Software tools for Complex Networks Analysis

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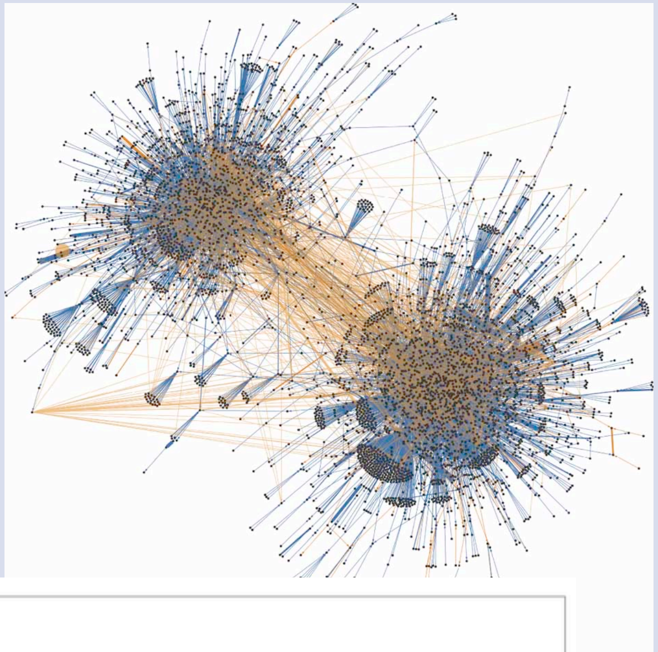
SCALE Team

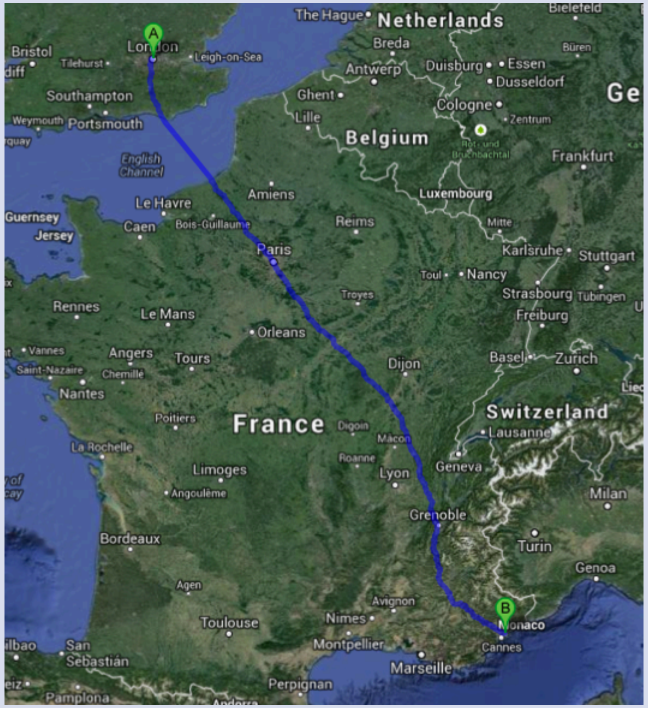
MOTIVATION

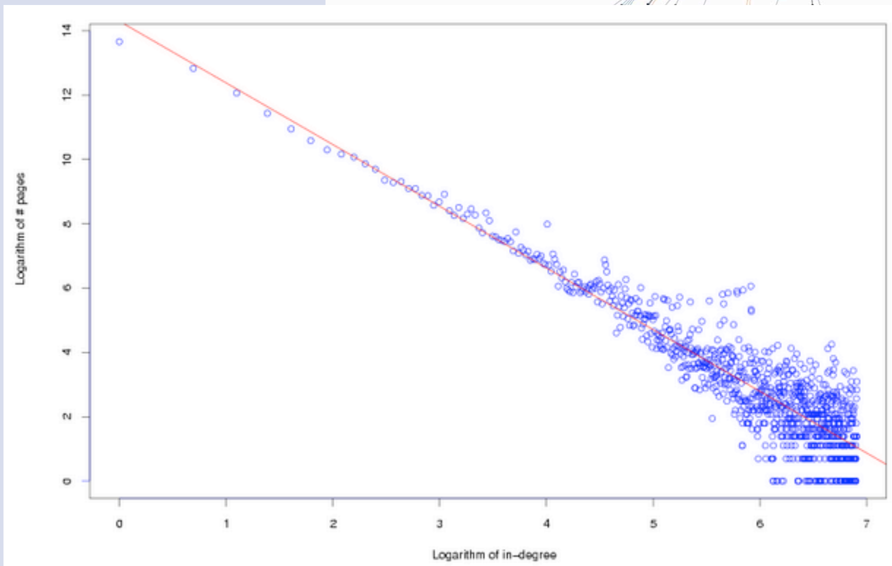
Why do we need tools ?

Source : nature.com



- Visualization
- Properties extraction
- Complex queries





Source : Boldi et al.

Graphs are everywhere

- RDF

```
("test1", writtenBy, "Sophie")
("test1", publishedIn, "Journal")
("test2", publishedIn, "Journal)
```

- SPARQL

```
SELECT ?s WHERE {
        ?s  writtenBy  ?a.
        ?a  hasName  "Sophie".
        ?s  publishedIn  "Journal".
    }
```

- Basically a sub-graph matching

Why are graphs different ?

- Graphs can be large
  - Facebook : 720M users, 69B friends in 2011
  - Twitter : 537M accounts, 23.95B links in 2012
- Low memory cost per vertex
  - 1 ID, 1 pointer/edge
- Low computation per vertex
- Graphs are not memory friendly
  - Random jumps to memory
- They are not hardware friendly!

Lots of frameworks

- Really lots of them
  - Matlab, NetworkX, GraphChi, Hadoop, Twister, Piccolo, Maiter, Pregel, Giraph, Hama, GraphLab, Pegasus, Snap, Neo4J, Gephi, Tulip, any DBMS,…
- Why so many ?
  - Not one size fits all
  - Different computational models
  - Different architecture

Possible taxonomy

- Generic vs Specialized
  - Hadoop vs GraphChi (or Giraph, GraphX…)
- Shared vs Distributed Memory
  - GraphChi vs Pregel
- Synchronous vs Asynchronous
  - Giraph vs Maiter
- Single vs Multi threaded
  - NetworkX vs GraphiChi

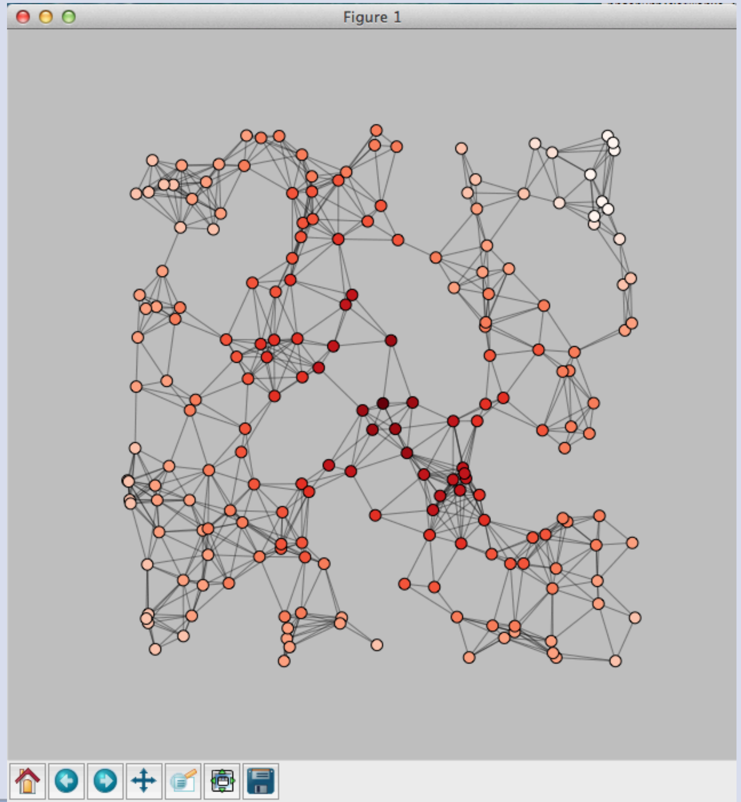
NETWORKX

Overview

- A Python package for complex network analysis
- Simple API
- Very flexible
  - Can attach any data to vertices and edges
  - Supports visualization
- Graphs generators
- http://networkx.github.io/

Dependencies

- Supports Python 2.7 (preferred) or 3.0
- If drawing support required
  - Numpy (http://www.numpy.org/)
  - Mathplotlib (http://matplotlib.org/)
  - Graphivz (http://graphviz.org/)



Examples

- Creating an empty graph

```
>>> import networkx as nx
>>> G=nx.Graph()
```

- Adding nodes

```
>>> G.add_node(1)
>>> G.add_nodes_from([2,3])
```

- Adding edges

```
>>> G.add_edge(2,3)
>>> G.add_edges_from([(1,2),(1,3)])
```

Examples (2)

- Graph generators

```
>>> K_5=nx.complete_graph(5)
>>> K_3_5=nx.complete_bipartite_graph(3,5)
```

- Stochastic graph generators

```
>>> er=nx.erdos_renyi_graph(100,0.15)
>>> ws=nx.watts_strogatz_graph(30,3,0.1)
>>> ba=nx.barabasi_albert_graph(100,5)
>>> red=nx.random_lobster(100,0.9,0.9)
```

- Reading from files

```
>>> mygraph=nx.read_gml("path.to.file")
```

Examples (3)

