MapReduce & Hadoop

CUNY The City College of New York
NYU Center for Urban Science + Progress

Why is MapReduce?

- By definition, big data is too large to handle by conventional means. Sooner or later, you just can't scale **up** anymore
  - machines cannot grow too large…
- But we can add more computers!
- MapReduce paradigm allows us to scale **out**
  - even with commodity hardware
  - first proposed in the big data world by Google

Jeffrey Dean and Sanjay Ghemawat. *MapReduce: Simplified Data Processing on Large Clusters.* 2004.

What is MapReduce?

- A programming paradigm (for big data processing)
  - Data is split into distributable chunks
  - Perform a series of transformations on those chunks
  - Transformations are run in parallel on the chunks (data parallelism)
- MapReduce is scalable by adding more machines to process chunks
  - scaling out on commodity hardware
- The foundation for Hadoop, which is an implementation of MapReduce

What is MapReduce?

- A programming paradigm that process data in 2 phases/operations: **map()**, and then **reduce()**
  - instead of map(), filter(), reduce() in Python, we are limited to only map() and reduce()
- In a nutshell — *that's it*:
  - Provide a data collection (separable records)
  - Apply a user-defined map function on each data record
  - Then reduce the mapped output with another user-defined function

MapReduce Pipeline

- MapReduce works on ***(key,value) pairs***

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INPUT: list of key-value pairs of (k1,v1)

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MAP: (k1,v1) ➔ [list of (k2,v2)]

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SHUFFLE: combine (k2,v2) ➔ (k2, [list of v2])

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REDUCE: (k2, [list of v2]) ➔ (k3,v3)

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Fixed pipeline

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REDUCE: (k2, [list of v2]) ➔ (k3,v3)

OUTPUT: list of (k3,v3)

User-defined functions executed in parallel

The classic example: WordCount

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- Given a set of documents, compute the frequency of each word
- INPUT **(k1, v1)**: (document:line number, text line)
- OUTPUT **(k3, v3)**: (word, frequency)

The classic example: WordCount

- The “Hello World” of MapReduce
- Given a set of documents, compute the frequency of each word
- INPUT **(k1, v1)**: (document:line number, text line)
- OUTPUT **(k3, v3)**: (word, frequency)
- INTERMEDIATE **(k2, v2)**: (word, 1)

The classic example: WordCount

- The “Hello World” of MapReduce
- Given a set of documents, compute the frequency of each word
- INPUT **(k1, v1)**: (document:line number, text line)
- OUTPUT **(k3, v3)**: (word, frequency)
- INTERMEDIATE **(k2, v2)**: (word, 1)
  - Transform each line to a list of words and their frequencies (=1)

The classic example: WordCount

- The “Hello World” of MapReduce
- Given a set of documents, compute the frequency of each word
- INPUT **(k1, v1)**: (document:line number, text line)
- OUTPUT **(k3, v3)**: (word, frequency)
- INTERMEDIATE **(k2, v2)**: (word, 1)
  - Transform each line to a list of words and their frequencies (=1)
  - Combine all tuples by words, and add all the frequency together

Example: Word Count

Input Data

```
the cat sat on the mat
the aardvark sat on the sofa
```

Result

aardvark	1
cat	1
mat	1
on	2
sat	2
sofa	1
the	4

Example: The WordCount Mapper (1)

Input Data (HDFS file)

```
the cat sat on the mat
the aardvark sat on the sofa
…
```

Record Reader

0	the cat sat on the mat
23	the aardvark sat on the sofa
52	…
…	…

Mapper

[*Cloudera Academic Resources*]

Example: The WordCount Mapper (2)

Input Data (HDFS file)

```
the cat sat on the mat
the aardvark sat on the sofa
…
```

Record Reader

0	the cat sat on the mat
23	the aardvark sat on the sofa
52	…
…	…

Mapper

map()

map()

the	1
cat	1
sat	1
on	1
the	1
mat	1

the	1
aardvark	1
sat	1
on	1
the	1
sofa	1

[Cloudera Academic Resources]

Example: WordCount Shuffle and Sort

Node 1

Mapper

the	1
cat	1
sat	1
on	1
the	1
mat	1
the	1
aardvark	1
sat	1
on	1
the	1
sofa	1

aardvark	1
cat	1
mat	1
on	1,1
sat	1,1
sofa	1
the	1,1,1,1

aardvark	1
cat	1
mat	1

elephant	1
mahout	1
sat	1,1

Node 2

Mapper

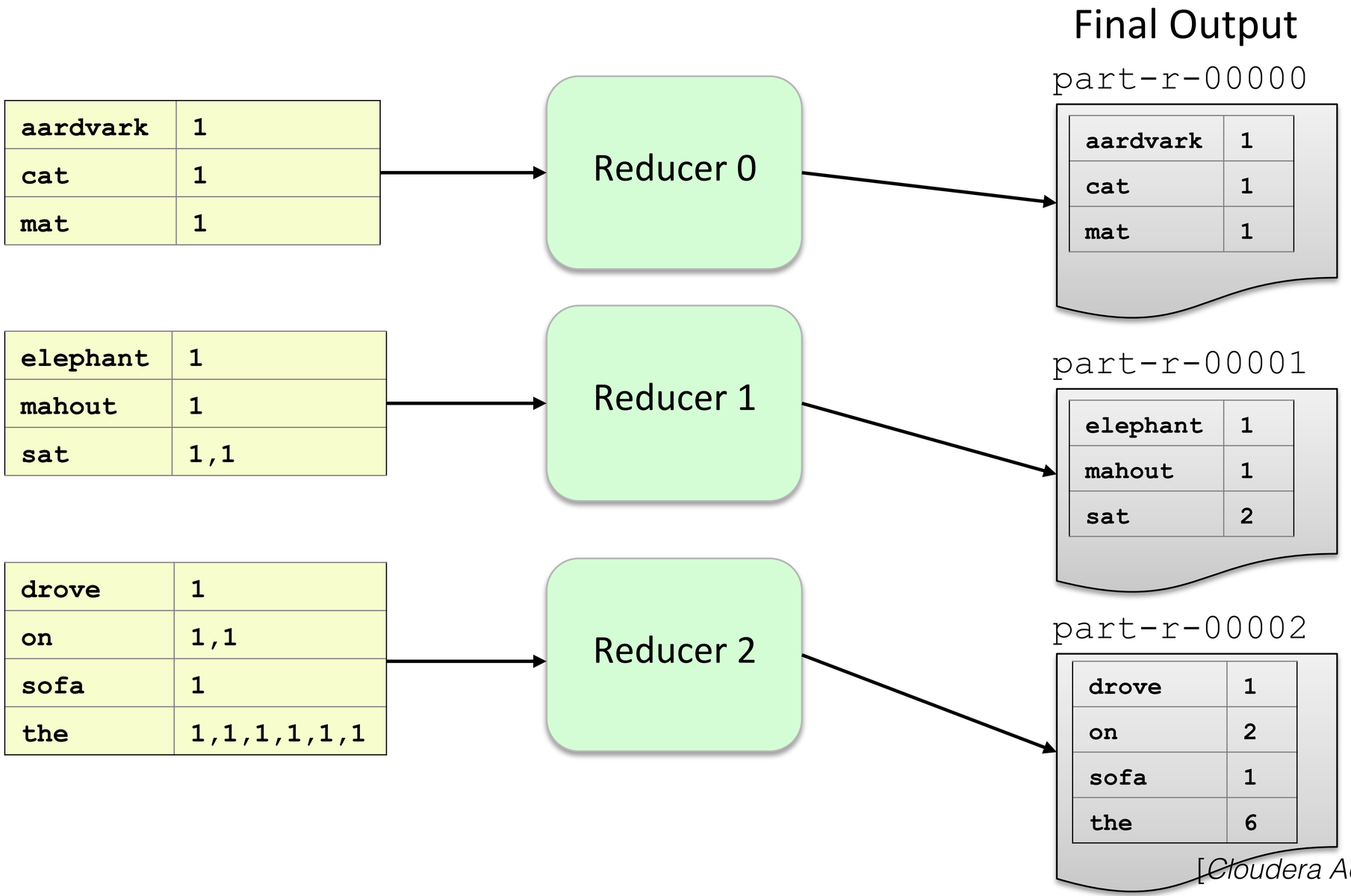
the	1
mahout	1
drove	1
the	1
elephant	1

drove	1
elephant	1
mahout	1
the	1,1

drove	1
on	1,1
sofa	1
the	1,1,1,1,1,1

[*Cloudera Academic Resources*]

Example: SumReducer (1)



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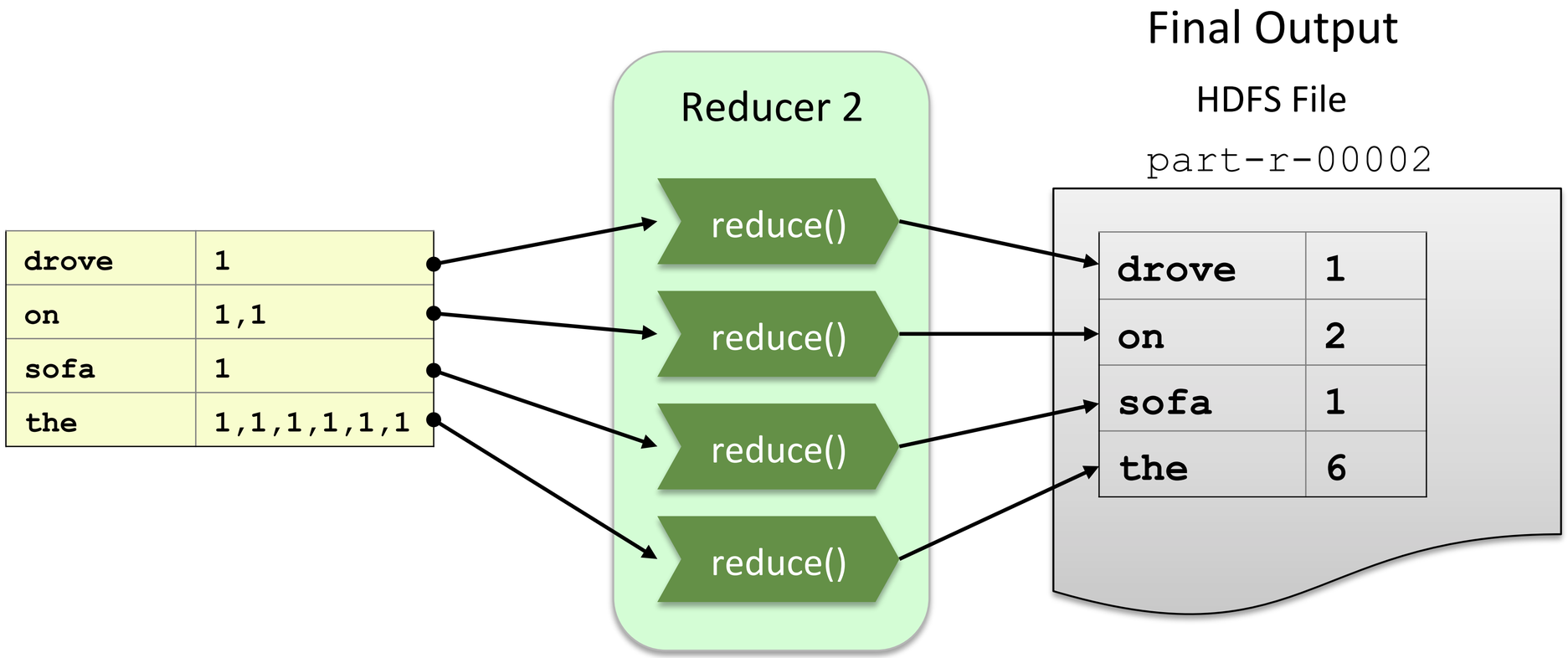
Example: SumReducer (2)



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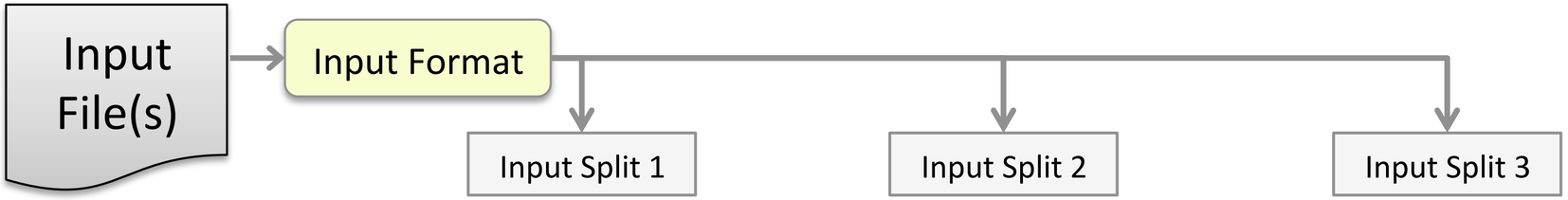
The MapReduce Flow



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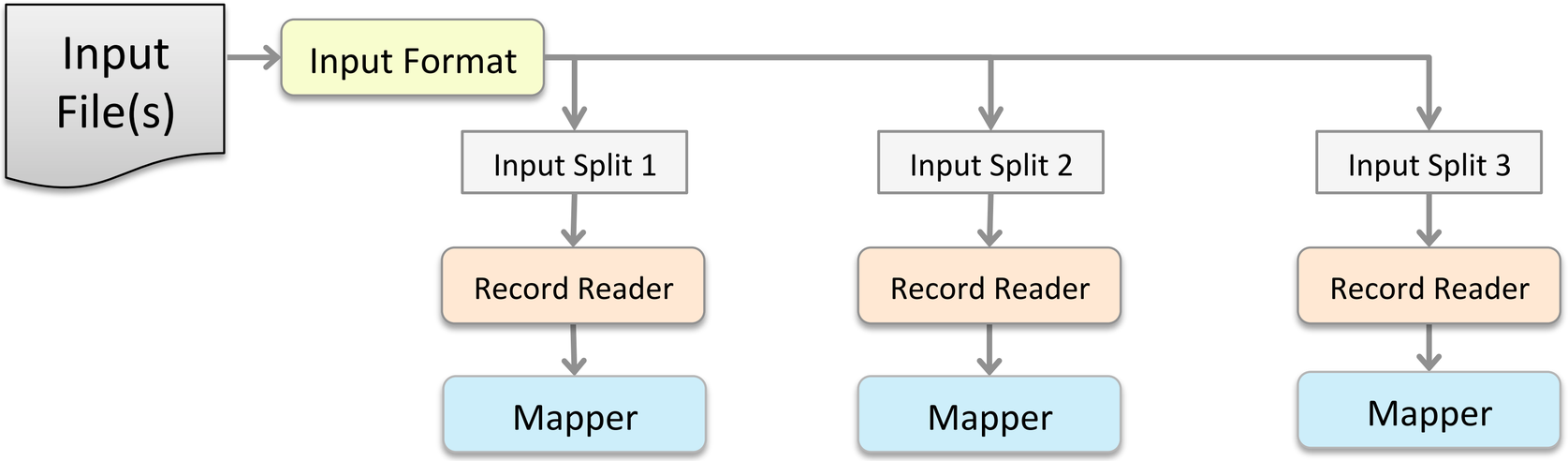

