Spark

An Efficient and Fault-Tolerant System for In-Memory Custer Computing

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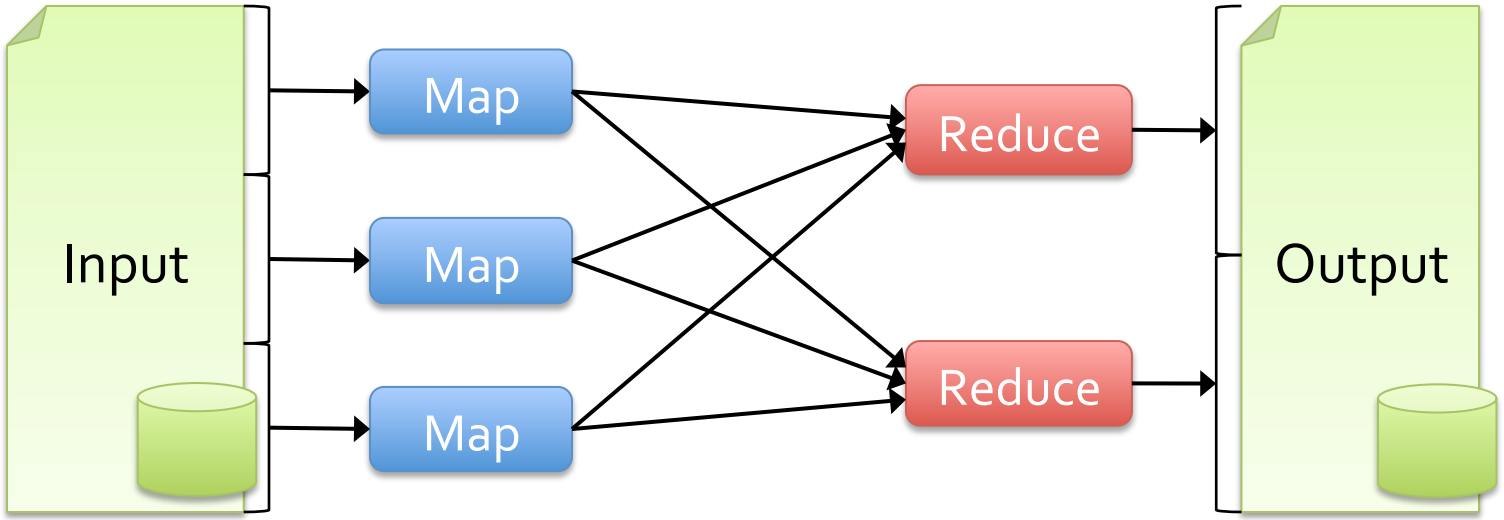
Motivation

Most current cluster programming models are based on *acyclic data flow* from stable storage to stable storage



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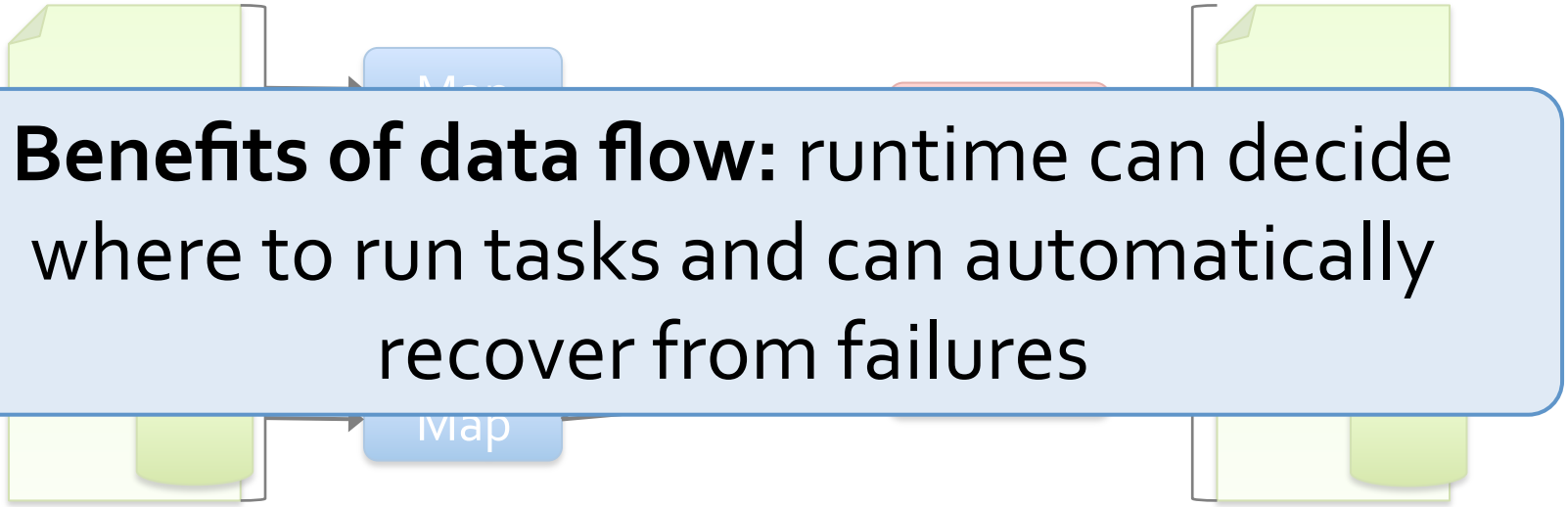


Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

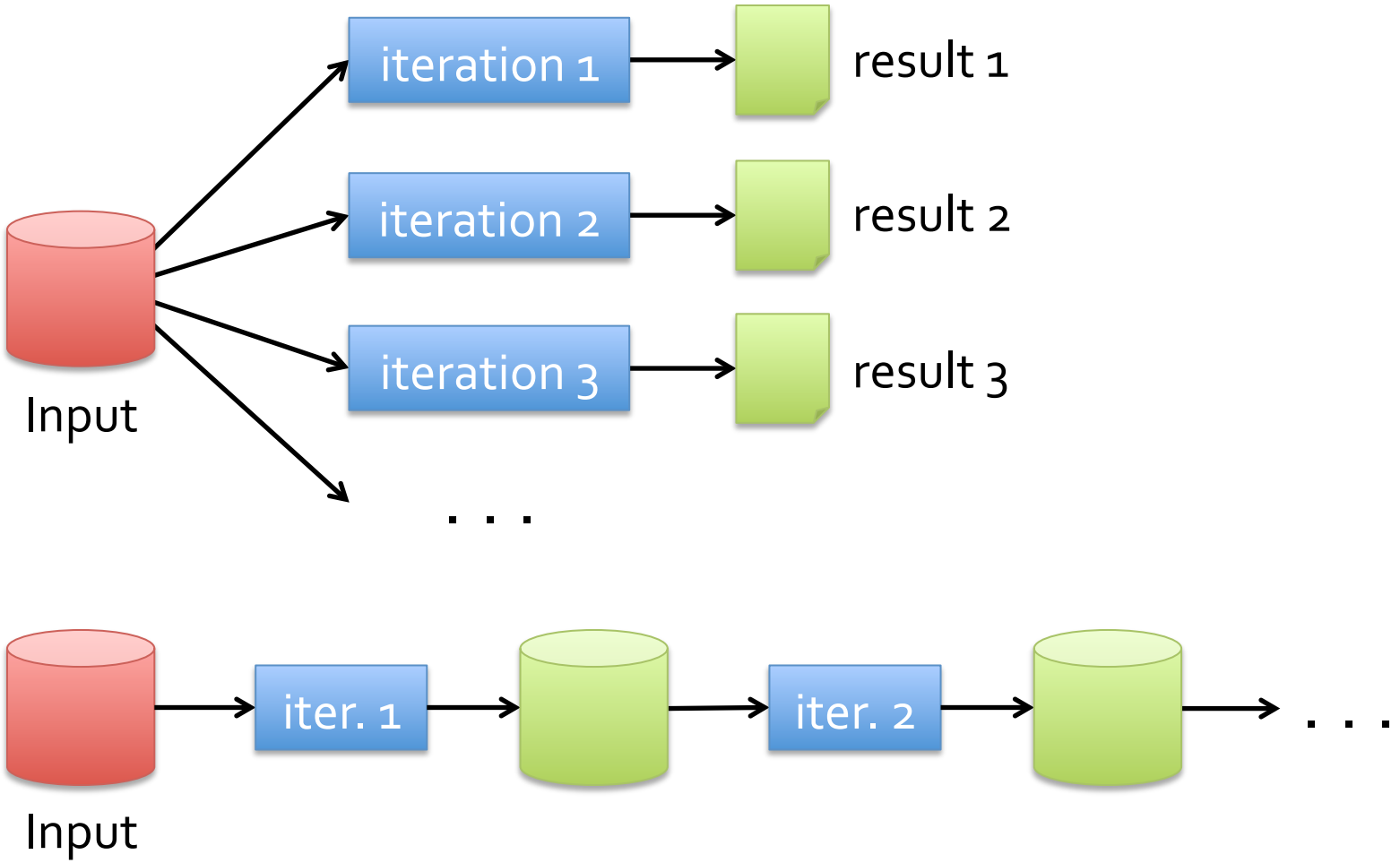
Motivation

Acyclic data flow is inefficient for applications that repeatedly reuse a *working set* of data:

