GraphX: *Unifying Table and Graph Analytics*

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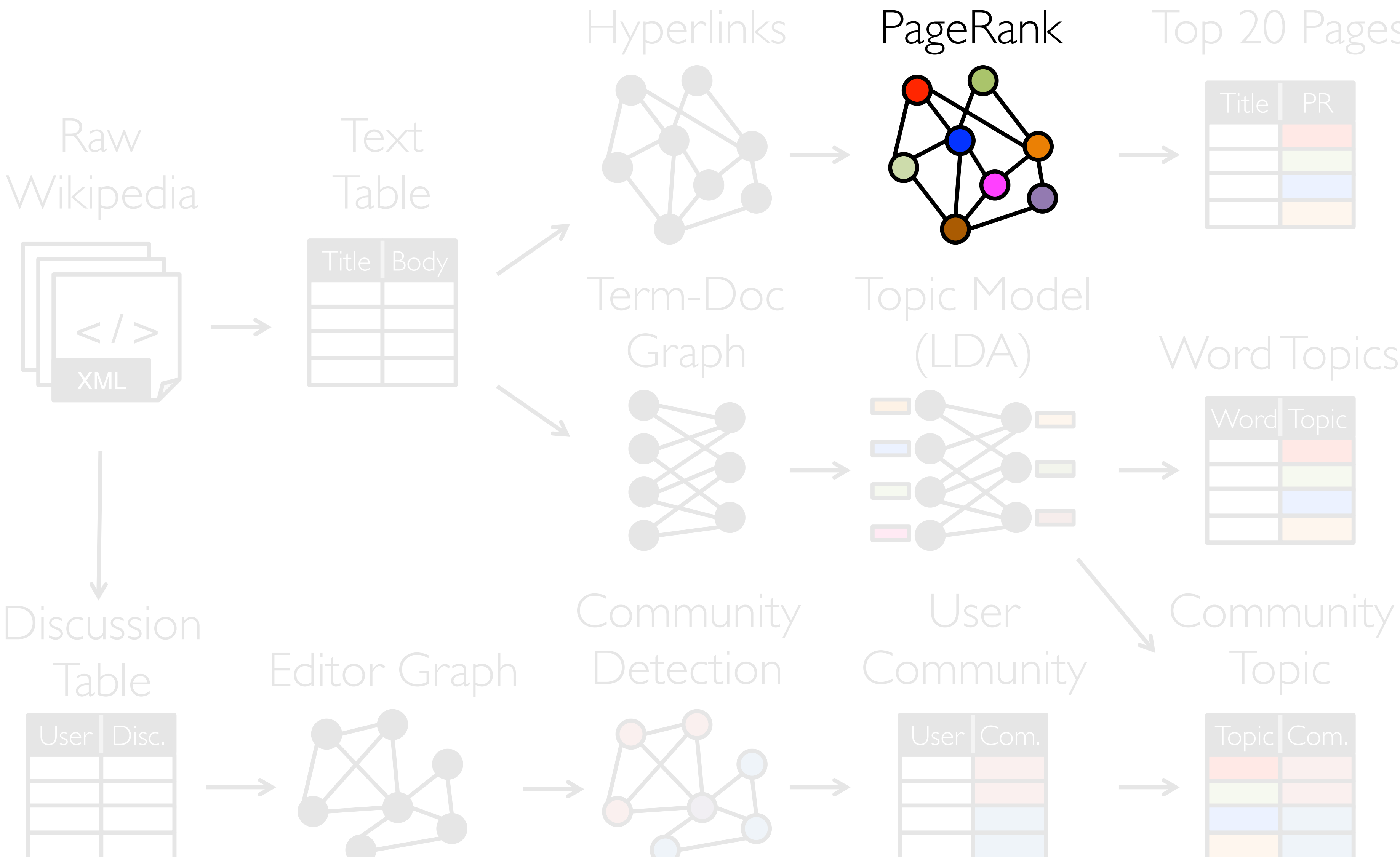
Joint work with Reynold Xin, Daniel Crankshaw, Ankur Dave, Michael Franklin, and Ion Stoica

IPDPS 2014

*These slides are best viewed in PowerPoint with animation.

Graphs are Central to Analytics



PageRank: Identifying Leaders

$$R[i] = 0.15 + \sum_{j \in \mathrm{Nbrs}(i)} w_{ji} R[j]$$

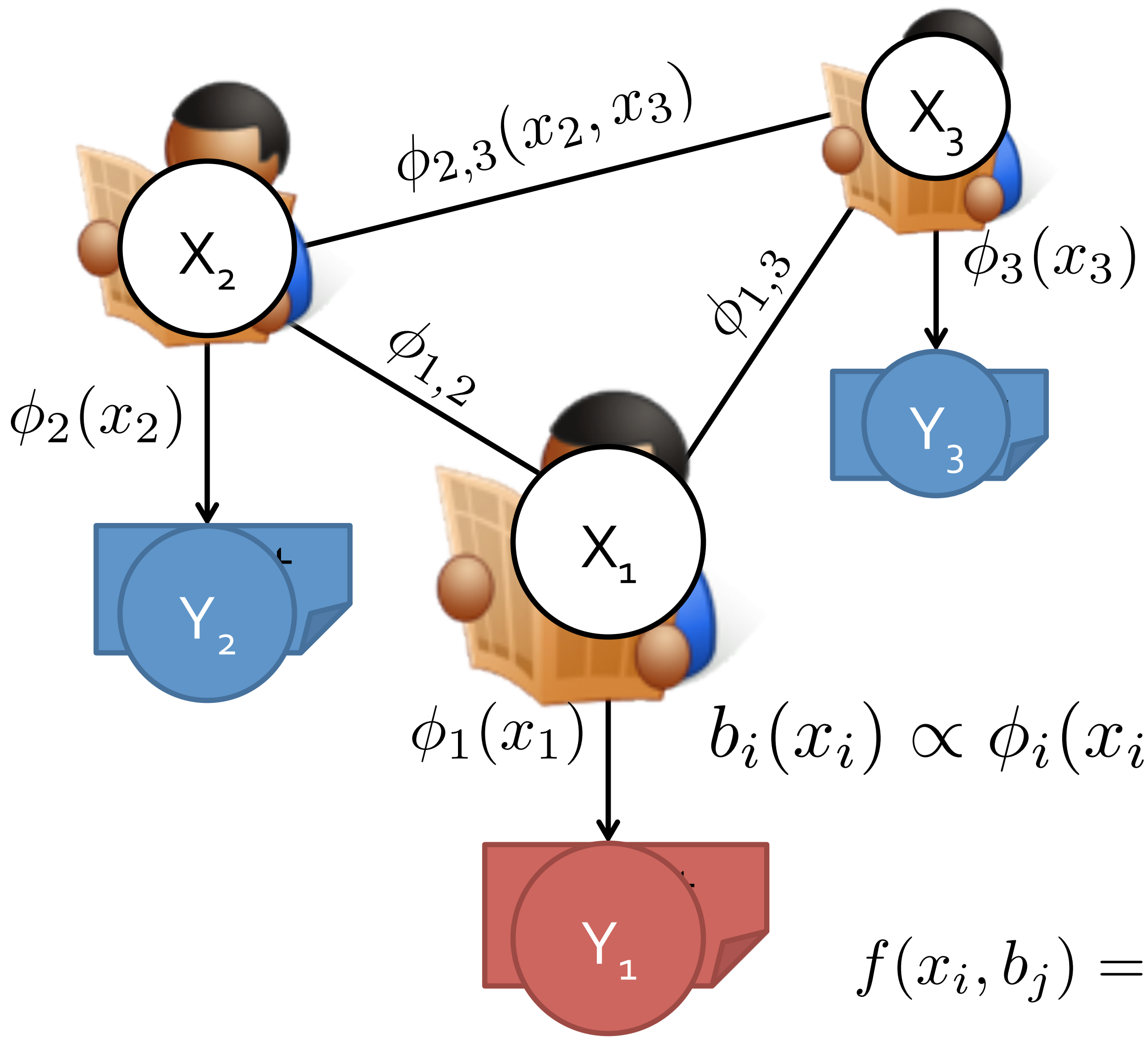
Rank of user *i*

Weighted sum of neighbors' ranks

Update ranks in parallel

Iterate until convergence

Mean Field Algorithm

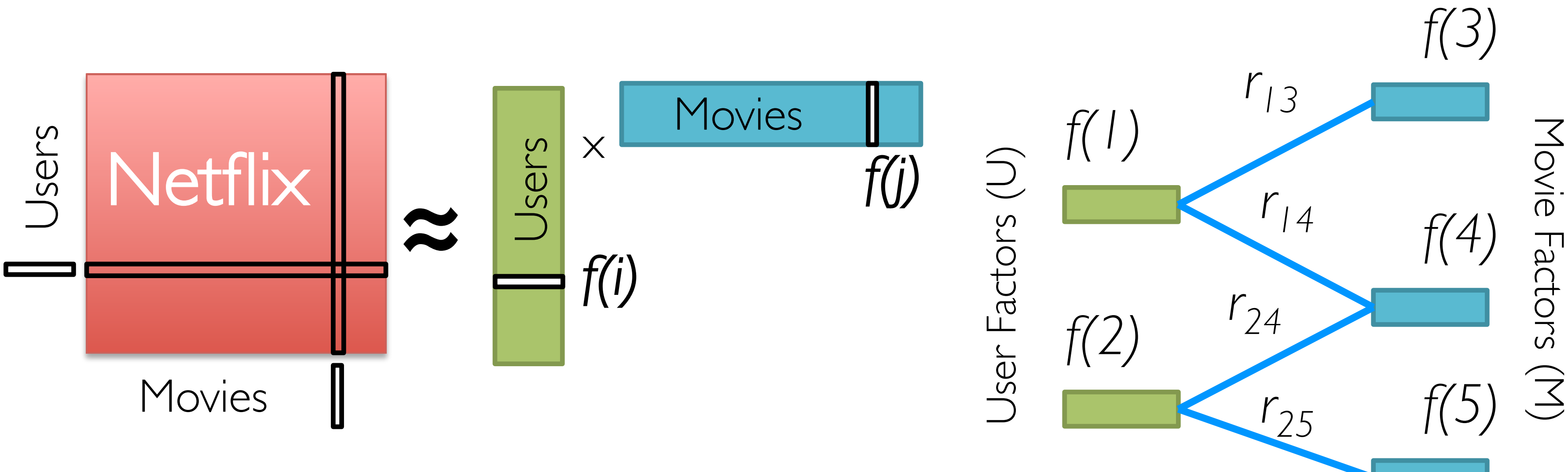


$$b_i(x_i) \propto \phi_i(x_i) \exp\left(\overbrace{\sum_{j \in N_i} f(x_i, b_j)}^{\text{Sum over Neighbors}} \right)$$

$$f(x_i, b_j) = \sum_{x_j} b_j(x_j) \log \phi_{i,j}(x_i, x_j)$$

Recommending Products

Low-Rank Matrix Factorization:

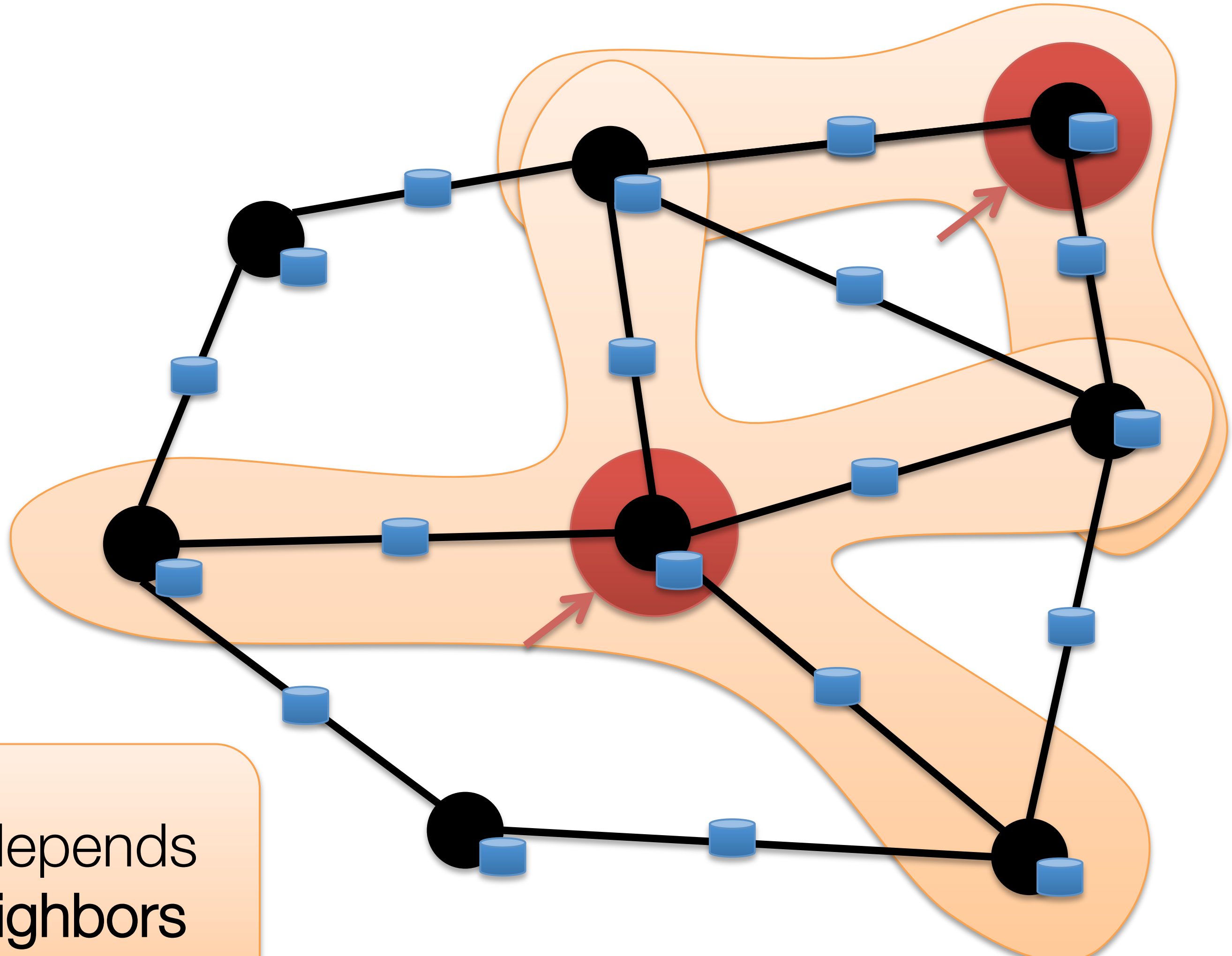


Iterate:

$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \mathrm{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

The Graph-Parallel Pattern

Model / Alg. State



Computation depends only on the **neighbors**

Many Graph-Parallel 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

MACHINE LEARNING

- Community Detection
  - Triangle-Counting
  - K-core Decomposition
  - K-Truss
- Graph Analytics
  - PageRank
  - Personalized PageRank
  - Shortest Path
  - Graph Coloring
- Classification
  - Neural Networks

SOCIAL NETWORK ANALYSIS

GRAPH ALGORITHMS

Graph-Parallel Systems

Pregel oogle

APACHE GIRAPH

GraphLab

Expose specialized APIs to simplify graph programming.

"Think like a Vertex."

- Pregel [SIGMOD'10]

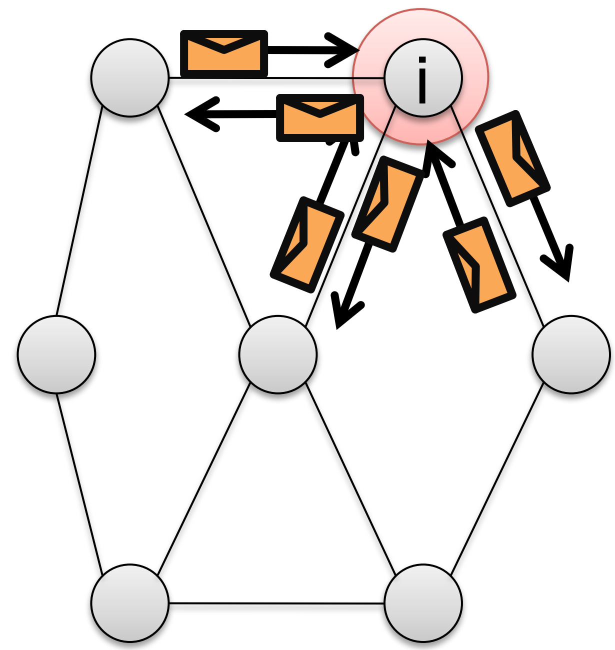
The Pregel (Push) Abstraction

Vertex-Programs interact by sending **messages.**

```
Pregel_PageRank(i, messages) :
  // Receive all the messages
  total = 0
  foreach( msg in messages) :
    total = total + msg

  // Update the rank of this vertex
  R[i] = 0.15 + total

  // Send new messages to neighbors
  foreach(j in out_neighbors[i]) :
    Send msg(R[i]) to vertex j
```



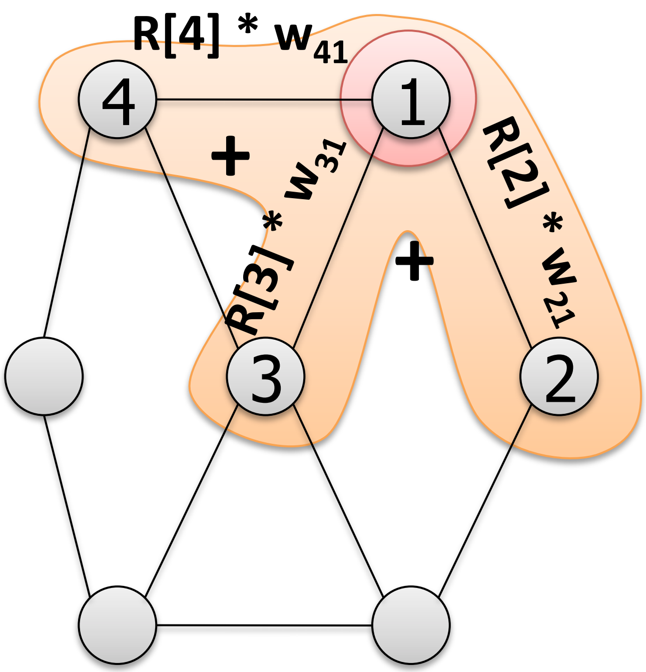
Malewicz et al. [PODC'09, SIGMOD'10]

The GraphLab (Pull) Abstraction

Vertex Programs directly **access** adjacent vertices and edges

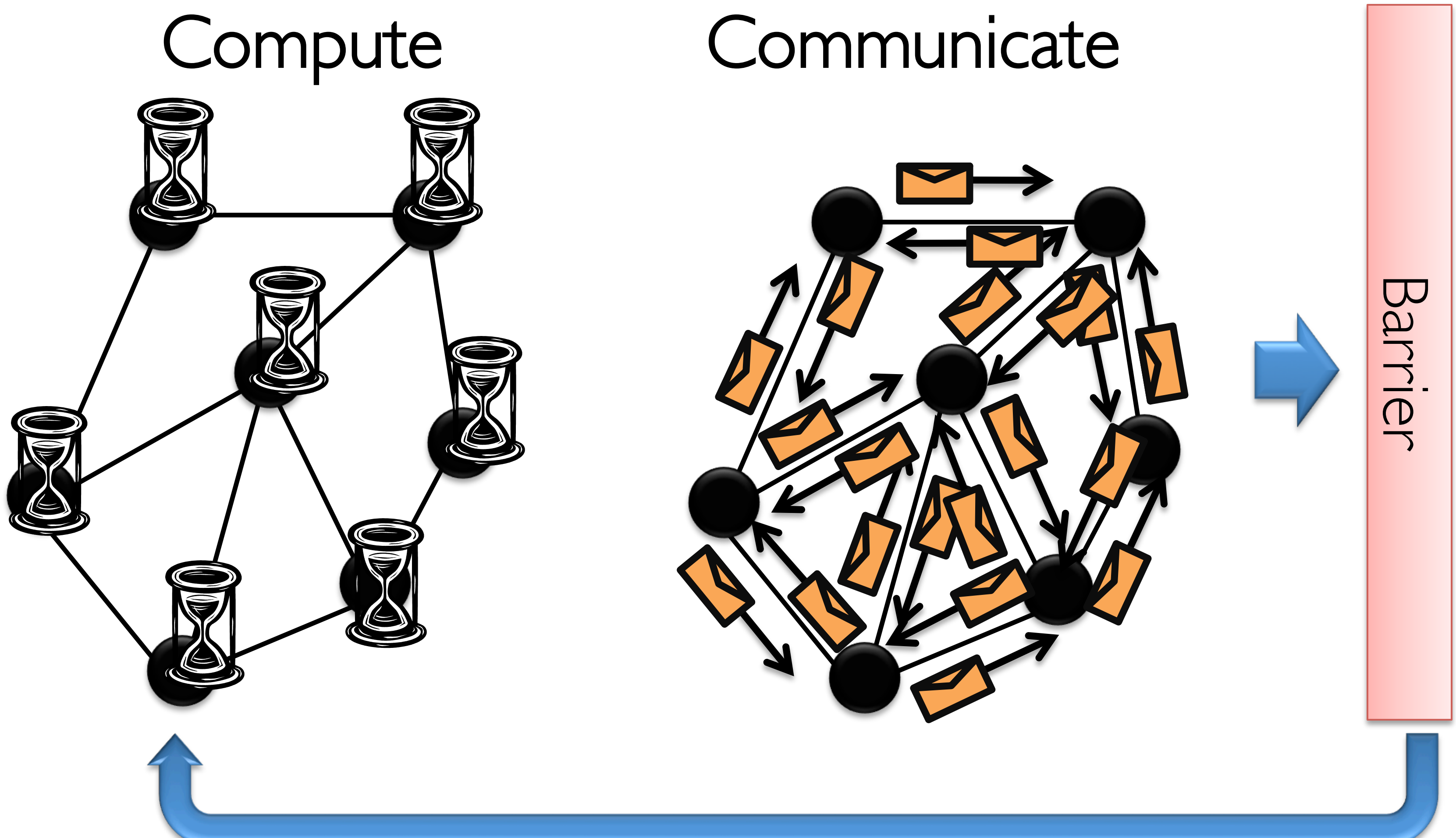
```
GraphLab_PageRank(i)
  // Compute sum over neighbors
  total = 0
  foreach( j in neighbors(i)):
    total = total + R[j] * w_ji

  // Update the PageRank
  R[i] = 0.15 + total
```



Data movement is managed by the system and not the user.

Iterative Bulk Synchronous Execution



Graph-Parallel Systems

Pregel oogle

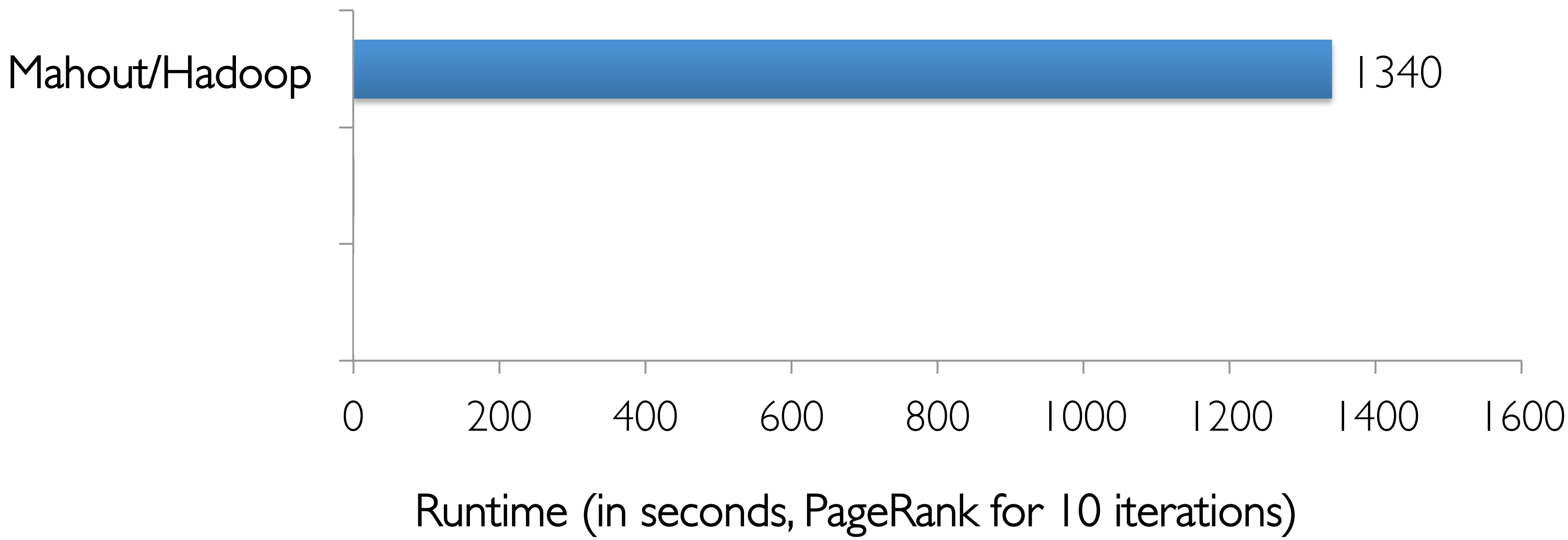
APACHE GIRAPH

GraphLab

Expose specialized APIs to simplify graph programming.

Exploit graph structure to achieve orders-of-magnitude performance gains over more general data-parallel systems.

