

# Apache Spark GraphX

By **Roy Levin**

<http://researcher.watson.ibm.com/researcher/view.php?person=il-ROYL>

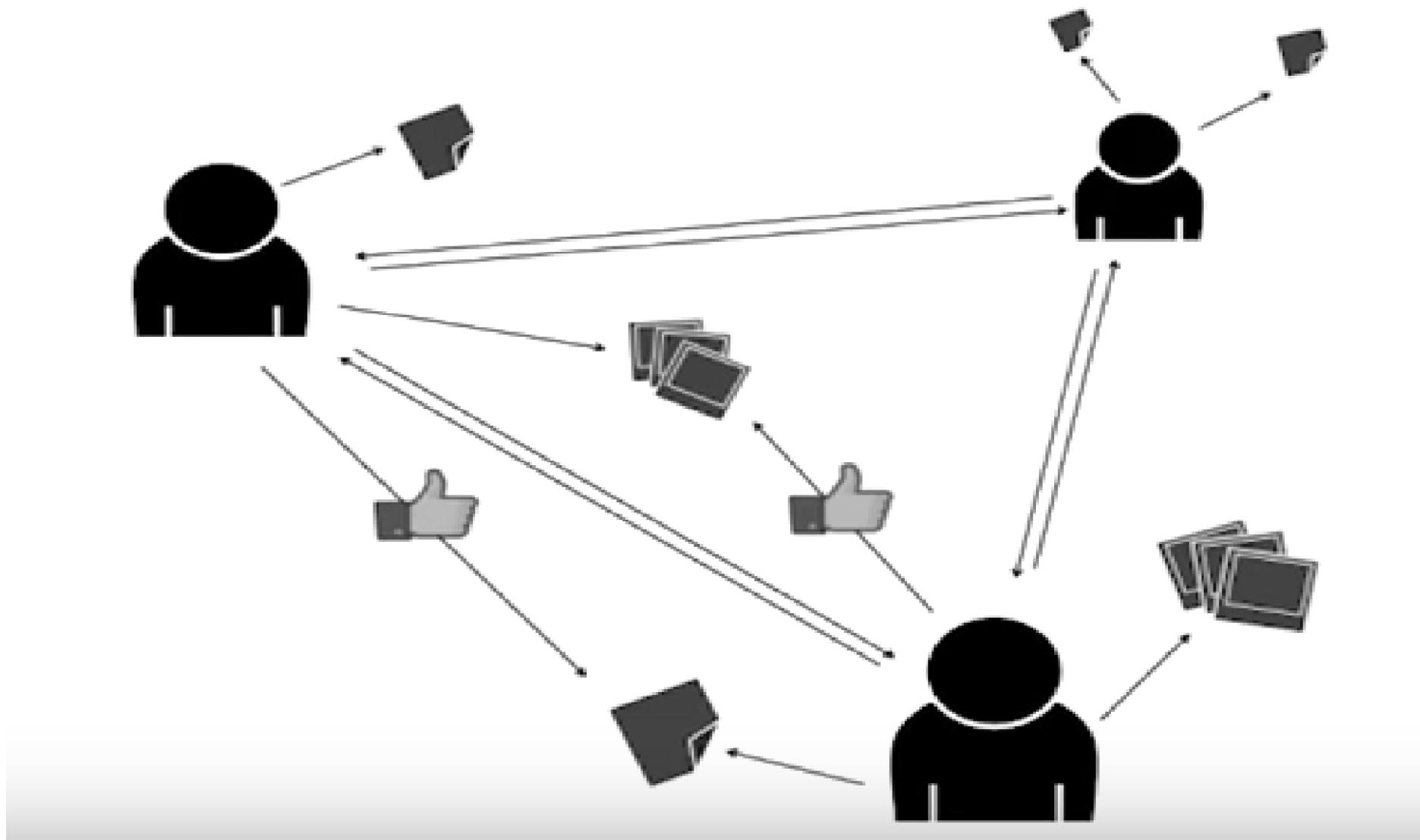
# Agenda

- **An Intro to Graph Processing**
- Why GraphX?
- How (to use) GraphX?
- How GraphX Works

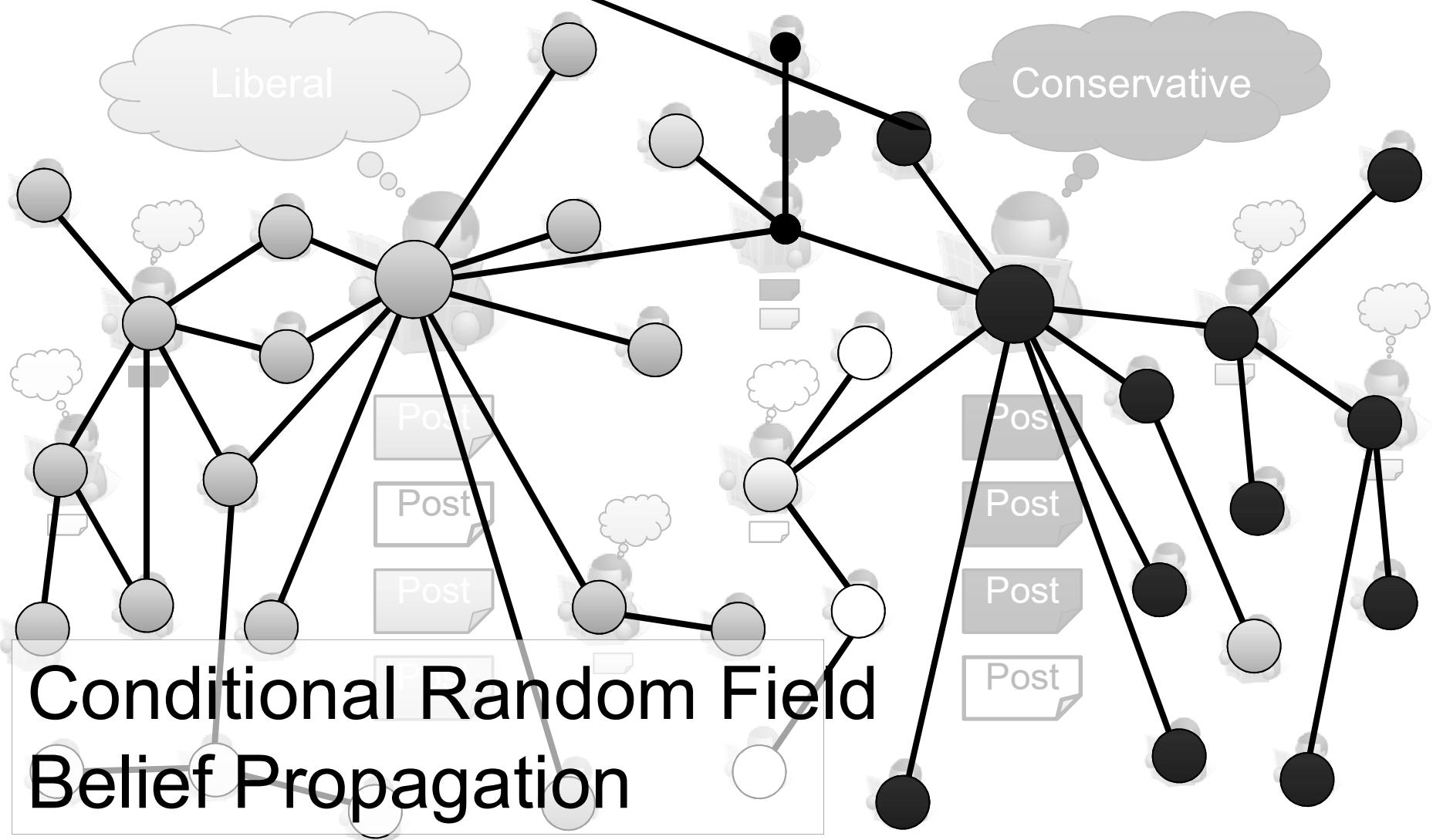
# Graphs are Essential to Data Mining and Machine Learning

- Identify influential people and information
- Find communities
- Understand people's shared interests
- Model complex data dependencies

# Example: Social Networks



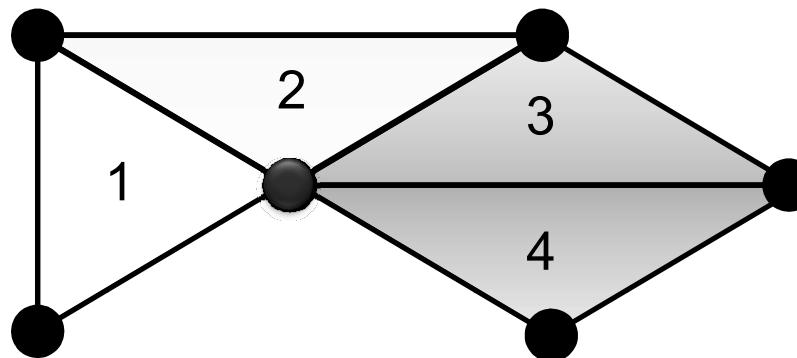
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# Triangle Counting

- Count triangles passing through each vertex

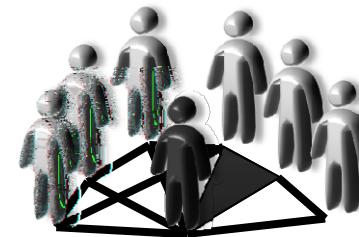
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- Measures **cohesiveness** of local community

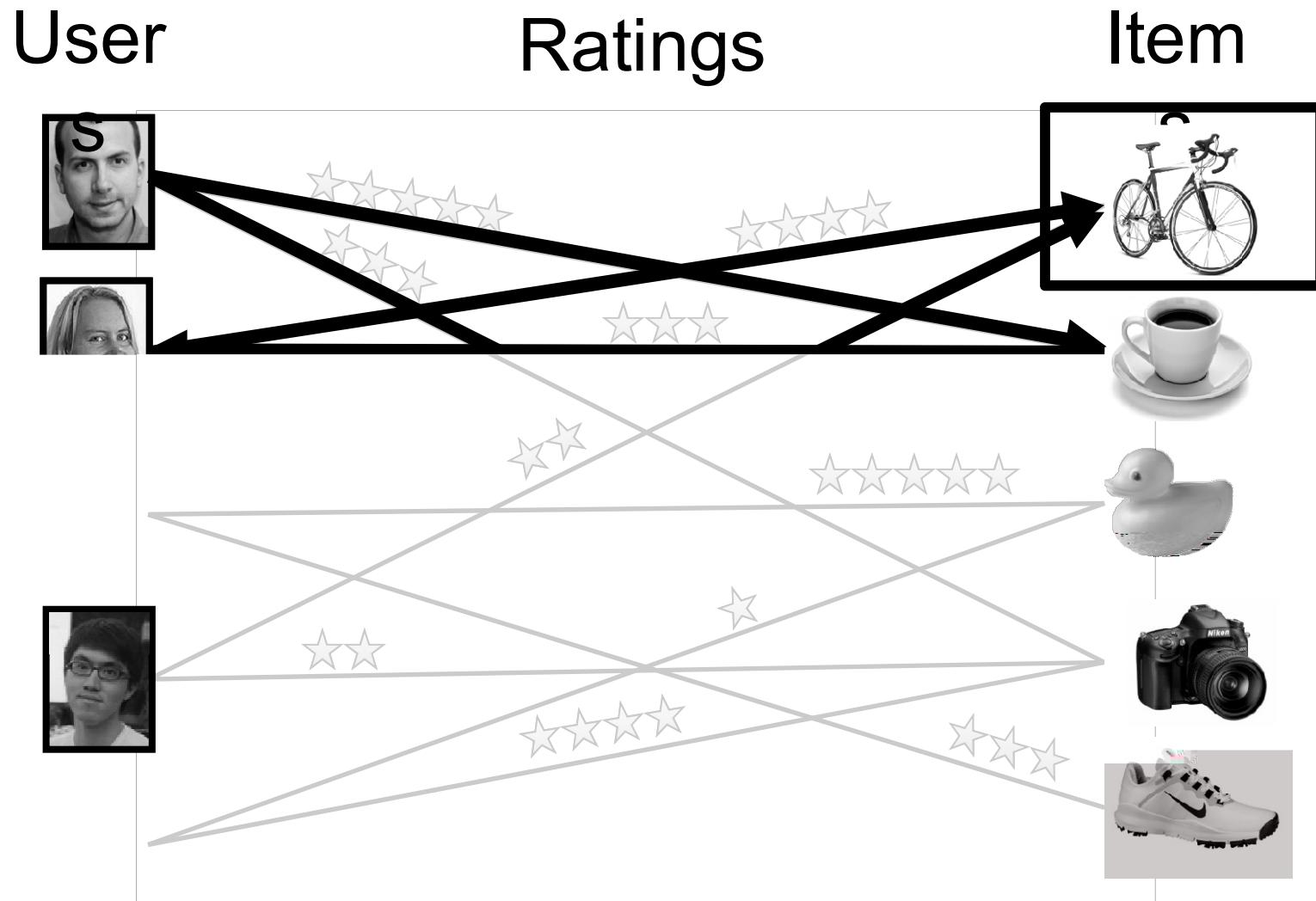


Fewer Triangles  
Weaker Community



More Triangles  
Stronger Community

# Collaborative Filtering



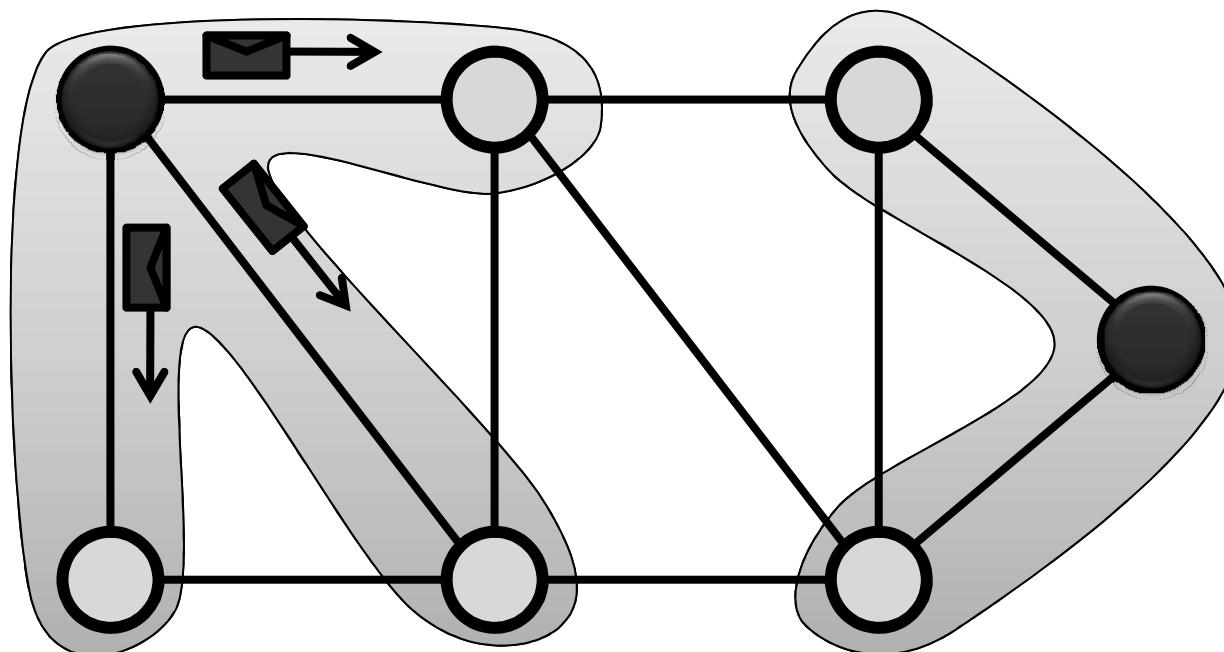
# Pregel

- Vertex-centric
- Runs in sequence of iterations called **super-steps**
- A vertex in super-step  $a$  can:
  - Read messages sent to it in super-step  $a$
  - Send messages to other vertices (they will receive the messages in step  $a + 1$ )
  - Modify its current state