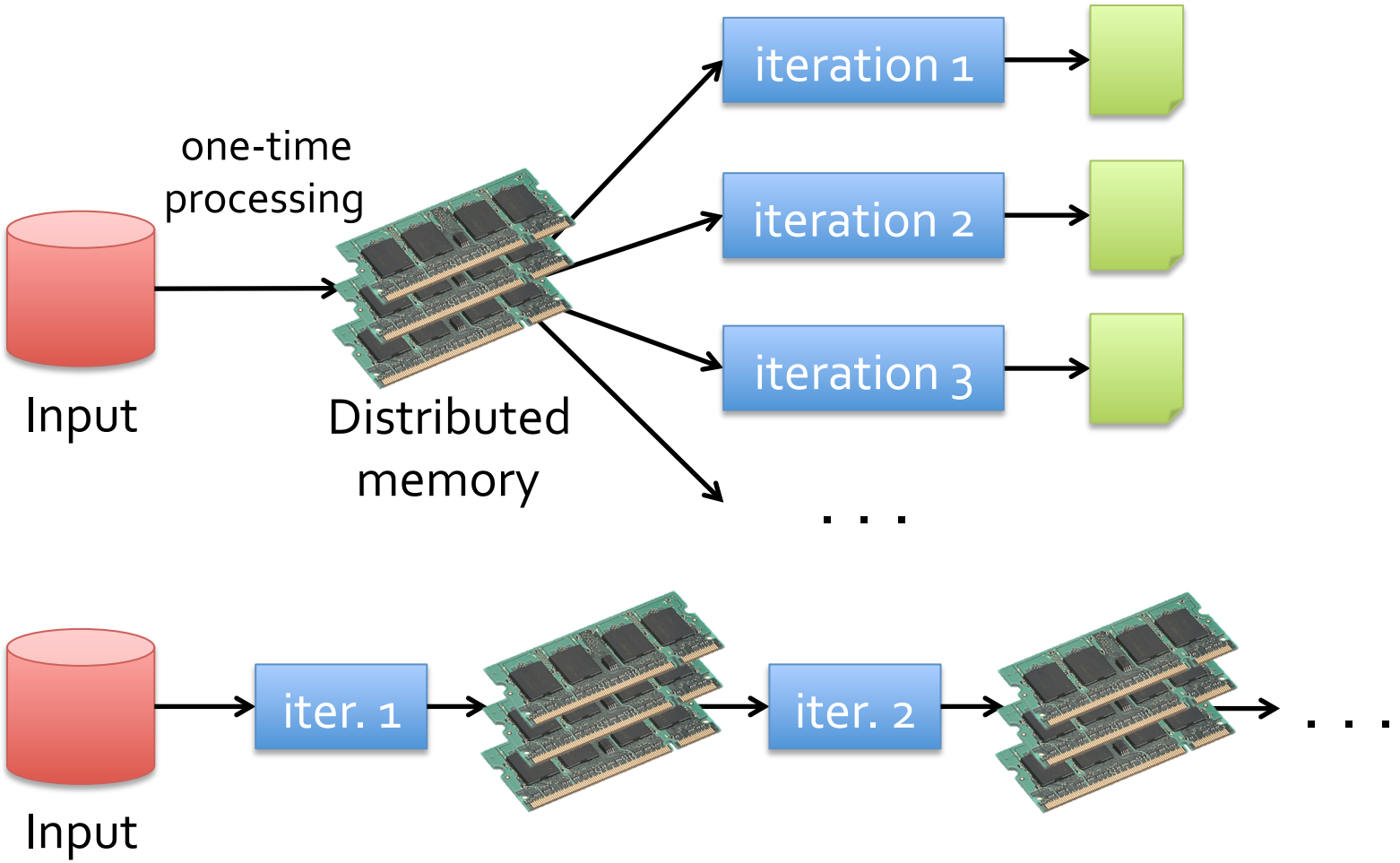
- » **Iterative** algorithms (machine learning, graphs)
- » **Interactive** data mining tools (R, Excel, Python)

With current frameworks, apps reload data from stable storage on each query

Example: Iterative Apps



Goal: Keep Working Set in RAM



Challenge

How to design a distributed memory abstraction that is both ***fault-tolerant*** and ***efficient***?

Challenge

Existing distributed storage abstractions have interfaces based on *fine-grained* updates

- » Reads and writes to cells in a table
- » E.g. databases, key-value stores, distributed memory

Requires replicating data or logs across nodes for fault tolerance

- » Expensive for data-intensive apps!

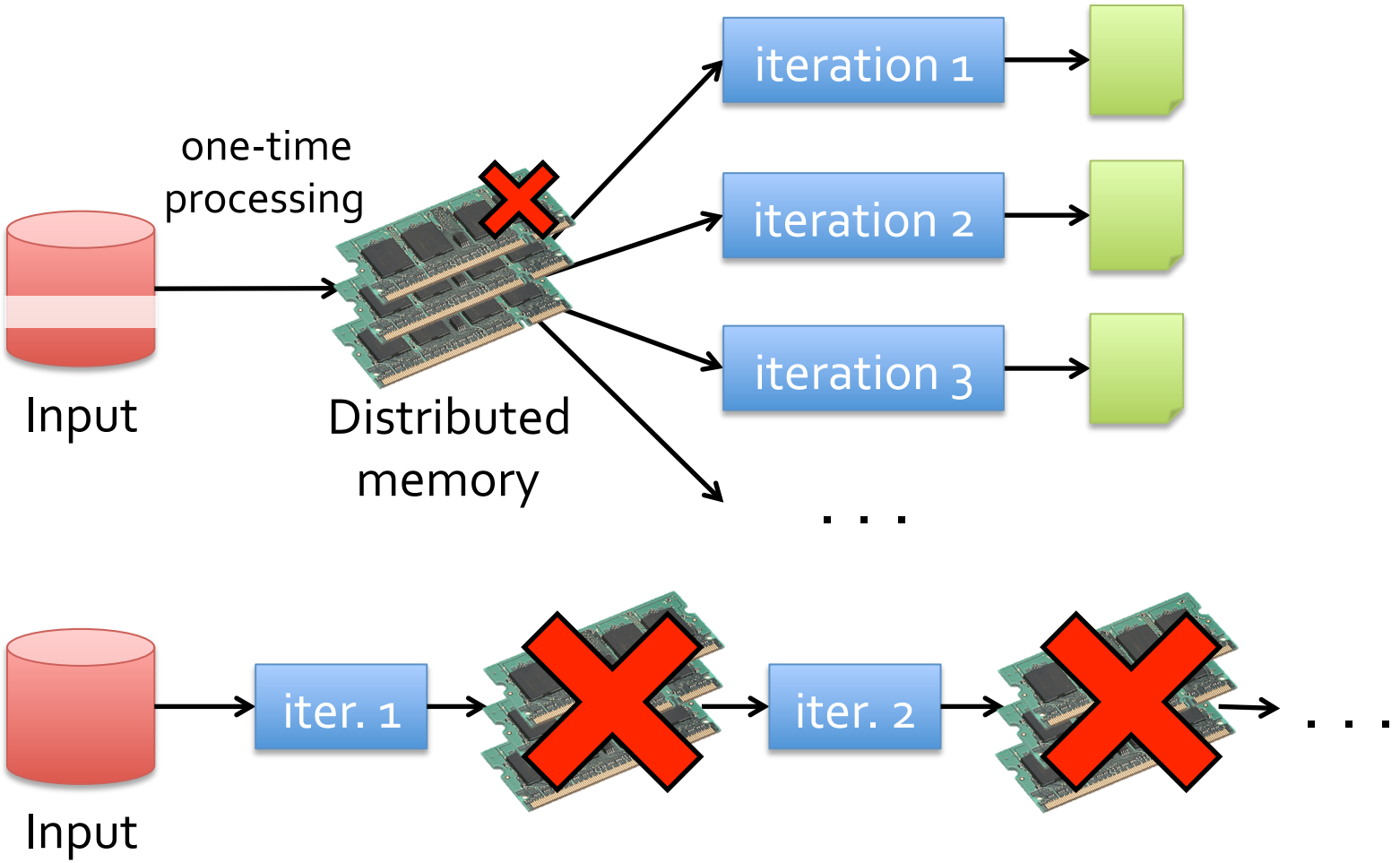
Solution: Resilient Distributed Datasets (RDDs)

