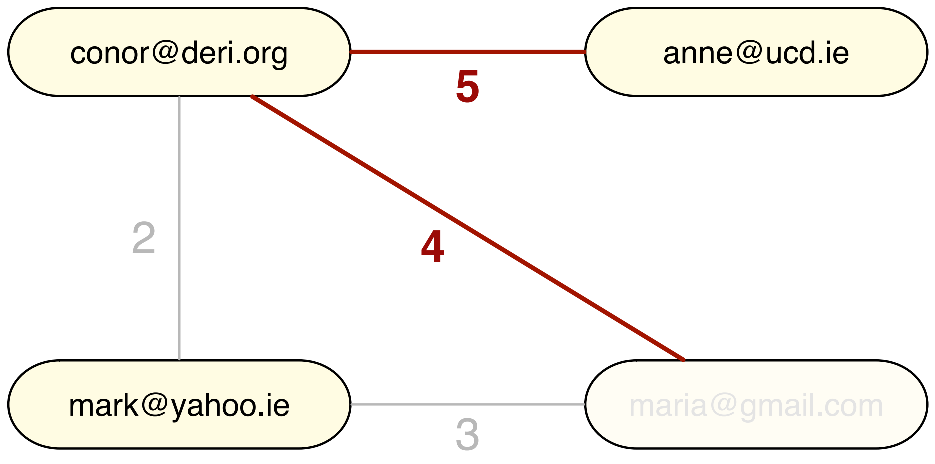
Note: nodes can be added to the graph "on the fly"

Select the subset of "strongly weighted" edges above a threshold...

```
estrong = [(u,v) for (u,v,d) in g.edges(data=True) if d["weight"] > 3]
```

```
>>> print estrong
[('conor@deri.org', 'anne@ucd.ie'), ('conor@deri.org', 'maria@gmail.com')]
```

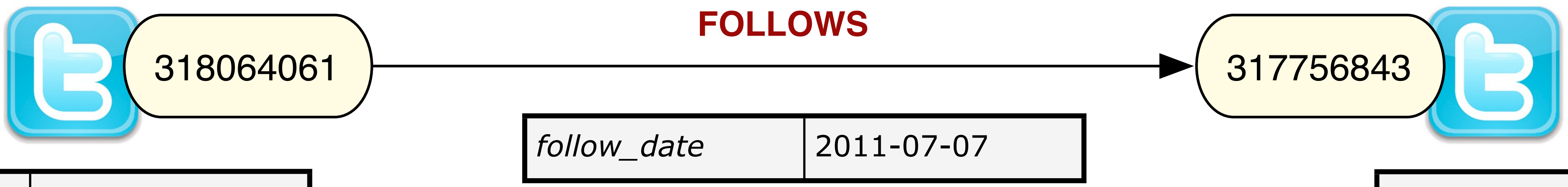
```
>>> print g.degree("conor@deri.org", weighted=False)
3
>>> print g.degree("conor@deri.org", weighted=True)
11
```



Weighted degree given by sum of edge weights.

Attributed Graphs

- Additional attribute data, relating to nodes and/or edges, is often available to compliment network data.



follow_date	2011-07-07

screen_name	peter78
location	Galway
time_zone	GMT
verified	FALSE

screen_name	mark763
location	London
time_zone	GMT
verified	FALSE

Create new nodes with attribute values

```
g.add_node("318064061", screen_name="peter78", location="Galway", time_zone="GMT")
g.add_node("317756843", screen_name="mark763", location="London", time_zone="GMT")
```

Add/modify attribute values for existing nodes

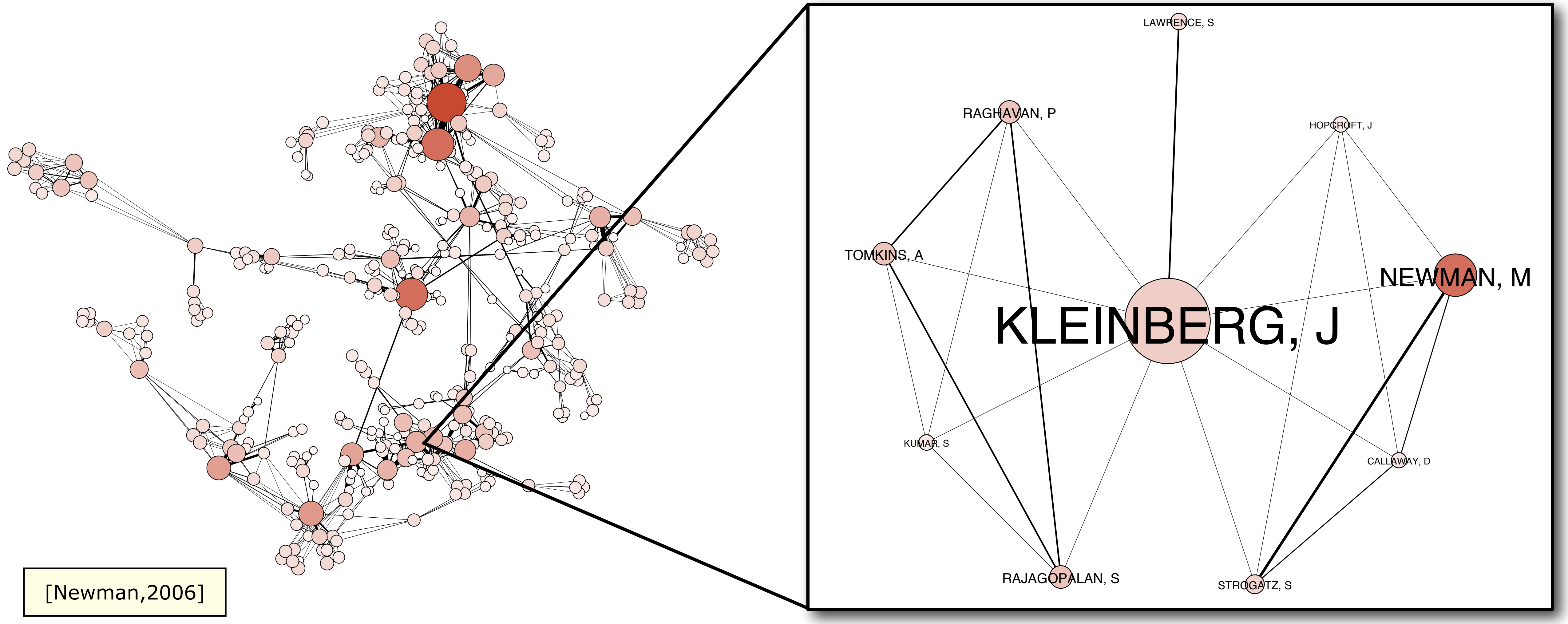
```
g.node["318064061"]["verified"] = False
g.node["317756843"]["verified"] = False
```

Create new edge with attribute values

```
g.add_edge("318064061", "317756843", follow_date=datetime.datetime.now())
```

Ego Networks

- Ego-centric methods really focus on the individual, rather than on network as a whole.
- By collecting information on the connections among the modes connected to a focal ego, we can build a picture of the **local** networks of the individual.



[Newman,2006]

NetworkX - Ego Networks

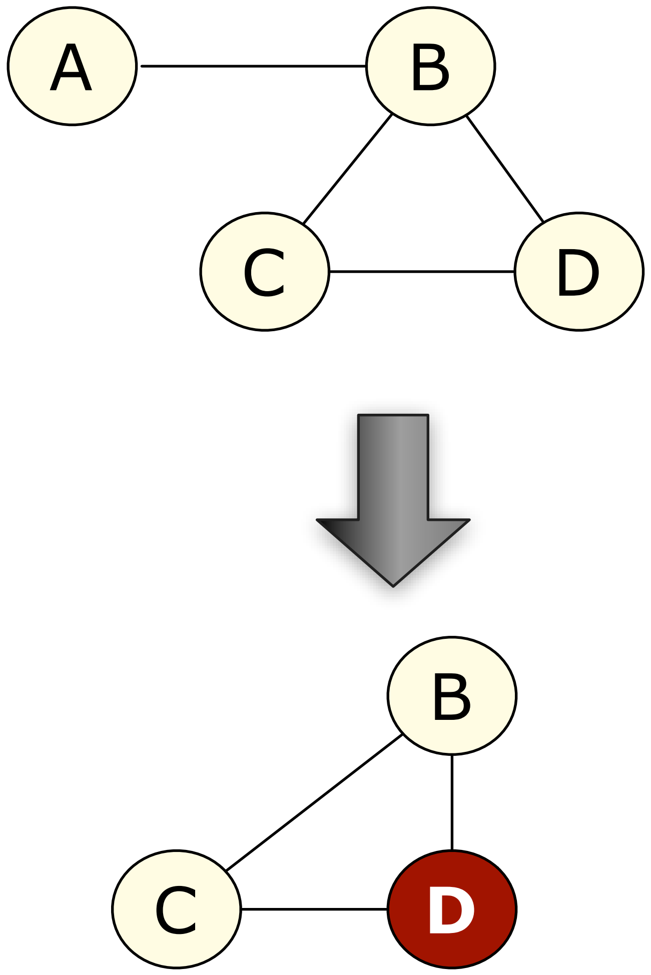
- We can readily construct an ego network subgraph from a global graph in NetworkX.

```
>>> g = networkx.read_adjlist("test.adj")
```

```
>>> ego = "d"
```

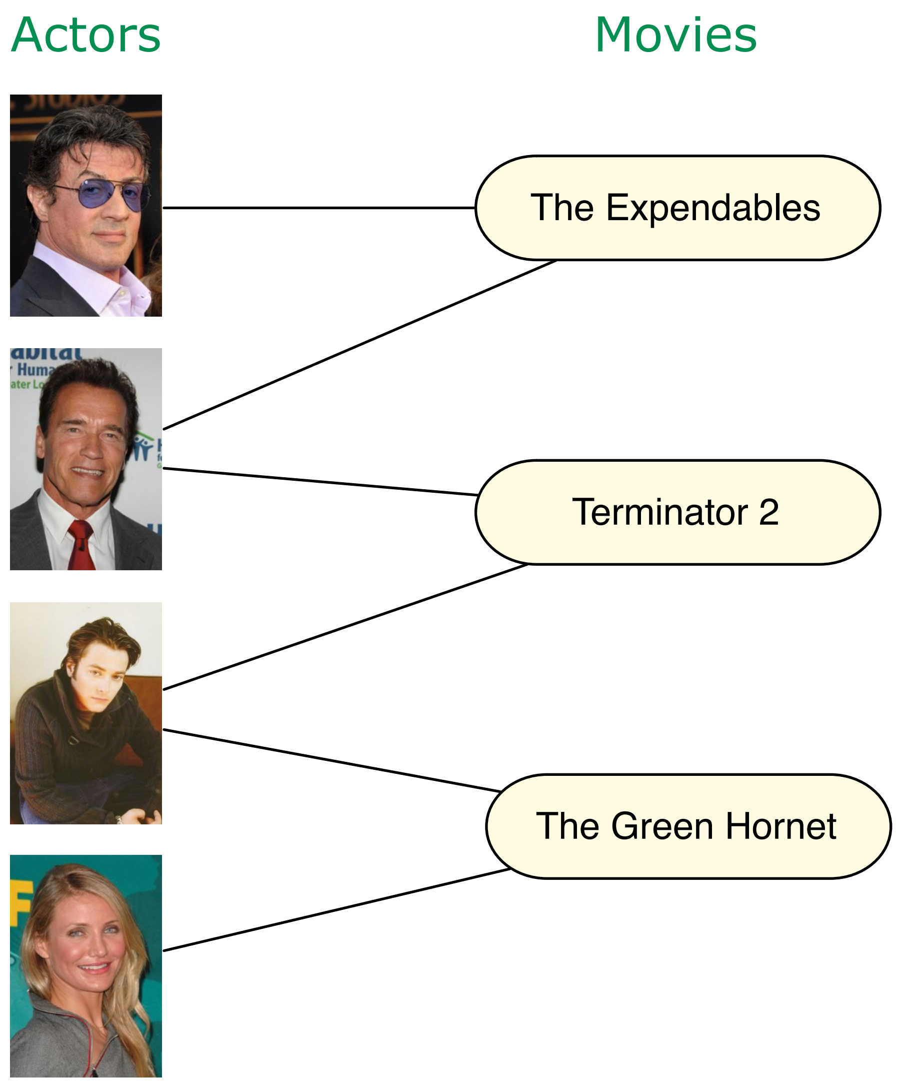
```
>>> nodes = set([ego])
>>> nodes.update(g.neighbors(ego))
>>> egonet = g.subgraph(nodes)
```

```
>>> print egonet.nodes()
['c', 'b', 'd']
>>> print egonet.edges()
[('c', 'b'), ('c', 'd'), ('b', 'd')]
```

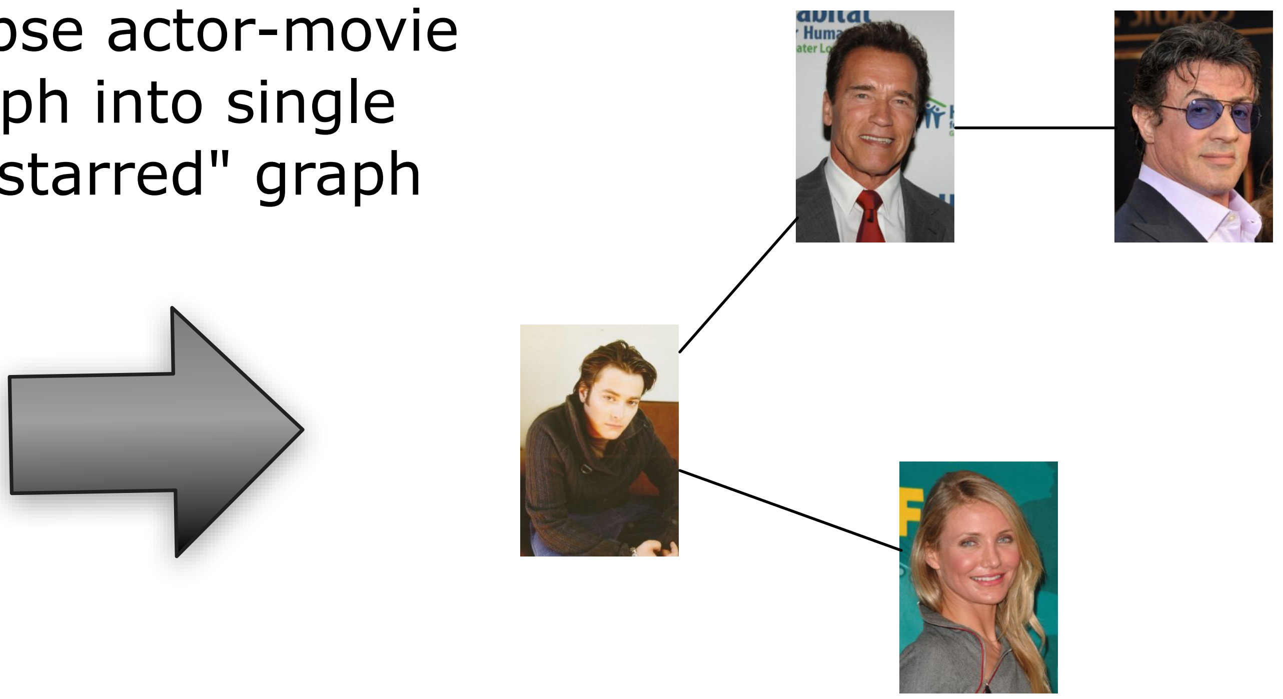


Bipartite Graphs

- In a bipartite graph the nodes can be divided into two disjoint sets so that no pair of nodes in the same set share an edge.



Collapse actor-movie graph into single "co-starred" graph



NetworkX - Bipartite Graphs

- NetworkX does not have a custom bipartite graph class.

➡ A standard graph can be used to represent a bipartite graph.

```
import networkx
from networkx.algorithms import bipartite
```

Import package for handling bipartite graphs

```
g = networkx.Graph()
```

Create standard graph, and add edges.

```
g.add_edges_from([("Stallone","Expendables"), ("Schwarzenegger","Expendables")])
g.add_edges_from([("Schwarzenegger","Terminator 2"), ("Furlong","Terminator 2")])
g.add_edges_from([("Furlong","Green Hornet"), ("Diaz","Green Hornet")])
```

```
>>> print bipartite.is_bipartite(g)
True
>>> print bipartite.bipartite_sets(g)
(set(['Stallone', 'Diaz', 'Schwarzenegger', 'Furlong']),
set(['Terminator 2', 'Green Hornet', 'Expendables']))
```

Verify our graph is bipartite, with two disjoint node sets.

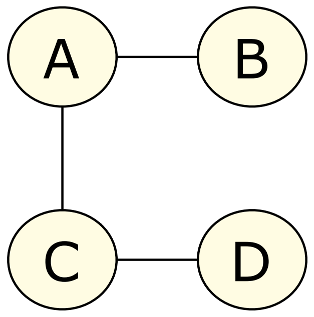
```
>>> g.add_edge("Schwarzenegger","Stallone")
>>> print bipartite.is_bipartite(g)
False
```

Graph is no longer bipartite!

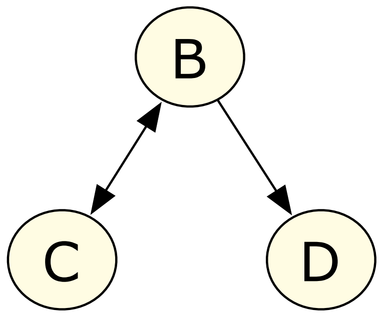
Multi-Relational Networks

- In many SNA applications there will be multiple kinds of relations between nodes. Nodes may be closely-linked in one relational network, but distant in another.

