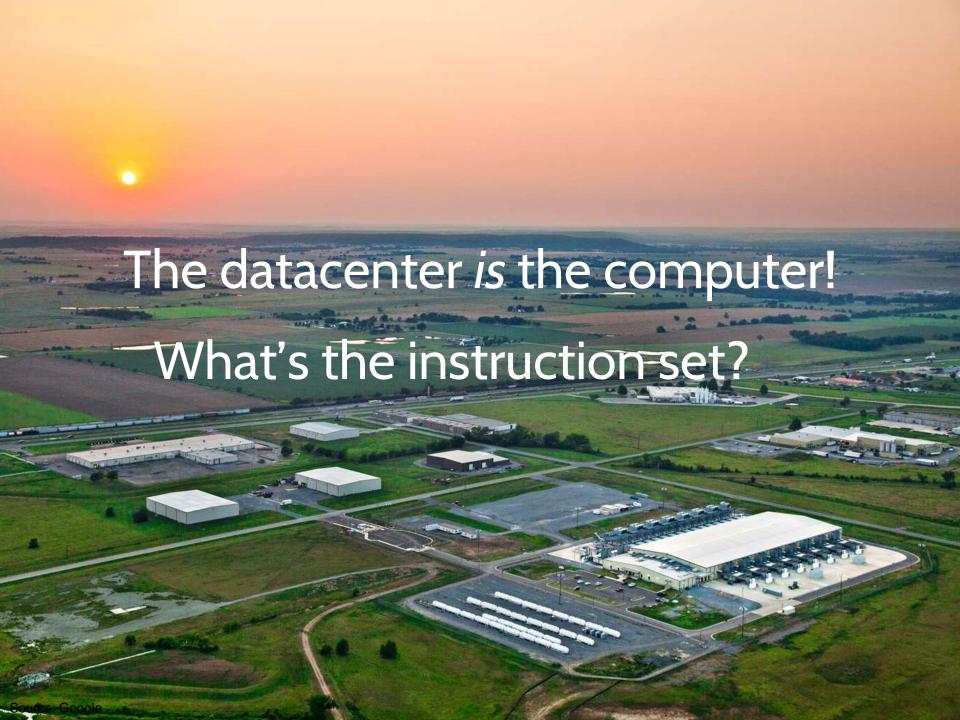
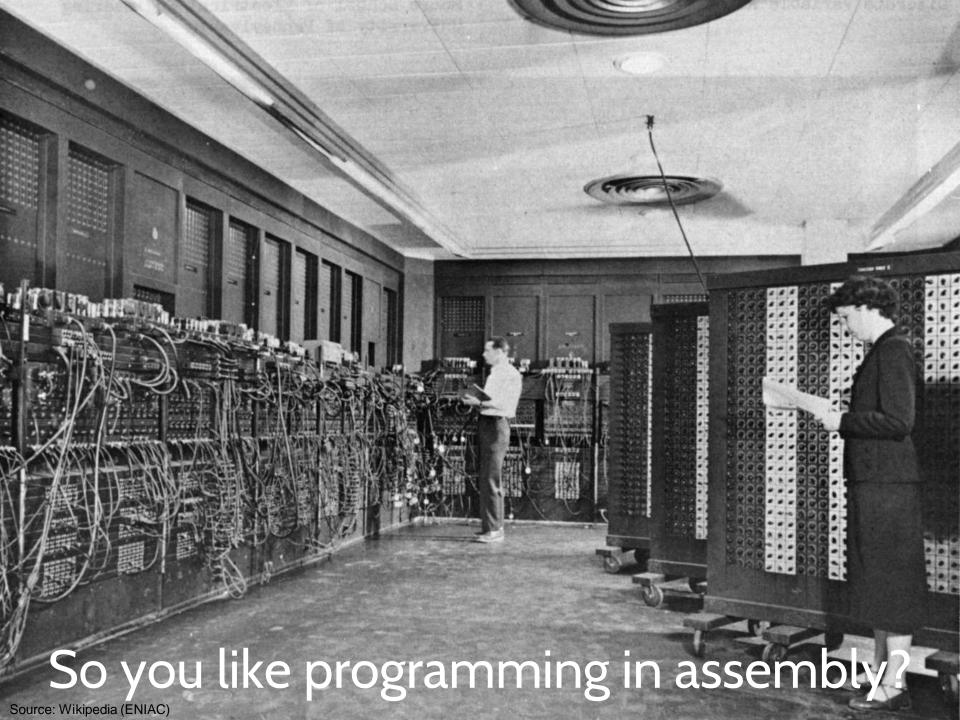
Introduction to Map/Reduce: From Hadoop to SPARK

Computer Science Department University of Crete, Greece

What we will cover...

- Dataflow Languages for Cluster Computing
- What is MapReduce?
- How does it work?
- A simple word count example
 - (the "Hello World!" of MapReduce)
- From MapReduce to Spark





Traditional Network Programming

Message-passing between nodes (e.g. MPI)

Very difficult to do at scale:

- How to split problem across nodes?
 - Must consider network & data locality

How to deal with failures? (inevitable at scale)

Even worse: stragglers (node not failed, but slow)

Ethernet networking not fast

• Have to write programs for each machine

Data Flow Models

Restrict the programming interface so that the system can do more automatically

Express jobs as graphs of high-level operators »System picks how to split each operator into tasks and where to run each task

Run parts twice fault recovery

Biggest example: MapReduce

Why Use a Data Flow Engine?

