BIG DATA - HADOOP

Outline

- Introduction to BigData / Hadoop
- HDFS Overview
- MapReduce Framework
- YARN Overview

Introduction to Big Data / Hadoop

- What is BigData?
- 3Vs – Volume, Velocity, Varity
- Big Data in Industry
- Hadoop Overview
- Hadoop Characteristics and Benefits
  - Accessible, Robust, Scalable, Simple
  - Economical, Reliable, Flexible
- Hadoop Architecture
- Hadoop Ecosystem
- Hadoop 1.x vs Hadoop 2.x vs Hadoop 3.x

What is Big Data?

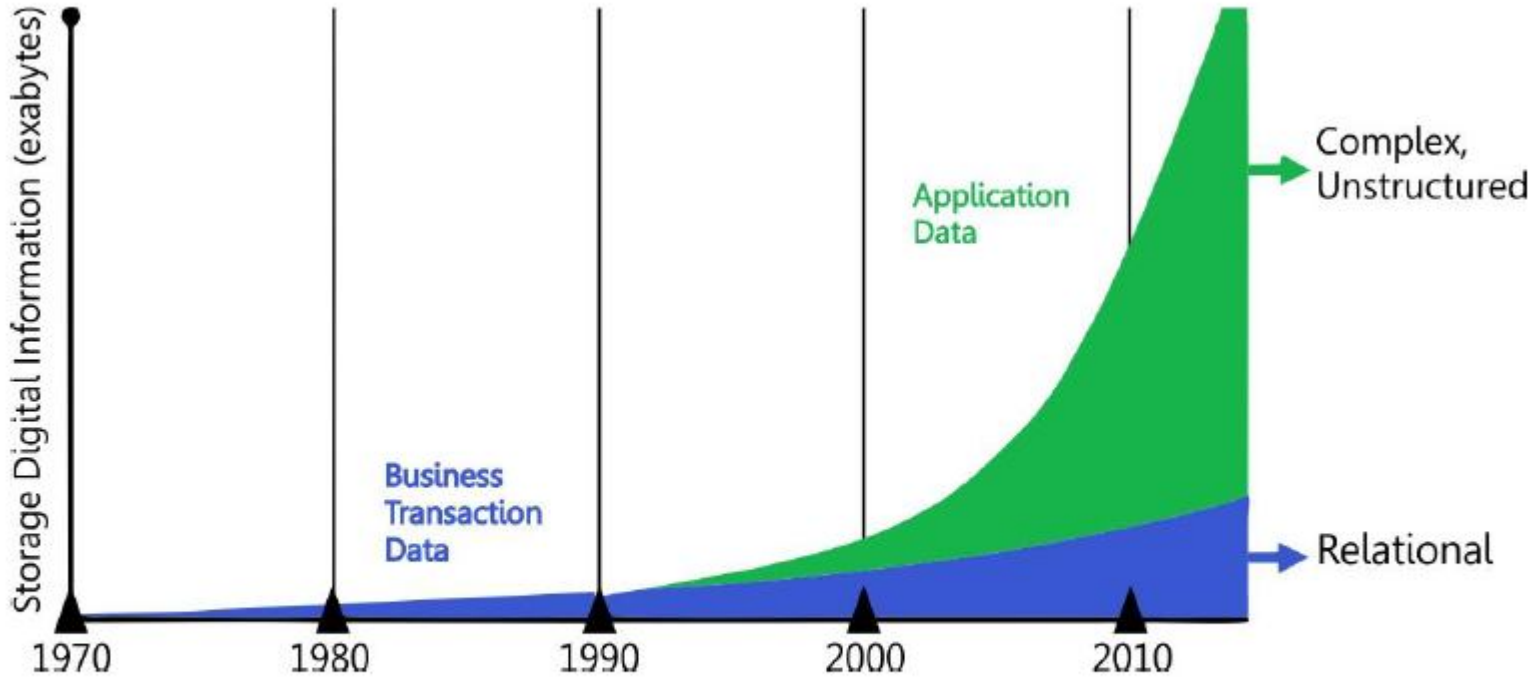
- Huge Amount of Data (Terabytes or Petabytes)
- Big data is the term for a collection of data sets so **large and complex** that it becomes **difficult** to process using on-hand database management tools or traditional data processing applications
- The challenges include capture, curation, storage, search, sharing, transfer, analysis, and visualization

Sources of Big Data Generation

- Systems / Enterprises generate huge amount of data from Terabytes to Petabytes of information

NYSE generates about one terabyte of new trade data per day to perform stock trading analytics to determine trends for optimal trades

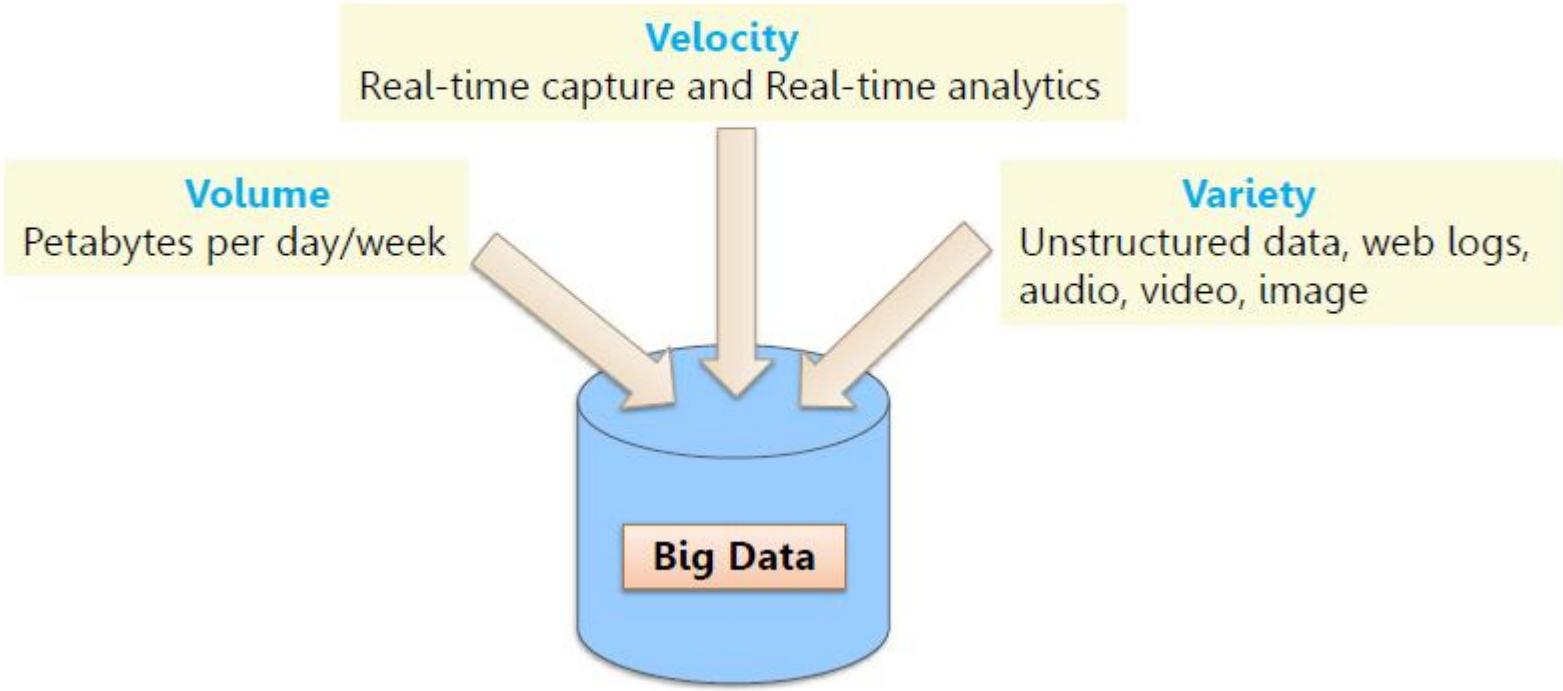
Challenges of Big Data World



- 2,500 exabytes of new information in 2012 with interest as primary driver
- Digital universe grew by 62% last year to 800K petabytes and will go to 1.2 "Zettabytes" this year

IBM’s Definition of Big Data

- IBM’s Definition – Big Data Characteristics
- http://www-01.ibm.com/software/data/bigdata/



Big Data in Industry

Web and e-tailing

- Recommendation Engines
- Ad Targeting
- Search Quality
- Abuse and Click Fraud Detection

Telecommunications

- Customer Churn Prevention
- Network Performance Optimization
- Calling Data Record (CDR) Analysis
- Analyzing Network to Predict Failure

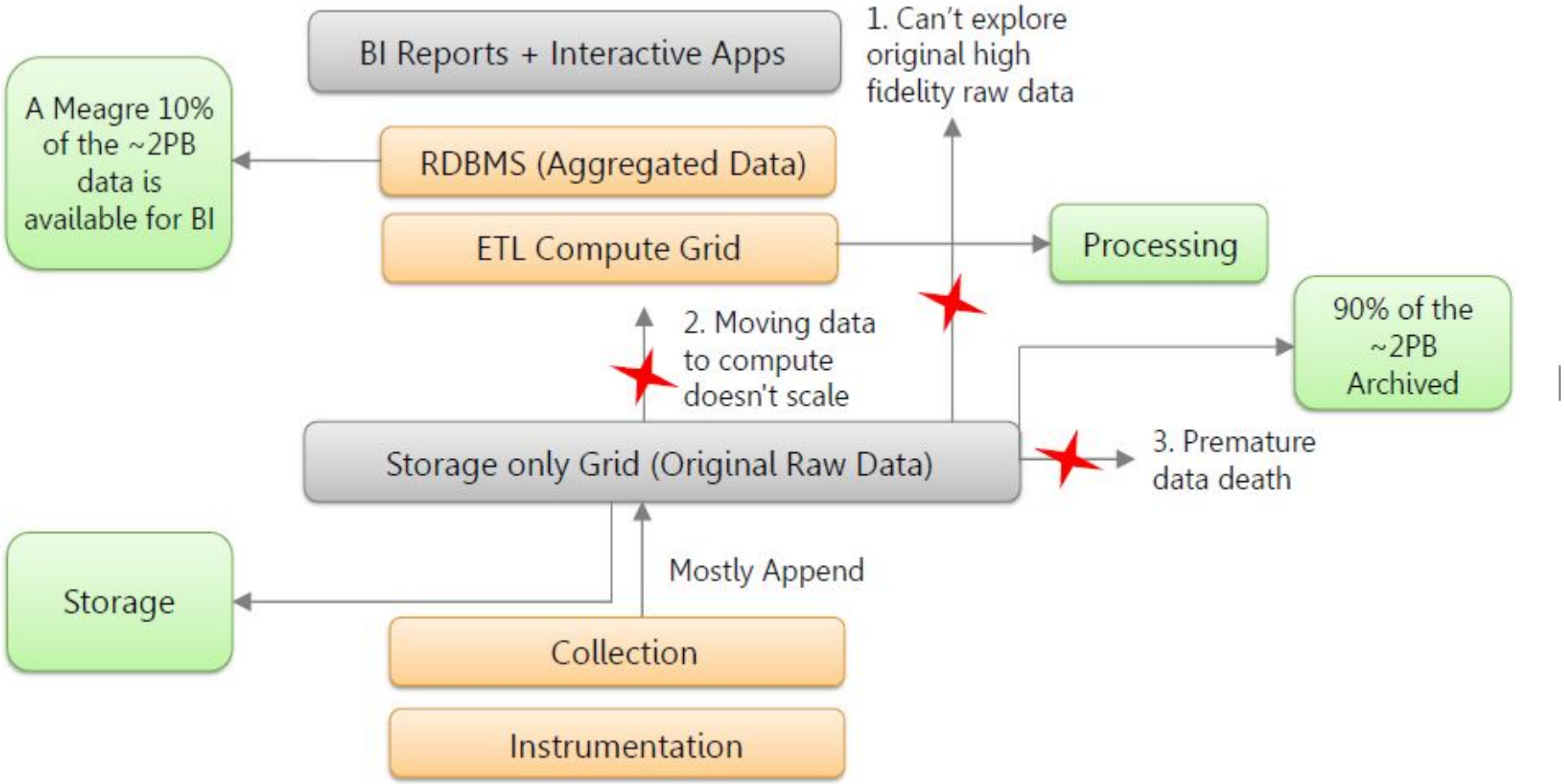
Government

- Fraud Detection and Cyber Security
- Welfare Schemes
- Justice

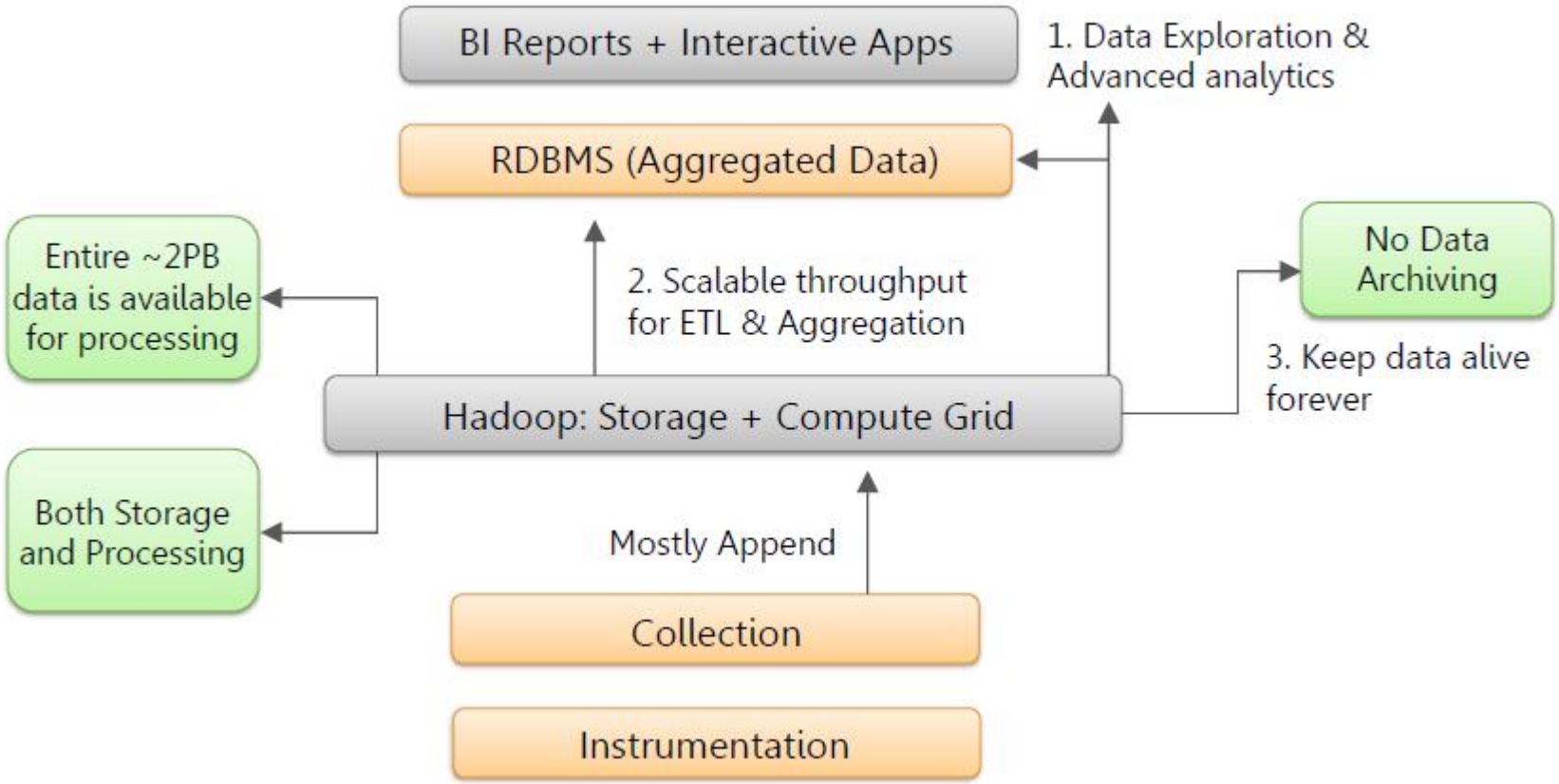
Healthcare and Life Sciences

- Health Information Exchange
- Gene Sequencing
- Serialization
- Healthcare Service Quality Improvements
- Drug Safety

Limitations of Traditional BI Architecture



Solution = Storage + Processing Layer

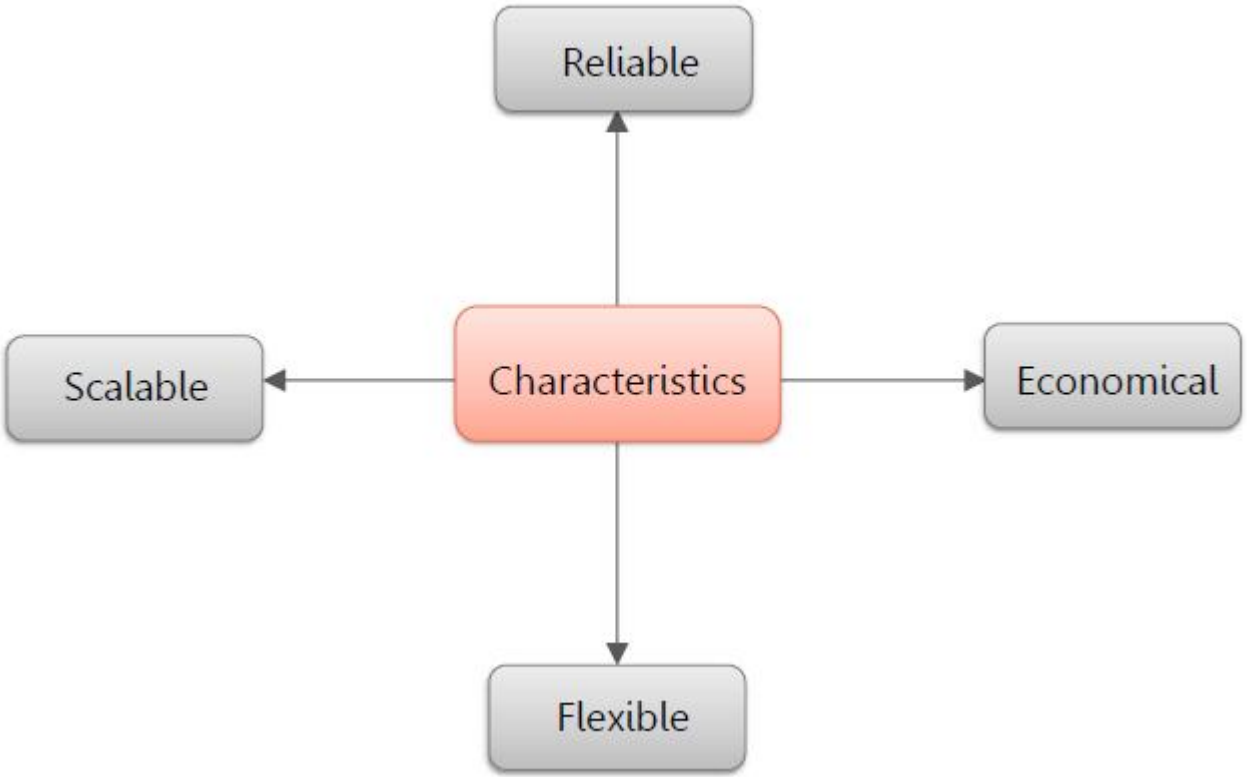


What is Hadoop?

