### Hadoop, a distributed framework for Big Data

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Big Data & Frameworks



- **4** Hadoop Basics
- **HDFS**
- **4** Yarn
- **4** MapReduce
- **4** Spark
- **4** Related Apache sub-projects (Pig, HBase, Hive)

## Apache Hadoop

 A framework for storing & processing Petabyte of data using commodity hardware and storage

- Apache project
- Implemented in Java
- Community of contributors is growing
  - Yahoo: HDFS and MapReduce
  - Powerset: HBase
  - Facebook: Hive and FairShare scheduler
  - IBM: Eclipse plugins

# What is Hadoope?

- Software platform that lets one easily write and run applications that process vast amounts of data. It includes:
  - MapReduce offline computing engine
- HDFS Hadoop distributed file system
  - HBase (pre-alpha) online data access
- 4 Yahoo! is the biggest contributor



- **Here's what makes it especially useful:**
- **4** Scalable: process petabytes.
- **4** Economical: processing across clusters (in thousands).
- Efficient: By distributing the data, it can process it in parallel on the nodes where the data is located.
- Reliable: It automatically maintains multiple copies of data and automatically redeploys computing tasks based on failures.

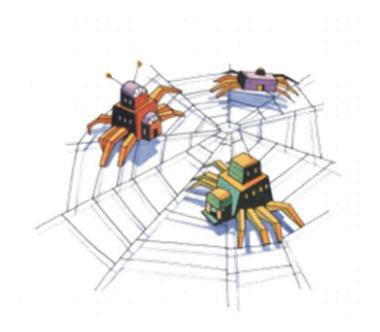


- Apache top level project, open-source implementation of frameworks for reliable, scalable, distributed computing and data storage.
- It is a flexible and highly-available architecture for large scale computation and data processing on a network of commodity hardware.





#### Designed to answer the question: "How to process big data with reasonable cost and time?"



# History of Hadoop

- Started as a sub-project of Apache Nutch
- A Nutch's job is to index the web and expose it for searching
- Started by Doug Cutting
- In 2004 Google publishes Google File System (GFS) and MapReduce framework papers
- The Google File System 2003





2003

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

The Google File System



MapReduce: Simplified Data Processing on Large Clusters

2004

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

Bigtable: A Distributed Storage System for Structured Data

Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C. Hsieh, Deborah A. Wallach Mike Burrows, Tushar Chandra, Andrew Fikes, Robert E. Gruber (Ingeff.sanjay.wiboshker.ackb.moha.dise.griber)@google.com

Google, Inc.

Abstract studies of a distributed storage system for managing inter data that is designed to scale to a very large predays of data across thousands of commoly restarys of data across thousands of commoly studies with a designed to scale to a very large predays of data across thousands of commoly studies with a designed to scale to a very large predays of data across thousands of commoly studies with a designed to scale to a very large predays of data across thousands of commoly studies with a scale storage thread to a study studies with a study of the study of the study studies with a study study study study studies with a study stu





2006

### History of Hadoop

- 2008 Hadoop Wins Terabyte Sort Benchmark (sorted 1 terabyte of data in 209 seconds, compared to previous record of 297 seconds)
- 2009 Avro and Chukwa became new members of Hadoop Framework family
- 2010 Hadoop's Hbase, Hive and Pig subprojects completed, adding more computational power to Hadoop framework
- 2011 ZooKeeper Completed
- 2013 Hadoop 1.1.2 and Hadoop 2.0.3 alpha.
  - Ambari, Cassandra, Mahout have been added



#### • <u>Hadoop:</u>

 an open-source software framework that supports dataintensive distributed applications, licensed under the Apache v2 license.

#### Goals / Requirements:

- Abstract and facilitate the storage and processing of large and/or rapidly growing data sets
  - Structured and non-structured data
  - Simple programming models
- High scalability and availability
- Use commodity (cheap!) hardware with little redundancy
- Fault-tolerance
- Move computation rather than data

### **Organization used hadoop**



Source: http://wiki.apache.org/hadoop/PoweredBy

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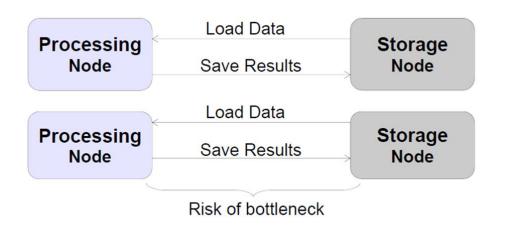
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## Hadoop system principles

- Scale-Out rather than Scale-Up
- **4** Bring code to data rather than data to code
- Deal with failures they are common
- **4** Abstract complexity of distributed and concurrent applications

### RTIFICIAL INTERDICENCE COde to Data

- Traditional data processing architecture
- Nodes are broken up into separate processing and storage nodes connected by high-capacity link
- Many data-intensive applications are not CPU demanding causing bottlenecks in network

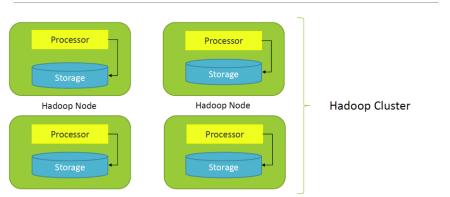




### **BRING CODE TO DATA**

Hadoop co-locates processors and storage Code is moved to data (size is tiny, usually in KBs) Processors execute code and access underlying local storage

Bring Code to Data



# Failures are Common

- **4** Given a large number machines, failures are common
- **4** Large warehouses may see machine failures weekly or even daily
- **4** Hadoop is designed to cope with node failures
- Data is replicated
- Tasks are retried

Frees developer from worrying about systemlevel challenges
processing pipelines, data partitioning, code distribution

**4** Allows developers to focus on application development and business logic



Cloudera Distribution for Hadoop (CDH)

MapR Distribution

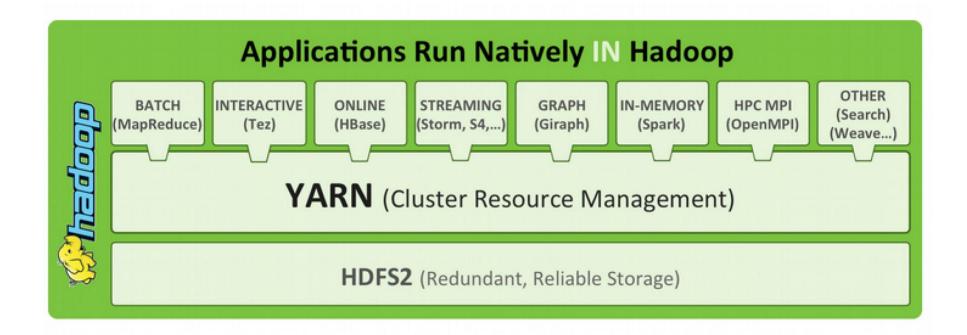
Hortonworks Data Platform (HDP)

