Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2016)

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

March 22, 2016

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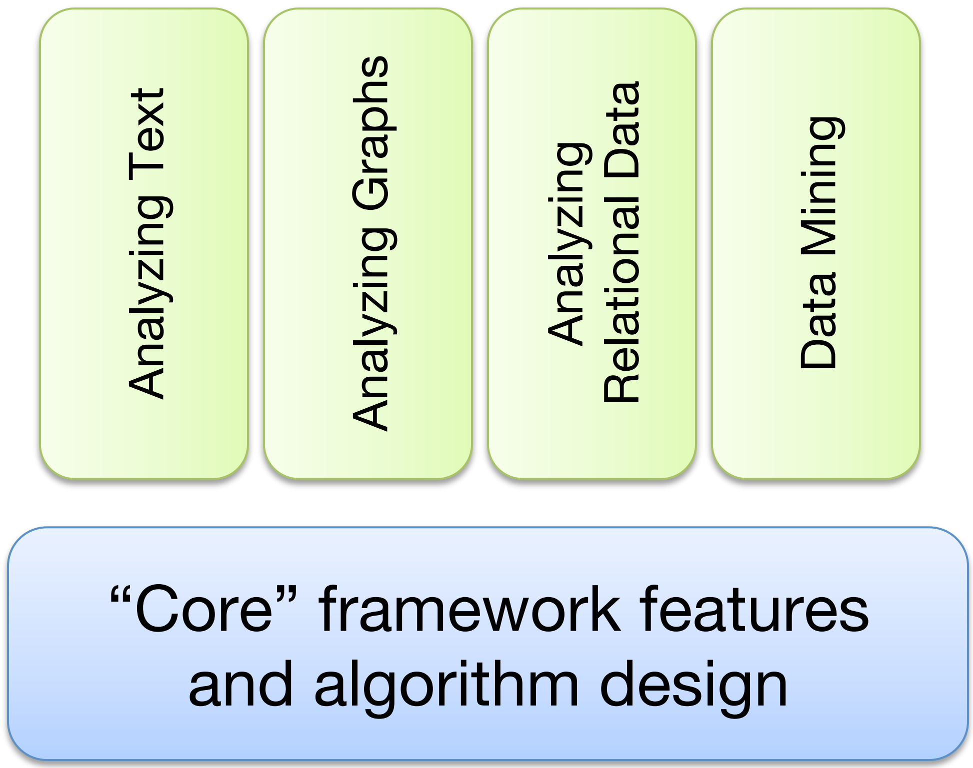
These slides are available at http://lintool.github.io/bigdata-2016w/

Structure of the Course



Characteristics of Graph Algorithms

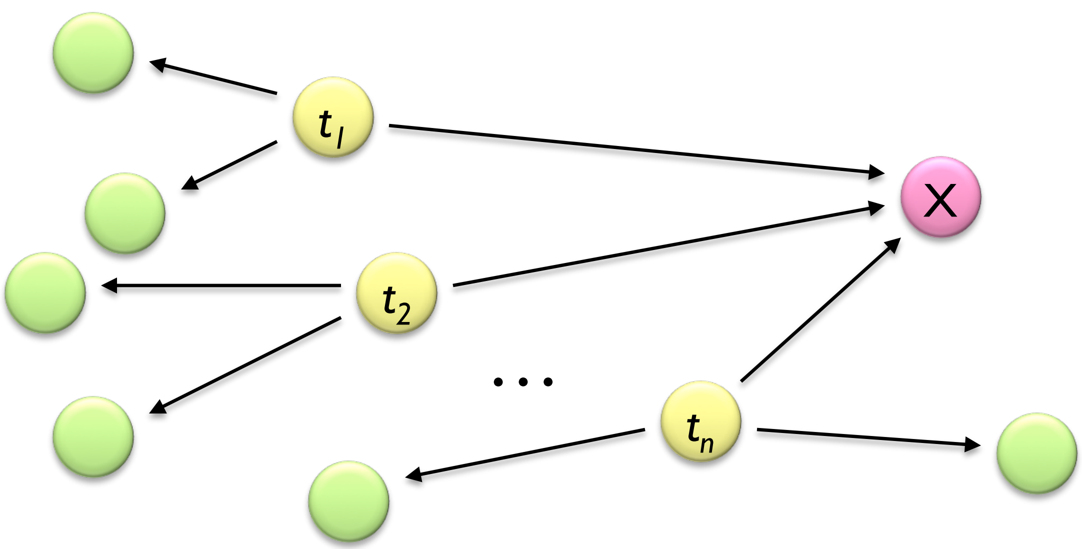
- Parallel graph traversals
  - Local computations
  - Message passing along graph edges
- Iterations

PageRank: Defined

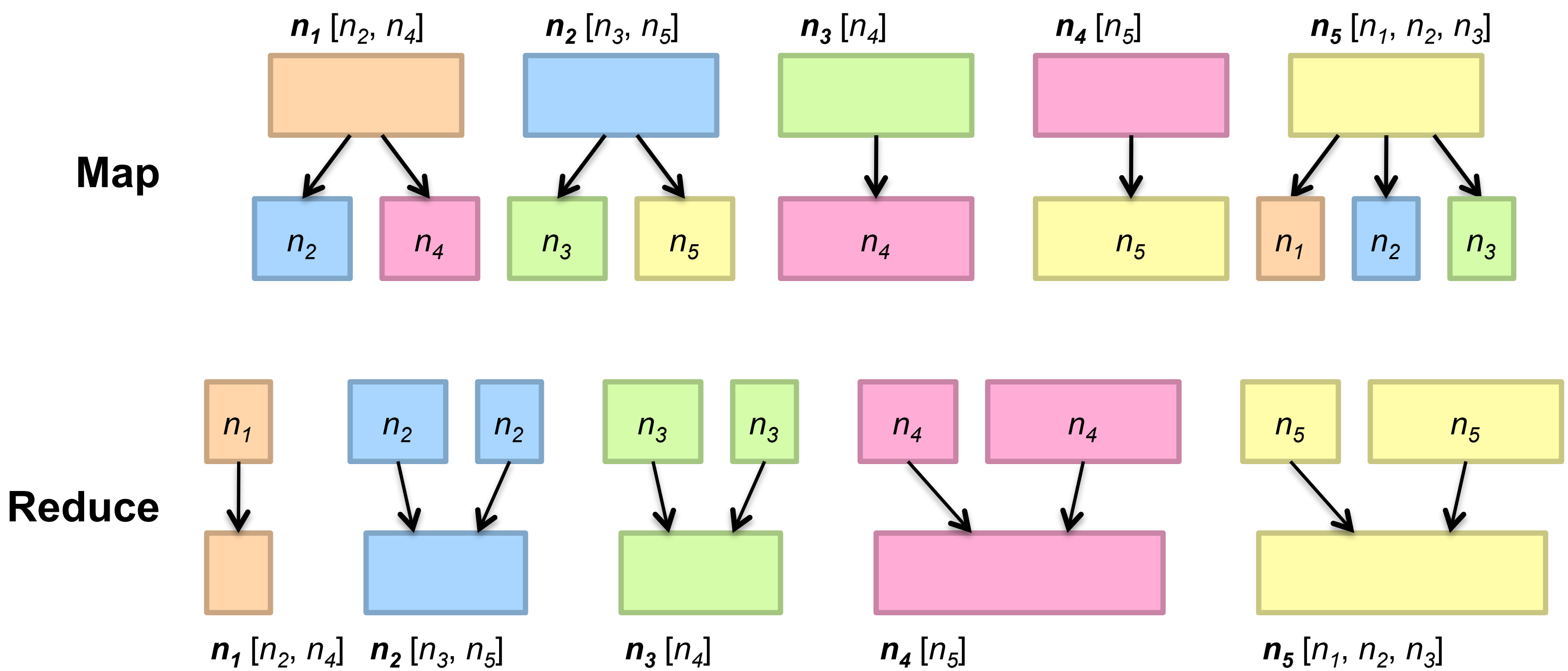
Given page x with inlinks $t_1 \ldots t_n$, where

- $C(t)$ 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



MapReduce Sucks

- Java verbosity
- Hadoop task startup time
- Stragglers
- Needless graph shuffling
- Checkpointing at each iteration

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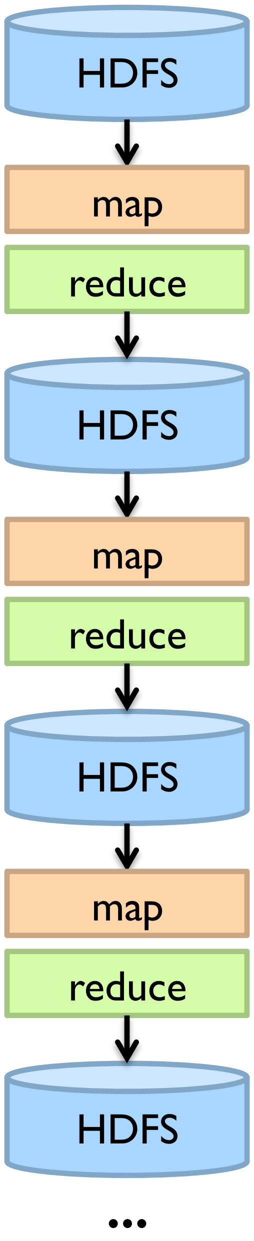
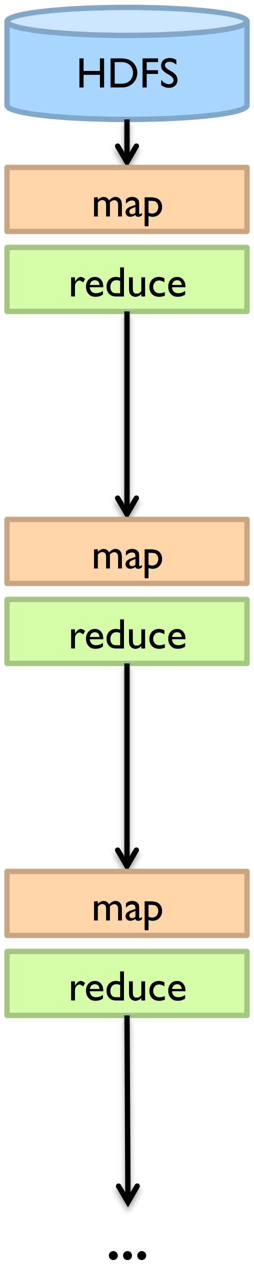
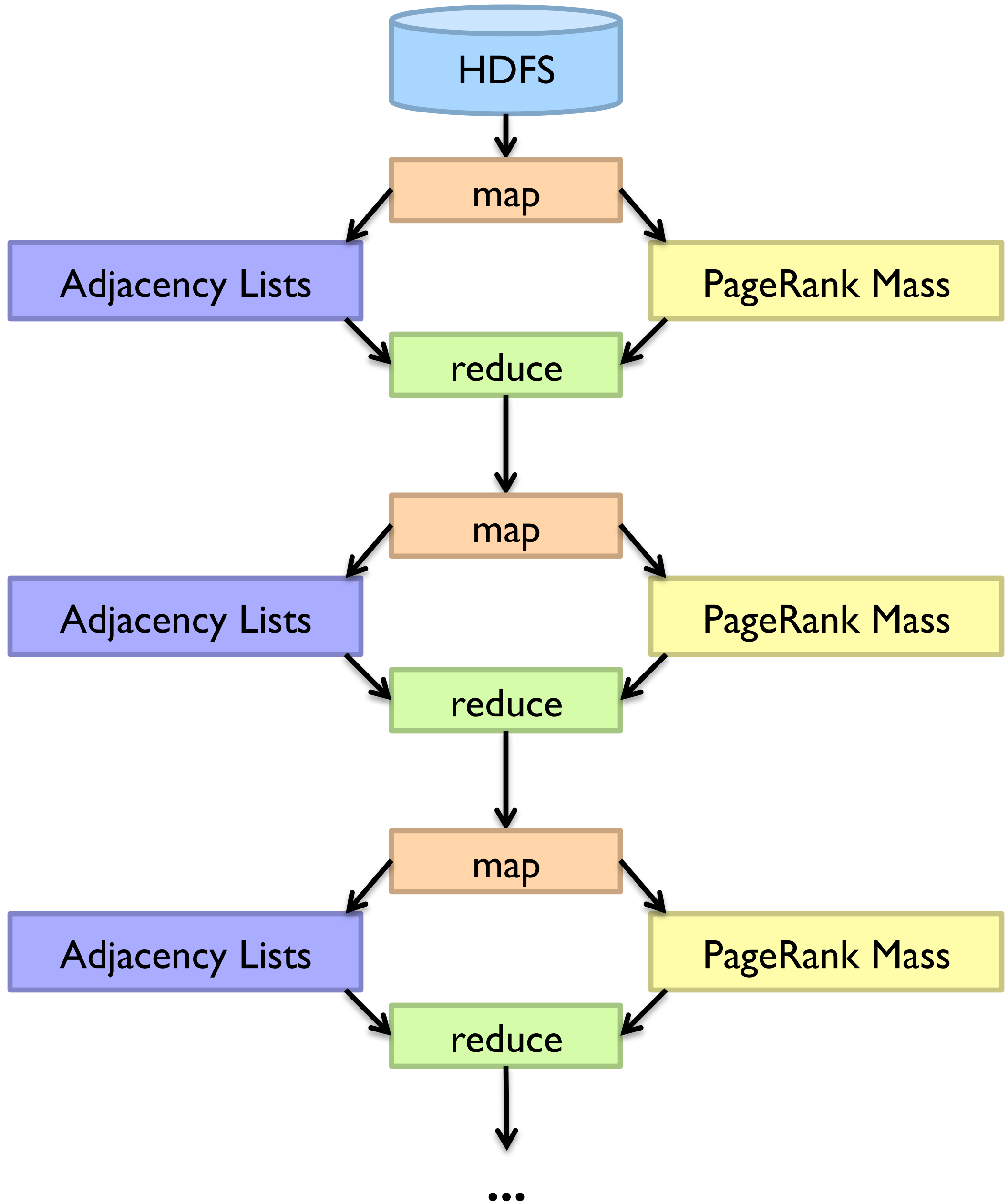
Spark to the rescue?

