One Trillion Edges

Graph Processing at Facebook Scale

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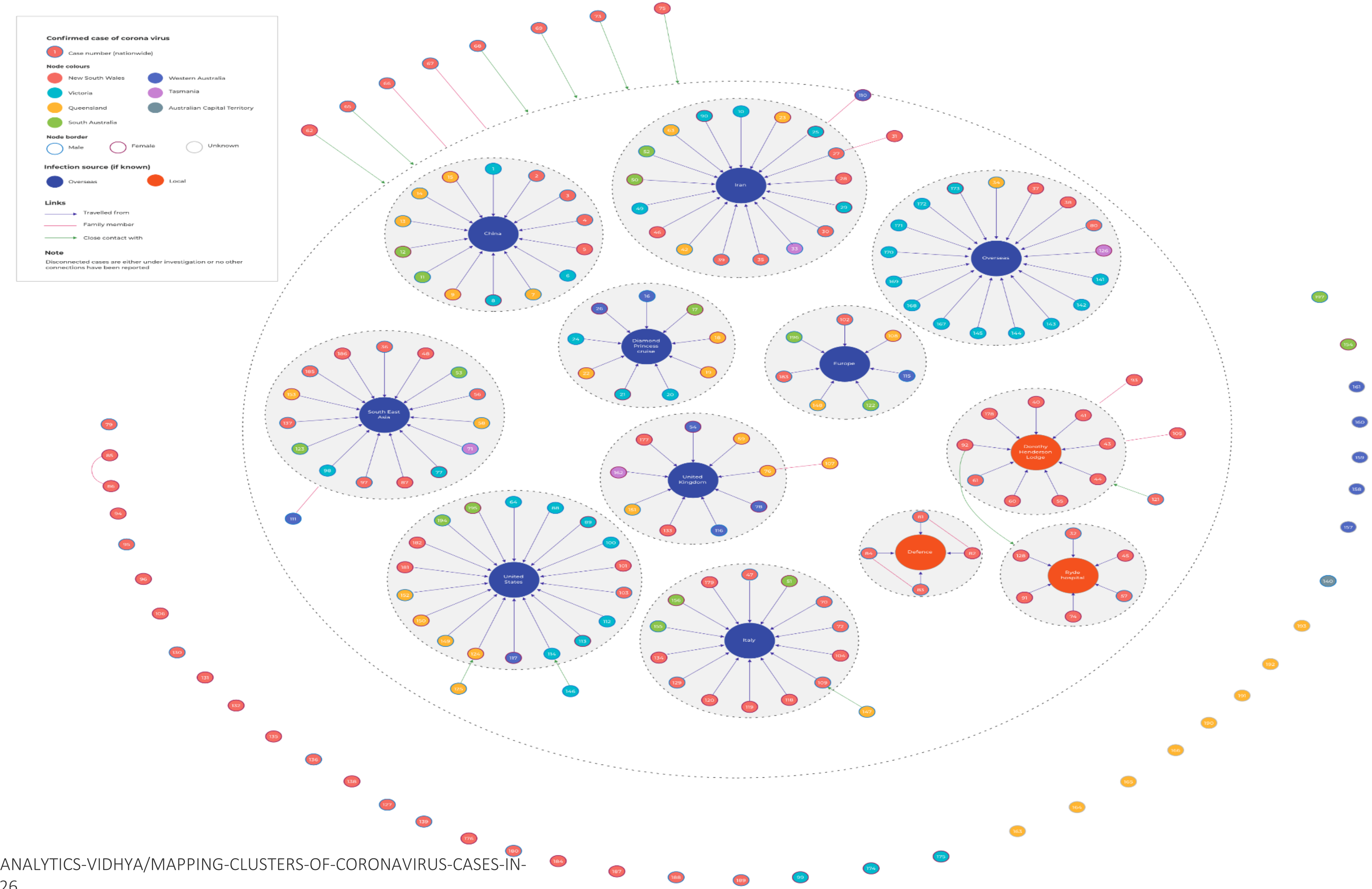
Graphs are Common



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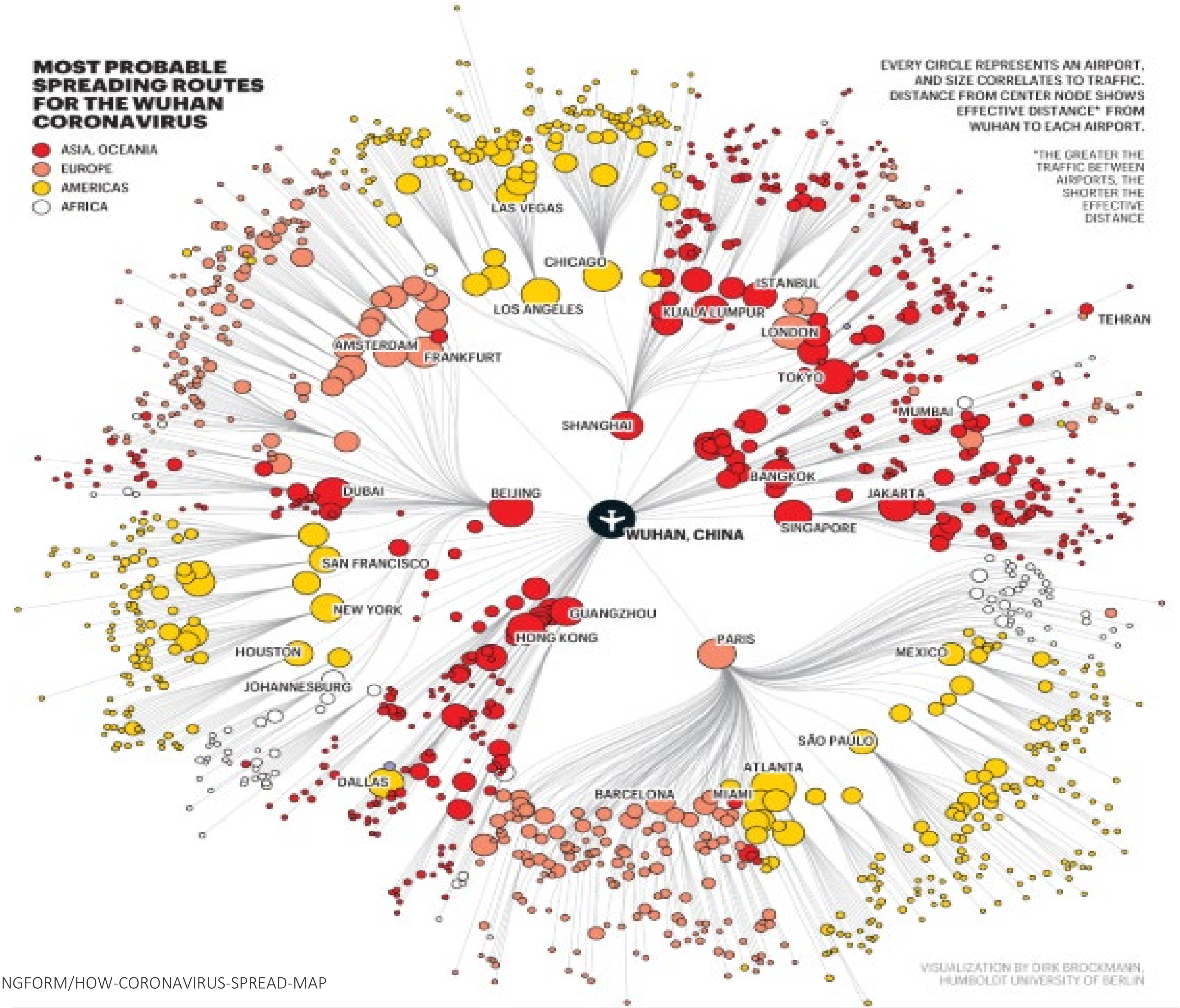
MOST PROBABLE SPREADING ROUTES FOR THE WUHAN CORONAVIRUS
ASIA, OCEANIA
EUROPE
AMERICAS
AFRICA
EVERY CIRCLE REPRESENTS AN AIRPORT, AND SIZE CORRELATES TO TRAFFIC. DISTANCE FROM CENTER NODE SHOWS EFFECTIVE DISTANCE* FROM WUHAN TO EACH AIRPORT.
*THE GREATER THE TRAFFIC BETWEEN AIRPORTS, THE SHORTER THE EFFECTIVE DISTANCE
LAS VEGAS
CHICAGO
LOS ANGELES
ISTANBUL
KUALA LUMPUR
LONDON
TEHRAN
AMSTERDAM
FRANKFURT
TOKYO
SHANGHAI
MUMBAI
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VISUALIZATION BY DIRK BROCKMANN, HUMBOLDT UNIVERSITY OF BERLIN

