iMapReduce:
A Distributed Computing Framework for Iterative Computation

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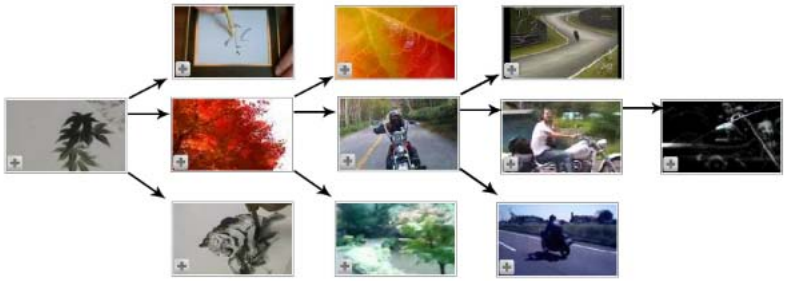
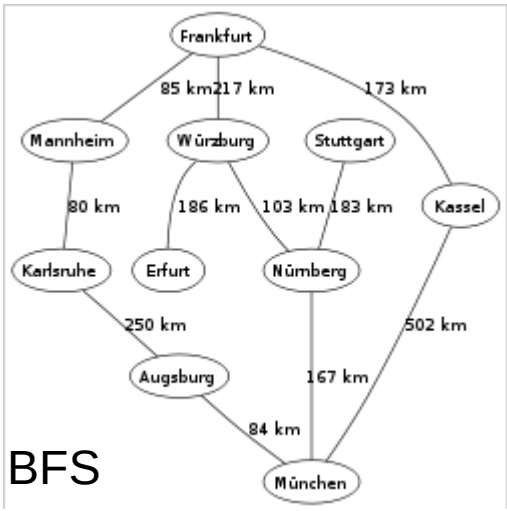
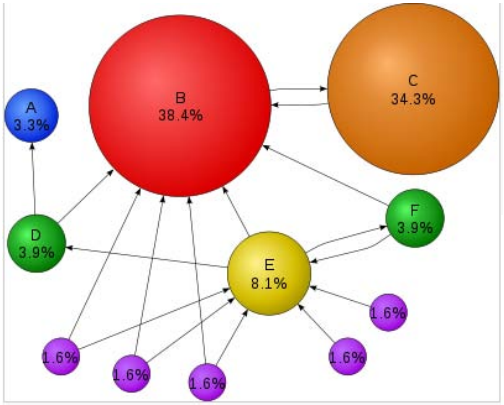
Iterative Computation Everywhere



