



Mining of Real-world Hypergraphs: Concepts, Patterns, and Generators

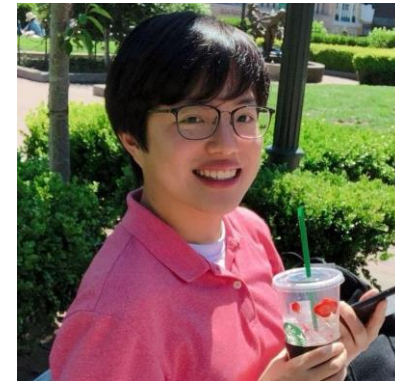
Part 2. Dynamic Structural Patterns



Geon Lee



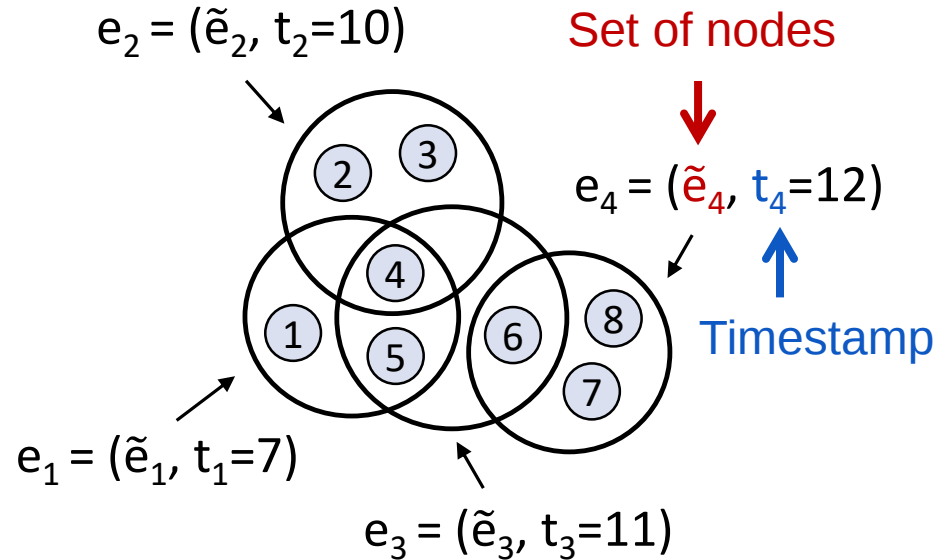
Jaemin Yoo



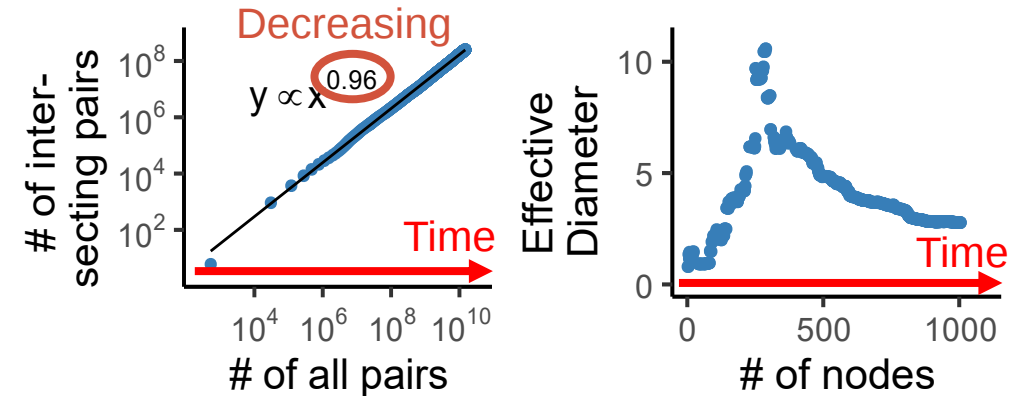
Kijung Shin

Part 2. Dynamic Structural Patterns

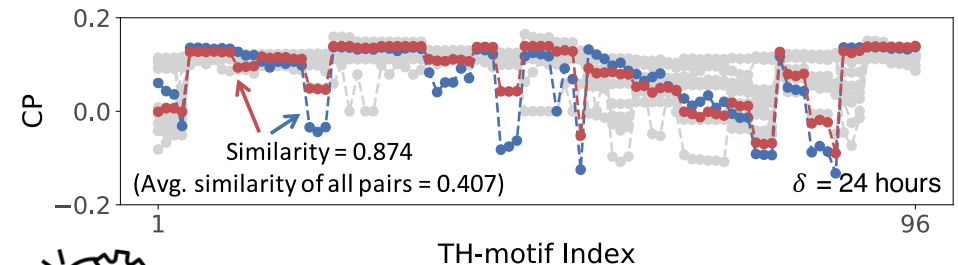
“Given a **dynamic** hypergraph, how can we analyze its structure?”



Input Temporal Hypergraph



Basic Patterns (**Part 2-1**)



Advanced Patterns (**Part 2-2**)

Roadmap

- **Part 1. Static Structural Patterns**
 - Basic Patterns
 - Advanced Patterns
- **Part 2. Dynamic Structural Patterns**
 - **Basic Patterns <<**
 - Advanced Patterns
- **Part 3. Generative Models**
 - Static Hypergraph Generator
 - Dynamic Hypergraph Generator

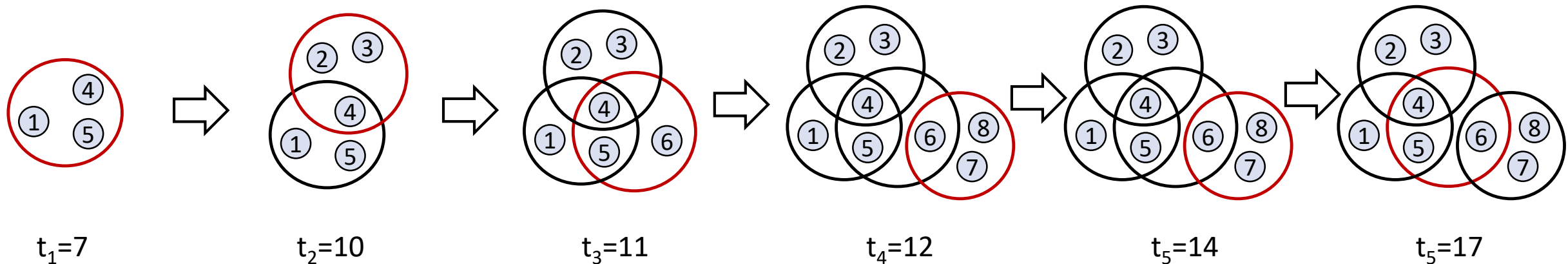


Part 2-1. Basic Dynamic Structural Patterns

		Part 1. 	Part 2. 
		Static Patterns	Dynamic Patterns
 Basic Patterns	Node-Level	DYHS20, KKS20, LCS21	BKT18, CS22
	Hyperedge-Level	KKS20, LCS21	BKT18, LS21, GLLB23, CBLK21
	Hypergraph-Level	BASJK18, DYHS20, KKS20	KKS20
 Advanced Patterns	Sub-hypergraph-Level	KBCYK23, BASJK18, LMMB22, LKS20, LCS21, LL23, BLS23	BASJK18, CJ21, LS21, CS22

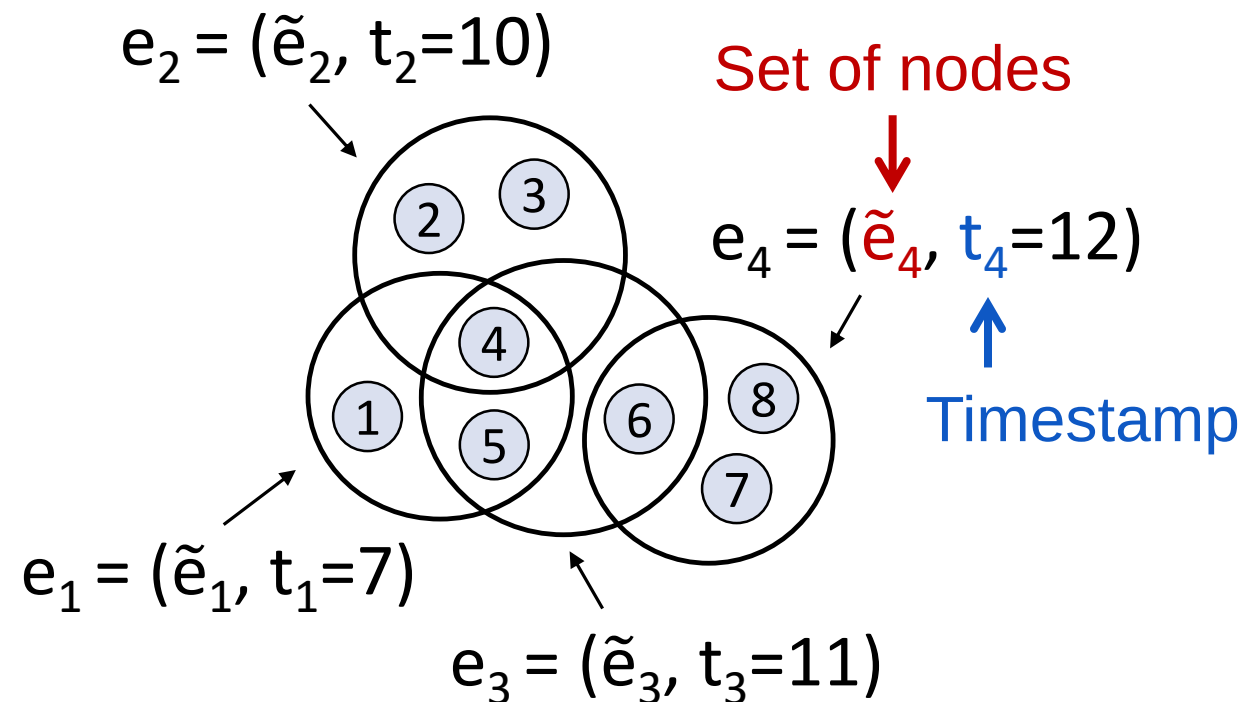
Background

- **Temporal hypergraphs** consist of **temporal hyperedges**.
 - Temporal hyperedges consisting of the same set of nodes can appear at different timestamps.



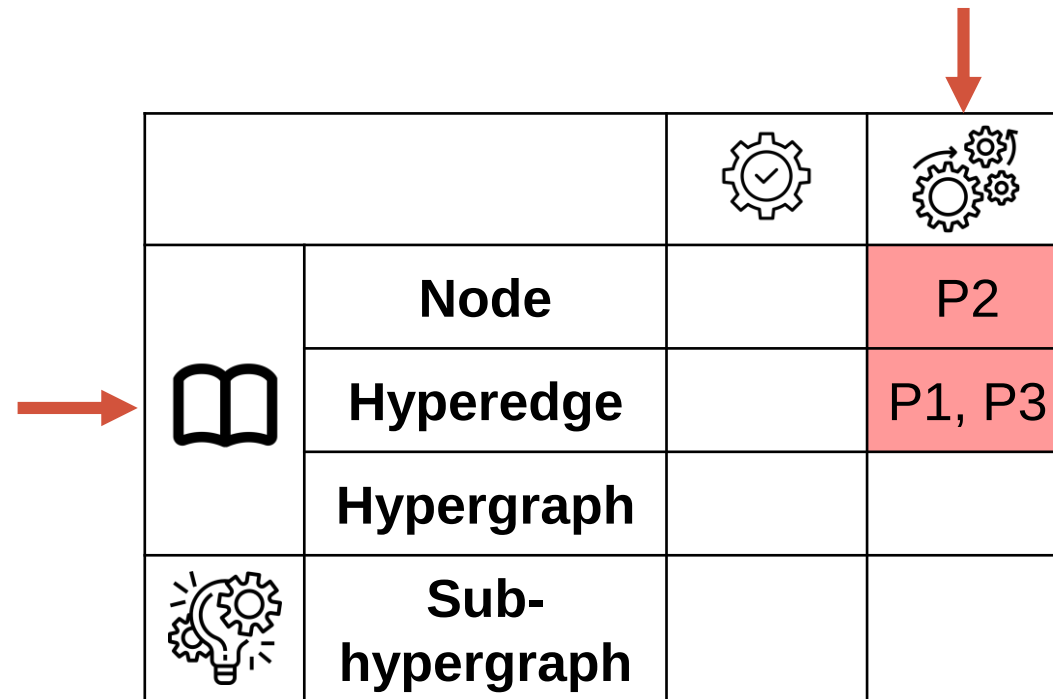
Background (cont.)

- Each **temporal hyperedge** consists of the set of nodes and the timestamp it arrived at.



BKT18: Three Basic Dynamic Patterns

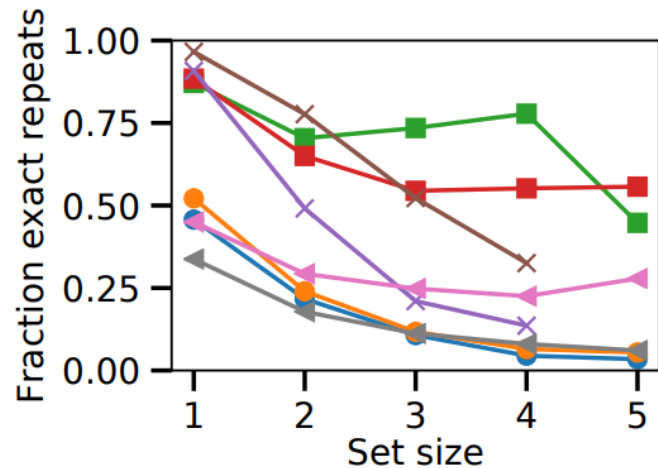
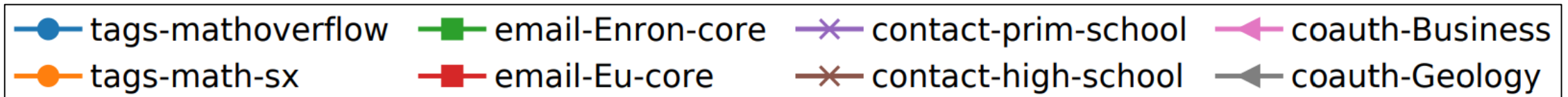
- **P1.** Repeat behavior
- **P2.** Subset correlation
- **P3.** Recency bias



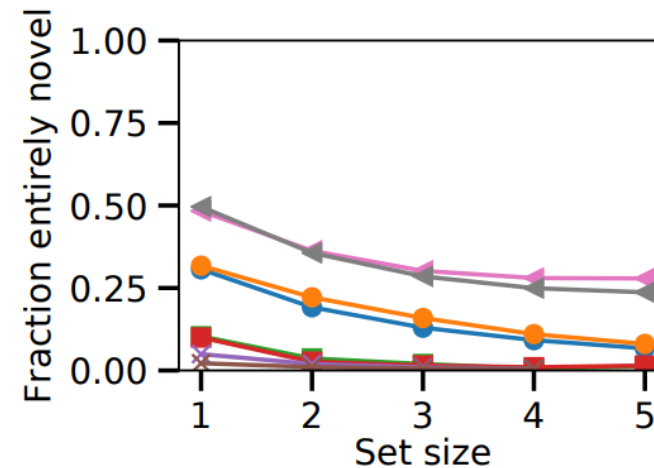
			
	Node		P2
	Hyperedge		P1, P3
	Sub-hypergraph		

Repeat Behavior

- Temporal hyperedges tend to **repeat** previous ones.



Exactly repeated hyperedges



Entirely novel hyperedges

Subset Correlation

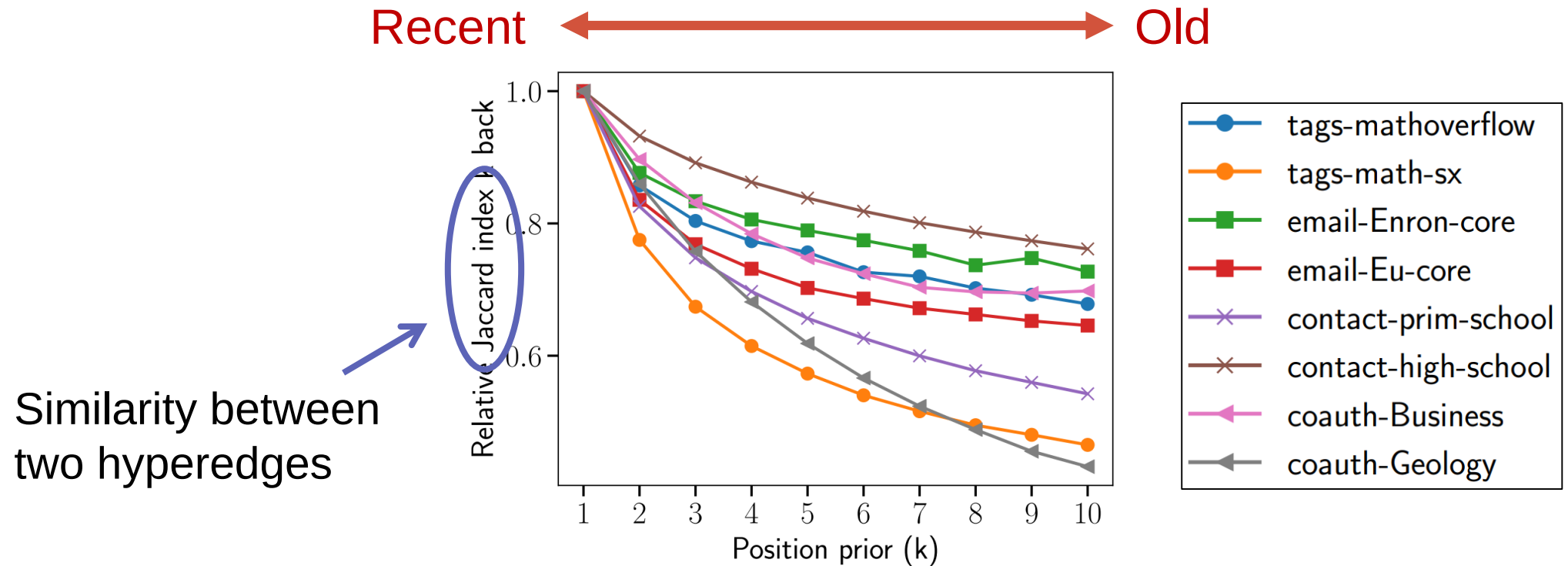
- Subsets of nodes tend to be **correlated**.
 - Size-2 and size-3 subsets co-appear in multiple temporal hyperedges.

