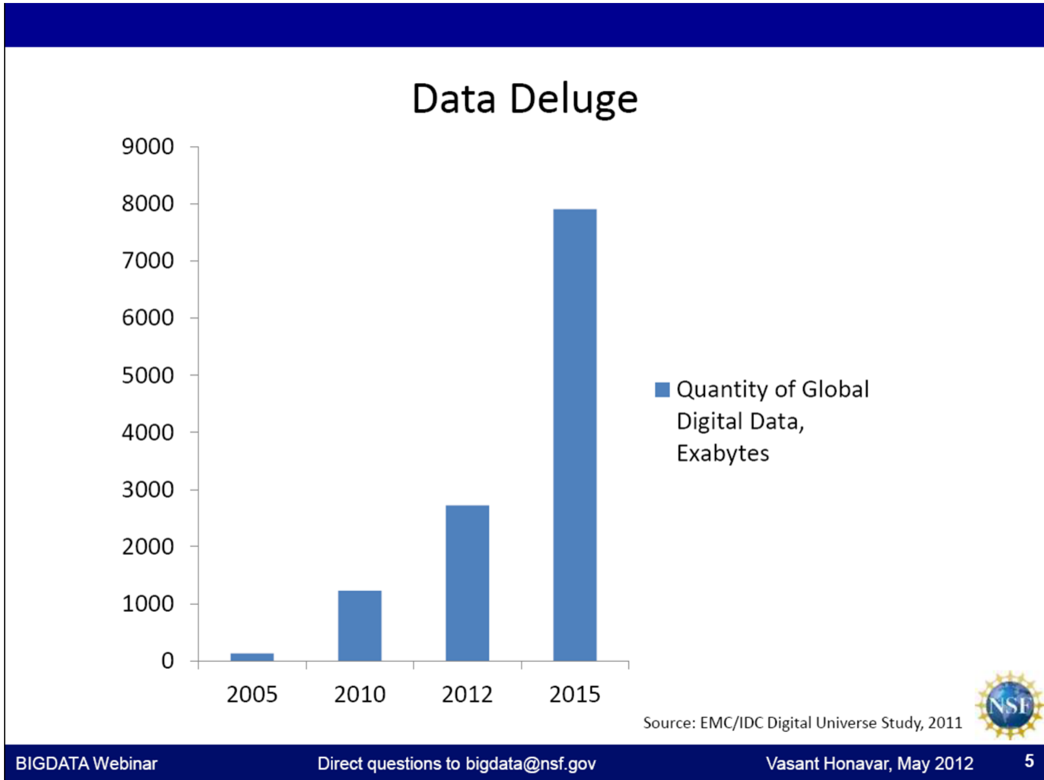
Hadoop

Data Deluge

- Billions of users connected through the Internet
  - WWW, FB, twitter, cell phones, …
  - 80% of the data on FB was produced last year
- Storage getting cheaper
  - Store more data!



Why Hadoop

- Drivers:
  - 500M+ unique users per month
  - Billions of interesting events per day
  - Data analysis is key
- Need massive scalability
  - PB's of storage, millions of files, 1000's of nodes
- Need cost effectively
  - Use commodity hardware
  - Share resources among multiple projects
  - Provide scale when needed
- Need reliable infrastructure
  - Must be able to deal with failures – hardware, software, networking
    - Failure is expected rather than exceptional
  - Transparent to applications
    - very expensive to build reliability into each application

The Hadoop infrastructure provides these capabilities

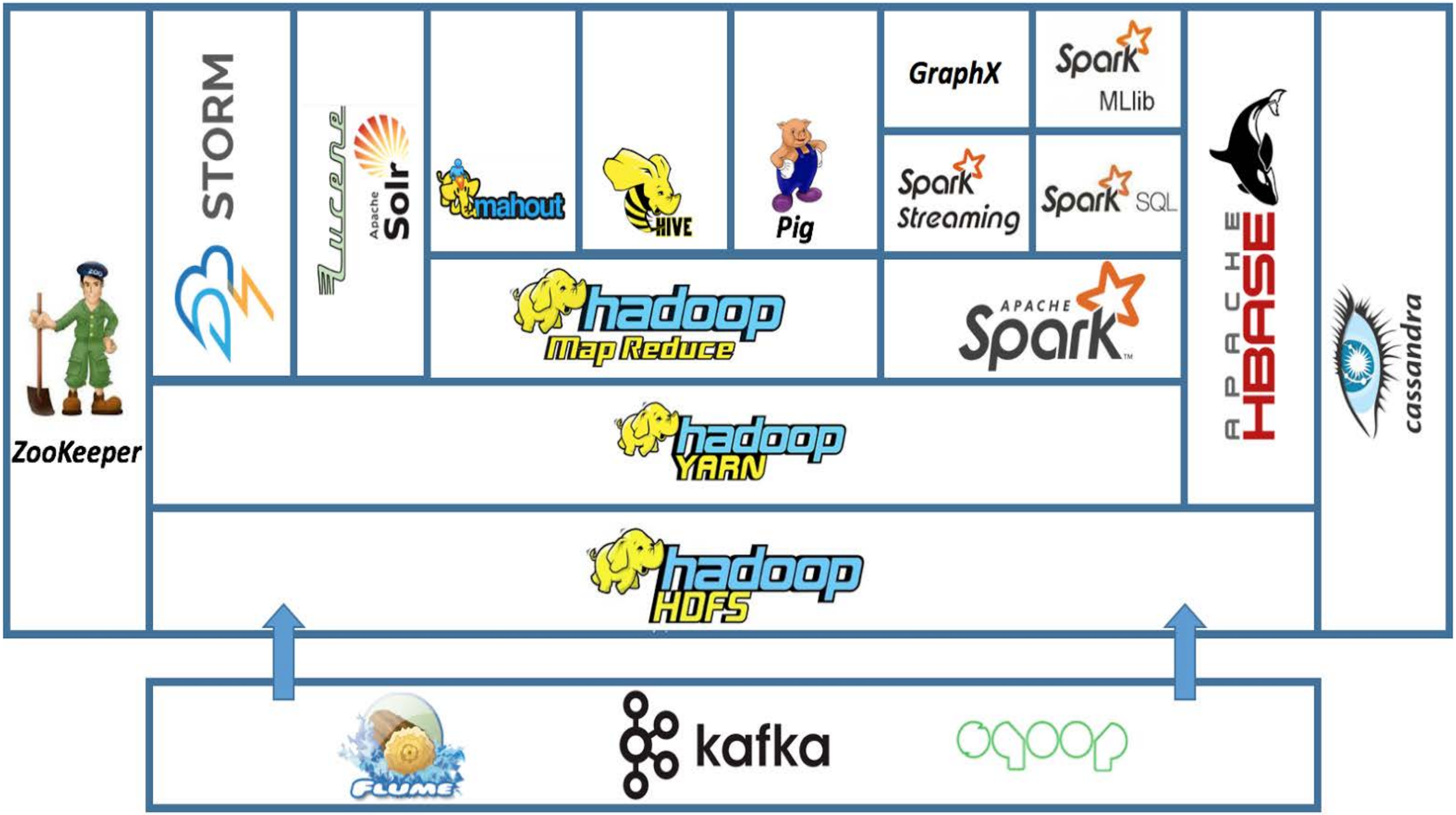
Introduction to Hadoop

- Apache Hadoop
  - Open Source – Apache Foundation project
    - Yahoo! is apache platinum sponsor
- History
  - Started in 2005 by Doug Cutting
  - Yahoo! became the primary contributor in 2006
    - They have scaled it from 20 node clusters to 10,000 node+ clusters today
  - They deployed large scale science clusters in 2007
  - They began running major production jobs in Q1, 2008
- Portable
  - Written in Java
  - Runs on commodity hardware
  - Linux, Mac OS/X, Windows, and Solaris

Growing Hadoop Ecosystem

- Hadoop Core
  - Distributed File System
  - MapReduce Framework
- Pig (initiated by Yahoo!)
  - Parallel Programming Language and Runtime
- Hbase (initiated by Powerset)
  - Table storage for semi-structured data
- Zookeeper (initiated by Yahoo!)
  - Coordinating distributed systems

- Hive (initiated by Facebook)
  - SQL-like query language and metastore


ZooKeeper
STORM
Lucene
Apache Solr
mahout
HIVE
Pig
GraphX
Spark MLlib
Spark Streaming
Spark SQL
hadoop Map Reduce
APACHE Spark
APACHE HBASE
cassandra
hadoop YARN
hadoop HDFS
FLUME
kafka
sqoop

M45 (open cirrus cluster)

- Collaboration with Major Research Universities (via open cirrus)
  - Carnegie Mellon University
  - The University of California at Berkeley
  - Cornell University
  - The University of Massachusetts at Amherst joined
- Seed Facility: Datacenter in a Box (DiB)
  - 500 nodes, 4000 cores, 3TB RAM, 1.5PB disk
  - High bandwidth connection to Internet
  - Located on Yahoo! corporate campus
- Runs Hadoop
- Has been used for Ten years

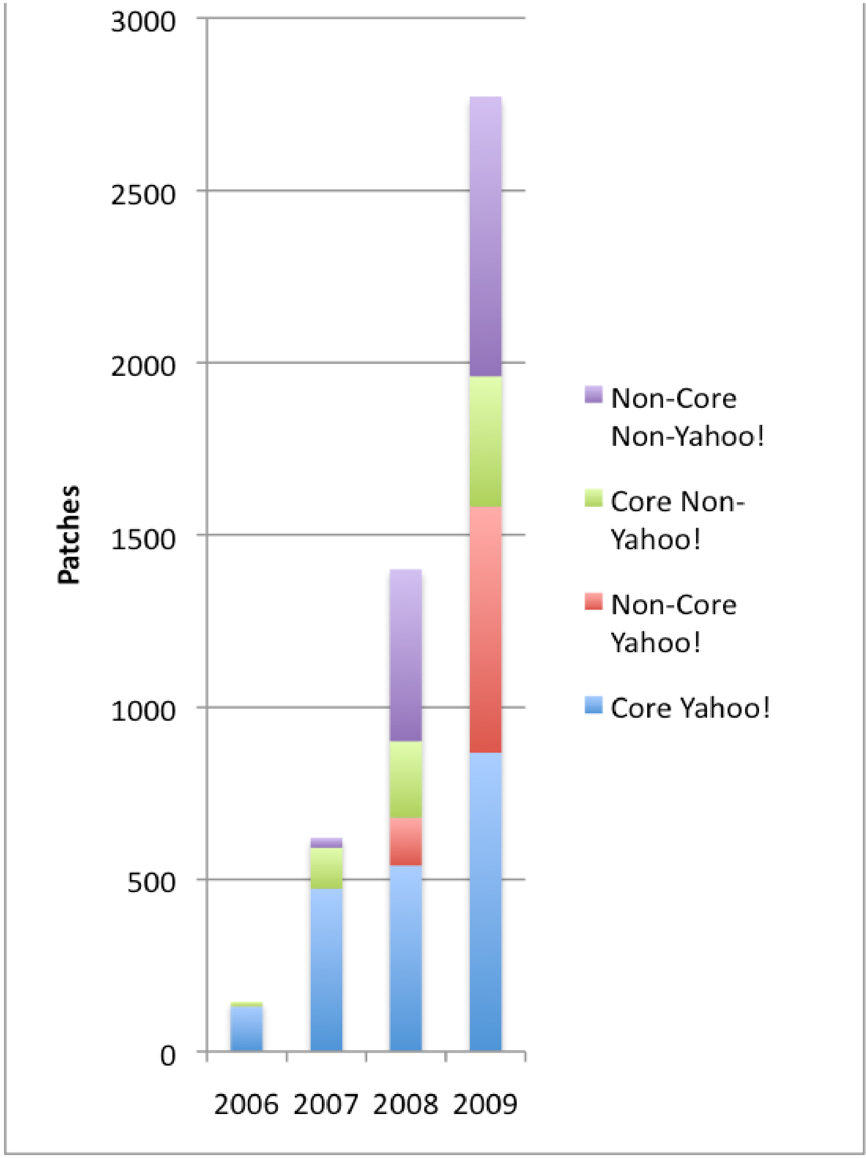
Hadoop Community

Apache Hadoop Community

- Hadoop is owned by the Apache Foundation
  - Provides legal and technical framework for **collaboration**
  - All code and intellectual property (IP) owned by non-profit foundation
- Anyone can join Apache's meritocracy
  - Users
  - Contributors
    - write patches
  - Committers
    - can commit patches
  - Project Management Committee
    - vote on new committers and releases
    - represent from many organizations
- Use, contribution, and diversity are growing

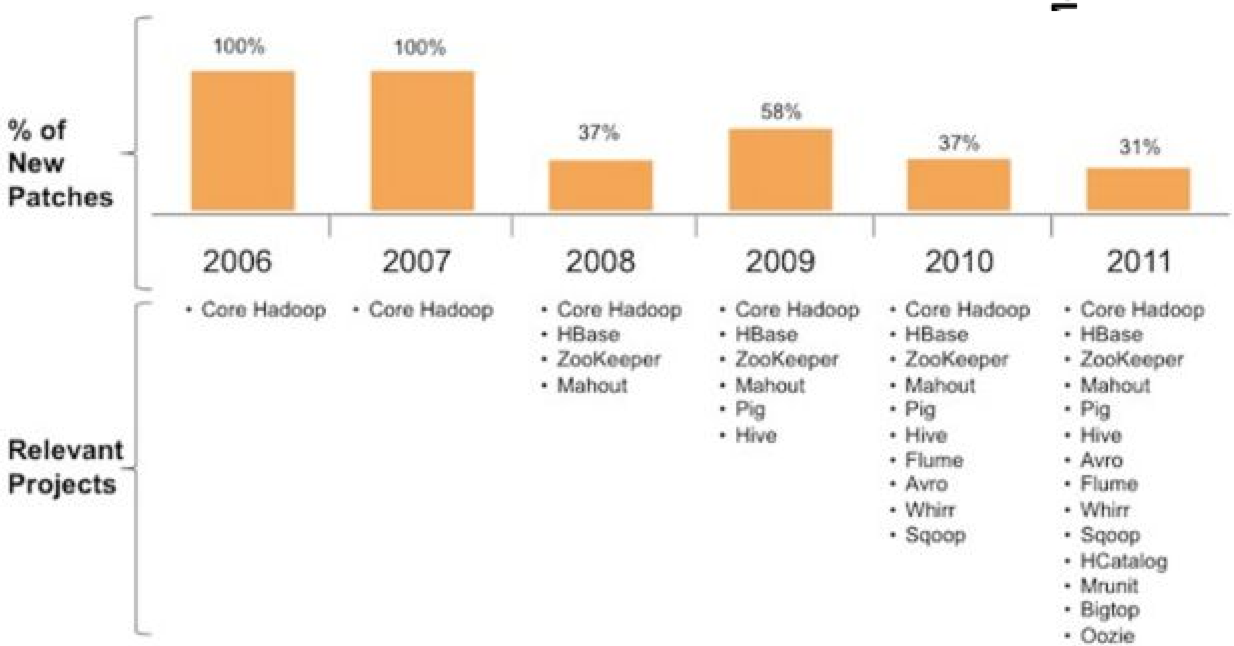
Contributions to Hadoop

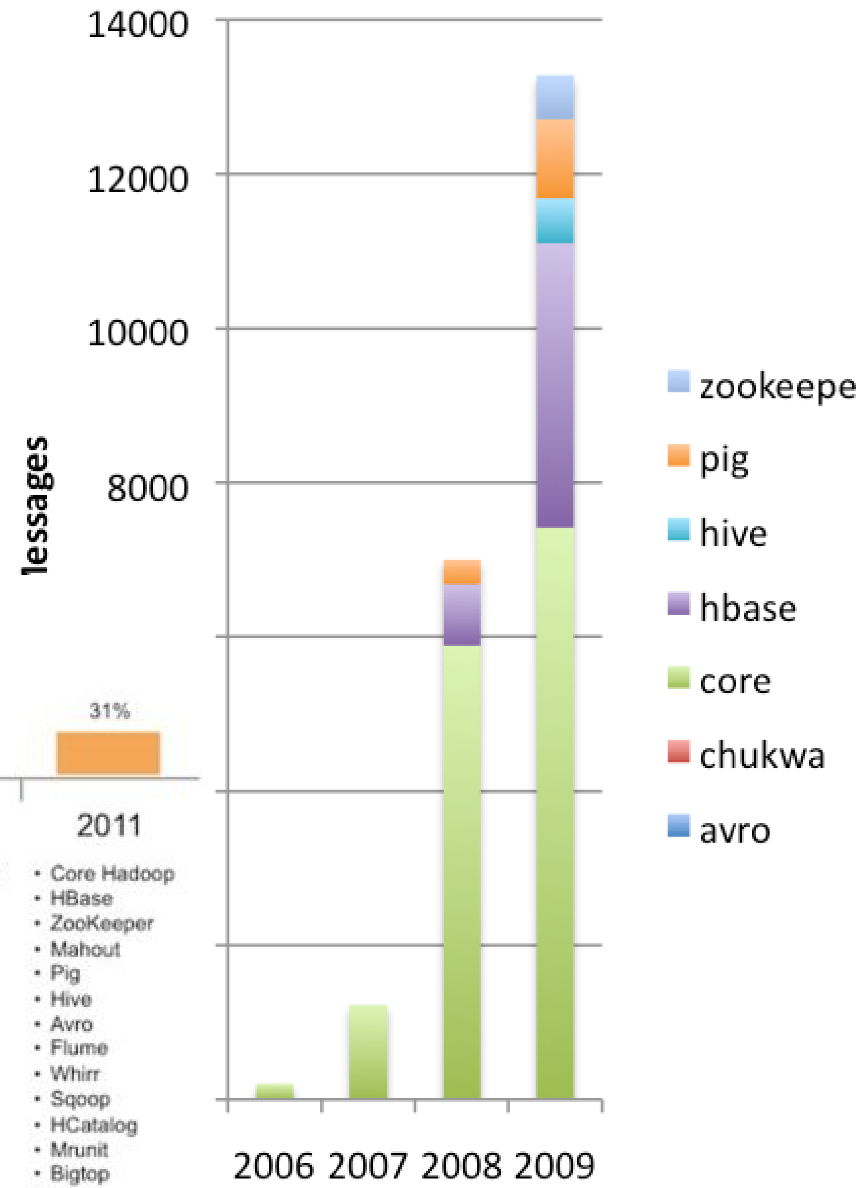
- Each contribution is a patch
- Divided by subproject
  - Core (includes HDFS and Map/Red)
  - Avro, Chukwa, HBase, Hive, Pig, and Zookeeper
- 2009 Non-Core > Core
- Core Contributors
  - 185 people (30% from Yahoo!)
  - 72% of patches from Yahoo!