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Other Common Graphs

- Web & Social Networks
  - Web graph, Citation Networks, Twitter, Facebook
- 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

Graphs are Huge!!!

- Real world web and social graphs are huge and continue to grow
  - Google estimated no. of web pages 30 trillion (2013)
  - Facebook has around 2 billion active users (2018)
  - Google has around 570 million users
  - Twitter claimed to have over 530 million users
- Relevant and personalized information for users relies strongly on iterative graph ranking algorithms (search results, social news, ads, etc)
  - In web graphs, page rank and its variants
  - In Social graphs, popularity rank, shared connection, shortest paths, etc.

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
- List is endless

Why Existing Solutions Fail?

- Shared memory algorithms don't scale!
- Graph algorithms are computationally expensive
- Do not fit naturally to Hadoop/MapReduce
  - Classical Map-Reduce Overheads (jobs startup/shutdown, reloading data from HDFS, shuffling)
  - Map-reduce programming model not good fit for graph algorithms
- Lot of work on parallel graph libraries for HPC
  - Storage & compute are (loosely) coupled, not fault tolerant
  - But everyone does not have a supercomputer
- Message Passing Interface
  - Not Fault-tolerant
  - Too generic

Pregel

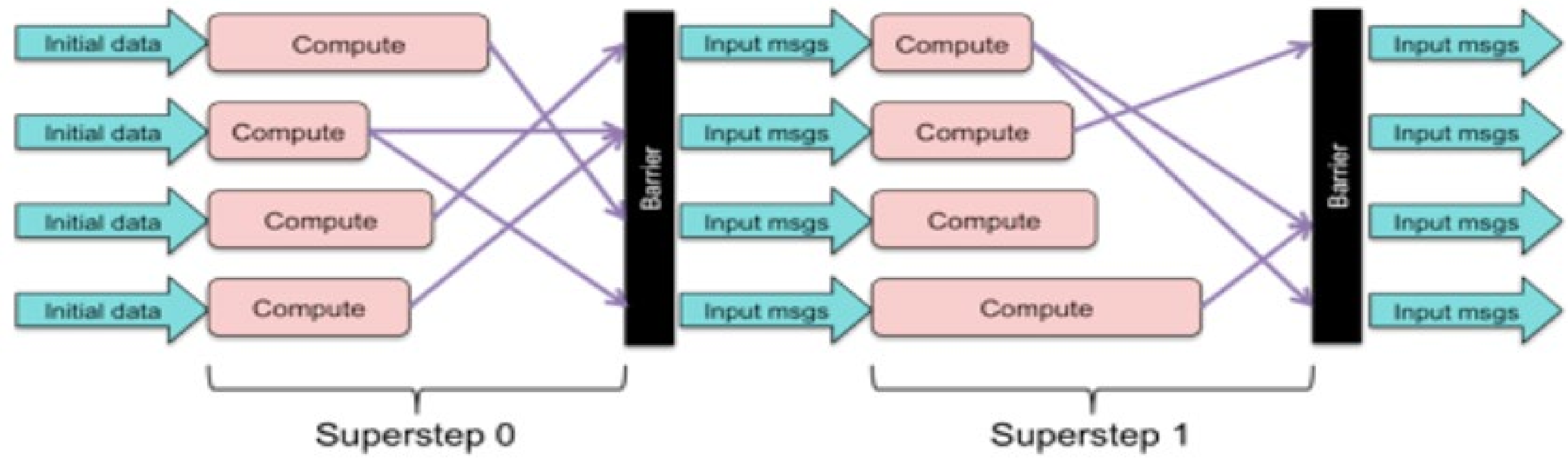
oogle

Overview of Pregel

- To overcome these challenges, google came up with Pregel
- Vertex-centric Model for writing Graph algorithms
  - Scalability
  - Expressibility in writing algorithms
  - Fault-tolerance
- The high level organization of Pregel programs is inspired by Valiant's Bulk Synchronous Parallel (BSP) model