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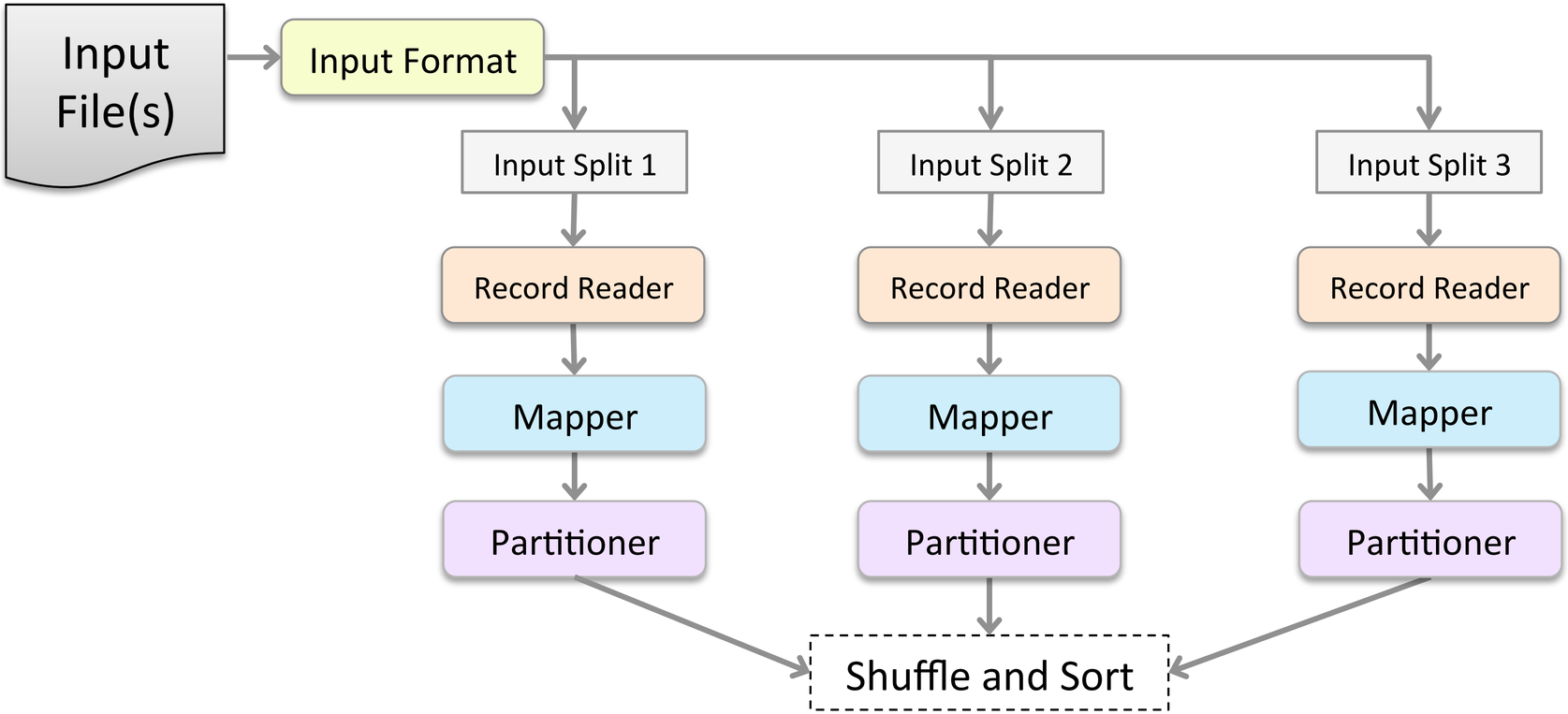

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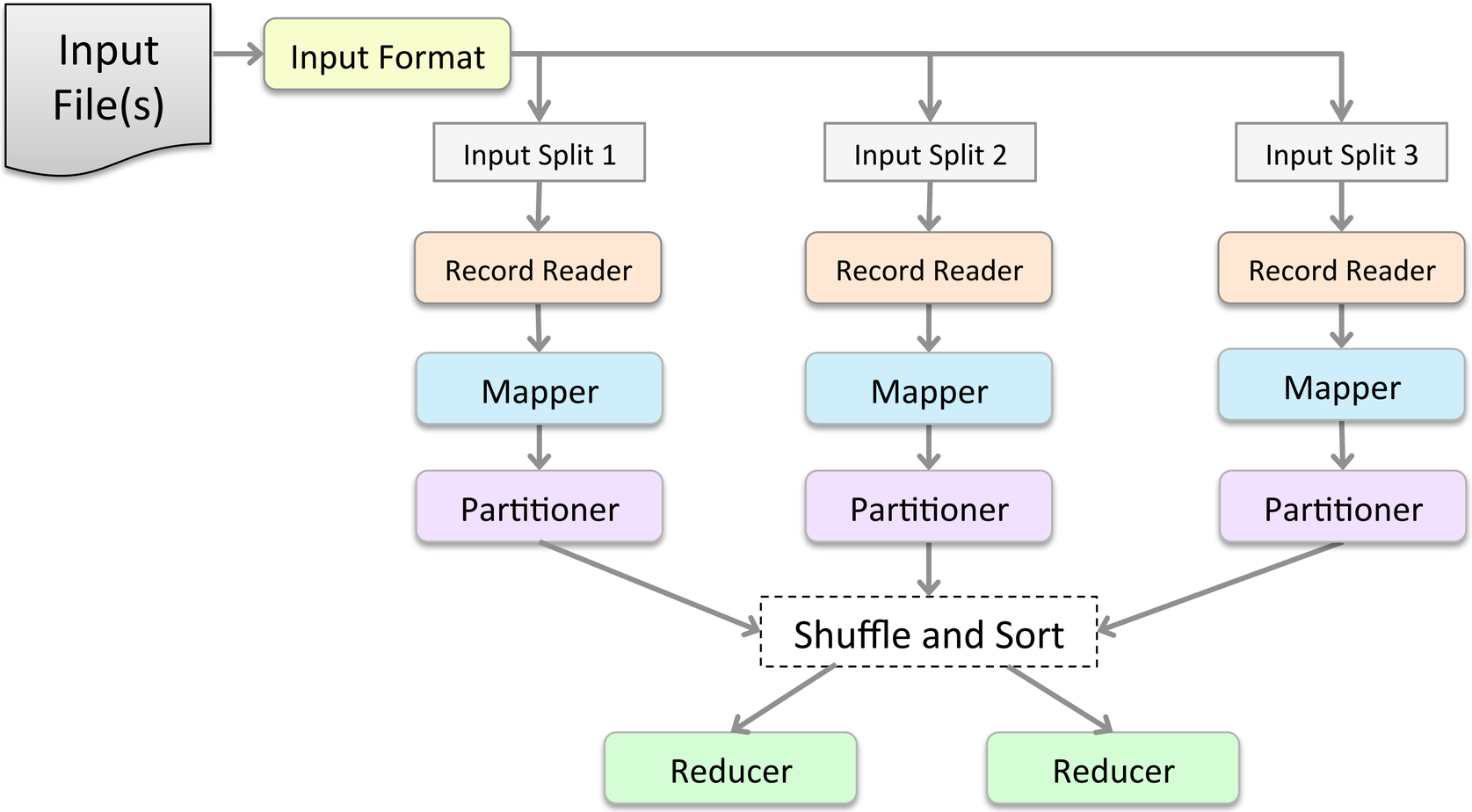
The MapReduce Flow



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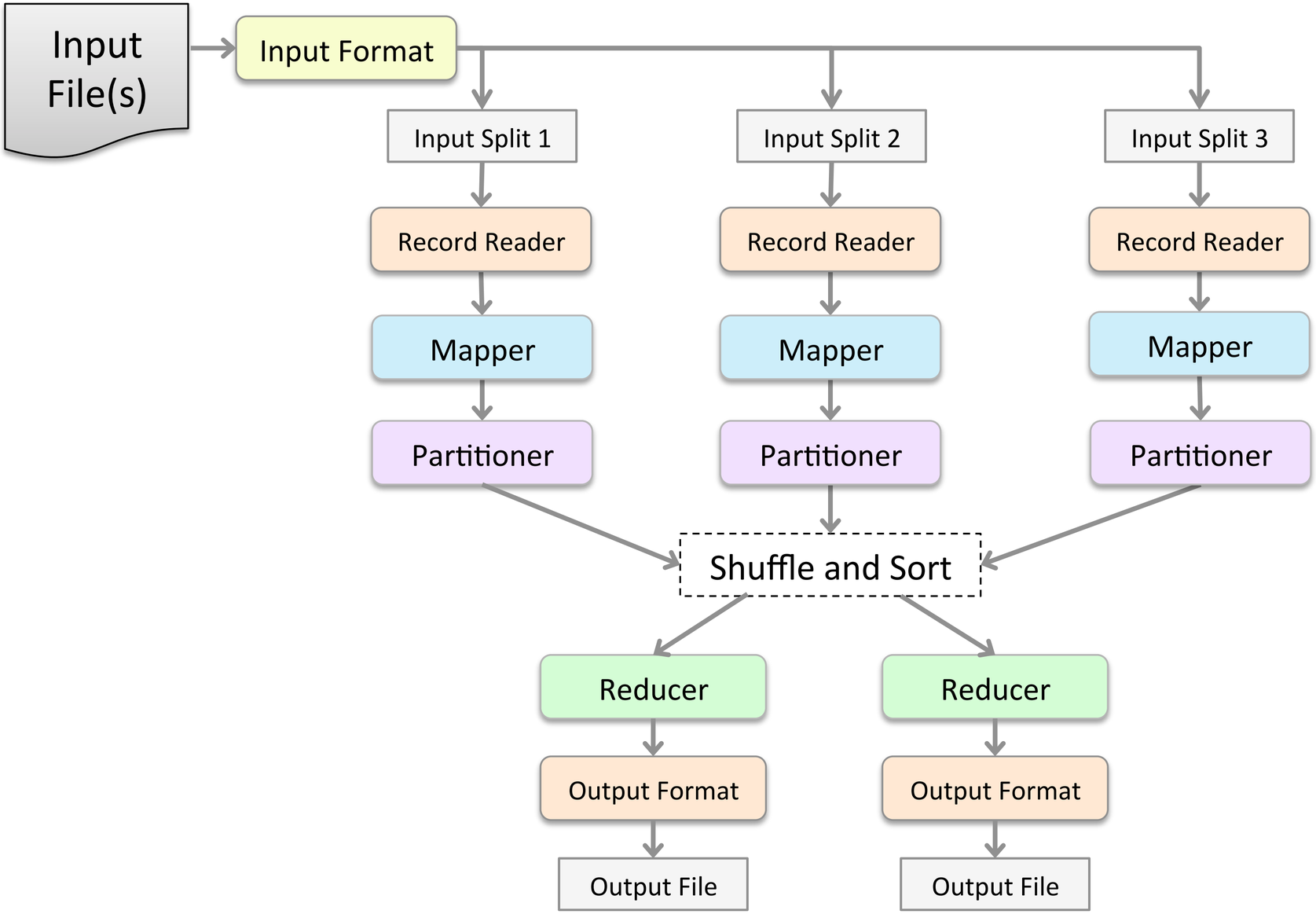

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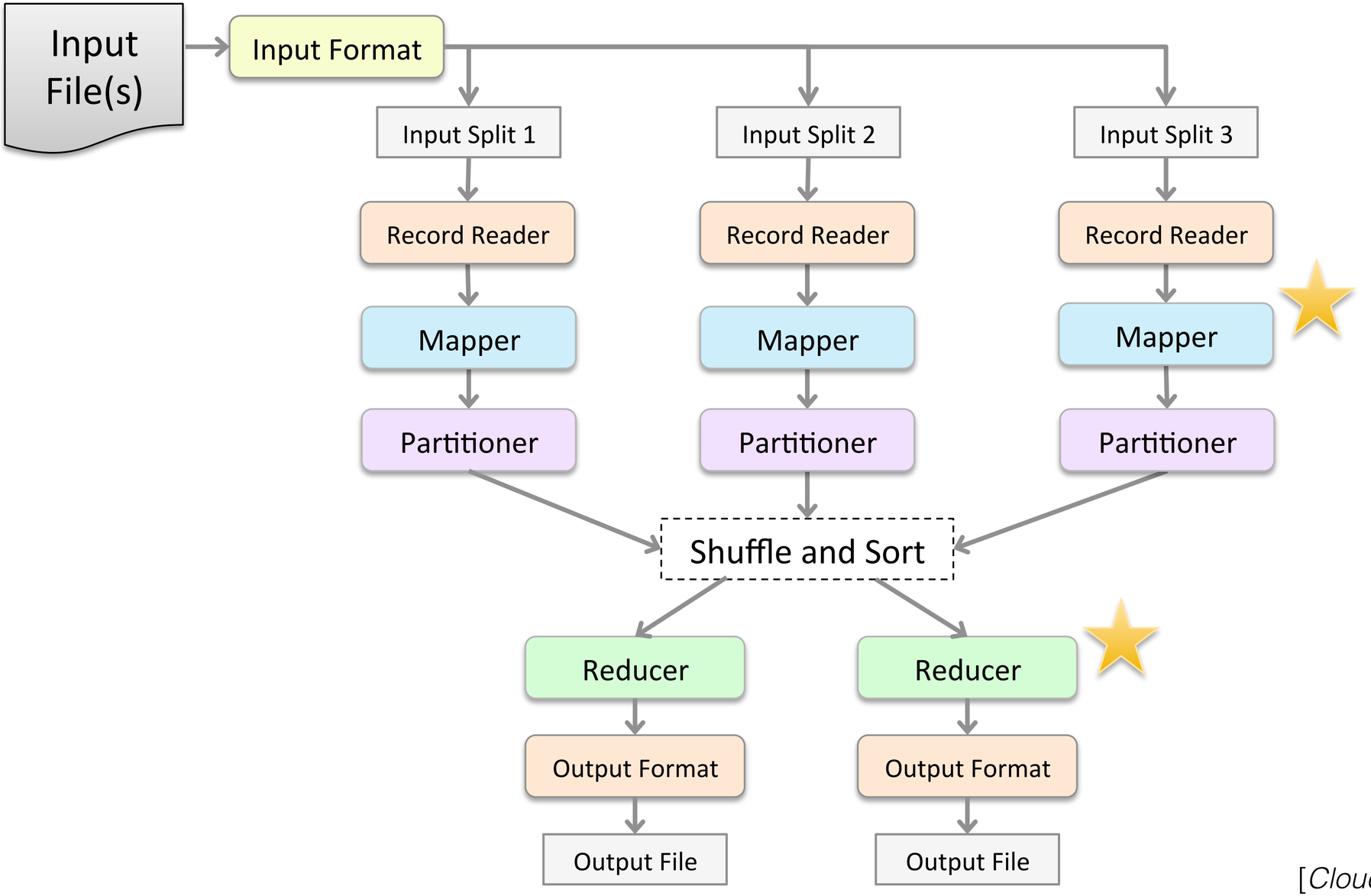

