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 (Manheim, GT)

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)
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Require faster **data sharing** across parallel jobs

Up for debate… as of 10/7/2014

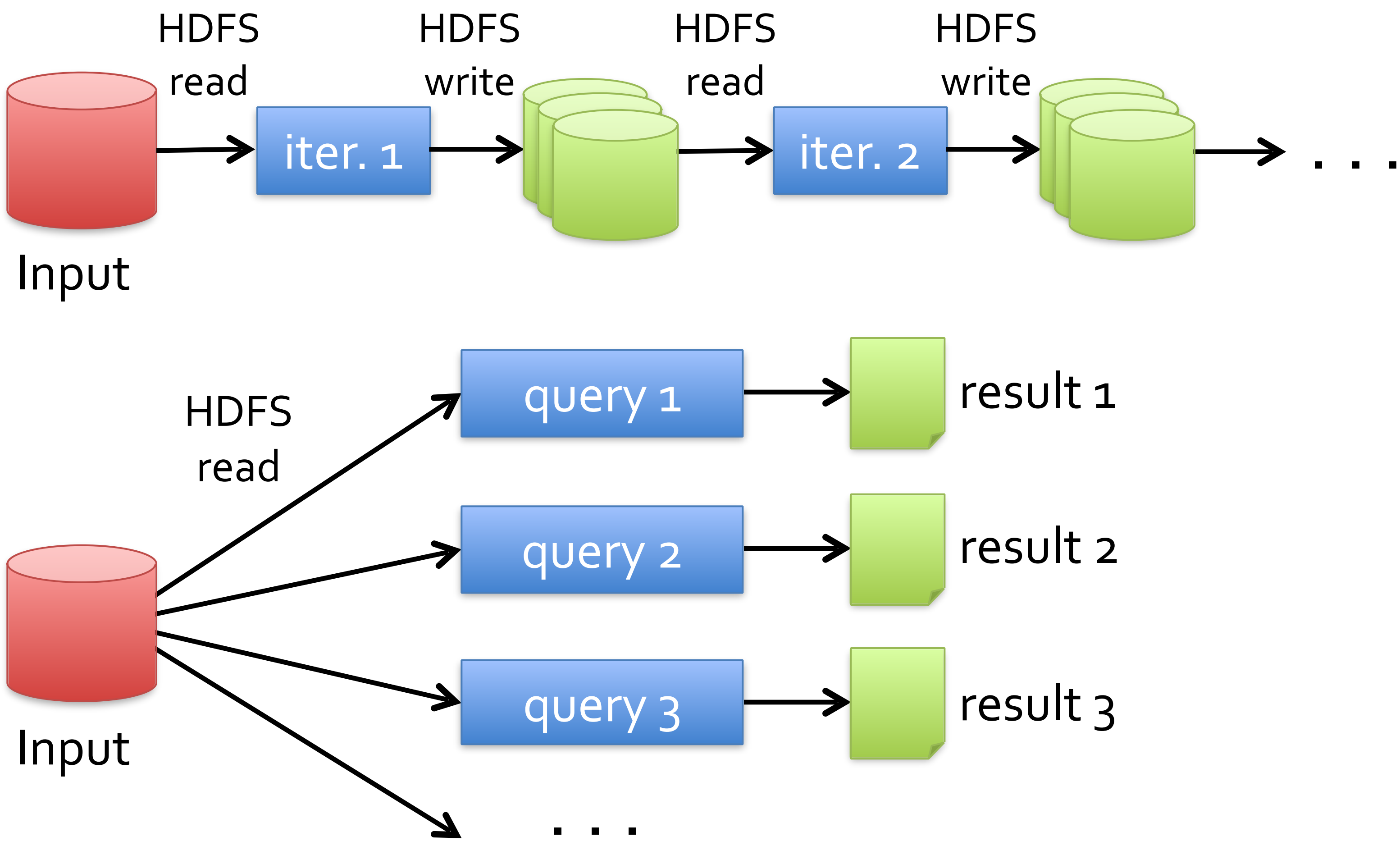
Is MapReduce dead?

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

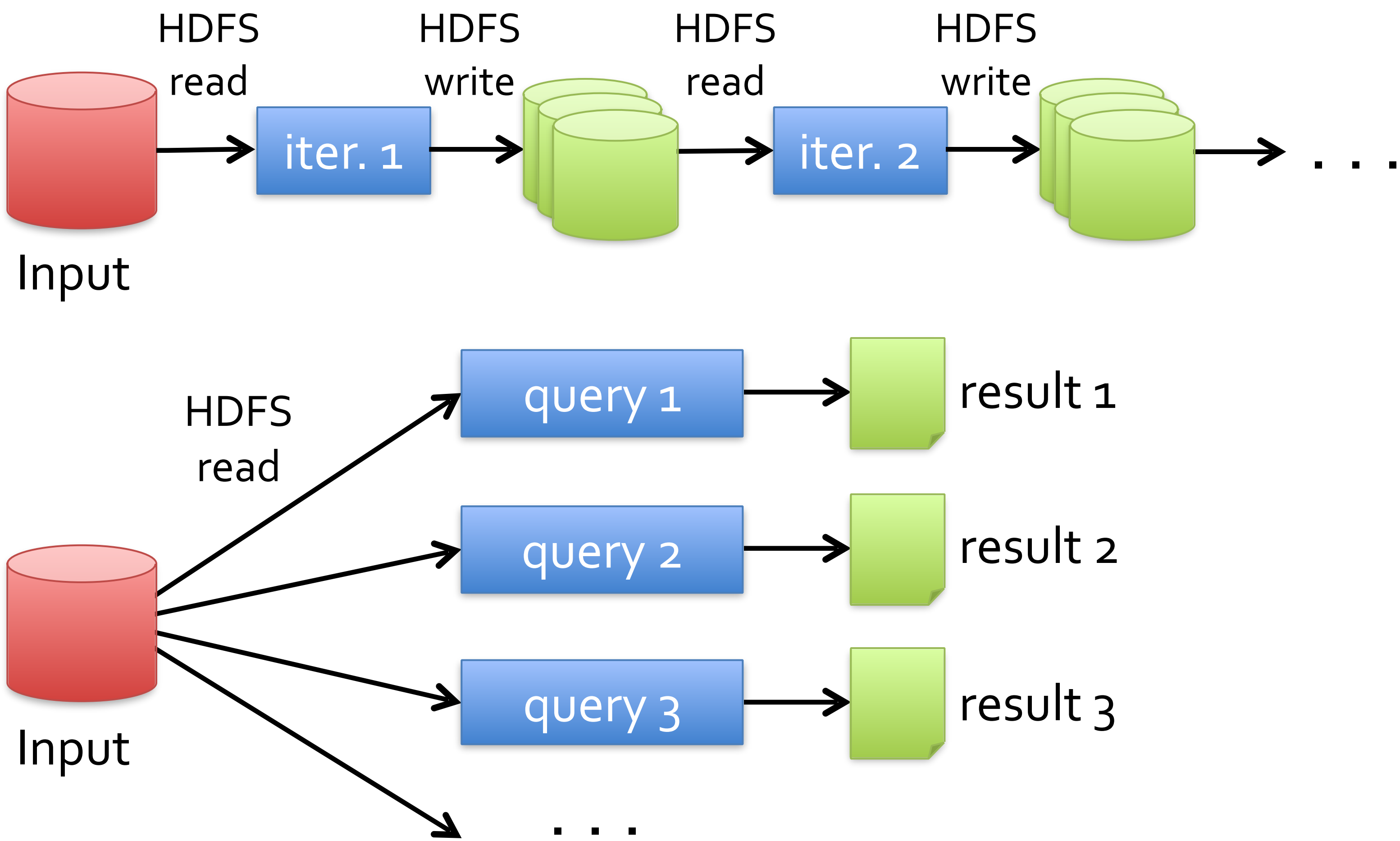
http://www.datacenterknowledge.com/archives/2014/06/25/google-dumps-mapreduce-favor-new-hyper-scale-analytics-system/

