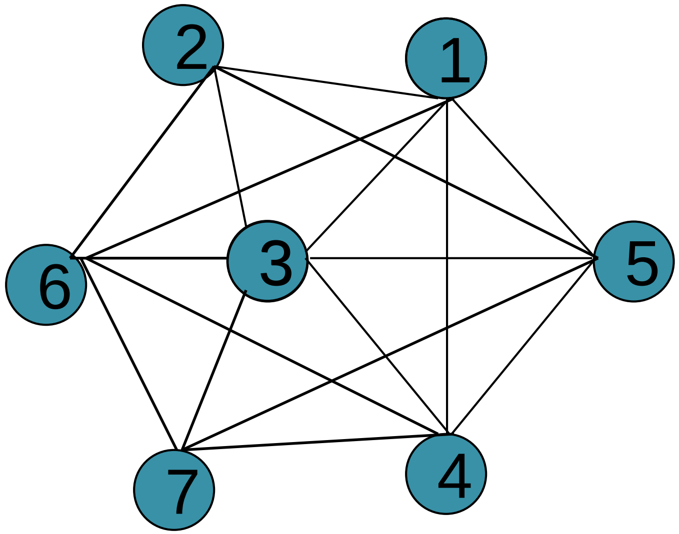
Additional approach for community detection

LCMA: Local Clique Merging Algorithm

- Observation that a maximal dense region covering vertices $\{v_1, \ldots, v_k\}$ in G_{ppi} must necessarily contain the local cliques (if any) of the vertices from $\{v_1, \ldots, v_k\}$.



{1, 3, 4, 5},

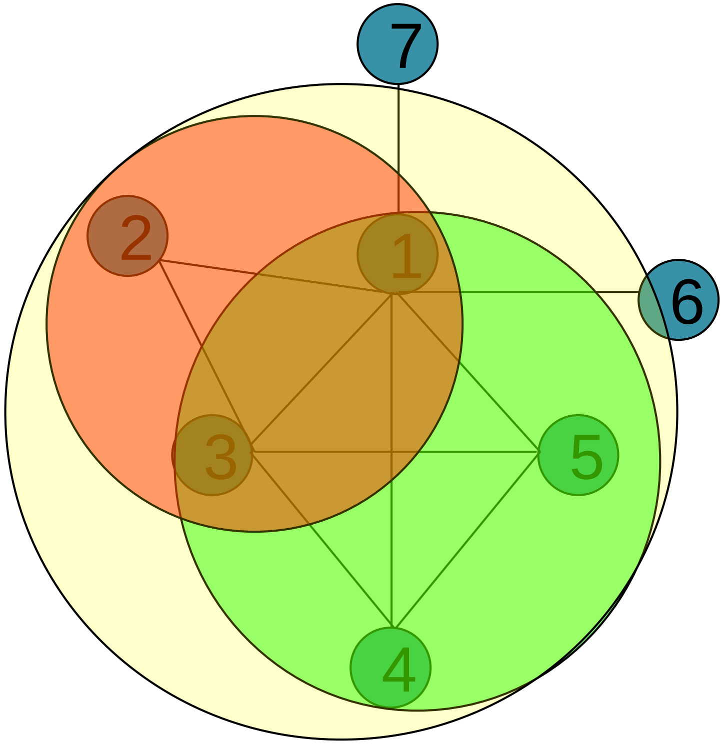
{1,2, 3, 6},

{1,2, 3, 5},

{7, 3, 4, 5},

{7, 3, 4, 6},

Local Clique Merging Algorithm (LCMA): from local cliques to maximal dense subgraphs