- Graph analysis

```
>>> nx.connected_components(G)
```

```
>>> nx.degree(G)
```

```
>>> pr=nx.pagerank(G,alpha=0.9)
```

- Graph drawing

```
>>> import matplotlib.pyplot as plt
>>> nx.draw(G)
>>> plt.show()
```

NetworkX - Conclusion

- Easy to use
  - Very good for prototyping/testing
- Centralized
  - Limited scalability
- Efficiency
  - Memory overhead

GRAPHCHI

Overview

- Single machine
  - Distributed systems are complicated!
- Disk-based system
  - Memory is cheap but limited
- Supports both static and dynamic graph
- Kyrola, Aapo and Blelloch, Guy and Guestrin, Carlos, ***GraphChi: Large-scale Graph Computation on Just a PC***, Proceedings of OSDI'12

Computational Model

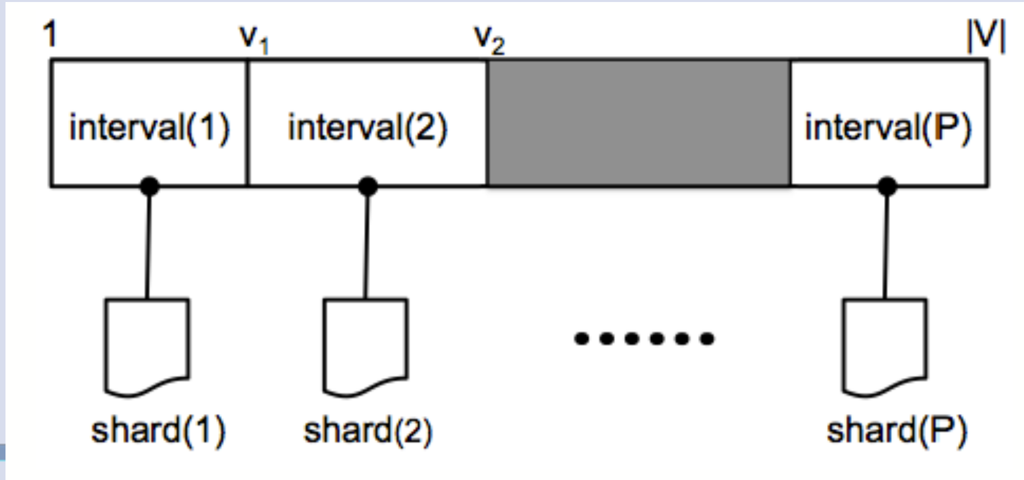
- Vertex centric
  - Vertices and Edges have associated values
  - Update a vertex values using edges values
- Typical update
  - Read values from edges
  - Compute new value
  - Update edges
- Asynchronous model
  - Always get the most recent value for edges
  - Schedule multiple updates

Storing graphs on disk

- Compressed Sparse Row (CSR)
  - Equivalent to adjacency sets
  - Store out-edges of vertex consecutively on Disk
  - Maintain index to adjacency sets for each vertex
- Very efficient for out-edges, not so for in-edges
  - Use *Compressed Sparse Column (CSC)*
- Changing edges values
  - On modification of out-edge : write to CSC
  - On reading of in-edge : read from CSR
  - Random read or random write ☹

Parallel Sliding Windows

- Minimize non sequential disk access
- 3 stages algorithm
- Storing graph on disk
  - Vertices *V* are split into *P* disjoints intervals
  - Store all edges that have **destination** in an interval in a *Shard*
  - Edges are stored by source order



From ***Kyrola and al.***

Parallel Sliding Windows (2)

- Loading subgraph of vertices in interval *p*
  - Load Shard(p) in memory
    - Get in-edges immediately
  - Out-edges are stored in the P-1 other shards
    - But ordered by sources, so easy to find
- Loading subgraph p+1
  - Slide a window over all shards
- Each interval requires *P* sequential reads

Parallel updates

- Once interval loaded, update in parallel
- Data races
  - Only a problem if considering edge with both endpoints in interval
  - Enforce sequential update
- Write back result to disk
  - Current shard totally rewritten
  - Sliding window of other shards rewritten

Example

Shard 1

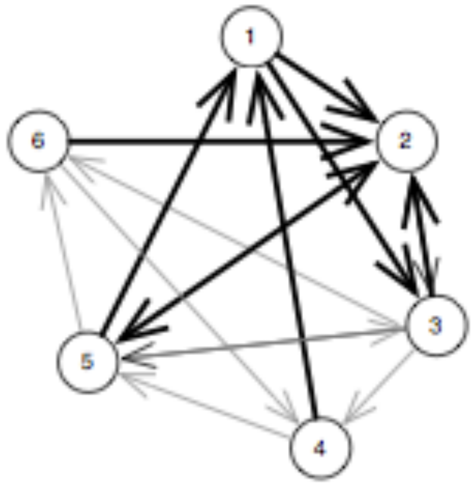
src	dst	value
1		
	2	0.3
3		
	2	0.2
4		
	1	1.4
5		
	1	0.5
	2	0.6
6		
	2	0.8

Shard 2

src	dst	value
1		
	3	0.4
2		
	3	0.3
3		
	4	0.8
5		
	3	0.2
6		
	4	1.9

Shard 3

src	dst	value
2		
	5	0.6
3		
	5	0.9
	6	1.2
4		
	5	0.3
5		
	6	1.1



Example

Shard 1

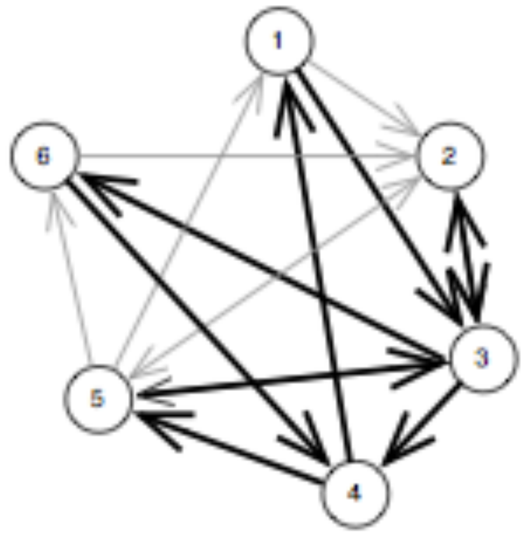
src	dst	value
1		
	2	0.273
3		
	2	0.22
4		
	1	1.54
5		
	1	0.55
	2	0.66
6		
	2	0.88

Shard 2

src	dst	value
1		
	3	0.364
2		
	3	0.273
3		
	4	0.8
5		
	3	0.2
6		
	4	1.9

Shard 3

src	dst	value
2		
	5	0.545
3		
	5	0.9
	6	1.2
4		
	5	0.3
5		
	6	1.1



Performance

- Mac Mini 2.5GHz, 8GB and 256GB SSD
- Shard creation

Graph name	Vertices	Edges	P	Preproc.
live-journal [3]	4.8M	69M	3	0.5 min
netflix [6]	0.5M	99M	20	1 min
domain [44]	26M	0.37B	20	2 min
twitter-2010 [26]	42M	1.5B	20	10 min
uk-2007-05 [11]	106M	3.7B	40	31 min
uk-union [11]	133M	5.4B	50	33 min
yahoo-web [44]	1.4B	6.6B	50	37 min

Performance (2)

Application & Graph	Iter.	Comparative result	GraphChi (Mac Mini)	Ref
Pagerank & domain	3	GraphLab[30] on AMD server (8 CPUs) **87 s**	**132 s**	-
Pagerank & twitter-2010	5	Spark [45] with 50 nodes (100 CPUs): **486.6 s**	**790 s**	[38]
Pagerank & V=105M, E=3.7B	100	Stanford GPS, 30 EC2 nodes (60 virt. cores), **144 min**	approx. **581 min**	[37]
Pagerank & V=1.0B, E=18.5B	1	Piccolo, 100 EC2 instances (200 cores) **70 s**	approx. **26 min**	[36]
Webgraph-BP & yahoo-web	1	Pegasus (Hadoop) on 100 machines: **22 min**	**27 min**	[22]
ALS & netflix-mm, D=20	10	GraphLab on AMD server: **4.7 min**	**9.8 min** (in-mem) **40 min** (edge-repl.)	[30]
Triangle-count & twitter-2010	-	Hadoop, 1636 nodes: **423 min**	**60 min**	[39]
Pagerank & twitter-2010	1	PowerGraph, 64 x 8 cores: **3.6 s**	**158 s**	[20]
Triange-count & twitter- 2010	-	PowerGraph, 64 x 8 cores: **1.5 min**	**60 min**	[20]

