

TechMesh London 2012
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dean@deanwampler.com
polyglotprogramming.com/talks

MapReduce and Its Discontents



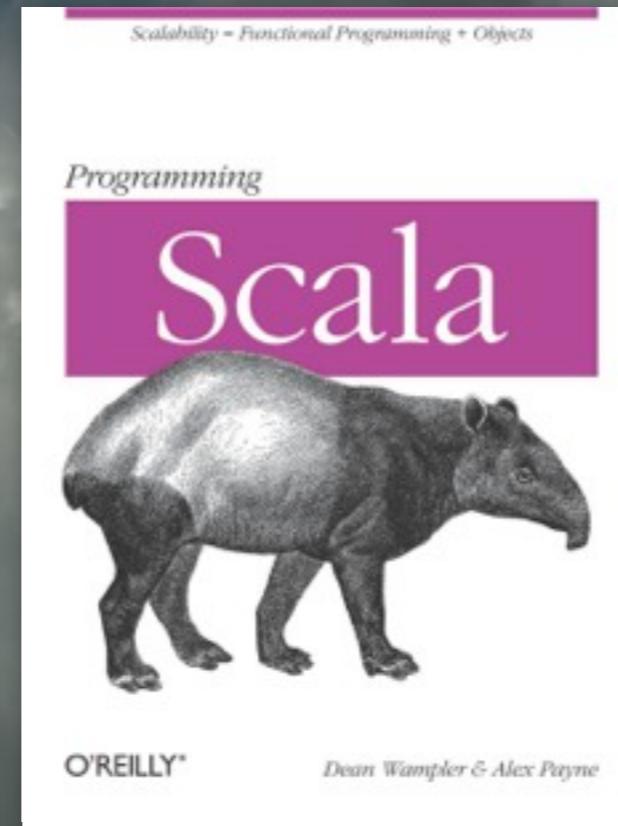
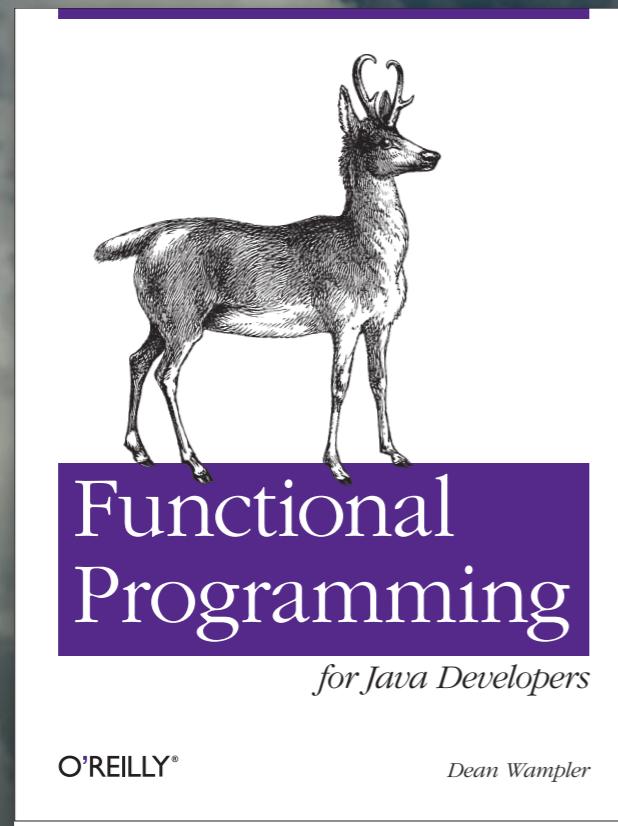
Thursday, April 11, 13

Beyond MapReduce: it's been a useful technology, but has a "first generation" feel. What's next?

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About Me...

dean@deanwampler.com
[@deanwampler](https://twitter.com/deanwampler)
github.com/deanwampler



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My books and contact information.

Big Data

Data so big that traditional solutions are too slow, too small, or too expensive to use.



It's a buzz word, but generally associated with the problem of data sets too big to manage with traditional SQL databases. A parallel development has been the NoSQL movement that is good at handling semistructured data, scaling, etc.



3 Trends

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Three trends influence my thinking...

Data Size ↑

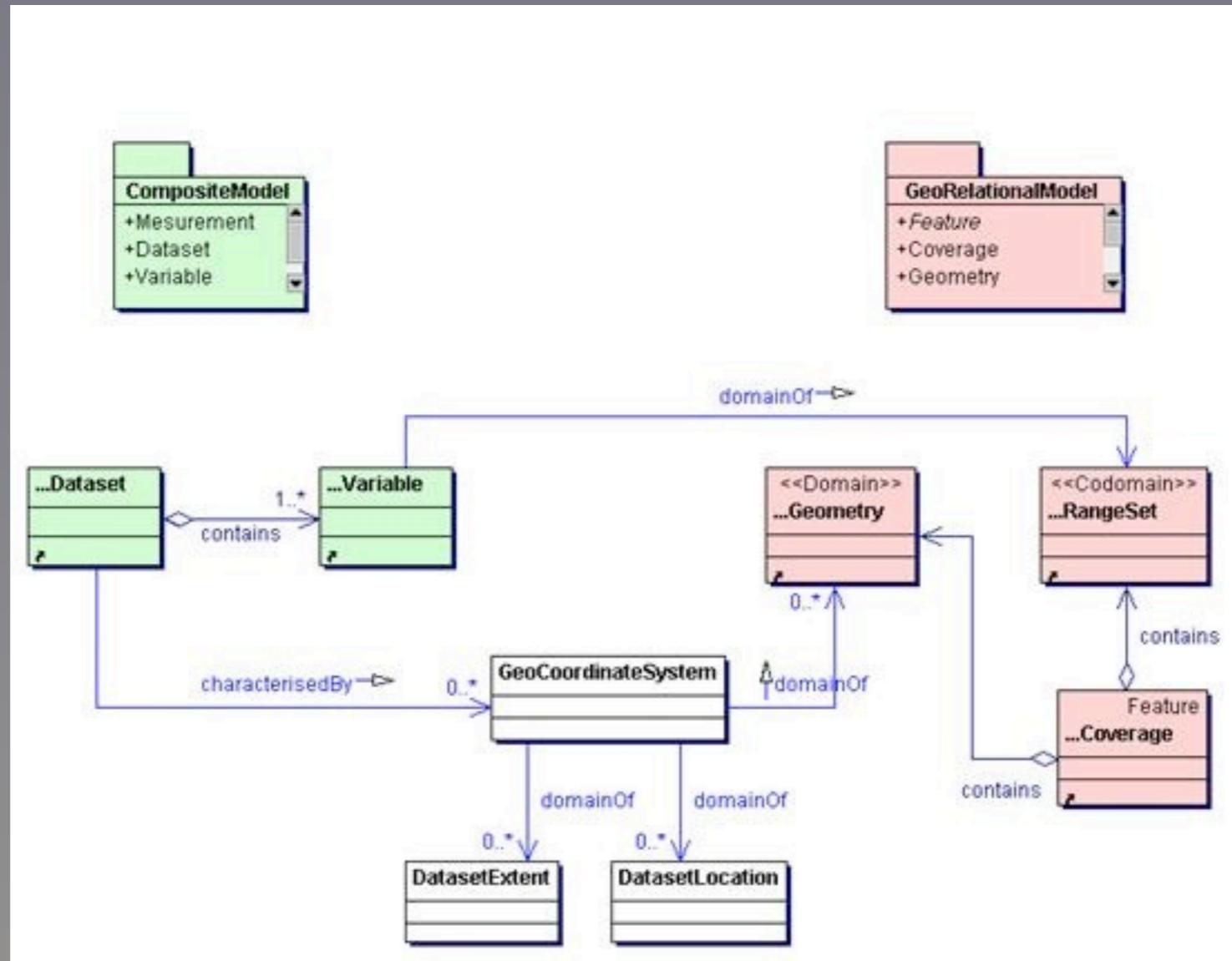


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Data volumes are obviously growing... rapidly.
Facebook now has over 600PB (Petabytes) of data in Hadoop clusters!

Formal Schemas



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There is less emphasis on “formal” schemas and domain models, i.e., both relational models of data and OO models, because data schemas and sources change rapidly, and we need to integrate so many disparate sources of data. So, using relatively-agnostic software, e.g., collections of things where the software is more agnostic about the structure of the data and the domain, tends to be faster to develop, test, and deploy. Put another way, we find it more useful to build somewhat agnostic applications and drive their behavior through data...

Data-Driven Programs ↑



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This is the 2nd generation “Stanley”, the most successful self-driving car ever built (by a Google-Stanford) team. Machine learning is growing in importance. Here, generic algorithms and data structures are trained to represent the “world” using data, rather than encoding a model of the world in the software itself. It’s another example of generic algorithms that produce the desired behavior by being application agnostic and data driven, rather than hard-coding a model of the world. (In practice, however, a balance is struck between completely agnostic apps and some engineering towards for the specific problem, as you might expect...)

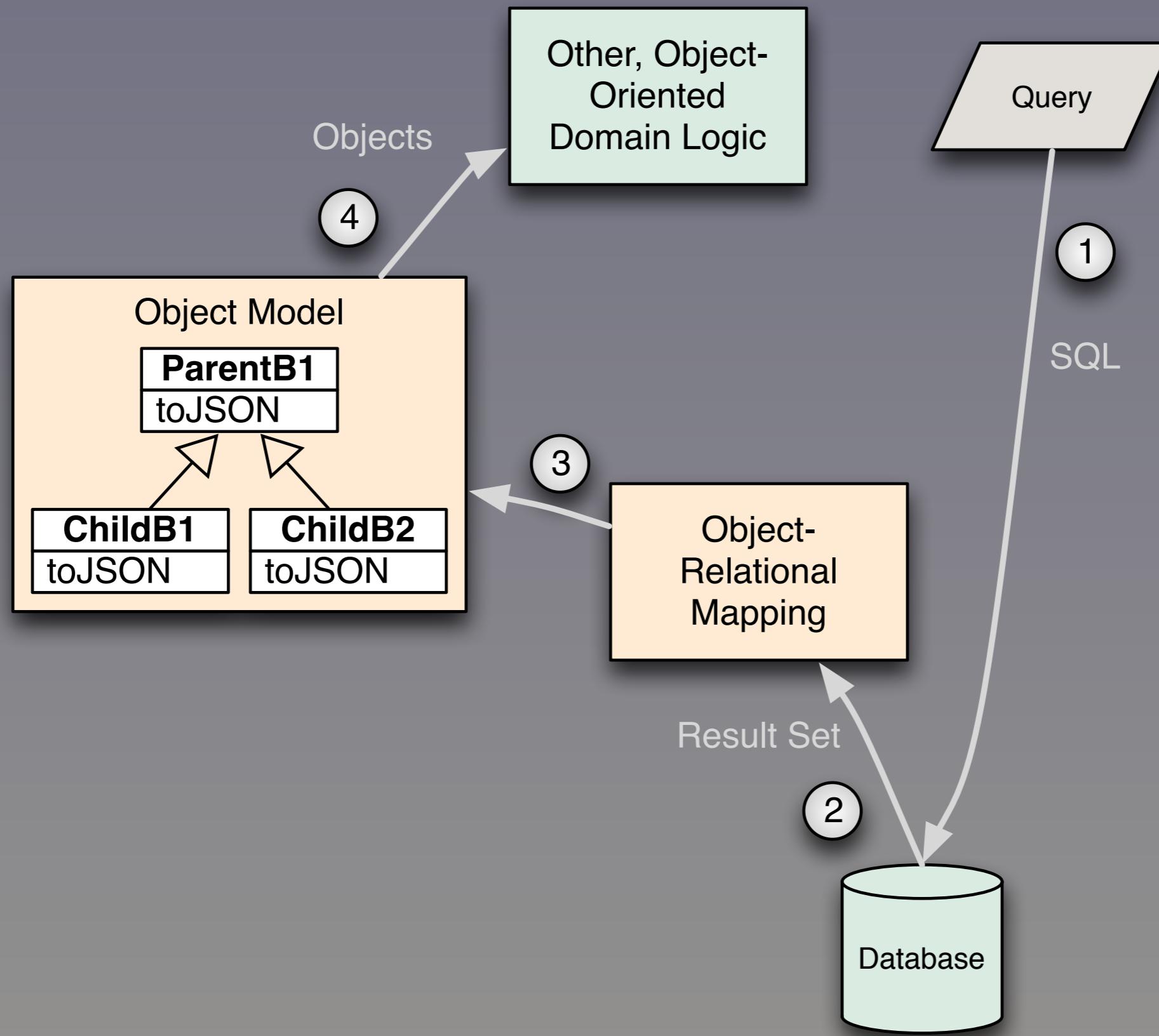


Big Data Architectures

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What should software architectures look like for these kinds of systems?

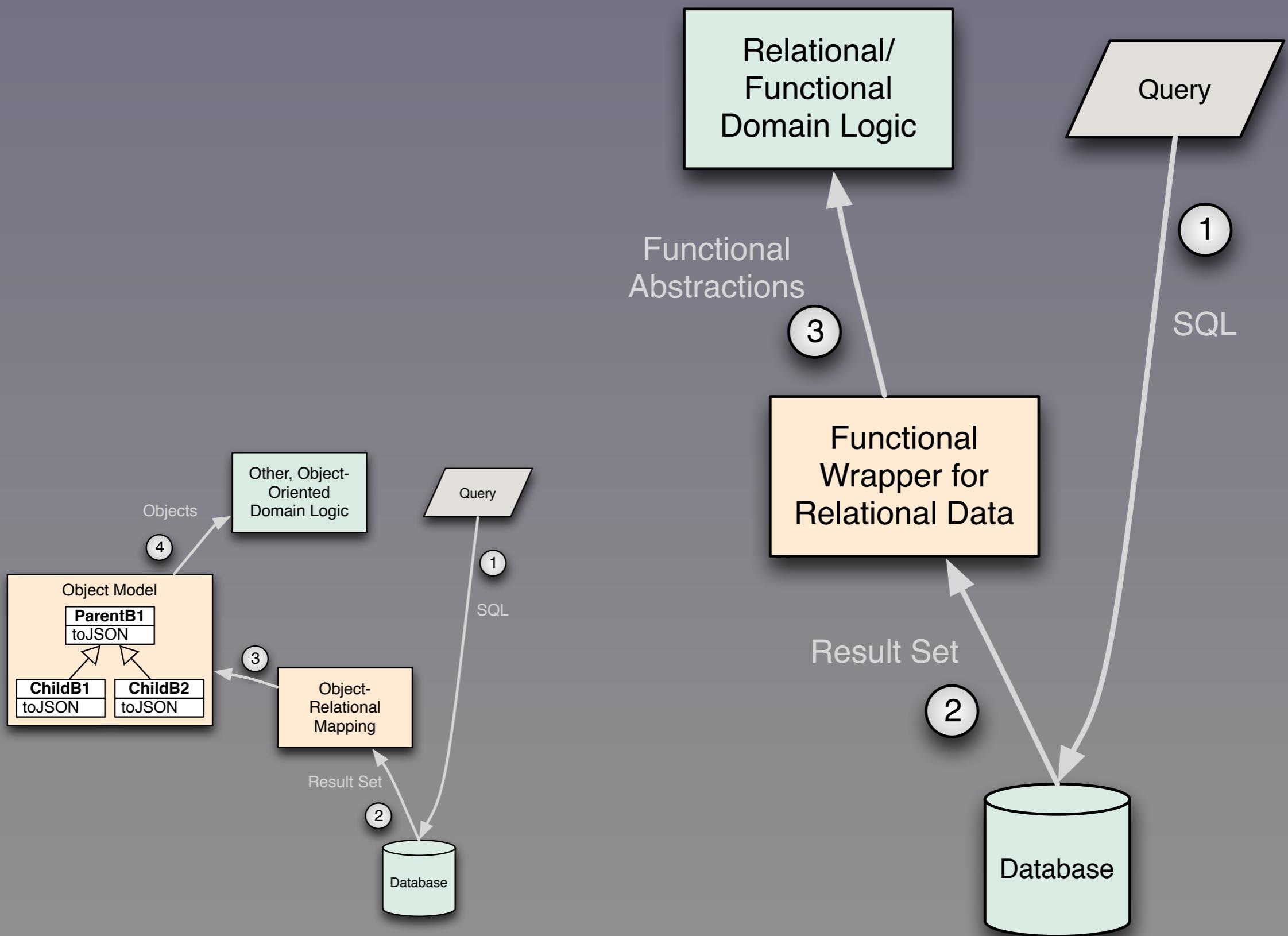


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Traditionally, we've kept a rich, in-memory domain model requiring an ORM to convert persistent data into the model. This is resource overhead and complexity we can't afford in big data systems. Rather, we should treat the result set as it is, a particular kind of collection, do the minimal transformation required to exploit our collections libraries and classes representing some domain concepts (e.g., Address, StockOption, etc.), then write functional code to implement business logic (or drive emergent behavior with machine learning algorithms...)