Apache Hadoop is a framework that allows the distributed processing of large data sets across clusters of commodity computers using a simple programming model

It is an Open-source Data Management with scale-out storage and distributed processing

Hadoop Key Characteristics



Hadoop Core Components

Hadoop is a system for large scale data processing. It has two main components:

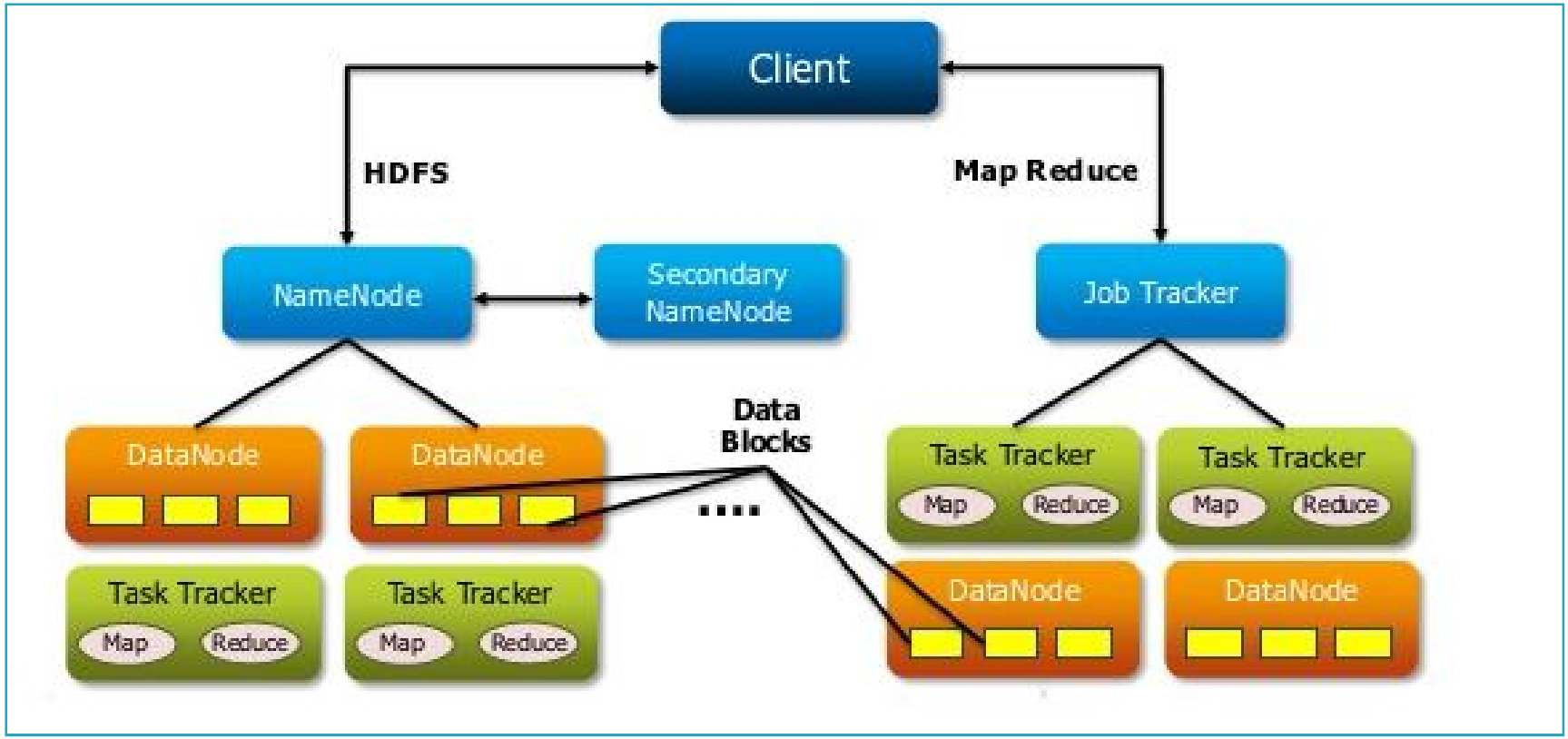
HDFS

- Distributed across "nodes"
- Natively redundant
- NameNode tracks locations

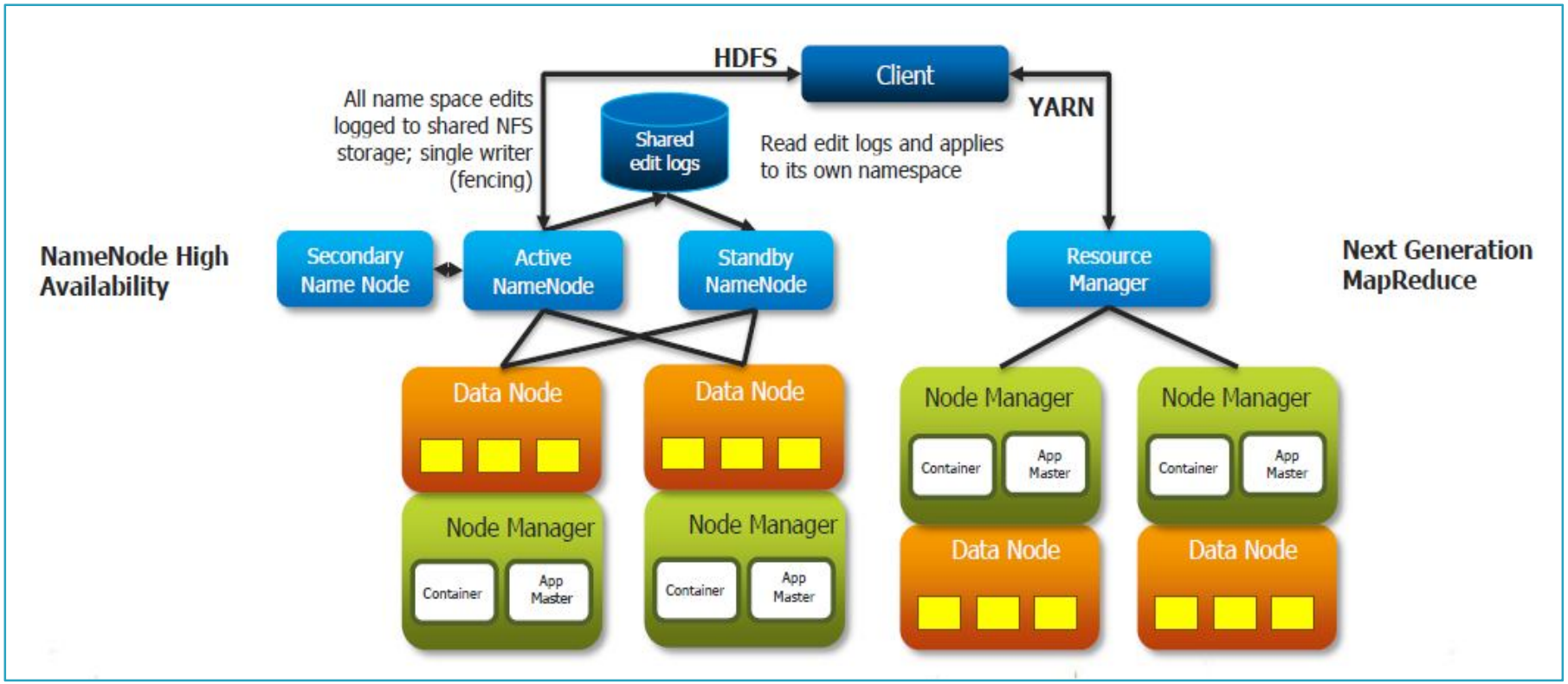
MapReduce

- Splits a task across processors
- "near" the data & assembles results
- Self-Healing, High Bandwidth
- Clustered storage
- JobTracker manages the TaskTrackers

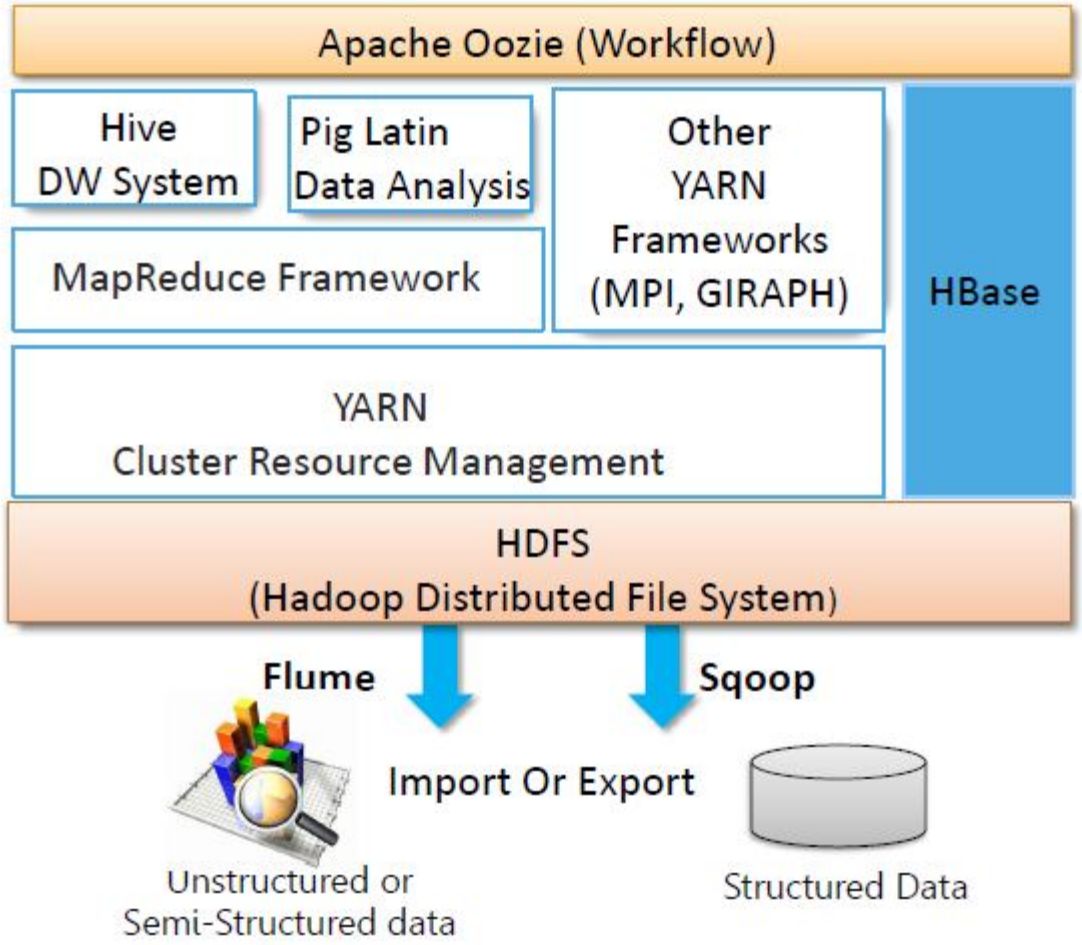
Hadoop Architecture (1.x)



Hadoop Architecture (2.x)



Hadoop EcoSystem



Different Hadoop Modes

You can use Hadoop in following modes:

Standalone (or Local) Mode

- No Hadoop daemons, entire process runs in a single JVM
- Suitable for running MapReduce programs during development
- Has no DFS access

Pseudo-Distributed Mode

- Hadoop daemons up, but on a single machine

Fully-Distributed/Clustered/Prod Mode

- Hadoop daemons run on a cluster of machines

Hadoop 1.X	Hadoop 2.X
Limited to 4,000 nodes per cluster	Up to 10,000 nodes per cluster
Jobtracker bottleneck	Efficient cluster utilization - YARN
Has only one namespace for handling HDFS	Supports multiple namespace for handling HDFS
Map and Reduce slots are static	Not restricted to Java
Has only one job - to run MapReduce	Any application can integrate with Hadoop

Hadoop 2.x vs Hadoop 3.x

Attributes	Hadoop 2.x	Hadoop 3.x
Handling Fault-tolerance	Through replication	Through erasure coding
Storage	Consumes 200% in HDFS	Consumes just 50%
Scalability	Limited	Improved
File System	DFS, FTP and Amazon S3	All features plus Microsoft Azure Data Lake File System
Manual Intervention	Not needed	Not needed
Scalability	Up to 10,000 nodes in a cluster	Over 10,000 nodes in a cluster
Cluster Resource Management	Handled by YARN	Handled by YARN
Data Balancing	Uses HDFS balancer for this purpose	Uses Intra-data node balancer

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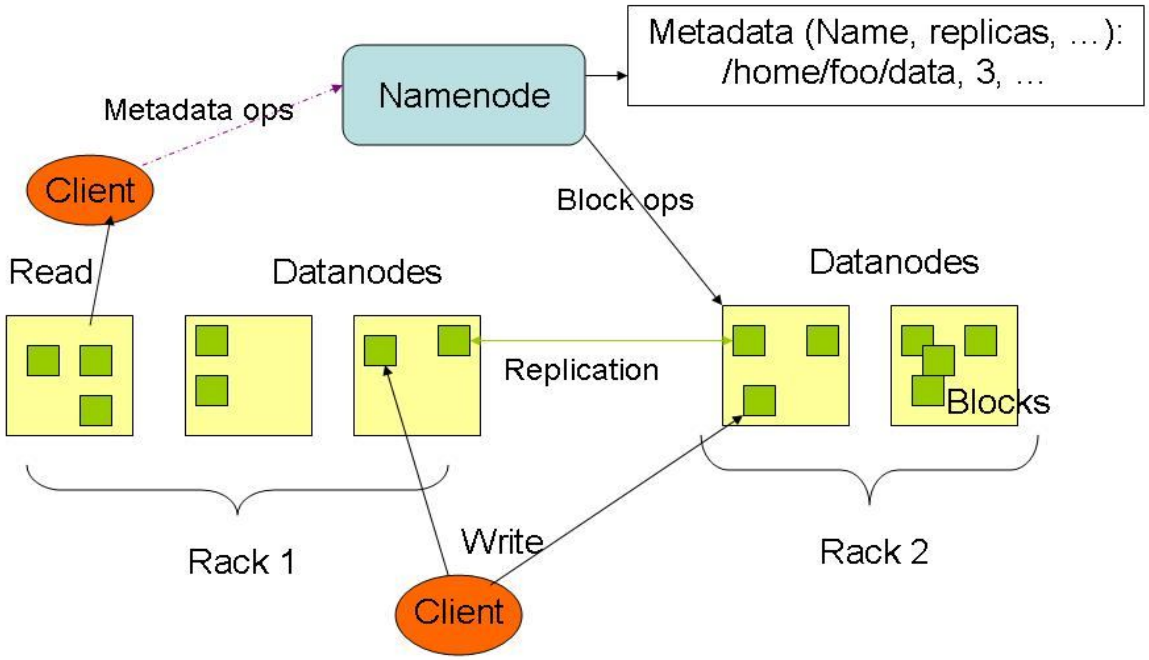
Hadoop Configuration Files

Configuration Filenames	Description of Log Files
hadoop-env.sh	Environment variables that are used in the scripts to run Hadoop
core-site.xml	Core Hadoop Configuration settings which are common to HDFS and MapReduce
hdfs-site.xml	HDFS Configuration settings for HDFS daemons, the NameNode, the secondary NameNode and the data nodes
mapred-site.xml	MapReduce specific Configuration settings
yarn-site.xml	Configuration settings for ResourceManager and NodeManager
masters	A list of machines (one per line) that each run a secondary NameNode
slaves	A list of machines (one per line) that each run a DataNode and a NodeManager

HDFS (Hadoop Distributed File System)

- HDFS Overview
- HDFS Architecture
- HDFS Components
  - Name Node
  - Secondary Name Node
  - Data Node
- HDFS File Write Anatomy
- HDFS File Read Anatomy
- Rack Awareness
- Hadoop File Formats
  - Text, Sequence, Avro, Parquet, ORC, etc.
- Hadoop Compression Techniques
  - Snappy, gzip, bgzip2, LZO, etc.
- Data Replication, Fault Tolerance, Resiliency, HA

HDFS Architecture



Name Node

Keeps Meta data in Main Memory

- The entire metadata is in main memory
- FS meta-data is not loaded from hard disk

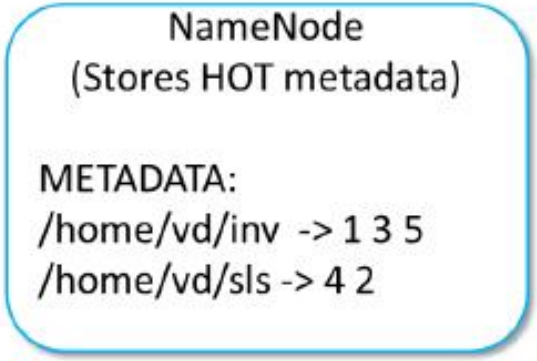
Metadata type

- Files in HDFS
- Data Blocks for each file
- DataNodes for each block
- File attributes, e.g. access time, replication factor, access control

Name Node (contd.)

