



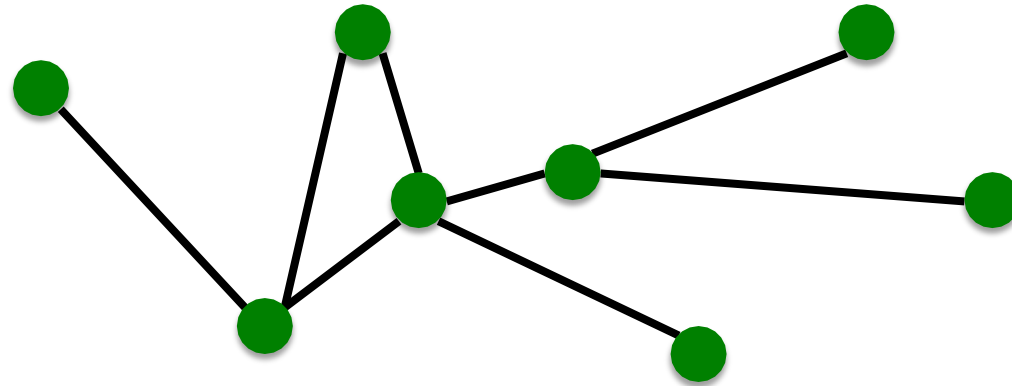
# Graph Computing

**Xiaoyang Wang**

## My Experience Survey

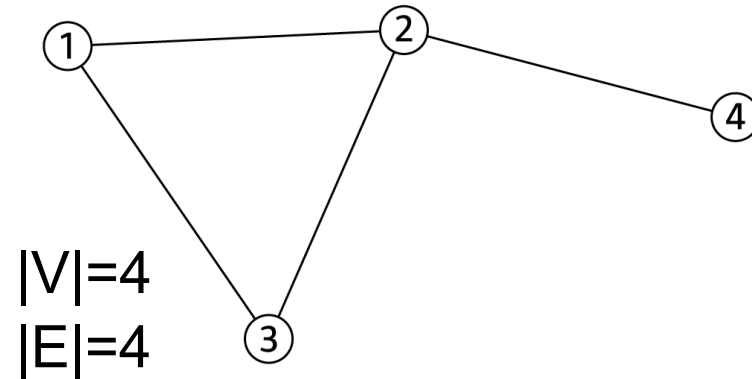
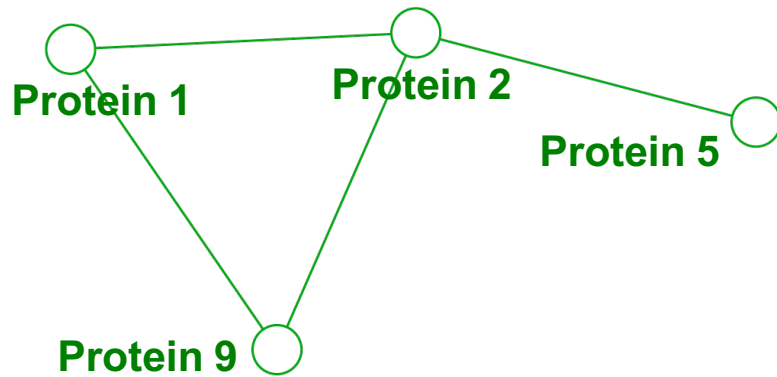
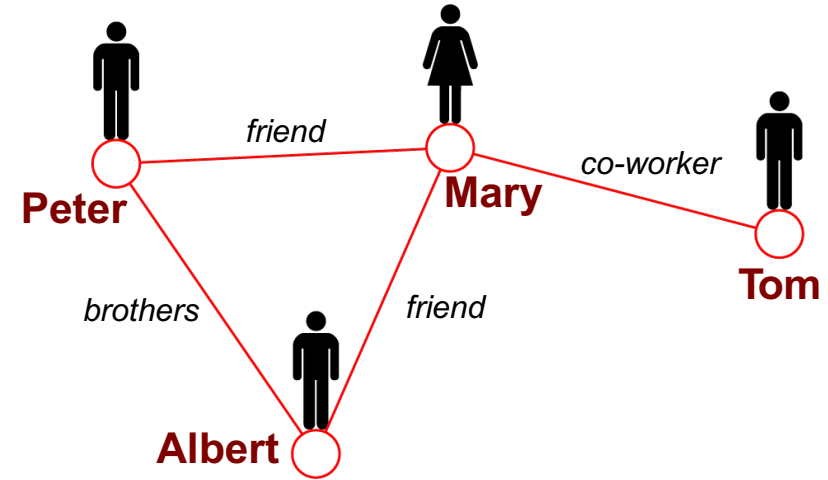
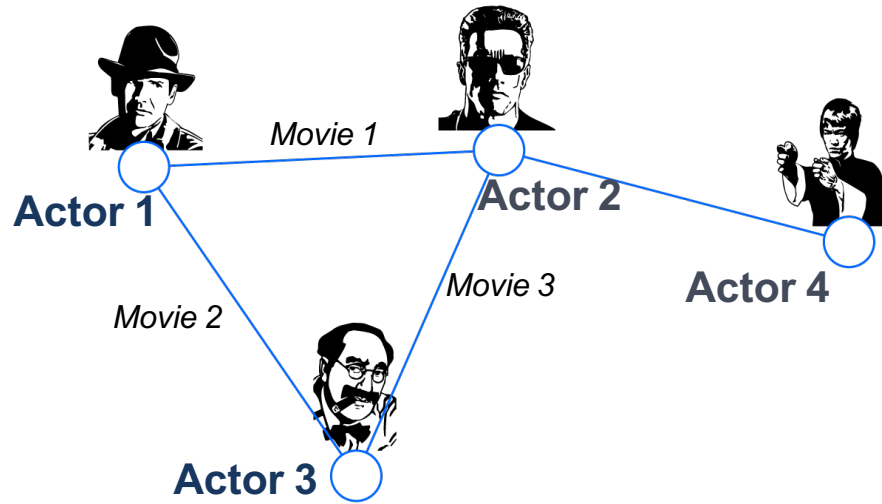
---

- The UNSW My Experience survey still open, participation is highly encouraged.
- *“Please participate in the my Experience Survey and take the opportunity to share your constructive thoughts on your 2022 learning experience.”*
- *Your contributions help your teachers and shape the future of education at UNSW.”*
- More information: <https://www.student.unsw.edu.au/myexperience>



- **Objects:** nodes, vertices  $V$
- **Interactions:** links, edges  $E$
- **Systems:** networks, graphs  $G(V, E)$

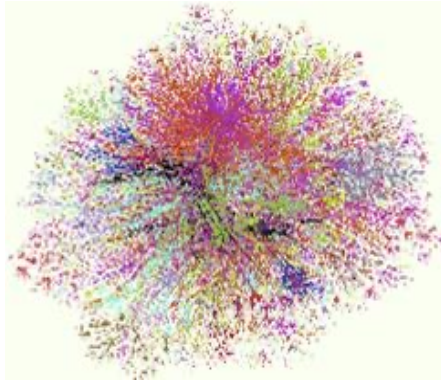
# Graph is a common language





# Graph is everywhere

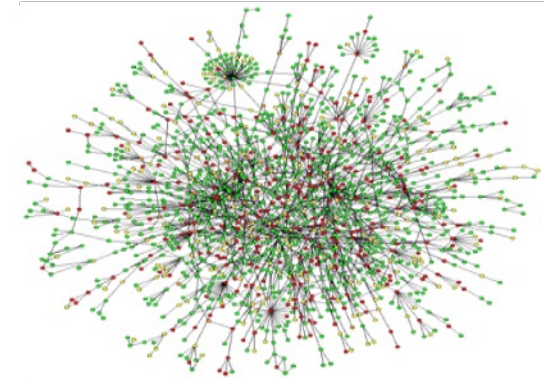
Common model across different fields:



Web Graph



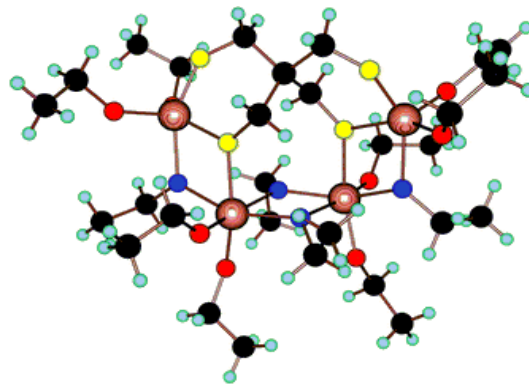
Social Network



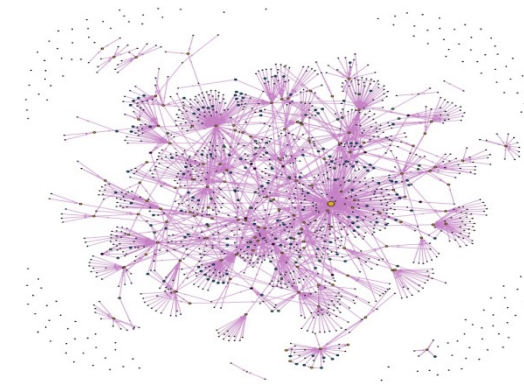
Protein Interaction Network



Road Network



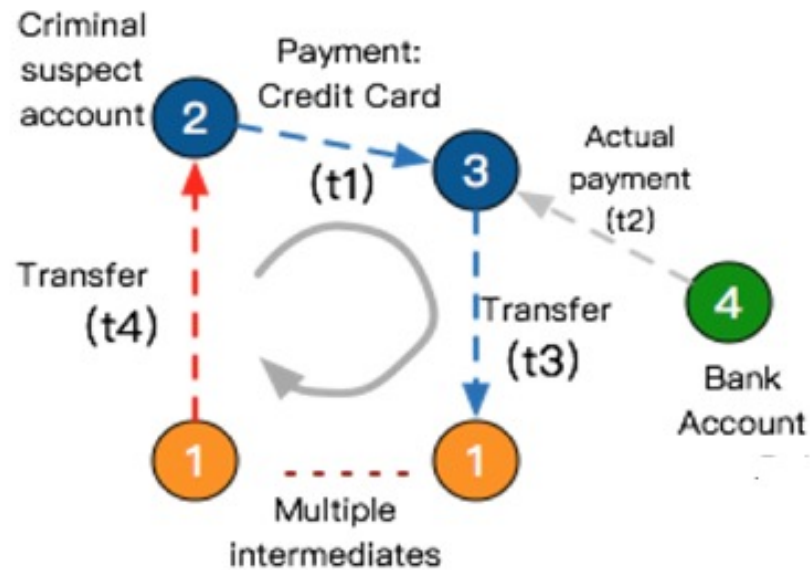
Chemical Compound



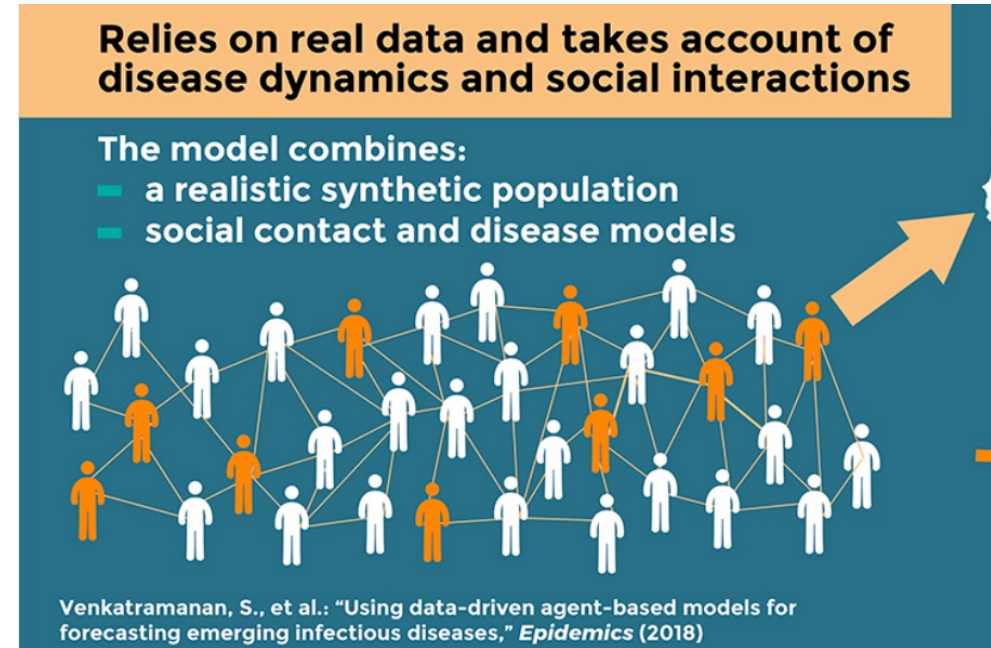
Ontology Graph

# Why graphs

- Networks / graphs are everywhere, and we live in a highly-connected world.
- In many applications, we need analyze in the context of networks, not just individuals.



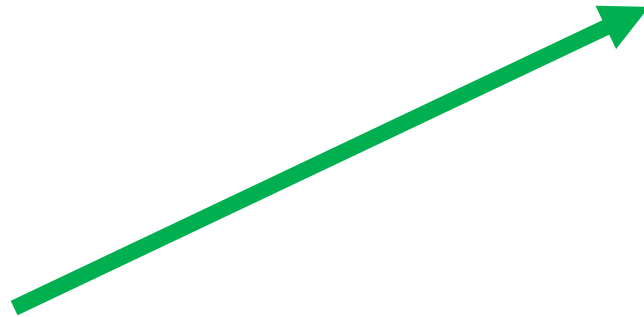
Money laundering detection



Predict the spread of information

# Why graphs

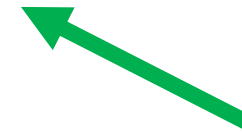
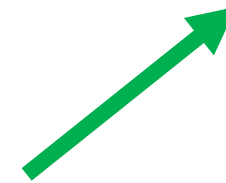
- Event Driven Investment





# Why graphs

- Can Computer Do It Automatically



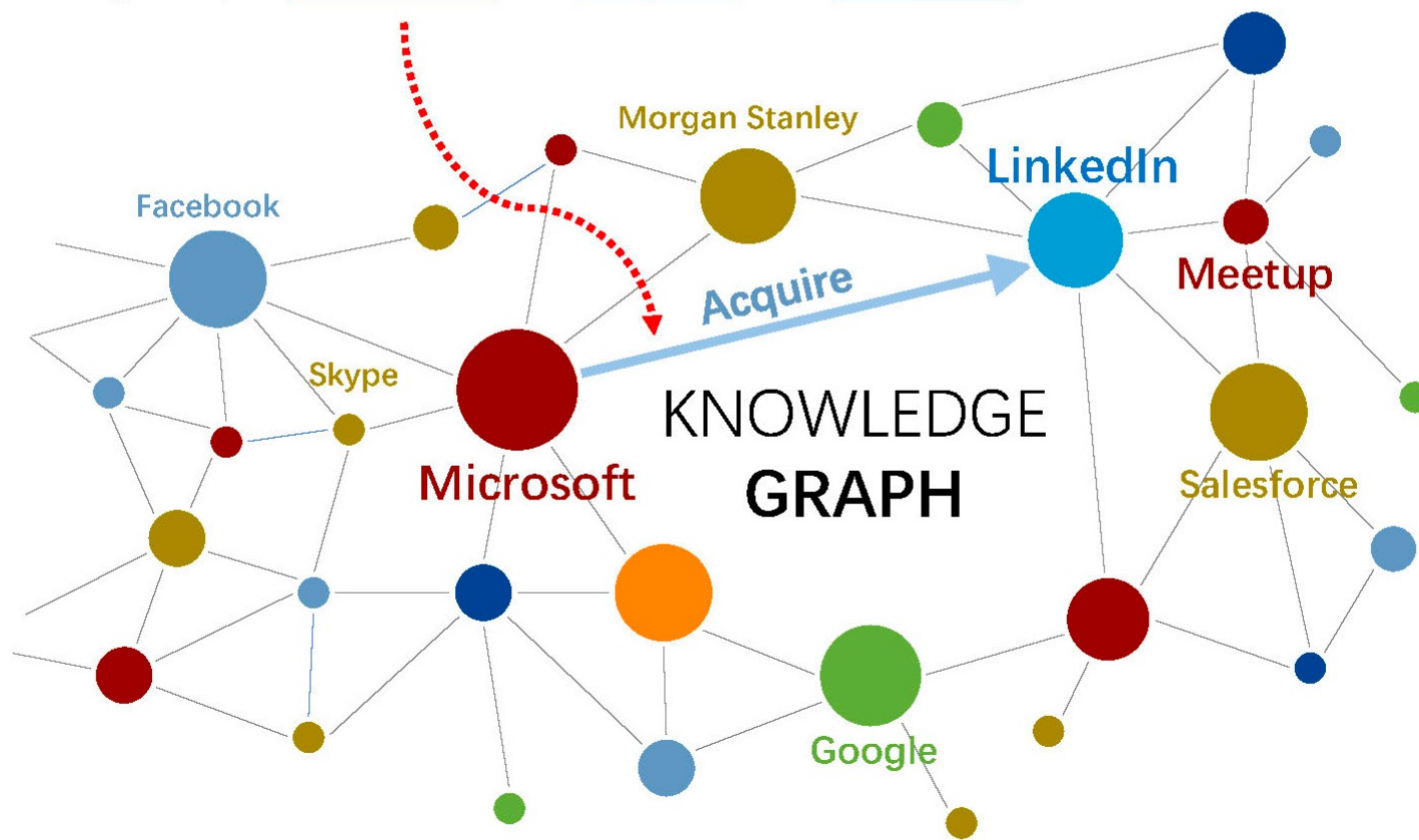
- Can We Do Better
- The financial market reaction of events is also influenced by the lead-lag effect, which is driven by internal relationships.
- For example, the event “Microsoft buys LinkedIn” will also influence the stock movements of upstream and downstream firms and competitors, such as Salesforce and Meetup.
- An event on a raw material will also impact various downstream products in different propagation speed over industrial chains, such as current energy crisis and cold weather.