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Input

- Data must be separable into records
  - Lines of text
  - Rows of tables
  - CSV: ***yes*** — JSON, XML: ***no*** (except independent JSONs/XMLs)
- Key/value pairs
  - Key = line number, record index
  - Value = text string, row data
- Keys are mostly ignored in many cases (e.g. just passing text lines)

Map phase

- Transform each input record using a user-defined function
  - **(k1,v1)** ➔ [**(k2,v2)**,…] — *could be an empty list*
- one-to-many relationship
  - vs. one-to-one of Python's map() higher order function
  - Python's filter() is part of the Map phase
- Under the hood, data are processed in a streaming fashion
  - [**(k1,v1)**] ➔ [**(k2,v2)**,…]
  - *generators* ➔ *generators*

Map Phase

pi	3.14

map()

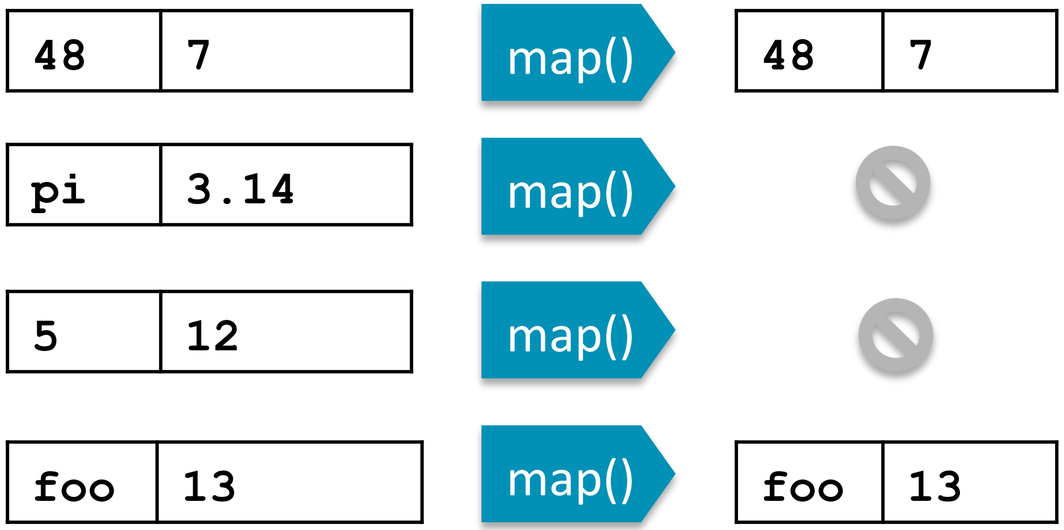
pi	3
pi	.
pi	1
pi	4

145	kale

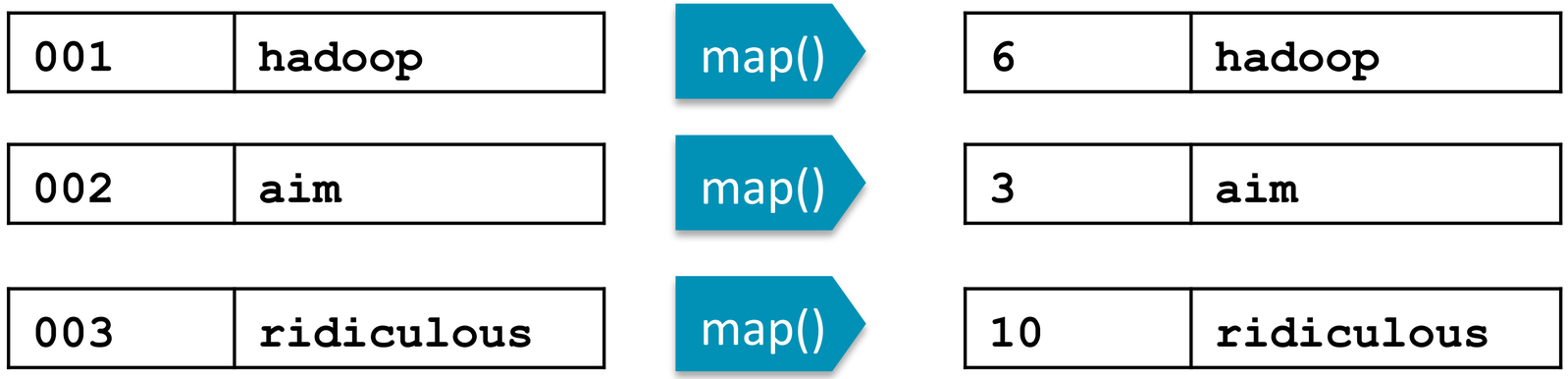
map()

145	k
145	a
145	l
145	e

Map Phase



Map Phase



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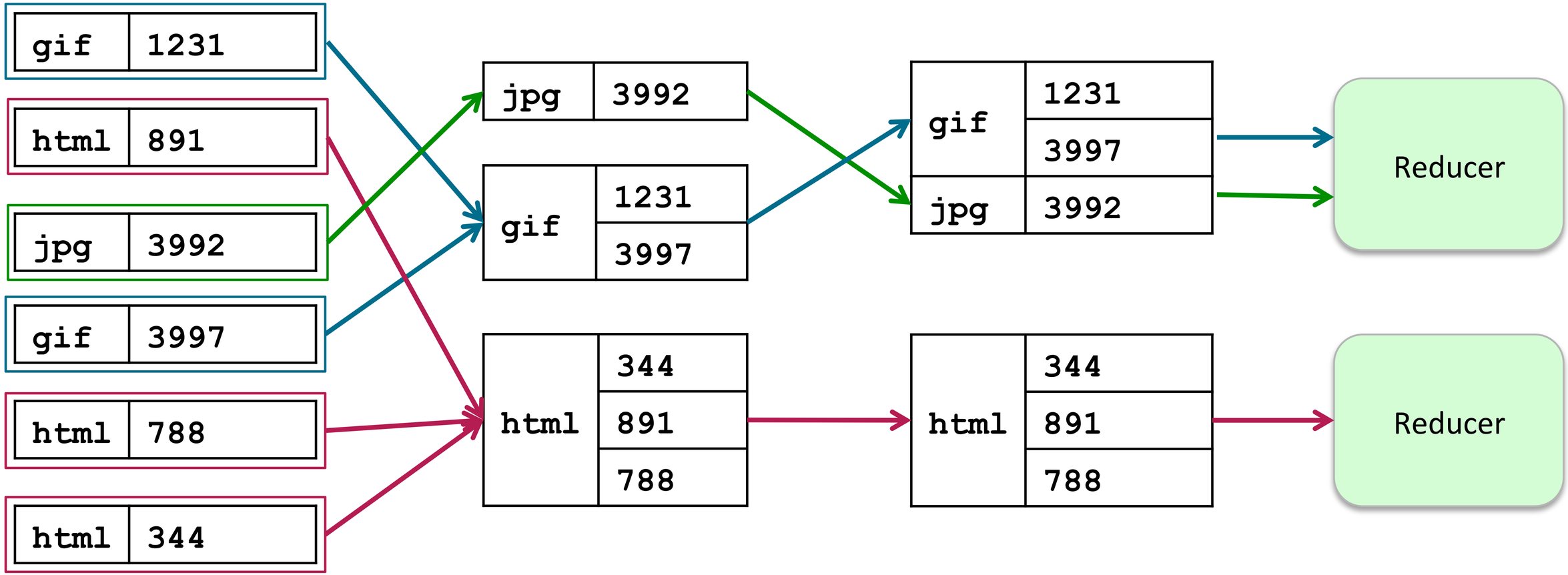
Shuffle & Sort Phase

- For each key **k2**, collect all **v2** from outputs of all map processes — *shuffling* into **(k2, [v2])**
  - Done by distributed partitioning and local sort
- Outputs are **(k2, [v2])** being distributed to “reducers”
- [**(k2,v2)**] ➔ **(k2, [v2])**
- **(k2,v2)** are *intermediate* key/value pairs

Shuffle & Short



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Reduce phase

- Transform the output of the Shuffle phase using a user-defined function
  - **(k2,[v2])** ➔ **(k3, v3)**
- Equivalent to reduceByKey() ~ groupByKey() x reduce()
  - vs. Python's reduce()
- Also process in streaming data chunks
  - [**(k2, [v2])**] ➔ [**(k3, v3)**]
- This phase is *optional*, can be omitted.

Reduce phase

the	1
	1
	1
	1

reduce()

the	1

SKU0021	34
	8
	19

reduce()

SKU0021	20.33

Output

- Redirect output from each reducer as an unsorted list of **(k3, v3)**
  - Store as separate files
  - Print to the console
  - Load data into databases

When to use MapReduce?

- Data parallelism problems (“embarrassingly parallel”)
  - Word count
  - Distributed grep
  - Reverse index
  - Document OCR
- Data must be splittable into chunks and records

More examples

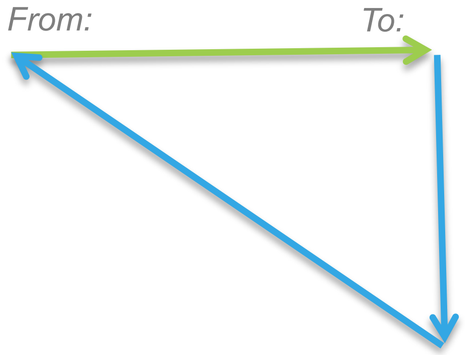
- Distributed grep – all lines matching a pattern
  - Map: filter by pattern
  - Reduce: output set
- Inverted index
  - Map: output (word,documentID)
  - Reduce: combines these into (word,[documentID])
- Joining data sets by BBL:
  - Map: process (BBL, feature value)
  - Reduce: combine (BBL, [list of features])

Example: Social Triangle

- Goal: inspect emails for To:From pairings to determine social relationship of any two contacts
  - A email B and B email A ➔ A~B is reciprocal
  - A email B but B doesn't email A ➔ A~B is directed

Date: Thu, 4 May 2000 09:55:00 -0700 (PDT)
From: walt.zimmerman@enron.com
To: michael.burke@enron.com, dana.gibbs@enron.com, lori.maddox@enron.com, susan.ralph@enron.com
Subject: Update on Steve Todoroff Prosecution--CONFIDENTIAL/SUBJECT TO ATTORNEY-CLIENT PRIVILEGE
Cc: steve.duffy@enron.com, stanley.horton@enron.com, jdegeeter@velaw.com

Social Triangle: First Directed Edge



Mapper1

Maps two regular expression searches:
To: Michael, Dan, Lori, Susan
From: Walt

Emits the outbound directed edge of the social graph:
<Key, Value> = <Walt, [Michael, Dan, Lori, Susan]>

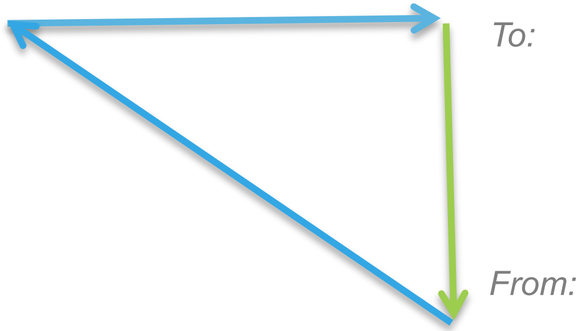
Reducer1

Gets the output from the mapper with different values
<Key, Value> = <Walt, [Michael, Dan, Lori, Susan]>
<Key, Value> = <Walt, [Lori, Susan, Jeff, Ken]>

Unions the values for the second directed edge:
<Key, Value> = <Walt, [Dan, Jeff, Ken, Lori, Michael, Susan]>

Social Triangle: Second Directed Edge

Mapper2



Reverses the previous Map:
To: Michael, Dan, Lori, Susan
From: Walt

Emits the inbound directed edge of the social graph:
<Key, Value> = <Susan, Walt>; <Lori, Walt>; <Dan, Walt>; etc

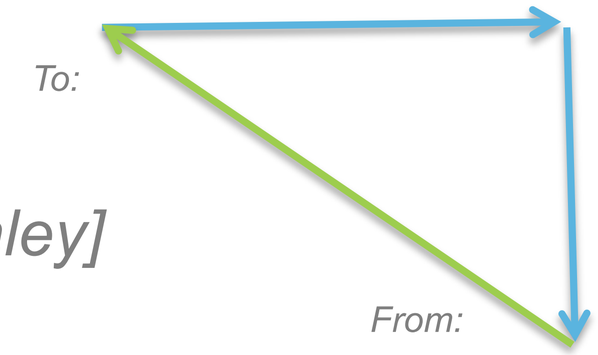
Reducer2

Gets the output from the mapper with different values
<Key, Value> = <Susan, Walt>
<Key, Value> = <Susan, Jeff>

