Large-Scale Matrix Operations Using a Data Flow Engine

Matei Zaharia

Outline

Data flow vs. traditional network programming

Limitations of MapReduce

Spark computing engine

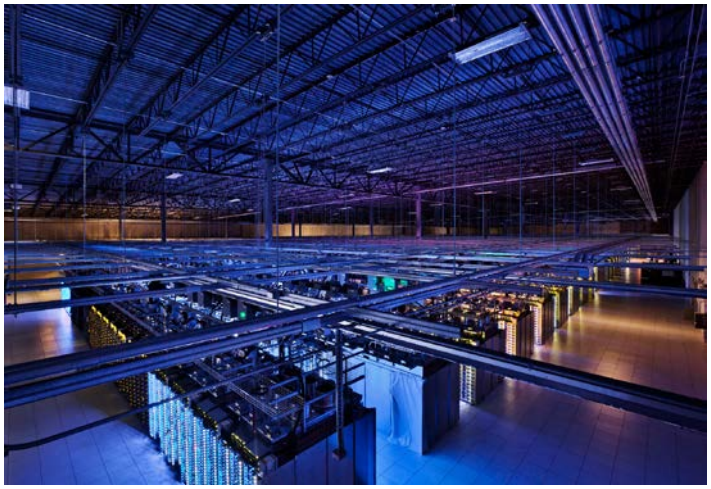
Matrix operations on Spark

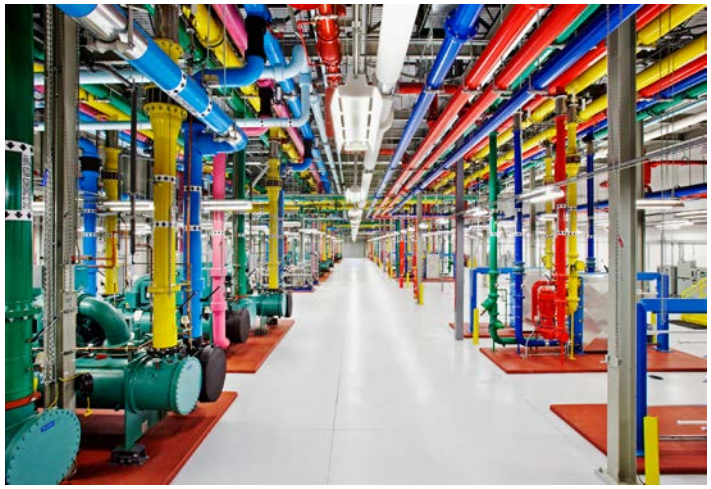
Problem

Data growing faster than processing speeds

Only solution is to parallelize on large clusters

- »Wide use in both enterprises and web industry





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Only solution is to parallelize on large clusters

- »Wide use in both enterprises and web industry

How do we program these things?

Traditional Network Programming

Message-passing between nodes (e.g. MPI)

Very difficult to do at scale:

- How to split problem across nodes?
  - Must consider network & data locality
- How to deal with failures? (inevitable at scale)
- Even worse: stragglers (node not failed, but slow)

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Rarely used in commodity datacenters

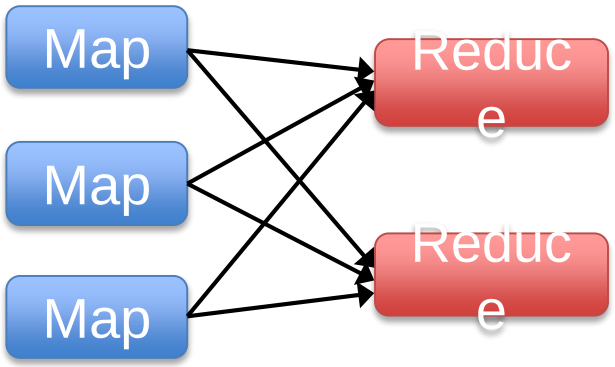
Data Flow Models

Restrict the programming interface so that the system can do more automatically

Express jobs as graphs of high-level operators

- System picks how to split each operator into tasks and where to run each task
- Run parts twice fault recovery

Biggest example: MapReduce



MapReduce for Matrix Operations

Matrix-vector multiply

Power iteration (e.g. PageRank)

Gradient descent methods

Stochastic SVD

Tall skinny QR

Many others!

Why Use a Data Flow Engine?

Ease of programming

- High-level functions instead of message passing

Wide deployment

- More common than MPI, especially “near” data

Scalability to very largest clusters

- Even HPC world is now concerned about resilience

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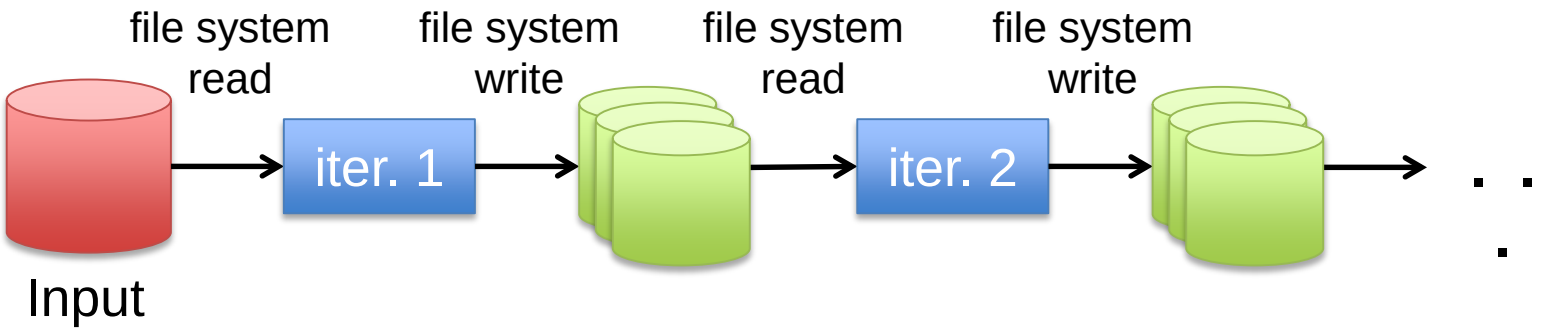
Limitations of MapReduce

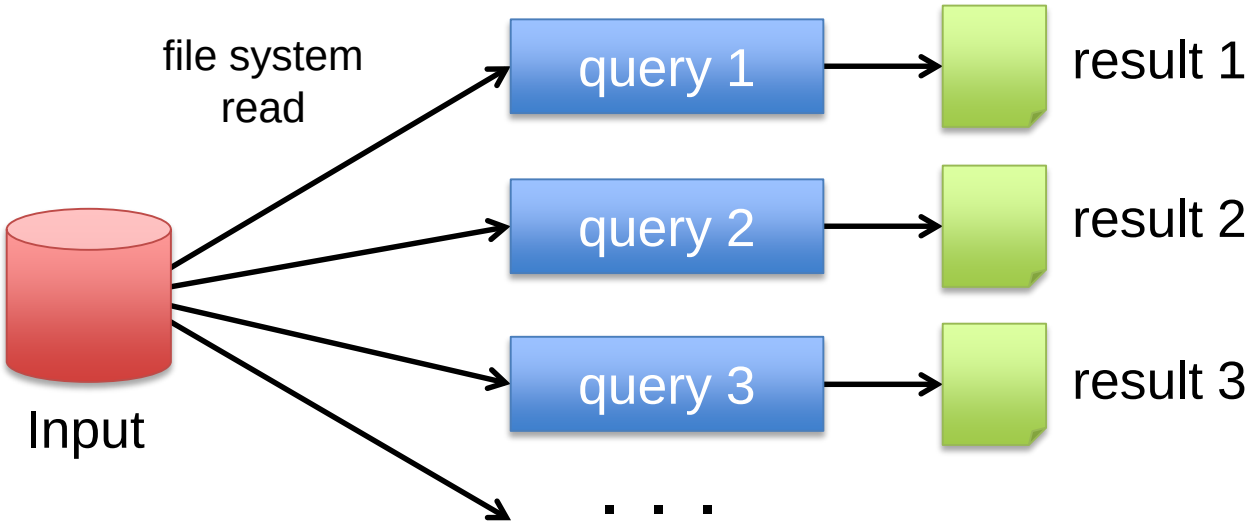
MapReduce is great at one-pass computation, but inefficient for *multi-pass* algorithms

