



# **Everything Evolves in Personalized PageRank**



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Motivation



- Proposed EvePPR Method
- Experiments
- Conclusion



## Personalized PageRank

- Methodology
  - Obtains broader attention within the trend of deep learning
  - E.g., PageRank-based Graph Representation Learning [1] and Graph Neural Networks [2]
- Applications [3]
  - Search Engine
  - Social Network Analysis
  - Recommender System
  - Bioinformatics
  - Many more ......







<sup>[2]</sup> Klicpera, et al. Predict then Propagate: Graph Neural Networks meet Personalized PageRank. ICLR 2019

<sup>[3]</sup> David F. Gleich. PageRank Beyond the Web. SIAM Rev. 2015

# PageRank in the Dynamic Setting

- Static Solution [1]
  - $\mathbf{v} = \alpha \mathbf{P} \mathbf{v} + (1 \alpha) \mathbf{h}$ 
    - $oldsymbol{v}$  is personalized PageRank vector
    - **P** is the transition matrix
    - **h** is the stochastic vector (e.g., personal interest)
- Dynamic Solution
  - Previous dynamic PPR works focus on modeling the evolving graph structure  $P^{(t)}$ , e.g.,
    - Gauss-Southwell [1]
    - Local Push [2]
    - Offset Score Propagation [3]

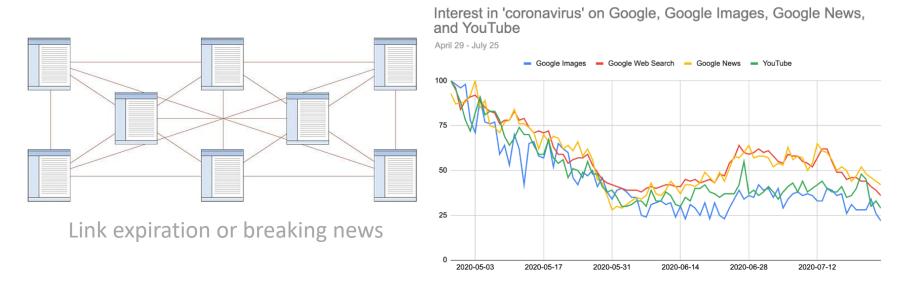


<sup>[2]</sup> Ohsaka et al. Efficient PageRank Tracking in Evolving Networks. KDD 2015

<sup>[3]</sup> Zhang et al. Approximate Personalized PageRank on Dynamic Graphs. KDD 2016

# PageRank in the Fully Dynamic Setting

- What if h is also evolving with time, like  $h^{(t)}$ ?
- E.g., web structure  $m{P}^{(t)}$  can evolve, as well as user interest  $m{h}^{(t)}$



• Then, how to solve  $\boldsymbol{v}^{(t)} = \alpha \boldsymbol{P}^{(t)} \boldsymbol{v}^{(t)} + (1 - \alpha) \boldsymbol{h}^{(t)}$ ?



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#### **Problem Setting and Theoretical Contribution**

- Input: Evolving graph structures  $\{P^{(1)}, P^{(2)}, ..., P^{(t)}\}$  and evolving stochastic vectors  $\{h^{(1)}, h^{(2)}, ..., h^{(t)}\}$
- Output: We aim to solve  $\{v^{(1)}, v^{(2)}, ..., v^{(t)}\}$  effectively and efficiently.
- Targeting this setting, we provide the solution EvePPR with theoretical time complexity and error bound.
- Also, we provide the fast and accuracy-comparable version,
  EvePPR-APP with theoretical analysis.



#### **EvePPR**

- Core Idea
  - When interests vary, i.e.,  $\Delta h = h^{(t)} h^{(t-1)}$ , decompose  $\Delta h$  into multiple single-source interests.
  - For each  $\Delta h(i) \neq 0$ , execute a single-source tracking  $v_{mid}$
  - Then, combine multiple  $oldsymbol{v}_{mid}$  to get  $oldsymbol{v}^{(t)}$
- Theoretical Analysis
  - At each timestamp t, EvePPR can get exact  $v^{(t)}$  satisfying  $v^{(t)} = \alpha P^{(t)} v^{(t)} + (1 \alpha) h^{(t)}$
  - The time complexity is  $O(m(l+1)log_{\alpha}\varepsilon)$ 
    - m and l is num. of non-zero entries of  $m{P}^{(t)}$  and  $m{h}^{(t)}$ , resp.
    - $\varepsilon$  is the tolerance to terminate the tracking



#### **EvePPR-APP**

- Core Idea
  - Trade off the tracking accuracy to tracking efficiency
  - Instead of decomposing  $\Delta h$  in EvePPR, use OSP [1] to get  $v_{mid}$  and refine  $v_{mid}$  through Gauss-Southwell [2] to get  $v^{(t)}$
- Theoretical Analysis
  - The time complexity is  $O\left(mlog_{\alpha}\varepsilon + n\left(\frac{(1+\alpha)\alpha}{(1+\alpha)^2}\right) + \frac{||\Delta h||_1}{\varepsilon}\right)$ 
    - m is num. of non-zero entries of  ${m P}^{(t)}$
    - $\varepsilon$  is the tolerance to terminate the tracking
  - The tracking error (i.e.,  $L_1$  norm) is bounded by  $\frac{n\varepsilon}{1-\alpha}$