Two Steps of LCMA Algorithm

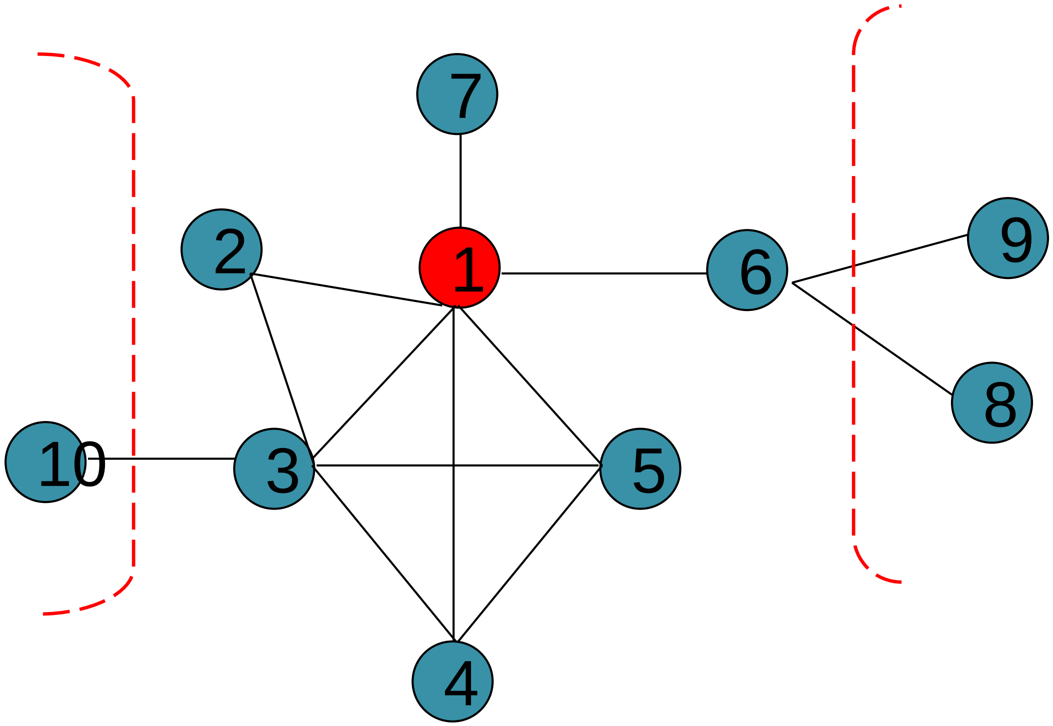
- 1. Computes the local cliques for all the vertices in G_{ppi}.
- 2.merge these local cliques to form maximal dense graphs.

Local neighborhood graph

For each vertex v_i from graph G_{ppi}, we first get its initial local neighborhood graph - namely, v_i, all its neighbors and the edges between the neighbors in graph G_{ppi}.

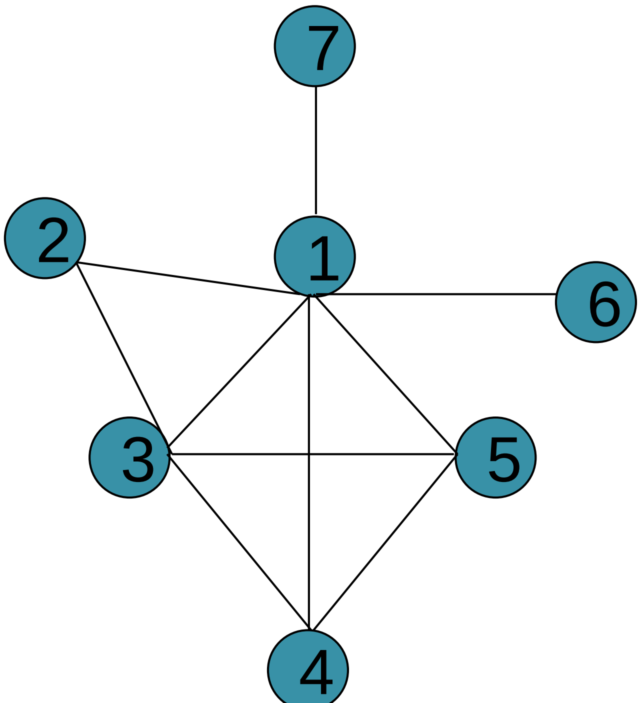
Definition 2 *Let a graph* $G = (V, E)$. *For each vertex* $v_i \in V$, *its local neighborhood graph* $G_{v_i} = (V_{v_i}, E_{v_i})$, *where* $V_{v_i} = \{v_i\} \cup \{v | v \in V, (v, v_i) \in E\}$, $E_{v_i} = \{(v_j, v_k) | (v_j, v_k) \in E, v_j, v_k \in V_{v_i}\}$.

