

 $p^{i}(s,t) = \Pr[A \text{ random walk starting from } s \text{ visits } t \text{ at the } i \text{-th hop}]$

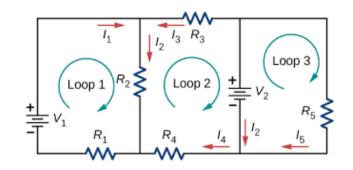
Effective Resistance

 $ER(s,t) = \sum \frac{p^{i}(s,s)}{d(s)} + \frac{p^{i}(t,t)}{d(s)} - \frac{p^{i}(s,t)}{d(s)} - \frac{p^{i}(t,s)}{d(s)} - \frac{p^{i}($

The ER of node pair (*s*, *t*) is a sum of the random walk probabilities of all possible numbers of hops between *s* and *t*. It describes the *dissimilarity* of nodes *s* and *t*.

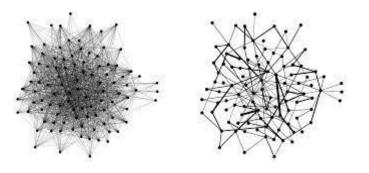
Applications of ER

- Electrical Circuit & Power Network Analysis

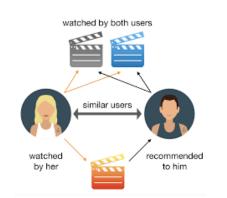




- Graph Sparsifiers



- Recommendation Systems



- Graph Clustering

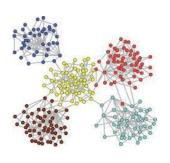
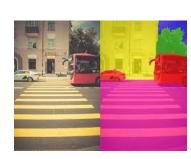
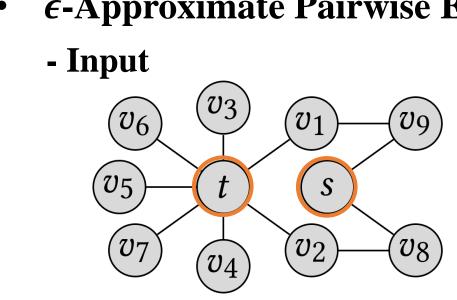


Image Segmentation





- Output

ERExact ER

- Existing works need

 λ is the 2nd largest eigenvalue of G's transition matrix, which is usually large (> 0.9) and thus leads to a large ℓ

- On Facebook graph (#nodes=4k, #edges=88k)

	$\epsilon = 0.5$	$\epsilon = 0.1$	$\epsilon = 0.05$
ł	42	57	64
r	2.94×10^6	139×10^6	710×10^{6}

Efficient Estimation of Pairwise Effective Resistance

Hong Kong Baptist University and Hong Kong University of Science and Technology (Guangzhou)

Problem Definition

ϵ-Approximate Pairwise ER Query

An undirected & unweighted graph G

Two nodes *s* and *t*

Error threshold ϵ

$$|(s,t) - ER'(s,t)| \le \epsilon$$

Approximate ER

Limitations of Existing Work

- either expensive matrix operations or a huge number of long random walks

The SOTA is a Monte-Carlo Approach - Maximum Random Walk Length

$$= \left[\frac{\log\left(\frac{4}{\epsilon(1-\lambda)}\right)}{\log(1/\lambda)} \right]$$

Too Large!

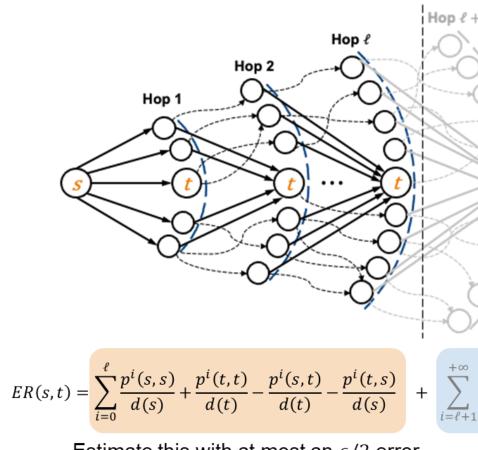
- Total #Random-Walks Needed (failure prob.=1%)

$$=\frac{40}{\epsilon^2}\cdot\ell^2\ln(800\ell)$$

Too Large!