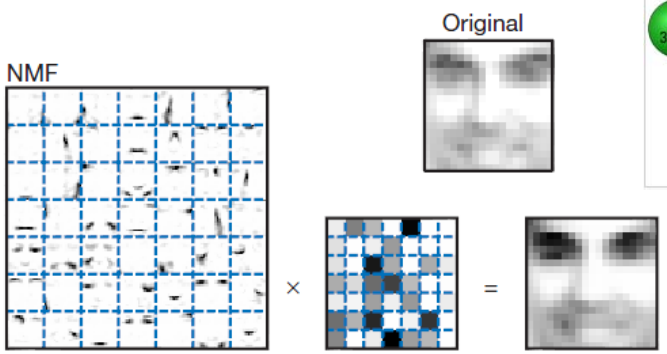
Video suggestion



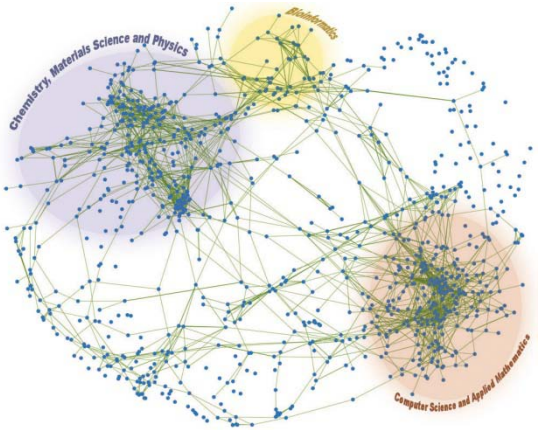
BFS



PageRank

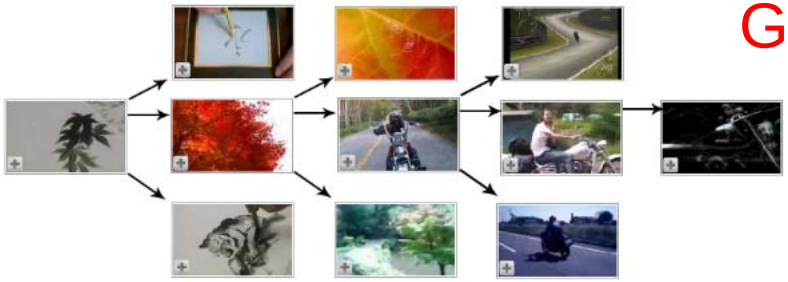


Pattern Recognition



Clustering

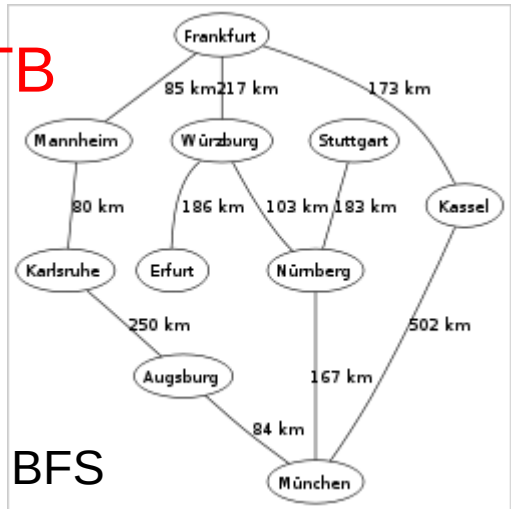
Iterative Computation on Massive Data



Video suggestion

100 million videos

Google maps 70.5TB



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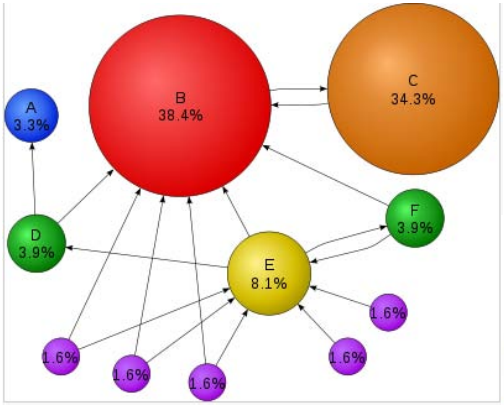
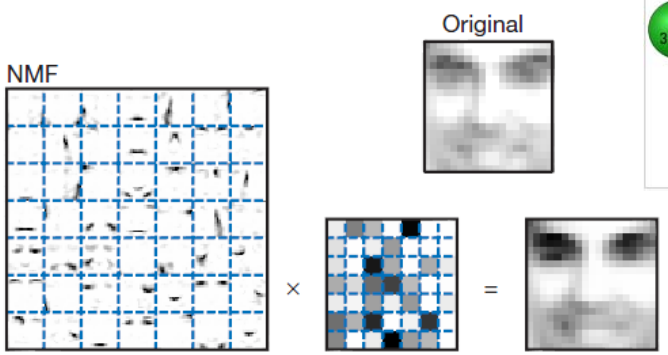


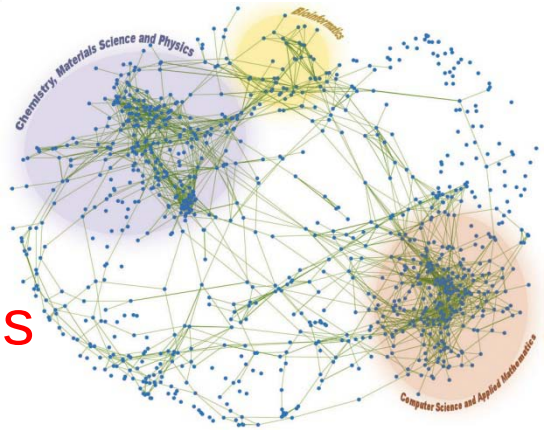
PageRank

29.7 billion pages



Pattern Recognition

500TB/yr hospital



700PB human genomics Clustering

Large-Scale Solution MapReduce

- Programming model
  - Map: distribute computation workload
  - Reduce: aggregate the partial results
- But, no support of iterative processing
  - Batched processing
  - Must design a series of jobs, do the same thing many times
    - Task reassignment, data loading, data dumping

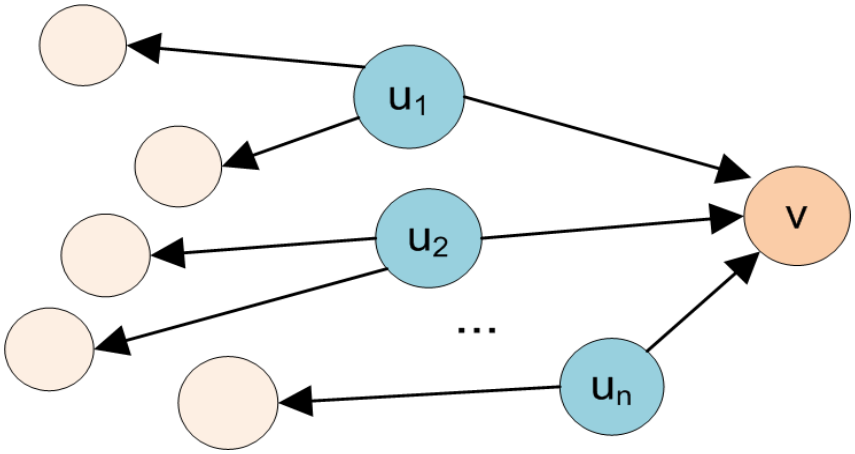
Outline

- Introduction & Motivation
- Example: PageRank in MapReduce
- System Design: iMapReduce
- Evaluation
- Conclusions