Local neighborhood graph



LCMA 1: Mining for local cliques

- Iteratively remove the loosely connected vertices



Density=8/12=0.67

|V|=7, |E|=10.

LCMA 1: Mining for local cliques from local neighborhood graph

- For each node in its local neighborhood graph, **iteratively remove the loosely connected vertices** until the density of local neighborhood graph does not increase.

- Paper proved that **the resulting graph is a fully connected graph, namely, clique**.

LCMA 2: Merging local cliques for maximal dense neighborhoods

To detect *larger* dense graphs which can match the larger complexes better, the LCMA algorithm performs a merging step after the local cliques have been identified

Definition 3 *Neighborhood Affinity. Given two neighborhoods (subgraphs) A and B, we define the Neighborhood Affinity NA between them as*

$$NA(A,B) = \frac{|A \cap B|^2}{|A| * |B|} \tag{10}$$

Equation quantifies the degree of similarity between neighborhoods. If two neighborhoods have larger intersection sets and similar sizes, then they are more similar and have bigger neighborhood affinity.

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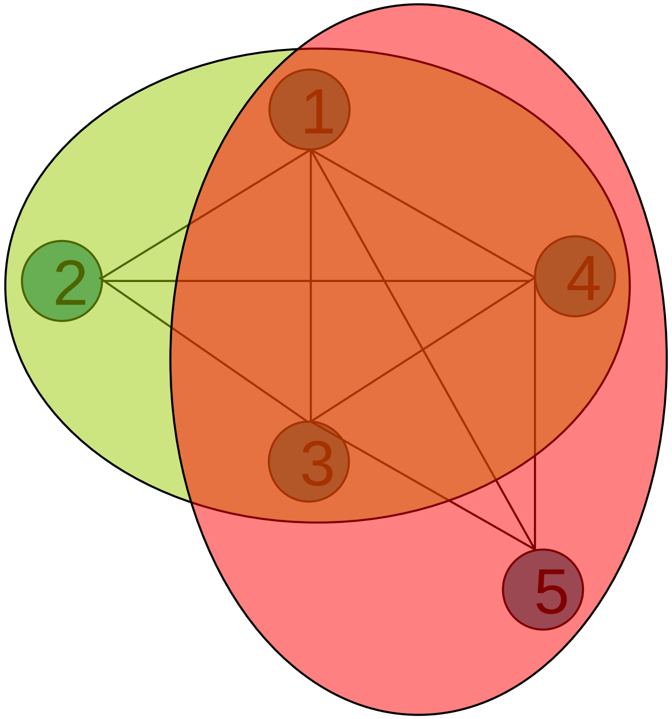
Example of the Neighborhood Affinity



$$A = (V_1, E_1)$$

$$V_1 = \{1,2,3,4\}$$

$$E_1 = \{(1,2),(1,3),(1,4),(2,3),(2,4),(3,4)\}$$

$$B = (V_2, E_2)$$

$$V_2 = \{1,3,4,5\}$$

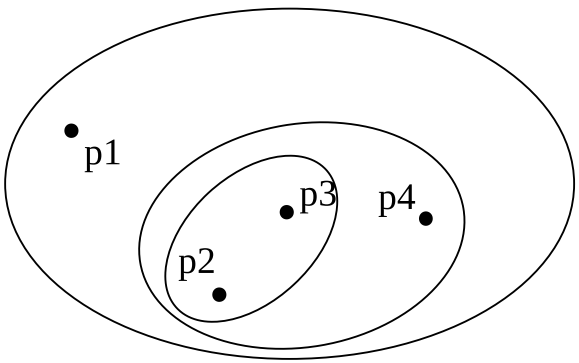
$$E_2 = \{(1,3),(1,4),(1,5),(3,4),(3,5),(4,5)\}$$