The **toJSON** methods are there because we often convert these object graphs back into fundamental structures, such as the maps and arrays of JSON so we can send them to the browser!



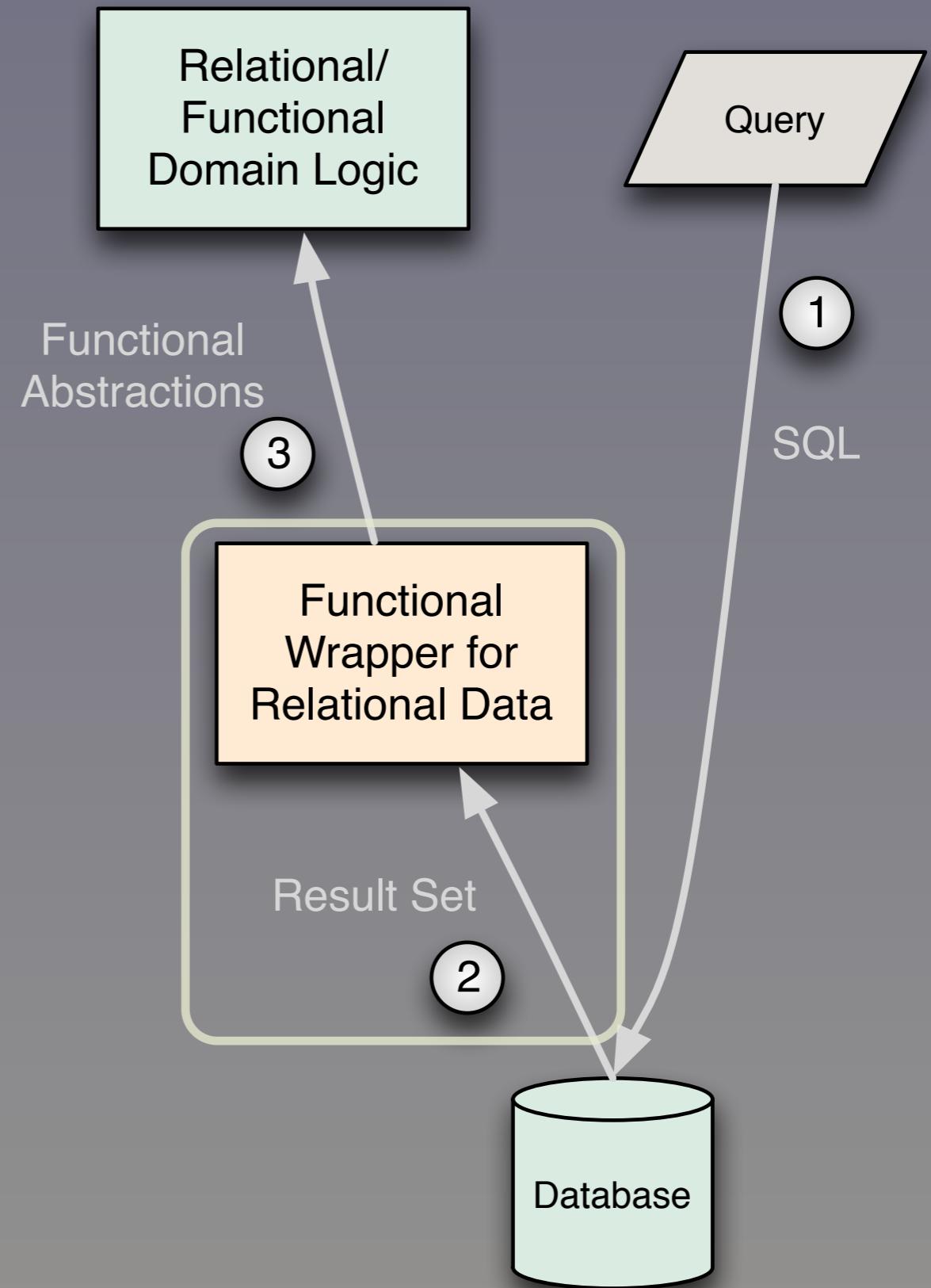
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But the traditional systems are a poor fit for this new world: 1) they add too much overhead in computation (the ORM layer, etc.) and memory (to store the objects). Most of what we do with data is mathematical transformation, so we're far more productive (and runtime efficient) if we embrace fundamental data structures used throughout (lists, sets, maps, trees) and build rich transformations into those libraries, transformations that are composable to implement business logic.

- Focus on:

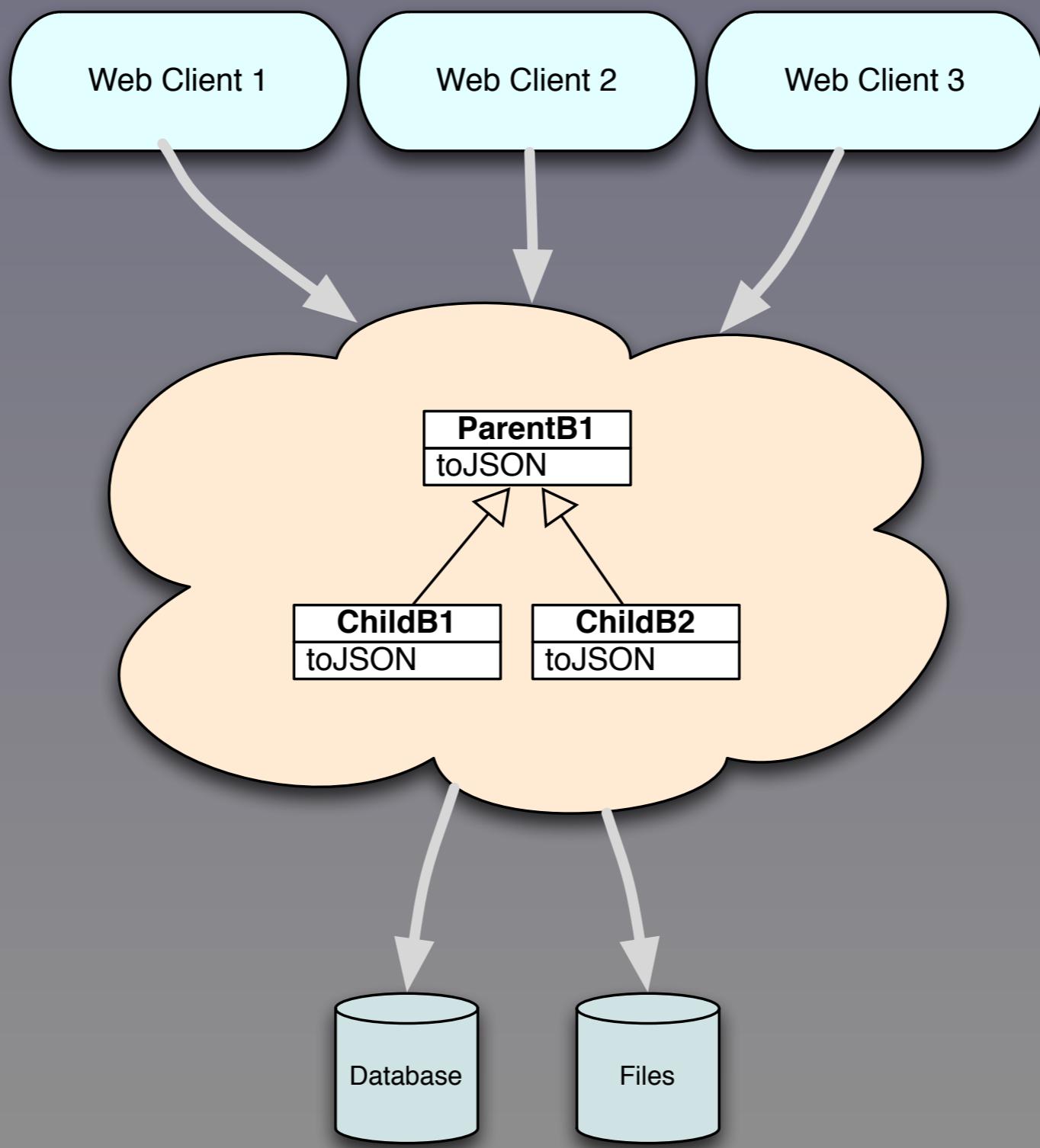
- Lists
- Maps
- Sets
- Trees
- ...



II

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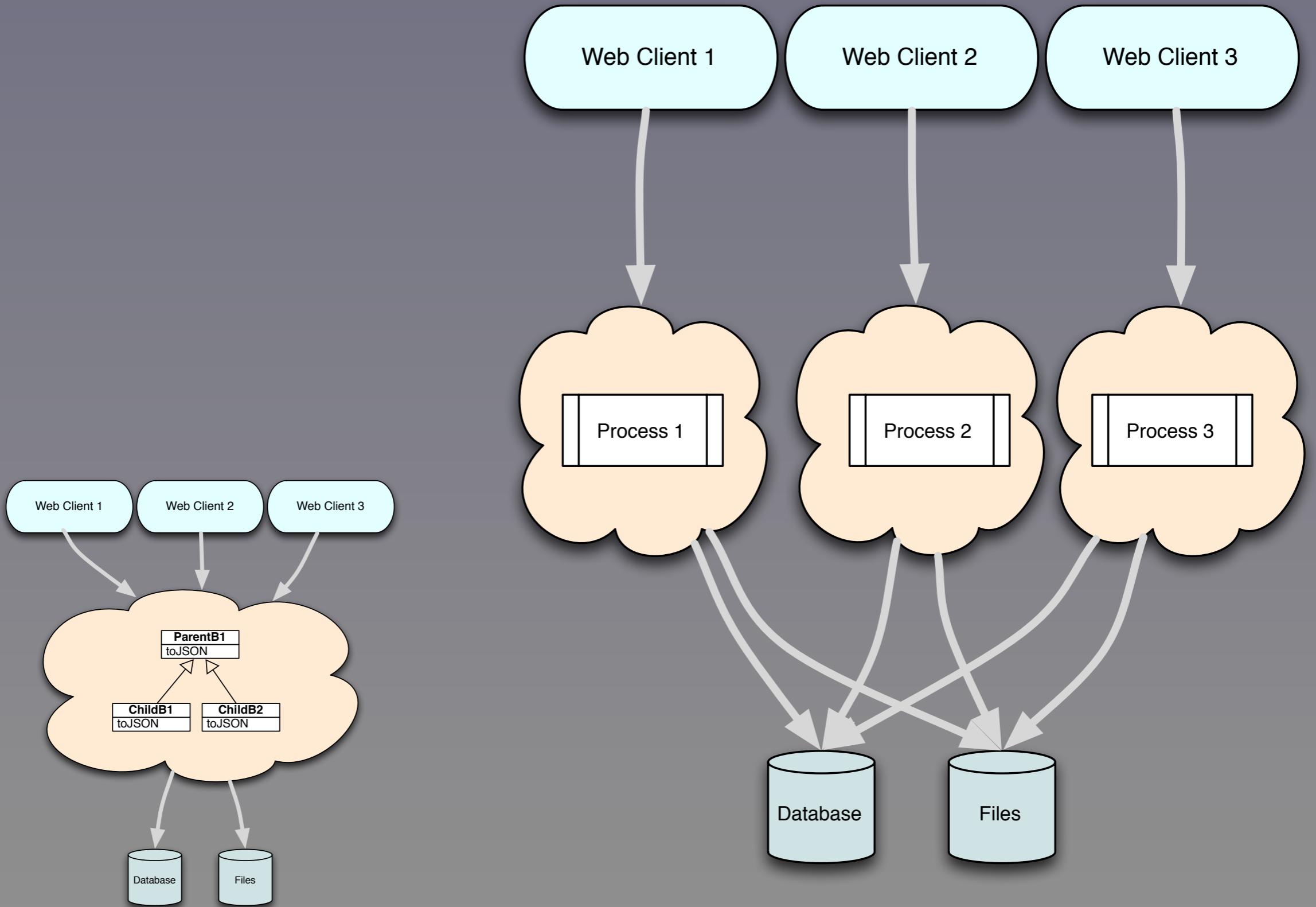
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In a broader view, object models tend to push us towards centralized, complex systems that don't decompose well and stifle reuse and optimal deployment scenarios. FP code makes it easier to write smaller, focused services that we compose and deploy as appropriate.



