Scala and the JVM for Big Data: Lessons from Spark - Extended Version

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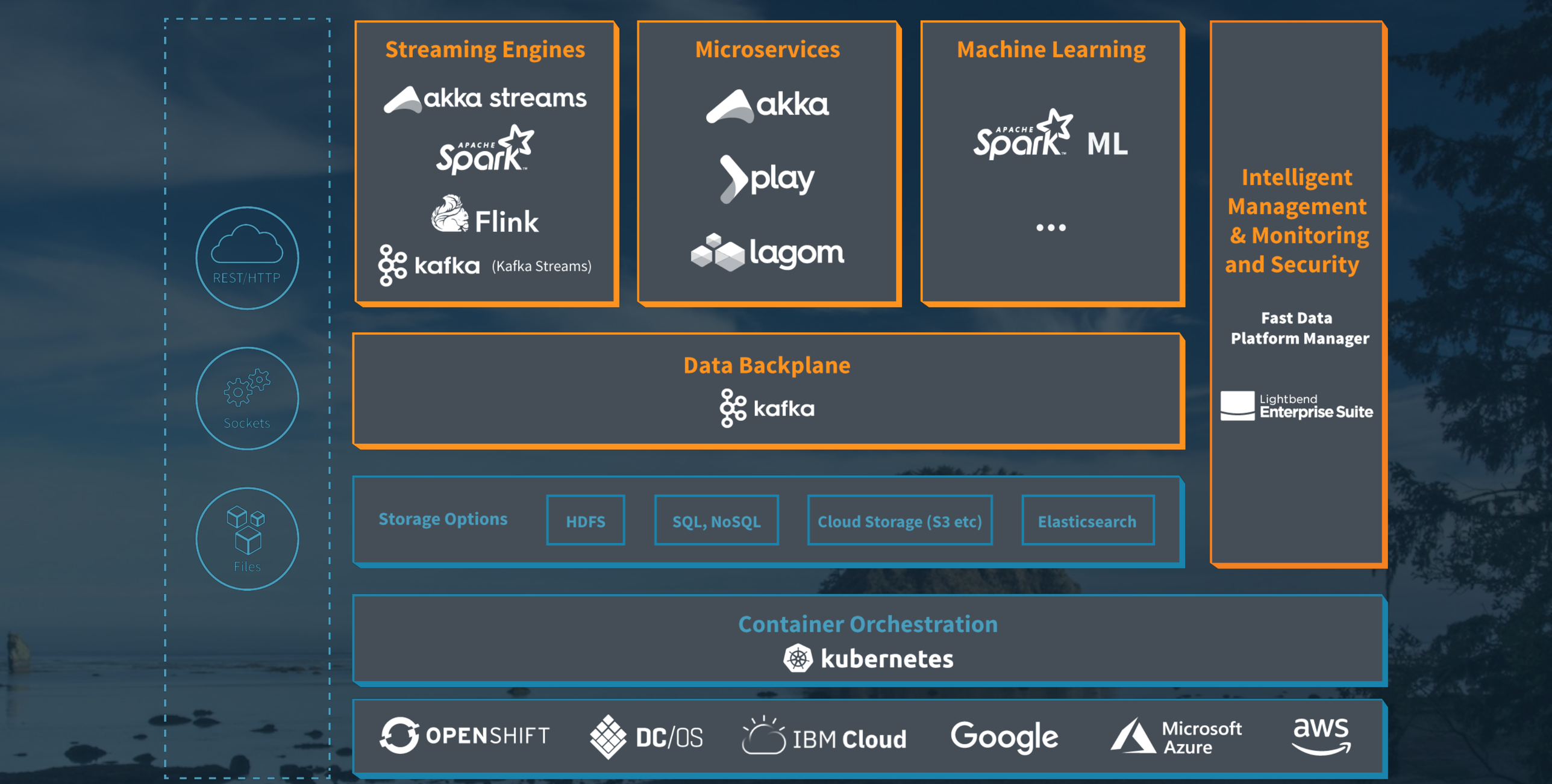
@deanwampler

