Scala and the JVM for Big Data: Lessons from Spark

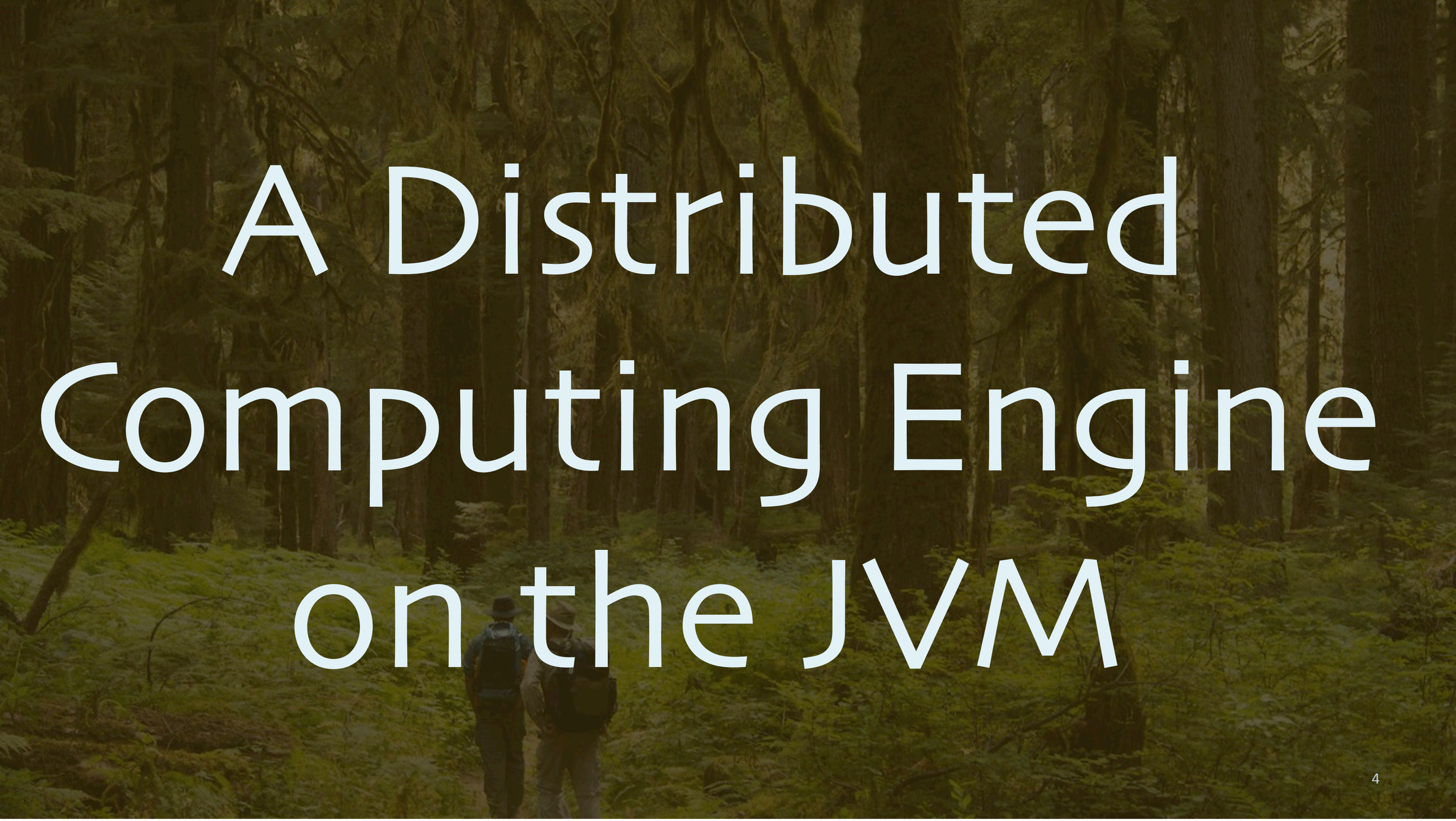
Strata+Hadoop World
Singapore
December 7, 2016

Photos from Olympic National Park, Washington State, USA, Aug. 2015.

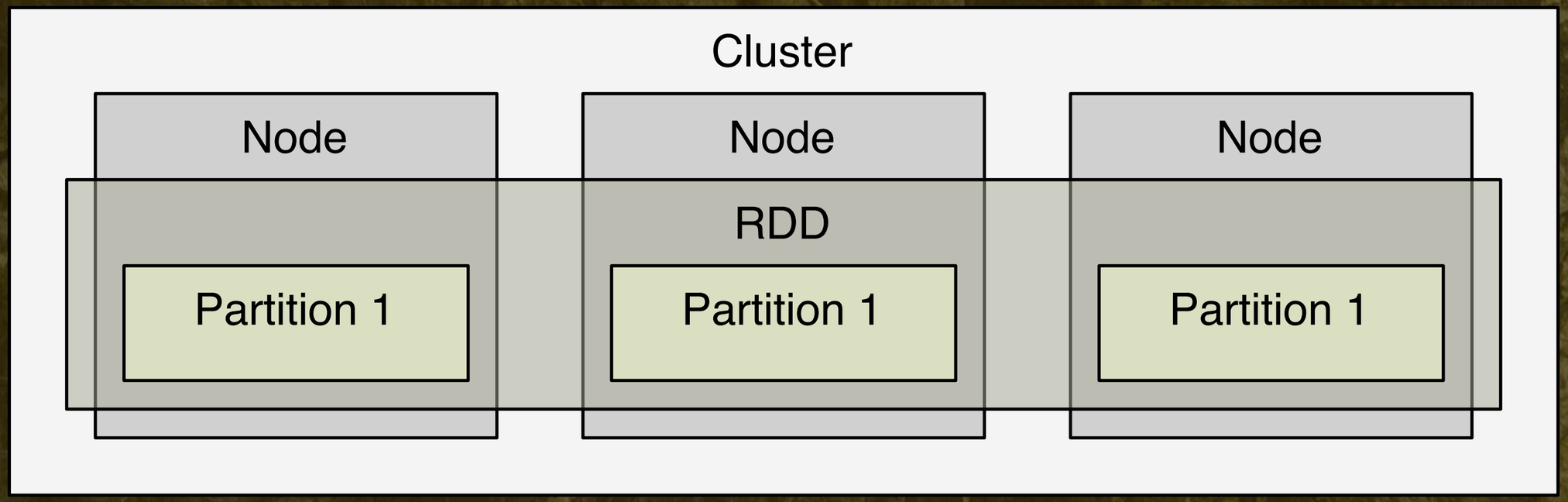
You can find this and my other talks here. There's an extended version of this talk there, too, with slides that I won't have time to cover today.

Spark

Scala has become popular for Big Data tools and apps, such as Spark. Why is Spark itself so interesting?



Spark is a general-purpose engine for writing JVM apps to analyze and manipulate massive data sets (although it works well for small ones, too), with the ability to decompose “jobs” into “tasks” that are distributed around a cluster.



Resilient Distributed Datasets

The core concept is a Resilient Distributed Dataset, a partitioned collection. They are resilient because if one partition is lost, Spark knows the lineage and can reconstruct it. However, you can also cache RDDs to eliminate having to walk back too far. RDDs are immutable, but they are also an abstraction, so you don't actually instantiate a new RDD with wasteful data copies for each step of the pipeline, but rather the end of each stage..

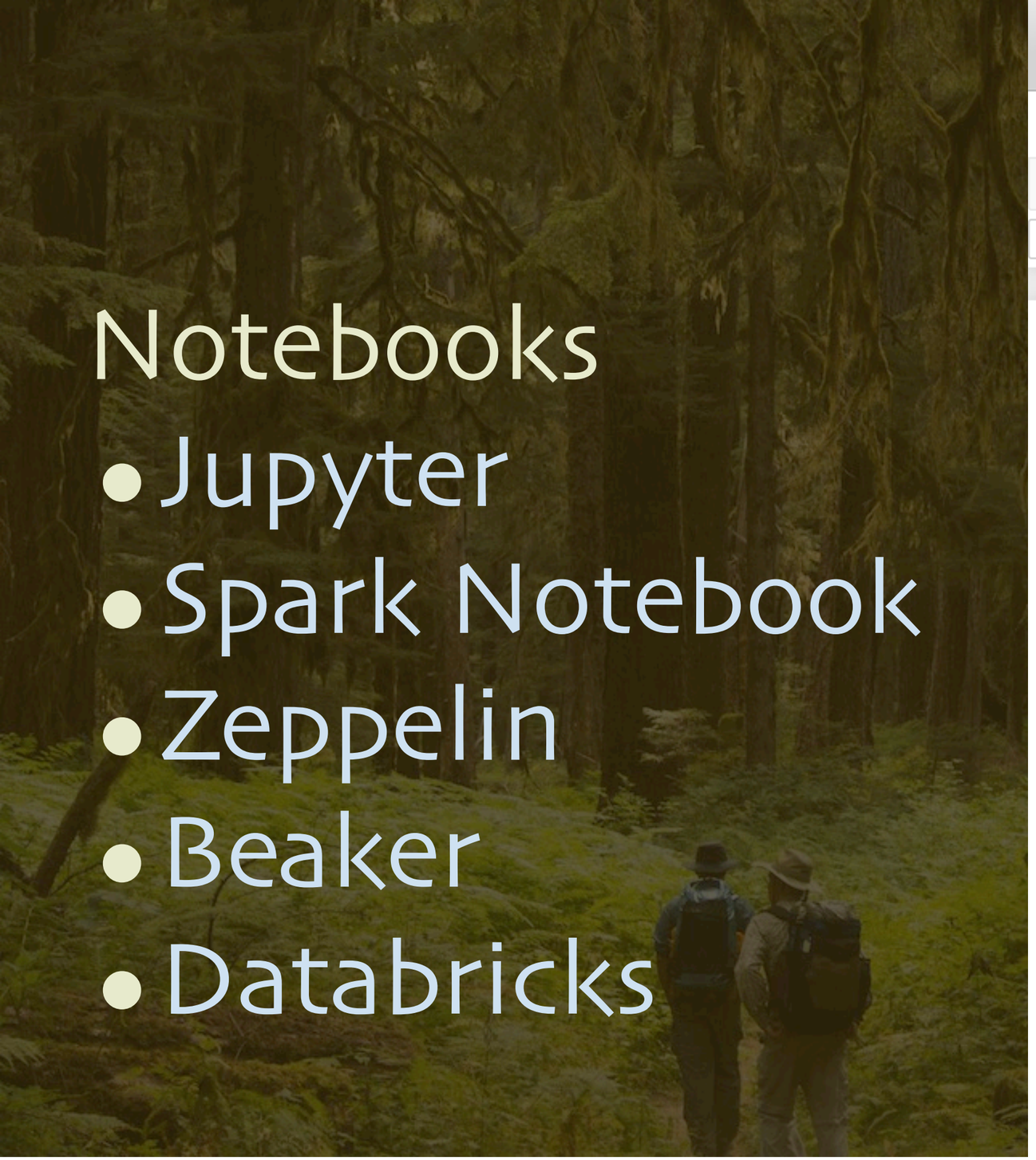
Productivity?

