# Fast Incremental SimRank on Link-Evolving Graphs

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### Outline

### Overview

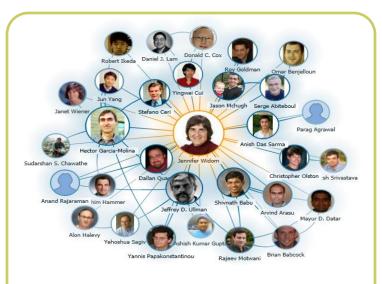
- Existing incremental method
- Our approaches
  - express ΔS as a rank-one Sylvester equation: O(Kn<sup>2</sup>)
  - prune "unaffected areas" of ΔS:
     O(K(nd+|AFF|)) with |AFF| < n<sup>2</sup>
- Empirical evaluations
- Conclusions

#### **Overview**

#### • Similarity Assessment plays a vital role in our lives.



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Articles  All fields SimRank Images  Journal/Book title	Author Volume Issue Page			
8 Evolution of trust networks in social web applications using supervised learning Original Research Article Procedia Computer Science, Volume 3, 2011, Pages 833-839 Kiyana Zolfaghar, Abdollah Aghaie				
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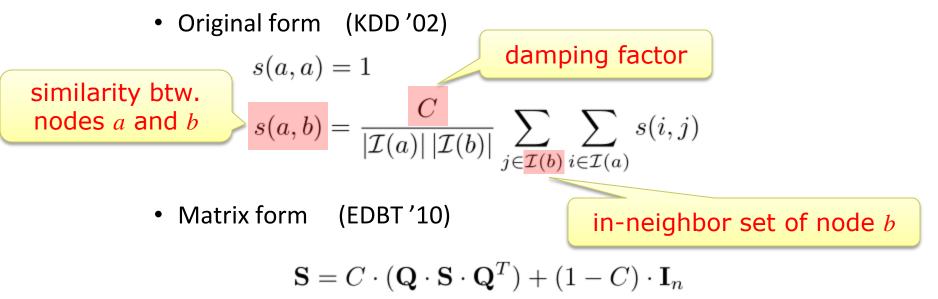
#### **Collaboration Network**

### **SimRank Overview**

- SimRank
  - An appealing link-based similarity measure (KDD '02)
  - Basic philosophy

Two vertices are similar if they are referenced by similar vertices.

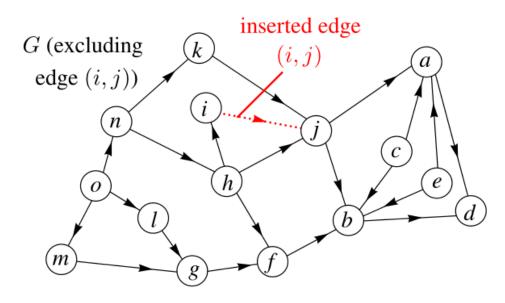
• Two Forms



# **Existing SimRank Algorithms**

- Batch Computations
  - All Pairs s(\*,\*)
  - Single Pair s(a,b)
  - Single Source s(\*,q)
  - Similarity Join s(x,y) for all x in A, and y in B.
- Incremental Paradigms:
  - link-evolving:
    - Li et. al. [EDBT 2010] needs O(r<sup>4</sup>n<sup>2</sup>) time for approximation.
  - node-evolving:
    - He et al. [KDD 2010] --- GPU based

### **Motivation**



Node-Pair	in $G$	in $G \cup \Delta G$	
	sim	sim <sub>true</sub>	sim <sub>Li et al.</sub>
(a,b)	0.075	0.062	0.073
(a,d)	0.000	0.006	0.002
(i,f)	0.246	0.246	0.246
(k,g)	0.128	0.128	0.128
(k,h)	0.288	0.288	0.288
(j, f)	0.206	0.138	0.206
(m,l)	0.160	0.160	0.160
(j,b)	0.000	0.030	0.001

- Li et al. [EDBT 2010] using SVD for incremental SimRank is approximate.
- When  $\Delta G$  is small, the "affected areas" of  $\Delta S$  are also small.