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

Data Sharing in MapReduce

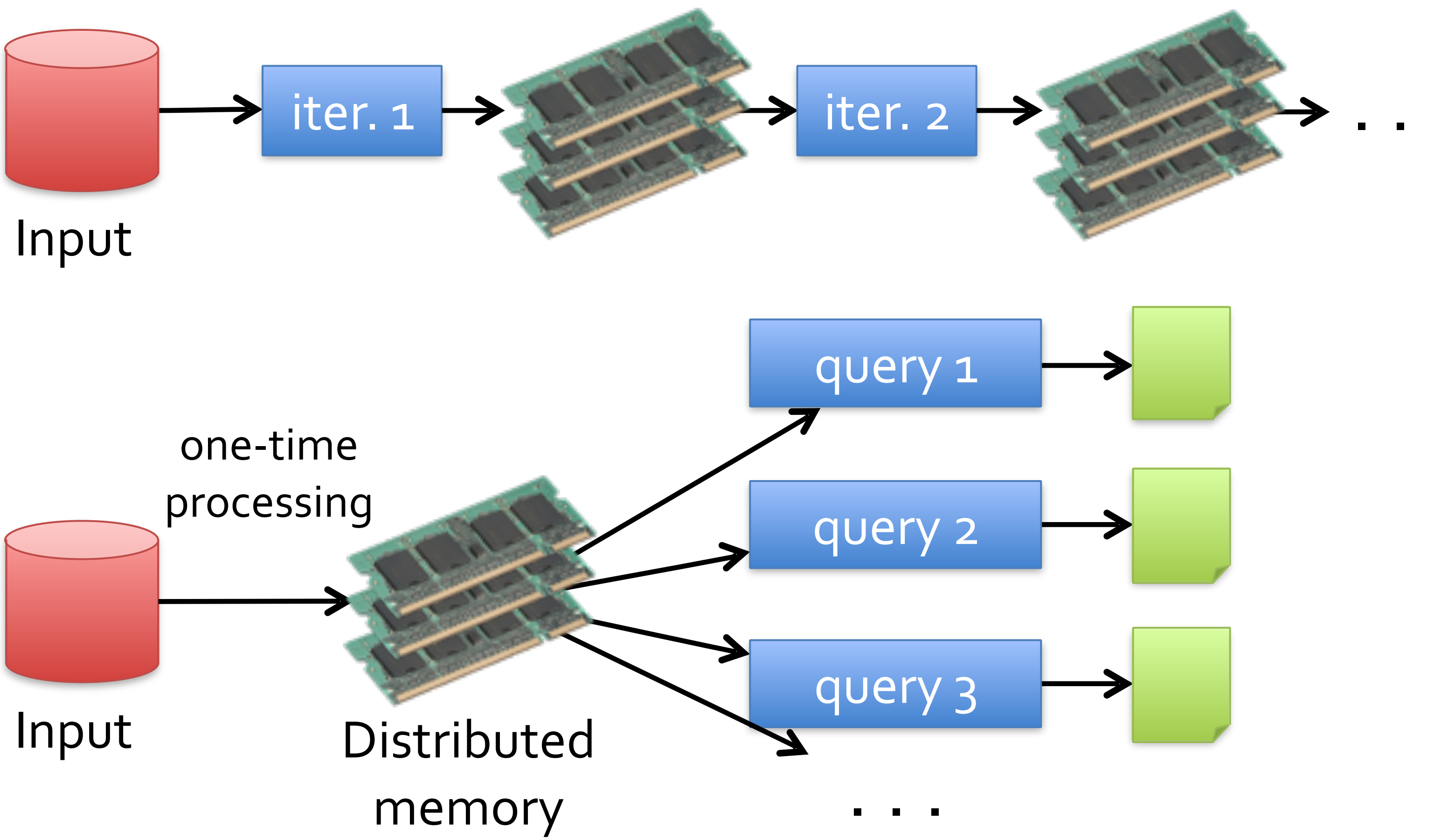


Data Sharing in MapReduce

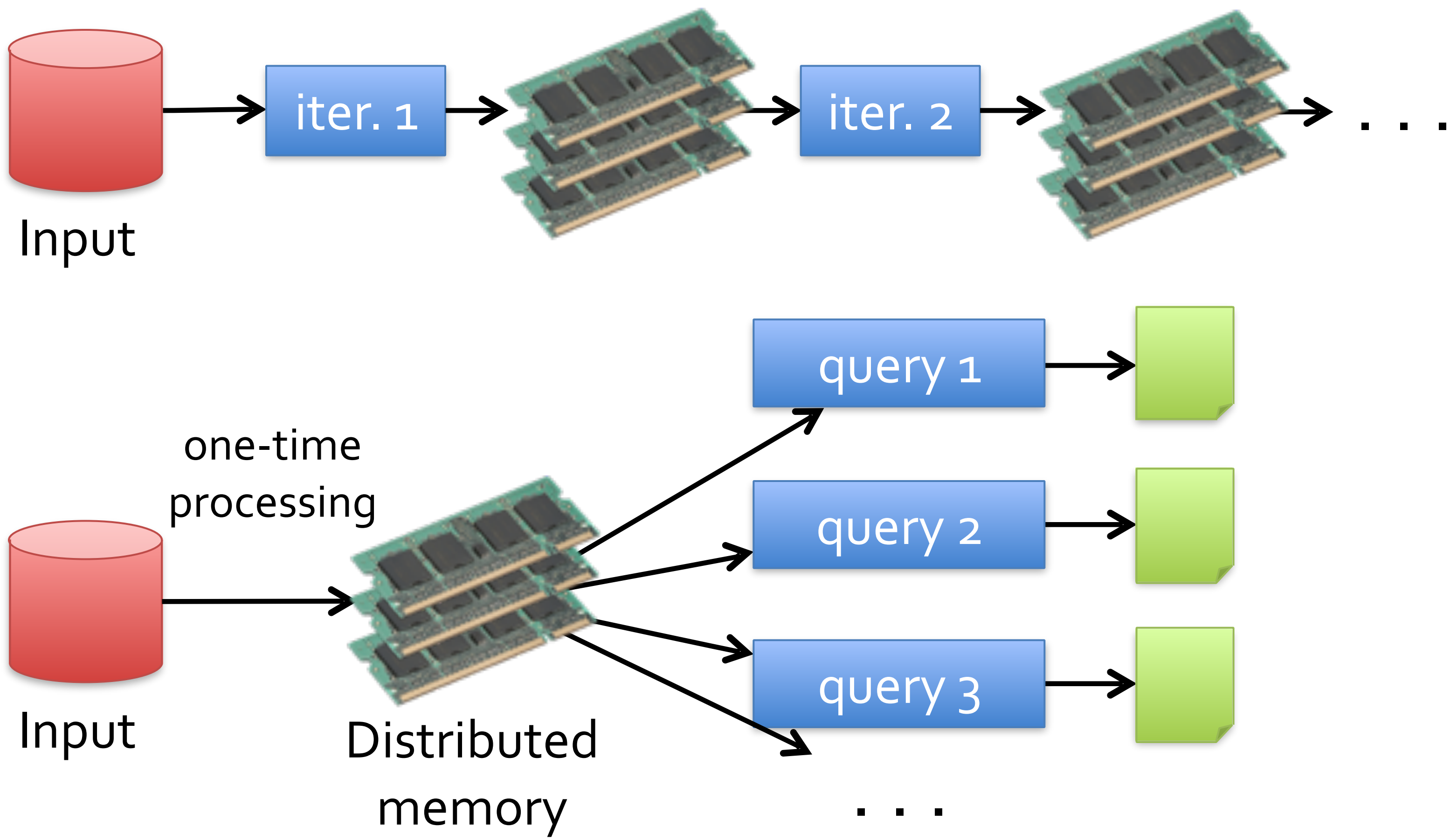


Slow due to replication, serialization, and disk IO

Data Sharing in Spark



Data Sharing in Spark



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

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

Example: Log Mining

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

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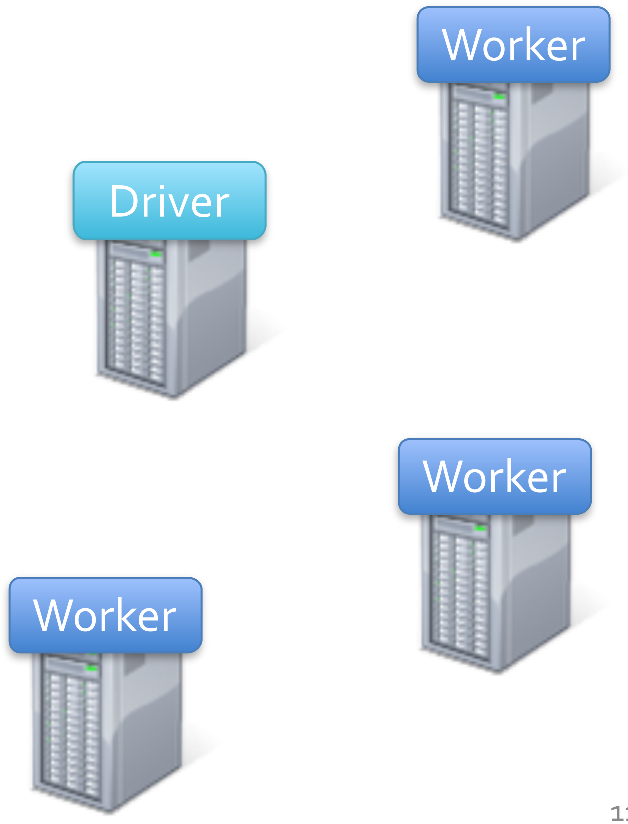

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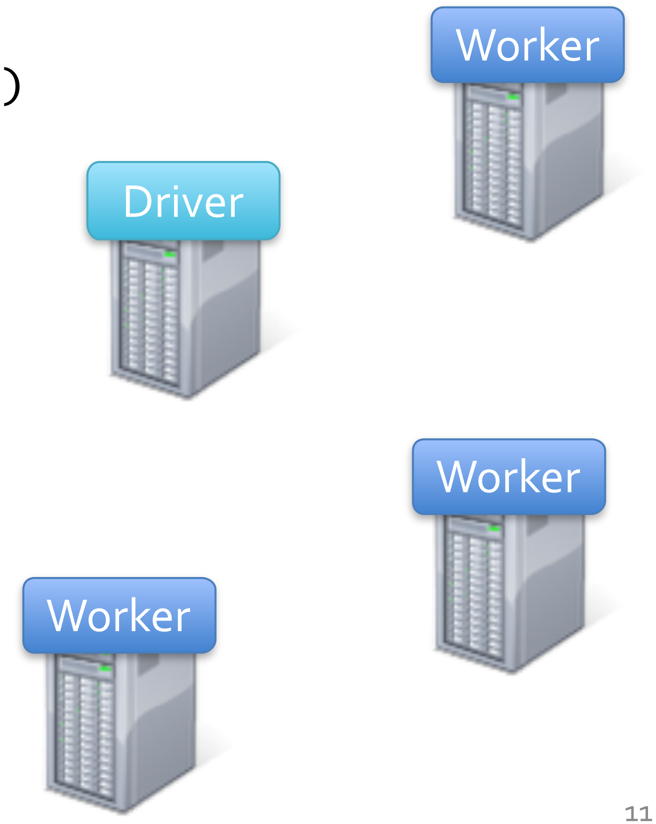

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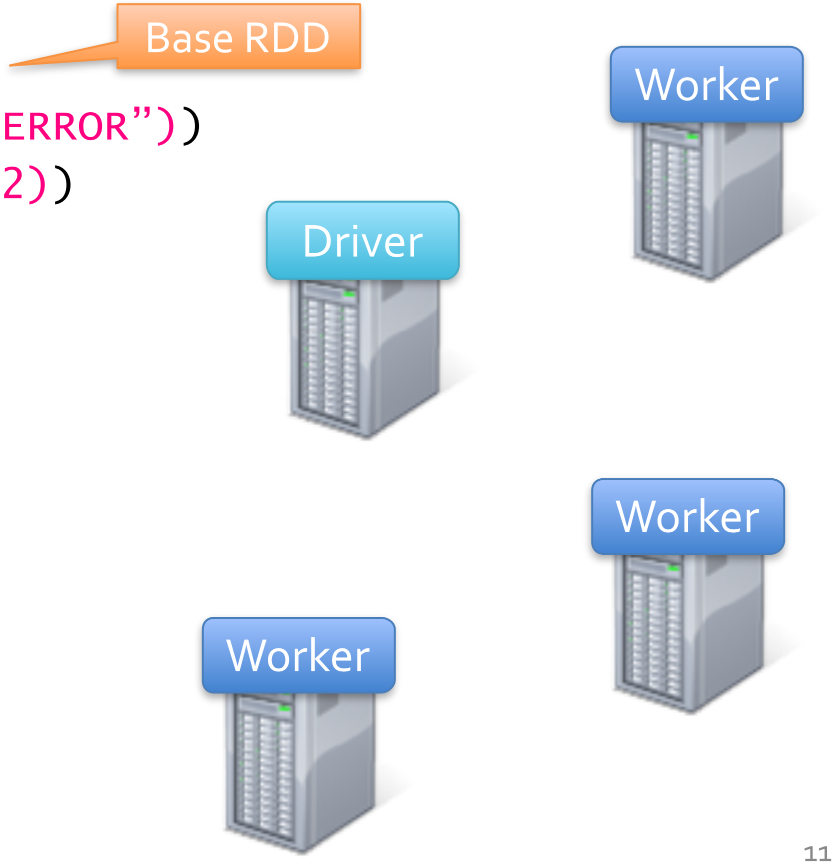

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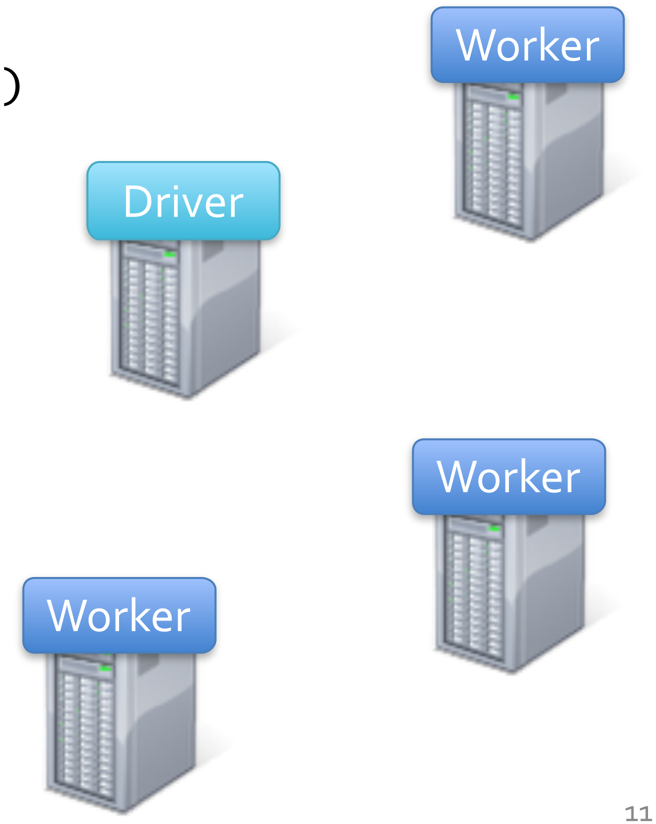

