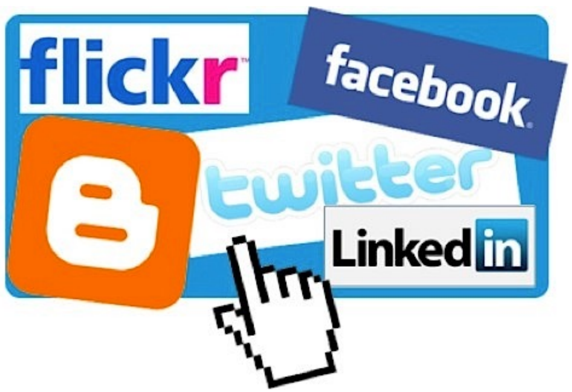
Extreme Computing

Distributed Graph Processing

THE UNIVERSITY of EDINBURGH

Amir Shaikhha, Fall 2023

Graphs are everywhere



Social networks

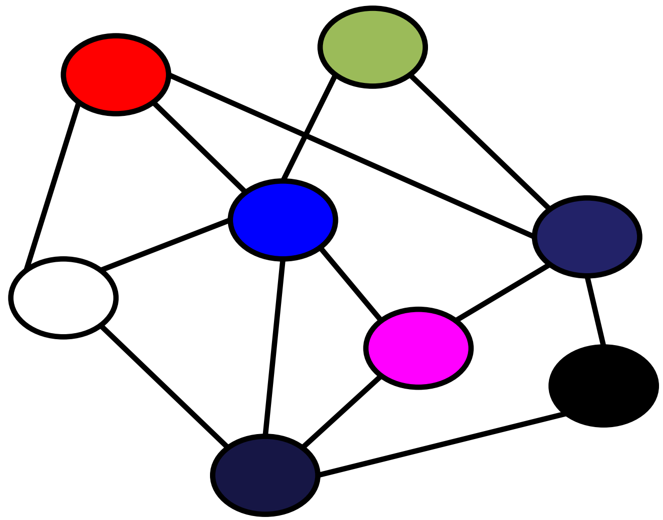
Web graph/search engine

E-commerce

Maps

Computational biology

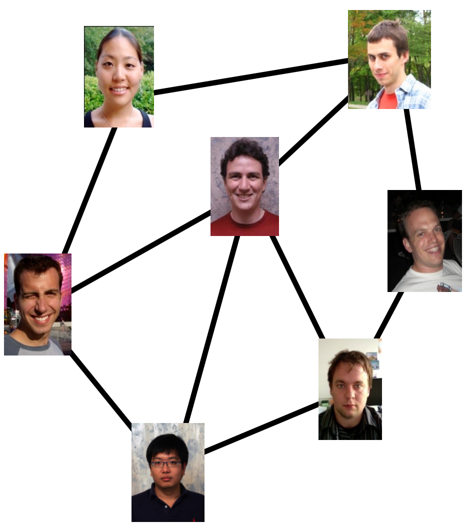
Example: PageRank



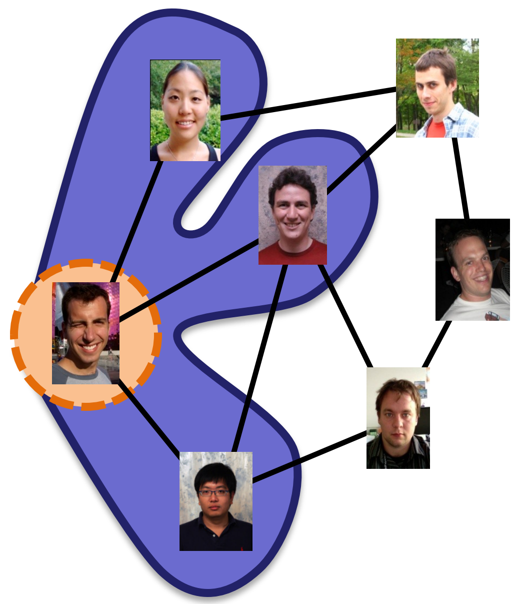
Web graph

Graph Parallel Algorithms

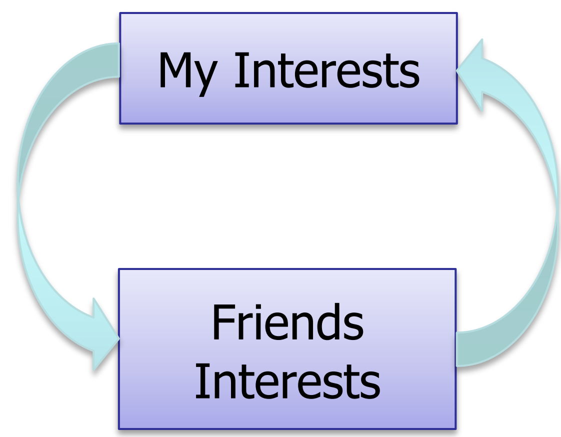
Dependency **Graph**



Local Updates



Iterative Computation



Many graph algorithms

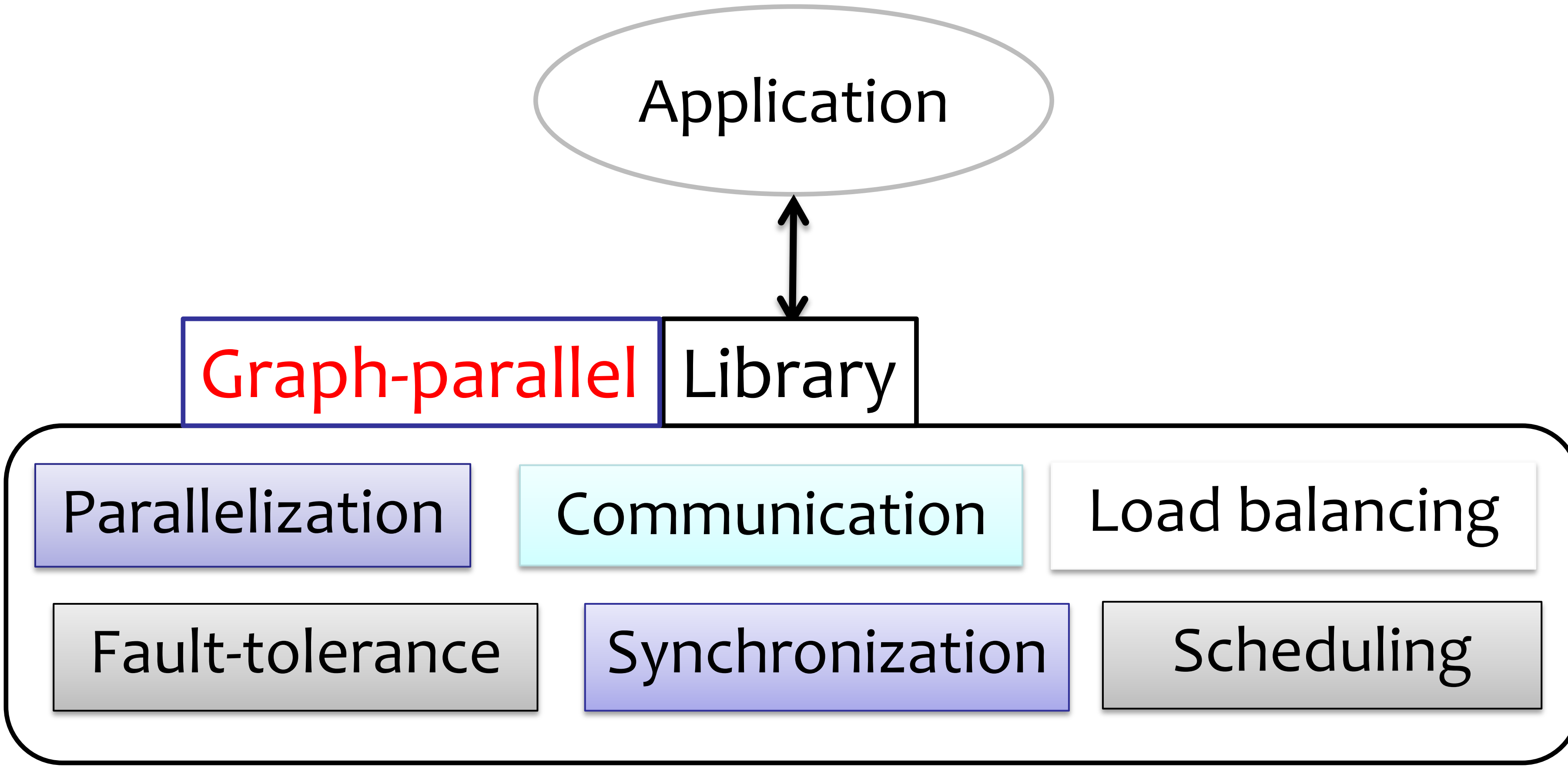
- Collaborative Filtering