Unions the values for the third directed edge:
<Key, Value> = <Susan, [Jeff, Ken, Walt]>

Social Triangle: Third Directed Edge

Mapper3



Join [inbound] and [outbound] lists by Key
Walt, [Jeff, Ken, Lori, Susan], [Jeff, Lori, Stanley]

Emits <Person, Person> pair with level of association:
<Key, Value> = <Walt: Jeff reciprocal>; <Walt:Stanley directed>,
etc

Reducer3

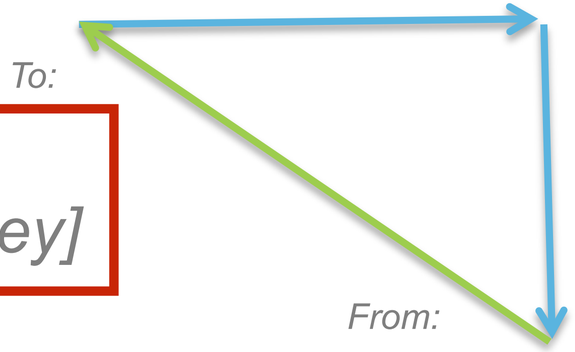
Reducer unions the output of the mappers and presents rules:
<Key, Value> = <Walt::Jeff, reciprocal>
<Key, Value> <Walt::Stanley, directed>

Social Triangle: Third Directed Edge

Another MapReduce Job

Mapper3

Join [inbound] and [outbound] lists by Key
Walt, [Jeff, Ken, Lori, Susan], [Jeff, Lori, Stanley]



Emits <Person, Person> pair with level of association:
<Key, Value> = <Walt: Jeff reciprocal>; <Walt:Stanley directed>,
etc

Reducer3

Reducer unions the output of the mappers and presents rules:
<Key, Value> = <Walt::Jeff, reciprocal>
<Key, Value> <Walt::Stanley, directed>

Designing MapReduce Algorithms

- Key decision: What should be done by **map**, and what by **reduce**?
  - **map** can do something to each individual key-value pair, but it can't look at other key-value pairs
    - Example: Filtering out key-value pairs we don't need
  - **map** can emit more than one intermediate key-value pair for each incoming key-value pair
    - Example: Incoming data is text, map produces (word,1) for each word
  - **reduce** can aggregate data; it can look at multiple values, as long as map has mapped them to the same (intermediate) key
    - Example: Count the number of words, add up the total cost, ...

Designing MapReduce Algorithms

- Need to get the intermediate format right!
  - If **reduce** needs to look at several values together, map must emit them using the same key!
- Work the algorithm bottom up
  - Look at the desired output (k3,v3), and what are needed to compute them to design your reducer and (k2,v2)
  - Then look at what are needed to compute (k2,v2), hopefully to get (k1,v1) and your mapper
- Sometime more than one MapReduce jobs are needed to finish a task

Filtering with MapReduce

- Goal: find lines/files/tuples with a particular characteristic

- Examples:
  - grep Web logs for requests to a specific domain
  - find in the Web logs the hostnames accessed by a particular IP
  - locate all the files that contain the words 'Apple' and 'Jobs'

- Generally: **map** does most of the work, utilizing one-to-many relationships to discard unqualified records. **reduce** may simply be the identity

Aggregation with MapReduce

- Goal: compute the maximum, the sum, the average, ..., over a set of values

- Examples:
  - Count the number of requests to a website
  - Count the number of CitiBike trips per station
  - Average the number of 311 calls by region

- Often: **map** may be simple or the identity, **reduce** does the aggregation

Lab 3 — Task 7

- Find the station with the highest number of bike pickups by genders
  - User type must be *'Subscriber'*

```
[('Female', ('W 21 St & 6 Ave', 107)),
 ('Male', ('8 Ave & W 31 St', 488)),
 ('Unknown', ('Pearl St & Hanover Square', 1))]
```

Bottom-up Approach

```
[('Female', ('W 21 St & 6 Ave', 107)),
 ('Male', ('8 Ave & W 31 St', 488)),
 ('Unknown', ('Pearl St & Hanover Square', 1))]
```

Bottom-up Approach

Bottom-up Approach

```
(gender, (station, max_count))
```

Bottom-up Approach

```
(gender, (station, max_count))
```

↑ *max()*

Bottom-up Approach

```
(gender, (station, max_count))
```

↑ *max()*

```
(gender, [(station, count)…])
```

Bottom-up Approach

```
(gender, (station, max_count))
```

↑ *max()*

```
(gender, [(station, count)…])
```

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
```

↑ *max()*

```
(gender, [(station, count)…])
```

↑ *?*

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

"Word Count"

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
((gender, station), count)
```

↑ *"Word Count"*

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
((gender, station), count)
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

↑ ?

```
((gender, station), count)
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

```
((gender, station), count)
(gender, station)
```

Bottom-up Approach

```
(gender, (station, max_count))
(gender, [(station, count)…])
```

↑ *"mapping"*

```
((gender, station), count)
(gender, station)
```

Bottom-up Approach

reduce (aggregate)

map (transform)

MapReduce (word count)

```
(gender, (station, max_count))

(gender, [(station, count)…])

(gender, station)
```

Bottom-up Approach

reduce (aggregate)

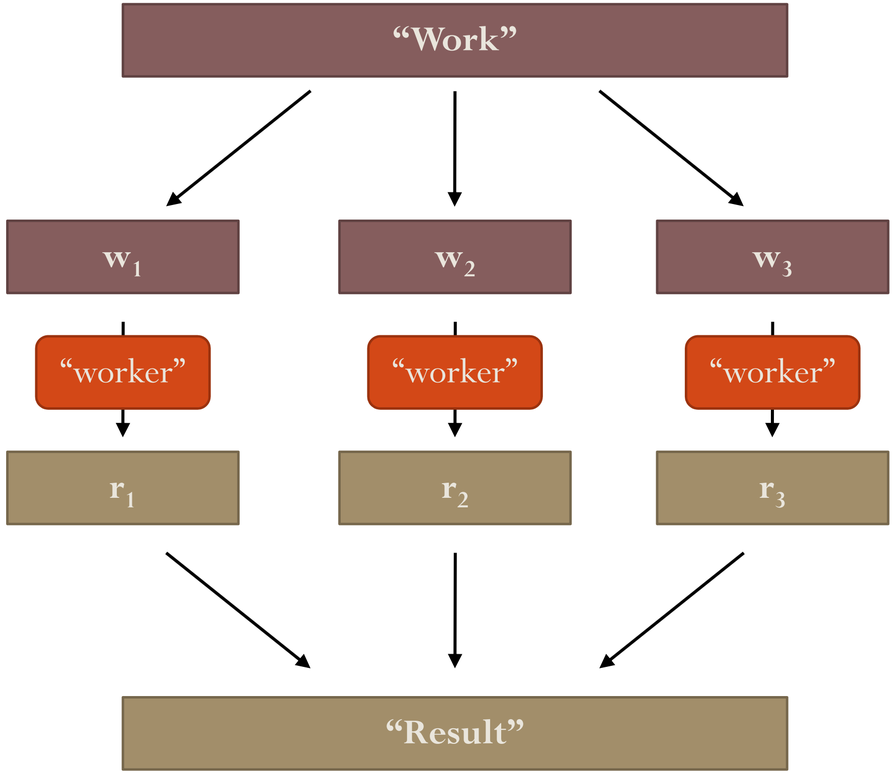
map (transform)

MapReduce (word count)

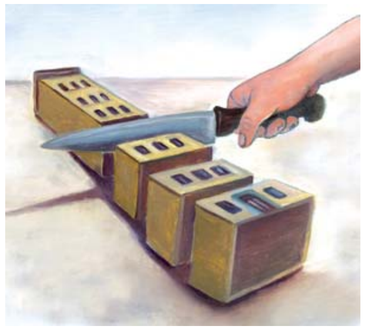
```
(gender, (station, max_count))

(gender, [(station, count)…])

((gender, station), count)

