

# Efficient Approximation Algorithms for Spanning Centrality

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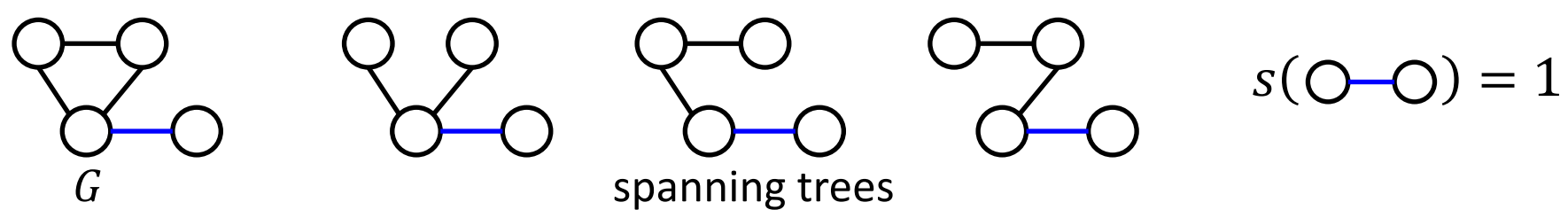
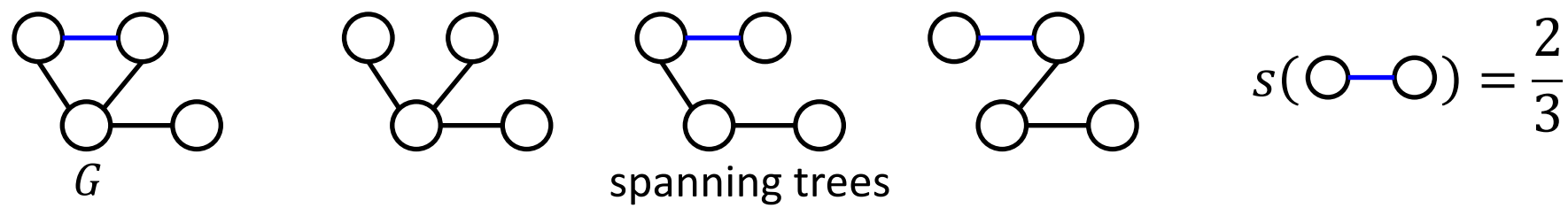
## Problem Definition

### Input:

an undirected and connected graph  $G$

### Spanning centrality $s(e_{i,j})$ of an edge $e_{i,j}$ :

the fraction of spanning trees of  $G$  that contains  $e_{i,j}$



A higher SC  $s(e_{i,j}) \rightarrow e_{i,j}$  is more crucial for connectedness

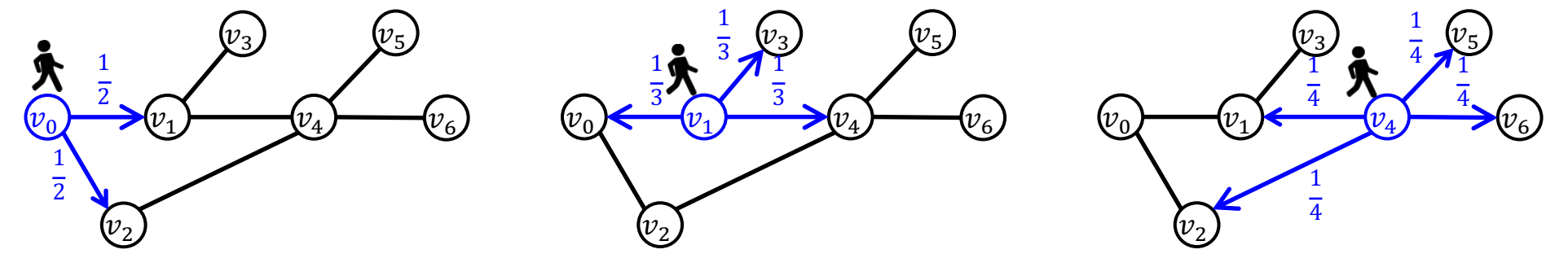
### $\epsilon$ -approximate All Edge Spanning Centrality (AESC):

the estimated SC  $\hat{s}(e_{i,j})$  for every edge  $e_{i,j}$  satisfying

$$|s(e_{i,j}) - \hat{s}(e_{i,j})| \leq \epsilon$$

## State of the Art

### Simple random walk from node $v_0$ :



$$d(v_i) = \text{\#neighbors of } v_i$$

$$p_\ell(v_i, v_j) = \text{Pr}[A \text{ simple random walk from } v_i \text{ visits } v_j \text{ at the } \ell\text{-th step}]$$