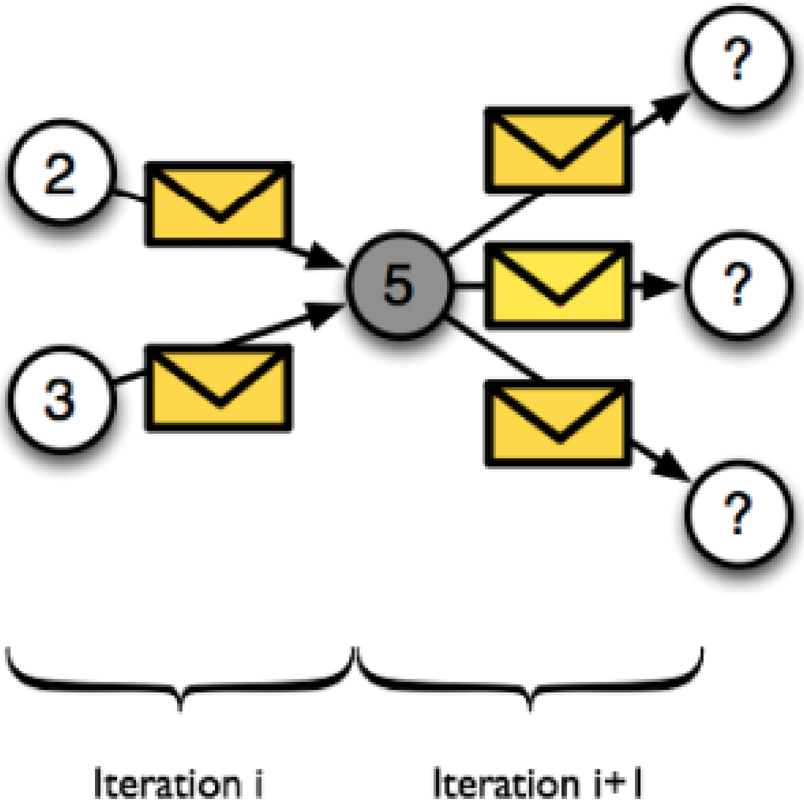
Bulk Synchronous Parallel (BSP)

- Computations consist of a sequence of iterations, called supersteps
  - Concurrent computation
  - Communication
  - Barrier synchronisation



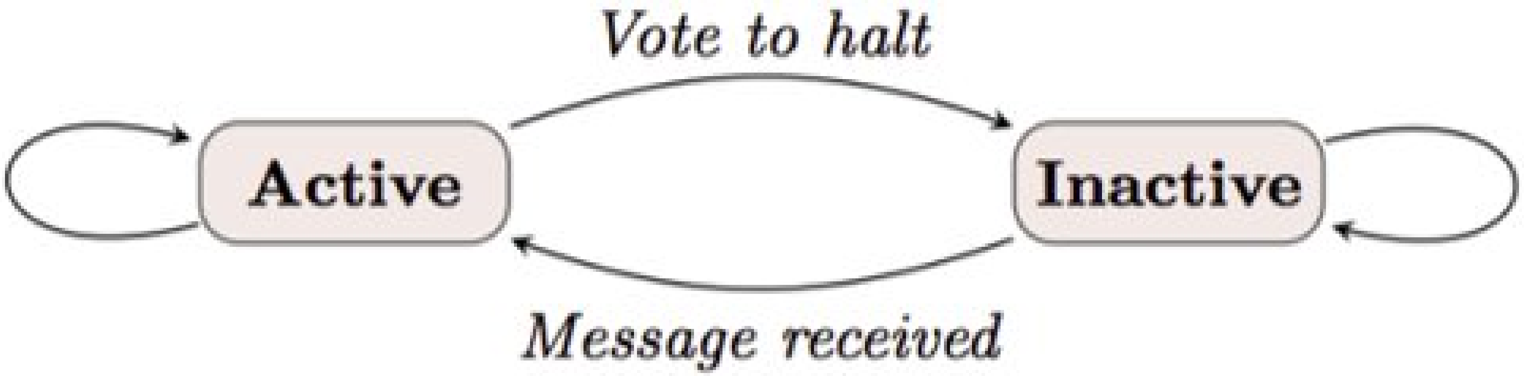
Vertex Centric Programming

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

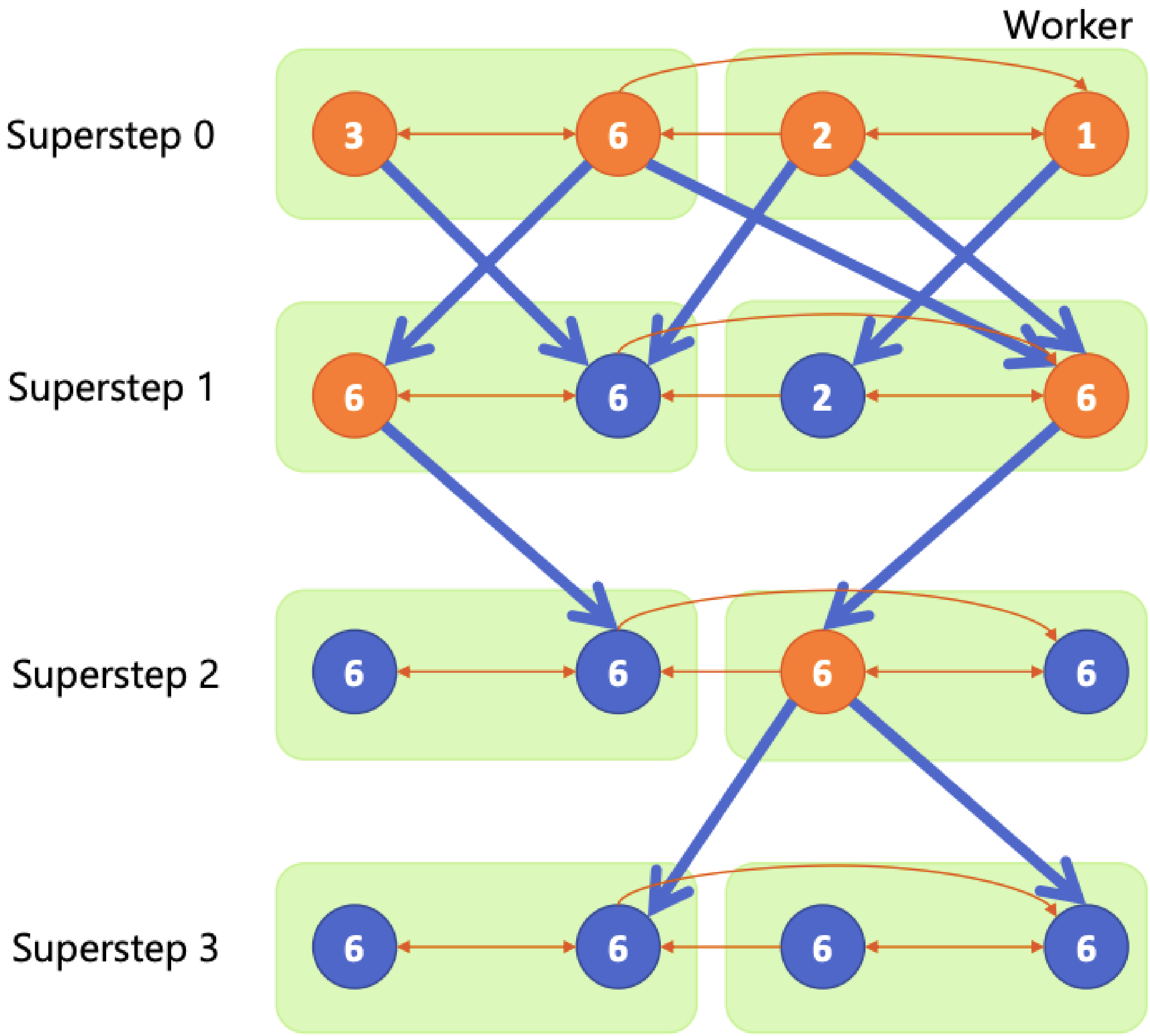


Vertex State Machine

- 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.