PageRank on the Live-Journal Graph



Spark is *4x faster* than Hadoop
GraphLab is *16x faster* than Spark

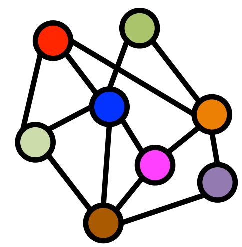
Triangle Counting on Twitter

40M Users, 1.4 Billion Links

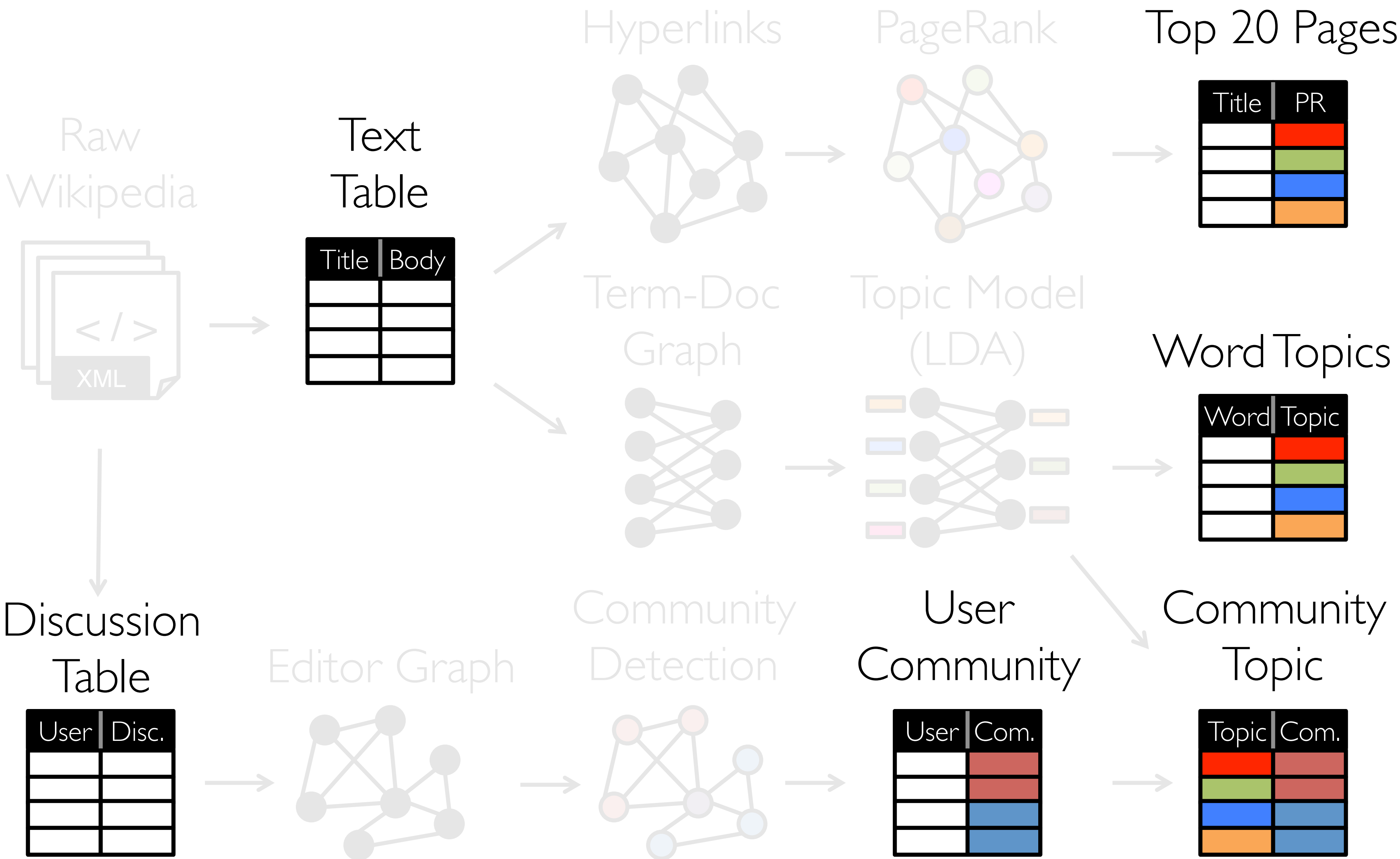
Counted: 34.8 Billion Triangles

S. Suri and S. Vassilvitskii, "Counting triangles and the curse of the last reducer," WWW'11

PageRank

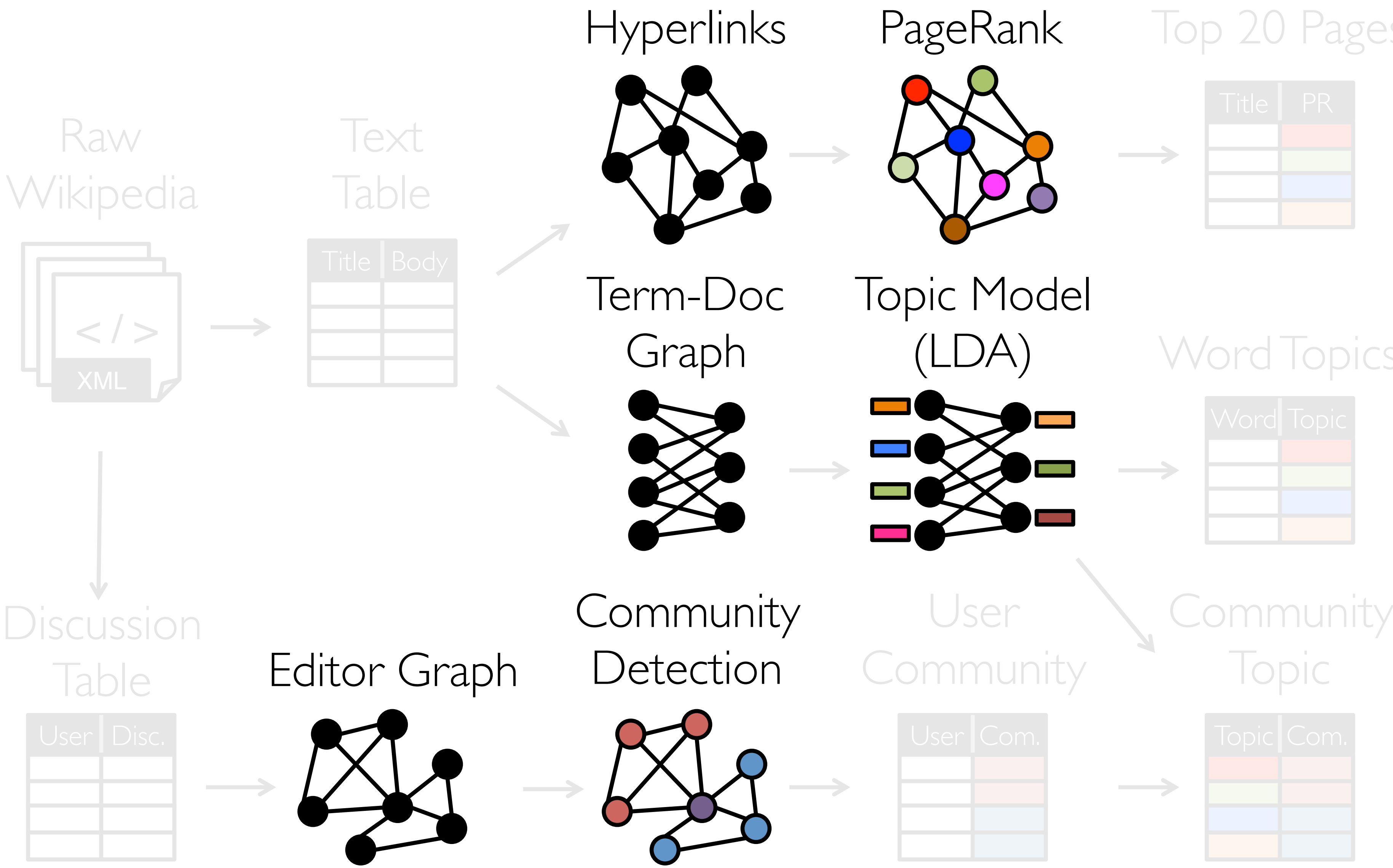


Tables



Raw Wikipedia
< / >
XML
Text Table
Title
Body
Hyperlinks
PageRank
Top 20 Pages
Title
PR
Term-Doc Graph
Topic Model (LDA)
Word Topics
Word
Topic
Discussion Table
User
Disc.
Editor Graph
Community Detection
User Community
User
Com.
Community Topic
Topic
Com.

Graphs



Hyperlinks
PageRank
Top 20 Pages
Title
PR
Raw Wikipedia
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XML
Text Table
Title
Body
Term-Doc Graph
Topic Model (LDA)
Word Topics
Word
Topic
Discussion Table
User
Disc.
Editor Graph
Community Detection
User Community
User
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Community Topic
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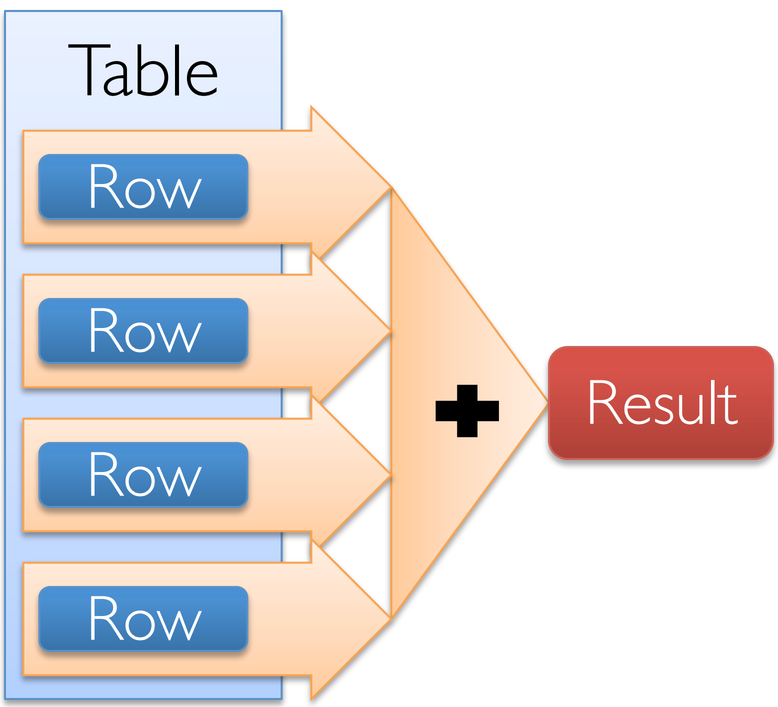
Com.

Separate Systems to Support Each View

Table View

Hadoop

Spark



Graph View

Pregel

GraphLab

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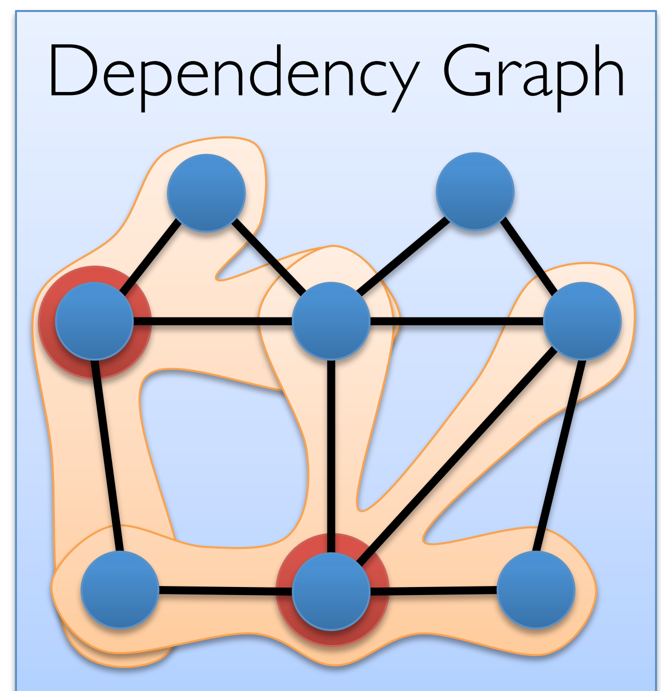


