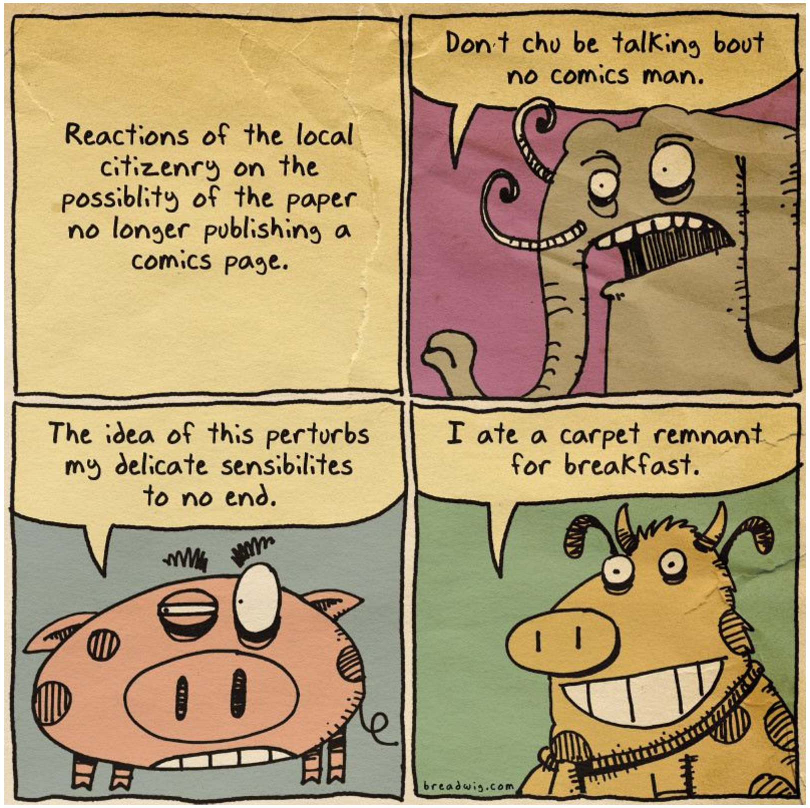
MapReduce Paradigm for Big Data

Delayed PS#4 deadline until Thursday

PS#5 will be up tonight



Distrubuted "Big" Data

One motivation of NoSQL databases was to distribute them across multiple network-connected servers

- Google MapReduce
  - Motivation and History
  - Google File System (GFS)
  - MapReduce:
    Schema, Example, MapReduce Framework
- Apache Hadoop
  - Hadoop Modules and Related Projects
  - Hadoop Distributed File System (HDFS)
  - Hadoop MapReduce
- Apache Spark

Big Data

- Big Data analytics (or data mining)
  - need to process large data volumes quickly
  - want to use a computing cluster (with distributed memory) instead of a super-computer (shared memory)

- Communication (sending data) between compute nodes is expensive

$\Rightarrow$ model of "move computing to data"

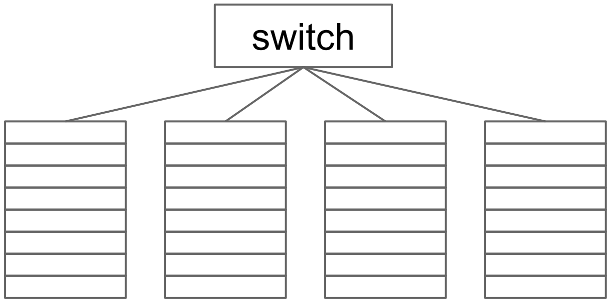
Big Data Processing

Computing cluster architecture:

1,000s of computing nodes

10,000s Gb of memory

10,000s Tb of data storage



racks with compute nodes

- HW failures are the rule rather than the exception, thus
  1. Files should be stored redundantly
     - over different racks to overcome also rack failures
  2. Computations must be divided into independent tasks
     - that can be restarted in case of a failure

MapReduce: Origins

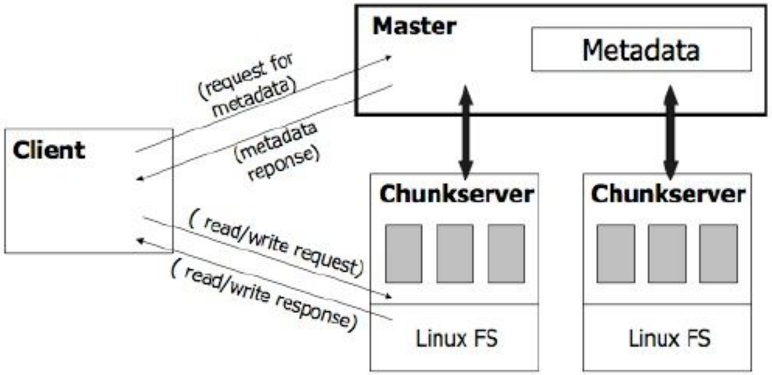
- In 2003, Google had the following problem:
  1. How to rank tens of billions of webpages by their "importance" (PageRank) in a "reasonable" amount of time?
  2. How to compute these rankings efficiently when the data is scattered across thousands of computers?
- Additional factors:
  1. Individual data files can be enormous (terabyte or more)
  2. The files were rarely updated
     - the computations were read-heavy, but not very write-heavy
     - If writes occurred, they were appended at the end of the file

Google's Solution

- Google found the following solutions:
  - Google File System (GFS)
    - A distributed file system
  - MapReduce
    - A ***simple*** programming *model* for distributed data processing

Google File System (GFS)

- Files are divided into chunks (typically 64 MB)
  - The chunks are replicated at three different machines
  - The chunk size and replication factor are tunable
- One machine is a master, the other chunkservers
  - The master keeps track of all file metadata
    - mappings from files to chunks and locations of the chunks
  - To find a file chunk, client queries the master, and then contacts the relevant chunkservers
  - The master's metadata files are also replicated



