MapReduce

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Ref

- MapReduce algorithm design, Jimmy Lin

Google™
processes 20 PB a day (2008)
crawls 20B web pages a day (2012)

JPMorganChase
150 PB on 50k+ servers
running 15k apps (6/2011)

ebay
>10 PB data, 75B DB
calls per day (6/2012)

INTERNET ARCHIVE
Wayback Machine: 240B web
pages archived, 5 PB (1/2013)

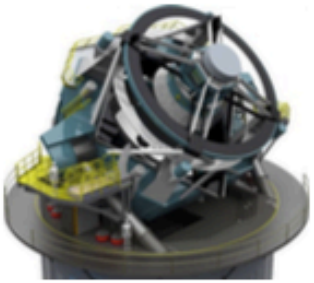
>100 PB of user data +
500 TB/day (8/2012)

facebook

amazon web services™
S3: 449B objects, peak 290k
request/second (7/2011)
1T objects (6/2012)

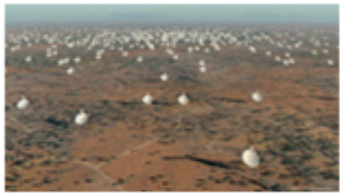
LHC: ~15 PB a year

CERN



LSST: 6-10 PB a year
(~2015)

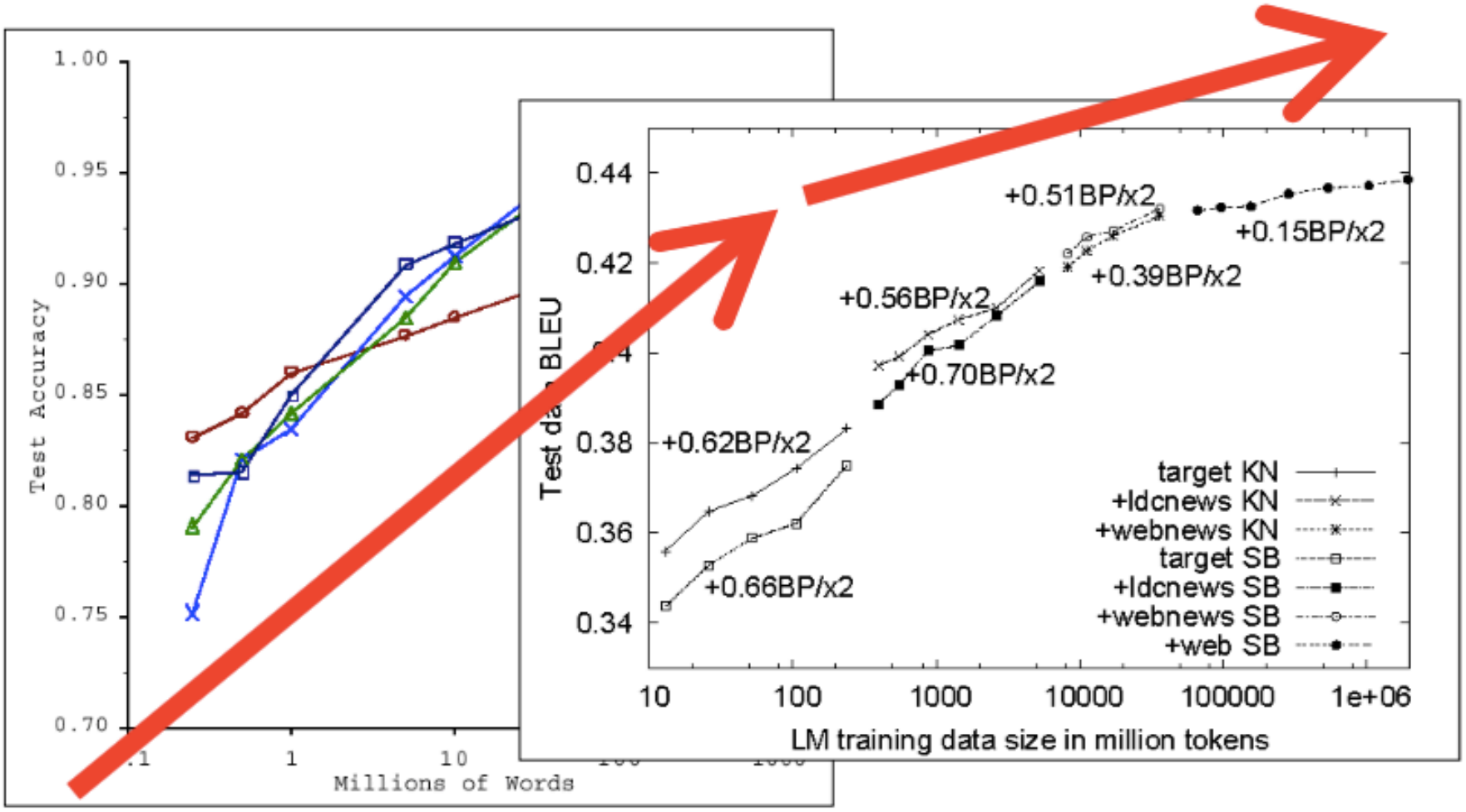
SKA: 0.3 – 1.5 EB
per year (~2020)



How much data?

No data like more data!

s/knowledge/data/g;



(Banko and Brill, ACL 2001)
(Brants et al., EMNLP 2007)

Source: Google

Typical Big Data Problem

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

Key idea: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)

MapReduce: A Real World Analogy

Coins Deposit

MapReduce: A Real World Analogy

Coins Deposit

Coins Counting Machine

MapReduce: A Real World Analogy

Coins Deposit

Mapper: Categorize coins by their face values

Reducer: Count the coins in each face value ***in parallel***

MapReduce

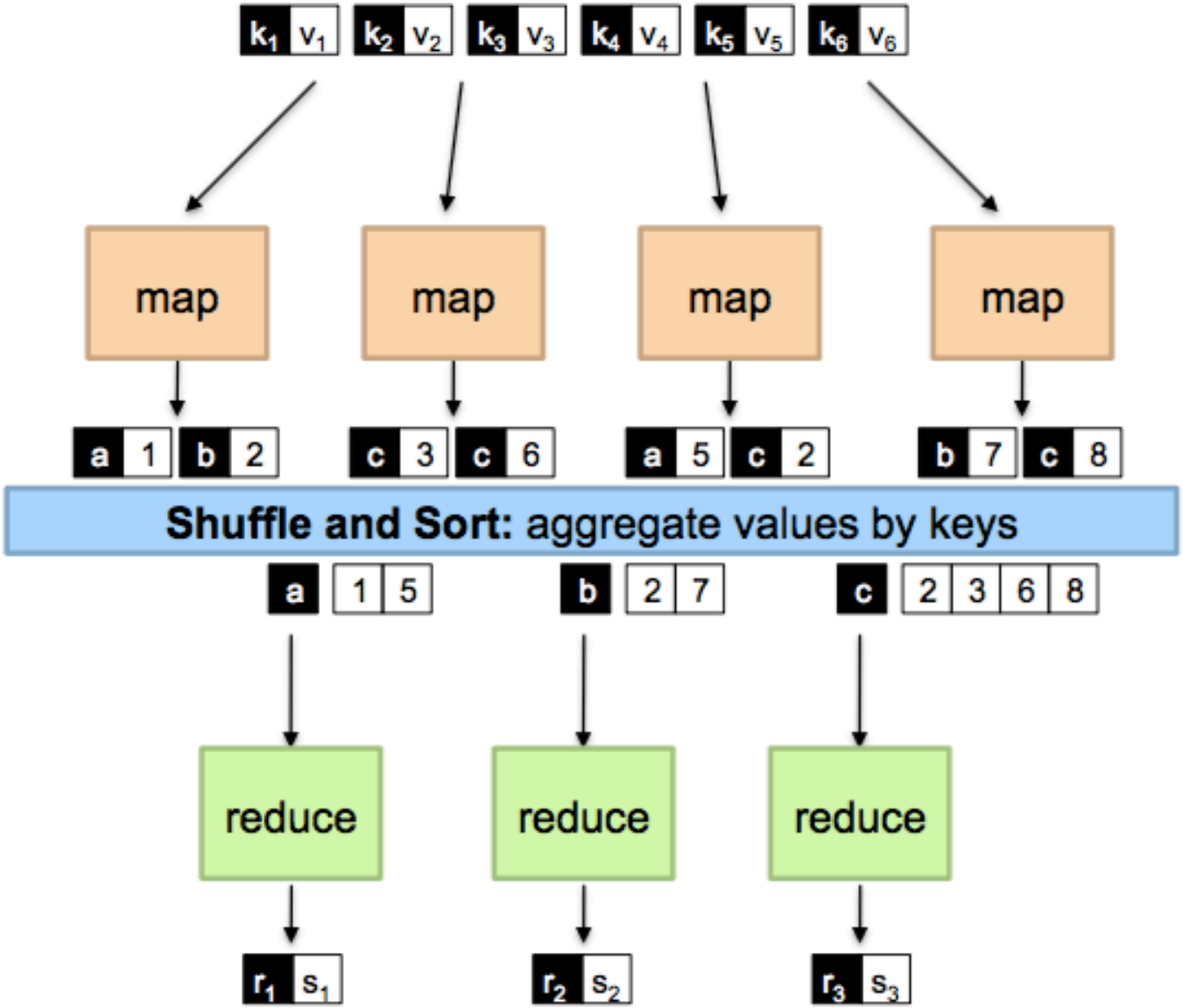
- Programmers specify two functions:

  map (k1, v1) → [<k2, v2>]

  reduce (k2, [v2]) → [<k3, v3>]

  (All values with the **same key** are sent to the same reducer)

- The execution framework handles everything else...


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
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

MapReduce

- Programmers specify two functions:

  Map (k1, v1) → <k2, v2>*

  Reduce (k2, list (v2)) → list (v3)

  (All values with the **same key** are sent to the same reducer)

- The execution framework handles everything else...

MapReduce "runtime"

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles "data distribution"
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed file system

Synchronization & ordering

- Barrier between map and reduce phases
  - But intermediate data can be copied over as soon as mappers finish
- Keys arrive at each reducer in sorted order
  - No enforced ordering *across* reducers

MapReduce

- Programmers specify two functions:

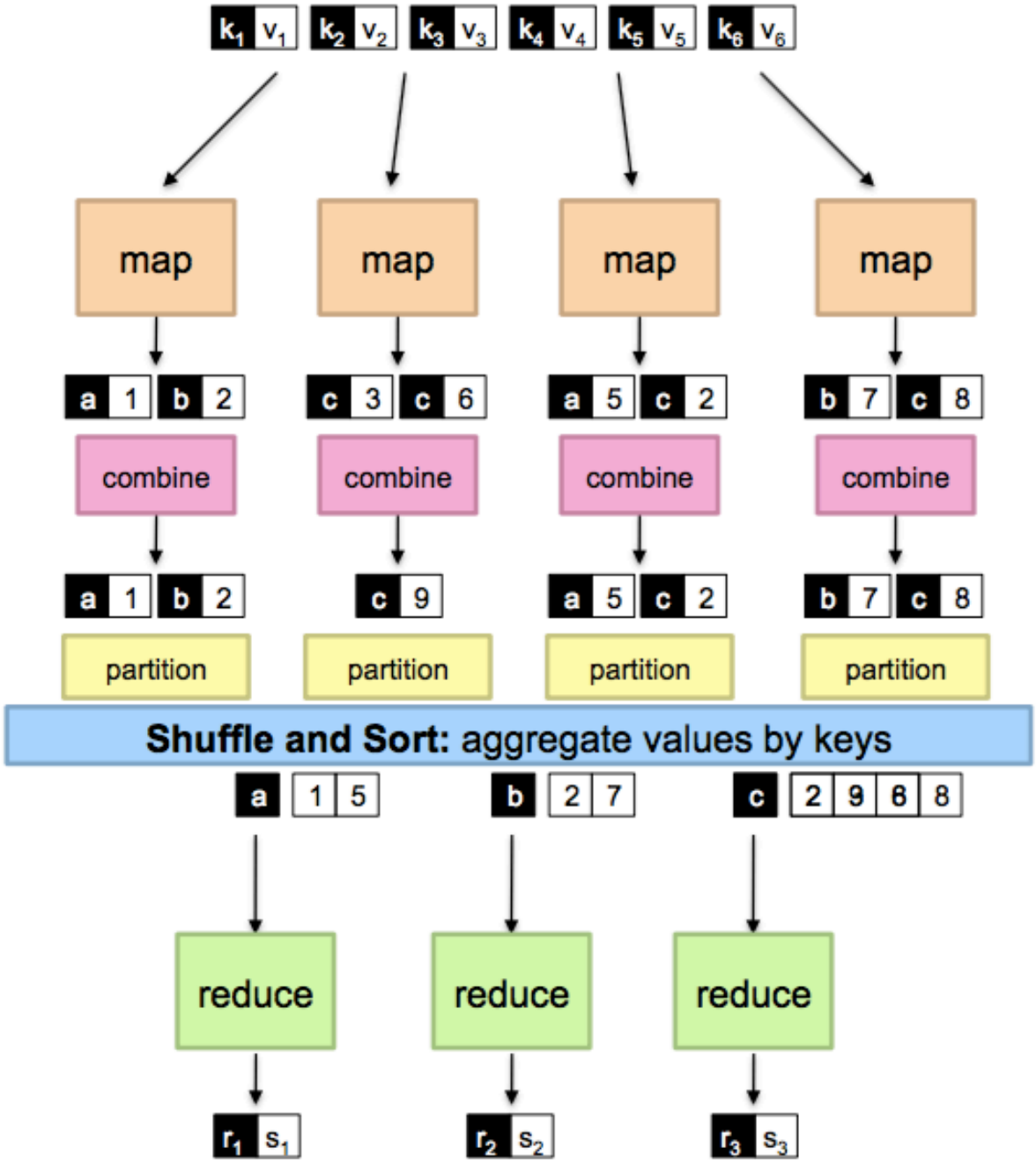
  Map (k1, v1) → <k2, v2>*

  Reduce (k2, list (v2)) → list (v3)

