UNIVERSITY OF WATERLOO

Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2017)

Week 11: Analyzing Graphs, Redux (1/2)

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University of Waterloo

These slides are available at http://lintool.github.io/bigdata-2017w/

Graph Algorithms, again?
(srsly?)

What makes graphs hard?

Irregular structure

Fun with data structures!

Irregular data access patterns

Fun with architectures!

Iterations

Fun with optimizations!

Characteristics of Graph Algorithms

Irregular structure and data access patterns!

Parallel graph traversals

Local computations

Message passing along graph edges

Iterations

PageRank: Defined

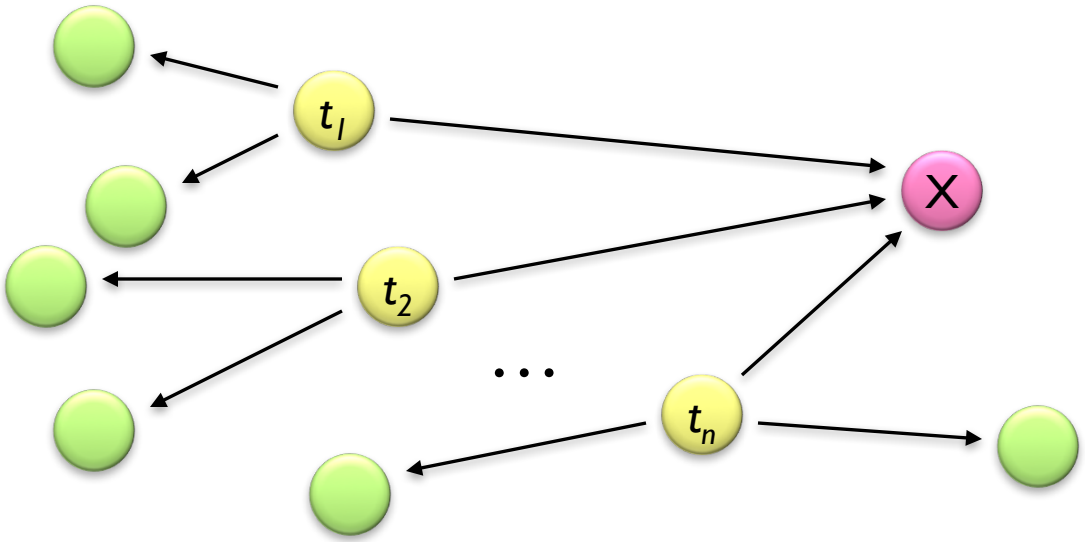
Given page *x* with inlinks $t_1 \ldots t_n$, where

C(t) is the out-degree of *t*

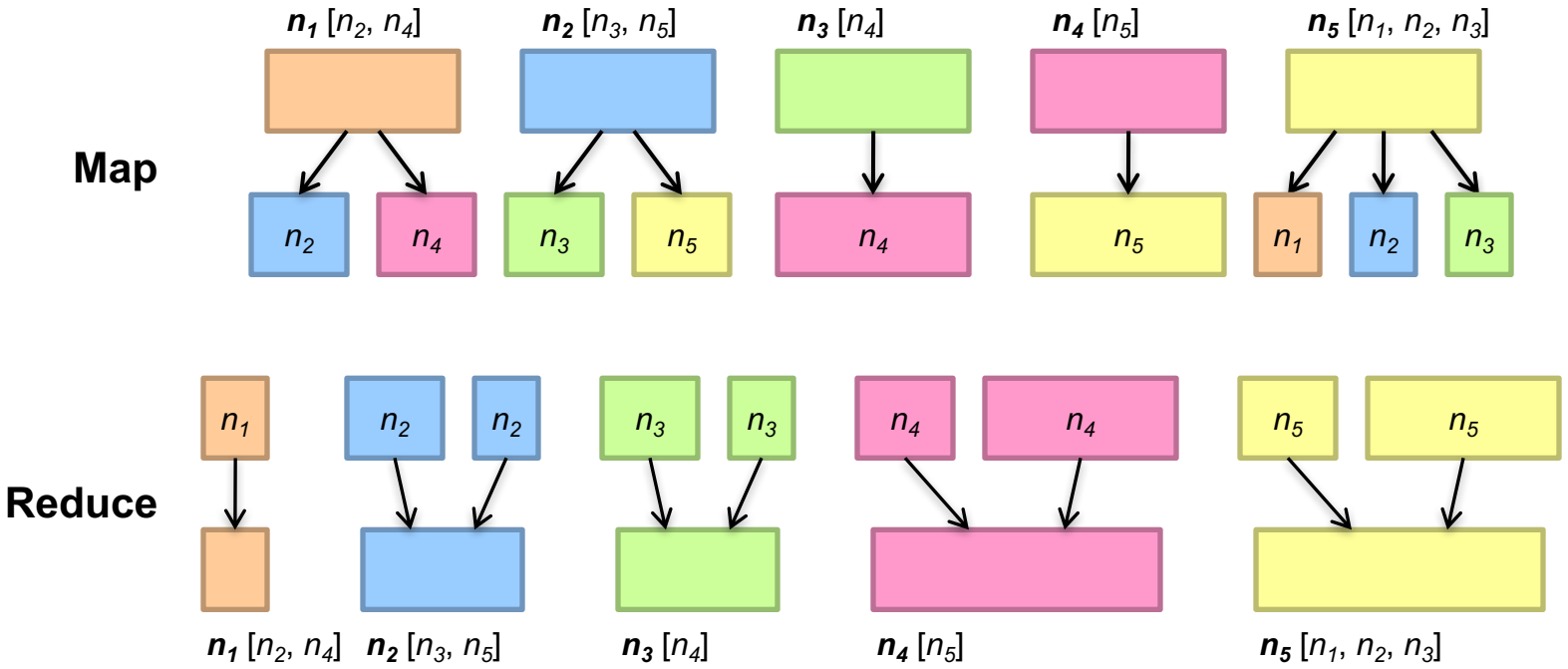
α is probability of random jump

N is the total number of nodes in the graph

$$PR(x) = \alpha \left(\frac{1}{N}\right) + (1-\alpha) \sum_{i=1}^{n} \frac{PR(t_i)}{C(t_i)}$$



