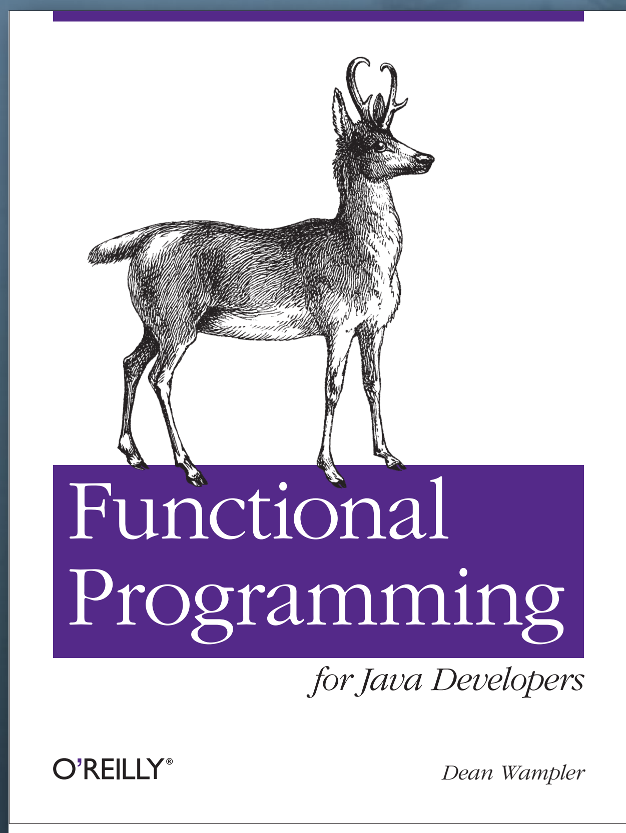
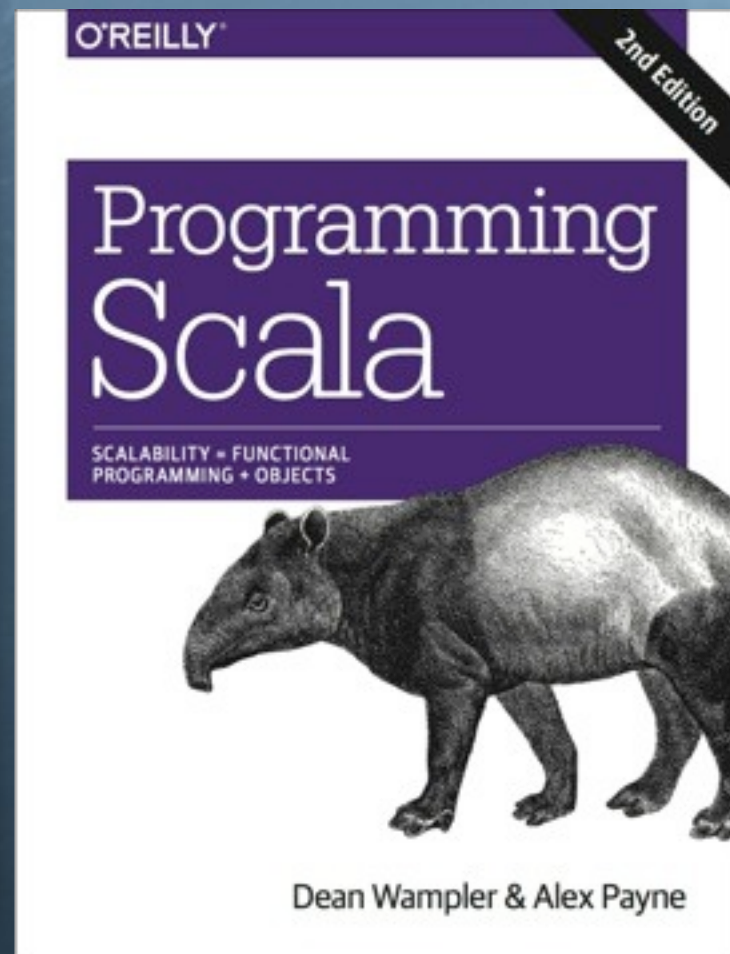
BIG DATA STATE OF THE ART: SPARK AND THE SQL RESURGENCE

Dean Wampler, Ph.D.
Typesafe

Dean Wampler

Typesafe





dean.wampler@typesafe.com
polyglotprogramming.com/talks
@deanwampler

About me. You can find this presentation and others on Big Data and Scala at polyglotprogramming.com.

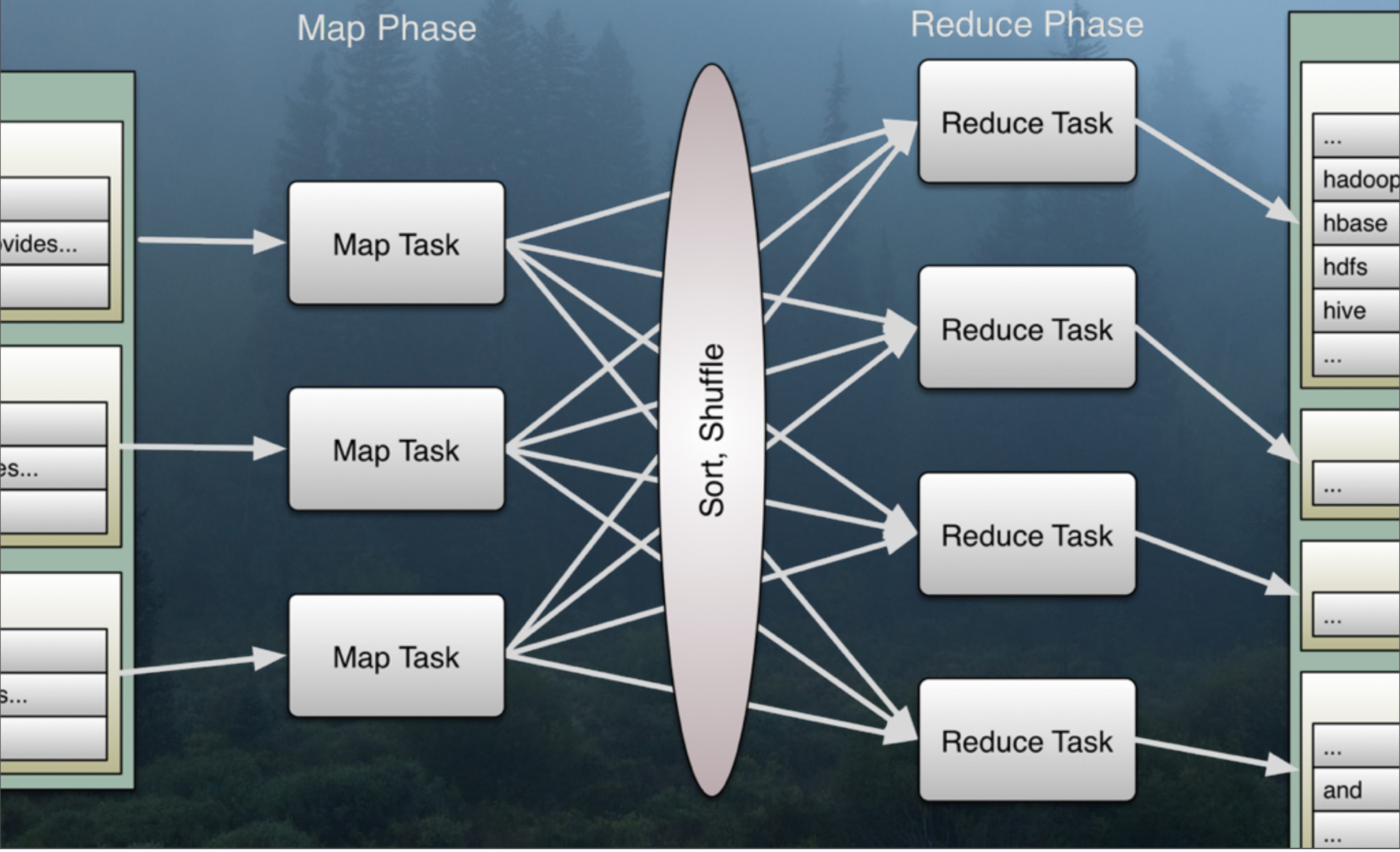

It's 2014


Hadoop has been very successful.
4


But it's not perfect
5

The limitations of MapReduce have become increasingly significant...

1 Map step + 1 Reduce step



Tuesday, September 30, 14

You get one map step and one reduce step. You can sequence jobs together when necessary.

Tuesday, September 30, 14

MapReduce is a restrictive model. Writing jobs requires arcane, specialized skills that few master.
It's not easy mapping arbitrary algorithms to this model. For example, algorithms that are naturally iterative are especially hard, because MR doesn't support iteration efficiently. For a good overview, see http://lintool.github.io/MapReduceAlgorithms/.

The limited model doesn't just impede developer productivity, it makes it much harder to build tools on top of the model, as we'll discuss.

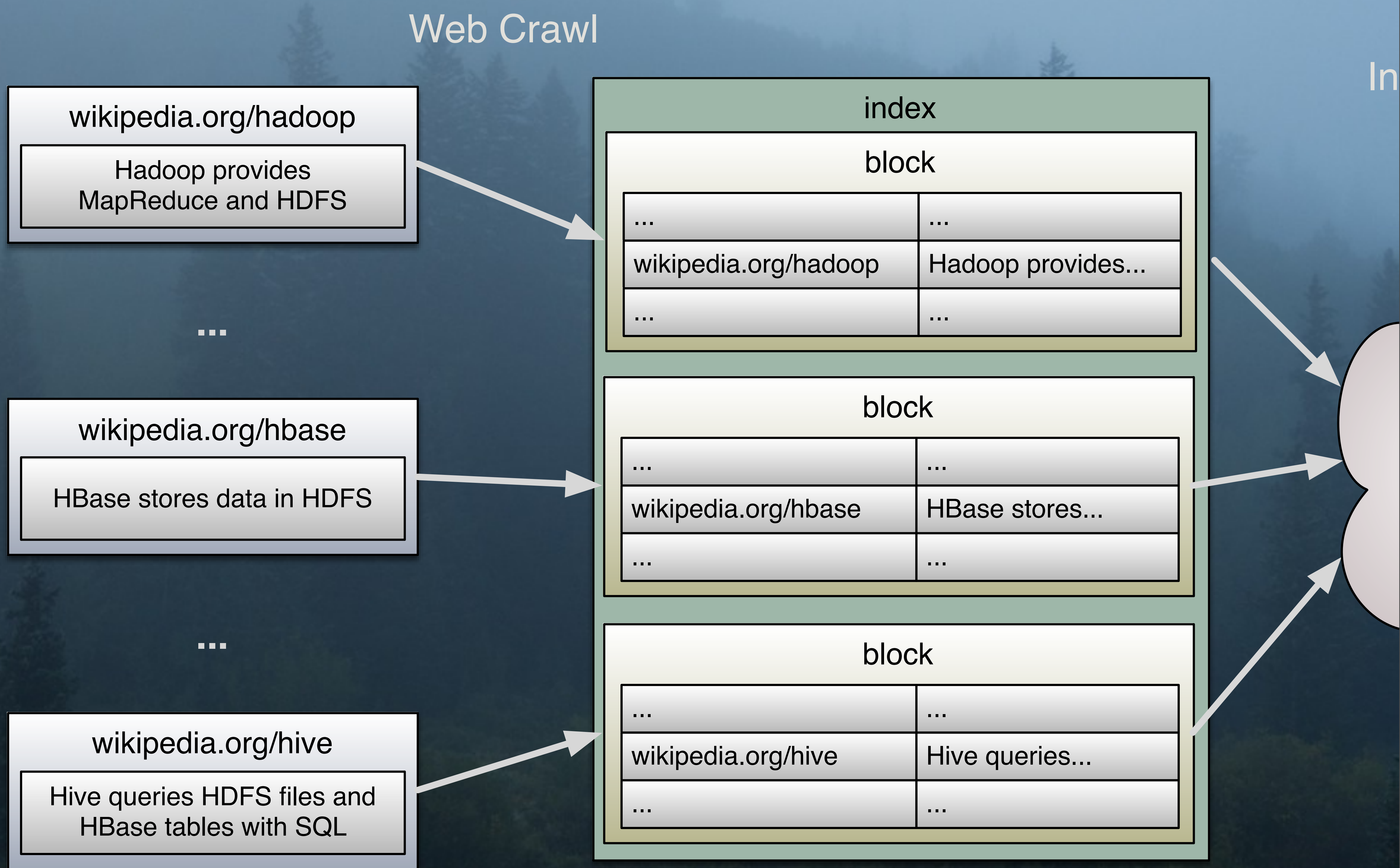
Tuesday, September 30, 14

And Hadoop's Java API only makes the problem harder, because it's very low level and offers limited or no support for many common idioms.