Ease of programming

High-level functions instead of message passing

Wide deployment

More common than MPI, especially "near" data

Scalability to very largest clusters

Even HPC world is now concerned about resilience

Examples: Pig, Hive, Scalding, Storm, Spark

Data-Parallel Dataflow Languages

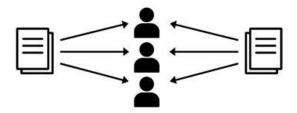
We have a collection of records, want to apply a bunch of operations to compute some result

Assumption: static collection of records (what's the limitation here?)

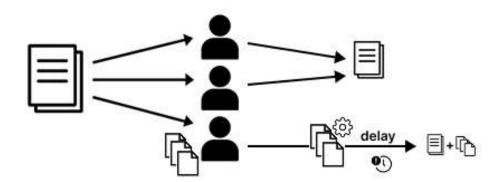
Example

In a group project the teacher gives all students exactly 5 questions from a fixed worksheet

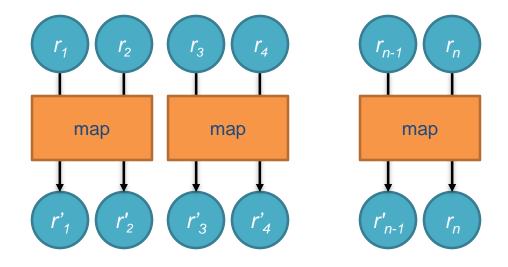
Everyone can solve the questions in parallel, and at the end the answers are collected at the same time



What if the teacher suddenly adds 10 new questions in only 1 student?



We Need Per-record Processing



Remarks: Easy to parallelize maps, record to "mapper" assignment is an implementation detail

What is MapReduce?

A <u>programming model</u> for processing large datasets in parallel on a cluster, by dividing the work into a set of independent tasks (introduced by Google in 2005)

All we <u>have to</u> do is provide the implementation of two methods:

- map()
- reduce()

...but we <u>can</u> do much more...

even that, is optional!

How does it work?

keys and values

- everything is expressed as (key, value) pairs
 - e.g. the information that the word "hello" appears 4 times in a text, could be expressed as: ("hello", 4)

Each map method receives a list of (key, value) pairs and emits a list of (key, value) pairs

• the intermediate output of the program

Each *reduce* method receives, for each unique intermediate key *k*, a **list** of all intermediate values that were emitted for *k*.