$$NA(A,B)$$

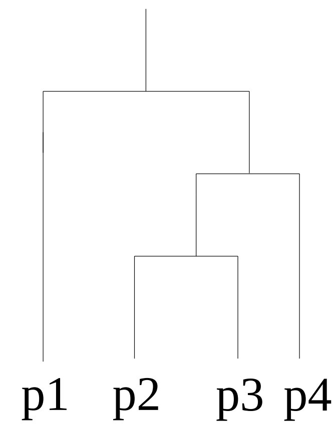
$$= \frac{|A \cap B|^2}{|A| * |B|}$$

$$= \frac{3*3}{4*4} = \frac{9}{16} = 0.5625$$

Agglomerative methods



Traditional Hierarchical Clustering

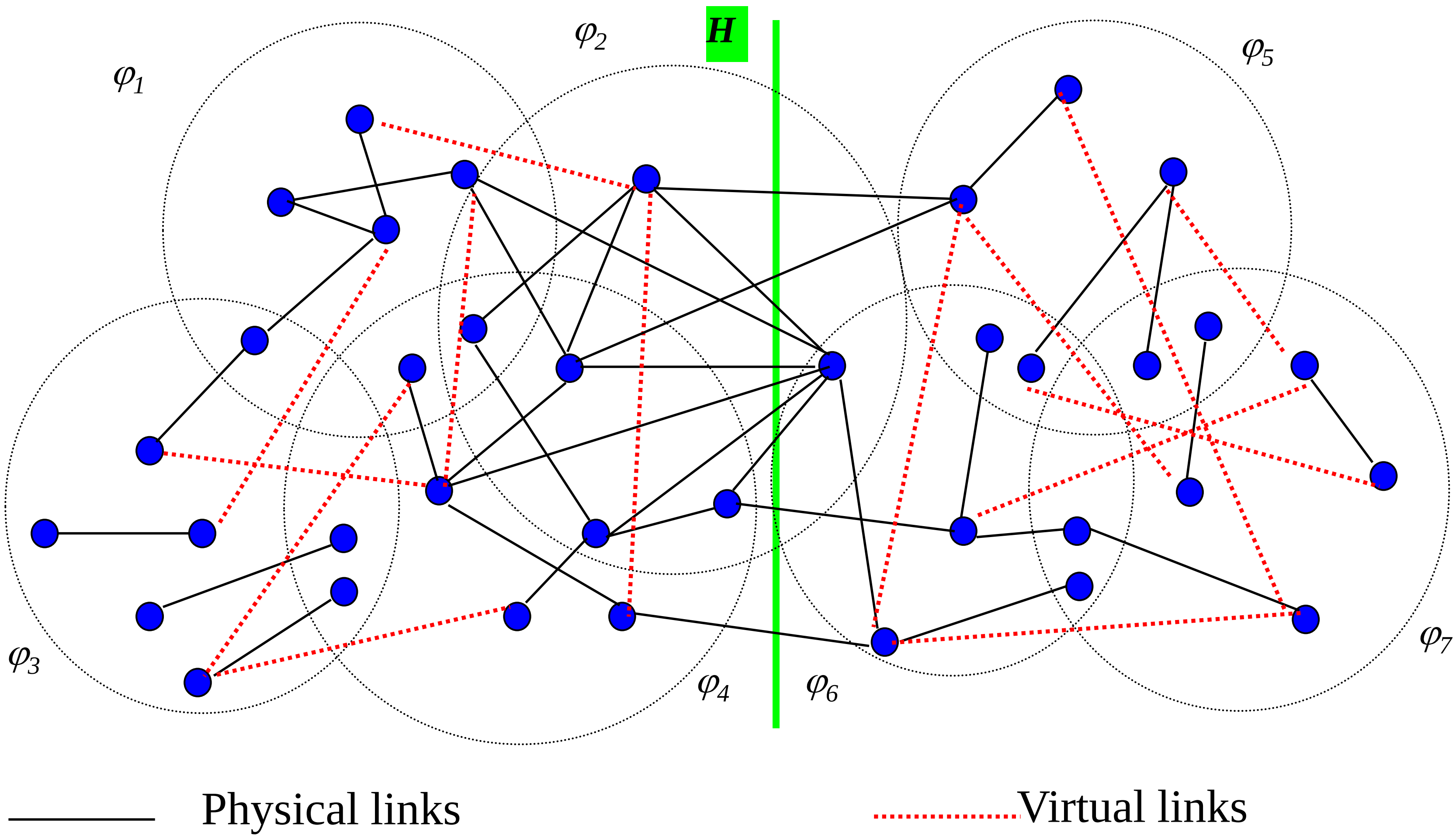


Traditional Dendrogram

Less links among the community members

- Social entities only *interact with limited community members*. As such, *there exist communities which do not have very dense connections among all its members*. This will make existing algorithms (mostly density-based) suffer.

Virtual Links enhance the connectivity among members within same communities



Virtual Links are content based

How to add virtual links

- For each node (crawl Web to get its additional information)
- Compute pair-wise content similarity
- If they are larger than certain threshold (i.e. average similarity among the known community members), then we regard them have virtual links