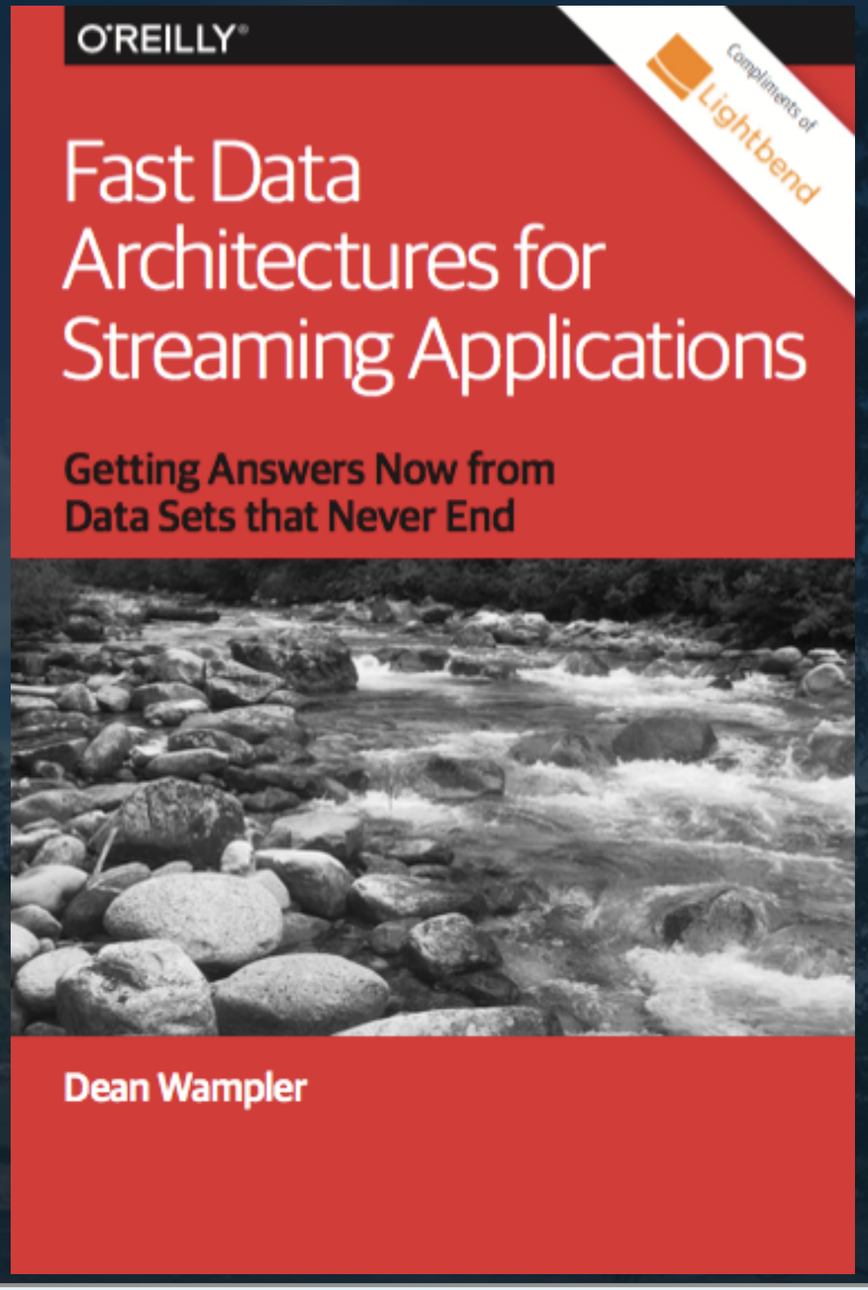
Lightbend



I lead the Lightbend Fast Data Platform project; streaming data and microservices