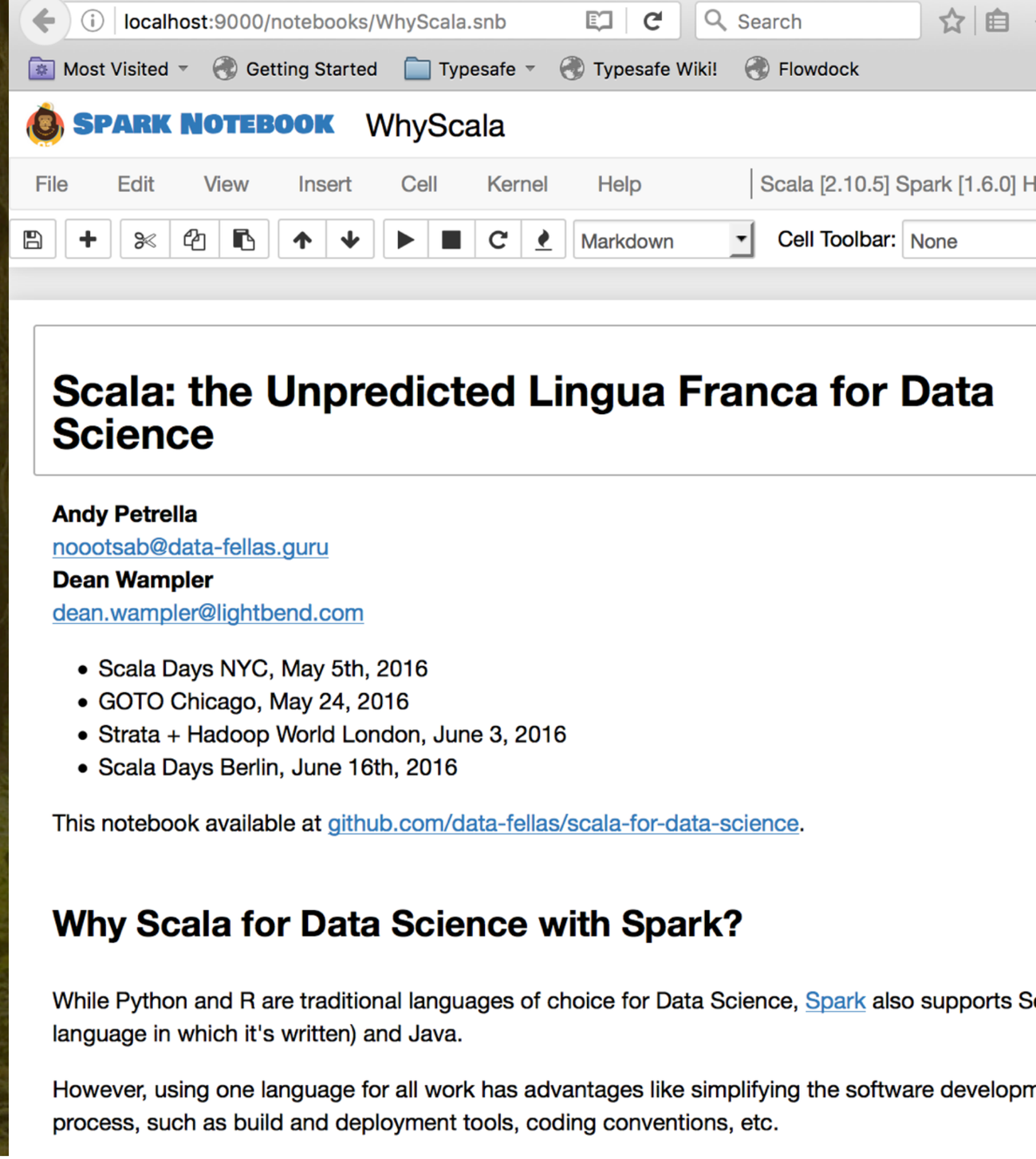
Very concise, elegant, functional APIs.

- Scala, Java
- Python, R
- ... and SQL!

We saw an example why this true.
While Spark was written in Scala, it has Java, Python, R, and even SQL APIs, too, which means it can be a single tool used across a Big Data organization, engineers and data scientists.

This is especially useful for the SQL queries we'll discuss, but also handy once you know the API for experimenting with data and/or algorithms. In fact, I tend to experiment in the REPL or Spark Notebook (next slide), then copy the code to a more "permanent" form, when it's supposed to be compiled and run as a batch program.





This is especially useful for the SQL queries we'll discuss, but also handy once you know the API for experimenting with data and/or algorithms. In fact, I tend to experiment in the REPL or Spark Notebook, then copy the code to a more "permanent" form, when it's supposed to be compiled and run as a batch program. Databricks is a commercial, hosted notebook offering.

Example: Inverted Index

Let’s look at a small, real actual Spark program, the Inverted Index.

Web Crawl

wikipedia.org/hadoop

Hadoop provides
MapReduce and HDFS

...

wikipedia.org/hbase

HBase stores data in HDFS

index

block

...	...
wikipedia.org/hadoop	Hadoop provides...
...	...

block

...	...
wikipedia.org/hbase	HBase stores...
...	...

Let’s look at a small, real actual Spark program, the Inverted Index.

Compute Inverted Index

index

block

...	...
wikipedia.org/hadoop	Hadoop provides...
...	...

block

...	...
wikipedia.org/hbase	HBase stores...
...	...

block

...	...
wikipedia.org/hive	Hive queries...
...	...

Miracle!!

inverse index

block

...	...
hadoop	(.../hadoop,1)
hbase	(.../hbase,1),(.../hive,1)
hdfs	(.../hadoop,1),(.../hbase,1),(.
hive	(.../hive,1)
...	...

block

...	...
...	...

block

...	...
...	...

block

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...	...

Let’s look at a small, real actual Spark program, the Inverted Index.

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

val sparkContext = new SparkContext(master, “Inv. Index”)
sparkContext.textFile("/path/to/input").
map { line =>
 val array = line.split(",", 2)
 (array(0), array(1))  // (id, content)
}.flatMap {
 case (id, content) =>
  toWords(content).map(word => ((word,id),1)) // toWords not shown
}.reduceByKey(_ + _).
map {
 case ((word,id),n) => (word,(id,n))
}.groupByKey.
mapValues {
 seq => sortByCount(seq)  // Sort the value seq by count, desc.
}.saveAsTextFile("/path/to/output")
```


All on one slide (30 point font). A very short program, which means your productivity is high and the “software engineering process” is drastically simpler. Spark 1.6.X syntax; Also works with 2.0.X.

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

val sparkContext = new
 SparkContext(master, “Inv. Index”)
sparkContext.textFile("/path/to/input").
map { line =>
 val array = line.split(",", 2)
 (array(0), array(1))
}.flatMap {
  case (id, contents) =>
   toWords(contents).map(w => ((w,id),1))
```


Let’s walk through it. I’ve zoomed in and reformatted a few lines to fit better. First, we create a SparkContext, the entry point into the program. “master” would point to the cluster or local machine.

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

val sparkCo
 SparkContext(master, "Inv. Index")
sparkContext.textFile("/path/to/input").
map { line =>
 val array = line.split(",", 2)
 (array(0), array(1))
}.flatMap {
 case (id,
  toWords(contents).map(w => ((w,id),1))
```

RDD[String]: .../hadoop, Hadoop provides...

RDD[(String,String)]: (.../hadoop,Hadoop provides...)

Using the sparkContext, read test data (the web crawl data). Assume it's comma-delimited and split it into the identifier (e.g., URL) and the contents. If the input is very large, multiple, parallel tasks will be spawned across the cluster to read and process each file block as a partition, all in parallel.

```
  val array = line.split(",", 2)
  (array(0), array(1))
}.flatMap {
  case (id, contents) =>
    toWords(contents).map(w => ((w,id),1))
}.reduceByKey(_ + _).
map {
  case ((word,id),n) => (word,(id,n))
}.groupByKey.
mapValues {
  seq => sortByCount(seq)
}.saveAsTextFile("/path/to/output")
```

RDD[((String,String),Int)]: ((Hadoop,.../hadoop),20)

An idiom for counting...
Flat map to tokenize the contents into words (using a “toWords” function that isn’t shown), then map over those words to nested tuples, where the (word, id) is the key, and see count of 1 is the value.
Then use reduceByKey, which is an optimized groupBy where we don’t need the groups, we just want to apply a function to reduce the values for each unique key. Now the records are unique (word,id) pairs and counts >= 1.

```
 val array = line.split(",", 2)
 (array(0), array(1))
}.flatMap {
 case (id, contents) =>
  toWords(contents).map(w => ((w,id),1))
}.reduceByKey(_ + _).
map {
 case ((word,id),n) => (word,(id,n))
}.groupByKey.
mapValues {
 seq => sortByCount(seq)
}.saveAsTextFile("/path/to/output")
```

RDD[(String,Iterable((String,Int))]: (Hadoop,seq(.../hadoop,20),...))

I love how simple this line is anon. function is; by moving the nested parentheses, we setup the final data set, where the words alone are keys and the values are (path, count) pairs. Then we group over the words (the “keys”).

```
 val array = line.split(",", 2)
 (array(0), array(1))
}.flatMap {
 case (id, contents) =>
  toWords(contents).map(w => ((w,id),1))
}.reduceByKey(_ + _).
map {
 case ((word,id),n) => (word,(id,n))
}.group
mapValues {
 seq => sortByCount(seq)
}.saveAsTextFile("/path/to/output")
```

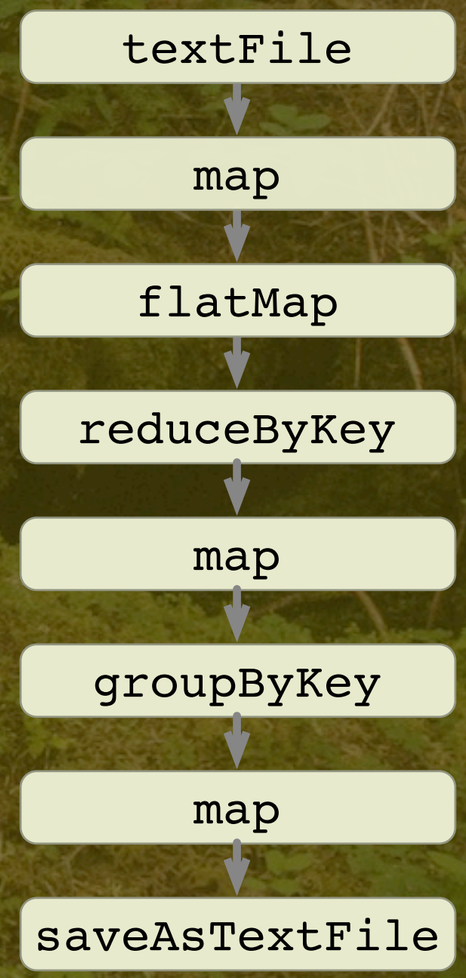
RDD[(String,Iterable((String,Int))]: (Hadoop,seq(.../hadoop,20),...))

Finally, for each unique word, sort the nested collection of (path,count) pairs by count descending (this is easy with Scala's Seq.sortBy method). Then save the results as text files.

Productivity?

Intuitive API:

- Dataflow of steps.
- Inspired by Scala collections and functional programming.

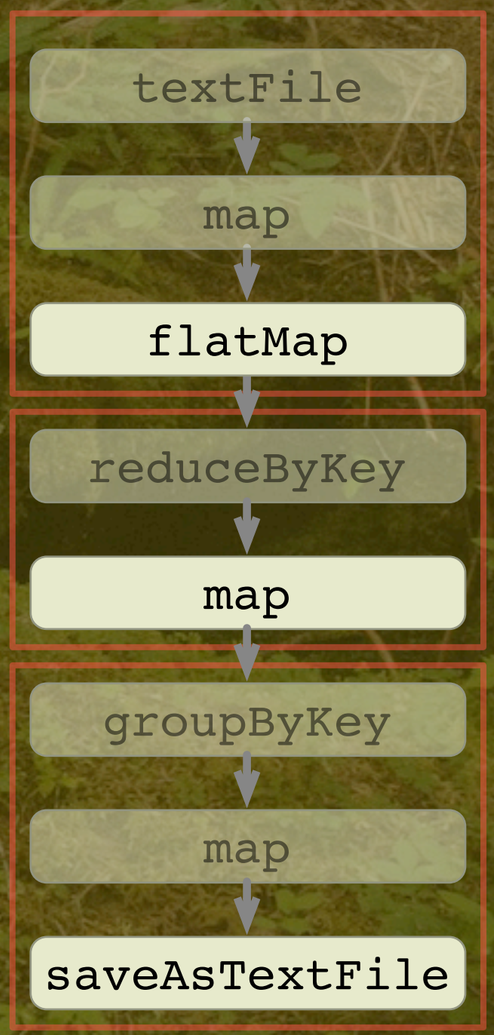


One you learn all these “operators” from functional programming, as expressed first in the Scala collections API and then adapted by Spark, you can quickly construct data flows that are intuitive, yet powerful.

Performance?

Lazy API:

- Combines steps into "stages".
- Cache intermediate data in memory.



How is Spark more efficient? Spark programs are actually "lazy" dataflows definitions that are only evaluated on demand. Because Spark has this directed acyclic graph of steps, it knows what data to attempt to cache in memory between steps (with programmable tweaks) and it can combine many logical steps into one "stage" of computation, for efficient execution while still providing an intuitive API experience.

The transformation steps that don't require data from other partitions can be pipelined together into a single JVM process (per partition), called a Stage. When you do need to bring together data from different partitions, such as group-bys, joins, reduces, then data must be "shuffled" between partitions (i.e., all keys of a particular value must arrive at the same JVM instance for the next transformation step). That triggers a new stage, as shown. So, this algorithm requires three stages and the RDDs are materialized only for the last steps in each stage.

Higher-Level APIs

Composable operators, performance optimizations, and general flexibility are a foundation for higher-level APIs...
A major step forward compared to MapReduce. Due to the lightweight nature of Spark processing, it can efficiently support a wider class of algorithms.

SQL: Datasets/ DataFrames

For data with a known, fixed schema.
Like Hive for MapReduce, a subset of SQL (omitting transactions and the U in CRUD) is relatively easy to implement as a DSL on top of a general compute engine like Spark. Hence, the SQL API was born, but it's grown into a full-fledged programmatic API supporting both actual SQL queries and an API similar to Python's DataFrame API for working with structured data in a more type-safe way (errr, at least for Scala). Datasets have statically-typed records while DataFrames are a special case where the fields are typed dynamically.

Example

```
import org.apache.spark.SparkSession
val spark = SparkSession.builder()
  .master("local")
  .appName("Queries")
  .getOrCreate()

val flights =
 spark.read.parquet(".../flights")
val planes =
 spark.read.parquet(".../planes")
flights.createOrReplaceTempView("flights")
planes. createOrReplaceTempView("planes")
flights.cache(); planes.cache()

val planes_for_flights1 = sqlContext.sql("""
  SELECT * FROM flights f
  JOIN planes p ON f.tailNum = p.tailNum LIMIT 100""")
```

```
val planes_for_flights2 =
 flights.join(planes,
  flights("tailNum") ===
  planes ("tailNum")).limit(100)
```


Example using SparkSQL to join two data sets (adapted from Typesafe's Spark Workshop training), data for flights and information about the planes.

