Indian Institute of Science
Bangalore, India
भारतीय विज्ञान संस्थान
बंगलौर, भारत

Department of Computational and Data Sciences

DS256:Jan17 (3:1)

L6:Distributed Graph Processing

Yogesh Simmhan

Assignment 2 (Storm)

- Deadline extension to Apr 8 (Sunday), 11:59PM
  - Submission instructions
- No class on Thu 29 Mar

Guest Lectures

- Robin Thomas, VMWare, Apr 5 4-5pm, CDS 102
  - Scalability in VMWare's IoT Architecture
- NetApp, Apr 10/12 (TBD), 4-5PM, CDS 102
  - Storage Area Networks and Big Data Platforms

Project

- Teams of 1 or 2
- Project proposal, teams by Apr 2, 11:59pm
  - 2 pages, IEEE 2 column format, PDF
  - Email to simmhan@iisc.ac.in with subject "DS256 Project Proposal:Lastname1, Lastname2"

1. Motivation
2. Related work
3. Contributions
4. Technical challenges addressed
5. Evaluation: Datasets, Scalability, Platforms, Cluster

- Proposal presentation, Apr 3
- Final project code, report due by Apr 24
- Demo, final presentation, Apr 28 Sat

Pregel: a system for large-scale graph processing

Malewicz, et al

SIGMOD 2010

Graphs are commonplace

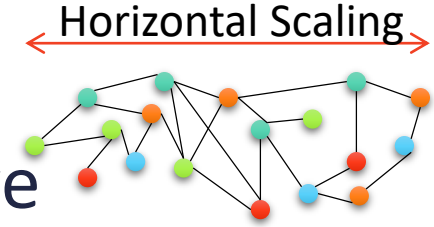
- Web & Social Networks
  - Web graph, Citation Networks, Twitter, Facebook, Internet
- Knowledge networks & relationships
  - Google's Knowledge Graph, NELL
- Cybersecurity
  - Telecom call logs, financial transactions, Malware
- Internet of Things
  - Transport, Power, Water networks
- Bioinformatics
  - Gene sequencing, Gene expression networks

Graph Algorithms

- Traversals: *Paths & flows between different parts of the graph*
  - Breadth First Search, Shortest path, Minimum Spanning Tree, Eulerian paths, MaxCut
- Clustering: *Closeness between sets of vertices*
  - Community detection & evolution, Connected components, K-means clustering, Max Independent Set
- Centrality: *Relative importance of vertices*
  - PageRank, Betweenness Centrality

When Had**p is just not good enough…

- Gap in frameworks for *dynamic graphs*
- Tuple/row/column-oriented frameworks
  - *E.g. Hadoop, Hive, Impala*
- Graph Databases & In-Memory
  - *E.g. Flock DB, Neo4J, MSR Trinity, Giraph*
  - Focus on large simple graphs, complex "queries", distributed in-memory
- Parallel Graph Frameworks
  - MPI, parallel computing, steep curve
  - Specialized HPC/shared-memory hardware

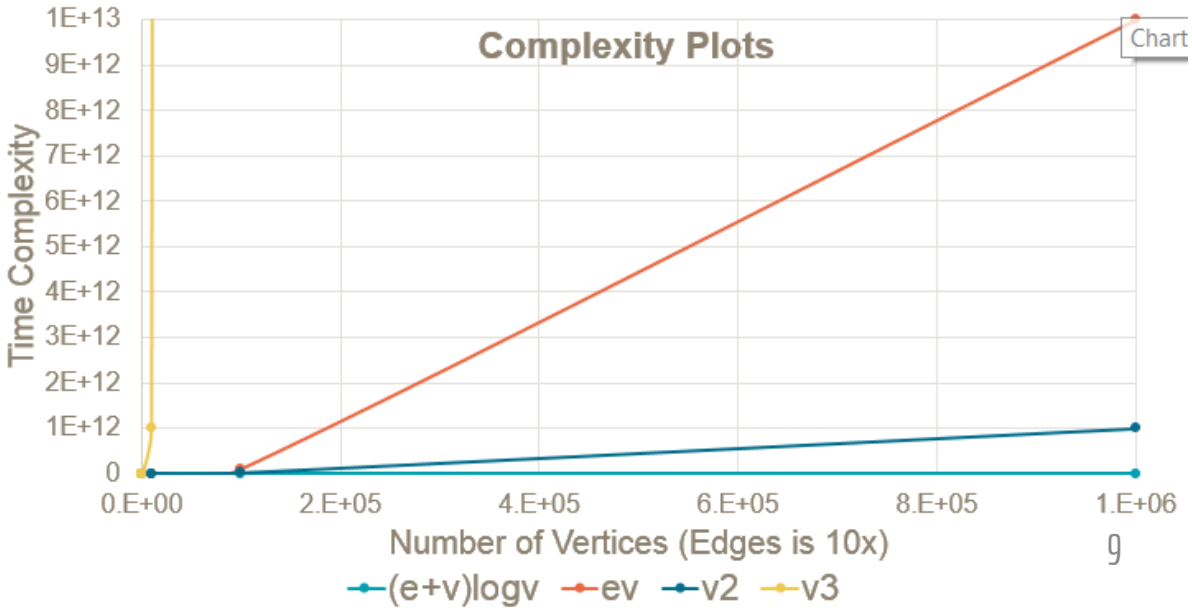


✓Storage & compute are (loosely)coupled

But, Graphs can be challenging

- Computationally complex algorithms
  - Shortest Path: O((E+V) log V) ~ O(EV)
  - Centrality: O(EV) ~ O(V^3)
  - Clustering: O(V) ~ O(V^3)
- *And these are for "shared-memory" algorithms*

Graph500.org's fastest supercomputer, ***K computer*** *with 524,288 cores performed at* ***17E+12 TEPS***



But, Graphs can be challenging

- Graphs sizes can be huge
  - Google's index contains 50B pages
  - Facebook has around 1.1B users
  - Twitter has around 530M users
  - Google+ has around 570M users

Apache Giraph, Claudio Martella, Hadoop Summit, Amsterdam, April 2014

But, Graphs can be challenging

- Shared memory algorithms don't scale!
- Do not fit naturally to *Hadoop/MapReduce*
  - Multiple MR jobs (iterative MR)
  - Topology & Data written to HDFS each time
  - *Tuple*, rather than graph-centric, abstraction
- Lot of work on *parallel graph libraries* for HPC
  - Boost Graph Library, Graph500
  - Storage & compute are (loosely) coupled, not fault tolerant
  - But everyone does not have a supercomputer ☺
- Processing and *querying* are different
  - Graph DBs not suited for analytics
  - Focus on large simple graphs, complex "queries"
  - *E.g. Neo4J, FlockDB, 4Store, Titan*

