# Distributed Systems

## 20. Other parallel frameworks

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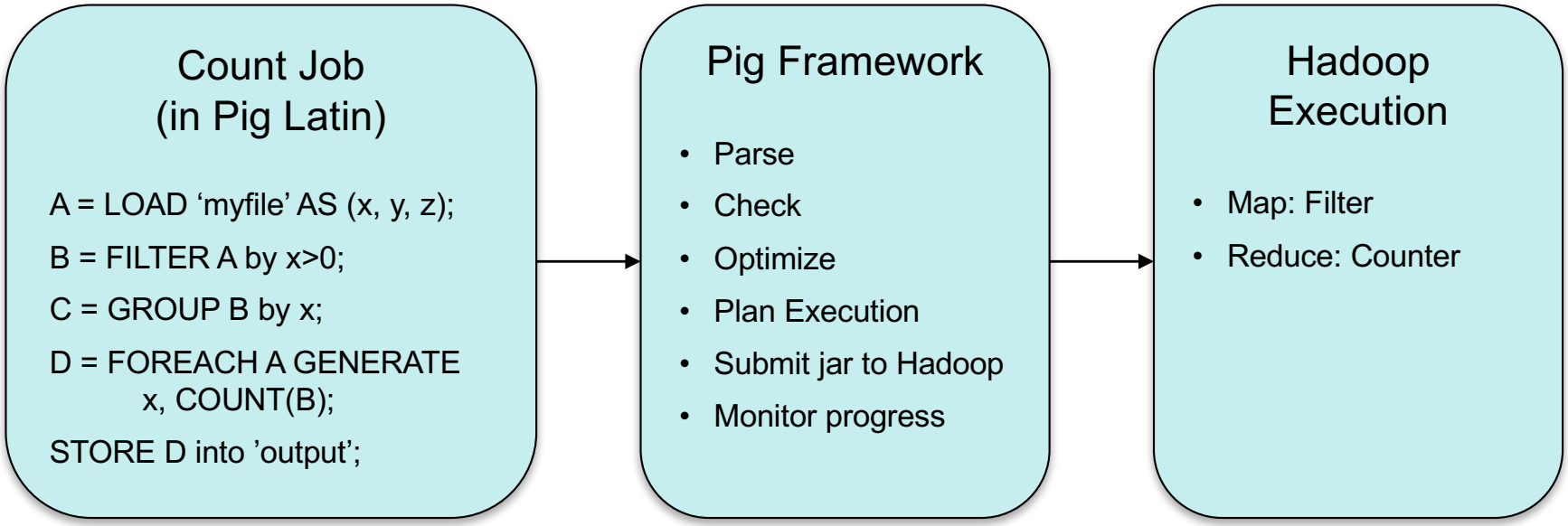
# Can we make MapReduce easier?

# Apache Pig

- Why?
  - Make it easy to use MapReduce via scripting instead of Java
  - Make it easy to use multiple MapReduce stages
  - Built-in common operations for join, group, filter, etc.
- How to use?
  - Use Grunt – the pig shell
  - Submit a script directly to pig
  - Use the PigServer Java class
  - PigPen – Eclipse plugin
- Pig compiles to several Hadoop MapReduce jobs

# Apache Pig


Count Job
(in Pig Latin)
A = LOAD 'myfile' AS (x, y, z);
B = FILTER A by x>0;
C = GROUP B by x;
D = FOREACH A GENERATE
x, COUNT(B);
STORE D into 'output';
Pig Framework
• Parse
• Check
• Optimize
• Plan Execution
• Submit jar to Hadoop
• Monitor progress
Hadoop
Execution
• Map: Filter
• Reduce: Counter

# Pig: Loading Data

Load/store relations in the following formats:

- PigStorage: field-delimited text
- BinStorage: binary files
- BinaryStorage: single-field tuples with a value of *bytearray*
- TextLoader: plain-text
- PigDump: stores using toString() on tuples, one per line

# Example

```
log = LOAD ‘test.log’ AS (user, timestamp, query);
grpd = GROUP log by user;
cntd = FOREACH grpd GENERATE group, COUNT(log);
fltrd = FILTER cntd BY cnt > 50;
srtd = ORDER fltrd BY cnt;
STORE srtd INTO ‘output’;
```

- Each statement defines a new dataset
  - Datasets can be given aliases to be used later
- FOREACH iterates over the members of a ”bag”
  - Input is grpd: list of log entries grouped by user
  - Output is group, COUNT(log): list of {user, count}
- FILTER applies conditional filtering
- ORDER applies sorting

See pig.apache.org
for full documentation

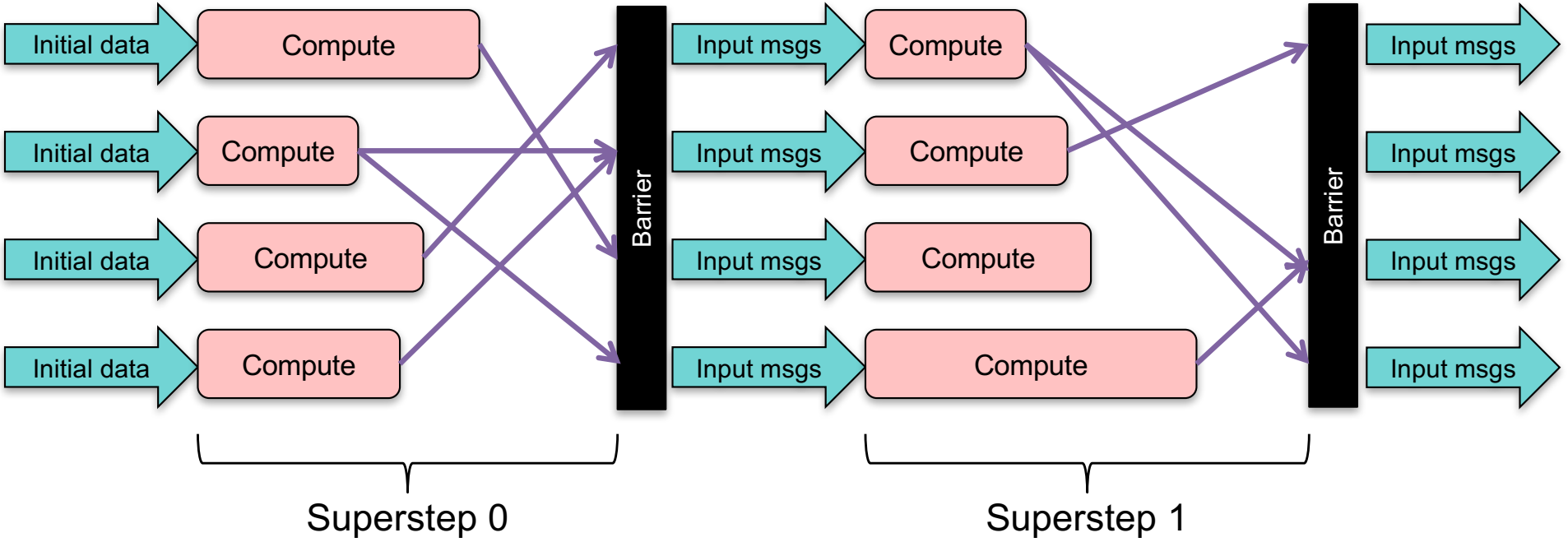
# MapReduce isn't always the answer

- MapReduce works well for certain problems
  - Framework provides
    - Automatic parallelization
    - Automatic job distribution

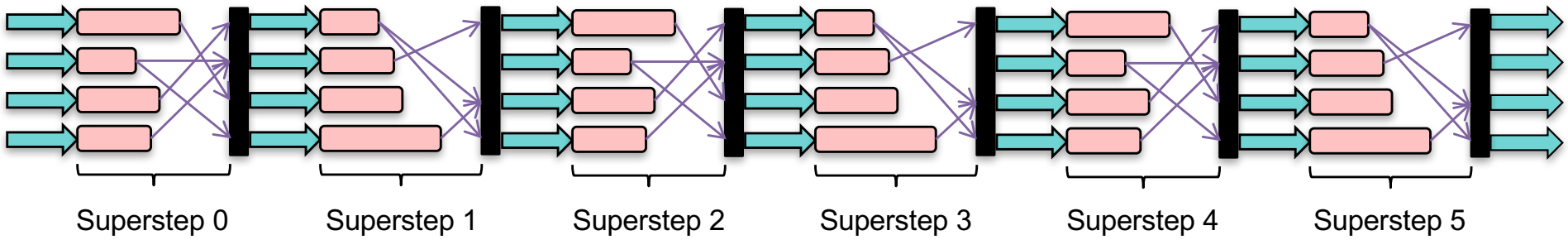
- For others:
  - May require many iterations
  - Data locality usually not preserved between Map and Reduce
    - Lots of communication between *map* and *reduce* workers

# Bulk Synchronous Parallel (BSP)

- Computing model for parallel computation
- Series of supersteps
  1. Concurrent computation
  2. Communication
  3. Barrier synchronization