```
import org.apache.spark.SparkSession
val spark = SparkSession.builder()
  .master("local")
  .appName("Queries")
  .getOrCreate()

val flights =
 spark.read.parquet(".../flights")
val planes =
 spark.read.parquet(".../planes")
flights.createOrReplaceTempView("flights")
planes. createOrReplaceTempView("planes")
flights.cache(); planes.cache()
```


We start with the new SparkSession introduced in Spark 2.0. (Use SQLContext in Spark 1.X)

```
import org.apache.spark.SparkSession
val spark = SparkSession.builder()
  .master("local")
  .appName("Queries")
  .getOrCreate()

val flights =
 spark.read.parquet(".../flights")
val planes =
 spark.read.parquet(".../planes")
flights.createOrReplaceTempView("flights")
planes. createOrReplaceTempView("planes")
flights.cache(); planes.cache()
```


Read the data as Parquet files, which include the schemas. Create temporary “views” (purely virtual) for SQL queries, and cache the tables for faster, repeated access.

```
planes. createOrReplaceTempView("planes")
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val planes_for_flights1 = sqlContext.sql("""
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val planes_for_flights2 =
 flights.join(planes,
  flights("tailNum") ===
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```

Returns another Dataset.

Use SQL to write the query. There are Dataset operations (DataFrames in Spark 1.X) we can then use on this result (the next part of the program uses this API to redo the query). A Dataset wraps an RDD, so we can also all RDD methods to work with the results. Hence, we can mix and match SQL and programmatic APIs to do what we need to do.

```
planes. createOrReplaceTempView("planes")
flights.cache(); planes.cache()

val planes_for_flights1 = sqlContext.sql("""
  SELECT * FROM flights f
  JOIN planes p ON f.tailNum = p.tailNum
LIMIT 100""")
```

Returns another Dataset.

```
val planes_for_flights2 =
 flights.join(planes,
  flights("tailNum") ===
  planes ("tailNum")).limit(100)
```


Use the Dataset DSL to write the query (more type safe). Also returns a new Dataset.

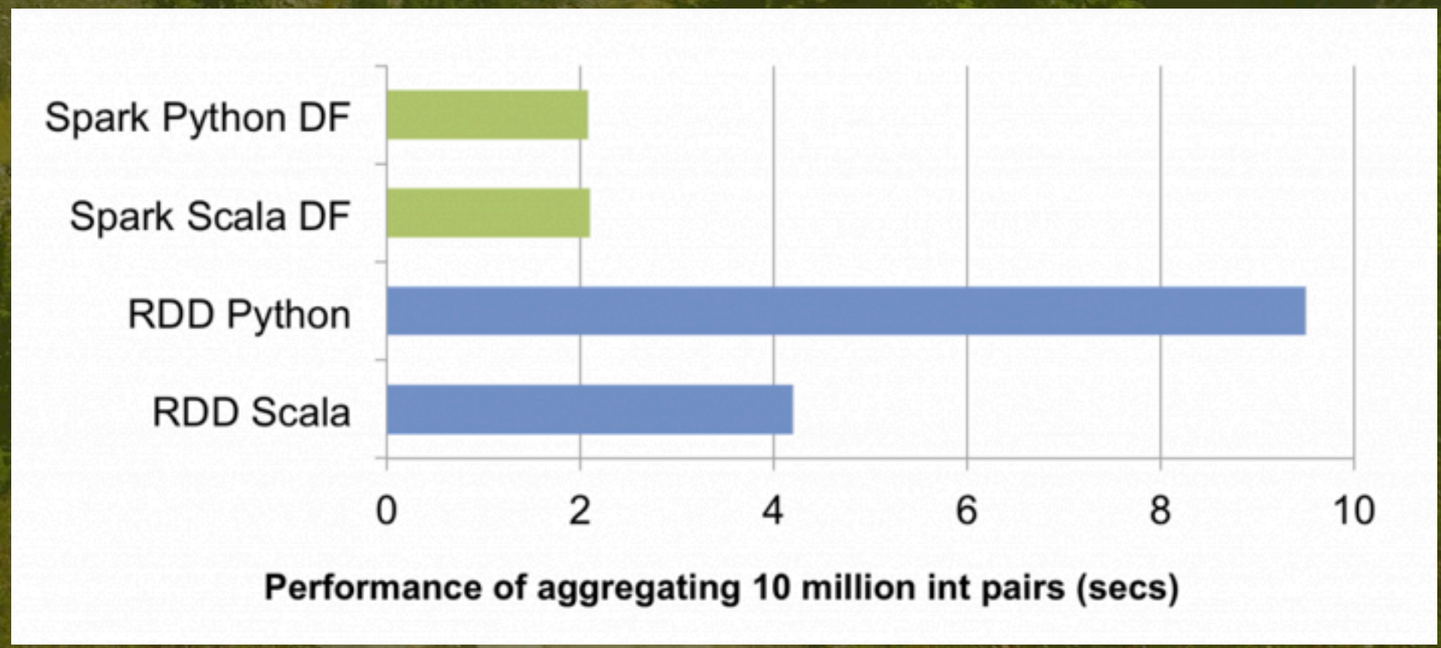
```
val planes_for_flights2 =
  flights.join(planes,
    flights("tailNum") ===
    planes ("tailNum")).limit(100)
```

Not an “arbitrary” anonymous function, but a “Column” instance.

Looks like an anonymous function, but actually it’s actually a join expression that constructs an instance of a “Column” type. By constraining what’s allowed here, Spark knows the exact expression used here and it can apply aggressive optimizations at run time.

Performance

The Dataset API has the same performance for all languages: Scala, Java, Python, R, and SQL!

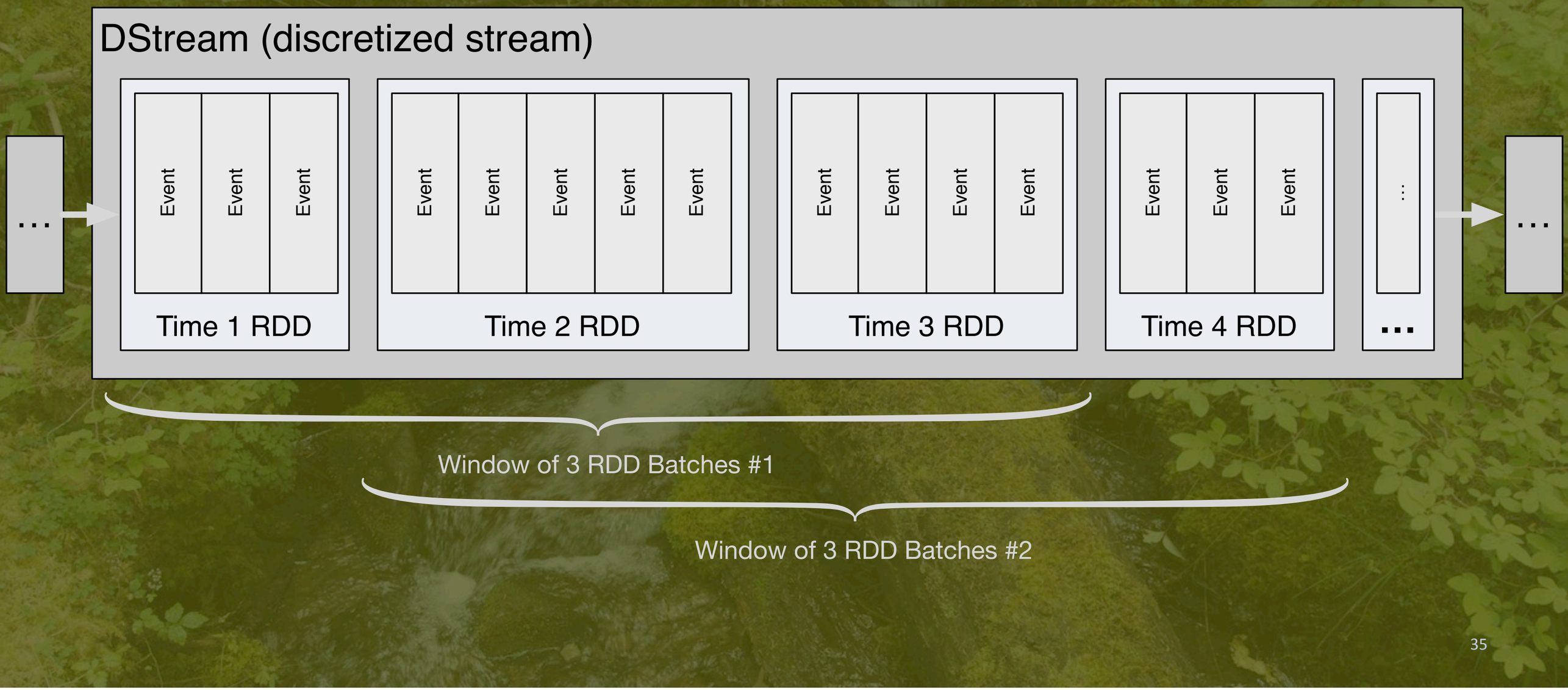


All the different language APIs are thin veneers on top of the Catalyst query optimizer and other Scala-based code. This performance independent of language choice is a major step forward. Previously for Hadoop, Data Scientists often developed models in Python or R, then an engineering team ported them to Java MapReduce. Previously with Spark, you got good performance from Python code, but about 1/2 the efficiency of corresponding Scala code. Now, the performance is the same.
Graph from: https://databricks.com/blog/2015/04/24/recent-performance-improvements-in-apache-spark-sql-python-dataframes-and-more.html

```
def join(right: Dataset[_], joinExprs: Column): DataFrame = {
def groupBy(cols: Column*): RelationalGroupedDataset = {
def orderBy(sortExprs: Column*): Dataset[T] = {
def select(cols: Column*): Dataset[...] = {
def where(condition: Column): Dataset[T] = {
def limit(n: Int): Dataset[T] = {
def intersect(other: Dataset[T]): Dataset[T] = {
def sample(withReplacement: Boolean, fraction, seed) = {
def drop(col: Column): DataFrame = {
def map[U](f: T => U): Dataset[U] = {
def flatMap[U](f: T => Traversable[U]): Dataset[U] ={
def foreach(f: T => Unit): Unit = {
def take(n: Int): Array[Row] = {
def count(): Long = {
def distinct(): Dataset[T] = {
def agg(exprs: Map[String, String]): DataFrame = {
```


So, the Dataset[T] API exposes a set of relational (-ish) operations, more limited than the general RDD API. This narrower interface enables broader (more aggressive) optimizations and other implementation choices underneath.