Apache BigTop Distribution

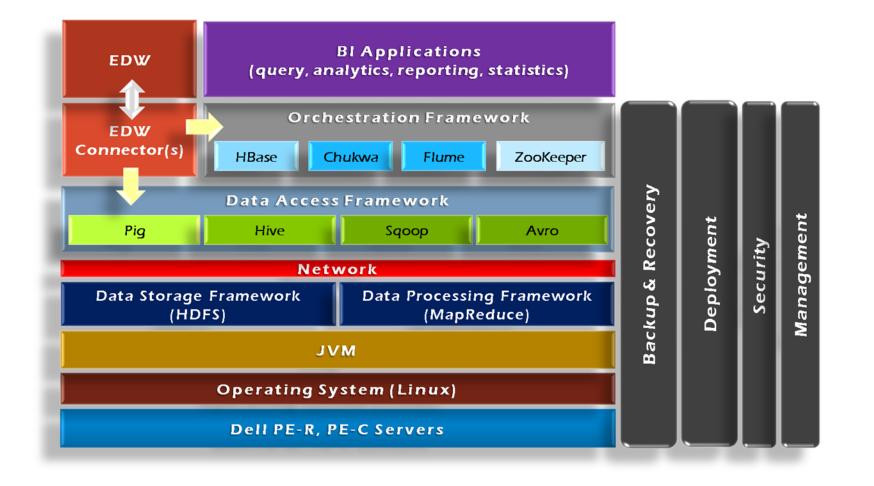






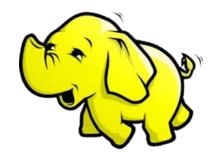








- HDFS : A distributed filesystem that runs on large clusters of commodity machines
- MapReduce : A distributed data processing model
- **Hbase : A distributed, column-oriented database.**

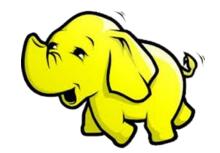


Hive : A distributed data warehouse. Hive manages data stored in HDFS and provides a query language based on SQL



# Fig : A data flow language and execution environment for exploring very large datasets

**4** ZooKeeper : A distributed, highly available coordination service.



### Hadoop Distributed File System

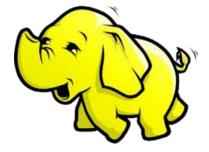
- **4** Appears as a single disk
- Runs on top of a native filesystem

**Ext3**,**Ext4**,...

- Based on Google's Filesystem GFS
- 4 Fault Tolerant

Can handle disk crashes, machine crashes, etc...

portable Java implementation



# HDFS is Good for...

### Storing large files

- Terabytes, Petabytes, etc...
- Millions rather than billions of files
- 100MB or more per file
- Streaming data
  - Write once and read-many times patterns
  - Optimized for streaming reads rather than random reads

### **4** "Cheap" Commodity Hardware

No need for super-computers, use less reliable commodity hardware

## HDFS is not so good for ...

#### Low-latency reads

High-throughput rather than low latency for small chunks of data

HBase addresses this issue

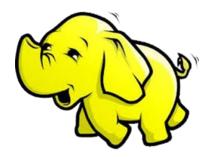
### Large amount of small files

Better for millions of large files instead of billions of small files

For example each file can be 100MB or more

### **4** Multiple Writers

Single writer per file





#### Master-Slave Architecture

#### HDFS Master "Namenode"

- Manages all filesystem metadata
- File name to list blocks + location mapping
- File metadata (i.e. "inode")
- Collect block reports from Datanodes on block locations
- Controls read/write access to files
- Manages block replication

#### HDFS Slaves "Datanodes"

- Notifies NameNode about block-IDs it has
- Serve read/write requests from clients
- Perform replication tasks upon instruction by namenode
- Rack-aware



#### NameNode:

- Stores metadata for the files, like the directory structure of a typical FS.
- The server holding the NameNode instance is quite crucial, as there is only one.
- Transaction log for file deletes/adds, etc. Does not use transactions for whole blocks or file-streams, only metadata.
- Handles creation of more replica blocks when necessary after a DataNode failure

#### DataNode:

- Stores the actual data in HDFS
- Can run on any underlying filesystem (ext3/4, NTFS, etc)
- Notifies NameNode of what blocks it has
- NameNode replicates blocks 2x in local rack, 1x elsewhere

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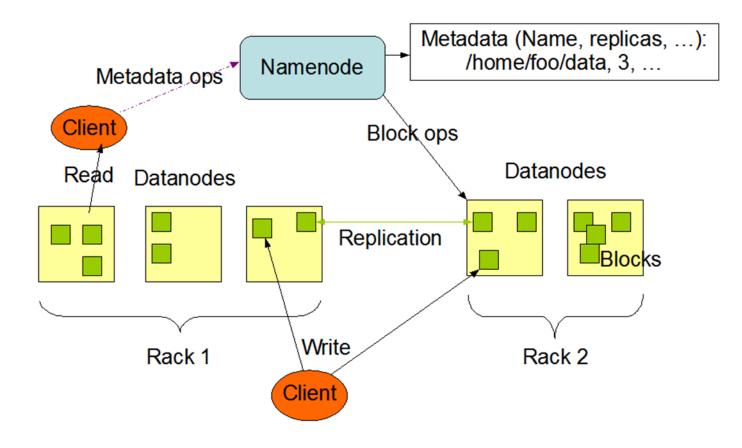
# HDFS Architecture

