



Hypercore Decomposition for Non-Fragile Hyperedges: Concepts, Algorithms, Observations, and Applications



Fanchen Bu



Geon Lee




Kijung Shin

Group Interactions are Everywhere

- **Ex 1: Collaboration** among researchers, e.g., co-authorship




Hypercore decomposition for non-fragile hyperedges:
concepts, algorithms, observations, and applications


Fanchen Bu¹ · Geon Lee² · Kijung Shin^{1,2} 



Improving the core resilience of real-world hypergraphs

Manh Tuan Do¹ · Kijung Shin^{1,2} 

Reciprocity in directed hypergraphs: measures, findings,
and generators

Sunwoo Kim¹ · Minyoung Choe¹ · Jaemin Yoo³ · Kijung Shin^{1,2} 

Datasets, tasks, and training methods for large-scale
hypergraph learning

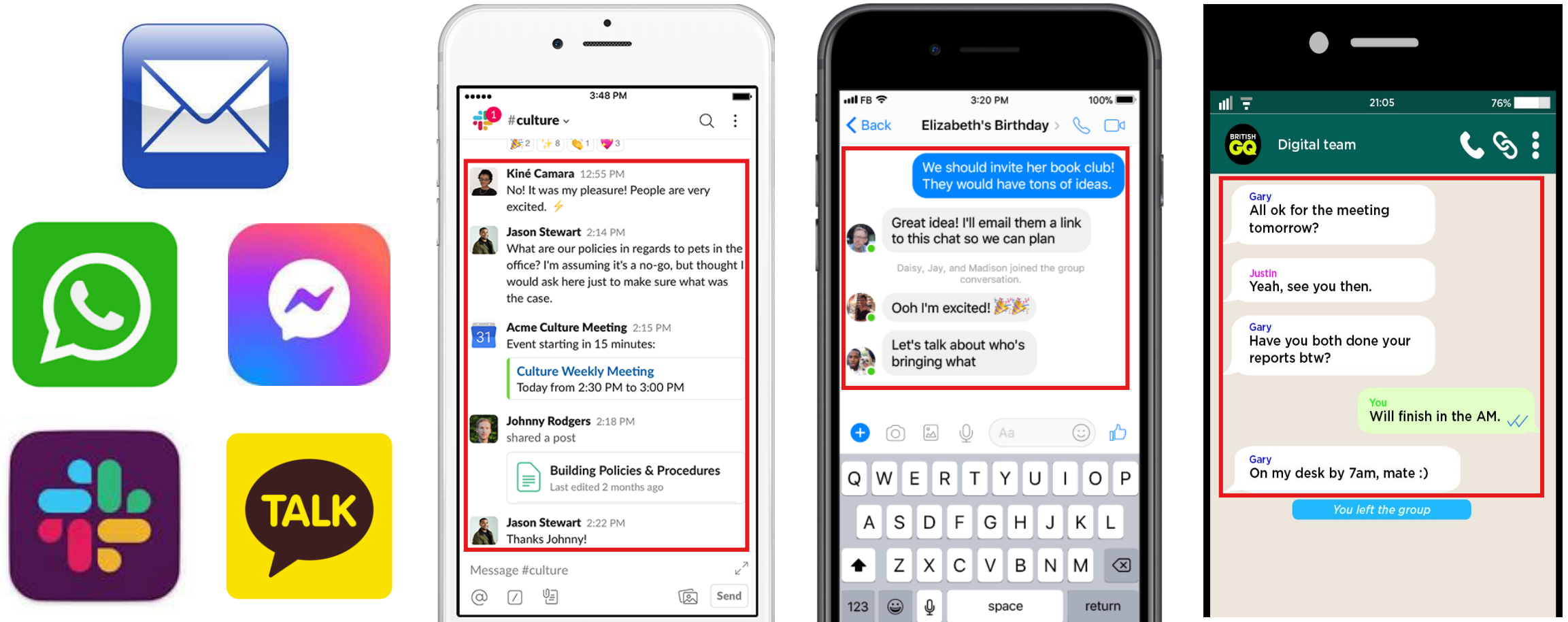
Sunwoo Kim¹ · Dongjin Lee² · Yul Kim³ · Jungho Park³ · Taeho Hwang³ ·
Kijung Shin^{1,2} 

Interplay between topology and edge weights in real-world
graphs: concepts, patterns, and an algorithm

Fanchen Bu¹ · Shinhwan Kang² · Kijung Shin^{1,2} 

Group Interactions are Everywhere (cont.)

- **Ex 2: Communication** among a group, e.g., emails, online group chats



Group Interactions are Everywhere (cont.)


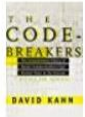

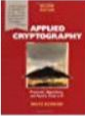
- **Ex 3:** Co-purchases of items on Ecommerce platforms



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Hypergraphs: A Good Model for Group Interactions

- **Q:** How can we represent real-world group interactions?
- **Hypergraphs** model group interactions among individuals or objects
- Each **hyperedge** is a subset of any number of nodes
- Each hyperedge indicates a **group interaction** among its members

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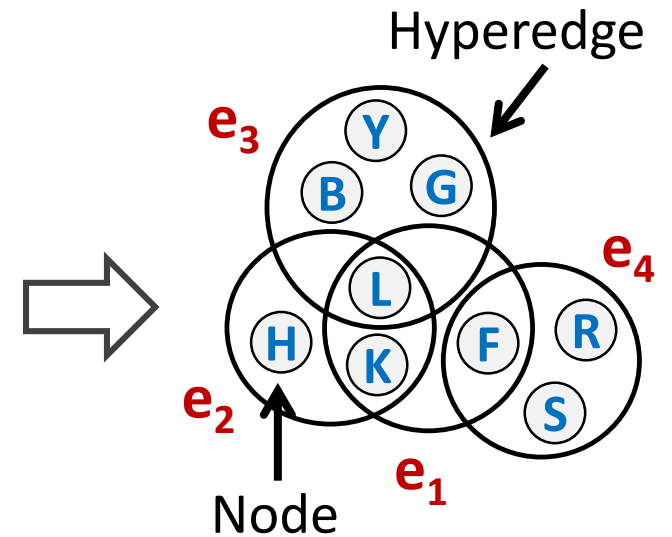
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Daniel Huttenlocher (H)	

Publications (Hyperedges)

e_1 : (L, K, F) KDD'05
e_2 : (L, H, K) WWW'10
e_3 : (Y, B, G, L) KDD'17
e_4 : (S, R, F) VLDB'87



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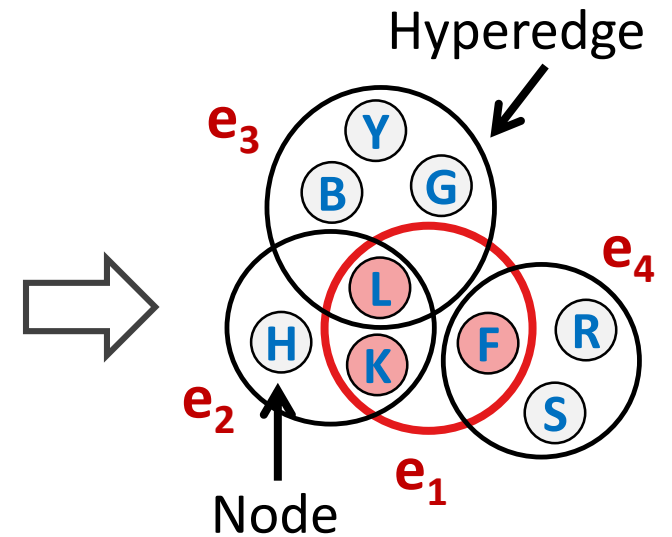
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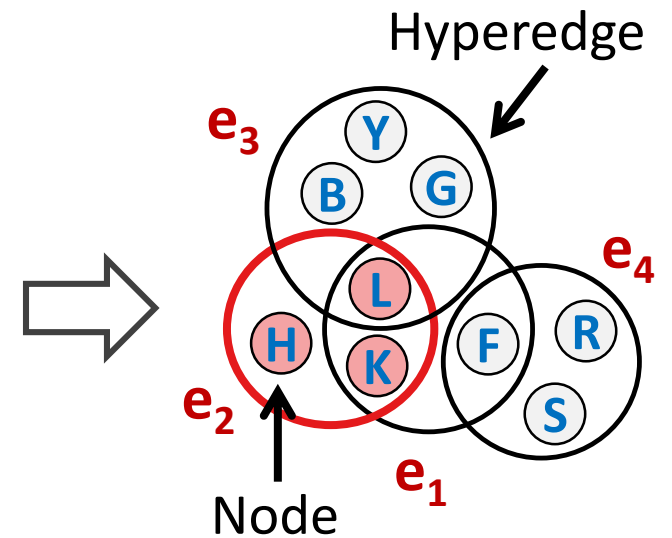
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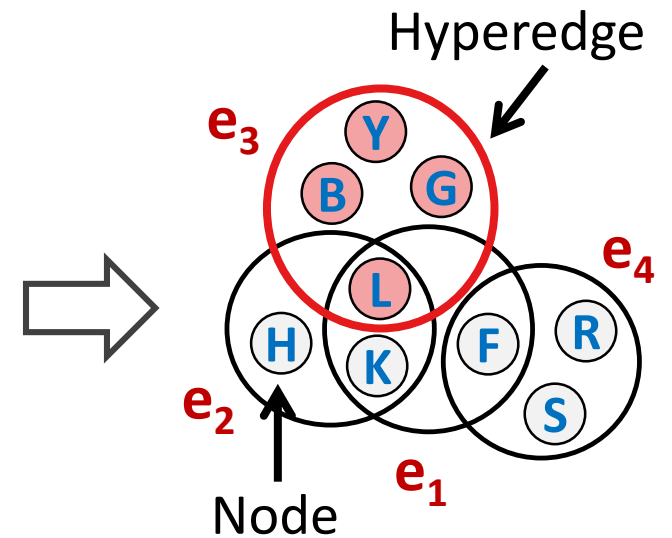
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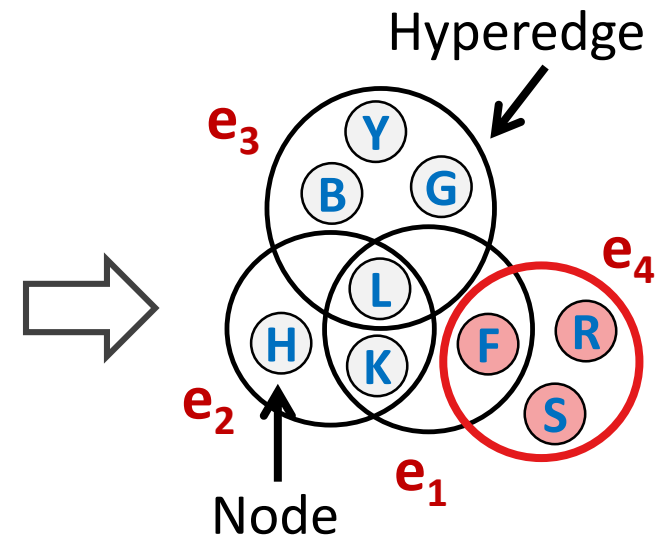
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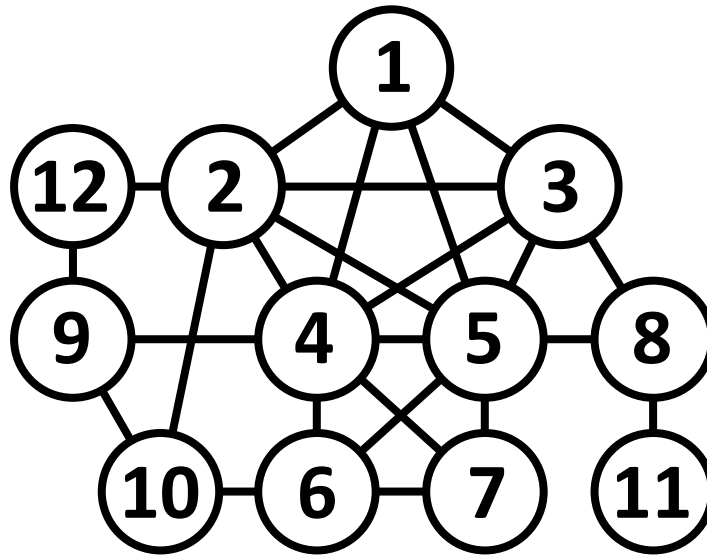
Roadmap

- **Concepts & Algorithms <<**
- Observations
- Applications
- Conclusions



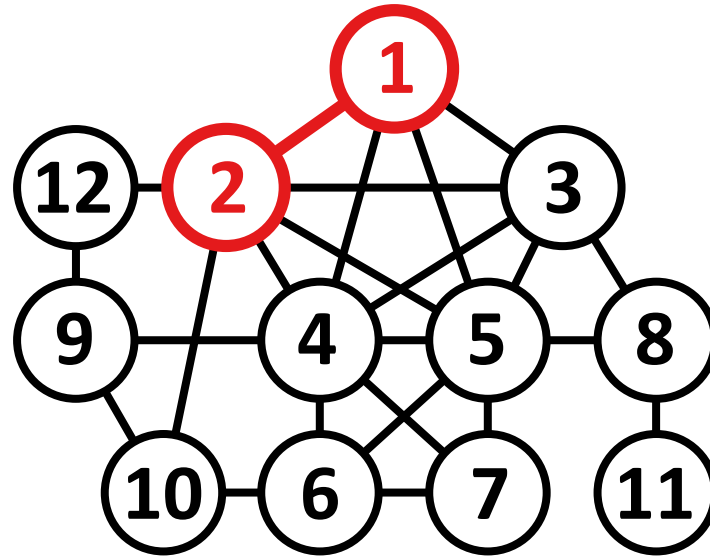
Important and useful k -cores

- The **k -core** $C_k(G)$ of a graph G is the **maximum subgraph** of G such that each node in $C_k(G)$ is **incident** to $\geq k$ edges
 - In (pairwise) graphs, each edge $e = (v_1, v_2)$ consists of a pair of nodes, v_1 and v_2 , and we say both v_1 and v_2 are incident to this edge e
 - The number of edges that a node v is incident to is also called the **degree** of v
 - It is maximum in the sense that **no node or edge can be added** into the k -core while still satisfying the conditions



