Tuesday, December 4, 12

On my website, this talk is called “MapReduce and Its Discontents”.
MR has been a useful technology, but it has a “first generation” feel. What’s next?

About Me...

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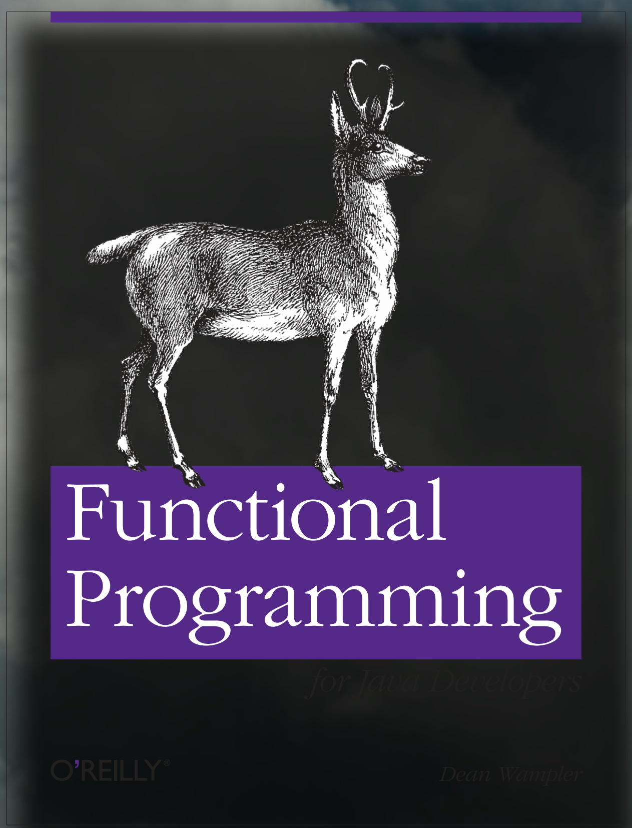
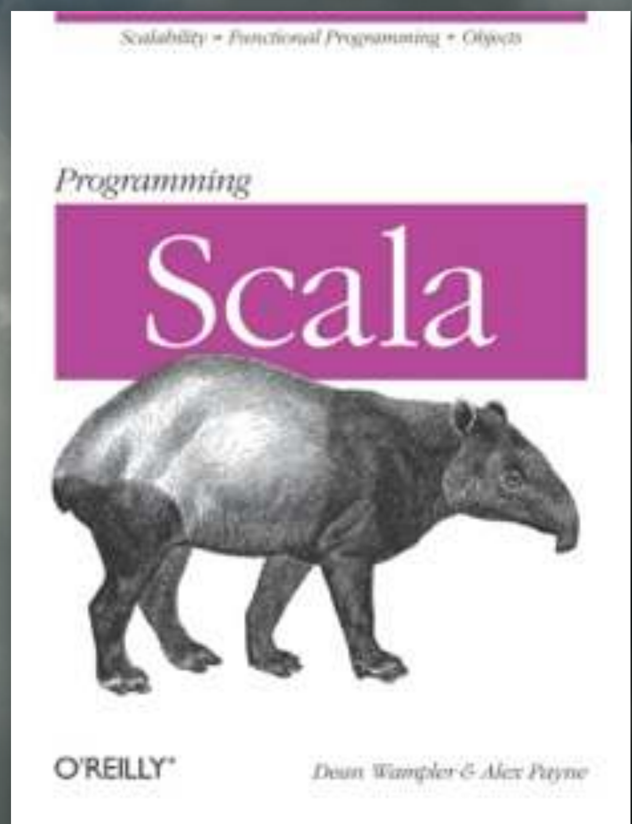
THiNK BIG ANALYTICS





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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.

Hat tip: Bob Korbus

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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.

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Three trends influence my thinking...

Data Size ⬆

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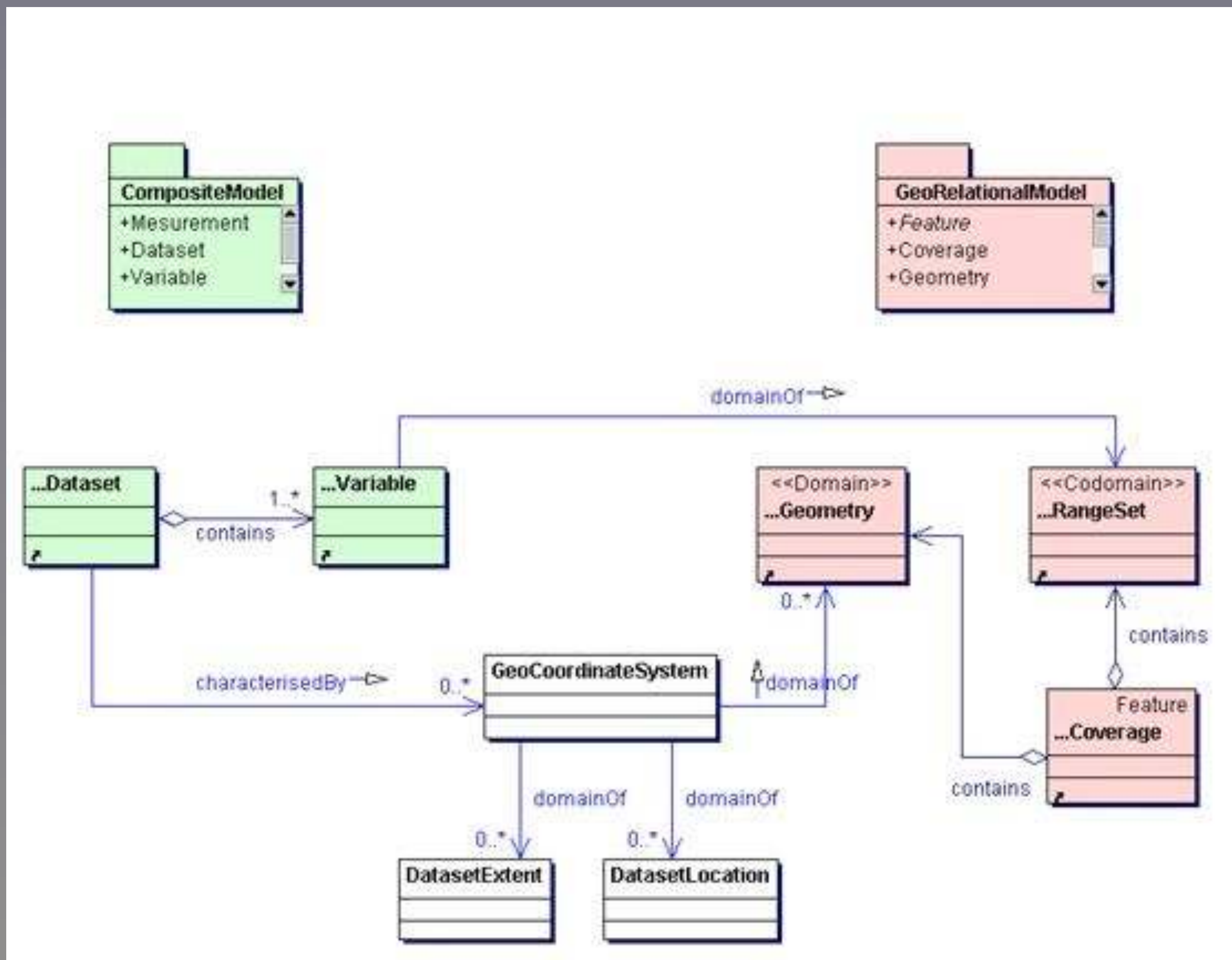
Data volumes are obviously growing… rapidly.
Facebook now has over 600PB (Petabytes) of data in Hadoop clusters!

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...)

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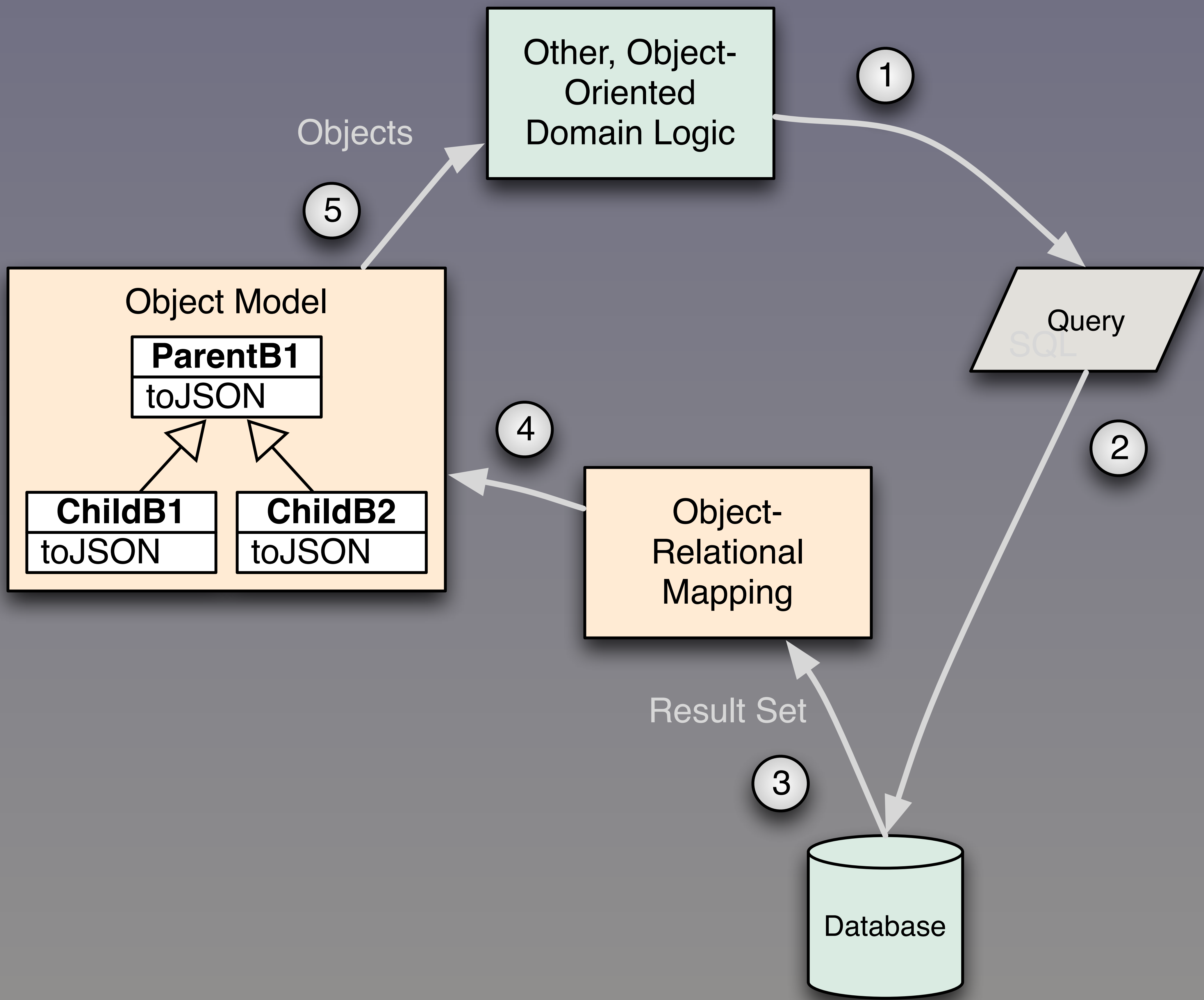
What should software architectures look like for these kinds of systems?