(gender, station)
```

MapReduce for Big Data

- Data parallelism — *scaling out*
  - Divide and Conquer
- Distributed computing
  - Data on different machines
- Bring compute to the data
  - Reduce transferring cost



Divide



Conquer

[Source: *Riccardo Torlone*]

What are the challenges?

- How do we distribute data across machines?
- How do we keep track of where the data are?
- How do we assign work units to machines?
- What if we have more work units than machines?
- What if a machine dies?
- Can we recover from a crash?

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- [illegible]
- **Distributed File System**
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Both

What is hadoop ?

People use “Hadoop” to mean one of four things:

- MapReduce paradigm.
- Massive unstructured data storage on commodity hardware.

(ideas)

- Java Classes for HDFS types and MapReduce job management.
- HDFS: The Hadoop distributed file system.

(actual Hadoop)

With Hadoop, you can do MapReduce jobs quickly and efficiently.

What is hadoop ?

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open-source!

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…in other words

- Hadoop = HDFS + MapReduce
- Hadoop = Big Data + Analytics

Two Main Components

Storage (Big Data)

- HDFS – Hadoop Distributed File System
- Reliable, redundant, distributed file system optimized for large files

MapReduce (Analytics)

- Programming model for processing sets of data
- Mapping inputs to outputs and reducing the output of multiple Mappers to one (or a few) answer(s)

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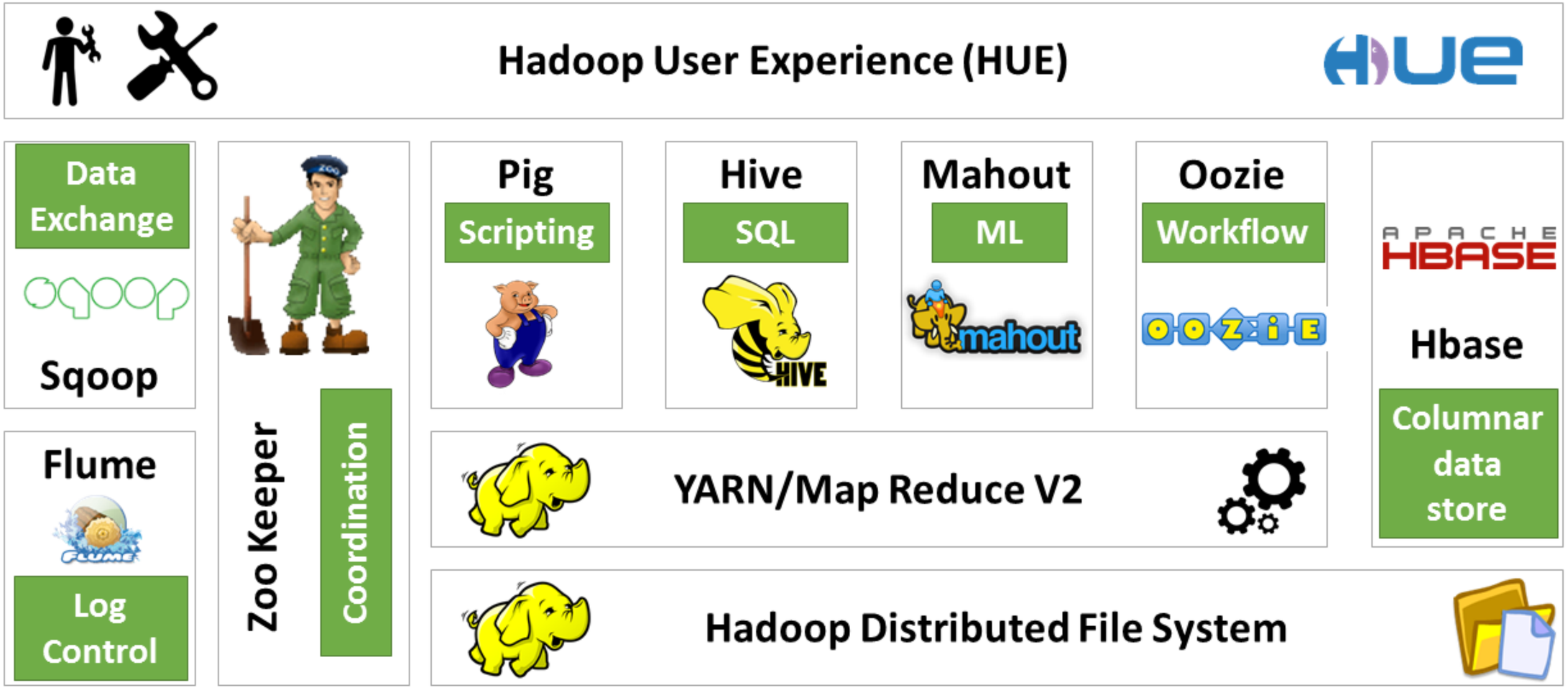
+ YARN (Yet Another Resource Negotiator)

Hadoop Ecosystem (use/support HDFS)



[Source: *Banyan*]

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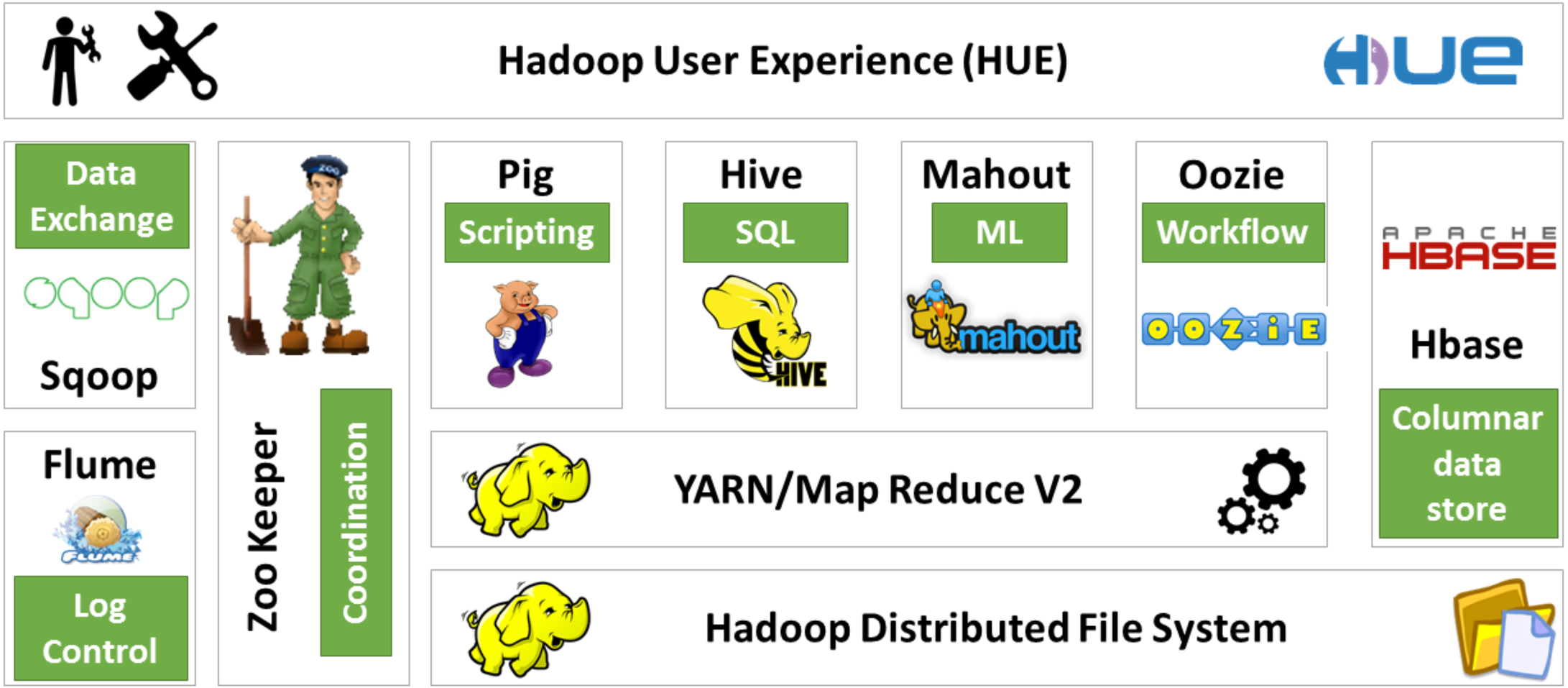


making data center become a computer

[Source: *Banyan*]

(Hadoop) Distributed File System

- Commodity hardware
- **Significant failure rates**
  - Nodes can fail over time
- “Modest” number of huge files
  - Multi-gigabyte files are common, if not encouraged
- Files are write-once, mostly appended to
  - Perhaps concurrently
- Large streaming reads over random access
  - High sustained throughput over low latency

[Source: *Riccardo Torlone*]

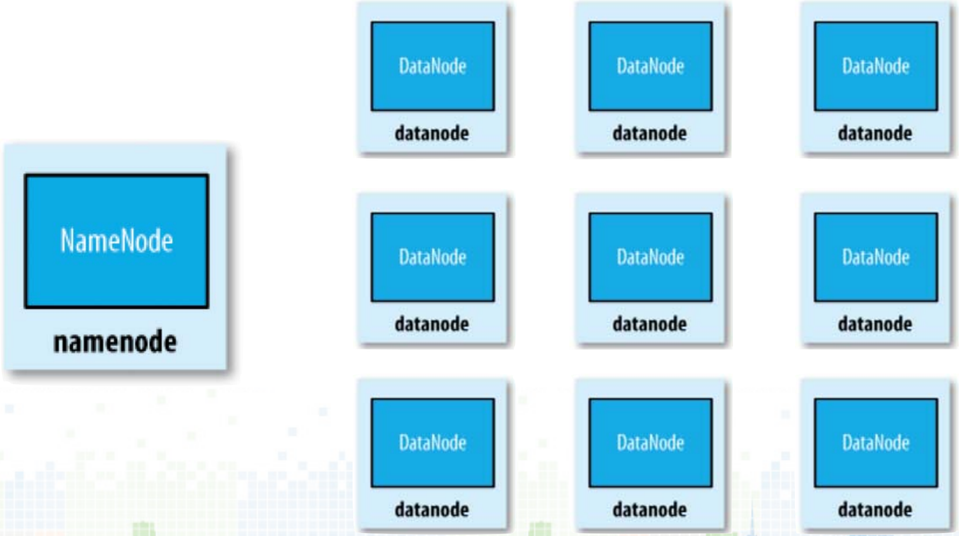
(H)DFS: Organization

- Files are divided into **chunks** (typically 64MB in size)
- Chunks are **replicated** at different compute nodes (usually 3+)
- Nodes holding copies of one chunk are located on different racks
- Chunk size and the degree of replication can be decided by the user
- A special file (the **master node**) stores, for each file, the positions of its chunks
- A directory for the file system knows where to find the master node
- Both the master node and the directory itself can be replicated
- All participants using the (H)DFS know where the directory copies are

[Source: *Riccardo Torlone*]

HDFS Implementation

- Master/slave architecture
- There are two types of nodes:
  - NameNode: a master server that manages the file system namespace and regulates access to files by clients
