Subgraphs and Community Structure of Networks

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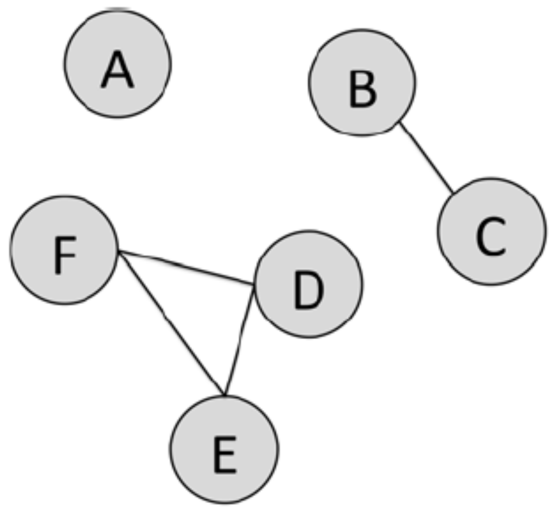
Subgraphs

- A subset of nodes and edges in a network
- Given a (social) network, what are some subgraphs of interest?

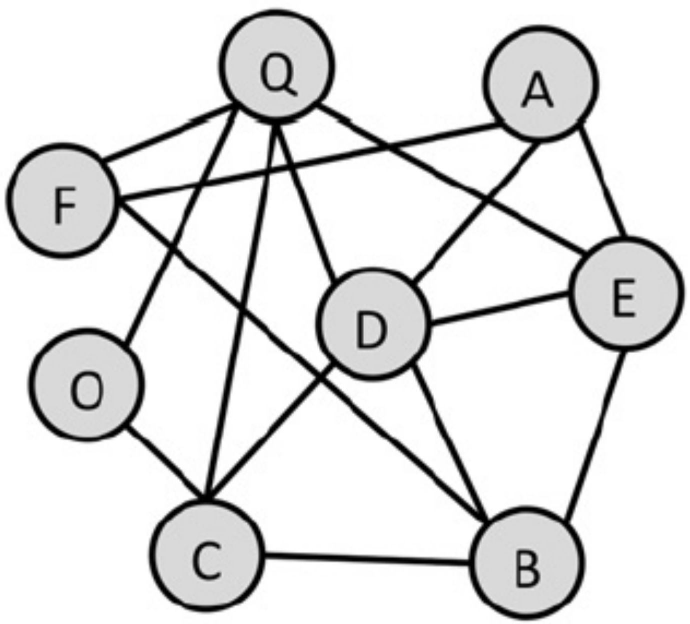
Subgraphs

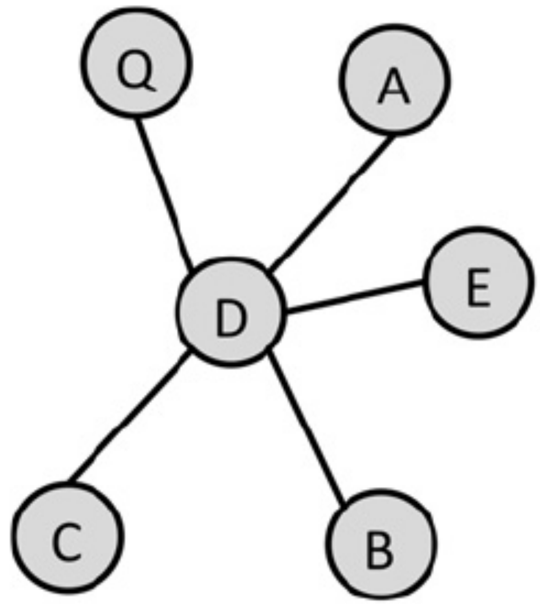
- A subset of nodes and edges in a network
- Given a (social) network, what are some subgraphs of interest?
  - Singletons: Isolated nodes
  - Connected components
  - Triads or triangles
  - Larger cliques



Egocentric networks

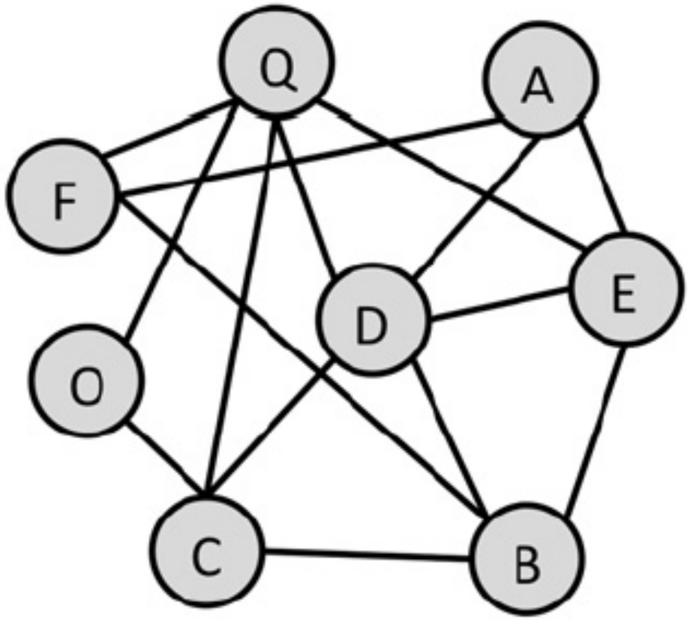
- From the perspective of a node (user)
- 1-degree egocentric network: a node and all its connections to its neighbors

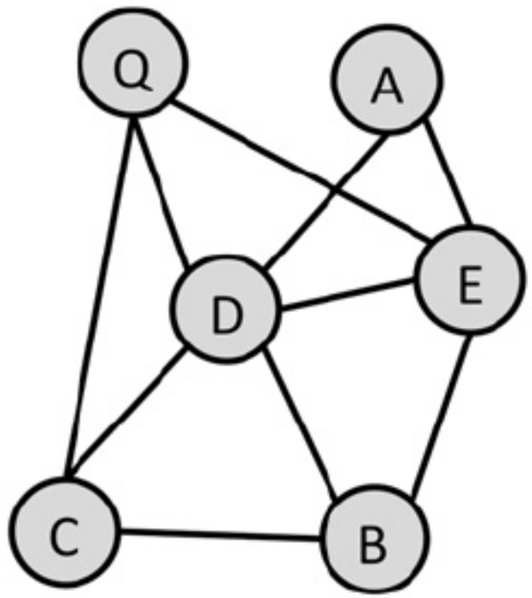




Egocentric networks

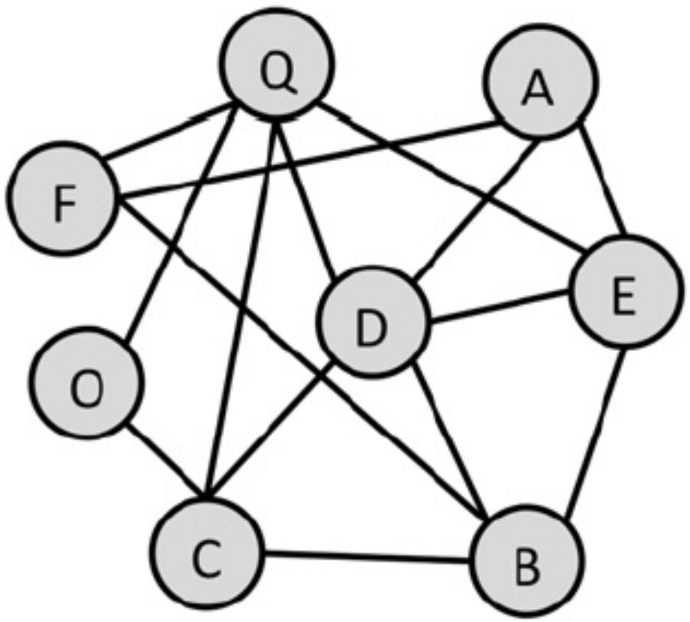
- 1.5-degree egocentric network: a node, all its connections to its neighbors, and the connections among the neighbors

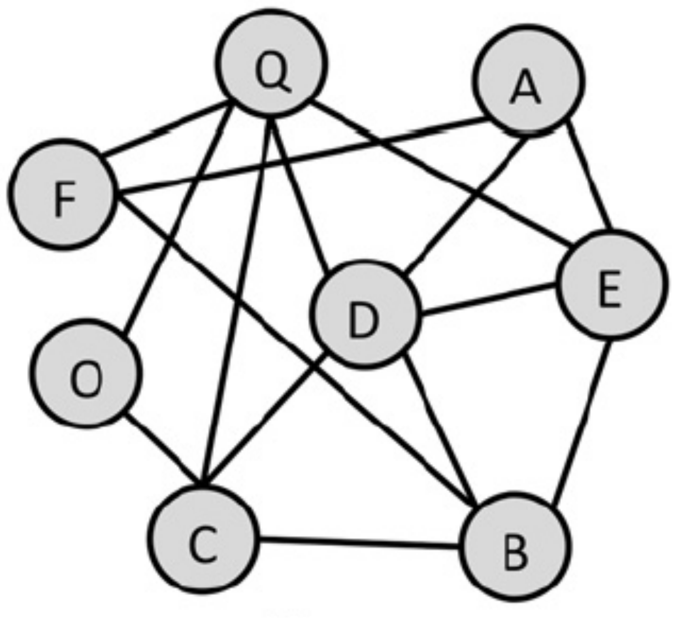




Egocentric networks

- 2-degree egocentric network: a node, all its neighbors, all neighbors of neighbors, and the connections among all these nodes





Communities

- Community or network cluster
  - Typically a group of nodes having more and / or better interactions among its members, than between its members and the rest of the network

- No unique formal definition

COMMUNITY DETECTION

Community detection algorithms

- Lot of applications – identifying similar nodes, close friends, recommendation, …

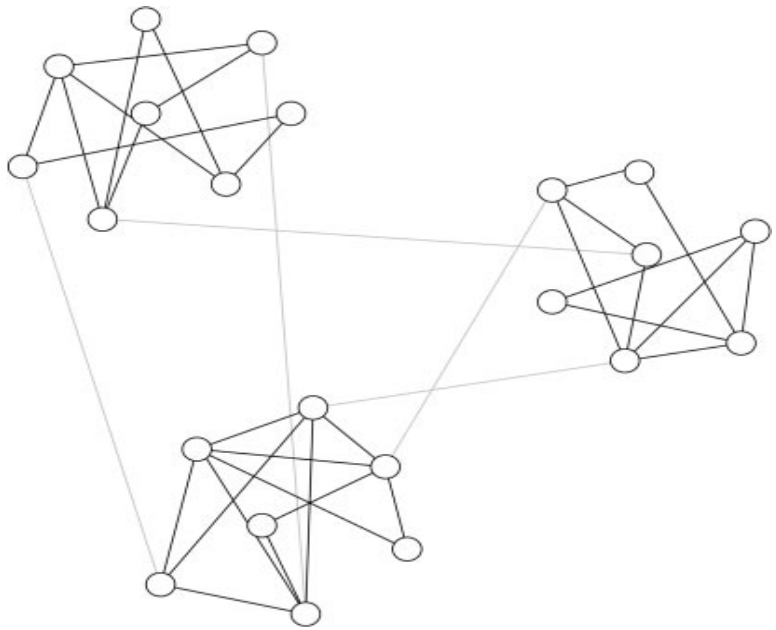
- Challenging
  - Communities are not well-defined
  - Number of communities in a network is not known

Two broad types of algorithms

- Detection of disjoint communities
  - Each community is a partition of the network
- Detection of overlapping communities
  - A node can be members of multiple communities

Algorithm by Girvan & Newman

- Community structure in social and biological networks, PNAS, 2002
- Focus on edges that are most "between" communities



Edge betweenness

- Edge betweenness of an edge *e*: fraction of shortest paths between all pairs of vertices, which run through *e*
- Edges between communities are likely to have high betweenness centrality
- Progressively remove edges having high betweenness centrality, to separate communities from one another