# 10 Why graphs

- How **News Text:** Microsoft officially closes its \$26.2B acquisition of LinkedIn



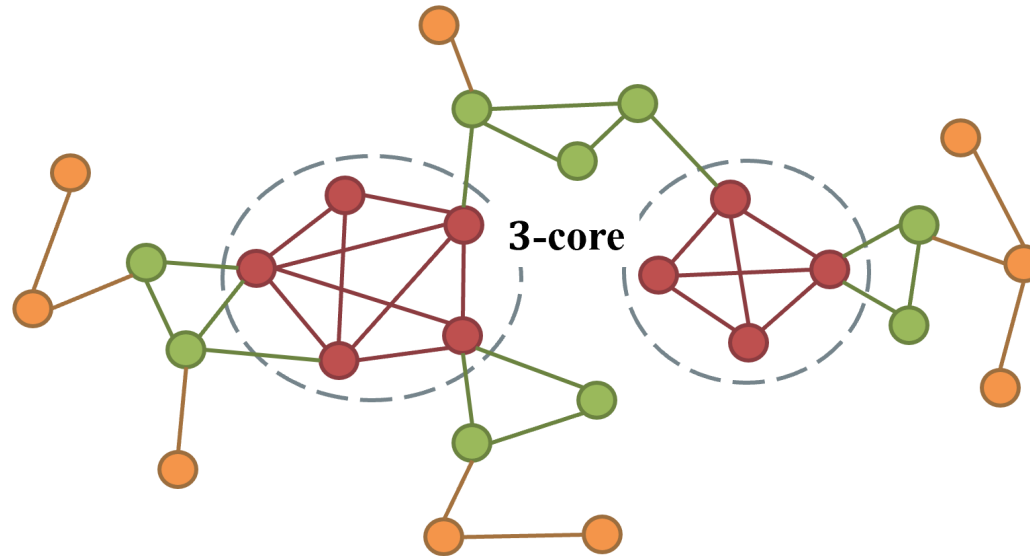
**Event Tuple:** (A=**Microsoft**, P=**acquire**, O=**LinkedIn**)



# Cohesive Subgraphs

---

- Clique,  $k$ -core,  $k$ -truss,  $k$ -ECC,  $k$ -VCC, .....
- In some models, a value  $k$  can be used to capture the cohesiveness of the subgraph.

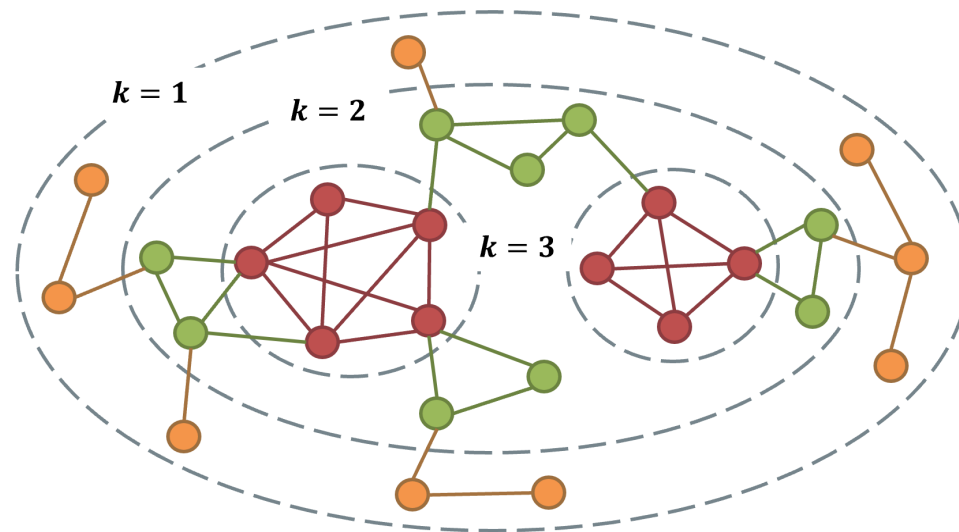


# Hierarchical Graph Decomposition

- Varying the possible  $k$  values (say  $k_1, k_2, \dots, k_h$ ) on the graph  $G$



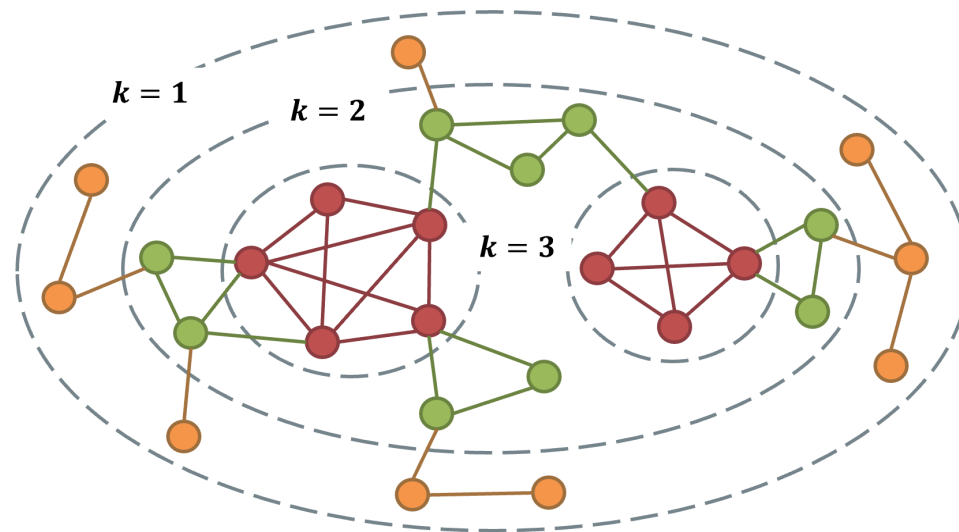
- $h$  subgraphs  $\{S_1, S_2, \dots, S_h\}$  with  $S_i \supseteq S_j$  for any  $i < j$ , where  $S_1 = G$  and  $S_i$  is a subgraph containing a set of connected components.





# Hierarchical Graph Decomposition

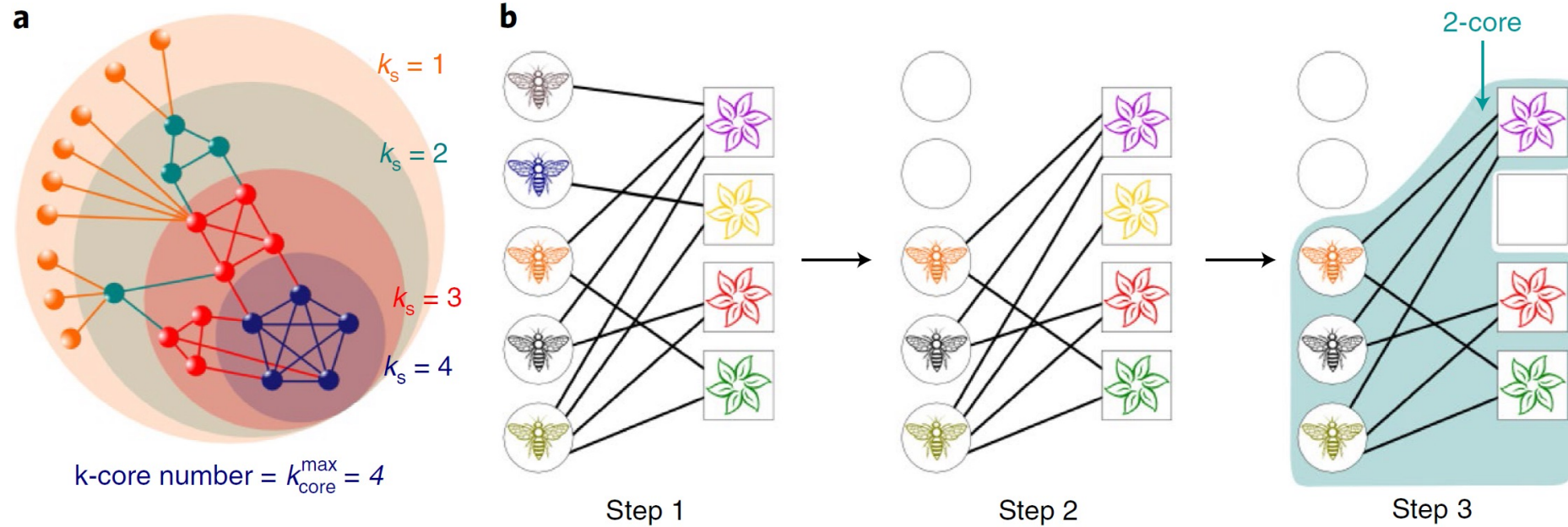
- Decomposition number of a vertex:  $dn(v) = i, v \in S_i$  and  $v \notin S_{i+1}$
- $k$ -core,  $k$ -truss,  $k$ -ECC, .....



- Network modeling and analysis
- Network Visualization
- Reasoning the collapse of a network
- Prevent Network Unraveling
- Discovering Influential Nodes
- Community Discovery
- Anomaly Detection
- Protein function prediction
- .....

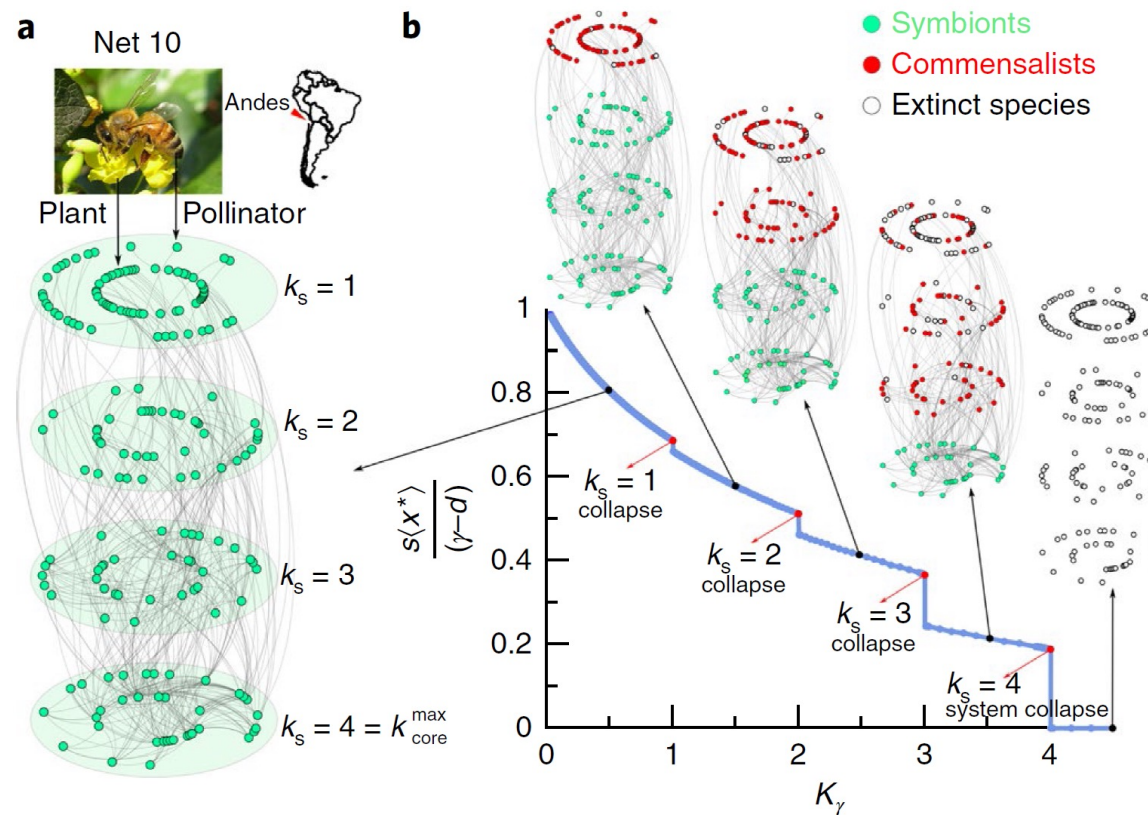
# 15 Application – Network Modeling and Analysis

Biology: a cohesive subgraph as a predictor of structural collapse in mutualistic ecosystems [Nature Physics 2018]



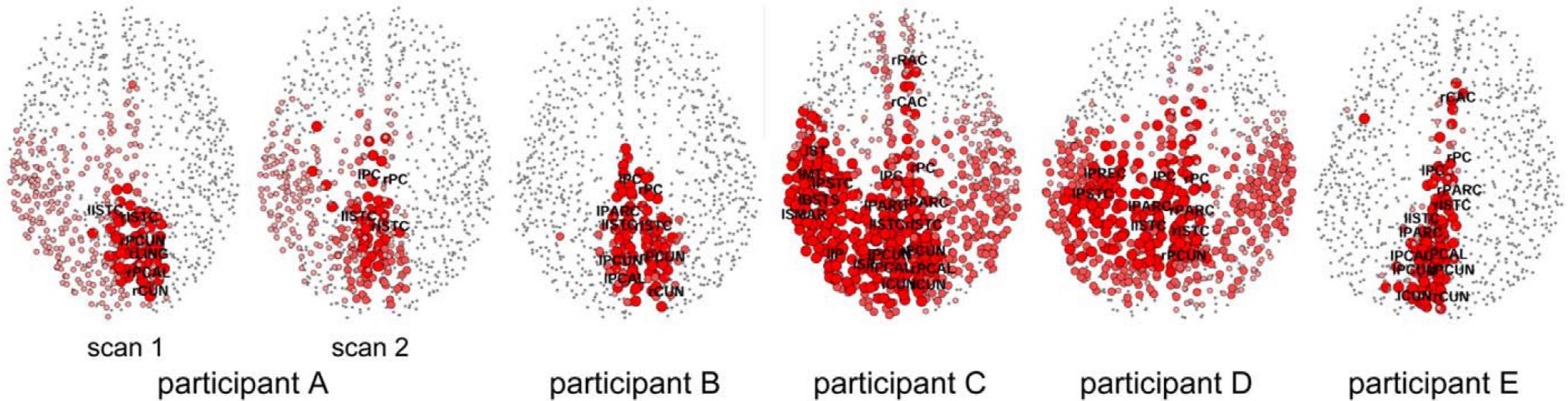
# 16 Application – Network Modeling and Analysis

Biology: the hierarchical decomposition reveals the tipping points of structural collapse in mutualistic ecosystems [Nature Physics 2018]



# 17 Application – Network Modeling and Analysis

Brain connectivity networks: mapping the Structural Core of Human Cerebral Cortex [PLoS Bio 2008]

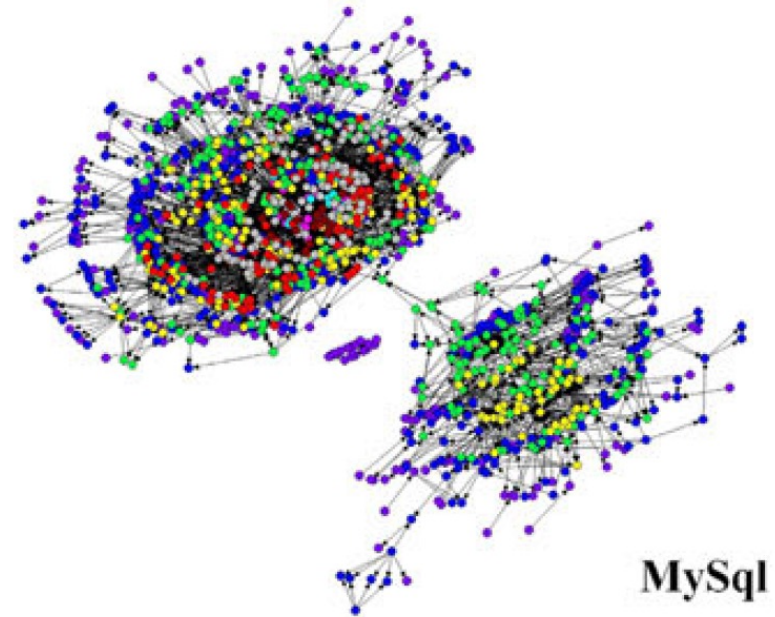
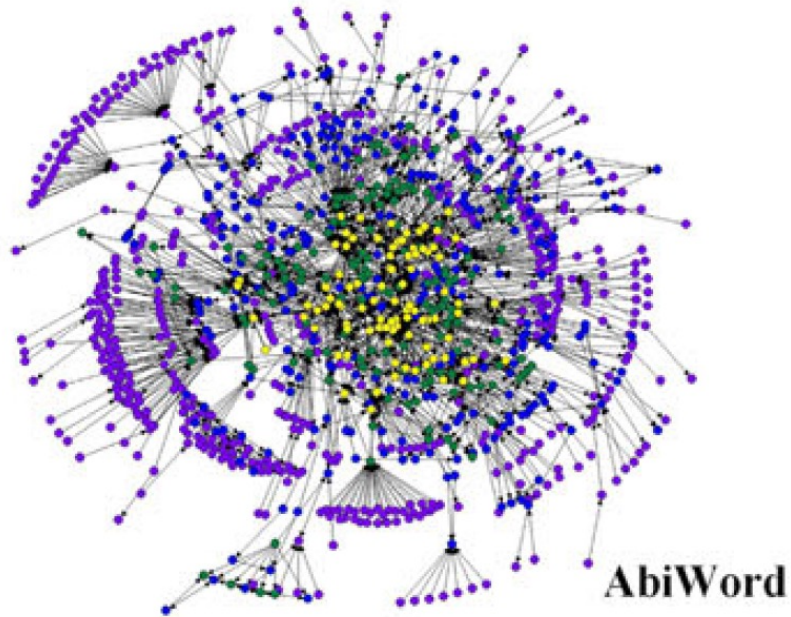




