Clustering
Lecture 8: MapReduce

Jing Gao
SUNY Buffalo

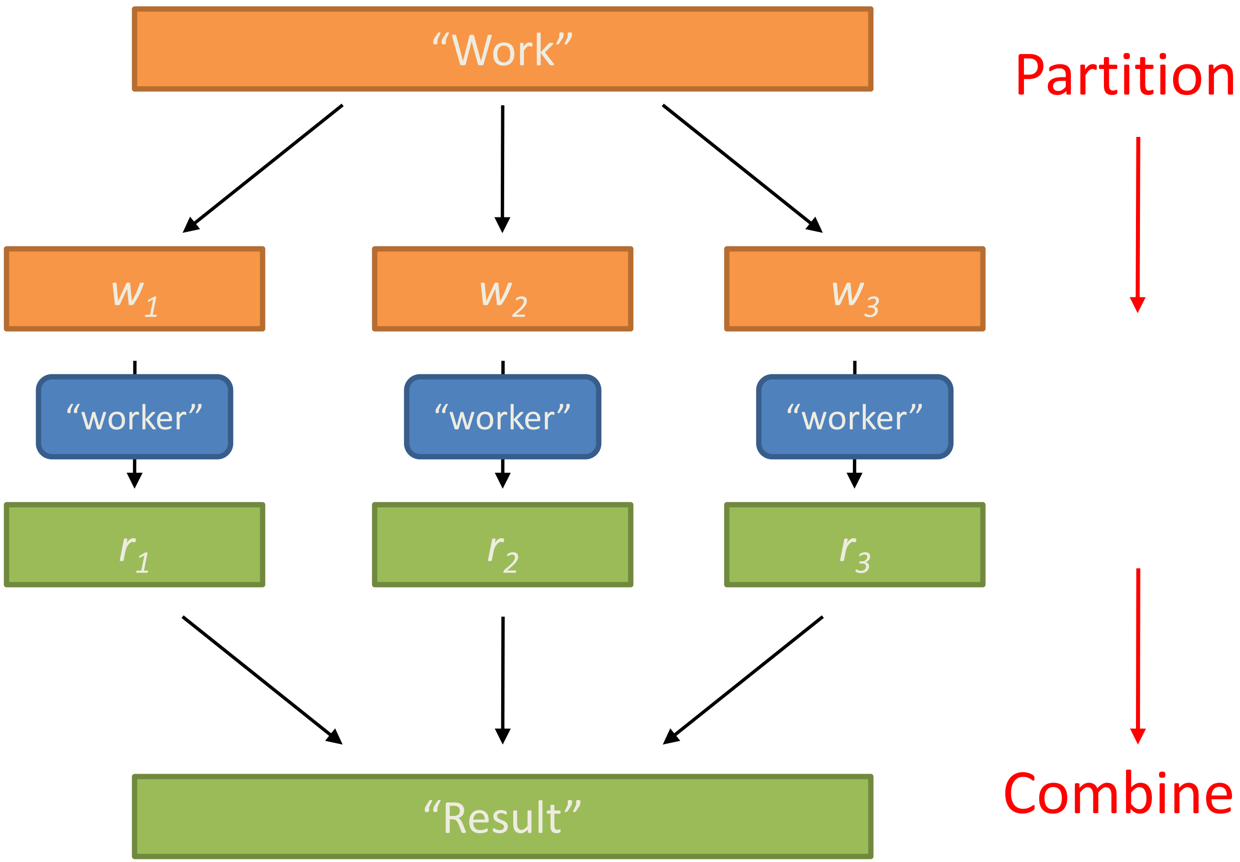
Outline

- **Basics**
  - Motivation, definition, evaluation
- **Methods**
  - Partitional
  - Hierarchical
  - Density-based
  - Mixture model
  - Spectral methods
- **Advanced topics**
  - Clustering ensemble
  - Clustering in MapReduce
  - Semi-supervised clustering, subspace clustering, co-clustering, etc.

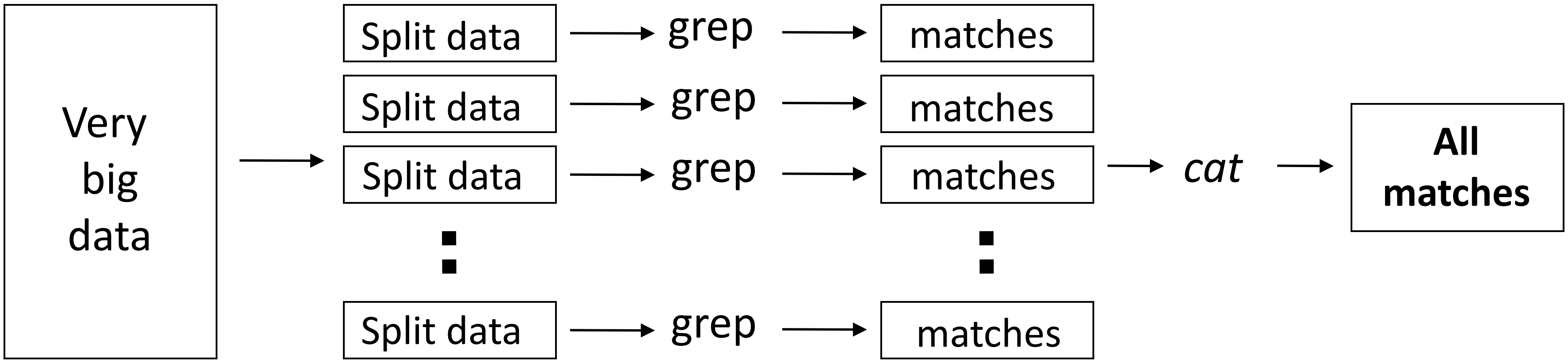
Big Data EveryWhere

- Lots of data is being collected and warehoused
  - Web data, e-commerce
  - purchases at department/ grocery stores
  - Bank/Credit Card transactions
  - Social Network

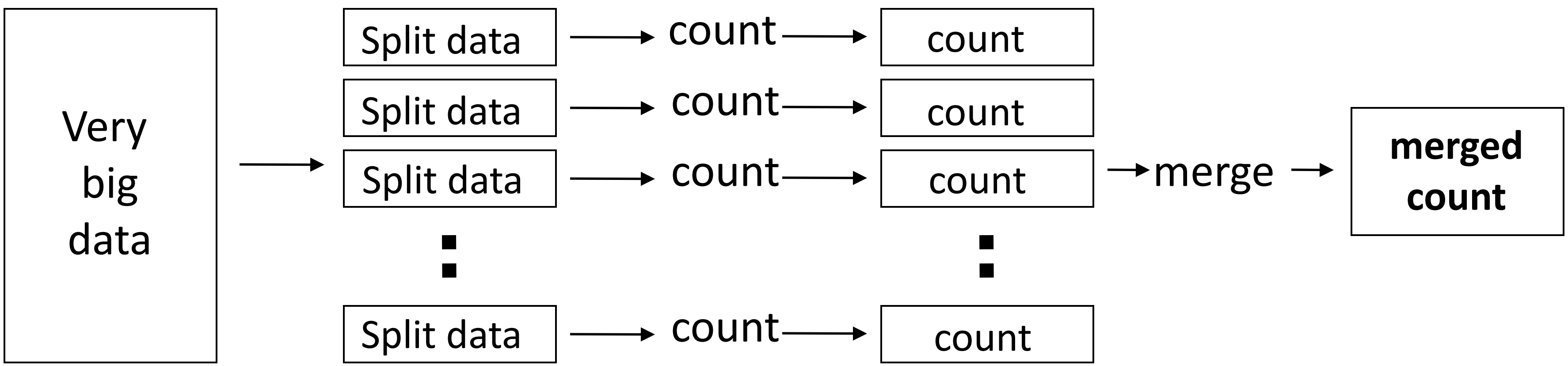
Divide and Conquer



Distributed Grep



Distributed Word Count



Parallelization Challenges

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?