  (All values with the **same key** are sent to the same reducer)
- The execution framework handles everything else...
- Not quite...usually, programmers also specify:

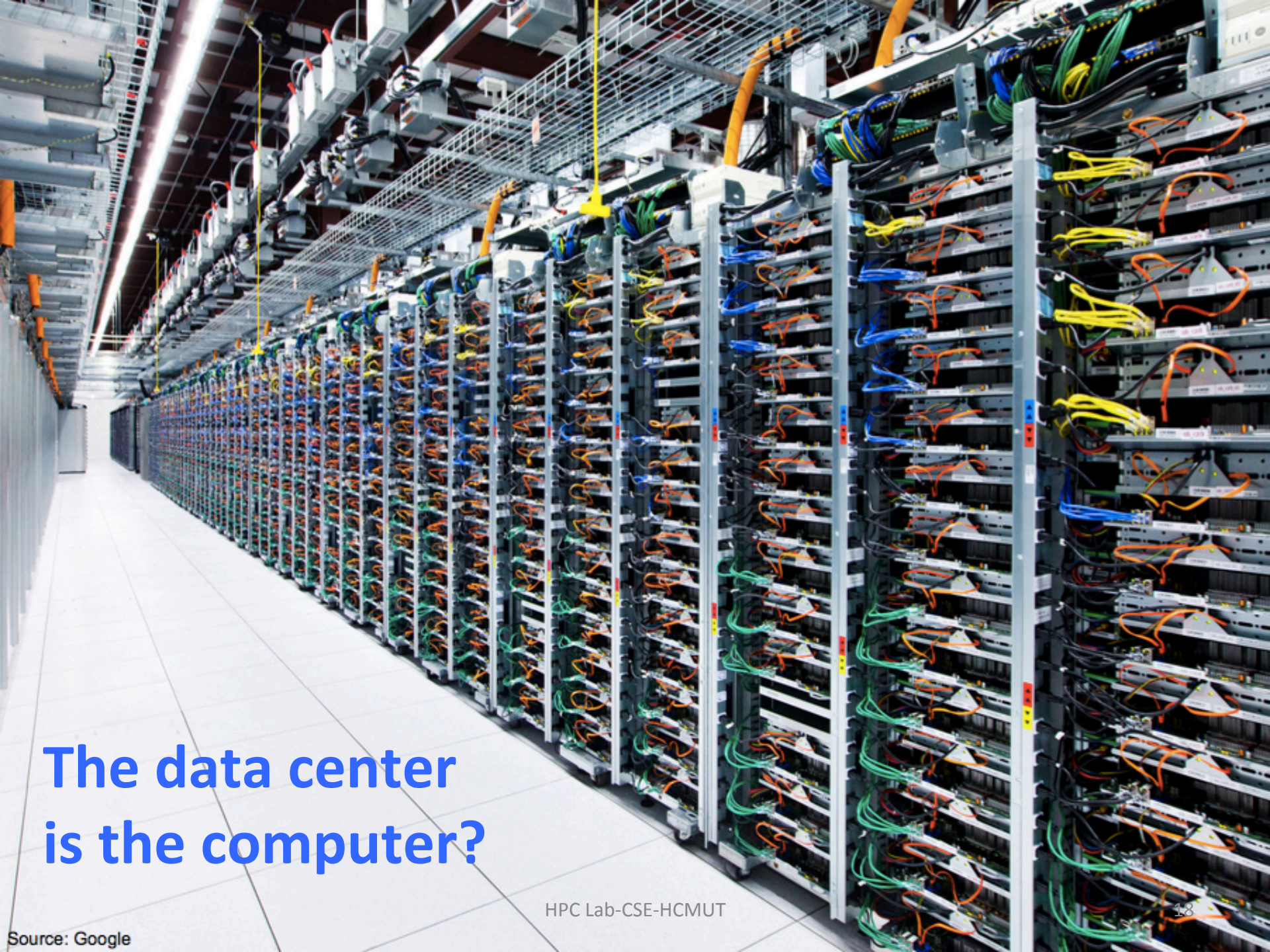
  partition (k2, number of partitions) → partition for k2
  - Often a simple hash of the key, e.g., hash(k') mod n
  - Divides up key space for parallel reduce operations

  combine (k2, v2) → <k2, v2>*
  - Mini-reducers that run in memory after the map phase
  - Used as an optimization to reduce network traffic


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

What's the big deal?

- Developers need the right level of abstraction
  - Moving beyond the von Neumann architecture
  - We need better programming models
- Abstractions hide low-level details from the developers
  - No more race conditions, lock contention, etc.
- MapReduce separating the *what* from *how*
  - Developer specifies the computation that need to be performed
  - Execution framework ("runtime") handles actual execution



The data center is the computer?

Source: Google

MapReduce can refers to…

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

MapReduce Implementations

- Google has a proprietary implementation in C++
  - Bindings in Java, Python
- Hadoop is an open-source implementation in Java
  - Development led by Yahoo, now an Apache project
  - Used in production at Yahoo, Facebook, Twitter, Linked In, Netflix, etc.
  - The *de facto* big data processing platform
  - Rapidly expanding software ecosystem
- Lots of custom research implementations
  - For GPUs, cell processors, etc.

MapReduce algorithm design

- The execution framework handles "everything else"...
  - 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

Apache Hadoop

Data volumes: Google Example

- Analyze 10 billion web pages
- Average size of a webpage: 20KB
- Size of the collection: 10 billion x 20KBs = 200TB
- HDD hard disk read bandwidth: 150MB/sec
- Time needed to read all web pages (without analyzing them): 2 million seconds = more than 15 days
- A single node architecture is not adequate

Data volumes: Google Example with SSD

- Analyze 10 billion web pages
- Average size of a webpage: 20KB
- Size of the collection: 10 billion x 20KBs = 200TB
- SSD hard disk read bandwidth: 550MB/sec
- Time needed to read all web pages (without analyzing them): 2 million seconds = more than 4 days
- A single node architecture is not adequate

Apache Hadoop

- Scalable fault-tolerant distributed system for Big Data
  - Distributed Data Storage
  - Distributed Data Processing
  - Borrowed concepts/ideas from the systems designed at Google (Google File System for Google's MapReduce)
  - Open source project under the Apache license
    - But there are also many commercial implementations (e.g., Cloudera, Hortonworks, MapR)

Hadoop History

- Dec 2004 - Google published a paper about GFS
- July 2005 - Nutch uses MapReduce
- Feb 2006 - Hadoop becomes a Lucene subproject
- Apr 2007 - Yahoo! runs it on a 1000-node cluster
- Jan 2008 - Hadoop becomes an Apache Top Level Project
- Jul 2008 - Hadoop is tested on a 4000 node cluster
- Feb 2009 - The Yahoo! Search Webmap is a Hadoop application that runs on more than 10,000 core Linux cluster
- June 2009 - Yahoo! made available the source code of its production version of Hadoop
- In 2010 Facebook claimed that they have the largest Hadoop cluster in the world with 21 PB of storage
  - On July 27, 2011 they announced the data has grown to 30PB.

Hadoop vs. HPC

- **Hadoop**
  - Designed for **Data intensive workloads**
  - Usually, no CPU demanding/intensive tasks
- **HPC** (High-performance computing)
  - A supercomputer with a high-level computational capacity
    - Performance of a supercomputer is measured in floating-point operations per second (FLOPS)
  - Designed for **CPU intensive tasks**
  - Usually it is used to process "small" data sets

Hadoop: main components

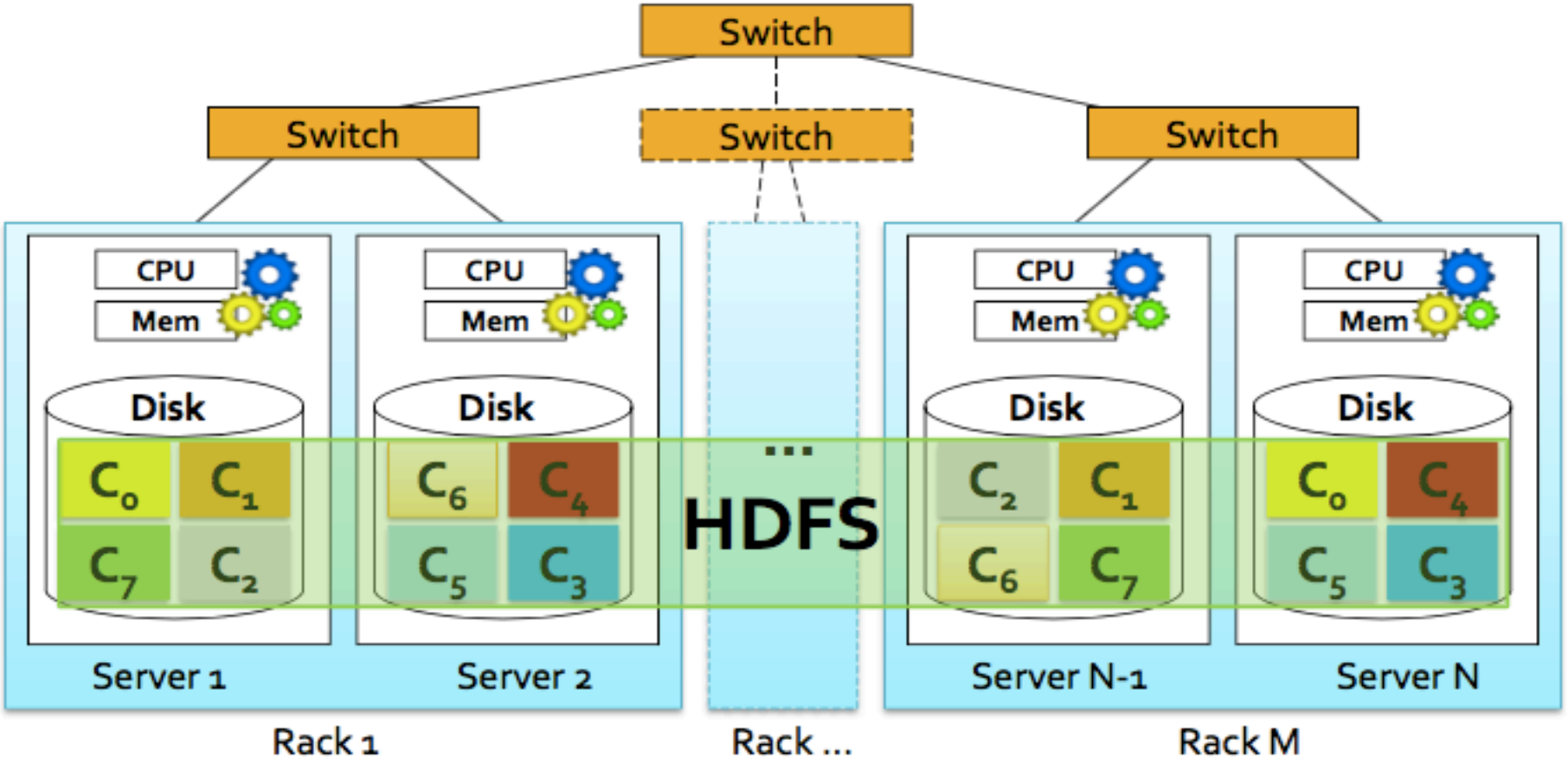
- Core components of Hadoop:
  - Distributed Big Data Processing Infrastructure based on the MapReduce programming paradigm
    - Provides a high-level abstraction view
      - Programmers do not need to care about task scheduling and synchronization
    - Fault-tolerant
      - Node and task failures are automatically managed by the Hadoop system
  - HDFS (Hadoop Distributed File System)
    - High availability distributed storage
    - Fault-tolerant