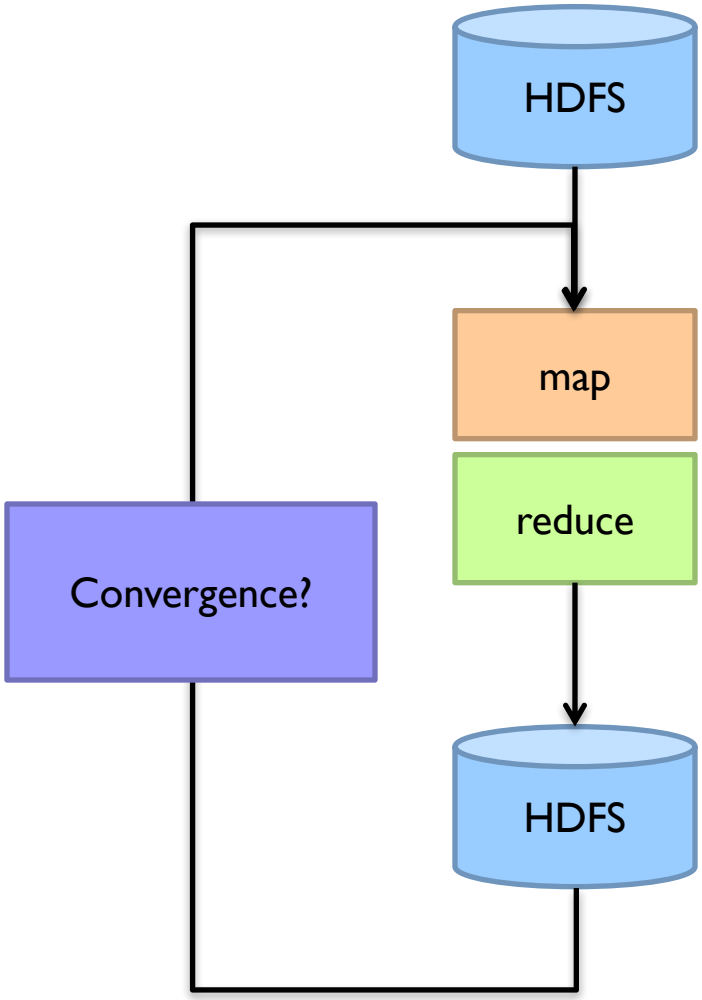
PageRank in MapReduce



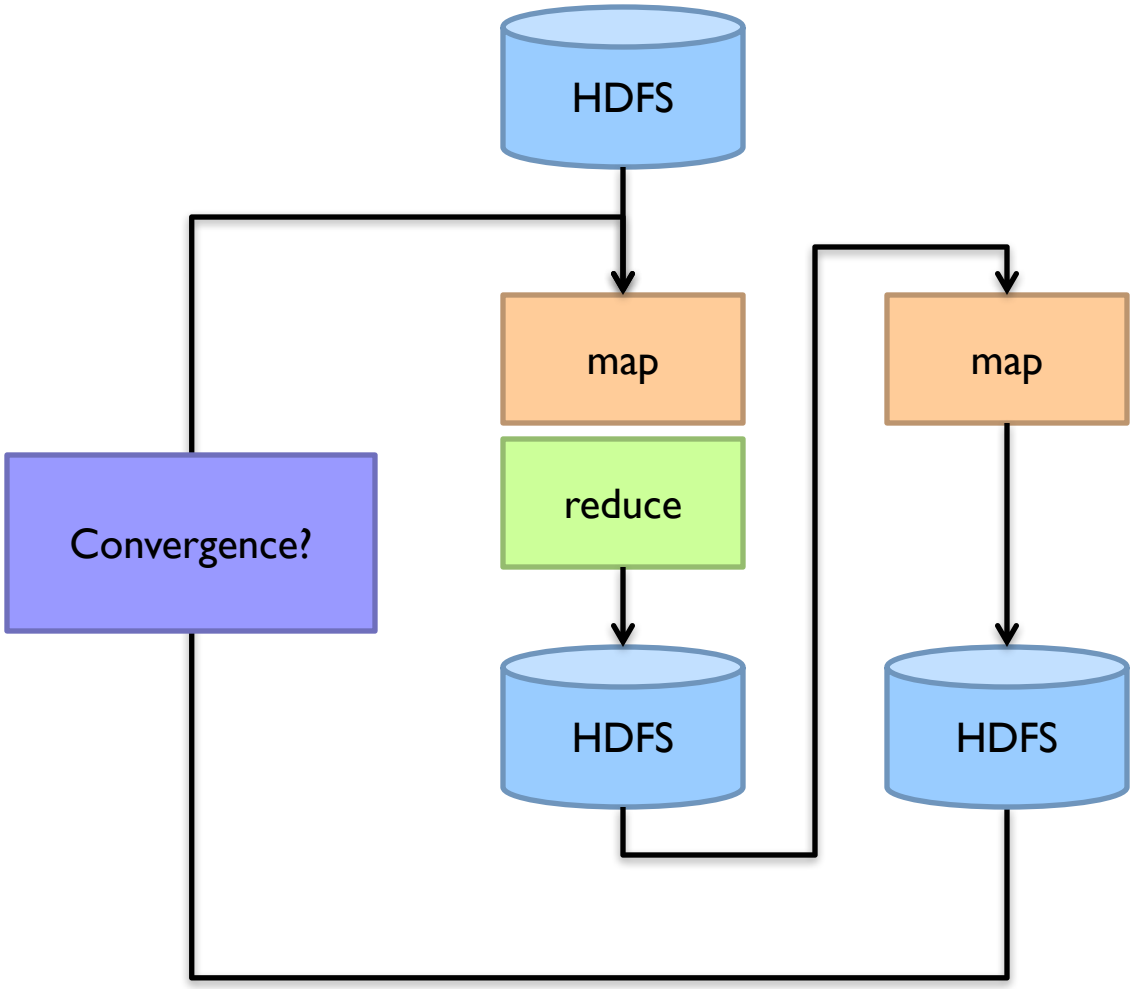
PageRank vs. BFS

	PageRank	BFS
Map	PR/N	d+1
Reduce	sum	min

BFS



PageRank



MapReduce Sucks

Java verbosity

Hadoop task startup time

Stragglers

Needless graph shuffling

Checkpointing at each iteration

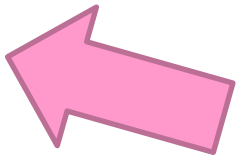
Characteristics of Graph Algorithms

Parallel graph traversals

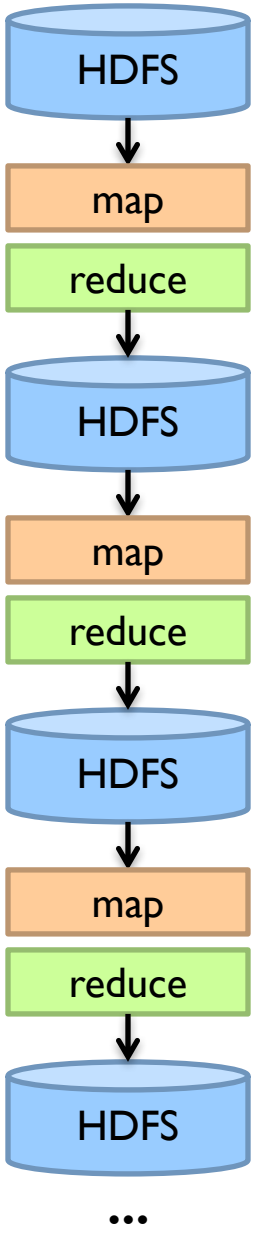
Local computations

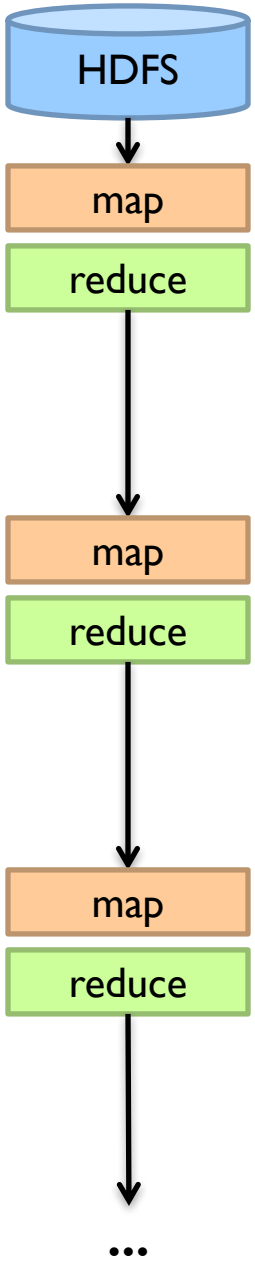
Message passing along graph edges

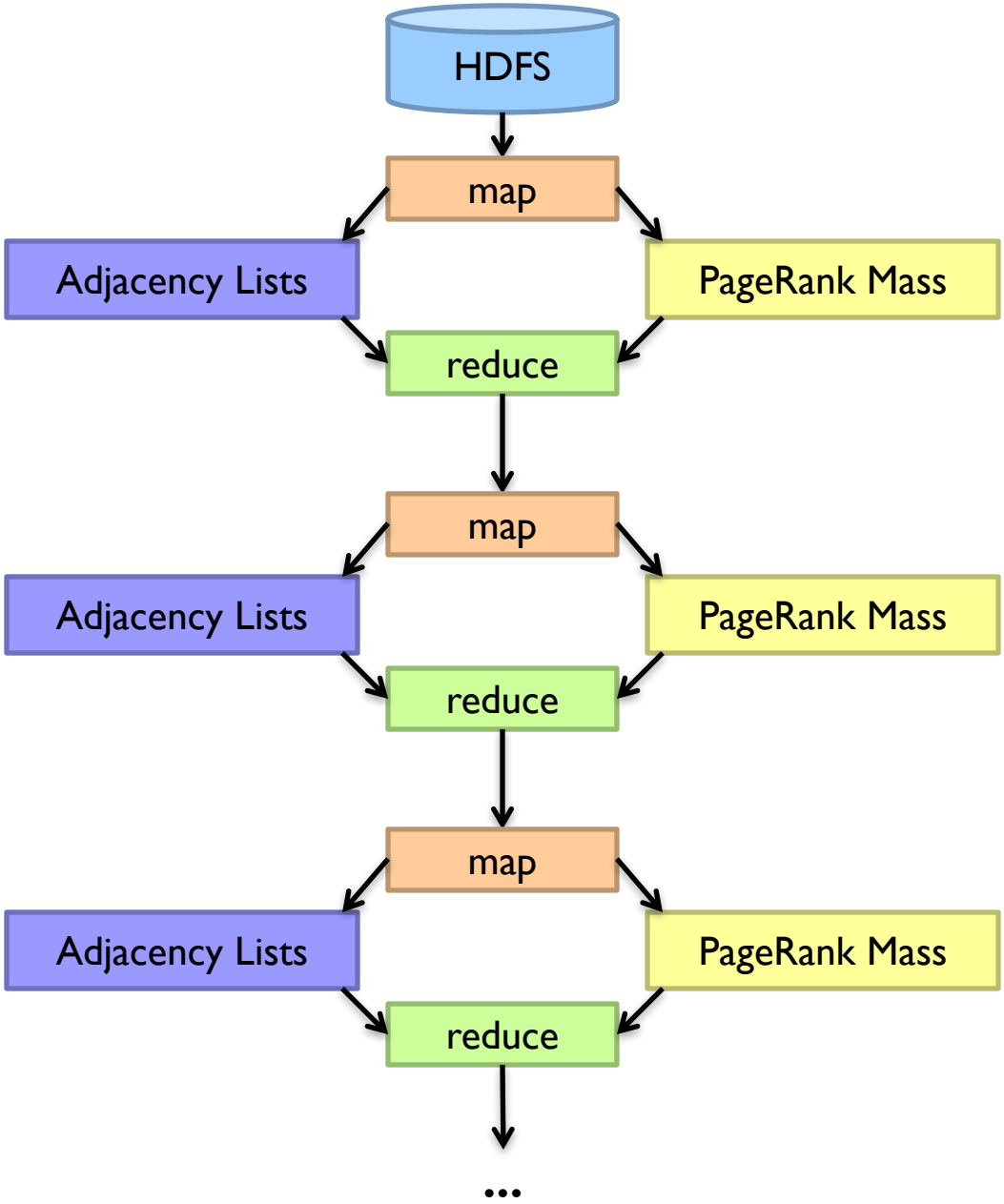
Iterations



Let's Spark!




HDFS
map
reduce
map
reduce
map
reduce
...


HDFS
map
Adjacency Lists
PageRank Mass
reduce
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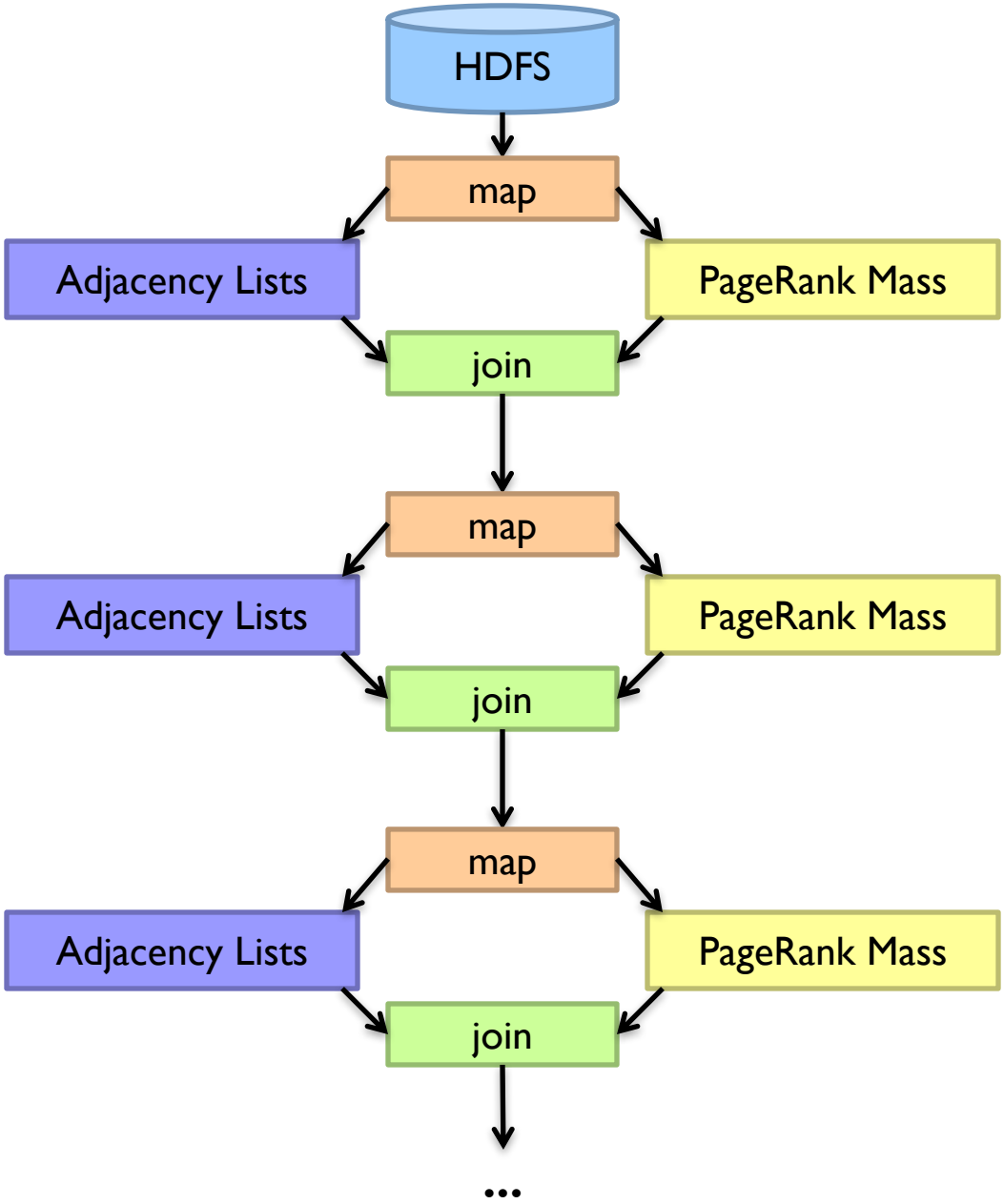
HDFS
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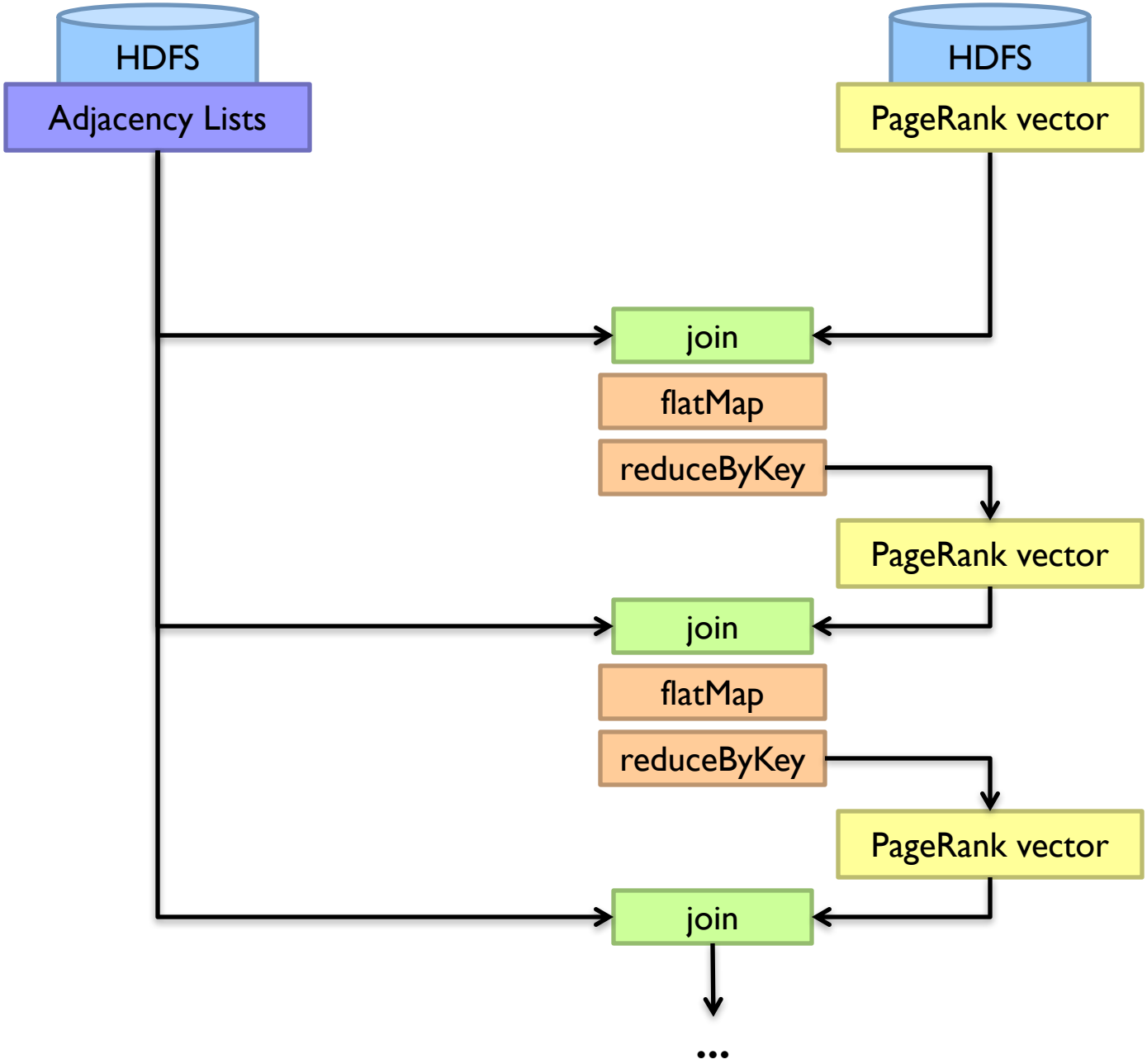
HDFS
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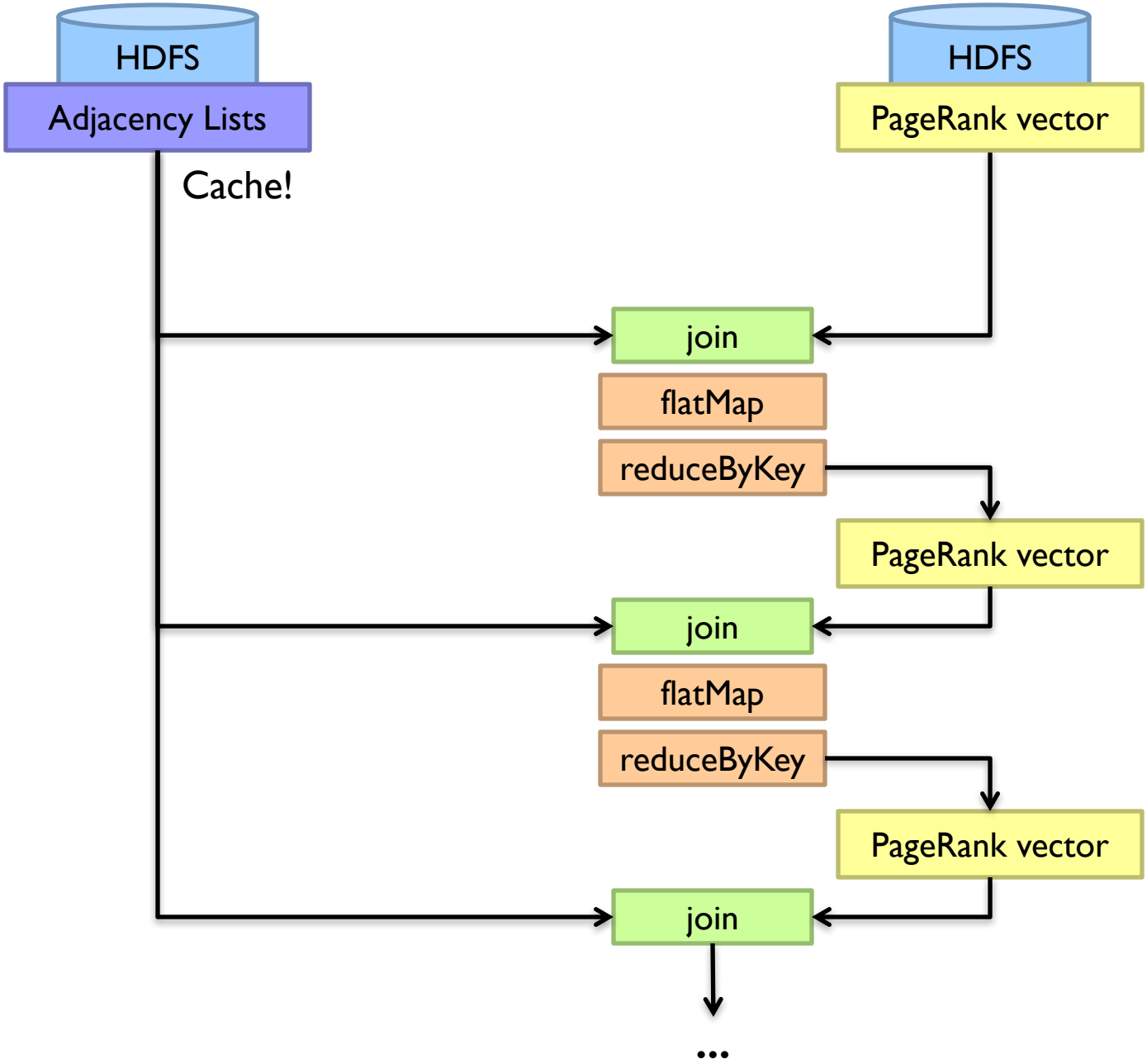
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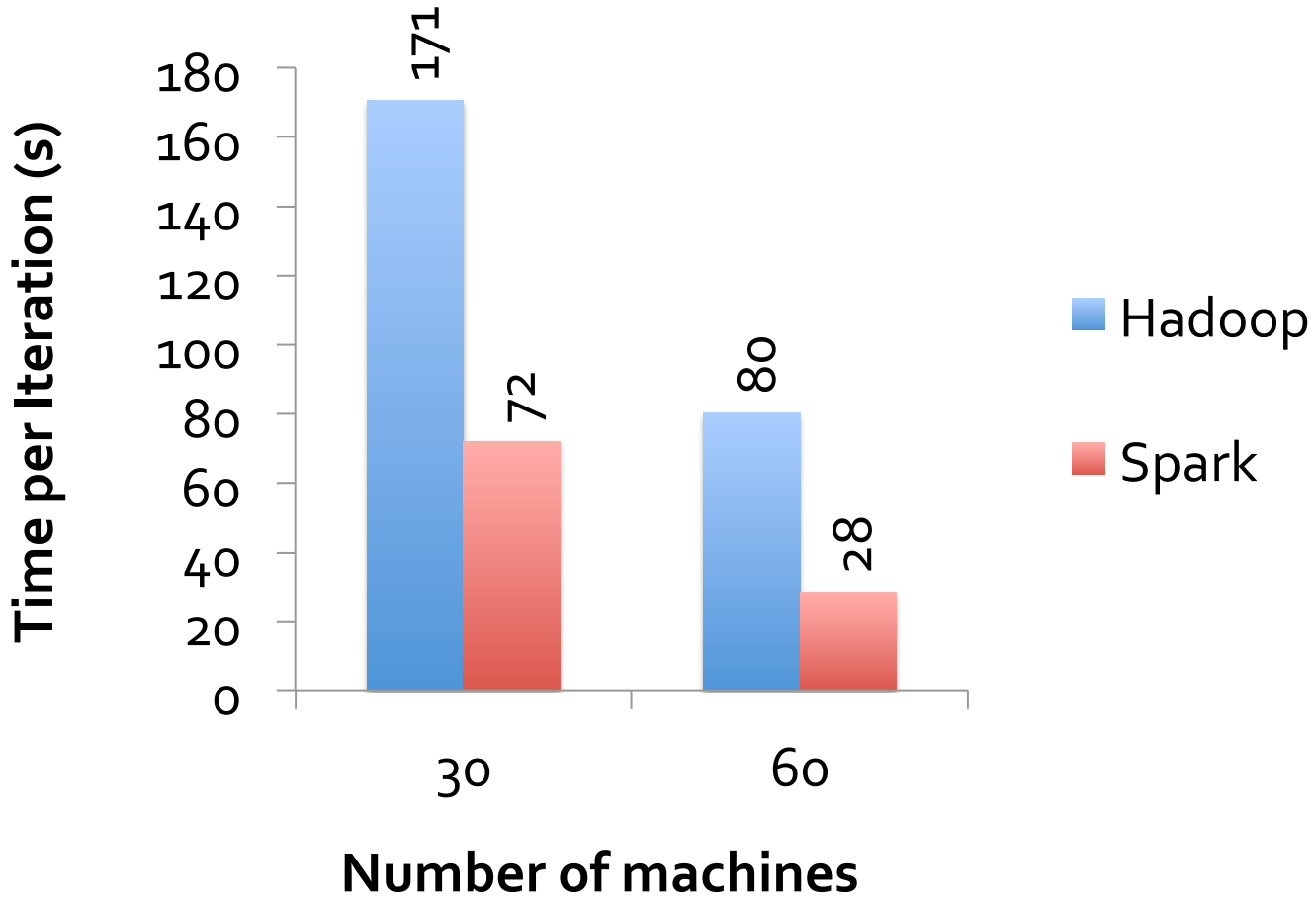
MapReduce vs. Spark



