STAT679
Computing for Data Science and Statistics

Lecture 15: MapReduce

Some slides adapted from C. Budak (UMichigan) and R. Burns (JHU)

Parallel processing and “big data”

The next few lectures will focus on “big data” and the MapReduce framework

This lecture: overview of the MapReduce framework

Next lectures:

Python package `mrjob`, which implements MapReduce

Apache Spark and the Hadoop file system

PySpark (if time permits)

The big data “revolution”

Sloan Digital Sky Survey https://www.sdss.org/

Generating so many images that most will never be looked at...

Genomics data: https://en.wikipedia.org/wiki/Genome_project

Web crawls

>20e9 webpages; ~400TB just to store pages (*without* images, etc)

Social media data

Twitter: ~500e6 tweets per day

YouTube: >300 hours of content uploaded per minute

(and that number is several years old, now)

Three aspects to big data

Volume: data at the TB or PB scale

Requires new processing paradigms

e.g., Distributed computing, streaming model

Velocity: data is generated at unprecedented rate

e.g., web traffic data, twitter, climate/weather data

Variety: data comes in many different formats

Databases, but also unstructured text, audio, video…

Messy data requires different tools

This requires a very different approach to computing from what we were accustomed to prior to about 2005.

How to count all the books in the library?

Peabody Library, Baltimore, MD USA

How to count all the books in the library?

I'll count this side...

Peabody Library, Baltimore, MD USA

...you count this side...

...and then we add our counts together.

Congratulations!

You now understand the MapReduce framework!

Basic idea:

Split up a task into independent subtasks

Specify how to combine results of subtasks to get your answer

Independent subtasks is a crucial point, here:

If we constantly have to share information, then it’s inefficient to split the task

Because we’ll spend more time communicating than actually counting

Assumptions of MapReduce

- Task can be split into pieces
- Pieces can be processed **in parallel**...
- ...with **minimal communication** between processes.
- Results of each piece can be combined to obtain answer.

Problems that have these properties are often described as being **embarrassingly parallel:** https://en.wikipedia.org/wiki/Embarrassingly_parallel

MapReduce: the workhorse of “big data”

Hadoop, Google MapReduce, Spark, etc are all based on this framework

1) Specify a “map” operation to be applied to every element in a data set
2) Specify a “reduce” operation for combining the list into an output

Then we split the data among a bunch of machines, and combine their results

MapReduce isn’t really new to you

You already know the **Map** pattern:

Python: `[f(x) for x in mylist]`

...and the **Reduce** pattern:

Python: `sum( [f(x) for x in mylist] )` (map and reduce)

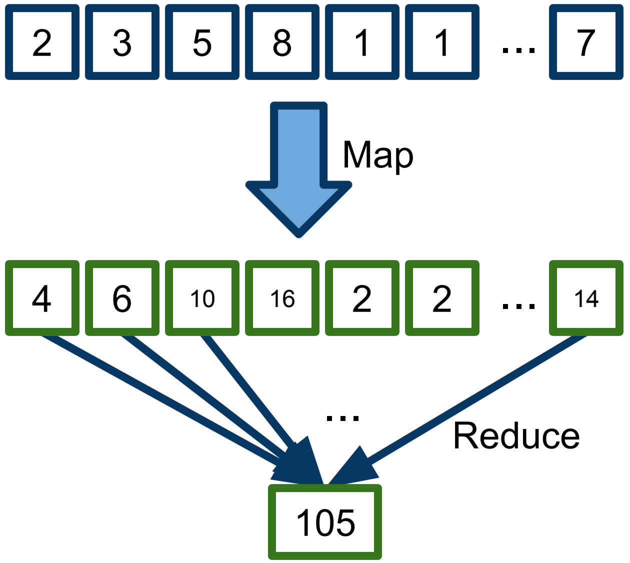
SQL: aggregation functions are like “reduce” operations

The only thing that’s new is the computing model

MapReduce, schematically, cartoonishly

Map: f(x) = 2x

Reduce: sum

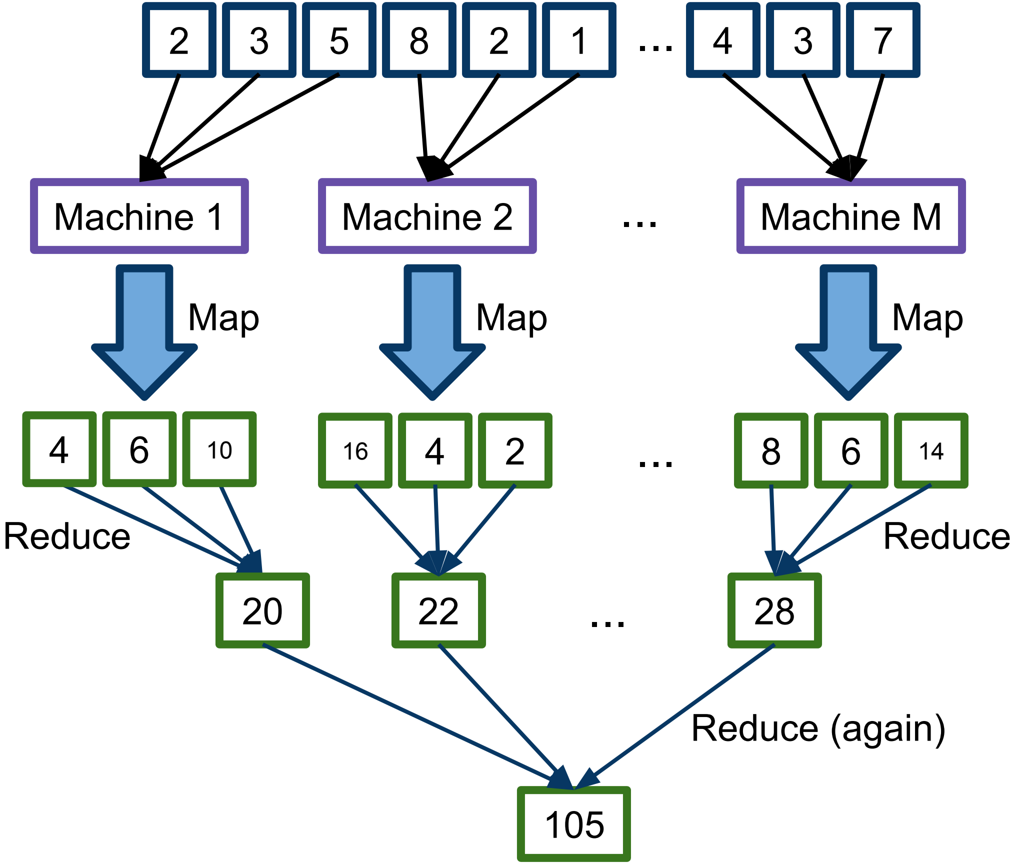


...but this hides the distributed computation.