Let's Spark!



(omitting the second MapReduce job for simplicity; no handling of dangling links)


HDFS
map
reduce
map
reduce
map
reduce
...


HDFS
map
Adjacency Lists
PageRank Mass
reduce
map
Adjacency Lists
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map
Adjacency Lists
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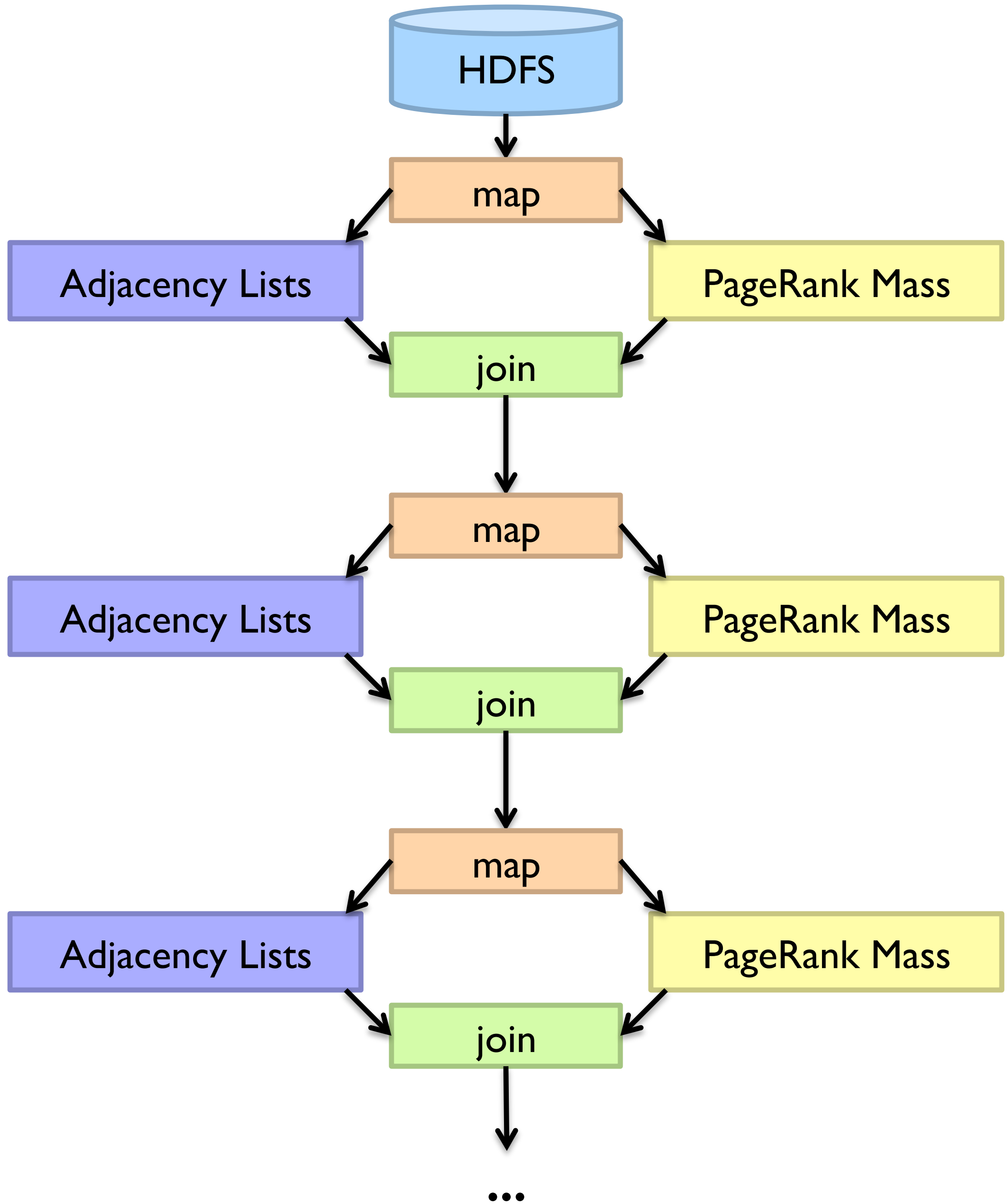
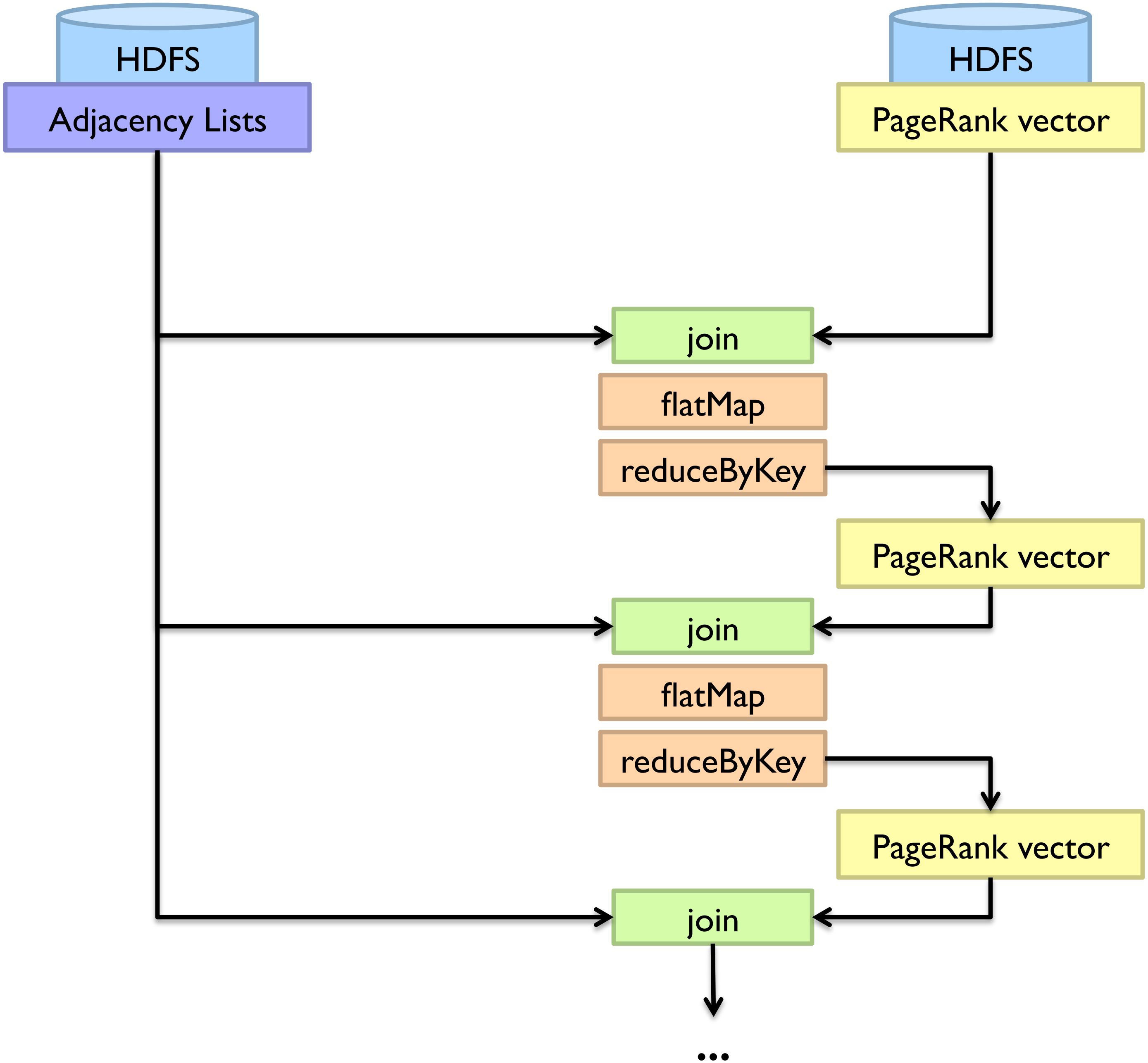
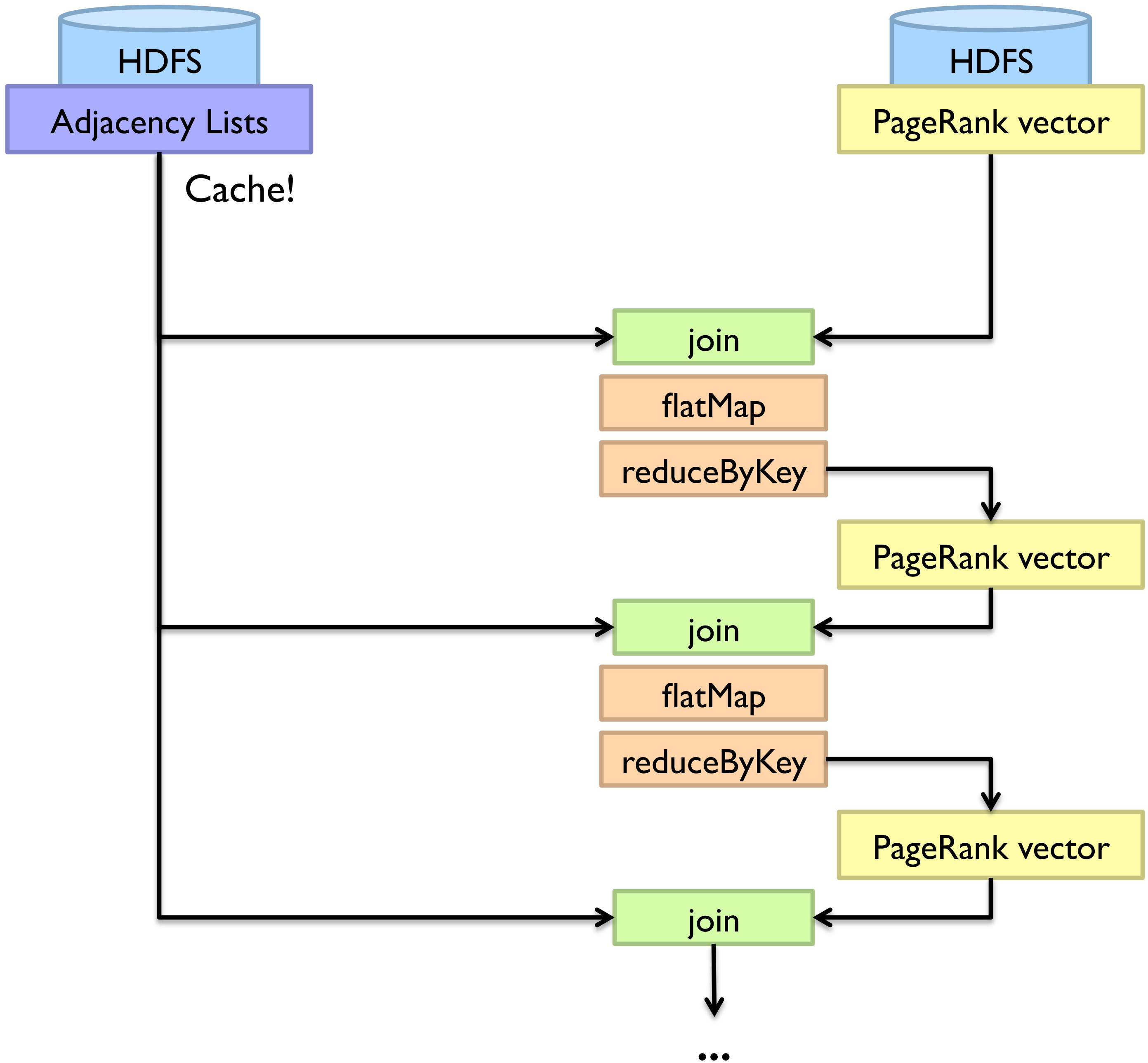
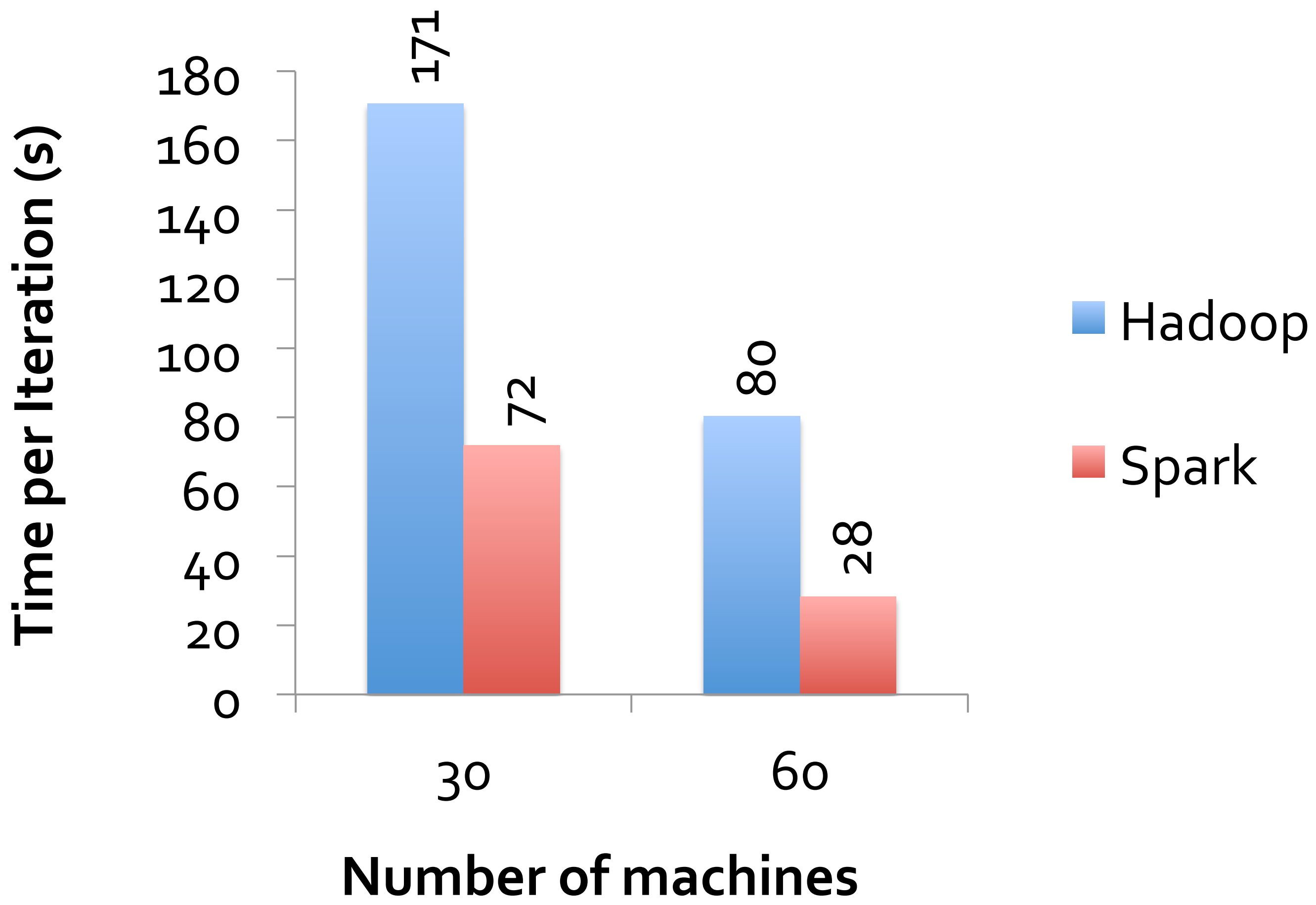
reduce
…