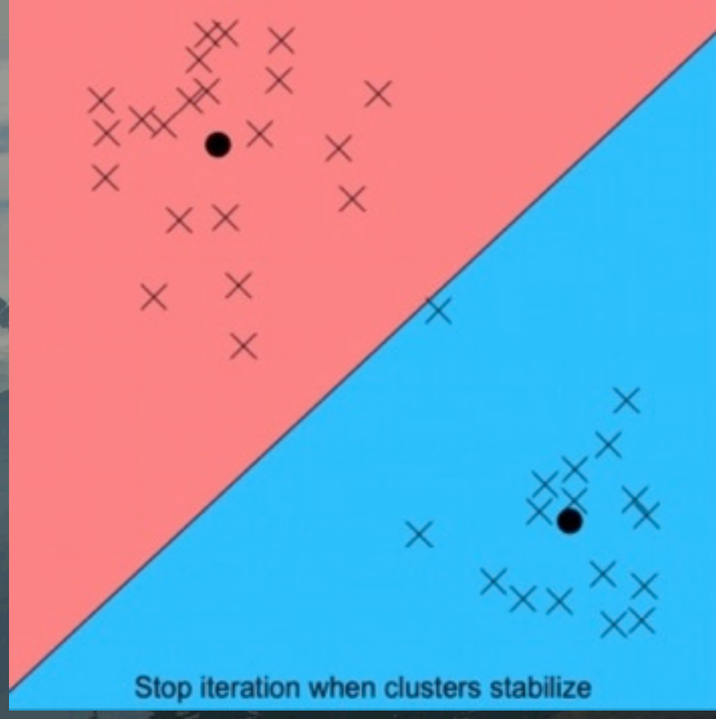

Structured
Streaming



For streaming in Spark 1.X, one RDD is created per batch iteration, with a DStream (discretized stream) holding all of them, which supports window functions. Spark started life as a batch-mode system, just like MapReduce, but Spark's dataflow stages and in-memory, distributed collections (RDDs - resilient, distributed datasets) are lightweight enough that streams of data can be time sliced (down to ~1 second) and processed in small RDDs, in a "mini-batch" style. This gracefully reuses all the same RDD logic, including your code written for RDDs, while also adding useful extensions like functions applied over moving windows of these batches. This idea of minibatches is slowly being removed from Spark so that lower latency streaming can be supported.

Many machine learning libraries are being implemented on top of Spark. An important requirement is the ability to do linear algebra and iterative algorithms quickly and efficiently, which is used in the training algorithms for many ML models. ML is the newer, Dataset-based library and MLlib is the older, deprecated, RDD-based library.

K-Means

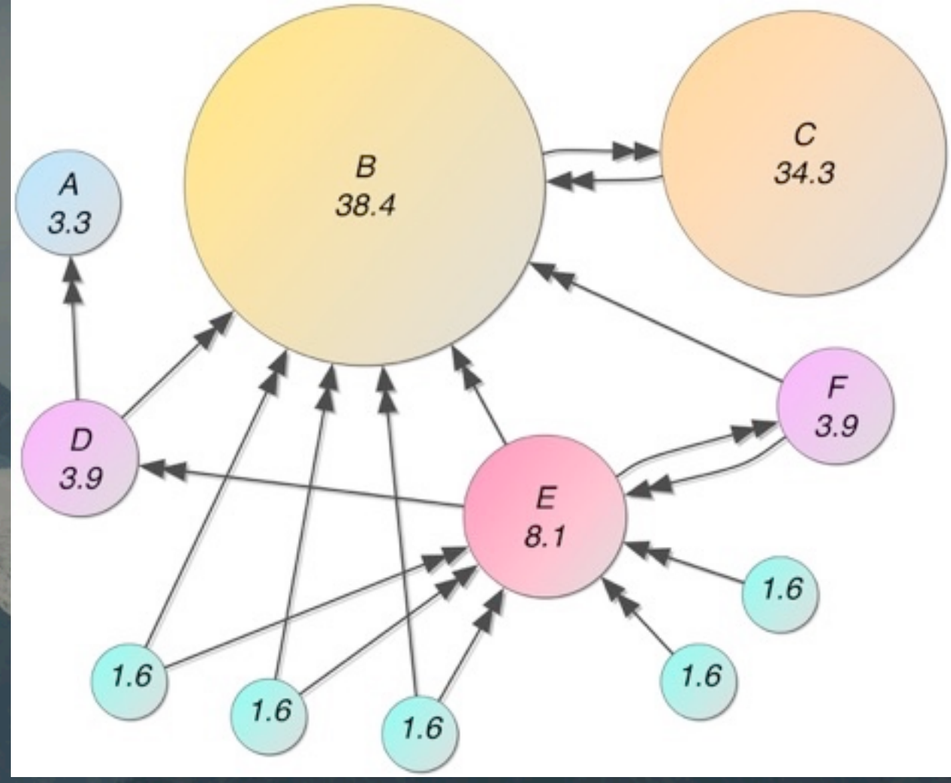


- Machine Learning requires:
- Iterative training of models.
- Good linear algebra perf.

Many machine learning libraries are being implemented on top of Spark. An important requirement is the ability to do linear algebra and iterative algorithms quickly and efficiently, which is used in the training algorithms for many ML models.
K-Means Clustering simulation: https://en.wikipedia.org/wiki/K-means_clustering

Similarly, efficient iteration makes graph traversal algorithms tractable, enabling “first-class” graph representations of data, like social networks.
This library is also in the process of being replaced with a new implementation.

PageRank



- Graph algorithms require:
- Incremental traversal.
- Efficient edge and node reps.

Similarly, efficient iteration makes graph traversal algorithms tractable, enabling “first-class” graph representations of data, like social networks.
Page Rank example: https://en.wikipedia.org/wiki/PageRank

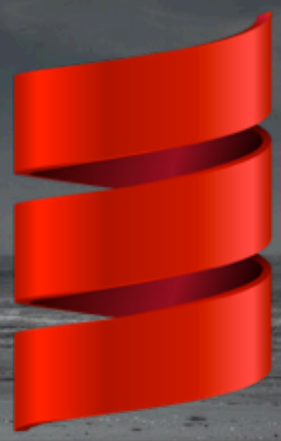
Foundation:

With that introduction, let's step back and look at the larger context, starting at the bottom; why is the JVM the platform of choice for Big Data?

20 Years of DevOps

We have 20 years of operations experience running JVM-based apps in production. We have many Java developers, some with 20 years of experience, writing JVM-based apps.

Tools and Libraries



Akka
Breeze
Algebird
Spire & Cats
Axle
...

We have a rich suite of mature(-ish) languages, development tools, and math-related libraries for building data applications...

http://akka.io - For resilient, distributed middleware.
https://github.com/scalanlp/breeze - A numerical processing library around LAPACK, etc.
https://github.com/twitter/algebird - A big data math library, developed at Twitter
https://github.com/non/spire - A numerical library
https://github.com/non/cats - A Category Theory library
http://axle-lang.org/ - DSLs for scientific computing.

Big Data Ecosystem

All this is why most Big Data tools in use have been built on the JVM, including Spark, especially those for OSS projects created and used by startups.

http://spark.apache.org
https://github.com/twitter/scalding
https://github.com/twitter/summingbird
http://kafka.apache.org
http://hadoop.apache.org
http://cassandra.apache.org
http://storm.apache.org
http://samza.apache.org
http://lucene.apache.org/solr/
http://h2o.ai

But no system is perfect. The JVM wasn't really designed with Big Data systems, as we call them now, in mind.

Richer data libs. in Python & R

First, a small, but significant issue; since Python and R have longer histories as Data Science languages, they have much richer and more mature libraries, e.g., statistics, machine learning, natural language processing, etc., compared to the JVM.

Garbage Collection

Garbage collection is a wonder thing for removing a lot of tedium and potential errors from code, but the default settings in the JVM are not ideal for Big Data apps.

GC Challenges

- Typical Spark heaps: 10s-100s GB.
- Uncommon for "generic", non-data services.

We'll explain the details shortly, but the programmer controls which data sets are cached to optimize usage.
See https://databricks.com/blog/2015/05/28/tuning-java-garbage-collection-for-spark-applications.html for a detailed overview of GC challenges and tuning for Spark.

GC Challenges

- Too many cached RDDs leads to huge old generation garbage.
- Billions of objects => long GC pauses.

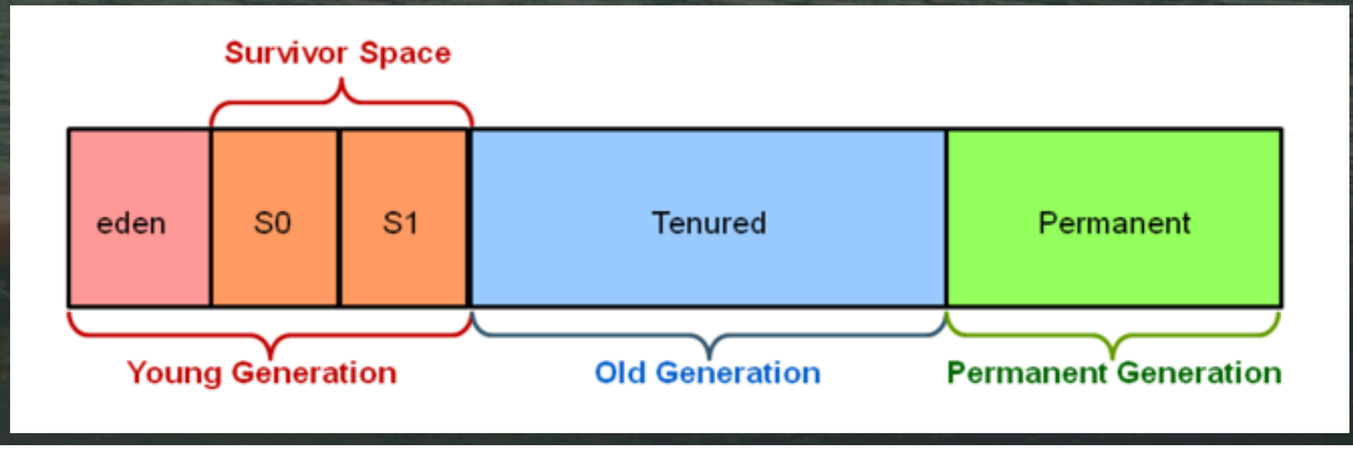


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Image from http://www.oracle.com/webfolder/technetwork/tutorials/obe/java/gc01/index.html.
Another example is the Hadoop Distributed File System Name Node service, which holds the file system's metadata in memory, often 10s-100sGB. At these sizes, there have been occurrences of multi-hour GC pauses. Careful tuning is required.

Tuning GC

- Best for Spark:
  - -XX:UseG1GC -XX:-ResizePLAB -Xms... -Xmx... -XX:InitiatingHeapOccupancyPercent=... -XX:ConcGCThread=...

databricks.com/blog/2015/05/28/tuning-java-garbage-collection-for-spark-applications.html

Summarizing a long, detailed blog post (https://databricks.com/blog/2015/05/28/tuning-java-garbage-collection-for-spark-applications.html) in one slide!
Their optimal settings for Spark for large data sets, before the “Tungsten” optimizations. The numbers elided (“...”) are scaled together.