Transaction Log

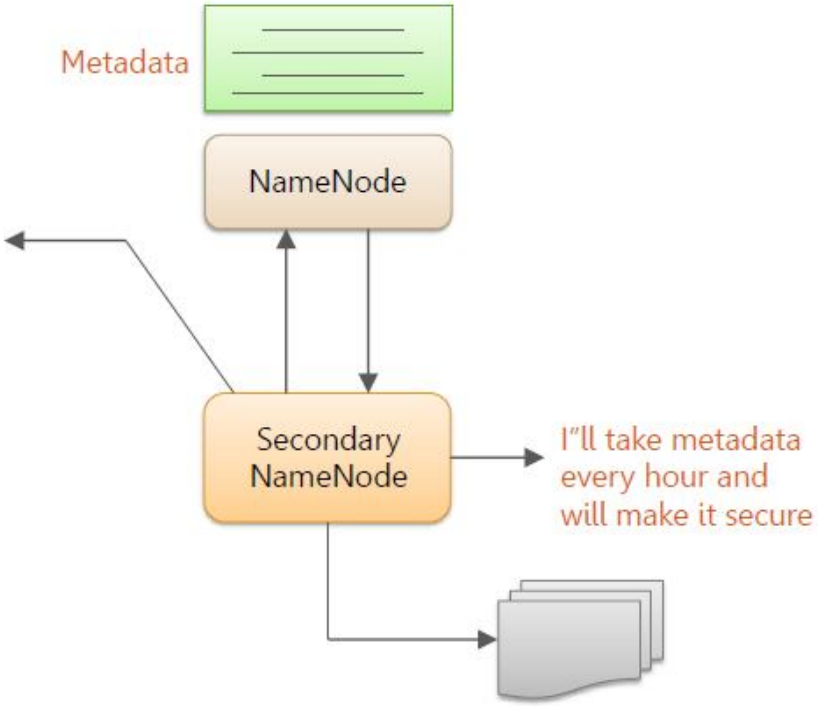
- Records file creations, file deletions. etc



NameNode:

- Keeps track of overall file directory structure and the placement of Data Block

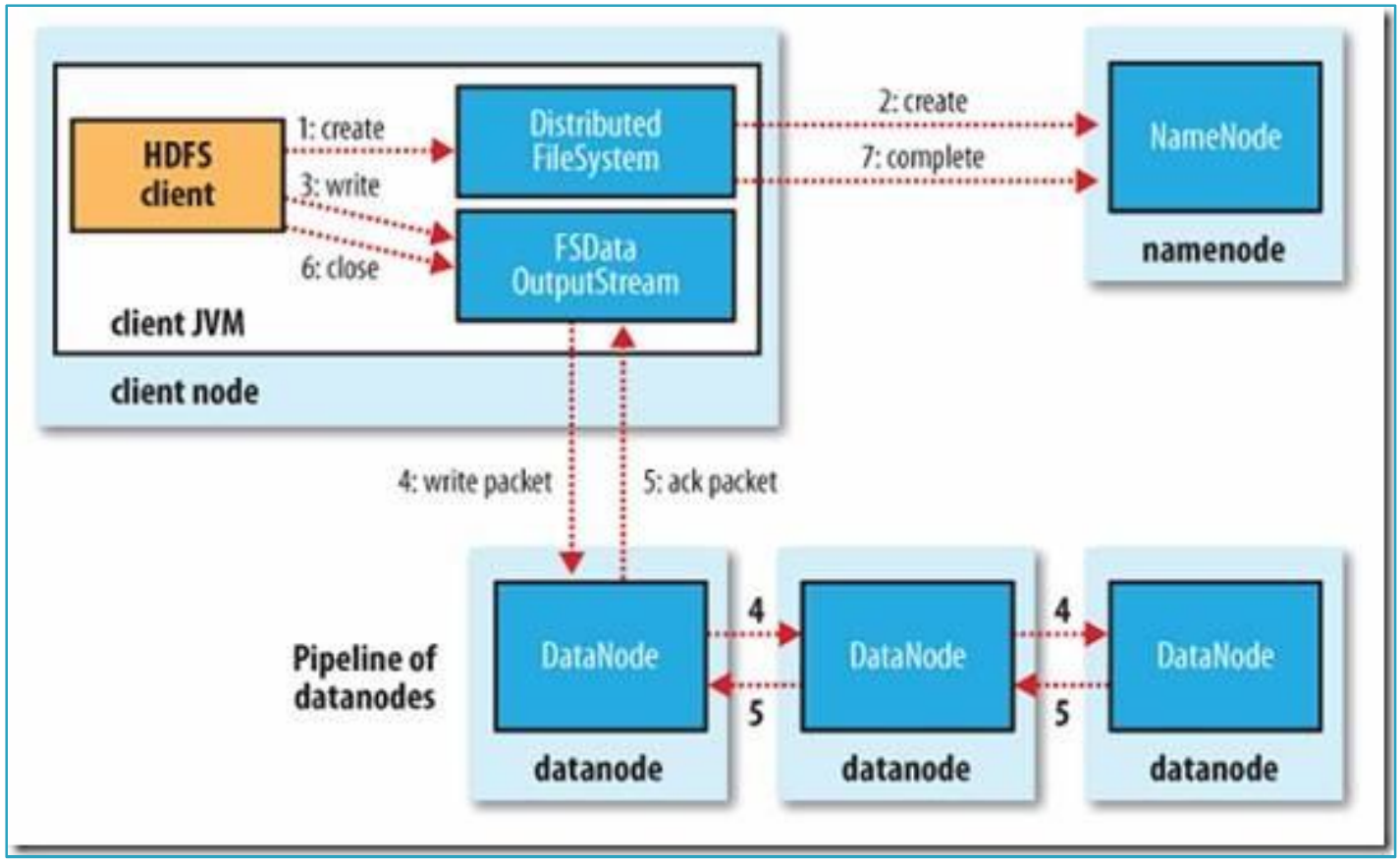
Secondary Name Node



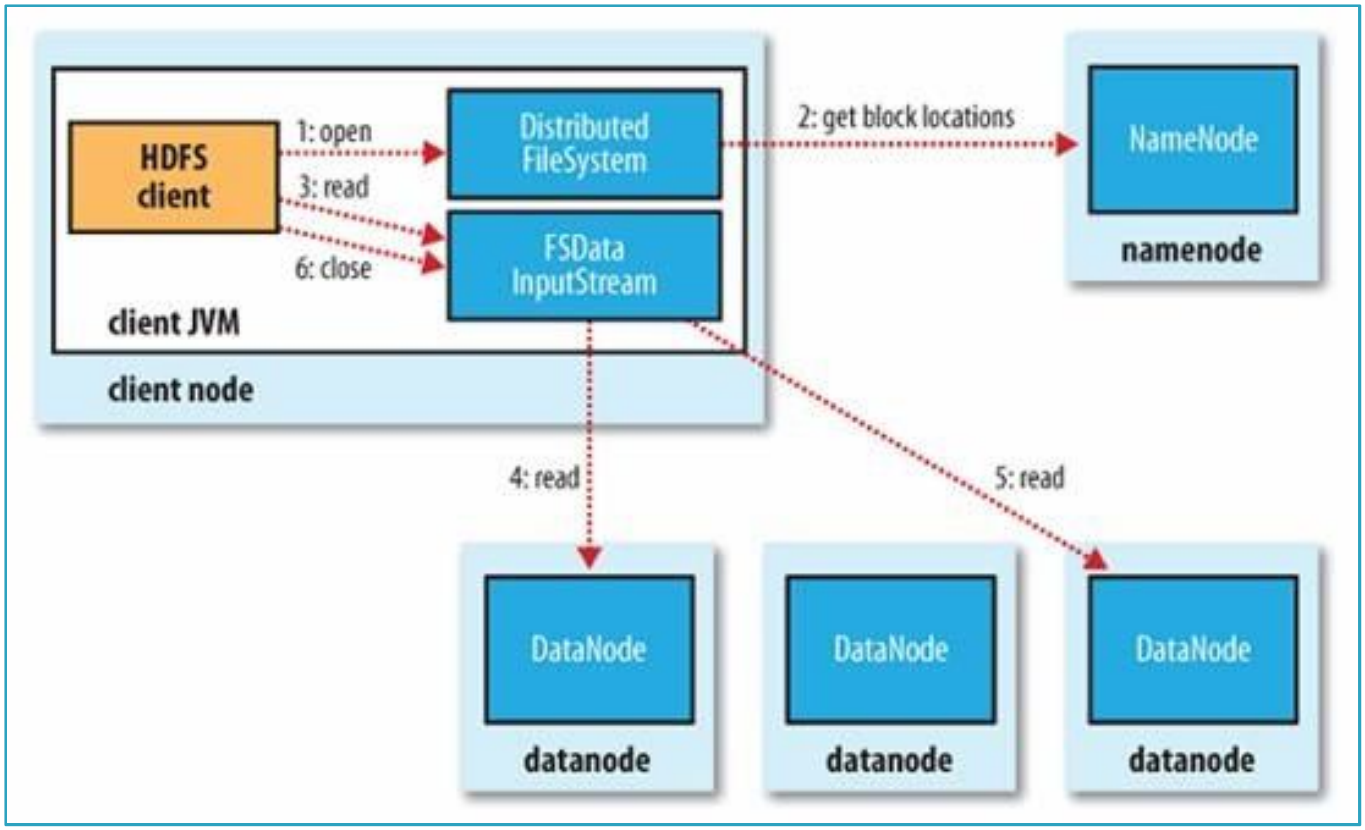
Secondary NameNode:

- In HDFS 1.0, not a hot standby for the NameNode
- By Default connects to NameNode every hour*
- Housekeeping, backup of NameNode metadata
- Saved metadata is used to bring up the Secondary NameNode

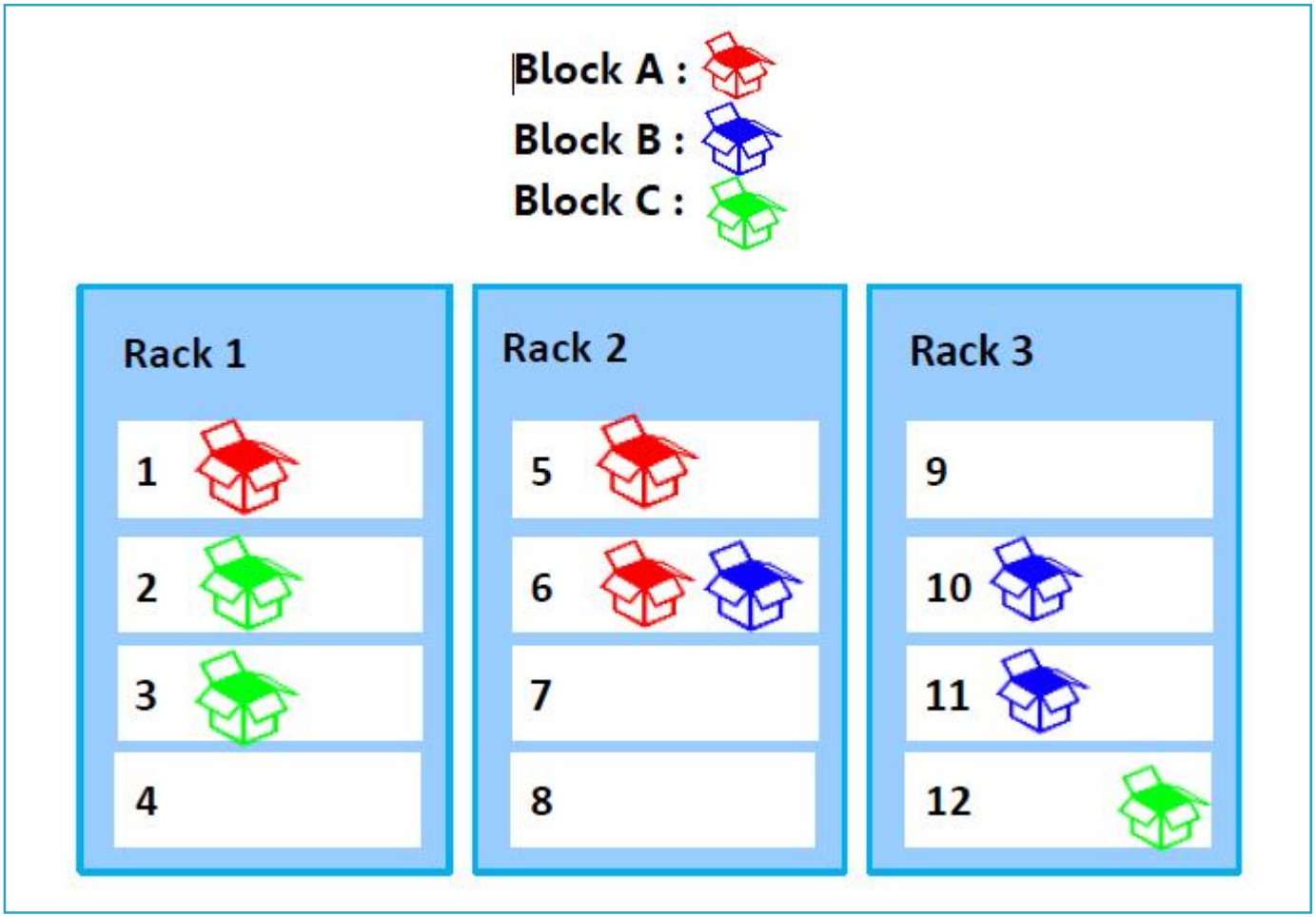
HDFS File Write Operation



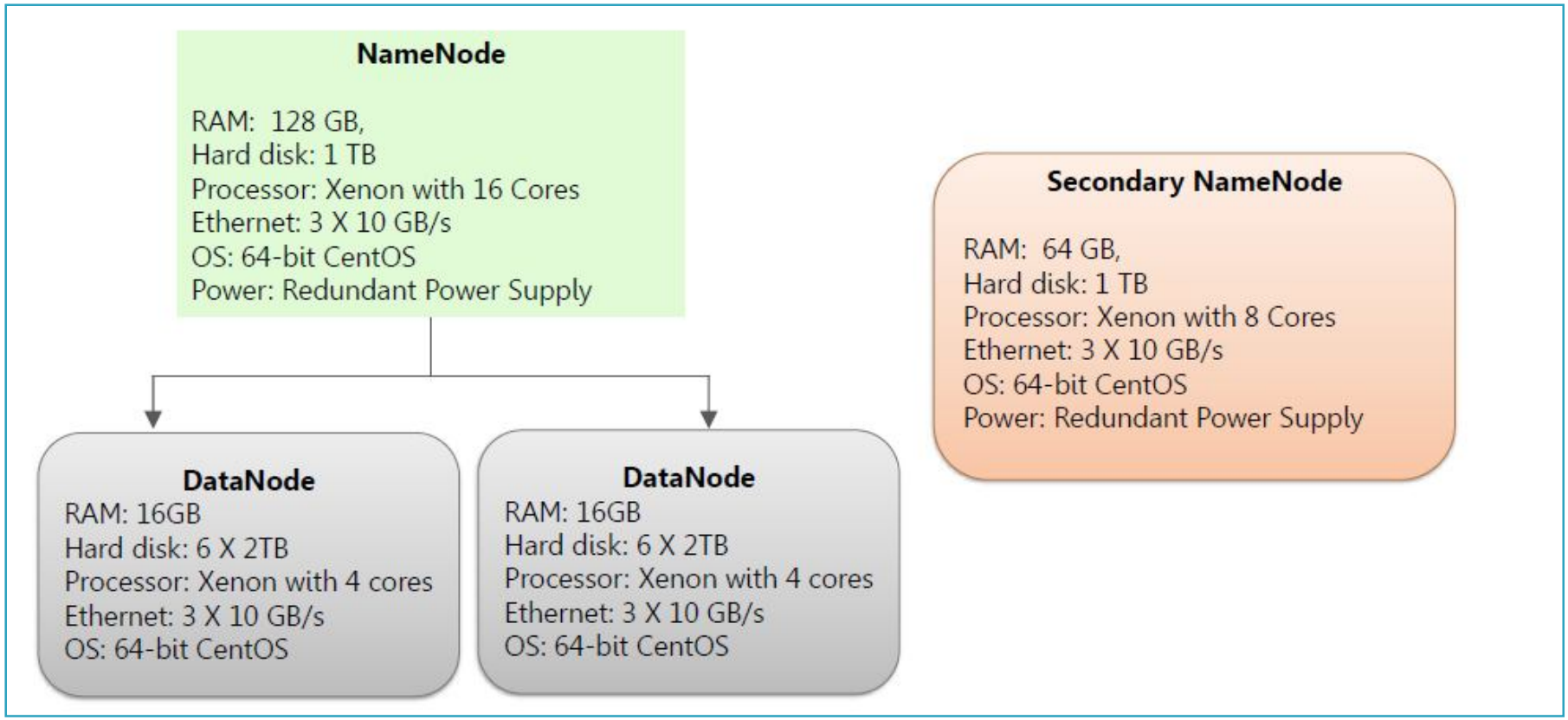
HDFS File Read Operation



Rack Awareness



Typical Production Hadoop Cluster



MapReduce Framework

- MapReduce Overview
- MapReduce Architecture
- MapReduce Concepts
  - Splits, Mappers, Reducers, Partitioners, Combiners and Counters
- Input / Output File Formats
- Map Side Join / Reduce Side Join
- YARN Overview
- YARN Components
  - Resource Manager, Node Manager, Container, App Master
- Job Scheduler
  - Fair Scheduler, Capacity Scheduler, etc.
- MR1 vs MR2
- MapReduce Job Execution
- Fault Tolerance, Resiliency, Reliability, HA

MapReduce Usecases

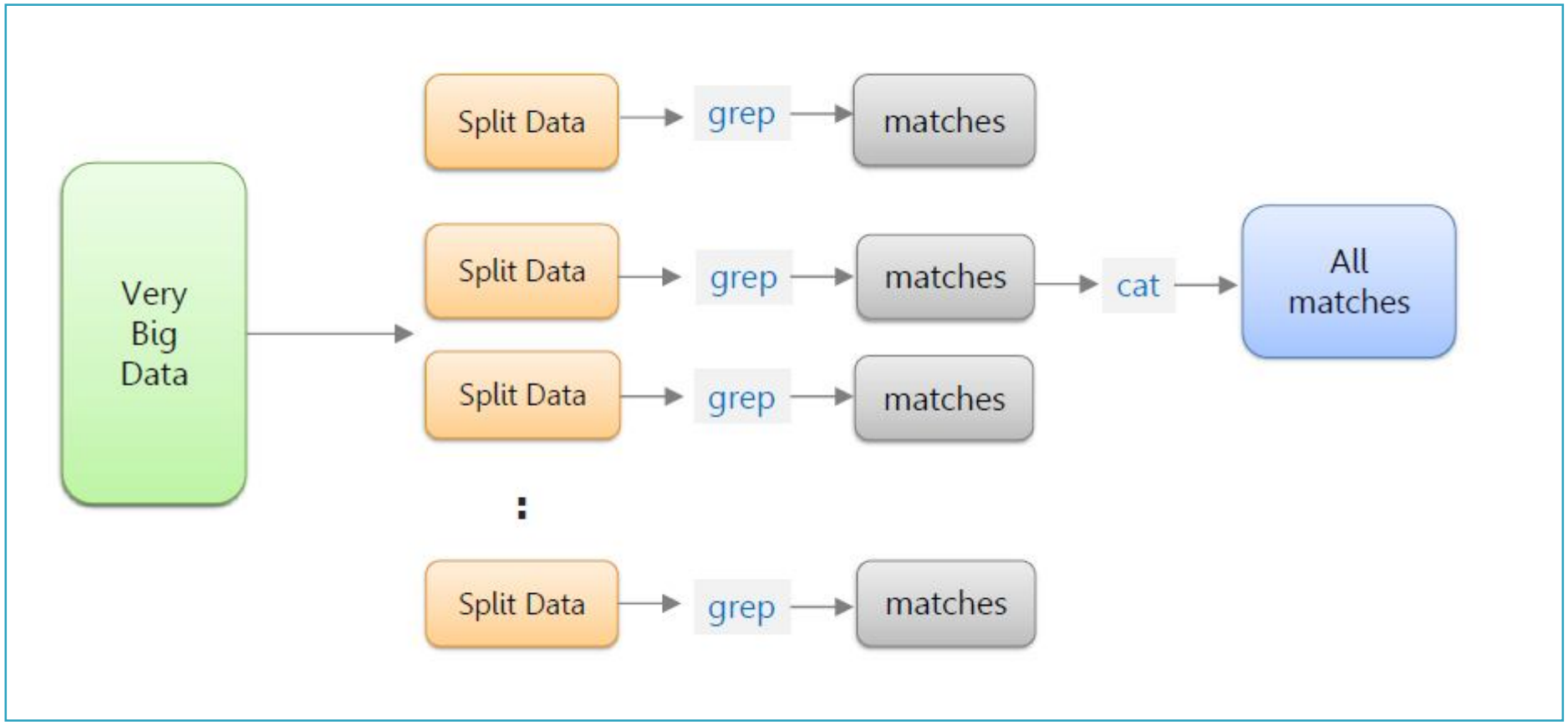
Problem Statement:

Find maximum stock market levels recorded in a span of 5 years

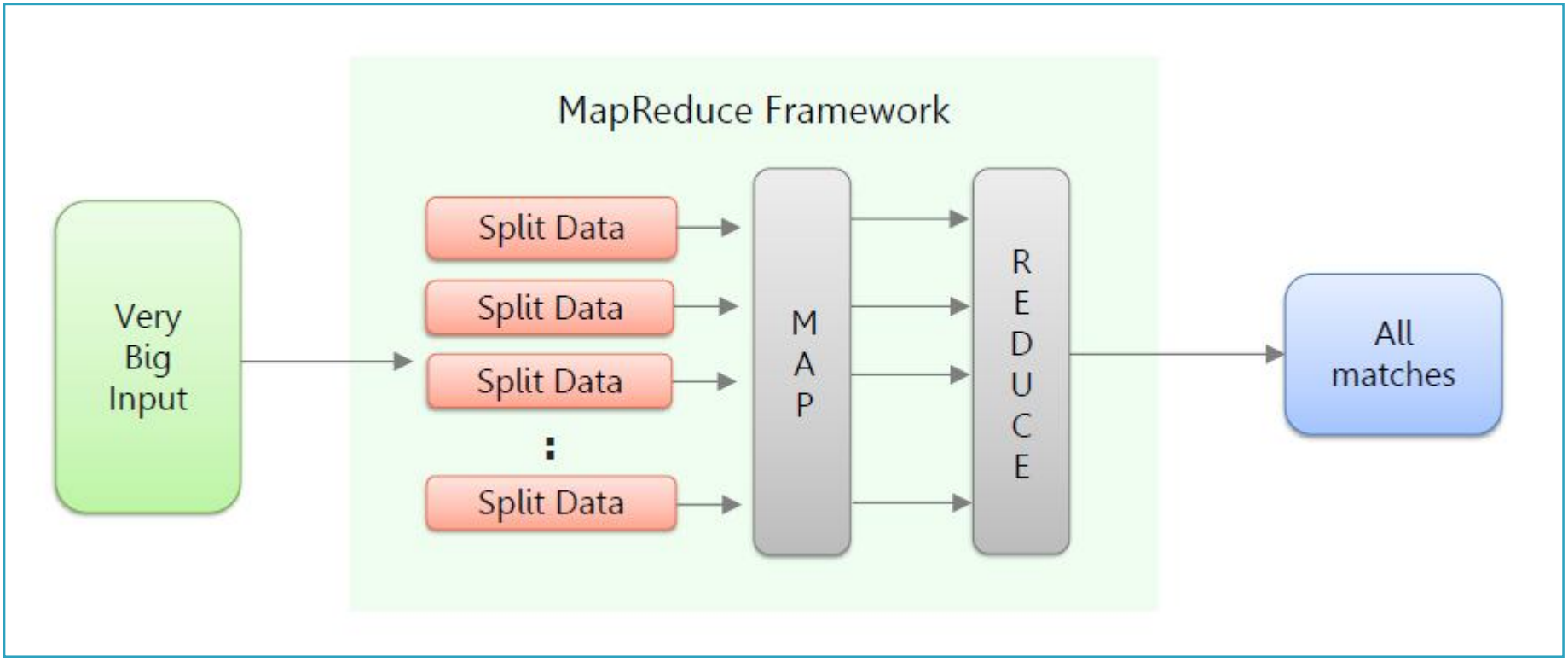
Problem Statement:

De-identify personal identifier information

Traditional Solution



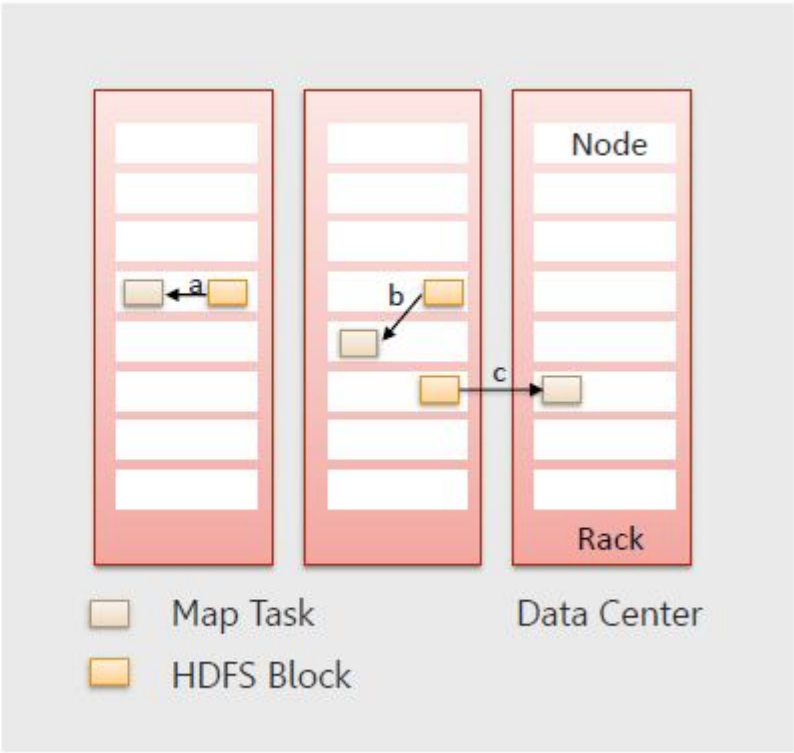
MapReduce Solution



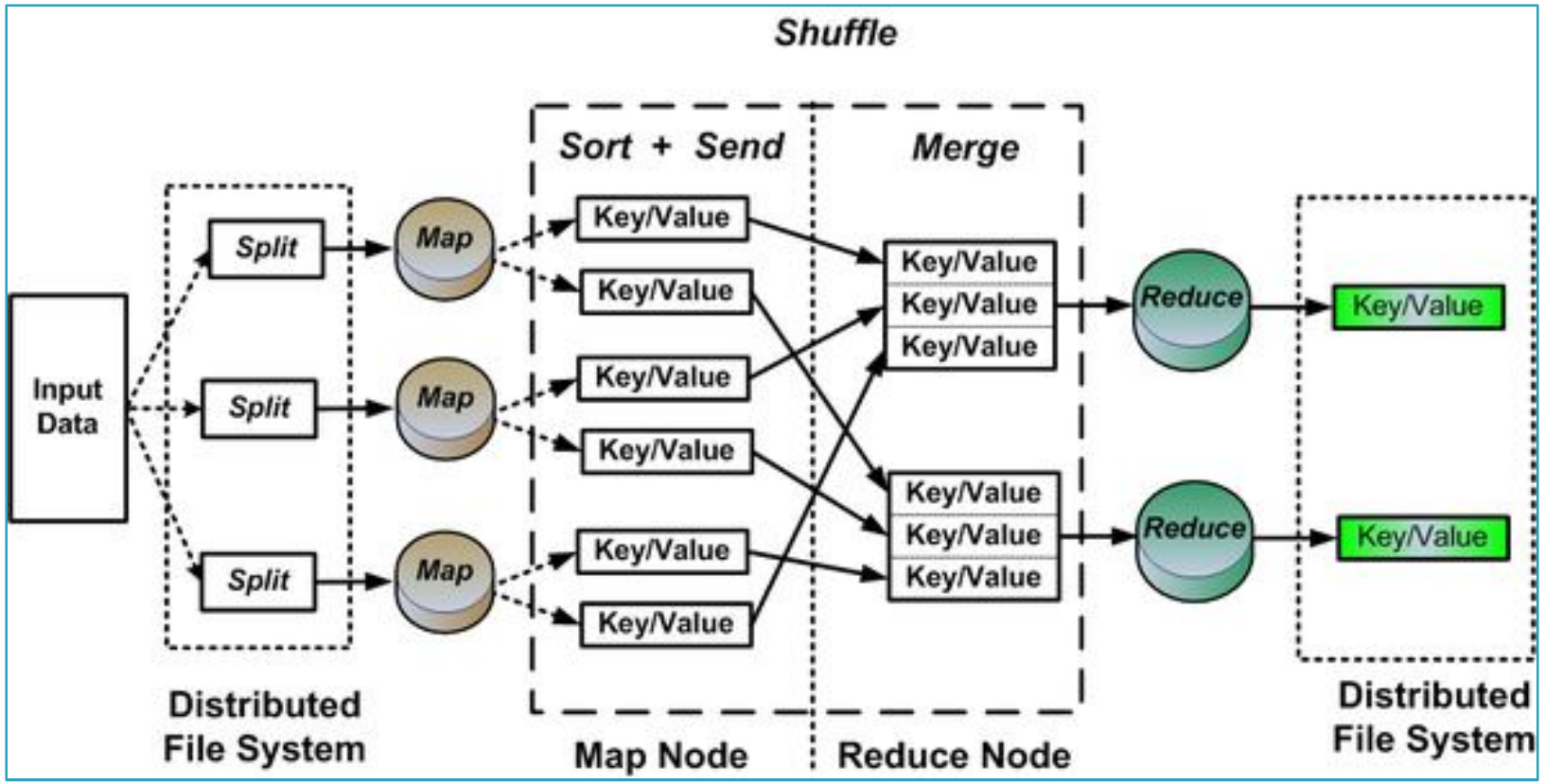
MapReduce Advantages

The two biggest advantages of Map Reduce are:

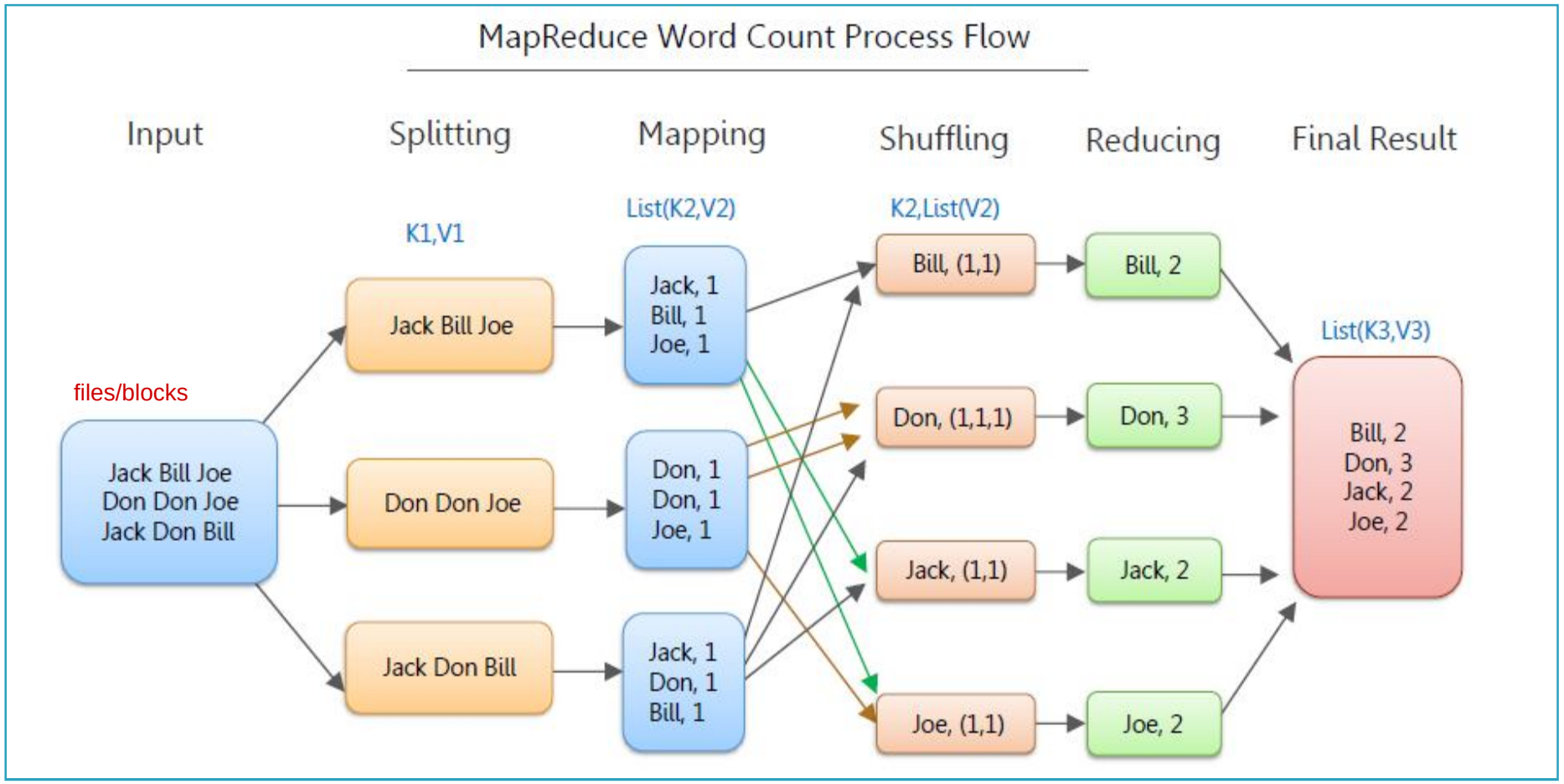
- It takes processing to the data
- It allows processing of data in parallel



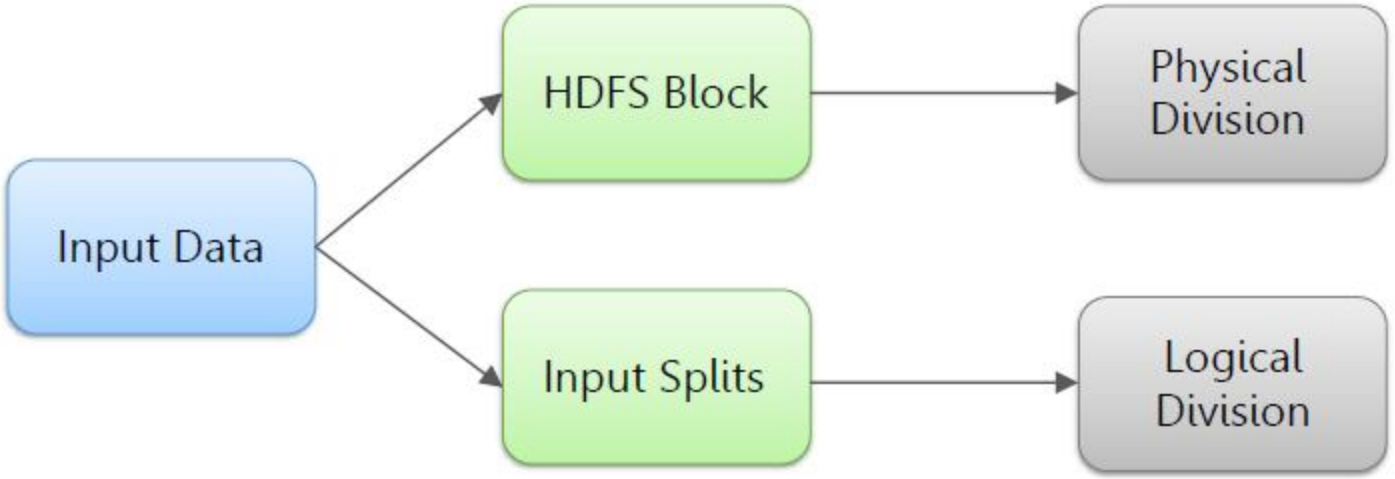
MapReduce Architecture



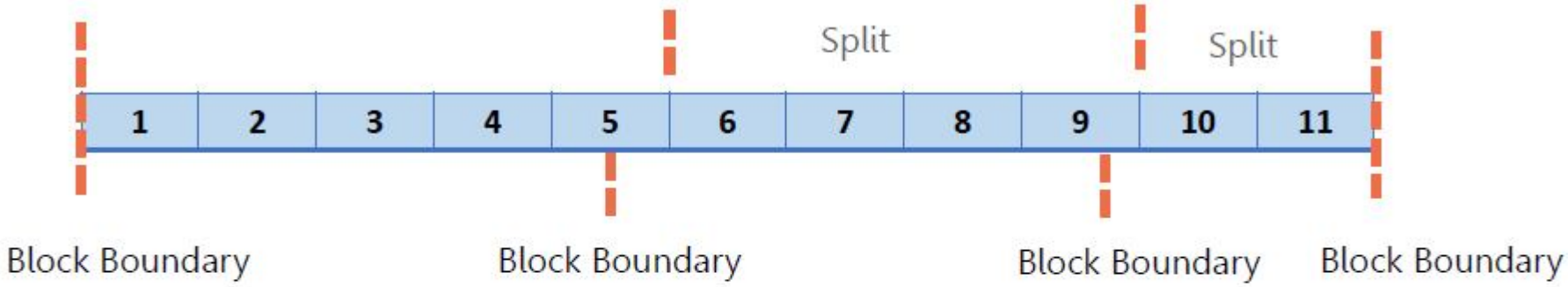
MapReduce Process Flow



Input Splits in MapReduce

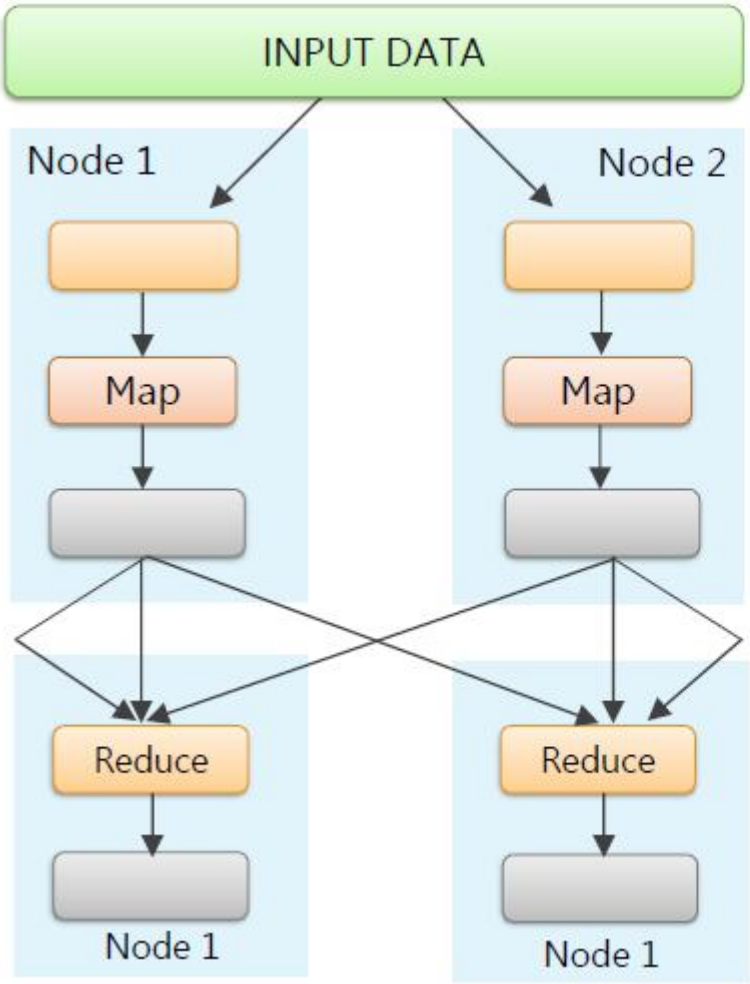


HDFS Blocks vs Input Splits



- In an ideal scenario, Block Size == Input Split Size
- However, Logical records rarely fit into HDFS blocks
- Logical Records may cross the block boundaries
- Deltas are read remotely