Common Theme?

- **Parallelization problems arise from**
  - Communication between workers (e.g., to exchange state)
  - Access to shared resources (e.g., data)
- **Thus, we need a synchronization mechanism**

Source: Ricardo Guimarães Herrmann

Managing Multiple Workers

- **Difficult because**
  - We don’t know the order in which workers run
  - We don’t know when workers interrupt each other
  - We don’t know the order in which workers access shared data
- **Thus, we need**
  - Semaphores (lock, unlock)
  - Conditional variables (wait, notify, broadcast)
  - Barriers
- **Still, lots of problems**
  - Deadlock, race conditions, ...
- **Moral of the story: be careful!**

Concurrency Challenge

- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters (even across datacenters)
  - In the presence of failures
  - In terms of multiple interacting services
- Not to mention debugging…
- The reality:
  - Lots of one-off solutions, custom code
  - Write you own dedicated library, then program with it
  - Burden on the programmer to explicitly manage everything

What’s the point?

- Right level of abstraction
  - multi-core/cluster environment
- Hide system-level details from the developers
  - No more race conditions, lock contention, etc.
- Separating the *what* from *how*
  - Developer specifies the computation that needs to be performed
  - Execution framework (“runtime”) handles actual execution

MapReduce

- **Key properties**
  - Google has used successfully is processing its “big-data” sets (~ 20000 peta bytes per day)
  - Users specify the computation in terms of a *map* and a *reduce* function
  - Underlying runtime system automatically parallelizes the computation across large-scale clusters of machines
  - Underlying system also handles machine failures, efficient communications, and performance issues

MapReduce can refer to…

- The programming model
- The execution framework (aka “runtime”)
- The specific implementation

Usage is usually clear from context!

Typical Large-Data Problem

Map

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Reduce

Key idea: provide a functional abstraction for these two operations

MapReduce Programming Model

- Programmers specify two functions:

  map (k, v) → [(k', v')]

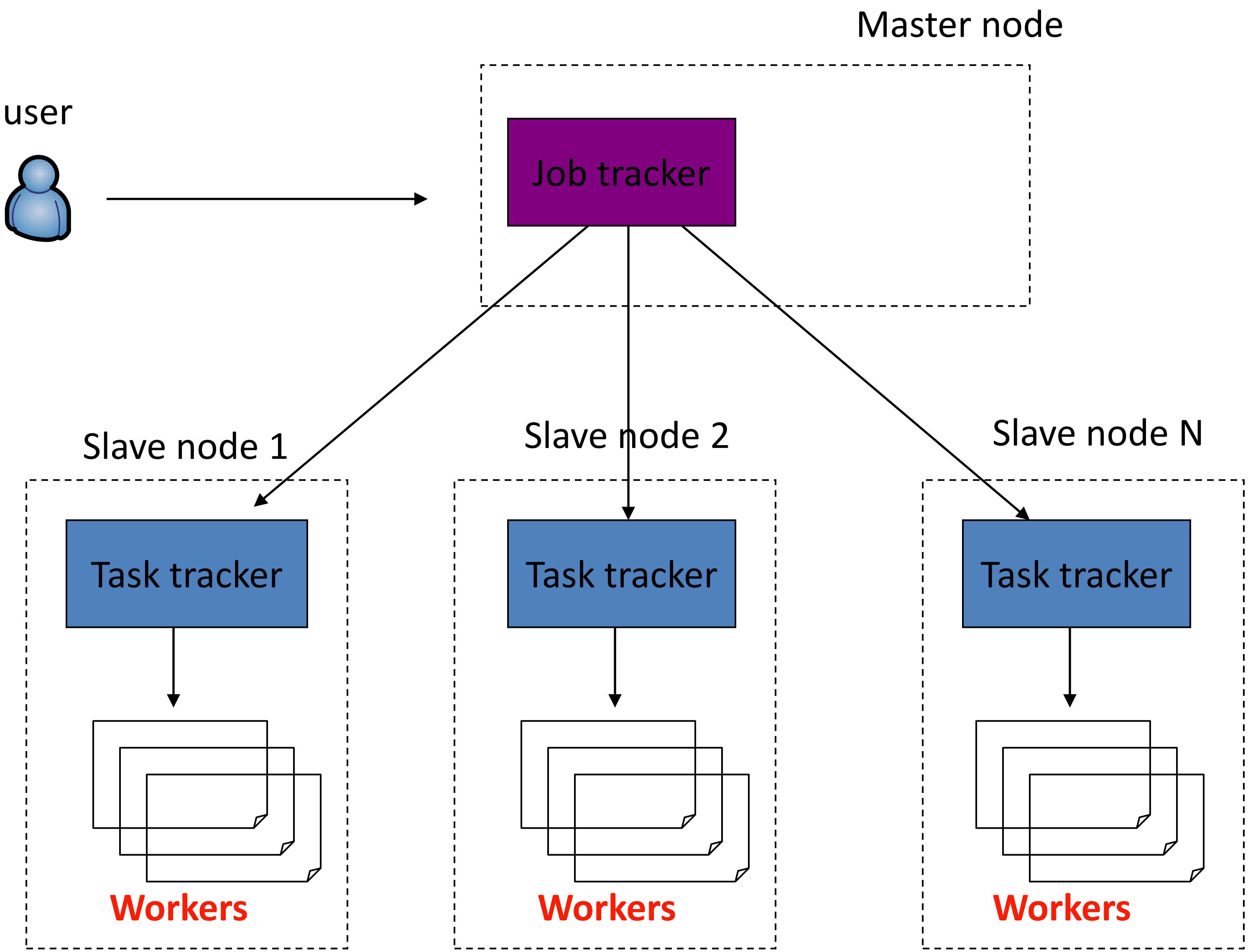
  reduce (k', [v']) → [(k', v')]

  – All values with the same key are sent to the same reducer
- The execution framework handles everything else…

"Everything Else"

- **The execution framework**
  - Scheduling: assigns workers to map and reduce tasks
  - "Data distribution": moves processes to data
  - Synchronization: gathers, sorts, and shuffles intermediate data
  - Errors and faults: detects worker failures and restarts
- **Limited control over data and execution flow**
  - All algorithms must expressed in m, r, c, p
- **You don't know:**
  - Where mappers and reducers run
  - When a mapper or reducer begins or finishes
  - Which input a particular mapper is processing
  - Which intermediate key a particular reducer is processing

Architecture Overview



MapReduce Implementations

- **Google MapReduce**
  - Not available outside Google
- **Hadoop**
  - An open-source implementation in Java
  - Development led by Yahoo, used in production
  - Now an Apache project
  - Rapidly expanding software ecosystem
- **Custom research implementations**
  - For GPUs, cell processors, etc.