Tuesday, September 30, 14

See compare and contrast MR with Spark, let’s use this classic algorithm.

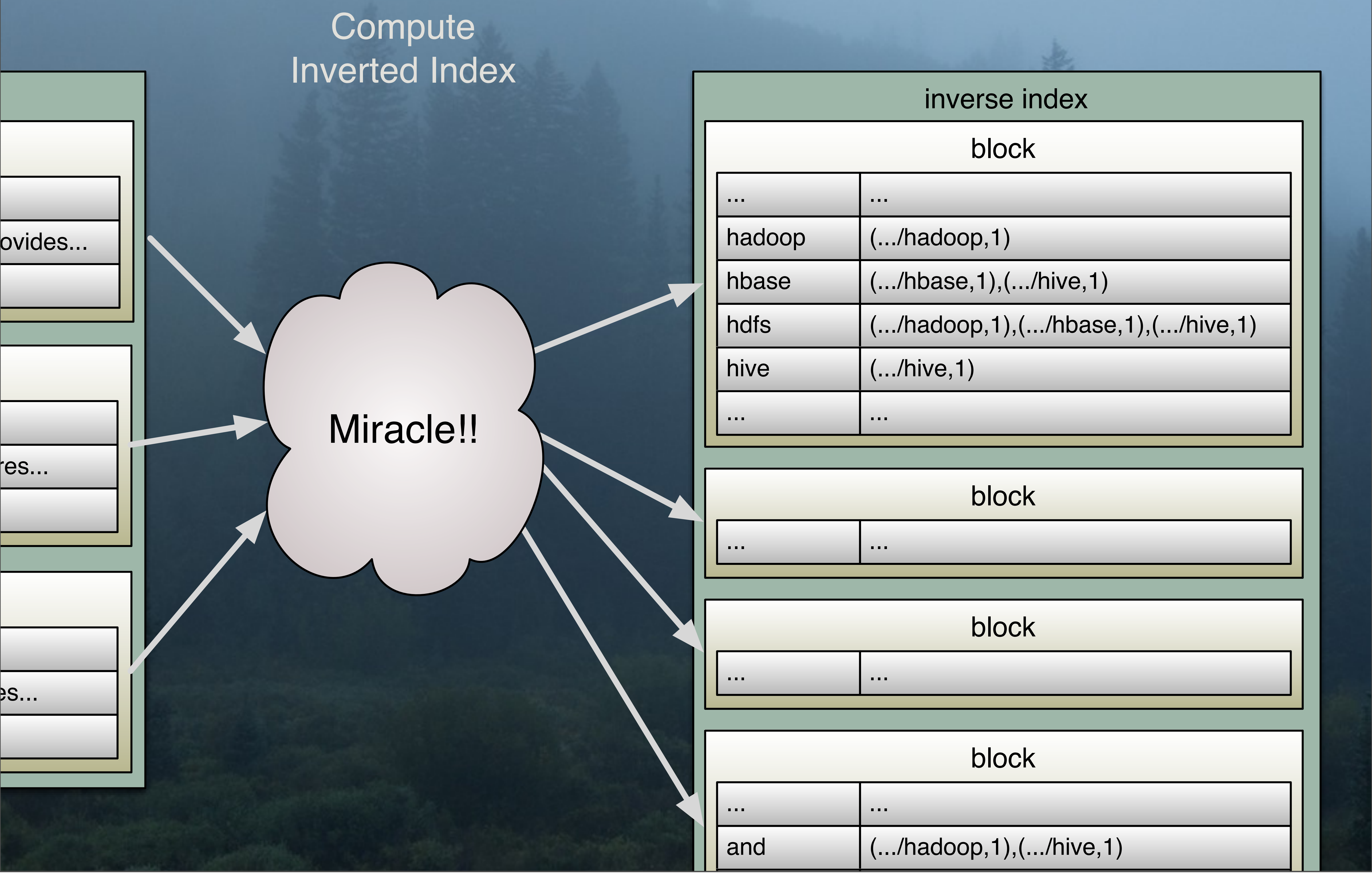
Inverted Index



Tuesday, September 30, 14

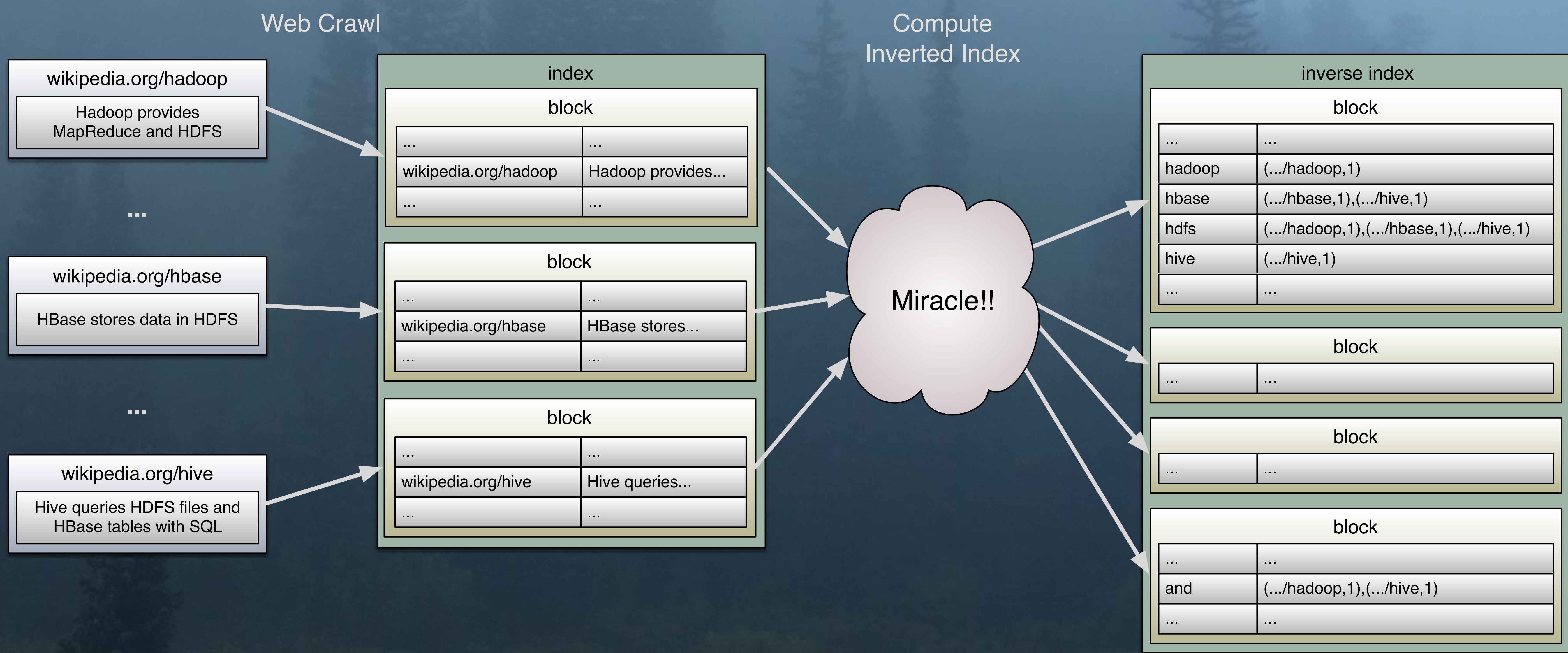
First we crawl the web to build a data set of document names/ids and their contents. Then we “invert” it; we tokenize the contents into words and build a new index from each word to the list of documents that contain the word and the count in each document. This is a basic data set for search engines.

Inverted Index



First we crawl the web to build a data set of document names/ids and their contents. Then we “invert” it; we tokenize the contents into words and build a new index from each word to the list of documents that contain the word and the count in each document. This is a basic data set for search engines.

Inverted Index



Altogether

Tuesday, September 30, 14

We'll implement the "miracle".

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

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapred.*;

public class LineIndexer {

 public static void main(String[] args) {
  JobClient client = new JobClient();
  JobConf conf =
   new JobConf(LineIndexer.class);

  conf.setJobName("LineIndexer");
  conf.setOutputKeyClass(Text.class);
```


I'm not going to explain many of the details. The point is to notice all the boilerplate that obscures the problem logic.
Everything is in one outer class. We start with a main routine that sets up the job.
I used yellow for method calls, because methods do the real work!! But notice that most of the functions in this code don't really do a whole lot of work for us...

```java
JobClient client = new JobClient();
JobConf conf =
 new JobConf(LineIndexer.class);

conf.setJobName("LineIndexer");
conf.setOutputKeyClass(Text.class);
conf.setOutputValueClass(Text.class);
FileInputFormat.addInputPath(conf,
 new Path("input"));
FileOutputFormat.setOutputPath(conf,
 new Path("output"));
conf.setMapperClass(
  LineIndexMapper.class);
conf.setReducerClass(
  LineIndexReducer.class);

client.setConf(conf);
```


boilerplate...

```
    LineIndexMapper.class);
  conf.setReducerClass(
    LineIndexReducer.class);

  client.setConf(conf);

  try {
   JobClient.runJob(conf);
  } catch (Exception e) {
   e.printStackTrace();
  }
}

public static class LineIndexMapper
  extends MapReduceBase
  implements Mapper<LongWritable, Text,
                    Text, Text> {
```


Tuesday, September 30, 14

main ends with a try-catch clause to run the job.

```java
public static class LineIndexMapper
 extends MapReduceBase
 implements Mapper<LongWritable, Text,
                  Text, Text> {
 private final static Text word =
  new Text();
 private final static Text location =
  new Text();

 public void map(
  LongWritable key, Text val,
  OutputCollector<Text, Text> output,
  Reporter reporter) throws IOException {

  FileSplit fileSplit =
   (FileSplit)reporter.getInputSplit();
  String fileName =
```


This is the LineIndexMapper class for the mapper. The map method does the real work of tokenization and writing the (word, document-name) tuples.

```
    FileSplit fileSplit =
     (FileSplit)reporter.getInputSplit();
    String fileName =
     fileSplit.getPath().getName();
    location.set(fileName);

    String line = val.toString();
    StringTokenizer itr = new
     StringTokenizer(line.toLowerCase());
    while (itr.hasMoreTokens()) {
     word.set(itr.nextToken());
     output.collect(word, location);
    }
  }
}
```


The rest of the LineIndexMapper class and map method.

```
public static class LineIndexReducer
 extends MapReduceBase
 implements Reducer<Text, Text,
                    Text, Text> {
 public void reduce(Text key,
  Iterator<Text> values,
  OutputCollector<Text, Text> output,
  Reporter reporter) throws IOException {
  boolean first = true;
  StringBuilder toReturn =
   new StringBuilder();
  while (values.hasNext()) {
   if (!first)
    toReturn.append(", ");
   first=false;
   toReturn.append(
    values.next().toString());
```


Tuesday, September 30, 14

The reducer class, LineIndexReducer, with the reduce method that is called for each key and a list of values for that key. The reducer is stupid; it just reformats the values collection into a long string and writes the final (word,list-string) output.

