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SAPIENZA
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Reduce and Aggregate: Similarity Ranking in Multi-Categorical Bipartite Graphs

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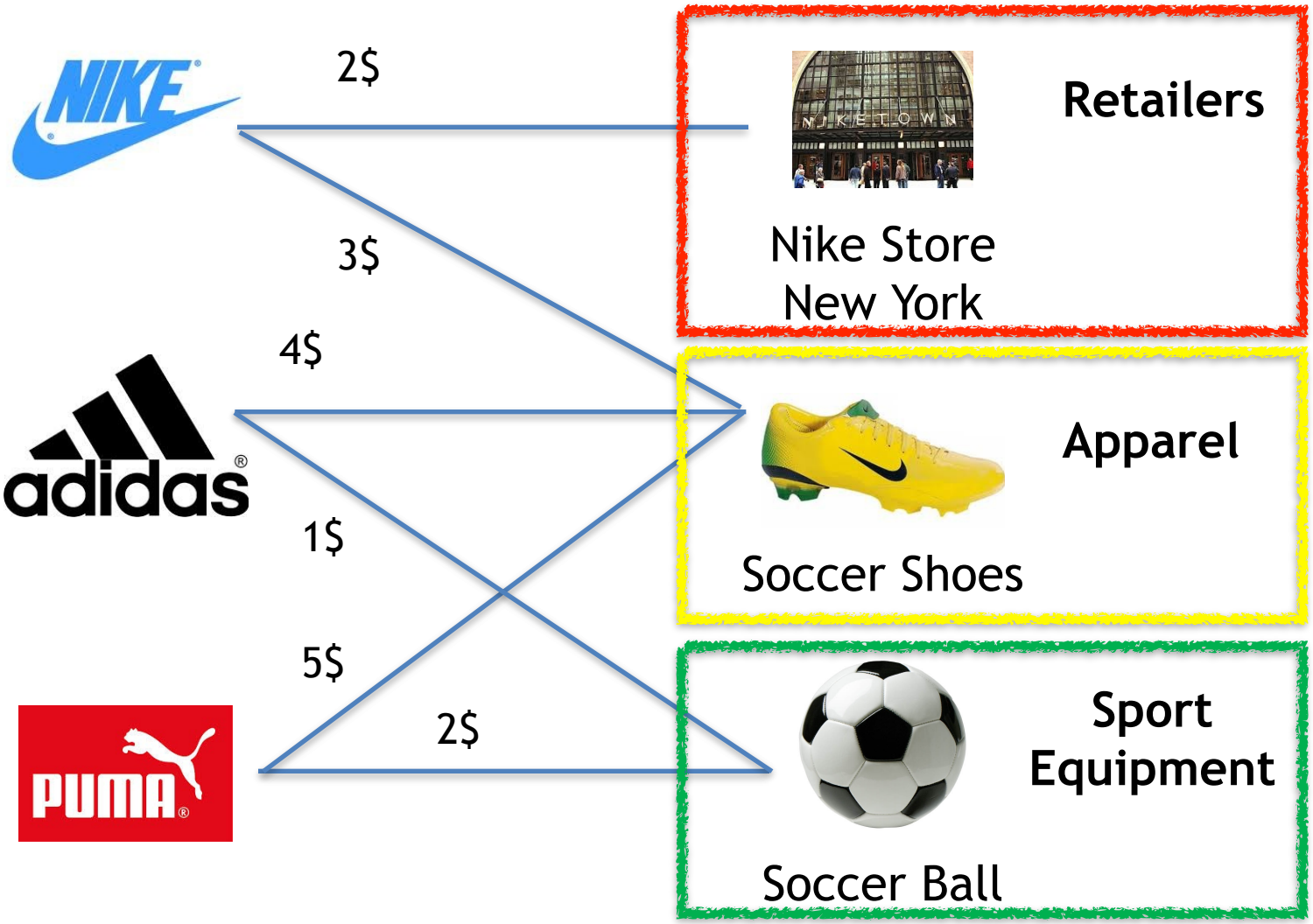
Motivation

- Recommendation Systems:
  - Bipartite graphs with **Users** and **Items.**
  - Identify similar users and suggest relevant items.
  - Concrete example: The **AdWords** case.

- Two key observations:
  - Items belong to different **categories.**
  - Graphs are often **lopsided.**

Modeling the Data as a Bipartite Graph

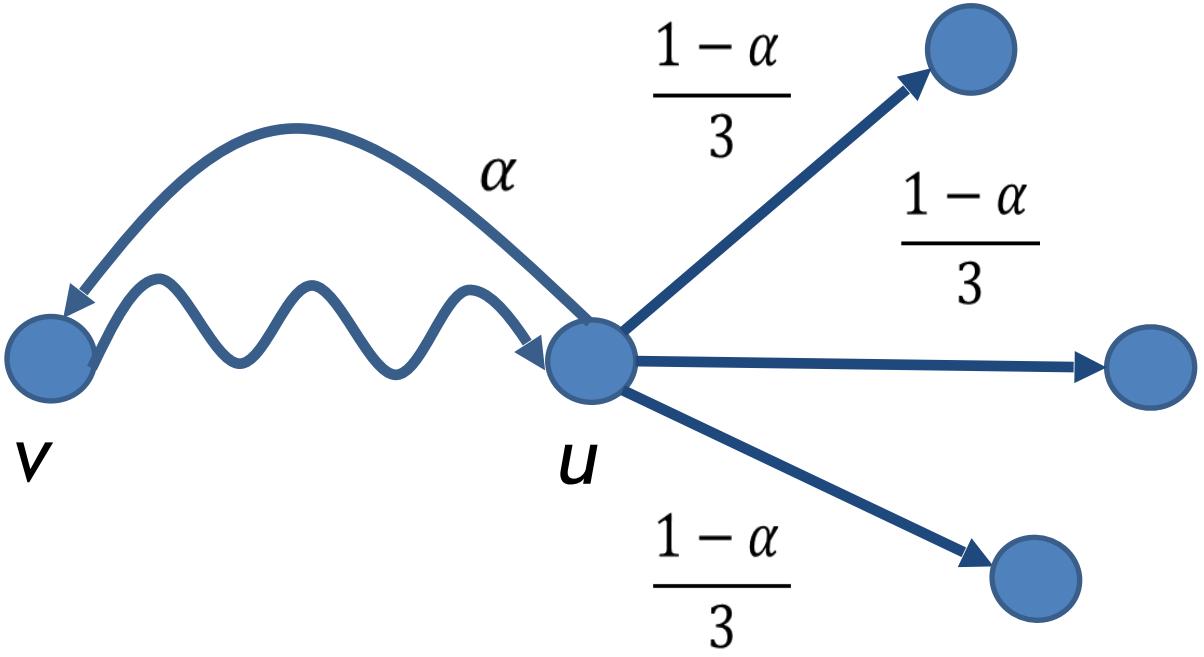


Millions of Advertisers

Billions of Queries

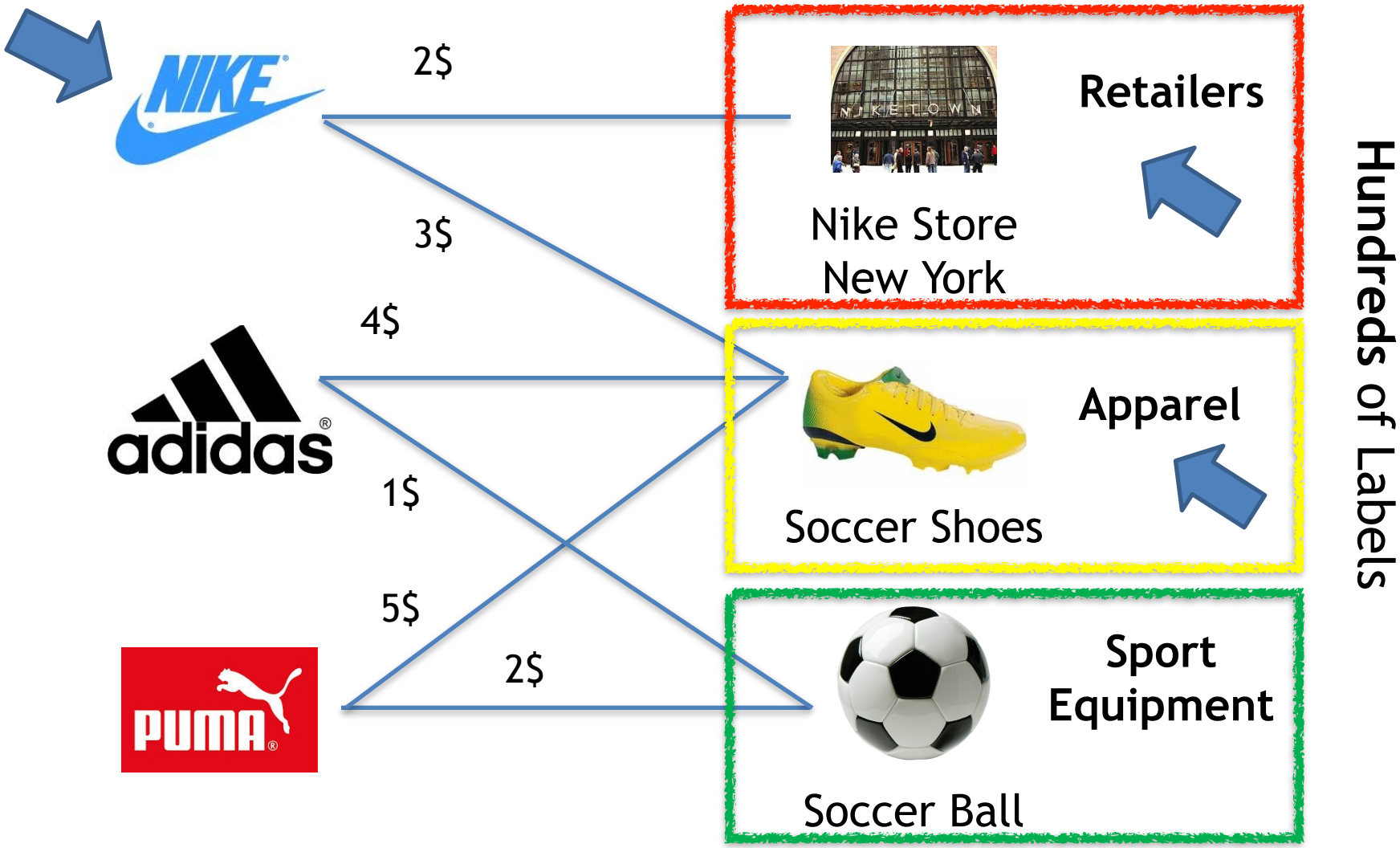
Personalized PageRank

For a node v (the seed) and a probability alpha



The stationary distribution assigns a similarity score to each node in the graph w.r.t. node v.