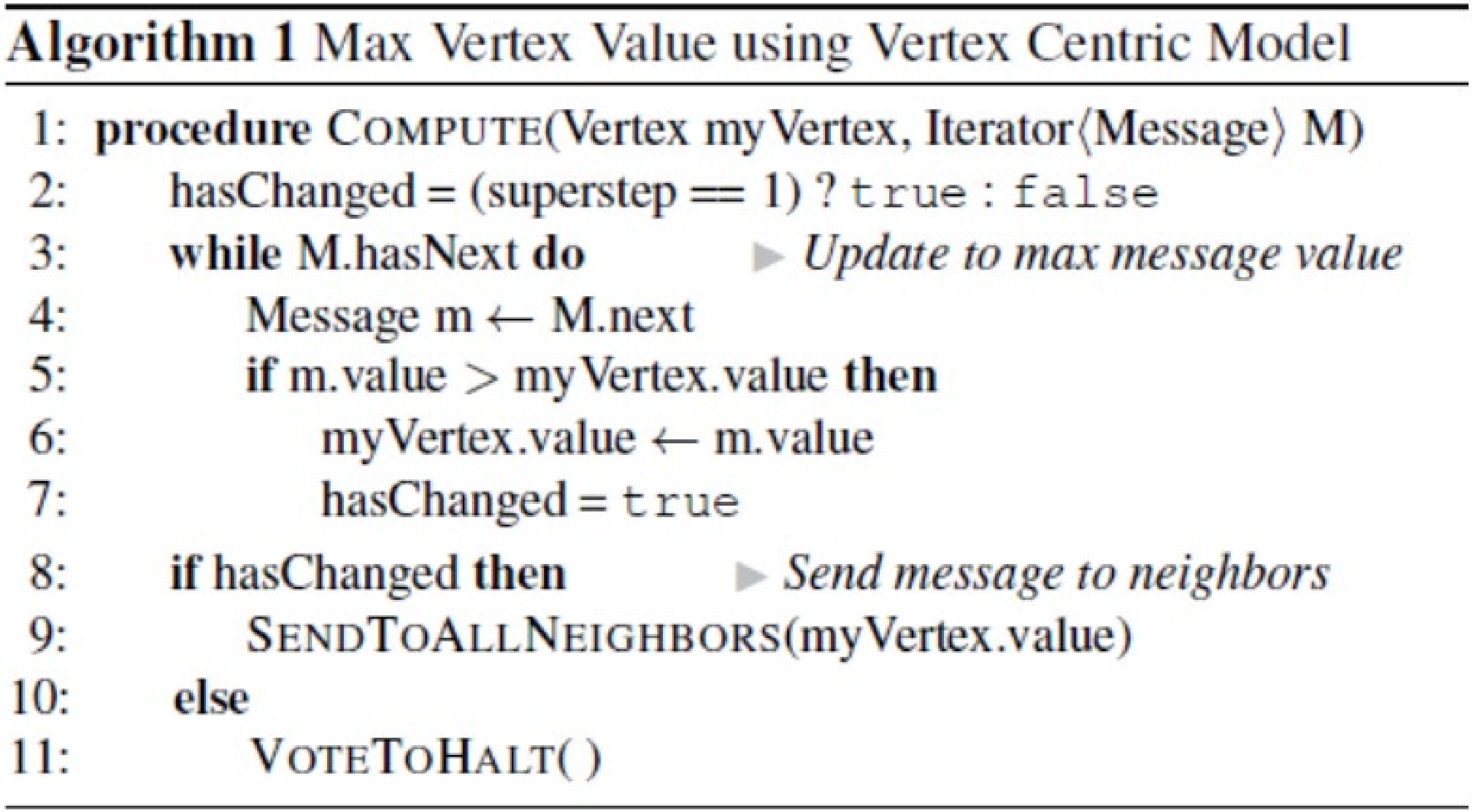
Example: Max Vertex Value



Blue Arrows are messages.

Blue vertices have voted to halt.

Max Vertex Value: Code



Algorithm 1 Max Vertex Value using Vertex Centric Model

```
procedure COMPUTE(Vertex myVertex, Iterator⟨Message⟩ M)
    hasChanged = (superstep == 1) ? true : false
    while M.hasNext do                    ▷ Update to max message value
        Message m ← M.next
        if m.value > myVertex.value then
            myVertex.value ← m.value
            hasChanged = true
    if hasChanged then                    ▷ Send message to neighbors
        SENDTOALLNEIGHBORS(myVertex.value)
    else
        VOTETOHALT( )
```

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

Why not Pregel?

- Requires its own computing infrastructure
- Not available unless you work at Google
- Master is Single Point of Failure