Then, it emits a list of (key, value) pairs

• the final output of the program

MapReduce – Input Data

e1

e2

۾

e4

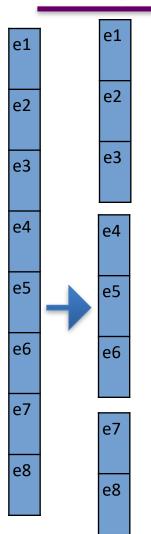
e.º

e6

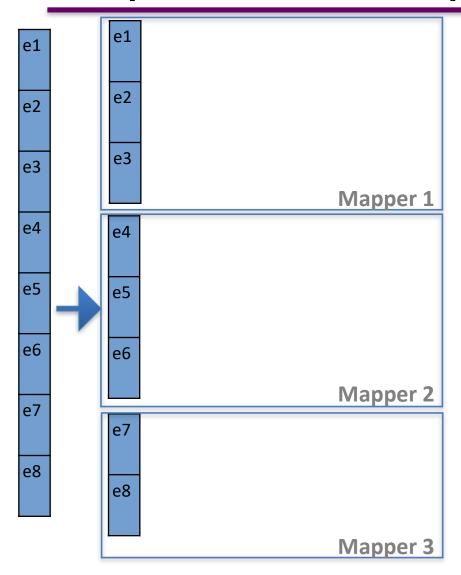
e7

e8

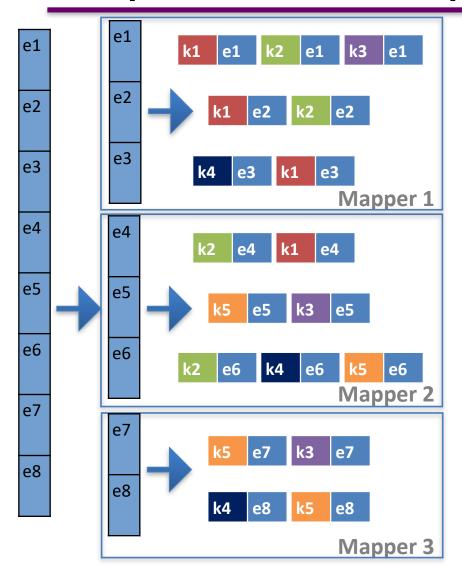
MapReduce – Input Data Splitting



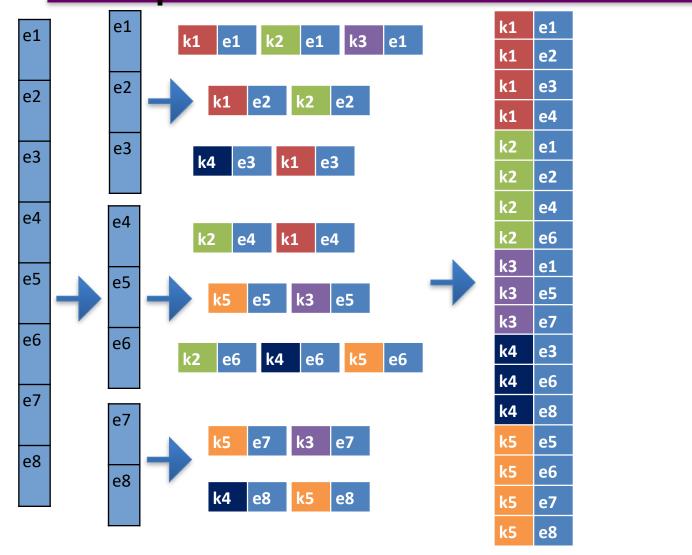
MapReduce – Mapper Input



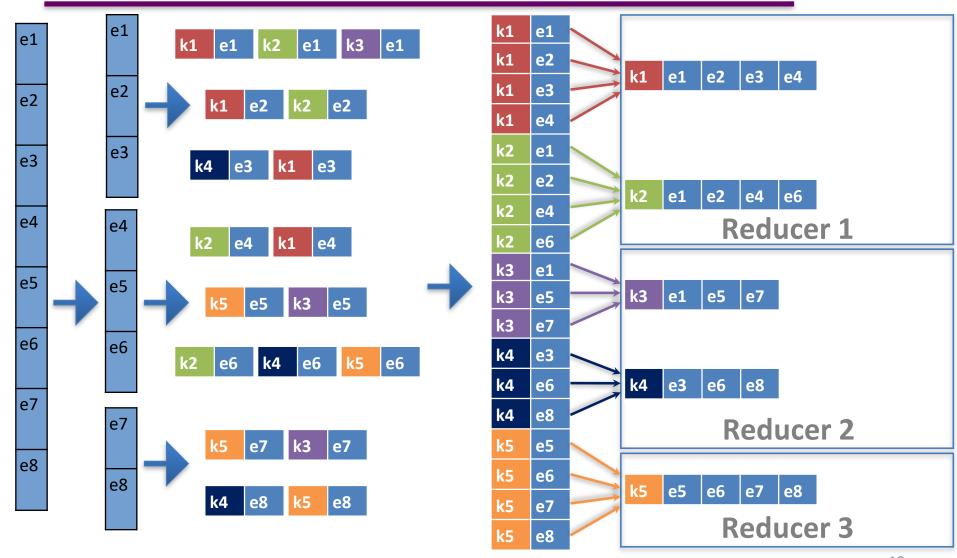
MapReduce – Mapper Output



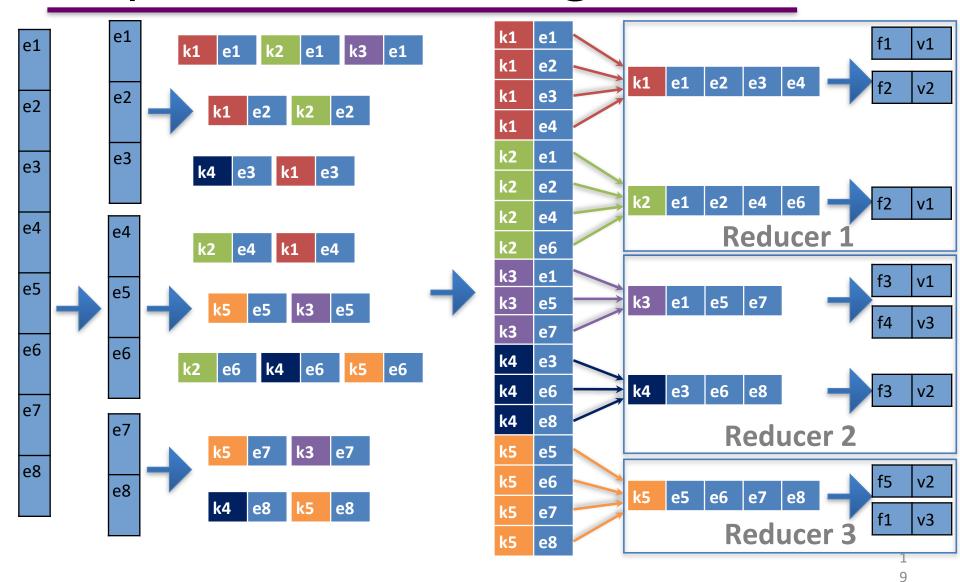
MapReduce – Shuffling & Sorting (simplified)



MapReduce – Reducing



MapReduce – Reducing





- Input: A list of (file-name, line) pairs
- Output: A list of (word, frequency) pairs for each unique word appearing in the input

