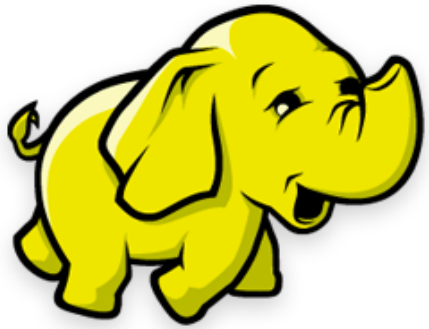
Apache Hadoop and MapReduce

COMP9313: Big Data Management

Thanks to Dr. Xin Cao for sharing useful materials for the preparation of this course

Hadoop



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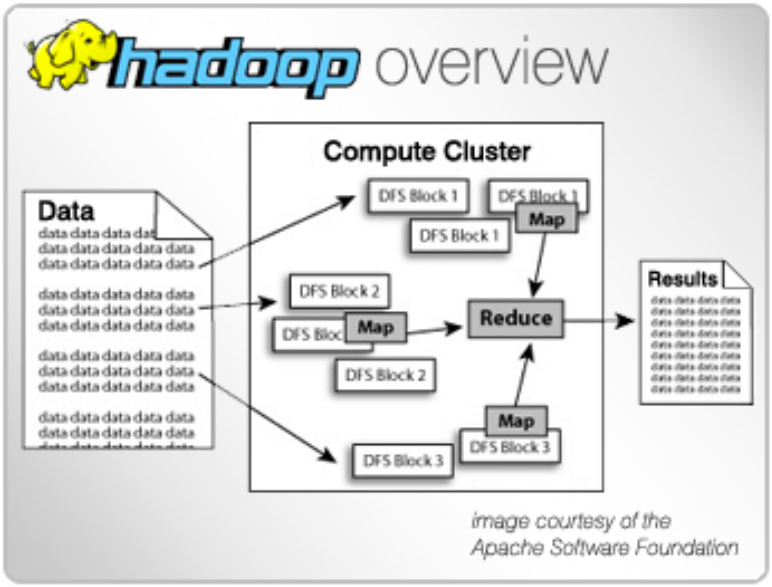
- Open-source data storage and processing platform
- Before the advent of Hadoop, storage and processing of big data was a big challenge
- Massively scalable, automatically parallelizable
  - Based on work from Google
    - Google: GFS + MapReduce + BigTable (Not open)
    - Hadoop: HDFS + Hadoop MapReduce + Hbase (opensource)
- Named by Doug Cutting in 2006 (worked at Yahoo! at that time), after his son's toy elephant

What's offered by Hadoop?

- Redundant, fault-tolerant data storage
- Parallel computation framework
- Job coordination
- Programmers do not need to worry about:
  - Where are files located?
  - How to handle failures and data loss?
  - How to distribute computation?
  - How to program for scaling?

Why use Hadoop?

- Cheap
  - Scales to Petabytes or more easily
- Fast
  - Parallel data processing
- Suitable
  - ... for particular types of big data problems



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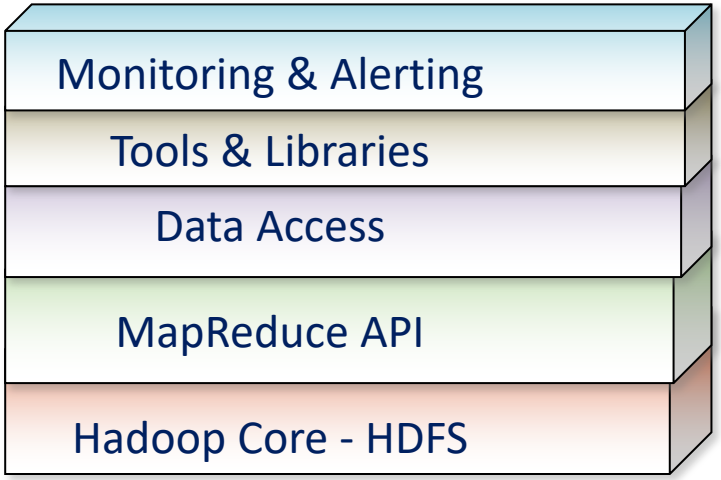
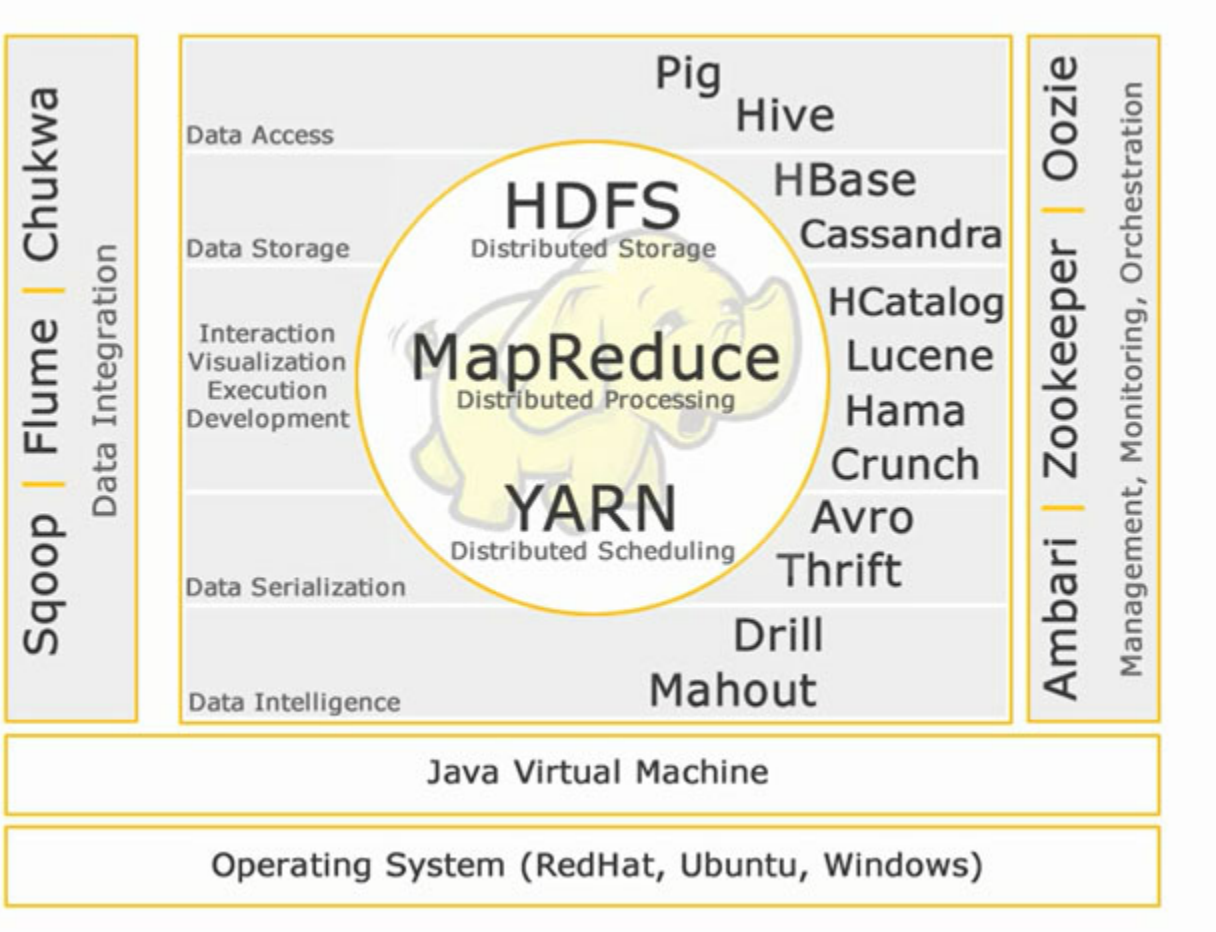
Hadoop is a set of Apache Frameworks...