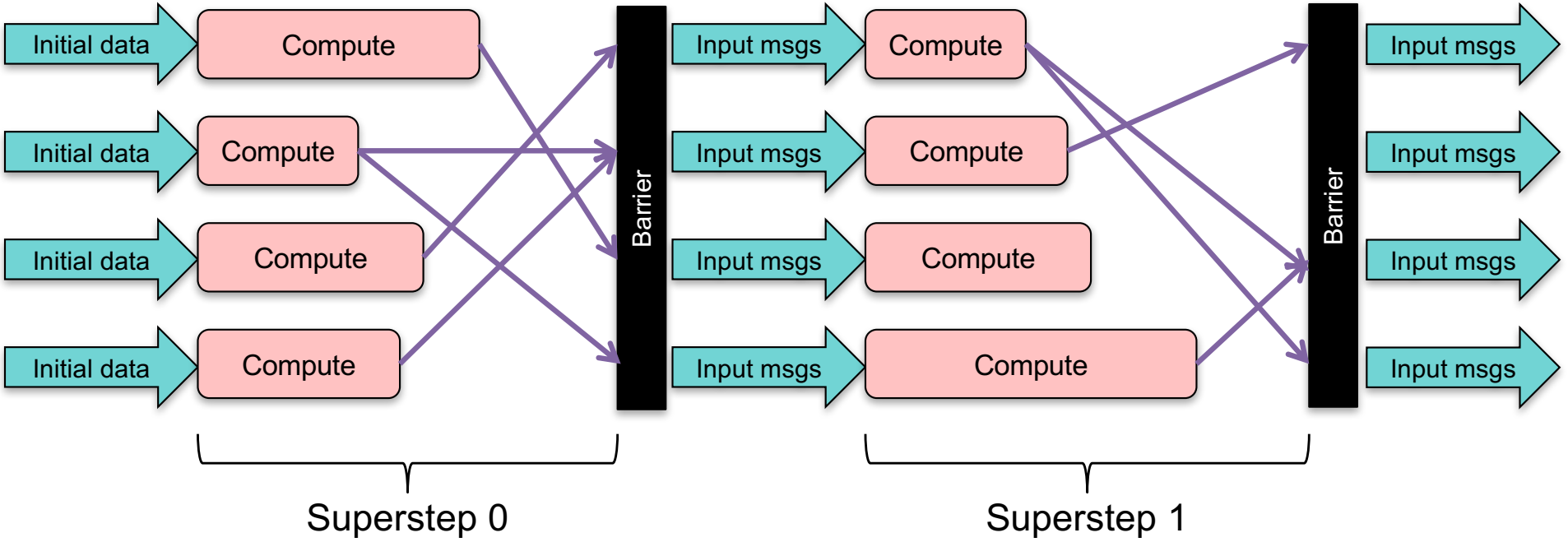
# Bulk Synchronous Parallel (BSP)



# Bulk Synchronous Parallel (BSP)

- Series of supersteps
  1. Concurrent computation
  2. Communication
  3. Barrier synchronization

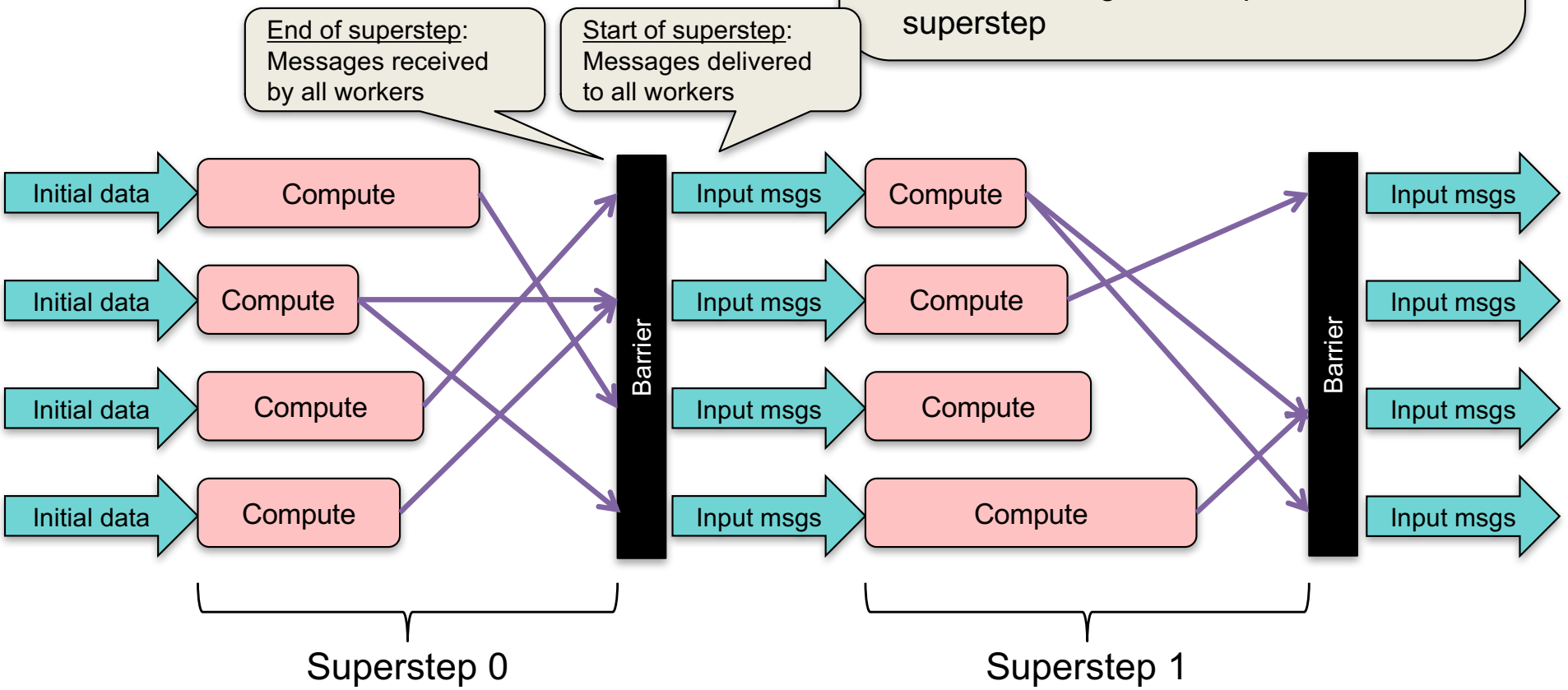
- Processes (workers) are randomly assigned to processors
- Each process uses only local data
- Each computation is asynchronous of other concurrent computation
- Computation time may vary



# Bulk Synchronous Parallel (BSP)

- Series of supersteps
  1. Concurrent computation
  2. Communication
  3. Barrier synchronization

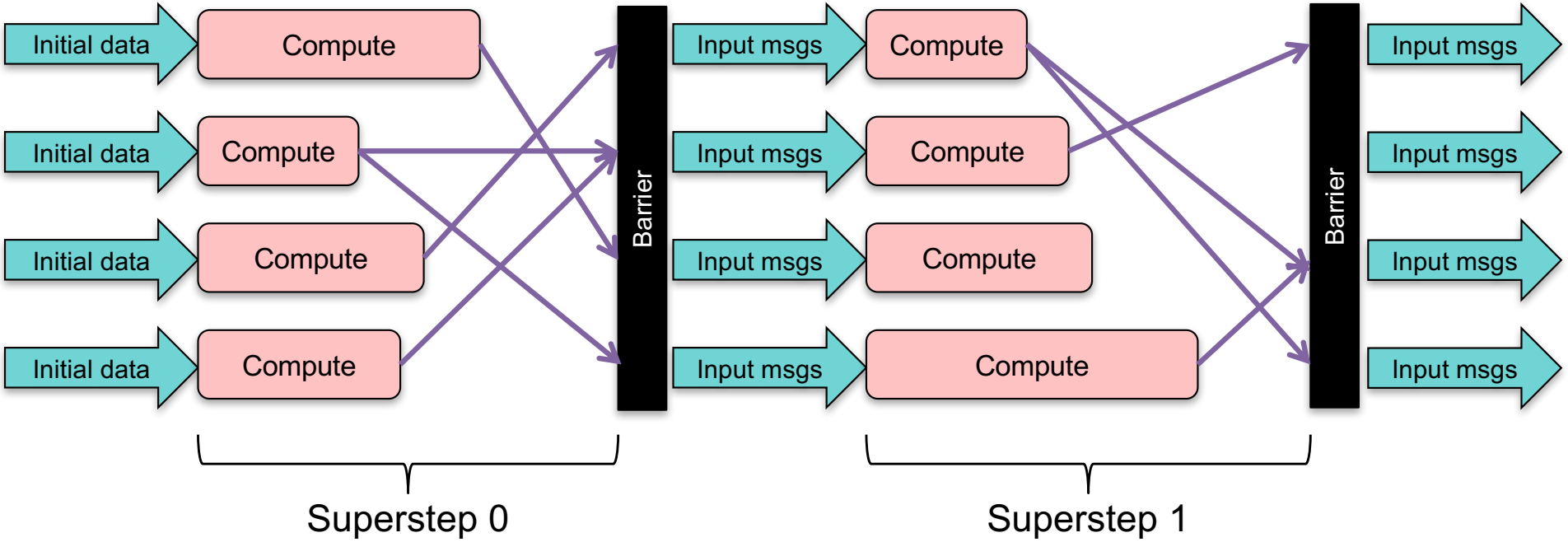
- Messaging is restricted to the end of a computation superstep
- Each worker sends a message to 0 or more workers
- These messages are inputs for the next superstep



# Bulk Synchronous Parallel (BSP)

- Series of supersteps
  1. Concurrent computation
  2. Communication
  3. Barrier synchronization

- The next superstep does not begin until **all** messages have been received
- Barriers ensure no deadlock: no circular dependency can be created
- Provide an opportunity to **checkpoint** results for fault tolerance
  - If failure, restart computation from last superstep