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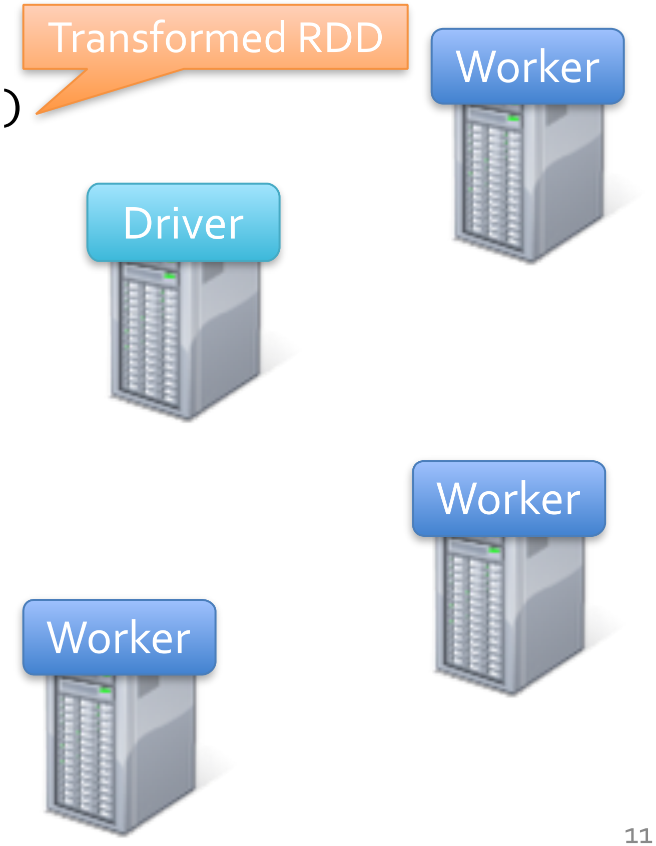

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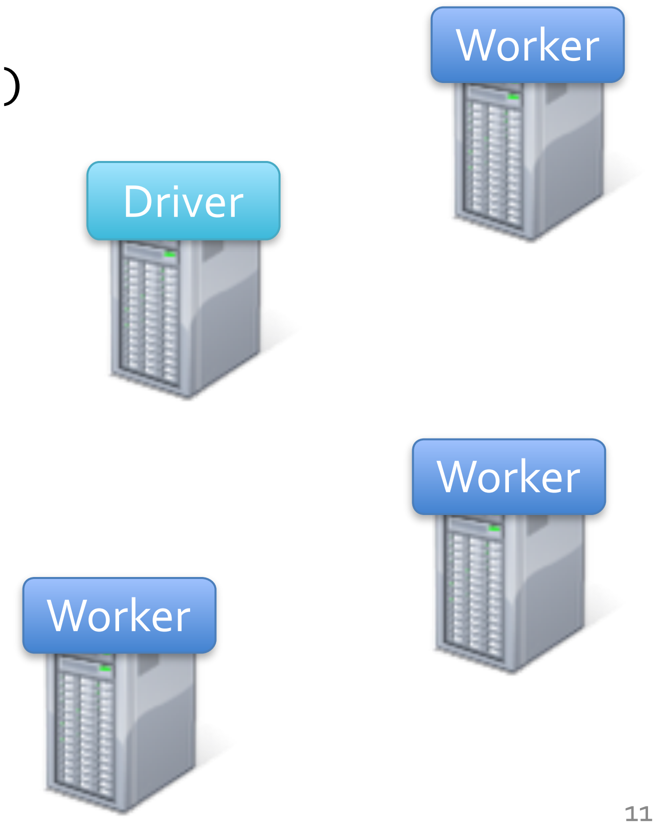

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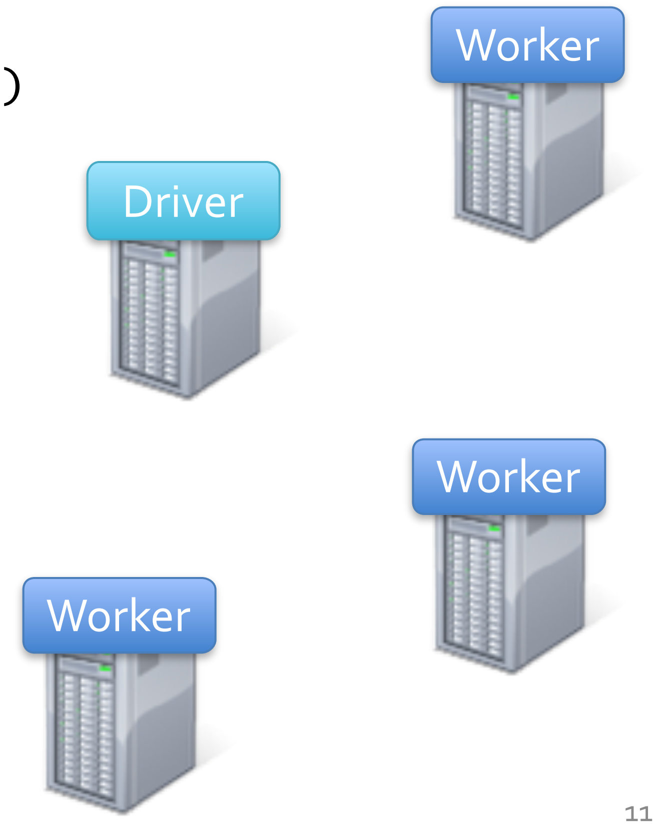

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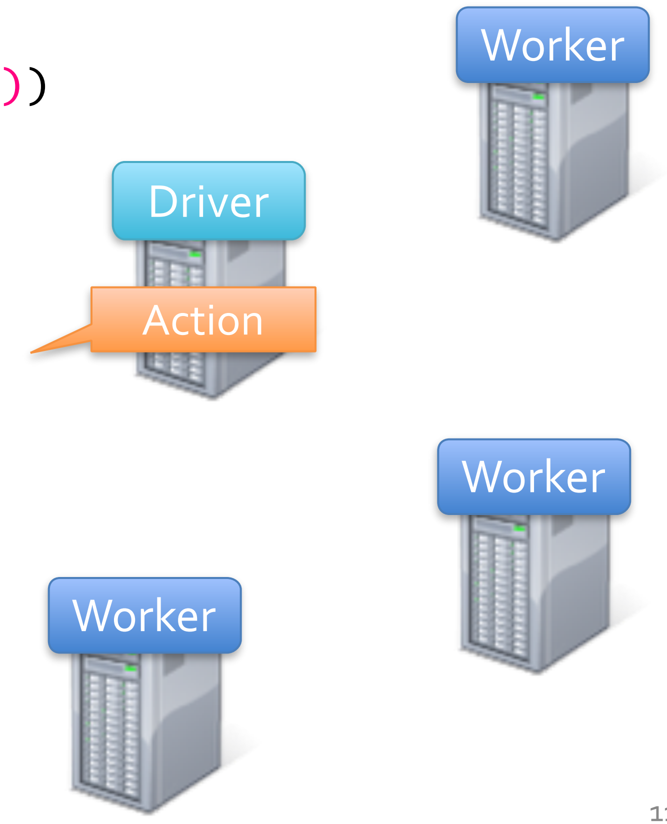

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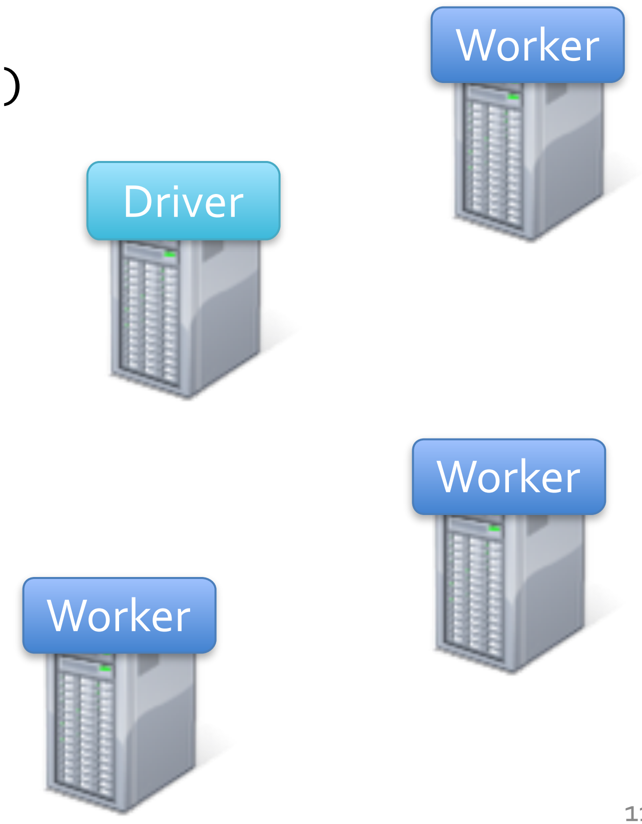

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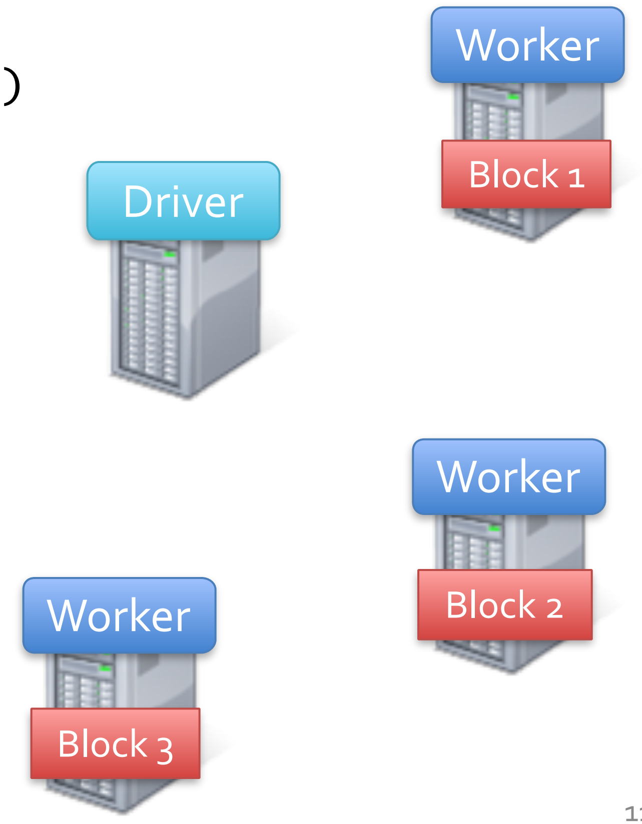

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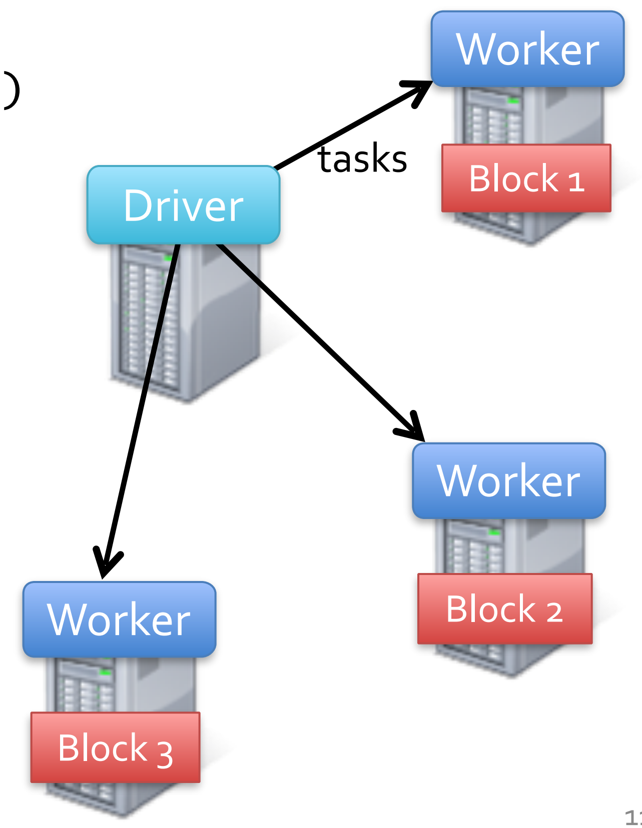