HDFS
map
Adjacency Lists
PageRank Mass
join
map
Adjacency Lists
PageRank Mass
join
map
Adjacency Lists
PageRank Mass
join
…


HDFS
Adjacency Lists
HDFS
PageRank vector
join
flatMap
reduceByKey
PageRank vector
join
flatMap
reduceByKey
PageRank vector
join
…


HDFS
Adjacency Lists
Cache!
HDFS
PageRank vector
join
flatMap
reduceByKey
PageRank vector
join
flatMap
reduceByKey
PageRank vector
join
…

MapReduce vs. Spark



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

MapReduce Sucks

- Java verbosity
- Hadoop task startup time
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What have we fixed?

Characteristics of Graph Algorithms

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Big Data Processing in a Nutshell

- Lessons learned so far:
  - Partition
  - Replicate
  - Reduce cross-partition communication
- What makes MapReduce/Spark fast?

Characteristics of Graph Algorithms

- Parallel graph traversals
  - Local computations
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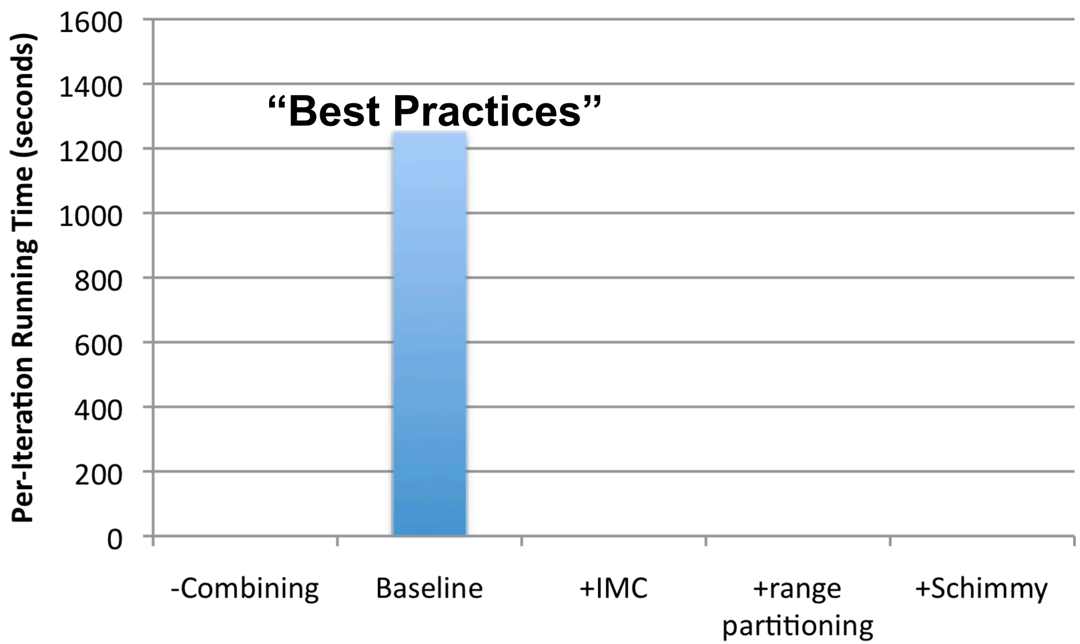
What's the issue?

Obvious solution: keep "neighborhoods" together!

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

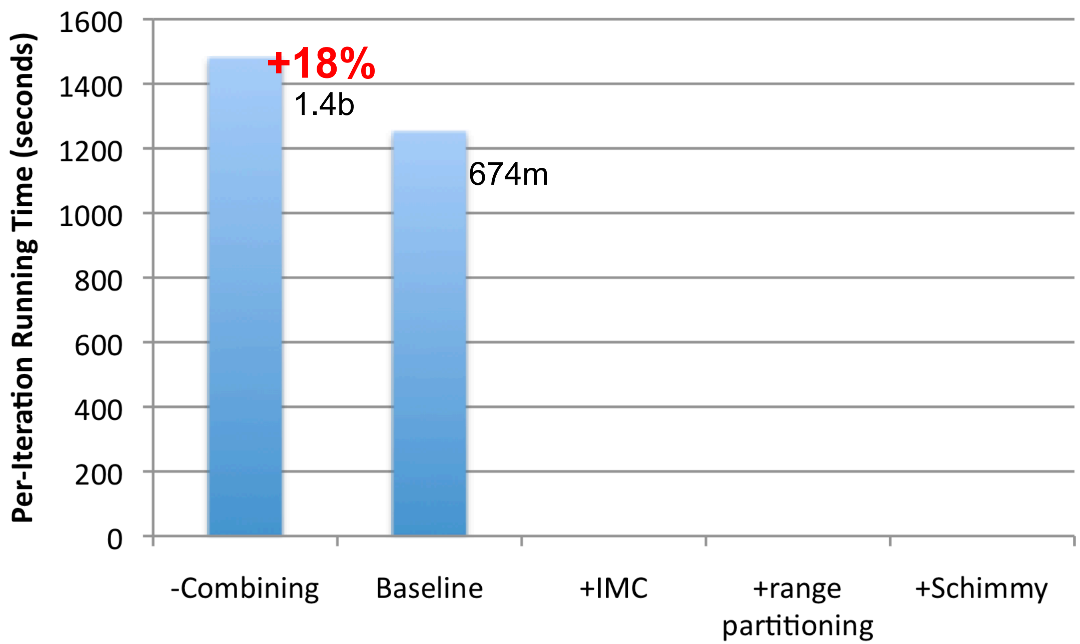
How much difference does it make?



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

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

How much difference does it make?



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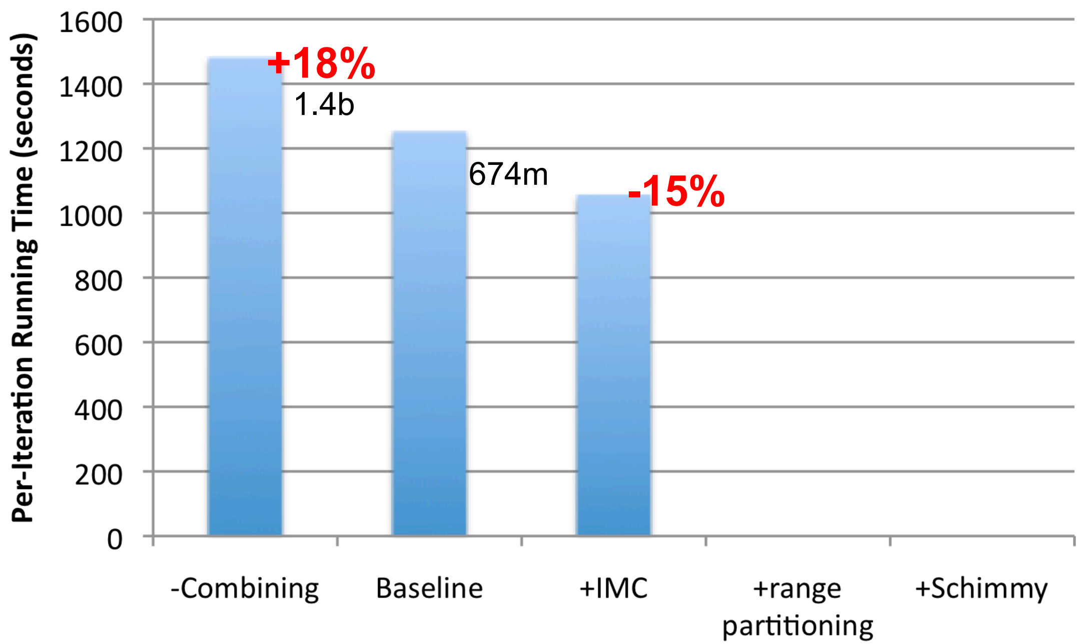