Who uses Hadoop?

- Amazon/A9
- Facebook
- Google
- IBM
- Joost
- Last.fm
- New York Times
- PowerSet
- Veoh
- Yahoo!
- ……

How do we get data to the workers?

What’s the problem here?

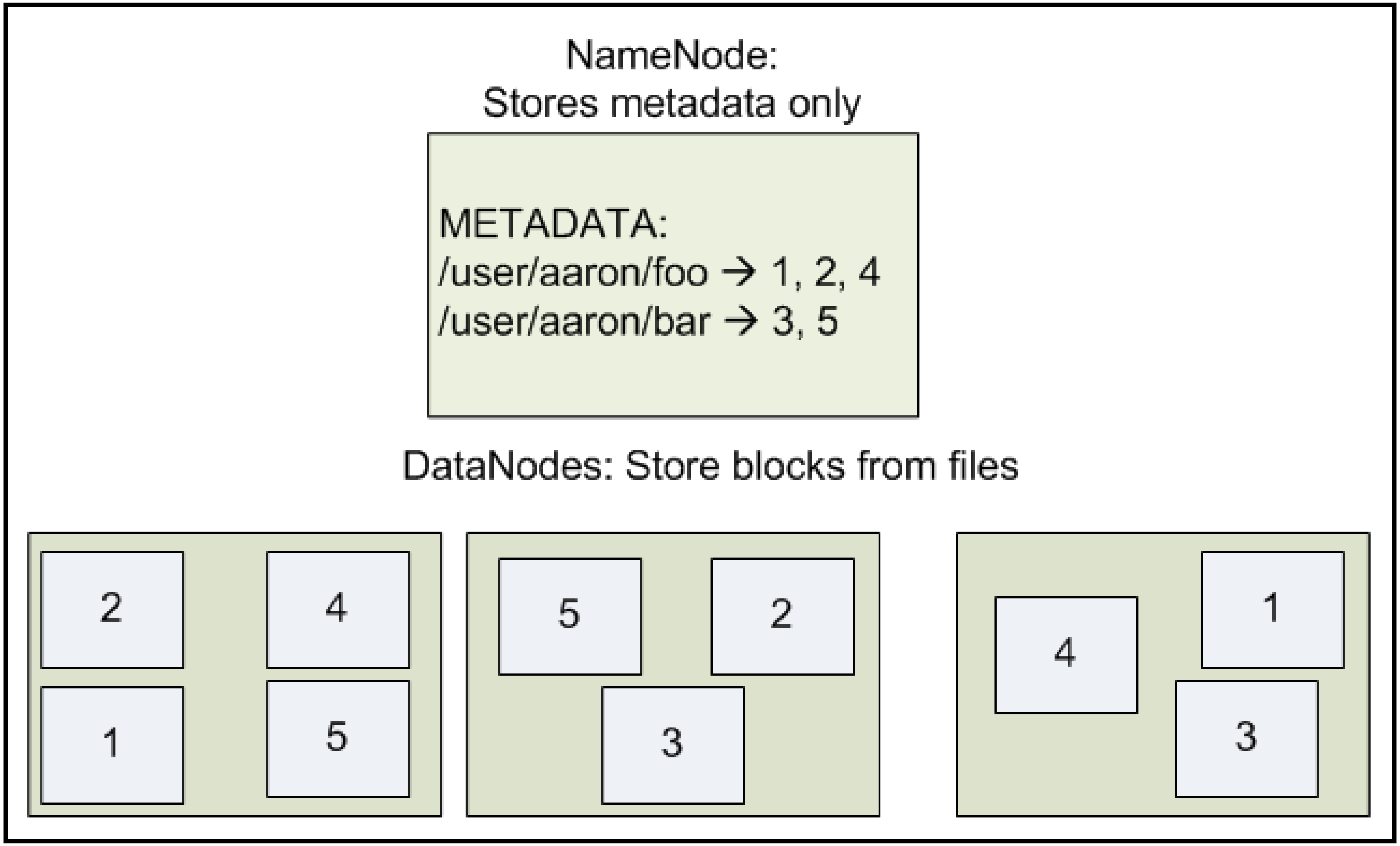
Distributed File System

- **Move workers to the data**
  - Store data on the local disks of nodes in the cluster
  - Start up the workers on the node that has the data local
- **Why?**
  - Not enough RAM to hold all the data in memory
  - Disk access is slow, but disk throughput is reasonable
- **A distributed file system**
  - GFS (Google File System) for Google's MapReduce
  - HDFS (Hadoop Distributed File System) for Hadoop