PageRank using MapReduce

```
1: class Mapper
2:     method Map(nid n, node N)
3:         p ← N.PageRank/|N.AdjacencyList|
4:         Emit(nid n, N)                          ▷ Pass along graph structure
5:         for all nodeid m ∈ N.AdjacencyList do
6:             Emit(nid m, p)                      ▷ Pass PageRank mass to neighbors

1: class Reducer
2:     method Reduce(nid m, [p1, p2, ...])
3:         M ← ∅
4:         for all p ∈ counts [p1, p2, ...] do
5:             if IsNode(p) then
6:                 M ← p                           ▷ Recover graph structure
7:             else
8:                 s ← s + p                       ▷ Sum incoming PageRank contributions
9:         M.PageRank ← s
10:        Emit(nid m, node M)
```

Lin, Fig 5.8

PageRank using MapReduce

- MR run over multiple iterations (typically 30)
  - *The graph structure itself must be passed from iteration to iteration!*
- Mapper will
  - Initially, load adjacency list and initialize default PR
    - `<v1, <v2>+>`
  - Subsequent iterations will load adjacency list and new PR
    - `<v1, <v2>+, pr1>`
  - Emit two types of messages from Map
    - PR messages and Graph Structure Messages
- Reduce will
  - Reconstruct the adjacency list for each vertex
  - Update the PageRank values for the vertex based on neighbour's PR messages
  - Write adjacency list and new PR values to HDFS, to be used by next Map iteration
    - `<v1, <v2>+, pr1'>`

Google's Pregel

- Google, to overcome, these challenges came up with Pregel.
  - Provides scalability
  - Fault-tolerance
  - Flexibility to express arbitrary algorithms

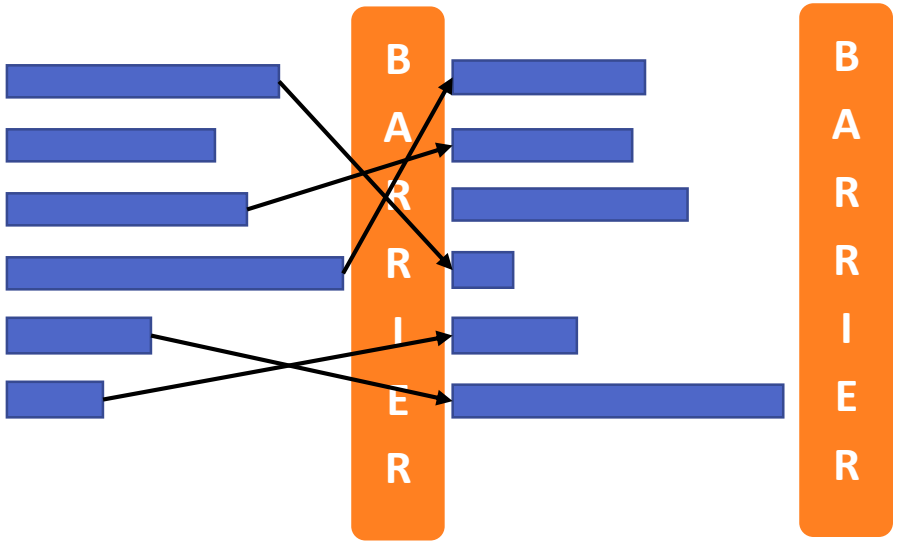
- The high level organization of Pregel programs is inspired by Valiant's Bulk Synchronous Parallel (BSP) model [1].

Slides courtesy "Pregel: A System for Large-Scale Graph Processing, Malewicz, et al, SIGMOD 2010"

[1] Leslie G. Valiant, A Bridging Model for Parallel Computation. Comm. ACM 33(8), 1990

Bulk Synchronous Parallel (BSP)

- Distributed execution model
  - Compute → Communicate → Compute → Communicate → …
  - Bulk messaging avoids comm. costs



Vertex-centric BSP

- Series of iterations (*supersteps*) .
- Each vertex *V* invokes a function in parallel.
- Can read messages sent in previous superstep (*S-1*).
- Can send messages, to be read at the next superstep (*S+1*).
- Can modify state of outgoing edges.

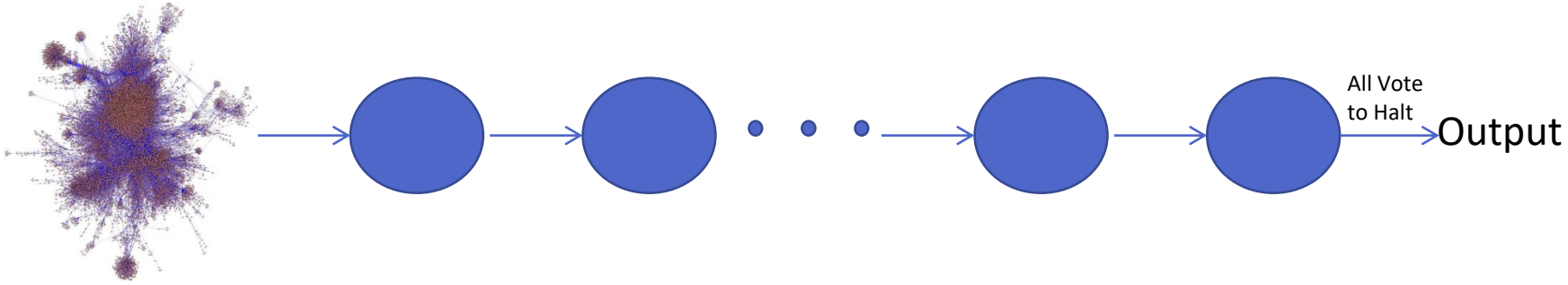
Advantage?

- In Vertex-Centric Approach
- Users focus on a *local action*
  - Think of **Map** method over tuple
- Processing each item *independently*.
- Ensures that Pregel programs are inherently free of *deadlocks* and *data races* common in asynchronous systems.

