

A Topological Visual Analysis Approach for Complex Networks

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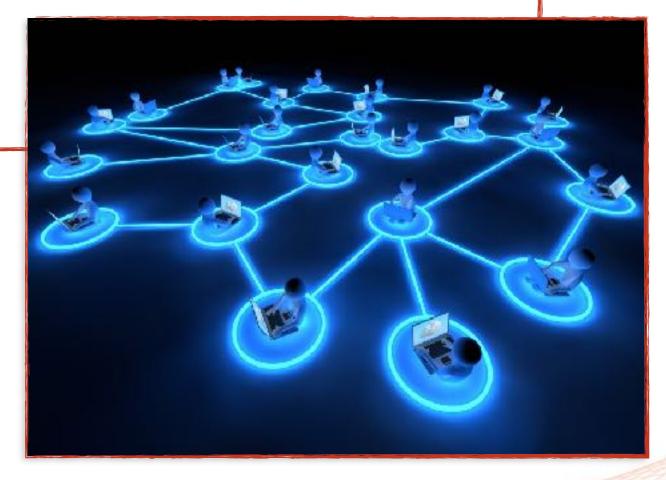
A *network* is a **complex system** consisting of **individuals** or **entities** connected by specific **ties** such as

- + Personal Relationship
- Shared Knowledge

### **Several Examples:**

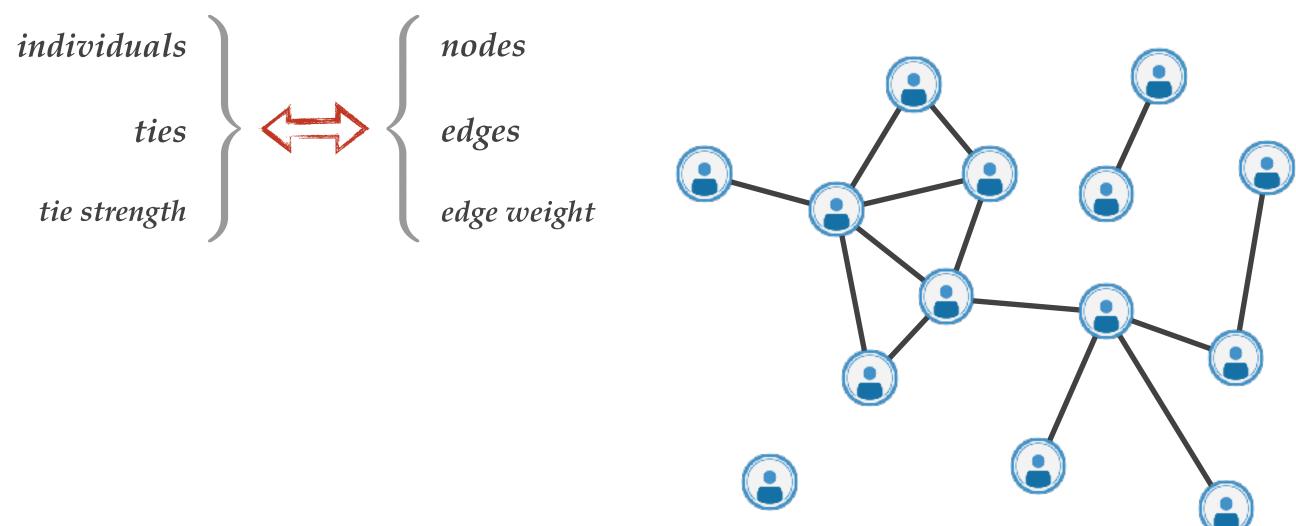
- **♦** Social Networks
- **♦** Sensor Networks
- ◆ Biological Networks
- **→ Collaborative** Networks





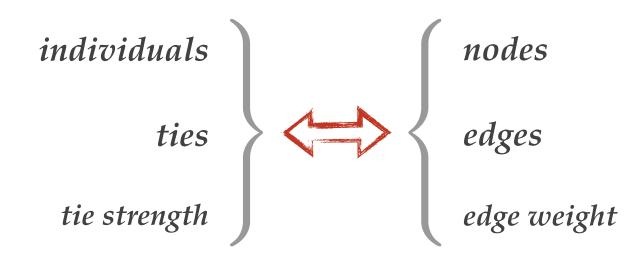


A network can be represented by a graph G=(V, E) such that:



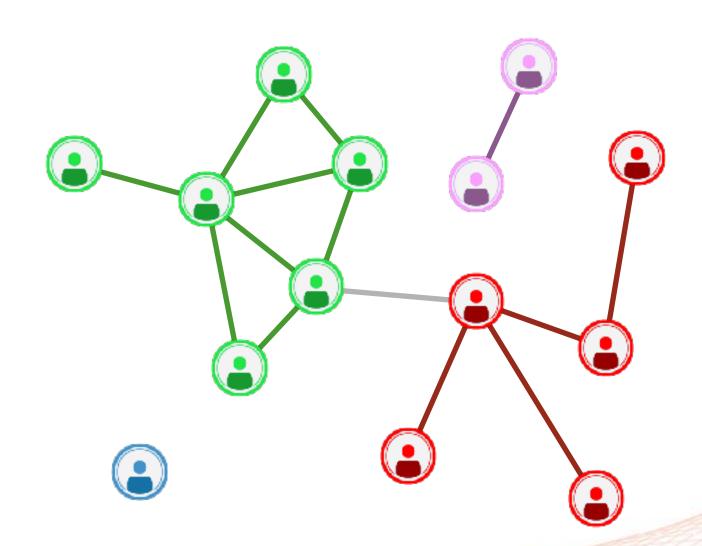


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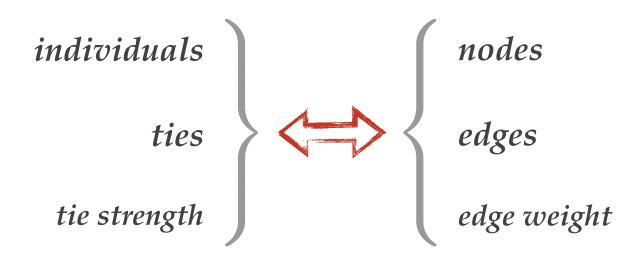
### **Network Analysis:**