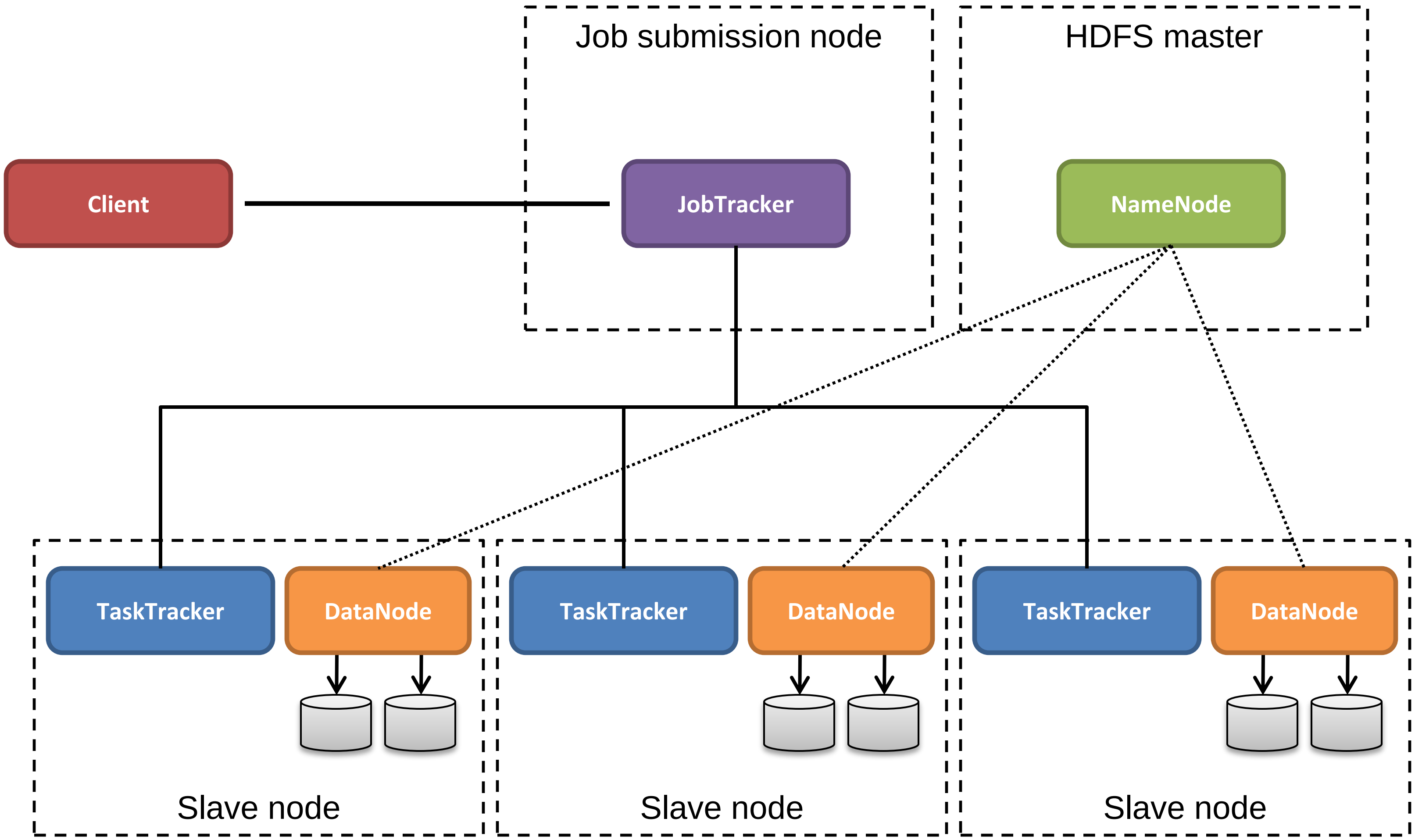
Distributed File System Design

- Chunk Servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Nodes in HDFS
  - Stores metadata
  - Might be replicated
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

Hadoop HDFS

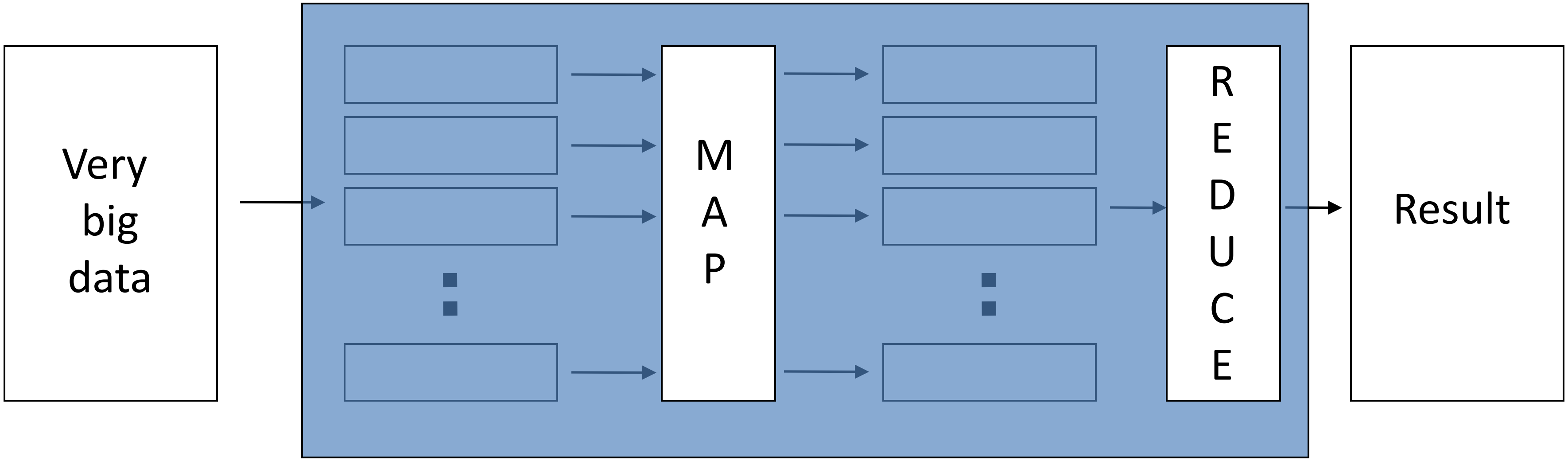

NameNode:
Stores metadata only
METADATA:
/user/aaron/foo → 1, 2, 4
/user/aaron/bar → 3, 5
DataNodes: Store blocks from files
2
4
1
5
5
2
3
4
1
3