Dataset	size-2 subset counts		size-3 subset counts	
	data	null model	data	null model
EMAIL-ENRON-CORE	5.82	4.34 ± 0.043	4.23	2.67 ± 0.038
EMAIL-EU-CORE	4.46	3.11 ± 0.008	3.23	2.08 ± 0.007
CONTACT-PRIM-SCHOOL	2.36	1.87 ± 0.003	1.35	1.09 ± 0.002
CONTACT-HIGH-SCHOOL	4.49	3.26 ± 0.007	2.09	1.35 ± 0.004
TAGS-MATHOVERFLOW	1.49	1.41 ± 0.002	1.18	1.15 ± 0.002
TAGS-MATH-SX	1.49	1.31 ± 0.001	1.21	1.12 ± 0.001
COAUTH-BUSINESS	1.50	1.30 ± 0.001	1.40	1.24 ± 0.001
COAUTH-GEOLOGY	1.29	1.15 ± 0.000	1.15	1.07 ± 0.000

Average number of times of size-2/3 subset appearance

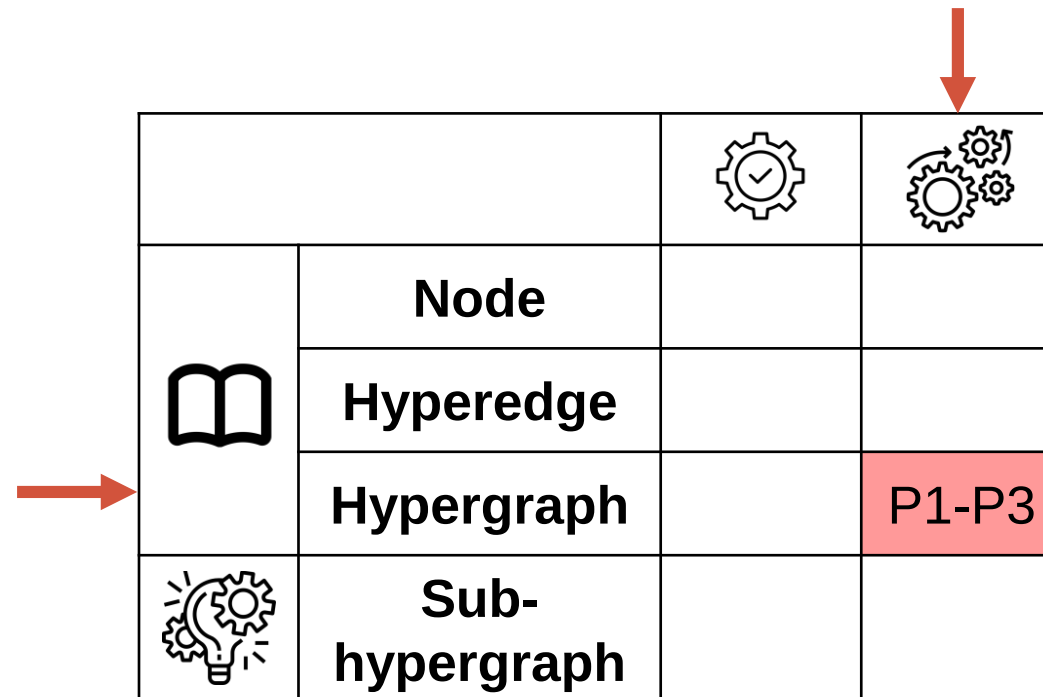
Recency Bias

- Temporal hyperedges tend to be similar to **recent** ones.



KKS20: Three Basic Dynamic Patterns

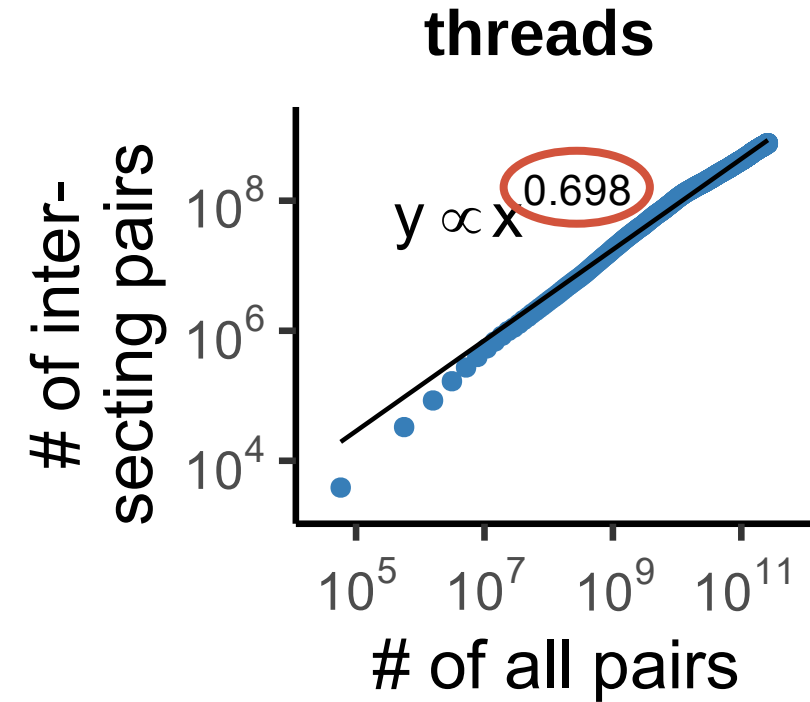
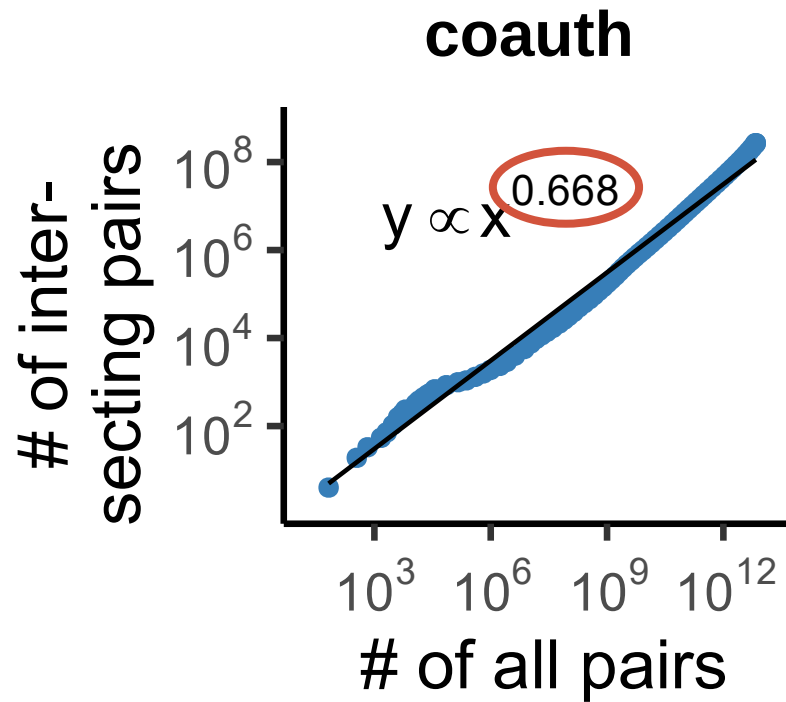
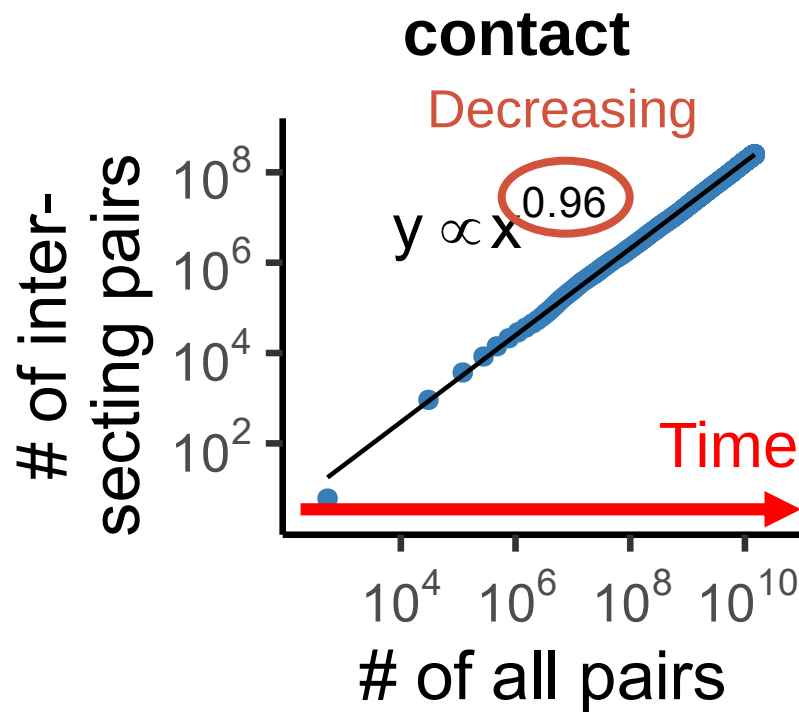
- **P1.** Diminishing overlaps
- **P2.** Densification
- **P3.** Shrinking diameter



			
	Node		
	Hyperedge		
	Hypergraph		P1-P3
	Sub-hypergraph		

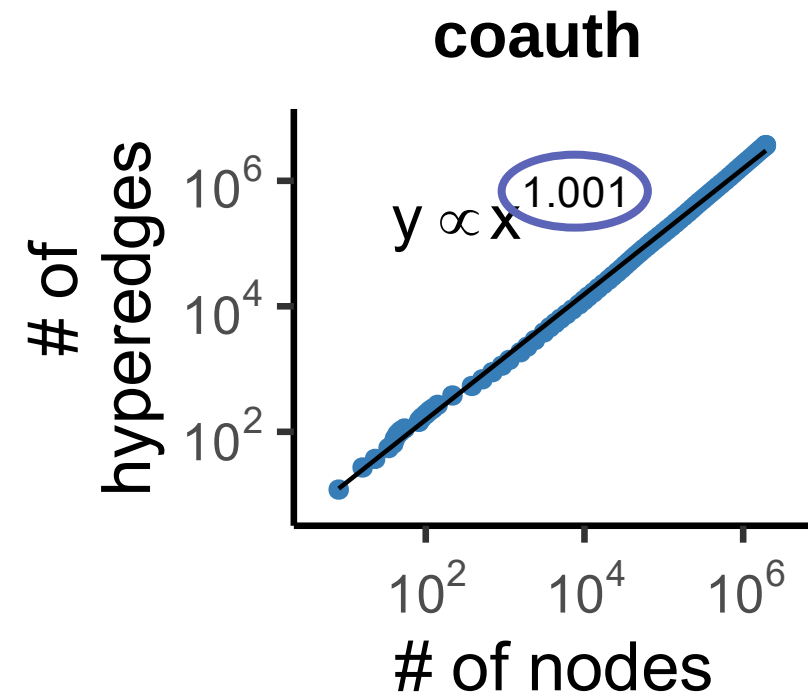
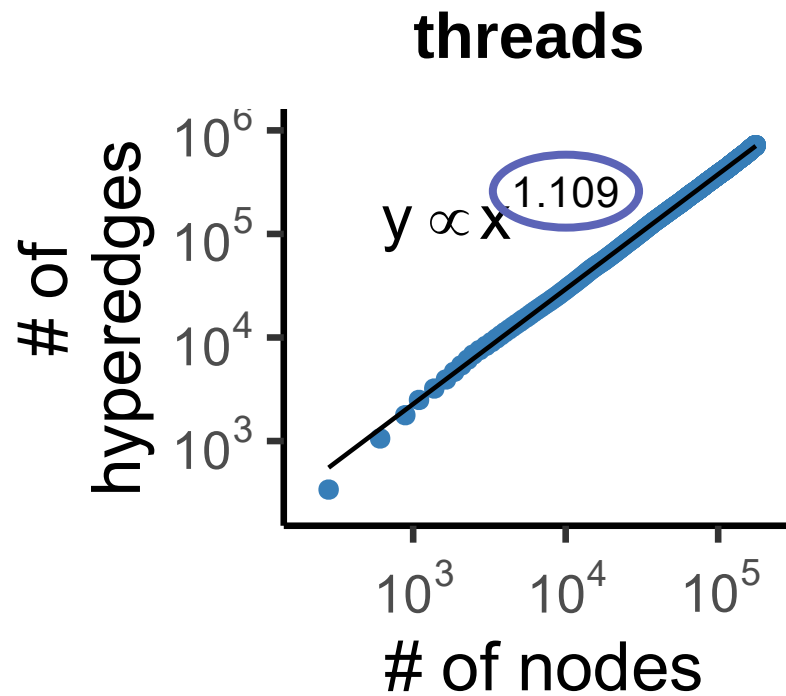
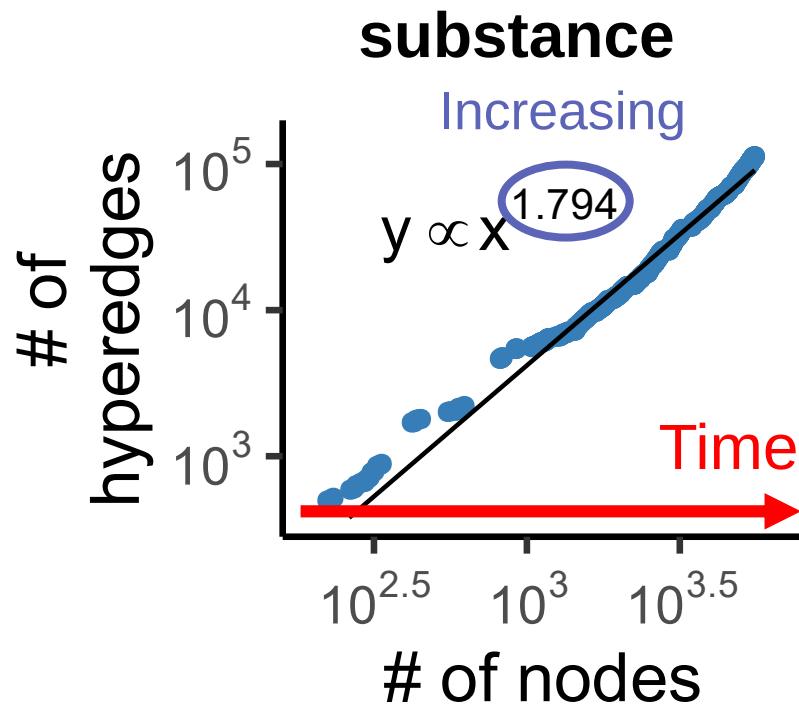
Diminishing Overlaps

- The overlap between hyperedges **decreases** over time.



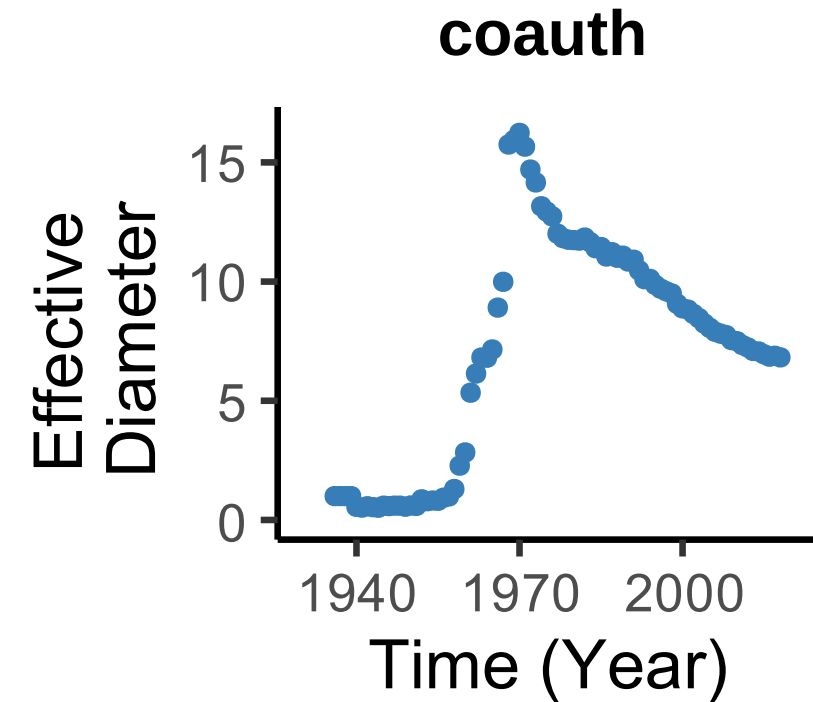
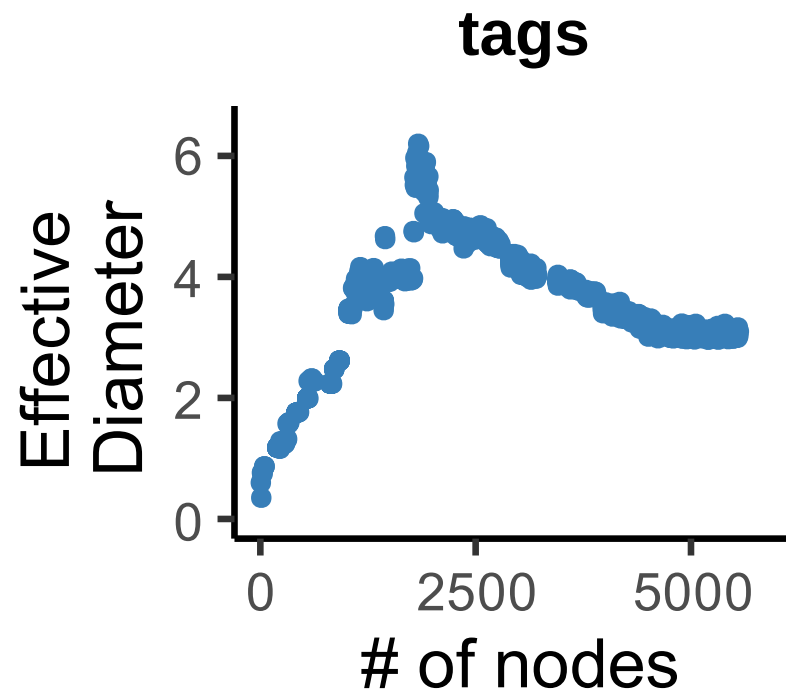
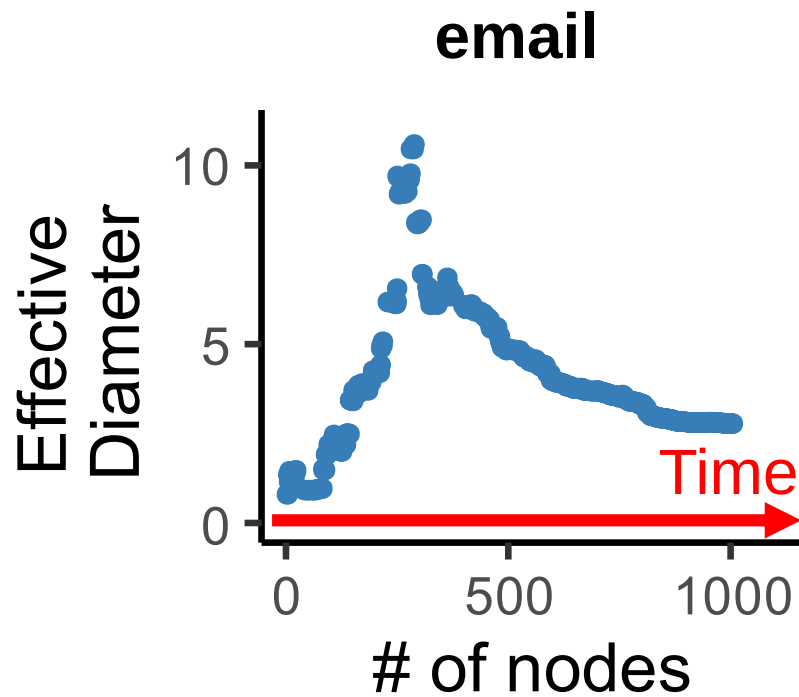
Densification

- Average node degree of the hypergraph **increases** over time.



