CSE 6242 / CX 4242 Data and Visual Analytics | Georgia Tech

Spark & Spark SQL

High-Speed In-Memory Analytics over Hadoop and Hive Data

Instructor: Duen Horng (Polo) Chau

Slides adopted from Matei Zaharia (MIT) and Oliver Vagner (TGI Fridays)

What is Spark?

http://spark.apache.org

Not a modified version of Hadoop

Separate, fast, MapReduce-like engine

- » **In-memory** data storage for very fast iterative queries
- » General execution graphs and powerful optimizations
- » Up to 40x faster than Hadoop

Compatible with Hadoop's storage APIs

- » Can read/write to any Hadoop-supported system, including HDFS, HBase, SequenceFiles, etc

What is Spark SQL?

(Formally called Shark)

Port of Apache Hive to run on Spark

Compatible with existing Hive data, metastores, and queries (HiveQL, UDFs, etc)

Similar speedups of up to 40x

Project History [latest: v1.1]

Spark project started in 2009 at UC Berkeley AMP lab, open sourced 2010

Became Apache Top-Level Project in Feb 2014

Shark/Spark SQL started summer 2011

Built by 250+ developers and people from 50 companies

Scale to 1000+ nodes in production

In use at Berkeley, Princeton, Klout, Foursquare, Conviva, Quantifind, Yahoo! Research, …

http://en.wikipedia.org/wiki/Apache_Spark

Why a New Programming Model?

MapReduce greatly simplified big data analysis

But as soon as it got popular, users wanted more:

- » More **complex**, multi-stage applications (e.g. iterative graph algorithms and machine learning)
- » More **interactive** ad-hoc queries

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» More **complex**, multi-stage applications (e.g. iterative graph algorithms and machine learning)

» More **interactive** ad-hoc queries

Require faster **data sharing** across parallel jobs

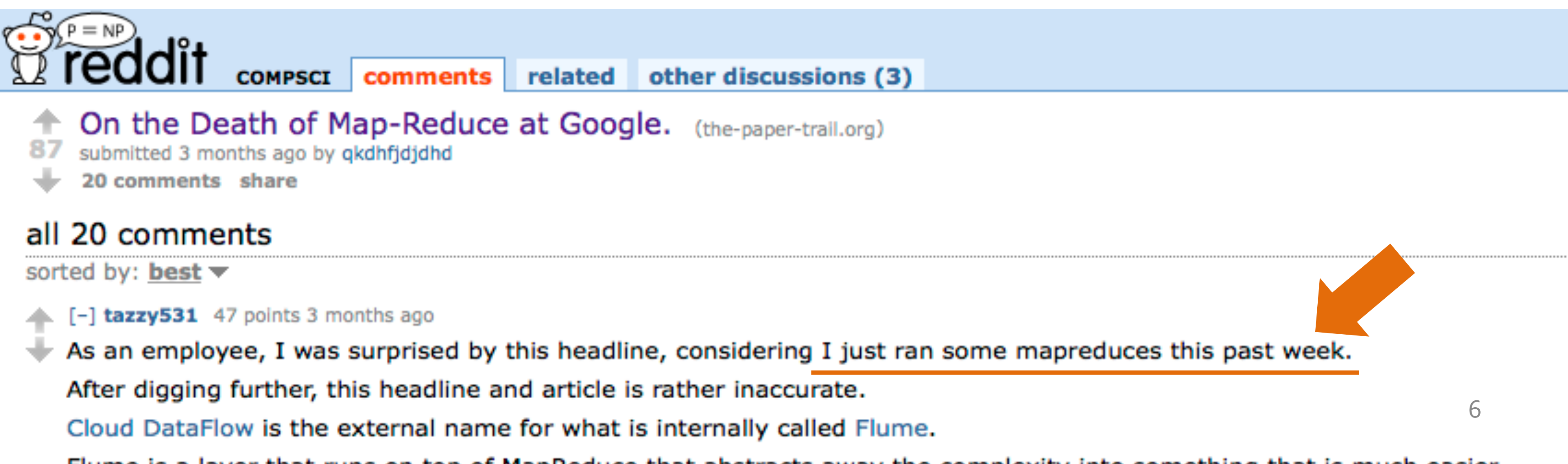
Up for debate… as of 10/7/2014

Is MapReduce dead?

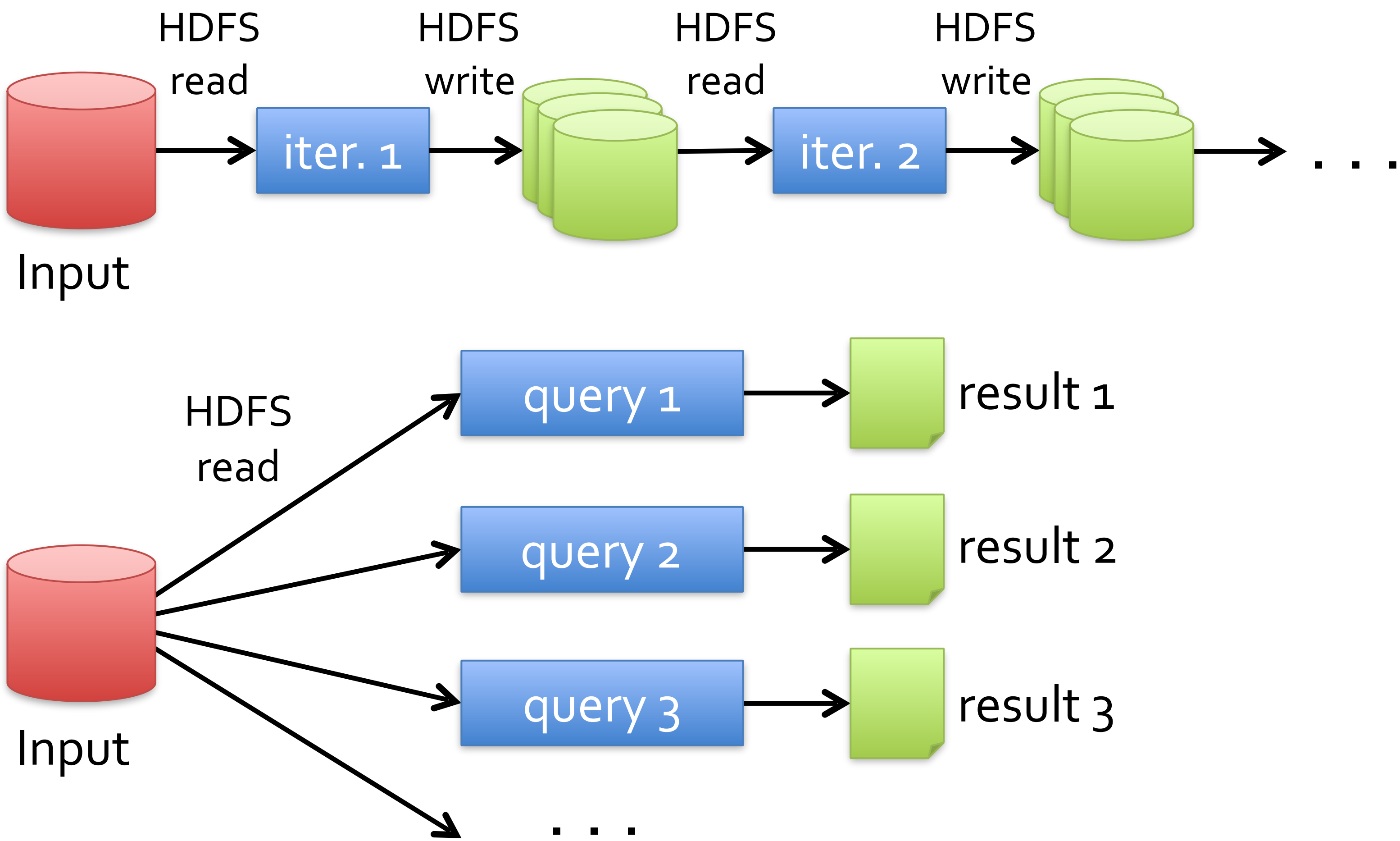
Google Dumps MapReduce in Favor of New Hyper-Scale Analytics System

http://www.datacenterknowledge.com/archives/2014/06/25/google-dumps-mapreduce-favor-new-hyper-scale-analytics-system/

http://www.reddit.com/r/compsci/comments/296aqr/on_the_death_of_mapreduce_at_google/