Hadoop Cluster Architecture



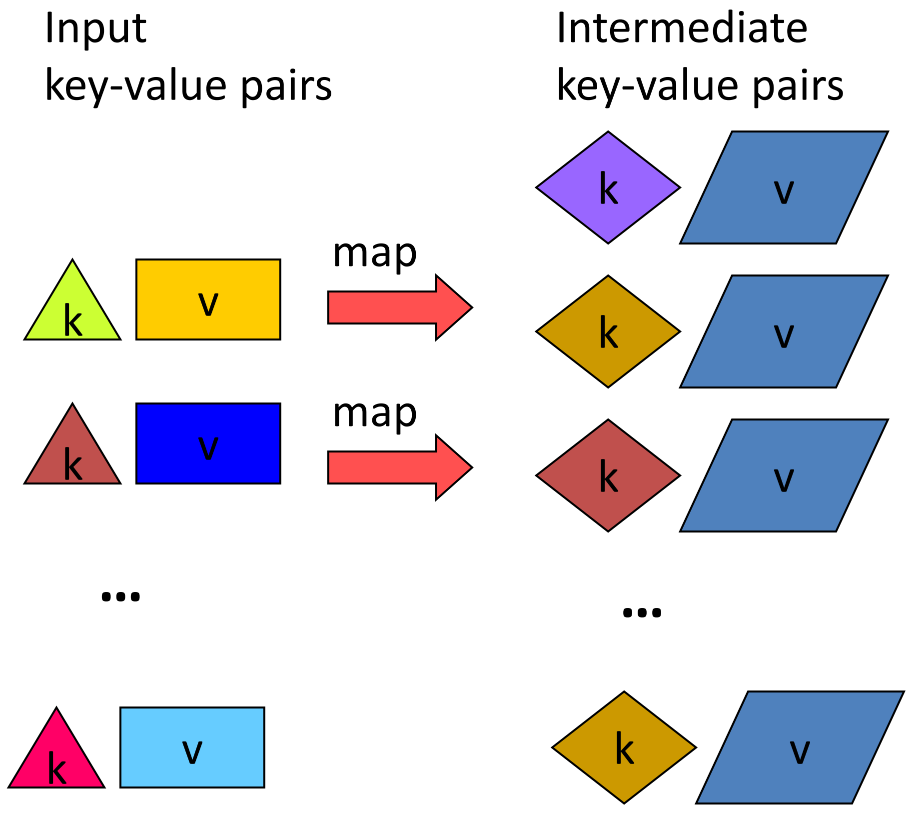
From Jimmy Lin's slides

Map+Reduce

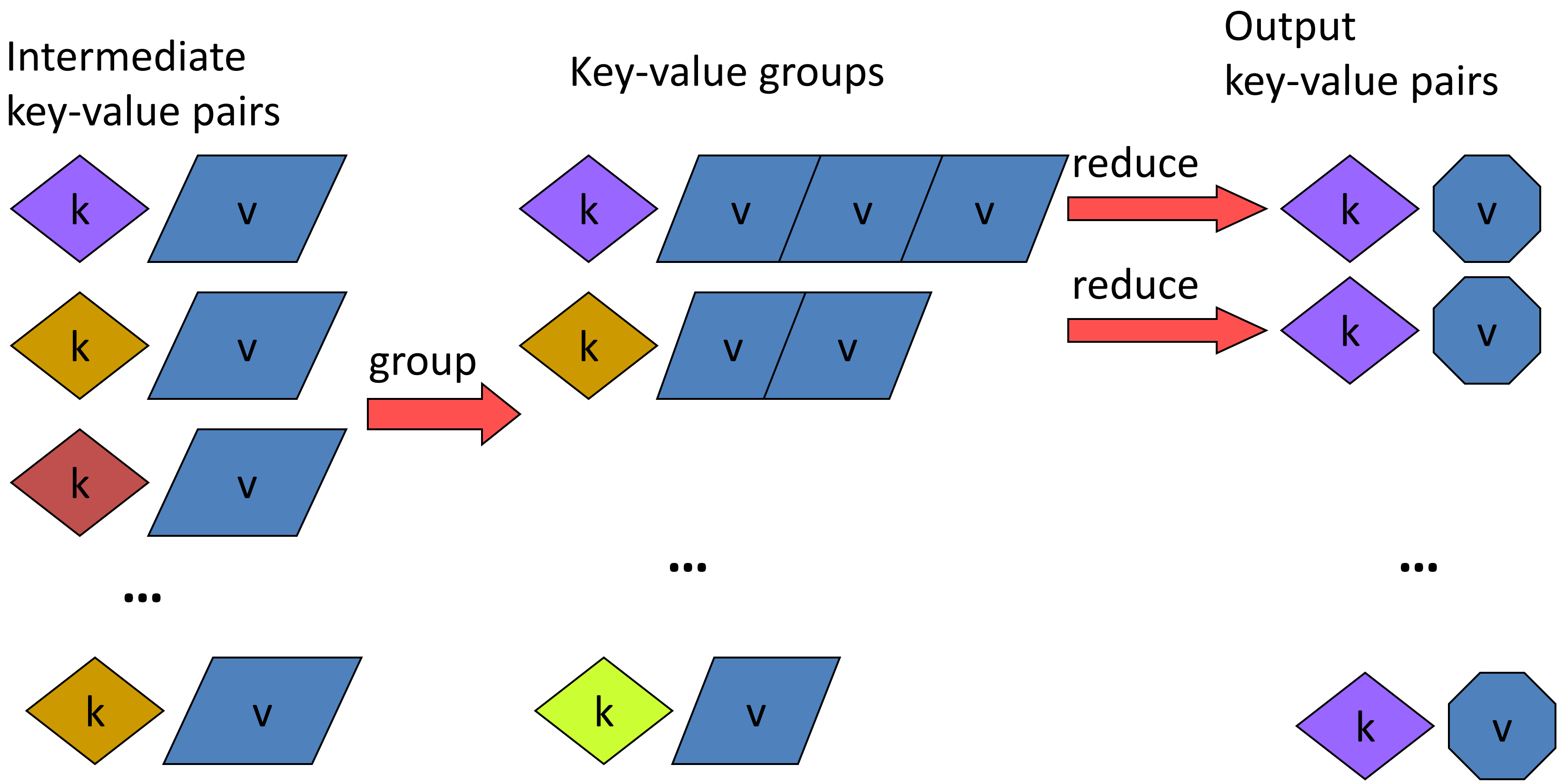


- Map:
  - Accepts *input* key/value pair
  - Emits *intermediate* key/value pair
- Reduce :
  - Accepts *intermediate* key/value* pair
  - Emits *output* key/value pair

The Map Step


Input
key-value pairs
Intermediate
key-value pairs
k
v
map
k
v
map
…
k
v
k
v
k
v
k
v
…
k
v

The Reduce Step



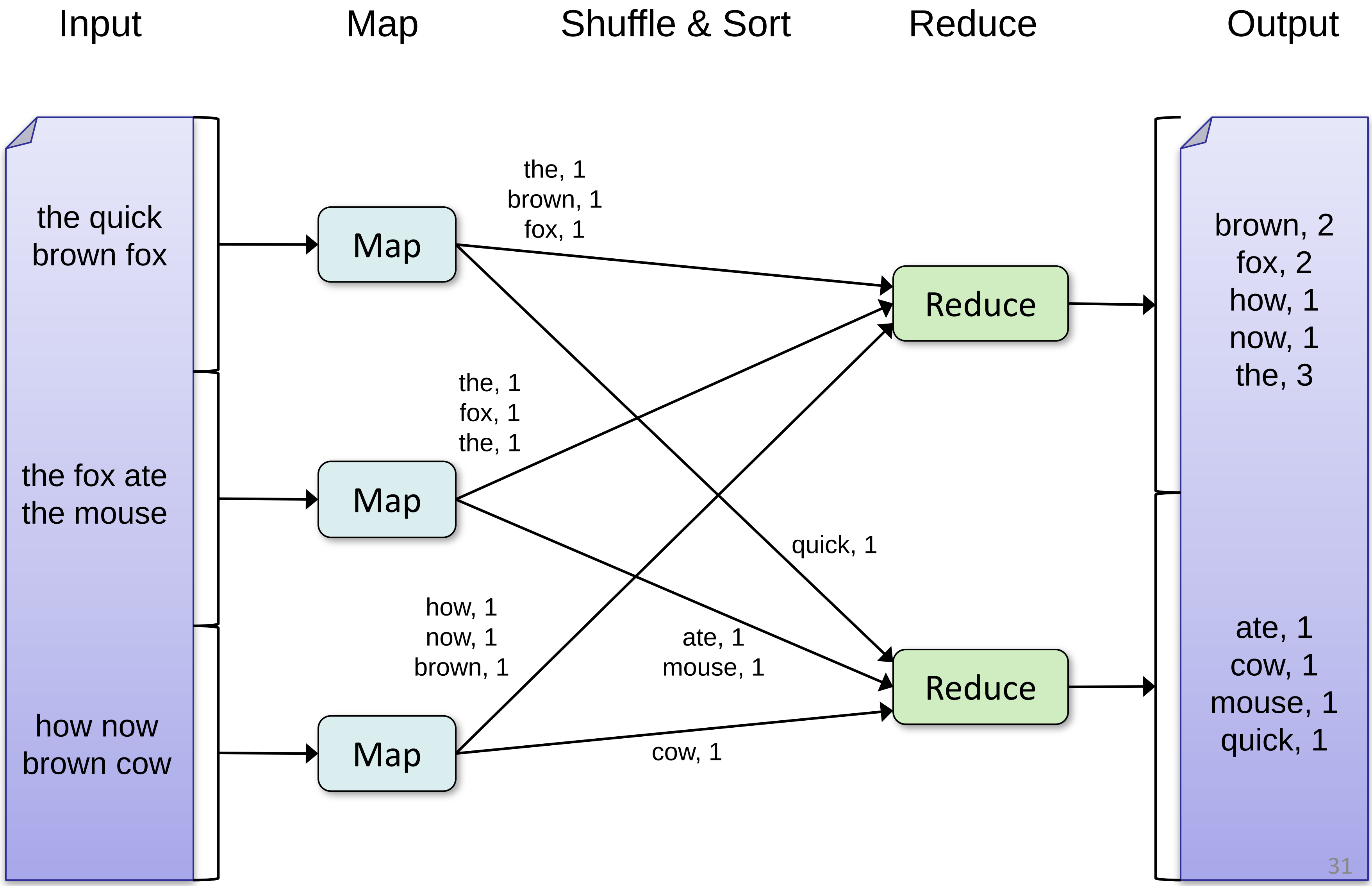
MapReduce

- Input: a set of key/value pairs
- User supplies two functions:
  - map(k,v) → list(k1,v1)
  - reduce(k1, list(v1)) → (k1,v2)
- (k1,v1) is an intermediate key/value pair
- Output is the set of (k1,v2) pairs