# The Graph-Parallel Abstraction

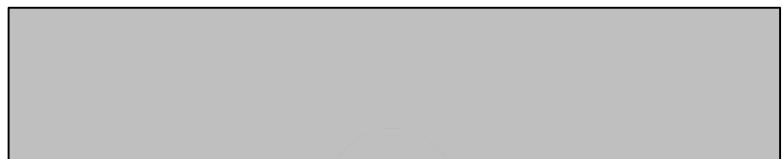
A user-defined **Vertex-Program** runs on each vertex  
**Graph** constrains **interaction** along edges

Using **messages** (e.g. **Pregel** [PODC'09, SIGMOD'10])

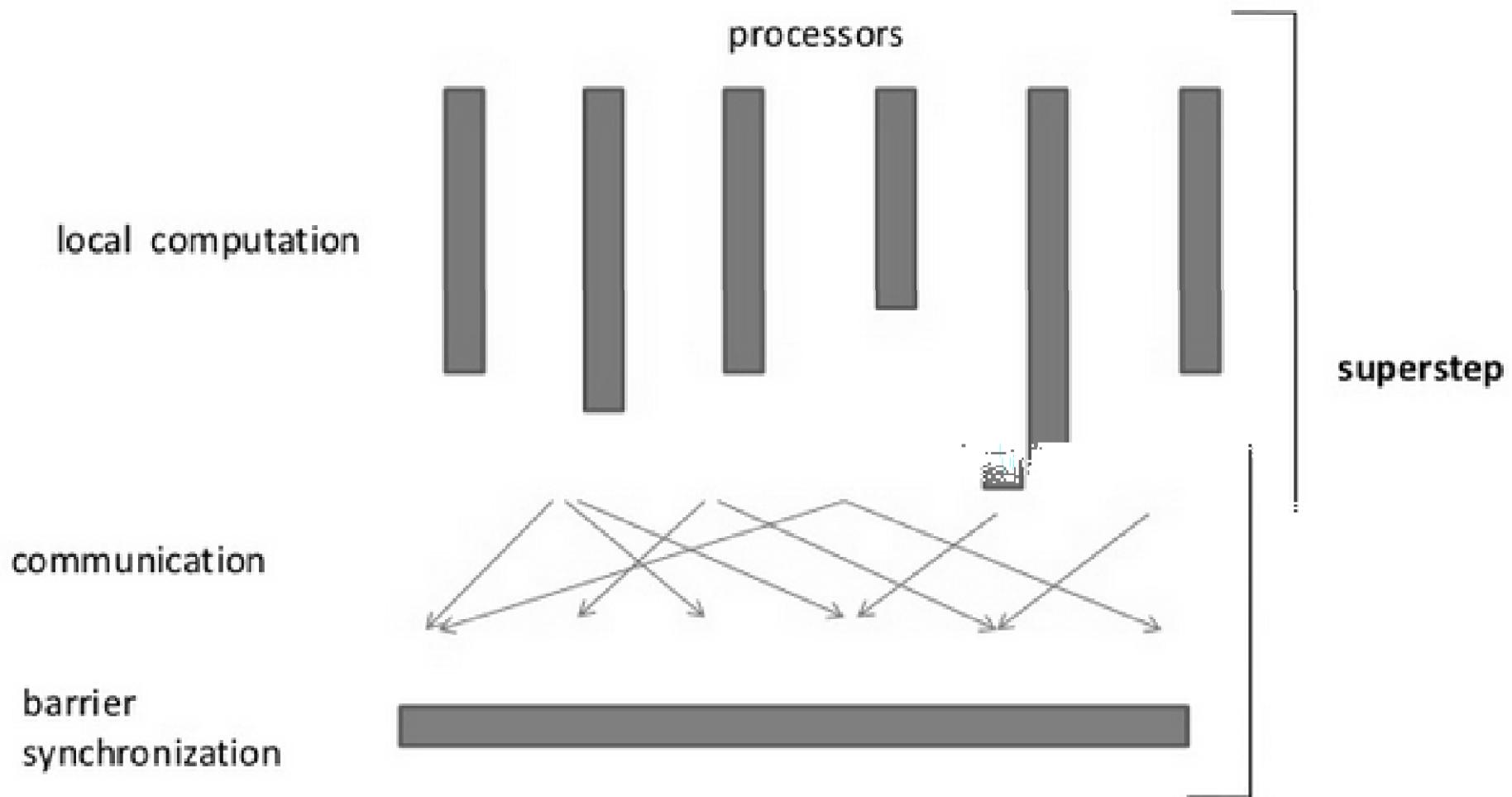


**Parallelism:** run multiple vertex programs simultaneously

# Computing PageRank the **Pregel** way



# Bulk Synchronous Parallel



# Graph Technology Components

Visualization

Gephi, Keylines, Linkurious, ...

Analytics Engines

Large scale! Used  
at Facebook for the  
Graph Search

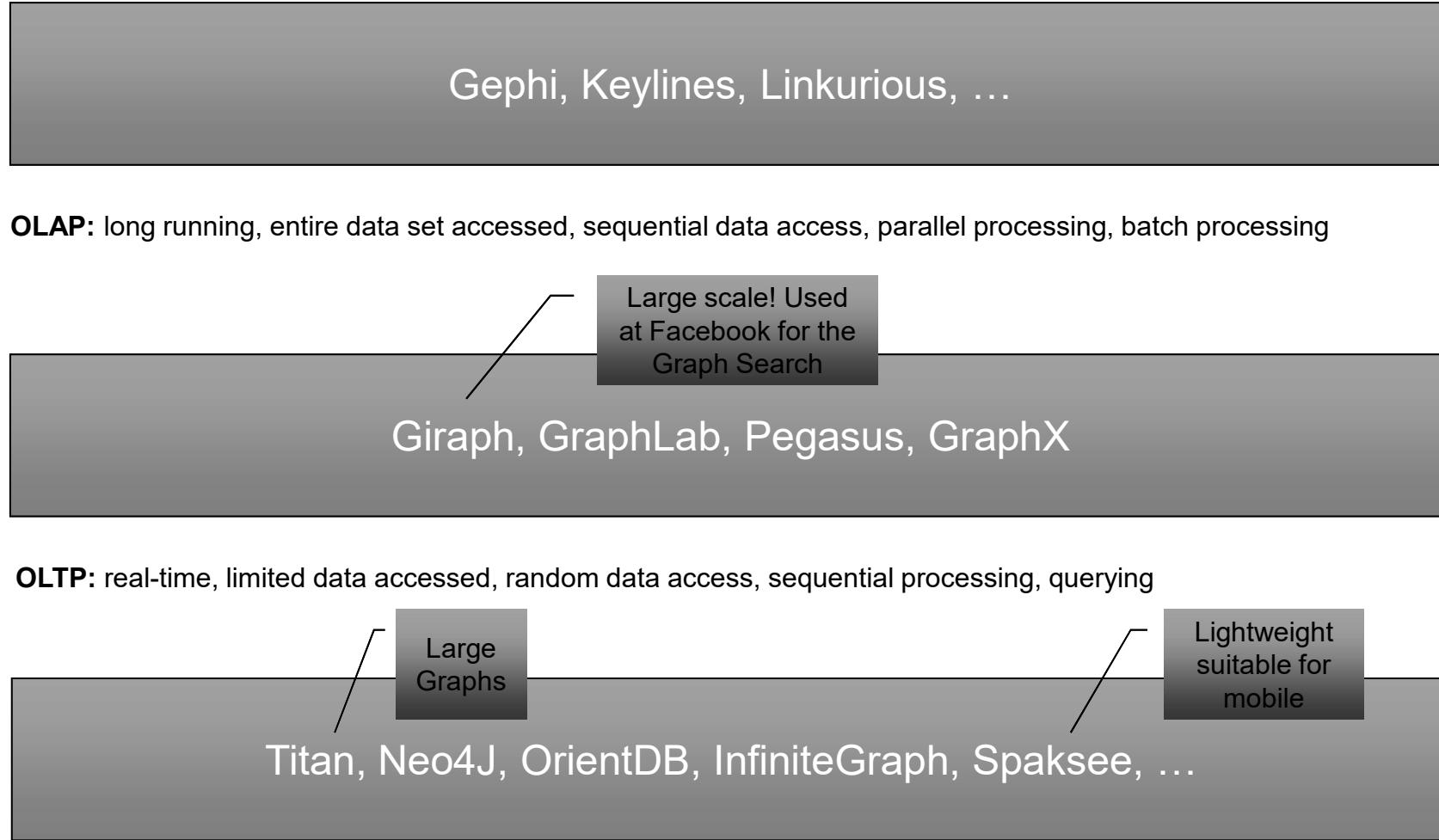
Giraph, GraphLab, Pegasus, GraphX

Storage

Large  
Graphs

Lightweight  
suitable for  
mobile

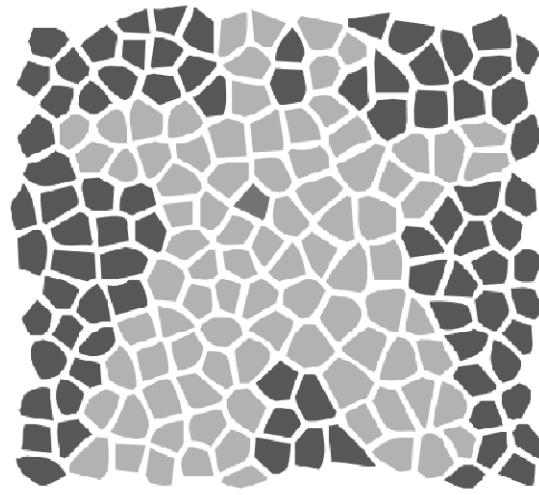
Titan, Neo4J, OrientDB, InfiniteGraph, Spaksee, ...



# Agenda

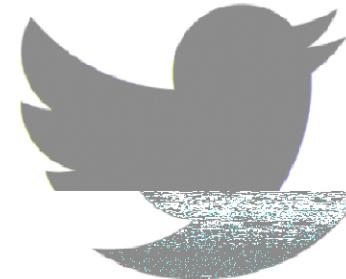
- An Intro to Graph Processing
- **Why GraphX?**
- How (to use) GraphX?
- How GraphX Works

