More Big Data Technologies

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Recap

- Technologies
  - SQL
  - NoSQL
    - Key-value stores, Column oriented DBs, Document DBs, and graph databases
- ML Algorithms
  - Supervised and unsupervised learning
  - Time series, association analysis

Today

- More Big Data Tech
  - Hadoop
  - Hive
  - Spark

Hadoop

- Open source software
  - Reliable, Scalable, Distributed Computing
- Can scale to thousands of machines
- Written in Java
- Supports many key ingredients for data-intensive applications
  - Map Reduce
  - HDFS (Hadoop Distributed File System)

Map Reduce

- Simple abstraction for scalable computing
  - Hides details of parallelization, fault-tolerance, and data balancing
- Can be viewed as a functional programming paradigm for expressing a broad range of big data analysis tasks

Example (warmup)

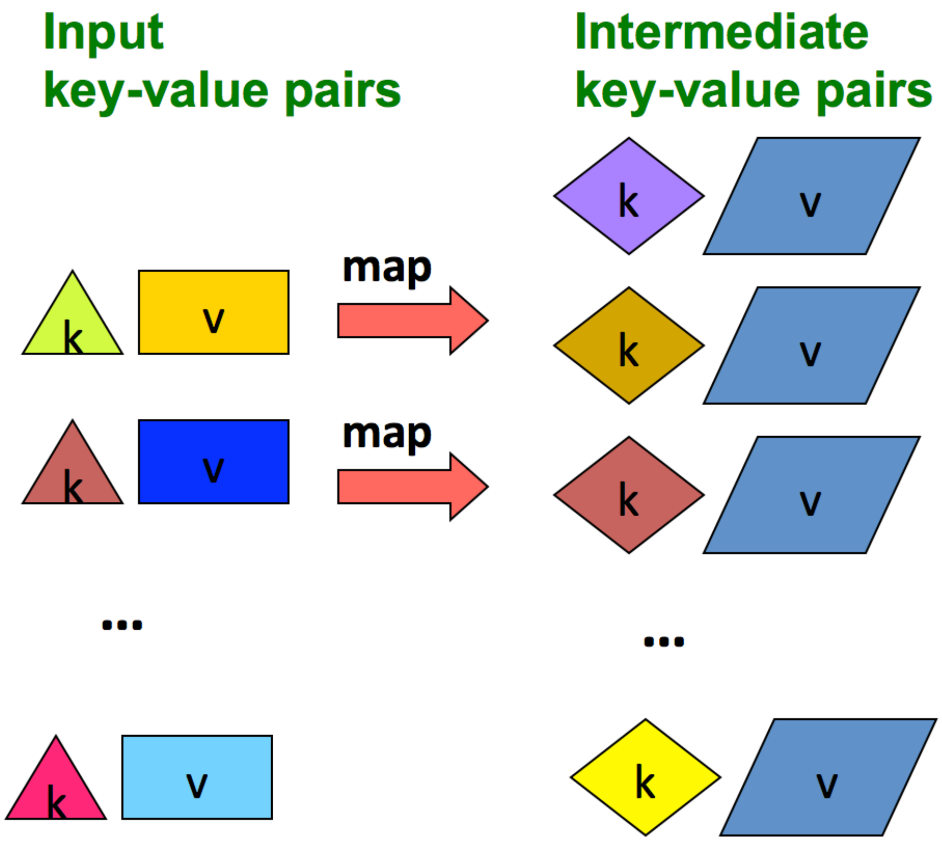
- We have a MASSIVE text document (file)
- Need to count the number of times each distinct word appears in the file
- Example application
  - Count support for political candidates in tweets
  - Analyze web server logs to find popular URLs
- Note:
  - File too large to fit into main memory