MapReduce

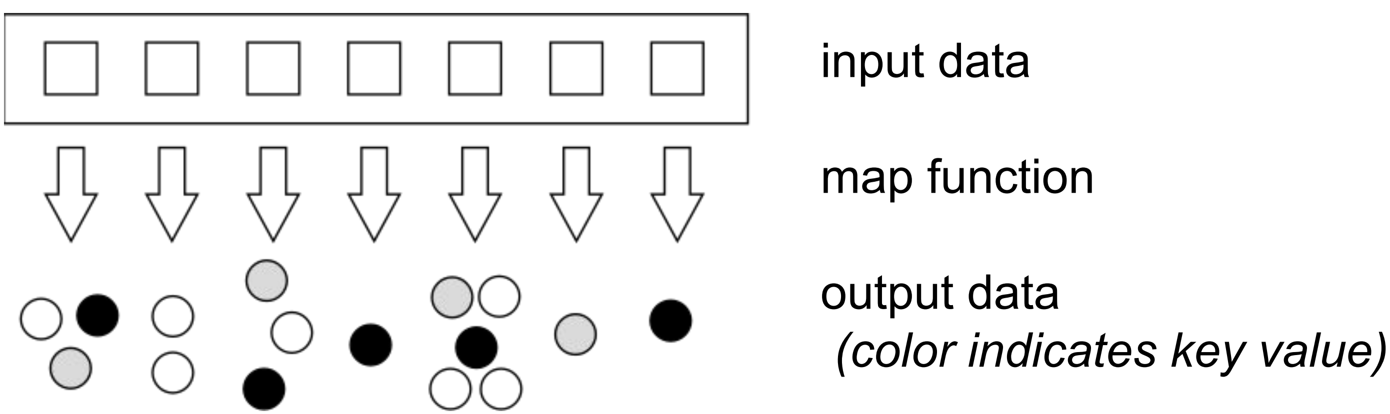
- MapReduce is a programming model that sits on the top of a Distributed File System
  - Originally: no data model – data is stored directly in files

- A distributed computational task has three phases:
  1. The map phase: data transformation
  2. The grouping phase
     - done automatically by the MapReduce Framework
  3. The reduce phase: data aggregation

- User defines only *map* & *reduce* functions

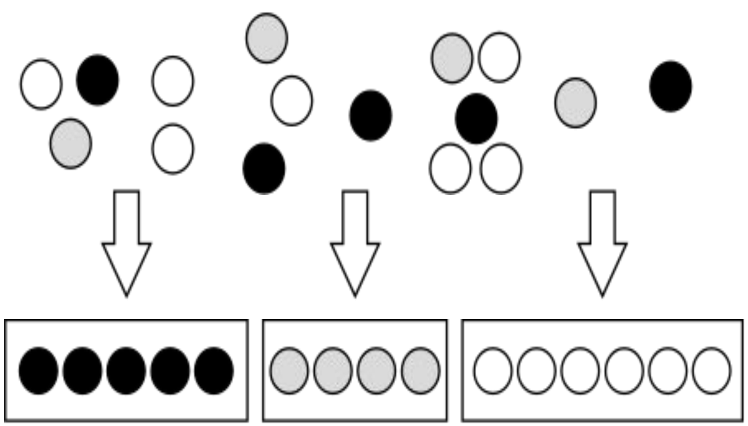
Map

- **Map function** simplifies the problem in this way:
  - Input: a single data item (e.g. line of text) from a data file
  - Output: zero or more (key, value) pairs
- The keys are similar to search "keys":
  - They do not have to be unique
  - A map task can produce several key-value pairs with the same key (even from a single input)
- **Map phase** applies the map function to all items



Grouping Phase

- Grouping (Shuffling): The key-value outputs from the map phase are grouped by key
  - Values sharing the same key are sent to the same reducer
  - These values are consolidated into a single list (key, list)
    - This is convenient for the reduce function
  - This phase is done automatically in the MapReduce framework

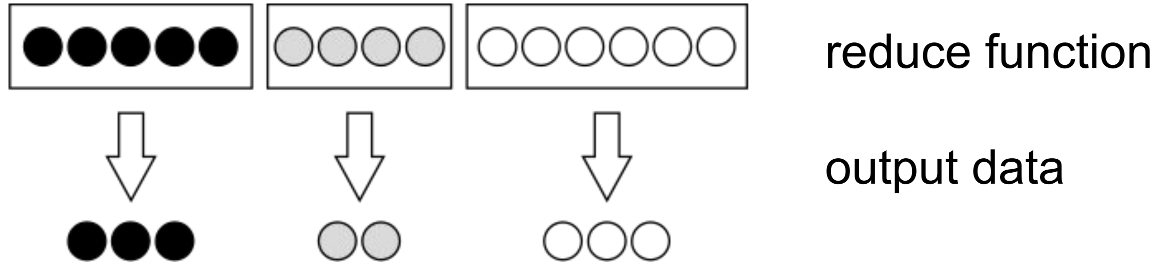


intermediate output
(color indicates key)