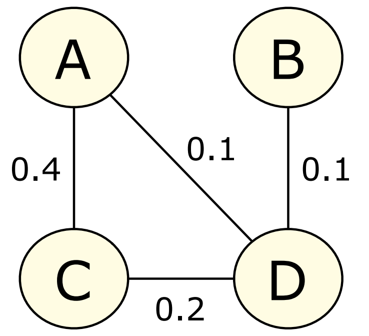
Scientific Research Network



Co-authorship Graph

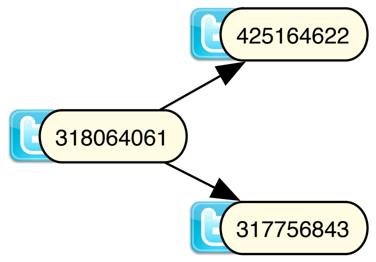


Citation Graph

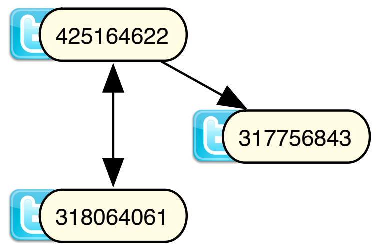


Content Similarity

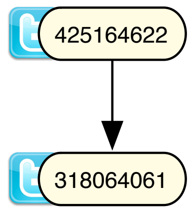
Microblogging Network



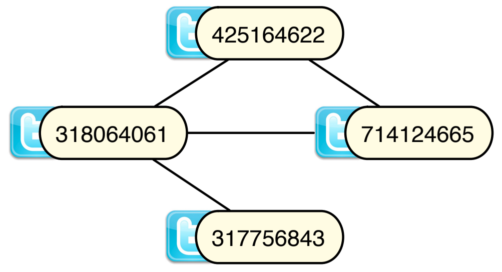
Follower Graph



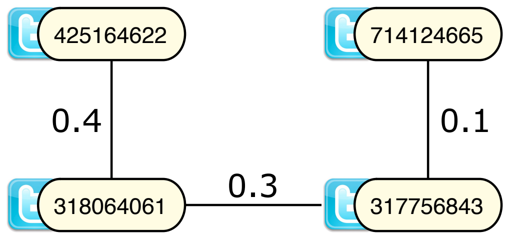
Reply-To Graph



Mention Graph



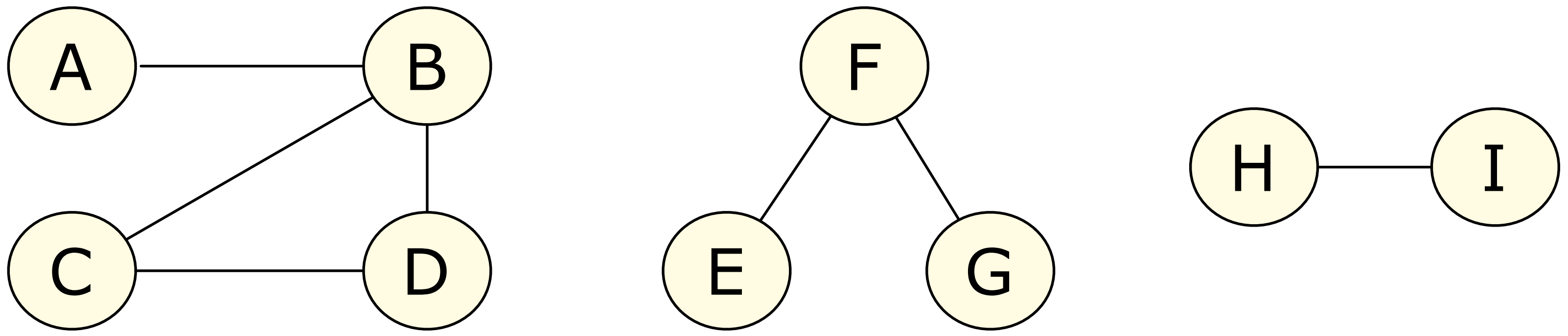
Co-Listed Graph



Content Similarity

Graph Connectivity - Components

- A graph is connected if there is a path between every pair of nodes in the graph.
- A connected component is a subset of the nodes where:
  1. A path exists between every pair in the subset.
  2. The subset is not part of a larger set with the above property.



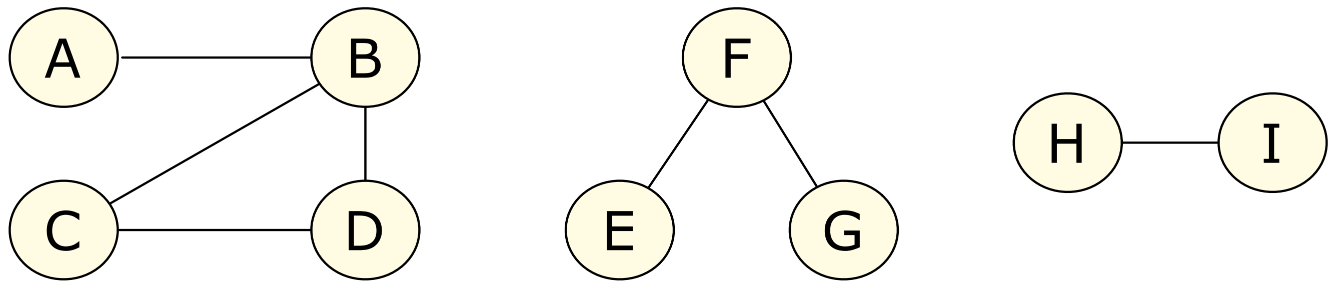
3 connected components

- In many empirical social networks a larger proportion of all nodes will belong to a single giant component.

NetworkX - Graph Connectivity

```
g = networkx.Graph()
g.add_edges_from([("a","b"),("b","c"),("b","d"),("c","d")])
g.add_edges_from([("e","f"),("f","g"),("h","i")])
```

Build undirected graph.



```
>>> print networkx.is_connected(g)
False
>>> print networkx.number_connected_components(g)
3
```

Is the graph just a single component?

If not, how many components are there?

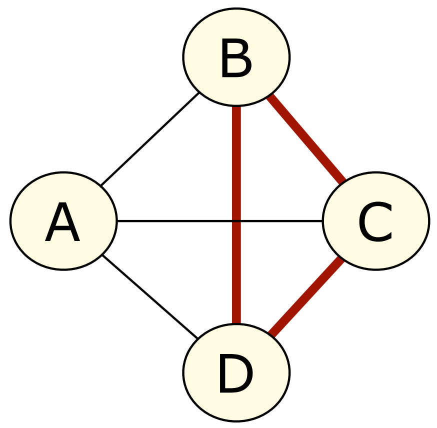
```
>>> comps = networkx.connected_component_subgraphs(g)
>>> print comps[0].nodes()
['a', 'c', 'b', 'd']
>>> print comps[1].nodes()
['e', 'g', 'f']
>>> print comps[2].nodes()
['i', 'h']
```

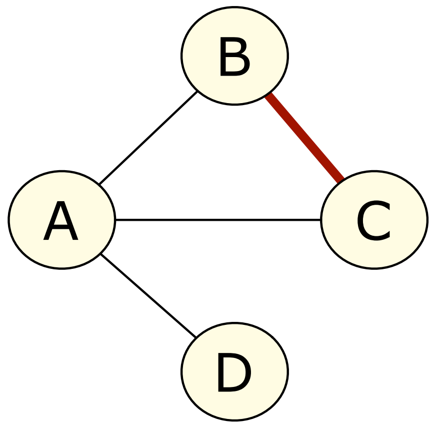
Find list of all connected components.

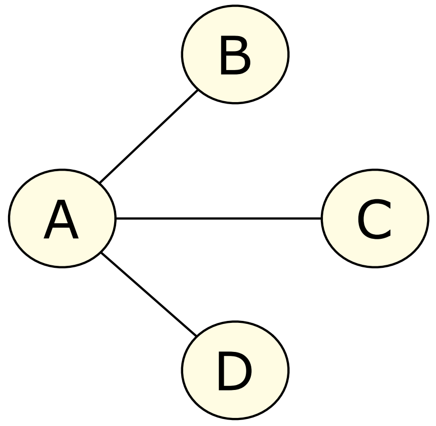
Each component is a subgraph with its own set of nodes and edges.

Clustering Coefficient

- The neighbourhood of a node is set of nodes connected to it by an edge, not including itself.
- The clustering coefficient of a node is the fraction of pairs of its neighbours that have edges between one another.





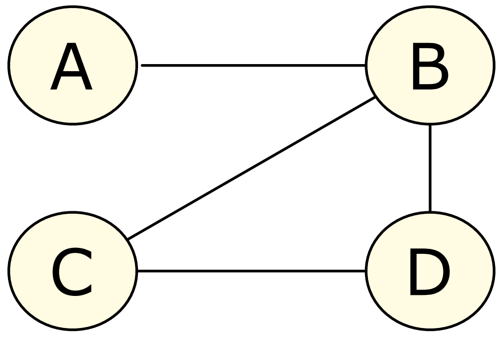


Node A: $CC = \frac{3}{3}$ $CC = \frac{1}{3}$ $CC = \frac{0}{3}$

- Locally indicates how concentrated the neighbourhood of a node is, globally indicates level of clustering in a graph.
- Global score is average over all nodes: $\bar{CC} = \frac{1}{n}\sum_{i=1}^{n} CC(v_i)$

NetworkX - Clustering Coefficient

```
g = networkx.Graph()
g.add_edges_from([("a","b"),("b","c"),("b","d"),("c","d")])
```



```
>>> print networkx.neighbors(g, "b")
['a', 'c', 'd']
```

Get list of neighbours for a specific node.

```
>>> print networkx.clustering(g, "b")
0.333333333333
```

Calculate coefficient for specific node.

```
>>> print networkx.clustering(g, with_labels=True)
{'a': 0.0, 'c': 1.0, 'b': 0.33333333333333331, 'd': 1.0}
```

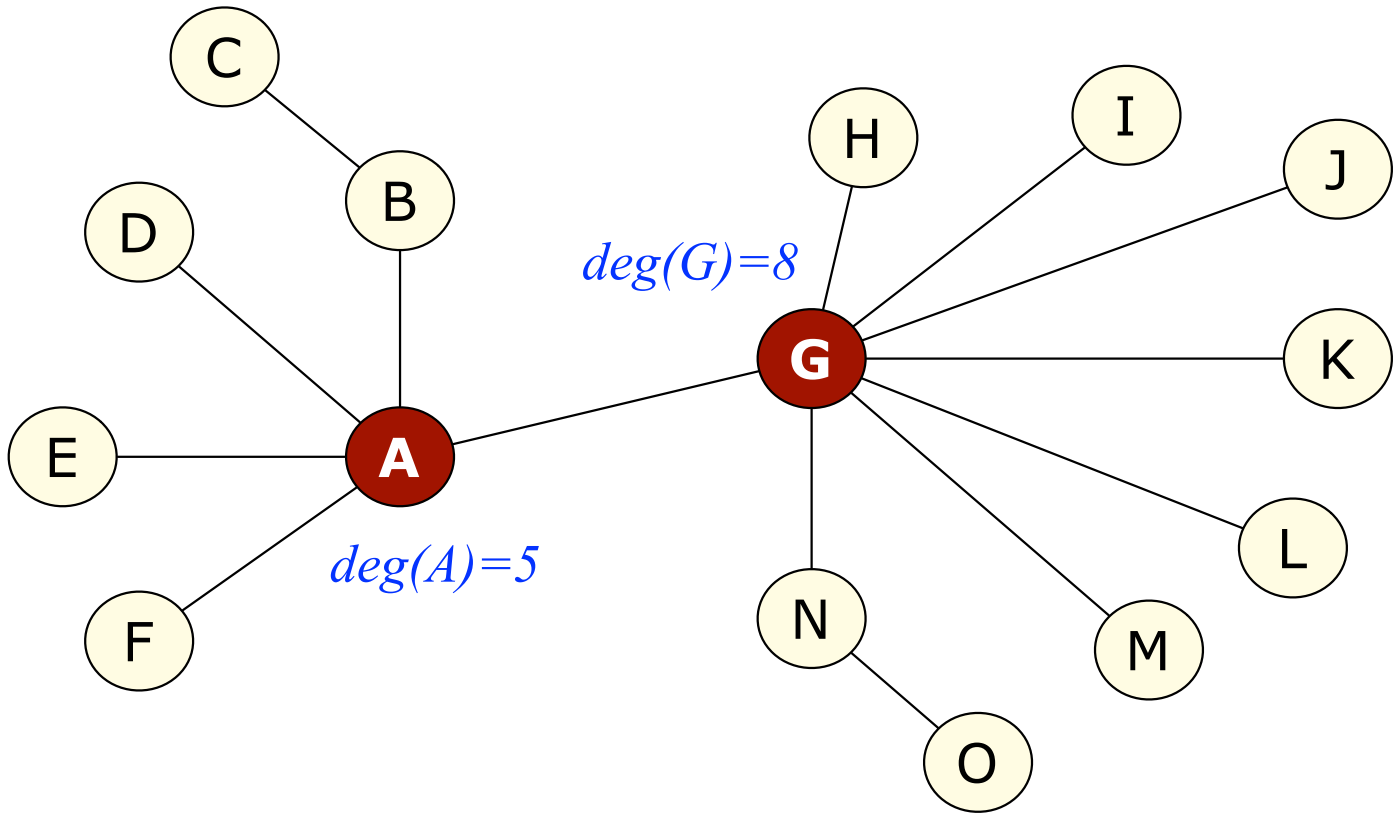
Build a map of coefficients for all nodes.

```
>>> ccs = networkx.clustering(g)
>>> print ccs
[0.0, 1.0, 0.33333333333333331, 1.0]
>>> print sum(ccs)/len(ccs)
0.583333333333
```

Calculate global clustering coefficient.

Measures of Centrality

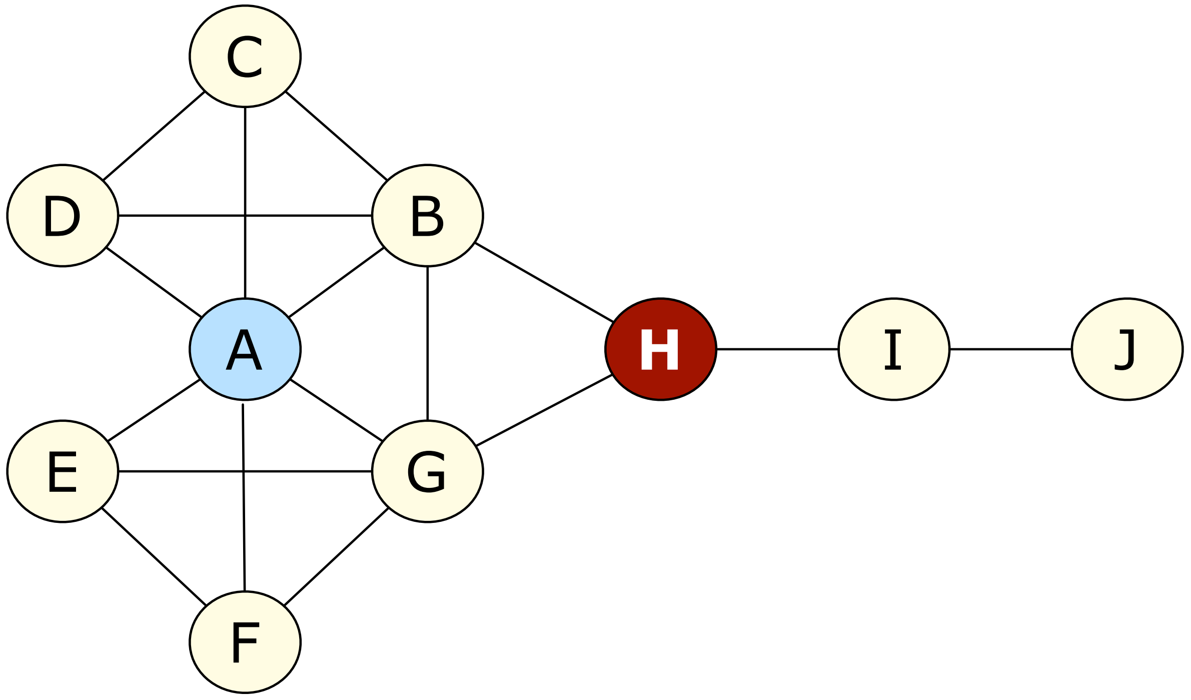
- A variety of different measures exist to measure the importance, popularity, or social capital of a node in a social network.
- Degree centrality focuses on individual nodes - it simply counts the number of edges that a node has.
- Hub nodes with high degree usually play an important role in a network. For directed networks, in-degree is often used as a proxy for popularity.



Betweenness Centrality

- A path in a graph is a sequence of edges joining one node to another. The path length is the number of edges.
- Often want to find the shortest path between two nodes.
- A graph's diameter is the longest shortest path over all pairs of nodes.

- Nodes that occur on many shortest paths between other nodes in the graph have a high betweenness centrality score.



Node "A" has high degree centrality than "B", as "B" has few direct connections.

Node "H" has higher betweenness centrality, as "H" plays a broker role in the network.

Eigenvector Centrality

- The eigenvector centrality of a node proportional to the sum of the centrality scores of its neighbours.

➡ A node is important if it connected to other important nodes.

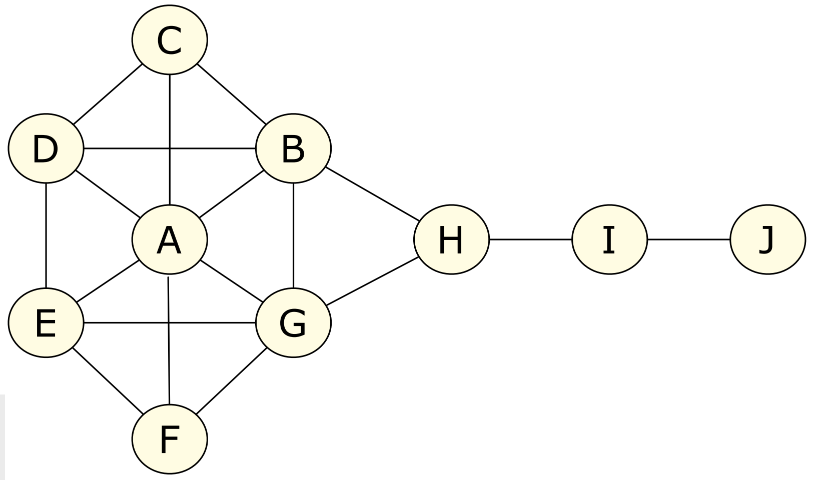
➡ A node with a small number of influential contacts may outrank one with a larger number of mediocre contacts.

- Computation:
  1. Calculate the eigendecomposition of the pairwise adjacency matrix of the graph.
  2. Select the eigenvector associated with largest eigenvalue.
  3. Element *i* in the eigenvector gives the centrality of the *i*-th node.