JVM Object Model

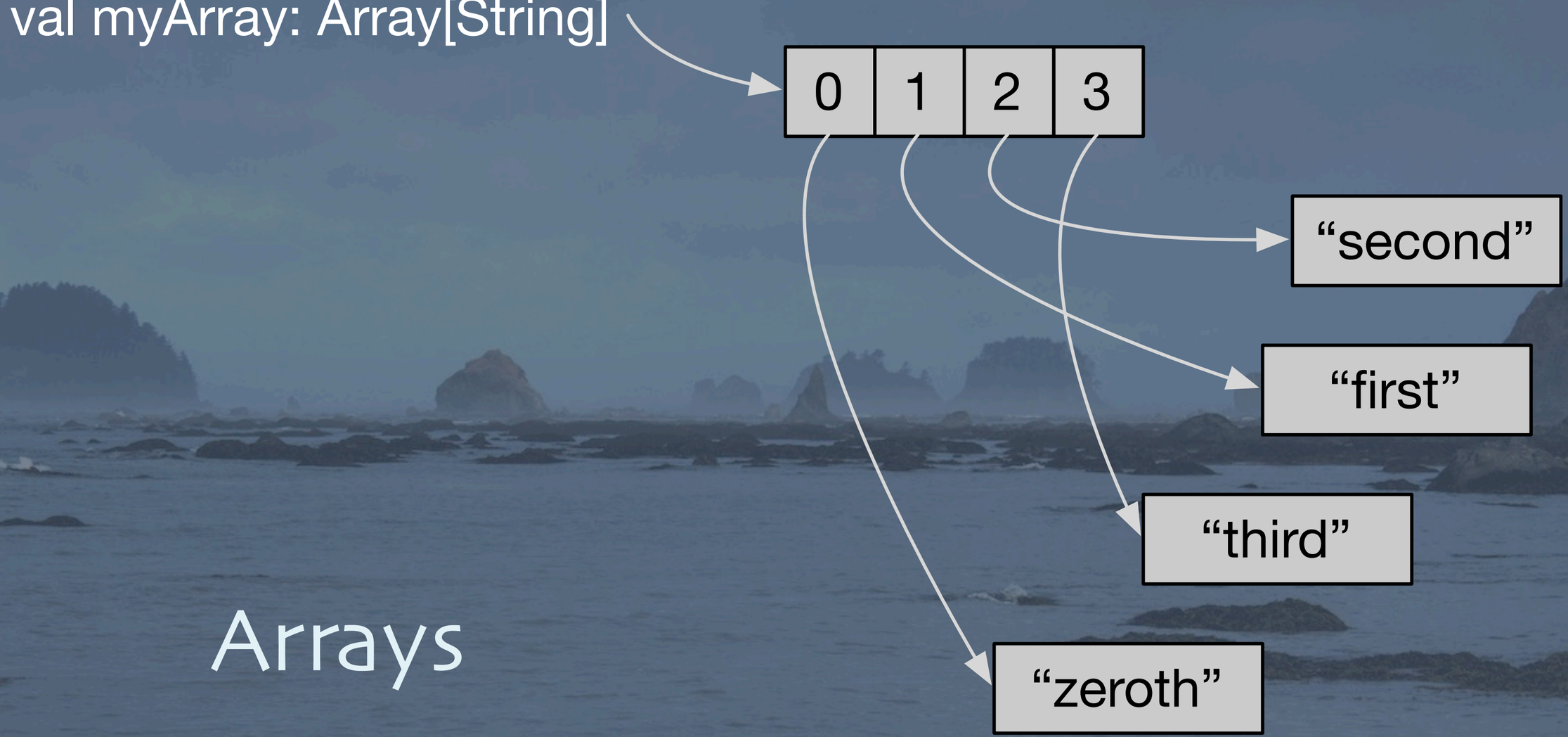
For general-purpose management of trees of objects, Java works well, but not for data orders of magnitude larger, where you tend to have many instances of the same “schema”.

Java Objects?

- "abcd": 4 bytes for raw UTF8, right?
- 48 bytes for the Java object:
  - 12 byte header.
  - 8 bytes for hash code.
  - 20 bytes for array overhead.
  - 8 bytes for UTF16 chars.

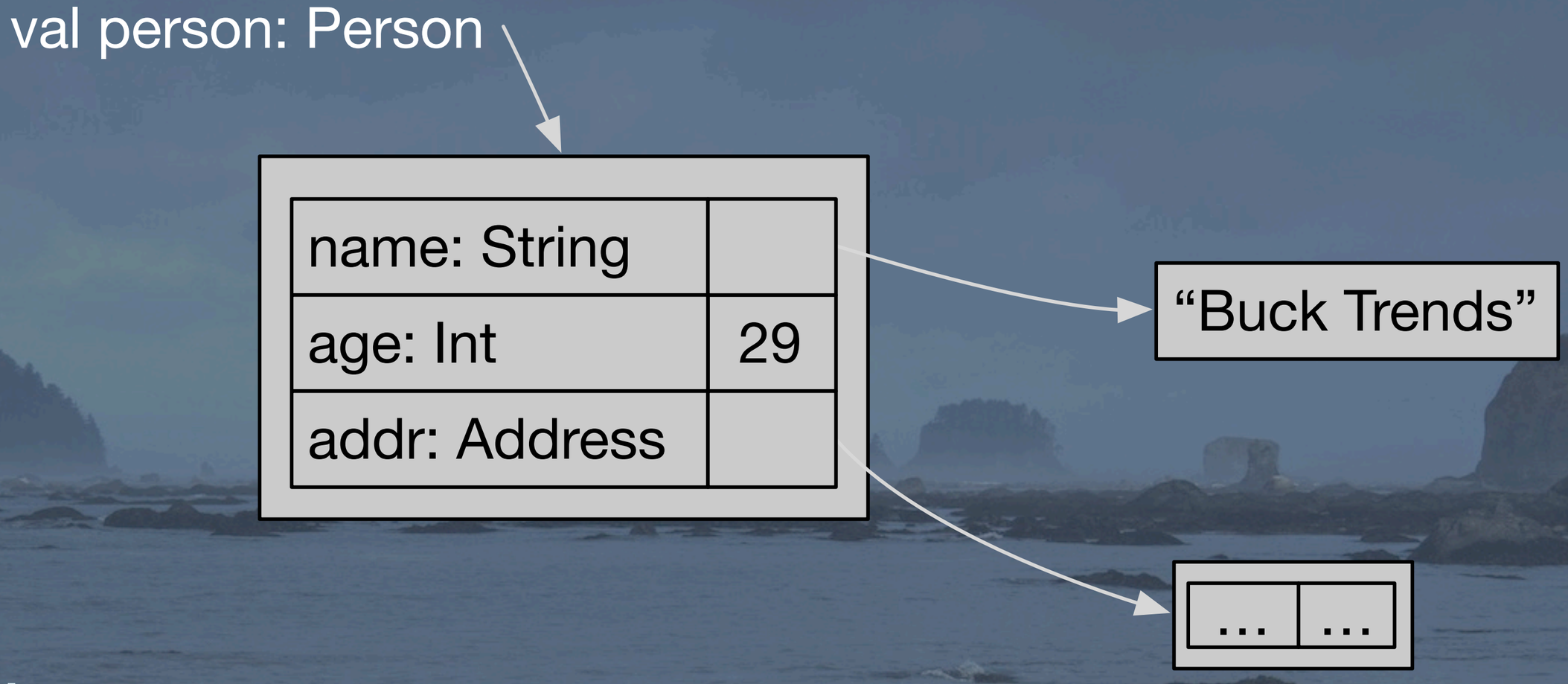
From http://www.slideshare.net/SparkSummit/deep-dive-into-project-tungsten-josh-rosen

Arrays



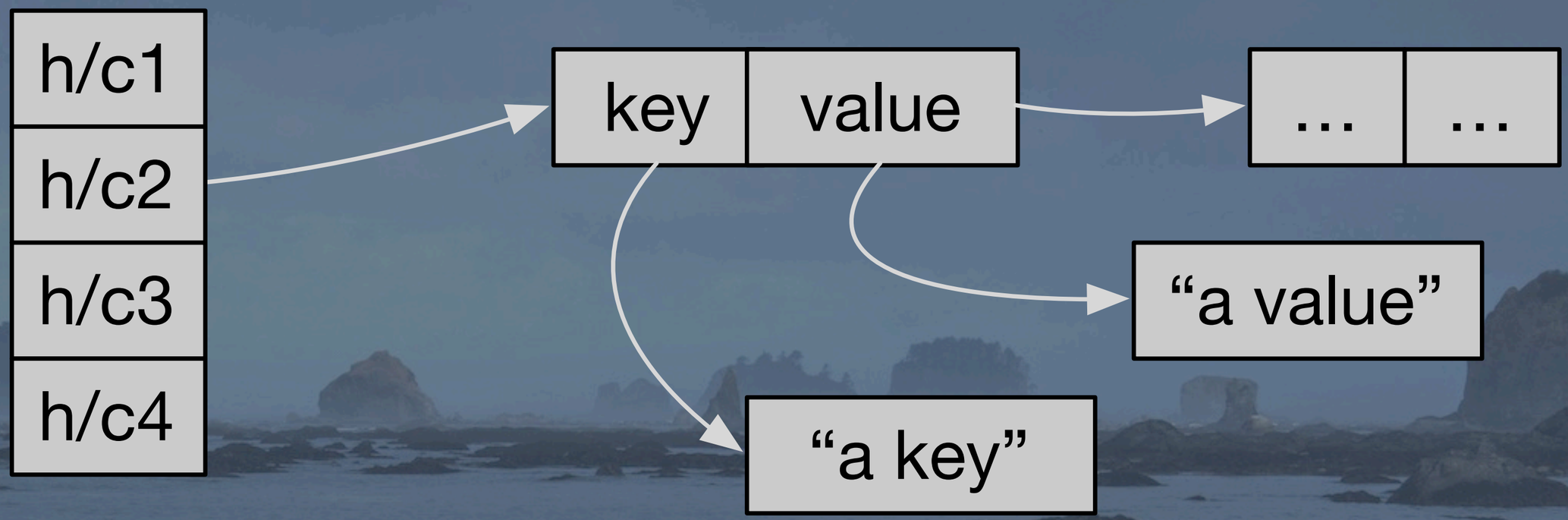
There’s the memory for the array, then the references to other objects for each element around the heap.

Class Instances



An example of the type that might represent a record for a “persons” table.
There’s the memory for the array, then the references to other objects for each element around the heap.

Hash Maps



For a given hash bucket, there’s the memory for the array, then the references to other objects for each element around the heap.

Improving Performance

Why obsess about this?
Spark jobs are CPU bound:

- Improve network I/O? ~2% better.
- Improve disk I/O? ~20% better.

Okay, so memory handling is an issue, but is it the major issue? Aren't Big Data jobs I/O bound anyway? MapReduce jobs tend to be CPU bound, but research by Kay Ousterhout (http://www.eecs.berkeley.edu/~keo/talks/2015_06_15_SparkSummit_MakingSense.pdf) and other observers indicate that for Spark, optimizing I/O only improve performance ~5% for network improvements and ~20% for disk I/O. So, Spark jobs tend to be CPU bound.

What changed?

- Faster HW (compared to ~2000)
  - 10Gbs networks
  - SSDs.

These are the contributing factors that make today's Spark jobs CPU bound while yesterday's MapReduce jobs were more I/O bound.

What changed?

- Smarter use of I/O
  - Pruning unneeded data sooner.
  - Caching more effectively.
  - Efficient formats, like Parquet.

These are the contributing factors that make today's Spark jobs CPU bound while yesterday's MapReduce jobs were more I/O bound.
We also use compression more than we used to.

What changed?

- But more CPU use today:
  - More Serialization.
  - More Compression.
  - More Hashing (joins, group-bys).

These are the contributing factors that make today's Spark jobs CPU bound while yesterday's MapReduce jobs were more I/O bound.

Improving Performance

To improve performance, we need to focus on the CPU, the:

- Better algorithms, sure.
- And optimize use of memory.

Okay, so memory handling is an issue, but is it the major issue? Aren't Big Data jobs I/O bound anyway? MapReduce jobs tend to be CPU bound, but research by Kay Ousterhout (http://www.eecs.berkeley.edu/~keo/talks/2015_06_15_SparkSummit_MakingSense.pdf) and other observers indicate that for Spark, optimizing I/O only improve performance ~5% for network improvements and ~20% for disk I/O. So, Spark jobs tend to be CPU bound.

