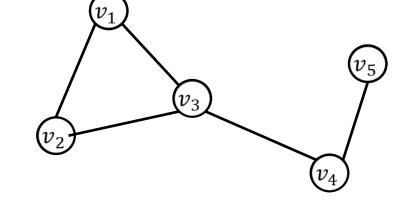
Global PageRank

PageRank is an algorithm of measuring the importance of website pages.

•
$$PR(v_i) = \frac{1-\alpha}{N} + \alpha \times \sum_{v_j \in N(v_i)} \frac{PR(v_j)}{L(v_j)}$$



Vectorize representation:

•
$$\vec{r} = \alpha P \vec{r} + \frac{1}{N} (1 - \alpha) \vec{1}$$

$$P^{T} = \begin{pmatrix} 0 & 1/2 & 1/2 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 1/3 & 1/3 & 0 & 1/3 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Calculate global PageRank

 Iterative process: Each vertex is initialized with a random PageRank value. Iteratively apply the transition function until convergence

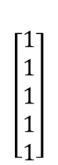
•
$$PR^{(t+1)}(v_i) = \frac{1-\alpha}{N} + \alpha \times \sum_{v_j \in N(v_i)} \frac{PR^{(t)}(v_j)}{L(v_j)}$$

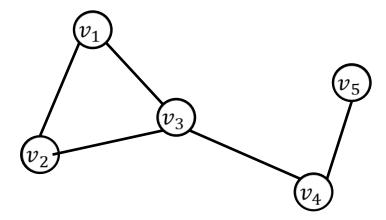
•
$$\overrightarrow{r^{(t+1)}} = \alpha P \overrightarrow{r^{(t)}} + \frac{1}{N} (1 - \alpha) \overrightarrow{1}$$

Output: global importance of each vertex

Personalized PageRank

- global PageRank:
 - $\vec{r} = \alpha P \vec{r} + \frac{1}{N} (1 \alpha) \vec{1}$

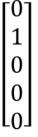


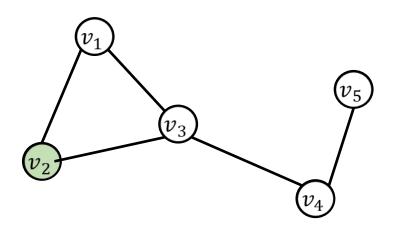


Randomly start from some vertex, each vertex has equal probability

- Personalized PageRank:
 - $\vec{r} = \alpha P \vec{r} + (1 \alpha) \vec{s}$

Start from target vertex





Accuracy and latency issue of PPR

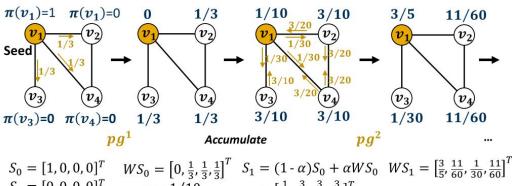
- Treat PPR as a linear equation:
 - $\vec{r} = (1 \alpha P)^{-1} (1 \alpha) \vec{s}$
 - Exact answer of PPR (very accurate)
 - Need to calculate the inverse of the transition matrix $O(n^3)$

Fast and approximate algorithm

• Information propagate in a local range, no need to apply the full transition matrix.

Graph Diffusion algorithm

- MELOPPR: Software/Hardware Co-design for Memory-efficient Low-latency Personalized PageRank
- Starting from target vertices, iteratively distribute the PageRank value to the neighbors
- Propagate k iterations -> can reach k hop neighbors
- k hop neighbors grows exponentially, large memory requirement
- More iteration higher accuracy



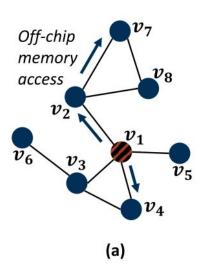
 $S_L = [0, 0, 0, 0]^T$

Multi-stage PPR

- PPR has linearity
 - $PPR(w_1\vec{u} + w_2\vec{v}) = w_1 * PPR(\vec{u}) + w_2 * PPR(\vec{v})$

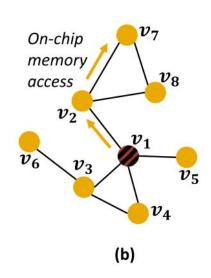
Low space, high accesses

- On-chip memory overhead : 0
- Off-chip memory access: O(G_L)