HDFS
(Hadoop File System)

HDFS

- HDFS is a distributed file system that is fault tolerant, scalable and extremely easy to expand
- HDFS is the primary distributed storage for Hadoop applications
- HDFS provides interfaces for applications to move themselves closer to data
- HDFS is designed to ‘just work’, however a working knowledge helps in diagnostics and improvements

HDFS: a distributed file system

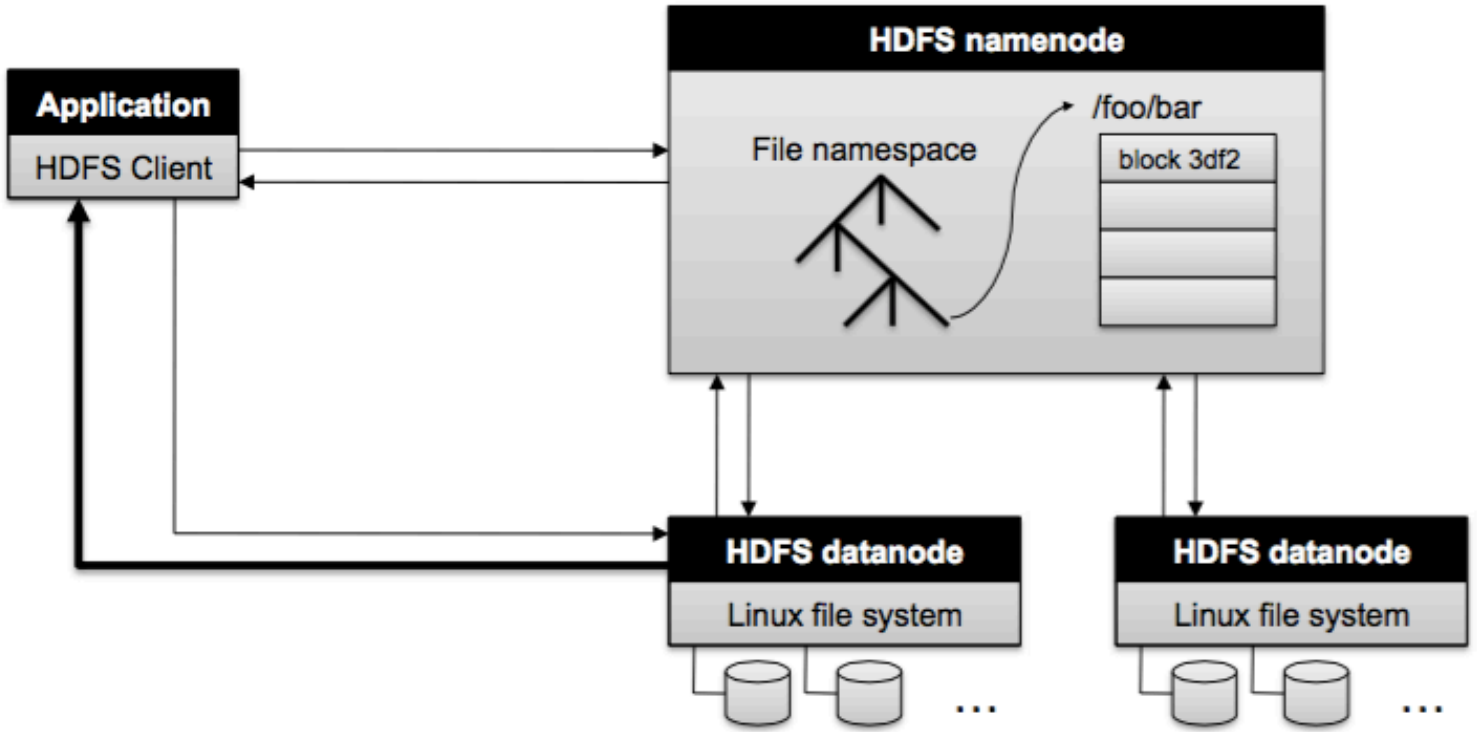


Example with number of replicas per chunk = 2

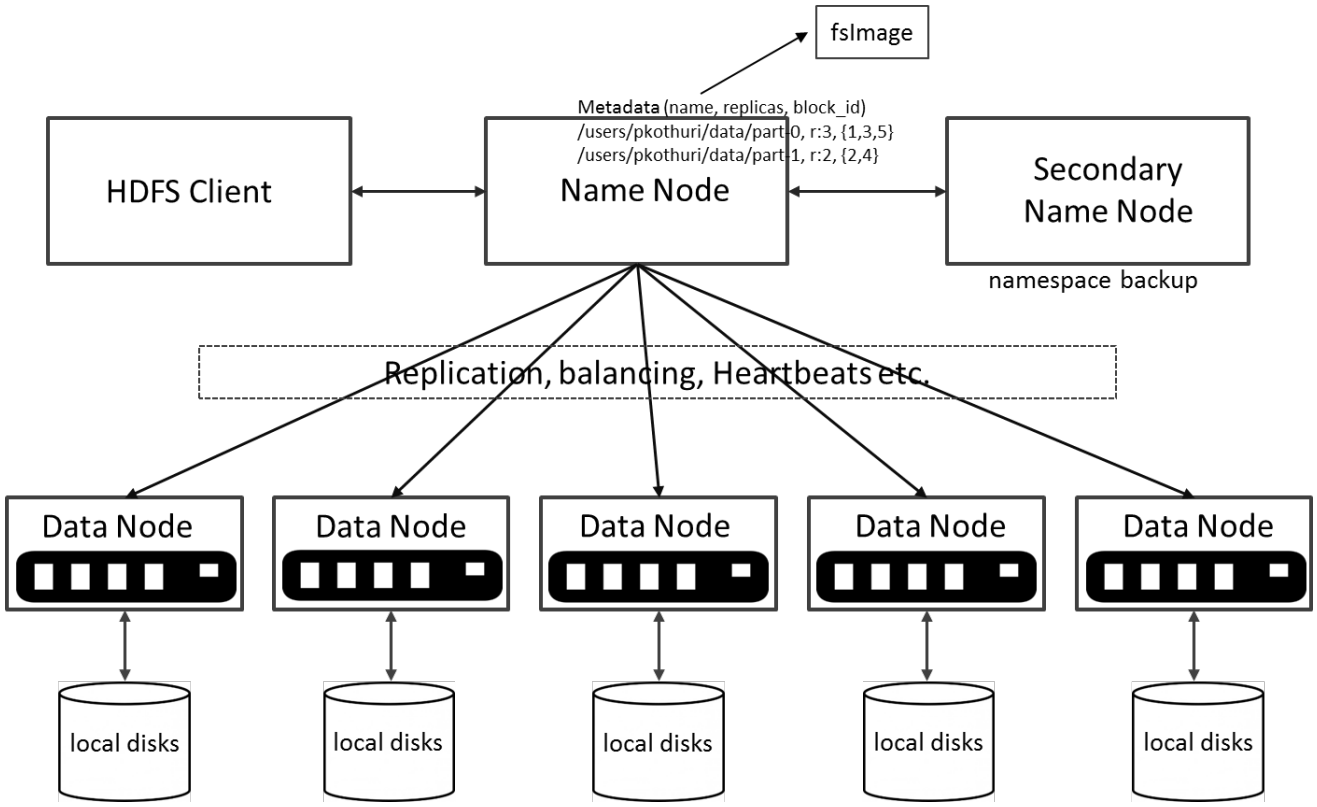
HDFS – Data Organization

- Each file written into HDFS is split into data blocks
- Each block is stored on one or more nodes
- Each copy of the block is called replica
- Block placement policy
  - First replica is placed on the local node
  - Second replica is placed in a different rack
  - Third replica is placed in the same rack as the second replica

HDFS architecture (1)



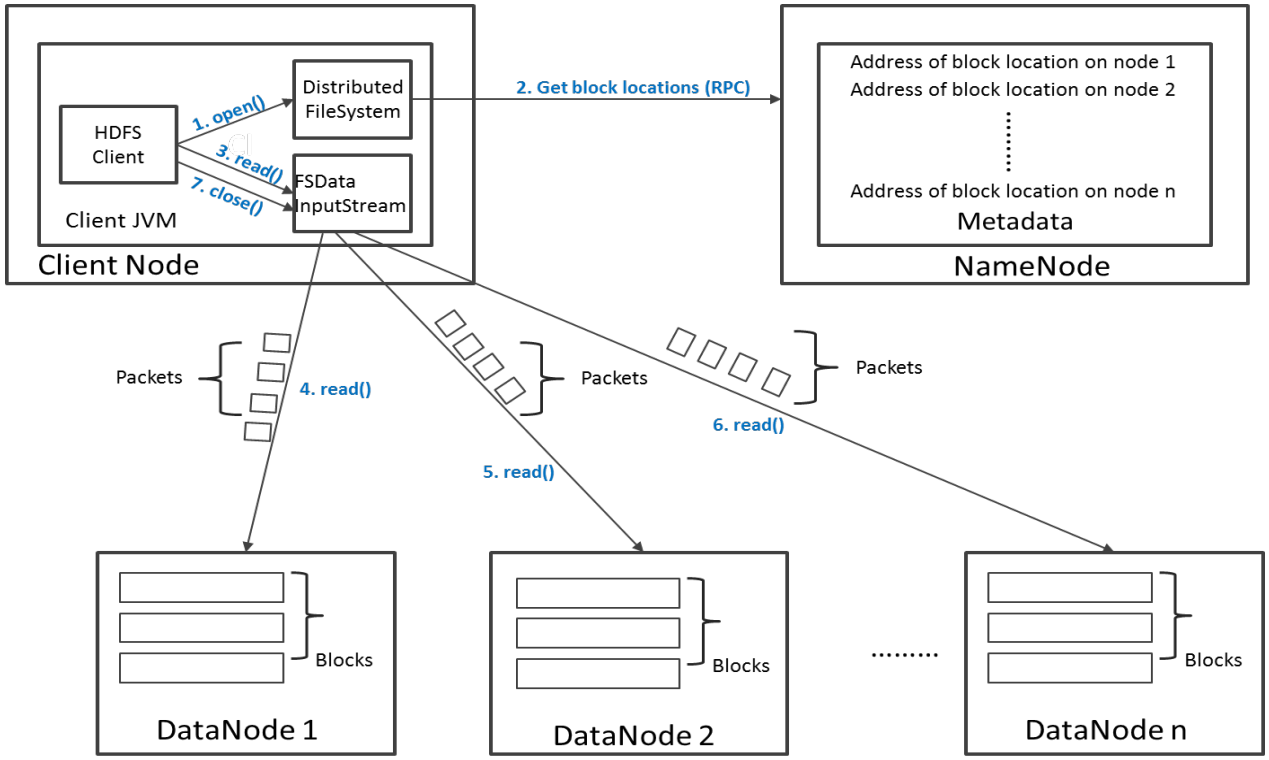
HDFS architecture (2)



