

A Higher-Order Temporal H-Index for Evolving Networks

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1) University of Liverpool 2) University of Vienna 3) University of Bonn



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(J. E. Hirsch, 2005)

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Static n-th Order H-Index (Lü et al., 2016)

Let \mathcal{M} be the set of finite multisets of integers.

- Function $\mathcal{H}: \mathcal{M} \rightarrow \mathbb{N}_0$ returns for a finite multiset of integers $S \subseteq \{j \mid j \in \mathbb{N}_0\}$ the maximum integer i such that there are at least i elements j in S with $j \geq i$.

n -th order H-index

n -th order H-index $s_u^{(n)}$ of a node $u \in V$ in a static graph $G = (V, E)$:

Let $s_u^{(0)} = \delta(u)$ the degree of node u , then

$$s_u^{(n)} = \mathcal{H} \left(\{s_v^{(n-1)} \mid v \in V \text{ and } v \text{ is neighbor of } u\} \right)$$

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Many networks change over time:

- **Prominent examples:** Social and online communication networks
- Highly dynamic networks
- Information spreads over time
- **H-index should take the dynamics into account**



We introduce n -th Order Temporal H-Index:

- **Ranking nodes:** Which nodes are important or central? Who can influence others well?
- **Core-like decomposition:** Find strongly connected subgraphs or communities?

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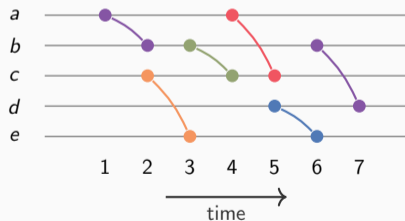


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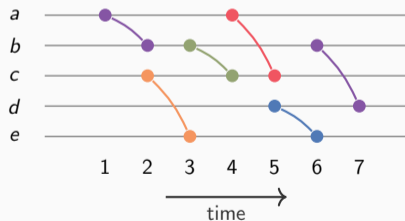
Temporal Network Model

- A **temporal network** is represented as $\mathcal{G} = (V, \mathcal{E})$
 - with (static) set of nodes V , and
 - set of temporal edges $\mathcal{E} = \{(u, v, t, \lambda)\}$, with $u, v \in V$ and $t, \lambda \in \mathbb{N}$
 - transition time λ equals time required to traverse the edge



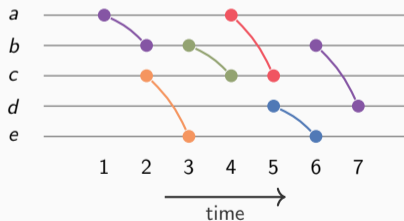
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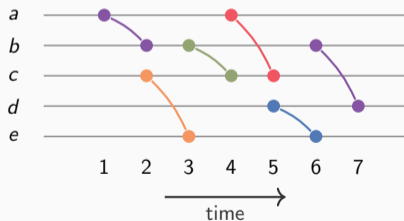
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What is a **useful adaption** of the n -th order H-index for temporal networks?

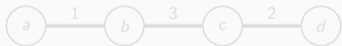
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- Information spreads along **temporal walks**
 - sequence of temporal edges, such that
 - consecutive edges share a common node, and
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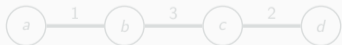
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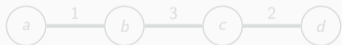
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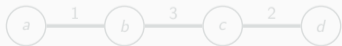
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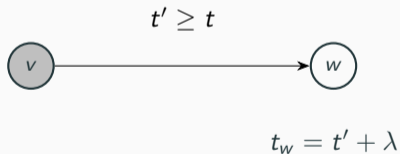
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Temporal Neighborhood

The multiset $\mathcal{N}(v, t)$ contains all pairs of nodes and times (w, t_w) such that there is a temporal edge from v to w leaving at time $t' \geq t$ and arriving at time t_w .