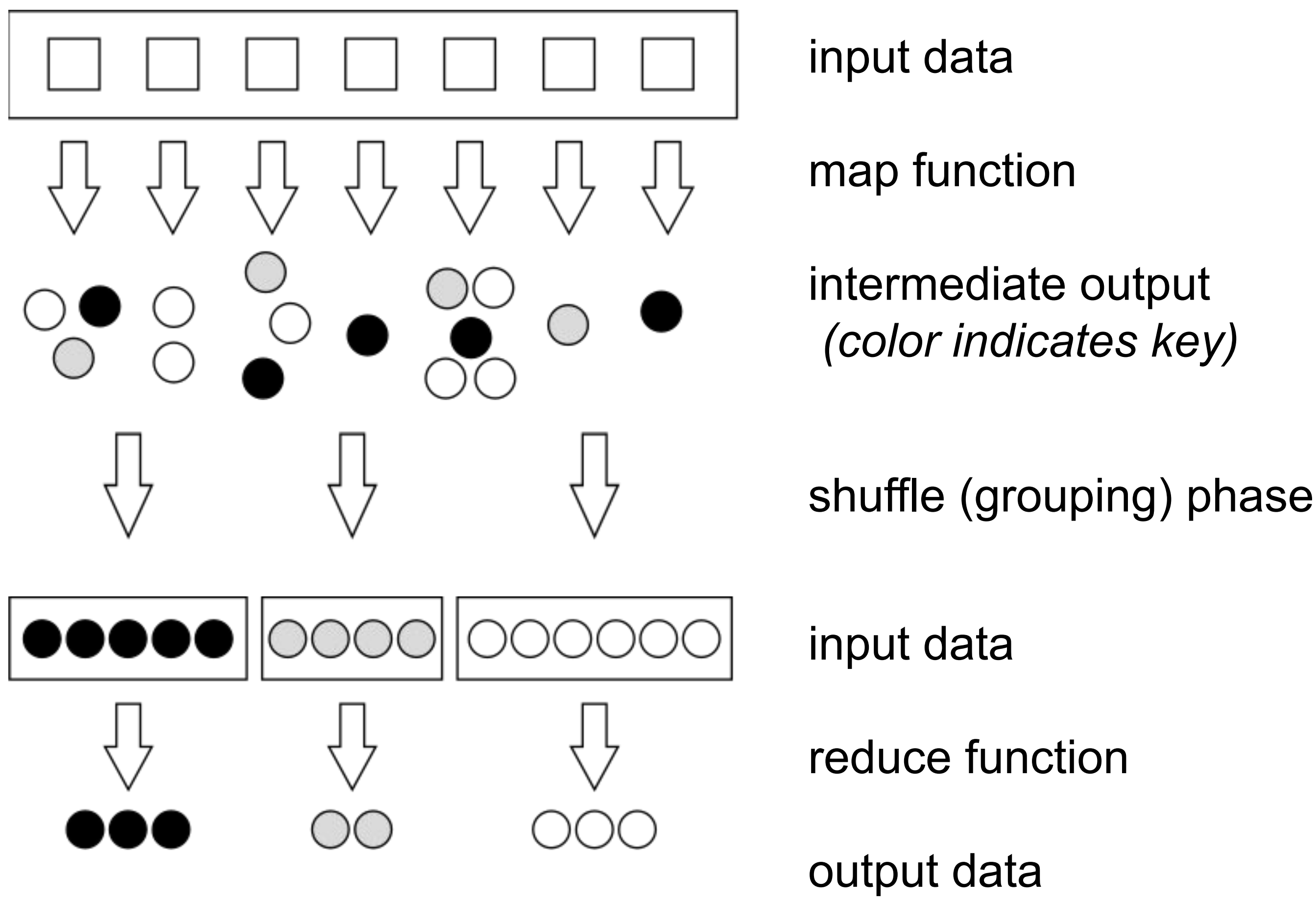
shuffle (grouping) phase

Reduce Phase

- Reduce: combines values with the same key
  - to achieve the final result(s) of the computational task
  - Input: (key, value-list)
    - value-list contains all values generated for given key in the Map phase
  - Output: (key, value-list)
    - zero or more output records



MapReduce, the full picture



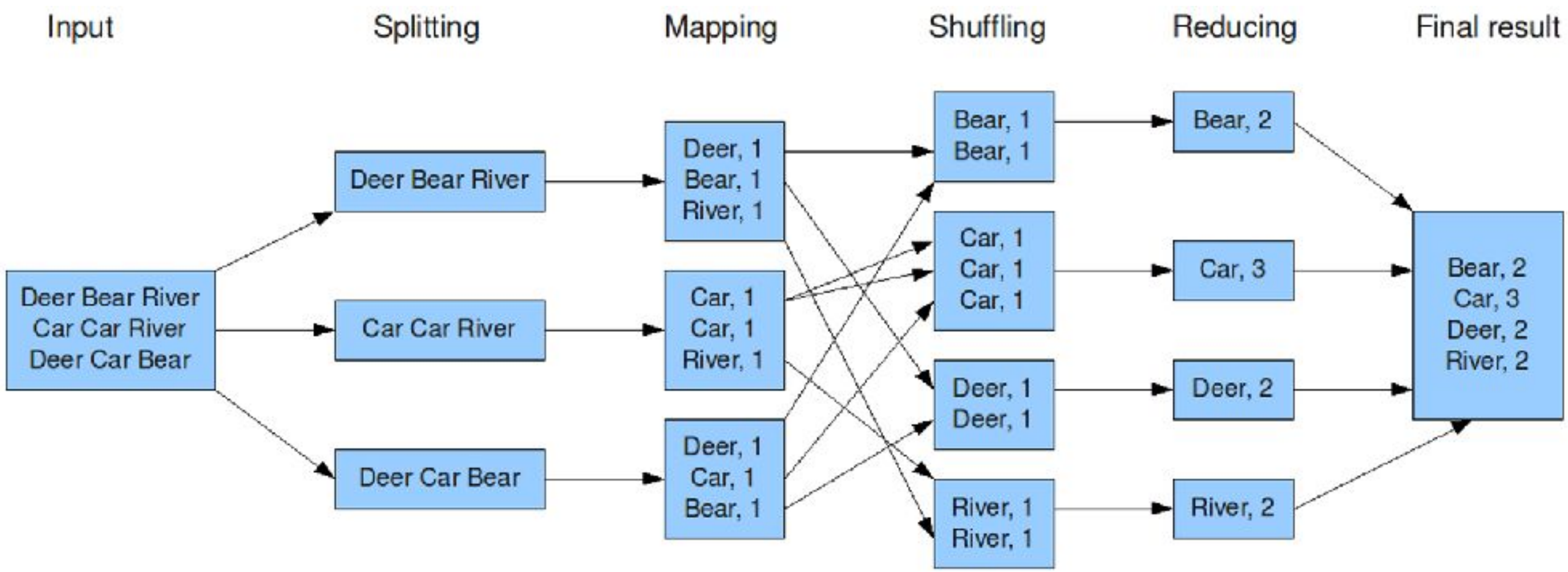
Example: Word Count

Task: Calculate word frequency in a set of documents

```
def map(key, value):
    """ key: document name (ignored)
        value: content of document (words) """
   for w in value.split(' '):
       emitIntermediate(w, 1)


def reduce(key, values):
    """ key: a word
        values: a list of counts """
    result = 0;
    for v in values:
        result += v
    emit(key, result)
```