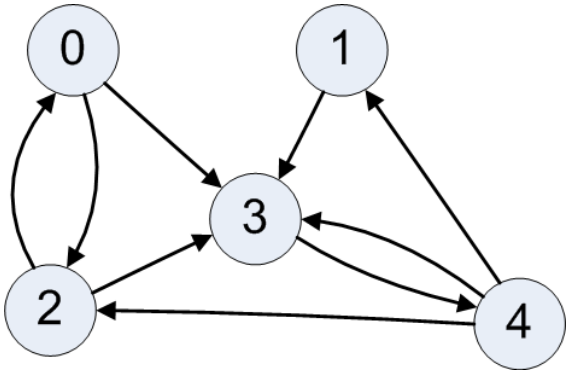
PageRank

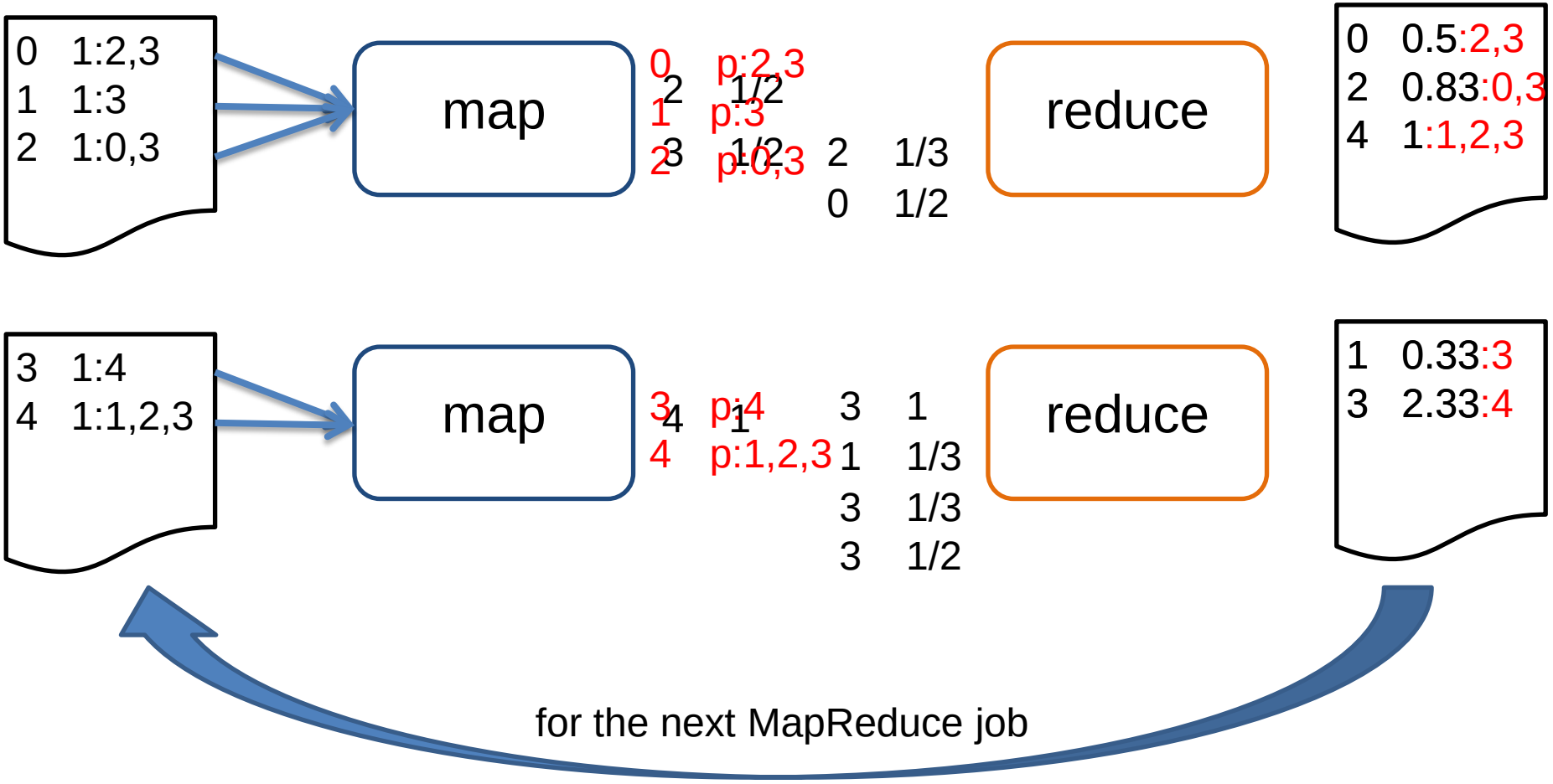
- Each node associated with a ranking score R
  - Evenly to its neighbors with portion d
  - Retain portion (1-d)

$$R^{k+1}(v) = d \cdot \left(\frac{R^k(u_1)}{N(u_1)} + \frac{R^k(u_2)}{N(u_2)} + \ldots + \frac{R^k(u_n)}{N(u_n)} \right) + (1-d) \cdot \frac{1}{|V|}$$



PageRank in MapReduce





Problems of Iterative Implementation

- 1. Multiple times job/task initializations
- 2. Re-shuffling the static data
- 3. Synchronization barrier between jobs

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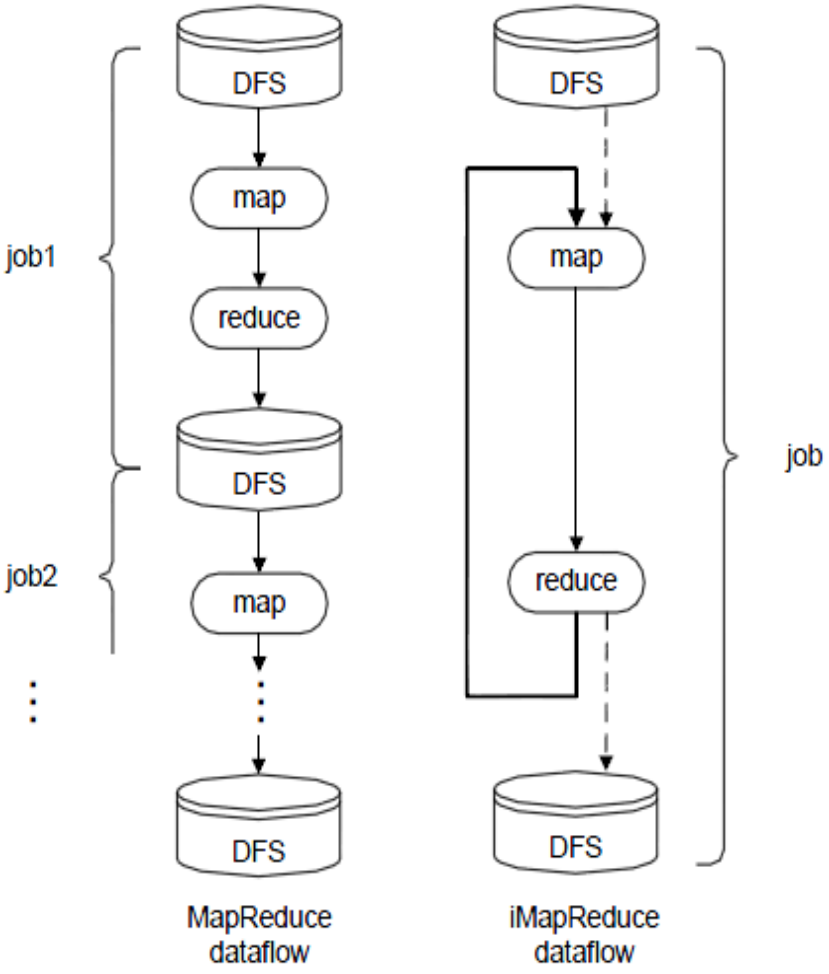
iMapReduce Solutions