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We define $h_{v,t}^{(0)} = |\mathcal{N}(v, t)|$.

- Captures node importance in terms of **temporal reachability**
- Nodes with high reachability are ranked high

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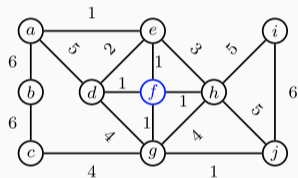
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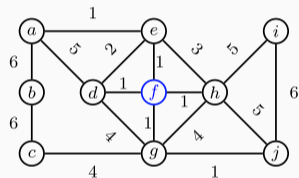
(a) \mathcal{G} with $\lambda = 1$ for all edges.



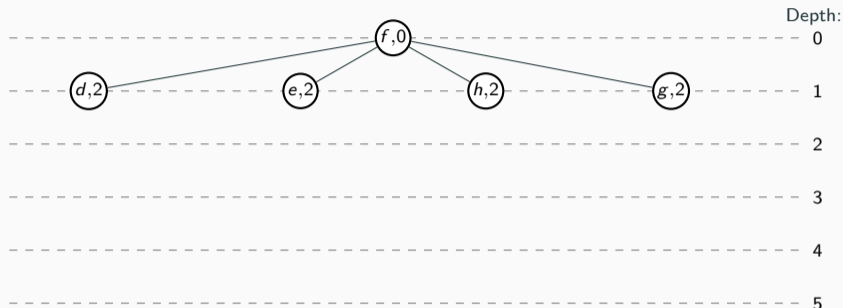
(b) The reachability tree $\Gamma(f)$ for vertex f in \mathcal{G} .