\* Retrieval of **global** structure



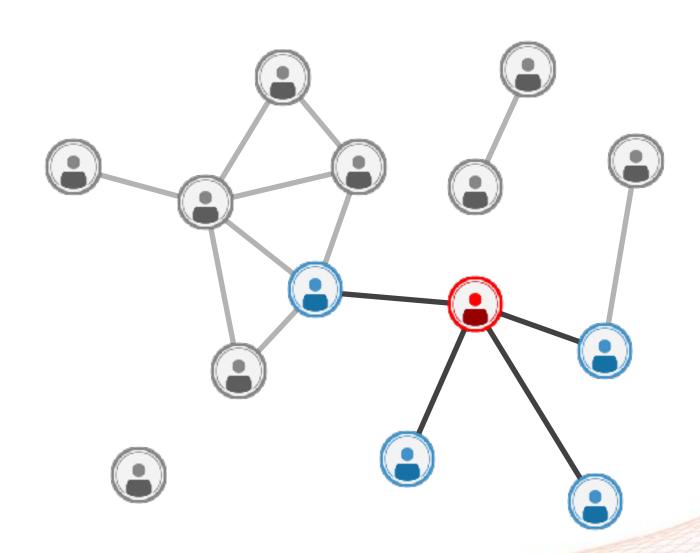


A network can be represented by a graph G=(V, E) such that:



### **Network Analysis:**

- \* Retrieval of **global** structure
- **→** *Local* study of each node





## Main Goal

### Propose a **general method** for

- performing global and local analyses
- interactively visualizing network structure according to different parameters in a single view
- comparing and characterize different networks

**Key Idea:** 

Adopt a *persistence-like* approach to *clique community* decomposition



### Outline

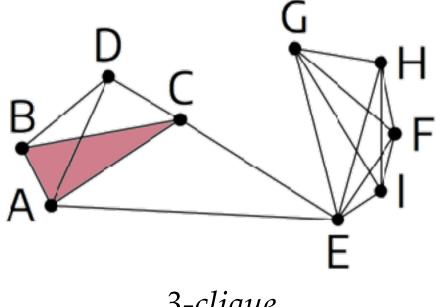
- Clique Communities
- **+** Clique Community Persistence
- Single Network Analysis
  - \* Interactive Visualization Tool based on Nested Graphs
- Network Comparison
  - \* **Distance** based on Persistence Indicator Functions
  - \* Clique Community Centrality Measure
- Conclusions and Future Developments



Given a network G=(V, E),

*k*-clique:

A complete subgraph of *k* vertices of *G* 



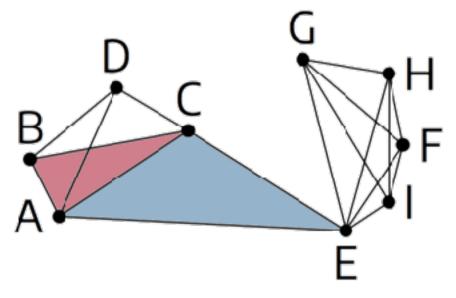
3-clique



Given a network G=(V, E),

*k*-clique:

A complete subgraph of *k* vertices of *G* 



3-adjacent

*k*-adjacency:

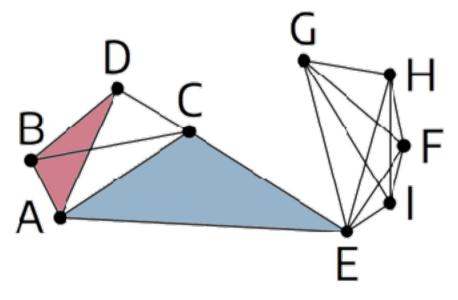
Two *k*-cliques are *k*-adjacent if they share *k*-1 nodes



Given a network G=(V, E),

*k*-clique:

A complete subgraph of *k* vertices of *G* 



non 3-adjacent

*k*-adjacency:

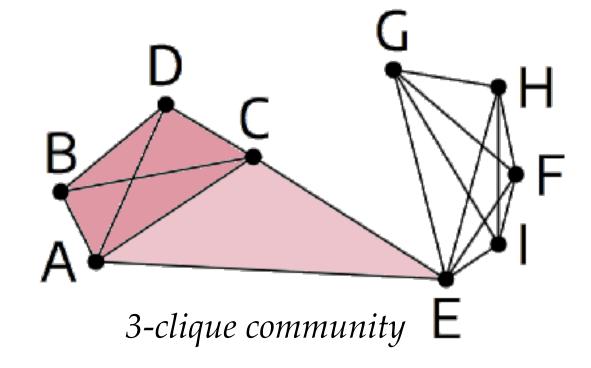
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Given a network G=(V, E),

*k*-clique Community:

**Maximal union** of *k*-cliques *pairwise connected* by a *sequence of k-adjacent cliques* 

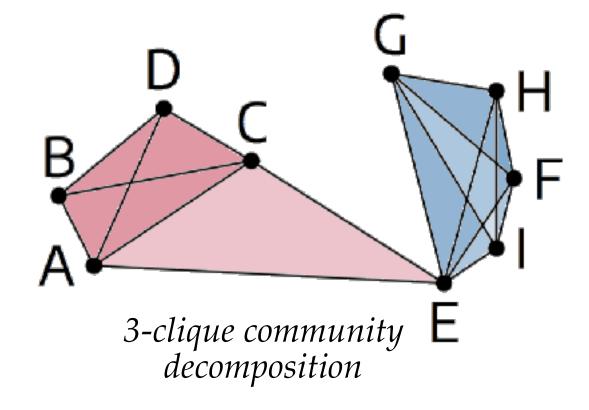




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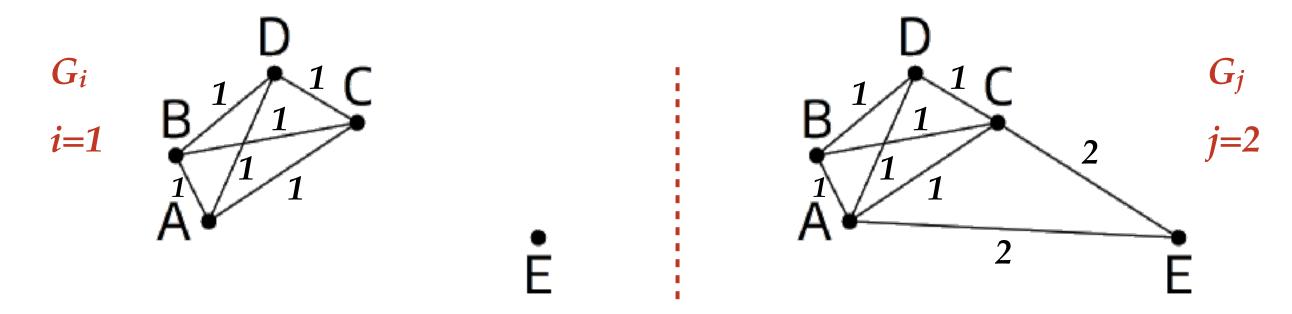
### *k*-clique Community Decomposition:

The **partition** of the *k*-cliques of *G* induced by the *k*-clique communities



Clique Communities & Weighted Networks:

Given a weighted network G and two threshold values i < j,

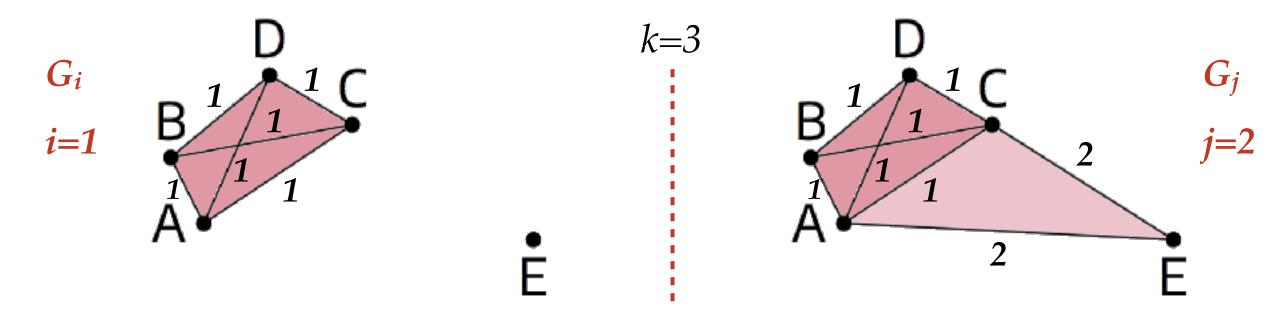


 $G_i$  is contained in  $G_i$ 



Clique Communities & Weighted Networks:

Given a weighted network G and two threshold values i < j,



Each k-clique community of  $G_i$  is **contained** in *exactly one* k-clique community of  $G_j$ 

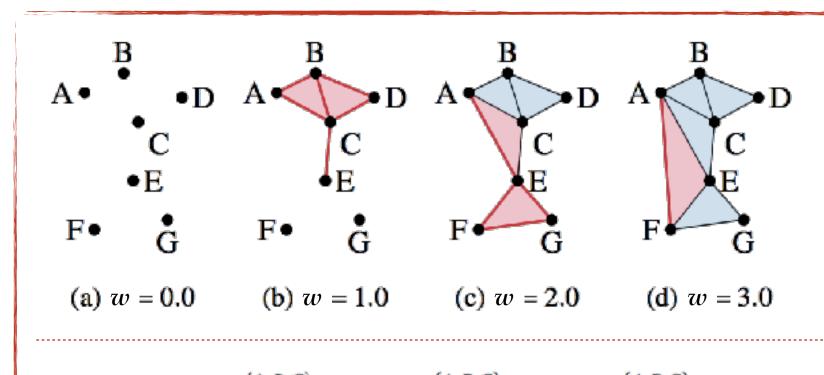


Fixing a value for *k* and varying the edge-weight threshold:

k = 3

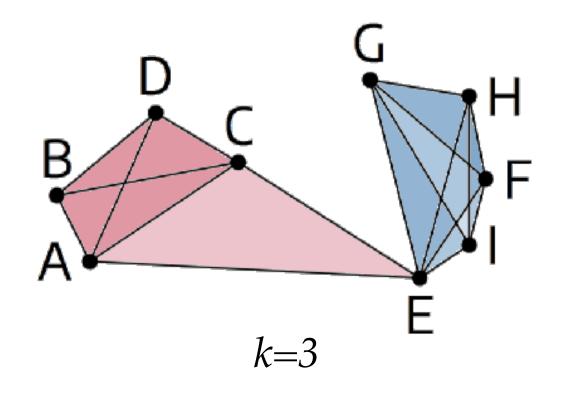
The evolution of k-clique communities of G can be tracked by:

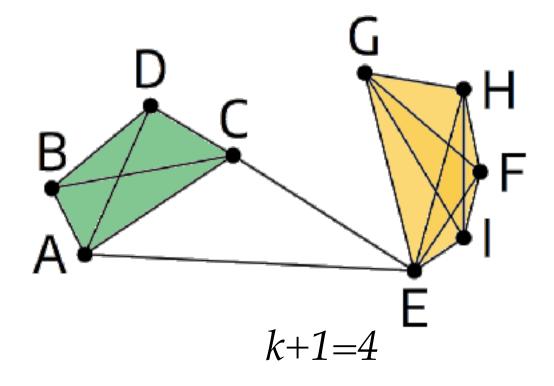
- building a sequence of *k*-dual graphs:
  - \*  $vertices \Leftrightarrow k$ -cliques
  - \* edges 
     \* adjacent k-cliques
- tracking the connected components of the sequence of k-dual graphs





Clique Communities & Multiple *k* Values:





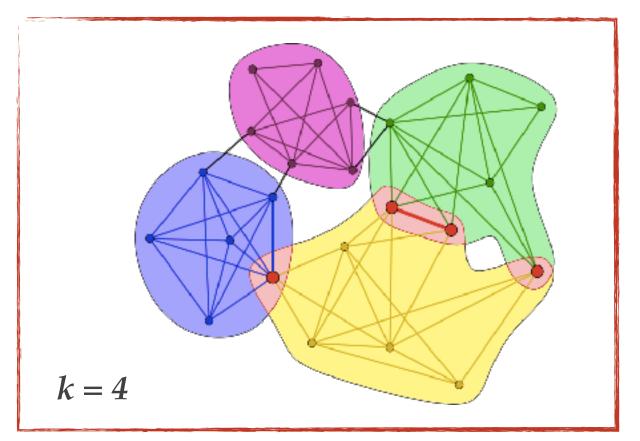
Each (k+1)-clique community of G is **contained** in *exactly one* k-clique community of G



### **Pros & Cons:**



- \* Reveal Highly Connected Communities
- \* Allow Overlaps
- \* Display a (double) Hierarchical Structure





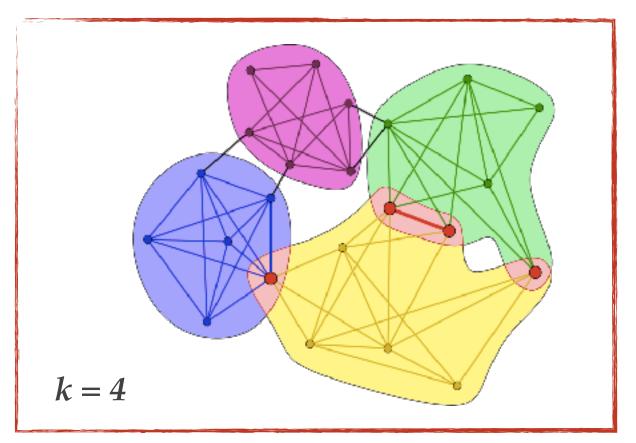
Focusing on a single value for k and weight threshold w provides just a partial view of the network structure



#### **Pros & Cons:**



- \* Reveal Highly Connected Communities
- \* Allow Overlaps
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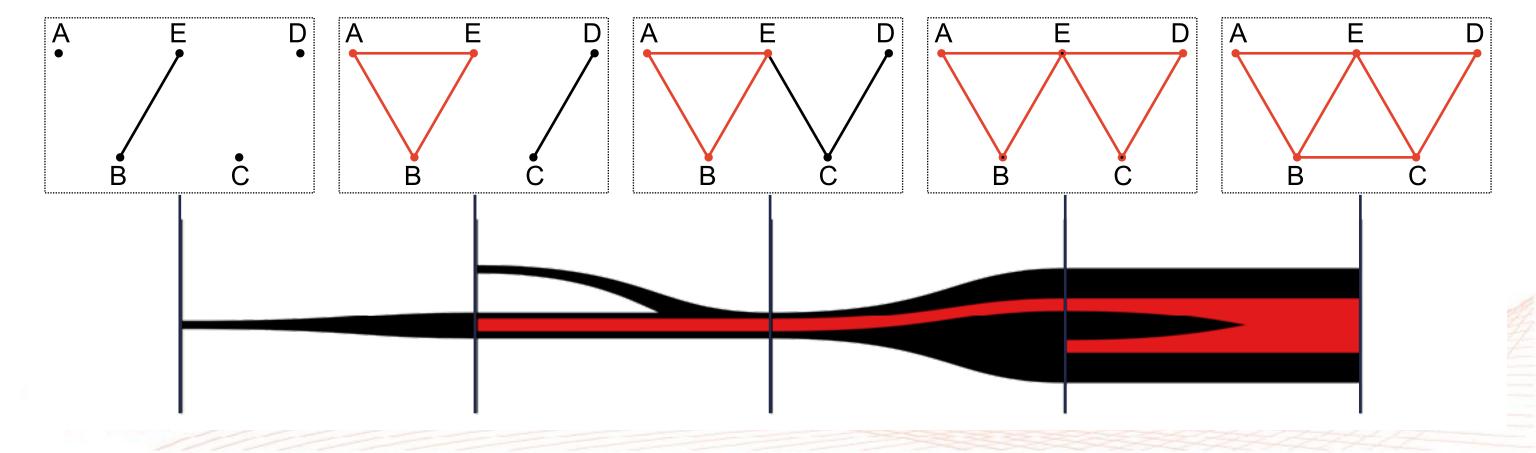
Develop a tool for simultaneously dealing with multiple k and w values



**Nested Graph:** 

[Lukasczyk et al., EuroVis 2017]