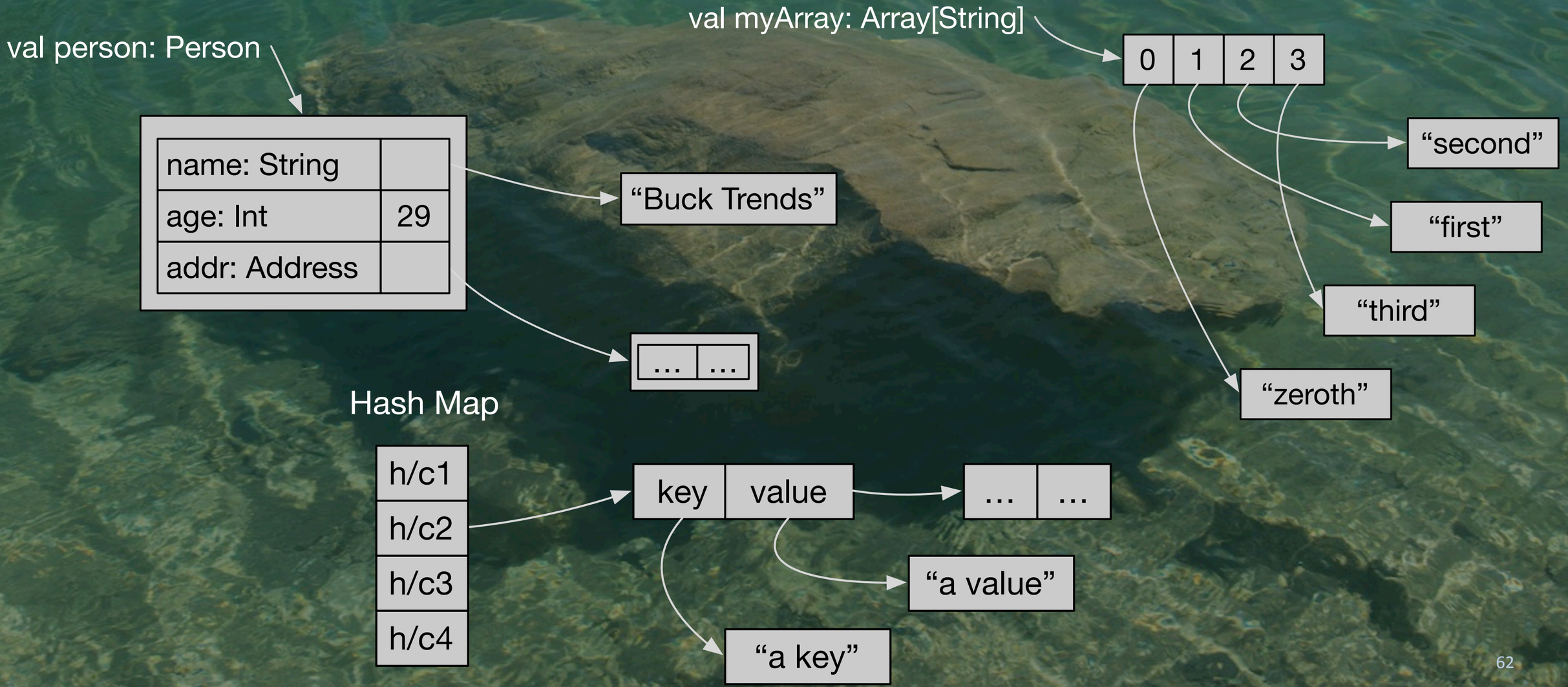
Project Tungsten

Initiative to greatly improve Dataset/DataFrame performance.

Project Tungsten is a multi-release initiative to improve Spark performance, focused mostly on the DataFrame implementation. References:
http://www.slideshare.net/databricks/2015-0616-spark-summit
http://www.slideshare.net/SparkSummit/deep-dive-into-project-tungsten-josh-rosen
https://databricks.com/blog/2015/04/28/project-tungsten-bringing-spark-closer-to-bare-metal.html

Goals

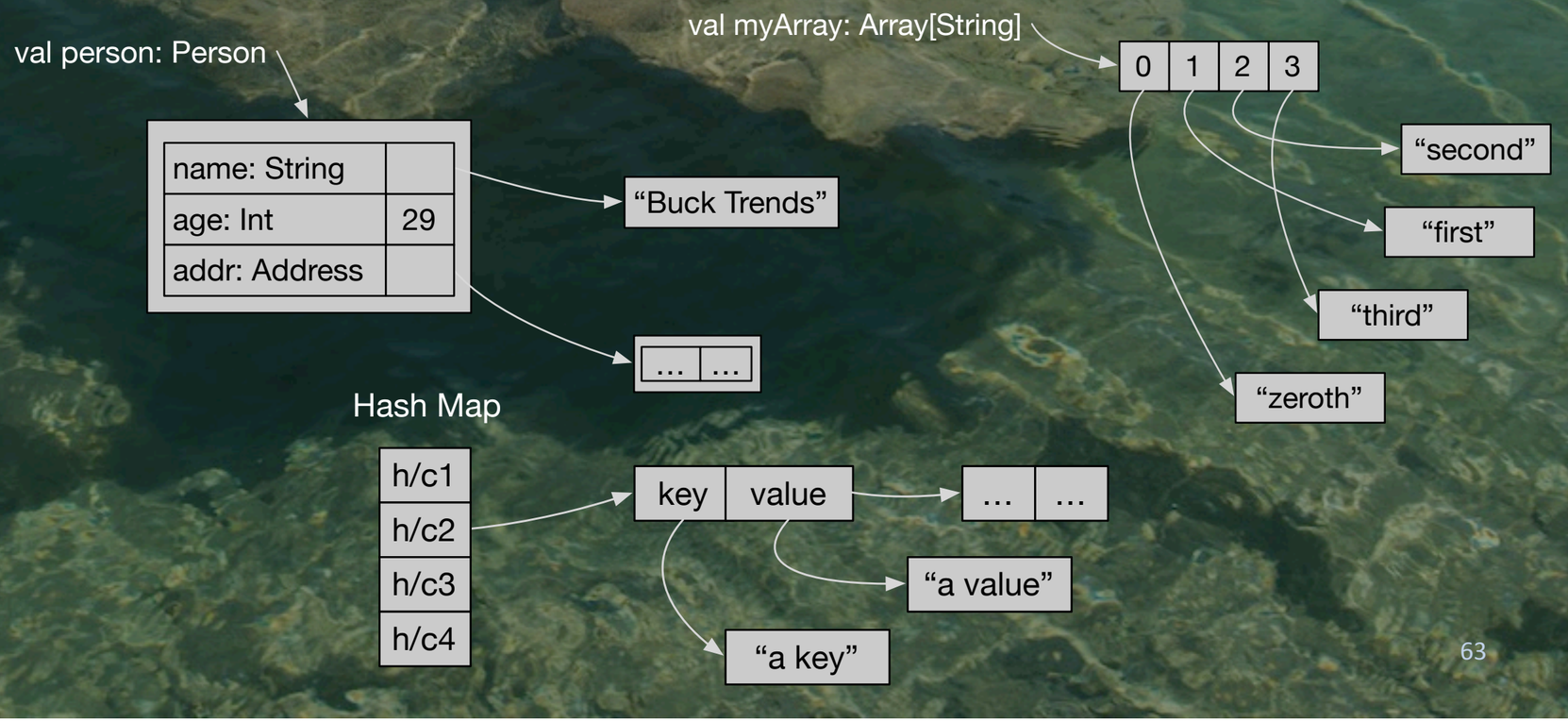
Reduce References



While this general-purpose model has given us the flexibility we need, it’s bad for big data, where we have a lot of data with the same format, same types, etc.

Reduce References

- Fewer, bigger objects to GC.
- Fewer cache misses



Eliminating references (the arrows) means we have better GC performance, because we'll have far fewer (but larger) to manage and collect. The size doesn't matter; it's just as efficient to collect a 1MB block as a 1KB block.
With fewer arrows, it's also more likely that the data we need is already in the cache!

Less Expression Overhead

```
sql("SELECT a + b FROM table")
```

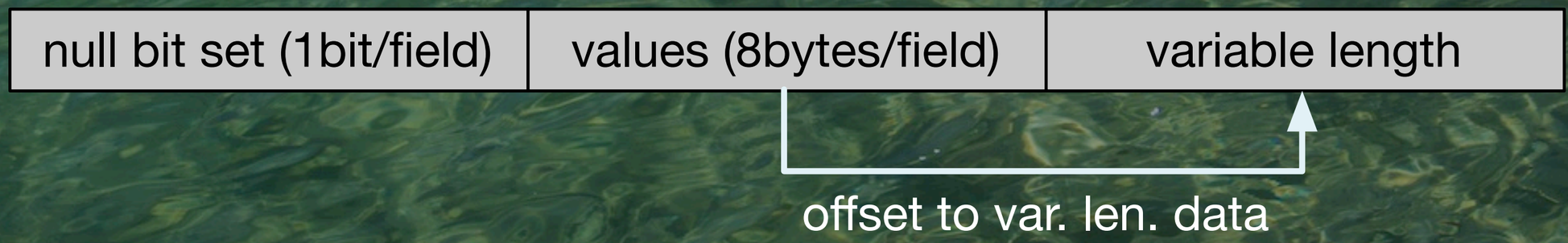
- Evaluating expressions billions of times:
  - Virtual function calls.
  - Boxing/unboxing.
  - Branching (if statements, etc.)

This is perhaps less obvious, but when you evaluate an expression billions of times, then the overhead of virtual function calls (even with the JVMs optimizations for polymorphic dispatch), the boxing and unboxing of primitives, and the evaluate of conditions adds up to noticeable overhead.

Implementation

Object Encoding

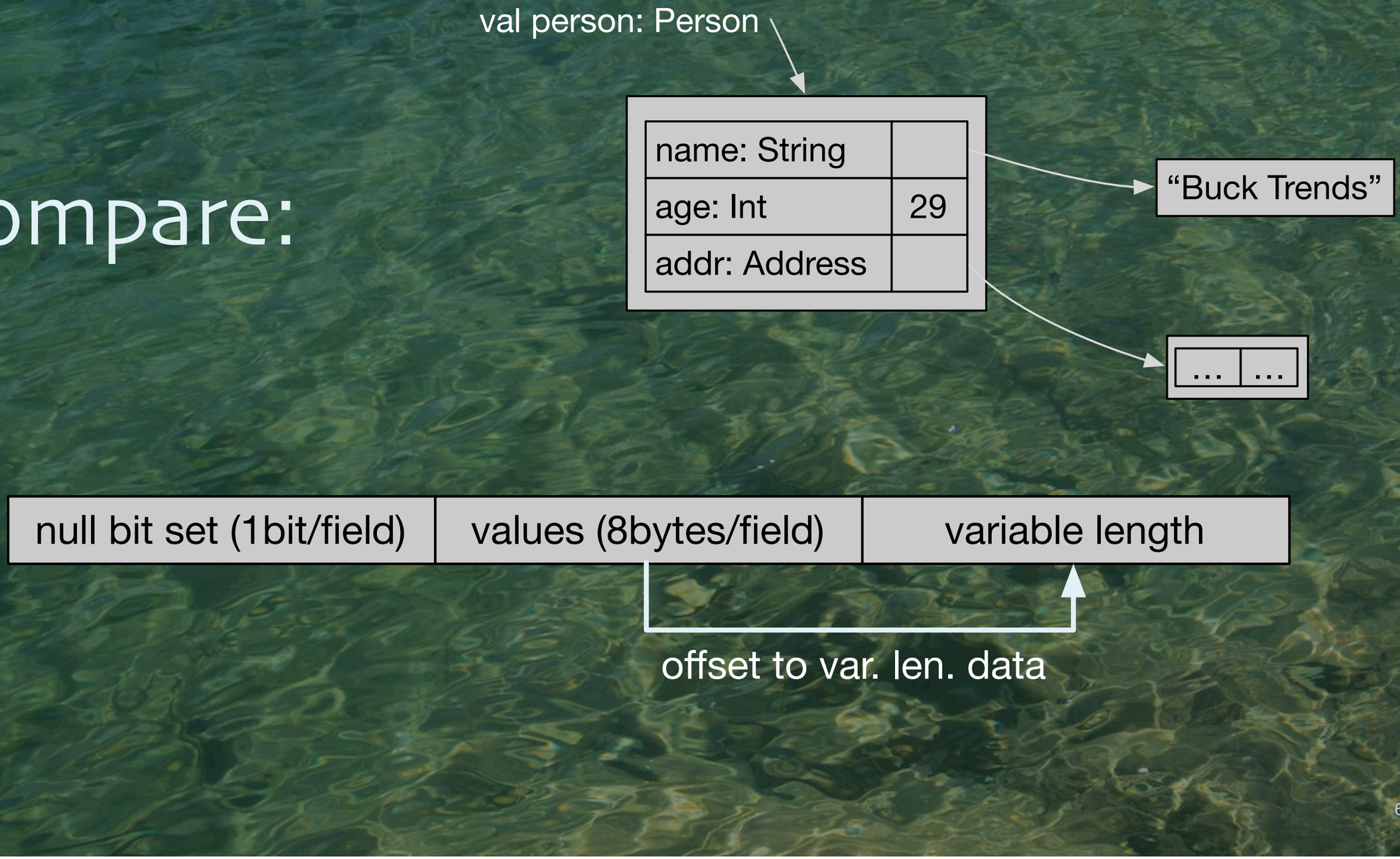
New CompactRow type:



- Compute hashCode and equals on raw bytes.