$$h_{f,0}^{(1)} =$$

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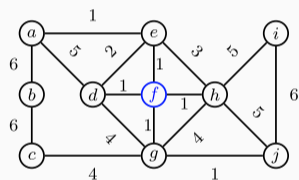
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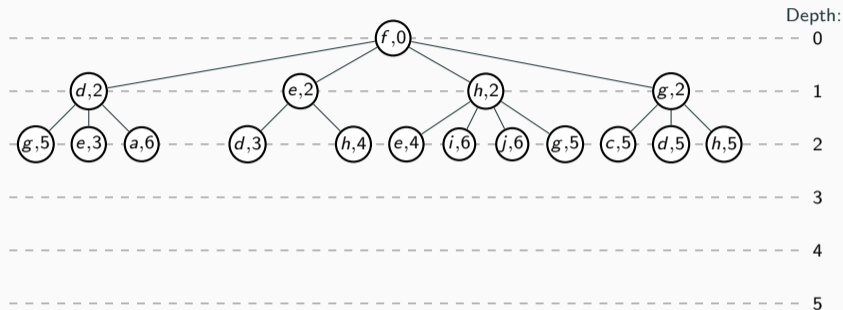
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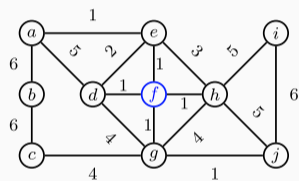
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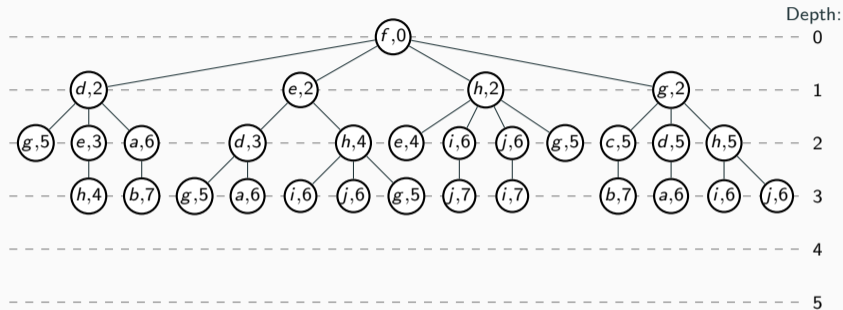
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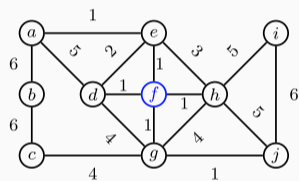
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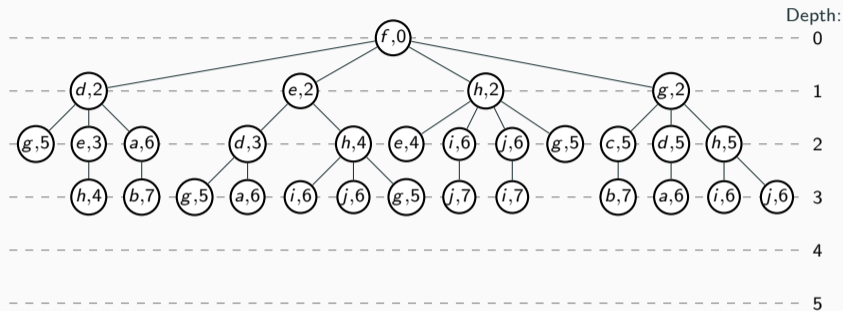
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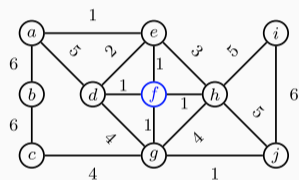
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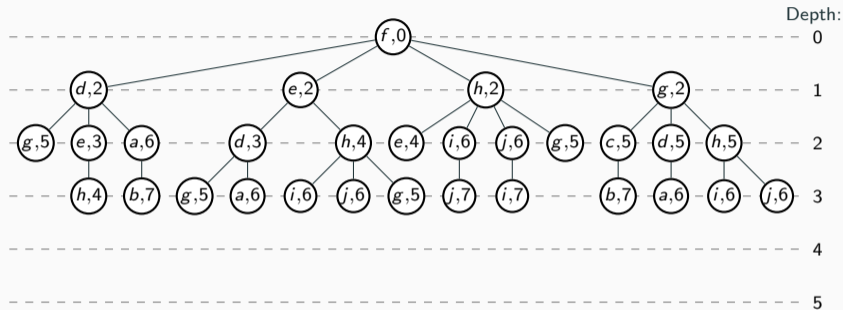
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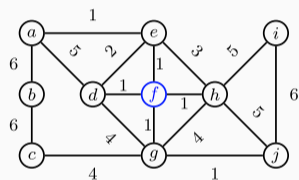