NetworkX - Measures of Centrality

```
import networkx
from operator import itemgetter
```

```
g = networkx.read_adjlist("centrality.edges")
```



```
dc = networkx.degree_centrality(g)
print sorted(dc.items(), key=itemgetter(1), reverse=True)
```

```
[('a', 0.66666666666666663), ('b', 0.55555555555555558), ('g', 0.55555555555555558), ('c', 0.33333333333333331),
('e', 0.33333333333333331), ('d', 0.33333333333333331), ('f', 0.33333333333333331), ('h', 0.33333333333333331),
('i', 0.22222222222222221), ('j', 0.1111111111111111)]
```

```
bc = networkx.betweenness_centrality(g)
print sorted(bc.items(), key=itemgetter(1), reverse=True)
```

```
[('h', 0.38888888888888884), ('b', 0.2361111111111111), ('g', 0.2361111111111111), ('i', 0.22222222222222221),
('a', 0.16666666666666666), ('c', 0.0), ('e', 0.0), ('d', 0.0), ('f', 0.0), ('j', 0.0)]
```

```
bc = networkx.eigenvector_centrality(g)
print sorted(bc.items(), key=itemgetter(1), reverse=True)
```

```
[('a', 0.17589997921479006), ('b', 0.14995290497083508), ('g', 0.14995290497083508), ('c', 0.10520440827586457),
('e', 0.10520440827586457), ('d', 0.10520440827586457), ('f', 0.10520440827586457), ('h', 0.078145778134411939),
('i', 0.020280613919932109), ('j', 0.0049501856857375875)]
```

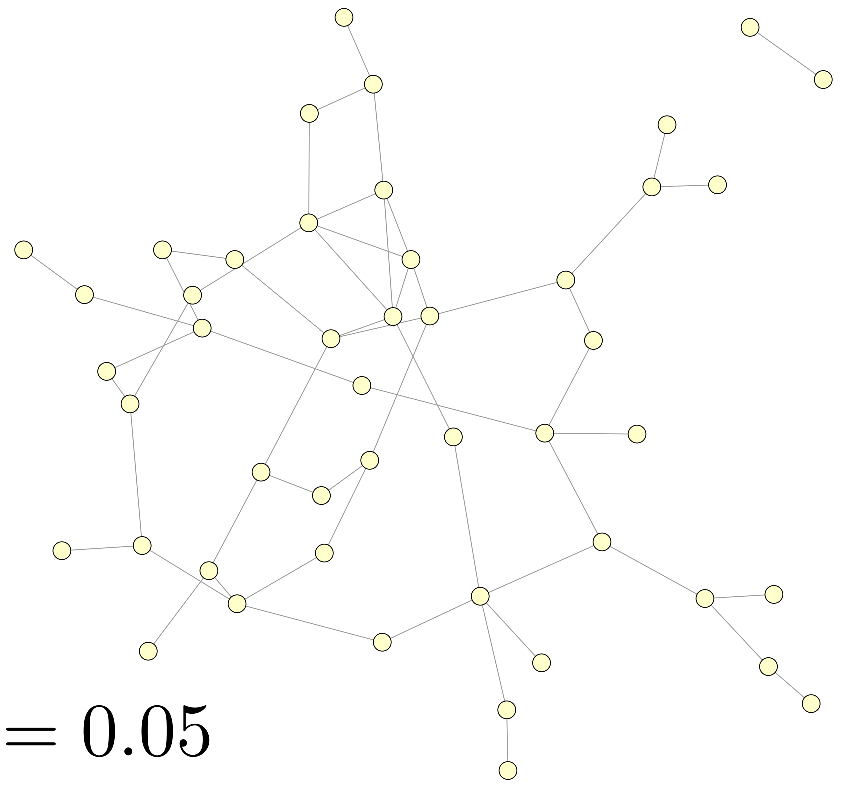
Random Networks

- Erdős–Rényi random graph model:
  - Start with a collection of *n* disconnected nodes.
  - Create an edge between each pair of nodes with a probability *p*, independently of every other edge.

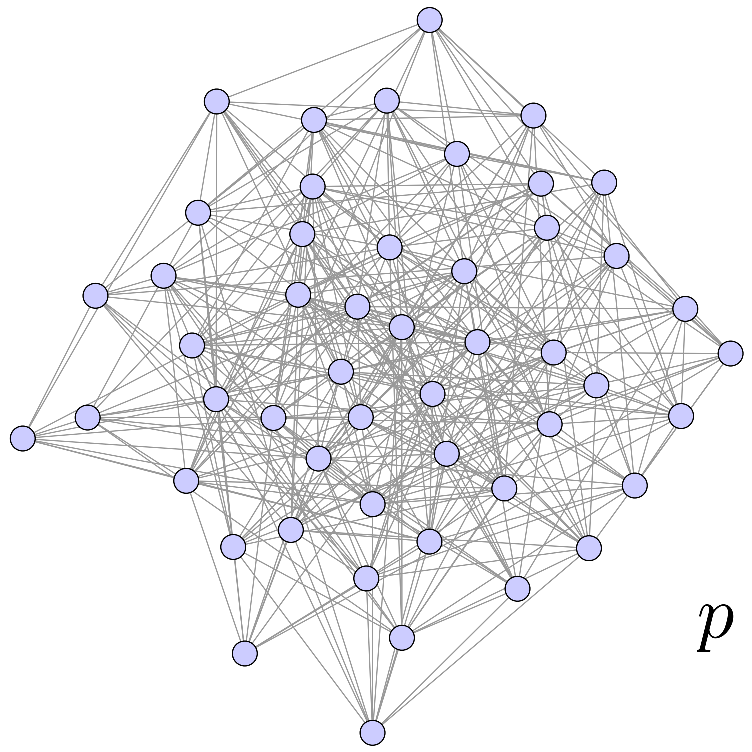
```
g1 = networkx.erdos_renyi_graph(50, 0.05)
```

```
g2 = networkx.erdos_renyi_graph(50, 0.3)
```

Specify number of nodes to create, and connection probability *p*.



$p = 0.05$



$p = 0.3$

Small World Networks

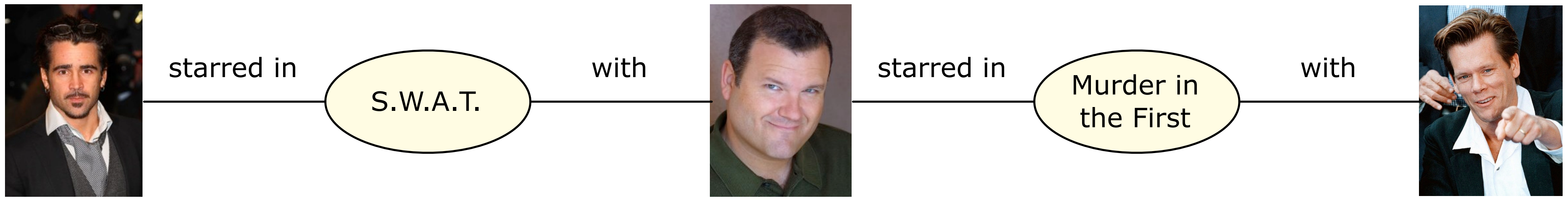
Milgram's Small World Experiment:

- Route a package to a stockbroker in Boston by sending them to random people in Nebraska and requesting them to forward to someone who might know the stockbroker.

➡ Although most nodes are not directly connected, each node can be reached from another via a relatively small number of hops.

Six Degrees of Kevin Bacon

- Examine the actor-actor "co-starred" graph from IMDB.
- The Bacon Number of an actor is the number of degrees of separation he/she has from Bacon, via the shortest path.



$\Rightarrow$ Bacon Number $= 2$

http://oracleofbacon.org

Small World Networks

- Take a connected graph with a high diameter, randomly add a small number of edges, then the diameter tends to drop drastically.
- Small-world network has many local links and few long range "shortcuts".

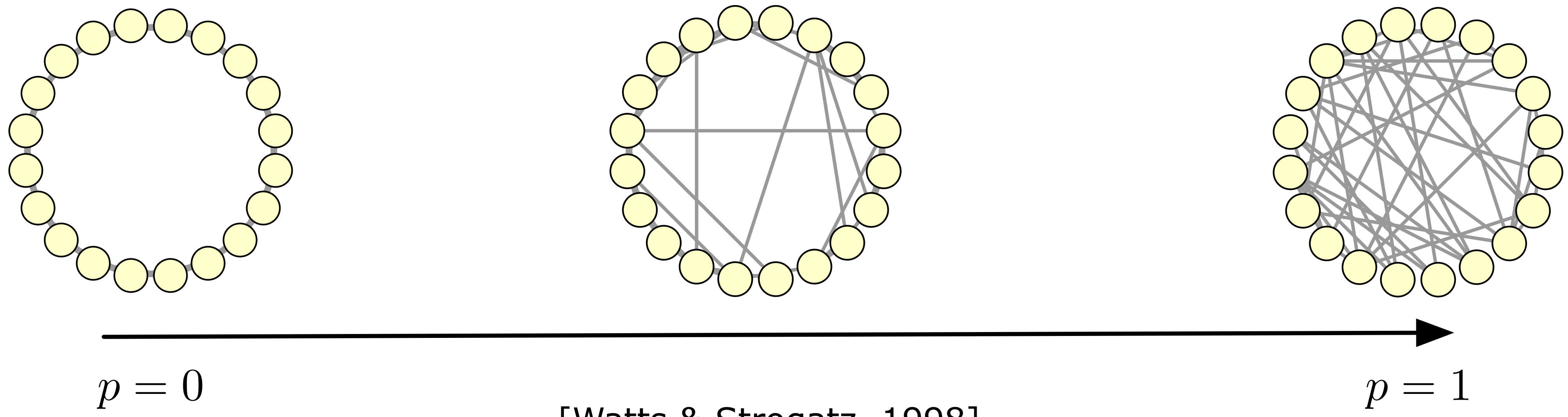
Typical properties:

- High clustering coefficient.
- Short average path length.
- Over-abundance of hub nodes.

[Watts & Strogatz, 1998]

Generating Small World Networks:

1. Create ring of *n* nodes, each connected to its *k* nearest neighbours.
2. With probability *p*, rewire each edge to an existing destination node.



[Watts & Strogatz, 1998]

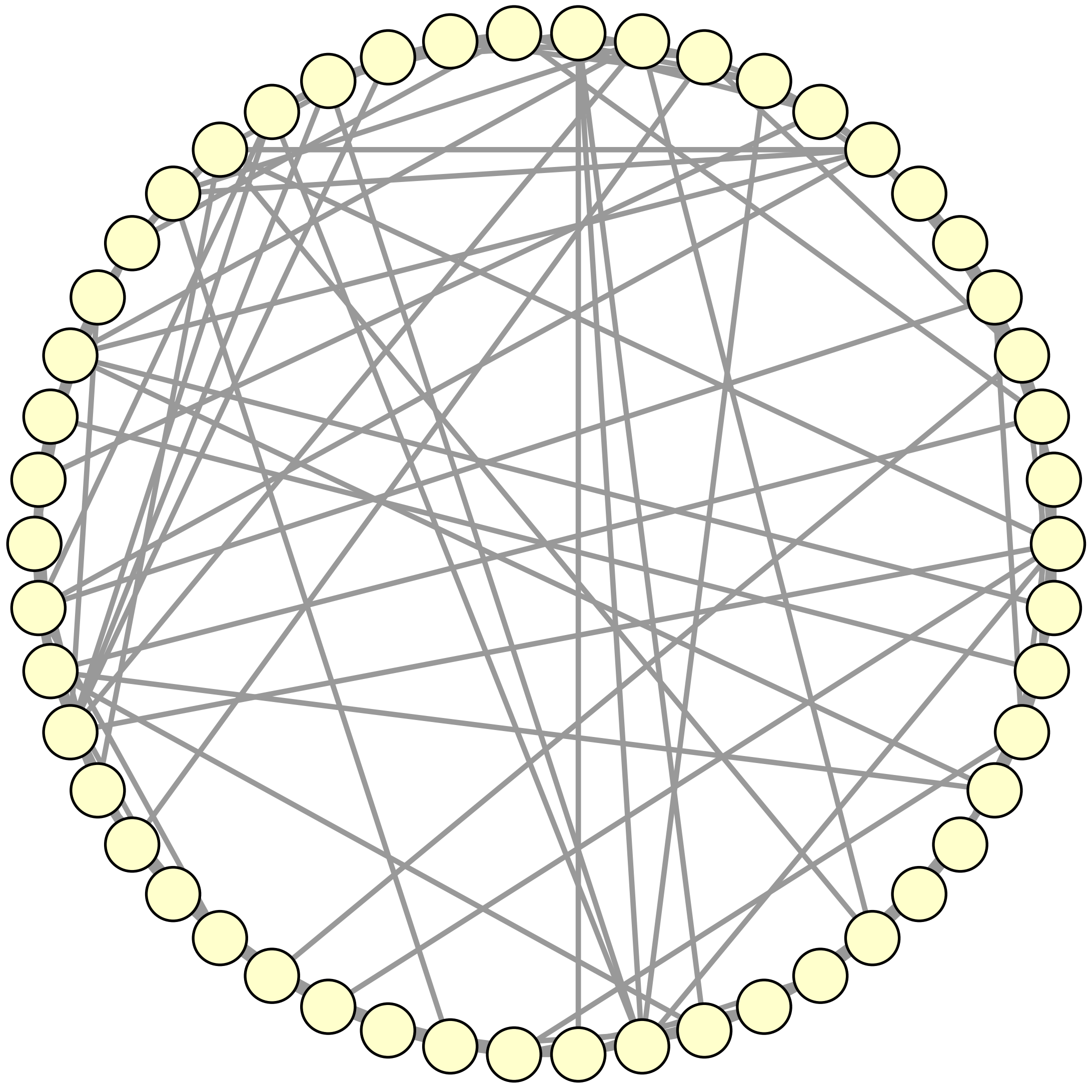
NetworkX - Small World Networks

- NetworkX includes functions to generate graphs according to a variety of well-known models:

  http://networkx.lanl.gov/reference/generators.html

```
n = 50
k = 6
p = 0.3
g = networkx.watts_strogatz_graph(n, k, p)
```

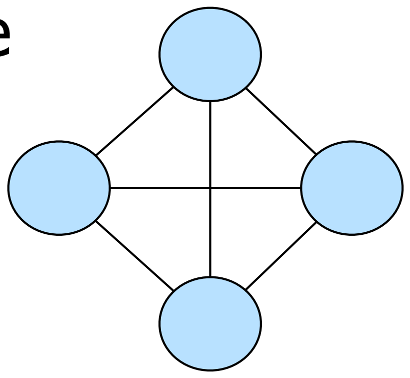
```
>>> networkx.average_shortest_path_length(g)
2.4506122448979597
```



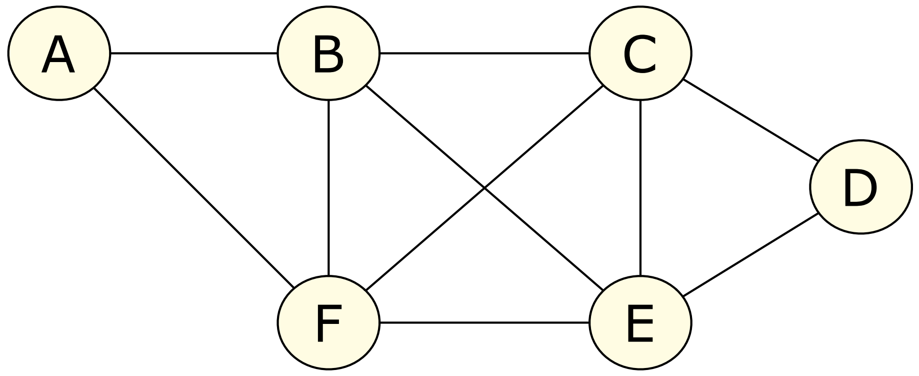
Community Finding

Cliques

- A clique is a social grouping where everyone knows everyone else (i.e. there is an edge between each pair of nodes).



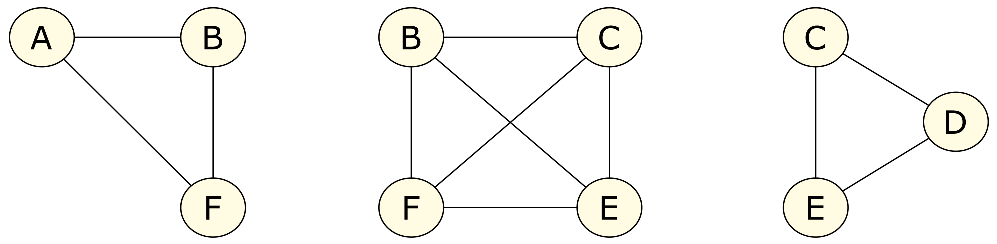
- A maximal clique is a clique that is not a subset of any other clique in the graph.
- A clique with size greater than or equal to that of every other clique in the graph is called a maximum clique.