Data Sharing in MapReduce



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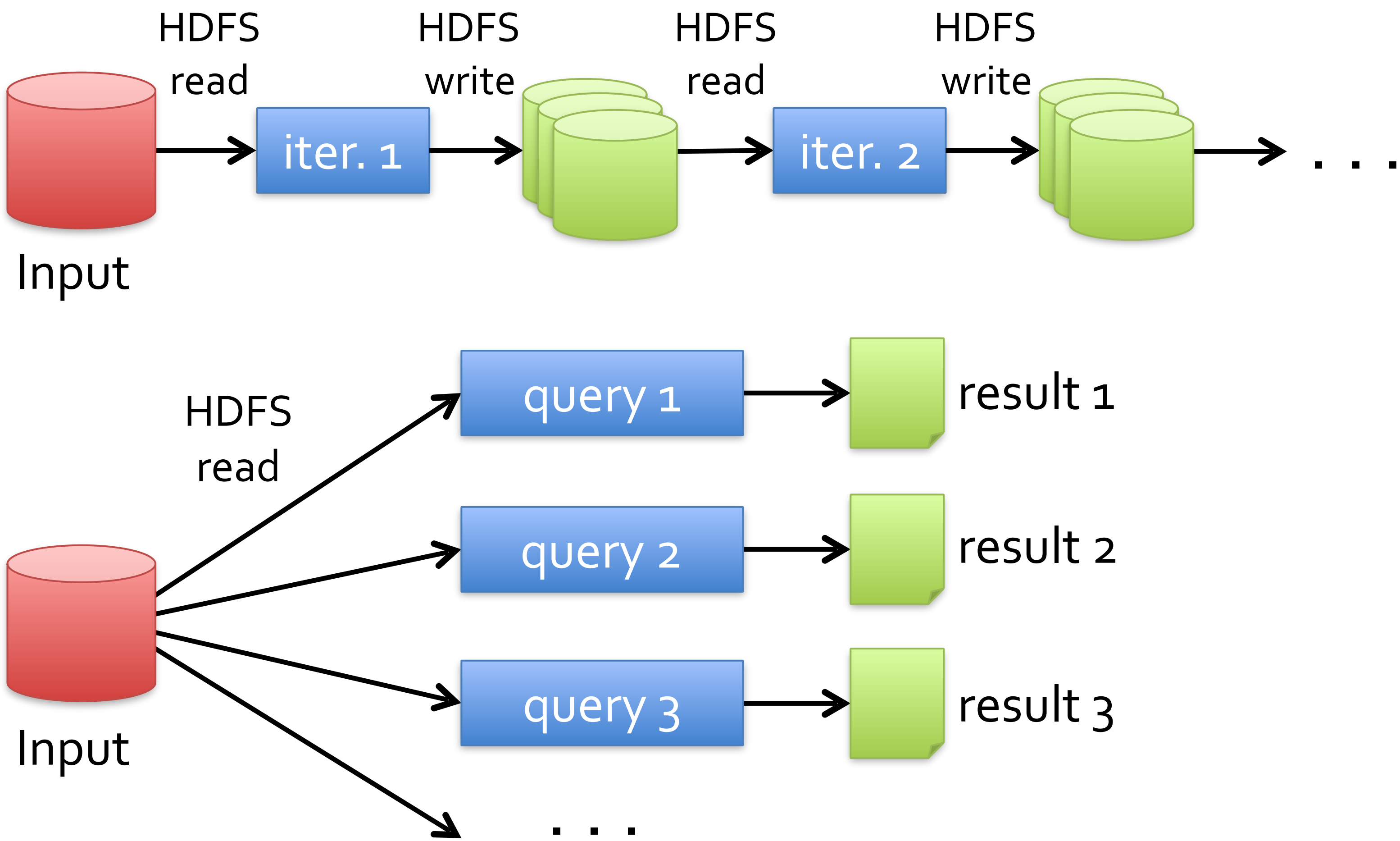
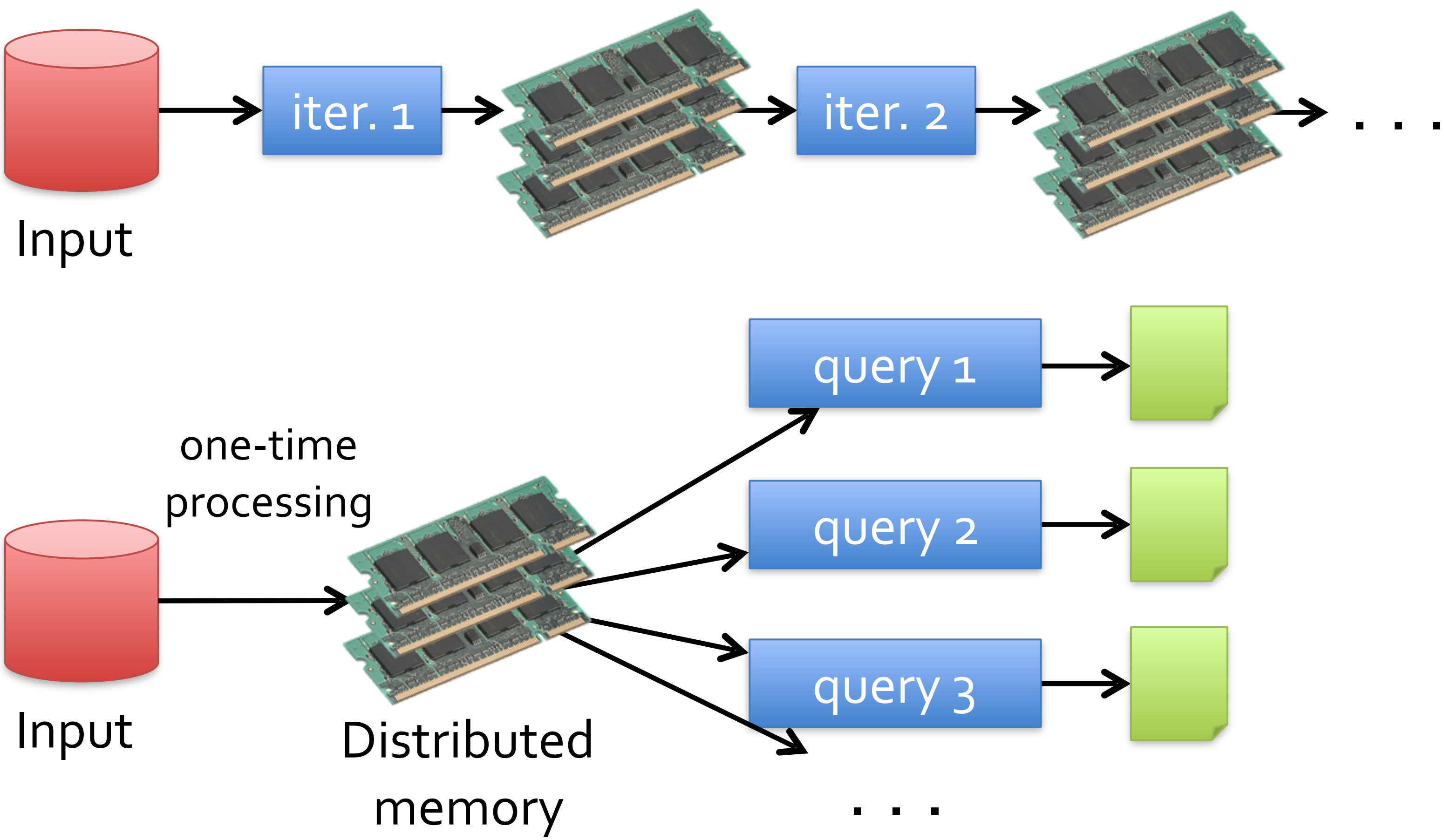


Slow due to replication, serialization, and disk IO

Data Sharing in Spark



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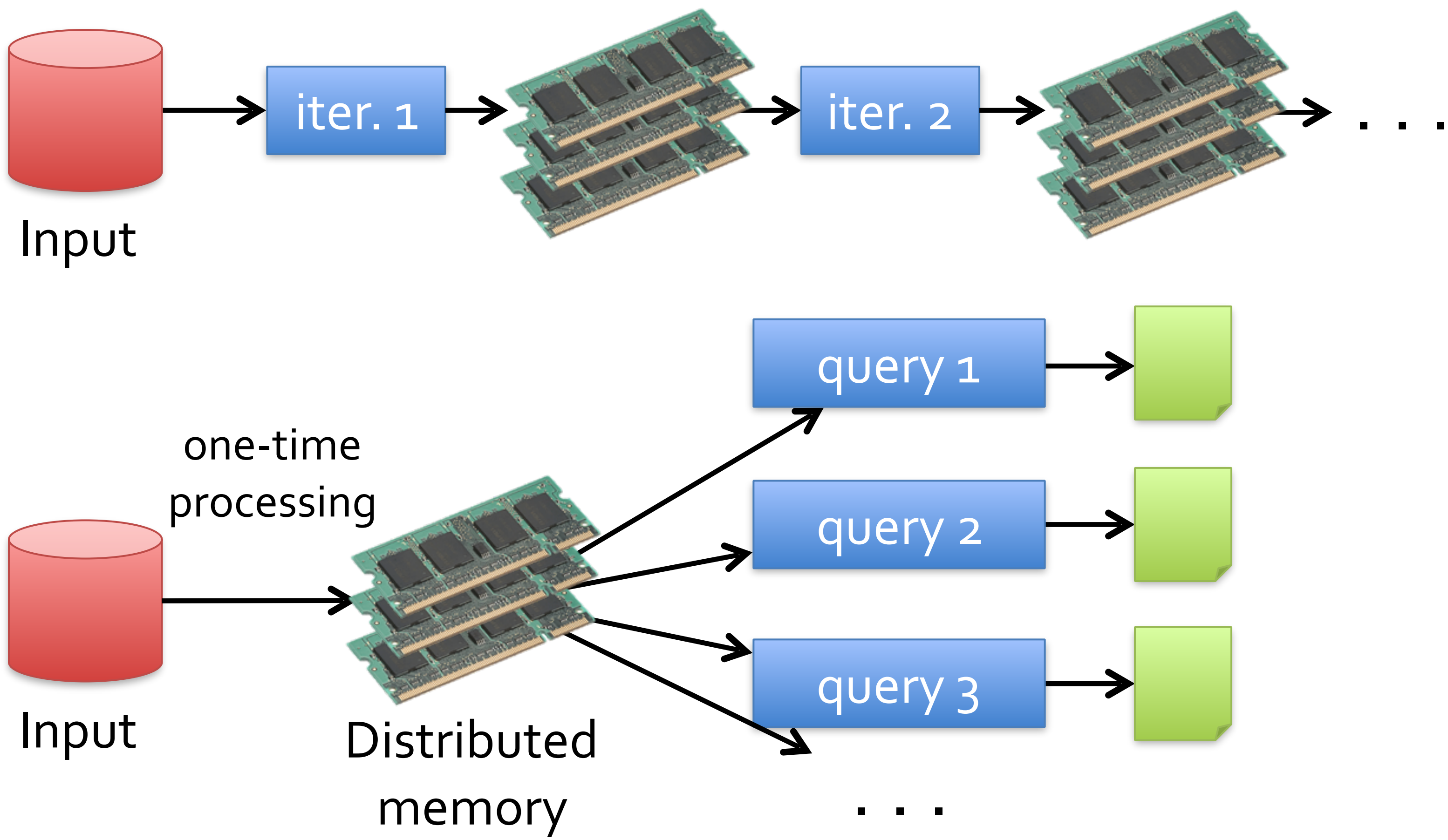

10-100× faster than network and disk

Spark Programming Model

Key idea: *resilient distributed datasets (RDDs)*

- Distributed collections of objects that can be cached in memory across cluster nodes
- Manipulated through various parallel operators
- Automatically rebuilt on failure

Interface

- Clean language-integrated API in Scala
- Can be used *interactively* from Scala, Python console
- Supported languages: Java, **Scala**, Python, R

http://www.scala-lang.org/old/faq/4

Functional programming in D3: http://sleptons.blogspot.com/2015/01/functional-programming-d3js-good-example.html

Scala vs Java 8: http://kukuruku.co/hub/scala/java-8-vs-scala-the-difference-in-approaches-and-mutual-innovations

Example: Log Mining

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

http://www.slideshare.net/normation/scala-dreaded

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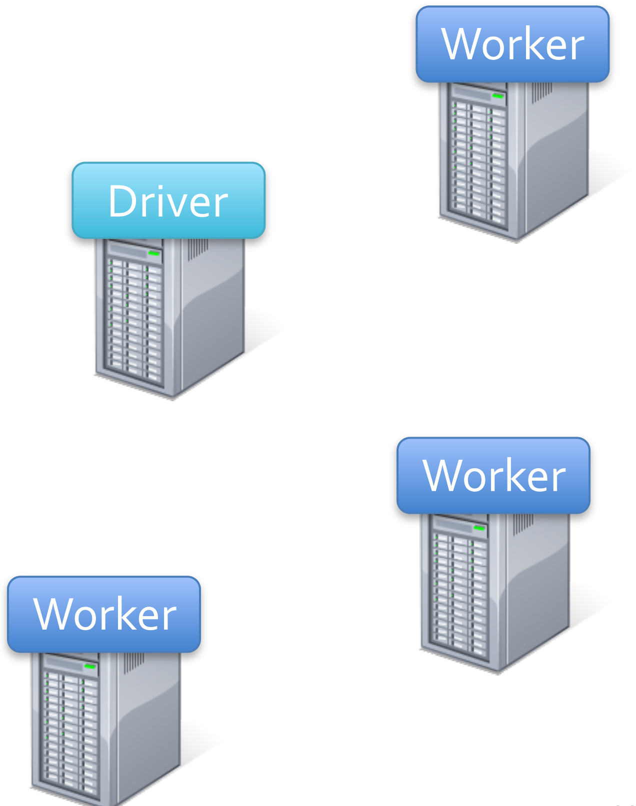

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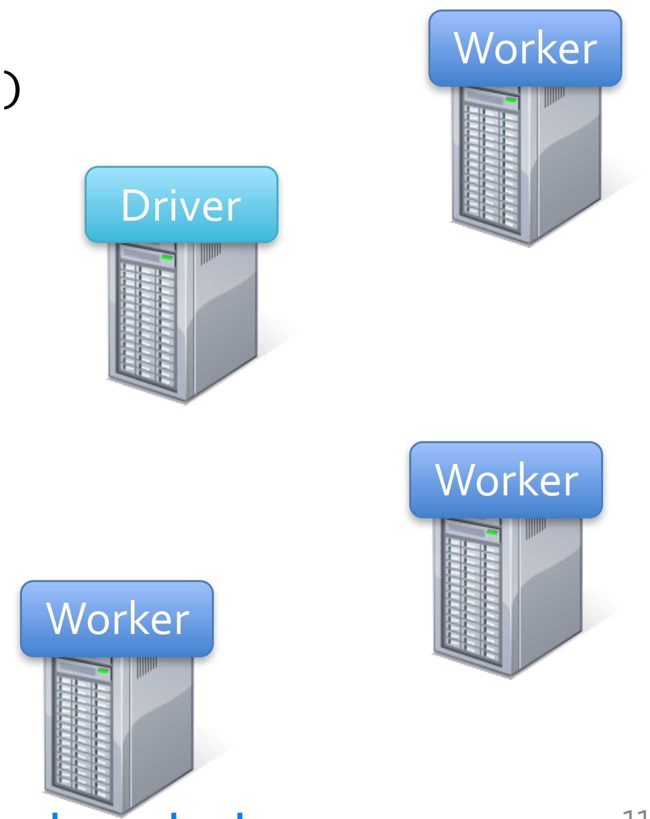

