GraphX : Graph Processing in a Distributed Dataflow Framework

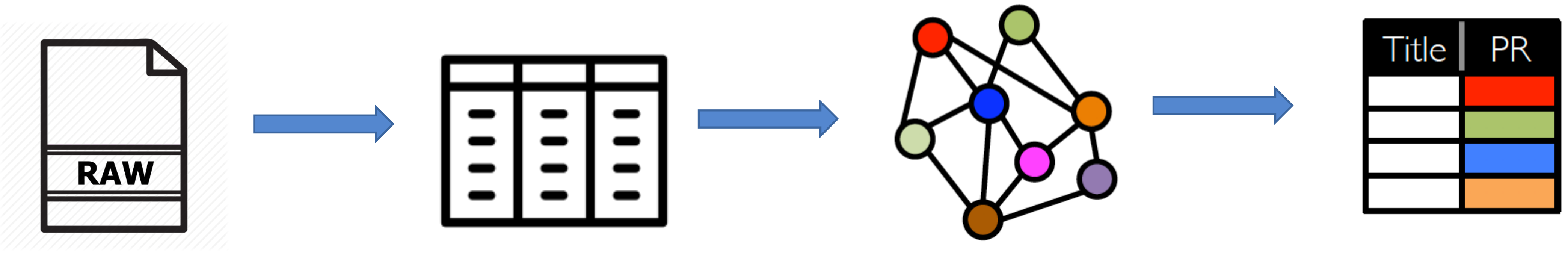
OSDI 2014

Bidyut Hota

Agenda

- Analytics space background
- Motivation
- Goal
- Approach
- Optimizations
- Results
- Flaws/Limitations
- Questions

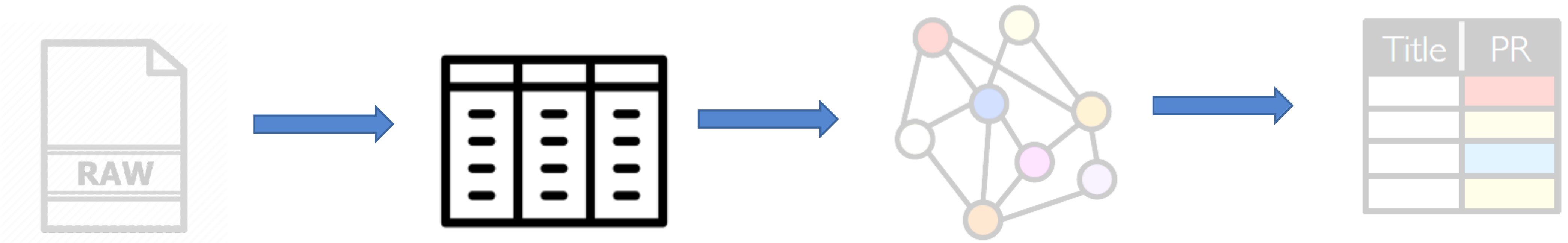
Real life Analytics Pipeline



Raw data | Link Table | Page Rank | Desired results

Eg. Google Knowledge graph :570MVertices, 18B Edges (as in Mid 2017)