# Specialized Graph Systems



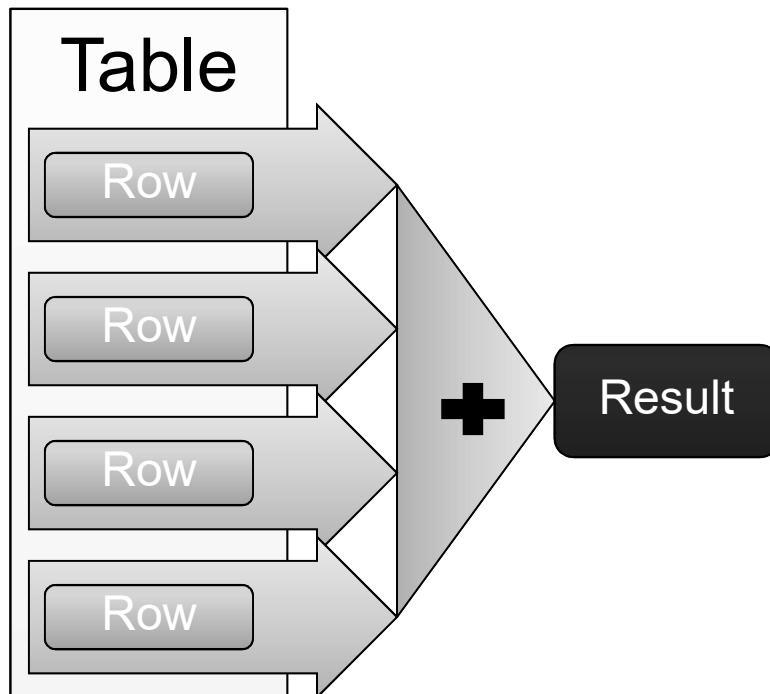
A P A C H E  
G I R A P H

Google Pregel

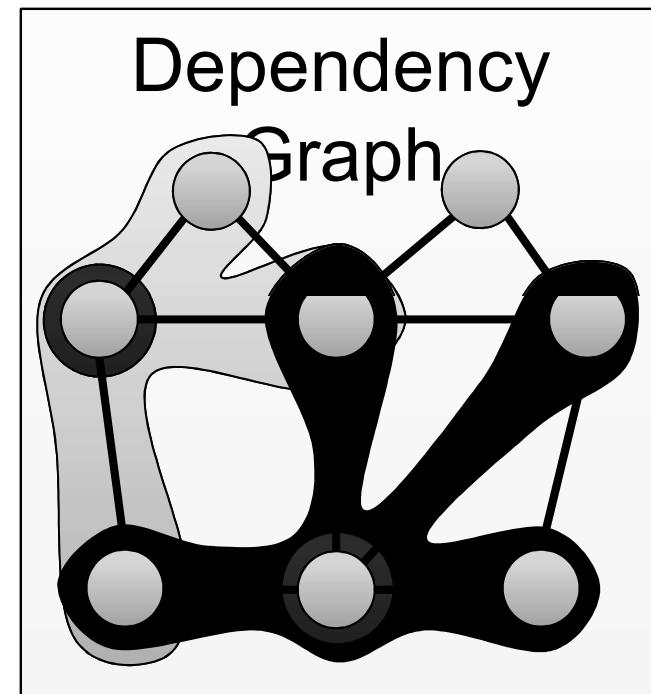


# A Disconnect Between Data and Graph Processing

## Data-Parallel



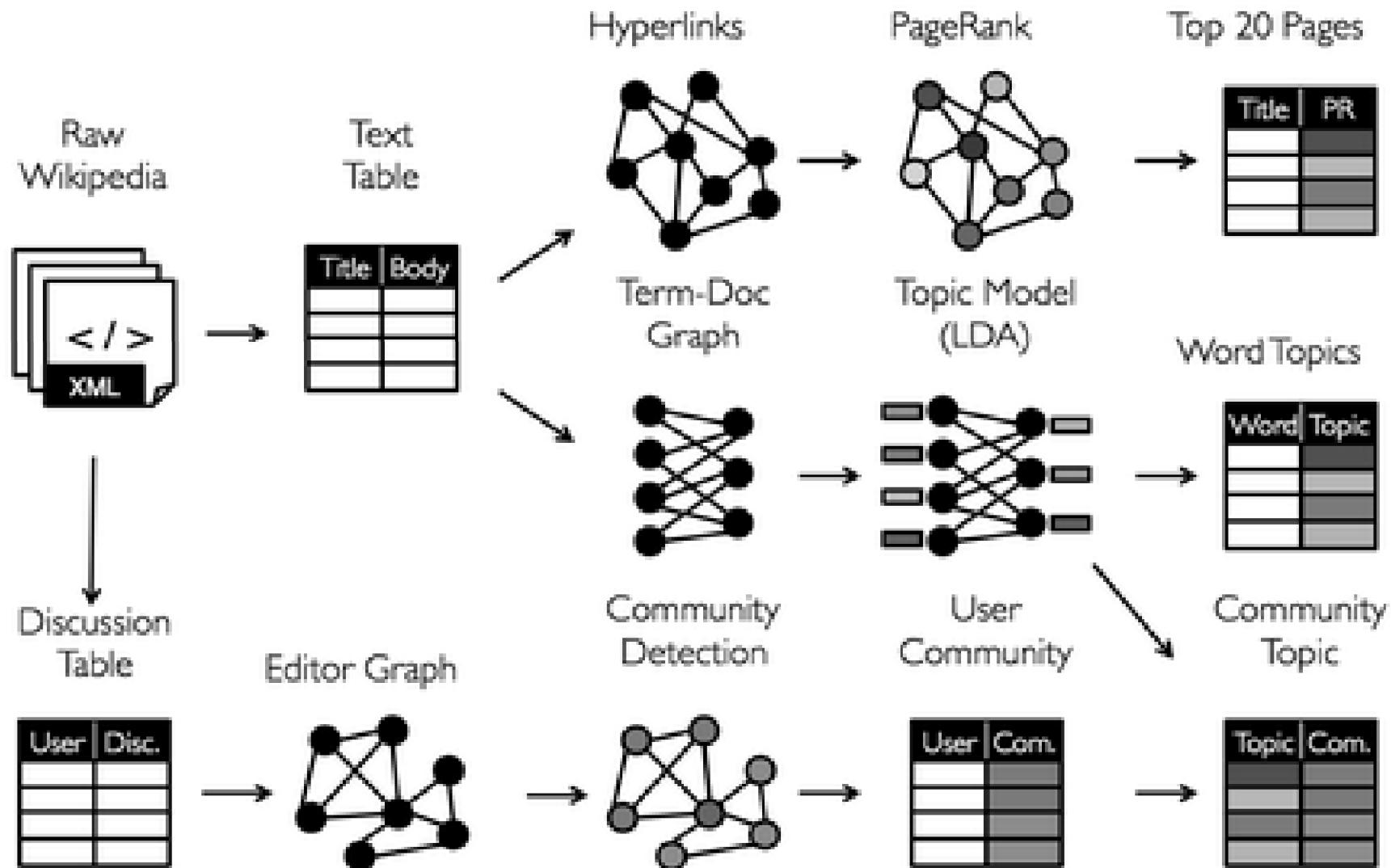
## Graph-Parallel



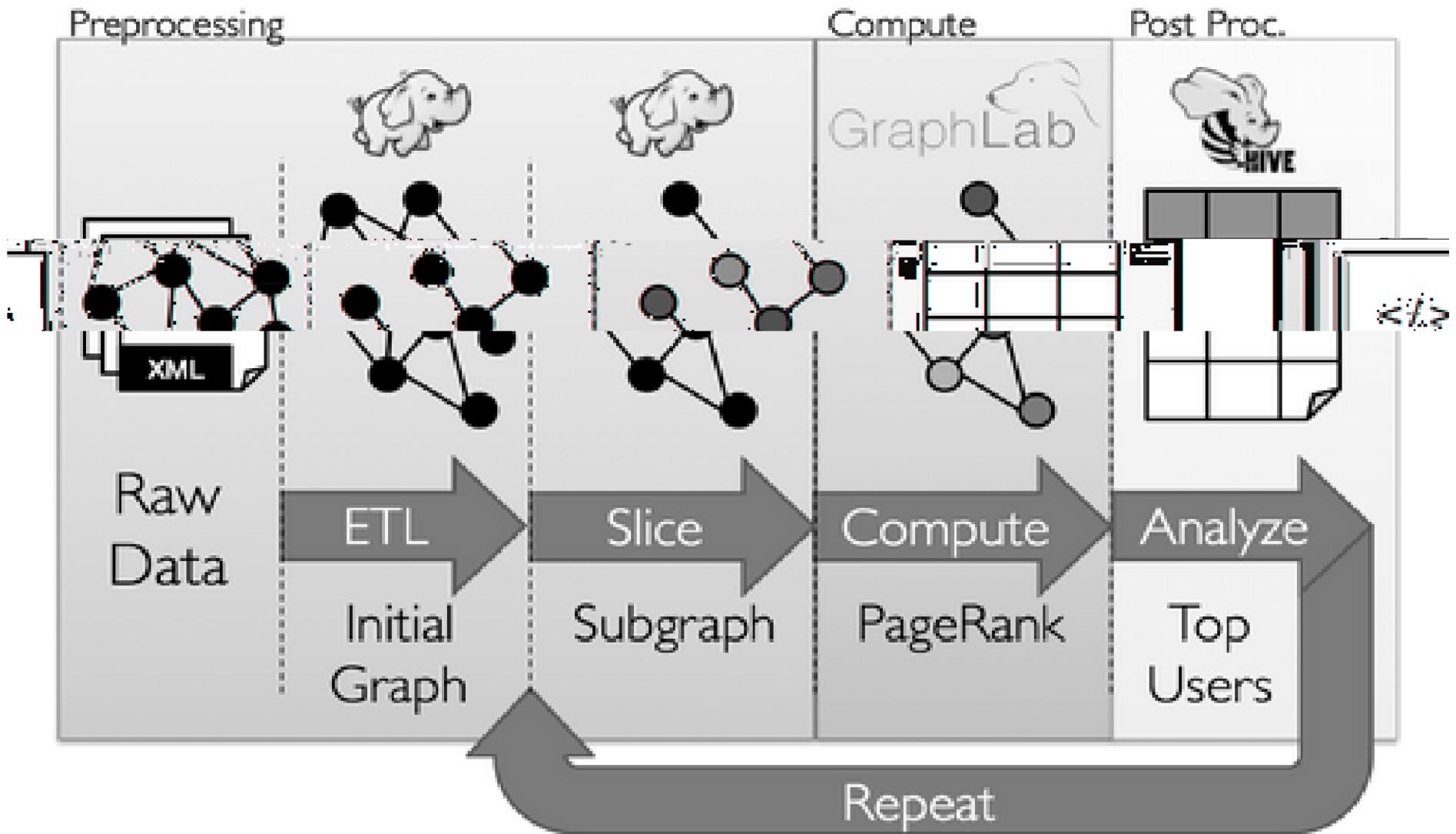
Pregel  
GraphLab<sup>15</sup>



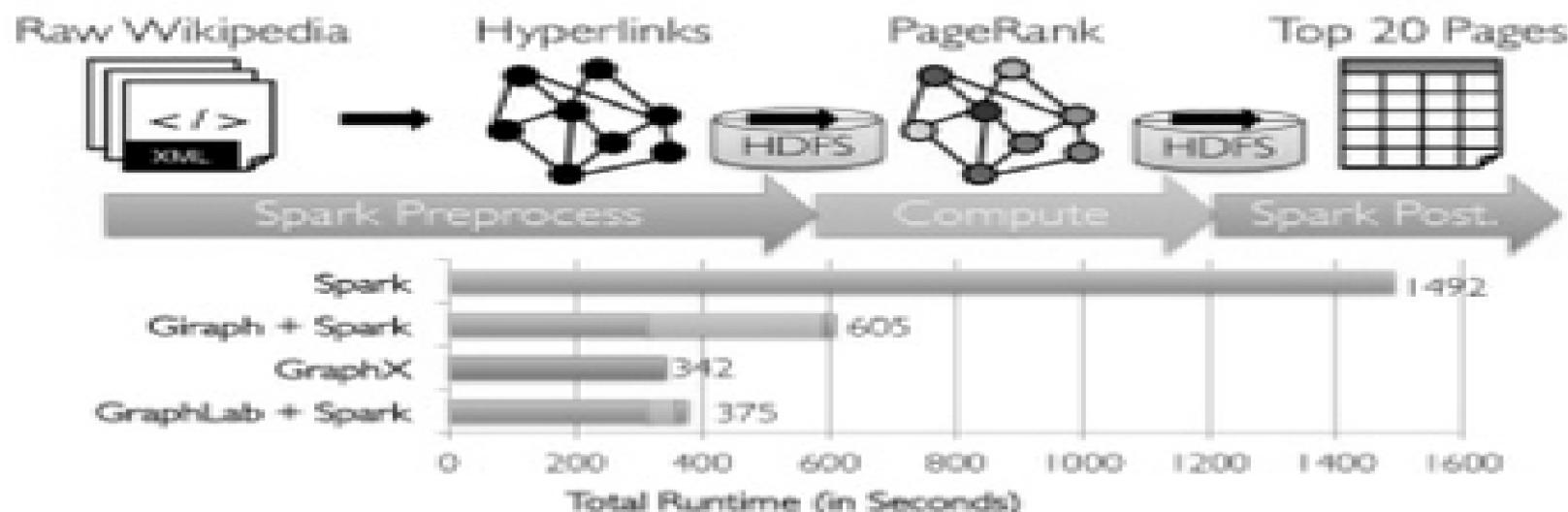
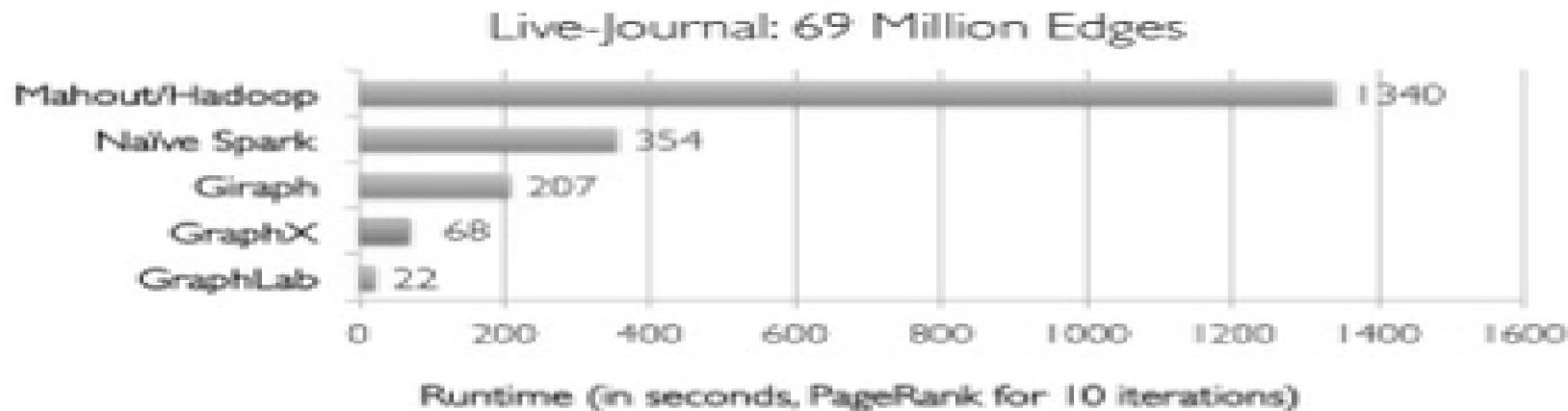
# Typical Graph Processing Pipeline



# An Example of this Pipeline



# Runtime Comparisons



# Agenda

- An Intro to Graph Processing
- Why GraphX?
- **How (to use) GraphX?**
- How GraphX Works

# GraphX Design Goals

- Blur distinction between tables & graphs
- Unify data & graph parallel processing
- Implement on top of Spark

# GraphX Key Idea

- Tables & Graphs are composable views of the same physical data
- View support operations that exploit semantics of the view to achieve efficient execution

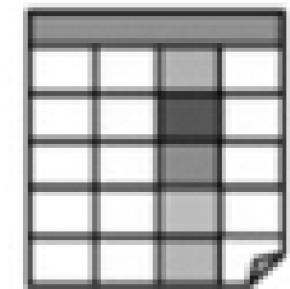
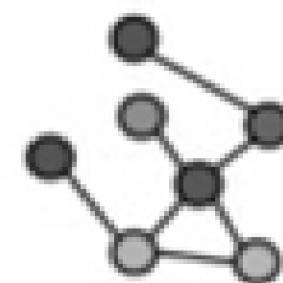
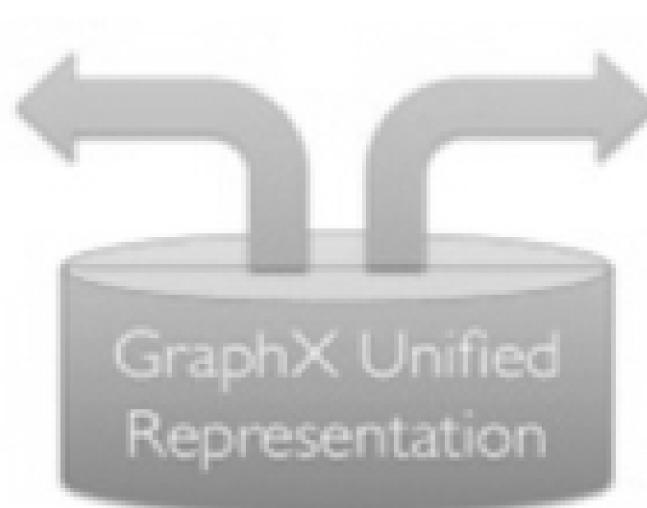


Table View



Graph View

# GraphX Structure

- VertexRDD maps IDs to vertex content
- EdgeRDD are of the form (ID1, ID2, ET)
- Triplets are a combination of Vertex & Edge RDDs



\* Some graph frameworks assume that the edges of a single vertex can fit in a single machine --- GraphX does not make this assumption!

# GraphX Structure

```
// Vertex collection
class VertexRDD[VD] extends RDD[(VertexId, VD)]  
  
// Edge collection
class EdgeRDD[ED] extends RDD[Edge[ED]]
case class Edge[ED](srcId: VertexId = 0, dstId: VertexId = 0,
                    attr: ED = null.asInstanceOf[ED])  
  
// Edge Triple
class EdgeTriplet[VD, ED] extends Edge[ED]
```