No efficient primitives for data sharing

- State between steps goes to distributed file system
- Slow due to replication & disk storage
- No control of data partitioning across steps

Example: Iterative Apps



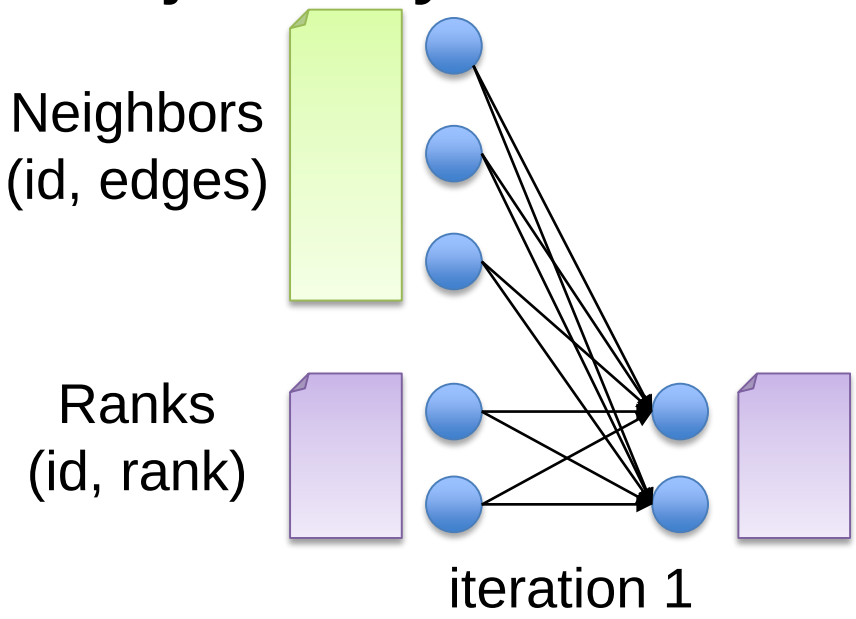


Commonly spend 90% of time doing I/O

Example: PageRank

Repeatedly multiply sparse matrix and vector

Requires repeatedly hashing together page adjacency lists and rank vector



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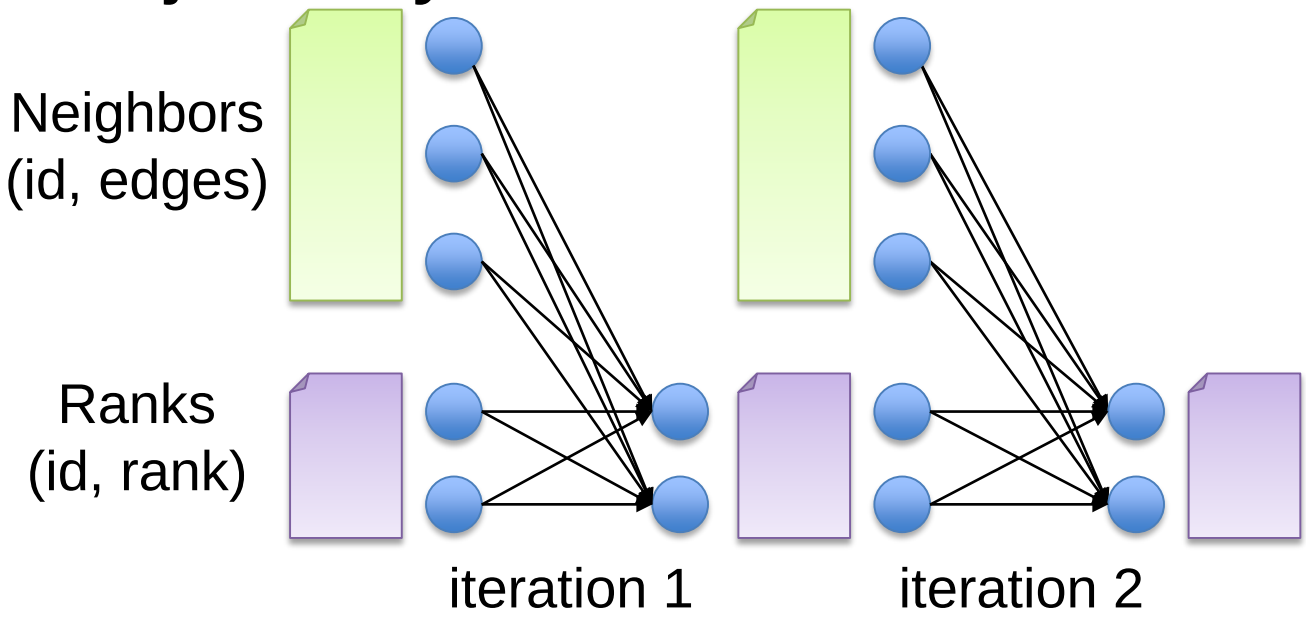

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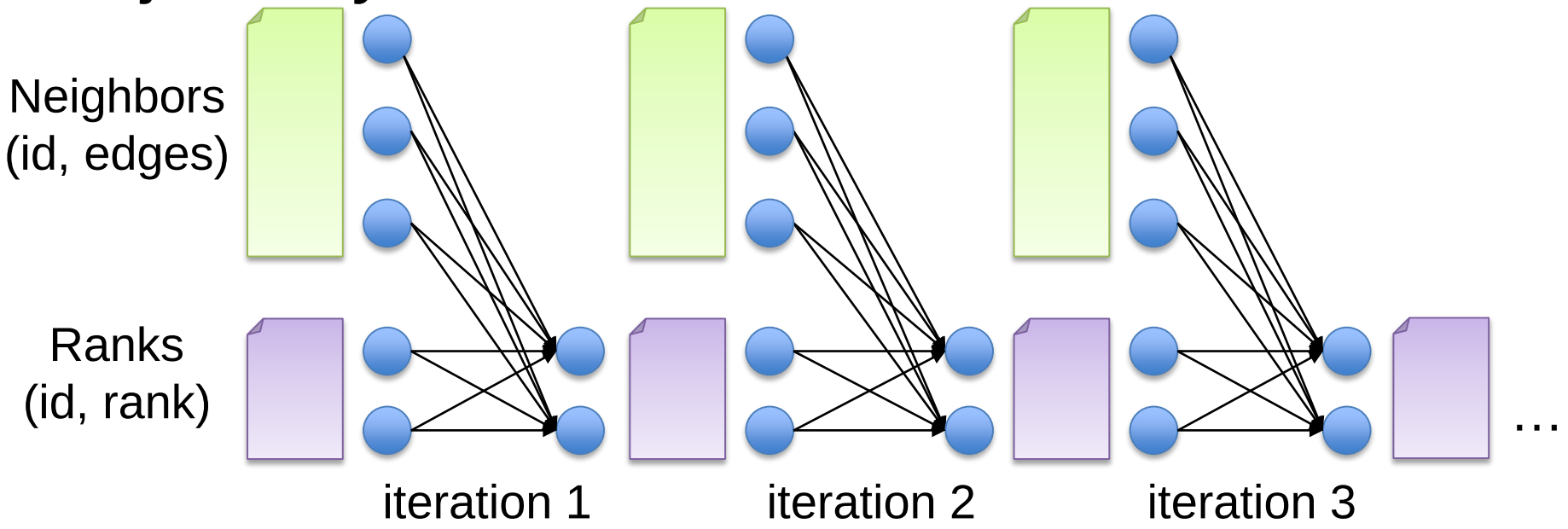