How MapReduce works

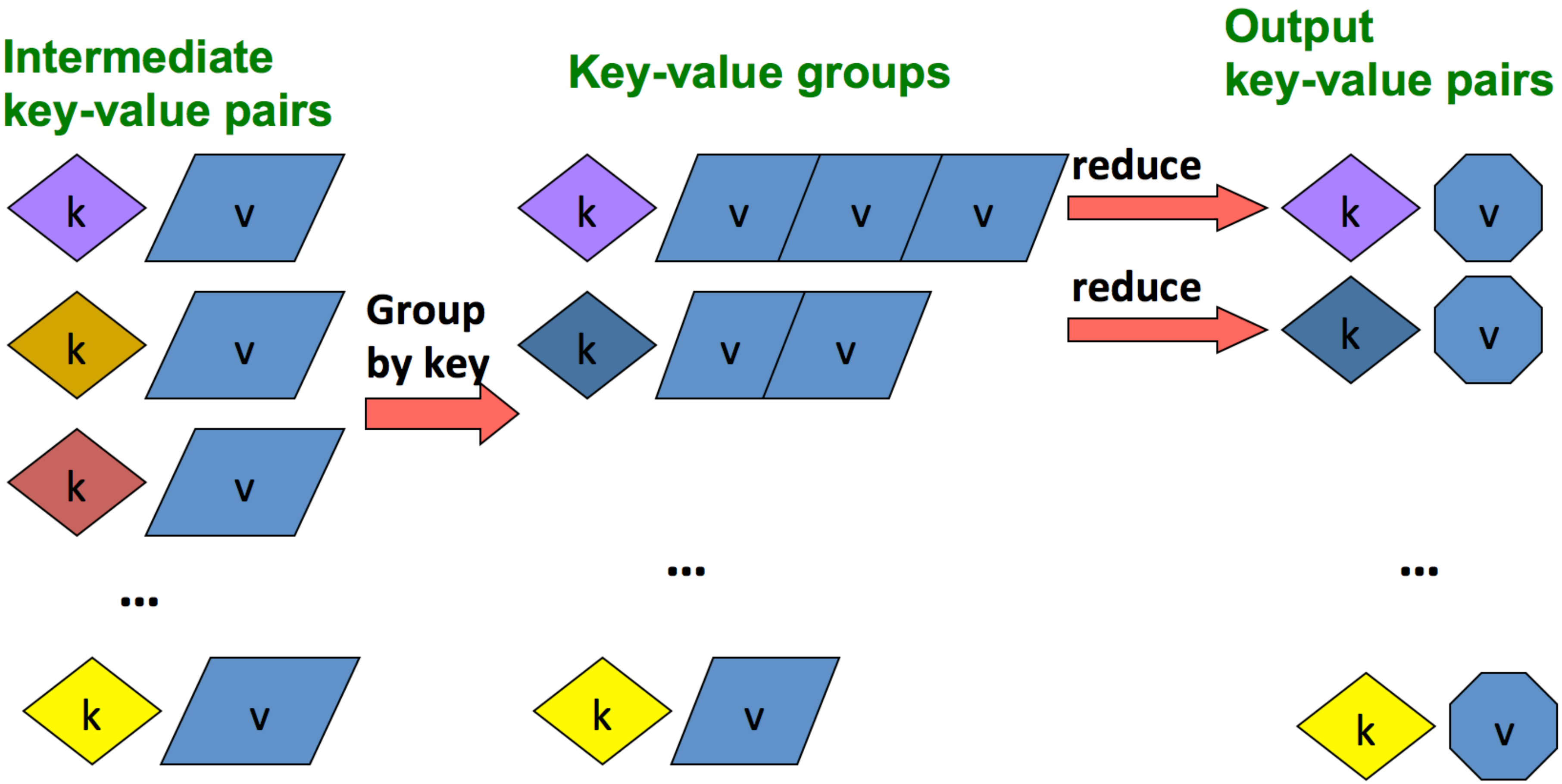
- Sequentially read a lot of data
- Map
  - Extract something you care about
- Group by key
  - Sort and shuffle
- Reduce
  - Aggregate, summarize, filter or transform
- Write the result

Outline stays the same, **Map** and **Reduce** change to fit the problem

MapReduce: Map Step



MapReduce: Reduce Step



In more detail

- **Input:** a set of key-value pairs
- Programmer specifies two methods:
  - **Map(k, v)** → <k', v'>*
    - Takes a key-value pair and outputs a set of key-value pairs
      - E.g., key is the filename, value is a single line in the file
    - There is one Map call for every *(k,v)* pair
  - **Reduce(k', <v'>*)** → <k', v''>*
    - **All values *v'* with same key *k'* are reduced together and processed in *v'* order**
    - There is one Reduce function call per unique key *k'*

MapReduce for word counting

Provided by the programmer

MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key

Provided by the programmer

Reduce:
Collect all values belonging to the key and output

The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/mache partnership. '"The work we're doing now -- the robotics we're doing -- is what we're going to need ....