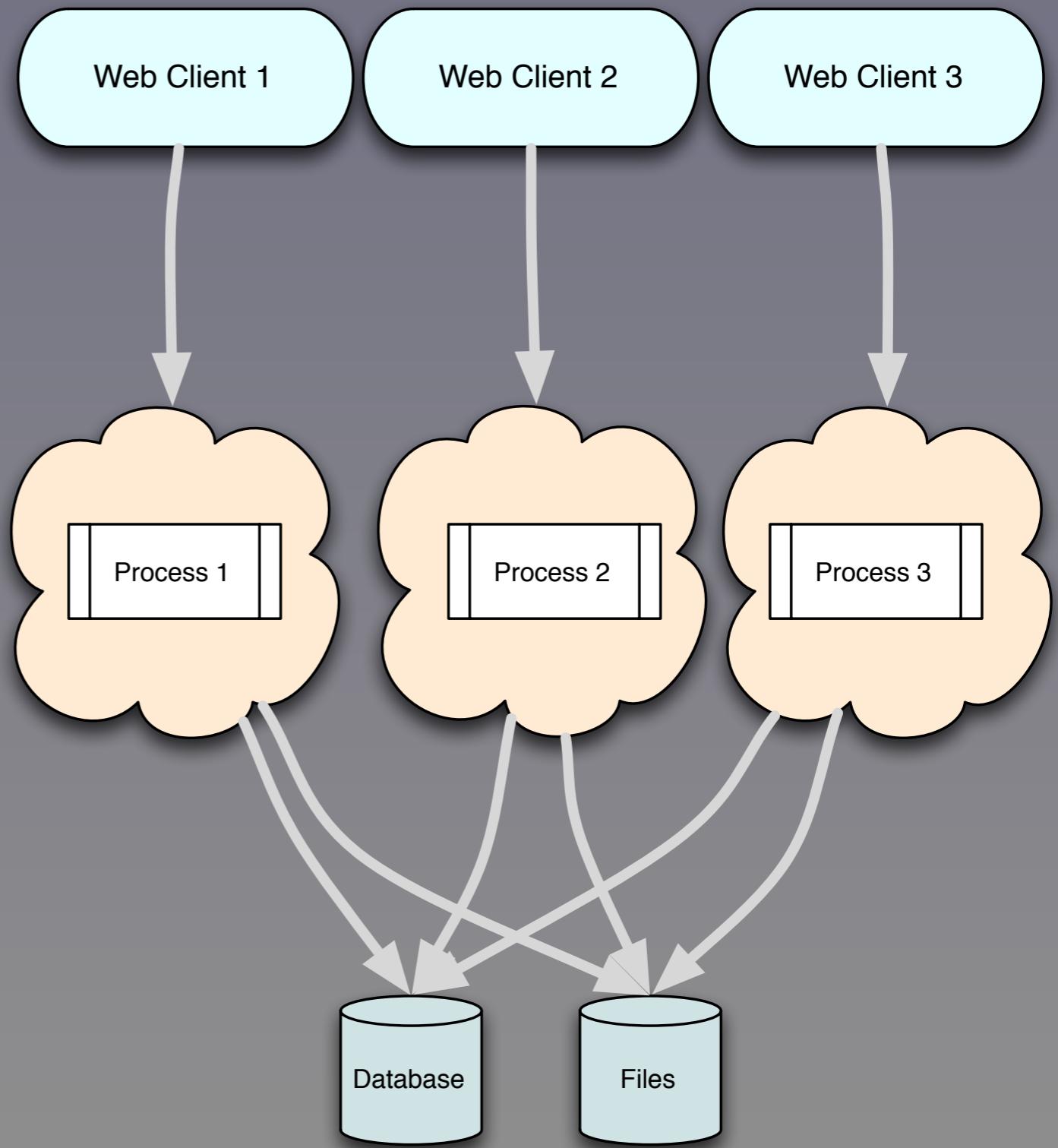
13

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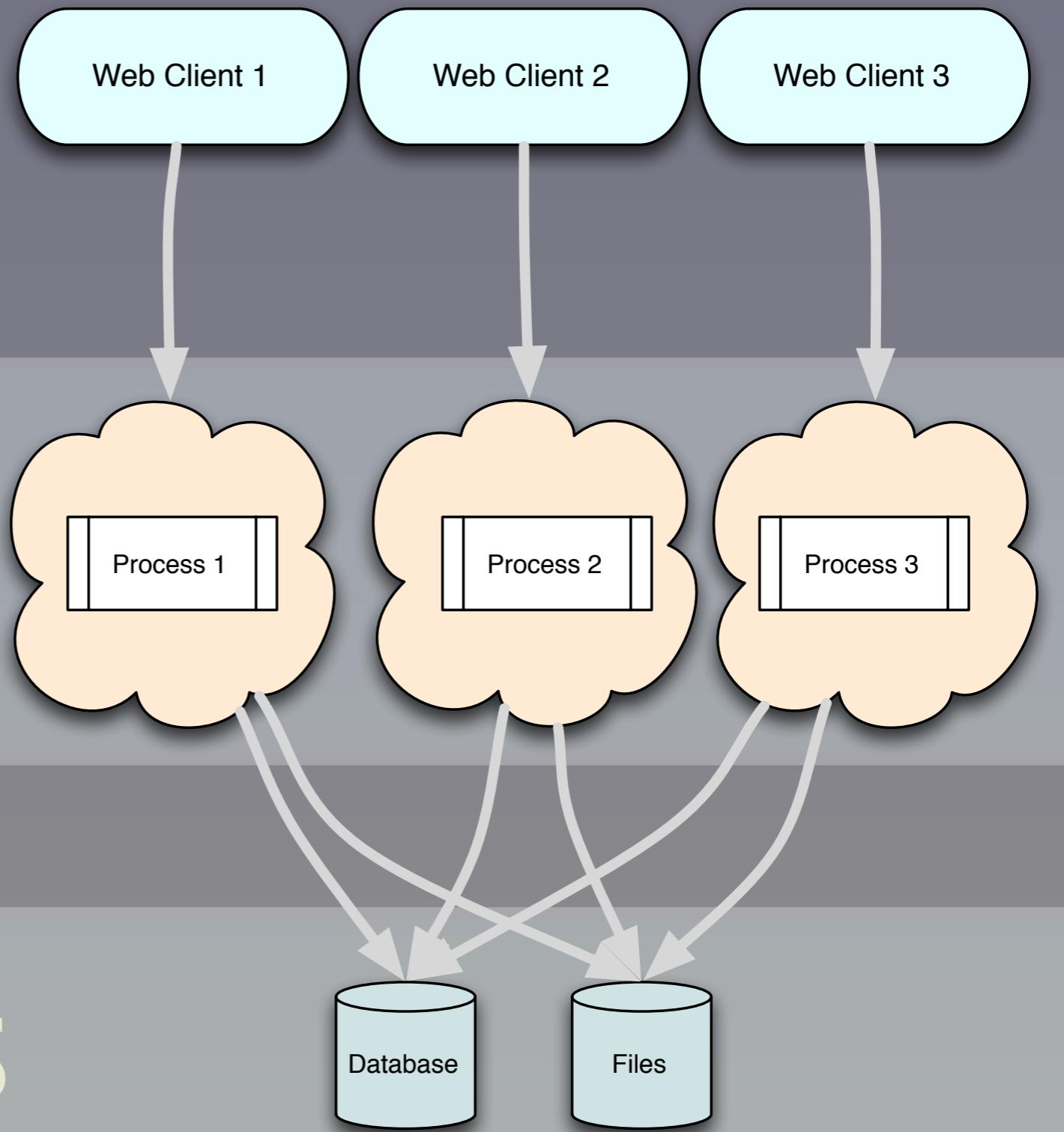
In a broader view, object models tend to push us towards centralized, complex systems that don't decompose well and stifle reuse and optimal deployment scenarios. FP code makes it easier to write smaller, focused services that we compose and deploy as appropriate. Each "ProcessN" could be a parallel copy of another process, for horizontal, "shared-nothing" scalability, or some of these processes could be other services...

Smaller, focused services scale better, especially horizontally. They also don't encapsulate more business logic than is required, and this (informal) architecture is also suitable for scaling ML and related algorithms.

- Data Size ↑
- Formal Schema ↓
- Data-Driven Programs ↑



- MapReduce

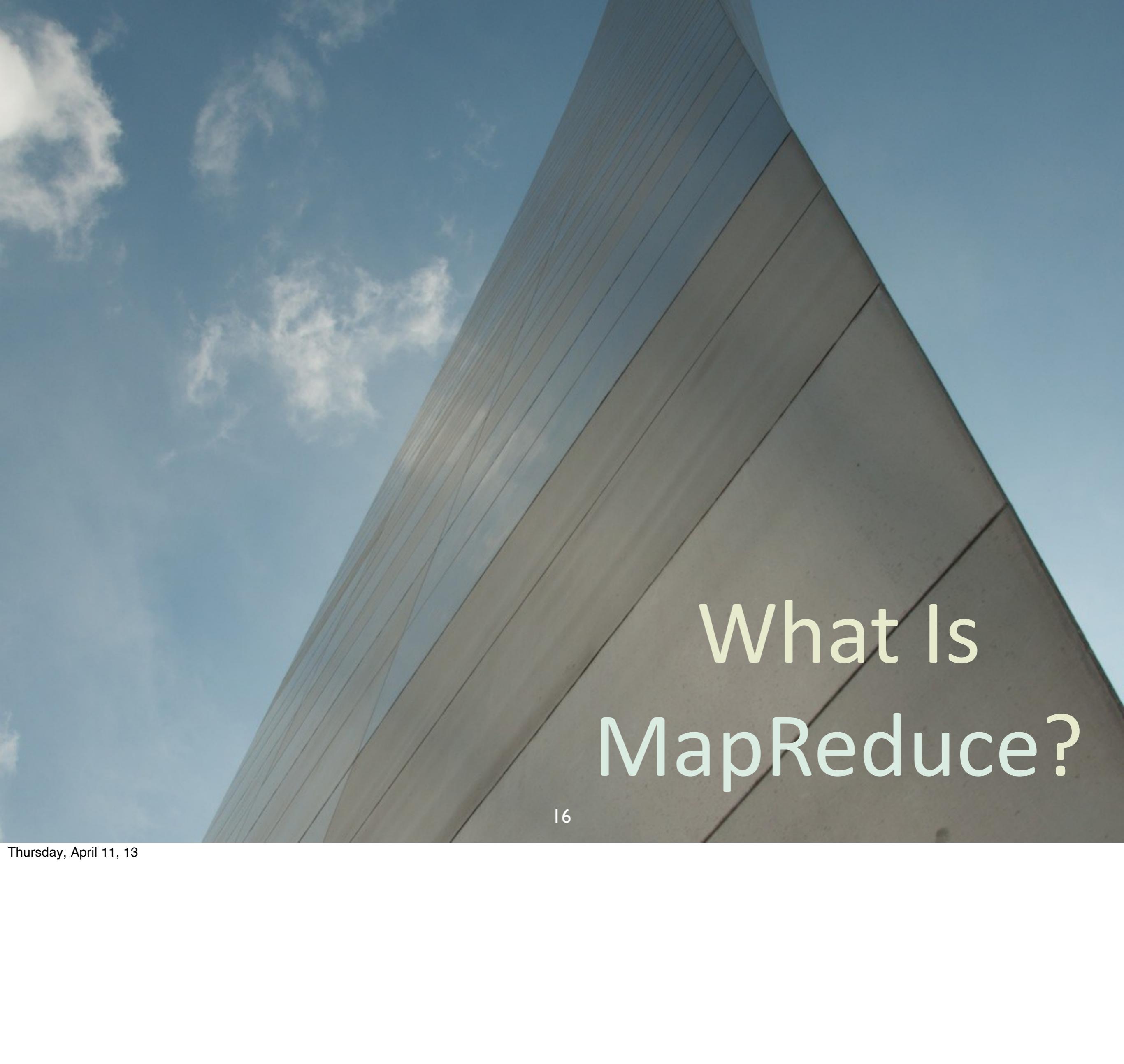


- Distributed FS

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And MapReduce + a distributed file system, like Hadoop's MapReduce and HDFS, fit this model.

The background of the slide features a photograph of a modern architectural structure, likely a stadium or arena, with a distinctive curved, light-colored facade made of many thin panels. The building is set against a clear blue sky with scattered white clouds.

What Is MapReduce?

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MapReduce in Hadoop

Let's look at a
MapReduce algorithm:
WordCount.

(The *Hello World* of big data...)

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Let's walk through the "Hello World" of MapReduce, the Word Count algorithm, at a conceptual level. We'll see actual code shortly!

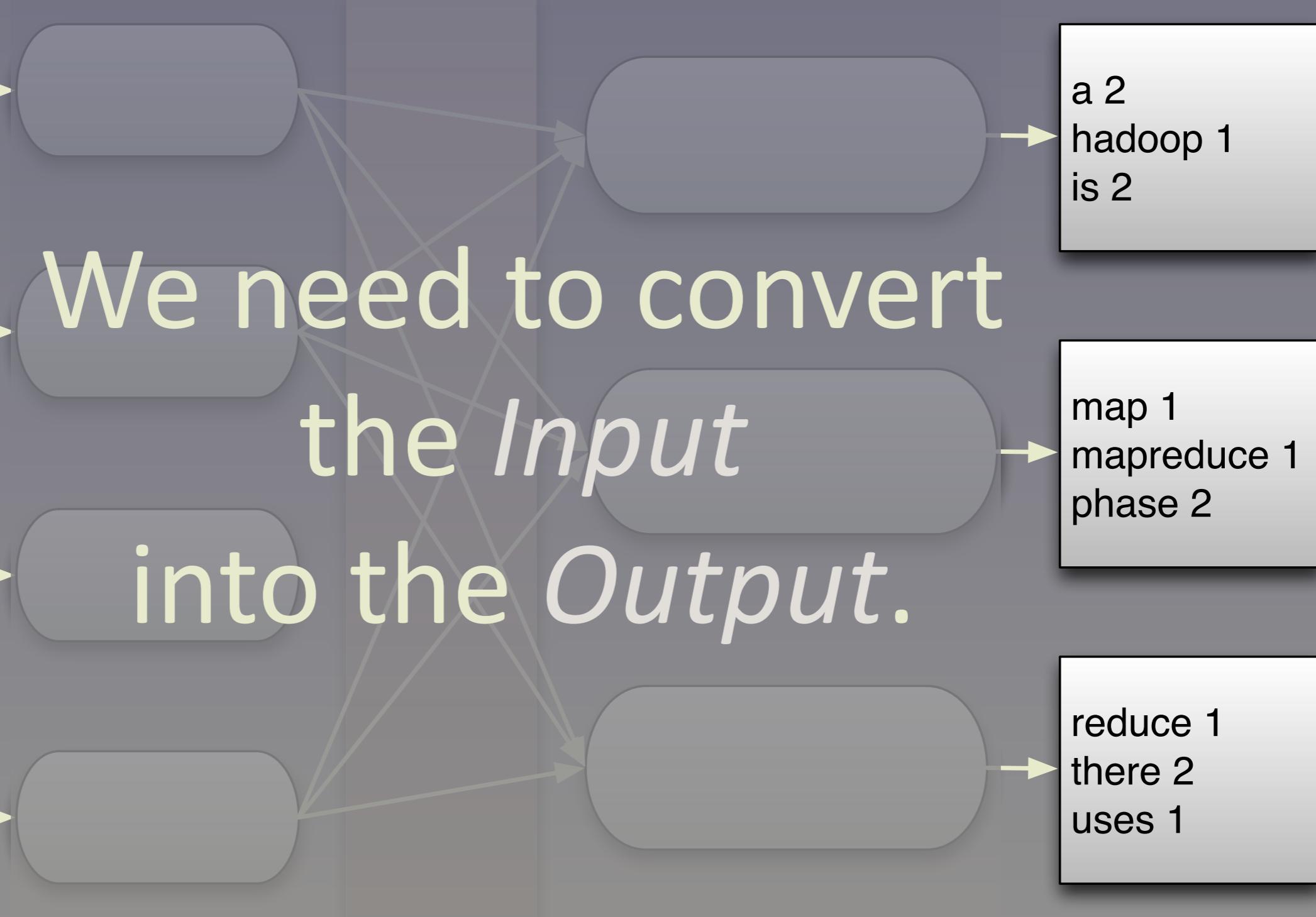
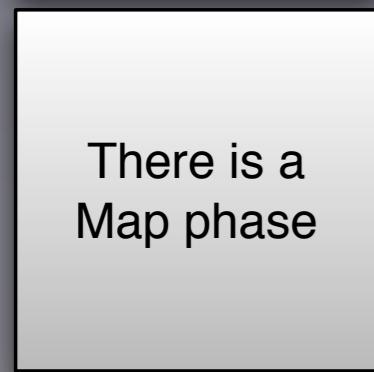
Input

Mappers

Sort,
Shuffle

Reducers

Output



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Four input documents, one left empty, the others with small phrases (for simplicity...). The word count output is on the right (we'll see why there are three output "documents"). We need to get from the input on the left-hand side to the output on the right-hand side.