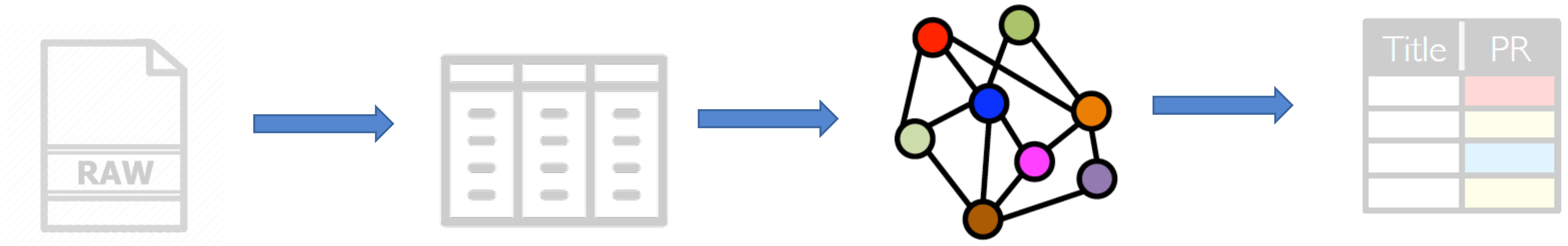
Real life Analytics Pipeline



Raw data Link Table Page Rank Desired results

Tables

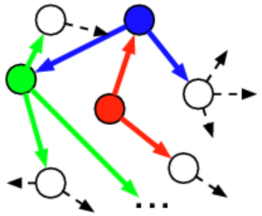
Real life Analytics Pipeline

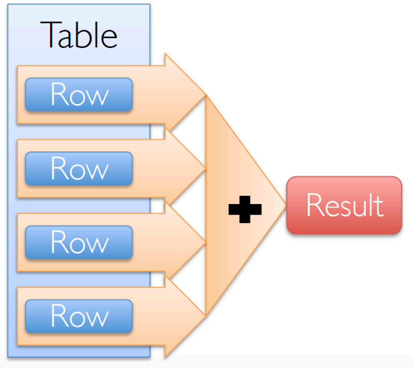


Raw data Link Table Page Rank Desired results

Graphs

Pregel GraphLab APACHE GIRAPH





hadoop

Spark

Systems landscape

Motivation

- Currently separate systems exist to compute on these data representation.
- Ability to combine data sources.
- Enhance dataflow frameworks to leverage inherent positives.

Current drawbacks of dataflow frameworks

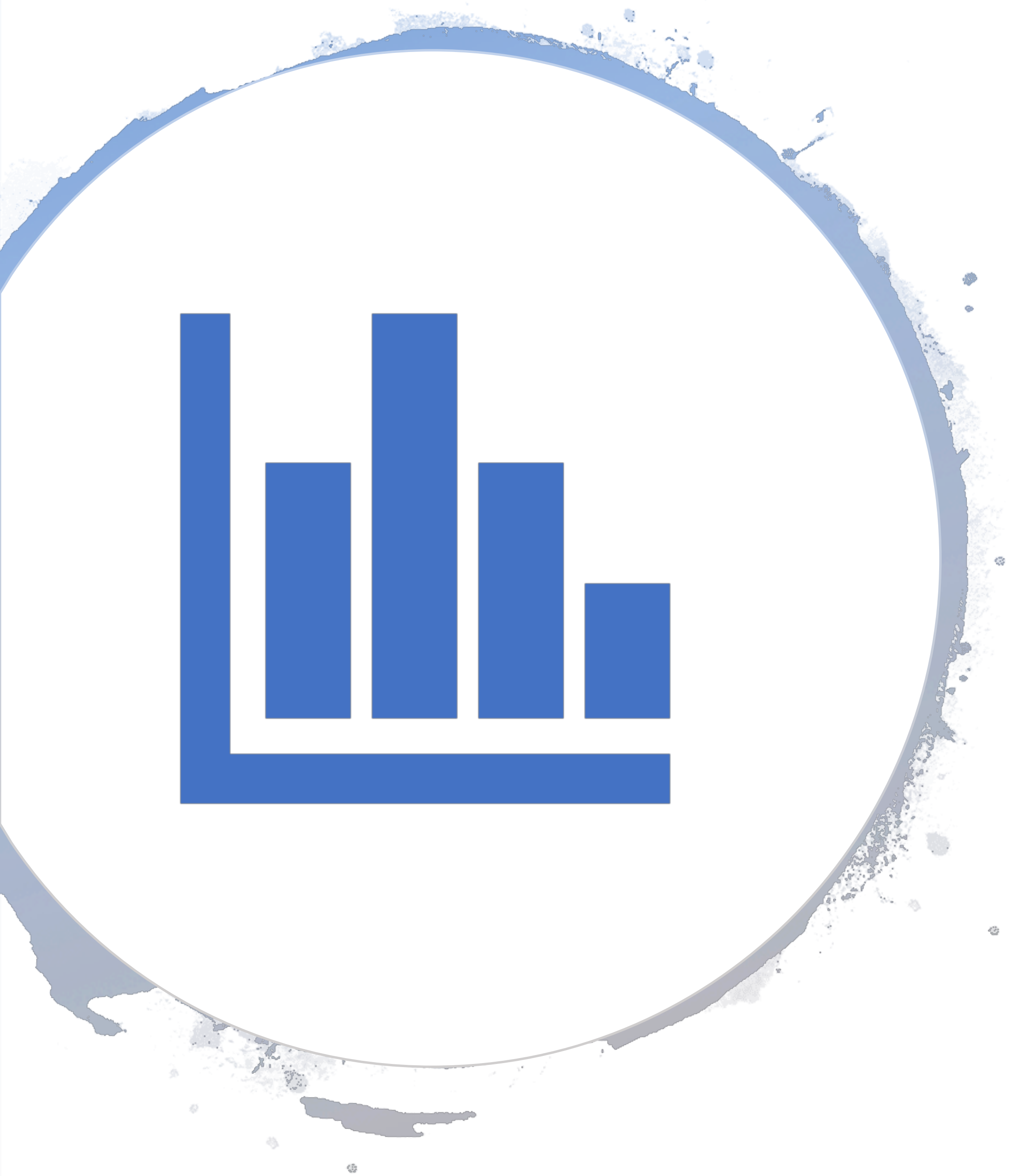
- Implementing iterative algorithms -> requires multiple stages of complex joins.
- Do not cover common patterns in graph algorithms -> Room for optimization.
- Unlike Spark, no fine grained control of data partitioning.