# GraphX Example

```
val sc: SparkContext

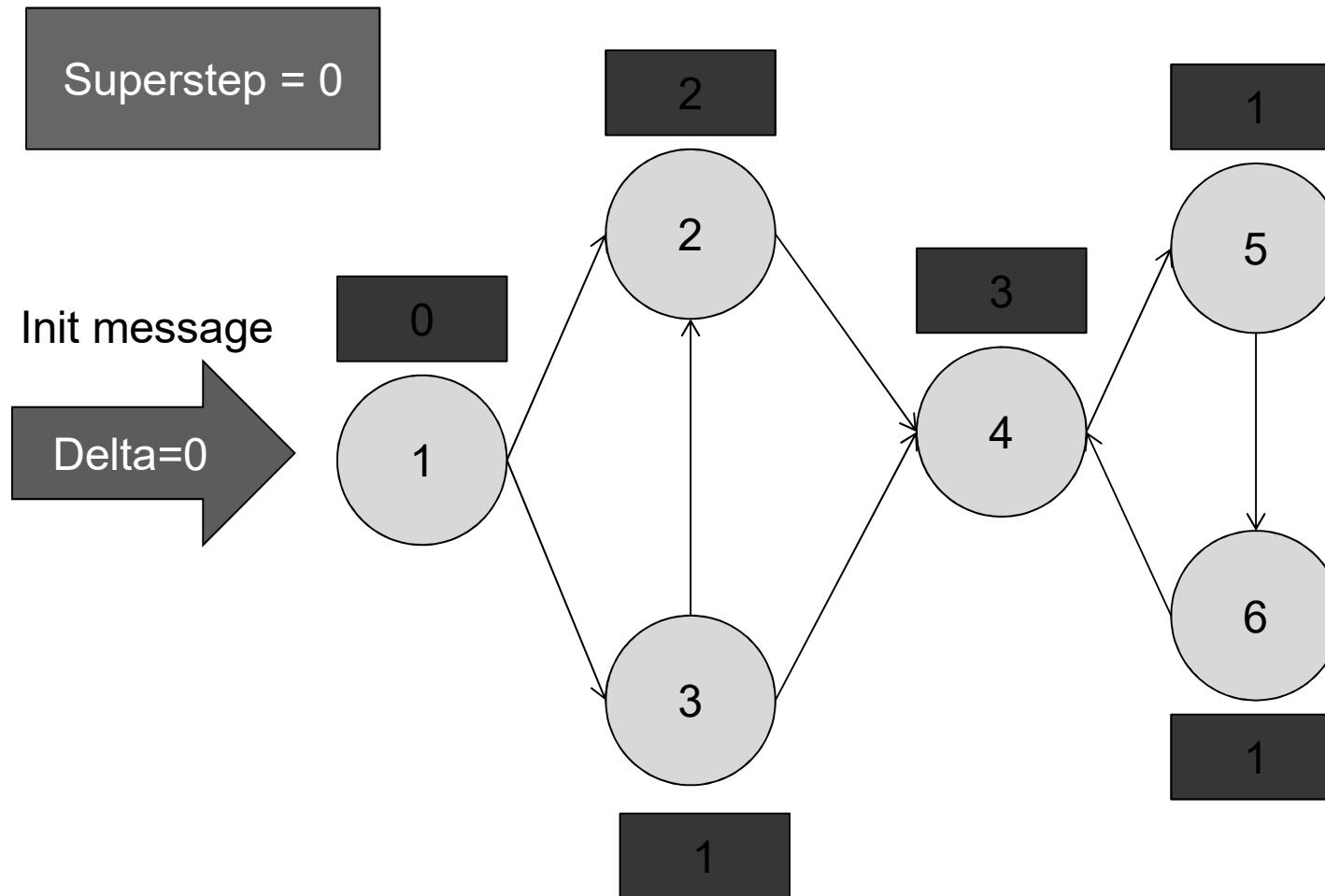
// Create an RDD for the vertices
val users: VertexRDD[(String, String)] = sc.parallelize(
  Array((3L, ("rxin", "student")), (7L, ("jgonzal", "postdoc")),
    (5L, ("franklin", "prof")), (2L, ("istoica", "prof"))))

// Create an RDD for edges
val relationships: EdgeRDD[String] = sc.parallelize(
  Array(Edge(3L, 7L, "collab"), Edge(5L, 3L, "advisor"),
    Edge(2L, 5L, "colleague"), Edge(5L, 7L, "pi")))

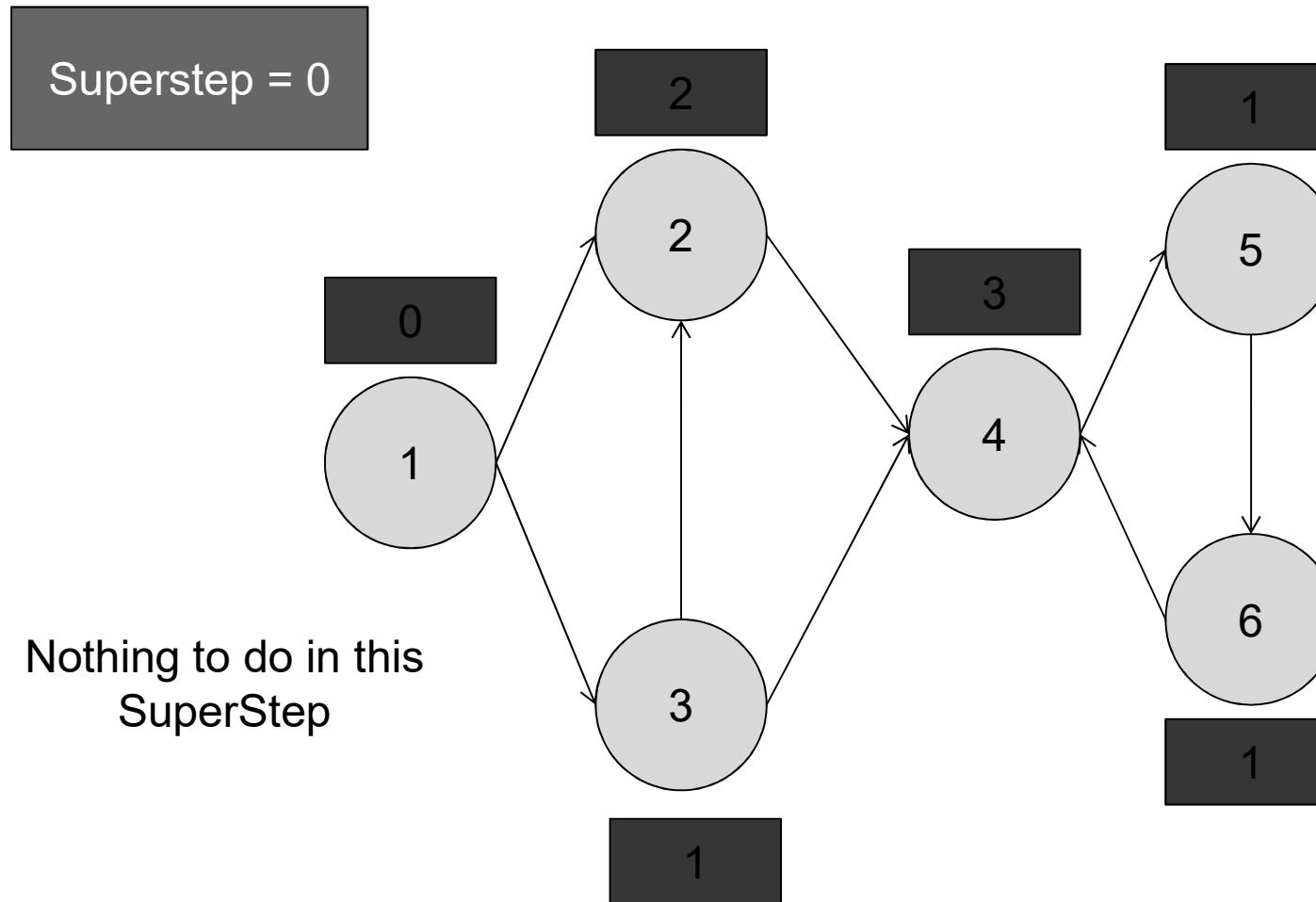
// Define a default user in case there are relationship with missing user
val defaultUser = ("John Doe", "Missing")

// Build the initial Graph
val userGraph: Graph[(String, String), String] =
  Graph(users, relationships, defaultUser)
```