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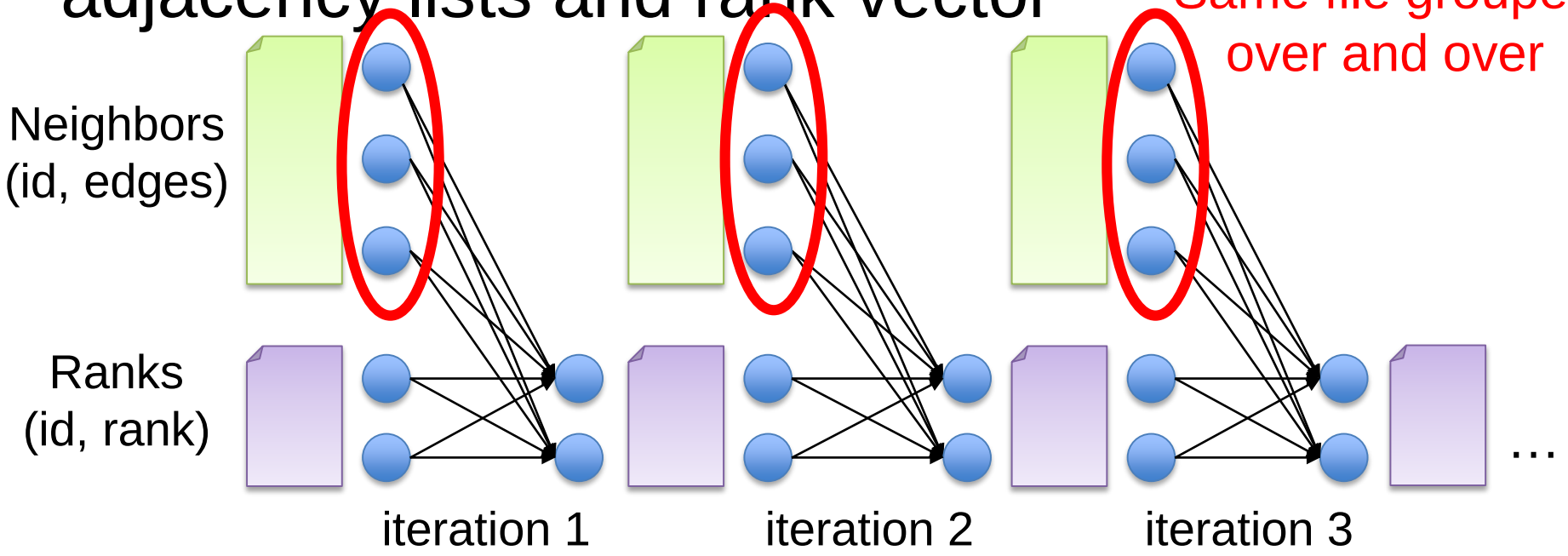


Spark Programming Model

Extends MapReduce with primitives for efficient data sharing

- »“Resilient distributed datasets”

Open source in Apache Incubator

- »Growing community with 100+ contributors

APIs in Java, Scala & Python

Resilient Distributed Datasets (RDDs)

Collections of objects stored across a cluster

User-controlled partitioning & storage (memory, disk, …)

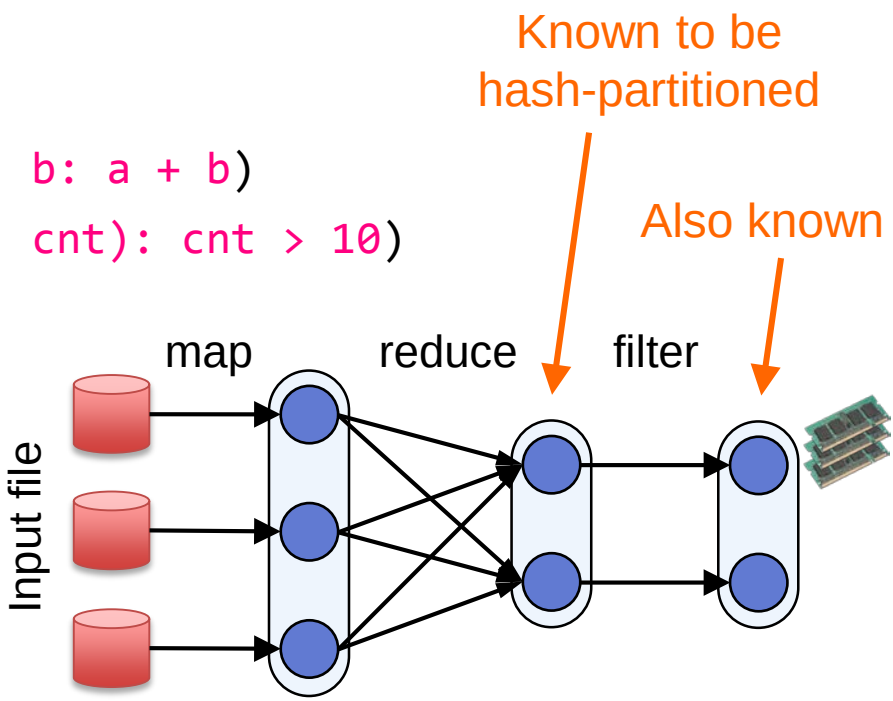
Automatically rebuilt on failure

```
urls = spark.textFile(“hdfs://...”)
records = urls.map(lambda s: (s, 1))
counts = records.reduceByKey(lambda a, b: a + b)
bigCounts = counts.filter(lambda (url, cnt): cnt > 10)
```

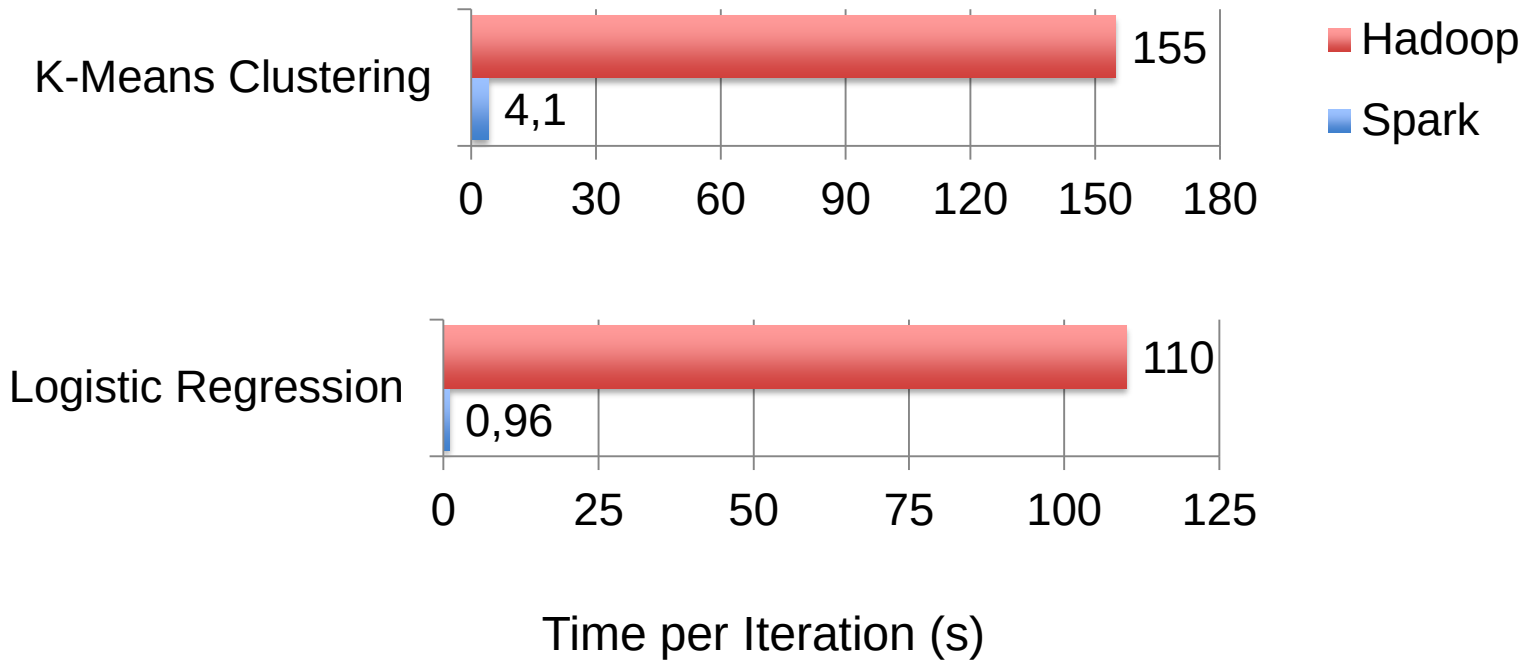
```
bigCounts.cache()

bigCounts.filter(
  lambda (k,v): “news” in k).count()

bigCounts.join(otherPartitionedRDD)
```