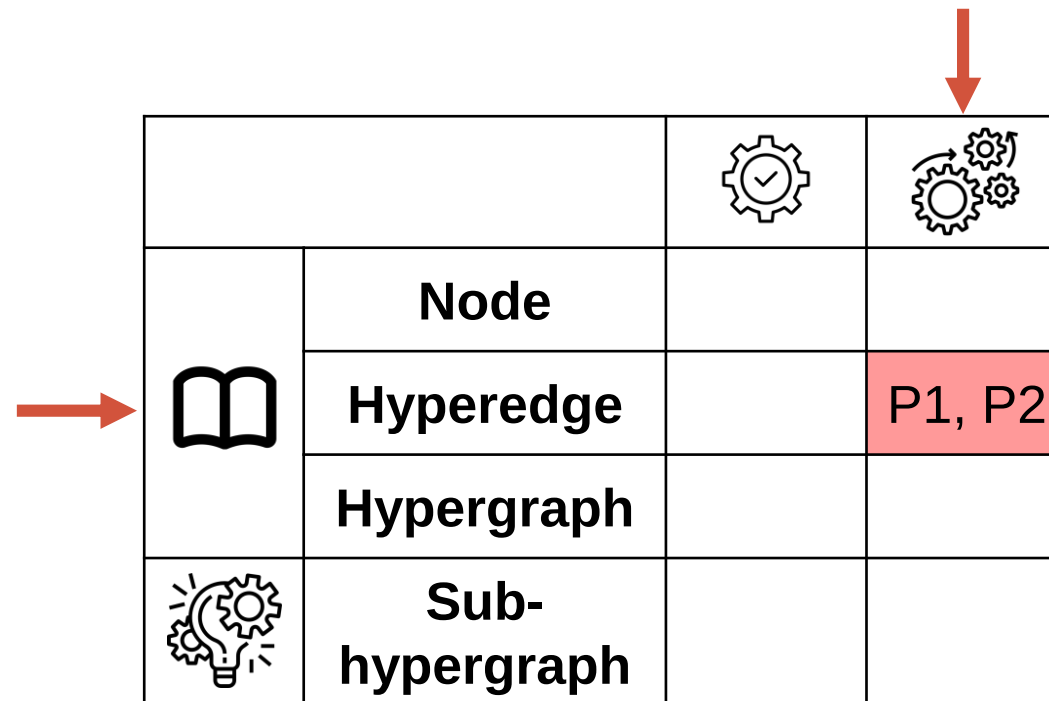
Shrinking Diameter

- Effective diameters eventually **decrease** over time.



LS21: Two Basic Dynamic Patterns

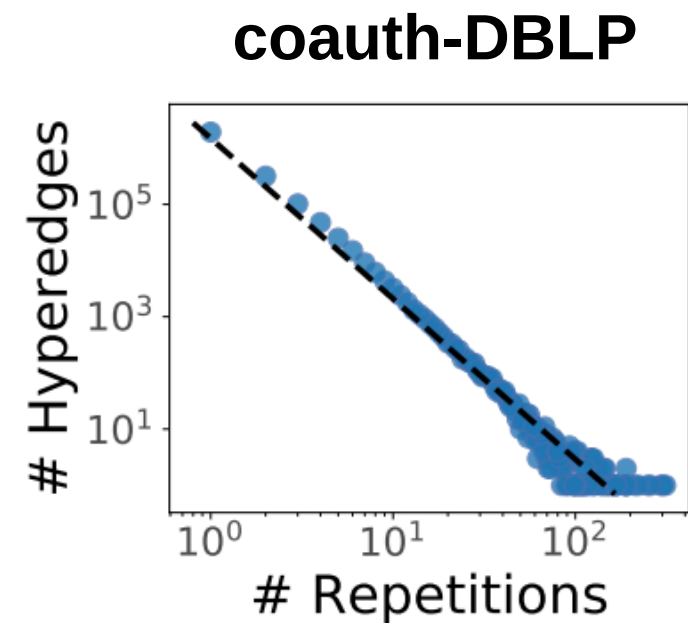
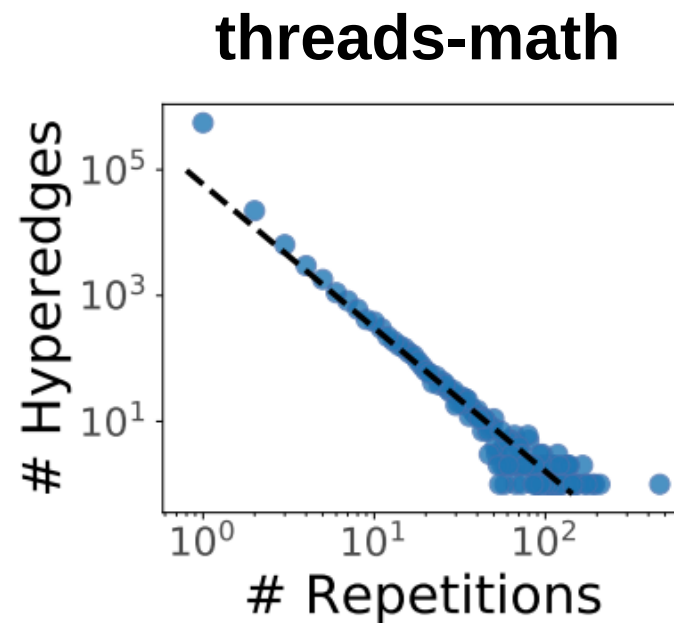
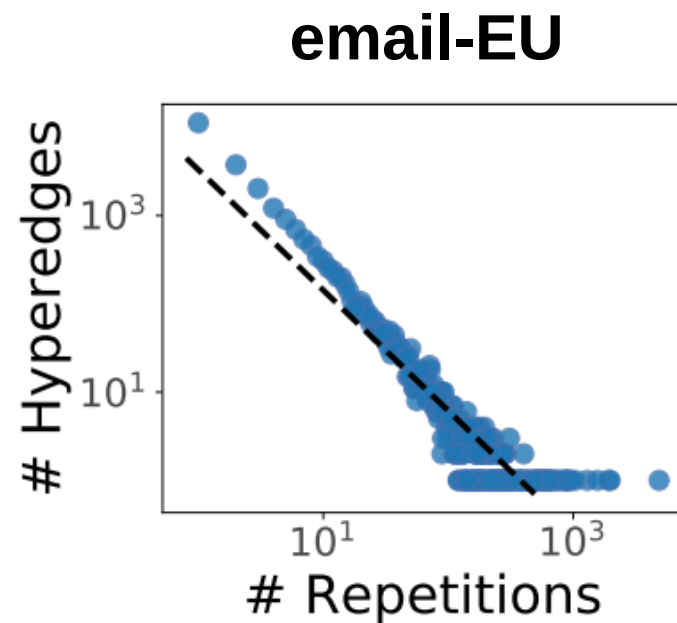
- **P1.** Hyperedge repetition
- **P2.** Temporal locality



			
	Node		
	Hyperedge		P1, P2
	Hypergraph		
	Sub-hypergraph		

Hyperedge Repetition

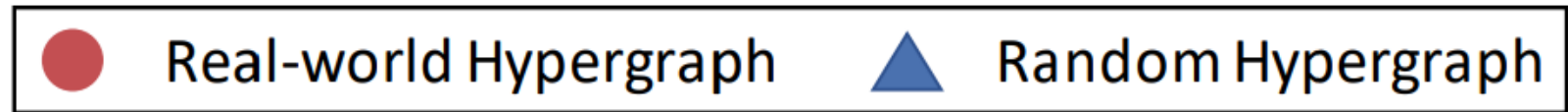
- Temporal hyperedges in real-world hypergraphs are **repetitive**.
- The number of repetitions is **heavy-tailed**.



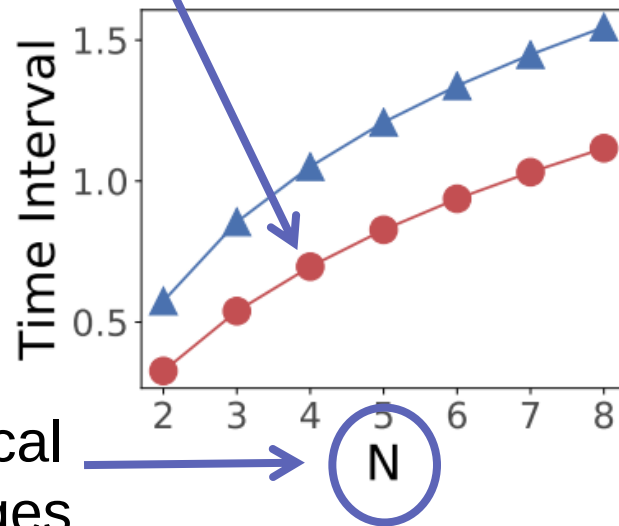
Temporal Locality

- Future temporal hyperedges are more likely to **repeat recent ones**.

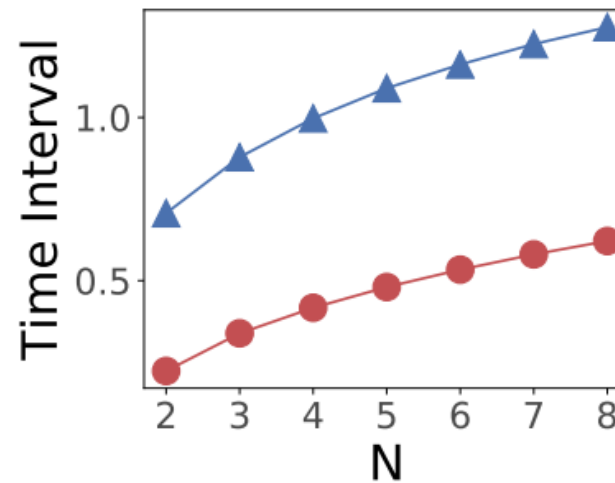
e.g., It took in average 0.7 time to repeat 4 times.



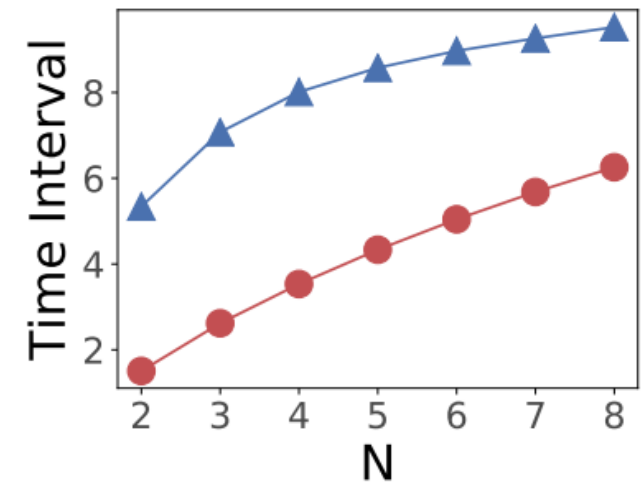
email-EU



threads-math



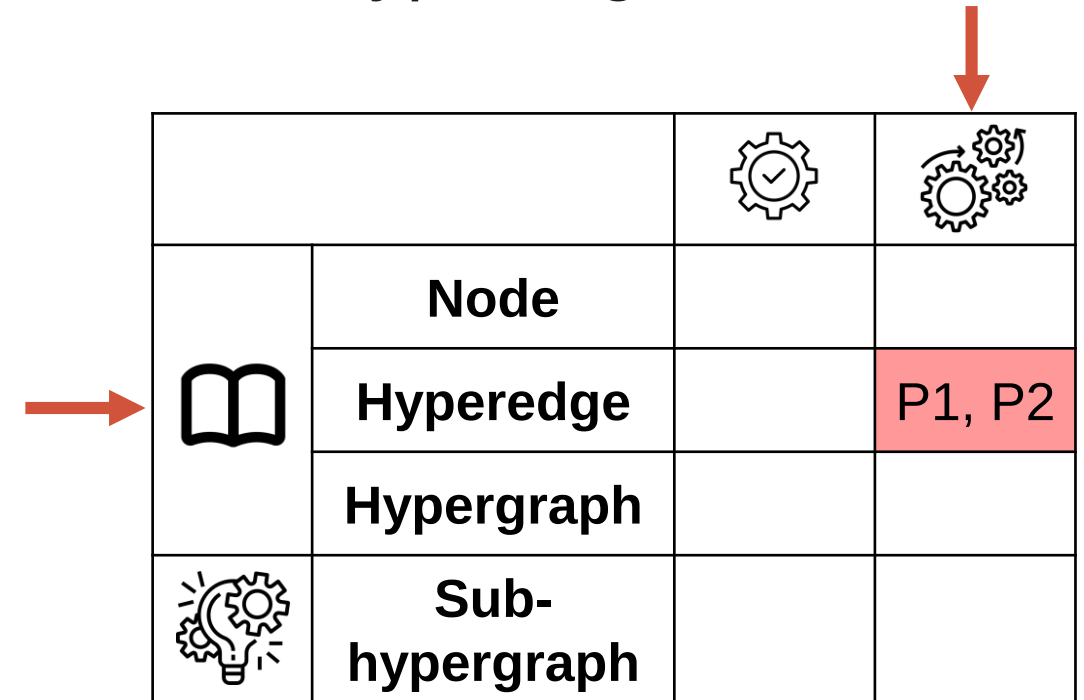
coauth-DBLP



Number of consecutive identical temporal hyperedges

GLLB23: Two Basic Dynamic Patterns

- **P1.** Temporal correlation between intra-order hyperedges
- **P2.** Temporal correlation between cross-order hyperedges



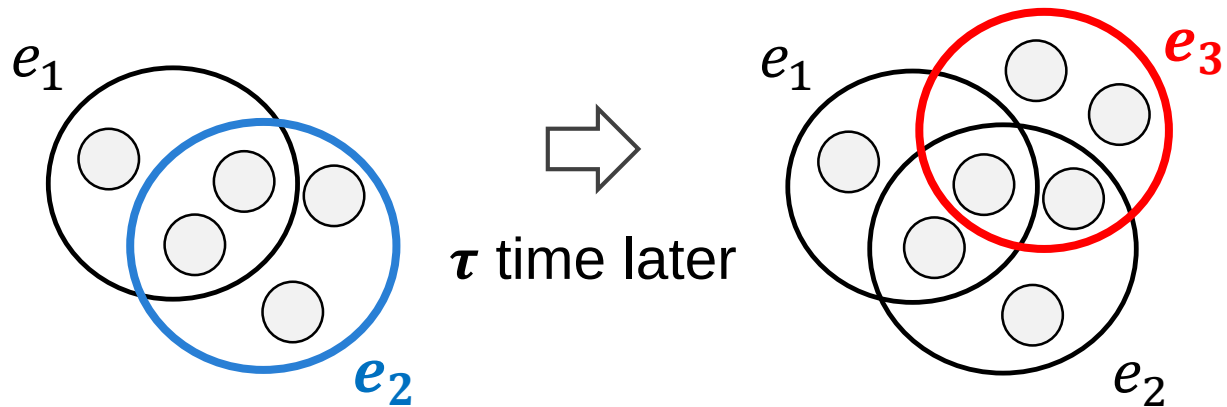
			
	Node		
	Hyperedge		P1, P2
	Hypergraph		
	Sub-hypergraph		

Temporal Correlations

?

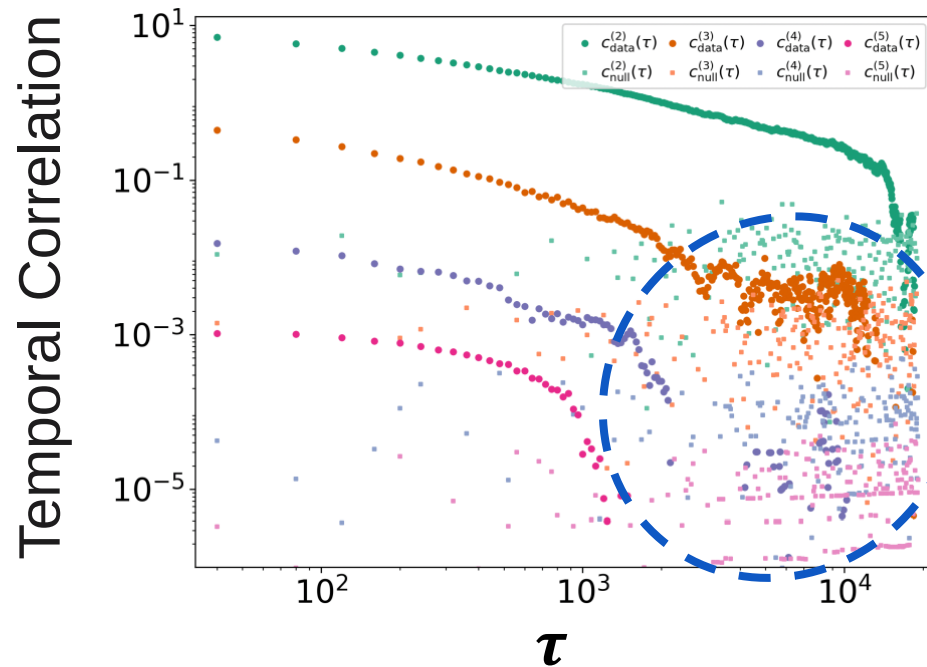
Question:How are hyperedges **temporally correlated**?**Answer:**

Temporal correlations between hyperedges are computed.
How does e_2 (before τ time) affect the formation of e_3 ?



Intra-Order Temporal Correlations

- Temporal correlations exist between hyperedges with the **same size**.
- Correlations decay slowly with the time interval τ .



Real-world

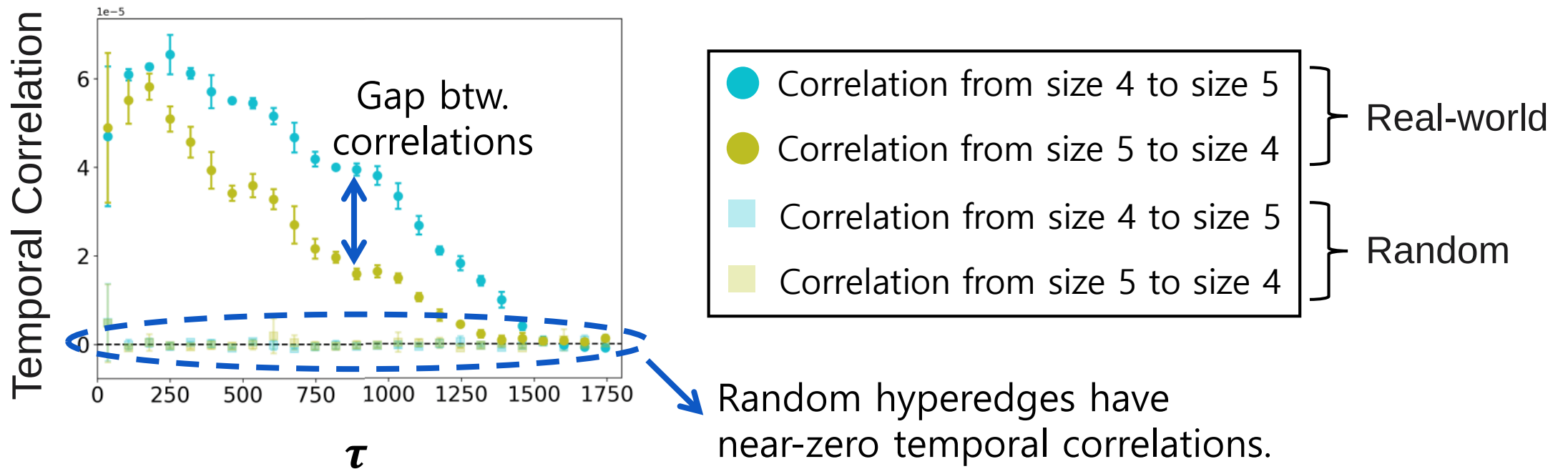
Random

● Size 2 hyperedges	■ Size 2 hyperedges
● Size 3 hyperedges	■ Size 3 hyperedges
● Size 4 hyperedges	■ Size 4 hyperedges
● Size 5 hyperedges	■ Size 5 hyperedges

Random hyperedges do not exhibit temporal correlations.