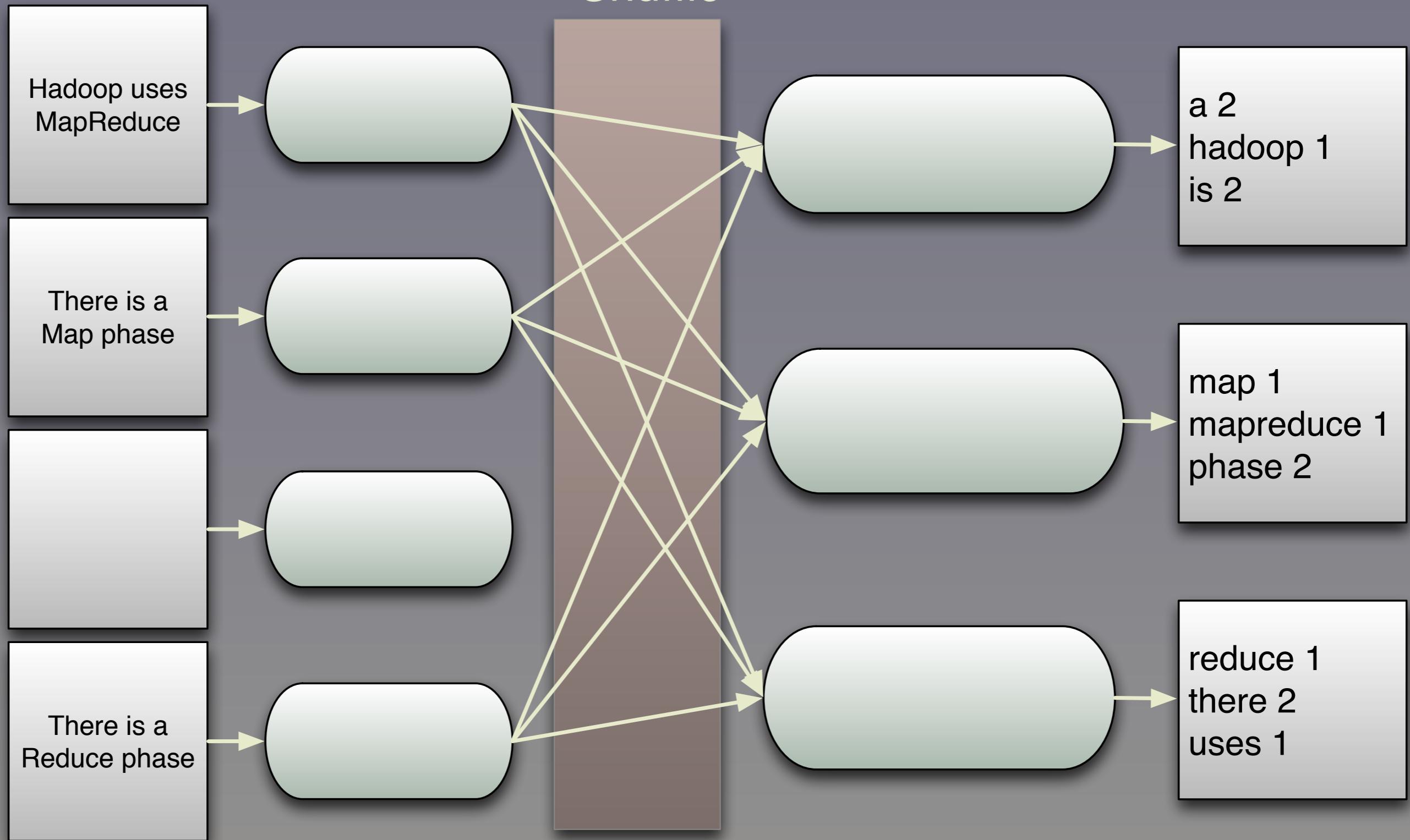
Input

Mappers

Sort, Shuffle

Reducers

Output

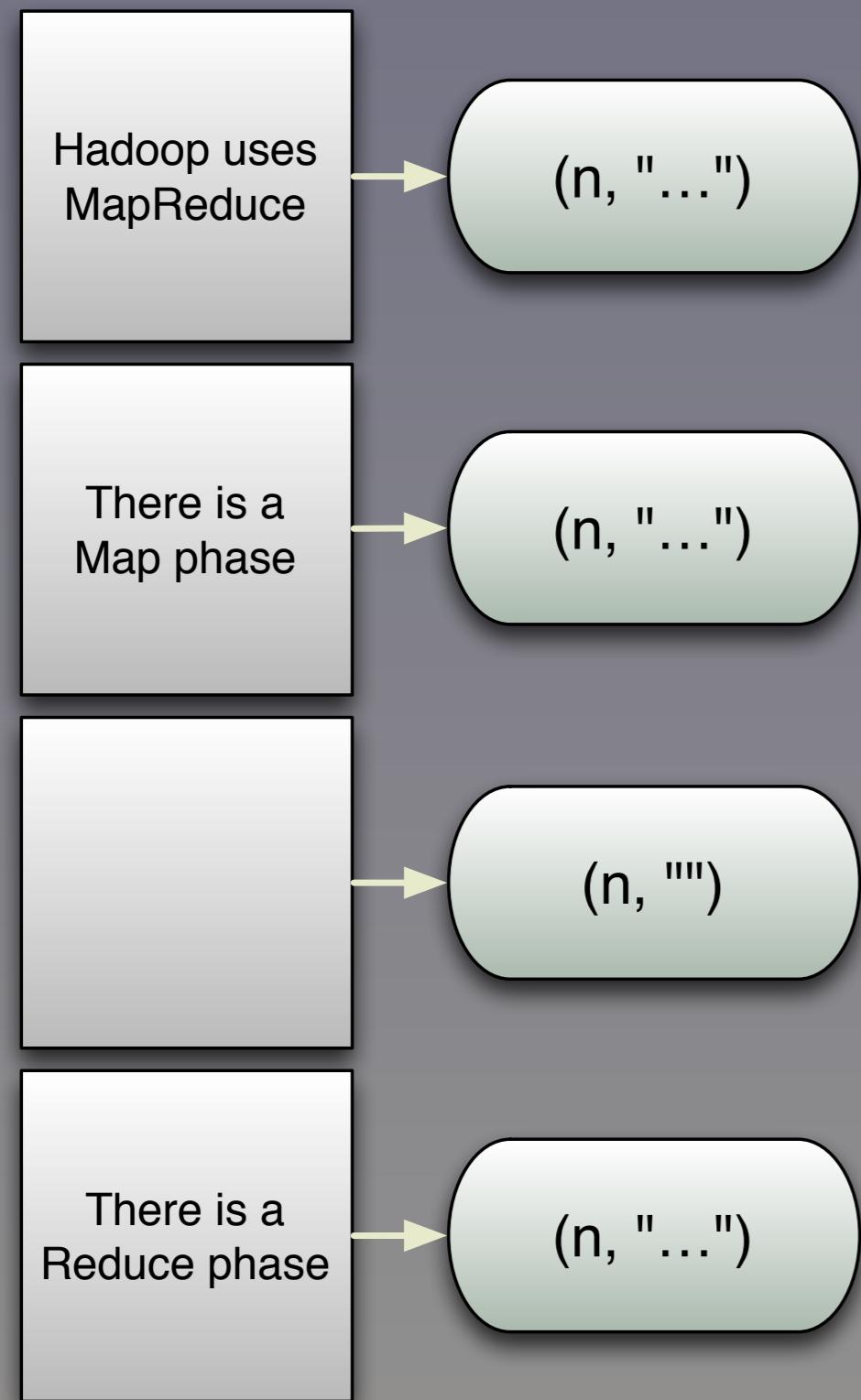


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Here is a schematic view of the steps in Hadoop MapReduce. Each Input file is read by a single Mapper process (default: can be many-to-many, as we'll see later). The Mappers emit key-value pairs that will be sorted, then partitioned and "shuffled" to the reducers, where each Reducer will get all instances of a given key (for 1 or more values). Each Reducer generates the final key-value pairs and writes them to one or more files (based on the size of the output).

Input Mappers

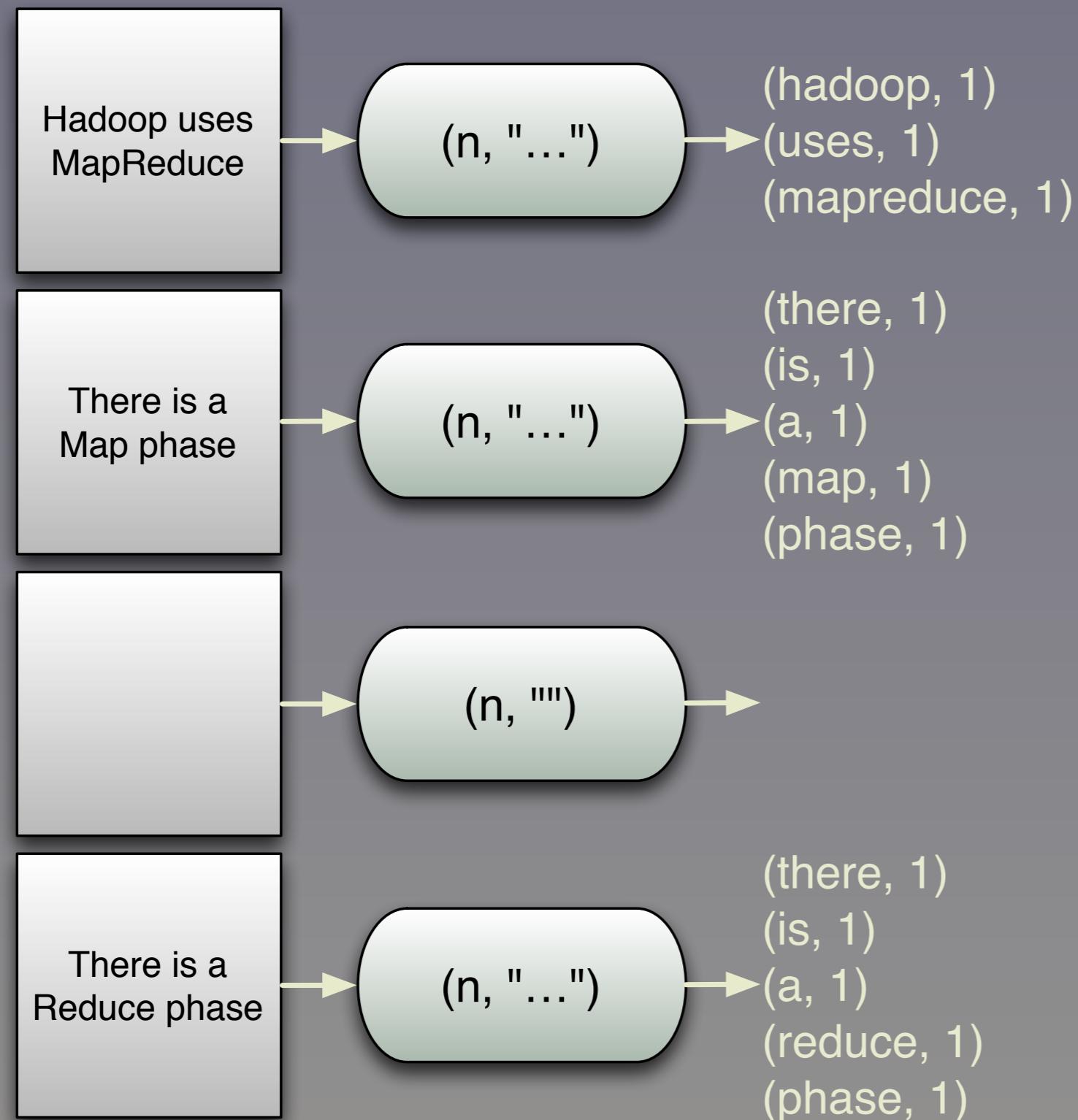


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Each document gets a mapper. All data is organized into key-value pairs; each line will be a value and the offset position into the file will be the key, which we don't care about. I'm showing each document's contents in a box and 1 mapper task (JVM process) per document. Large documents might get split to several mapper tasks.
The mappers tokenize each line, one at a time, converting all words to lower case and counting them...

Input Mappers



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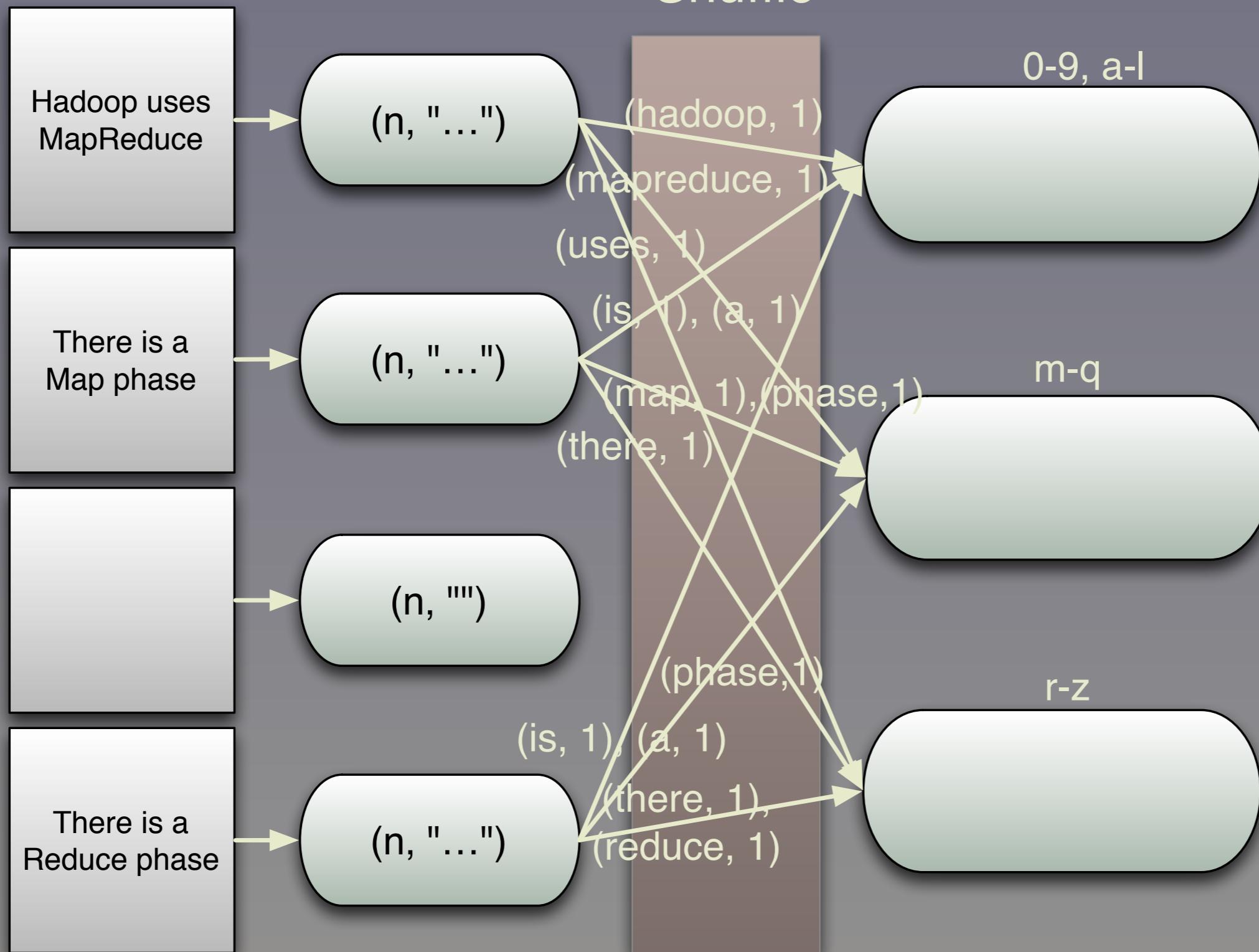
The mappers emit key-value pairs, where each key is one of the words, and the value is the count. In the most naive (but also most memory efficient) implementation, each mapper simply emits (word, 1) each time “word” is seen. However, this is IO inefficient! Note that the mapper for the empty doc. emits no pairs, as you would expect.