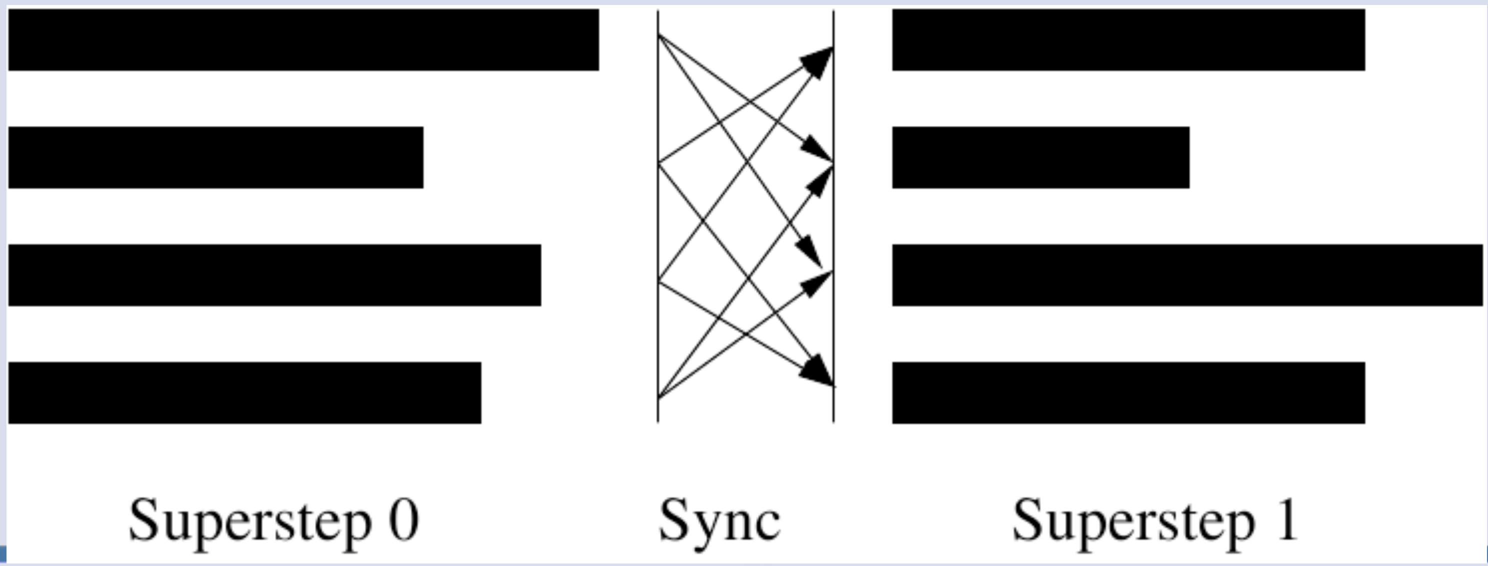
GOOGLE PREGEL

Overview

- Directed graphs
- Distributed Framework Based on the *Bulk Synchronous Parallel* model
- *Vertex Centric* computation model
- Private framework with C++ API
- Grzegorz Malewicz, Matthew H. Austern, Aart J.C Bik, James C. Dehnert, Ilan Horn, Naty Leiser, and Grzegorz Czajkowski. 2010. **Pregel: a system for large-scale graph processing.** In *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data* (SIGMOD '10)

Model of Computation (1)

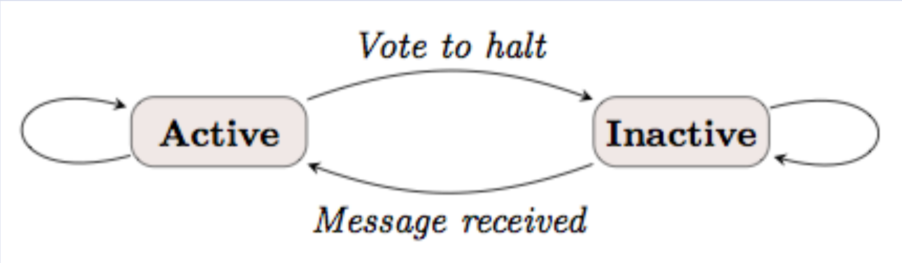
- BSP : model for parallel programming
  - Takes into account communication/synchronization
  - Series of super-steps (iterations)
    - Performs local computations
    - Communicate with others
    - Barrier



From : http://www.multicorebsp.com/

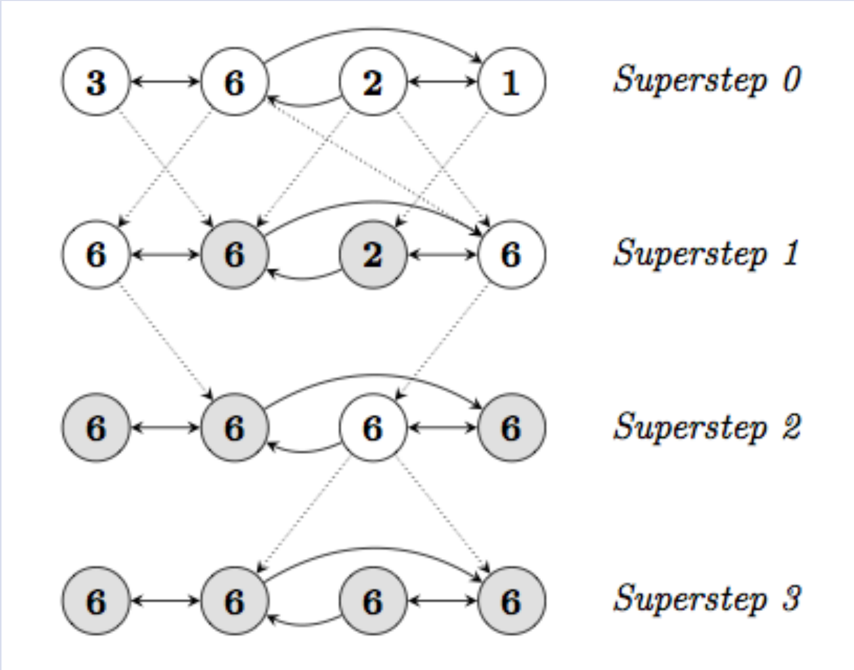
Model of Computation (2)

- Vertex Centric
  - Each vertex execute a function in parallel
- Can read messages sent at previous super-step
- Can send messages to be read at next super-step
  - Not necessarily following edges
- Can modify state of outgoing edges
- Run until all vertices agree to stop and no message in transit



From ***Malewicz and al.***

Maximum Value Example



*From **Malewicz and al.***

Implementation and Execution (1)

- User provides a graph, some input (vertex and edges values) and a program
- The program is executed on all nodes of a cluster
  - One node become the master, other are workers
- The graph is divided into partitions by the master
  - Vertex Id used to compute partition index (*e.g. hash(Id) mod N*)
- Partitions are assigned to workers
- User input file is partitioned (no fancy hash) and sent to workers
  - If some input is not for the worker, it will pass it along

Implementation and Execution (2)

- The master request worker to perform superstep
  - At the end, each worker reports the number of active vertices for next superstep
- Aggregators can be used at end of super-step to reduce communications
  - Perform reduction on values before sending
- If no more active vertices, Master can halt computation
- What about failures ?
  - Easy to checkpoint workers at end of superstep
  - If failure, rollback to previous checkpoint
  - If master fails… too bad ☹

PageRank in Pregel

$$PR(p_i) = \frac{1-d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)}$$

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

From ***Malewicz and al.***

Performance

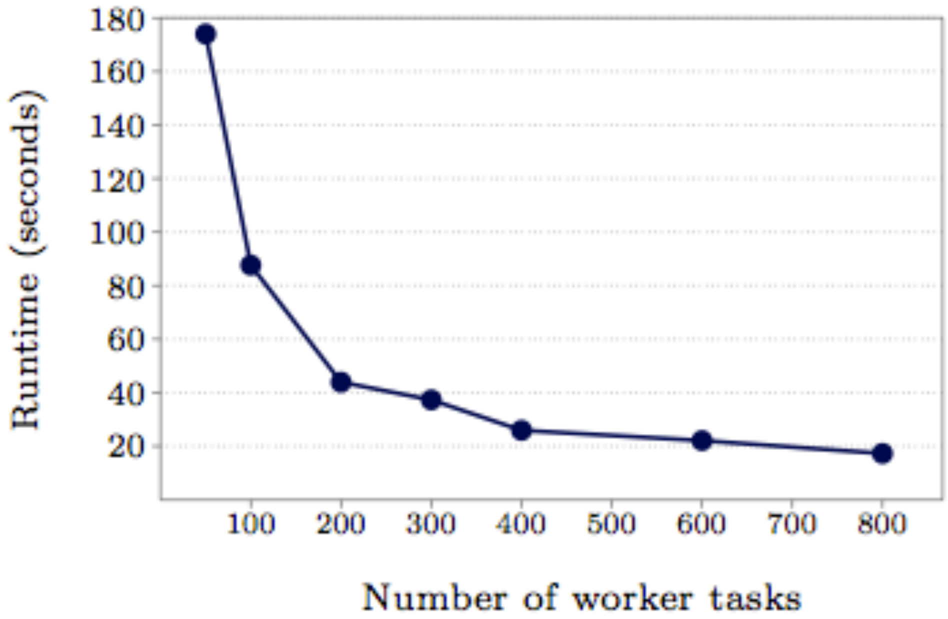


Figure 7: SSSP—1 billion vertex binary tree: varying number of worker tasks scheduled on 300 multicore machines