MapReduce, schematically (slightly more accurately)

Map: f(x) = 2x

Reduce: sum



Fundamental unit of MapReduce: (key,value) pairs

Examples:

- Linguistic data: <word, count>
- Enrollment data: <student, major>
- Climate data: <location, wind speed>

Values can be more complicated objects in some environments

- e.g., lists, dictionaries, other data structures
  - Social media data: <person, list_of_friends>
- Apache Hadoop doesn’t support this directly
  - but can be made to work via some hacking
- mrjob and Spark are a little more flexible

Less boring example: word counts

Suppose we have a giant collection of books...

e.g., Google ngrams: https://books.google.com/ngrams/info

...and we want to count how many times each word appears in the collection.

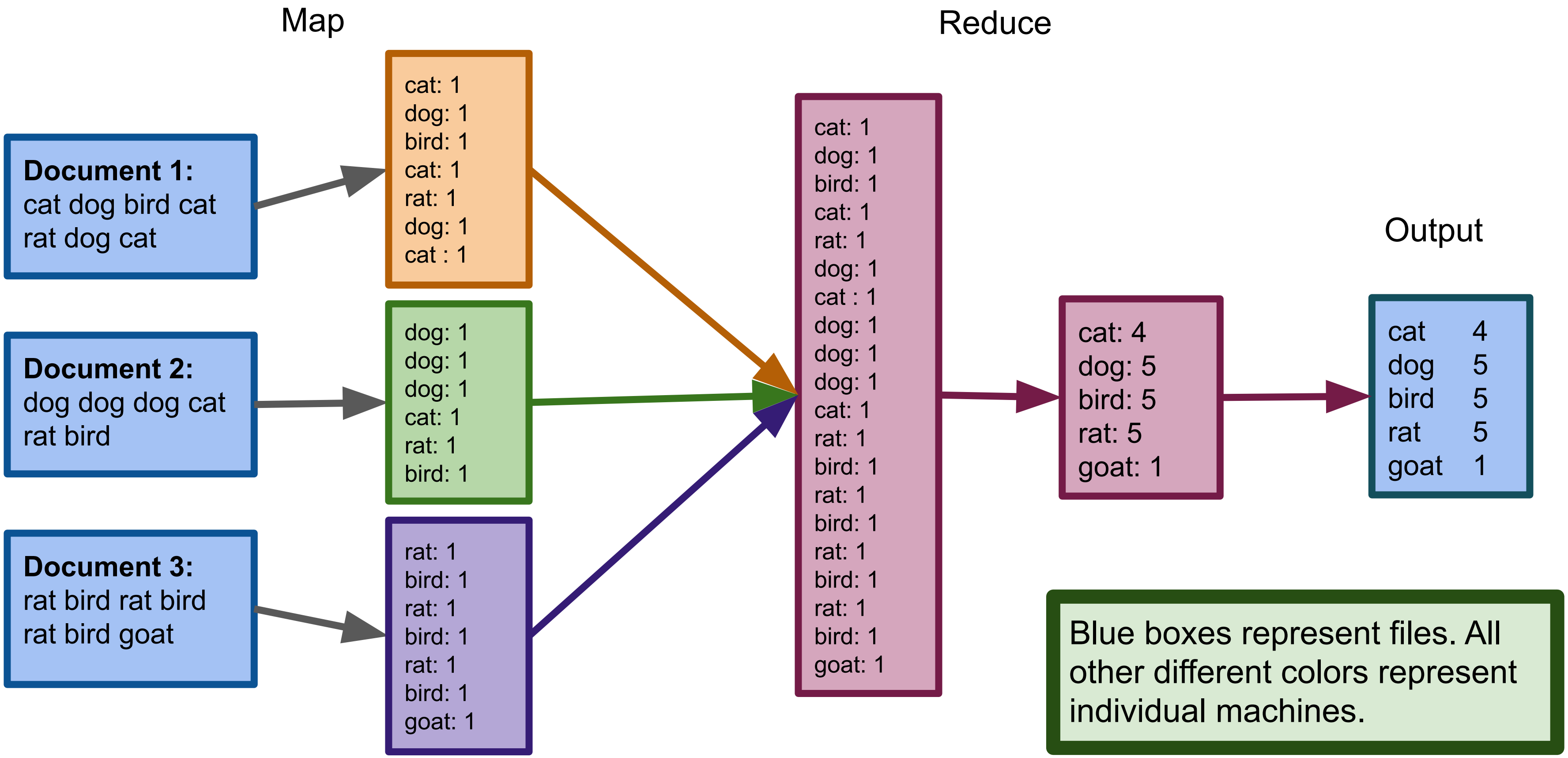
Divide and Conquer!

1. Everyone takes a book, and makes a list of (word,count) pairs.
2. Combine the lists, adding the counts with the same **word** keys.