(The, 1)
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(recently, 1)
...

(crew, 2)
(space, 1)
(the, 3)
(shuttle, 1)
(recently, 1)
...

In more detail

```
map(key, value):
// key: document name; value: text of the document
  for each word w in value:
   emit(w, 1)


reduce(key, values):
// key: a word; value: an iterator over counts
   result = 0
   for each count v in values:
      result += v
   emit(key, result)
```

MapReduce as SQL

- select count(*) ← **Reducer**

  from DOCUMENT

  group by word

Mapper

Why is this a big deal?

Map-Reduce environment takes care of:

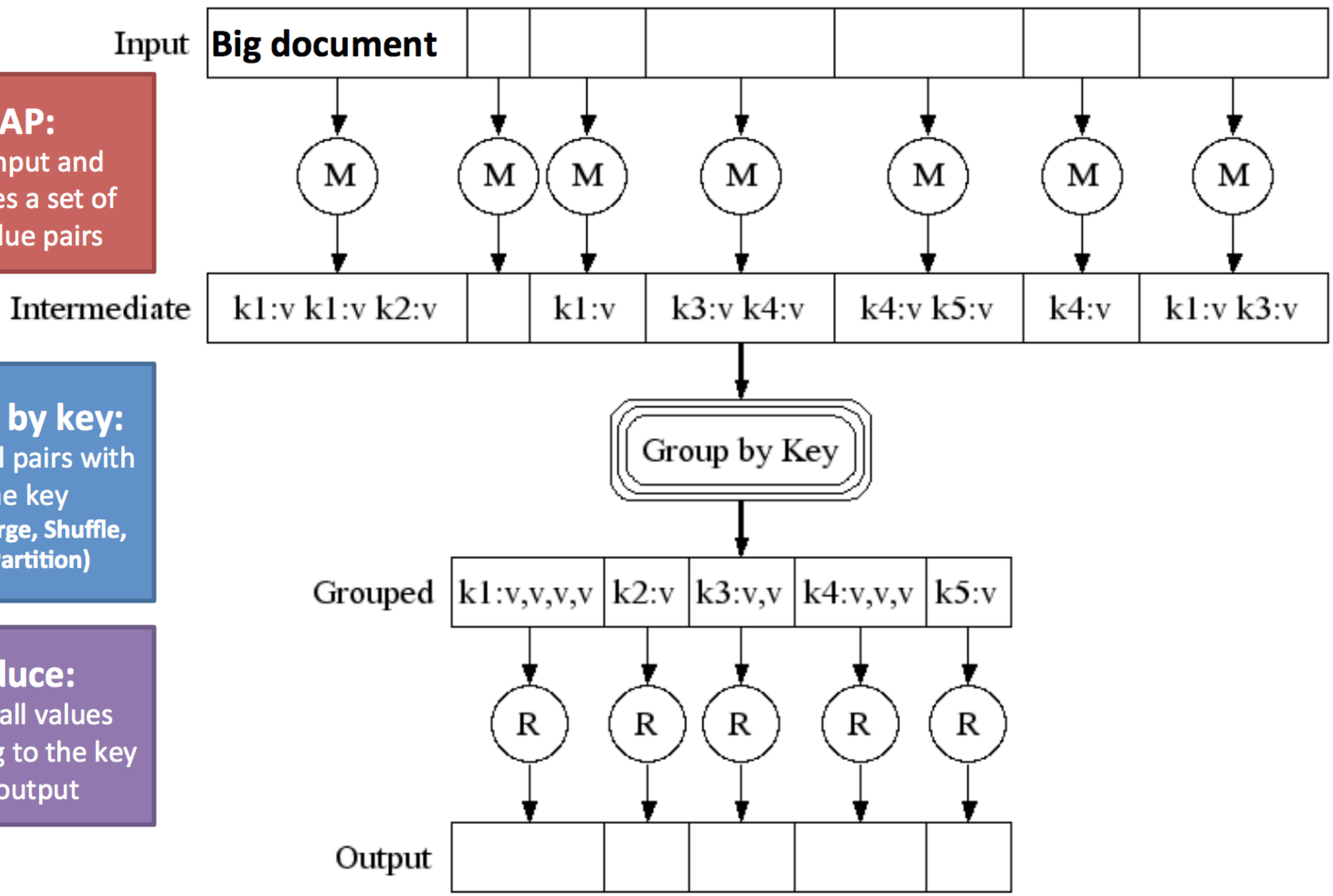
- Partitioning the input data
- Scheduling the program's execution across a set of machines
- Performing the **group by key** step
- Handling machine failures
- Managing required inter-machine communication