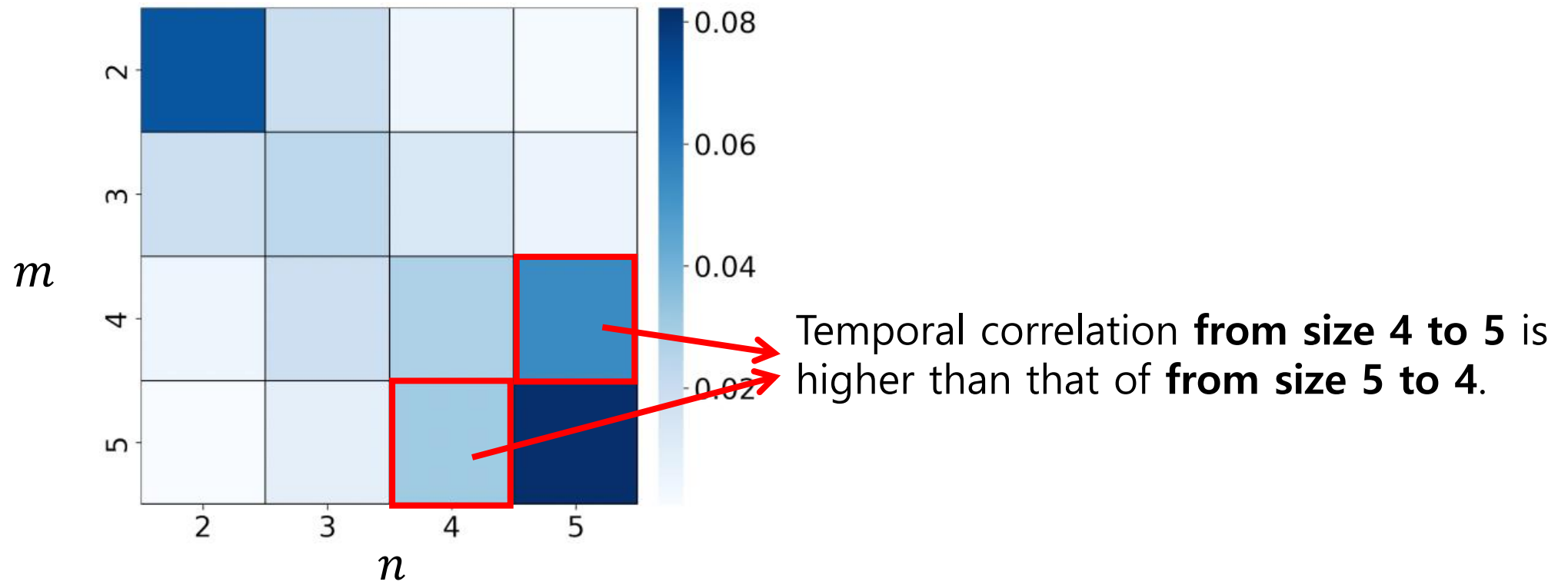
Cross-Order Temporal Correlations

- Temporal correlations exist between hyperedges with **different sizes**.



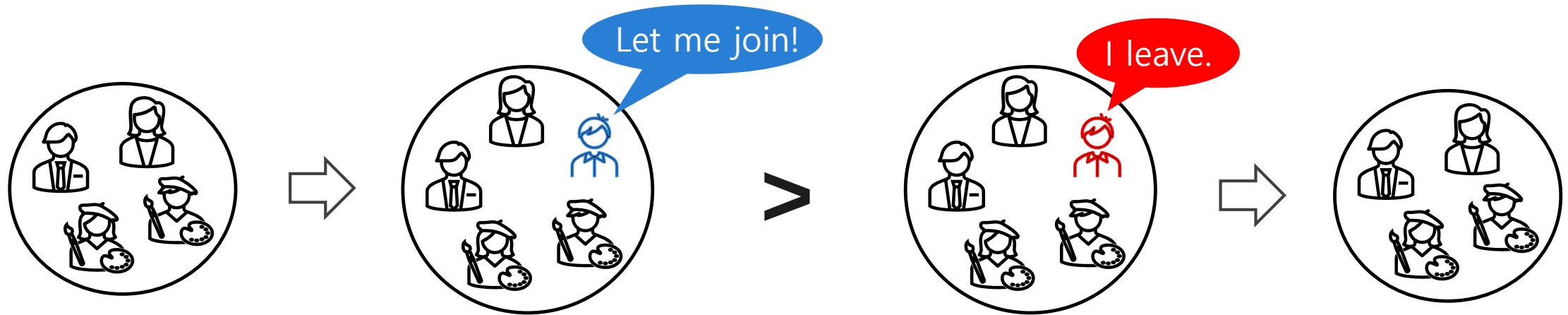
Cross-Order Temporal Correlations (cont.)

- Cross-order temporal correlations are **asymmetric**.



Cross-Order Temporal Correlations (cont.)

- The **asymmetry** suggests the formation or loss of group interactions.

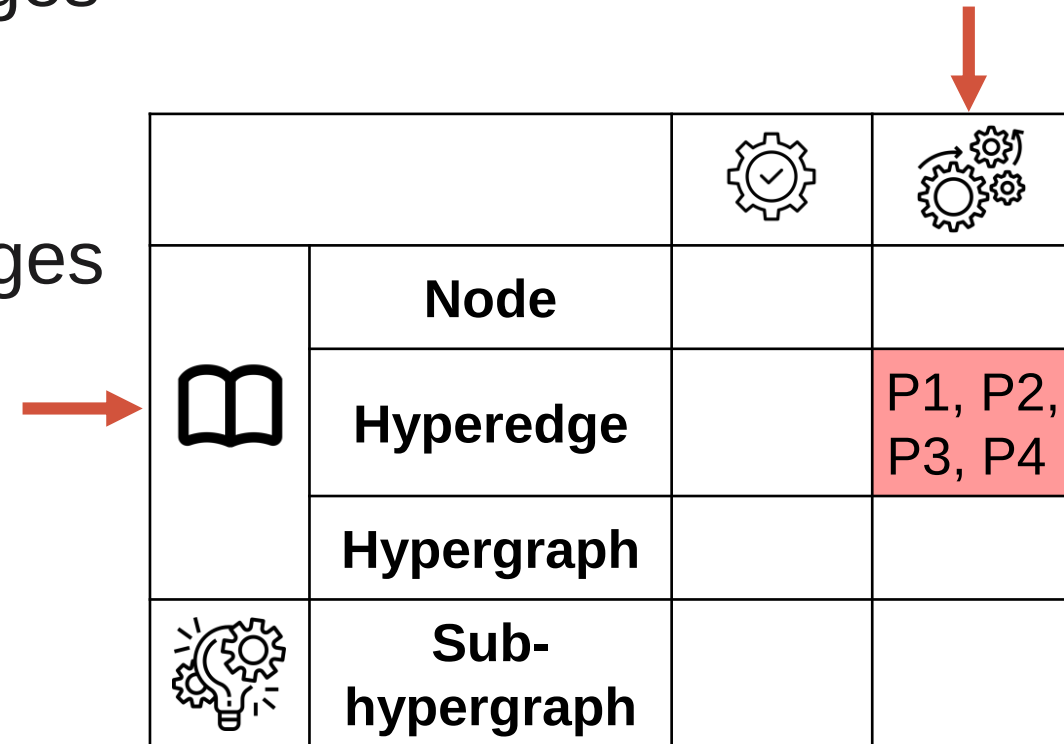


Temporal correlation **from size 4 to size 5**

Temporal correlation **from size 5 to size 4**

CBLK21: Four Basic Dynamic Patterns

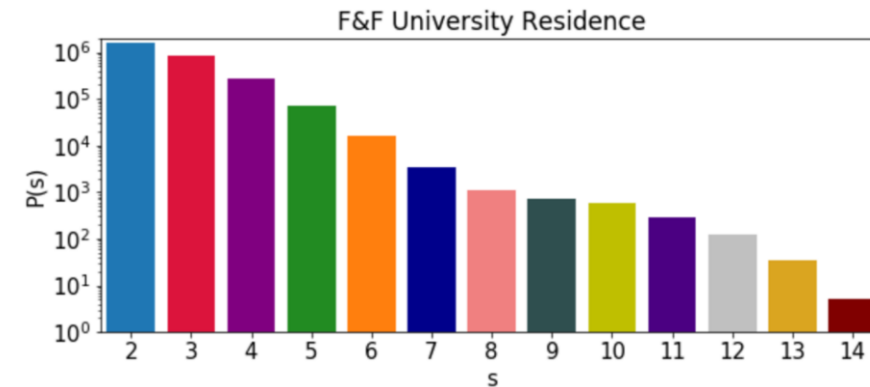
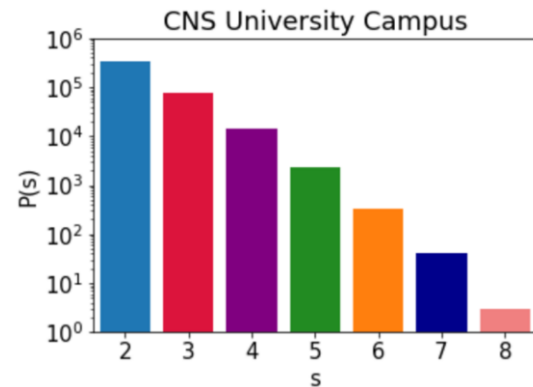
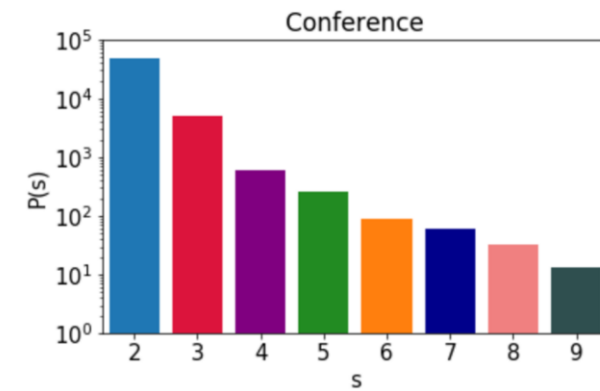
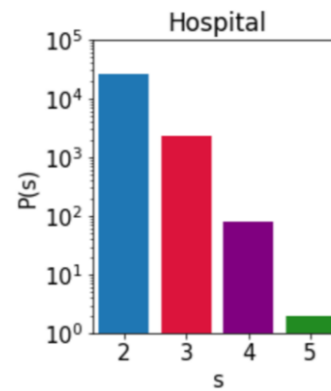
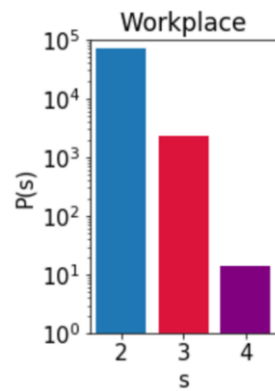
- **P1.** Hyperedge sizes and frequencies
- **P2.** Temporal heterogeneity of hyperedges
- **P3.** Bursty behavior of hyperedges
- **P4.** Temporal reinforcement of hyperedges



			
	Node		
	Hyperedge		P1, P2, P3, P4
	Hypergraph		
	Sub-hypergraph		

Hyperedge Sizes and Frequencies

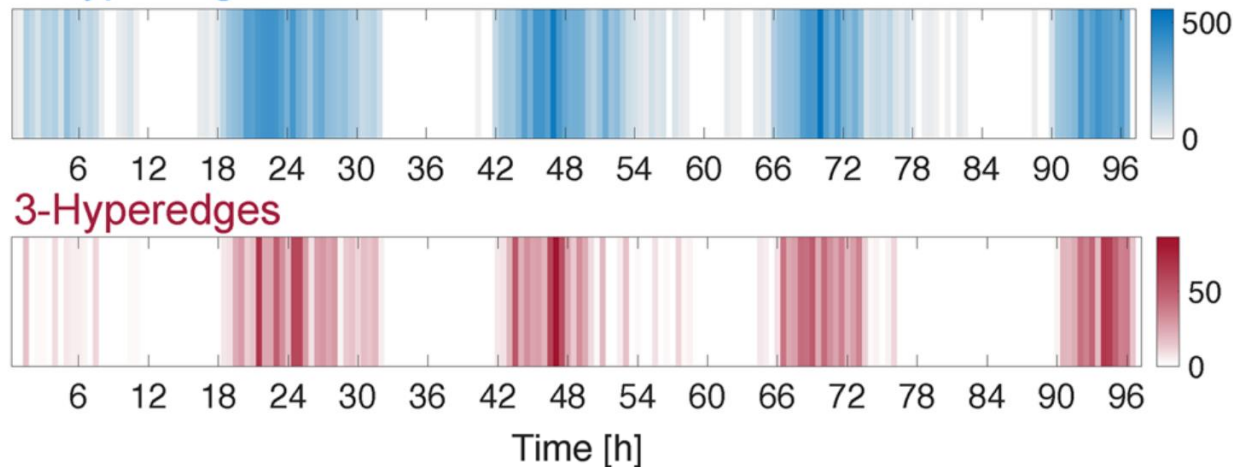
- **Smaller hyperedges** are more numerous in a real-world dataset.



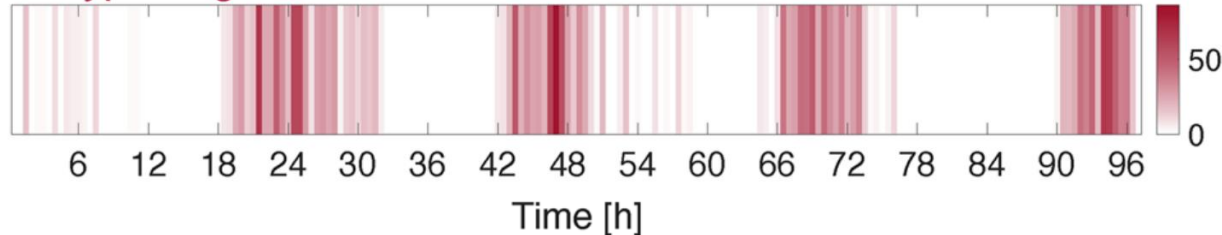
Temporal Heterogeneity of Hyperedges

- Emergence of hyperedges is strongly **heterogeneous in time**.
 - Bursty patterns of hyperedges are not independent of size.

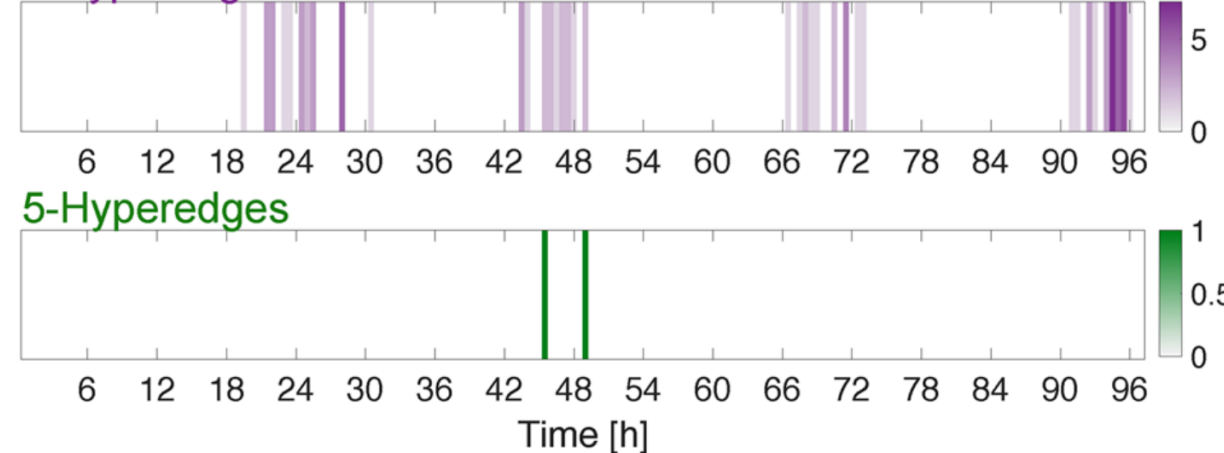
2-Hyperedges



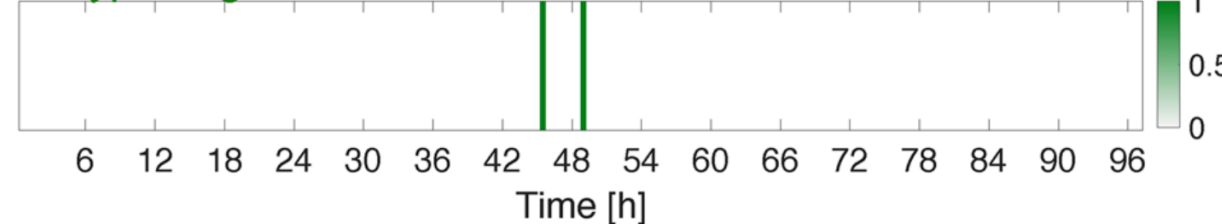
3-Hyperedges



4-Hyperedges

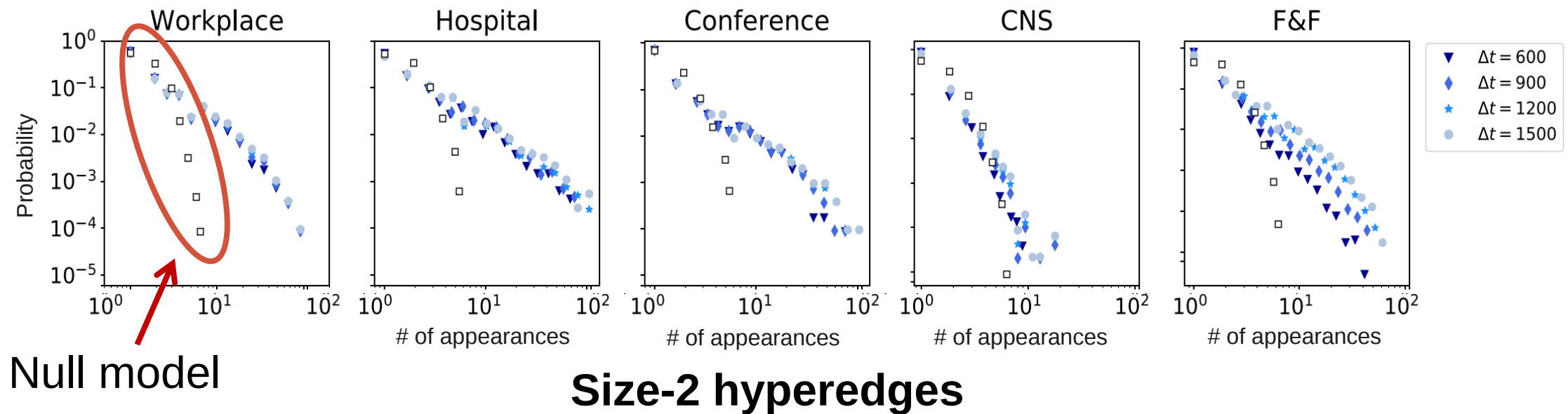


5-Hyperedges



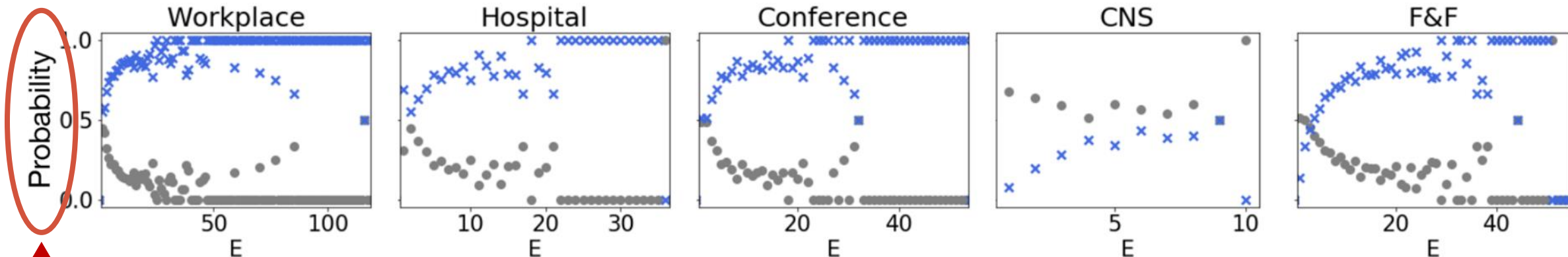
Bursty Behavior of Hyperedges

- Hyperedges in real-world hypergraphs are likely to **repeatedly appear within a short time (Δt)** and the distribution of their numbers of appearances are **heavy-tailed**.