# 18 Application – Network Modeling and Analysis

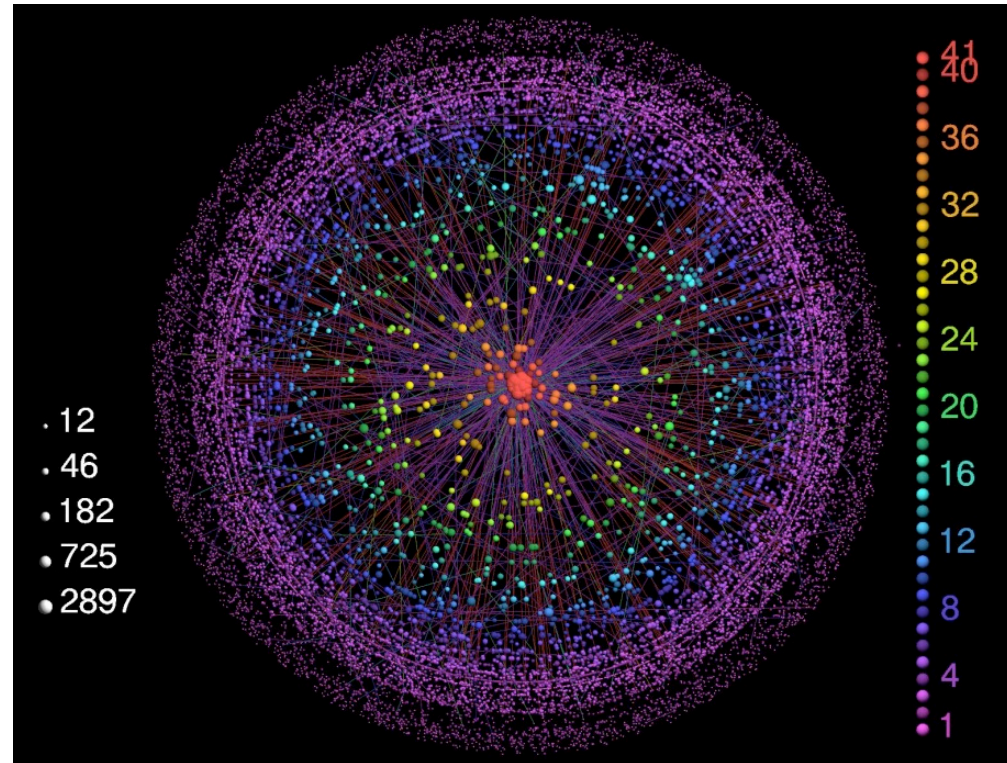
---

Software systems: analyzing the static structure of large-scale software systems  
[J Supercomput 2010]



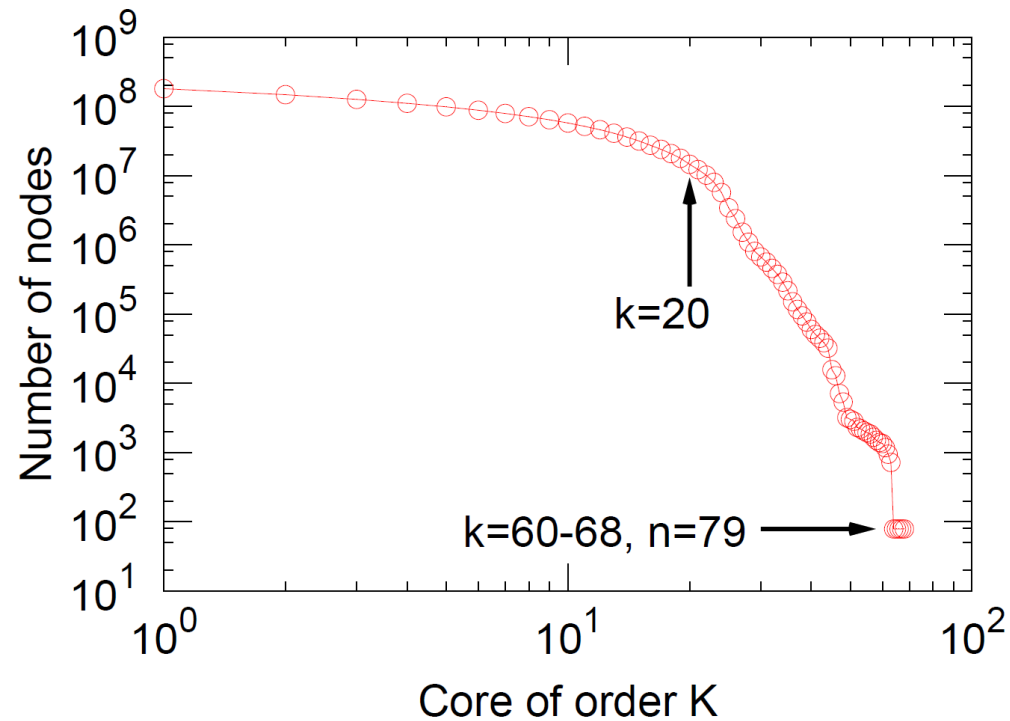
# 19 Application – Network Modeling and Analysis

Internet networks: modeling Internet topology using k-shell decomposition [PNAS 2007] [NHM 2008]



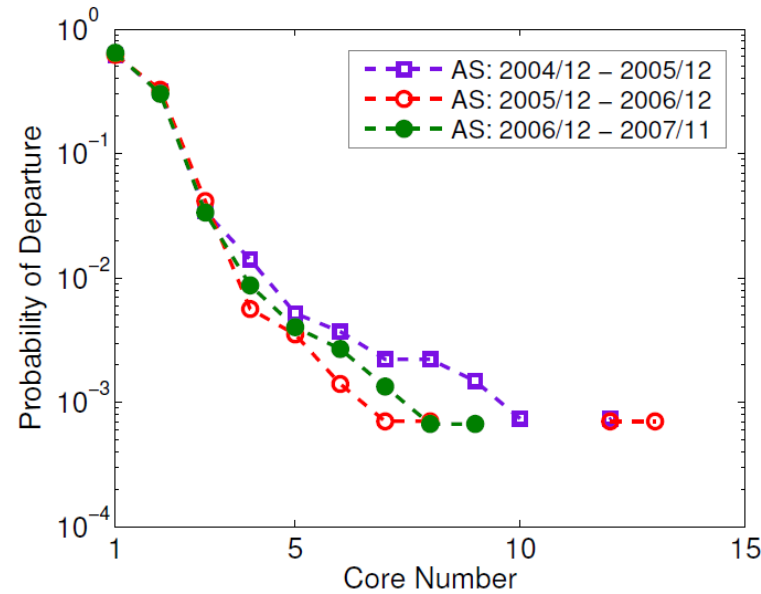
# 20 Application – Network Modeling and Analysis

Message networks: analysing the large instant-messaging network (Microsoft Messenger system) [WWW 2008]

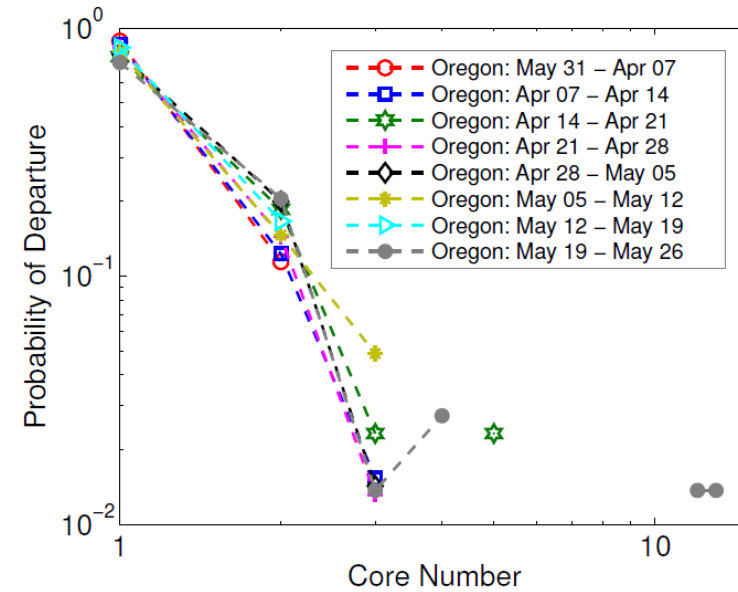




Social networks: modeling engagement dynamics in social graphs [CIKM 2013]  
[Social Networks 1983]



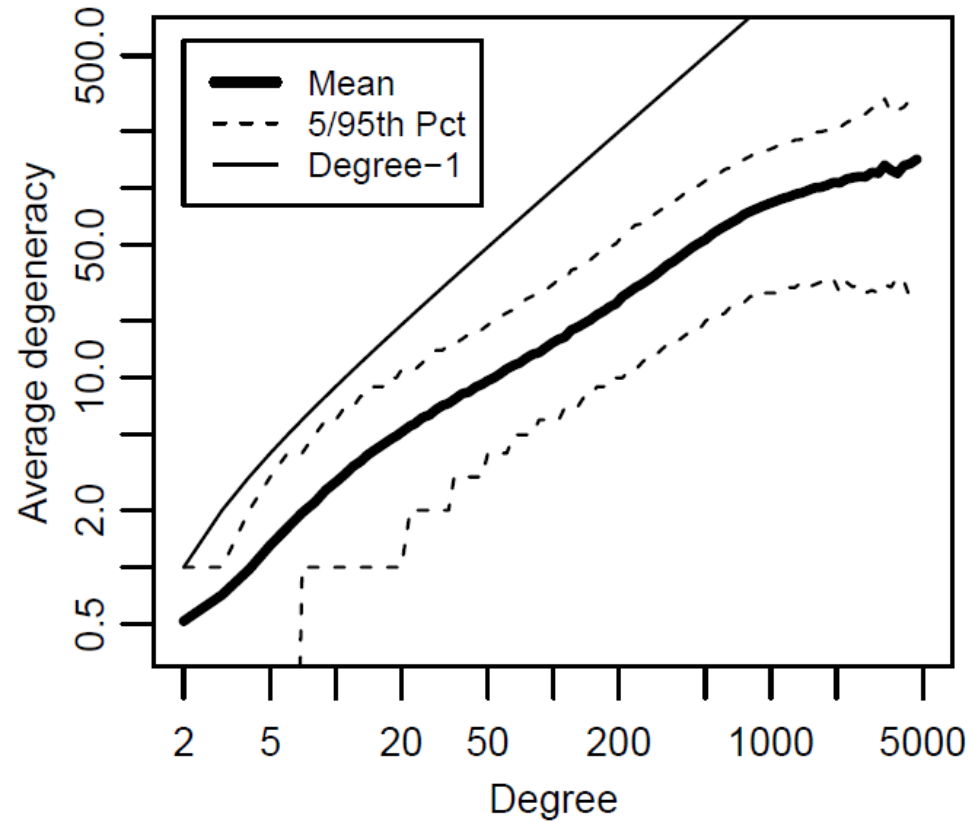
(a) CAIDA



(b) OREGON

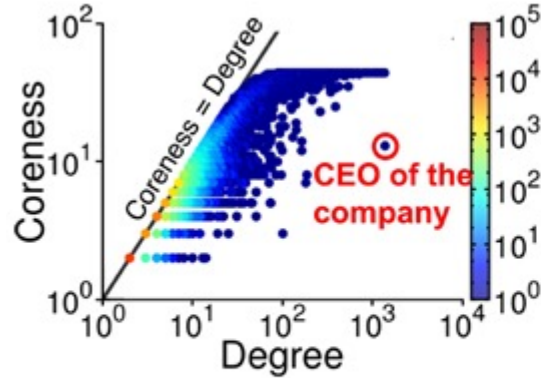
# 22 Application – Network Modeling and Analysis

Social networks: the anatomy of the Facebook social graph [Corr 2011]

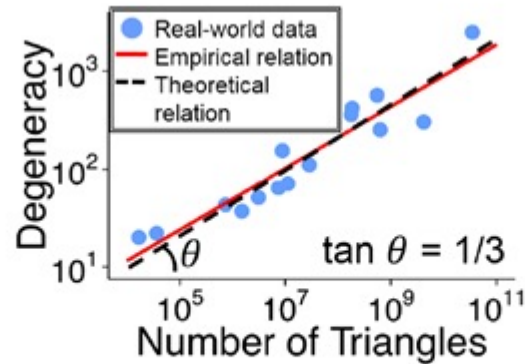


# 23 Application – Network Modeling and Analysis

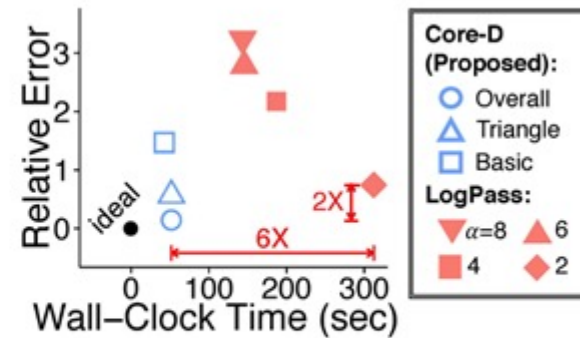
Complex networks: pattern and anomaly analysis using k-core analysis [ICDM 2016] [KAIS 2018]



(a) P1: MIRROR PATTERN  
A1: Anomaly Detection



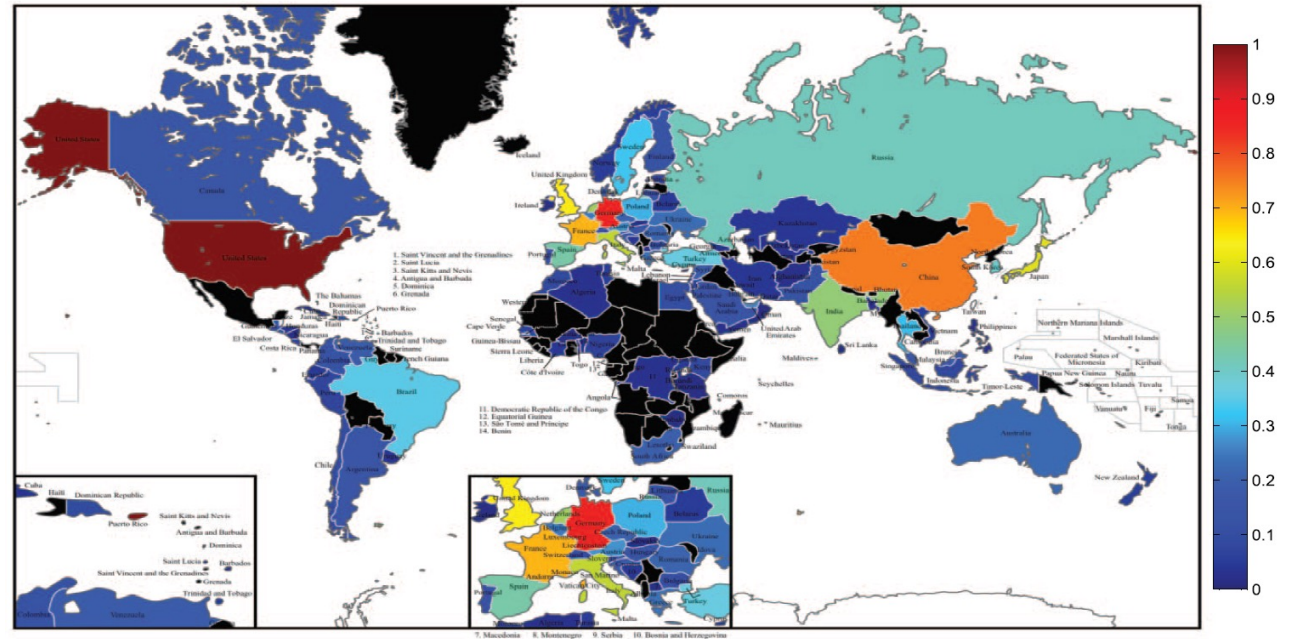
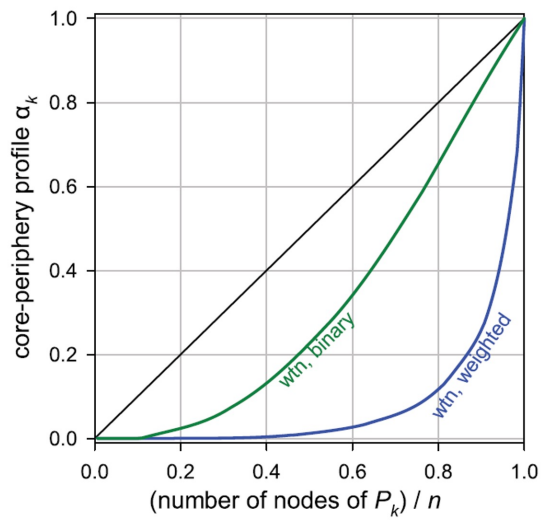
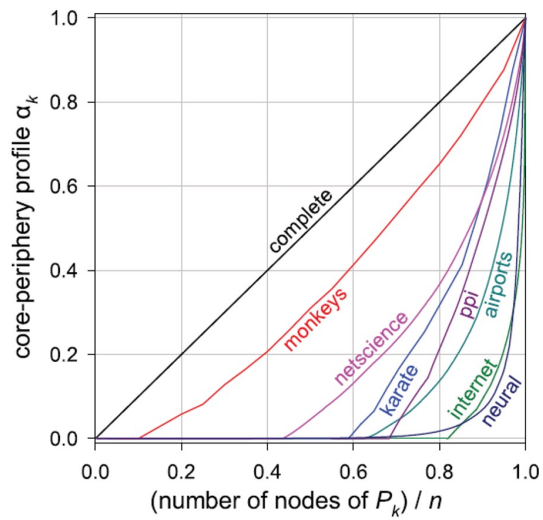
(b) P2: CORE-TRIANGLE PATTERN