# BSP Implementation: Apache Hama

- Hama: BSP framework on top of HDFS
  - Provides automatic parallelization & distribution
  - Uses Hadoop RPC
    - Data is serialized with Google Protocol Buffers
  - Zookeeper for coordination (Apache version of Google's Chubby)
    - Handles notifications for Barrier Sync
- Good for applications with data locality
  - Matrices and graphs
  - Algorithms that require a lot of iterations

hama.apache.org

# Hama programming (high-level)

- Pre-processing
  - Define the number of peers for the job
  - Split initial inputs for each of the peers to run their supersteps
  - Framework assigns a unique ID to each worker (peer)

---

- Superstep: the worker function is a superstep
  - ***getCurrentMessage()*** – input messages from previous superstep
  - Compute – your code
  - ***send(peer, msg)*** – send messages to a peer
  - ***sync()*** – synchronize with other peers (barrier)

---

- File I/O

*Bigtable*

  - Key/value model used by Hadoop MapReduce & HBase
  - ***readNext(key, value)***
  - ***write(key, value)***

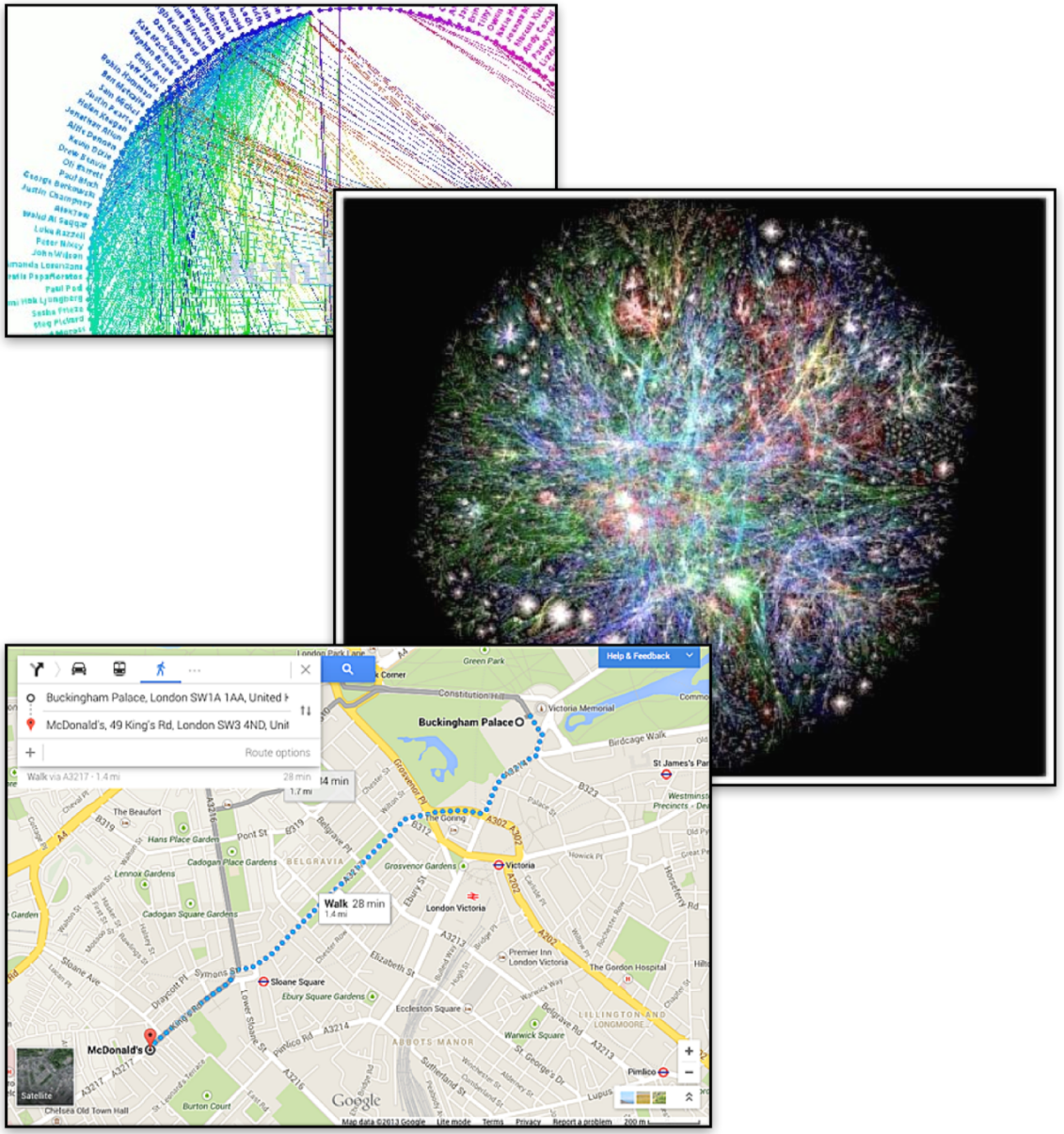
# For more information

- Architecture, examples, API
- Take a look at:
  - Apache Hama project page
    - http://hama.apache.org
  - Hama BSP tutorial
    - https://hama.apache.org/hama_bsp_tutorial.html
  - Apache Hama Programming document
    - http://bit.ly/1aiFbXS
      http://people.apache.org/~tjungblut/downloads/hamadocs/ApacheHamaBSPProgrammingmodel_06.pdf

# Graph computing

# Graphs are common in computing

- Social links
  - Friends
  - Academic citations
  - Music
  - Movies
- Web pages
- Network connectivity
- Roads
- Disease outbreaks



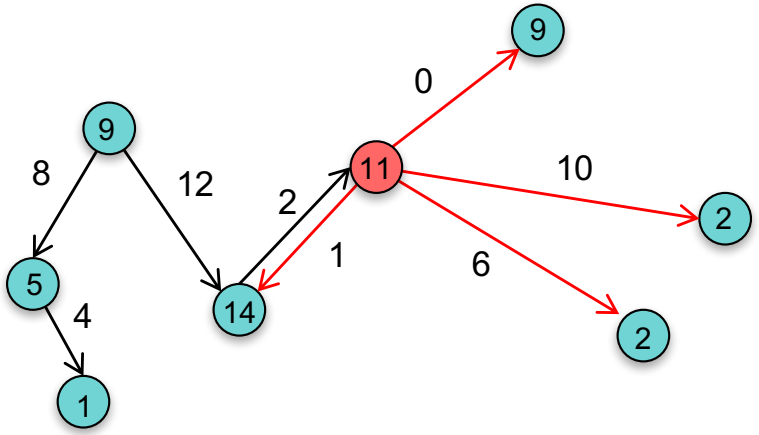
# Processing graphs on a large scale is hard

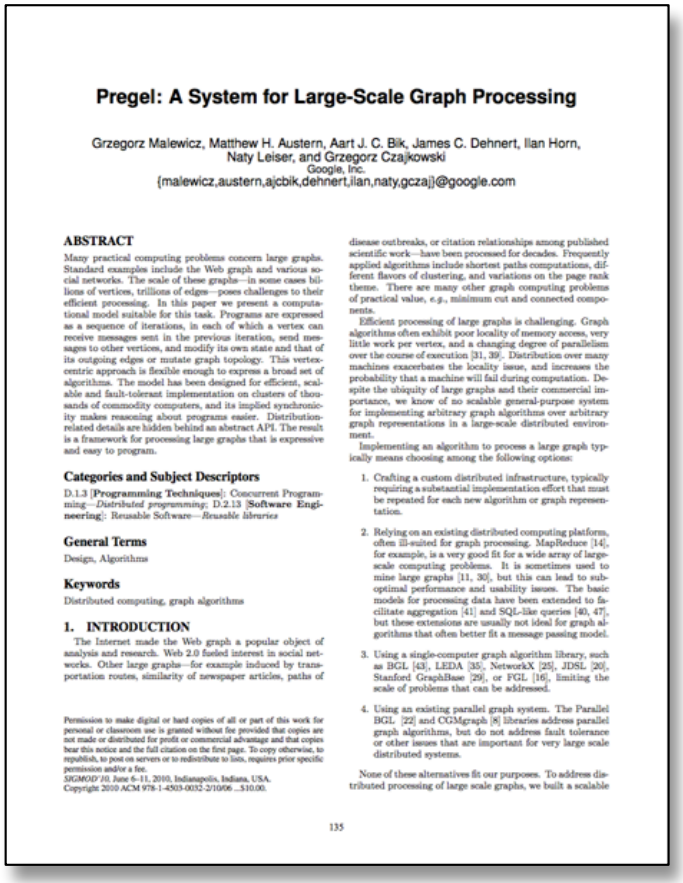
- Computation with graphs
  - Poor locality of memory access
  - Little work per vertex
- Distribution across machines
  - Communication complexity
  - Failure concerns
- Solutions
  - Application-specific, custom solutions
  - MapReduce or databases
    - But require many iterations (and a lot of data movement)
  - Single-computer libraries: limits scale
  - Parallel libraries: do not address fault tolerance
  - BSP: ***close*** but too general

# Pregel: a vertex-centric BSP

## Input: directed graph

- A vertex is an object
  - Each vertex uniquely identified with a name
  - Each vertex has a modifiable value
- Directed edges: links to other objects
  - Associated with source vertex
  - Each edge has a modifiable value
  - Each edge has a target vertex identifier



Pregel: A System for Large-Scale Graph Processing

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ABSTRACT

Many practical computing problems concern large graphs. Standard examples include the Web graph and various social networks. The scale of these graphs—in some cases billions of vertices, trillions of edges—poses challenges to their efficient processing. In this paper we present a computational model suitable for this task. Programs are expressed as a sequence of iterations, in each of which a vertex can receive messages sent in the previous iteration, send messages to other vertices, and modify its own state and that of its outgoing edges or mutate graph topology. This vertex-centric approach is flexible enough to express a broad set of algorithms. The model has been designed for efficient, scalable and fault-tolerant implementation on clusters of thousands of commodity computers, and its implied synchronicity makes reasoning about programs easier. Distribution-related details are hidden behind an abstract API. The result is a framework for processing large graphs that is expressive and easy to program.