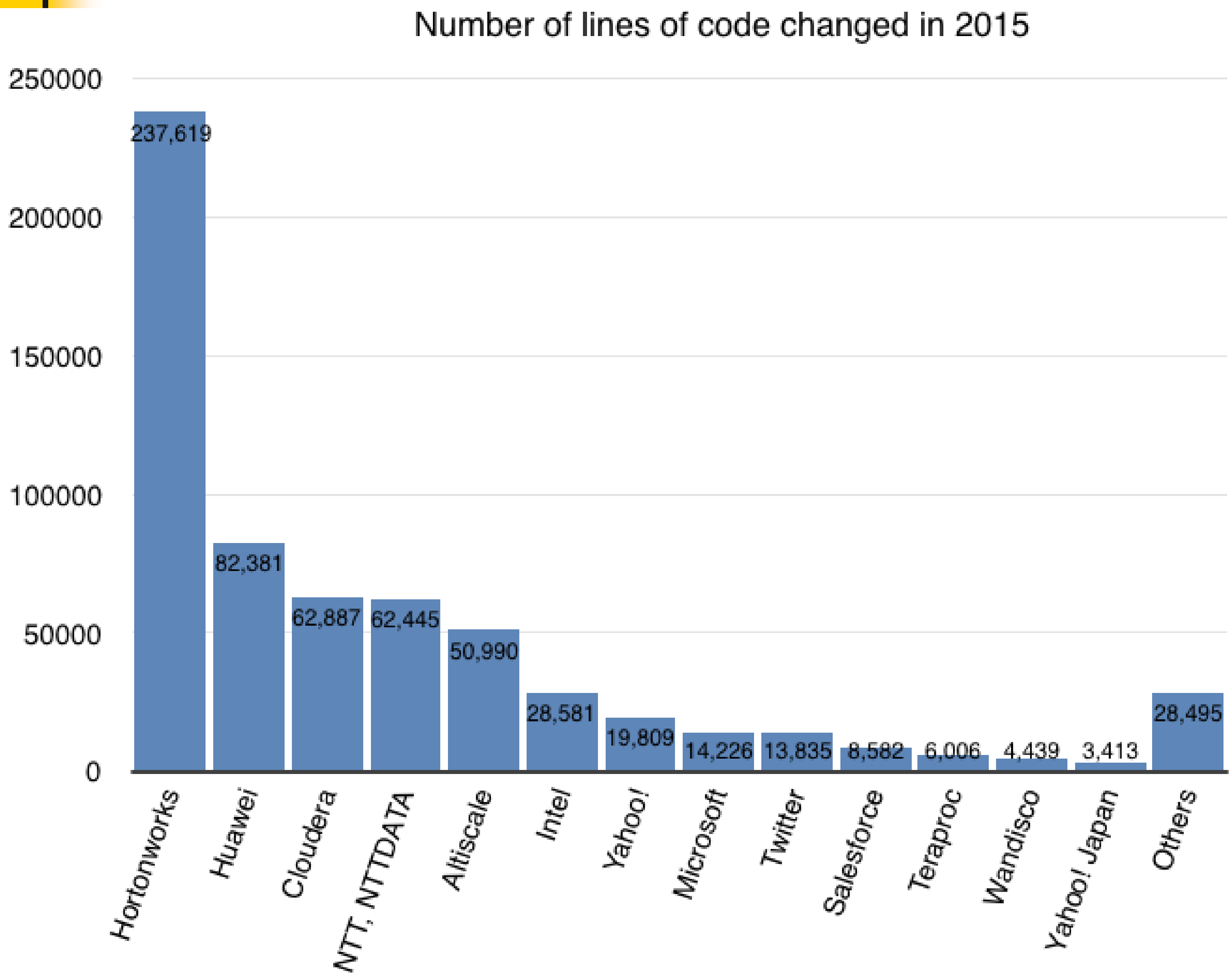


Growing Sub-Project

- User list traffic is best indicator of usage.
- Only Core, Pig, and HBase have existed > 12 months
- All sub-projects are growing



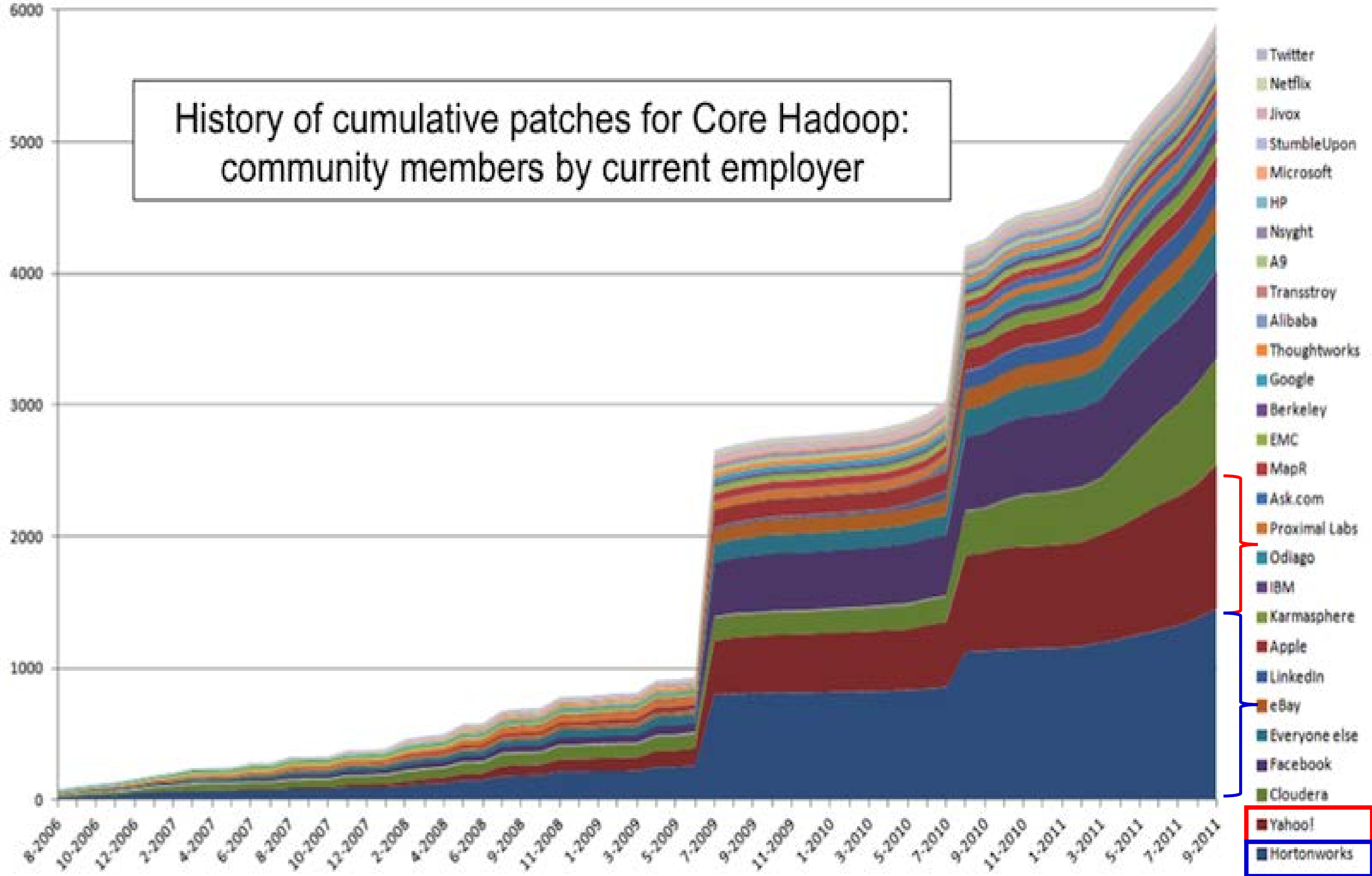




Number of lines of code changed in 2015
250000
200000
150000
100000
50000
0
237,619
82,381
62,887
62,445
50,990
28,581
19,809
14,226
13,835
8,582
6,006
4,439
3,413
28,495
Hortonworks
Huawei
Cloudera
NTT, NTTDATA
Altiscale
Intel
Yahoo!
Microsoft
Twitter
Salesforce
Teraproc
Wandisco
Yahoo! Japan
Others

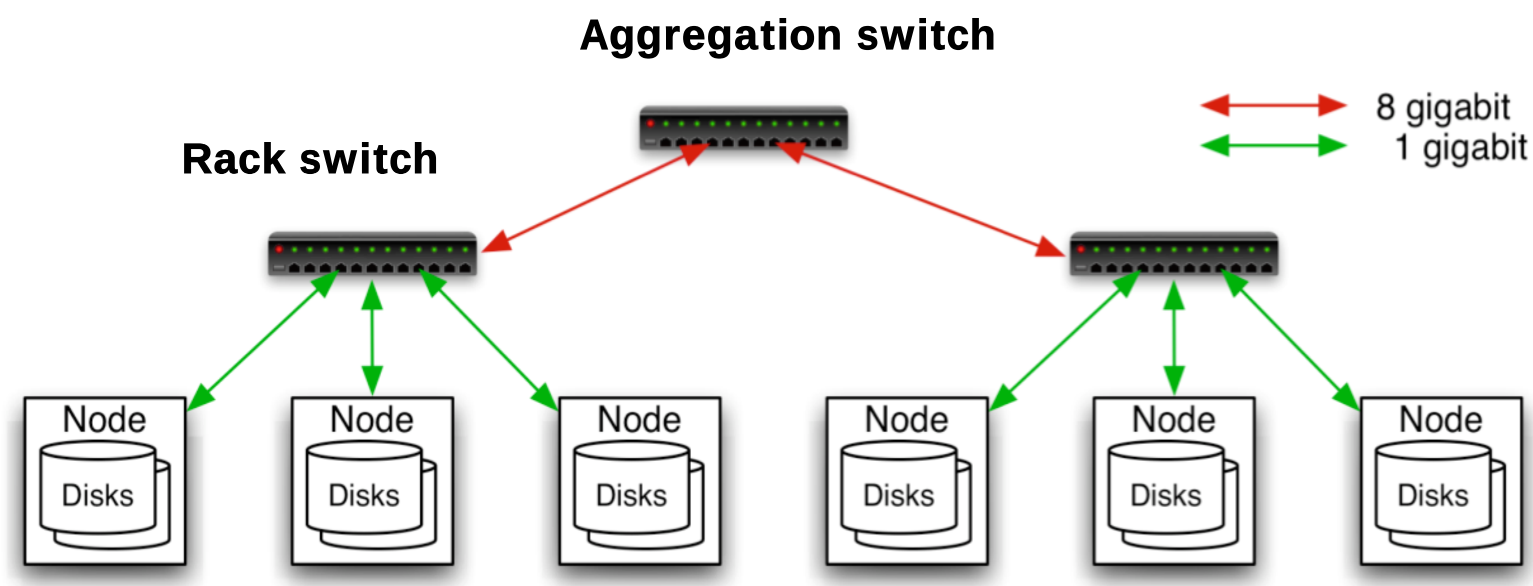

2012
2014
2016
2018
2020
Global Hadoop market is expected to reach
$5.24 Billion in 2020

The Community Effect



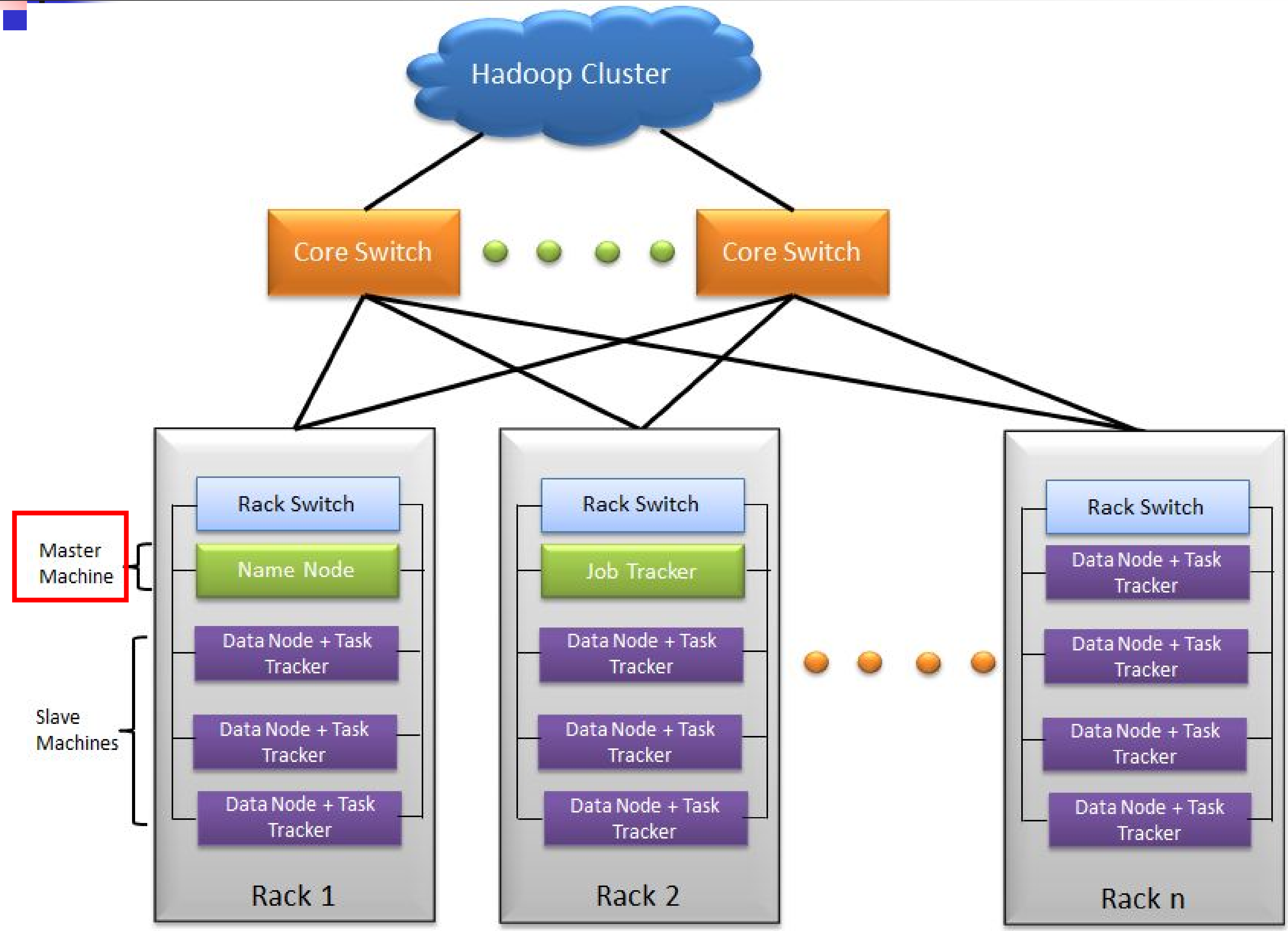
Hadoop Architecture

Typical Hadoop Cluster (Facebook)



- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 Gbps bandwidth in rack, 8 Gbps out of rack
- Node specs (Facebook):
  8-16 cores, 32 GB RAM, 8×1.5 TB disks, no RAID

Typical Hadoop Cluster



Challenges of Cloud Environment

- Cheap nodes encounter failure, especially when you have many
  - Mean time between failures for 1 node = 3 years
  - Mean time between failures for 1000 nodes = 1 day
- **Solution:** Build fault tolerance in the system

- Commodity network implies low bandwidth
- **Solution:** Effectively computer the data

- Programming distributed system is hard
- **Solution:** Restricted programming model: users write data-parallel "map" and "reduce" functions, system handles work distribution and failures

Enter the World of Distributed Systems

- Distributed Systems/Computing
  - *Loosely coupled* set of computers, communicating through message passing, solving a common goal
- Distributed computing is *challenging*
  - Dealing with *partial failures* (examples?)
  - Dealing with *asynchrony* (examples?)

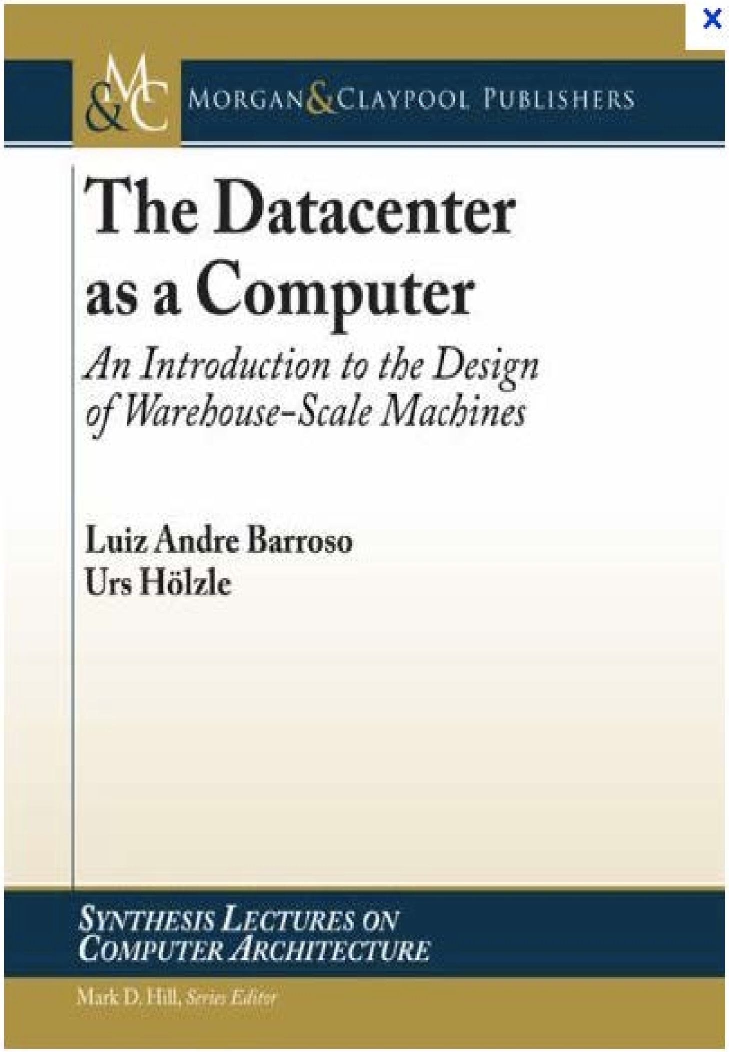
network and computers

- Distributed Computing versus Parallel Computing?
  - distributed computing = parallel computing + partial failures

Dealing with Distribution

- We have seen several of the tools that help with distributed programming
  - Message Passing Interface (MPI)
  - Distributed Shared Memory (DSM)
  - Remote Procedure Calls (RPC)
- But, distributed programming is still very hard
  - Programming for scale, fault-tolerance, consistency, …

The Datacenter is the new Computer



- *"Program"* == Web search, email, map/reduce, …
- *"Computer"* == 10,000's computers, storage, network
- Warehouse-sized facilities and workloads
- *Built from <u>less reliable</u> components than traditional datacenters*

Distributed File System

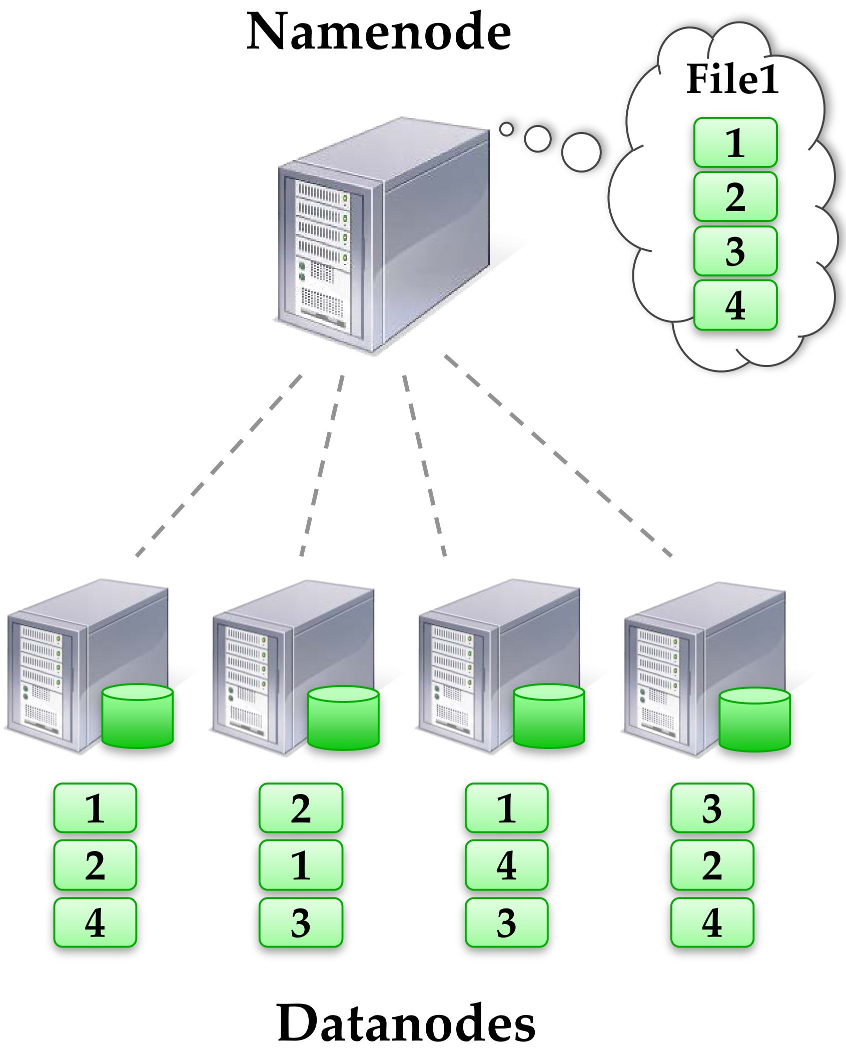
- Single petabyte file system for entire cluster
  - Managed by **a single namenode**.
  - Files are written, read, renamed, deleted, append-only.
  - Optimized for streaming reads of large files.
- Files are divided into large blocks.
  - Transfer to the client
  - CRC 32 is used in data with checksum
  - For reliability, **replicated to several datanodes**,
- Client library talks to both **namenode** and **datanodes**
  - Data is not sent through the namenode.
  - Throughput of file system scales nearly linearly.
- Access from Java, C, or command line.