**Problem** (INCREMENTAL SIMRANK COMPUTATION)**Given**: G, S, ΔG, and C.**Compute**: ΔS to S.

• For every edge update,  $\Delta Q$  has a rank-one structure

 $\mathbf{\Delta Q} = \mathbf{u} \cdot \mathbf{v}^T$ 

$$\Delta \mathbf{Q} = \mathbf{u}^T$$

• Characterize  $\Delta S$  as

 $\mathbf{\Delta S} = \mathbf{M} + \mathbf{M}^T$  , where M satisfies

$$\mathbf{M} = C \cdot \tilde{\mathbf{Q}} \cdot \mathbf{M} \cdot \tilde{\mathbf{Q}}^T + C \cdot \mathbf{u} \cdot \mathbf{w}^T$$

compute M via mat-vec multiplication

In comparison

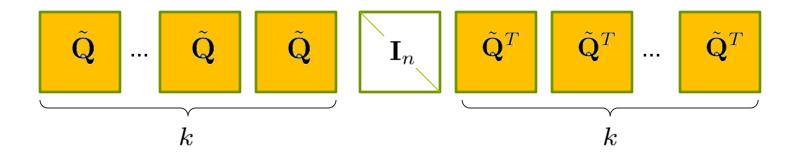
$$\tilde{\mathbf{S}} = C \cdot \tilde{\mathbf{Q}} \cdot \tilde{\mathbf{S}} \cdot \tilde{\mathbf{Q}}^T + (1 - C) \cdot \mathbf{I}_n$$

compute  $\widetilde{\mathsf{S}}$  via mat-mat multiplication

• Based on

$$\mathbf{X} = \sum_{k=0}^{\infty} \mathbf{A}^k \cdot \mathbf{C} \cdot \mathbf{B}^k \quad \Leftrightarrow \quad \mathbf{X} = \mathbf{A} \cdot \mathbf{X} \cdot \mathbf{B} + \mathbf{C}$$
 we have

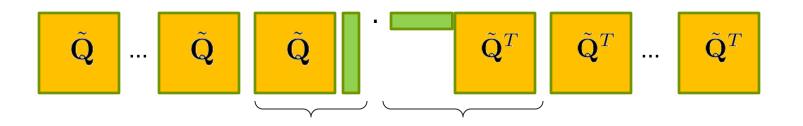
$$\mathbf{M} = \sum_{k=0}^{\infty} C^{k+1} \cdot \tilde{\mathbf{Q}}^{k} \cdot \mathbf{u} \cdot \mathbf{w}^{T} \cdot \left(\tilde{\mathbf{Q}}^{T}\right)^{k},$$
$$\tilde{\mathbf{S}} = (1-C) \cdot \sum_{k=0}^{\infty} C^{k} \cdot \tilde{\mathbf{Q}}^{k} \cdot \mathbf{I}_{n} \cdot \left(\tilde{\mathbf{Q}}^{T}\right)^{k}.$$



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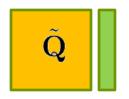
$$\tilde{\mathbf{Q}}$$
 ...  $\tilde{\mathbf{Q}}$  ...  $\tilde{\mathbf{Q}}^T$  ...  $\tilde{\mathbf{Q}}^T$ 

• Based on

$$\mathbf{X} = \sum_{k=0}^{\infty} \mathbf{A}^k \cdot \mathbf{C} \cdot \mathbf{B}^k \quad \Leftrightarrow \quad \mathbf{X} = \mathbf{A} \cdot \mathbf{X} \cdot \mathbf{B} + \mathbf{C}$$
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$$\mathbf{M} = \sum_{k=0}^{\infty} C^{k+1} \cdot \qquad = \sum_{k=0}^{\infty} C^{k+1} \cdot$$

### Challenges

• For every edge update,  $\Delta Q$  has a rank-one structure

 $\mathbf{\Delta Q} = \mathbf{u} \cdot \mathbf{v}^T$ 

$$\Delta \mathbf{Q} = \mathbf{\mathbf{u}}^T$$

• Characterize  $\Delta S$  as

 $\mathbf{\Delta S} = \mathbf{M} + \mathbf{M}^T$  , where M satisfies

$$\mathbf{M} = C \cdot \tilde{\mathbf{Q}} \cdot \mathbf{M} \cdot \tilde{\mathbf{Q}}^T + C \cdot \mathbf{u} \cdot \mathbf{w}^T$$

Finding u, v, w is challenging !!