Temporal Reinforcement of Hyperedges

- There exists **temporal reinforcement** in real-world hypergraphs, i.e., the longer the length of an interaction, the higher chances the interaction will not break down.



Prob. that after interactions at least E times, the hyperedge to appear within Δt

Size-2 hyperedges

Roadmap

- **Part 1. Static Structural Patterns**
 - Basic Patterns
 - Advanced Patterns
- **Part 2. Dynamic Structural Patterns**
 - Basic Patterns
 - **Advanced Patterns <<**
- **Part 3. Generative Models**
 - Static Hypergraph Generator
 - Dynamic Hypergraph Generator



Part 2-2. Advanced Dynamic Structural Patterns

		Part 1. 	Part 2. 
		Static Patterns	Dynamic Patterns
 Basic Patterns	Node-Level	DYHS20, KKS20, LCS21	BKT18, CS22
	Hyperedge-Level	KKS20, LCS21	BKT18, LS21, GLLB23, CBLK21
	Hypergraph-Level	BASJK18, DYHS20, KKS20	KKS20
 Advanced Patterns	Sub-hypergraph-Level	KBCYK23, BASJK18, LMMB22, LKS20, LCS21, LL23, BLS23	BASJK18, CJ21, LS21, CS22

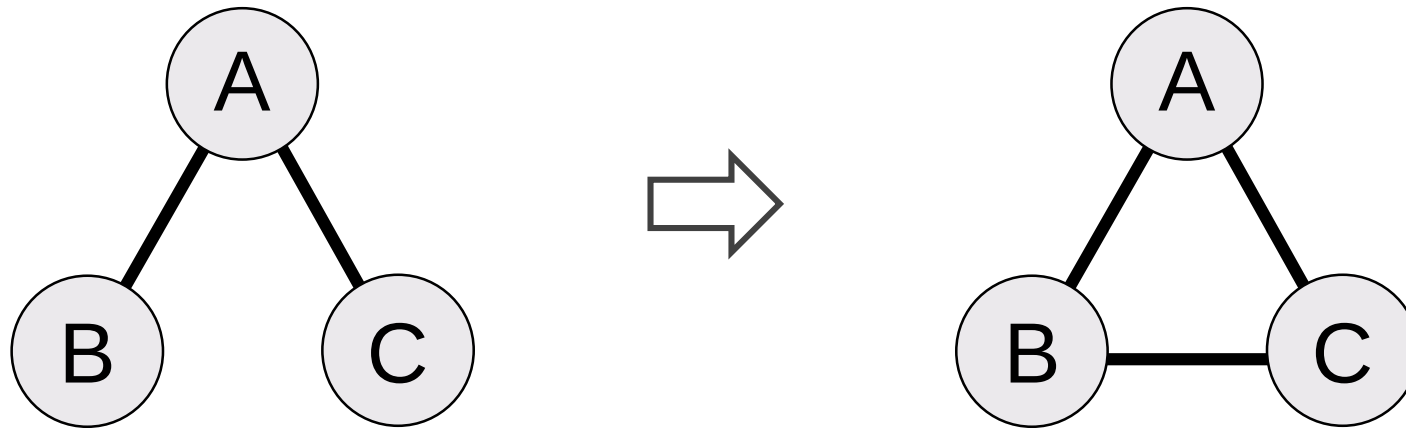
BASJK18: One Advanced Dynamic Pattern

- **P1.** Simplicial closure

			
	Node		
	Hyperedge		
	Hypergraph		
	Sub-hypergraph		P1

Background

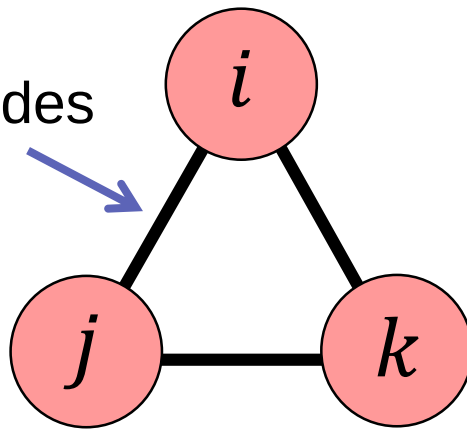
- **Triadic closure** in networks is a tendency of forming a triangle.



Recap: Open and Closed Triangles

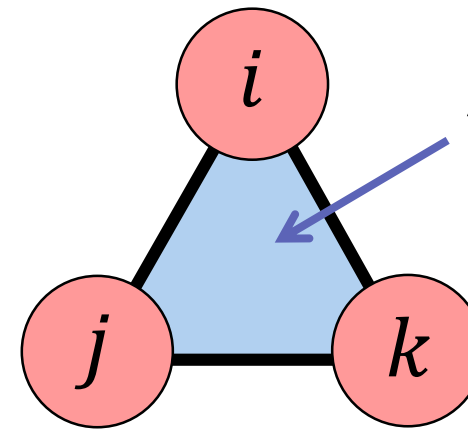
- There are two types of **triangles** in hypergraphs.
 - Static observations can be found at Part 1.

Any hyperedge that contains the pair of nodes



Open Triangle

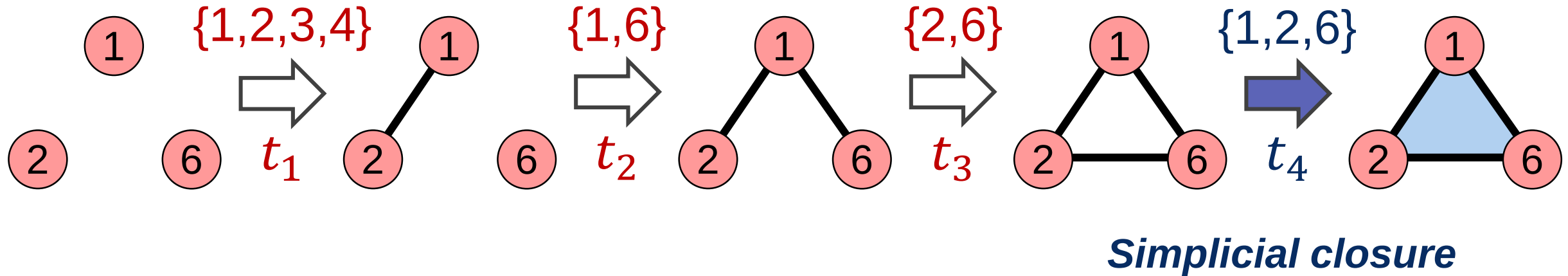
Any hyperedge that contains all 3 nodes



Closed Triangle

Simplicial Closure

- **Simplicial closure** is an event of forming a **closed triangle**.



Structural Factors of Simplicial Closure

?

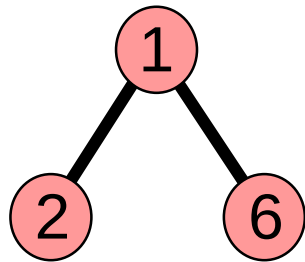
Questions:

How does the simplicial closure occur?

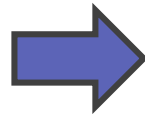
Can we predict it from the structure of the projected graph?

Approach:

First 80% of the data (in time)

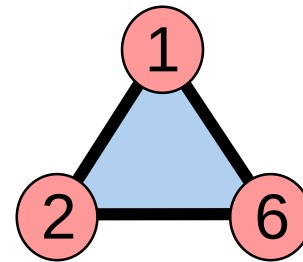


Triplets not in
closed triangle



Compute the ratio

Last 20% of the data (in time)

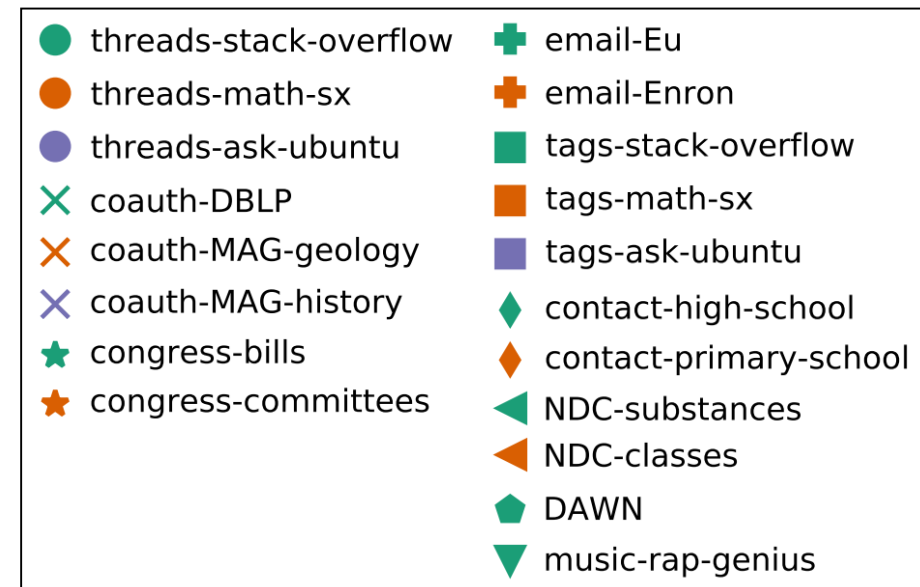
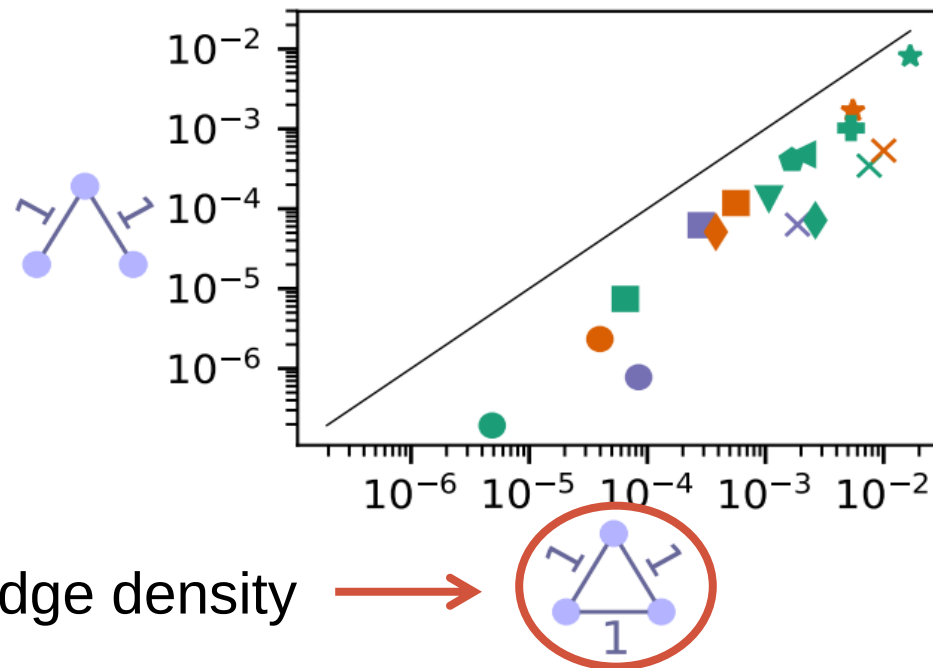


Closed triangle

!

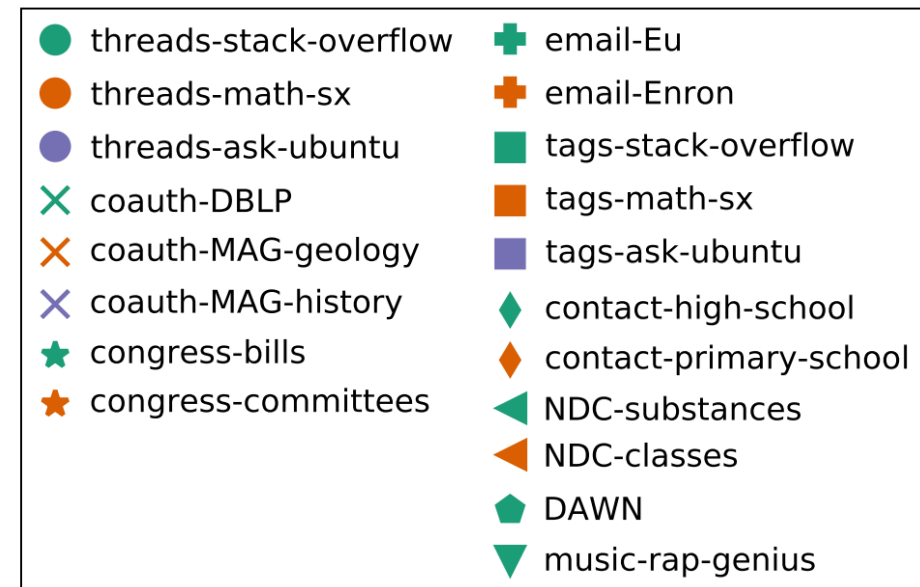
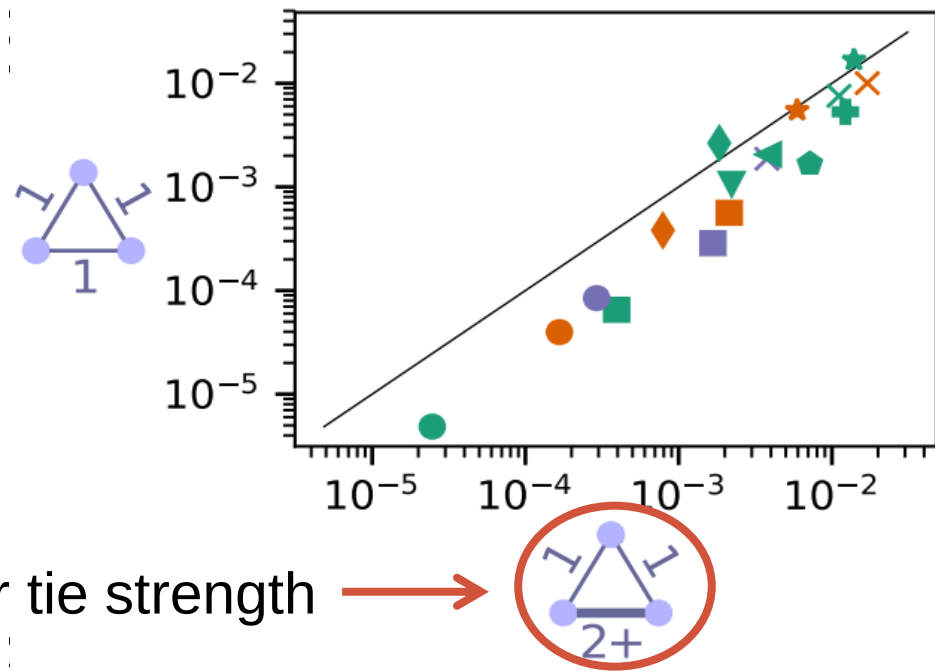
Edge Density vs. Simplicial Closure

- Increased **edge density** increases simplicial closure probability.



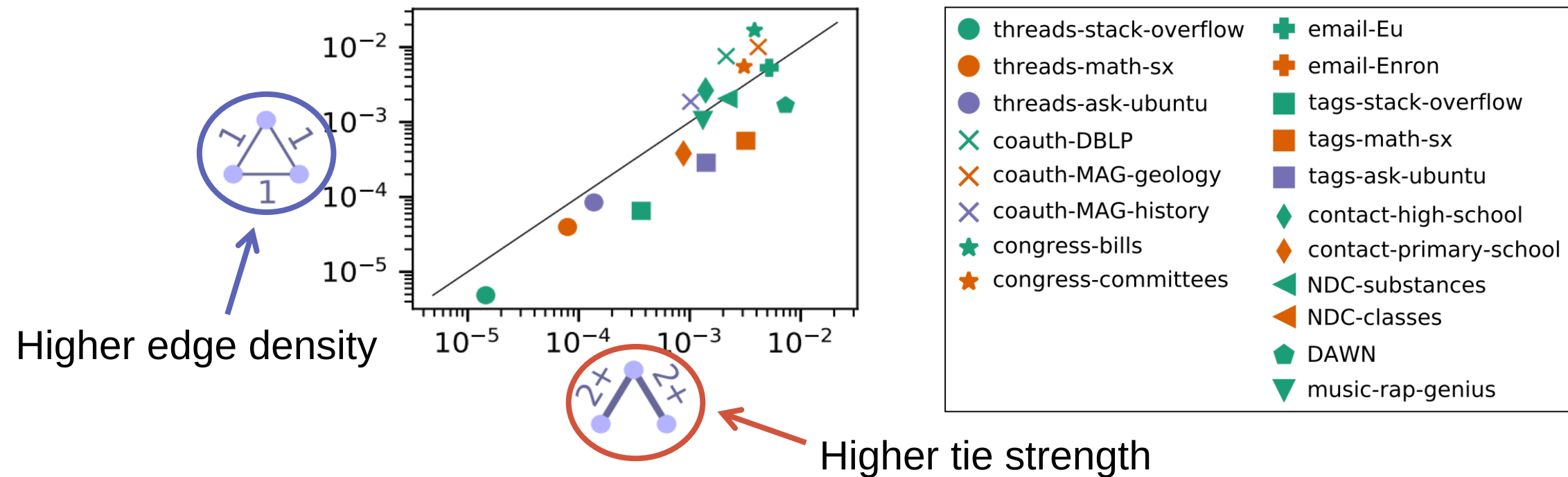
Tie Strength vs. Simplicial Closure

- Increased **tie strength** increases simplicial closure probability.



Edge Density vs. Tie Strength

- Relative importance of **edge density** and **tie strength** depends on the dataset.