Provide an interface based on *coarse-grained* transformations (e.g. map, group-by, join, …)

Efficient fault recovery using *lineage*

- » Log one operation to apply to many elements
- » Recompute lost partitions of RDD on failure
- » No cost if nothing fails

RDD Recovery



Generality of RDDs

Despite coarse-grained interface, RDDs can express surprisingly many parallel algorithms

- » These naturally *apply the same operation to many items*

Capture many current programming models

- » Data flow models: MapReduce, Dryad, SQL, …
- » Specialized models for iterative apps: BSP (Pregel), iterative MapReduce, incremental (CBP)

Support new apps that these models don't

Outline

Spark programming interface

Applications

Implementation

Demo

Spark Programming Interface

Language-integrated API in Scala

Can be used interactively from Scala interpreter

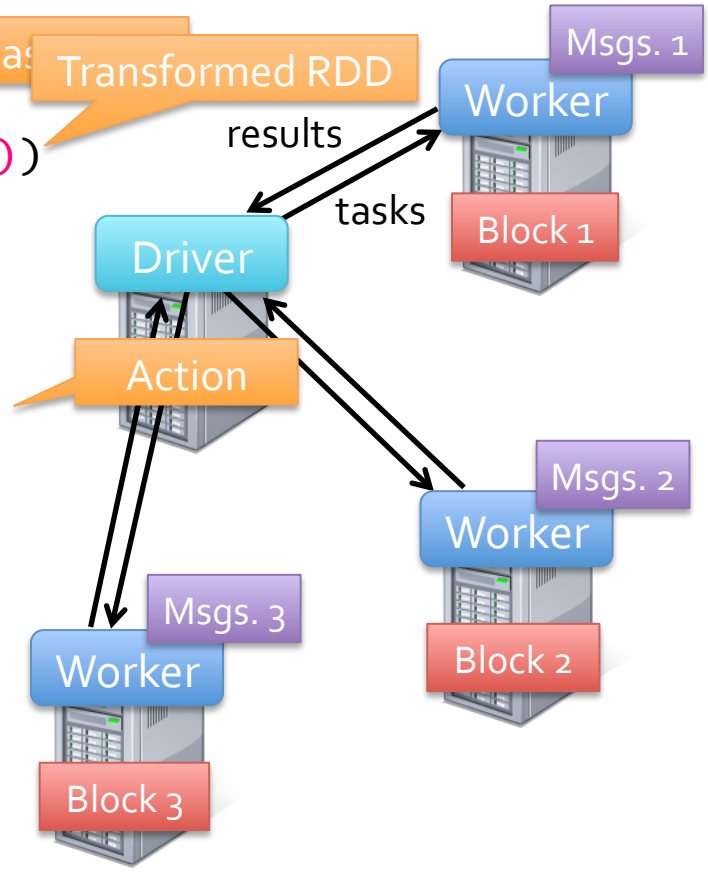
RDDs look like standard Scala collections

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.persist()