### Finding u, v

• For every edge update,  $\Delta Q$  has a rank-one structure

$$\Delta \mathbf{Q} = \mathbf{u} \cdot \mathbf{v}^T$$

$$\Delta \mathbf{Q} = \mathbf{u}^T$$

where

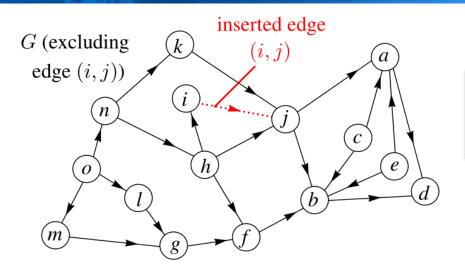
(1) for edge (i, j) insertion,

$$\mathbf{u} = \begin{cases} \mathbf{e}_j & (d_j = 0) \\ \frac{1}{d_j + 1} \mathbf{e}_j & (d_j > 0) \end{cases}, \quad \mathbf{v} = \begin{cases} \mathbf{e}_i & (d_j = 0) \\ \mathbf{e}_i - [\mathbf{Q}]_{j,\star}^T & (d_j > 0) \end{cases}$$

(2) for edge (i, j) deletion,

$$\mathbf{u} = \begin{cases} \mathbf{e}_j & (d_j = 1) \\ \frac{1}{d_j - 1} \mathbf{e}_j & (d_j > 1) \end{cases}, \quad \mathbf{v} = \begin{cases} -\mathbf{e}_i & (d_j = 1) \\ [\mathbf{Q}]_{j,\star}^T - \mathbf{e}_i & (d_j > 1) \end{cases}$$

#### Example



$$[\tilde{\mathbf{Q}}]_{j,\star} = \begin{bmatrix} 0 & \cdots & 0 & \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} & 0 & \cdots & 0 \end{bmatrix}$$

• Since the old  $[\mathbf{Q}]_{j,\star} = \begin{bmatrix} 0 \cdots 0 & \frac{1}{2} & 0 & 0 & \frac{1}{2} & 0 & \cdots & 0 \end{bmatrix} \in \mathbb{R}^{1 \times 15}$ , after insertion:  $\Delta \mathbf{Q} = \mathbf{u} \cdot \mathbf{v}^T$  with  $\mathbf{u} = \frac{1}{d_j + 1} \mathbf{e}_j = \frac{1}{3} \mathbf{e}_j = \begin{bmatrix} 0 \cdots 0 & \frac{1}{3} & 0 & \cdots & 0 \end{bmatrix}^T \in \mathbb{R}^{15 \times 1},$  $\mathbf{v} = \mathbf{e}_i - [\mathbf{Q}]_{j,\star}^T = \begin{bmatrix} 0 \cdots 0 & -\frac{1}{2} & 1 & 0 & -\frac{1}{2} & 0 & \cdots & 0 \end{bmatrix}^T \in \mathbb{R}^{15 \times 1}.$ 

### **Finding w**

• For every edge update,  $\Delta Q$  has a rank-one structure

$$\Delta \mathbf{Q} = \mathbf{u} \cdot \mathbf{v}^T$$
 Step 1

$$\Delta \mathbf{Q} = \mathbf{u}^T$$

• Characterize  $\Delta S$  as

Step 3 
$$\Delta S = M + M^T$$
, where M satisfies  
 $M = C \cdot \tilde{Q} \cdot M \cdot \tilde{Q}^T + C \cdot u \cdot w^T$  (1)

**Theorem** There exists 
$$\mathbf{w} \neq \mathbf{y} + \frac{\lambda}{2}\mathbf{u}$$
 with  
 $\mathbf{y} = \mathbf{Q} \cdot \mathbf{z}, \quad \mathbf{Step 2} \cdot \mathbf{z}, \quad \mathbf{z} = \mathbf{S} \cdot \mathbf{v}$ 

s.t. Eq.(1) is a rank-one Sylvester Equation w.r.t. M.