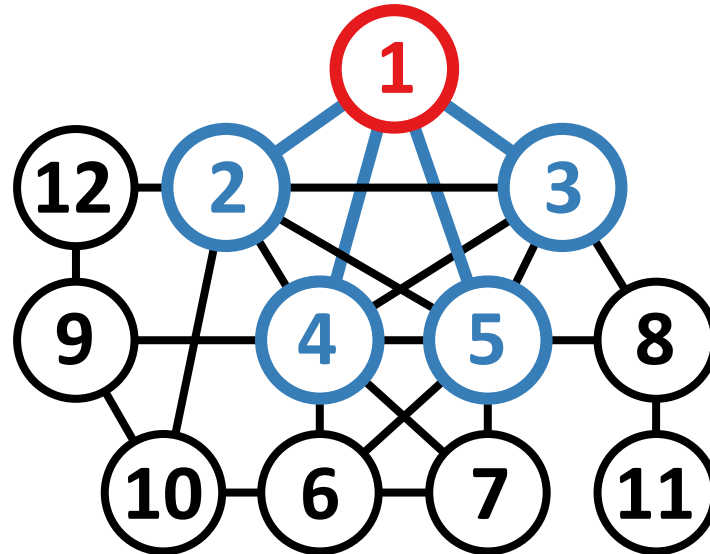
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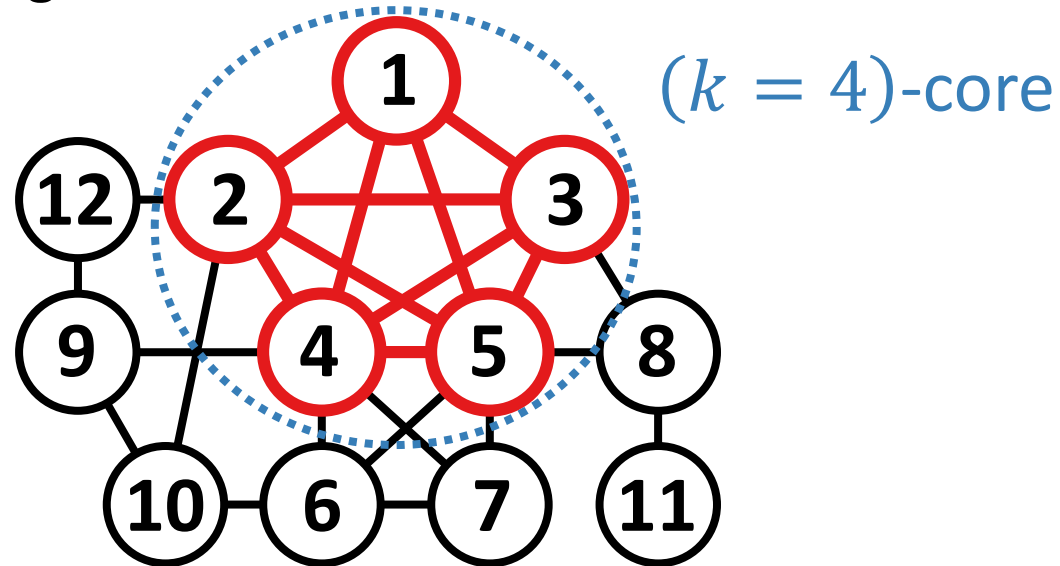
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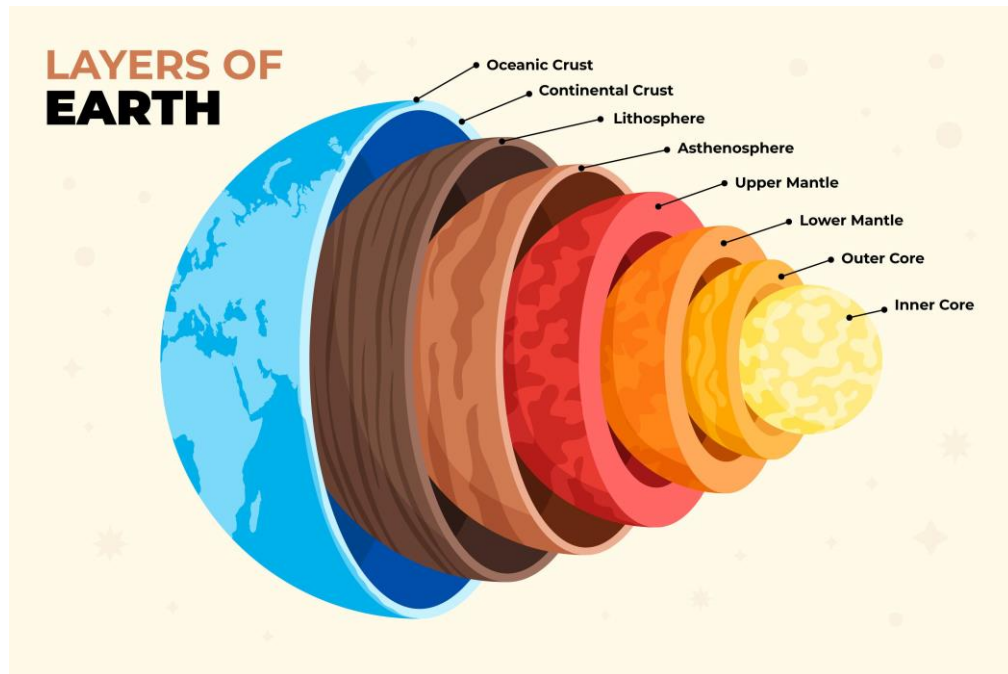
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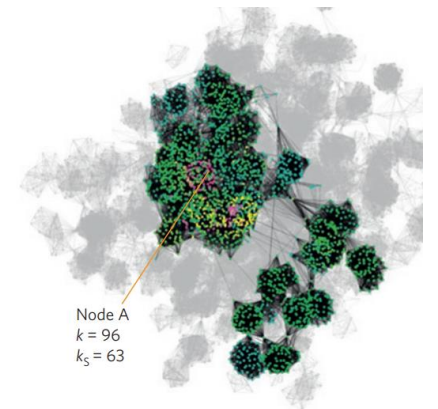
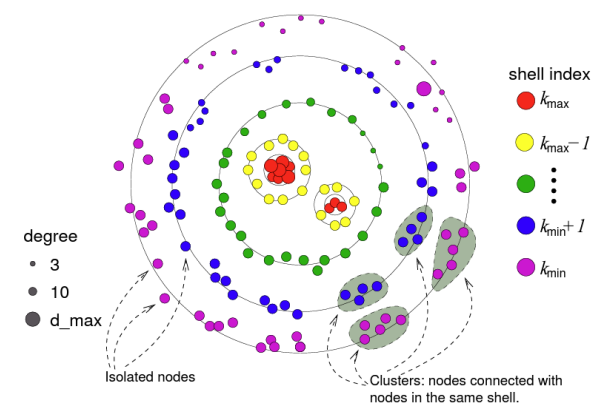
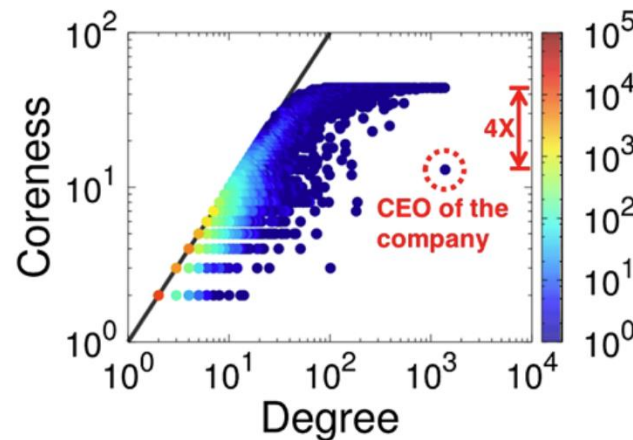
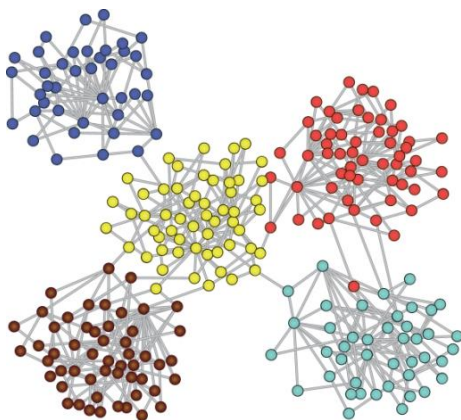
Important and useful k -cores

- The k -core $C_k(G)$ of a graph G is the **maximum subgraph** of G such that each node in $C_k(G)$ is **incident** to $\geq k$ edges
 - We can obtain the k -core by keeping removing nodes violating the conditions
 - Whenever a node is removed, **all its incident edges are removed** too



Important and useful k -cores

- The k -core $C_k(G)$ of a graph G is the **maximum subgraph** of G such that each node in $C_k(G)$ is **incident** to $\geq k$ edges
- **Applications:** community detection, anomaly detection, network visualization, important-node identification, ...



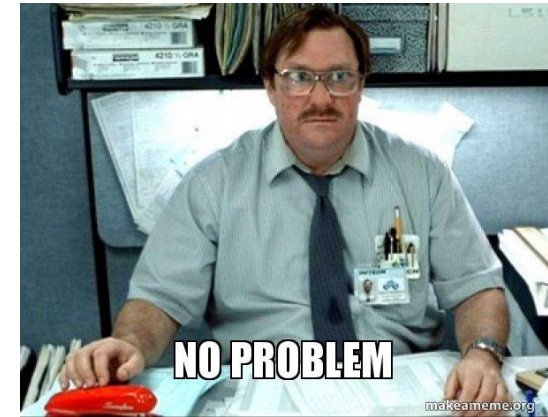
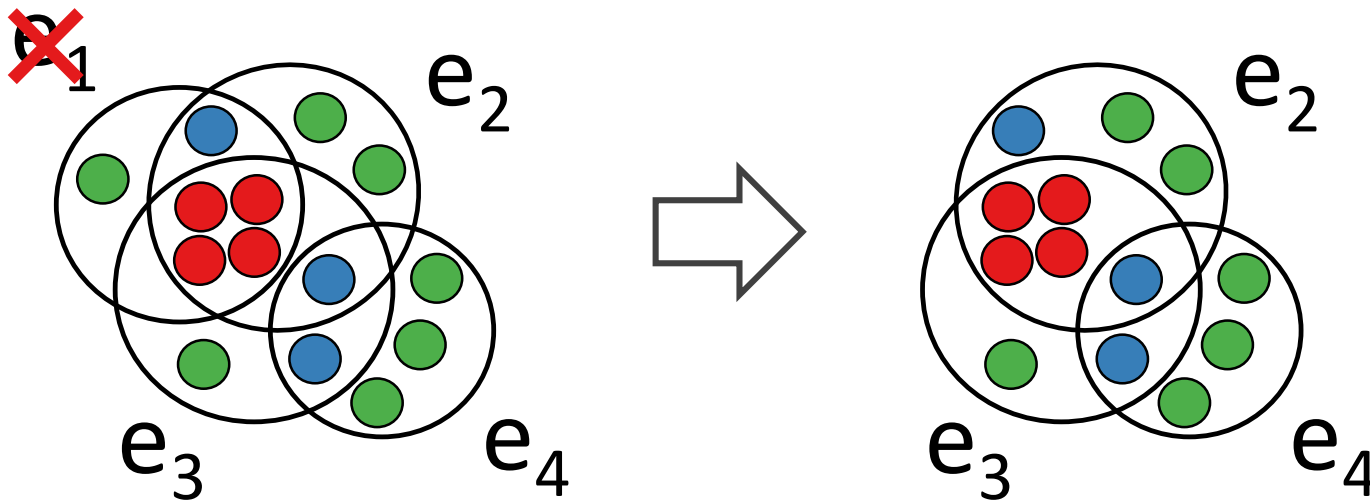
Hypercores: k -cores in hypergraphs

- **Q:** How can we generalize k -cores in hypergraphs?
- The **k -core** $C_k(G)$ of a graph G is the maximum **subgraph** of G such that each node in $C_k(G)$ is incident to $\geq k$ **edges**
- The **k -hypercore** $C_k(H)$ of a hypergraph H is the max. **subhypergraph** of H such that each node in $C_k(H)$ is incident to $\geq k$ **hyperedges**
- **Q:** What kind of subhypergraphs should we allow?



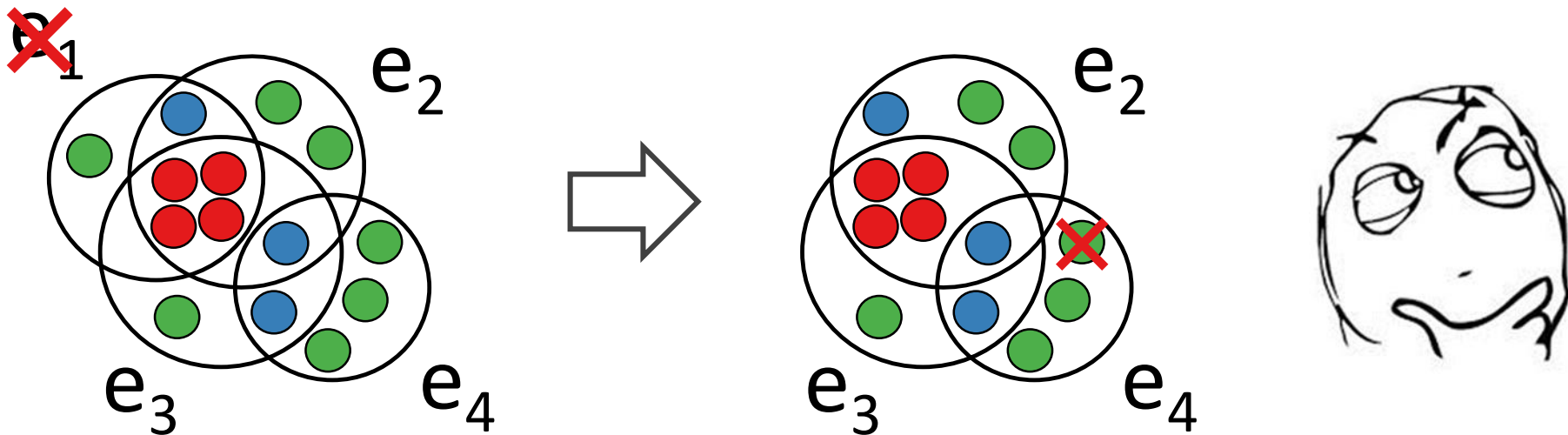
Hypercores: k -cores in hypergraphs

- The k -hypercore $C_k(H)$ of a hypergraph H is the max. **subhypergraph** of H such that each node in $C_k(H)$ is incident to $\geq k$ **hyperedges**
- **Q:** What kind of **subhypergraphs** should be allowed in k -hypercores?
 - Simply removing **some of the hyperedges**?



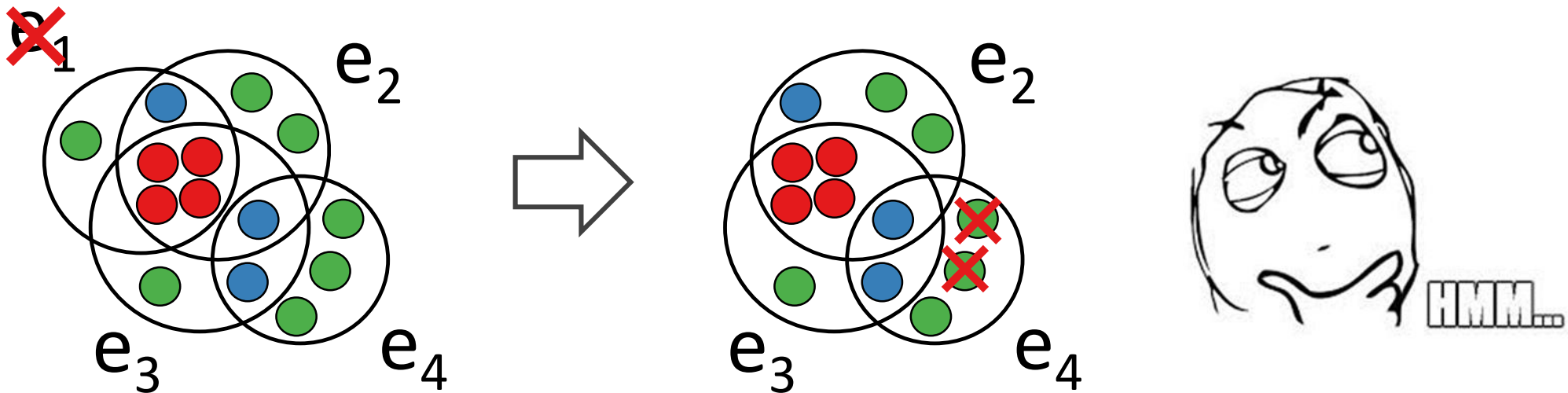
Hypercores: k -cores in hypergraphs

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- **Q:** What kind of **subhypergraphs** should be allowed in k -hypercores?
 - What if we remove **some of the nodes** from a **hyperedge**?