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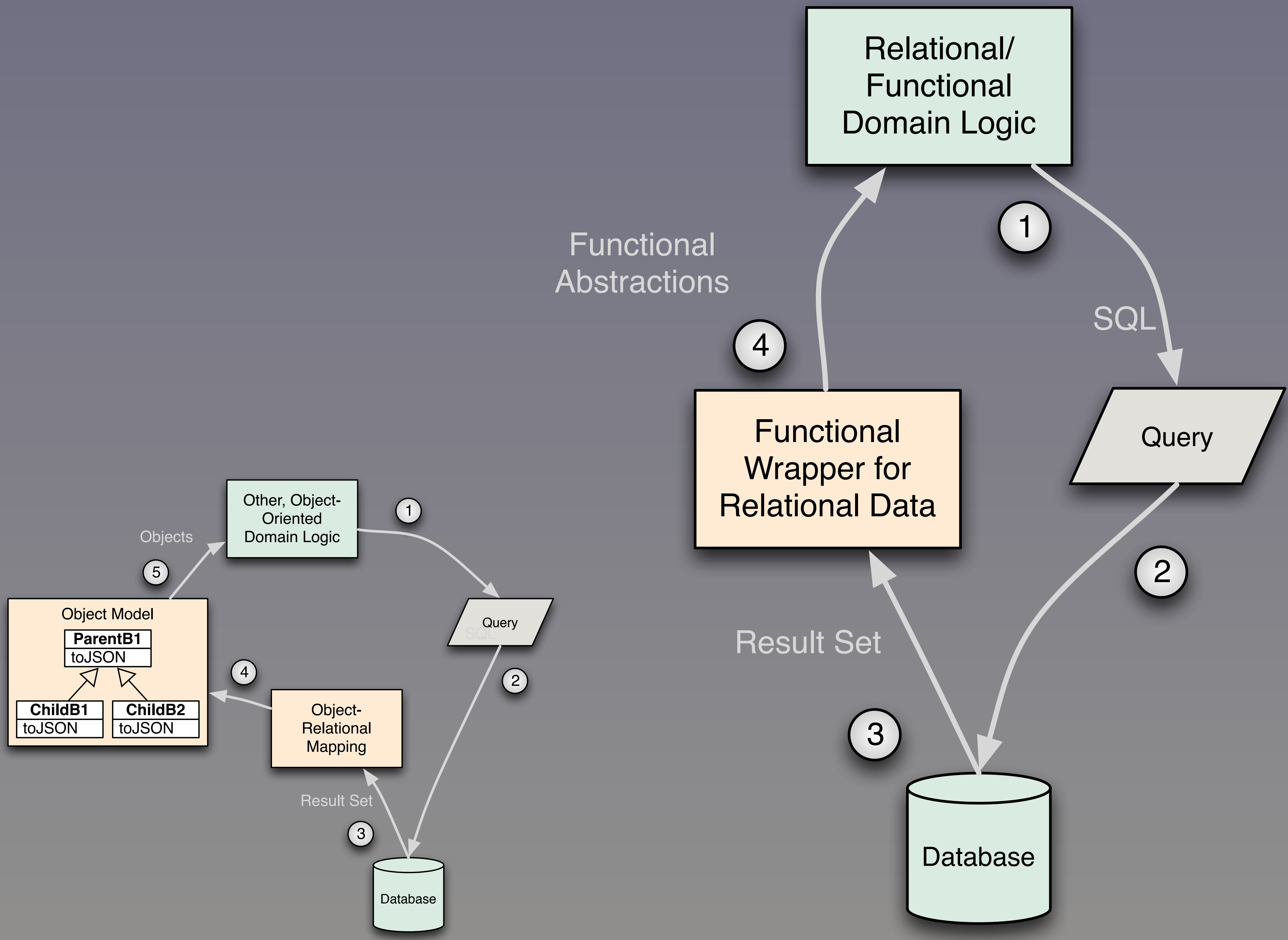
Traditionally, we've kept a rich, in-memory domain model requiring an ORM to convert persistent data into the model. This is resource overhead and complexity we can't afford in big data systems. Rather, we should treat the result set as it is, a particular kind of collection, do the minimal transformation 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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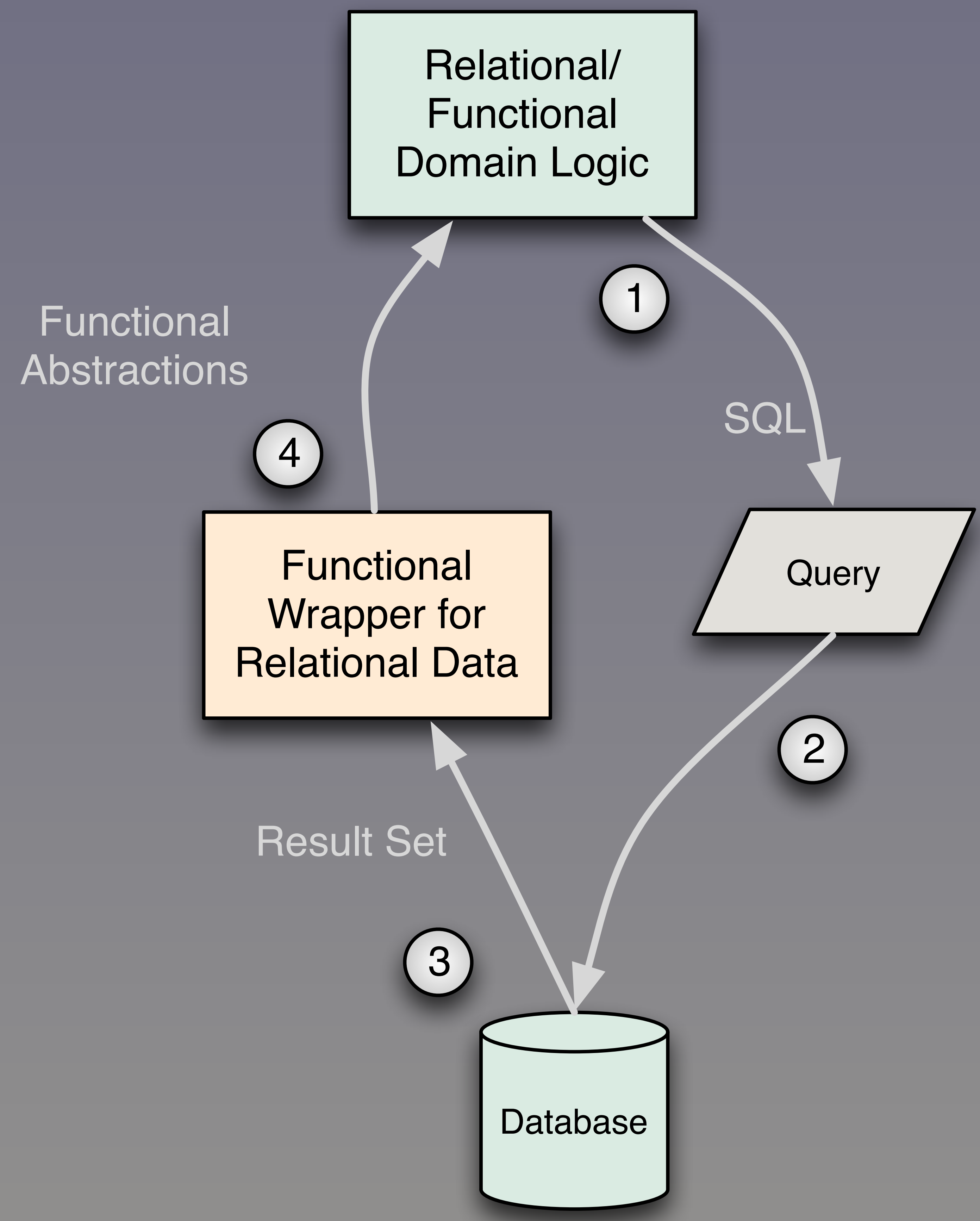
But the traditional systems are a poor fit for this new world: 1) they add too much overhead in computation (the ORM layer, etc.) and memory (to store the objects). Most of what we do with data is mathematical transformation, so we're far more productive (and runtime efficient) if we embrace fundamental 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
  - ...



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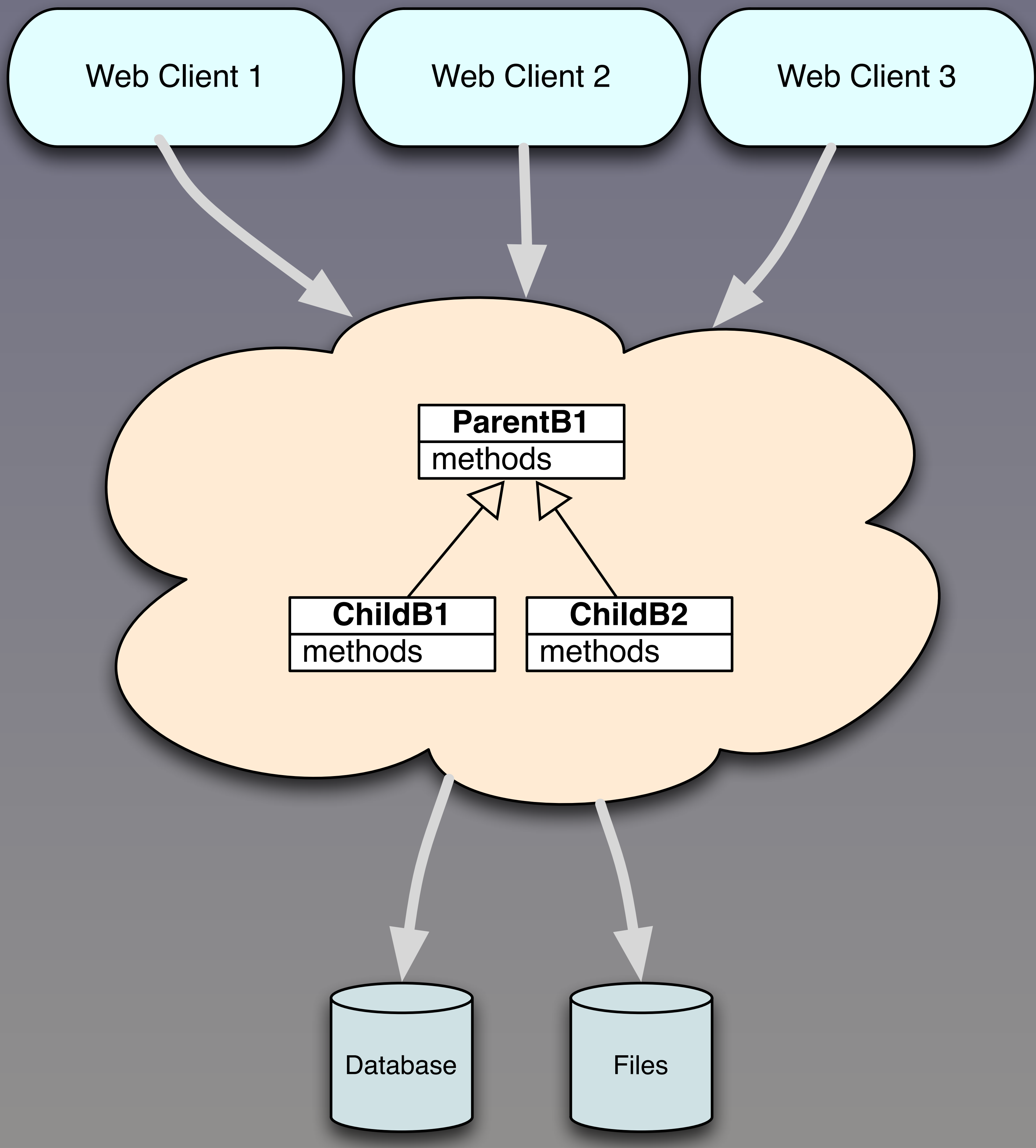
But the traditional systems are a poor fit for this new world: 1) they add too much overhead in computation (the ORM layer, etc.) and memory (to store the objects). Most of what we do with data is mathematical transformation, so we're far more productive (and runtime efficient) if we embrace fundamental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