Find all maximal cliques in the specified graph:

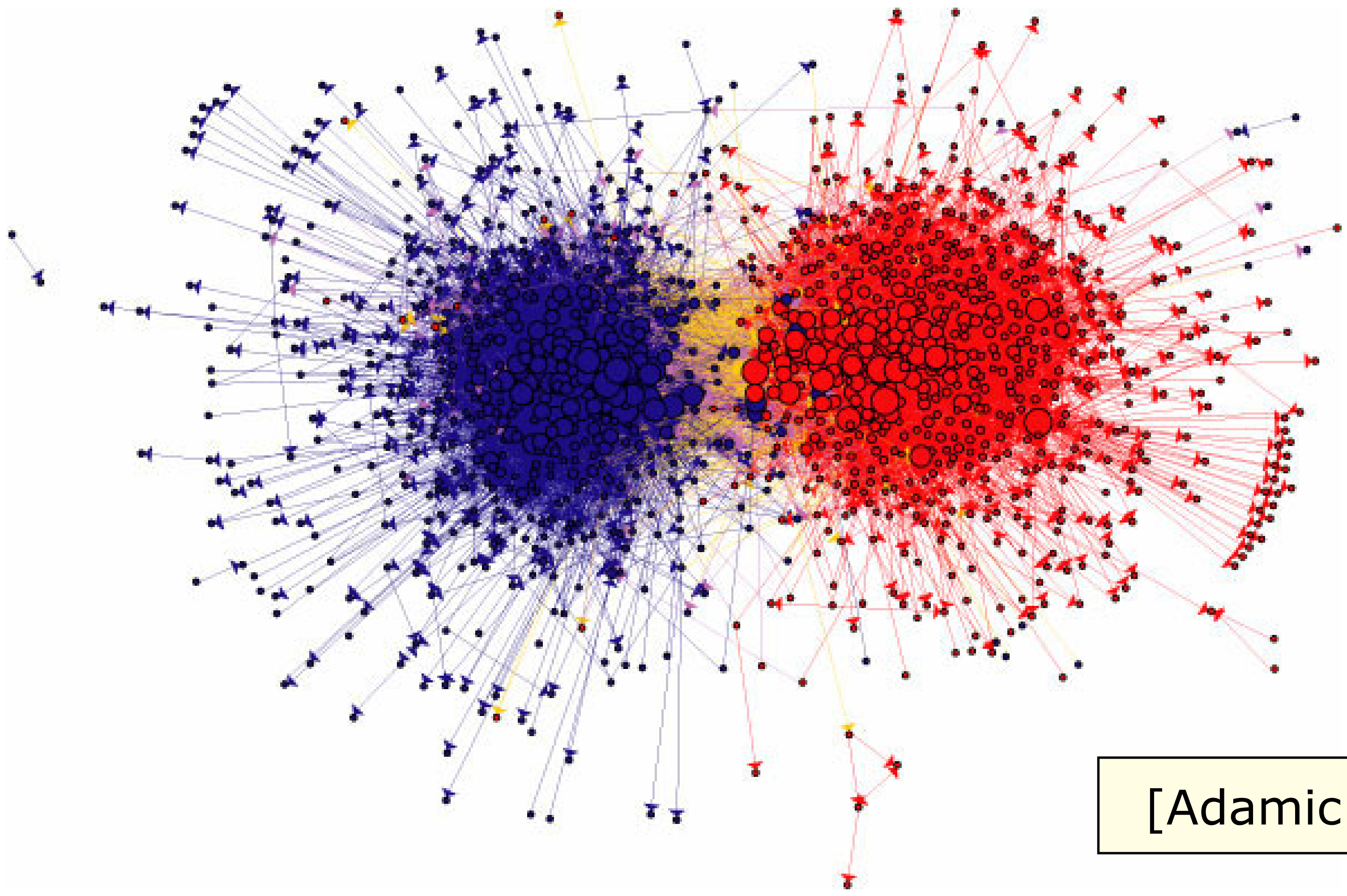
```
>>> cl = list( networkx.find_cliques(g) )
```

```
>>> print cl
[['a', 'b', 'f'], ['c', 'e', 'b', 'f'], ['c', 'e', 'd']]
```



Community Detection

- We will often be interested in identifying communities of nodes in a network...

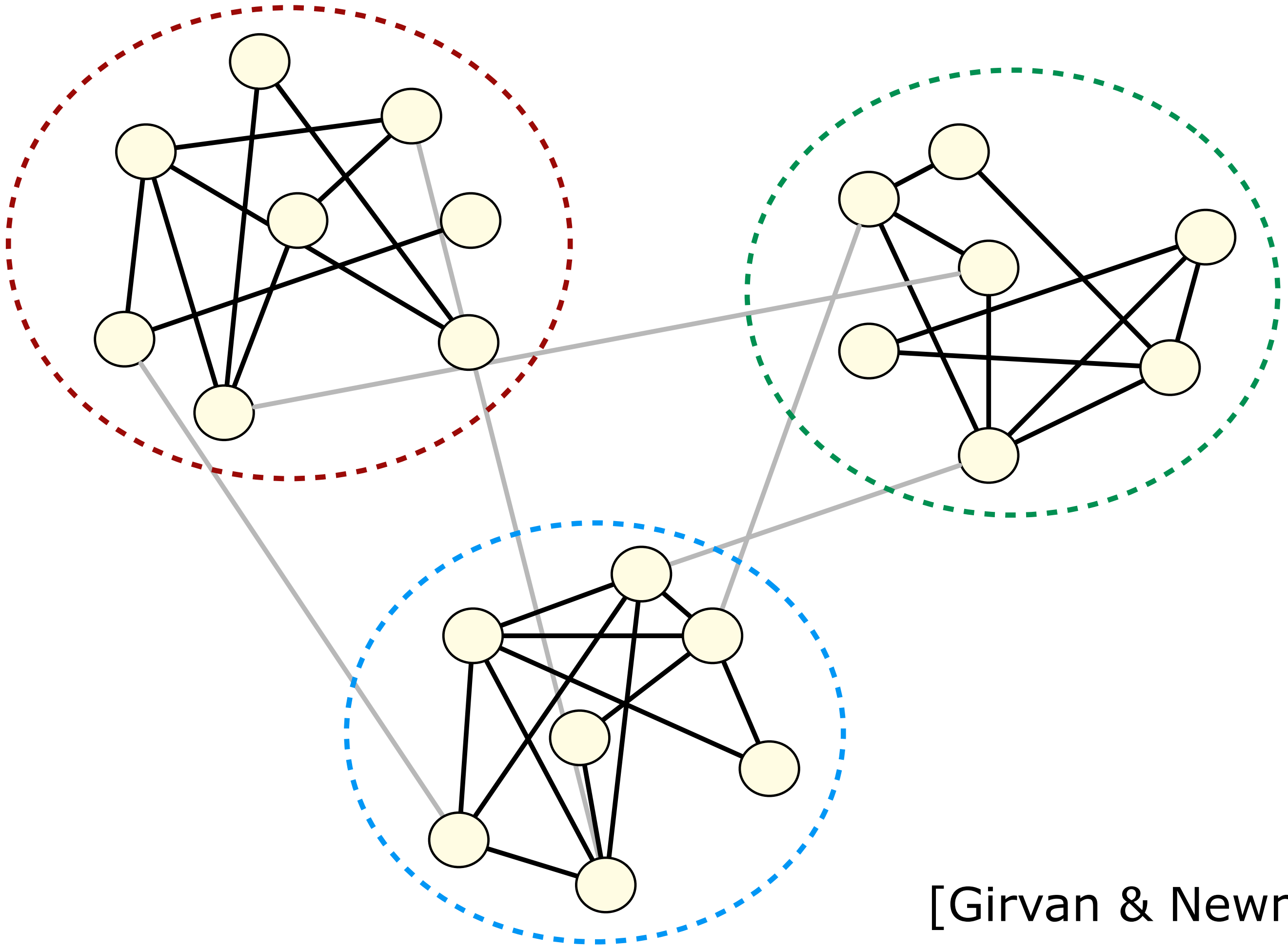


[Adamic & Glance,2005]

- Example: Two distinct communities of bloggers discussing 2004 US Presidential election.

Community Detection

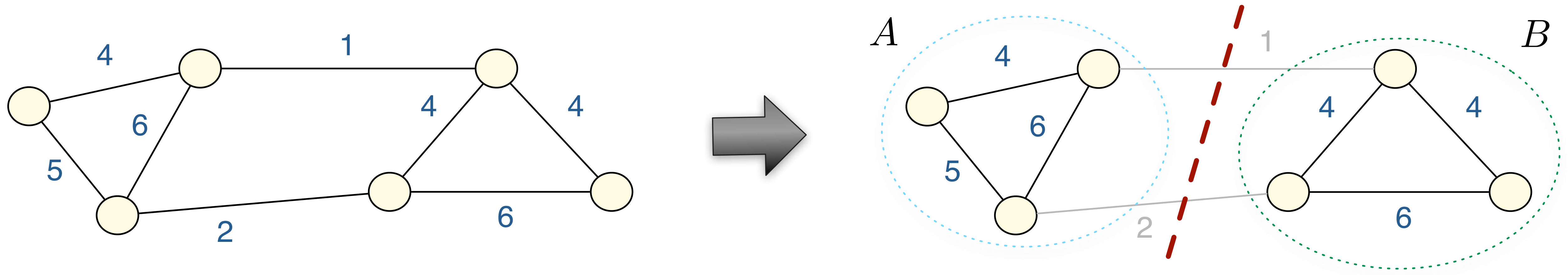
- A variety of definitions of community/cluster/module exist:
  - A group of nodes which share common properties and/or play a similar role within the graph [Fortunato, 2010].
  - A subset of nodes within which the node-node connections are dense, and the edges to nodes in other communities are less dense [Girvan & Newman, 2002].



[Girvan & Newman, 2002]

Graph Partitioning

- **Goal:** Divide the nodes in a graph into a user-specified number of disjoint groups to optimise a criterion related to number of edges cut.



- Min-cut simply involves minimising number (or weight) of edges cut by the partition.

$$cut(A, B) = 3$$

- Recent approaches use more sophisticated criteria (e.g. normalised cuts) and apply multi-level strategies to scale to large graphs.

  Graclus [Dhillon et al, 2007] http://www.cs.utexas.edu/users/dml/Software/graclus.html

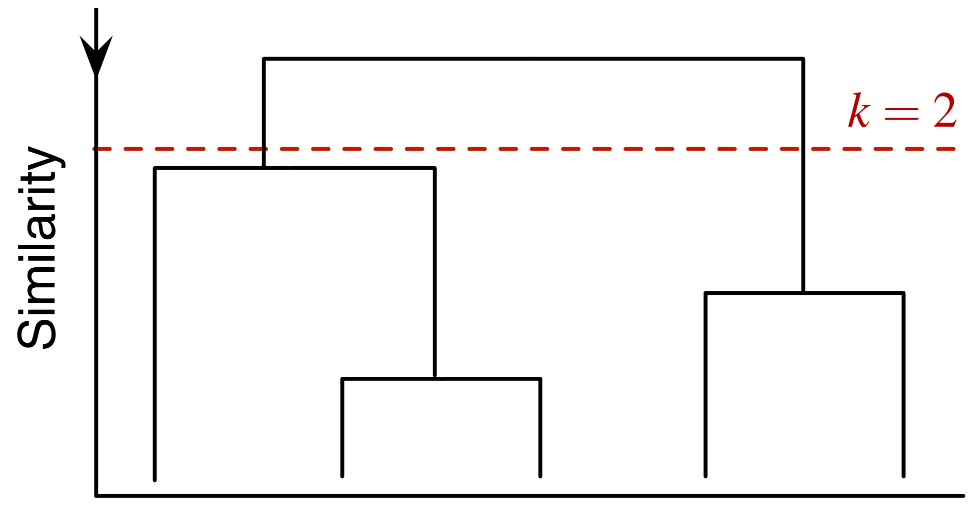
Issues: Requirement to pre-specify number of partitions, cut criteria often make strong assumptions about cluster structures.

Hierarchical Clustering

- Construct a tree of clusters to identify groups of nodes with high similarity according to some similarity measure.
- Two basic families of algorithm...
  1. Agglomerative: Begin with each node assigned to a singleton cluster. Apply a bottom-up strategy, merging the most similar pair of clusters at each level.
  2. Divisive: Begin with single cluster containing all nodes. Apply a top-down strategy, splitting a chosen cluster into two sub-clusters at each level.

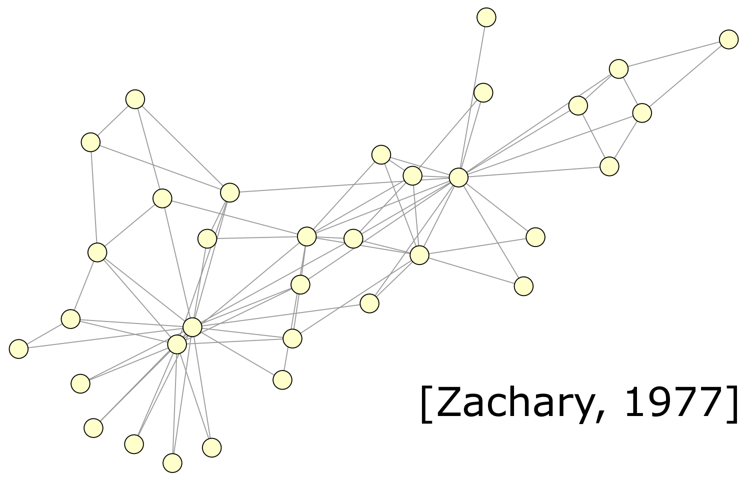
<u>Issues for Community Detection:</u>

- How do we choose among many different possible clusterings?
- Is there really a hierarchical structure in the graph?
- Often scales poorly to large graphs.



NetworkX - Hierarchical Clustering

- We can apply agglomerative clustering to a NetworkX graph by calling functions from the NumPy and SciPy numerical computing packages.



[Zachary, 1977]

```
import networkx
import numpy, matplotlib
from scipy.cluster import hierarchy
from scipy.spatial import distance
```

```
g = networkx.read_edgelist("karate.edgelist")
```

```
path_length=networkx.all_pairs_shortest_path_length(g)
n = len(g.nodes())
distances=numpy.zeros((n,n))
for u,p in path_length.iteritems():
   for v,d in p.iteritems():
      distances[int(u)-1][int(v)-1] = d
sd = distance.squareform(distances)
```

Build pairwise distance matrix based on shortest paths between nodes.

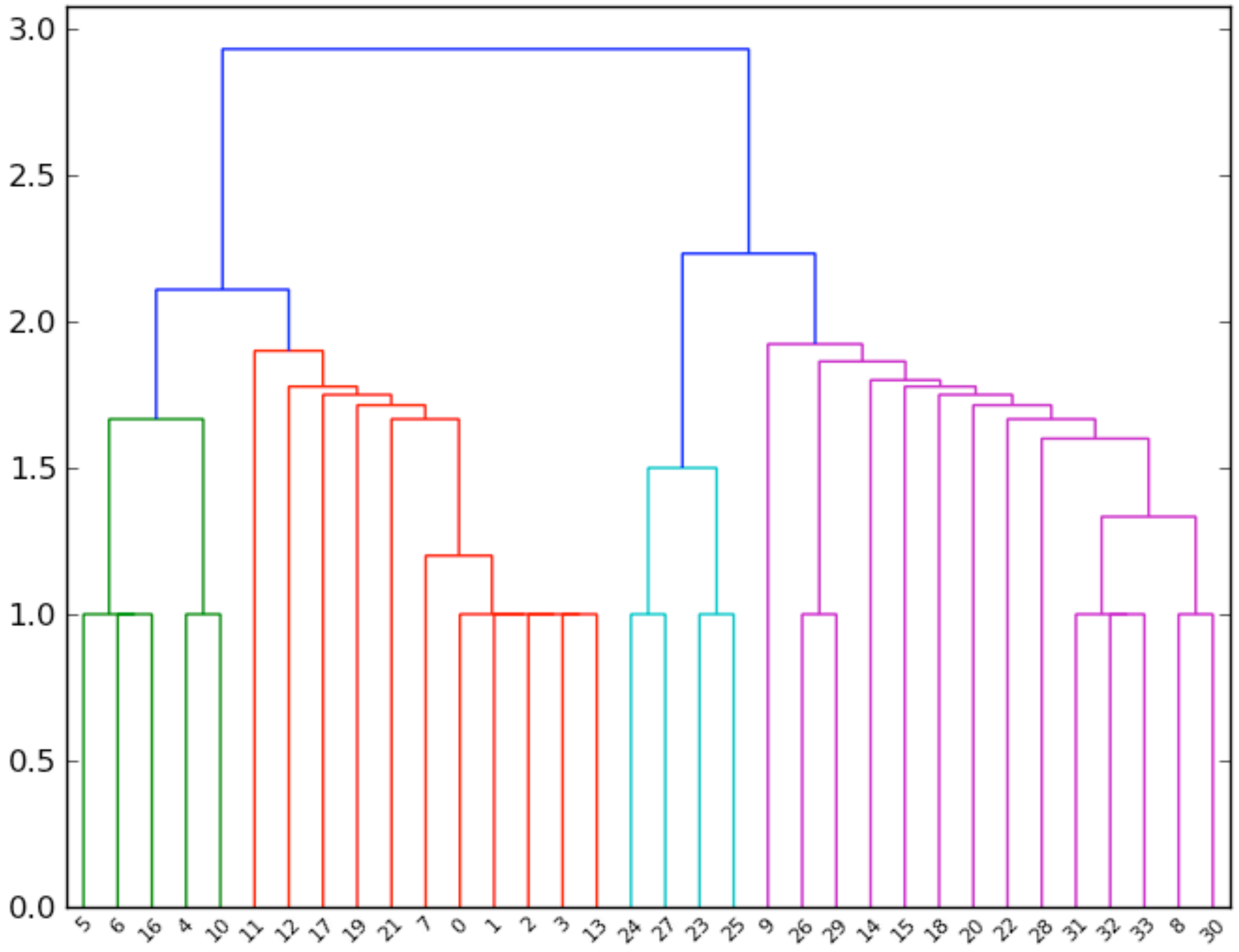
```
hier = hierarchy.average(sd)
```

Apply average-linkage agglomerative clustering.

NetworkX - Hierarchical Clustering

```
hierarchy.dendrogram(hier)
matplotlib.pylab.savefig("tree.png",format="png")
```

Build the dendrogram, then write image to disk.



Modularity Optimisation

- Newman & Girvan [2004] proposed measure of partition quality....
  - ➡ Random graph shouldn't have community structure.
  - ➡ Validate existence of communities by comparing actual edge density with expected edge density in random graph.

$$Q = (\text{number of edges within communities}) - (\text{expected number within communities})$$

- Apply agglomerative technique to iteratively merge groups of nodes to form larger communities such that modularity increases after merging.
- Recently efficient greedy approaches to modularity maximisation have been developed that scale to graphs with up to 10^9 edges.

Louvain Method [Blondel et al, 2008] http://findcommunities.googlepages.com

Issues for Community Detection:

- Total number of edges in graph controls the resolution at which communities are identified [Fortunato, 2010].
- Is it realistic/useful to assign nodes to only a single community?