MapReduce Flow

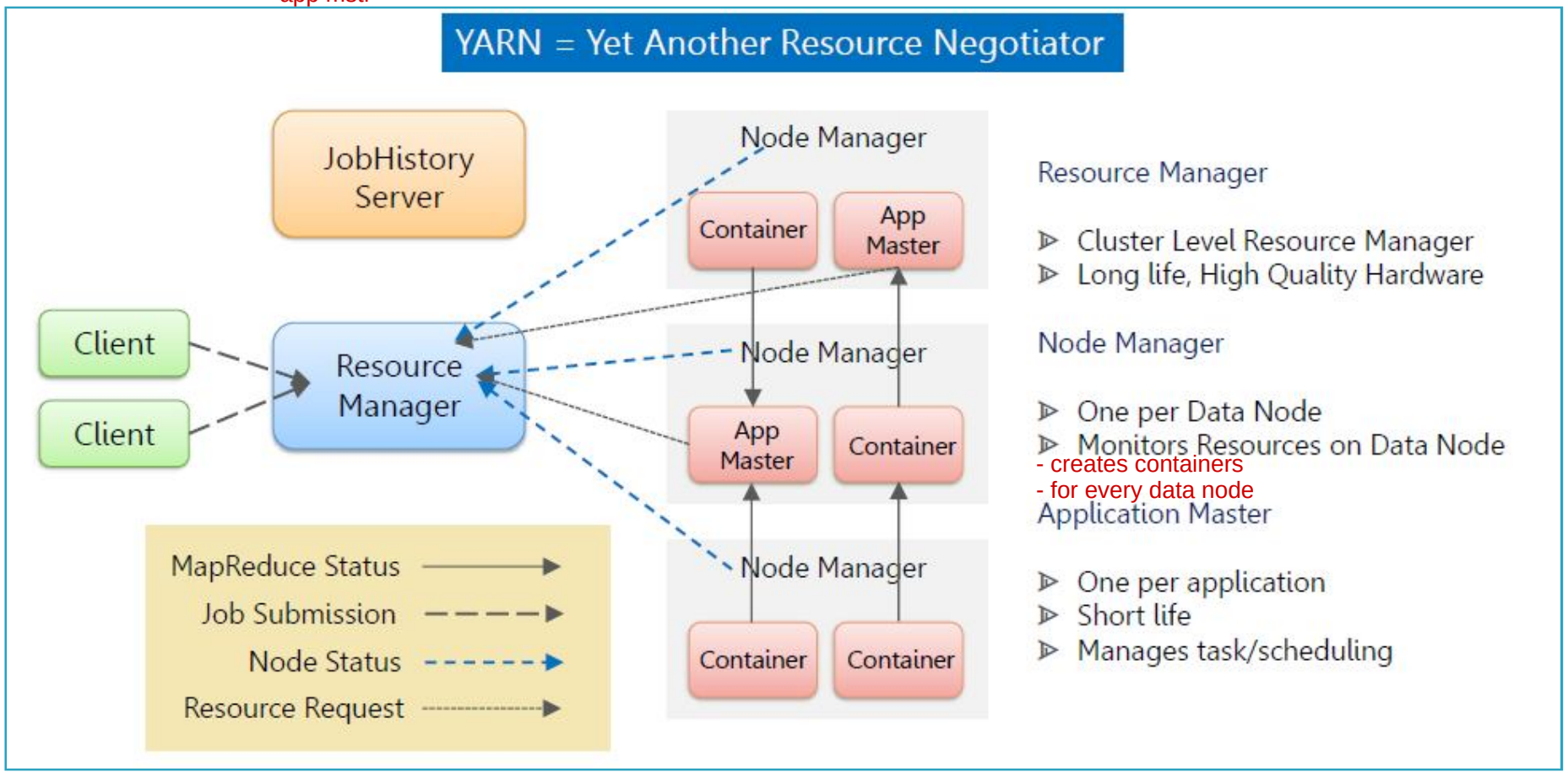


1. Input data is present in data nodes
2. Map tasks = Input Splits
3. Mappers produce intermediate data
4. Data is exchanged among nodes in "shuffling"
5. All data of same key goes to same reducer
6. Reducer output is stored at output location

- replaces Job tracker => single point of failure, not scalable

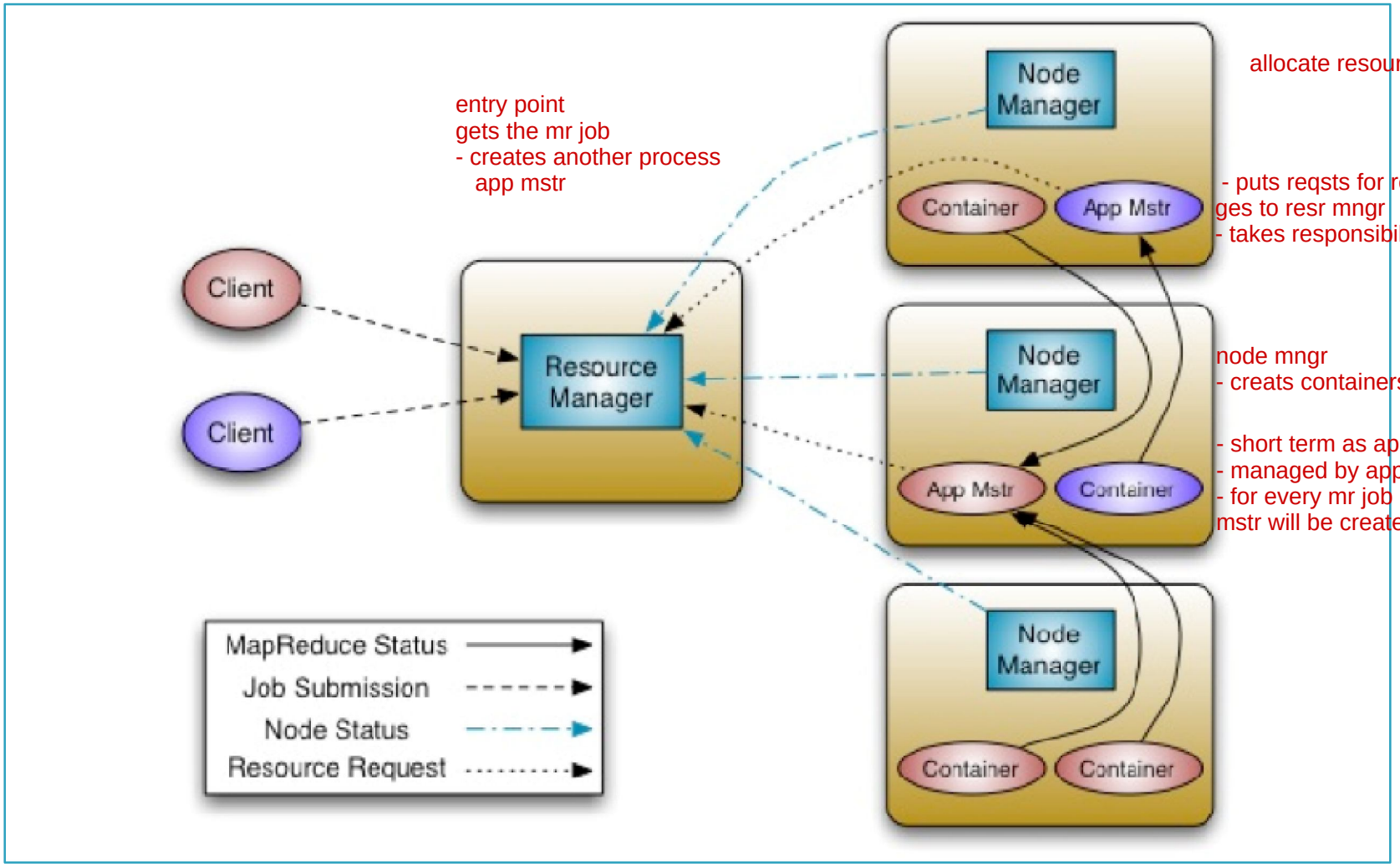
YARN

4 daemons
short term
- app mstr
- containers
long term
- resource mngr
- app mstr



YARN Architecture

task tracker => resource mngr + app mstr



entry point
gets the mr job
- creates another process
  app mstr

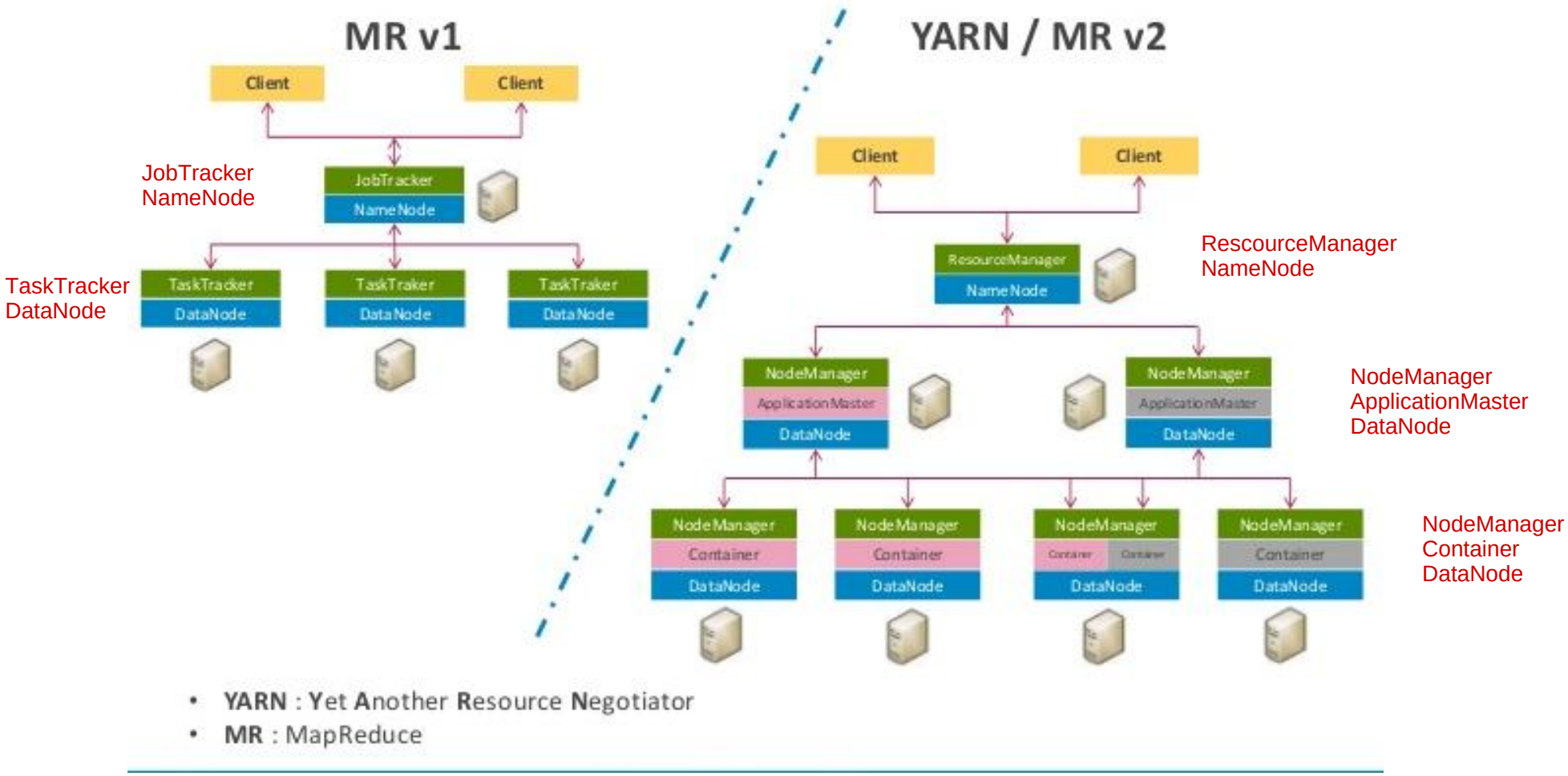
allocate resources.

- puts reqsts for resources and ges to resr mngr
- takes responsibility for exe tasks

node mngr
- creats containers

- short term as app mstr
- managed by app mstr
- for every mr job new c and app mstr will be created

MR1 vs YARN/MR2 Architecture



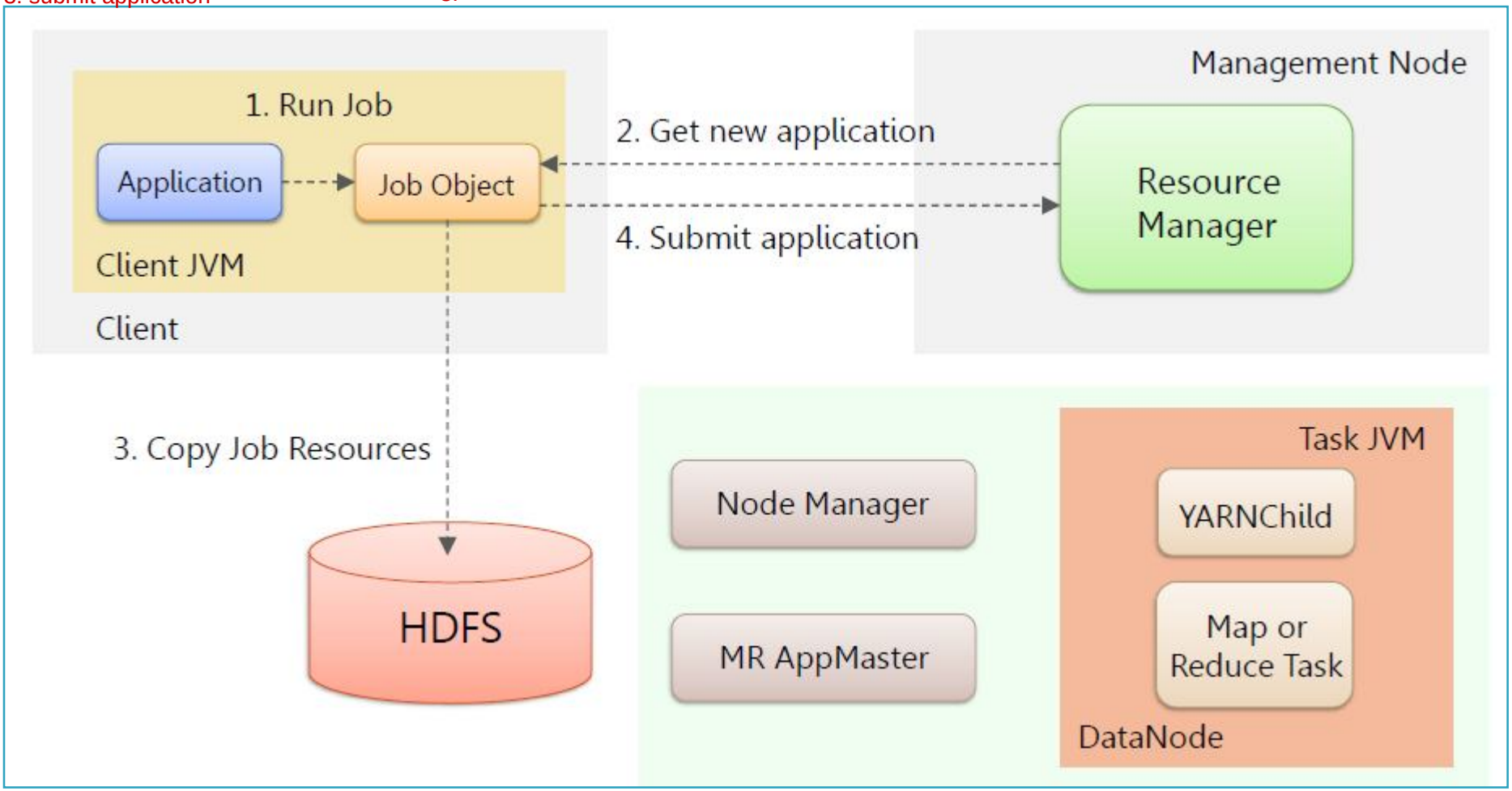
MR Job Execution YARN Flow

Phase 1
1: run job by running cmd
2: python script will be copied to hdfs
3: submit application

Phase 2
1: req goes to resource mgr
2: rs mgr reqts node mgr to create app mstr
3:

Phase 3
1: creates container
2: acquiring resources
3: map red tasks running

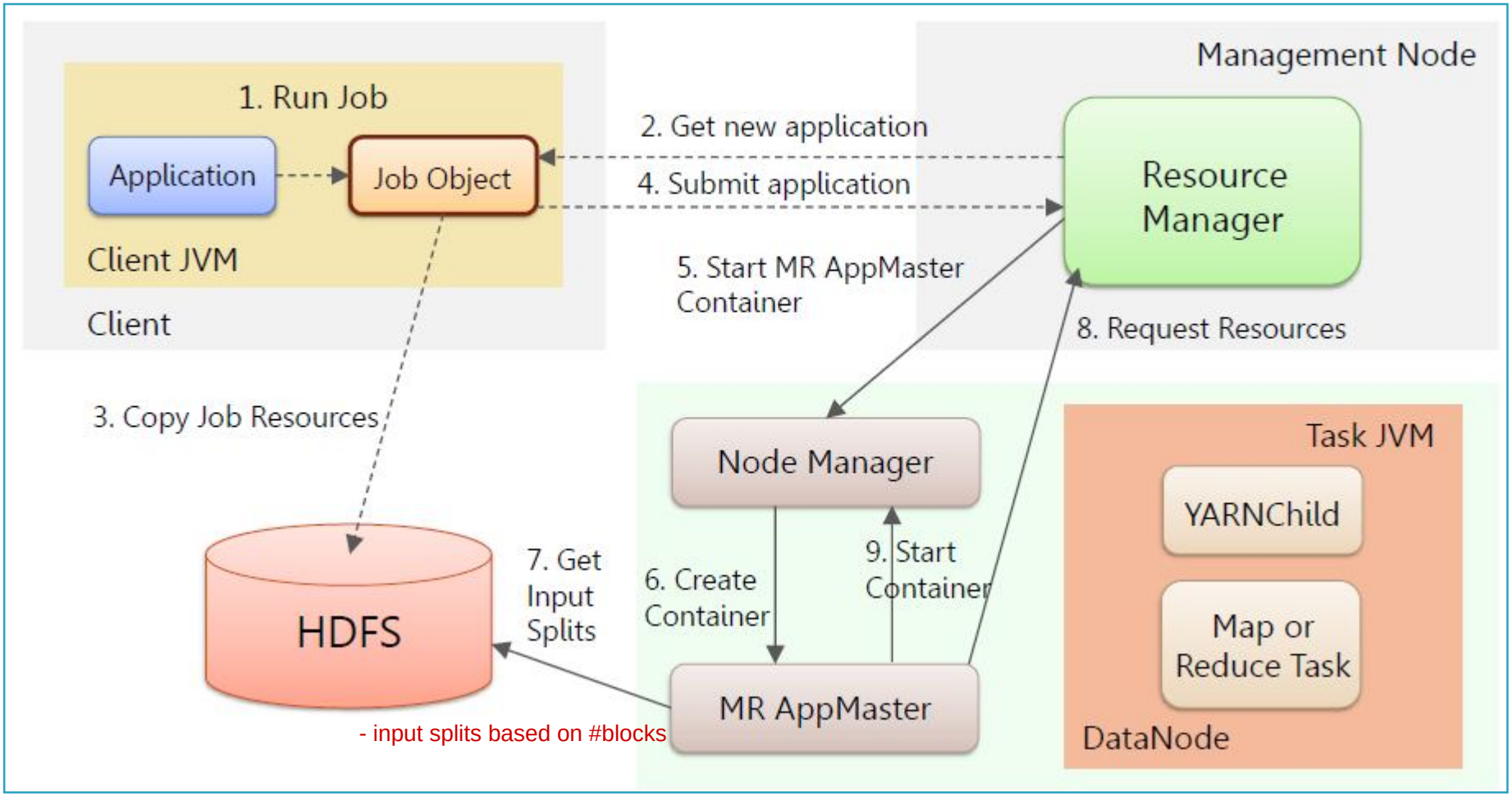
Moniter from
localhost:8042



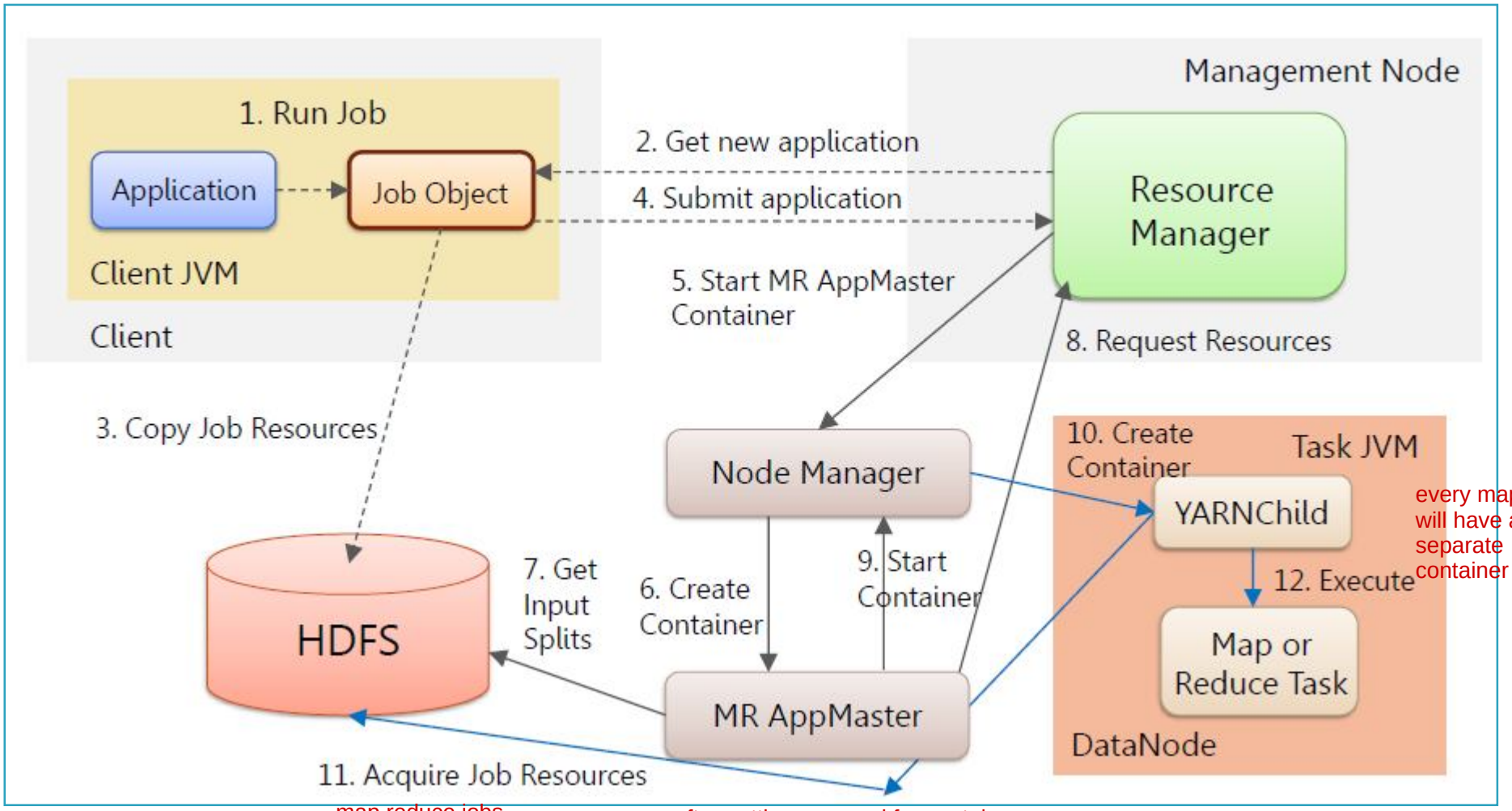
Counters: metrics
- input format counter
- output format counter
- sys counters
- job counters

Job history server:
- mr job history
$mr-jobhistory-daemon.sh start historyserver
$mr-jobhistory-daemon.sh stop historyserver
port: 19888

MR Job Execution YARN Flow



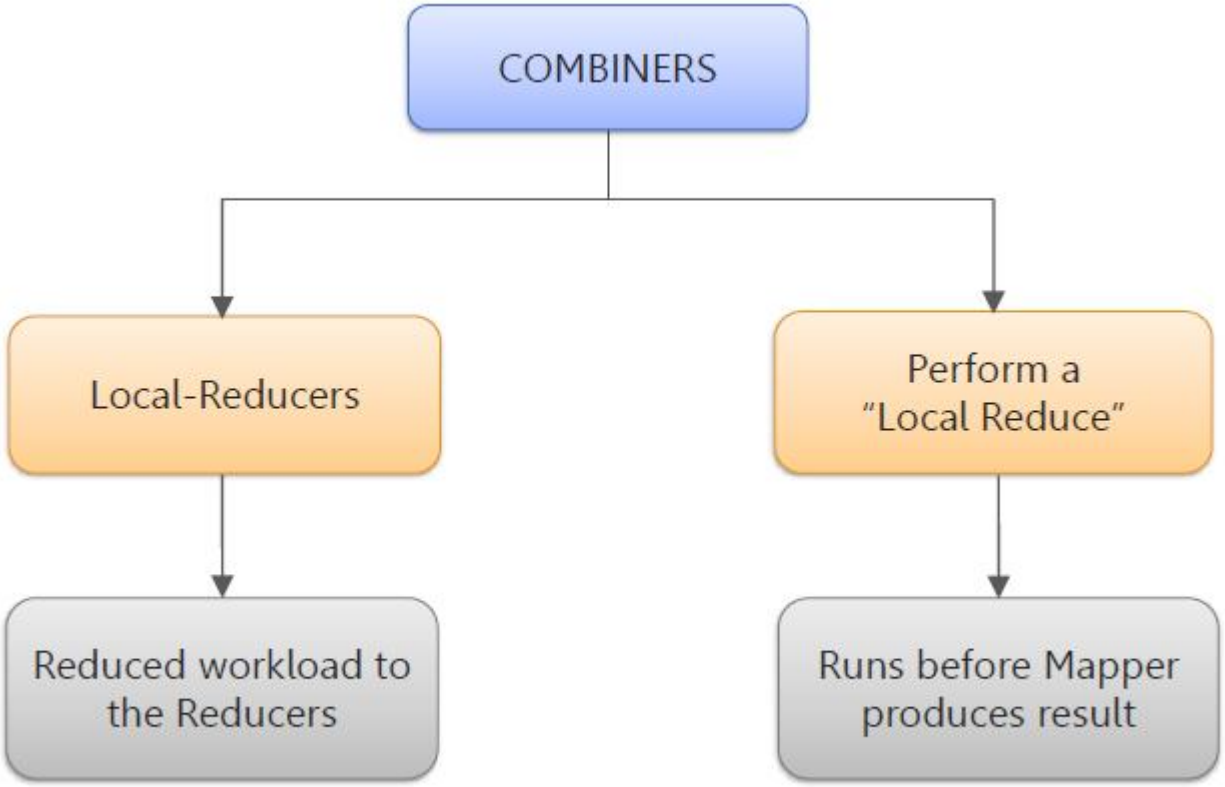
MR Job Execution YARN Flow



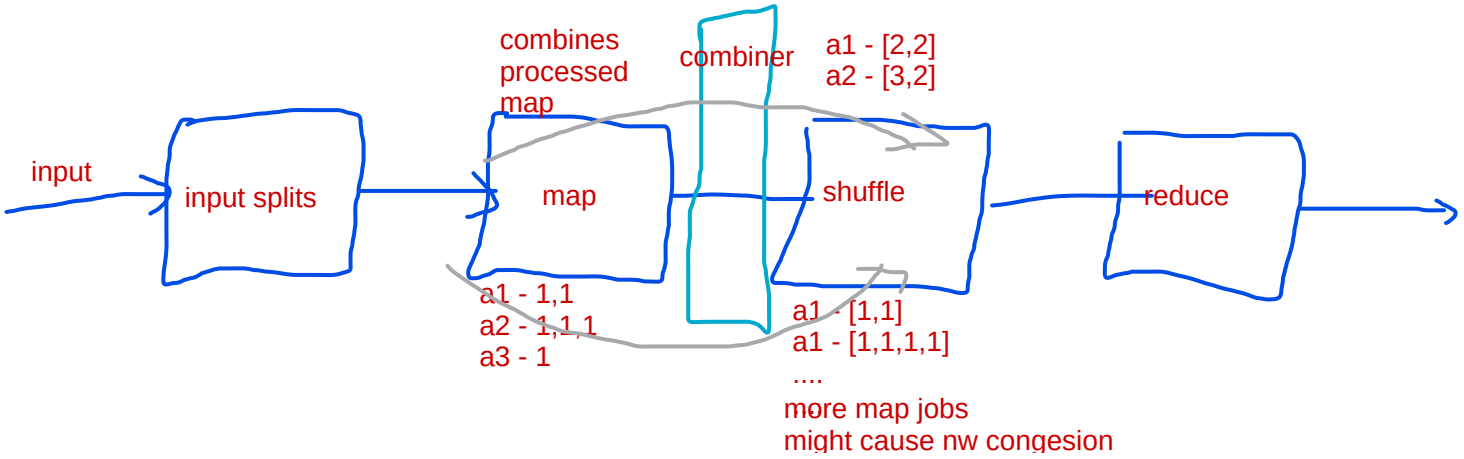
MR Advanced Concepts

Combiner

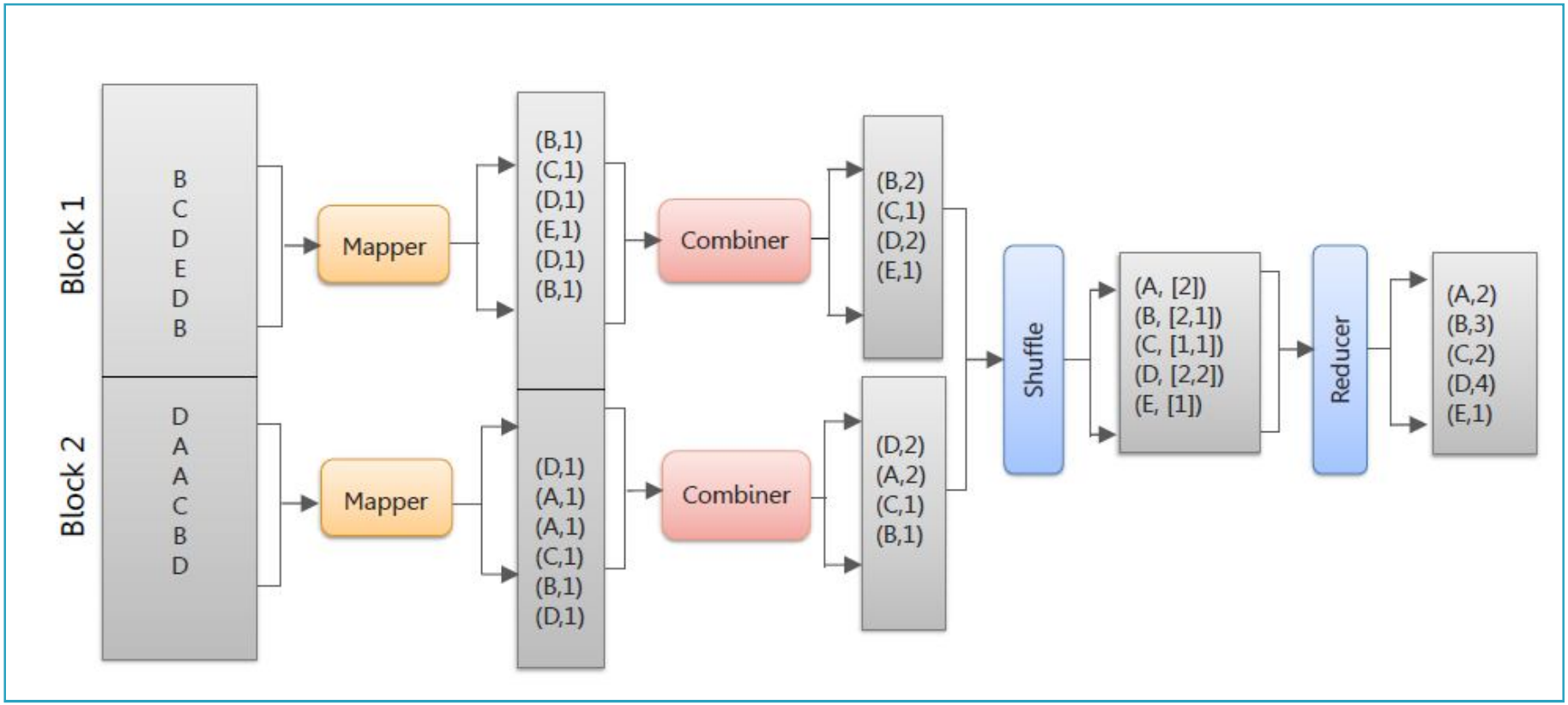
Local Reducer
-



- part of map task



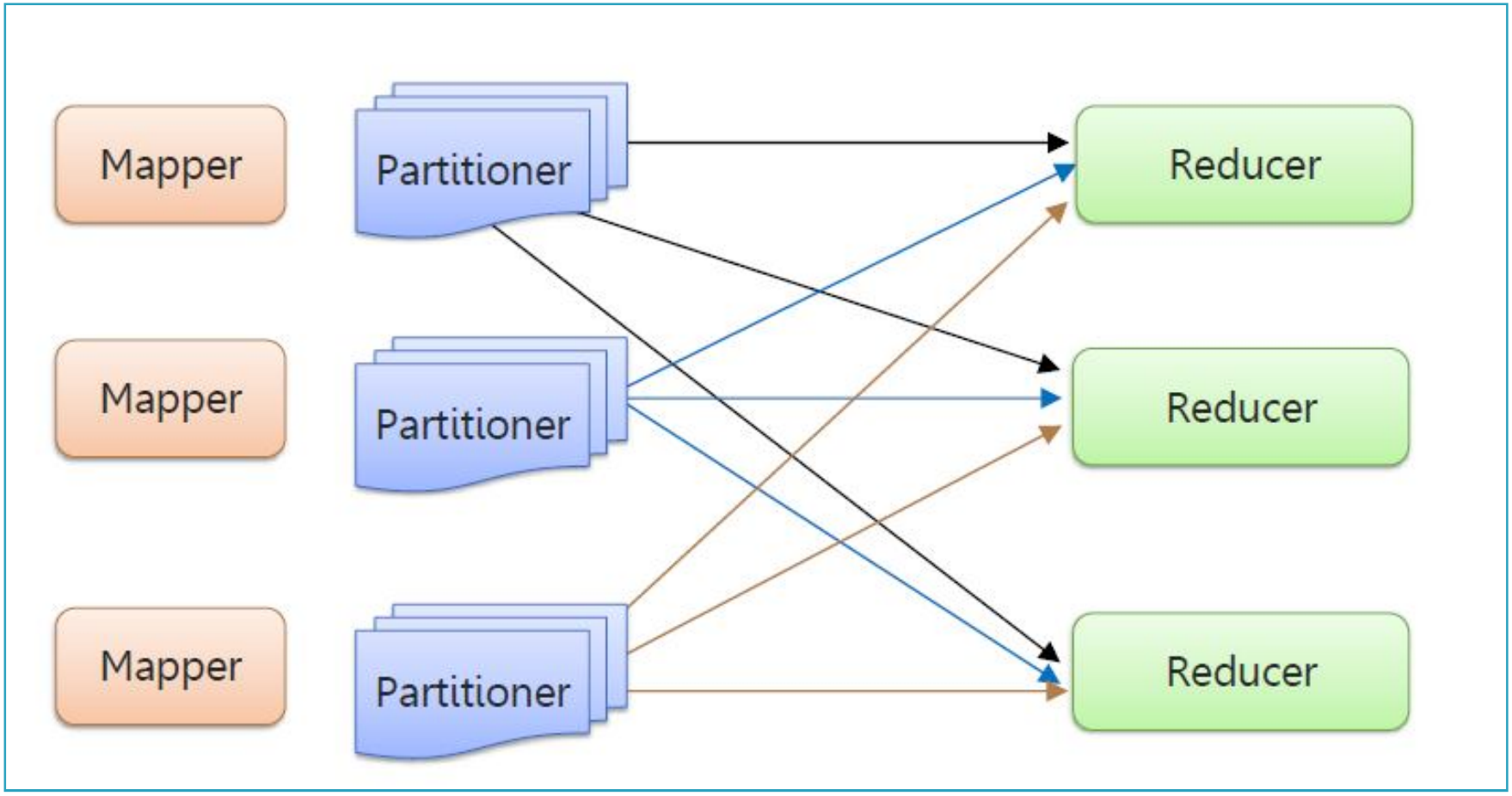
Combiner in Action



- can have more than one reducer?
-- yes
-- gives multiple outputs
-- ex. gen stats for countries, each reducer will reduce for particular country.