- Data storage (HDFS)
  - Runs on commodity hardware
  - Horizontally scalable
- Processing (MapReduce)
  - Parallelized (scalable) processing
  - Fault Tolerant
- Other Tools / Frameworks
  - Data Access
    - Hbase (column store), Hive (Data warehousing), Pig (high-level language on top of Hadoop), Mahout (library for ML / Data Analytics)
  - Tools
    - Hue (SQL Cloud editor), Sqoop (data transfer Hadoop / Structured stores)



Hadoop ecosystem



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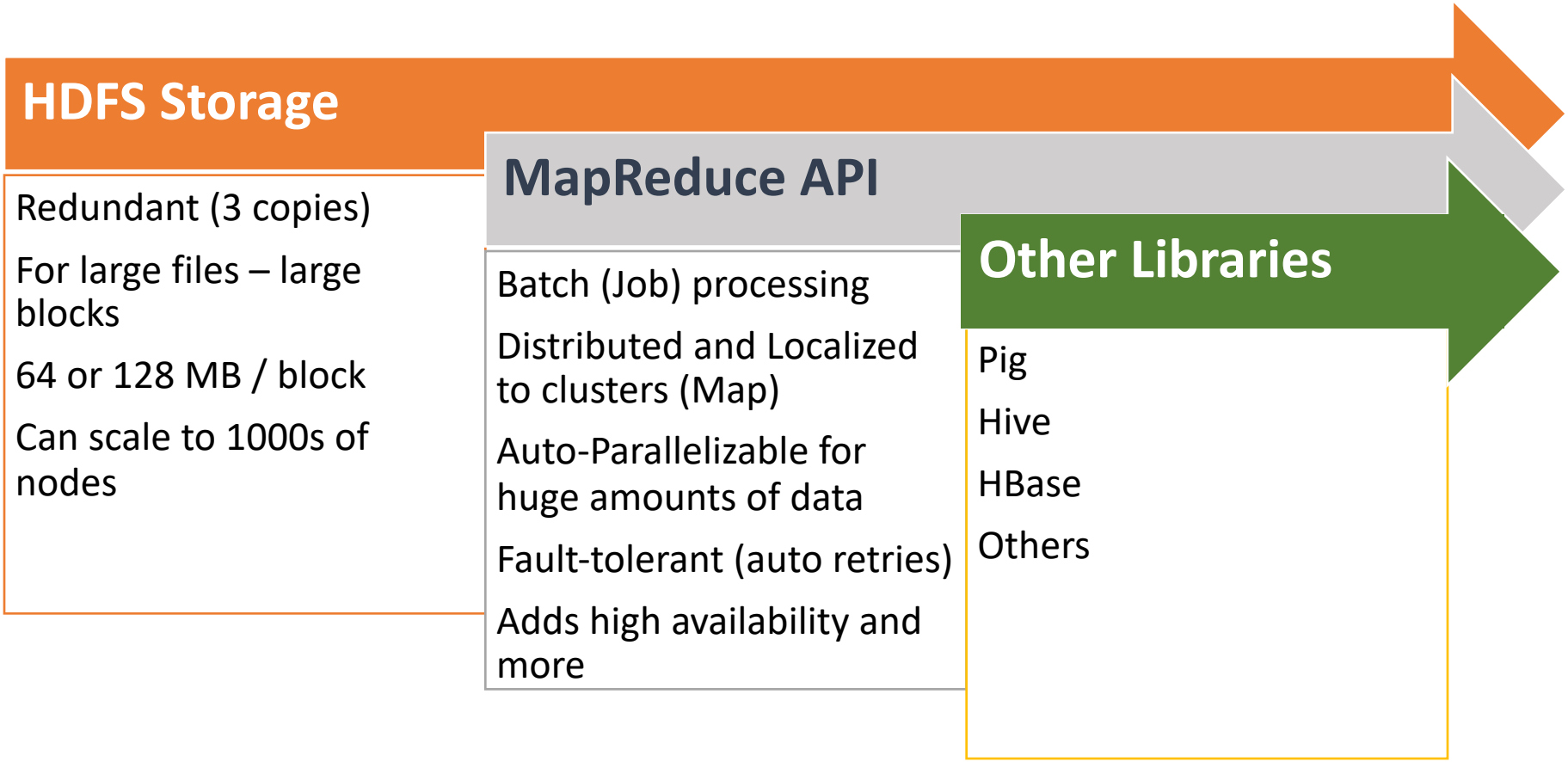
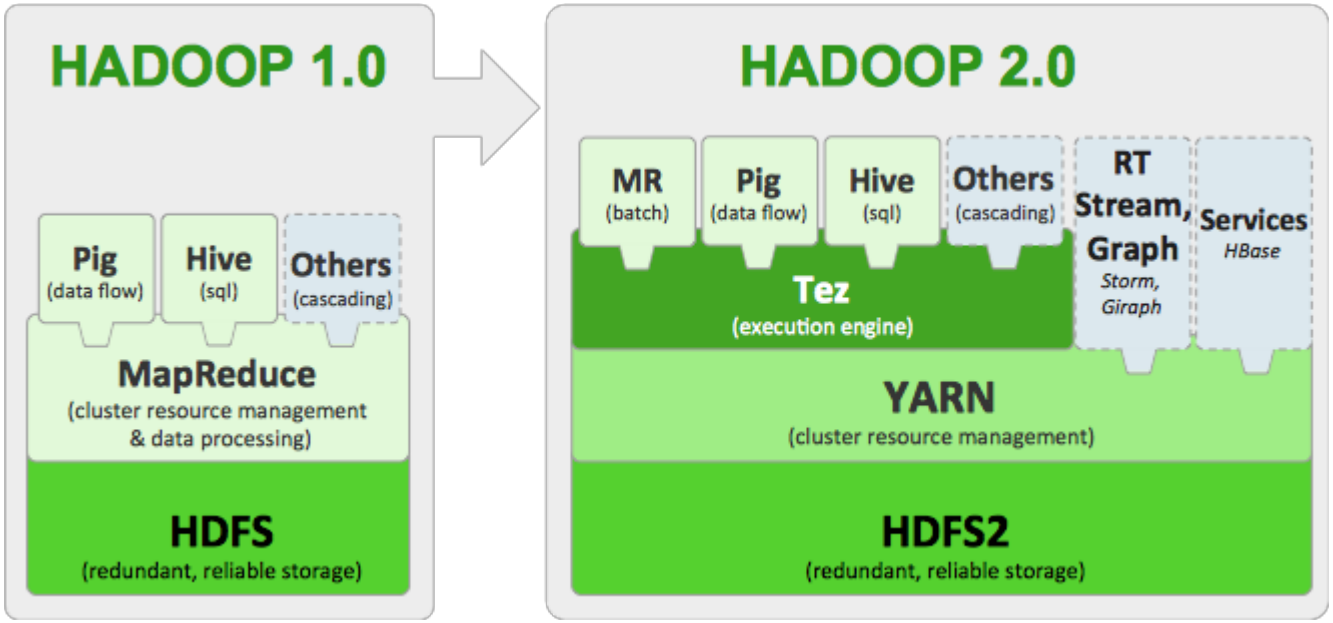
Core Parts of a Hadoop Distribution



Hadoop 1.0 vs Hadoop 2.0

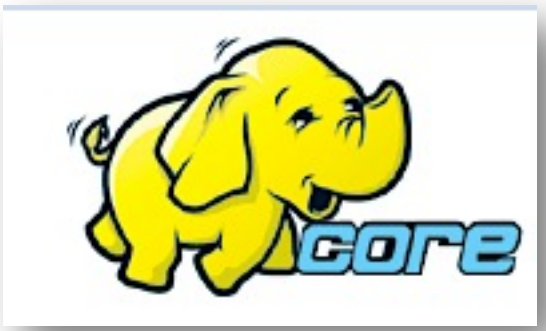
- Single Use System
  - Batch apps
- Multi-Purpose Platform
  - Batch, Interactive, Online, Streaming



Hadoop YARN *(Yet Another Resource Negotiator)*: a resource-management platform responsible for managing computing resources in clusters and using them for scheduling of users' applications