### Secondary Namenode

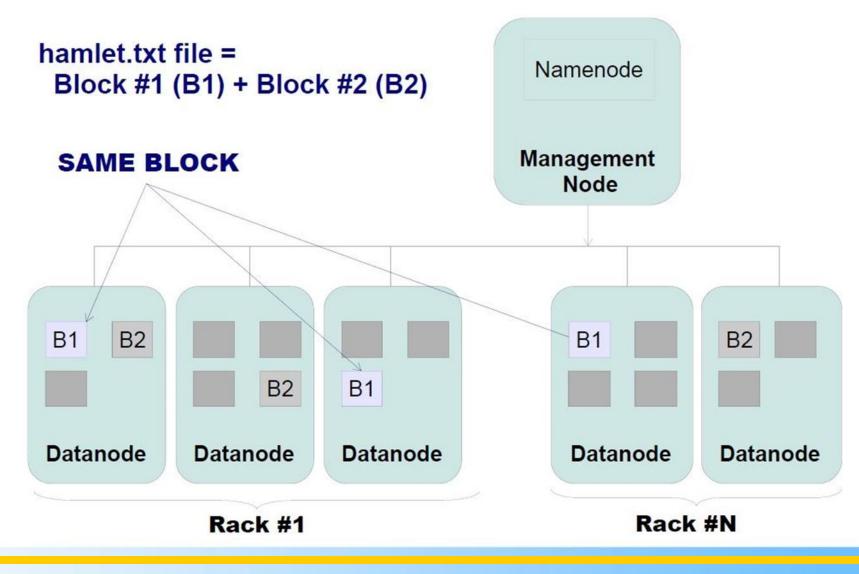
- Performs house keeping work so Namenode doesn't have to
- Requires similar hardware as Namenode machine
- Not used for high-availability not a backup for Namenode



#### **HDFS** Architecture



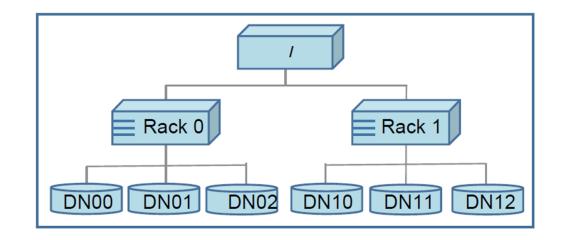
Files and Blocks



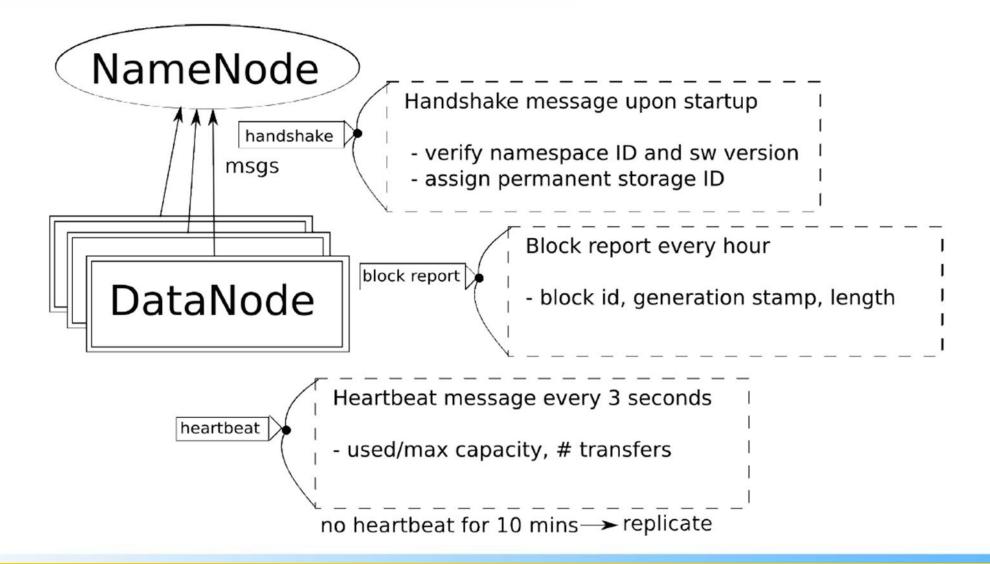
## REPLICA MANGEMENT

**4** A common practice is to spread the nodes across multiple racks

- **4** improve data reliability, availability, and network bandwidth utilization
- **4** Namenode determines replica placement



### HDFS Component Communication





- During startup each DataNode connects to the NameNode and performs a handshake
- **4** The purpose is to verify the namespace ID and the software version
- **4** After the handshake the DataNode registers with the NameNode



**4** A block report contains the *block id*, the length for each block replica

### **4** The first is sent immediately after the DataNode registration

**4** Subsequent block reports are sent every hour.

### Uring normal operation DataNodes send heartbeats to the NameNode to confirm that the DataNode is operating and the block replicas it hosts are available.

**Heartbeats from a DataNode also carry information about:** 

- Total storage capacity
- Fraction of storage in use

heartbeats

The default heartbeat interval is three seconds

## Resd,Write, Append,Delete

**4** Using the FileSystem API:

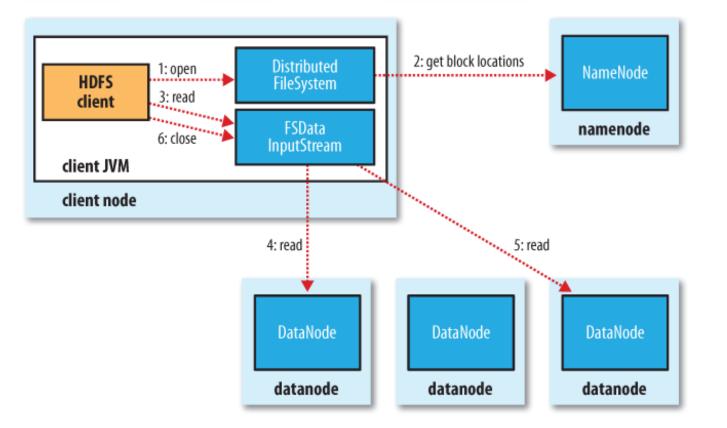
**4** an open() method to get the input stream for a file

4 The create() methods for writing

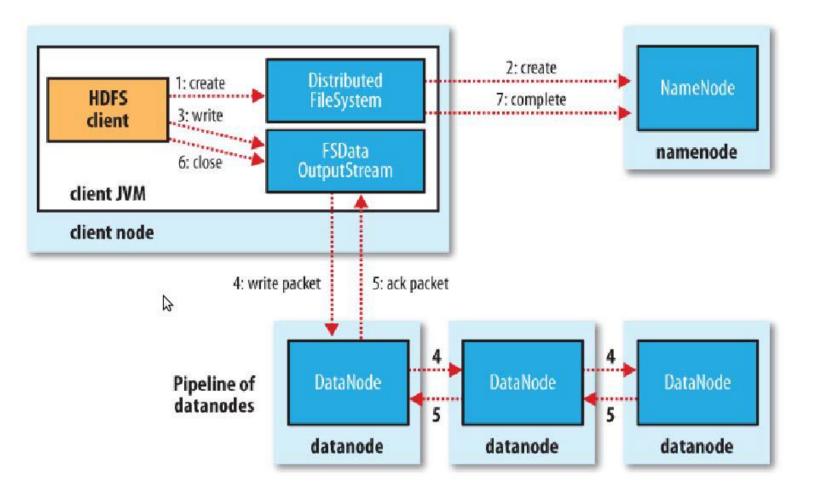
append to an existing file using the append() method