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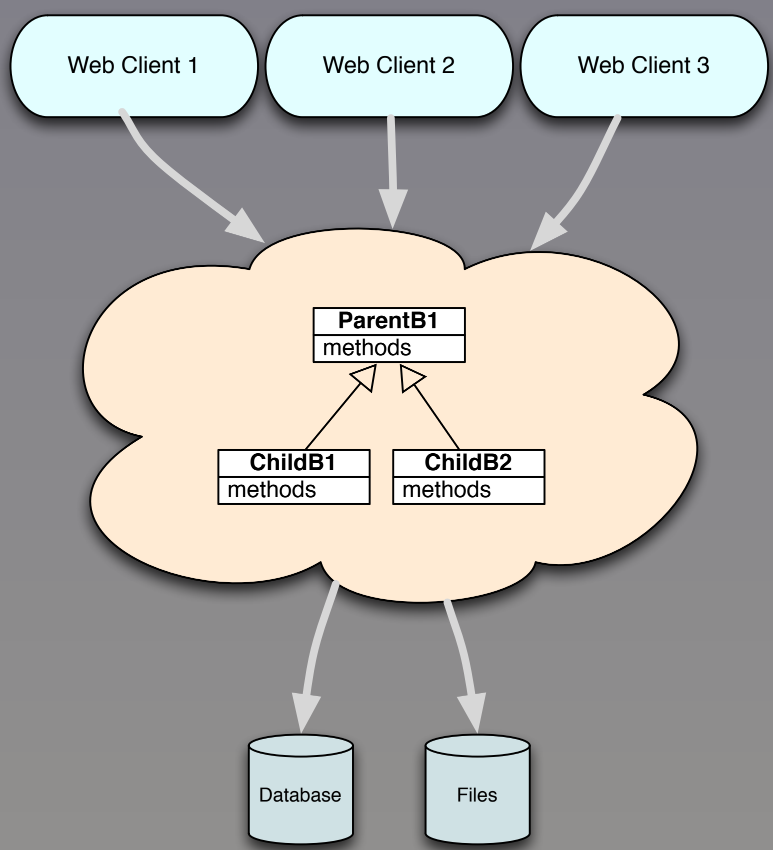
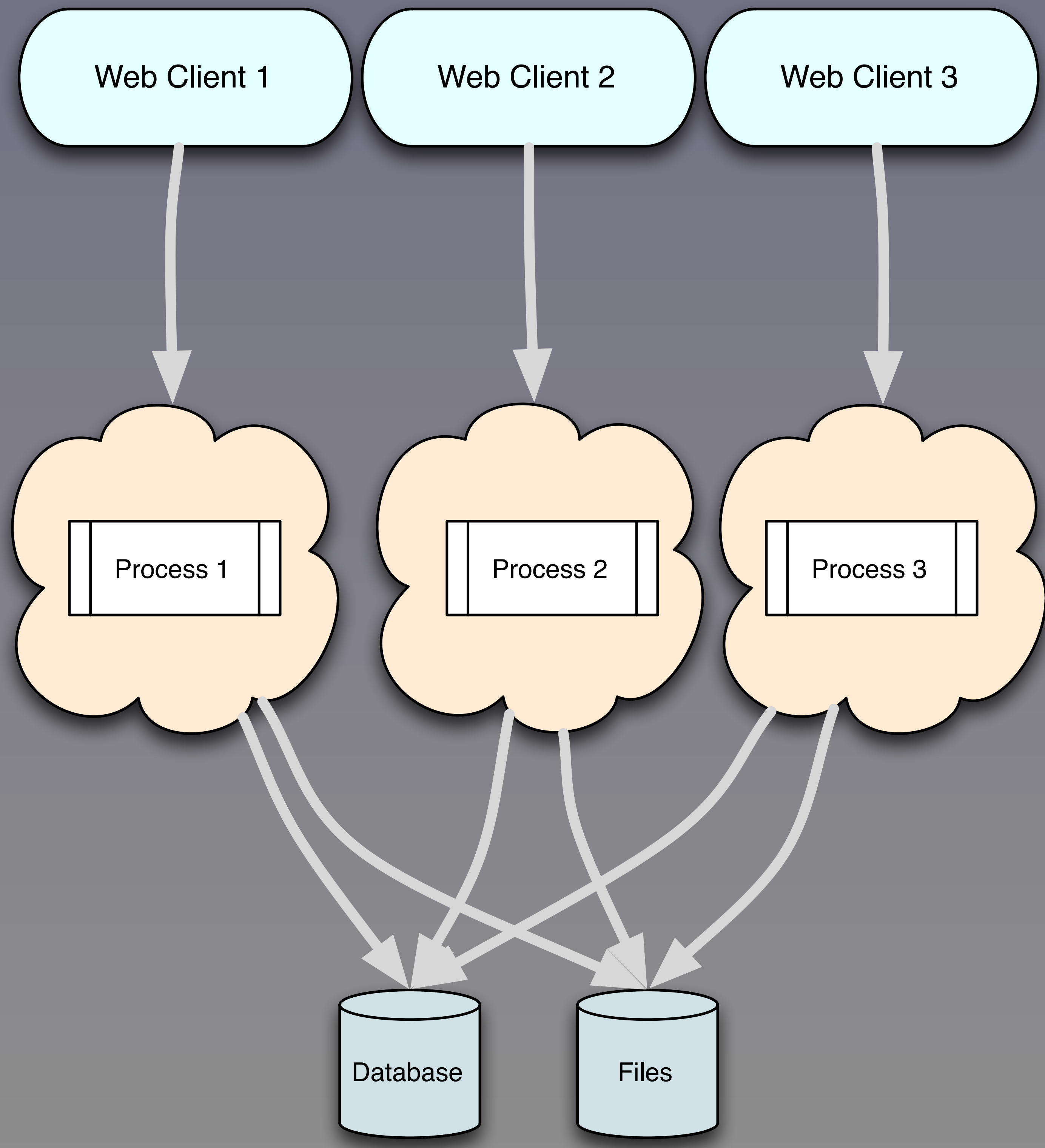
In a broader view, object models tend to push us towards centralized, complex systems that don't decompose well and stifle reuse and optimal deployment scenarios. FP code makes it easier to write smaller, focused services that we compose and deploy as appropriate.





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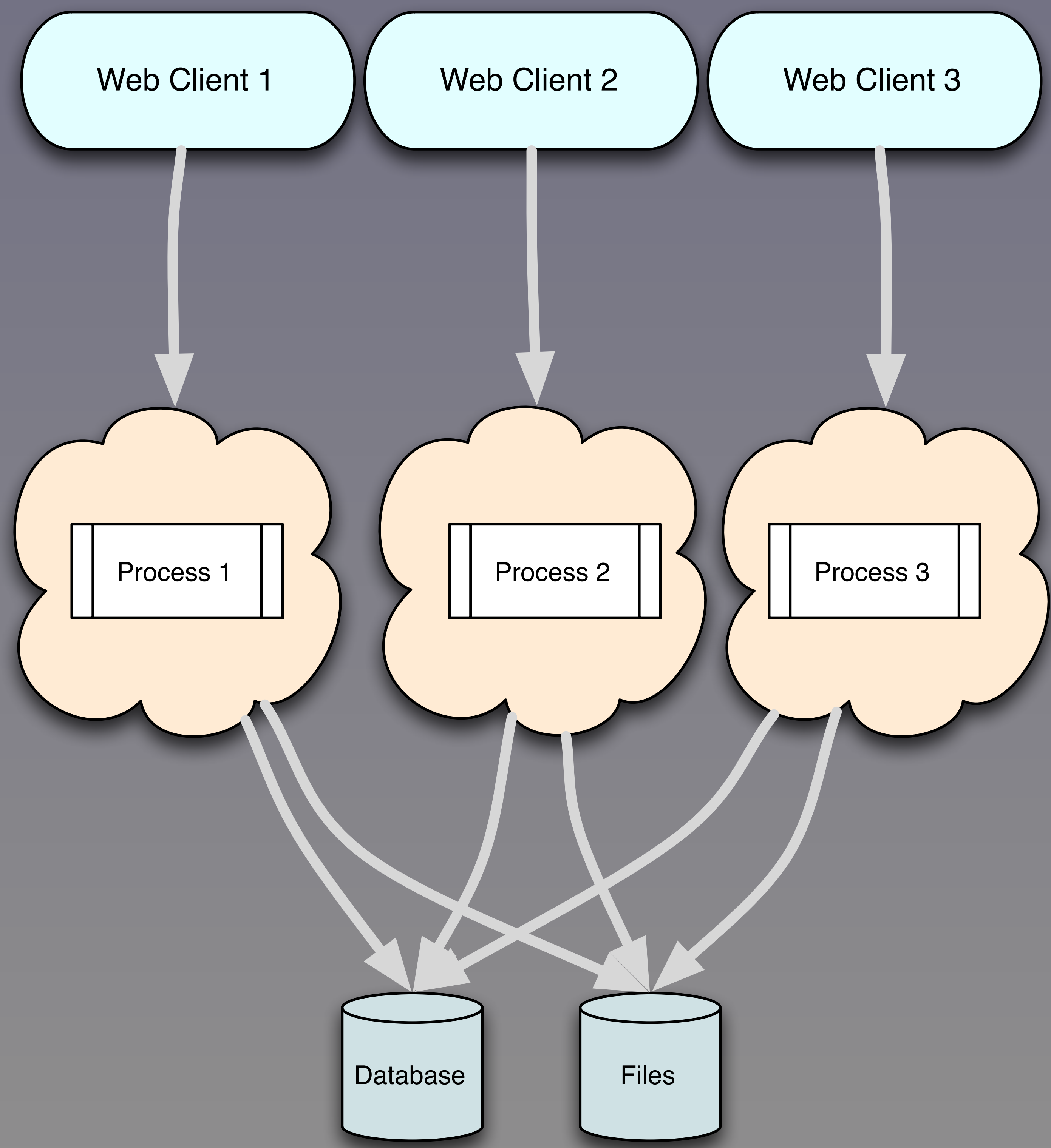
In a broader view, object models tend to push us towards centralized, complex systems that don't decompose well and stifle reuse and optimal deployment scenarios. FP code makes it easier to write smaller, focused services that we compose and deploy as appropriate. Each "ProcessN" could be a parallel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



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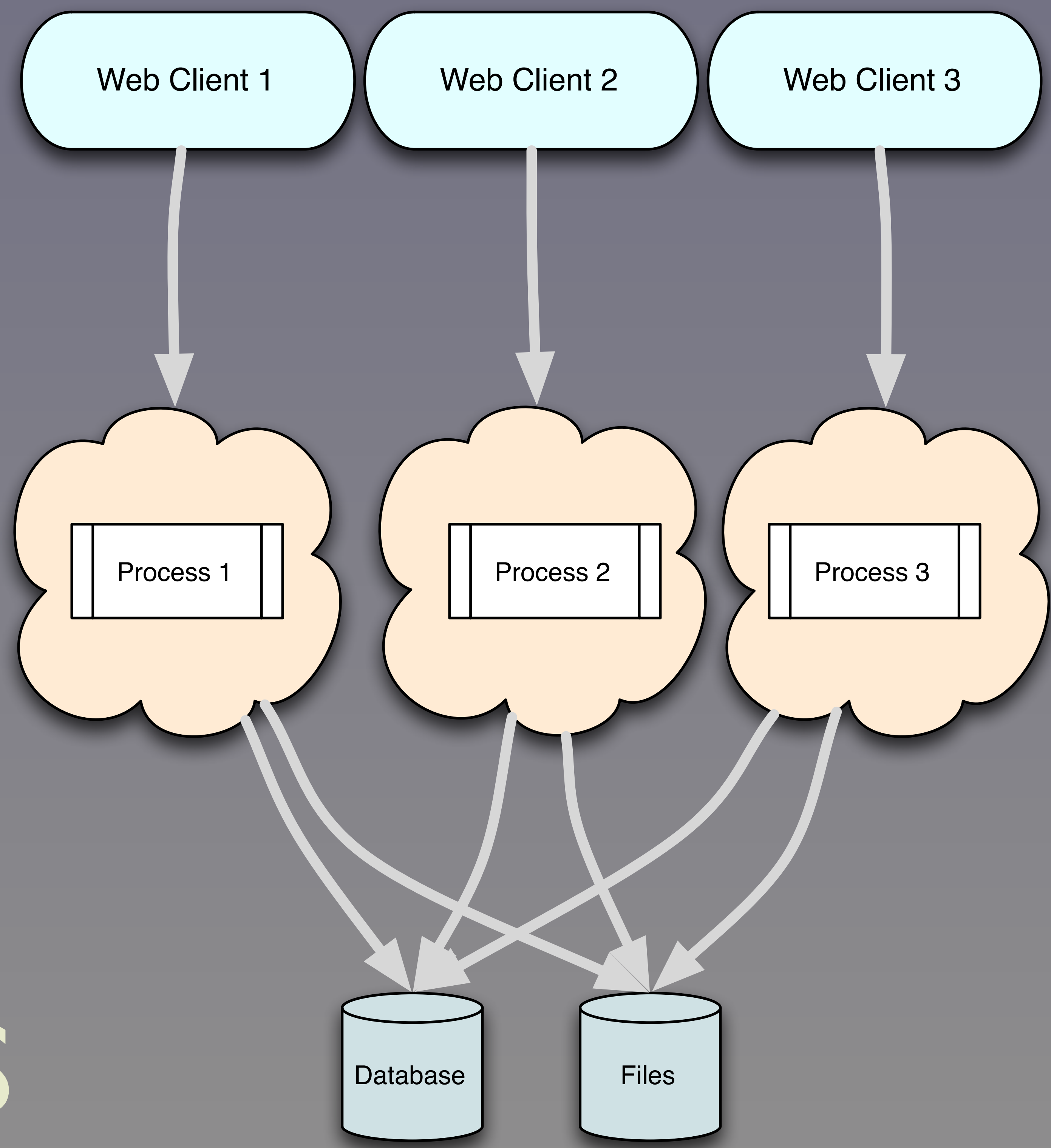
And this structure better fits the trends I outlined at the beginning of the talk.