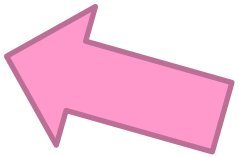
Source: http://ampcamp.berkeley.edu/wp-content/uploads/2012/06/matei-zaharia-part-2-amp-camp-2012-standalone-programs.pdf

Characteristics of Graph Algorithms

Parallel graph traversals

Local computations

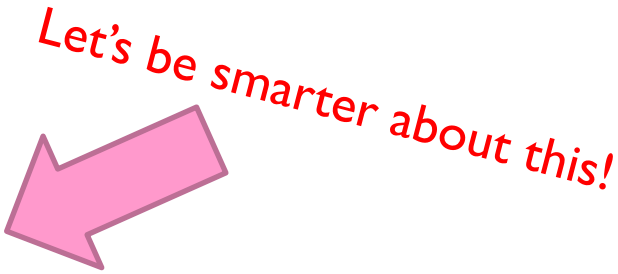
Message passing along graph edges



Iterations

Even faster?

Big Data Processing in a Nutshell



Partition

Replicate

Reduce cross-partition communication

Simple Partitioning Techniques

Hash partitioning

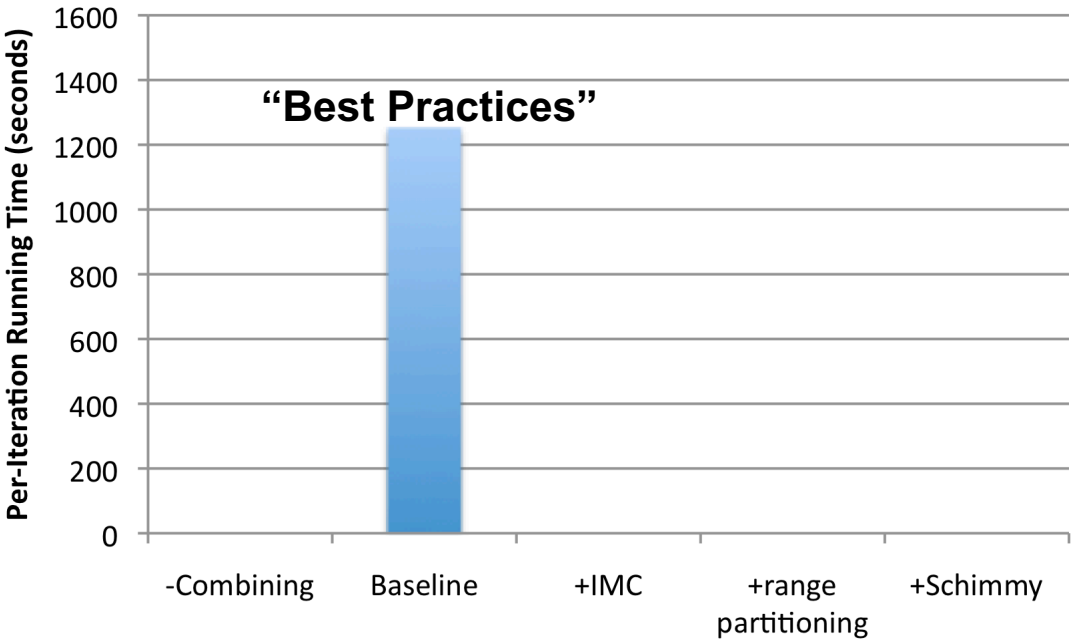
Range partitioning on some underlying linearization

Web pages: lexicographic sort of domain-reversed URLs

Social networks: sort by demographic characteristics

Geo data: space-filling curves

How much difference does it make?



PageRank over webgraph
(40m vertices, 1.4b edges)

Lin and Schatz. (2010) Design Patterns for Efficient Graph Algorithms in MapReduce.

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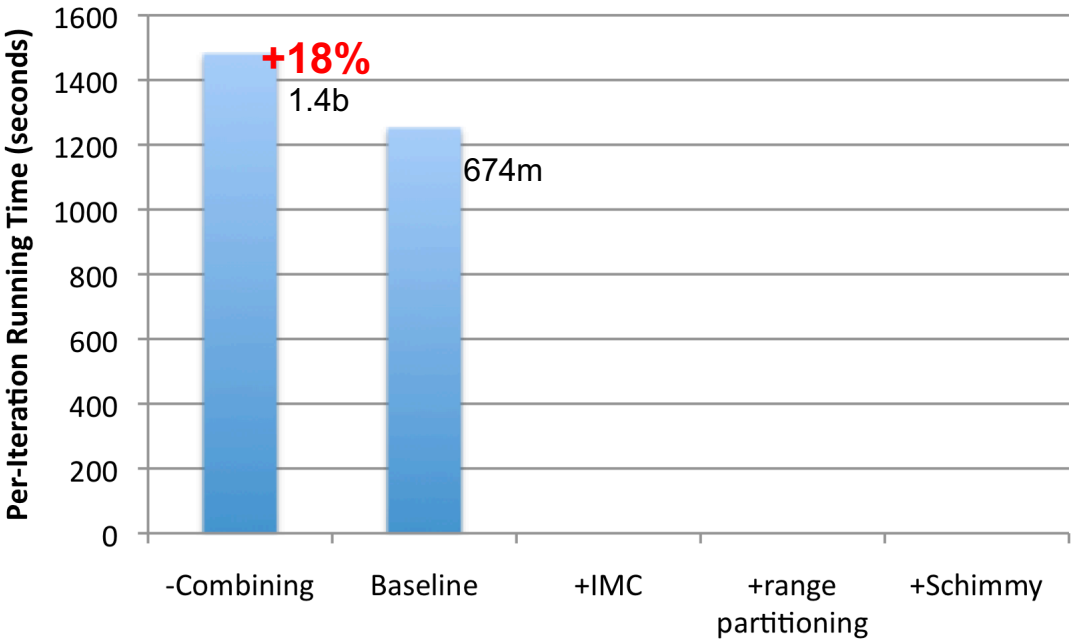

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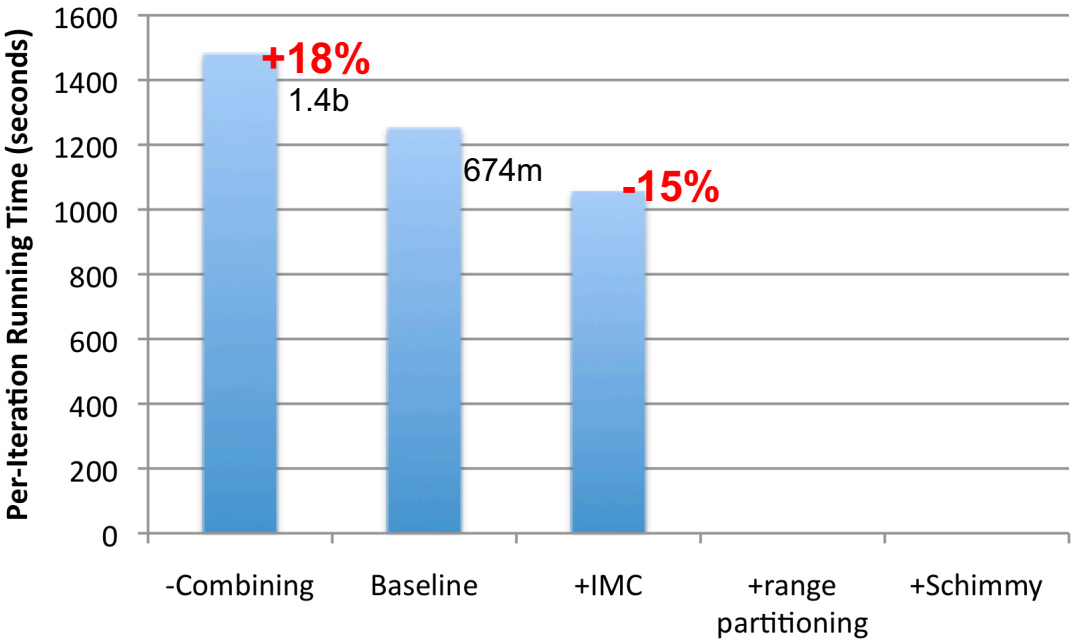

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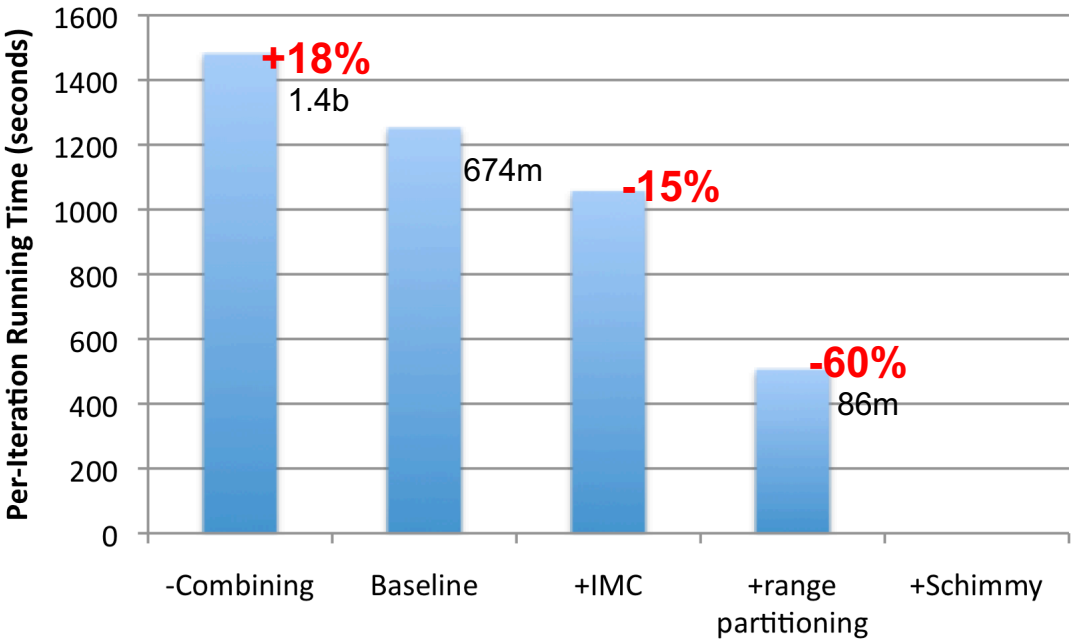

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Schimmy Design Pattern

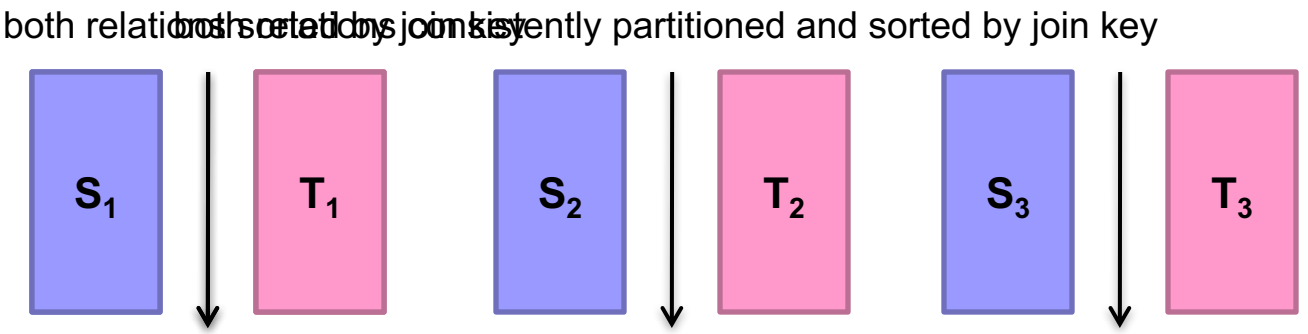
Basic implementation contains two dataflows:

Messages (actual computations)

Graph structure ("bookkeeping")

