



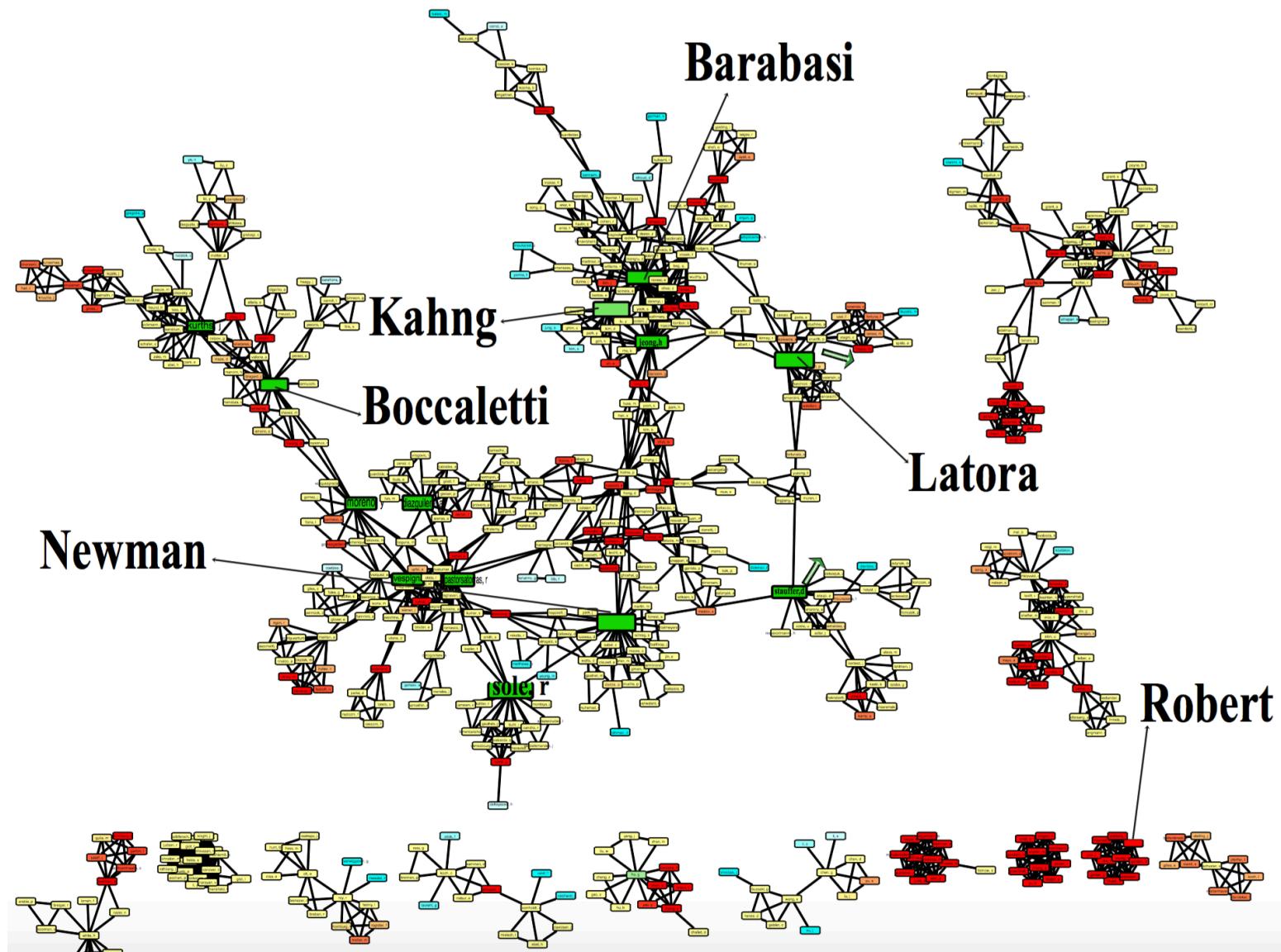
# Panther: Fast Top-K Similarity Search on Large Networks

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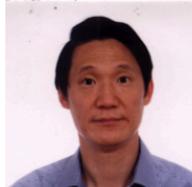
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# Related Work and Challenges

1

Share many direct/indirect common neighbors.