Current drawbacks of specialized systems

- Lacking ability for combining graphs with unstructured or tabular data
- Systems favoring snapshot recovery rather than fault tolerance like in Spark

What can we leverage?

- Immutability of RDD’s
- Reusing indices across graph and collection views over iterations.
- Increase in performance

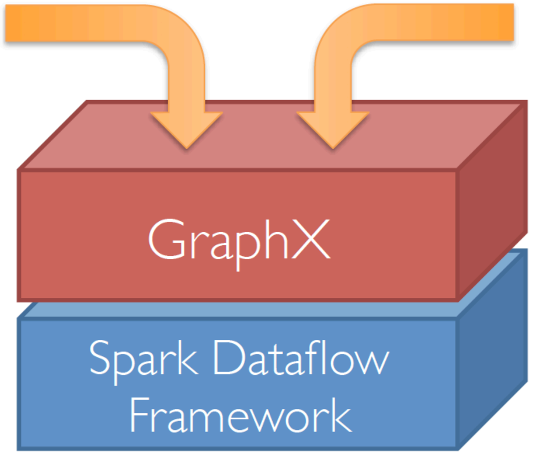


Goal

- General purpose distributed frameworks for graph computations
- Comparable performances to specialized graph processing systems

Approach

- Unifies Tabular view and Graph view
- Imbibe the best of specialized systems
- Graph representation on dataflow frameworks
- Optimizations
- Develop GraphX API on top of Spark



Graph approach: Page Rank example

- Eg. Page Rank algorithm
- Graph parallel abstraction
- Define a vertex program
- Terminate when vertex programs vote to halt

```
def PageRank(v: Id, msgs: List[Double]) {
  // Compute the message sum
  var msgSum = 0
  for (m <- msgs) { msgSum += m }
  // Update the PageRank
  PR(v) = 0.15 + 0.85 * msgSum
  // Broadcast messages with new PR
  for (j <- OutNbrs(v)) {
    msg = PR(v) / NumLinks(v)
    send_msg(to=j, msg)
  }
  // Check for termination
  if (converged(PR(v))) voteToHalt(v)
}
```

