Data-Intensive Distributed Computing

CS 451/651 (Fall 2025)

UNIVERSITY OF WATERLOO

Batch Processing I

(v1.01)

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Jimmy Lin
David R. Cheriton School of Computer Science
University of Waterloo

These slides are available at `https://lintool.github.io/cs451-2025f/`

Key Questions

What's MapReduce and how does it work with HDFS?

What challenges do communication and skew present in scaling out?

Why is local aggregation important?

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

How do you write a program that runs across 100 machines?

Implications

Must create higher levels of abstraction

Must think about fault tolerance from the beginning

The essence of abstraction is preserving information that is relevant in a given context, and forgetting information that is irrelevant in that context.

– computer scientist John V. Guttag


THIS IS THE WAY

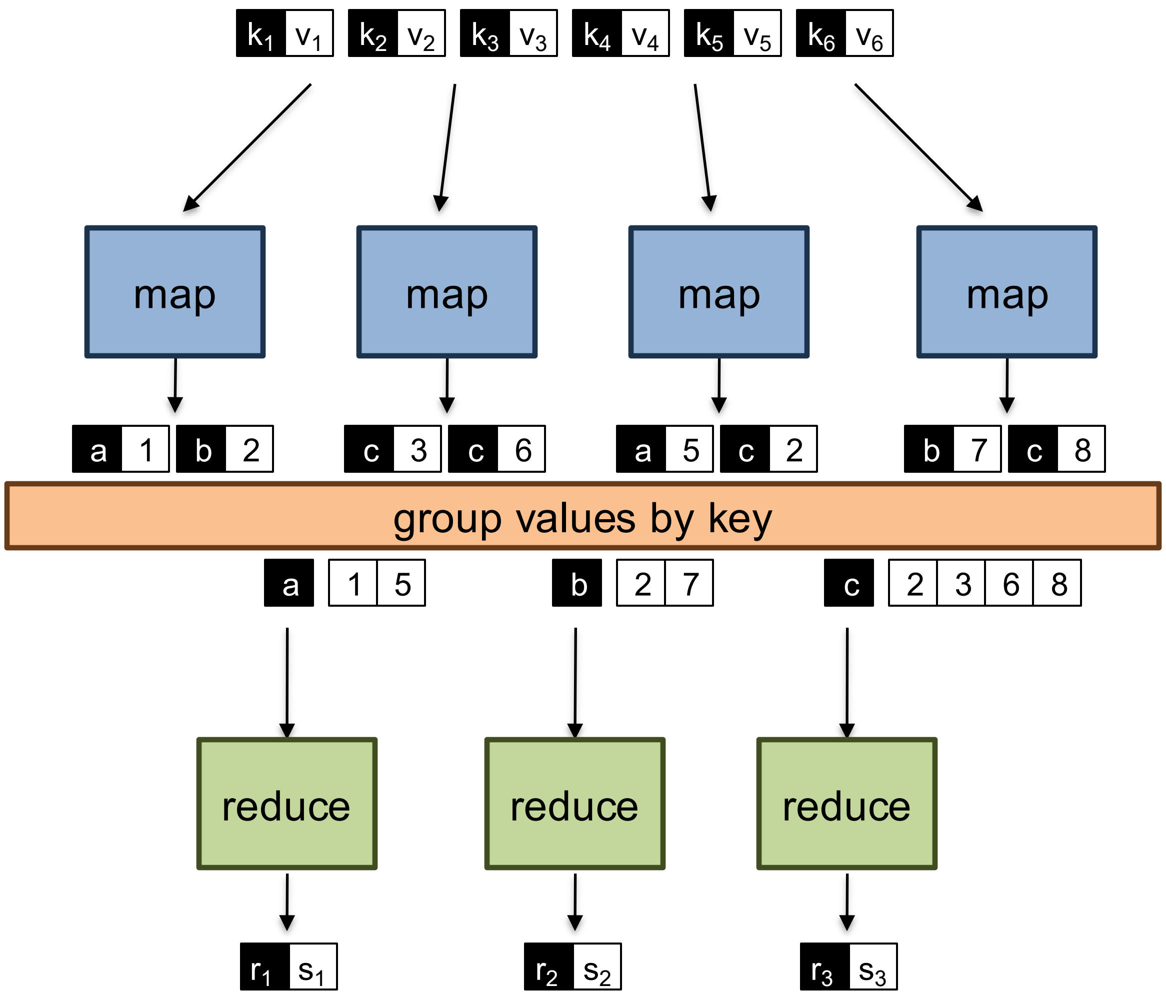
MapReduce

Programmer specifies two functions:

$$\texttt{map}\ (k_1, v_1) \rightarrow \mathrm{List}[(k_2, v_2)]$$

$$\texttt{reduce}\ (k_2, \mathrm{List}[v_2]) \rightarrow \mathrm{List}[(k_3, v_3)]$$

All values with the same key are sent to the same reducer


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
group values by key
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

The datacenter *is* the computer!