(c) A2: CORE-D Algorithm

# 24 Application – Network Modeling and Analysis

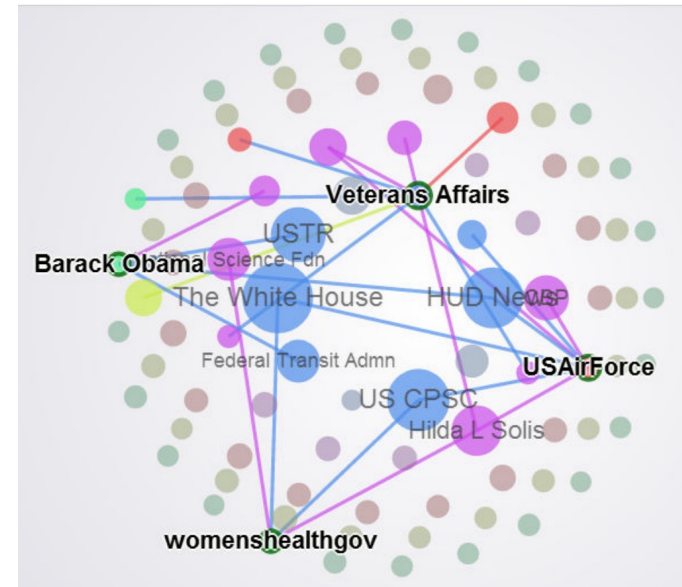
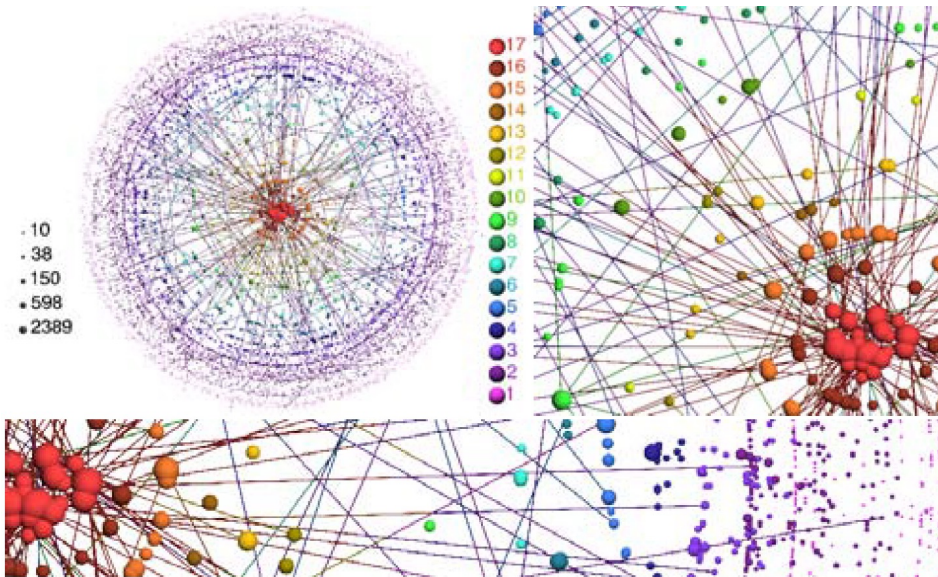
## Complex networks: pcore-periphery network structure [Scientific reports 2013]



world trade network

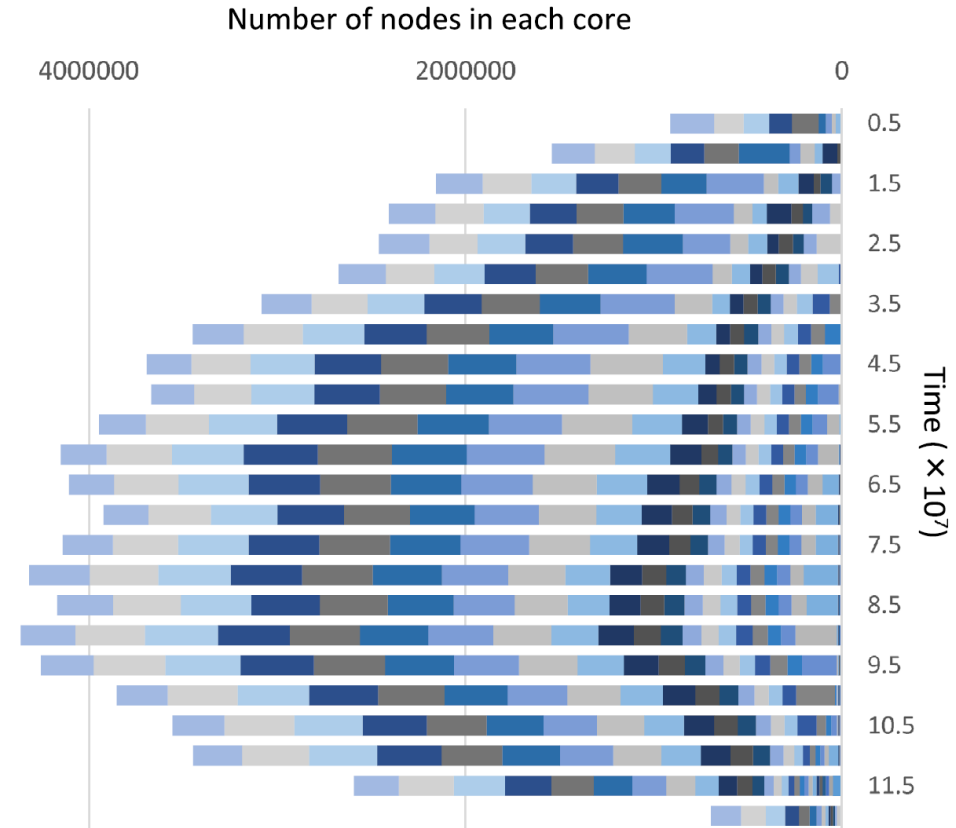
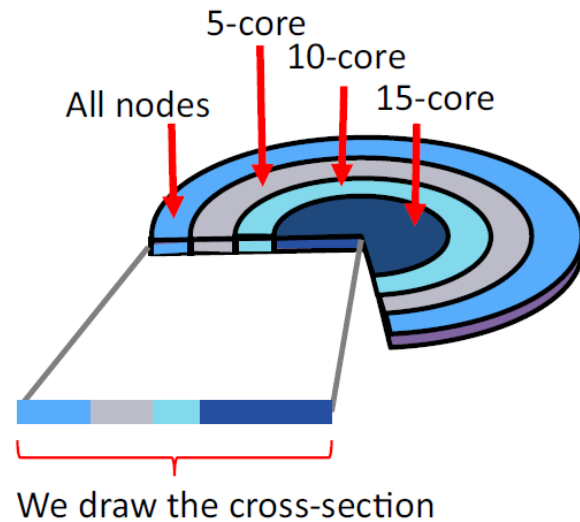
# Application – Network Visualization

Large scale networks fingerprinting and visualization using hierarchical decomposition [NIPS 2006] [VLDB 2012] [ICDE 2012] [KDD 2012]



# Application – Reasoning the collapse of a social network

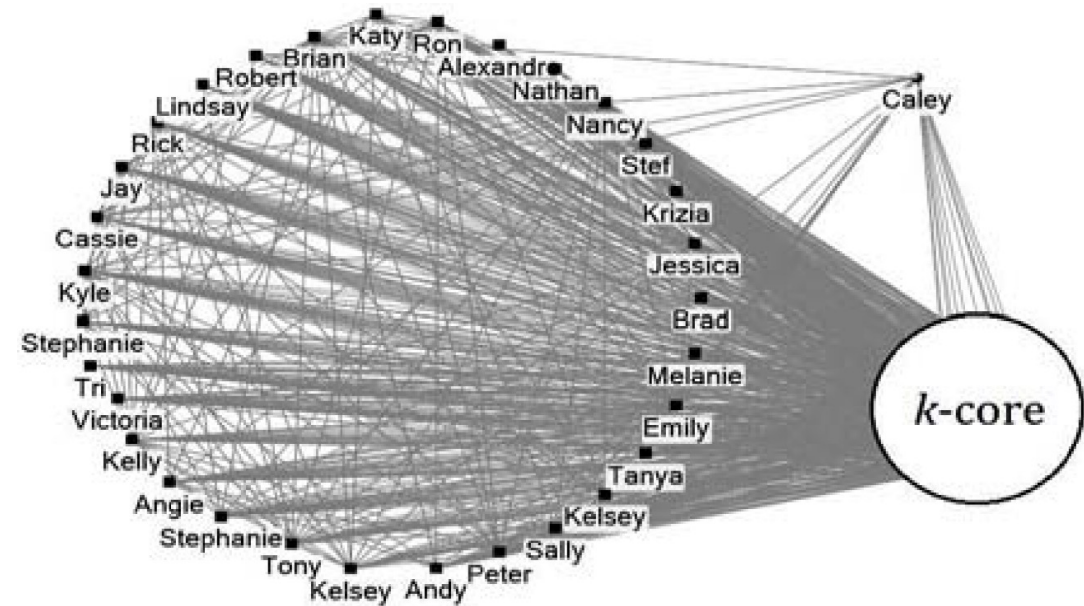
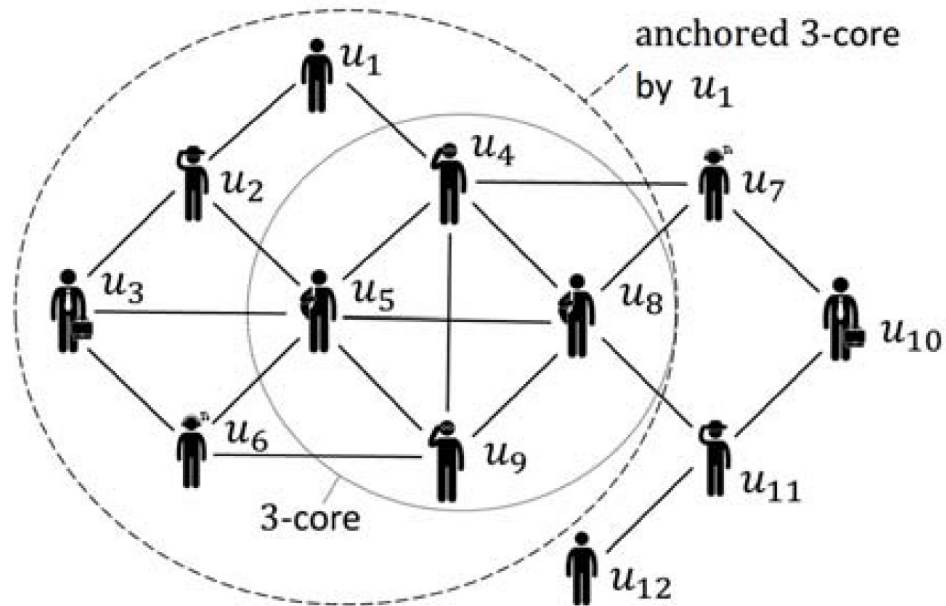
Friendster network: revealing the mechanism of collapse [SNAM 2017] [COSN 2013]





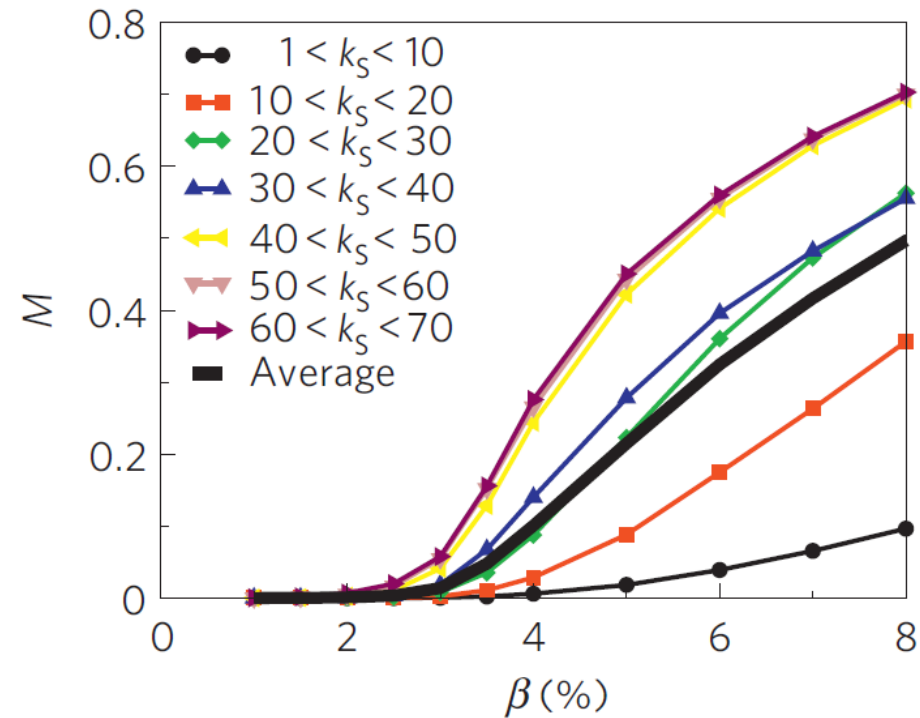
# Application – Prevent Network Unraveling

The Anchored Core and Truss Problems [SIAM J Discrete Math 2015]. The algorithms [VLDB 2017] [ICDE 2018].



## 28 Application – Discovering Influential Nodes

The most effective spreaders are located in the core of the network, fairly independent of their degree. [Nature Physics 2010]

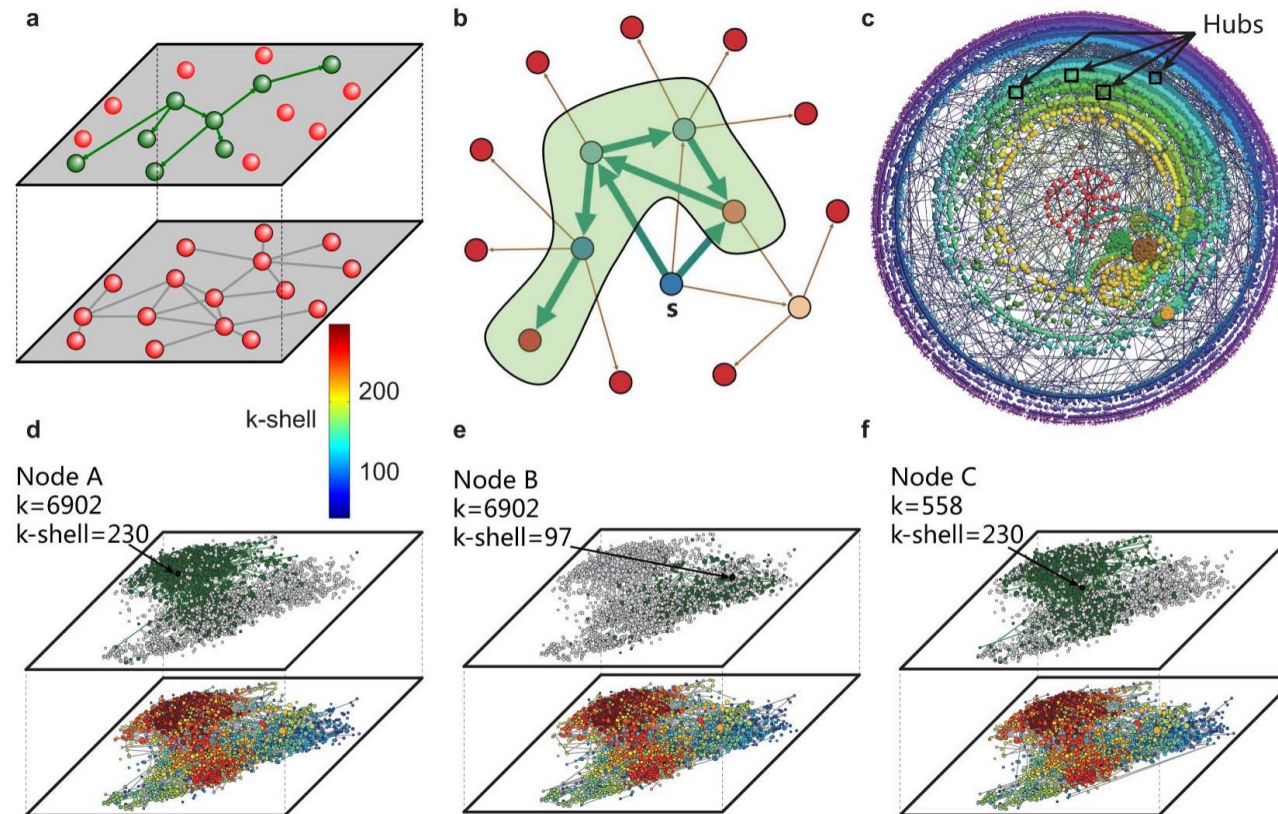




# Application – Discovering Influential Nodes

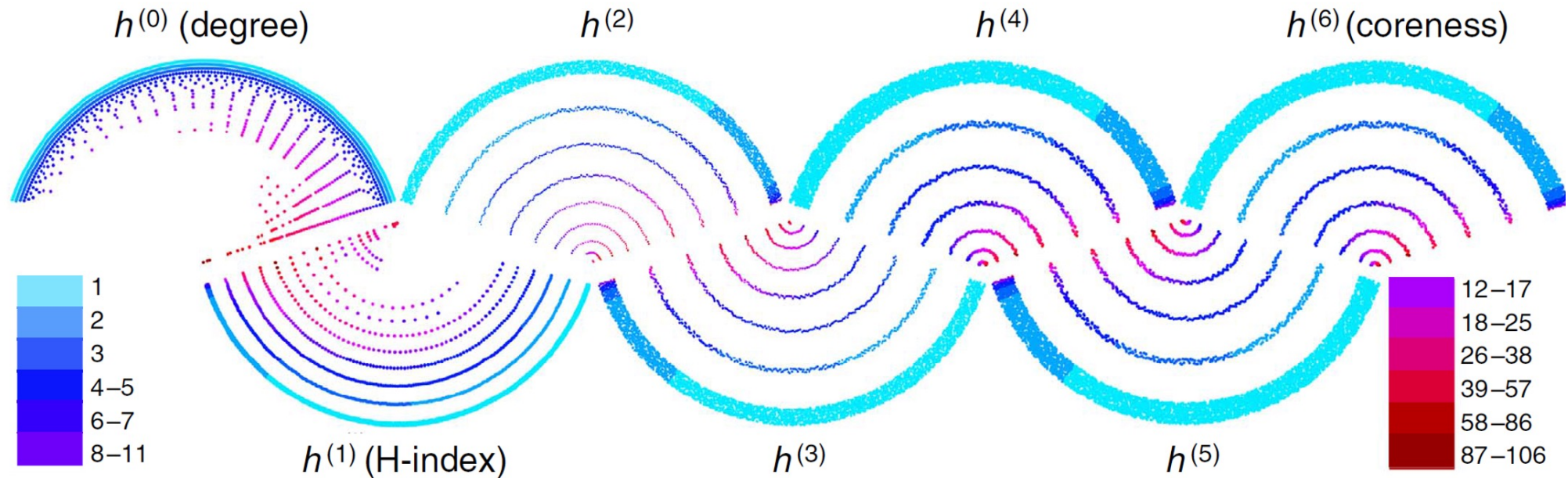
The widely-used degree and PageRank fail in ranking users' influence.