Schimmy: separate the two dataflows, shuffle only the messages

Basic idea: merge join between graph structure and messages



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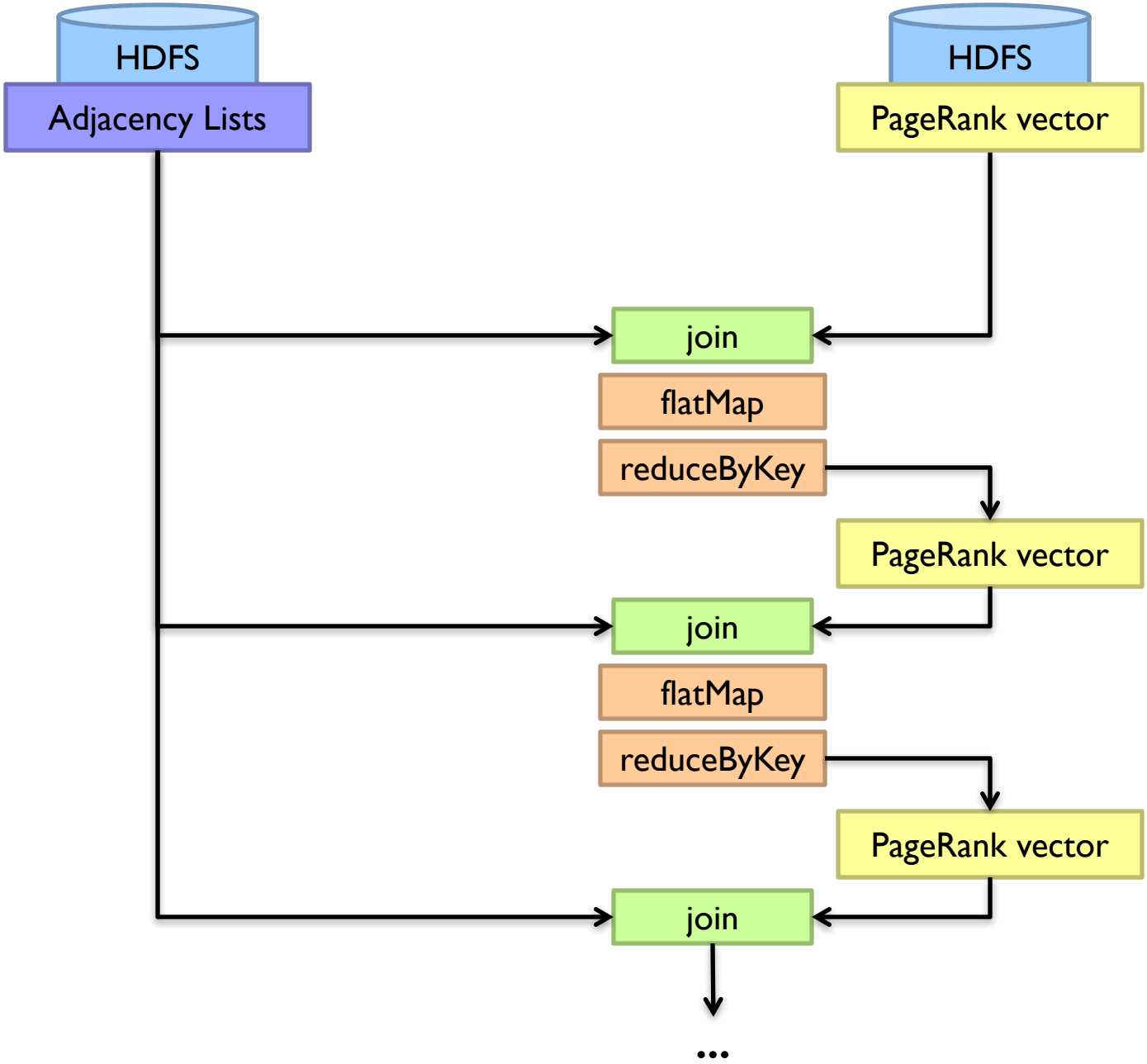
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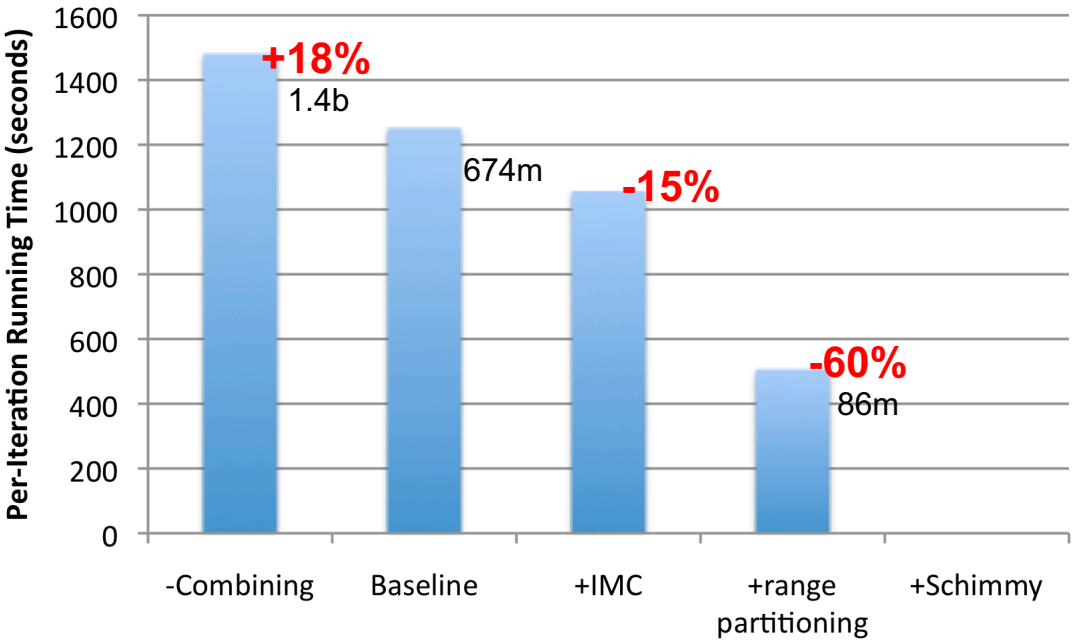

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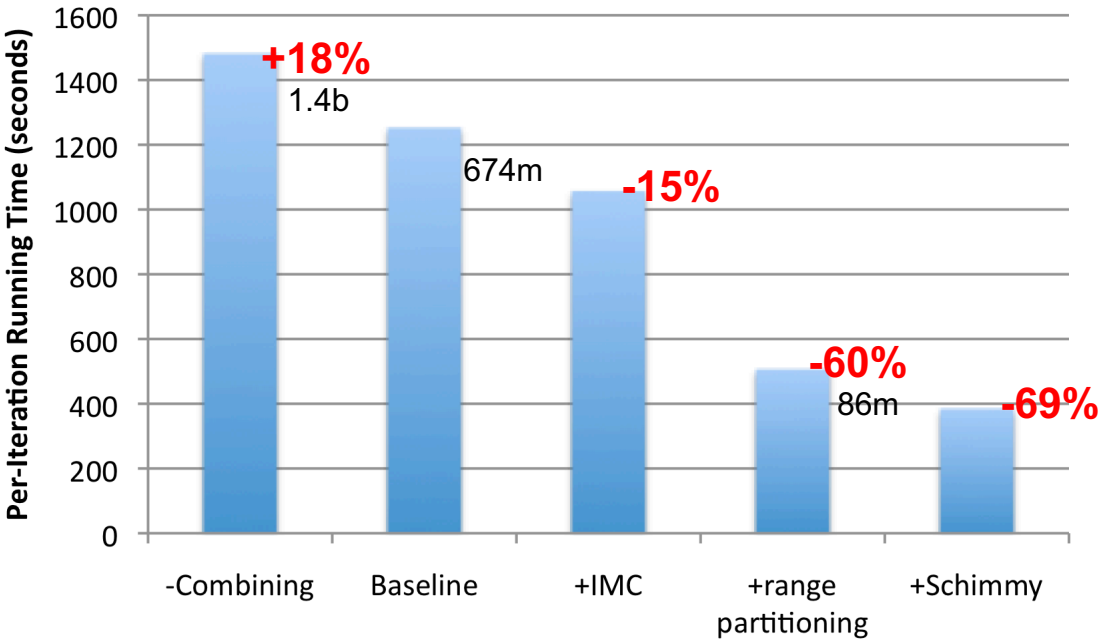

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Simple Partitioning Techniques

Hash partitioning

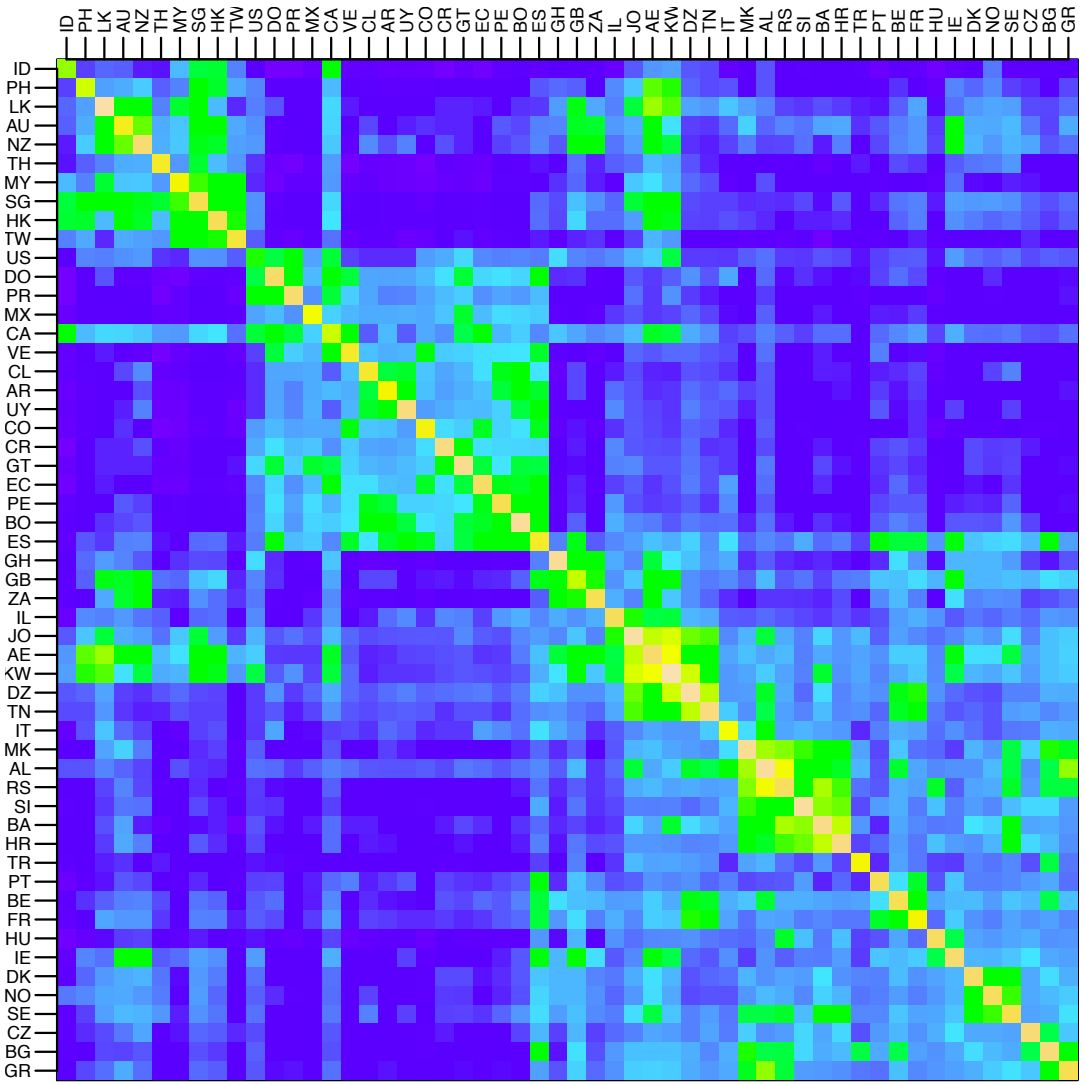
Range partitioning on some underlying linearization

Web pages: lexicographic sort of domain-reversed URLs

Social networks: sort by demographic characteristics

Geo data: space-filling curves

Country Structure in Facebook



Analysis of 721 million active users (May 2011)

54 countries w/ >1m active users, >50% penetration

Ugander et al. (2011) The Anatomy of the Facebook Social Graph.

Simple Partitioning Techniques

Hash partitioning

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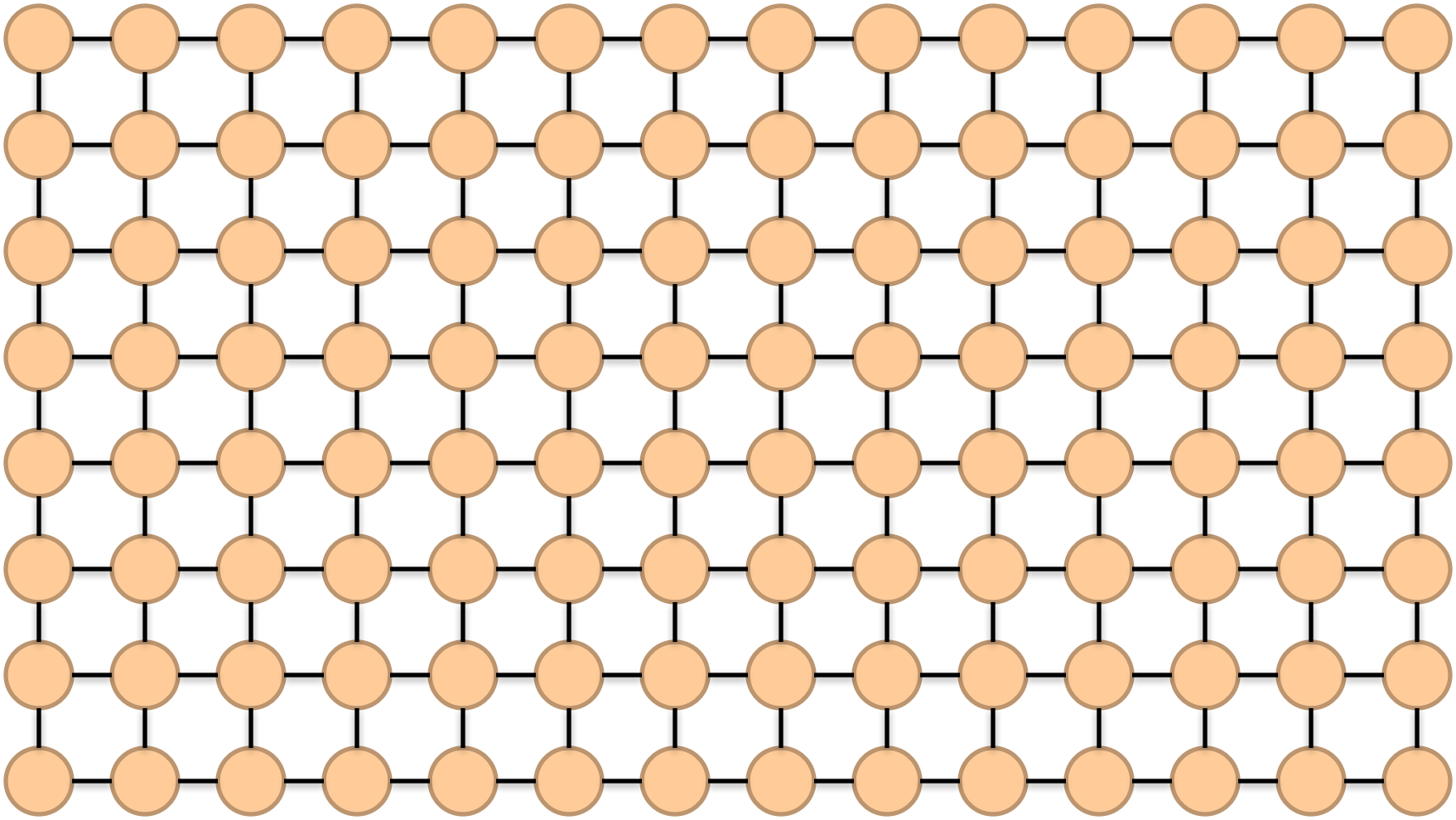
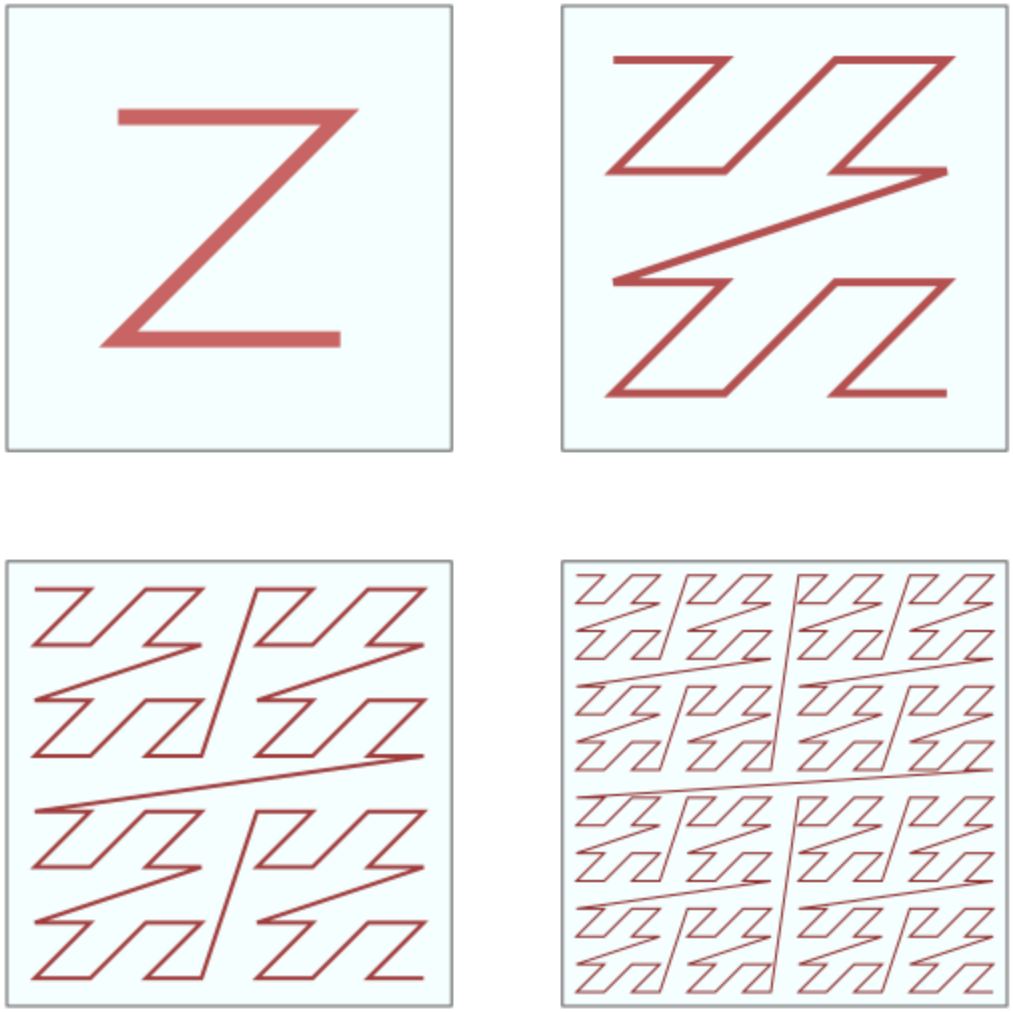
Aside: Partitioning Geo-data