What's the instruction set?

Source: Google

“Hello World” MapReduce: Word Count

```
def map(key: Long, value: String) = {
  for (word <- tokenize(value)) {
    emit(word, 1)
  }
}

def reduce(key: String, values: Iterable[Int]) = {
  for (value <- values) {
    sum += value
  }
  emit(key, sum)
}
```

MapReduce

Programmer specifies two functions:

$$\texttt{map}\ (k_1, v_1) \rightarrow \mathrm{List}[(k_2, v_2)]$$

$$\texttt{reduce}\ (k_2, \mathrm{List}[v_2]) \rightarrow \mathrm{List}[(k_3, v_3)]$$

All values with the same key are sent to the same reducer

The “runtime” handles everything else…

MapReduce “Runtime”

Handles scheduling

Assigns workers to map and reduce tasks

Handles “data distribution”

Moves processes to data

Handles coordination

Groups and shuffles intermediate data

Handles errors and faults

Detects worker failures and restarts

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

How do you write a program that runs across 100 machines?

Implications

Must create higher levels of abstraction

Must think about fault tolerance from the beginning

tl;dr – MapReduce takes care of it!

</end> ?

More? Why do you care?

The essence of abstraction is preserving information that is relevant in a given context, and forgetting information that is irrelevant in that context.

– computer scientist John V. Guttag

1. All abstractions are *leaky*
2. Important to develop intuitions
3. What do you want to be?
4. Curiosity

You don't have to be an engineer to be be a racing driver,
but you do have to have mechanical sympathy

– Formula One driver Jackie Stewart

MapReduce

Programmer specifies two functions:

map $(k_1, v_1) \rightarrow \text{List}[(k_2, v_2)]$

reduce $(k_2, \text{List}[v_2]) \rightarrow \text{List}[(k_3, v_3)]$

All values with the same key are sent to the same reducer

That's it?

Not quite…

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Ideal scaling characteristics:

Twice the data, twice the running time

Twice the resources, half the running time

Why can't we achieve this?

1. Communication is unavoidable
2. Skew creates idle workers

Ideal Scaling: Why not?