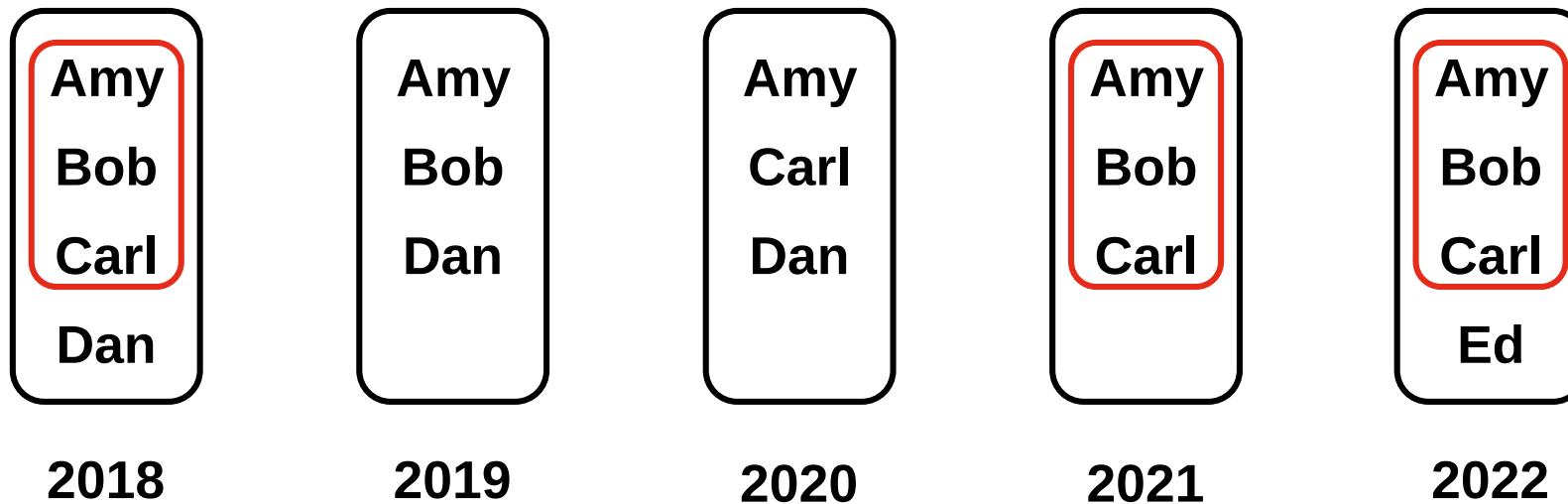
CS22: One Advanced Dynamic Pattern

- **P1.** Persistence of higher-order interactions (HOIs)

			
	Node		
	Hyperedge		
	Hypergraph		
	Sub-hypergraph		P1

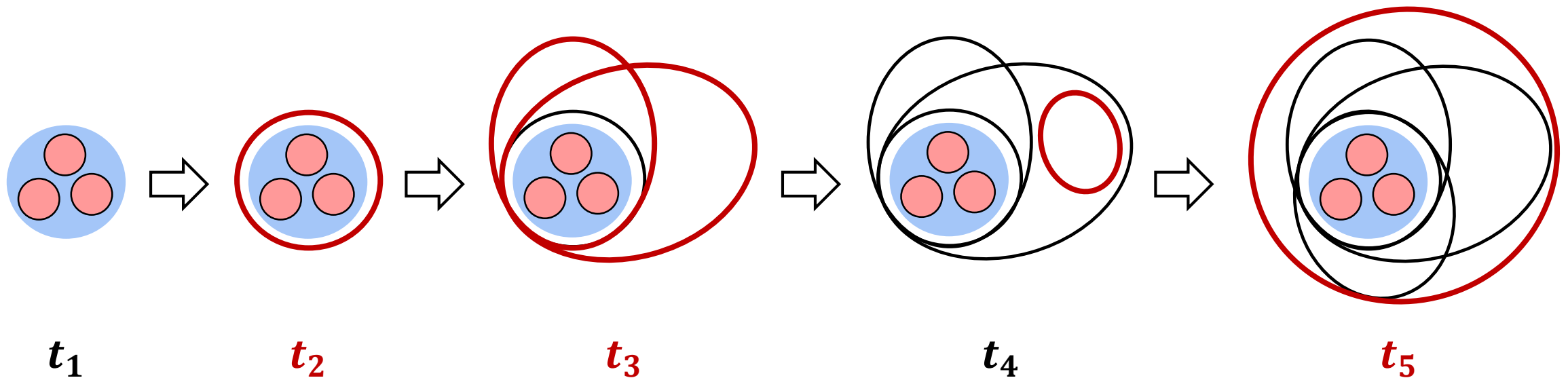
Higher-Order Interaction

- A **higher-order interaction (HOI)** is the co-appearance of a set of nodes in any hyperedge.
- HOIs can appear **repeatedly** over time.



Persistence of HOIs

- **Persistence** of an HOI S over time range T is the number of time units in T when S co-appears in any hyperedge.
- **Example: Persistence = 3**



Group Features and Persistence

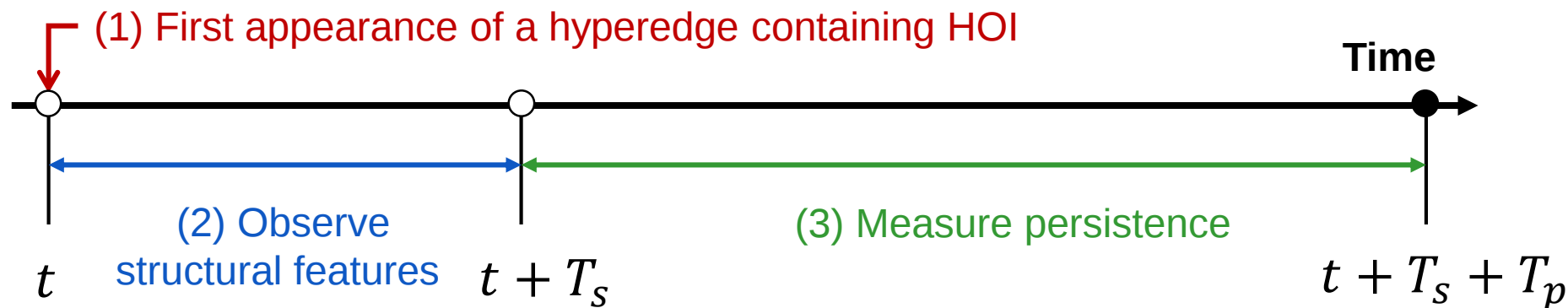
?

Questions:

What structural features are related to HOI persistence?

Answer:

We examine relations between various structural features and HOI persistence with the following setting:



Group Features and Persistence (cont.)

- Basic structural features of each HOI S :

- $\#$: number of hyperedges including S
- Σ : sum of sizes of hyperedges containing S
- $\cup$: number of hyperedges overlapping S
- $\Sigma \cup$: sum of sizes of hyperedges overlapping S
- $\cap$: number of common neighbors of S
- $\mathcal{H}$: entropy in sizes of hyperedges containing S

- Group structural features of each HOI S :

(1) $\#$, (2) $\#/\cup$, (3) $\Sigma/(\Sigma \cup)$, (4) $\cap$, (5) $\#/\cap$, (6) $\Sigma/\cap$, (7) $\Sigma/\#$, (8) $\mathcal{H}$

Group Features and Persistence (cont.)

- HOI persistence is **positively correlated** with:
 - The **number of hyperedges** containing the HOI
 - The **entropy of the sizes of hyperedges** containing the HOI

	Size of HOIs	#	$\frac{\#}{U}$	$\frac{\Sigma}{\Sigma U}$	$\cap$	$\frac{\#}{\cap}$	$\frac{\Sigma}{\cap}$	$\frac{\Sigma}{\#}$	$\mathcal{H}$
Normalized mutual information → MI	2	0.13	0.11	<u>0.14</u>	0.05	0.10	0.12	0.10	0.15
	3	<u>0.11</u>	0.06	0.08	0.05	0.08	0.09	0.08	0.12
	4	<u>0.11</u>	0.05	0.07	0.06	0.07	0.10	0.07	0.12
	Avg.	<u>0.12</u>	0.08	0.10	0.05	0.08	0.11	0.08	0.13
Pearson correlation coefficient → CC	2	0.36	0.09	0.09	0.17	0.19	0.26	-0.08	<u>0.32</u>
	3	0.31	0.10	0.10	0.05	0.16	0.20	-0.09	<u>0.25</u>
	4	0.30	0.13	0.13	-0.01	0.17	0.20	-0.10	<u>0.24</u>
	Avg.	0.32	0.10	0.11	0.07	0.17	0.22	-0.09	<u>0.27</u>

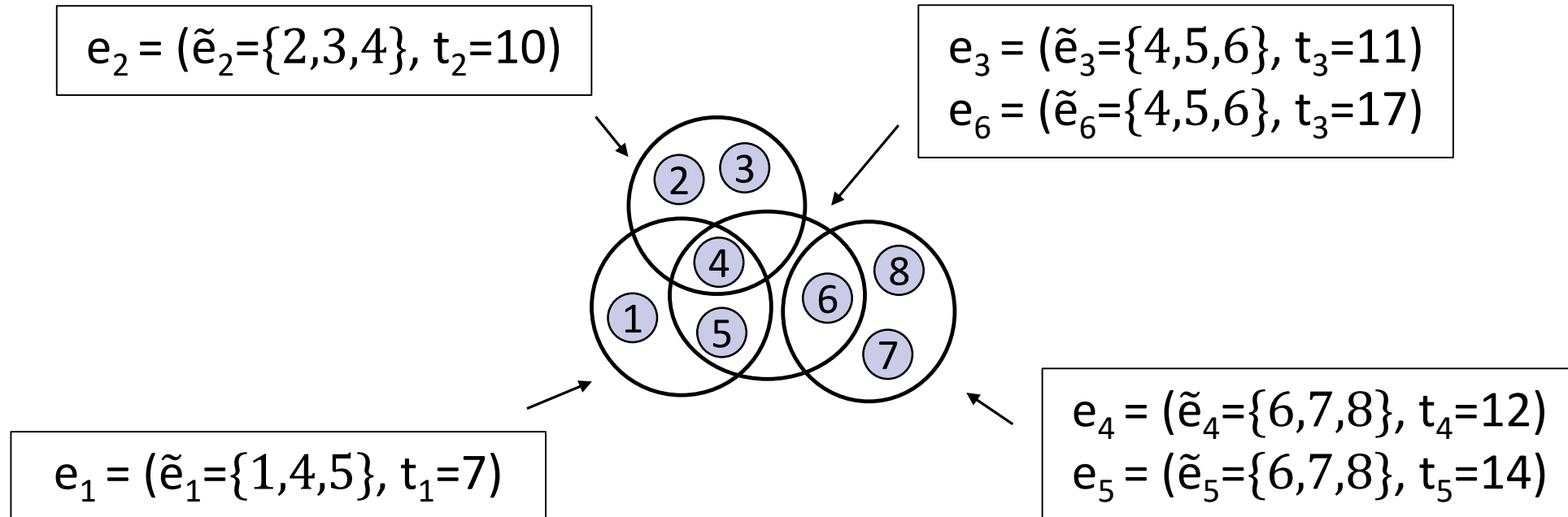
LS21: One Advanced Dynamic Pattern

- **P1.** Temporal hypergraph motifs (TH-motifs)

			
	Node		
	Hyperedge		
	Hypergraph		
	Sub-hypergraph		P1

Temporal Hypergraph Motifs: Definition

“How can we define motifs in temporal hypergraphs?”



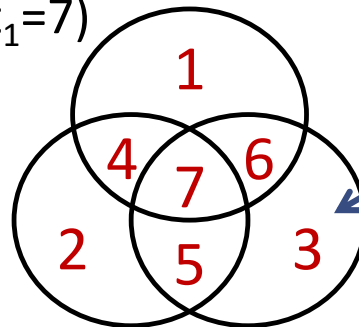
Temporal Hypergraph Motifs: Definition (cont.)

?

Question:How can we capture **structural** properties of hypergraphs?**Answer:**

We consider the **emptiness of seven subsets** of three connected temporal hyperedges.

$$e_1 = (\tilde{e}_1, t_1=7)$$



Is it empty?

$$e_2 = (\tilde{e}_2, t_2=10)$$

$$e_3 = (\tilde{e}_3, t_3=11)$$

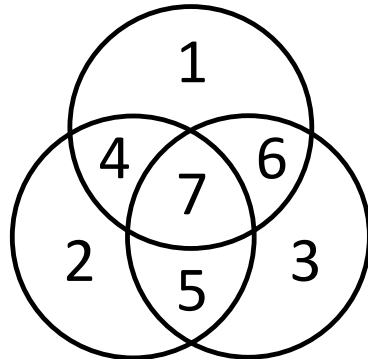
!

Temporal Hypergraph Motifs: Definition (cont.)

?

Question:How can we capture **temporal** properties of hypergraphs?**Answer:**The three temporal hyperedges should **arrive within δ time**.

$$e_1 = (\tilde{e}_1, t_1=7)$$



$$e_2 = (\tilde{e}_2, t_2=10)$$

$$e_3 = (\tilde{e}_3, t_3=11)$$

$$\max(t_1, t_2, t_3) - \min(t_1, t_2, t_3) \leq \delta$$

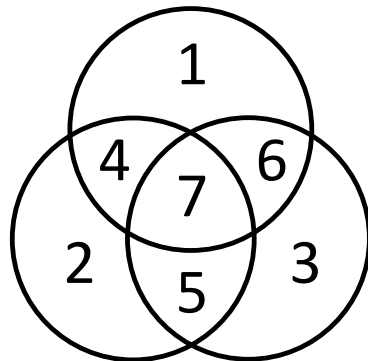
!

Temporal Hypergraph Motifs: Definition (cont.)

?

Question:How can we capture **temporal** properties of hypergraphs?**Answer:**The **order** of the three temporal hyperedges is considered.

$$e_1 = (\tilde{e}_1, t_1=7)$$



$$e_2 = (\tilde{e}_2, t_2=10)$$

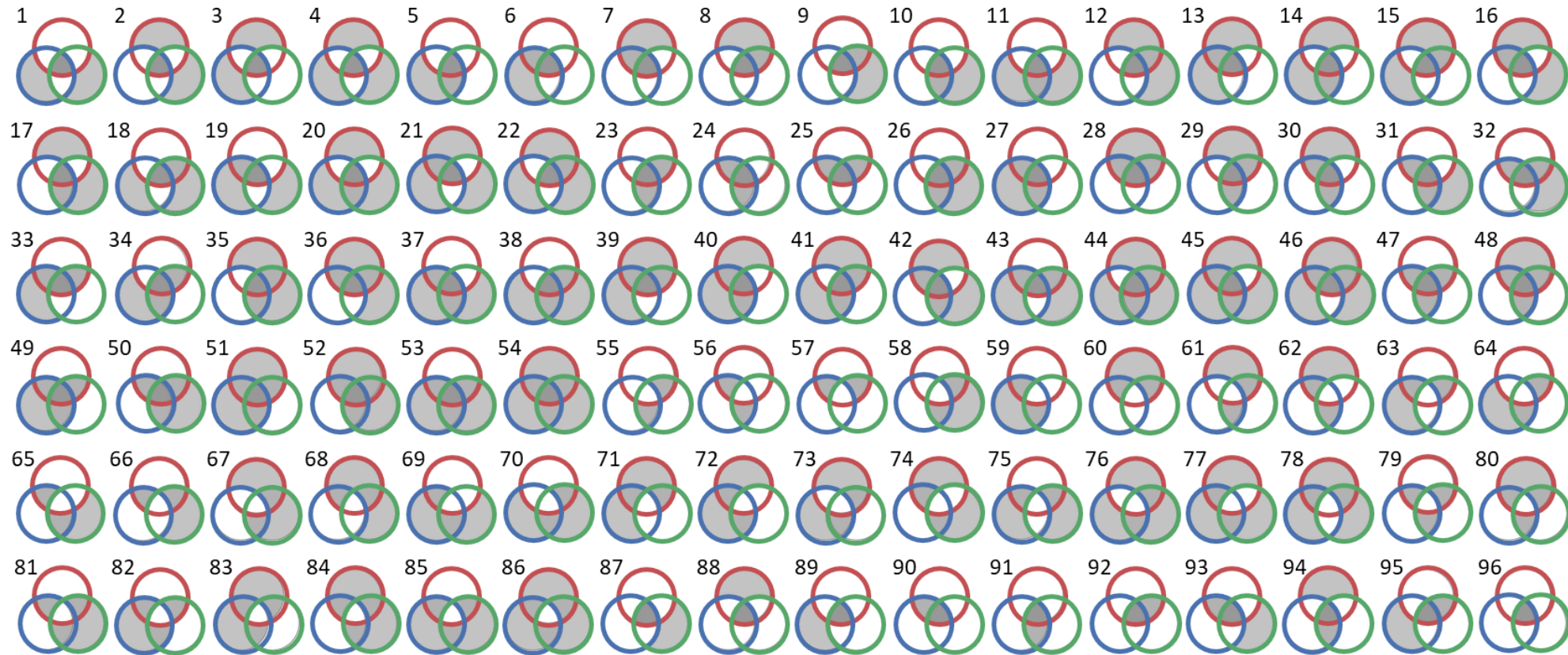
$$e_3 = (\tilde{e}_3, t_3=11)$$

$$e_1 \rightarrow e_2 \rightarrow e_3$$

!

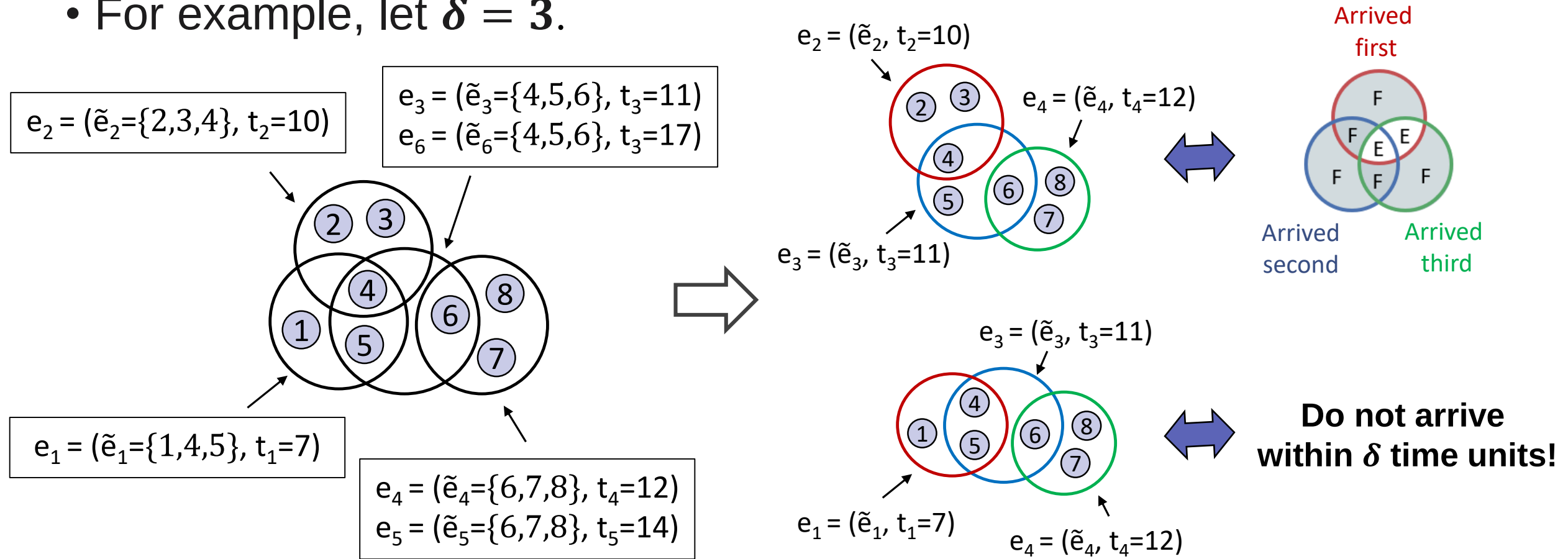
Temporal Hypergraph Motifs: Definition (cont.)