The best spreaders are consistently located in the k-core across dissimilar social platforms. [Scientific Reports 2014]

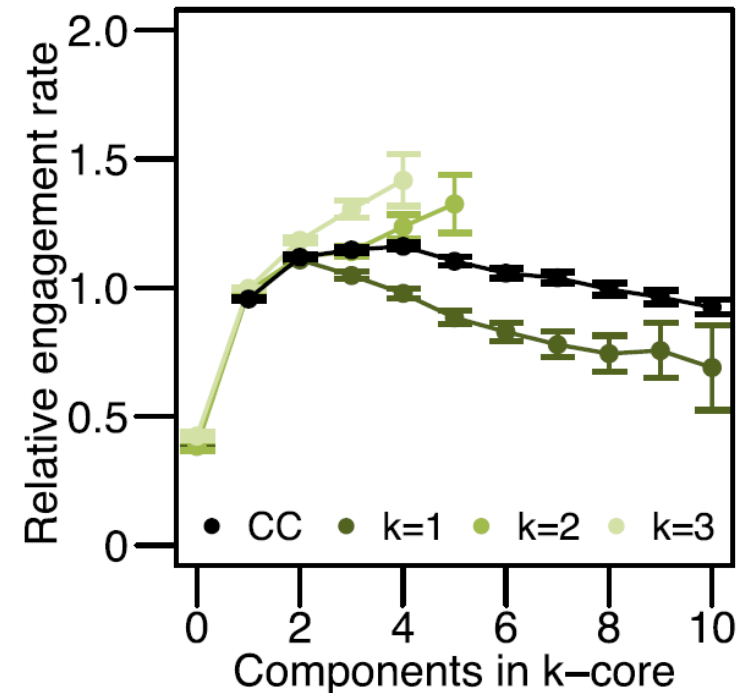
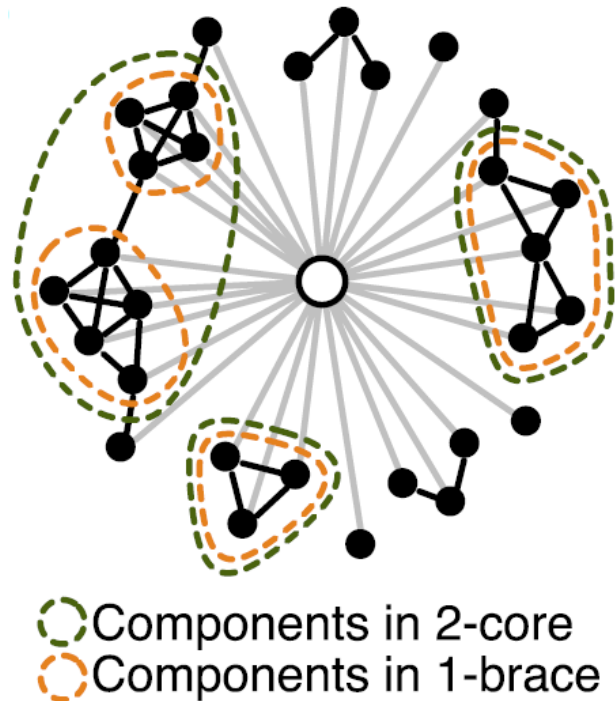


# 30 Application – Evaluating Node Influence

The H-index of a network node and its relation to degree and coreness [Nature Com 2016]

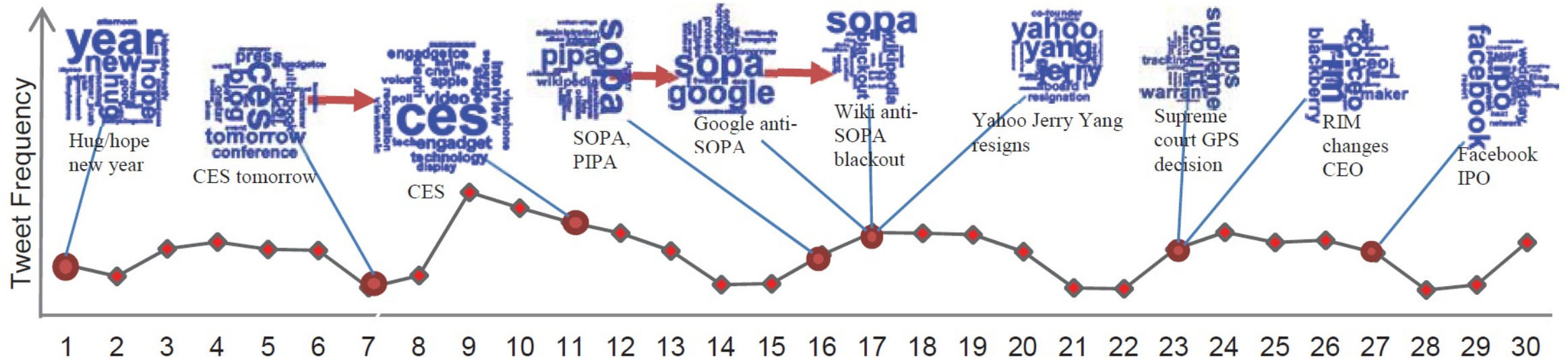


Evaluating social contagion based structural diversity [PNAS 2012]



# Application – Community Discovery

Online social streams: a context-aware story-teller [CIKM 2014]



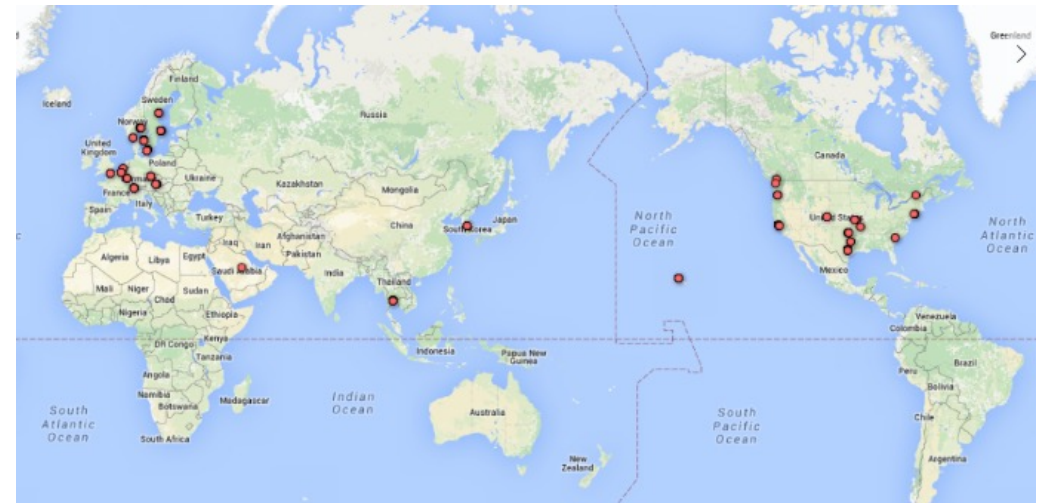


## Application – Community Discovery

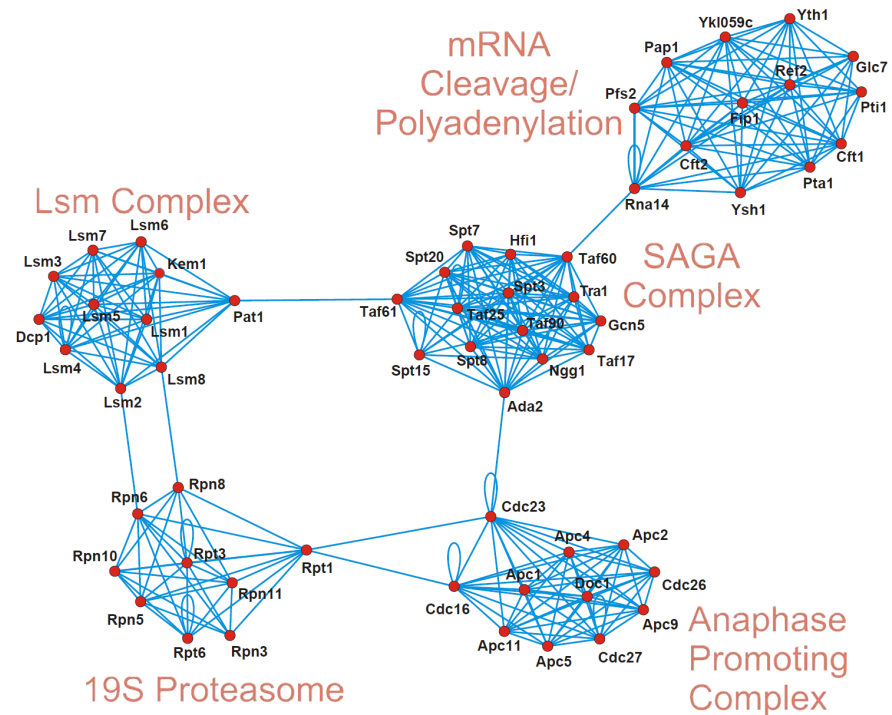
Social networks: persistent community search [ICDE 2018], spatial community search [ICDE 2018], attributed community detection [VLDB 2017] [VLDB 2017] [VLDB 2018] , influential community search [VLDB 2015]



Blogosphere in US

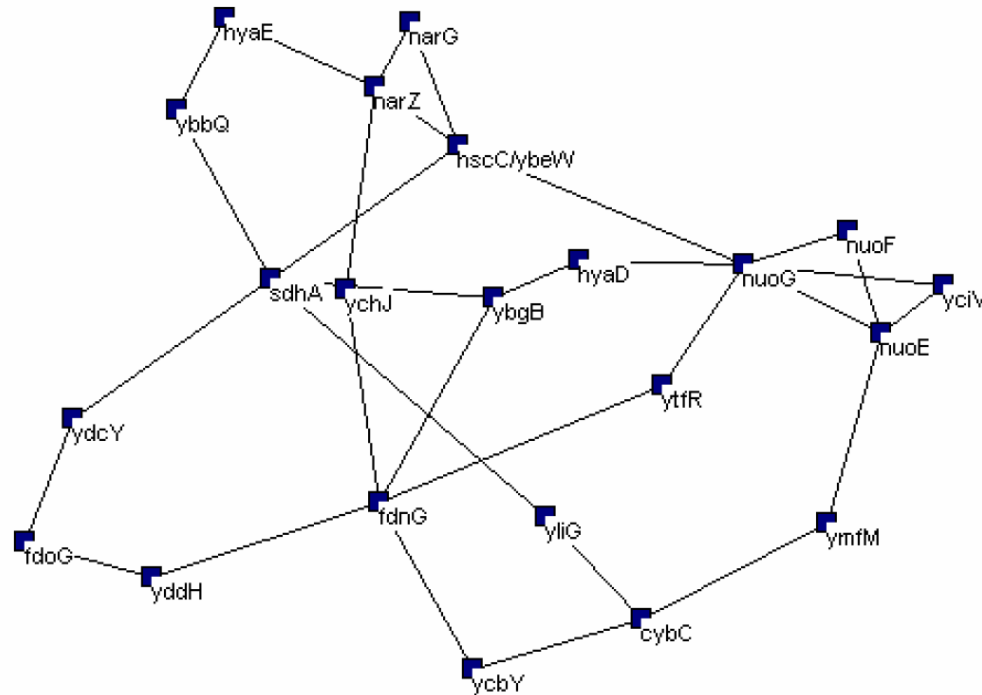


Communities in Gowalla

Protein interaction networks: finding molecular complexes [BMC Bio 2003]

## Application – Protein Function Prediction

Protein interaction networks: prediction of protein functions based on k-cores of the networks and amino acid sequences [Genome Info 2003]



- **Graph clustering**

Giatsidis, Christos, et al. "Corecluster: A degeneracy based graph clustering framework." *AAAI*. 2014.

- **Graph similarity**

Nikolentzos, Giannis, et al. "A Degeneracy Framework for Graph Similarity." *IJCAI*. 2018.

- **Community evaluation**

Giatsidis, Christos, Dimitrios M. Thilikos, and Michalis Vazirgiannis. "Evaluating cooperation in communities with the k-core structure." *ASONAM*, 2011.

- **Influence maximization**

Elsharkawy, Sarah, et al. "Effectiveness of the k-core nodes as seeds for influence maximisation in dynamic cascades." *International Journal of Computers 2* (2017).

- **Graph generating**

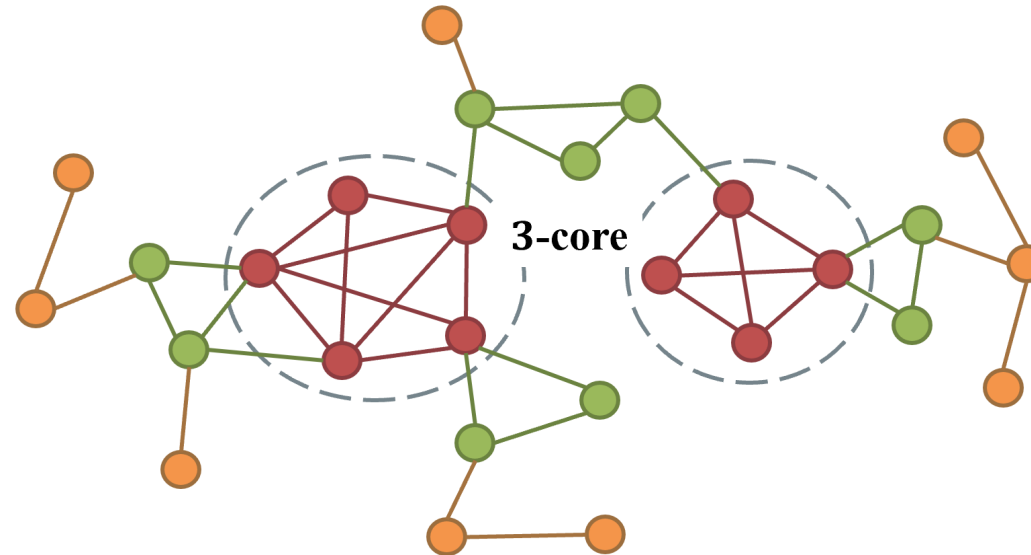
Baur, Michael, et al. "Generating graphs with predefined k-core structure." *Proceedings of the European Conference of Complex Systems*. 2007.





**K-CORE**

K-core is a maximal subgraph in which each vertex has at least  $k$  neighbors in the subgraph.



*Erdős, Paul, and András Hajnal. "On chromatic number of graphs and set-systems." Acta Mathematica Hungarica 17.1-2 (1966): 61-99.*

# Computing the k-Core

Iteratively remove every vertex whose degree is less than  $k$ .