Hadoop Components

- Distributed file system (HDFS)
  - Single namespace for entire cluster
  - Replicates data **3x** for fault-tolerance
- MapReduce framework
  - Runs jobs submitted by users
  - Manages work distribution & fault-tolerance
  - Collocated with file system (i.e., allocate the jobs to the file system)

Hadoop Distributed File System

- Files split into 128MB blocks
- Blocks replicated across several datanodes (often 3)
- Namenode stores metadata (file names, locations, etc)
- Optimized for large files, sequential reads
- Files are append-only



What is MapReduce?

- **MapReduce** is a programming model for processing large data sets.
  - Programming model for data-intensive computing on commodity clusters
  - MapReduce is typically used to do distributed computing on clusters of computers
- Pioneered by Google
  - Processes 20 PB of data per day
- Popularized by Apache Hadoop project
  - Used by Yahoo!, Facebook, Amazon, …

Map/Reduce features

- Java, C++, and text-based APIs
  - Java and C++ use object concept
  - Text-based (streaming) APIs for scripting or legacy apps
  - Higher level interfaces: Pig, Hive, Jaql
- Automatic re-execution on failure
  - In a large cluster, some nodes are always slow or flaky
  - Framework re-executes failed tasks
- Locality optimizations
  - For large data, bandwidth is a problem for transmission data
  - Map-Reduce queries HDFS considering locations of input data
  - Map tasks are scheduled close to the inputs when possible

MapReduce Insights

- Restricted key-value model
  - Same **fine-grained operation** (Map & Reduce) repeated on big data
  - Operations must be **deterministic**
  - Operations must be **no side effects**
  - Only communication is through the **shuffle**
    - Data from the mapper tasks is prepared and moved to the nodes where the reducer tasks will be run.
  - Operation (Map & Reduce) outputs are saved on disk.

MapReduce Insights

- The mapper is applied to every **key-value pair** in the input which is originally stored on the underlying distributed file system.
- The result of mapper is an arbitrary number of intermediate key-value pairs, and then these pairs will be sorted and grouped by the same key, finally be passed to reducer (reduce function) as input.
- Shuffle can strongly affects the efficiency of MapReduce tasks.

shuffle

Who Use MapReduce?

Industry

- Google:
  - Index building for Google Search
  - Article clustering for Google News
  - Statistical machine translation
- Yahoo!:
  - Index building for Yahoo! Search
  - Spam detection for Yahoo! Mail
- Facebook:
  - Data mining
  - Advertising optimization
  - Spam detection

Who Use MapReduce?

Academic

- For research:
  - Analyzing Wikipedia conflicts (PARC)
  - Natural language processing (CMU)
  - Climate simulation (Washington)
  - Bioinformatics (Maryland)
  - Particle physics (Nebraska)
  - ...

Google Cloud Infrastructure

- Google File System (GFS), 2003
  - Distributed File System for entire cluster
  - Single namespace

The Google File System

Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung
Google*

ABSTRACT

We have designed and implemented the Google File System, a scalable distributed file system for large distributed data-intensive applications. It provides fault tolerance while running on inexpensive commodity hardware, and it delivers high aggregate performance to a large number of clients.

While sharing many of the same goals as previous distributed file systems, our design has been driven by observations of our application workloads and technological environment, both current and anticipated, that reflect a marked departure from some earlier file system assumptions. This has led us to reexamine traditional choices and explore radically different design points.

The file system has successfully met our storage needs. It is widely deployed within Google as the storage platform

1. INTRODUCTION

We have designed and implemented the Google File System (GFS) to meet the rapidly growing demands of Google's data processing needs. GFS shares many of the same goals as previous distributed file systems such as performance, scalability, reliability, and availability. However, its design has been driven by key observations of our application workloads and technological environment, both current and anticipated, that reflect a marked departure from some earlier file system design assumptions. We have reexamined traditional choices and explored radically different points in the design space.

First, component failures are the norm rather than the exception. The file system consists of hundreds or even thousands of storage machines built from inexpensive com-

- Google MapReduce (MR), 2004
  - Runs queries/jobs on data
  - Manages work distribution & fault-tolerance
  - Colocated with file system

MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat
jeff@google.com, sanjay@google.com
Google, Inc.

Abstract

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a key/value pair to generate a set of intermediate key/value pairs, and a *reduce* function that merges all intermediate values associated with the same intermediate key. Many real world tasks are expressible in this model, as shown in the paper.

Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the pro-

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually large and the computations have to be distributed across hundreds or thousands of machines in order to finish in a reasonable amount of time. The issues of how to parallelize the computation, distribute the data, and handle failures conspire to obscure the original simple computation with large amounts of complex code to deal with these issues.

As a reaction to this complexity, we designed a new abstraction that allows us to express the simple computations we were trying to perform but hides the messy details of parallelization, fault-tolerance, data distribution and load balancing in a library. Our abstraction is in-

- Apache open source versions Hadoop DFS and Hadoop MR

GFS/HDFS Insights

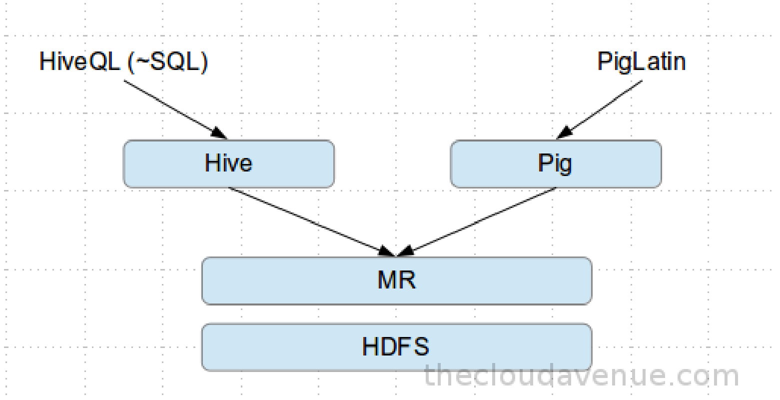
- **Petabyte** storage
  - Files split into large blocks (128 MB) and replicated across several nodes
  - Big blocks allow high throughput sequential reads/writes
- Use **commodity** hardware
  - Failures are the norm anyway because buy cheaper hardware
- No complicated consistency models
  - Single writer, append-only data

MapReduce Pros

- Distribution is completely **transparent**
  - Not a single line of distributed programming (ease, correctness)
- Automatic **fault-tolerance**
  - Determinism enables running failed tasks somewhere else again
  - Saved intermediate data enables just re-running failed reducers
- Automatic **scaling**
  - As operations as side-effect free, they can be distributed to any number of machines dynamically
- Automatic **load-balancing**
  - Move tasks and speculatively execute duplicate copies of slow tasks (*stragglers)*

MapReduce Cons

- Restricted programming model
  - Not always natural to express problems in this model
  - Low-level coding necessary
  - Little support for iterative jobs (lots of disk access)
  - High-latency (batch processing)
- Addressed by follow-up research
  - **Pig** and **Hive** for high-level coding
  - **Spark** for iterative and low-latency jobs



MapReduce Goals

- Scalability process large data volumes:
  - Scan 100 TB on 1 node at 50 MB/s = 24 days
  - Using 1000-node cluster to scan = 35 minutes

- Cost-efficiency:
  - Commodity nodes (cheap, but unreliable)
  - Commodity network (low bandwidth)
  - Automatic fault-tolerance (fewer administration)
  - Easy to use (fewer programmers)

MapReduce Programming Model

- Data type: key-value records

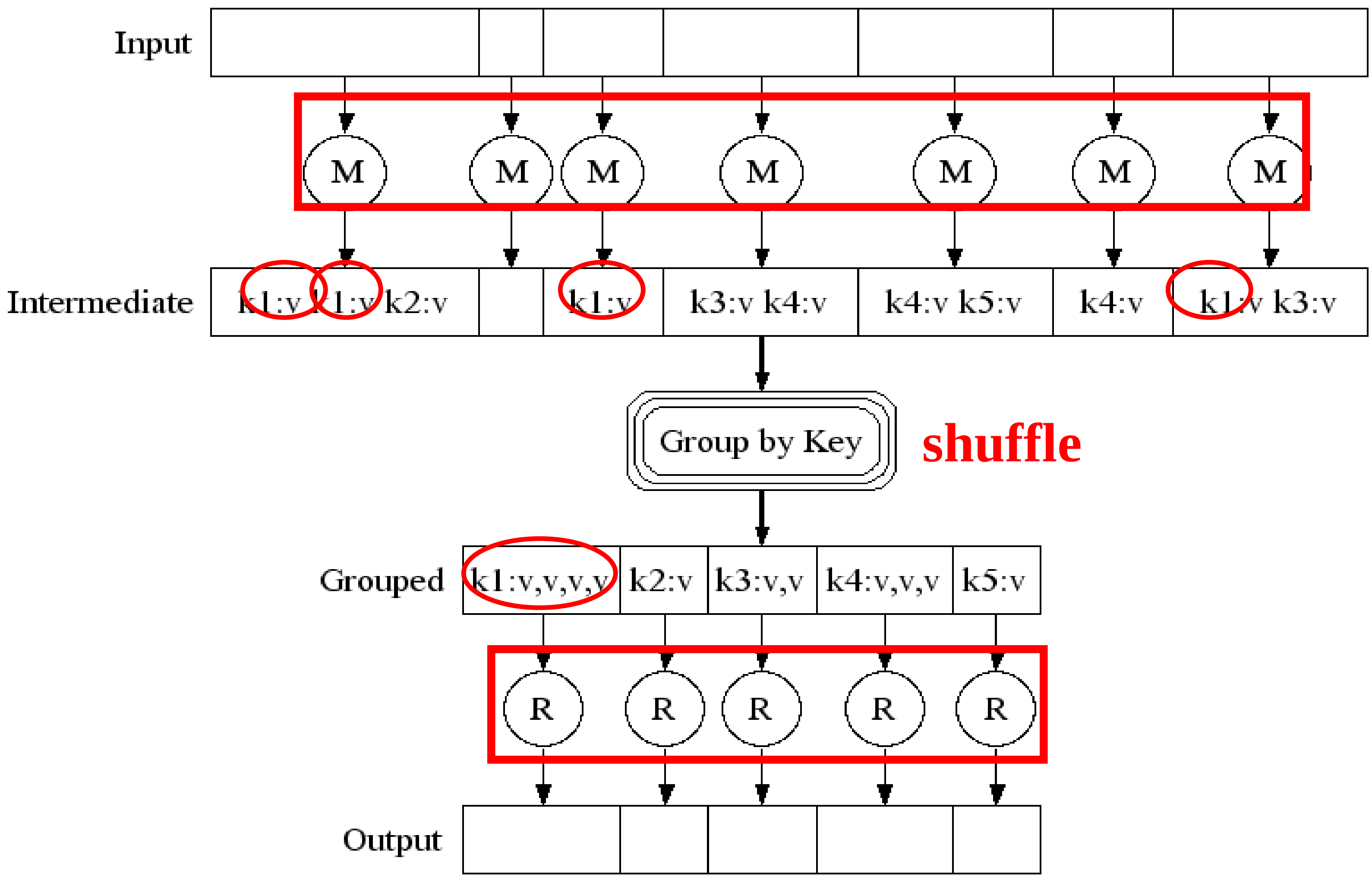
- Map function:

$$(K_{in}, V_{in}) \rightarrow list(K_{inter}, V_{inter})$$

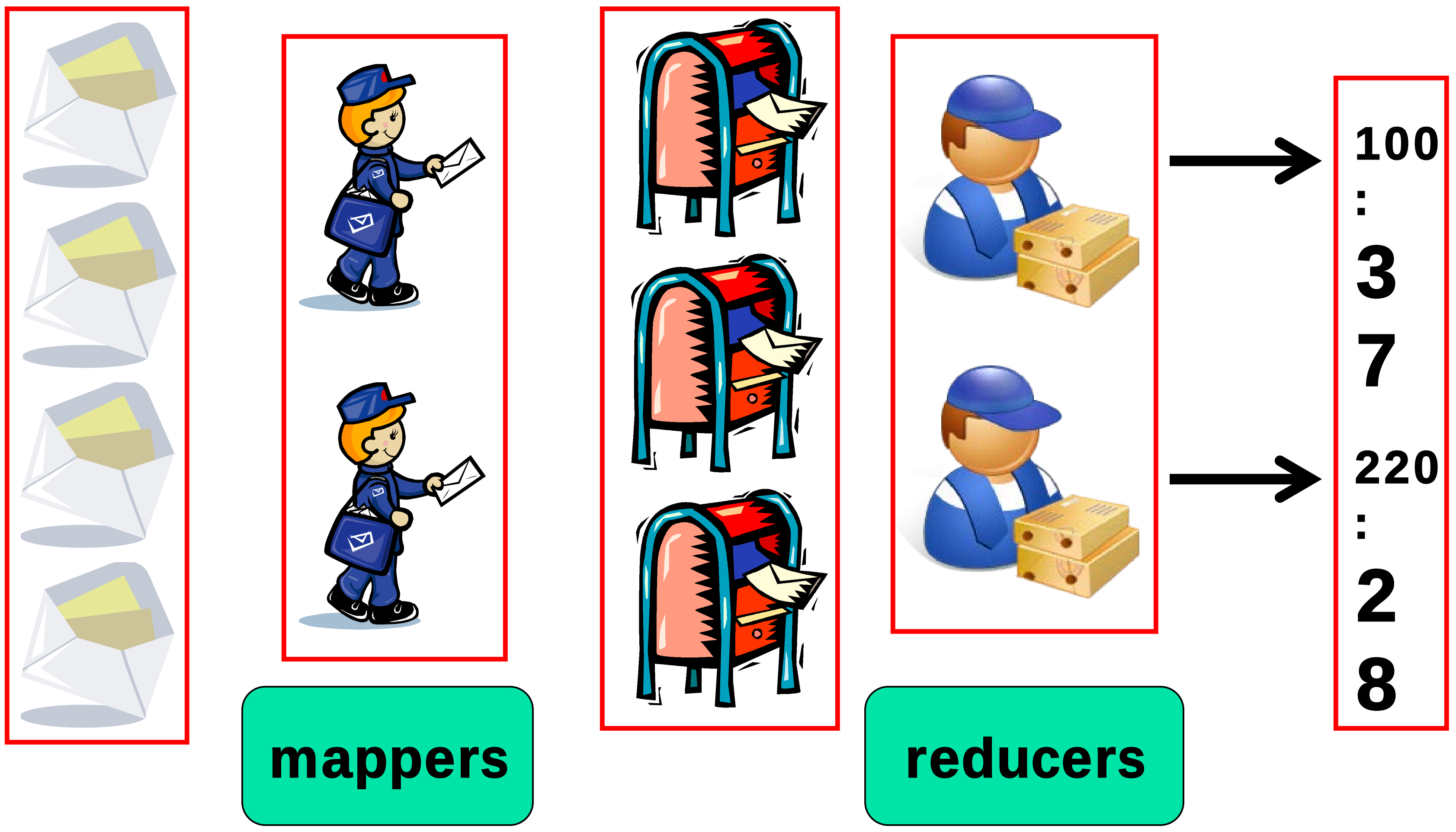
- Reduce function:

$$(K_{inter}, list(V_{inter})) \rightarrow list(K_{out}, V_{out})$$

Hadoop Programming – Map/Reduce



Map / Reduce

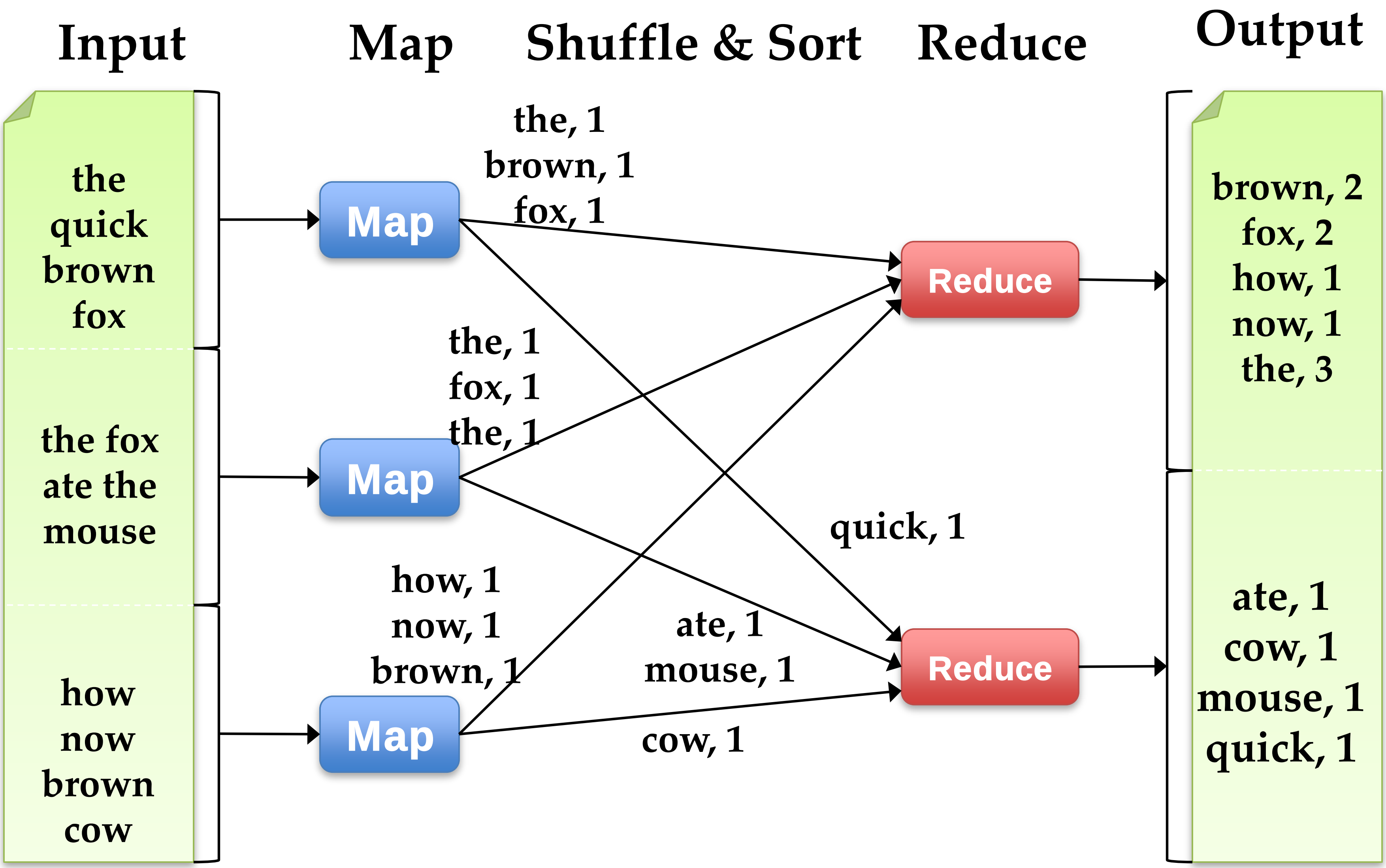


Example: Word Count (Python)

```
def mapper(line):
    foreach word in line.split():
        output(word, 1)


def reducer(key, values):
    output(key, sum(values))
```