  - Alternating Least Squares
  - Stochastic Gradient Descent
  - Tensor Factorization
- Structured Prediction
  - Loopy Belief Propagation
  - Max-Product Linear Programs
  - Gibbs Sampling
- Semi-supervised ML
  - Graph SSL
  - CoEM
- Community Detection
  - Triangle-Counting
  - K-core Decomposition
  - K-Truss
- Graph Analytics
  - PageRank
  - Personalized PageRank
  - Shortest Path
  - Graph Coloring
- Classification
  - Neural Networks

Graph processing framework

Pregel
oogle

APACHE
GIRAPH

Graph processing frameworks



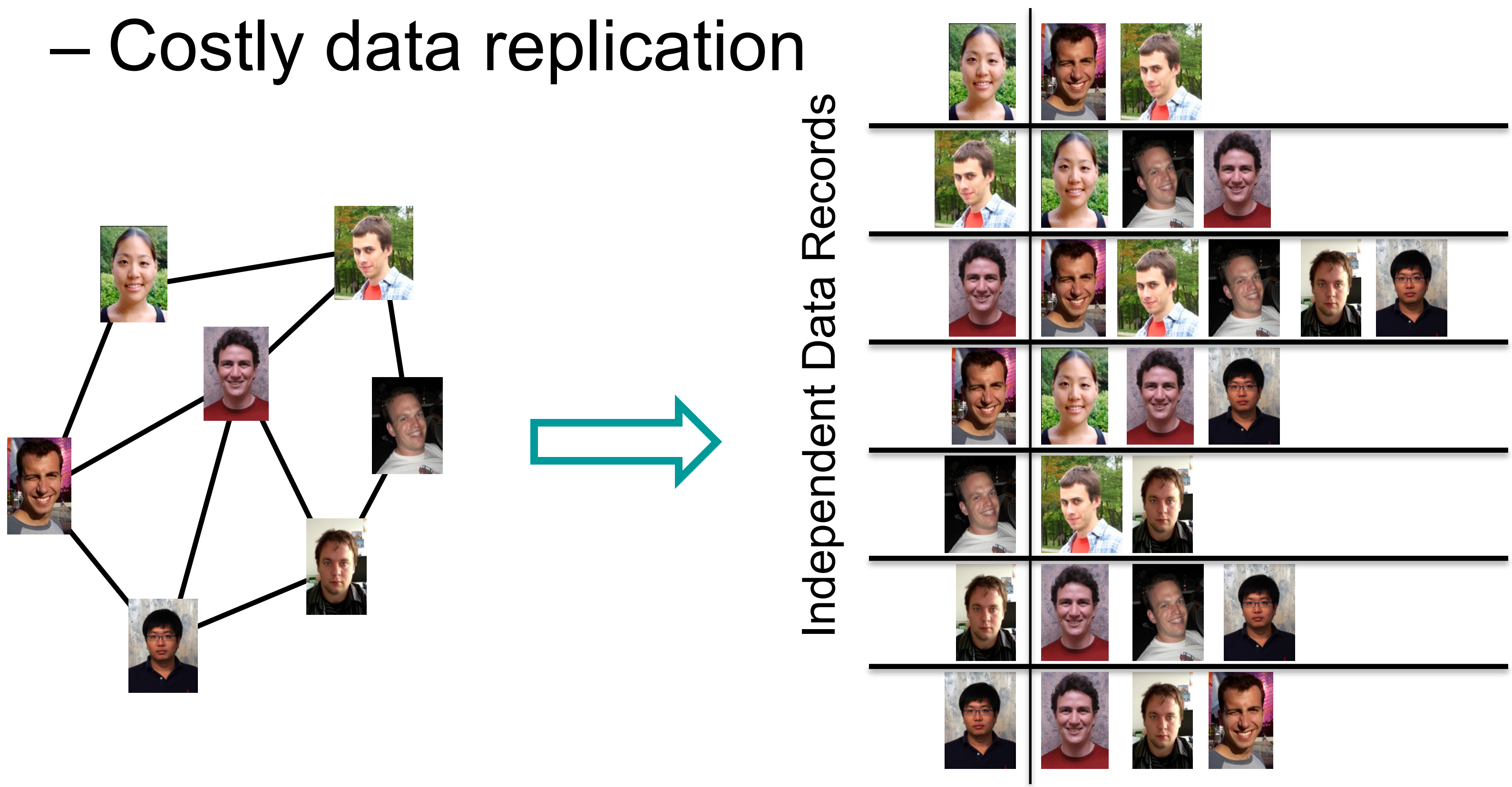
Why do we need a new framework?