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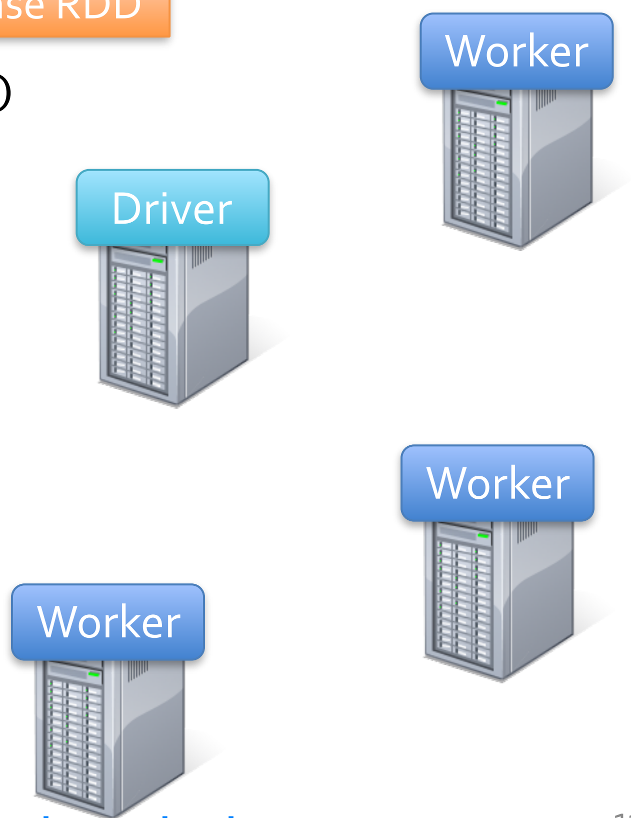
Base RDD



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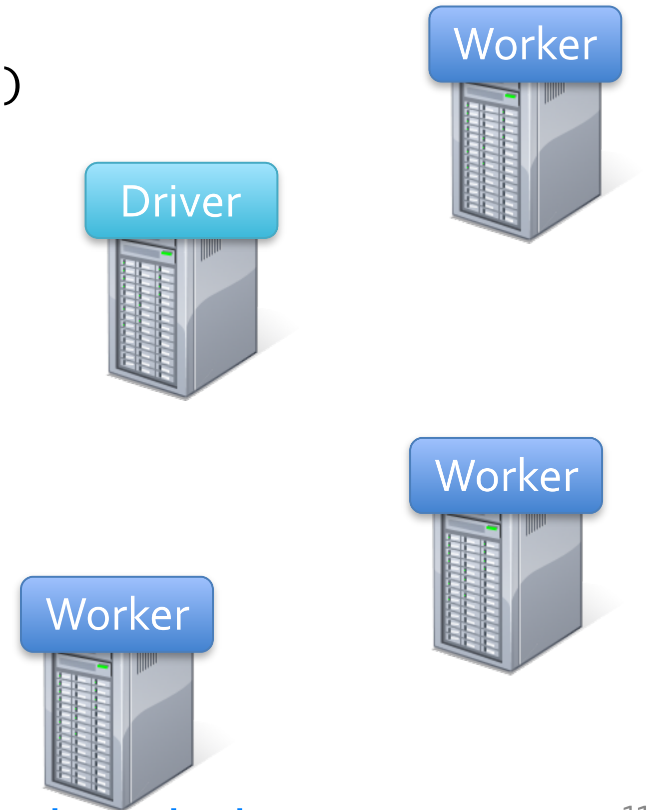

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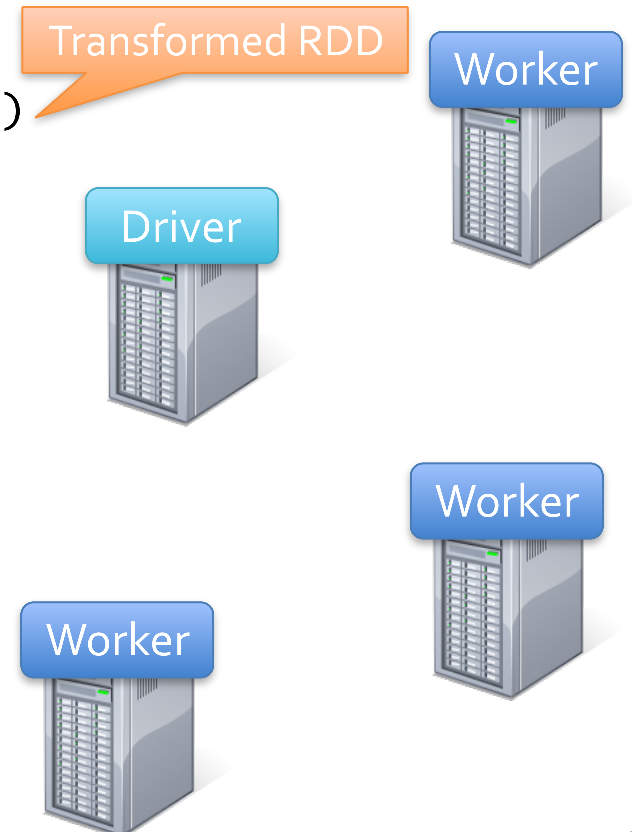

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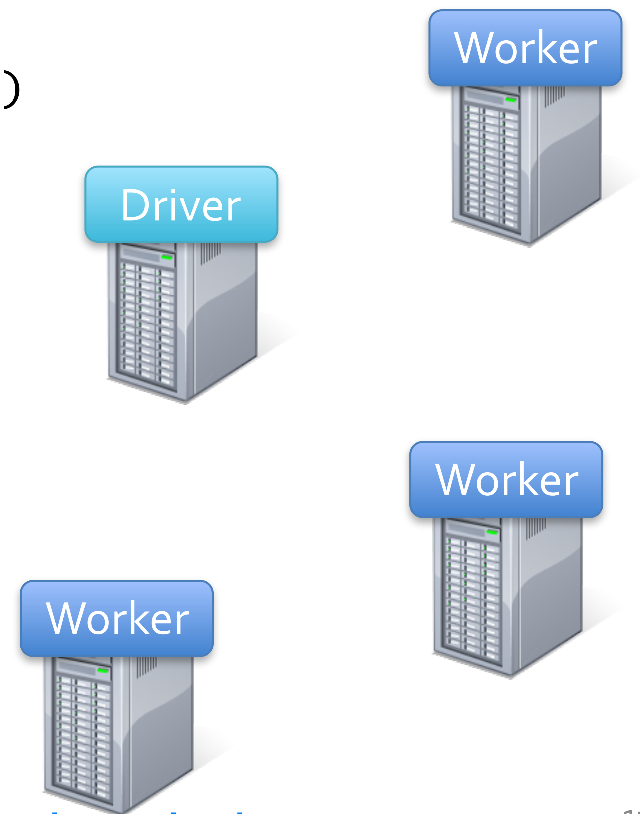

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cachedMsgs.filter(_.contains("foo")).count
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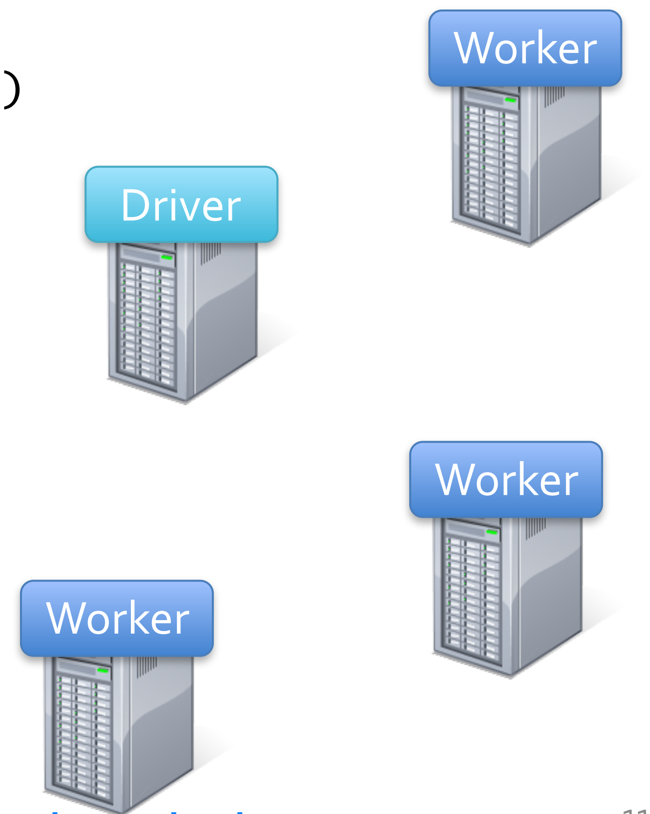

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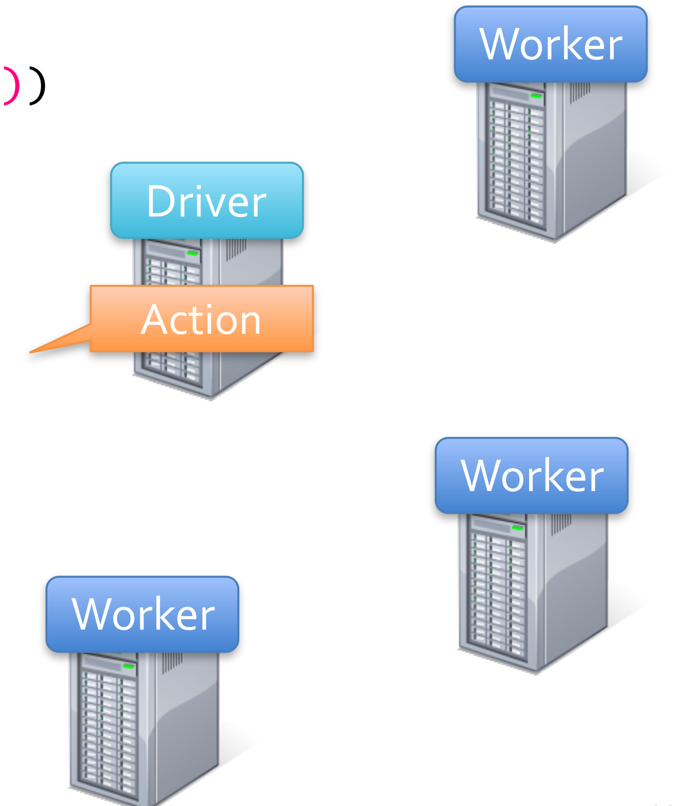

