Apache Spark

28-01-2016
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A Data-Parallel Approach

Restrict the programming interface so that the system can do more automatically. Use ideas from functional programming:

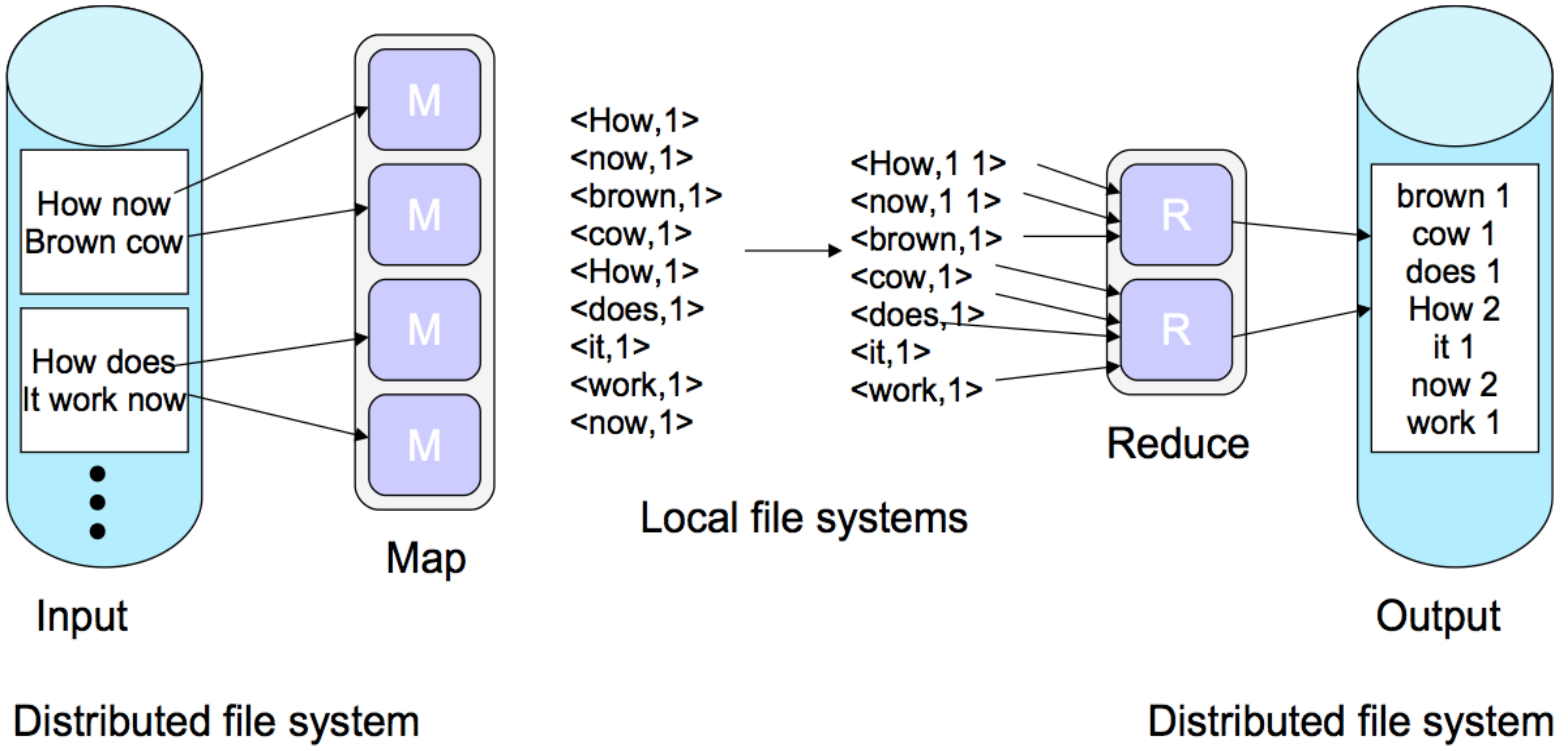
“Here is a function, apply it to all of the data”

- I do not care where it runs (the system should handle that)
- Feel free to run it twice on different nodes (no side effects!)

MapReduce Programming Model

Map function: $(K_1, V_1) \longrightarrow list(K_2, V_2)$

Reduce function: $(K_2, list(V_2)) \longrightarrow list(K_3, V_3)$



Problems with MapReduce

- Difficulty to convert problem to MR algorithm:
  MR not expressive enough?

- Performance issues due to disk I/O between every job:
  Unsuited for iterative algorithms or interactive use

Higher Level Frameworks

HIVE

cascading

APACHE GIRAPH

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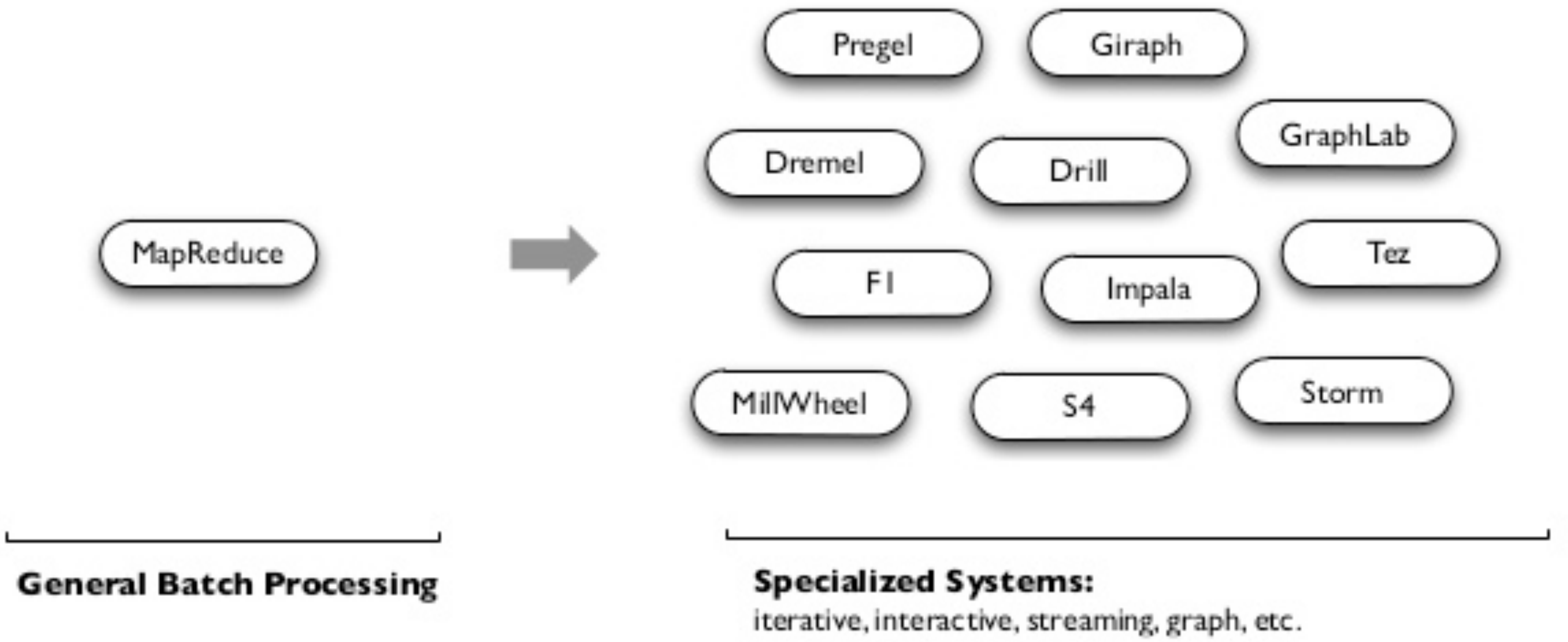
Specialized systems