messages.filter(_.contains("foo")).count
messages.filter(_.contains("bar")).count
. . .
```

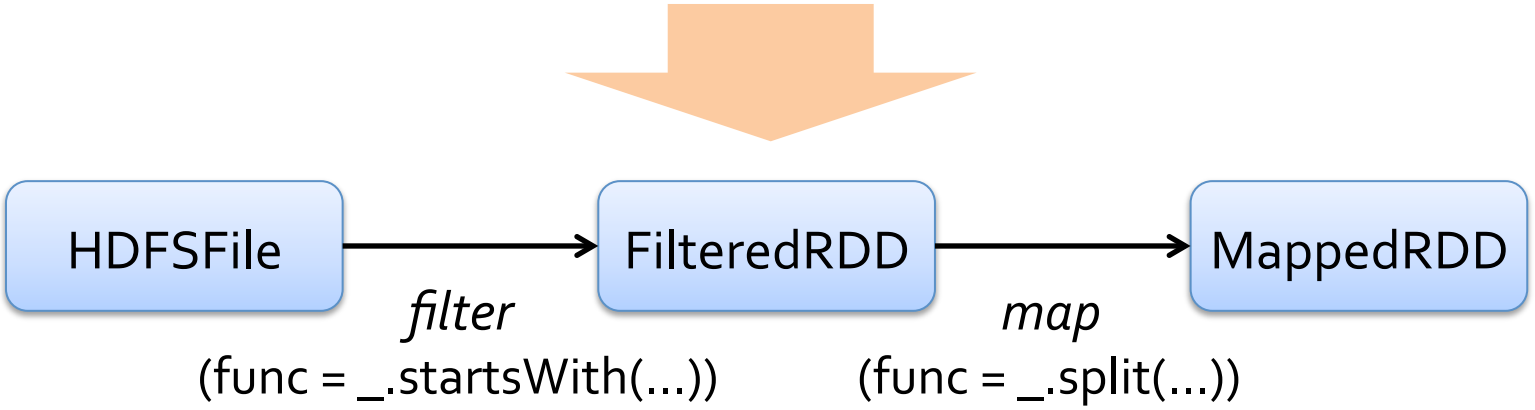


Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

Fault Tolerance

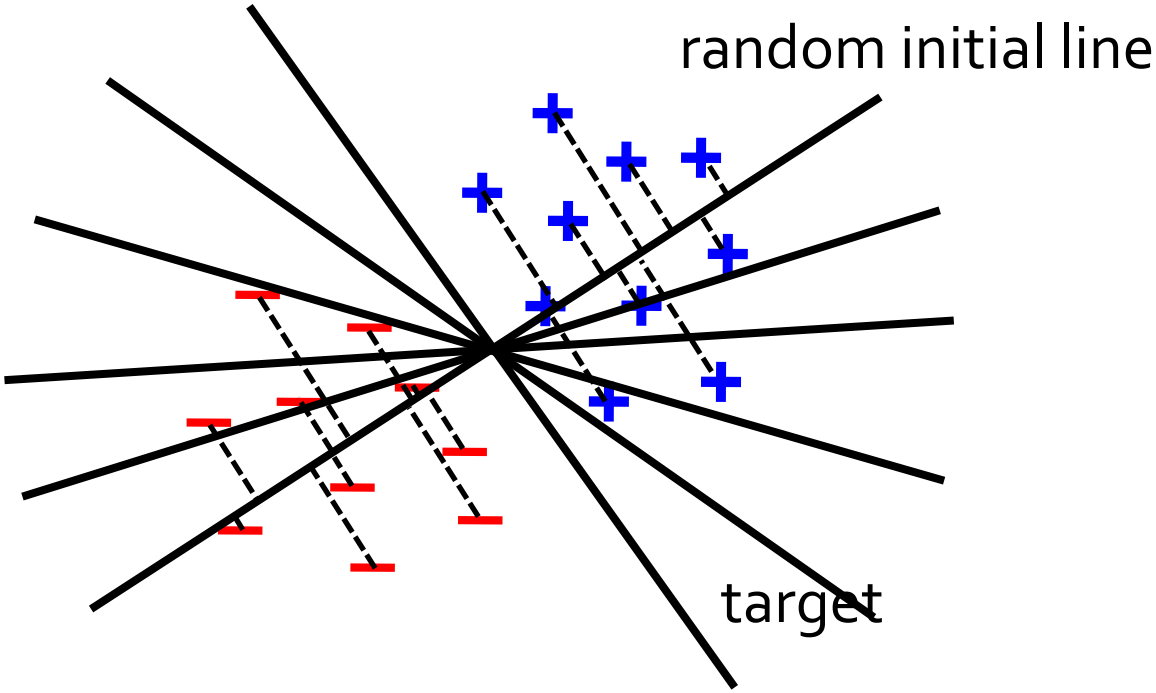
RDDs maintain *lineage* information that can be used to reconstruct lost partitions