- 1. Multiple job/task initializations
  - Iterative processing
- 2. Re-shuffling the static data
  - Maintain static data locally
- 3. Synchronization barrier between jobs
  - Asynchronous map execution

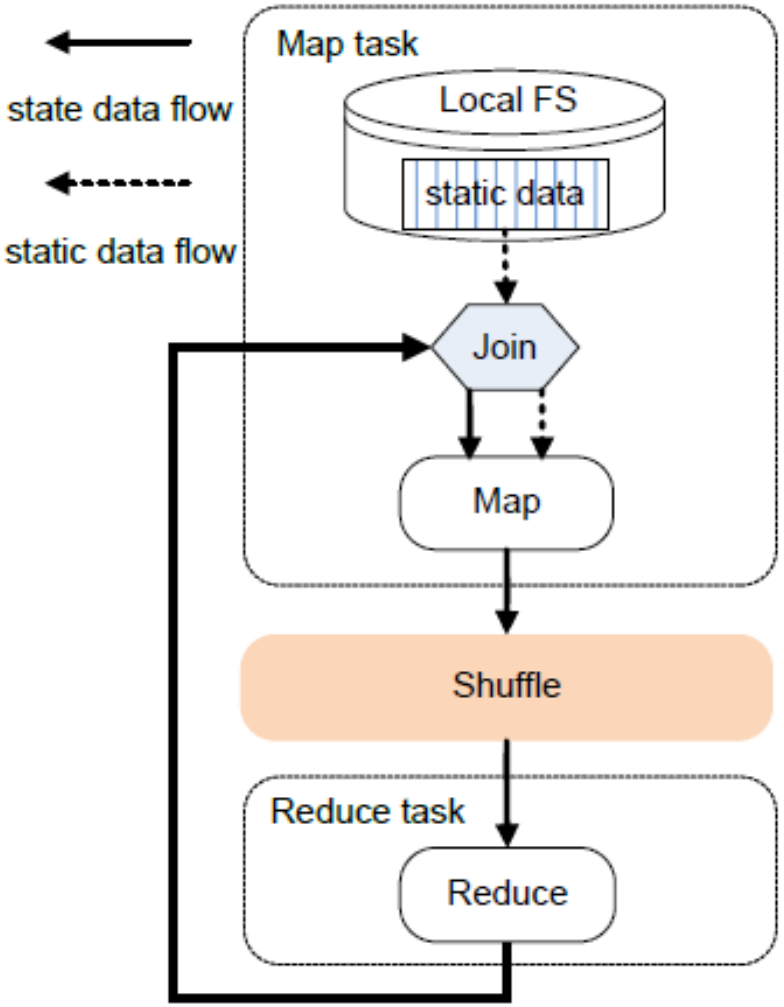
Iterative Processing

- Reduce → Map
  - Load/dump once
  - Persistent map/reduce task
  - Each reduce task has a correspondent map task
  - Locally connected