- Virtual links can be used to do friend recommendation

Virtual Link - Predicting friendship

- Input: two people
- Output: should they be Facebook friends?

Virtual Links

- <u>Input</u>: two people
- <u>Output</u>: should they be Facebook friends?

- **Features:**
  - **friends list**
  - **school**
  - **home town**
  - **Music**
  - **hobbies**
  - **...**

Peter, Julia, …
NUS, IIT,
Hyderabad, India
Rock
Tennis, running
…

Celia, Julia, …
NUS, Tsinghua
Beijing, China
Rock
Tennis,
…

Big SIMILARITY?

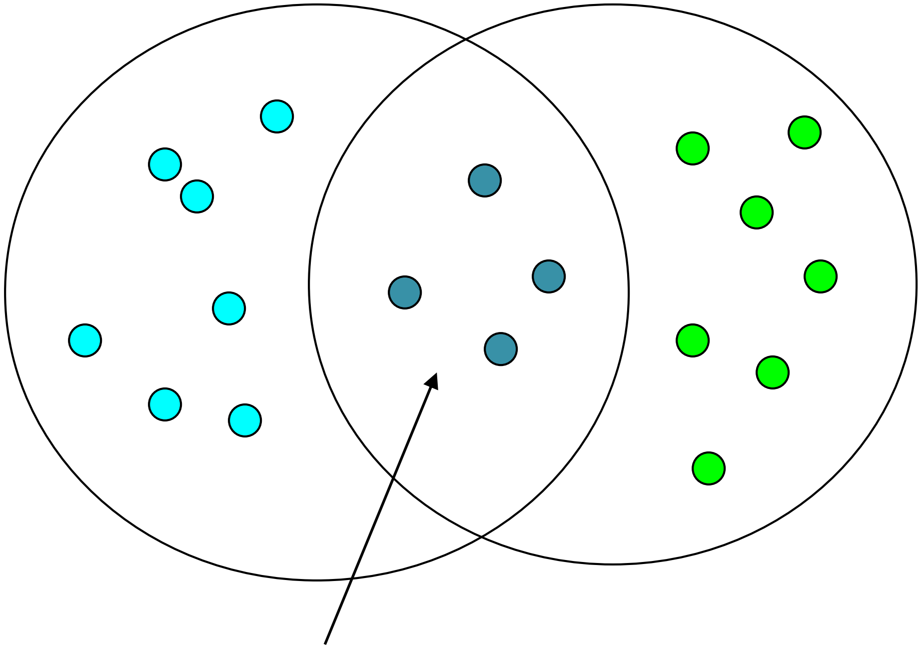
Yes!

Merge small dense graphs by computing similarity measures

- Communities can consist of the people from different small dense graphs . It is thus necessary to combine them together to form those bigger communities.
- We evaluate the similarities between graphs by the following *three different similarity measures*.