- Why don’t we just MapReduce?

- How would you implement Graph processing in MapReduce?

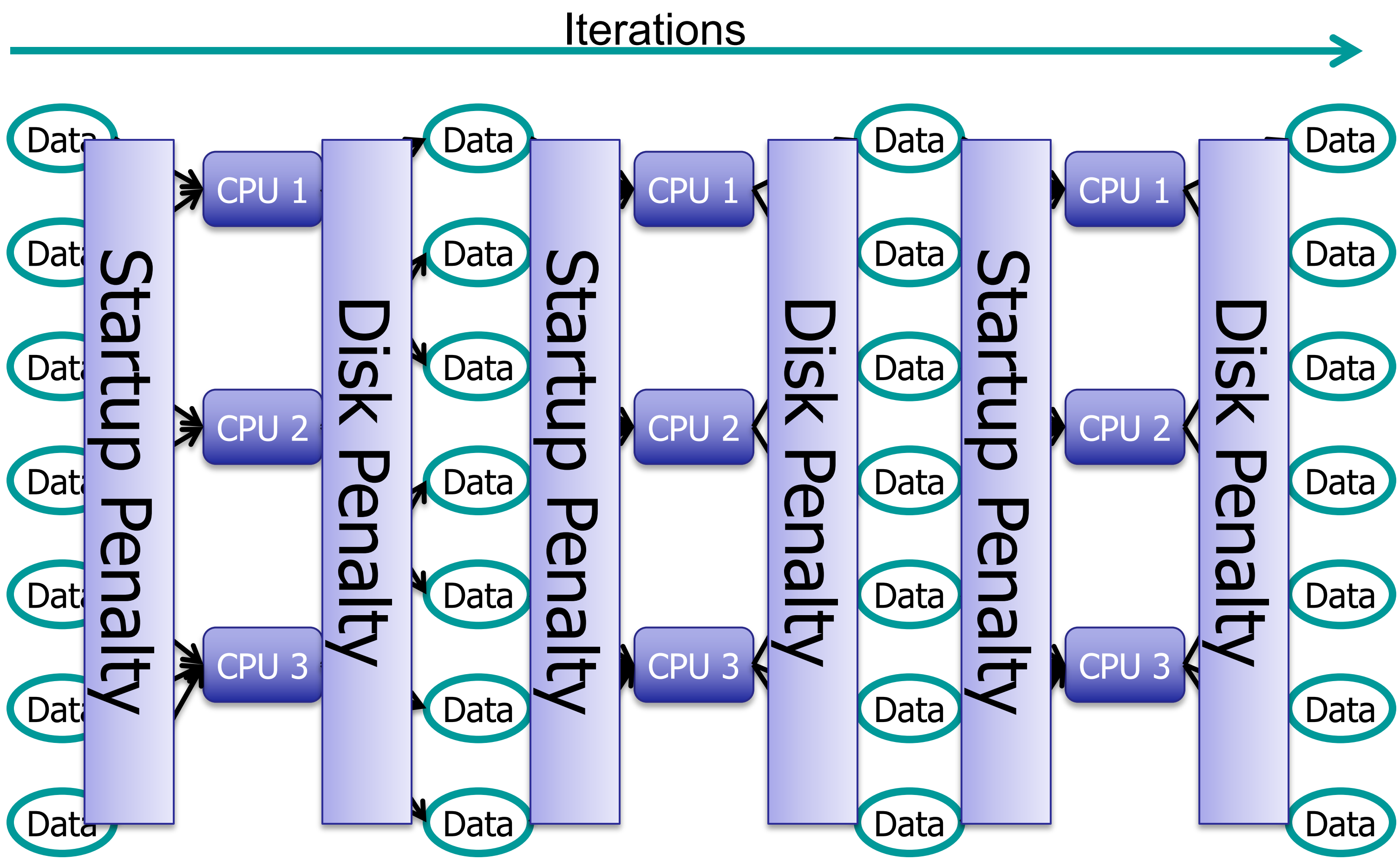
Data Dependencies are Difficult

- Difficult to express dependent data in MR
  - Substantial data transformations
  - User managed graph structure
  - Costly data replication