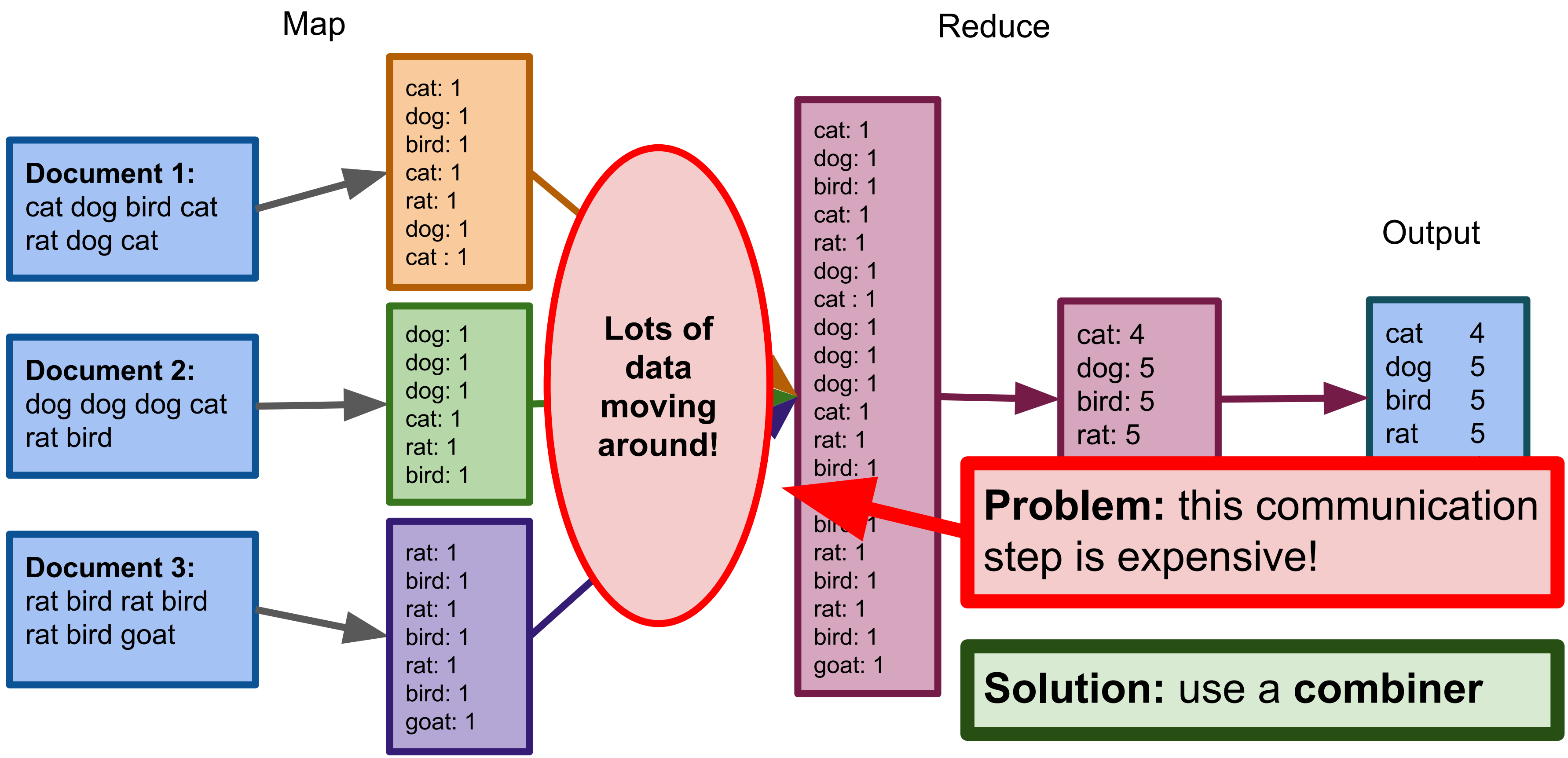
This still fits our framework, but it's a little more complicated…

...and it's just the kind of problem that MapReduce is designed to solve.