Input

Mappers

Sort, Shuffle

Reducers



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The mappers themselves don't decide to which reducer each pair should be sent. Rather, the job setup configures what to do and the Hadoop runtime enforces it during the Sort/Shuffle phase, where the key-value pairs in each mapper are sorted by key (that is locally, not globally) and then the pairs are routed to the correct reducer, on the current machine or other machines.

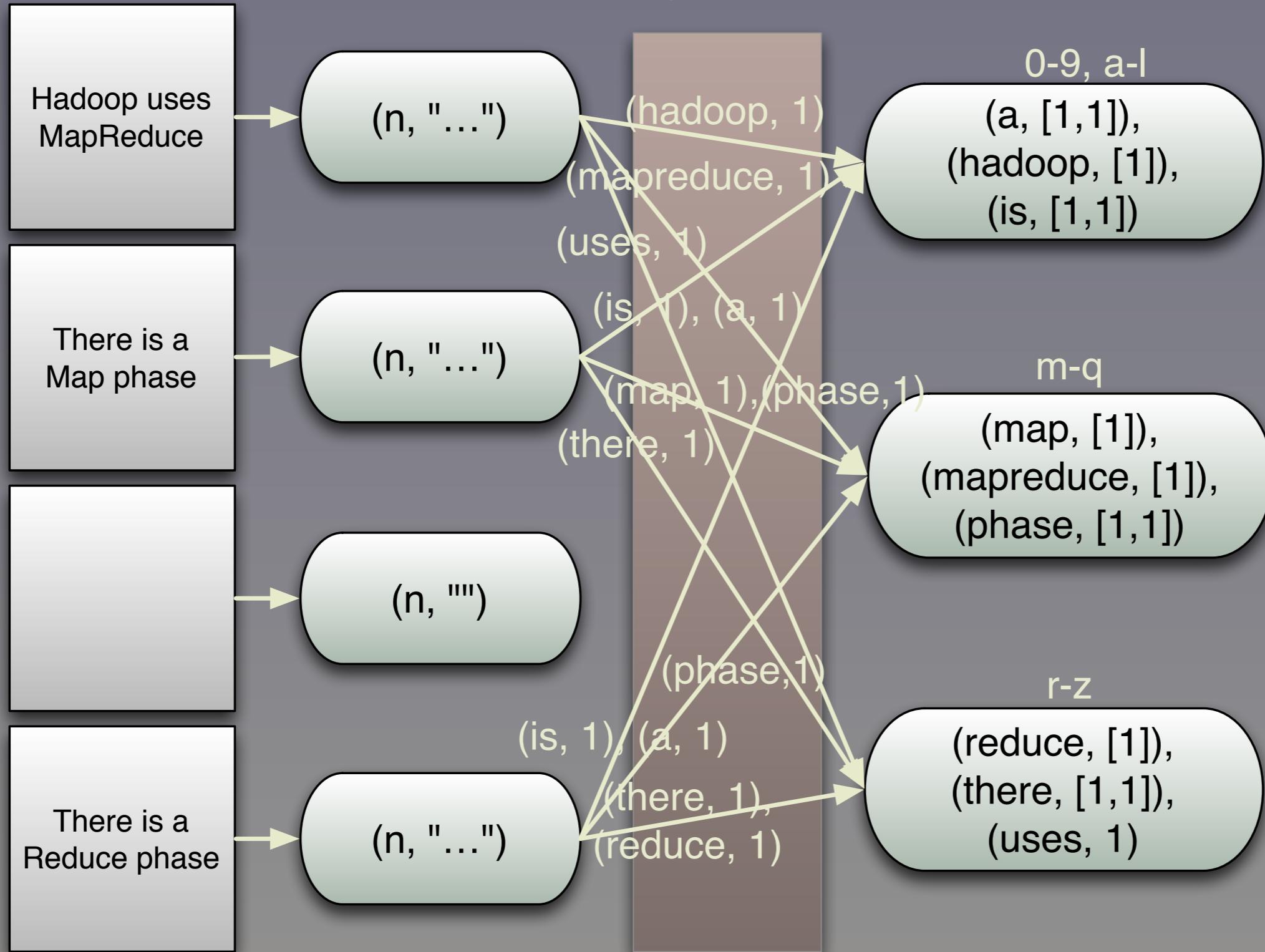
Note how we partitioned the reducers, by first letter of the keys. (By default, MR just hashes the keys and distributes them modulo # of reducers.)

Input

Mappers

Sort, Shuffle

Reducers

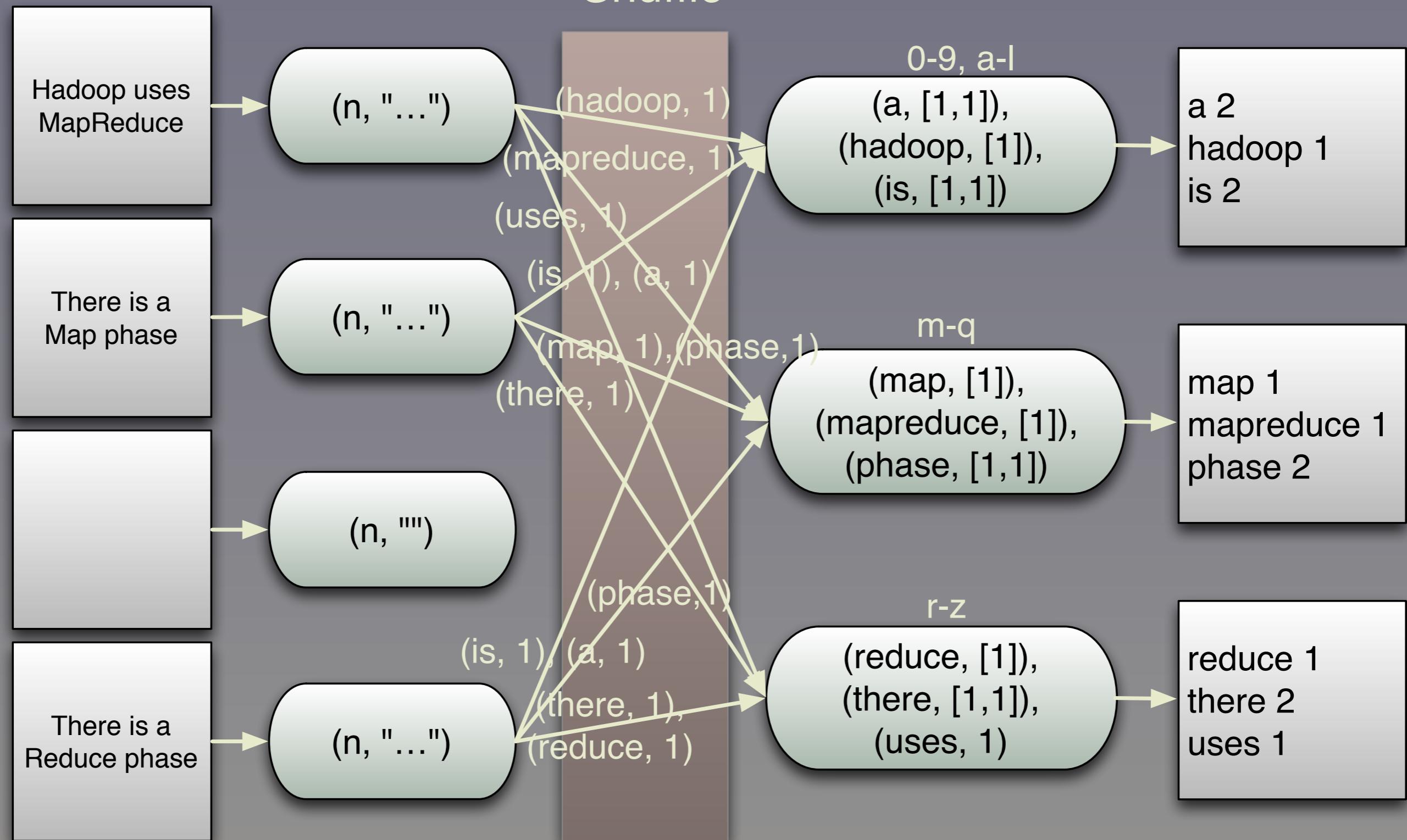


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The reducers are passed each key (word) and a collection of all the values for that key (the individual counts emitted by the mapper tasks). The MR framework creates these collections for us.

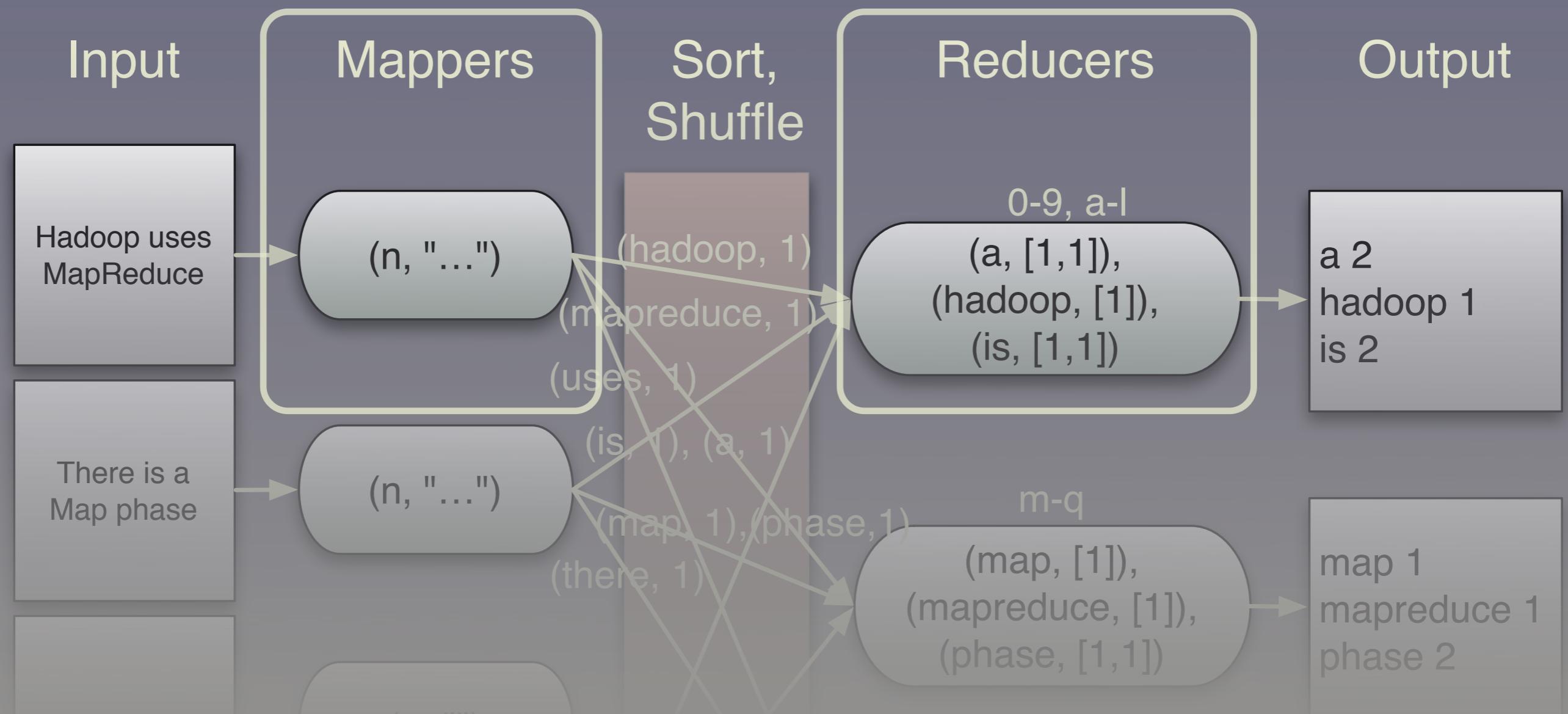
Input Mappers Sort, Shuffle Reducers Output



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The final view of the WordCount process flow. The reducer just sums the counts and writes the output. The output files contain one line for each key (the word) and value (the count), assuming we're using text output. The choice of delimiter between key and value is up to you, but tab is common.



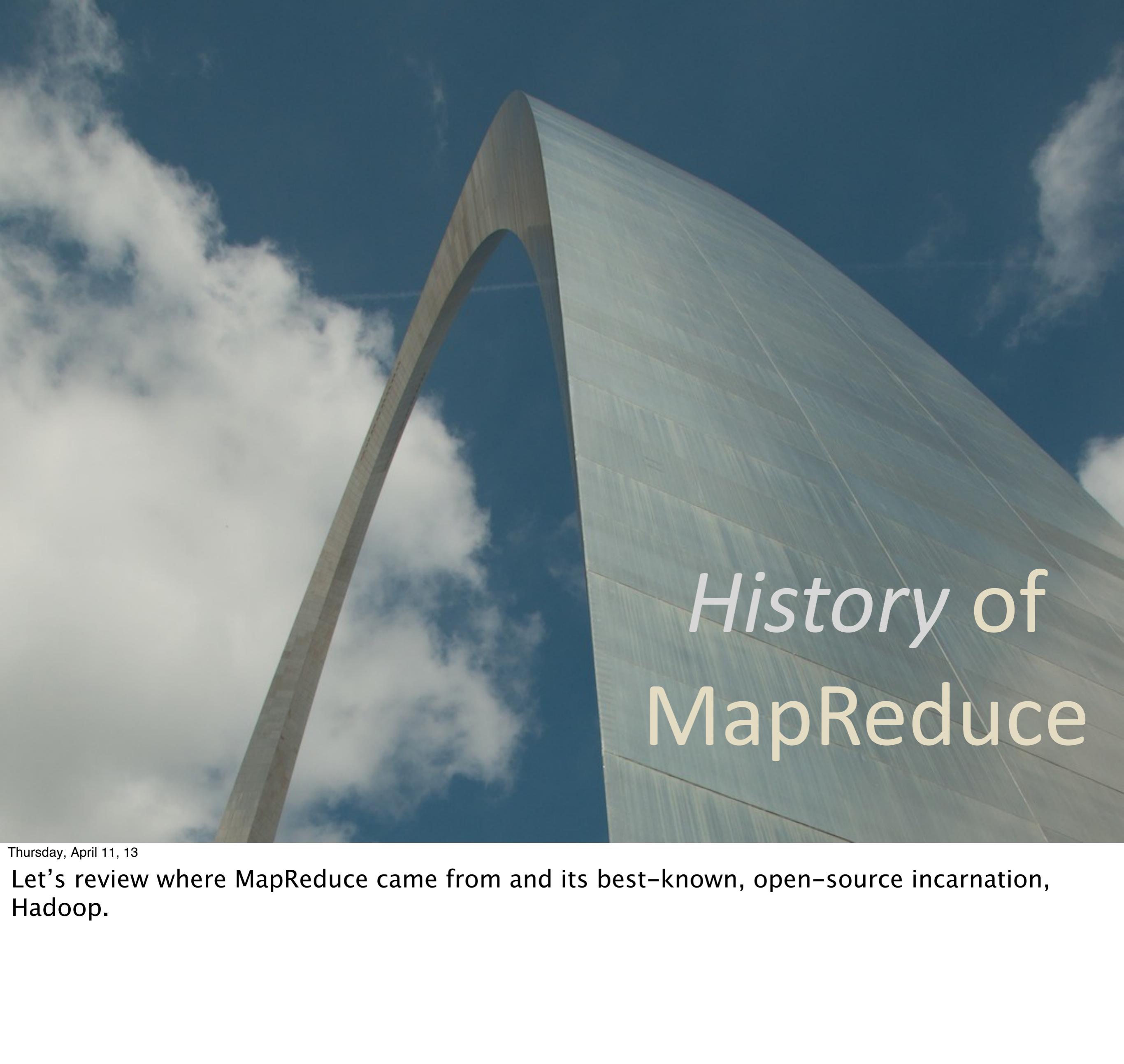
Map:

- Transform *one* input to *0-N* outputs.