http://www.slideshare.net/rxin/stanford-cs347-guest-lecture-apache-spark

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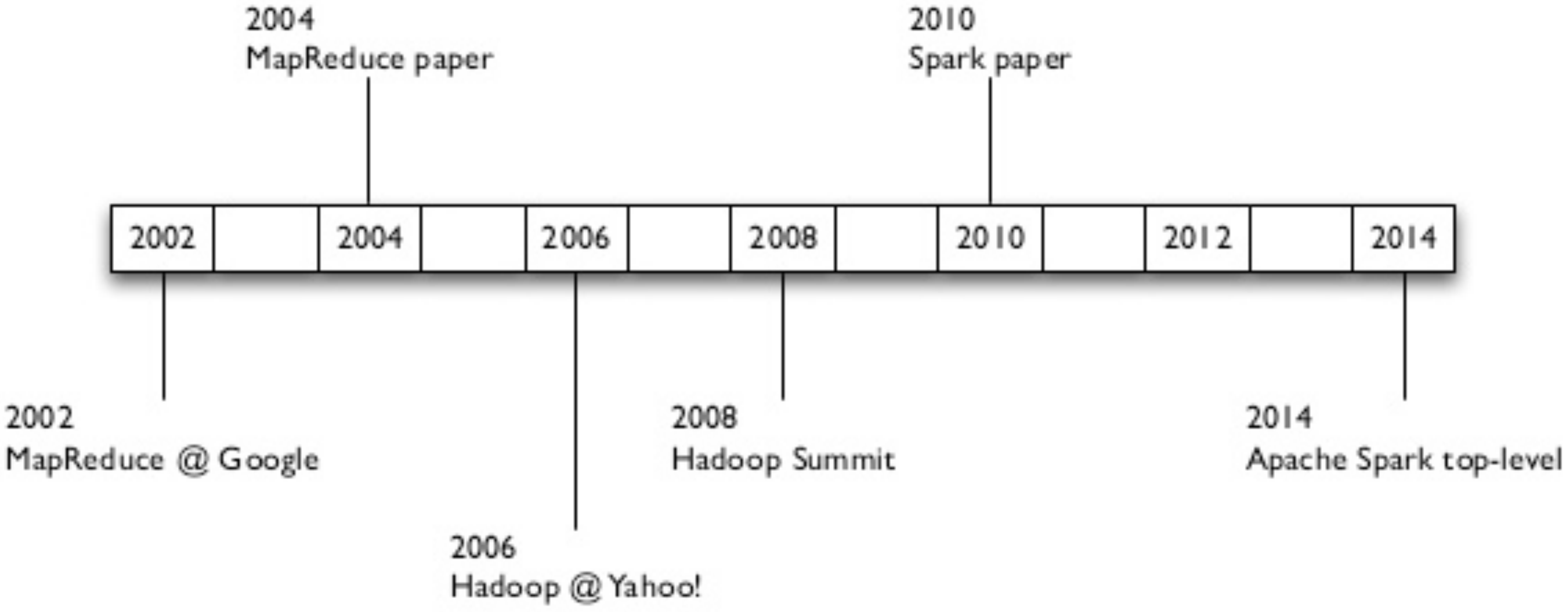
Solved?

- Performance issues solved only partially
- How about workflows that need multiple components?

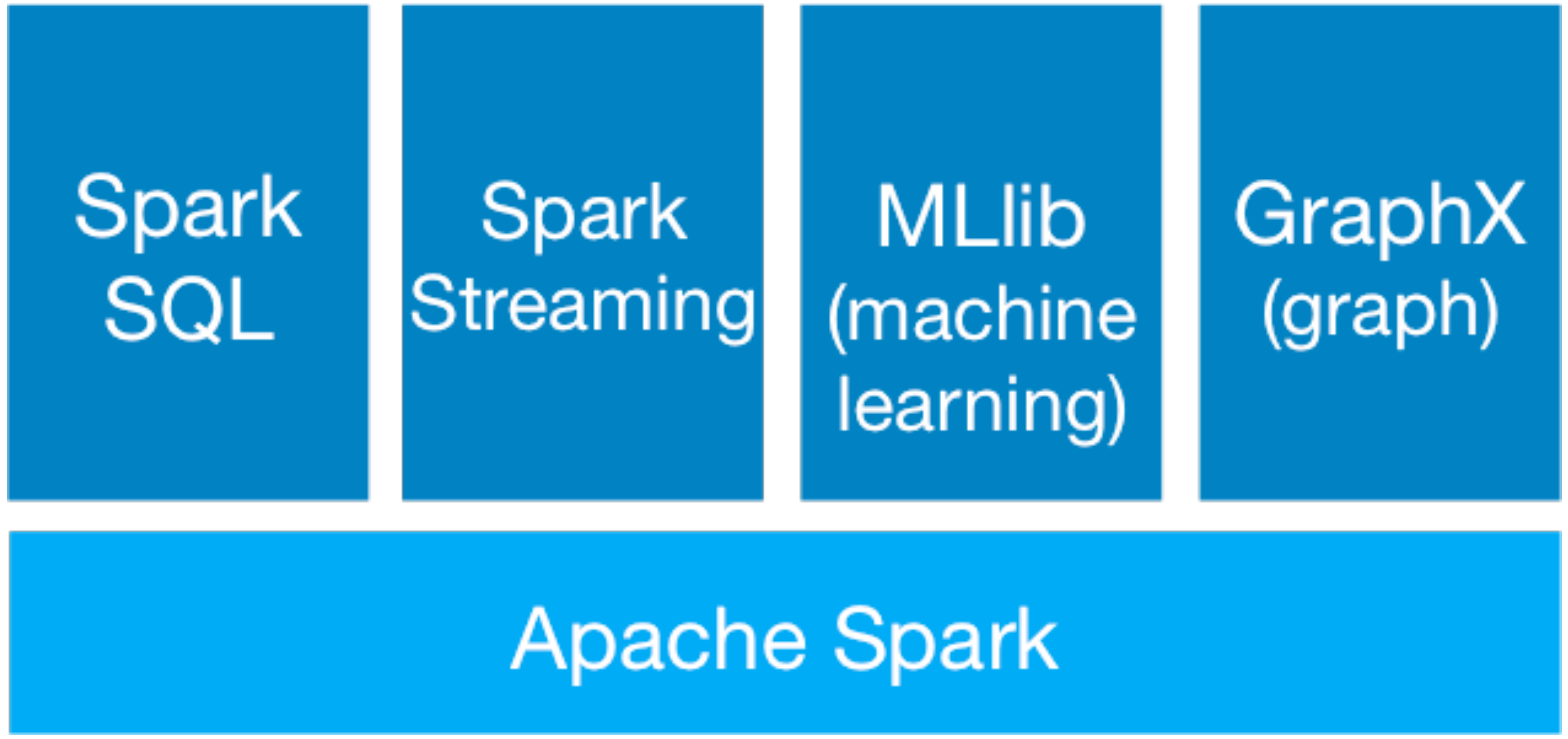
Enter Spark


2004
MapReduce paper
2010
Spark paper
2002
2004
2006
2008
2010
2012
2014
2002
MapReduce @ Google
2006
Hadoop @ Yahoo!
2008
Hadoop Summit
2014
Apache Spark top-level

Spark’s approach

- General purpose processing framework for DAG’s
- Fast data sharing
- Idiomatic API (if you know Scala)

Spark ecosystem



Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

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Abstract

We present Resilient Distributed Datasets (RDDs), a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner. RDDs are motivated by two types of applications that current computing frameworks handle inefficiently: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarse-

tion, which can dominate application execution times.