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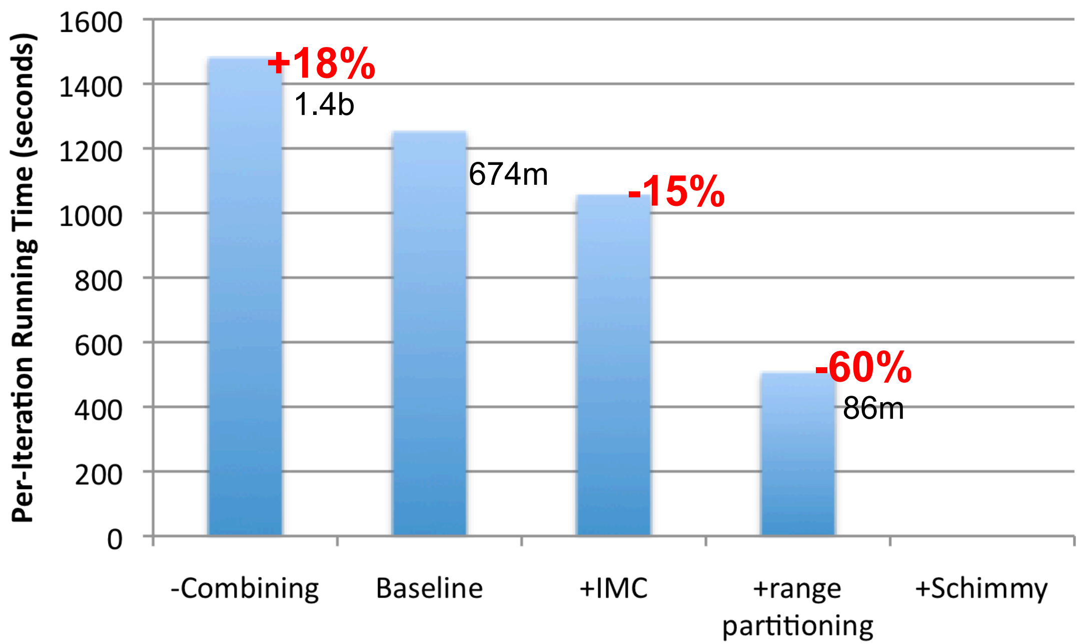

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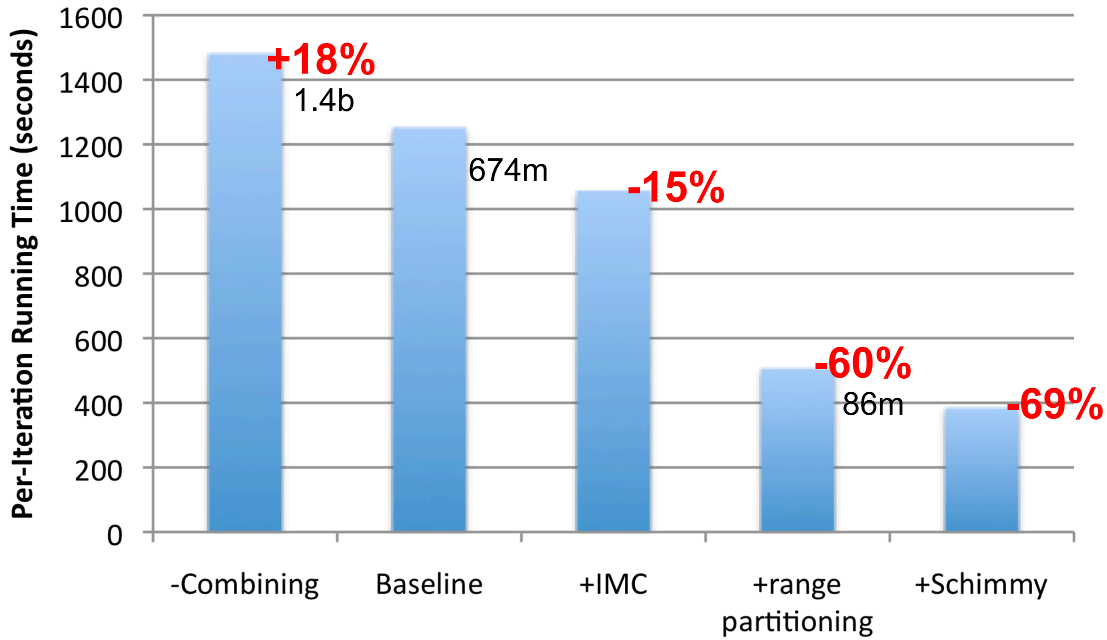

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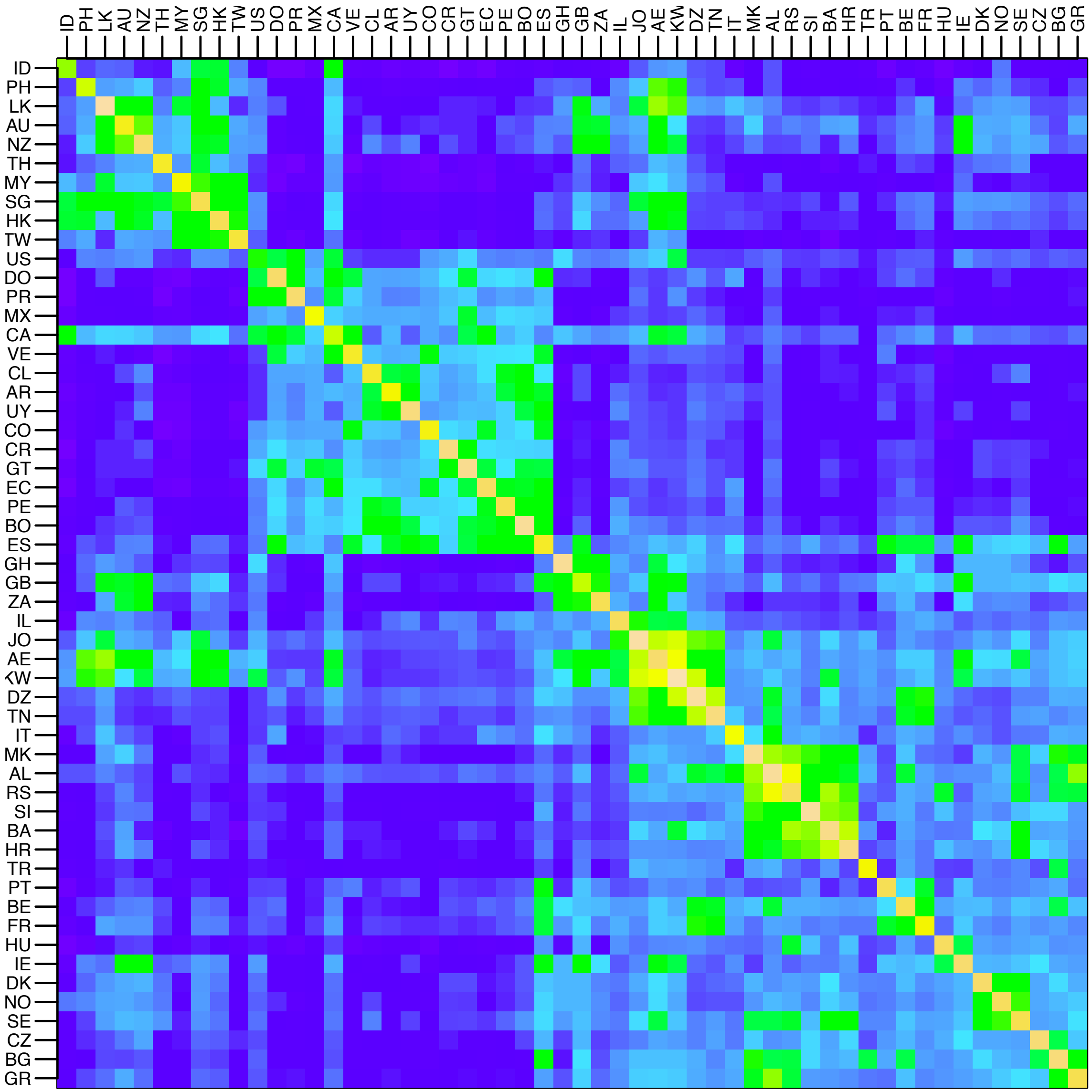
Lin and Schatz. (2010) Design Patterns for Efficient Graph Algorithms in MapReduce.

Country Structure in Facebook

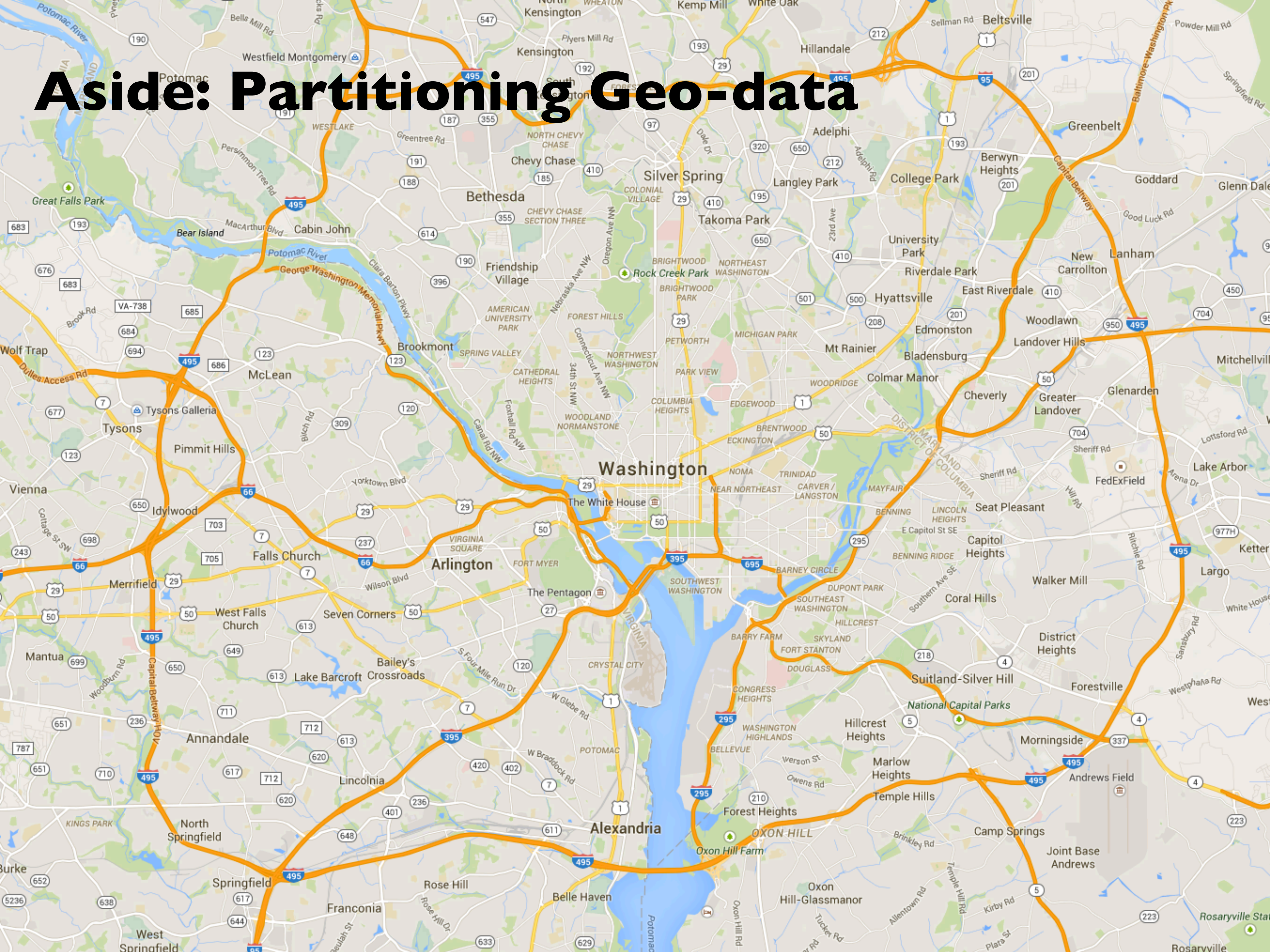


Analysis of 721 million active users (May 2011)