The Problem



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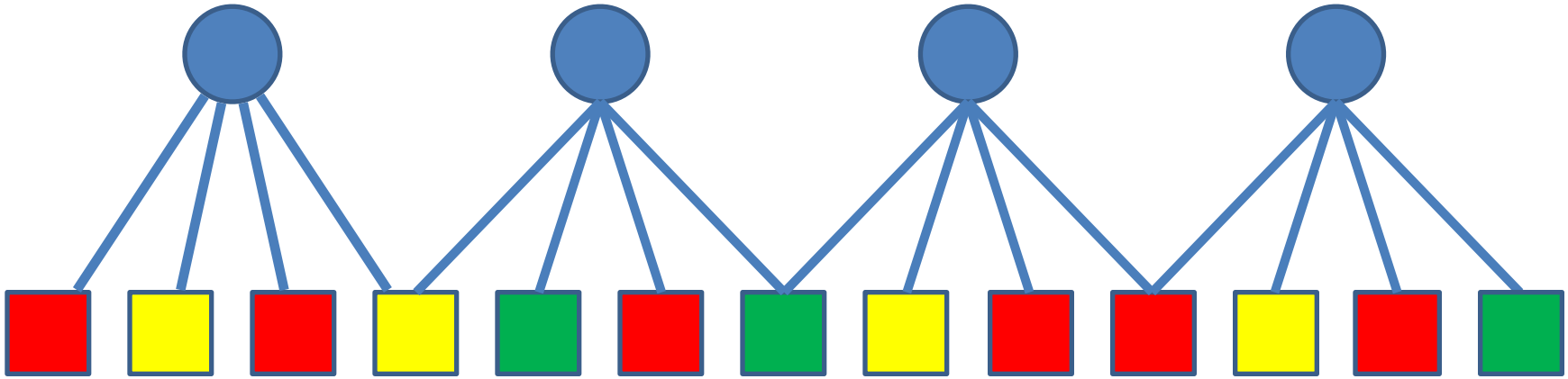
Other Applications

- General approach applicable to several contexts:
  - **User**, **Movies**, **Genres**: find similar users and suggest movies.
  - **Authors**, **Papers**, **Conferences**: find related authors and suggest papers to read.

Semi-Formal Problem Definition

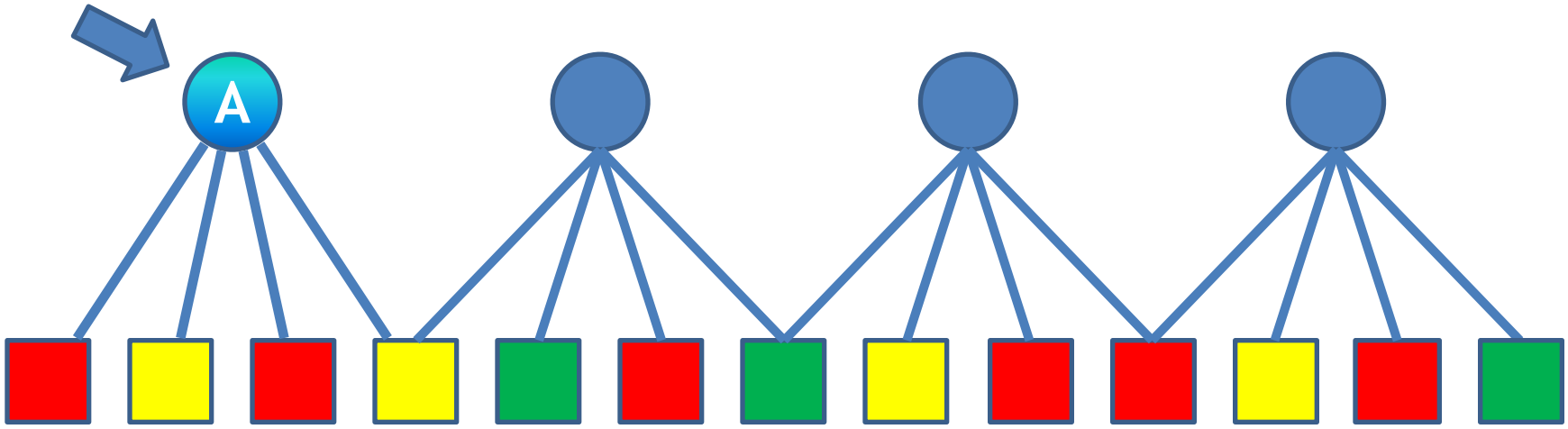
Advertisers



Queries

Semi-Formal Problem Definition

Advertisers



Queries

Semi-Formal Problem Definition

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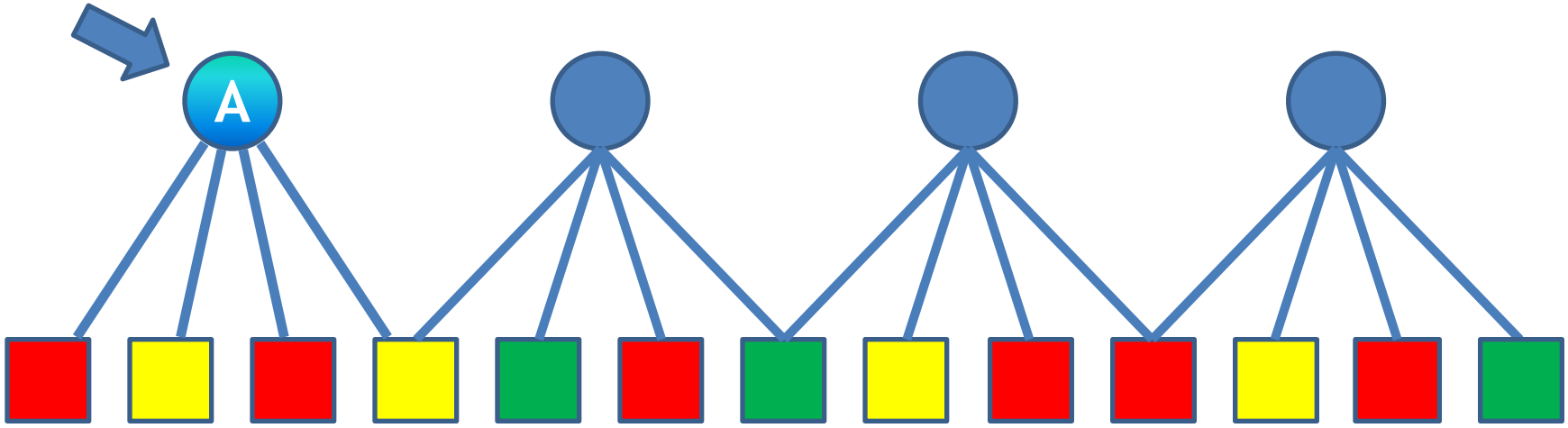
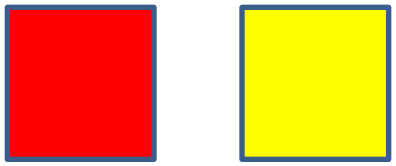


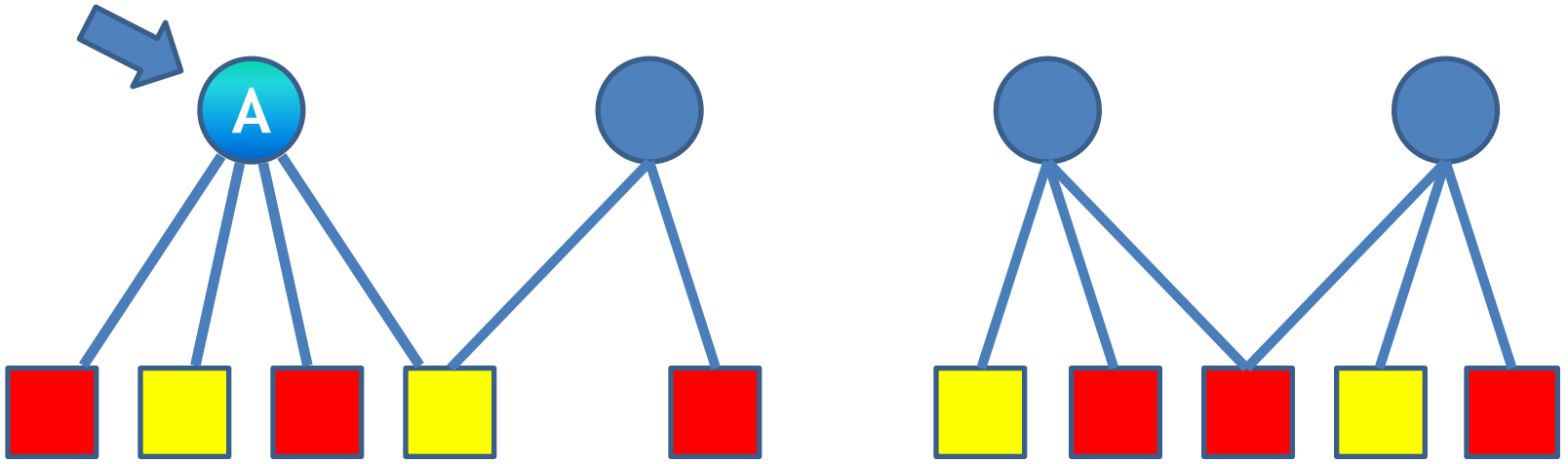
Queries

Labels:



Semi-Formal Problem Definition

Advertisers



Queries

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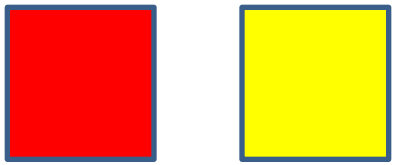


Goal:
Find the nodes most "similar" to A.

How to Define Similarity?

- We address the computation of several node similarity measures:
  - Neighborhood based: Common neighbors, Jaccard Coefficient, Adamic-Adar.
  - Paths based: Katz.
  - Random Walk based: Personalized PageRank.
- Experimental question: which measure is useful?
- Algorithmic questions:
  - Can it scale to **huge** graphs?
  - Can we compute it in **real-time**?