  - DataNode: holds data blocks, attached to storage devices
  -



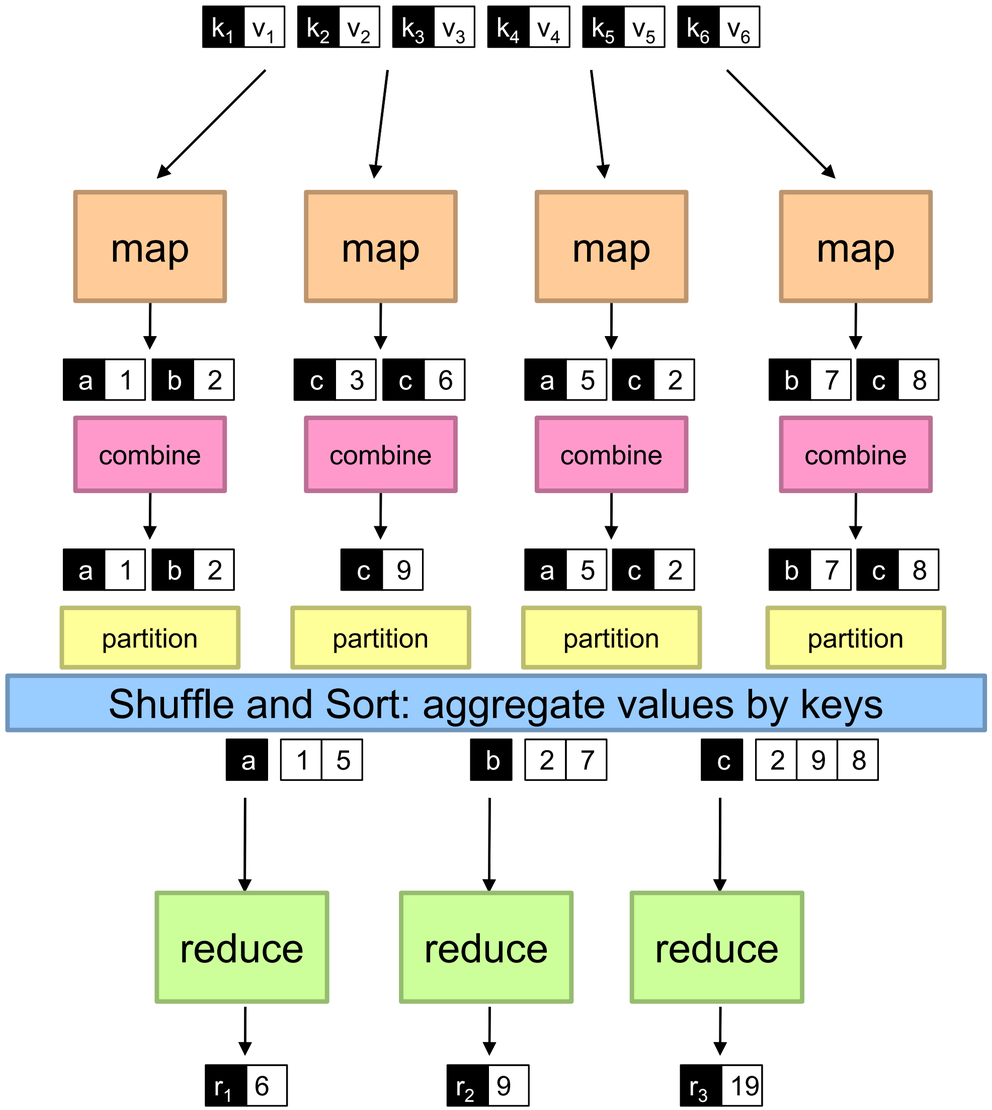
[Source: *Riccardo Torlone*]

HDFS Notes

- Designed to support **Fault Tolerance**
- However, without the NameNode HDFS cannot be used
  - The NameNode machine is a single point of failure
  - It is important to make the namenode resilient to failure

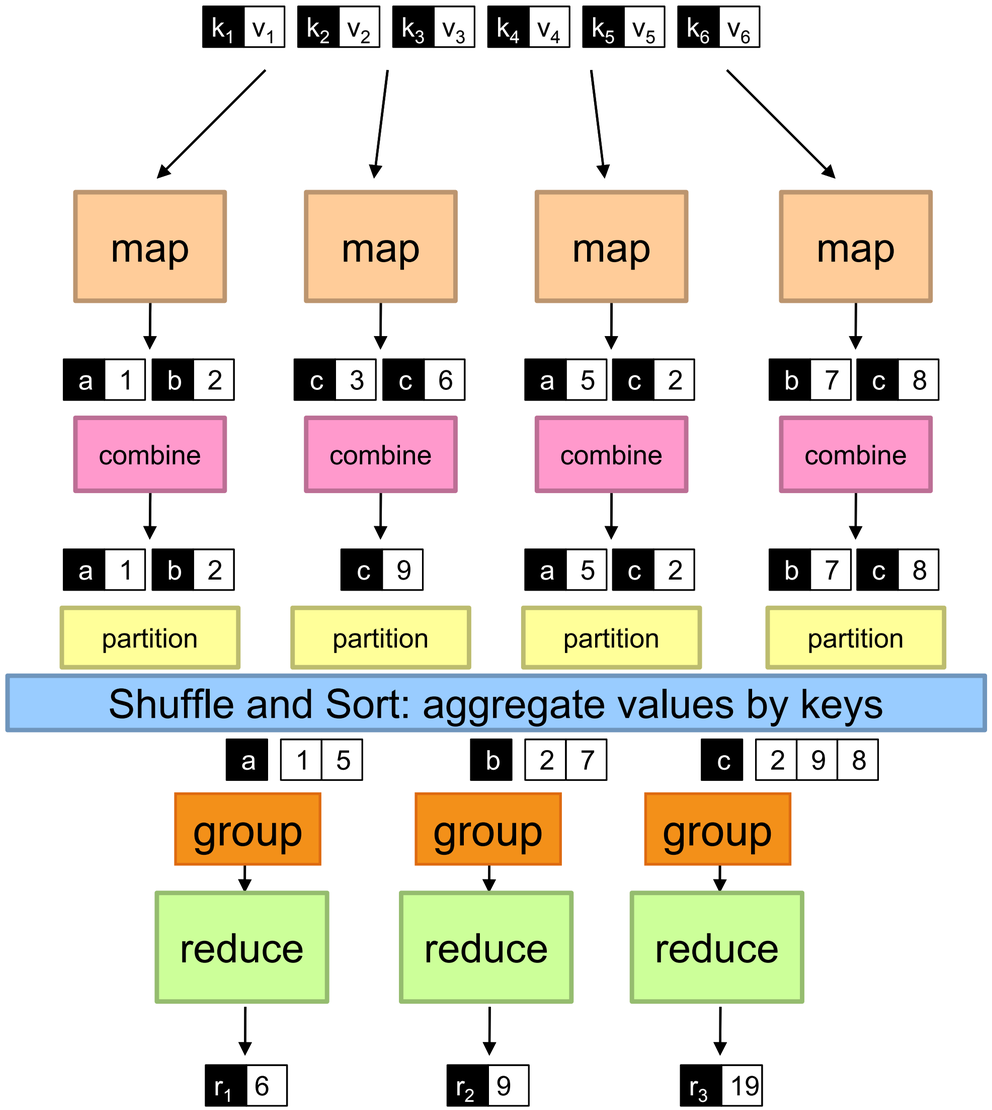
[Source: *Riccardo Torlone*]

Hadoop and MapReduce



[Source: *Jimmy Lin*]

Hadoop and MapReduce



[Source: *Jimmy Lin*]

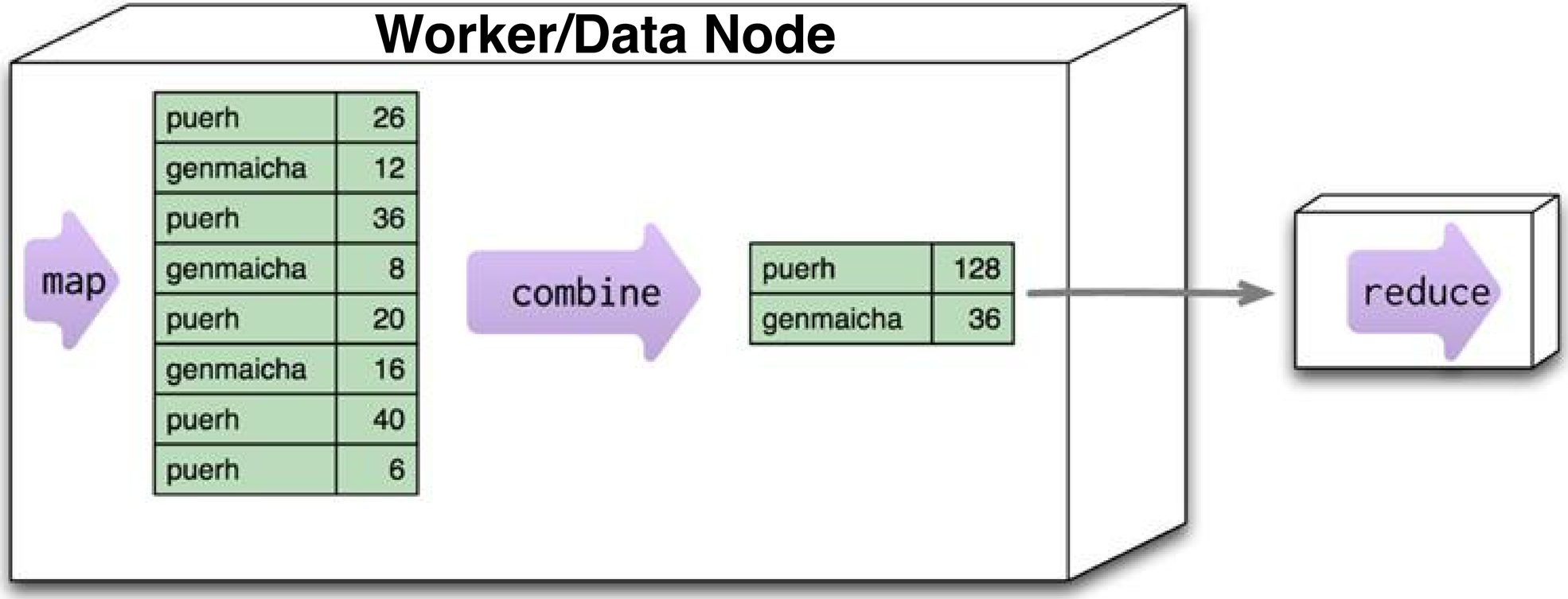
Combiners

- Certain functions can be decomposed into partial steps:
  - Can take counts of two sub-partitions, sum them up to get a complete count for the partition
  - Can take maxes of two sub-partitions, max them to get a complete max for the partition

- Multiple map jobs on the same machine may write to the same reduce key

-

Combiner Example



[Source: *Riccardo Torlone*]

Combiner Example (vs. Reducer)

dragonwell	ann
puerh	ann
puerh	brian
genmaicha	claire
puerh	david
dragonwell	ann
hojicha	ann
puerh	claire
genmaicha	claire

dragonwell	1
puerh	**4**
genmaicha	1
hojicha	1

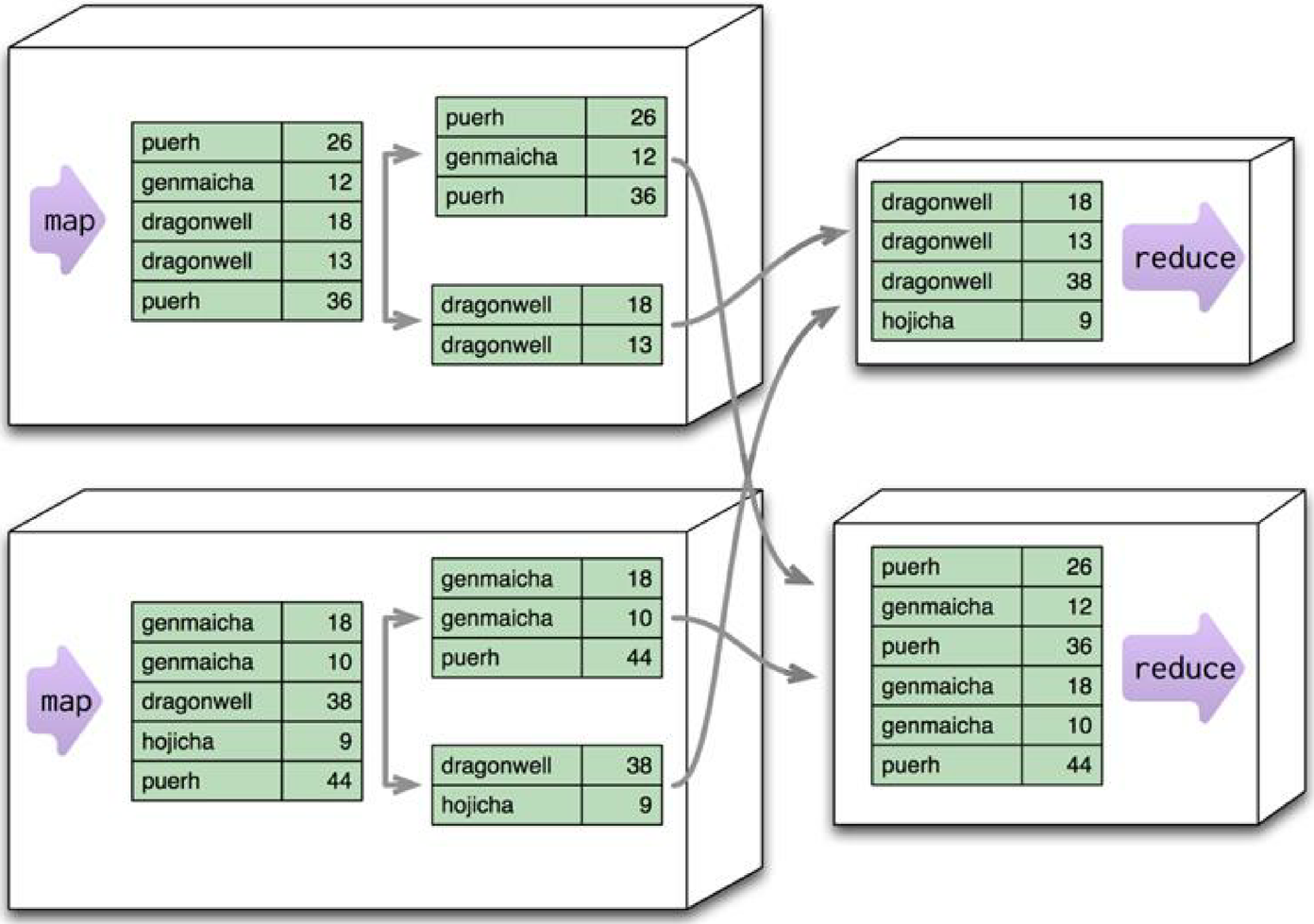
Counting unique names per Last Name

[Source: *Riccardo Torlone*]

Partitioners

- We can also specify a partitioner that:
  - divides up the intermediate key space
  - assigns intermediate key-value pairs to reducers
  - n partitions ➔ n reducers (n can be specified by users)
- The simplest partitioner assigns approximately the same number of keys to each reducer
- Partitioner only considers the key and ignores the value
- Optionally, users can specify their own hash function or other method for assigning keys to Reduce tasks (group).
- However, whatever algorithm is used, each key is assigned to one and only one Reducer

Partitioners Example

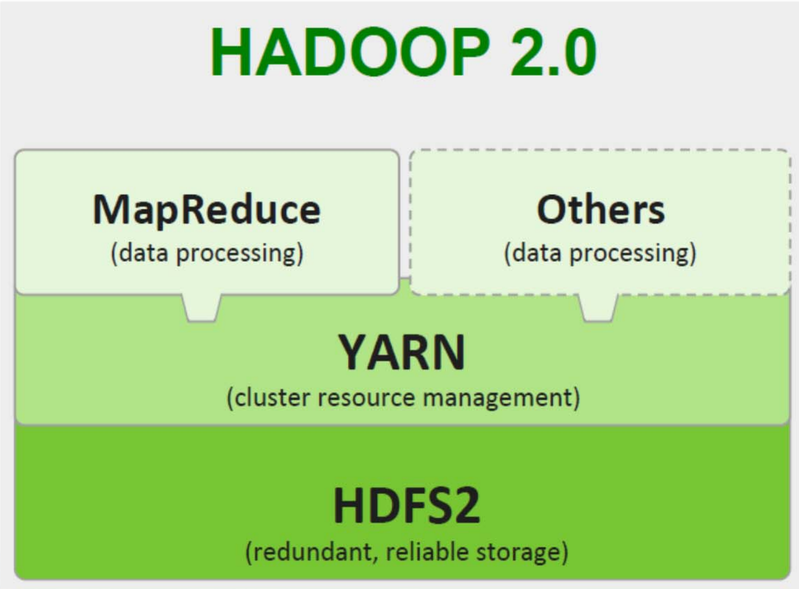


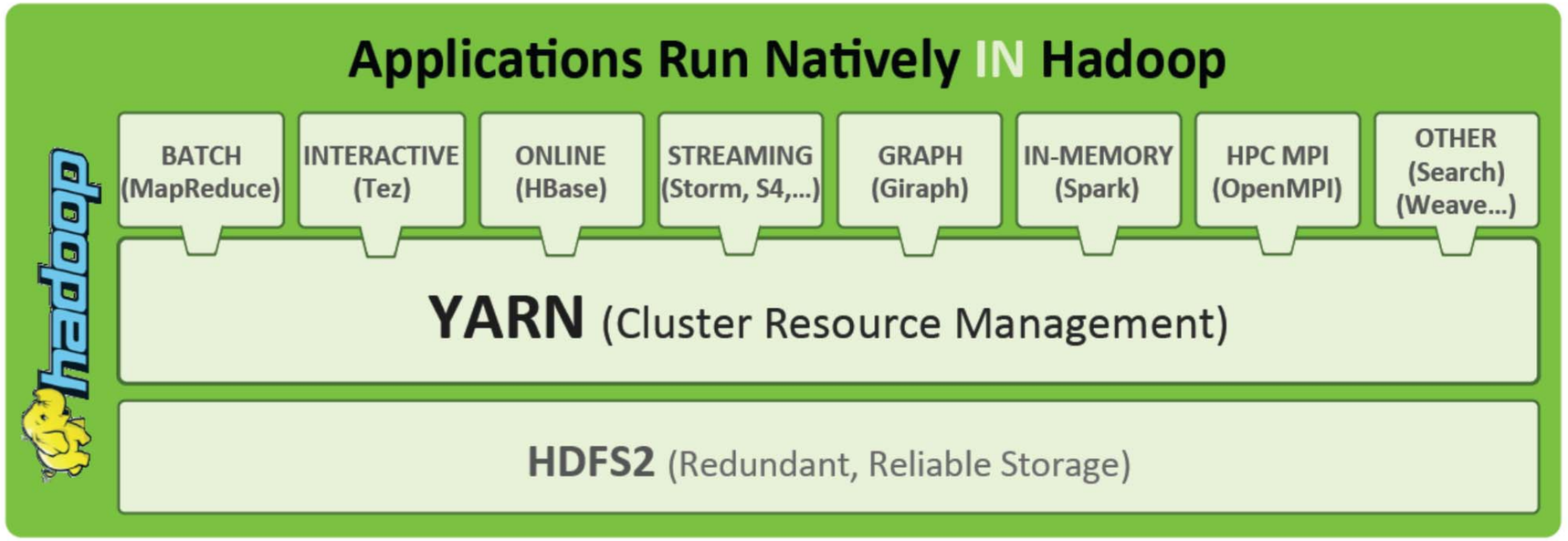
YARN

- MapReduce job lifecycle is handled by YARN — a resource negotiator
  - beyond batch execution

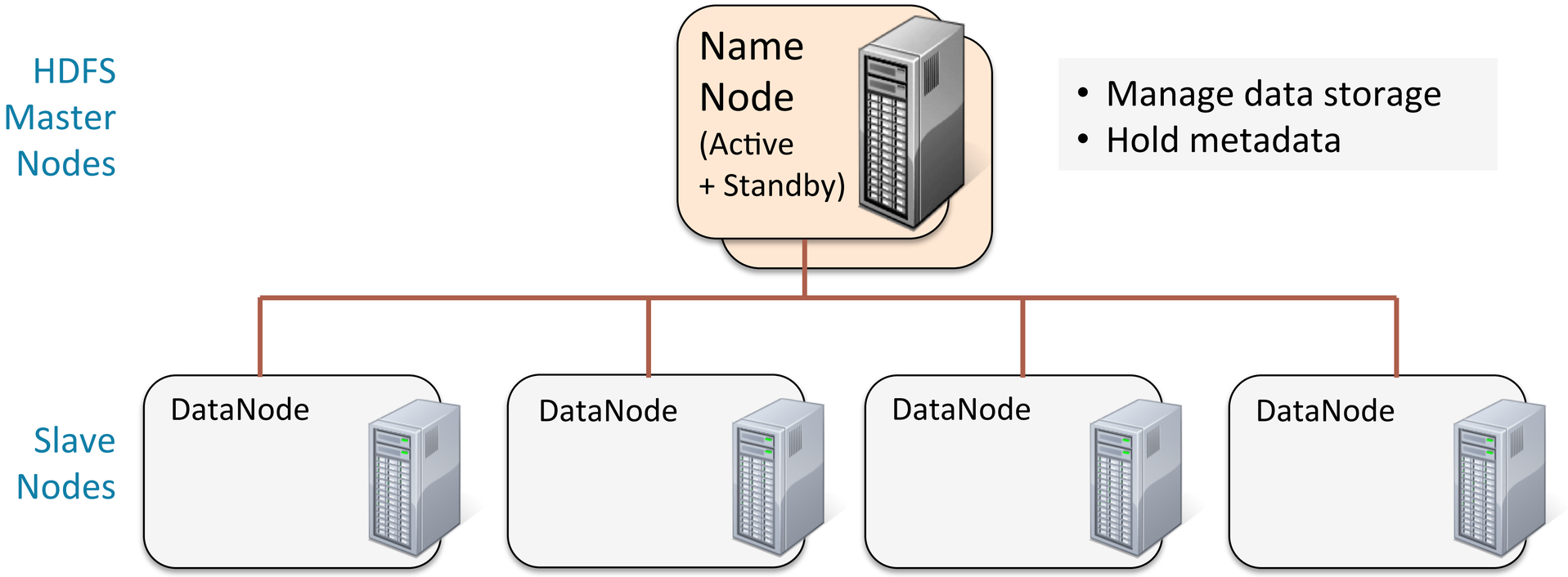
Multi Purpose Platform

Batch, Interactive, Online, Streaming, …



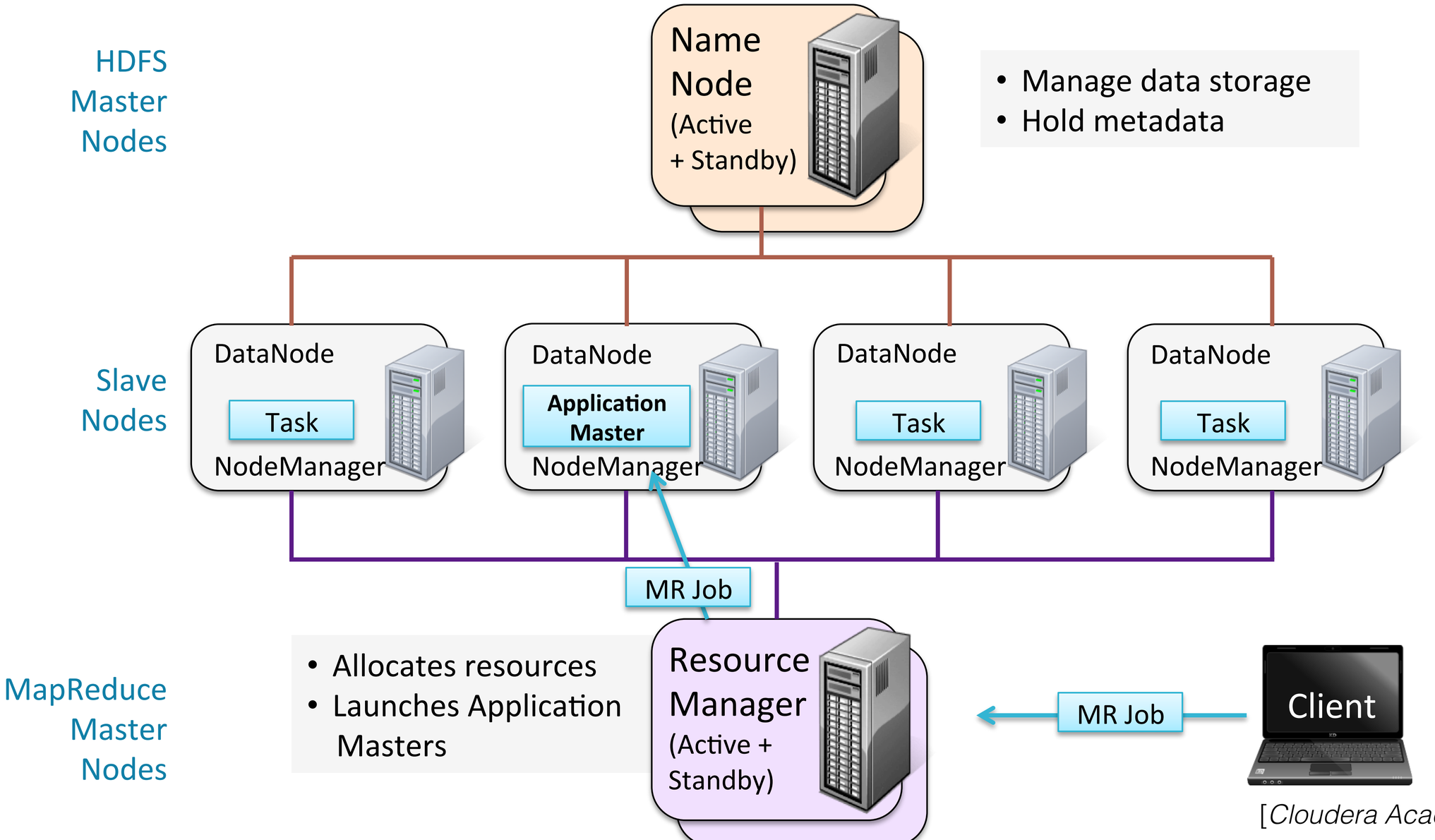


Basic Cluster Configuration: HDFS



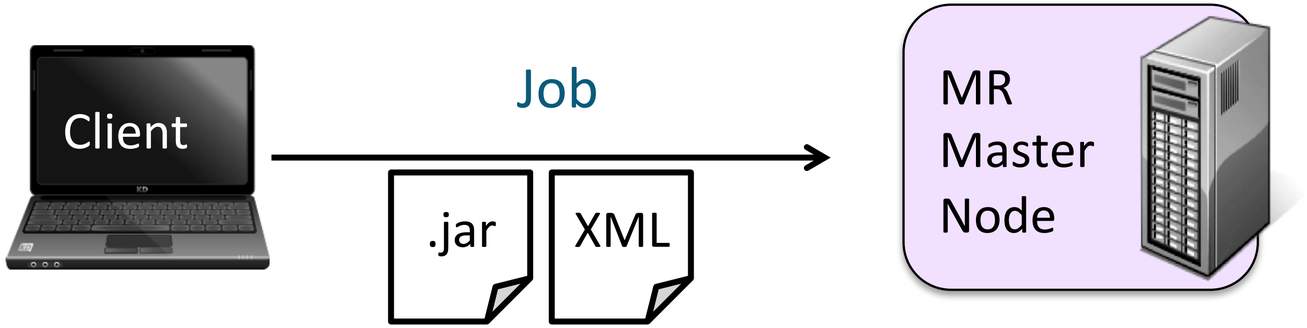
- Manage data storage
- Hold metadata

Basic Cluster Configuration: HDFS + MapReduce v2

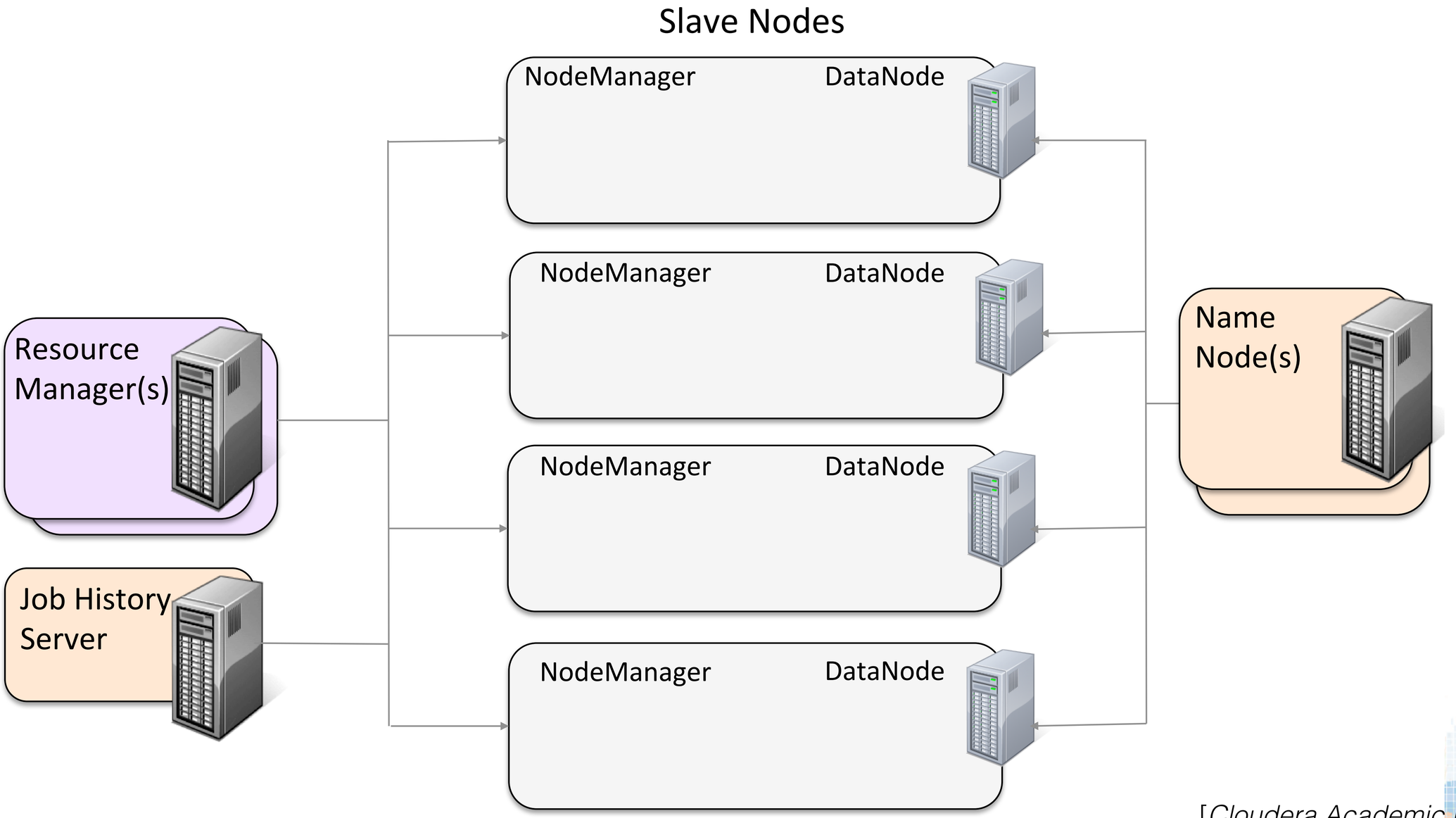


[*Cloudera Academic Resources*]

Submitting A Job



A MapReduce v2 Cluster



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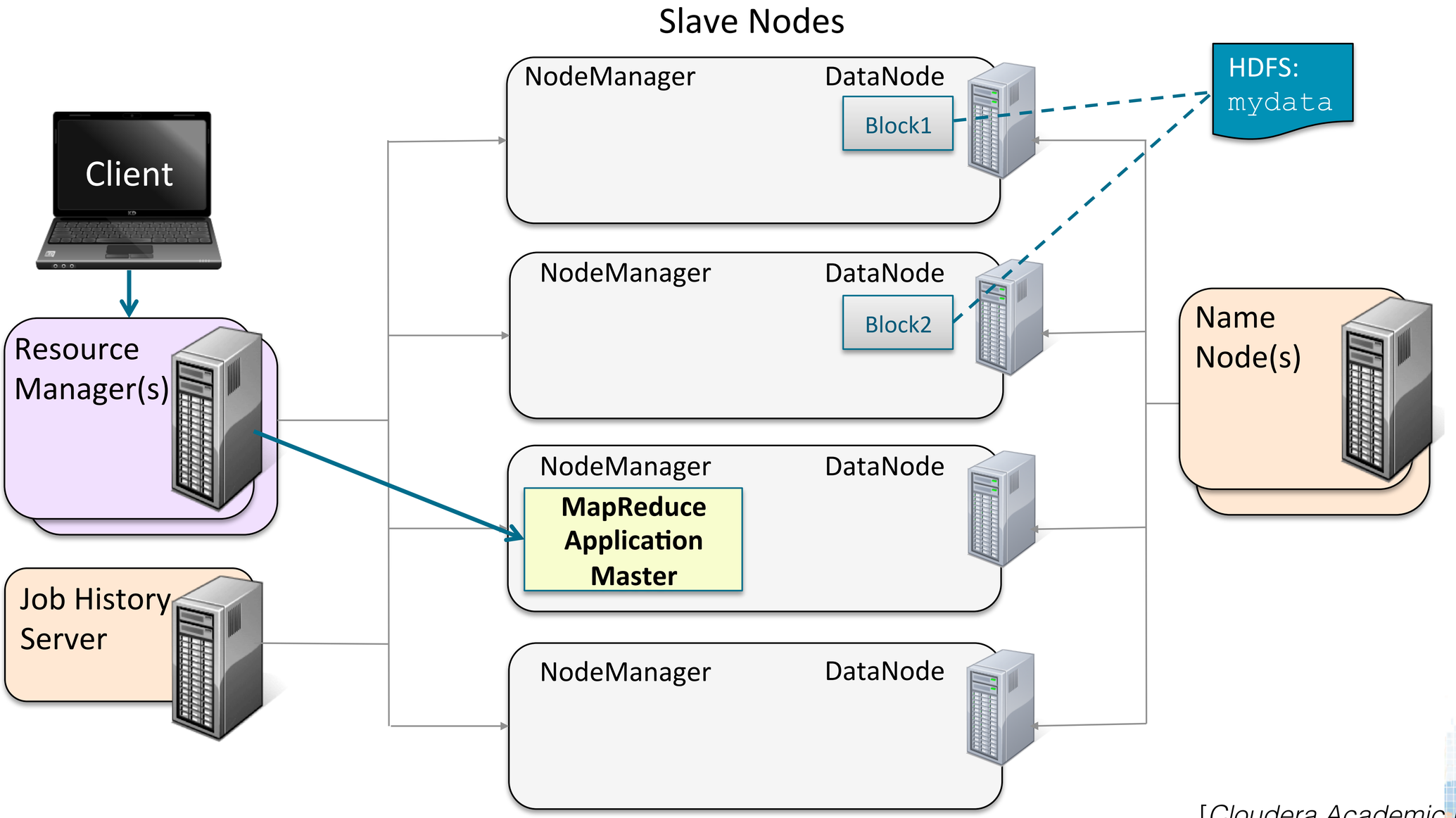
Running a Job on a MapReduce v2 Cluster (1)



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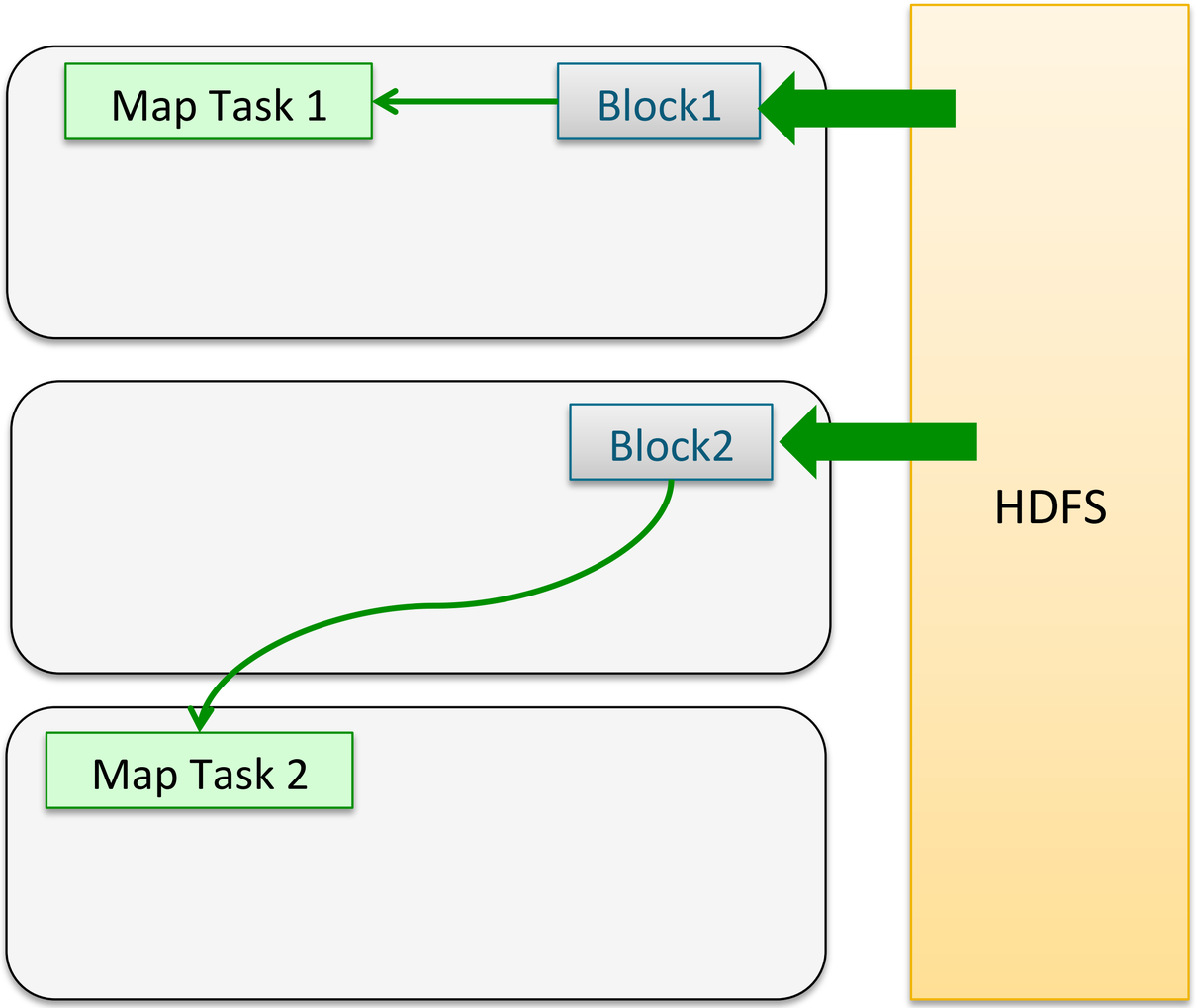
Job Data: Mapper Data Locality

When possible, Map tasks run on a node where the block of data to be processed is stored locally

Otherwise, the Map task will transfer the data across the network and then process that data



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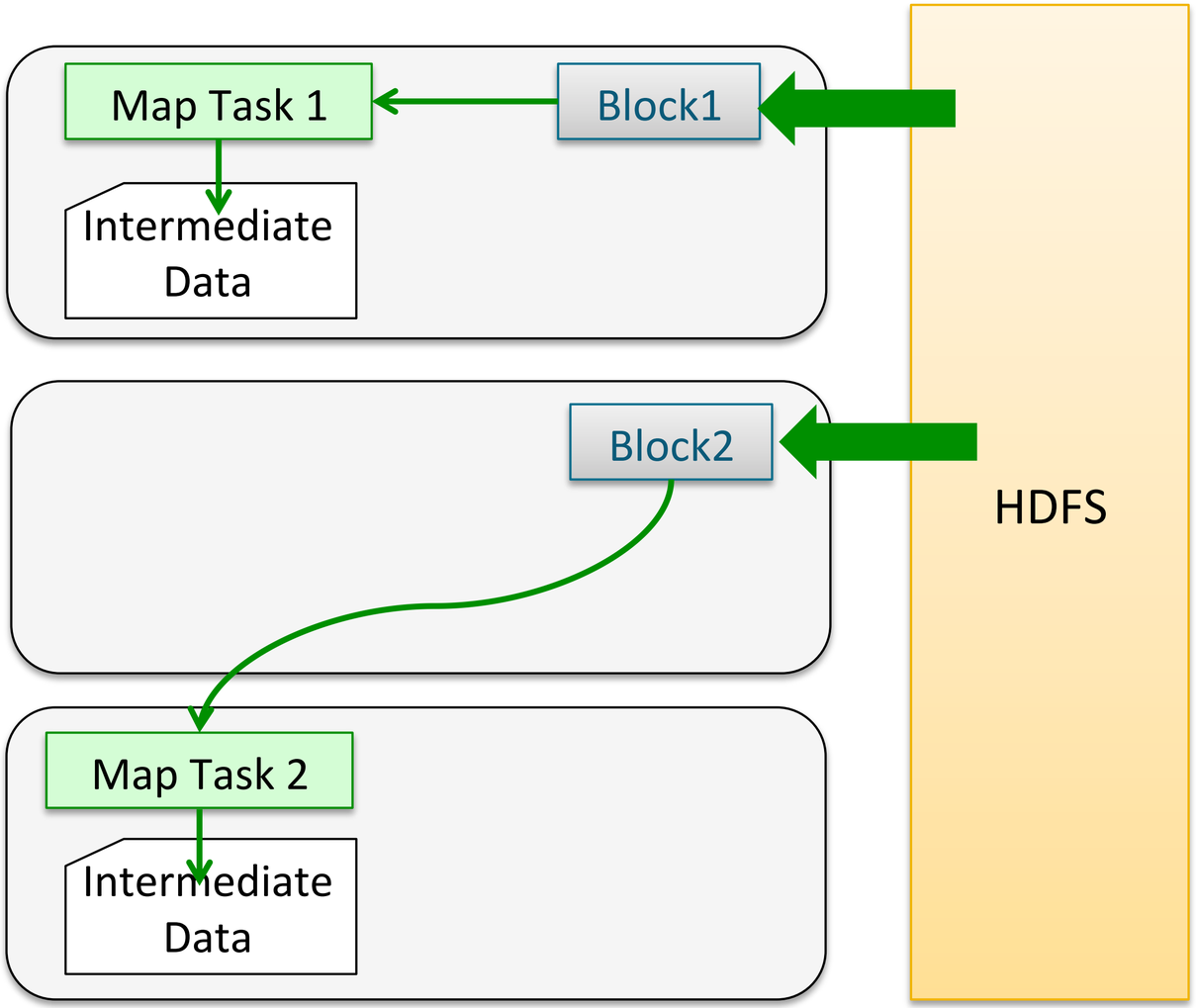
Job Data: Intermediate Data

Map task intermediate data is stored on the local disk (not HDFS)