Apache Giraph
Implements *Pregel* Abstraction

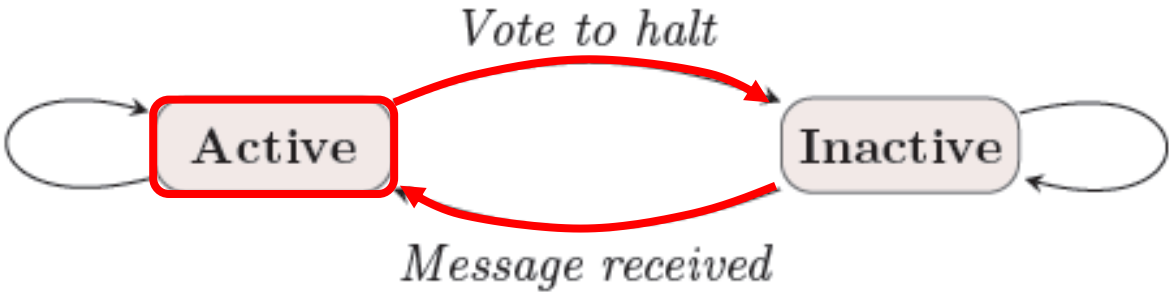
- Google's Pregel, SIGMOD 2010
  - Vertex-centric Model
  - Iterative BSP computation
- Apache Giraph donated by Yahoo
  - Feb 6, 2012: Giraph 0.1-incubation
  - May 6, 2013: Giraph 1.0.0
  - Nov 19, 2014: Giraph 1.1.0
- Built on Hadoop Ecosystem

Model of Computation



- A Directed Graph is given to Pregel.
- It runs the computation at each vertex.
- Until all nodes vote for halt.
- Pregel gives you a directed graph back.

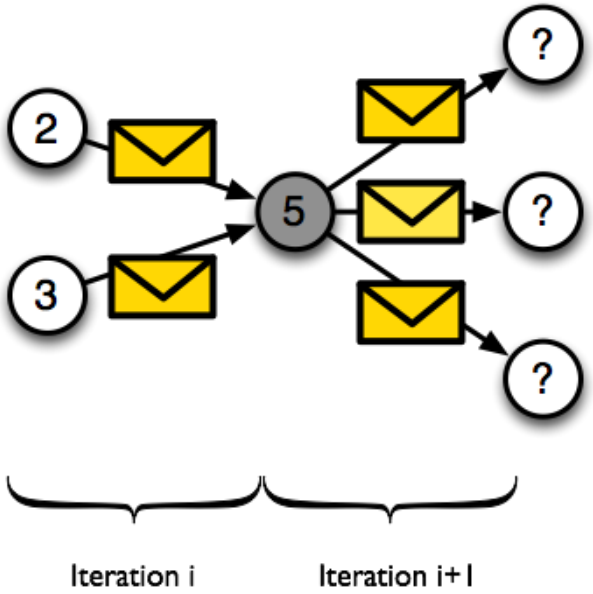
Vertex State Machine



- Algorithm termination is based on every vertex *voting to halt*.
- In superstep 0, every vertex is in the *active* state.
- A vertex deactivates itself by voting to halt.
- It can be reactivated by receiving an (external) message.

Vertex Centric Programming

- Vertex Centric Programming Model
  - Logic written from perspective on a single vertex. Executed on all vertices.
- Vertices know about
  - Their own value(s)
  - Their outgoing edges



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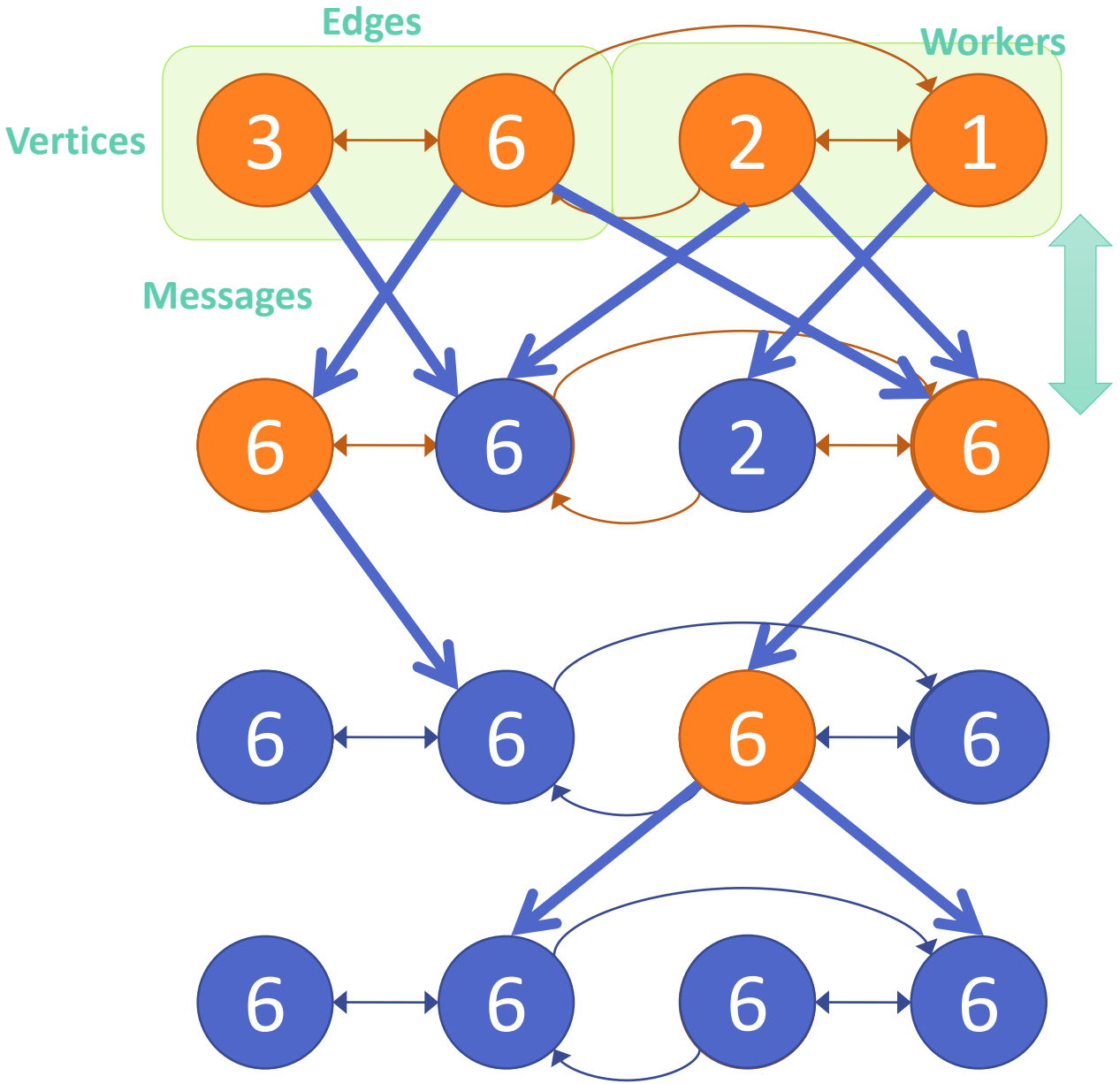


Blue Arrows are messages.