Recognizing this problem, researchers have developed specialized frameworks for some applications that require data reuse. For example, Pregel [22] is a system for iterative graph computations that keeps intermediate data in memory, while HaLoop [7] offers an iterative MapReduce interface. However, these frameworks only support specific computation patterns (*e.g.,* looping a series of MapReduce steps), and perform data sharing implicitly for these patterns. They do not provide abstractions for more general reuse, *e.g.*, to let a user load several datasets

https://www.cs.berkeley.edu/~matei/papers/2012/nsdi_spark.pdf

RDD properties

- Collection of objects/elements
- Spread over many machines
- Built through parallel transformations
- Immutable

RDD origins

There are two ways to create a RDD from scratch

Parallelised collections:
distribute existing single-machine collections (List, HashMap)

Hadoop datasets:
files from HDFS-compatible filesystem (Hadoop InputFormat)

Operations on RDDs

Transformations:

- Lazily computed
- Create new RDD
- Example: ‘map’

Actions:

- Triggers computation
- Example: ‘count’, ‘saveAsTextFile’

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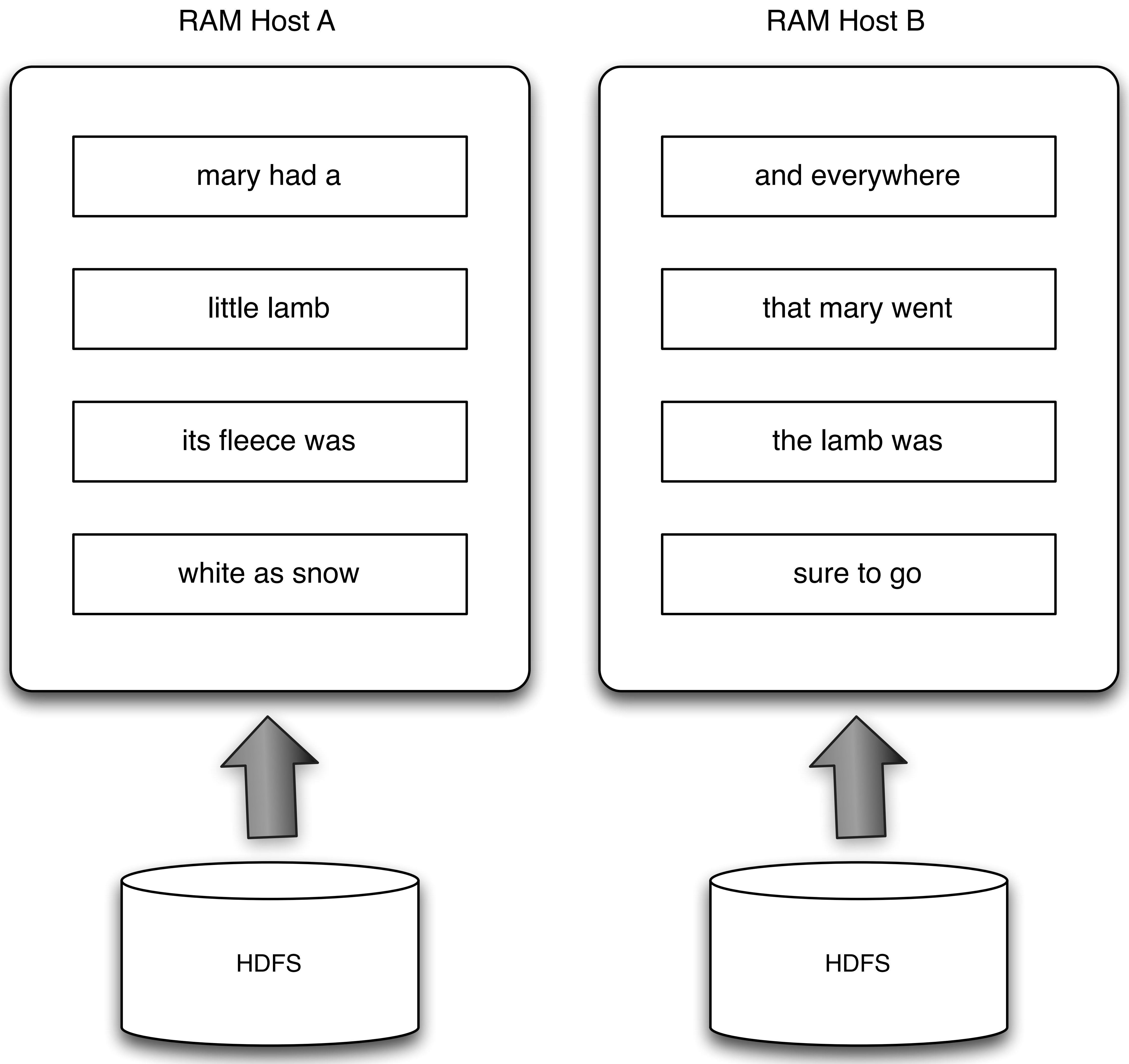
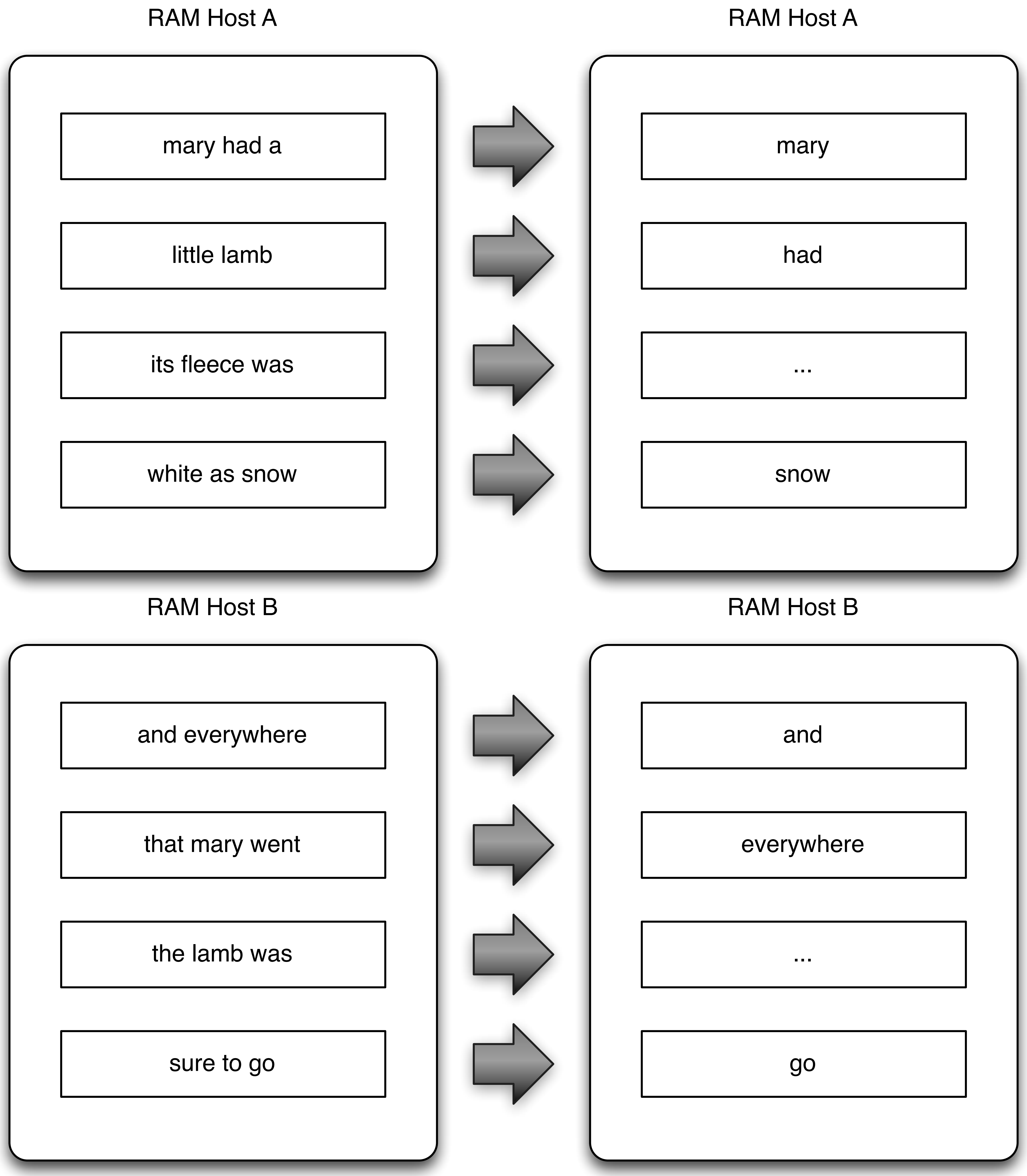
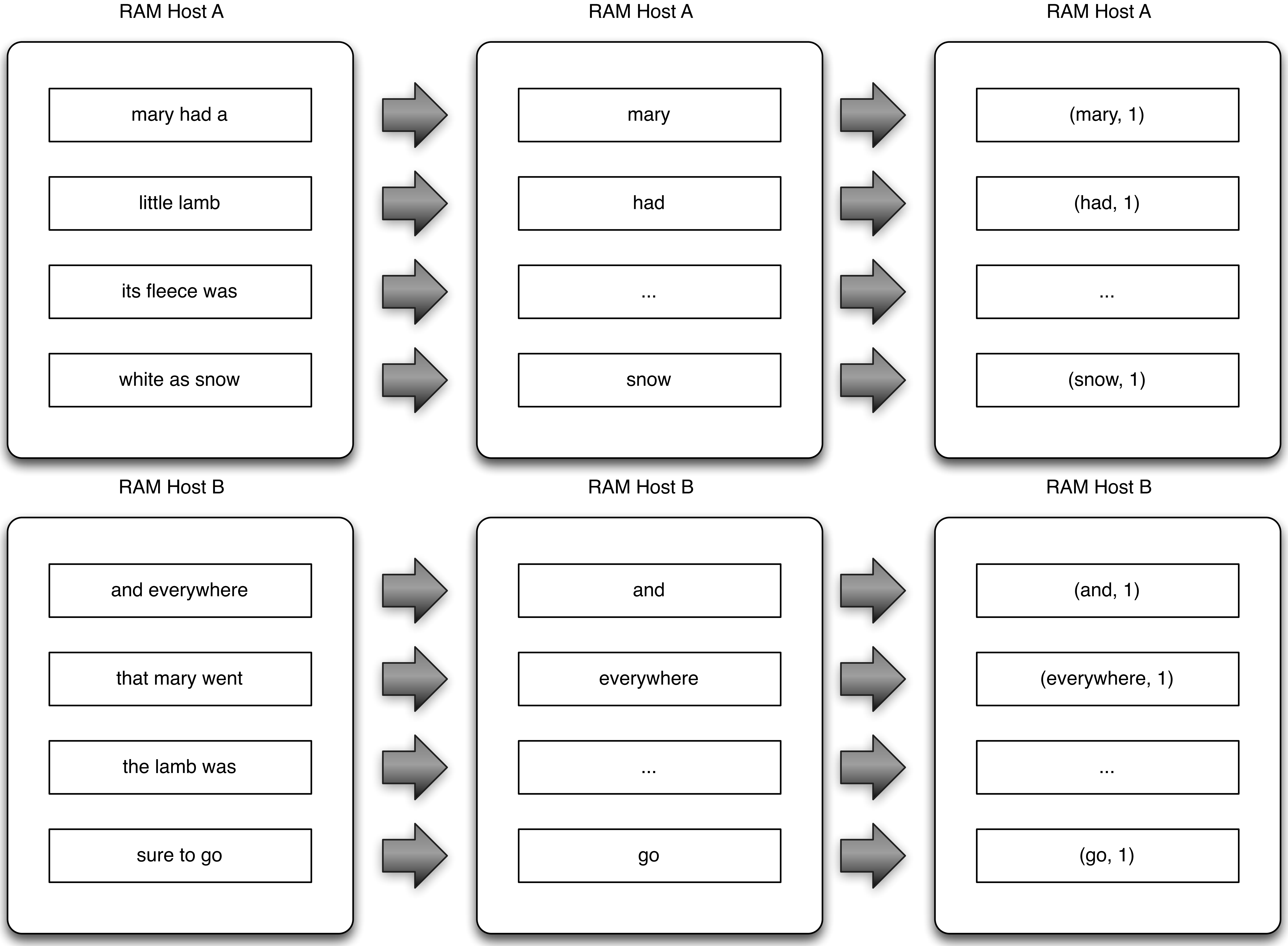
An RDD from HDFS






```
rdd.flatMap(lambda s: s.split(" "))
```