Common Hadoop Distributions

- Open Source
  - Apache
- Commercial
  - Cloudera
  - Hortonworks
  - MapR
  - AWS MapReduce
  - Microsoft Azure HDInsight (Beta)



Setting up for Hadoop Development

Hadoop Binaries

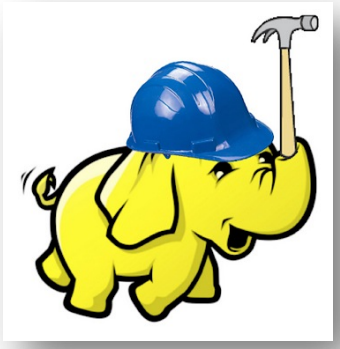
- **Local install**
  - Linux
  - Windows
- **Cloudera's Demo VM**
  - Need Virtualization software, i.e. VMware, etc…
- **Cloud**
  - AWS
  - Microsoft (Beta)
  - Others

Data Storage

- **Local**
  - File System
  - HDFS Pseudo-distributed (single-node)
- **Cloud**
  - AWS
  - Azure
  - Others

MapReduce

- Local
- Cloud

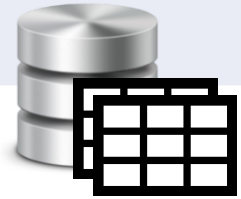


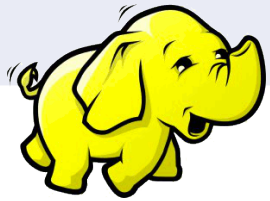
Other Libraries & Tools

- Vendor Tools
- Libraries

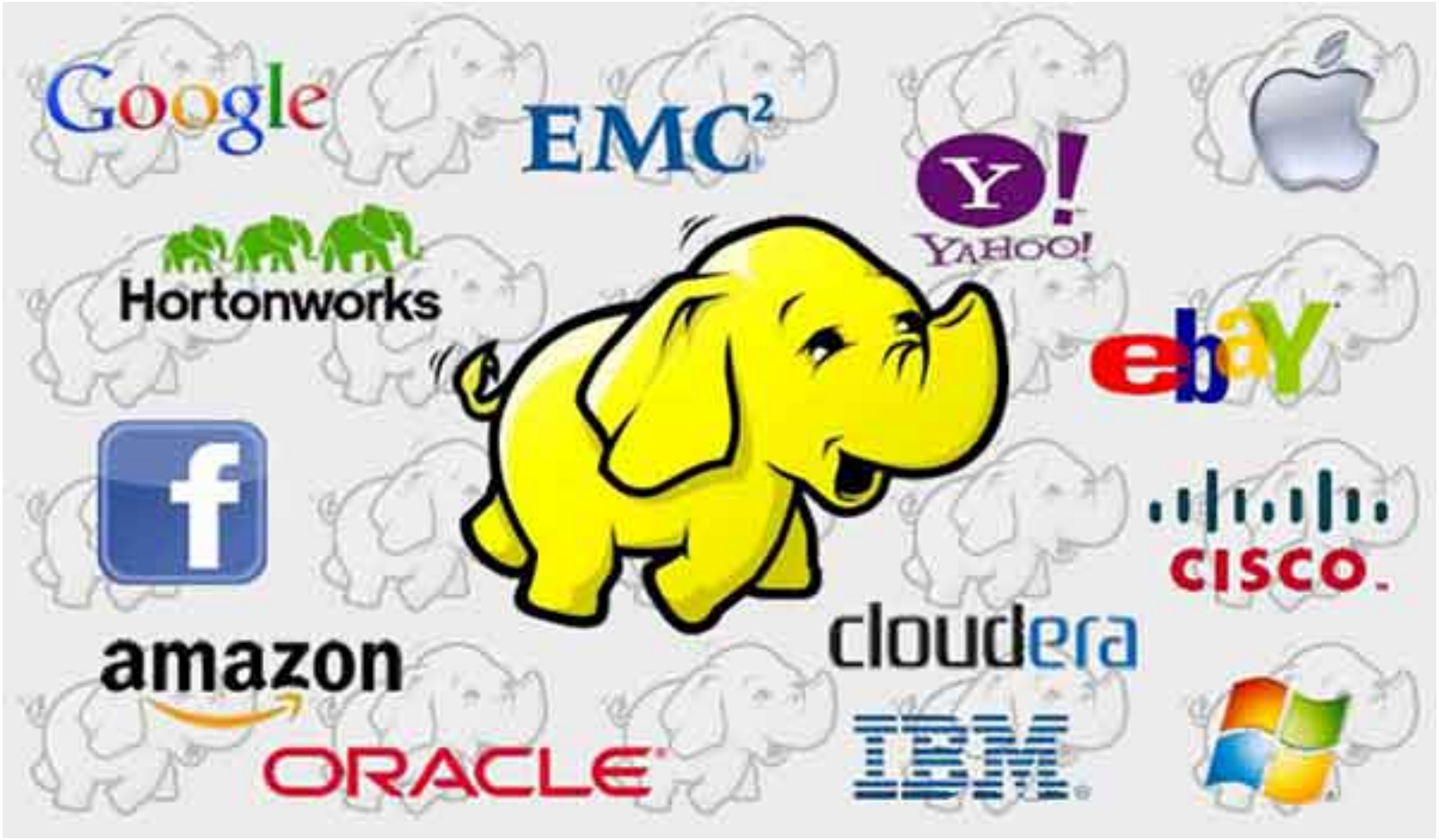
RDMS vs Hadoop

Feature	RDBMS	Hadoop
Data variety	Mainly structured data	Structured, semi-structured and unstructured data
Data storage	Average size data (GBs)	Used for large datasets (TBs, PTs)
Querying	SQL	HQL (Hive Query Language)
Schema	Required on write (static schema)	Required on read (dynamic schema)
Speed	Read are fast	Both read and write are fast
Use case	OLTP (Online Transaction Processing)	Analytics (audio, video, logs), data discovery
Data objects	Works on relational tables	Works on key/value pairs
Scalability	Vertical	Horizontal
Hardware profile	High-end servers	Commodity / Utility hardware
Integrity	ACID	Low





Companies using Hadoop



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MapReduce

What is MapReduce?

- Originated from Google, [OSDI'04]
  - MapReduce: Simplified Data Processing on Large Clusters
  - Jeffrey Dean and Sanjay Ghemawat (paper)
- Programming model for parallel data processing
- Hadoop can run MapReduce programs written in various languages:
  e.g. Java, Ruby, Python, C++
- For large-scale data processing
  - Exploits large set of commodity computers
  - Executes process in distributed manner
  - Offers high availability

Motivation for MapReduce (1)

- Typical big data problem challenges:
  - How do we break up a large problem into smaller tasks that can be executed in parallel?
  - How do we assign tasks to workers distributed across a potentially large number of machines?
  - How do we ensure that the workers get the data they need?
  - How do we coordinate synchronization among the different workers?
  - How do we share partial results from one worker that is needed by another?
  - How do we accomplish all of the above in the face of software errors and hardware faults?