```
    boolean first = true;
    StringBuilder toReturn =
     new StringBuilder();
    while (values.hasNext()) {
     if (!first)
      toReturn.append(", ");
     first=false;
     toReturn.append(
      values.next().toString());
    }
    output.collect(key,
     new Text(toReturn.toString()));
   }
  }
}
```


Tuesday, September 30, 14
EOF

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

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapred.*;

public class LineIndexer {

 public static void main(String[] args) {
  JobClient client = new JobClient();
  JobConf conf =
   new JobConf(LineIndexer.class);

  conf.setJobName("LineIndexer");
  conf.setOutputKeyClass(Text.class);
  conf.setOutputValueClass(Text.class);
  FileInputFormat.addInputPath(conf,
   new Path("input"));
  FileOutputFormat.setOutputPath(conf,
   new Path("output"));
  conf.setMapperClass(
    LineIndexMapper.class);
  conf.setReducerClass(
    LineIndexReducer.class);

  client.setConf(conf);

  try {
   JobClient.runJob(conf);
  } catch (Exception e) {
   e.printStackTrace();
  }
 }

 public static class LineIndexMapper
  extends MapReduceBase
  implements Mapper<LongWritable, Text,
                   Text, Text> {
  private final static Text word =
   new Text();
  private final static Text location =
   new Text();

  public void map(
   LongWritable key, Text val,
   OutputCollector<Text, Text> output,
   Reporter reporter) throws IOException {

   FileSplit fileSplit =
    (FileSplit)reporter.getInputSplit();
   String fileName =
    fileSplit.getPath().getName();
   location.set(fileName);

   String line = val.toString();
   StringTokenizer itr = new
    StringTokenizer(line.toLowerCase());
   while (itr.hasMoreTokens()) {
    word.set(itr.nextToken());
    output.collect(word, location);
   }
  }
 }

 public static class LineIndexReducer
  extends MapReduceBase
  implements Reducer<Text, Text,
                     Text, Text> {
  public void reduce(Text key,
   Iterator<Text> values,
   OutputCollector<Text, Text> output,
   Reporter reporter) throws IOException {
   boolean first = true;
   StringBuilder toReturn =
    new StringBuilder();
   while (values.hasNext()) {
    if (!first)
     toReturn.append(", ");
    first=false;
    toReturn.append(
     values.next().toString());
   }
   output.collect(key,
    new Text(toReturn.toString()));
  }
 }
}
```

Altogether

Tuesday, September 30, 14

The whole shebang (6pt. font) This would take a few hours to write, test, etc. assuming you already know the API and the idioms for using it.

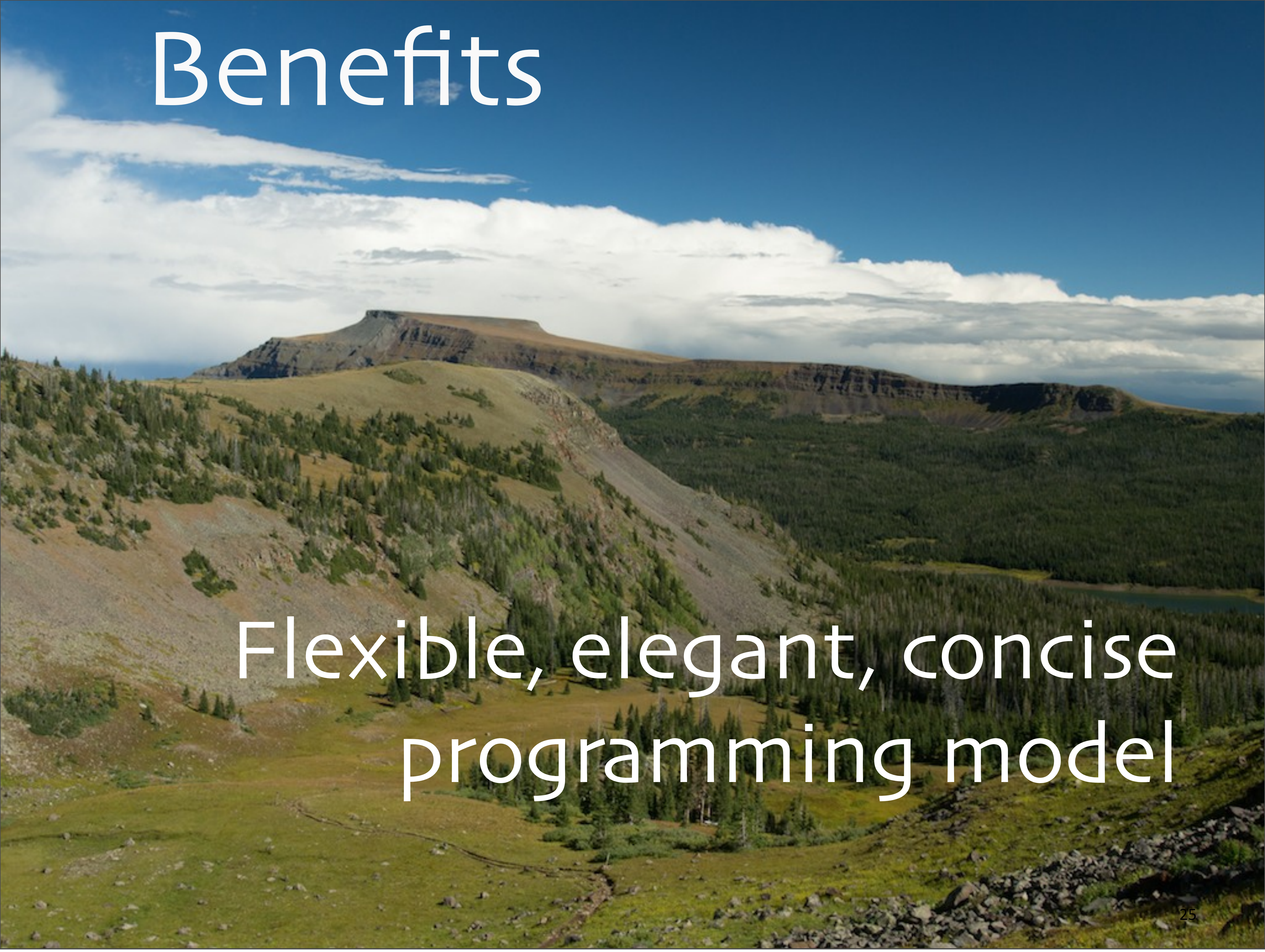
You can't do event-stream processing (a.k.a. "real-time") with MapReduce, only batch mode processing.

A complex sequence of jobs results in fully flushing data to disk at the end of each job in the sequence, even though it will be immediately reread by the next job!