`rdd.flatMap(lambda s: s.split(" "))` `rdd.map(lambda w: (w, 1))`

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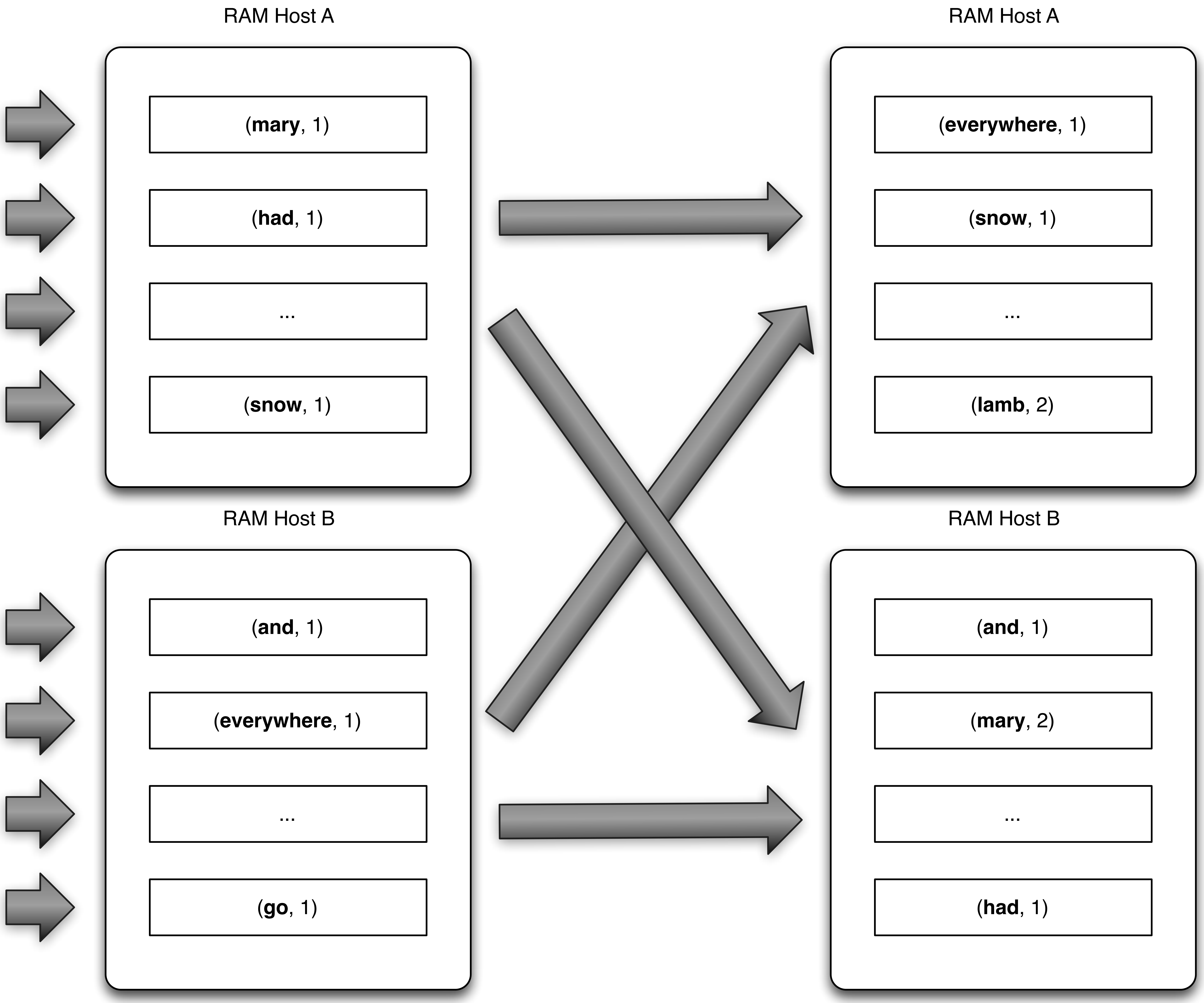


rdd.reduceByKey(lambda x, y: x + y)

Transformations

RDD's are created from other RDD's using transformations:

map(f) => pass every element through function *f*

reduceByKey(f) => aggregate values with same key using *f*

Transformations

RDD’s are created from other RDD’s using transformations:

map(f) => pass every element through function *f*

reduceByKey(f) => aggregate values with same key using *f*

filter(f) => select elements for which function *f* is true

flatMap(f) => similar to map, but one-to-many

join(r) => joined dataset with RDD *r*

union(r) => union with RDD *r*

sample, intersection, distinct, groupByKey, sortByKey, cartesian…

Actions

Transformations give no output (no side-effects) and don’t result in any real work (laziness)