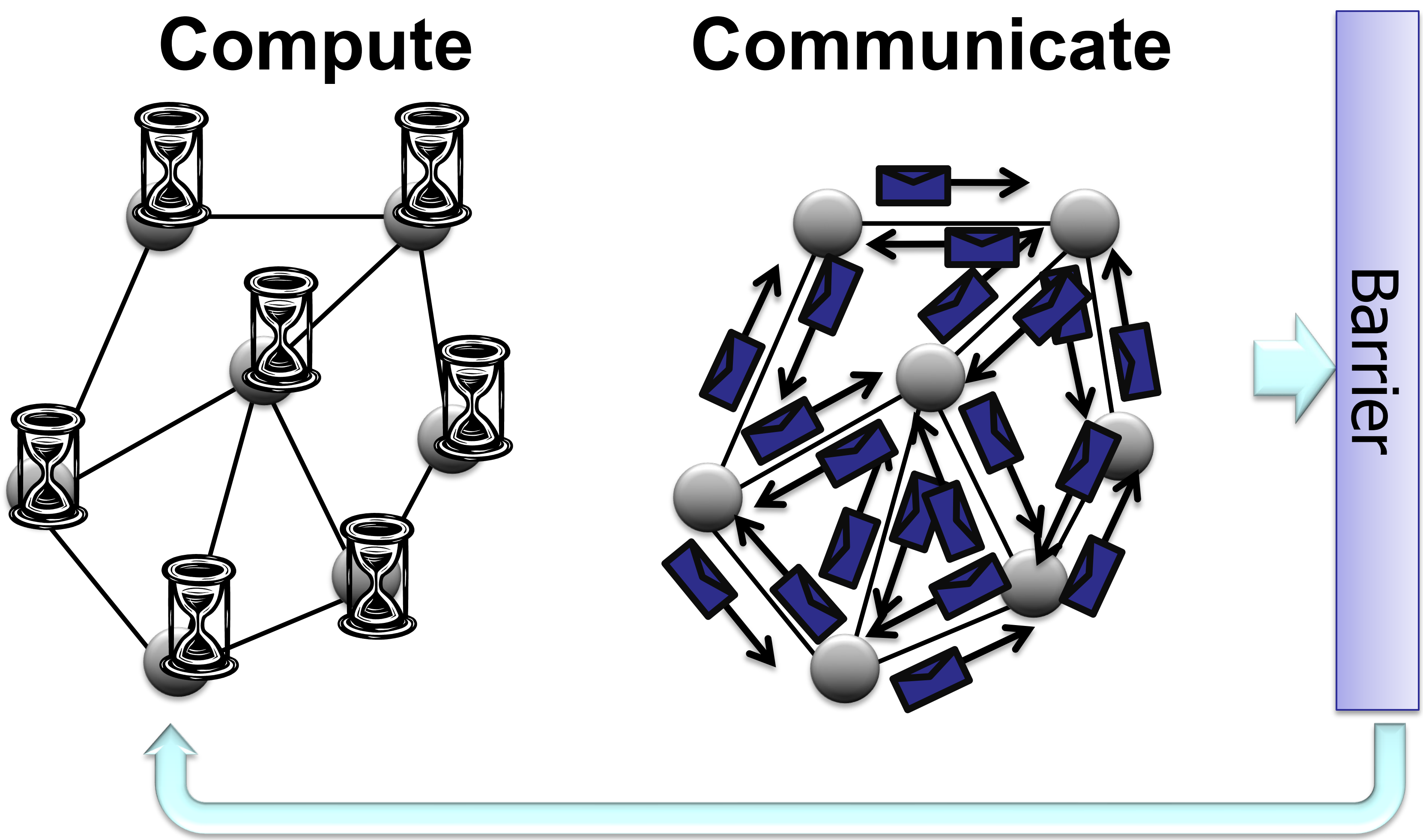


Iterative Computation is Difficult

- System is not optimized for iteration:

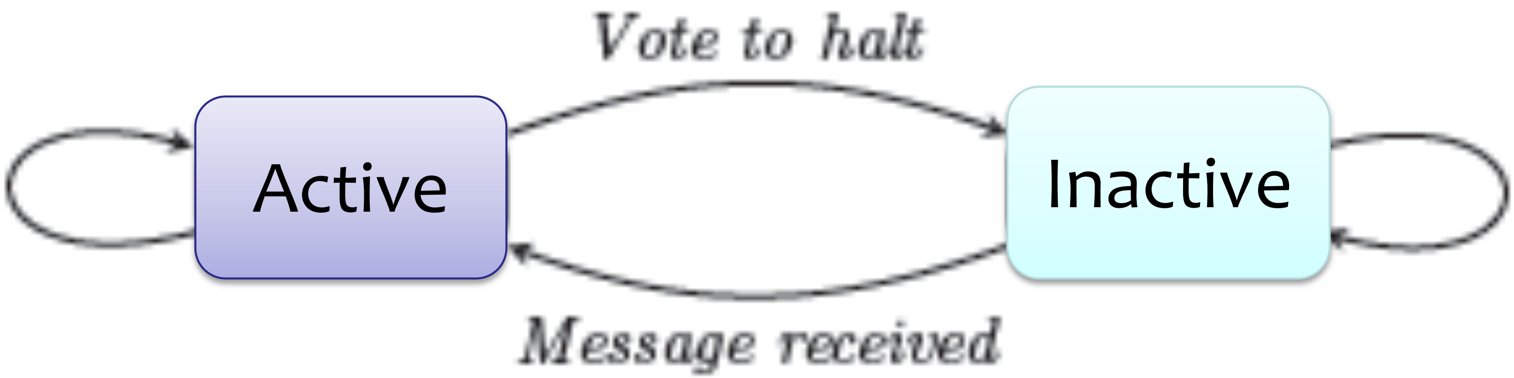


Pregel: Bulk Synchronous Parallel



http://dl.acm.org/citation.cfm?id=1807184

Vertex centric API

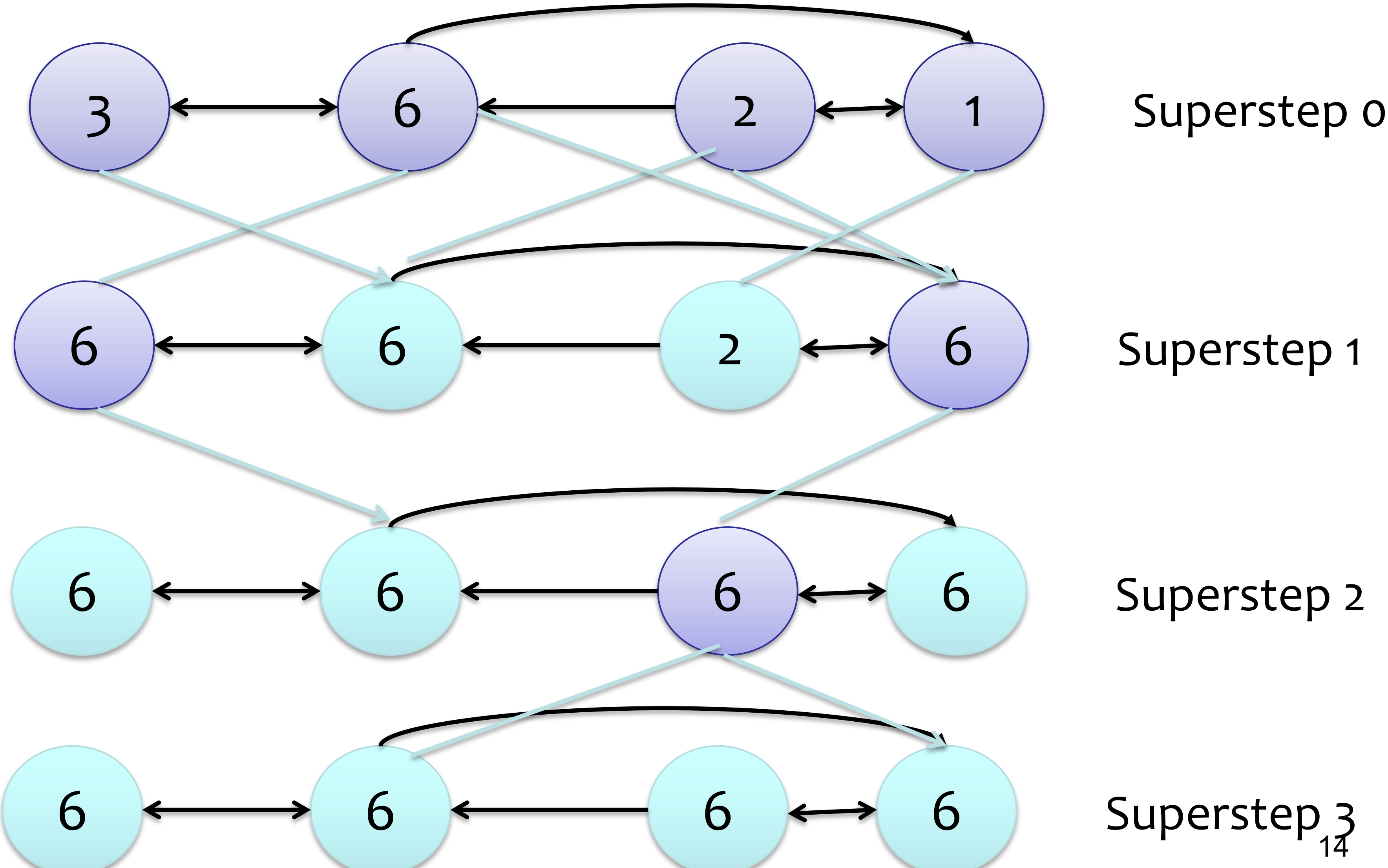


Programming API

```
Class Vertex{
    //Main methods
    Compute(MessageIterator *msgs);
    SendMsgTo(dest, msg);
    VoteToHalt();

    //Auxiliary methods
    GetValue();
    MutableValue();
    GetOutEdgeIterator();
    SuperStep();
}
```

Example: maximum value



Example: PageRank

$$PageRank\ of\ site = \sum \frac{PageRank\ of\ inbound\ link}{Number\ of\ links\ on\ that\ page}$$