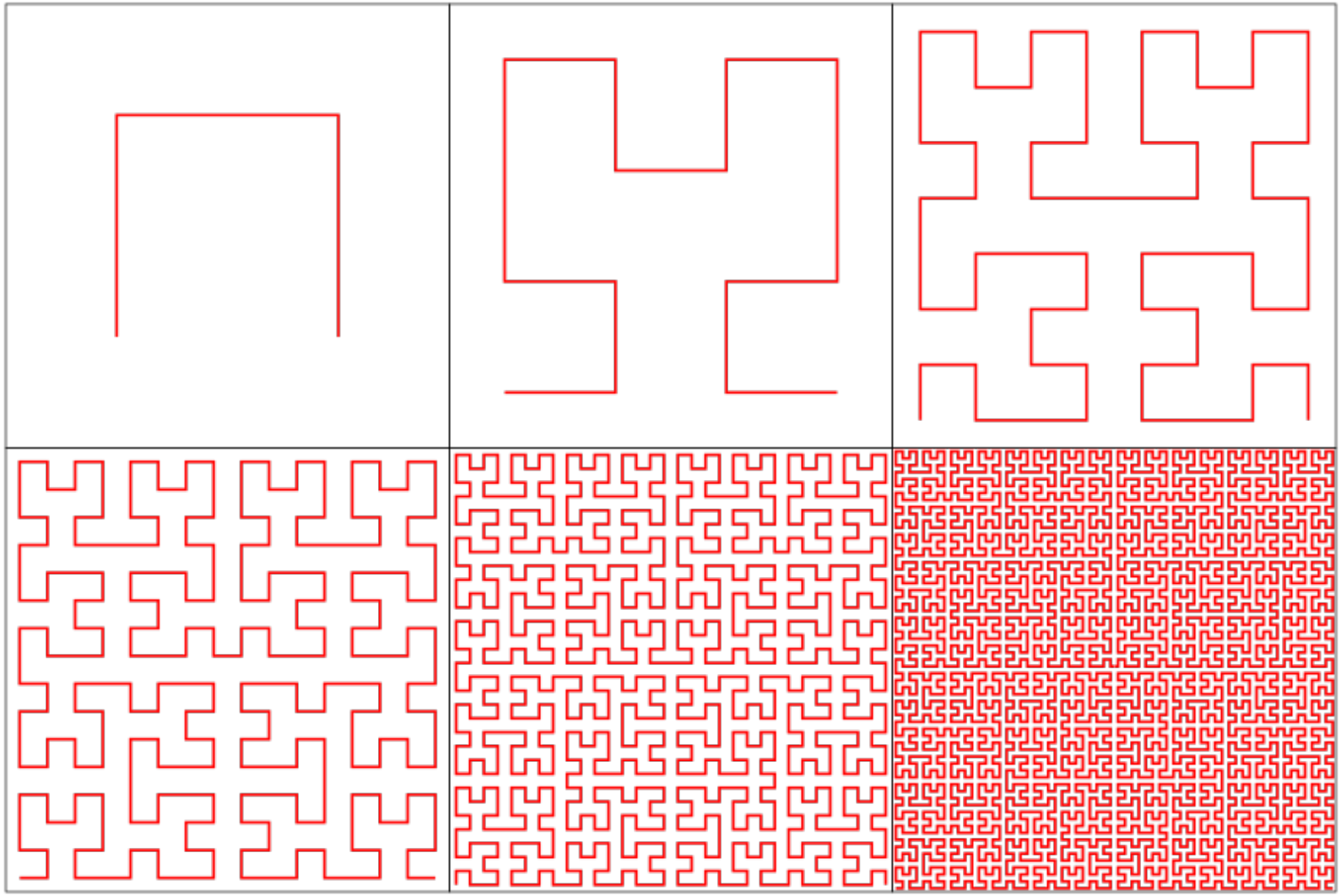
Geo-data = regular graph



Space-filling curves: Z-Order Curves



Space-filling curves: Hilbert Curves



Simple Partitioning Techniques

Hash partitioning

Range partitioning on some underlying linearization

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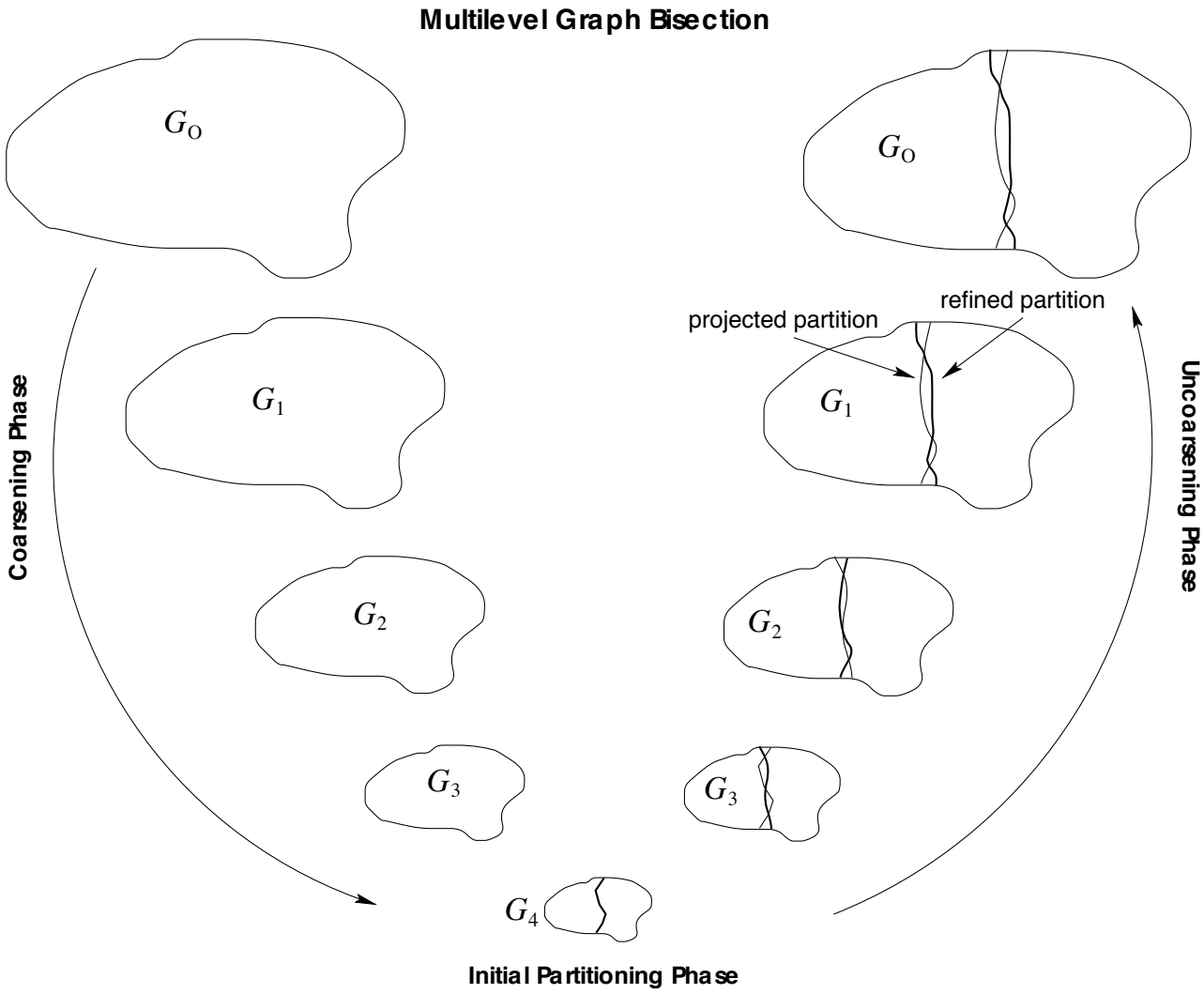
But what about graphs in general?

Source: http://www.flickr.com/photos/fusedforces/4324320625/

General-Purpose Graph Partitioning

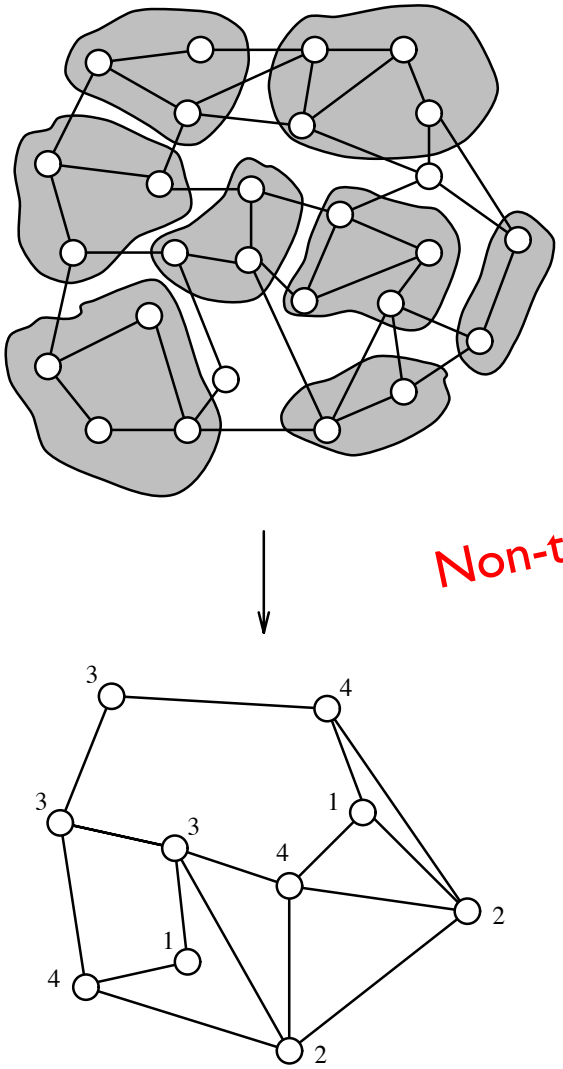
Recursive bisection
Graph coarsening

General-Purpose Graph Partitioning



Karypis and Kumar. (1998) A Fast and High Quality Multilevel Scheme for Partitioning Irregular Graphs.

Graph Coarsening



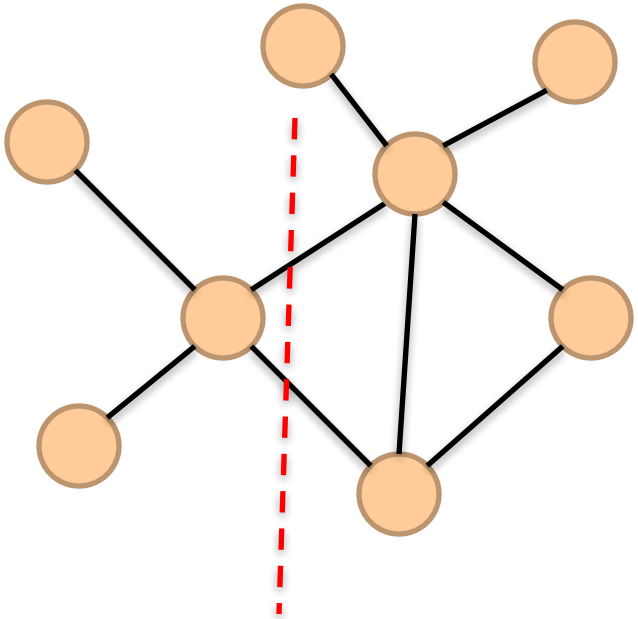
Non-trivial problem itself!

Karypis and Kumar. (1998) A Fast and High Quality Multilevel Scheme for Partitioning Irregular Graphs.

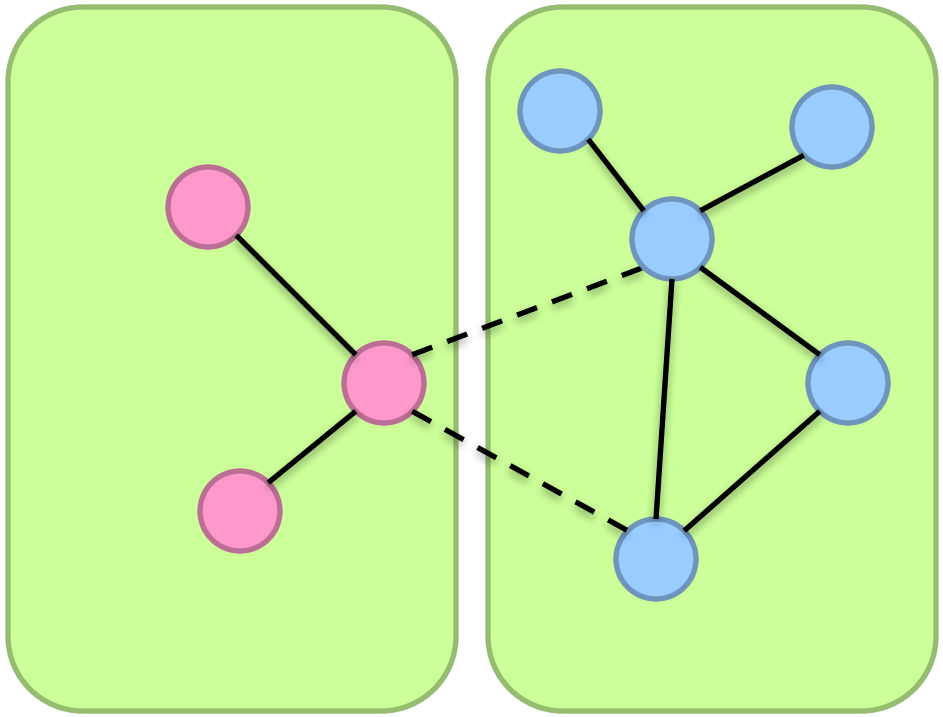
Graph Coarsening Challenges

Difficult to identify dense neighborhoods in large graphs
Local methods to the rescue?