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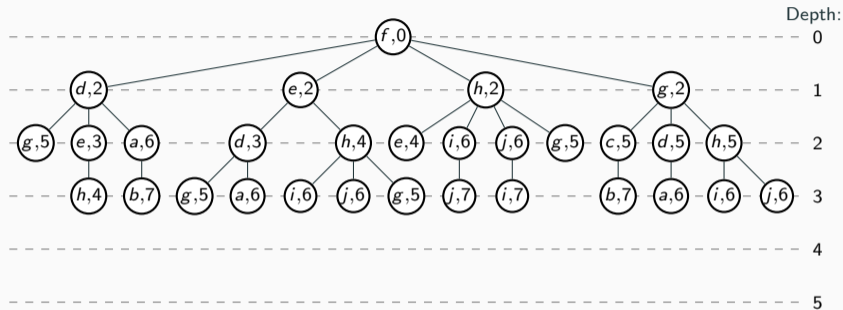
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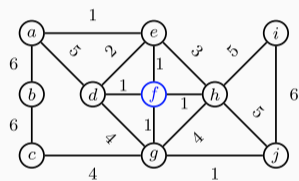
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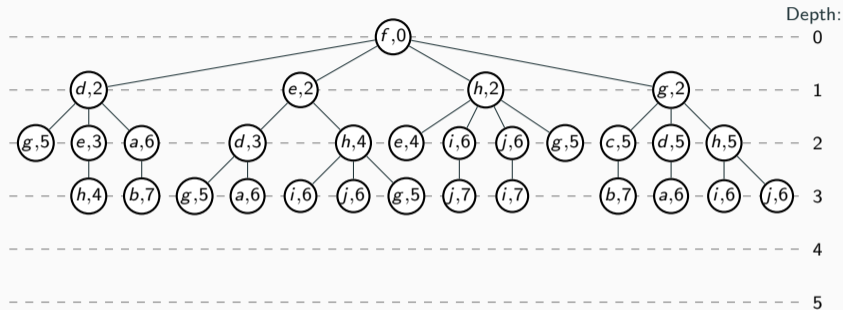
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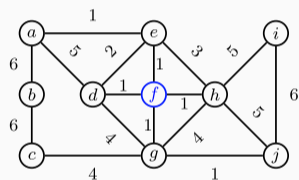
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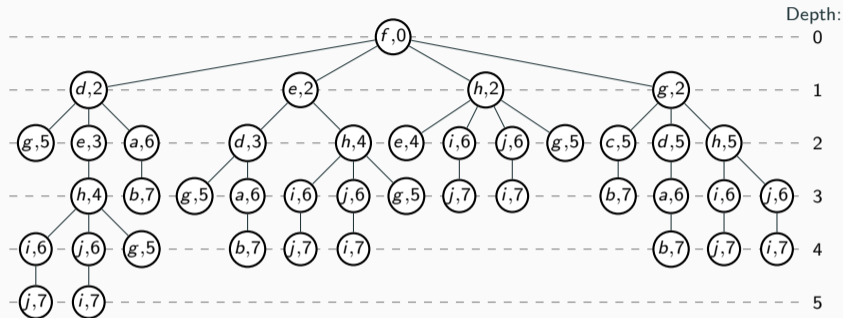
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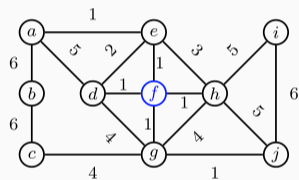
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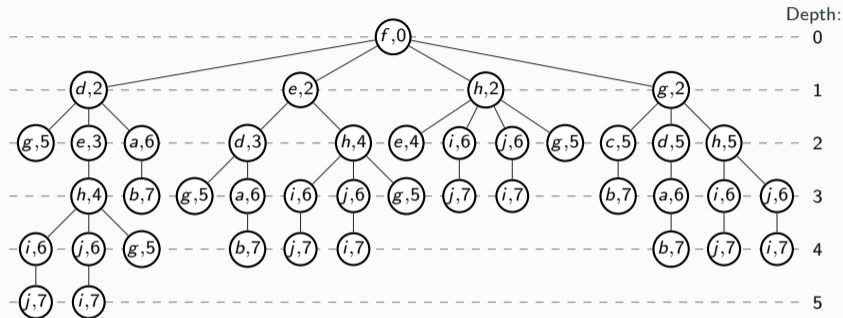
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For $h_v^{(n)} = k > 1$, there are at least $\frac{k^{(n+2)} - k}{k-1}$ descendants u of the root r in $\Gamma(v)$ with $d(u) \leq n$.