2

Disconnected, but share similar structure.

Method	Time Complexity	Space Complexity
SimRank [kdd'02]	$O(IN^2d^2)$	$O(N^2)$
TopSim [ICDE'12]	$O(NTd^T)$	$O(N+M)$
RWR [KDD'04]	$O(IN^2d)$	$O(N^2)$
RoleSim [KDD'11]	$O(IN^2d^2)$	$O(N^2)$
ReFex [KDD'11]	$O(N+I(fM+Nf^2))$	$O(N+Mf)$

- ❖ Find top-K similar vertices for any vertex in a network
- ❖  $d$ : average degree,  $f$ : feature number,  $T$ : path length

## Challenges

- C1 : How to design a similarity method that applies to both similarities?
- C2: Computational efficiency challenge.



# Our Approach: Panther

1

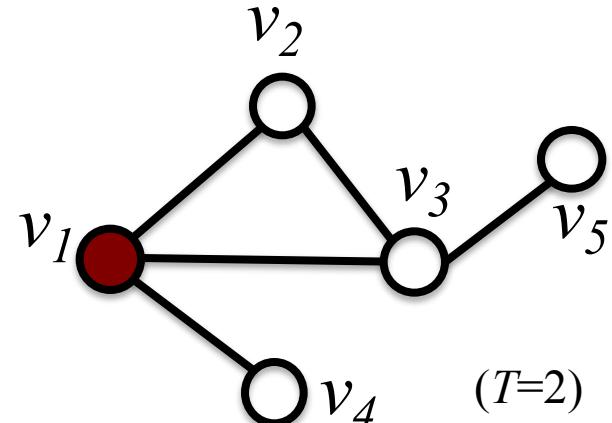
# Path Similarity

**Intuition:** two vertices are similar if they frequently appear on the same paths.

$$S_{ps}(v_i, v_j) = \frac{\sum_{p \in P(v_i, v_j)} w(p)}{\sum_{p \in \Pi} w(p)}$$

- A path is a  $T$ -length sequence of vertices  $p = (v_1, \dots, v_{T+1})$ .
- $\Pi$  is all the  $T$ -paths in  $G$ .
- Path weight:

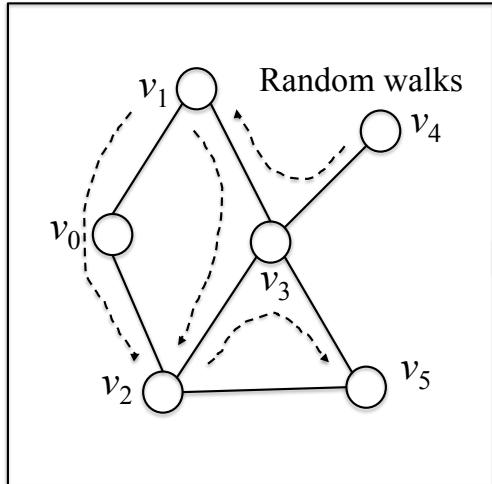
$$w(p) = \prod_{i=1, j=i+1}^T t_{ij}. \quad t_{ij} = \frac{w_{ij}}{\sum_{v_k \in \mathcal{N}(v_i)} w_{ik}}$$



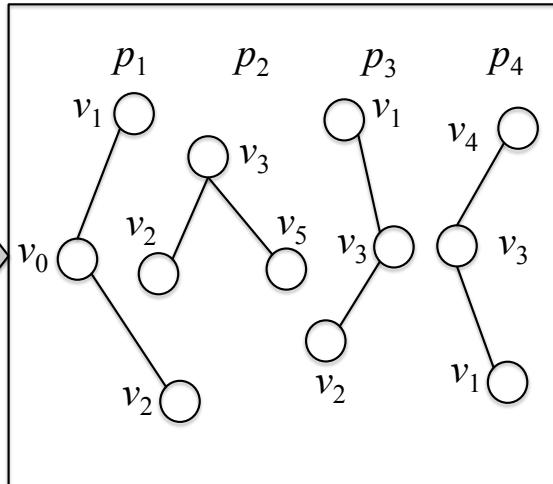
$$\begin{aligned} S_{ps}(v_1, v_2) &= 0.37, \\ S_{ps}(v_1, v_3) &= 0.42, \\ S_{ps}(v_1, v_4) &= 0.39, \\ S_{ps}(v_1, v_5) &= 0.09. \end{aligned}$$