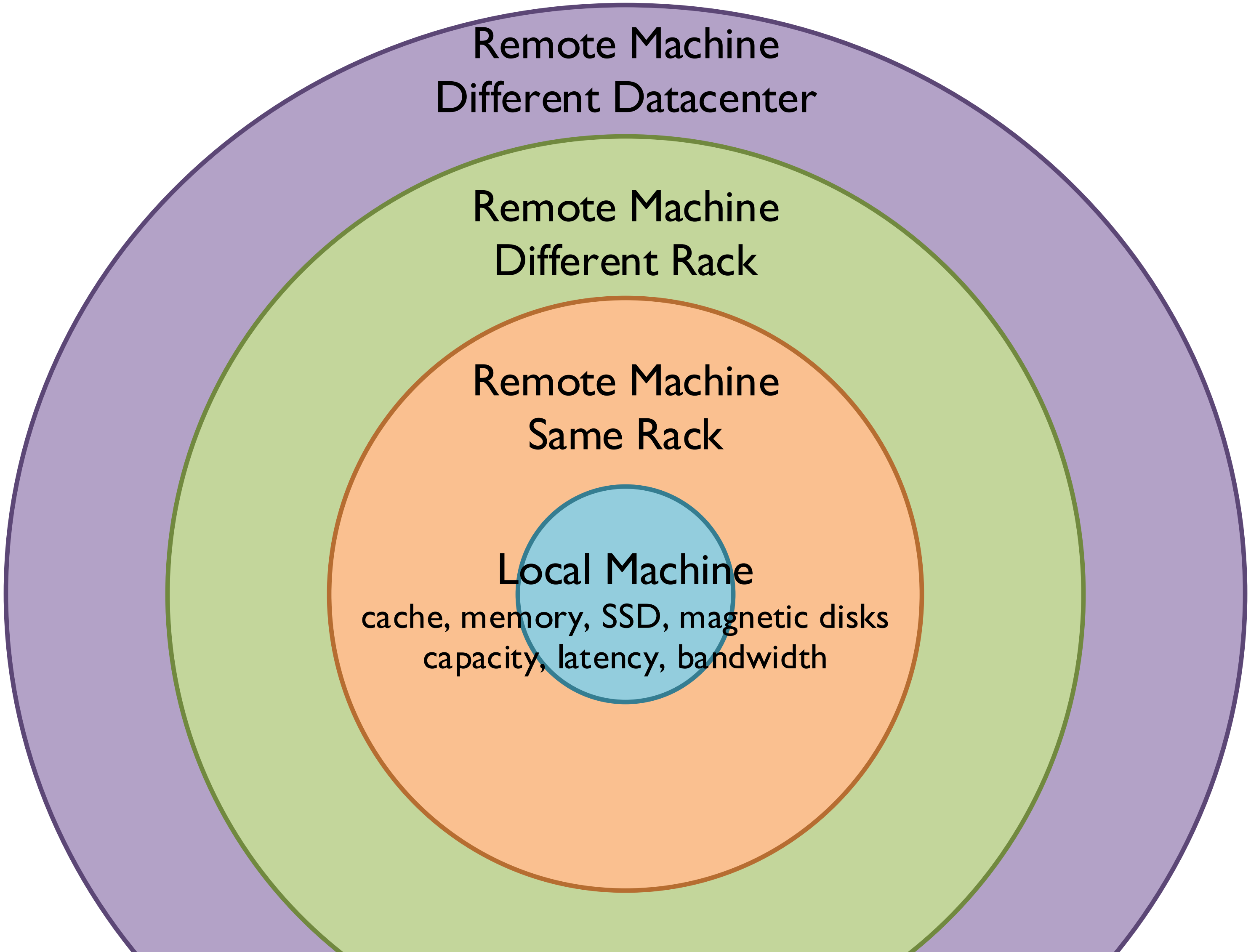
Communication is unavoidable

Workers need to share intermediate results…
Which requires communication across machines…
Which requires synchronization…
Which kills performance.

Skew creates idle workers

Tasks are never divided perfectly evenly…
And even if they are, processing times can be unpredictable…
Which leads to idle workers.

Storage Hierarchy



tl;dr – communication is costly

So let's reduce the amount of data shuffling!
How? Aggregate intermediate results locally!

MapReduce

four

Programmer specifies ~~two~~ functions:

$\texttt{map}\ (k_1,\ v_1) \rightarrow \texttt{List}[(k_2,\ v_2)]$

$\texttt{reduce}\ (k_2,\ \texttt{List}[v_2]) \rightarrow \texttt{List}[(k_3,\ v_3)]$

All values with the same key are sent to the same reducer

$\texttt{partition}\ (k',\ p) \rightarrow 0\ \ldots\ p\text{-}1$

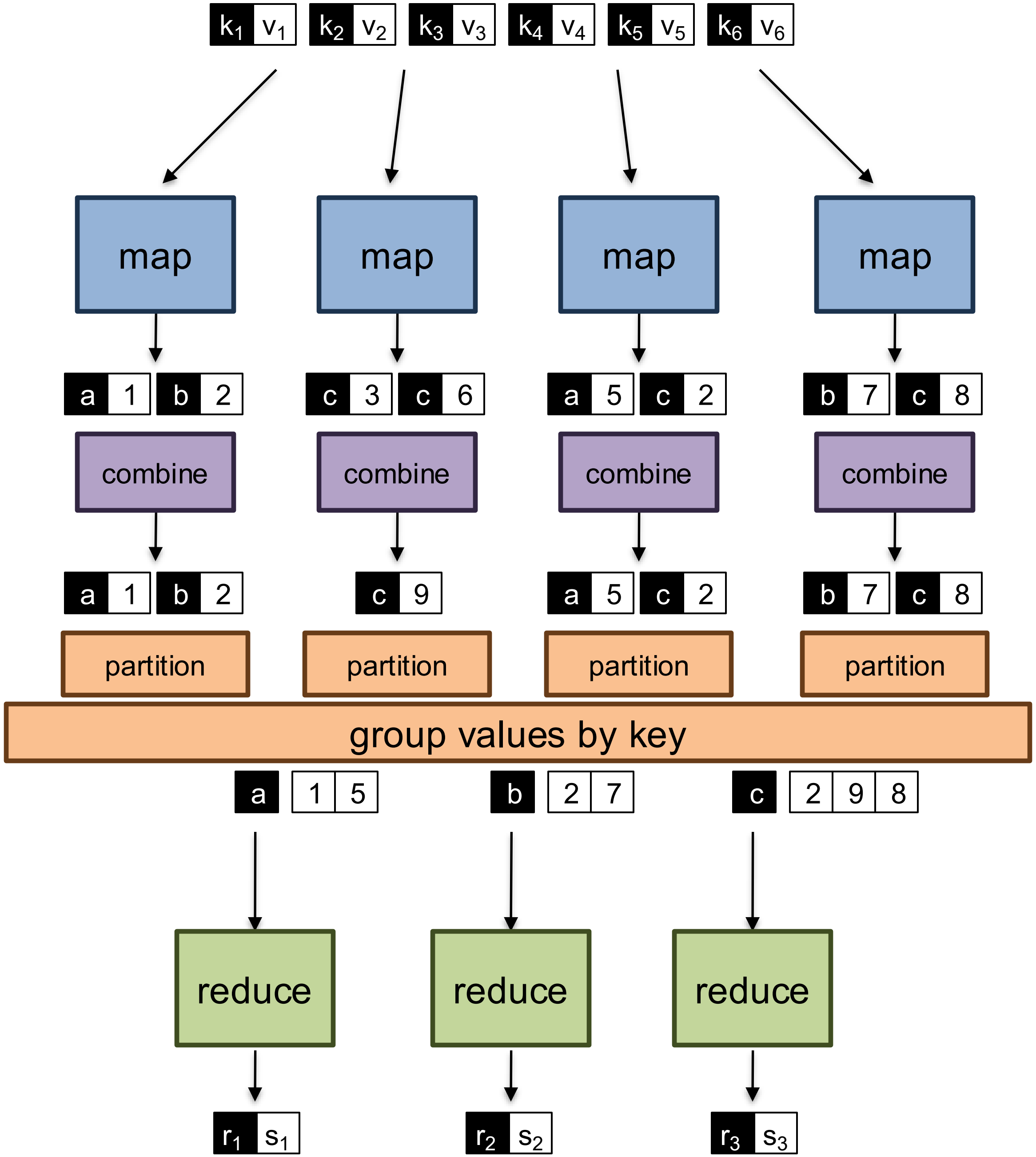
Often a simple hash of the key, e.g., `hash(k') mod n`