- MapReduce
- Distributed FS



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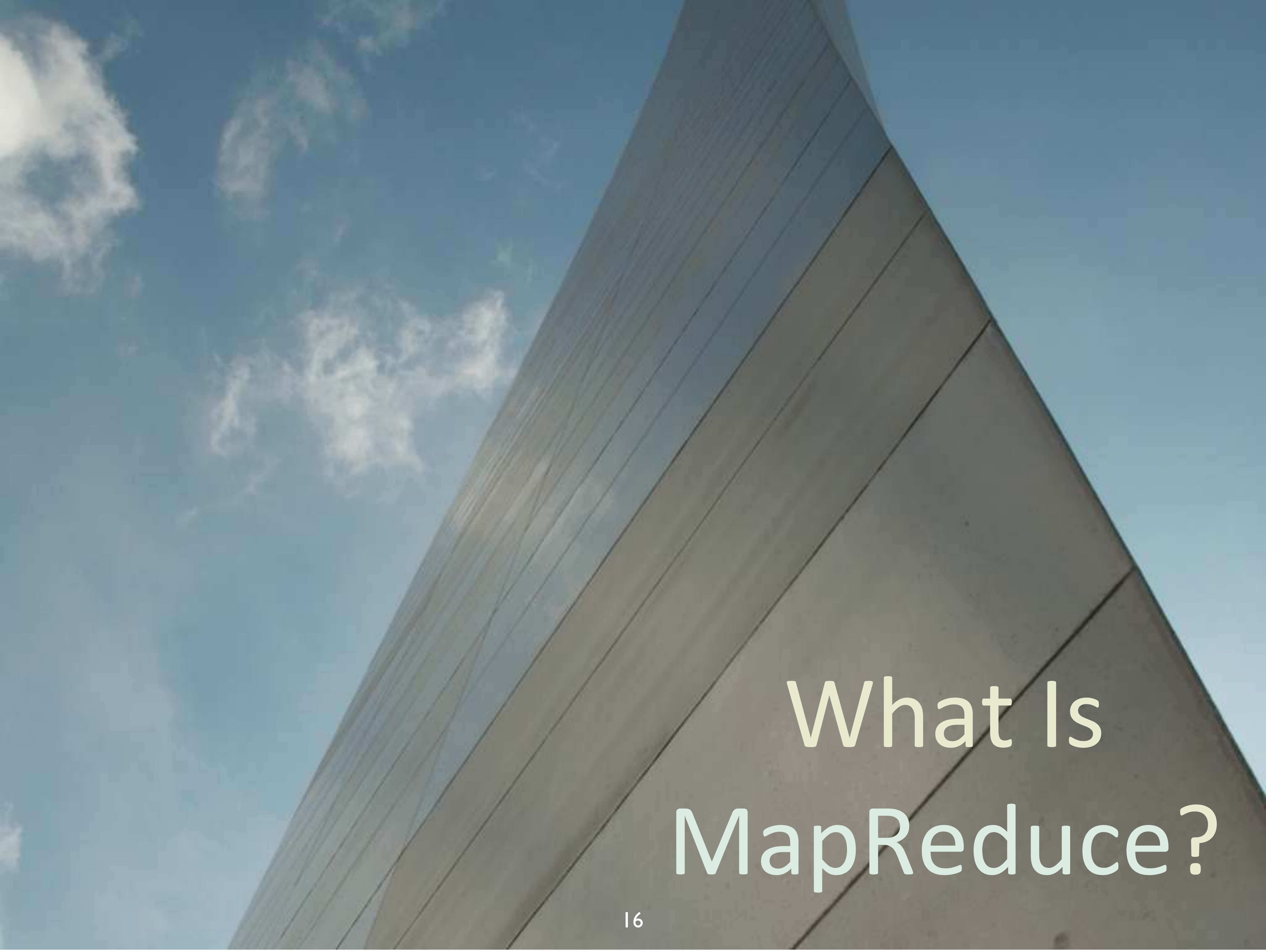
And MapReduce + a distributed file system, like Hadoop's MapReduce and HDFS, fit this model.


What Is MapReduce?
16

MapReduce in Hadoop

Let's look at a *MapReduce* algorithm: *WordCount*.

(The *Hello World* of *MapReduce*…)

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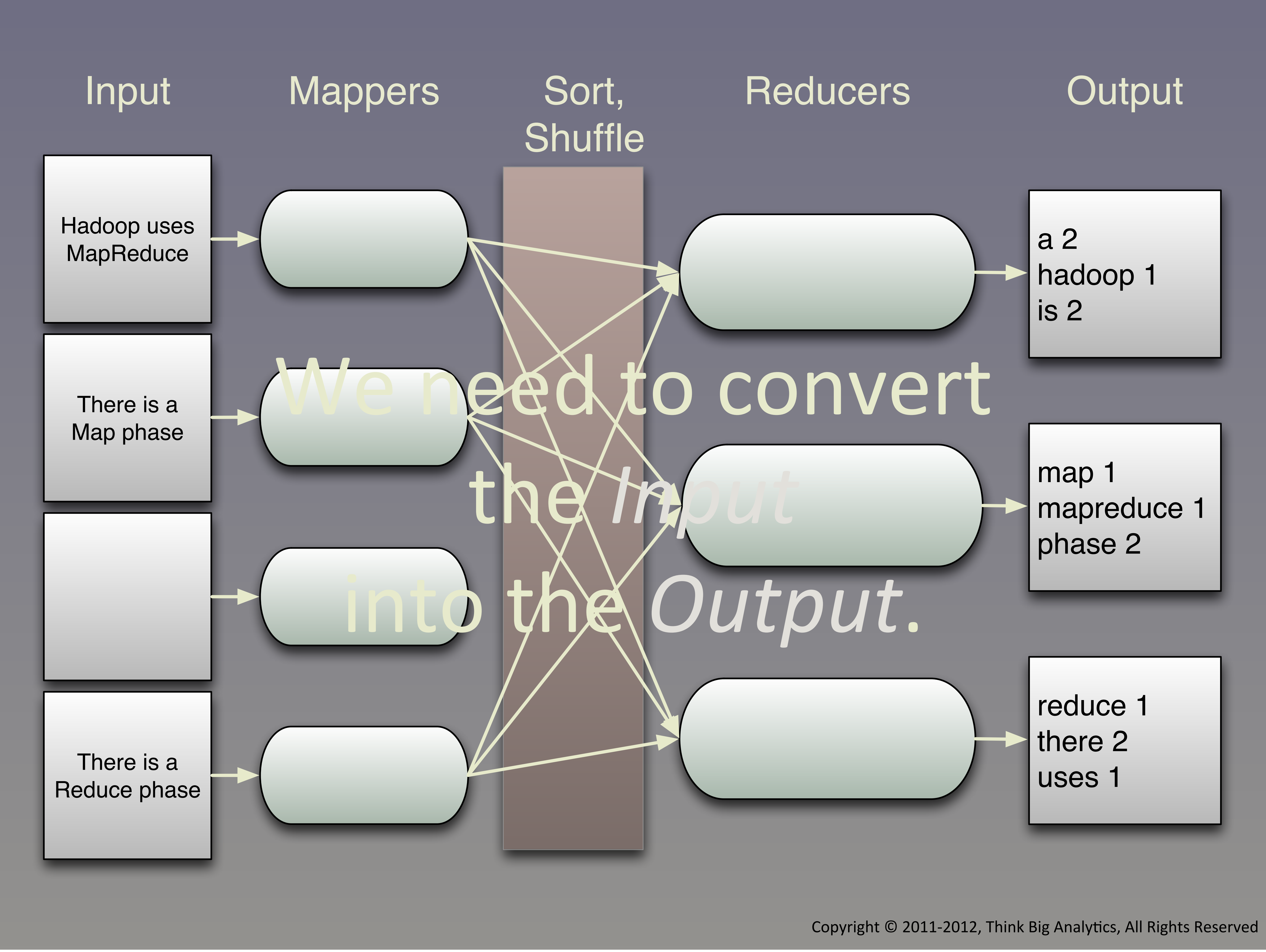
Let's walk through the "Hello World" of MapReduce, the Word Count algorithm, at a conceptual level. We'll see actual code shortly!



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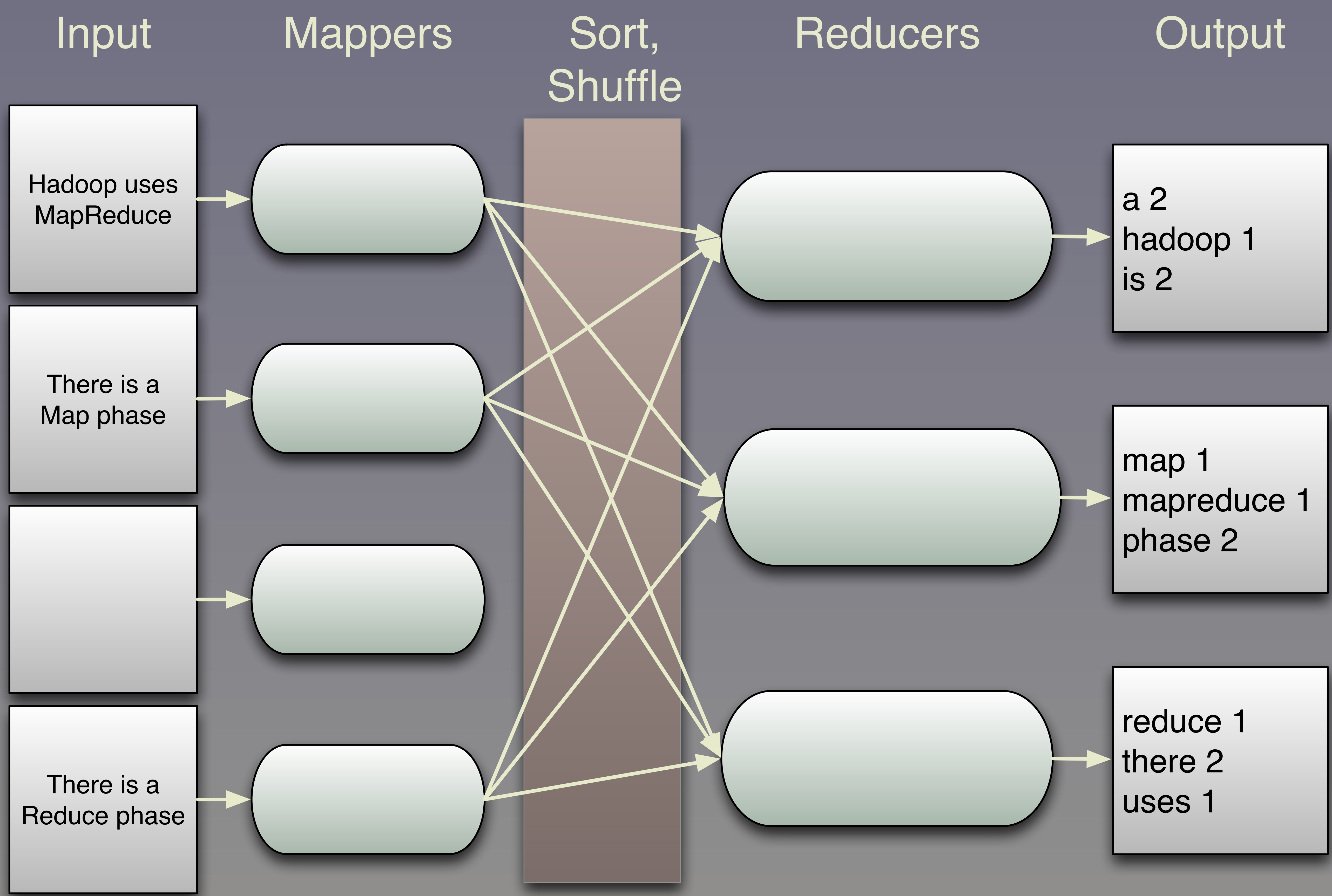
Four input documents, one left empty, the others with small phrases (for simplicity…). The word count output is on the right (we'll see why there are three output "documents"). We need to get from the input on the left-hand side to the output on the right-hand side.



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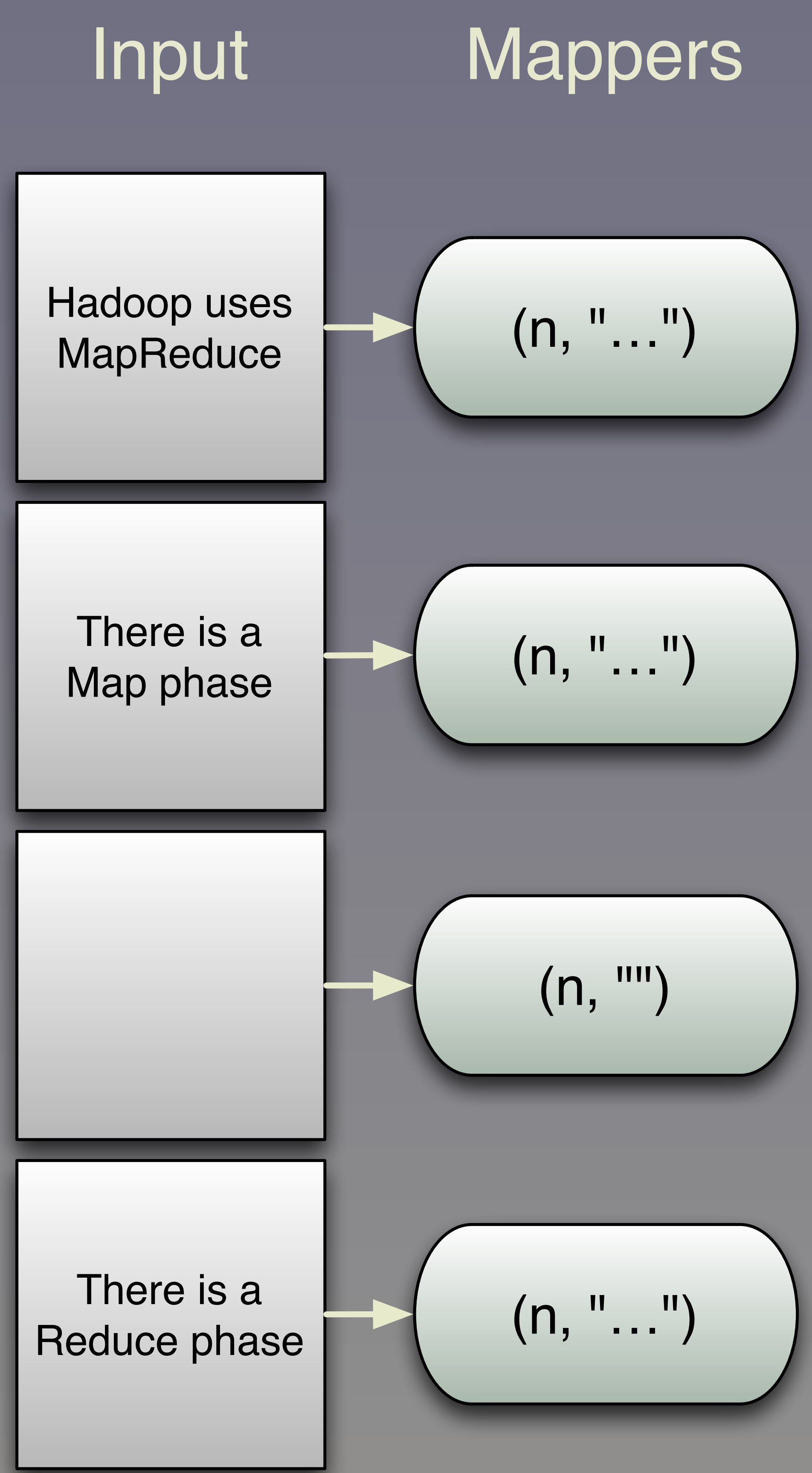
Here is a schematic view of the steps in Hadoop MapReduce. Each Input file is read by a single Mapper process (default: can be many-to-many, as we'll see later).
The Mappers emit key-value pairs that will be sorted, then partitioned and "shuffled" to the reducers, where each Reducer will get all instances 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).