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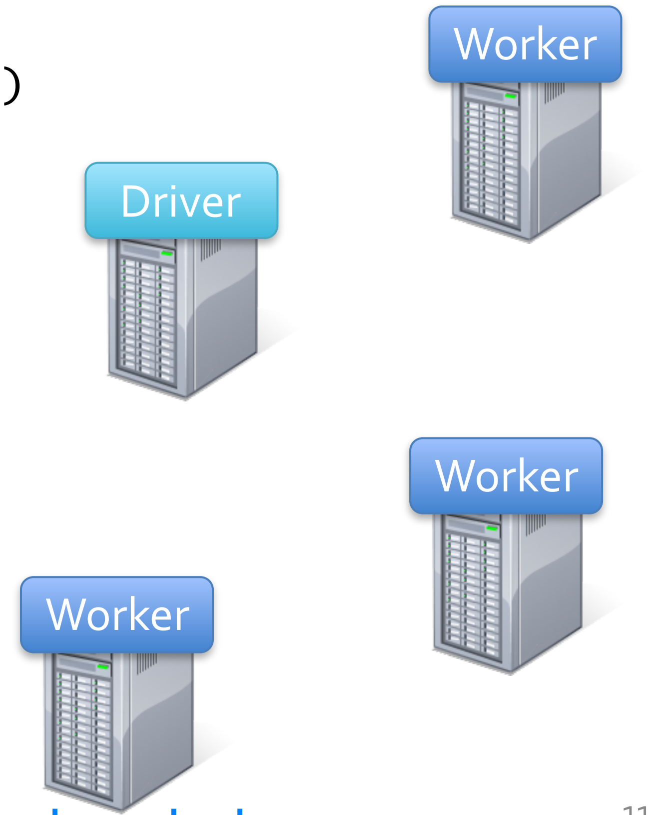

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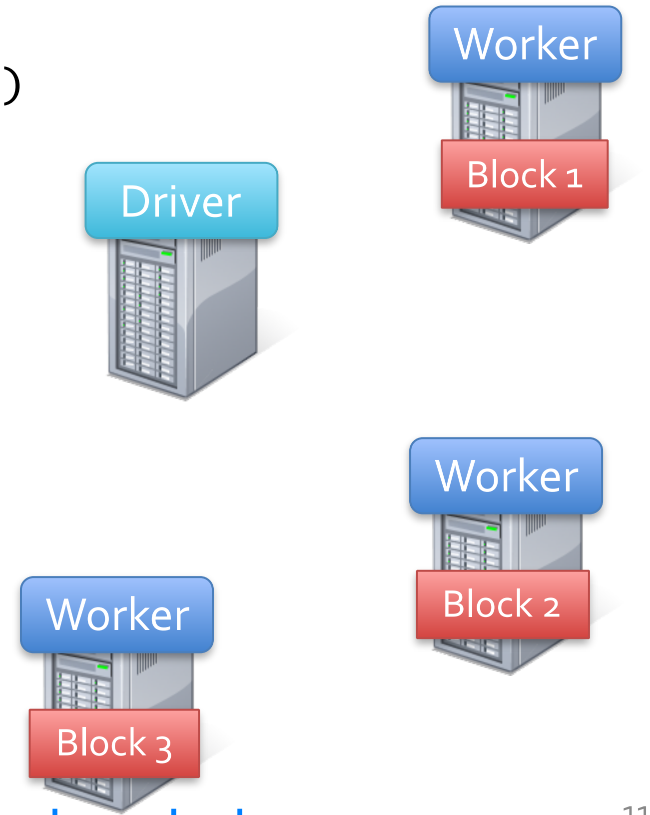

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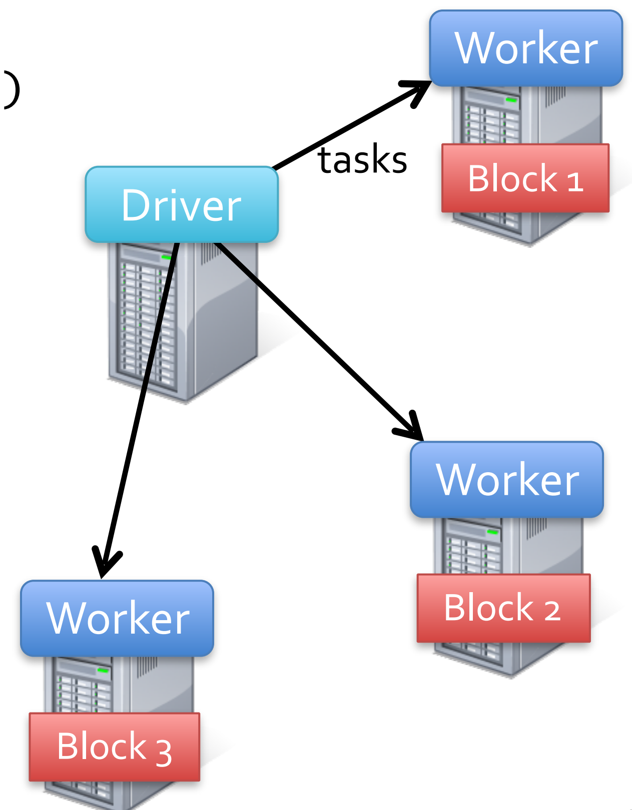

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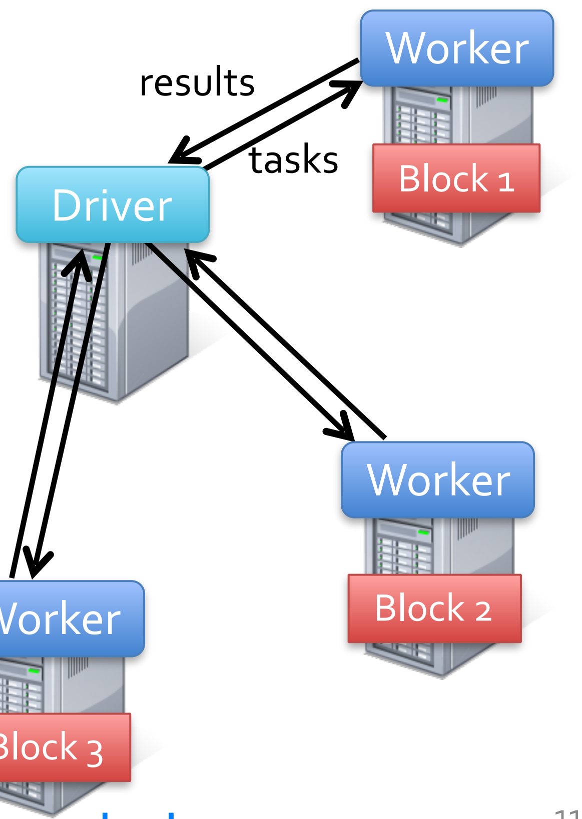

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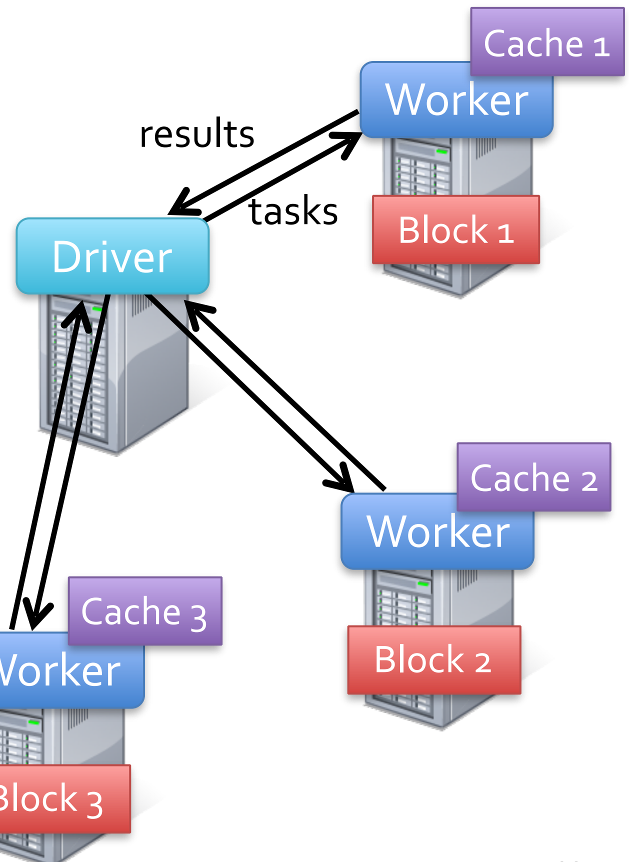

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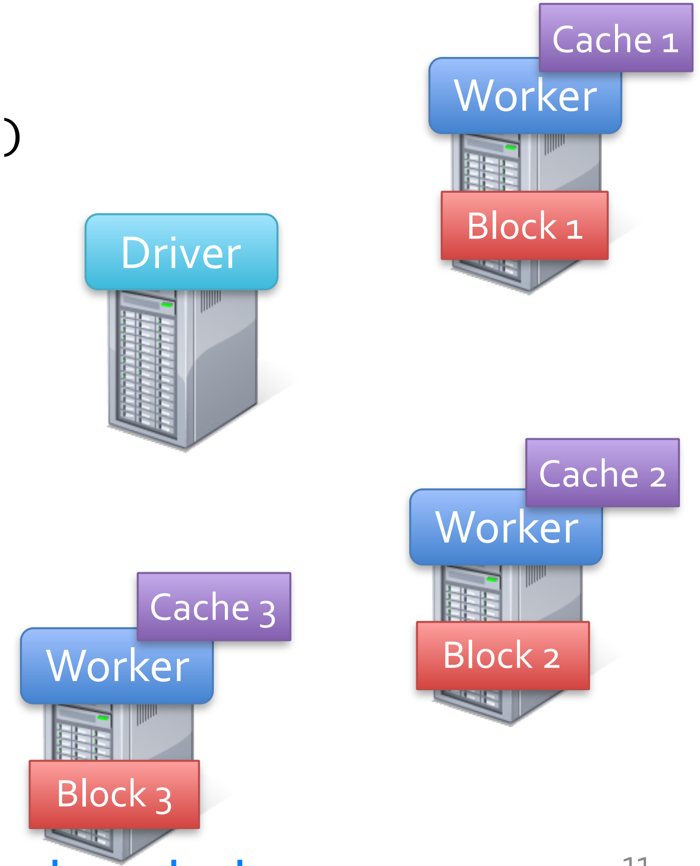

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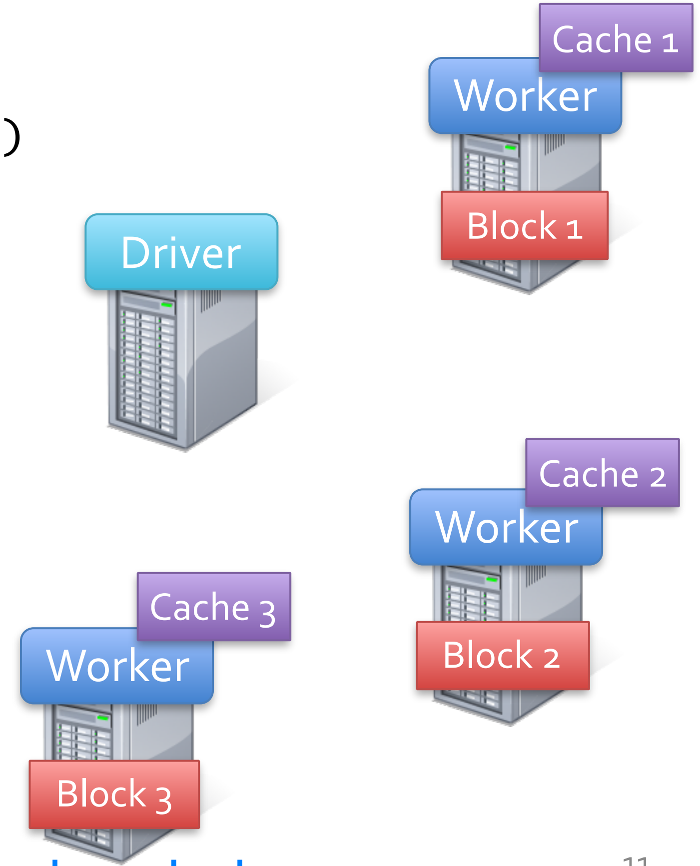