Tuesday, September 30, 14

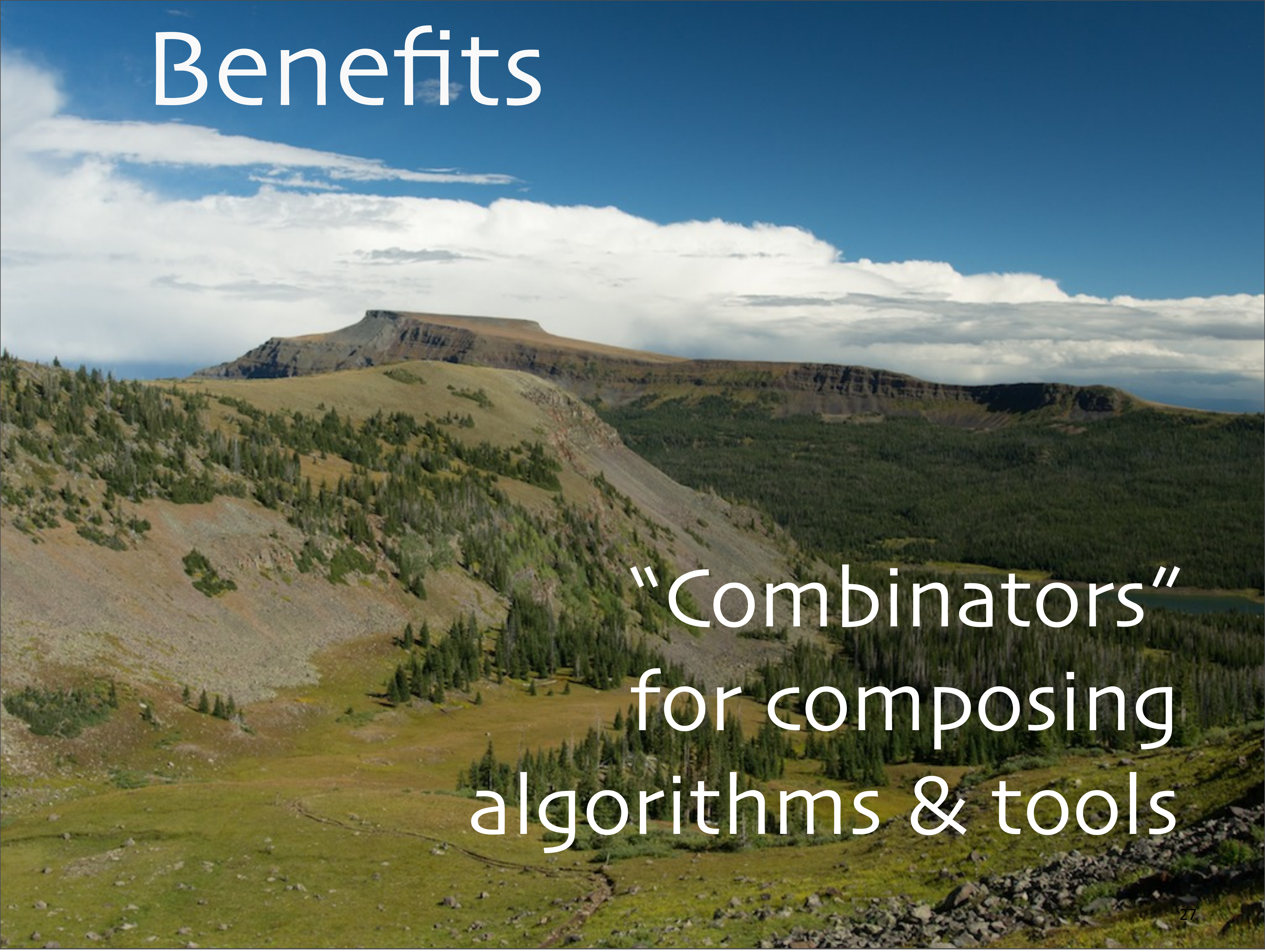
http://spark.apache.org

Benefits



Flexible, elegant, concise programming model


Benefits
Written in Scala,
with Java &
Python APIs
26



Tuesday, September 30, 14

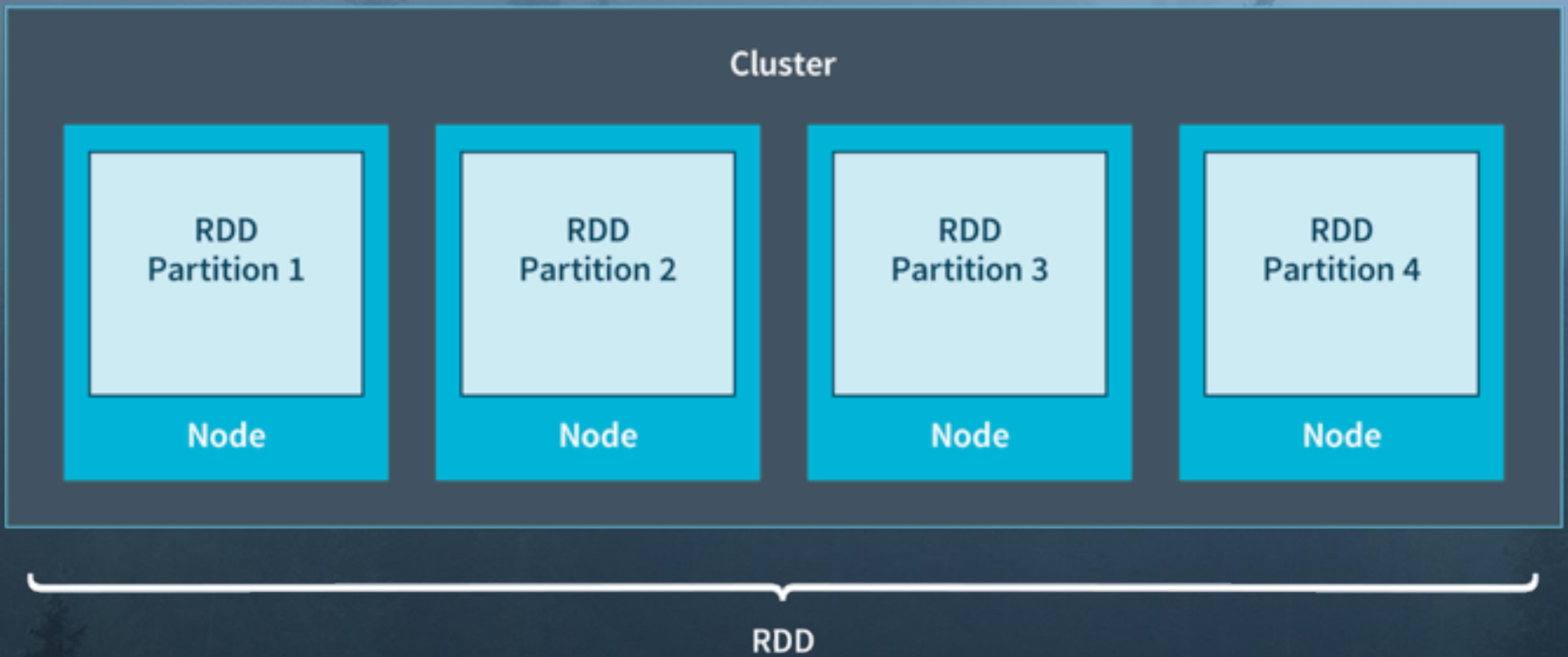
Once you learn the core set of primitives, it’s easy to compose non-trivial algorithms with little code.

Tuesday, September 30, 14

Not restricted to Hadoop, when you don’t need it, e.g., because you want to “enhance” existing applications with data analytics, running in the same infrastructure.

Tuesday, September 30, 14

Data is shared over the cluster in RDDs. This is the core abstraction everyone else builds on.


Cluster
RDD
Partition 1
Node
RDD
Partition 2
Node
RDD
Partition 3
Node
RDD
Partition 4
Node
RDD

Tuesday, September 30, 14

Let’s see our example rewritten in Spark.

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

object InvertedIndex {
 def main(args: Array[String]) = {

  val sc = new SparkContext(
   "local", "Inverted Index")

  sc.textFile("data/crawl")
  .map { line =>
    val array = line.split("\t", 2)
    (array(0), array(1))
  }
  .flatMap {
    case (path, text) =>
      text.split("""\W+""").map {
```


It starts with imports, then declares a singleton object (a first-class concept in Scala), with a main routine (as in Java).
The methods are colored yellow again. Note this time how dense with meaning they are this time.

You being the workflow by declaring a SparkContext (in “local” mode, in this case). The rest of the program is a sequence of function calls, analogous to “pipes” we connect together to perform the data flow.

Next we read one or more text files. If “data/crawl” has 1 or more Hadoop-style “part-NNNNN” files, Spark will process all of them (in parallel if running a distributed configuration; they will be processed synchronously in local mode).

sc.textFile returns an RDD with a string for each line of input text. So, the first thing we do is map over these strings to extract the original document id (i.e., file name), followed by the text in the document, all on one line. We assume tab is the separator. “(array(0), array(1))” returns a two-element “tuple”. Think of the output RDD has having a schema “String fileName, String text”.

```
}
.flatMap {
  case (path, text) =>
   text.split("""\W+""") map {
    word => (word, path)
   }
}
.map {
  case (w, p) => ((w, p), 1)
}
.reduceByKey {
  case (n1, n2) => n1 + n2
}
.map {
  case ((w, p), n) => (w, (p, n))
}
.groupBy {
  case (w, (p, n)) => w
```


Tuesday, September 30, 14

flatMap maps over each of these 2-element tuples. We split the text into words on non-alphanumeric characters, then output collections of word (our ultimate, final “key”) and the path. Each line is converted to a collection of (word,path) pairs, so flatMap converts the collection of collections into one long “flat” collection of (word,path) pairs.

Then we map over these pairs and add a single count of 1.

reduceByKey does an implicit “group by” to bring together all occurrences of the same (word, path) and then sums up their counts.
Note the input to the next map is now ((word, path), n), where n is now >= 1. We transform these tuples into the form we actually want, (word, (path, n)).

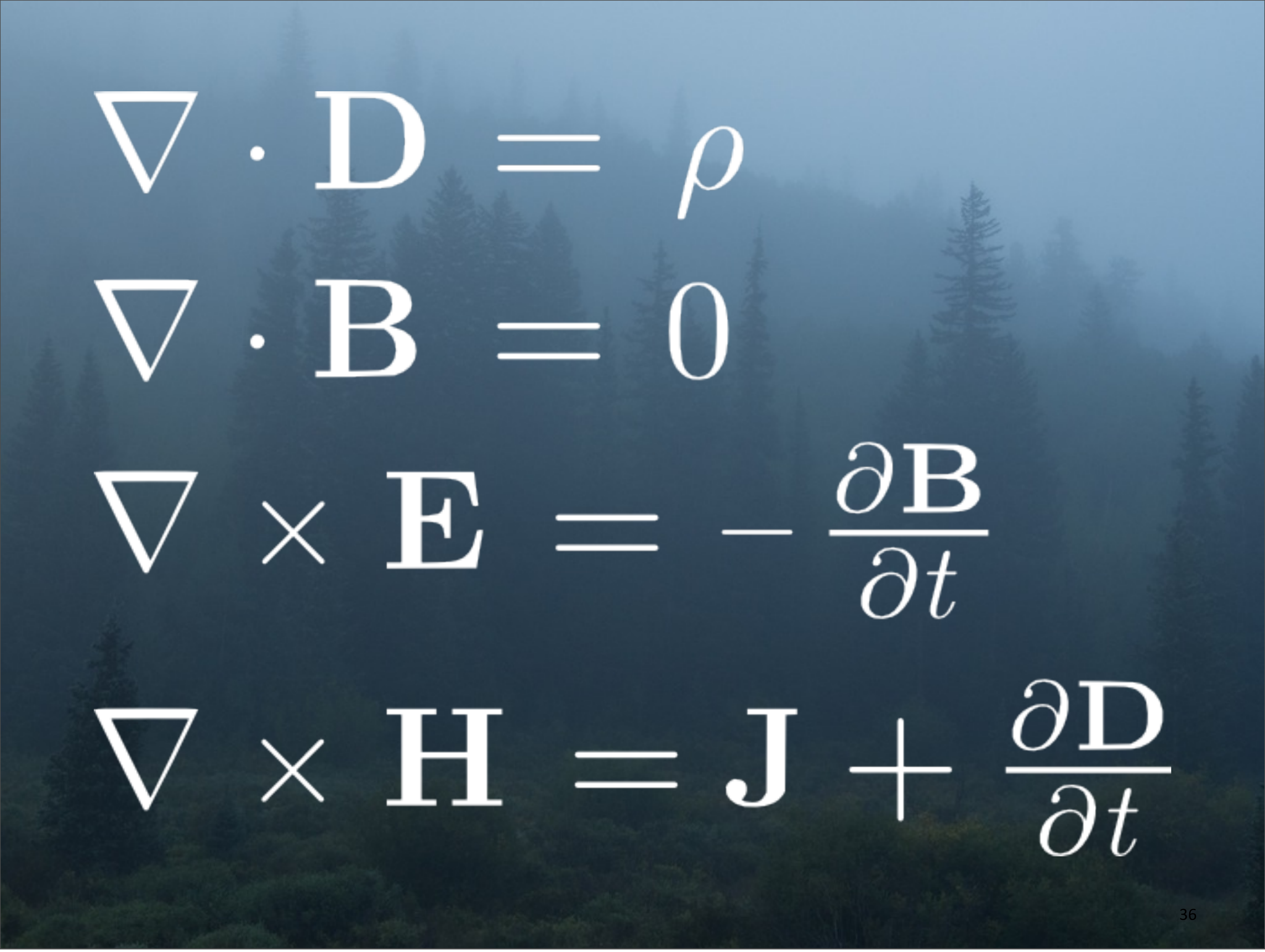
```scala
    }
    .groupBy {
      case (w, (p, n)) => w
    }
    .map {
      case (w, seq) =>
        val seq2 = seq map {
          case (_, (p, n)) => (p, n)
        }
        (w, seq2.mkString(", "))
    }
    .saveAsTextFile(argz.outpath)

    sc.stop()
  }
}
```


Now we do an explicit group by to bring all the same words together. The output will be (word, (word, (path1, n1)), (word, (path2, n2)), ...).
The last map removes the redundant “word” values in the sequences of the previous output. It outputs the sequence as a final string of comma-separated (path,n) pairs.
We finish by saving the output as text file(s) and stopping the workflow.