Ex:
```
messages = textFile(...).filter(_.startsWith("ERROR"))
                        .map(_.split('\t')(2))
```



Example: Logistic Regression

Goal: find best line separating two sets of points



Logistic Regression Code

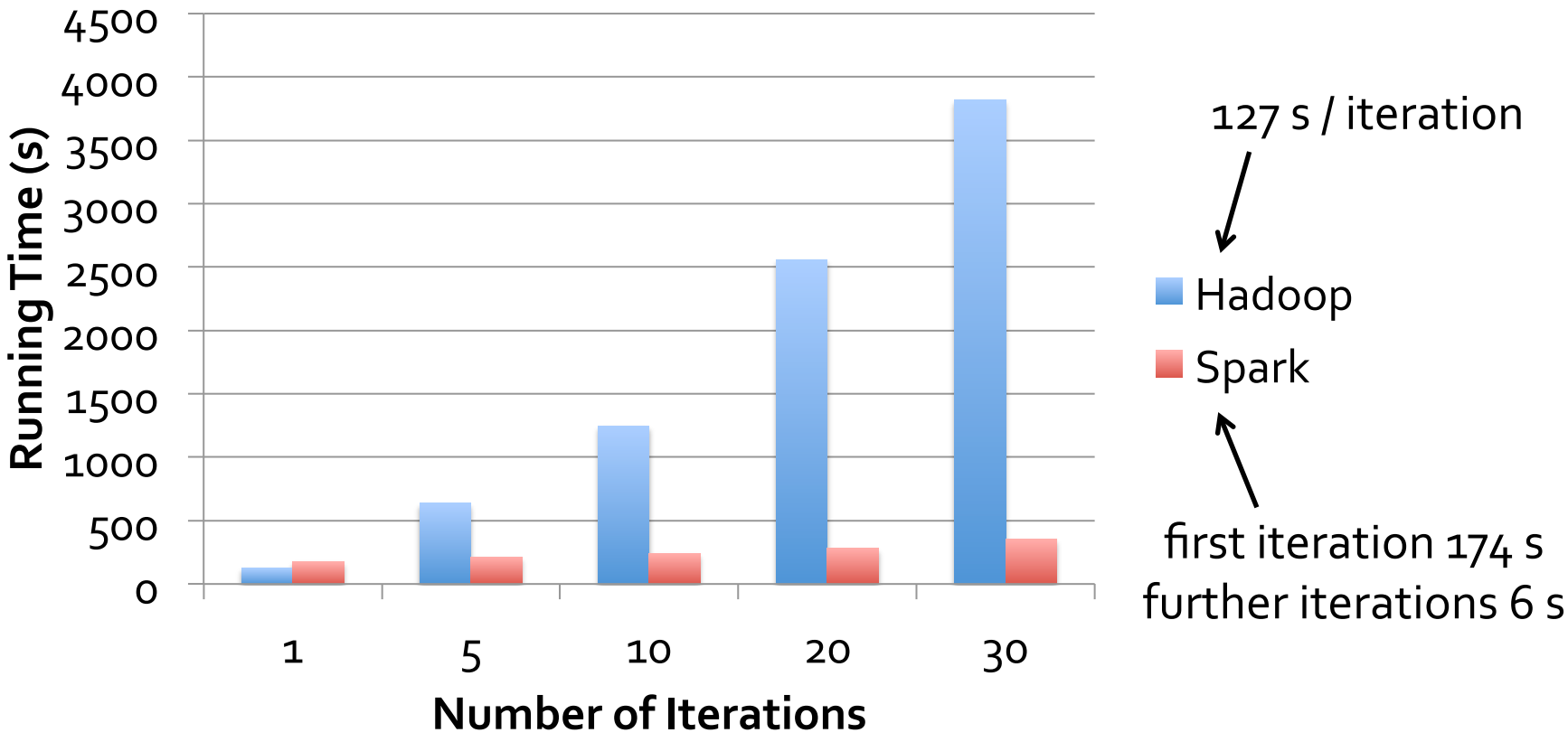
```
val data = spark.textFile(...).map(readPoint).persist()