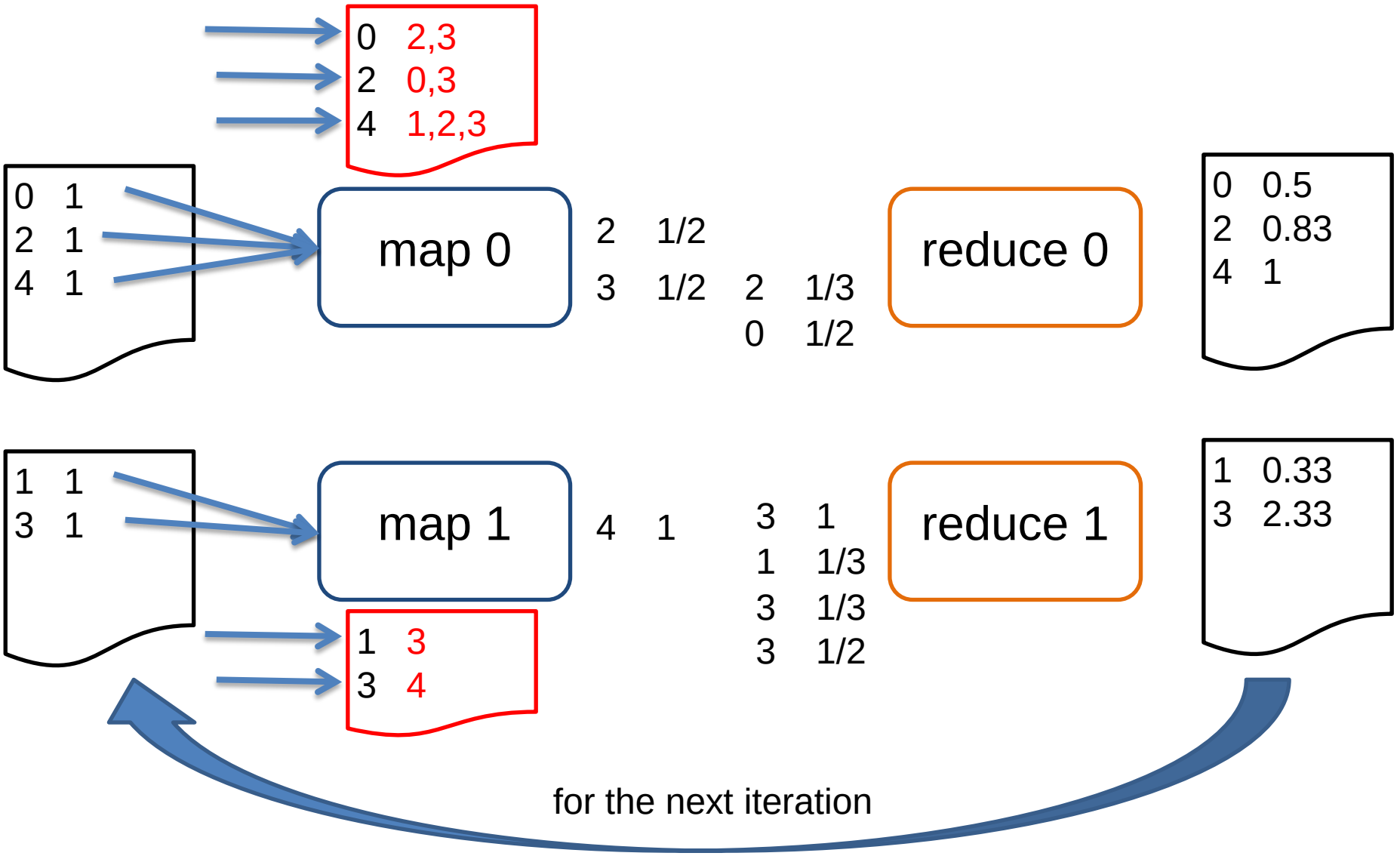


Maintain Static Data Locally

- Iterate state data
  - Update iteratively
- Maintain static data
  - Join with state data at map phase

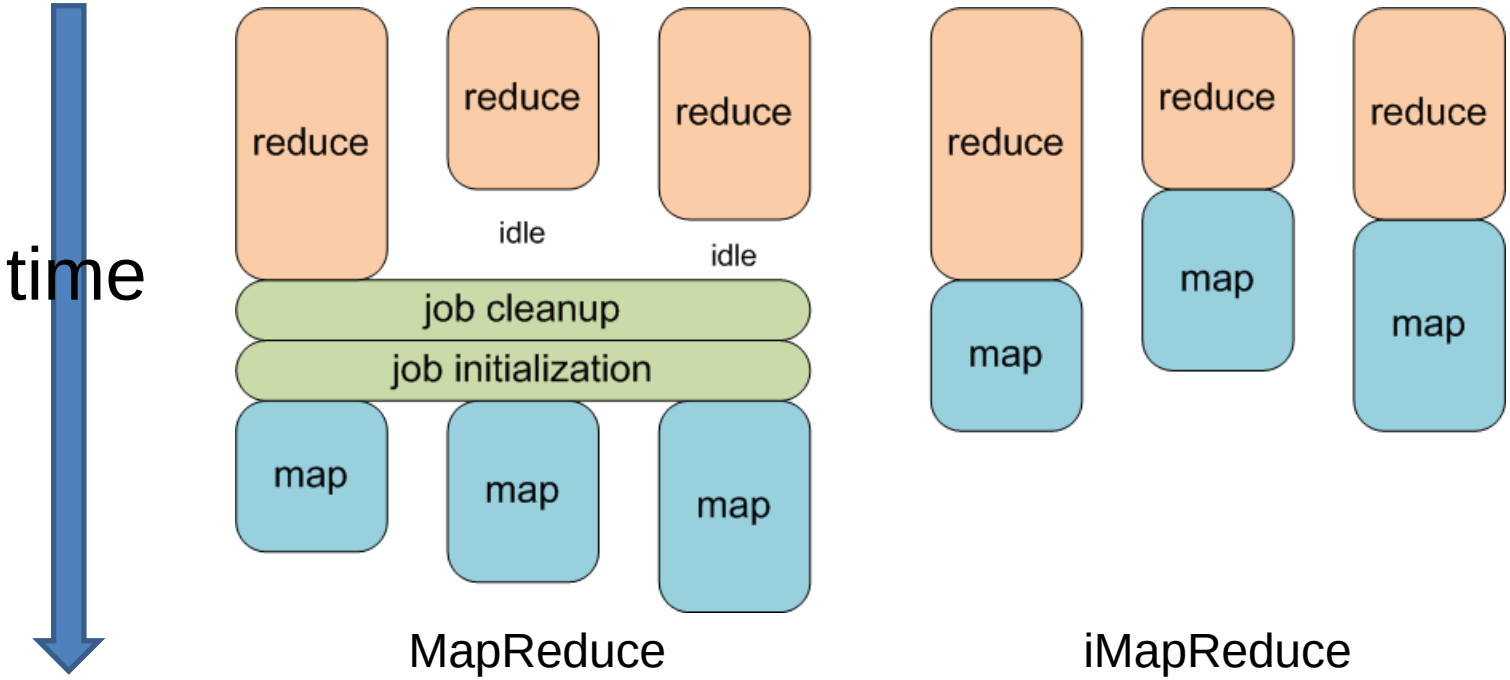


State Data ⋈ Static Data



Asynchronous Map Execution

- Persistent socket reduce -> map
- Reduce completion directly trigger map
- Map tasks no need to wait



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Experiment Setup

- Cluster
  - Local cluster: 4 nodes
  - Amazon EC2 cluster: 80 small instances
- Implemented algorithms
  - Shortest path, PageRank, K-Means
- Data sets