**4** Use the delete() method on FileSystem to permanently remove files or directories

# Reading Data From HDFS



# ARTIFICIAL INTERDICENCE Writing Data To HDFS

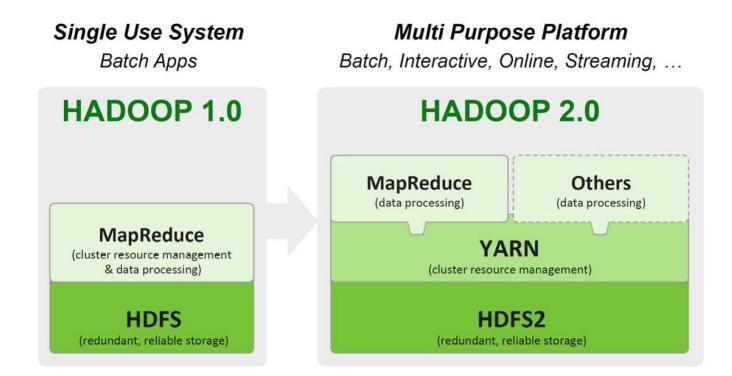


#### Hadoop MapReduce Classic

YARN

- **4** MapReduce Classic Limitations:
- **4** Scalability
- Maximum Cluster size 4,000 nodes
- Maximum concurrent tasks 40,000
- Coarse synchronization in JobTracker
- •Availability
- Failure kills all queued and running jobs
- Hard partition of resources into map and reduce slots
- Low resource utilization
- Lacks support for alternate paradigms and services
- Iterative applications implemented using MapReduce are 10x slower

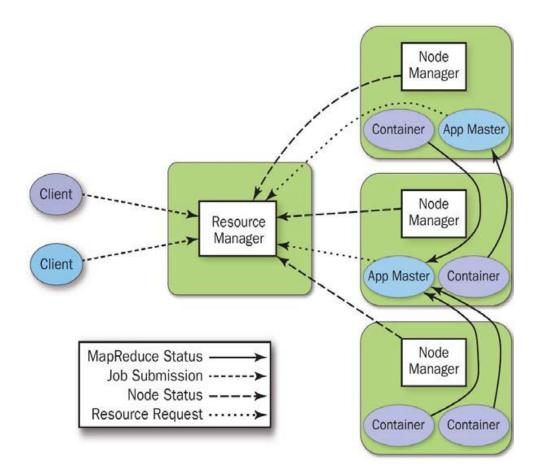
### Hadoop as Next-Gen Platform



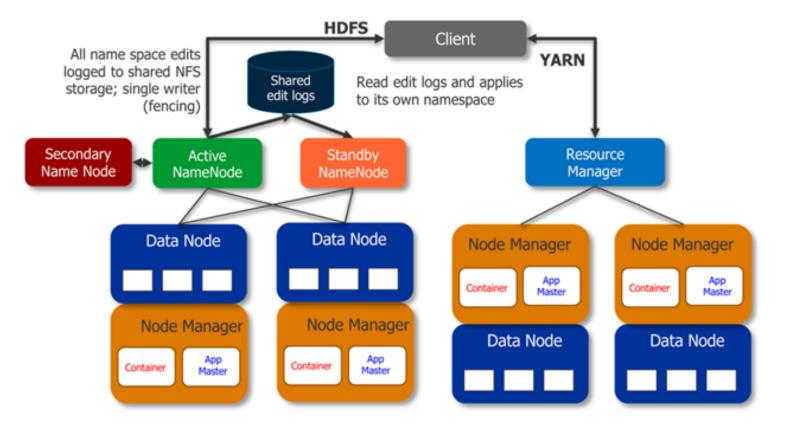


- 4 YARN Architecture and Concepts
- **4** Application
- Application is a job submitted to the framework
- Example Map Reduce Job
- Container
- Basic unit of allocation
- Fine-grained resource allocation across multiple resource types (memory, cpu, disk, network,
- \pm gpu etc.)
- container\_0 = 2GB, 1CPU
- container\_1 = 1GB, 6 CPU
- Replaces the fixed map/reduce slots





## Hadoop Architecture



## What is MapReduce?

- Parallel programming model meant for large clusters
- User implements Map() and Reduce()
- Parallel computing framework
- Libraries take care of EVERYTHING else
- Parallelization
- 4 Fault Tolerance
- Data Distribution
- Load Balancing
- Useful model for many practical tasks (large data)

- Map and Reduce
- Functions borrowed from functional programming languages (eg. Lisp)
- **4** Map()
- Process a key/value pair to generate intermediate key/value pairs•
- Reduce()
- **4** Merge all intermediate values associated with the same key

### Map Reduce

Data

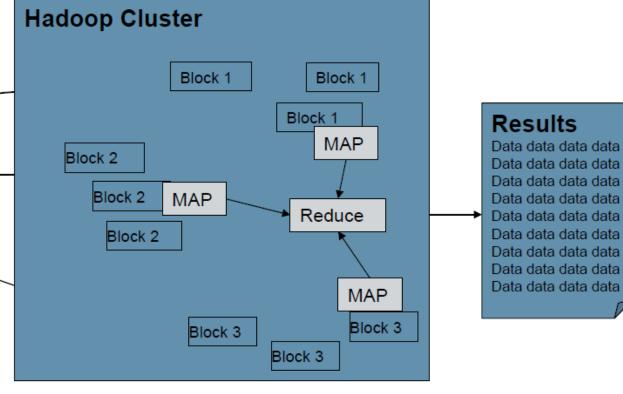
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Data data