$O(m + n)$

---

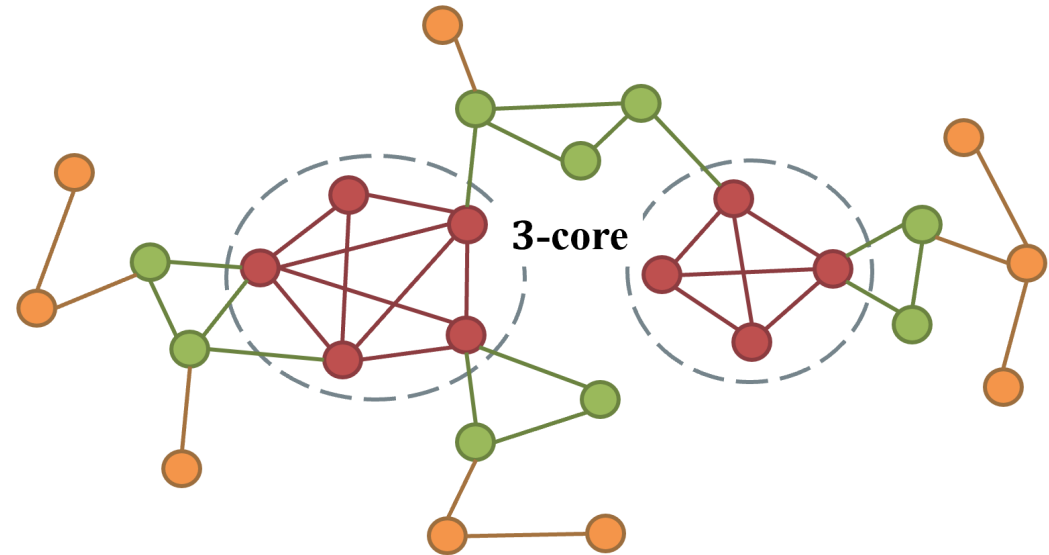
**Algorithm : ComputeCore( $G, k$ )**

---

**Input** :  $G$  : a graph,  $k$  : degree constraint

**Output** :  $C_k(G)$

- 1 **while exists**  $v \in G$  with  $deg(v, G) < k$  **do**
  - 2      $G \leftarrow G \setminus \{v \cup E(v, G)\};$
  - 3 **return**  $G$
- 



# Computing the k-Core

Iteratively remove every vertex whose degree is less than  $k$ .

$O(m + n)$

---

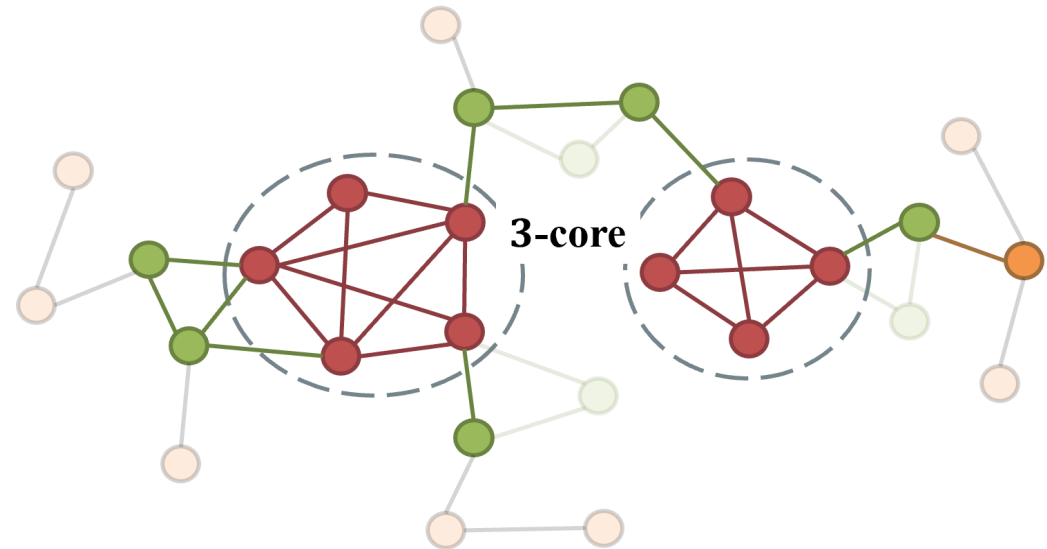
**Algorithm : ComputeCore( $G, k$ )**

---

**Input** :  $G$  : a graph,  $k$  : degree constraint

**Output** :  $C_k(G)$

- 1 **while exists**  $v \in G$  with  $\text{deg}(v, G) < k$  **do**
  - 2      $G \leftarrow G \setminus \{v \cup E(v, G)\};$
  - 3 **return**  $G$
- 



# Computing the k-Core

Iteratively remove every vertex whose degree is less than  $k$ .

$O(m + n)$

---

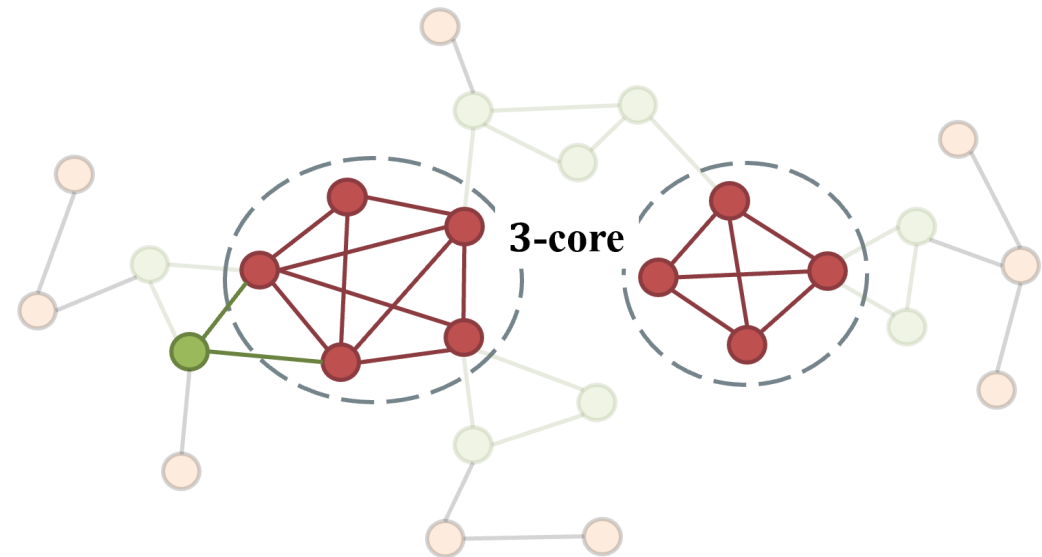
**Algorithm : ComputeCore( $G, k$ )**

---

**Input** :  $G$  : a graph,  $k$  : degree constraint

**Output** :  $C_k(G)$

- 1 **while** exists  $v \in G$  with  $\text{deg}(v, G) < k$  **do**
  - 2      $G \leftarrow G \setminus \{v \cup E(v, G)\};$
  - 3 **return**  $G$
- 



Iteratively remove every vertex whose degree is less than  $k$ .

$O(m + n)$

---

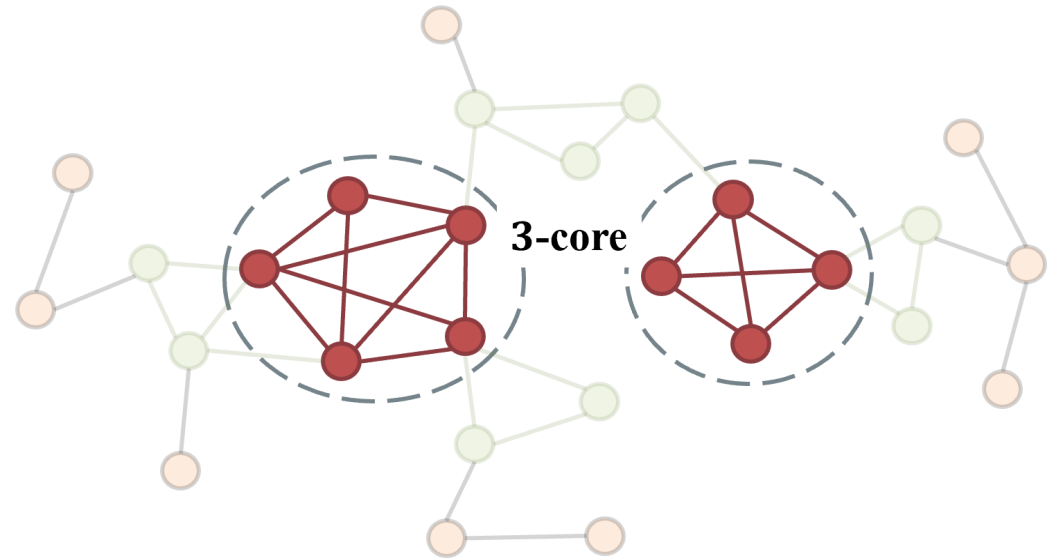
**Algorithm : ComputeCore( $G, k$ )**

---

**Input** :  $G$  : a graph,  $k$  : degree constraint

**Output** :  $C_k(G)$

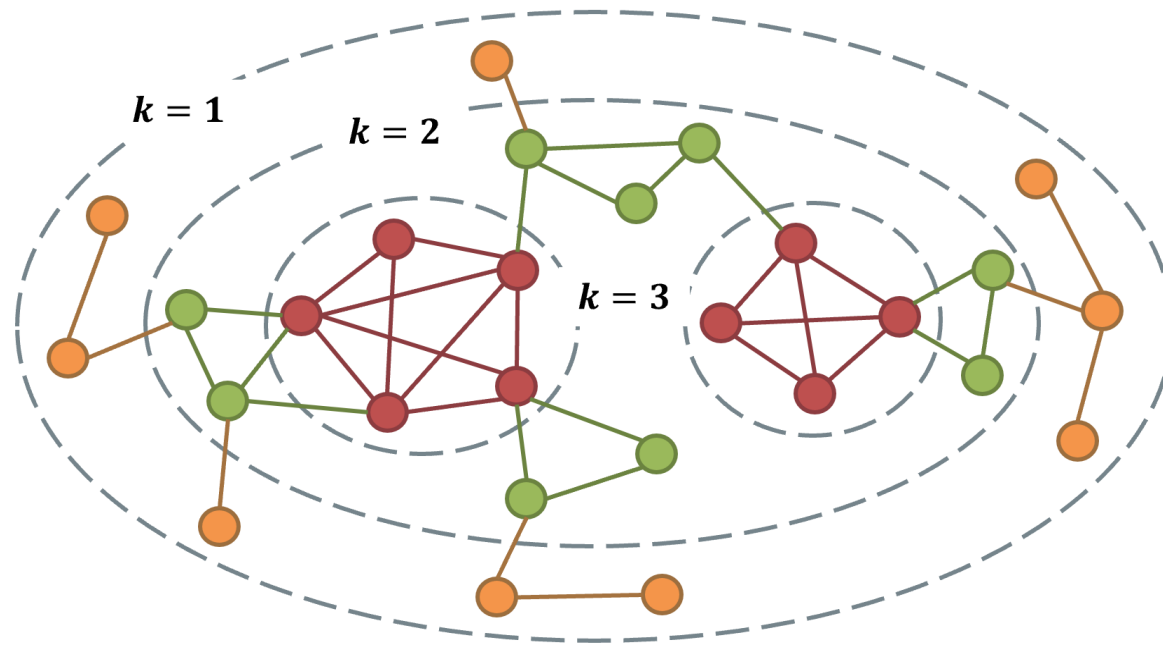
- 1 **while** exists  $v \in G$  with  $\text{deg}(v, G) < k$  **do**
  - 2      $G \leftarrow G \setminus \{v \cup E(v, G)\};$
  - 3 **return**  $G$
- 



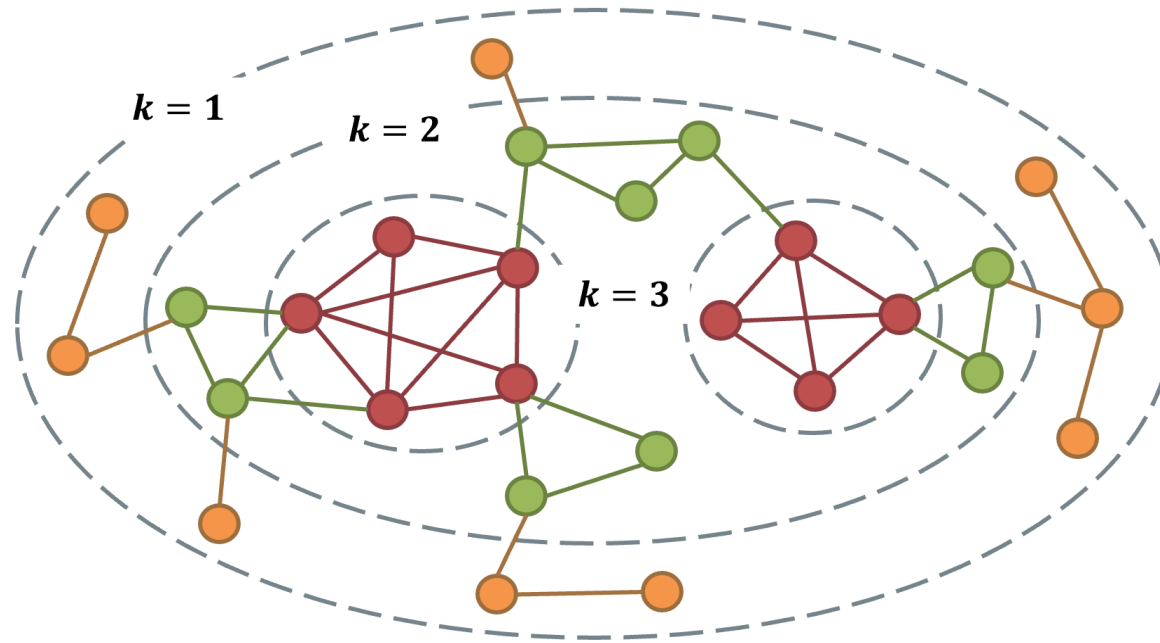


# Core Number of a Vertex $v$

$k(v)$  = the largest  $k$  such that the  $k$ -core contains  $v$



Compute the core number of every vertex.



The following algorithms are optional, as long as you know how to compute the core number of a given graph.

Global-view: peel low-degree vertices iteratively from the whole graph.

Local-view 1: update the upper bound of core number for each vertex until converge

# 46 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

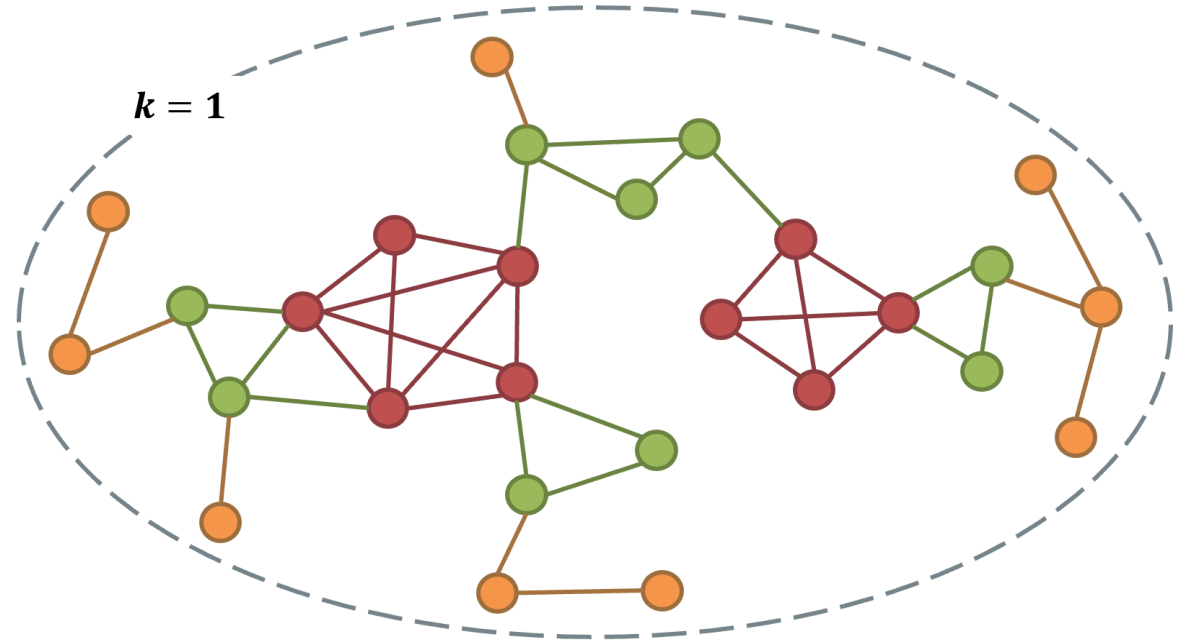
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 47 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

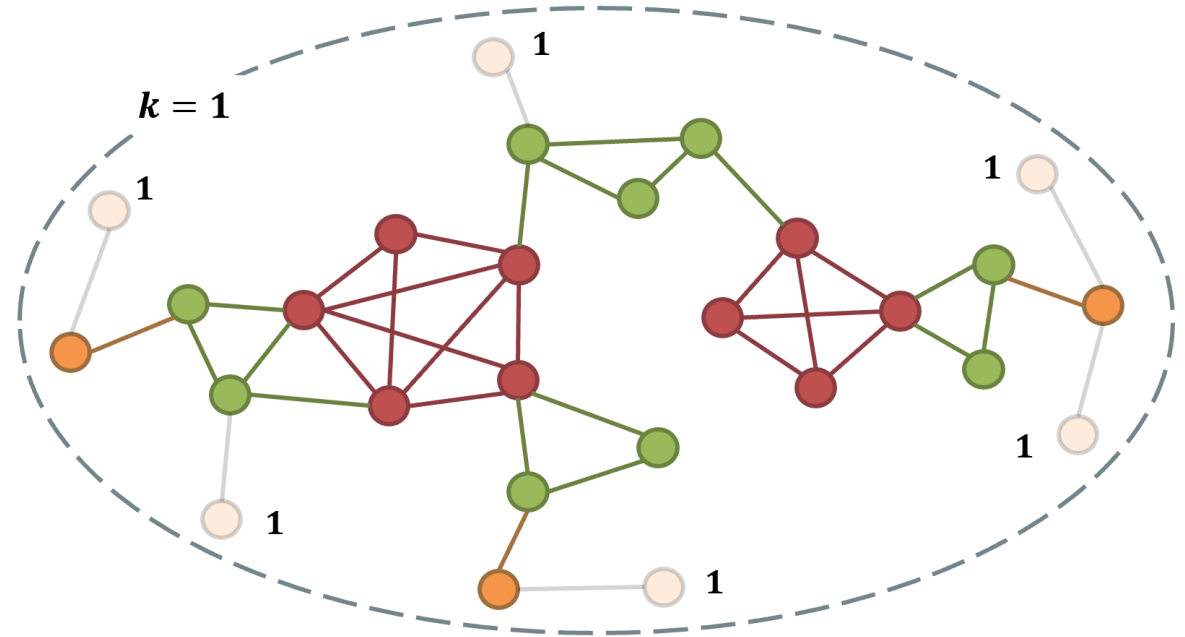
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 48 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