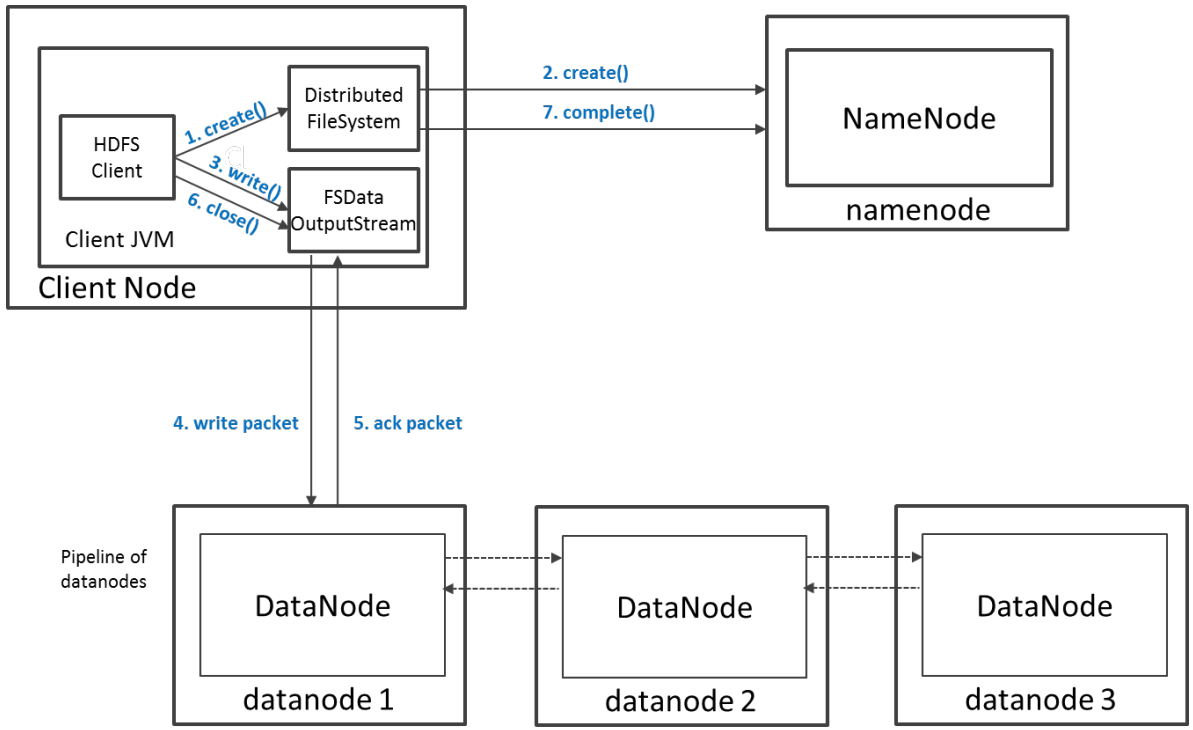
There are two (*and a half*) types of machines in a HDFS cluster

- NameNode is the heart of an HDFS filesystem, it maintains and manages the file system metadata. E.g; what blocks make up a file, and on which datanodes those blocks are stored
- DataNode where HDFS stores the actual data, there are usually quite a few of these

Read operation in HDFS



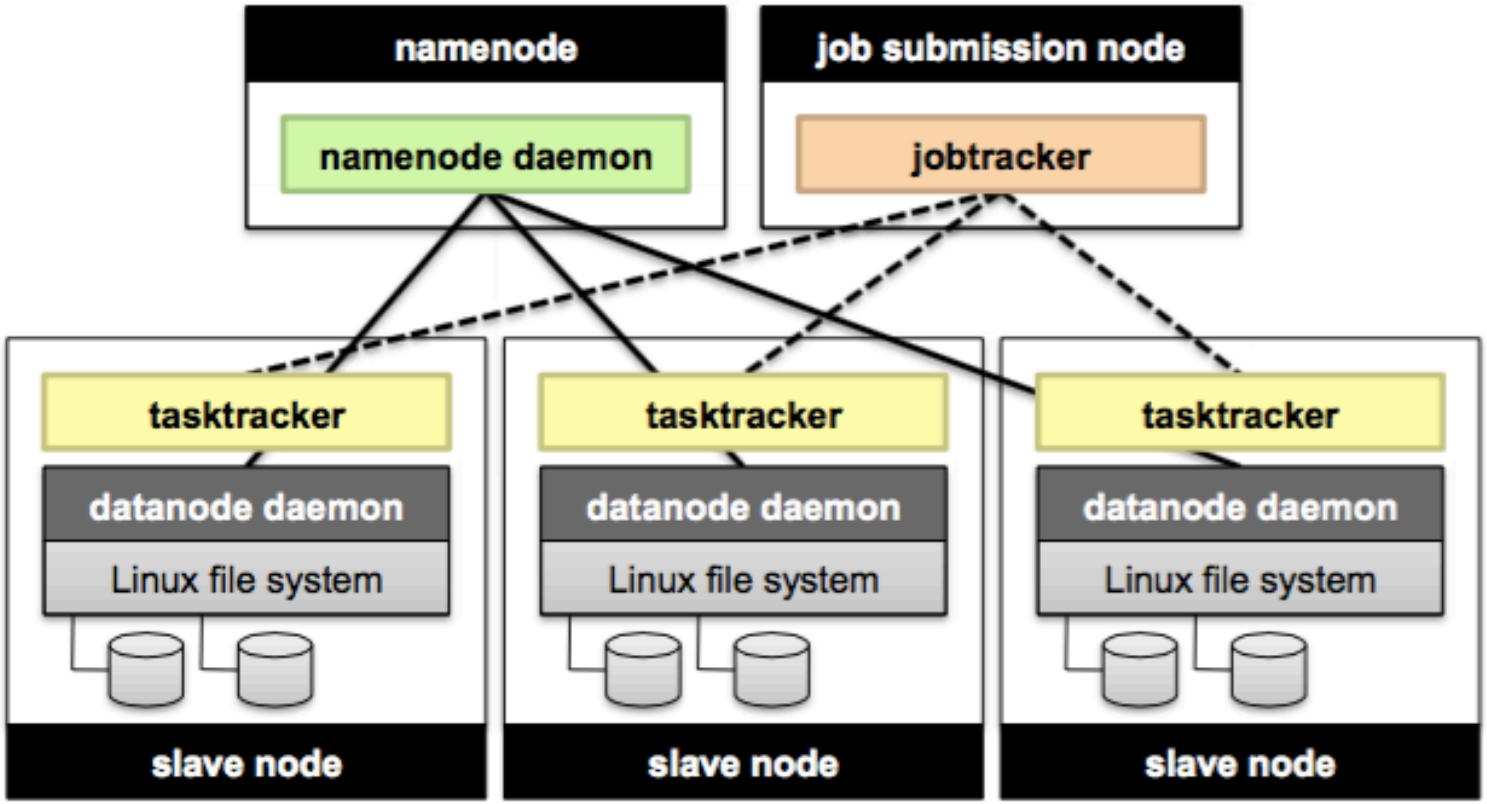
Write operation in HDFS



Unique features of HDFS

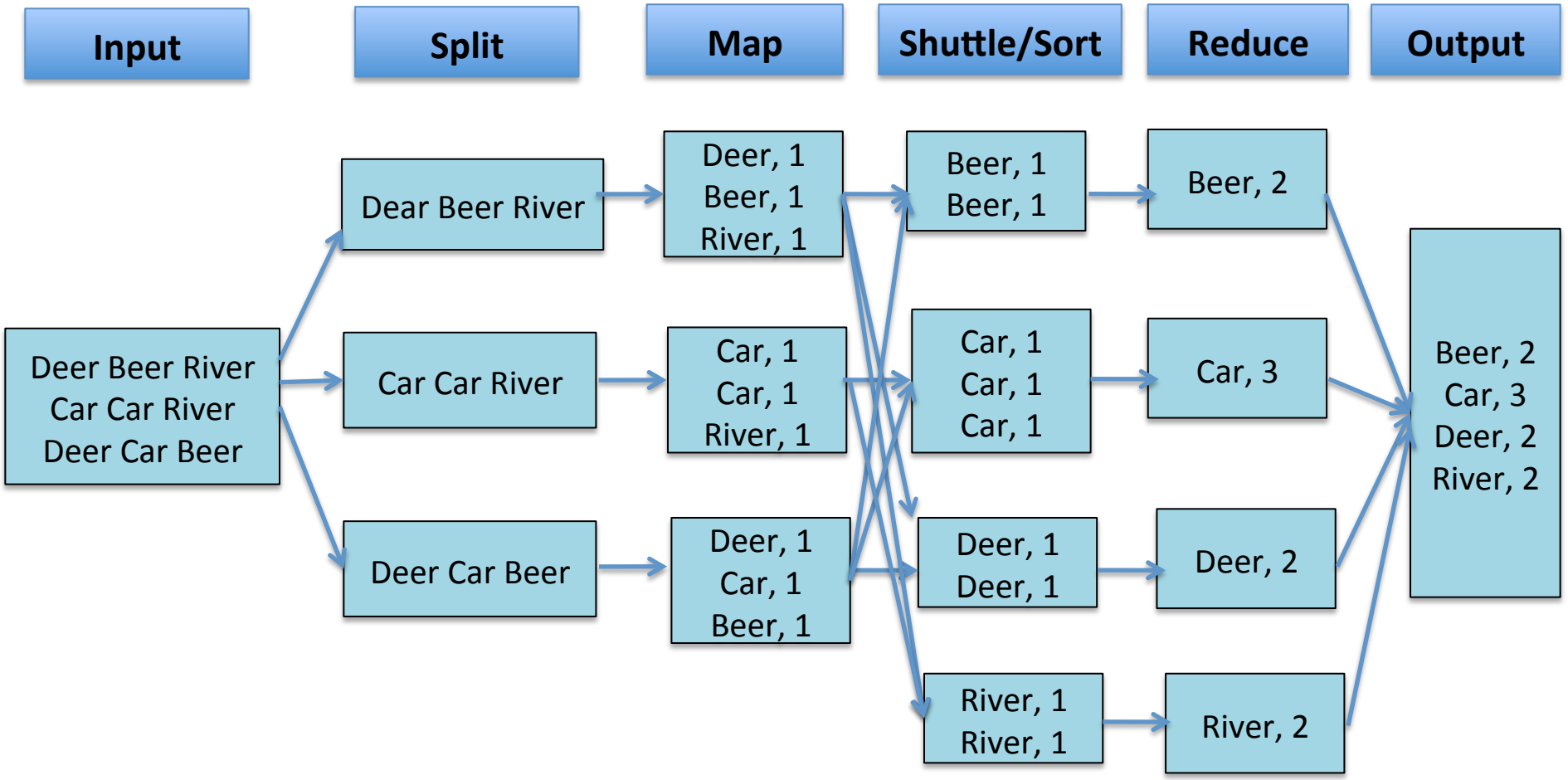
- HDFS also has a bunch of unique features that make it ideal for distributed systems:
  - Failure tolerant - data is duplicated across multiple DataNodes to protect against machine failures. The default is a replication factor of 3 (every block is stored on three machines).
  - Scalability - data transfers happen directly with the DataNodes so your read/write capacity scales fairly well with the number of DataNodes
  - Space - need more disk space? Just add more DataNodes and re-balance
  - Industry standard - Other distributed applications are built on top of HDFS (HBase, Map-Reduce)
- HDFS is designed to process large data sets with write-once-read-many, it is not for low latency access