Example: Word Count (2)



MapReduce: Combiner

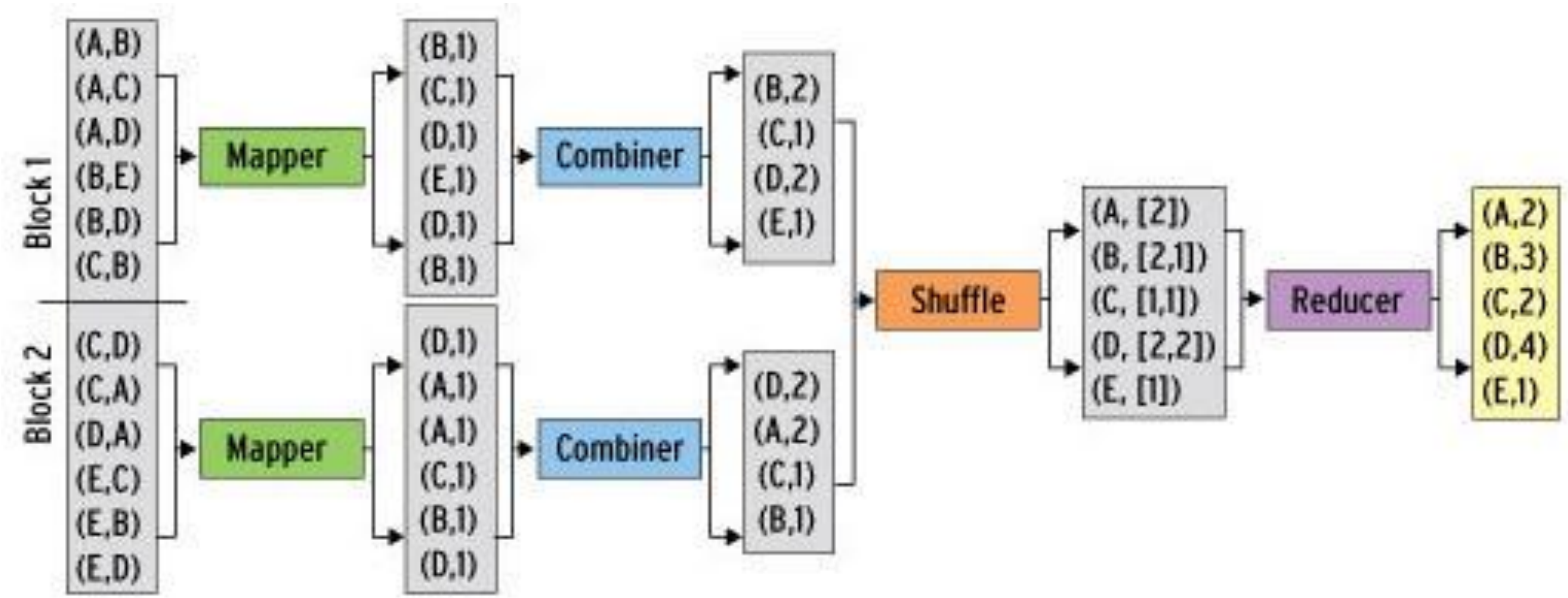
- If the reduce function is commutative & associative
  - The values can be combined in any order and combined in parts (grouped)
    - with the same result (e.g. Word Counts)
- … opportunities for optimization
  - Apply the same reduce function right immediately after the map phase, before shuffling and then distribute to reducer nodes
- This (optional) step is known as the combiner
  - Note: it's still necessary to run the reduce phase

Example: Word Count, Combiner

Task: Calculate word frequency in a set of documents

```
def combine(keyValuePairs):
    """ keyValuePairs: a list counts """
    result = {}
    for k, v in keyValuePairs:
        result[k] = result.get(k,0) + v
    for k, v in result:
       emit(k, v);
```