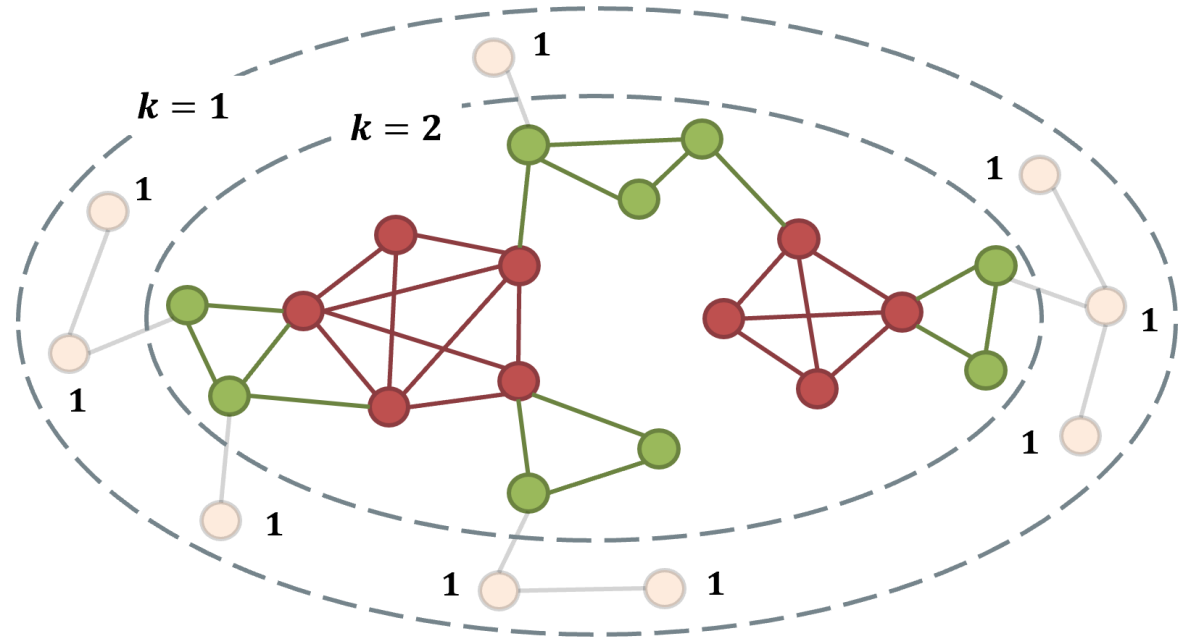
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).



# 49 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

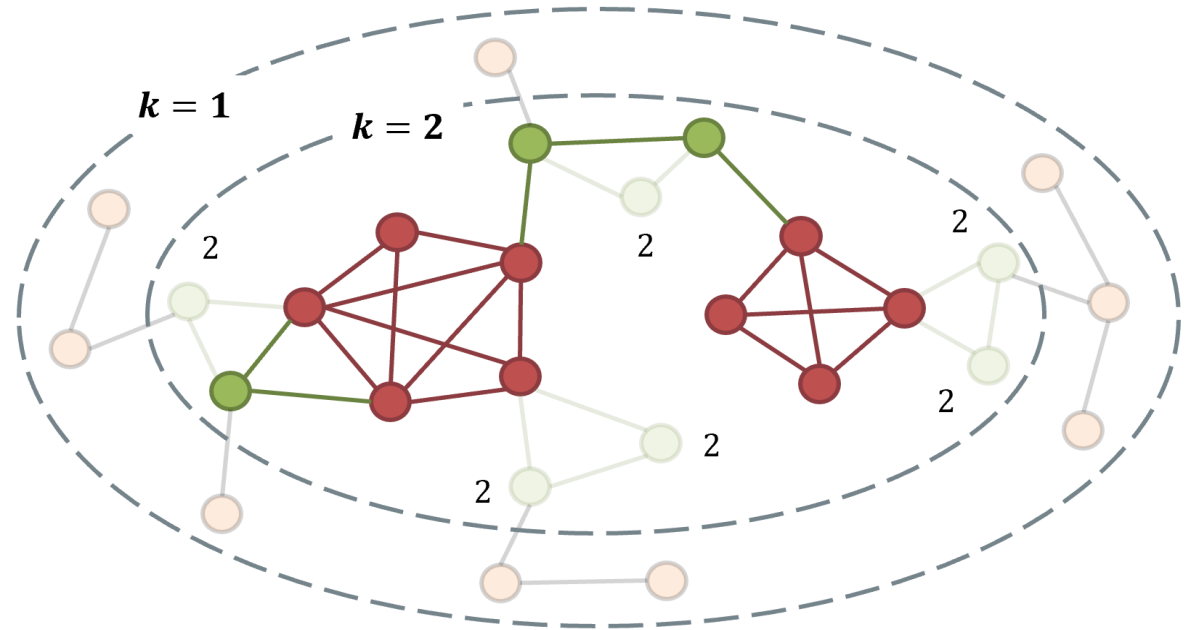
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 50 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

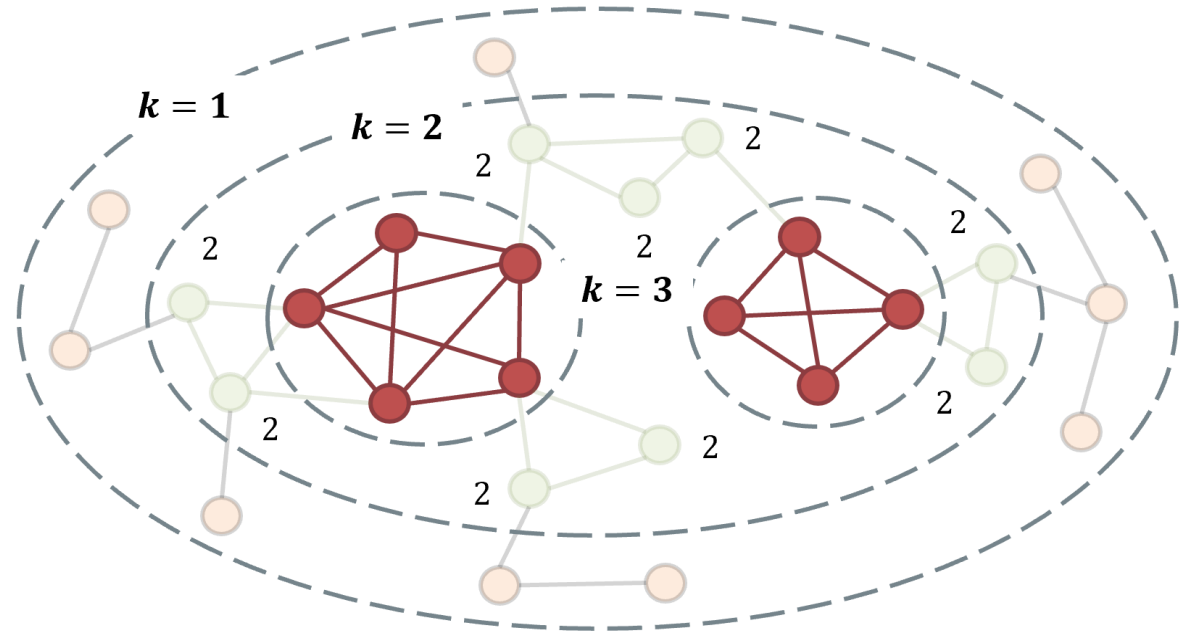
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 51 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

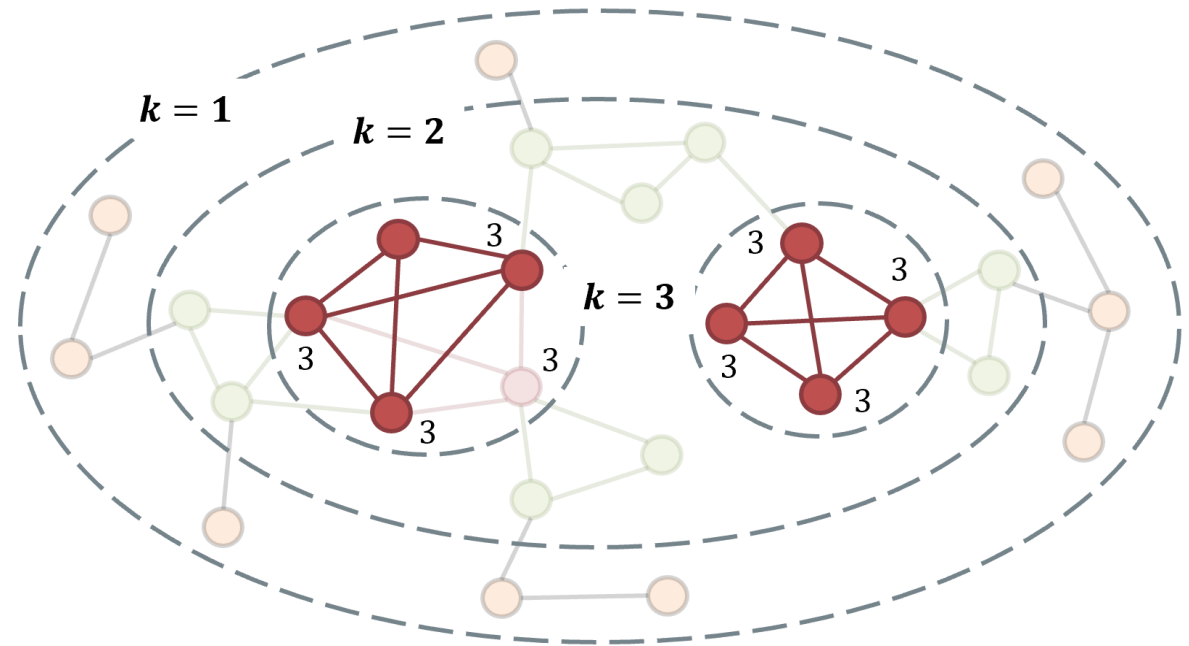
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 52 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

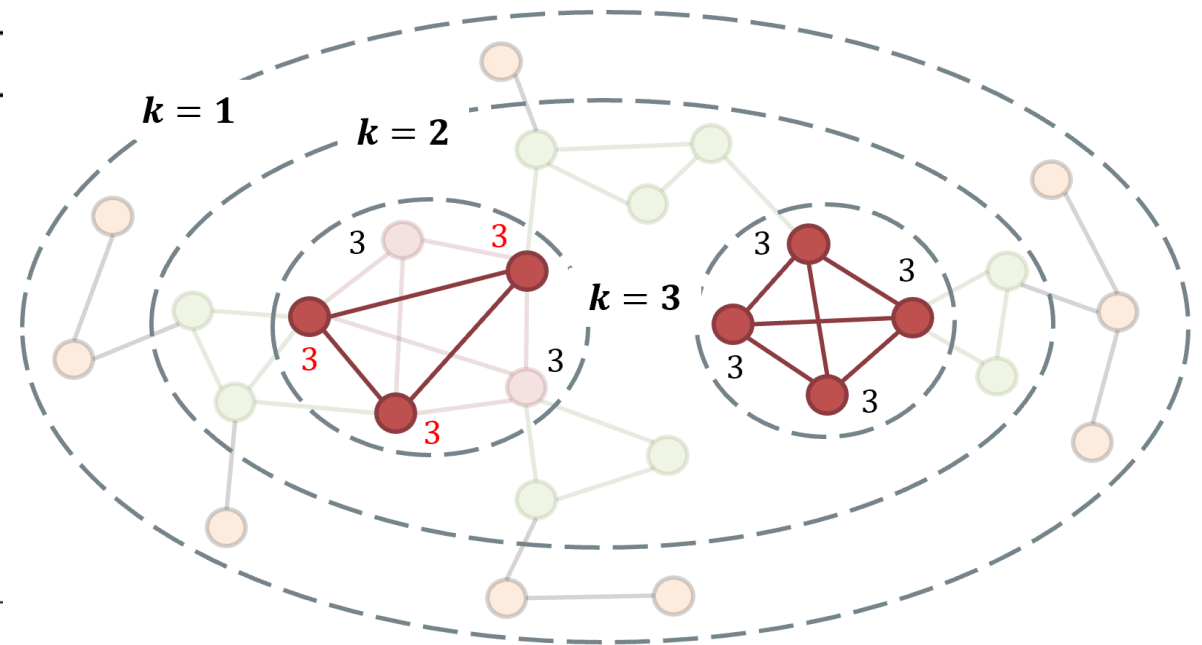
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 53 Core Decomposition: Global-view (Peeling)

Iteratively delete the vertex with the lowest degree.  $O(m+n)$

---

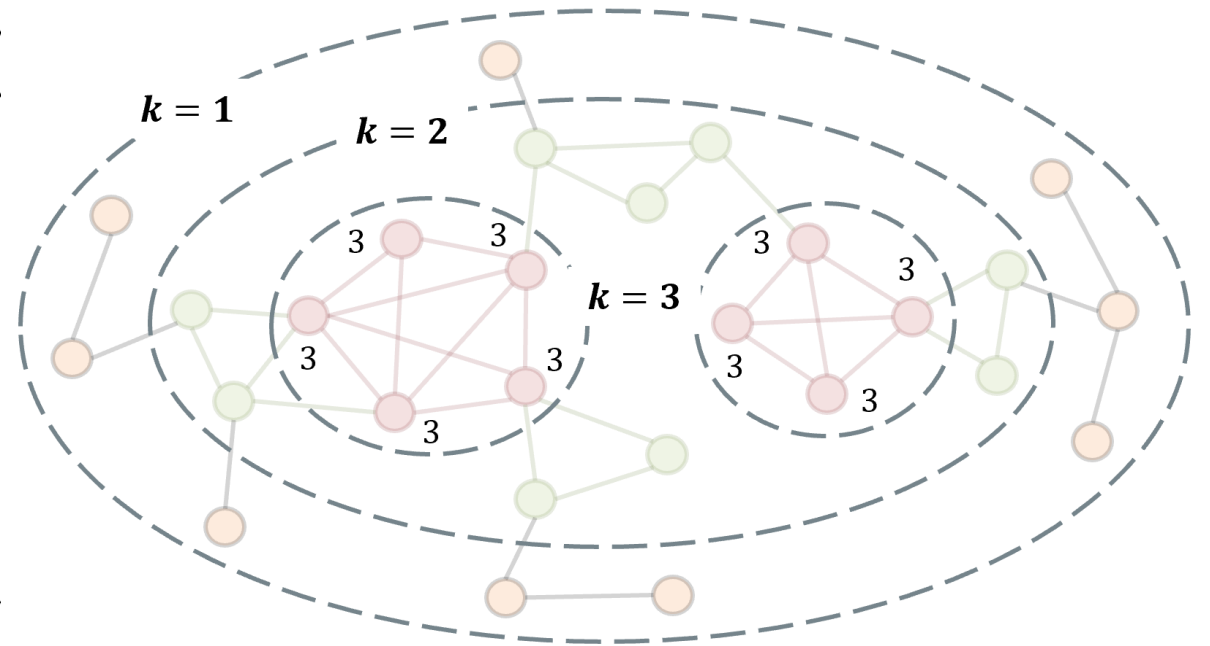
## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

- 1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;
  - 2 order the vertices in  $V$  in increasing order of their degrees;
  - 3 **for each**  $u \in V$  **in the order do**
  - 4      $cn(u) \leftarrow d(u)$ ;
  - 5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**
  - 6          $d(v) \leftarrow d(v) - 1$ ;
  - 7         reorder  $V$  accordingly;
  - 8 **return**  $cn(u)$  **of every**  $u \in V$
- 



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

# 54 Core Decomposition: Global-view (Peeling)

Using bin-sort  $\rightarrow O(m+n)$

---

## Algorithm : CoreDecomposition

---

**Input** :  $G = (V, E)$  : a graph

**Output** :  $\{cn(u) \mid u \in V\}$ : core number of every vertex in  $G$

1  $d(u) \leftarrow deg(u, G)$  for every  $u \in V$ ;

2 order the vertices in  $V$  in increasing order of their degrees;

3 **for each**  $u \in V$  **in the order do**

4      $cn(u) \leftarrow d(u)$ ;