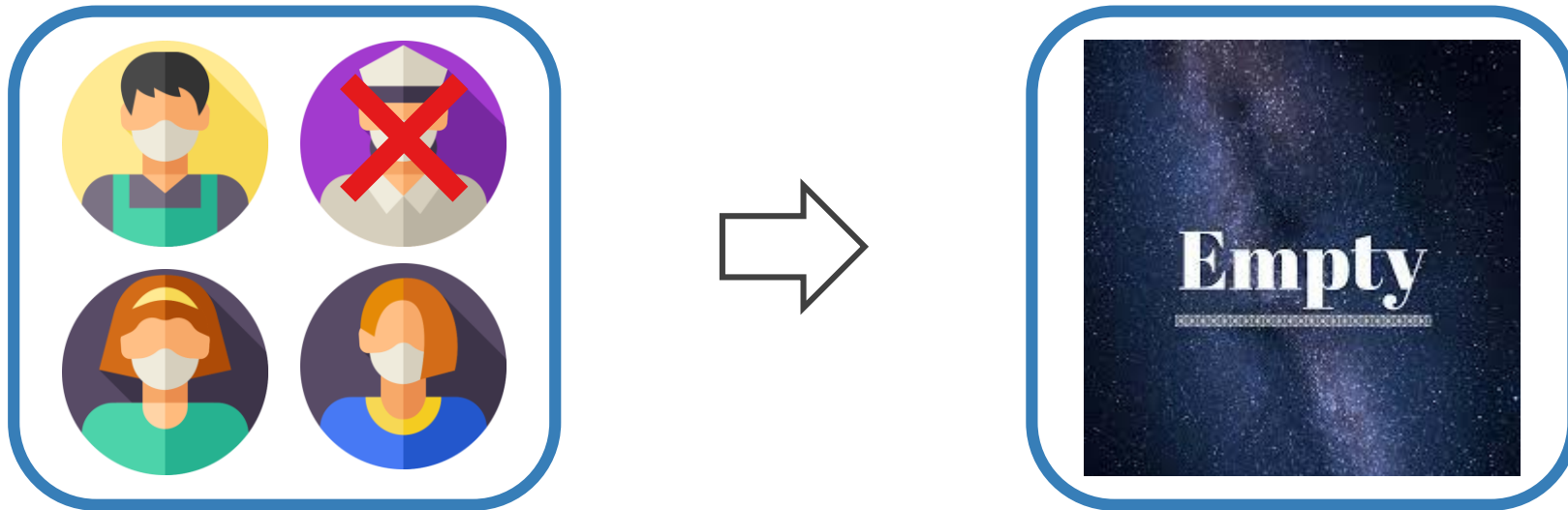
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- **Q:** What kind of **subhypergraphs** should be allowed in k -hypercores?
 - **How many** nodes are allowed to leave a hyperedge?



A Naïve Definition with Fragile Hyperedges

- Hyperedges are **fragile**, with **every** member **indispensable**
- A hyperedge is kept only if **all** the constituent nodes remain
- But this is **NOT** realistic!



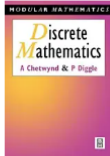
Real-World Groups are Not Fragile

- Many real-world groups still remain valid even if some members leave




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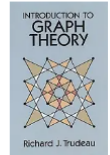
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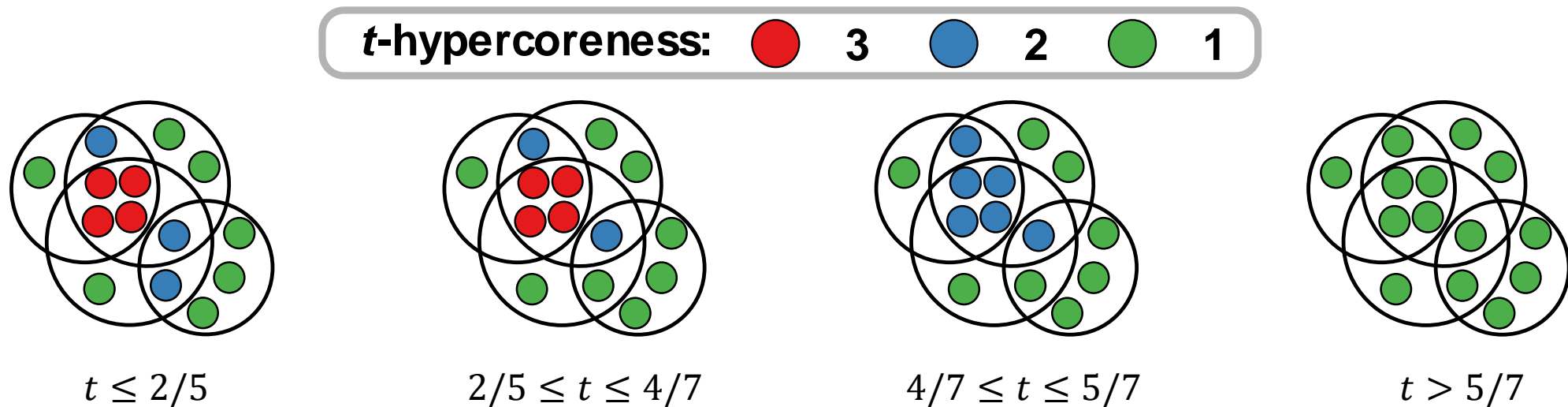
Definition: (k, t) -Hypercores

- Given a hypergraph $H = (V, E)$, a positive integer k , and $t \in [0, 1]$
- The (k, t) -hypercore $C_{k,t}(H)$ of H , is the maximum subhypergraph of H such that
 - Each **node** in $C_{k,t}(H)$ is incident to $\geq k$ hyperedges
 - Each **hyperedge** in $C_{k,t}(H)$ contains $\geq t$ proportion of the original constituent nodes (and at least two nodes)
- **Example:** $t = 3/4$



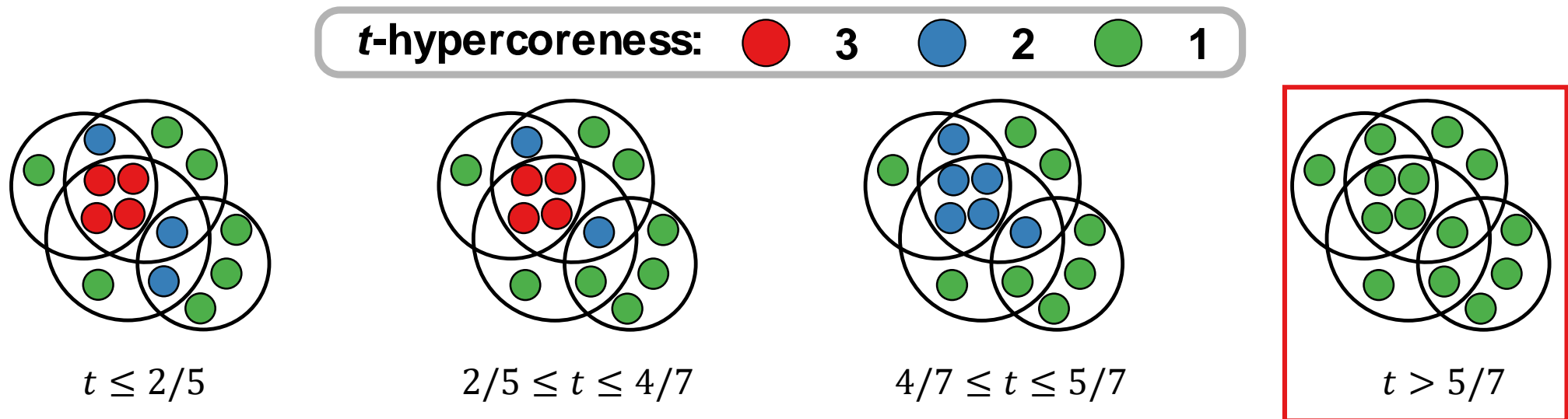
Related Concepts: t -Hypercoreness & k -Fraction

- The **t -hypercoreness** $c_t(v)$ of a node v is the **maximum** k^* such that v is in the (k^*, t) -hypercore
- The **k -fraction** $f_k(v)$ of a node v is the maximum t^* such that v is in the (k, t^*) -hypercore
- **Example:** Different (k, t) -hypercore structures with different t values



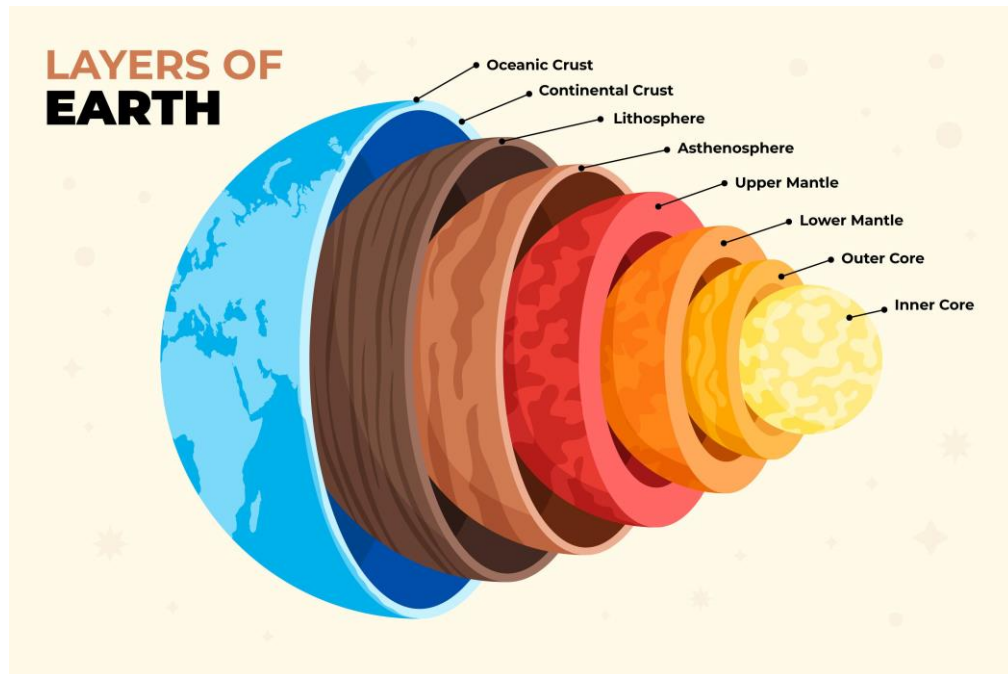
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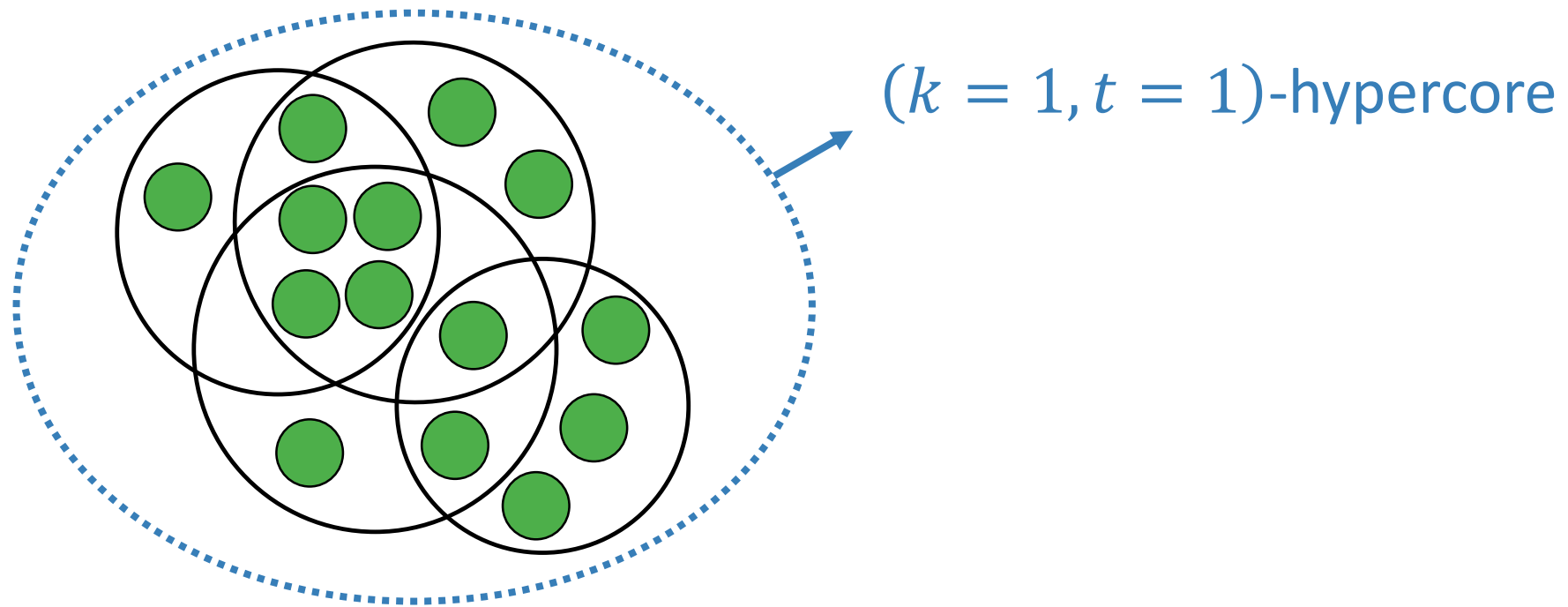
Computation Algorithms: Find the Core

- **Peeling:** We repeatedly remove nodes and hyperedges violating the conditions, until the conditions are satisfied
- **Time complexity: Linear** to the total size of the input hypergraph
 - Specifically, $O(\sum_{e \in E} |e|)$



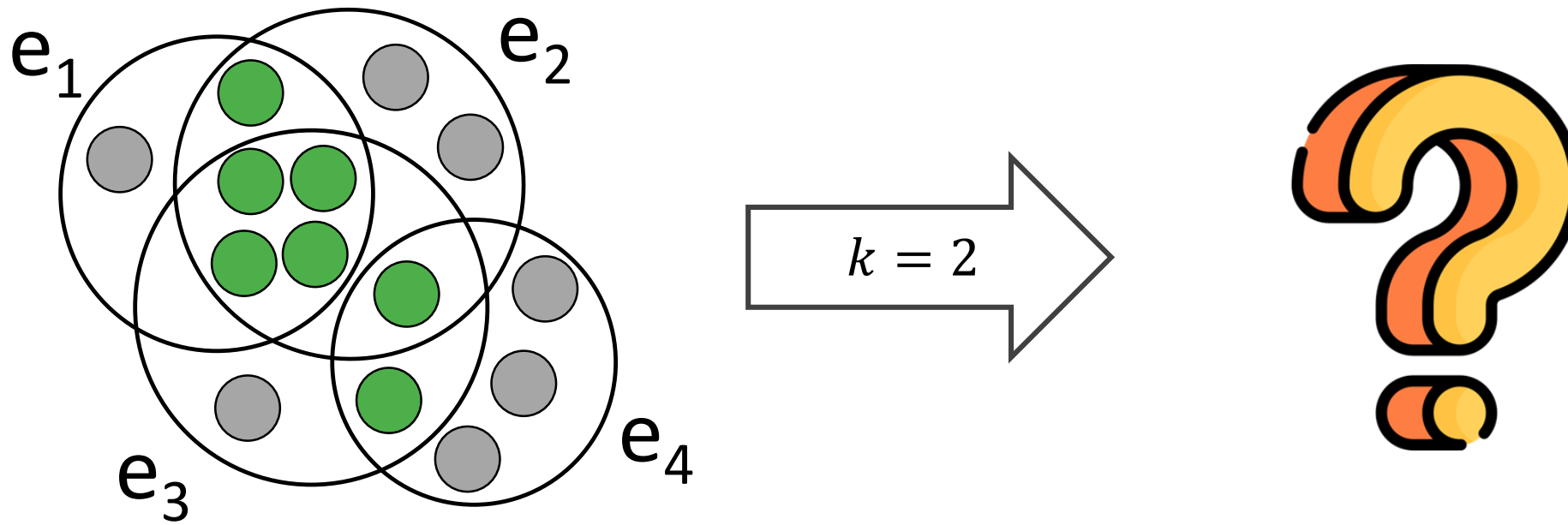
Computation Algorithms: Example ($t = 1$)