Reduce:

- Collect *multiple* inputs into one output.

To recap, a “map” transforms one input to one output, but this is generalized in MapReduce to be one to 0-N. The output key-value pairs are distributed to reducers. The “reduce” collects together multiple inputs with the same key into

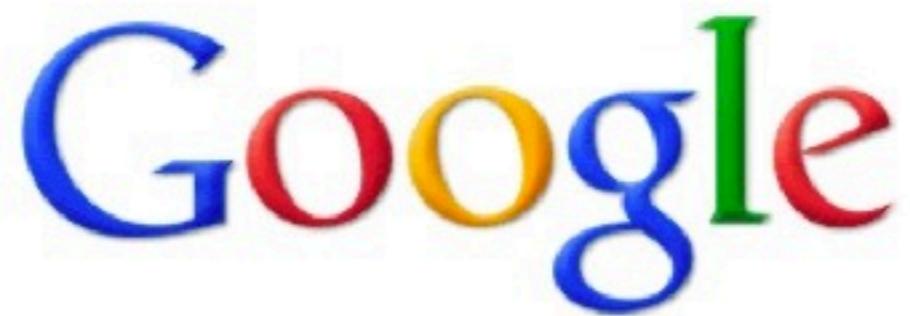
A photograph of a modern architectural structure, possibly a library or concert hall, featuring a large glass-enclosed entrance and a curved, light-colored facade. The sky is blue with scattered white clouds.

History of MapReduce

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Let's review where MapReduce came from and its best-known, open-source incarnation, Hadoop.

How would you *index the web?*

A screenshot of a Google search interface. The search bar contains the partial query "What is the meanin". Below the search bar, a list of suggested completions appears, all starting with "what is the meaning of":

- what is the meaning of life
- what is the meaning of life 42
- what is the meaning of pumped up kicks
- what is the meaning of halloween
- what is the meaning of love
- what is the meaning of labor day
- what is the meaning of slope
- what is the meaning of homecoming
- what is the meaning of my last name
- what is the meaning of a promise ring

At the bottom of the interface are two buttons: "Google Search" and "I'm Feeling Lucky".

How would you *index the web?*

Google

what is the meaning of life

Search

About 48,900,000 results (0.26 seconds)

Everything

Images

Maps

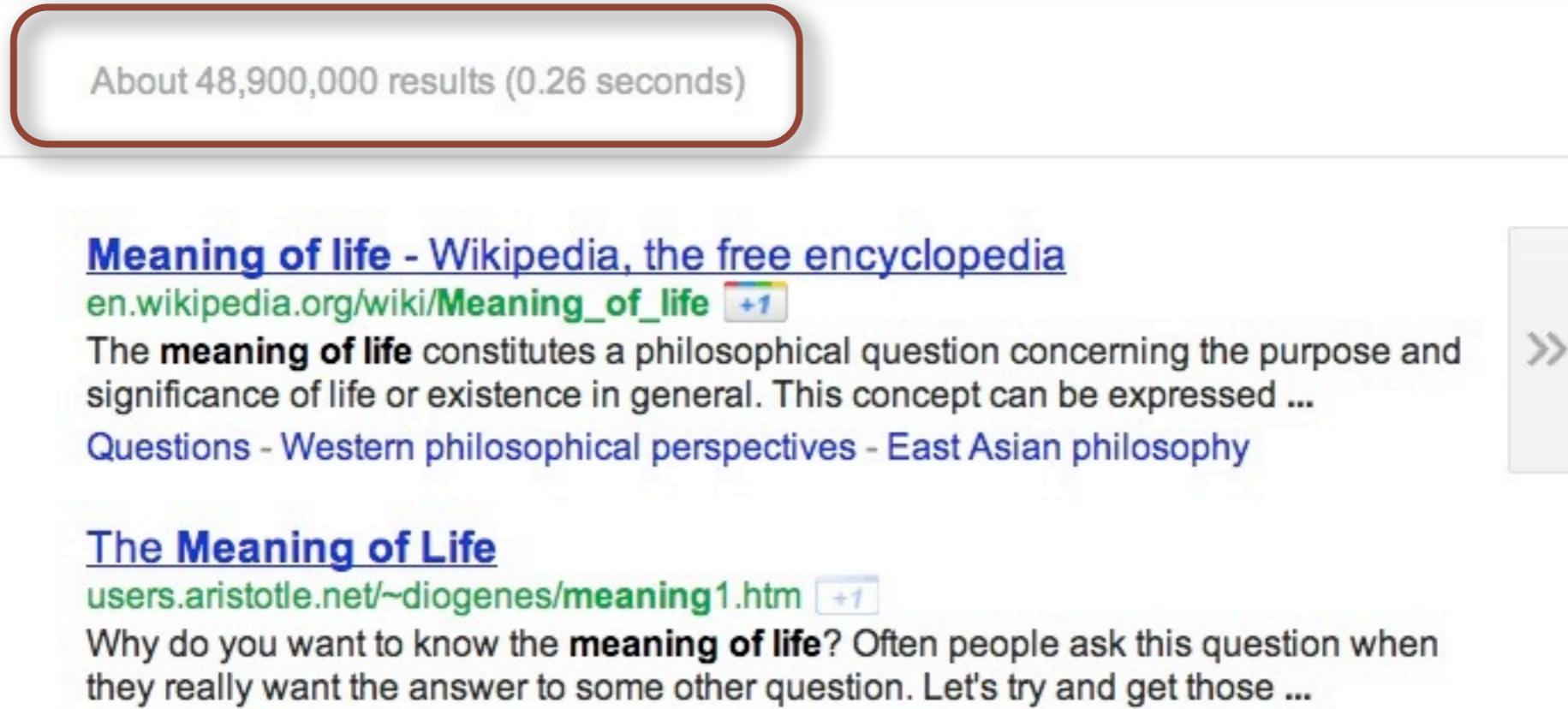
Videos

News

Shopping

[Meaning of life - Wikipedia, the free encyclopedia](#)
en.wikipedia.org/wiki/Meaning_of_life +1
The **meaning of life** constitutes a philosophical question concerning the purpose and significance of life or existence in general. This concept can be expressed ...
[Questions - Western philosophical perspectives - East Asian philosophy](#)

[The Meaning of Life](#)
users.aristotle.net/~diogenes/meaning1.htm +1
Why do you want to know the **meaning of life**? Often people ask this question when they really want the answer to some other question. Let's try and get those ...



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Did Google search the entire web in 0.26 seconds to find these ~49M results?

You ask a *phrase* and
the *search engine* finds
the *best match* in
billions of web pages.

Actually, Google
computes the *index*
that *maps terms* to
pages in *advance*.

Google's famous *Page Rank* algorithm.

In the early 2000s,
Google invented server
infrastructure to support
PageRank, etc...

Google File System

for Storage

2003

The Google File System

Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung

Google*

ABSTRACT

We have designed and implemented the Google File System, a scalable distributed file system for large distributed data-intensive applications. It provides fault tolerance while running on inexpensive commodity hardware, and it delivers high aggregate performance to a large number of clients.

While sharing many of the same goals as previous distributed file systems, our design has been driven by observations of our application workloads and technological envi-

1. INTRODUCTION

We have designed and implemented the Google File System (GFS) to meet the rapidly growing demands of Google's data processing needs. GFS shares many of the same goals as previous distributed file systems such as performance, scalability, reliability, and availability. However, its design has been driven by key observations of our application workloads and technological environment, both current and anticipated, that reflect a marked departure from some earlier

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A distributed file system provides horizontal scalability and resiliency when file blocks are duplicated around the cluster.

MapReduce for Computation

2004

MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

Abstract

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually large and the computations have to be distributed across hundreds or thousands of machines in order to finish in a reasonable amount of time. The issues of how to par-

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The compute model for processing all that data is MapReduce. It handles lots of boilerplate, like breaking down jobs into tasks, distributing the tasks around the cluster, monitoring the tasks, etc. You write your algorithm to the MR programming model.

*About this time, Doug
Cutting, the creator of
Lucene, and Mike
Cafarella was working
on Nutch...*

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Lucene is an open-source text search engine. Nutch is an open source web crawler.

They started clean-
room versions of
MapReduce and *GFS*...

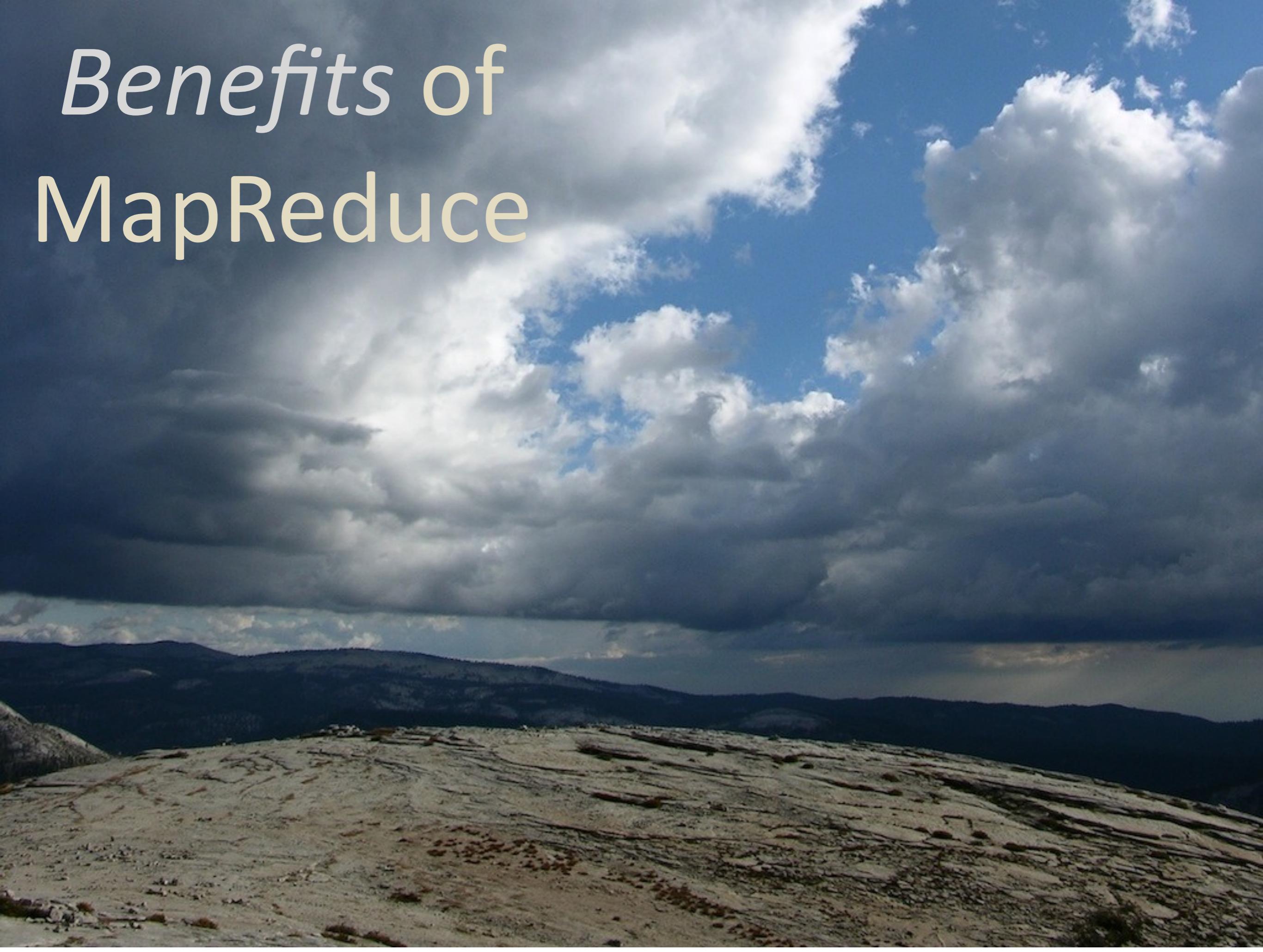
By 2006 , they became
part of a separate
Apache project,
called *Hadoop*.



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The name comes from a toy, stuffed elephant that Cutting's son owned at the time.

Benefits of MapReduce



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The best way to
approach *Big Data* is to
scale *Horizontally*.

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We can't build vertical systems big enough and if we could, they would cost a fortune!

Hadoop Design Goals

Maximize I/O
Performance!!

*And parallelize execution,
run on server-class,
commodity hardware.*

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Maximizing disk and network I/O is critical, because it's the largest throughput bottleneck. So, optimization is a core design goal of Hadoop (both MR and HDFS). It affects the features and performance of everything in the stack above it, including high-level programming tools!

By design, Hadoop is
great for batch mode
data crunching.

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... but less so for “real-time” event handling, as we’ll discuss...

MapReduce and its Discontents



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Is MapReduce the end of the story? Does it meet all our needs? Let's look at a few problems...

#1

It's hard to *implement*
many *Algorithms*
in *MapReduce*.

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Even word count is not “obvious”. When you get to fancier stuff like joins, group-bys, etc., the mapping from the algorithm to the implementation is not trivial at all. In fact, implementing algorithms in MR is now a specialized body of knowledge...

#2

For *Hadoop* in
particularly,
the *Java API* is
hard to use.