Figure : PageRank in Pregel

Approach

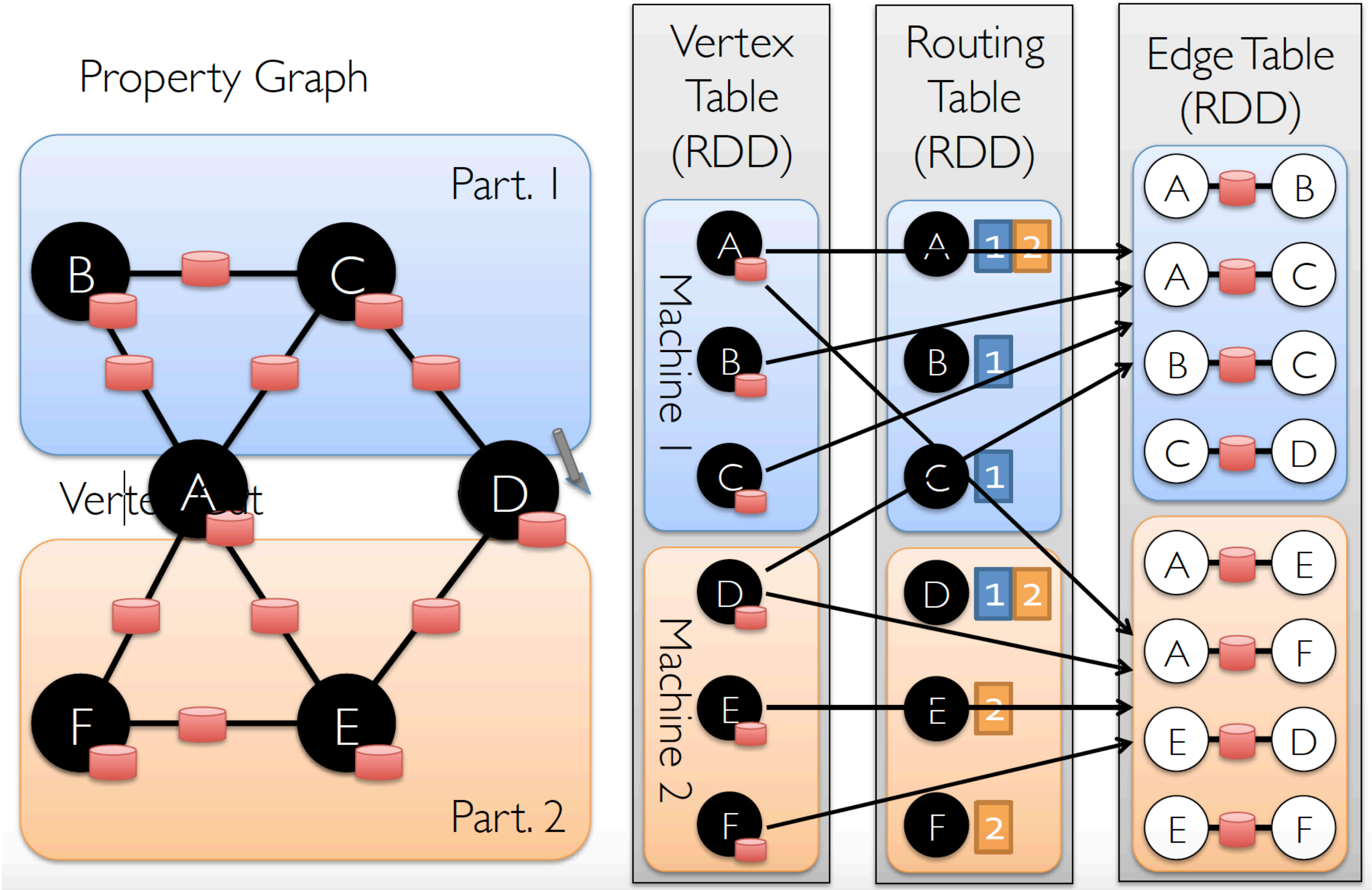
- GAS (Gather Apply Scatter)

```
def Gather(a: Double, b: Double) = a + b
def Apply(v, msgSum) {
  PR(v) = 0.15 + 0.85 * msgSum
  if (converged(PR(v))) voteToHalt(v)
}
def Scatter(v, j) = PR(v) / NumLinks(v)
```

How to apply this in dataflow frameworks?