# Panther<sub>ps</sub>

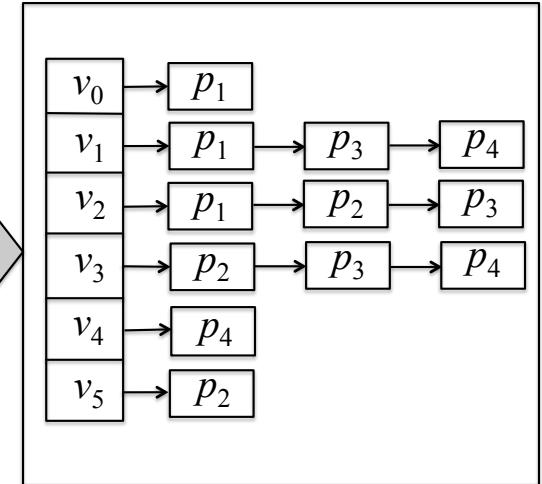
Basic idea: random path sampling



(a) Input network



(b) Random paths



(c) Vertex-to-path index

Simplified path similarity:

$$S_{ps}(v_i, v_j) = \frac{|P(v_i, v_j)|}{R} \quad O(RT) \quad \xrightarrow{\hspace{1cm}} \quad O(dT)$$

# Theoretical Analysis

- How many random paths shall we sample?

Domain and range set	Upper bound of range set's VC dimension	Distribution
Theorem 1	1  Let $\mathcal{R}$ be a range set on a domain $\mathcal{D}$ , with $VC(\mathcal{R}) \leq d$ . and let $\phi$ be a distribution on $\mathcal{D}$ . Given $\varepsilon, \delta \in (0, 1)$ , let $S$ be a set of $ S $ points sampled from $\mathcal{D}$ according to $\phi$ , with	2  $ S  = \frac{c}{\varepsilon^2} \left( d + \ln \frac{1}{\delta} \right)$ ,  where $c$ is a universal positive constant. Then $S$ is a $\varepsilon$ -approximation to $(\mathcal{R}, \phi)$ with probability of at least $1 - \delta$ .

Required sample size

# Theoretical Analysis

- Domain:  $\Pi$
- Range set:  $\mathcal{R}_G = \{P_{v_i, v_j} : v_i, v_j \in V\}$
- VC bound:  $VC(\mathcal{R}_G) \leq \log_2 \binom{T}{2} + 1$
- Distribution:  $\phi(p) = \text{prob}(p) = \frac{w(p)}{\sum_{p \in \Pi} w(p)}$
- Path similarity  $\frac{\sum_{p \in P_{v_i, v_j}} w(p)}{\sum_{p \in P} w(p)}$  is  $\phi(P_{v_i, v_j})$
- Conclusion
$$R = \frac{c}{\varepsilon^2} \left( \log_2 \binom{T}{2} + 1 + \ln \frac{1}{\delta} \right)$$
  - $R$  random paths can guarantee  $\varepsilon$  and  $1 - \delta$ .

# Proof of

$$VC(\mathcal{R}_G) \leq \log_2 \binom{T}{2} + 1$$

Assume  $VC(\mathcal{R}_G) = l$  and  $l > \log_2 \binom{T}{2} + 1$

A set  $Q$  of size  $l$  can be shattered by  $\mathcal{R}_G$

A 1-1 correspondence exists between each subset in  $Q$  and each range  $P_i$  in  $\mathcal{R}_G$

