

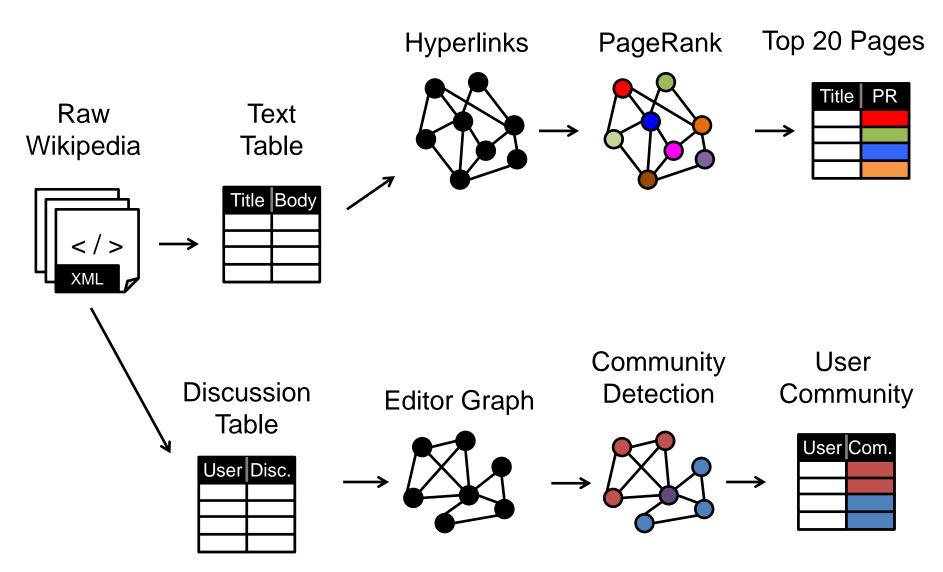
Unifying Data-Parallel and Graph-Parallel Analytics

Cloud Computing Research Topic

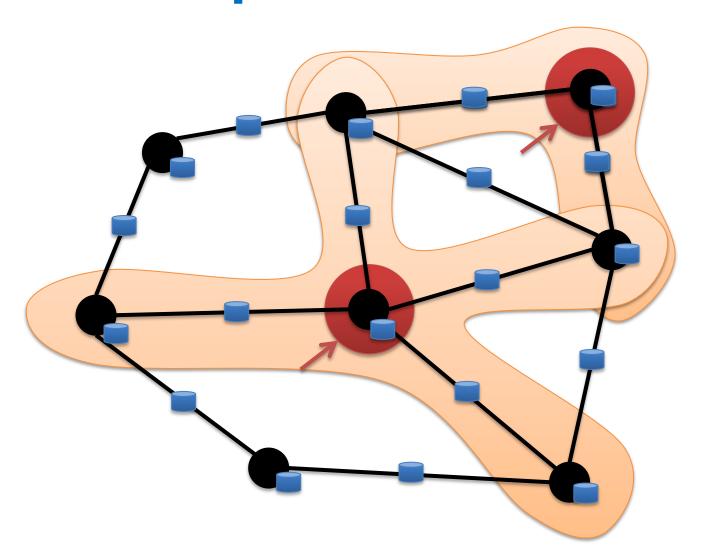
Fatemeh Shafiee Kashif Rabbani

May 2018

Graphs are Central to Analytics



The Graph-Parallel Pattern



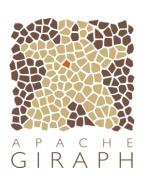
Computation depends only on the **neighbors**

Graph-Parallel Algorithms

- Classification: Neural Networks
- Community Detection : Triangle-Counting
- Semi-supervised ML: Graph SSL
- Collaborative Filtering: Alternating Least Squares
- Graph Analytics: PageRank, Shortest Path, Graph Coloring
- Structured Prediction : Max-Product, Linear Programs

Current Graph-Parallel Systems







Separate Systems to Support Each View

Table View





Graph View





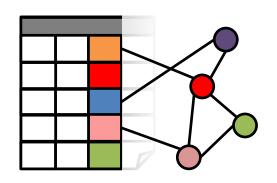
What are the Problems?

- Having separate systems for each view is difficult to use and inefficient
- Difficult to Program and Use
- Users must Learn, **Deploy**, and **Manage** multiple systems
- Extensive data movement and duplication across the network and file system

Solution: GraphX

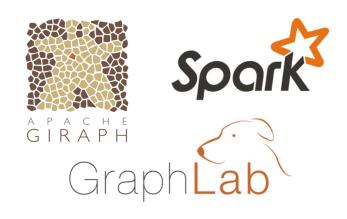
New API

Blurs the distinction between Tables and Graphs



New System

Combines Data-Parallel Graph-Parallel Systems



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

What is GraphX?