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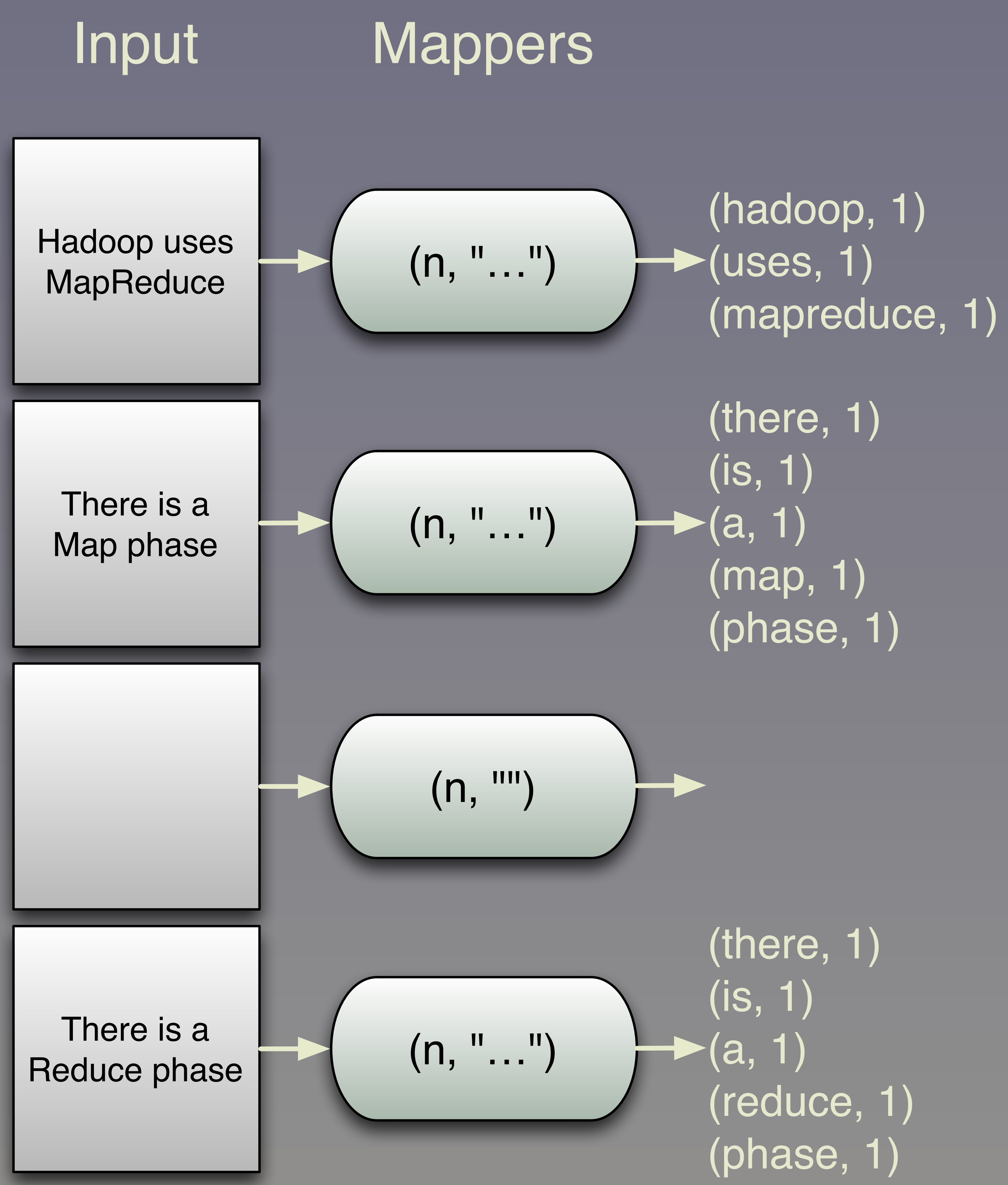
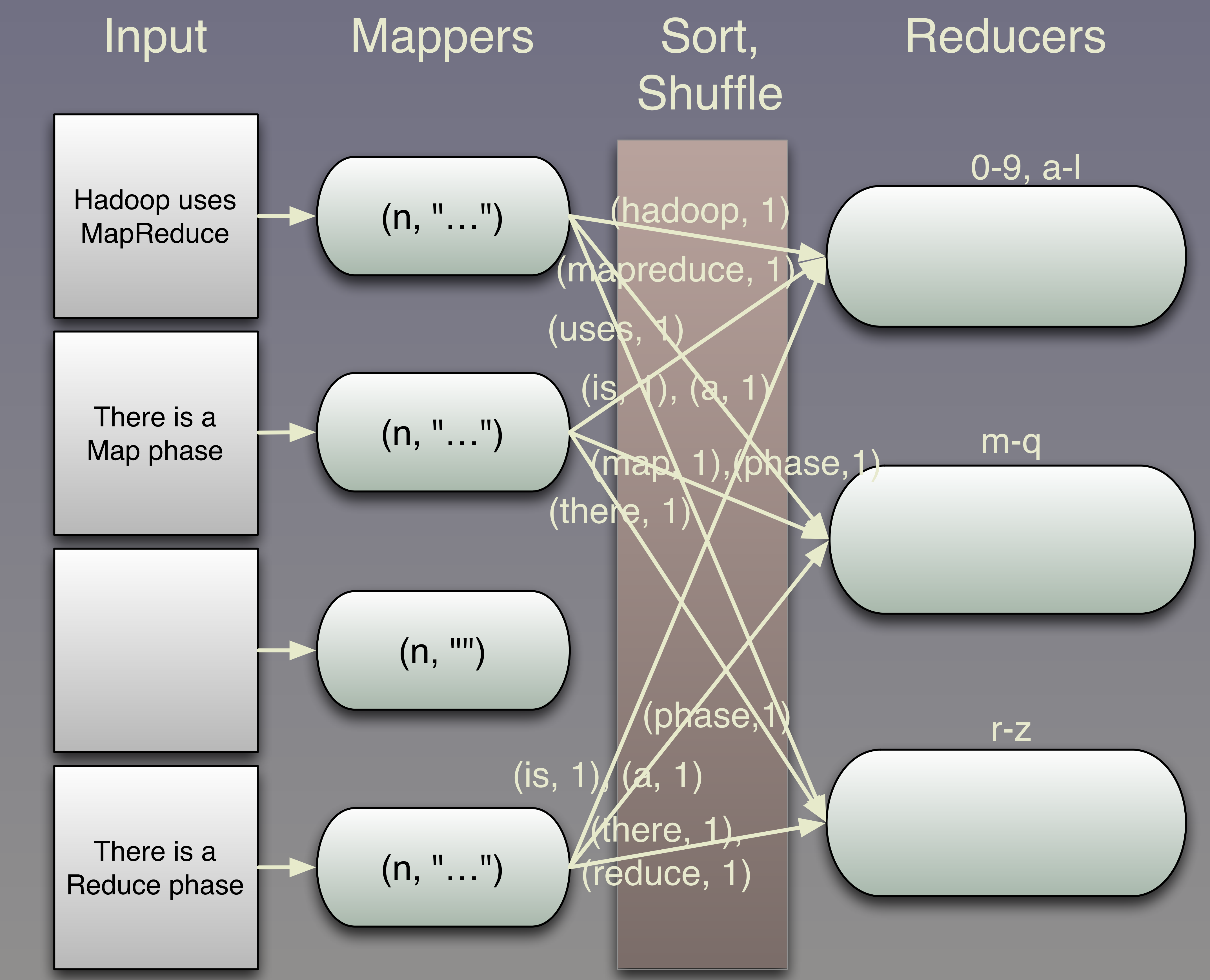
Each document gets a mapper. All data is organized into key-value pairs; each line will be a value and the offset position into the file will be the key, which we don't care about. I'm showing each document's contents in a box and 1 mapper task (JVM process) per document. Large documents might get split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



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.



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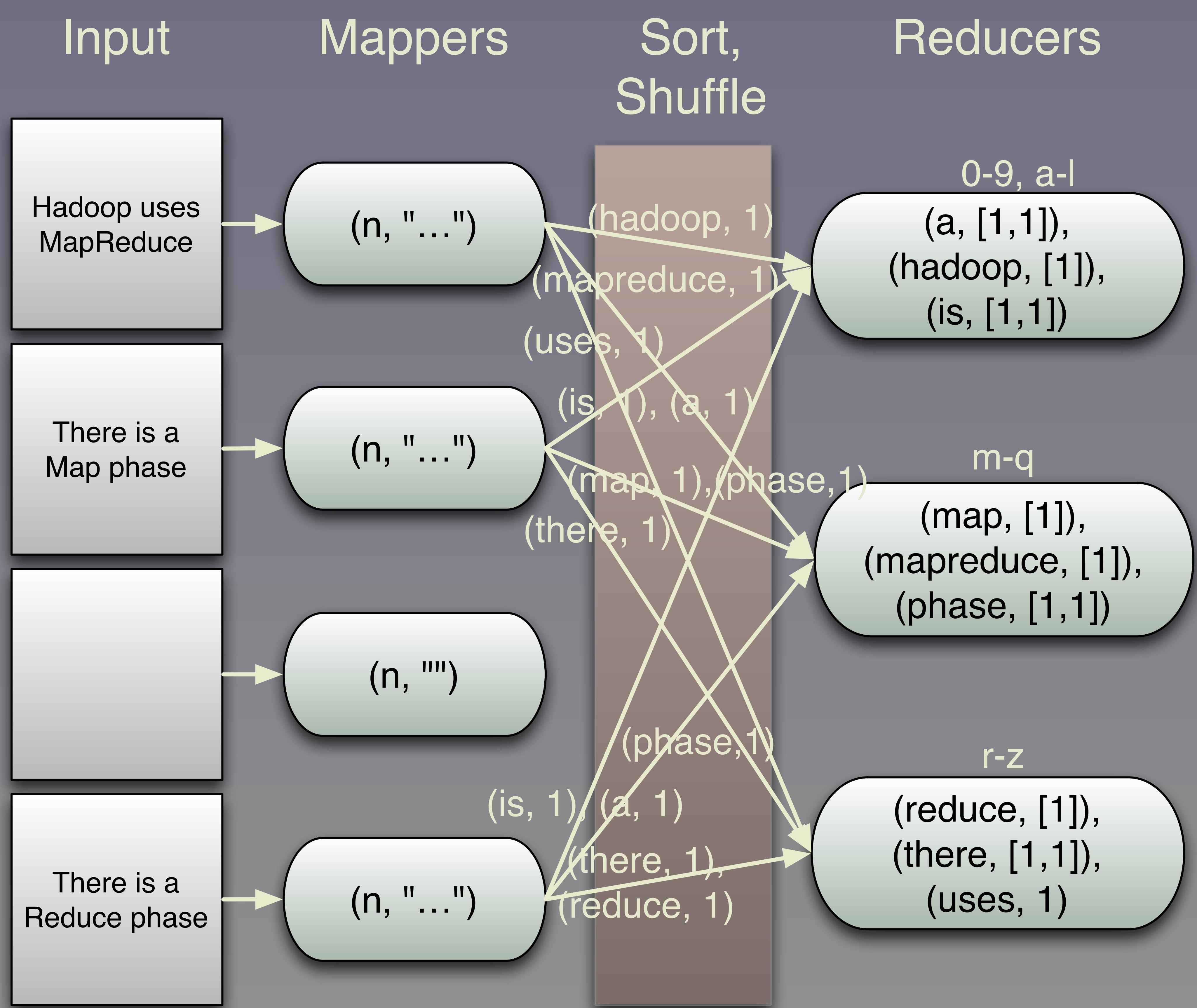
The mappers themselves don't decide to which reducer each pair should be sent. Rather, the job setup configures what to do and the Hadoop runtime enforces it during the Sort/Shuffle phase, where the key-value pairs in each mapper are sorted by key (that is locally, not globally) and then the pairs are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