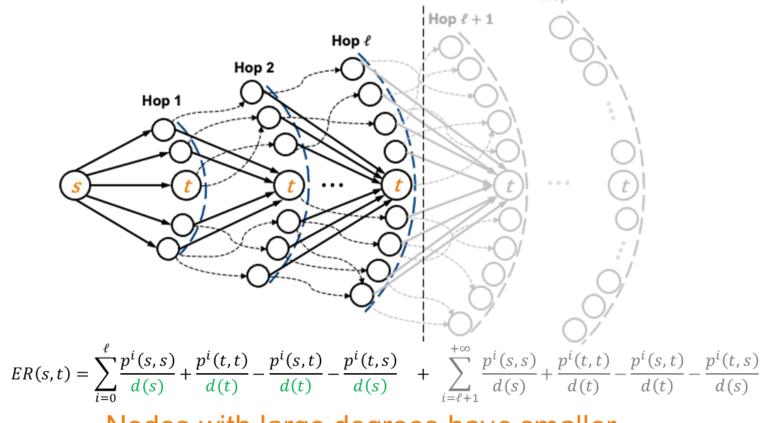
Reducing Random Walk Length

Finding a Maximum Random Walk Length



Estimate this with at most an $\epsilon/2$ error

Utilizing Node Degrees



Nodes with large degrees have smaller maximum random walk lengths

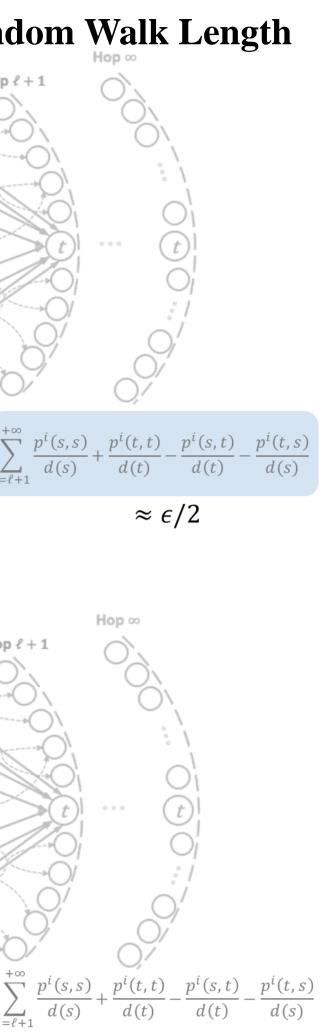
Our Maximum Random Walk Length

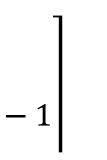
$$\ell = \left[\frac{\log\left(\frac{2}{d(s)} + \frac{2}{d(t)}\right)}{\epsilon(1-\lambda)} \right]$$

On Facebook graph (#nodes=4k, #edges=88k)

	$oldsymbol{\epsilon}=0.5$	$\epsilon = 0.1$	$\epsilon = 0.05$
ł	42	57	64
Our ℓ	6	21	28
r	2.94×10^{6}	139×10^{6}	710×10^{6}
Our r	48.8×10^{3}	17.2×10^{6}	126×10^{6}

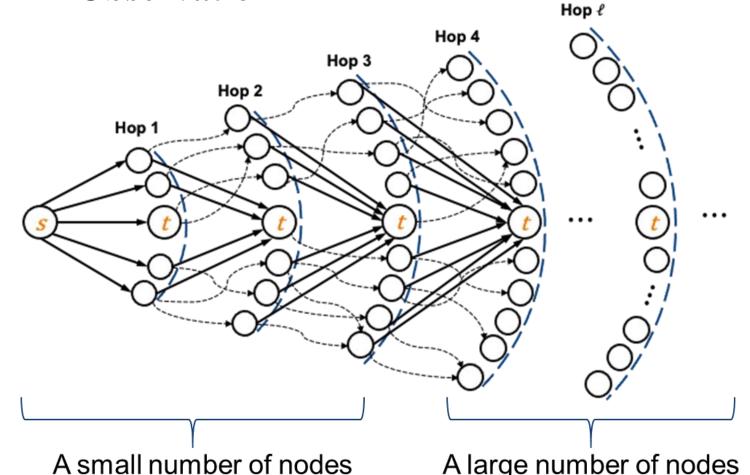
Renchi Yang and Jing Tang





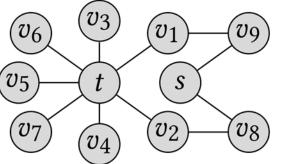
Pruning Random Walks

An Observation

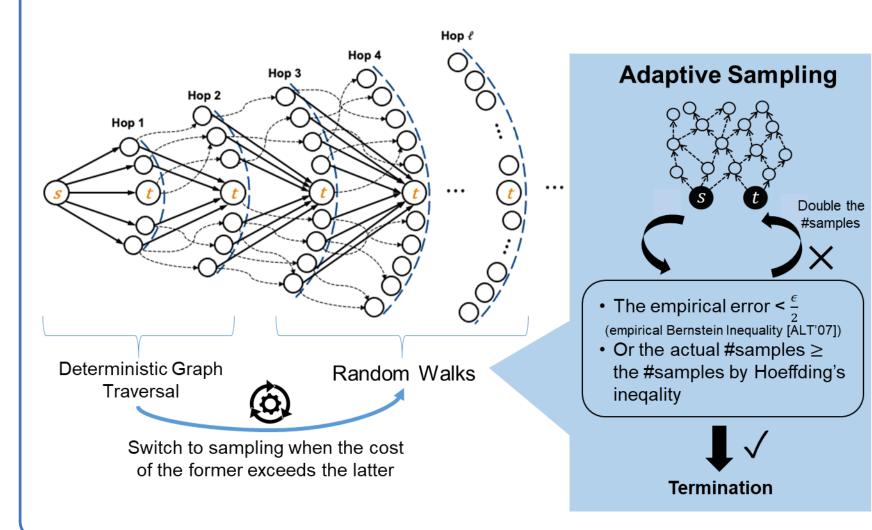


#Path & #Random-Walks from Node s to Node t

Нор	1	2	3	4	5	6	7	8
#paths	9	13	61	97	439	723	3231	5387
#random walks	31	122	275	488	762	1097	1493	1949



- Deterministic search is better when #hops is small
- Sampling is better when #hops is large
- **Combining Deterministic Graph Traversal and Random Walks in an Adaptive Manner**





JNIVERSITY OF SCIENCE AND ECHNOLOGY (GUANGZHOU

Experimental Setup

Dataset	#nodes	#edges	Avg. degree
Facebook	4.04K	88.2K	43.69
DBLP	317.1K	1.05M	6.62
YouTube	1.13M	2.99M	5.27
Orkut	3.07M	117.2M	76.28
LiveJournal	4M	34.68M	17.35
Friendster	65.6M	1.81B	55.06

- Our Methods (AMC (only random walks), GEER (deterministic graph traversal + random walks)) against 5 competitors: EXACT, TP/TPC (KDD'21), RP (STOC'08), and SMM (our baseline)
- Linux machine with an Intel Xeon(R) Gold 6240@2.60GHz 32-core processor and 377GB of RAM