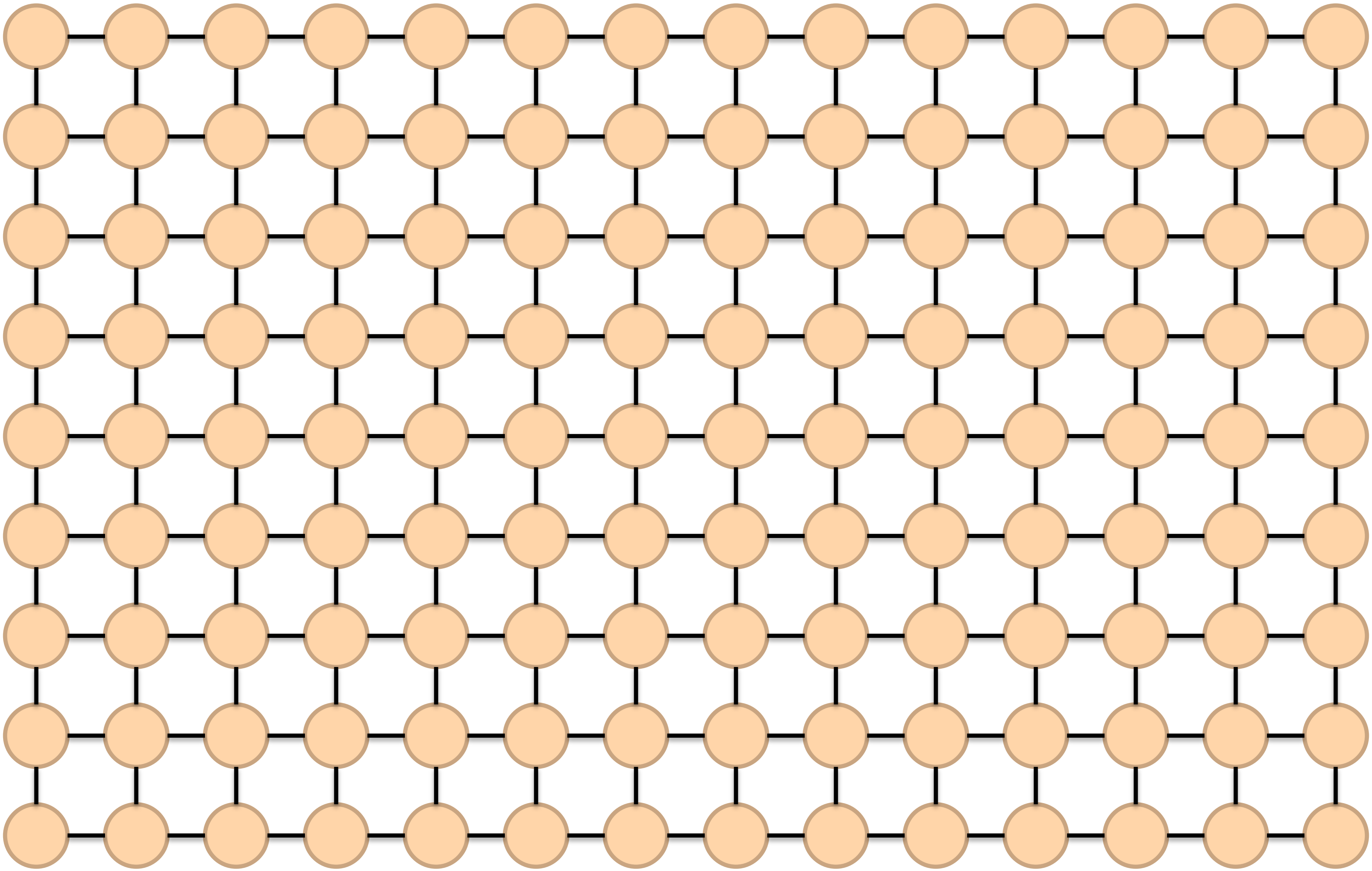
54 countries w/ >1m active users, >50% penetration