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It holds that $h_v^{(n)} = 0$ for all $n > \Delta(\mathcal{G})$ with $\Delta(\mathcal{G})$ being the max. temporal walk length.

So far:

- Adapted n -th order H-index for temporal networks
- Rank nodes according to spreading capabilities

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- For increasing n , the **static n -th order H-index** converges to the core number of u
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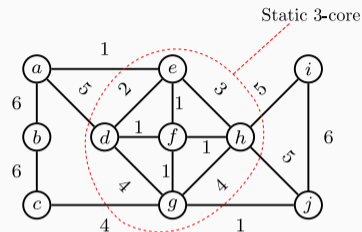
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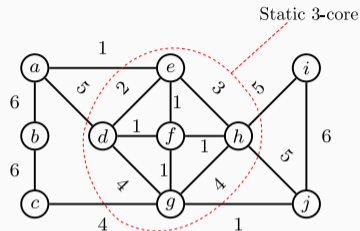
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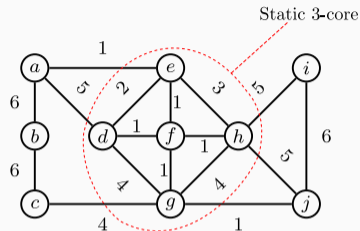
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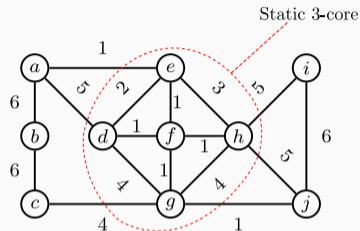
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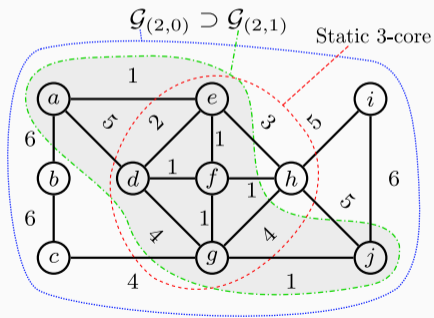


Core-like Decomposition

Temporal (n, k) -Pseudocore

Let $k, n \in \mathbb{N}$. The temporal (n, k) -pseudocore of \mathcal{G} is a maximal induced temporal subgraph $\mathcal{G}_{(n,k)}$ of \mathcal{G} such that for all $v \in V(\mathcal{G}_{(n,k)})$ the n -th order temporal H-index $h_v^{(n)} \geq k$ in \mathcal{G} .

- (n, k) -pseudocore: Temporal subgraph containing nodes with similar temporal activity and importance in the network \mathcal{G}
- For a node v in a (n, k) -pseudocore $\mathcal{G}_{(n,k)}$, the inequality $h_v^{(n)} \geq k$ does not hold necessarily with respect to $\mathcal{G}_{(n,k)}$

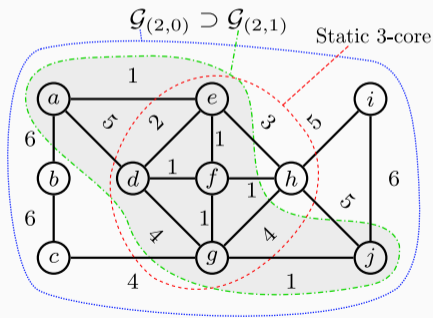


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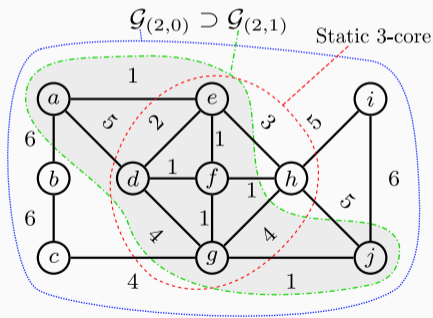


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Two algorithms

- Naive recursive algorithm
- Streaming algorithm
 - Single pass over edges in reverse chronological order
 - Computes for each node i -th order H-indices for $0 \leq i \leq n$

Algorithm	Running Time	Space	Edge Trans. Times	Results for $\forall i \in [n]$
RECURS	$\mathcal{O}(V n(\delta_{\max})^2)$	$\mathcal{O}(V n\delta_{\max})$	individual	\times
STREAM	$\mathcal{O}(\mathcal{E} n\delta_{\max})$	$\mathcal{O}(V n\delta_{\max})$	uniform	\checkmark

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Streaming Algorithm

- Streaming algorithm of the temporal edges in **reverse chronological order** of time steps
- Manages for each $v \in V$ and $1 \leq i \leq n$ a multiset of i -th order H-indices of the neighbors
- When edge $(u, v, t) \in \mathcal{E}$ is processed
 1. Update degree $|\mathcal{N}(u, t)|$
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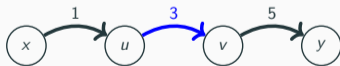
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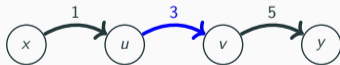
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1. Running Times

Running times in seconds (s). OOT: out of time (time limit 12h).