Divides up key space for parallel reduce operations

$\texttt{combine}\ (k_2,\ \texttt{List}[v_2]) \rightarrow \texttt{List}[(k_2,\ v_2)]$

Mini-reducers that run in memory after the map phase

Used as an optimization to reduce the amount of data shuffling



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
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
group values by key
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
r_1 s_1
r_2 s_2
r_3 s_3

Word Count: Baseline

```
class Mapper {
  def map(key: Long, value: String) = {
    for (word <- tokenize(value)) {
      emit(word, 1)
    }
  }
}

class Reducer {
  def reduce(key: String, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
    }
    emit(key, sum)
  }
}
```

What's the impact of combiners?

Word Count: Mapper Histogram

```
class Mapper {
  def map(key: Long, value: String) = {
    val counts = new Map()
    for (word <- tokenize(value)) {
      counts(word) += 1
    }

    for ((k, v) <- counts) {
      emit(k, v)
    }
  }
}
```

Are combiners still needed?

Ideal Scaling: Why not?

Communication is unavoidable

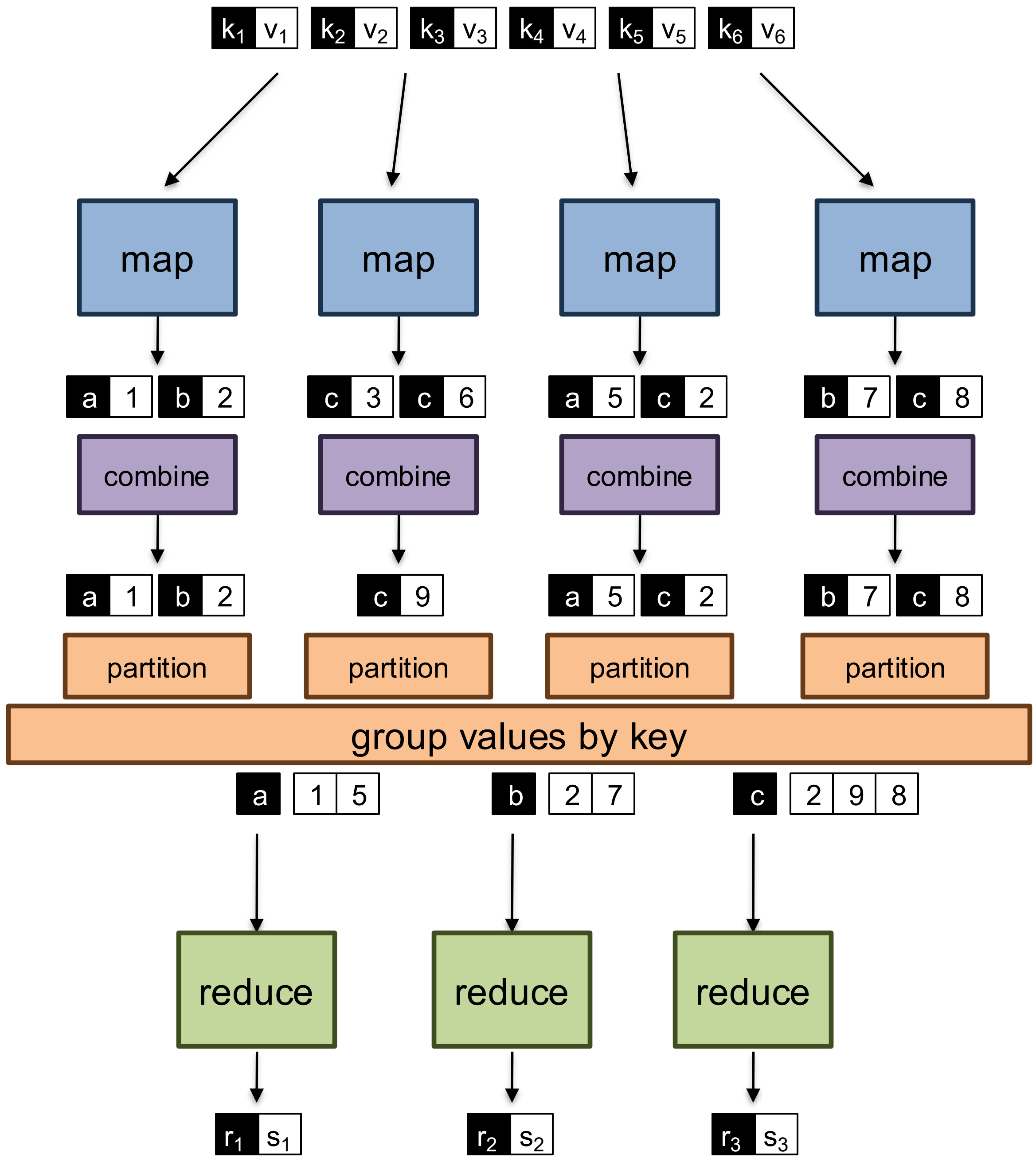
Workers need to share intermediate results…
Which requires communication across machines…
Which requires synchronization…
Which kills performance.