Performance



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Using cache(), keep neighbors in RAM

Using partitioning, avoid repeated hashing

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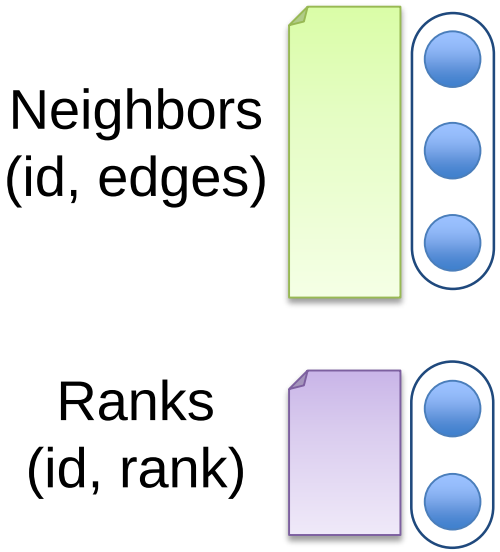

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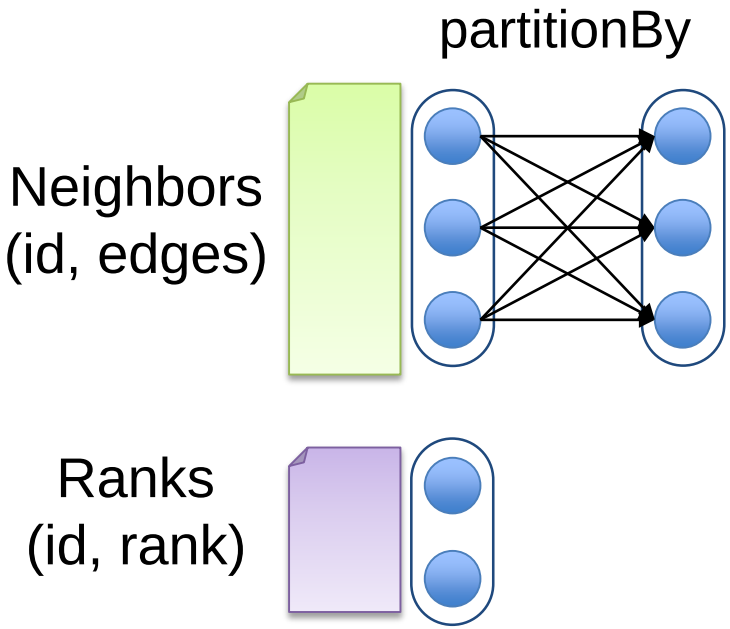

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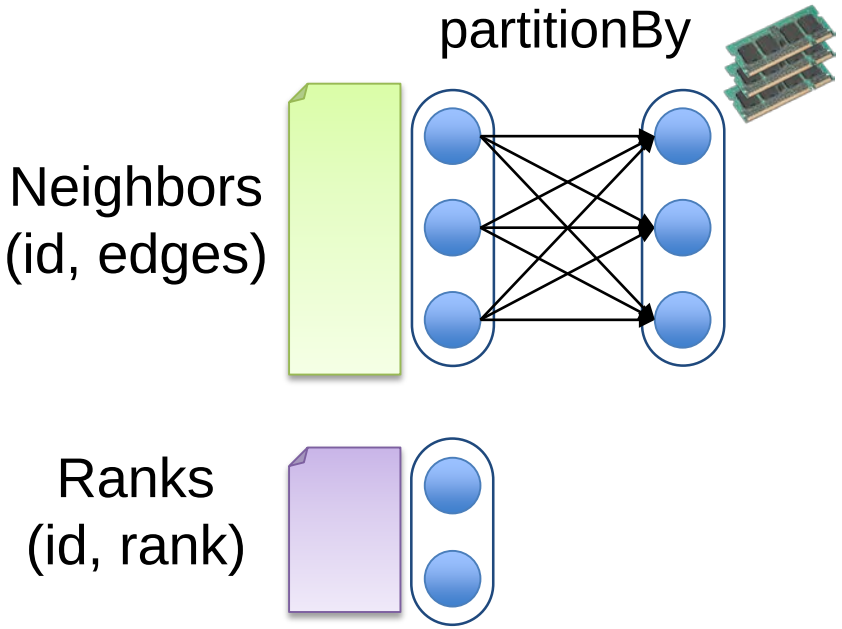

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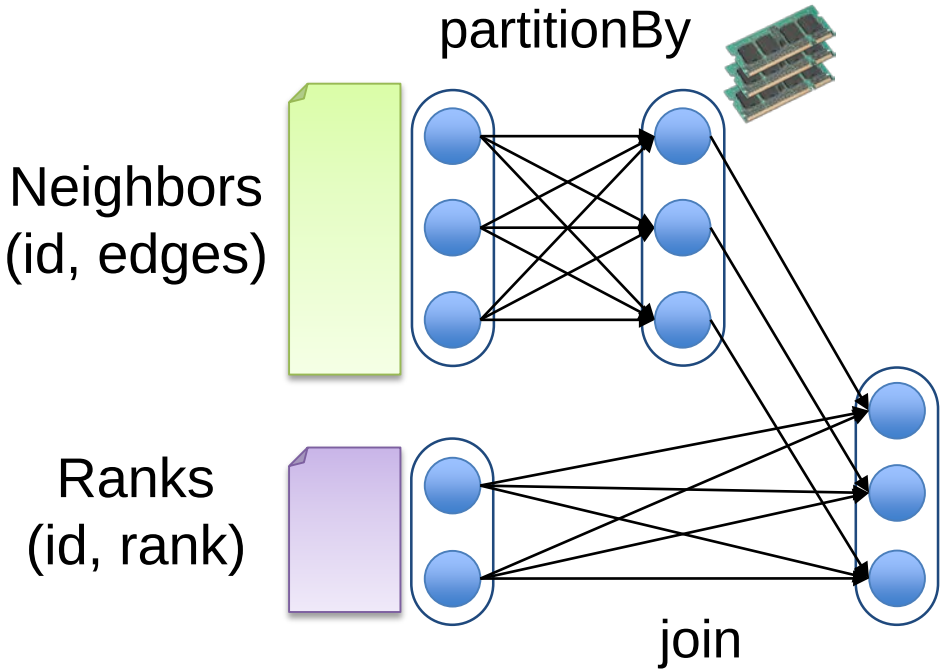