Diagrammatic notation

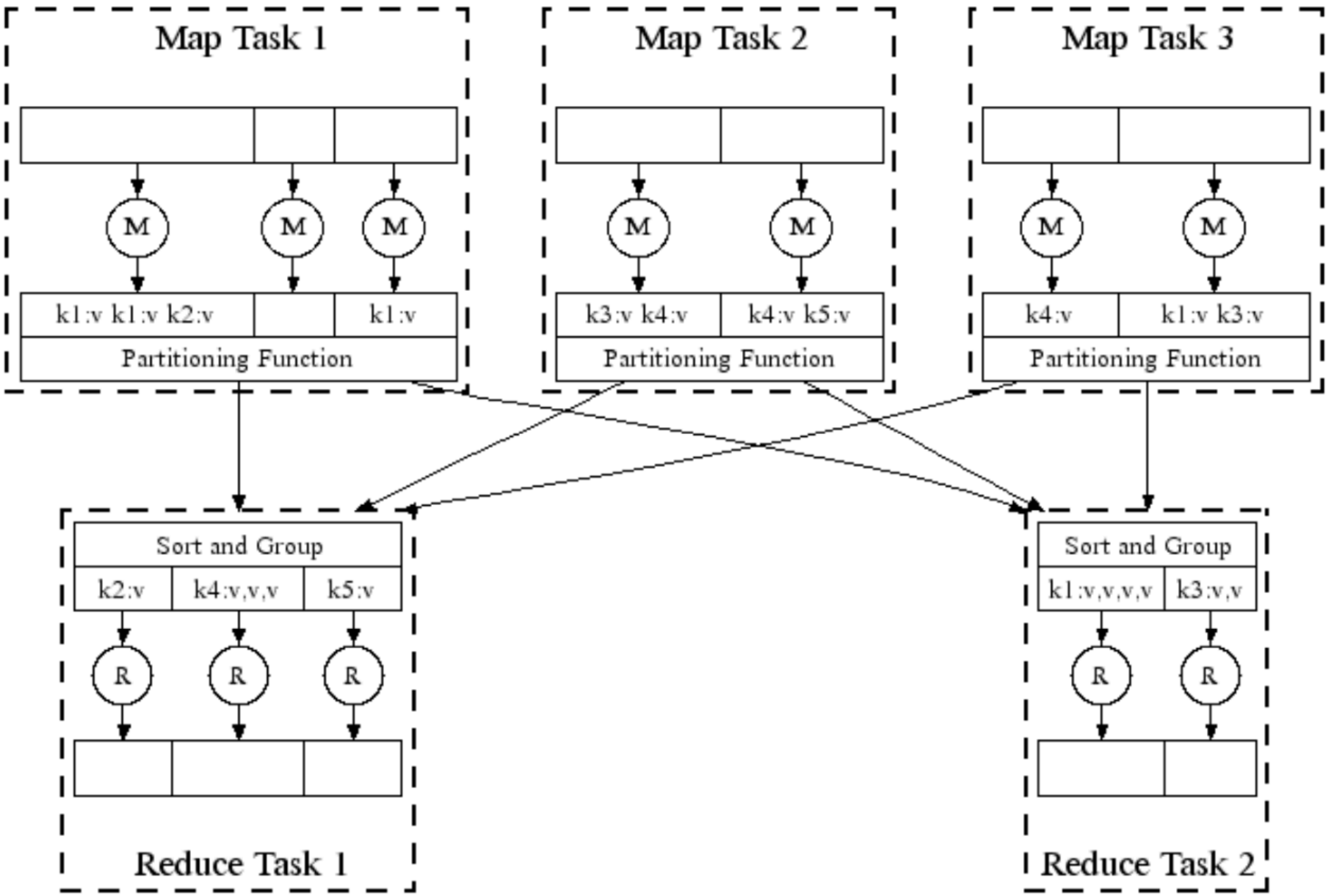
MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