Having separate systems for each view is difficult to use and inefficient

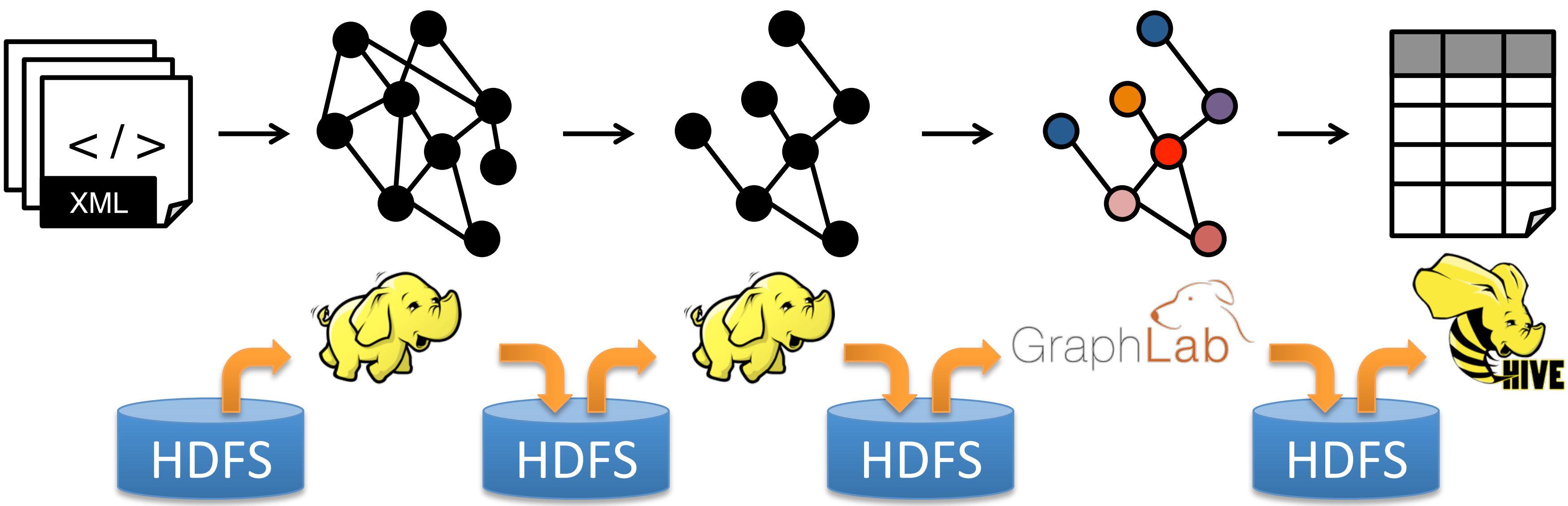
Difficult to Program and Use

Users must *Learn*, *Deploy*, and *Manage* multiple systems

Leads to brittle and often complex interfaces

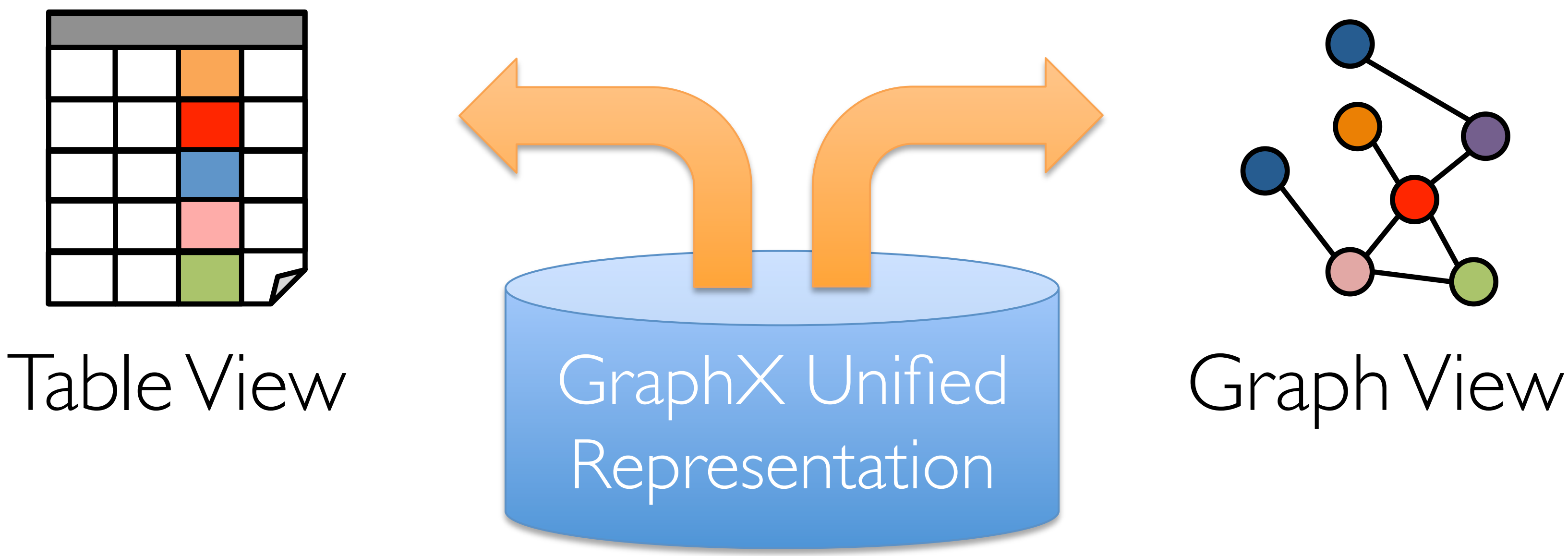
Inefficient

Extensive data movement and duplication across the network and file system



Limited reuse internal data-structures across stages

GraphX Solution: Tables and Graphs are *views* of the *same physical* data



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

Graphs → Relational Algebra

1. Encode graphs as distributed tables
2. Express graph computation in relational algebra
3. Recast graph systems optimizations as:
    1. Distributed join optimization
    2. Incremental materialized maintenance

Integrate Graph and Table data processing systems.

Achieve performance parity with specialized systems.

Distributed Graphs as Distributed Tables

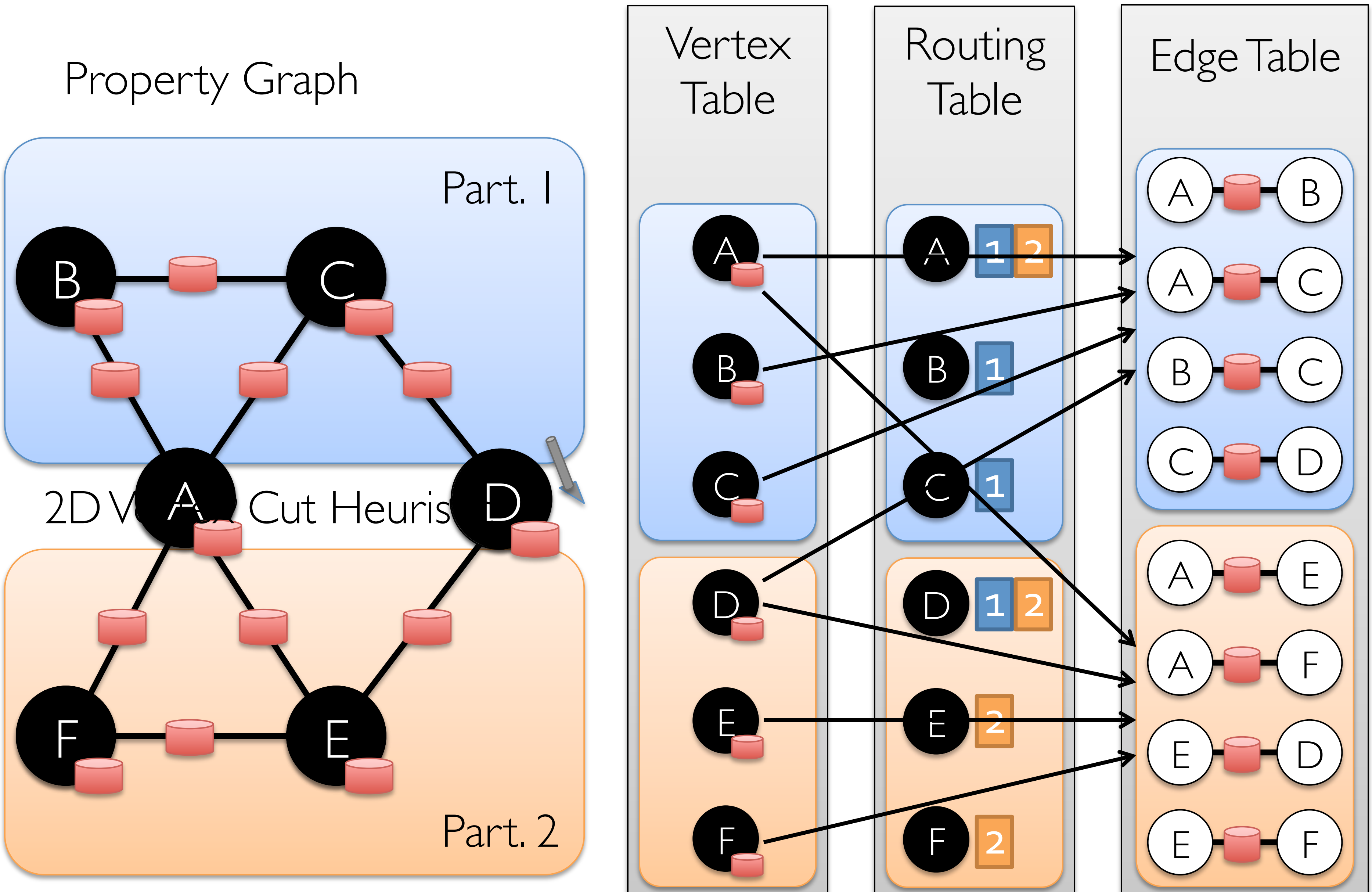


Table Operators

Table 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`	`...`

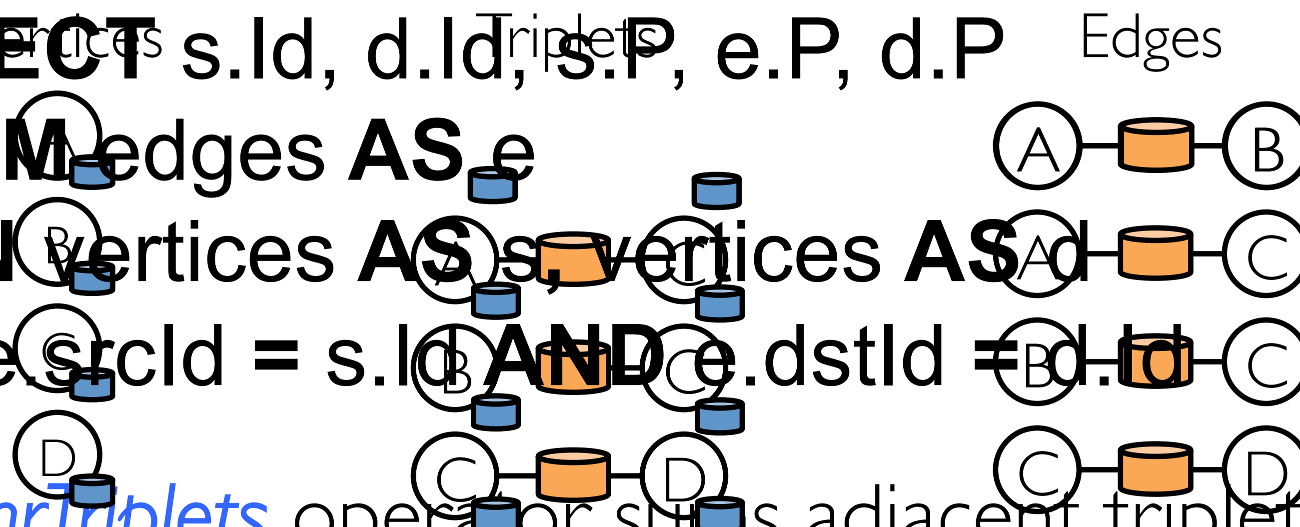
Graph Operators

```
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] => 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]
}
```

Triplets Join Vertices and Edges

The *triplets* operator joins vertices and edges:

SELECT s.Id, d.Id, s.P, e.P, d.P
FROM edges **AS** e
JOIN vertices **AS** s, vertices **AS** d
ON e.srcId = s.Id **AND** e.dstId = d.Id



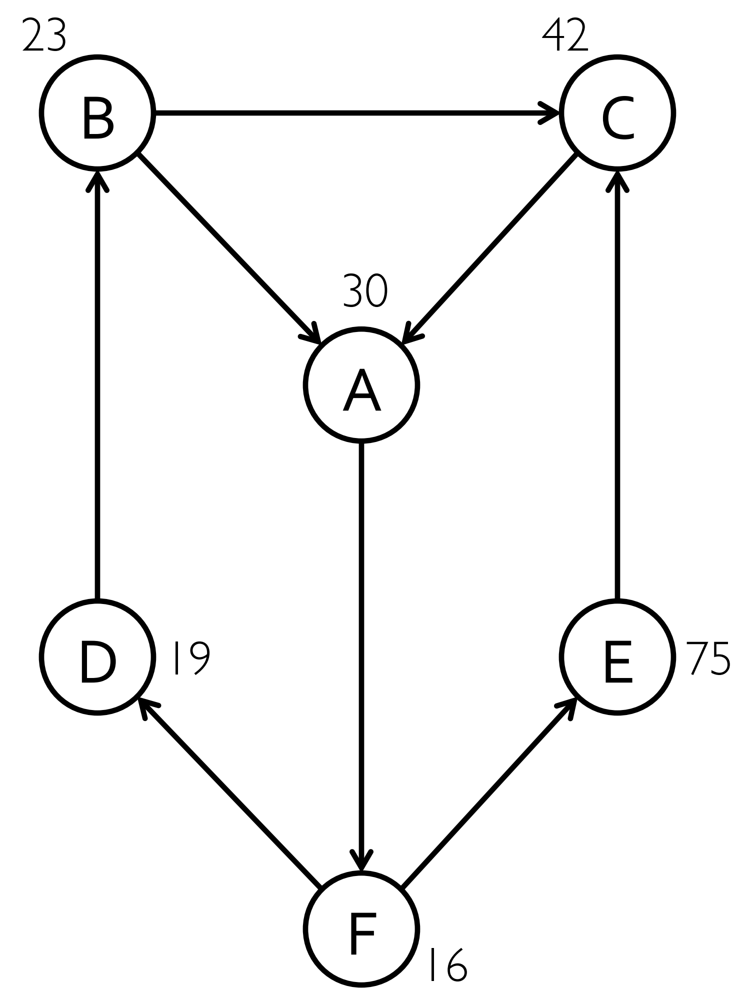
The *mrTriplets* operator sums adjacent triplets.