Apache Spark Ecosystem

Spark SQL DataFrames **Streaming**

MLlib Machine Learning Graph Computation

Apache Spark Core API

R

SQL

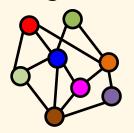
Python

Scala

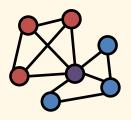
Java



PageRank



Community Detection

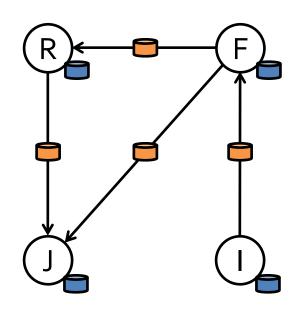


Triangle Count



Property Graph

Property Graph



Vertex Property Table

Id	Property (V)	
Rxin	(Stu., Berk.)	
Jegonzal	(PstDoc, Berk.)	
Franklin	(Prof., Berk)	
Istoica	(Prof., Berk)	

Edge Property Table

SrcId	Dstld	Property (E)
rxin	jegonzal	Friend
franklin	rxin	Advisor
istoica	franklin	Coworker
franklin	jegonzal	PI ⁹

RDD Operators

RDD operators are inherited from Spark:

map reduce sample

filter count take

groupBy fold first

sort reduceByKey partitionBy

union groupByKey mapWith

join cogroup pipe

leftOuterJoin cross save

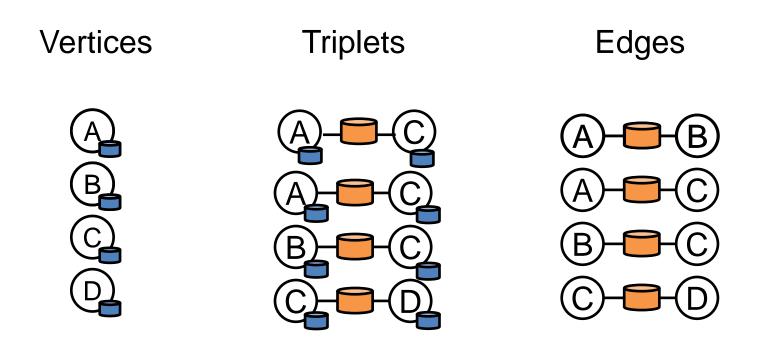
rightOuterJoin zip ...

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) ]
   def triplets: Table [ ((Id, V), (Id, V), E) ]
   // Transformations --
   def reverse: Graph[V, E]
   def subgraph(pV: (Id, V) => Boolean,
                 pE: Edge[V, E] \Rightarrow Boolean): Graph[V, E]
   def mapV(m: (Id, V) \Rightarrow T): Graph[T, E]
   def mapE(m: Edge[V, E] \Rightarrow 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]) \Rightarrow List[(Id, T)],
                    reduceF: (T, T) \Rightarrow T: Graph[T, E]
```

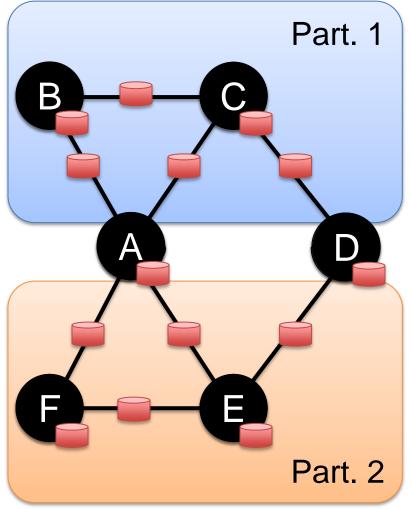
Triplets Join Vertices and Edges

The *triplets* operator joins vertices and edges

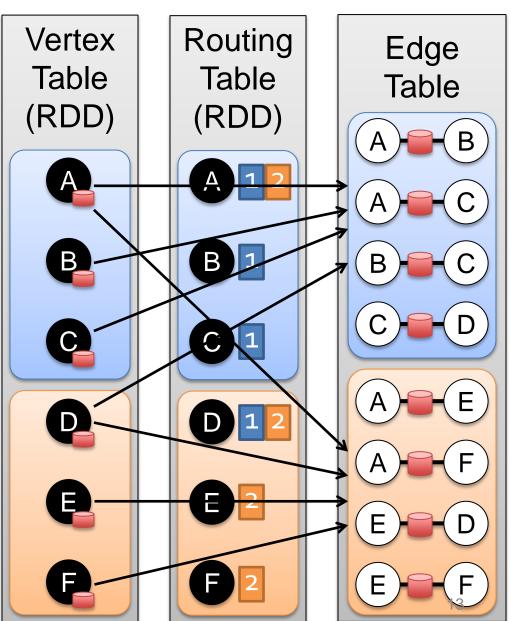


GraphX System Design

Property Graph



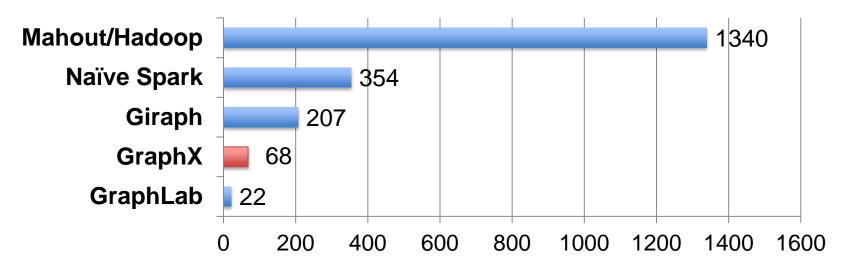
Distributed Graphs as Tables (RDDs)



Ref: https://amplab.cs.berkeley.edu/

Performance Comparisons

Live-Journal: 69 Million Edges

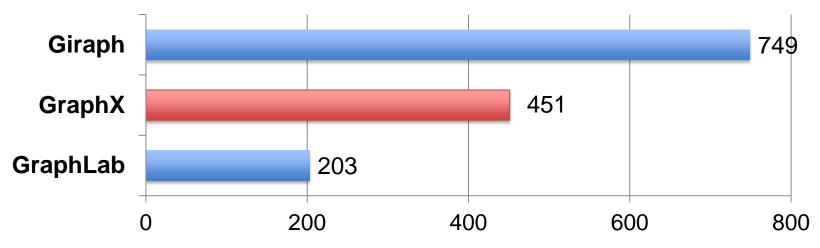


Runtime (in seconds, PageRank for 10 iterations)

GraphX is roughly 3x slower than GraphLab

GraphX scales to larger graphs

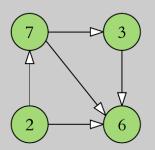
Twitter Graph: 1.5 Billion Edges



Runtime (in seconds, PageRank for 10 iterations)

GraphX is roughly 2x slower than GraphLab Scala + Java overhead: Lambdas, GC time, etc. No shared memory parallelism 15

Initial Graph:



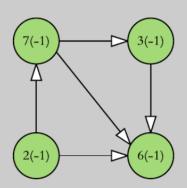
define f to be:

```
val originalValue = value
val value = (messages :+ value).min

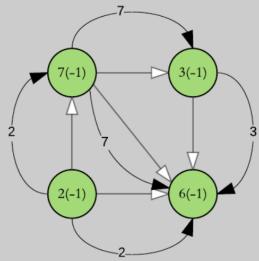
if (originalValue == value)
   inactive()
else
   neighbours.foreach(sendMessage)
```

Superstep 0:

Initialise the graph with -1 picked as the originalValue



All active vertices send its value as message to its neighbouring vertices



Superstep 1:

Receive messages from the previous superstep

2

7(-1)

3(-1)

3(-1)

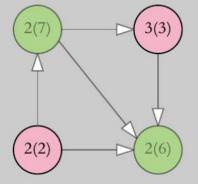
7

6(-1)

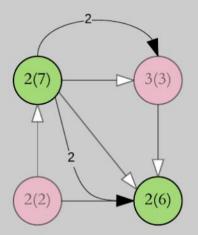
2

7

Mutate the value of the vertices and make vertices with
originalValue == value
inactive

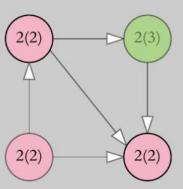


For vertices that are still active, send its value as message to its neighbouring vertices

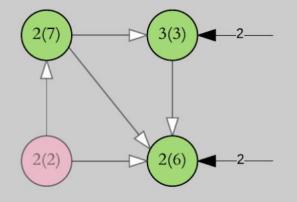


Superstep 2:

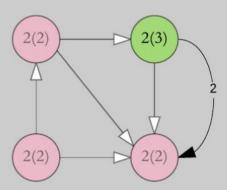
Mutate the value of the vertices and make vertices with
originalValue == value
inactive



Receive message from the previous superstep

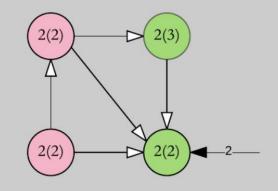


For vertices that are still active, send its value as message to its neighbouring vertices

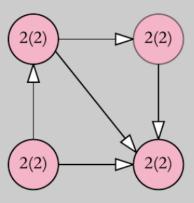


Superstep 3:

Receive message from the previous superstep



Mutate the value of the vertices and make vertices with
originalValue == value
inactive



Interesting Use Cases

Building a Graph of **US Businesses**

RADIUS

Using Spark GraphX to detect communities at Alibaba

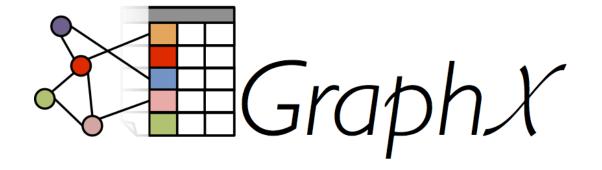


 Spark, GraphX, and Blockchains: Building a Behavioral Analytics Platform for Fraud, and C BLOCKCYPHER **Finance**



Multi-Label Graph Analysis and Computations Using GraphX





Thank you