*From **Malewicz and al.***

Performance

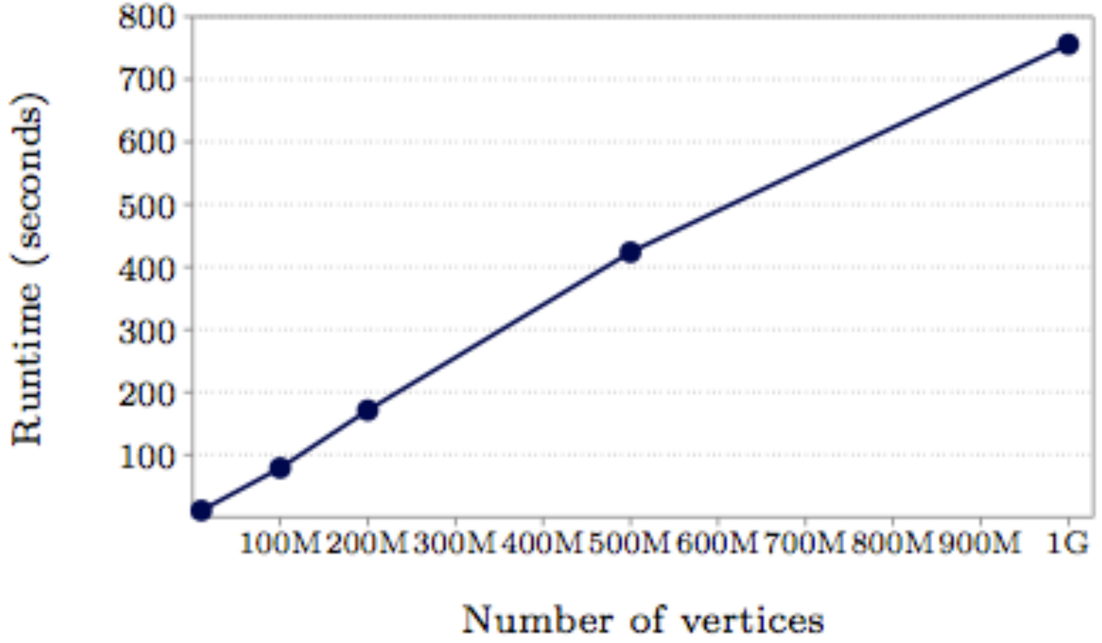


Figure 9: SSSP—log-normal random graphs, mean out-degree 127.1 (thus over 127 billion edges in the largest case): varying graph sizes on 800 worker tasks scheduled on 300 multicore machines

*From **Malewicz and al.***

MAPREDUCE

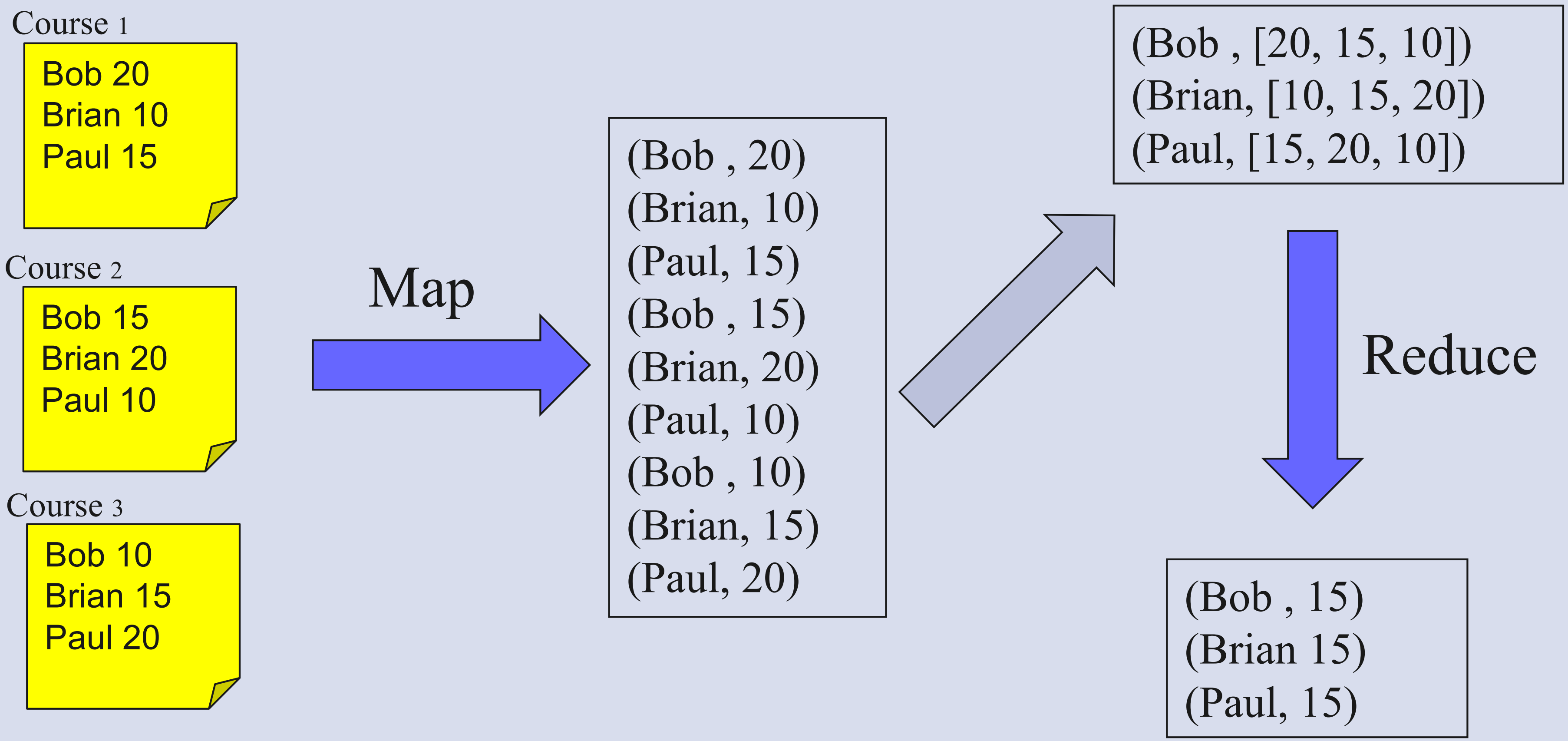
Map Reduce operations

- Input data are (key, value) pairs
- 2 operations available : map and reduce
- Map
  - Takes a (key, value) and generates other (key, value)
- Reduce
  - Takes a key and all associated values
  - Generates (key, value) pairs
- A map-reduce algorithm requires a mapper and a reducer
- Re-popularized by Google
  - **MapReduce: Simplified Data Processing on Large Clusters**
    Jeffrey Dean and Sanjay Ghemawat, OSDI'04

Map Reduce example

- Compute the average grade of students
  - For each course, the professor provides us with a text file
  - Text file format : lines of "student grade"
- Algorithm (non map-reduce)
  - For each student, collect all grades and perform the average
- Algorithm (map-reduce)
  - Mapper
    - Assume the input file is parsed as (student, grade) pairs
    - So … do nothing!
  - Reducer
    - Perform the average of all values for a given key

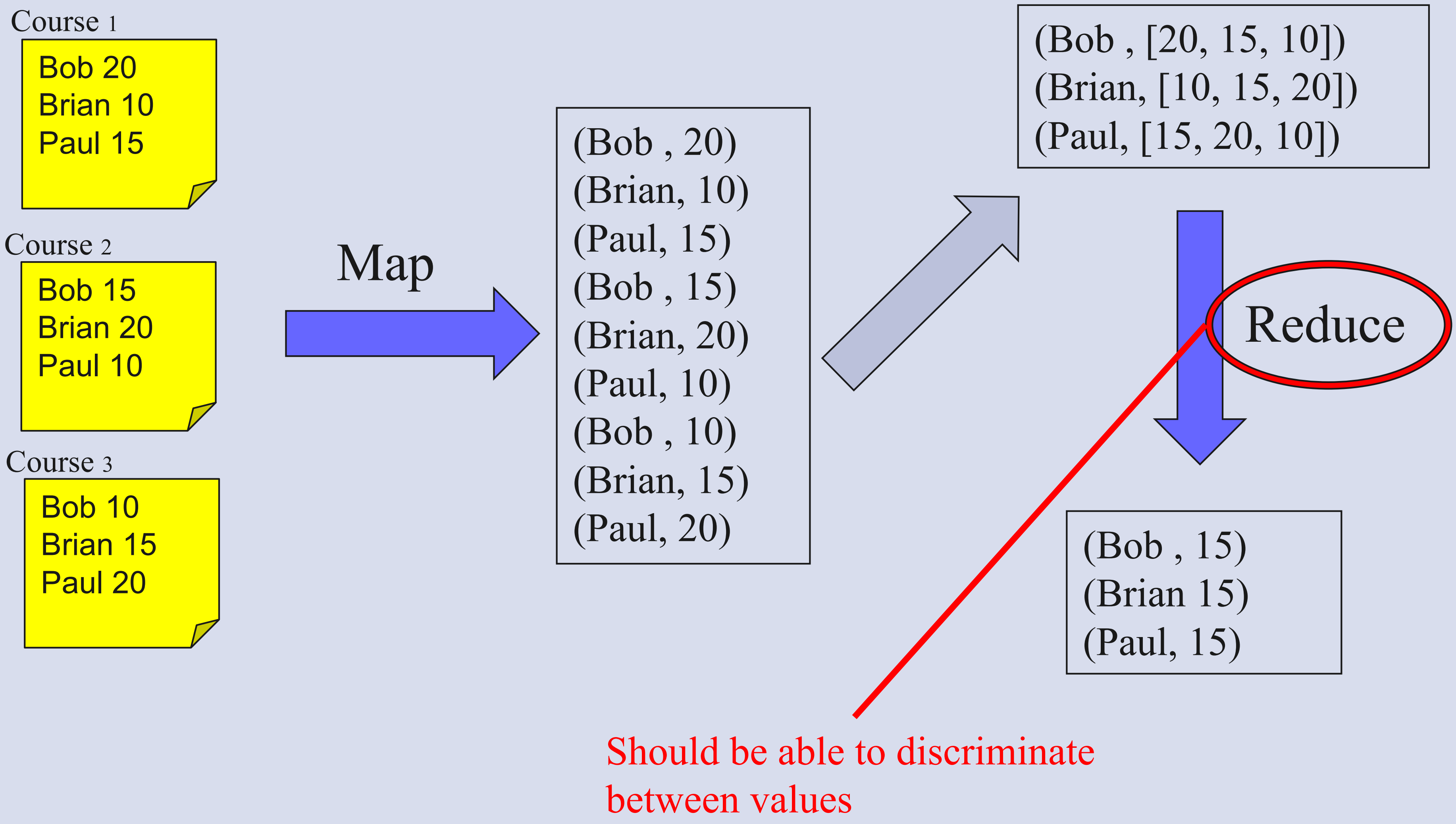
Map Reduce example



Map Reduce example… too easy ☺

- Ok, this was easy because
  - We didn't care about technical details like reading inputs
  - All keys are "equals", no weighted average
- Now can we do something more complicated ?
- Let's computed a weighted average
  - Course 1 has weight 5
  - Course 2 has weight 2
  - Course 3 has weight 3
- What is the problem now ?