Apache Giraph

Open-Source Implementation of Pregel

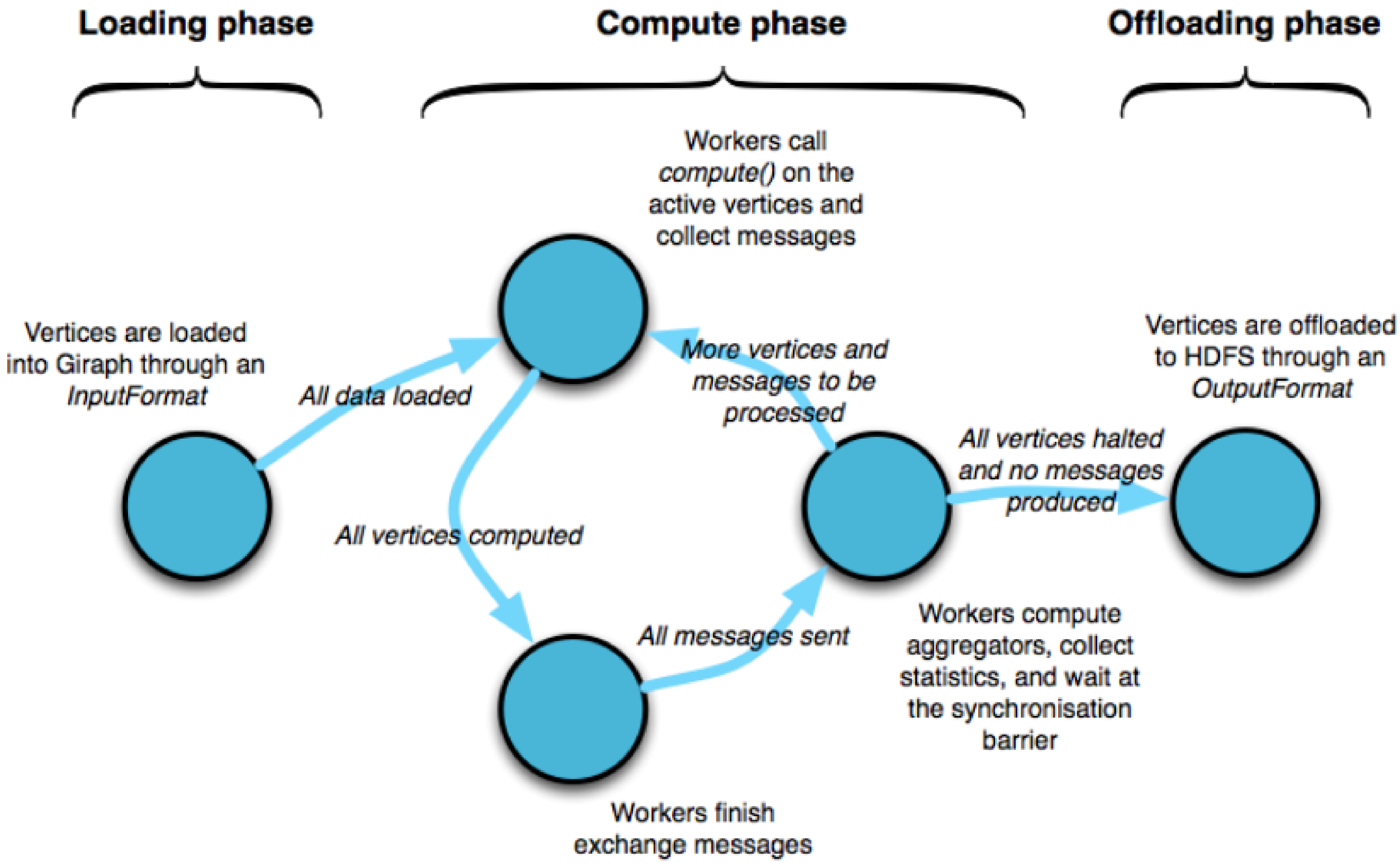
Giraph

- Leverage Hadoop Installations around the world for iterative graph processing
  - Big Data today is processed on Hadoop with map-reduce computing model
  - Map-reduce with Hadoop is widely deployed
- Bulk Synchronous Processing (BSP) Computing Model
  - Input data loaded once during the application, all messaging in memory
- Fault-tolerant/Dynamic Graph Processing Infrastructure
  - Automatically adjust to available resources on Hadoop grid
  - No single point of failure except Hadoop namenode and Jobtracker
  - Relies on Zookeeper as a fault-tolerant coordination service
- Vertex Centric API to do graph processing in a BSP computing model
  - Inspired by Pregel
- Open Source

Giraph API

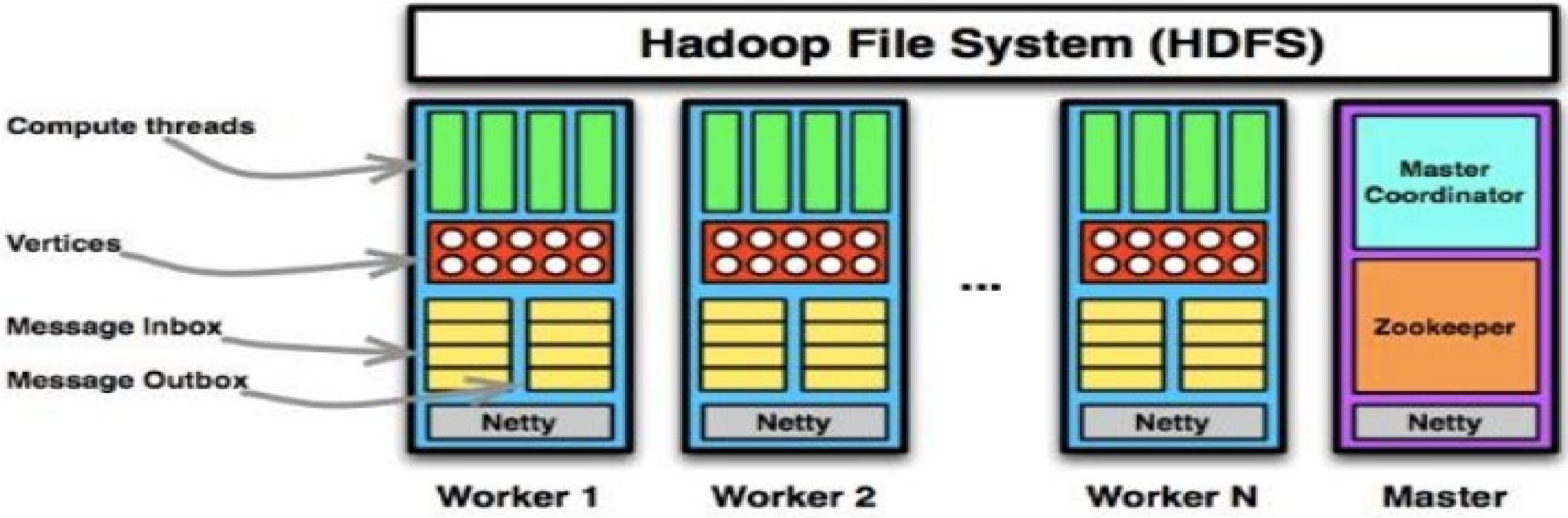
- void compute(Iterator msgs)
  - getSuperstep()
  - getVertexValue()
  - edges = iterator() //list of edges
  - sendMsg(edge, value)
  - sendMsgToAllEdges(value)
  - VoteToHalt()
- Messages Passing
  - Message ordering not guaranteed
  - Can send messages to any node
  - Message is delivered exactly once

Giraph Job Lifetime


Loading phase
Compute phase
Offloading phase
Workers call *compute()* on the active vertices and collect messages
Vertices are loaded into Giraph through an *InputFormat*
All data loaded
More vertices and messages to be processed
Vertices are offloaded to HDFS through an *OutputFormat*
All vertices halted and no messages produced
All vertices computed
All messages sent
Workers compute aggregators, collect statistics, and wait at the synchronisation barrier
Workers finish exchange messages

Giraph Architecture

- Master (responsible for coordination)
  - Assigns partitions to workers, Synchronization
- Workers (responsible for vertices)
  - Operates on set of vertices called partitions
  - Invokes active vertices, sends/receive and assign messages
- Zookeeper (responsible for computation state)
  - Keeps track of the computation state



Fault Tolerance

- Checkpointing
  - The master periodically (alternate supersteps) instructs the workers to save the state of their partitions to HDFS.
  - e.g., Vertex values, edge values, incoming messages.
- Failure detection
  - Using regular “ping” messages.
- Recovery
  - The master reassigns graph partitions to the currently available workers.
  - The workers all reload their partition state from most recent available checkpoint.
- No single point of failure from BSP threads
- Hadoop single point of failure still exists

Additional Features

Combiners

- Sending a message to another vertex that exists on a different machine has some overhead.
- 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.
- Runs on both the client side and server side
  - Client side saves memory and message traffic
  - Server side saves memory
- Exceedingly useful in certain contexts (e.g., 4x speedup on shortest-path computation).