```
  }
  .map {
    case (w, p) => ((w, p), 1)
  }
  .reduceByKey {
    case (n1, n2) => n1 + n2
  }
  .map {
    case ((w, p), n) => (w, (p, n))
  }
  .groupBy {
    case (w, (p, n)) => w
  }
  .map {
    case (w, seq) =>
      val seq2 = seq map {
        case (_, (p, n)) => (p, n)
```

Chain combinators together

The yellow functions are our composable - and elegant - combinators.



$$\nabla \cdot \mathbf{D} = \rho$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}$$

$$\nabla \times \mathbf{H} = \mathbf{J} + \frac{\partial \mathbf{D}}{\partial t}$$

Tuesday, September 30, 14

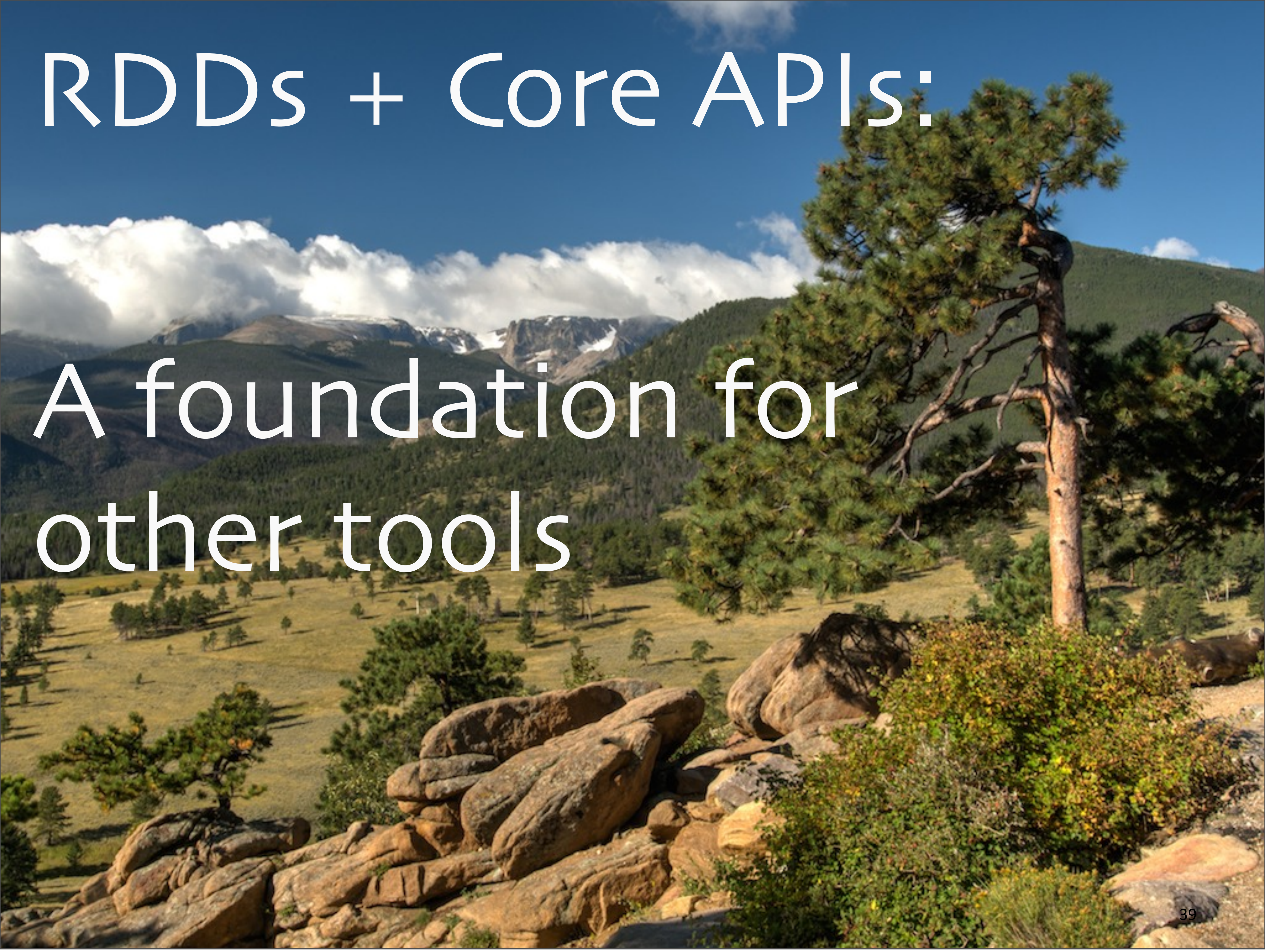
Another example of a beautiful and profound DSL, in this case from the world of Physics: Maxwell’s equations: http://upload.wikimedia.org/wikipedia/commons/c/c4/Maxwell'sEquations.svg

Altogether

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

object InvertedIndex {
 def main(args: Array[String]) = {

  val sc = new SparkContext(
   "local", "Inverted Index")

  sc.textFile("data/crawl")
  .map { line =>
    val array = line.split("\t", 2)
    (array(0), array(1))
  }
  .flatMap {
    case (path, text) =>
     text.split("""\W+""") map {
      word => (word, path)
     }
  }
  .map {
    case (w, p) => ((w, p), 1)
  }
  .reduceByKey {
    case (n1, n2) => n1 + n2
  }
  .map {
    case ((w, p), n) => (w, (p, n))
  }
  .groupBy {
    case (w, (p, n)) => w
  }
  .map {
    case (w, seq) =>
      val seq2 = seq map {
        case (_, (p, n)) => (p, n)
      }
      (w, seq2.mkString(", "))
  }
  .saveAsTextFile(argz.outpath)

  sc.stop()
 }
}
```

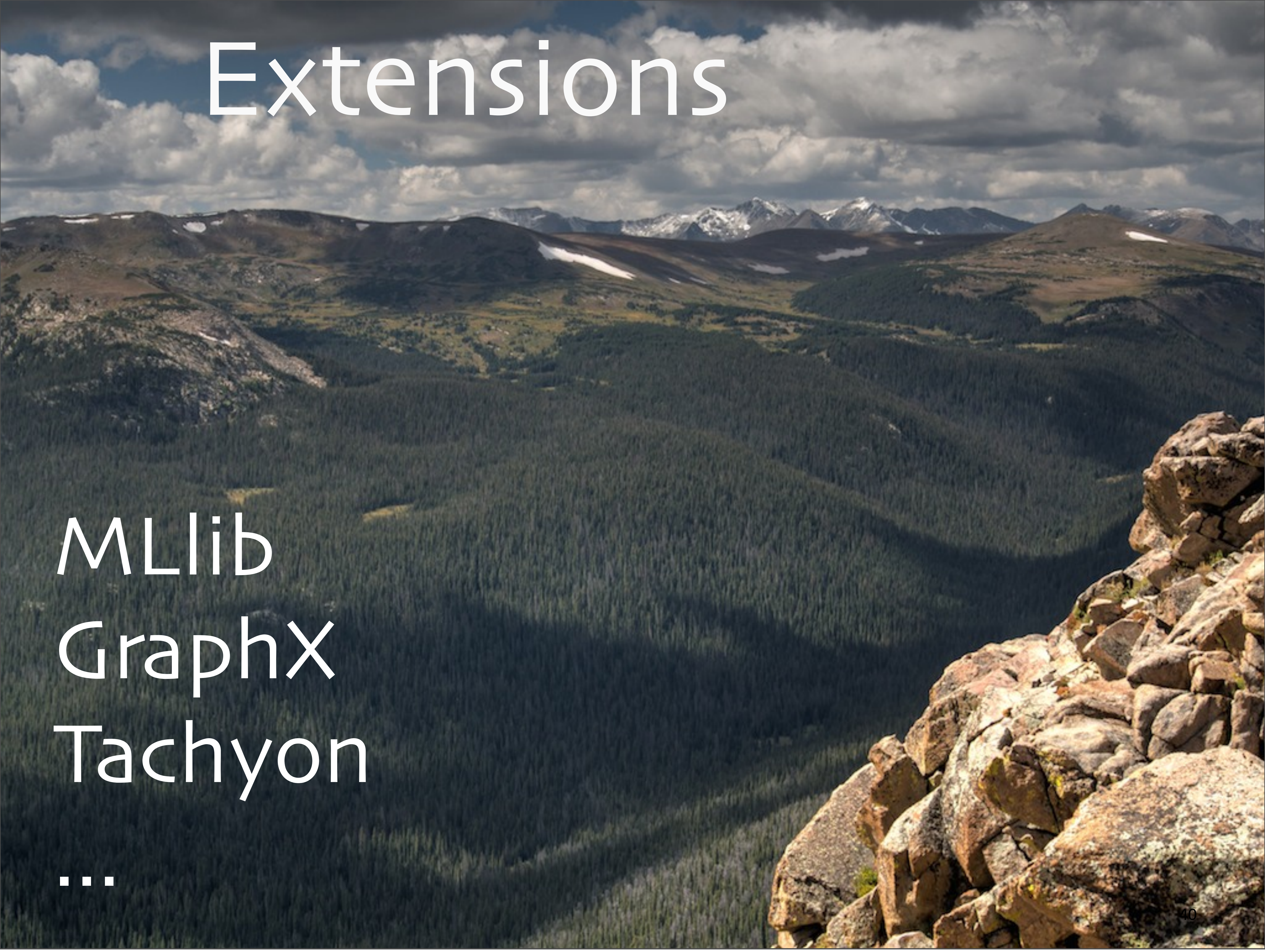
Tuesday, September 30, 14

When you have a concise, flexible API, you can turn a “software development project” into a script! It transforms your productivity.



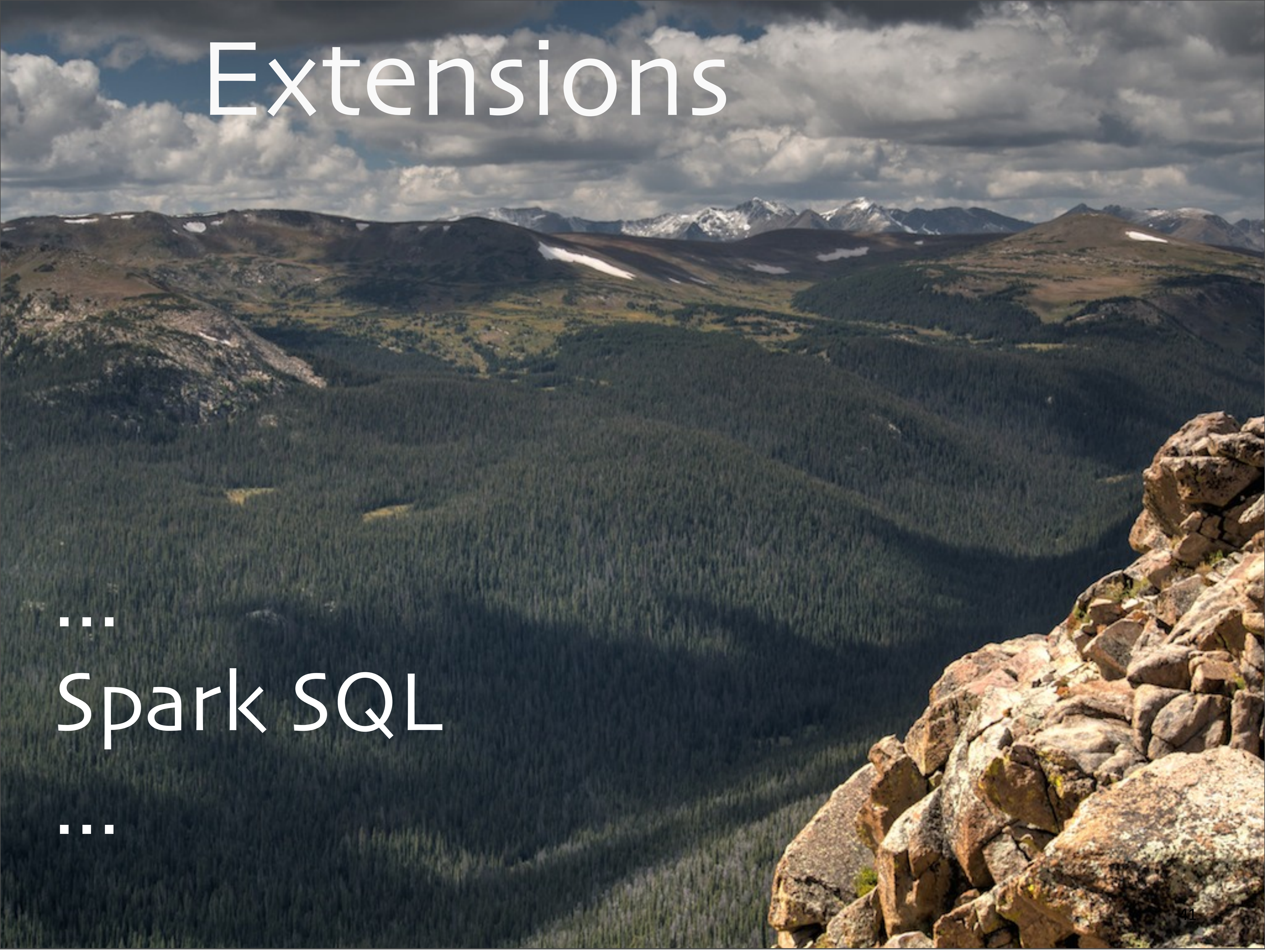
Tuesday, September 30, 14

The good API also provides an excellent foundation for other tools to build on.



Tuesday, September 30, 14

MLlib - a growing library of machine learning algorithms.
GraphX - for representing data as a graph and applying graph algorithms to it.
Tachyon - an experiment to generalize Spark’s caching mechanism into a standalone service, so data is shareable between apps and more durable. I believe it will be transformative!



Tuesday, September 30, 14

Let's look at the SQL abstractions layered on top.

Tuesday, September 30, 14

Best of both worlds: SQL for concision, the RDD API for Turing-complete, general-purpose computing. Also adds elegant handling of the “schema” for data.

Tuesday, September 30, 14

Let's us query Hadoop Hive "tables". We can create or delete them, too.

New feature. Can read JSON records and infer their schema. Can write RDD records as JSON.