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  val gradient = data.map(p =>
    (1 / (1 + exp(-p.y*(w dot p.x))) - 1) * p.y * p.x
  ).reduce((a,b) => a+b)
  w -= gradient
}

println("Final w: " + w)
```

Logistic Regression Performance



Spark Applications

City traffic prediction (Mobile Millennium)

In-memory OLAP & anomaly detection (Conviva)

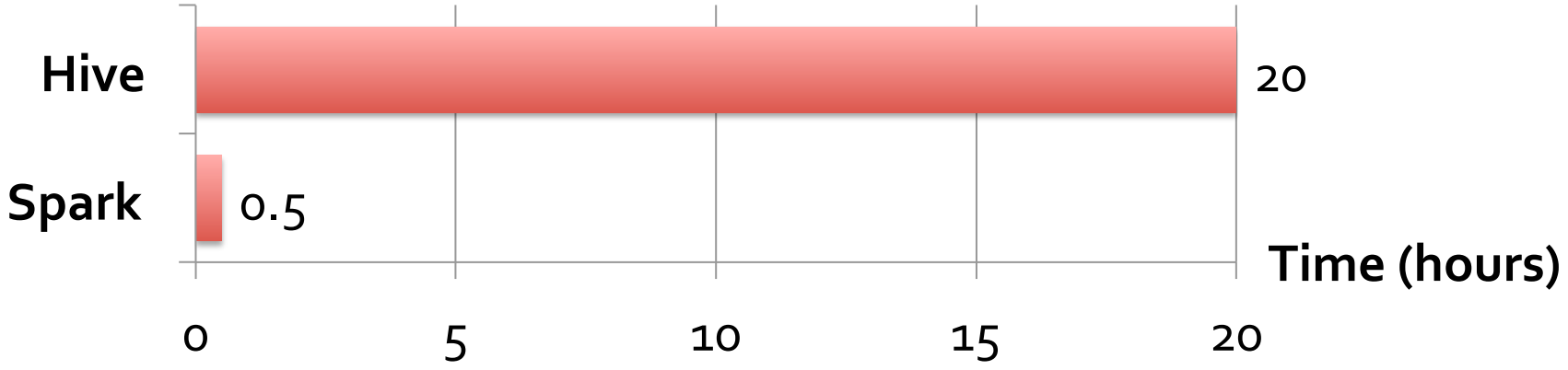
Twitter spam classification (Monarch)

Matrix factorization for collaborative filtering

Time series analysis

…

Conviva GeoReport



Aggregations on many keys w/ same WHERE clause

40× gain comes from:

- » Not re-reading unused columns or filtered records
- » Avoiding repeated decompression
- » In-memory storage of deserialized objects

Cluster Programming Models

RDDs can express many proposed data-parallel programming models

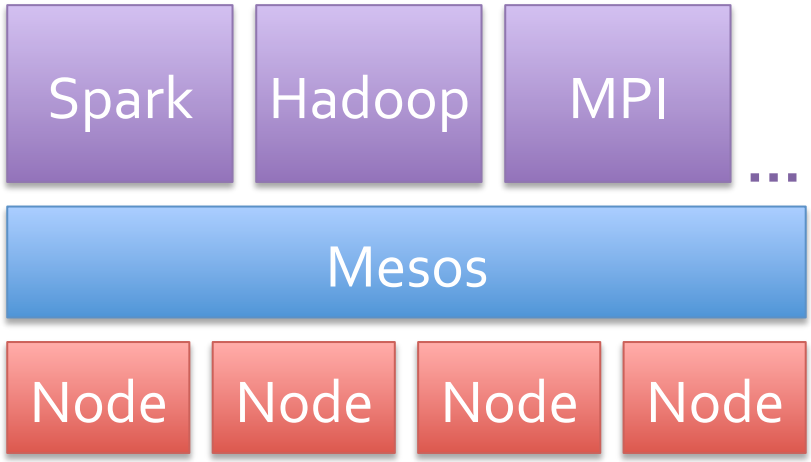
- » **MapReduce, DryadLINQ**
- » **Pregel** => implemented as Bagel [200 LOC]
- » **Iterative MapReduce** => ported HaLoop [200 LOC]
- » **SQL** => Hive on Spark (Shark) [3000 LOC]

Allow apps to efficiently *intermix* these models

Implementation

Runs on the Mesos cluster manager to share resources with Hadoop & other apps

Can read from any Hadoop input source (HDFS, S3, …)



No changes to Scala language or compiler

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Conclusion

RDDs offer a simple and efficient programming model for a broad range of applications