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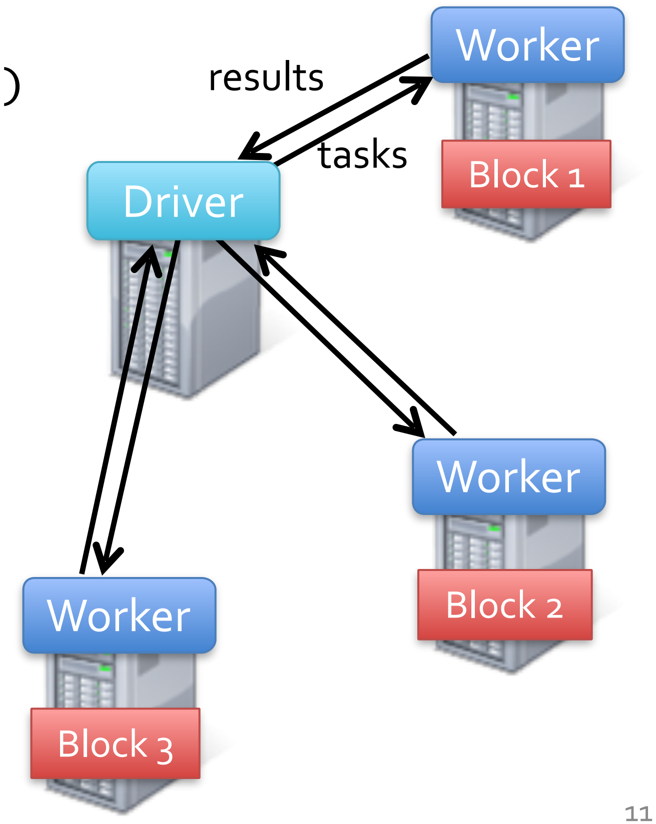

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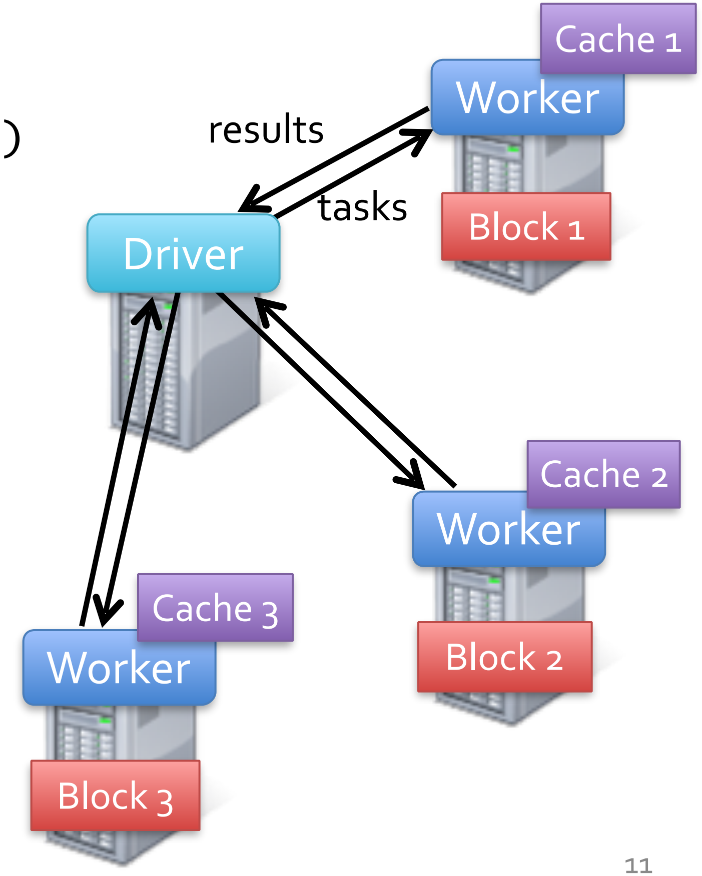

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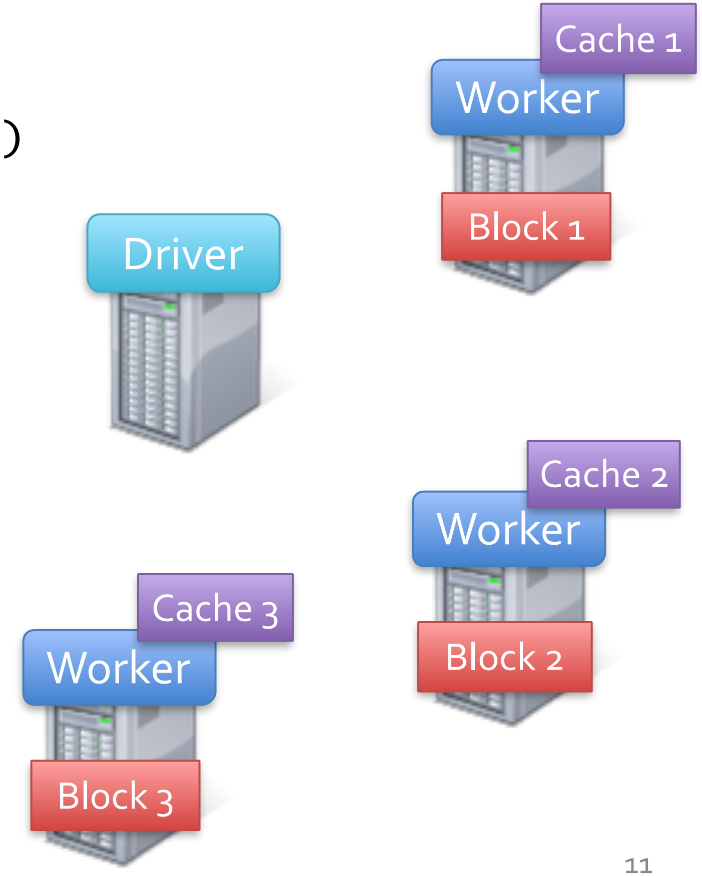

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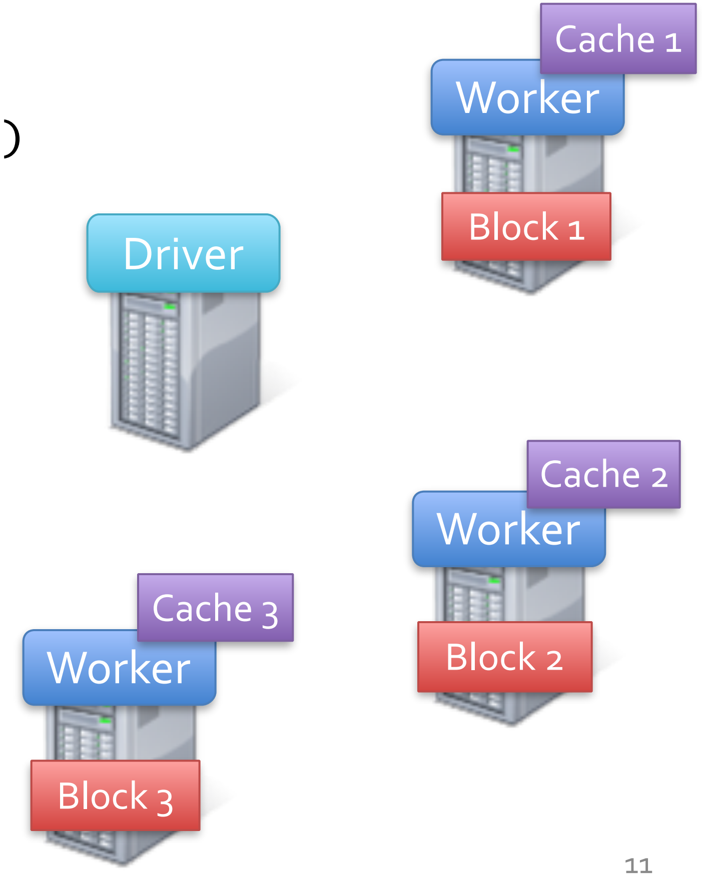

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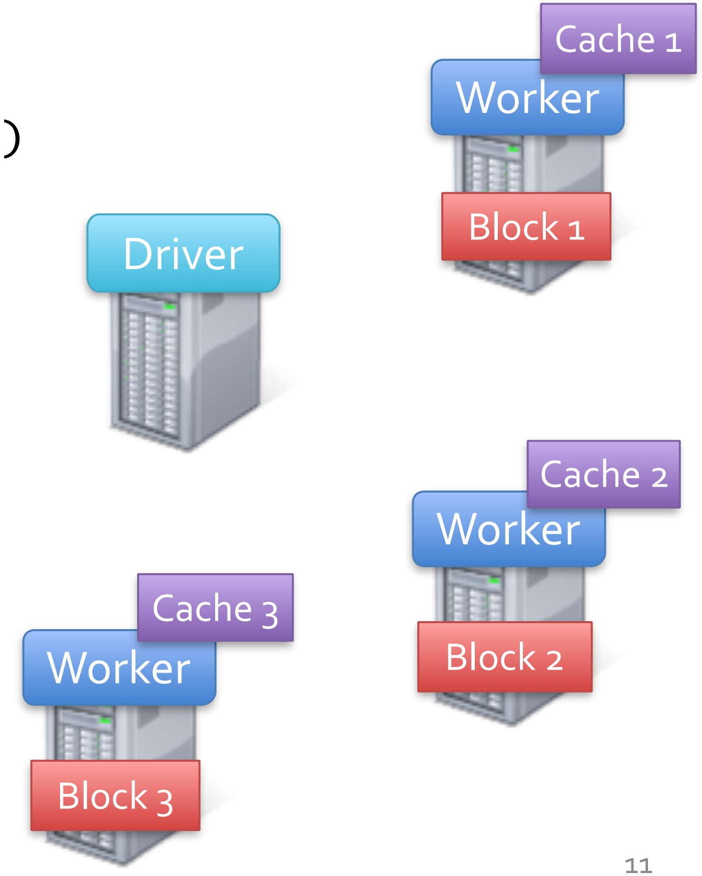

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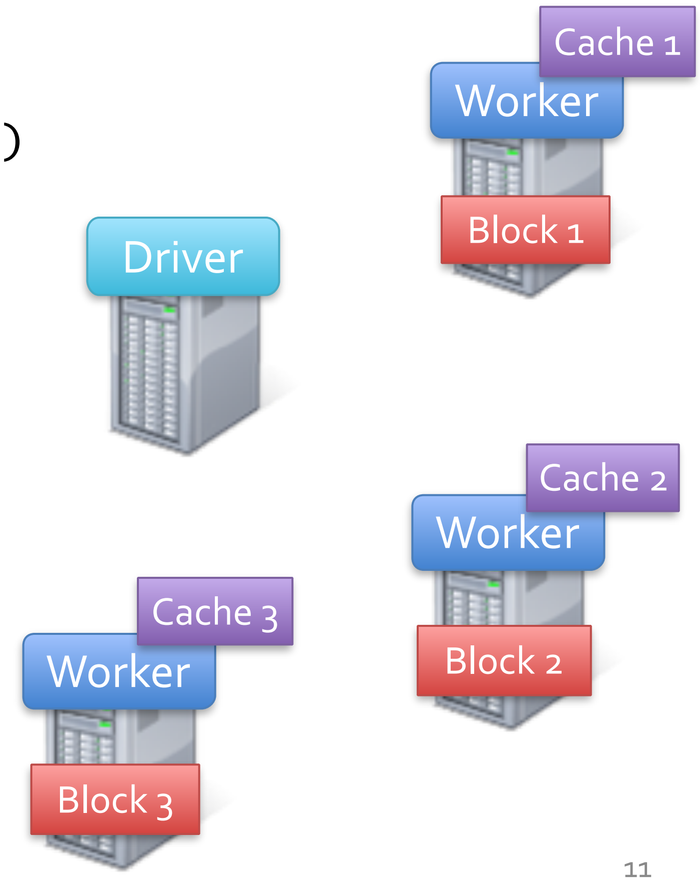