Word Count with Combiner

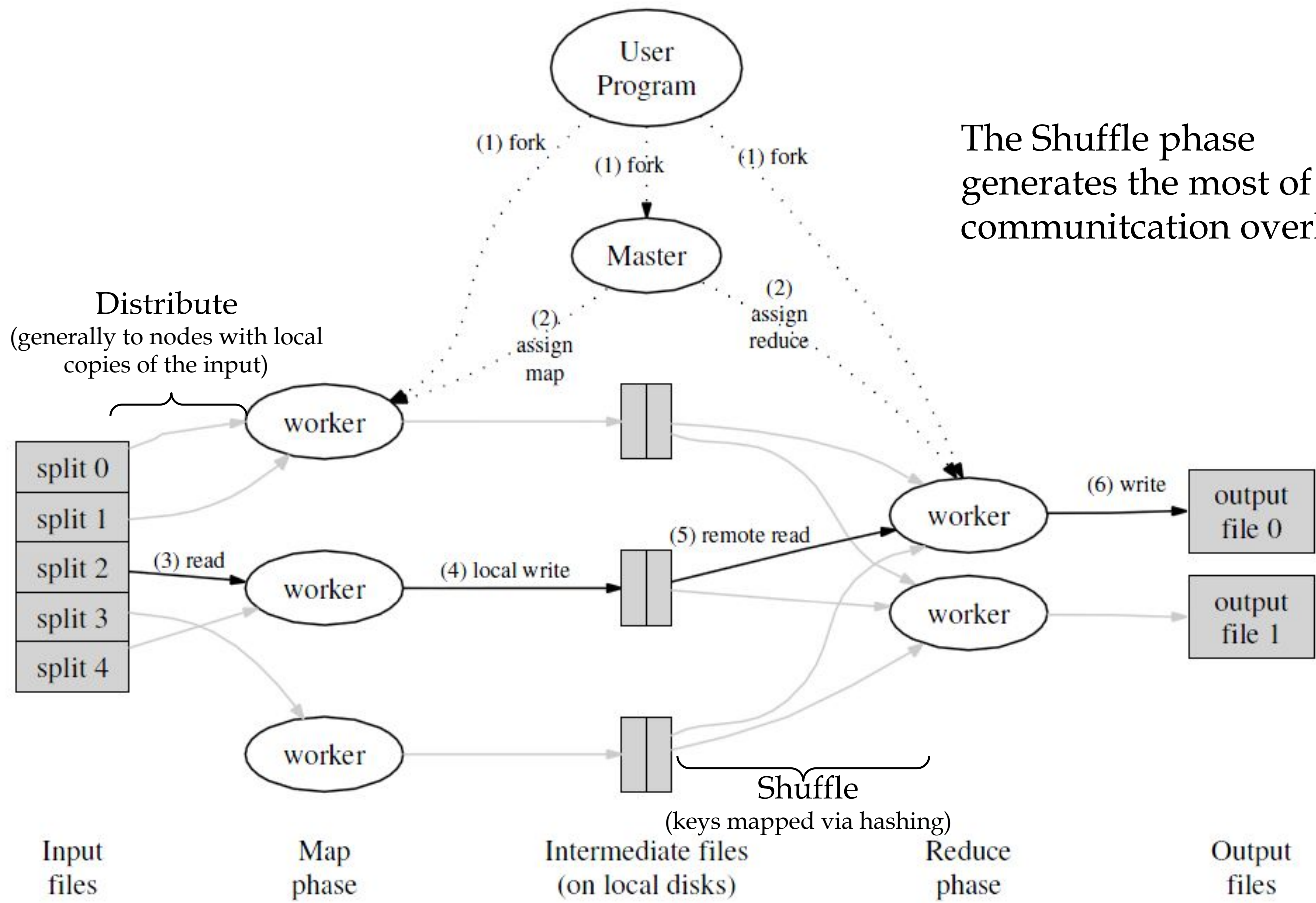


MapReduce Framework

- MapReduce framework takes care of
  - Distributing and parallelizing of the computation
  - Monitoring of the whole distributed task
  - The grouping phase
    - putting together intermediate results
  - Recovering from any failures

- User defines only map & reduce functions
  - but can define also other additional functions

MapReduce Framework



The Shuffle phase generates the most of the communitcation overhead

MapReduce: Example II

Task: Calculate graph of web links

- what pages reference (<a href=””>) each page (backlinks)

```
def map(url, html):
    """ url: web page URL
        html: HTML text of the page """
    for tag, contents in html:
        if tag.type == 'a':
            emitIntermediate(tag.href, url)


def reduce(key, values):
    """ key: target URLs
        values: a list of source URLs """
    emit(key, values)
```

Example II: Result

Input: `(page_URL, HTML_code)`

```
("http://cnn.com", "<html>...<a href="http://cnn.com">link</a>...</html>")
("http://nbc.com", "<html>...<a href="http://cnn.com">link</a>...</html>")
("http://fox.com",
   "<html>... <a href="http://cnn.com">x</a>...
              <a href="http://nbc.com">y</a>...
              <a href="http://fox.com">z</a>... </html>")
```

Intermediate output after Map phase:

```
("http://cnn.com", "http://cnn.com")
("http://cnn.com", "http://nbc.com")
("http://cnn.com", "http://fox.com")
("http://nbc.com", "http://fox.com")
("http://fox.com", "http://fox.com")
```

Intermediate result after shuffle phase (the same as output after Reduce phase):

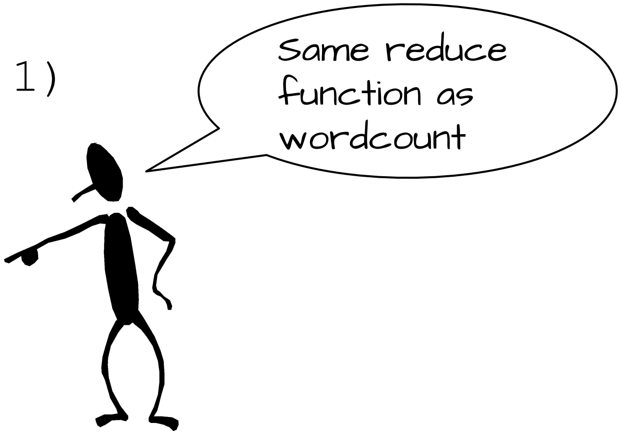
```
("http://cnn.com", ["http://cnn.com", "http://nbc.com", "http://fox.com"] )
("http://nbc.com", [ "http://fox.com" ])
("http://fox.com", [ "http://fox.com" ])
```

MapReduce: Example III

Task: What are the lengths of words in the input text

- output = how many words are in the text for each length

```
def map(key, text):
    """ key: document name (ignored)
        text: content of document (words) """
    for w in text.split(' '):
        emitIntermediate(length(w), 1)
```




```
def reduce(key, values):
    """ key: a length
        values: a list of counts """
    result = 0;
    for v in values:
        result += v
    emit(key, result)
```

MapReduce: Features

- MapReduce uses a "shared nothing" architecture
  - Nodes operate independently,
    - nodes share no memory
    - nodes need not share disk
  - Common feature of many NoSQL systems

- Data is partitioned (sharded) and replicated over many nodes
  - Pro: Large number of read/write operations per second
  - Con: Coordination problem – which nodes have my data, and when?