Vertex overlapping based similarity

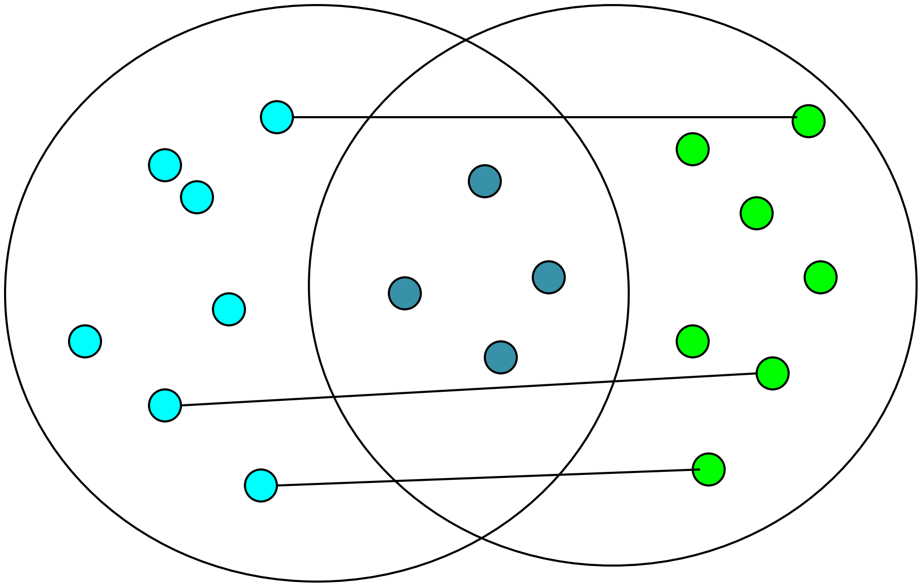
$$Vex\_sim(\varphi_i, \varphi_j) = \frac{|V_i \cap V_j|}{|V_i \cup V_j|} / K_{vex}$$



If two graphs share a high proportion of members, then they should be combined into same community.

Physical link based similarity

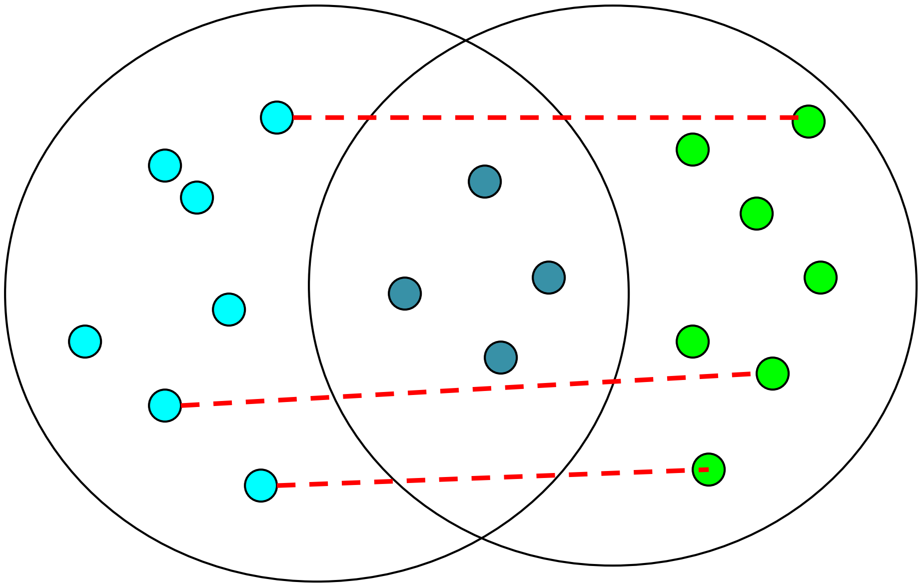
$$PL\_sim(\varphi_i,\varphi_j)=\frac{|\{(v_i,v_j)\,|\,(v_i,v_j)\in\varphi_k, k\neq i, k\neq j, v_i\in V_i\setminus V_j, v_j\in V_j\setminus V_i\}|}{|V_i\setminus V_j|*|V_j\setminus V_i|}/K_{PL}$$



Physical link based similarity: evaluates how closely the members from different graphs interact with each other.