Blue vertices have voted to halt.

Pregel: A System for Large-Scale Graph Processing, Malewicz, et al, SIGMOD 2010

Max Vertex

Algorithm 1 Max Vertex Value using Vertex Centric Model

```
1:  procedure COMPUTE(Vertex myVertex, Iterator⟨Message⟩ M)
2:      hasChanged = (superstep == 1) ? true : false
3:      while M.hasNext do            ▶ Update to max message value
4:          Message m ← M.next
5:          if m.value > myVertex.value then
6:              myVertex.value ← m.value
7:              hasChanged = true
8:      if hasChanged then            ▶ Send message to neighbors
9:          SENDTOALLNEIGHBORS(myVertex.value)
10:     else
11:         VOTETOHALT( )
```

GoFFish: A Sub-Graph Centric Framework for Large-Scale Graph Analytics, Simmhan, et al, EuroPar 2014

Advantages

- Makes distributed programming easy
  - No locks, semaphores, race conditions
  - Separates computing from communication phase
- Vertex-level parallelization
  - Bulk message passing for efficiency
- Stateful (in-memory)
  - Only messages & checkpoints hit disk

Apache Giraph: API

```
void compute(Iterator<IntWritable> msgs)
    getSuperstep()
    getVertexValue()
    edges = iterator()
    sendMsg(sinkVtx, value)
    sendMsgToAllEdges(value)
    voteToHalt()
```

Message passing

- No guaranteed message delivery order.
- Messages are delivered exactly once.
- Can send messages to any node.
  - Though, typically to neighbors

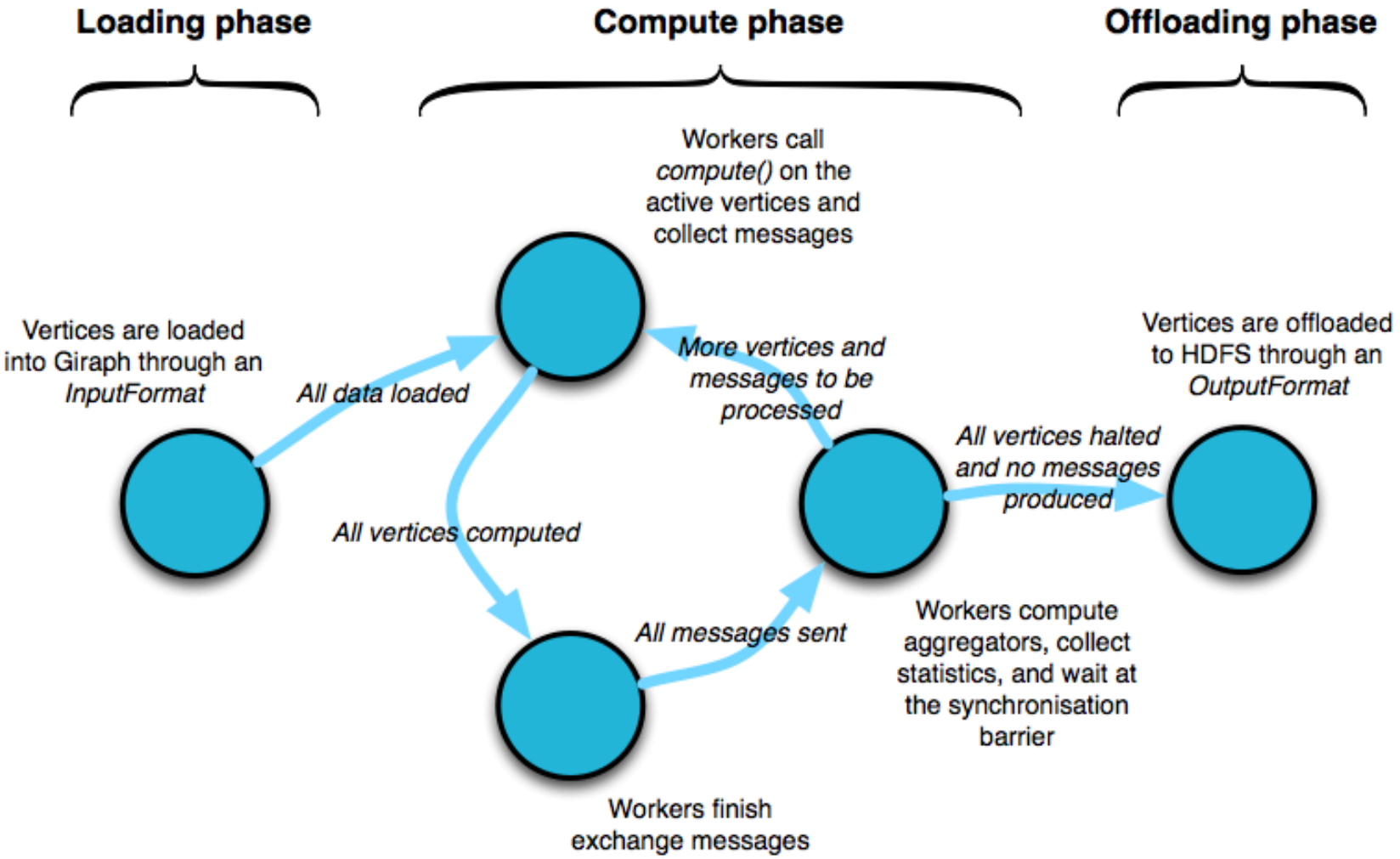
```
public class MaxVertexVertex extends IntIntNullIntVertex {
    public void compute(Iterator<IntWritable> messages)
            throws IOException {
        int currentMax = getVertexValue().get();
        // first superstep is special,
        // because we can simply look at the neighbors
        if (getSuperstep() == 0) {
            Iterator<IntWritable> edges = iterator();
            while(edges.hasNext()) {
                int neighbor = edges.next().get();
                if (neighbor > currentMax) {
                   currentMax = neighbor;
                }
            } ...
```

Based on org.apache.giraph.examples.ConnectedComponentsVertex

```
    ...
    // only need to send value if it is not the own id
    if (currentMax != getVertexValue().get()) {
      setVertexValue(new IntWritable(currentMax));
    Iterator<IntWritable> edges = iterator();
    while(edges.hasNext()) {
      int neighbor = edges.next().get();
      if (neighbor < currentMax) {
        sendMsg(new IntWritable(neighbor),
          getVertexValue());
      }
    }
  }
  voteToHalt();
  return;
} // end getSuperstep==0
```

```
    boolean changed = false; // getSuperstep != 0
    // did we get a smaller id?
    while (messages.hasNext()) {
      int candidateMax = messages.next().get();
      if (candidateMax > currentMax) {
            currentMax = candidateMax;
            changed = true;
        }
    }
    // propagate new component id to the neighbors
    if (changed) {
        setVertexValue(new IntWritable(currentMax));
        sendMsgToAllEdges(getVertexValue());
    }
    voteToHalt();
} // end compute()
```