Motivation for MapReduce (2)

- There was need for an abstraction that hides many system-level details from the programmer.
- MapReduce addresses this challenge by providing a simple abstraction for the developer, transparently handling most of the details behind the scenes in a **scalable**, **robust**, and **efficient** manner.
- MapReduce separates the **what** from the **how**

Typical Big Data Problem

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

Key idea:
Provide a **functional abstraction** for these two operations

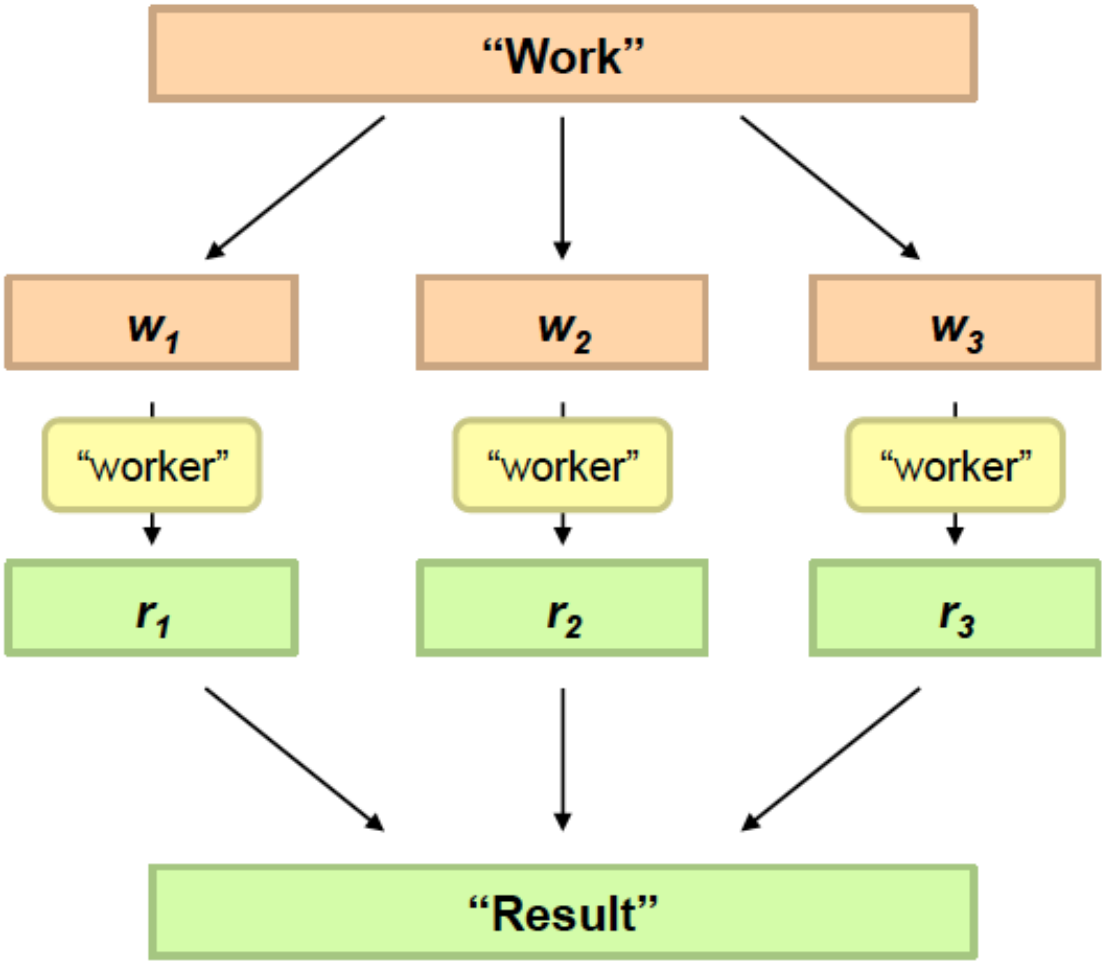
The Idea of MapReduce (1)

- Inspired by the map and reduce functions in functional programming
- We can view map as a transformation over a dataset
  - This transformation is specified by the function *f*
  - Each functional application happens in isolation
  - The application of *f* to each element of a dataset can be parallelized in a straightforward manner
- We can view reduce as an aggregation operation
  - The aggregation is defined by the function *g*
  - Data locality: elements in the list must be "brought together"
  - If we can group elements of the list, also the reduce phase can proceed in parallel
- The framework coordinates the map and reduce phases:
  - Grouping intermediate results happens in parallel

The Idea of MapReduce (2)

- 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 (HDFS)
- 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

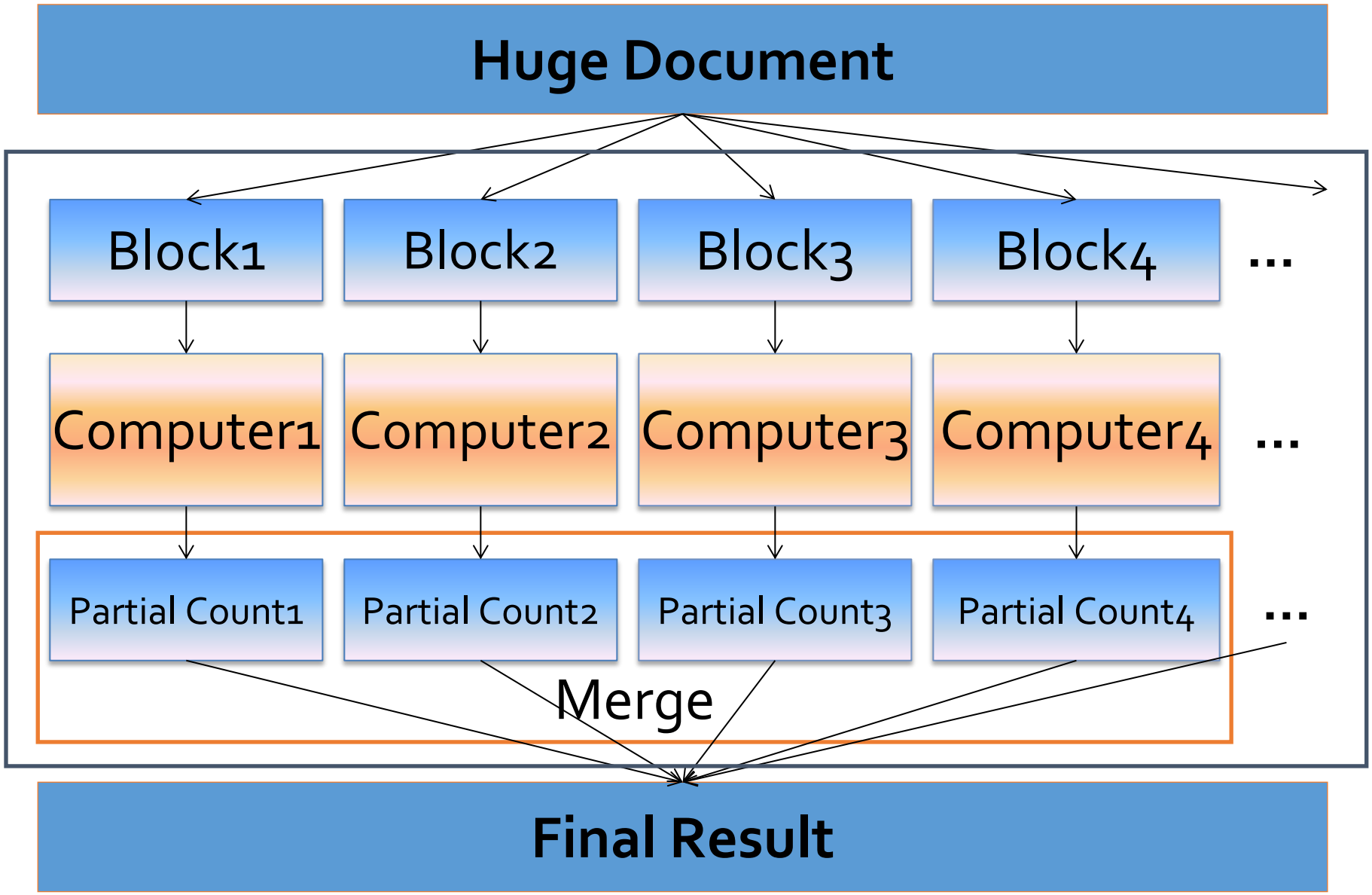
Philosophy to Scale for Big Data Processing