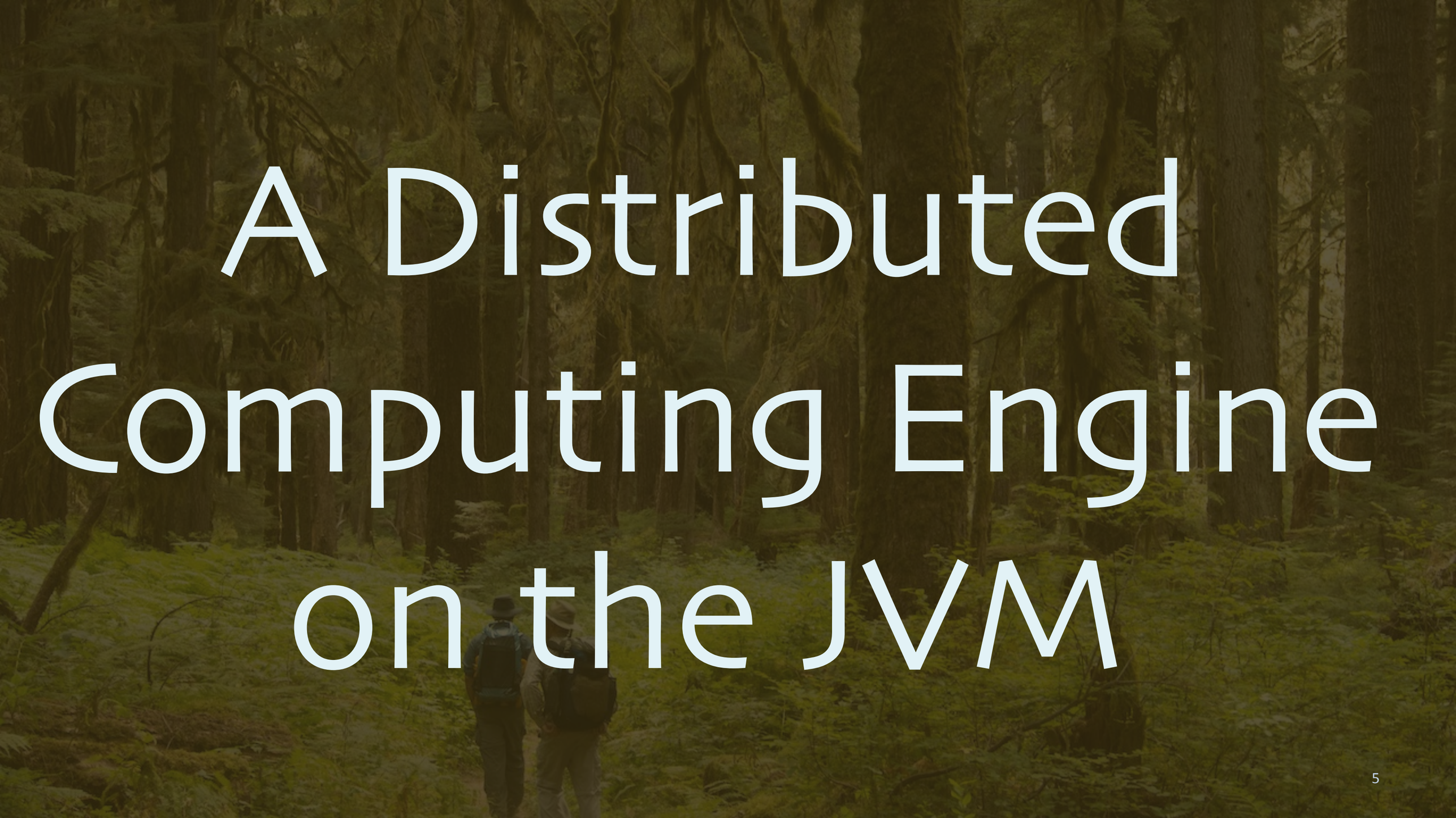
Free as in 🍺

New second edition!
lbnd.io/fast-data-book

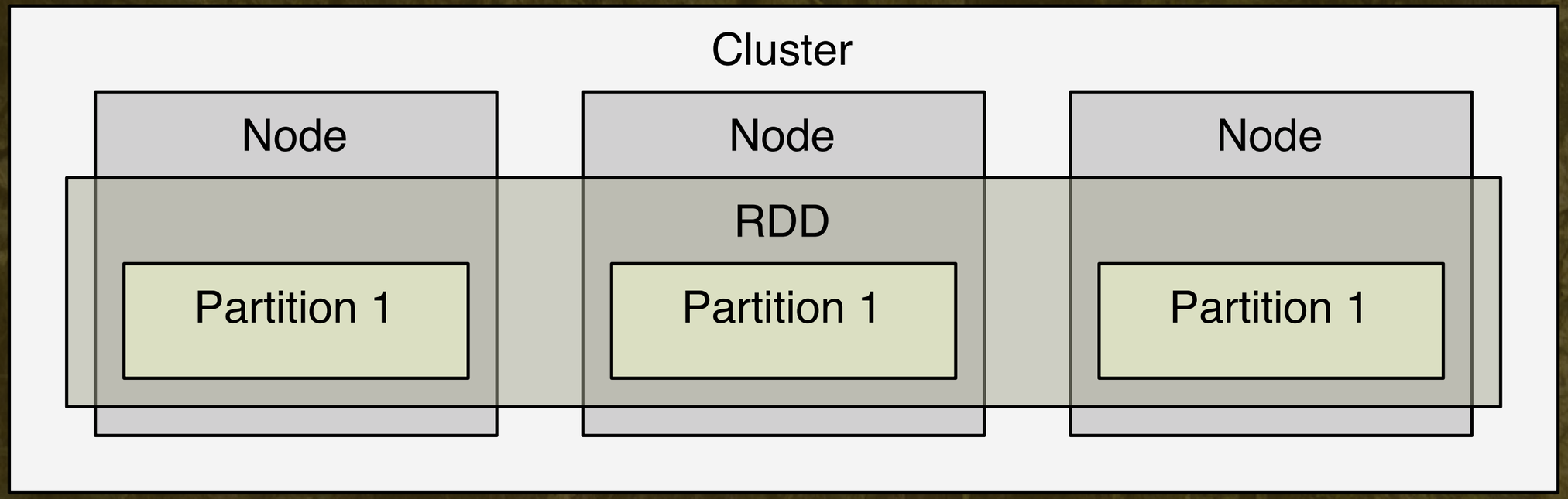