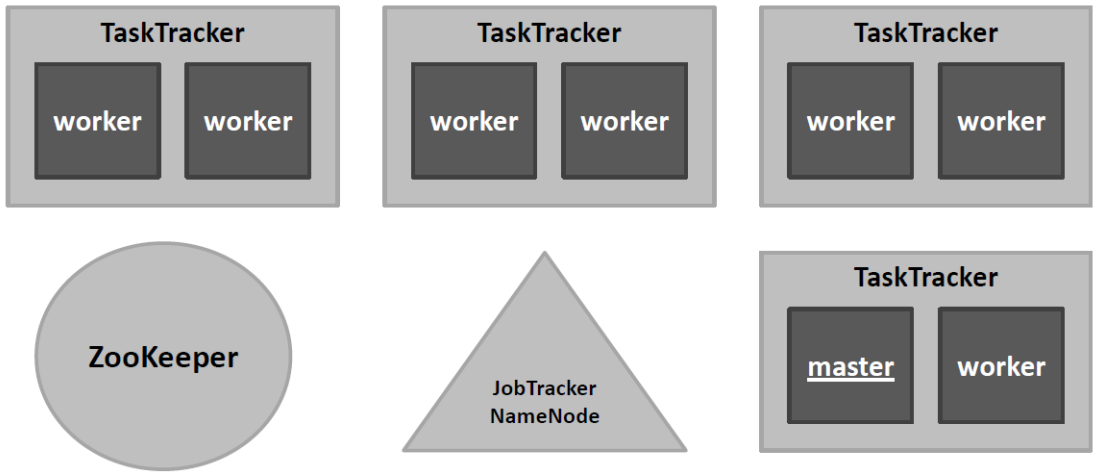
Apache Giraph



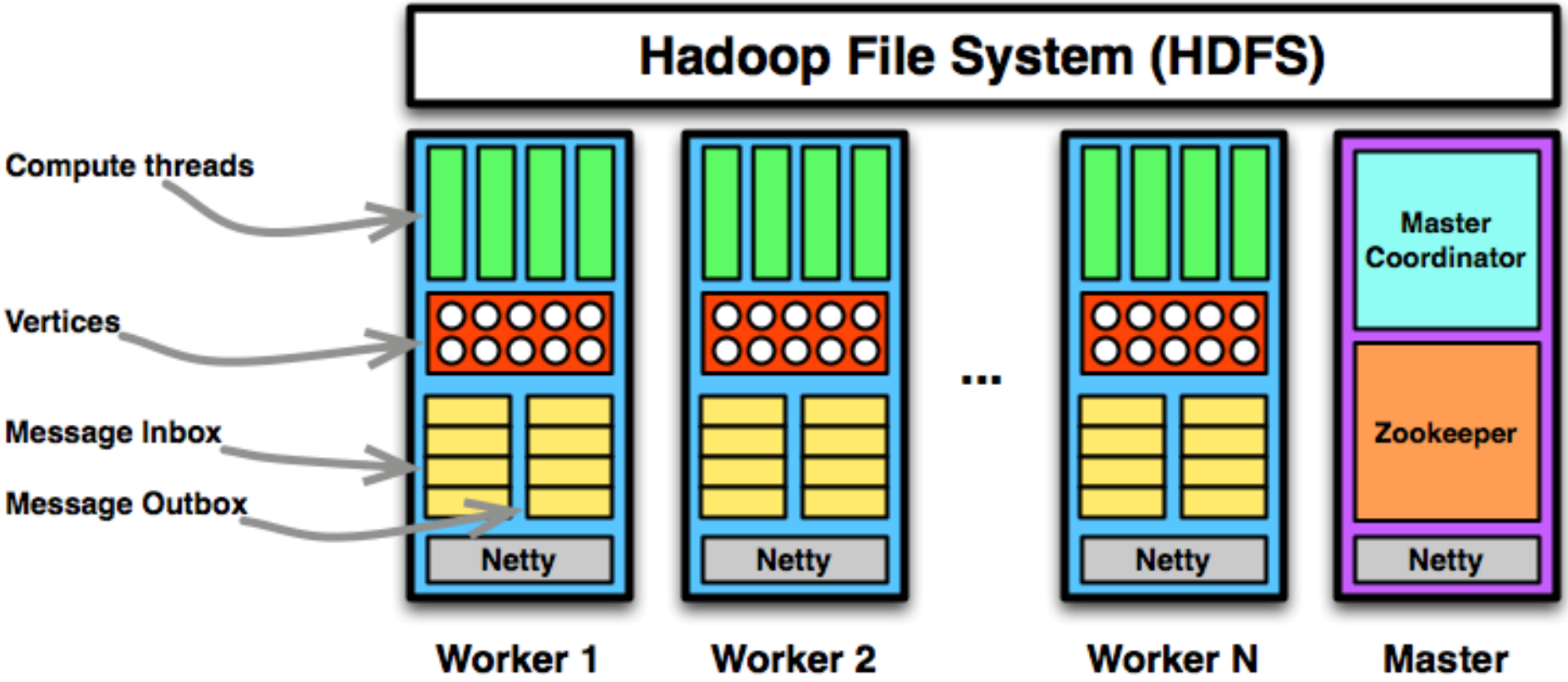
Apache Giraph, Claudio Martella, Hadoop Summit, Amsterdam, April 2014

Giraph Architecture

- Hadoop Map-only Application
- **ZooKeeper**: responsible for **computation state**
  - Partition/worker mapping, global #superstep
- **Master**: responsible for **coordination**
  - Assigns partitions to workers, synchronization
- **Worker:** responsible for **vertices**
  - Invokes active vertices compute() function, sends, receives and assigns messages