SELECT t.dstId, *reduce*(*map*(t)) **AS** sum
FROM triplets **AS** t **GROUPBY** t.dstId

Example: Oldest Follower

Calculate the number of older followers for each user?

```
val olderFollowerAge = graph
  .mrTriplets(
    e => // Map
     if(e.src.age < e.dst.age) {
       (e.srcId, 1)
     else { Empty }
    ,
    (a,b) => a + b // Reduce
  )
  .vertices
```



We express *enhanced* Pregel and GraphLab abstractions using the GraphX operators in less than 50 lines of code!

Enhanced Pregel in GraphX

```
pregelPR(i, messageSum):
  // Receive all the messages
  total = 0
  foreach( msg in messageList) :
    total = total + msg

  // Update the rank of this vertex
  R[i] = 0.15 + total

  // Send new messages to neighbors
  foreach(j in out_neighbors[i]) :
    Send msg(R[i]/E[i,j]) to vertex
```

messageSum

Require Message Combiners

```
combineMsg(a, b):
  // Compute sum of two messages
  return a + b

sendMsg(i→j, R[i], R[j], E[i,j]):
  // Compute single message
  return msg(R[i]/E[i,j])
```

Remove Message Computation from the Vertex Program

Malewicz et al. [PODC'09, SIGMOD'10]

PageRank in GraphX

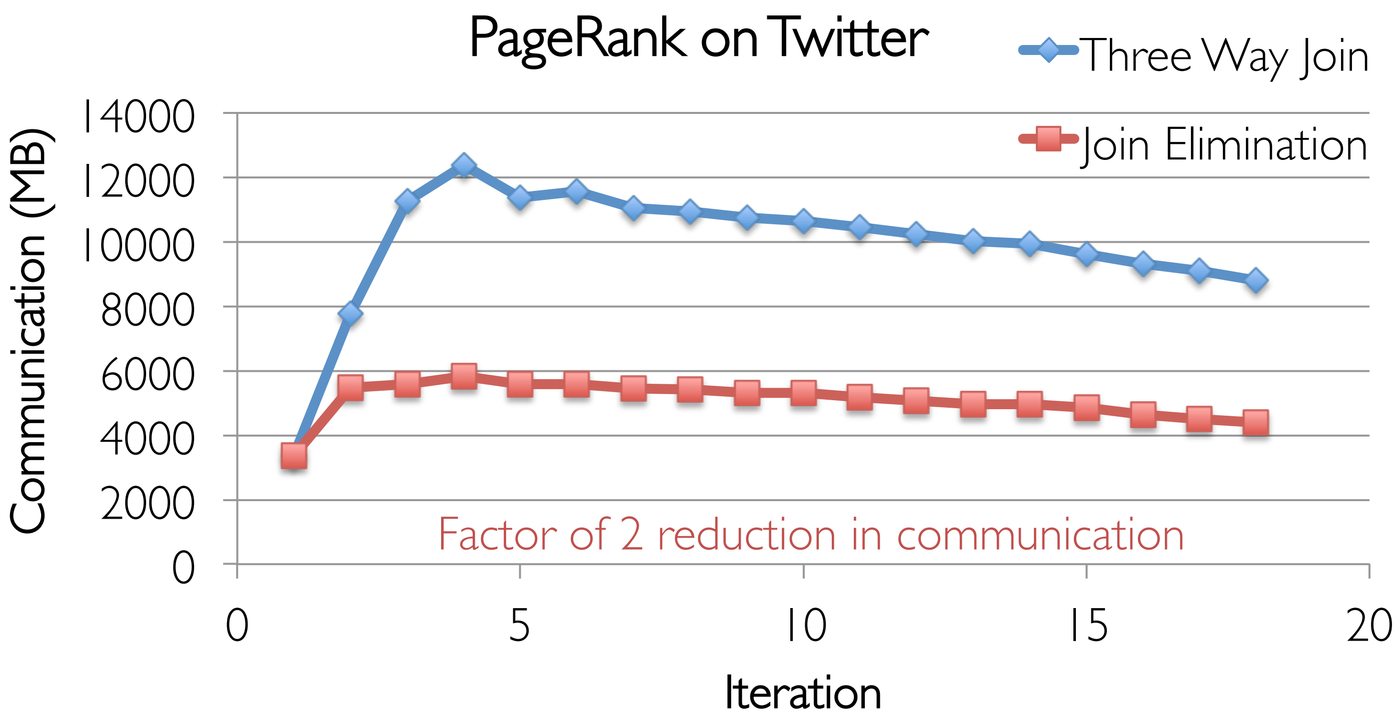
```
// Load and initialize the graph
val graph = GraphBuilder.text("hdfs://web.txt")
val prGraph = graph.joinVertices(graph.outDegrees)

// Implement and Run PageRank
val pageRank =
  prGraph.pregel(initialMessage = 0.0, iter = 10)(
    (oldV, msgSum) => 0.15 + 0.85 * msgSum,
    triplet => triplet.src.pr / triplet.src.deg,
    (msgA, msgB) => msgA + msgB)
```

Join Elimination

Identify and bypass joins for unused triplet fields

```
sendMsg(i→j, R[i], R[j], E[i,j]):
  // Compute single message
  return msg(R[i]/E[i,j])
```



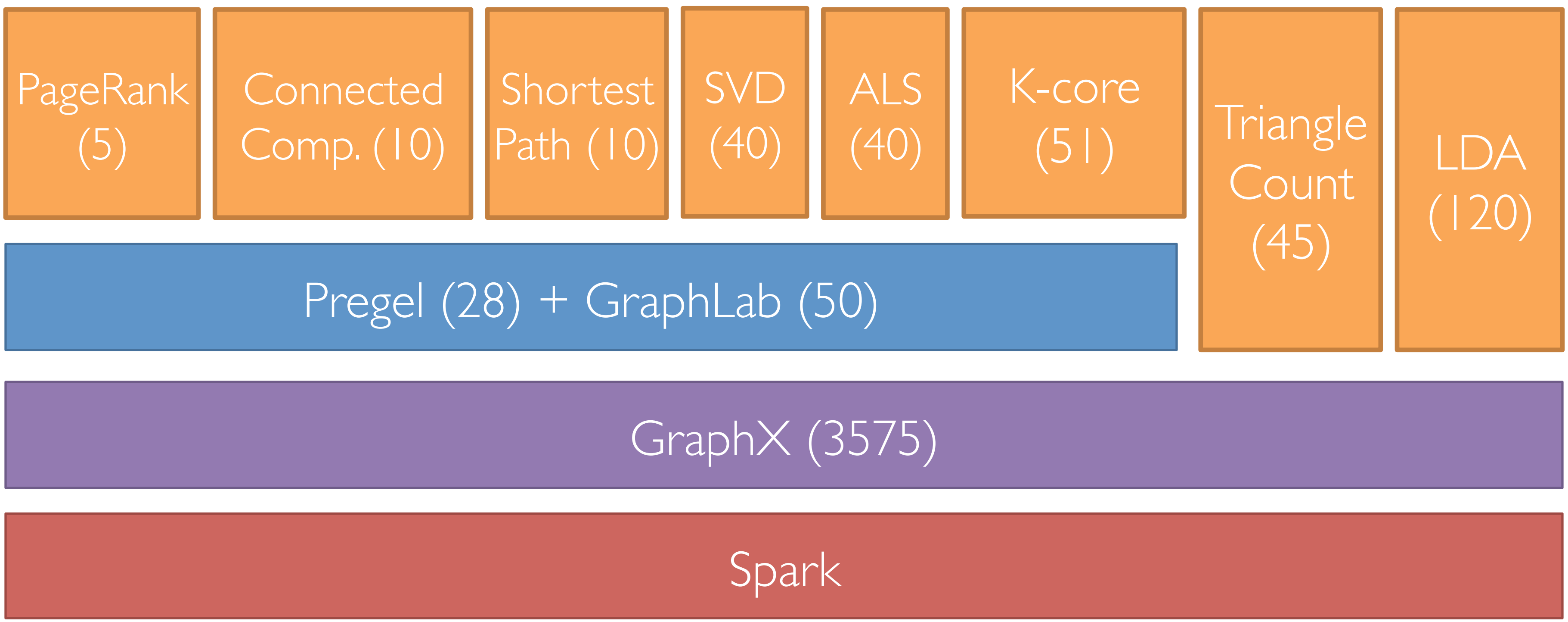
We express the Pregel and GraphLab *like* abstractions using the GraphX operators in less than 50 lines of code!

By composing these operators we can construct entire graph-analytics pipelines.

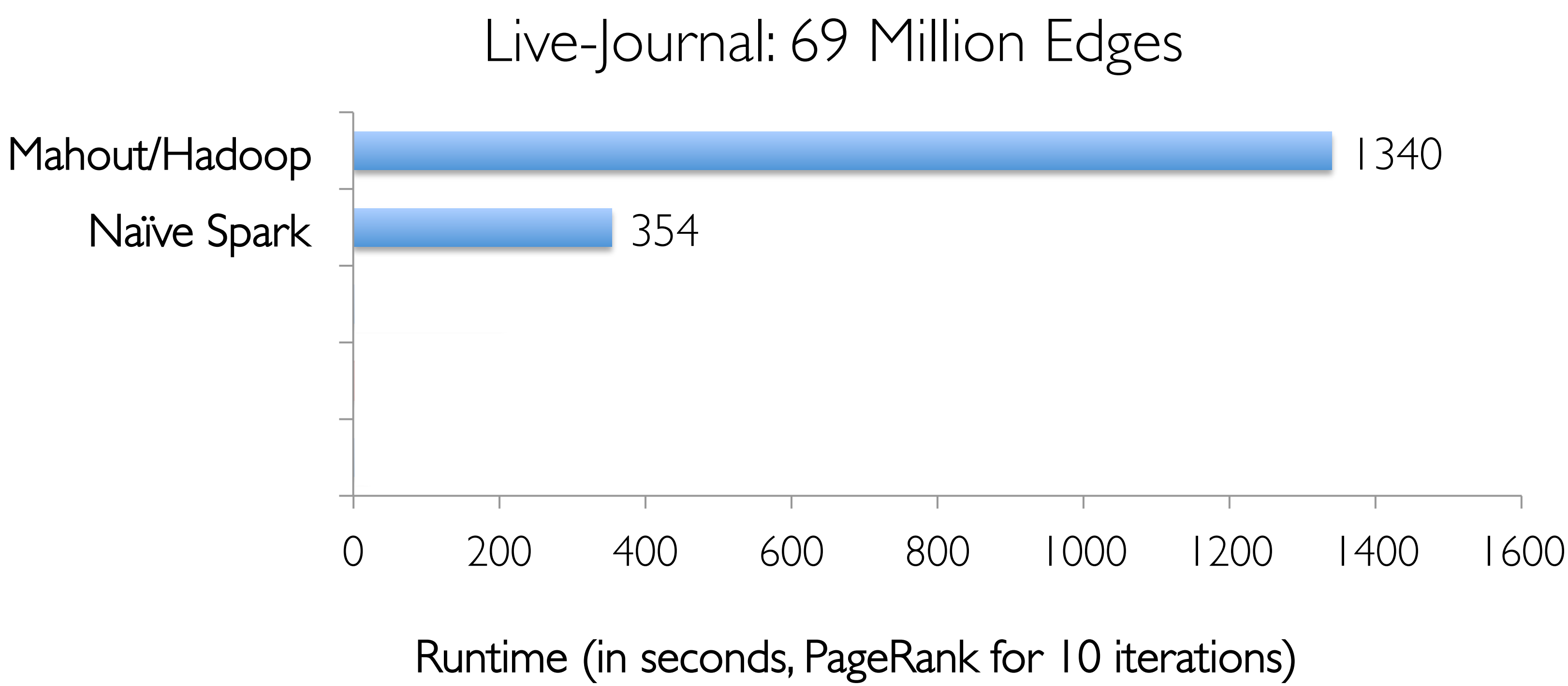
Example Analytics Pipeline

```
// Load raw data tables
val verts = sc.textFile("hdfs://users.txt").map(parserV)
val edges = sc.textFile("hdfs://follow.txt").map(parserE)
// Build the graph from tables and restrict to recent links
val graph = new Graph(verts, edges)
val recent = graph.subgraph(edge => edge.date > LAST_MONTH)
// Run PageRank Algorithm
val pr = graph.PageRank(tol = 1.0e-5)
// Extract and print the top 25 users
val topUsers = verts.join(pr).top(25).collect
topUsers.foreach(u => println(u.name + '\t' + u.pr))
```