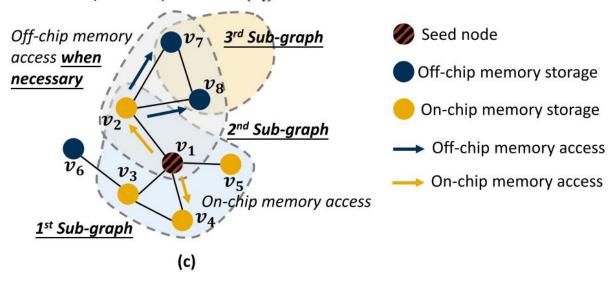
Low accesses, high space

- On-chip memory overhead : $O(G_L)$
- Off-chip memory access: 0



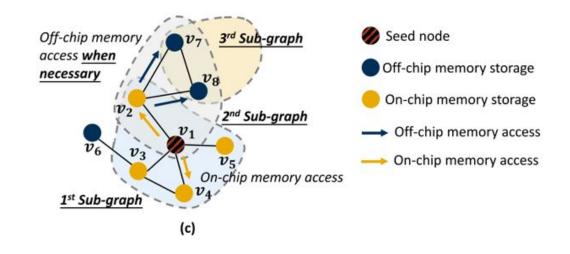
Balanced space and accesses (Ours)

- On-chip memory overhead : $O(G_l)$
- Off-chip memory access : $O(G_l)$



Multi-stage PPR

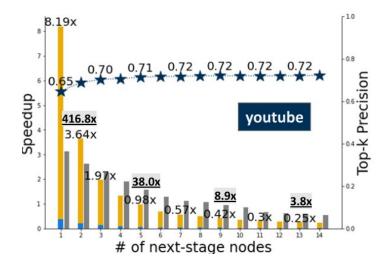
- k iterations $\rightarrow l_1 + l_2 = k$ iteration
 - Example; 2 iterations $\rightarrow 1 + 1 = 2$ iteration
- In the first l_1 iteration, reach the l_1 hop neighbors of the target vertex. Then start from each l_1 hop neighbors, perform PPR l_2 iteration.
- $GD^l(S)$: pagerank vector start from initialization for l iterations.



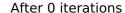
$$\mathcal{GD}^{(l_1+l_2)}(S_0) = \mathcal{GD}^{(l_1)}(S_0) - \alpha^{l_1} S_{l_1}^r + \alpha^{l_1} \sum_{v \in G_{l_1}(s)} \mathcal{GD}^{(l_2)}(S_{l_1,v}^r)$$

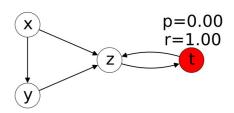
MELOPPR

- Fast, memory efficient
- No guaranteed error bound
- Error measure:
 - $\hat{T}(s,k)$: top-k important vertices selected by the algorithm
 - T(s,k): top k important vertices in the ground truth
 - Precision: $prec(s,k) = |\{v | v \in \hat{T}(s,k) \land c \in T(s,k)\}|/k$

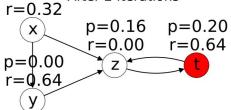


Approximate Personalized PageRank using local push

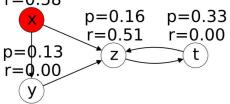




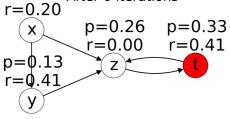
$$p=0.00$$
 After 2 iterations



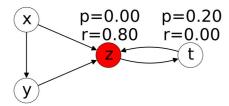
p=0.00 After 4 iterations r=0.58



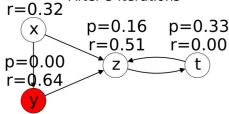
p=0.12 After 6 iterations r=0.20



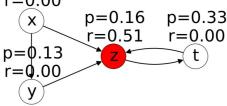
After 1 iteration



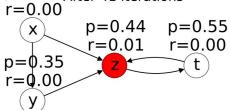
p=0.00 After 3 iterations



p=0.12 After 5 iterations r=0.00



p=0.32_{After 41} iterations



${\tt ApproximatePageRank}\ (v,\alpha,\epsilon) \colon$

- 1. Let $p = \vec{0}$, and $r = \chi_v$.
- 2. While $\max_{u \in V} \frac{r(u)}{d(u)} \ge \epsilon$:
 - (a) Choose any vertex u where $\frac{r(u)}{d(u)} \ge \epsilon$.
 - (b) Apply $push_u$ at vertex u, updating p and r.
- 3. Return p, which satisfies $p = \operatorname{apr}(\alpha, \chi_v, r)$ with $\max_{u \in V} \frac{r(u)}{d(u)} < \epsilon$.

${\tt push}_u(p,r) \colon$

- 1. Let p' = p and r' = r, except for the following changes:
 - (a) $p'(u) = p(u) + \alpha r(u)$.
 - (b) $r'(u) = (1 \alpha)r(u)/2$.
 - (c) For each v such that $(u, v) \in E$: $r'(v) = r(v) + (1 \alpha)r(u)/(2d(u))$.
- 2. Return (p', r').

local push

- Convergent until an error bound ϵ is reached
- No guaranteed execution time
- The computation complexity has a upper bound $O(\frac{1}{\epsilon})$
- Can be applied to dynamic graph:
 - Approximate Personalized PageRank on Dynamic Graphs
 - When a new edge is added, the complexity of updating the PPR has the complexity of O(1).