- Originally defined for connected components in scalar fields
- → Illustrates *evolutions across two parameters*



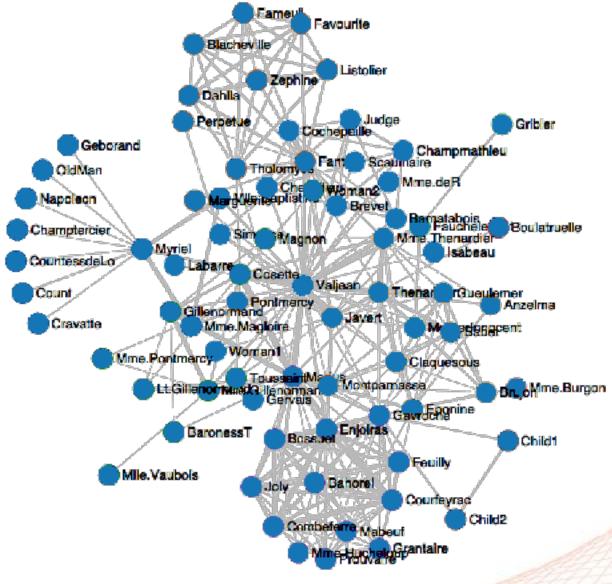
### "Les Misérables" Network:

- Co-occurrence network between the characters in Victor Hugo's novel "Les Misérables"
  - 77 nodes
  - 254 edges