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

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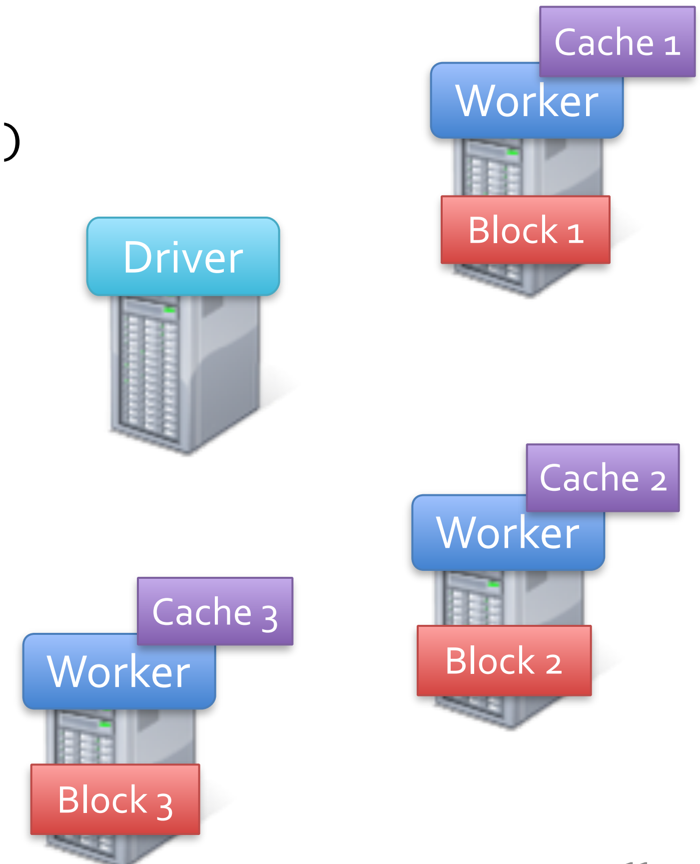
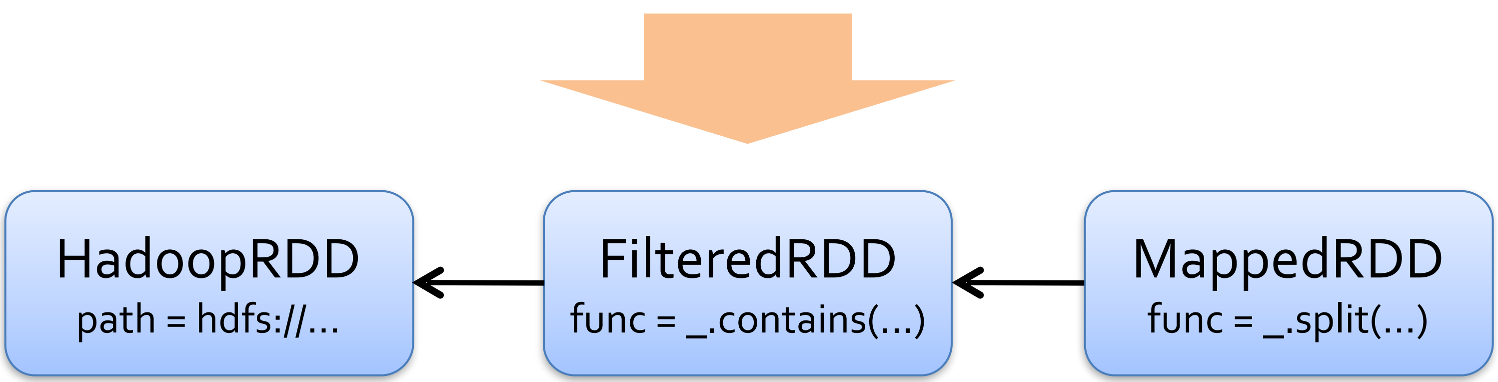


Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

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: Word Count (Python)

```
file = spark.textFile("hdfs://...")

file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

Word count in Spark's Python API

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

Example: Logistic Regression

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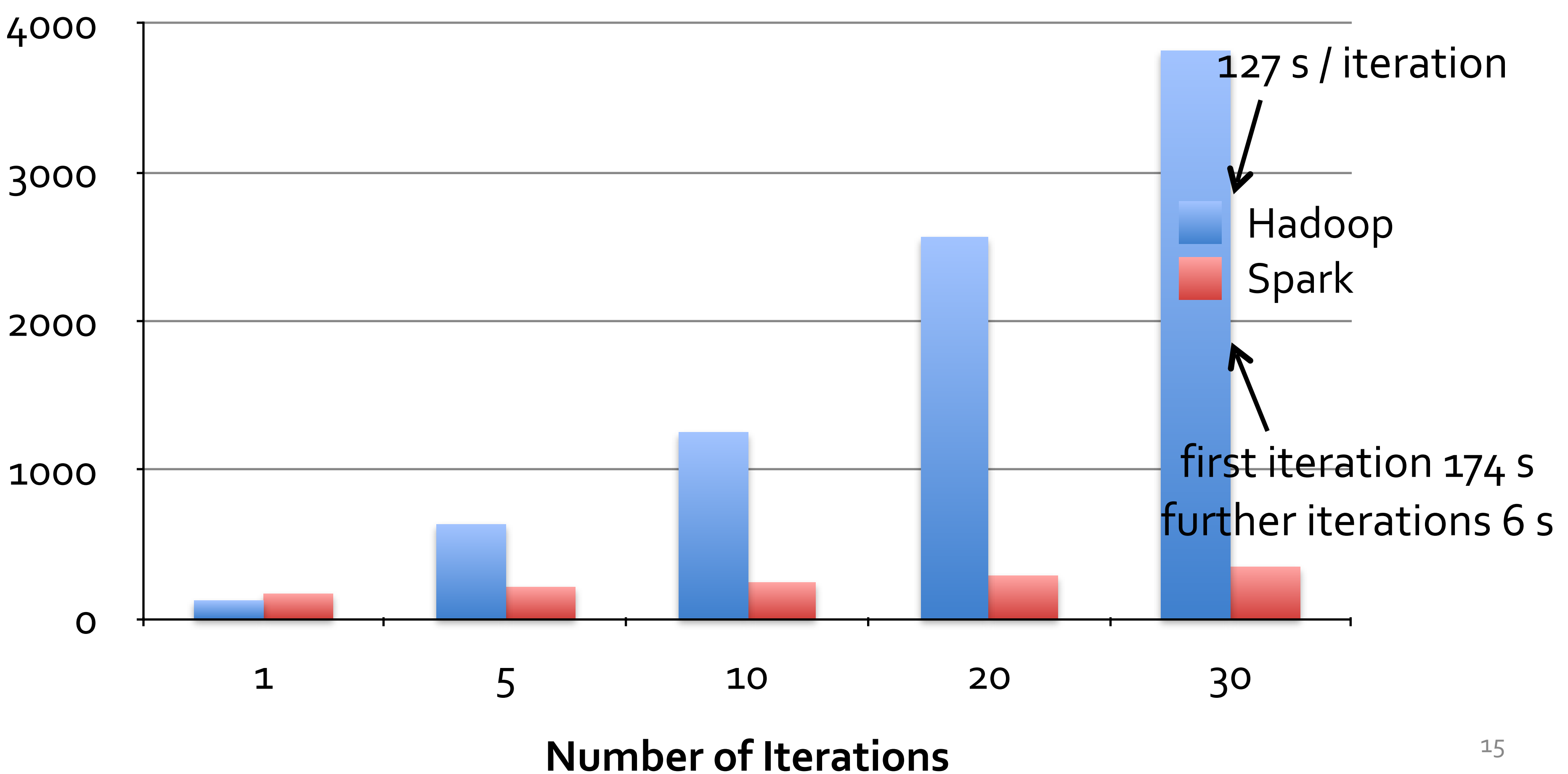
Repeated MapReduce steps to do gradient descent

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

Use Cases

In-memory analytics & anomaly detection (Conviva)

Interactive queries on data streams (Quantifind)

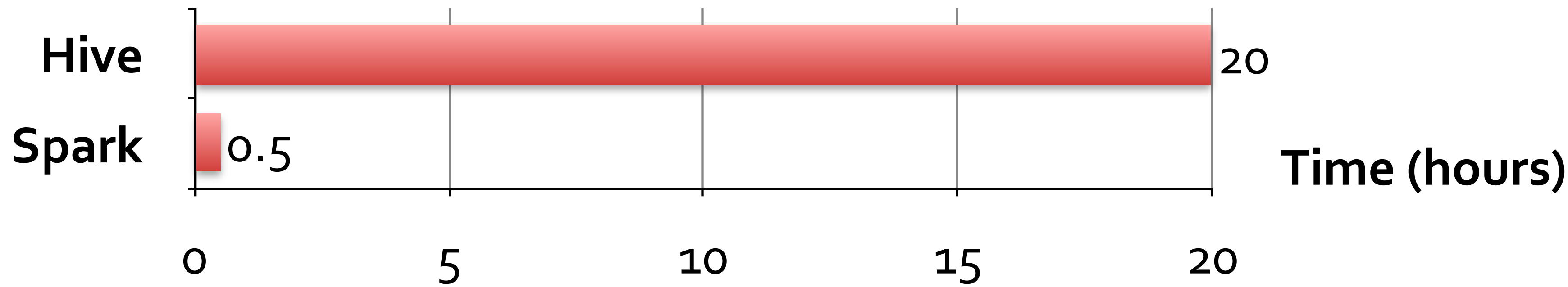
Exploratory log analysis (Foursquare)

Traffic estimation w/ GPS data (Mobile Millennium)

Twitter spam classification (Monarch)

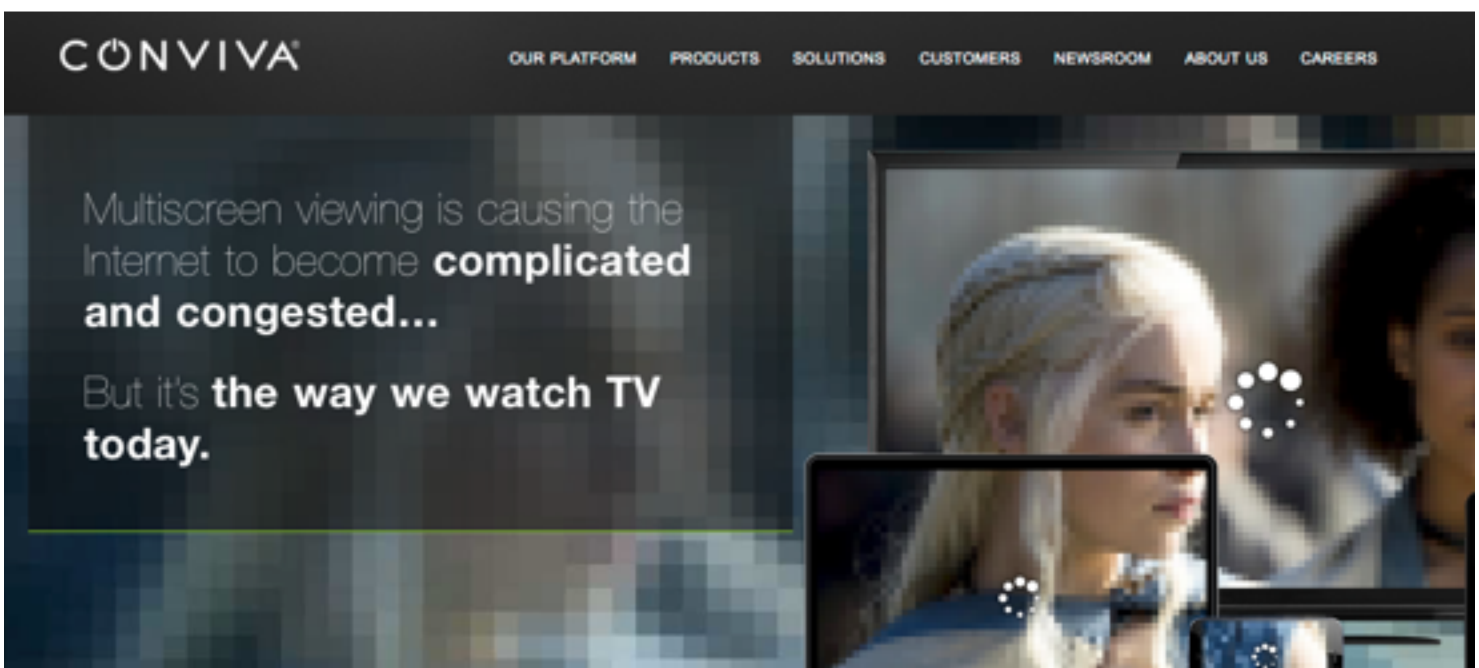
. . .

Conviva GeoReport



Group aggregations on many keys w/ same filter

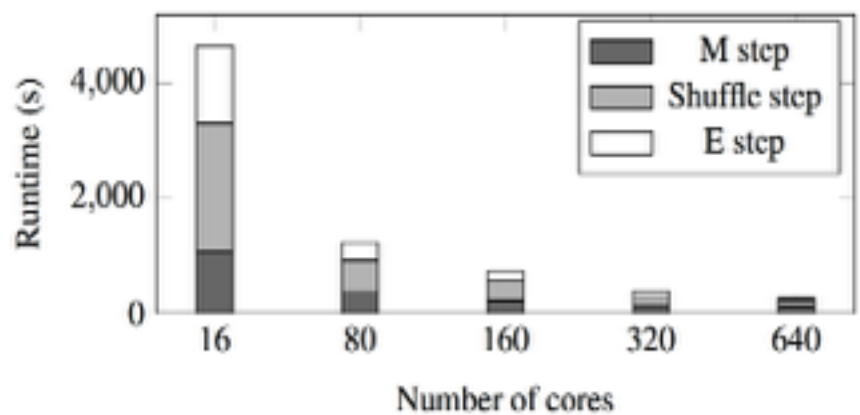
40× gain over Hive; avoid repeated reading, deserialization, filtering



Mobile Millennium Project

Estimate city traffic from crowdsourced GPS data

Iterative EM algorithm scaling to 160 nodes



Credit: Tim Hunter, with support of the Mobile Millennium team; P.I. Alex Bayen; traffic.berkeley.edu

Spark SQL: Hive on Spark

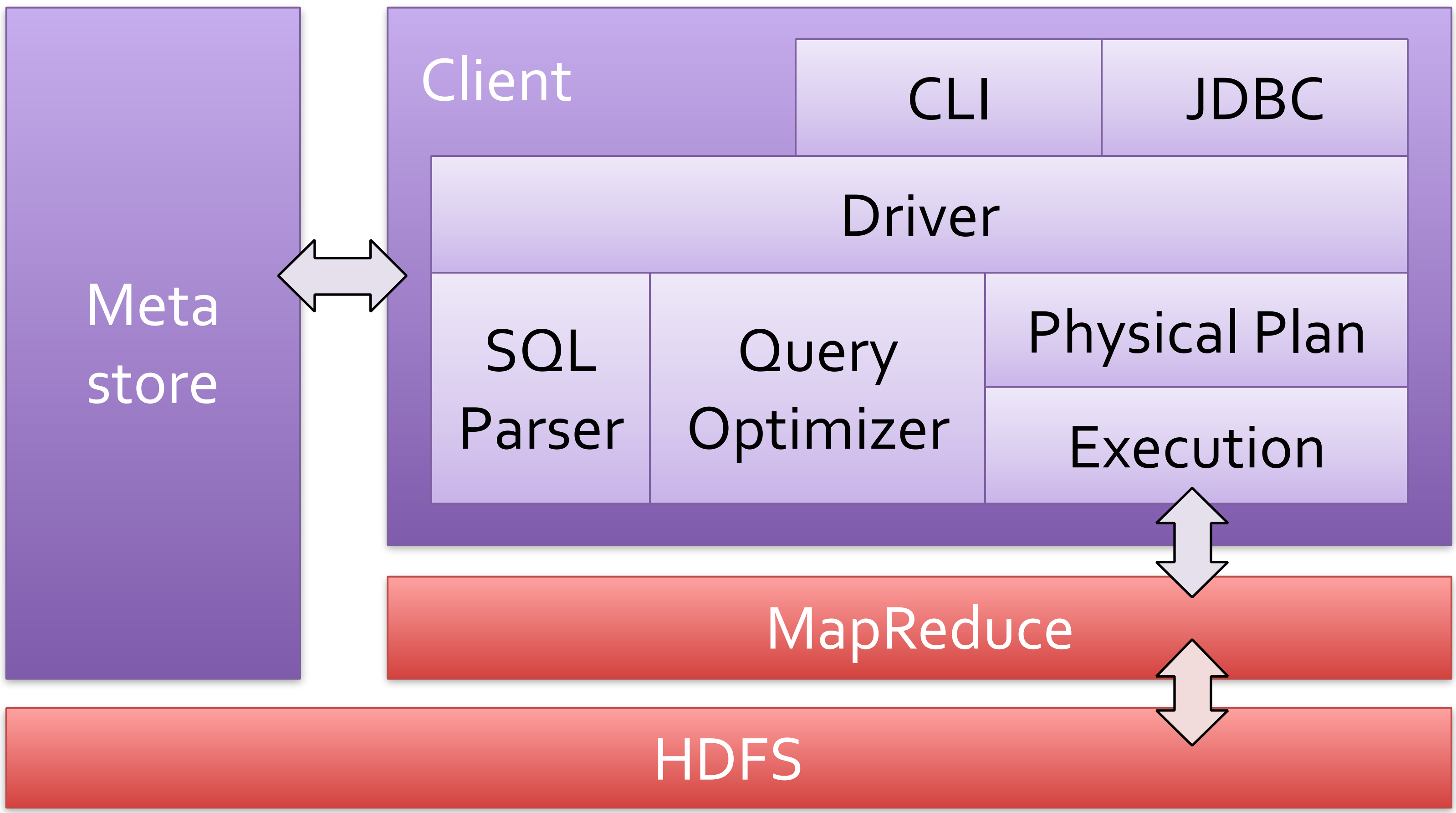
Motivation

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

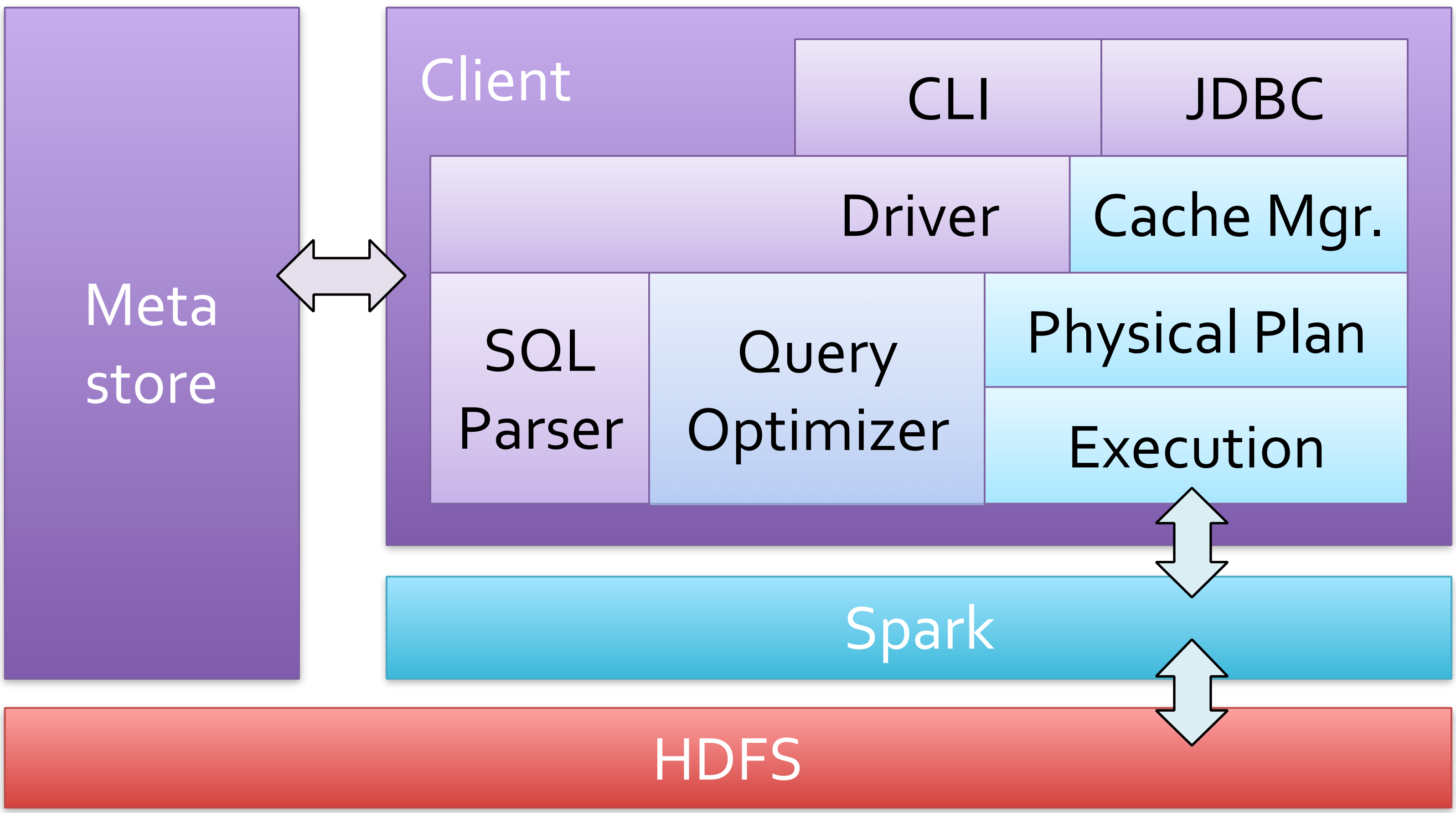
Scala is good for programmers, but many data users only know SQL

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

1	john	4.1
2	mike	3.5
3	sally	6.4

Column Storage

1	2	3
john	mike	sally
4.1	3.5	6.4

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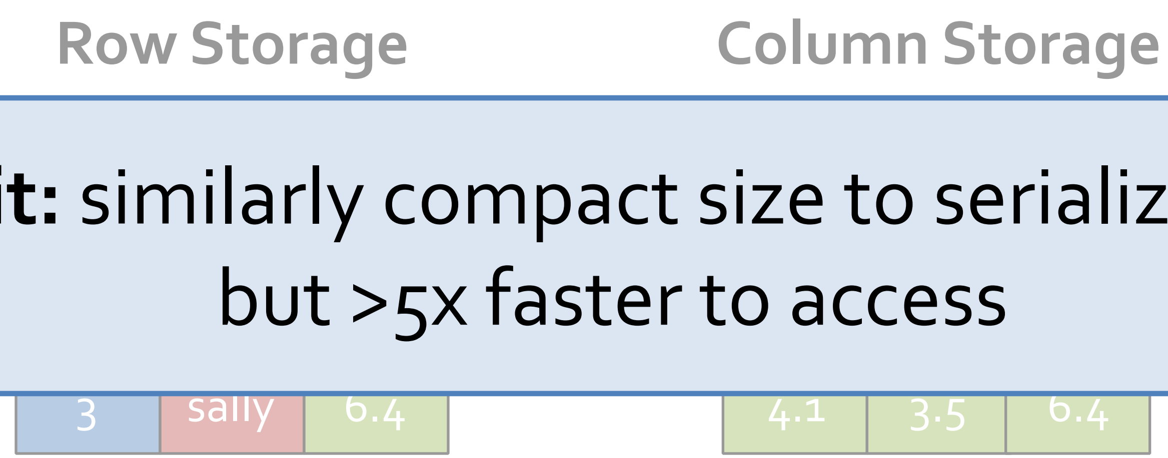


Benefit: similarly compact size to serialized data, but >5x faster to access

Using Shark

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

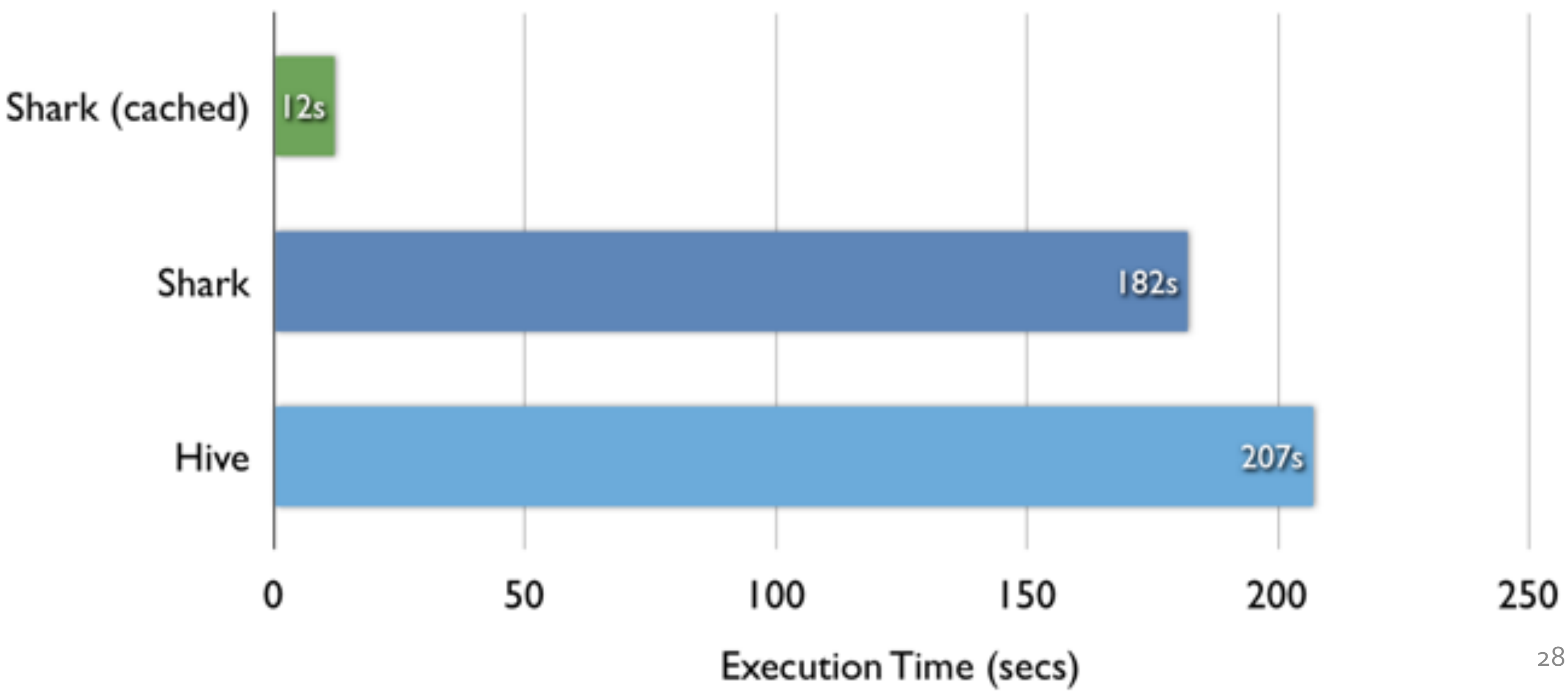
Run standard HiveQL on it, including UDFs

» A few esoteric features are not yet supported

Can also call from Scala to mix with Spark

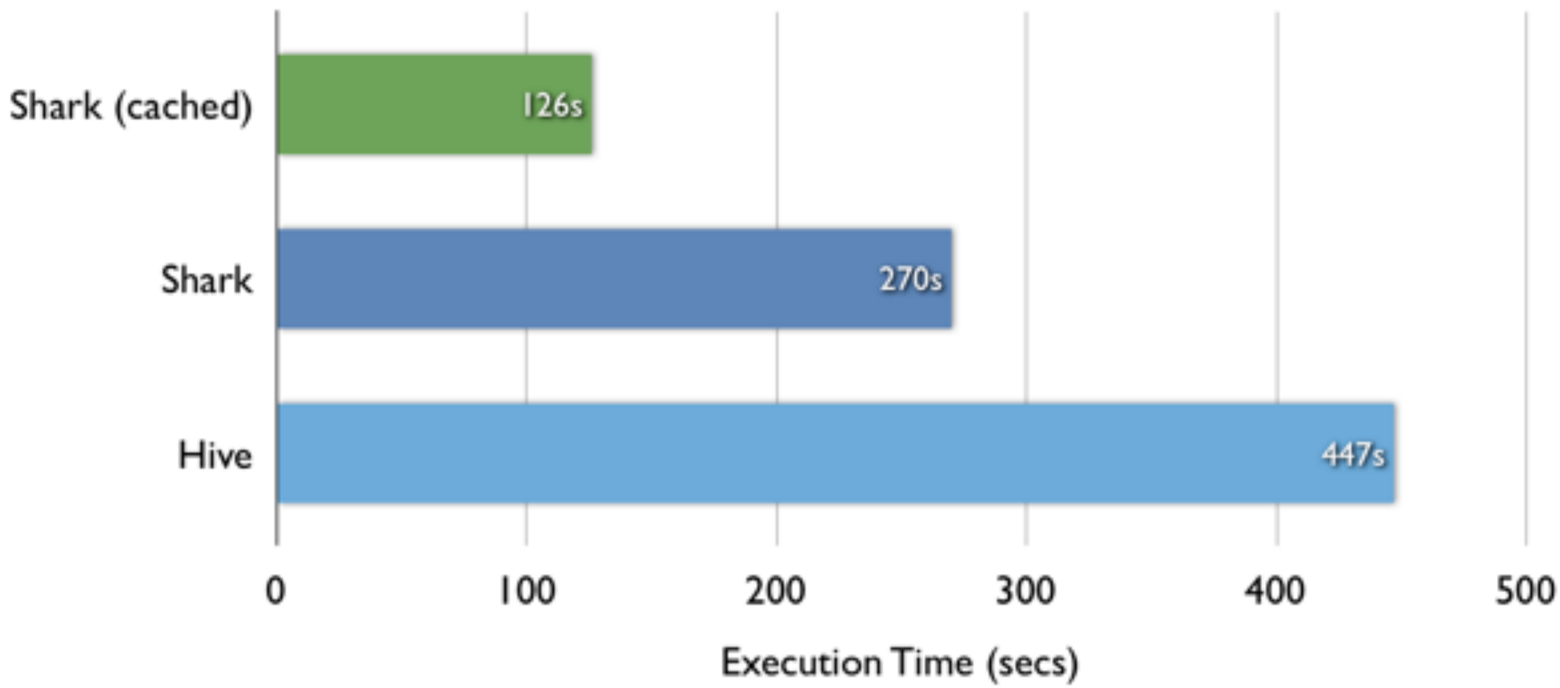
Benchmark Query 1