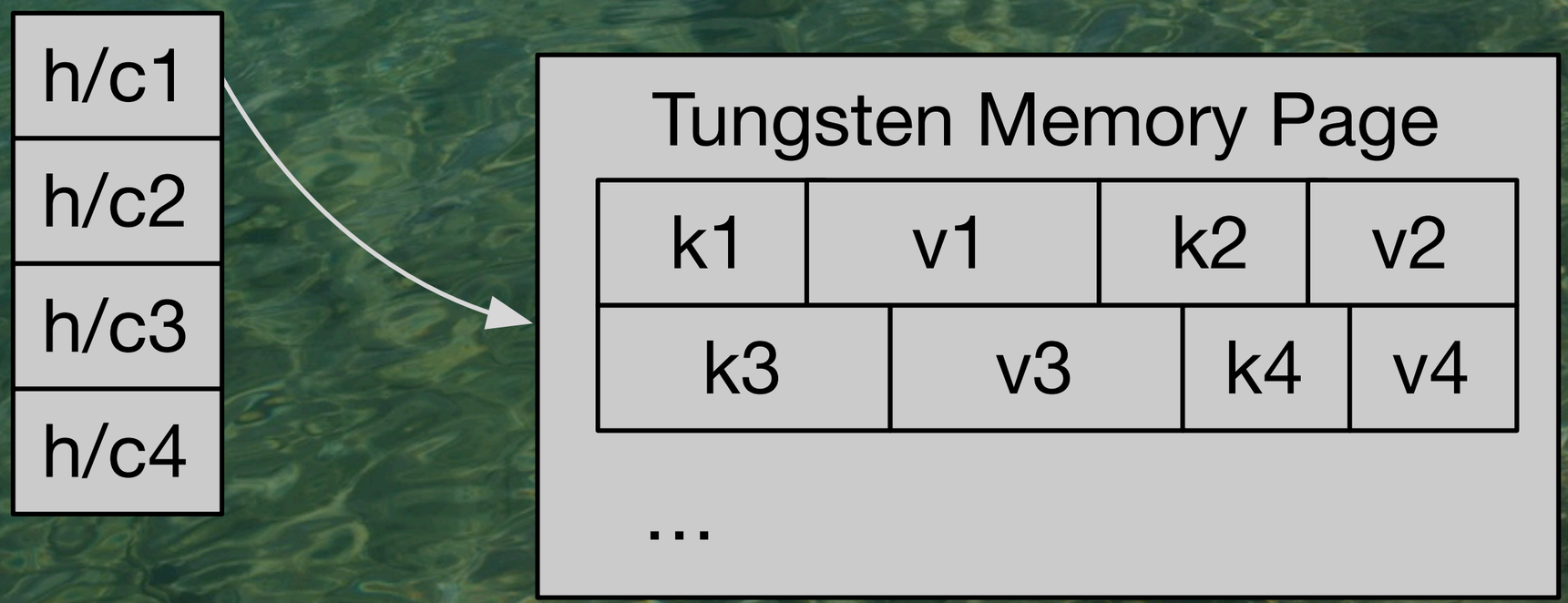
The new Compact Row format (for each record) uses a bit vector to mark values that are null, then packs the values together, each in 8 bytes. If a value is a fixed-size item and fits in 8 bytes, it's inlined. Otherwise, the 8 bytes holds a reference to a location in variable-length segment (e.g., strings).
Rows are 8-byte aligned. Hashing and equality can be done on the raw bytes.

- Compare:



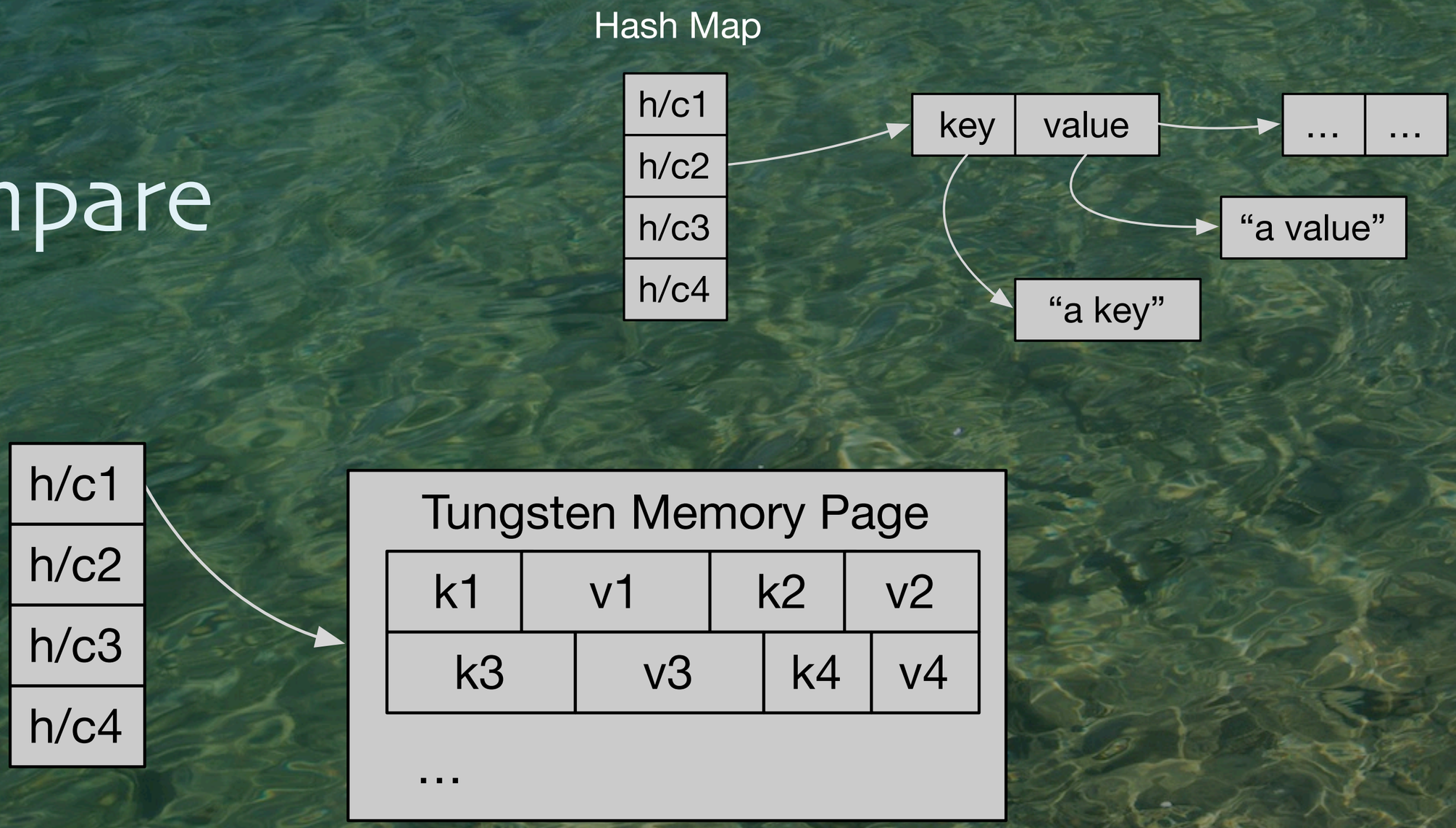
An object spread over the heap vs. a single byte array encoding.

- BytesToBytesMap:



BytesToBytesMap eliminates almost all the reference indirections. The memory pages are on or off heap, but managed by Tungsten using sun.misc.Unsafe.

- Compare



Many fewer arrows!

Memory Management

- Some allocations off heap.
  - sun.misc.Unsafe.

Unsafe allows you to manipulate memory directory, like in C/C++.

Less Expression Overhead

```
sql("SELECT a + b FROM table")
```

- Solution:
  - Generate custom byte code.
    - Spark 1.X - for subexpressions.

To eliminate virtual function calls, boxing overhead and branching, generate custom byte code for expressions.

Less Expression Overhead

```
sql("SELECT a + b FROM table")
```

- Solution:
  - Generate custom byte code.
    - Spark 1.X - for subexpressions.
    - Spark 2.0 - for whole queries.

To eliminate virtual function calls, boxing overhead and branching, generate custom byte code for expressions.

No Value Types (Planned for Java 9 or 10)

Value types would let you write simple classes with a single primitive field, then the compiler doesn't heap allocate instances, but puts them on the stack, like primitives today. Under consideration for Java 10. Limited support already in the Scala compiler.

```
case class Timestamp(epochMillis: Long) {

  def toString: String = { ... }

  def add(delta: TimeDelta): Timestamp = {
    /* return new shifted time */
  }

  ...
}
```

Don’t allocate on the heap; just push the primitive long on the stack. (scalac does this now.)

Value types would let you write simple classes with a single primitive field, then the compiler doesn’t heap allocate instances, but puts them on the stack, like primitives today. Under consideration for Java 10. Limited support already in the Scala compiler.

Long operations aren't atomic

According to the JVM spec

That is, even though longs are quite standard now and we routinely run 64bit CPUs (small devices the exception), long operations are not guaranteed to be atomic, unlike int operations.

No Unsigned Types

What's factorial(-1)?

Back to issues with the JVM as a Big Data platform...
Unsigned types are very useful for many applications and scenarios. Not all integers need to be signed!
Arrays are limited to 2^(32-1) elements, rather than 2^(32)!

Arrays Indexed with Ints

Byte Arrays limited to 2GB!

2GB is quite small in modern big data apps and servers now approaching TBs of memory! Why isn't it 4GB, because we *signed* ints, not *unsigned* ints!

```
scala> val N = 1100*1000*1000
N2: Int = 1100000000 // 1.1 billion

scala> val array = Array.fill[Short](N)(0)
array: Array[Short] = Array(0, 0, ...)

scala> import
org.apache.spark.util.SizeEstimator

scala> SizeEstimator.estimate(array)
res3: Long = 2200000016   // 2.2GB
```


One way this bites you is when you need to serialize a data structure larger than 2GB. Keep in mind that modern Spark heaps could be 10s of GB and 1TB of memory per server is coming on line!
Here's a real session that illustrates what can happen.

```
scala> val b = sc.broadcast(array)
...broadcast.Broadcast[Array[Short]] = ...

scala> SizeEstimator.estimate(b)
res0: Long = 2368

scala> sc.parallelize(0 until 100000).
     | map(i => b.value(i))
```


One way this bites you is when you need to serialize a data structure larger than 2GB. Keep in mind that modern Spark heaps could be 10s of GB and 1TB of memory per server is coming on line!
Here's a real session that illustrates what can happen.

```
scala> SizeEstimator.estimate(b)
res0: Long = 2368

scala> sc.parallelize(0 until 100000).
     | map(i => b.value(i))

java.lang.OutOfMemoryError:
        Requested array size exceeds VM limit
    at java.util.Arrays.copyOf(...)
    ...
```

Boom!

Even though a 1B-element Short array is fine, as soon as you attempt to serialize it, it won't fit in a 2B-element Byte array. Our 2.2GB short array can't be serialized into a byte array, because it would take more than 2^31-1 bytes and we don't have that many available elements, due to (signed) integer indexing.

But wait... I actually lied to you...

I implied this is a problem with broadcast variables, but it's not...

Spark handles large broadcast variables by breaking them into blocks.

Spark serializes and distributes smaller blocks for broadcast variables (and also when shuffling data between tasks), so it doesn't attempt to create an Array[Byte] that's larger than 2B elements. So what really happened?