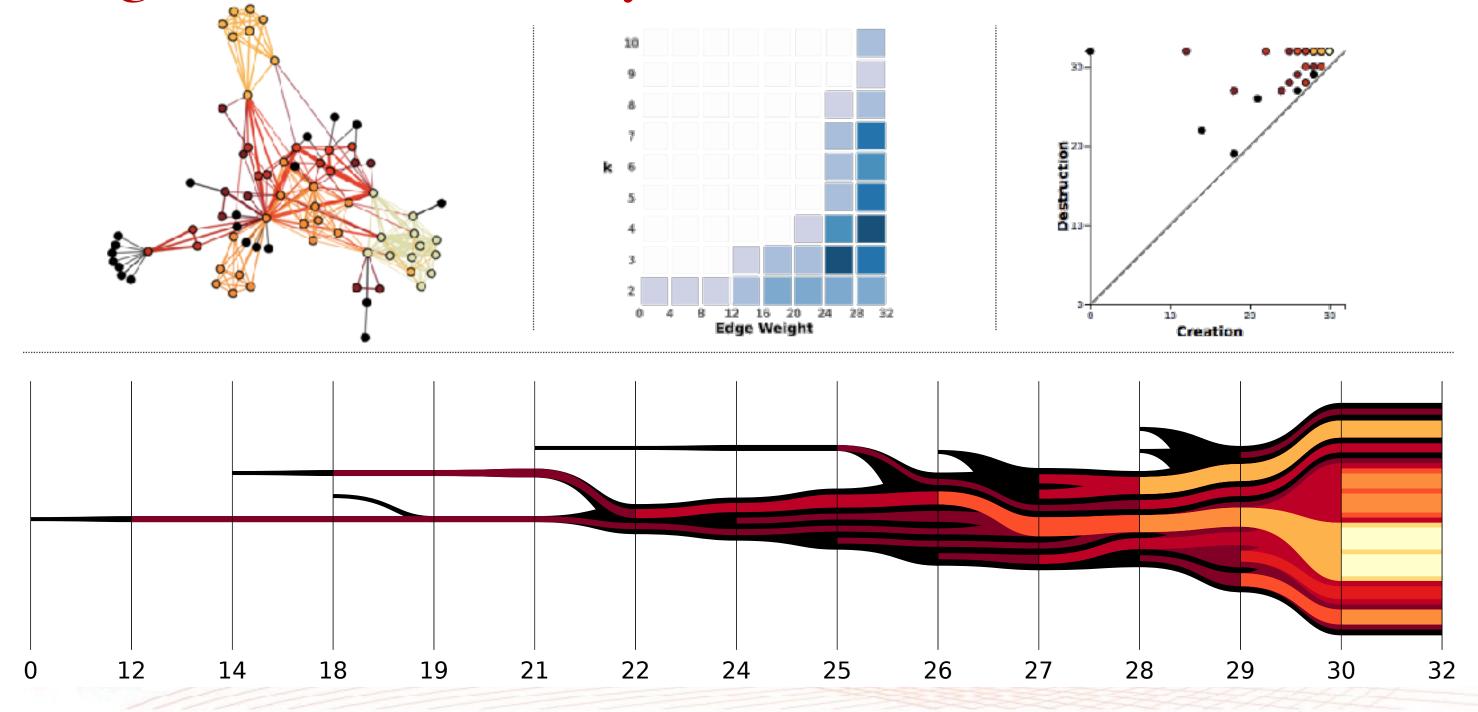
inverse of the

→ edge weight 
→ number of co-occurrences

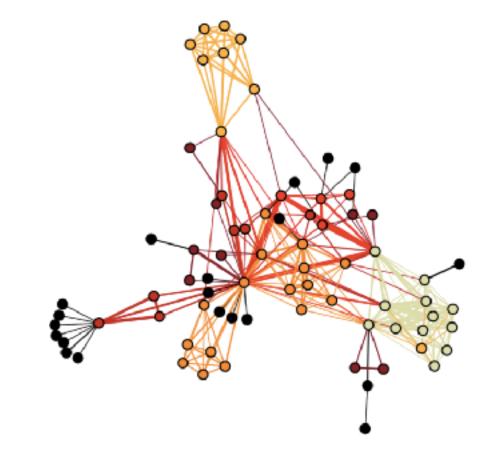
between two characters

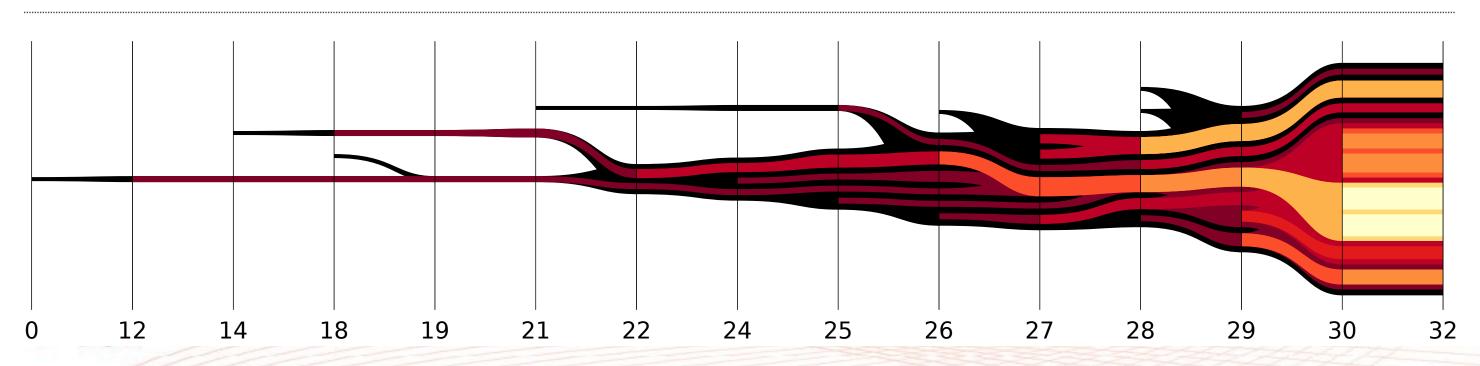






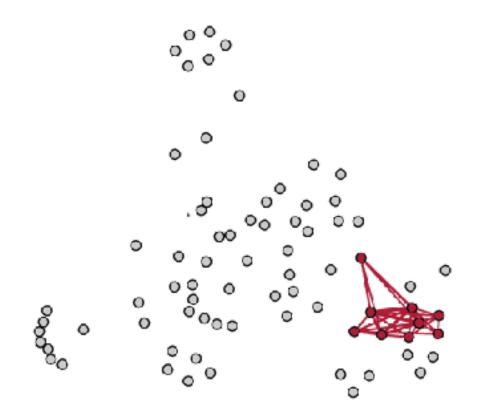
Nested-based visualization tool allows the user for



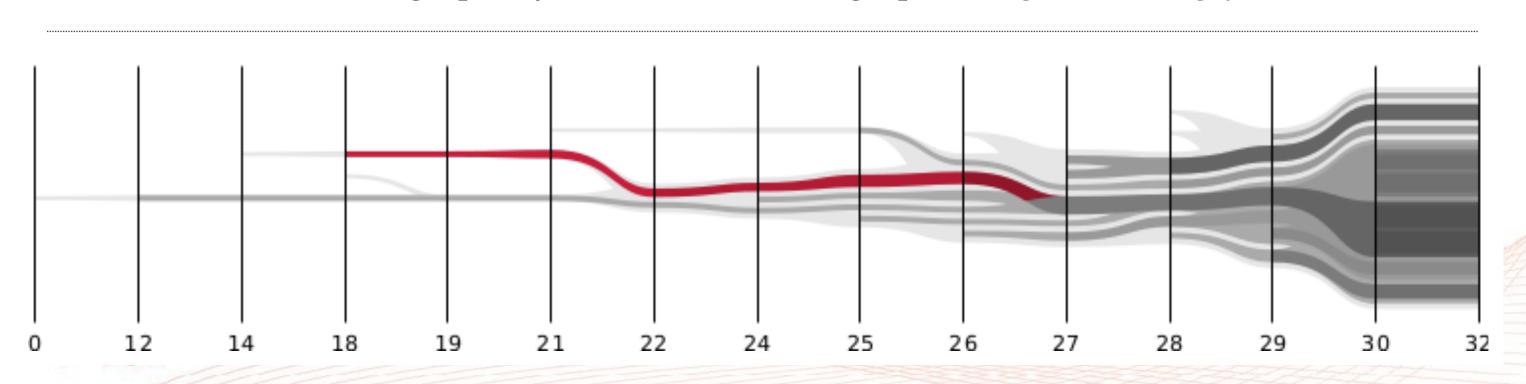


Nested-based visualization tool allows the user for

- \* focusing on the evolution of a specific clique community
- \* selecting and interactivity exploring different edge weights and clique degrees