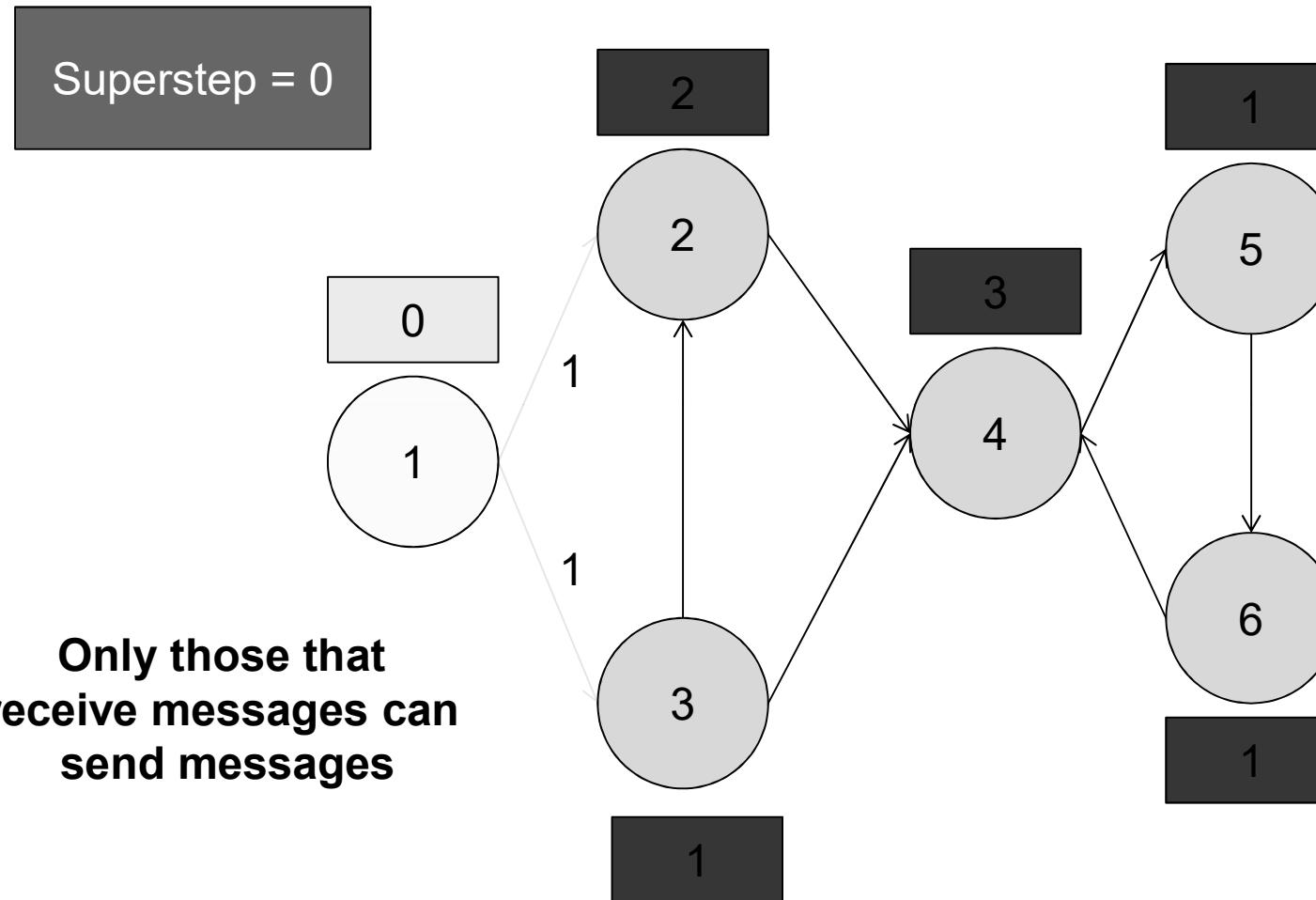
# Is DAG Pregel Example



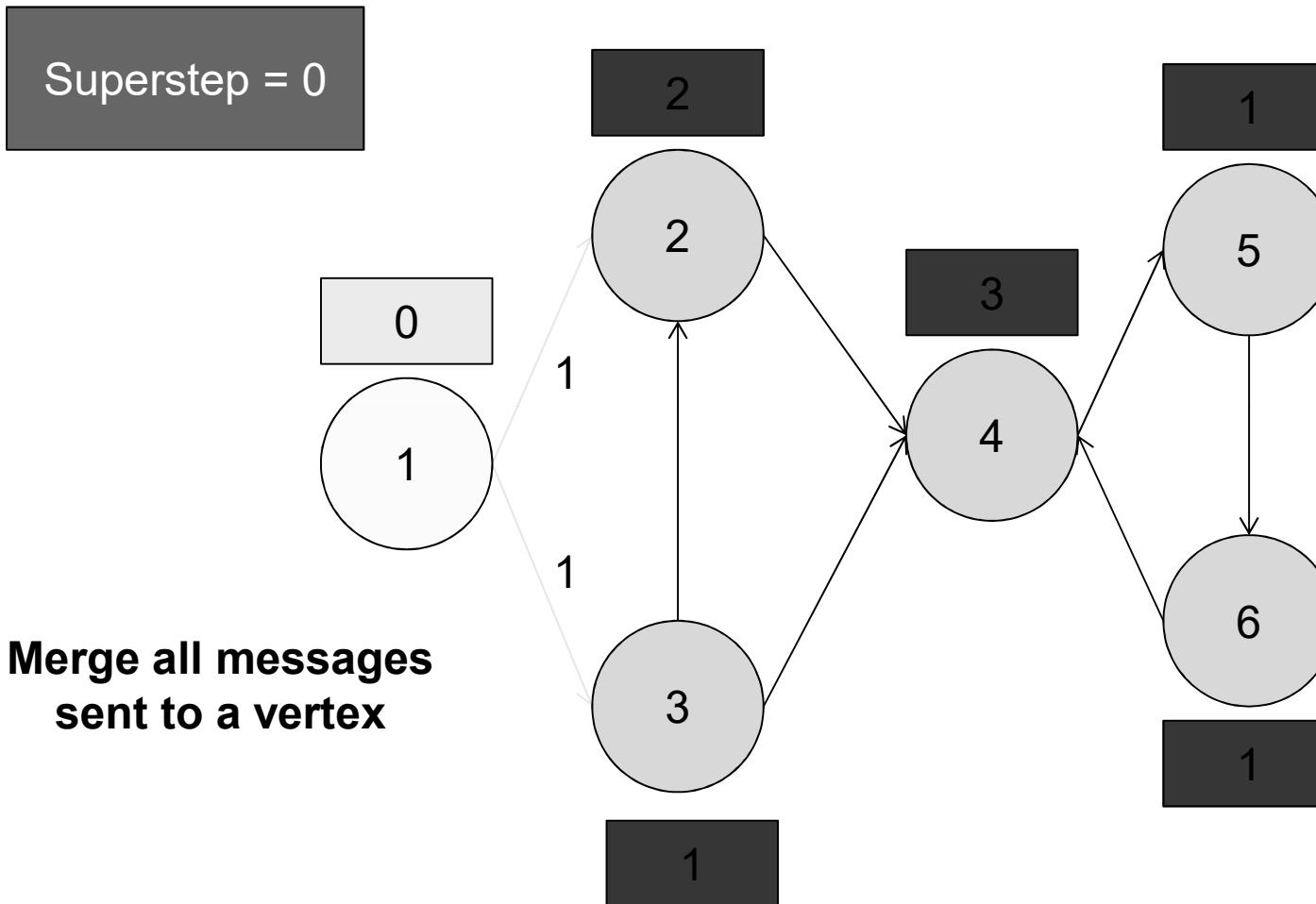
# Is DAG Pregel: vprog



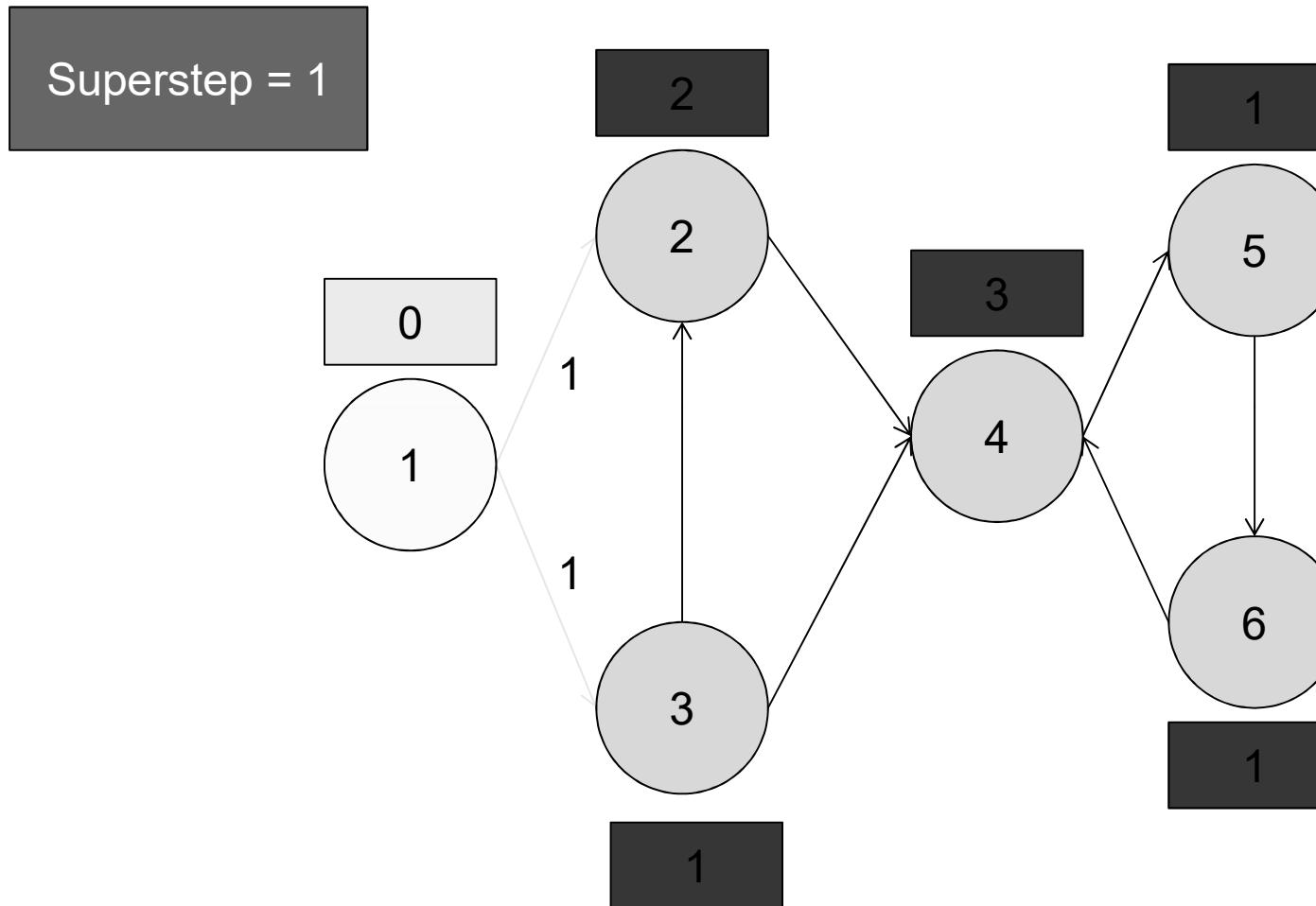
# Is DAG Pregel: sendMsg



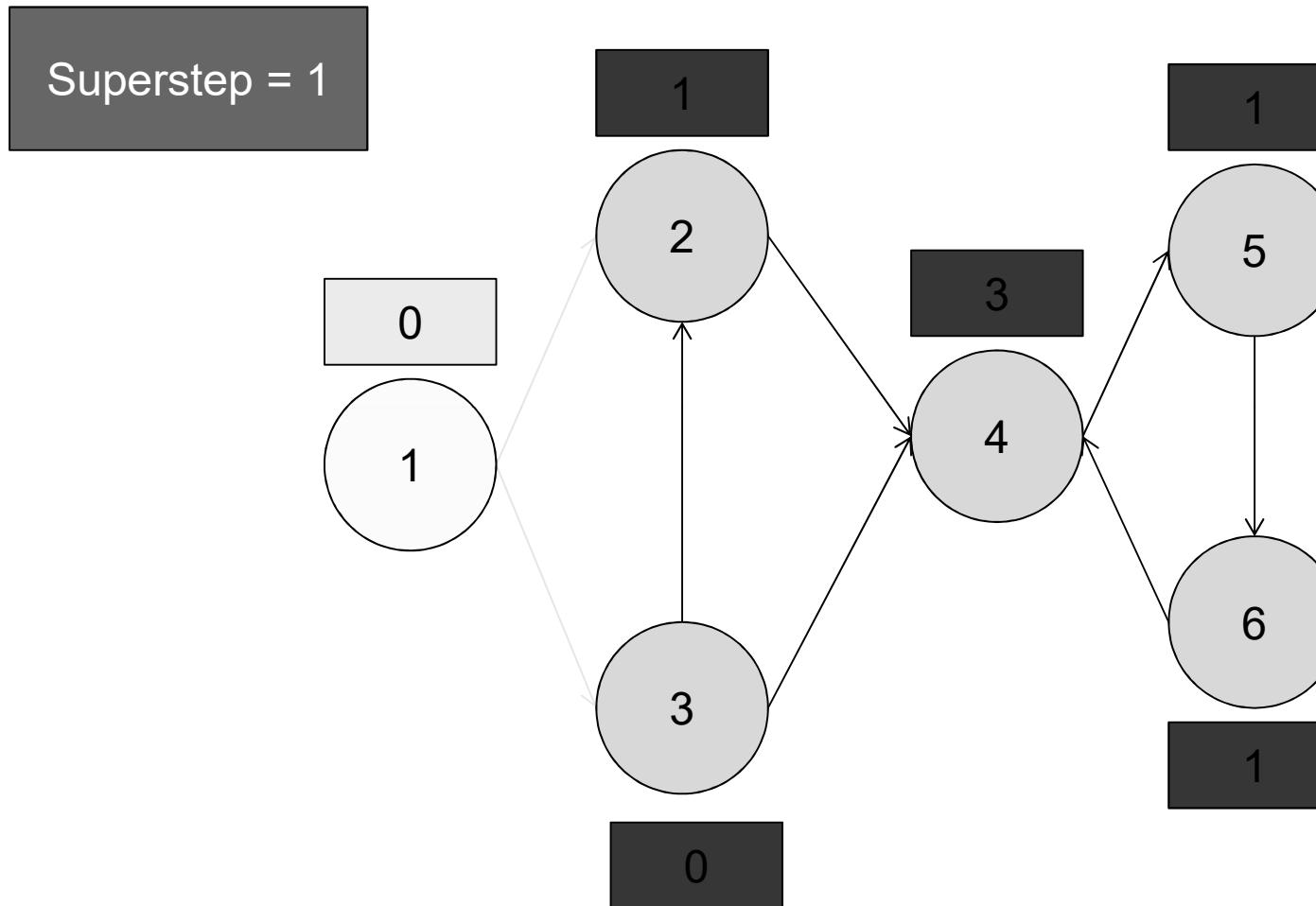
# Is DAG Pregel: mergeMsg



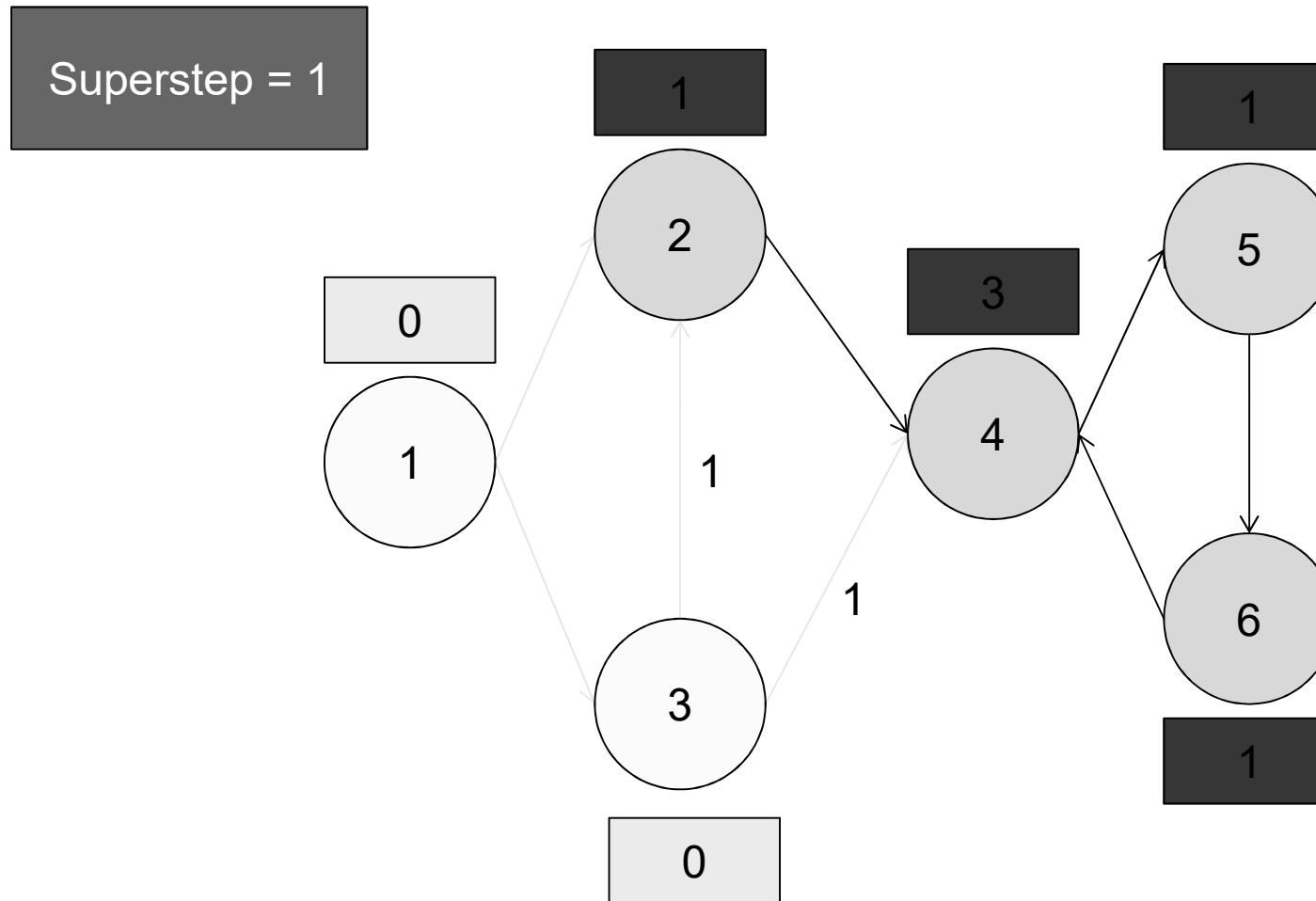
# Is DAG Pregel: vprog



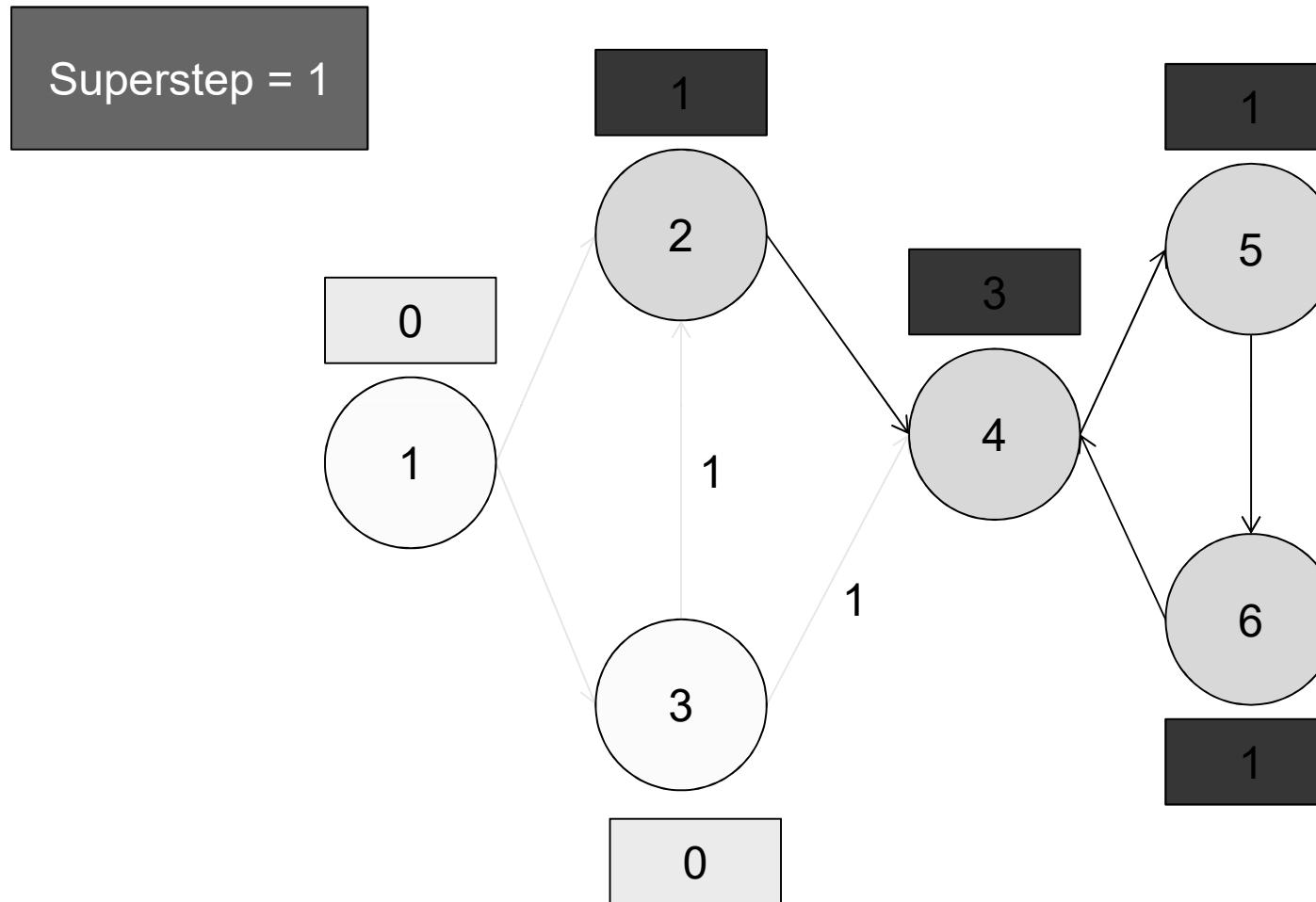
# Is DAG Pregel: vprog



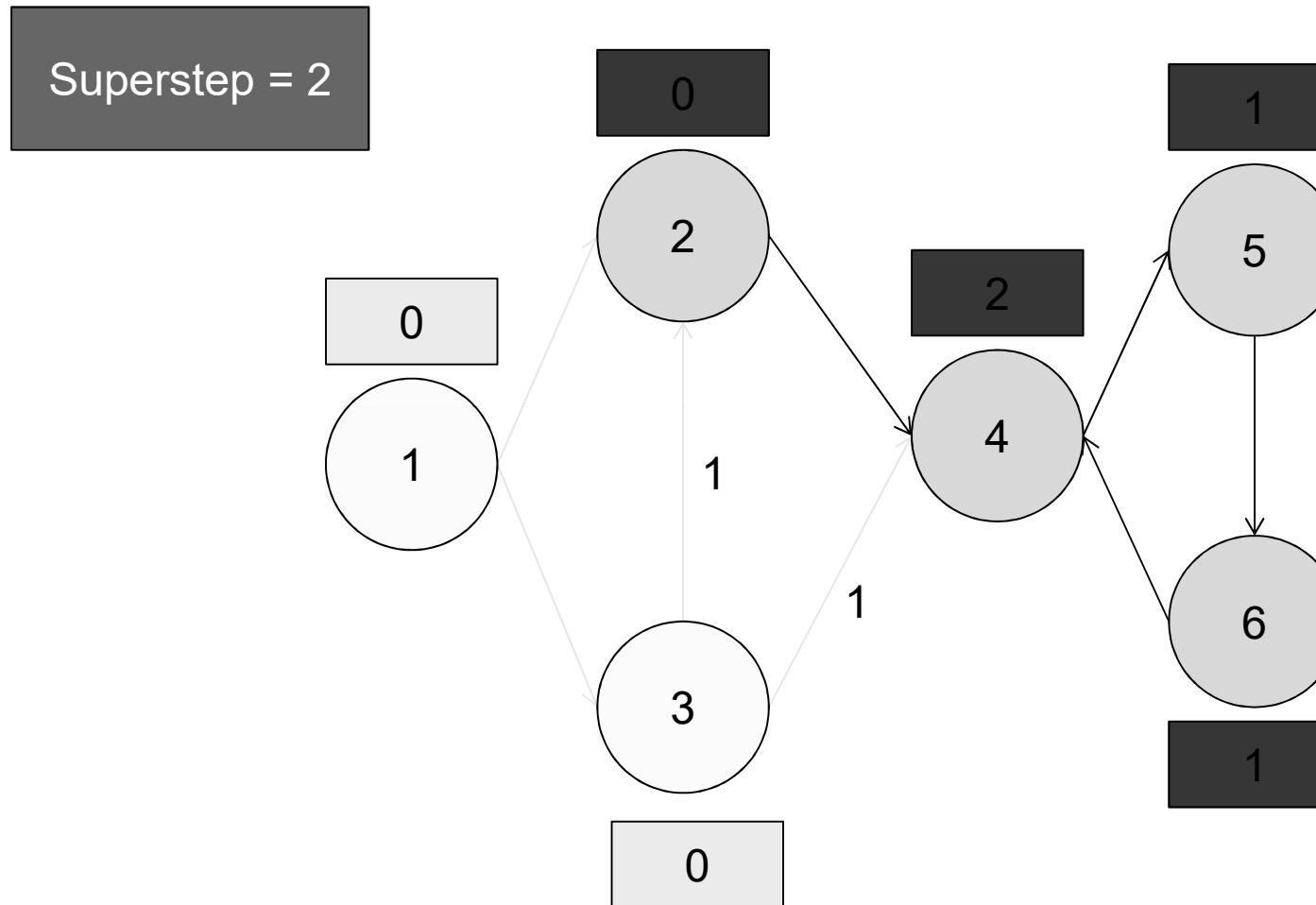
# Is DAG Pregel: sendMsg



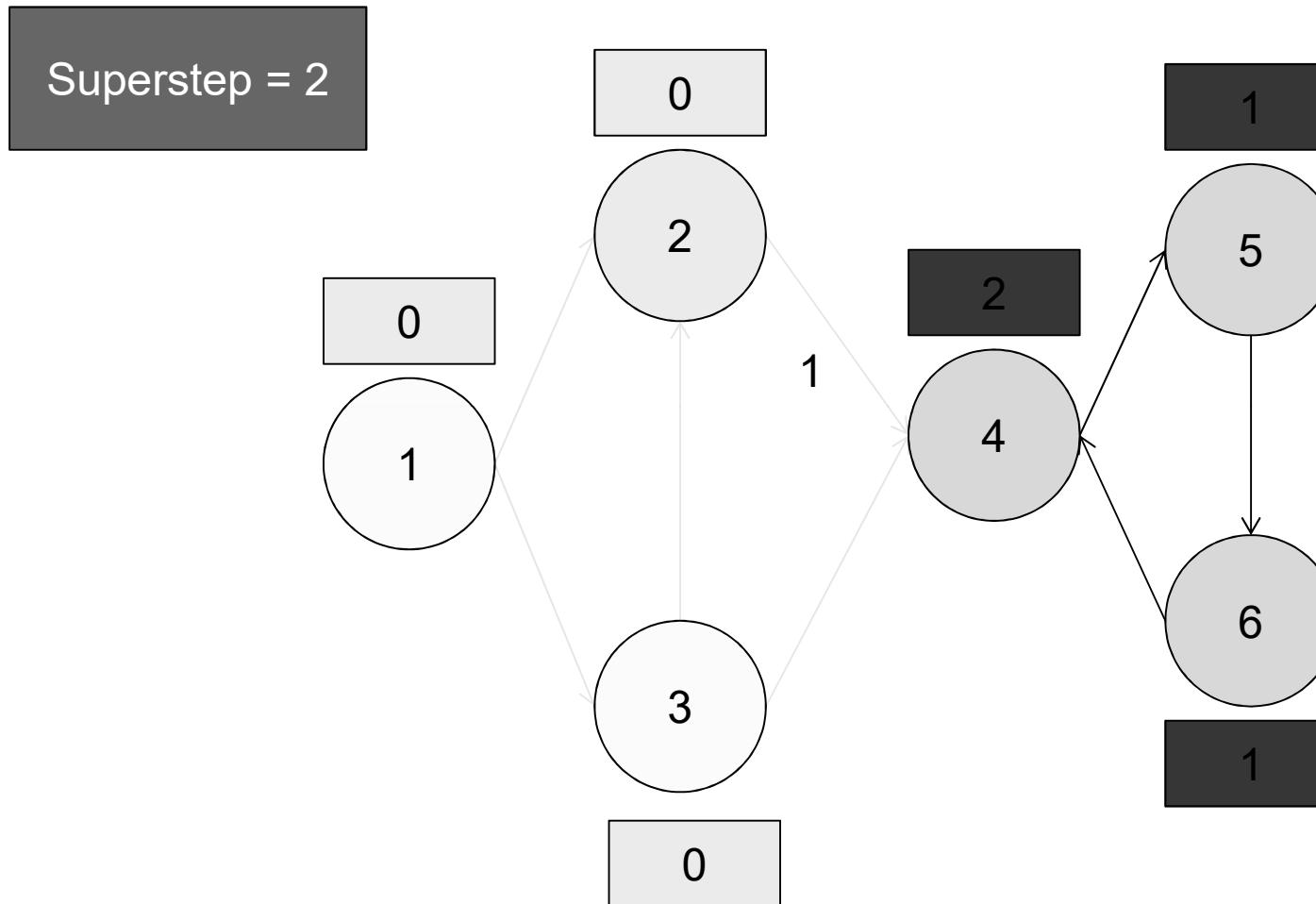
# Is DAG Pregel: mergeMsg



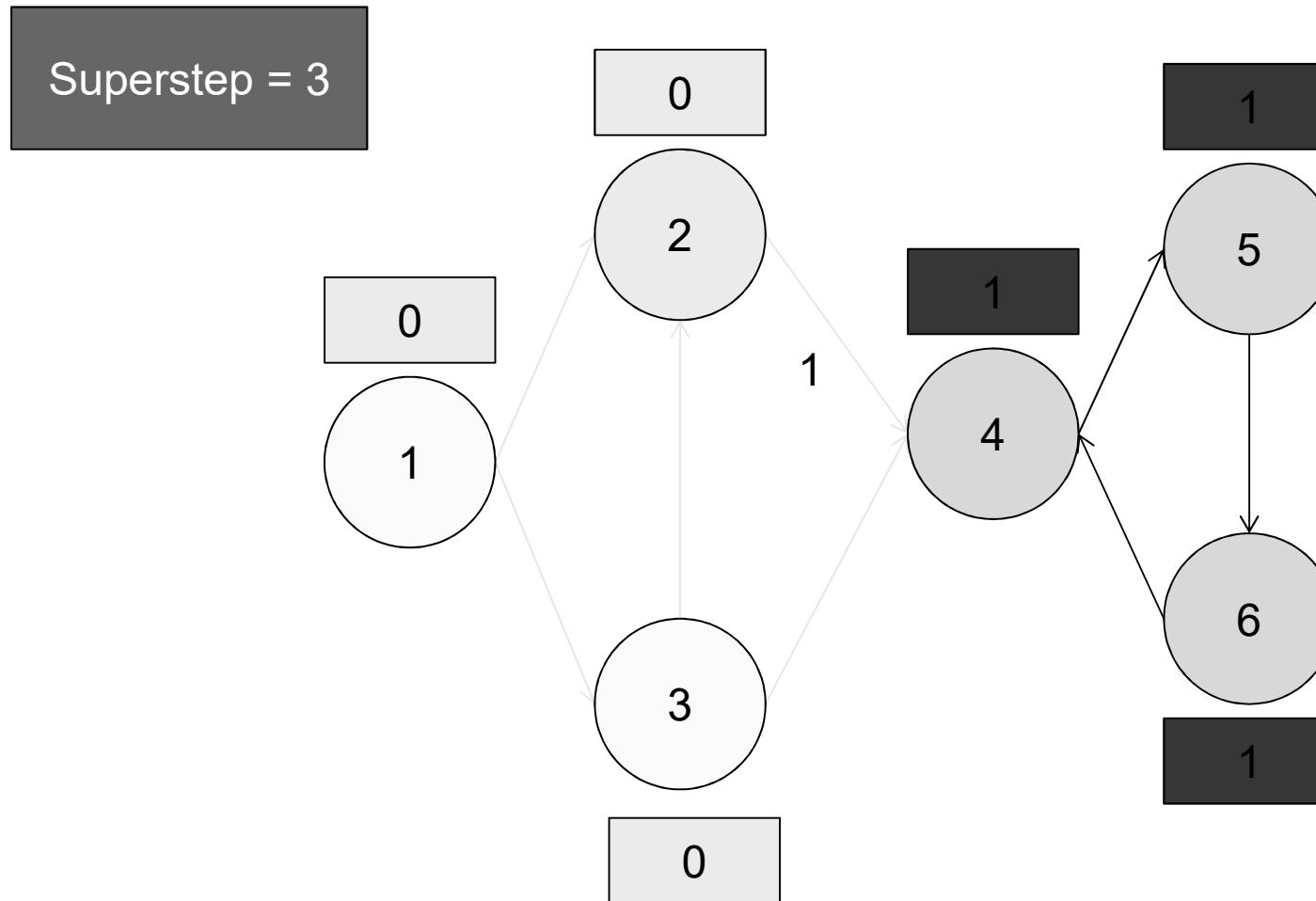
# Is DAG Pregel: vprog



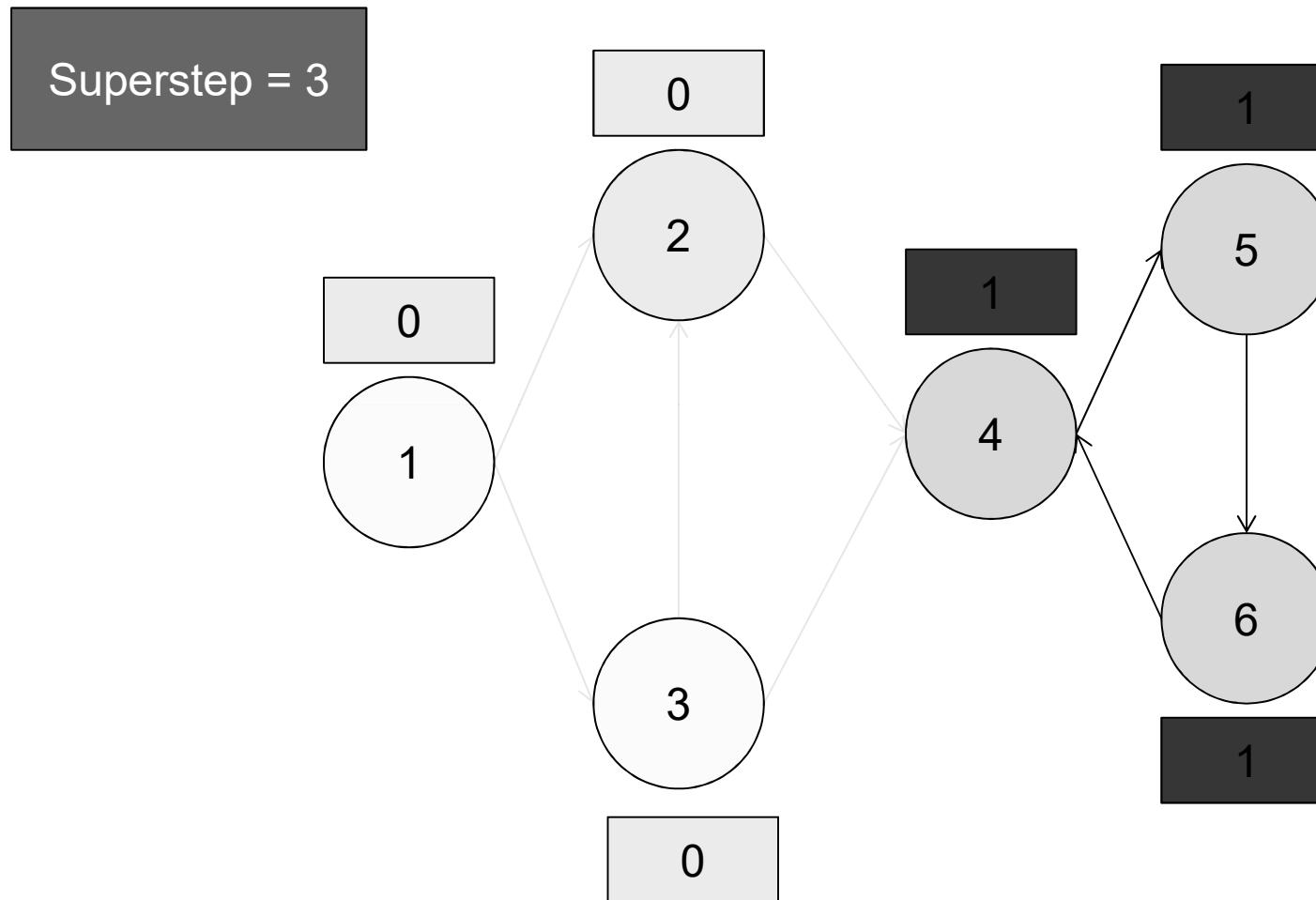
# Is DAG Pregel: sendMsg



# Is DAG Pregel: vprog



# Is DAG Pregel: sendMsg



# Final (non-pregel) Step

- Is a DAG iff all vertex incounts are zero
- This requires something like:
  - `-filter(_.deg != 0).isEmpty`**

# Looking at the Code

```
def isDag(): Boolean = {