Our Contribution

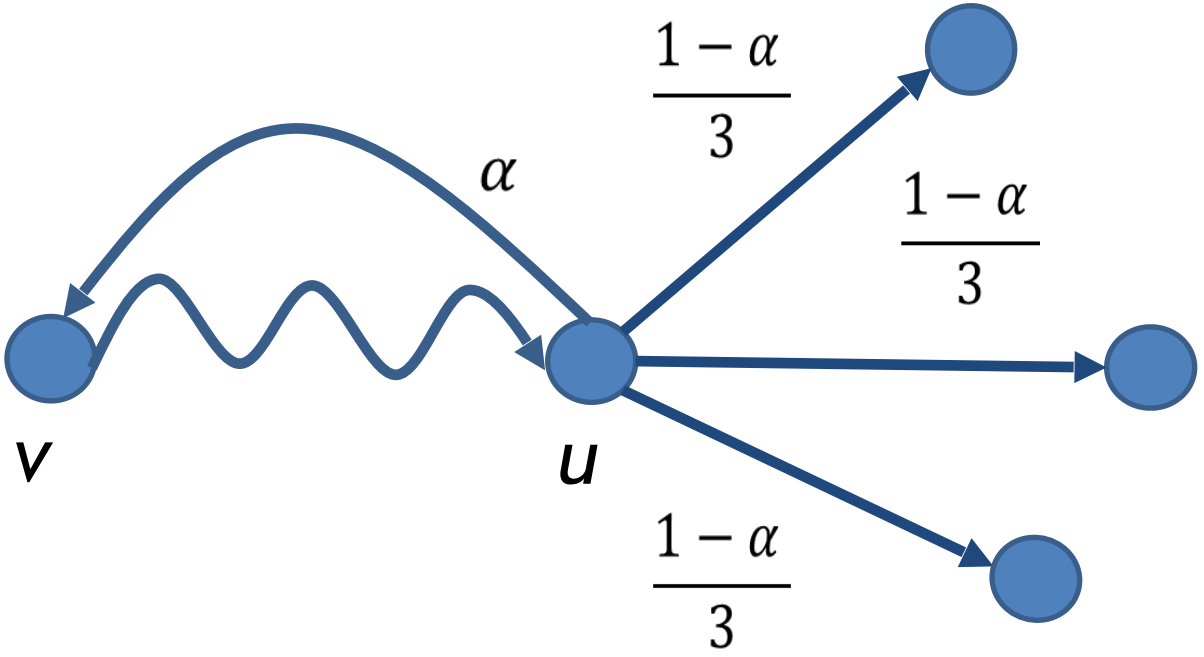
- **Reduce and Aggregate:** general approach to induce real-time similarity rankings in multi-categorical bipartite graphs, that we apply to several similarity measures.

- Theoretical guarantees for the precision of the algorithms.

- Experimental evaluation with real world data.

Personalized PageRank

For a node v (the seed) and a probability alpha

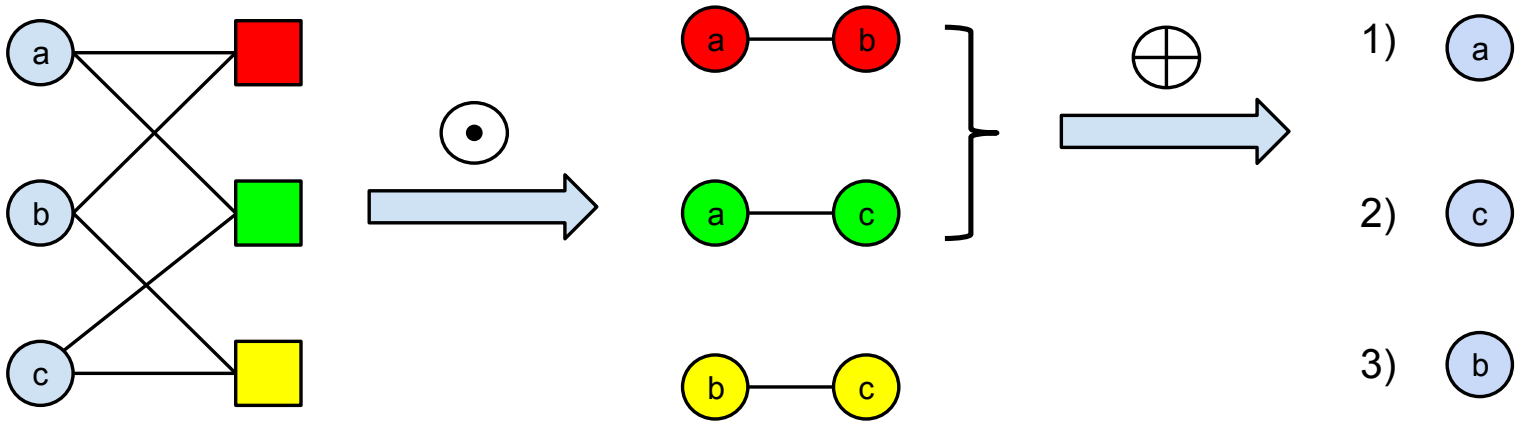


The stationary distribution assigns a similarity score to each node in the graph w.r.t. node v.

Challenges

- Our graphs are too big (**billions** of nodes) even for very large-scale MapReduce systems.
- MapReduce is not real-time.
- We cannot pre-compute the rankings for each subset of labels.

Reduce and Aggregate

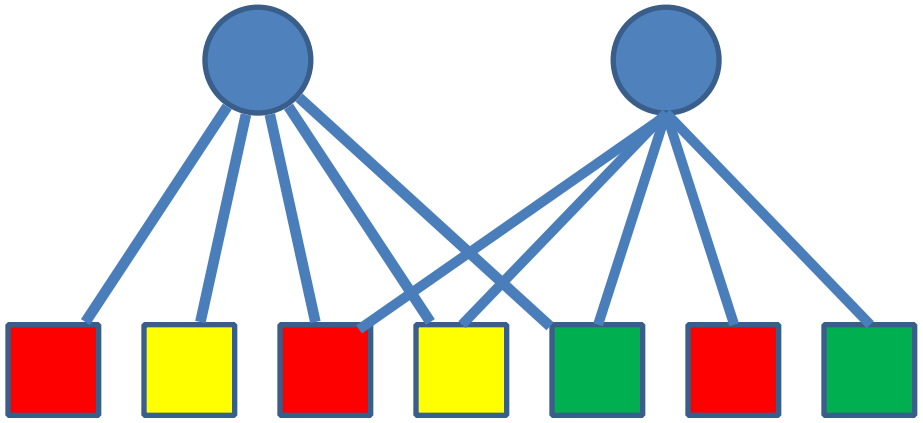


Reduce: Given the bipartite and a category construct a graph with only A nodes that preserves the ranking on the entire graph.

Aggregate: Given a node v in A and the reduced graphs of the subset of categories interested determine the ranking for v.

Reduce (Precomputation)

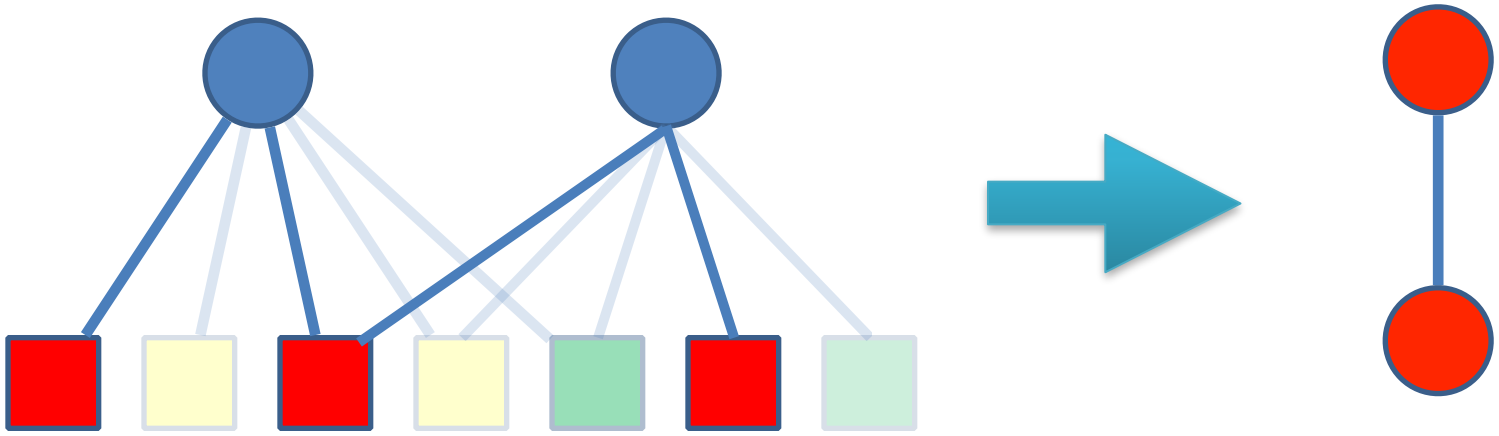
Advertisers



Queries

Reduce (Precomputation)

Advertisers



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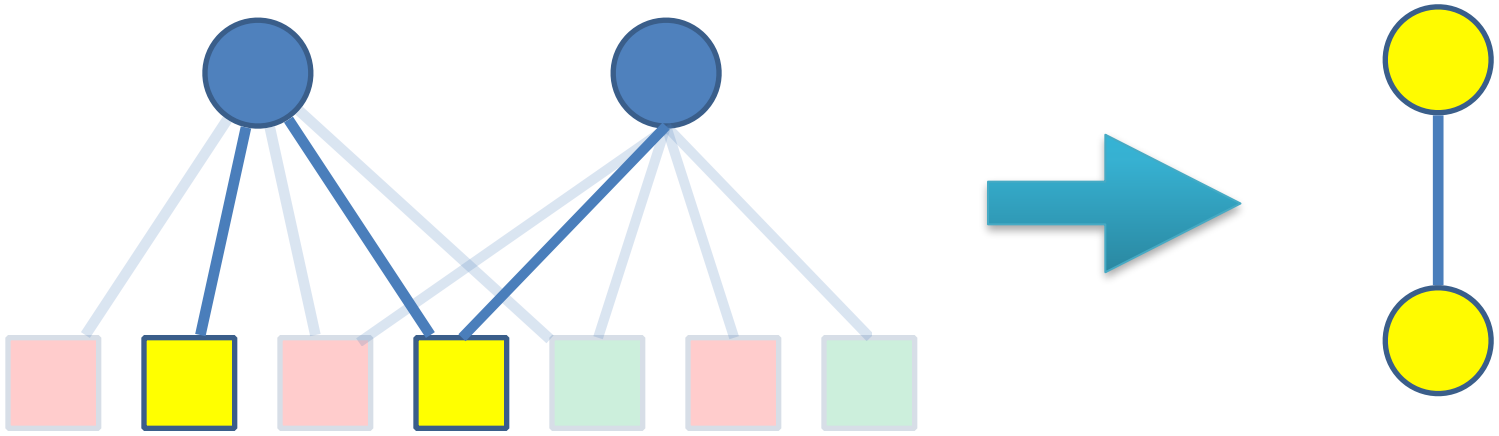
Advertisers