Applicability of MapReduce

- MR is always applicable if the problem is trivially parallelized

- Two problems:
  1. The programming model is limited (only two phases with a given schema)
  2. There is no data model - it works on nebulous "data chunks" that the application understands.

- Google's answer to the 2nd problem was BigTable
  - The first column-family system (2005)
  - Subsequent systems: HBase (over Hadoop), Cassandra,...

Apache Hadoop

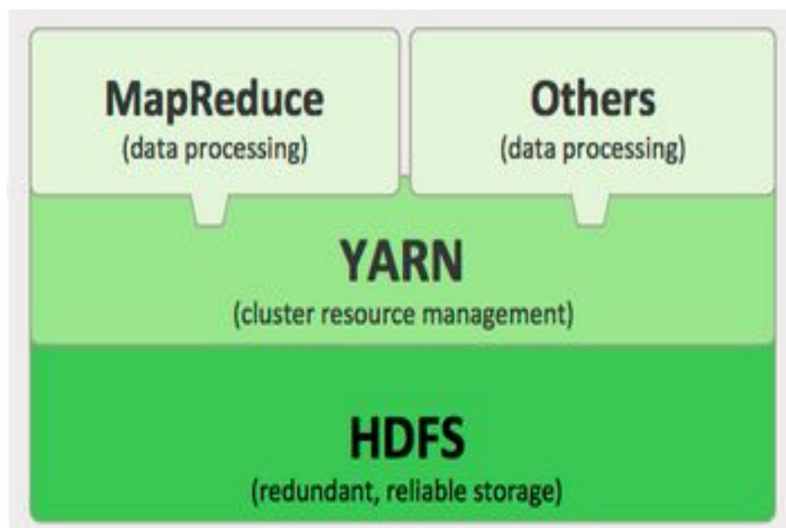
- Open-source MapReduce framework
  - Implemented in Java
  - Named for author's (Doug Cutting) son's yellow toy elephant

web: http://hadoop.apache.org/

- Able to run applications on large clusters of commodity hardware
  - Multi-terabyte data-sets
  - Thousands of nodes
- A reimplementation and redesign of Google's MapReduce and Google File System

Hadoop: Modules

- Hadoop Common
  - Common support functions for other Hadoop modules
- Hadoop Distributed File System (HDFS)
  - Distributed file system
  - High-throughput access to application data
- Hadoop YARN
  - Job scheduling and cluster resource management
- Hadoop MapReduce
  - YARN-based system for parallel data processing



source: https://goo.gl/NPuuJr

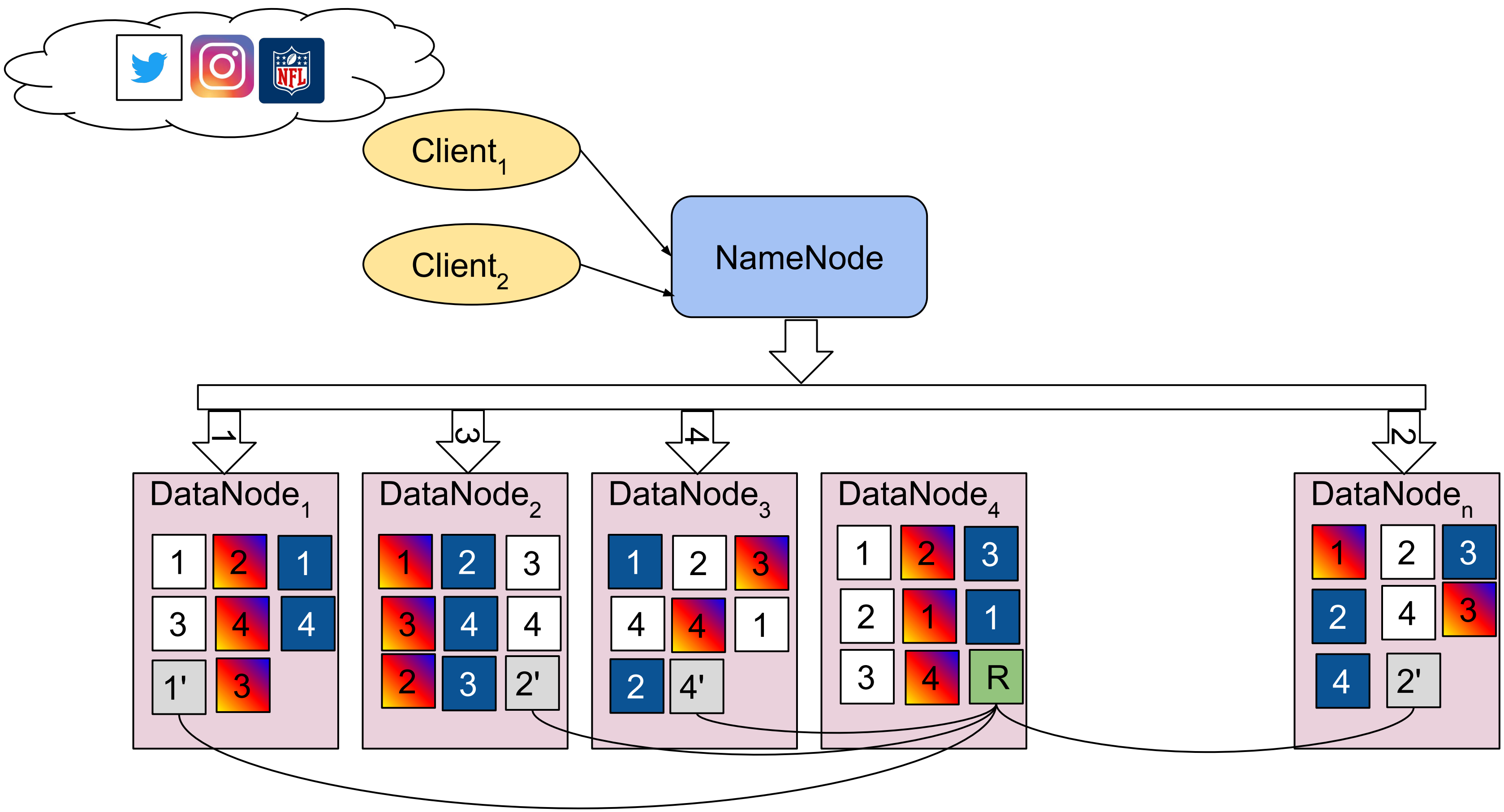
HDFS: Data Characteristics

- Assumes:
  - Streaming data access
    - files are read sequentially from the beginning to end
  - Batch processing rather than interactive user access
- Very large data sets and files
- Write-once / read-many
  - A file once created does not change often
  - This assumption simplifies consistancy
- Typical applications for this model:
  MapReduce, web-crawlers, data warehouses, …