Categories and Subject Descriptors

D.1.3 [Programming Techniques]: Concurrent Programming—*Distributed programming*; D.2.13 [Software Engineering]: Reusable Software—*Reusable libraries*

General Terms

Design, Algorithms

Keywords

Distributed computing, graph algorithms

1. INTRODUCTION

The Internet made the Web graph a popular object of analysis and research. Web 2.0 fueled interest in social networks. Other large graphs—for example induced by transportation routes, similarity of newspaper articles, paths of disease outbreaks, or citation relationships among published scientific work—have been processed for decades. Frequently applied algorithms include shortest paths computations, different flavors of clustering, and variations on the page rank theme. There are many other graph computing problems of practical value, e.g., minimum cut and connected components.

Efficient processing of large graphs is challenging. Graph algorithms often exhibit poor locality of memory access, very little work per vertex, and a changing degree of parallelism over the course of execution [31, 39]. Distribution over many machines exacerbates the locality issue, and increases the probability that a machine will fail during computation. Despite the ubiquity of large graphs and their commercial importance, we know of no scalable general-purpose system for implementing arbitrary graph algorithms over arbitrary graph representations in a large-scale distributed environment.

Implementing an algorithm to process a large graph typically means choosing among the following options:

1. Crafting a custom distributed infrastructure, typically requiring a substantial implementation effort that must be repeated for each new algorithm or graph representation.
2. Relying on an existing distributed computing platform, often ill-suited for graph processing. MapReduce [14], for example, is a very good fit for a wide array of large-scale computing problems. It is sometimes used to mine large graphs [11, 30], but this can lead to sub-optimal performance and usability issues. The basic models for processing data have been extended to facilitate aggregation [41] and SQL-like queries [40, 47], but these extensions are usually not ideal for graph algorithms that often better fit a message passing model.
3. Using a single-computer graph algorithm library, such as BGL [43], LEDA [35], NetworkX [25], JDSL [20], Stanford GraphBase [29], or FGL [16], limiting the scale of problems that can be addressed.
4. Using an existing parallel graph system. The Parallel BGL [22] and CGMgraph [8] libraries address parallel graph algorithms, but do not address fault tolerance or other issues that are important for very large scale distributed systems.

None of these alternatives fit our purposes. To address distributed processing of large scale graphs, we built a scalable

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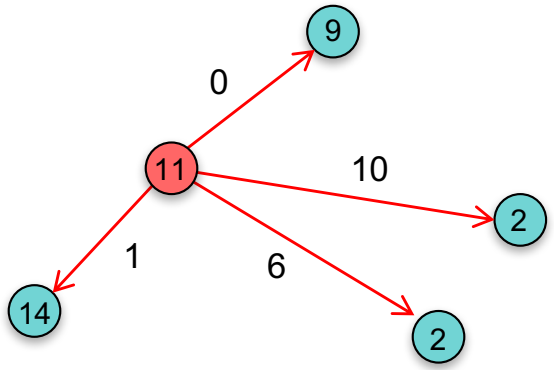
http://googleresearch.blogspot.com/2009/06/large-scale-graph-computing-at-google.html

# Pregel: computation

## Computation: series of supersteps

- Same user-defined function **runs on each vertex**
  - Receives messages sent from the previous superstep
  - May modify the state of the vertex or of its outgoing edges
  - Sends messages that will be received in the next superstep
    - Typically to outgoing edges
    - But can be sent to any known vertex
  - May modify the graph topology

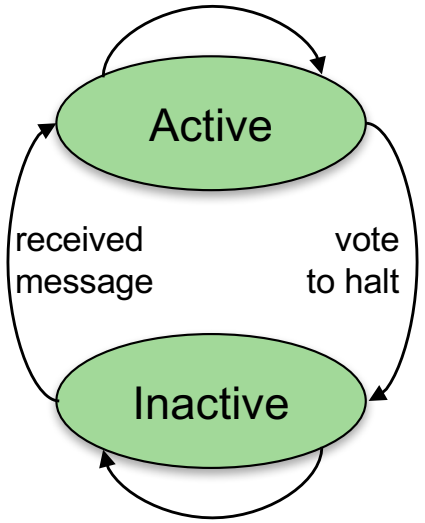
- Each superstep ends with a **barrier** (synchronization point)



# Pregel: termination

Pregel terminates when every vertex votes to halt

- Initially, every vertex is in an *active* state
  - Active vertices compute during a superstep
- Each vertex may choose to deactivate itself by **voting to halt**
  - The vertex has no more work to do
  - Will not be executed by Pregel
  - UNLESS the vertex receives a message
    - Then it is reactivated
    - Will stay active until it votes to halt again
- Algorithm terminates when all vertices are inactive and there are no messages in transit




Vertex State Machine

# Pregel: output

- Output is the set of values output by the vertices
- Often a directed graph
  - May be non-isomorphic to original since edges & vertices can be added or deleted

  … Or summary data

# Examples of graph computations

- Shortest path to a node
  - Each iteration, a node sends the shortest distance received to all neighbors
- Cluster identification
  - Each iteration: get info about clusters from neighbors.
  - Add myself
  - Pass useful clusters to neighbors (e.g., within a certain depth or size)
    - May combine related vertices
    - Output is a smaller set of disconnected vertices representing clusters of interest
- Graph mining
  - Traverse a graph and accumulate global statistics
- Page rank
  - Each iteration: update web page ranks based on messages from incoming links.

# Simple example: find the maximum value

- Each vertex contains a value
- In the first superstep:
  - A vertex sends its value to its neighbors
- In each successive superstep:
  - If a vertex learned of a larger value from its incoming messages, it sends it to its neighbors
  - Otherwise, it votes to halt
- Eventually, all vertices get the largest value
- When no vertices change in a superstep, the algorithm terminates

# Simple example: find the maximum value

Semi-pseudocode:

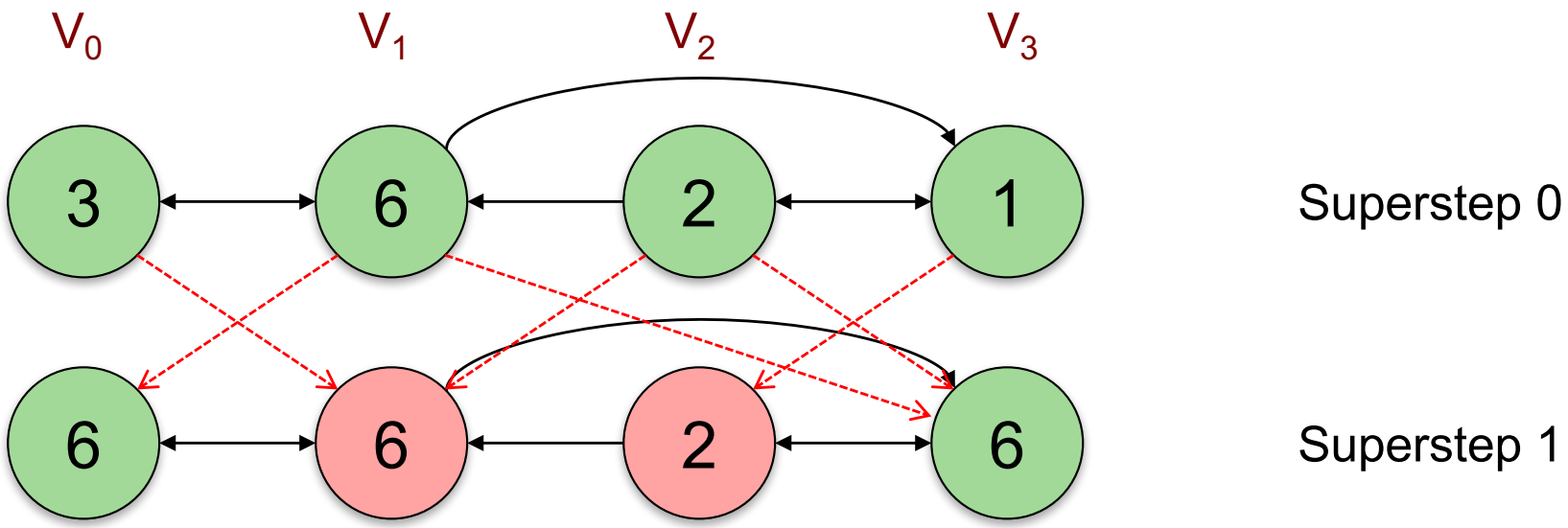
1. vertex value type; 2. edge value type (none!); 3. message value type

```
class MaxValueVertex
    : public Vertex<int, void, int> {
  void Compute(MessageIterator *msgs) {
    int maxv = GetValue();
    for (; !msgs->Done(); msgs->Next())
        maxv = max(msgs.Value(), maxv);

    if (maxv > GetValue()) || (step == 0)) {
        *MutableValue() = maxv;
        OutEdgeIterator out = GetOutEdgeIterator();
        for (; !out.Done(); out.Next())
            sendMessageTo(out.Target(), maxv)
    } else
        VoteToHalt();
    }
  }
};
```