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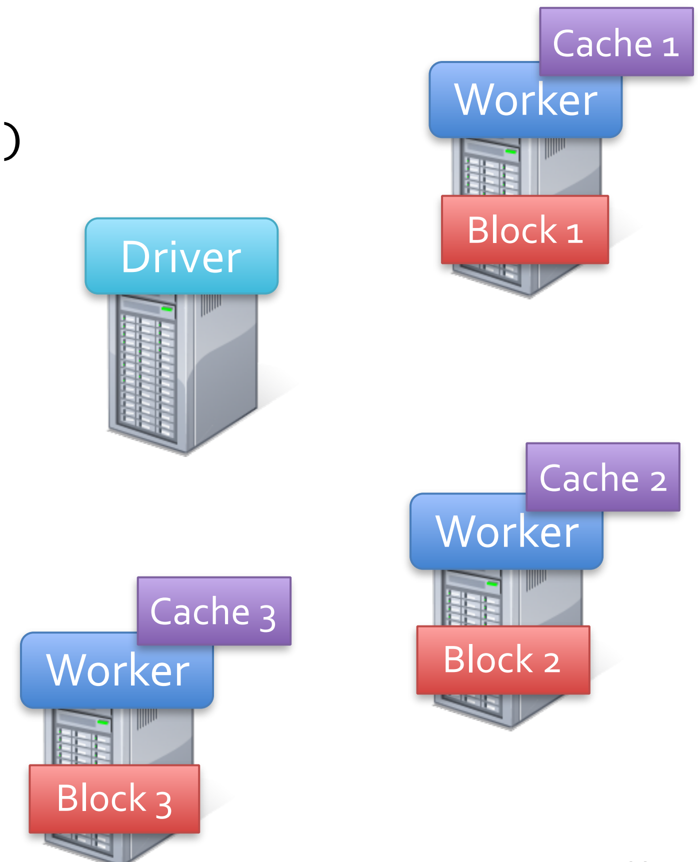

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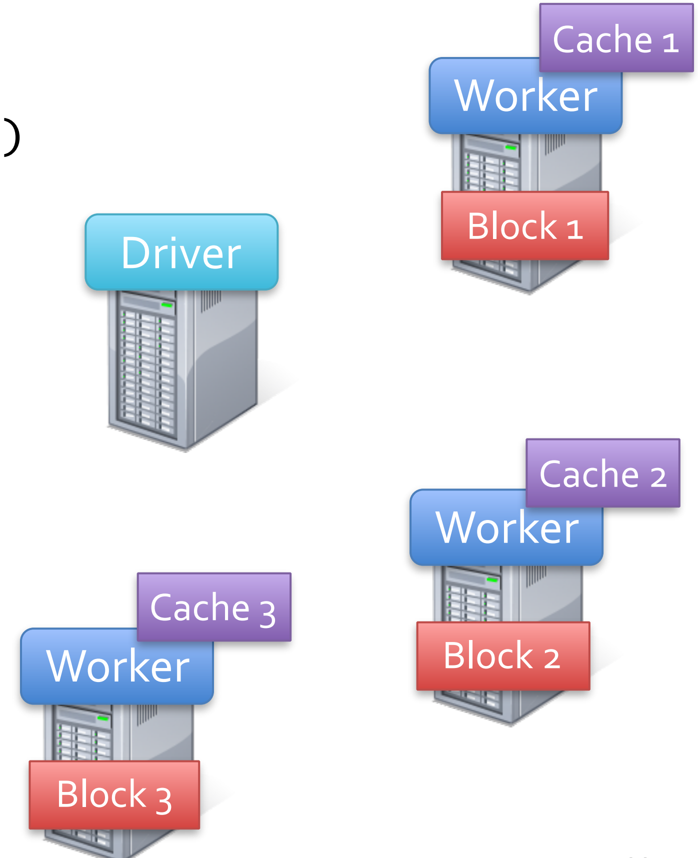

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

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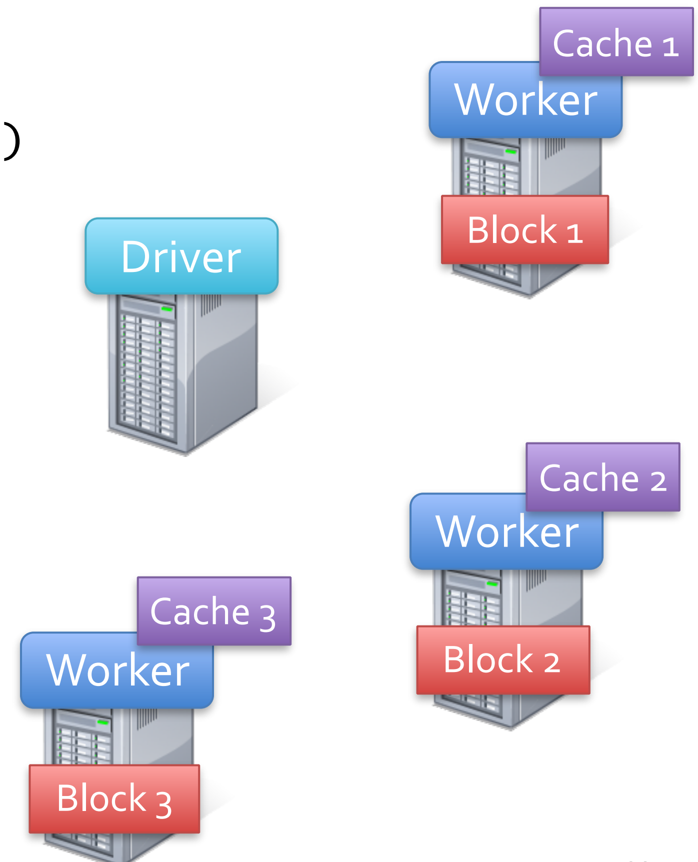

Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

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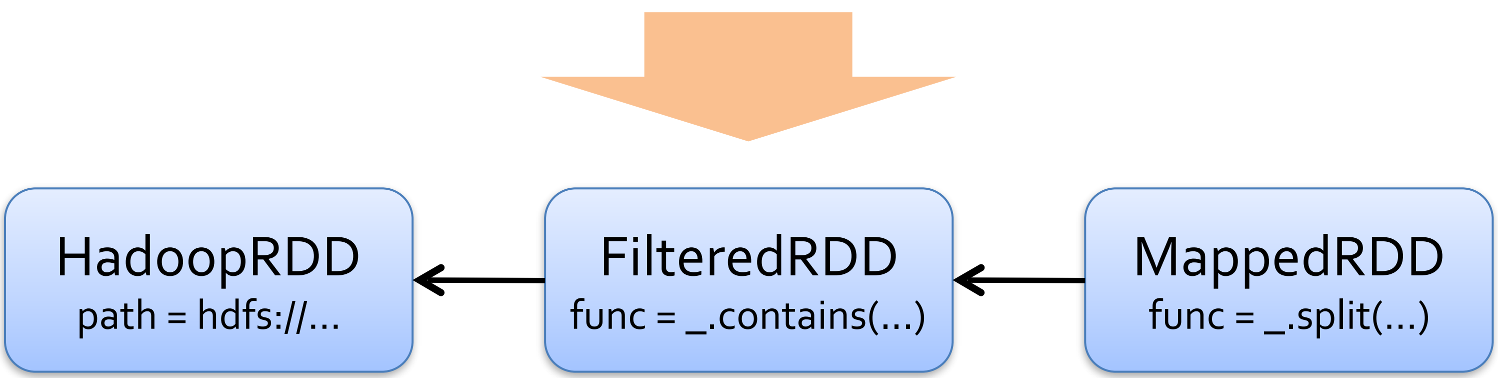
Fault Tolerance

RDDs track the series of transformations used to build them (their *lineage*) to recompute lost data

E.g:
```
messages = textFile(...).filter(_.contains("error"))
                        .map(_.split('\t')(2))
```



Example: Logistic Regression

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

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(_ + _)
  w -= gradient
}

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

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Load data in memory once

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Initial parameter vector

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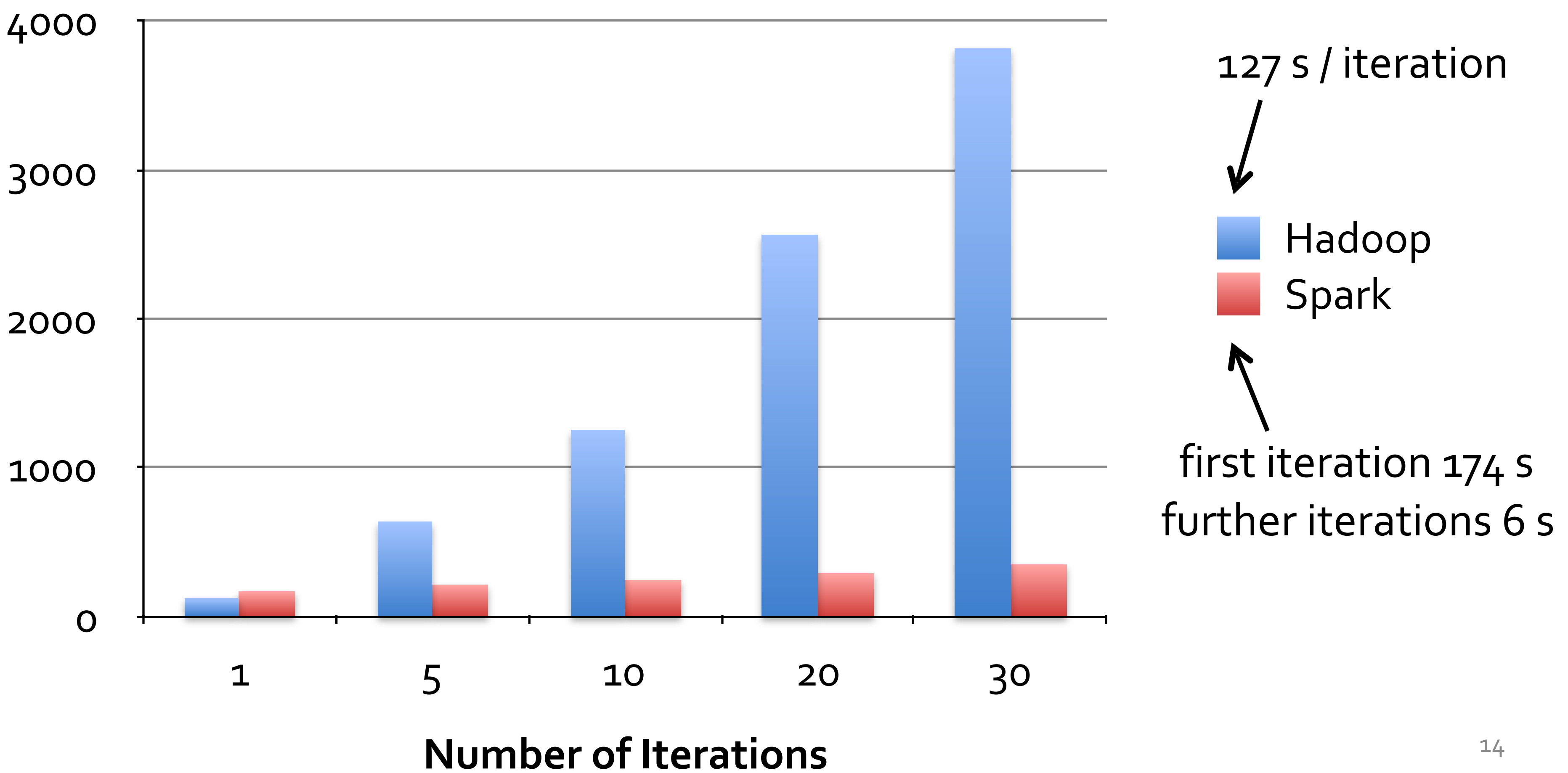
Repeated MapReduce steps to do gradient descent