The GraphX Stack (Lines of Code)

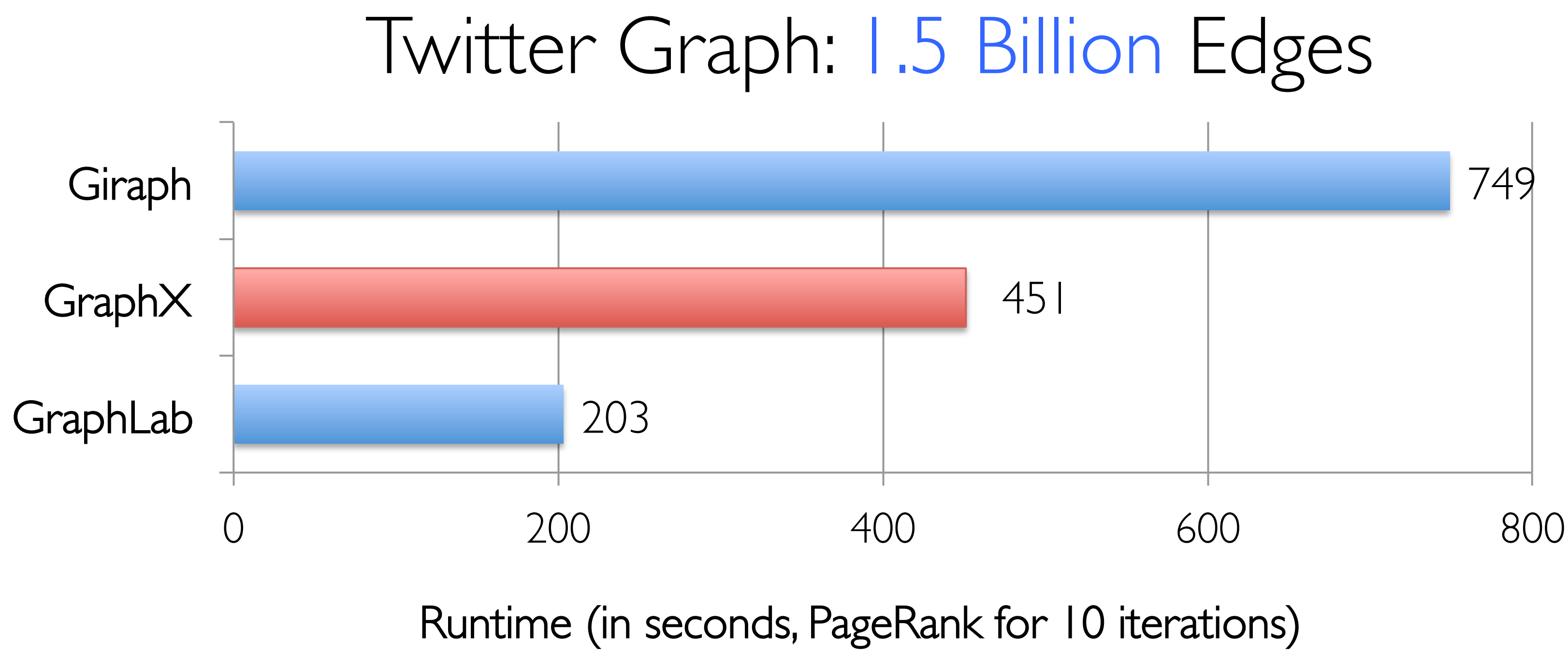


Performance Comparisons



GraphX is roughly 3x slower than GraphLab

GraphX scales to larger graphs



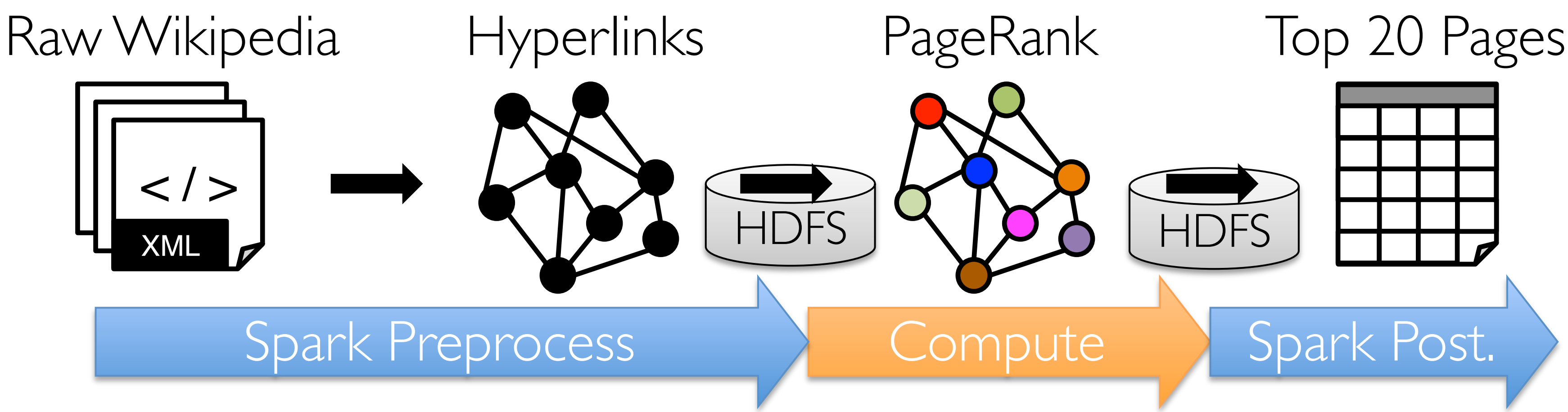
GraphX is roughly 2x slower than GraphLab

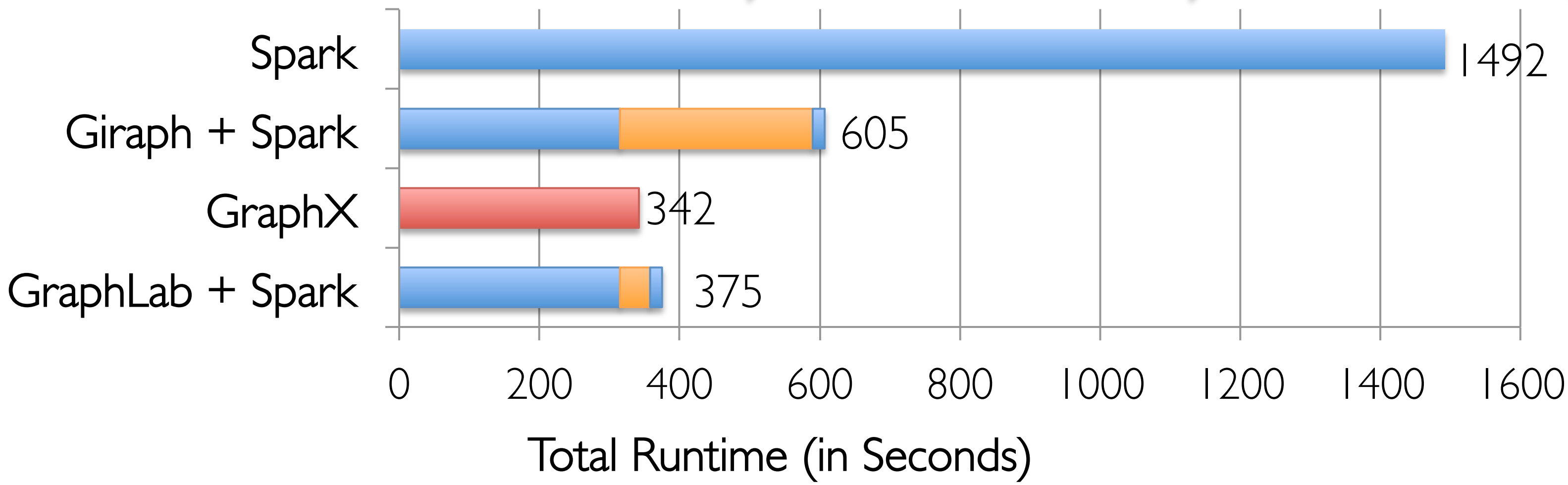
- » Scala + Java overhead: Lambdas, GC time, …
- » No shared memory parallelism: 2x increase in comm.

PageRank is just one stage….

What about a pipeline?

A Small Pipeline in GraphX

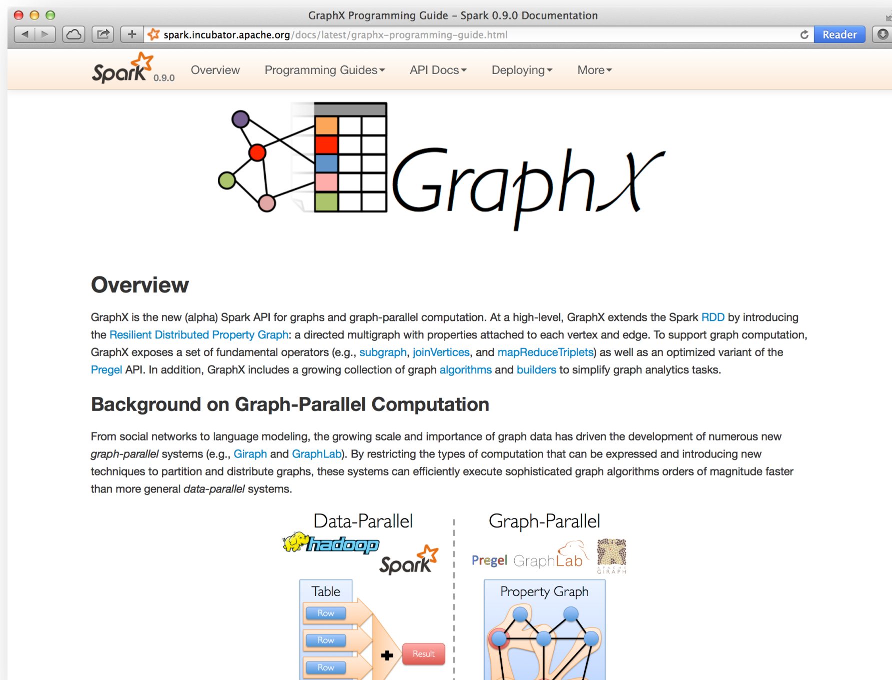




Timed end-to-end GraphX is *faster* than GraphLab

Status

Part of Apache Spark

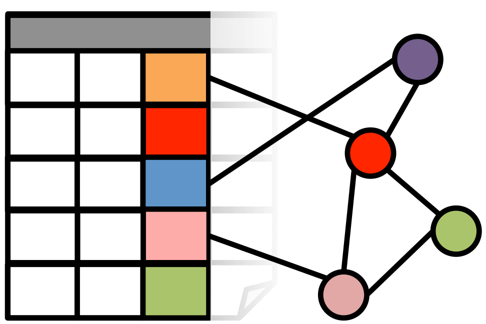


In production at several large technology companies

GraphX: Unified Analytics

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

A Case for Algebra in Graphs

A standard algebra is essential for graph systems:

- e.g.: SQL → proliferation of relational system

By embedding graphs in *relational algebra:*

- Integration with tables and preprocessing
- Leverage advances in relational systems
- Graph opt. recast to relational systems opt.

Conclusions

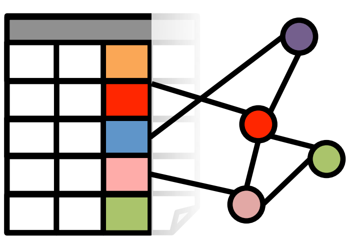
Composable domain specific views and operators

Single system that efficiently spans the pipeline

Graphs through the lens of database systems

» Graph-Parallel Pattern → Triplet joins in relational alg.