Combiners help here!

Skew creates idle workers

Tasks are never divided perfectly evenly…
And even if they are, processing times can be unpredictable…
Which leads to idle workers.

What about partitioners?



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
group values by key
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

MapReduce

That's it!

Programmer specifies ~~two~~ four functions:

map $(k_1, v_1) \rightarrow$ List[(k_2, v_2)]

reduce $(k_2,$ List[v_2]$) \rightarrow$ List[(k_3, v_3)]

All values with the same key are sent to the same reducer

partition (k', p) → 0 ... p-1

Often a simple hash of the key, e.g., `hash(k') mod n`

Divides up key space for parallel reduce operations

combine $(k_2,$ List[v_2]$) \rightarrow$ List[(k_2, v_2)]

Mini-reducers that run in memory after the map phase

Used as an optimization to reduce the amount of data shuffling

Which means…

You have limited control over data and execution flow!

All algorithms must be 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

…

Abstractions

Pros

You don’t have to worry about it.

You don’t need to know what’s going on.

Cons

You can’t worry about it (even if you wanted to).

You don’t know what’s going on (even if you wanted to).

Recap, why combiners?

Combiner Design

Combiners and reducers share same method signature

Sometimes, reducers can serve as combiners

Often, not…

Combiner are optional optimizations

Should not affect algorithm correctness

May be run 0, 1, or multiple times

Reducers are guaranteed to run *exactly* once

Can reducers be used as combiners?

Example: find average of integers associated with the same key

Computing the Mean: Version 1

```
class Mapper {
  def map(key: String, value: Int) = {
    emit(key, value)
  }
}

class Reducer {
  def reduce(key: String, values: Iterable[Int]) {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    emit(key, sum/cnt)
  }
}
```

Why can’t we use reducer as combiner?

Computing the Mean: Version 2

```
class Mapper {
  def map(key: String, value: Int) =
    context.write(key, value)
}
class Combiner {
  def reduce(key: String, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    emit(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, sum/cnt)
  }
}
```

Why doesn't this work?

Computing the Mean: Version 3

```
class Mapper {
  def map(key: String, value: Int) =
    context.write(key, (value, 1))
}
class Combiner {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: String, values: Iterable[Pair]) = {
    for ((s, c) <- values) {
      sum += s
      cnt += c
    }
    emit(key, sum/cnt)
  }
}
```

Fixed? Yes!

Another Example

Term co-occurrence matrix for a text collection

$M = N \times N$ matrix (N = vocabulary size)

M_{ij}: number of times i and j co-occur in some context

(for concreteness, let's say context = sentence)

Why?

Large Counting Problems

Term co-occurrence matrix for a text collection
= specific instance of a large counting problem

A large event space (number of terms)
A large number of observations (the collection itself)
Goal: keep track of interesting statistics about the events

Basic approach

Mappers generate partial counts
Reducers aggregate partial counts

How do we aggregate partial counts efficiently?

First Try: "Pairs"

Each mapper takes a sentence:

Generate all co-occurring term pairs

For all pairs, emit (a, b) → count

Reducers sum up counts associated with these pairs

Use combiners!

