Introduction to Map/Reduce: From Hadoop to SPARK

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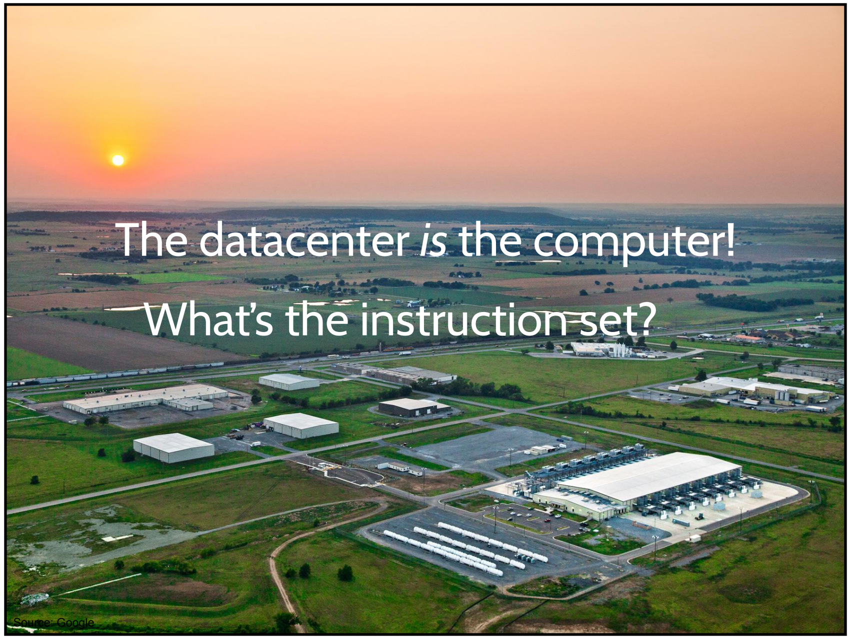
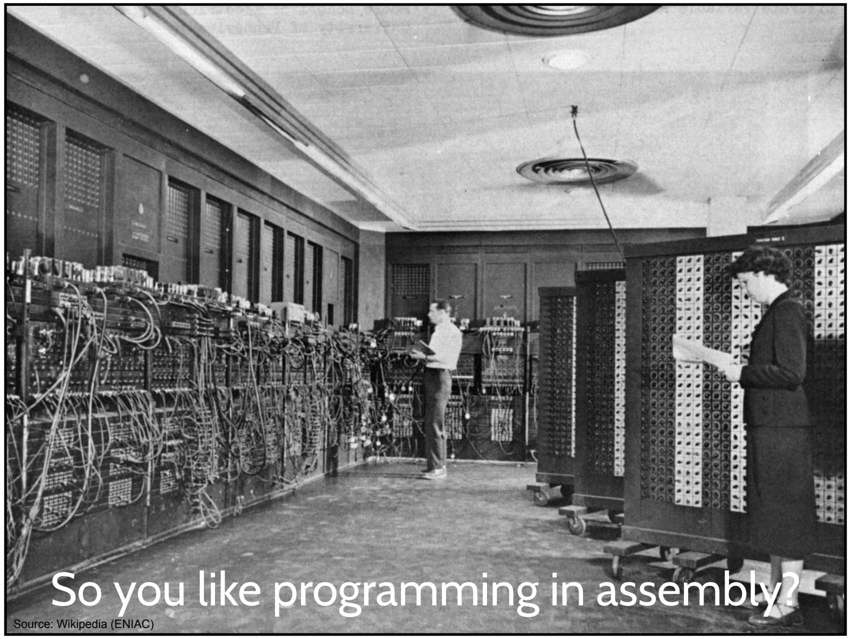
What we will cover…

- 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


The datacenter *is* the computer!
What's the instruction set?
Source: Google


So you like programming in assembly?
Source: Wikipedia (ENIAC)

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

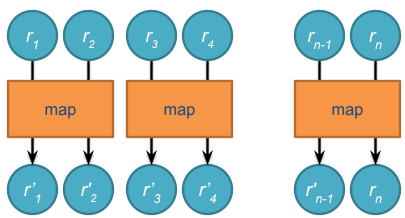
Data-Parallel Dataflow Languages

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?)