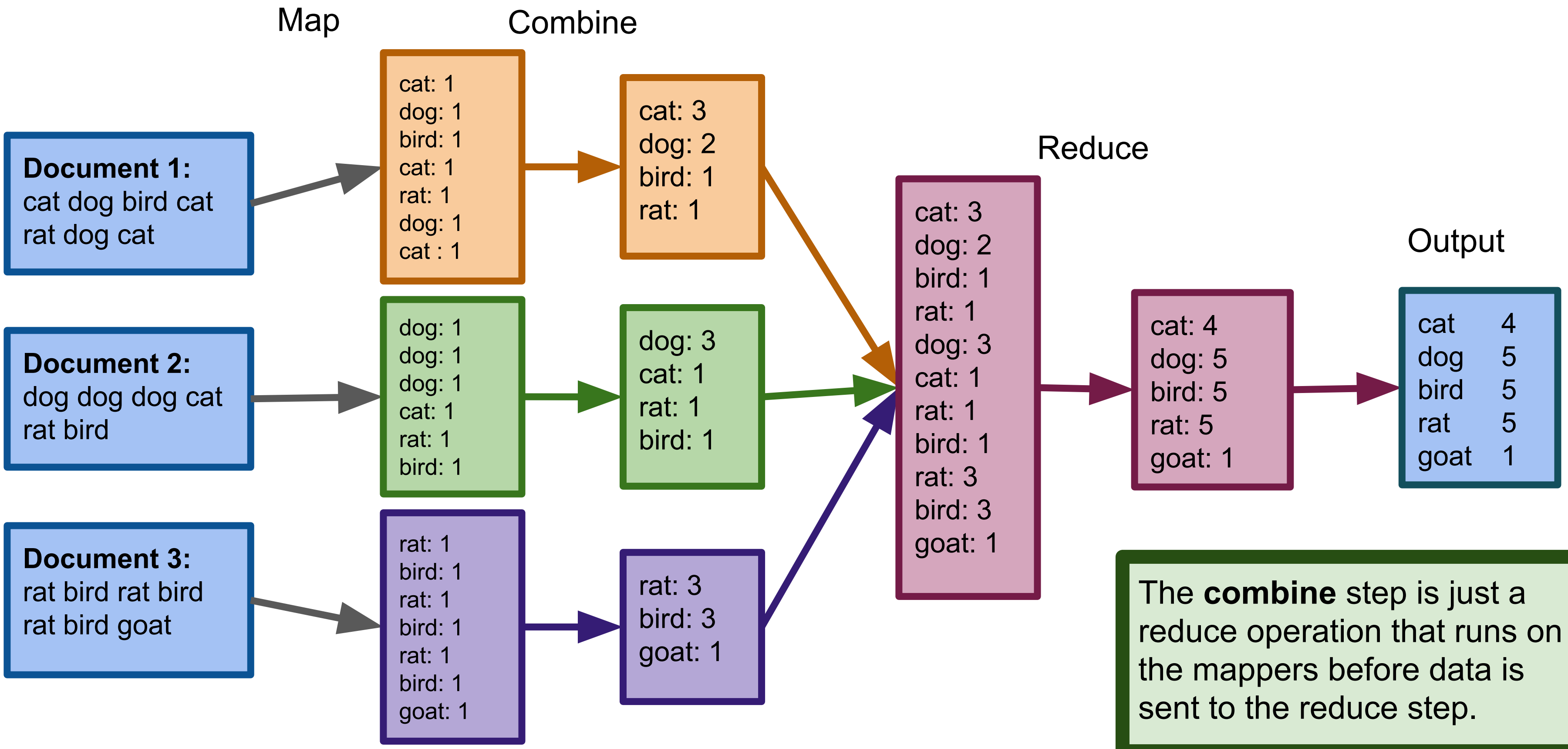
Counting words in MapReduce: version 1



Counting words in MapReduce: version 1

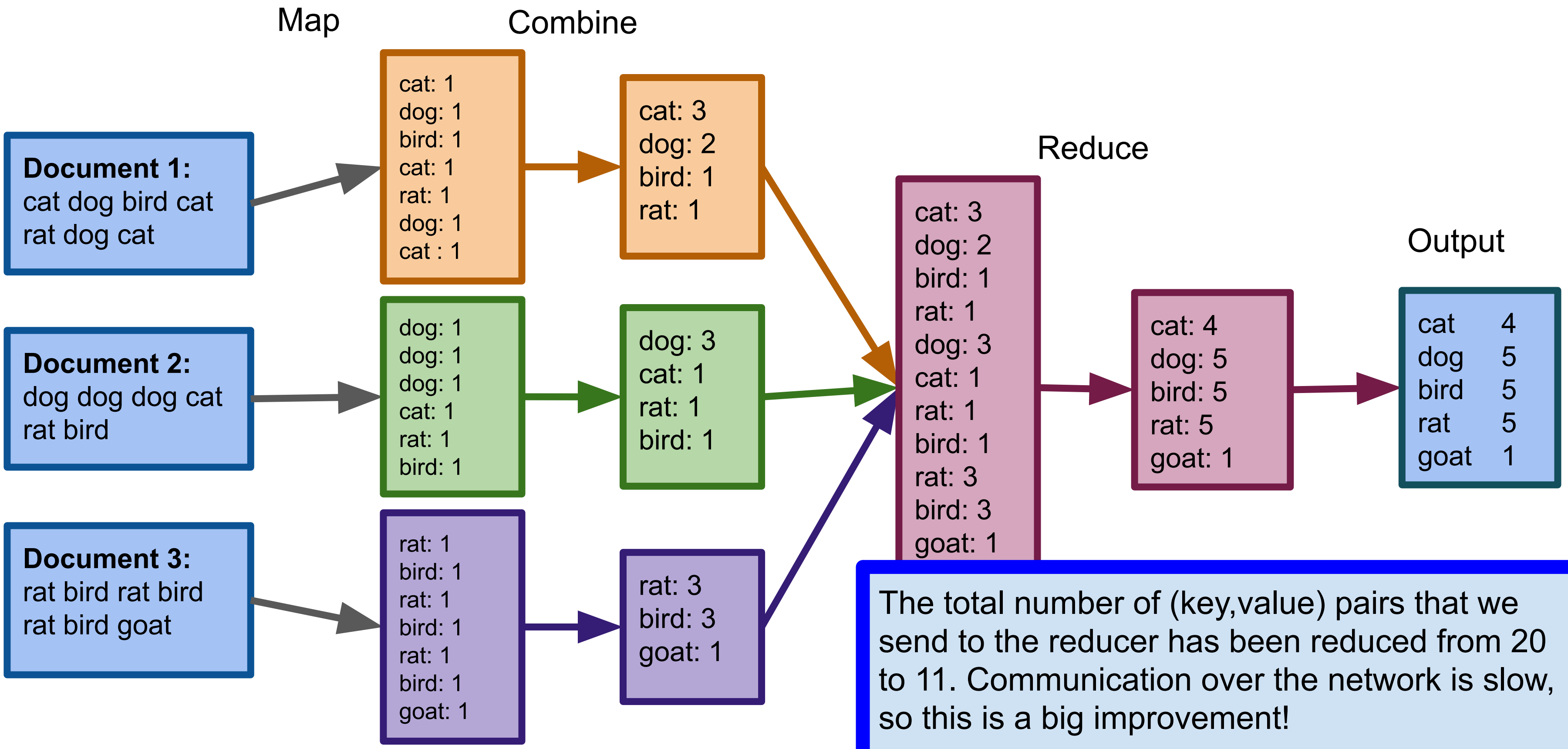


Counting words in MapReduce: version 2



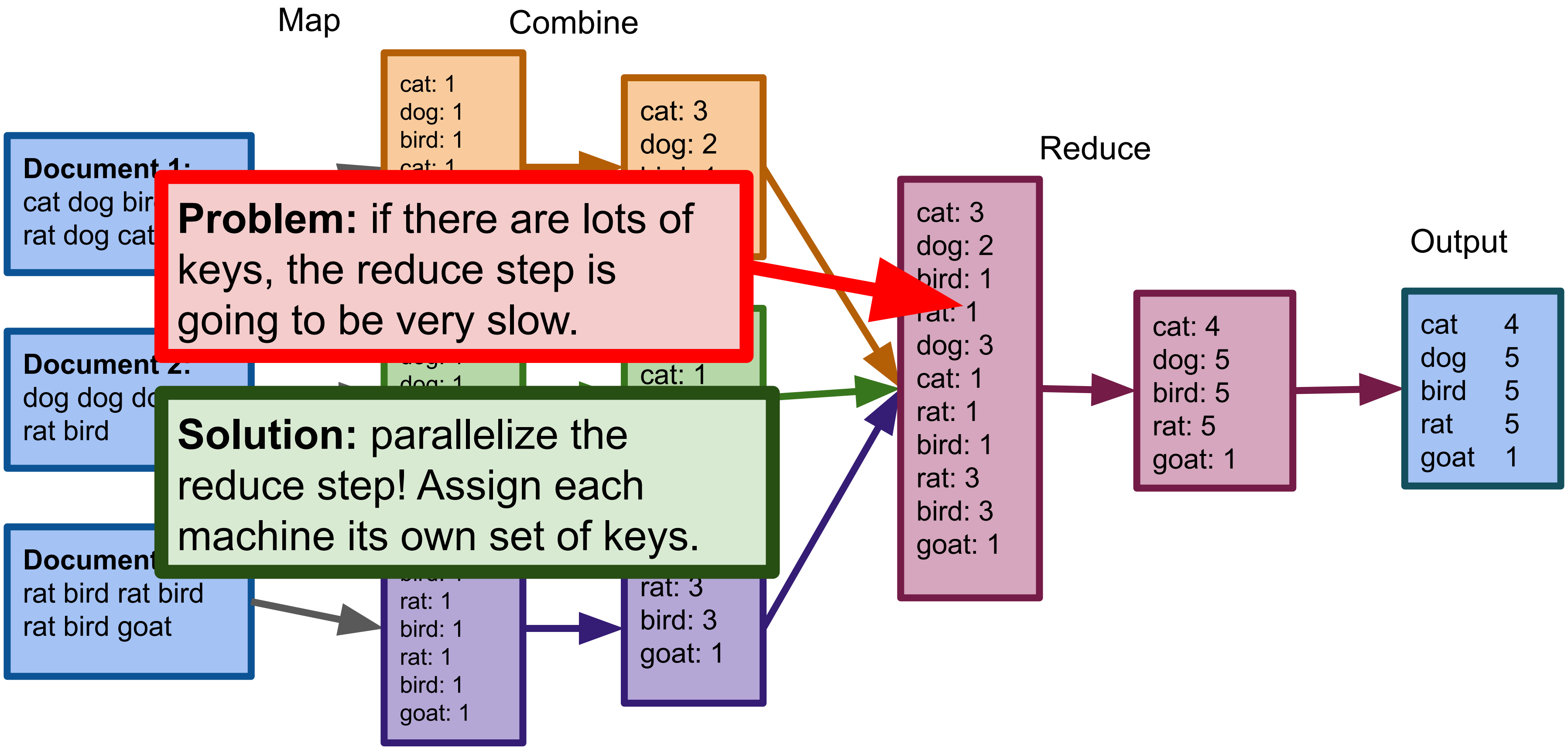
The **combine** step is just a reduce operation that runs