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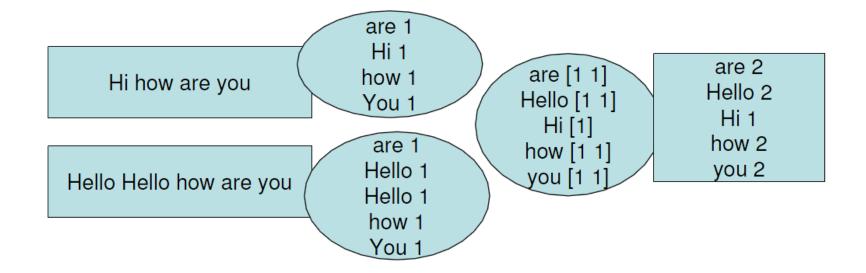
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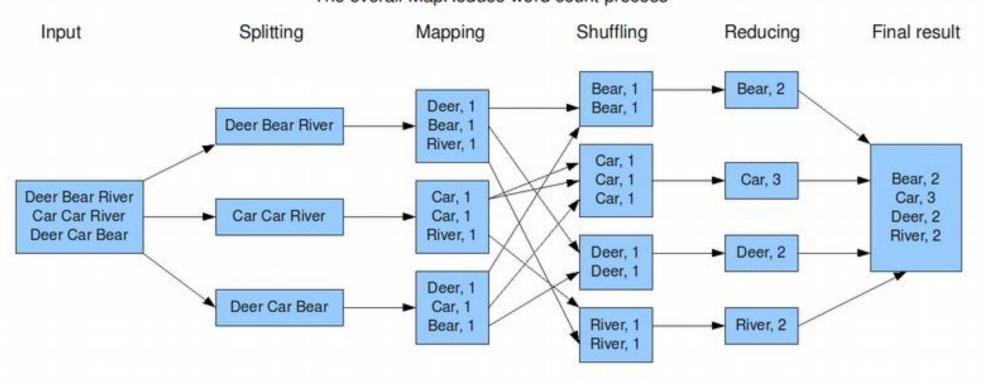


**Big Data & FrameWorks** 

## Distributed Processing







#### The overall MapReduce word count process

### **Map-Reduce on Large Clusters**

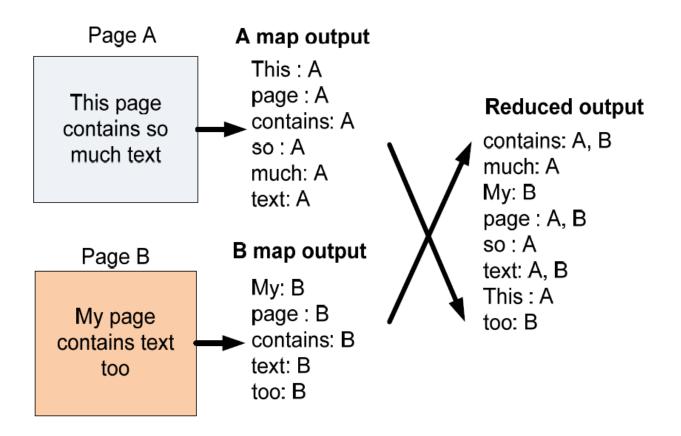
#### **4** Motivation and Demand:

- Tend to be very short, code-wise
- Represent a data flow

| Load a large set of records onto a set of machines         | Key/Value Pairs |
|--|-----------------|
| Extract / transform something of interest from each record | "Map"           |
| Shuffle intermediate results between the machines          |                 |
| Aggregate intermediate results                             | "Reduce"        |
| Store end result   |                 |

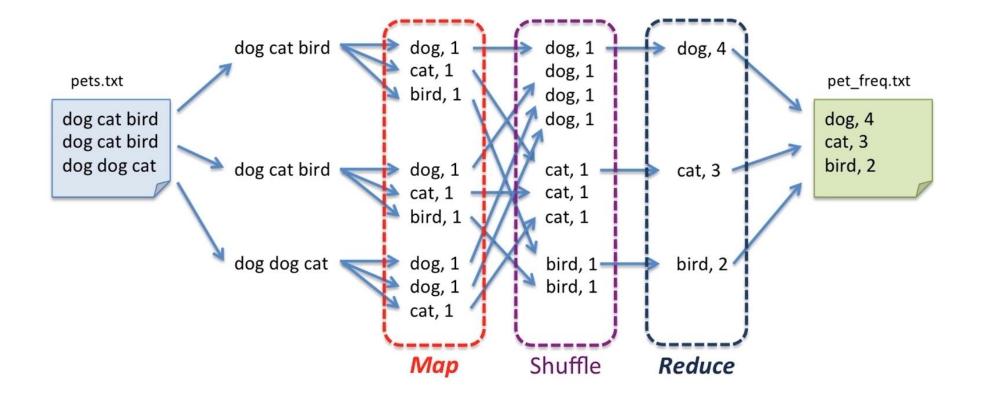
### Map-Reduce (Cont.)

### Index: Data Flow



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## Map-Reduce (Cont.)



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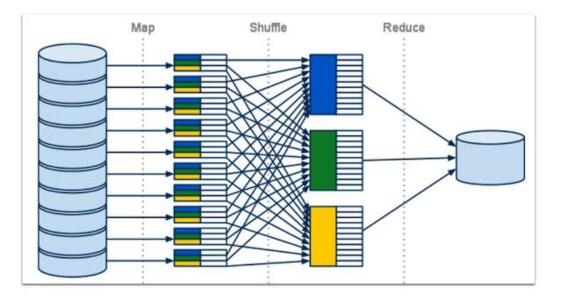
### Map-Reduce (Cont.)

#### **4** Each step has one Map phase and one Reduce phase

Convert any into MapReduce pattern

#### Great solution for one-pass computations

Not very efficient for Multi-pass computations and algorithms



### Map/Reduce in Python

- import sys
- for line in sys.stdin:
- line = line.strip()
- words = line.split()
- for word in words:
- print '%s\t%s' % (word,1)



- from operator import itemgetter
- import sys
- current\_word = None
- current\_count = 0
- word = None
- for line in sys.stdin:
- line = line.strip()
- word, count = line.split('\t', 1)



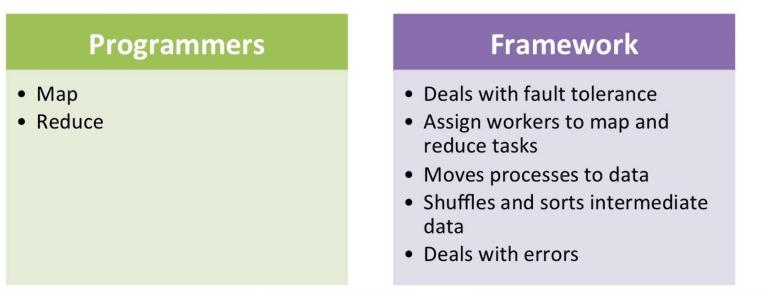
- try:
- count = int(count)
- except ValueError:
- continue
- if current\_word == word:
- current\_count += count
- else:
- if current\_word:
- print '%s\t%s' % (current\_word, current\_count)
- current\_count = count
- current\_word = word
- if current\_word == word:
- print '%s\t%s' % (current\_word, current\_count)

**Big Data & FrameWorks** 

## Hadoop Framework

#### **4** Features :

- Open Source Framework for Processing Large Data
- Work on Cheap and Unreliable Clusters
- Known in Companies who deal with Big Data Applications
- Compatible with Java, Python and Scala



## Hadoop Framework (Cont.)

#### MapReduce Framework

Assign work for different nodes

#### Hadoop Distributed File System (HDFS)

Primary storage system used by Hadoop applications.