    val dag = g.outerJoinVertices(g.inDegrees){
        case(vid, vt, oInDeg) => oInDeg.getOrElse(0)
    }
}

import IsDagUtil._

val resG = dag.pregel(
    initialMsg = -1,
    maxIterations = Int.MaxValue,
    activeDirection = EdgeDirection.Out
)(vprog, sendMsg, mergeMsg)

resG.vertices.filter(_._2 > 0).isEmpty
}
```

# **GraphX**

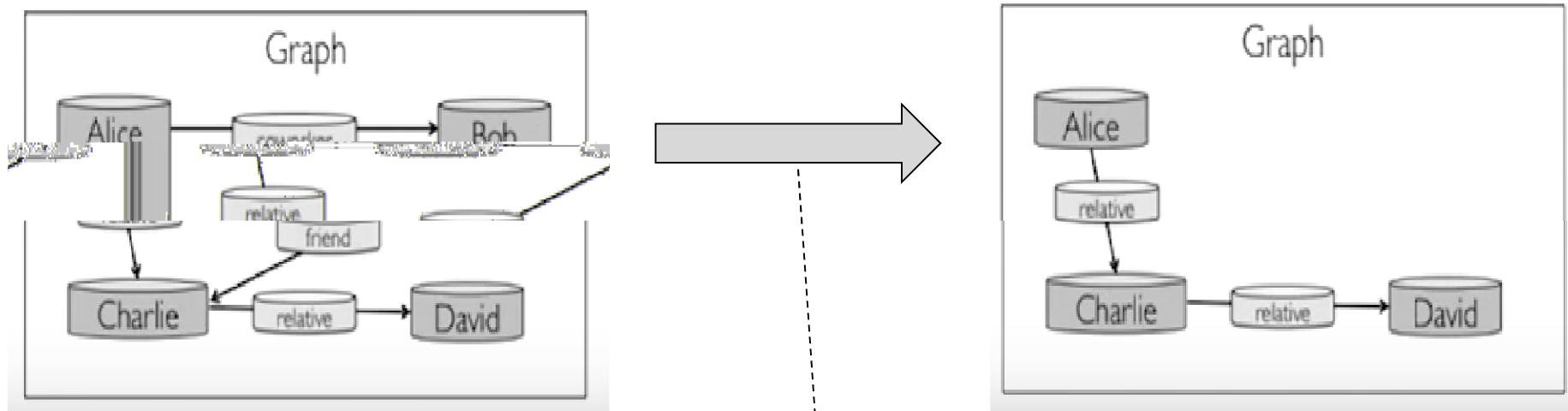
# **APIs**

# GraphX APIs

```
def mapVertices[VD2](map: (VertexId, VD) ⇒ VD2): Graph[VD2, ED]
def mapEdges[ED2](map: (Edge[ED]) ⇒ ED2): Graph[VD, ED2]
def mapTriplets[ED2](map: (EdgeTriplet[VD, ED]) ⇒ ED2): Graph[VD, ED2]
```

```
def reverse: Graph[VD, ED]
def subgraph(
    epred: (EdgeTriplet[VD, ED]) ⇒ Boolean,
    vpred: (VertexId, VD) ⇒ Boolean): Graph[VD, ED]
def mask[VD2, ED2](other: Graph[VD2, ED2]): Graph[VD, ED] // subgraph based on other
def groupEdges(merge: (ED, ED) ⇒ ED): Graph[VD, ED] // merge parallel edges
```