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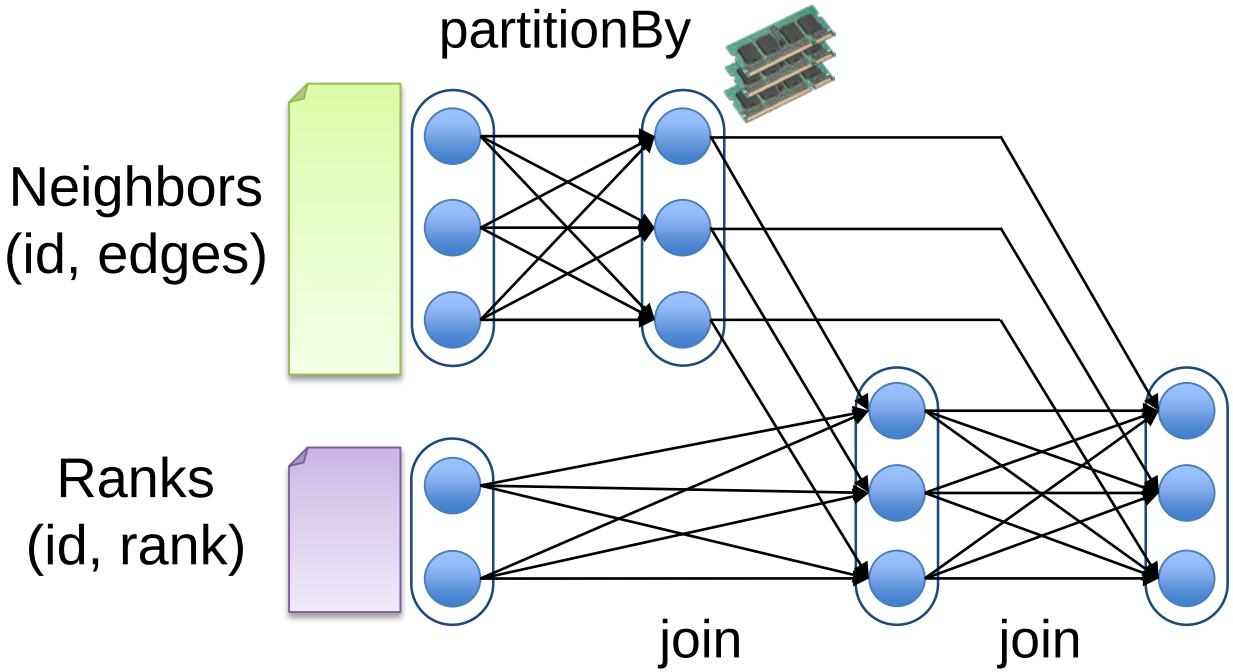

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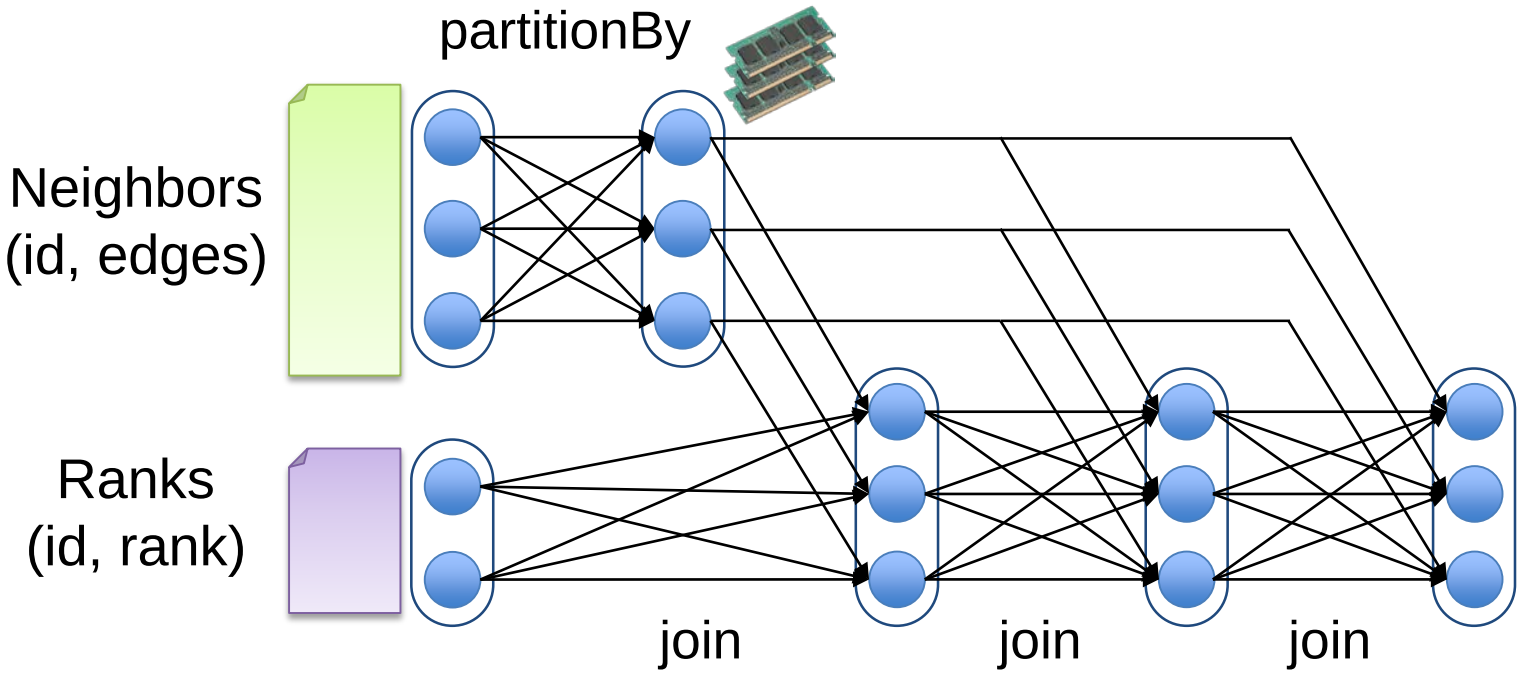

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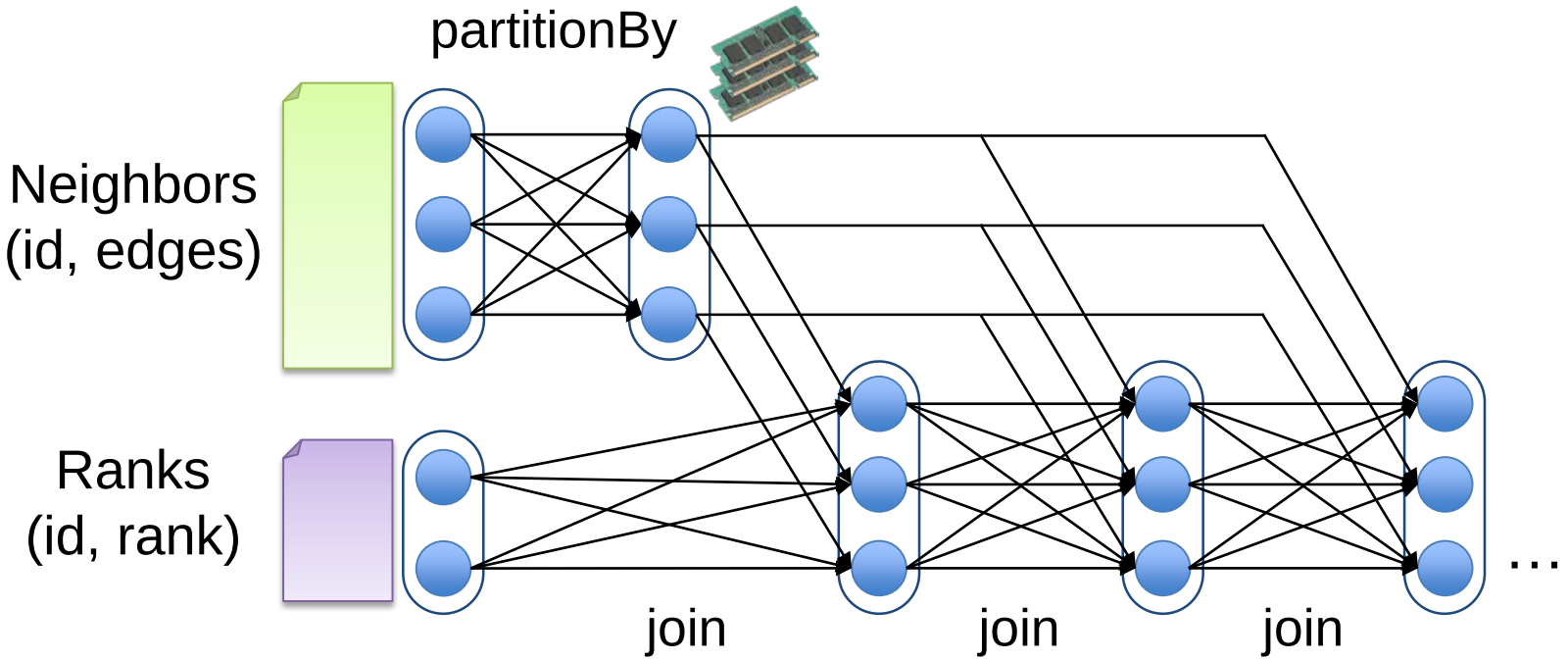