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The Hadoop Java API is even more verbose and tedious to use than it should be.

```

import org.apache.hadoop.io.*;
import org.apache.hadoop.mapred.*;
import java.util.StringTokenizer;

class WCMapper extends MapReduceBase
    implements Mapper<LongWritable, Text, Text, IntWritable> {

    static final IntWritable one = new IntWritable(1);
    static final Text word = new Text(); // Value will be set in a non-thread-safe way!

    @Override
    public void map(LongWritable key, Text valueDocContents,
                    OutputCollector<Text, IntWritable> output, Reporter reporter) {
        String[] tokens = valueDocContents.toString().split("\\s+");
        for (String wordString: tokens) {
            if (wordString.length > 0) {
                word.set(wordString.toLowerCase());
                output.collect(word, one);
            }
        }
    }
}

class Reduce extends MapReduceBase
    implements Reducer[Text, IntWritable, Text, IntWritable] {

    public void reduce(Text keyword, java.util.Iterator<IntWritable> valuesCounts,
                      OutputCollector<Text, IntWritable> output, Reporter reporter) {
        int totalCount = 0;
        while (valuesCounts.hasNext()) {
            totalCount += valuesCounts.next().get();
        }
        output.collect(keyword, new IntWritable(totalCount));
    }
}

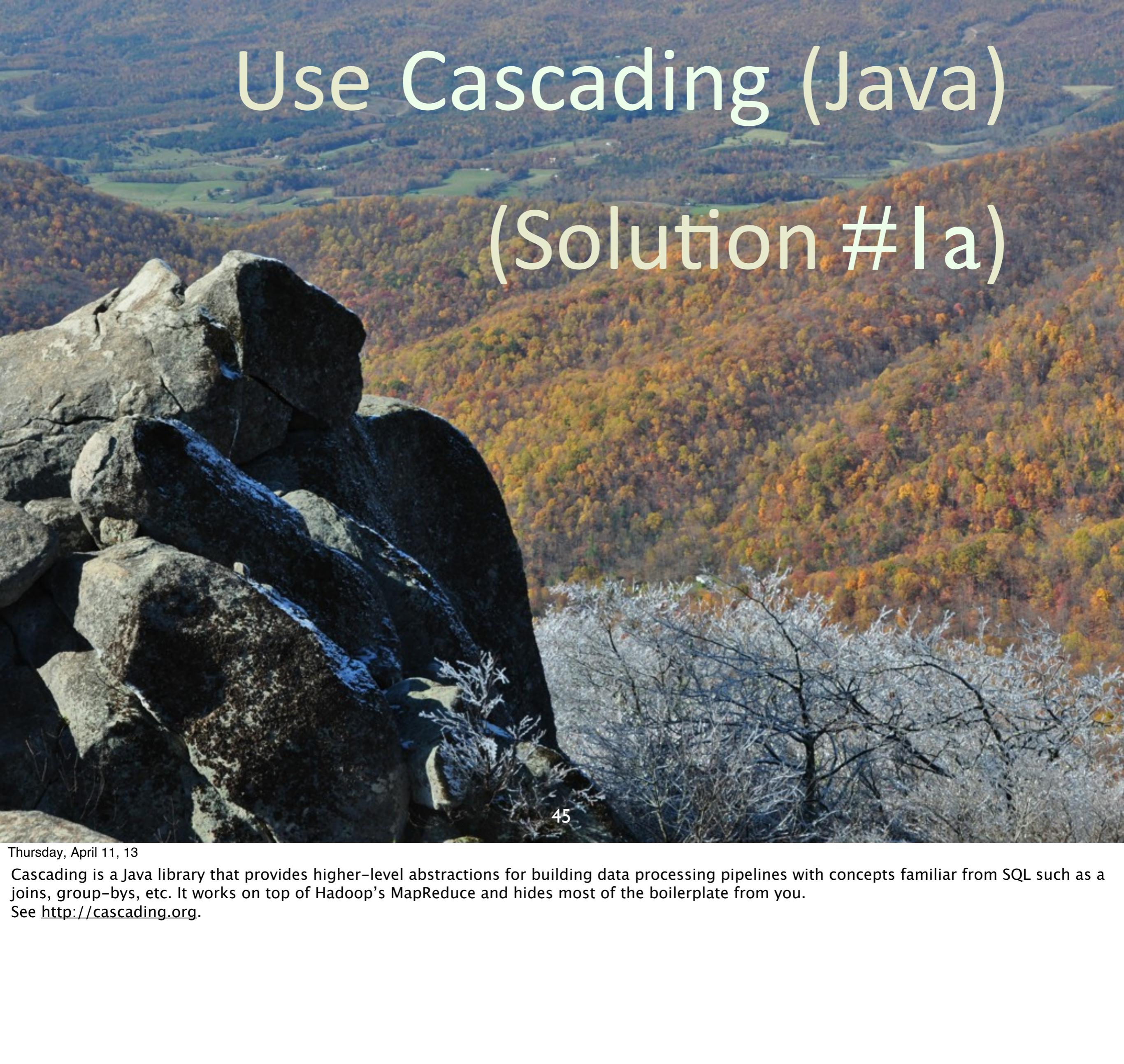
```

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This is intentionally too small to read and we're not showing the main routine, which doubles the code size. The algorithm is simple, but the framework is in your face. In the next several slides, notice which colors dominate. In this slide, it's green for types (classes), with relatively few yellow functions that implement actual operations.

The main routine I've omitted contains boilerplate details for configuring and running the job. This is just the "core" MapReduce code. In fact, Word Count is not too bad, but when you get to more complex algorithms, even conceptually simple ideas like relational-style joins and group-bys, the corresponding MapReduce code in this API gets complex and tedious very fast!



Use Cascading (Java)

(Solution #1a)

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Cascading is a Java library that provides higher-level abstractions for building data processing pipelines with concepts familiar from SQL such as a joins, group-bys, etc. It works on top of Hadoop's MapReduce and hides most of the boilerplate from you.
See <http://cascading.org>.

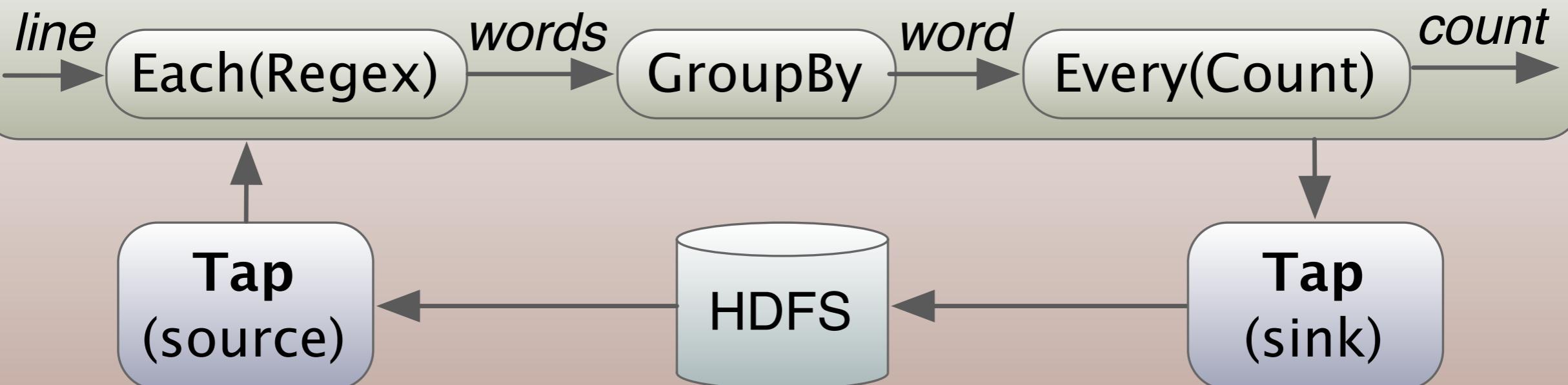
Cascading Concepts

Data flows consist of source and sink Taps connected by Pipes.

Word Count

Flow

Pipe ("word count assembly")



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Schematically, here is what Word Count looks like in Cascading. See <http://docs.cascading.org/cascading/1.2/userguide/html/ch02.html> for details.

```

import org.cascading.*;
...
public class WordCount {
    public static void main(String[] args) {
        String inputPath = args[0];
        String outputPath = args[1];
        Properties properties = new Properties();
        FlowConnector.setApplicationJarClass( properties, Main.class );

        Scheme sourceScheme = new TextLine( new Fields( "line" ) );
        Scheme sinkScheme = new TextLine( new Fields( "word", "count" ) );
        Tap source = new Hfs( sourceScheme, inputPath );
        Tap sink = new Hfs( sinkScheme, outputPath, SinkMode.REPLACE );

        Pipe assembly = new Pipe( "wordcount" );

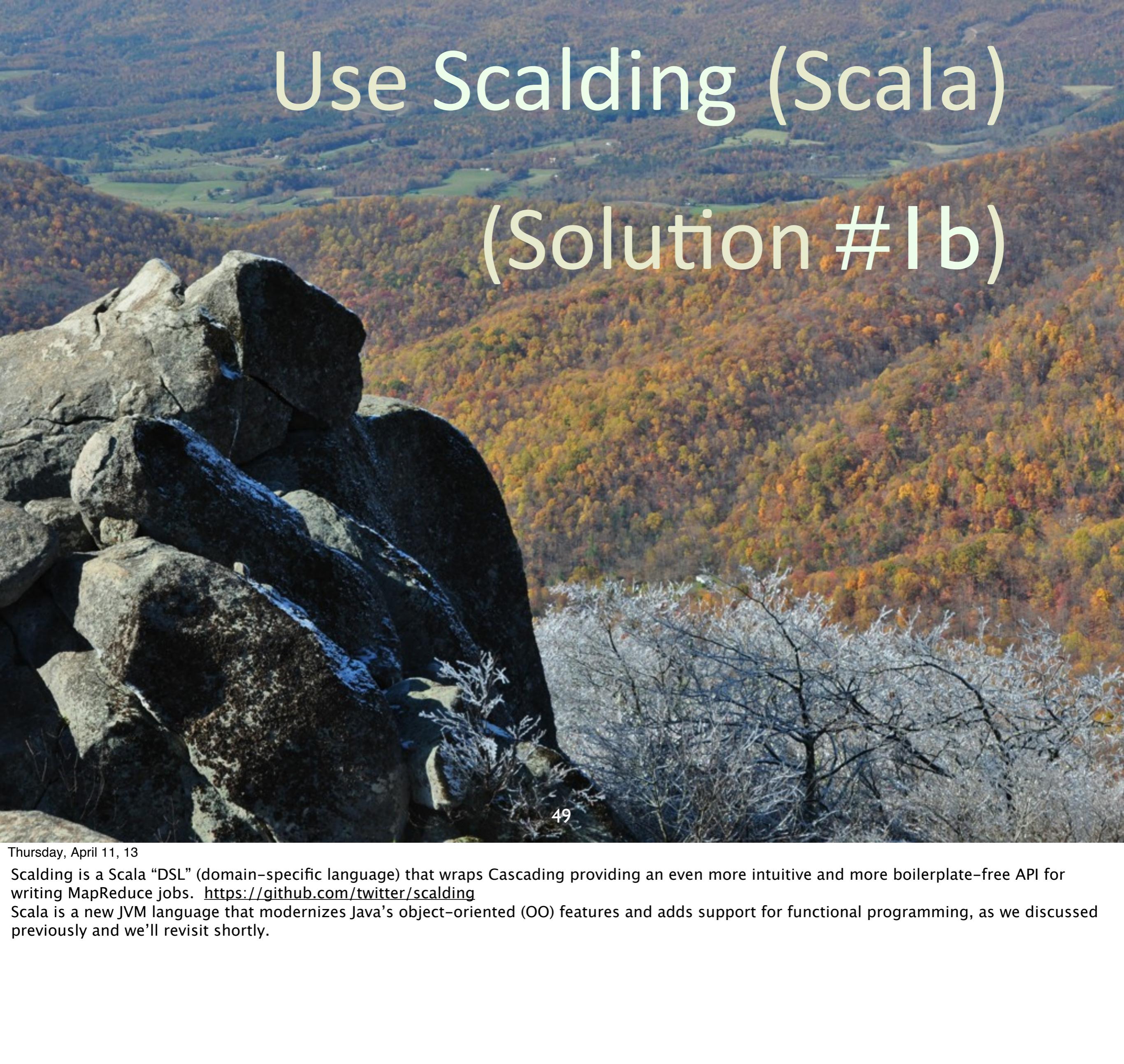
        String regex = "(?<!\\pL)(?=\\pL)[^ ]*(?=<\\pL)(?!\\pL)";
        Function function = new RegexGenerator( new Fields( "word" ), regex );
        assembly = new Each( assembly, new Fields( "line" ), function );
        assembly = new GroupBy( assembly, new Fields( "word" ) );
        Aggregator count = new Count( new Fields( "count" ) );
        assembly = new Every( assembly, count );

        FlowConnector flowConnector = new FlowConnector( properties );
        Flow flow = flowConnector.connect( "word-count", source, sink, assembly );
        flow.complete();
    }
}

```

Here is the Cascading Java code. It's cleaner than the MapReduce API, because the code is more focused on the algorithm with less boilerplate, although it looks like it's not that much shorter. HOWEVER, this is all the code, where as previously I omitted the setup (main) code. See <http://docs.cascading.org/cascading/1.2/userguide/html/ch02.html> for details of the API features used here; we won't discuss them here, but just mention some highlights.

Note that there is still a lot of green for types, but at least the API emphasizes composing behaviors together.



Use Scalding (Scala)

(Solution #1b)

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Scalding is a Scala “DSL” (domain-specific language) that wraps Cascading providing an even more intuitive and more boilerplate-free API for writing MapReduce jobs. <https://github.com/twitter/scalding>

Scala is a new JVM language that modernizes Java’s object-oriented (OO) features and adds support for functional programming, as we discussed previously and we’ll revisit shortly.

```
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String => line.trim.toLowerCase.split("\\\\w+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

That's It!!

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This Scala code is almost pure domain logic with very little boilerplate. There are a few minor differences in the implementation. You don't explicitly specify the "Hfs" (Hadoop Distributed File System) taps. That's handled by Scalding implicitly when you run in "non-local" model. Also, I'm using a simpler tokenization approach here, where I split on anything that isn't a "word character" [0-9a-zA-Z_].

There is little green, in part because Scala infers type in many cases. There is a lot more yellow for the functions that do real work!

What if MapReduce, and hence Cascading and Scalding, went obsolete tomorrow? This code is so short, I wouldn't care about throwing it away! I invested little time writing it, testing it, etc.

Other Improved APIs:

- Crunch (Java) & Scrunch (Scala)
- Scoobi (Scala)
- ...

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See <https://github.com/cloudera/crunch>.

Others include Scoobi (<http://nicta.github.com/scoobi/>) and Spark, which we'll discuss next.

A scenic view of a mountain range during autumn. The foreground is dominated by large, dark, craggy rocks. In the middle ground, there are bare, frost-covered branches of trees. The background consists of rolling hills and mountains covered in a dense forest of trees with orange, yellow, and green leaves. The sky is clear and blue.

Use Spark (Scala) (Solution #2)

Spark is a Hadoop MapReduce alternative:

- Distributed computing with in-memory caching.
- Up to 30x faster than MapReduce.

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See <http://www.spark-project.org/>

Why isn't it more widely used? 1) lack of commercial support, 2) only recently emerged out of academia.

Spark is a Hadoop MapReduce alternative:

- Originally designed for machine learning applications.

```
object WordCountSpark {  
    def main(args: Array[String]) {  
        val file = spark.textFile(args(0))  
        val counts = file.flatMap(line => line.split("\\\\w+"))  
                      .map(word => (word, 1))  
                      .reduceByKey(_ + _)  
        counts.saveAsTextFile(args(1))  
    }  
}
```

Also that's it!
Note it's similar to the MapReduce API,
but far more concise.

Use Hive, Shark, or Impala

(Solution #3)

Use SQL when you can!

- Hive: SQL on top of MapReduce.
- Shark: Hive ported to Spark.
- Impala: HiveQL with new, faster back end.

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See <http://hive.apache.org/> or my book for Hive, <http://shark.cs.berkeley.edu/> for shark, and <http://www.cloudera.com/content/cloudera/en/products/cloudera-enterprise-core/cloudera-enterprise-RTQ.html> for Impala. Impala is very new. It doesn't yet support all Hive features.

SQL!