Tuesday, September 30, 14

It's a bit tricky to use the inverted index data, because of the variable list of (docid, N) values, so we'll use the crawl data, which is easier for our purposes.

```scala
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark.sql.{
  SQLContext, SchemaRDD}
import org.apache.spark.rdd.RDD

case class CrawlRecord(
  docid: String, contents: String)

def makeCrawlRecord(line: String) = {...}

def dosql(qry: String, n: Int = 100) =
  sql(qry).collect.take(n) foreach println

val crawlData = "/path/to/directory"

val sc = new SparkContext("...", "Crawl")
```


Starts out like a typical Spark program...
Defines a "case class" (think normal Java class where the args are automatically turned into fields) to represent each record.
Defines a method to parse each input line and output a CrawlRecord (details omitted)
Defines a helper method to take a SQL query as a string, run it using the "sql(...)" method provided by SparkSQL, grab the first n elements and print them, one per line.
Finally, defines the path to the input for the crawl data.

```
val sc = new SparkContext("...", "Crawl")

val crawl = for {
  line <- sc.textFile(crawlData)
  cr <- makeCrawlRecord(line)
} yield cr

crawl.registerAsTable("crawl")
crawl.printSchema

dosql("""
  SELECT docid, contents FROM crawl
  LIMIT 10""")

val crawlPerWord = crawl flatMap {
  case CrawlRecord(docid, contents) =>
    contents.trim.split("""[^\w']""") map
```


The for loop takes each line of input and parses it into a CrawlRecord. So, “crawl” has the type RDD[CrawlRecord]. Then we register it as a table and print its schema.
Now run a query!

```scala
val crawlPerWord = crawl flatMap {
  case CrawlRecord(docid, contents) =>
    contents.trim.split("""[^\w']""") map
(word => CrawlRecord(docid, word))
}

crawlPerWord.registerAsTable("crawl2")
crawlPerWord.cache

dosql("SELECT * FROM crawl2 LIMIT 10")
dosql("""
  SELECT DISTINCT * FROM crawl2
  WHERE contents = 'management'""")
dosql("""
  SELECT contents, COUNT(*) AS c
  FROM crawl2
  GROUP BY contents
```


Create a new, similar RDD where the records are the docids with each word in the document, not one record for each docid with the entire contents.

Register this RDD as a table and this time cache it in memory, since we'll write several queries against it.

```
crawlPerWord.registerAsTable("crawl2")
crawlPerWord.cache

dosql("SELECT * FROM crawl2 LIMIT 10")
dosql("""
  SELECT DISTINCT * FROM crawl2
  WHERE contents = 'management'""")
dosql("""
  SELECT contents, COUNT(*) AS c
  FROM crawl2
  GROUP BY contents
  ORDER BY c DESC LIMIT 100""")
```


Tuesday, September 30, 14

Run several queries.


Extensions
... and
Streaming.

Tuesday, September 30, 14

A clever extension to the existing batch-oriented RDD model; use smaller batches! So, it's not a replacement for true event-processing systems, like Storm, message queues.

Tuesday, September 30, 14

We get all the familiar RDD functions, “for free”, plus functions for working with windows of batches.


DStream (discretized stream)
...
Event
Event
Event
Time 1 RDD
Event
Event
Event
Event
Event
Time 2 RDD
Event
Event
Event
Event
Time 3 RDD
Event
Event
Event
Time 4 RDD
...
...
...
Window of 3 RDD Batches #1
Window of 3 RDD Batches #2

Tuesday, September 30, 14

Continue using the crawl data, but “pretend” we’re reading it live from a socket.

```
// ... imports, etc.
val sc = new SparkContext(...)
val ssc = new StreamingContext(
  sc, Seconds(60))
ssc2.addStreamingListener(
  /*... listener for end of data ...*/)
val sqlc = new SQLContext(sc)
import sqlc._

val inputDStream =
  sc.socketTextStream(server,
port).flatMap(_.split("\n"))

val crawlWords = for {
  line <- inputDStream
```

“Batch” size

We won’t show everything now, just the interesting bits...
We create a SparkContext, then wrap it with a new StreamingContext object, where we’ll grab the records in 60-second increments, AND a SQLContext as before (optional).
We also add listener for stream events, such as end of input (not shown).

```
val inputDStream =
  sc.socketTextStream(server,
port).flatMap(_.split("\n"))

val crawlWords = for {
  line <- inputDStream
  cr1 <- CrawlRecord.parse(line)
  word <- cr1.contents.trim.split(
    """[^\w']""")
} yield (CrawlRecord(cr1.docid, word))

crawlWords.window(
  Seconds(300), Seconds(60))
  .foreachRDD { rdd =>
    rdd.registerAsTable("crawlWords")
    dosql("""
```

Window size,
“skip size.

The DStream holds the RDDs mentioned previously. Here, we listen to a socket of text data, splitting the input on line feeds, then we parse the lines as before into CrawlRecord(docid,contents), but then parse again into CrawlRecord(docid,word) records.

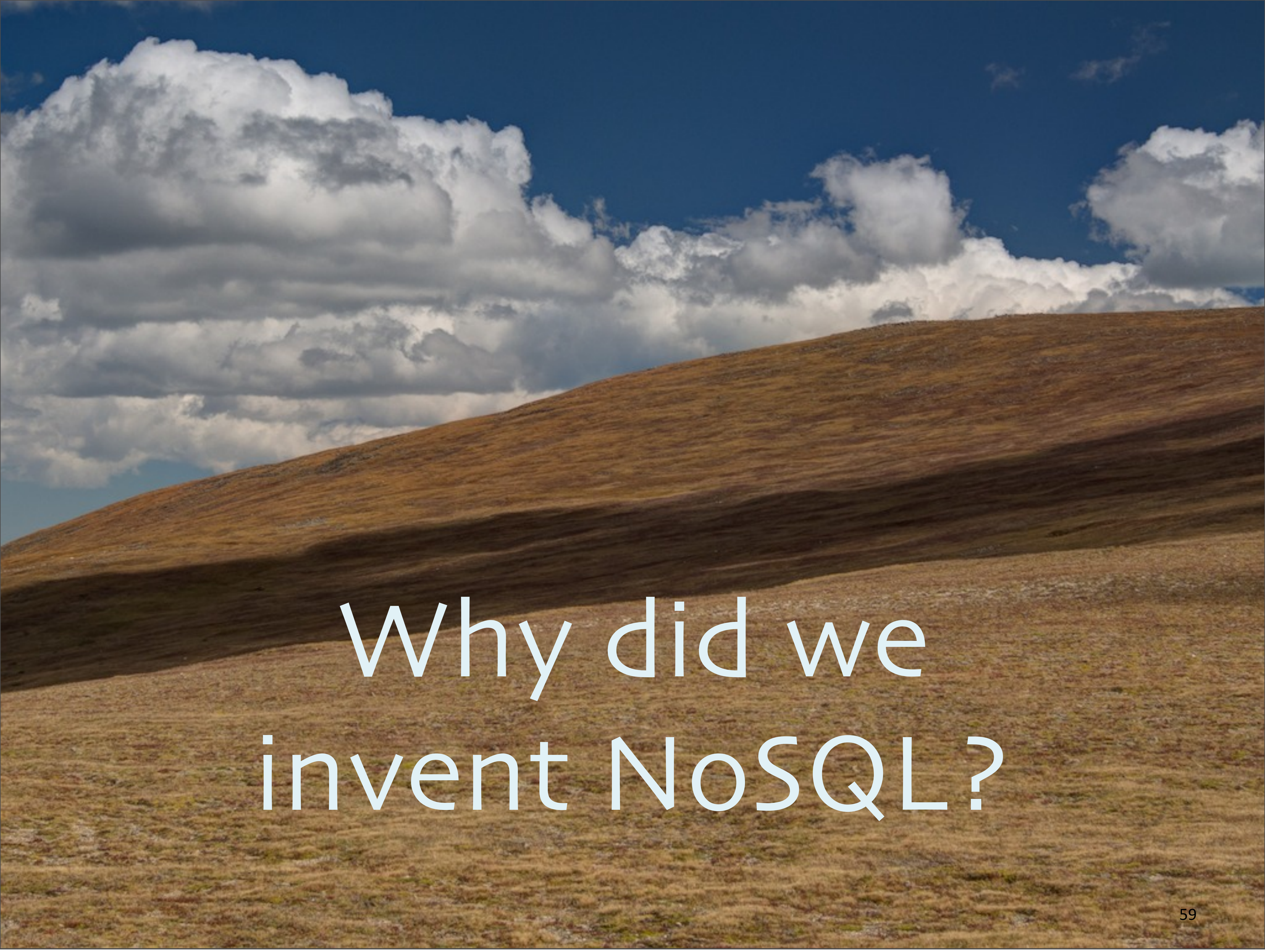
```
} yield (CrawlRecord(cr1.docid, word))

crawlWords.window(
  Seconds(300), Seconds(60))
  .foreachRDD { rdd =>
    rdd.registerAsTable("crawlWords")
    dosql("""
      SELECT contents, COUNT(*) AS c
      FROM crawlWords
      GROUP BY contents
      ORDER BY c DESC LIMIT 100""")
  }

ssc2.start()
ssc2.awaitTermination()
```


Tuesday, September 30, 14

Let’s run queries over windows of time slices. Our slices are 60 seconds, so we’ll query over the last 5 slices.
The query is the same as the last one in the SQL example.
Finally, we start the pipeline and wait for it to complete (forever?).

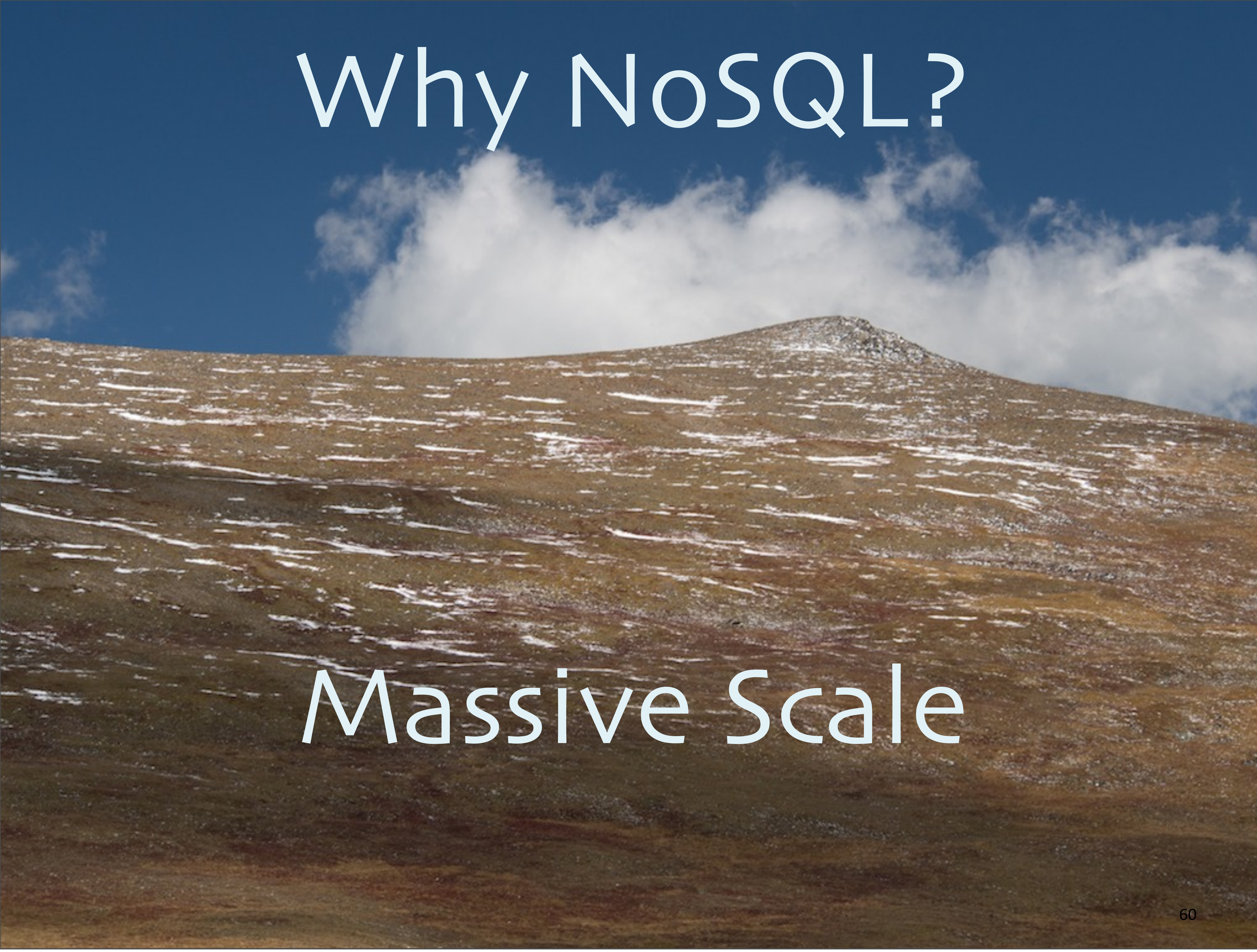
Tuesday, September 30, 14

So, SQL is very useful for “structured” data in Hadoop. In fact, SQL has experienced a renaissance in Big Data