### SC in a view of simple random walk [Peng et al. KDD'21]:

$$s(e_{i,j}) = \sum_{\ell=0}^{+\infty} \frac{p_\ell(v_i, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)} - \frac{p_\ell(v_j, v_i)}{d(v_i)}$$

Shorten by a derived length threshold  $\tau$

TOO LARGE

$$s_\tau(e_{i,j}) = \sum_{\ell=0}^{\tau} \frac{p_\ell(v_i, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)} - \frac{p_\ell(v_j, v_i)}{d(v_i)}$$

Estimated by random walk samplings

TOO MANY

$$\hat{s}(e_{i,j}) = \hat{s}_\tau(e_{i,j})$$

## Our Proposal

### Separate the random walk interpretation of SC into three parts:

Switch when the cost of step 2 exceeds step 3

#### Step 1:

improved length threshold  $\tau_{i,j}$  personalized to each  $e_{i,j}$

$$\sum_{\ell=\tau+1}^{+\infty} \frac{p_\ell(v_i, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)} - \frac{p_\ell(v_j, v_i)}{d(v_i)}$$

#### Step 2:

Deterministic graph traversal in a reverse manner for the first  $\tilde{\tau}$  steps

$$\sum_{\ell=0}^{\tilde{\tau}} \frac{p_\ell(v_i, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)} - \frac{p_\ell(v_j, v_i)}{d(v_i)}$$

#### Step 3:

Random walk samplings for the rest  $\tau - \tilde{\tau}$  steps

$$\sum_{\ell=\tilde{\tau}+1}^{\tau} \frac{p_\ell(v_i, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)} - \frac{p_\ell(v_j, v_i)}{d(v_i)}$$

endpoints with larger degrees

decomposed by graph spectral property

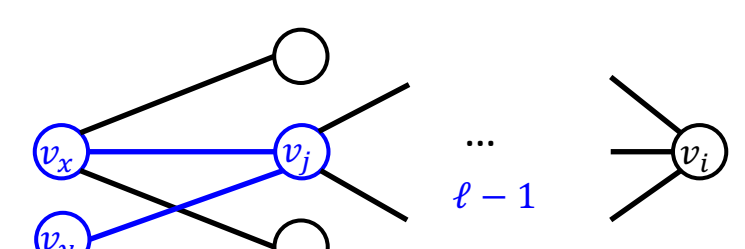
$$\sum_{\ell=0}^{\tilde{\tau}} \frac{p_\ell(v_i, v_i)}{d(v_i)} - \frac{p_\ell(v_j, v_i)}{d(v_i)} + \frac{p_\ell(v_j, v_j)}{d(v_j)} - \frac{p_\ell(v_i, v_j)}{d(v_j)}$$

$$\sum_{v_x} \frac{p_{\tilde{\tau}}(v_x, v_i)}{d(v_i)} \left( \sum_{\ell=1}^{\tau-\tilde{\tau}} p_\ell(v_i, v_x) - p_\ell(v_j, v_x) \right)$$

smaller SC values and smaller  $\tau$

utilize eigenvectors and eigenvalues of  $G$

rely on  $p_\ell(v_*, v_i)$



deterministic traversal reversely from  $v_i$

$$p_\ell(v_x, v_i) + \frac{p_{\ell-1}(v_j, v_i)}{d(v_x)} = \frac{p_{\ell-1}(v_j, v_i)}{3}$$

$$p_\ell(v_y, v_i) + \frac{p_{\ell-1}(v_j, v_i)}{d(v_y)} = p_{\ell-1}(v_j, v_i)$$