 $\mathbf{z} = \mathbf{S} \cdot \mathbf{v}$  $\mathbf{y} = \mathbf{Q} \cdot \mathbf{z}$  $\mathbf{Q} = \mathbf{Q} \cdot \mathbf{z}$  $\mathbf{Q} = \mathbf{Q} \cdot \mathbf{z}$ 

## **Complexity Analysis**

• Time complexity:  $O(Kn^2)$ Step 1. Find  $\mathbf{u}, \mathbf{v}$  s.t.  $\Delta \mathbf{Q} = \mathbf{u} \cdot \mathbf{v}^T$ 

$$\mathbf{u} = \begin{cases} \mathbf{e}_j & (d_j = 0) \\ \frac{1}{d_j + 1} \mathbf{e}_j & (d_j > 0) \end{cases}, \quad \mathbf{v} = \begin{cases} \mathbf{e}_i & (d_j = 0) \\ \mathbf{e}_i - [\mathbf{Q}]_{j,\star}^T & (d_j > 0) \end{cases}$$

Step 2. Find w s.t.  $\mathbf{M} = C \cdot \tilde{\mathbf{Q}} \cdot \mathbf{M} \cdot \tilde{\mathbf{Q}}^T + C \cdot \mathbf{u} \cdot \mathbf{w}^T$ 

initialize 
$$\boldsymbol{\xi}_0 \leftarrow C \cdot \mathbf{u}, \quad \boldsymbol{\eta}_0 \leftarrow \mathbf{w}, \quad \mathbf{M}_0 \leftarrow C \cdot \mathbf{u} \cdot \mathbf{w}^T$$
  
for  $k = 0, 1, 2, \cdots$   
 $\boldsymbol{\xi}_{k+1} \leftarrow C \cdot \tilde{\mathbf{Q}} \cdot \boldsymbol{\xi}_k, \quad \boldsymbol{\eta}_{k+1} \leftarrow \tilde{\mathbf{Q}} \cdot \boldsymbol{\eta}_k$   
 $\mathbf{M}_{k+1} \leftarrow \boldsymbol{\xi}_{k+1} \cdot \boldsymbol{\eta}_{k+1}^T + \mathbf{M}_k$ 

#### Step 3. Compute $\Delta S$ as

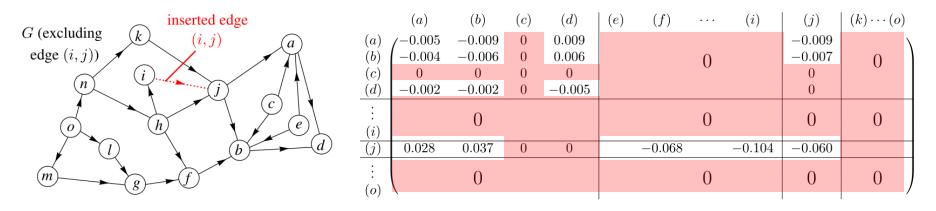
$$\mathbf{\Delta S} = \mathbf{M} + \mathbf{M}^T$$



No mat-mat multiplications

### Pruning

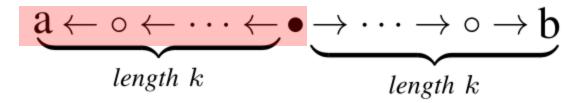
- Key observation:
  - When link updates are small, "affected areas" in ΔS (or M) are often small as well.



- Challenge:
  - How to identify only "unaffected areas" in ΔS to skip unnecessary recomputations for link update ?

### **Paths Aggregation**

- $[\mathbf{A}^k]_{i,j}$  counts # of length-k paths from node i to j.
- $[\mathbf{S}]_{a,b}$  counts the weighted sum of paths:



$$\mathbf{S} = C \cdot (\mathbf{Q} \cdot \mathbf{S} \cdot \mathbf{Q}^T) + (1 - C) \cdot \mathbf{I}_n$$
  
$$\Leftrightarrow \quad [\mathbf{S}]_{a,b} = (1 - C) \cdot \sum_{k=0}^{\infty} C^k \cdot [\mathbf{Q}^k \cdot (\mathbf{Q}^T)^k]_{a,b}$$

Q is the weighted (*i.e.*, row-normalized) matrix of  $A^T$ 

### Paths captured by M

$$\Delta \mathbf{S} = \mathbf{M} + \mathbf{M}^T \qquad \qquad \mathbf{M} = C \cdot \tilde{\mathbf{Q}} \cdot \mathbf{M} \cdot \tilde{\mathbf{Q}}^T + C \cdot \mathbf{u} \cdot \mathbf{w}^T$$