MapReduce & HDFS

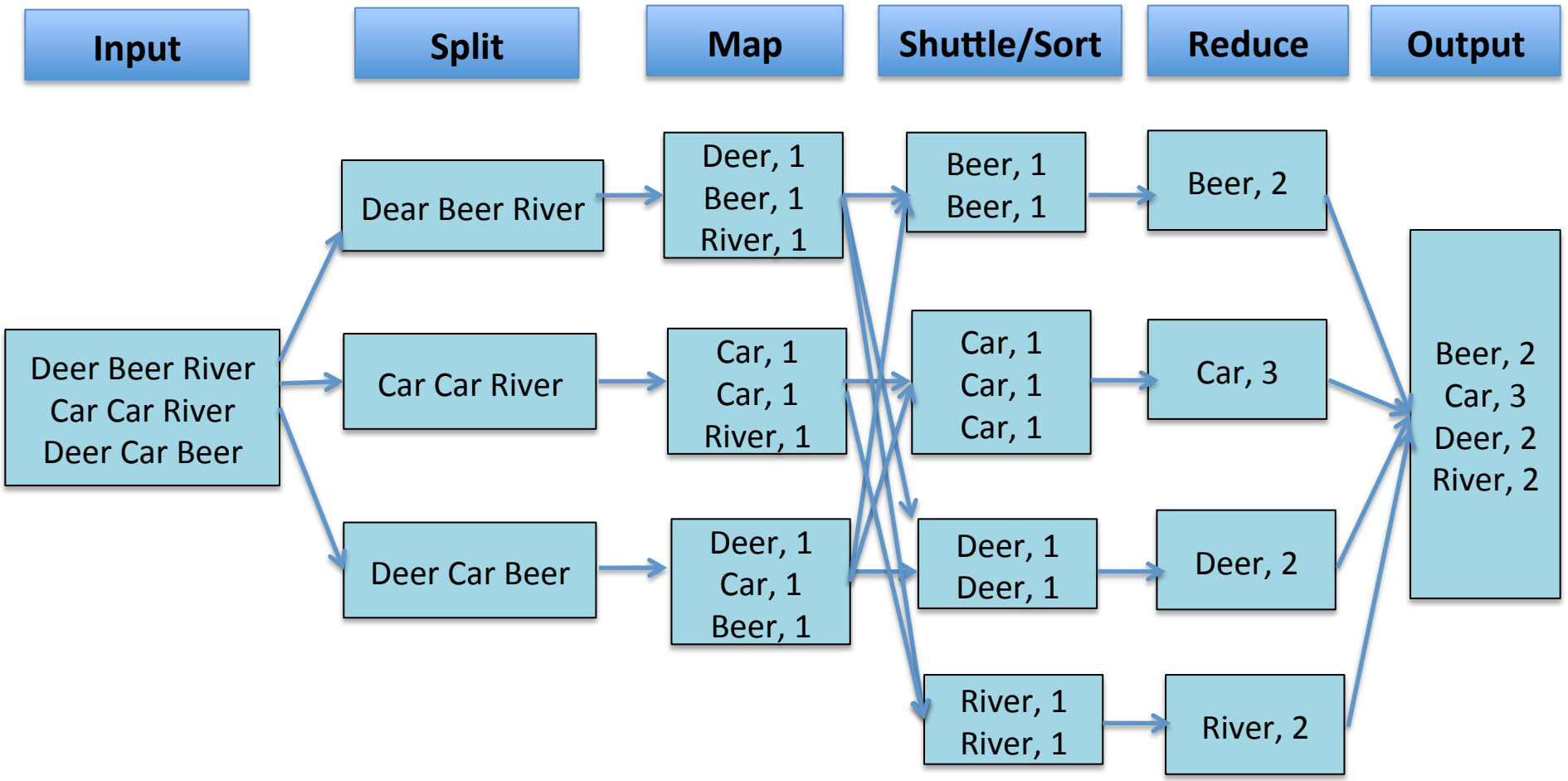


Algorithm & programming

MapReduce Example: Word Count



MapReduce Example: Word Count



Q: What are the Key and Value Pairs of Map and Reduce?

Map: Key=word, Value=1

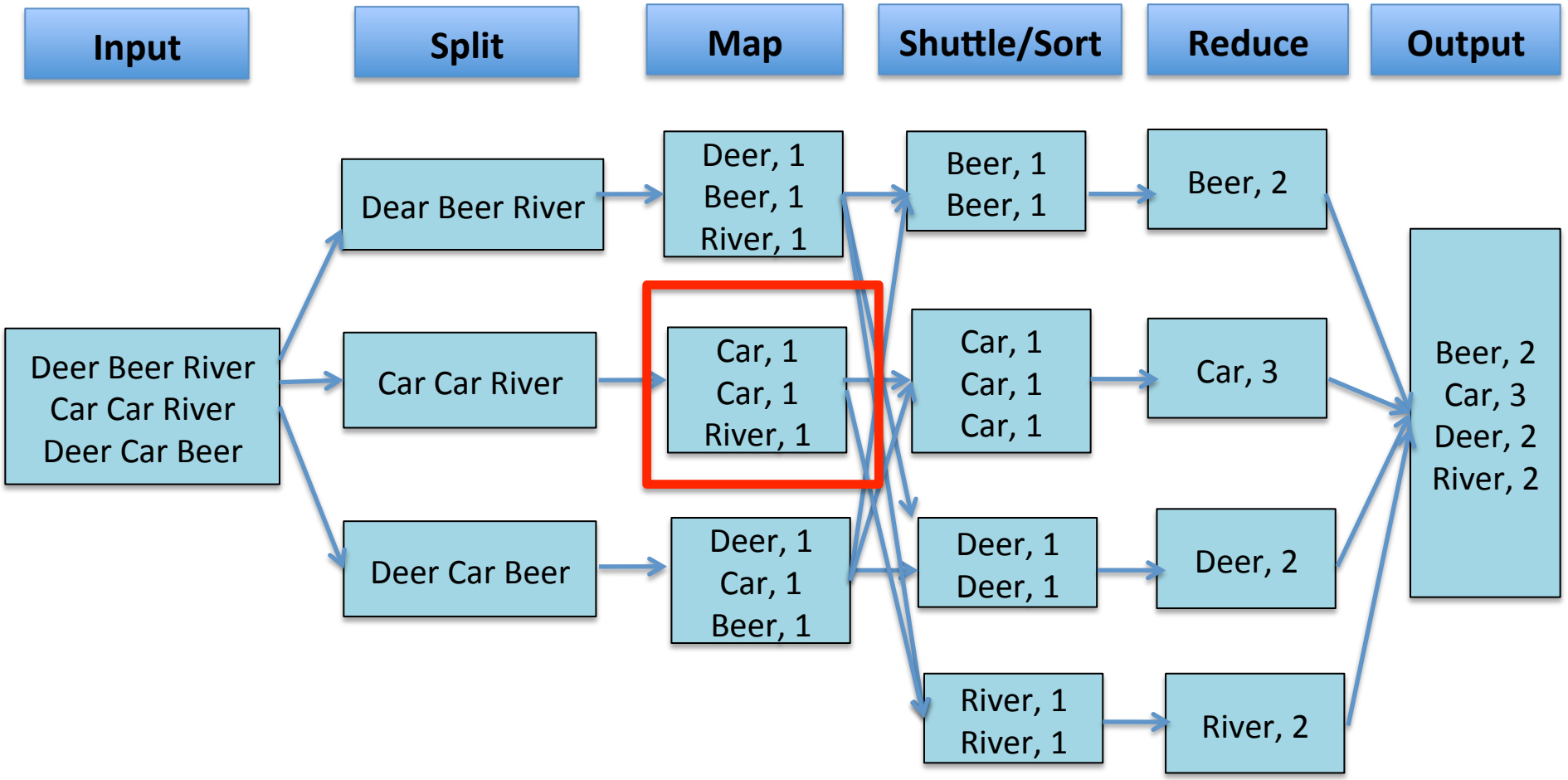
Reduce: Key=word, Value=aggregated count

Word Count: baseline

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         for all term t ∈ doc d do
4:             Emit(term t, count 1)
```

```
1: class Reducer
2:     method Reduce(term t, counts [c1, c2, ...])
3:         sum ← 0
4:         for all count c ∈ counts [c1, c2, ...] do
5:             sum ← sum + c
6:         Emit(term t, count s)
```

MapReduce Example: Word Count

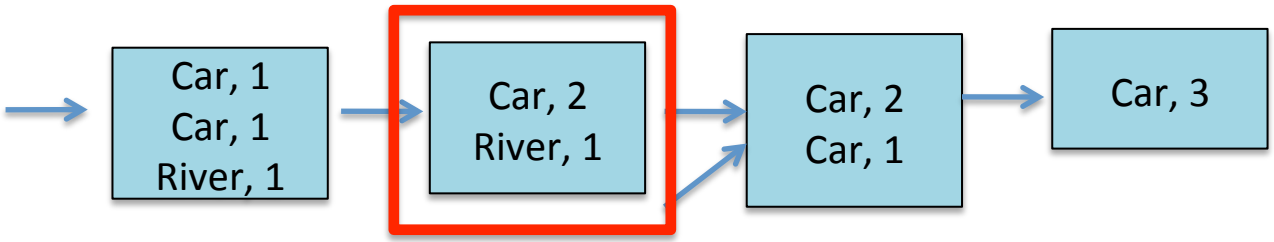


Q: Do you see any place we can improve the efficiency?

Local aggregation at mapper will be able to improve MapReduce efficiency.

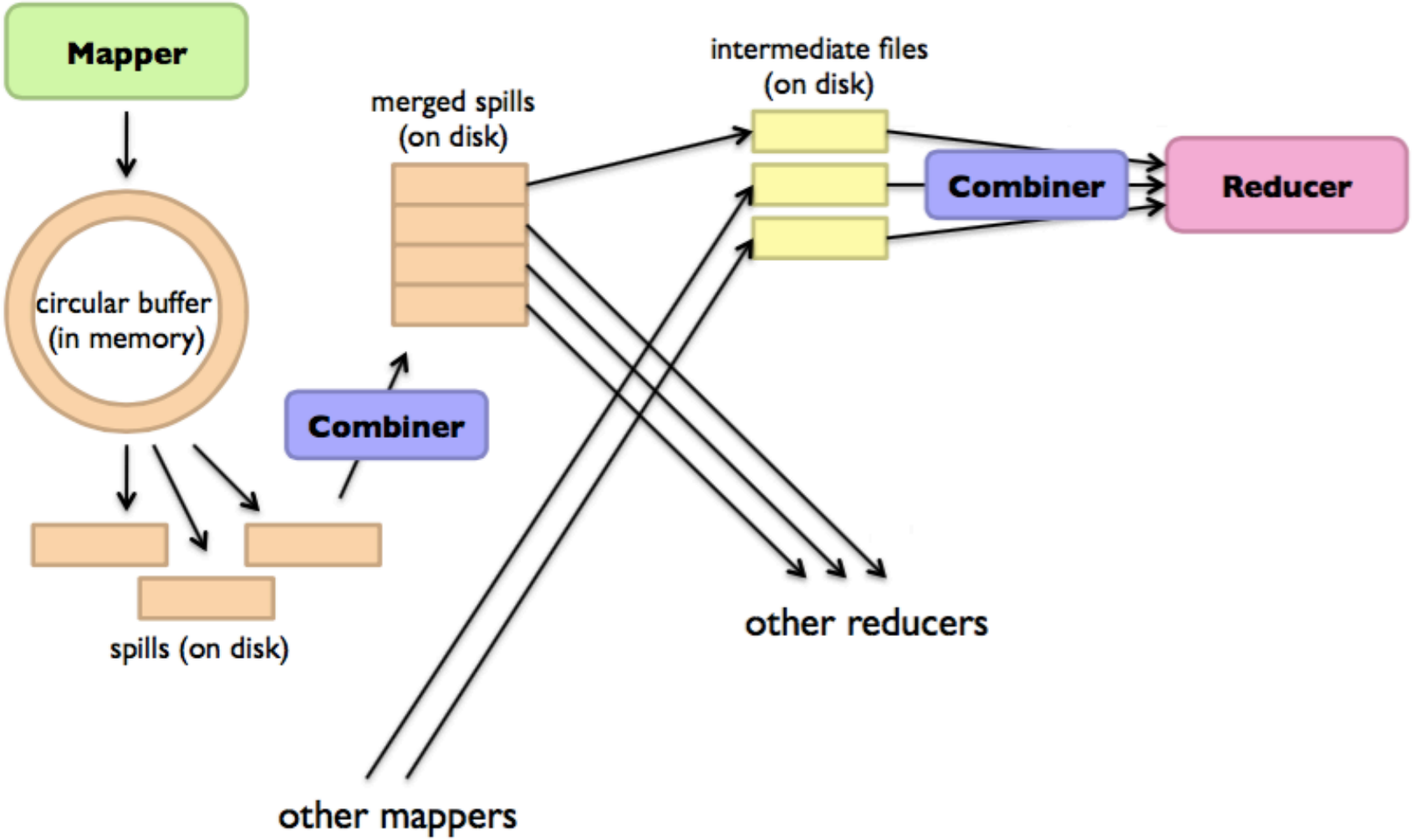
MapReduce: Combiner

- **Combiner:** do local aggregation/combine task at mapper

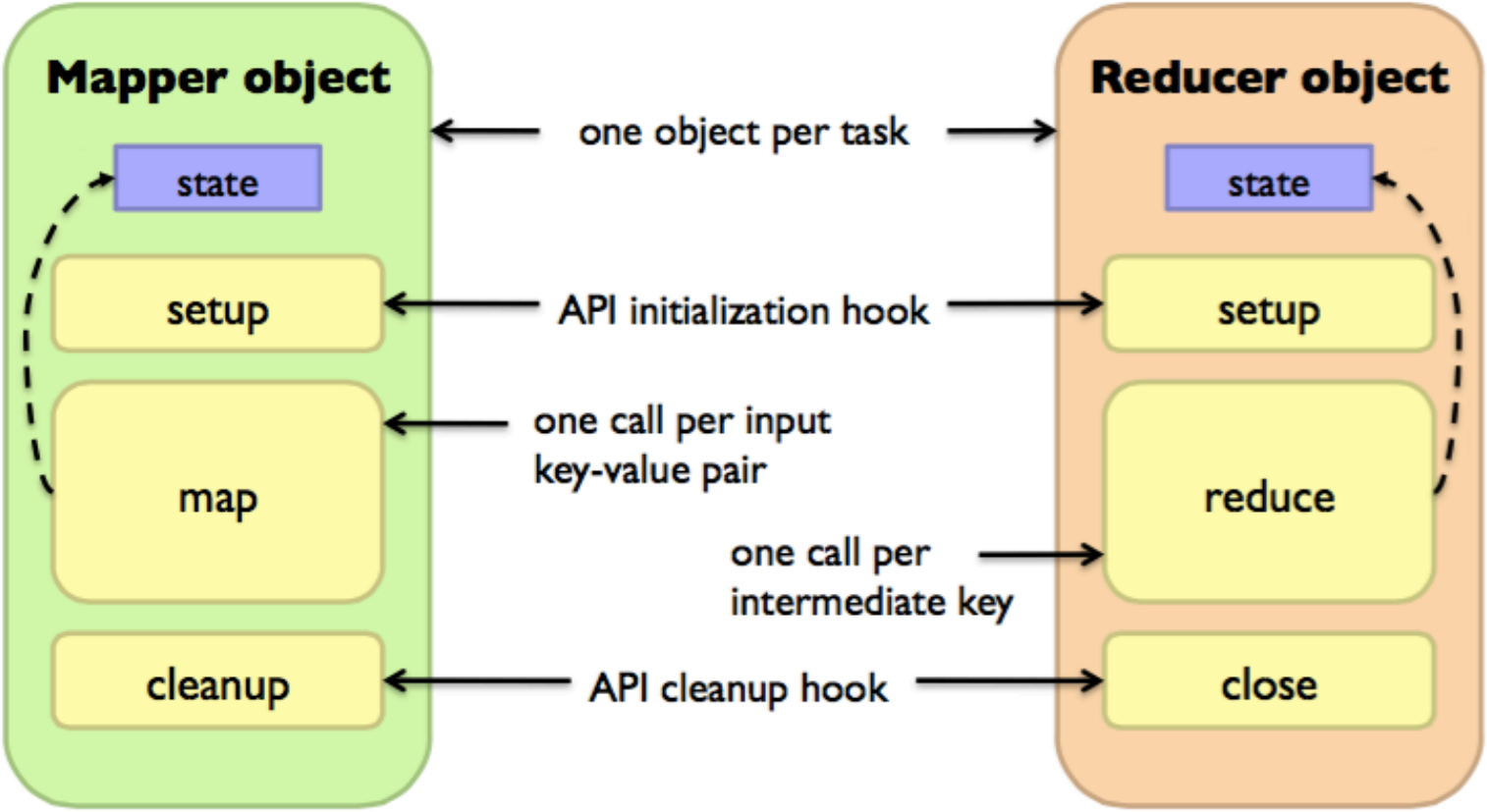


- **Q: What are the benefits of using combiner:**
  - Reduce memory/disk requirement of Map tasks
  - Reduce network traffic
- **Q: Can we remove the reduce function?**
  - No, reducer still needs to process records with same key but from *different mappers*
- **Q: How would you implement combiner?**
  - It is the same as Reducer!

Shuffle and sort



Preserving state



Implementation don't

- Don't unnecessarily create objects
  - Object creation is costly
  - Garbage collection is costly
- Don't buffer objects
  - Processes have limited heap size (remember, commodity machines)
  - May work for small datasets, but won't scale!

Word Count: version 1