- **Example:** how we obtain a (k, t) -hypercore



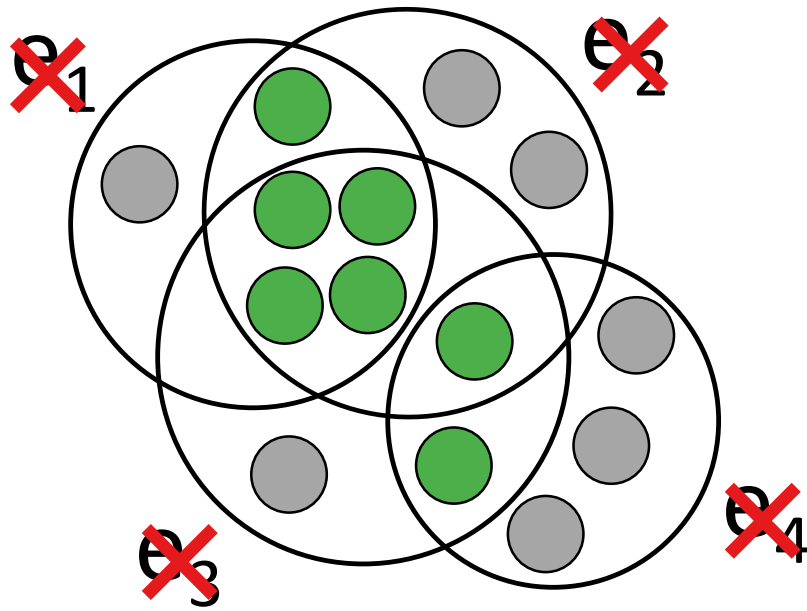
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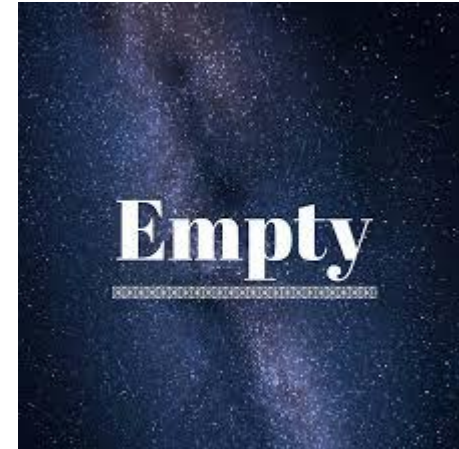


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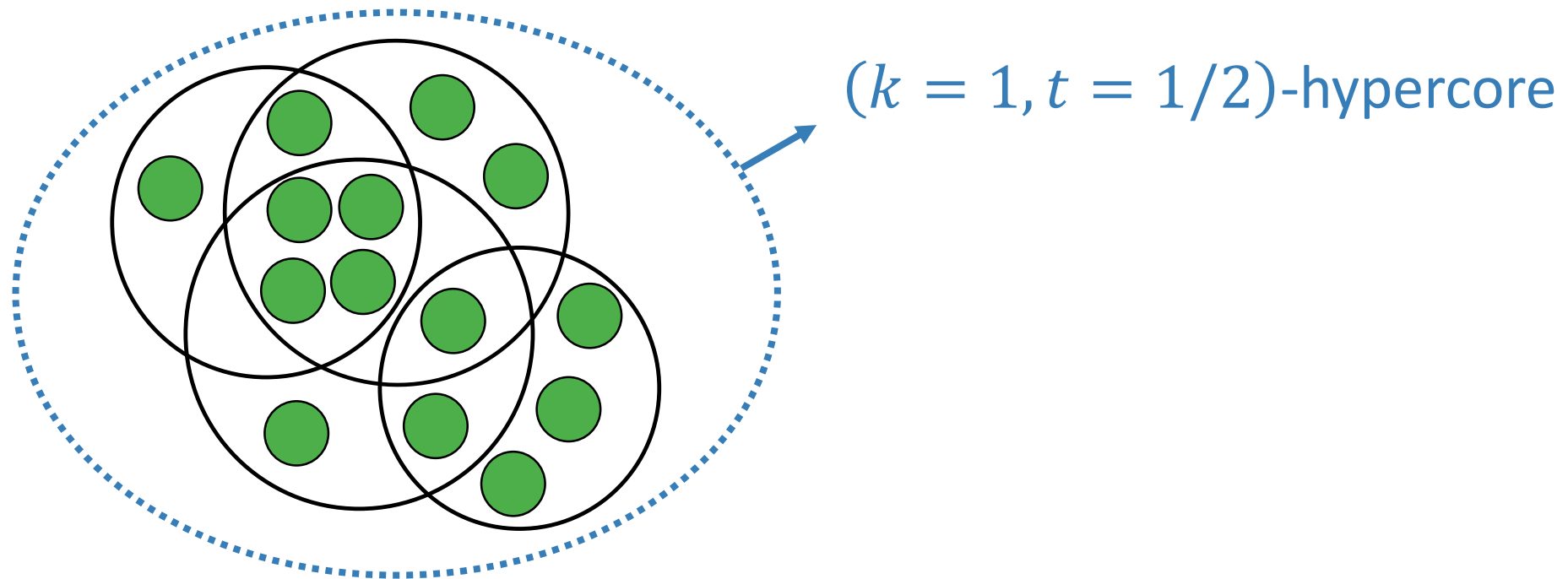


$k = 2$



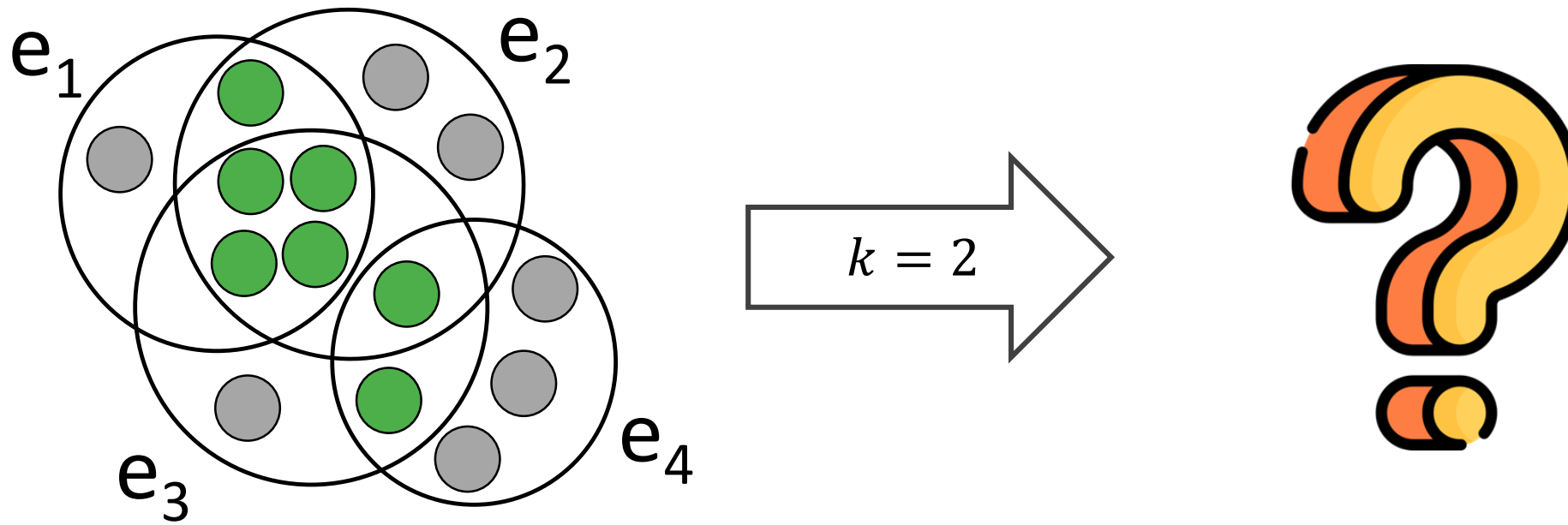
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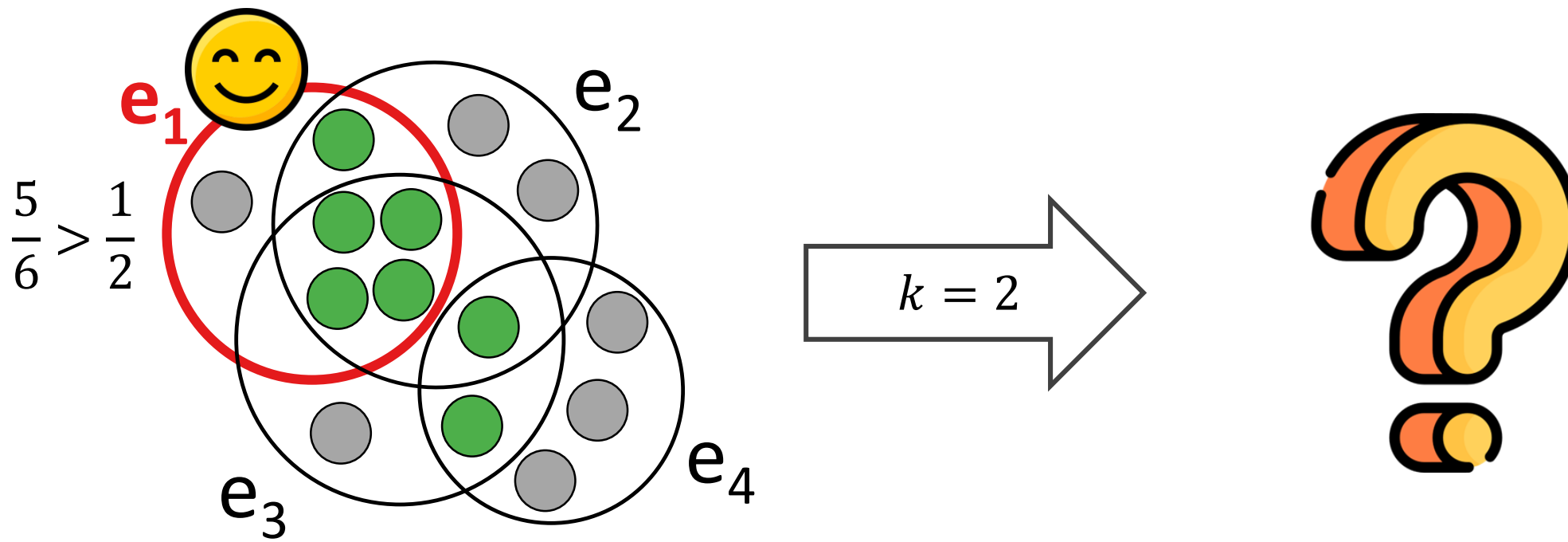
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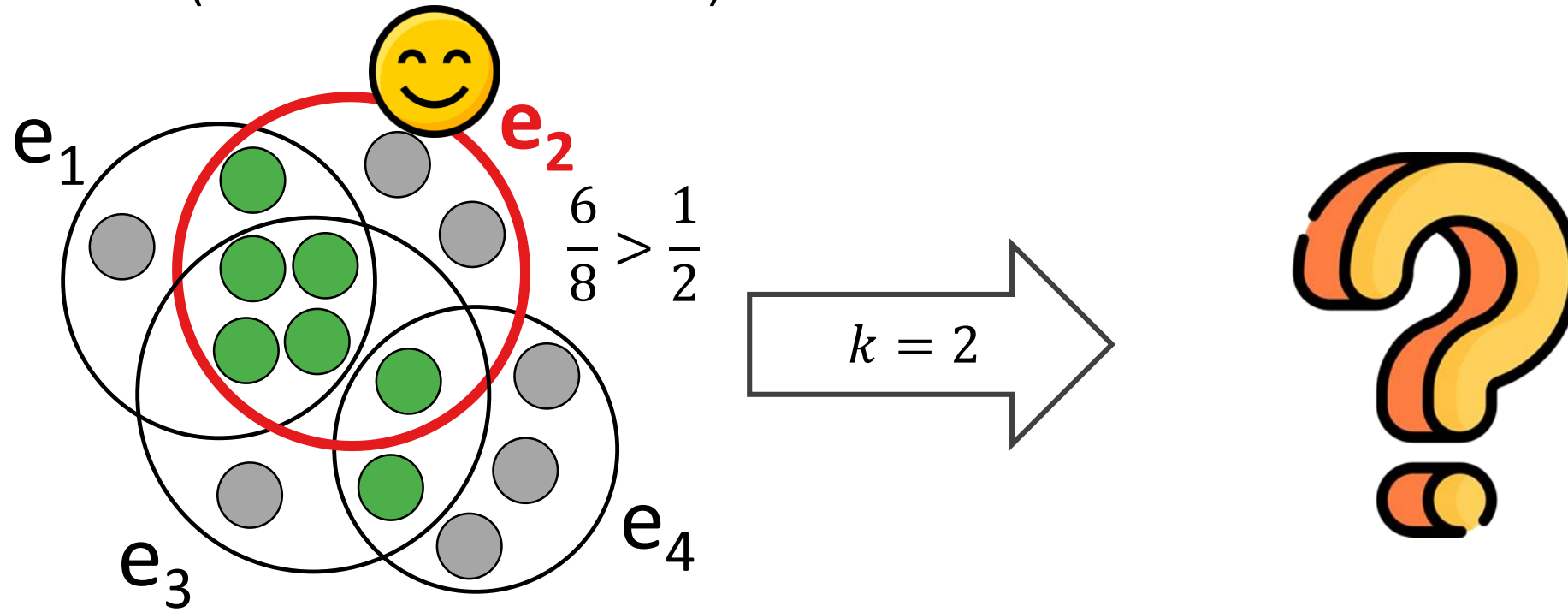
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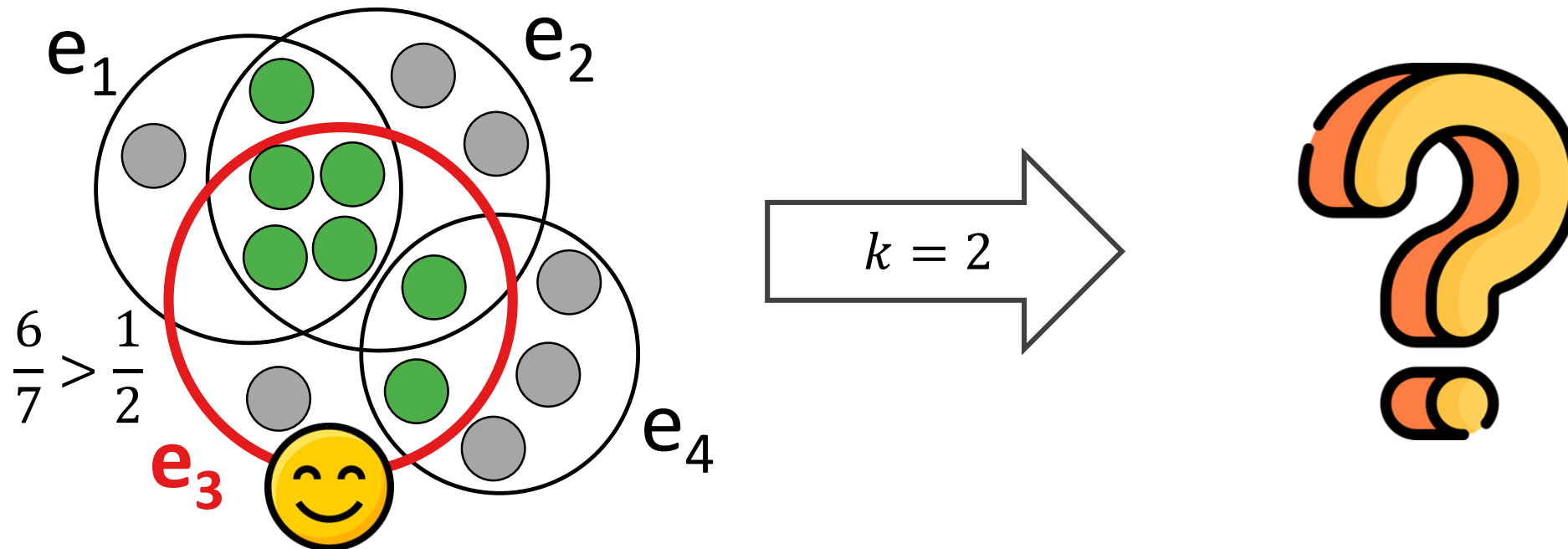
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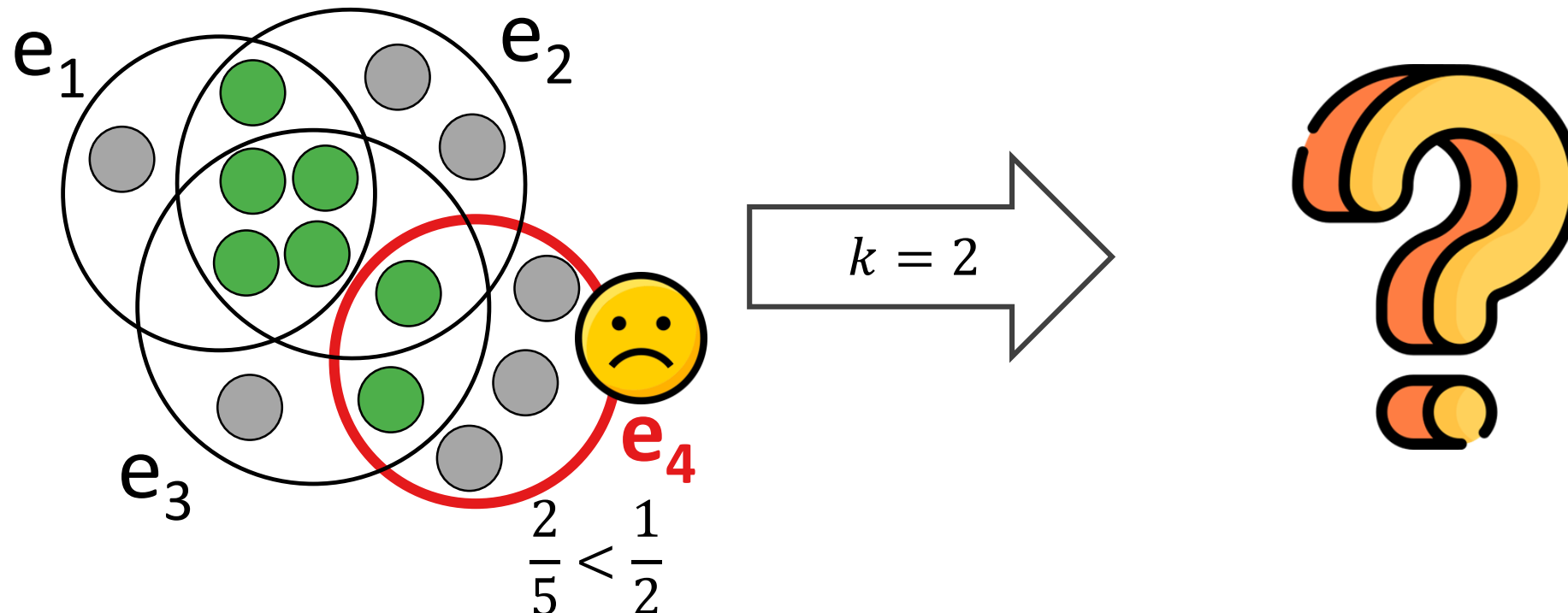
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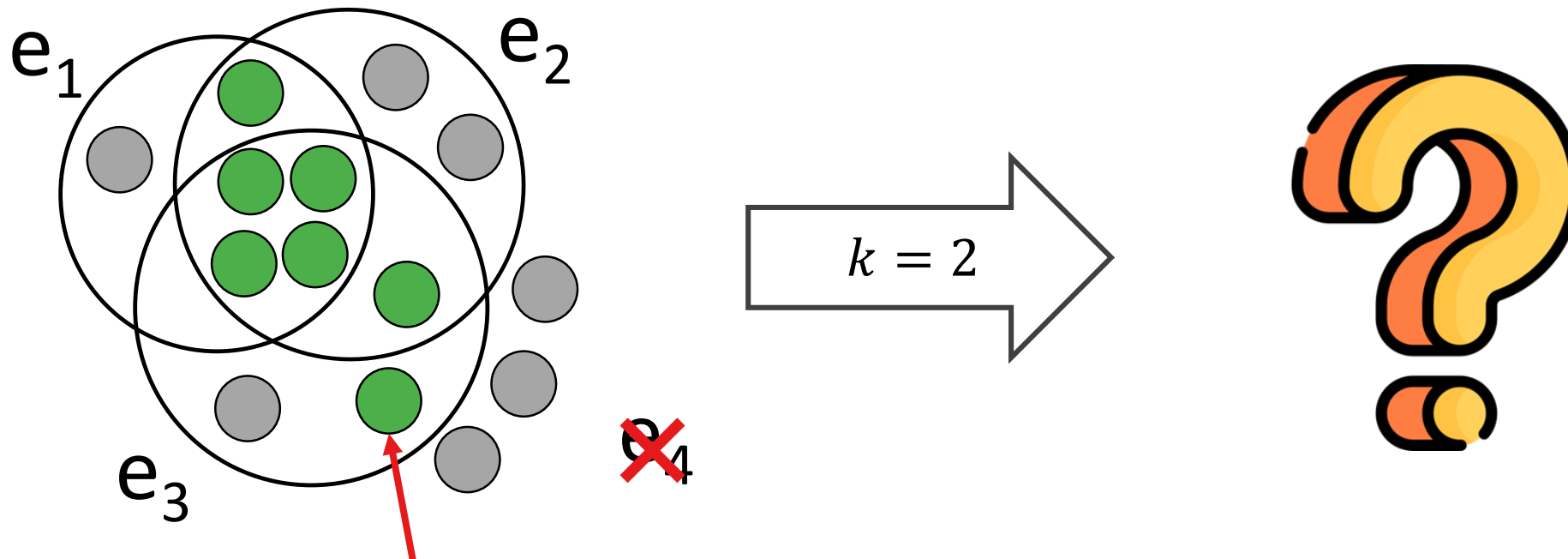
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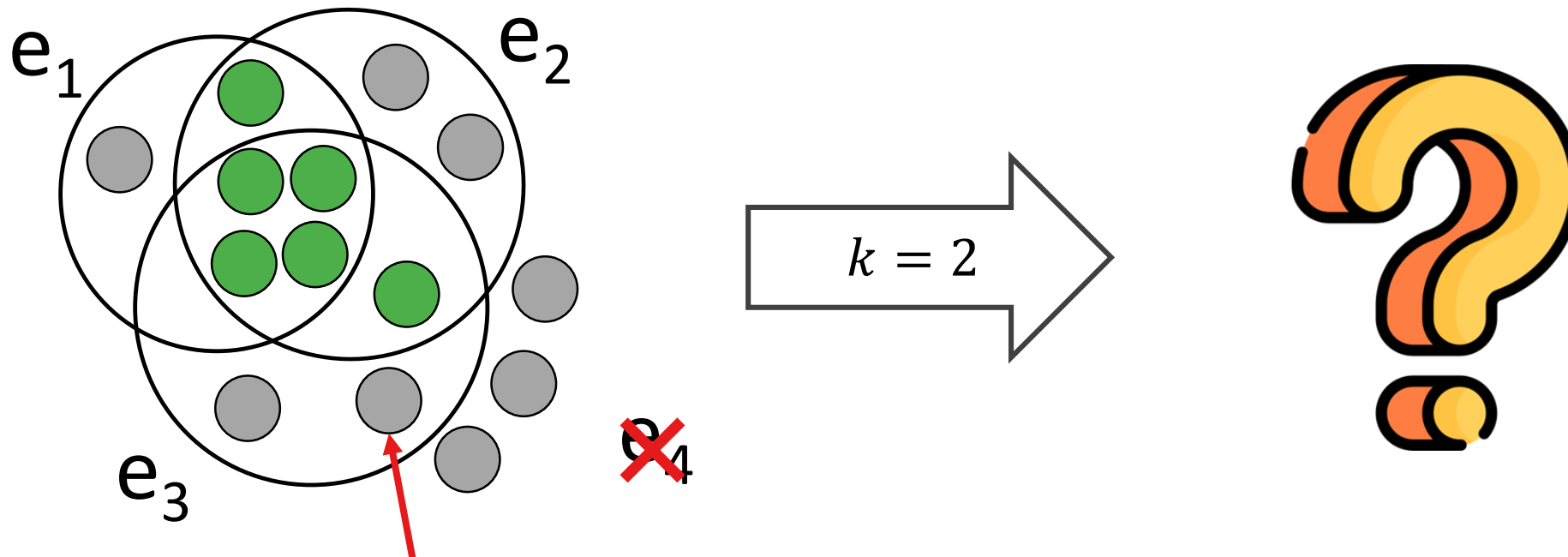
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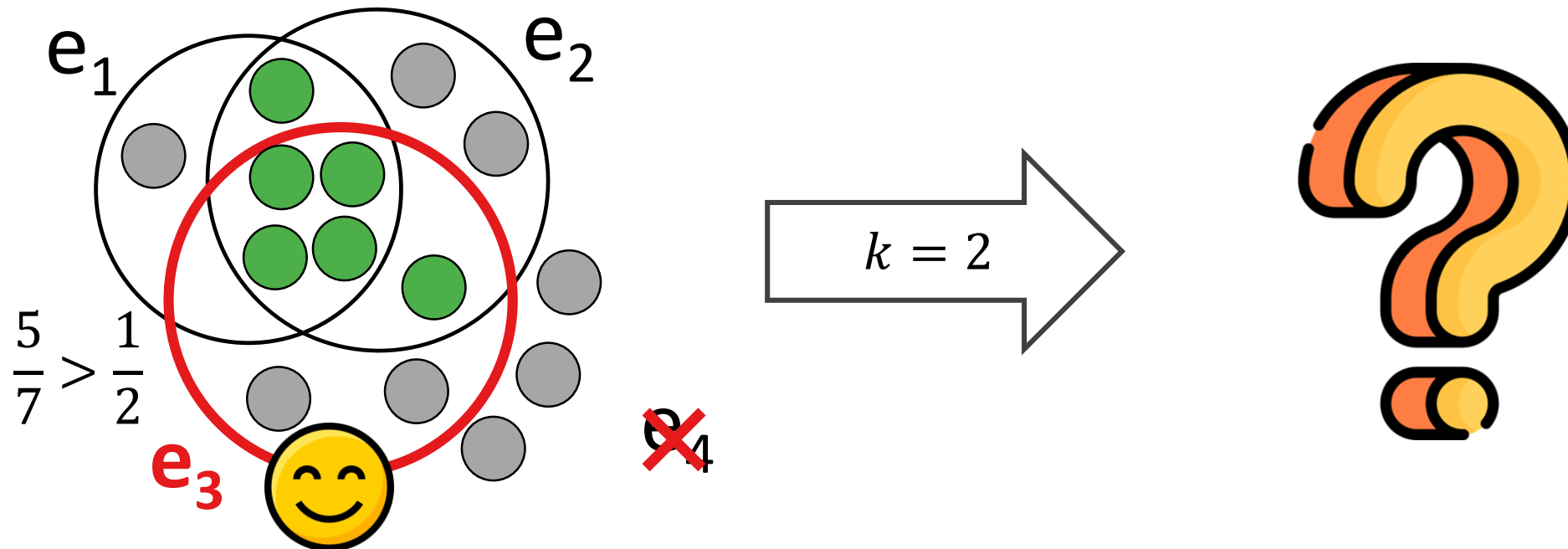
Computation Algorithms: Example ($t = 1/2$)