Word Count Execution

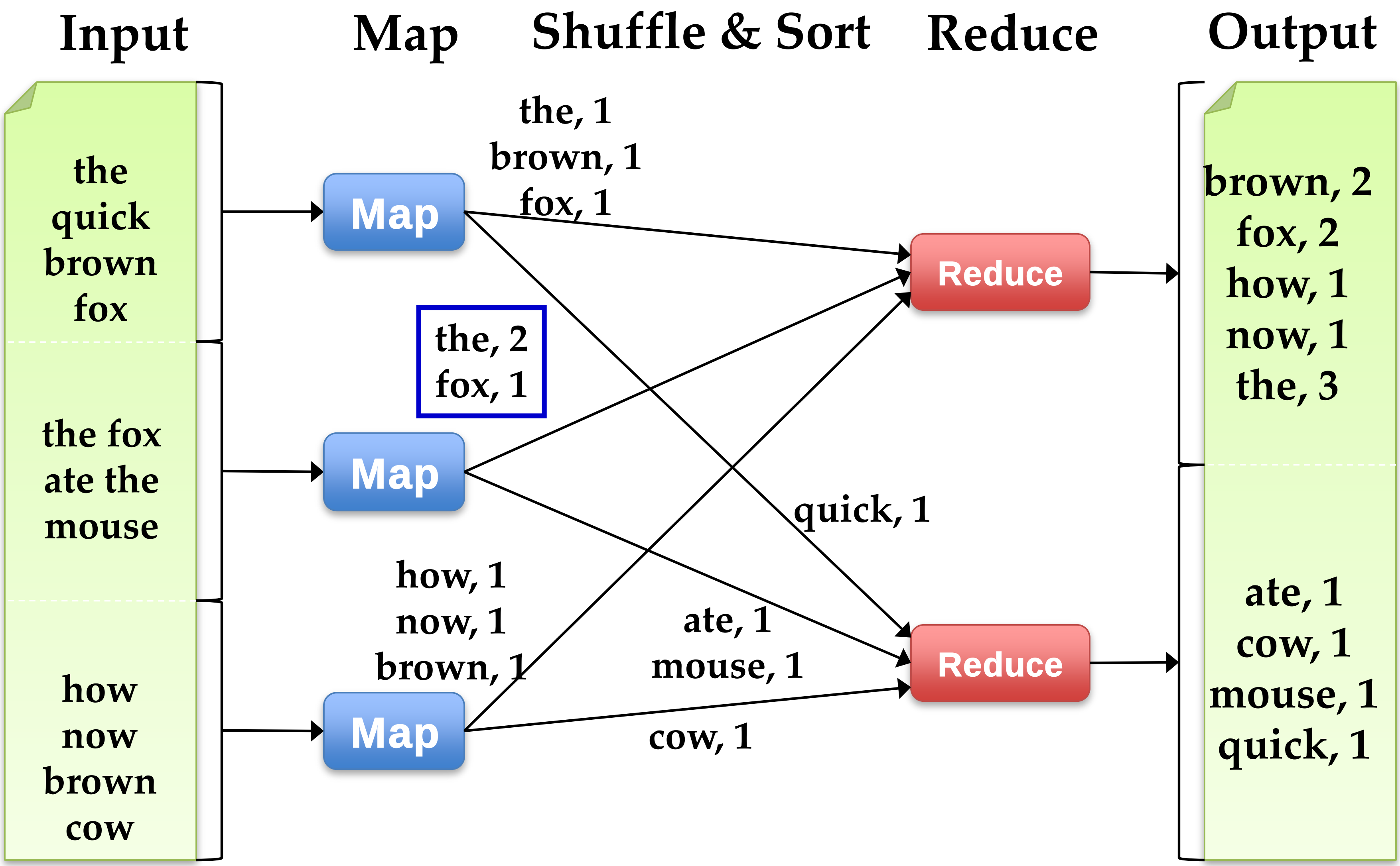


An Optimization using the Combiner

- Local reduce function for repeated keys produced by same map
- For associative options like sum, count, max.
- Decreases amount of intermediate data
- Example: local counting for Word Count:

```
def combiner(key, values):
    output(key, sum(values))
```

Word Count with Combiner



MapReduce Execution Details

- Mappers preferentially scheduled on same node or same rack as their input block
  - Minimize bandwidth use to improve performance
- Mappers <u>save outputs to local disk</u> before serving to reducers
  - Allows recovery if a reducer crashes
  - Allows running more reducers than number of nodes

Fault Tolerance in MapReduce

1. If a **task** crashes:
   - Retry on another node
     - Find for the map because it had no dependencies
     - Find for the reduce because outputs of map are on disk
   - If the same task repeatedly fails, fail for the job or ignore that input block

- **Note: For the fault tolerance in work, user tasks must be deterministic and side-effect-free**

Fault Tolerance in MapReduce

2. If a **node** crashes:
   - Relaunch its current tasks on other nodes
   - Relaunch any maps in which the node previously ran
     - Note that their output files were lost along with the crashed node
3. If a **task** is going slowly (straggler):
   - Launch second copy of the task on another node
   - Take the output of whichever copy finishes first, and kill the other one
   - This action is critical for performance in large clusters (many possible causes of stragglers)

Some issues

- By providing a restricted data-parallel programming model, MapReduce can control job execution in useful ways:
  - Automatic division of job into tasks
  - Be placed near data for computing
  - Load balancing
  - Recovery from failures & stragglers

Outline

- MapReduce architecture
- Sample applications
- Introduction to Hadoop
- Higher-level query languages: Pig & Hive
- Current research

1. Search

- **Input:** (lineNumber, line) records
- **Output:** lines matching a given pattern

- **Map:**

```
if(line matches pattern):
    output(line)
```

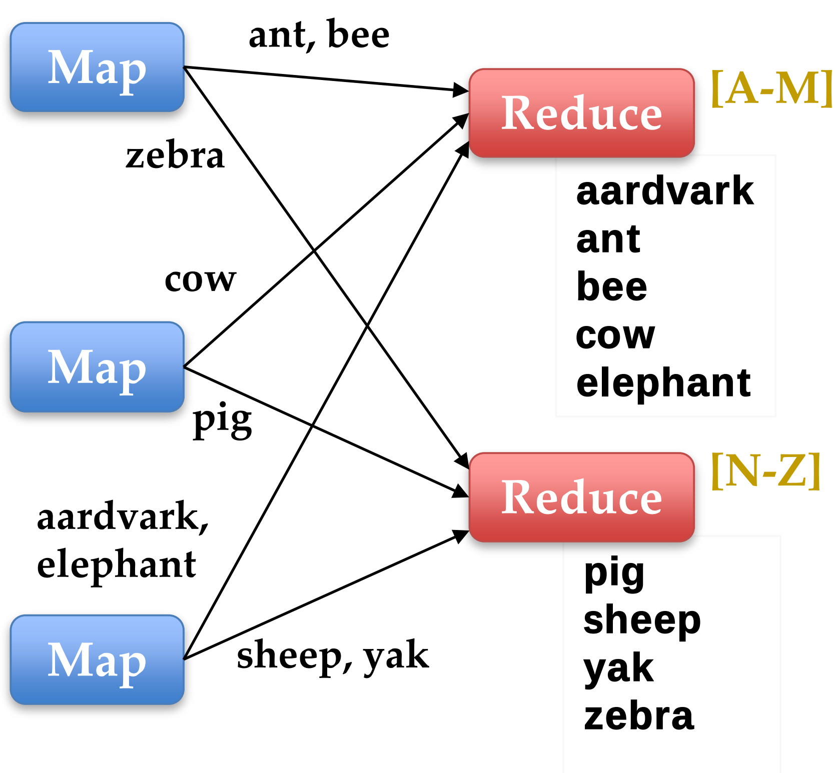
- **Reduce:** identity function
  - Alternative: no reducer (map-only job)

2. Sort

- **Input:** (key, value) records
- **Output:** same records and sorted by key

- **Map:** identity function
- **Reduce:** identify function

- **Trick:** Pick partitioning function *p* such that $k_1 < k_2 \Rightarrow p(k_1) < p(k_2)$



3. Inverted Index

- **Input:** (filename, text) records
- **Output:** list of files containing each word

- **Map:**

```
foreach word in text.split():
  output(word, filename)
```

- **Combine:** unique filenames for each word

- **Reduce:**

```
def reduce(word, filenames):
    output(word, sort(filenames))
```

Inverted Index Example

hamlet.txt

to be or not to be

to, hamlet.txt
be, hamlet.txt
or, hamlet.txt
not, hamlet.txt

12th.txt

be not afraid of greatness

be, 12th.txt
not, 12th.txt
afraid, 12th.txt
of, 12th.txt
greatness, 12th.txt

afraid, (12th.txt)
be, (12th.txt, hamlet.txt)
greatness, (12th.txt)
not, (12th.txt, hamlet.txt)
of, (12th.txt)
or, (hamlet.txt)
to, (hamlet.txt)

4. Most Popular Words

- **Input:** (filename, text) records
- **Output:** the 100 words occurring in most files

- Two-stage solution:
  - **Job 1:**
    - Create inverted index, giving (word, list(file)) records
  - **Job 2:**
    - Map each (word, list(file)) to (count, word)
    - Sort these records by count as in sort job

- Optimizations:
  - Map to (word, 1) instead of (word, file) in Job 1
  - Estimate count distribution in advance by sampling

5. Numerical Integration (積分)

- **Input:** (start, end) records for sub-ranges to integrate
  - Can implement using custom InputFormat
- **Output:** integral of **f(x)** over entire range

- **Map:**

```
def map(start, end):
 sum = 0
 for(x = start; x < end; x += step):
      sum += f(x) * step
 output("", sum)
```

- **Reduce:**

```
def reduce(key, values):
 output(key, sum(values))
```

Outline

- MapReduce architecture
- Sample applications
- Introduction to Hadoop
- Higher-level query languages: Pig & Hive
- Current research

Introduction to Hadoop

- Download from hadoop.apache.org
- To install locally, unzip and set `JAVA_HOME`
- Docs: hadoop.apache.org/common/docs/current

- Three ways to write jobs:
  - Java API
  - Hadoop Streaming (for Python, Perl, etc)
  - Pipes API (C++)

Word Count Using Map in Java

```
public static class MapClass extends MapReduceBase
   implements Mapper<LongWritable, Text, Text, IntWritable> {

   private final static IntWritable ONE = new IntWritable(1);

   public void map(LongWritable key, Text value,
                   OutputCollector<Text, IntWritable> output,
                   Reporter reporter) throws IOException {
     String line = value.toString();
     StringTokenizer itr = new StringTokenizer(line);
     while (itr.hasMoreTokens()) {
      output.collect(new Text(itr.nextToken()), ONE);
    }
   }
 }
```

Word Count Using Reduce in Java

```java
public static class Reduce extends MapReduceBase
   implements Reducer<Text, IntWritable, Text, IntWritable> {

   public void reduce(Text key, Iterator<IntWritable> values,
                      OutputCollector<Text, IntWritable> output,
                      Reporter reporter) throws IOException {
     int sum = 0;
     while (values.hasNext()) {
       sum += values.next().get();
     }
     output.collect(key, new IntWritable(sum));
   }
 }
```

Word Count (Main Function)

```
public static void main(String[] args) throws Exception {
   JobConf conf = new JobConf(WordCount.class);
   conf.setJobName("wordcount");

   conf.setMapperClass(MapClass.class);
   conf.setCombinerClass(Reduce.class);
   conf.setReducerClass(Reduce.class);

   FileInputFormat.setInputPaths(conf, args[0]);
   FileOutputFormat.setOutputPath(conf, new Path(args[1]));

   conf.setOutputKeyClass(Text.class); // out keys are words (strings)
   conf.setOutputValueClass(IntWritable.class); // values are counts

   JobClient.runJob(conf);
 }
```

Word Count in Python

- Mapper.py

mapper.py

```
#!/usr/bin/env python

import sys

# input comes from STDIN (standard input)
for line in sys.stdin:
    # remove leading and trailing whitespace
    line = line.strip()
    # split the line into words
    words = line.split()
    # increase counters
    for word in words:
        # write the results to STDOUT (standard output);
        # what we output here will be the input for the
        # Reduce step, i.e. the input for reducer.py
        #
        # tab-delimited; the trivial word count is 1
        print '%s\t%s' % (word, 1)</pre>
```

```python
#!/usr/bin/env python

from operator import itemgetter
import sys

current_word = None
current_count = 0
word = None

# input comes from STDIN
for line in sys.stdin:
    # remove leading and trailing whitespace
    line = line.strip()

    # parse the input we got from mapper.py
    word, count = line.split('\t', 1)

    # convert count (currently a string) to int
    try:
        count = int(count)
    except ValueError:
        # count was not a number, so silently
        # ignore/discard this line
        continue

    # this IF-switch only works because Hadoop sorts map output
    # by key (here: word) before it is passed to the reducer
    if current_word == word:
        current_count += count
    else:
        if current_word:
            # write result to STDOUT
            print '%s\t%s' % (current_word, current_count)
        current_count = count
        current_word = word

# do not forget to output the last word if needed!
if current_word == word:
    print '%s\t%s' % (current_word, current_count)
```

Results

```
# very basic test
hduser@ubuntu:~$ echo "foo foo quux labs foo bar quux" | /home/hduser/mapper.py
foo     1
foo     1
quux    1
labs    1
foo     1
bar     1
quux    1
```

```
hduser@ubuntu:~$ echo "foo foo quux labs foo bar quux" | /home/hduser/mapper.py | sort -k1,1 | /home/hduser/reducer.py
bar     1
foo     3
labs    1
quux    2
```

HDFS Running

- hduser@ubuntu:/usr/local/hadoop$ bin/hadoop jar contrib/streaming/hadoop-*streaming*.jar -mapper /home/hduser/mapper.py -reducer /home/hduser/reducer.py -input /user/hduser/gutenberg/* -output /user/hduser/gutenberg-output

  additionalConfSpec_:null

  null=@@@userJobConfProps_.get(stream.shipped.hadoopstreaming

  packageJobJar: [/app/hadoop/tmp/hadoop-unjar54543/]

  [] /tmp/streamjob54544.jar tmpDir=null

  […] INFO mapred.FileInputFormat: Total input paths to process : 7

  […] INFO streaming.StreamJob: getLocalDirs(): [/app/hadoop/tmp/mapred/local]

  […] INFO streaming.StreamJob: Running job: job_201510011615_0021

  […]

  […] INFO streaming.StreamJob: map 0% reduce 0%

  […] INFO streaming.StreamJob: map 43% reduce 0%

  […] INFO streaming.StreamJob: map 86% reduce 0%

  […] INFO streaming.StreamJob: map 100% reduce 0%

  […] INFO streaming.StreamJob: map 100% reduce 33%

  […] INFO streaming.StreamJob: map 100% reduce 70%

  […] INFO streaming.StreamJob: map 100% reduce 77%

  […] INFO streaming.StreamJob: map 100% reduce 100%

  […] INFO streaming.StreamJob: Job complete: job_201510011615_0021

  […] INFO streaming.StreamJob: Output: /user/hduser/gutenberg-output

  hduser@ubuntu:/usr/local/hadoop$

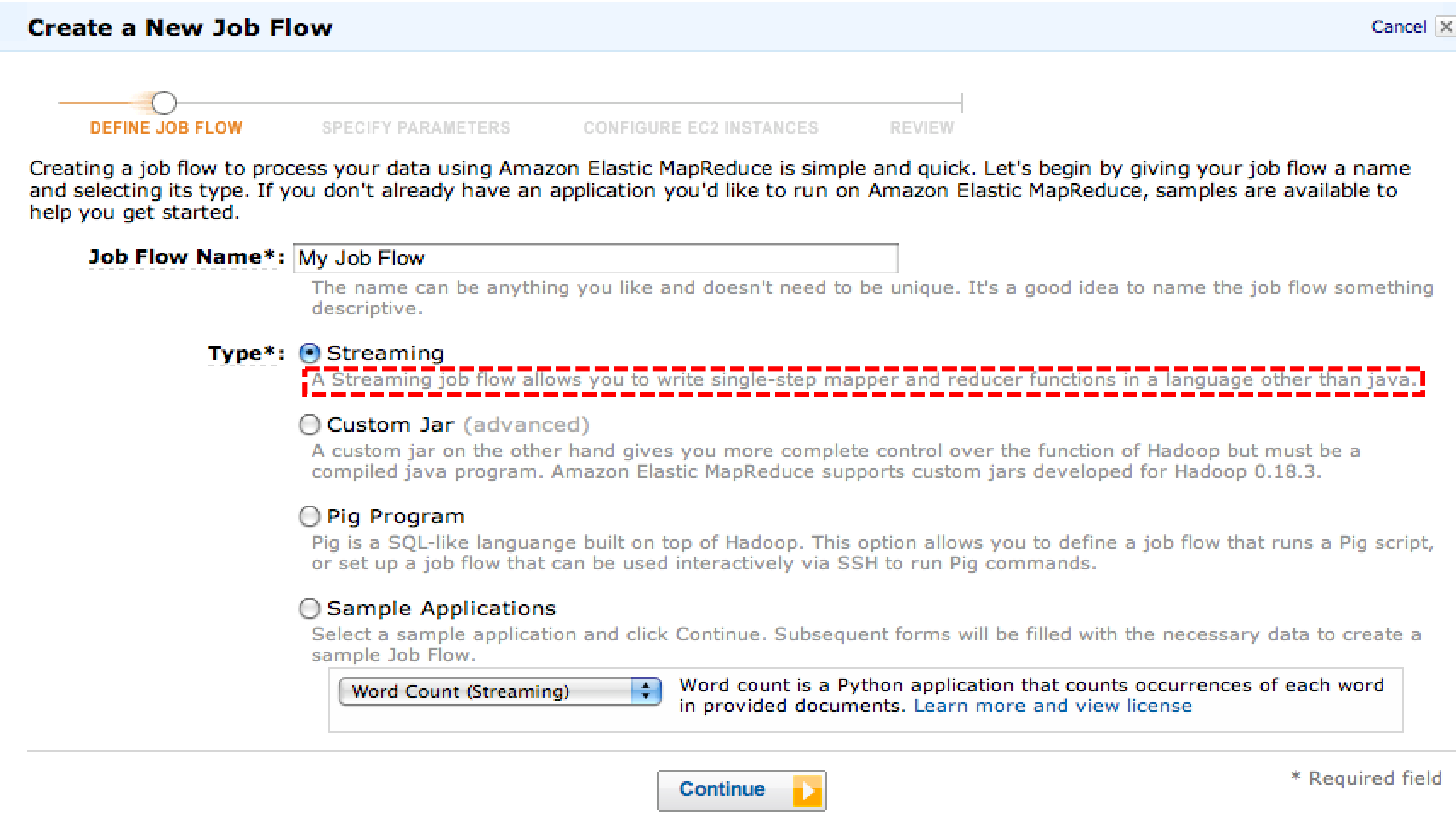
Results

- hduser@ubuntu:/usr/local/hadoop$ bin/hadoop dfs -ls /user/hduser/gutenberg-output
  Found 1 items
  /user/hduser/gutenberg-output/part-00000 <r 1> 903193 2016-09-20 13:00
  hduser@ubuntu:/usr/local/hadoop$
  hduser@ubuntu:/usr/local/hadoop$ bin/hadoop dfs -cat /user/hduser/gutenberg-output/part-00000
  "(Lo)cra" 1
  "1490 1
  "1498," 1
  "35" 1
  "40," 1
  "A 2
  "AS-IS". 2
  "A_ 1
  "Absoluti 1
  [...]
  hduser@ubuntu:/usr/local/hadoop$