Word Count

- We have a large collection of documents
- Count the number of times each distinct word appears in the collection of documents

Word Count Execution



Word Count using MapReduce

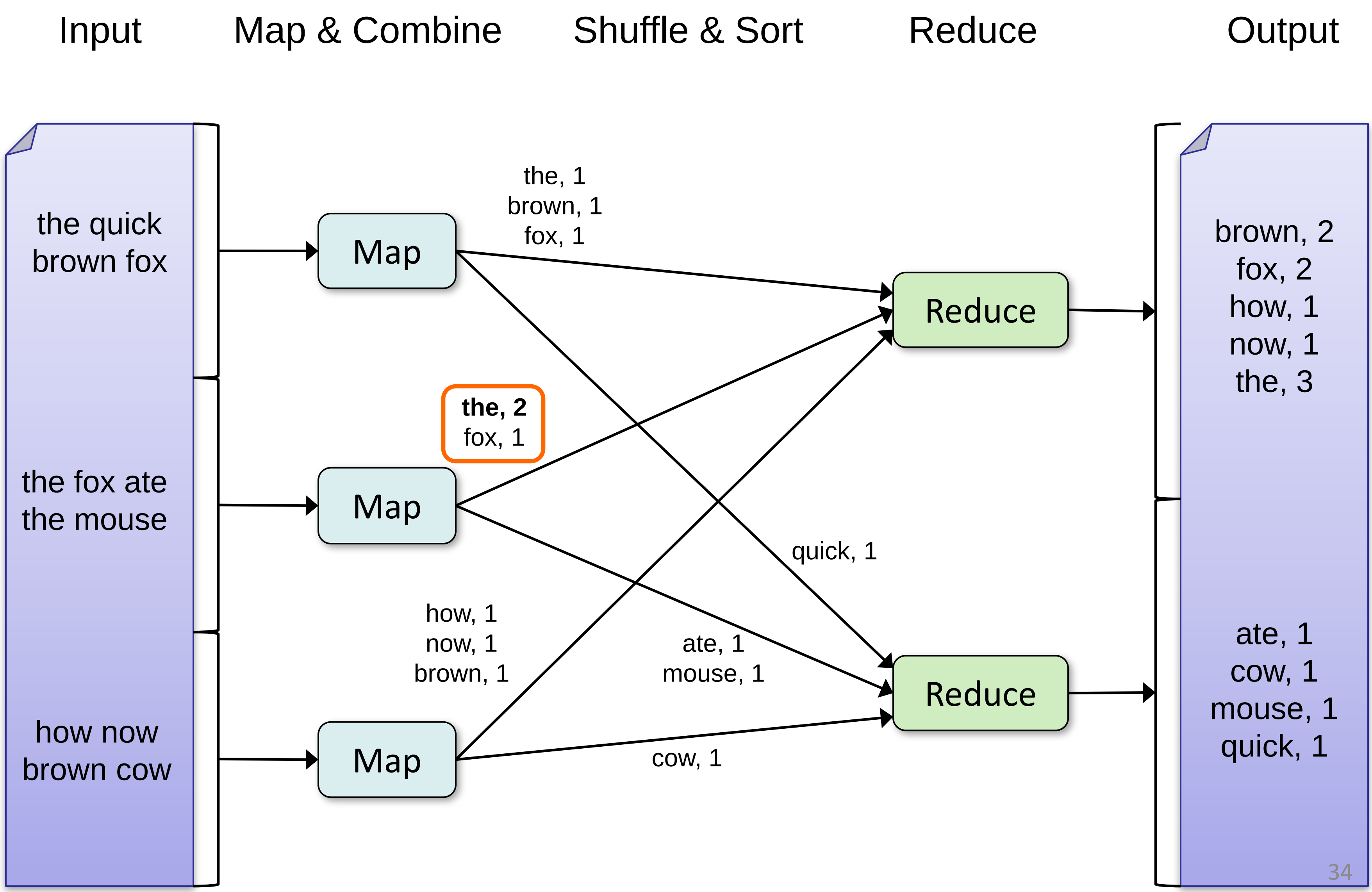
```
map(key, value):
// key: document name; value: text of document
    for each word w in value:
        emit(w, 1)

reduce(key, values):
// key: a word; value: an iterator over counts
        result = 0
        for each count v in values:
                result += v
        emit(result)
```

Combiners

- Often a map task will produce many pairs of the form (k,v1), (k,v2), … for the same key k
  - E.g., popular words in Word Count
- Can save network time by pre-aggregating at mapper
- For associative ops. like sum, count, max
- Decreases size of intermediate data
- Example: local counting for Word Count:

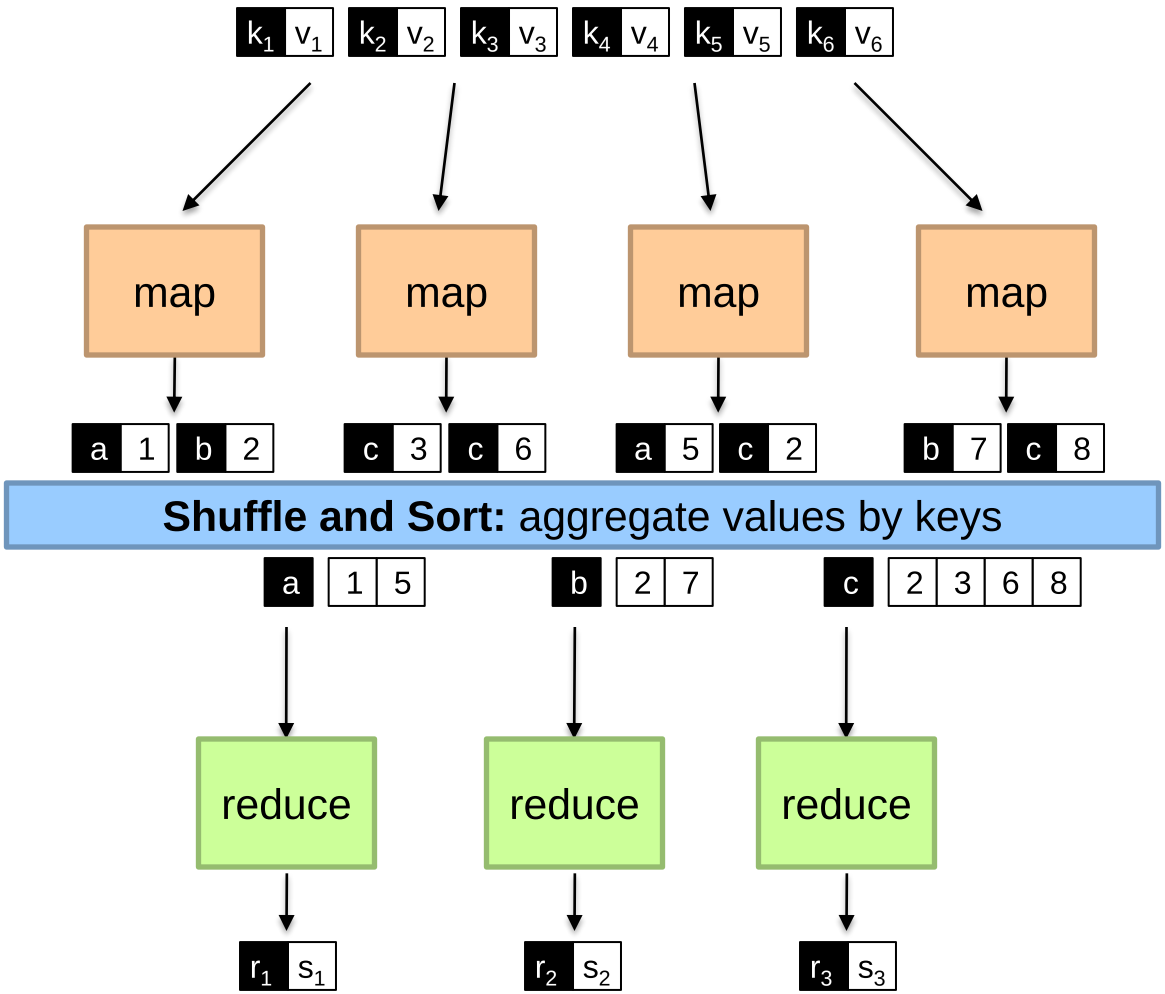
```
def combiner(key, values):
  output(key, sum(values))
```