This is actually a limitation of the Scala REPL (“read, evaluate, print, loop” - i.e., the interpreter), which was never intended to support very large heaps. Let’s see what actually happened...

```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  at java.util.Arrays.copyOf(...)
  ...
  at java.io.ByteArrayOutputStream.write(...)
  ...
  at java.io.ObjectOutputStream.writeObject(...)
  at ...spark.serializer.JavaSerializationStream
          .writeObject(...)
  ...
  at ...spark.util.ClosureCleaner$.ensureSerializable(..)
  ...
  at org.apache.spark.rdd.RDD.map(...)
```


This is actually a limitation of the Scala REPL (shell), which was never intended to support very large heaps. Let's see what actually happened...

```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  at java.util.Arrays.copyOf(...)
  ...
  at java.io.ByteArrayOutputStream.write(...)
  ...
  at java.io.ObjectOutputStrea
  at ...spark.serializer.JavaS
          .writeObject(...)
  ...
  at ...spark.util.ClosureClea
  ...
  at org.apache.spark.rdd.RDD.map(...)
```

Pass this closure to RDD.map:

```
i => b.value(i)
```


When RDD.map is called, Spark verifies that the “closure” (anonymous function) that’s passed to it is clean, meaning it can be serialized. Note that it references “b” outside its body, i.e., it “closes over” b.

```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  at java.util.Arrays.copyOf(...)
  ...
  at java.io.ByteArrayOutputSt
  ...
  at java.io.ObjectOutputStrea
  at ...spark.serializer.JavaS
          .writeObject(...)
  ...
  at ...spark.util.ClosureCleaner$.ensureSerializable(..)
  ...
  at org.apache.spark.rdd.RDD.map(...)
```

Verify that it's "clean" (serializable).

```
i => b.value(i)
```


ClosureCleaner does this serialization check (among other things).

```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  at java.util.Arrays.copyOf(...)
  ...
  at java.io.ByteArrayOutputStream.write(...)
  ...
  at java.io.ObjectOutputStream.writeObject(...)
  at ...spark.serializer.JavaSerializationStream
          .writeObject(...)
  ...
  at ...spark.util.ClosureClea
  ...
  at org.apache.spark.rdd.RDD.r
```

...which it does by serializing to a byte array...

ClosureCleaner does this serialization check (among other things).

```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  at java.util.Arrays.copyOf(...)
  ...
  at java.io.ByteArrayOutputSt
  ...
  at java.io.ObjectOutputStrea
  at ...spark.serializer.JavaSe
          .writeObject(...)
  ...
  at ...spark.util.ClosureClea
```

...which requires copying an array...

What array???

```
i => b.value(i)
```

```
...
scala> val array = Array.fill[Short](N)(0)
...
```

ClosureCleaner does this serialization check (among other things).

It’s because of the way Scala has to wrap your REPL expressions into objects...

- You write:

```
scala> val array = Array.fill[Short](N)(0)
scala> val b = sc.broadcast(array)
scala> sc.parallelize(0 until 100000).
     | map(i => b.value(i))
```


I'm greatly simplifying the actual code that's generated. In fact, there's a nested object for every line of REPL code! The synthesized name $iwC is real.

```
scala> val array = Array.fill[Short](N)(0)
scala> val b = sc.broadcast(array)
scala> sc.parallelize(0 until 100000).
     | map(i => b.value(i))
```

- Scala compiles:

```
class $iwC extends Serializable {
 val array = Array.fill[Short](N)(0)
 val b = sc.broadcast(array)

 class $iwC extends Serializable {
   sc.parallelize(...).map(i => b.value(i))
 }
}
```


I'm greatly simplifying the actual code that's generated. In fact, there's a nested object for every line of REPL code! The synthesized name $iwC is real.

```
scala> val array = Array.fill[Short](N)(0)
scala> val b = sc.broadcast(array)
scala> sc.parallelize(0 until 100000).
```

- Scala compiles:

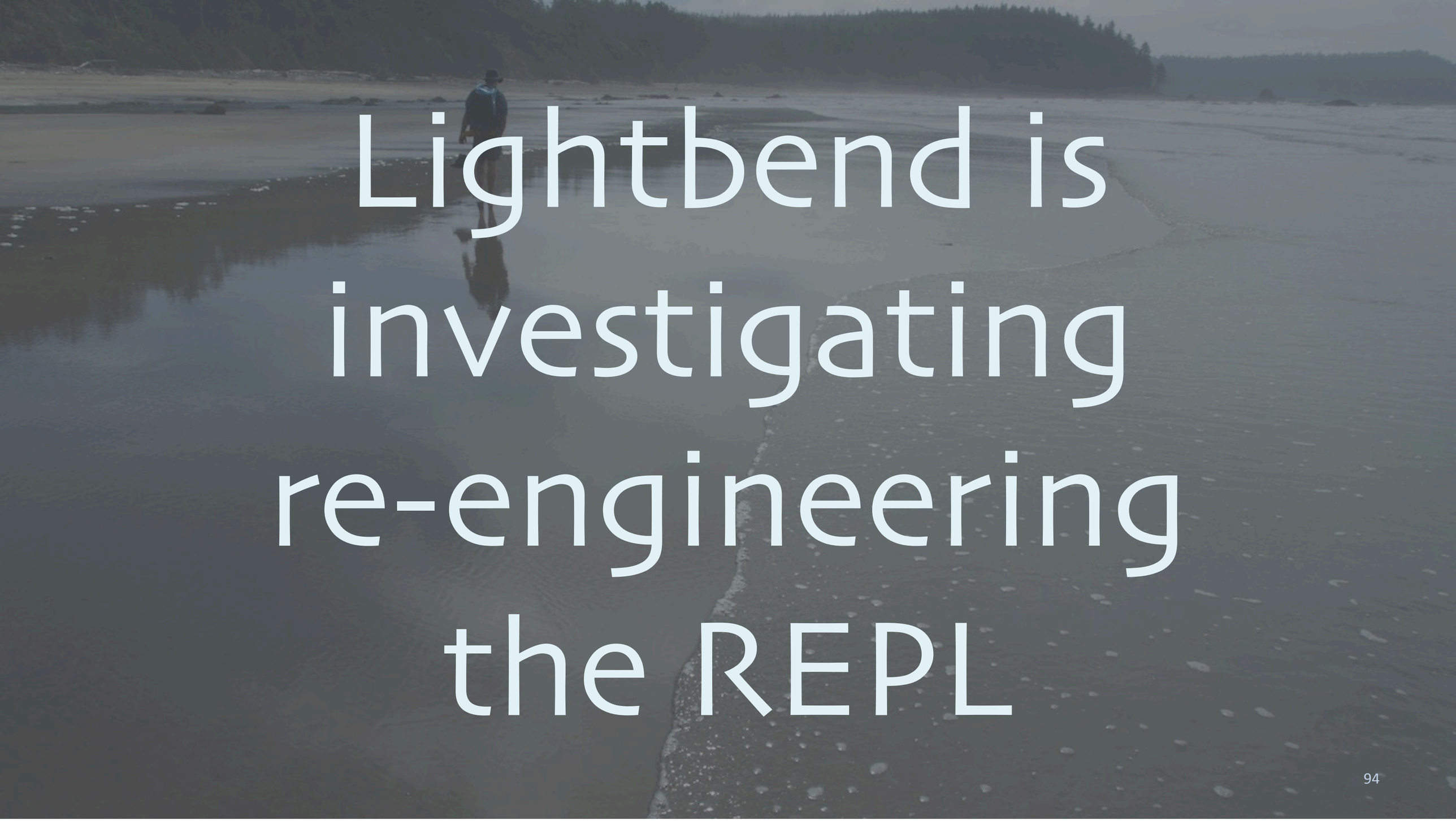
… sucks in the whole object!

```
class $iwC extends Serializable {
  val array = Array.fill[Short](N)(0)
  val b = sc.broadcast(array)

  class $iwC extends Se
    sc.parallelize(...).map(i => b.value(i))
  }
}
```

So, this closure over “b”…

I’m greatly simplifying the actual code that’s generated. In fact, there’s a nested object for every line of REPL code!
The synthesized name $iwC is real.
Note that “array” and “b” become fields in these classes.



We’re looking into design changes that would better support Big Data scenarios and avoid these issue.

Workarounds...

- Transient is often all you need:

```
scala> @transient val array =
     |   Array.fill[Short](N)(0)
scala> ...
```


This is enough in this example because when serializing over those generated objects, the array will be skipped.

```
object Data {   // Encapsulate in objects!
  val N = 1100*1000*1000
  val array = Array.fill[Short](N)(0)
  val getB = sc.broadcast(array)
}
object Work {
  def run(): Unit = {
    val b = Data.getB // local ref!
    val rdd = sc.parallelize(...).
      map(i => b.value(i)) // only needs b
    rdd.take(10).foreach(println)
}}
```


It's not shown, but you could paste this into the REPL. A more robust approach. You don't need to wrap everything in objects. "Work" is probably not needed, but the local variable "b" is very valuable to grabbing just what you need inside an object and not serialiazing the whole "Data" instance.

Okay, all things considered, the JVM is a great platform for Big Data.
Scala has emerged as the de facto “data engineering” language, as opposed to data science, where Python, R, SAS, Matlab, and Mathematica still dominate (although Scala has its passionate advocates here, too.)

You can find this talk and a longer version of it with more details at polyglotprogramming.com/talks

lightbend.com/fast-data-platform

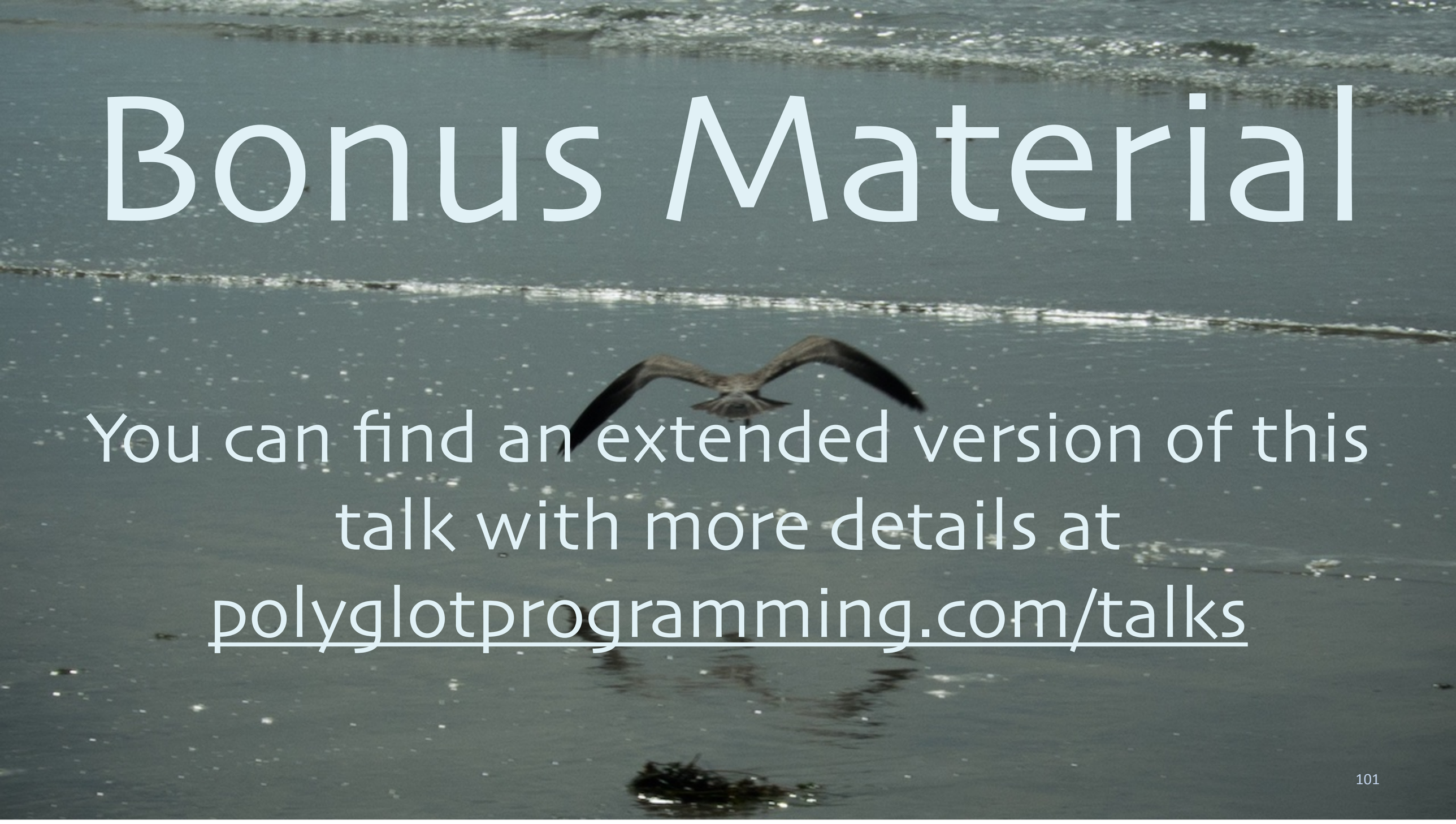
dean.wampler@lightbend.com
@deanwampler

Thank You!

Lightbend

I've thought a lot about the evolution of big data to more stream-oriented "fast data". Please follow this link for more information

Bonus Material



You can find an extended version of this talk with more details at

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