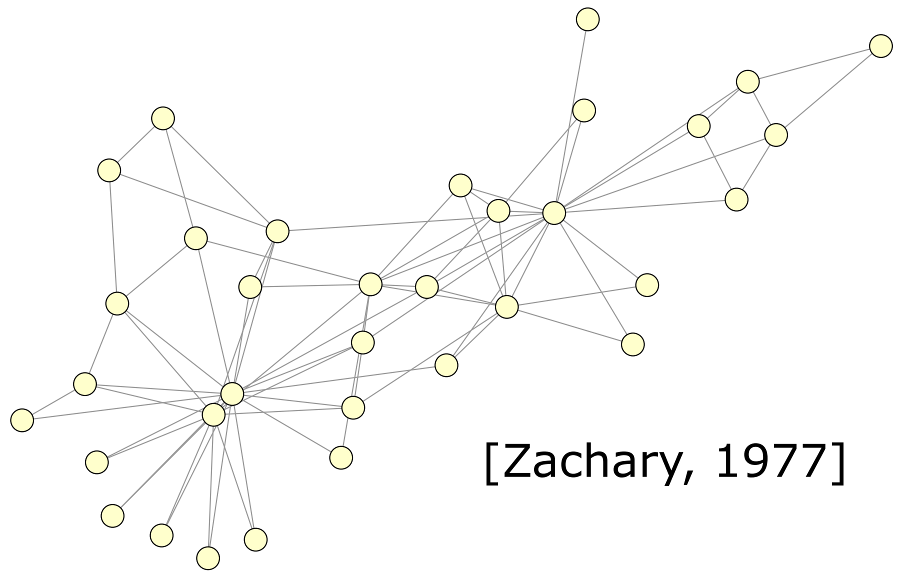
NetworkX - Modularity Optimisation

- Python implementation of the Louvain algorithm available: http://perso.crans.org/aynaud/communities/community.py

```
g = networkx.read_edgelist("karate.edges")
```

Apply Louvain algorithm to the graph

```
import community
partition = community.best_partition( g )
```


[Zachary, 1977]

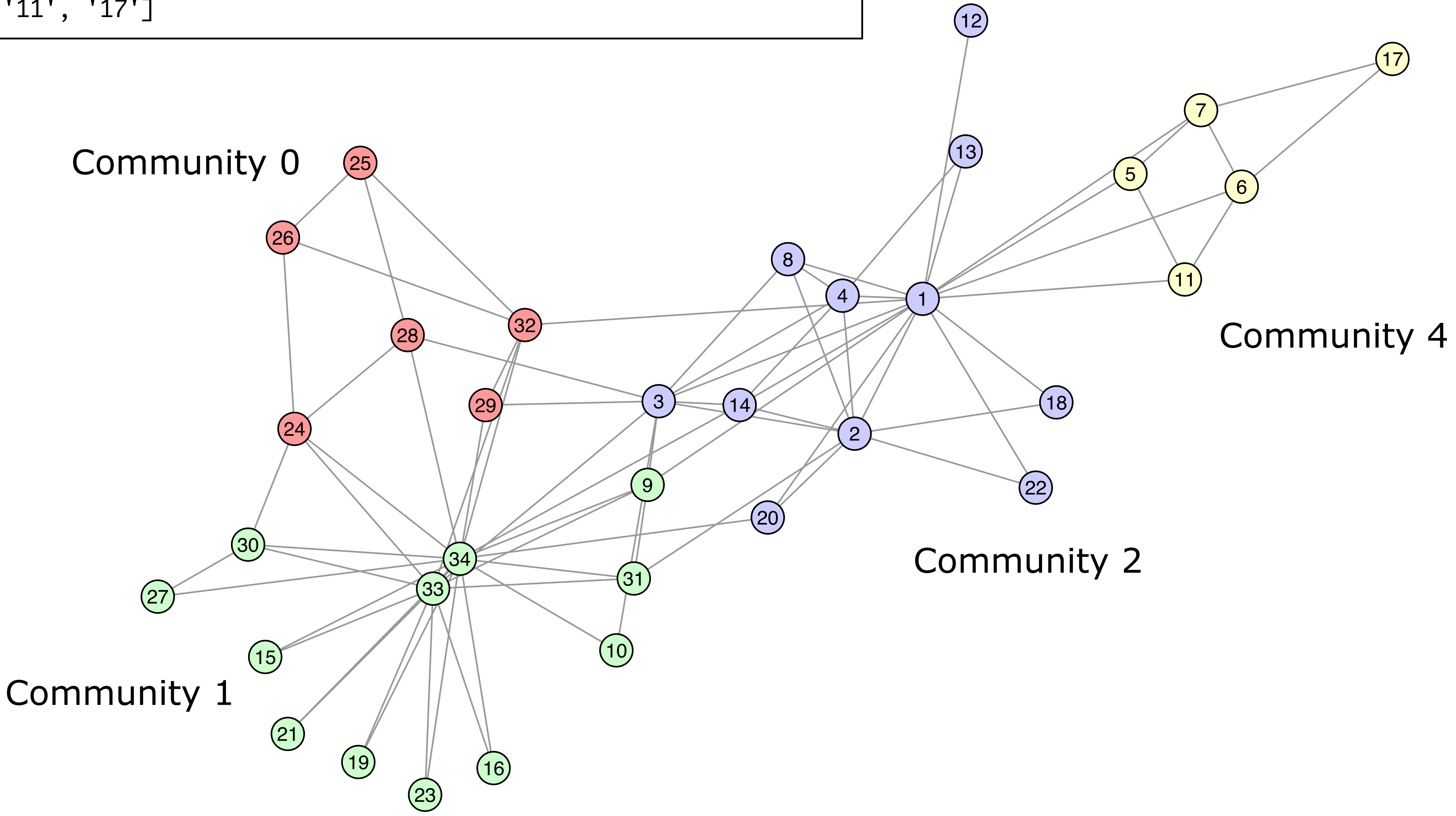
Print nodes assigned to each community in the partition

```
for i in set(partition.values()):
   print "Community", i
   members = list_nodes = [nodes for nodes in partition.keys() if partition[nodes] == i]
   print members
```

```
Community 0
['24', '25', '26', '28', '29', '32']
Community 1
['27', '21', '23', '9', '10', '15', '16', '33', '31', '30', '34', '19']
Community 2
['20', '22', '1', '3', '2', '4', '8', '13', '12', '14', '18']
Community 3
['5', '7', '6', '11', '17']
```

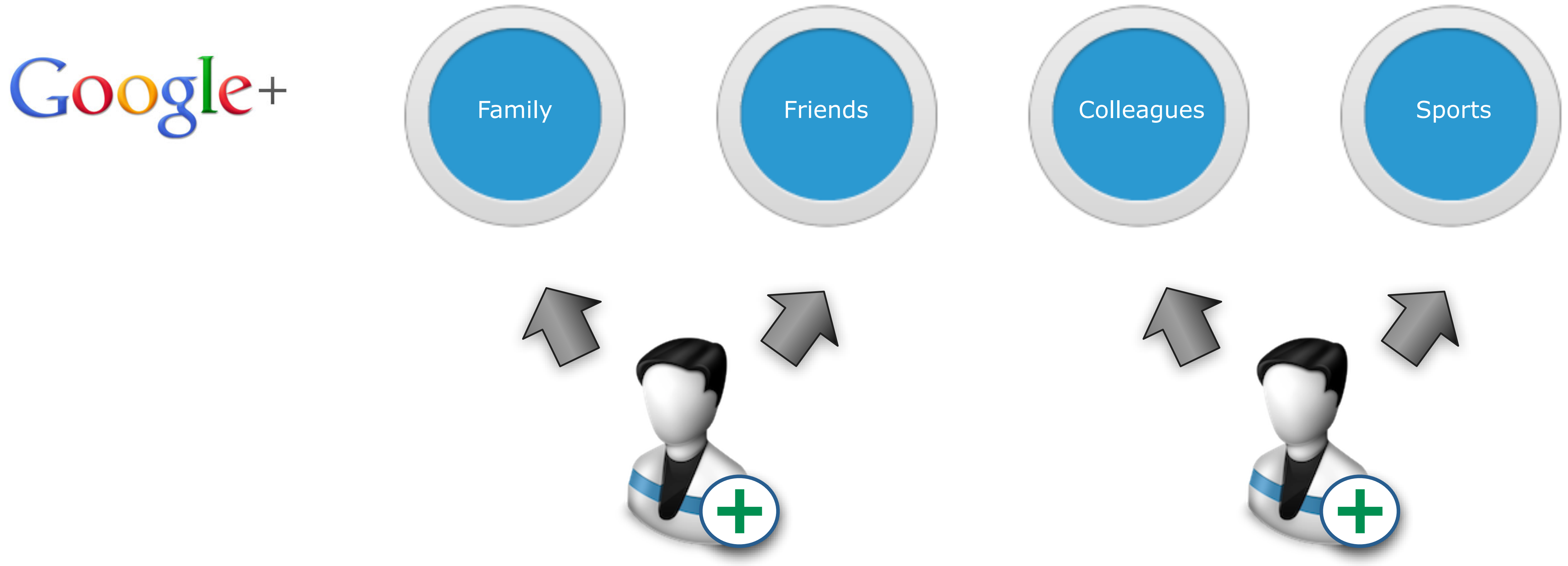
NetworkX - Modularity Optimisation

```
Community 0
['24', '25', '26', '28', '29', '32']
Community 1
['27', '21', '23', '9', '10', '15', '16', '33', '31', '30', '34', '19']
Community 2
['20', '22', '1', '3', '2', '4', '8', '13', '12', '14', '18']
Community 3
['5', '7', '6', '11', '17']
```



Overlapping v Non-Overlapping

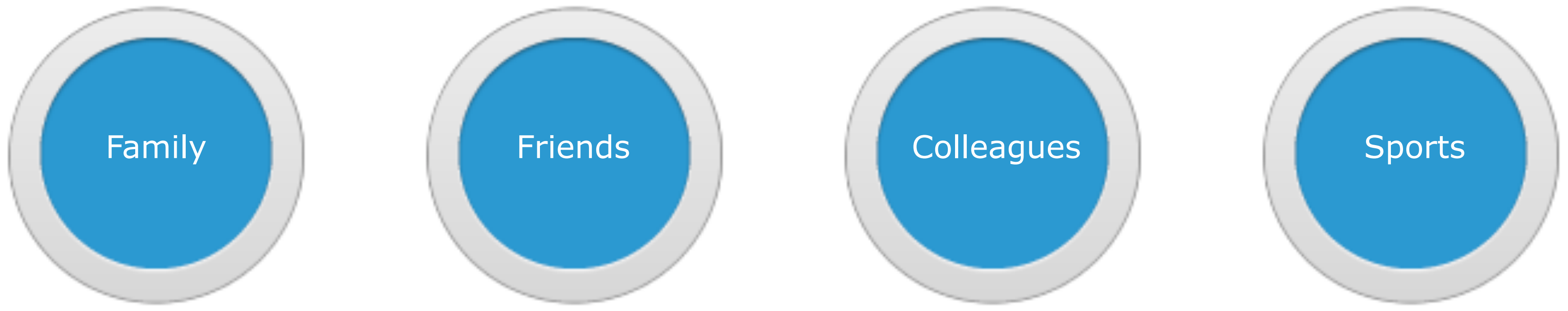
- Do disjoint non-overlapping communities make sense in empirical social networks?



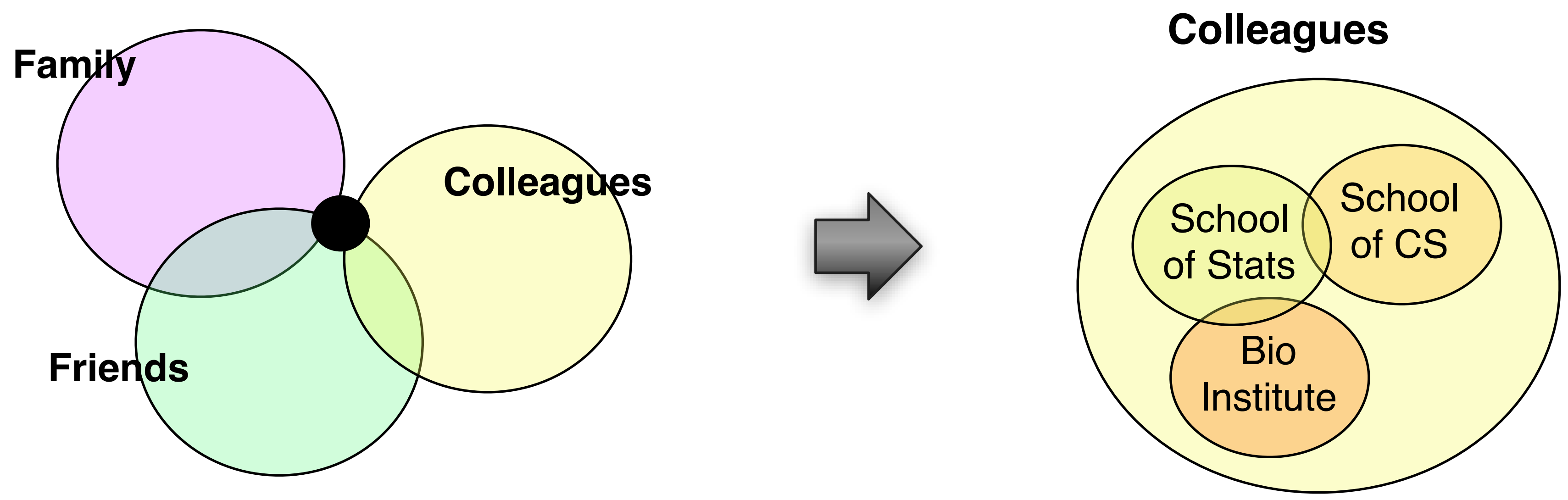
Overlapping v Non-Overlapping

- Do disjoint non-overlapping communities make sense in empirical social networks?

Google+



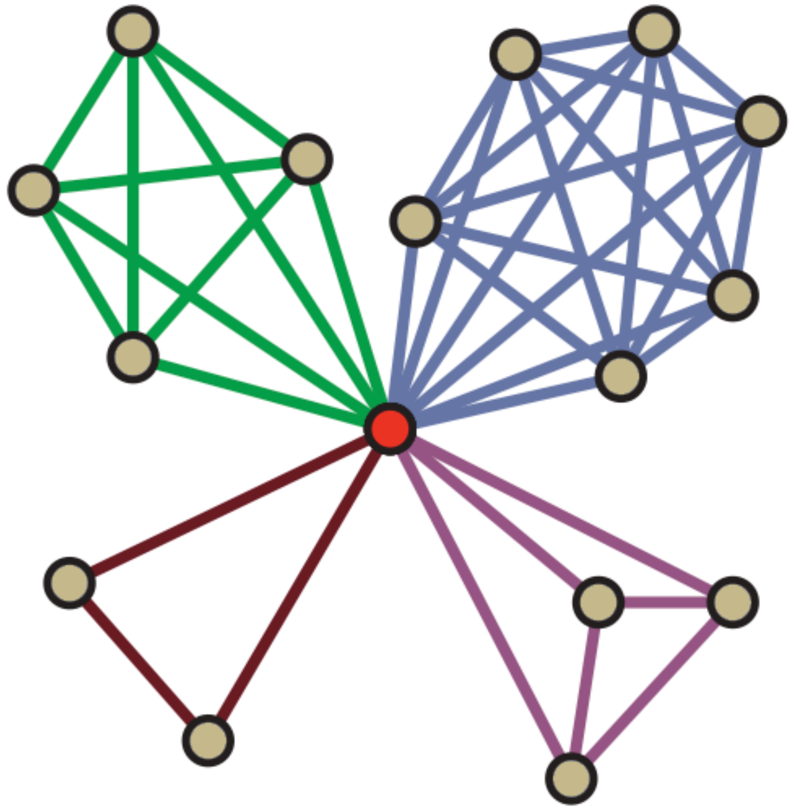
Overlapping communities may exist at different resolutions.

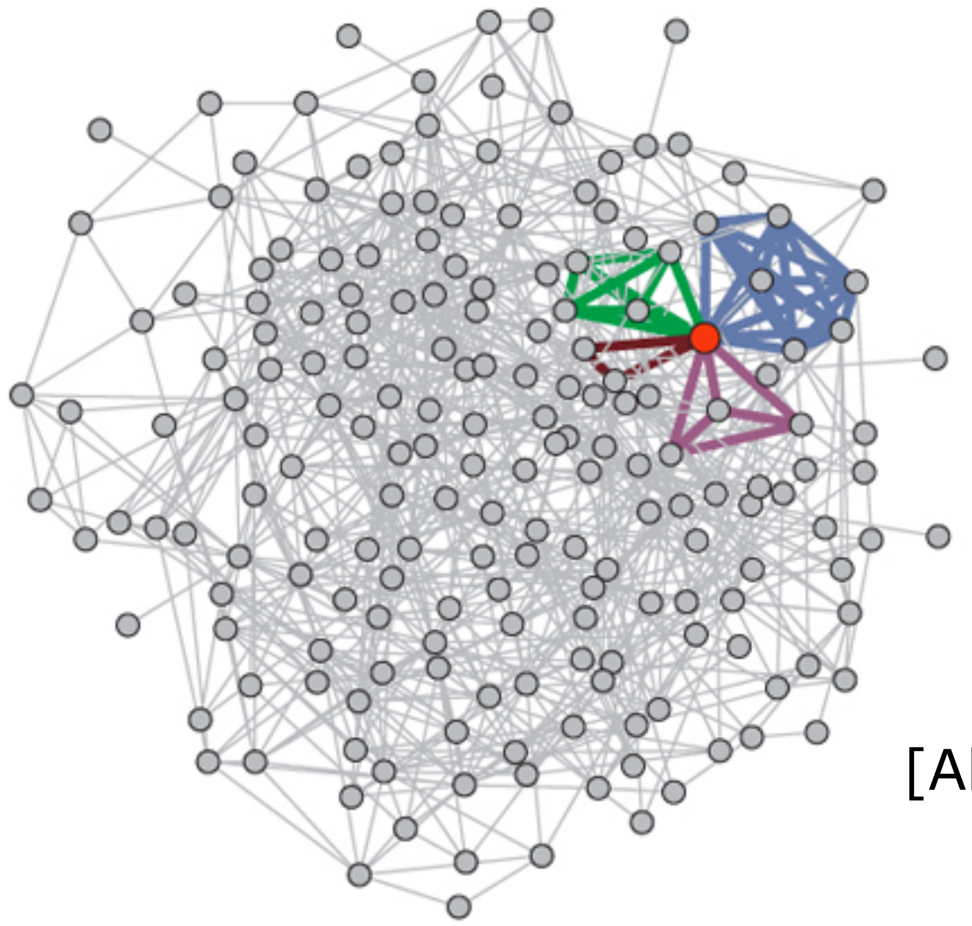


Overlapping v Non-Overlapping

- Distinct "non-overlapping" communities rarely exist at large scales in many empirical networks [Leskovec et al, 2008].

➡ Communities overlap pervasively, making it impossible to partition the networks without splitting communities [Reid et al, 2011].