Logistic Regression Performance



Supported Operators

`map`	`reduce`	`sample`
`filter`	`count`	`cogroup`
`groupBy`	`reduceByKey`	`take`
`sort`	`groupByKey`	`partitionBy`
`join`	`first`	`pipe`
`leftOuterJoin`	`union`	`save`
`rightOuterJoin`	`cross`	`...`

Spark Users

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YAHOO! RESEARCH

University of California Berkeley

PRINCETON UNIVERSITY

UCSF

Spark SQL: Hive on Spark

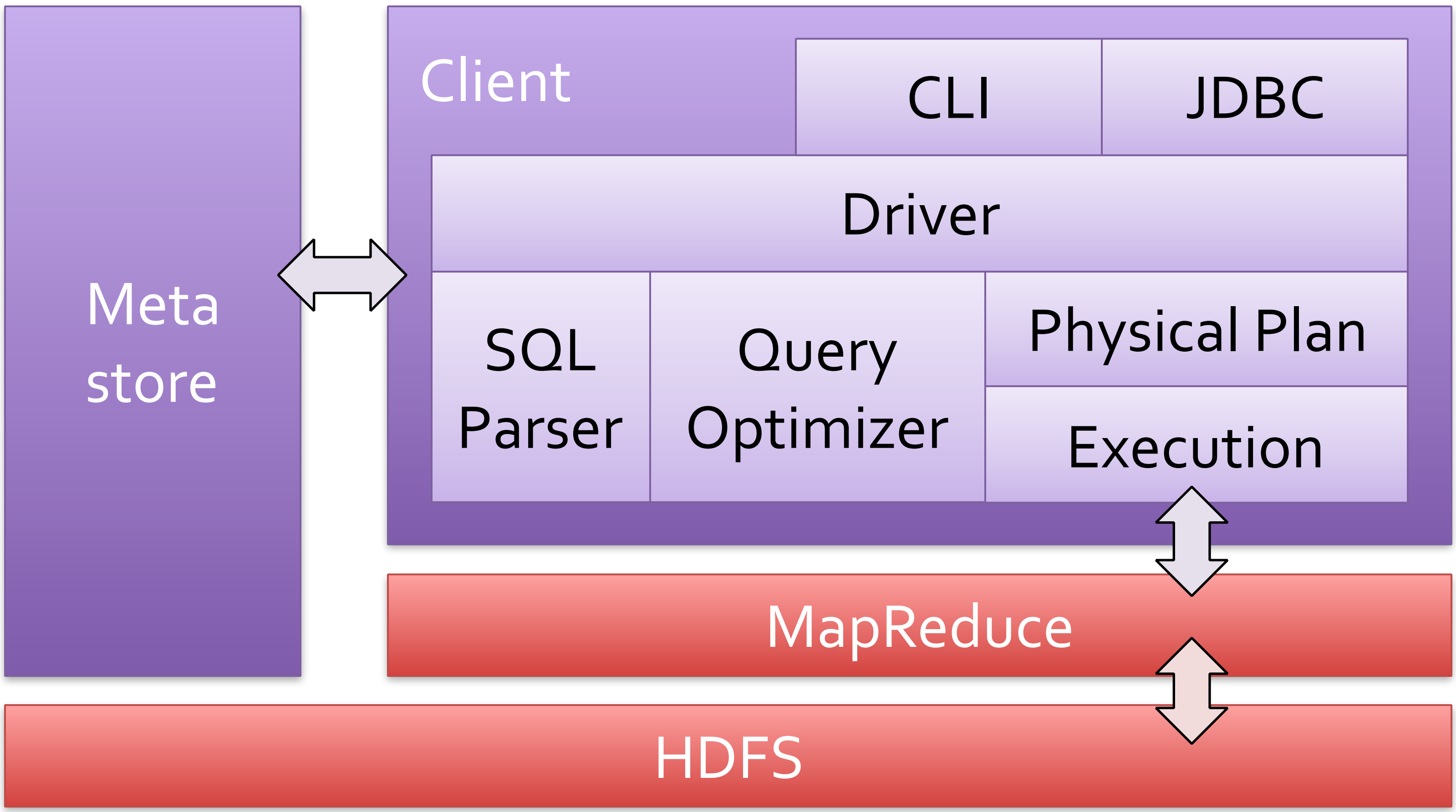
Motivation

Hive is great, but Hadoop's execution engine makes even the smallest queries take minutes

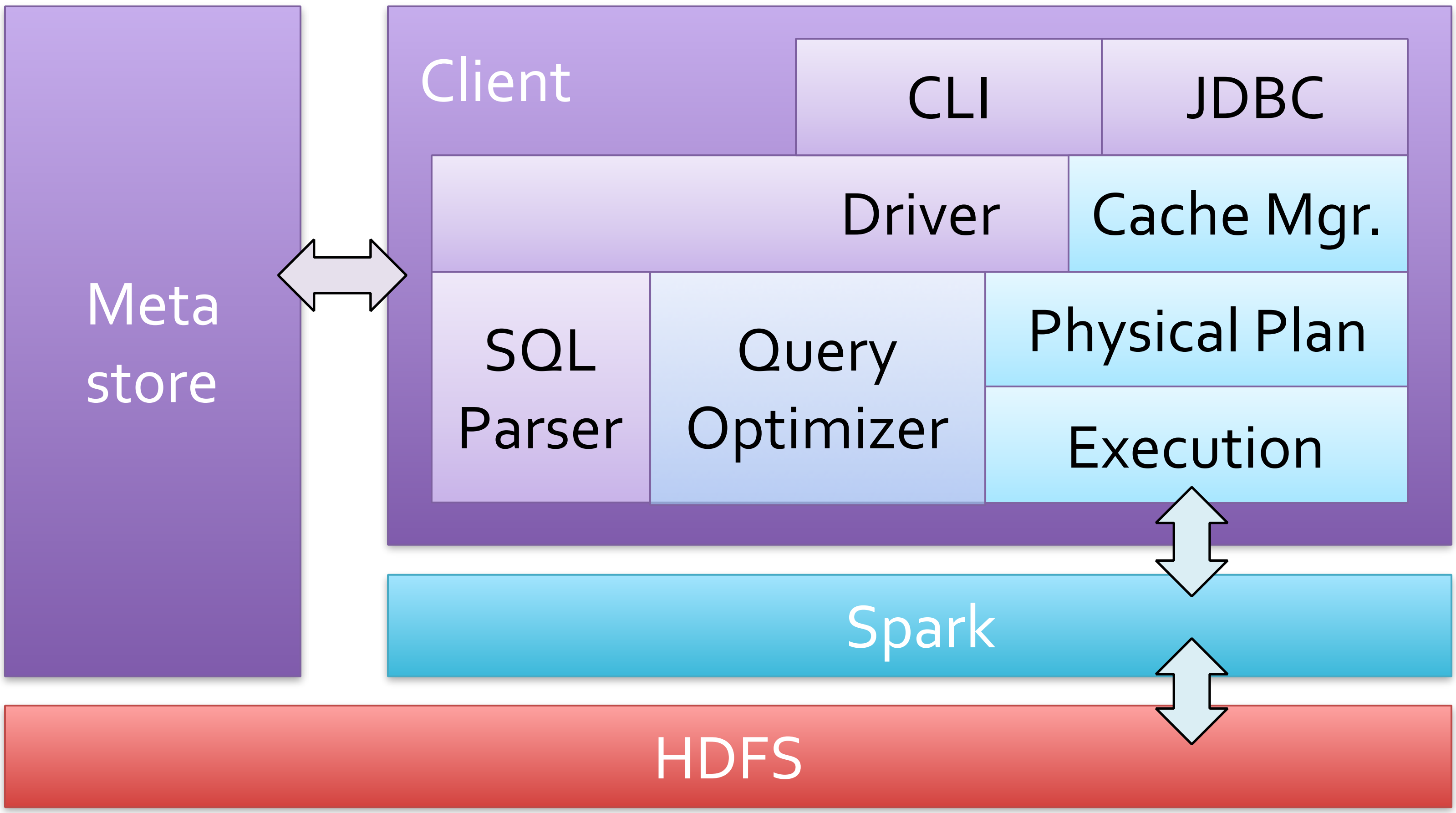
Scala is good for programmers, but many data users only know SQL

Can we extend Hive to run on Spark?

Hive Architecture



Spark SQL Architecture



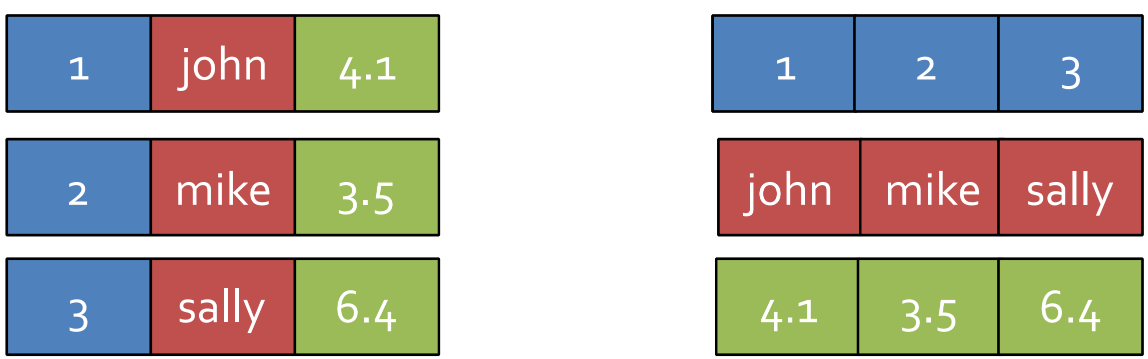
[Engle et al, SIGMOD 2012]

Efficient In-Memory Storage

Simply caching Hive records as Java objects is inefficient due to high per-object overhead

Instead, Spark SQL employs column-oriented storage using **arrays of primitive types**

Row Storage **Column Storage**



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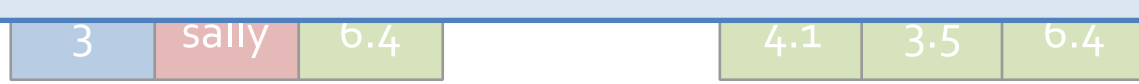
Row Storage