Girvan-Newman algorithm

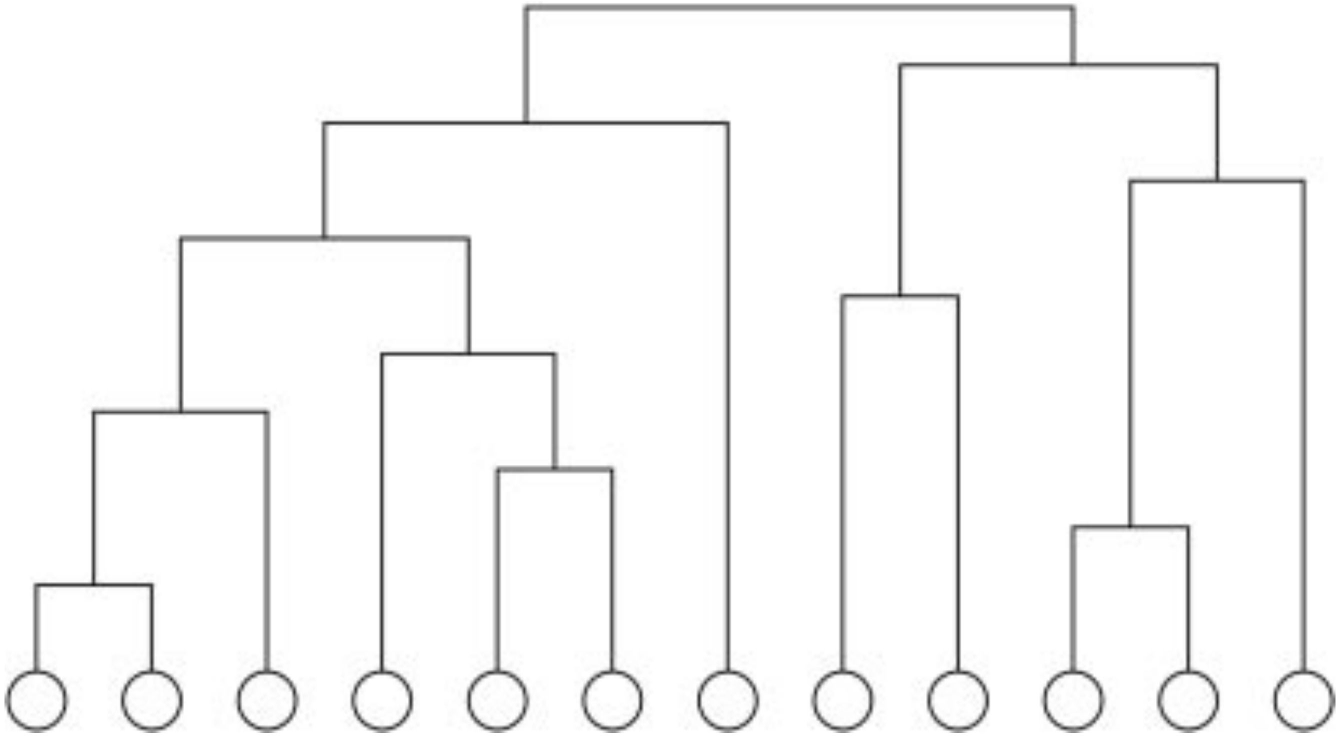
1. Compute betweenness centrality for all edges
2. Remove the edge with highest betweenness centrality
3. Re-compute betweenness centrality for all edges affected by the removal
4. Repeat steps 2 and 3 until no edges remain

- Time complexity
  - Graph of n vertices and m edges: betweenness centrality of all edges can be computed in $O(mn)$ time
  - Hence, worst case time complexity: $O(m^2n)$

How many communities?

- Community structure of a graph is hierarchical, with smaller communities nested within larger ones
- Represented as a hierarchical clustering tree: dendrogram
- A “slice” through the tree at any level gives a certain number of communities
- Which level to slice at?

An example dendrogram



Hierarchical clustering algorithms

- Agglomerative algorithms (bottom-up)
  - Clusters / communities iteratively merged if their similarity is sufficiently high
- Divisive algorithms (top-down)
  - Clusters / communities iteratively split by removing edges

- Both can be represented by dendrograms
- Need some way to decide at what level to slice the dendrogram – what is a good community structure?

What is a good community structure?

- A few large communities, or many small communities?
- Often depends on the end application

- Example: find communities in an OSN for
  - Application 1: personalized recommendation to users
  - Application 2: map user-accounts to data centers located in some places

Objective functions for CD

- Community or network cluster
  - Typically a group of nodes having more and / or better interactions among its members, than between its members and the rest of the network

- Typical CD algorithms
  - Choose an objective function that captures the above intuition
  - Optimize the objective function using heuristics or approximation algorithms

OBJECTIVE FUNCTIONS FOR COMMUNITY DETECTION

Empirical Comparison of Algorithms for Network Community Detection, Leskovec et al., WWW 2010

Various objective functions

- Two criteria of interest for measuring how well a particular set *S* of nodes represents a community
  - Number of edges among the nodes within *S*
  - Number of edges between nodes in *S* and rest of network

- Two types of objective functions
  - Single criterion – considers any one of the above criteria
  - Multi criterion – considers both the above criteria

Multi-criterion scores

- Consider both the criteria for measuring quality of a set S of nodes

- Lower values of $f(S)$ signify a more community-like set of nodes

Notations

- $G = (V, E)$ is the network.
- $n = |V|$ = number of nodes
- $m = |E|$ = number of edges
- $d(u) = k_u$ = degree of node u

- S: set of nodes
- n_s = number of nodes in S
- m_s = number of edges within S (both nodes in S)
- c_s = number of edges on the boundary of S

Expansion

$$f(S) = \frac{c_S}{n_S}$$

- Number of edges per node in S, that points outside the set S

Internal density

$$f(S) = 1 - \frac{m_S}{n_S(n_S - 1)/2}$$

- Internal edge density of the set S

Cut Ratio

$$f(S) = \frac{c_S}{n_S(n - n_S)}$$

- Fraction of all possible edges leaving the set S

Conductance

$$f(S) = \frac{c_S}{2m_S + c_S}$$

- Fraction of total edge volume that points outside the cluster
- Edge volume = sum of node-degrees
- Denominator: total connection from nodes in S to all nodes in graph G

Normalized Cut

$$f(S) = \frac{c_S}{2m_S + c_S} + \frac{c_S}{2(m - m_S) + c_S}$$

- Originally proposed in “Normalized cuts and Image Segmentation” by Shi et al, IEEE TPAMI, 2000
- Some doubts about the denominator of the second term

Normalized cut – original definition

- Partition graph G = (V, E) into two partitions A and B

$$cut(A,B) = \sum_{u \in A, v \in B} w(u,v).$$

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}, \qquad (2)$$

where $assoc(A,V) = \sum_{u \in A, t \in V} w(u,t)$ is the total connection from nodes in A to all nodes in the graph and $assoc(B,V)$ is similarly defined.

- According to this definition, denominator of second term likely to be $2(m - m_s - c_s) + c_s = 2(m - m_s) - c_s$

Maximum Out Degree Fraction (ODF)

$$\max_{u \in S} \frac{|\{(u,v) : v \notin S\}|}{d(u)}$$

- Maximum fraction of edges of a node in S, that points outside the set S

Average ODF

$$f(S) = \frac{1}{n_S} \sum_{u \in S} \frac{|\{(u,v) : v \notin S\}|}{d(u)}$$

- Average fraction of edges of nodes in S, that points outside S

Flake ODF

$$f(S) = \frac{|\{u : u \in S, |\{(u,v) : v \in S\}| < d(u)/2\}|}{n_S}$$

- Fraction of nodes in S that have fewer edges pointing inside S, than to outside S

Observations by Leskovec et al.

- Internal density and Maximum-ODF are not good measures for community quality
  - Does not show much variation, except for very small communities

- Cut ratio has high variance
  - communities of similar sizes can have very different numbers of edges pointing outside

- Both very low variance and very high variance undesirable for objective functions for CD

Observations by Leskovec et al.

- Flake-ODF prefers larger communities

- Conductance, expansion, normalized cut, average-ODF all exhibit qualitatively similar behavior and give best scores to similar clusters

Single-criterion scores

- Consider only one of the two criteria for measuring quality of a set S of nodes

- Two simple single-criterion scores:
  - Volume: Sum of degrees of the nodes in *S*
  - Edges Cut: c_s: Number of edges needed to be removed to disconnect nodes in *S* from the rest of the network

Modularity-based measures

- A set of nodes is a good community if the number of edges within the set is significantly more than what can be expected by random chance

- Modularity $Q = 1/K * (m_s - E(m_s))$
  - Number of edges m_s within set S, minus expected number of edges within the set S
  - K is a constant, used for normalization

Modularity ratio

$$\frac{m_S}{E(m_S)}$$

- Alternative measure of how well set S represents a community
- Ratio of the number of edges among nodes in S, and expected number of such edges

Expected number of edges

- Null model: Erdos-Renyi random network having the same node degree sequence as given network

- Randomized realization of a given network, realized in practice using Configuration Model
  - Cut each edge into two half-edges or stubs
  - Randomly connect each stub to any stub
  - Expected to have no community structure

Mathematical definition of Modularity

- For two particular nodes *i* and *j* :
  - Number of edges between the nodes: A_{ij}
  - Degrees: k_i, k_j
  - Expected number of links between i and j: $k_i\, k_j\, /2m$

- Do the nodes *i* and *j* have more edges than expected by random chance?

$$A_{ij} - k_i\, k_j\, /2m$$

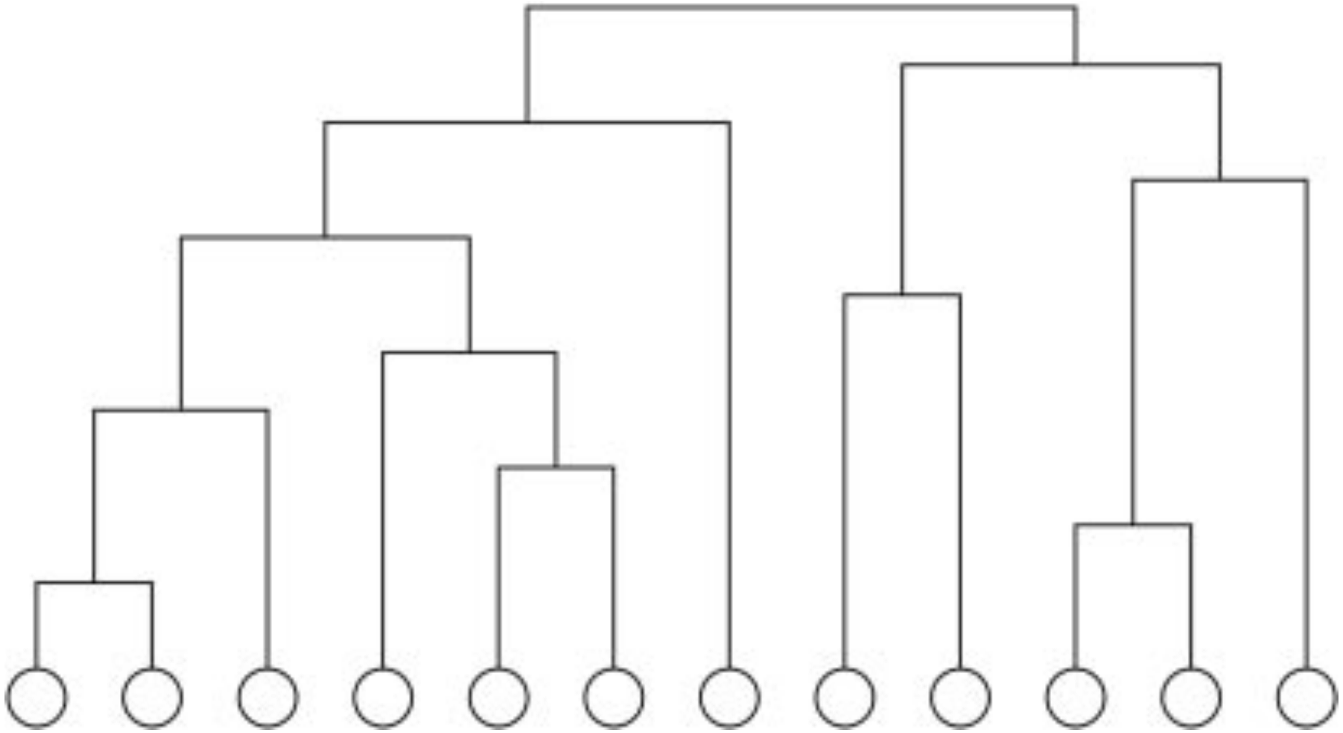
Modularity for a given network

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(C_i, C_j)$$

- The delta function is 1 if both nodes *i* and *j* are in the same community ($C_i = C_j$), 0 otherwise
- Consider a network with two communities c1, c2
  - Q is the fraction of edges that fall within c1 or c2, minus the expected number of edges within c1 and c2 for a random graph with the same node degree distribution as the given network