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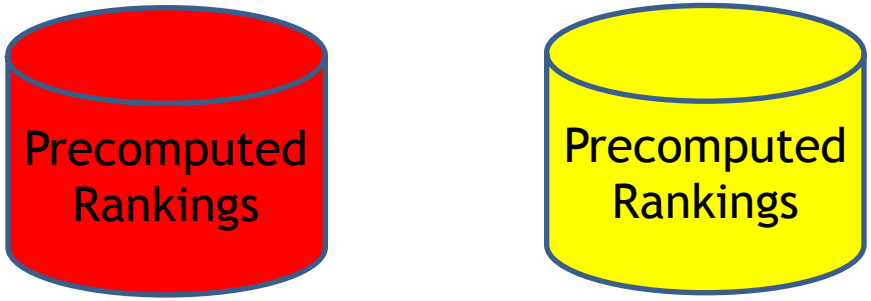
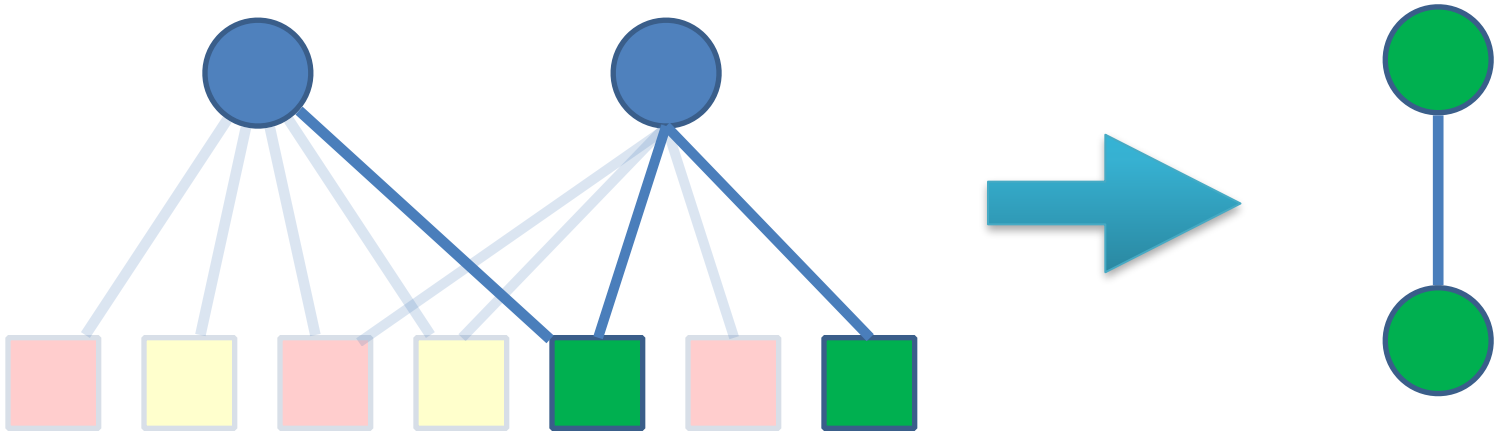


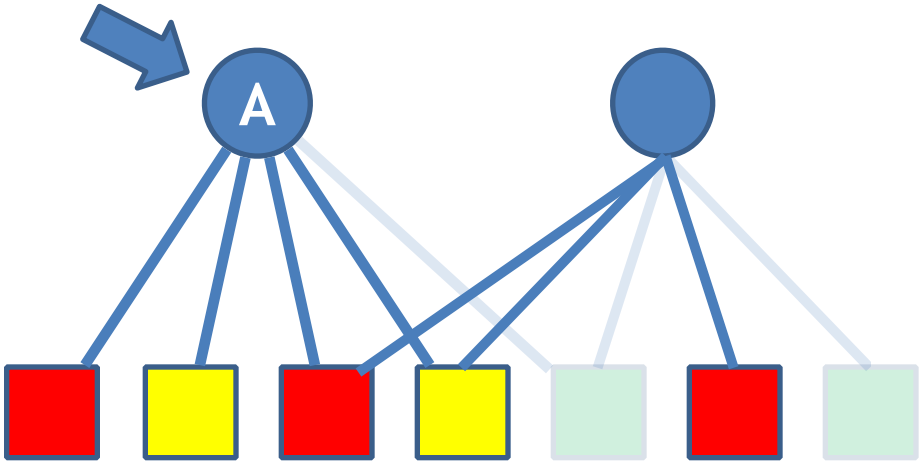
Reduce (Precomputation)

Advertisers

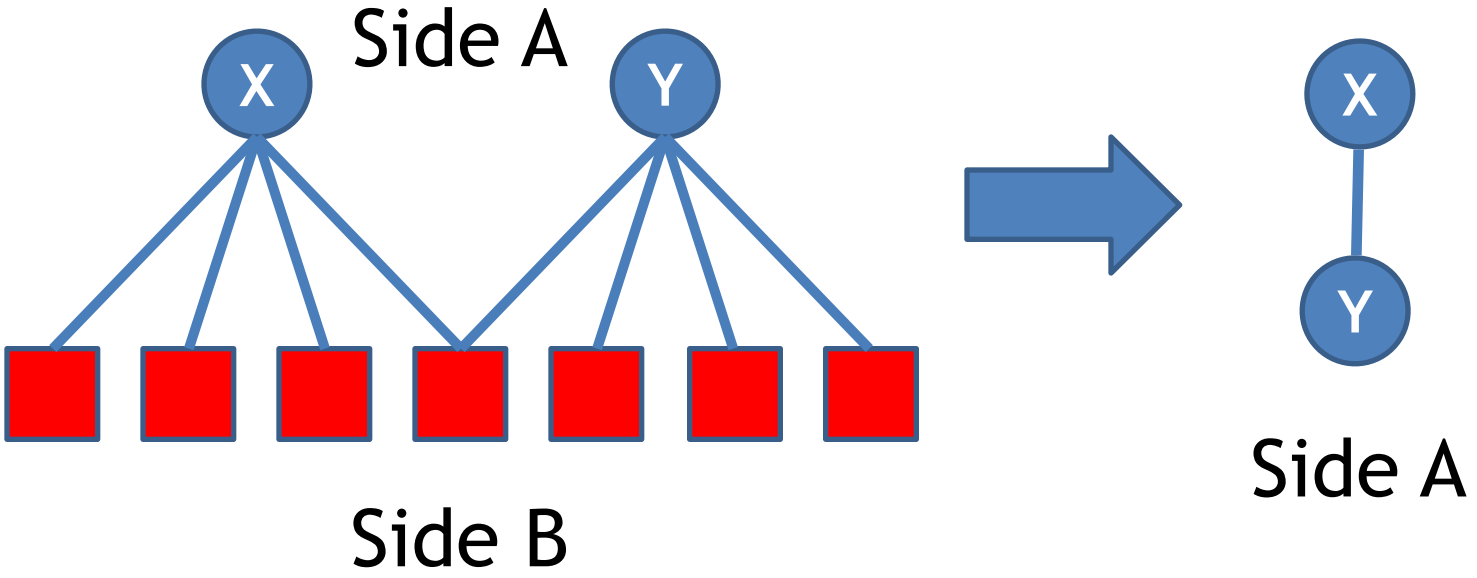


Queries

Aggregate (Run Time)



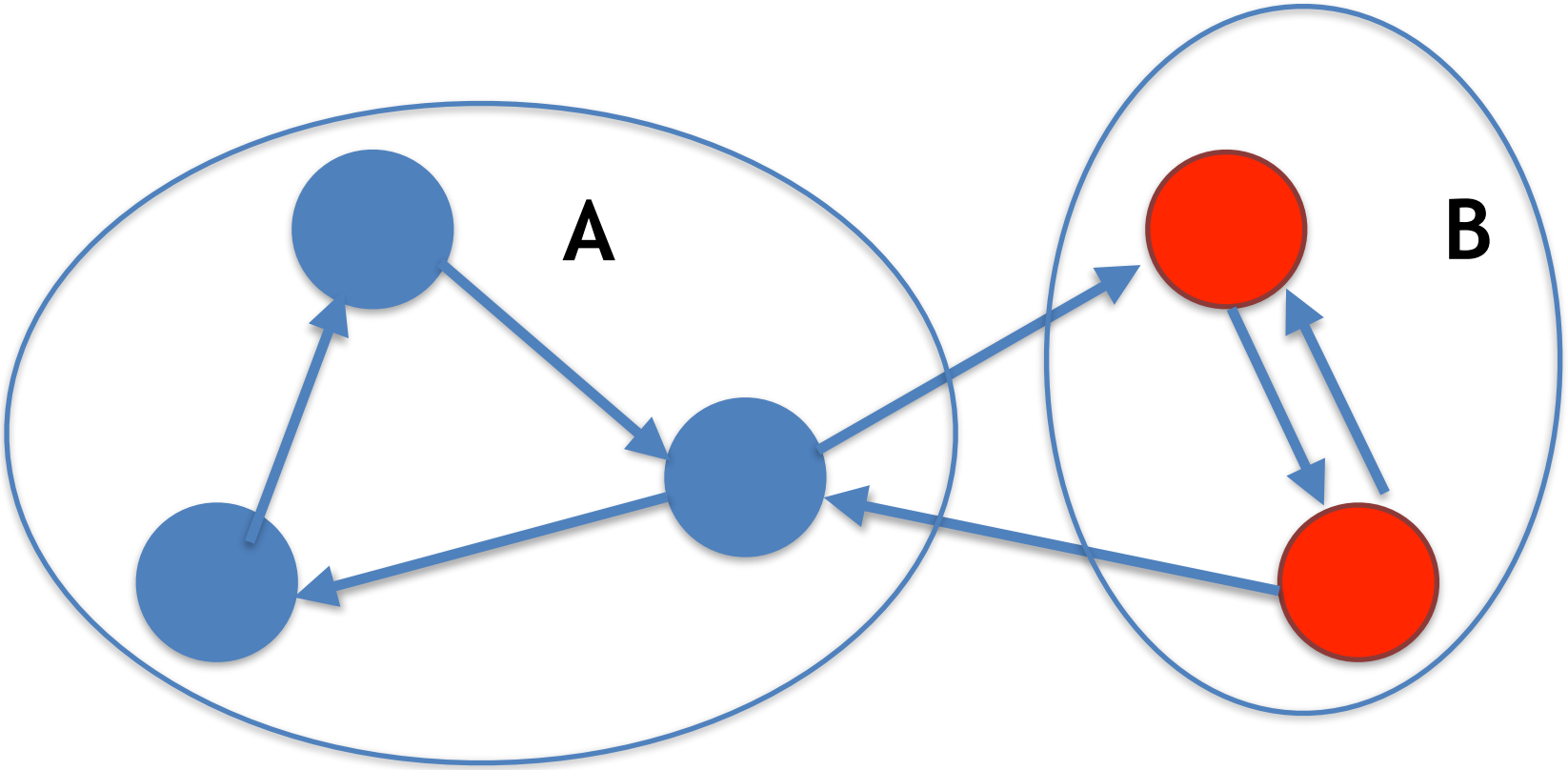
Reduce for Personalized PageRank



- Markov Chain state aggregation theory (Simon and Ado, ’61; Meyer ’89, etc.).
- **750x** reduction in the number of node while preserving correctly the PPR distribution on the **entire graph**.