Copies each piece of data and distributes to individual nodes

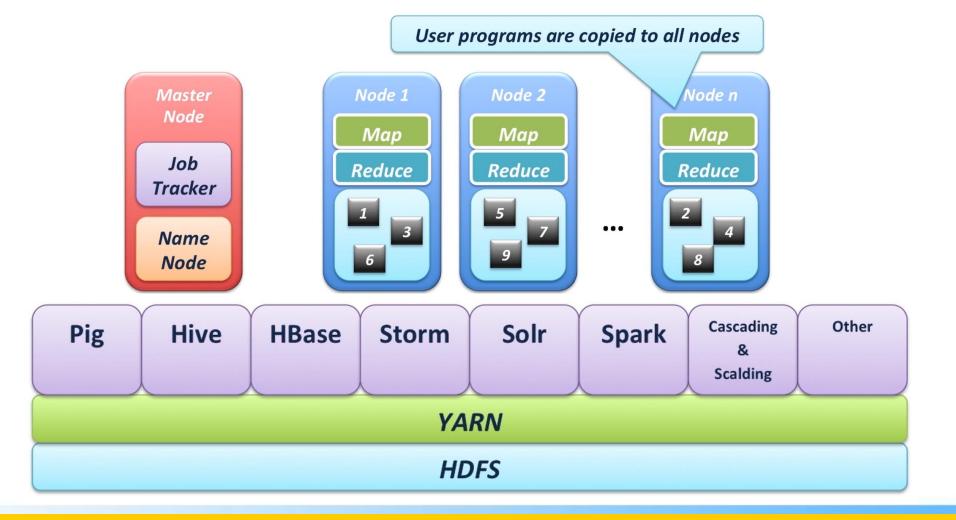
Name Node (Meta Data) and Data Nodes (File Blocks)

- Redundant information (Three times by default)
- Machines in a given cluster are cheap and unreliable
- Decreases the risk of catastrophic failure
  - » Even in the event that numerous nodes fail

Links together the file systems on different nodes to make an integrated big file system (Parallel Processing)

# Hadoop Framework (Cont.)

#### **Hadoop V.2**: Hadoop NextGen MapReduce (YARN)



## Hadoop Framework (Cont.)

### Hadoop Programming

Java 📕

Full control of MapReduce , Cascading (Open Java Library)

Python , Scala, Ruby

**4** Data Retrieval / Query Language

Hive

SQL- Like Language

### Pig

Data Flow Language (Simple and Out of Small Steps)

Scalding

Library built on top of Scala (Elegant Model)



atforms & tools for big data analytics in healthcare

|                   |   | Platfor  | m/Tool  | Description  |  |
|-------------------|---|--|---|--|--|
| 1                 |   | The Hadoop<br>Distributed<br>File System<br>(HDFS) |   | HDFS enables the underlying storage for the Hadoop cluster. It divides the data into smaller parts and<br>listributes it across the various servers/nodes.   |  |
|                   | MapReduce   |  |   | apReduce provides the interface for the distribution of sub-tasks and the gathering of outputs. When<br>hs are executed, MapReduce tracks the processing of each server/node.  |  |
|                   | La  | IG and PIG<br>tin (Pig and<br>Latin)               | is con<br>the Pi  | programming language is configured to assimilate all types of data (structured/unstructured, etc.).<br>Imprised of two key modules: the language itself, called PigLatin, and the runtime version in which glatin code is executed.                              |  |
|                   | Hive Hive Hive to ty  |  | Hive is<br>Hadoop<br>to typica  | a runtime Hadoop support architecture that leverages Structure Query Language (SQL) with the<br>p platform. It permits SQL programmers to develop Hive Query Language (HQL) statements aking<br>al SQL statements.   |  |
| Zou               | unctional, declarative query language designed to process large data sets. To facilitate parallel |  |   |  |  |
| across big        |   | oss big cl   | clusters.   |  |  |
| Cassand           | dra   |  |   | lumn-oriented database management system that sits on top of HDFS. It uses a non-SQL<br>lso a distributed database system. It is designated as a top-level project modeled to<br>distributed across many utility servers. It also provides reliable service with |  |
| ere, all open sou |   | opensi   | o wiki Abacho Casa  |  |  |
| I De Luca         |   | e projec<br>e projec                               | t is used widely for text analytics/searches and has been in this a NoSQL system. |  |  |
| )                 | Avr   | o facilitate                                       | es data   | Serializati  |  |
| ut                | AAab  |  |   | serialization services. Versioning and version control are additional useful features<br>r Apache project whose goal is to generate free applications of distributed and<br>hing algorithms that support big data analytics on the Hadoop platform.              |  |
|                   |   |  |   | a data analytics on the Hadoop platform.   |  |

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## Big Data Programming

4 R – Java- Python and Scala (Commonly Used)

#### 4 Three References : ( Recommended to Read)

- https://www.linkit.nl/knowledge-base/177/4\_most\_used\_languages\_in\_big\_data\_projects\_Java
- https://www.linkit.nl/knowledge-base/226/4\_most\_used\_languages\_in\_big\_data\_projects\_R
- https://www.linkit.nl/eng/knowledge-

base/196/4\_most\_used\_languages\_in\_big\_data\_projects\_Python



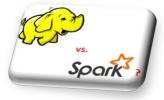
### Apache Spark Framework

#### Spark Features (More than Distributed Processing)

- Ease of use, and sophisticated analytics
- In-memory data storage and near real-time processing
- Holds intermediate results in memory
- Store as much as data in memory and then goes to disk