Word Count with Combiner

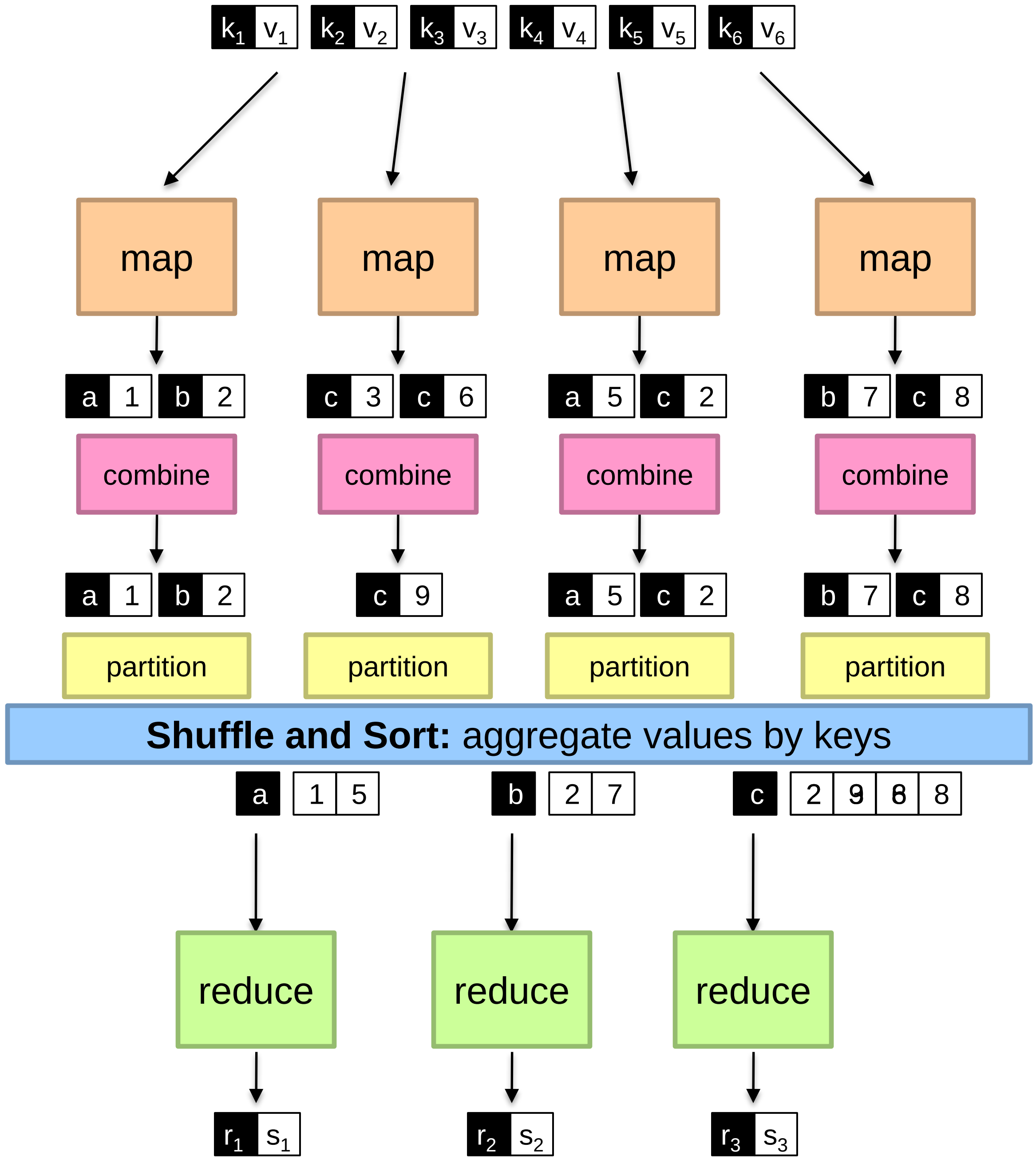


Partition Function

- Inputs to map tasks are created by contiguous splits of input file
- For reduce, we need to ensure that records with the same intermediate key end up at the same worker
- System uses a default partition function e.g., hash(key) mod R
- Sometimes useful to override
  - Balance the loads
  - Specific requirement on which key value pairs should be in the same output files



k_1 v_1 k_2 v_2 k_3 v_3 k_4 v_4 k_5 v_5 k_6 v_6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r_1 s_1
r_2 s_2
r_3 s_3



k1 v1 k2 v2 k3 v3 k4 v4 k5 v5 k6 v6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

How to MapReduce K-means

- **Partition $\{x_1,\ldots,x_n\}$ into K clusters**
  – K is predefined
- **Initialization**
  – Specify the initial cluster centers (centroids)
- **Iteration until no change**
  – For each object x_i
    - Calculate the distances between x_i and the K centroids
    - (Re)assign x_i to the cluster whose centroid is the closest to x_i

  – Update the cluster centroids based on current assignment

K-Means Map/Reduce Design

<u>Traditional</u>

AssignCluster():

- For each point p

  Assign p the closest c

UpdateCentroids ():

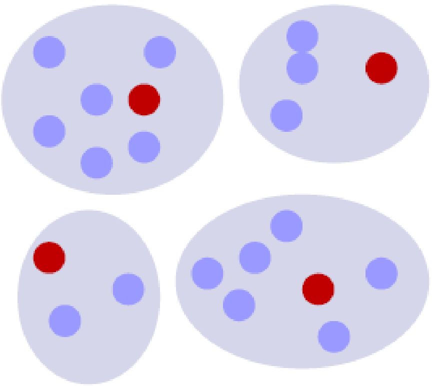
- For each cluster

  Update cluster center

Kmeans ()