```
1: class Mapper
2:     method Map(docid a, doc d)
3:         H ← new AssociativeArray
4:         for all term t ∈ doc d do
5:             H{t} ← H{t} + 1                ▷ Tally counts for entire document
6:         for all term t ∈ H do
7:             Emit(term t, count H{t})
```

Word Count: version 2

```
1: class Mapper
2:     method Initialize
3:         H ← new AssociativeArray
4:     method Map(docid a, doc d)
5:         for all term t ∈ doc d do
6:             H{t} ← H{t} + 1                ▷ Tally counts across documents
7:     method Close
8:         for all term t ∈ H do
9:             Emit(term t, count H{t})
```

Key idea: preserve state across input key-value pairs!

Are combiners still need?

Design pattern for local aggregation

- "In-mapper combining"
  - Fold the functionality of the combiner into the mapper by preserving state across multiple map calls
- Advantages
  - Speed
  - Why is this faster than actual combiners?
- Disadvantages
  - Explicit memory management required
  - Potential for order-dependent bugs

Combiner design

- Combiners and reducers share same method signature
  - Sometimes, reducers can serve as combiners
  - Often, not…
- Remember: combiner are optional optimizations
  - Should not affect algorithm correctness
  - May be run 0, 1, or multiple times
- Example: find average of integers associated with the same key

Computing the Mean: version 1

```
1: class Mapper
2:     method Map(string t, integer r)
3:         Emit(string t, integer r)

1: class Reducer
2:     method Reduce(string t, integers [r_1, r_2, ...])
3:         sum ← 0
4:         cnt ← 0
5:         for all integer r ∈ integers [r_1, r_2, ...] do
6:             sum ← sum + r
7:             cnt ← cnt + 1
8:         r_avg ← sum/cnt
9:         Emit(string t, integer r_avg)
```

Why can't we use Reducer as Combiner?

Computing the Mean: version 2

```
1: class Mapper
2:     method Map(string t, integer r)
3:         Emit(string t, integer r)
```

```
1: class Combiner
2:     method Combine(string t, integers [r_1, r_2, ...])
3:         sum ← 0
4:         cnt ← 0
5:         for all integer r ∈ integers [r_1, r_2, ...] do
6:             sum ← sum + r
7:             cnt ← cnt + 1
8:         Emit(string t, pair (sum, cnt))          ▷ Separate sum and count
```

```
1: class Reducer
2:     method Reduce(string t, pairs [(s_1, c_1), (s_2, c_2) ...])
3:         sum ← 0
4:         cnt ← 0
5:         for all pair (s, c) ∈ pairs [(s_1, c_1), (s_2, c_2) ...] do
6:             sum ← sum + s
7:             cnt ← cnt + c
8:         r_avg ← sum/cnt
9:         Emit(string t, integer r_avg)
```

Why doesn't this work?

Computing the Mean: version 3

```
1: class Mapper
2:     method Map(string t, integer r)
3:         Emit(string t, pair (r, 1))
```

```
1: class Combiner
2:     method Combine(string t, pairs [(s_1, c_1), (s_2, c_2) ...])
3:         sum ← 0
4:         cnt ← 0
5:         for all pair (s, c) ∈ pairs [(s_1, c_1), (s_2, c_2) ...] do
6:             sum ← sum + s
7:             cnt ← cnt + c
8:         Emit(string t, pair (sum, cnt))
```

```
1: class Reducer
2:     method Reduce(string t, pairs [(s_1, c_1), (s_2, c_2) ...])
3:         sum ← 0
4:         cnt ← 0
5:         for all pair (s, c) ∈ pairs [(s_1, c_1), (s_2, c_2) ...] do
6:             sum ← sum + s
7:             cnt ← cnt + c
8:         r_avg ← sum/cnt
9:         Emit(string t, pair (r_avg, cnt))
```

Computing the Mean: version 4