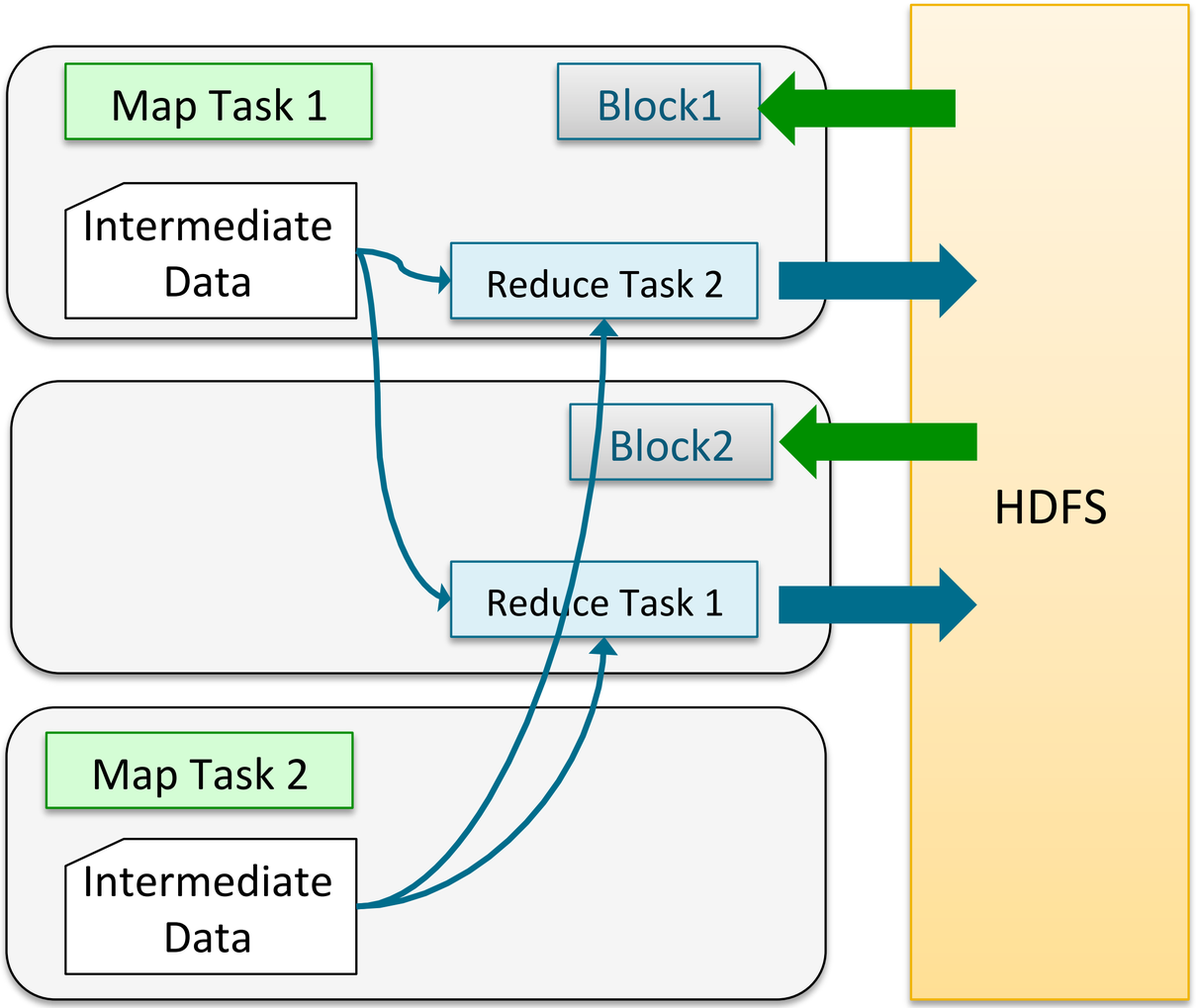
[*Cloudera Academic Resources*]

Job Data: Shuffle and Sort

There is no concept of data locality for Reducers

Intermediate data is transferred across the network to the Reducers

Reducers write their output to HDFS



Hadoop Runtime Tasks

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Get data to the workers
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed FS

Fault-Tolerance

- The worst thing that can happen is that the compute node executing the Master fails
  - In this case, the entire map-reduce job must be restarted.
- Other failures will be detected and managed by the Master, and the map-reduce job will complete eventually.
- Failure of a worker
  - the tasks assigned to this Worker will have to be redone
  - the Master:
    - sets the status of each failed tasks to idle
    - reschedules them on a Worker when one becomes available

Hadoop Operation Modes

- Java MapReduce Mode
  - Write Mapper, Combiner, Reducer functions in Java using Hadoop Java APIs
  - Read records one at a time
- Streaming Mode
  - Uses *nix pipes and standard input and output streams!
  - Any language (Python, Ruby, C, Perl, Tcl/Tk, etc.)
  - Input can be a line at a time, or a stream at a time

Hadoop Streaming Jobs

- Reducers receive independent key/value pairs (not lists of values)
- The mapper and reducer must be in executable form
  - Complete Python programs (.py file) that get sent to worker nodes
- Some features are not exposed, e.g. custom format and/or partitioner
- Input and output are handled through **stdin** and **stdout**
  - Might not perform as well/efficient as native codes

Hadoop Streaming Example

	Script to invoke Hadoop
1	`Hadoop jar $HADOOP_INSTALL/contrib/streaming/hadoop-*-streaming.jar \`
2	`-input input/ \  # relative to HDFS`
3	`-output output \  # relative to HDFS`
4	`-mapper mapper.py \`
5	`-reducer reducer.py \`
6	`-file scripts/mapper.py \`
7	`-file scripts/reducer.py`

Example Mapper

Code	Comments
import sys	
for line in sys.stdin	# input comes from STDIN
line = line.strip()	# strip leading/trailing whitespace
words = line.split()	# split line based on whitespace
for word in words: print ‘%s\t %s %(word, 1)	# for each word in the collection words # write word and count of “1”, tab delimited

Example Reducer

Code	Code, continued
cur_count = 0	if cur_word == word:
cur_word = None	cur_count += count
for line in sys.stdin	else:
line = line.strip()	if cur_word:
word, count = line.split("\t",1)	print '%s\t%s' (cur_word, cur_count)
try	cur_count, cur_word = (count, word)
count = int(count)	if cur_word == word:
except ValueError:	print '%s\t%s' %(cur_word, cur_count)
continue	

Hadoop Streaming

- Operate on streaming “chunks” of data
  - By default only reads and writes lines of text
- **“group-by-key” has to be done manually**
- Allow for Python **scripts** for mappers, reducers and combiners
- Can control the number of reducers and mappers
- Intermediate keys are split by tabs ‘\t’ by default
- More customizations (e.g. partitioner) have to be done in Java

Hadoop Streaming Mapper