OR

$$PR(u) = (1 - d) + d \times \sum \frac{PR(v)}{N(v)}$$

Rank of webpage *i*

Weighted sum of neighbors' ranks

Iterate until it converges

Example: PageRank

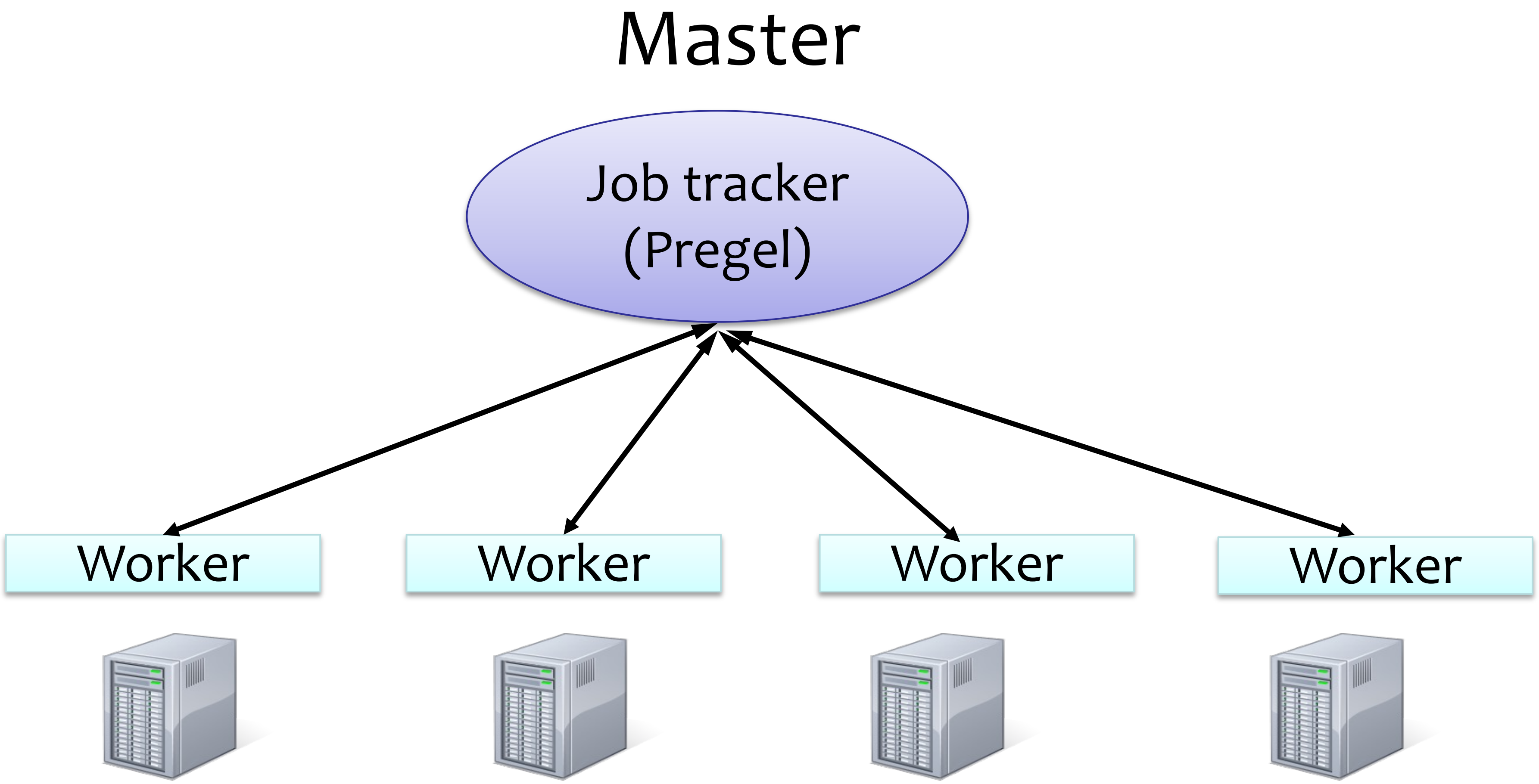
```
class PageRankVertex
    : public Vertex<double, void, double> {
 public:
  virtual void Compute(MessageIterator* msgs) {
    if (superstep() >= 1) {
      double sum = 0;
      for (; !msgs->Done(); msgs->Next())
        sum += msgs->Value();
      *MutableValue() =
          0.15 / NumVertices() + 0.85 * sum;
    }

    if (superstep() < 30) {
      const int64 n = GetOutEdgeIterator().size();
      SendMessageToAllNeighbors(GetValue() / n);
    } else {
      VoteToHalt();
    }
  }
};
```

Additional features

- Combiners
- Aggregators
- Topology mutations
  - Partial ordering
    - Removal first (Edge → vertex removal)
    - Addition (vertex → edge addition)
  - Handlers
    - User-defined functions to resolve conflicts
- Input/output
  - File, GFS, BigTable, etc.