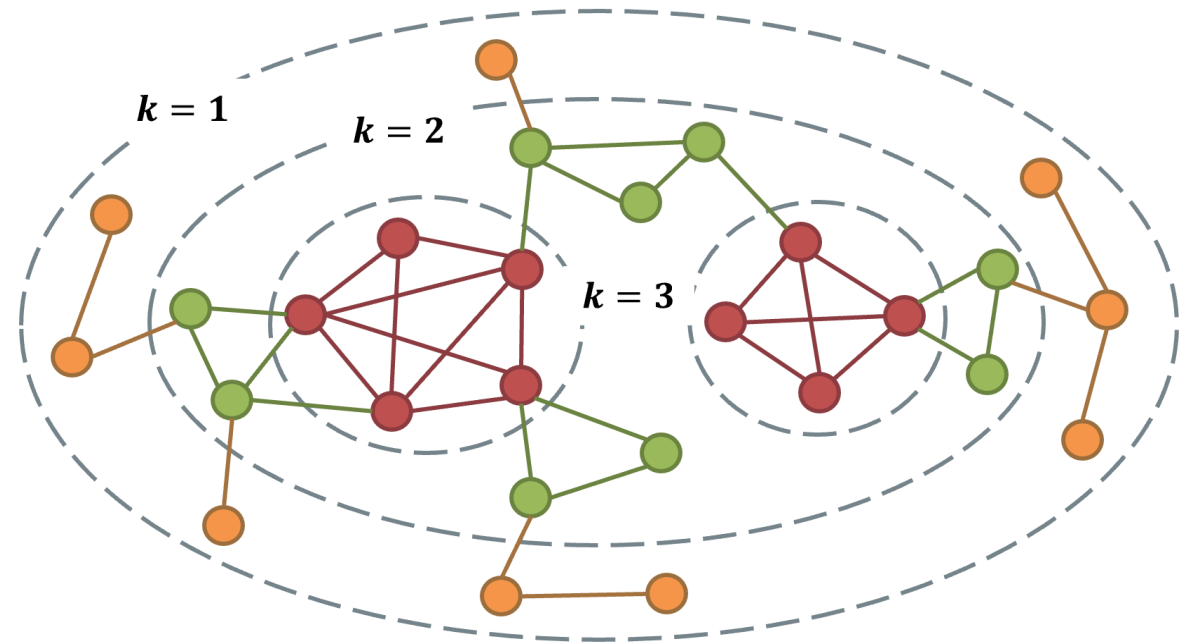
5     **for each**  $v \in N(u)$  **with**  $d(v) > d(u)$  **do**

6          $d(v) \leftarrow d(v) - 1$ ;

7         reorder  $V$  accordingly;

8 **return**  $cn(u)$  of every  $u \in V$

---



Batagelj, Vladimir, and Matjaz Zaversnik. "An  $O(m)$  algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

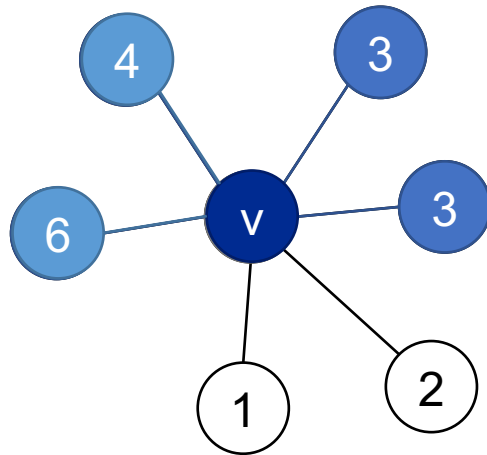


Locality Theorem:

Given a vertex and its core number  $k$ :

There exists at least  $k$  neighbors with core number  $k$ ;

There does not exist  $k+1$  neighbors with core number  $k+1$ .



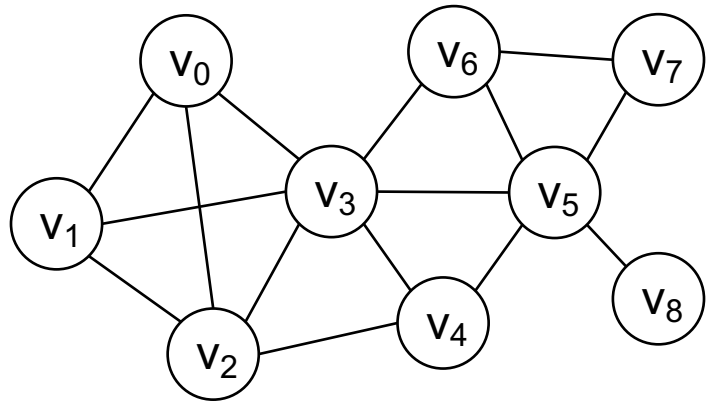
Core( $v$ ) = 3

4 neighbors with core number at least 3

Core( $v$ ) = 4

Only 2 neighbors with core number at least 4

# 56 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

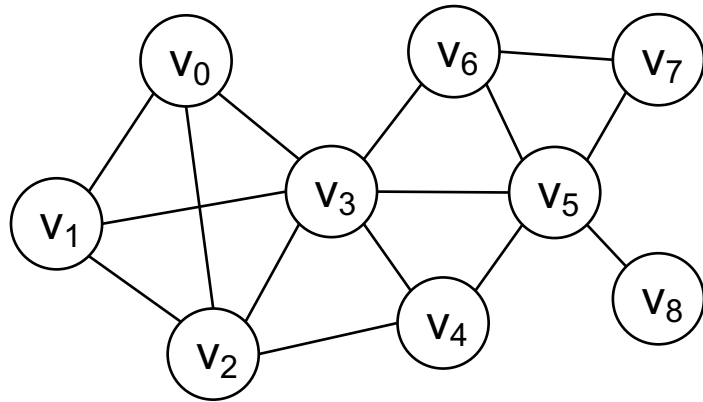
Initialize the core number by degree

Iteration **1**

isContinue **False**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	4	6	3	5	3	2	1

# Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
 There exists at least  $k$  neighbors with core number  $k$ ;  
 There does not exist  $k+1$  neighbors with core number  $k+1$ .

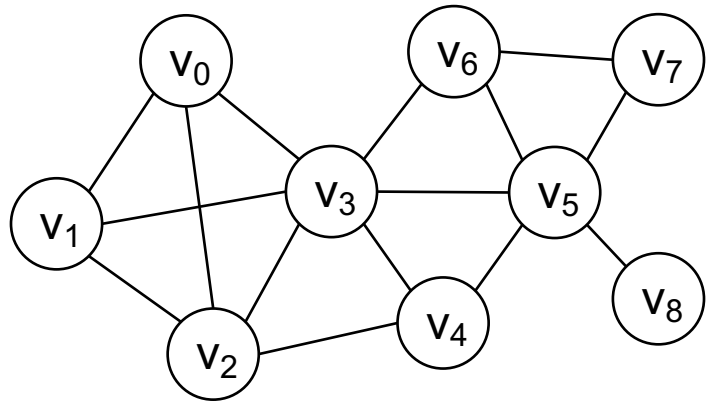
Initialize the core number by degree

Iteration **1**

isContinue **False**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	4	6	3	5	3	2	1

# 58 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

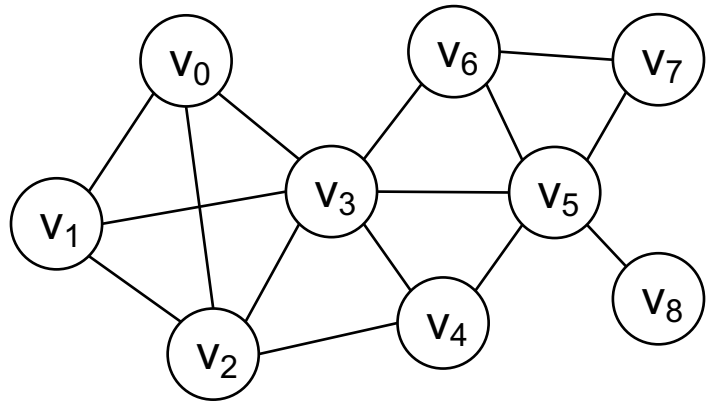
Initialize the core number by degree

Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	6	3	5	3	2	1

# 59 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

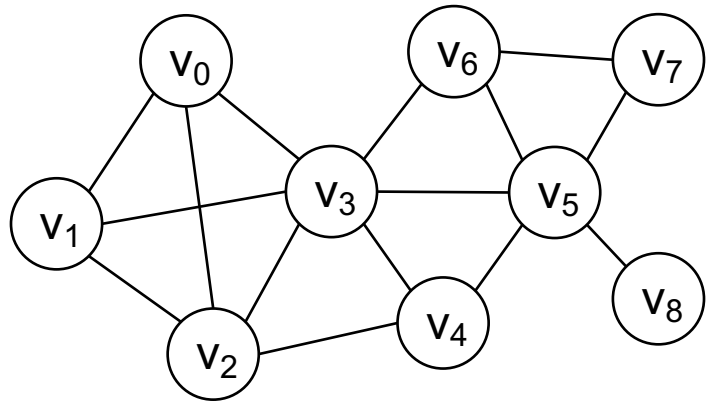
Initialize the core number by degree

Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	5	3	2	1

# 60 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

Initialize the core number by degree

Iteration **1**

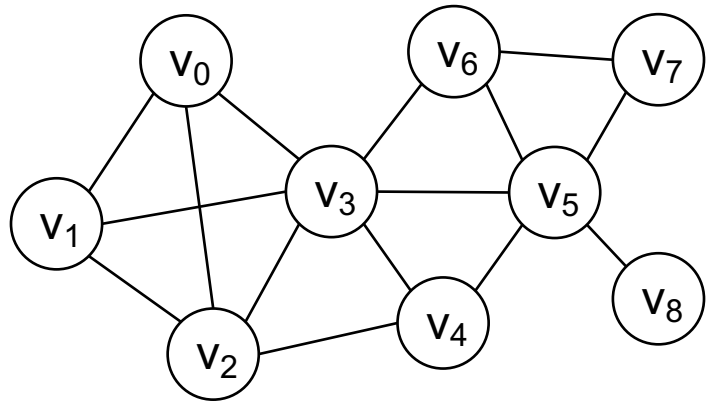
isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	5	3	2	1





# 62 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

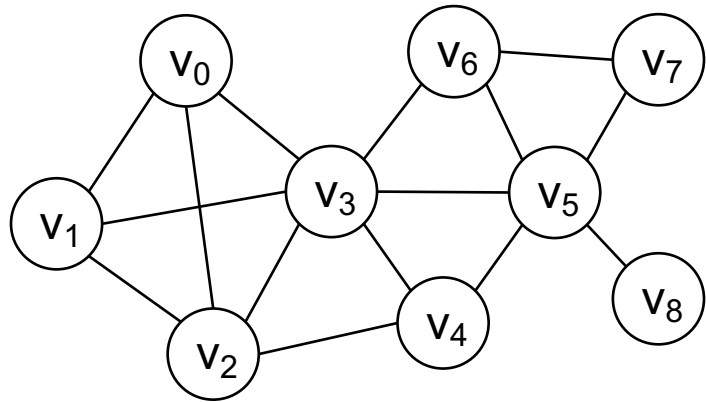
Initialize the core number by degree

Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	3	2	2	1

# 63 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

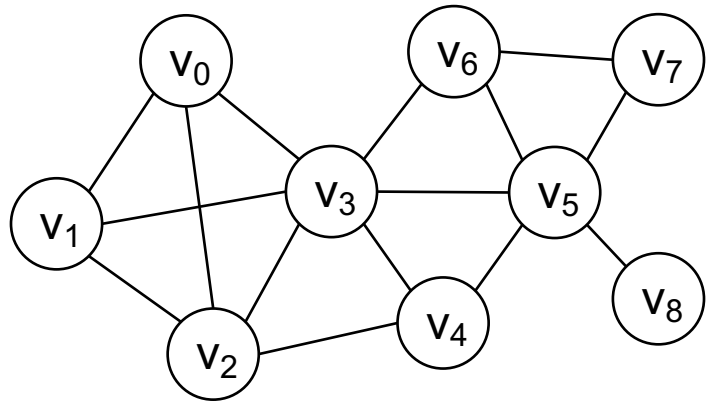
Initialize the core number by degree

Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	3	2	2	1

# 64 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

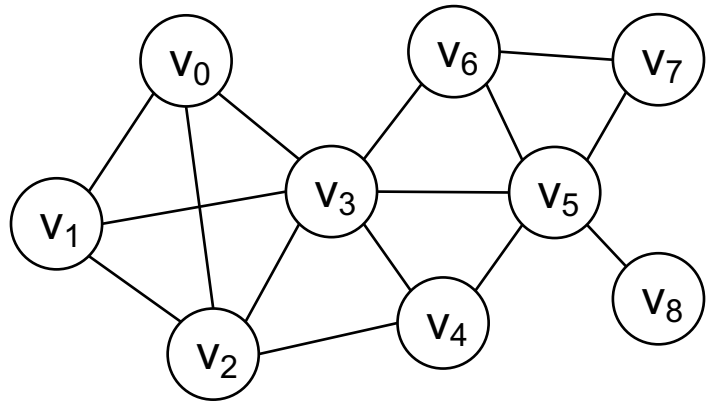
Initialize the core number by degree

Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	3	2	2	1

# 65 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

Initialize the core number by degree

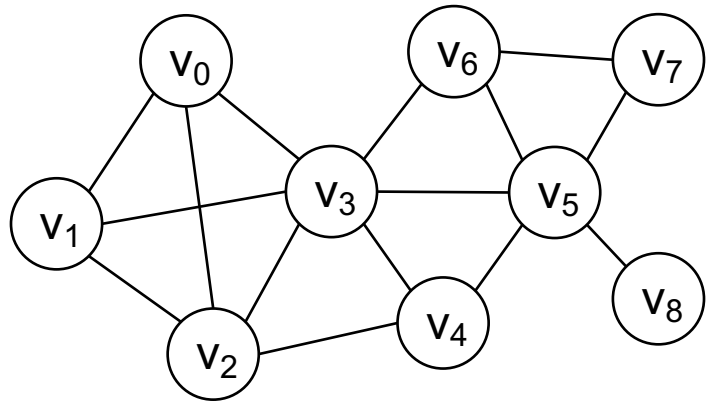
Iteration **1**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	3	2	2	1



# 66 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

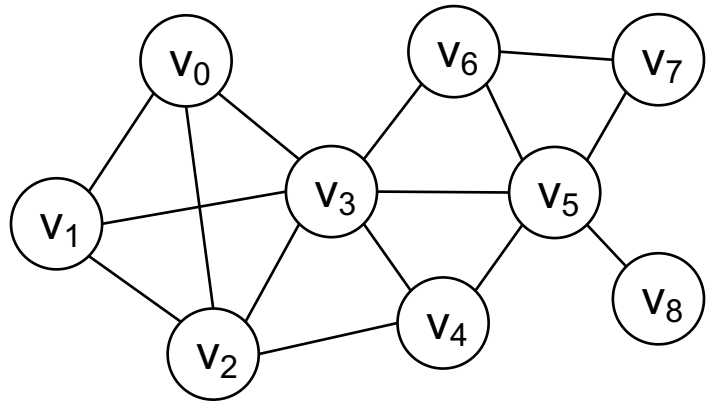
Initialize the core number by degree

Iteration **2**

isContinue **False**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	3	2	2	1

# 67 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

Initialize the core number by degree

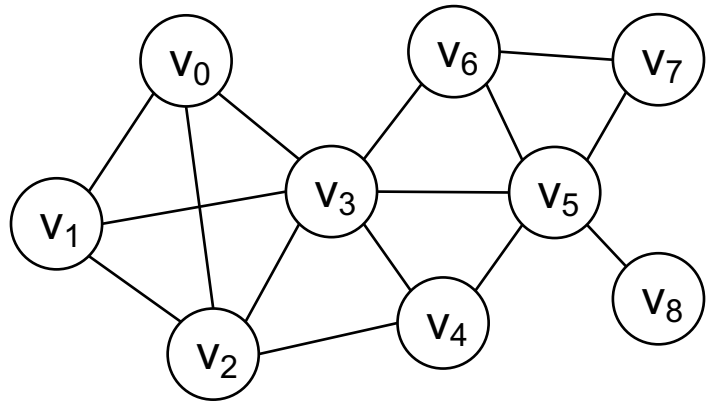
Iteration **2**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	3	2	2	2	1



# 68 Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
There exists at least  $k$  neighbors with core number  $k$ ;  
There does not exist  $k+1$  neighbors with core number  $k+1$ .

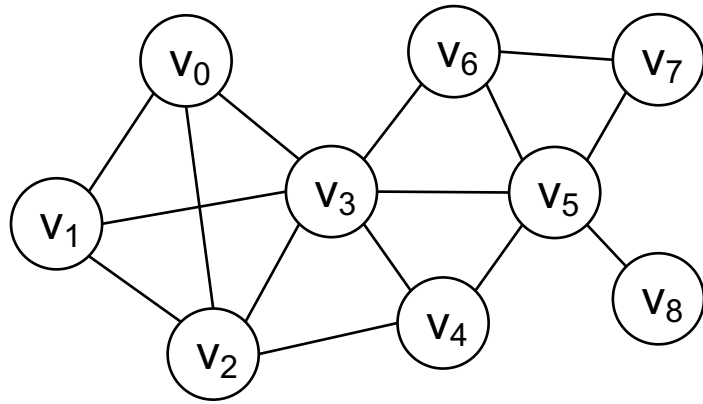
Initialize the core number by degree

Iteration **3**

isContinue **True**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	2	2	2	2	1

# Core Decomposition: Local-view (Converging)



Given a vertex and its core number  $k$ :  
 There exists at least  $k$  neighbors with core number  $k$ ;  
 There does not exist  $k+1$  neighbors with core number  $k+1$ .

Initialize the core number by degree

Iteration **4**

isContinue **False**

ID	0	1	2	3	4	5	6	7	8
Core	3	3	3	3	2	2	2	2	1