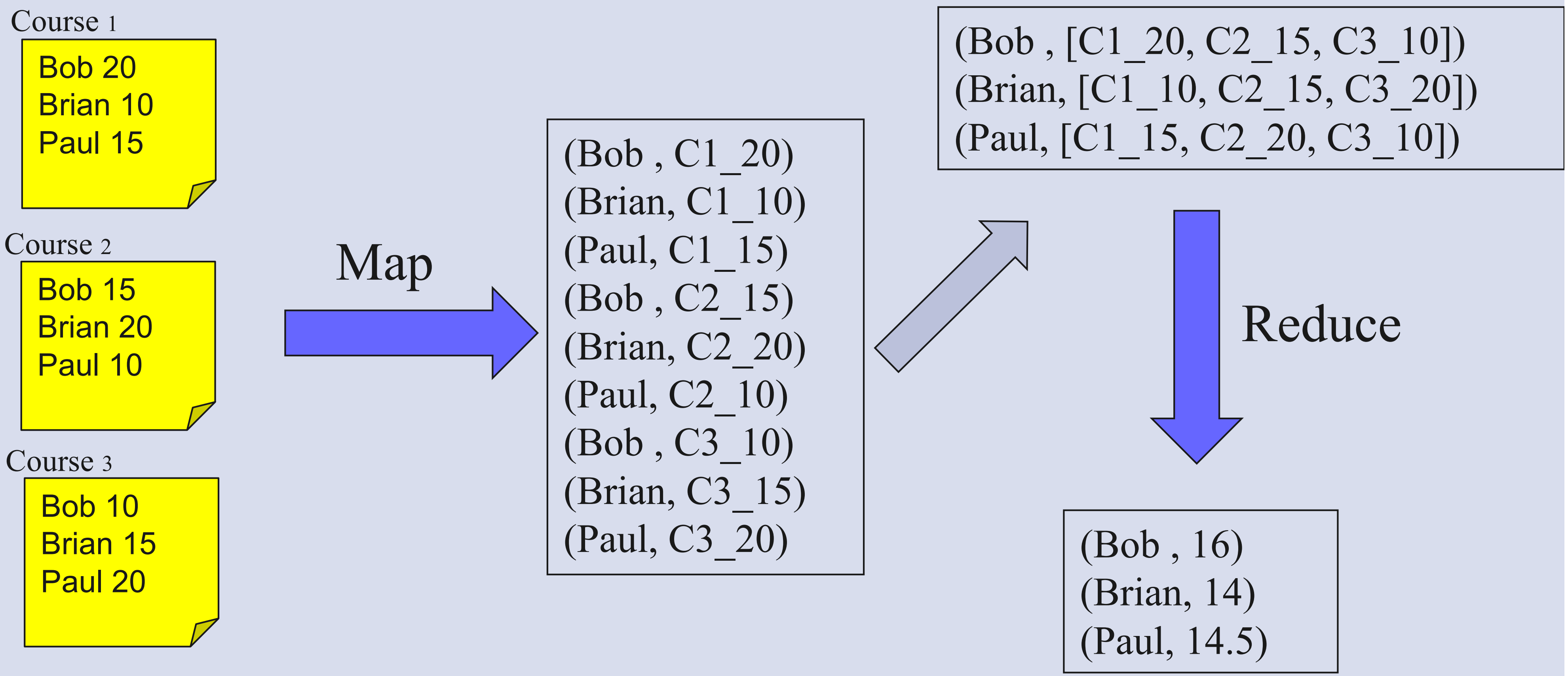
Map Reduce example



Map Reduce example - advanced

- How discriminate between values for a given key
  - We can’t … unless the values look different
- New reducer
  - Input : (Name, [course1_Grade1, course2_Grade2, course3_Grade3])
  - Strip values from course indication and perform weighted average
- So, we need to change the input of the reducer which comes from… the mapper
- New mapper
  - Input : (Name, Grade)
  - Output : (Name, courseName_Grade)
  - The mapper needs to be aware of the input file

Map Reduce example - 2



What is Hadoop ?

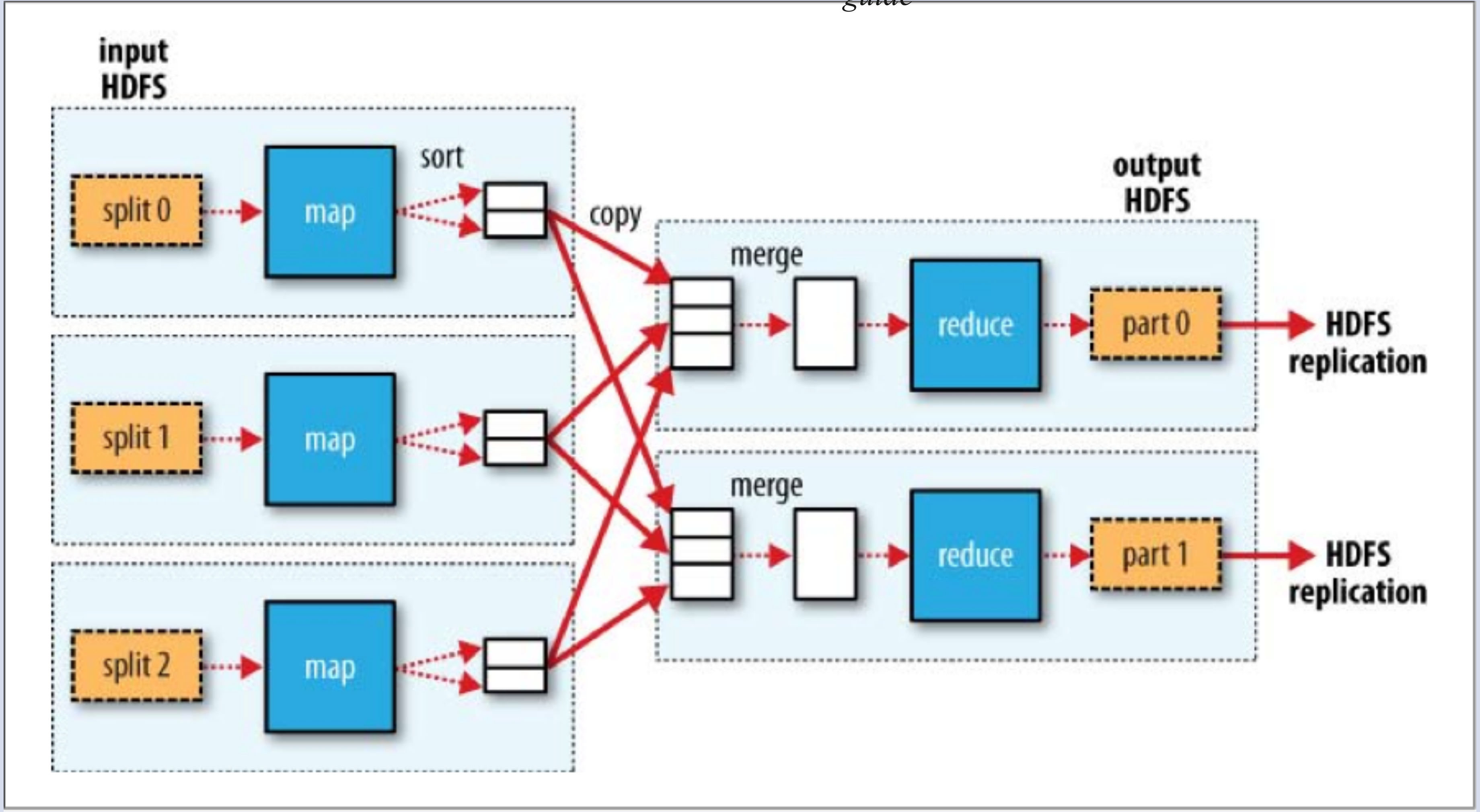
- A set of software developed by Apache for distributed computing
- Many different projects
  - MapReduce
  - HDFS : Hadoop Distributed File System
  - Hbase : Distributed Database
  - ….
- Written in Java
  - Bindings for your favorite languages available
- Can be deployed on any cluster easily

Hadoop Job

- An Hadoop job is composed of a map operation and (possibly) a reduce operation
- Map and reduce operations are implemented in a *Mapper* subclass and a *Reducer* subclass
- Hadoop will start many instances of *Mapper* and *Reducer*
  - Decided at runtime but can be specified
- Each instance will work on a subset of the keys called a *Splits*

Hadoop workflow

Source : Hadoop the definitive guide



Graphs and MapReduce

- How to write a graph algorithm in MapReduce?
- Graph representation ?
  - Use adjacency matrix