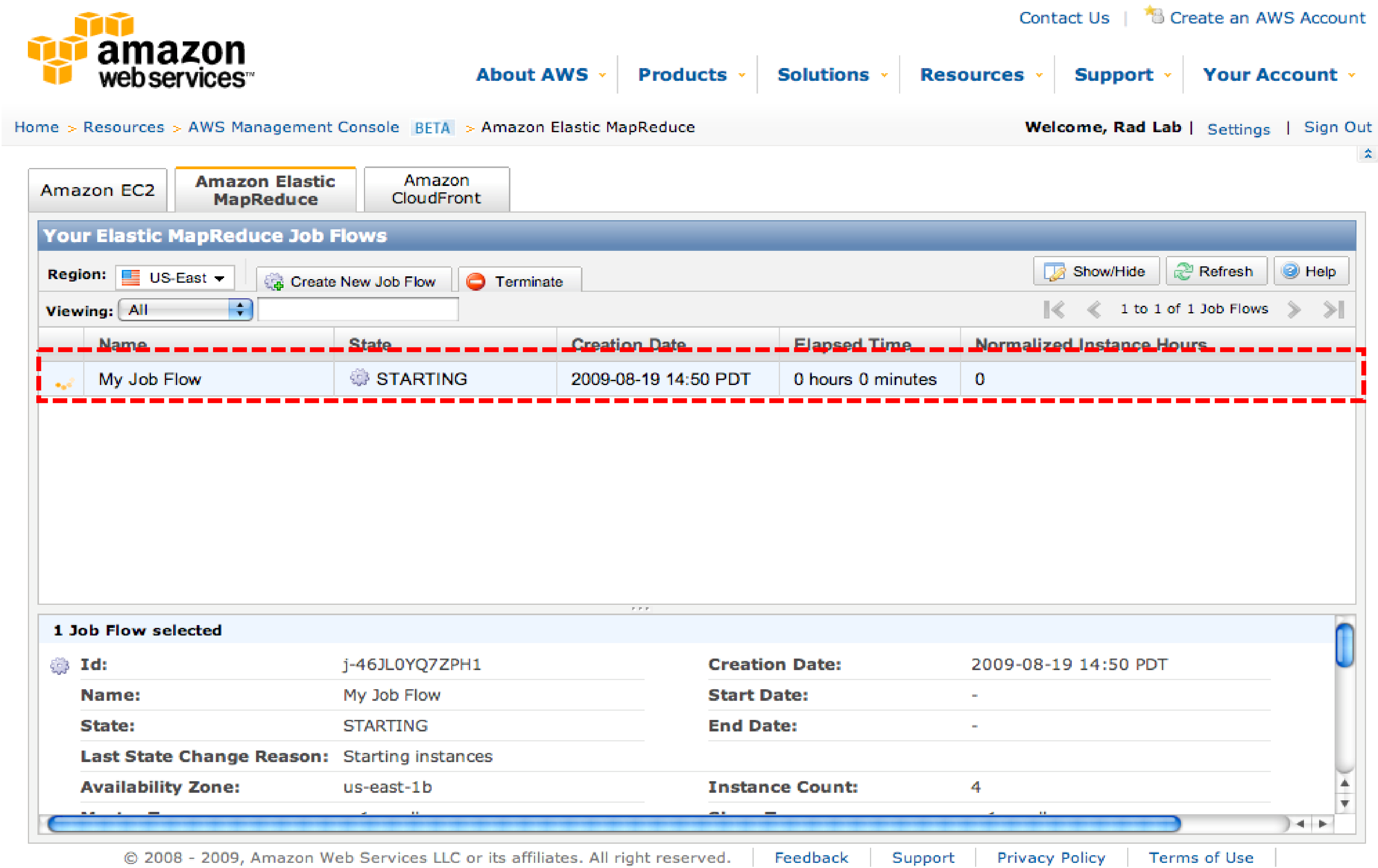
Amazon Elastic MapReduce

- Web interface and command-line tools for running Hadoop jobs on EC2
- Data stored in Amazon S3
- Monitors job and shuts machines after use

Elastic MapReduce UI



Elastic MapReduce UI



Outline

- MapReduce architecture
- Sample applications
- Introduction to Hadoop
- Higher-level query languages: Pig & Hive
- Current research

Motivation

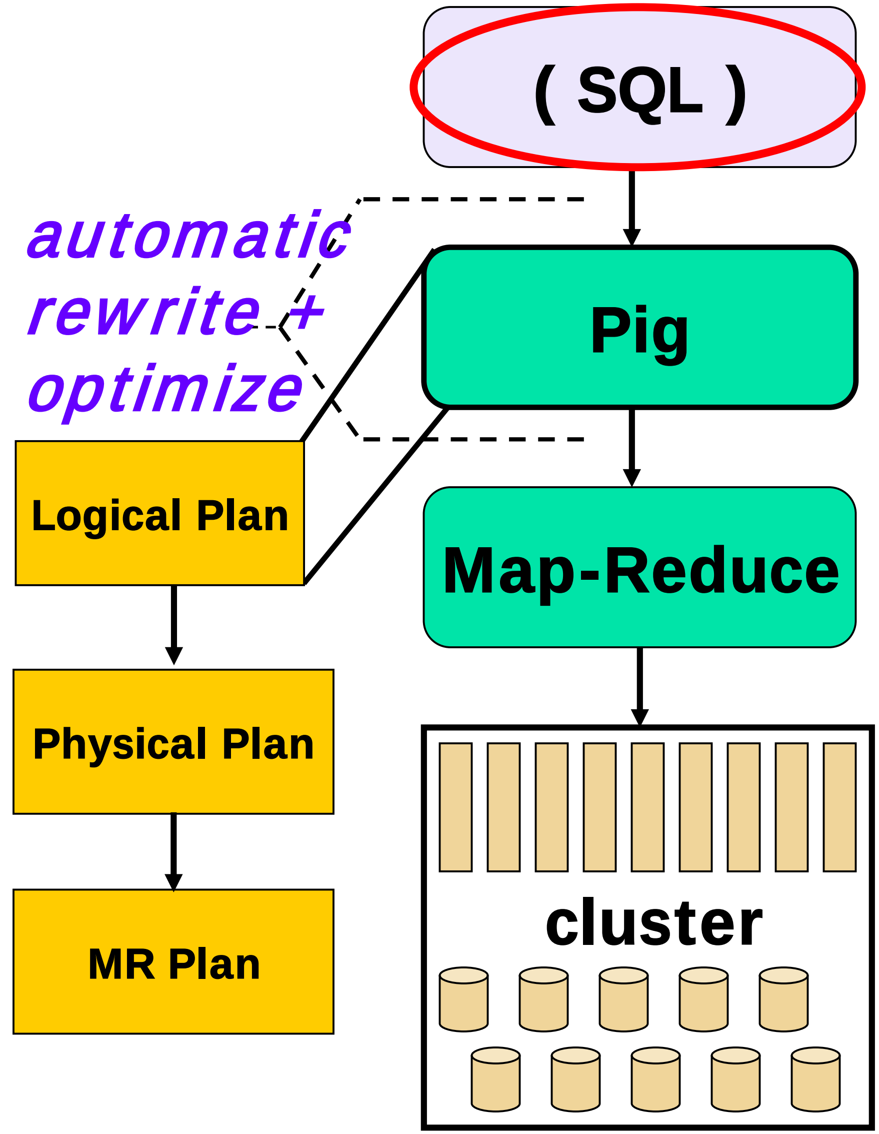
- MapReduce is powerful: many algorithms can be expressed as a series of MapReduce jobs
- But it's fairly low-level: must think about keys, values, partitioning, etc.
- Can we capture common "job patterns"?

Pig

- Started at Yahoo's research
- Runs about 50% of Yahoo!'s jobs
- Features:
  - Expresses sequences of MapReduce jobs
  - Data model: nested "bags" of items
  - Provides relational (SQL) operators (JOIN, GROUP BY, etc.)
  - Easy to plug in Java functions

Pig script → MapReduce

- Do not understand below MapReduce operations
- Pig transfers logical plan to MR plan



Pig Example

- Show users aged 18-25

```
Users = LOAD 'users.txt'
        USING PigStorage(',') AS (name, age);
Fltrd = FILTER Users
        BY age >= 18 AND age <= 25;
Names = FOREACH Fltrd GENERATE name;

STORE Names INTO 'names.out';
```

How to execute

- Local:
  - `pig` **`-x local`** `foo.pig`
- Hadoop (HDFS):
  - `pig foo.pig`
  - `pig` **`-Dmapred.job.queue.name=xxx`** `foo.pig`
    - `hadoop queue -showacls`

How to execute

- Interactive pig shell
  - `$ pig`
  - grunt> _

Load Data

```
Users = LOAD 'users.txt'
        USING PigStorage(',') AS (name, age);
```

- LOAD … AS …
- PigStorage(‘,’) to specify separator

```
John,18
Mary,20
Bob,30
```

name	age
John	18
Mary	20
Bob	30

Filter

```
Fltrd = FILTER Users
        BY age >= 18 AND age <= 25;
```

- FILTER ... BY ...
  - constraints can be composite

name	age
John	18
Mary	20
Bob	30

→

name	age
John	18
Mary	20

Generate / Project

```
Names = FOREACH Fltrd GENERATE name;
```

- FOREACH ... GENERATE

name	age
John	18
Mary	20

name
John
Mary

Store Data

```
STORE Names INTO 'names.out';
```

- STORE … INTO …
  - PigStorage(‘,’) to specify separator if multiple fields

Command - JOIN

```
Users = LOAD 'users' AS (name, age);
Pages = LOAD 'pages' AS (user, url);
Jnd   = JOIN Users BY name, Pages BY
user;
```

name	age
John	18
Mary	20
Bob	30

user	url
John	yaho
Mary	goog
Bob	bing

→

name	age	user	url
John	18	John	yaho
Mary	20	Mary	goog
Bob	30	Bob	bing

Command - GROUP

```
Grpd  = GROUP Jnd by url;
describe Grpd;
```

name	age	url
John	18	yhoo
Mary	20	goog
Dee	25	yhoo
Kim	40	bing
Bob	30	bing

→

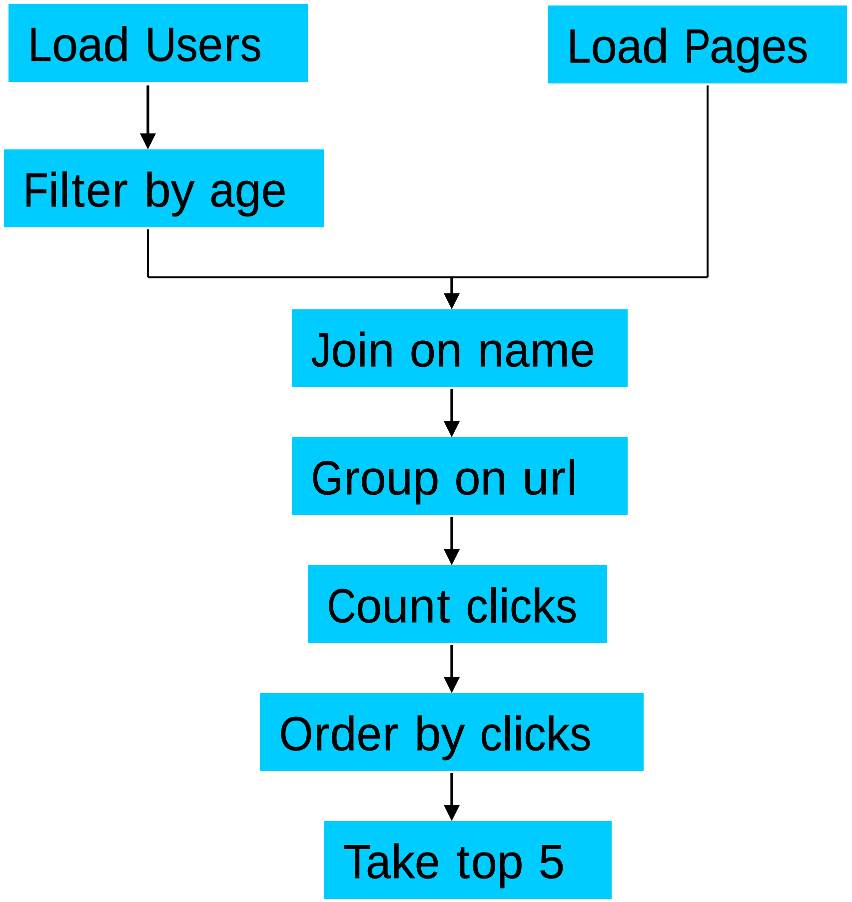
yhoo	(John, 18, yhoo) (Dee, 25, yhoo)
goog	(Mary, 20, goog)
bing	(Kim, 40, bing) (Bob, 30, bing)

Other Commands

- PARALLEL – controls #reducer
- ORDER – sort by a field
- COUNT – eval: count #elements
- COGROUP – structured JOIN
- More at http://hadoop.apache.org/pig/docs/r0.5.0/piglatin_reference.html

An Example Problem

- Suppose you have user data in one file, website data in another, and you need to find the top 5 most visited pages by users aged 18-25.



Example from http://wiki.apache.org/pig-data/attachments/PigTalksPapers/attachments/ApacheConEurope09.ppt

Pig Latin

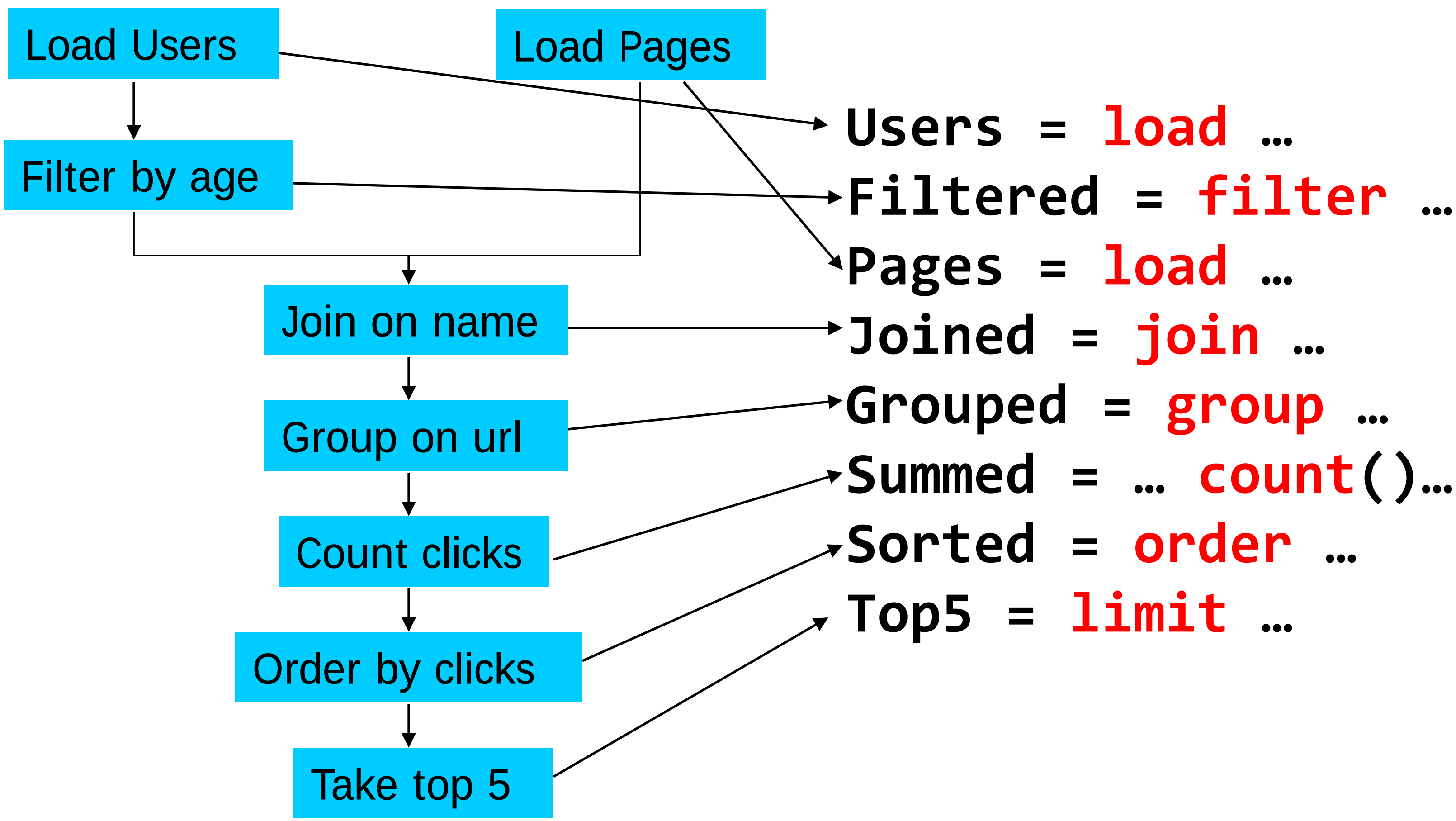
```
Users    = load 'users' as (name, age);
Filtered = filter Users by
                  age >= 18 and age <= 25;
Pages    = load 'pages' as (user, url);
Joined   = join Filtered by name, Pages by user;
Grouped  = group Joined by url;
Summed   = for each Grouped generate group,
                   count(Joined) as clicks;
Sorted   = order Summed by clicks desc;
Top5     = limit Sorted 5;

store Top5 into 'top5sites';
```

Example from http://wiki.apache.org/pig-data/attachments/PigTalksPapers/attachments/ApacheConEurope09.ppt

Translation to MapReduce

Notice how naturally the components of the job translate into Pig Latin.