Results from RDD’s via actions:

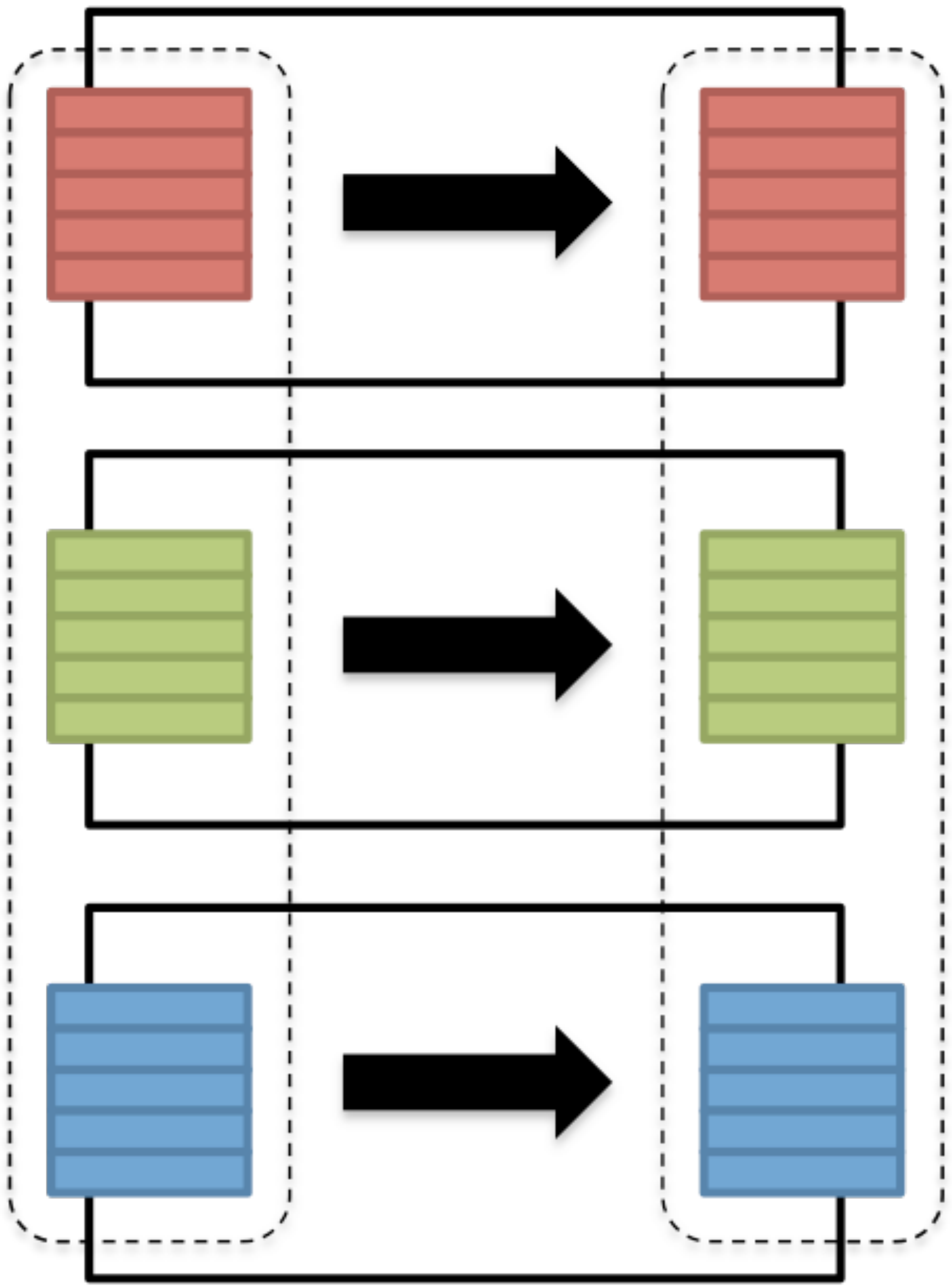
- count() => return the number of elements
- take(n) => select the first *n* elements
- saveAsTextFile(file) => store dataset as file

Lineage, laziness & persistence

- Spark stores lineage information for every RDD partition
- Intermediate RDDs are computed only when needed
- By default RDDs are not retained in memory
  — use the cache/persist methods on ‘hot’ RDDs