on the mappers before data is sent to the reduce step.

Counting words in MapReduce: version 2

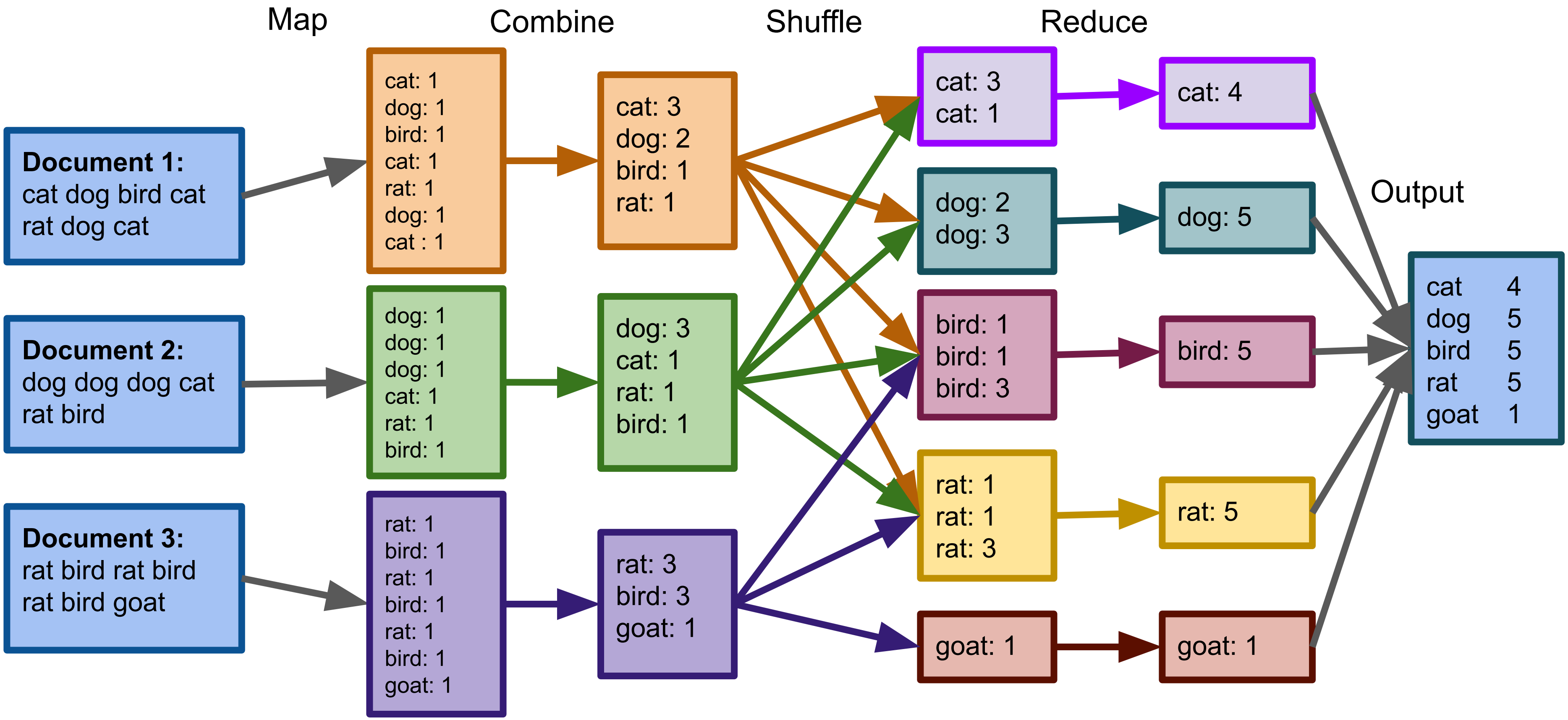


The total number of (key,value) pairs that we send to the reducer has been reduced from 20 to 11. Communication over the network is slow, so this is a big improvement!