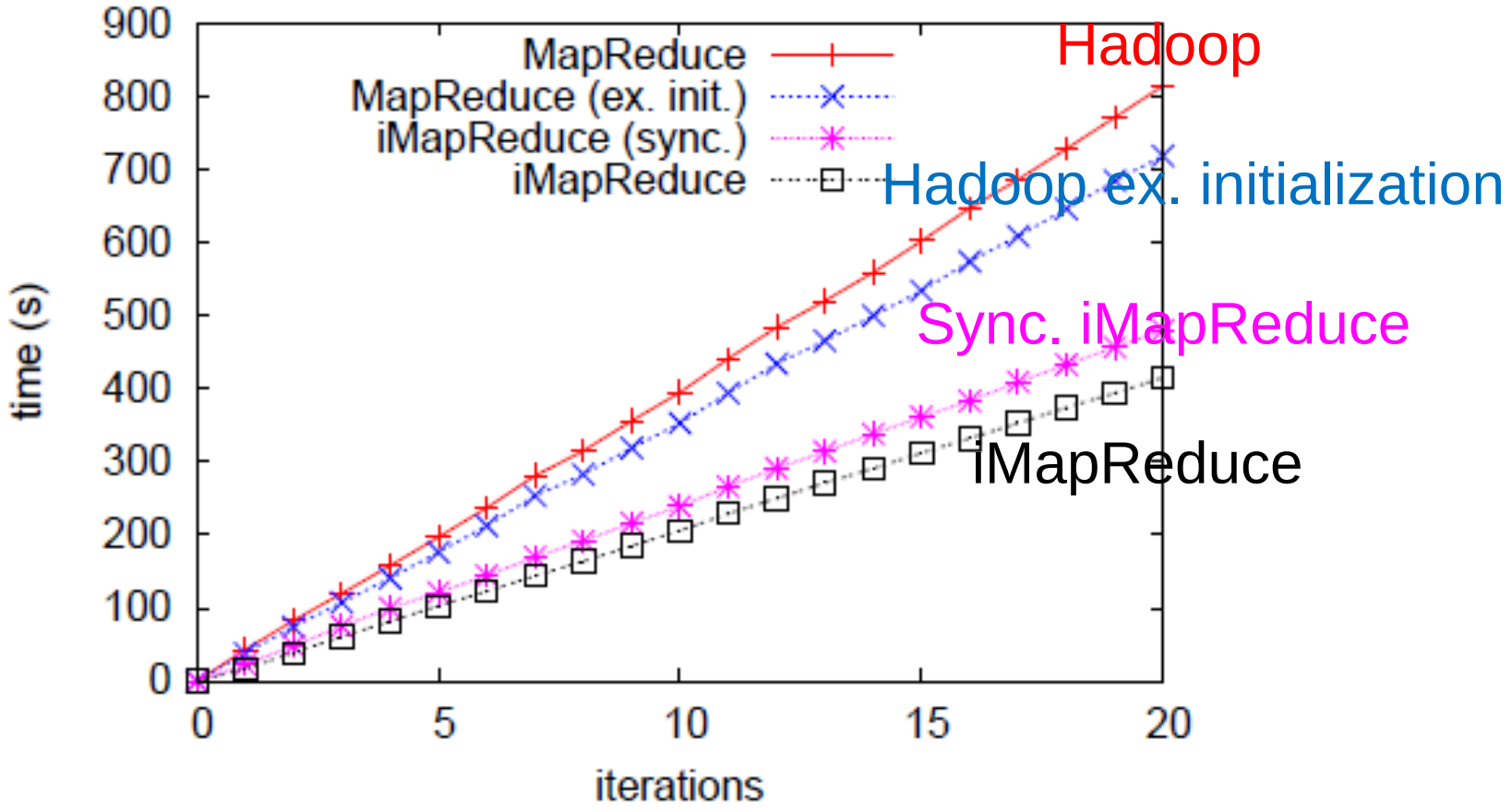
graph	# of nodes	# of edges	file size
DBLP	310,556	1,518,617	16MB
Facebook	1,204,004	5,430,303	58MB
SSPP-s	1M	7,868,140	87MB
SSPP-m	10M	78,873,968	958MB
SSPP-l	50M	369,455,293	5.19GB

SSSP

graph	# of nodes	# of edges	file size
Google	916,417	6,078,254	49MB
Berk-Stan	685,230	7,600,595	57MB
PageRank-s	1M	7,425,360	61MB
PageRank-m	10M	75,061,501	690MB
PageRank-l	30M	224,493,620	2.26GB