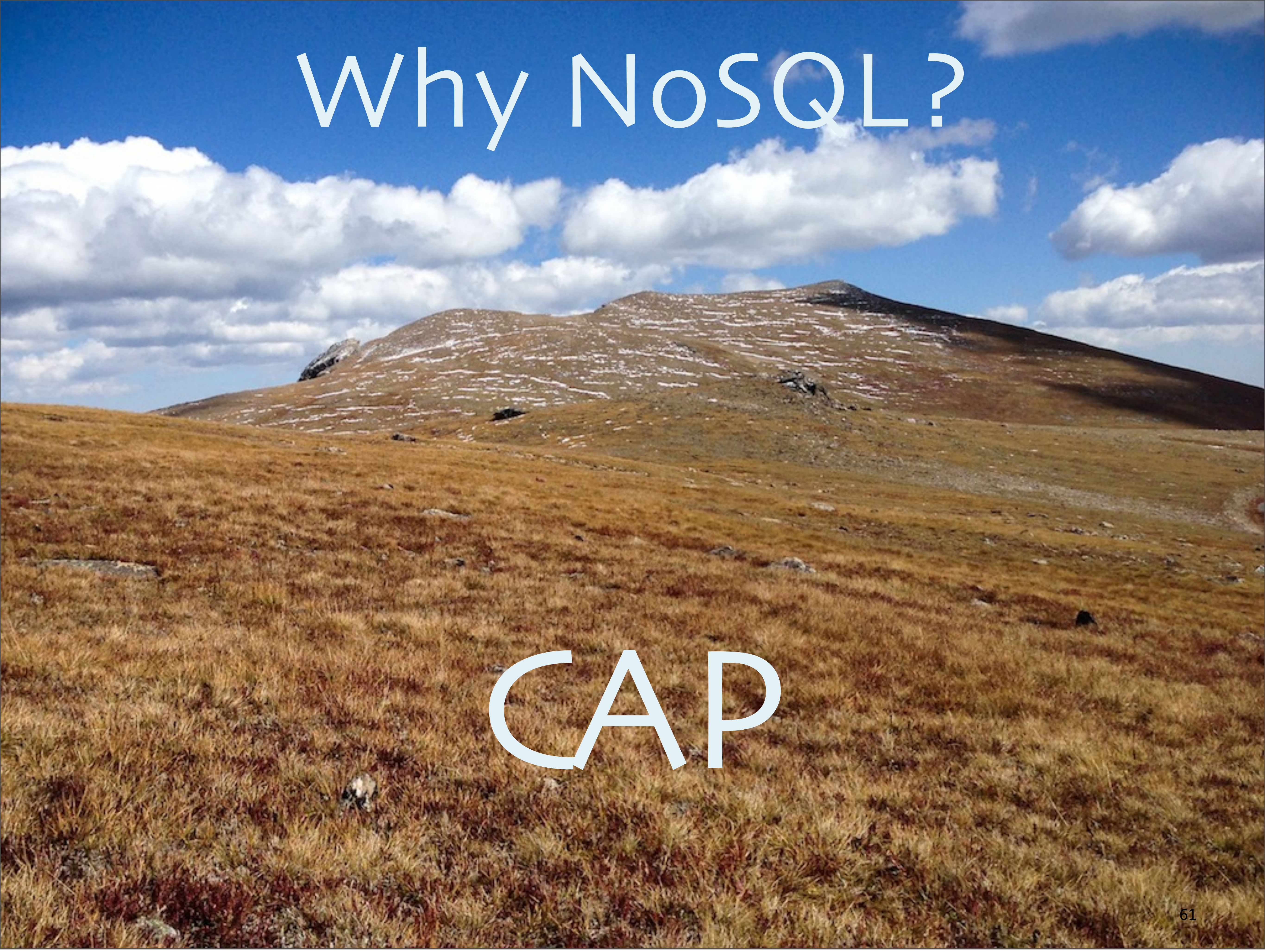


Tuesday, September 30, 14

First, why did NoSQL emerge in the first place?

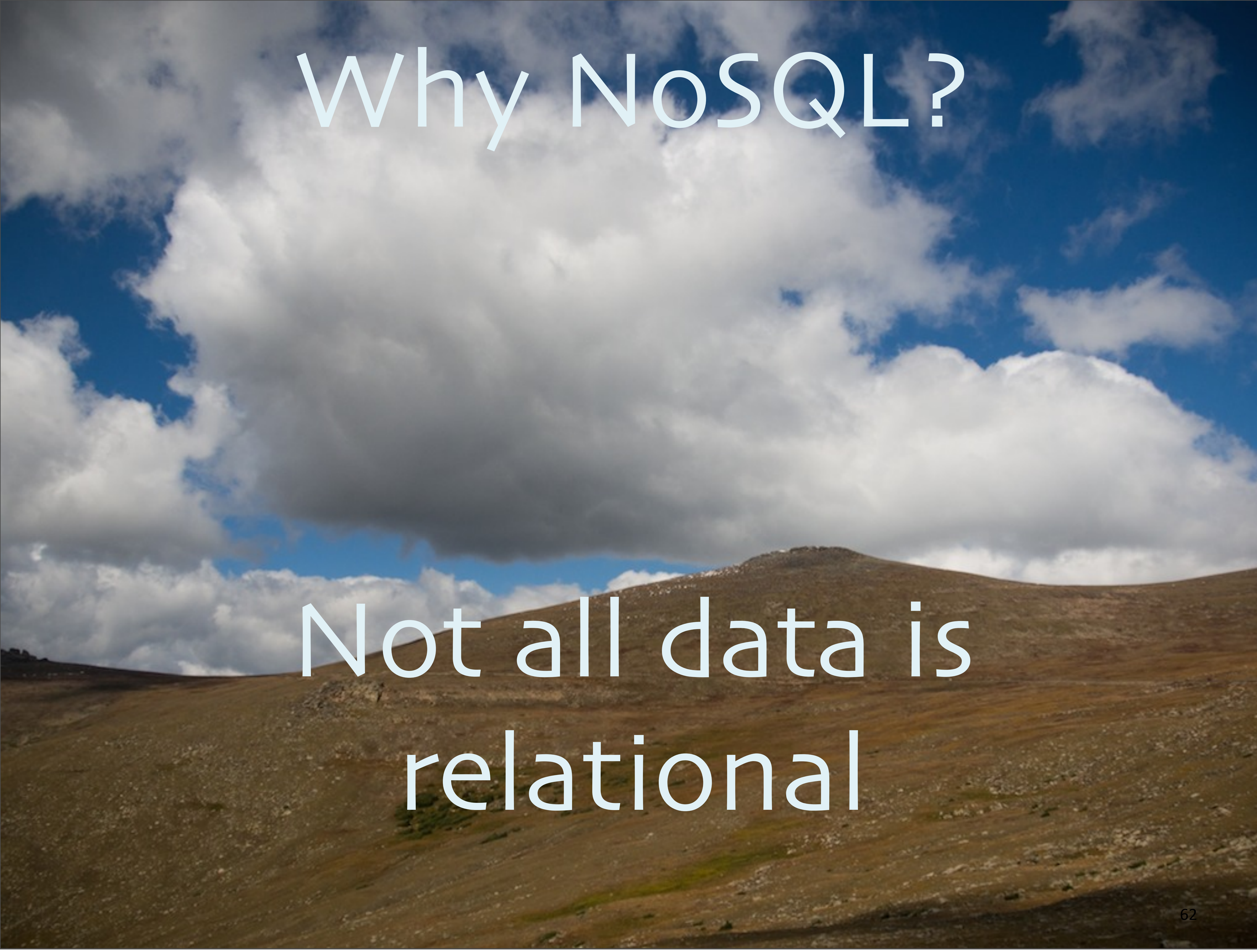


1. We needed to manage unprecedented data set sizes, economically. Existing Relational tools couldn’t handle the size, especially at low cost.



Tuesday, September 30, 14

Sometimes remaining available and accepting eventual consistency is the tradeoff we want when partitions occur. Relational is CP, if a partition happens we prefer consistency, so the DB won't be available until the partition is resolved. But many apps can accept lack of consistency if they can still remain available.



Tuesday, September 30, 14

Key-value stores, hierarchical data, e.g.,JSON/XML docs, etc. are alternative forms that work better for many scenarios.

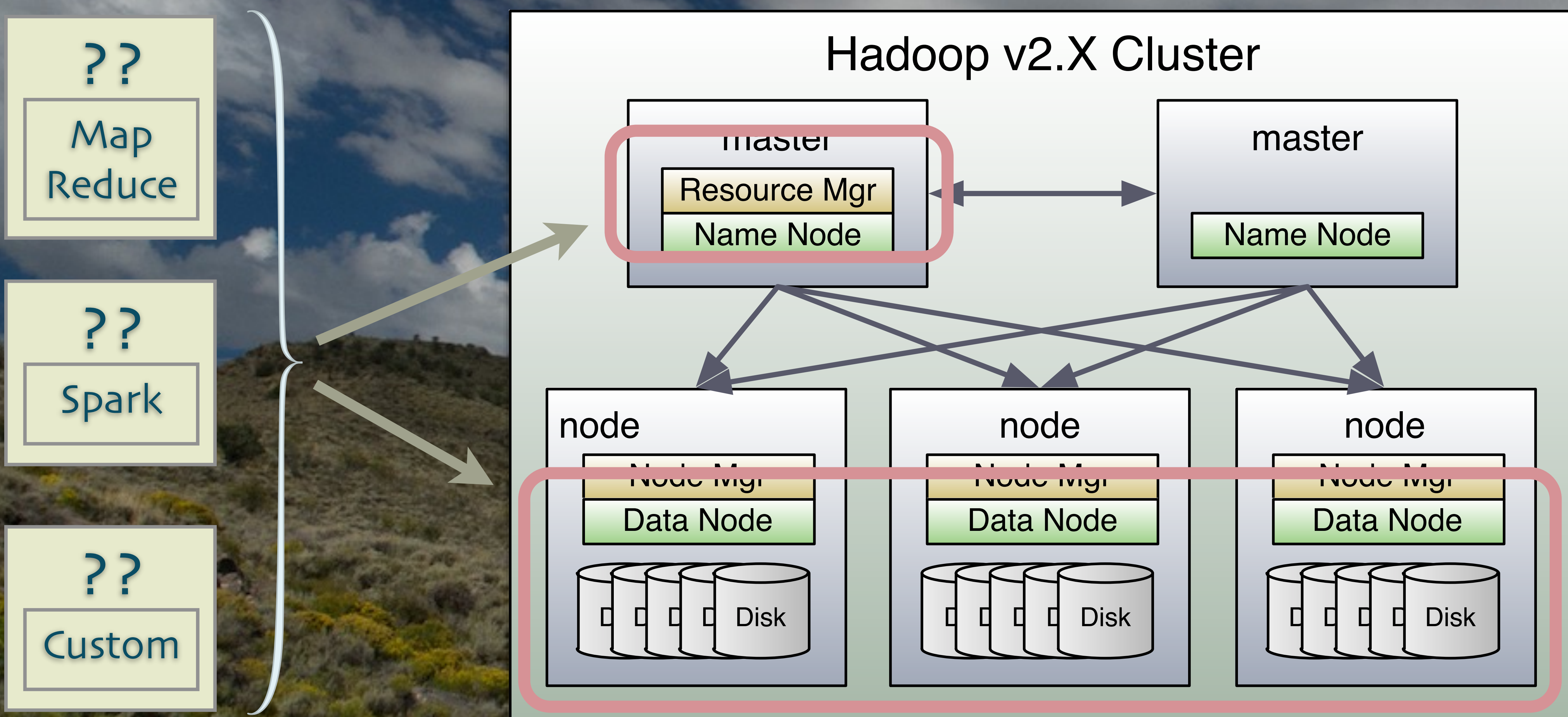
Tuesday, September 30, 14

Even so-called “unstructured data”, like tweets and other text, are quickly processed to extract structure of some kind.