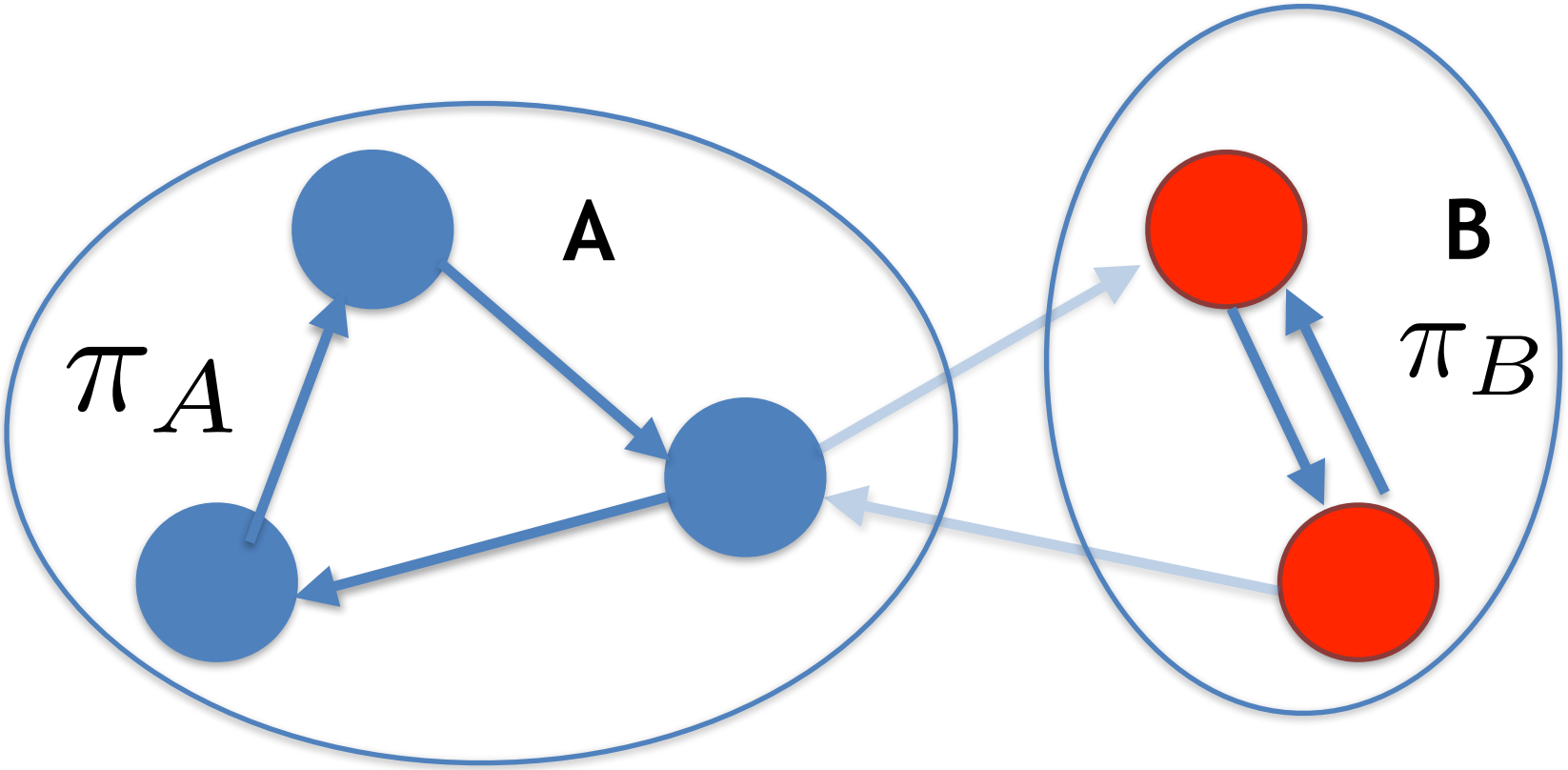
Run-time Aggregation

Koury et al. Aggregation-Disaggregation Algorithm



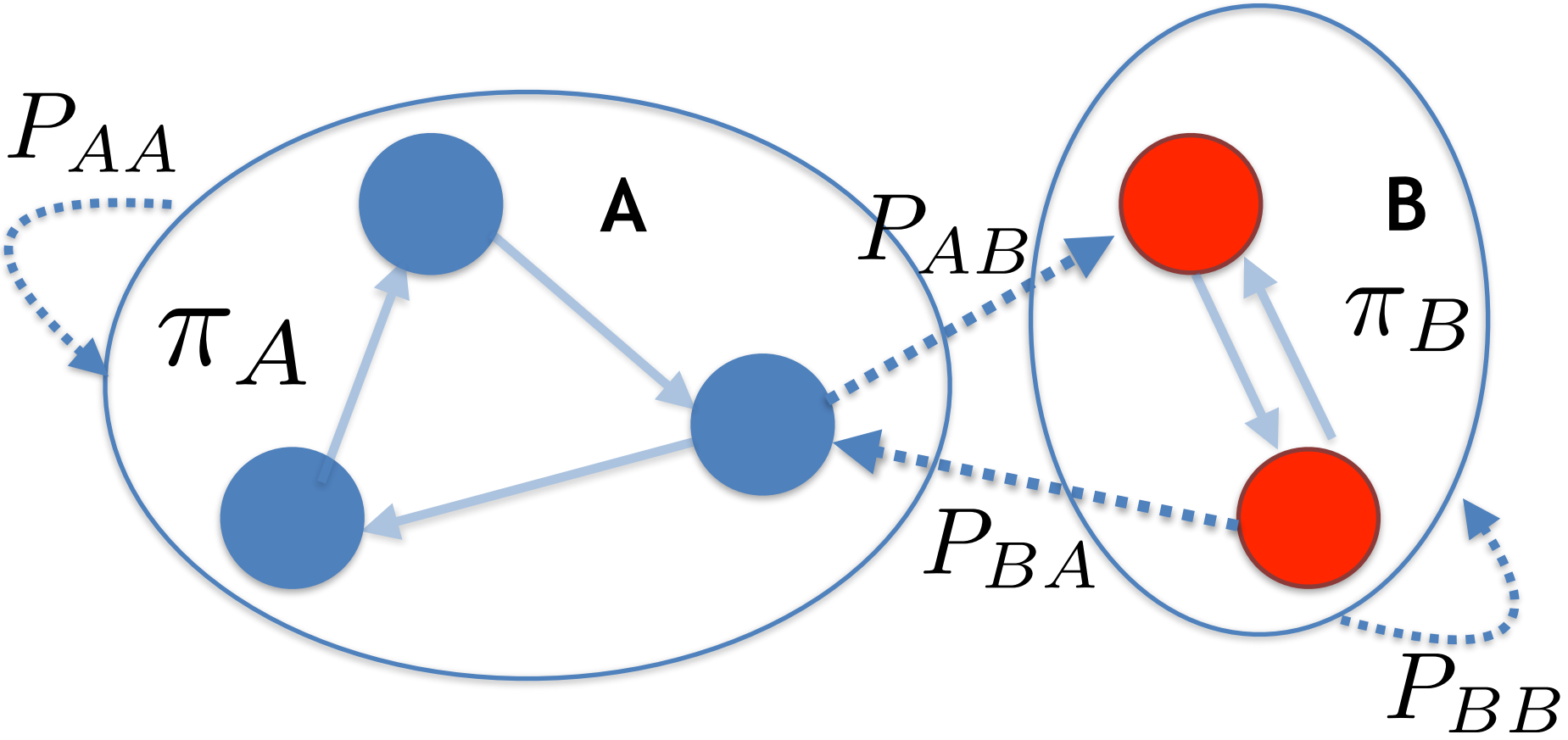
Step 1: Partition the Markov chain into **DISJOINT** subsets

Koury et al. Aggregation-Disaggregation Algorithm



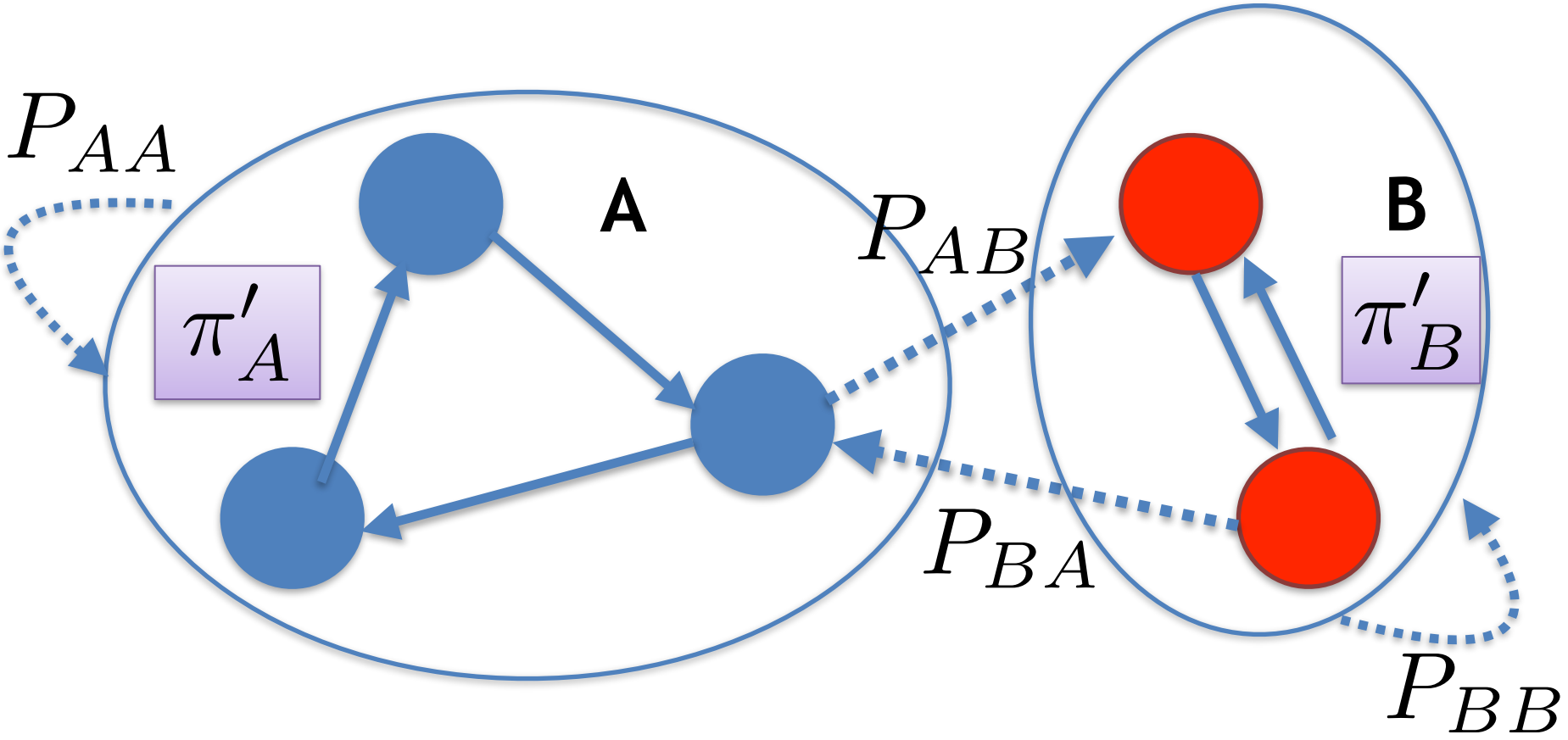
Step 2: Approximate the stationary distribution on each subset independently.