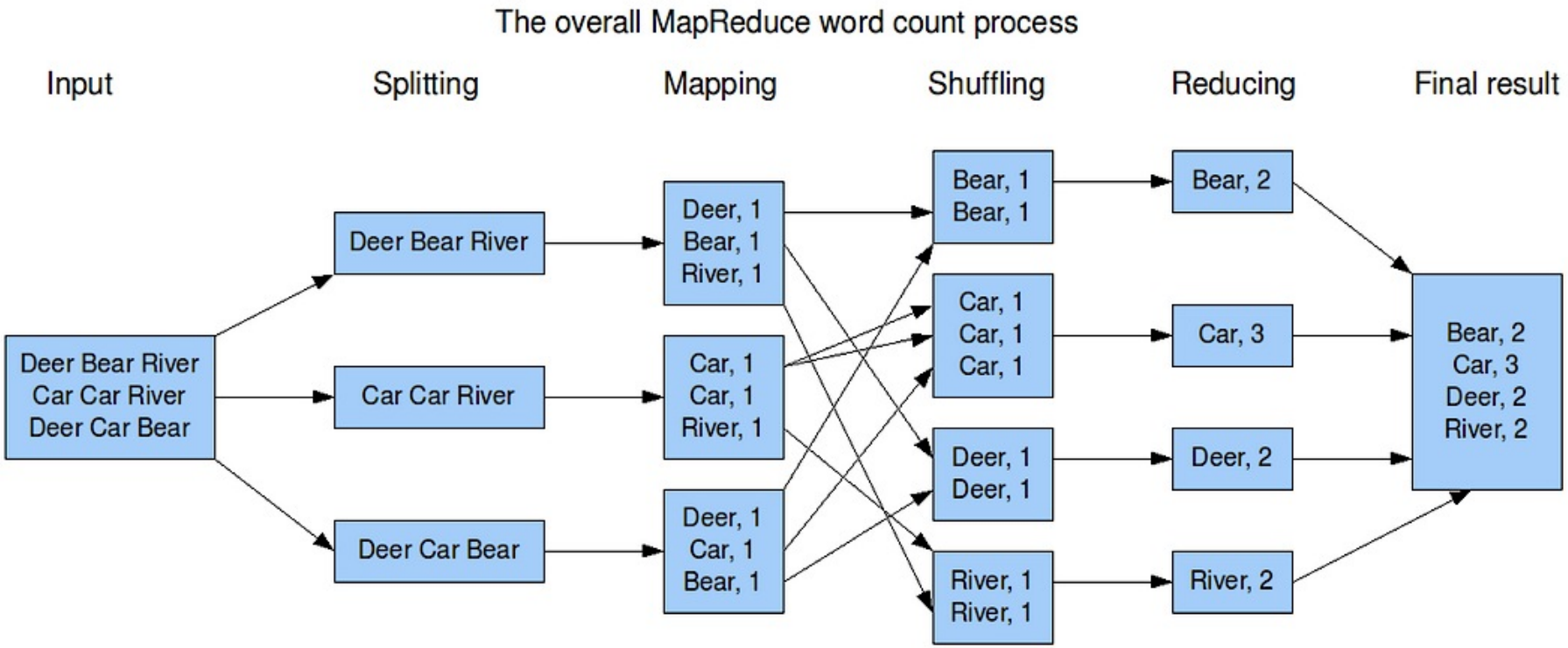
Divide Work

Combine Results

Distributed Word Count



MapReduce Example - WordCount



- Hadoop MapReduce is an implementation of MapReduce
  - MapReduce is a computing paradigm (Google)
  - Hadoop MapReduce is an open-source software

Data Structures in MapReduce

- Key-value pairs are the basic data structure in MapReduce
  - Keys and values can be: integers, float, strings, raw bytes, etc.
  - They can also be arbitrary data structures
- The design of MapReduce algorithms involves:
  - Imposing the key-value structure on arbitrary datasets
    - E.g.: for a collection of Web pages, input keys may be URLs and values may be the HTML content
  - In some algorithms, input keys uniquely identify a record
  - Keys can be combined in complex ways to design various algorithms

Map and Reduce Functions

- Programmers specify two functions:
  - **map** (k_1, v_1) → list [<k_2, v_2>]
    - Map transforms the input into key-value pairs to process
  - **reduce** (k_2, list [v_2]) → [<k_3, v_3>]
    - Reduce aggregates the list of values for each key
    - All values with the same key are sent to the same reducer
  - list [<k_2, v_2>] will be grouped according to key k_2 as (k_2, list [v_2])

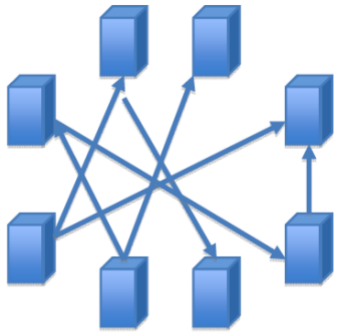
- The MapReduce environment takes in charge of everything else…

- A complex program can be decomposed as a succession of Map and Reduce tasks

Understanding MapReduce

- Map>>
  - (K1, V1) →
    - Info in
    - Input Split
  - list (K2, V2)
    - Key / Value out (intermediate values)
    - One list per local node
    - Can implement local Reducer (or Combiner)

- Shuffle/Sort>>



- Reduce
  - (K2, list(V2)) →
    - Shuffle / Sort phase precedes Reduce phase
    - Combines Map output into a list
  - list (K3, V3)
    - Usually aggregates intermediate values

(input) <k1, v1> → **map** → <k2, v2> → **shuffle/sort** → <k2, list(V2)> → **reduce** → <k3, v3> *(output)*

WordCount - Mapper

- Let's count number of each word in documents (e.g., Tweets/Blogs)
  - Reads input pair <k1,v1>
    - The input to the mapper is in format of <docID, docText>:

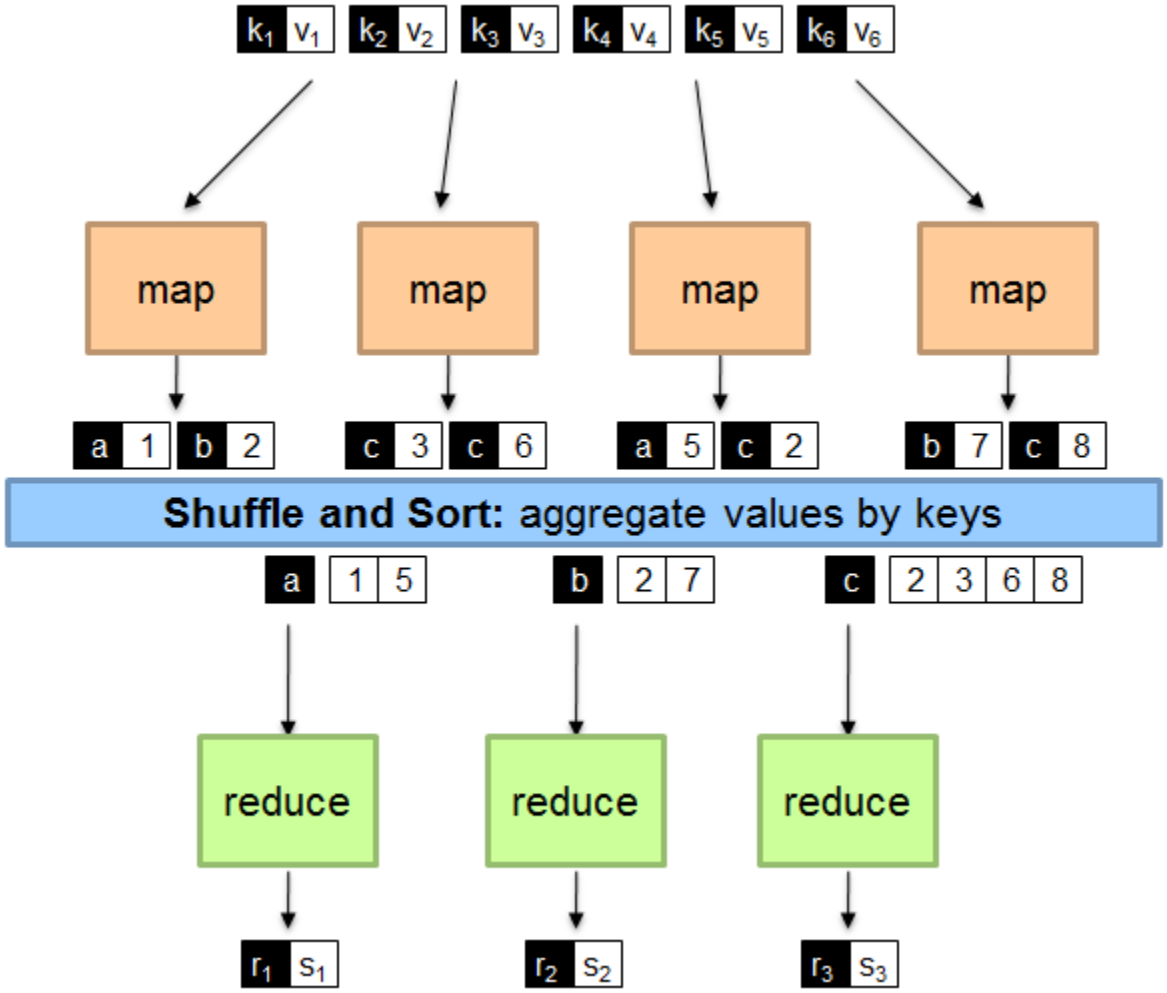
    <D1,"Hello World" >,<D2,"Hello Hadoop Bye Hadoop" >
  - Outputs pairs <k2, v2>
    - The output of the mapper is in format of <term, 1>:

    <Hello, 1><World, 1><Hello, 1><Hadoop, 1><Bye, 1><Hadoop, 1>
  - After shuffling and sort, reducer receives <k2, list(v2)>

    <Hello, {1, 1}><World, {1}><Hadoop, {1, 1}><Bye, {1}>
  - The output is in format of <k3, v3>:

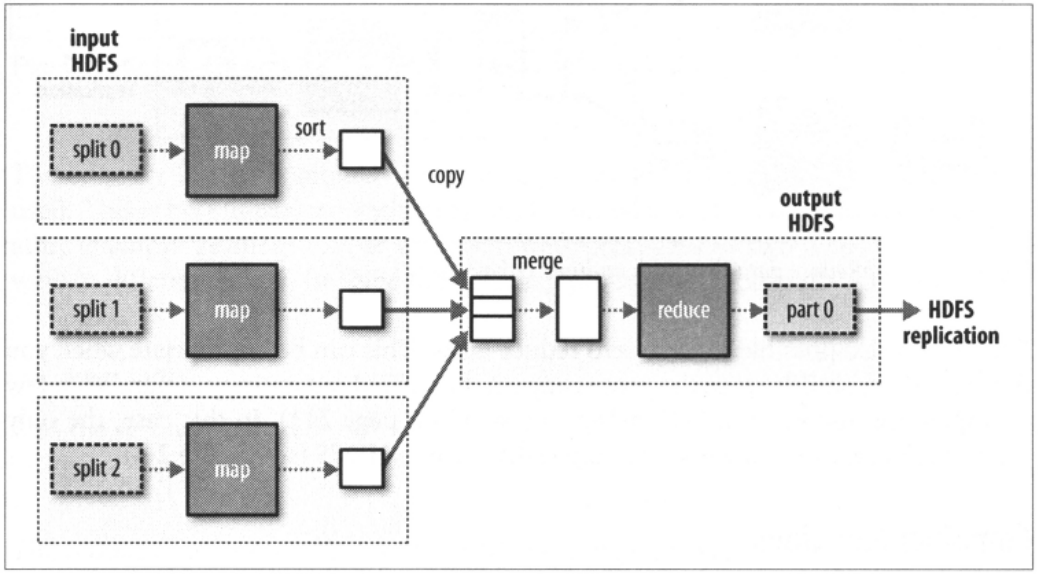
    <Hello, 2><World, 1><Hadoop, 2><Bye, 1>

WordCount - Mapper



Shuffle and Sort

- Shuffle
  - Input to the Reducer is the sorted output of the mappers. In this phase the framework fetches the relevant partition of the output of all the mappers, via HTTP.
- Sort
  - The framework groups Reducer inputs by keys (since different Mappers may have output the same key) in this stage.
- Hadoop framework handles the Shuffle and Sort step .



Word Count MapReduce in Java

MapReduce Program

- A MapReduce program consists of the following 3 parts:
  - Driver → main (would trigger the map and reduce methods)
  - Mapper
  - Reducer
  - Include the map reduce and main methods in 3 different classes
- Check detailed information of all classes at: https://hadoop.apache.org/docs/r2.7.2/api/allclasses-noframe.html

Mapper

```
public static class TokenizerMapper
    extends Mapper<Object, Text, Text, IntWritable> {
        private final static IntWritable one = new IntWritable(1);
        private Text word = new Text();

        public void map(Object key, Text value, Context context) throws
                IOException, InterruptedException {
            StringTokenizer itr = new
                    StringTokenizer(value.toString());
            while (itr.hasMoreTokens()) {
                word.set(itr.nextToken());
                context.write(word, one);
            }
        }
}
```

Mapper Explanation

- Maps input key/value pairs to a set of intermediate key/value pairs.

```
//Map class header
public static class TokenizerMapper
        extends Mapper<Object, Text, Text, IntWritable>{
```

- Class Mapper<KEYIN,VALUEIN,KEYOUT,VALUEOUT>
  - KEYIN,VALUEIN -> (k1, v1) -> (docid, doc)
  - KEYOUT,VALUEOUT ->(k2, v2) -> (word, 1)

```
// IntWritable: A serializable and comparable object for integer
private final static IntWritable one = new IntWritable(1);
/* Text: stores text using standard UTF8 encoding. It provides methods to serialize, deserialize, and compare texts at byte level*/
private Text word = new Text();
/* hadoop supported data types for the key/value pairs, in package org.apache.Hadoop */
```

What's Writable?

- Hadoop defines its own "box" classes for strings (Text), integers (IntWritable), etc.
- All values must implement interface Writable
- All keys must implement interface WritableComparable
- Writable is a serializable object which implements a simple, efficient, serialization protocol

Writable Wrappers

Java primitive	Writable implementation
boolean	BooleanWritable
byte	ByteWritable
short	ShortWritable
int	IntWritable VIntWritable
float	FloatWritable
long	LongWritable VLongWritable
double	DoubleWritable

Java class	Writable implementation
String	Text
byte[]	BytesWritable
Object	ObjectWritable
null	NullWritable

Java collection	Writable implementation
array	ArrayWritable ArrayPrimitiveWritable TwoDArrayWritable
Map	MapWritable
SortedMap	SortedMapWritable
enum	EnumSetWritable

Mapper Explanation (Cont'd)

//Map method header

public void map(Object key, Text value, Context context) throws IOException, InterruptedException

- Object key/Text value: Data type of the input Key and value to the mapper
- Context: An inner class of Mapper, used to store the context of a running task. Here it is used to collect data output by either the Mapper or the Reducer, i.e. intermediate outputs or the output of the job
- Exceptions: IOException, InterruptedException
- This function is called once for each key/value pair in the input split. Your application should override this to do your job.