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

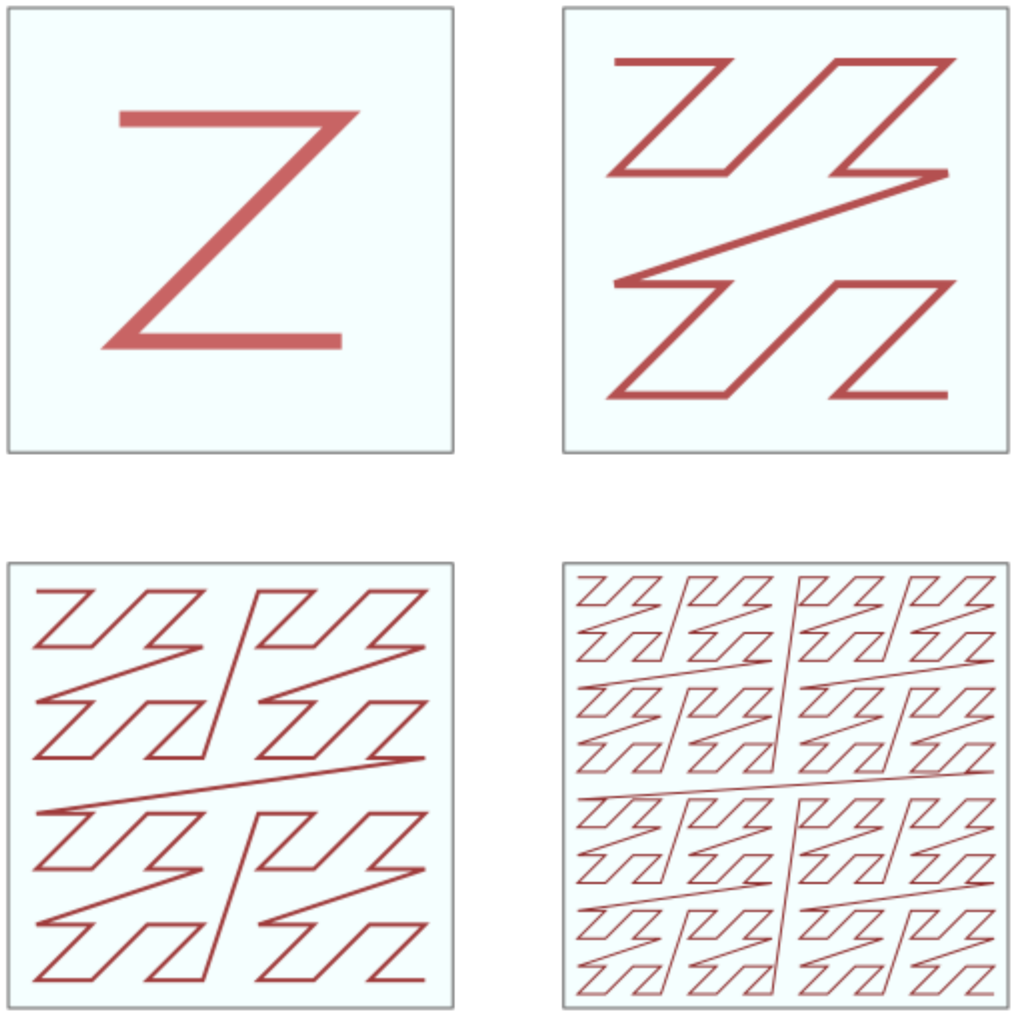
Aside: Partitioning Geo-data



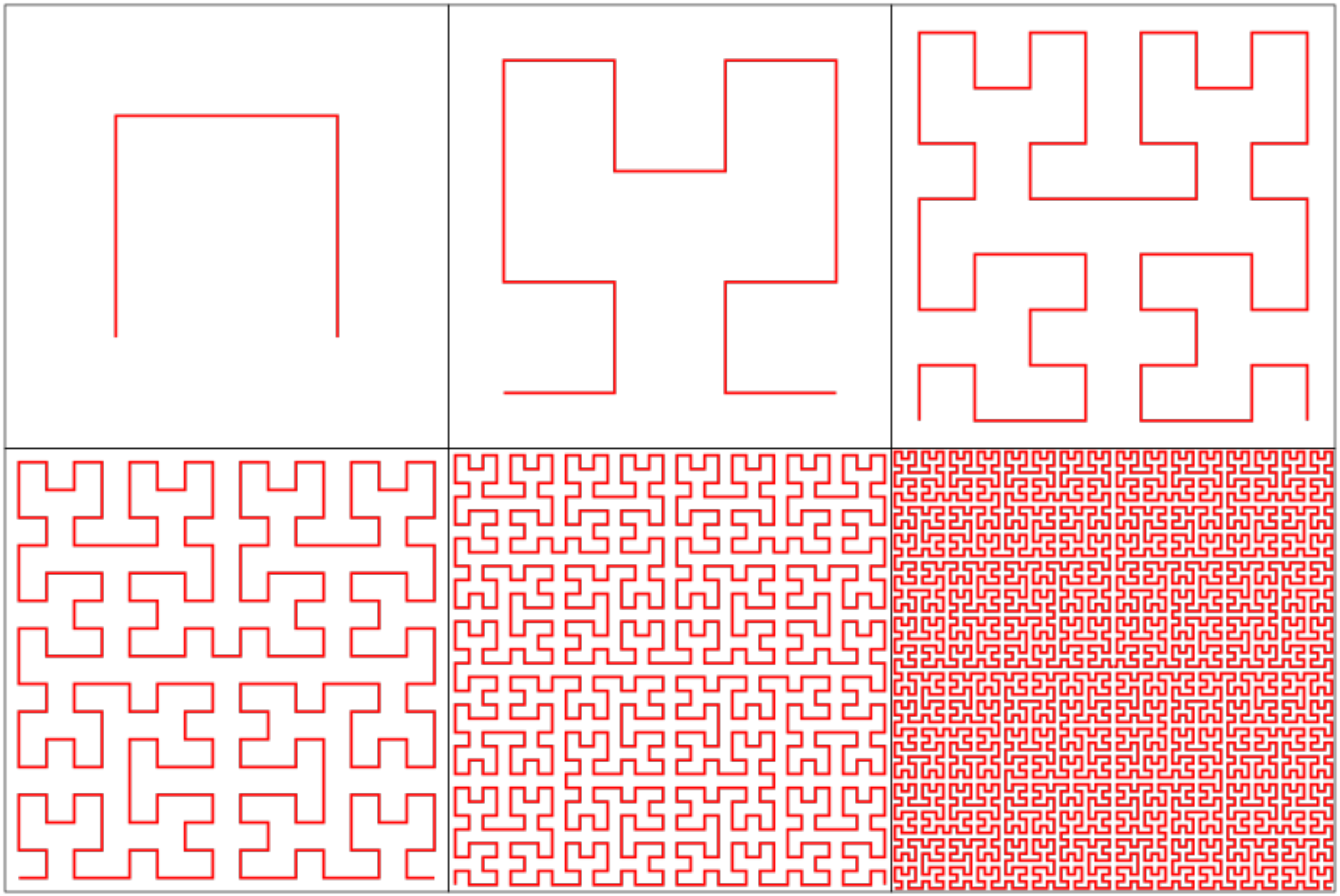
Geo-data = regular graph



Space-filling curves: Z-Order Curves

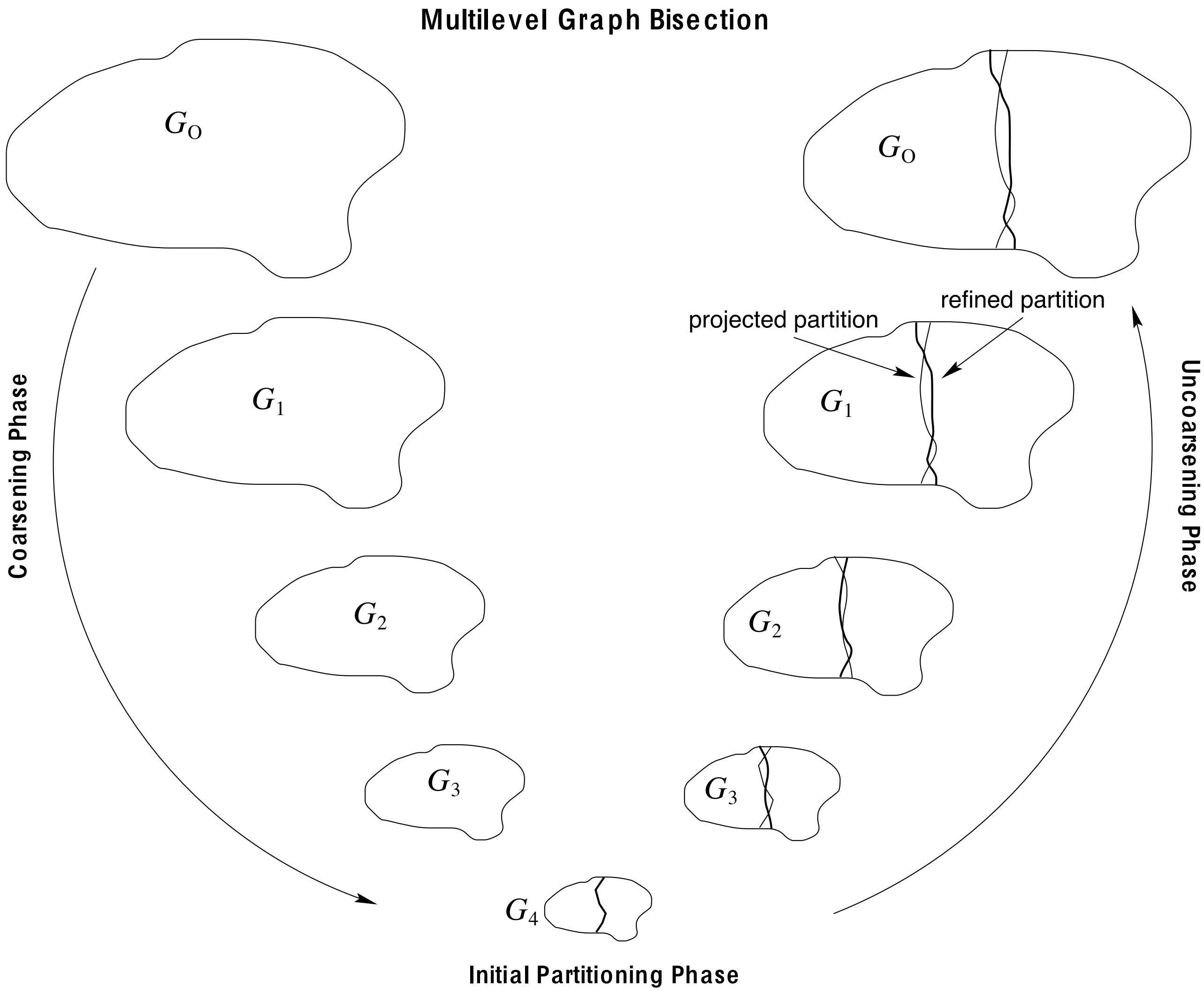


Space-filling curves: Hilbert Curves



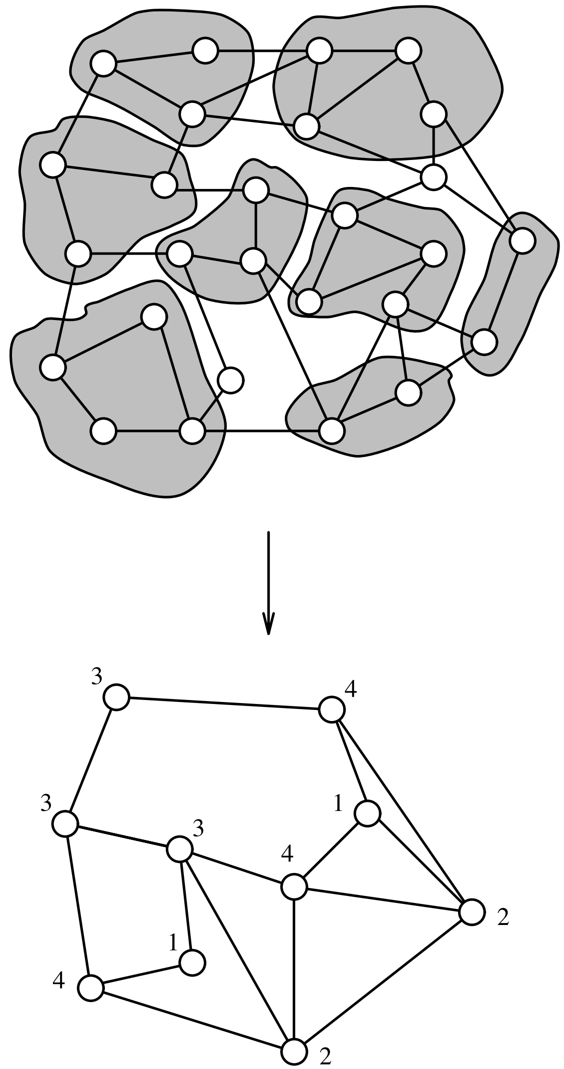
Source: http://www.flickr.com/photos/fusedforces/4324320625/

General-Purpose Graph Partitioning



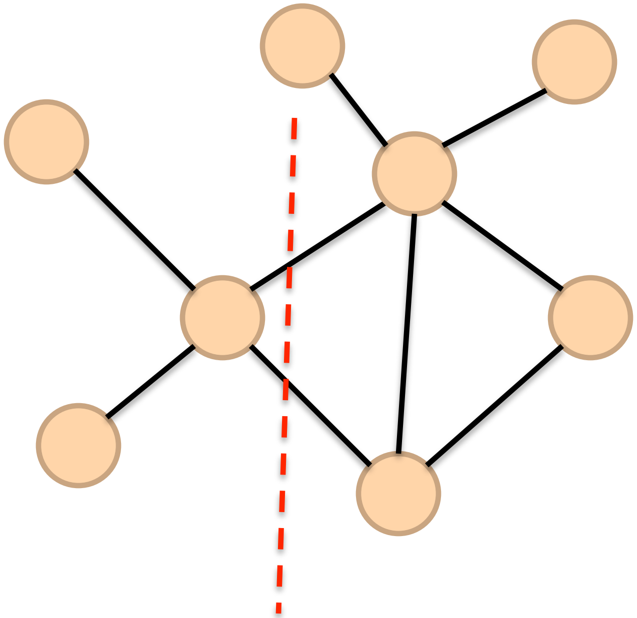
Karypis and Kumar. (1998) A Fast and High Quality Multilevel Scheme for Partitioning Irregular Graphs.

Graph Coarsening

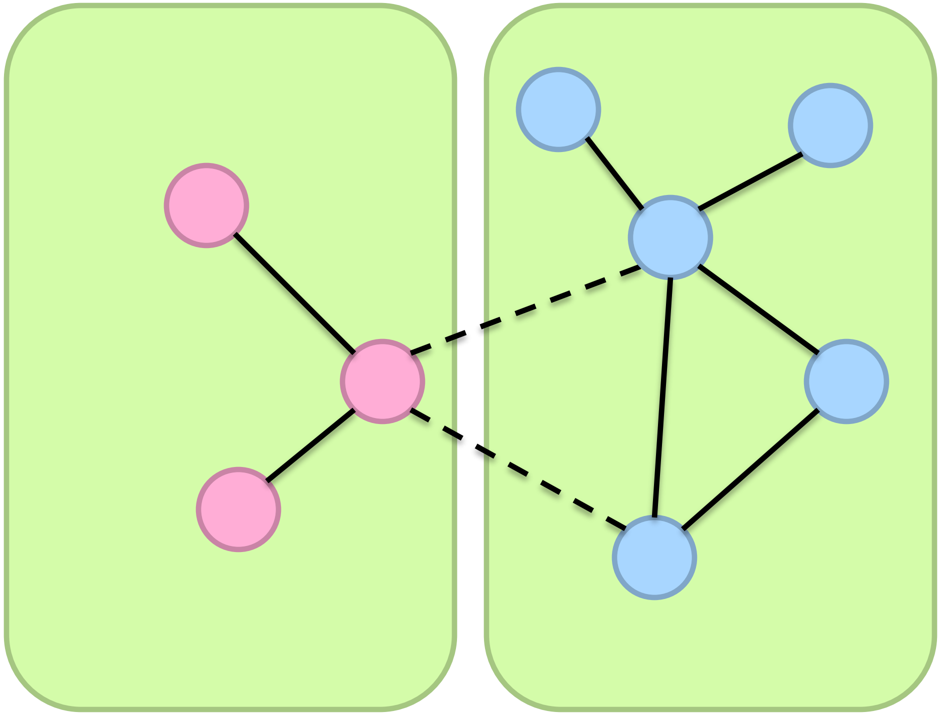


Karypis and Kumar. (1998) A Fast and High Quality Multilevel Scheme for Partitioning Irregular Graphs.

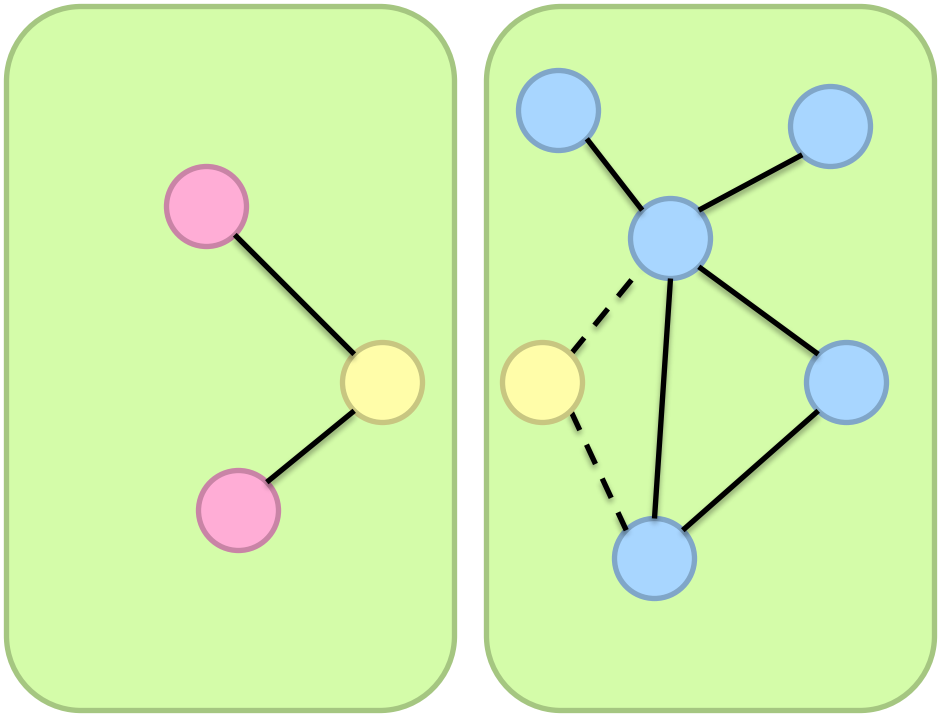
Partition



Partition



Partition + Replicate



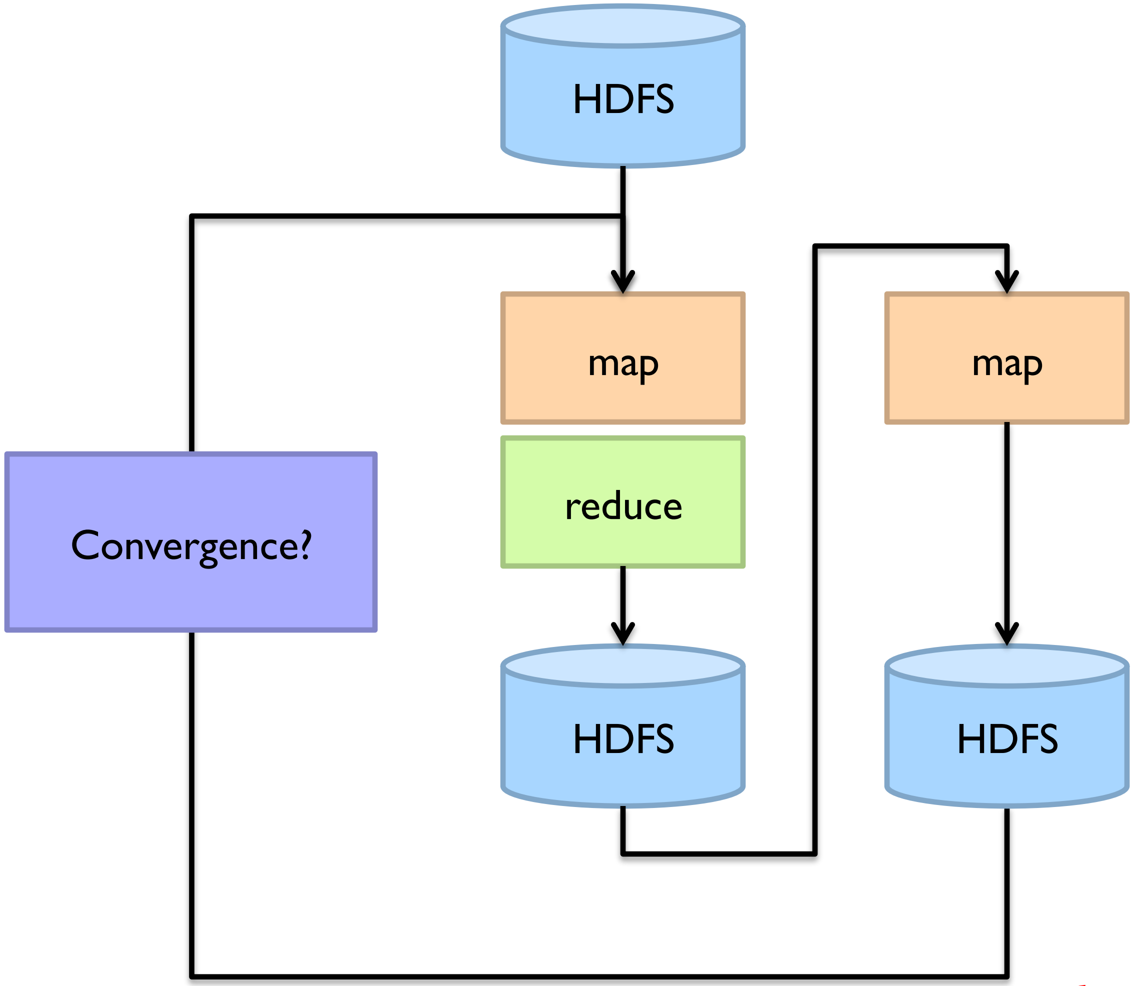
What's the issue?