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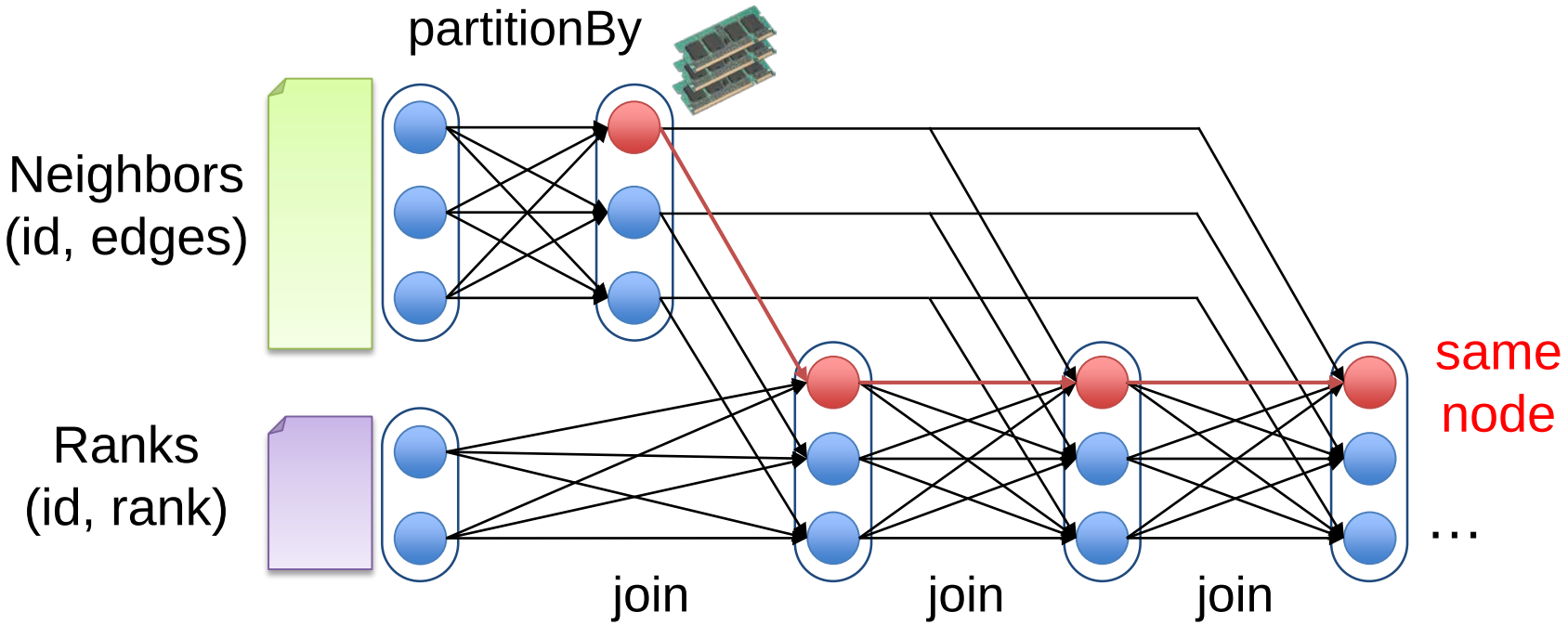

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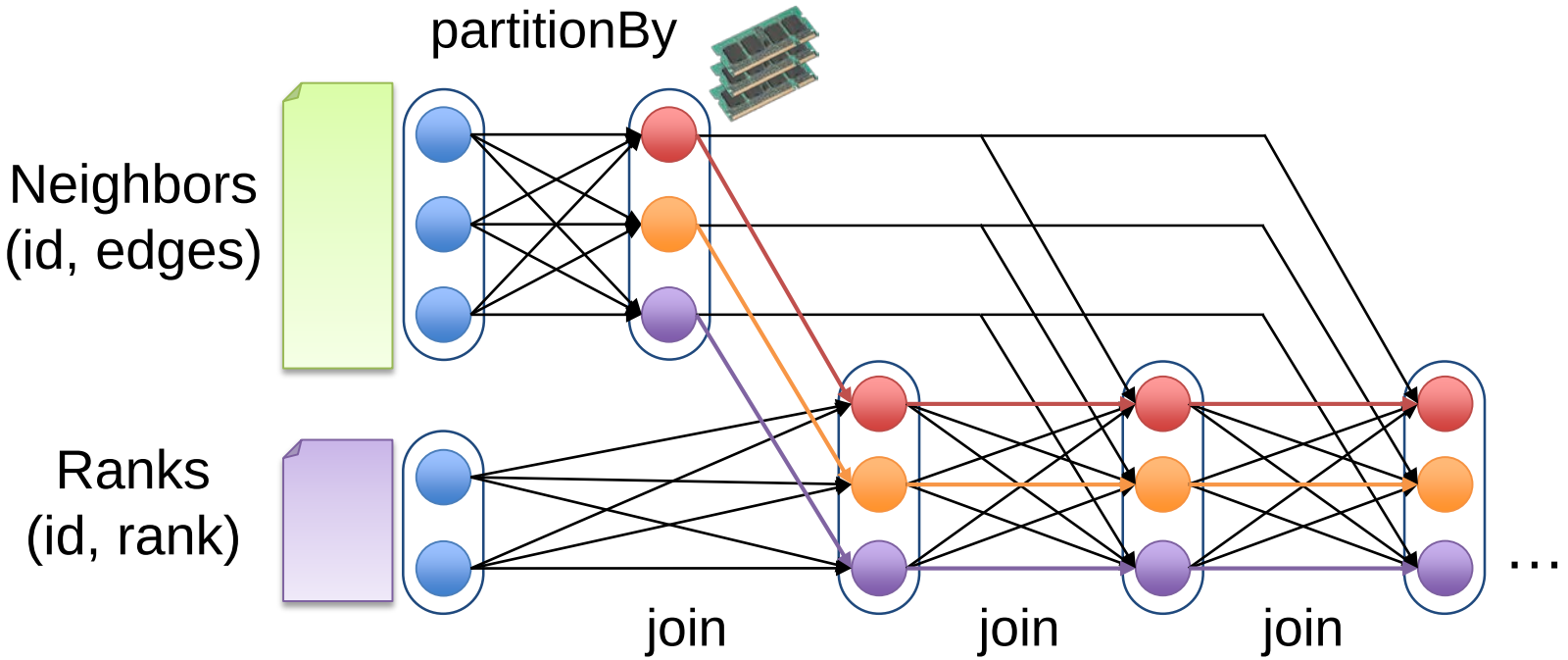
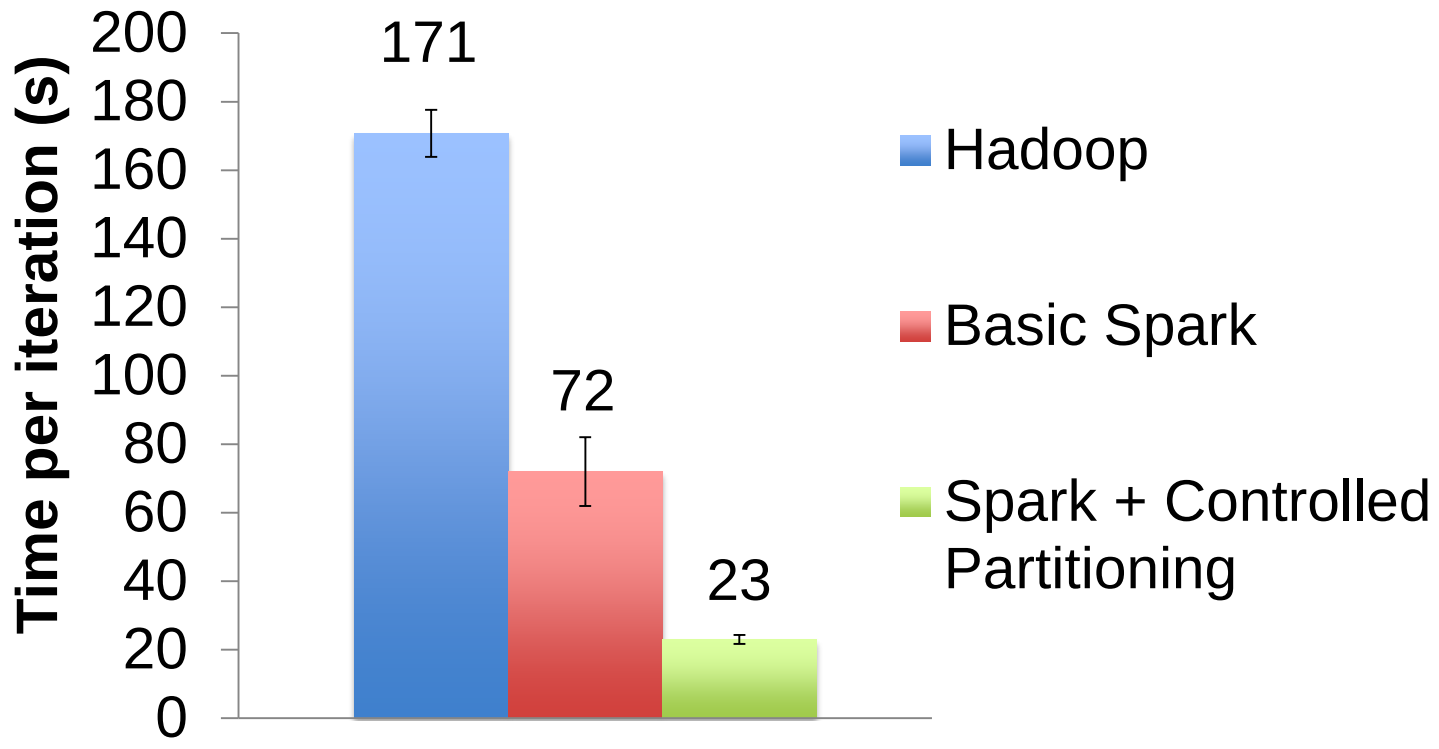