Using modularity for CD

- Approach 1: use Modularity to decide at which level to slice the dendrogram



Using modularity for CD

- Approach 1: use Modularity to decide at which level to slice the dendrogram

- Approach 2: Optimize modularity
  - Exhaustive maximization is NP-hard
  - Heuristics and approximations used

Greedy algorithm for maximizing Q

- Fast algorithm for detecting community structure in networks, Newman, PRE 69(6), 2004

- Greedy agglomerative hierarchical clustering
  - Start with n clusters, each containing a single node
  - Add edges such that the new partitioning gives the maximum increase (minimum decrease) of modularity wrt the previous partitioning
  - A total of *n* partitionings found, with number of clusters varying from *n* to 1
  - Select the partitioning having highest modularity

Most popular Q optimization algorithm

- Louvain algorithm:
  - https://perso.uclouvain.be/vincent.blondel/research/louvain.html

- Optimization in two steps
  - Step 1: look for small communities - optimizing Q locally
  - Step 2: aggregate nodes in the same community and build a new network whose nodes are the communities
  - Repeat iteratively until a maximum of modularity is attained and a hierarchy of communities is produced
  - Time: approx $O(n \log n)$

For reading

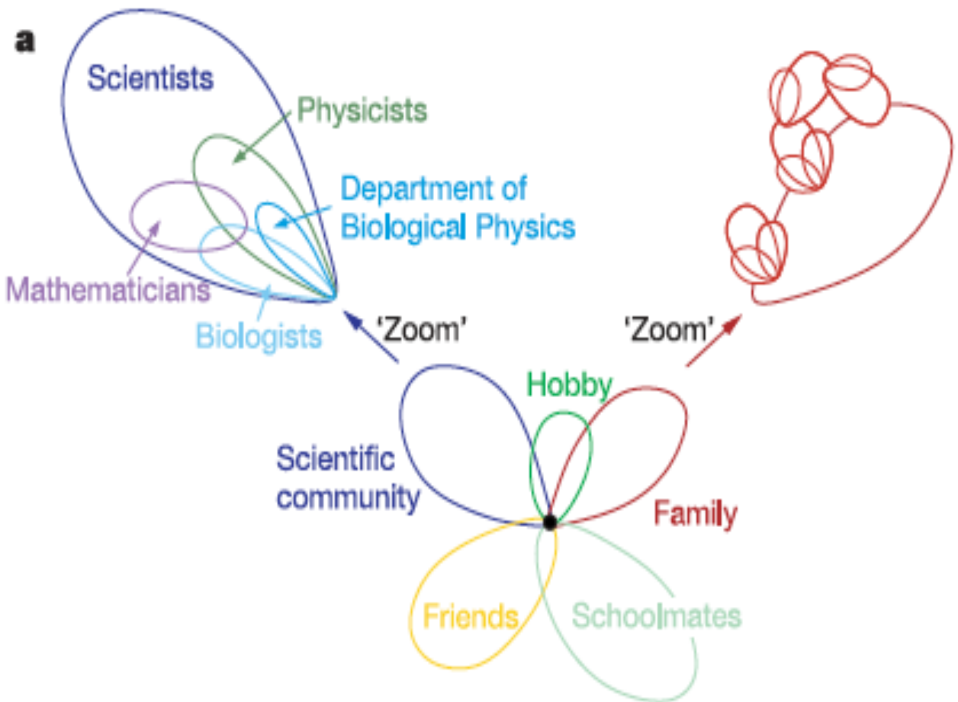
- Many subsequent works have suggested improvements for maximizing modularity
  - Reducing time complexity
  - Normalizing with number of edges to minimize bias towards larger communities
  - …

- Read “Community detection in graphs” by Fortunato, Physics Reports, 2010.

OVERLAPPING COMMUNITY DETECTION

Overlapping communities

- Nodes in real networks are often parts of multiple overlapping communities



Two algorithms

- Clique Percolation Method
  - Uncovering the overlapping community structure of complex networks in nature and society, Palla et al., Nature Letters, vol. 435, 2005

- Link communities
  - Link communities reveal multiscale complexity in networks, Ahn et al., Nature Letters, vol. 466, 2010

Clique Percolation Method

- Concept:
  - Internal edges of communities likely to be part of cliques
  - Inter-community edges unlikely to be part of cliques

- Adjacent *k*-cliques: two *k*-cliques are adjacent if they share *k-1* nodes

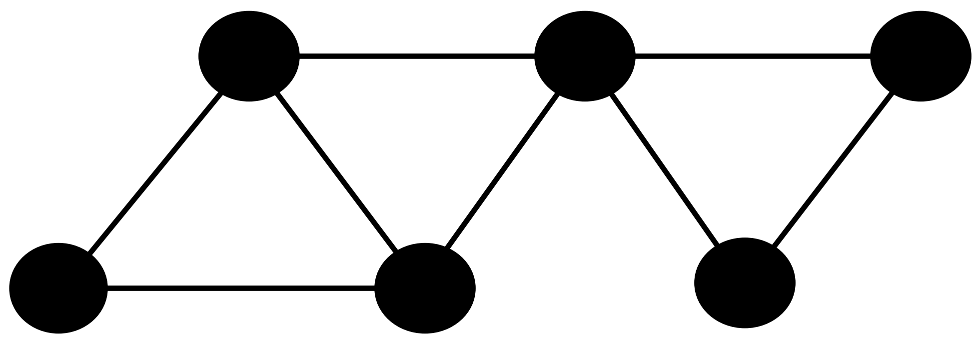
Some material on CPM borrowed from slides by Eugene Lim

k-Clique Communities

- **Adjacent k-cliques**

Two k-cliques are adjacent when they share **k-1** nodes

k = 3



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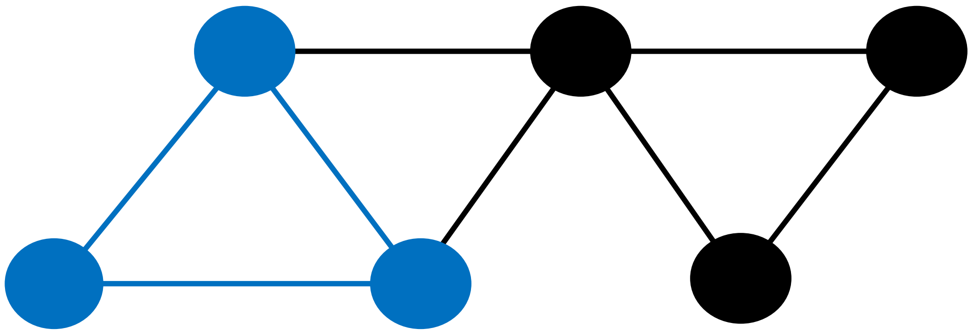

Clique 1

k-Clique Communities

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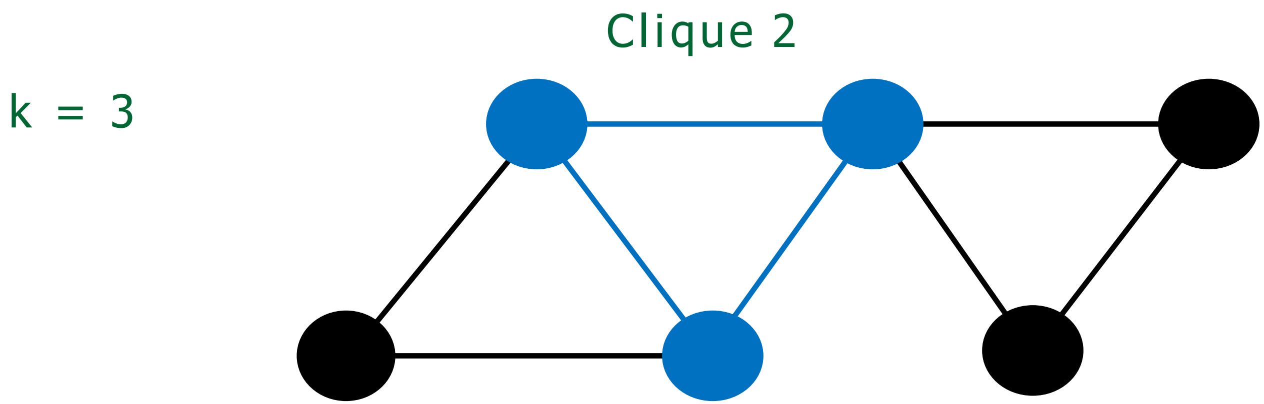

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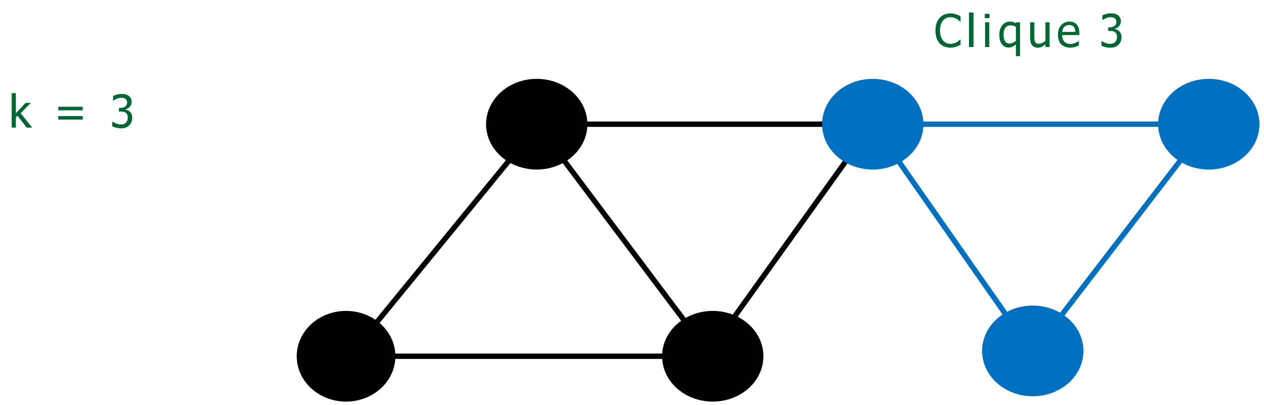

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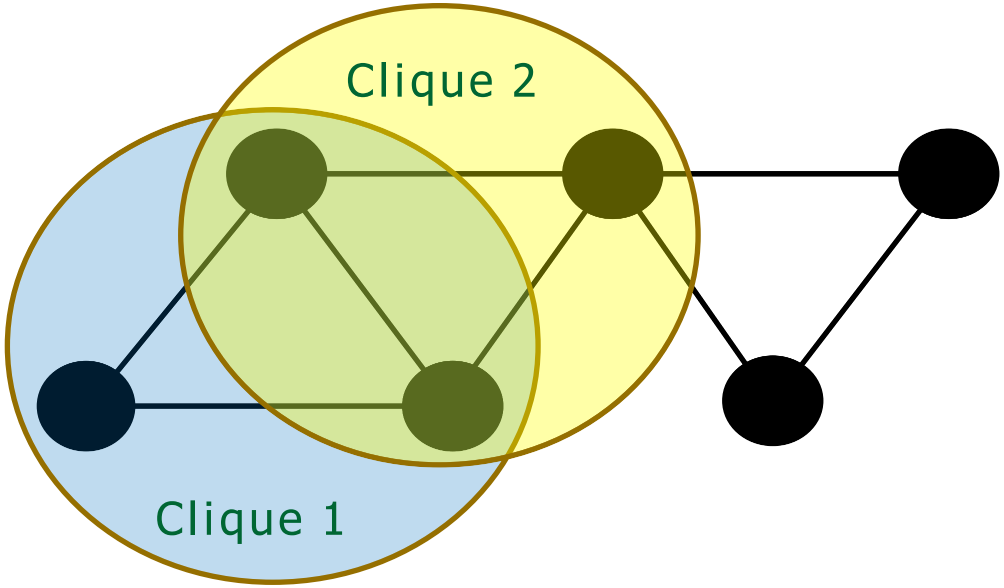