```
#!/usr/bin/env python
import sys, time

def parseRecords():
    for line in sys.stdin:
        line = line.strip('\n')
        yield line.split()

def mapper():
    for words in parseRecords():
        for w in words:
            print '%s\t%s' % (w,1)

if __name__=='__main__':
    mapper()
```

Hadoop Streaming Reducer

```
#!/usr/bin/env python
import itertools, operator, sys

def parsePairs():
    for line in sys.stdin:
        yield tuple(line.strip('\n').split('\t'))

def reducer():
    for key, pairs in itertools.groupby(parsePairs(),
                                        operator.itemgetter(0)):
        count = sum(int(i[1]) for i in pairs)
        print '%s\t%s' % (key, count)

if __name__=='__main__':
    reducer()
```

How to debug Hadoop program?

- Using the mapreduce.py package for testing algorithm correctness
- Testing your mapper.py and reducer.py locally for streaming logics

```
cat input.txt | ./mapper.py | sort -k 1,1 | ./reducer.py > output.txt
```

Hadoop Python packages

- Pydoop
- MRJob
  - Can only run in stand-alone modes

Common Mistakes to Avoid

- Mapper and reducer should be **stateless**
  - Don't use static variables - after map + reduce return, they should remember nothing about the processed data!
  - Reason: No guarantees about which key-value pairs will be processed by which workers!

```
HashMap h = new HashMap();
map(key, value) {
  if (h.contains(key)) {
    h.add(key,value);
    emit(key, "X");
  }
}
```

Wrong!

Common Mistakes to Avoid

- Mapper must not map **too much data** to the **same key**
  - In particular, don't map everything to the same key!! Otherwise the reduce worker will be overwhelmed!
- It's okay if some reduce workers have more work than others

```
map(key, value) {
  emit("FOO", key + " " + value);
}
```

Wrong!

Thanks!

- Questions?