Koury et al. Aggregation-Disaggregation Algorithm



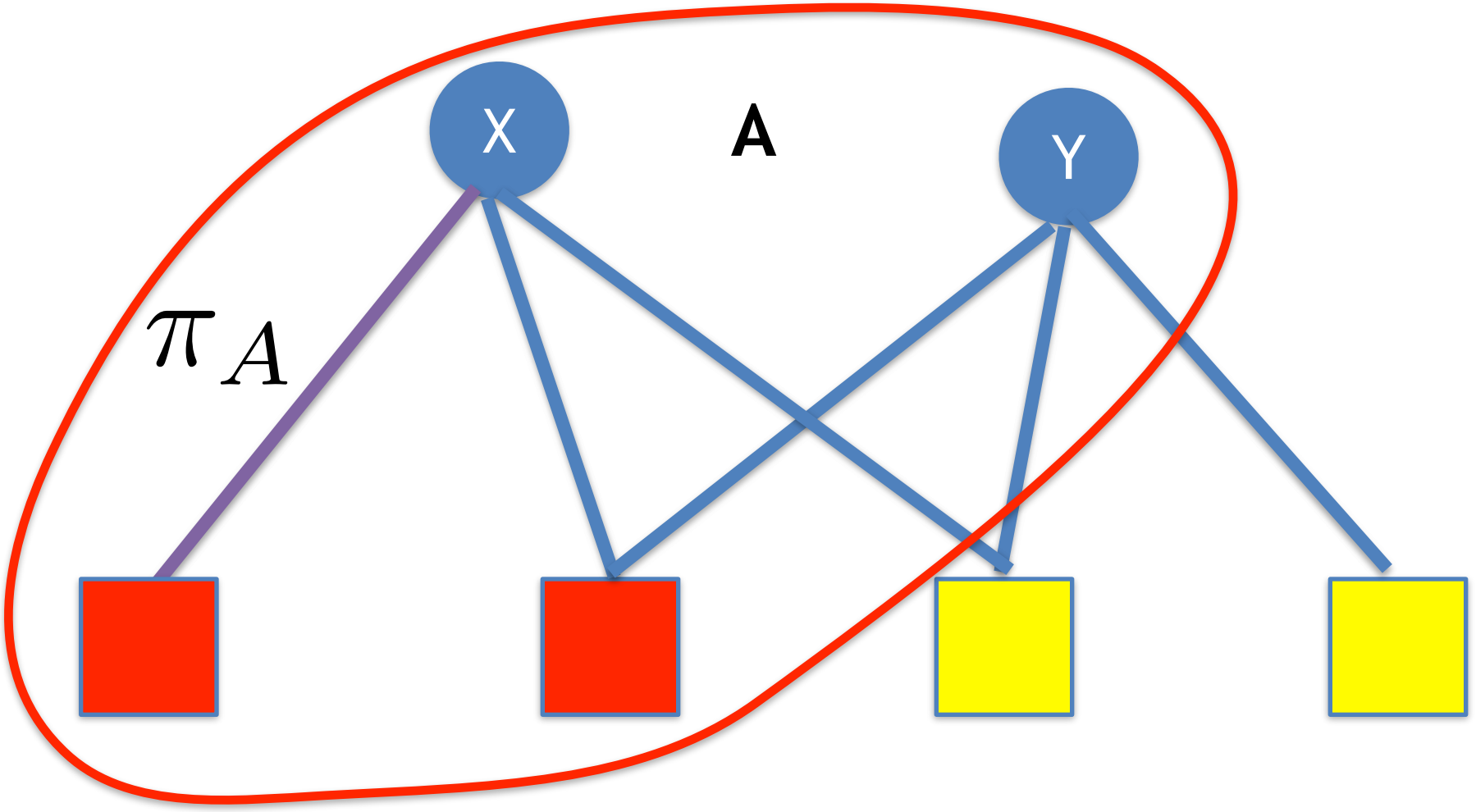
Step 3: Consider the transition between subsets.

Koury et al. Aggregation-Disaggregation Algorithm



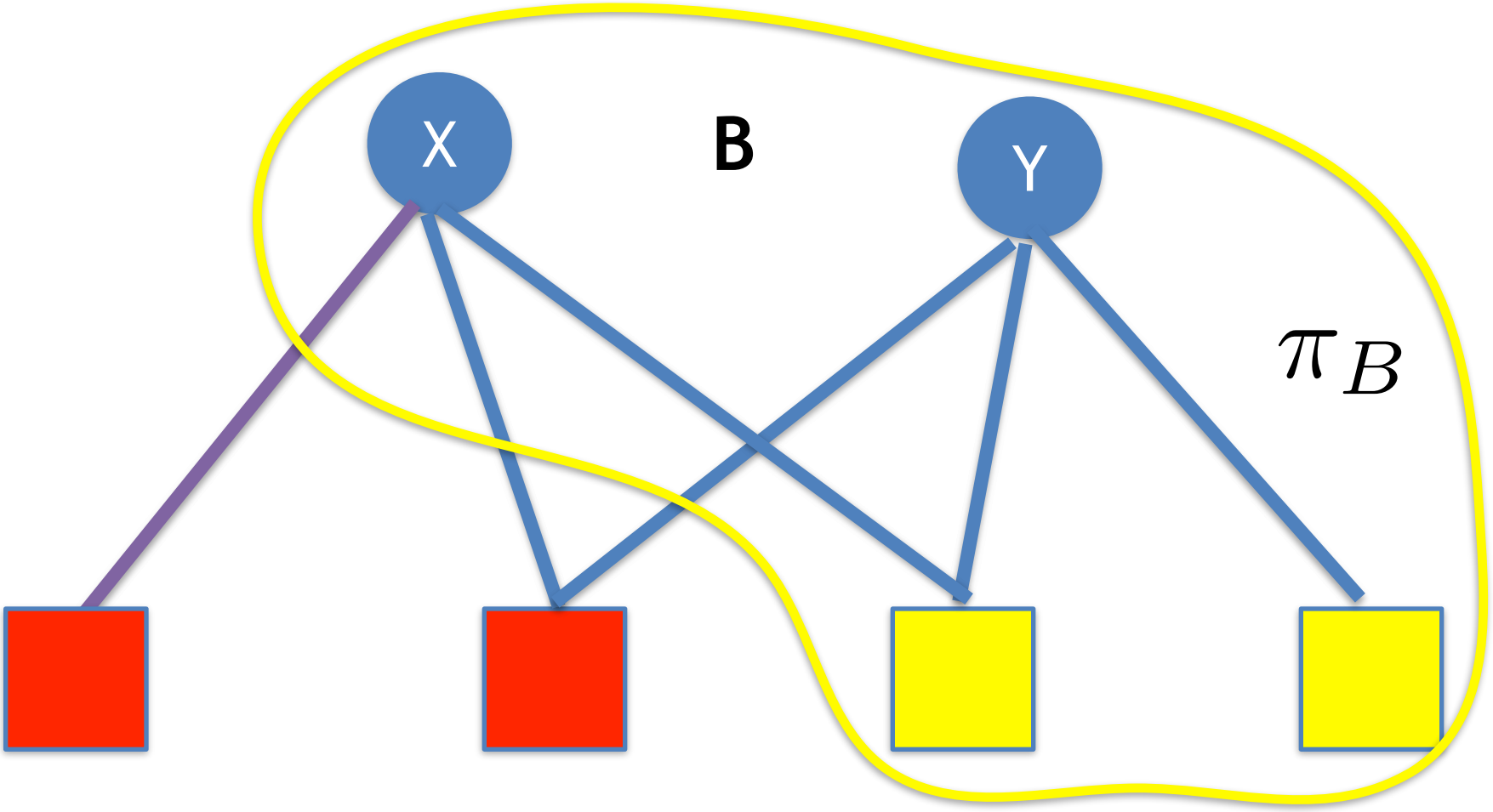
Step 4: Aggregate the distributions. **Repeat** until convergence.

Aggregation in PPR



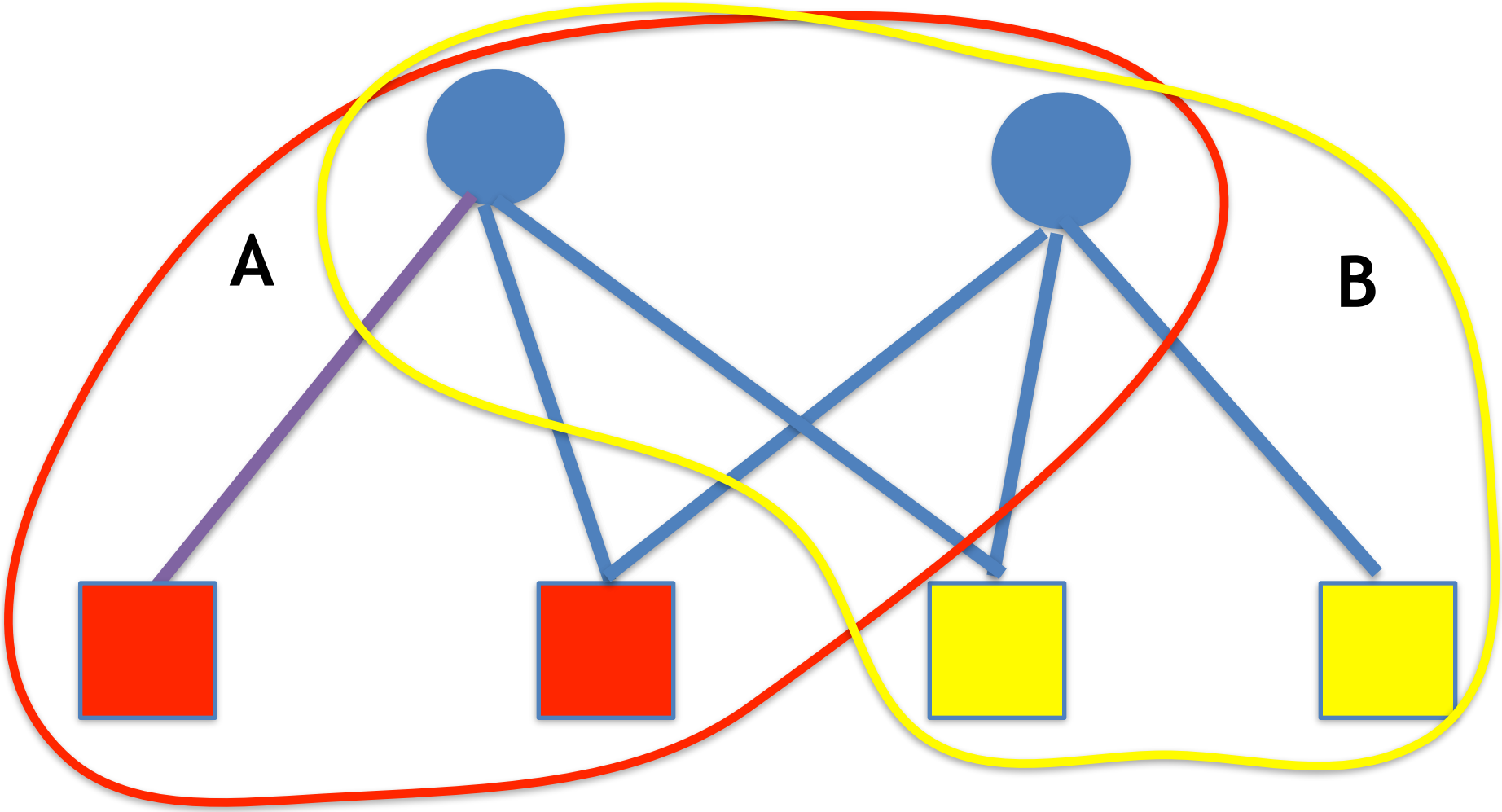
Precompute the stationary distributions individually