- There exist **96 temporal hypergraph motifs (TH-motifs)**.



Temporal Hypergraph Motifs: Example

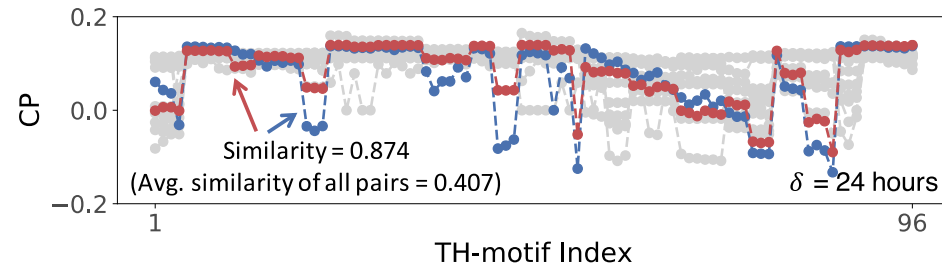
- For example, let $\delta = 3$.



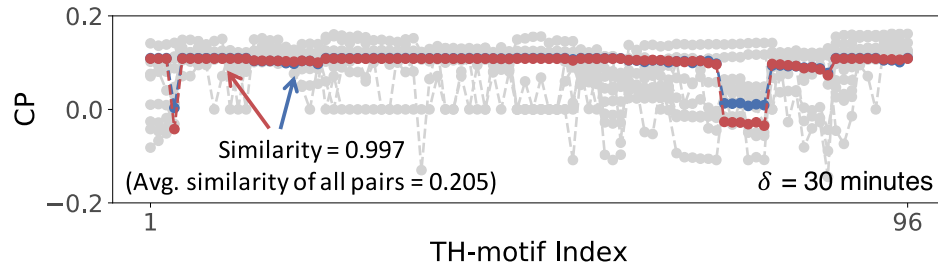
Comparison across Domains

- TH-motifs play a key role in capturing **structural** & **temporal** patterns.

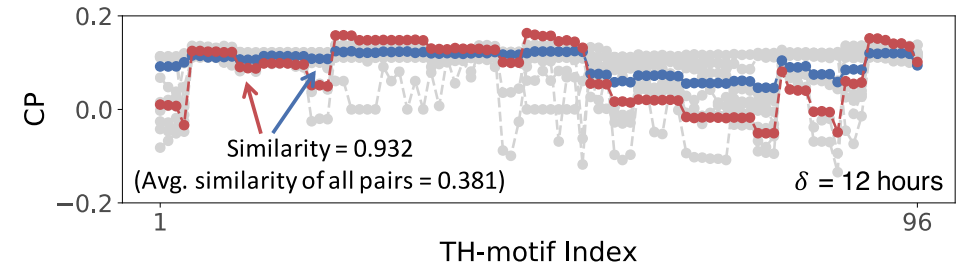
Email domain



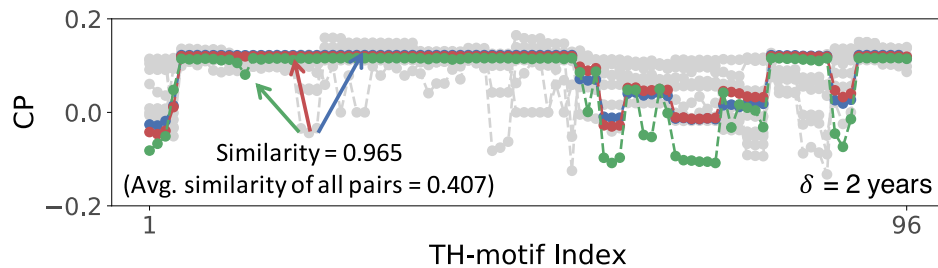
Contact domain



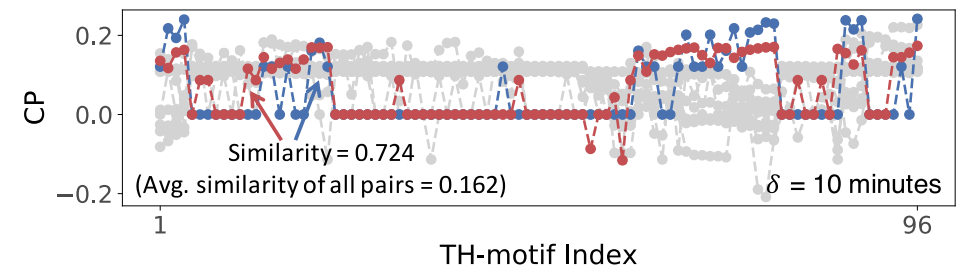
Tags domain



Coauthorship domain

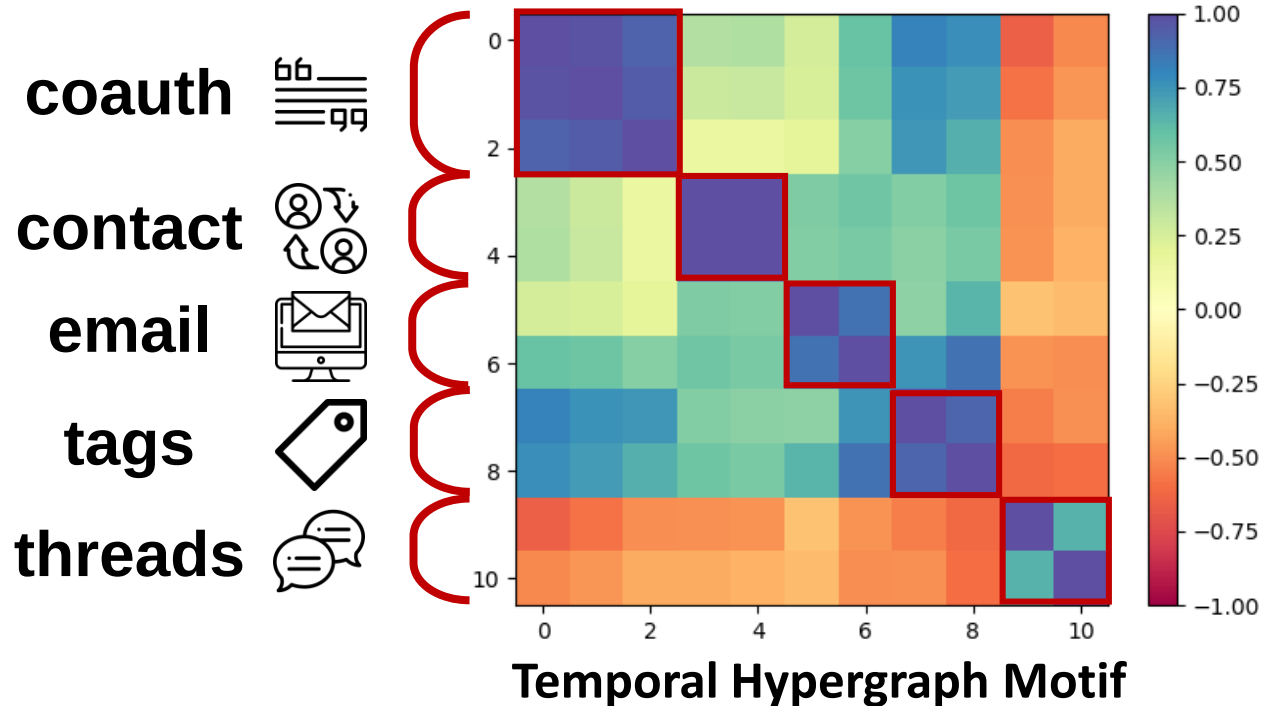


Threads domain

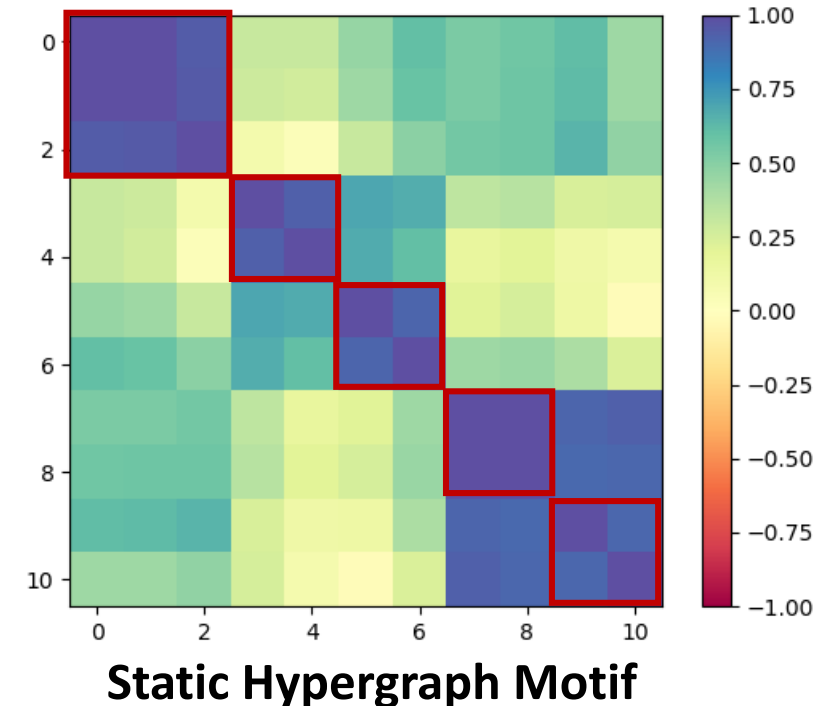


Comparison across Domains (cont.)

- TH-motifs play a key role in capturing **structural & temporal** patterns.



- Within-domain: 0.900 **Gap: 0.759**
- Between-domain: 0.141 **Times: 6.38X**



- Within-domain: 0.951 **Gap: 0.517**
- Between-domain: 0.434 **Times: 2.19X**

CK21: Four Advanced Dynamic Patterns

- **P1.** Intersection size of ego-networks
- **P2.** Spread of alter-networks
- **P3.** Anthropic principles of ego-networks
- **P4.** Novelty rate of ego-networks

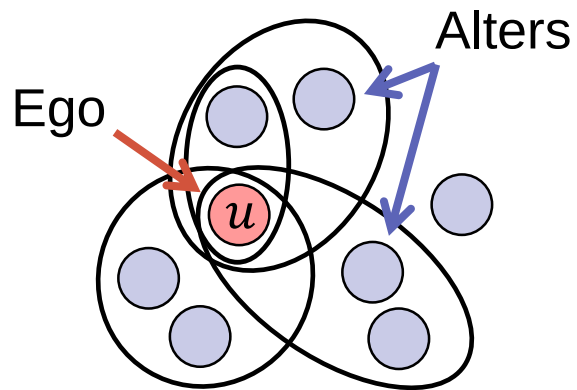
			 ↓
	Node		
	Hyperedge		
	Hypergraph		
	Sub-hypergraph		P1, P2, P3, P4

→

Hypergraph Ego-networks

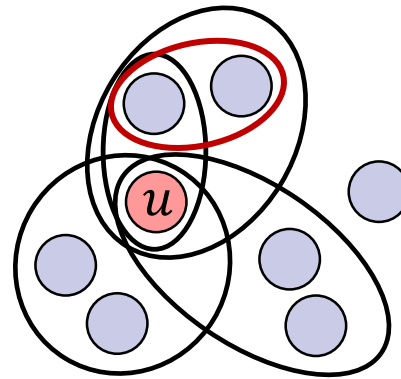
- There are three types of **hypergraph ego-networks**.

Star ego-network



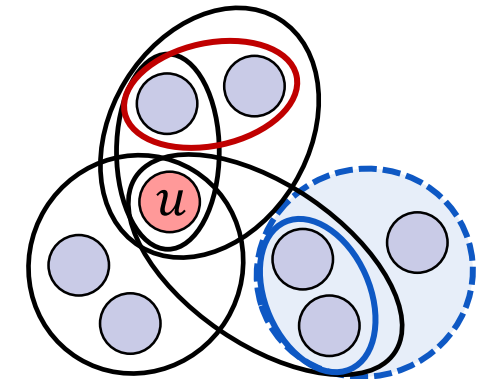
Hyperedges containing the ego-node.

Radial ego-network



Hyperedges containing ego-node **or** its neighbors.

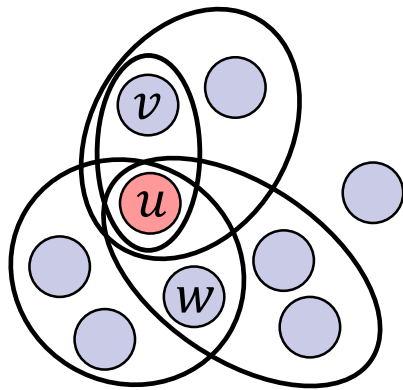
Contracted ego-network



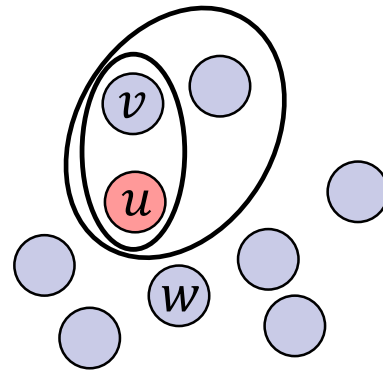
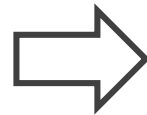
Hyperedges containing ego-node or its neighbors
+ **sub-hyperedges** containing them

Hypergraph Alter-networks

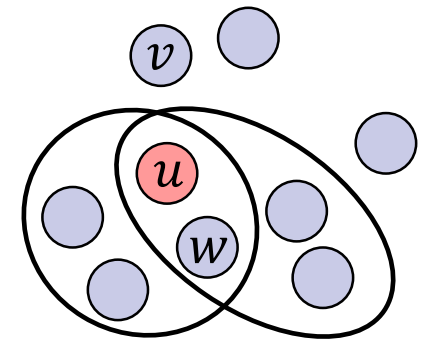
- An **alter-network** of node v in **ego-network** of node u is the collection of hyperedges in the ego-network that contain v .



Ego-network of u



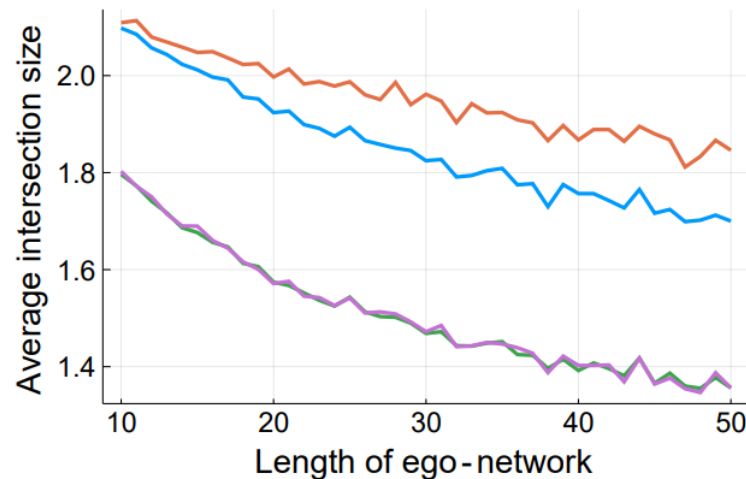
Alter-network of v



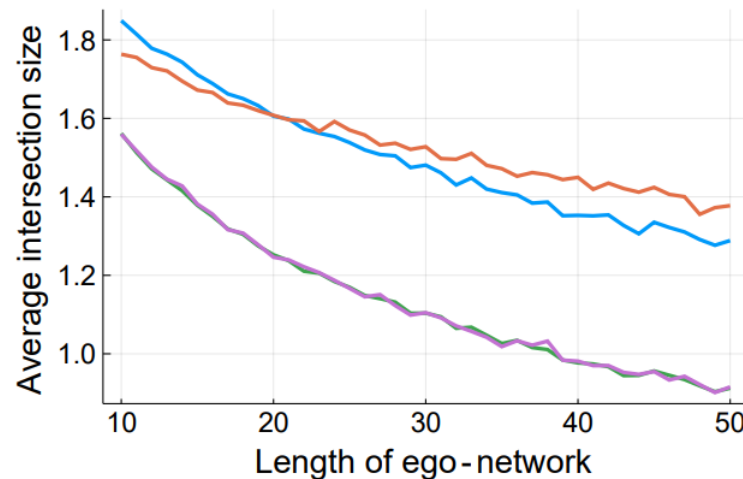
Alter-network of w

Intersection Size of Ego-networks

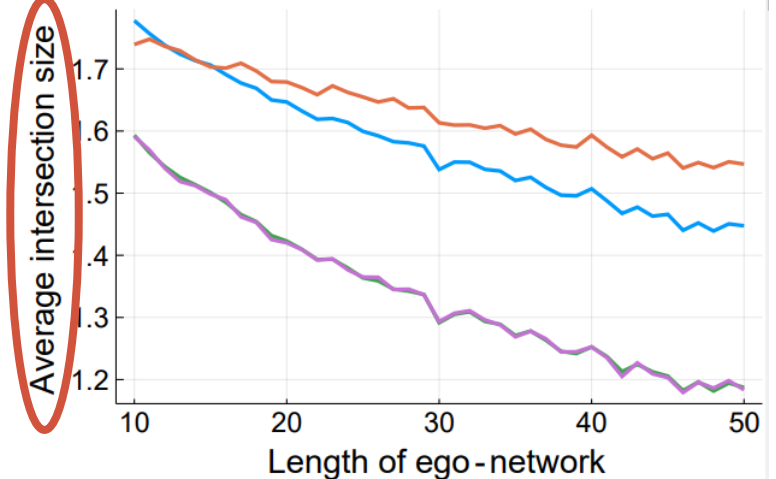
- Temporally adjacent hyperedges are similar.