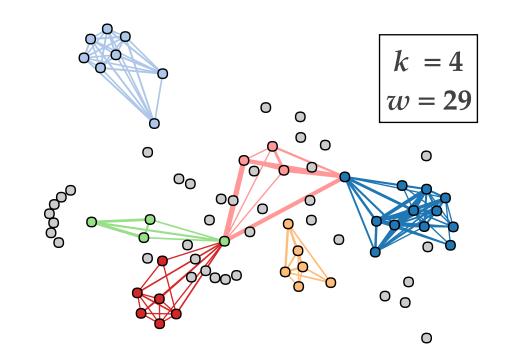


while the force-directed graph layout and the nested graph *change accordingly* 

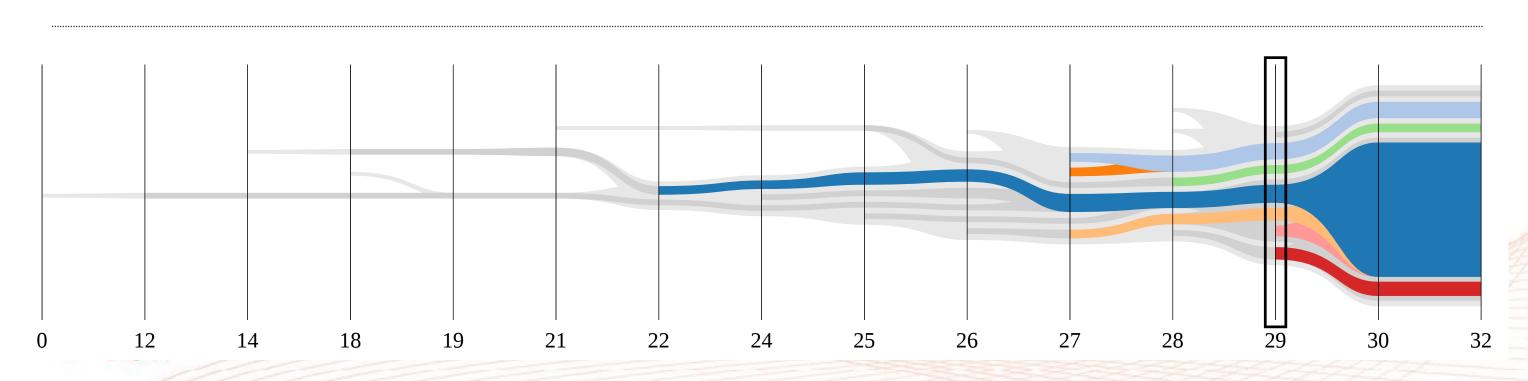


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while the force-directed graph layout and the nested graph *change accordingly* 

### **Intuitively:**

edge-weight variation  $\Leftrightarrow$  reveal the core part of a communitiy clique-degree variation  $\Leftrightarrow$  analyze community according to different granularities



Clique community persistence enables the introduction of *comparison measures*:

- \* Persistence indicator function (PIF)
- → PIF-based distance
- \* Clique community centrality measure



### **Persistence Indicator Function:**

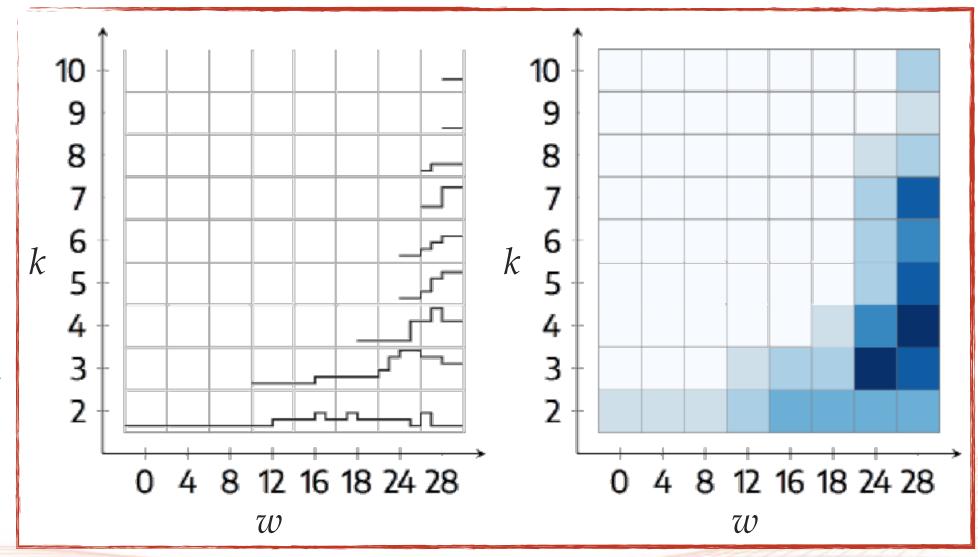
Defined as the function

$$f_k:\mathbb{R}\longrightarrow\mathbb{N}$$

assigning







PIF-based Distance:

Given two persistence indicator functions f and g,

**PIF-based distance** is defined to be the  $L_p$  distance between f and g:

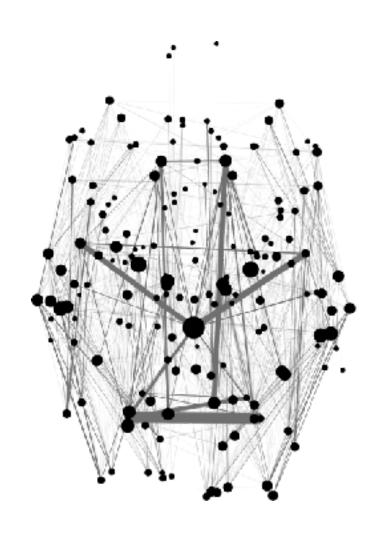
$$dist(f,g) = \left( \int_{\mathbb{R}} |f(x) - g(x)|^p dx \right)^{\frac{1}{p}}$$

- Quantifies dissimilarities between PIFs
- ◆ Easier to be computed than Wasserstein and bottleneck distances
- Highly correlated to Wasserstein distance



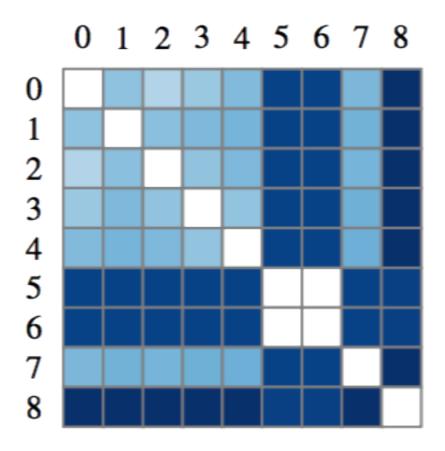
### **Brain Networks:**

- \* Biological networks representing variants of human brain connectivity
  - 9 instances considered
- → nodes 
   ⇔ brain areas
- ◆ edges ⇔ fibers connecting different areas