The theory behind Lightbend Fast Data Platform

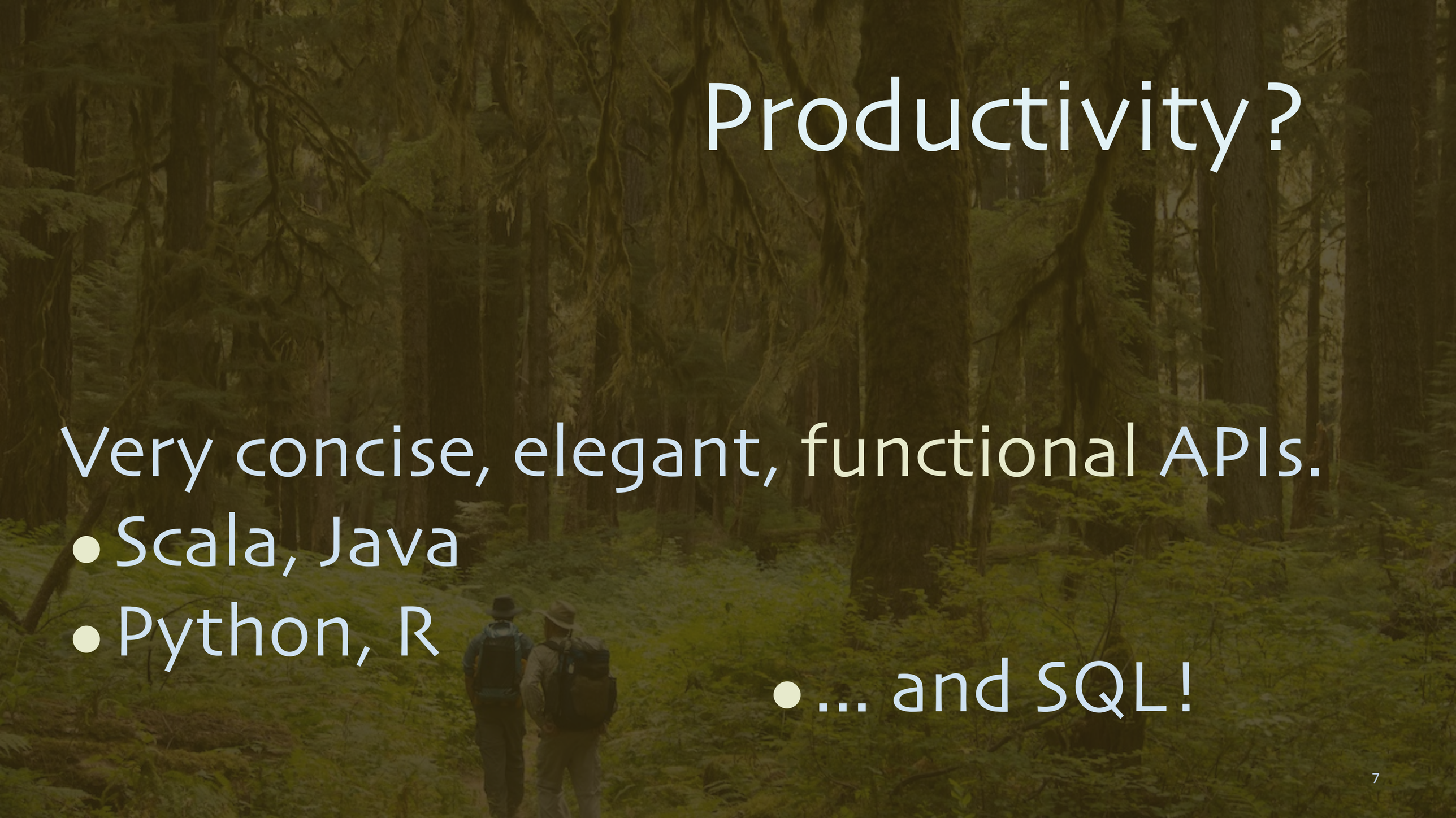

Spark



A Distributed Computing Engine on the JVM



Resilient Distributed Datasets