```
1: class Mapper
2:     method Initialize
3:         S ← new AssociativeArray
4:         C ← new AssociativeArray
5:     method Map(string t, integer r)
6:         S{t} ← S{t} + r
7:         C{t} ← C{t} + 1
8:     method Close
9:         for all term t ∈ S do
10:            Emit(term t, pair (S{t}, C{t}))
```

Are combiners still need?

Word Count & sorting

- **New Goal:** output all words sorted by their frequencies (total counts) in a document.
- **Question:** How would you adopt the basic word count program to solve it?
- **Solution:**
  - **Sort words by their counts in the reducer**
  - **Problem: what happens if we have more than one reducer?**

Word Count & sorting

- **New Goal:** output all words sorted by their frequencies (total counts) in a document.
- **Question:** How would you adopt the basic word count program to solve it?
- **Solution:**
  - **Do two rounds of MapReduce**
  - **In the 2nd round, take the output of WordCount as input but *switch key and value pair*!**
  - **Leverage the sorting capability of *shuffle/sort* to do the global sorting!**

Word Count & top K words

- **New Goal:** output the top K words sorted by their frequencies (total counts) in a document.
- **Question:** How would you adopt the basic word count program to solve it?
- **Solution:**
  - **Use the solution of previous problem and only grab the top K in the final output**
  - **Problem: is there a more efficient way to do it?**

Word Count & top K words

- **New Goal:** output the top K words sorted by their frequencies (total counts) in a document.
- **Question:** How would you adopt the basic word count program to solve it?
- **Solution:**
  - **Add a sort function to the *reducer* in the first round and only output the top K words**
  - **Intuition: the *global top K must be a local top K* in any reducer!**

MapReduce In-class Exercise

- **Problem:** Find the maximum monthly temperature for each year from weather reports
- **Input:** A set of records with format as:

  <Year/Month, Average Temperature of that month>

  - (200707,100), (200706,90)

  - (200508, 90), (200607,100)

  - (200708, 80), (200606,80)
- **Question:** write down the Map and Reduce function to solve this problem
  - Assume we split the input by line

Mapper and Reducer of Max Temperature

- Map(key, value){

  // key: line number

  // value: tuples in a line

  for each tuple t in value:

  Emit(t->year, t->temperature);}

- Reduce(key, list of values){

  // key: year

  //list of values: a list of monthly temperature

  int max_temp = -100;

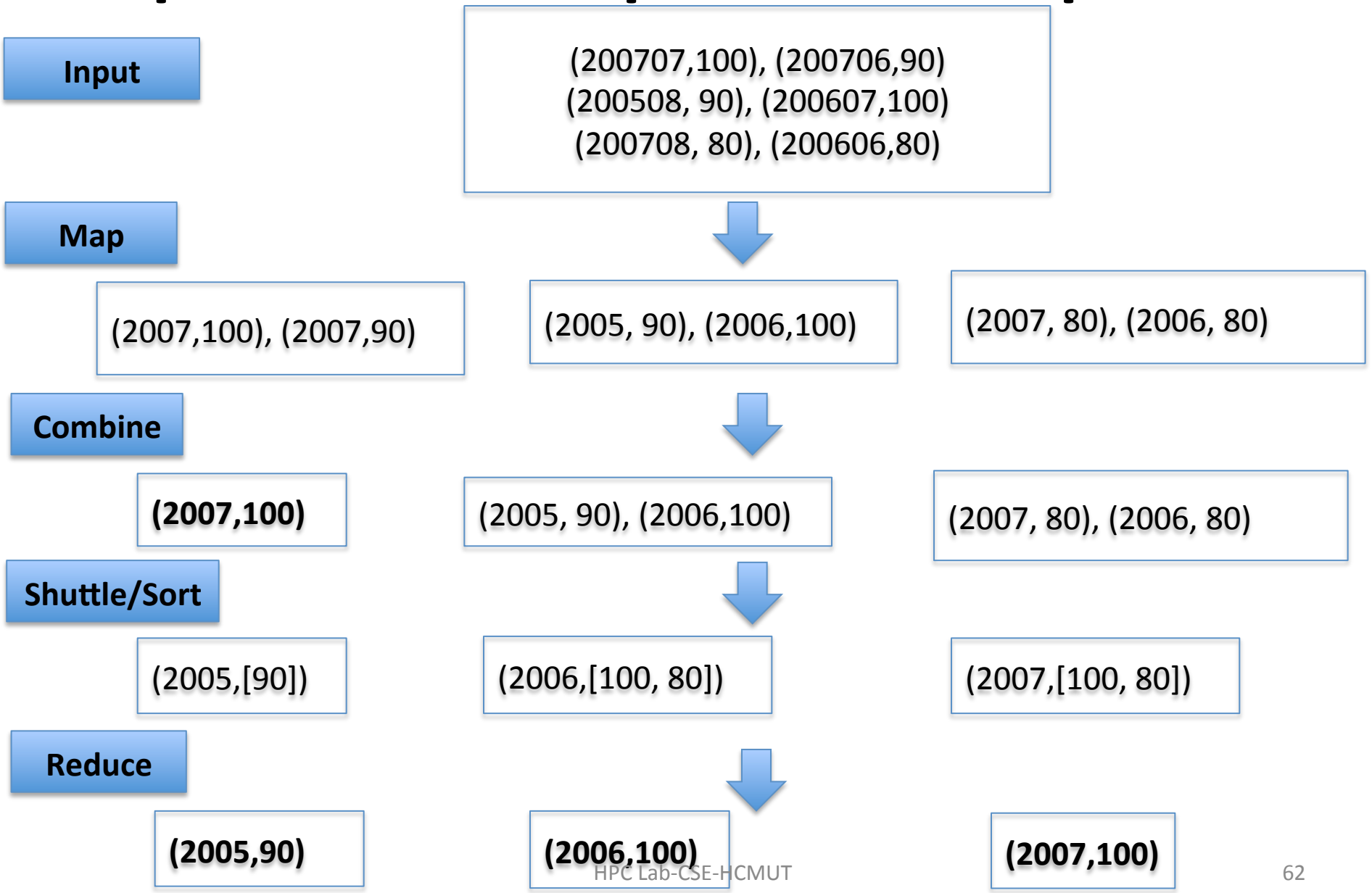
  for each v in values:

  max_temp= max(v, max_temp);

  Emit(key, max_temp);}

Combiner is the same as Reducer

MapReduce Example: Max Temperature



MapReduce In-class Exercise

- **Key-Value Pair of Map and Reduce:**
  - **Map:** (year, temperature)
  - **Reduce:** (year, maximum temperature of the year)

- **Question: How to use the above Map Reduce program *(that contains the combiner)* with slight changes to find the average monthly temperature of the year?**

Mapper and Reducer of Average Temperature

- Map(key, value){

  // key: line number

  // value: tuples in a line

  for each tuple t in value:

  Emit(t->year, t->temperature);}

- Reduce(key, list of values){

  // key: year

  // list of values: a list of monthly temperatures

  int total_temp = 0;

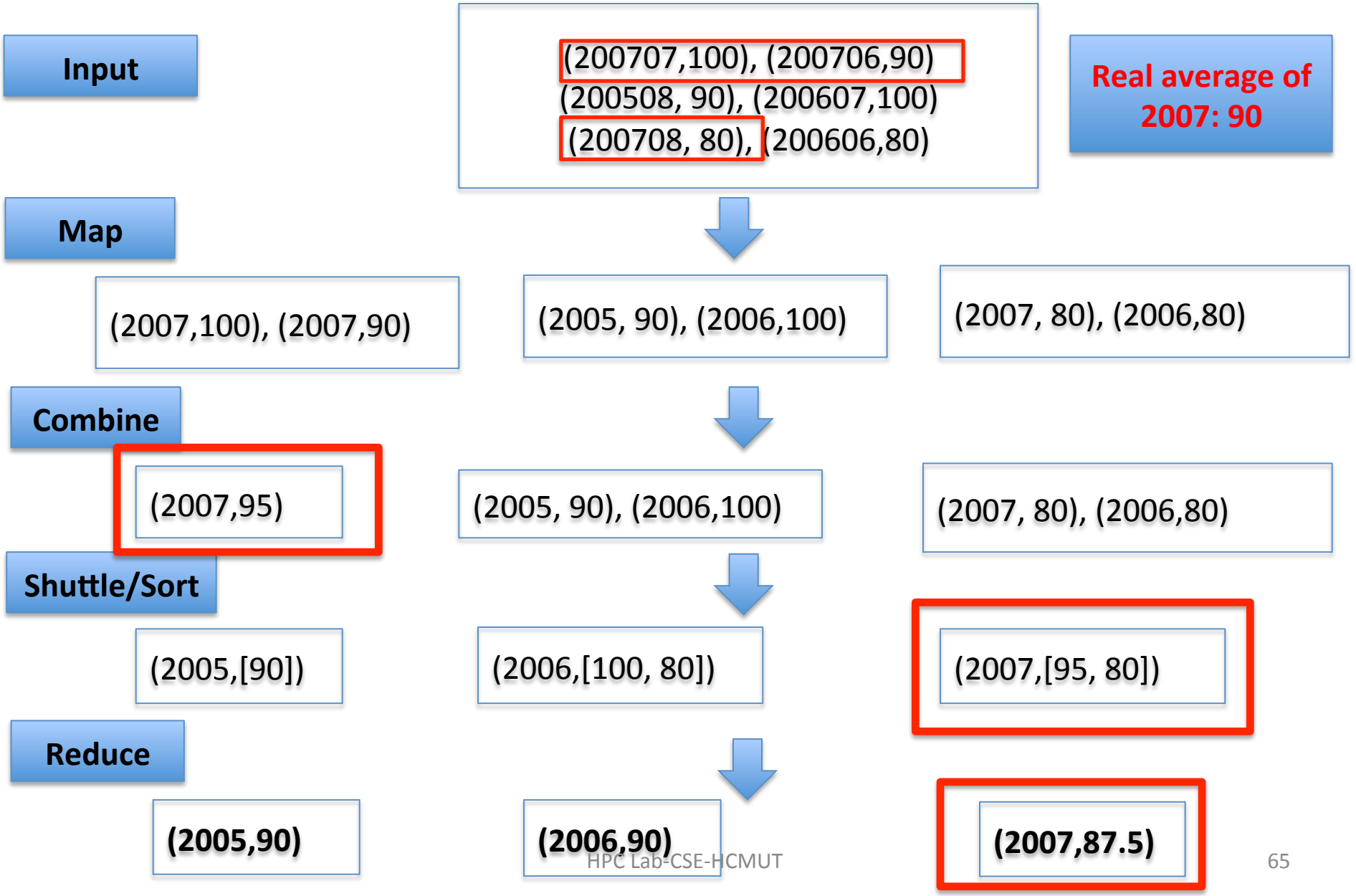
  for each v in values:

  total_temp= total_temp+v;

  Emit(key, total_temp/size_of(values));}

Combiner is the same as Reducer

MapReduce Example: Average Temperature

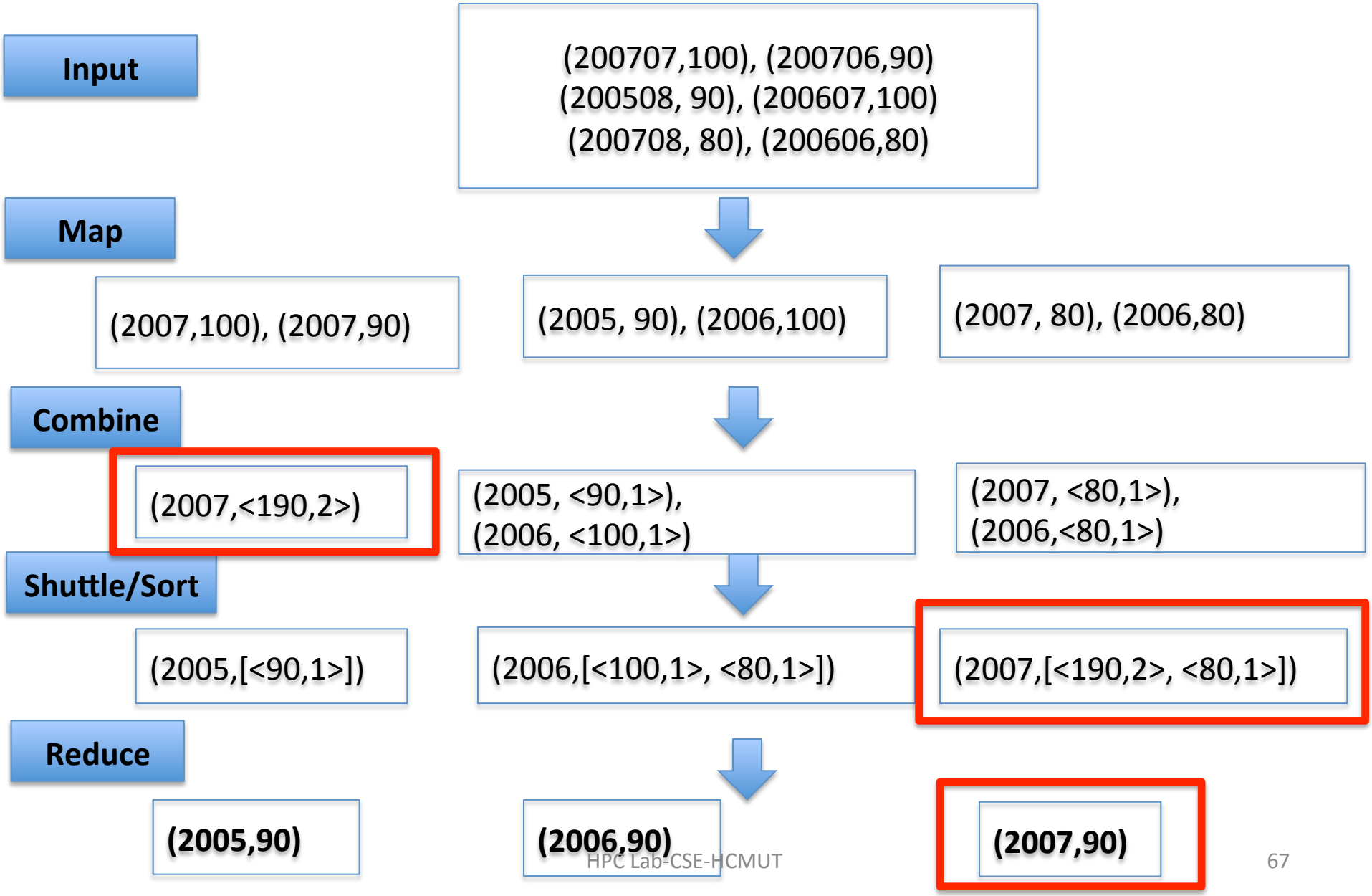


MapReduce In-class Exercise

- **The problem is with the combiner!**
- **Here is a simple counterexample:**
  - (2007, 100), (2007,90) -> (2007, 95)
    (2007,80)->(2007,80)
  - Average of the above is: (2007,87.5)
  - However, the real average is: (2007,90)

- **However, we can do a small trick to get around this**
  - Mapper: (2007, 100), (2007,90) -> (2007, <190,2>)
    (2007,80)->(2007,<80,1>)
  - Reducer: (2007,<270,3>)->(2007,90)

MapReduce Example: Average Temperature



Mapper and Reducer of Average Temperature

- Map(key, value){
  // key: line number
  // value: tuples in a line
  for each tuple t in value:
    Emit(t->year, t->temperature);}

- **Reduce (key, list of values)**{
  // key: year
  // list of values: a list of <temperature sums, counts> tuples
  int total_temp = 0;
  int total_count=0;
  for each v in values:
    total_temp= total_temp+v->sum;