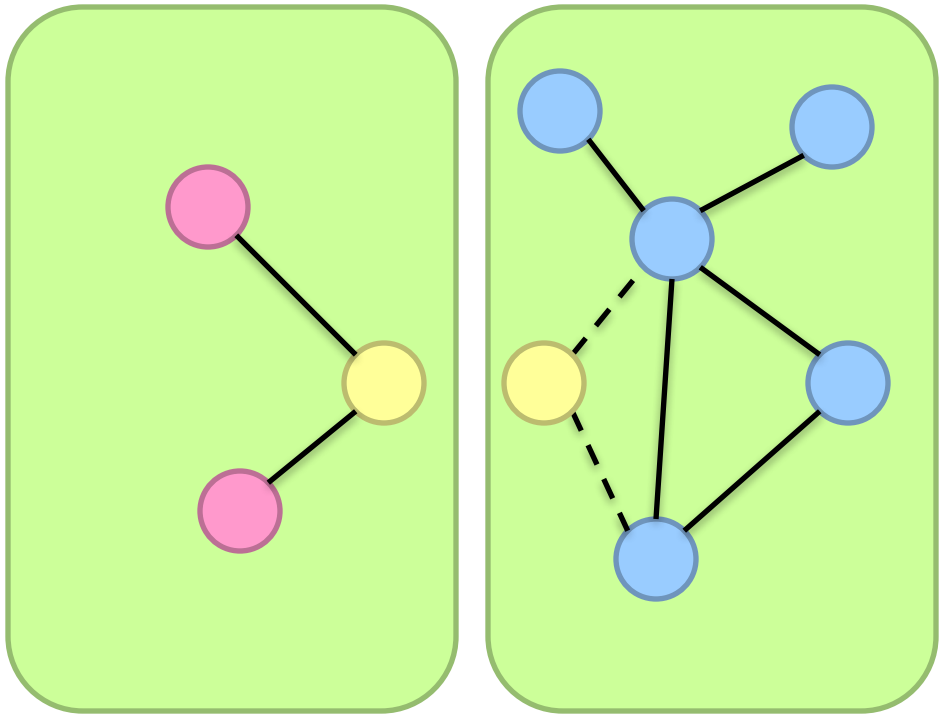
Partition



Partition



Partition + Replicate

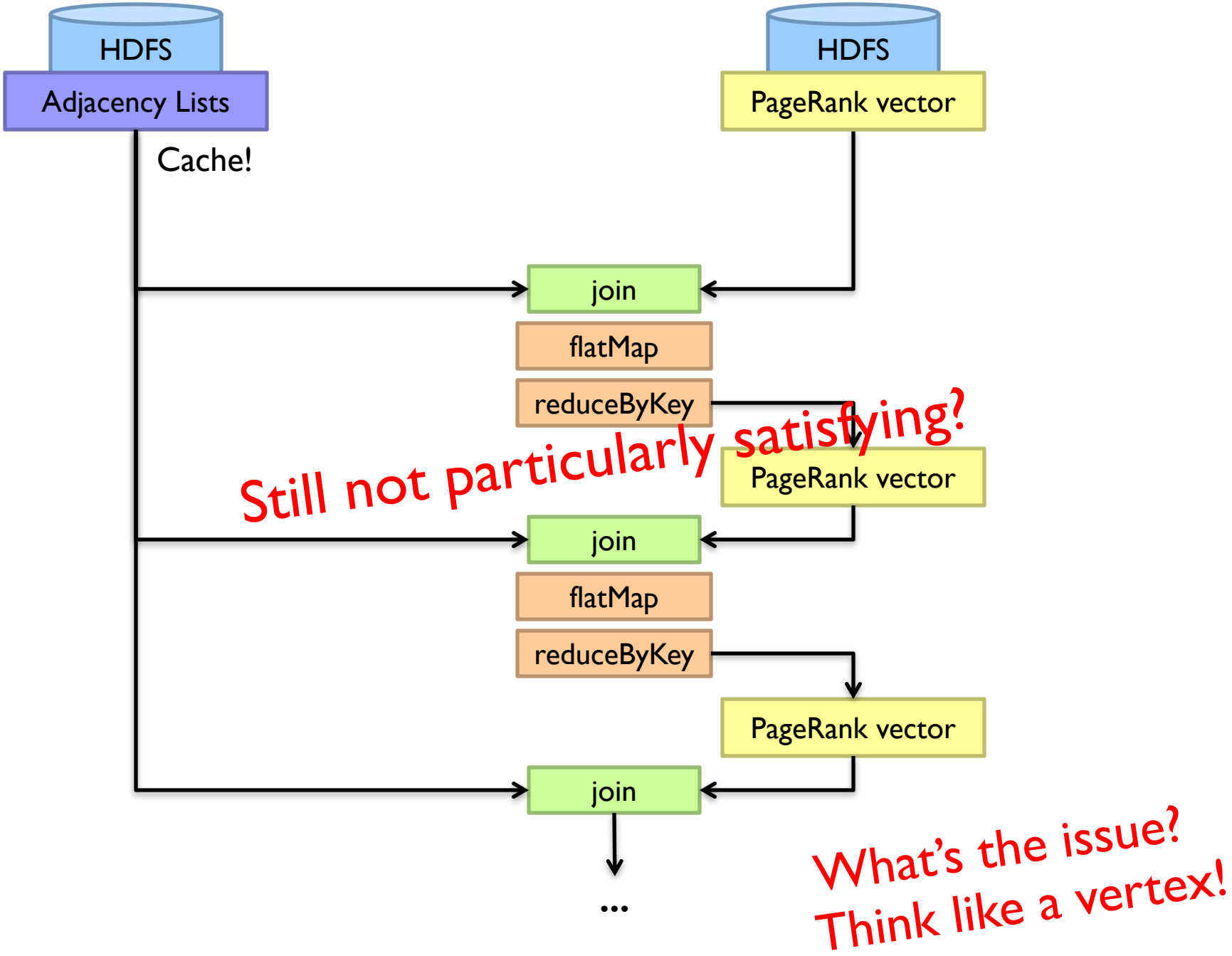


What's the issue?

The fastest current graph algorithms combine smart partitioning with asynchronous iterations

Graph Processing Frameworks

Source: Wikipedia (Waste container)


HDFS
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Still not particularly satisfying?
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flatMap
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...
What's the issue?
Think like a vertex!

Pregel: Computational Model

Based on Bulk Synchronous Parallel (BSP)

Computational units encoded in a directed graph

Computation proceeds in a series of supersteps

Message passing architecture

Each vertex, at each superstep:

Receives messages directed at it from previous superstep

Executes a user-defined function (modifying state)

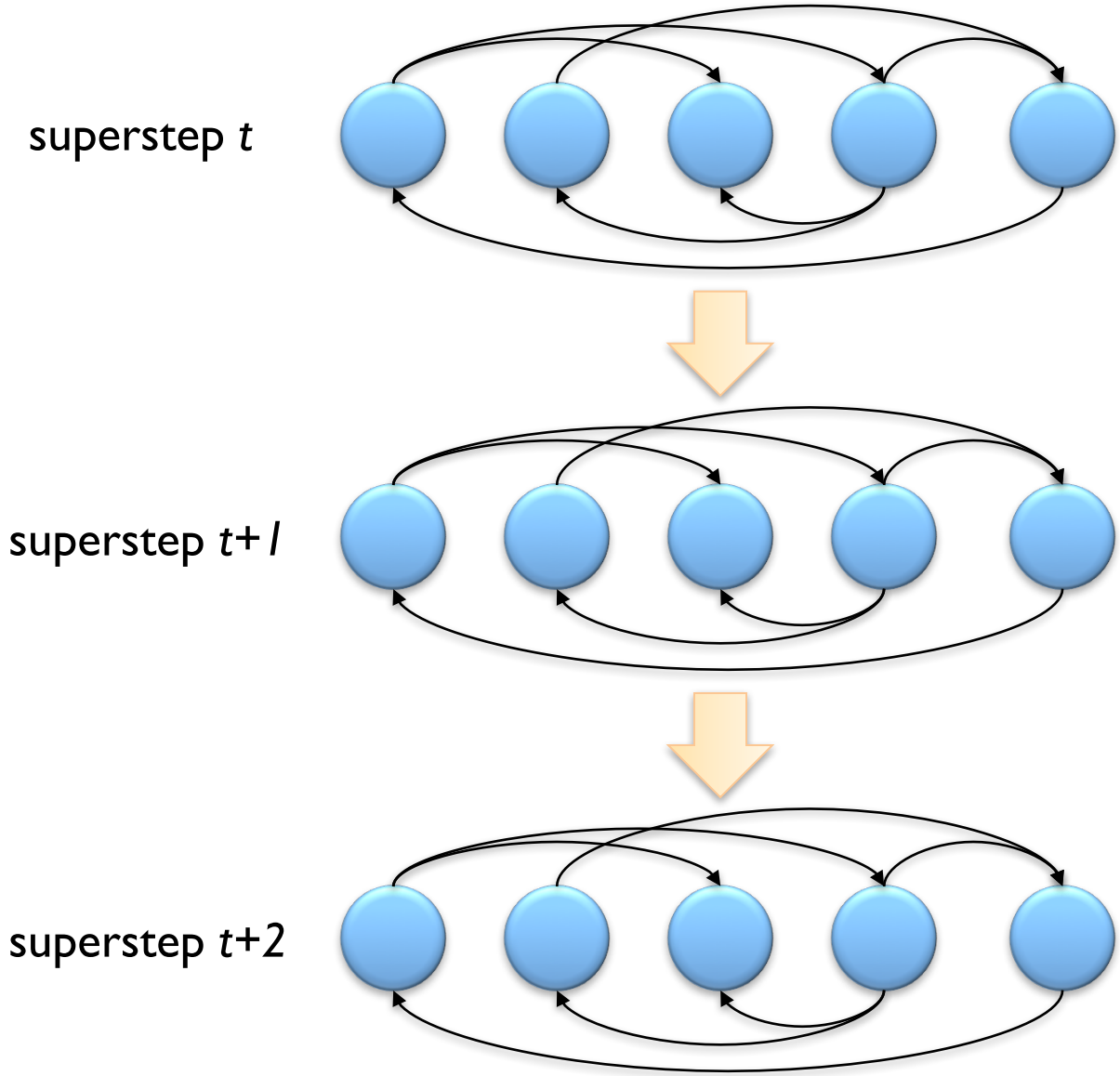
Emits messages to other vertices (for the next superstep)

Termination:

A vertex can choose to deactivate itself

Is "woken up" if new messages received

Computation halts when all vertices are inactive



Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

Pregel: Implementation

Master-Worker architecture

Vertices are hash partitioned (by default) and assigned to workers

Everything happens in memory

Processing cycle:

Master tells all workers to advance a single superstep

Worker delivers messages from previous superstep, executing vertex computation

Messages sent asynchronously (in batches)

Worker notifies master of number of active vertices

Fault tolerance

Checkpointing

Heartbeat/revert

Pregel: SSSP

```
class ShortestPathVertex : public Vertex<int, int, int> {
  void Compute(MessageIterator* msgs) {
    int mindist = IsSource(vertex_id()) ? 0 : INF;
    for (; !msgs->Done(); msgs->Next())
      mindist = min(mindist, msgs->Value());
    if (mindist < GetValue()) {
      *MutableValue() = mindist;
      OutEdgeIterator iter = GetOutEdgeIterator();
      for (; !iter.Done(); iter.Next())
        SendMessageTo(iter.Target(),
                      mindist + iter.GetValue());
    }
    VoteToHalt();
  }
};
```

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

Pregel: PageRank

```
class PageRankVertex : public Vertex<double, void, double> {
public:
  virtual void Compute(MessageIterator* msgs) {
    if (superstep() >= 1) {
      double sum = 0;
      for (; !msgs->Done(); msgs->Next())
        sum += msgs->Value();
      *MutableValue() = 0.15 / NumVertices() + 0.85 * sum;
    }

    if (superstep() < 30) {
      const int64 n = GetOutEdgeIterator().size();
      SendMessageToAllNeighbors(GetValue() / n);
    } else {
      VoteToHalt();
    }
  }
};
```

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

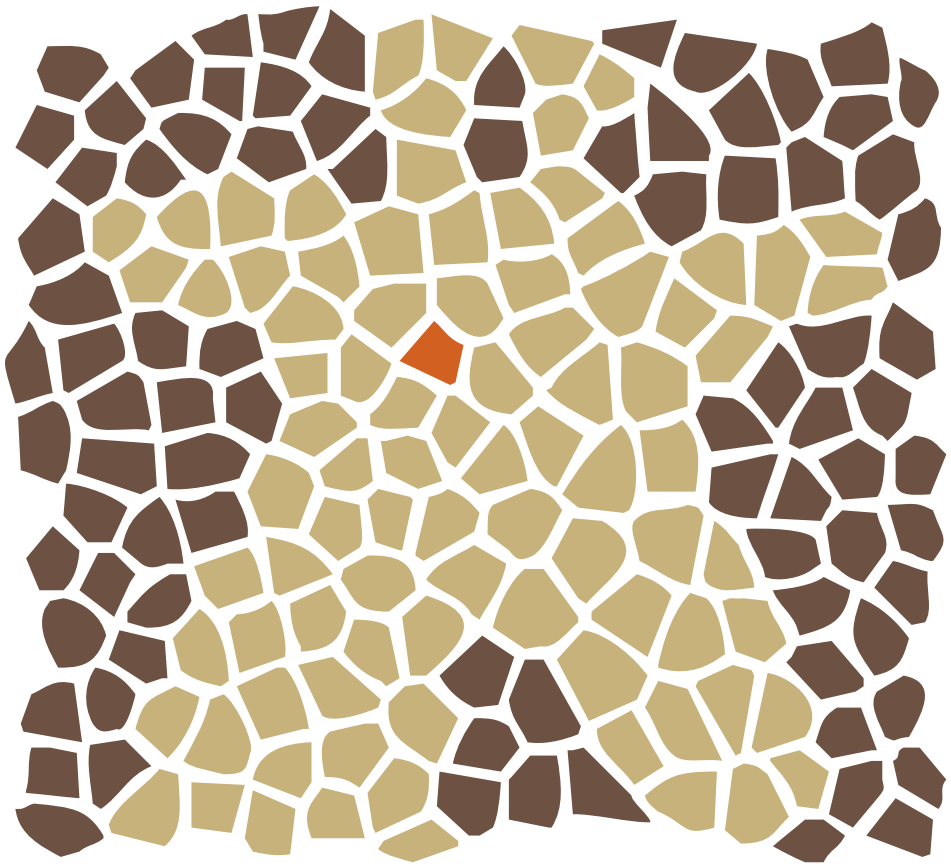
Pregel: Combiners

```
class MinIntCombiner : public Combiner<int> {
  virtual void Combine(MessageIterator* msgs) {

  int mindist = INF;
  for (; !msgs->Done(); msgs->Next())
    mindist = min(mindist, msgs->Value());
    Output("combined_source", mindist);
  }

};
```

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.