Productivity?

Very concise, elegant, functional APIs.

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

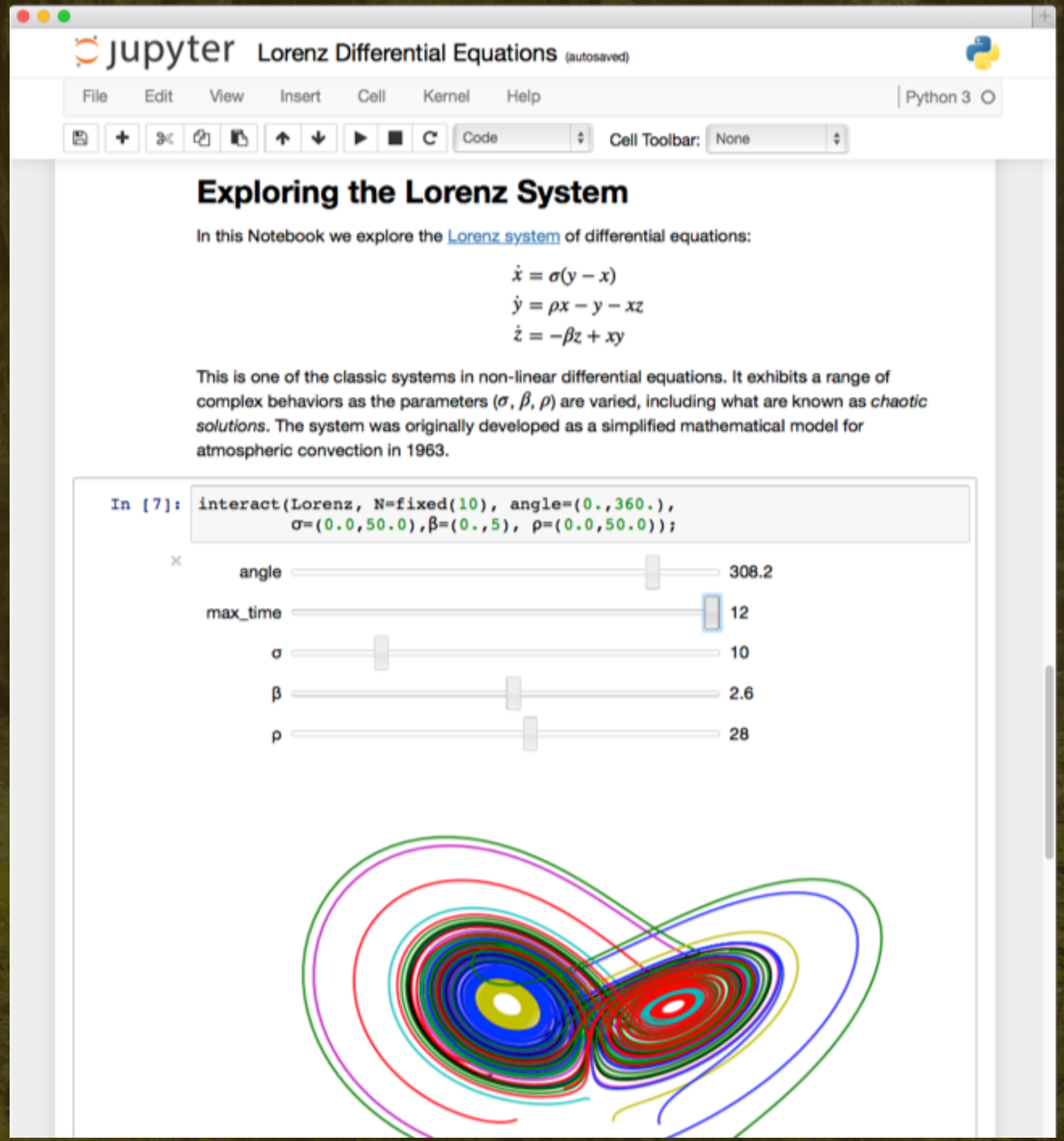
Productivity?