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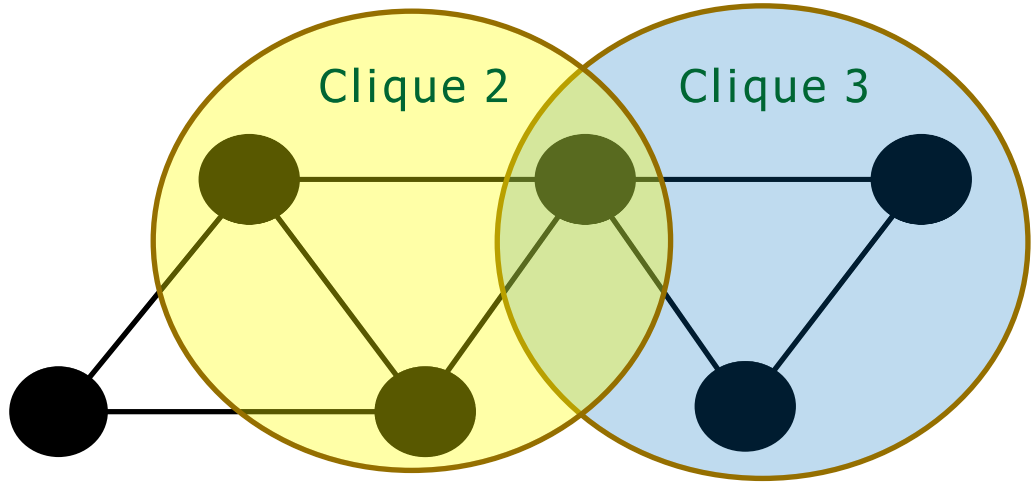

k-Clique Communities

- **k-clique community**

  Union of all k-cliques that can be reached from each other

  through a series of adjacent k-cliques

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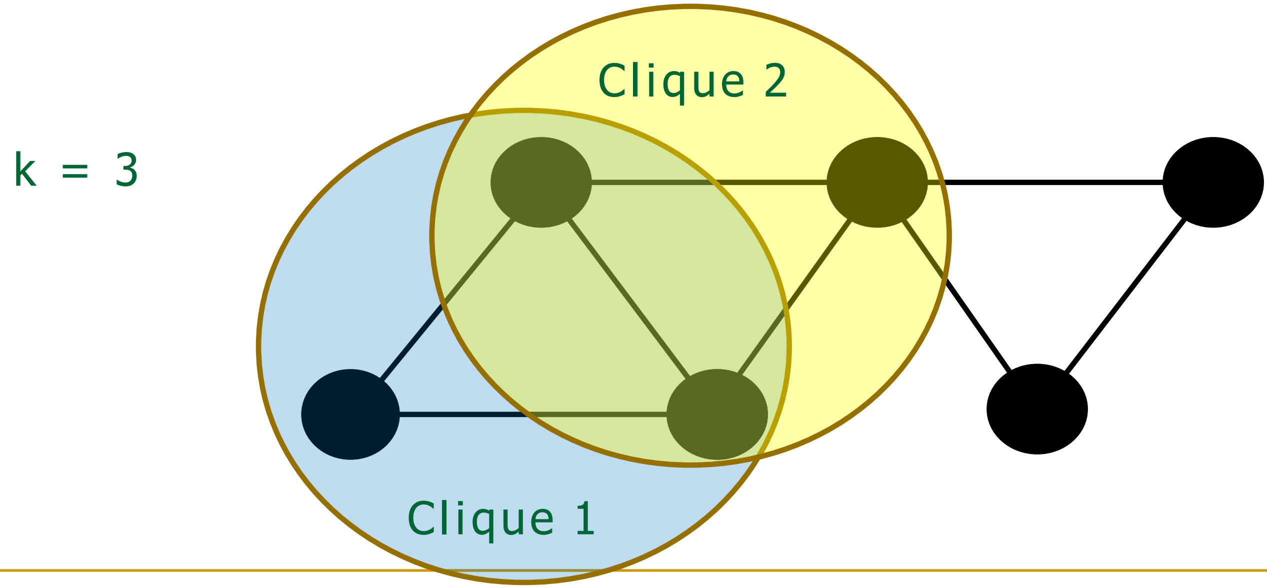

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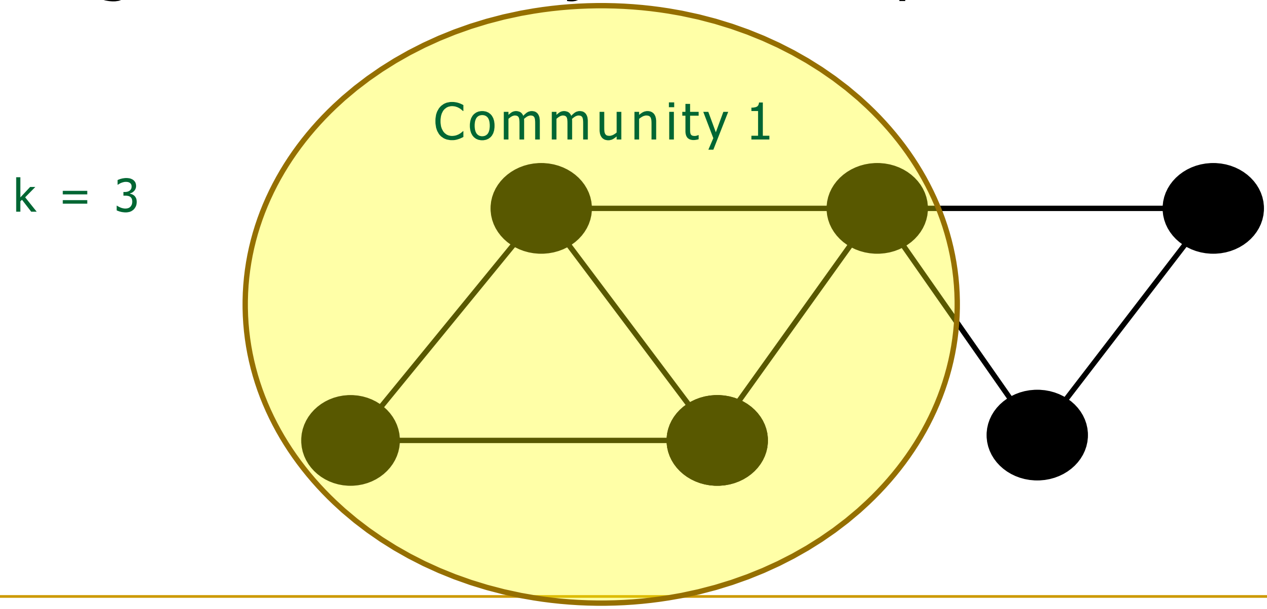

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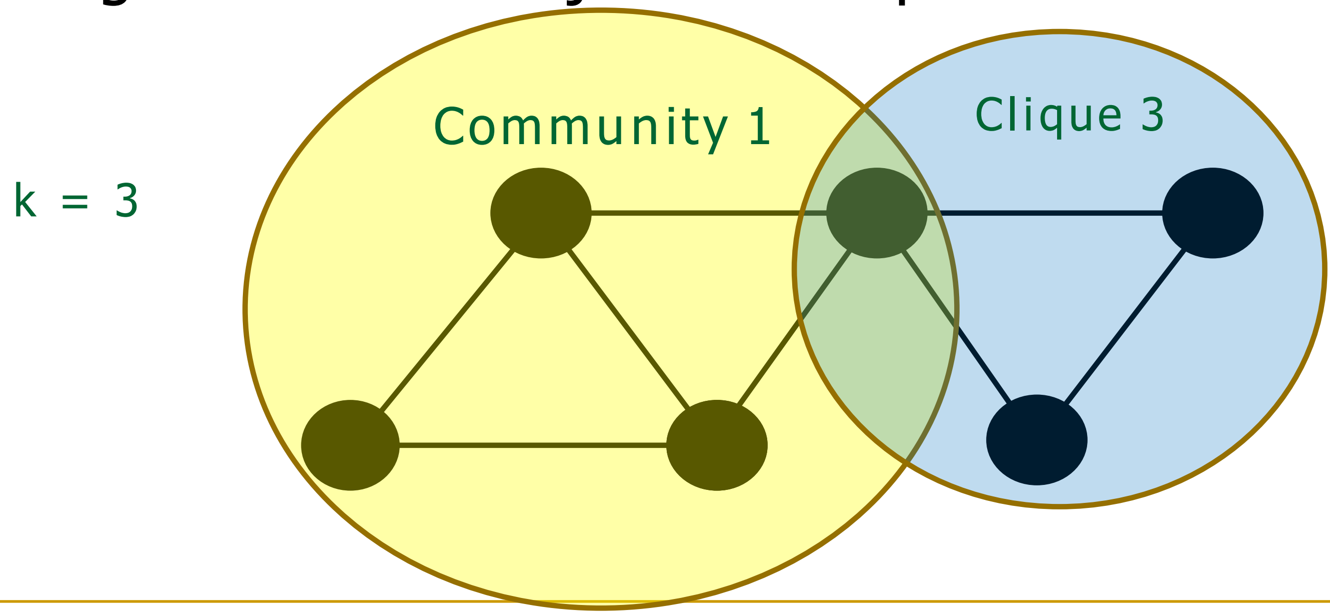

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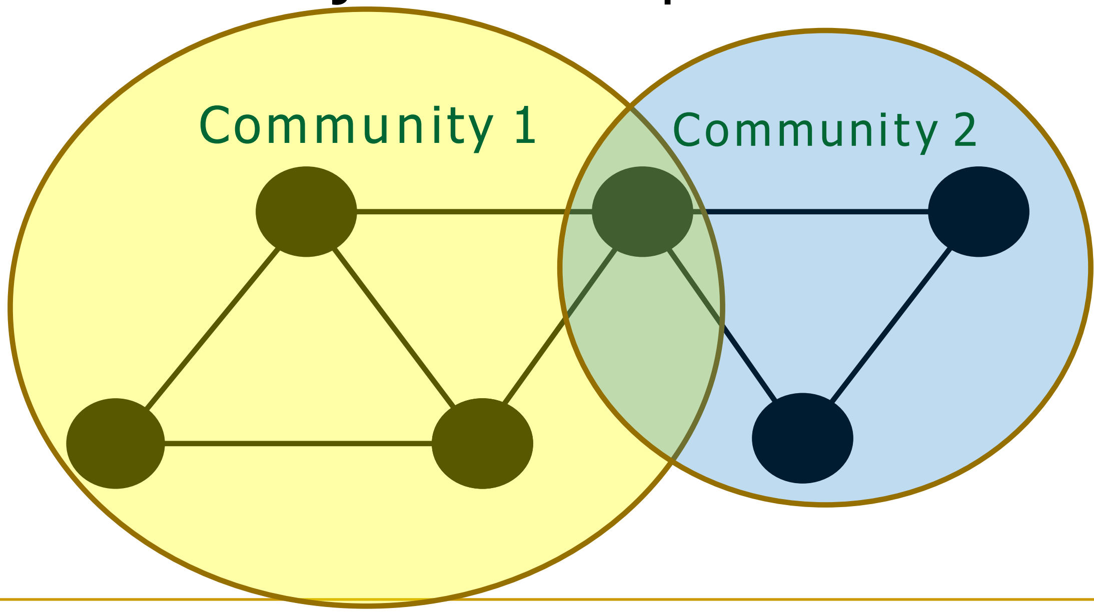