Two New Approaches for SQL

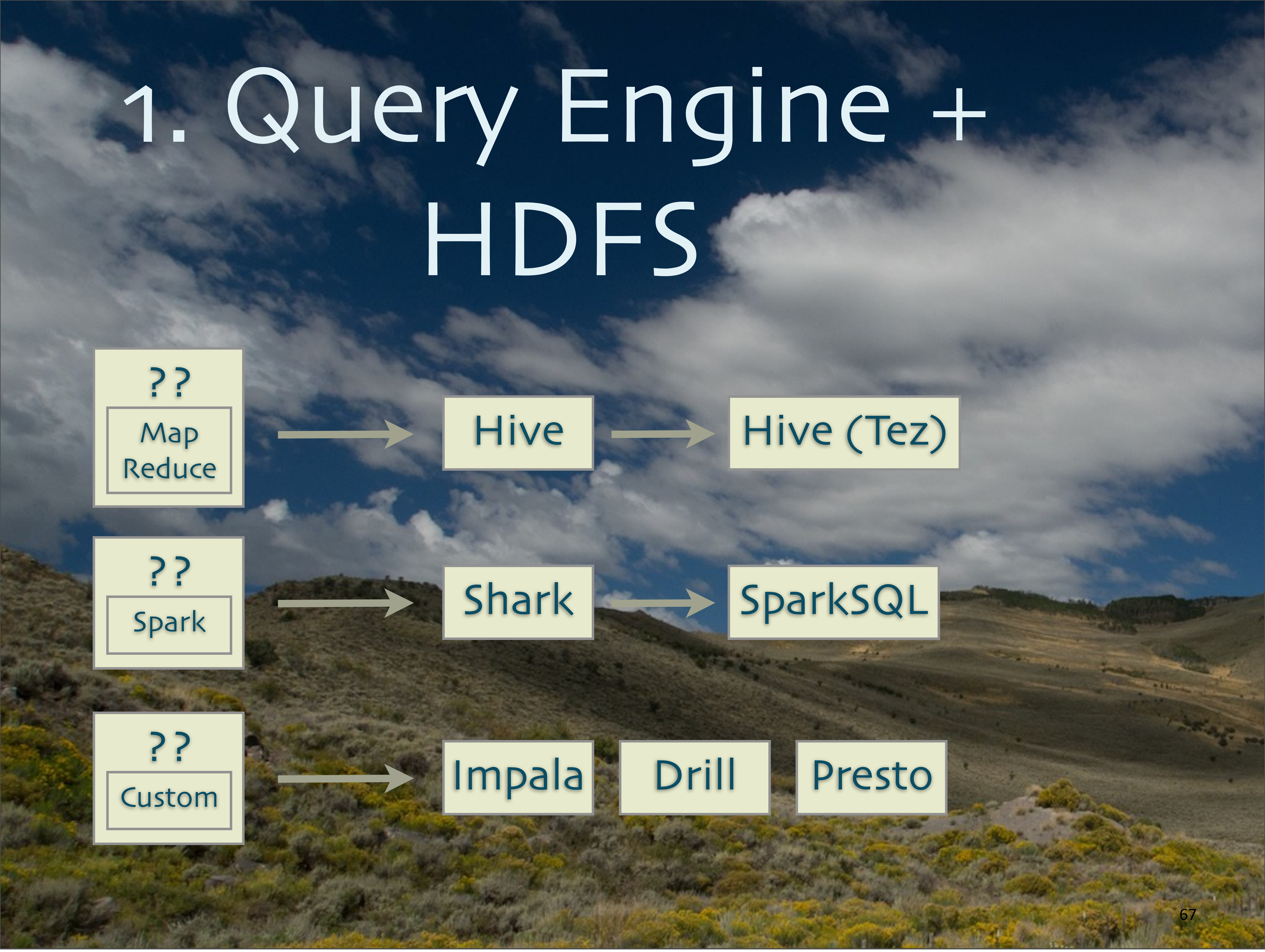
First idea, put SQL-based query abstractions on top of simple storage, like flat files in HDFS, MapRFS, S3, etc. The query abstractions can be a “DSL” implemented in a generic framework like MapReduce or Spark, or with a custom query engine optimized for the job.

1. Query Engine + HDFS



Tuesday, September 30, 14

You could write engines in MR, Spark, or something custom, which may offer less flexibility, but better performance.



Tuesday, September 30, 14

Hive, developed at Facebook, pioneered SQL on Hadoop. It has recently been ported to a new, higher-performance engine called Tez. Tez is a competitor to Spark, but isn't gaining the same traction.
The Spark team ported Hive to Spark and achieved 30x+ performance improvements. Shark is now deprecated; it's being replaced with a better engineered query engine called Catalyst, inside SparkSQL.
Impala was the first custom query engine, inspired by Google's Dremel. It holds the current performance records for SQL on Hadoop. Presto is a Facebook project. Drill is another Apache project. It's more portable across Hadoop platforms than Impala, but not as fast.

Tuesday, September 30, 14

These are new, relational databases, separate from Hadoop altogether. The leverage the scalability and resiliency lessons of NoSQL, but restore the relational model.

Google Spanner is globally distributed with *global transactions*. The others are commercial projects.

Tuesday, September 30, 14

Gazing into the foggy future...

Tuesday, September 30, 14

Mesos may be all that many teams need, if they don't already have Hadoop (YARN), and especially if they have other infrastructure running on Mesos. (Technically, you can run Hadoop on Mesos, too.)

Tuesday, September 30, 14

In general, people are pursuing flexible ways of deploying big data apps, especially when they integrate with other systems running in different cloud or virtualization environments.

Tuesday, September 30, 14

I think Tachyon will be disruptive when it's mature.

Check out this high-performance computing engine. https://github.com/0xdata/h2o They are integrating it with Spark.
See Cliff Click's talk!

Recap

Spark

Replaces MapReduce

Spark

Supports Streaming and Batch

Spark

Integrates SQL, ML, & Graph libraries

SQL

Works great in Hadoop!

SQL

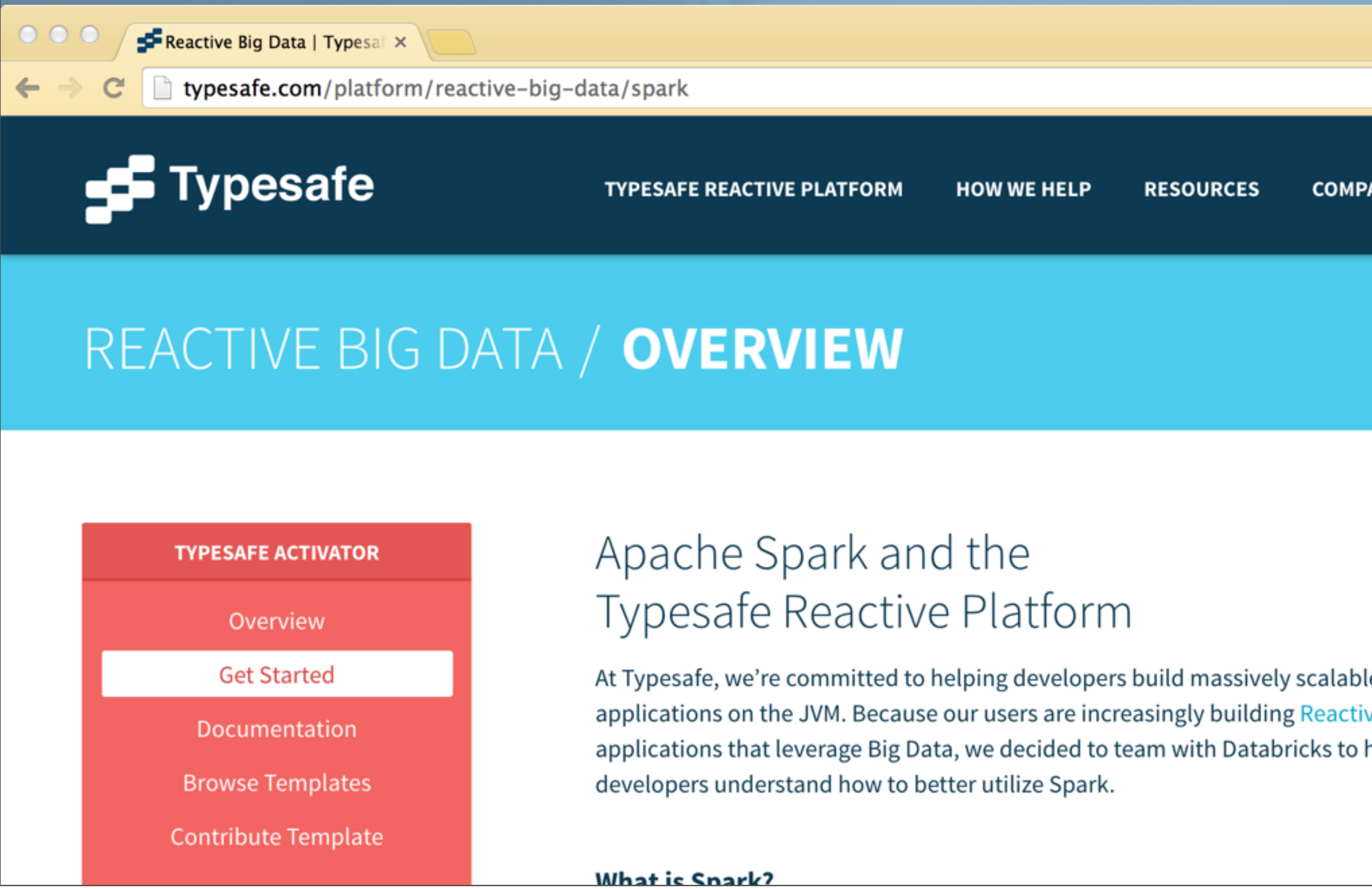
NewSQL DBs improve Relational scalability


SQL
The world needs NoSQL and NewSQL
81

Prediction

Mesos-based environments will grow.

More Stuff by Me...



I have a 1-day Spark Workshop I'm teaching for Typesafe. See this page for details, as well as a whitepaper and blog post on Spark that I wrote.

Tuesday, September 30, 14

About me. You can find this presentation and others on Big Data and Scala at polyglotprogramming.com.
Photo: Time lapse at night in Colorado.