*find maximum value*

*send maximum value to all edges*

# Simple example: find the maximum value

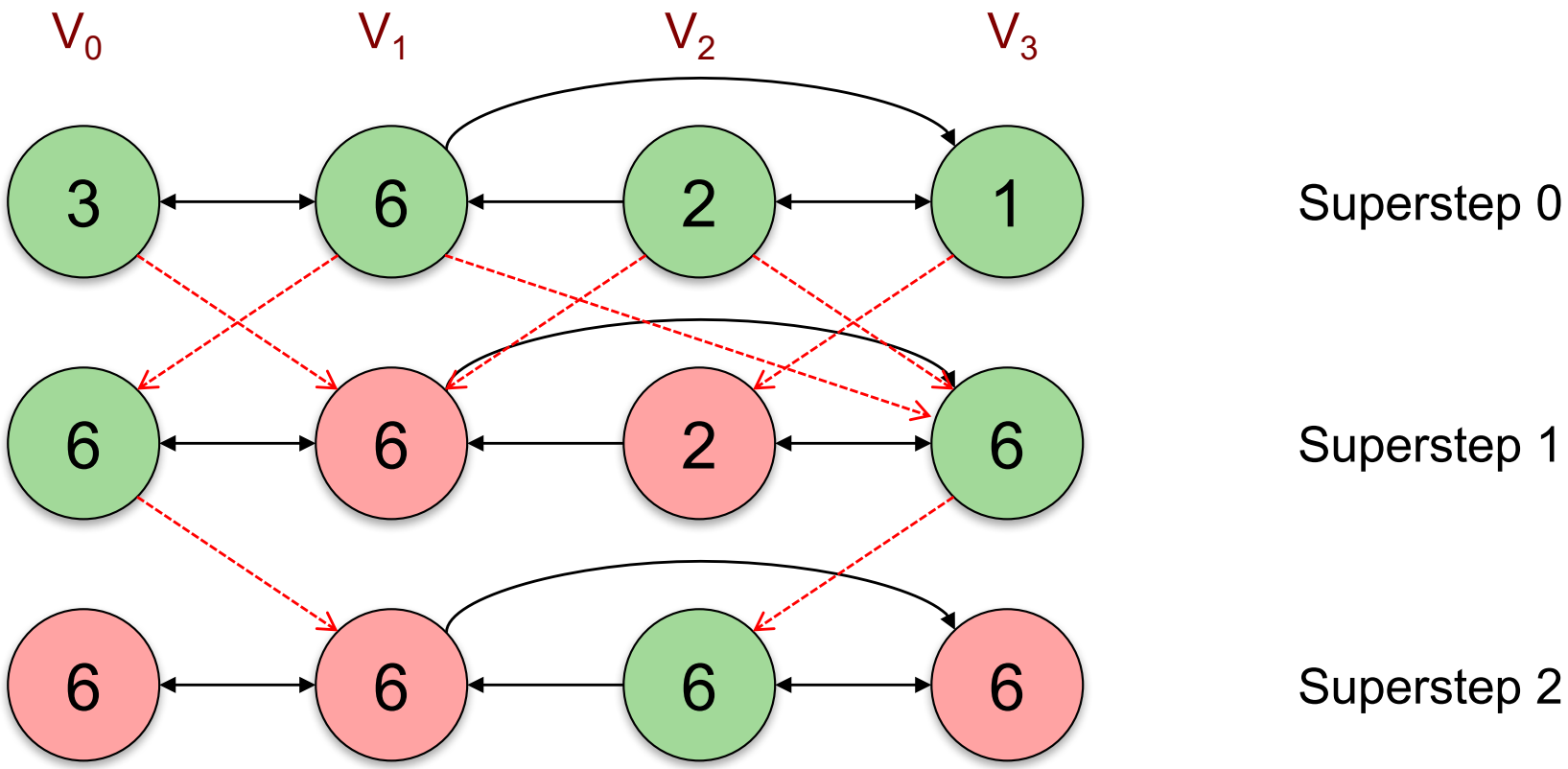



Superstep 0: Each vertex propagates its own value to connected vertices

Superstep 1: $V_0$ updates its value: 6 > 3
$V_3$ updates its value: 6 > 1
$V_1$ and $V_2$ do not update so vote to halt

Active vertex  Inactive vertex

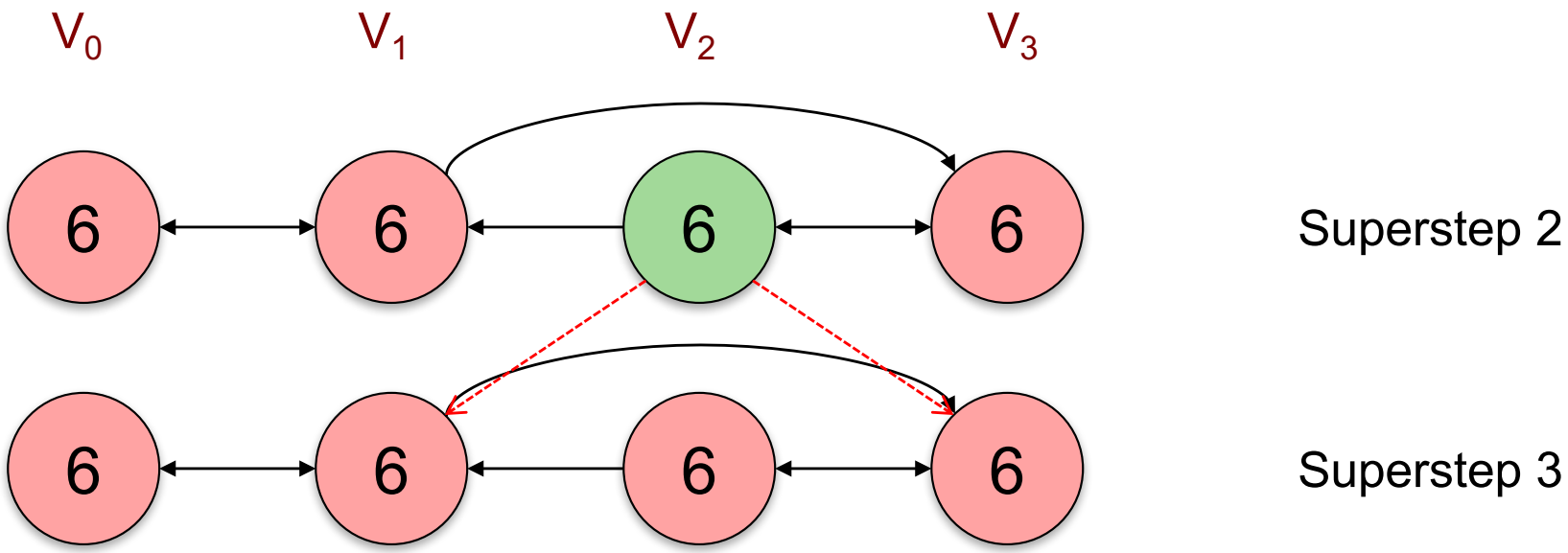
# Simple example: find the maximum value




Superstep 2: $V_1$ receives a message – becomes active
$V_3$ updates its value: 6 > 2
$V_1$, $V_2$, and $V_3$ do not update so vote to halt