Pairs: Pseudo-Code

```
class Mapper {
  def map(key: Long, value: String) = {
    for (u <- tokenize(value)) {
      for (v <- neighbors(u)) {
        emit((u, v), 1)
      }
    }
  }
}

class Reducer {
  def reduce(key: Pair, values: Iterable[Int]) = {
    for (value <- values) {
      sum += value
    }
    emit(key, sum)
  }
}
```

Pairs: Pseudo-Code

One more thing…

```
class Partitioner {
  def getPartition(key: Pair, value: Int, numTasks: Int): Int = {
    return key.left % numTasks
  }
}
```

“Pairs” Analysis

Advantages

Easy to implement, easy to understand

Disadvantages

Lots of pairs to sort and shuffle around (upper bound?)

Fewer opportunities for combiners to work

Another Try: "Stripes"

Idea: group together pairs into an associative array

(a, b) → 1
(a, c) → 2
(a, d) → 5
(a, e) → 3
(a, f) → 2

a → { b: 1, c: 2, d: 5, e: 3, f: 2 }

Each mapper takes a sentence:

Generate all co-occurring term pairs

For each term, emit a → { b: count_b, c: count_c, d: count_d … }

Reducers perform element-wise sum of associative arrays

$$
\begin{array}{rl}
 & a \rightarrow \{\, b{:}\ 1, \qquad\quad d{:}\ 5,\ e{:}\ 3 \,\} \\
+ & a \rightarrow \{\, b{:}\ 1,\ c{:}\ 2,\ d{:}\ 2, \qquad\quad f{:}\ 2 \,\} \\
\hline
 & a \rightarrow \{\, b{:}\ 2,\ c{:}\ 2,\ d{:}\ 7,\ e{:}\ 3,\ f{:}\ 2 \,\}
\end{array}
$$

Key idea: data structure to bring together intermediate results

Stripes: Pseudo-Code

```
class Mapper {
  def map(key: Long, value: String) = {
    for (u <- tokenize(value)) {
      val map = new Map()
      for (v <- neighbors(u)) {
        map(v) += 1
      }
      emit(u, map)
    }
  }
}
```

a → { b: 1, c: 2, d: 5, e: 3, f: 2 }

```
class Reducer {
  def reduce(key: String, values: Iterable[Map]) = {
    val map = new Map()
    for (value <- values) {
      map += value
    }
    emit(key, map)
  }
}
```

	a →	{ b: 1,		d: 5,	e: 3 }	
+	a →	{ b: 1,	c: 2,	d: 2,		f: 2 }
	a →	{ b: 2,	c: 2,	d: 7,	e: 3,	f: 2 }

“Stripes” Analysis

Advantages

Far less sorting and shuffling of key-value pairs
Can make better use of combiners

Disadvantages

More difficult to implement
Underlying object more heavyweight
Overhead associated with data structure manipulations
Fundamental limitation in terms of size of event space

Stripes >> Pairs?

Tradeoffs

Developer code vs. framework

CPU vs. RAM vs. disk vs. network

Number of key-value pairs: sorting and shuffling data across the network

Size and complexity of each key-value pair: de/serialization overhead

Cost of manipulating data structures

Opportunities for local aggregation

Tradeoffs

Pairs:

Generates a *lot* more key-value pairs
Fewere combining opportunities
More sorting and shuffling
Simple aggregation at reduce

Stripes:

Generates fewer key-value pairs (but more complex values)
More opportunities for combining
Less sorting and shuffling
More complex (slower) aggregation at reduce

(At scale, stripes are faster)

Hrm. Can we generalize?

(Yes, but next time…)

Deep(-er) Dive: How does this all work?

Where do we place the data?
Where do we place the compute?

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

Where do we place the data?

Trick #1: Partition

Trick #2: Replicate

Answer:
GFS! (circa 2003)

Remember: There are no solutions, only tradeoffs!

GFS: Assumptions

Commodity hardware over "exotic" hardware

Scale "out", not "up"

High component failure rates

Inexpensive commodity components fail all the time

"Modest" number of huge files

Multi-gigabyte files are common, if not encouraged

Files are write-once, mostly appended to

Logs are a common case

Large streaming reads over random access

Design for high sustained throughput over low latency

GFS: Design Decisions

Files stored as chunks

Fixed size (64MB)

Reliability through replication

Each chunk replicated across 3+ chunkservers

Single master to coordinate access and hold metadata

Simple centralized management

No data caching

Little benefit for streaming reads over large datasets

Simplify the API: not POSIX!