	V_1	V_2	V_3
V_1	0	0	1
V_2	1	0	1
V_3	1	1	0

- Line based representation
  - V_1 : 0, 0, 1
  - V_2 : 1, 0, 1
  - V_3 : 1, 1, 0
- Size $|V|^2$ with tons of 0 …

Sparse matrix representation

- Only encode useful values, i.e. non 0
  - $V_1 : (V_3, 1)$
  - $V_2 : (V_1, 1), (V_3, 1)$
  - $V_3 : (V_1, 1), (V_2, 1)$
- And if equal weights
  - $V_1 : V_3$
  - $V_2 : V_1, V_3$
  - $V_3 : V_1, V_2$

Single Source Shortest Path

- Find the shortest path from one source node *S* to others
- Assume edges have weight 1
- General idea is BFS
  - Distance(*S*) = 0
  - For all nodes *N* reachable from S
    - Distance(*N*) = 1
  - For all nodes *N* reachable from other set of nodes *M*
    - Distance(N) = 1+ min(Distance(M))
  - And start next iteration

MapReduce SSSP

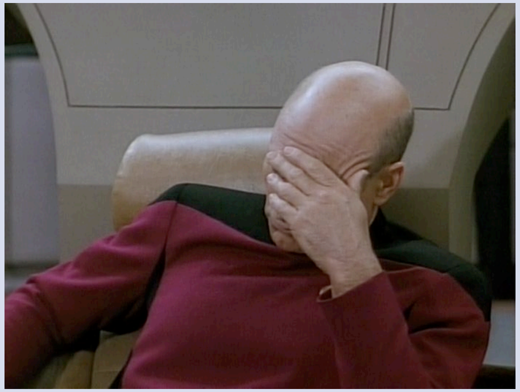
- Data
  - Key : node N
  - Value : (d, adjacency list of N)
    - d distance from S so far
- Map :
  - $\forall m \in$ adjacency list: emit (m, d + 1)
- Reduce :
  - Keep minimum distance for each node
- This basically advances the frontier by one hop
  - Need more iterations

MapReduce SSSP (2)

- How to maintain graph structure between iterations
  - Output adjacency list in mapper
  - Have special treatment in reducer
- Termination ?
  - Eventually ☺
  - Stops when no new distance is found… (any idea how?)

Seriously ?

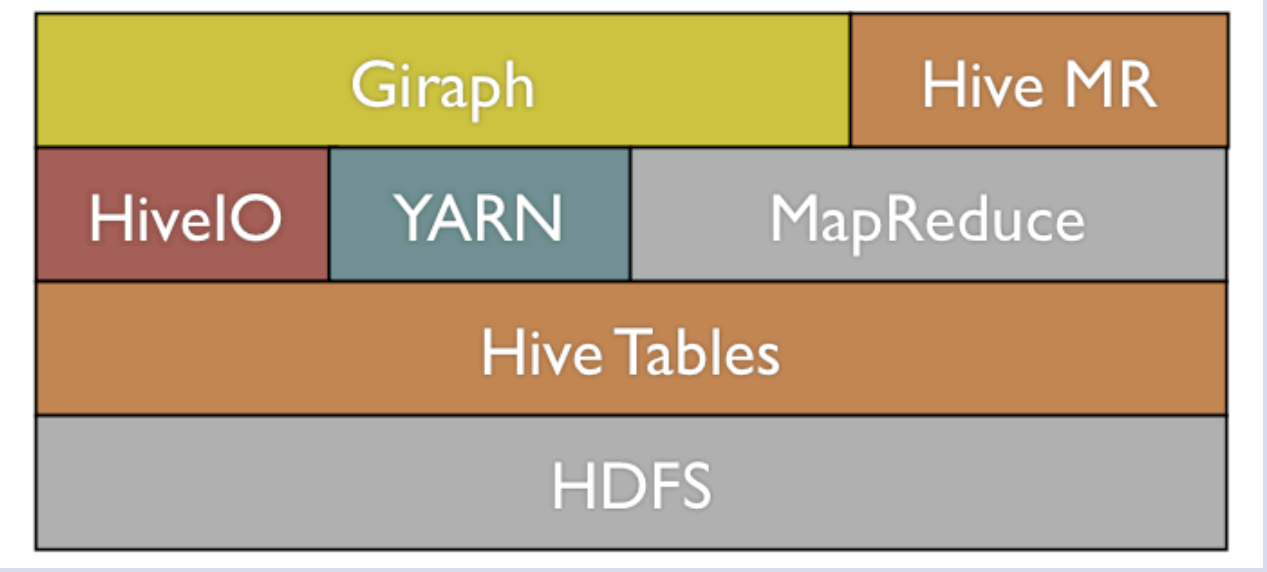
- MapReduce + Graphs is easy



- But everyone is MapReducing the world!
  - Because they are forced to
  - And because of Hadoop
- Hadoop gives
  - A scalable infrastructure (computation and storage)
  - Fault tolerance
- So let's use Hadoop as an underlying infrastructure

Giraph

- Built on top of Hadoop
- Vertex centric and BSP model ☺
  - Giraph jobs run as MapReduce



Source : https://m.facebook.com/notes/facebook-engineering/scaling-apache-giraph-to-a-trillion-edges/10151617006153920/

SPARK AND GRAPHX

Spark

- Addresses limitations of Hadoop
  - Disk intensive
  - No support for iteration (cycles)
- Spark
  - In-Memory computation
  - Workflows with cycles
  - Still relies on Map-Reduce like operations
  - Multi languages support : Scala, Java, Python, R
- https://spark.apache.org/

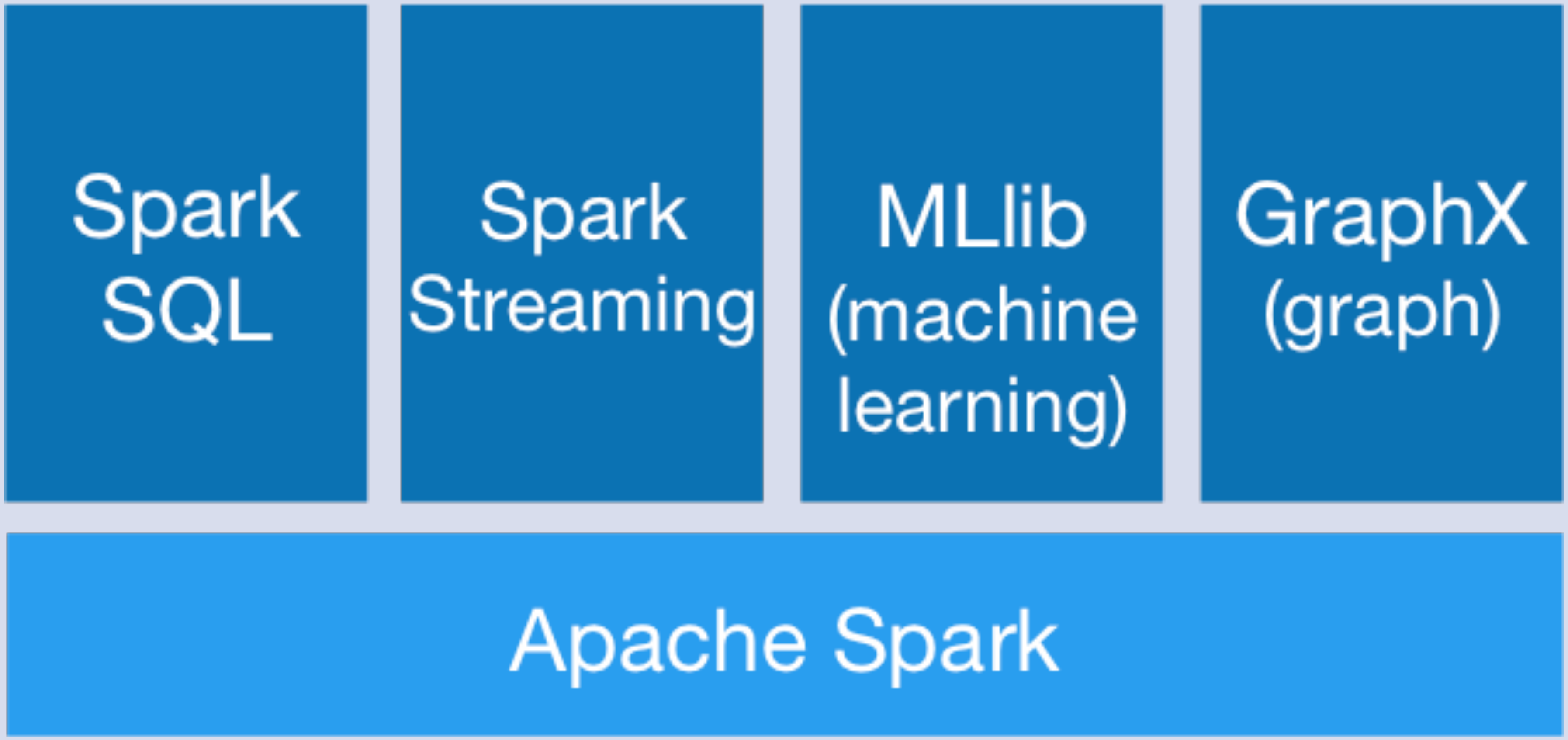
Resilient Distributed Datasets

- RDDs
  - Array-like data structure
  - Mostly in-memory
  - Partitioned
  - Fault tolerant
  - Immutable ← very important !
- RDDs are created through **transformations**
  - Of raw data or another RDD
  - Example : map, filter, reduceByKey, groupBy…
- RDDs support **actions**
  - Example : collect, count, reduce, save…
- Transformations are lazy