- Map, group-by, join dataflow operators

Representing Property graphs as Tables

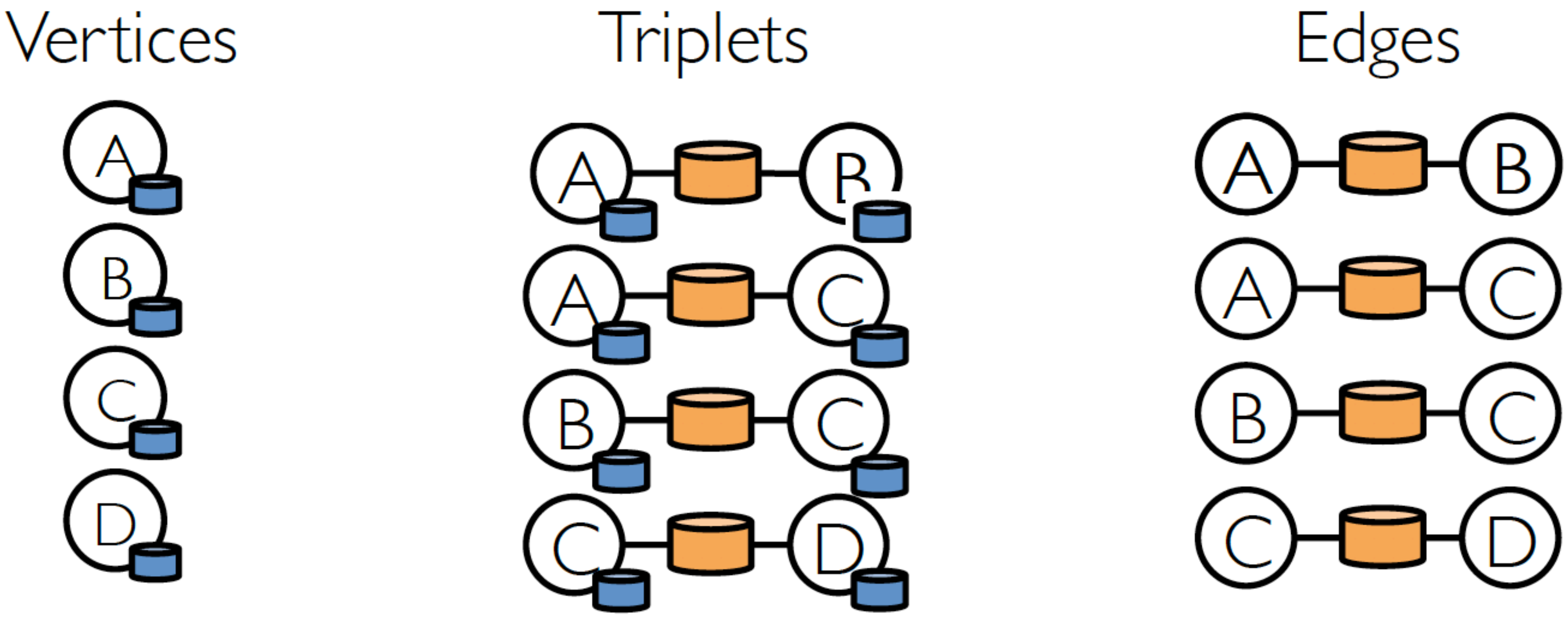


Never transfer edges

GraphX API

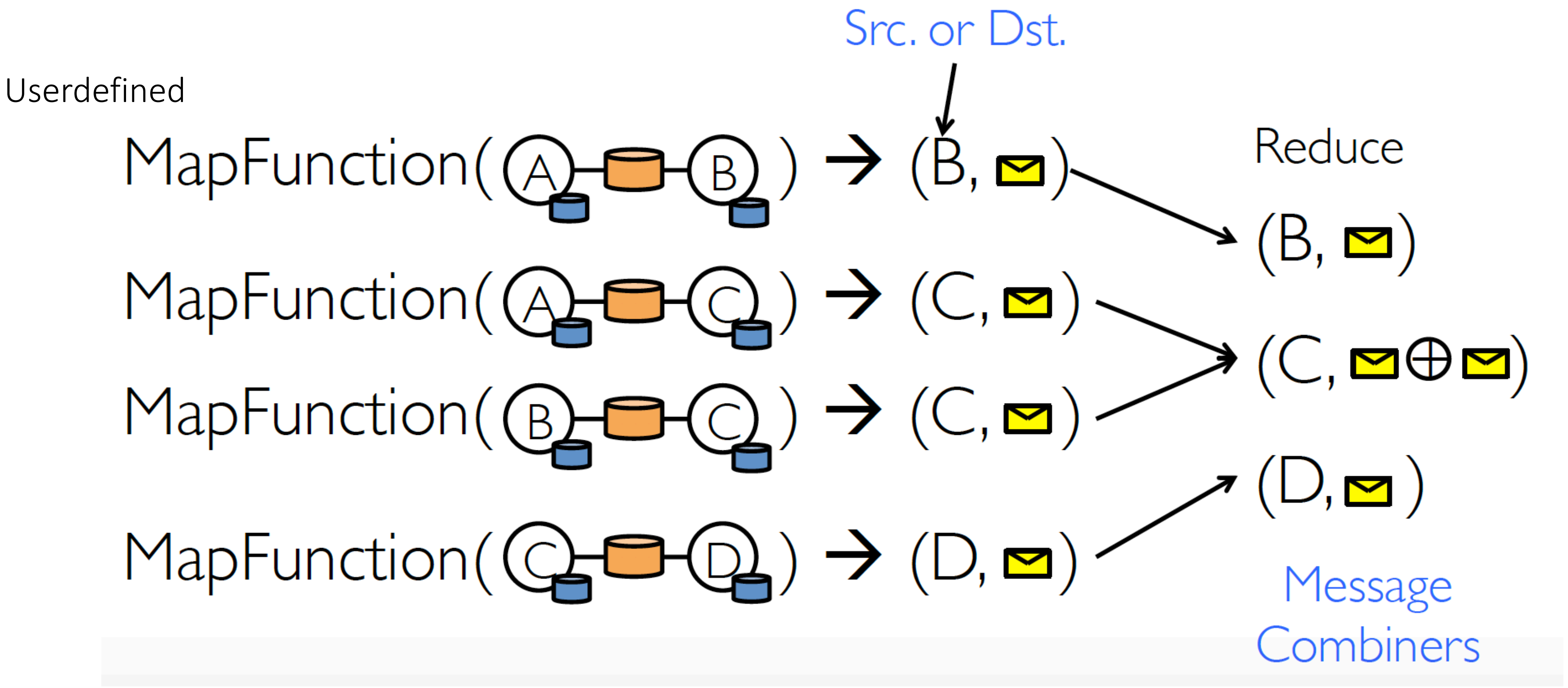
```
class Graph[V, E] {
  // Constructor
  def Graph(v: Collection[(Id, V)],
            e: Collection[(Id, Id, E)])
  // Collection views
  def vertices: Collection[(Id, V)]
  def edges: Collection[(Id, Id, E)]
  def triplets: Collection[Triplet]
  // Graph-parallel computation
  def mrTriplets(f: (Triplet) => M,
      sum: (M, M) => M): Collection[(Id, M)]
  // Convenience functions
  def mapV(f: (Id, V) => V): Graph[V, E]
  def mapE(f: (Id, Id, E) => E): Graph[V, E]
  def leftJoinV(v: Collection[(Id, V)],
      f: (Id, V, V) => V): Graph[V, E]
  def leftJoinE(e: Collection[(Id, Id, E)],
      f: (Id, Id, E, E) => E): Graph[V, E]
  def subgraph(vPred: (Id, V) => Boolean,
      ePred: (Triplet) => Boolean)
    : Graph[V, E]
  def reverse: Graph[V, E]
}
```