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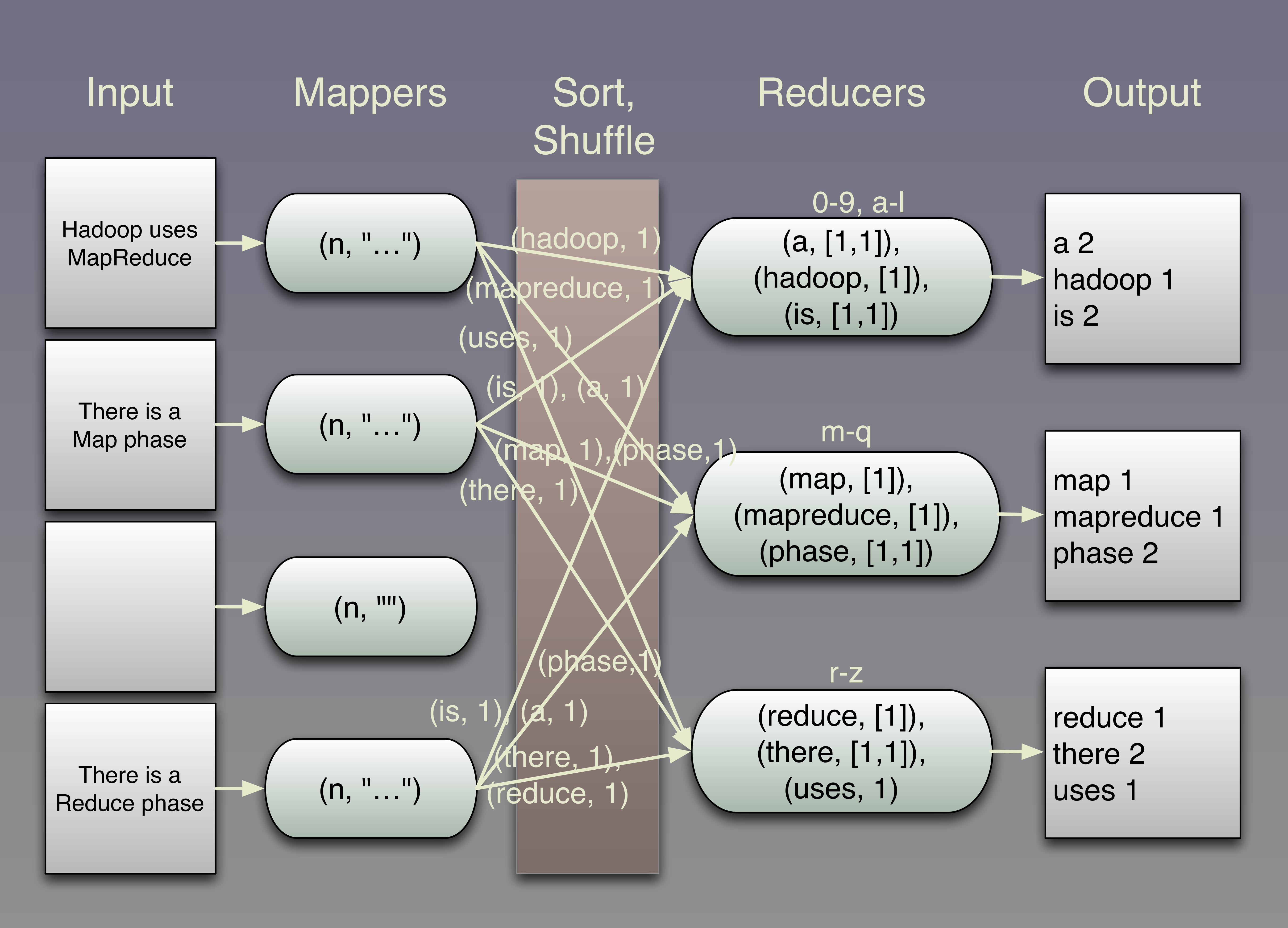
The reducers are passed each key (word) and a collection of all the values for that key (the individual counts emitted by the mapper tasks). The MR framework creates these collections for us.



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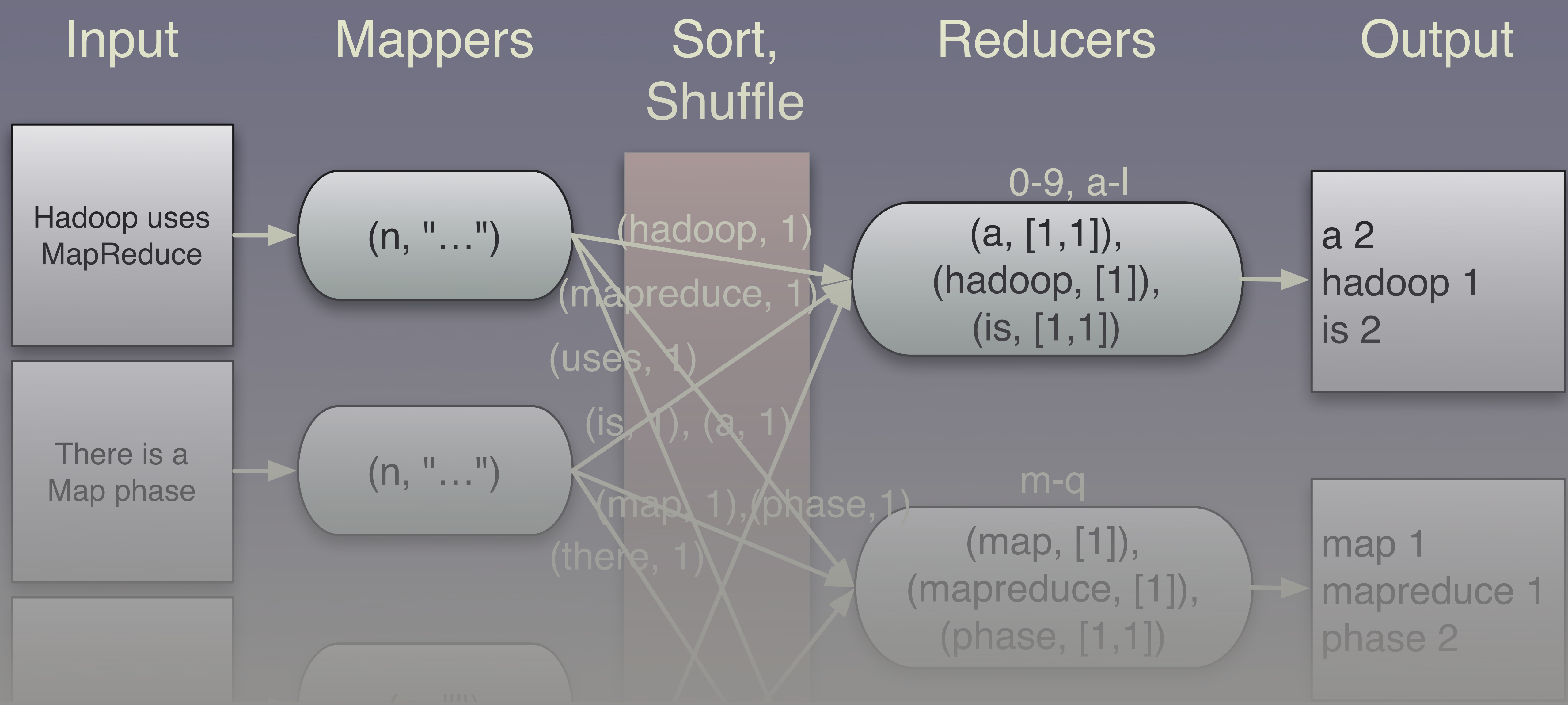
The final view of the WordCount process flow. The reducer just sums the counts and writes the output. The output files contain one line for each key (the word) and value (the count), assuming we're using text output. The choice of delimiter between key and value is up to you, but tab is common.



Map:

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

Reduce:

- Collect *multiple* inputs into *one* output.

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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

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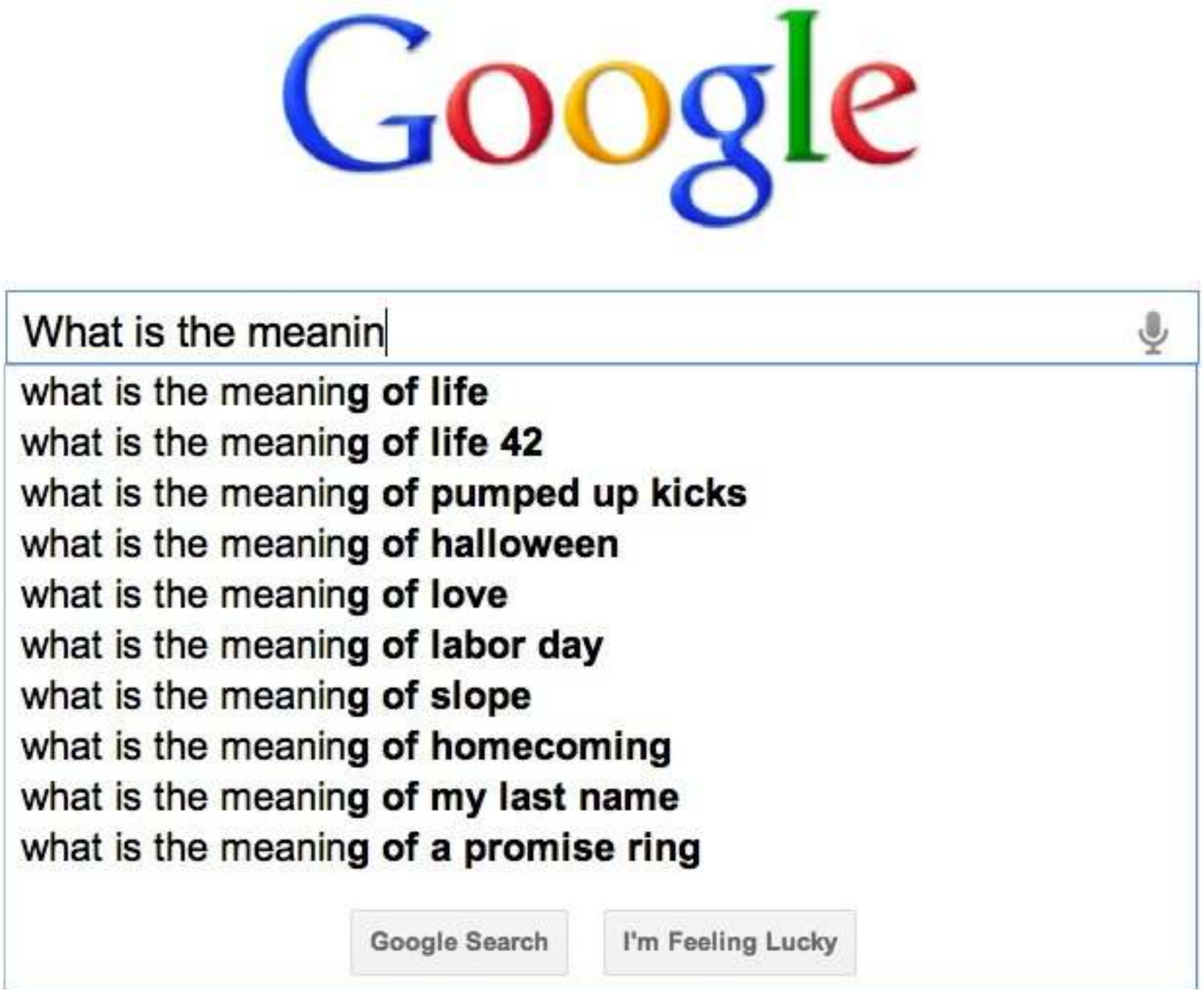
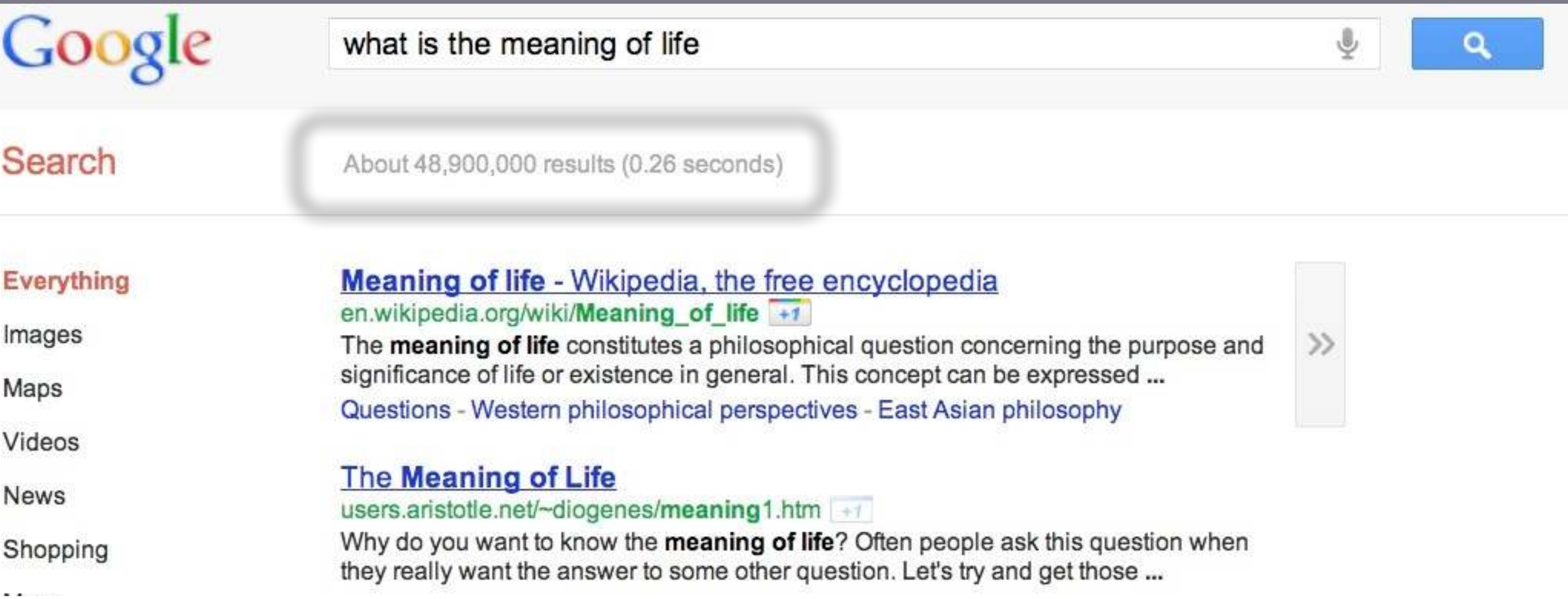
Let’s review where MapReduce came from and its best-known, open-source incarnation, Hadoop.