Example : Word Count

```
val textFile = sc.textFile(”…")
val counts = textFile.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)
counts.saveAsTextFile(”….")
```

Spark Stack



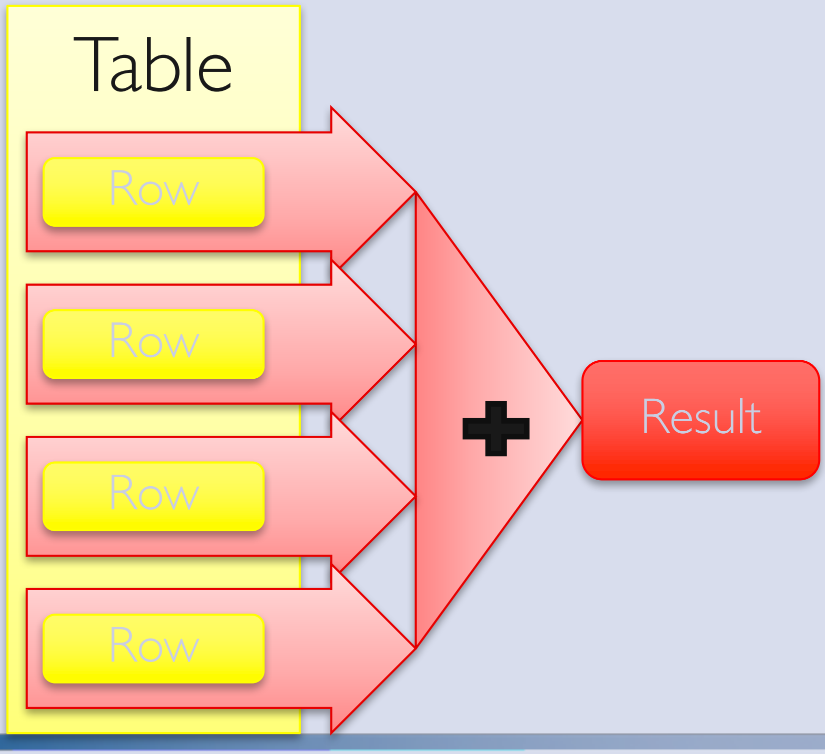
http://spark.apache.org/

Separate Systems to Support Each View

Table View

hadoop

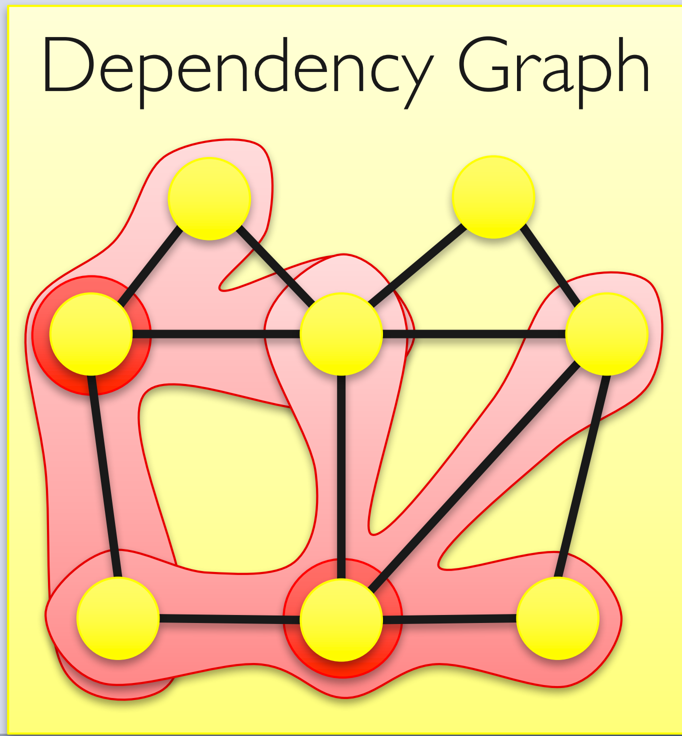
Spark



Graph View

Pregel GraphLab

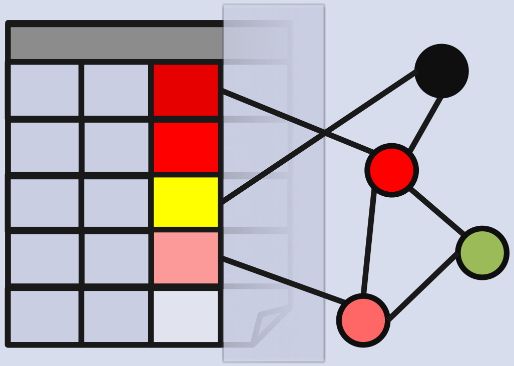
APACHE GIRAPH



Solution: The GraphX Unified Approach

New API

Blurs the distinction between Tables and Graphs



New System

Combines Data-Parallel Graph-Parallel Systems

APACHE GIRAPH

Spark

GraphLab

Enabling users to easily and efficiently express the entire graph analytics pipeline

GraphX: Graph Processing in a Distributed Dataflow Framework, OSDI 2014

Abstractions

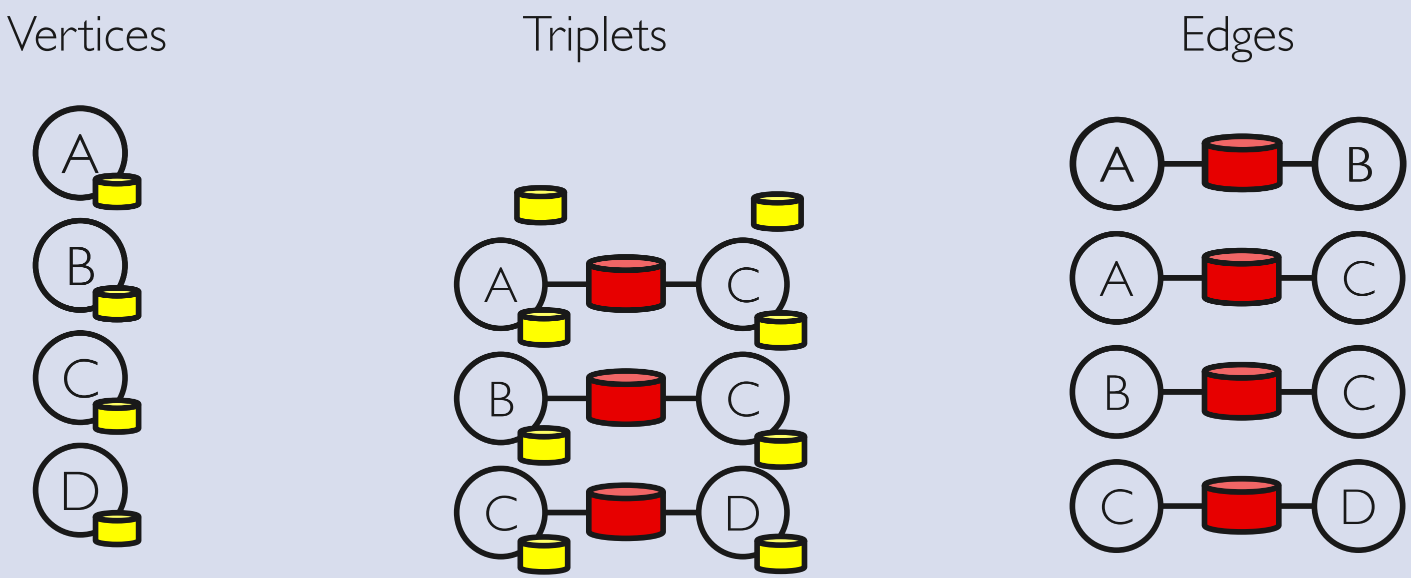
- Graphs are represented by 2 collections
  - Vertex RDD (IDs, Properties)
  - Edges RDD(sIDs, dIDs, Properties)
- Graphs have multiple propertes
  - edges, vertices
- Most graphs operations can be expressed as analyzing or joining collections
  - *Join stage* (build a triple view)
  - *Group-by-stage* (reduce-like)
  - *Map operations*

Building a Graph

```
import org.apache.spark.graphx._
import org.apache.spark.rdd.RDD

val vertices :  VertexRDD[String] = ….

val edges : EdgeRDD[Int] = ….

val graph : Graph(vertices, edges) = …

graph.edges.count()
```

Triplets Join Vertices and Edges

- The ***triplets*** view joins vertices and edges:



SELECT src.id, dst.id, src.attr, e.attr, dst.attr
FROM edges **AS** e
    LEFT JOIN vertices **AS** src, vertices **AS** dst **ON** e.srcId = src.Id **AND**
     e.dstId = dst.Id

Triplet view

```
graph.triplets
```

- Each Triplet contains
  - srcId and srcAttr
  - dstId and dstAttr
  - attr

Aggregate Messages

- Applies a user defined function to each edge triplet
  - The messages
- Applies a user defined function to aggregate the messages at destination vertex

```
def aggregateMessages[Msg: ClassTag](
  sendMsg: EdgeContext[VD, ED, Msg] => Unit,
  mergeMsg: (Msg, Msg) => Msg,
  tripletFields: TripletFields = TripletFields.All) : VertexRDD[Msg]
}
```