APACHE

GIRAPH

Giraph Architecture

Master – Application coordinator

Synchronizes supersteps

Assigns partitions to workers before superstep begins

Workers – Computation & messaging

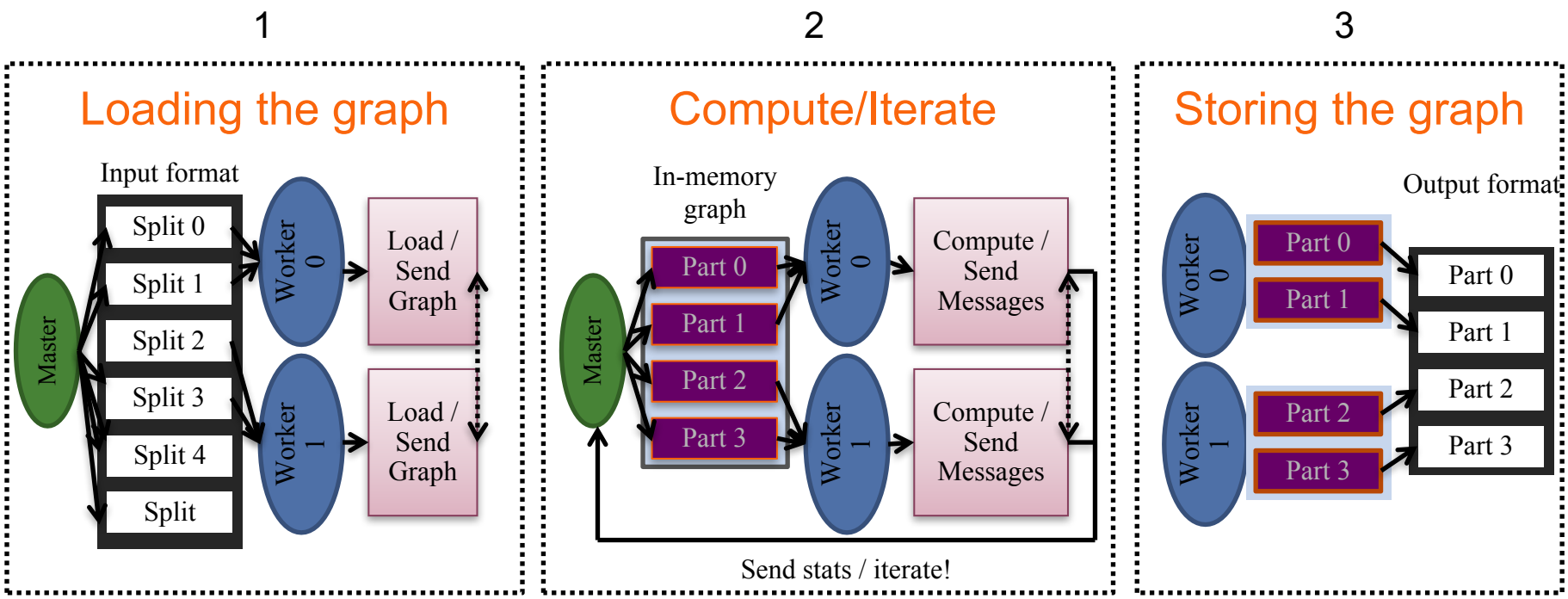
Handle I/O – reading and writing the graph

Computation/messaging of assigned partitions

ZooKeeper

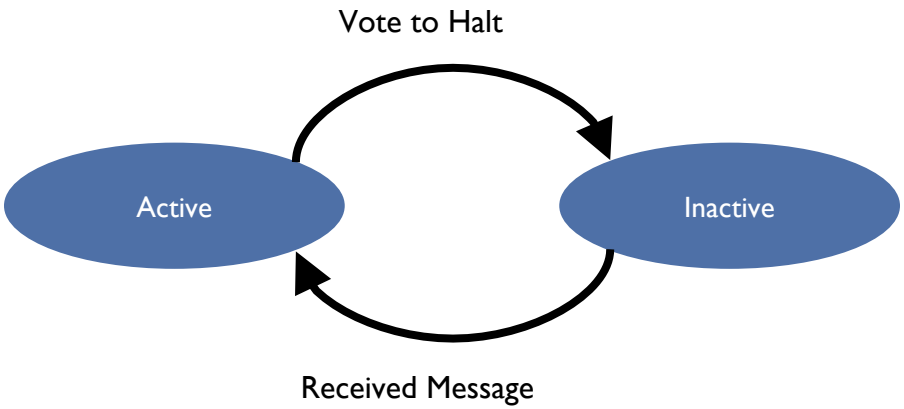
Maintains global application state

Giraph Dataflow

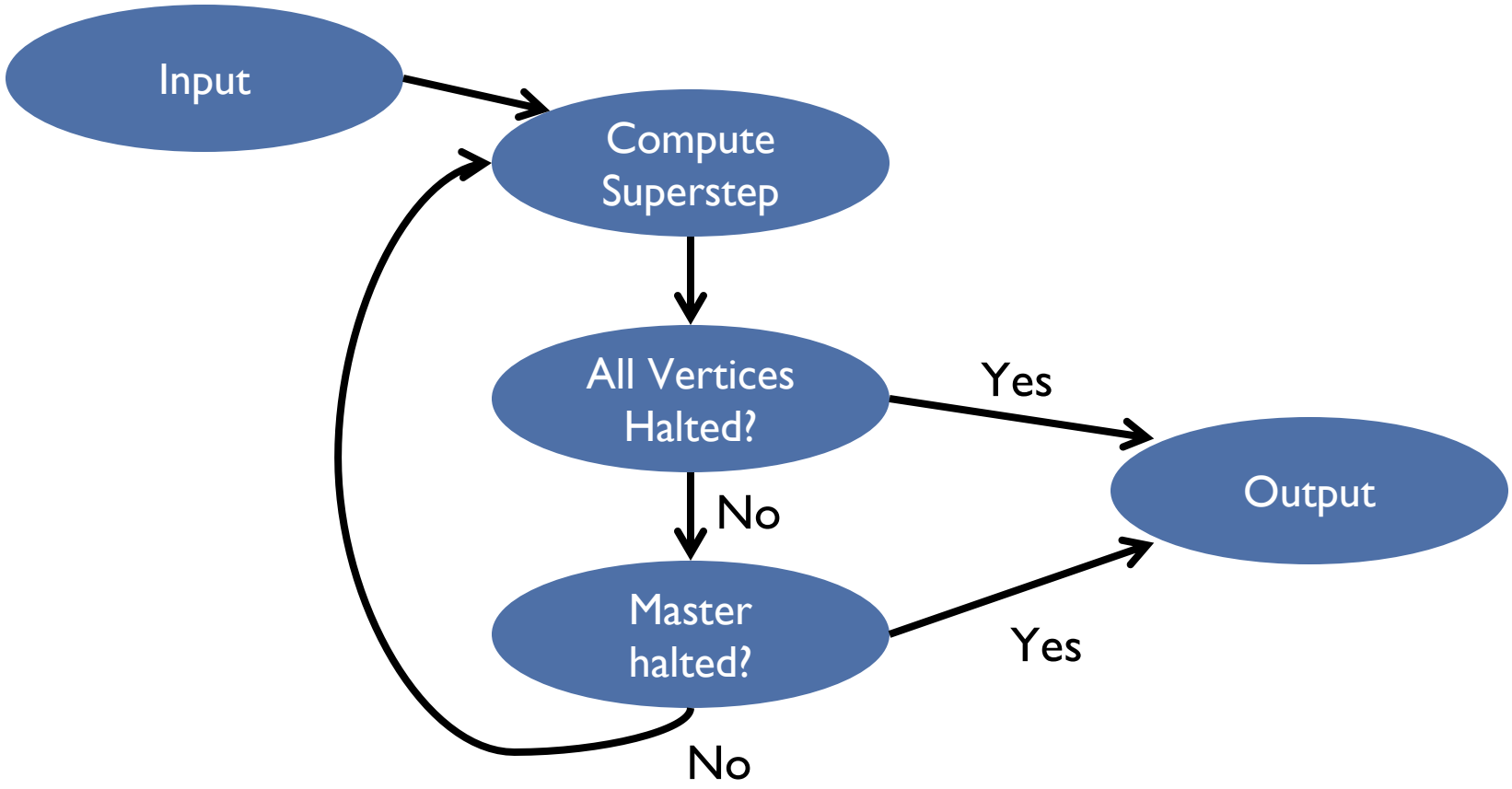


Giraph Lifecycle

Vertex Lifecycle



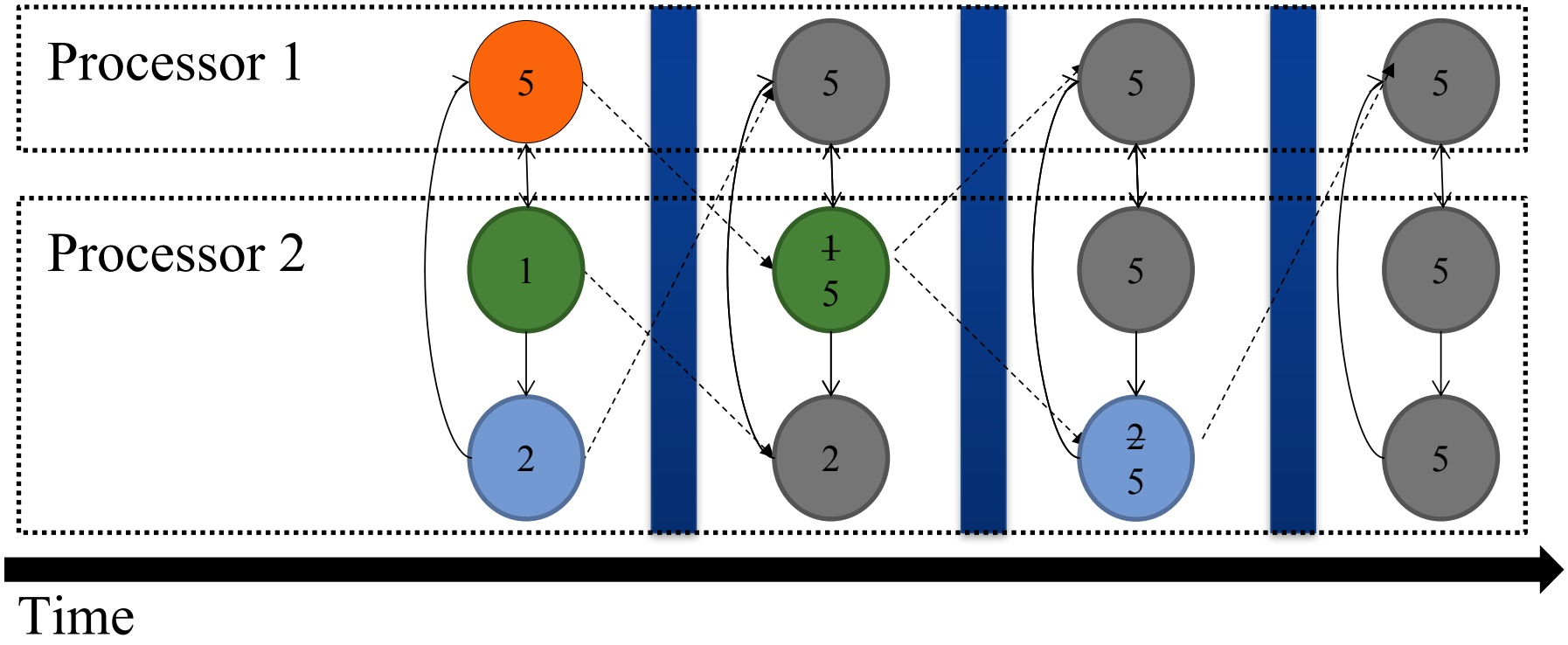
Giraph Lifecycle

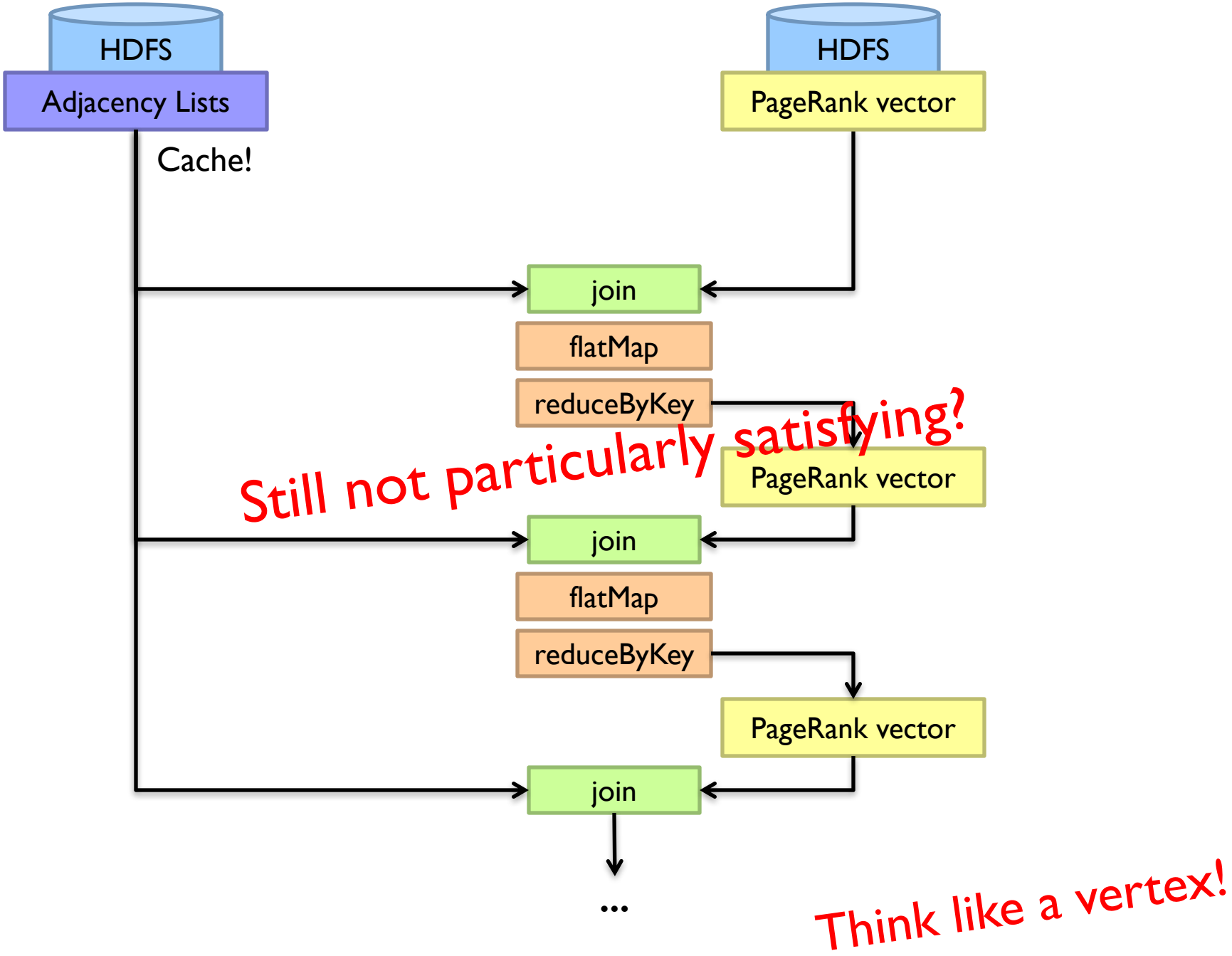


Giraph Example

```
public class MaxComputation extends BasicComputation<IntWritable, IntWritable,
    NullWritable, IntWritable> {
  @Override
  public void compute(Vertex<IntWritable, IntWritable, NullWritable> vertex,
      Iterable<IntWritable> messages) throws IOException
  {
    boolean changed = false;
    for (IntWritable message : messages) {
      if (vertex.getValue().get() < message.get()) {
        vertex.setValue(message);
        changed = true;
      }
    }
    if (getSuperstep() == 0 || changed) {
      sendMessageToAllEdges(vertex, vertex.getValue());
    }
    vertex.voteToHalt();
  }
}
```