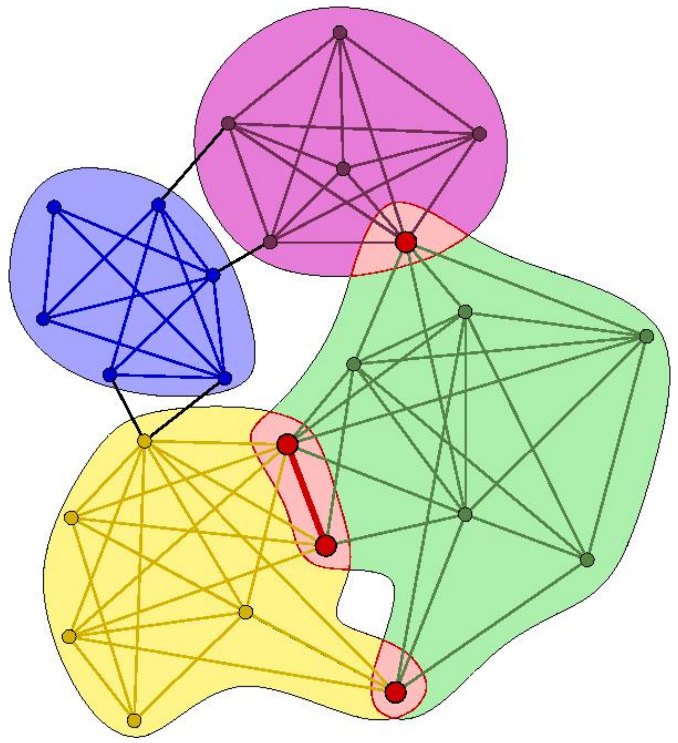

Community overlap at an ego level


Community overlap at a global level

[Ahn et al, 2010]

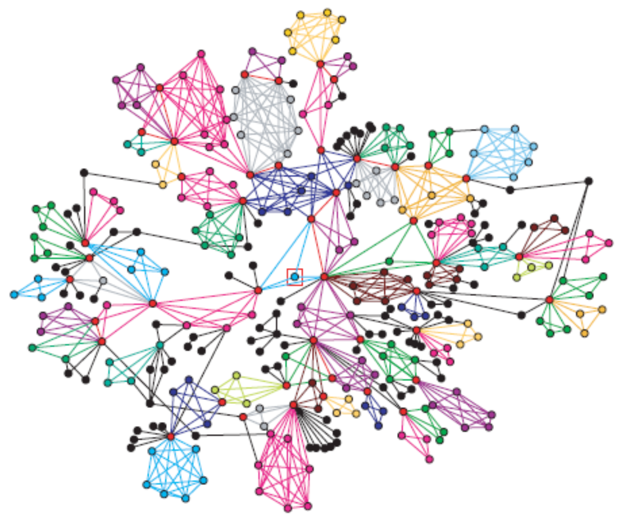
Overlapping Community Finding

- **CFinder**: algorithm based on the clique percolation method [Palla et al, 2005].
- Identify *k*-cliques: a fully connected subgraph *k* nodes.
- Pair of *k*-cliques are "adjacent" if they share *k−1* nodes.
- Form overlapping communities from maximal union of *k*-cliques that can be reached from each other through adjacent *k*-cliques.



Set of overlapping communities
built from 4-cliques.

Co-authorship Network



[Palla et al, 2005]

http://cfinder.org

Overlapping Community Finding

- **Greedy Clique Expansion (GCE)**: identify distinct cliques as seeds, expands the seeds by greedily optimising a local fitness function [Lee et al, 2010].

  https://sites.google.com/site/greedycliqueexpansion

- **MOSES**: scalable approach for identifying highly-overlapping communities [McDaid et al, 2010].
  - Randomly select an edge, greedily expand a community around the edge to optimise an objective function.
  - Delete "poor quality" communities.
  - Fine-tune communities by re-assigning individual nodes.

  https://sites.google.com/site/aaronmcdaid/moses

NetworkX - Overlapping Communities

- No built-in support for overlapping algorithms, but we can use the MOSES tool to analyse graphs represented as edge lists.

```
import networkx
g = networkx.watts_strogatz_graph(60, 8, 0.3)
edgepath = "test_moses.edgelist"
networkx.write_weighted_edgelist(g, edgepath)
```

Build a graph, write it to a temporary edge-list file.

Apply MOSES tool to the edge-list file

```
import subprocess
outpath="test_moses.comms"
proc = subprocess.Popen(["/usr/bin/moses", edgepath, outpath])
proc.wait()
```

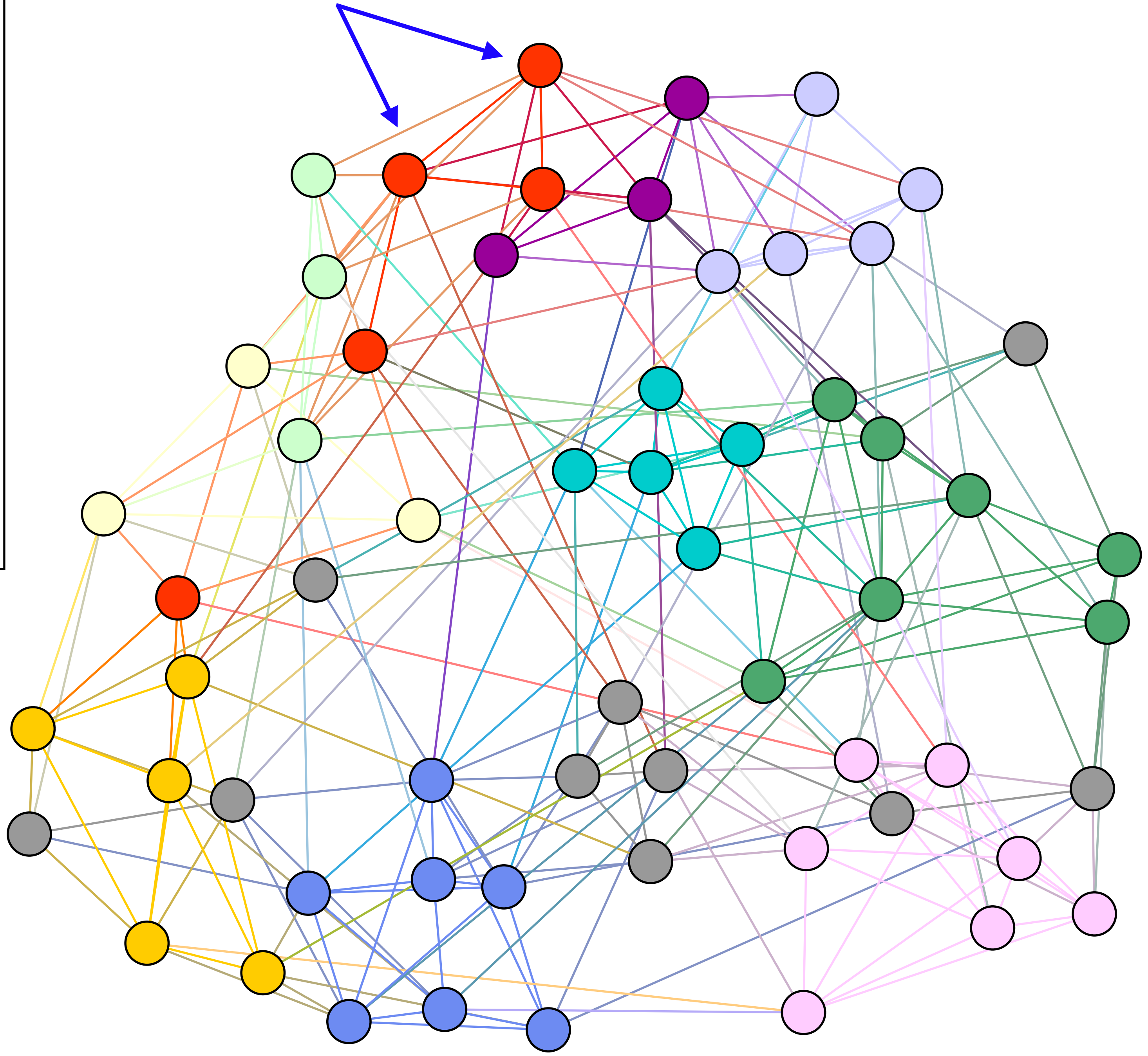
Parse the output of MOSES

```
lines = open(outpath,"r").readlines()
print "Identified %d communities" % len(lines)
for l in lines:
   print set(lines[i].strip().split(" "))
```

NetworkX - Overlapping Communities

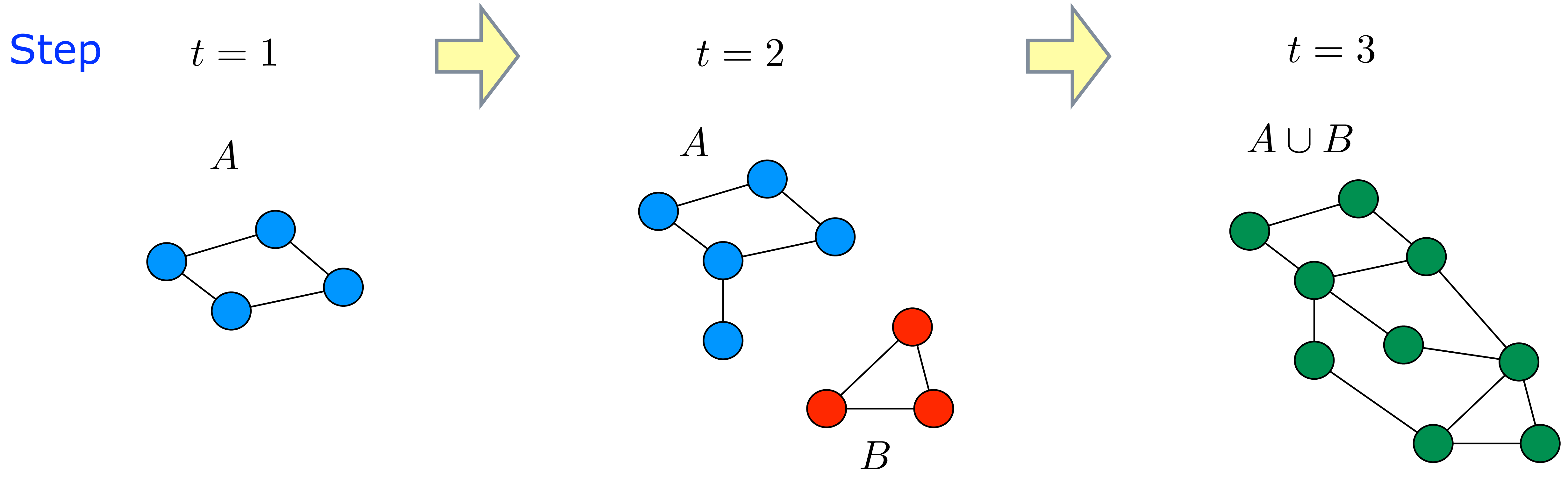
```
Identified 9 communities
Community 0
set(['48', '49', '46', '47', '45', '51', '50'])
Community 1
set(['54', '56', '51', '53', '52'])
Community 2
set(['39', '38', '37', '42', '40', '41'])
Community 3
set(['20', '21', '17', '16', '19', '18', '15'])
Community 4
set(['33', '32', '36', '35', '34'])
Community 5
set(['48', '46', '44', '45', '43', '40'])
Community 6
set(['59', '58', '56', '0', '3', '2'])
Community 7
set(['24', '25', '26', '27', '31', '30', '28'])
Community 8
set(['10', '5', '4', '7', '6', '9', '8'])
```

Nodes assigned to multiple communities



Dynamic Community Finding

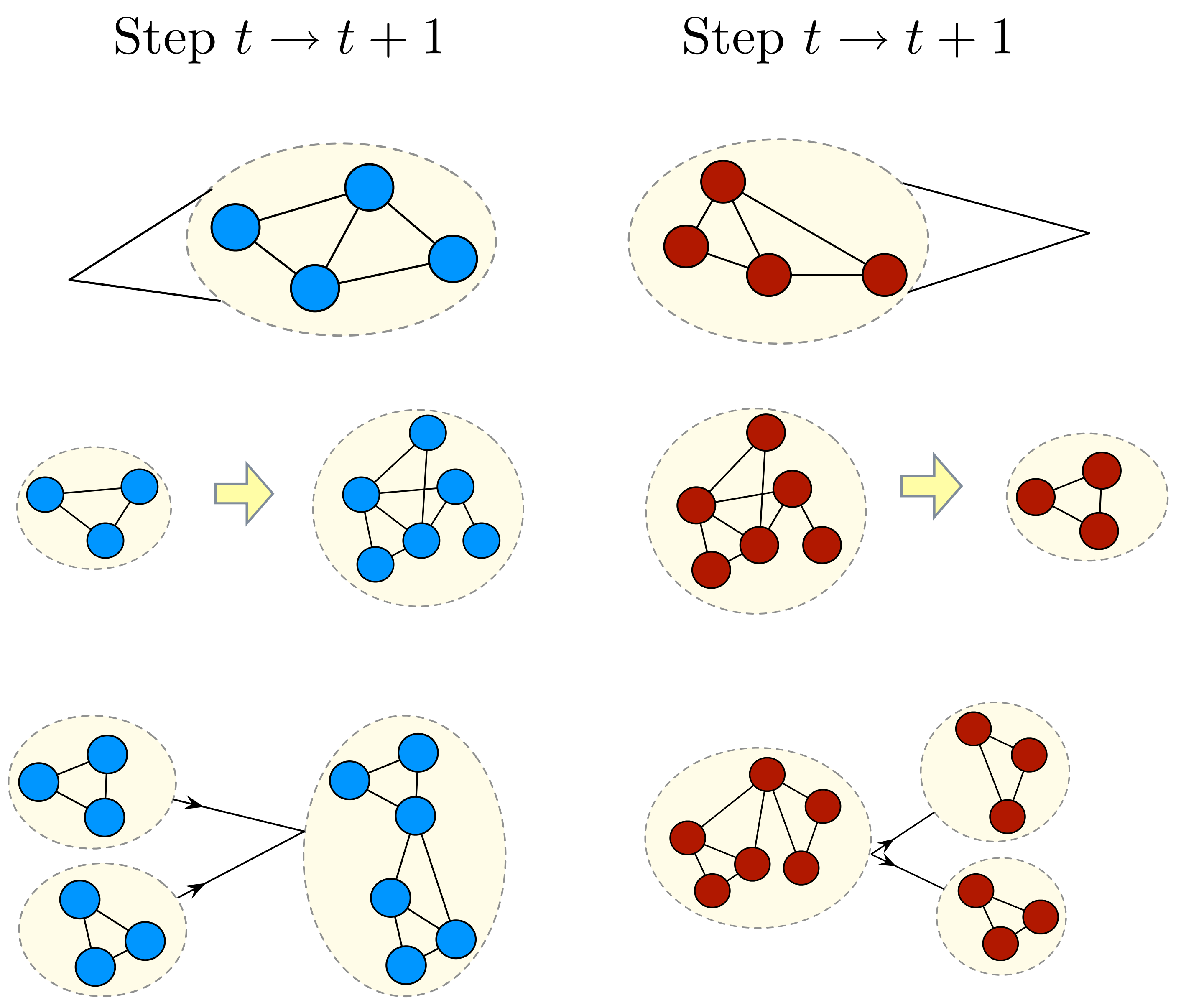
- In many SNA tasks we will want to analyse how communities in the network form and evolve over time.
- Often perform this analysis in an "offline" manner by examining successive snapshots of the network.



Dynamic Community Finding

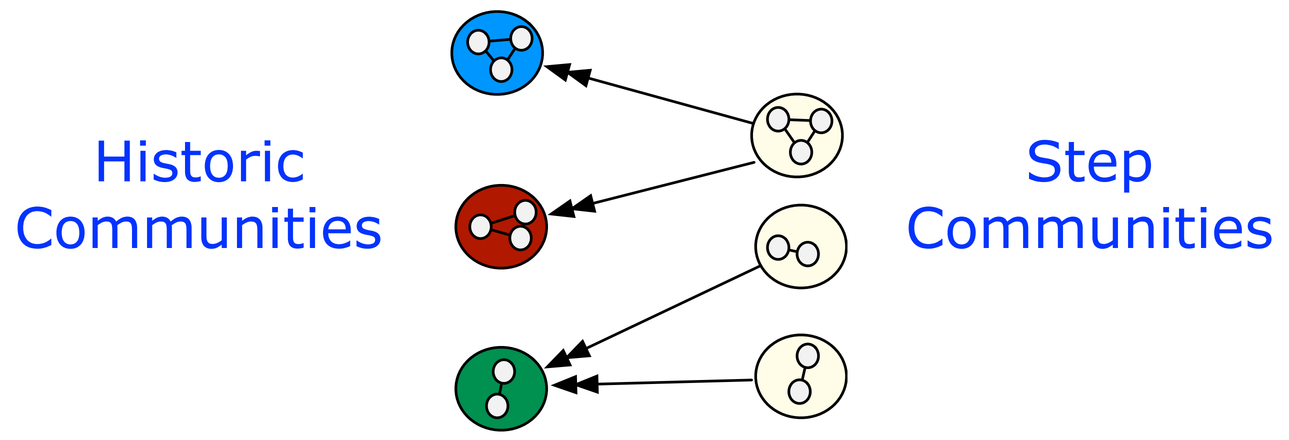
- We can characterise dynamic communities in terms of key life-cycle events [Palla et al, 2007; Berger-Wolf et al, 2007]

  - Birth & Death of communities
  - Expansion & Contraction of communities
  - Merging & Splitting of communities



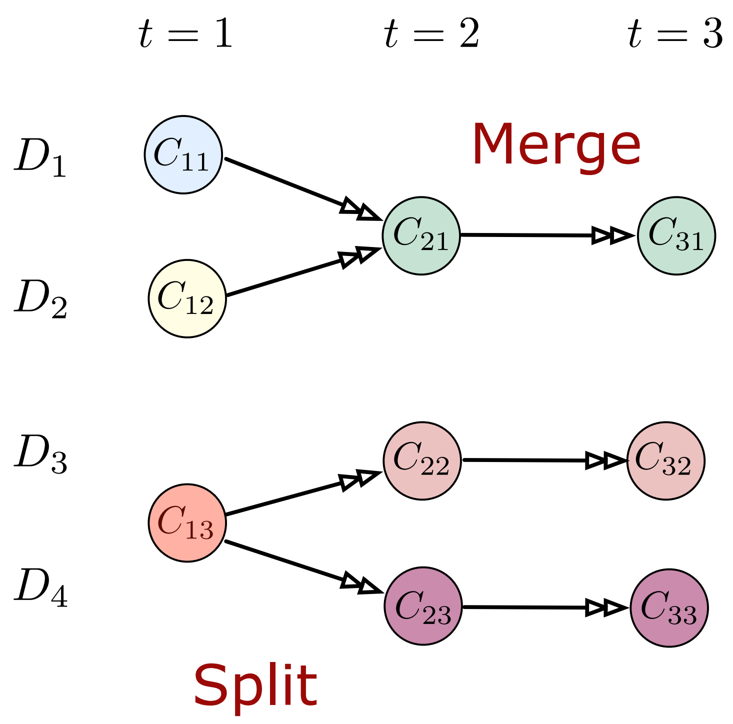
Dynamic Community Finding

- Apply community finding algorithm to each snapshot of the graph.
- Match newly-generated "step communities" with those that have been identified in the past.



