

# IRWR: Incremental Random Walk with Restart



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## RWR Overview

### Random Walk with Restart (RWR)

- An appealing link-based node-proximity measure (ICDM '06)
- Basic philosophy

The proximity of  $u$  w.r.t. query  $q$  is defined as the limiting probability that a random surfer, starting from  $q$ , and then either moving to one of its out-neighbors, or restarting from  $q$ , will eventually arrive at  $u$ .

### Matrix Formula

$$[\mathbf{P}]_{*,q} = (1-c) \cdot \mathbf{A} \cdot [\mathbf{P}]_{*,q} + c \cdot \mathbf{e}_q$$

proximities of node  $u$  w.r.t. query  $q$

column normalized adjacency matrix

restarting prob.

## Motivations

### Prior Work

- Existing computational methods are in a batch style, with the aim to accelerate the matrix inversion:

$$[\mathbf{P}]_{*,q} = c(\mathbf{I} - (1-c) \cdot \mathbf{A})^{-1} \cdot \mathbf{e}_q$$

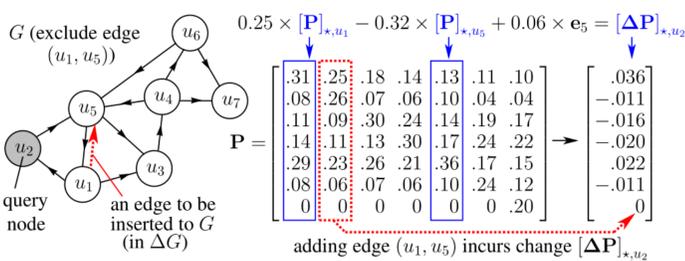
- B\_LIN and NB\_LIN need  $O(|V|^2)$  time and space for computing all node proximities via SVD. [ICDM '06]
- k-dash uses LU decomposition, yielding  $O(|E| + |V|)$ , to find top-k highest proximity. [PVLDB '12]
- Our Contributions
  - devise an exact and fast incremental algorithm (IRWR) computing any node proximity in  $O(1)$  time for every link update

## Problem Statement

### Problem (Incremental Update for RWR)

**Given:** a graph  $G$ , proximities  $P$  for  $G$ , changes  $\Delta G$  to  $G$ , a query node  $q$ , and a restarting probability  $c \in (0,1)$ .

**Compute:** changes to the proximities w.r.t.  $q$  exactly.



## Challenges

### Observations

- The update proximity of RWR can be expressed as the linear combination of the old proximities.
- Convert **matrix-vector** multiplications into **vector scaling and additions**.

### Challenge

- It seems hard to determine the scalars  $\alpha, \beta, \lambda$  for

$$[\Delta \mathbf{P}]_{*,u_2} = \alpha \cdot [\mathbf{P}]_{*,u_1} + \beta \cdot [\mathbf{P}]_{*,u_5} + \lambda \cdot \mathbf{e}_5$$

## Our Results on IRWR

- For edge update  $(i, j)$ , the changes to  $P$  can be computed as

$$[\Delta \mathbf{P}]_{*,q} = \frac{(1-c)[\mathbf{P}]_{j,q}}{1-(1-c)[\mathbf{y}]_j} \cdot \mathbf{y}, \text{ where}$$

For edge insertion,

$$\mathbf{y} = \begin{cases} \frac{1}{c} [\mathbf{P}]_{*,i} & (d_j = 0) \\ \frac{1}{c(d_j+1)} ([\mathbf{P}]_{*,i} - \frac{1}{1-c} [\mathbf{P}]_{*,j}) + \frac{1}{(1-c)(d_j+1)} \mathbf{e}_j & (d_j > 0) \end{cases}$$

For edge deletion,

$$\mathbf{y} = \begin{cases} -\frac{1}{c} [\mathbf{P}]_{*,i} & (d_j = 1) \\ \frac{1}{c(d_j-1)} (\frac{1}{1-c} [\mathbf{P}]_{*,j} - [\mathbf{P}]_{*,i}) - \frac{1}{(1-c)(d_j-1)} \mathbf{e}_j & (d_j > 1) \end{cases}$$

## Key Rationale

$$\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{a}\mathbf{e}_j^T \text{ with } \mathbf{a} = \begin{cases} \mathbf{e}_i & (d_j = 0) \\ \frac{1}{d_j+1} (\mathbf{e}_i - [\mathbf{A}]_{*,j}) & (d_j > 0) \end{cases}$$

Rank-one update

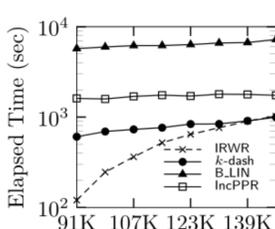
$$[\tilde{\mathbf{P}}]_{*,q} = [\mathbf{P}]_{*,q} + (1-c)\gamma \cdot \mathbf{z}$$

$$\text{with } \gamma = \frac{[\mathbf{P}]_{j,q}}{1-(1-c)[\mathbf{z}]_j} \text{ and } \mathbf{z} = (\mathbf{I} - (1-c)\mathbf{A})^{-1} \mathbf{a}$$

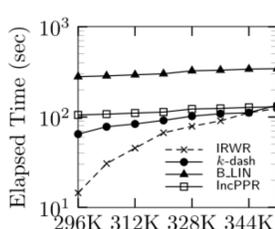
$$\begin{aligned} (\mathbf{I} - (1-c)\mathbf{A})^{-1} \mathbf{A} &= \sum_{k=0}^{\infty} (1-c)^k \mathbf{A}^{k+1} \\ &= \frac{1}{1-c} ((\mathbf{I} - (1-c)\mathbf{A})^{-1} - \mathbf{I}) = \frac{1}{1-c} (\frac{1}{c} \mathbf{P} - \mathbf{I}) \end{aligned}$$

Avoid matrix inversion

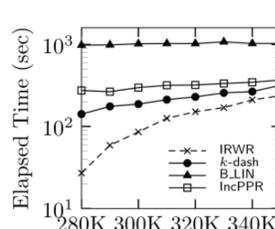
## Experimental Evaluations



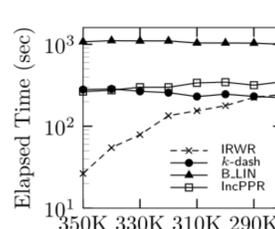
(a) p2p-Gnutella



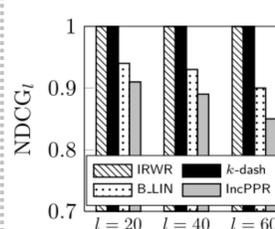
(b) cit-HepPh



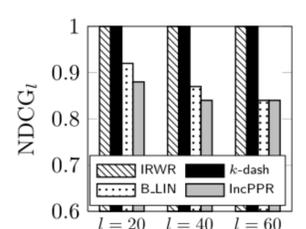
(c) edge insertions



(d) edge deletions



(e) p2p-Gnutella



(f) cit-HepPh

Speedup on Real Datasets

Speedup on Synthetic Datasets

Exactness on Real Datasets