```
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

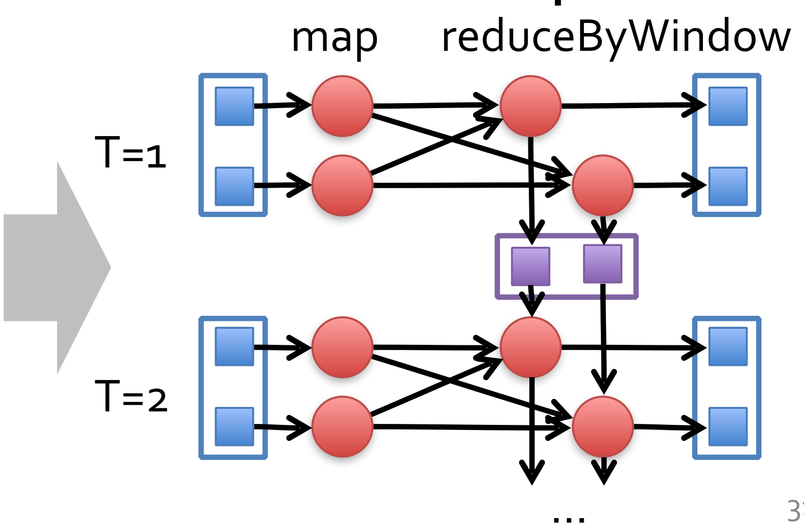
Streaming Spark

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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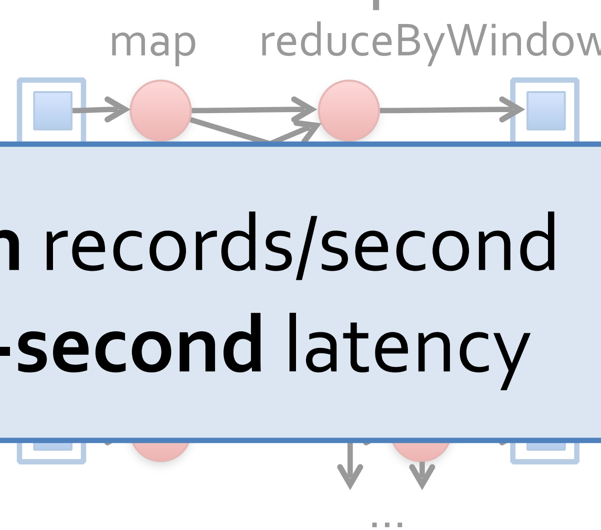

Result: can process **42 million** records/second (4 GB/s) on 100 nodes at **sub-second** latency

[Zaharia et al, HotCloud 2012]

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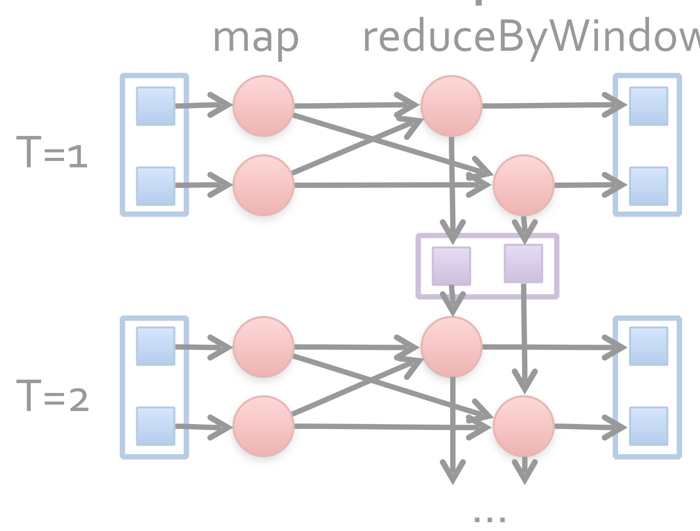
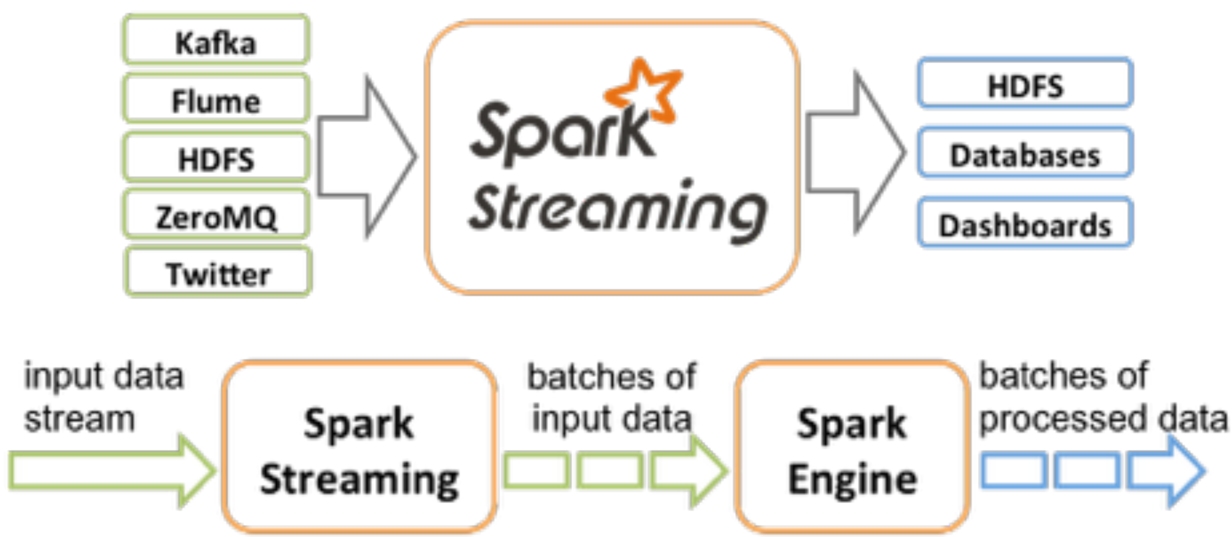