We Need Per-record Processing



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

What is MapReduce?

A programming model 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 have to do is provide the implementation of two methods:

- map()
- reduce()

...but we can 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

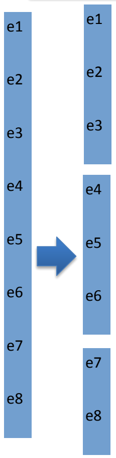
- the intermediate output of the program

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

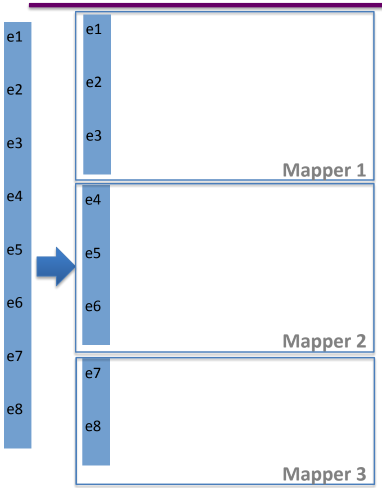
- the final output of the program

MapReduce – Input Data

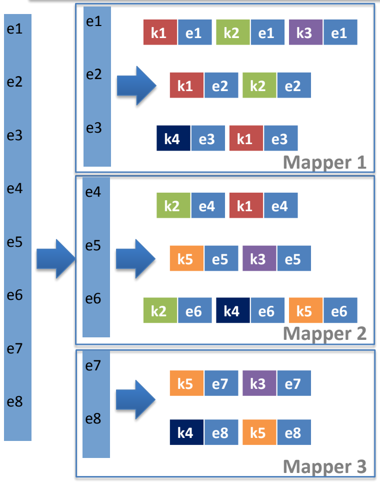
MapReduce – Input Data Splitting



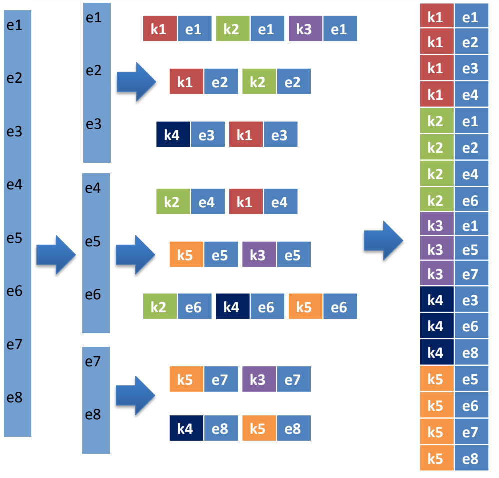
MapReduce – Mapper Input



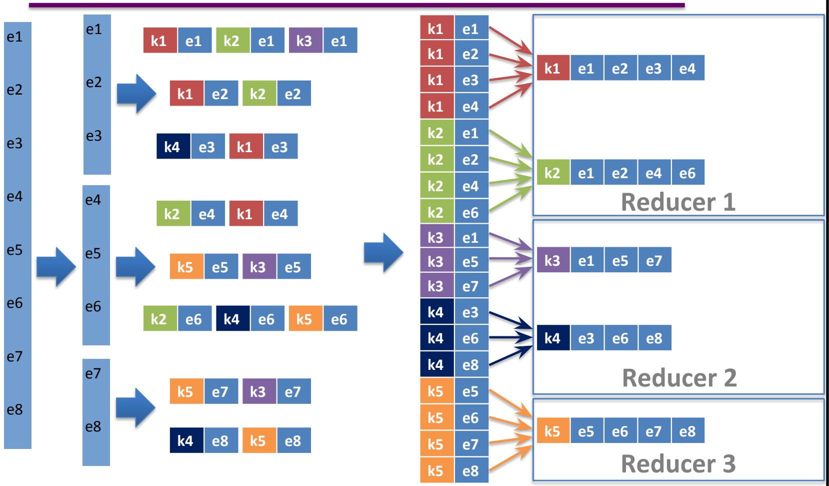
MapReduce – Mapper Output



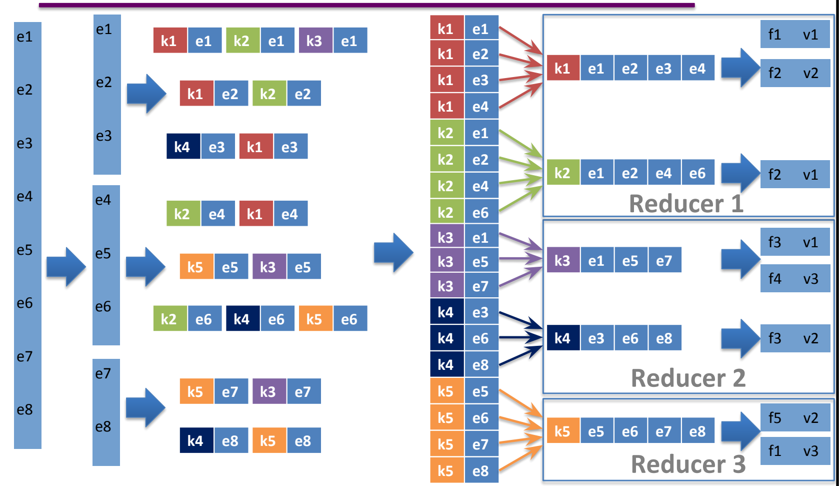
MapReduce – Shuffling & Sorting (simplified)



MapReduce – Reducing



MapReduce – Reducing



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

<u>Idea:</u>

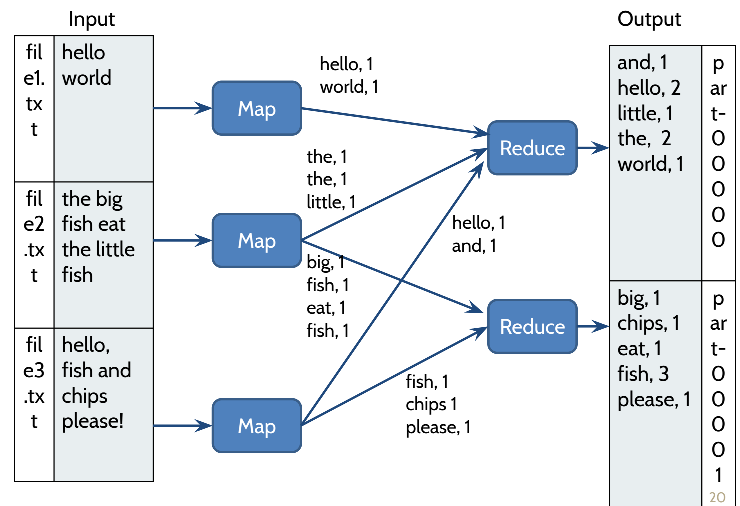
Map:

`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

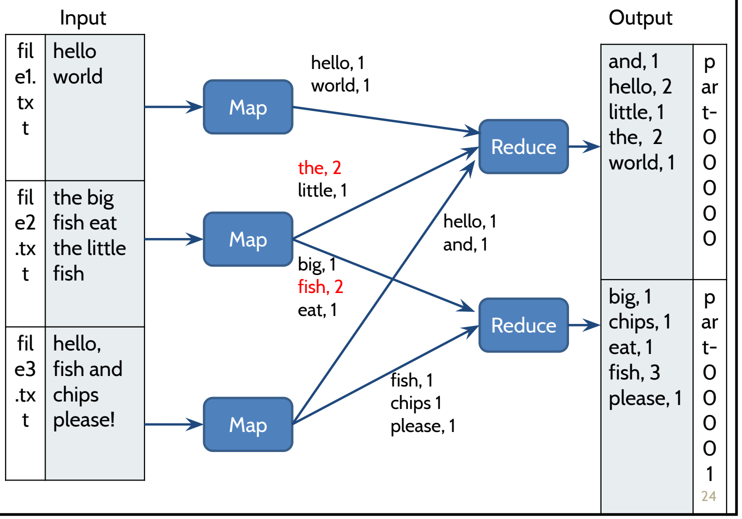
```
public static class Reduce extends Reducer<Text,
  IntWritable, Text, IntWritable>

   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



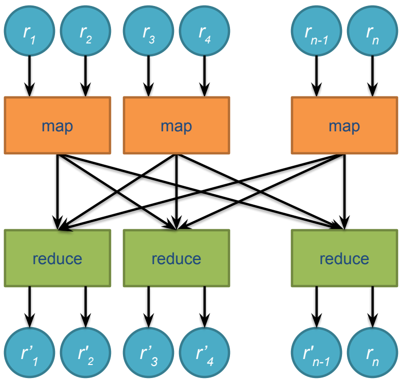
Map Alone Isn't Enough!

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

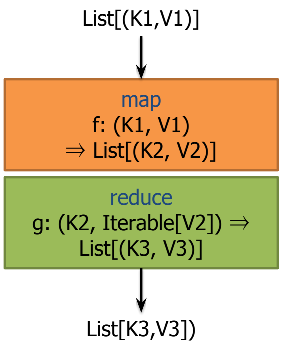
Once we resolve the addressing, apply another computation

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

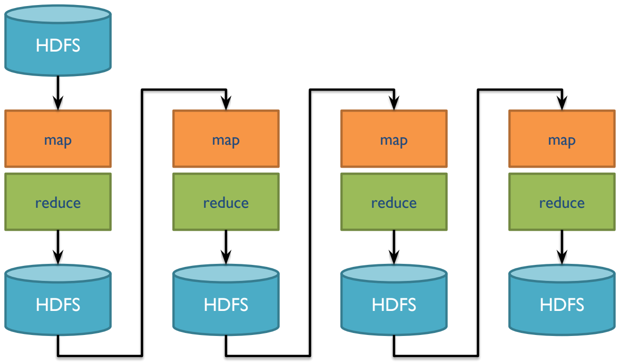
MapReduce