» Graph Systems → Distributed join optimizations



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http://tinyurl.com/ampgraphx

UC BERKELEY

Thanks!

http://amplab.cs.berkeley.edu/projects/graphx/

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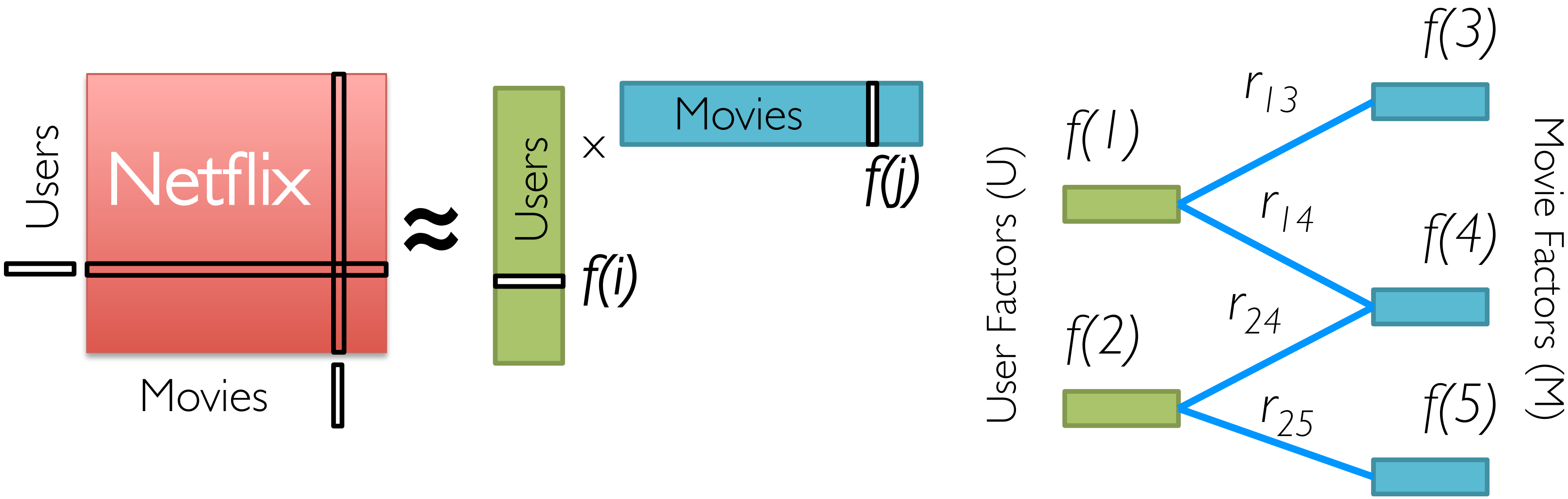
Recommending Products

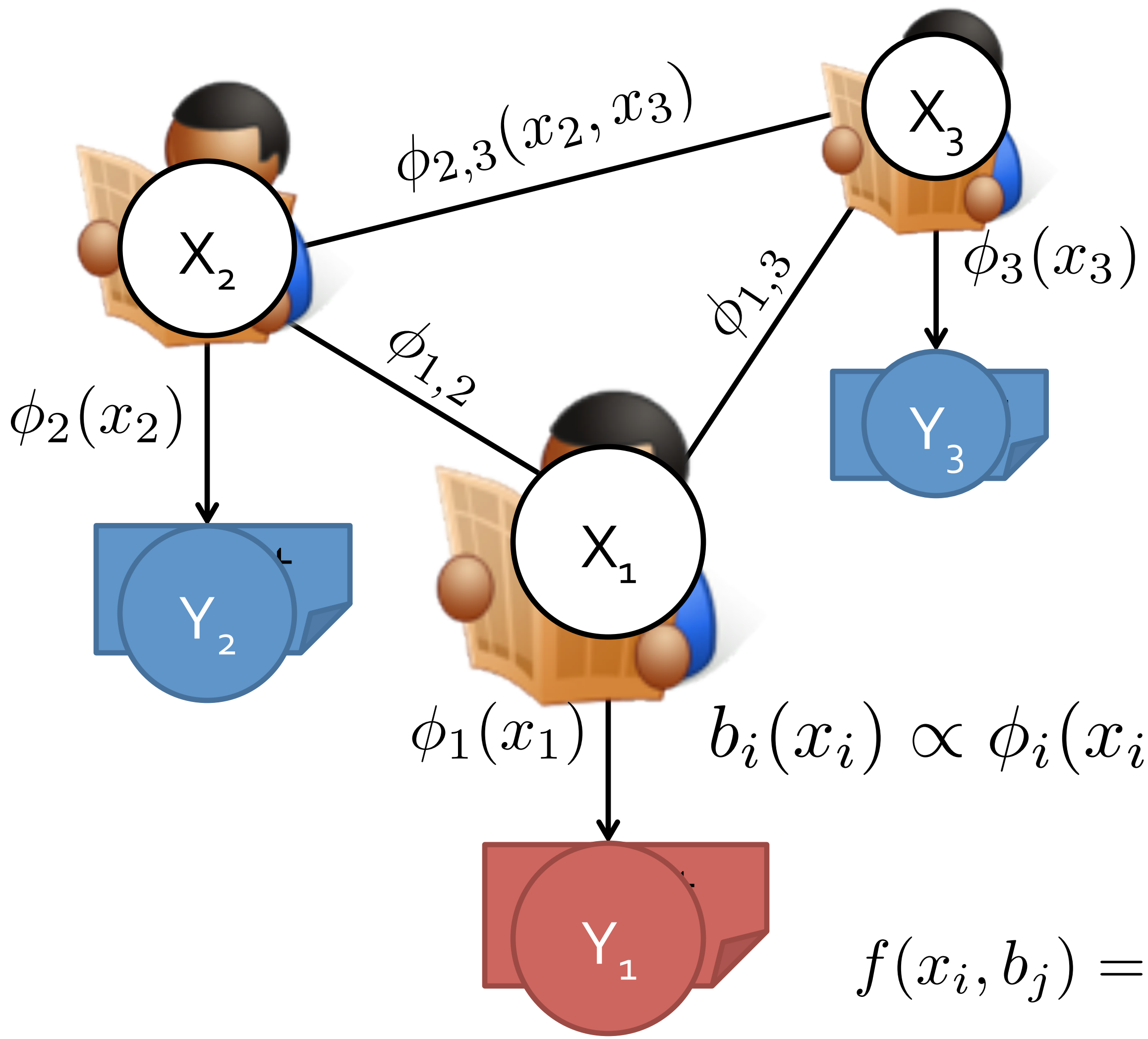
Low-Rank Matrix Factorization:



Iterate:

$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \mathrm{Nbrs}(i)} \left(r_{ij} - w^T f[j] \right)^2 + \lambda ||w||_2^2$$

Mean Field Algorithm

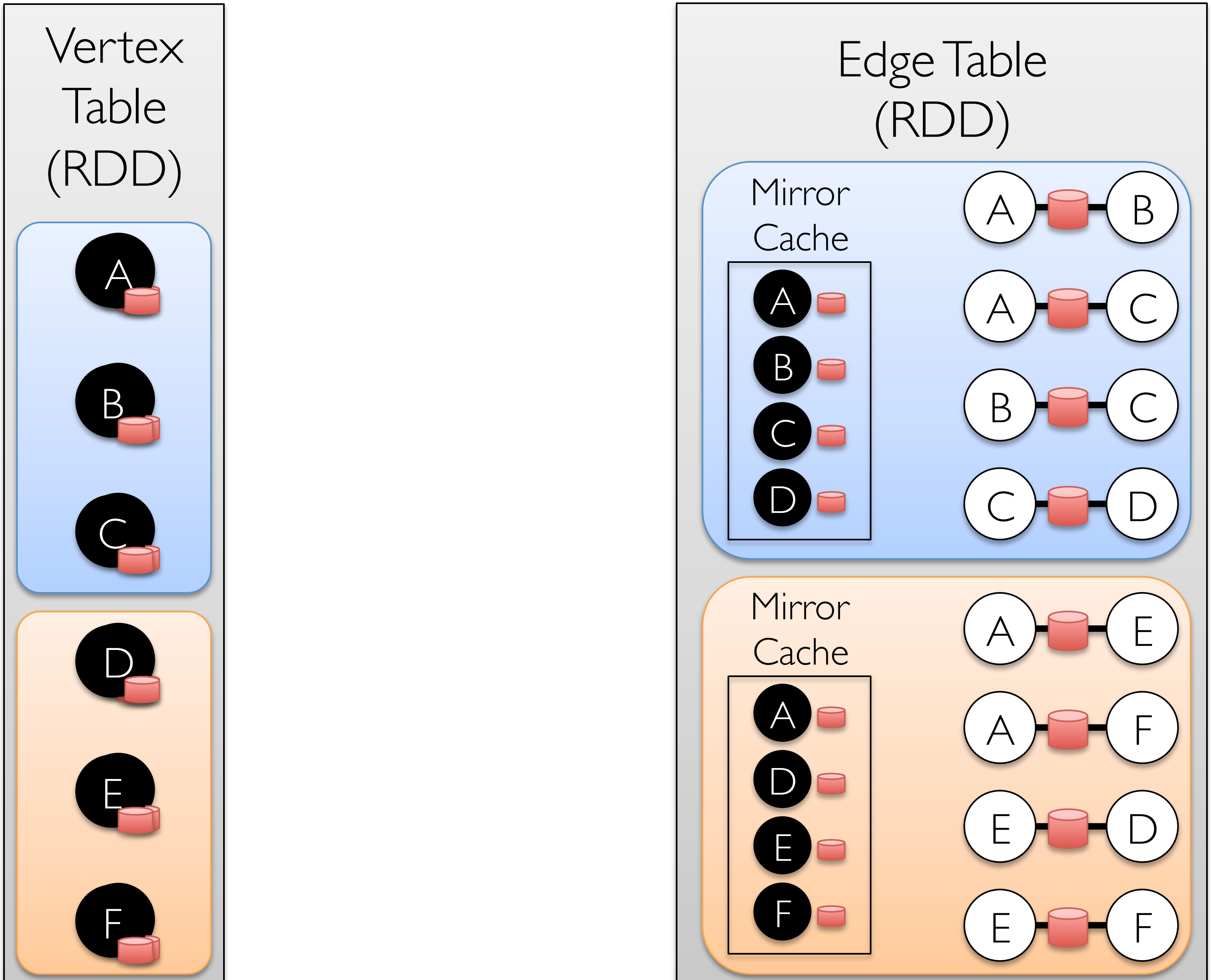


$$b_i(x_i) \propto \phi_i(x_i) \exp\left(\overbrace{\sum_{j \in N_i} f(x_i, b_j)}^{\text{Sum over Neighbors}} \right)$$

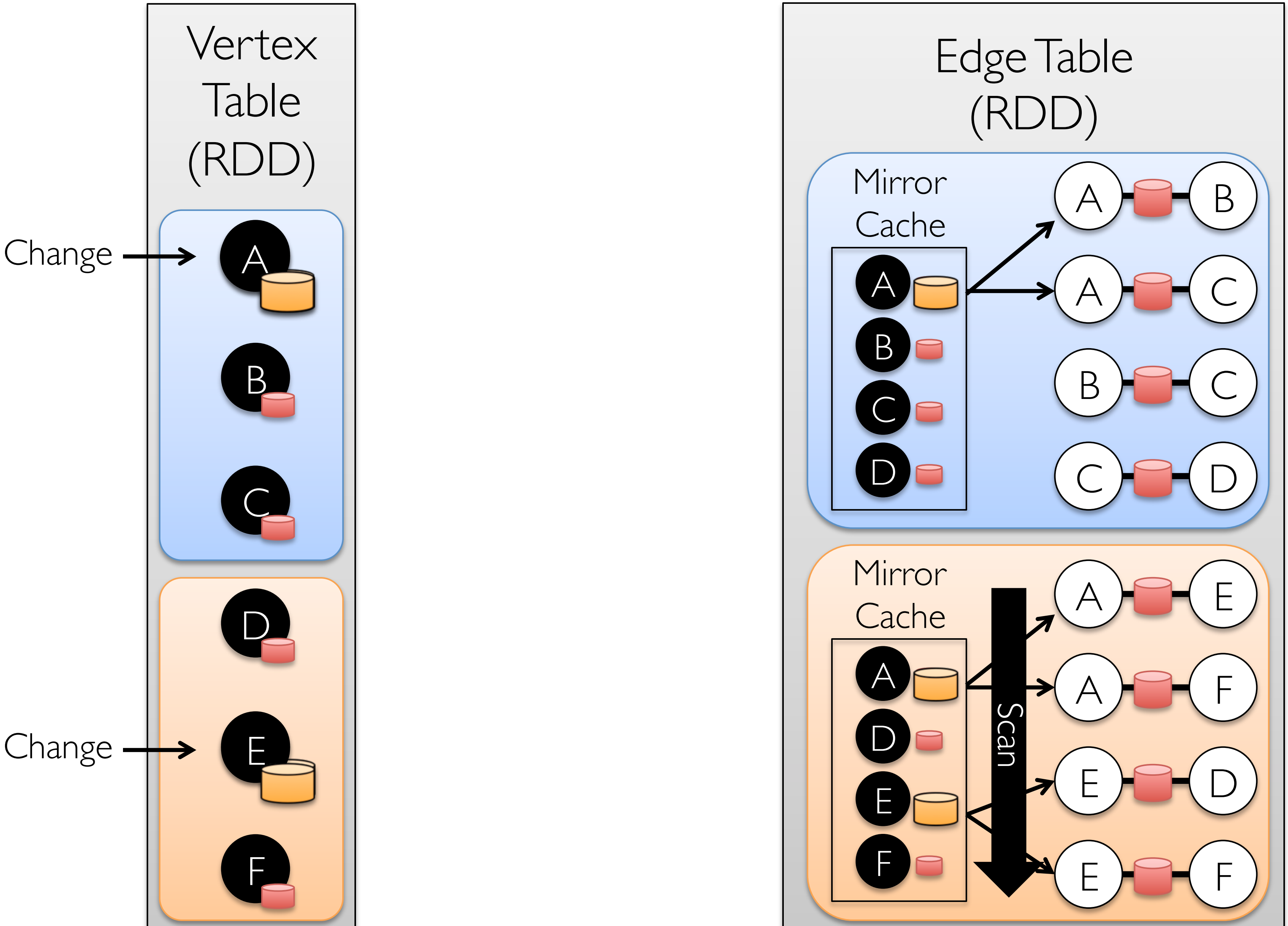
$$f(x_i, b_j) = \sum_{x_j} b_j(x_j) \log \phi_{i,j}(x_i, x_j)$$