### **Brain Networks:**



Variant	Density	Diam. (weighted)	Avg. degree (weighted)
0	0.125	4 (60.0)	21.21 (2300.3)
1	0.124	4 (60.0)	21.06 (2296.0)
2	0.124	4 (60.0)	21.13 (2295.2)
3	0.124	4 (60.0)	21.16 (2282.0)
4	0.124	4 (60.0)	21.15 (2279.3)
5	0.125	4 (60.0)	21.19 (2264.0)
6	0.125	4 (60.0)	21.19 (2264.0)
7	0.124	4 (60.0)	21.16 (2279.6)
8	0.125	4 (60.0)	21.20 (2257.5)

PIF-based distance reveals differences between networks that common graph measures are incapable of detecting



### **Clique Community Centrality:**

Clique community centrality of a node v is defined as

$$centrality(v) = \sum_{C \ni v} pers(C)$$

#### where

- ◆ C is any clique community containing v
- → pers(C) is the "lifespan" of C

Nodes belonging to high-persistence communities are identified as relevant



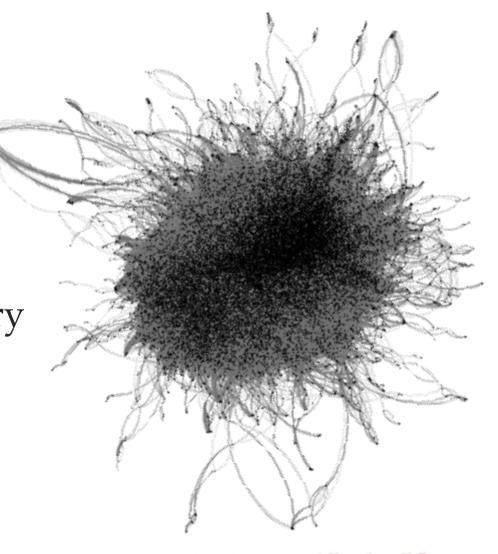
### Condensed matter collaboration:

- Collaborative networks describing scientist coauthorship of the "Condensed Matter" arXiv category
  - \* 3 snapshots in time considered (1999, 2003, 2005)
- Network sizes:
  - \* 16K 40K nodes
  - ❖ 47K 175K edges

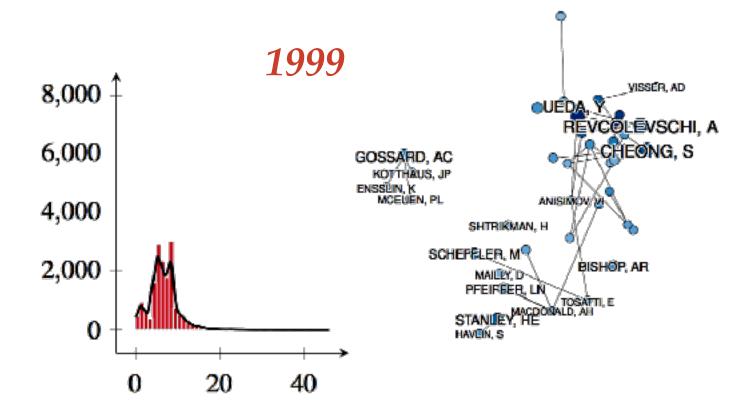


- evaluating the evolution of network connectivity
- filtering away the less relevant nodes

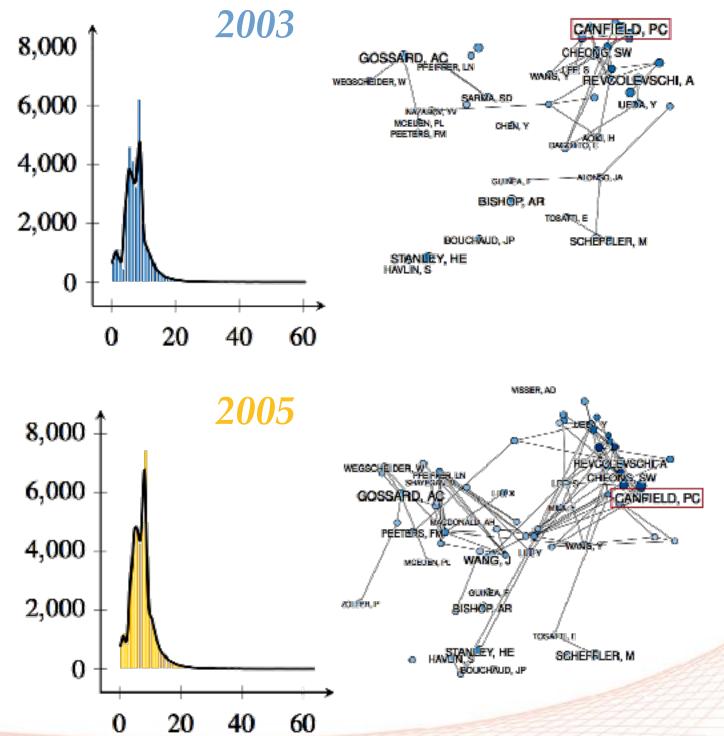




### Condensed matter collaboration:



Density estimates of the clique community centrality values



### Conclusions

### **To Summarize:**

In our work, we propose a *new method* based on *clique community persistence* for analyzing *global* and *local properties* of complex networks

This method leads to the design and the introduction of

- an interactive visualization tool based on nested graphs
- new criteria and distances for network comparison

### **Future Developments:**

- Extend to **time-varying** non-weighted networks
- ◆ Improve clique community computation

# Thank you

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