The fastest current graph algorithms combine smart partitioning with asynchronous iterations

Graph Processing Frameworks

Source: Wikipedia (Waste container)

MapReduce PageRank



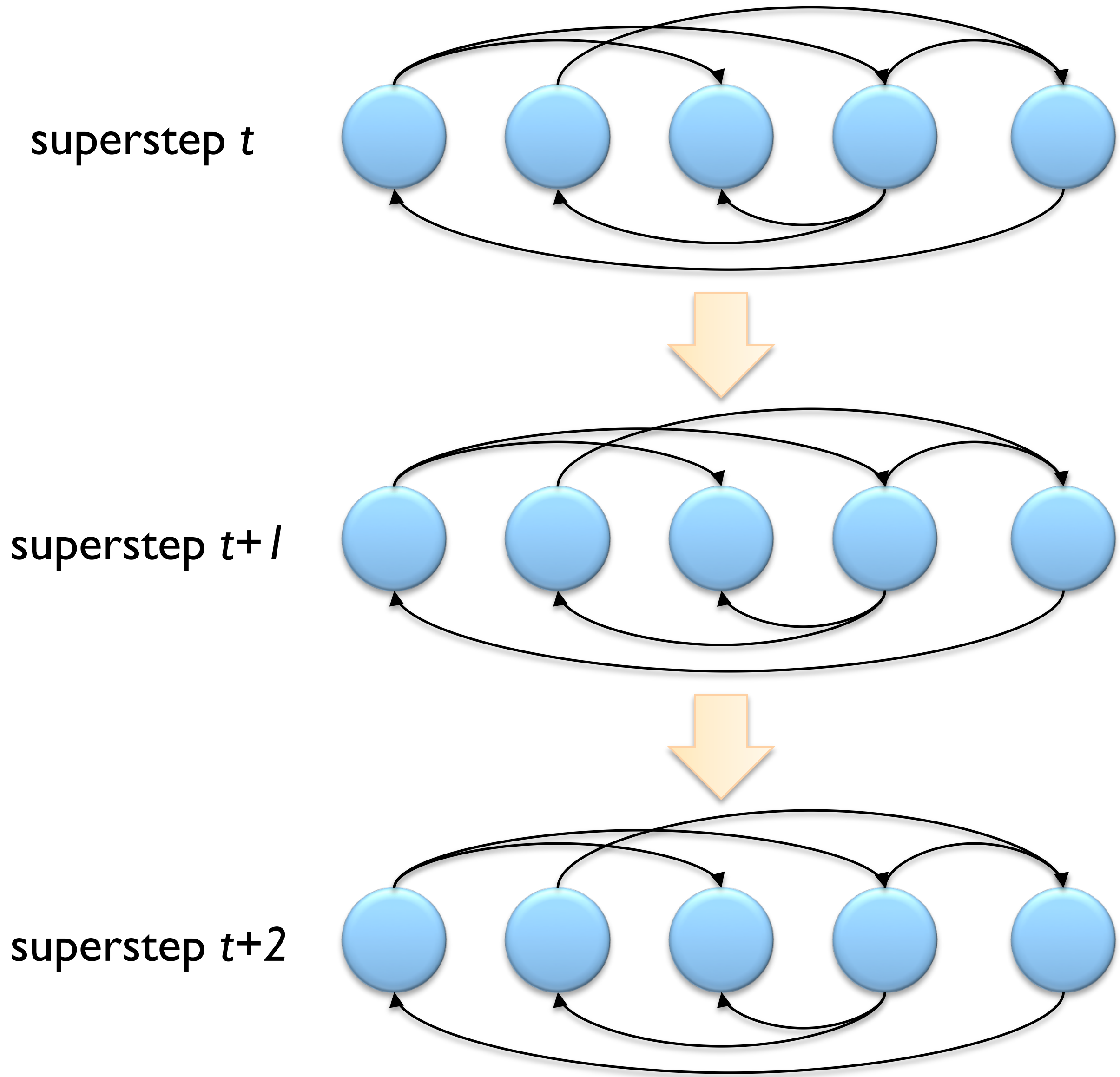
What's the issue?
Think like a vertex!

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



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

Pregel: Implementation

- Master-Slave 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

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: 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: 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

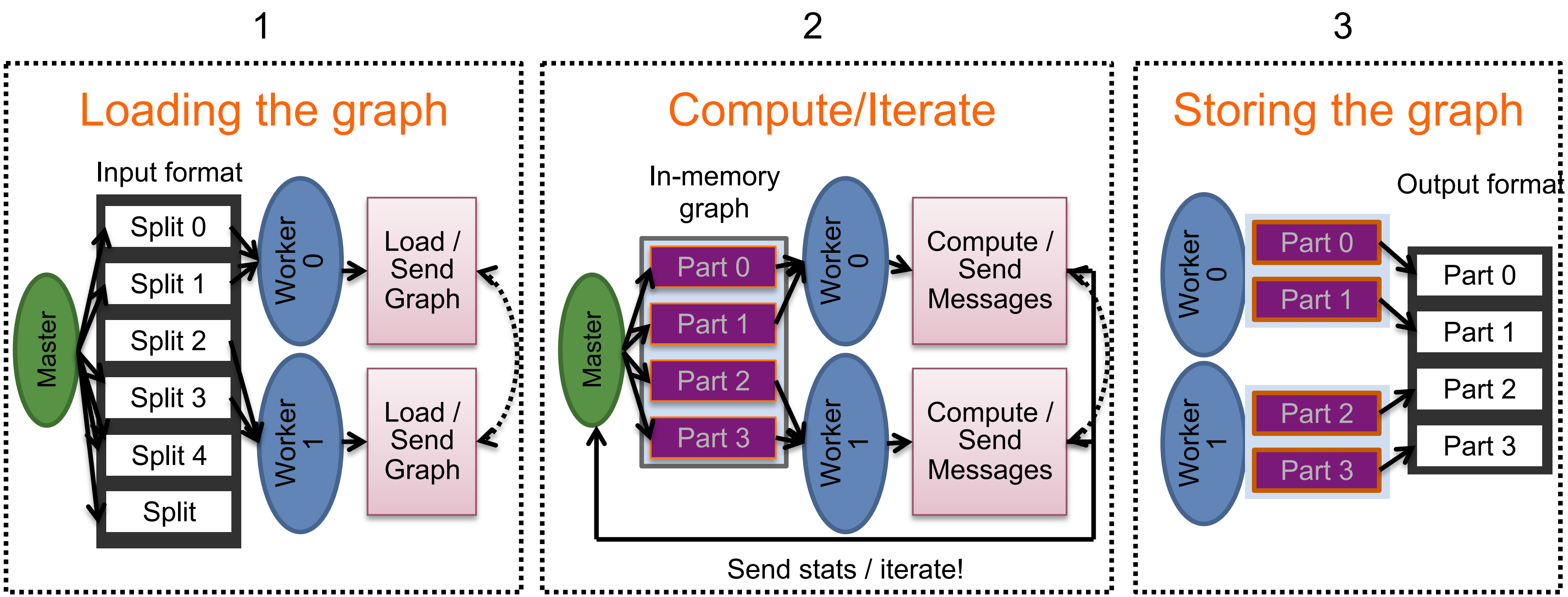
GIRAPH

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

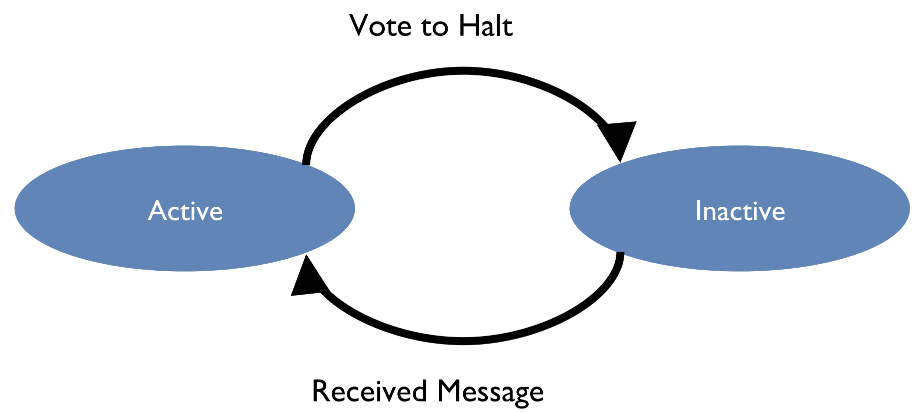
Giraph slides borrowed from Joffe (2013)