- **Example:** how we obtain a (k, t) -hypercore
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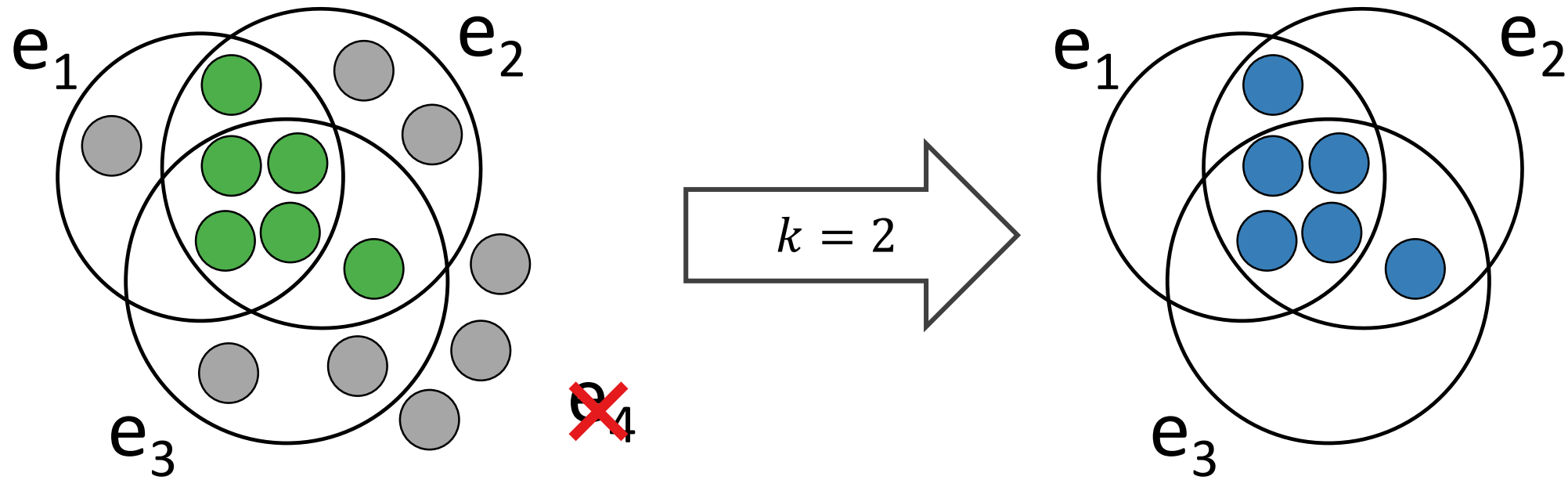
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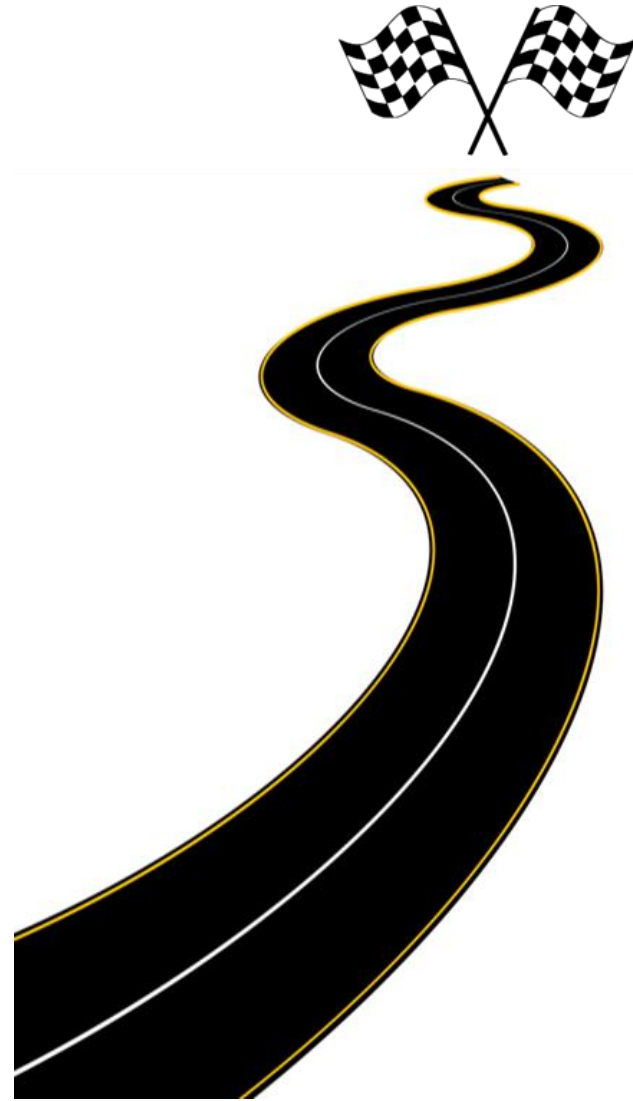
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Roadmap

- Concepts & Algorithms
- **Observations <<**
- Applications
- Conclusions



Real-World Hypergraph Datasets

- **Datasets:** 14 real-world hypergraphs from 6 different domains

- # nodes: 143 – 2.3M
- # hyperedges: 1,047 – 8.6M



- **Source:** <https://www.cs.cornell.edu/~arb/data/>

Dataset	$ V $	$ E $	max./avg. $d(v)$	max./avg. $ e $
coauth-DBLP	1,831,126	2,169,663	846 / 4.06	25 / 3.42
coauth-Geology	1,087,111	908,516	716 / 3.21	25 / 3.84
NDC-classes	1,149	1,047	221 / 5.57	24 / 6.11
NDC-substances	3,438	6,264	578 / 14.51	25 / 7.96
contact-high	327	7,818	148 / 55.63	5 / 2.33
contact-primary	242	12,704	261 / 126.98	5 / 2.42
email-Enron	143	1,457	116 / 31.43	18 / 3.09
email-Eu	979	24,399	910 / 86.93	25 / 3.49
tags-ubuntu	3,021	145,053	12,930 / 164.56	5 / 3.43
tags-math	1,627	169,259	13,949 / 363.80	5 / 3.50
tags-SO	49,945	5,517,054	520,468 / 427.77	5 / 3.87
threads-ubuntu	90,054	115,987	2,170 / 2.97	14 / 2.31
threads-math	153,806	535,323	11,358 / 9.08	21 / 2.61
threads-SO	2,321,751	8,589,420	34,925 / 9.75	25 / 2.64