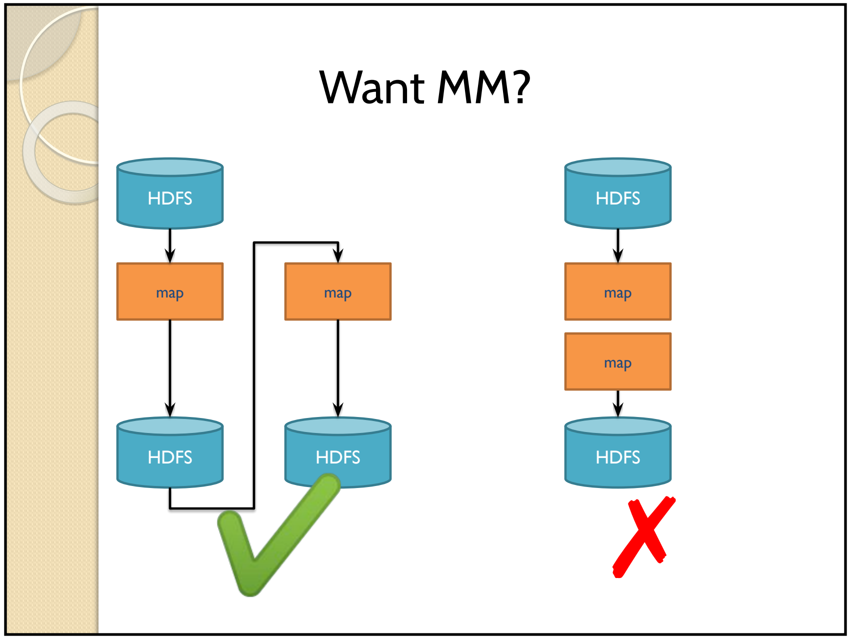
MapReduce



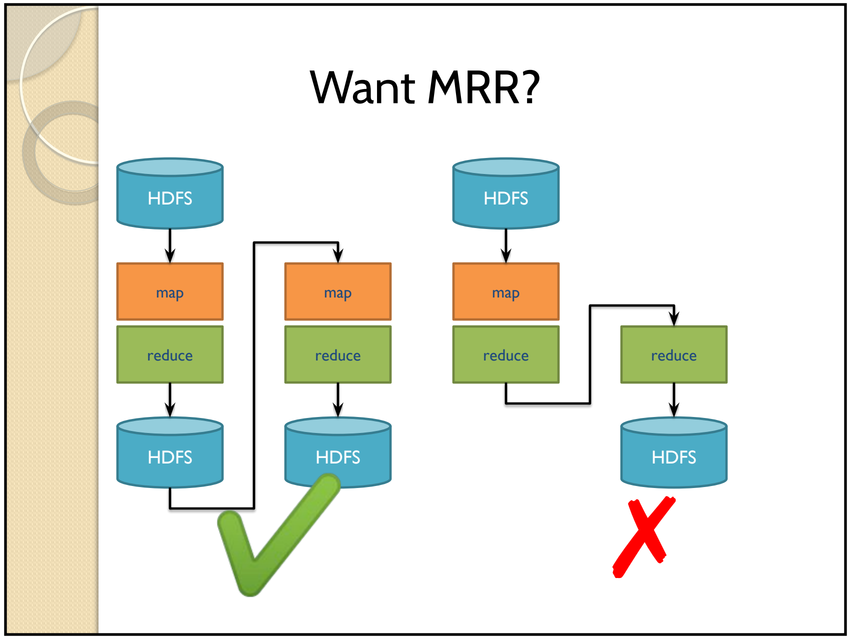
MapReduce Workflows



What's wrong?



Want MM?
HDFS
map
map
HDFS
HDFS
HDFS
map
map
HDFS



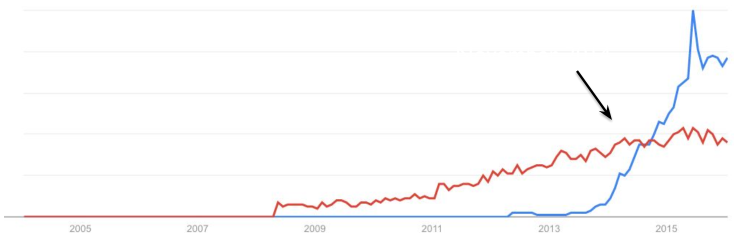
Want MRR?
HDFS
map
reduce
map
reduce
HDFS
HDFS
HDFS
map
reduce
reduce
HDFS

Spark

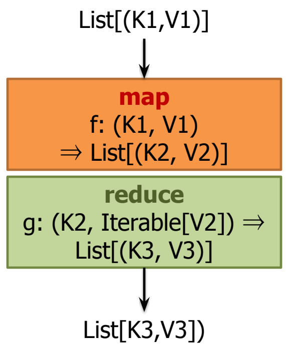
Answer to "What's beyond MapReduce?"

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

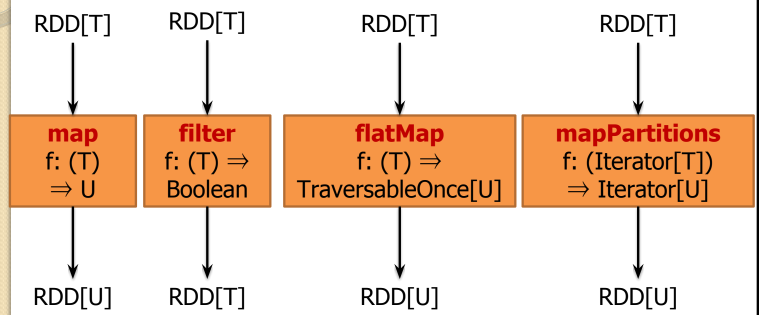
Spark vs. Hadoop Popularity



MapReduce

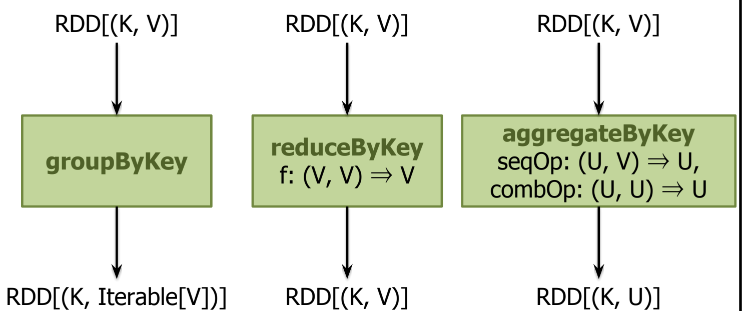