Reduce:
Collect all values belonging to the key and output

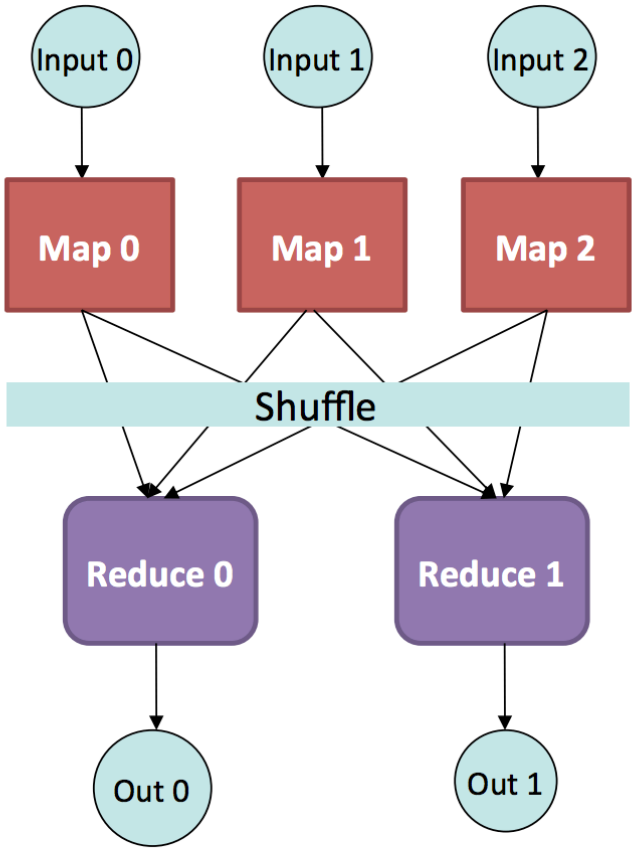


MapReduce in parallel



MapReduce in parallel

- Programmer specifies:
  - Map and Reduce and input files
- **Workflow:**
  - Read inputs as a set of key-value-pairs
  - **Map** transforms input kv-pairs into a new set of k'v'-pairs
  - Sorts & Shuffles the k'v'-pairs to output nodes
  - All k'v'-pairs with a given k' are sent to the same **reduce**
  - **Reduce** processes all k'v'-pairs grouped by key into new k''v''-pairs
  - Write the resulting pairs to files
- All phases are distributed with many tasks doing the work



Data Flow

- Input and final output are stored on a distributed file system (FS):
  - Scheduler tries to schedule map tasks "close" to physical storage location of input data

- Intermediate results are stored on local FS of Map and Reduce workers

- Output is often input to another MapReduce task

Coordination: Master

- Master node takes care of coordination:
  - **Task status:** (idle, in-progress, completed)
  - **Idle tasks** get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its *R* intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle
  - Reduce task is restarted
- **Master failure**
  - MapReduce task is aborted and client is notified

Other problems suitable for MR

- Counting, size determination, many statistical estimation routines
- Graph analytics
  - e.g, finding degrees, degree distribution
- Many machine learning algorithms can be cast in terms of MR
  - Often need to “dumb” your algorithms down!