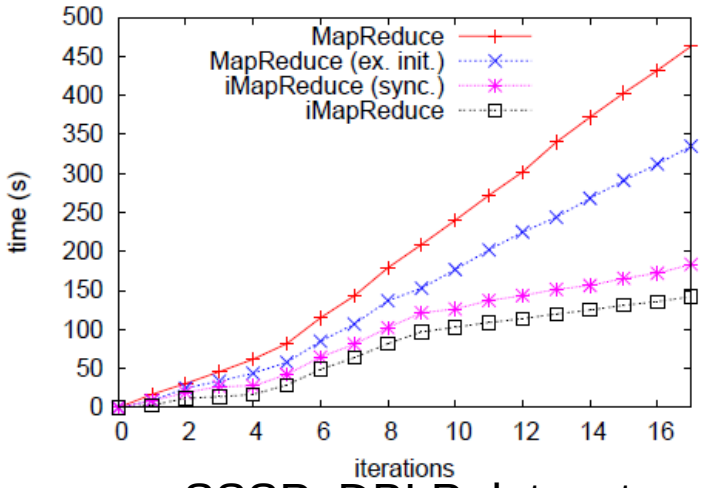
PageRank

Results on Local Cluster

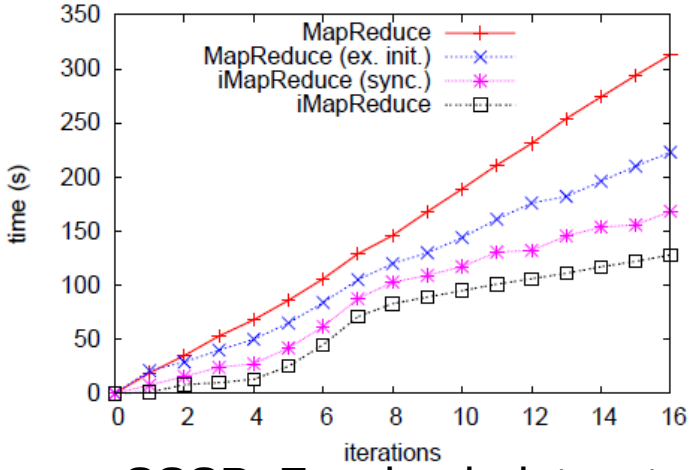


PageRank: google webgraph

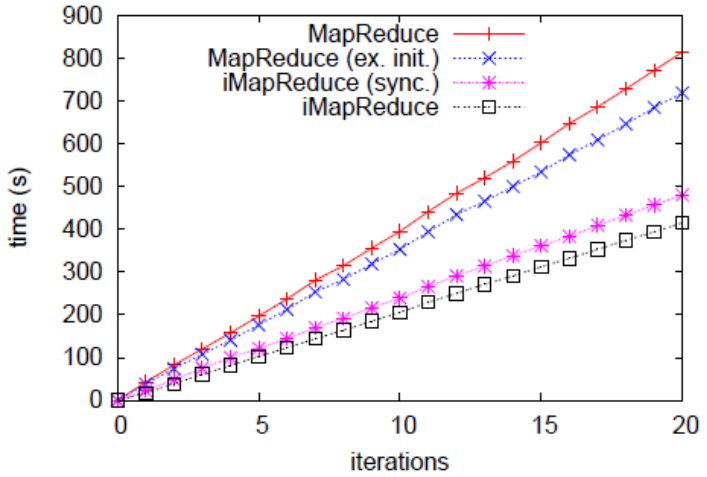
Results cont.