Push many issues onto the client (e.g., data layout)

HDFS = GFS clone (same basic ideas)

From GFS to HDFS

Terminology differences:

GFS master = Hadoop namenode

GFS chunkservers = Hadoop datanodes

Implementation differences:

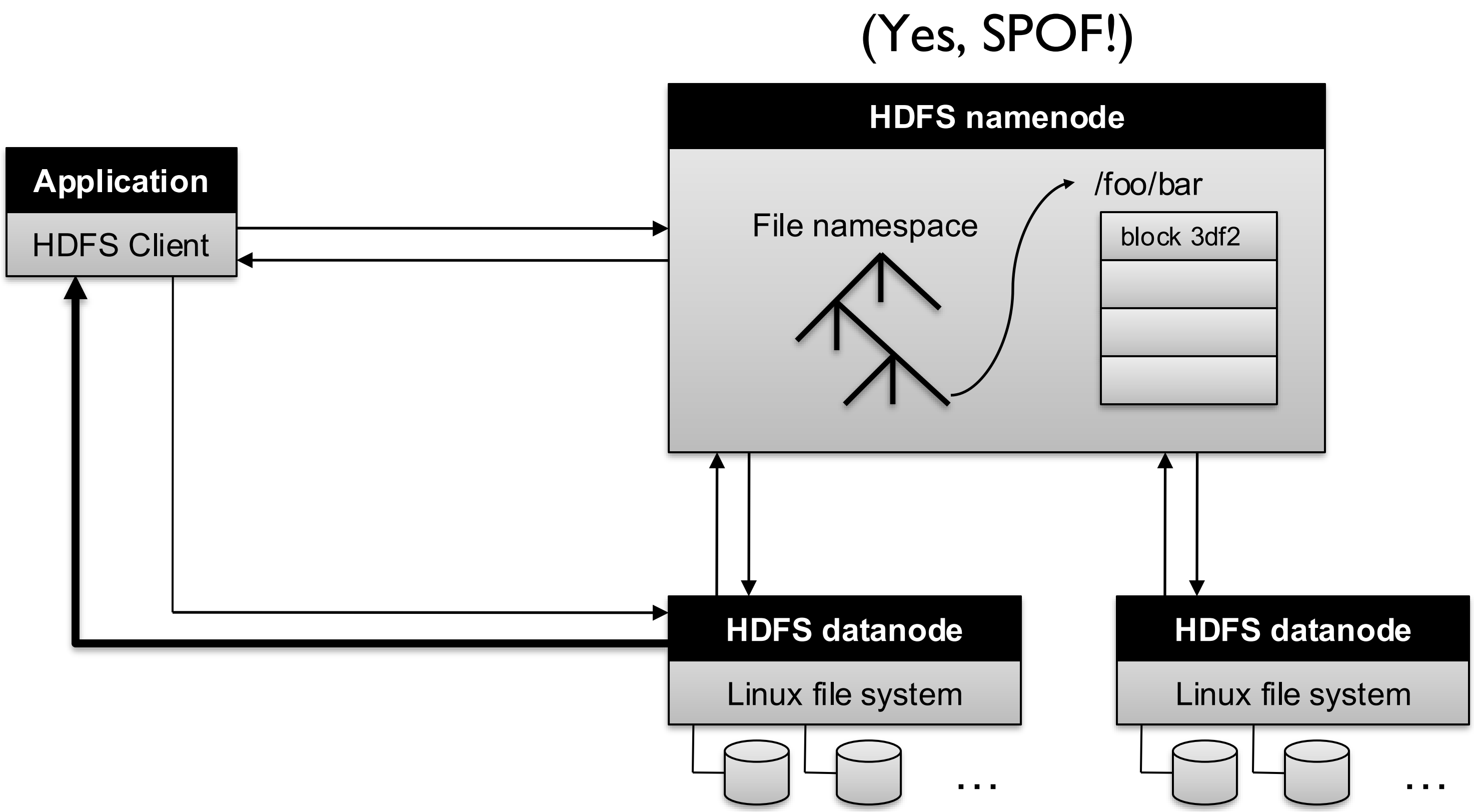
Different consistency model for file appends

Implementation language

Performance

For the most part, we'll use Hadoop terminology…

HDFS Architecture



Adapted from (Ghemawat et al., SOSP 2003)

Namenode Responsibilities

Managing the file system namespace

Holds file/directory structure, file-to-block mapping, metadata (ownership, access permissions, etc.)

Coordinating file operations

Directs clients to datanodes for reads and writes

No data is moved through the namenode

Maintaining overall health

Periodic communication with the datanodes

Block re-replication and rebalancing

Garbage collection

Deep(-er) Dive: How does this all work?

Where do we place the data?
Where do we place the compute?