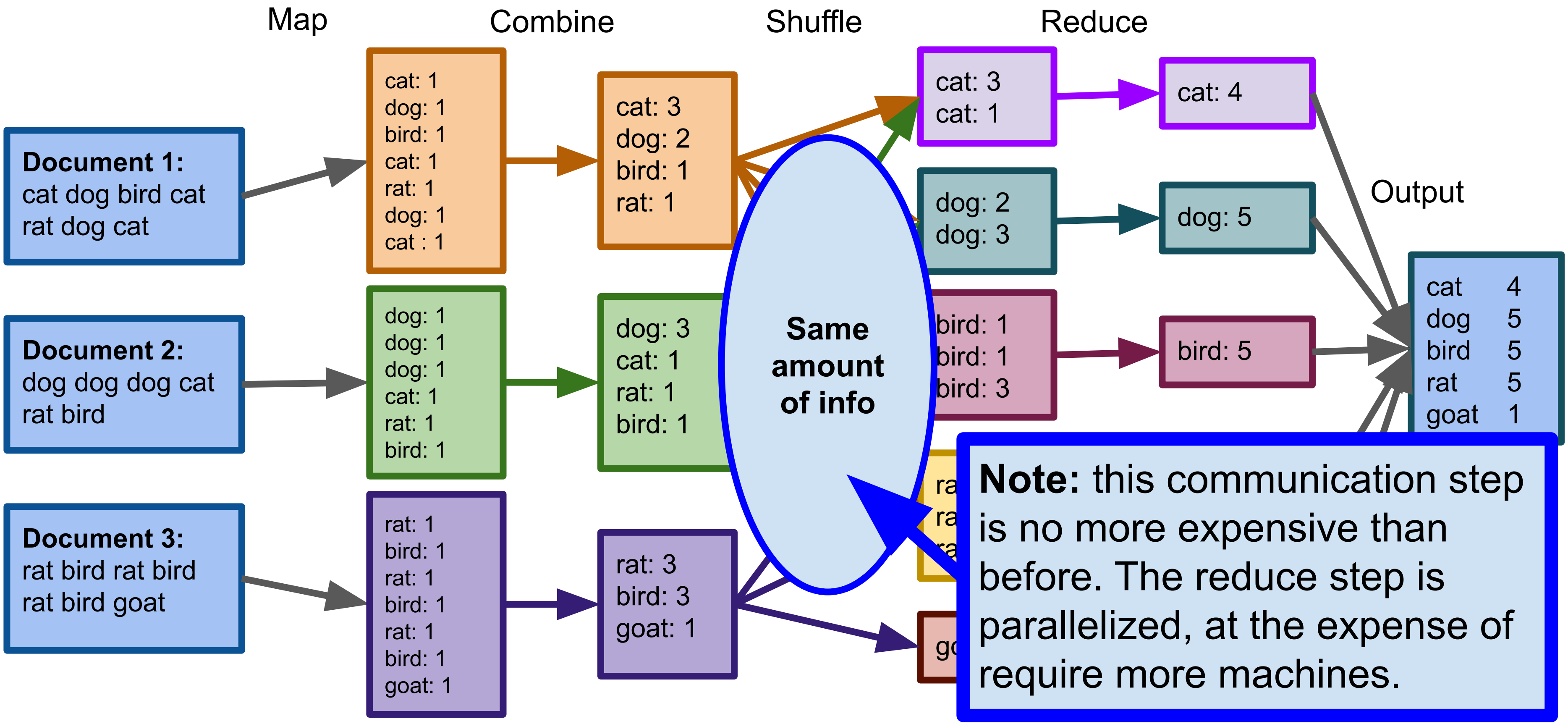
Counting words in MapReduce: version 2



Counting words in MapReduce version 3



Counting words in MapReduce version 3



Note: this communication step is no more expensive than before. The reduce step is parallelized, at the expense of require more machines.

A prototypical MapReduce program

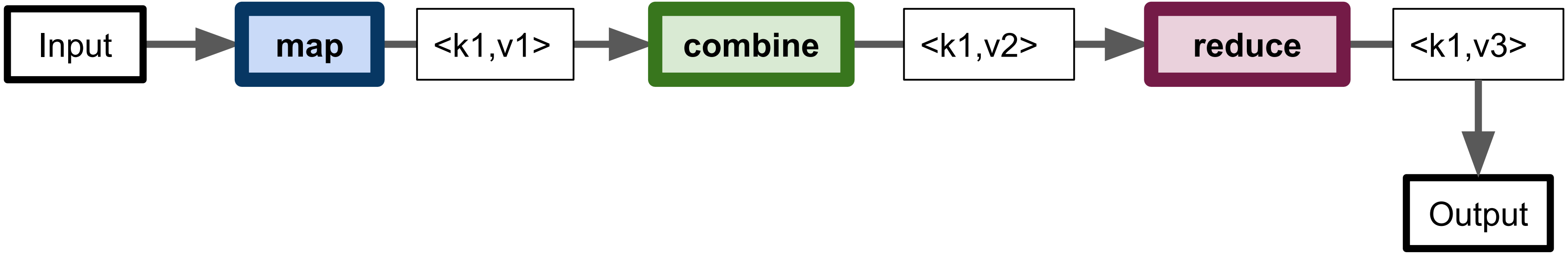
1. Read records (i.e., pieces of data) from file(s)

2. **Map:**
   For each record, extract information you care about
   Output this information in <key,value> pairs

3. **Combine:**
   Sort and group the extracted <key,value> pairs based on their keys

4. **Reduce:**
   For each group, summarize, filter, group, aggregate, etc. to obtain some new value, v2
   Output the <key, v2> pair as a row in the results file

A prototypical MapReduce program



Note: this output could be made the input to another MR program. We call one of these input->map->combine->reduce->output chains a **step**. Different platforms differ in how these steps are executed, a topic we'll discuss in our next two lectures.