Jaccard Similarity Score

$$\frac{|C \cap F_i|}{|C \cup F_i|} > \theta$$



Dynamic community tracking software

http://mlg.ucd.ie/dynamic

[Greene et al, 2010]

Applications

Application - Mapping Blog Networks

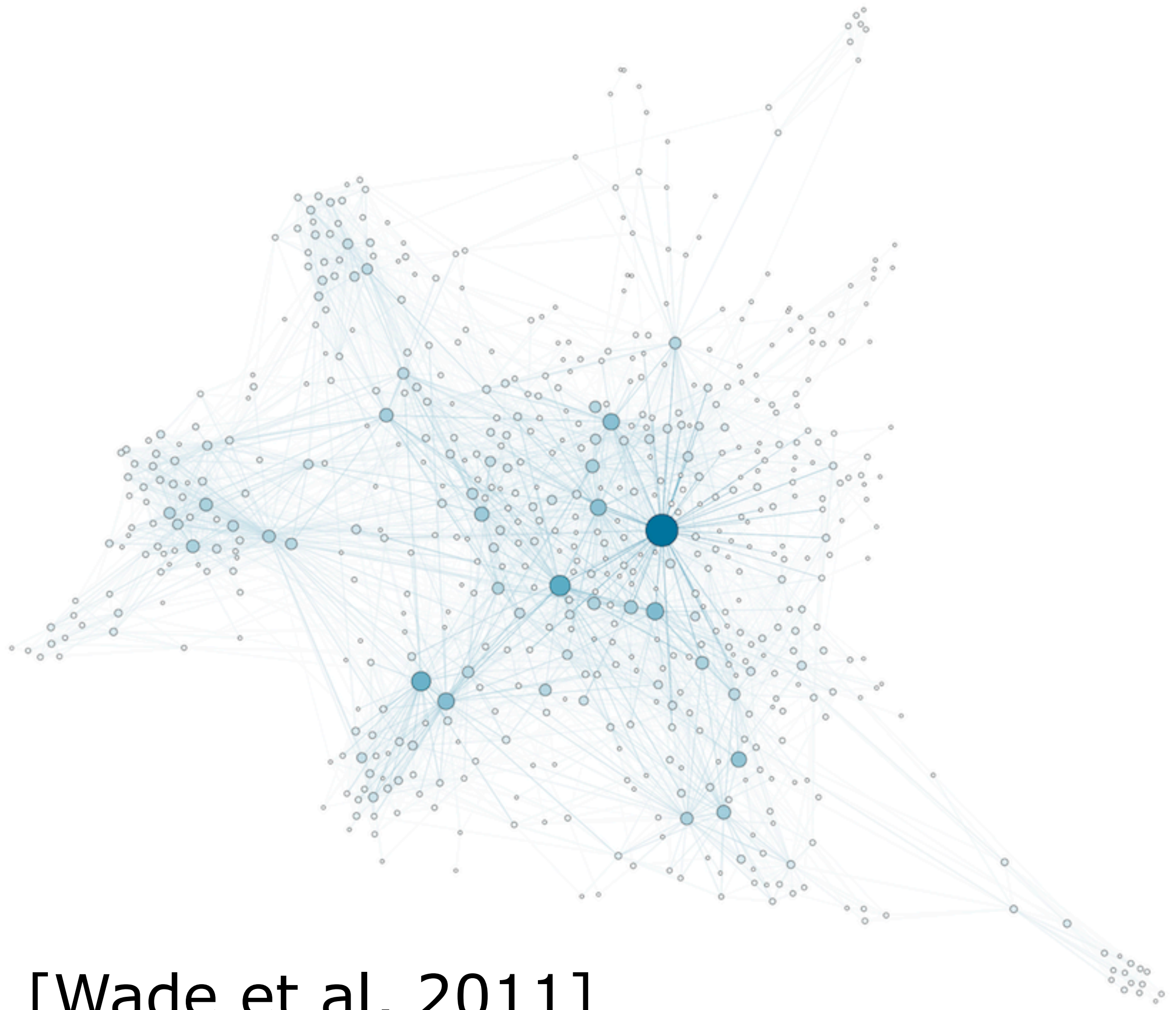
- **Motivation:** Literary analysis of blogs is difficult when corpus contains hundreds of blogs and hundreds of thousands of posts.

➡ Use a data-driven approach to select a topically representative set from 635 blogs in the Irish blogosphere during 1997-2011.

Multi-Relational Networks

1. Blogroll: unweighted graph with edges representing permanent or nearly-permanent links between blogs.
2. Post-link: weighted graph with edges representing non-permanent post content links between blogs.
3. Content profile: text content from all available posts for a given blog.

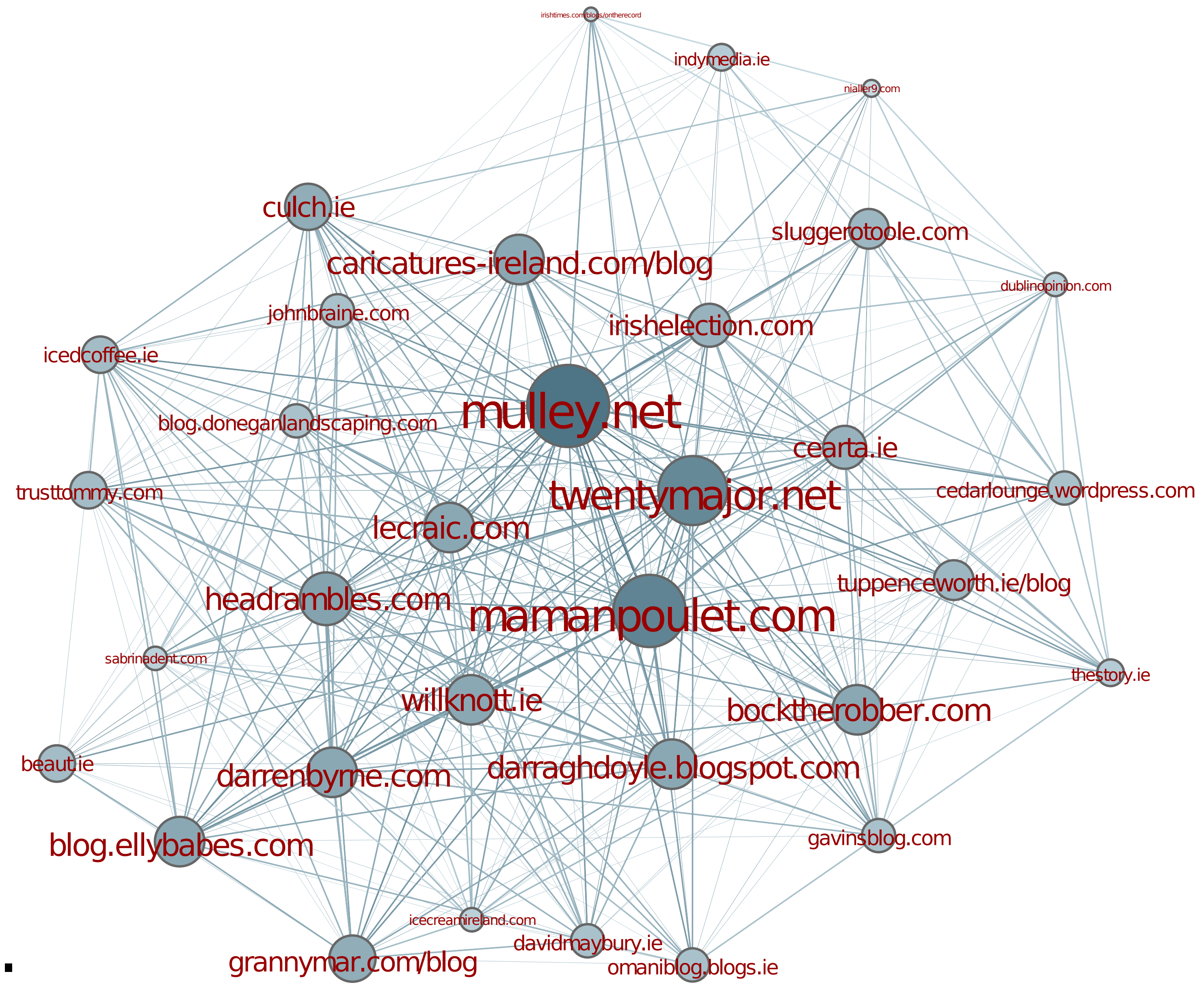
http://mlg.ucd.ie/blogs



[Wade et al, 2011]

Application - Mapping Blog Networks

- Initially applied centrally measures to identify representatives blogs in blogroll and post-link graphs.

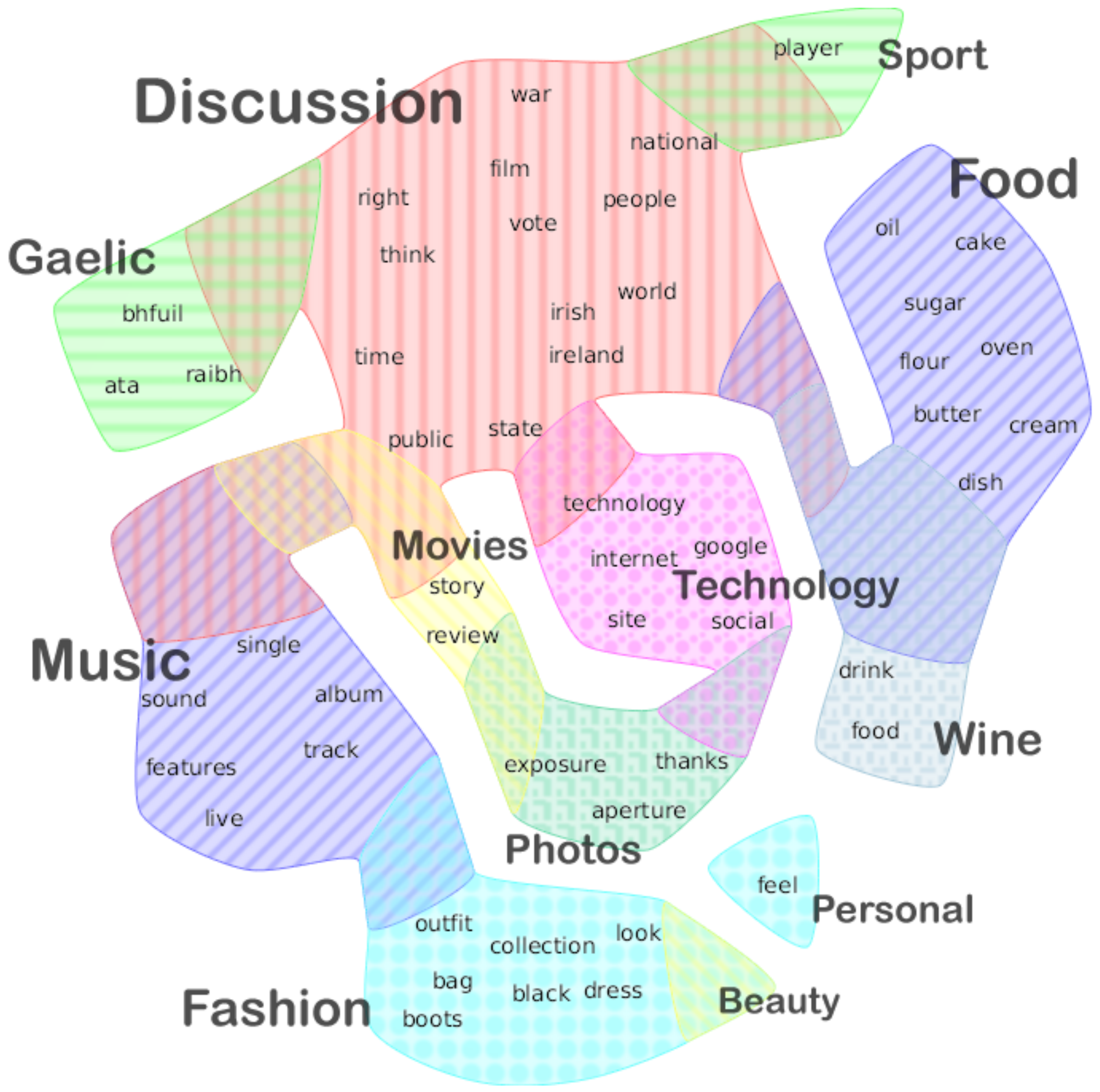


<u>Limitations:</u>

Influential blogs are identified. But they do not necessarily provide good coverage of the wider Irish blogosphere.

Application - Mapping Blog Networks

- Apply text clustering techniques on content view to identify clusters of blogs discussing coherent topics.
- Generated a clustering with 12 distinct communities...

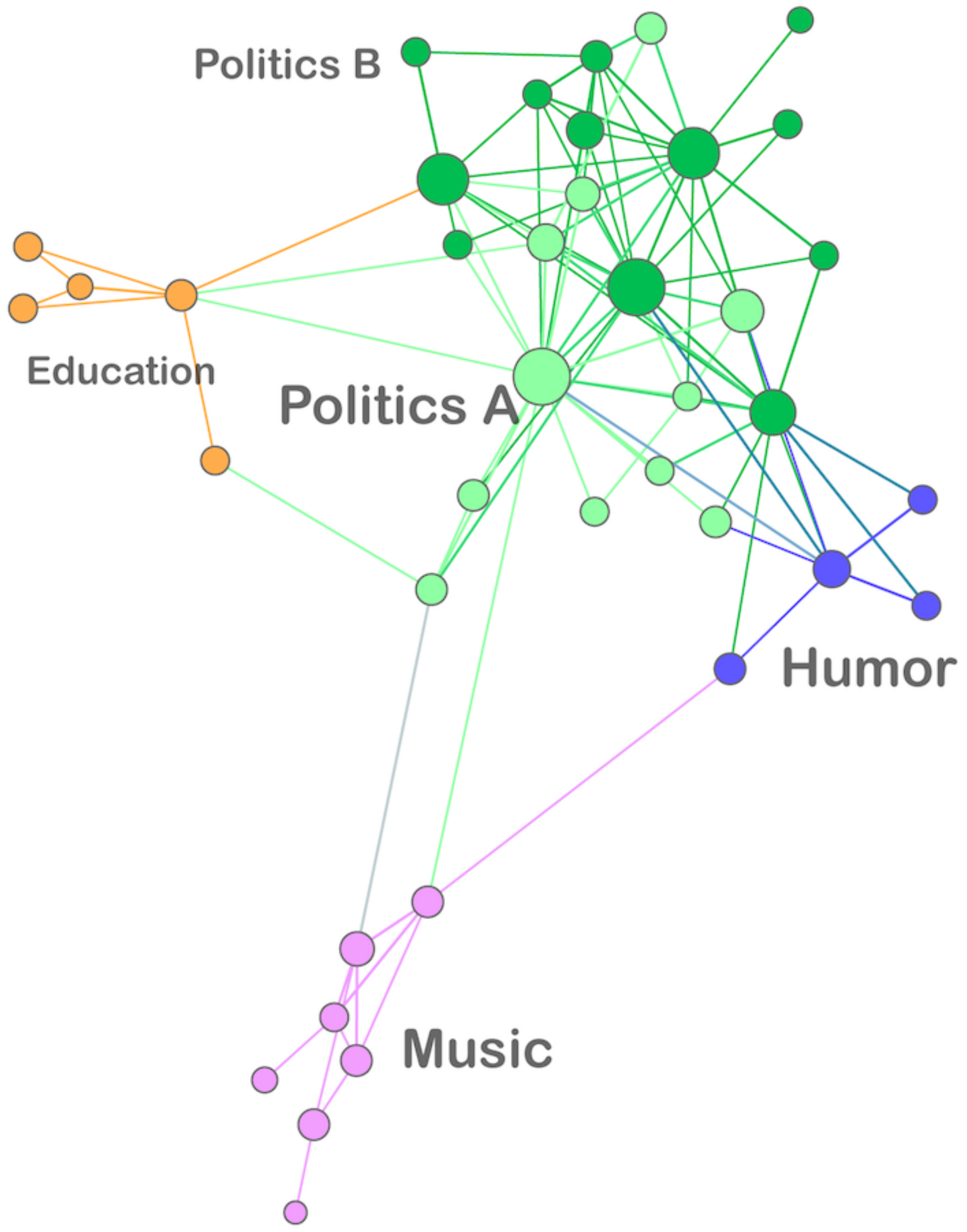


- The "Discussion" community was least coherent in terms of content, and includes blogs pertaining to a number of topics.