Interactive shell (REPL)

- Scala, Python, R, and SQL

Notebooks

- Jupyter
- Spark Notebook
- Zeppelin
- Databricks



Example: 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...
...	...

Compute Inverted Index

index

block

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

block

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

Miracle!!

inve

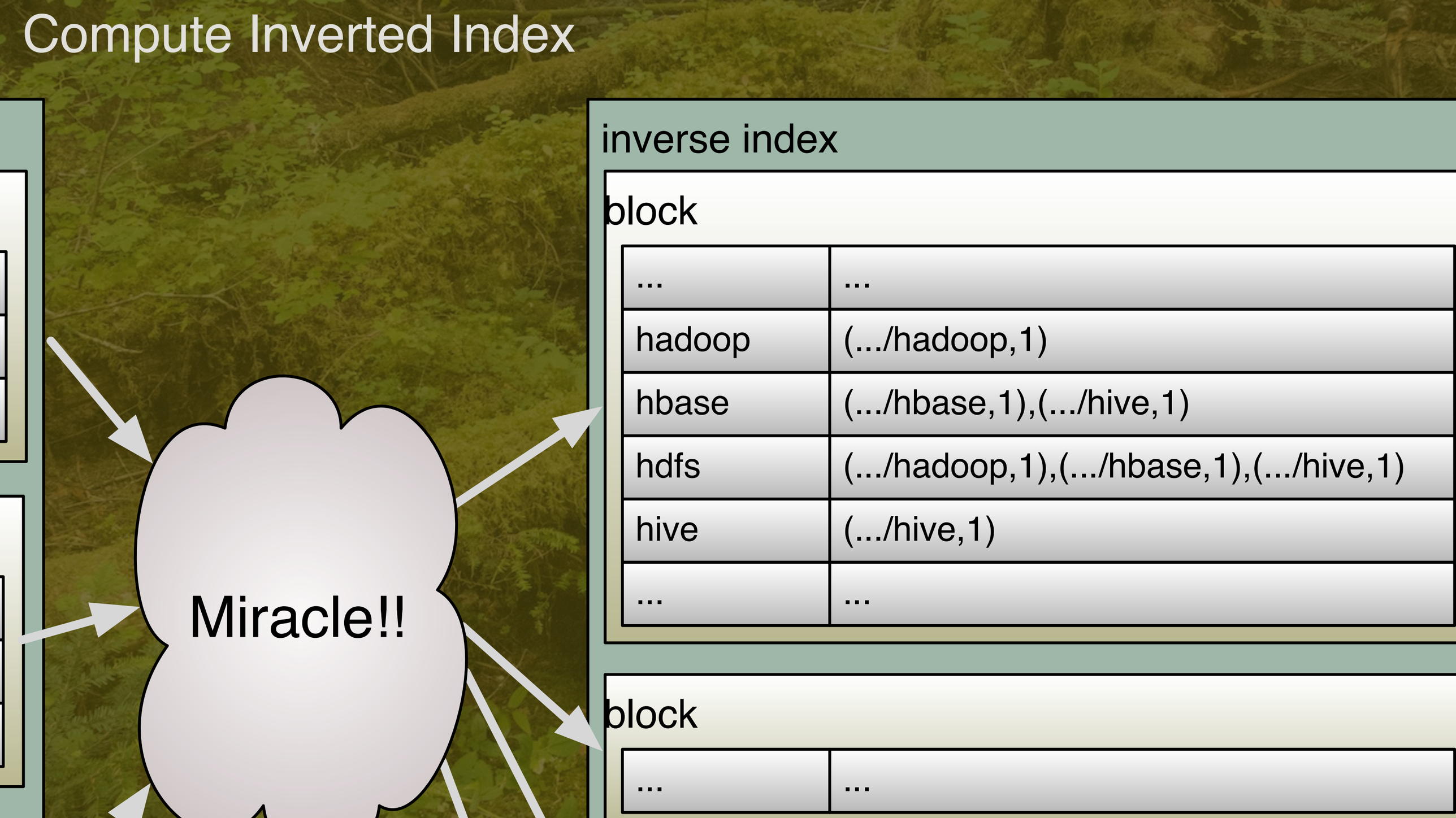
bloc

...
ha
hb
hd
hiv
...

bloc

...