- **Coauth:** Co-authorship
- **NDC:** National Drug Code
- **Tags and threads** are collected from different sub-sites on an online Q&A platform <https://stackexchange.com/>

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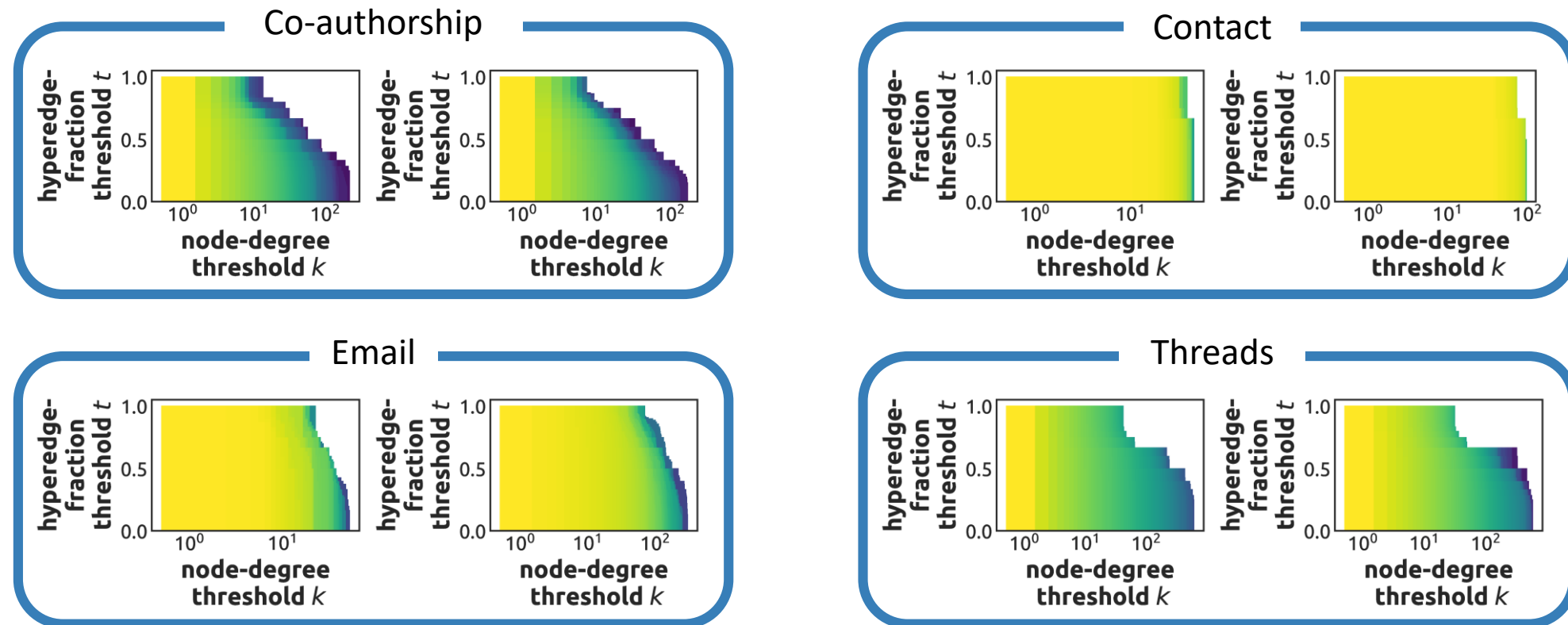


Domain	Nodes	Hyperedges
coauth	Researchers	Publications
NDC	Classes/Substances	Drugs
contact	People	Communications
email	Senders/Receivers	Emails
tags	Tags	Questions
threads	Users	Threads

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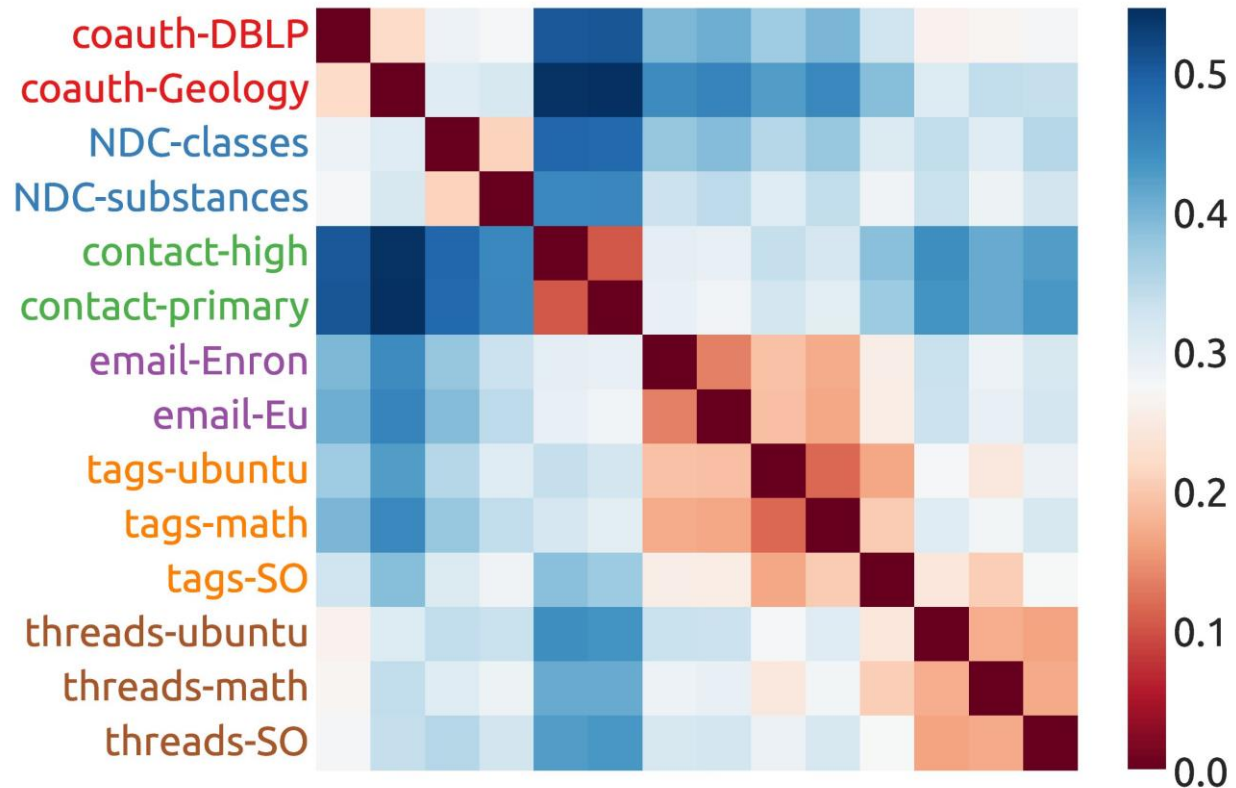
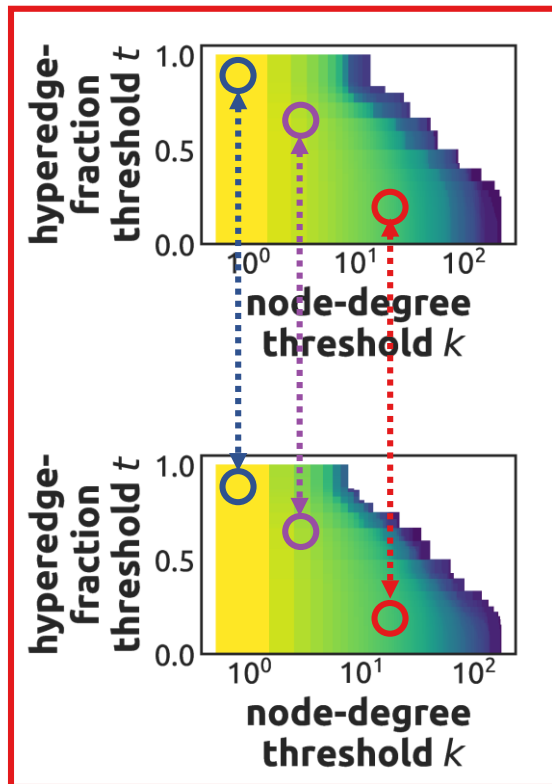
Observation 1: Domain-Based Patterns of Hypercore Sizes

- **Observation:** Real-world hypergraphs in the same domain have similar patterns of hypercore sizes with different k and t values
- **Color of each pixel:** The normalized size of the (k, t) -hypercore



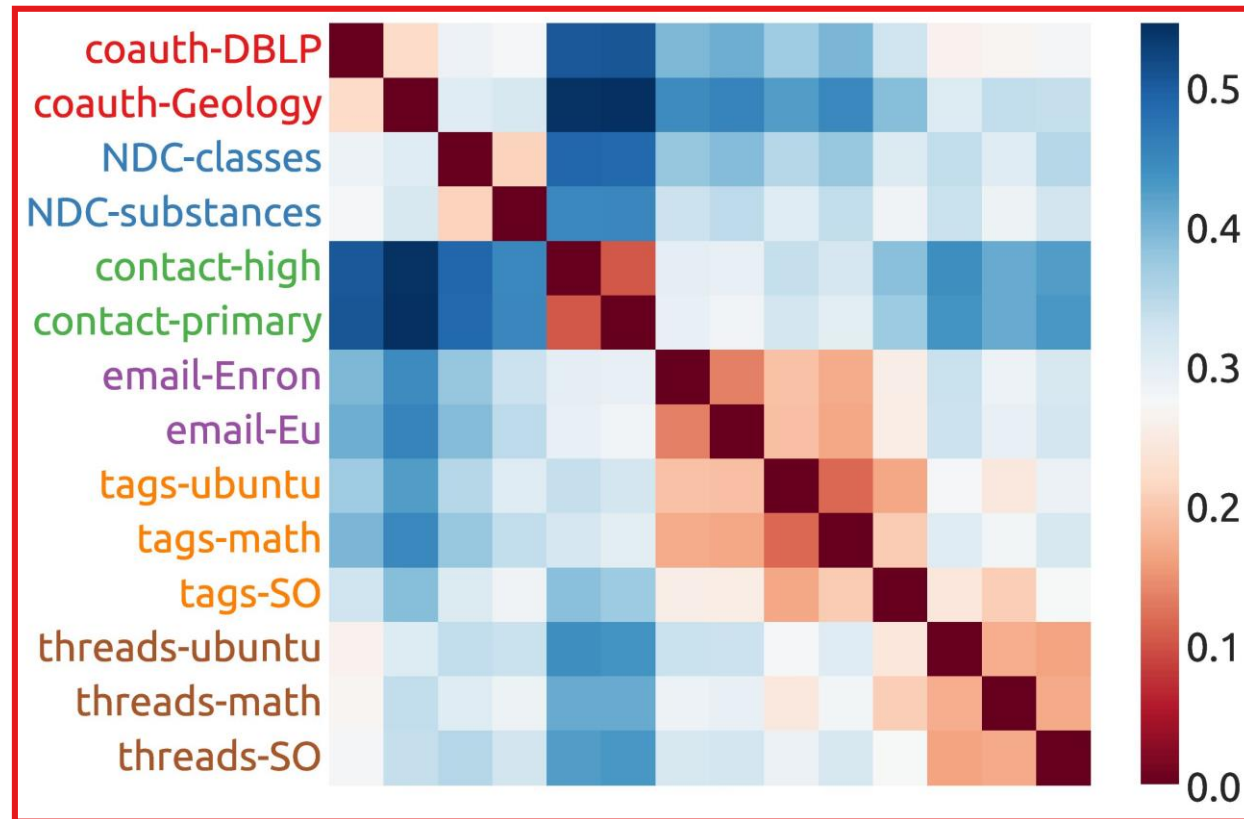
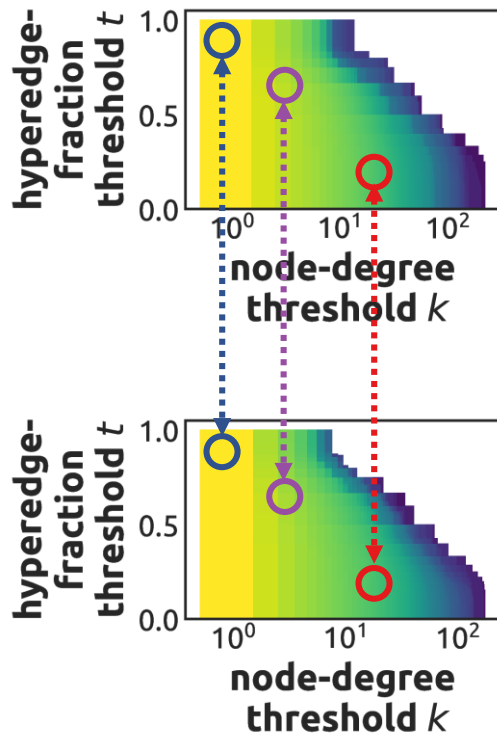
Observation 1: Pairwise Distance

- We define a **distance metric** to compare the patterns of hypercore sizes between different hypergraphs, which can be interpreted as the average **pixel-level difference** between the plots in the previous page