Map-like Operations



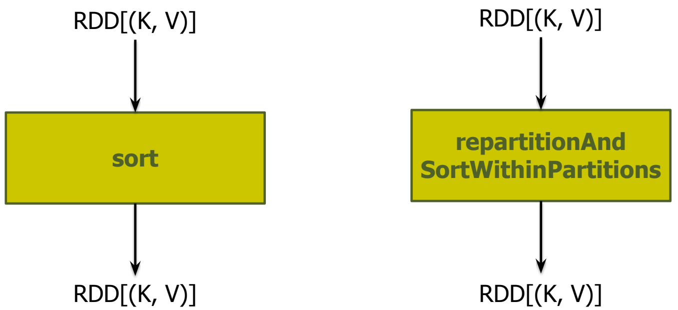
(Not meant to be exhaustive)

Reduce-like Operations

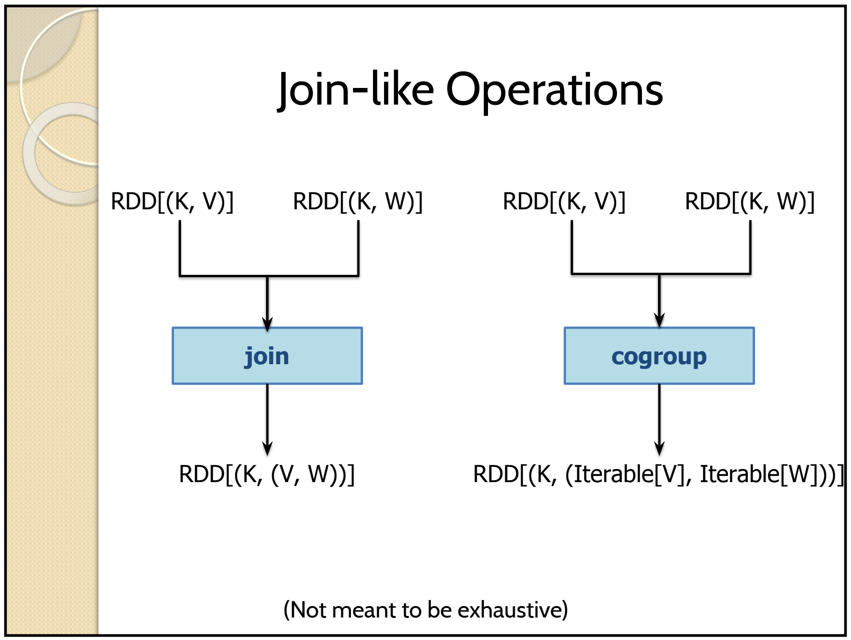


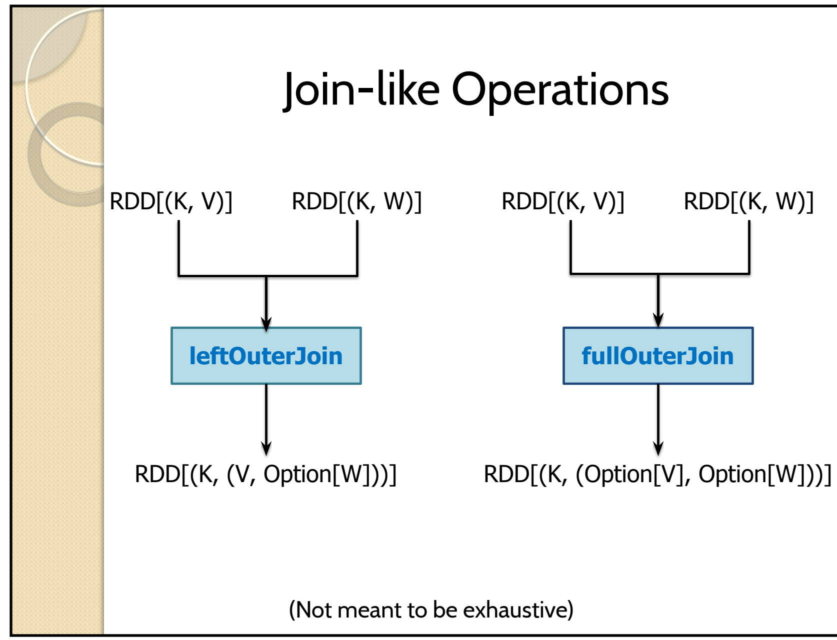
(Not meant to be exhaustive)

Sort Operations

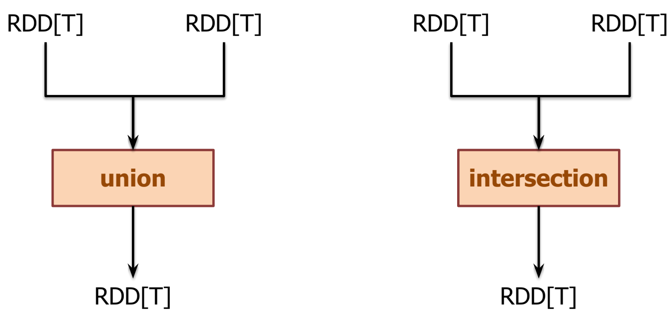


(Not meant to be exhaustive)


Join-like Operations
RDD[(K, V)]
RDD[(K, W)]
join
RDD[(K, (V, W))]
RDD[(K, V)]
RDD[(K, W)]
cogroup
RDD[(K, (Iterable[V], Iterable[W]))]
(Not meant to be exhaustive)

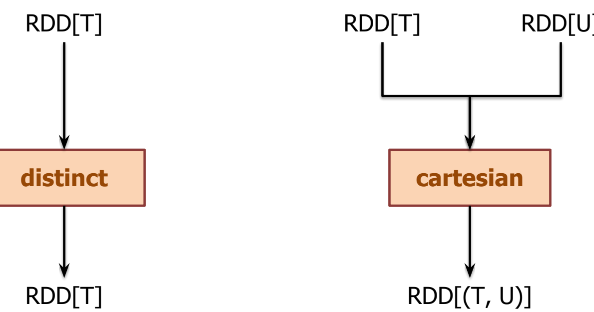

Join-like Operations
RDD[(K, V)]