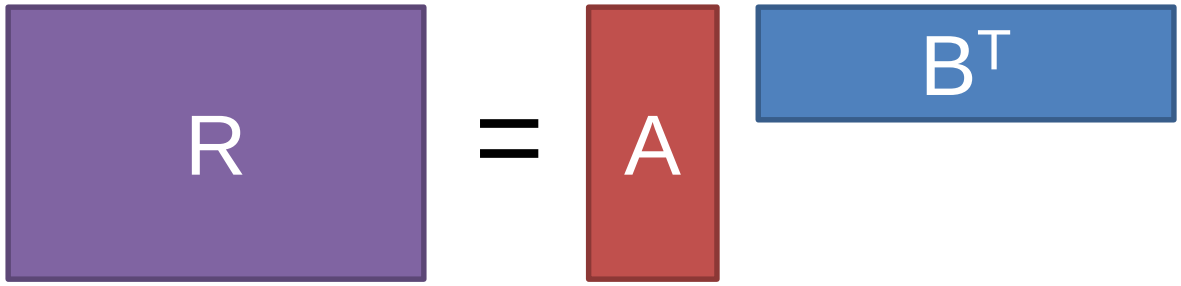
PageRank Code

```
# RDD of (id, neighbors) pairs
links = spark.textFile(...).map(parsePage)
            .partitionBy(128).cache()

ranks = links.mapValues(lambda v: 1.0)  # RDD of (id, rank)

for i in range(ITERATIONS):
    ranks = links.join(ranks).flatMap(
        lambda (id, (links, rank)):
            [(d, rank/links.size) for d in links]
    ).reduceByKey(lambda a, b: a + b)
```

PageRank Results



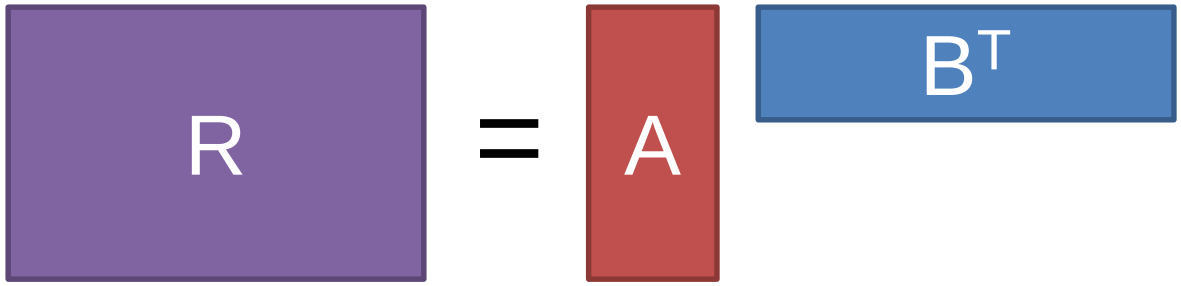
Alternating Least Squares



1. Start with random A_1, B_1
2. Solve for A_2 to minimize $||R - A_2 B_1^T||$
3. Solve for B_2 to minimize $||R - A_2 B_2^T||$
4. Repeat until convergence