• Expansion of M

$$[\mathbf{M}]_{a,b} = \frac{1}{d_j+1} \left( \underbrace{\sum_{k=0}^{\infty} C^{k+1} \cdot [\tilde{\mathbf{Q}}^k]_{a,j} [\mathbf{S}]_{i,\star} \mathbf{Q}^T \cdot [(\tilde{\mathbf{Q}}^T)^k]_{\star,b}}_{\text{Part 1}} - \underbrace{\sum_{k=0}^{\infty} C^k [\tilde{\mathbf{Q}}^k]_{a,j} [\mathbf{S}]_{j,\star} [(\tilde{\mathbf{Q}}^T)^k]_{\star,b}}_{\text{Part 2}} \right)$$

$$+ \mu \underbrace{\sum_{k=0}^{\infty} C^{k+1} [\tilde{\mathbf{Q}}^k]_{a,j} [(\tilde{\mathbf{Q}}^T)^k]_{j,b}}_{\text{Part 3}} \right)$$

• Three types of paths identified by M

• P1:  

$$\begin{array}{c} [\tilde{\mathbf{Q}}^{k}]_{a,j} & [\mathbf{S}]_{i,\star} \\ a \leftarrow \cdots \leftrightarrow \leftarrow j \\ ength \ k \end{array} \stackrel{(i \leftarrow \cdots \leftrightarrow \leftarrow \bullet \rightarrow \cdots \leftrightarrow \rightarrow \star}{all \ symmetric \ in-link \ paths \ for \ node-pair \ (i,\star)} \stackrel{(i \leftarrow \cdots \leftrightarrow \rightarrow \bullet)}{\longrightarrow} \\ ength \ k \end{array}$$
• P2:  

$$\begin{array}{c} [\tilde{\mathbf{Q}}^{k}]_{a,j} & [\mathbf{S}]_{j,\star} \\ a \leftarrow \cdots \leftrightarrow \leftarrow j \\ ength \ k \end{array} \stackrel{(i \leftarrow \cdots \leftrightarrow \leftarrow \bullet \rightarrow \cdots \leftrightarrow \rightarrow \star}{\longrightarrow} \\ ength \ k \end{array} \stackrel{(i \leftarrow \cdots \leftrightarrow \leftarrow \bullet)}{\longrightarrow} \\ ength \ k \end{array}$$
• P3:  

$$\begin{array}{c} [\tilde{\mathbf{Q}}^{k}]_{a,j} & [\tilde{\mathbf{Q}}^{T}]_{j,h} \\ ength \ k \end{array} \stackrel{(i \leftarrow \cdots \leftrightarrow \leftarrow \bullet)}{\longrightarrow} \\ ength \ k \end{array}$$

### **Unaffected Areas**

- Since M merely tallies these paths, node-pairs without having such paths could be safely pruned.
- Iteratively Pruning:

Let 
$$\mathcal{F}_1 := \{b \mid b \in \mathcal{O}(y), \exists y, s.t. [\mathbf{S}]_{i,y} \neq 0\}$$
  
 $\mathcal{F}_2 := \begin{cases} \varnothing & (d_j = 0) \\ \{y \mid [\mathbf{S}]_{j,y} \neq 0\} & (d_j > 0) \end{cases}$   
 $\mathcal{A}_k \times \mathcal{B}_k := \begin{cases} \{j\} \times (\mathcal{F}_1 \cup \mathcal{F}_2 \cup \{j\}) & (k = 0) \\ \{(a, b) \mid a \in \tilde{\mathcal{O}}(x), b \in \tilde{\mathcal{O}}(y), \exists x, \exists y, s.t. [\mathbf{M}_{k-1}]_{x,y} \neq 0\} & (k > 0) \end{cases}$ 

Then

$$[\mathbf{M}_k]_{a,b} = 0 \quad for \ all \ (a,b) \notin (\mathcal{A}_k \times \mathcal{B}_k) \cup (\mathcal{A}_0 \times \mathcal{B}_0)$$