HDFS: Basic Components

- Master/slave architecture
- HDFS exposes a file system namespace
  - Files are internally split into blocks and distrubuted over servers called "DataNodes"
  - Blocks are relatively large (64 MB by default)
- NameNode - master server
  - Manages the file system namespace
    - Opening/closing/renaming files and directories
    - Arbitrates file access
  - Determines mapping of blocks to DataNodes
- DataNode - manages file blocks
  - Block read/write/creation/deletion/replication
  - Usually one per physical node

HDFS: Schema



Client1
Client2
NameNode
1
3
4
2
DataNode1
1 2 1
3 4 4
1' 3
DataNode2
1 2 3
3 4 4
2 3 2'
DataNode3
1 2 3
4 4 1
2 4'
DataNode4
1 2 3
2 1 1
3 4 R
DataNoden
1 2 3
2 4 3
4 2'

HDFS: NameNode

- NameNode has a structure called FsImage
  - Entire file system namespace + mapping of blocks to files + file system properties
  - Stored in a file in NameNode’s local file system
  - Designed to be compact
    - Loaded in NameNode’s memory (4 GB of RAM is sufficient)

- NameNode uses a transaction log called EditLog
  - to record every change to the file system’s meta data
    - E.g., creating a new file, change in replication factor of a file, ..
  - EditLog is stored in the NameNode’s local file system

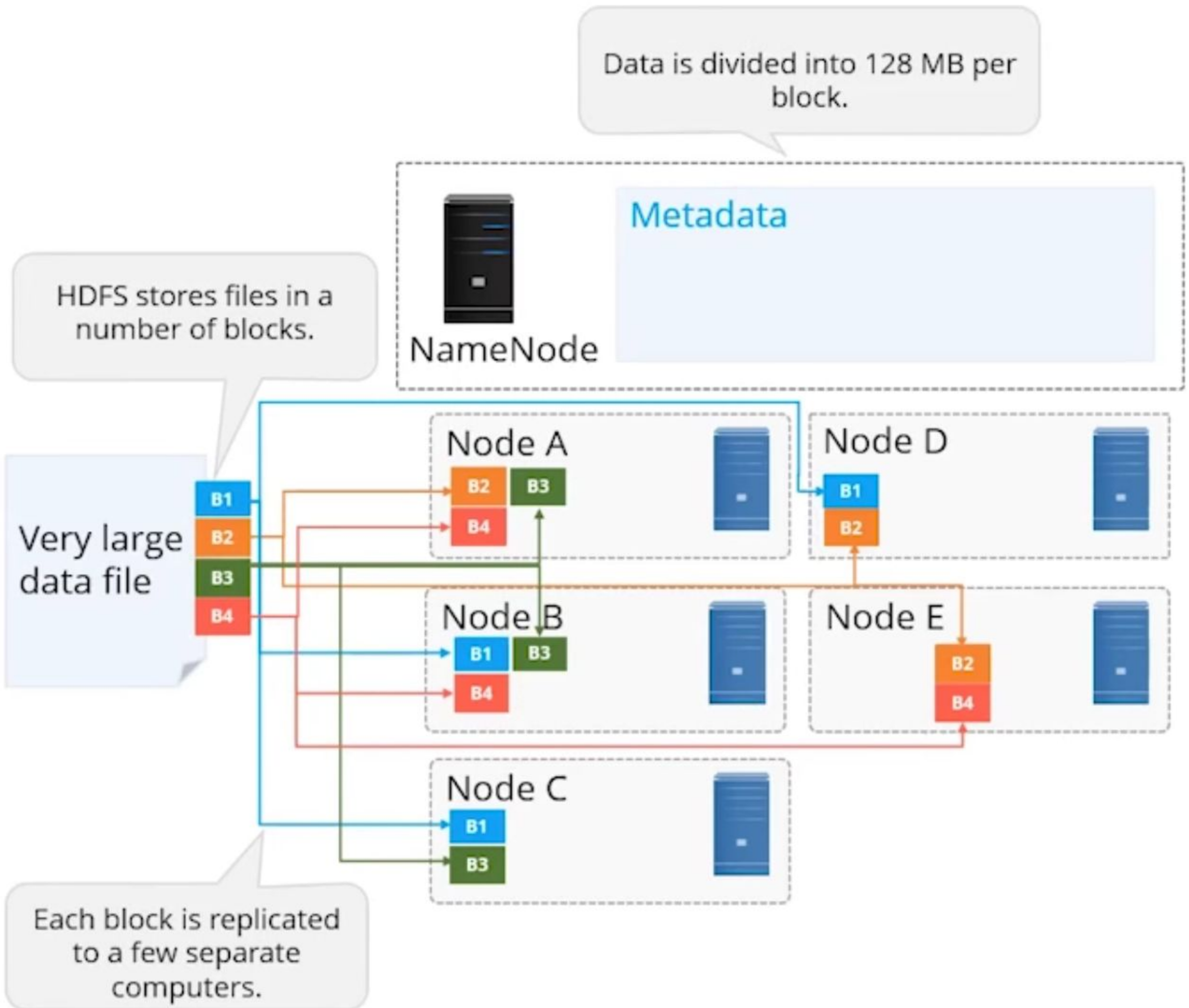
HDFS: DataNode

- Stores data blocks as files on its local file system
  - Each HDFS block is a separate file
  - Has no knowledge about HDFS file system
- When the DataNode starts up:
  - It generates a list of all HDFS blocks = BlockReport
  - It sends the report to NameNode