ALS on Spark

Joint work with
Joey Gonzales,
Virginia Smith

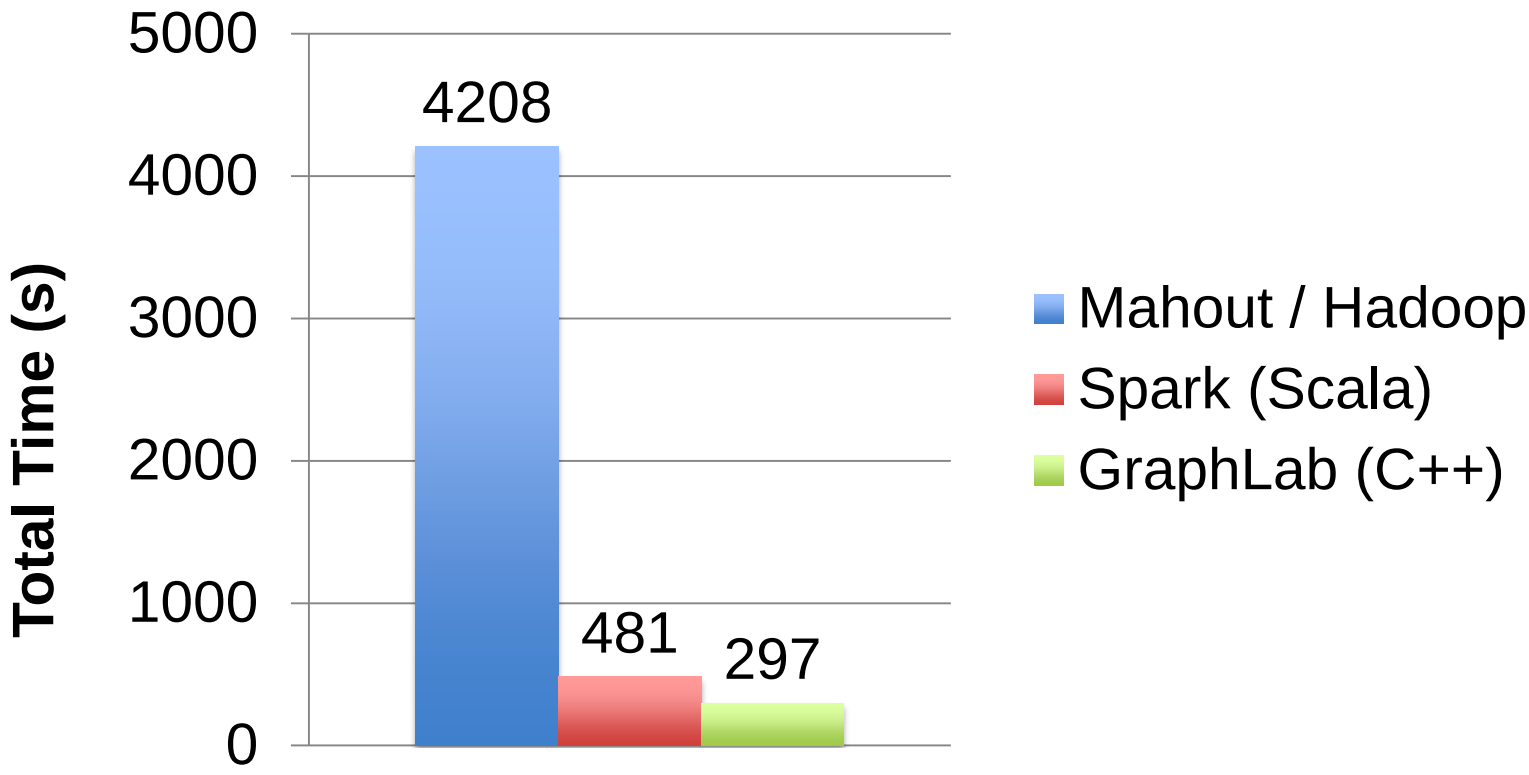


Cache 2 copies of R in memory, one partitioned by rows and one by columns

Keep A & B partitioned in corresponding way

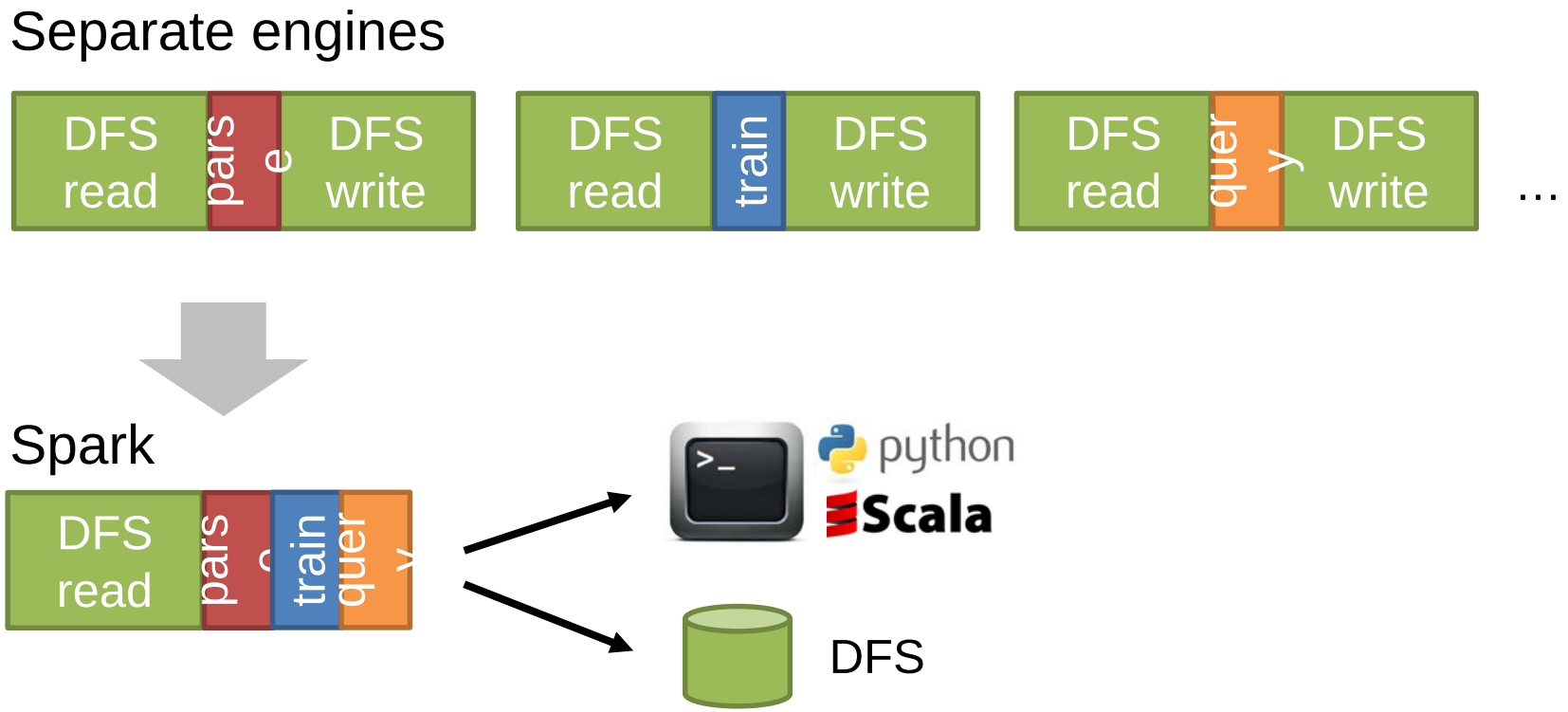
Operate on blocks to lower communication

ALS Results


Total Time (s)
5000
4000
3000
2000
1000
0
4208
481
297
Mahout / Hadoop
Spark (Scala)
GraphLab (C++)

Benefit for Users

Same engine performs data extraction, model training and interactive queries



Other Projects on Spark

MLlib: built-in Spark library for ML

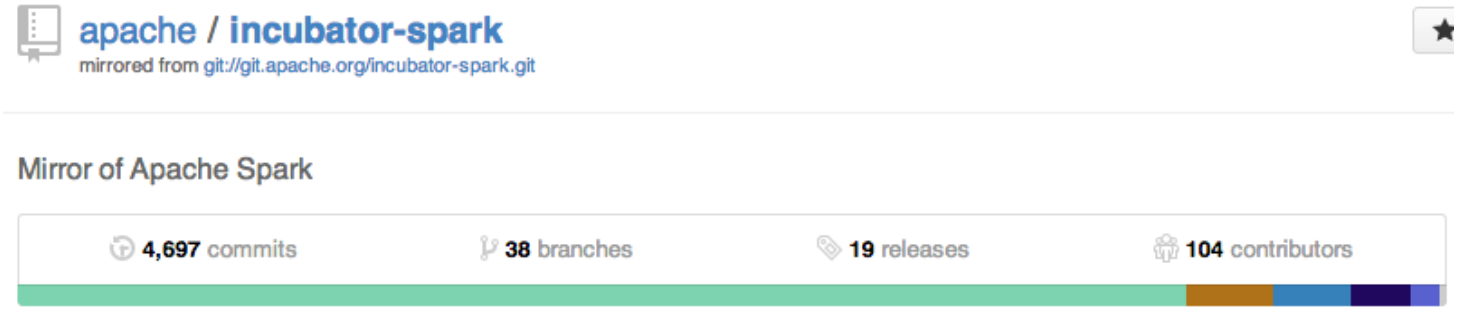
- Includes ALS, K-means||, various algorithms on SGD
- Frankin, Gonzales et al. [MLOSS '13]

MLI: Matlab-like language for writing apps

- Basic ALS in 35 lines of code
- Evan Sparks, Ameet Talwalkar et al. [ICDM '13]

Spark Community

100+ developers, 25+ companies contributing;
most active development community after Hadoop



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Conclusion

Data flow engines are becoming an important platform for matrix algorithms

Spark offers a simple programming model that greatly speeds these up

More info: spark.incubator.apache.org