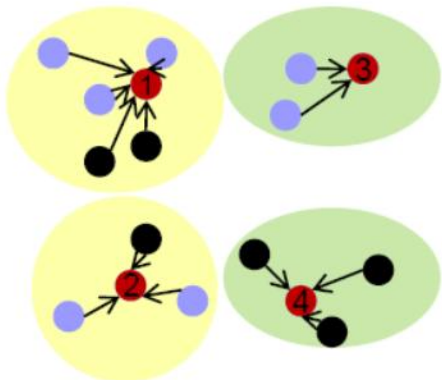
- While not converge:
  - AssignCluster()
  - UpdateCentroids()

AssignCluster()



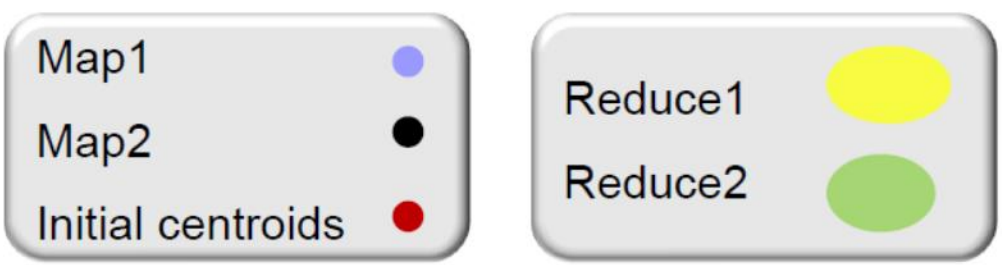
UpdateCentroid()

K-Means Map/Reduce Design



Map: assign each **p** to closest centroids

Reduce: update each centroid with its new location (total, count)



KmeansIter()

Map(p) // Assign Cluster

- For c in clusters:
  - If dist(p,c)<minDist,
    then minC=c, minDist = dist(p,c)
- Emit(minC.id, (p, 1))

Reduce() //Update Centroids

- For all values (p, c) :
  - total += p; count += c;
- Emit(key, (total, count))

MapReduce K-means Algorithm

- **Driver**
  - Runs multiple iteration jobs using mapper+combiner+reducer
- **Mapper**
  - Configure: A single file containing cluster centers
  - Input: Input data points
  - Output: (data id, cluster id)
- **Reducer**
  - Input: (data id, cluster id)
  - Output: (cluster id, cluster centroid)
- **Combiner**
  - Input: (data id, cluster id)
  - Output: (cluster id, (partial sum, number of points))

MapReduce Characteristics

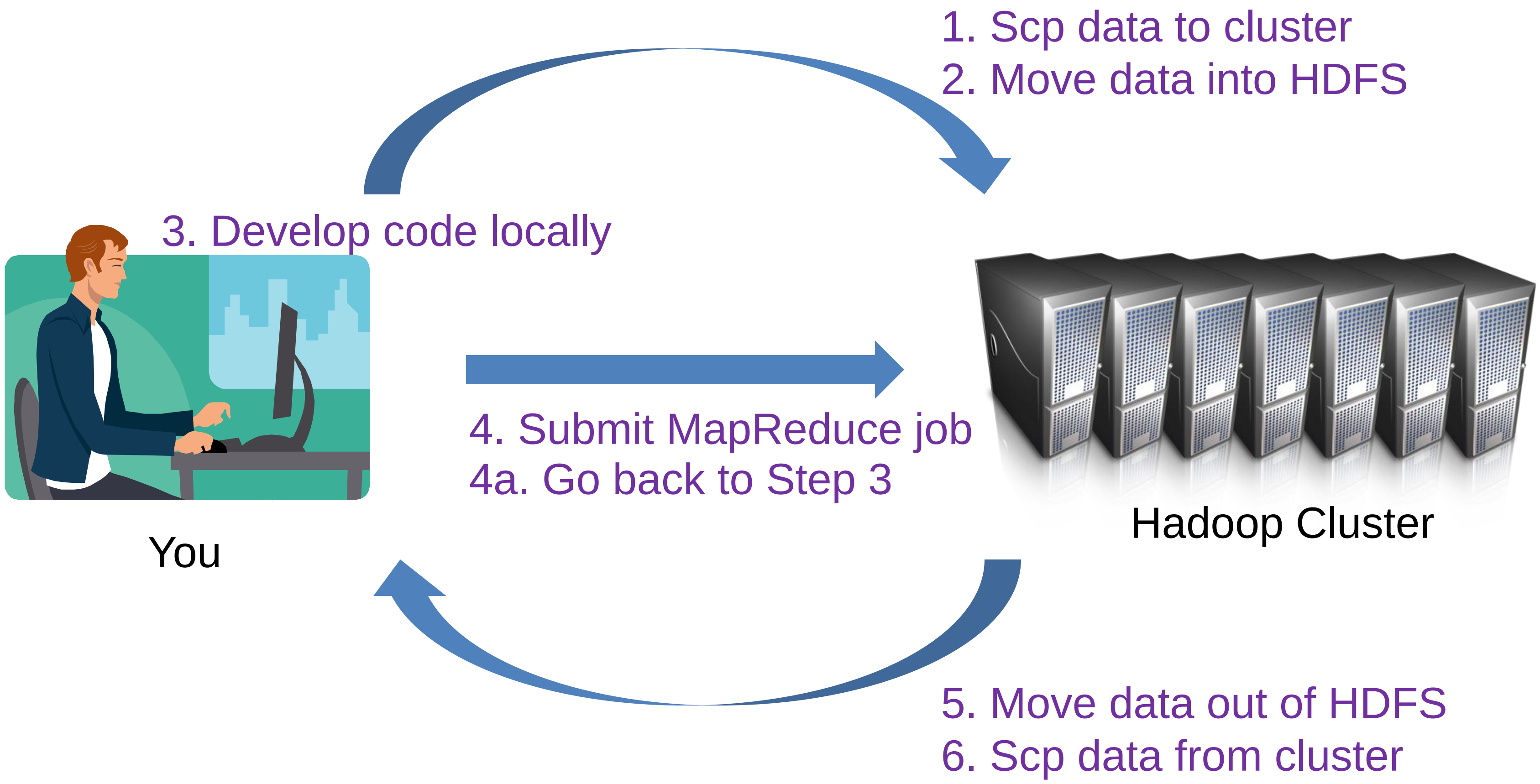
- Very large scale data: peta, exa bytes
- Map and Reduce are the main operations: simple code
- There are other supporting operations such as combine and partition
- All the map should be completed before reduce operation starts
- Map and reduce operations are typically performed by the same physical processor
- Number of map tasks and reduce tasks are configurable
- Operations are provisioned near the data
- Commodity hardware and storage
- Runtime takes care of splitting and moving data for operations
- Special distributed file system, such as Hadoop Distributed File System

MapReducable?

	One Iteration	Multiple Iterations	Not good for MapReduce
Clustering	Canopy	KMeans	
Classification	Naïve Bayes, kNN	Gaussian Mixture	SVM
Graphs		PageRank	
Information Retrieval	Inverted Index	Topic modeling (PLSI, LDA)	

- One-iteration algorithms are perfect fits
- Multiple-iteration algorithms are OK fits
  - but **small shared info** have to be synchronized across iterations (typically through filesytem)
- Some algorithms are not good for MapReduce framework
  - Those algorithms typically require **large shared info** with a lot of synchronization.
  - Traditional parallel framework like MPI is better suited for those.

Development Cycle



Take-away Message

- MapReduce programming model
- How to design map, reduce, combiner, partition functions
- Which tasks can be easily MapReduced and which cannot