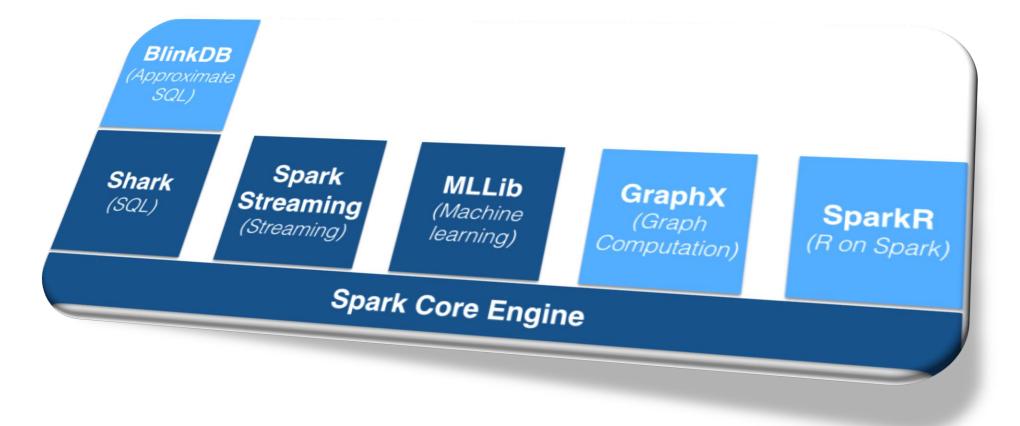
### Spark vs Hadoop

On top of existing HDFS



- Data sets that are diverse in nature (Text, Videos, ...)
- Variety in source of data (Batch v. real-time streaming data).
- 100 times faster in memory, 10 times faster when running on disk.

## ARTHFICTAL INTERCENCE Apache Spark Framework (Cont.)



### Apache Spark Framework (Cont.)

Compatible with Java, Scala and Python

Perform Data Analytics and Machine Learning

- SQL Queries, Streaming Data
- Machine Learning and Graph Data Processing
  - Spark MLlib, Spark's Machine Learning library

#### **4** Spark and data stored in a Cassandra database

(Case Study)





## Apache Flink

Apache Flink is an open source platform

Distributed stream and batch data processing."

- https://flink.apache.org/
- **4** The definition in wikipedia:

https://en.wikipedia.org/wiki/Apache\_Flink



## Apache Flink (Cont.)

**4** written in Java and Scala, consists of:

Big data processing engine:

Distributed and scalable streaming dataflow engine

**4** Several APIs in Java / Scala / Python:

DataSet API – Batch processing

DataStream API – Real-Time streaming analytics

#### **4** Domain-Specific Libraries:

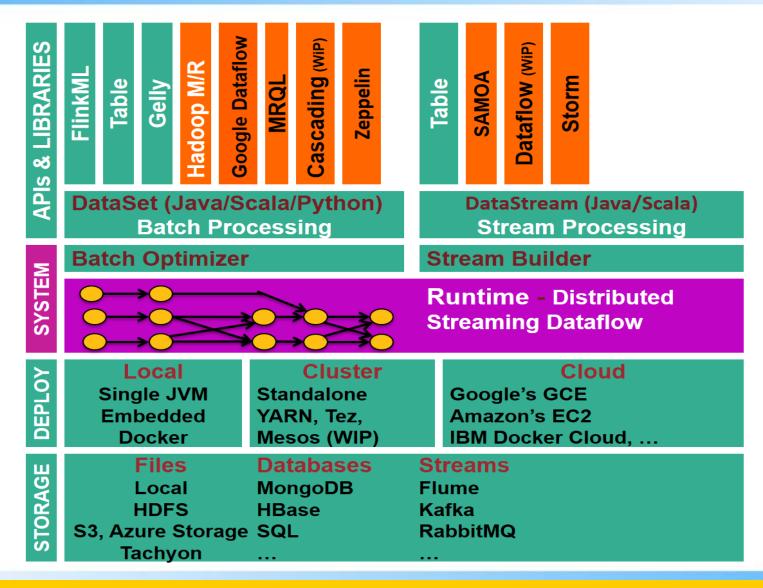
FlinkML: Machine Learning Library for Flink

Gelly: Graph Library for Flink

Table: Relational Queries

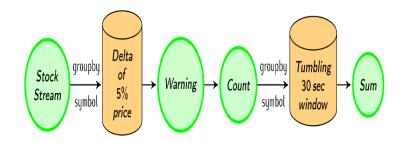
FlinkCEP: Complex Event Processing for Flink

### **Apache Flink (Cont.)**

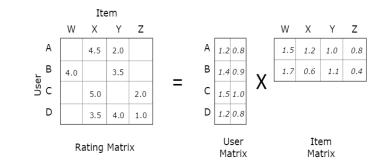


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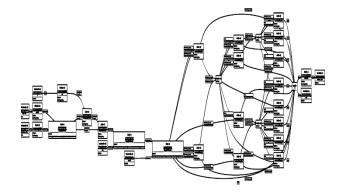
## ARTIFICATE MINISTER APAche Flink (Cont.)



#### **Real-Time stream processing**



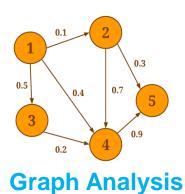
#### **Machine Learning**



**Batch Processing** 

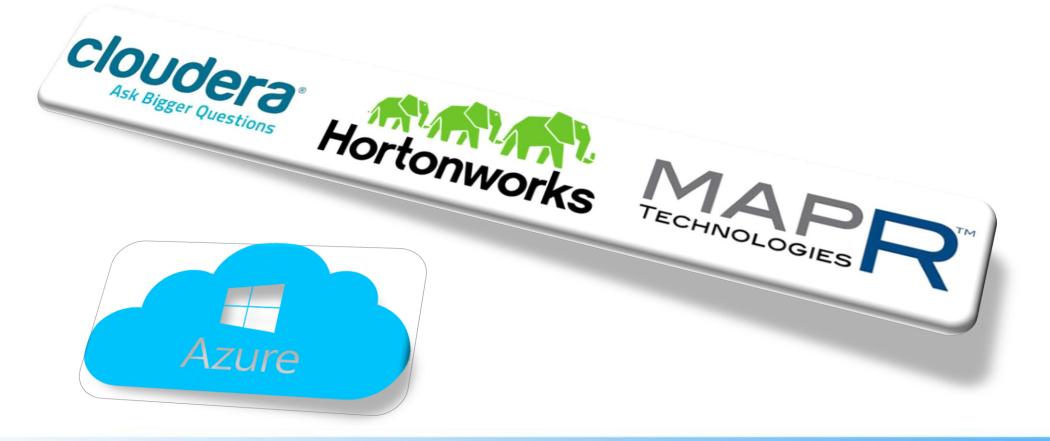
DataSet APIDataStream APIBatch ProcessingStream Processing