$$|\{P_i | p \in P_i \text{ and } P_i \in \mathcal{R}_G\}| = 2^{l-1}$$

$$\mathcal{R}_G = \{P_{v_i, v_j} : v_i, v_j \in V\}$$

$$\binom{T}{2} < 2^{l-1}$$

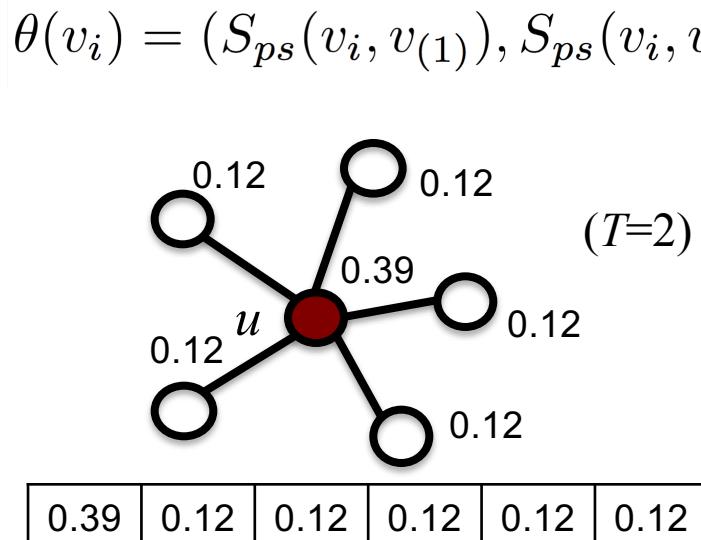
A path belongs only to the ranges w.r.t a pair of vertices in the path

$$|\{P_i | p \in P_i \text{ and } P_i \in \mathcal{R}_G\}| = \binom{T}{2} < 2^{l-1}$$

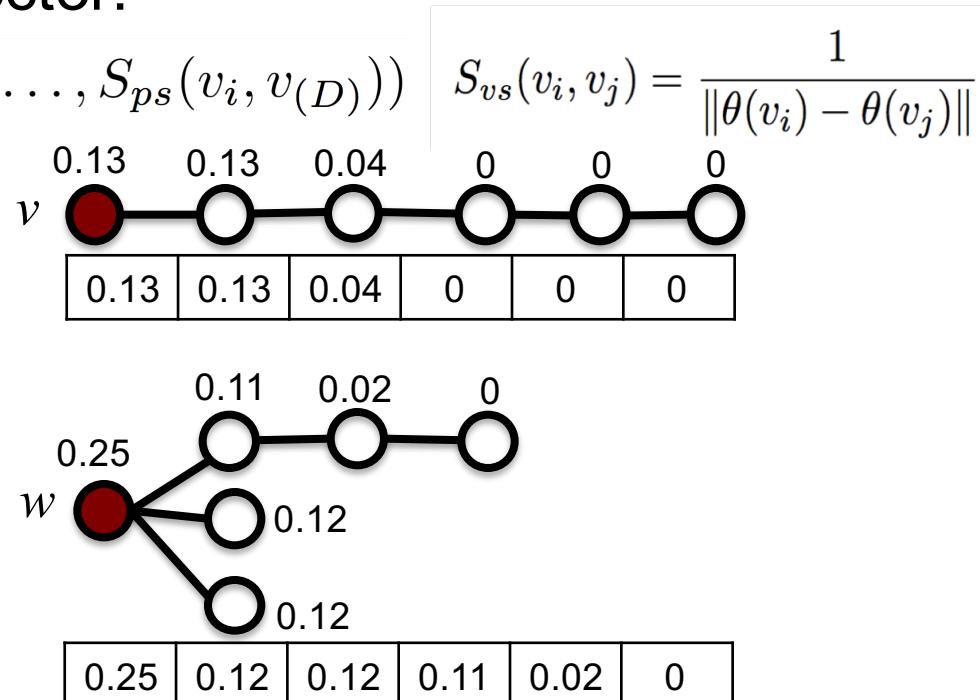
Contradiction

# Vector Similarity and Panther<sub>vs</sub>

- Limitation of path similarity: bias to close neighbors.
- Vector Similarity:** the probability distributions of a vertex linking to all other vertices are similar if their topology structures are similar.
- Panther<sub>vs</sub>**: Use top- $D$  path similarities calculated by Panther<sub>ps</sub> to represent a vector:



$$S_{vs}(u, w) = 0.27 > S_{vs}(u, v) = 0.16$$



# Time Complexity

Method	Time Complexity	Space Complexity
SimRank	$O(IN^2d^2)$	$O(N^2)$
TopSim	$O(NTd^\top)$	$O(N+M)$
RWR	$O(IN^2d)$	$O(N^2)$
RoleSim	$O(IN^2d^2)$	$O(N^2)$
ReFex	$O(N+I(fM+Nf^2))$	$O(N+Mf)$
Panther <sub>ps</sub>	$O(RTc+NdT)$	$O(RT+Nd)$
Panther <sub>vs</sub>	$O(RTc+NdT+Nc)$	$O(RT+Nd+ND)$