Example : get largest incoming edge

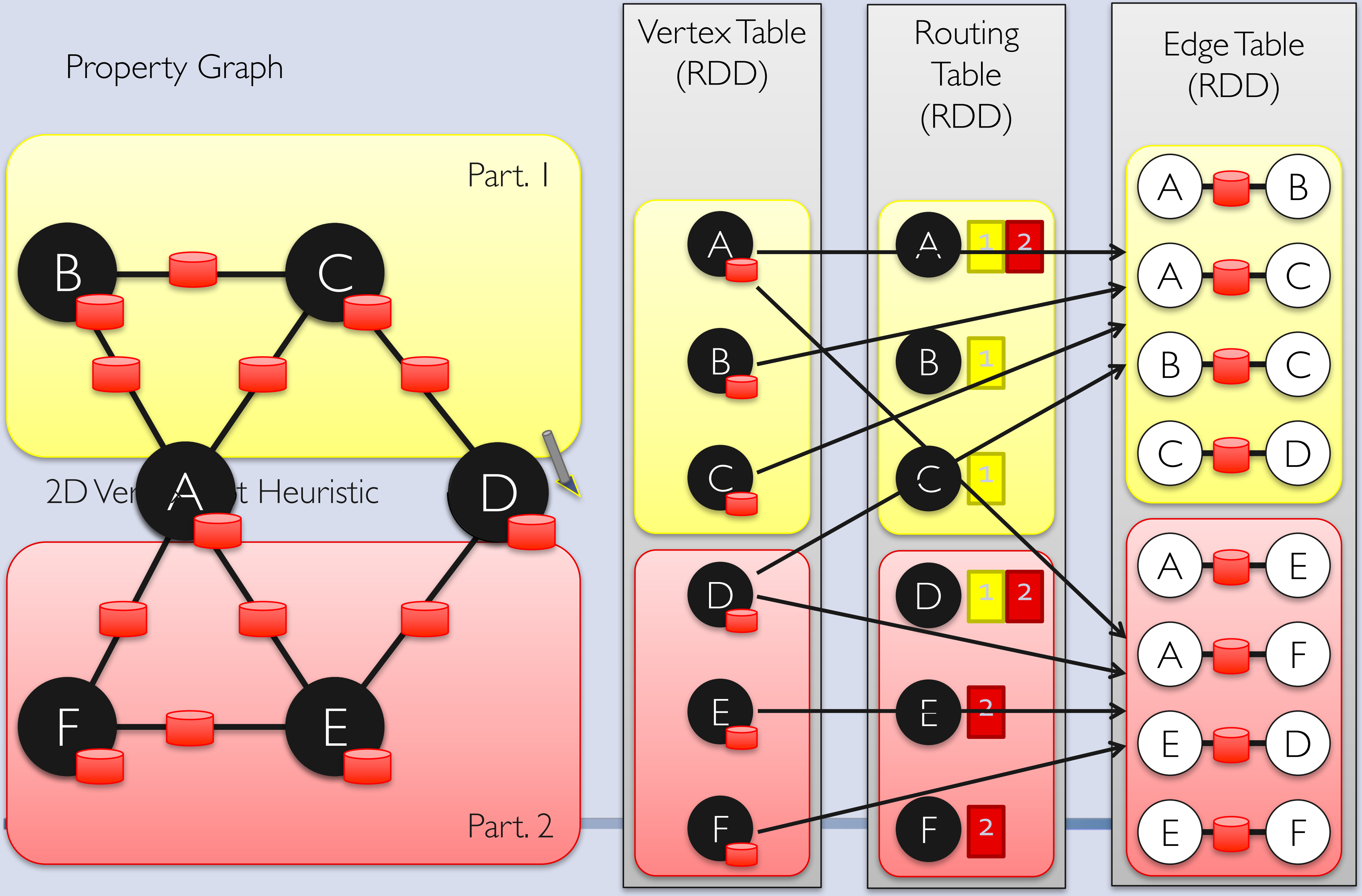
- For each vertex compute the largest incoming edge
  - Message is edge attribute value
  - Merge function is max

```
graph.aggregateMessages[Int](
        triplet => {
            triplet.sendToDst(triplet.attr)
        },
       (a,b) => Math.max(a,b)
)
```

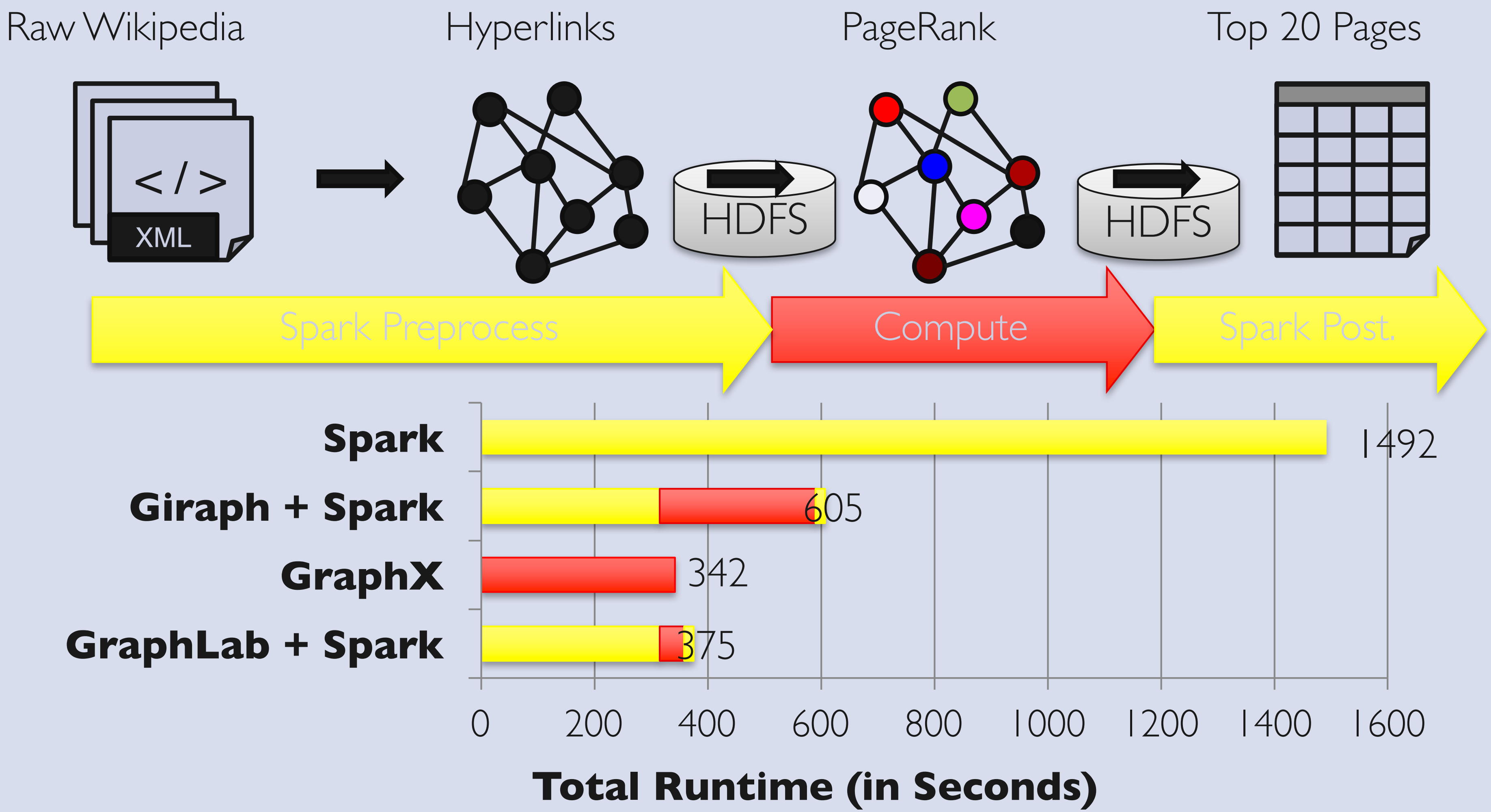
Misc operations

- RDD -> Array
  - take(n)
- Compute the degree of each vertex
  - graph.inDegrees/outDegrees
- Collect edges for all vertices
  - **val** coll = graph.collectNeighborIds(EdgeDirection.X) with X In, Out, Either
- Get all edges of a given vertice id
  - coll.lookup(id)

Distributed Graphs as Tables (RDDs)



A Small Pipeline in GraphX



Timed end-to-end GraphX is *faster* than GraphLab

Conclusion

- So many frameworks to choose from…
- Criteria
  - What is the size of your graph ?
  - What algorithms do you want to run ?
  - How fast do you want your results ?
- Distributed frameworks are no silver bullet
  - Steeper learning curve
  - Add new problems (data distribution, faults…)

Food for thought

- Distributed partitioning is a hot topic
  - But what is a good partitioner ?
- The network might not be a bottleneck anymore
  - RDMA + Infiniband == profit !
  - *The end of slow networks: it's time for a redesign,* Carsten Binnig, Andrew Crotty, Alex Galakatos, Tim Kraska, and Erfan Zamanian, Proc. VLDB Endow. 2016,
- Hardware contention is an issue
  - *Performance Impact of Resource Contention in Multicore Systems*, R. Hood, H. Jin, P. Mehrotra, J. Chang, J. Djomehri, S. Gavali, D. Jespersen, K. Taylor, R. Biswas, IPDPS 2010

Resources

- Slides
  - http://www.slideshare.net/shatteredNirvana/pregel-a-system-for-largescale-graph-processing
  - *http://courses.cs.washington.edu/courses/cse490h/08au/lectures/algorithms.pdf*
  - http://www.cs.kent.edu/~jin/Cloud12Spring/GraphAlgorithms.pptx
  - https://amplab.cs.berkeley.edu/wp-content/uploads/2014/02/graphx@strata2014_final.pptx