Example: WordCount

- Input: A list of (file-name, line) pairs
- Output: A list of (word, frequency) pairs for each unique word appearing in the input

Idea:

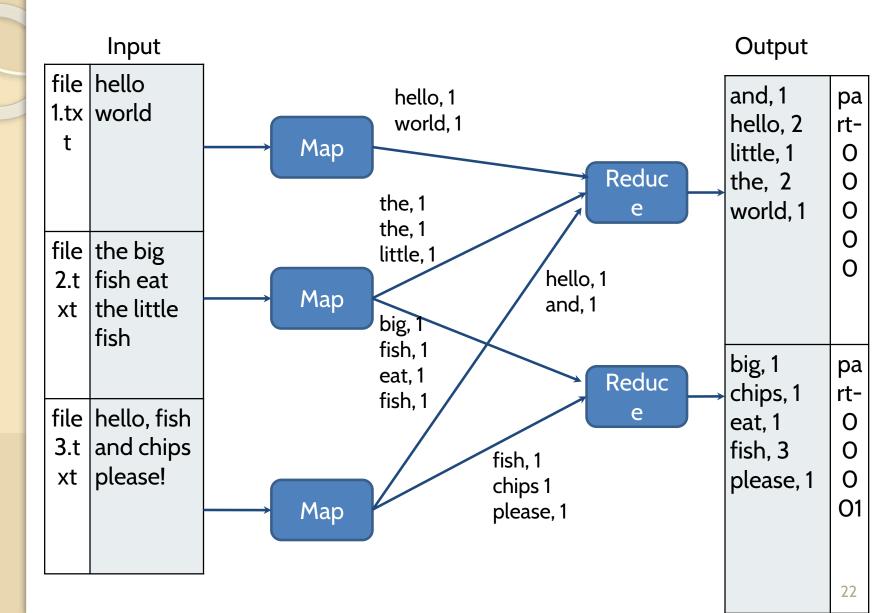
Map:

for each word w, emit a (w, 1) pair

Reduce:

for each (w, list(1,1,...,1)), sum up the 1's and emit a (w, 1+1+...+1)) pair

Example: WordCount



WordCount Mapper

```
public static class Map extends Mapper<LongWritable, Text, Text,
  IntWritable> {
  private final static IntWritable one = new IntWritable(1);
  private Text word = new Text();
 public void map(LongWritable key, Text value, Context context)
 throws
                                                 IOException,
  InterruptedException {
       String line = value.toString();
       StringTokenizer tokenizer = new StringTokenizer(line);
       while (tokenizer.hasMoreTokens()) {
          word.set(tokenizer.nextToken());
          context.write(word, one);
```



WordCount Reducer

```
public static class Reduce extends Reducer<Text, IntWritable,
 Text, IntWritable>
 public void reduce(Text key, Iterable<IntWritable> values,
 Context context)
                        throws IOException, InterruptedException {
       int sum = 0;
       for (IntWritable val : values) {
          sum += val.get();
       context.write(key, new IntWritable(sum));
```



Combiner: a local, mini-reducer

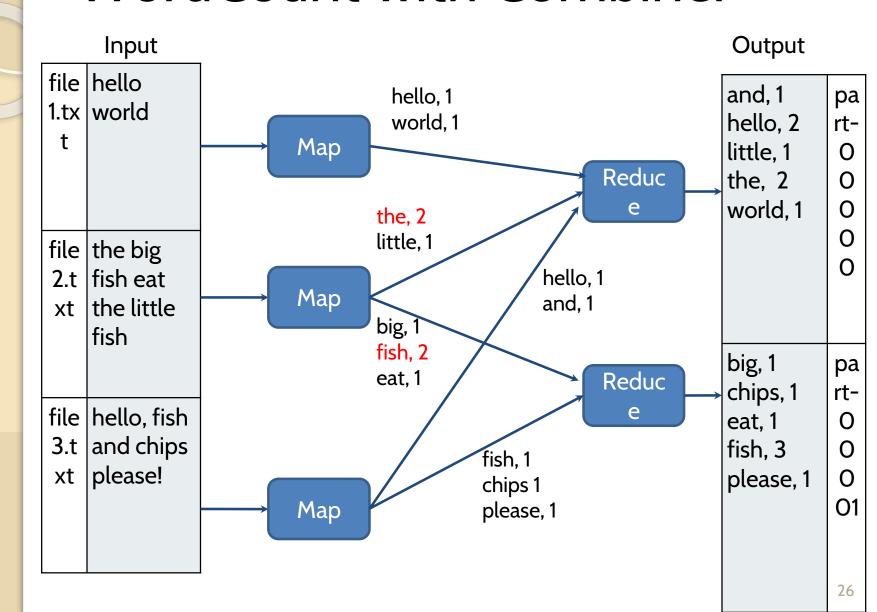
- An optional class that works like a reducer, run locally
 - for the output of each mapper
- Goal:
 - reduce the network traffic from mappers to reducers
 - could be a bottleneck
 - reduce the workload of the reducers

WordCount Example:

We could sum up the local 1's corresponding to the same key and emit a temporary word count to the reducer