Giraph Architecture



- Checkpointing of supersteps possible

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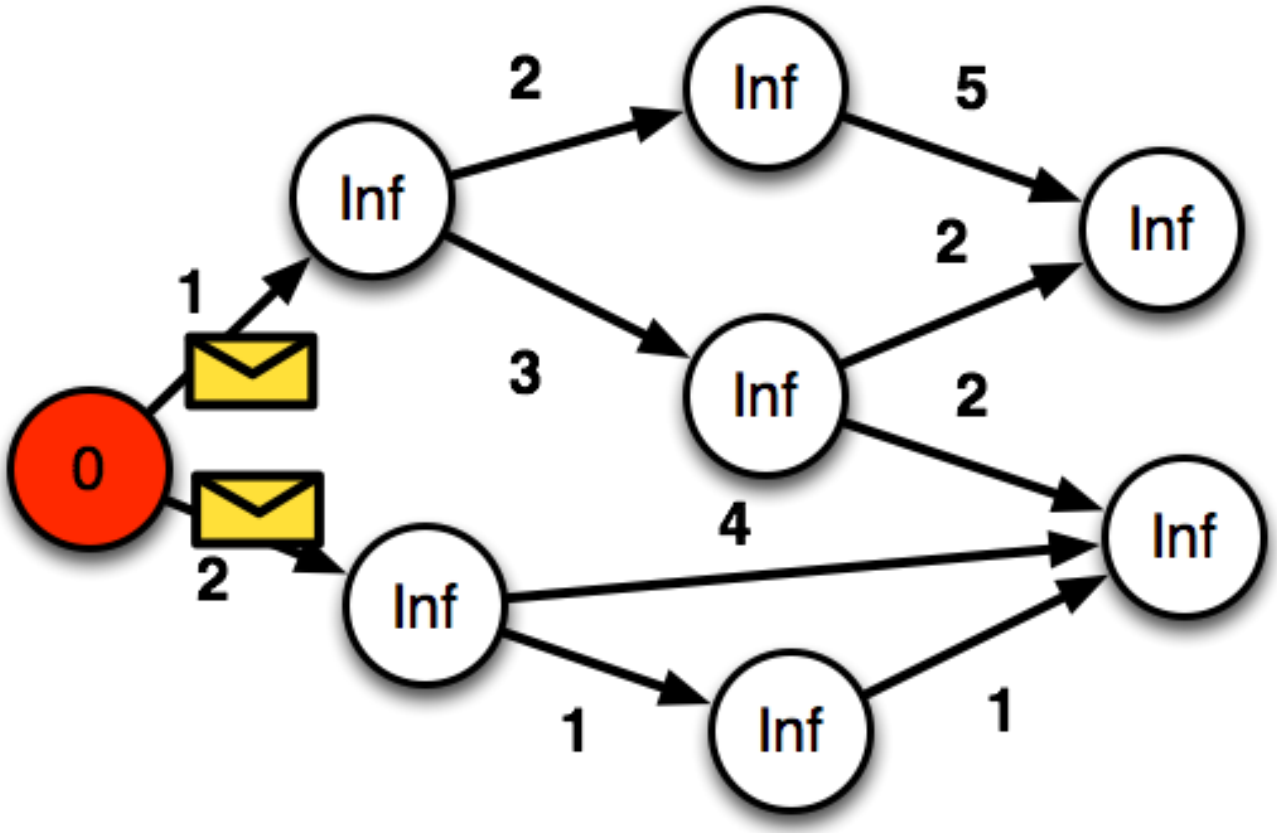
Shortest Path

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

In the 1st superstep, only the source vertex will update its value (from INF to zero)