Random path sampling →  $RTc$   
 Top-k similarity search for any vertex →  $NdT$   
 Build and query kd-tree →  $Nc$   
 Random path sampling →  $RT$   
 Top-k similarity search for any vertex →  $Nd$   
 Build and query kd-tree →  $ND$

Random path →  $RT$   
 Vertex-to-path index →  $Nd$   
 Kd-tree →  $ND$



# Experiments

# Evaluation Aspects

- Efficiency Performance
- Accuracy Performance
- Parameter Sensitivity Analysis

# Efficiency Performance

Tencent  
network

Preprocessing time + top- $k$  similarity search time

$ V $	$ E $	RWR [(KDD'04)]	TopSim [ICDE'12]	RoleSim [KDD'11]	ReFex [KDD'11]	$\text{Panther}_{\text{ps}}$	$\text{Panther}_{\text{vs}}$
6,523	10,000	+7.79hr	+38.58m	+37.26s	3.85s+0.07s	0.07s+0.26s	0.99s+0.21s
25,844	50,000	+>150hr	+11.20hr	+12.98m	26.09s+0.40s	0.28s+1.53s	2.45s+4.21s
48,837	100,000		+30.94hr	+1.06hr	2.02m+0.57s	0.58s+3.48s	5.30s+5.96s
169,209	500,000		+>120hr	+>72hr	17.18m+2.51s	8.19s+16.08s	27.94s+24.17s
230,103	1,000,000				31.50m+3.29s	15.31s+30.63s	49.83s+22.86s
443,070	5,000,000				24.15hr+8.55s	50.91s+2.82m	4.01m+1.29m
702,049	10,000,000				>48hr	2.21m+6.24m	8.60m+6.58m
2,767,344	50,000,000					15.787m+1.36hr	1.60hr+2.17hr
5,355,507	100,000,000					44.09m+4.50hr	5.61hr+6.47hr
26,033,969	500,000,000					4.82hr+25.01hr	32.90hr+47.34hr
51,640,620	1,000,000,000					13.32hr+80.38hr	98.15hr+120.01hr

Can scale up to  
handle 1 billion edges

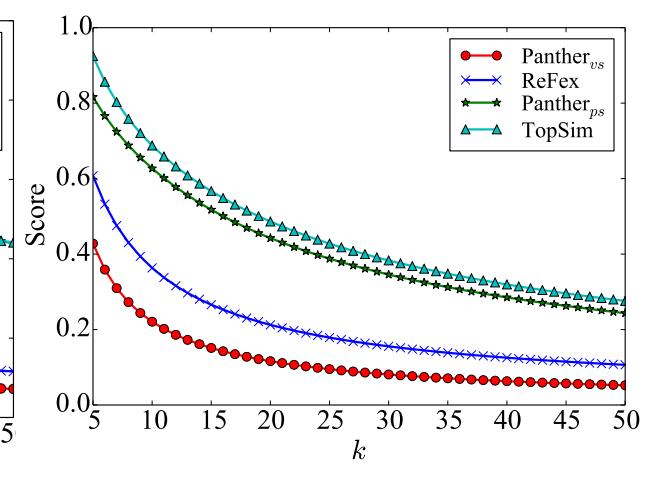
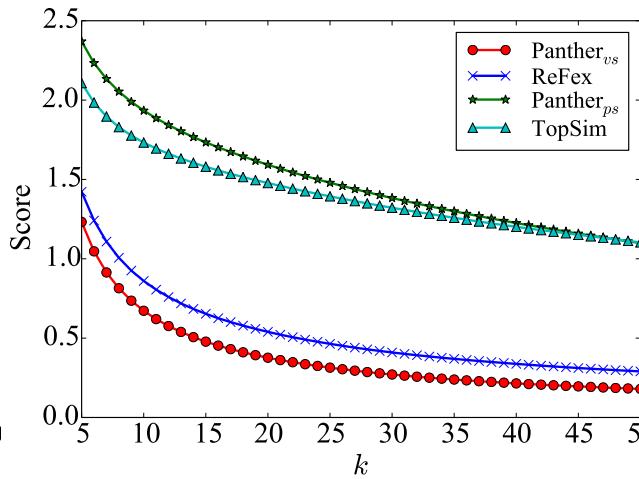
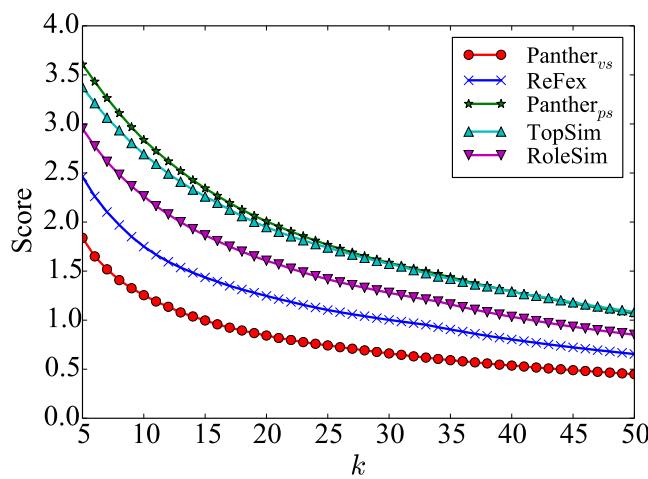
270X speed up