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Translation to MapReduce

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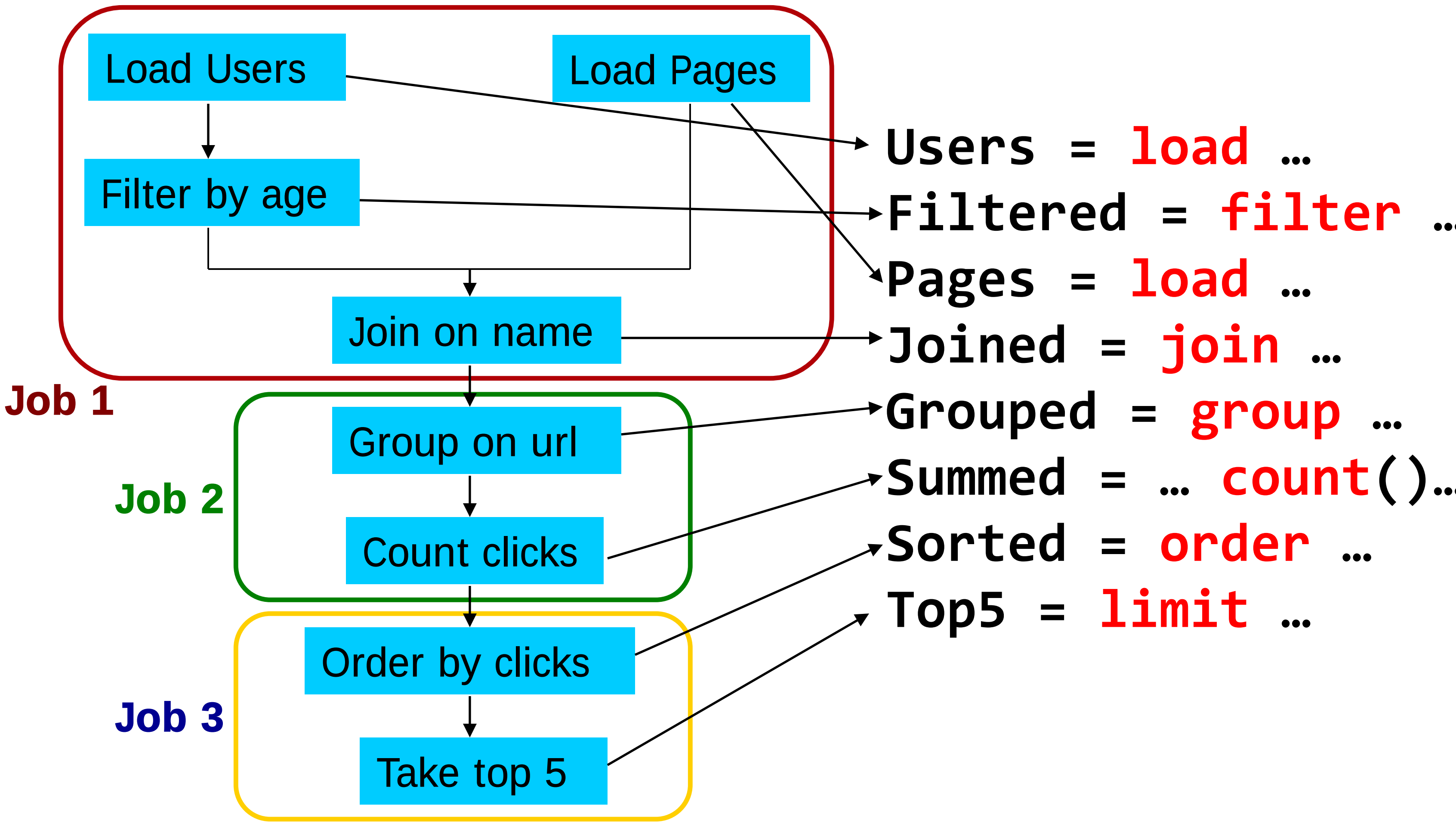


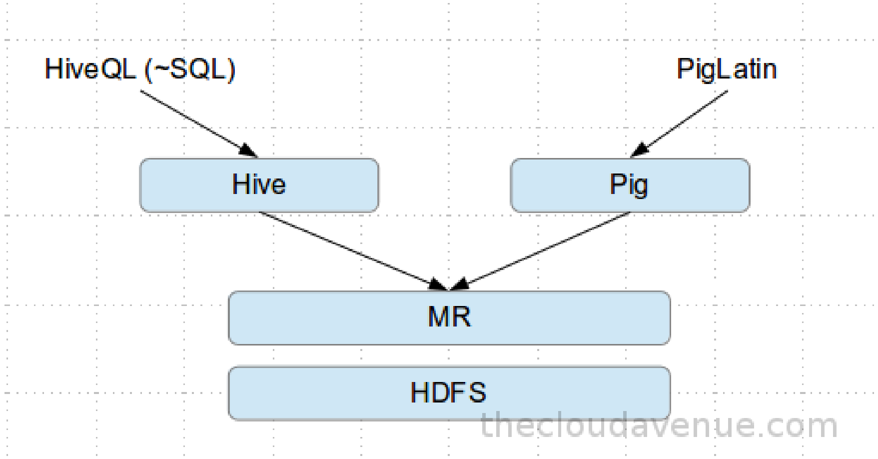
Example from http://wiki.apache.org/pig-data/attachments/PigTalksPapers/attachments/ApacheConEurope09.ppt

Hive

- Developed at Facebook
- Used for most jobs of Facebook
- Relational database built on Hadoop
  - Maintains table schema
  - SQL-like query language (which can also call Hadoop streaming scripts)
  - Supports table partitioning, complex data types, sampling, some query optimization

Hive Query Language

- Basic SQL
  - From clause sub-query
  - ANSI JOIN (equi-join only)
  - Multi-Table insert
  - Multi group-by
  - Sampling
  - Objects Traversal
- Extensibility
  - Pluggable Map-reduce scripts using TRANSFORM



Hive Query Language

- JOIN

  SELECT t1.a1 as c1, t2.b1 as c2

  FROM t1 JOIN t2 ON (t1.a2 = t2.b2);

- INSERTION

  INSERT OVERWRITE TABLE t1

  SELECT * FROM t2;

Hive Query Language

- Insertion

```
INSERT OVERWRITE TABLE sample1 '/tmp/hdfs_out'
   SELECT * FROM sample WHERE ds='2016-09-24';

INSERT OVERWRITE DIRECTORY '/tmp/hdfs_out'
  SELECT * FROM sample WHERE ds='2016-09-24';

INSERT OVERWRITE LOCAL DIRECTORY '/tmp/hive-
   sample-out' SELECT * FROM sample;
```

Hive Query Language

- Map Reduce

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

FROM (FROM session_table
SELECT sessionid, tstamp, data
DISTRIBUTE BY sessionid SORT BY tstamp
)
REDUCE sessionid, tstamp, data USING 'session_reducer.sh';
```

Hive Query Language

- Example of multi-table insert query and its optimization

```
FROM (SELECT a.status, b.school, b.gender
        FROM status_updates a JOIN profiles b
            ON (a.userid = b.userid AND a.ds='2016-09-24' )) subq1

INSERT OVERWRITE TABLE gender_summary
                        PARTITION(ds='2016-09-24')
SELECT subq1.gender, COUNT(1)
GROUP BY subq1.gender