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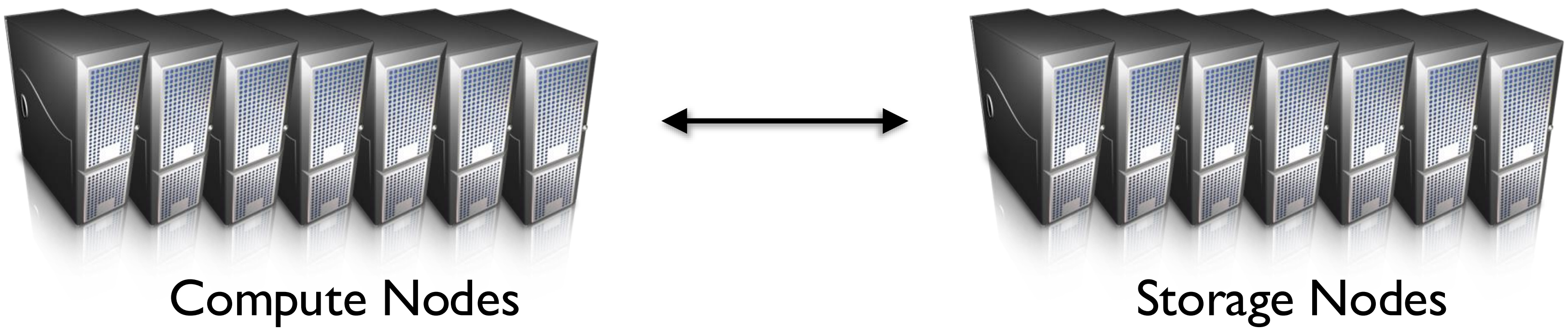
Where do we place the compute?

Trick #1: Partition

Trick #2: Replicate

Remember: There are no solutions, only tradeoffs!

Compute meets Data!



Move data to compute?
Move compute to data?

Basic Cluster Components

Namenode (NN)

Holds HDFS metadata

Jobtracker (JT)

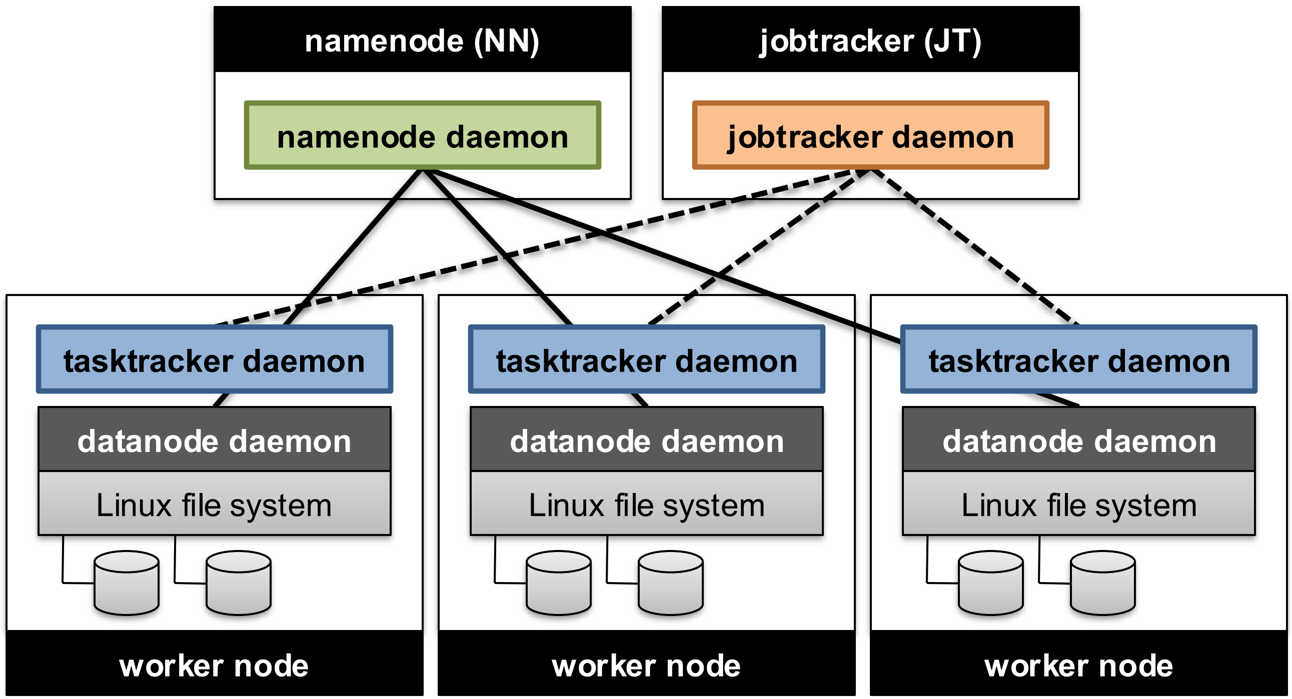
Coordinator for MapReduce jobs

On *each* of the worker machines:

Tasktracker (TT): contains multiple task slots

Datanode (DN): serves HDFS data blocks

Putting everything together…



Key idea: align map tasks with HDFS blocks


EXPRESSWAY
TOYOTA
COROLLA LE
ONTARIO
HADOOP
YOURS TO DISCOVER