- fewer pairs are sent to the network
- the reducers save some operations

WordCount with Combiner



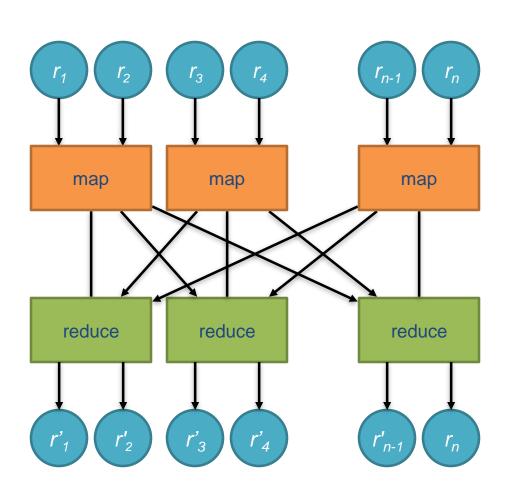
Map Alone Isn't Enough!

Where do intermediate results go?
We need an addressing mechanism!
What's the semantics of the group by?

Once we resolve the addressing, apply another computation

That's what we call reduce! (What's with the sorting then?)

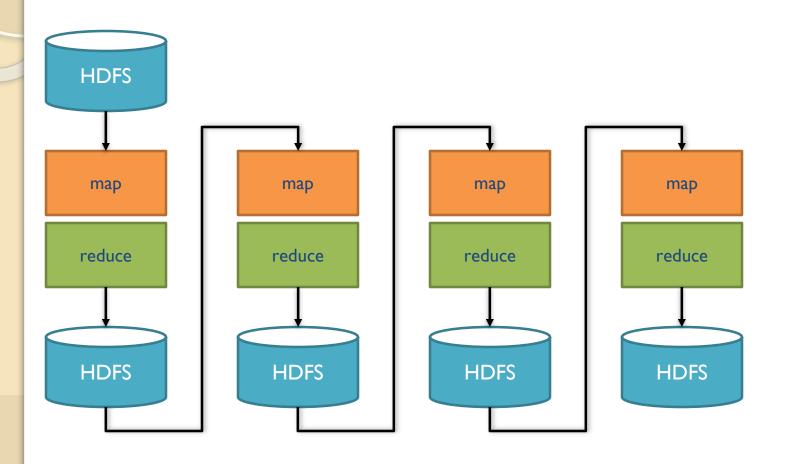
MapReduce



MapReduce

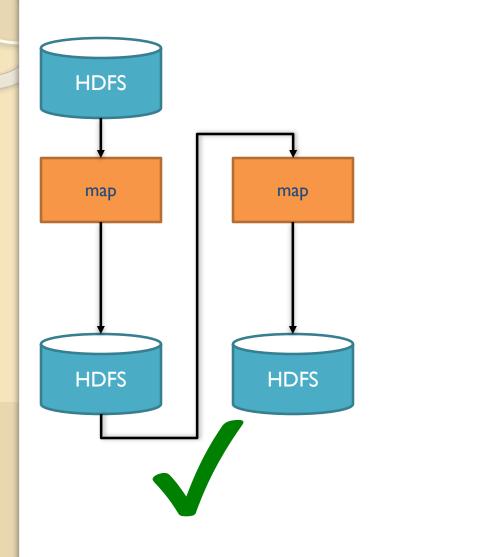
```
List[(K1,V1)]
           map
       f: (K1, V1)
    \Rightarrow List[(K2, V2)]
         reduce
g: (K2, Iterable[V2]) \Rightarrow
     List[(K3, V3)]
       List[K3,V3])
```

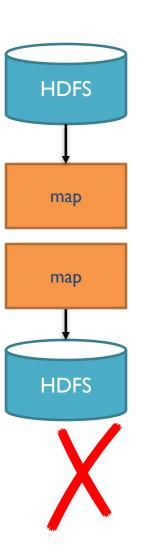
MapReduce Workflows



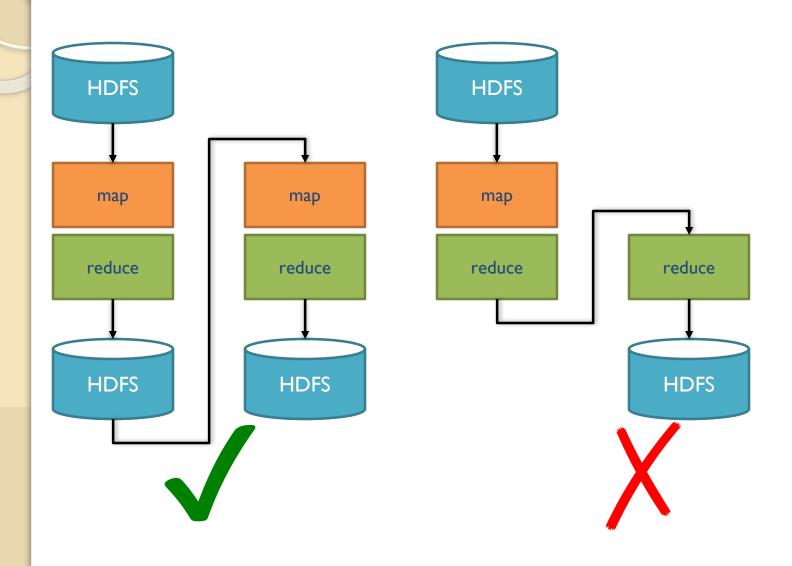
What's wrong?