Active vertex  Inactive vertex

# Simple example: find the maximum value

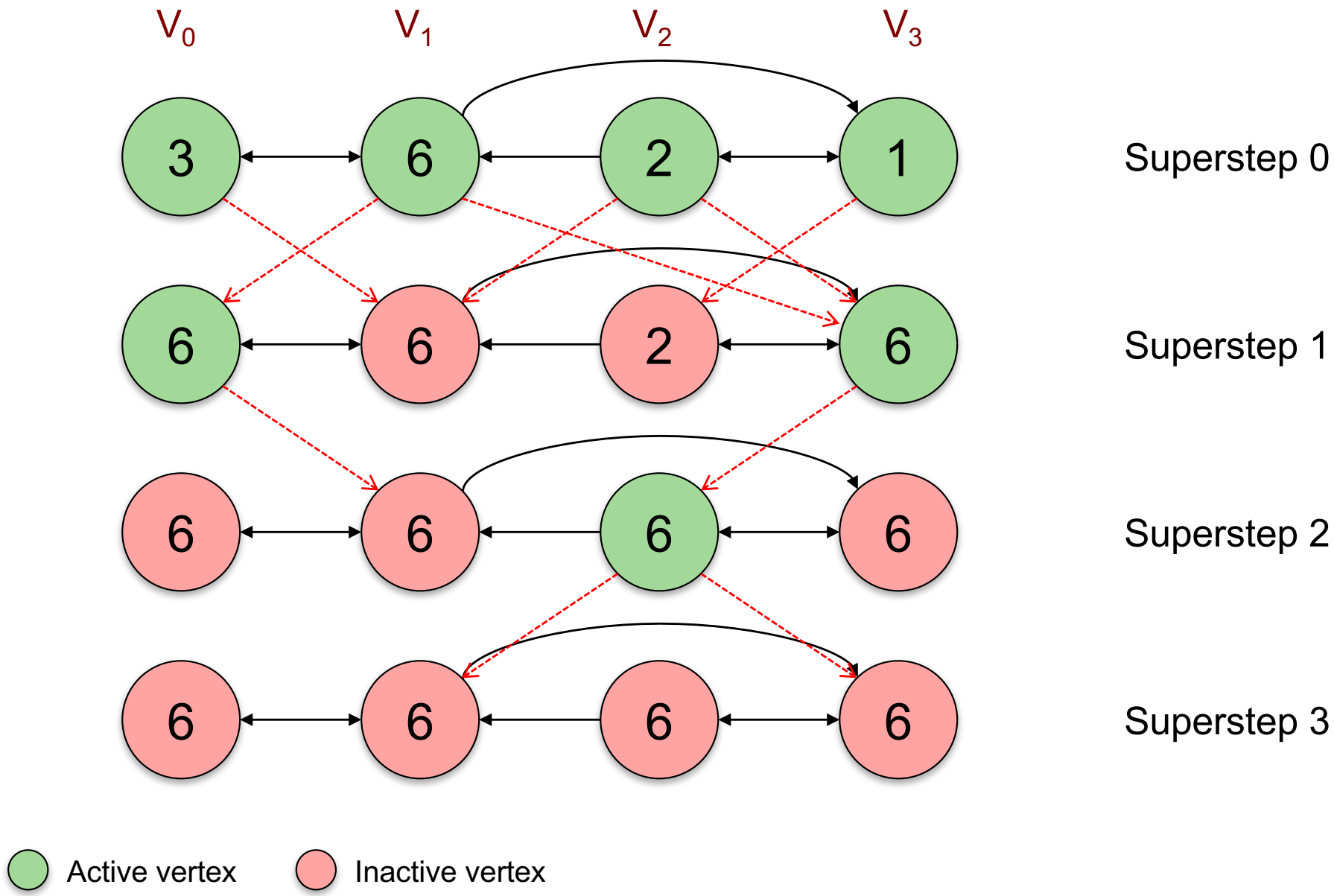



Superstep 3: $V_1$ receives a message – becomes active
$V_3$ receives a message – becomes active
No vertices update their value – **all vote to halt**

Done!

Active vertex  Inactive vertex

# Summary: find the maximum value



# Locality

- Vertices and edges remain on the machine that does the computation

- To run the same algorithm in MapReduce
  - Requires chaining multiple MapReduce operations
  - Entire graph state must be passed from *Map* to *Reduce*

    … and again as input to the next *Map*

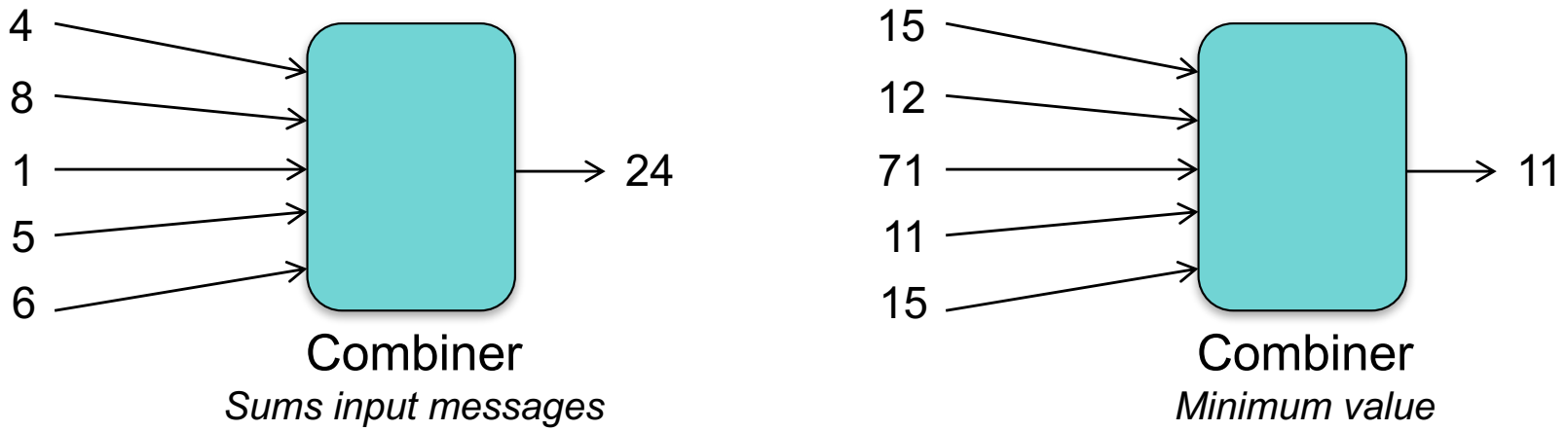
# Pregel API: Basic operations

- A user subclasses a Vertex class
- Methods
  - **Compute**(MessageIterator*): Executed per active vertex in each superstep
    - MessageIterator identifies incoming messages from previous supersteps
  - **GetValue**(): Get the current value of the vertex
  - **MutableValue**(): Set the value of the vertex
  - **GetOutEdgeIterator**(): Get a list of outgoing edges
    - .**Target**(): identify target vertex on an edge
    - .**GetValue**(): get the value of the edge
    - .**MutableValue**(): set the value of the edge
  - **SendMessageTo**(): send a message to a vertex
    - Any number of messages can be sent
    - Ordering among messages is not guaranteed
    - A message can be sent to *any* vertex (but our vertex needs to have its ID)

# Pregel API: Advanced operations

## Combiners

- Each message has an overhead – let's reduce # of messages
  - Many vertices are processed per worker (multi-threaded)
  - Pregel can combine messages targeted to one vertex into one message
- Combiners are application specific
  - Programmer subclasses a Combiner class and overrides Combine() method
- No guarantee on which messages may be combined



# Pregel API: Advanced operations

## Aggregators

- **Handle global data**
- A vertex can provide a value to an aggregator during a superstep
  - Aggregator combines received values to one value
  - Value is available to all vertices in the next superstep
- User subclasses an Aggregator class
- Examples
  - Keep track of total edges in a graph
  - Generate histograms of graph statistics
  - Global flags: execute until some global condition is satisfied
  - Election: find the minimum or maximum vertex

# Pregel API: Advanced operations

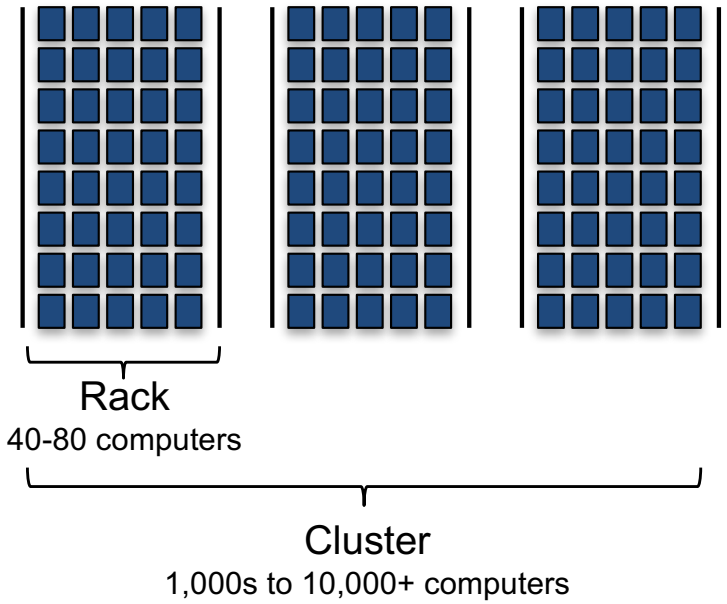
## Topology modification

- Examples
  - If we're computing a spanning tree: remove unneeded edges
  - If we're clustering: combine vertices into one vertex
- Add/remove edges/vertices
- Modifications visible in the next superstep

# Pregel Design

# Execution environment

- Many copies of the program are started on a cluster of machines
- One copy becomes the **master**
  - Will not be assigned a portion of the graph
  - Responsible for coordination
- Cluster's name server = chubby
  - Master registers itself with the name service
  - Workers contact the name service to find the master



# Partition assignment

- Master determines # partitions in graph
- One or more partitions assigned to each worker
  - Partition = set of vertices
  - Default: for *N* partitions

    hash(vertex ID) mod *N* ⇒ worker

    May deviate: e.g., place vertices representing the same web site in one partition

  - More than 1 partition per worker: improves load balancing

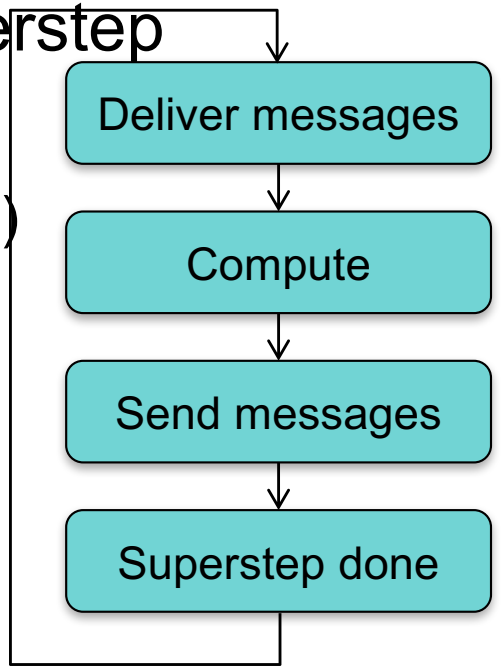
- Worker
  - Responsible for its section(s) of the graph
  - Each worker knows the vertex assignments of other workers

# Input assignment

- Master assigns parts of the input to each worker
  - Data usually sits in GFS or Bigtable
- Input = set of records
  - Record = vertex data and edges
  - Assignment based on file boundaries
- Worker reads input
  - If it belongs to any of the vertices it manages, messages sent locally
  - Else worker sends messages to remote workers
- After data is loaded, all vertices are active