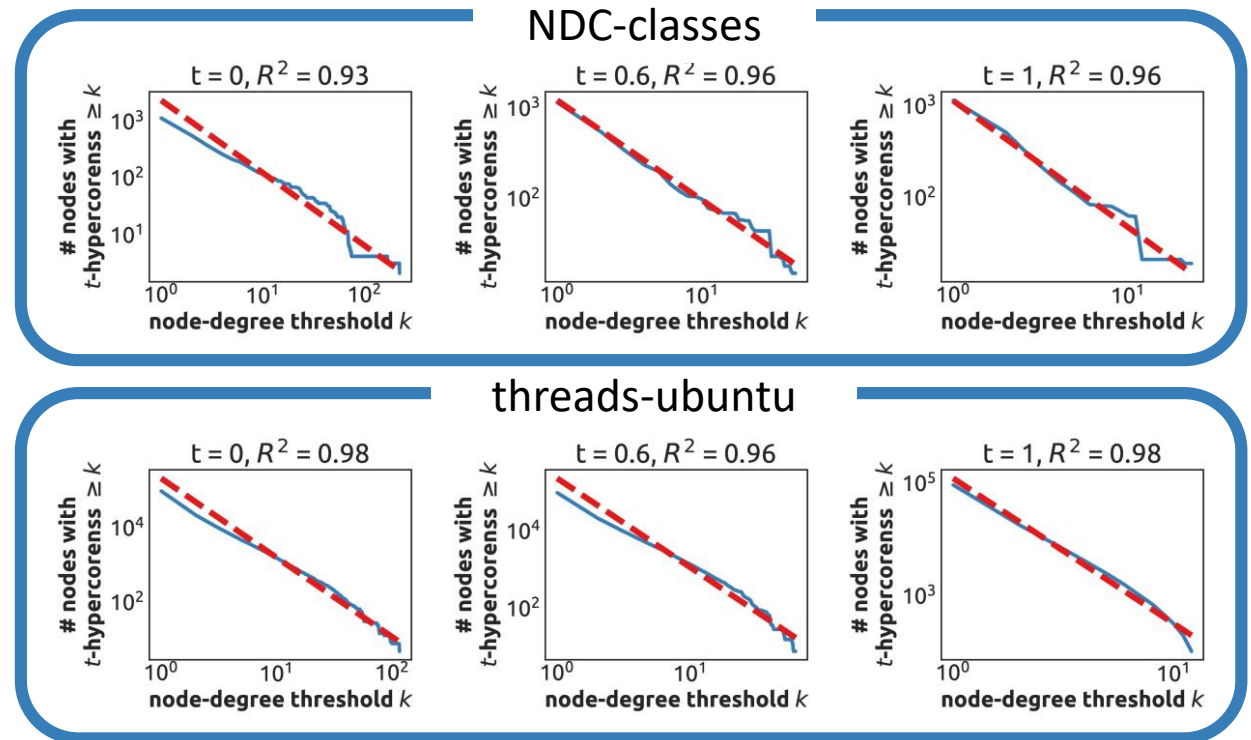
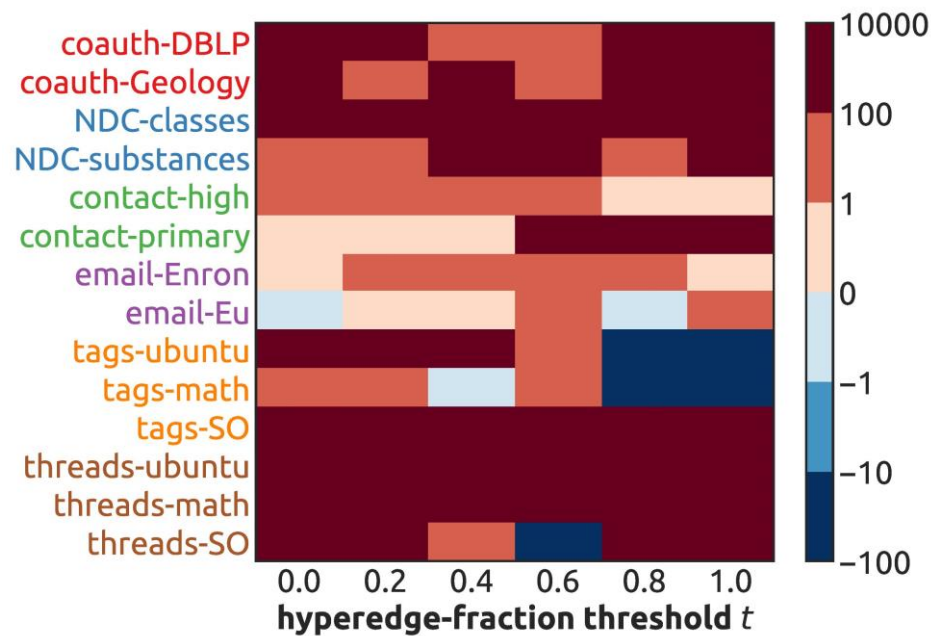
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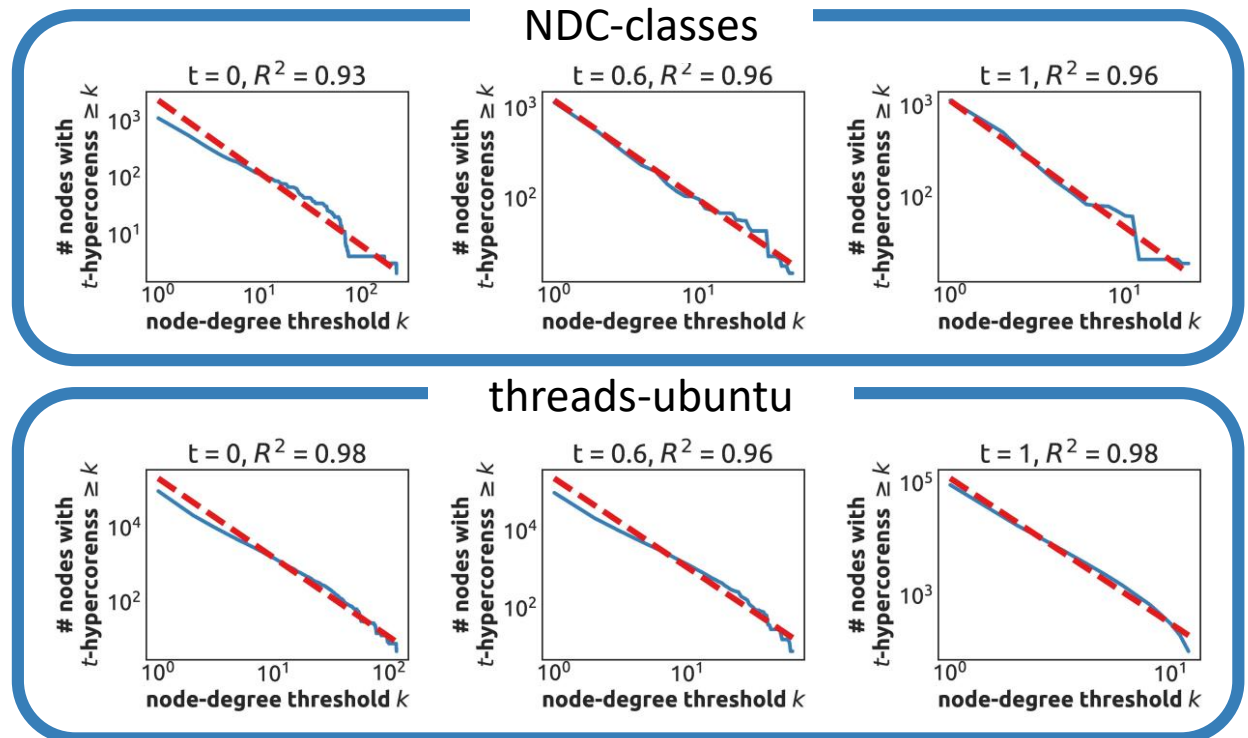
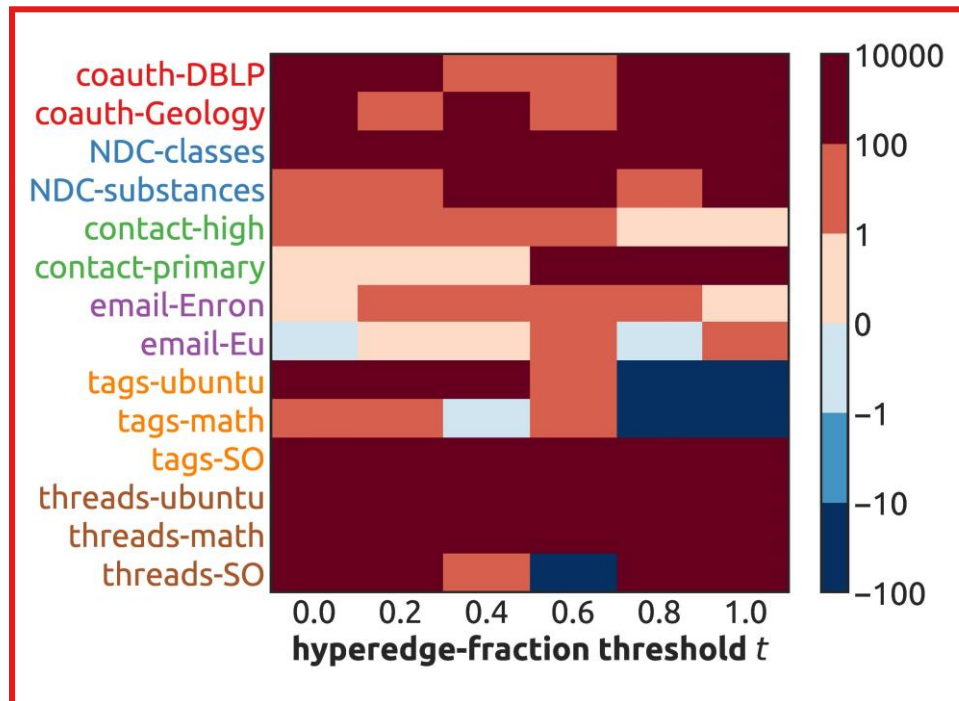
Observation 2: Heavy-Tailed Hypercoreness Distributions

- **Observation:** In real-world hypergraphs, t -hypercoreness follows **heavy-tailed** distributions regardless of t . In some datasets, the t -hypercoreness strongly follows a **power law**.
- **Left: Red colors** indicates heavy-tailed distributions



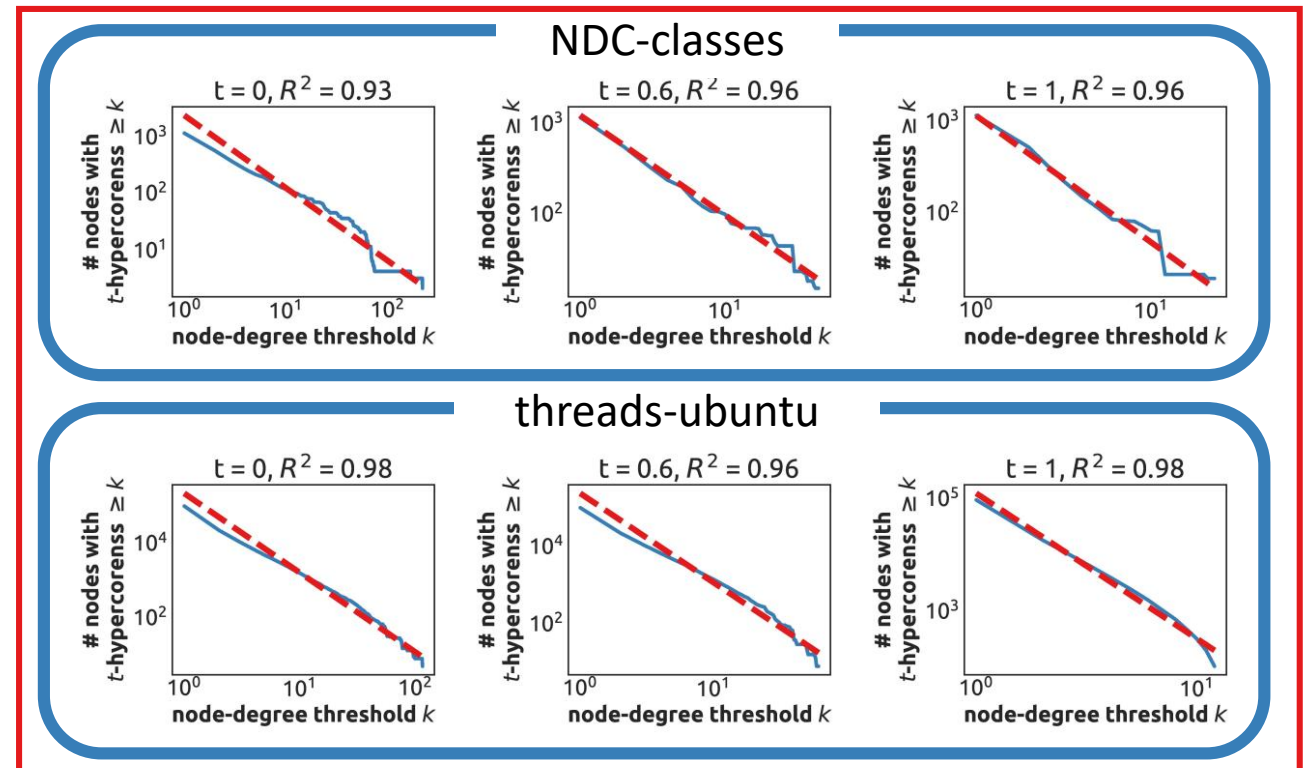
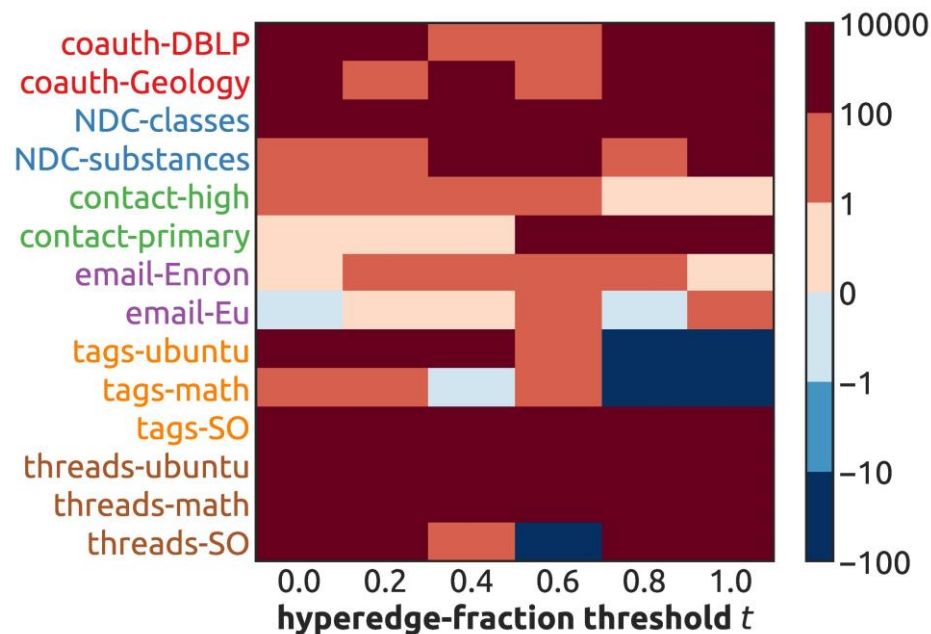
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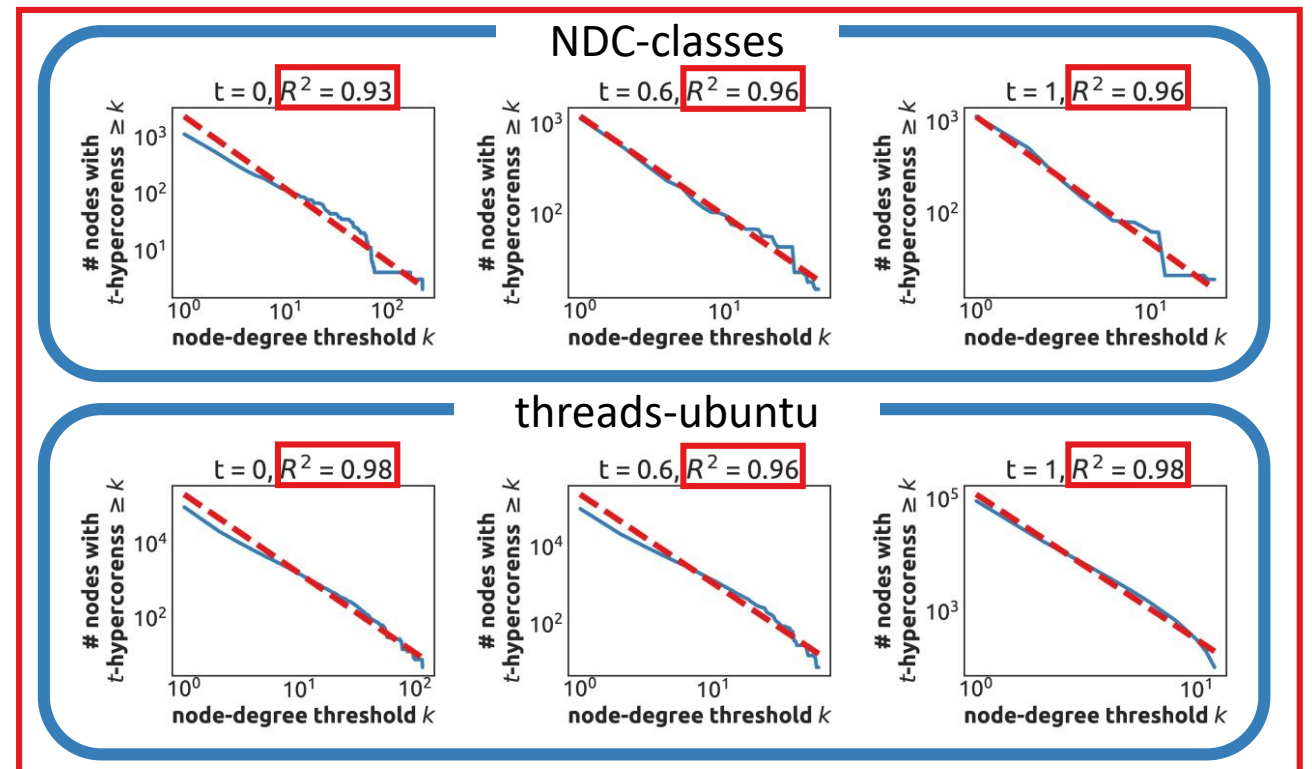
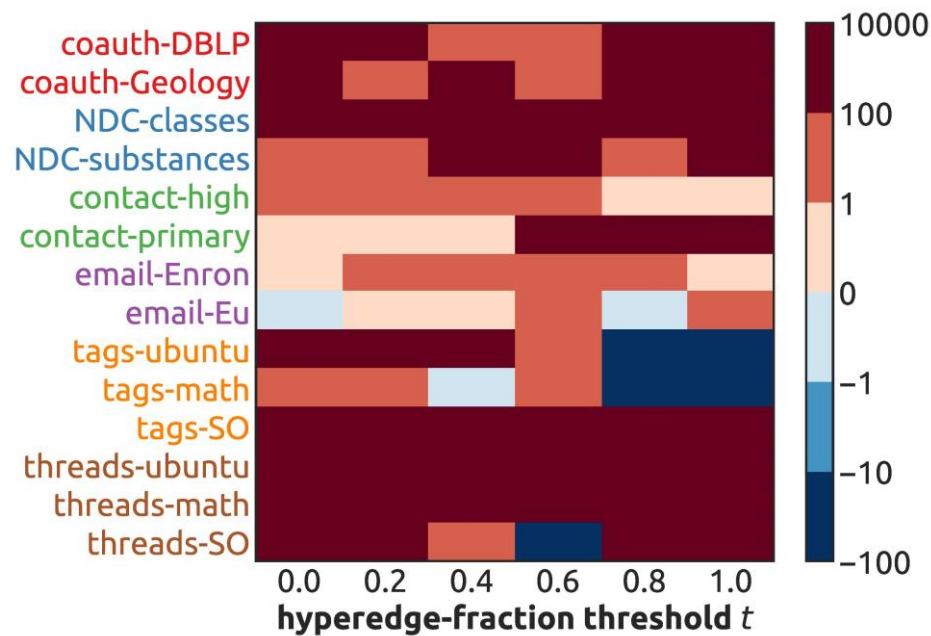
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Observation 3: t -Hypercoreness is Different