Shortest Path



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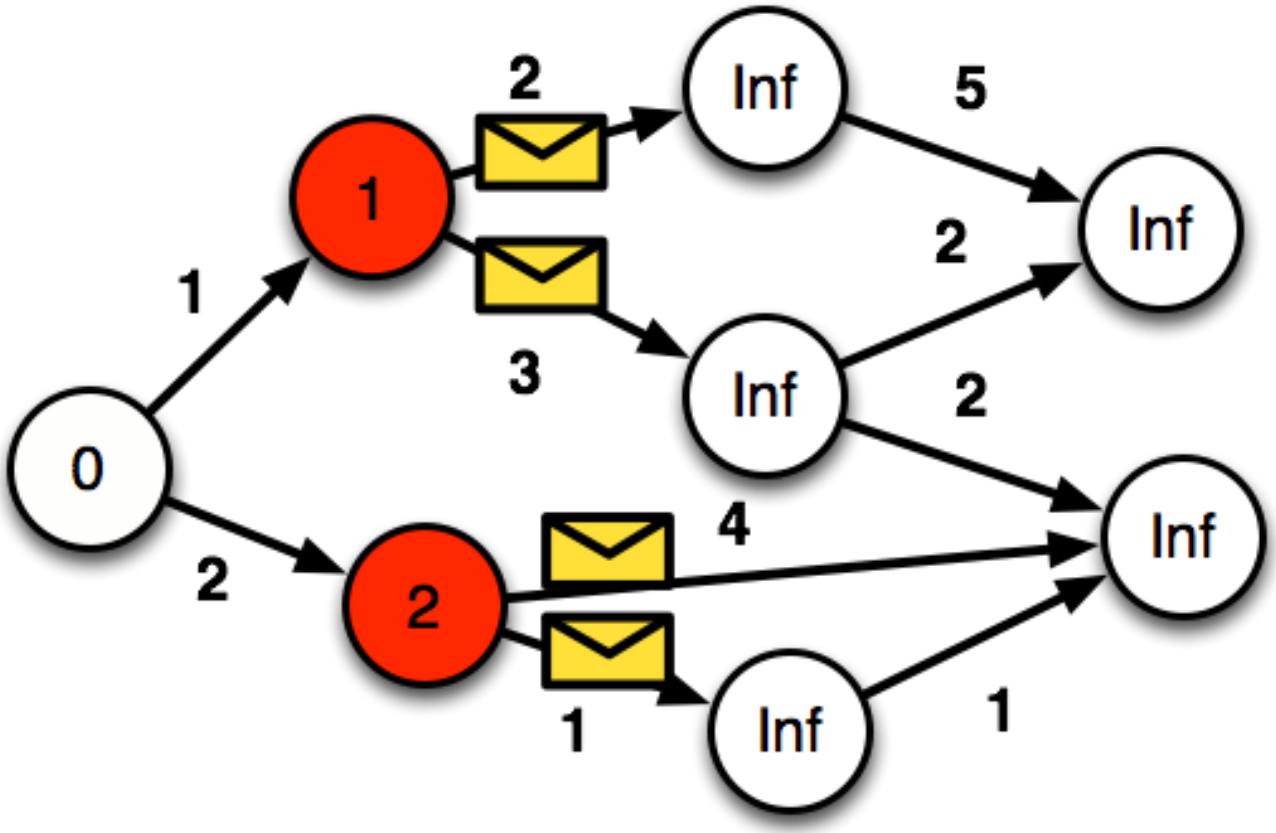
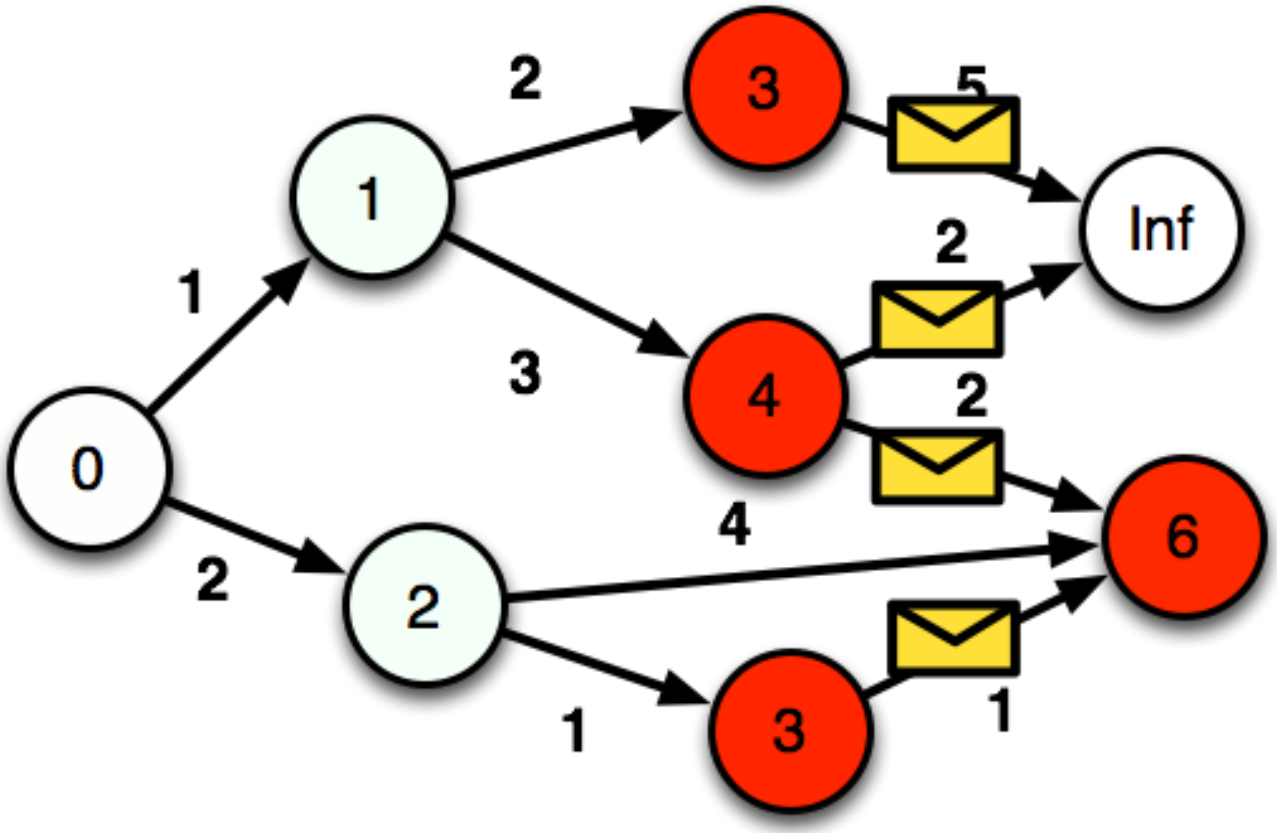
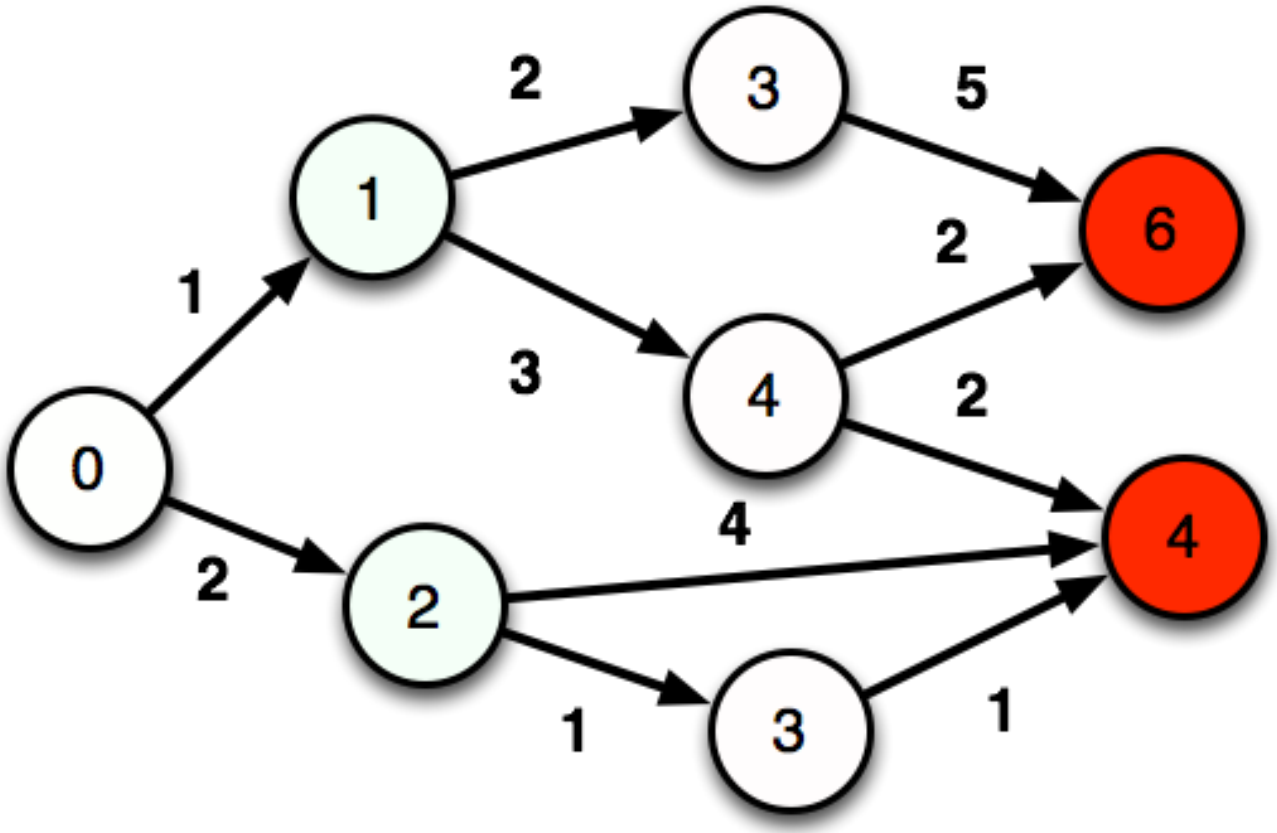
Shortest Path