Algorithm

- Locate maximal cliques
- Convert from cliques to k-clique communities

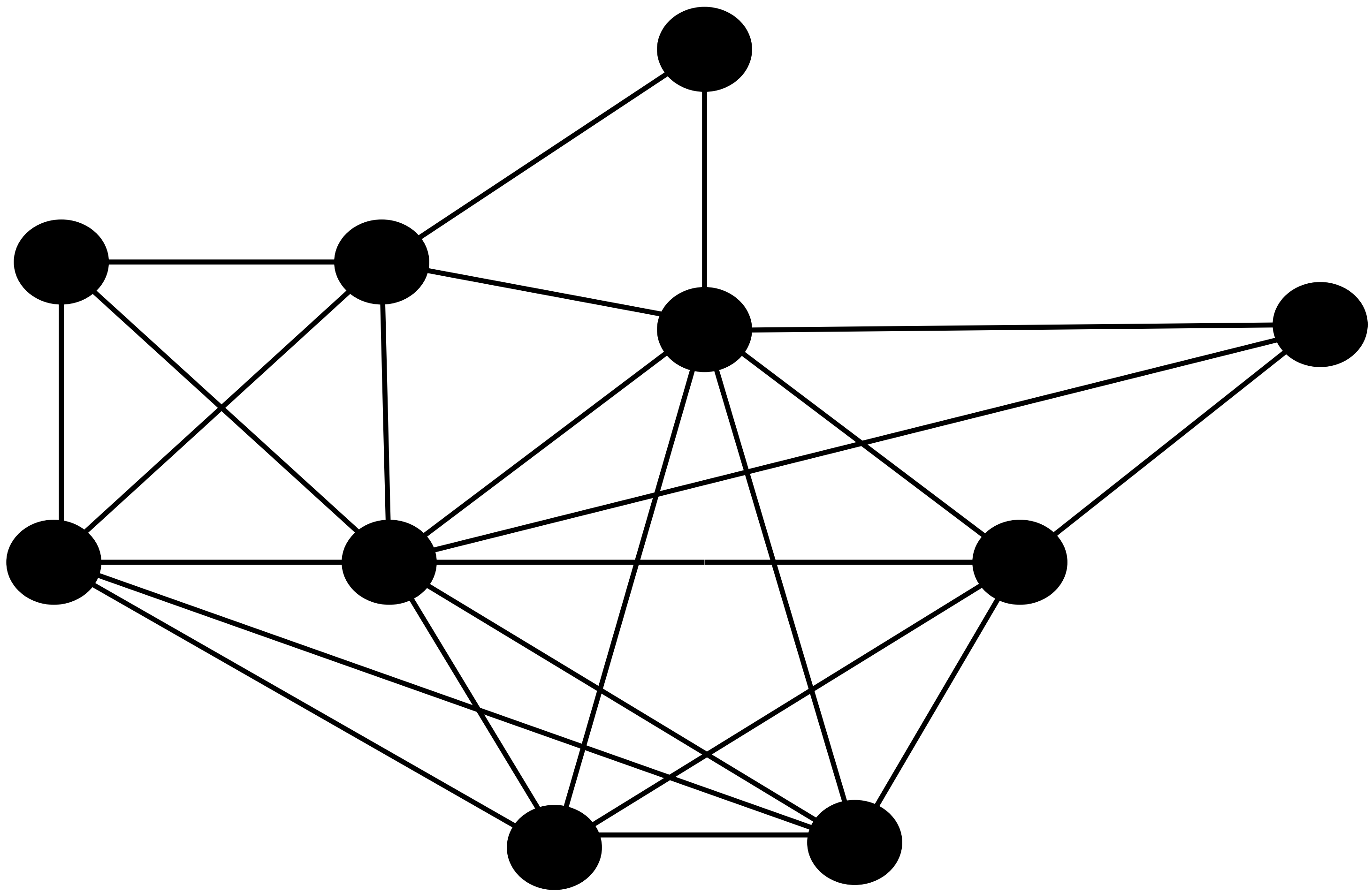
Locate Maximal Cliques

- Largest possible clique size can be determined from degrees of vertices
- Starting from this size, find all cliques, then reduce size by 1 and repeat

Algorithm

- Locate maximal cliques
- Convert from cliques to k-clique communities

Cliques to k-Clique Communities



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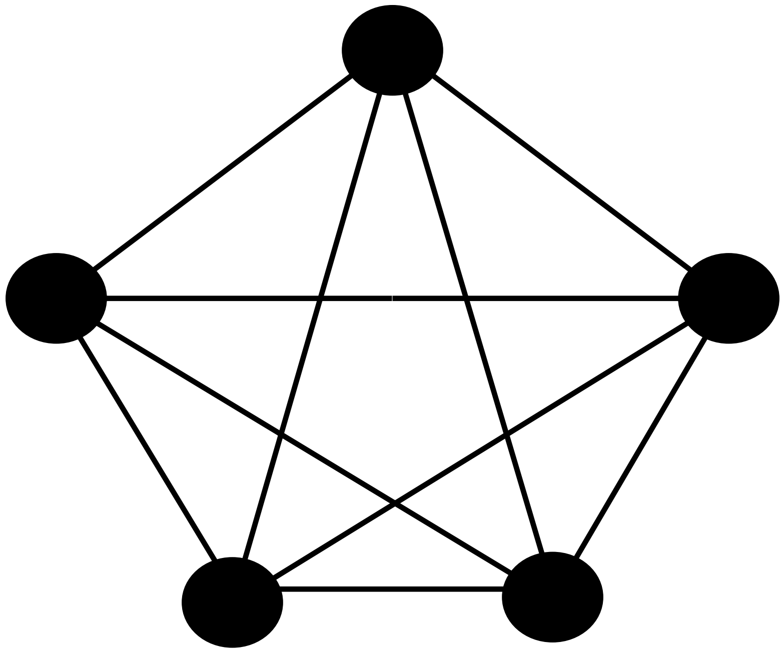
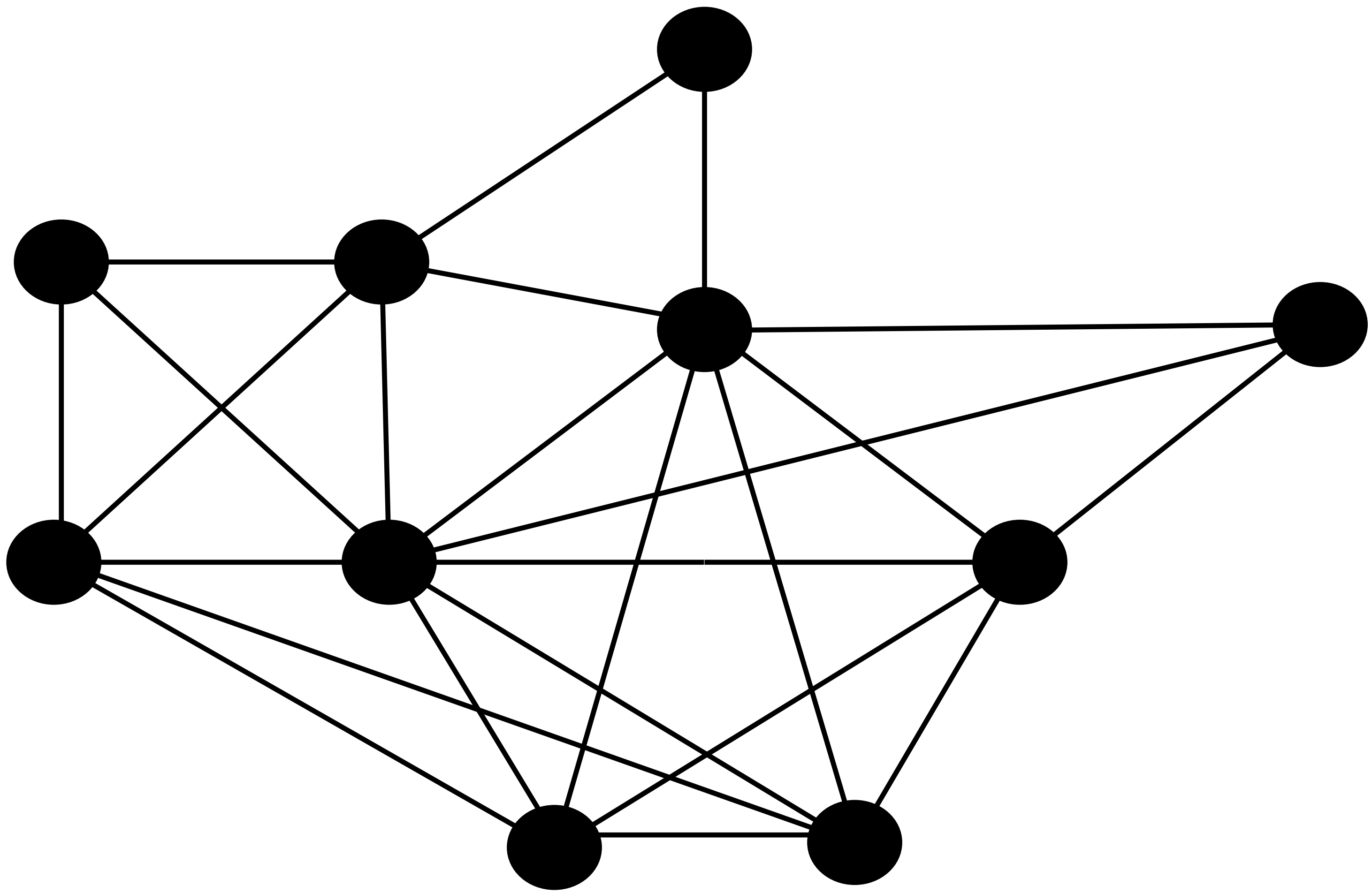


Clique 1: 5-clique

Cliques to k-Clique Communities



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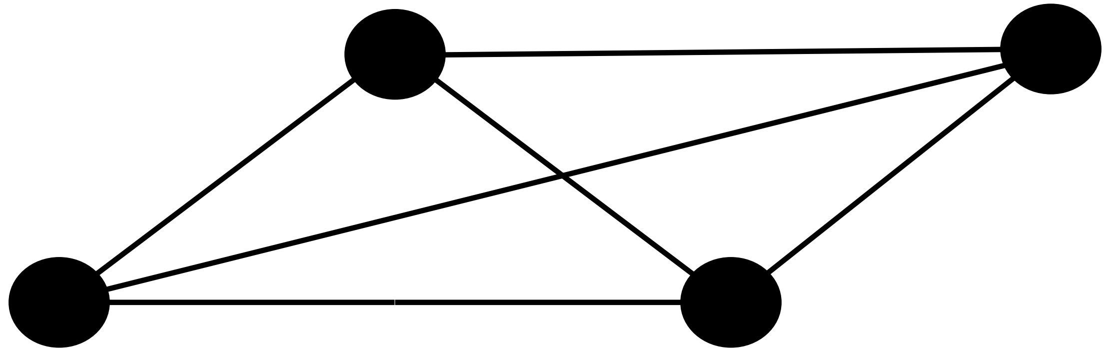
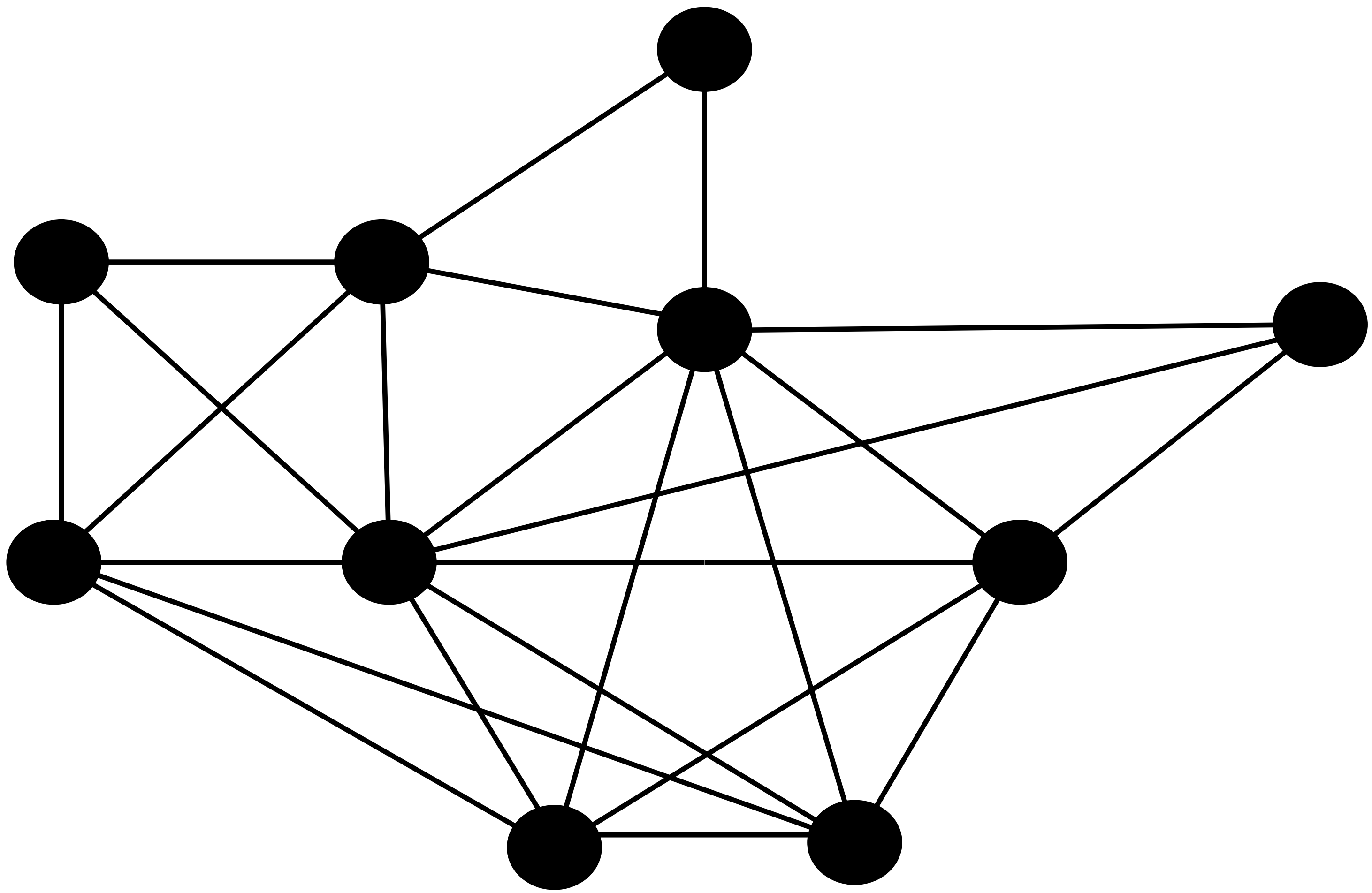