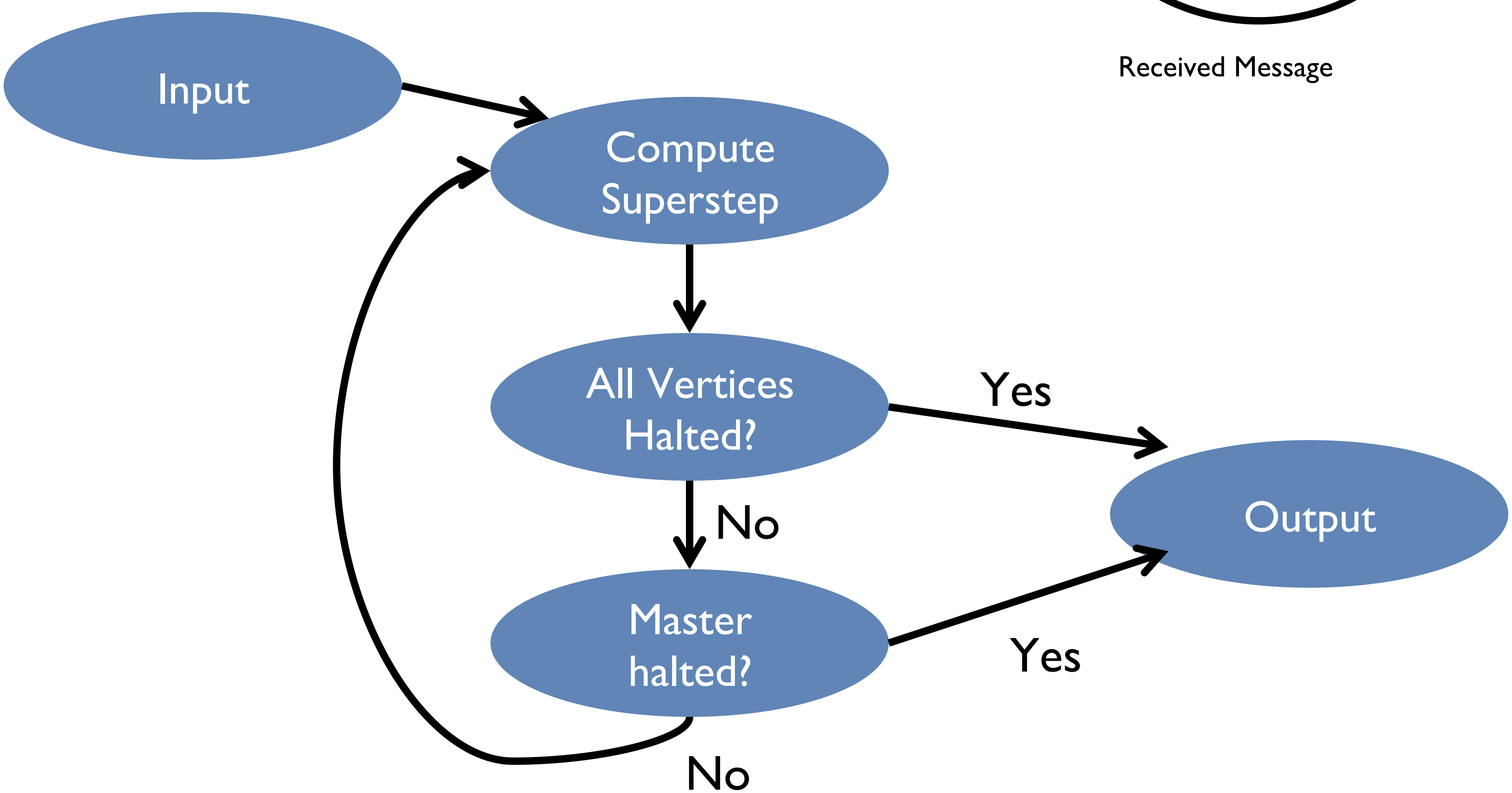
Giraph Dataflow



Giraph Lifecycle

Vertex Lifecycle

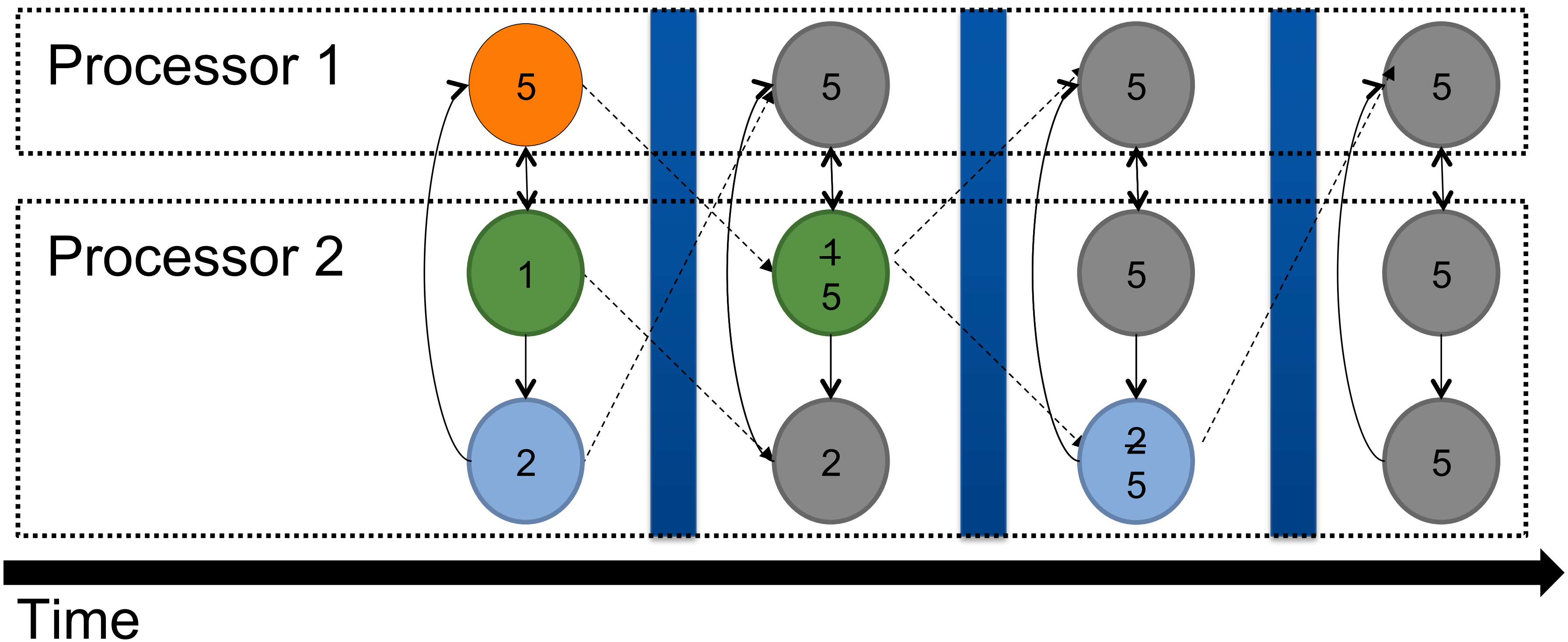




Giraph Example

```java
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();
  }
}
```

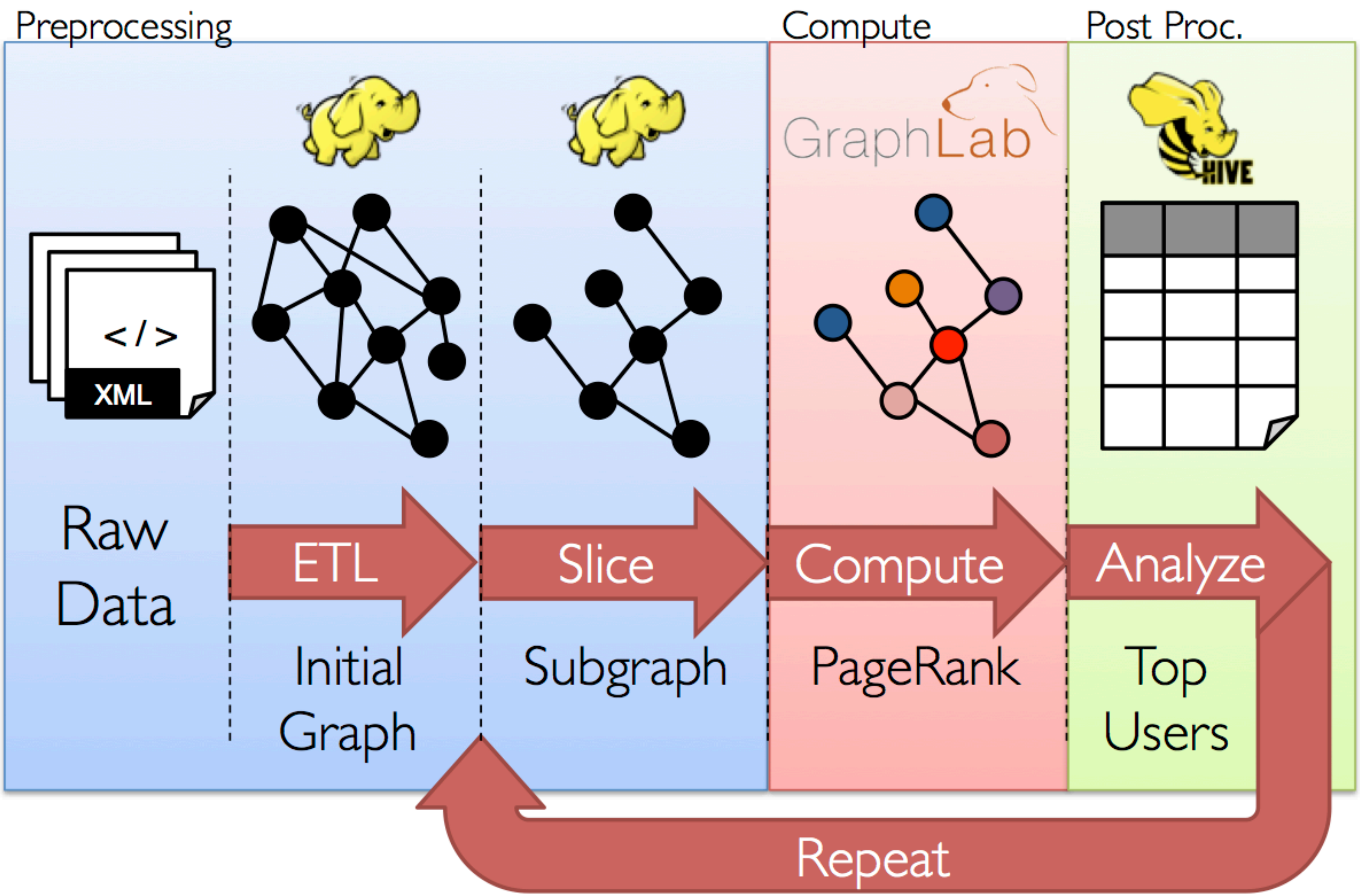
Execution Trace



Graph Processing Frameworks

Source: Wikipedia (Waste container)

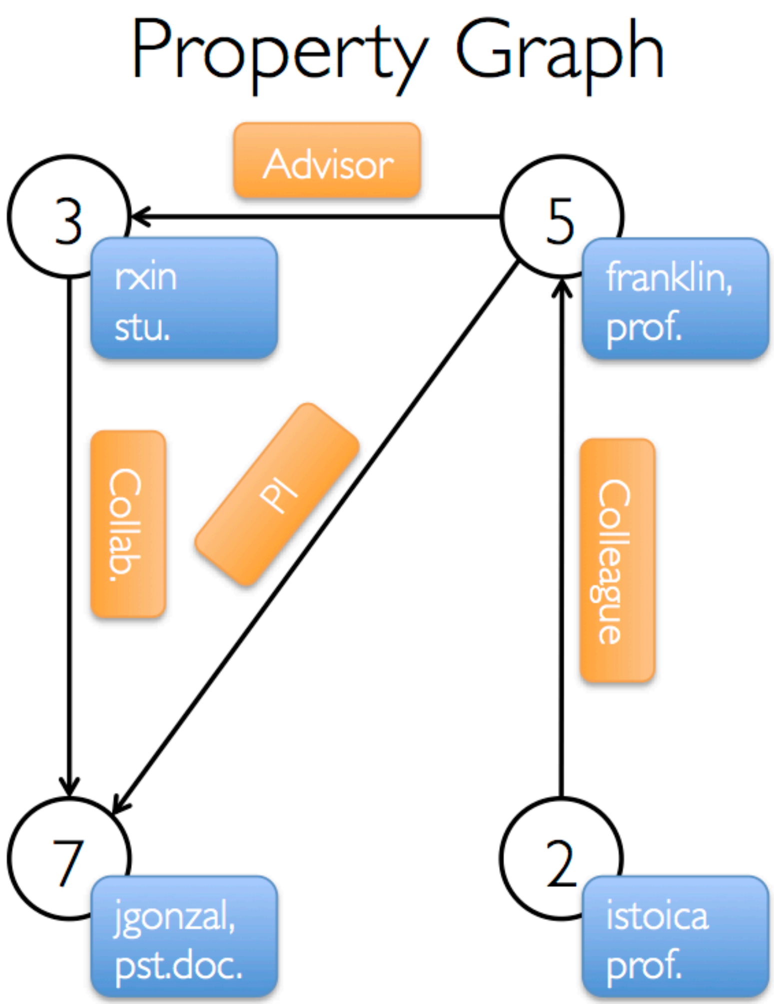
GraphX: Motivation



GraphX = Spark for Graphs

- Integration of record-oriented and graph-oriented processing
- Extends RDDs to Resilient Distributed Property Graphs
- Property graphs:
  - Present different views of the graph (vertices, edges, triplets)
  - Support map-like operations
  - Support distributed Pregel-like aggregations

Property Graph: Example



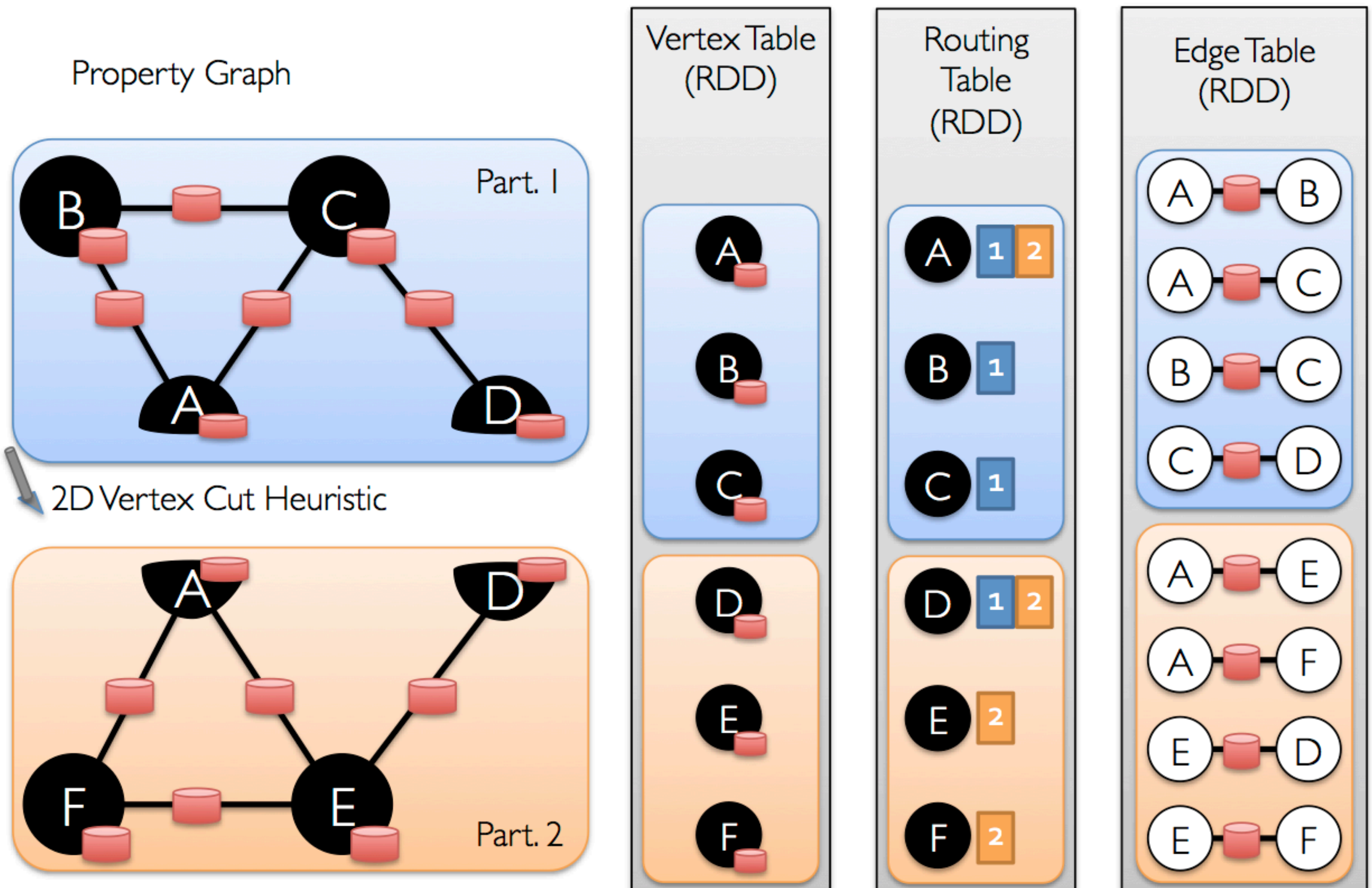
Vertex Table

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

Underneath the Covers



Source: Wikipedia (Japanese rock garden)