INSERT OVERWRITE TABLE school_summary
                        PARTITION(ds='2016-09-24')
SELECT subq1.school, COUNT(1)
GROUP BY subq1.school
```

Summary

- MapReduce's data-parallel programming model hides complexity of distribution and fault tolerance

- Principal philosophies:
  - Scale, so you can throw problems to hardware
  - Cheap, saving hardware, programmer and administration costs but can own fault tolerance

- Hive and Pig further simplify programming

- MapReduce is not suitable for all problems, but it may save you a lot of time.

Outline

- MapReduce architecture
- Sample applications
- Introduction to Hadoop
- Higher-level query languages: Pig & Hive
- Current research

Cloud Programming Research

- More general execution engines
  - **Dryad** (Microsoft): general task directed acyclic graph
  - **S4** (Yahoo!): streaming computation
  - **Pregel** (Google): in-memory iterative graph algs.
  - **Spark** (Berkeley): general in-memory computing
- Language-integrated interfaces
  - Run computations directly from host language
  - **DryadLINQ** (MS), **FlumeJava** (Google), **Spark**

Spark

Fast, Interactive, Language-Integrated Cluster Computing

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael Franklin, Scott Shenker, Ion Stoica

www.spark-project.org

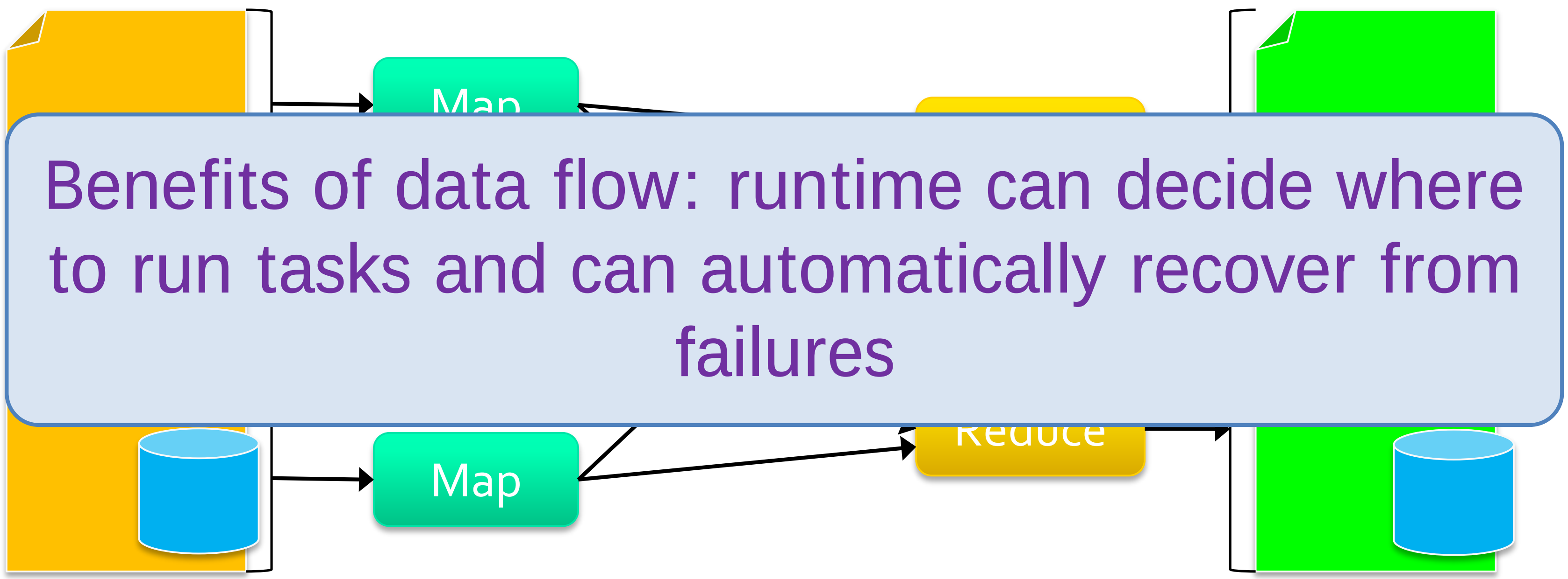
amplab UC BERKELEY

Project Goals

- Extend the MapReduce model to better support two common classes of analytics apps:
  - **Iterative** algorithms (machine learning, graphs)
  - **Interactive** data mining (R, excel, python)
- Enhance programmability:
  - Integrate into **Scala** programming language
  - Allow interactive use from Scala interpreter
- Acyclic data flow is inefficient for applications that repeatedly reuse a working set of data.
- With current frameworks, apps reload data from stable storage on each query

Motivation

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



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

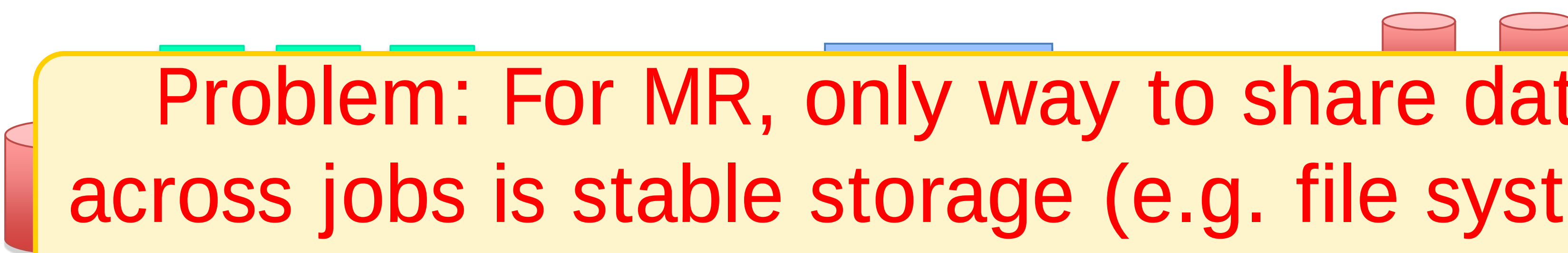
Spark Motivation

- MapReduce simplified “big data” analysis on large, unreliable clusters
- However, many organizations started using it widely, users wanted more:
  - More complex, multi-stage applications
  - More interactive queries
  - More low-latency online processing

Spark Motivation

- Complex jobs, interactive queries and online processing all need one thing that MapReduce lacks:

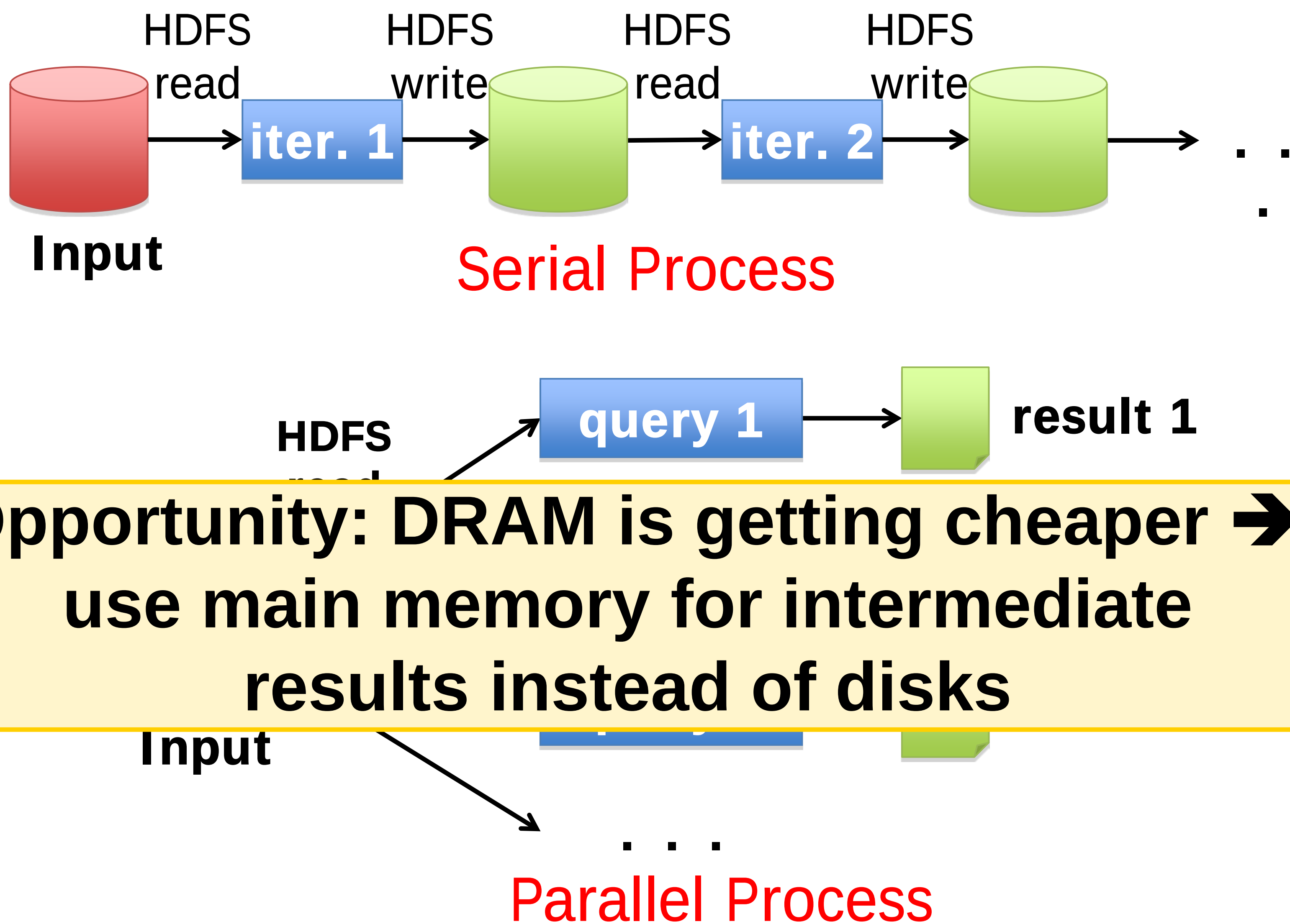
  Efficient primitives for **data sharing**



Problem: For MR, only way to share data across jobs is stable storage (e.g. file system) -> slow!

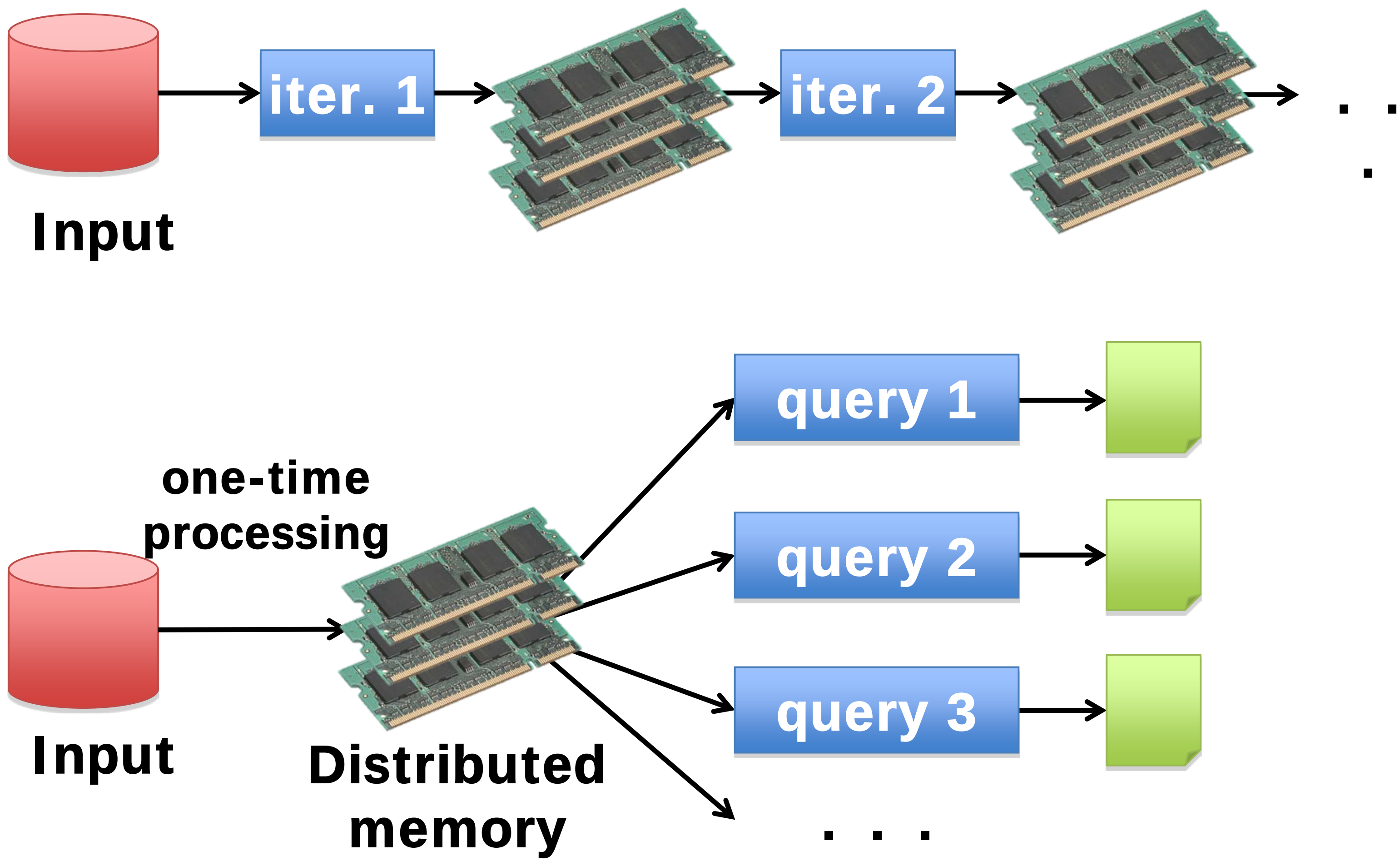
Iterative job **Interactive mining** **Stream processing**

Example: Data Sharing



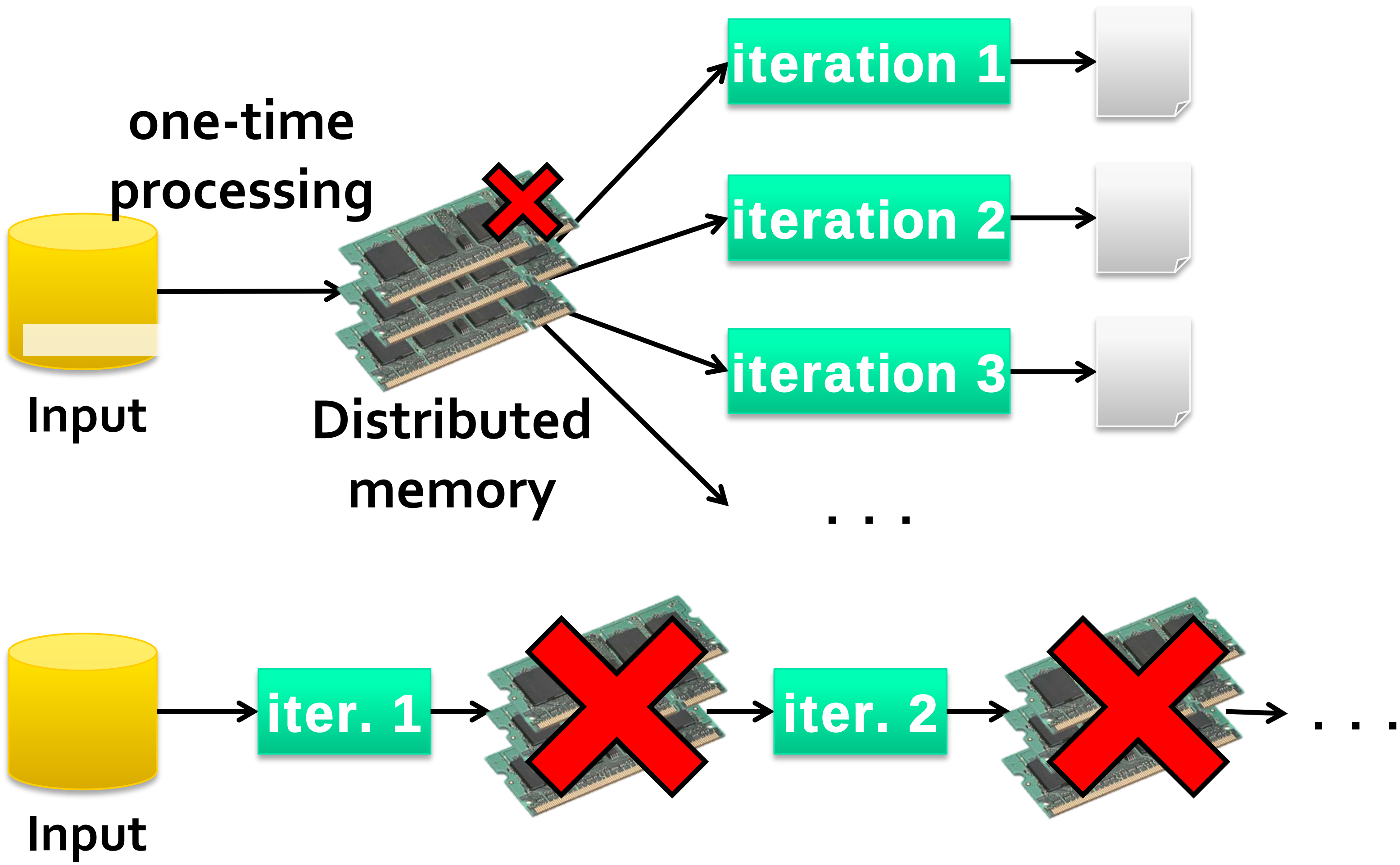
Opportunity: DRAM is getting cheaper → use main memory for intermediate results instead of disks

Goal: Data Sharing in Memory



10~100× faster than network and disk

Resilient Distributed Datasets (RDDs) Recovery



RDD

- A read-only multiset of data items distributed over a cluster of machines, that is maintained in a fault-tolerant way.
- MapReduce programs read input data from disk, map a function across the data, reduce the results of the map, and store reduction results on disk.
- Spark's RDDs function as a working set for distributed programs that offers a (deliberately) restricted form of distributed shared memory

Solution: RDDs

- Partitioned collections of records that can be stored in memory across the cluster

- Manipulated through a diverse set of transformations (*map*, *filter*, *join*, etc)

- Fault recovery without costly replication
  - Remember the series of transformations that built an RDD (from its lineage) to **recompute** lost data

Programming Model

Resilient distributed datasets (RDDs)

- Immutable, partitioned collections of objects
- Created through parallel ***transformations*** (map, filter, groupBy, join, ...) on data in stable storage
- Can be ***cached*** for efficient reuse

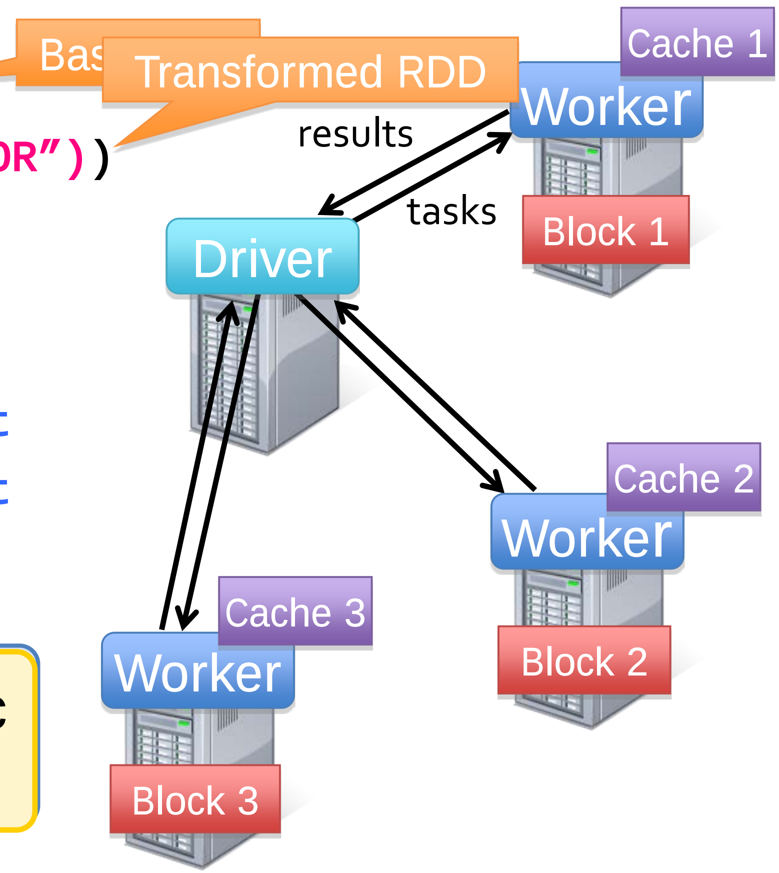
Actions on RDDs

- Count, reduce, collect, save, ...

Example: Log Mining

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

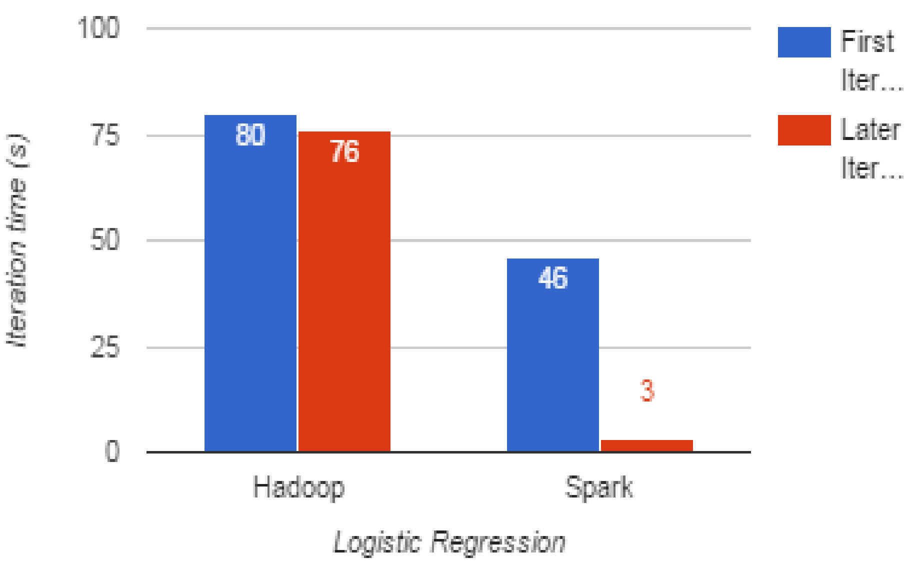
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
messages.cache()

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

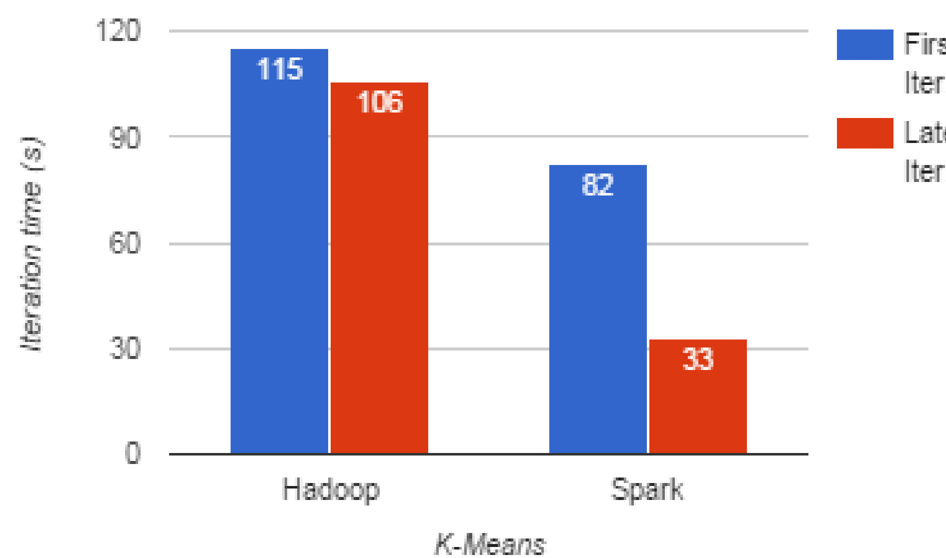


Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

Evaluation

10 iterations on 100GB data using 25-100 machines



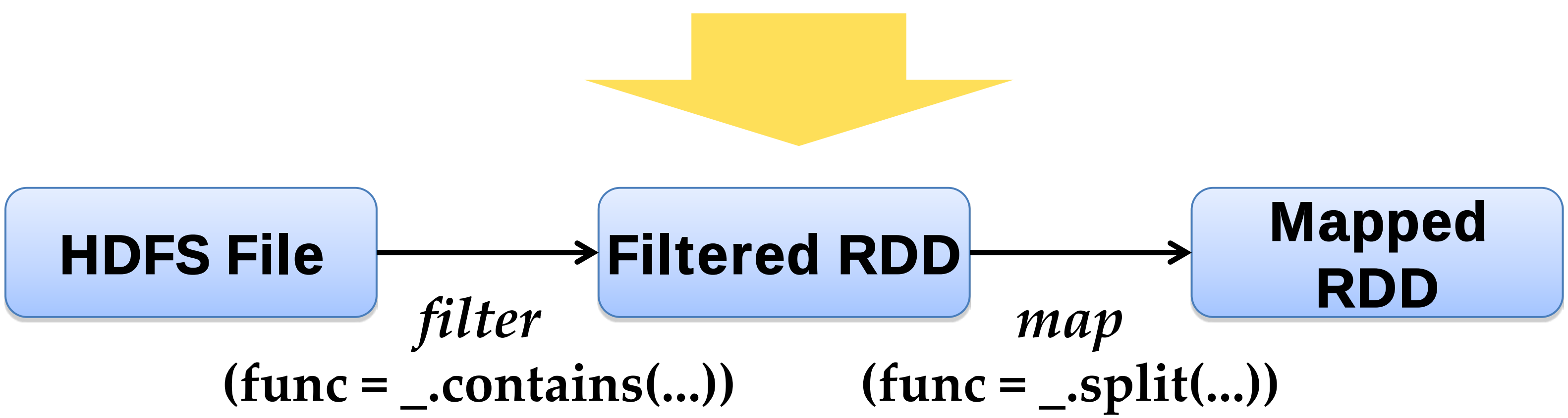


Fault Recovery

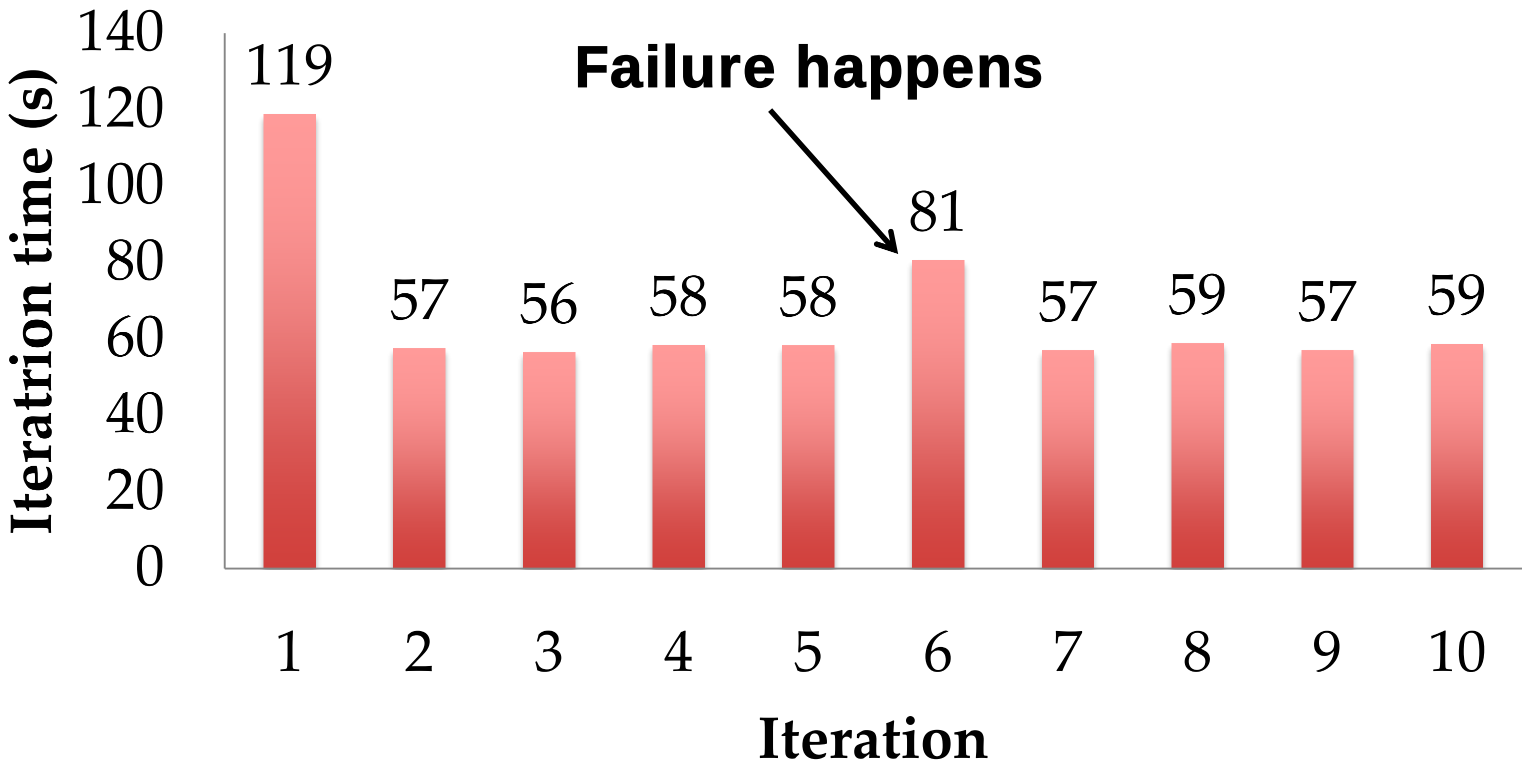
RDDs track **lineage** information that can be used to efficiently reconstruct lost partitions

Ex:

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

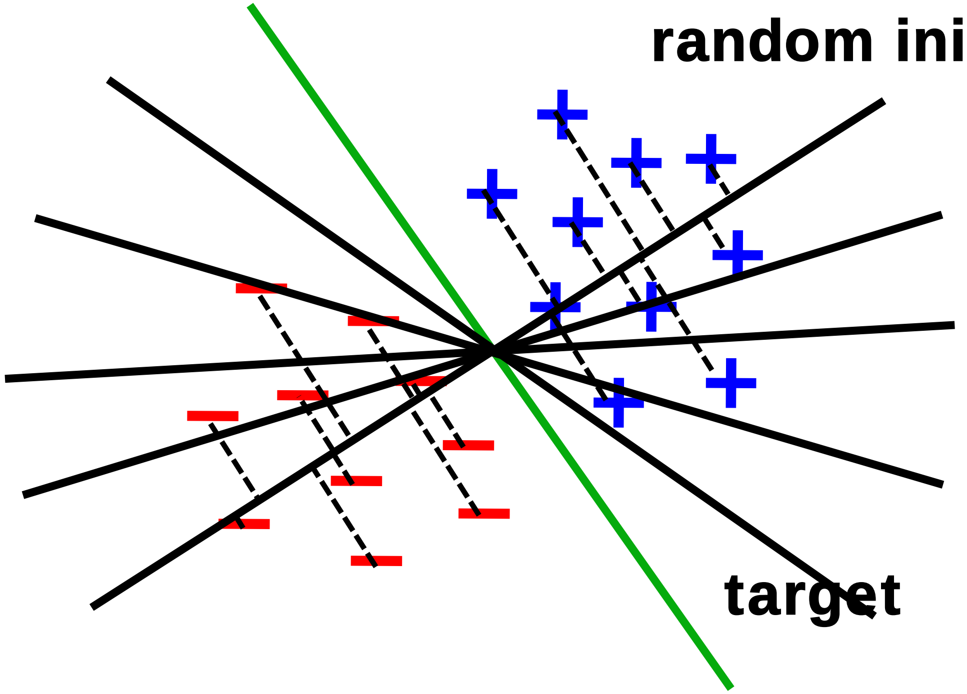


Fault Recovery Results



Example: Logistic Regression

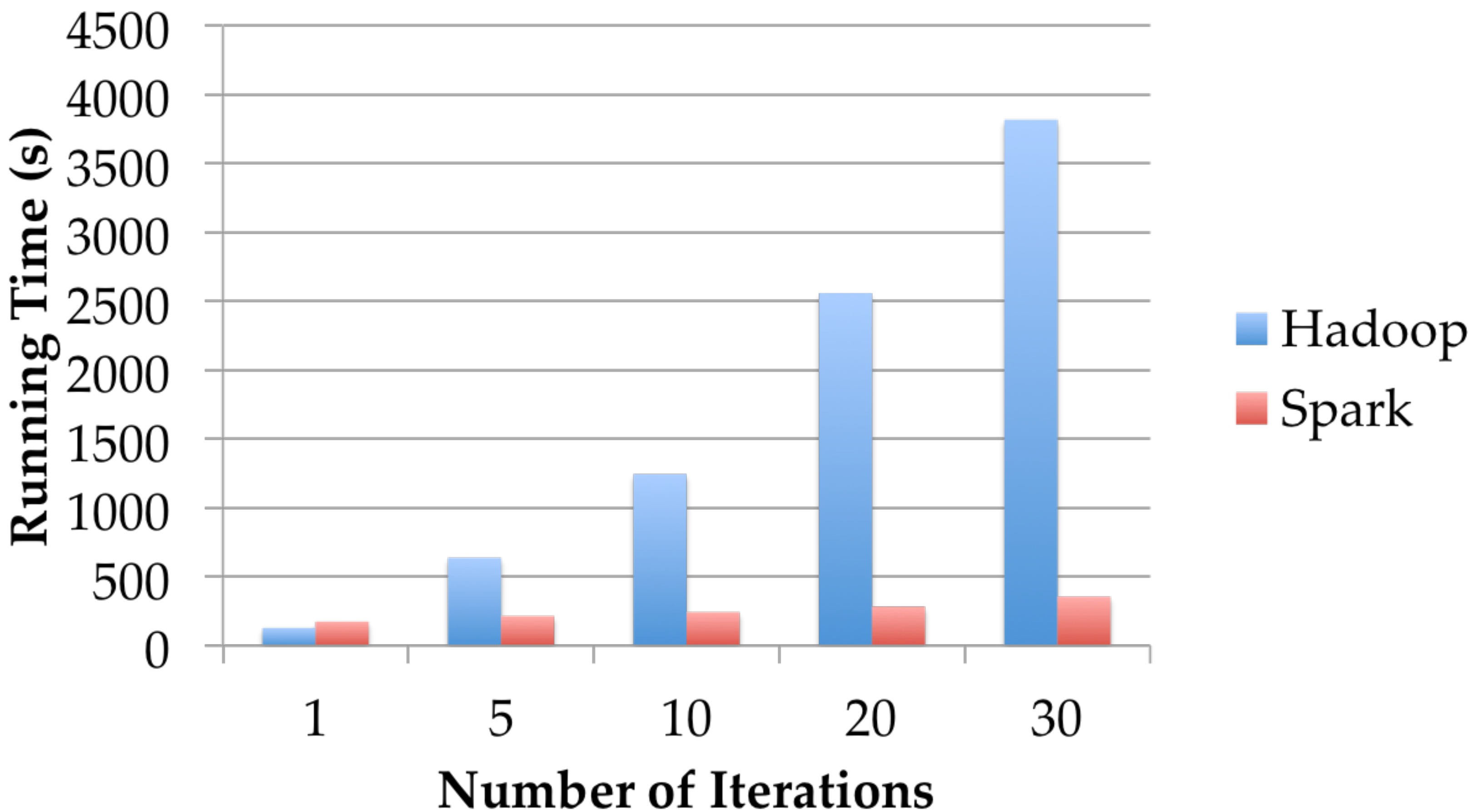
Find best line separating two sets of points



Logistic Regression Code