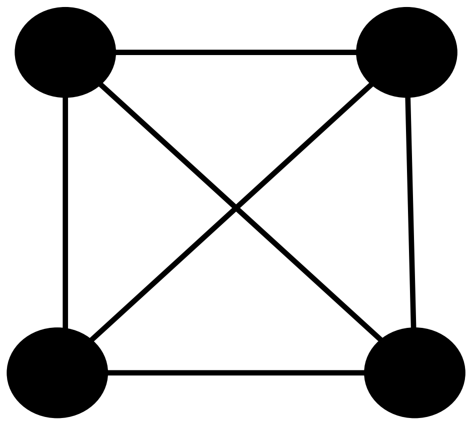
Clique 2: 4-clique

Cliques to k-Clique Communities



Cliques to k-Clique Communities

Clique 3: 4-clique



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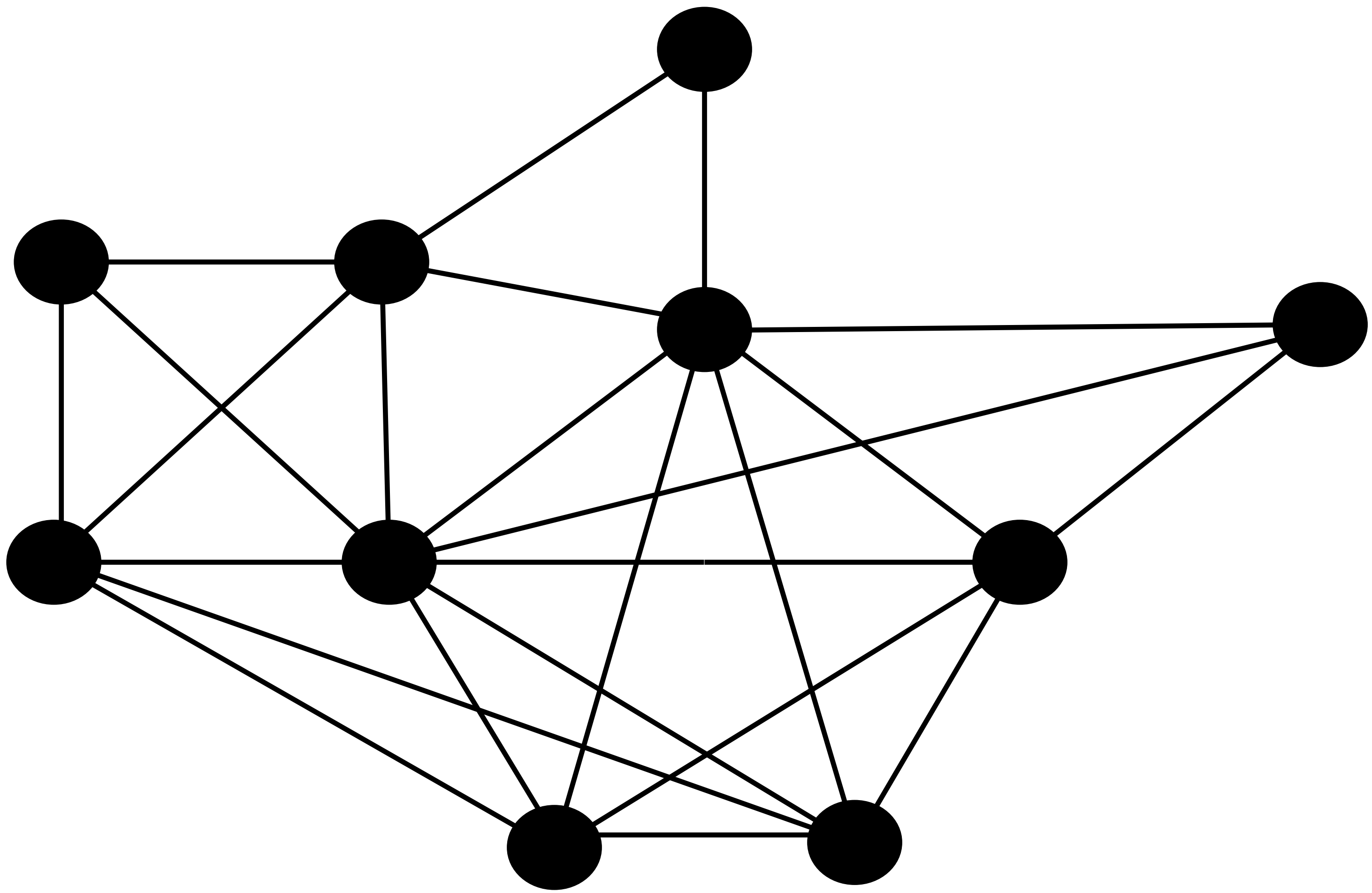

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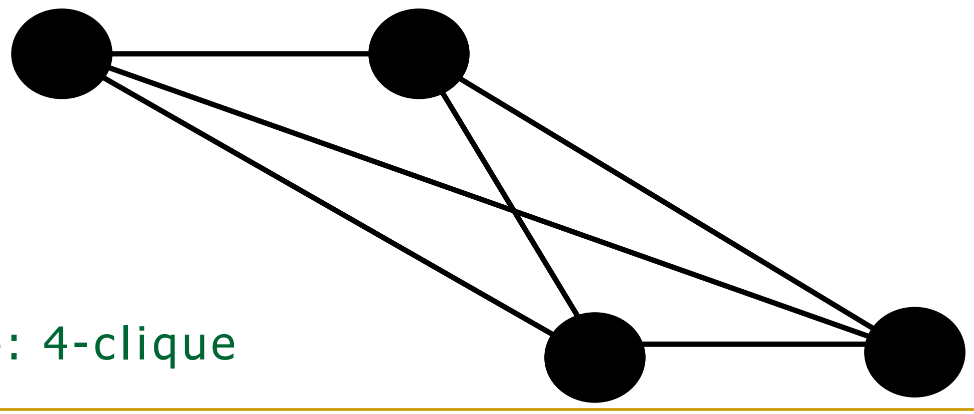
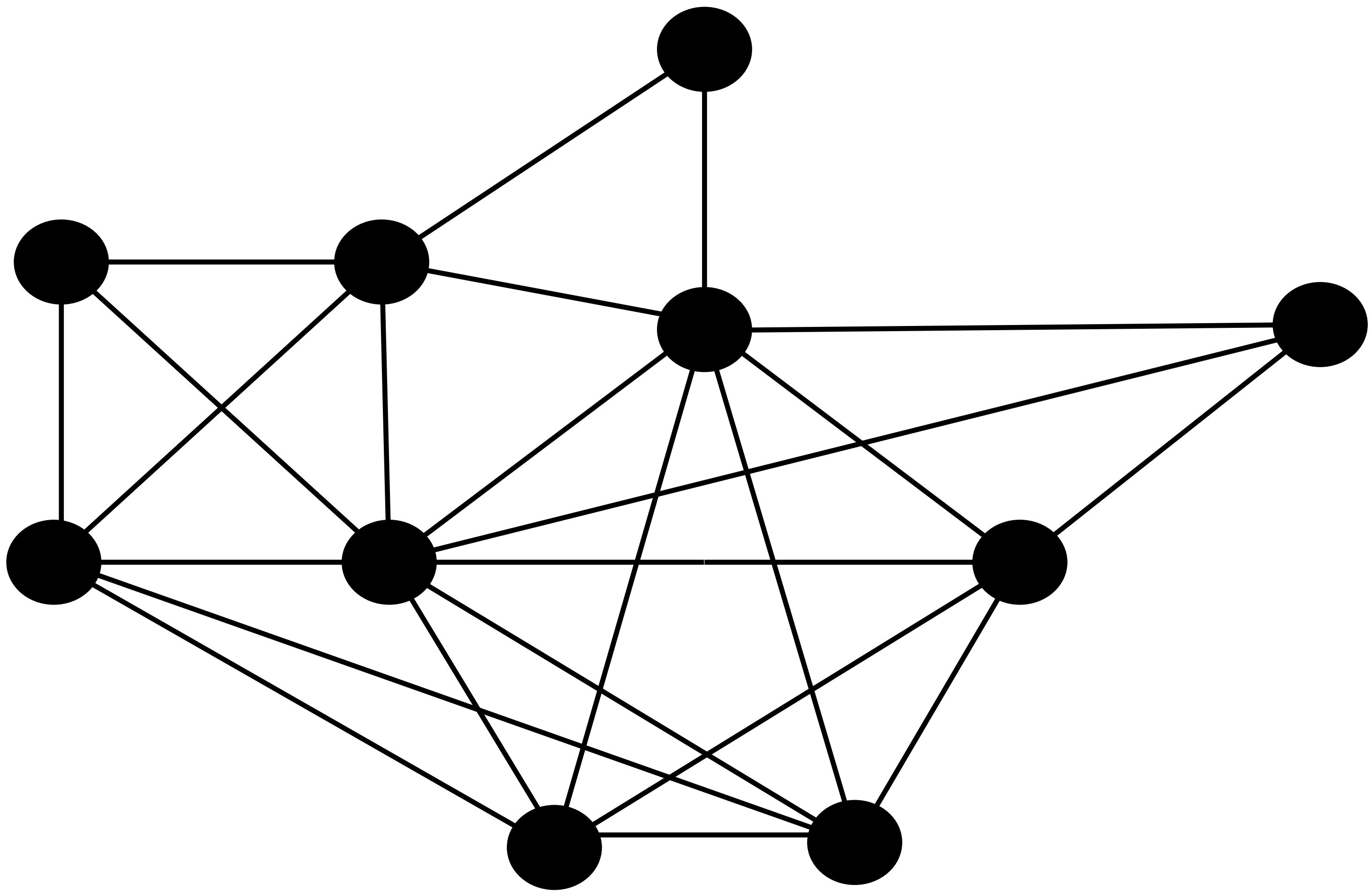
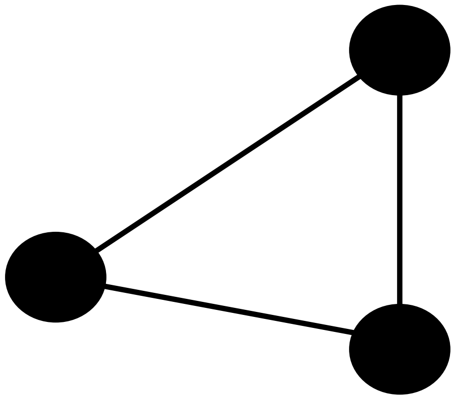