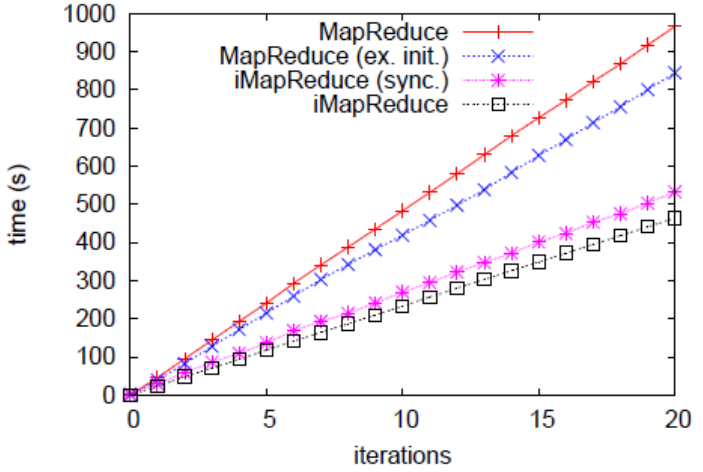
SSSP: DBLP dataset



SSSP: Facebook dataset



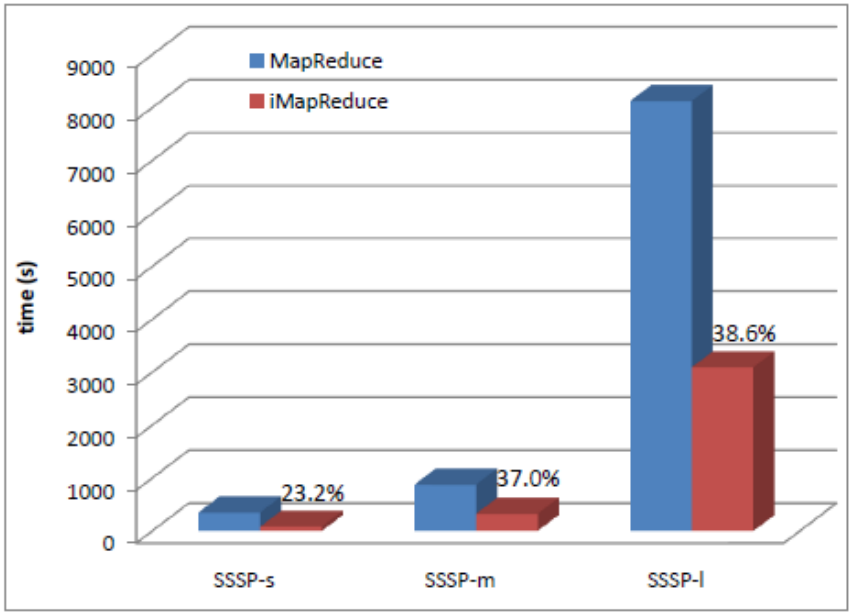
PageRank: google webgraph



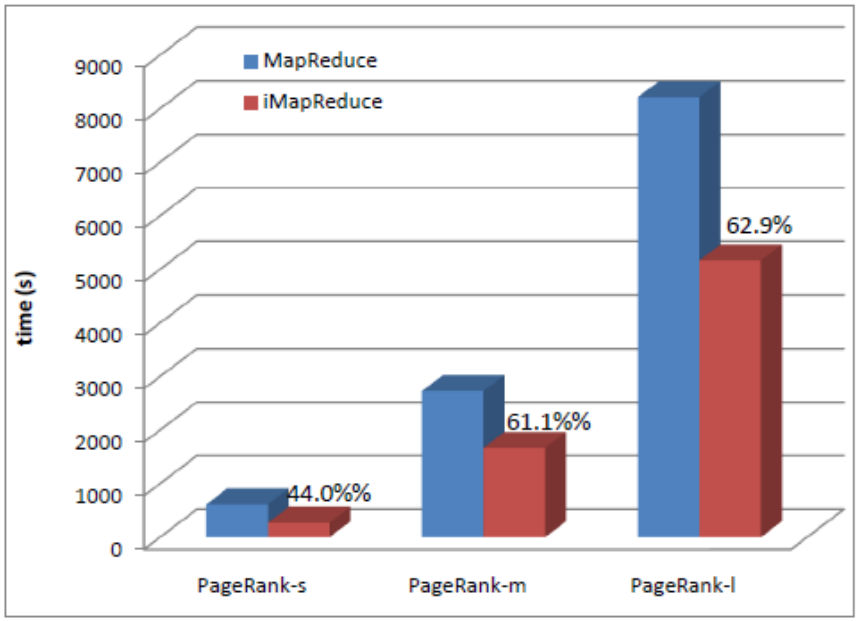
PageRank: Berk-Stan webgraph

Scale to Large Data Sets

- On Amazon EC2 cluster
- Various-size graphs

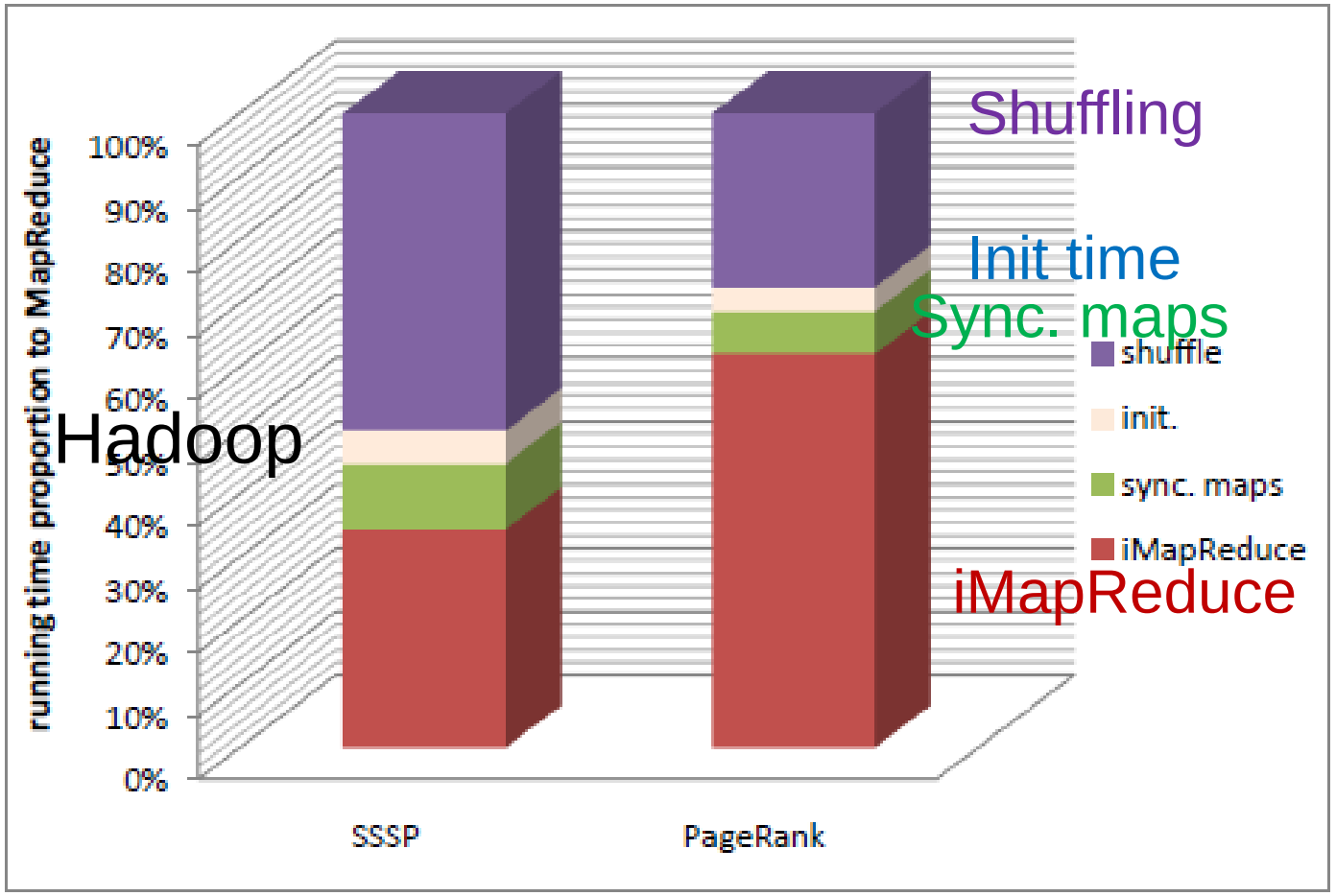


SSSP



PageRank

Different Factors on Running Time Reduction



Conclusion

- iMapReduce reduces running time by
  - Reducing the overhead of job/task initialization
  - Eliminating the shuffling of static data
  - Allowing asynchronous map execution
- Achieve a factor of 1.2x to 5x speedup
- Suitable for most iterative computations

Q & A

- Thank you!