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.
- Commutative and associate operations that are performed globally.
- 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.*

Application

Shortest Path

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

In the 0th superstep, only source vertex will update its value

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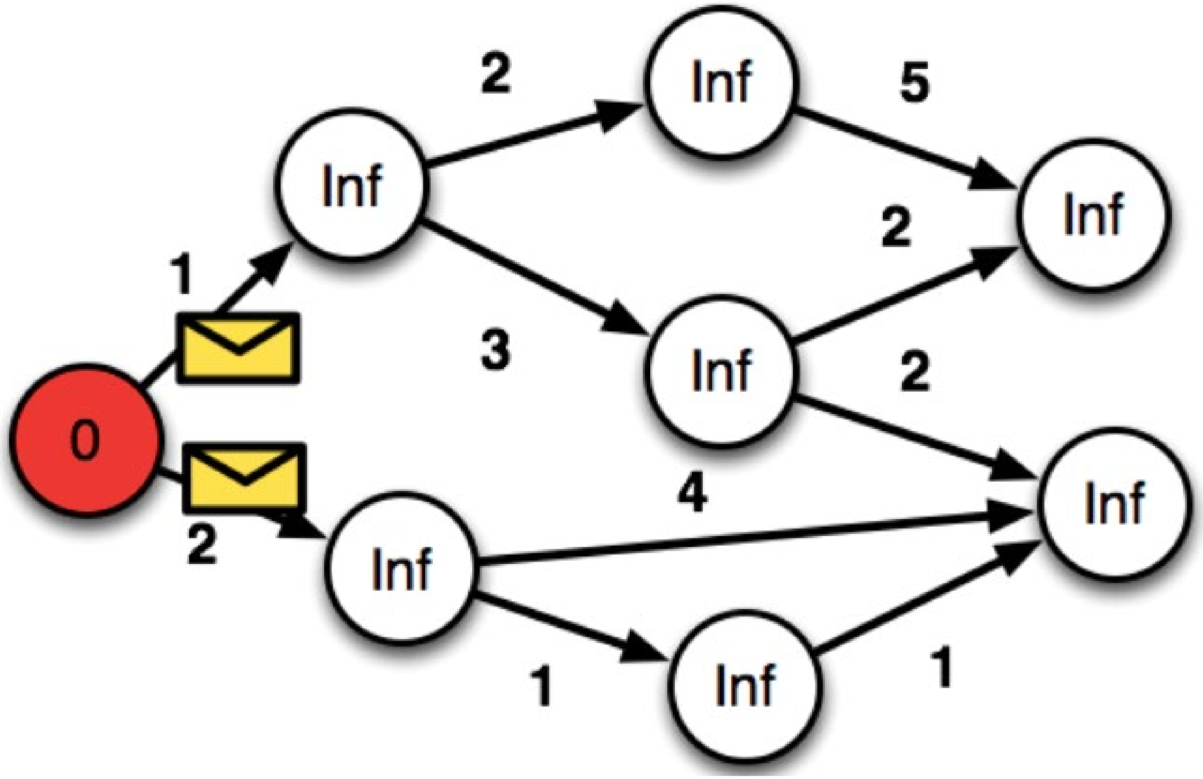
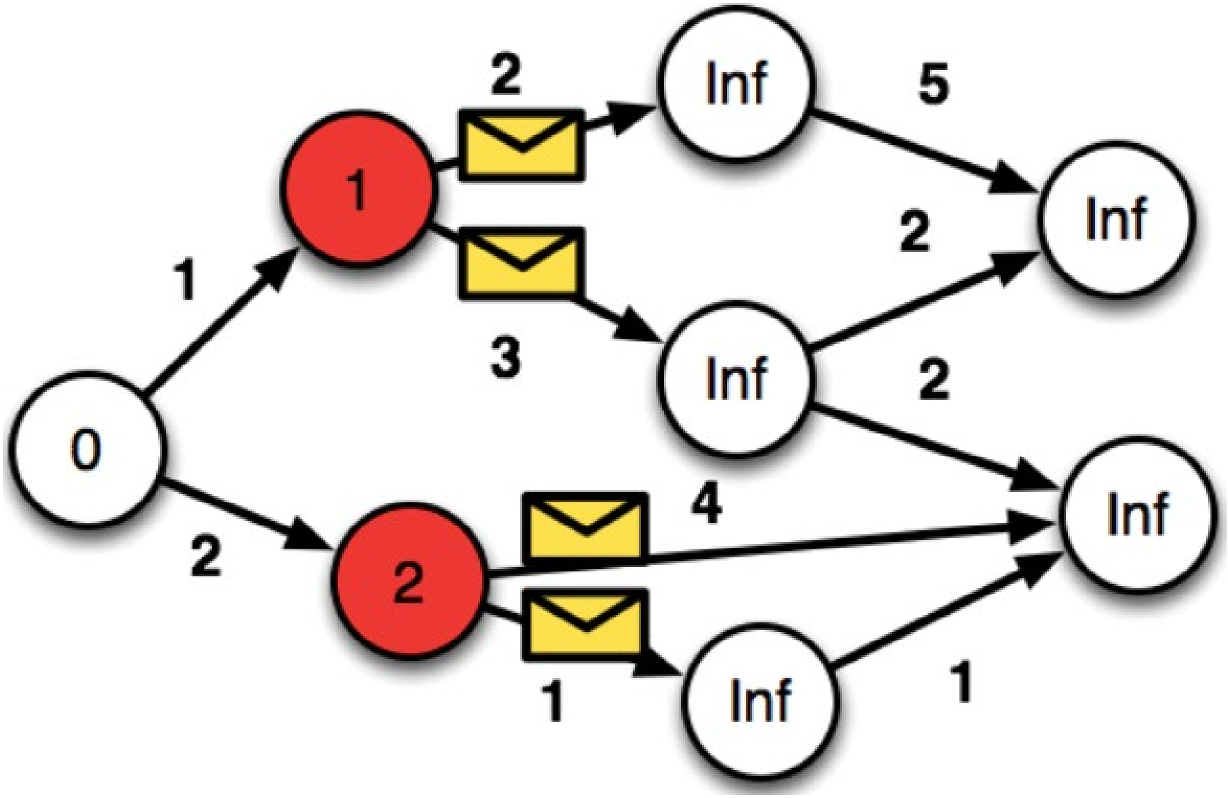
Shortest Path