GraphX System Design

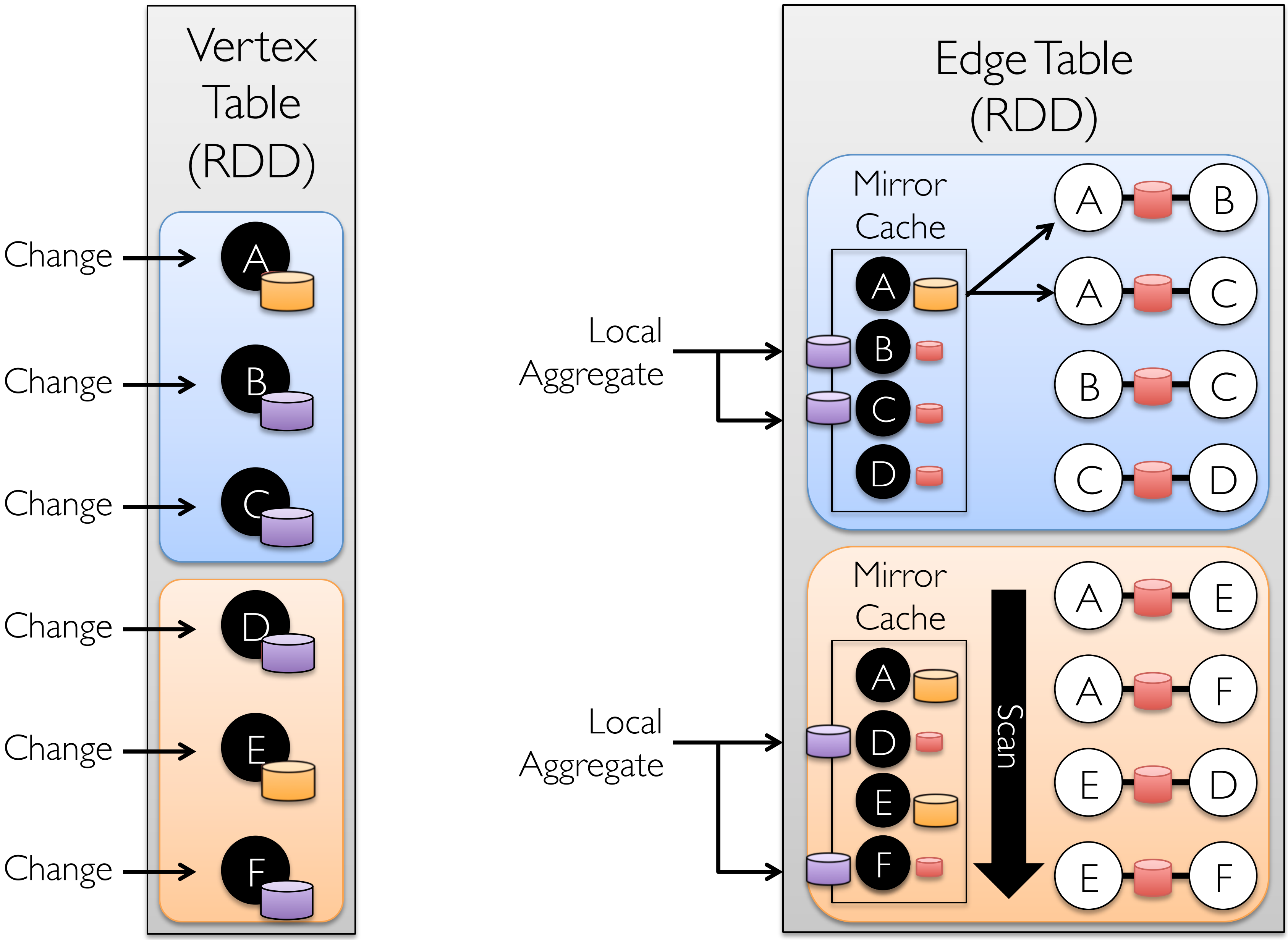
Caching for Iterative mrTriplets



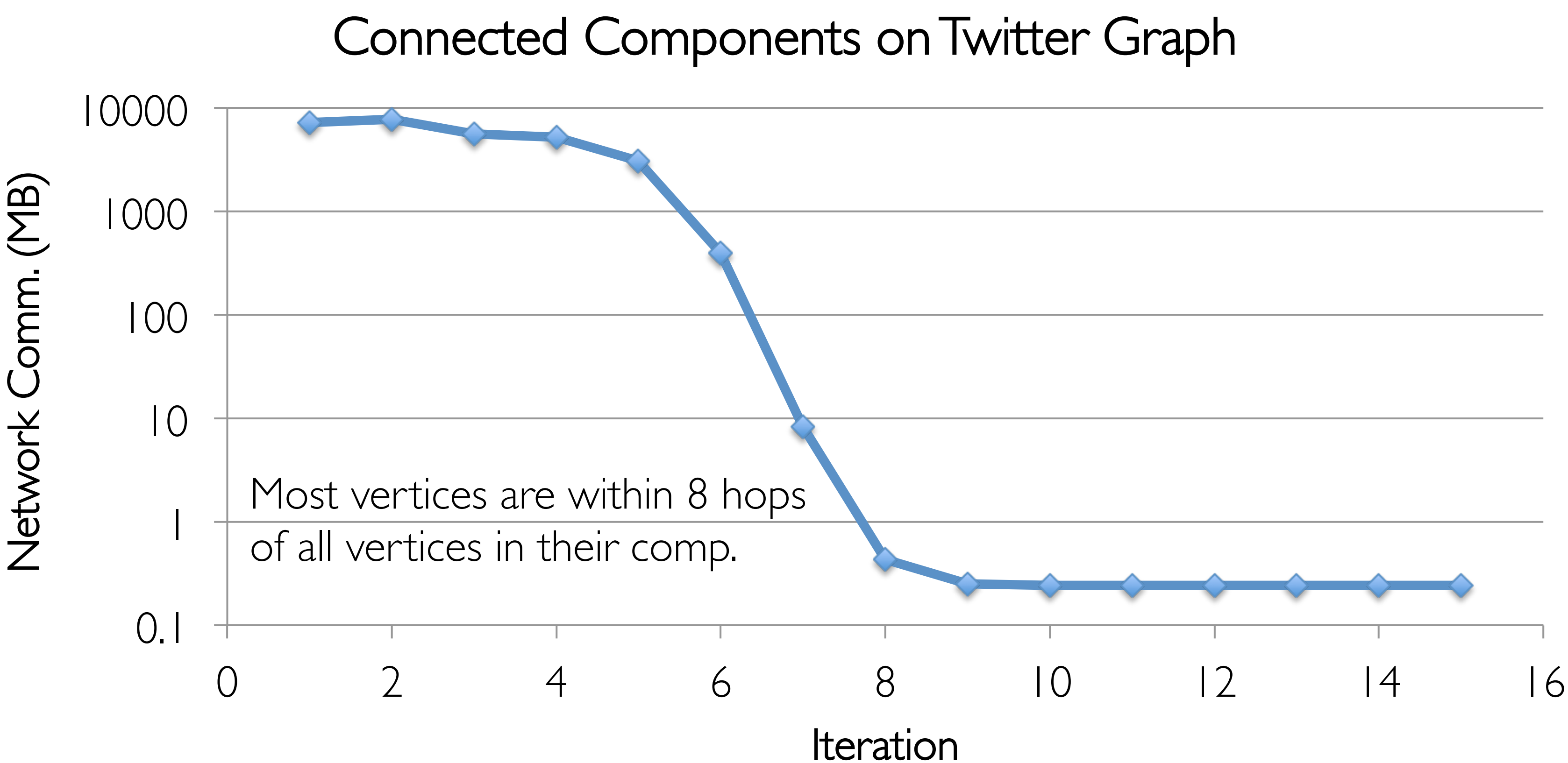
Incremental Updates for Iterative mrTriplets



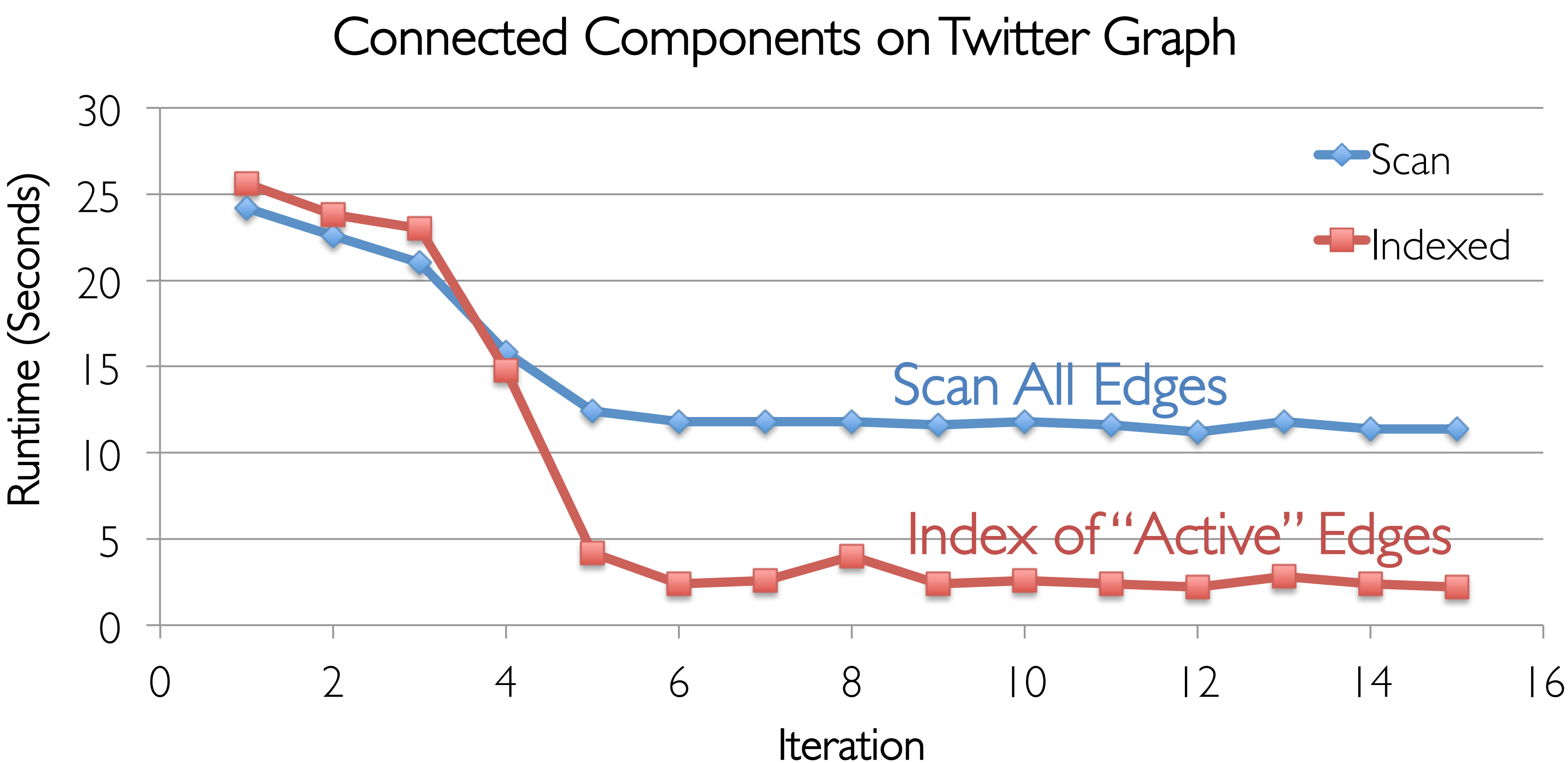
Aggregation for Iterative mrTriplets



Reduction in Communication Due to Cached Updates



Benefit of Indexing *Active* Edges



Additional Query Optimizations

Indexing and Bitmaps:

» To accelerate joins across graphs

» To efficiently construct sub-graphs

Substantial Index and Data Reuse:

» Reuse routing tables across graphs and sub-graphs

» Reuse edge adjacency information and indices