```
CREATE TABLE docs (line STRING);
LOAD DATA INPATH '/path/to/docs' INTO TABLE docs;

CREATE TABLE word_counts AS
SELECT word, count(1) AS count FROM
(SELECT explode(split(line, '\W+')) AS word FROM docs) w
GROUP BY word
ORDER BY word;
```

Word Count, again...
... in HiveQL

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This is how you could implement word count in Hive. We're using some Hive built-in functions for tokenizing words in each "line", the one "column" in the docs table, etc., etc.

Impala

- HiveQL front end.
- C++ and Java back end.
- Provides up to 100x performance improvement!
- Developed by Cloudera.

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See <http://www.cloudera.com/content/cloudera/en/products/cloudera-enterprise-core/cloudera-enterprise-RTQ.html>. However, this was just announced a few ago (at the time of this writing), so it's not production ready quite yet...

#3

It's not suitable for
“*real-time*”
event processing.

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For typical web/enterprise systems, “real-time” is up to 100s of milliseconds, so I’m using the term broadly (but following common practice in this industry). True real-time systems, such as avionics, have much tighter constraints.



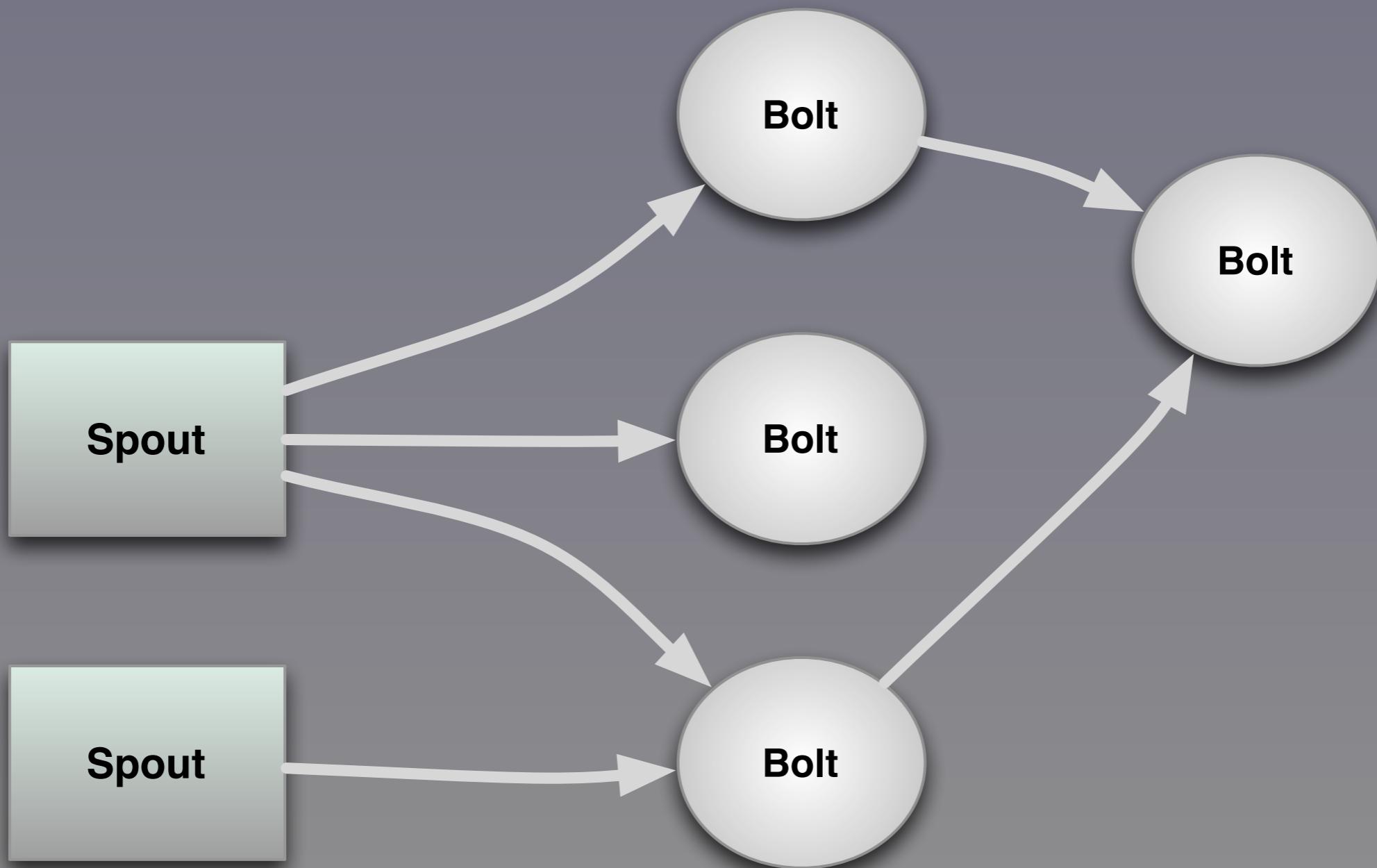
Storm!

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*Storm implements
reliable, distributed
“real-time”
event processing.*

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<http://storm-project.net/> Created by Nathan Marz, now at Twitter, who also created Cascalog, the Clojure wrapper around Cascading with added Datalog (logic programming) features.



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In Storm terminology, Spouts are data sources and bolts are the event processors. There are facilities to support reliable message handling, various sources encapsulated in Spouts and various targets of output. Distributed processing is baked in from the start.

Databases?



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SQL or NoSQL Databases?

- Since databases are designed for fast, transactional updates, consider a database for event processing.

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Use a SQL database unless you need the scale and looser schema of a NoSQL database!

#4

It's not ideal for
graph processing.

Google's Page Rank

- Google invented MapReduce,
- ... but MapReduce is not ideal for Page Rank and other graph algorithms.

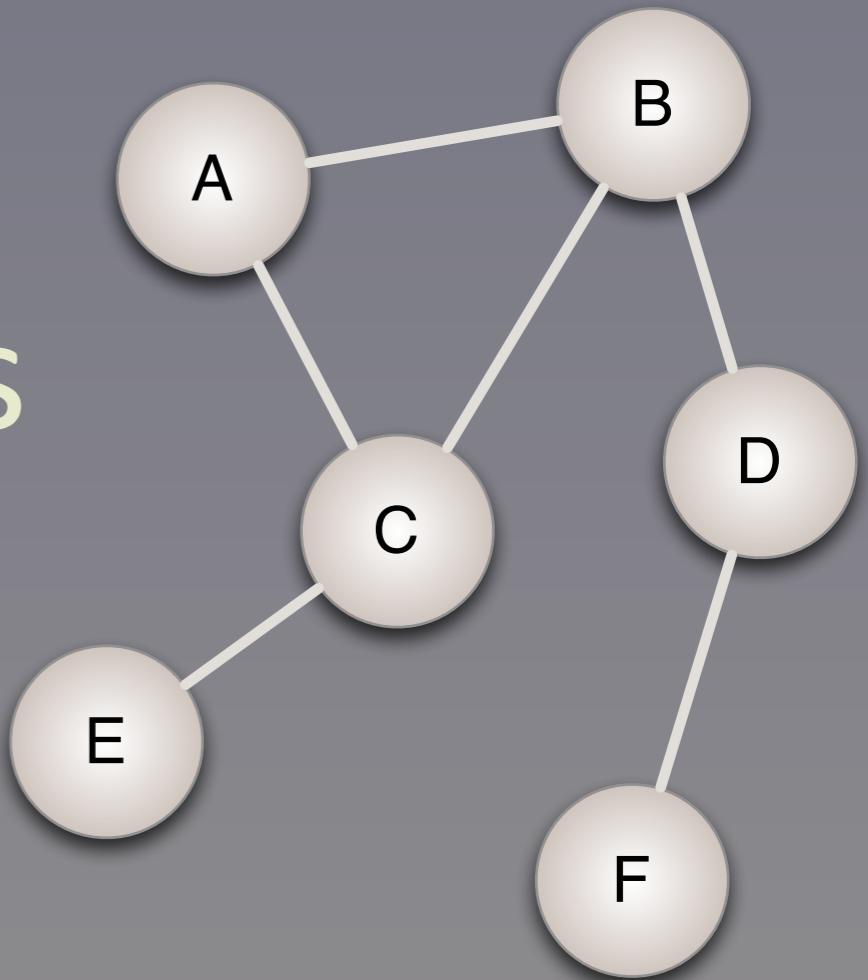
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Recall that PageRank is the famous algorithm invented by Sergey Brin and Larry Page to index the web. It's the foundation of Google's search engine.

Why not MapReduce?

- 1 MR job for each iteration that updates all n nodes/edges.
- Graph saved to disk after each iteration.
- ...



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The presentation <http://www.slideshare.net/shatteredNirvana/pregel-a-system-for-largescale-graph-processing> itemizes all the major issues with using MR to implement graph algorithms. In a nutshell, a job with a map and reduce phase is waaay to course-grained...

Use Graph Processing (Solution #4)

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A good summary presentation: <http://www.slideshare.net/shatteredNirvana/pregel-a-system-for-largescale-graph-processing>

Google's Pregel

- Pregel: New graph framework for Page Rank.
- Bulk, Synchronous Parallel (BSP).
 - Graphs are first-class citizens.
 - Efficiently processes updates...

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Pregel is the name of the river that runs through the city of Königsberg, Prussia (now called Kaliningrad, Ukraine). 7 bridges crossed the river in the city (including to 5 to 2 islands between river branches). Leonhard Euler invented graph theory when we analyzed the question of whether or not you can cross all 7 bridges without retracing your steps (you can't).

Open-source Alternatives

- Apache Giraph.
- Apache Hama.
- Aurelius Titan.

All are
somewhat
immature.

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<http://incubator.apache.org/giraph/>

<http://hama.apache.org/>

<http://thinkaurelius.github.com/titan/>

None is very mature nor has extensive commercial support.

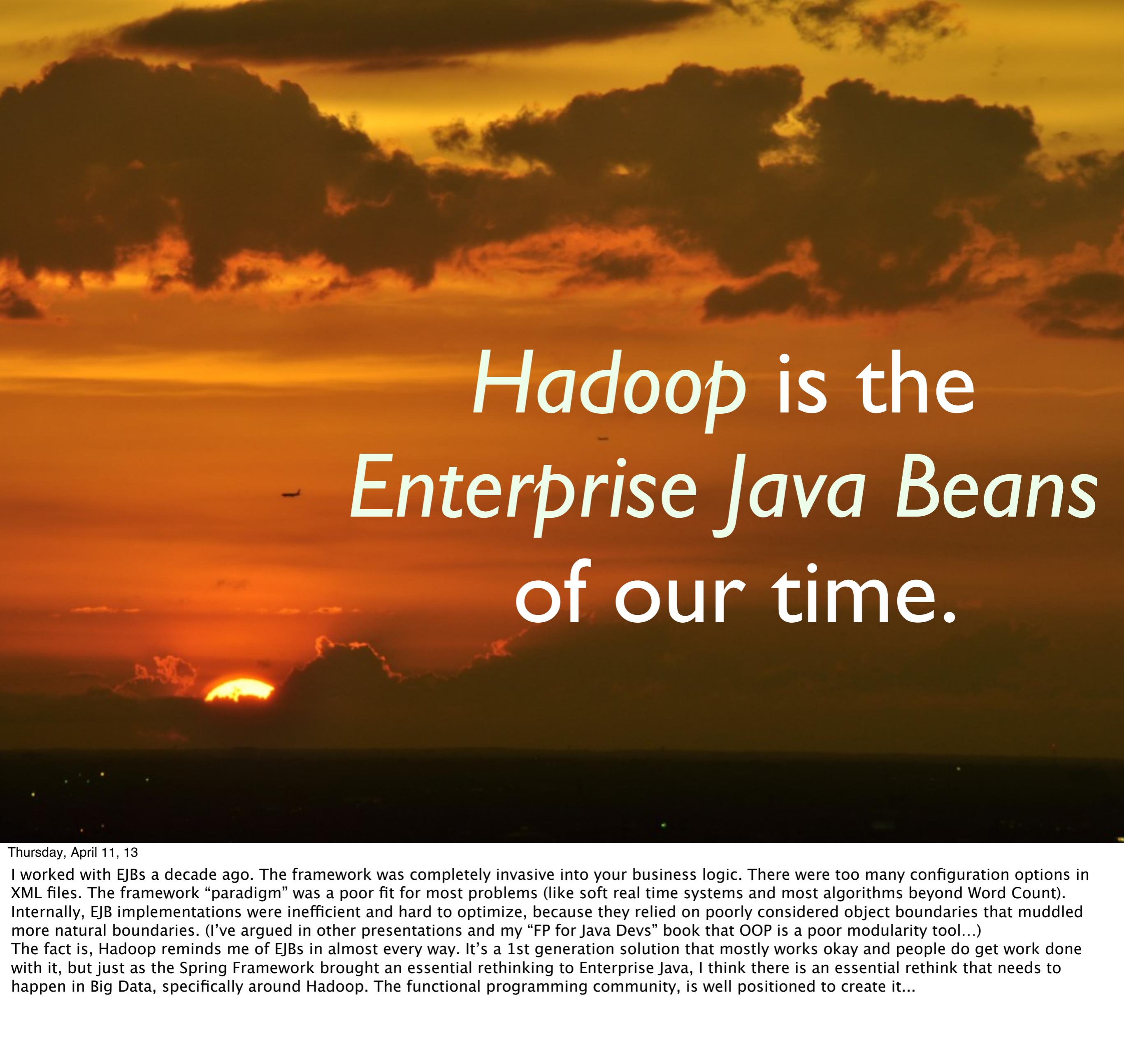
A Manifesto...



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To bring this altogether, I think we have opportunities for a better way...



*Hadoop is the
Enterprise Java Beans
of our time.*

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I worked with EJBs a decade ago. The framework was completely invasive into your business logic. There were too many configuration options in XML files. The framework “paradigm” was a poor fit for most problems (like soft real time systems and most algorithms beyond Word Count). Internally, EJB implementations were inefficient and hard to optimize, because they relied on poorly considered object boundaries that muddled more natural boundaries. (I’ve argued in other presentations and my “FP for Java Devs” book that OOP is a poor modularity tool...) The fact is, Hadoop reminds me of EJBs in almost every way. It’s a 1st generation solution that mostly works okay and people do get work done with it, but just as the Spring Framework brought an essential rethinking to Enterprise Java, I think there is an essential rethink that needs to happen in Big Data, specifically around Hadoop. The functional programming community, is well positioned to create it...

Stop using Java!



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Java has taken us a long way and the JVM remains one of our most valuable tools. But the language is really wrong language for data purposes and its continued use by Big Data vendors is slowing down overall progress, as well as application developer productivity, IMHO. Java emphasizes the wrong abstractions, objects instead of mathematically-inspired functional programming constructs, and Java encourages inflexible bloat because it's verbose compared to more modern alternatives and objects (at least class-based ones...) are far less reusable and flexible than people realize.



Functional Languages improve Big Data productivity!

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Why is Functional Programming better for Big Data? The work we do with data is inherently mathematical transformations and FP is inspired by math. Hence, it's naturally a better fit, much more so than object-oriented programming. And, modern languages like Scala, Clojure, Erlang, F#, OCaml, and Haskell are more concise and better at eliminating boilerplate, while still providing excellent performance.

Note that one reason SQL has succeeded all these years is because it is also inspired by math, e.g., set theory.



Functional Collections.

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We already have the right model in the collection APIs that come with functional languages. They are far better engineered for intuitive data transformations. They provide the right abstractions and hide boilerplate. In fact, they make it relatively easy to optimize implementations for parallelization. The Scala collections offer parallelization with a tiny API call. Spark and Cascading transparently distribute collections across a cluster.

Erlang, Akka: Actor-based, Distributed Computation

Fine Grain Compute Models.

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We can start using new, more efficient compute models, like Spark, Pregel, and Impala today. Of course, you have to consider maturity, viability, and support issues in large organizations. So if you want to wait until these alternatives are more mature, then at least use better APIs for Hadoop! For example, Erlang is a very mature language with the Actor model backed in. Akka is a Scala distributed computing model based on the Actor model of concurrency. It exposes clean, low-level primitives for robust, distributed services (e.g., Actors), upon which we can build flexible big data systems that can handle soft real time and batch processing efficiently and with great scalability.

Final Thought:



A large, rugged mountain peak with vertical rock faces and patches of snow at the base. The sky is clear and blue.



Luke Wroblewski

@lukew

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The new tech mullet: simple mobile interactions up front, big data in the back.

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A final thought about Big Data...



Questions?

TechMesh London 2012
December 5, 2012

@deanwampler
dean@deanwampler.com

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