Want MM?





Want MRR?



Spark

Answer to "What's beyond MapReduce?"

Brief history:

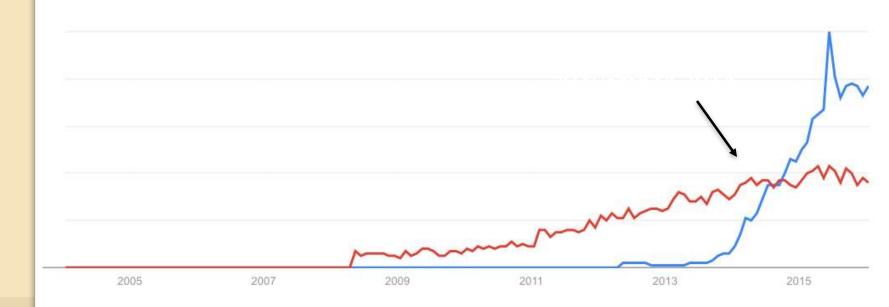
Developed at UC Berkeley AMPLab in 2009

Open-sourced in 2010

Became top-level Apache project in February 2014

Commercial support provided by DataBricks

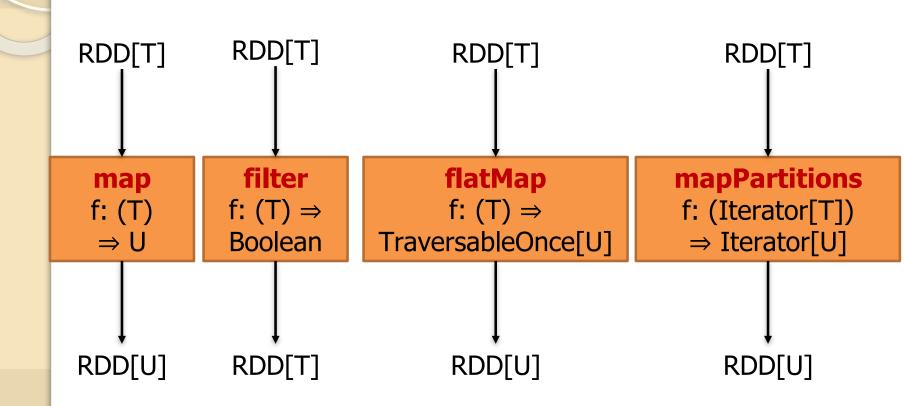
Spark vs. Hadoop Popularity



MapReduce

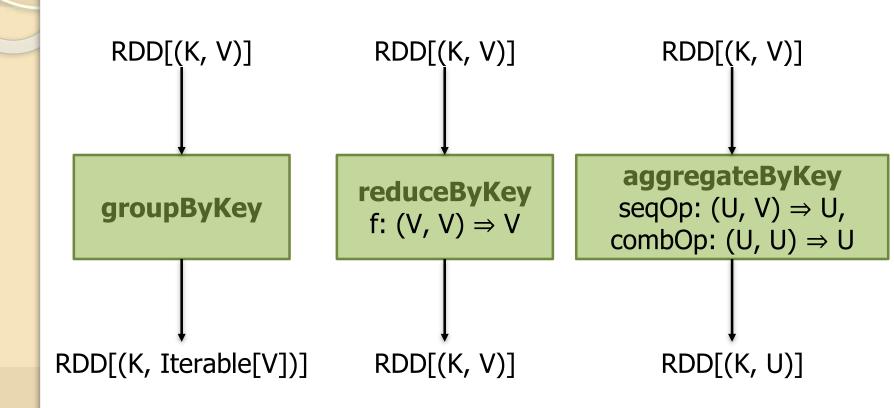
```
List[(K1,V1)]
           map
       f: (K1, V1)
    \Rightarrow List[(K2, V2)]
         reduce
g: (K2, Iterable[V2]) \Rightarrow
     List[(K3, V3)]
      List[K3,V3])
```

Map-like Operations

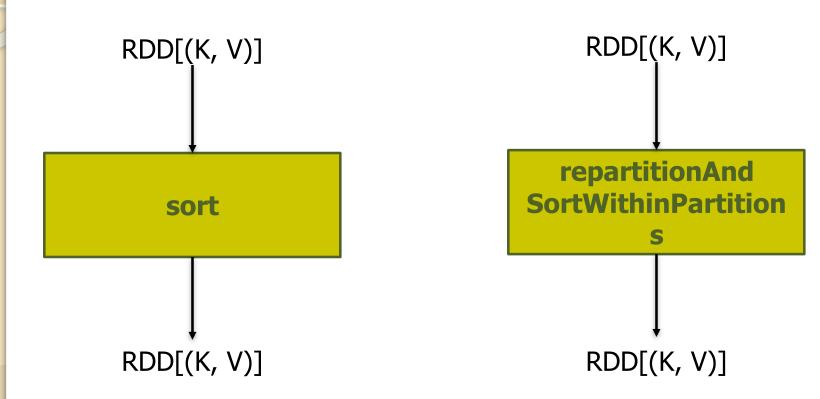


(Not meant to be exhaustive)