Mapper Explanation (Cont'd)

```
//Use a string tokenizer to split the document into words
StringTokenizer itr = new StringTokenizer(value.toString());
//Iterate through each word and a form key value pairs
while (itr.hasMoreTokens()) {
//Assign each word from the tokenizer(of String type) to a Text 'word'
        word.set(itr.nextToken());
//Form key value pairs for each word as <word, one> using context
        context.write(word, one);
}
```

- Map function produces Map.Context object
  - Map.context() takes *(k, v)* elements
- Any (WritableComparable, Writable) can be used

Reducer

```
public static class IntSumReducer
      extends Reducer<Text,IntWritable,Text,IntWritable> {
            private IntWritable result = new IntWritable();


            public void reduce(Text key, Iterable<IntWritable> values,
            Context context) throws IOException,
InterruptedException{
                        int sum = 0;
                        for (IntWritable val : values) {
                                    sum += val.get();
                        }
                        result.set(sum);
                        context.write(key, result);
            }
}
```

Reducer Explanation

```
//Reduce Header similar to the one in map with different key/value data type
public static class IntSumReducer
    extends Reducer<Text, IntWritable, Text, IntWritable>
//data from map will be <"word",{1,1,..}>, so we get it with an Iterator and thus we can go through the sets of values
public void reduce(Text key, Iterable<IntWritable> values, Context context) throws IOException, InterruptedException{
//Initialize a variable 'sum' as 0
        int sum = 0;
//Iterate through all the values with respect to a key and sum up all of them
        for (IntWritable val : values) {
            sum += val.get();
        }
// Form the final key/value pairs results for each word using context
        result.set(sum);
        context.write(key, result);
```

Main (Driver)

```
public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```

Main (Driver)

- Given the Mapper and Reducer code, the main() method starts the MapReduction running
- The Hadoop system picks up a bunch of values from the command line on its own
- Then the main() also specifies a few key parameters of the problem in the Job object
- Job is the primary interface for a user to describe a map-reduce job to the Hadoop framework for execution (such as what Map and Reduce classes to use and the format of the input and output files)
- Other parameters, i.e. the number of machines to use, are optional and the system will determine good values for them if not specified
- Then the framework tries to faithfully execute the job as described by the job object

Main Explanation

```
//Creating a Configuration object and a Job object, assigning a job name for identification purposes

Configuration conf = new Configuration();

Job job = Job.getInstance(conf, "word count");
```

- Job Class: It allows the user to configure the job, submit it, control its execution, and query the state. Normally the user creates the application, describes various facets of the job via Job and then submits the job and monitor its progress.

```
//Setting the job's jar file by finding the provided class location

job.setJarByClass(WordCount.class);

//Providing the mapper and reducer class names

job.setMapperClass(TokenizerMapper.class);

job.setReducerClass(IntSumReducer.class);

//Setting configuration object with the Data Type of output Key and Value for map and reduce

job.setOutputKeyClass(Text.class);

job.setOutputValueClass(IntWritable.class);
```

Main Explanation (Cont'd)

```
/* The HDFS input and output directory to be fetched from the command line */
FileInputFormat.addInputPath(job, new Path(args[0]));
FileOutputFormat.setOutputPath(job, new Path(args[1]));
/* Submit the job to the cluster and wait for it to finish */
System.exit(job.waitForCompletion(true) ? 0 : 1);
```

Running the Code

- Configure environment variables

```
export JAVA_HOME=…
export PATH=${JAVA_HOME}/bin:${PATH}
export HADOOP_CLASSPATH=${JAVA_HOME}/lib/tools.jar
```

- Compile WordCount.java and create a jar:

```
$ hadoop com.sun.tools.javac.Main WordCount.java
$ jar cf wc.jar WordCount*.class
```

- Put files to HDFS

```
$ hdfs dfs –put YOURFILES input
```

- Run the application

```
$ hadoop jar wc.jar WordCount  input output
```

- Check the results

```
$ hdfs dfs –cat output/*
```

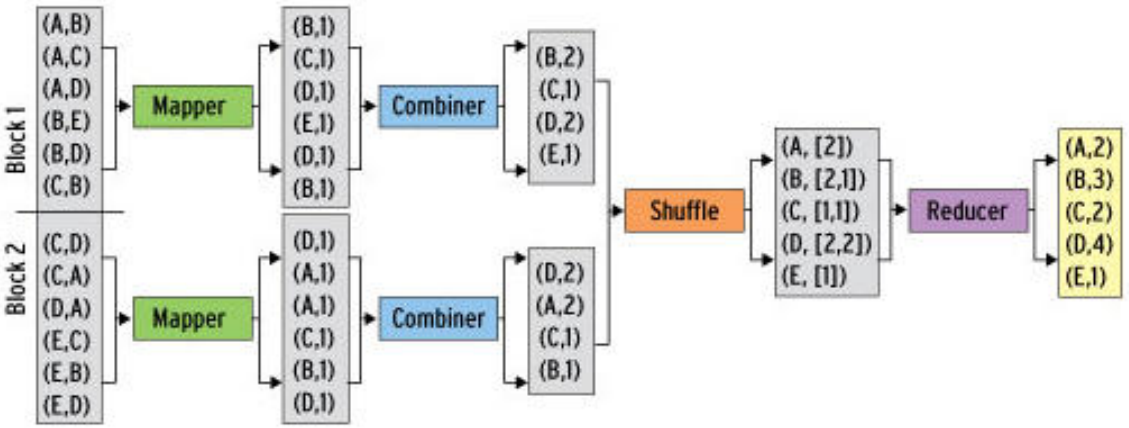
```
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;

public class WordCount {

  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }

  public static class IntSumReducer
       extends Reducer<Text,IntWritable,Text,IntWritable> {
    private IntWritable result = new IntWritable();

    public void reduce(Text key, Iterable<IntWritable> values,
                       Context context
                       ) throws IOException, InterruptedException {
      int sum = 0;
      for (IntWritable val : values) {
        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }

  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
```

Combiners

- Often a Map task will produce many pairs of the form $(k,v_1), (k,v_2), \ldots$ for the same key k
  - E.g., popular words in the word count example
- Combiners are a general mechanism to reduce the amount of intermediate data, thus saving network time
  - They could be thought of as "mini-reducers"
- Warning!
  - The use of combiners must be thought carefully
    - Optional in Hadoop: the correctness of the algorithm cannot depend on computation (or even execution) of the combiners
    - A combiner operates on each map output key. It must have the same output key-value types as the Mapper class.
    - A combiner can produce summary information from a large dataset because it replaces the original Map output
  - Works only if reduce function is commutative and associative
    - In general, reducer and combiner are not interchangeable

Combiners in WordCount

- Combiner combines the values of all keys of a single mapper node (single machine):



- Much less data needs to be copied and shuffled!
- If combiners take advantage of all opportunities for local aggregation we have at most $m \times V$ intermediate key-value pairs
  - m: number of mappers
  - V: number of unique terms in the collection
- Note: not all mappers will see all terms

Combiners in WordCount

- In WordCount.java, you only need to add the follow line to Main:

  job.setCombinerClass(IntSumReducer.class);

  - This is because in this example, Reducer and Combiner do the same thing
  - Note: In most cases, this is not true!
  - You need to write an extra combiner class
- Given two files:
  - file1: Hello World Bye World
  - file2: Hello Hadoop Bye Hadoop
- The first map emits:
  - < Hello, 1> < World, 2> < Bye, 1>
- The second map emits:
  - < Hello, 1> < Hadoop, 2> < Bye, 1>

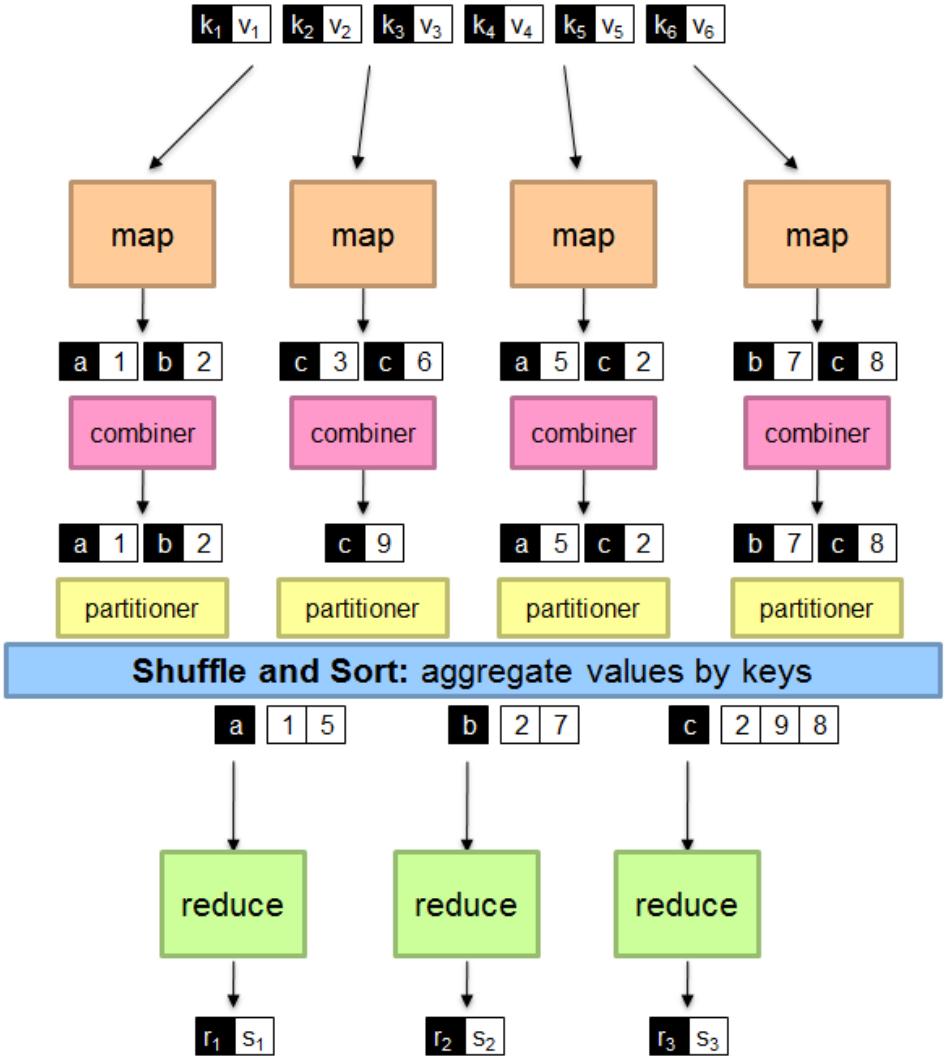
Partitioner

- Partitioner controls the partitioning of the keys of the intermediate map-outputs.
  - The key (or a subset of the key) is used to derive the partition, typically by a *hash function*.
  - The total number of partitions is the same as the number of reduce tasks for the job.
    - This controls which of the m reduce tasks the intermediate key (and hence the record) is sent to for reduction.
- System uses HashPartitioner by default:
  - hash(key) mod R
- Sometimes useful to override the hash function:
  - E.g., **hash(hostname(URL)) mod R** ensures URLs from a host end up in the same output file
    - https://www.unsw.edu.au/faculties and https://www.unsw.edu.au/about-us will be stored in one file
- Job sets Partitioner implementation (in Main)

MapReduce Recap

- Programmers must specify:
  - map $(k_1, v_1) \rightarrow [(k_2, v_2)]$
  - reduce $(k_2, [v_2]) \rightarrow [<k_3, v_3>]$
  - All values with the same key are reduced together
- Optionally, also:
  - combine (k2, [v2]) → [<k3, v3>]
    - Mini-reducers that run in memory after the map phase
    - Used as an optimization to reduce network traffic
  - partition (k2, number of partitions) → partition for k2
    - Often a simple hash of the key, e.g., hash(k2) mod n
    - Divides up key space for parallel reduce operations
- The execution framework handles everything else…

MapReduce Recap



For Large Datasets

- Data stored in HDFS (organized as blocks)
- Hadoop MapReduce Divides input into fixed-size pieces***, input splits***
  - Hadoop creates one map task for each split
  - Map task runs the user-defined map function for each *record* in the split
  - Size of a split is normally the size of a HDFS block (e.g., 64Mb)
- Data locality optimization
  - Run the map task on a node where the input data resides in HDFS
  - This is the reason why the split size is the same as the block size
    - The largest size of the input that can be guaranteed to be stored on a single node
    - If the split spanned two blocks, it would be unlikely that any HDFS node stored both blocks

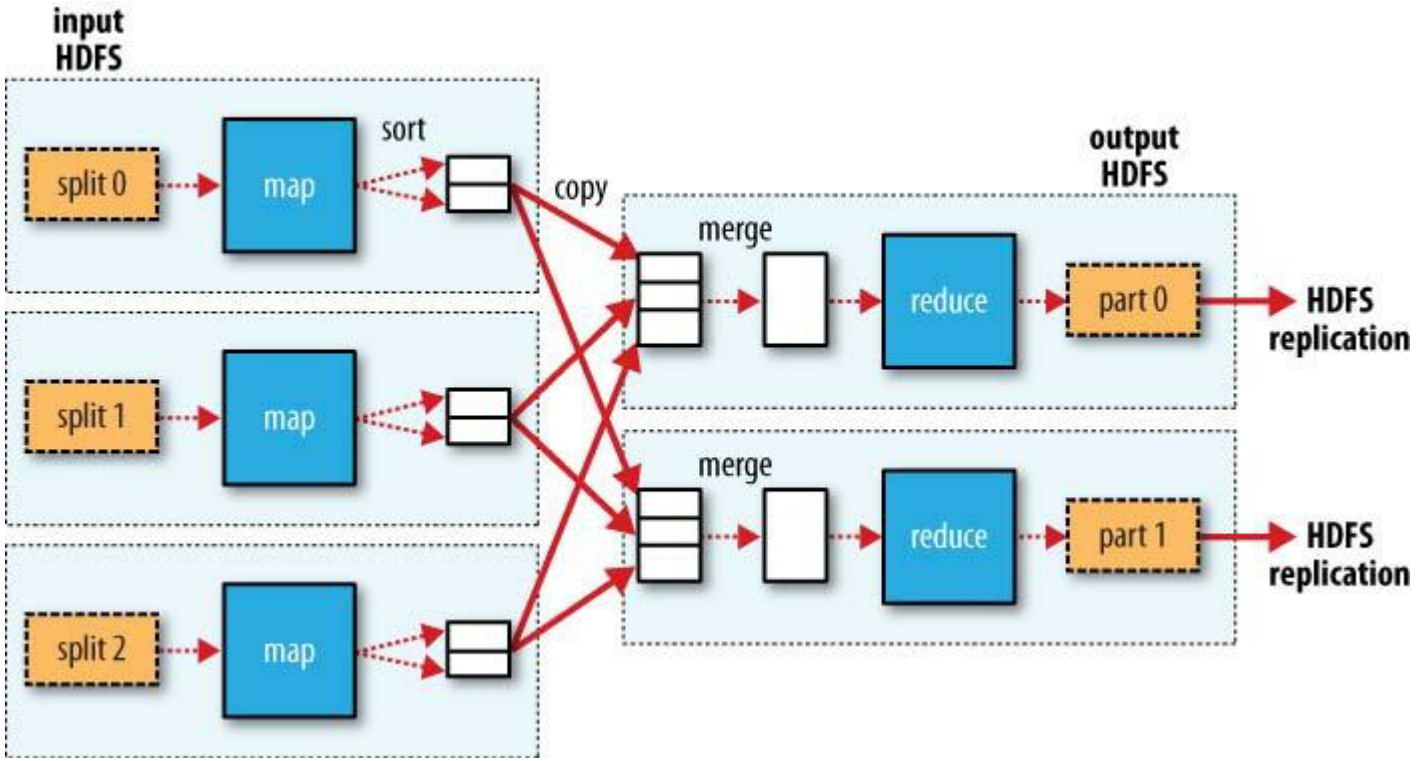
For Large Datasets

- Map tasks write their output to local disk (not to HDFS)
  - Map output is intermediate output
  - Once the job is complete the map output can be thrown away
  - Storing it in HDFS with replication, would be overkill
  - If the node of map task fails, Hadoop will automatically rerun the map task on another node

- Reduce tasks don't have the advantage of data locality
  - Input to a single reduce task is normally the output from all mappers
  - Output of the reduce is stored in HDFS for reliability
  - The number of reduce tasks is not governed by the size of the input, but is specified independently

More Detailed MapReduce Dataflow

- When there are multiple reducers, the map tasks partition their output:
  - One partition for each reduce task
  - The records for every key are all in a single partition
  - Partitioning can be controlled by a user-defined partitioning function



Thanks