Column Storage

Benefit: similarly compact size to serialized data, but >5x faster to access



Using Spark SQL

```
CREATE TABLE mydata_cached AS SELECT …
```

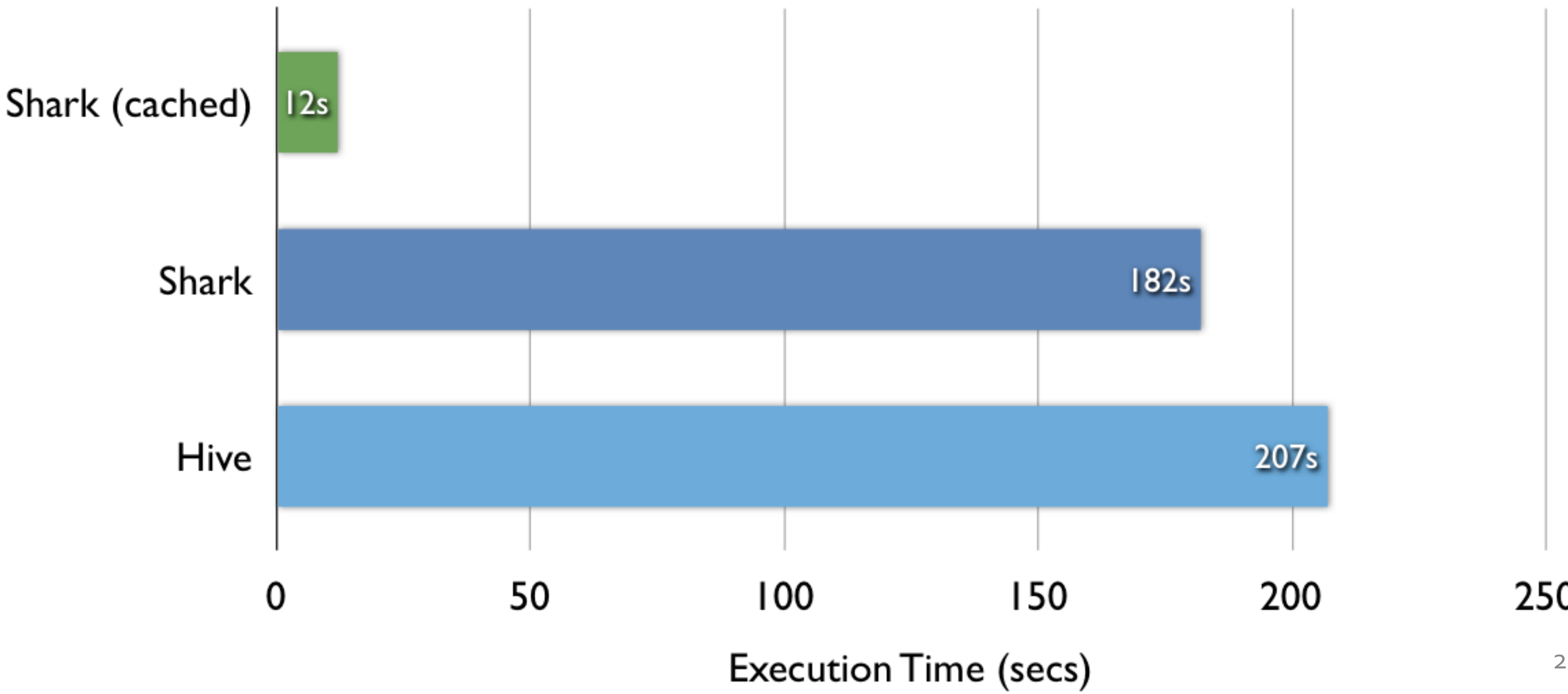
Run standard HiveQL on it, including UDFs

» A few esoteric features are not yet supported

Can also call from Scala to mix with Spark

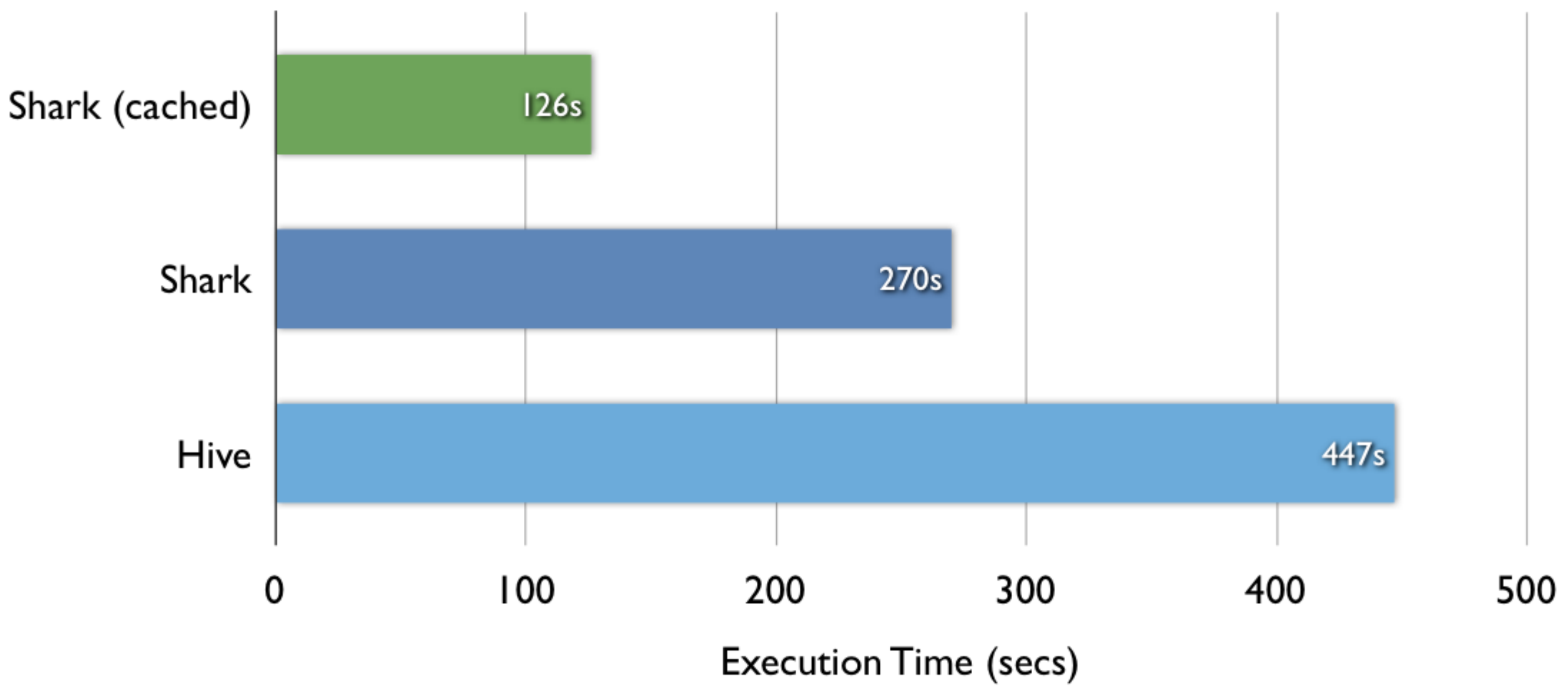
Benchmark Query 1

```
SELECT * FROM grep WHERE field LIKE '%XYZ%';
```



Benchmark Query 2

```
SELECT sourceIP, AVG(pageRank), SUM(adRevenue) AS earnings
FROM rankings AS R, userVisits AS V ON R.pageURL = V.destURL
WHERE V.visitDate BETWEEN '1999-01-01' AND '2000-01-01'
GROUP BY V.sourceIP
ORDER BY earnings DESC
LIMIT 1;
```



What's Next?

Recall that Spark's model was motivated by two emerging uses (interactive and multi-stage apps)

Another emerging use case that needs fast data sharing is **stream processing**

» Track and update state in memory as events arrive

» Large-scale reporting, click analysis, spam filtering, etc

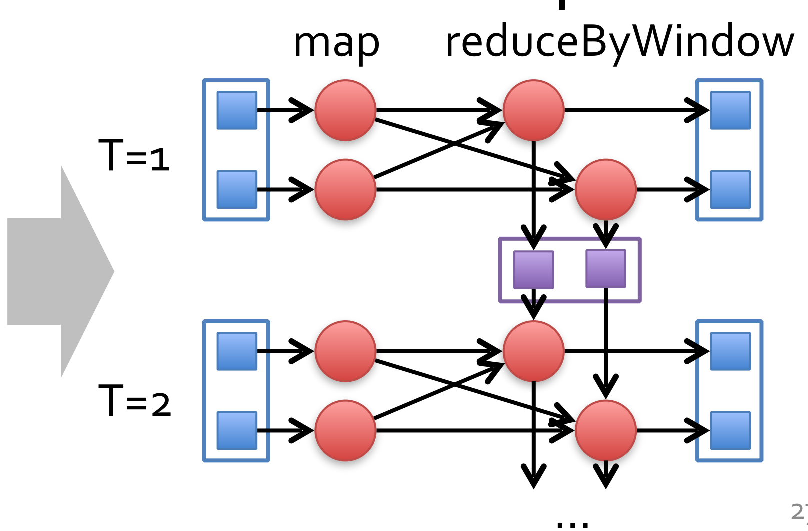
Streaming Spark

Extends Spark to perform streaming computations

Runs as a series of small (~1 s) batch jobs, keeping state in memory as fault-tolerant RDDs

Intermix seamlessly with batch and ad-hoc queries

```
tweetStream
 .flatMap(_.toLower.split)
 .map(word => (word, 1))
 .reduceByWindow("5s", _ + _)
```



[Zaharia et al, HotCloud 2012]

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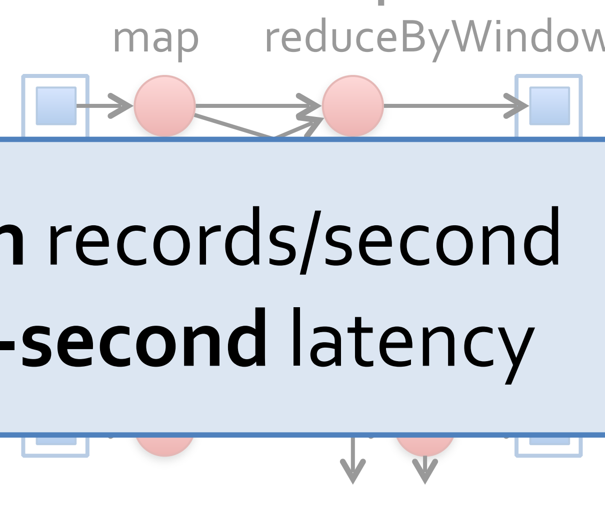

tweetStream

Result: can process **42 million** records/second (4 GB/s) on 100 nodes at **sub-second** latency

[Zaharia et al, HotCloud 2012]