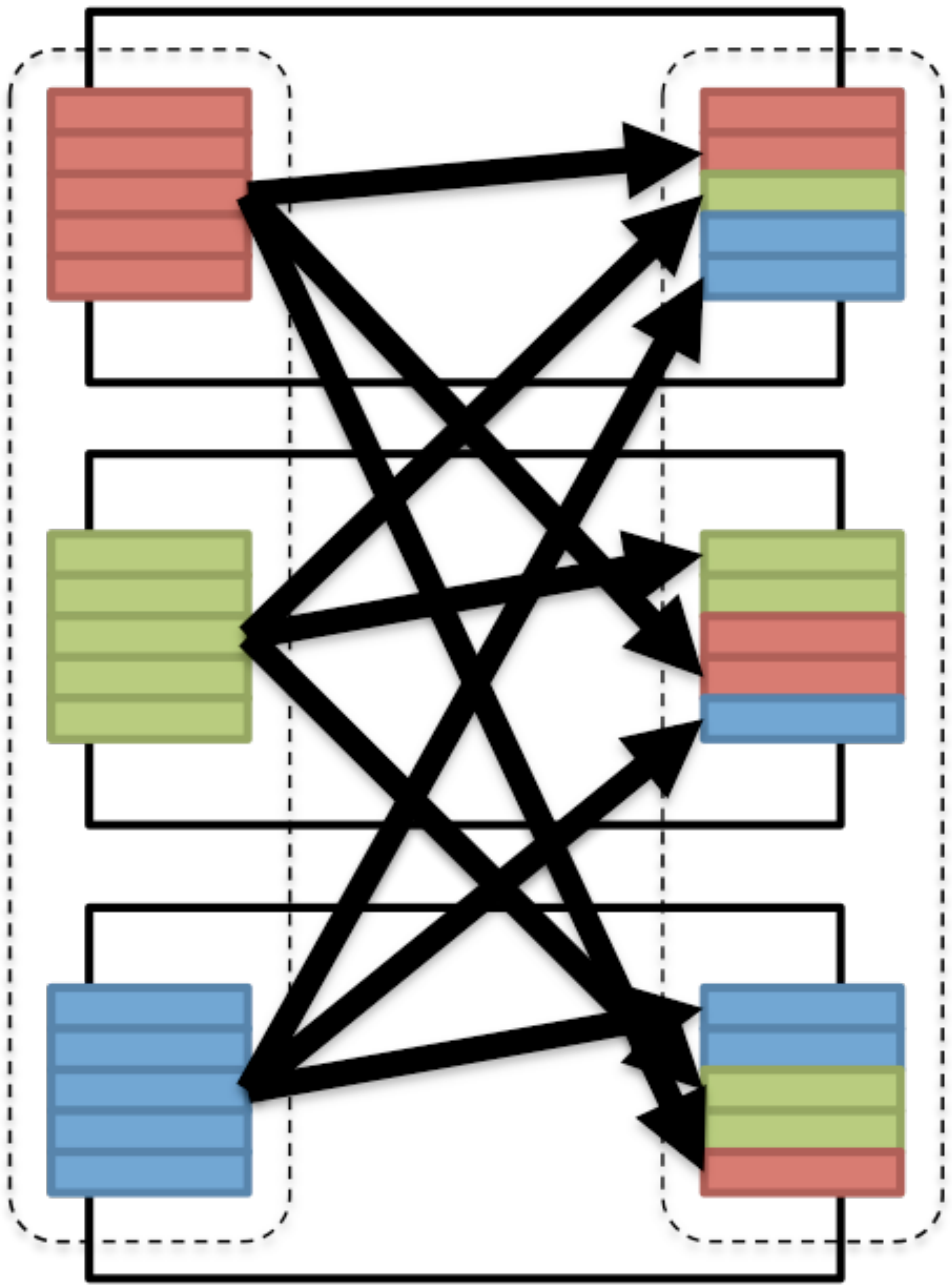
Narrow transformation

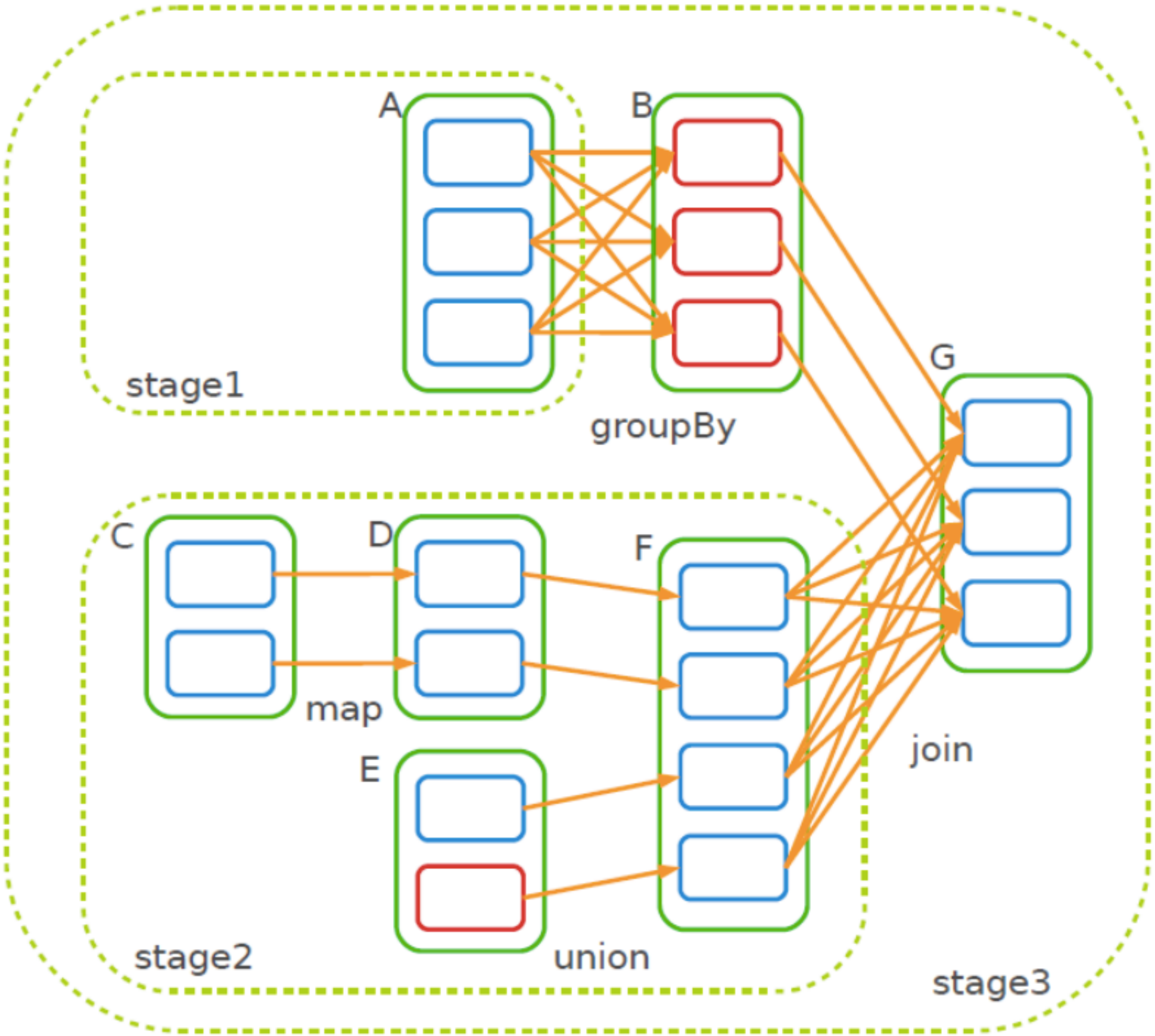
- Input and output stays in same partition
- No data movement is needed



Wide transformation

- Input from other partitions are required
- Data shuffling is needed before processing




A
B
G
stage1
groupBy
C
D
F
map
join
E
stage2
union
stage3

PairRDDs

RDDs of (key, value) tuples are ‘special’

A number of transformations only for PairRDDs:

- reduceByKey, groupByKey
- join, cogroup

Spark: a general framework

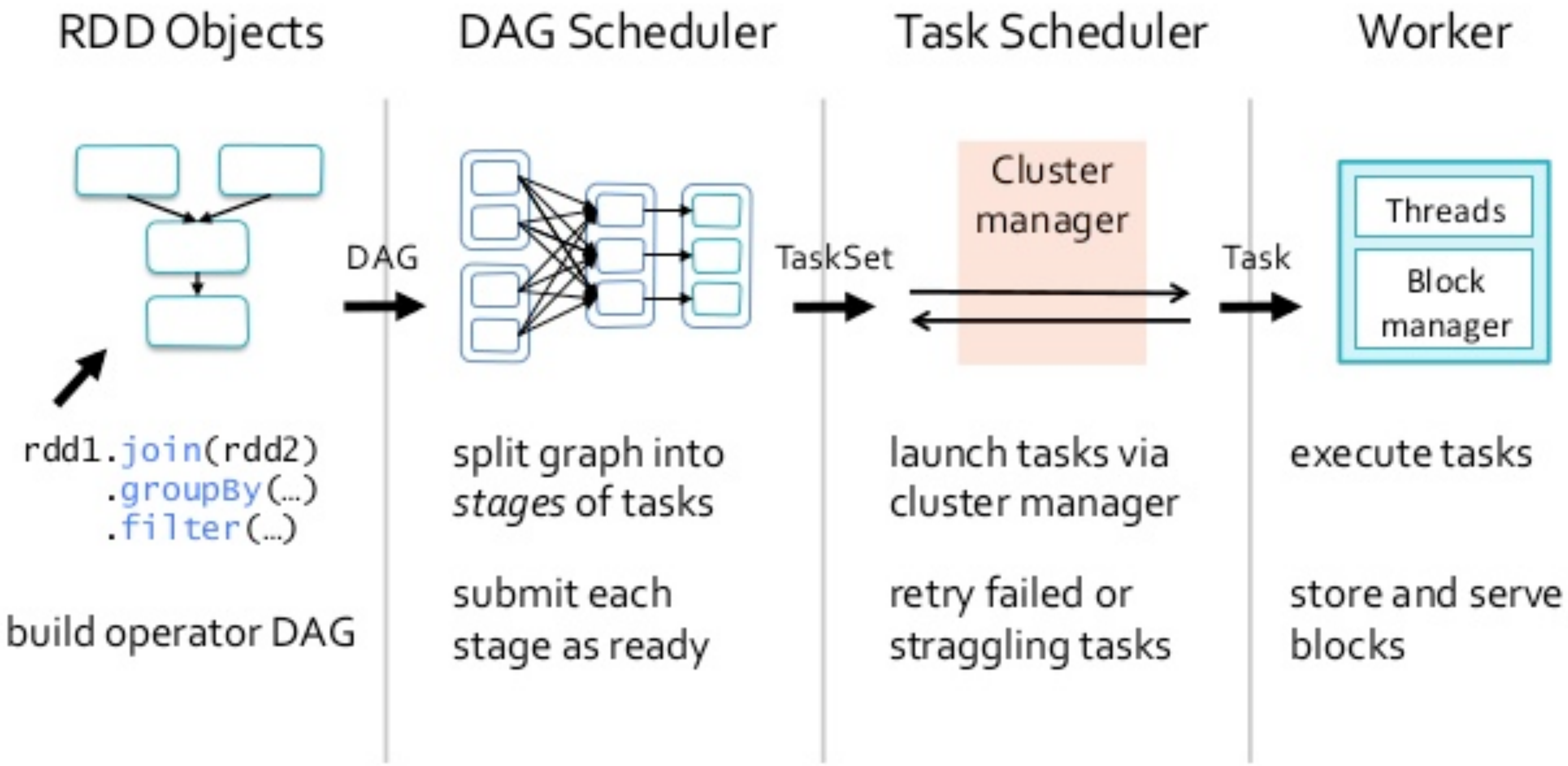
Spark aims to generalize MapReduce to support new applications with a more efficient engine, and simpler for the end users.