all  $p_{\tilde{\tau}}(v_*, v_i)$  are known in step 2

estimate by generating random walks from  $v_i$  and  $v_j$

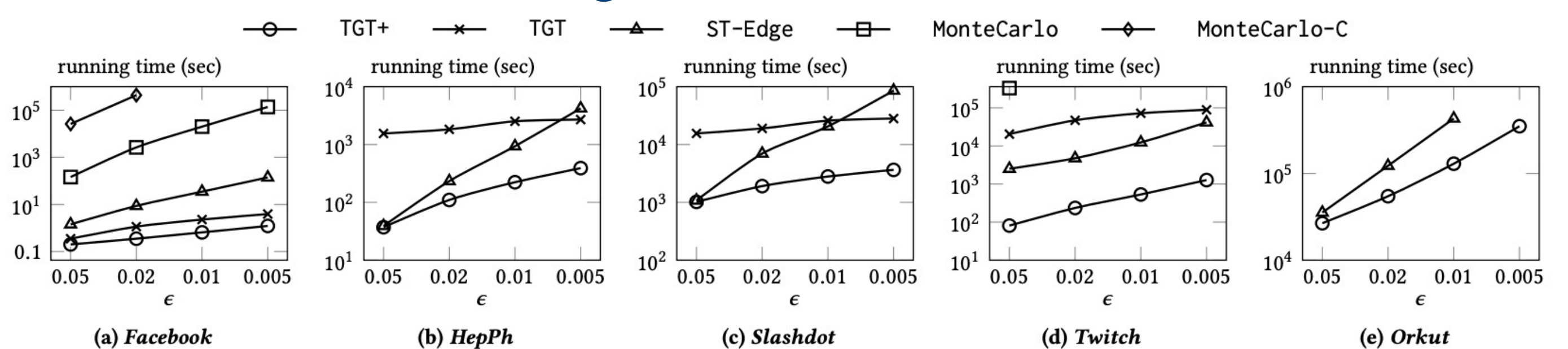
utilize the degree information of two endpoints

## Experiments

### $\epsilon$ -approximate AESC solutions:

- spanning tree sampling: ST-Edge
- random walk sampling with our  $\tau$ :
  - MonteCarlo, MonteCarlo-C
- our proposal:
  - TGT (steps 1-2), TGT+ (steps 1-3)

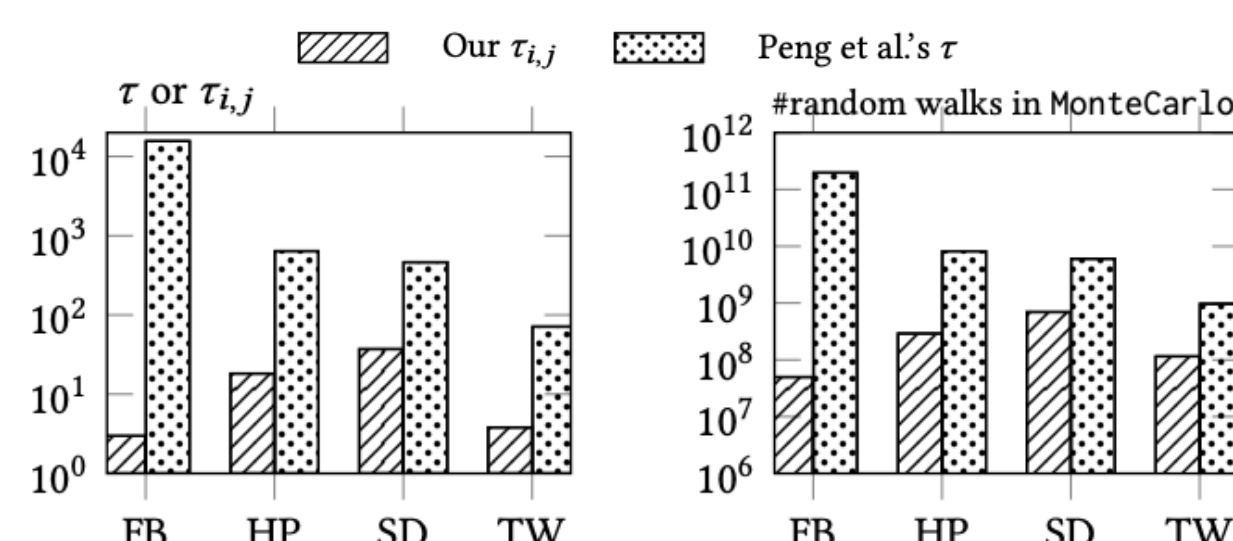
### Running time vs. absolute error



### Datasets

Name	#nodes	#edges
Facebook [30]	4,039	88,234
HepPh [20]	34,401	420,784
Slashdot [22]	77,360	469,180
Twitch [35]	168,114	6,797,557
Orkut [50]	3,072,441	117,185,082

### $\tau$ comparison



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