Using the dataflow operators



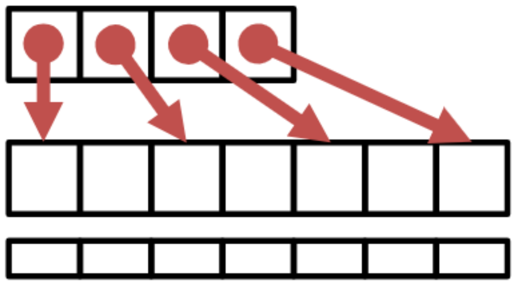
Logical representation Join of vertices table on edges table

Using the dataflow operators on vertex program

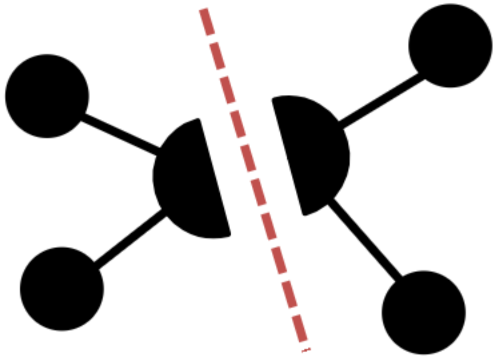


Optimizations

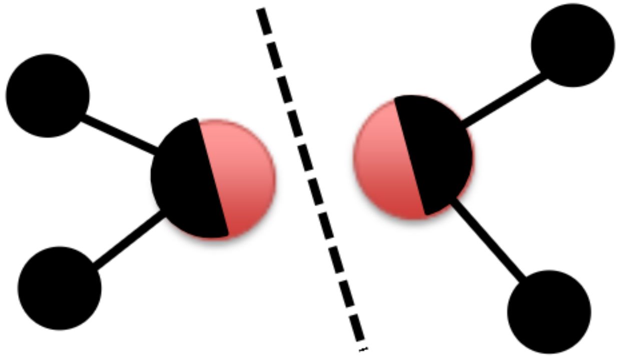
Specialized Data Structure



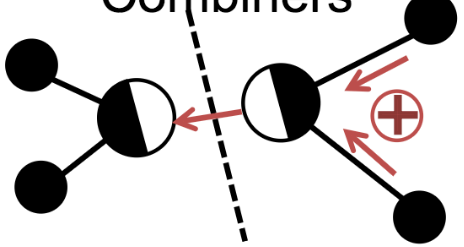
Vertex-cut Partitioning