Shortest Path



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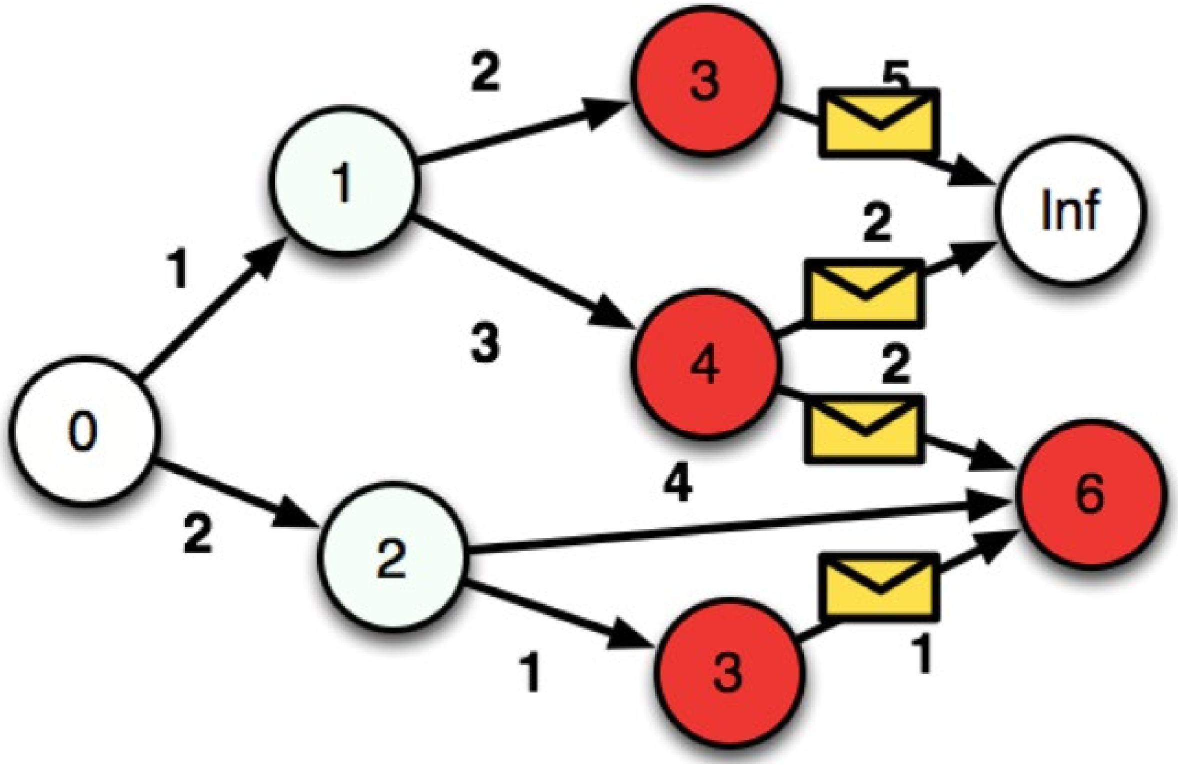

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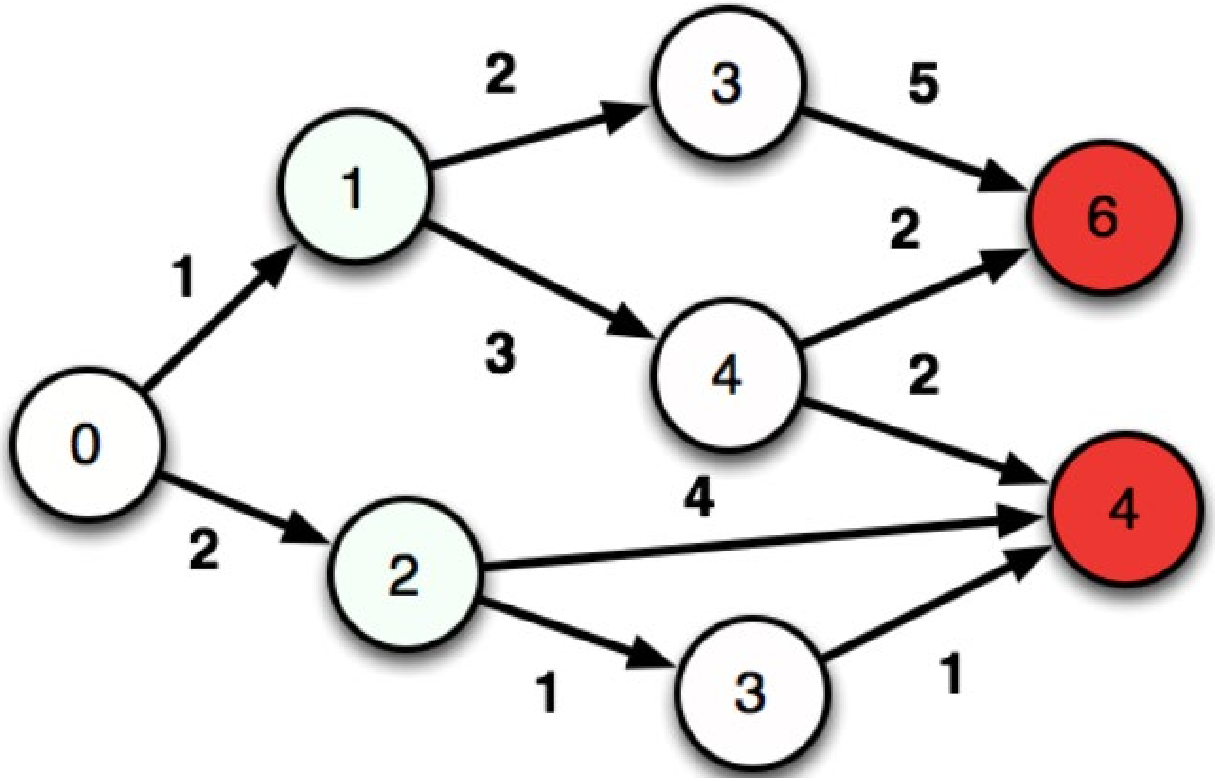
Shortest Path