390X speed up

❖  $T=5$ ,  $c=0.5$ ,  $\varepsilon=\sqrt{1/|E|}$  and  $\delta=0.1$ ,  $R=16,609,640$

# Accuracy Performance of Panther<sub>ps</sub>

- Evaluate how Panther<sub>ps</sub> can approximate common neighbors.
- The score represents the improvement over a random method.



KDD

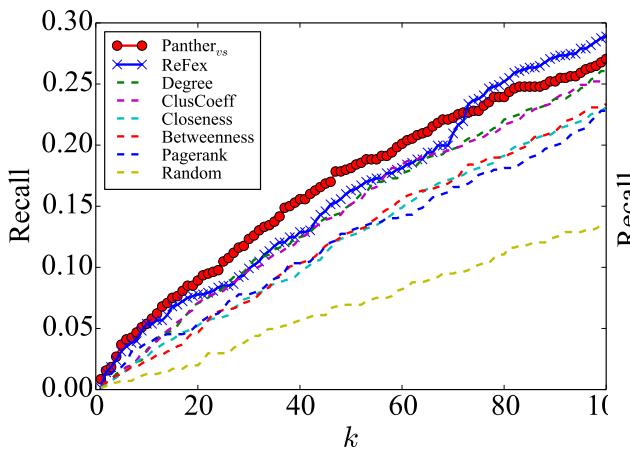
Twitter

Mobile

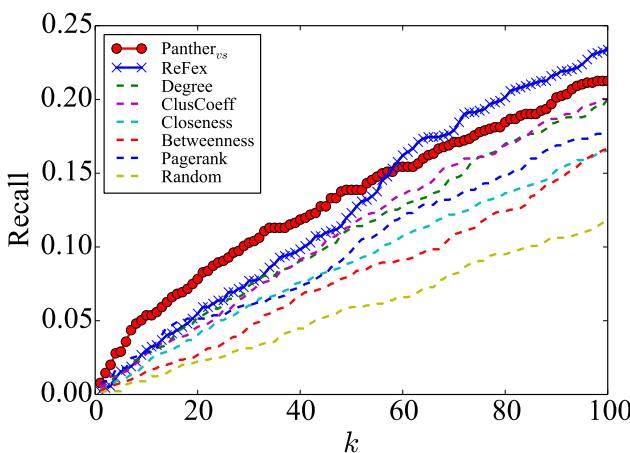
- ❖ Co-author networks:  $|V|=3K$ ,  $|E| = 7K$ .
- ❖ Twitter network:  $|V| = 100K$ ,  $|E| = 500K$ .
- ❖ Mobile network:  $|V| = 200K$ ,  $|E| = 200K$ .