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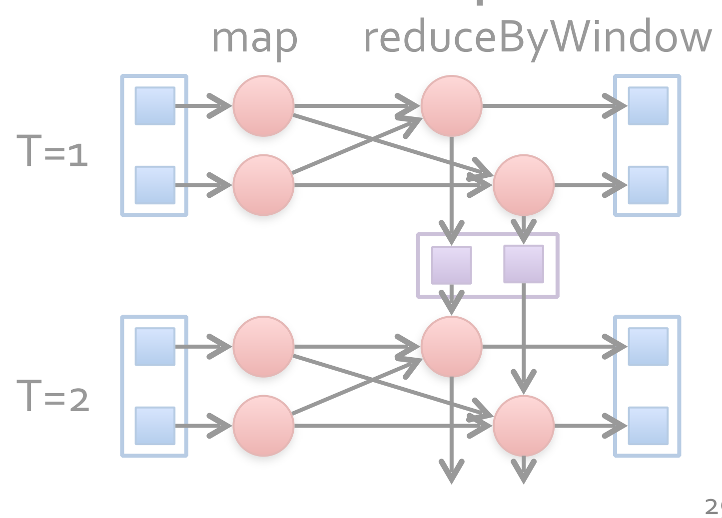
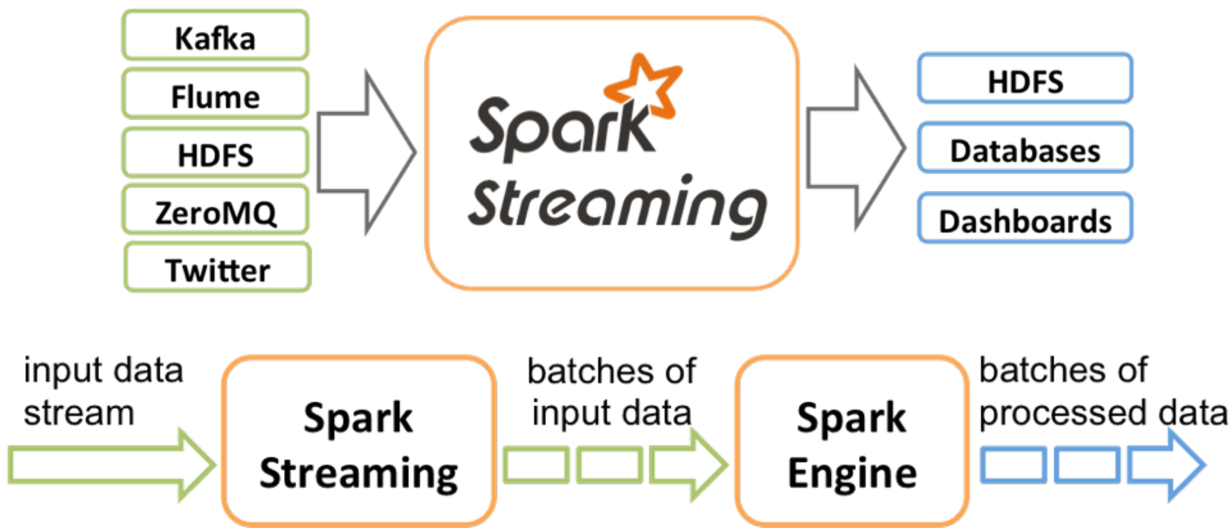
 .reduceByWindow(5, _ + _)
```



[Zaharia et al, HotCloud 2012]

Spark Streaming

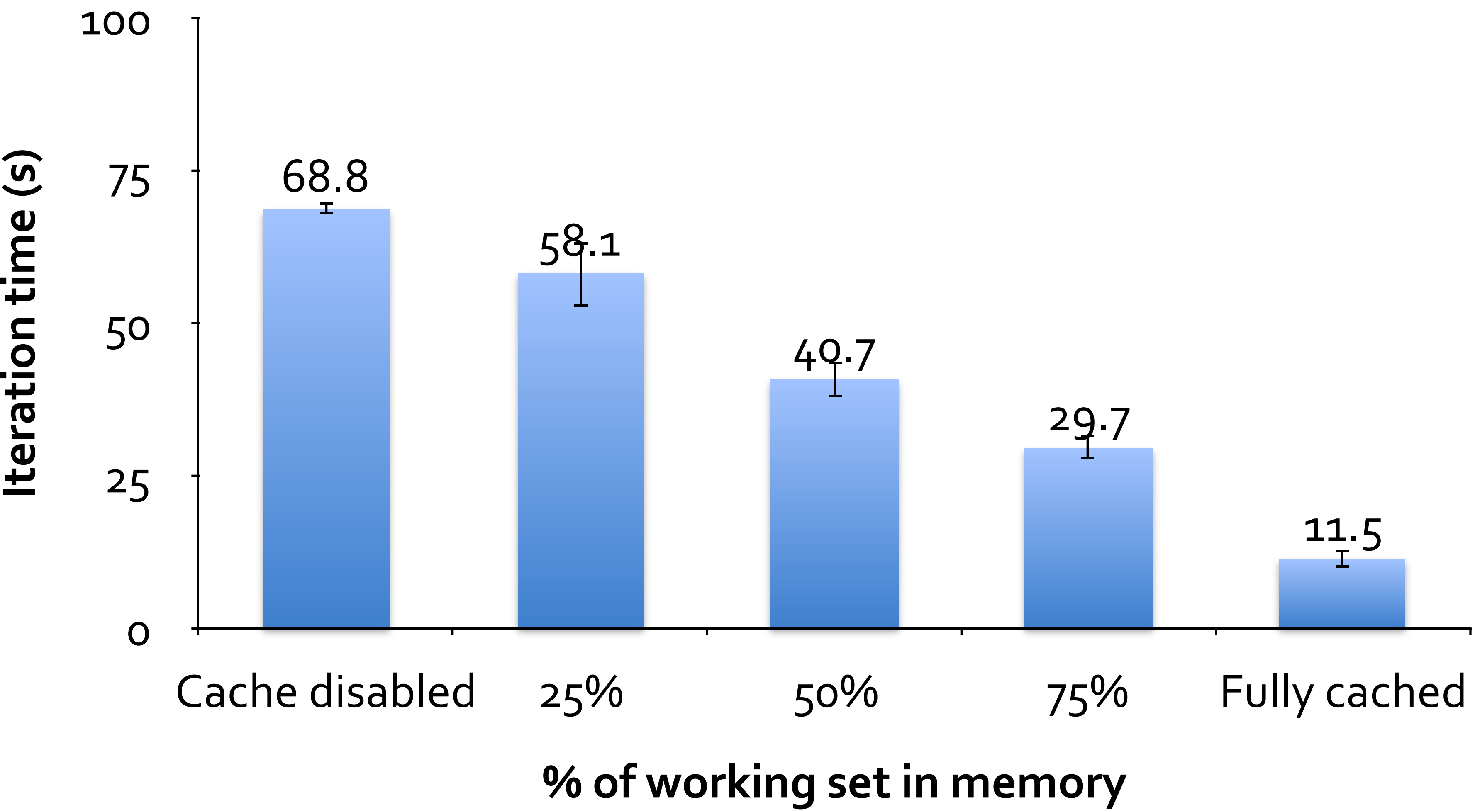
Create and operate on RDDs from live data streams at set intervals



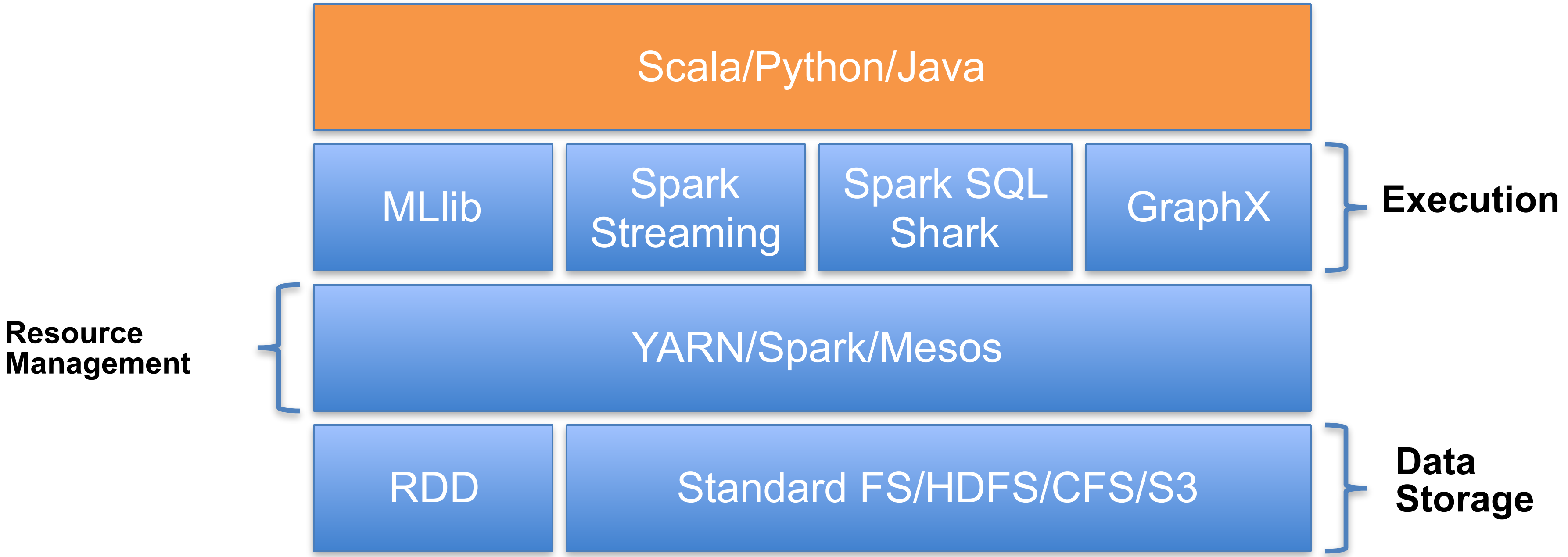
Data is divided into batches for processing

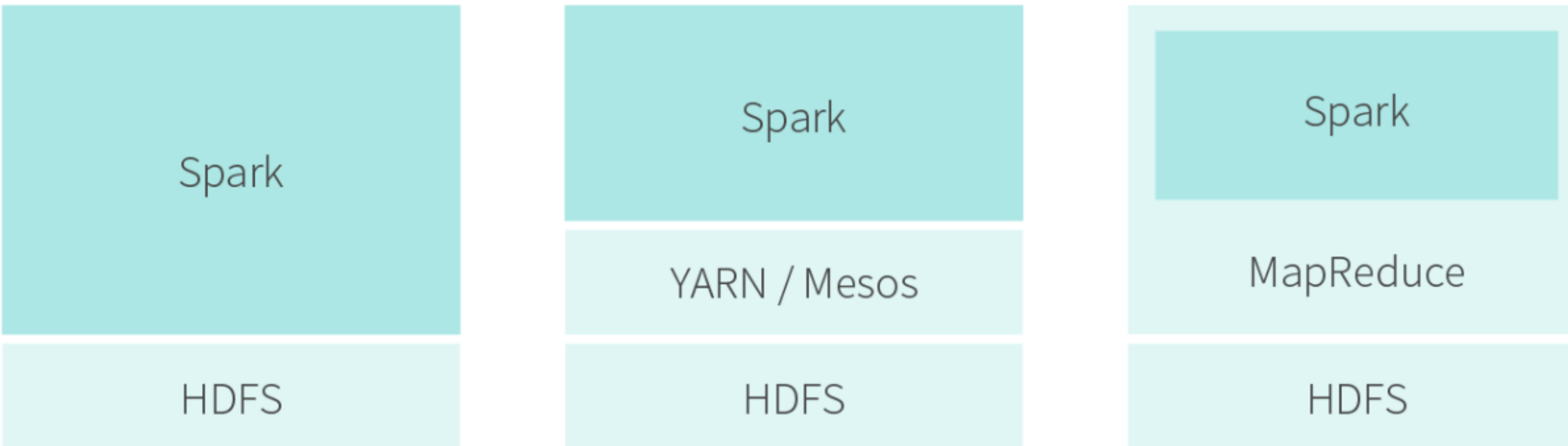
Streams may be combined as a part of processing or analyzed with higher level transforms

Behavior with Not Enough RAM



SPARK PLATFORM





Standalone

Hadoop 2.x
(YARN)

Hadoop V1
(SIMR)

MLlib

Scalable machine learning library

Interoperates with NumPy

Available algorithms in 1.0

- » Linear Support Vector Machine (SVM)
- » Logistic Regression
- » Linear Least Squares
- » Decision Trees
- » Naïve Bayes
- » Collaborative Filtering with ALS
- » K-means
- » Singular Value Decomposition
- » Principal Component Analysis
- » Gradient Descent

GraphX

Parallel graph processing

Extends RDD -> Resilient Distributed Property Graph

- Directed multigraph with properties attached to each vertex and edge

Limited algorithms

- PageRank
- Connected Components
- Triangle Counts

Alpha component

Commercial Support

Databricks

» Not to be confused with DataStax
» Found by members of the AMPLab
» Offering
  - Certification
  - Training
  - Support
  - DataBricks Cloud

databricks
making big data simple