Write programs in terms of distributed datasets and operations on them

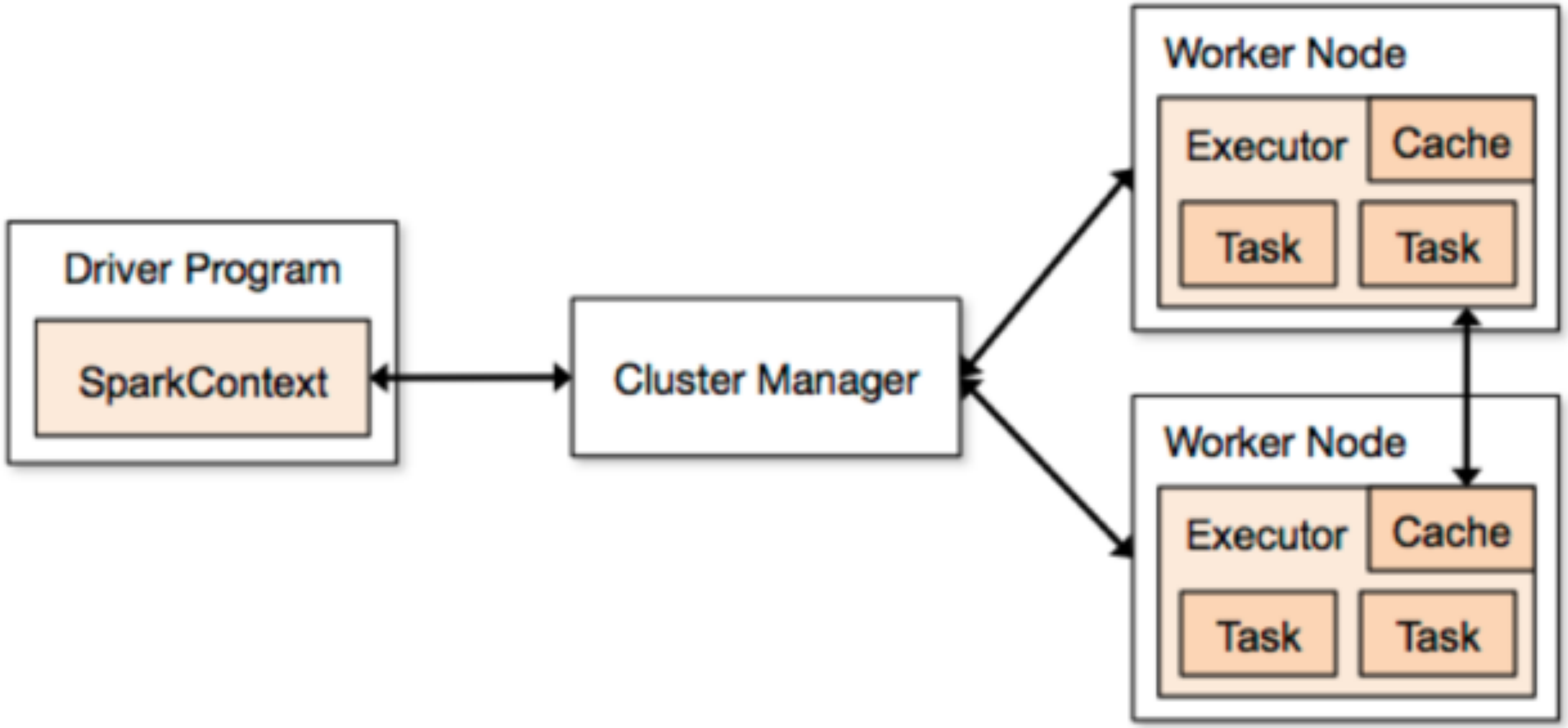
Accessible from multiple programming languages:

- Scala
- Java
- Python
- R (only via dataframes)

Execution Process



An Executing Application



Shared variables

- In general: avoid!
- When needed: read-only
- Two helpful types:
  broadcast variables, accumulators

Broadcast variables

- Wrapper around an object
- Copy send once to every worker
- Use case: lookup-table
- Should fit in the main memory of a single worker
- Can only be used read-only

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Accumulators

- Special variable to which workers can only “add”
- Only the driver can read
- Similar to MapReduce counters

RDD limitations

- Reading structured data sources (schema)
- Tuple juggling

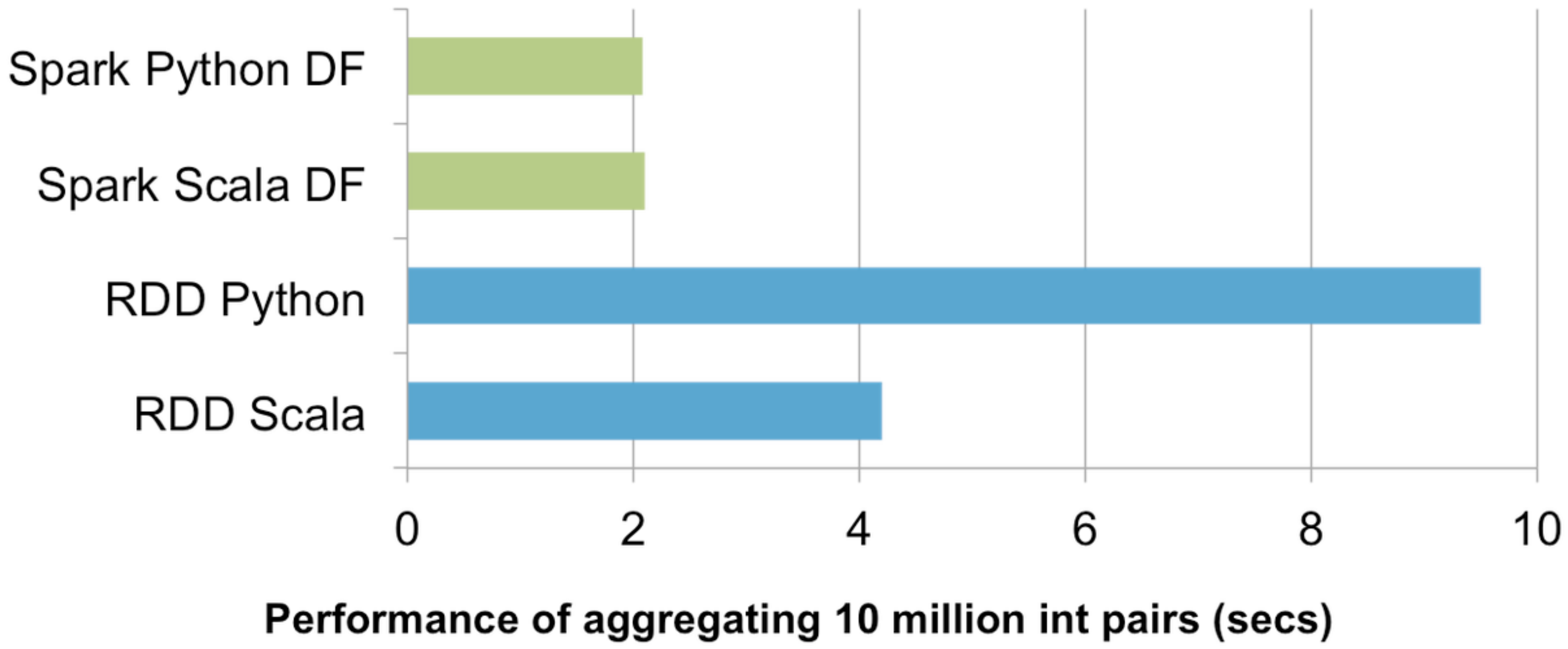
  ([a, b, c]) => (a, [a, b, c]) => (c, [a, b, c]) etc