[Zaharia et al, HotCloud 2012]

Spark Streaming

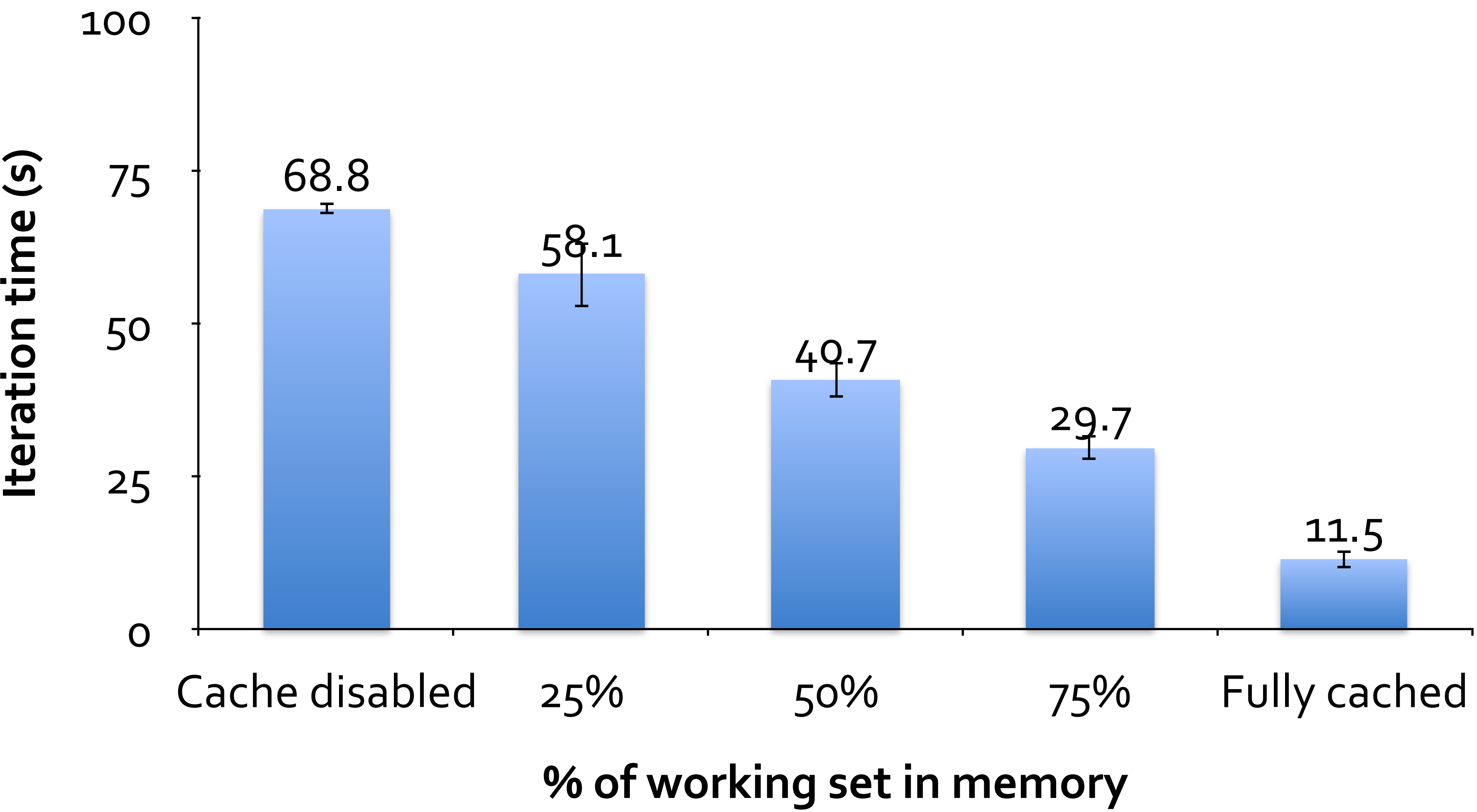
Create and operate on RDDs from live data streams at set intervals



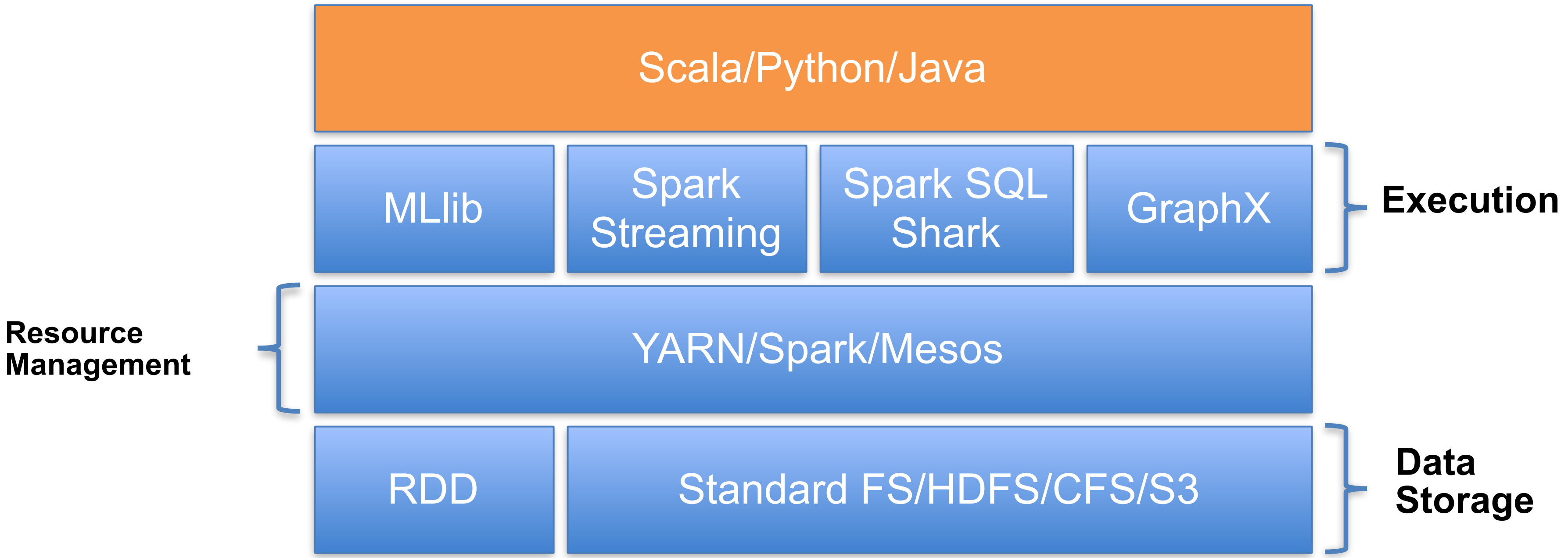
Data is divided into batches for processing

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

Behavior with Not Enough RAM



SPARK PLATFORM




Spark
HDFS
Standalone
Spark
YARN / Mesos
HDFS
Hadoop 2.x
(YARN)
Spark
MapReduce
HDFS
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

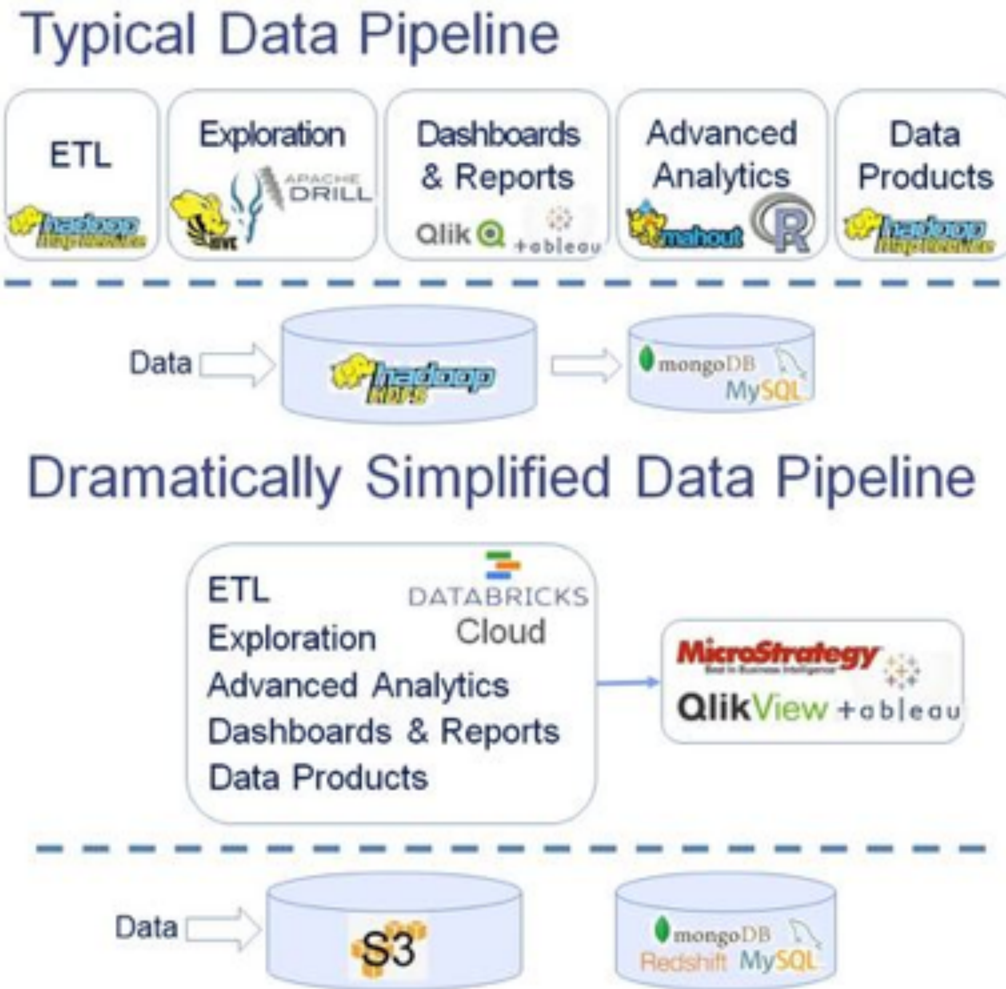
Commercial Support

Databricks

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

Commercial Support

Databricks Cloud



https://databricks.com