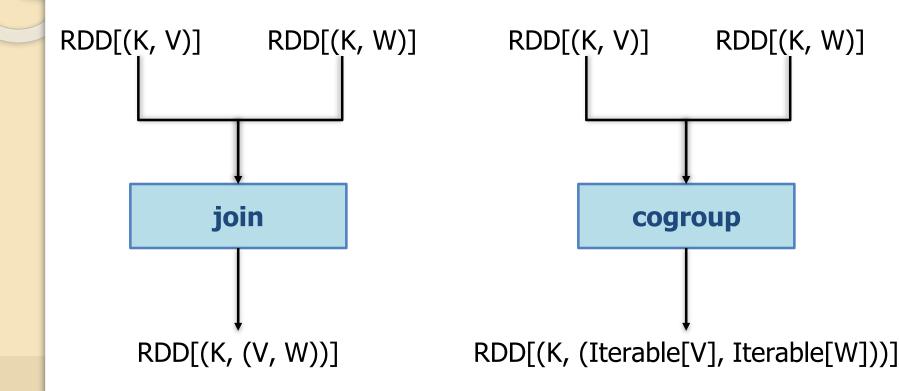
Reduce-like Operations



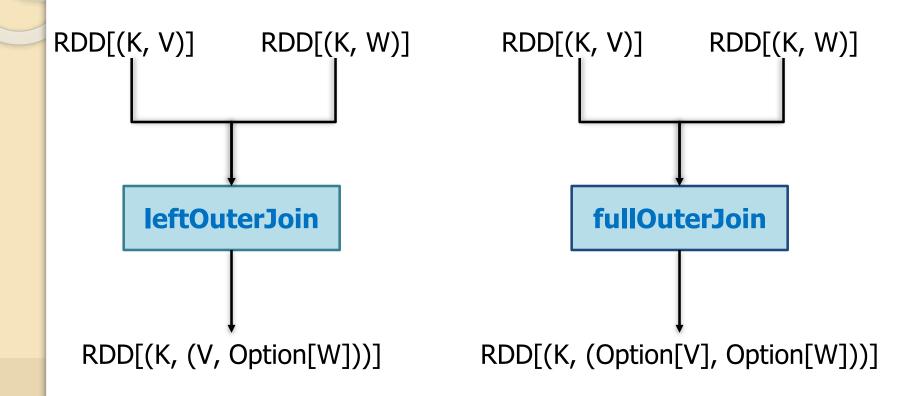
Sort Operations



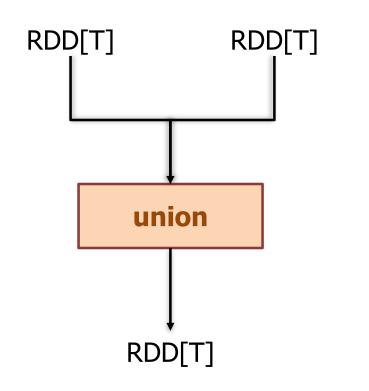
Join-like Operations

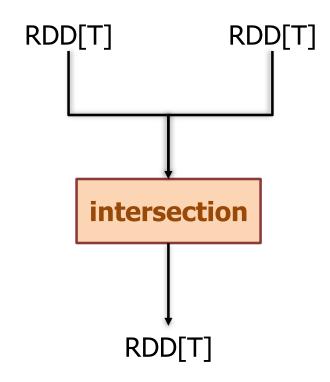


Join-like Operations

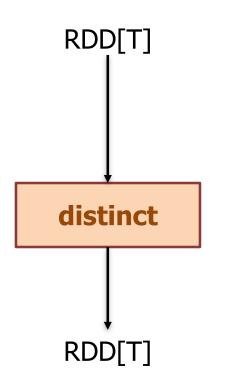


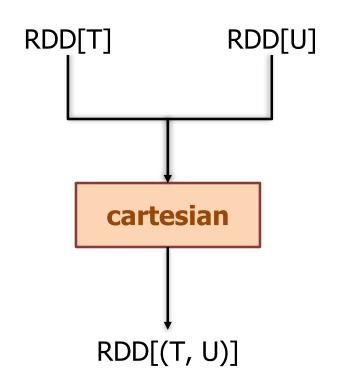
Set-ish Operations



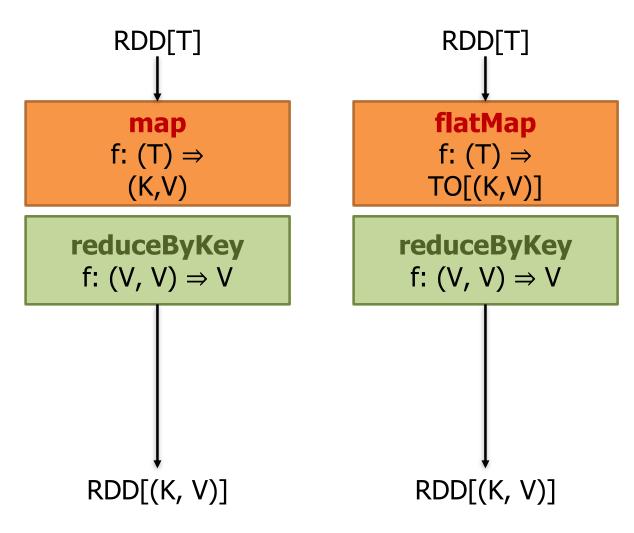


Set-ish Operations

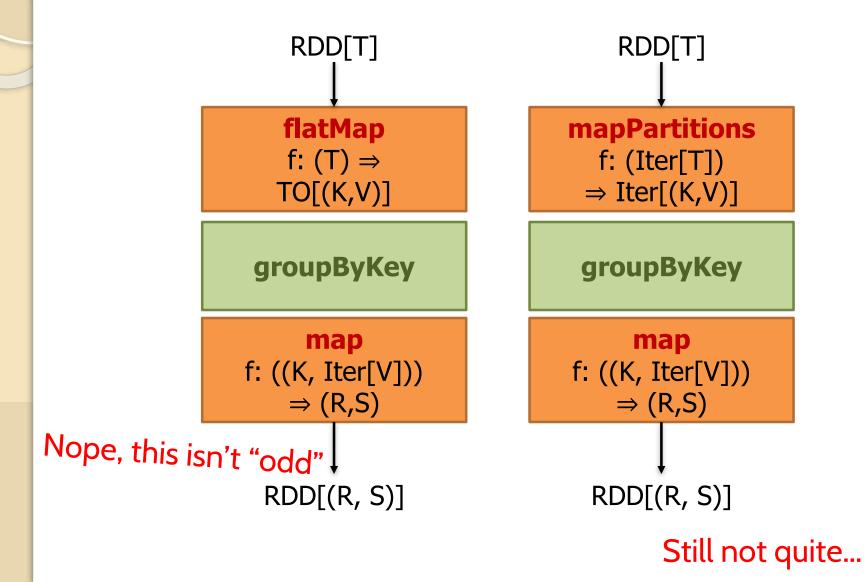




MapReduce in Spark?



MapReduce in Spark?



Don't focus on Java verbosity!

```
val textFile = sc.textFile(args.input())
textFile
 .map(object mapper {
  def map(key: Long, value: Text) =
    tokenize(value).foreach(word => write(word, 1))
  })
 .reduce(object reducer {
  def reduce(key: Text, values: Iterable[Int]) = {
   var sum = 0
    for (value <- values) sum += value
   write(key, sum)
  })
 .saveAsTextFile(args.output())
```

Spark Word Count

```
val textFile = sc.textFile(args.input())

textFile
   .flatMap(line => tokenize(line))
   .map(word => (word, 1))
   .reduceByKey(_ + _)
   .saveAsTextFile(args.output())

   (x, y) => x + y
```

Aside: Scala tuple access notation, e.g., a._1

Install Spark

Let's get started using Apache Spark, in just four easy steps... Step 1: Install Java JDK 6/7 on MacOSX or Windows oracle.com/technetwork/java/javase/downloads/jdk7-downloads-1880260.html follow the license agreement instructions then click the download for your OS need JDK instead of JRE (for Maven, etc.) this is much simpler on Linux: sudo apt-get -y install openjdk-7-jdk Step 2: Download the latest Spark version 2.4.4 open spark.apache.org/downloads.html with a browser double click the archive file to open it connect into the newly created directory