Execution Trace

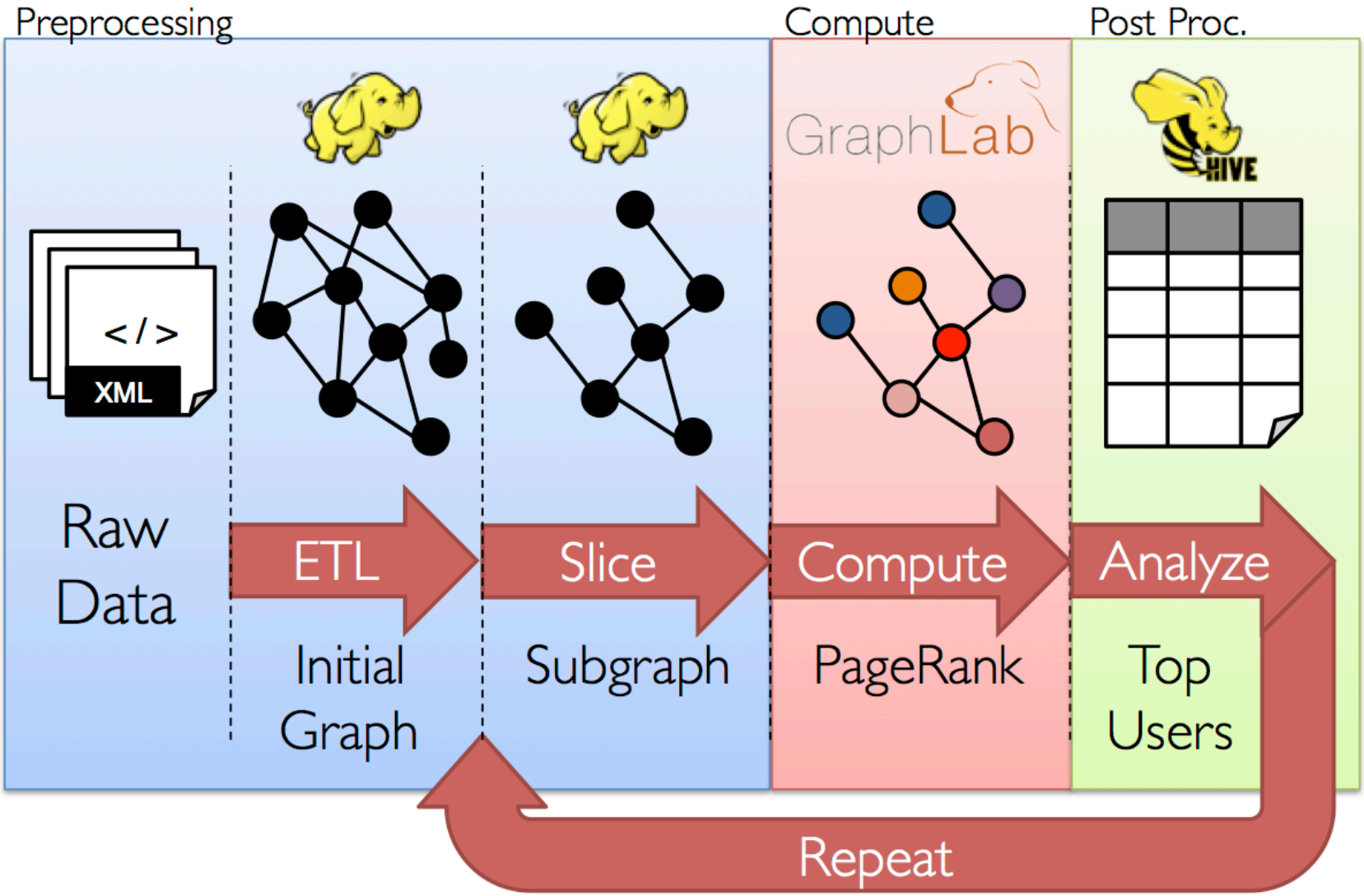



HDFS
Adjacency Lists
Cache!
HDFS
PageRank vector
join
flatMap
reduceByKey
PageRank vector
Still not particularly satisfying?
join
flatMap
reduceByKey
PageRank vector
join
...
Think like a vertex!

Graph Processing Frameworks

Source: Wikipedia (Waste container)

GraphX: Motivation



GraphX = Spark for Graphs

Integration of record-oriented and graph-oriented processing

Extends RDDs to Resilient Distributed Property Graphs

Supported operations

Map operations over views of the graph (vertices, edges, triplets)

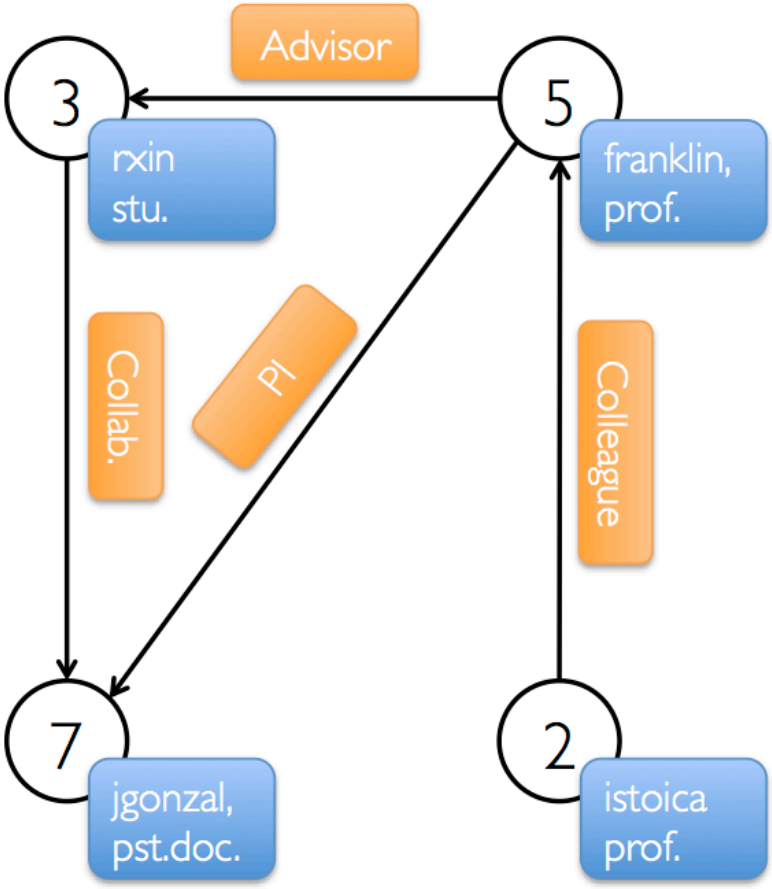
Pregel-like computations

Neighborhood aggregations

Join graph with RDDs

Property Graph: Example

Property Graph



Vertex Table

Id	Property (V)
3	(rxin, student)
7	(jgonzal, postdoc)
5	(franklin, professor)
2	(istoica, professor)

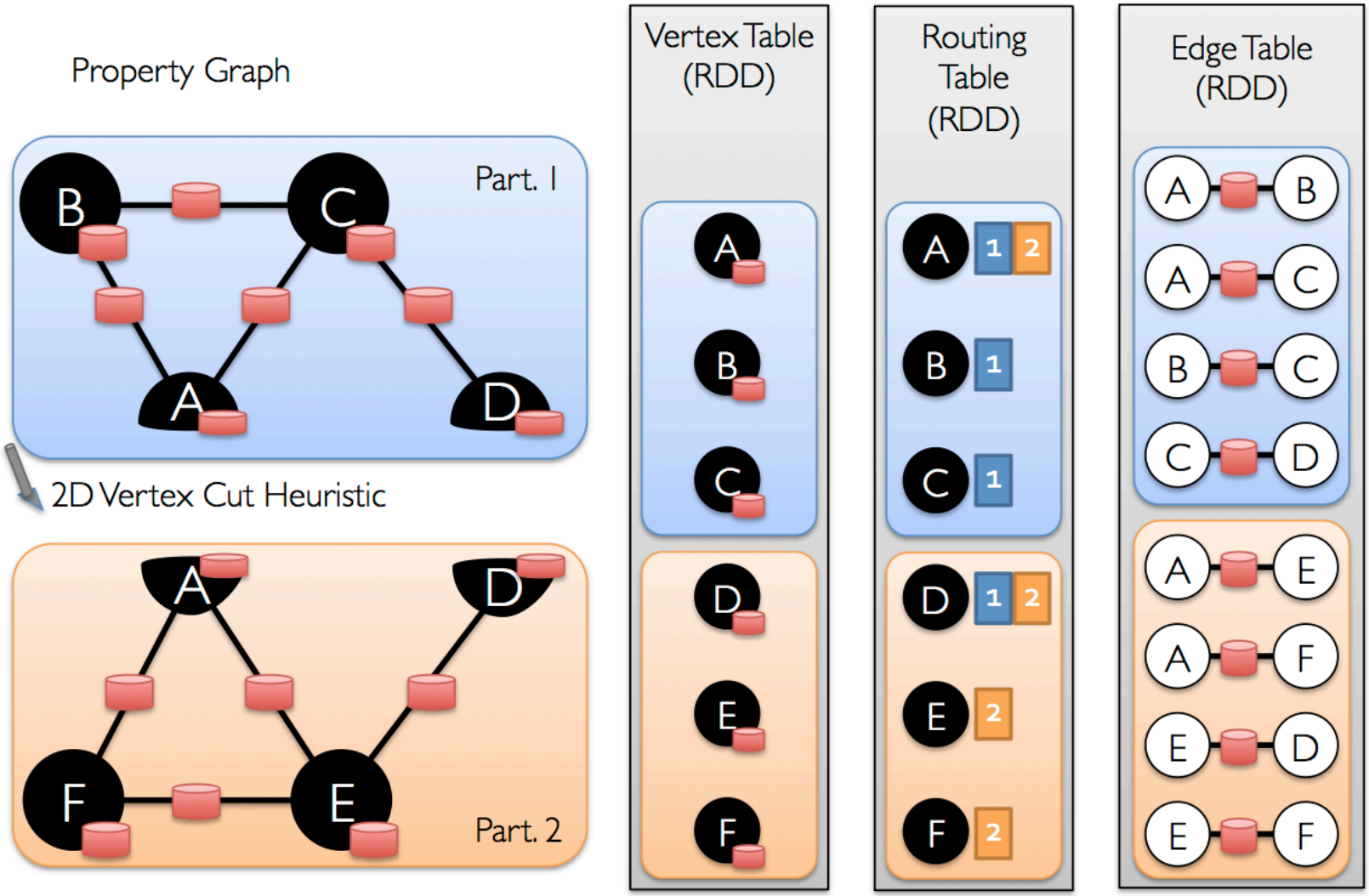
Edge Table

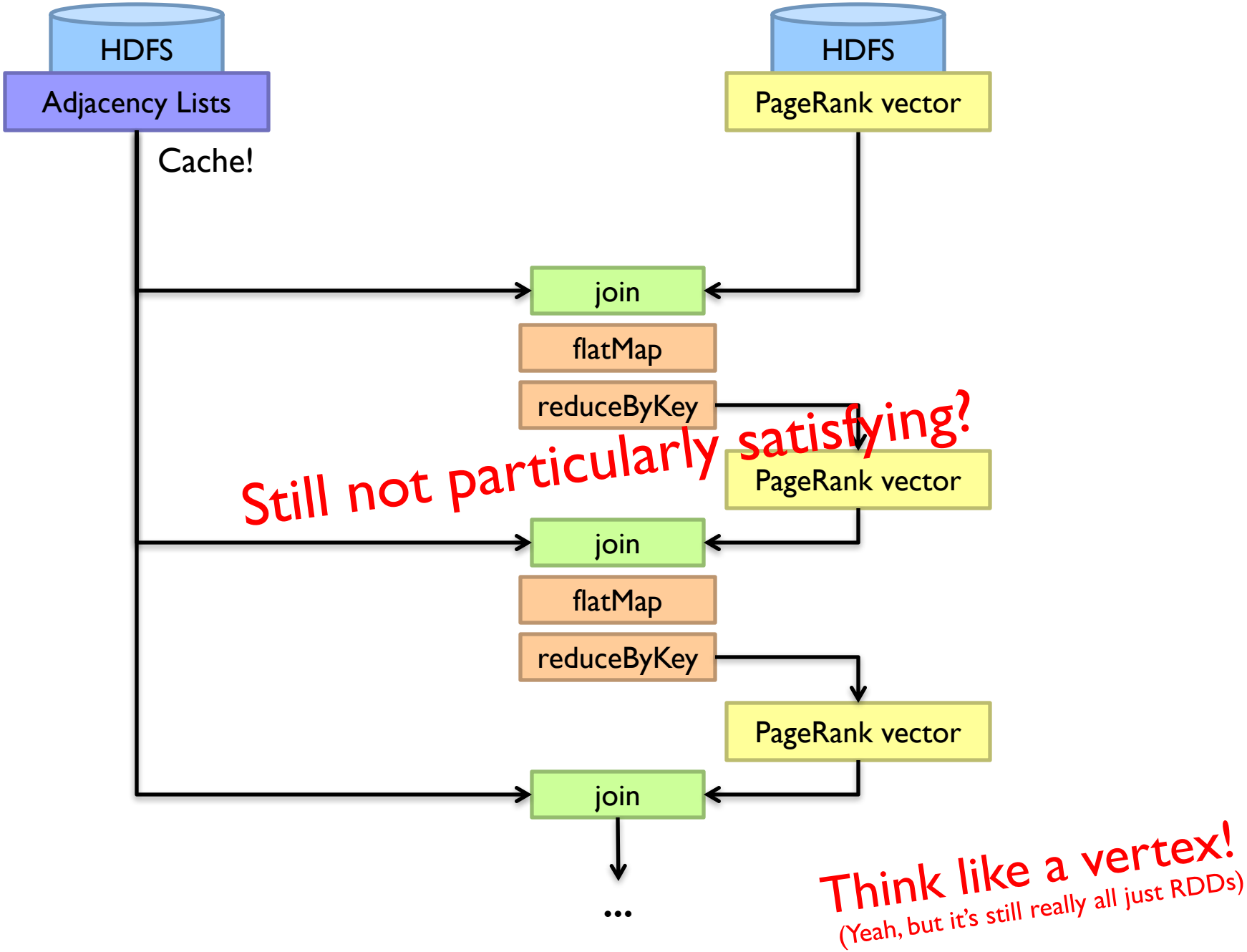
SrcId	DstId	Property (E)
3	7	Collaborator
5	3	Advisor
2	5	Colleague
5	7	PI

Property Graphs in SparkX

```
class Graph[VD, ED] {
  val vertices: VertexRDD[VD]
  val edges: EdgeRDD[ED]
}
```

Underneath the Covers

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join
...
Think like a vertex!
(Yeah, but it's still really all just RDDs)

Source: Wikipedia (Japanese rock garden)