Clarifying terminology

MapReduce: a large-scale computing framework initially developed at Google

Later open-sourced via the Apache Foundation as **Hadoop MapReduce**

Apache Hadoop: a set of open source tools from the Apache Foundation

Includes Hadoop MapReduce, Hadoop HDFS, Hadoop YARN

Hadoop MapReduce: implements the MapReduce framework

Hadoop YARN: resource manager that schedules Hadoop MapReduce jobs

Hadoop Distributed File System (HDFS): distributed file system

Designed for use with Hadoop MapReduce

Runs on same commodity hardware that MapReduce runs on

Note that there are a host of other loosely related programs, such as Apache Hive, Pig, Mahout and HBase, most of which are designed to work atop HDFS.

MapReduce: vocabulary

Cluster: a collection of devices (i.e., computers)

- Networked to enable fast communication, typically for purpose of distributed computing
- Jobs scheduled by a program like Sun/Oracle grid engine, Slurm, TORQUE or YARN
  - https://en.wikipedia.org/wiki/Job_scheduler

Node: a single computing "unit" on a cluster

- Roughly, computer==node, but can have multiple nodes per machine
- Usually a piece of commodity (i.e., not specialized, inexpensive) hardware

Step: a single map->combine->reduce "chain"

- A step need not contain all three of map, combine and reduce
- **Note:** some documentation refers to each of map, combine and reduce as steps

Job: a sequence of one or more MapReduce steps

More terminology (useful for reading documentation)

NUMA: non-uniform memory access

Local memory is much faster to access than memory elsewhere on network

https://en.wikipedia.org/wiki/Non-uniform_memory_access

Commodity hardware: inexpensive, mass-produced computing hardware

As opposed to expensive specialized machines

E.g., servers in a data center

Hash function: a function that maps (arbitrary) objects to integers

Used in MapReduce to assign keys to nodes in the reduce step

So MapReduce makes things much easier

Instead of having to worry about splitting the data, organizing communication between machines, etc., we only need to specify:

Map

Combine (optional)

Reduce

and the Hadoop backend will handle everything else.

MapReduce: under the hood

MR job consists of:

A **job tracker** or **resource manager** node

A number of **worker** nodes

Resource manager:

schedules and assigns tasks to workers

monitors workers, reschedules tasks if a worker node fails

https://en.wikipedia.org/wiki/Fault-tolerant_computer_system

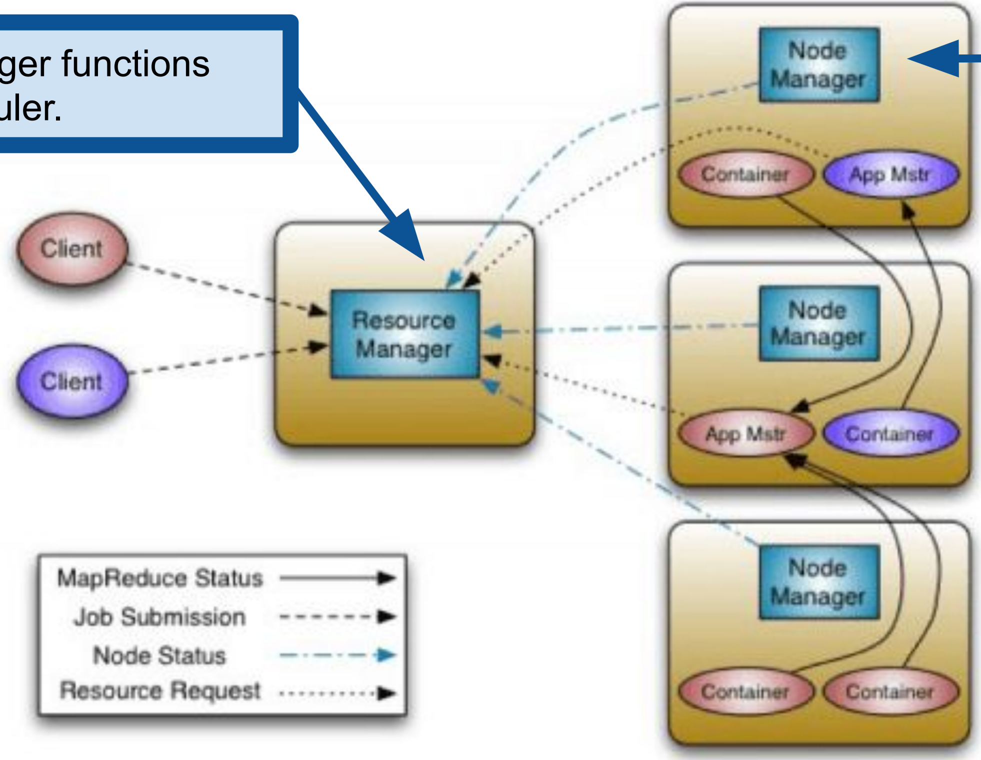
Worker nodes:

Perform computations as directed by resource manager

Communicate results to downstream nodes (e.g., Mapper -> Reducer)

Hadoop v2 YARN schematic

Resource manager functions only as a scheduler.



Note: manager is a process (i.e., program) that runs on a node and controls processing of data on that node.

So everything except allocation of tasks is performed at the **worker nodes**. Even much of the resource allocation is done by worker nodes via the **ApplicationMaster**.

Image credit: https://hortonworks.com/blog/apache-hadoop-yarn-concepts-and-applications/

You do not have to commit any of this to memory, or even understand it all. The important point here is that **Hadoop/YARN hides a whole bunch of complexity** from you so that you don't have to worry about it.