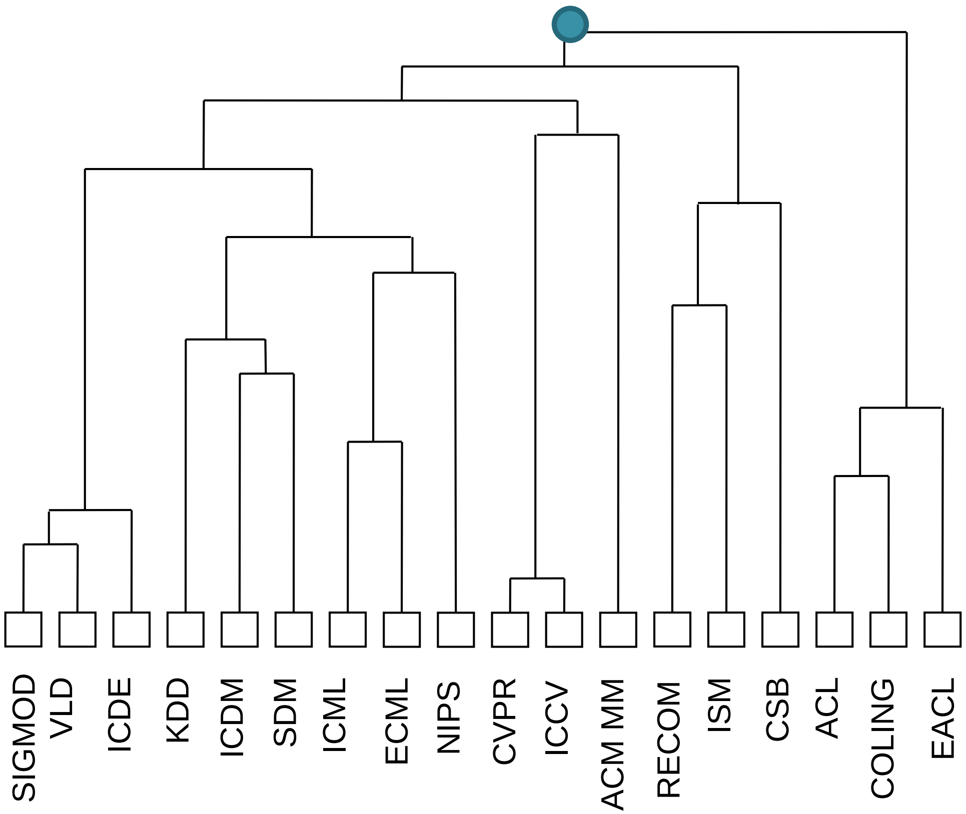
Virtual link based similarity

$$VL\_sim(\varphi_i,\varphi_j)=\frac{|\{(v_i,v_j)\,|\,v_i\in\varphi_i, v_j\in\varphi_j, consim(v_i,v_j)>\delta, v_i\in V_i\setminus V_j, v_j\in V_j\setminus V_i\}|}{|V_i\setminus V_j|*|V_j\setminus V_i|}/K_{VL}$$