```
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)
```

Logistic Regression Performance



Example: Collaborative Filtering

Goal: predict users' movie ratings based on past ratings of other movies

$$R = \begin{array}{cc} \begin{pmatrix} 1 & ? & ? & 4 & 5 & ? & 3 \\ ? & ? & 3 & 5 & ? & ? & 3 \\ 5 & ? & 5 & ? & ? & ? & 1 \\ 4 & ? & ? & ? & ? & 2 & ? \end{pmatrix} & \text{Users} \\ \text{Movies} & \end{array}$$

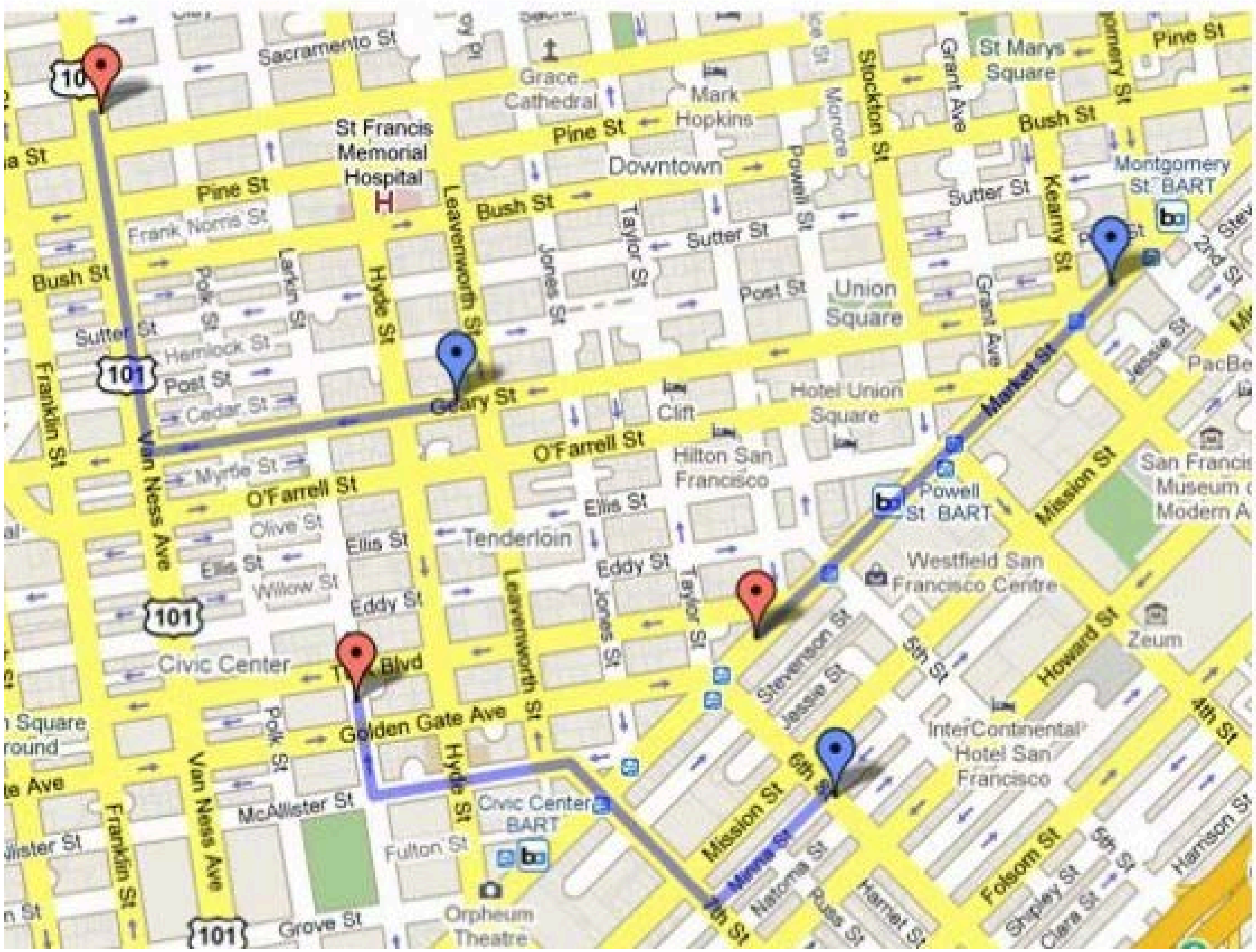
Spark Applications

- In-memory data mining on Hive data (Conviva)
- Predictive analytics (Quantified)
- City traffic prediction (Mobile Millennium)
- Twitter spam classification (Monarch)
- Collaborative filtering via matrix factorization
- Time series analysis
- Network simulation

...

Mobile Millennium Project

Estimate city traffic using GPS observations from probe vehicles
(e.g. SF taxis)

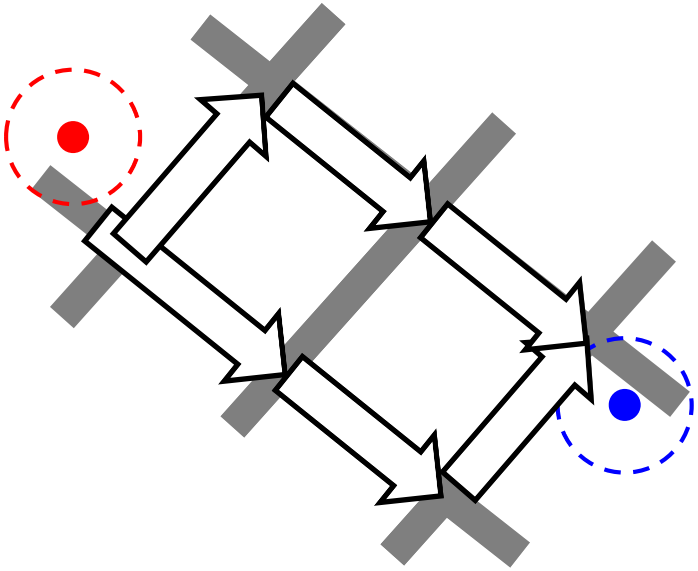


Sample Data

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

Challenge

- Data is noisy and sparse (1 sample/minute)
- Must infer path taken by each vehicle in addition to travel time distribution on each link



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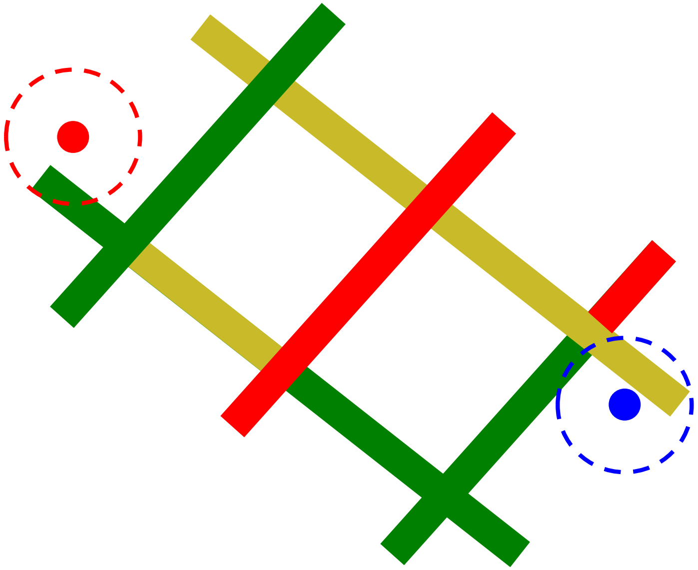
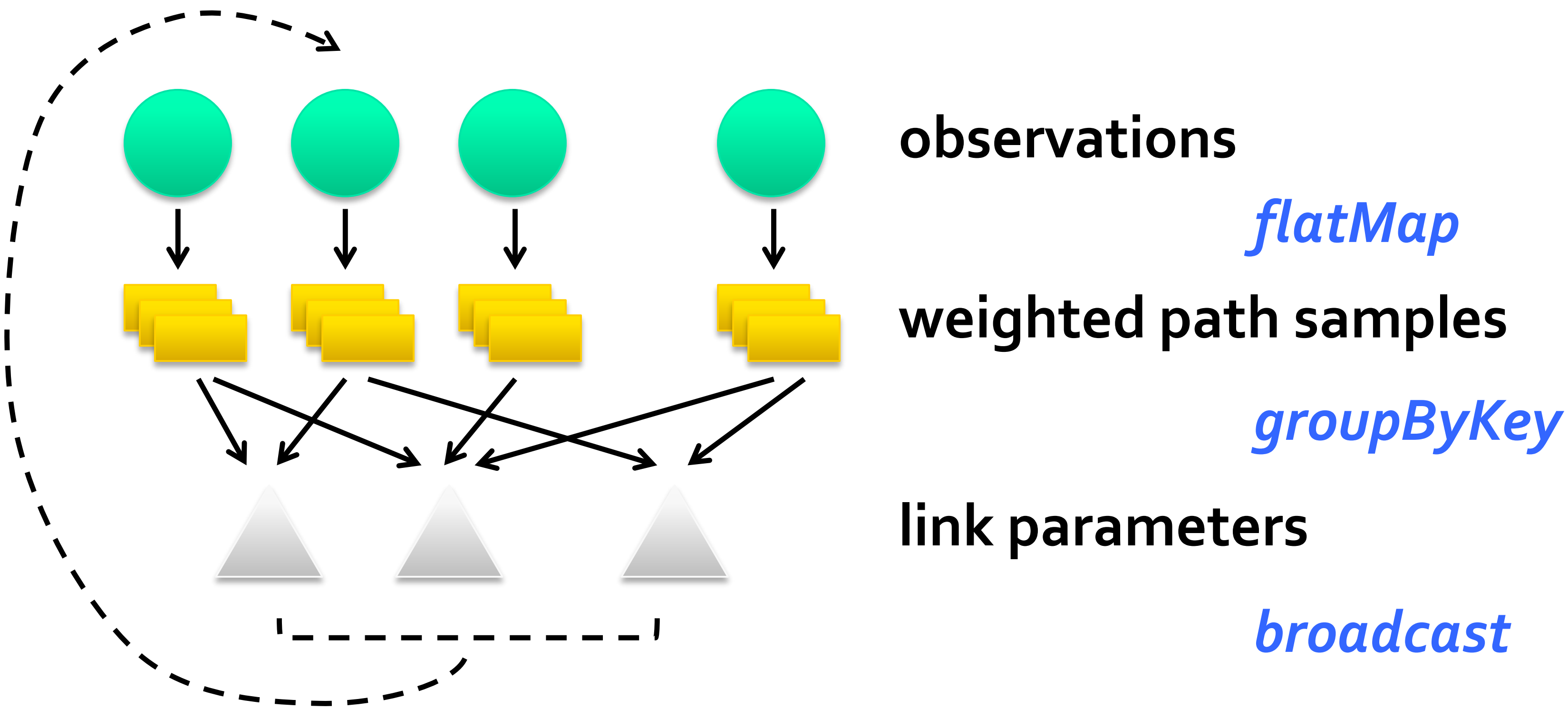


Solution

EM algorithm to estimate paths and travel time distributions simultaneously



Frameworks Built on Spark

- Pregel on Spark (Bagel)
  - Google message passing model for graph computation
  - 200 lines of code
- Hive on Spark (Shark)
  - 3000 lines of code
  - Compatible with Apache Hive
  - ML operators in Scala

Scala is an object-functional programming and scripting language for general software applications, statically typed, designed to concisely express solutions in an elegant, type-safe and lightweight manner.

Scala "Hello World" example

- Edit

```scala
object HelloWorld extends App {
  println("Hello, World!")
}
```

- Compiler

```
$ scalac HelloWorld.scala
```

- Run

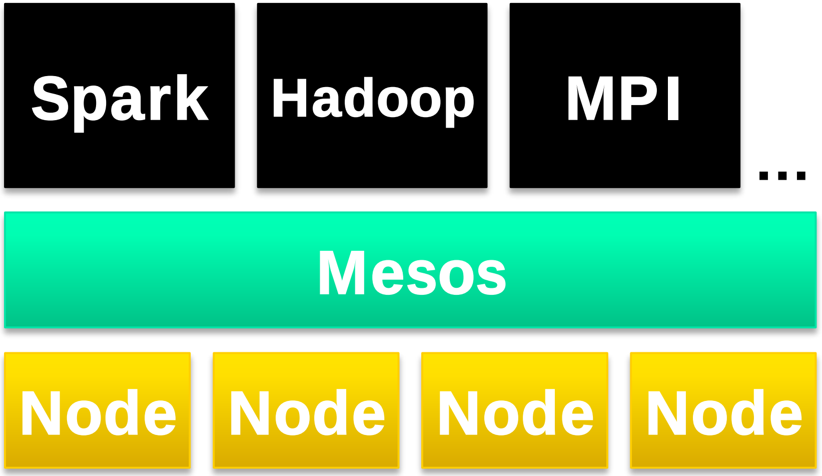
```
$ scala HelloWorld
```

Implementation

Runs on Apache Mesos to share resources with Hadoop & other apps

Can read from any Hadoop input source (e.g. HDFS)

- No changes to Scala compiler



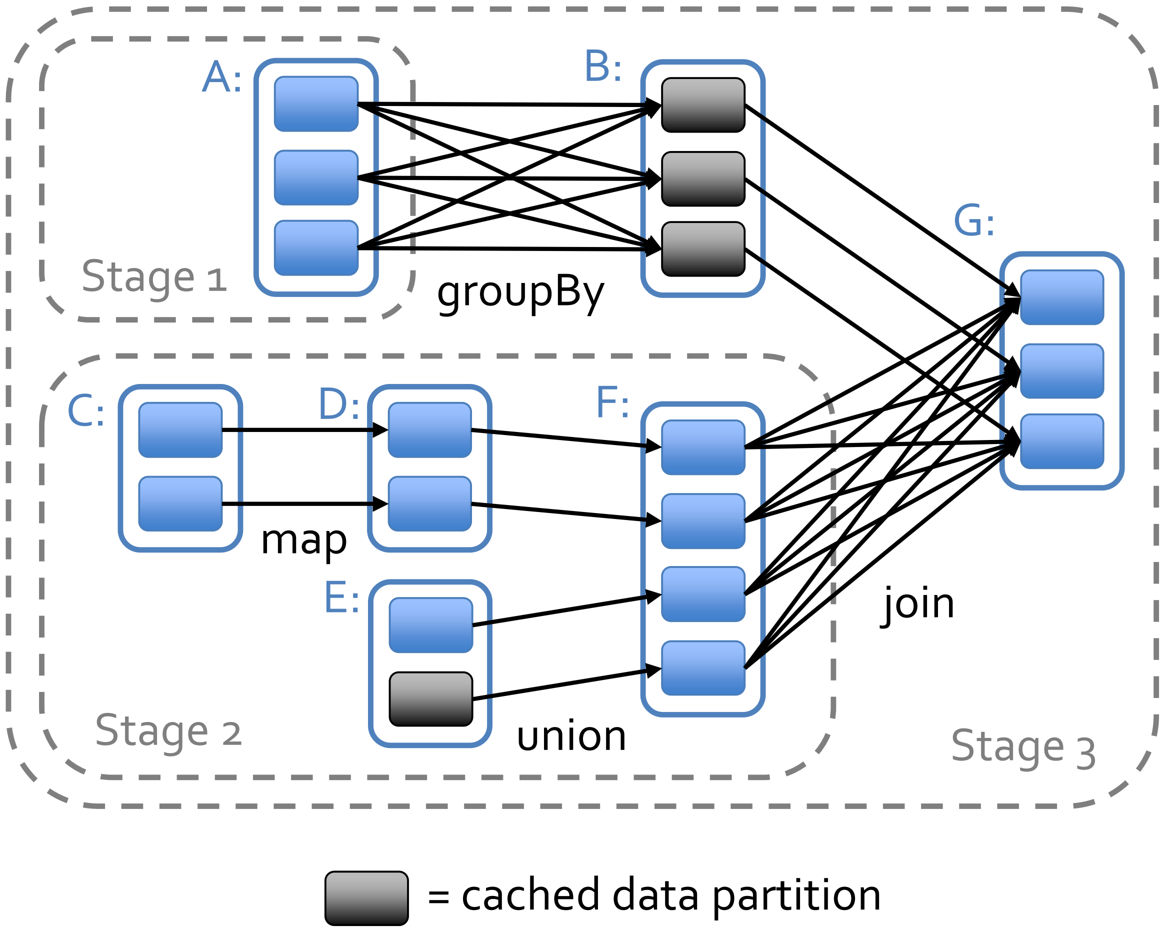
Spark Scheduler

Dryad-like DAGs

Pipelines functions within a stage

Cache-aware work reuse & locality

Partitioning-aware to avoid shuffles



If You Want to Try It Out

- **www.spark-project.org**
- To run locally, just need Java installed
- Easy scripts for launching on Amazon EC2
- Can call into any Java library from Scala

Other Resources

- Hadoop: http://hadoop.apache.org/common
- Pig: http://hadoop.apache.org/pig
- Hive: http://hadoop.apache.org/hive
- Spark: http://spark-project.org

- Hadoop video tutorials: www.cloudera.com/hadoop-training

- Amazon Elastic MapReduce: http://aws.amazon.com/elasticmapreduce/

Q&A

- For more information:
  - http://hadoop.apache.org/
  - http://developer.yahoo.com/hadoop/

- Who uses Hadoop?:
  - http://wiki.apache.org/hadoop/PoweredBy