Run Spark with Shel

Step 3: Run Spark Shel we'll run Spark's interactive shell... ./bin/spark-shell then from the "scala>" REPL prompt, let's create some data... val data = 1 to 10000 Step 4: Create an RDD create an RDD based on that data... val distData = sc.parallelize(data) then use a filter to select values less than 10... distData.filter(_ < 10).collect() Check your output: gist.github.com/ceteri/f2c3486062c9610eac1d#file-O1-repl-txt

Run Spark with Scala

If using Scala, you can use <u>metals</u> for project management <u>Download</u> <u>starter code here.</u>

Install JDK 11+, sbt, and the Metals extension in VS Code and create a project.

You can either run the full project by running :

\$ sbt run

or Press `Ctrl+Shift+B` and pick **sbt: compile (watch)** to auto-compile.

Optional Downloads

Python:

For Python 2.7, check out Anaconda by Continuum Analytics for a full-featured platform: store.continuum.io/cshop/anaconda/

Maven

Java builds later also require Maven, which you can download at: maven.apache.org/download.cgi

Resources

- Jimmy Lin. CS 489/698 Big Data Infrastructure, Winter 2017.
 David R. Cheriton School of Computer Science, University of Waterloo http://lintool.github.io/bigdata-2017w/ This work is licensed under a Creative Commons Attribution
 Noncommercial-Share Alike 3.0 United States
- First part of this tutorial was adapted from <u>https://developer.yahoo.com/hadoop/tutorial/index.html</u>, under a <u>Creative Commons Attribution 3.0 Unported License</u>.