HDFS: Blocks & Replication

- HDFS can store very large files across a cluster
  - Each file is a sequence of blocks
  - All blocks in the file are of the same size
    - Except the last one
    - Block size is configurable per file (default 128MB)
    - Use of large files promotes high I/O throughput
  - Blocks are replicated for fault tolerance
    - Number of replicas is configurable per file
- NameNode receives HeartBeat and BlockReport from each DataNode
  - BlockReport: list of all blocks on a DataNode

HDFS: Block Replication

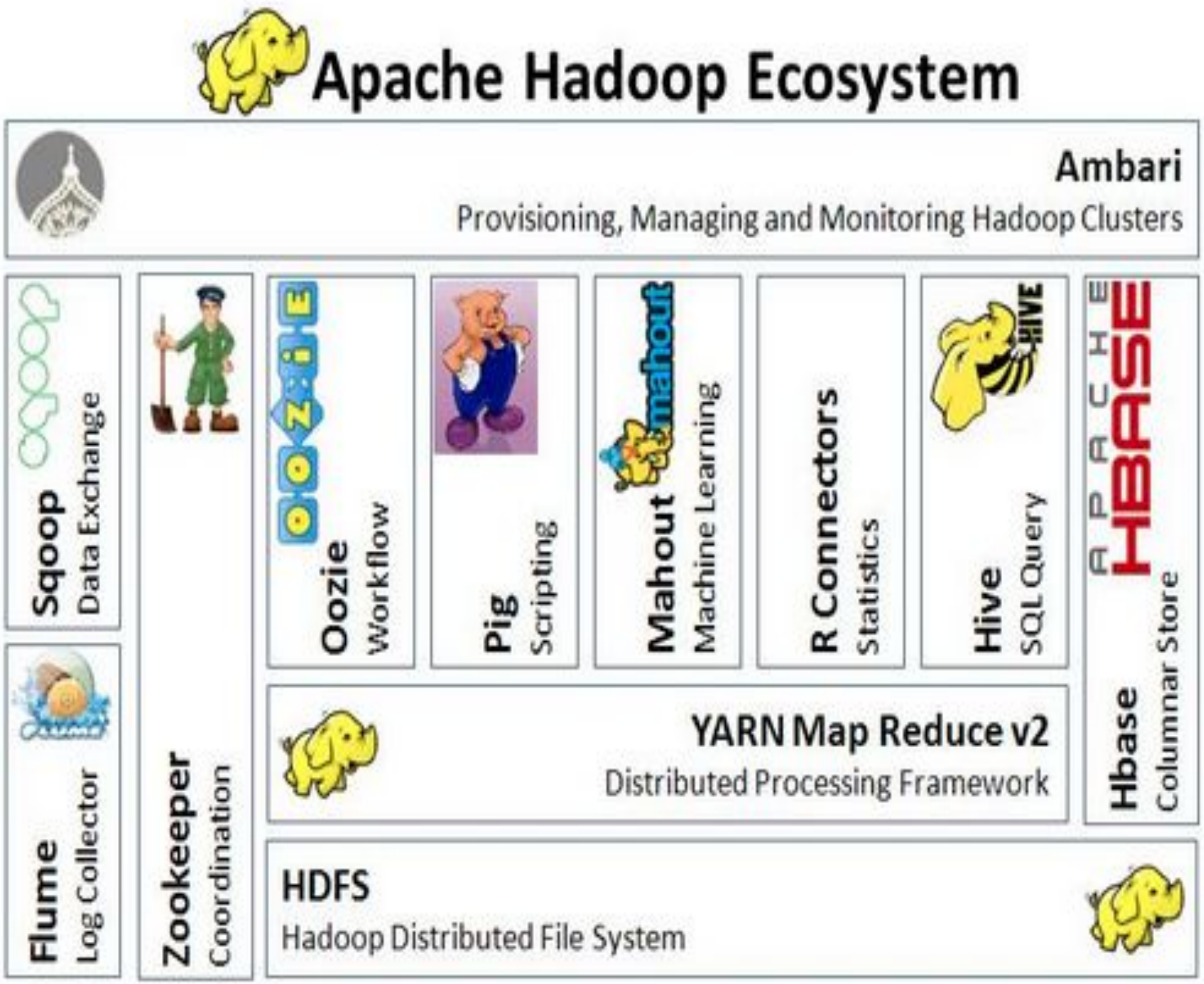


HDFS: Reliability

- Primary objective: to store data reliably in case of:
  - NameNode failure
  - DataNode failure
  - Network partition
    - a subset of DataNodes can lose connectivity with NameNode
- NameNode expects a periodic HeartBeat message from every datanode.
- In case of absence of a HeartBeat message
  - NameNode marks DataNodes without HeartBeat and does not send any I/O requests to them
  - A long period w/o a heartbeat from a DataNode typically results in re-replication
  - Tells another datanode with a replicate of the dead node's datablock to send a copy to some other "live" datanode

Hadoop: MapReduce

- Hadoop MapReduce requires:
  - Distributed file system (typically HDFS)
  - Engine that can distribute, coordinate, monitor and gather the results (typically YARN)
- Two main components:
  - JobTracker (master) = scheduler
    - tracks the whole MapReduce job
    - communicates with HDFS NameNode to run the task close to the data
  - TaskTracker (slave on each node) – is assigned a Map or a Reduce task (or other operations)
    - Each task runs in its own JVM



source: http://www.dineshonjava.com/2014/11/hadoop-architecture.html#.WLU6aBLyso8

Next time

- A shallow dive into the Hadoop Eco system
- Primarily, Pig and Hive