- Flexibility hinders optimiser

SparkSQL & DataFrames

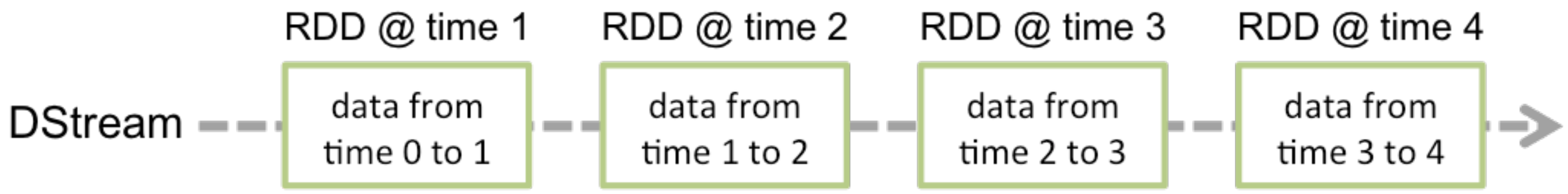
- Inspiration from SQL & Pandas
- Columnar data representation
- Automatically reading data in Avro, CSV, JSON, .. format
- Easy conversion from/to RDD's

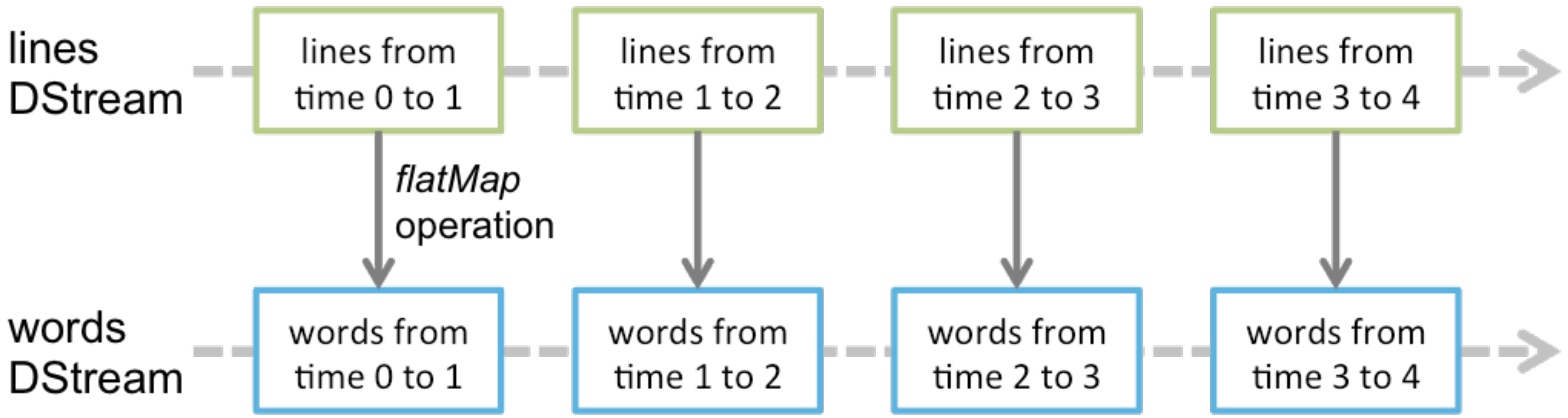
DataFrame performance



https://databricks.com/blog/2015/04/24/recent-performance-improvements-in-apache-spark-sql-python-dataframes-and-more.html

Discretized Streams





http://spark.apache.org/docs/latest/streaming-programming-guide.html

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Spark Streaming

Spark uses microbatches to get close to real-time performance
Intervals for batch creation can be set

http://spark.apache.org/docs/latest/streaming-programming-guide.html

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Streaming data sources

- Kafka
- Flume
- HDFS/S3
- Kinesis
- Twitter
- TCP socket
- Pluggable interface, write your own

Machine Learning Library (MLlib)

Common machine learning algorithms on top of Spark:

- classification: SVM, naive Bayes
- regression: logistic regression, decision trees, isotonic regression
- clustering: K-means, PIC, LDA
- collaborative filtering: alternating least squares
- dimensionality reduction: SVD, PCA

Deployment

- Stand-alone cluster
- On cluster scheduler (YARN / Mesos)
- Local, single machine
  (easy way to get started: docker-stacks)

Usage

- Interactive shell:
  - spark-shell (Scala)
  - pyspark (Python)
- Notebook
- Standalone application
  - spark-submit <jar> / <py>

Distributed data store

amazon web services™ S3

cassandra

hadoop HDFS

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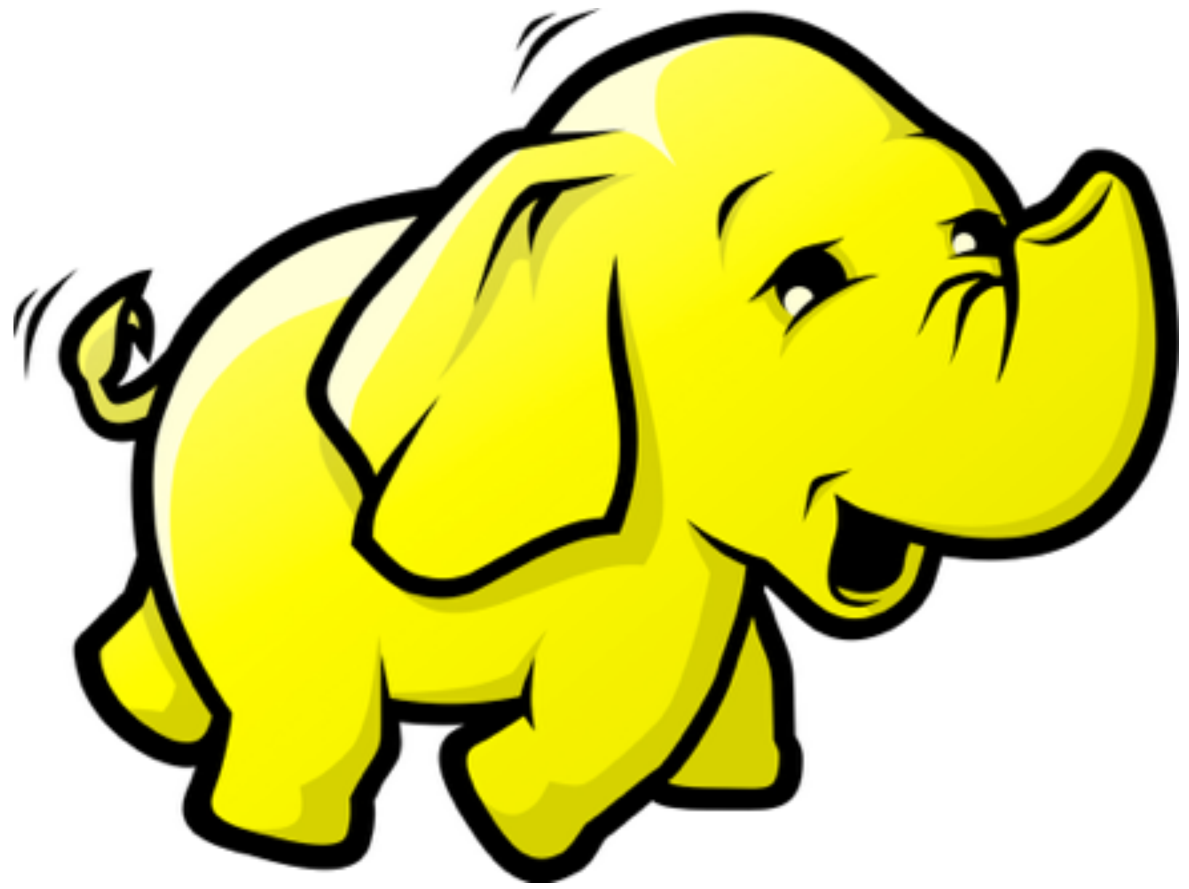
Summary

- Spark replaces MapReduce
- RDDs enable fast distributed data processing
- Learn Scala

Intermezzo

There are only two hard things in Computer Science:
cache invalidation and naming things.

-- Phil Karlton



https://pixelastic.github.io/pokemonorbigdata/