    total_count=total_count+v->count;
  Emit(key,**total_temp/total_count**);}

- **Combine(key, list of values)**{
  // key: year
  // list of values: a list of monthly temperature
  int total_temp = 0;
  for each v in values:
    total_temp= total_temp+v;
  Emit(key,**<total_temp,size_of(values)>**);}

MapReduce In-class Exercise

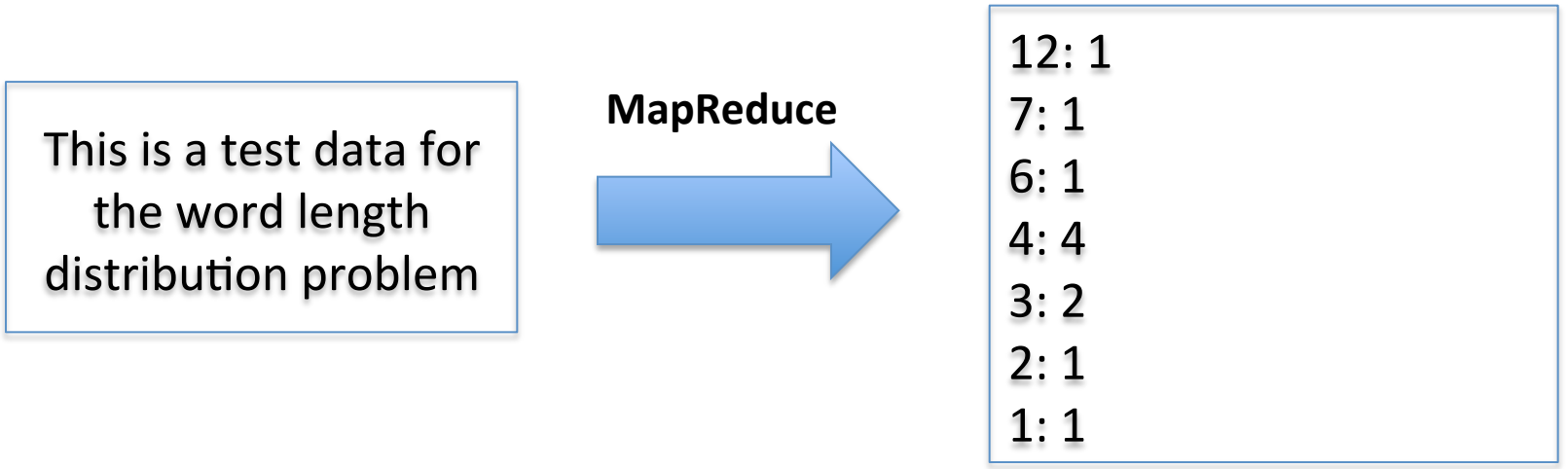
- **Functions that can use combiner are called *distributive*:**
  - Distributive: Min/Max(), Sum(), Count(), TopK()
  - Non-distributive: Mean(), Median(), Rank()

Gray, Jim*, et al. "Data cube: A relational aggregation operator generalizing group-by, cross-tab, and sub-totals." Data Mining and Knowledge Discovery 1.1 (1997): 29-53.

*Jim Gray received Turing Award in 1998

Map Reduce Problems Discussion

- **Problem 1:** Find Word Length Distribution
- **Statement:** Given a set of documents, use Map-Reduce to find the length distribution of all words contained in the documents
- **Question:**
  - What are the Mapper and Reducer Functions?



Mapper and Reducer of Word Length Distribution

- Map(key, value){

  // key: document name

  // value: words in a document

  for each word w in value:

  Emit(length(w), w);}

- Reduce(key, list of values){

  // key: length of a word

  // list of values: a list of words with the same length

  Emit(key, size_of(values));}

Map Reduce Problems Discussion

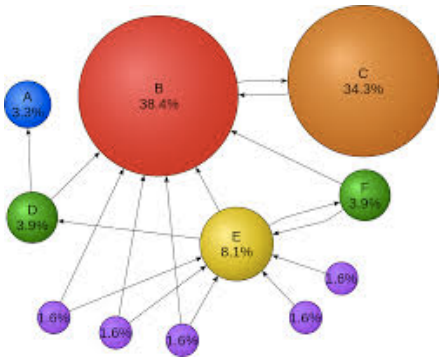
- **Problem 1:** Find Word Length Distribution
- **Mapper and Reducer:**
  - Mapper(document)

    { Emit (**Length(word), word**) }
  - Reducer(output of map)

    { Emit (Length(word), **Size of (List of words at a particular length))**}

Map Reduce Problems Discussion

- **Problem 2:** Indexing & Page Rank
- **Statement:** Given a set of web pages, each page has a **page rank** associated with it, use Map-Reduce to find, for each word, *a list of pages (sorted by rank)* that contains that word
- **Question:**
  - What are the Mapper and Reducer Functions?



MapReduce

Word 1: [page x1, page x2, ..]

Word 2: [page y1, page y2, …]

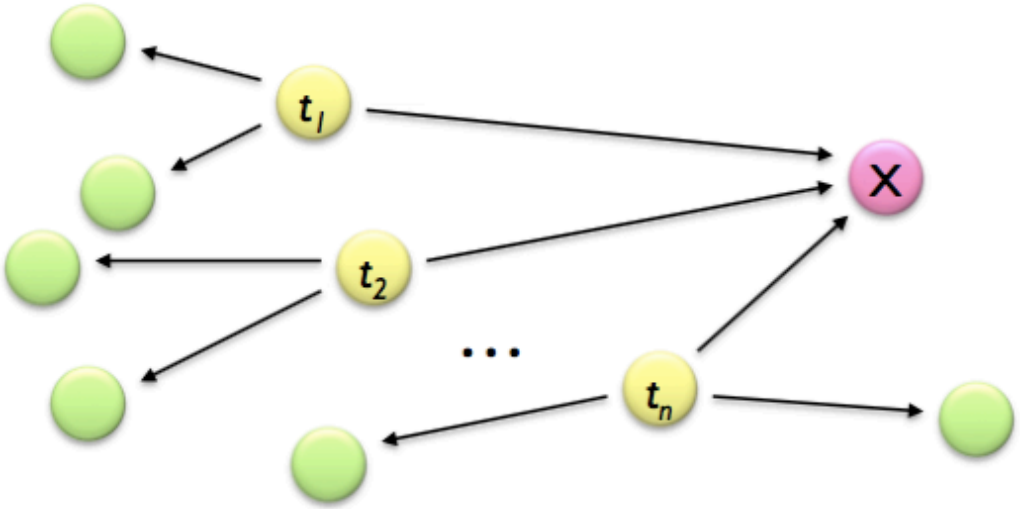
…

Page Rank

Given page *x* with inlinks $t_1 \ldots t_n$, where

- *C(t)* is the out-degree of *t*
- α is probability of random jump
- *N* is the total number of nodes in the graph

$$PR(x) = \alpha \left(\frac{1}{N}\right) + (1-\alpha) \sum_{i=1}^{n} \frac{PR(t_i)}{C(t_i)}$$



Mapper and Reducer of Indexing and PageRank

- Map(key, value){

  // key: a page

  // value: words in a page

  for each word w in value:

  Emit(w, <page_id, page_rank>);}

- Reduce(key, list of values){

  // key: a word

  // list of values: a list of pages containing that word

  sorted_pages=sort(values, page_rank)

  Emit(key, sorted_pages);}

Map Reduce Problems Discussion

- **Problem 2:** Indexing and Page Rank
- **Mapper and Reducer:**
  - Mapper(page_id, <page_text, page_rank>)

    { Emit (**word, <page_id, page_rank>**) }
  - Reducer(output of map)

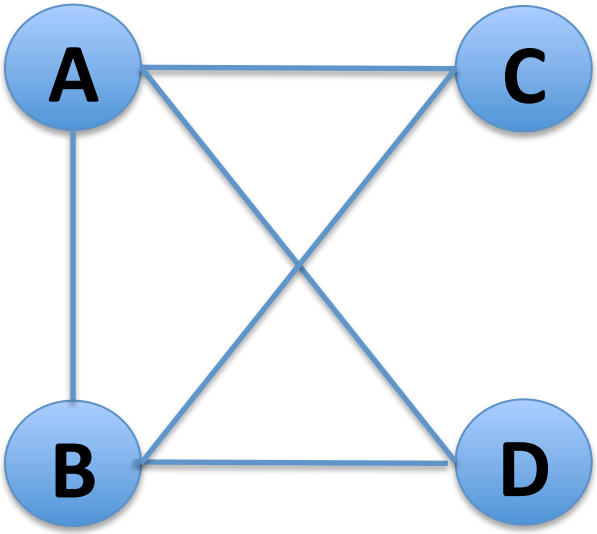
    { Emit (word, **List of pages contains the word sorted by their page_ranks)**}

Map Reduce Problems Discussion

- **Problem 3:** Find Common Friends
- **Statement:** Given a group of people on online social media (e.g., Facebook), each has a list of friends, use Map-Reduce to find *common friends* of any two persons who are friends
- **Question:**
  - What are the Mapper and Reducer Functions?

Map Reduce Problems Discussion

- **Problem 3:** Find Common Friends
- **Simple example:**



Input:

A -> B,C,D

B-> A,C,D

C-> A,B

D->A,B

MapReduce

Output:

(A ,B) -> C,D

(A,C) -> B

(A,D) -> ..

….

Mapper and Reducer of Common Friends

- Map(key, value){
  // key: person_id
  // value: the list of friends of the person
  for each friend f_id in value:
    Emit(<person_id, f_id>, value);}
- Reduce(key, list of values){
  // key: <friend pair>
  // list of values: a set of friend lists related with the friend pair
  for v1, v2 in values:
    common_friends = v1 intersects v2;
  Emit(key, common_friends);}

Map Reduce Problems Discussion

- **Problem 3:** Find Common Friends
- **Mapper and Reducer:**
  - Mapper(friend list of a person)

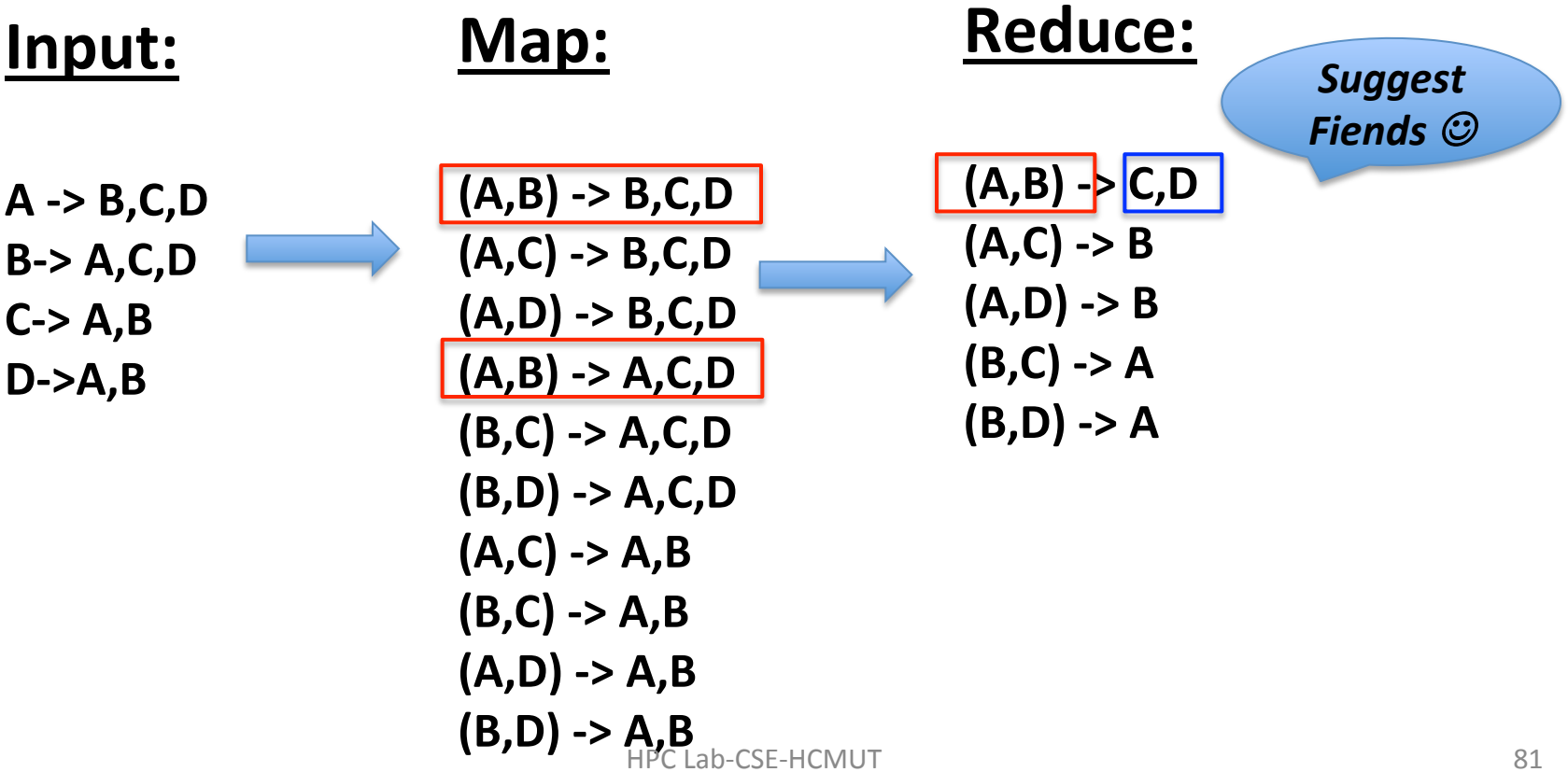
    { for each person in the friend list:

    Emit (**<friend pair>, <list of friends>**) }
  - Reducer(output of map)

    { Emit (<friend pair>, **Intersection of two (i.e, the one in friend pair) friend lists)**}

Map Reduce Problems Discussion

- **Problem 3:** Find Common Friends
- **Mapper and Reducer:**



Enjoy MR and Hadoop☺