# Computation

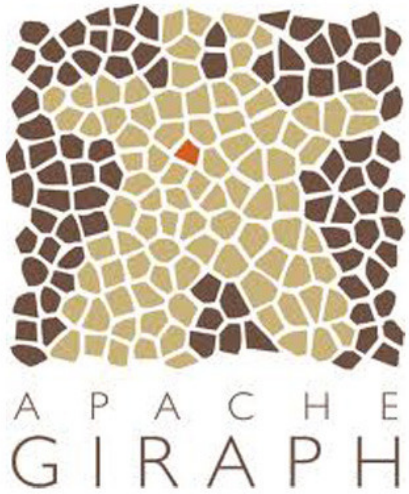
- Master tells each worker to perform a superstep
- Worker:
  - Iterates through vertices (one thread per partition)
  - Calls *Compute()* method for each active vertex
  - Delivers messages from the previous superstep
  - Outgoing messages
    - Sent asynchronously
    - Delivered before the end of the superstep
- When done
  - worker tells master how many vertices will be active in the next superstep
- Computation done when no more active vertices in the cluster
  - Master may instruct workers to save their portion of the graph



# Handling failure

- **Checkpointing**
  - Controlled by master … every *N* supersteps
  - Master asks a worker to checkpoint at the start of a superstep
    - Save state of partitions to persistent storage
      - Vertex values
      - Edge values
      - Incoming messages
  - Master is responsible for saving aggregator values
- Master sends "ping" messages to workers
  - If worker does not receive a ping within a time period
    ⇒ Worker terminates
  - If the master does not hear from a worker
    ⇒ Master marks worker as failed
- When failure is detected
  - Master reassigns partitions to the current set of workers
  - **All** workers reload partition state from most recent checkpoint

# Pregel outside of Google




Apache Giraph

- Initially created at Yahoo
- Used at Facebook to analyze the social graph of users
- Runs under Hadoop MapReduce framework
  - Runs as a *Map*-only job
  - Adds fault-tolerance to the master by using ZooKeeper for coordination
  - Uses Java instead of C++

*== Chubby*

# Conclusion

- Vertex-centric approach to BSP
- Computation = set of supersteps
  - Compute() called on each vertex per superstep
  - Communication between supersteps: barrier synchronization
- Hides distribution from the programmer
  - Framework creates lots of workers
  - Distributes partitions among workers
  - Distributes input
  - Handles message sending, receipt, and synchronization
  - A programmer just has to think from the viewpoint of a vertex
- Checkpoint-based fault tolerance

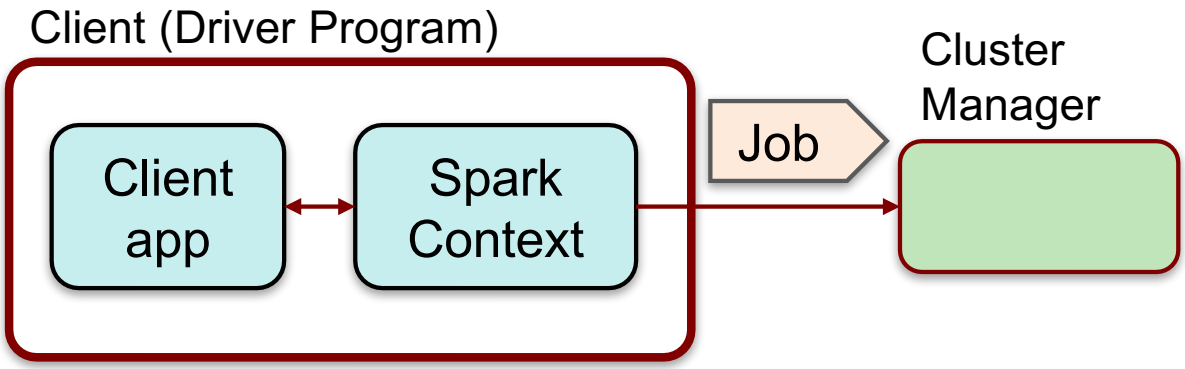
# Spark: Generalizing MapReduce

# Apache Spark

- Goal: Generalize MapReduce
  - Similar shard-and-gather approach to MapReduce
  - Add fast data sharing & general DAGs
- Generic data storage interfaces
  - Storage agnostic: use HDFS, Cassandra database, whatever
  - Resilient Distributed Data (RDD) sets
    - An RDD is a chunk of data that gets processed – a large collection of stuff
  - In-memory caching
- More general functional programming model
  - *Transformation* and *action*
  - In Map-Reduce, *transformation* = *map*, *action* = *reduce*

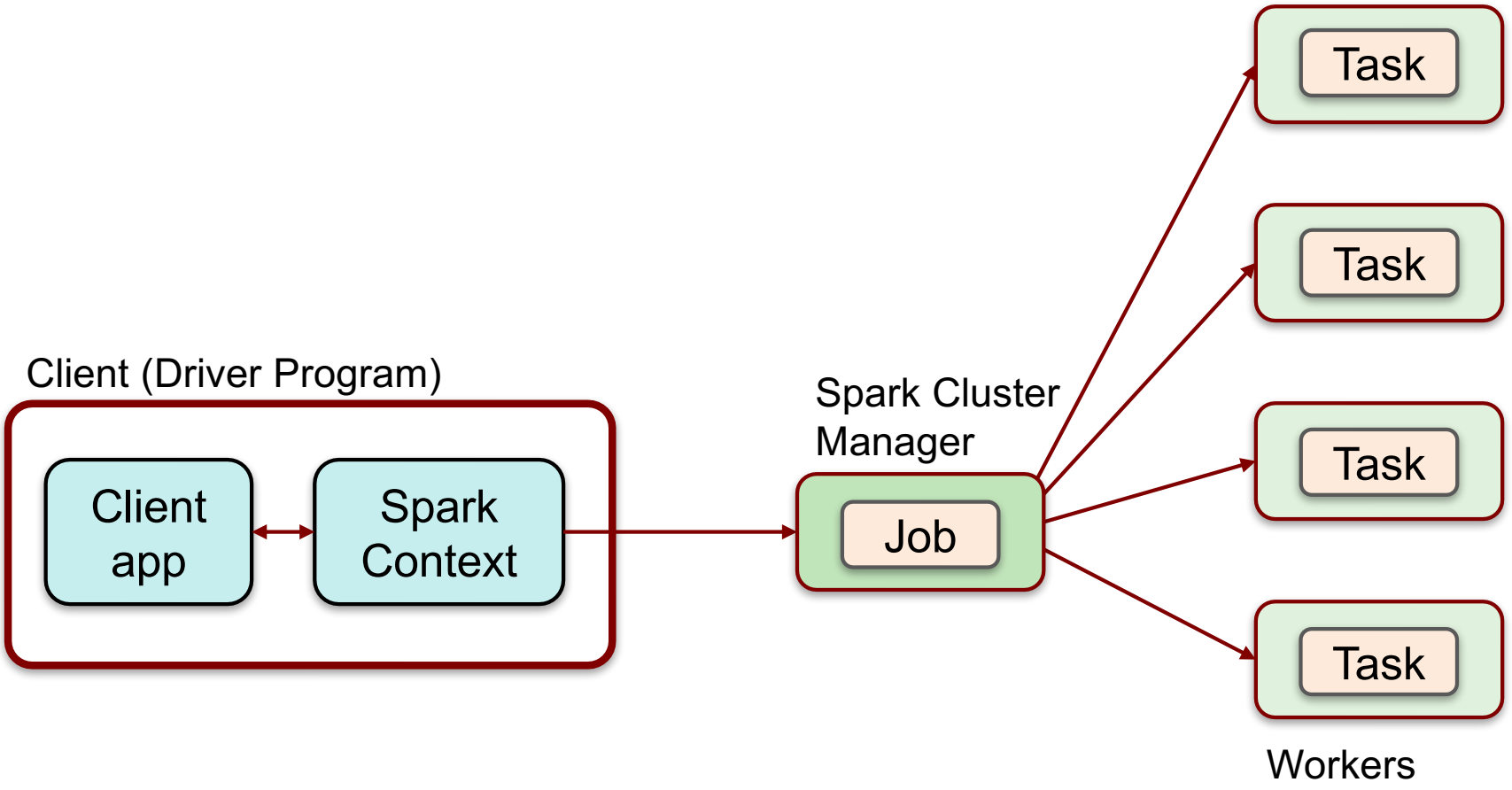
# High-level view

- Job = bunch of transformations & actions on RDDs



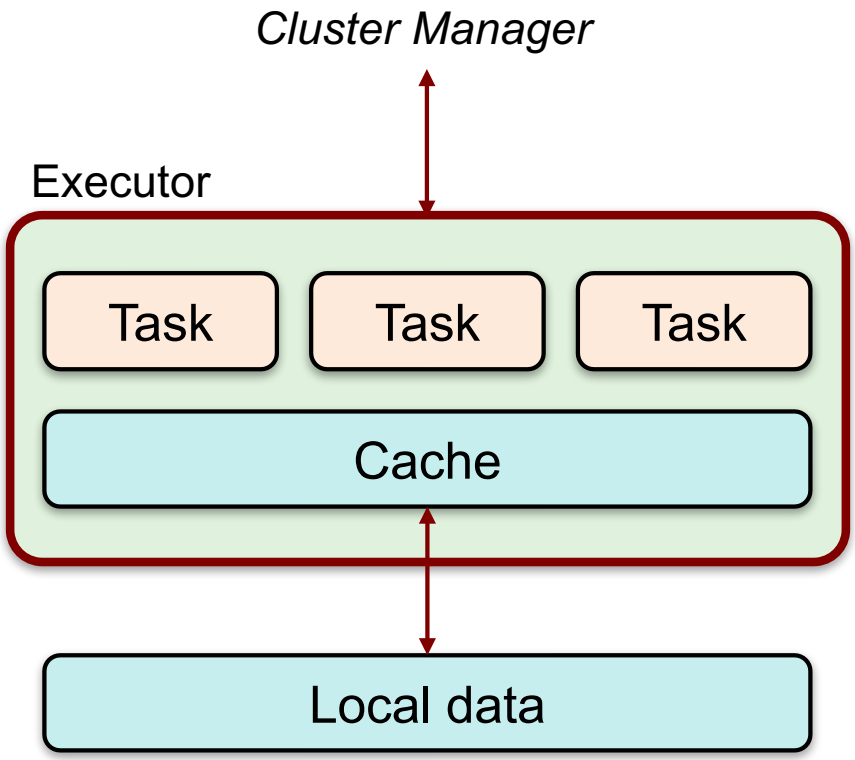
# High-level view

- Cluster manager breaks the job into tasks
- Sends tasks to worker nodes where the data lives