# Accuracy Performance of Panther<sub>vs</sub>

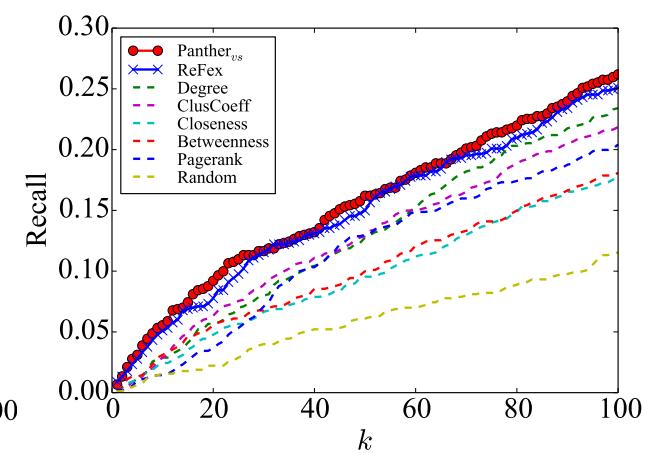
- Identity Resolution
  - Assume the same authors in different networks of the same domain are similar to each other.
- Settings
  - Given any two co-author networks, e.g., KDD and ICDM, if the top- $k$  similar vertices from ICDM consists of the query author from KDD, we say that the method hits a correct instance.