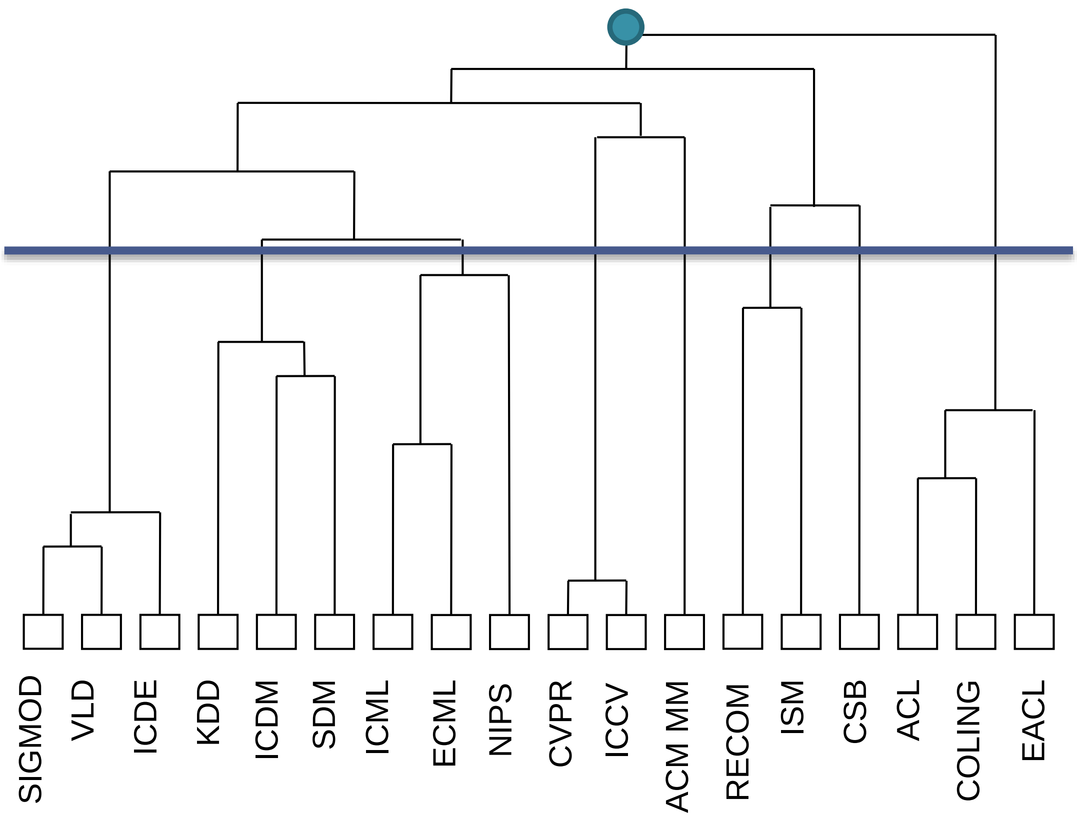
Connect those people from different graphs whose content similarity is equal to or higher than the average similarity between people within randomly selected events.

Overall Idea of ECODE Algorithm



- Hierarchical clustering approach
- Detect similar graphs in terms of *overlapping vertices* and *physical/virtual links*, and then merging them to form bigger communities

ECODE Algorithm



Automatic stopping criteria: automatically terminates when the *quality of the detected communities become maximal*

Compute the quality of the current level of the tree
Link based method

- The hierarchical clustering will result in a tree (one big community). The merging process can be stopped if *the current merging step does not improve the quality of the current level of tree*.
- Newman has proposed a quality function Q (**modularity**) to evaluate the goodness of a tree

$$Q = \sum_i (e_{ii} - a_i^{\,2})$$

where e_{ii} is the number of links in the same group connecting the vertices (intralinks) and a_i is the sum of edges from the vertices in group i to another group j (interlinks)

Compute the quality of the current level of the tree
Content based method

- There are many interactions across different communities, instead of using the physical links, we use the content/feature-based approach.

$$Q = \sum_i (cossim(i,i) - \sum_j cossim(i,j)^2)$$

- It favors a community substructure which has in overall bigger intra-similarity and less inter-similarity in terms of their topics and content.
- The algorithm can stop at a level of tree with the maximal *Q* value.

References

1. Xiao-Li Li, Chuan-Sheng Foo, Kar Leong Tew, See-Kiong Ng, "Searching for Rising Stars in Bibliography Networks", DASFAA 2009, Australia.
2. Xiao-Li Li, Soon-Heng Tan, Chuan-Sheng Foo and See-Kiong Ng. "Interaction Graph Mining for Protein Complexes Using Local Clique Merging." in *Genome Informatics, Vol. 16, No.2.* 2005.
3. Xiao-Li Li, Aloysius Tan, Philip S. Yu, See-Kiong Ng, ECODE: Event-Based Community Detection from Social Networks, DASFAA 2011, Hong Kong.