Data set	Graph size		$n = 8$		$n = 16$		$n = 32$		$n = 64$	
	$ V $	$ \mathcal{E} $	RECURS	STREAM	RECURS	STREAM	RECURS	STREAM	RECURS	STREAM
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<i>Infectious</i>	10972	415912	18.81	1.02	39.87	1.98	76.73	4.19	144.48	8.51
<i>FacebookWall</i>	63731	817035	31.11	3.48	69.01	6.03	135.03	11.31	310.44	22.49
<i>Enron</i>	86806	1133968	411.59	4.89	866.53	11.03	1882.11	24.45	4226.25	52.33
<i>AskUbuntu</i>	134035	257305	1.23	0.21	2.50	0.38	5.31	0.72	13.15	1.44
<i>Digg</i>	279630	1731652	62.80	3.33	120.30	6.84	229.93	13.83	364.88	27.61
<i>Wikipedia</i>	1870709	39953145	4863.44	117.03	10332.81	230.70	21998.44	457.65	OOT	861.95
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2. Comparison of reachability scores

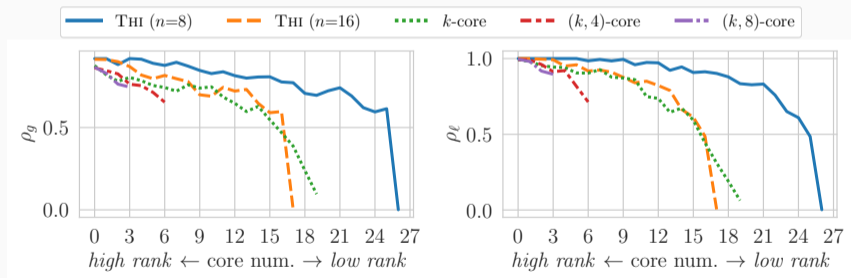
Let $r: V \times V \rightarrow \{0, 1\}$ the indicator function for temporal reachability, i.e., $r(u, v) = 1$ iff u can reach v via a temporal walk. For pseudocore $\mathcal{G}_{(n,k)} = (V', \mathcal{E}')$:

- **global reachability score:** $\rho_g = \frac{\sum_{u \in V', v \in V} r(u, v)}{|V'| \cdot |V|}$
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(a) FacebookMsg – global

(b) FacebookMsg – local

3. Use Case: Influential Spreader Identification

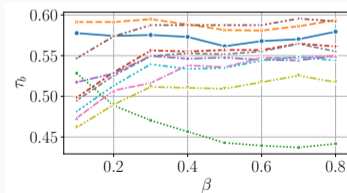
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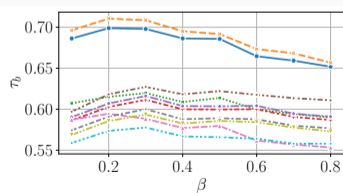
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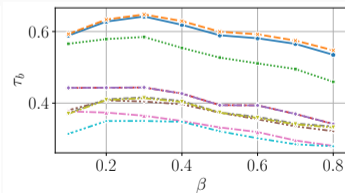
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(a) Malawi



(b) FacebookMsg



(c) Email

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- Obtained **inward** and **outward** variants based on incoming and outgoing temporal walks
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- Effective pseudocore decomposition
- We showed that the n -th order temporal H-index can be a successful heuristic for identifying possible super-spreaders



[Link to our paper](#)

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