- **Observation:** t -Hypercoreness is statistically different **from other existing centrality measures**
 - **Meaning:** t -Hypercoreness can provide unique insights of a hypergraph
- **Observation:** Even for the same hypergraph, with **varying t values**, the t -hypercoreness can be statistically different **from each other**
 - **Meaning:** Using different t values can provide us different insights



Roadmap

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Application 1: Influential-Node Identification

- **Spoiler:** In real-world hypergraphs, t -hypercoreness with a proper t value **identifies influential nodes** well
- **Set-up:** We use a widely-used **epidemic model**, the SIR model
 - A **single initially infected node**
 - Infected nodes can infect susceptible nodes **in the same hyperedge**
 - Infected nodes have some probability to **recover** (and become immune)
 - The process terminates with only **susceptible** and **recovered** nodes



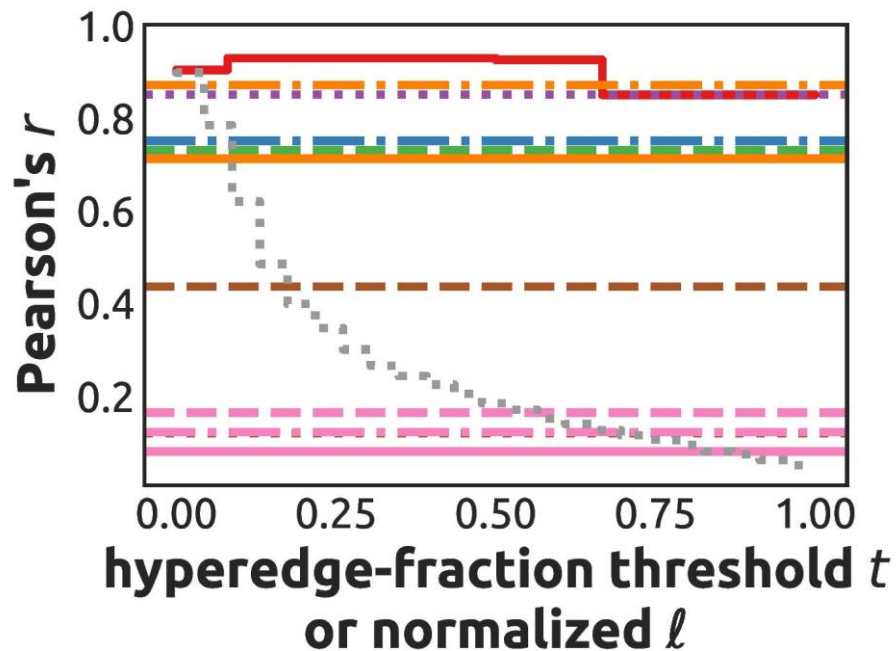
Application 1: Influential-Node Identification

- **Spoiler:** In real-world hypergraphs, t -hypercoreness with a proper t value **identifies influential nodes** well
- **Influence:** We measure the **influence** of each node v as the number of **ever-infected nodes** when v is the initially infected node
 - **Ever-infected nodes:** the nodes in the recovered state in the end
 - The influence of each node is measured by **simulations**

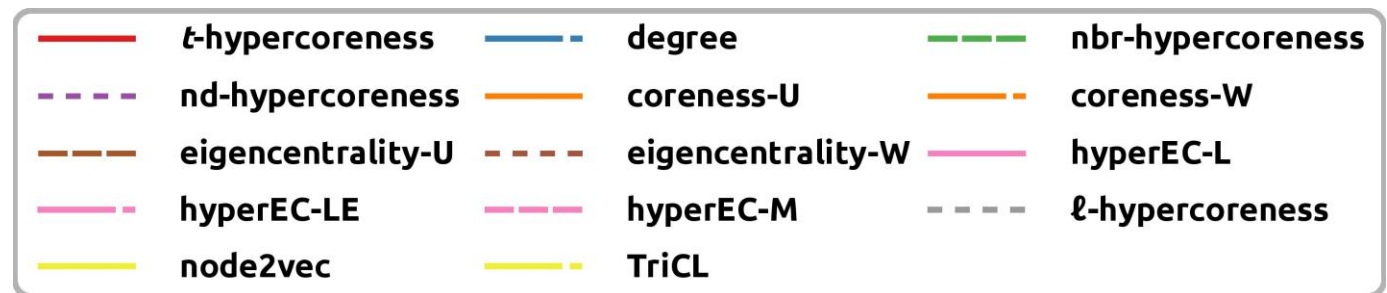


Application 1: Results

- **Metric:** For each considered measure, we compute the **Pearson's r** **between** the values of the **measure** and the **influences** of the nodes
 - The higher Pearson's r, the better
- **Result summary:** t -Hypercoreness with a proper t usually has **high correlation** with the influences of nodes

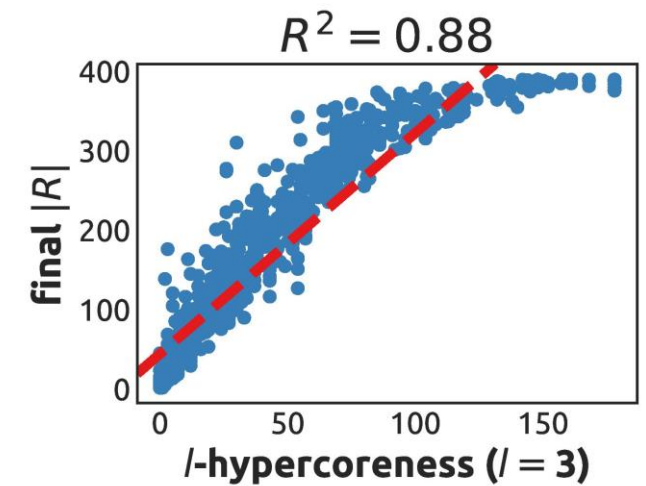
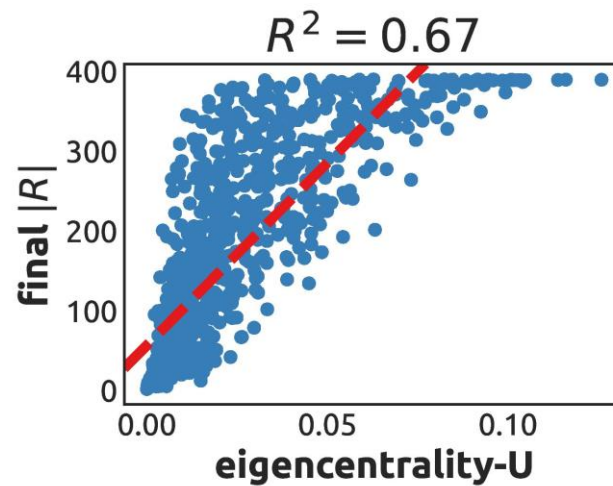
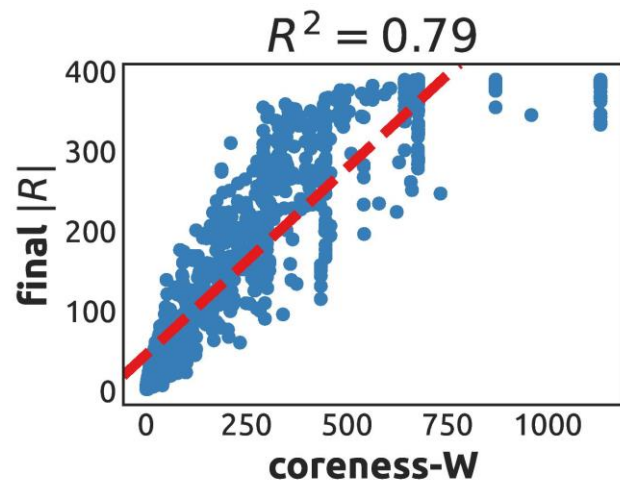
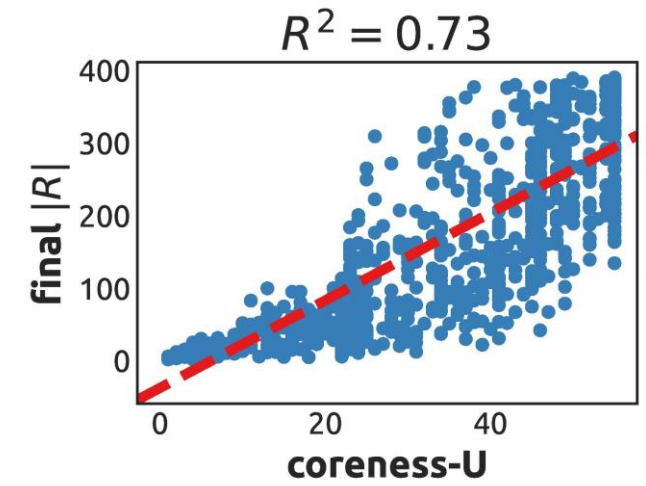
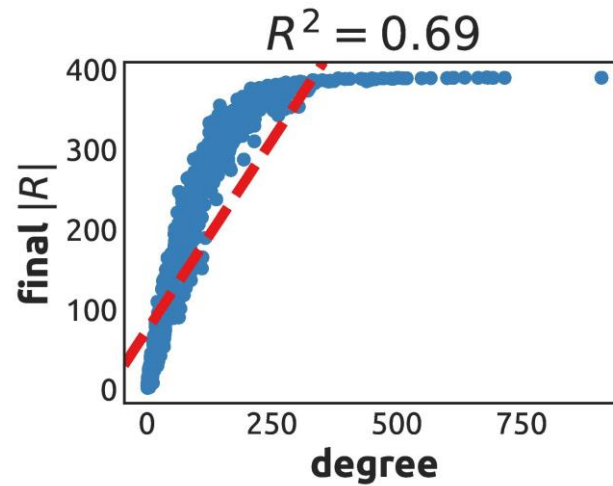
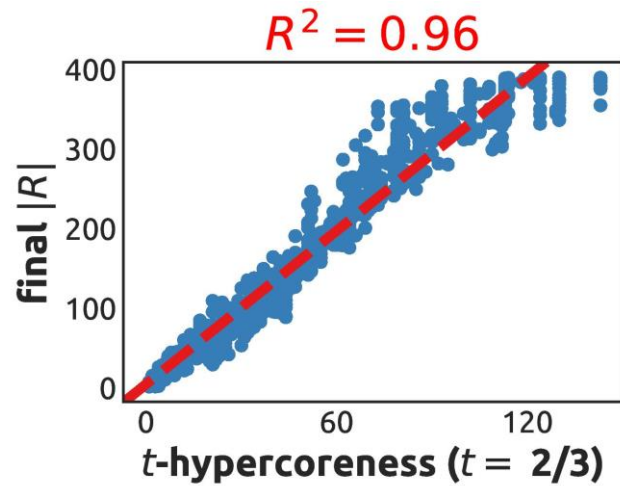


- **Dataset:** coauth-DBLP



Application 1: Results

- **Dataset:** email-Eu

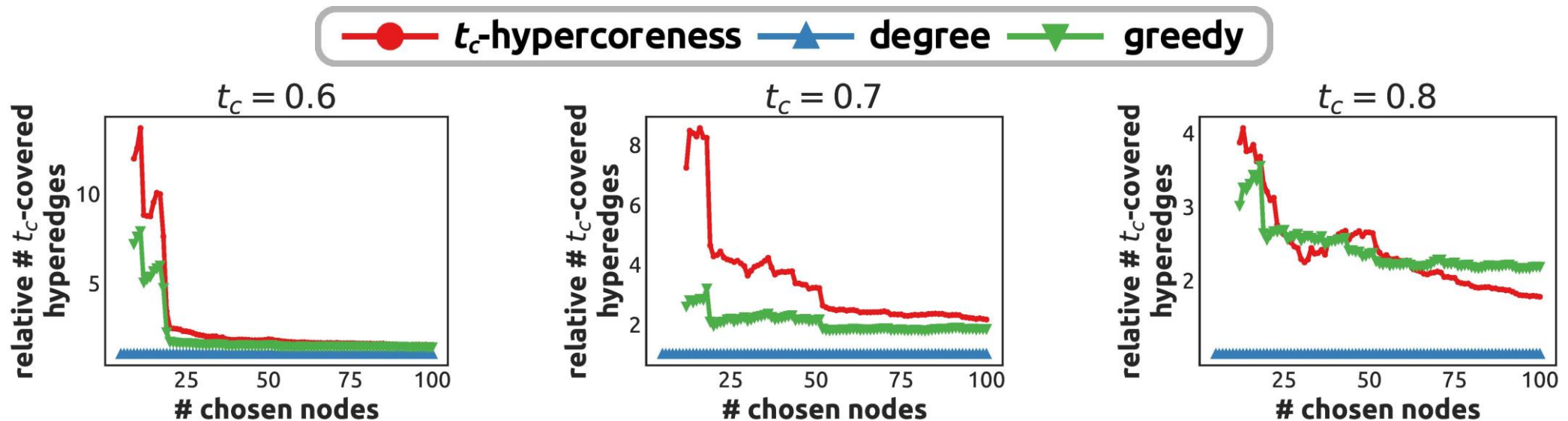


Application 2: Dense Substructure Discovery

- **Spoiler:** (k, t) -Hypercores can be used to efficiently and effectively find dense substructures
- **Set-up:** We consider a **vertex cover** problem
 - **Given:** A hypergraph H , # nodes to choose k_c , and the cover threshold t_c
 - **Aim to:** Choose k_c nodes to maximize # covered hyperedges
 - A hyperedge is **covered** if $\geq t_c$ proportion of its constituent nodes are chosen
- **Considered methods:**
 - **t_c -Hypercoreness:** The k_c nodes with the highest t_c -hypercoreness
 - **Degree:** The k_c nodes with the highest degree
 - **Greedy:** Greedily increases the number of covered hyperedges

Application 2: Results

- We vary k_c from 10 to 100 and vary $t_c \in \{0.6, 0.7, 0.8\}$
- The performance of the **degree** method is used as the reference one
- **Result summary:** Overall, t_c -hypercoreness outperforms the other two methods, i.e., covers more hyperedges
- Below are the results averaged over all the datasets



Application 3: Hypergraph Vulnerability Detection

- **TL;DR:** The concept of (k, t) -hypercores can be used to detect **vulnerability** in hypergraphs
- We consider an **optimization problem** on hypergraphs using the concept of (k, t) -hypercores
- We aim to remove a small number of nodes from a given hypergraph so that the size of a (k, t) -hypercore is minimized
 - Such nodes are **vulnerable nodes** in the hypergraph
 - We can pay attention to and **protect** such nodes in real-world applications



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Conclusions

- Our contributions are summarized as follows:

- ✓ **Novel concepts** generalizing k -cores to hypergraphs, with
- ✓ **Theoretical properties** and **practical computational algorithms**
- ✓ **Various observations** utilizing the proposed concepts
- ✓ **Extensive applications** showing the usefulness of the proposed concepts



Code: bit.ly/hypercore_code