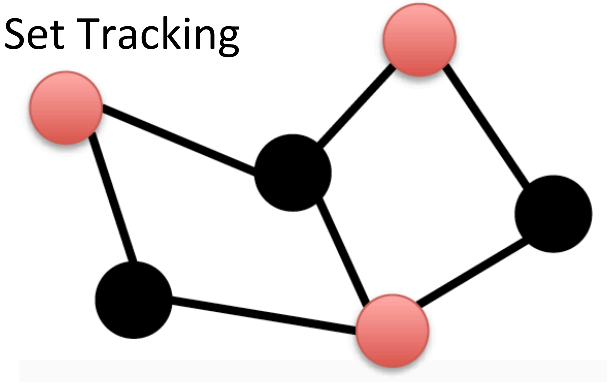
Remote caching



Message Combiners

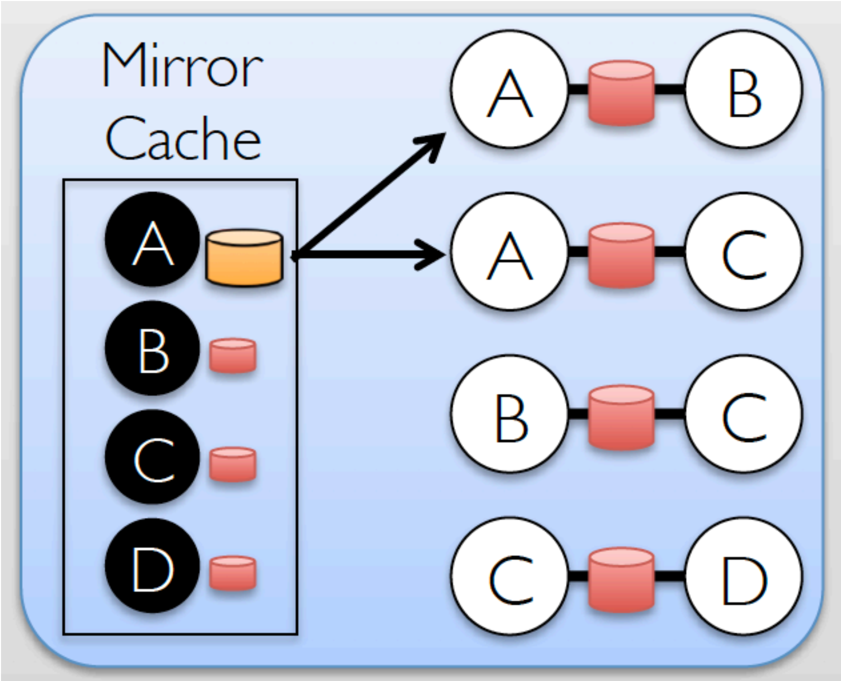


Active Set Tracking



Implementing Optimizations

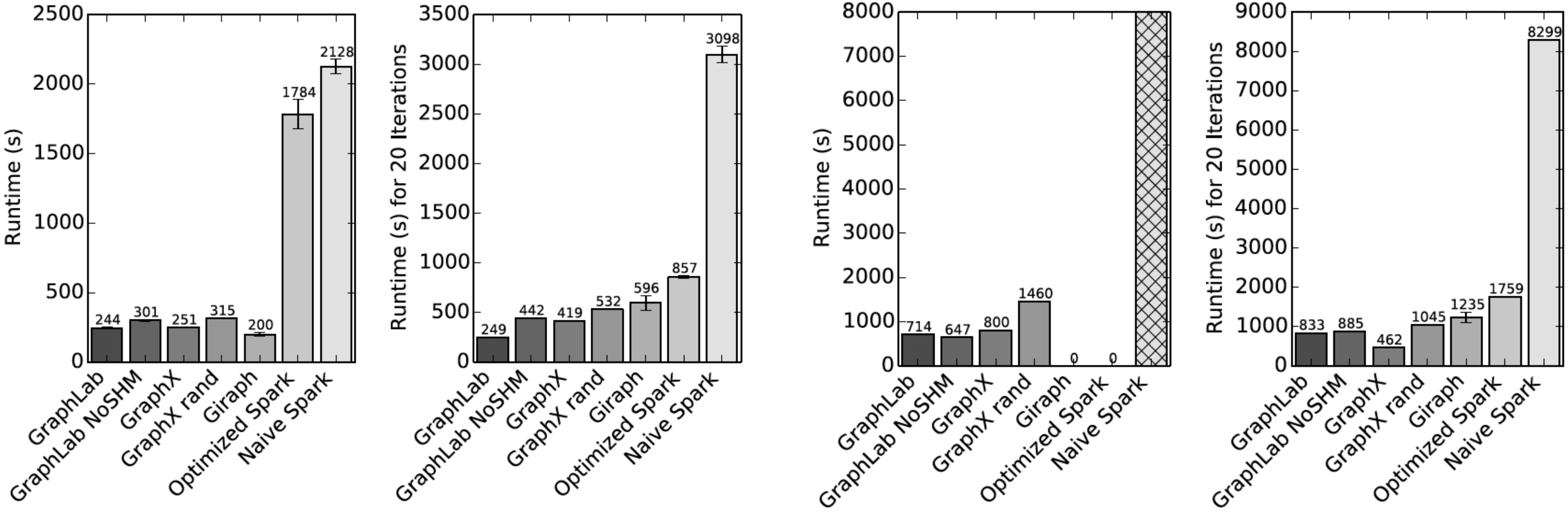
- Reusable Hash index
- Sequential scan or clustered scan based on active set (Dynamic)
- Incremental updates
- Automatic Join elimination