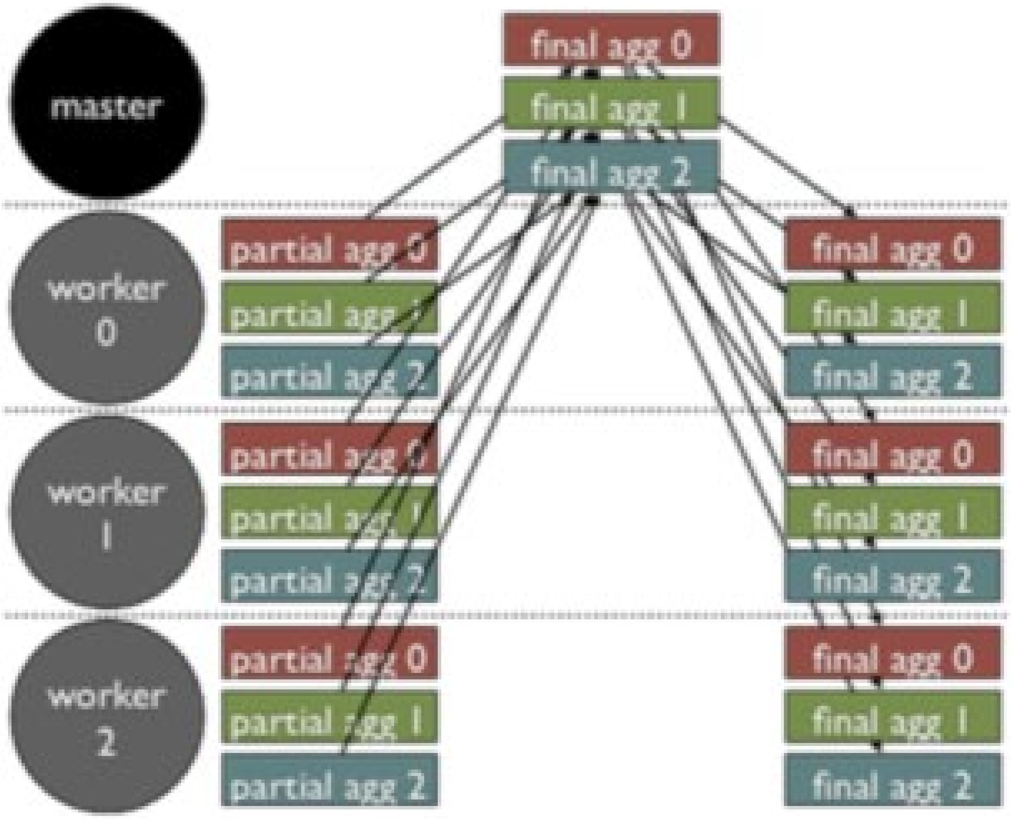


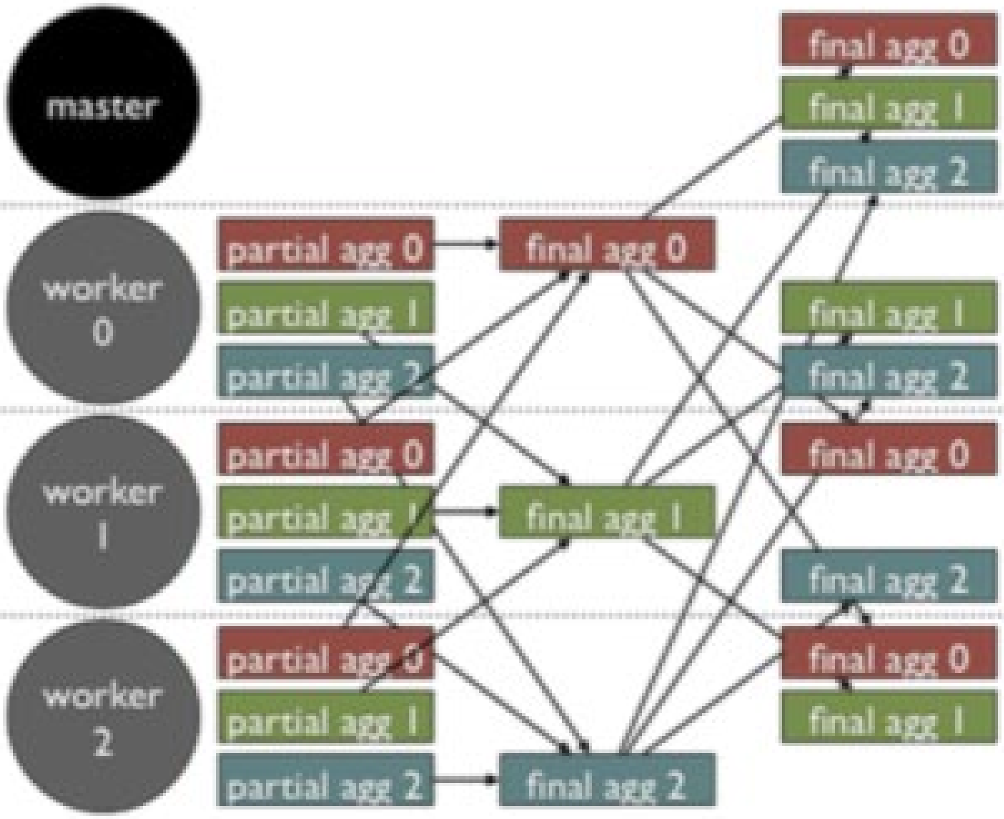
Ready to Process Trillion Edges

Platform Improvement

- Efficient Memory Management (MM)
  - Vertex and Edge data stored using serialized byte array
  - Better MM -> Less GC
- Support for Multi-Threading
  - Maximized resource utilization
  - Linear speed-up for CPU bound applications like K-Means Clustering
- Flexible IO Format
  - Reduces Pre-processing
  - Allows Vertex and Edge data to be loaded from different sources
- Sharded Aggregator
  - Aggregator responsibilities are balanced across workers
  - Different Aggregators can be assigned to different workers.

Sharded Aggregator





Compute Model Extensions

- Master Compute
  - Allows centralized execution of computation
- Worker Phases
  - Special methods which by-pass Pregel Model, but add ease of usability
  - Applicability is application specific
- Computation Composability
  - Decouples Vertex and Computation
  - Existing Computation implementation can be decoupled for multiple applications
- Superstep Splitting
  - Master runs same “Message Heavy” Superstep for fixed number of iterations
  - For an iteration, vertex computation invoked if vertex passes hash function
  - Example : Friends-of-Friends Computation

Take Away

- Giraph is a graph processing infrastructure that runs on existing Hadoop infrastructure
- Open source- available on GitHub
- Scales to “Trillion” edge graph

THANK
YOU