Back to Hadoop

- Hadoop provides
  - Map reduce (MR)
  - Distributed, fault-tolerant file system (HDFS)
    - E.g., Store files multiple times for reliability and to avoid copying costs over the network

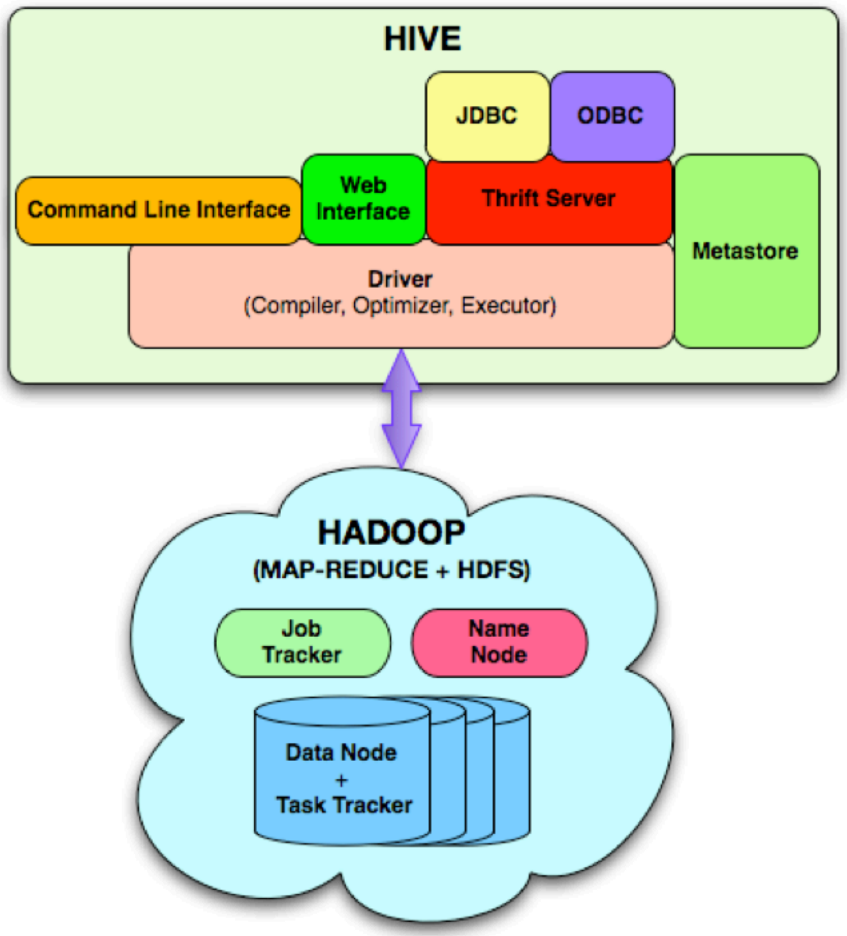
Criticisms of Hadoop/MR

- Still a bit low-level
- Analytic pipelines can get quite complex
- Researchers started developing higher-level substrates/layers over MR
  - Yahoo: Pig
  - Facebook: Hive

Hive

- Supports queries expressed in SQL-like language called HiveQL which are compiled into MR jobs that are executed on Hadoop.
  - Also allows MR scripts!
- Helps structure data into classical concepts like tables, rows, columns, and partitions