Runtime Distributed Streaming Dataflow





Cloud Computing Platform & Services
(Cloudera, Hortonworks, MapR, Azure)



### Apache Spark

- Processing engine; instead of just "map" and "reduce", defines a large set of operations (transformations & actions)
- Operations can be arbitrarily combined in any order
- **4** Open source software
- Supports Java, Scala and Python
- 4 Key construct: Resilient Distributed Dataset (RDD)

# RDD Operations

| Transformations  | Actions   |
|--|---|
| map (func)<br>flatMap(func)<br>filter(func)<br>groupByKey()<br>reduceByKey(func)<br>mapValues(func)<br>sample()<br>union(other)<br>distinct()<br>sortByKey() | reduce(func)<br>collect()<br>count()<br>first()<br>take(n)<br>saveAsTextFile(path)<br>countByKey()<br>foreach(func)<br> |
|  |   |

### Sample Spark transformations

- # <u>map(func)</u>: Return a new distributed dataset formed by passing each element of the source through a function func.
- filter(func): Return a new dataset formed by selecting those elements of the source on which func returns true
- union(otherDataset): Return a new dataset that contains the union of the elements in the source dataset and the argument.

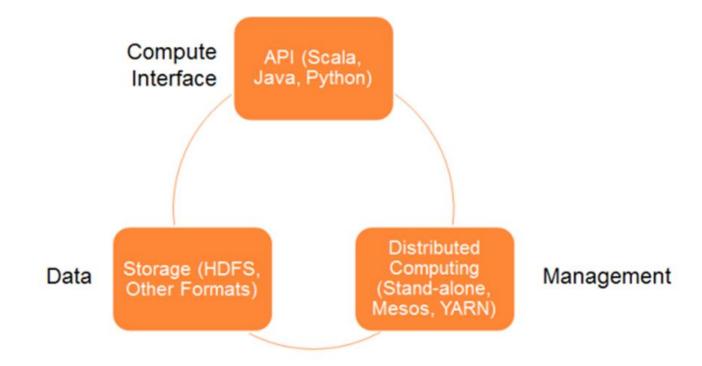
## ARTIFICIAL INTEREMENT Sample Spark Actions

- intersection(otherDataset): Return a new RDD that contains the intersection of elements in the source dataset and the argument.
- distinct([numTasks])): Return a new dataset that contains the distinct elements of the source dataset
- Join(otherDataset, [numTasks]): When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key. Outer joins are supported through leftOuterJoin, rightOuterJoin, and fullOuterJoin.

## Sample Spark Actions

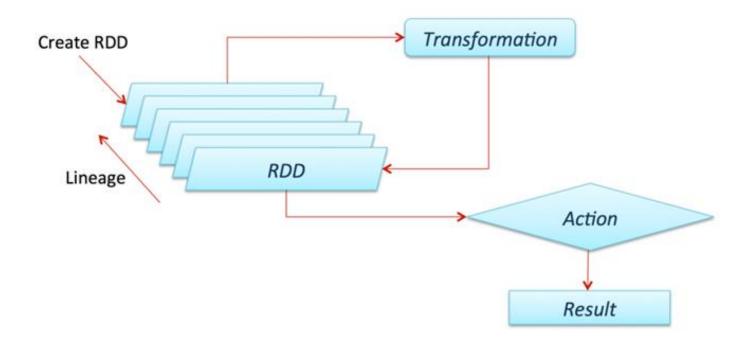
- Final states and returns one). The function should be commutative and associative so that it can be computed correctly in parallel.
- <u>collect()</u>: Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.
- <u>count()</u>: Return the number of elements in the dataset.







Fault tolerance because an RDD know how to recreate and re-compute the datasets. RDDs are immutable.





| Hadoop   | Spark  |
|--|--|
| Map & Reduce -> suitable for on-<br>pass computations  | multi-step data pipelines using directed acyclic graph ( <u>DAG</u> ) pattern. |
| Clusters are hard to set up and manage   | supports in-memory data sharing across DAGs.                                   |
| need to integrate with Mahout<br>(Machine Learning) and Storm<br>(Streaming data processing) | Spark as an alternative to Hadoop<br>MapReduce                                 |

#### Gray sort competition: Winner Spark-based (previously MR)

#### Sort benchmark, Daytona Gray: sort of 100 TB of data (1 trillion records)

|                            | Hadoop MR<br>Record           | Spark<br>Record (2014)              |                         |  |
|----------------------------|-------------------------------|-------------------------------------|-------------------------|--|
| Data Size                  | 102.5 TB                      | 100 TB                              |                         |  |
| Elapsed Time               | 72 mins                       | 23 mins                             | Spark-based             |  |
| # Nodes                    | 2100                          | 206                                 | System                  |  |
| # Cores                    | 50400 physical                | 6592 virtualized                    | 3x faster               |  |
| Cluster disk<br>throughput | 3150 GB/s<br>(est.)           | 618 GB/s                            | with 1/10<br># of nodes |  |
| Network                    | dedicated data center, 10Gbps | virtualized (EC2) 10Gbps<br>network |                         |  |
| Sort rate                  | <b>1.42 TB/min</b>            | <b>4.27 TB/min</b>                  |                         |  |
| Sort rate/node             | 0.67 GB/min                   | 20.7 GB/min                         |                         |  |

http://databricks.com/blog/2014/11/05/spark-officially-sets-a-new-record-in-large-scale-sorting.html

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ARTIFICIAL I

### Spark vs. Hadoop MapReduce

- **4** Performance: Spark normally faster but with caveats
- Spark can process data in-memory; Hadoop MapReduce persists back to the disk after a map or reduce action
- Spark generally outperforms MapReduce, but it often needs lots of memory to do well; if there are other resource-demanding services or can't fit in memory, Spark degrades
- MapReduce easily runs alongside other services with minor performance differences, & works well with the 1-pass jobs it was designed for
- Ease of use: Spark is easier to program
- Data processing: Spark more general
- **4** Maturity: Spark maturing, Hadoop MapReduce mature

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