Star ego-network



Radial ego-network



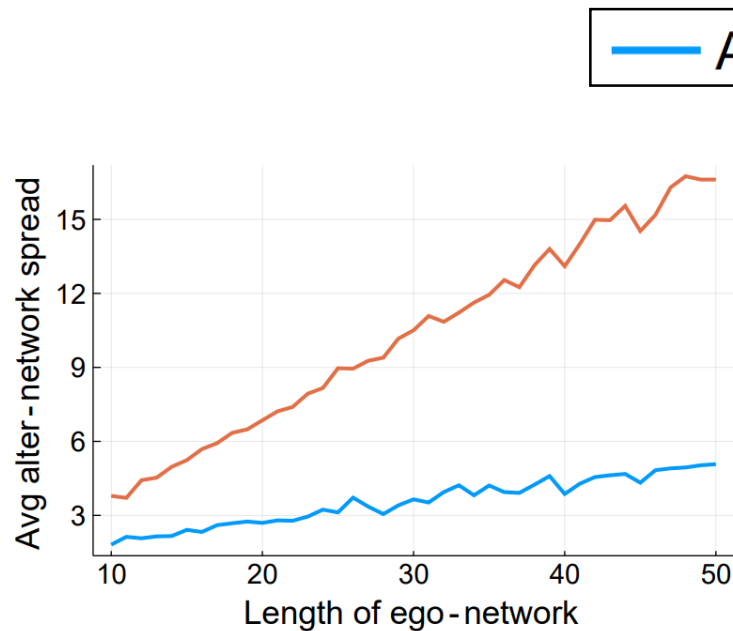
Contracted ego-network

Average intersection size of ego-network $\{s_1, \dots, s_m\}$:

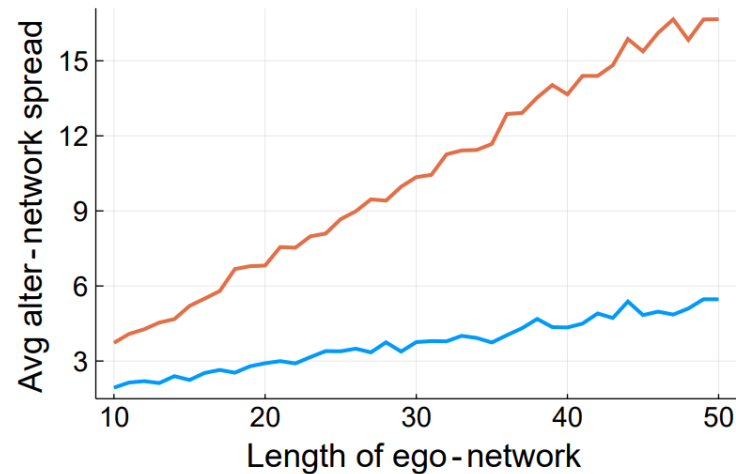
$$\frac{\sum_{i=1}^{m-1} |s_i \cap s_{i+1}|}{m-1}$$

Spread of Alter-networks

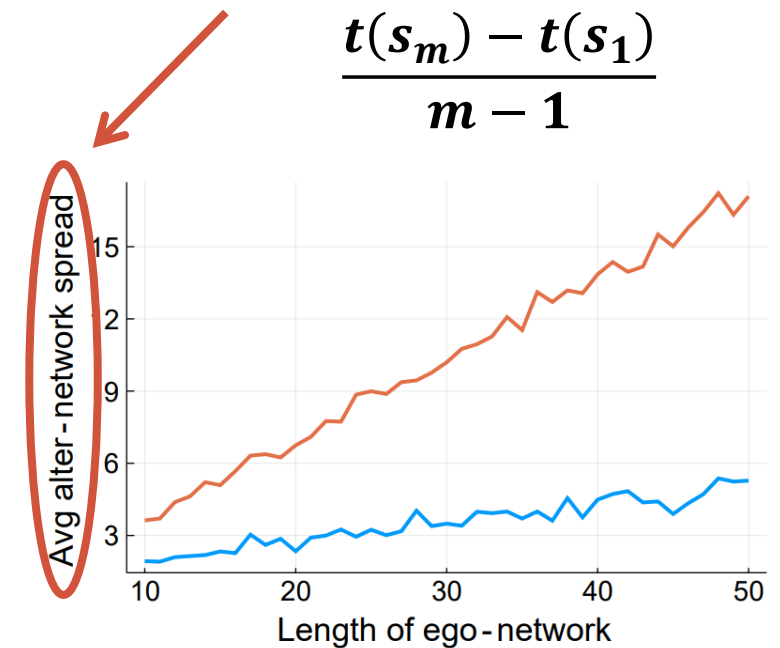
- Spread of **alter networks** is temporally local.



Star ego-network



Radial ego-network



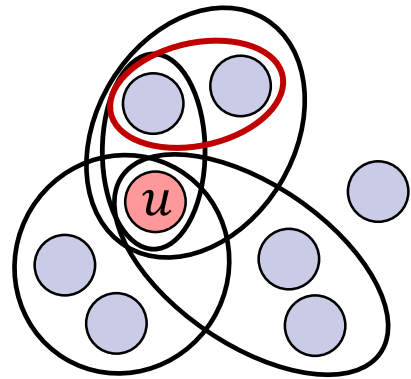
Contracted ego-network

Average spread time of alter-network $\{s_i, \dots, s_m\}$:

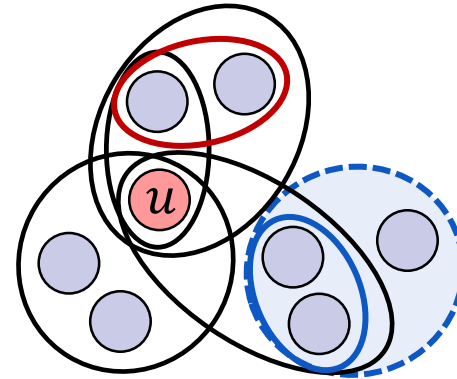
$$\frac{t(s_m) - t(s_1)}{m - 1}$$

Anthropic Principle of Ego-networks

- **Radial & contracted ego-networks** may include hyperedges without ego-node u .
- These hyperedges may arrive **before** the ego-node entered it.



Radial ego-network



Contracted ego-network

Anthropic Principle of Ego-networks (cont.)

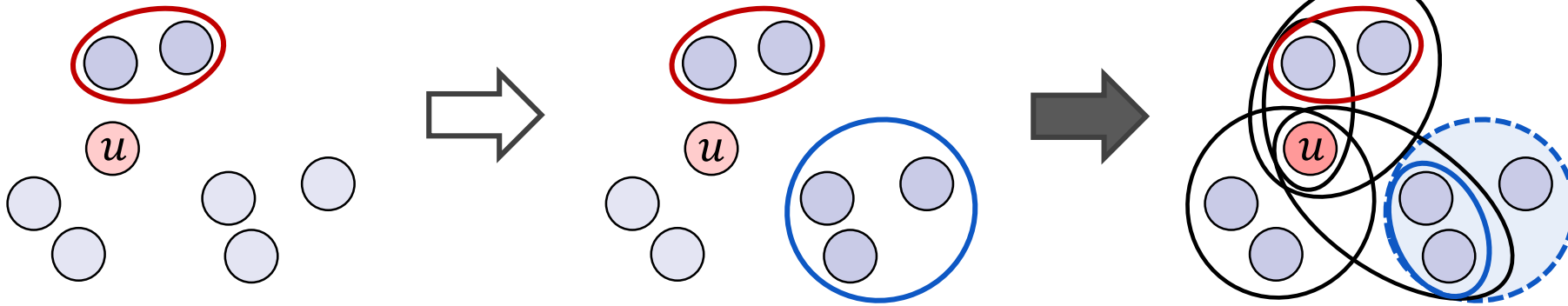
?

Question:

Across real-world radial & contracted ego-networks, at what timestamp does the ego-node arrive?

Answer:

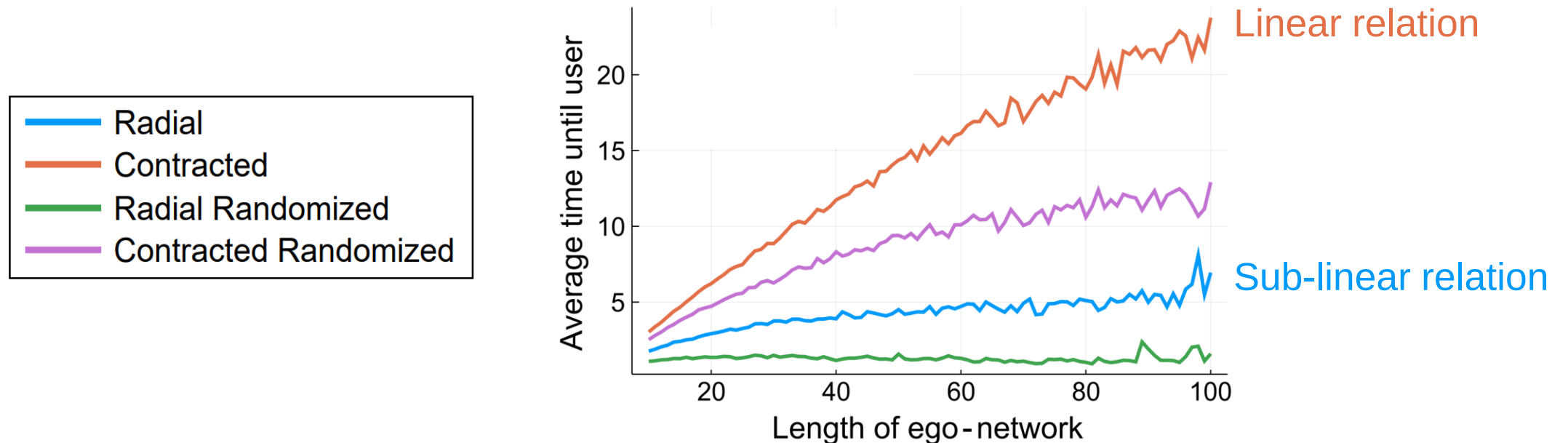
Timestamps of the ego-node arrival are observed.



!

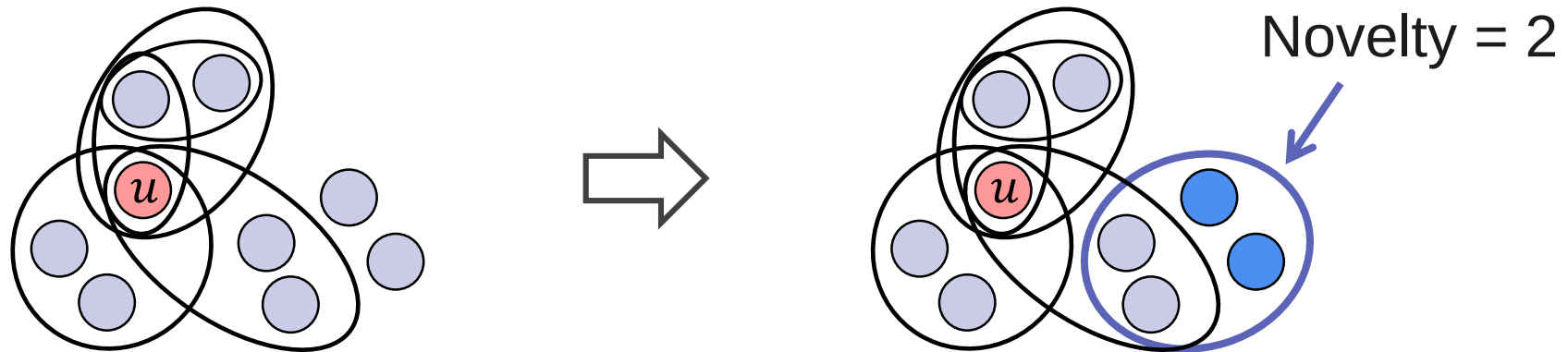
Anthropic Principle of Ego-networks (cont.)

- The **ego-node** tends to arrive...
 - before or around the fifth timestamp in **radial ego-networks**,
 - at linear timestamp to the size in **contracted ego-networks**.



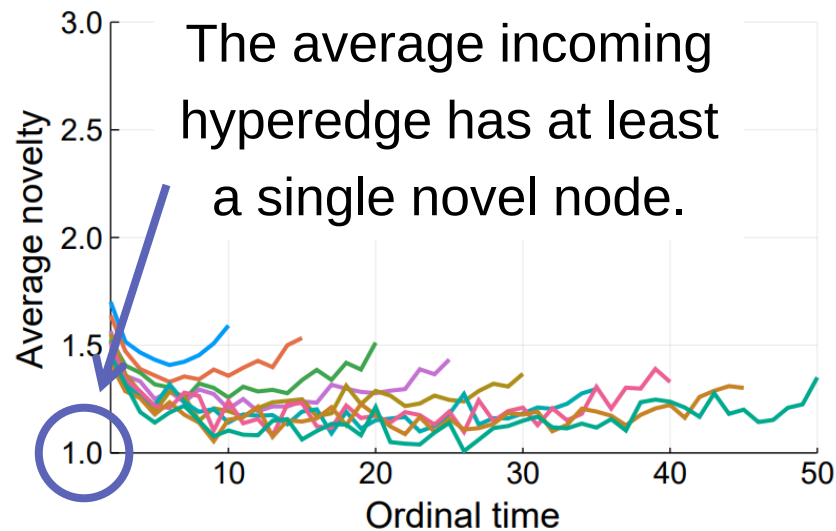
Novelty Rate of Ego-networks

- **Novelty** of a hyperedge is the number of nodes in the hyperedge that have never been contained in any previous hyperedges.

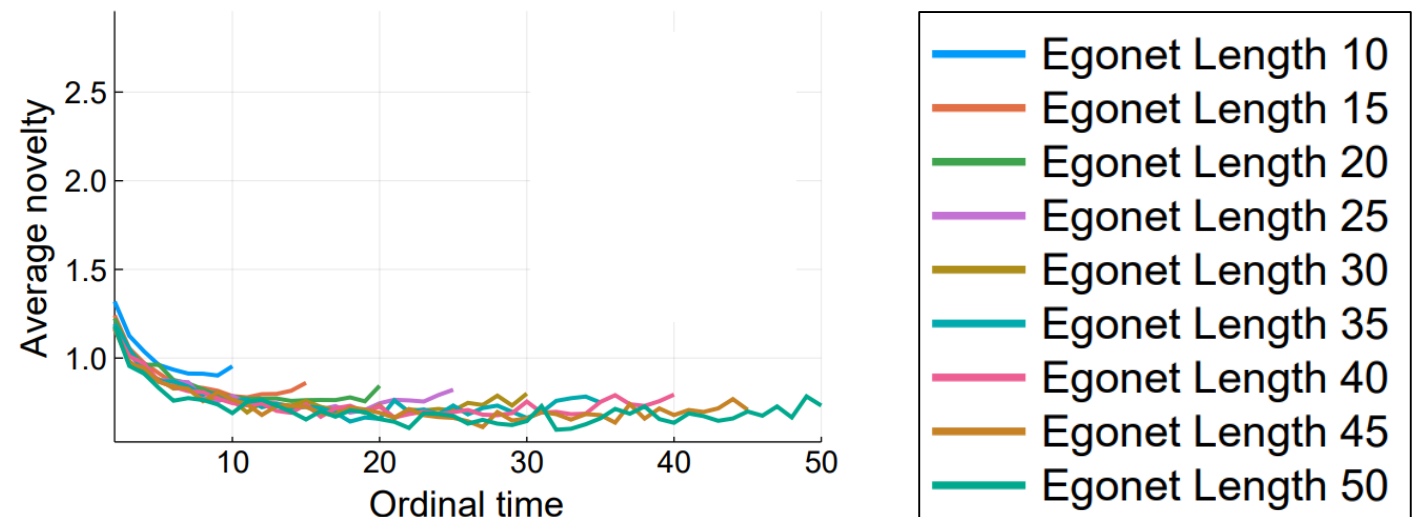


Novelty Rate of Ego-networks (cont.)

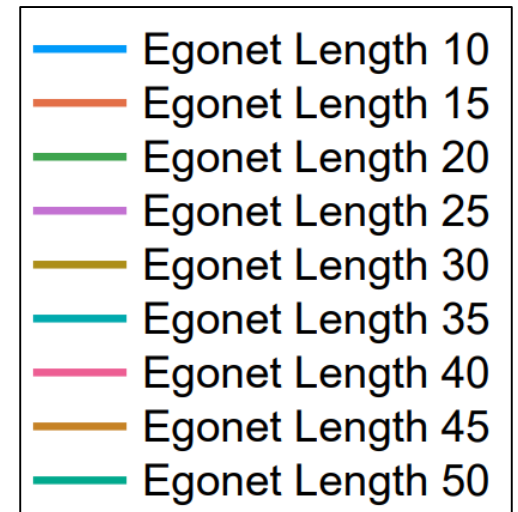
- Novelty slowly & gradually **decreases** in **star & radial ego-networks**.



Star ego-network

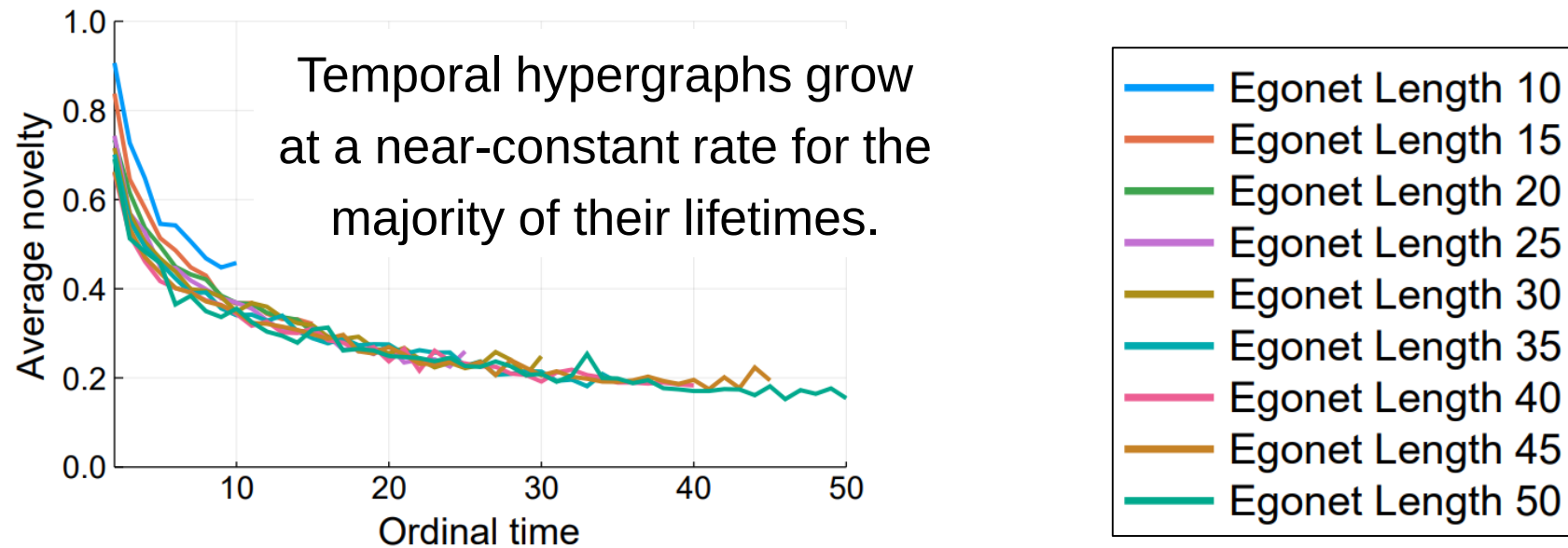


Radial ego-network



Novelty Rate of Ego-networks (cont.)

- Novelty always **decreases** in **contracted ego-networks**.



Contracted ego-network

References

1. [BASJK18] Benson, Austin R., et al. “Simplicial Closure and Higher-order Link Prediction.” PNAS 115(48):E11221–E11230, 2018.
2. [BKT18] Benson, Austin R., Ravi Kumar, and Andrew Tomkins, “Sequences of Sets.” KDD 2018.
3. [CBLK21] Cencetti, Giulia, et al. “Temporal Properties of Higher-order Interactions in Social Networks.” Scientific reports 11(1):1–10, 2021.
4. [CK21] Comrie, Cazamere, and Jon Kleinberg. “Hypergraph Ego-networks and Their Temporal Evolution.” ICDM 2021.
5. [CS22] Choo, Hyunjin, and Kijung Shin. “On the Persistence of Higher-order Interactions in Real-world Hypergraphs.” SDM 2022.
6. [KKS20] Kook, Yunbum, Jihoon Ko, and Kijung Shin. “Evolution of Real-world Hypergraphs: Patterns and Models without Oracles.” ICDM 2020.

References (cont.)

7. [LS21] Lee, Geon, and Kijung Shin. “THyMe+: Temporal Hypergraph Motifs and Fast Algorithms for Exact Counting.” ICDM 2021.
8. [GLLB23] Gallo, Luca, et al. “Higher-order Correlations Reveal Complex Memory in Temporal Hypergraphs. arXiv (2023).