Partitioner

- default partitioner -- Hash partitioner - doesn't know to which red a particular record should go
- custom partitioner - works based on key, to map reducer
- reducer output format => part-r-00000 - can create up to 1,00,000 reducers -- r for reducer
*- no reducer needed - validation, transformation, filtering, cleansing and where no processing/ops
 -- then no need of shuffling, format => part-m-00000



Map Side Join

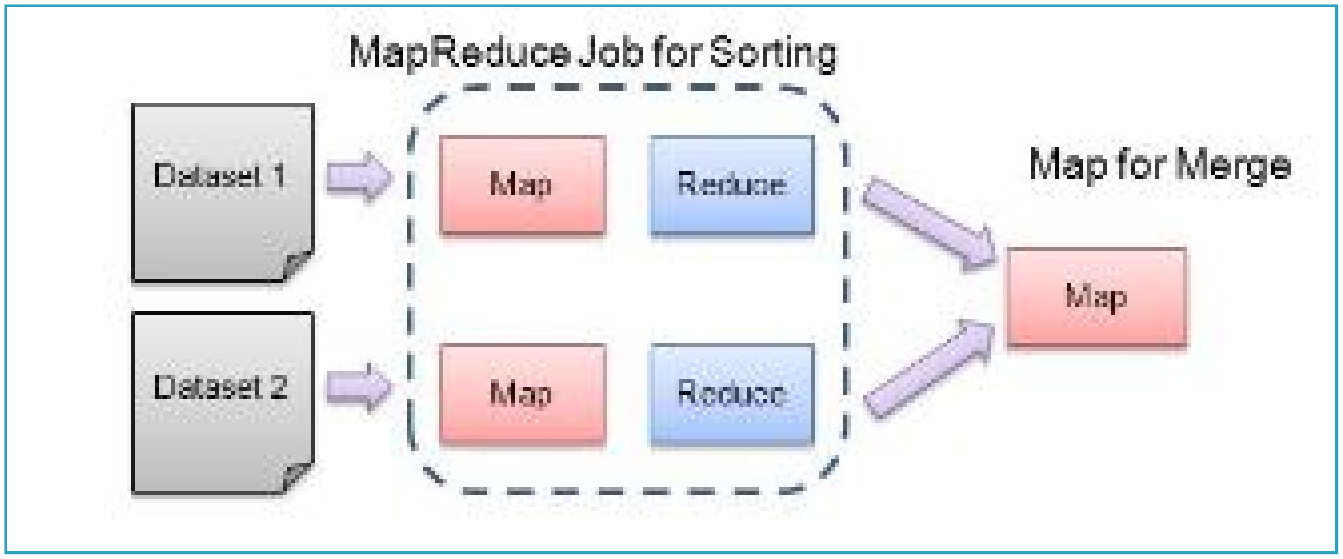
Joins
- map side join
- reduce side join
- joins based on keys
-
- multiple input files -- multiple input splits
- different map tasks to read data from different files
- keys from both map jobs should have same key in op

map side join
- if data of different size, f1 << f2

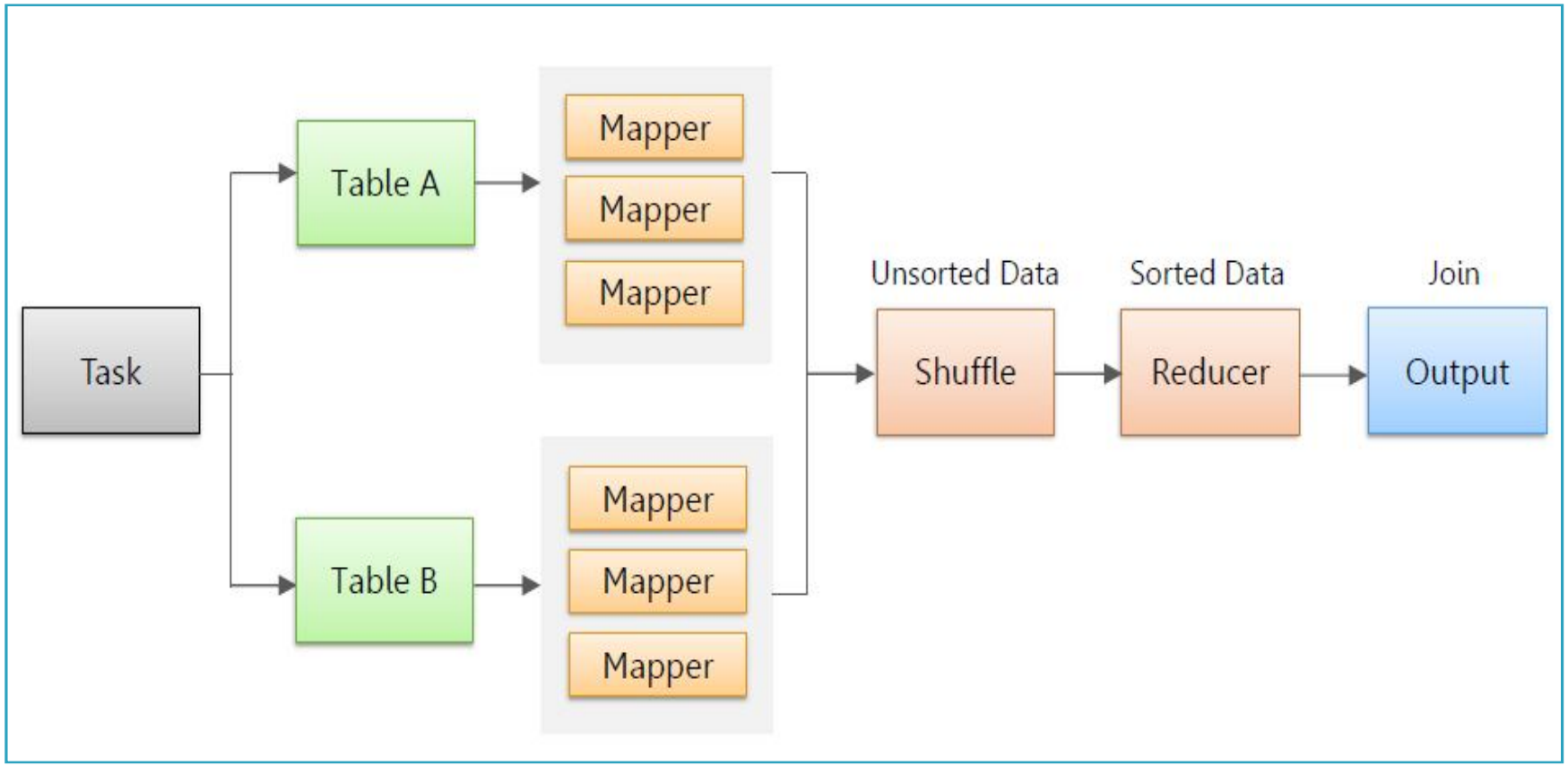
reducer side join
- both are big and f1 ~= f 2
- takes more resources and time

hive qry may translated to either map side or reducer side join

- A map-side join works by performing the join before the data reaches the map function
- Requirements
  - Each input dataset must be divided into the same number of partitions
  - It must be sorted by the same key (the join key) in each source
  - All the records for a particular key must reside in the same partition
- Above requirements actually fit the description of the output of a MapReduce job
  - A map-side join can be used to join the outputs of several jobs that had the same number of reducers, the same keys, and output files that are not splittable



Reduce Side Join

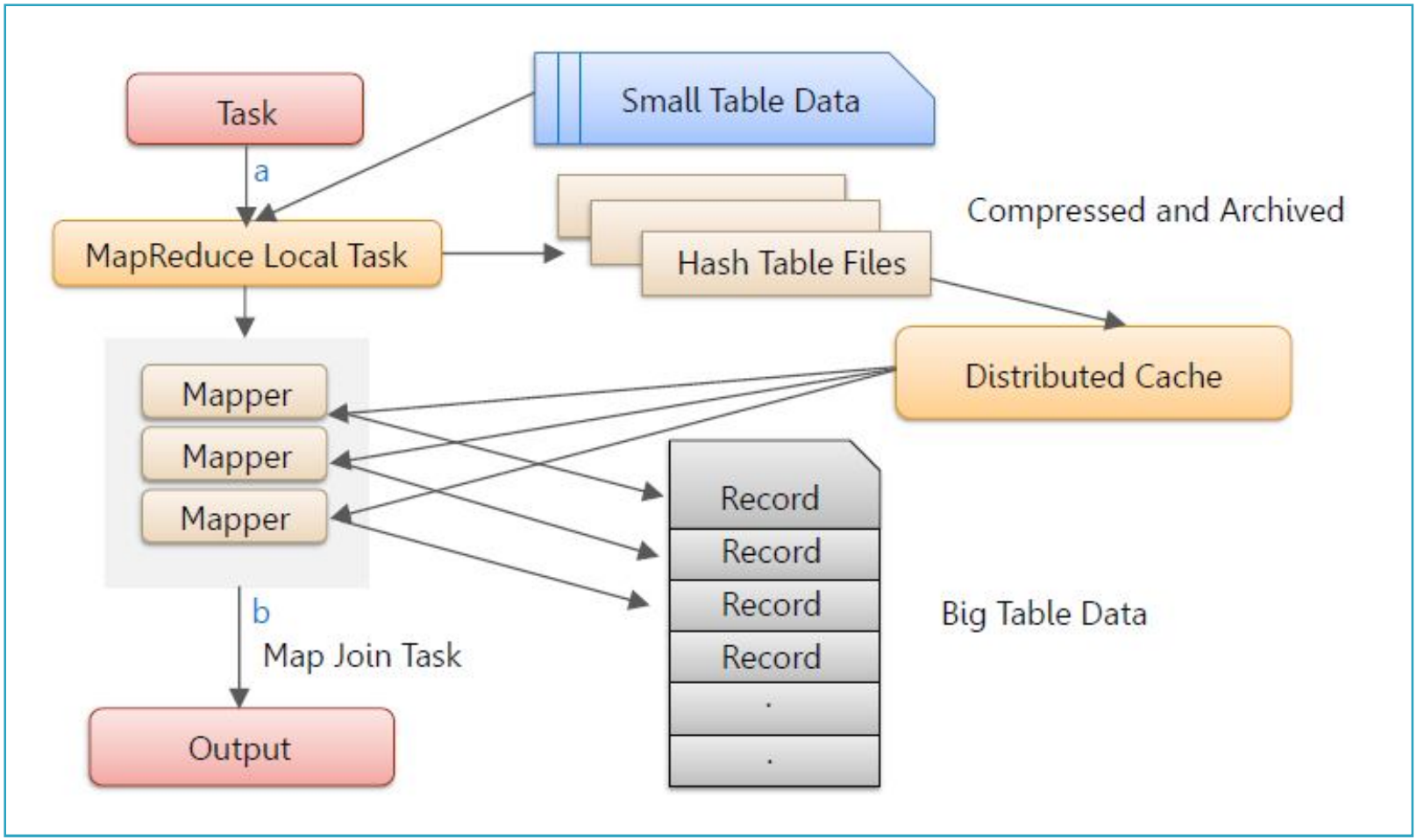


Distributed Cache

- At times, we might need to refer a relatively smaller amount of data in Map Reduce jobs
  Examples: Master Files, Lookup files, Cross Reference Files etc.
- Map Reduce provides Distributed Cache facility. This allows to cache files (text, archives, jars etc.) needed by applications
- Files are copied only once per job and should not be modified by the application or externally while the job is executing
- Both Mappers and reducers can access these files
- DistributedCache can be used to distribute simple, read-only data/text files and/or more complex types such as archives, jars etc via the JobConf
- Programmer need to be careful to not use too many cache files
- The ideal size for distributed cache file is <= 100 to 150 MB

if data of different size, f1 <<< f2
- reference data. ex: countries, departments, plans, diseases
- which are very small and won't grow/change
- we can go for Map side join but better approach would be distributed Cache
- like broadcast vars, central data, etc

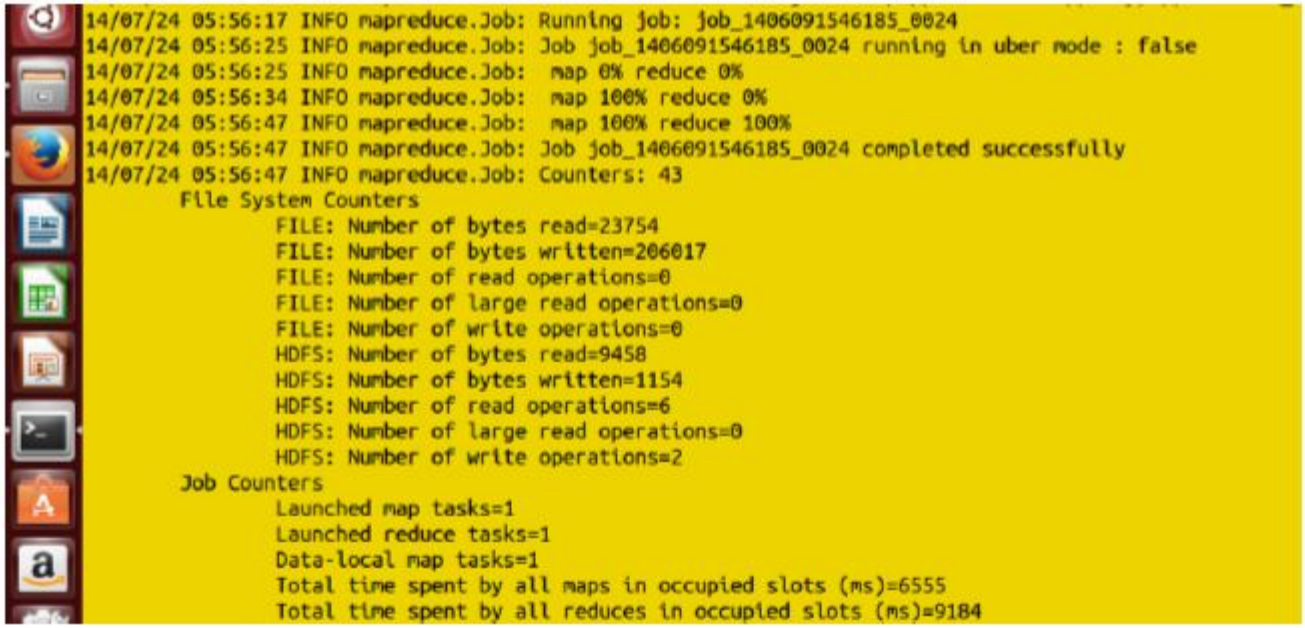
Distributed Cache (contd.)



Counters

- Counters are lightweight objects in Hadoop that allow you to keep track of system progress in both the map and reduce stages of processing

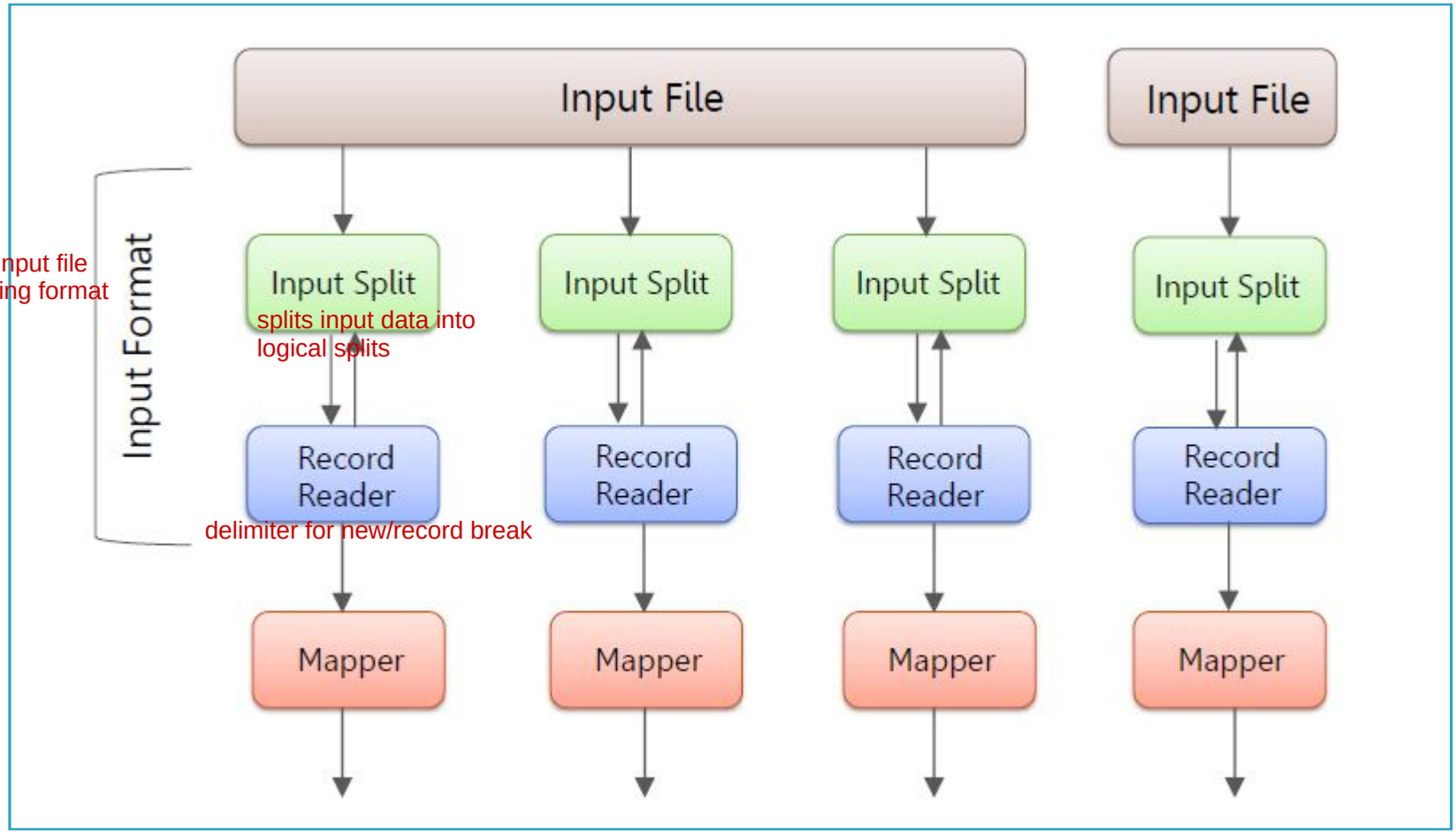
- Counters are used to gather information about the data we are analysing, like how many types of records were processed, how many invalid records were found while running the job, and so on