# Example: subgraph



```
graph.subgraph(vpred = (_, name) => name != "Bob")
```

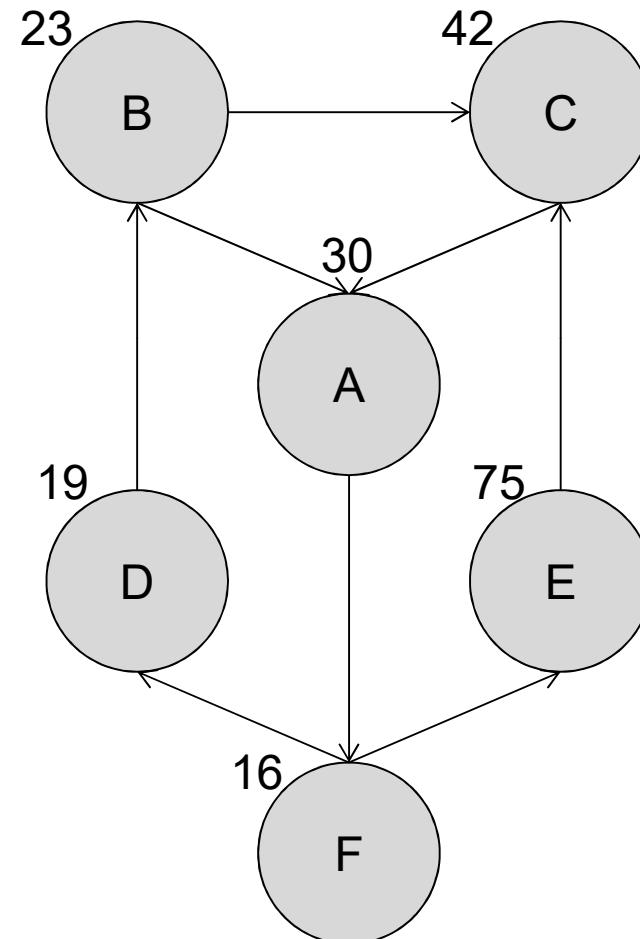
# GraphX APIs

```
def outerJoinVertices[U, VD2](  
    other: RDD[(VertexId, U)])  
    (mapFunc: (VertexId, VD, Option[U]) ⇒ VD2): Graph[VD2, ED]  
def aggregateMessages[A](  
    sendMsg: (EdgeContext[VD, ED, A]) ⇒ Unit,  
    mergeMsg: (A, A) ⇒ A): VertexRDD[A]
```

# Age Of Oldest Follower

```
val oldestFollowersAge: VertexRDD[Int] =  
  graph.aggregateMessages(  
    ctx => ctx.sendToDst(ctx.srcAttr),  
    (c1, c2) => Math.max(c1, c2)  
)
```

```
class EdgeContext[VD, ED, A] {  
  def attr: ED  
  
  def srcAttr: VD  
  def dstAttr: VD  
  
  def srcId: VertexId  
  def dstId: VertexId  
  
  def sendToDst(msg: A): Unit  
  def sendToSrc(msg: A): Unit  
}
```

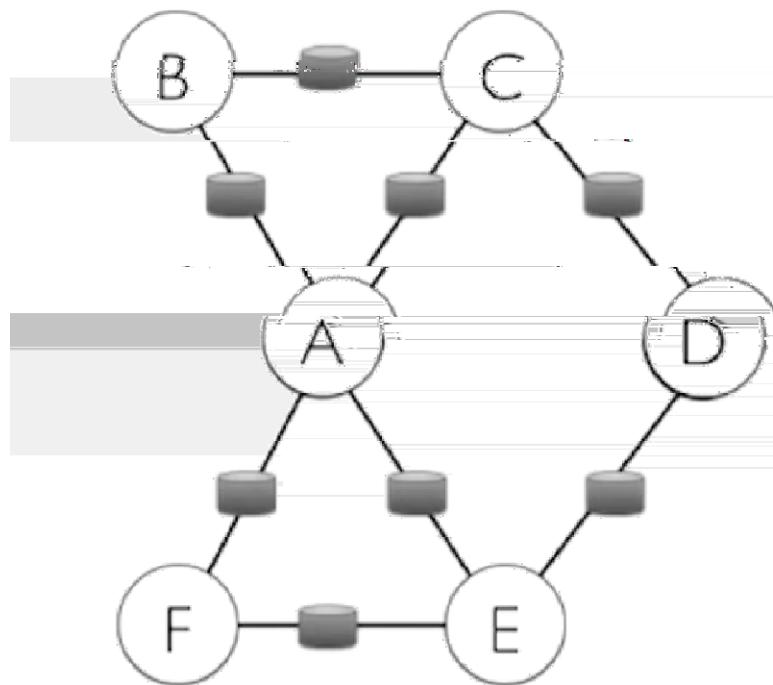


# Agenda

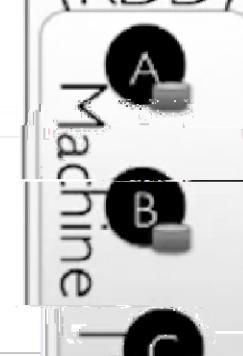
- An Intro to Graph Processing
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# A Graph as-a Table

Property Graph

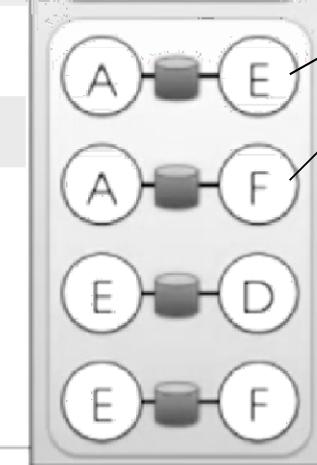
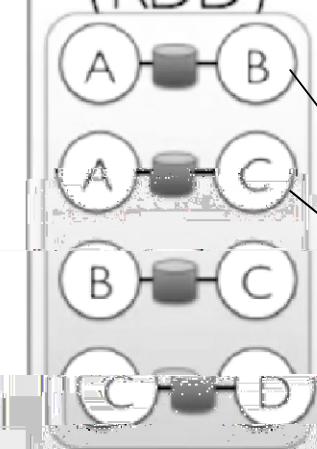


Vertex Table  
(RDD)



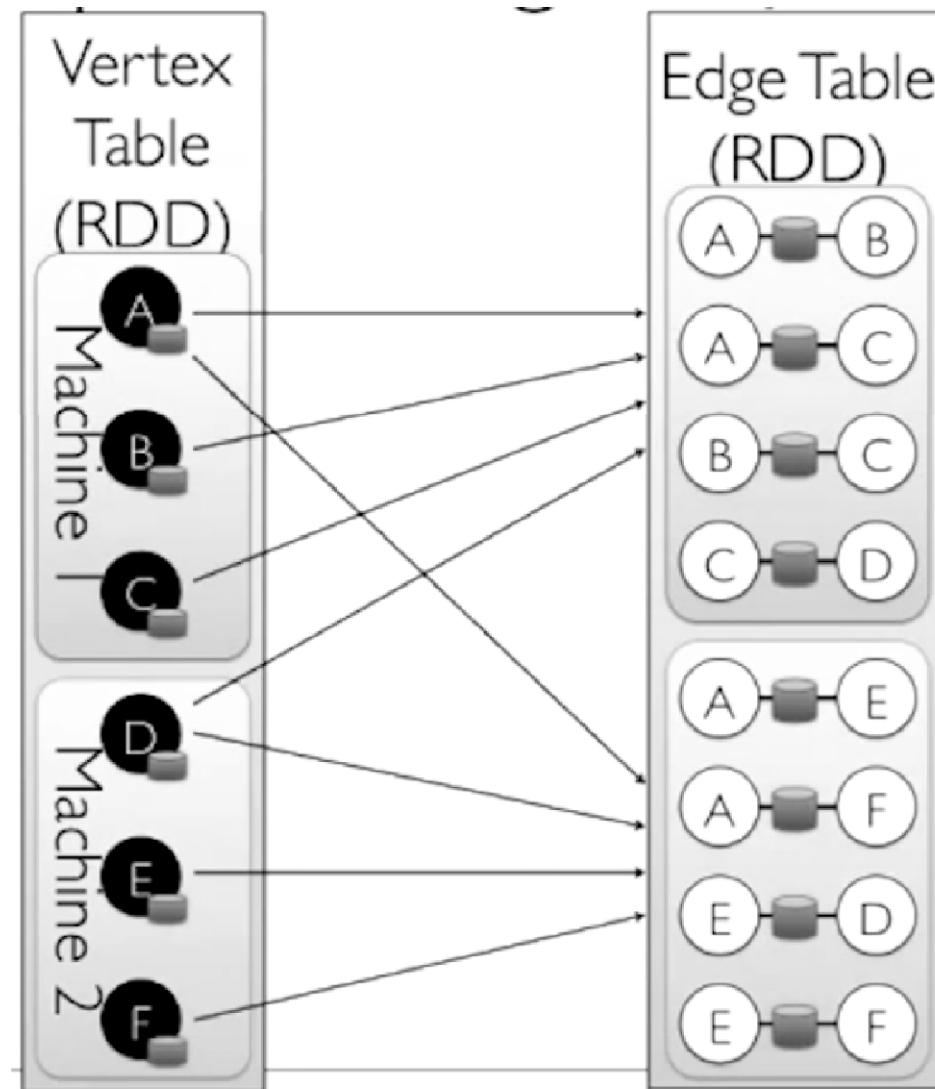
Machine 2

Edge Table  
(RDD)