KDD-ICDM



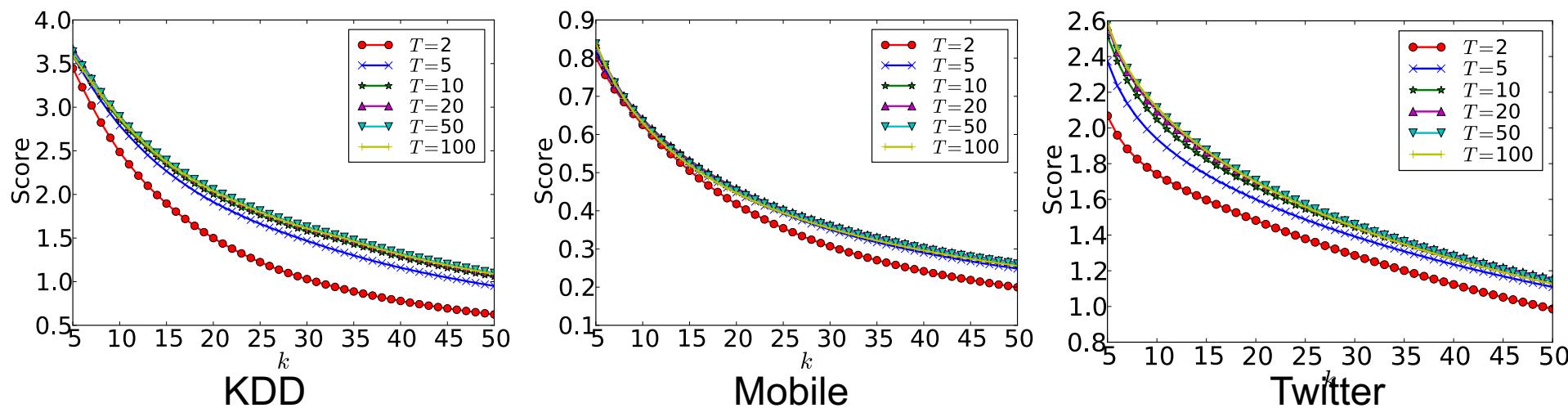
SIGIR-CIKM



SIGMOD-ICDE

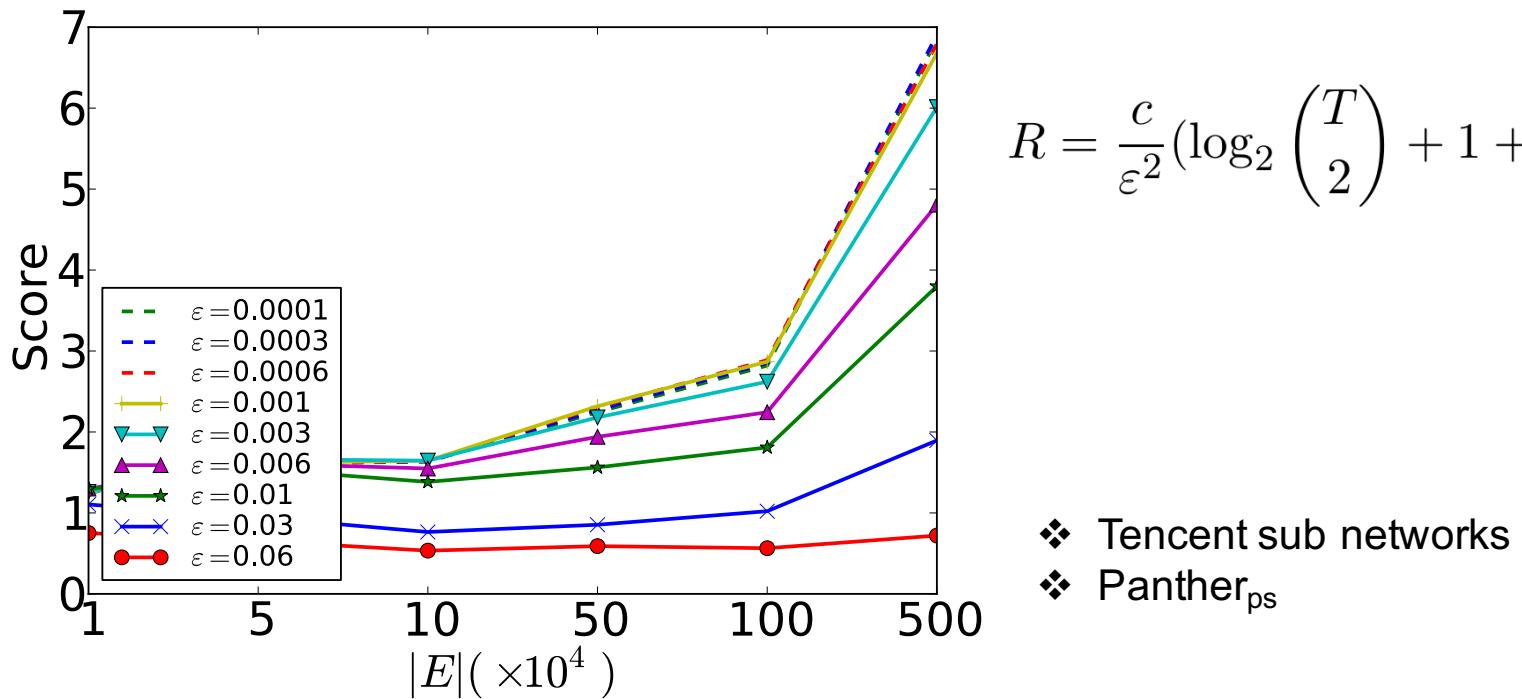
# Parameter Analysis: Path Length $T$

- The performance gets better when  $T$  increases.
- The performance almost becomes stable When  $T \geq 5$ .



Effect of path length  $T$  on the accuracy performance of Panther<sub>ps</sub>.

# Parameter Analysis: Error Bound $\varepsilon$



$$R = \frac{c}{\varepsilon^2} \left( \log_2 \binom{T}{2} + 1 + \ln \frac{1}{\delta} \right)$$

❖ Tencent sub networks  
❖ Panther<sub>ps</sub>

- When  $|E|/(1/\varepsilon)^2$  ranges from 5 to 20, scores of Panther<sub>ps</sub> are almost convergent.
- The value  $(1/\varepsilon)^2$  is almost linearly positively correlated with the number of edges in a network.

# Conclusion

- Methods:
  - Solve two similarity metrics efficiently.
- Theoretic analysis:
  - Sampling size is only related to path length given error-bound and confidence level.
- Empirical evaluations:
  - When  $|V| = 0.5$  million and  $|E|=5$  million,  $\text{Panther}_{\text{ps}}$  achieves a  $390 \times$  speed-up and  $\text{Panther}_{\text{vs}}$  achieves a  $270x$  speed-up.
  - Panther can scale up to a network with 1 billion edges.



# Thank You

Code & Data:

<http://aminer.org/Panther>