Hive architecture



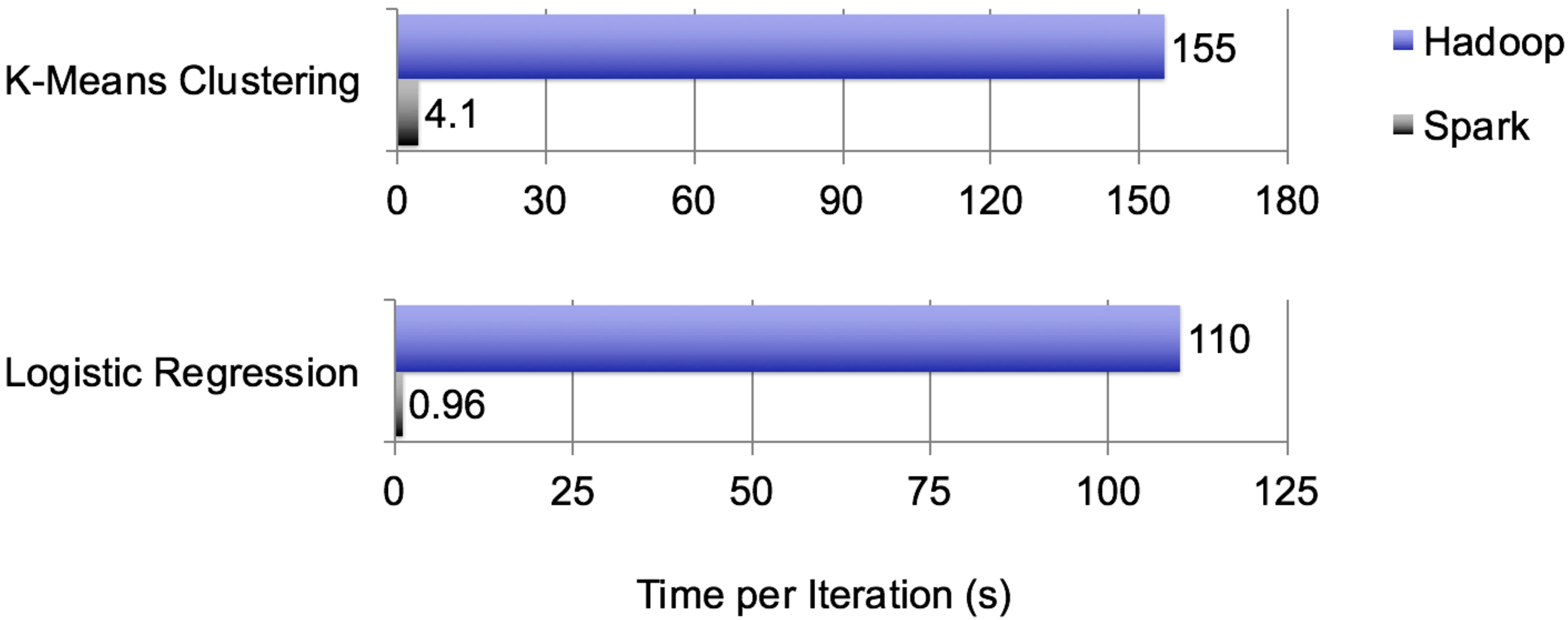
Wordcount in Hive

```
FROM (
MAP doctext USING 'python wc_mapper.py' AS
   (word, cnt)
FROM docs
CLUSTER BY word
) a
REDUCE word, cnt USING 'pythonwc_reduce.py';
```

Apache Spark

- From AMP Lab at Berkeley
- Spark vs Hadoop
  - Like Hadoop, works on distributed data collections
  - Unlike Hadoop, does not provide its own file system
    - But can use HDFS!
- Primarily suited for in-memory analytics;
  - can be 10X faster than MR for batch processing
  - can be 100X faster than MR for in-memory analytics

Example performance



Resilient Distributed Datasets (RDDs)

- Even though data is not written to disk at each step, fault recovery/resiliency is built in because data is distributed across the cluster
  - Immutable collections of objects spread across a cluster
  - Built through parallel transformations (map, filter, etc)
  - Automatically rebuilt on failure
  - Controllable persistence (e.g. caching in RAM)

Using Spark

- APIs in Java, Scala and Python
- Transformations (e.g. map, filter, groupBy, join)
  - Lazy operations to build RDDs from other RDDs
- Actions (e.g. count, collect, save)
  - Return a result or write it to storage
- Spark can read/write to any storage system / format that has a plugin for Hadoop!
  - Examples: HDFS, S3, HBase, Cassandra, Avro, SequenceFile
  - Reuses Hadoop's InputFormat and OutputFormat APIs

What we have learnt thus far

- Map Reduce
- Hadoop
- Hive
- Spark