Clique 4: 4-clique

Cliques to k-Clique Communities

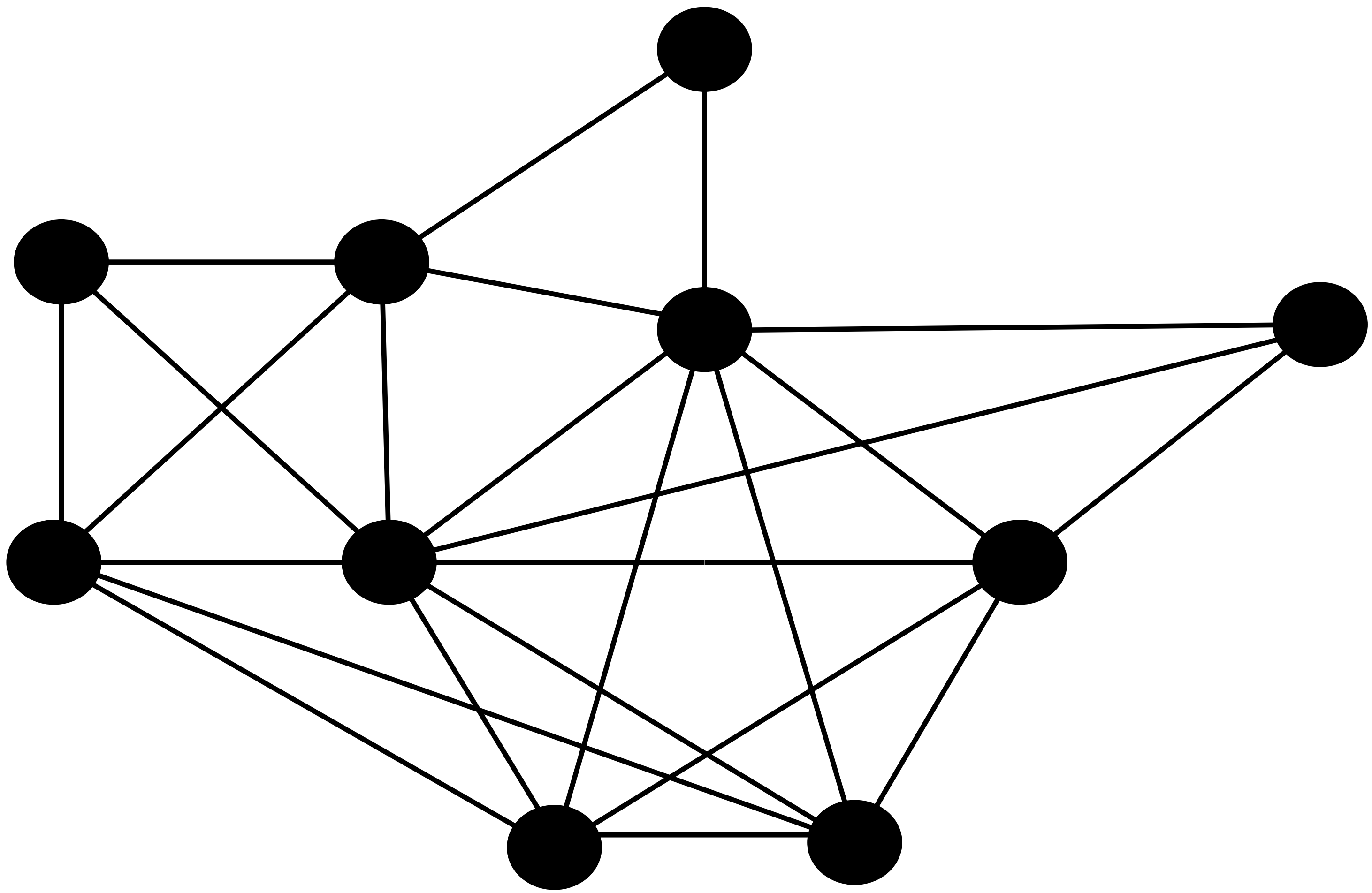


Cliques to k-Clique Communities



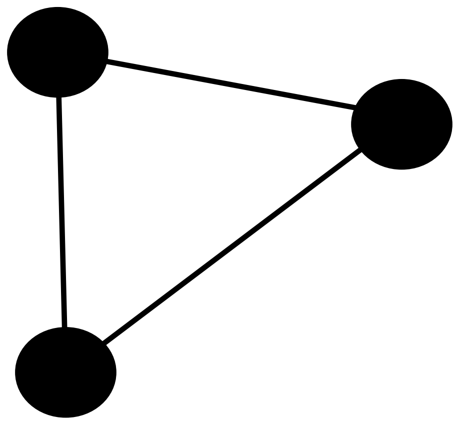
Clique 5: 3-clique

Cliques to k-Clique Communities



Cliques to k-Clique Communities

Clique 6: 3-clique



Cliques to k-Clique Communities

Clique-Clique overlap matrix

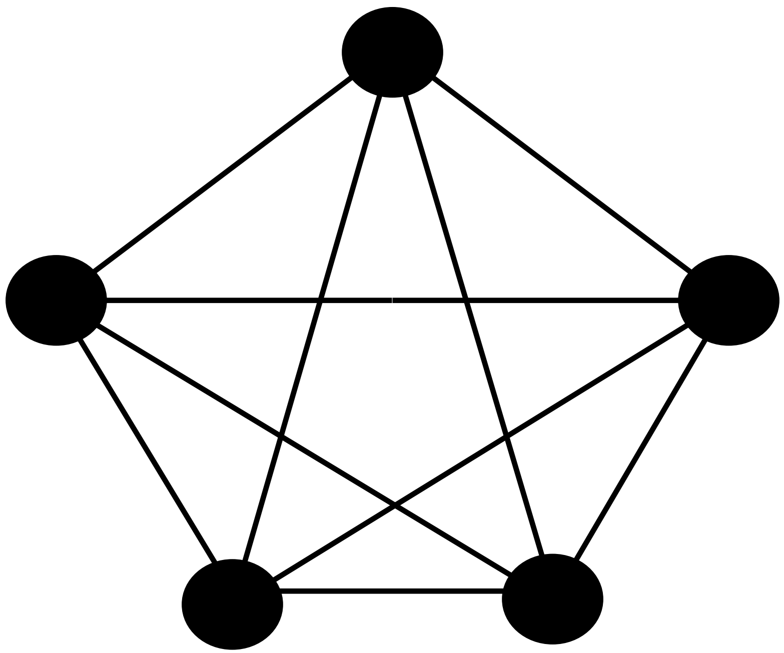
	1	2	3	4	5	6
1	5					
2		4				
3			4			
4				4		
5					3	
6						3

Cliques to k-Clique Communities

Clique-Clique overlap matrix

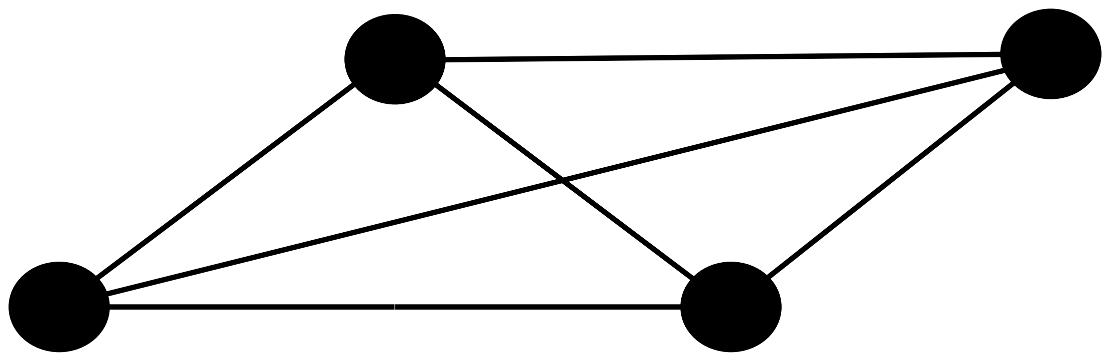
	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	3	2
6	2	2	2	1	2	3

Cliques to k-Clique Communities



Clique 1: 5-clique

Cliques to k-Clique Communities



Clique 2: 4-clique

Cliques to k-Clique Communities

Clique-Clique overlap matrix

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	3	2
6	2	2	2	1	2	3

Cliques to k-Clique Communities

- For a given value of k, k-clique communities:
  - Connected clique components in which neighboring cliques linked to each other by at least k-1 common nodes

- How to find k-clique communities from the clique-clique overlap matrix?
  - Erase every diagonal element smaller than k
  - Erase every off-diagonal element smaller than k-1
  - Replace remaining elements by 1
  - Carry out a component analysis of this matrix

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	3	2
6	2	2	2	1	2	3

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	3	2
6	2	2	2	1	2	3

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	0	2
6	2	2	2	1	2	0

Delete if less than k

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	0	2
6	2	2	2	1	2	0

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	1	3	1	2
2	3	4	1	1	1	2
3	1	1	4	2	1	2
4	3	1	2	4	0	1
5	1	1	1	0	0	2
6	2	2	2	1	2	0

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	0	3	0	0
2	3	4	0	0	0	0
3	0	0	4	0	0	0
4	3	0	0	4	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0

Delete if less than k-1

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	5	3	0	3	0	0
2	3	4	0	0	0	0
3	0	0	4	0	0	0
4	3	0	0	4	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0

Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	1	1	0	1	0	0
2	1	1	0	0	0	0
3	0	0	1	0	0	0
4	1	0	0	1	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0

Change all non-zeros to 1

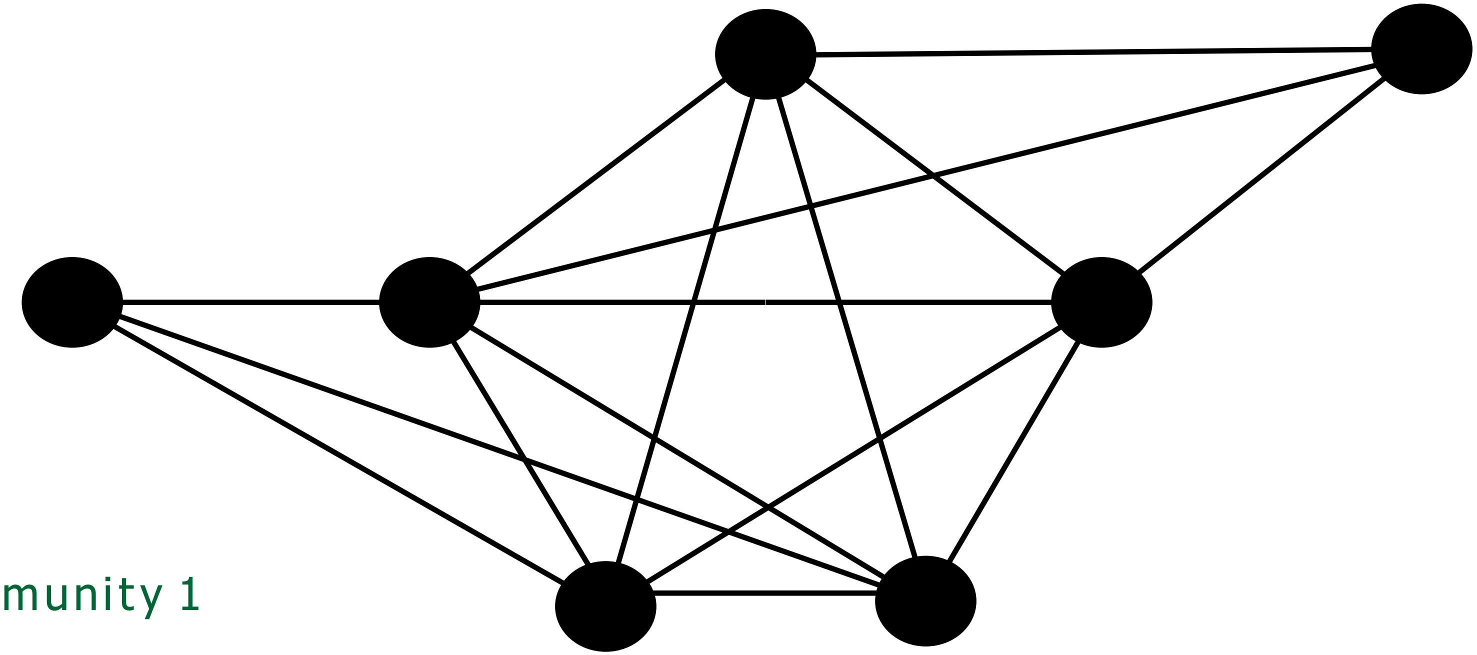
Cliques to k-Clique Communities

k=4

	1	2	3	4	5	6
1	1	1	0	1	0	0
2	1	1	0	0	0	0
3	0	0	1	0	0	0
4	1	0	0	1	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0