How would you *index* the *web*?



How would you *index* the *web*?



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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

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-

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* was working on *Nutch*...

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

He implemented clean-room versions of *MapReduce* and *GFS*...

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

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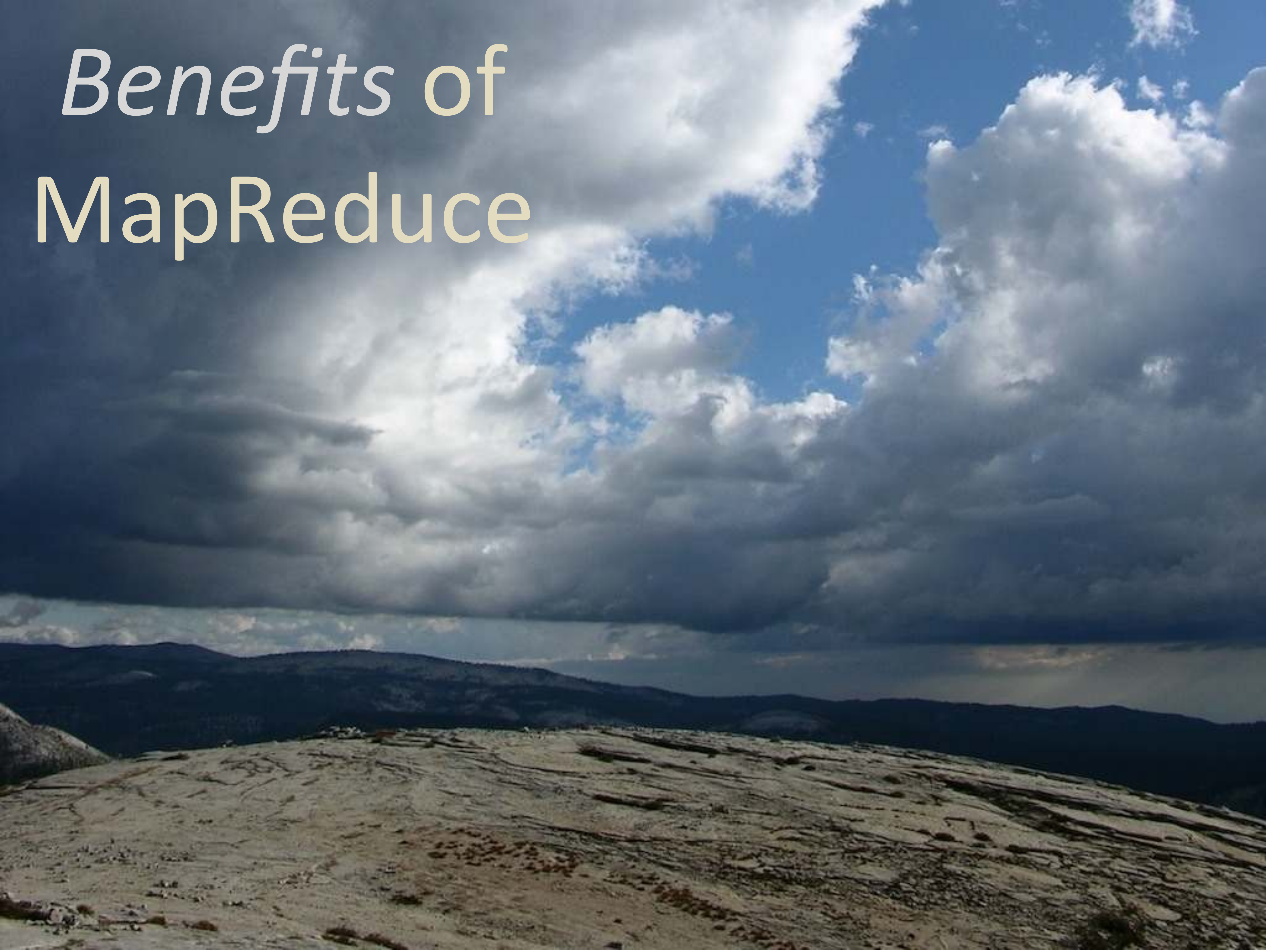
The name comes from a toy, stuffed elephant that Cutting's son owned at the time.

Benefits of MapReduce



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

Minimize I/O Overhead!!

Oh, and run on *server-class, commodity* hardware.

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True of Google's GFS and MapReduce, too. Minimizing disk and network I/O latency/ overhead 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...

Hadoop also has a *vibrant community* that's evolving the platform.

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For the IT manager, especially at large, cautious organizations.

Commercial support is available from many companies.

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From Hadoop-oriented companies like Cloudera, MapR, and HortonWorks, to integrators like IBM and Greenplum.

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 WCReduce 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));
  }
}
```


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 additional boilerplate 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!

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I claimed we should be using FP for big data, so why not use SQL when you can! Here are 3 options.

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, 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.

Use SQL when you can!

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

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.

Impala

- Copied from Google's Dremel.
- C++ and Java back end.
- Provides up to 100x performance improvement!
- Developed by Cloudera.

See http://www.cloudera.com/content/cloudera/en/products/cloudera-enterprise-core/cloudera-enterprise-RTQ.html. However, this was just announced recently, so it's not production ready quite yet...

Use Cascading (Java)

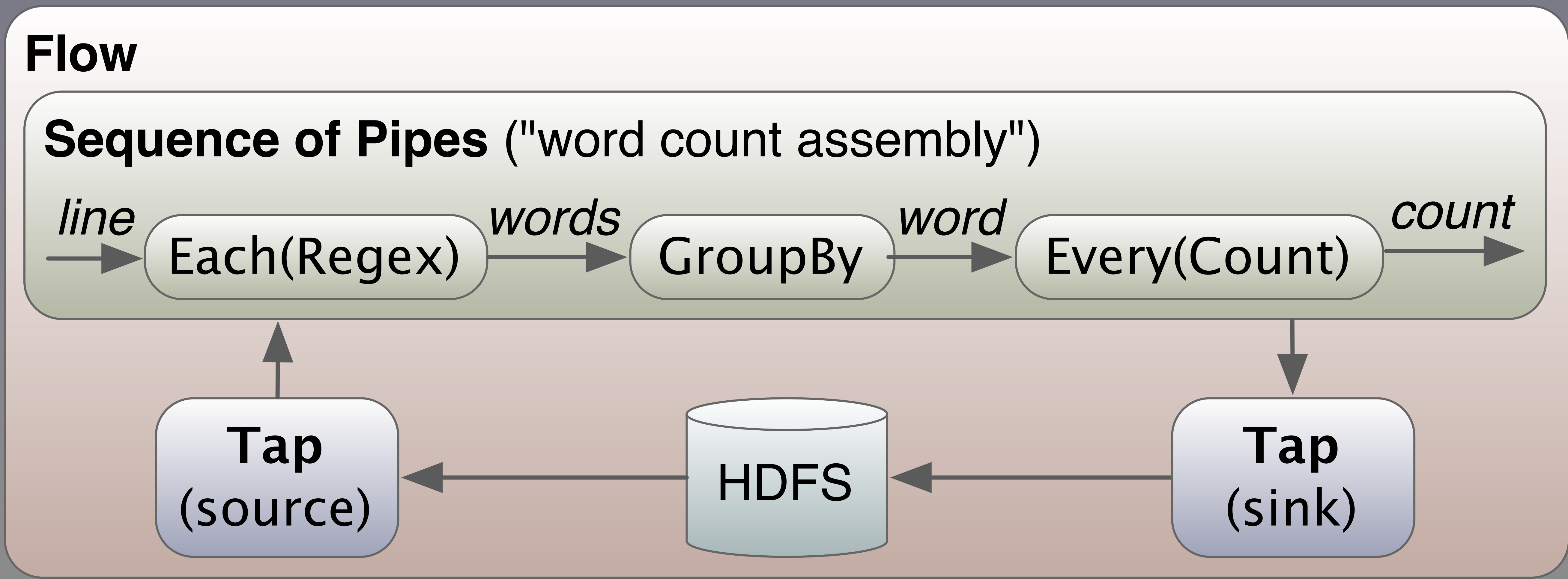
(Solution #2a)

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



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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.

```java
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 #2b)

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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.

```scala
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!!

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.

Use Spark (Scala)

(Solution #3)

Spark is an Alternative to Hadoop MapReduce:

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

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 an Alternative to Hadoop MapReduce:

- Originally designed for machine learning applications.