Aggregation in PPR



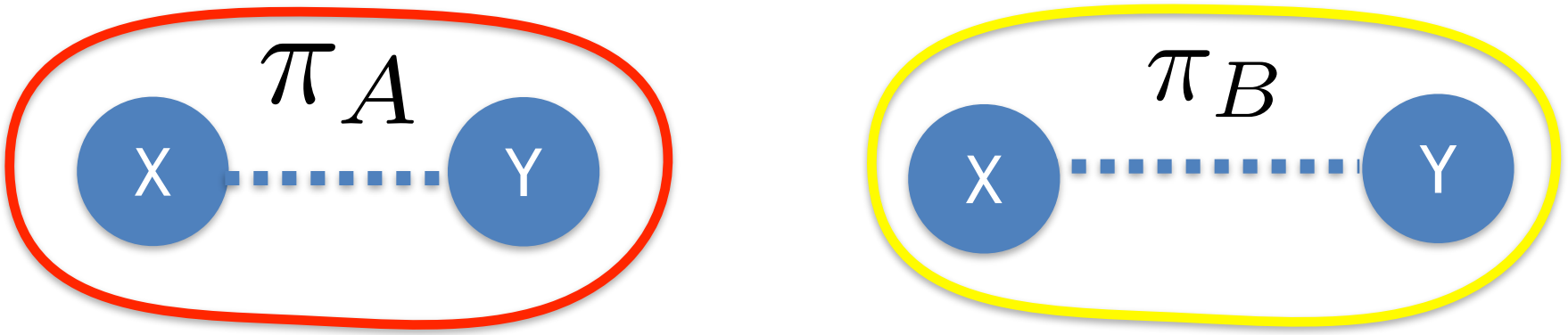
Precompute the stationary distributions individually

Aggregation in PPR



The two subsets are not disjoint!

Our Approach



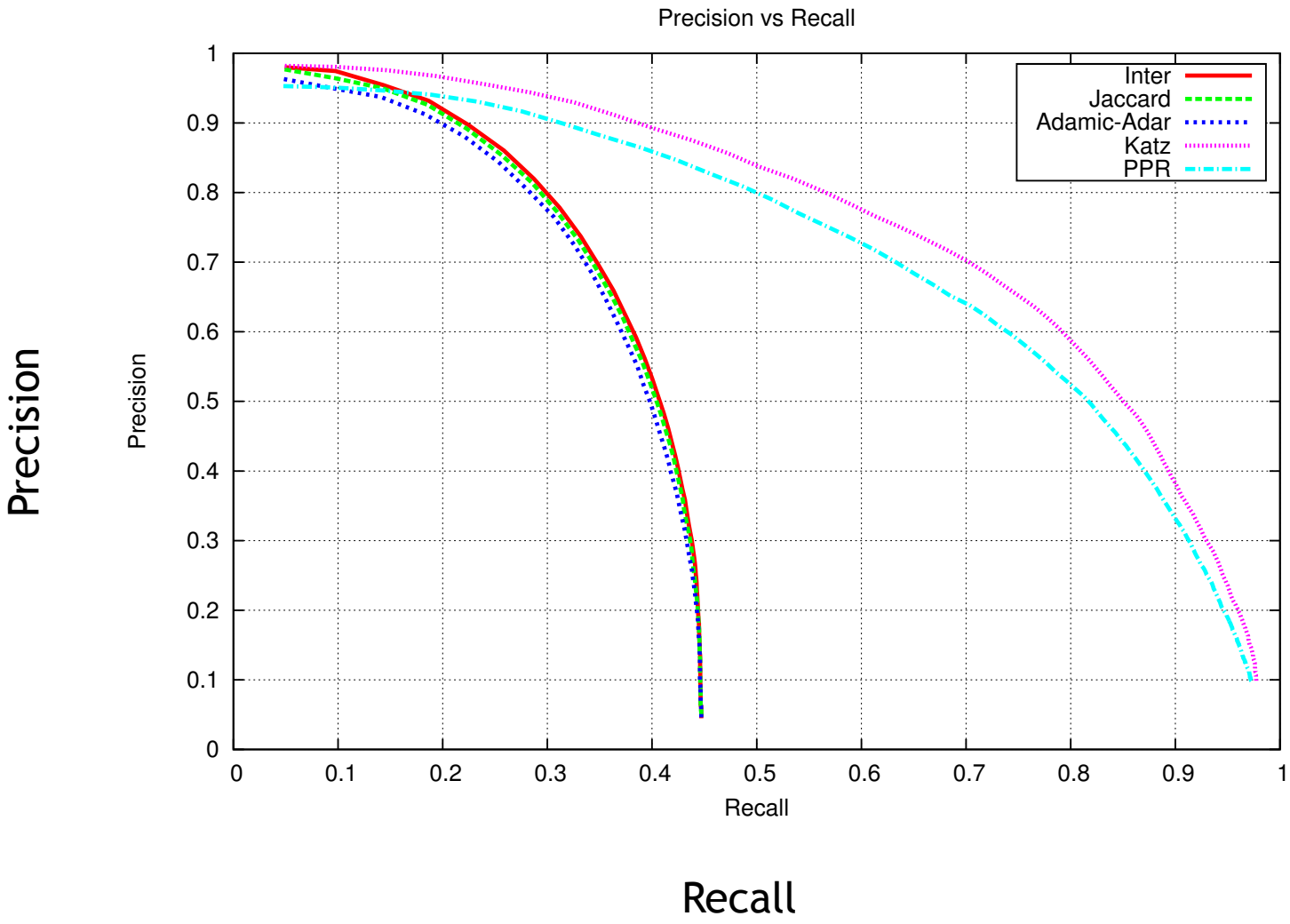
- The algorithm is based **only** on the reduced graphs with Advertiser-Side nodes.

- The aggregation algorithm is scalable and converges to the correct distribution.

Experimental Evaluation

- We experimented with publicly available and proprietary datasets:
  - Query-Ads graph from Google AdWords > 1.5 billions nodes, > 5 billions edges.
  - DBLP Author-Papers and Patent Inventor-Inventions graphs.
- Ground-Truth clusters of competitors in Google AdWords.