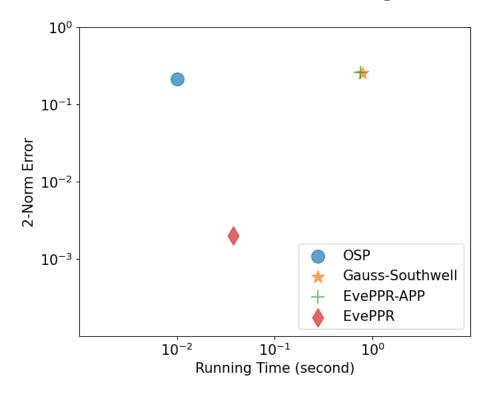


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# PageRank Tracking Experiment

Our method is fast and has less tracking errors



Tracking Error and Running Time of Different PageRank Algorithms in MathOverflow Network (24,818 nodes and 506,550 edges)

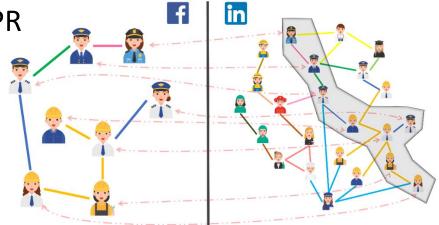


## **Application Experiment – Graph Alignment**

- Node similarity retrieval across graphs [1]
- Can be rewritten in the form of PPR

$$s = \alpha \widetilde{W} s + (1 - \alpha) h$$

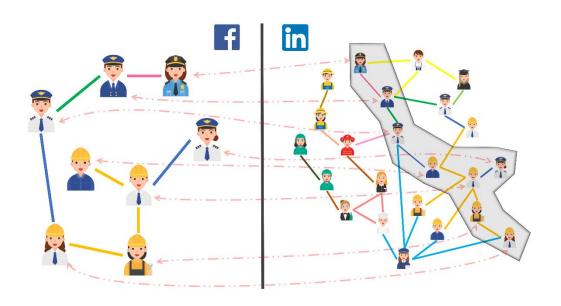
 W encodes graph topology, node feature, edge feature of two graphs, and h encodes the prior aligning knowledge



- $\mathbf{s} \in \mathbb{R}^{n_1 \times n_2}$  encodes node-pair similarity
- Our EvePPR in the fully dynamic setting allows graph topology, node feature, edge feature, and prior aligning knowledge from two graphs co-evolve, i.e.,  $\widetilde{\pmb{W}}^{(t)}$  and  $\pmb{h}^{(t)}$

## **Application Experiment – Graph Alignment**

#### Real-World Datasets



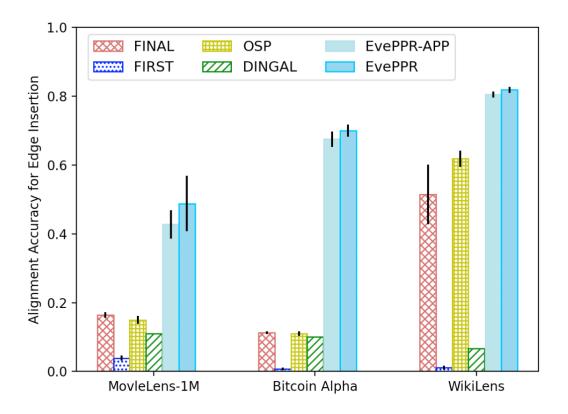
Extracted Subgraphs	Format	V	E
MovieLens-1M	Bipartite	90	375
Bitcoin Alpha	Unipartite	100	423
WikiLens	Bipartite	150	553

Graphs	Format	V	E	Time Span
MovieLens-1M	Bipartite	9,746	1,000,209	35 months
Bitcoin Alpha	Unipartite	3,783	24,186	64 months
WikiLens	Bipartite	5,437	26,937	46 months



#### **Application Experiment – Graph Alignment**

Our method achieves highest alignment accuracy



Alignment Accuracy of Different Graph Alignment Algorithms in Different Networks



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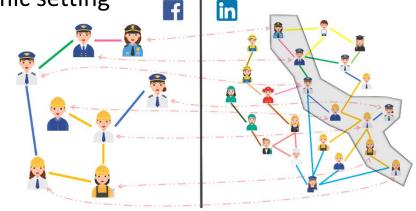


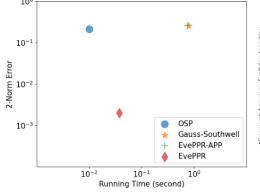
#### **Conclusion**

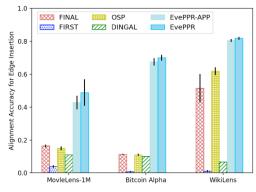
- Problem
  - Tracking PPR solution in the fully dynamic setting
- Algorithm: EvePPR
  - Bounded accuracy
  - Bounded time complexity
  - Approximation solution

#### Evaluation

- Effectiveness in PPR tracking
- Efficiency in PPR tracking
- Knowledge graph alignment
- Ablation studies













#### Thanks!



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