Shortest Path



Shortest Path



PageRank, recursively

$$P(n) = \alpha \left(\frac{1}{|G|} \right) + (1 - \alpha) \sum_{m \in L(n)} \frac{P(m)}{C(m)}$$

- P(n) is PageRank for webpage/URL ‘n’
  - Probability that you’re in vertex ‘n’
- |G| is number of URLs (vertices) in graph
- α is probability of random jump
- L(n) is set of vertices that link to ‘n’
- C(m) is out-degree of ‘m’

PageRank using MapReduce

```
1: class Mapper
2:     method Map(nid n, node N)
3:         p ← N.PageRank/|N.AdjacencyList|
4:         Emit(nid n, N)                          ▷ Pass along graph structure
5:         for all nodeid m ∈ N.AdjacencyList do
6:             Emit(nid m, p)                      ▷ Pass PageRank mass to neighbors

1: class Reducer
2:     method Reduce(nid m, [p1, p2, ...])
3:         M ← ∅
4:         for all p ∈ counts [p1, p2, ...] do
5:             if IsNode(p) then
6:                 M ← p                           ▷ Recover graph structure
7:             else
8:                 s ← s + p                       ▷ Sum incoming PageRank contributions
9:         M.PageRank ← s
10:        Emit(nid m, node M)
```

Lin, Fig 5.8

Application – Page Rank

Store and carry PageRank

```
class PageRankVertex
        : public Vertex<double, void, double> {
public:
  virtual void Compute(MessageIterator* msgs) {
        if (superstep() == 0) *MutableValue() = 1 / NumVertices();
        else
        if (superstep() >= 1) {
                double sum = 0;
                while((m = msgs->Next()) != NULL)
                        sum += m->Value();
                *MutableValue() = 0.15 / NumVertices() + 0.85 * sum;
        }
        if (superstep() < 30) {
                const int64 n = GetOutEdgeIterator().size();
                SendMessageToAllNeighbors(GetValue() / n);
        } else
                VoteToHalt();
  }
};
```

Combiners

- Sending a message to remote vertex has overhead
  - Can we merge multiple *incoming* message into one?
- User specifies a way to reduce many messages into one value (ala Reduce in MR)
  - by overriding the **Combine()** method.
  - Must be commutative and associative.

```
originalMessage =
 combine(vid, originalMessage, messageToCombine)
```

- Exceedingly useful in certain contexts (e.g., 4x speedup on shortest-path computation).
  - e.g. for MAX, om = om < mtc ? mtc : om

MasterCompute

- Runs before slave compute()
- Has a global view
- A place for aggregator manipulation

- `MasterCompute`: Executed on master
- `WorkerContext`: Executed per worker
- `PartitionContext`: Executed per partition

Aggregators

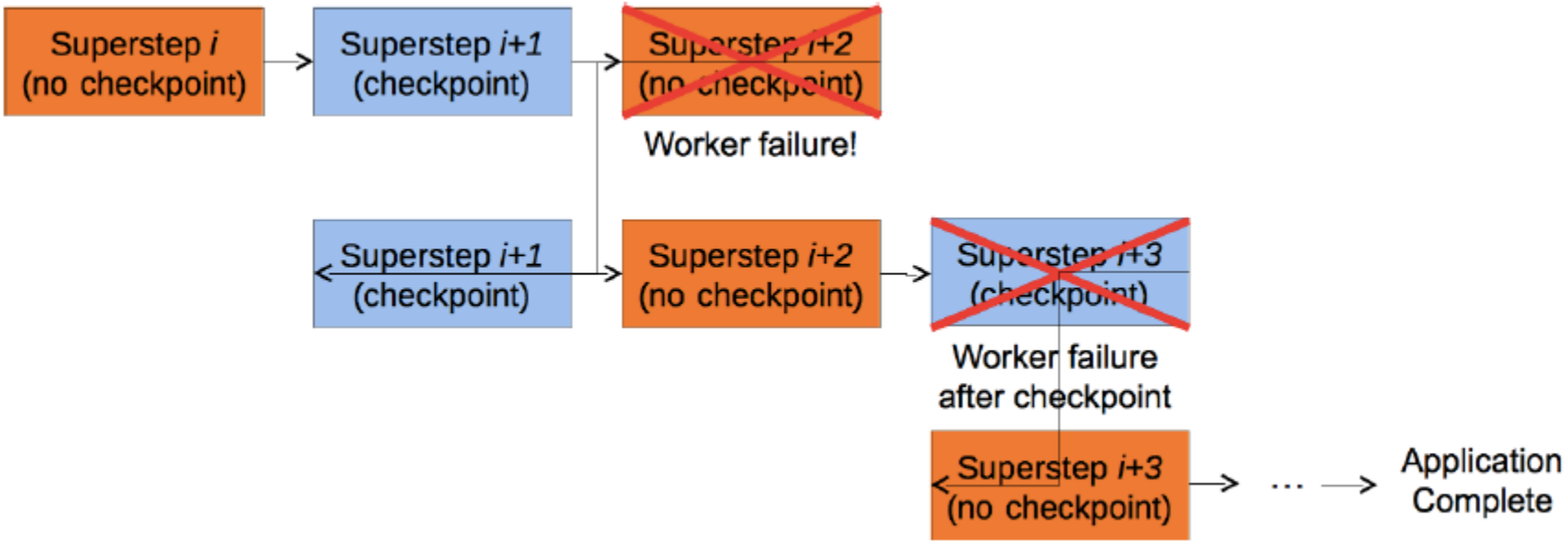
- A mechanism for global communication, monitoring, and data.
  - Each vertex can produce a value in a superstep S for the Aggregator to use.
  - The Aggregated value is available to all the vertices in superstep S+1.
- Implemented using Master Compute
- Aggregators can be used for statistics and for global communication.
  - E.g., **Sum** applied to out-edge count of each vertex.
    - generates the total number of edges in the graph and communicate it to all the vertices.

Partitioner

- Maps vertices to partitions that are operated by workers
  - Default is a hash partitioner
- Done once at the start of the application
- Called at the end of each superstep, for dynamic migration of partitions

Checkpointing

- Optionally capture the state of vertex, messages at periodic supersteps, e.g. 2
- Globally revert to last checkpoint superstep on failure



Topology mutations

- Some graph algorithms need to change the graph's topology.
  - E.g. A clustering algorithm may need to replace a cluster with a node
- Vertices can create / destroy vertices at will.
- Resolving conflicting requests:
  - Partial ordering:

    E Remove,V Remove,V Add, E Add.
  - User-defined handlers:

    You fix the conflicts on your own.