Additional optimizations:

- Memory based shuffle
- Batching and columnar structure
- Variable Integer encoding

Results



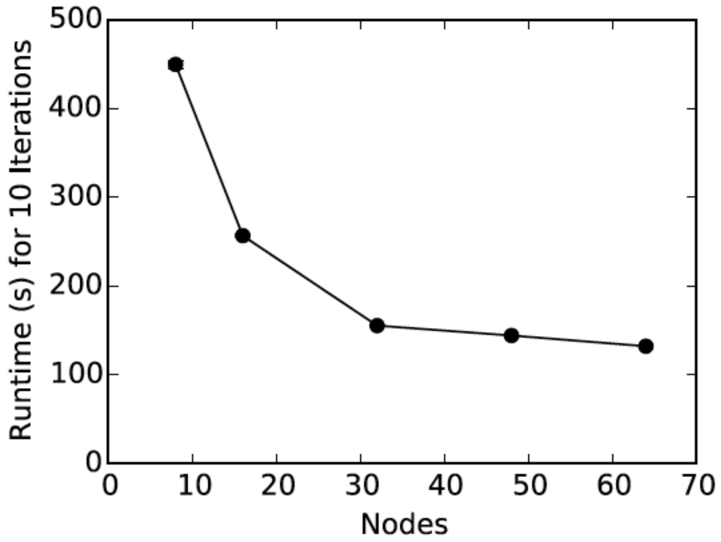
(a) Conn. Comp. Twitter

(b) PageRank Twitter

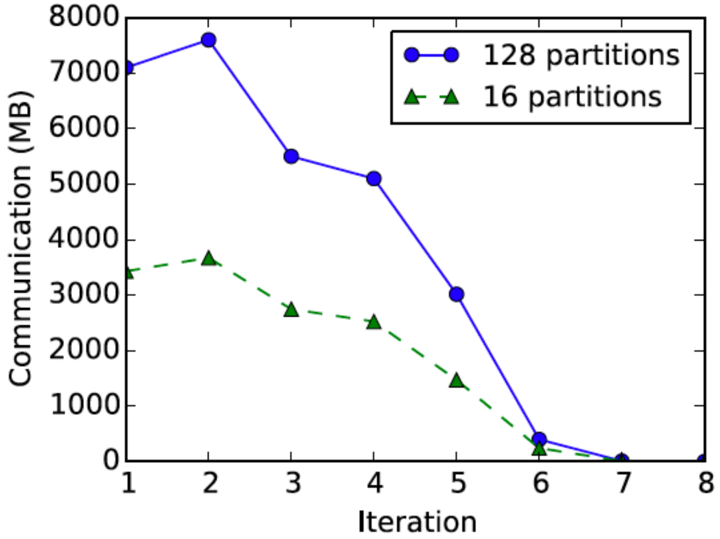
(c) Conn. Comp. uk-2007-05*

(d) PageRank uk-2007-05

Results



Scaling for PageRank
on Twitter dataset



Effect of partitioning on
communication

Current Flaws

- Is not optimized for dynamic graphs.
- Requires incremental updates to routing table.
- Is not designed for streaming applications.
- Asynchronous graph computation not available. This is where Naiad will outperform.

Questions