Image credit: https://hortonworks.com/blog/apache-hadoop-yarn-concepts-and-applications/

Hadoop Distributed File System (HDFS)

Storage system for Hadoop

File system is **distributed** across multiple nodes on the network

- In contrast to, say, all of your files being on one computer

Fault tolerant

- Multiple copies of files are stored on different nodes
- If nodes fail, recovery is still possible

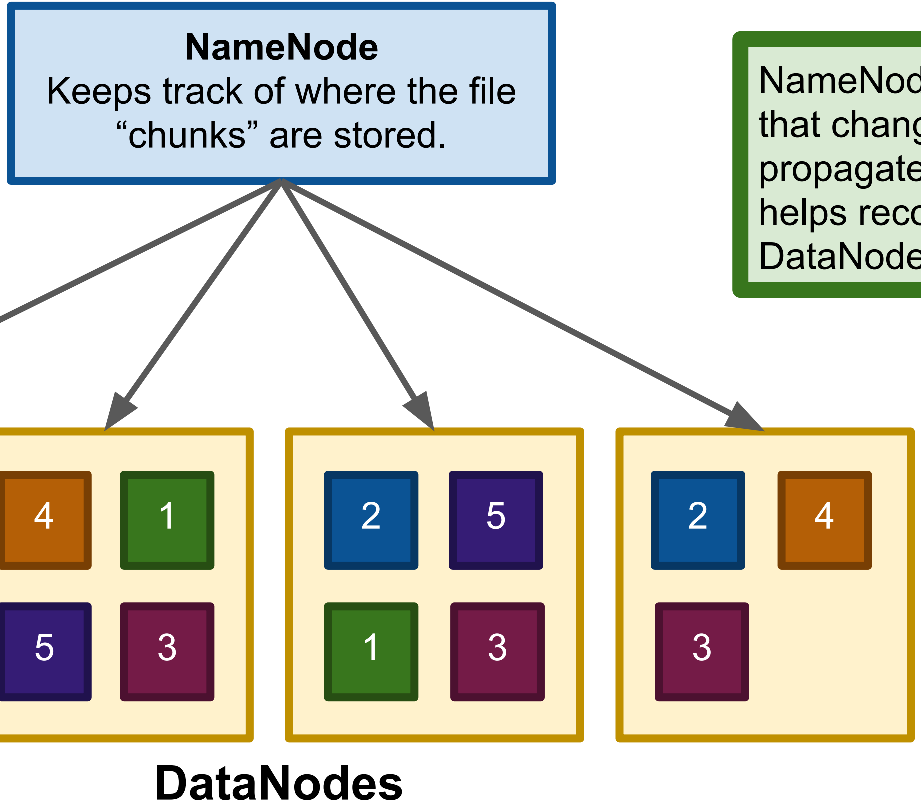
High-throughput

- Many large files, accessible by multiple readers and writers, simultaneously

Details: https://www.ibm.com/developerworks/library/wa-introhdfs/index.html

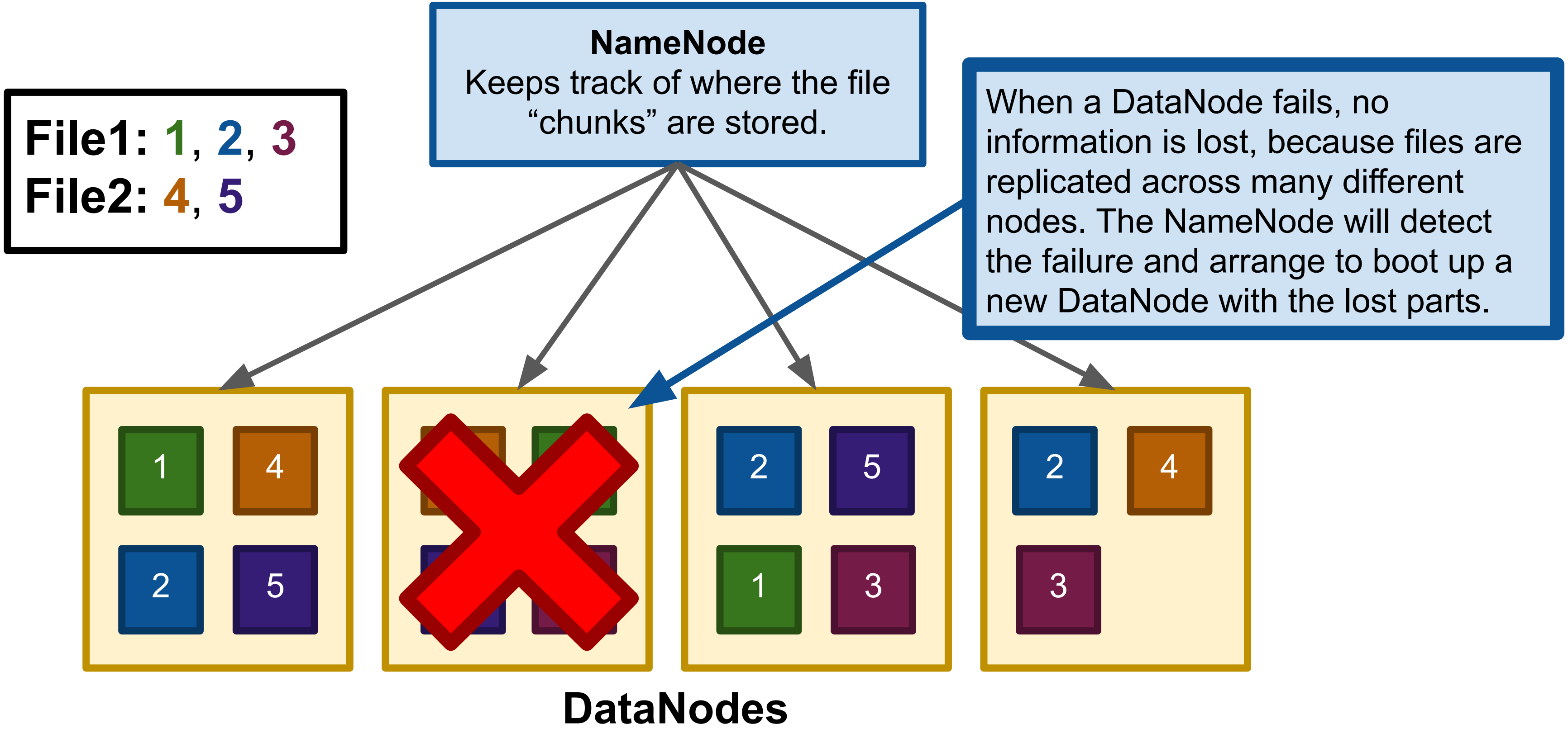
HDFS Schematic

File1: 1, 2, 3
File2: 4, 5



NameNode also ensures that changes to files are propagated correctly and helps recover from DataNode failures.

HDFS Schematic



HDFS Schematic

NameNode

NameNode also ensures

Again, the important point is that HDFS does all the hard work so you don't have to!

DataNodes