Implementation

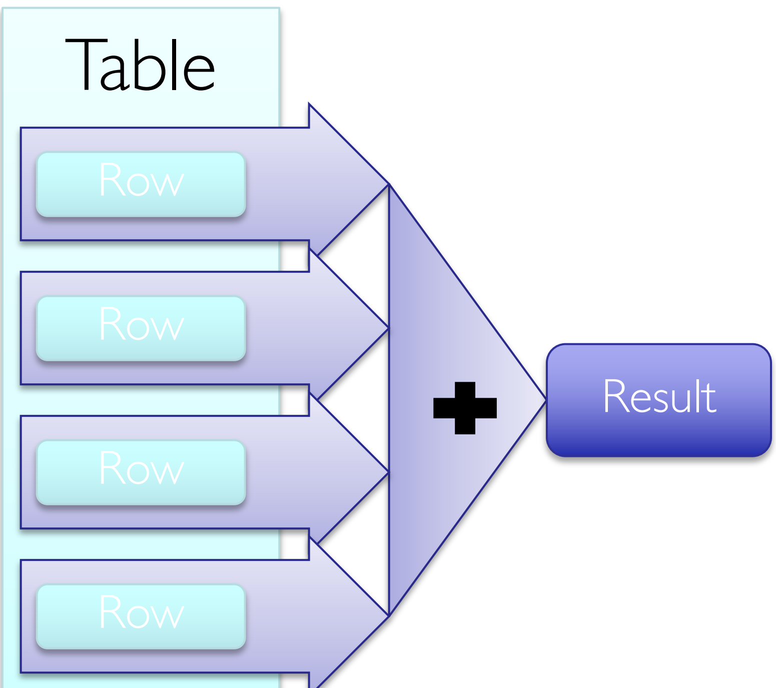


Fault tolerance

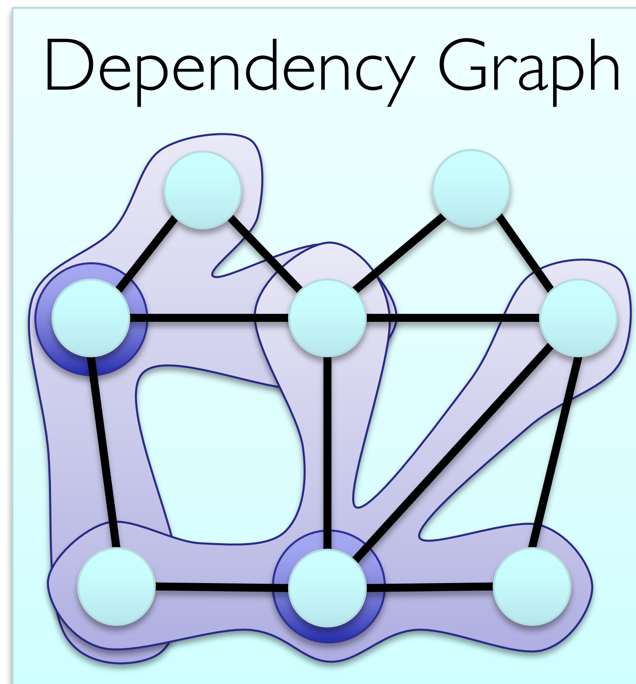
- Achieved through checkpointing
- At the beginning of a super-step, master instructs the workers to take a check-point
- When a worker fails --- the master re-assigns the partition to a new worker, and restarts from the latest checkpoint

Distributed Collections Views

Table View



Graph View



Spark Software Stack

Spark SQL (SQL)	MLlib (Machine Learning)	GraphX (Graph processing)	Spark Streaming (Streaming)	Other Spark libraries

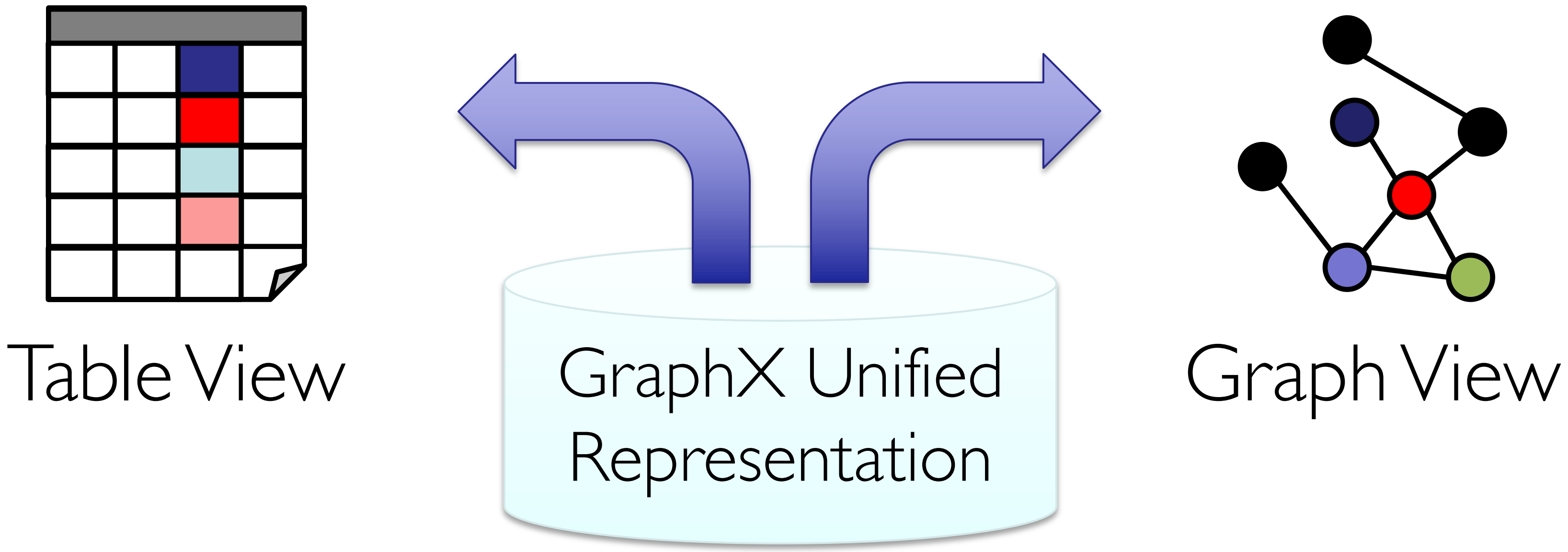
Spark Core
Processing Engine

Mesos / YARN / Standalone
Cluster Resource Management

HDFS / Amazon S3 / OpenStack Swift / Cassandra
Distributed File System & Storage

GraphX

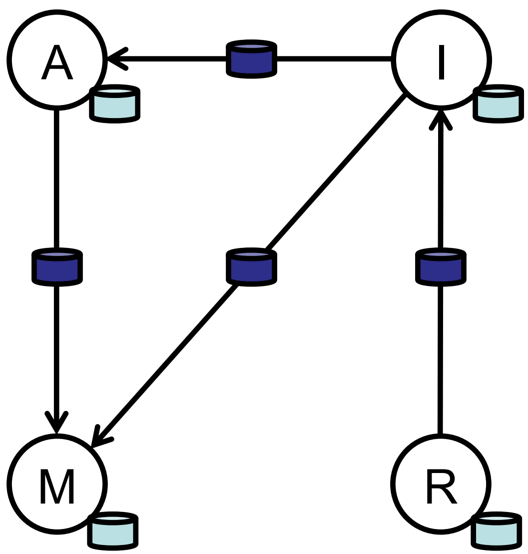
- Tables and Graphs are composable views of the same physical data



- Each view has its own operators that exploit the semantics of the view to achieve efficient execution

View a Graph as a Table

Property Graph



Vertex Property Table

Id	Property (V)
A	(P1, P4)
M	(P2,P4)
I	(P3, P4)
R	(P3, P4)