RDD[(K, W)]
leftOuterJoin
RDD[(K, (V, Option[W]))]
RDD[(K, V)]
RDD[(K, W)]
fullOuterJoin
RDD[(K, (Option[V], Option[W]))]
(Not meant to be exhaustive)

Set-ish Operations



(Not meant to be exhaustive)

Set-ish Operations



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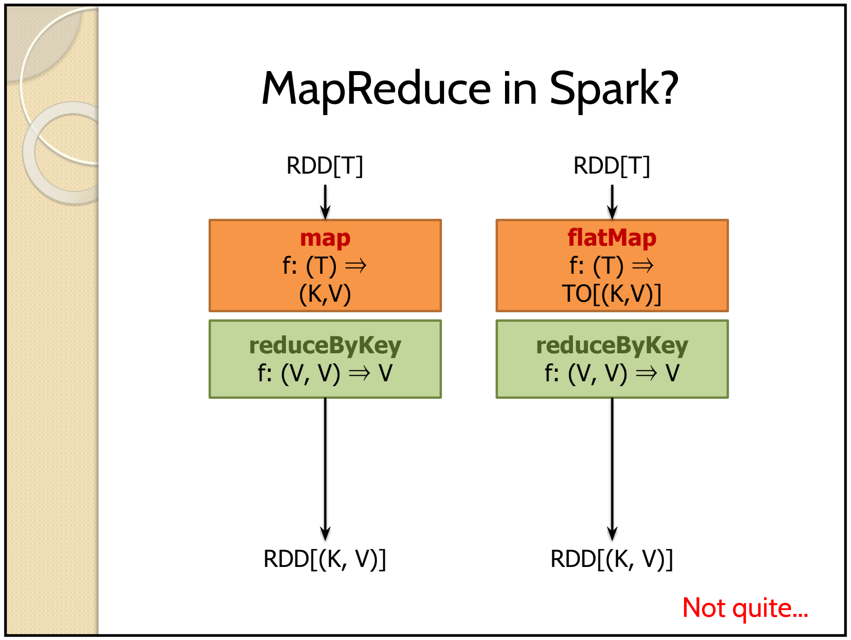
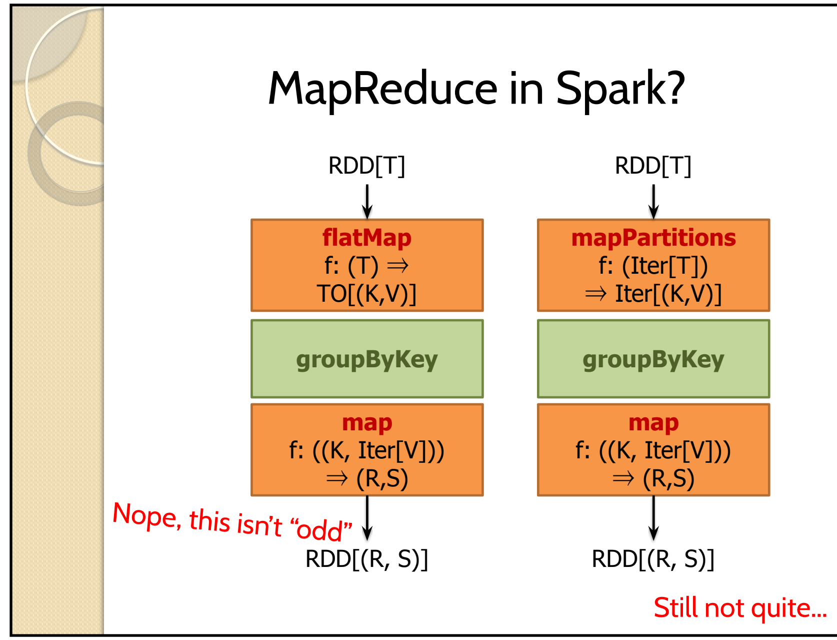

MapReduce in Spark?
RDD[T]
map
f: (T) ⇒ (K,V)
reduceByKey
f: (V, V) ⇒ V
RDD[(K, V)]
RDD[T]
flatMap
f: (T) ⇒ TO[(K,V)]
reduceByKey
f: (V, V) ⇒ V
RDD[(K, V)]
Not quite…


MapReduce in Spark?
RDD[T]
flatMap
f: (T) ⇒ TO[(K,V)]
groupByKey
map
f: ((K, Iter[V])) ⇒ (R,S)
Nope, this isn't "odd"
RDD[(R, S)]
RDD[T]
mapPartitions
f: (Iter[T]) ⇒ Iter[(K,V)]
groupByKey
map
f: ((K, Iter[V])) ⇒ (R,S)
RDD[(R, S)]
Still not quite…

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`

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())
```

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

Install Spark

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-01-repl-txt

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
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