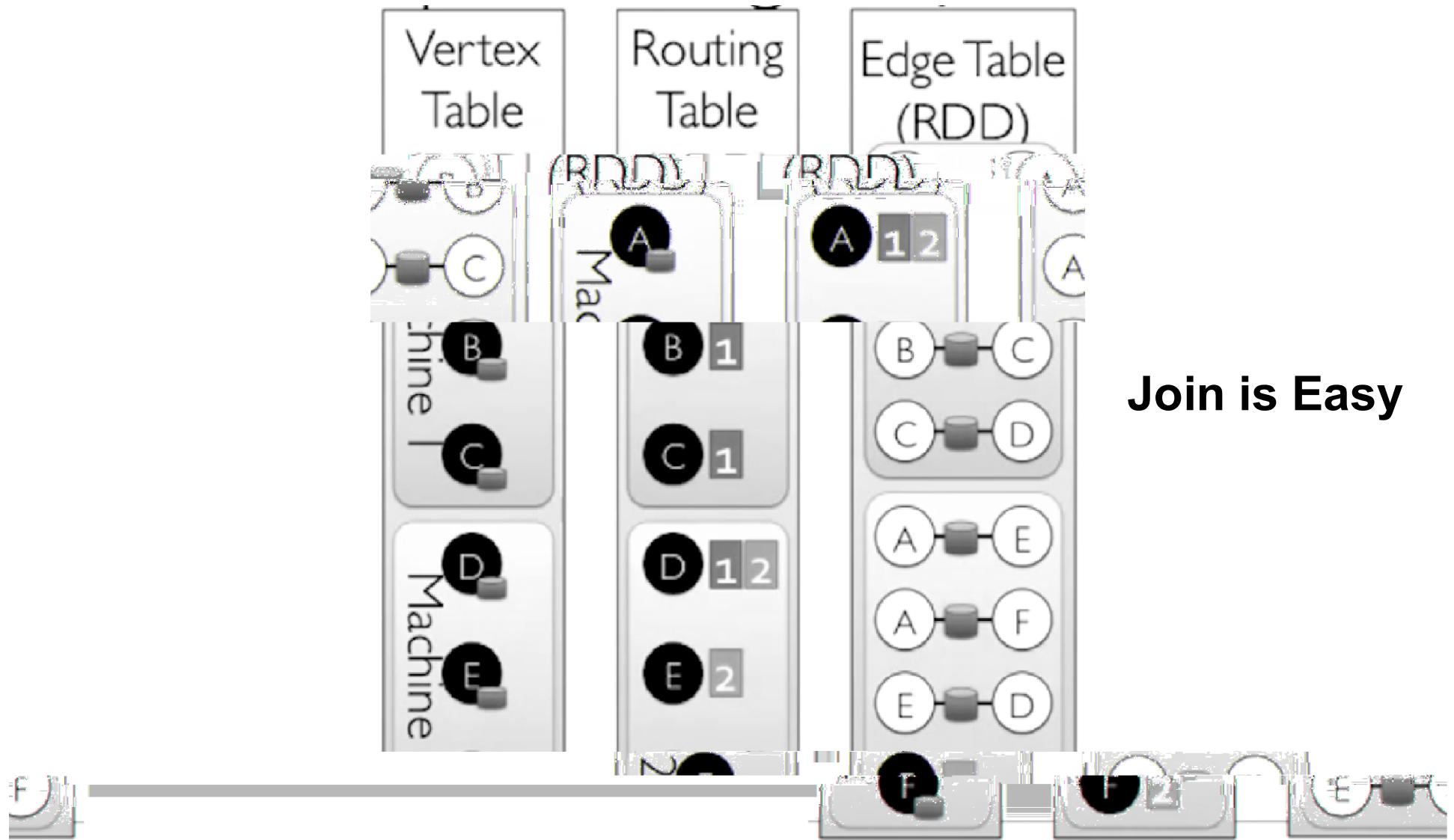


**Spanned across multiple nodes**

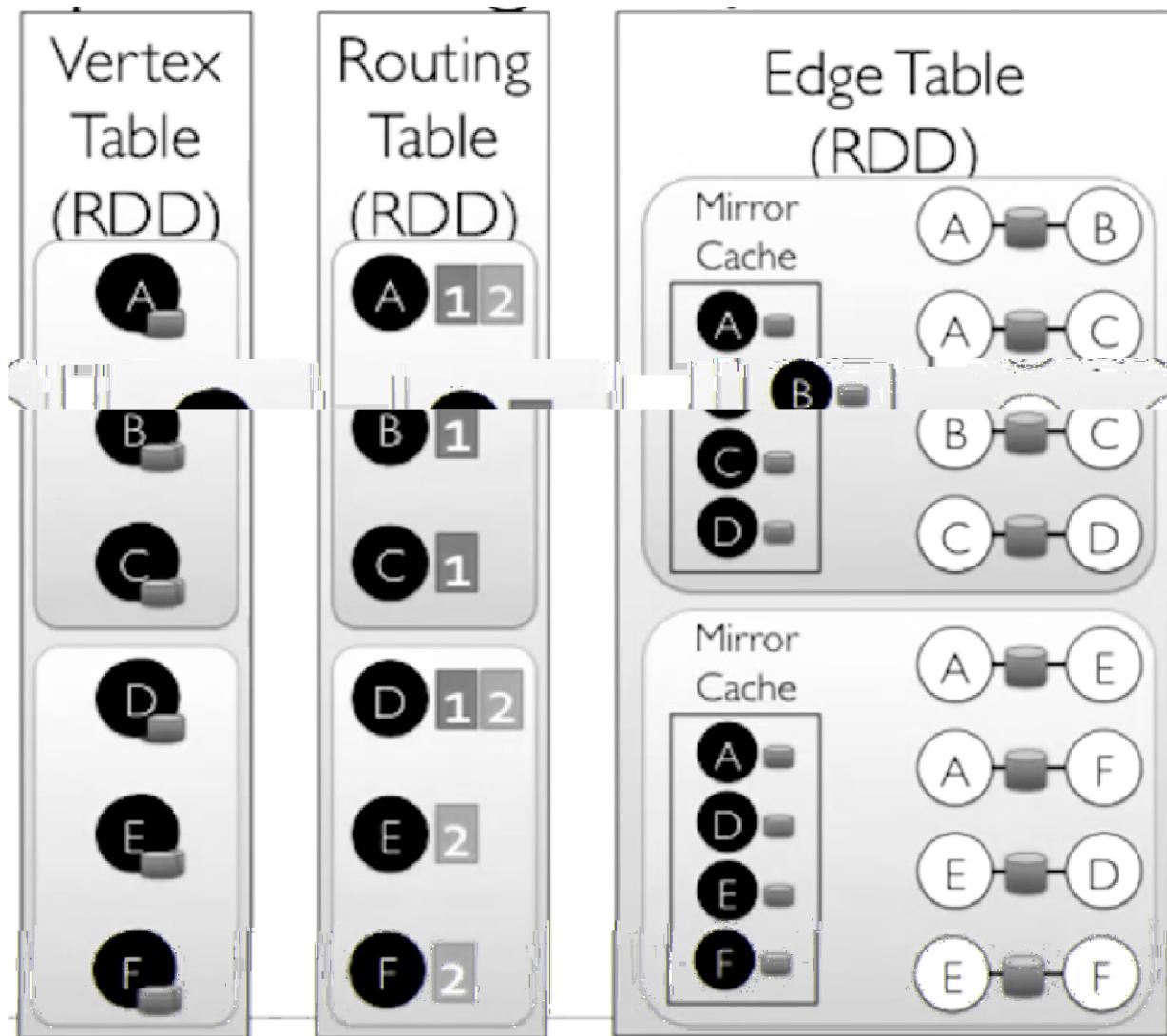
# Triplets Under the Hood



# Triplets Under the Hood

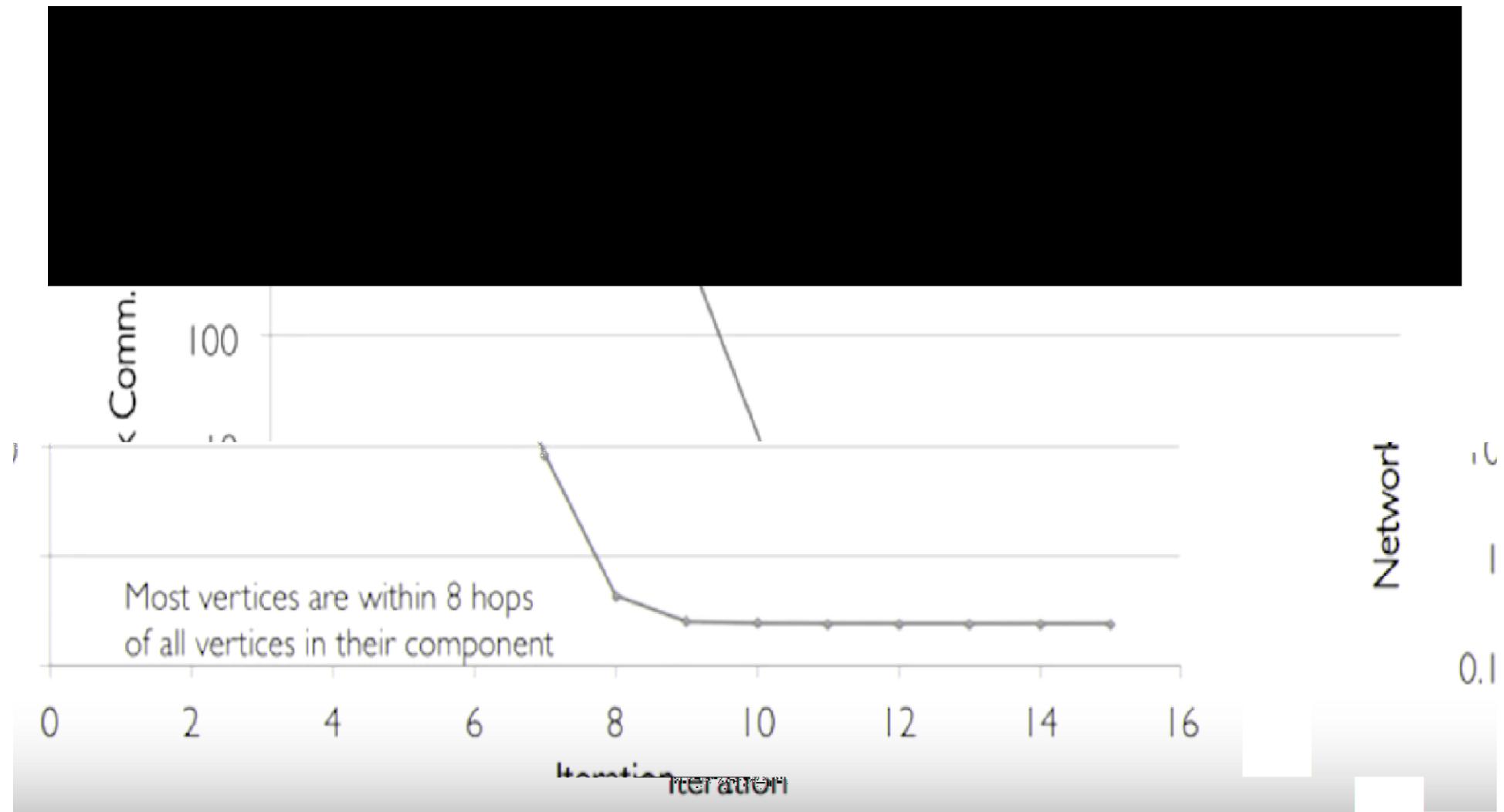


# Triplets Under the Hood



**Send only  
vertex  
properties  
that  
changed**

# Reduction in Communication Due to Caching



# **Graph Partitioning**

# Graph Partitioning

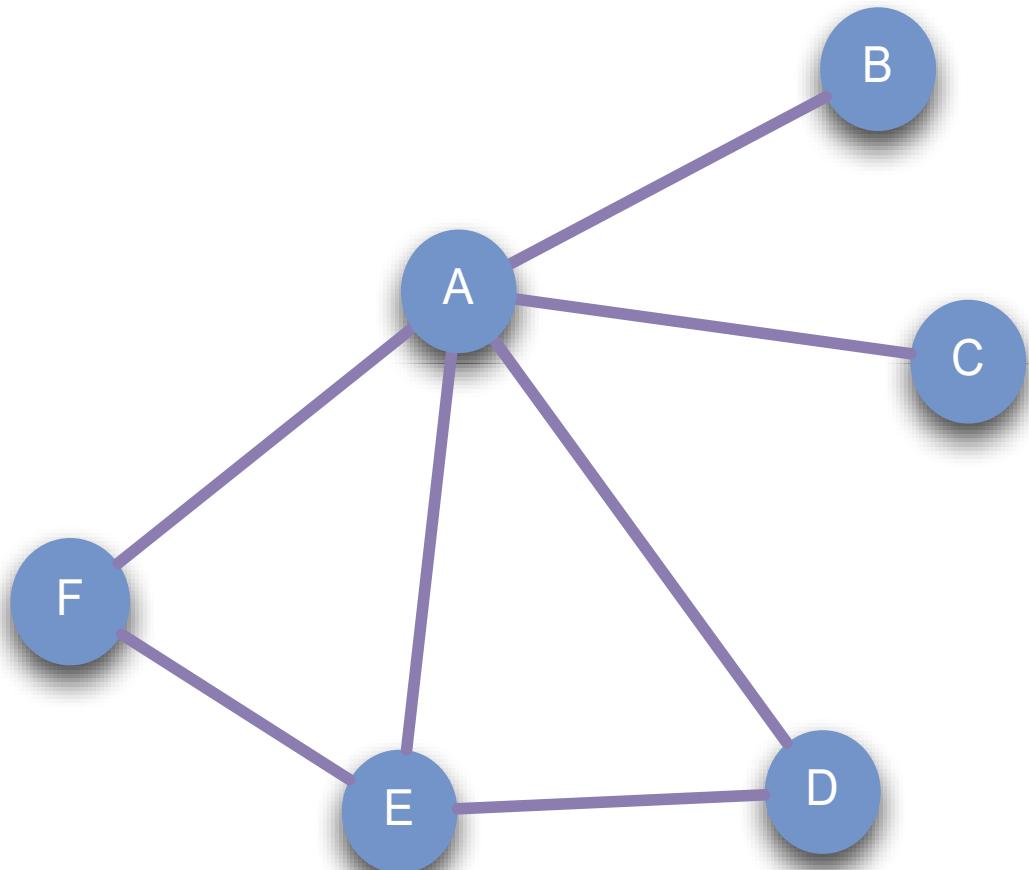
- **Goal:** create a balanced graph partition
- **Challenges:**
  - Problem is NPH
  - Heuristics exist but they are complex and there is a chicken & egg problem here

# GraphX Partitioning

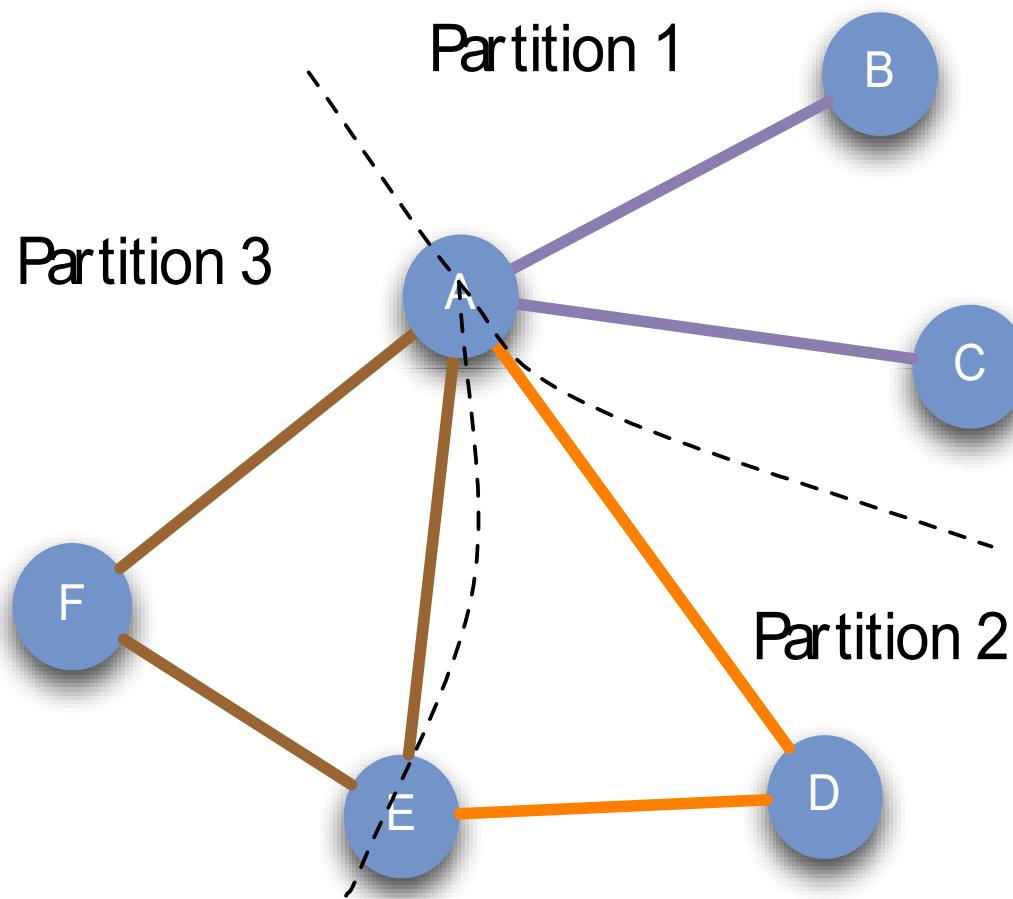
- Controls edge partitioning
- Four built in partitioning strategies
- Can also write custom partitioning
- Partitioning can be based on vertex/edge

```
g.partitionBy(PartitionStrategy.EdgePartition2D, numPartitions)
```

# Vertex Cut Partitioning



# Vertex Cut Partitioning



# Support Partitioning Strategies

```
trait PartitionStrategy {  
    def getPartition(src: VertexId, dst: VertexId, numParts: PartitionID): PartitionID  
}
```

- **RandomVertexCut** – select edge partition based on **(src, dst)** hash
- **CanonicalRandomVertexCut** – same as above only canonical
- **EdgePartition1D** – partitioning based only on source vertex id (bad for hypernodes)

# Partition As Sparse Matrix

## EdgePartition2D

	$v_0$	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$	$v_7$	$v_8$	$v_9$	$v_{10}$	$v_{11}$
$v_0$	*				*	*	*	*	*			
$v_1$	*	*	*				*			*		
$v_2$	*	*			*			*				*
$v_3$			*	*		*	*	*				*
$v_4$	*				*					*		
$v_5$	*				*					*		
$v_6$						*		*				*
$v_7$				*	*							
$v_8$						*		*			*	
$v_9$	*					*				*		*
$v_{10}$						*	*	*	*		*	*
$v_{11}$					*			*	*		*	

# Partition As Sparse Matrix

## EdgePartition2D

	$v_0$	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$	$v_7$	$v_8$	$v_9$	$v_{10}$	$v_{11}$
$v_0$	*				*	*	*	*	*			
$v_1$	*	*	*				*			*		
$v_2$		*	$p_0$	*		*	$p_1$	*		*	$p_2$	
$v_3$			*	*		*	*	*				*
$v_4$		*				*				*		
$v_5$		*			*					*		
$v_6$			$p_3$				$p_4$	*		*	$p_5$	*
$v_7$				*		*						
$v_8$						*			*		*	
$v_9$		*					*			*		*
$v_{10}$			$p_6$				*	*	*	*	*	$p_8$
$v_{11}$					*				*	*	*	

# Summary

1. Graph-parallel processing on Spark
2. Unify tables/graphs processing
3. Work being done to improve performance  
brining it closer to specialized engines  
such as GraphLab

# References

- <http://ampcamp.berkeley.edu/amp-camp-one-berkeley-2012>
- <http://www.slideshare.net/payberah/graph-processing-powergraph-and-graphx>
- <http://www.slideshare.net/payberah/pregec-43904273>
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- <https://www.youtube.com/watch?v=Y7hq5MudV9M>
- <http://note.yuhc.me/2015/03/graphx-partition-strategy/>