Edge Property Table

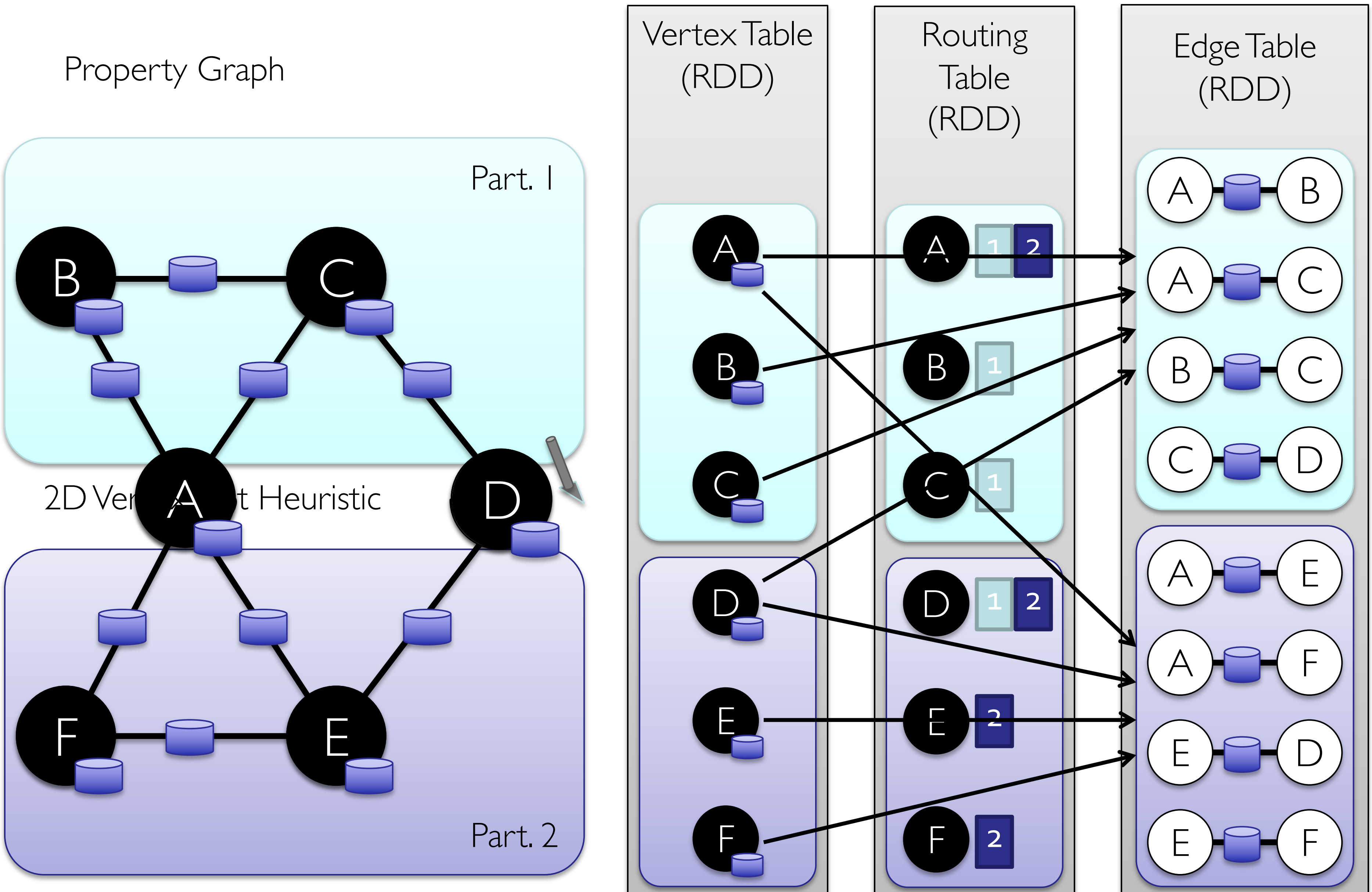
SrcId	DstId	Property (E)
A	M	P5
I	M	P6
I	A	P7
R	I	P8

Graph Operators

```
class Graph [ V, E ] {
  def Graph(vertices: Table[ (Id, V) ],
            edges: Table[ (Id, Id, E) ])

     // Table Views -----------------
     def vertices: Table[ (Id, V) ]
     def edges: Table[ (Id, Id, E) ]
     // Transformations ------------------------------
     def reverse: Graph[V, E]
     def subgraph(pV: (Id, V) => Boolean,
                  pE: Edge[V,E] => Boolean): Graph[V,E]
     def mapV(m: (Id, V) => T ): Graph[T,E]
     def mapE(m: Edge[V,E] => T ): Graph[V,T]
     // Joins ----------------------------------------
     def joinV(tbl: Table [(Id, T)]): Graph[(V, T), E ]
     def joinE(tbl: Table [(Id, Id, T)]): Graph[V, (E, T)]
     // Computation ----------------------------------
     def mrTriplets(mapF: (Edge[V,E]) => List[(Id, T)],
                    reduceF: (T, T) => T):Graph[T, E]
}
```

Distributed Graphs as RDDs



Summary

- Graph processing with Pregel/Giraph
  - Bulk Synchronous Programming (BSP) model
- Graph processing on Spark with GraphX
- Resources:
  - Giraph: http://giraph.apache.org/
  - GraphX: https://spark.apache.org/graphx/
  - GraphLab: http://graphlab.org/
  - Okapi: http://grafos.ml/

Resources

- Compulsory reading:
  - Pregel [SIGMOD'10]
    https://kowshik.github.io/JPregel/pregel_paper.pdf
- Recommended reading
  - GraphX [OSDI'14]
    - Graph processing framework built on top of Spark
  - GraphLab [OSDI'12]
    - Edge-centric graph processing framework

QUESTIONS?