Achieve fault tolerance efficiently by providing *coarse-grained* operations and tracking lineage

Open source: **www.spark-project.org**

Related Work

DryadLINQ, FlumeJava
- » Similar "distributed collection" API, but cannot reuse datasets efficiently *across* queries

Relational databases
- » Lineage/provenance, logical logging, materialized views

GraphLab, Piccolo, BigTable, RAMCloud
- » Fine-grained writes similar to distributed shared memory

Iterative MapReduce (e.g. Twister, HaLoop)
- » Implicit data sharing for a fixed computation pattern

Caching systems (e.g. Nectar)
- » Store data in files, no explicit control over what is cached

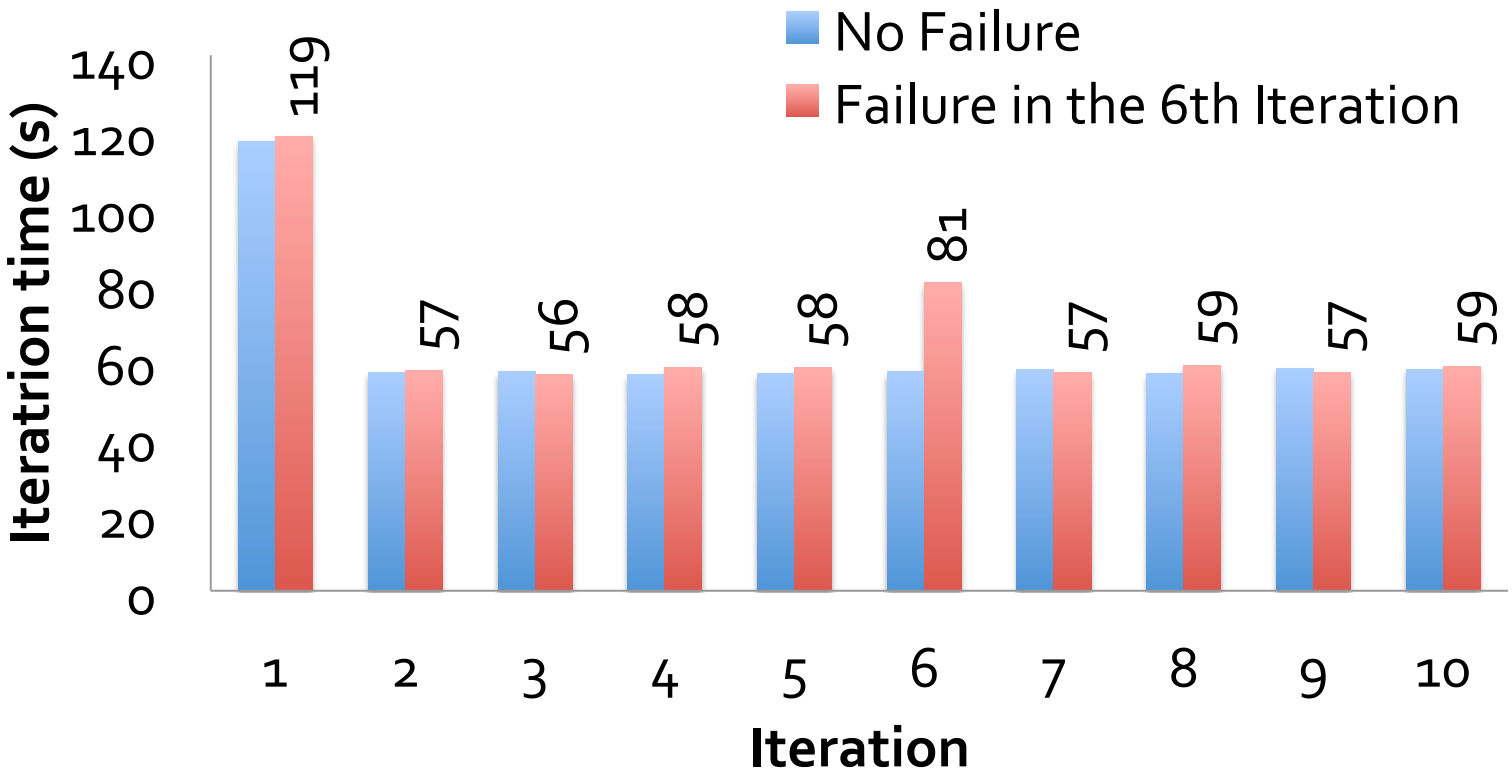
RDDs vs Distributed Shared Memory

Concern	RDDs	Distr. Shared Mem.
Reads	Fine-grained	Fine-grained
Writes	Bulk transformations	Fine-grained
Consistency	Trivial (immutable)	Up to app / runtime
Fault recovery	Fine-grained and low-overhead using lineage	Requires checkpoints and program rollback
Straggler mitigation	Possible using speculative execution	Difficult
Work placement	Automatic based on data locality	Up to app (but runtime aims for transparency)

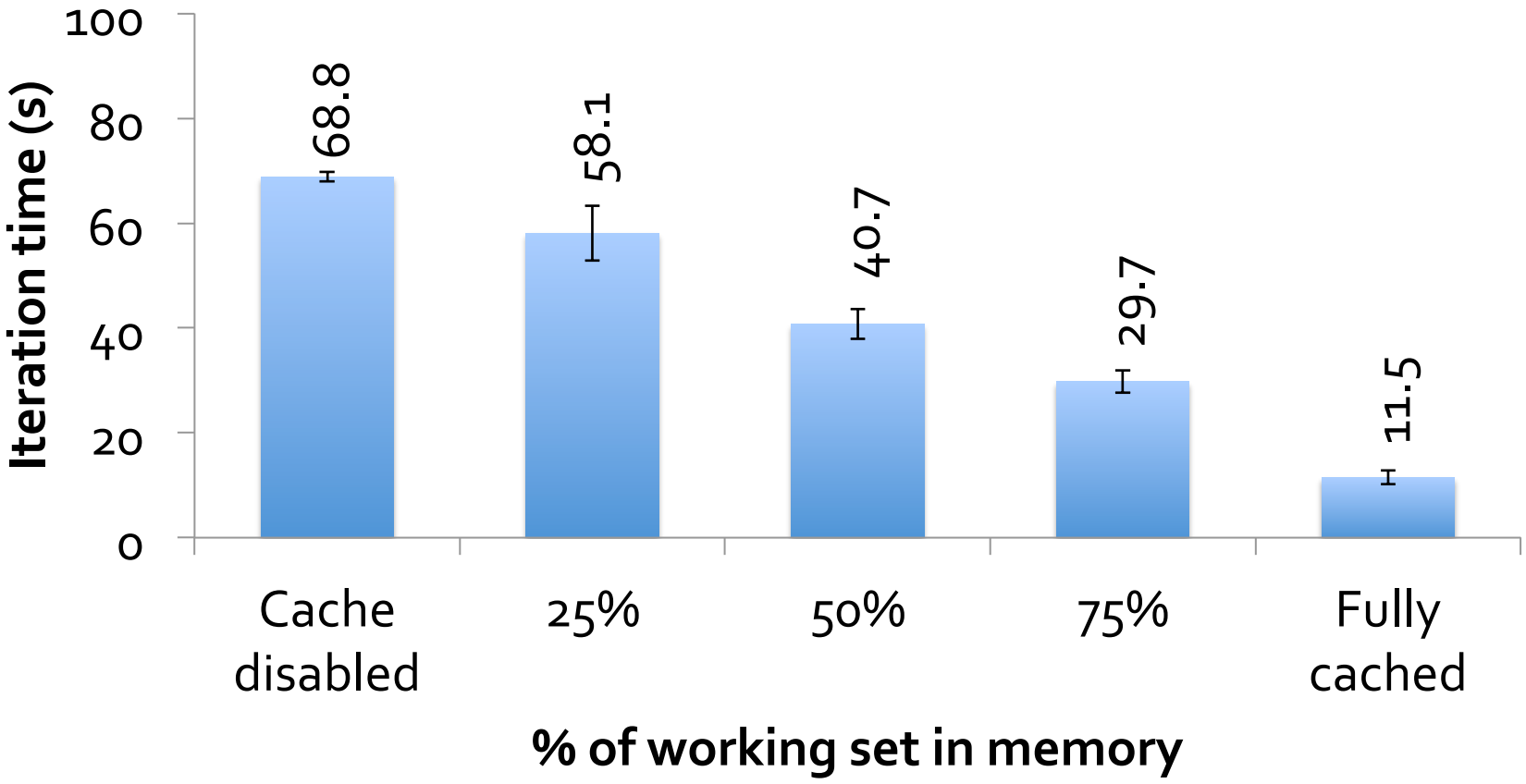
Spark Operations

Transformations (define a new RDD)	map filter sample groupByKey reduceByKey sortByKey	flatMap union join cogroup cross mapValues
Actions (return a result to driver program)	collect reduce count save lookupKey	

Fault Recovery Results



Behavior with Not Enough RAM



PageRank Results