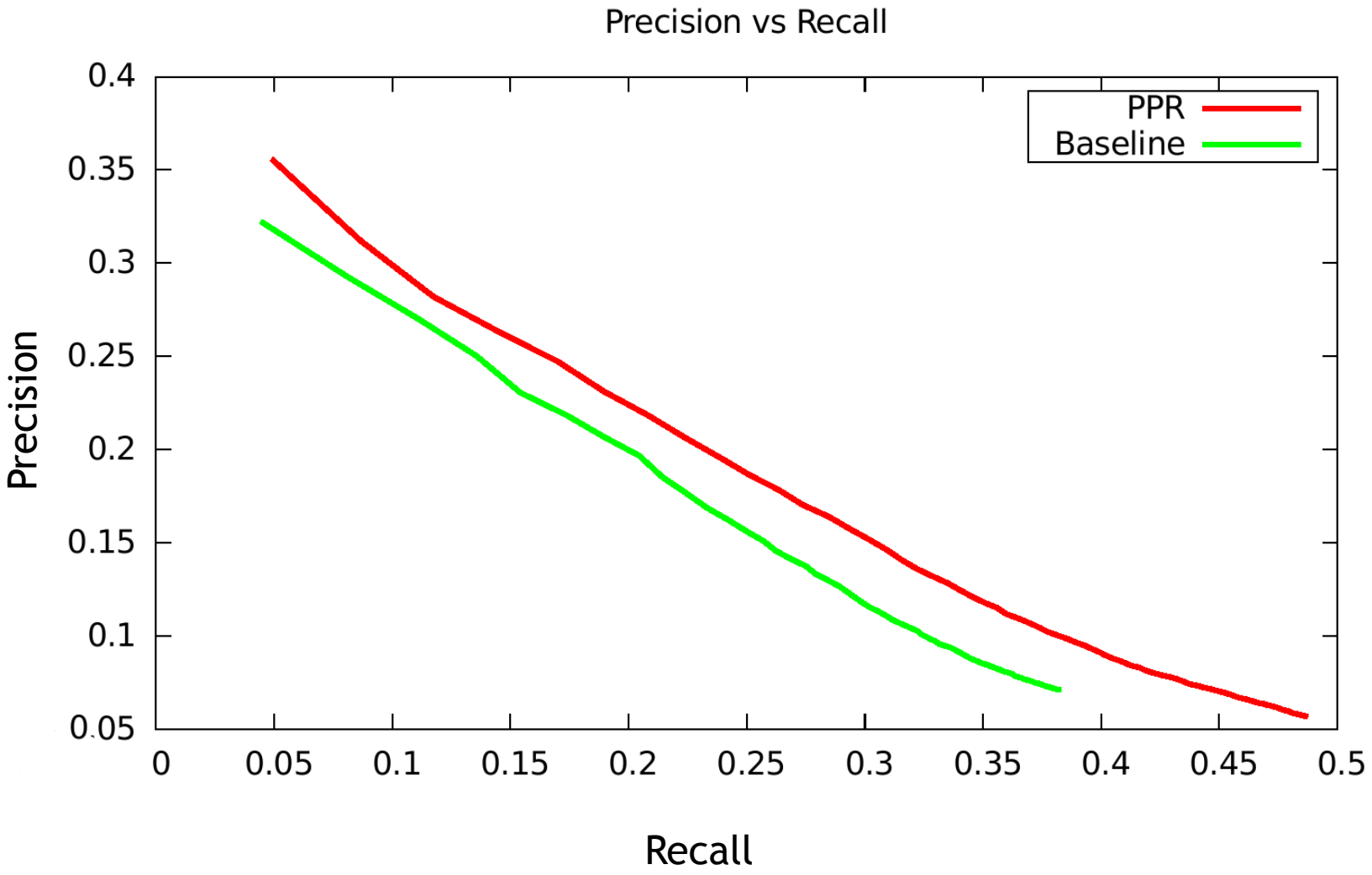
Patent Graph



Precision

Recall

Google AdWords



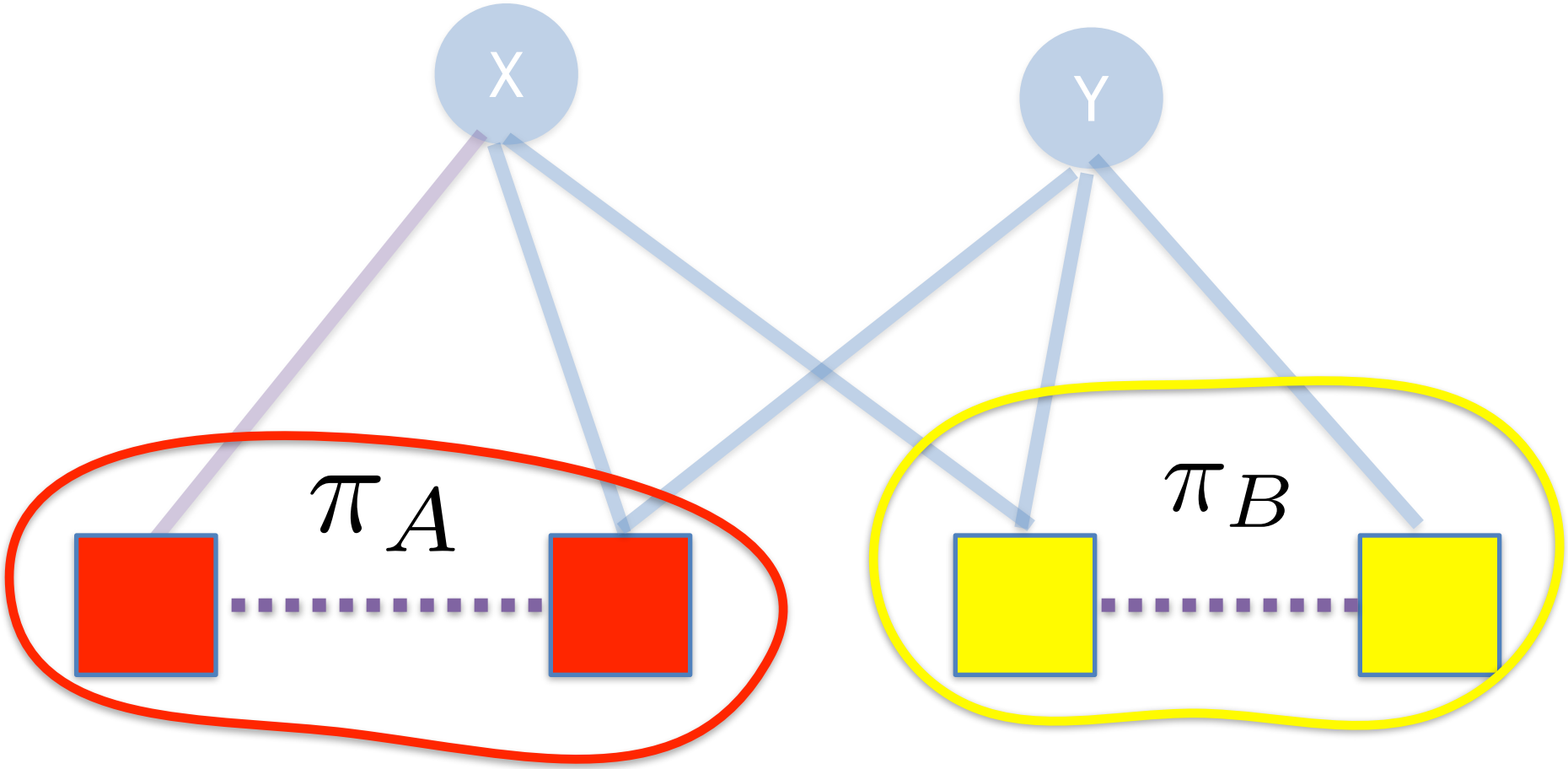
Conclusions and Future Work

- It is possible to compute several similarity scores on very large bipartite graphs in real-time with good accuracy.

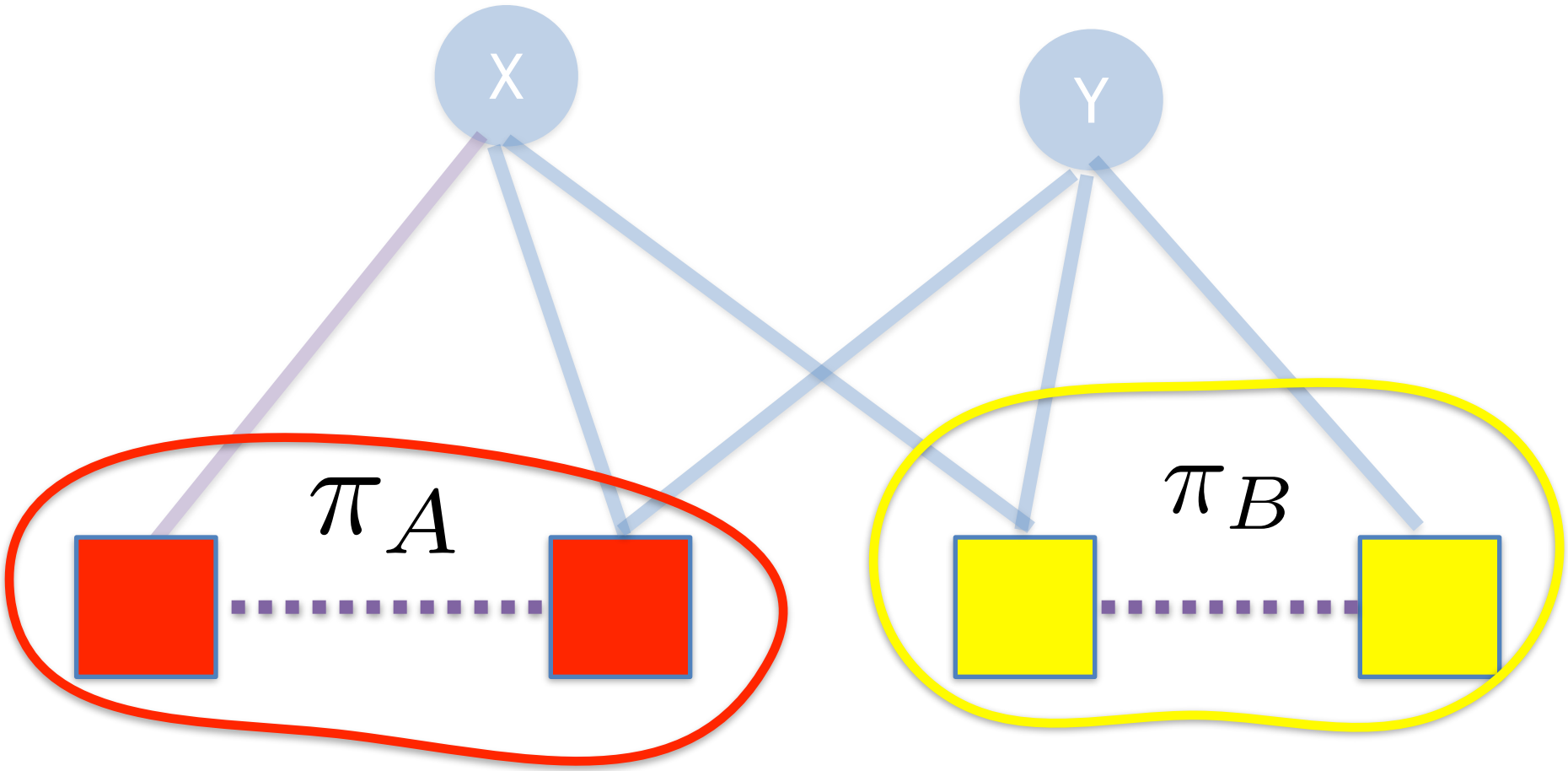
- Future work could focus on the case where categories are not disjoint is relevant.

Thank you for your attention

Reduction to the Query Side

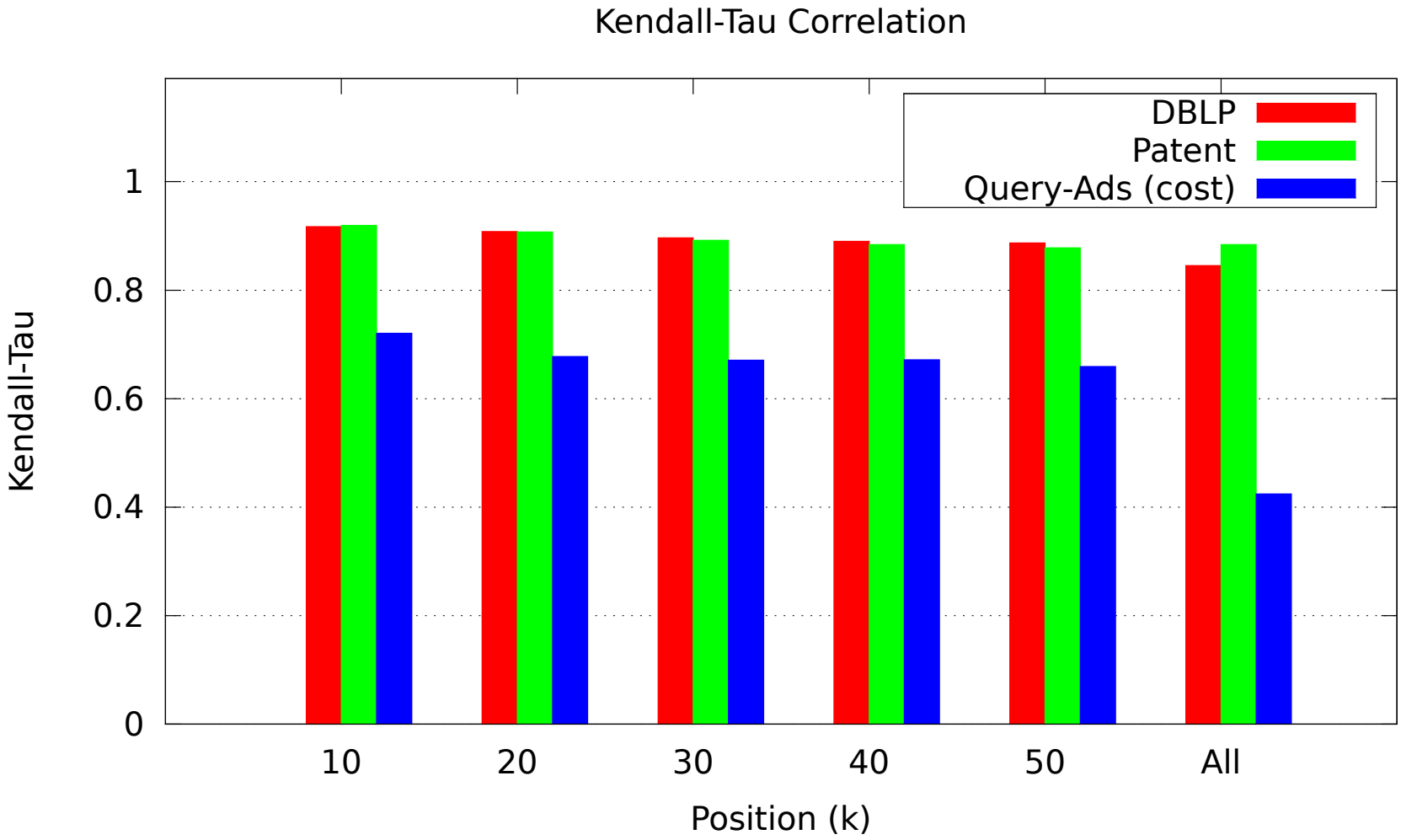


Reduction to the Query Side



This is the larger side of the graph.

Convergence after One Iteration



Convergence