Custom counter: ex: to count the # rows which have null in cols
- accumulator

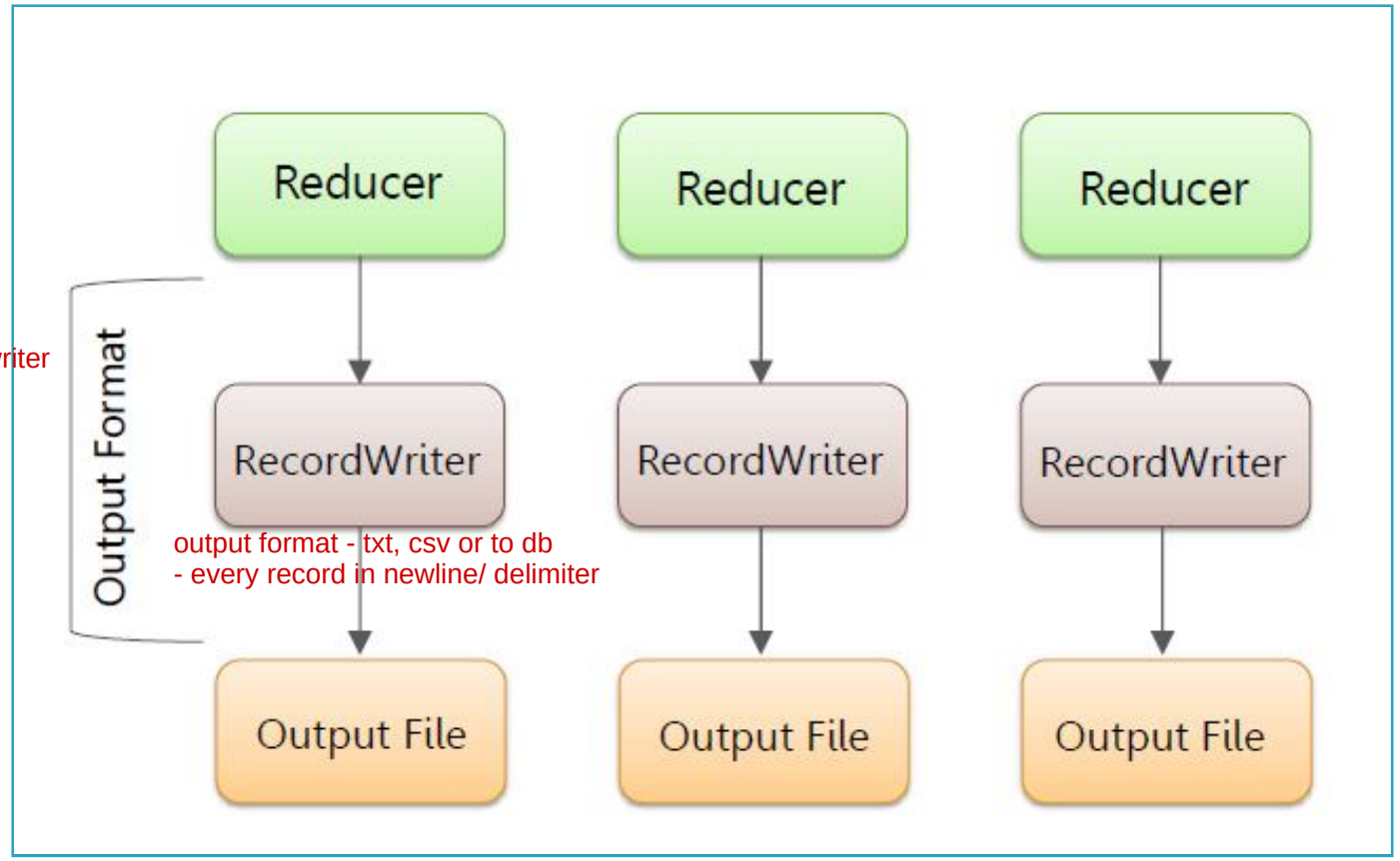
Hadoop Input Formats

read data from input file
use corresponding format

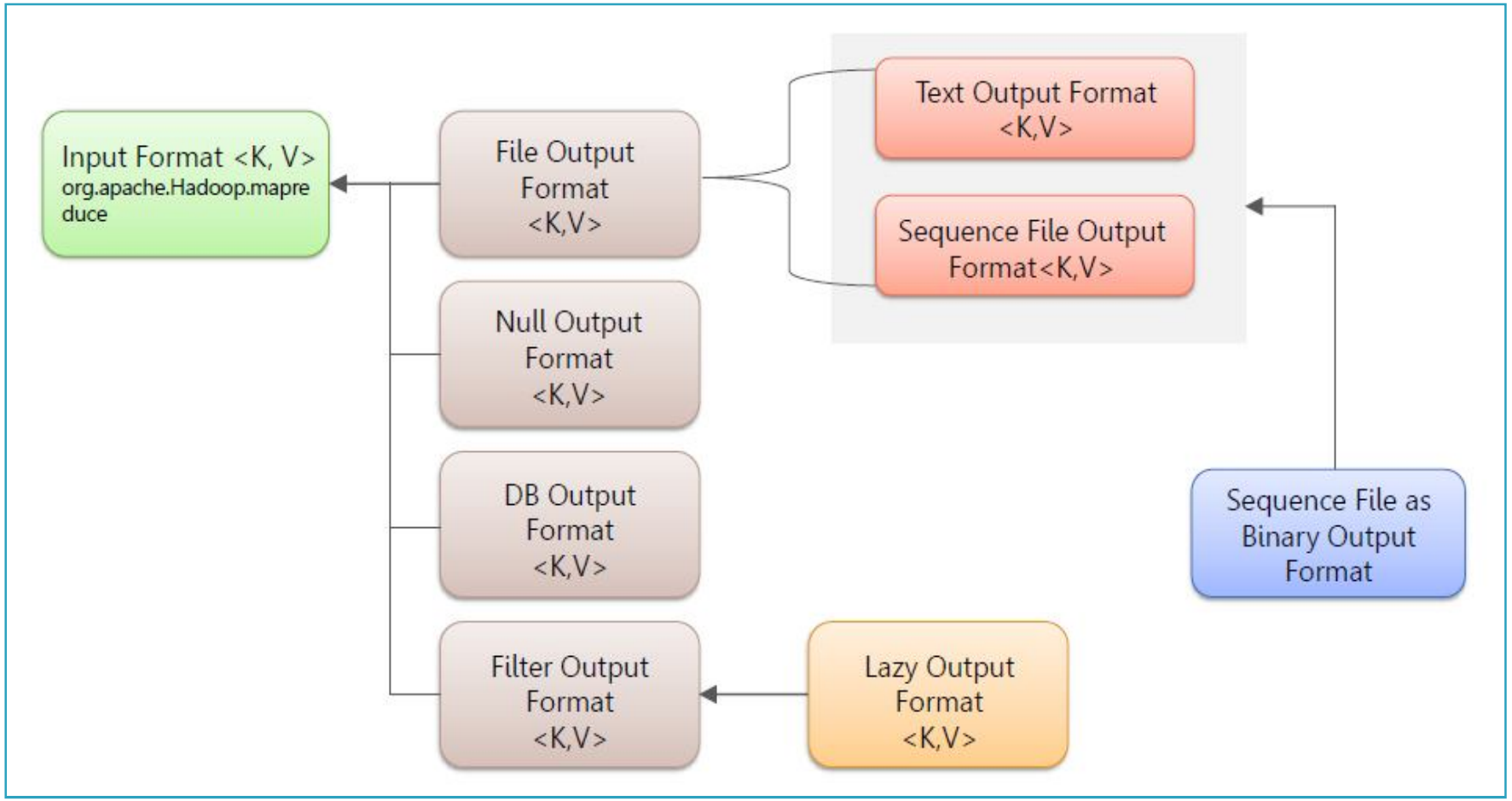


Hadoop Output Formats

out format clss
-no more splitting at writer



Hadoop Output Formats – Class Hierarchy



HDFS File Formats – Sequence File

In HDFS

- SequenceFile is one of the solutions to small file problem in Hadoop.
- Small file is significantly smaller than the HDFS block size(128MB).
- Each file, directory, block in HDFS is represented as object and occupies 150 bytes.
- 10 million files, would use about 3 gigabytes of memory of NameNode.
- A billion files is not feasible.

In MapReduce

- Map tasks usually process a block of input at a time (using the default FileInputFormat).
- The more the number of files is, the more number of Map task need and the job time can be much more slower.

Small file scenarios

- The files are pieces of a larger logical file.
- The files are inherently small, for example, images.

HDFS File Formats – Sequence File

- The concept of SequenceFile is to put each small file to a larger single file.
- For example, suppose there are 10,000 100KB files, then we can write a program to put them into a single SequenceFile like below, where you can use filename to be the key and content to be the value.

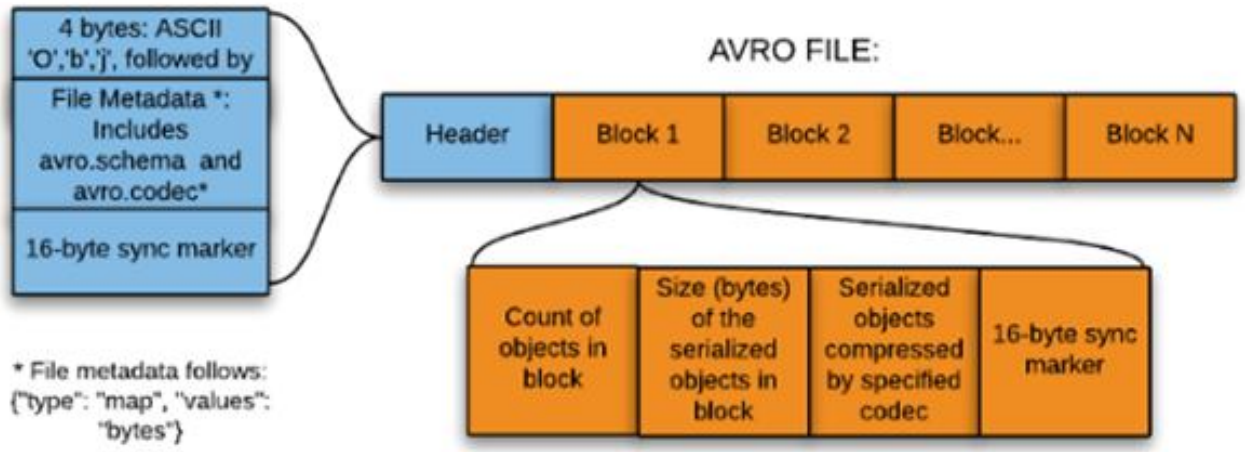
(source: csdn.net)

- Some benefits:
  1. A smaller number of memory needed on NameNode. Continue with the 10,000 100KB files example,
     - Before using SequenceFile, 10,000 objects occupy about 4.5MB of RAM in NameNode.
     - After using SequenceFile, 1GB SequenceFile with 8 HDFS blocks, these objects occupy about 3.6KB of RAM in NameNode.
  2. SequenceFile is splittable, so is suitable for MapReduce.

HDFS File Formats – Avro

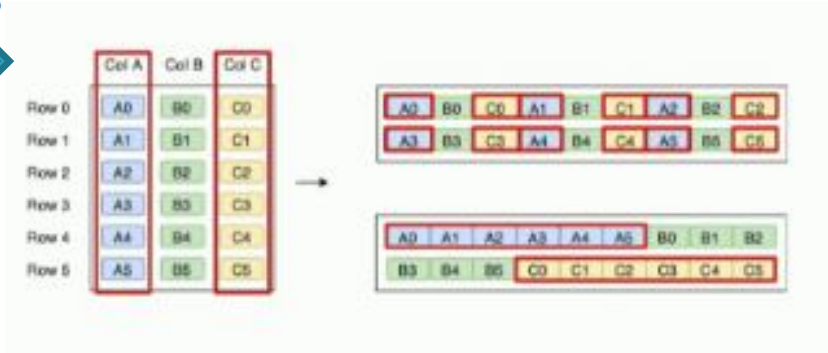
- Row-based (store data in rows): row-based databases are best for write-heavy transactional workloads
- Support serialization
- Fast binary format
- Support block compression and splittable
- Support schema evolution (the use of JSON to describe the data, while using binary format to optimize storage size)
- Stores the schema in the header of file so data is *self-describing*.

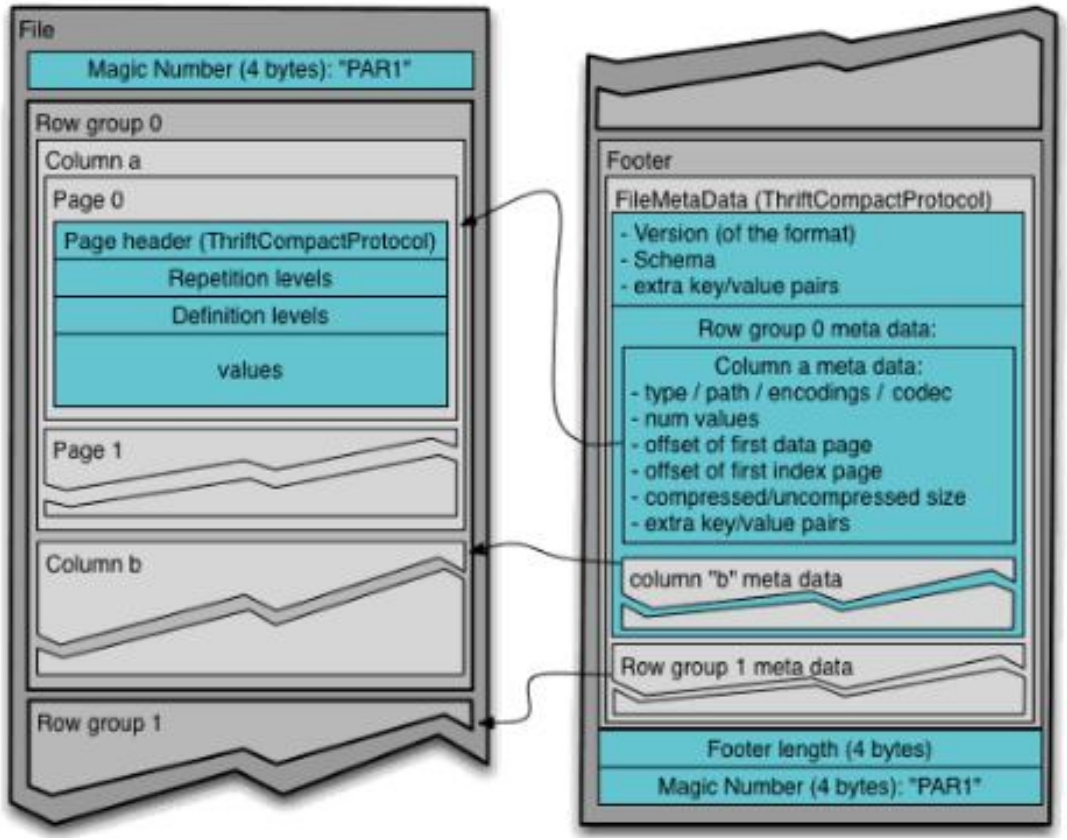
```
{
  "namespace": "customer.avro",
  "type": "record",
  "name": "customer",
  "fields": [
     {"name": "name",    "type": "string"},
     {"name": "age",     "type": "int"},
     {"name": "address", "type": "string"},
     {"name": "phone",   "type": "string"},
     {"name": "email",   "type": "string"},
  ]
}
```



HDFS File Formats – Parquet

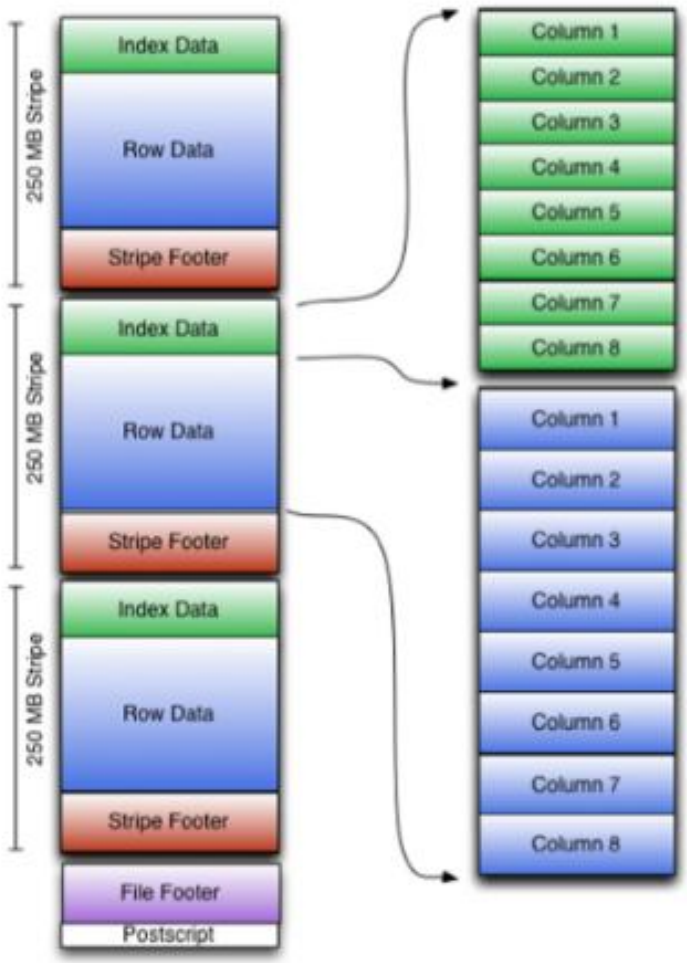
- Column-oriented (store data in columns): column-oriented data stores are optimized for read-heavy analytical workloads
- High compression rates (up to 75% with Snappy compression)
- Only required columns would be fetched/read (reducing the disk I/O)
- Can be read and write using Avro API and Avro Schema
- Support predicate pushdown (reducing disk I/O cost)



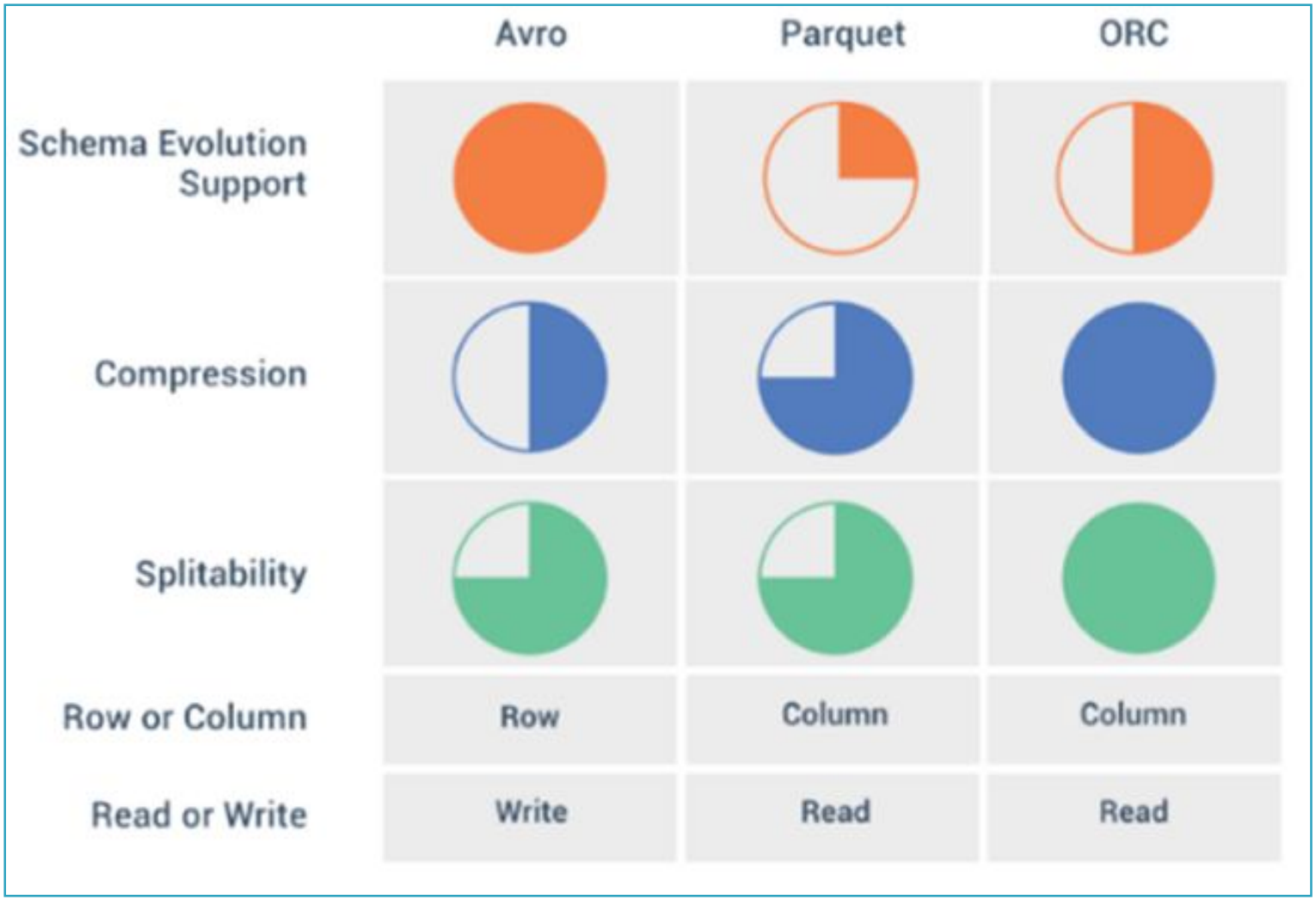


HDFS File Formats – ORC (Optimized Row Columnar)

- Column-oriented (store data in columns): column-oriented data stores are optimized for read-heavy analytical workloads
- High compression rates (ZLIB)
- Hive type support (datetime, decimal, and the complex types like struct, list, map, and union)
- Metadata stored using Protocol Buffers, which allows addition and removal of fields
- Compatible on HiveQL
- Support serialization



File Formats Comparison



	Avro	Parquet	ORC
Schema Evolution Support			
Compression			
Splitability			
Row or Column	Row	Column	Column
Read or Write	Write	Read	Read

Thank You!