```scala
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))
  }
}
```

Even more succinct.

Note that there are only 3 explicit types required.

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This spark example is actually closer in a few details, i.e., function names used, to the original Hadoop Java API example, but it cuts down boilerplate to the bare minimum.

#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!

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

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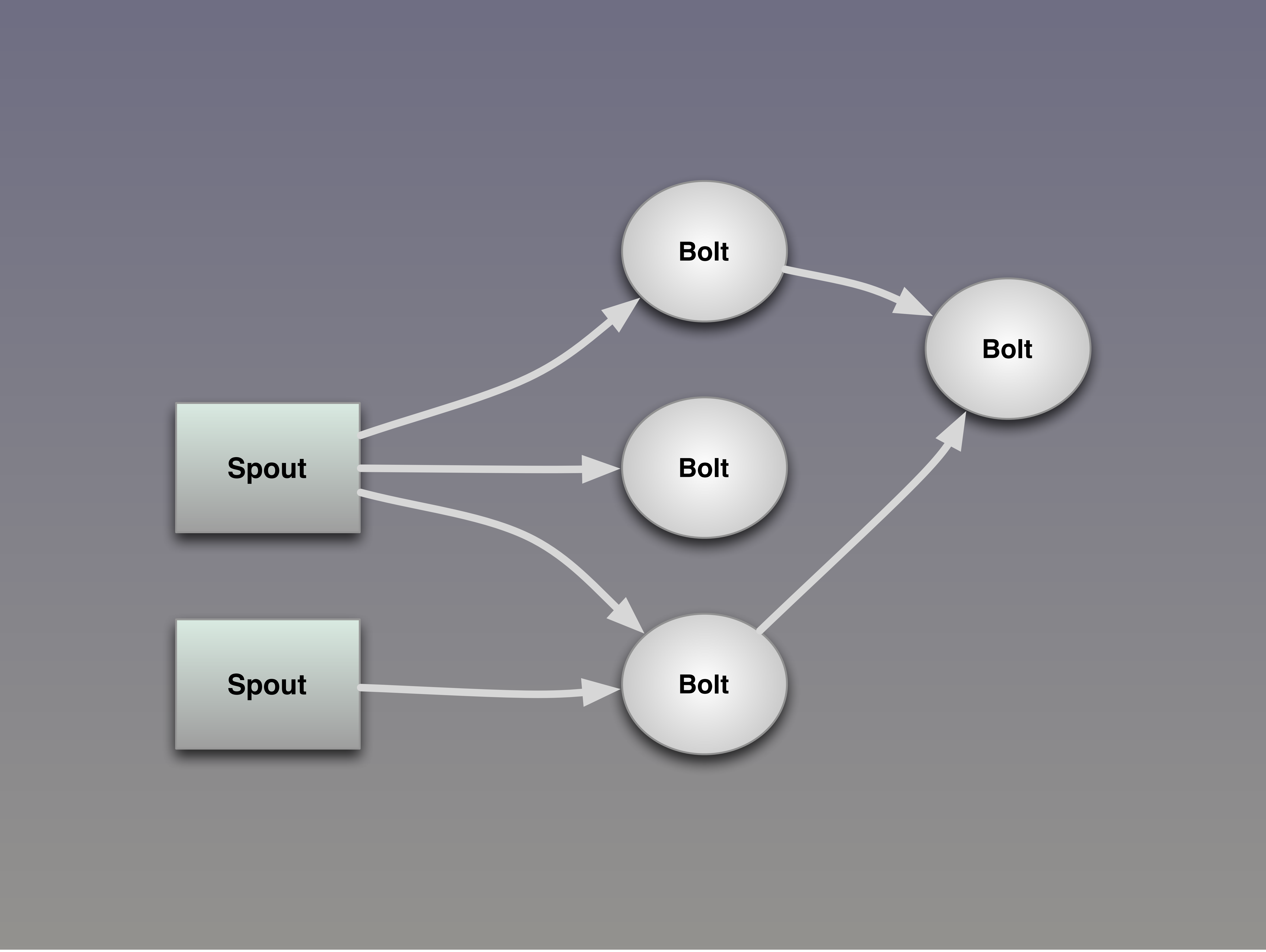
http://storm-project.net/ Created by Nathan Marz, now at Twitter, who also created Cascalog, the Clojure wrapper around Cascading with added Datalog (logic programming) features.



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 Sprouts and various targets of output. Distributed processing is baked in from the start.


Databases?

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*.

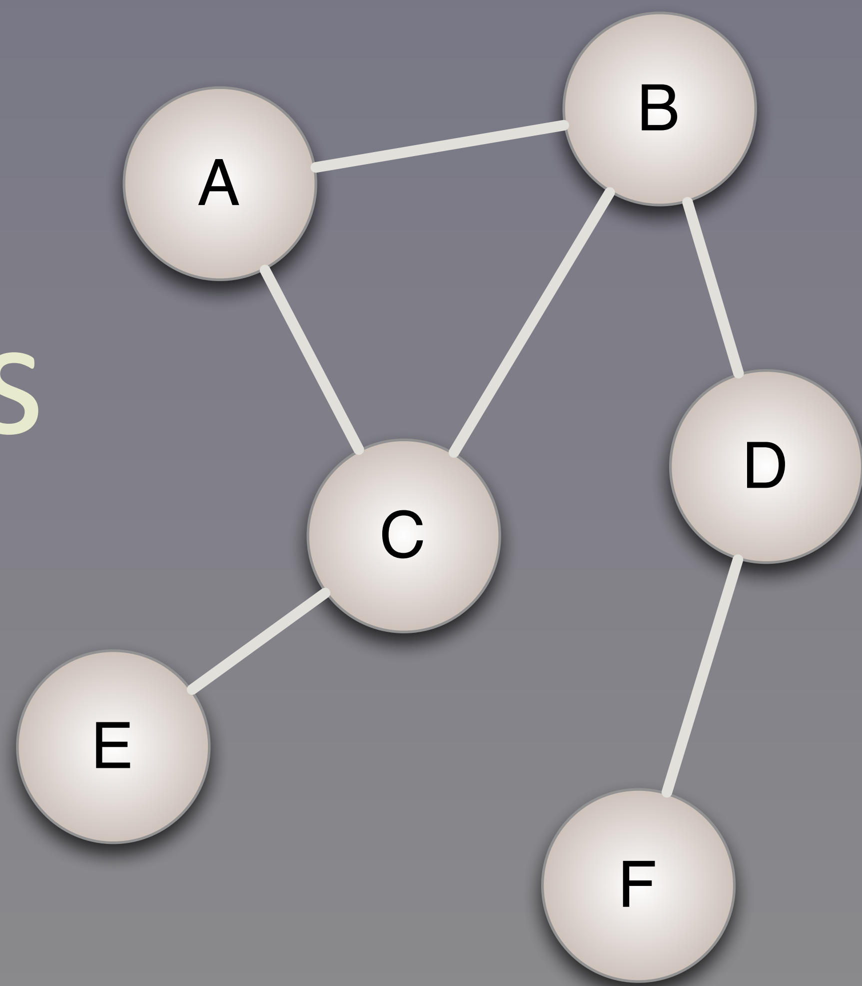
Google's Page Rank

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

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...

Pregel is intended to replace MR for PageRank, but I've heard they haven't actually been able to switch over to it yet. "Pregel" is 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 he 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.

http://incubator.apache.org/giraph/
http://hama.apache.org/
http://thinkaurelius.github.com/titan/
None is very mature nor has extensive commercial support.

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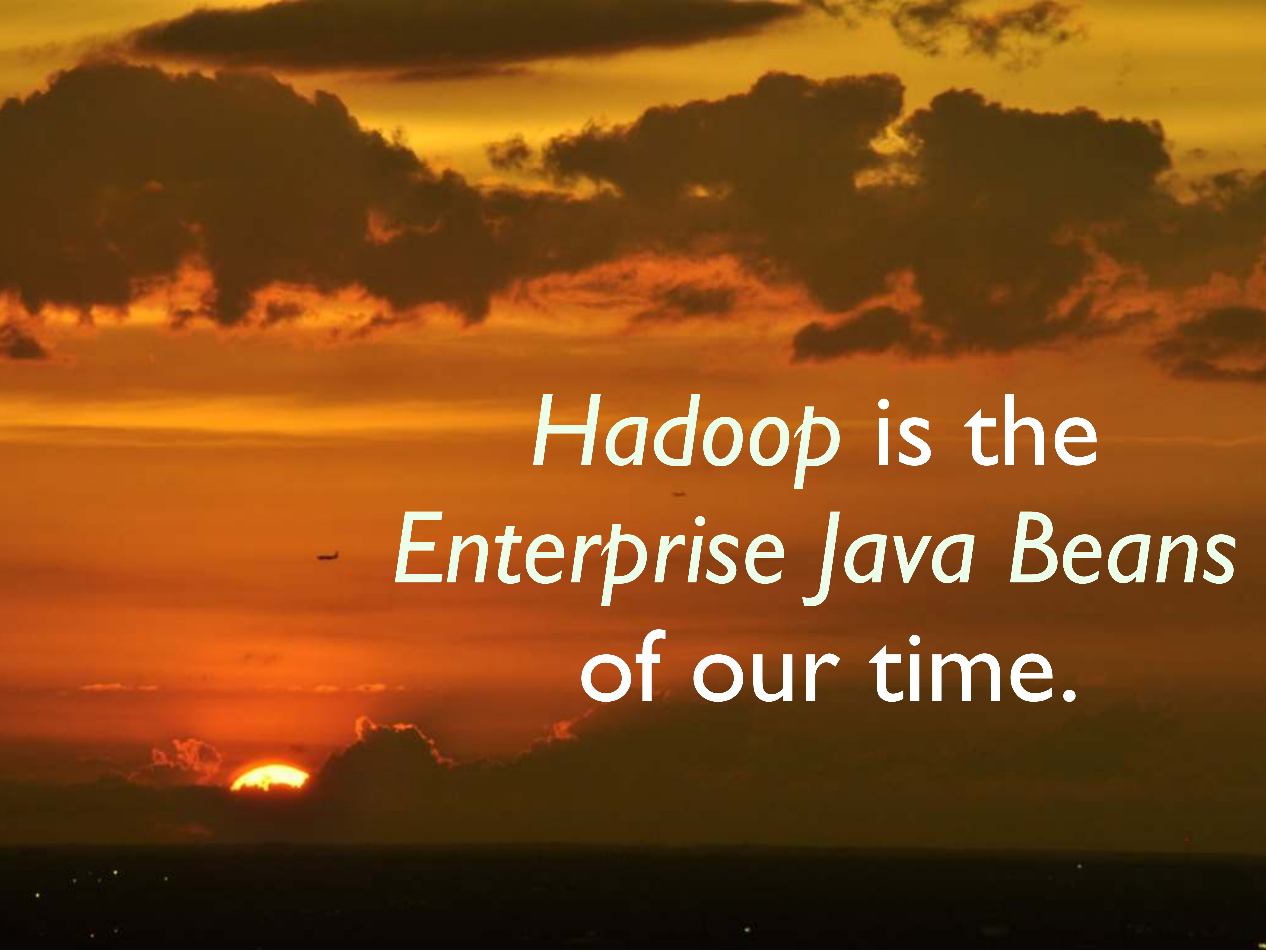
To bring this altogether, I think we have opportunities for a better way...



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...

Java has taken us a long way and made many organizations successful over the years. Also, the JVM remains one of our most valuable tools in all of IT. But the language is really wrong 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. They also contribute to focusing on the wrong concepts, structure instead of behavior.

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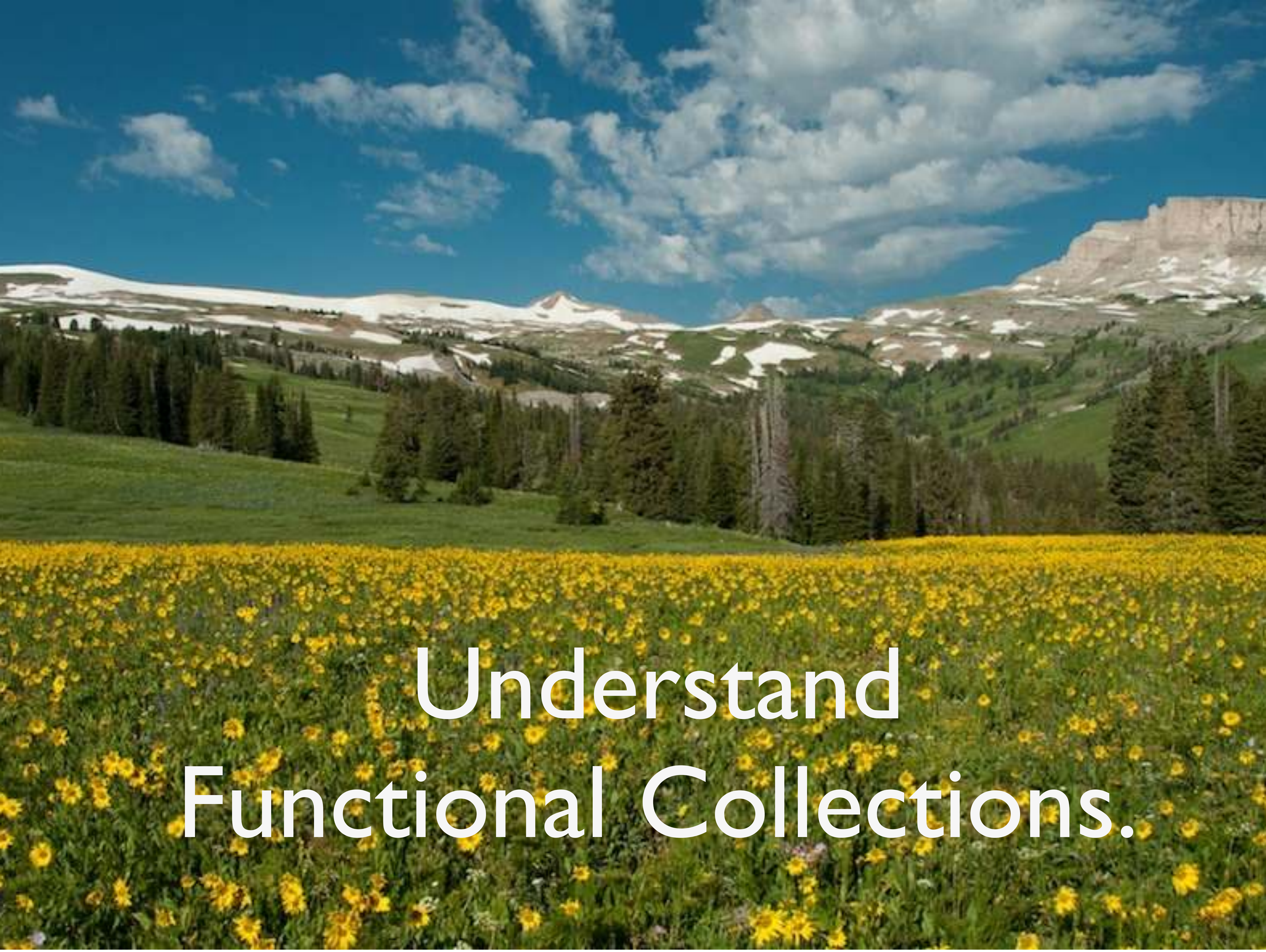
Why is Functional Programming better for Big Data? The work we do with data is inherently mathematical transformations and FP is inspired by math. Hence, it's naturally a better fit, much more so than object-oriented programming. And, modern languages like Scala, Clojure, Erlang, F#, OCaml, and Haskell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



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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.

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.

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A final thought about Big Data...

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