# Worker node

- One or more **executors**
  - JVM process
  - Talks with cluster manager
  - Receives tasks
    - JVM code (e.g., compiled Java, Clojure, Scala, JRuby, …)
    - Task = **transformation** or **action**
  - Data to be processed (RDD)
    - Local to the node
  - Cache
    - Stores frequently-used data in memory
    - Key to high performance



# Data & RDDs

- Data organized into RDDs:
  - Big data: partition it across lots of computers
- How are RDDs created?
  1. Create from any file stored in HDFS or other storage supported in Hadoop (Amazon S3, HDFS, HBase, Cassandra, etc.)
     - Created externally (e.g., event stream, text files, database)
     - Example:
       - Query a database & make query the results an RDD
       - Any Hadoop InputFormat, such as a list of files or a directory
  2. Streaming sources (via *Spark Streaming*)
     - Fault-tolerant stream with a sliding window
  3. An RDD can be the output of a Spark *transformation* function
     - Example, filter out data, select key-value pairs

# Properties of RDDs

- **Immutable**
  - You cannot change it – only create new RDDs
  - The framework will eventually collect unused RDDs
- **Typed**
  - Contain some parsable data structure – e.g., key-value set
- Created from – and thus **dependent** on other RDDs
  - Either original source data or computed from one or more other RDDs
- **Partitioned** – parts of an RDD may go to different servers
  - Function can be defined for computing each split
  - Default partitioning function = *hash(key) mod server_count*
- **Ordered** (optional)
  - Elements in an RDD can be sorted

# Operations on RDDs

- Two types of operations on RDDs
- **Transformations**
  - Lazy – not computed immediately
  - Transformed RDD is recomputed when an action is run on it
    - **Work backwards**:
      - What RDDs do you need to apply to get an action?
      - What RDDs do you need to apply to get the input to this RDD?
  - RDD can be persisted into memory or disk storage
- **Actions**
  - Finalizing operations
    - *Reduce*, *count*, *grab samples*, *write to file*

# Spark Transformations

| Transformation | Description |
|---|---|
| **map**(func) | Pass each element through a function *func* |
| **filter**(func) | Select elements of the source on which *func* returns true |
| **flatmap**(func) | Each input item can be mapped to 0 or more output items |
| **sample**(withReplacement, fraction, seed) | Sample a *fraction* fraction of the data, with or without replacement, using a given random number generator seed |
| **union**(otherdataset) | Union of the elements in the source data set and *otherdataset* |
| **distinct**([numtasks]) | The distinct elements of the source dataset |

# Spark Transformations

| Transformation | Description |
|---|---|
| **groupByKey**([numtasks]) | When called on a dataset of (K, V) pairs, returns a dataset of (K, seq[V]) pairs |
| **reduceByKey**(func, [numtasks]) | Aggregate the values for each key using the given *reduce* function |
| **sortByKey**([ascending], [numtasks]) | Sort keys in ascending or descending order |
| **join**(otherDataset, [numtasks]) | Combines two datasets, (K, V) and (K, W) into (K, (V, W)) |
| **cogroup**(otherDataset, [numtasks]) | Given (K, V) and (K, W), returns (K, Seq[V], Seq[W]) |
| **cartesian**(otherDataset) | For two datasets of types T and U, returns a dataset of (T, U) pairs |

# Spark Actions

| Action | Description |
|---|---|
| **reduce**(func) | Aggregate elements of the dataset using *func*. |
| **collect**(func, [numtasks]) | Return all elements of the dataset as an array |
| **count**() | Return the number of elements in the dataset |
| **first**() | Return the first element of the dataset |
| **take**(n) | Return an array with the first *n* elements of the dataset |
| **takeSample**(withReplacement, fraction, seed) | Return an array with a random sample of *num* elements of the dataset |

# Spark Actions

| Action | Description |
|---|---|
| **saveAsTextFile**(path) | Write dataset elements as a text file |
| **saveAsSequenceFile**(path) | Write dataset elements as a Hadoop SequenceFile |
| **countByKey** () | For (K, V) RDDs, return a map of (K, Int) pairs with the count of each key |
| **foreach**(func) | Run *func* on each element of the dataset |

# Data Storage

- Spark does not care how source data is stored
  - RDD connector determines that
  - E.g., read RDDs from tables in a Cassandra DB; write new RDDs to Cassandra tables

- RDD Fault tolerance
  - RDDs track the sequence of transformations used to create them
  - Enables recomputing of lost data
    - Go back to the previous RDD and apply the transforms again

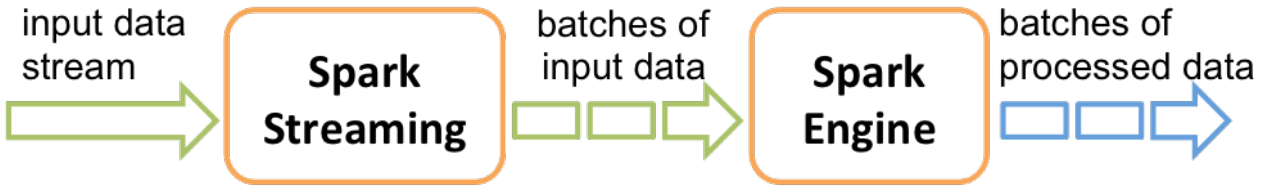
# Example: processing logs

- Transform (creates new RDDs)
  - Grab error message from a log
  - Grab only ERROR messages & extract the source of error
- Actions : Count mysql & php errors

```
// base RDD
val lines = sc.textFile("hdfs://...")

// transformed RDDs
val errors = lines.filter(_.startsWith("ERROR"))
val messages = errors.map(_.split("\t")).map(r => r(1))
messages.cache()

// action 1
messages.filter(_.contains("mysql")).count()

// action 2
messages.filter(_.contains("php")).count()
```

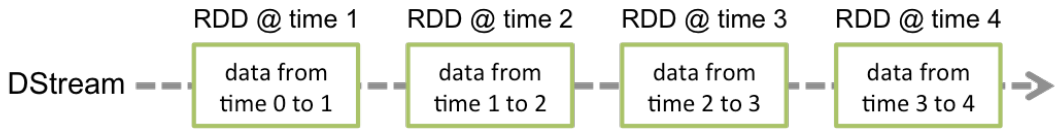
# Spark Streaming

- Map-Reduce & Pregel expect static data
- Spark Streaming enables processing live data streams
  - Same programming operations
  - Input data is chunked into batches
    - Programmer specifies time interval

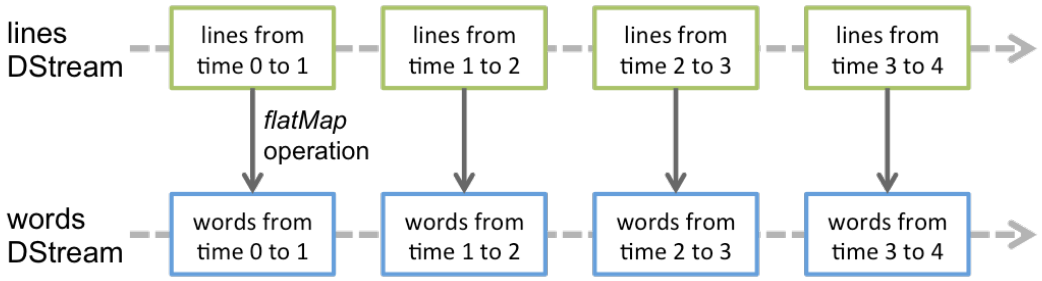


# Spark Streaming: DStreams

- Discretized Stream = DStream
  - Continuous stream of data (from source or a transformation)
  - Appears as a continuous series of RDDs, each for a time interval




  - Each operation on a DStream translates to operations on the RDDs




  - Join operations allow combining multiple streams

# Spark Summary

- Supports streaming
  - Handle continuous data streams via Spark Streaming
- Fast
  - Often up to 10x faster on disk and 100x faster in memory than MapReduce
  - General execution graph model
    - No need to have ”useless” phases just to fit into the model
  - In-memory storage for RDDs
- Fault tolerant: RDDs can be regenerated
  - You know what the input data set was, what transformations were applied to it, and what output it creates

# The end