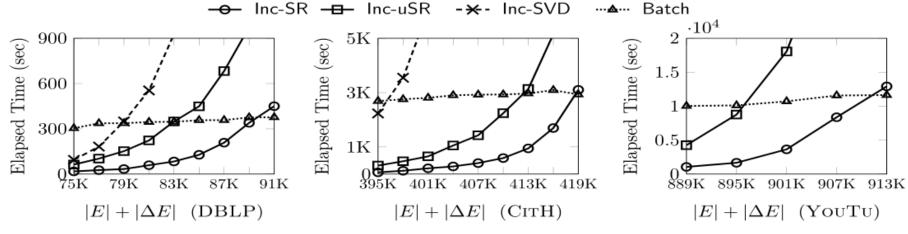
• Complexity: O(K(nd+|AFF|)) with

$$|\mathsf{AFF}| := \operatorname{avg}_{k \in [0,K]}(|\mathcal{A}_k| \cdot |\mathcal{B}_k|)$$

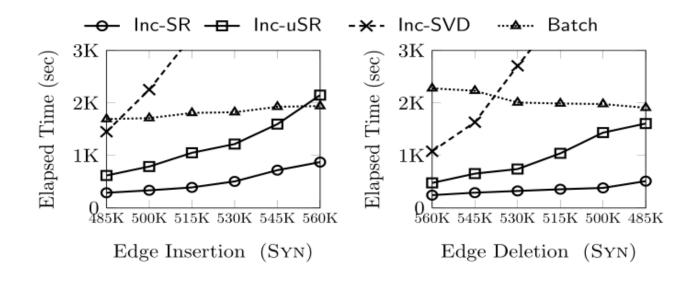
## **Experimental Settings**

- Datasets
  - Real: DBLP, CITH, YOUTU
  - Synthetic: GraphGen generator
- Compared Algorithms
  - Inc-SR : Our Incremental SimRank with Pruning
  - Inc-uSR : Our Incremental SimRank without Pruning
  - Inc-SVD [EDBT '10]: the best known link-update algorithm
  - Batch, the batch SimRank via fine-grained memoization
- Evaluations
  - Time Efficiency
  - Effectiveness of Pruning
  - Intermediate Memory
  - Exactness

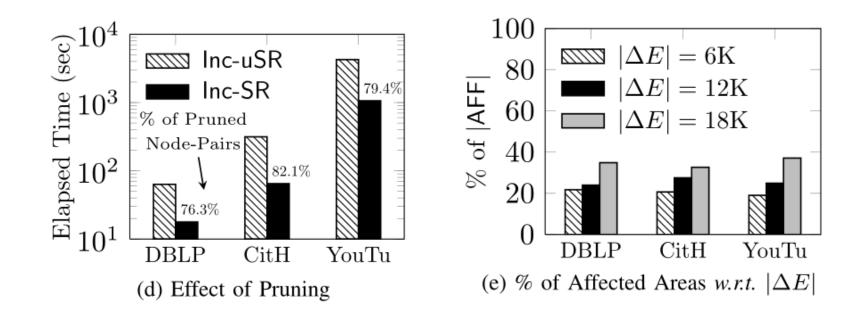
#### **Time Efficiency**



(a) Time Efficiency of Incremental SimRank on Real Data



#### **Effectiveness of Pruning**



#### **Intermediate Memory & Exactness**

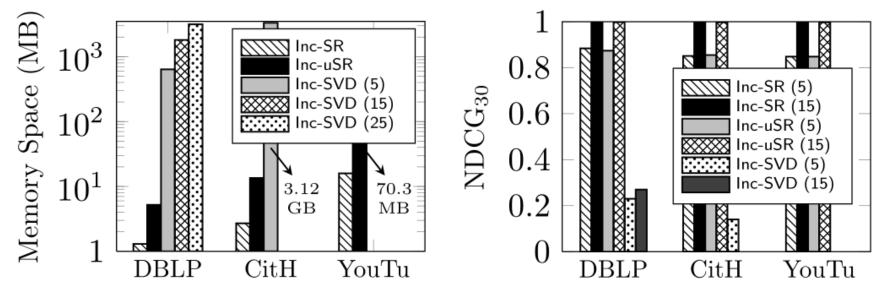


Fig. 3: Memory Space Fig.

Fig. 4: NDCG<sub>30</sub> Exactness

### Conclusions

- Two efficient methods are proposed to incrementally compute SimRank on link-evolving graphs
  - ΔS is characterized via a rank-one Sylvester equation, improving the time to O(Kn<sup>2</sup>) for every link update.
  - A pruning strategy skipping unnecessary recomputations, which further reduces the time to O(K(nd + |AFF|)).
- Empirical evaluations to show the superiority of our methods from several times to one order of magnitude.

# Thank you!



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