Cliques to k-Clique Communities

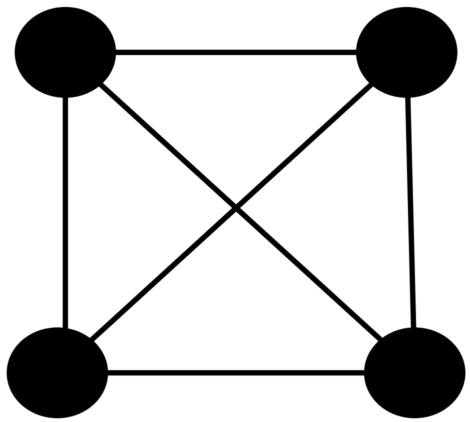
k=4



Community 1

Cliques to k-Clique Communities

k=4



Community 2

Clique Percolation Method: Analysis

- Believed to be non-polynomial
- No closed formula can be given
- However, claimed to be efficient on real systems

- Limitations
  - Fail to give meaningful covers for graph with few cliques
  - With too many cliques, might give a trivial community structure

Link communities

- A node might belong to multiple communities
  - For a person: family, co-workers, friends, …
- A link often exists for one dominant reason
  - Two people are in the same family, or are co-workers
- Link community: a set of closely inter-related links

Identifying Link communities

- Hierarchical clustering with a similarity between links to build a dendrogram
  - Each leaf of the dendrogram is a link from the original network
  - Branches of the dendrogram are link communities

- Slice the dendrogram at a suitable level
- Each link placed in a single community
- Each node inherits membership of the communities of all its links

For hierarchical clustering

- Two questions to be answered
- How to measure similarity between items?
- At which level to slice the dendrogram?

Similarity measure between links

- Node i and its neighboring nodes: $n_+(i)$

- Similarity measured only between pairs of links which share a node
- Similarity between e_{ik} and e_{jk}:

$$S(e_{ik}, e_{jk}) = |n_+(i) \cap n_+(j)| / |n_+(i) \cup n_+(j)|$$

Which level to slice the dendrogram?

- Measure: Partition density *D*
  - Total number of links in network: M
  - { P_1, P_2, …, P_C }: partition of links into C subsets
  - P_c has n_c nodes and m_c links

$$D_c = \frac{m_c - (n_c - 1)}{n_c(n_c - 1)/2 - (n_c - 1)}$$

  - Partition density is average of D_c weighted by the fraction of links present in P_c

$$D = \frac{2}{M} \sum_c m_c \frac{m_c - (n_c - 1)}{(n_c - 2)(n_c - 1)}$$

How to evaluate a CD algorithm?

- Assume a known community structure $X = \{x_1, x_2, \ldots, x_I\}$
- An algorithm finds a community structure $Y = \{y_1, y_2, \ldots, y_J\}$
- How close is Y to X?
- Several existing measures
  - Purity
  - Rand index
  - Normalized Mutual Information (NMI) [has been extended to overlapping communities]
- Generalized Measures for the Evaluation of Community Detection Methods, by Labatut (https://arxiv.org/abs/1303.5441)

DIFFERENT TYPES OF GROUPS IN A SOCIAL NETWORK

Different methods to identify groups

- Identifying groups based on network structure – community detection algorithms
- How about identifying groups based on content, e.g., text or profile attributes?
- Deep Twitter Diving: Exploring Topical Groups in Microblogs at Scale, Bhattacharya et al., CSCW 2014

Identified topical groups in Twitter

Topical Groups = Experts + Seekers

Experts: Users who have expertise on the topic

Seekers: Users who are interested in the topic

@BarackObama
Expert on Politics

@BarackObama
Seeker on Basketball

Identifying topical groups at scale

- Crawled data for first 38 million users in Twitter
- 88 Million lists, 1.5 Billion social links
- Identified 36 thousand topical groups

Diversity: Topics and Group Size

No. of seekers	Number of experts					
	< 100	100 – 500	500 – 1K	1K – 5K	5K – 10K	> 10K
< 1K	**(5416)** *geology*, *karate*, *malaria*, *neurology*, *tsunami*, psychiatry, radiology, pediatrics, dermatology, dentistry	**(132)** volleyball, philosophers, tarot, perfume, florists, copy-writers, taxi, esperanto				
1K – 5K	**(915)** *biology*, *chemistry*, *swimmers*, astrophysics, multi-media, semiconductor, renewable-energy, breast-cancer, judaism	**(428)** *painters*, *astrology*, *sociology*, *geography*, *forensics*, anthropology, genealogy, archaeology, gluten, diabetes, neuroscience	**(17)** architects, insurance, second-life, police, progressives, creativity			
5K – 10K	**(166)** *malware*, gnu, robot, chicago-sports, gospel-music, space-exploration, wall-street	**(202)** horror, agriculture, atheism, attorneys, furniture, art-galleries, ubuntu	**(34)** *psychology*, poetry, catholic, hospitals, autism, jazz	**(2)** coffee, dealers		
10K – 50K	**(174)** ipod, ipad, virus, Liverpool-FC, choreographers, heavy-metal, backstreet-boys, world-cup,	**(312)** *olympics*, *physics*, *theology*, *earthquake*, opera, makeup, Adobe, wrestlers, typography, american-idol	**(146)** *tennis*, *linux*, *astronomy*, yoga, animation, manga, doctors, realtors, wildlife, rugby, forex, php, java,	**(67)** *law*, *history*, *beer*, *golf*, librarians, theatre, military, poker, conservatives, vegan		
50K–100K	**(7)** bbc-radio, UK-celebs, christian-leaders, superstars	**(61)** *hackers*, *programmers*, bicycle, GOP, fantasy-football, NCAA, wwe, sci-fi	**(35)** *medicine*, *cyclists*, investors, recipes, NHL, xbox, triathlon, Google	**(37)** hotels, museums, hockey, architecture, charities, weather, space		
> 100K	**(3)** headlines, brits	**(49)** pop-culture, gospel, BBC, reality-tv, bollywood	**(58)** *religion*, actresses, gadgets, graphic-design, directors, lifestyle, gossip, commentators, youtube	**(140)** *books*, *government*, *comedy*, *environment*, *baseball*, *soccer*, *hollywood*, *iphone*, *economics*, money	**(25)** *fashion*, *education*, *wine*, photography, radio, restaurants, science, SEO	**(17)** *music*, *tech*, *business*, *politics*, *food*, *sports*, *celebs*, *health*, media, bloggers, travel, writers

A Small Number of Very Popular Groups

No. of seekers	Number of experts					
	< 100	100 – 500	500 – 1K	1K – 5K	5K – 10K	> 10K
< 1K	**(5416)** *geology*, *karate*, *malaria*, *neurology*, *tsunami*, psychiatry, radiology, pediatrics, dermato	**(132)** volleyball, philosophers, tarot, perfume, florists, copy-writers, taxi, esperanto				
1K – 5K	**(915)** istry, astroph media, renewal breast-c					
5K – 10K	**(166)** robot, gospel- explora					
10K – 50K	**(174)** virus, choreog metal, world-c					
50K–100K	**(7)** bl celebs, leaders, superstars	GOP, fantasy-football, NCAA, wwe, sci-fi	xbox, triathlon, Google	architecture, chari-ties, weather, space		
> 100K	**(3)** headlines, brits	**(49)** pop-culture, gospel, BBC, reality-tv, bollywood	**(58)** *religion*, actresses, gadgets, graphic-design, directors, lifestyle, gossip, com-mentators, youtube	**(140)** *books*, *govern-ment*, *comedy*, *en-vironment*, *baseball*, *soccer*, *hollywood*, *iphone*, *economics*, money	**(25)** *fashion*, *education*, *wine*, photog-raphy, radio, restaurants, science, SEO	**(17)** *music*, *tech*, *business*, *politics*, *food*, *sports*, *celebs*, *health*, media, bloggers, travel, writers

(37) hotels, mu-seums, hockey, architecture, chari-ties, weather, space		
(140) *books*, *govern-ment*, *comedy*, *en-vironment*, *baseball*, *soccer*, *hollywood*, *iphone*, *economics*, money	**(25)** *fashion*, *education*, *wine*, photog-raphy, radio, restaurants, science, SEO	**(17)** *music*, *tech*, *business*, *politics*, *food*, *sports*, *celebs*, *health*, media, bloggers, travel, writers

Thousands of Specialized Niche Groups

No. of seekers	Number of experts					
	< 100	100 – 500	500 – 1K	1K – 5K	5K – 10K	> 10K
< 1K	(5416) *geology*, *karate*, *malaria*, *neurology*, *tsunami*, psy… radiology, pe… dermatology, de…	(132) volleyball, philosophers, tarot, …				
1K – 5K	(915) *biology*, … *istry*, *sw*… astrophysics, … media, semicon… renewable-energ… breast-cancer, ju…					
5K – 10K	(166) *malware*… robot, chicago… gospel-music, … exploration, wal…					
10K – 50K	(174) ipod, … virus, Liverp… choreographers, … metal, backstre… world-cup, …					
50K–100K	(7) bbc-radio, … celebs, ch… leaders, supersta…	… NCAA, wwe, sci-fi		… ties, weather, space		
> 100K	(3) headlines, brits	(49) pop-culture, gospel, BBC, reality-tv, bollywood	(58) *religion*, actresses, gadgets, graphic-design, directors, lifestyle, gossip, commentators, youtube	(140) *books*, *government*, *comedy*, *environment*, *baseball*, *soccer*, *hollywood*, *iphone*, *economics*, money	(25) *fashion*, *education*, *wine*, photography, radio, restaurants, science, SEO	(17) *music*, *tech*, *business*, *politics*, *food*, *sports*, *celebs*, *health*, media, bloggers, travel, writers

(5416) *geology*, *karate*, *malaria*, *neurology*, *tsunami*, psychiatry, radiology, pediatrics, dermatology, dentistry	**(132)** volleyball, philosophers, tarot, perfume, florists, copywriters, taxi, esperanto
(915) *biology*, *chemistry*, *swimmers*, astrophysics, multi-media, semiconductor, renewable-energy, breast-cancer, judaism	**(428)** *painters*, *astrology*, *sociology*, *geography*, *forensics*, anthropology, genealogy, archaeology, gluten, diabetes, neuroscience

Breaking the Twitter stereotype

- Twitter stereotype
  - Popular news on few topics such as sports, entertainment, politics, technology
  - Celebrity gossip, current news, and chatter

- Breaking the stereotype
  - Majority of the population discuss few popular topics, but
  - Smaller groups interested in thousands of niche, specialized topics

Detecting topical groups

- We followed content-based approach to identify topical groups
- Could community detection algorithms be used on the social network to detect them?
- Applied BGLL / Louvain algorithm on the Twitter subscription network to identify communities

Detecting topical groups

- Louvain largely unable to detect topical groups, especially the smaller ones (on niche topics)

- Communities detected by Louvain fare better on structural measures like cut-ratio, conductance

- Topical groups do not have good structural quality
  - Poor values for standard community quality metrics such as cut-ratio and conductance

Why do groups form?

- "Common Identity and Bond Theory"
  - Prentice et. al. "Asymmetries in Attachments to Groups and to Their Members: Distinguishing Between Common-Identity and Common-Bond Groups", Personality and Social Psychology Bulletin, 1994
- Identity based groups
- Bond based groups

Common Identity and Bond Theory

Identity Based Groups

Low Reciprocity
Low Personal Interactions
High Topicality of discussions

Examples:
Fans at a football match,
Attendees at a conference

Bond Based Groups

High Reciprocity
High Personal Interactions
Low Topicality of discussions

Examples:
Family, personal friends

Analysis of 50 topical groups

- Low reciprocity among members
- Few one-to-one interactions
- Most tweets posted by experts are related to topic
- → Topical groups are identity-based which are difficult to detect via community detection algorithms