Application - Mapping Blog Networks

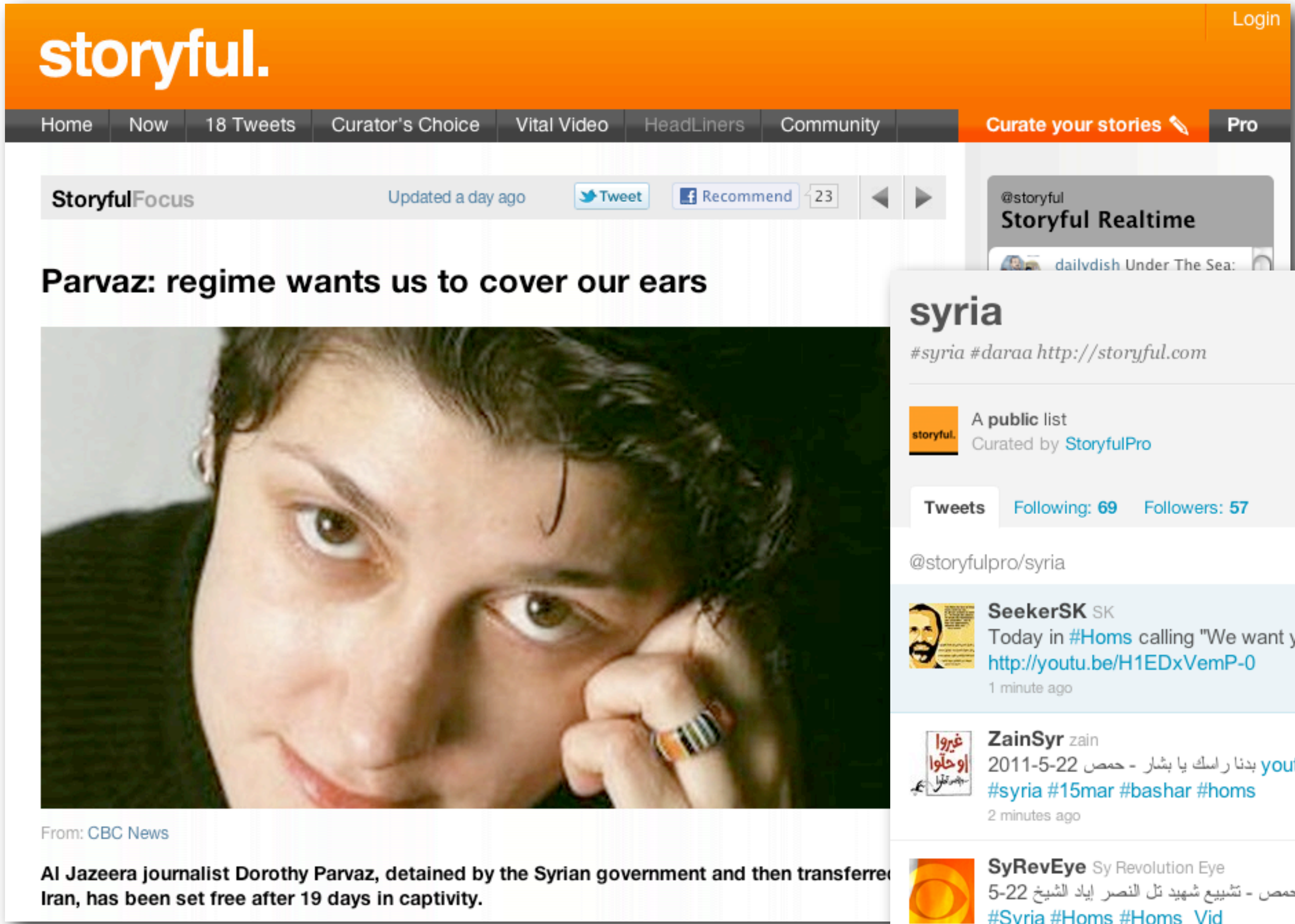
- Applied GCE overlapping community finding algorithm to the blogroll and post-link graphs on the subgraphs induced by the "Discussion" cluster.
- Identified "stable" communities that were present in both the blog-roll and post-link networks.

➡ Identified representative blogs as those with high in-degree in the blogroll subgraphs for each of the resulting communities.



Application - Microblogging

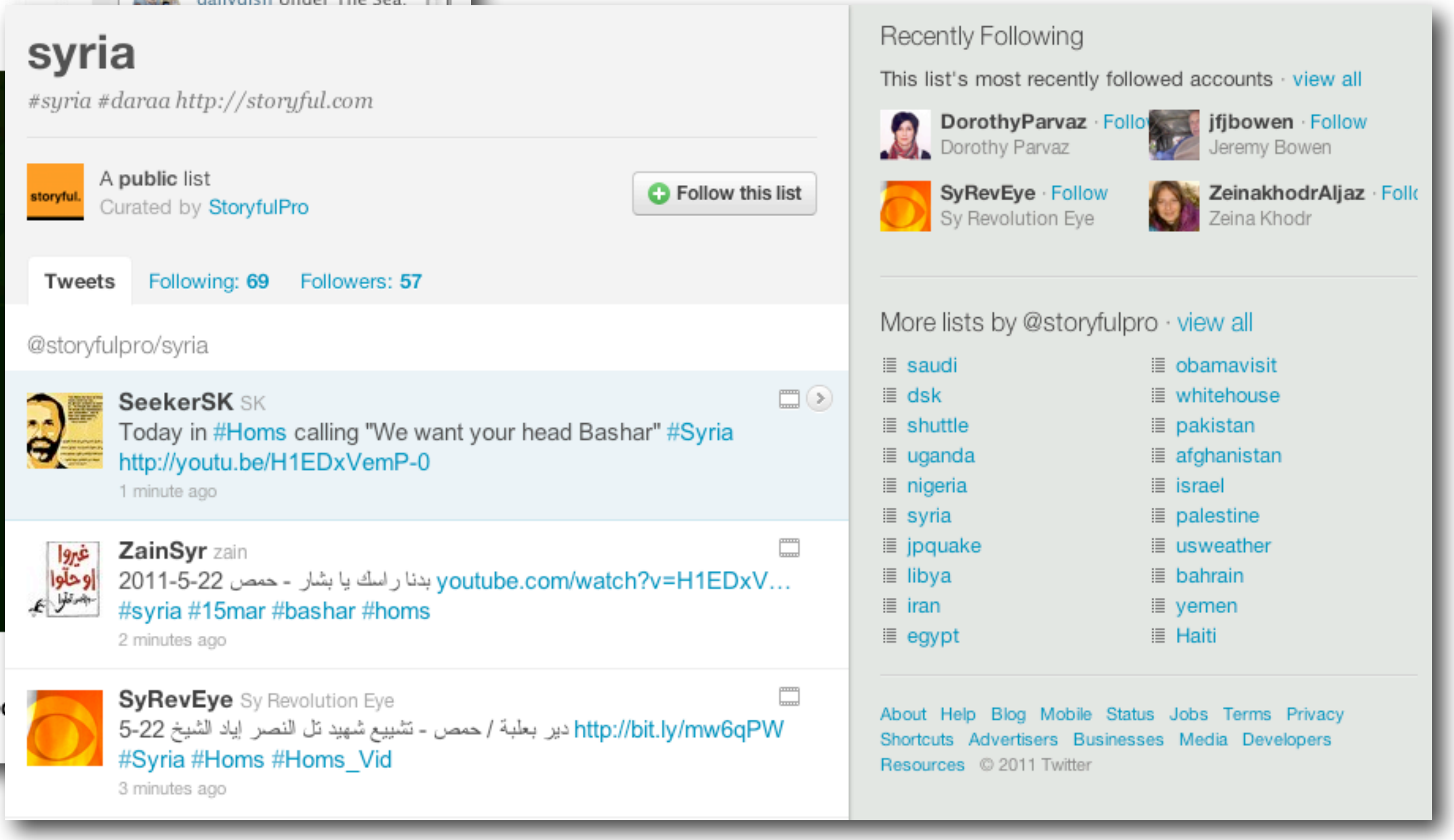
- **Storyful.com:** Journalists struggling to cope with a "tsunami of user-generated content" on social media networks.



Parvaz: regime wants us to cover our ears

From: CBC News

Al Jazeera journalist Dorothy Parvaz, detained by the Syrian government and then transferre
Iran, has been set free after 19 days in captivity.



syria

#syria #daraa http://storyful.com

A public list
Curated by StoryfulPro

@storyfulpro/syria

SeekerSK SK
Today in #Homs calling "We want your head Bashar" #Syria http://youtu.be/H1EDxVemP-0
1 minute ago

ZainSyr zain
2011-5-22 بدنا راسك يا بشار - حمص youtube.com/watch?v=H1EDxV…
#syria #15mar #bashar #homs
2 minutes ago

SyRevEye Sy Revolution Eye
5-22 دير بعلبة / حمص - تشييع شهيد تل النصر اياد الشيخ http://bit.ly/mw6qPW
#Syria #Homs #Homs_Vid
3 minutes ago

Recently Following

This list's most recently followed accounts · view all

DorothyParvaz · Follo Dorothy Parvaz	**jfjbowen** · Follow Jeremy Bowen
SyRevEye · Follow Sy Revolution Eye	**ZeinakhodrAljaz** · Foll Zeina Khodr

More lists by @storyfulpro · view all

saudi	obamavisit
dsk	whitehouse
shuttle	pakistan
uganda	afghanistan
nigeria	israel
syria	palestine
jpquake	usweather
libya	bahrain
iran	yemen
egypt	Haiti

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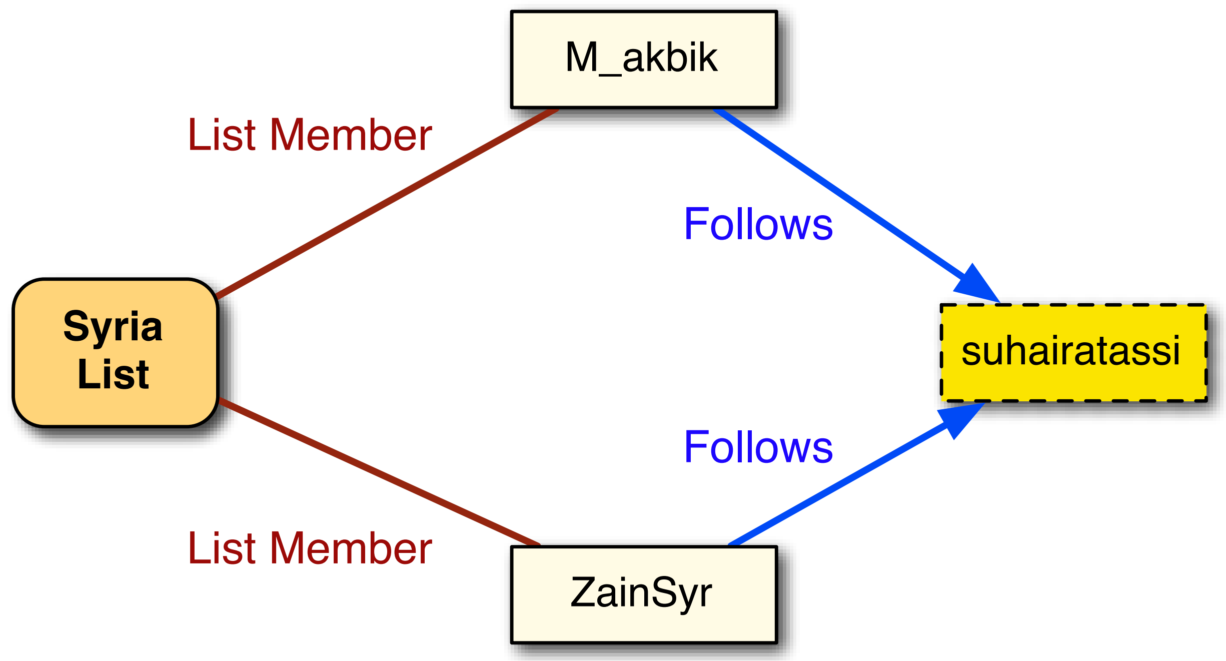
Resources © 2011 Twitter

Application - Microblogging

- A community of users evolves on Twitter around a breaking news story.

➡ Support the content curation process by augmenting curated lists by recommending authoritative sources from the community that are relevant to the news story.

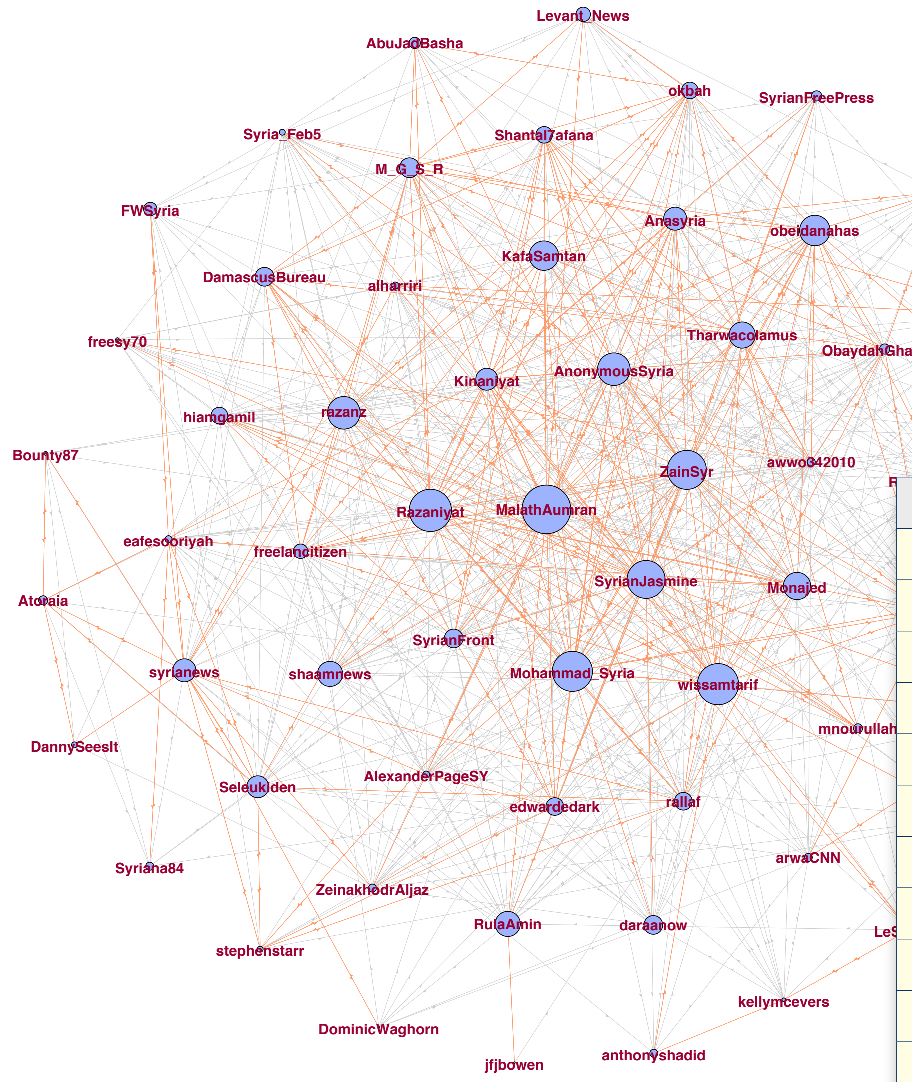


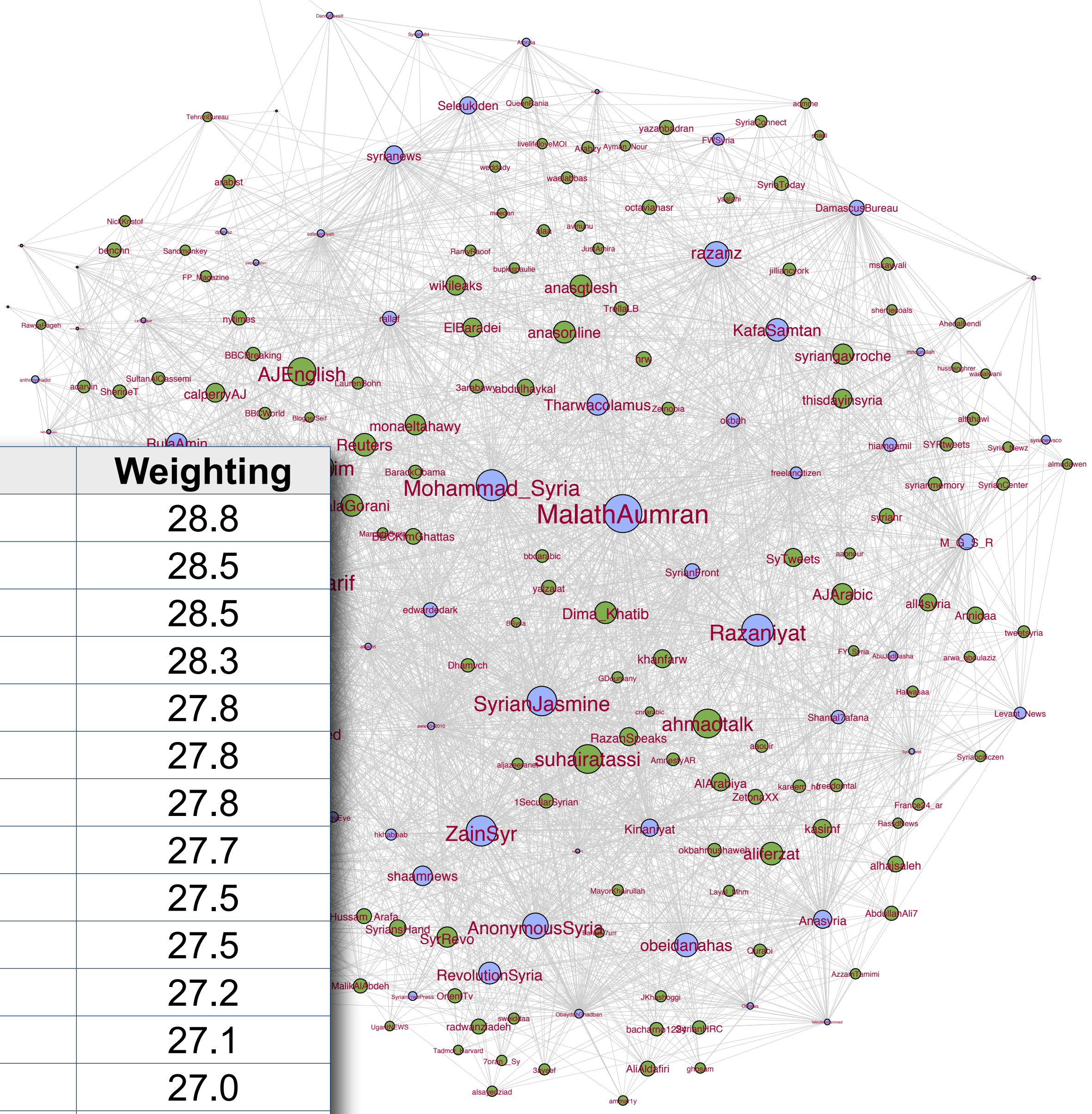
Relations:

- ☐ Follower links
- ☐ Co-listed
- ☐ Shared URLs
- ☐ Retweets
- ☐ Co-location
- ☐ Mentions
- ☐ Content similarity

Application - Microblogging

- Performed analysis to recommend additional Twitter users to augment the "Syria" list curated by Storyful.





Rank	Screen Name	Weighting
1	suhairatassi	28.8
2	aliferzat	28.5
3	syriangavroche	28.5
4	Annidaa	28.3
5	ahmadtalk	27.8
6	Dhamvch	27.8
7	bacharno1224	27.8
8	radwanziadeh	27.7
9	alhajsaleh	27.5
10	MalikAlAbdeh	27.5
11	ZetonaXX	27.2
12	SyrianHRC	27.1
13	anasonline	27.0
14	SyTweets	26.8
15	AbdullahAli7	26.7

Tutorial Resources

- **NetworkX**: Python software for network analysis (v1.5)
  http://networkx.lanl.gov
- Python 2.6.x / 2.7.x
  http://www.python.org
- **Gephi**: Java interactive visualisation platform and toolkit.
  http://gephi.org
- Slides, full resource list, sample networks, sample code snippets online here:
  http://mlg.ucd.ie/summer

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