Compute 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")
```

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

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}.flatMap {
 case (id,
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```

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

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

```
 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)

```
 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))
}.groupBy
mapVal
 seq =>
}.saveAsTextFile("/path/to/output")
```

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

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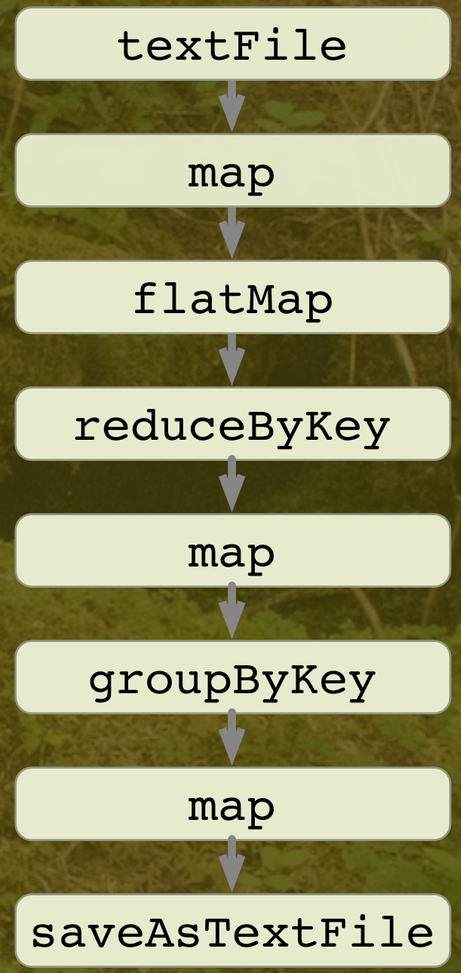

RDD[(String,Iterable((String,Int))]: (Hadoop,seq(.../hadoop,20),...))

Productivity?

Intuitive API:

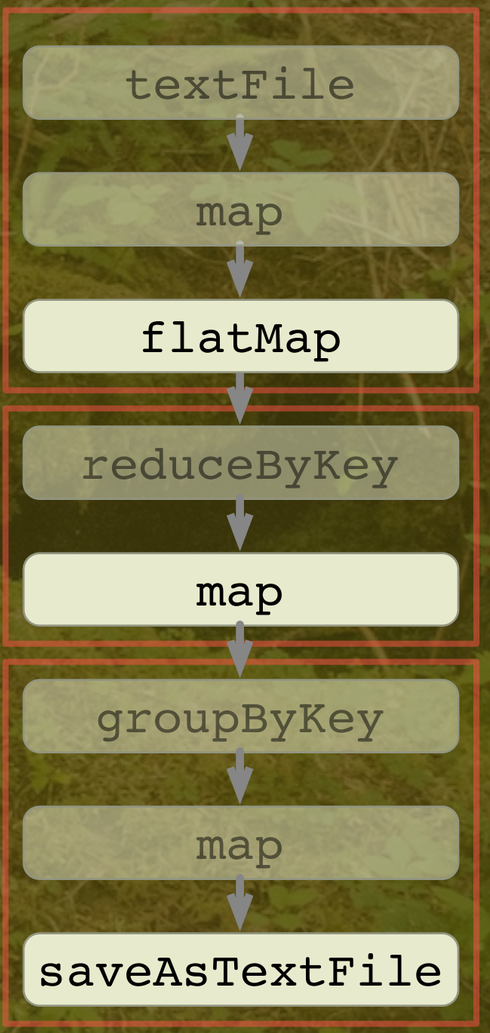
- Dataflow of steps.
- Inspired by Scala collections and functional programming.



Performance?

Lazy API:

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



Higher-Level APIs


SQL:
Datasets/
DataFrames

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)
```

```
import org.apache.spark.SparkSession
val spark = SparkSession.builder()
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```
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,
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```
planes. createOrReplaceTempView("planes")
flights.cache(); planes.cache()

val planes_for_flights1 = sqlContext.sql("""
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Returns another Dataset.

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val planes_for_flights2 =
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```
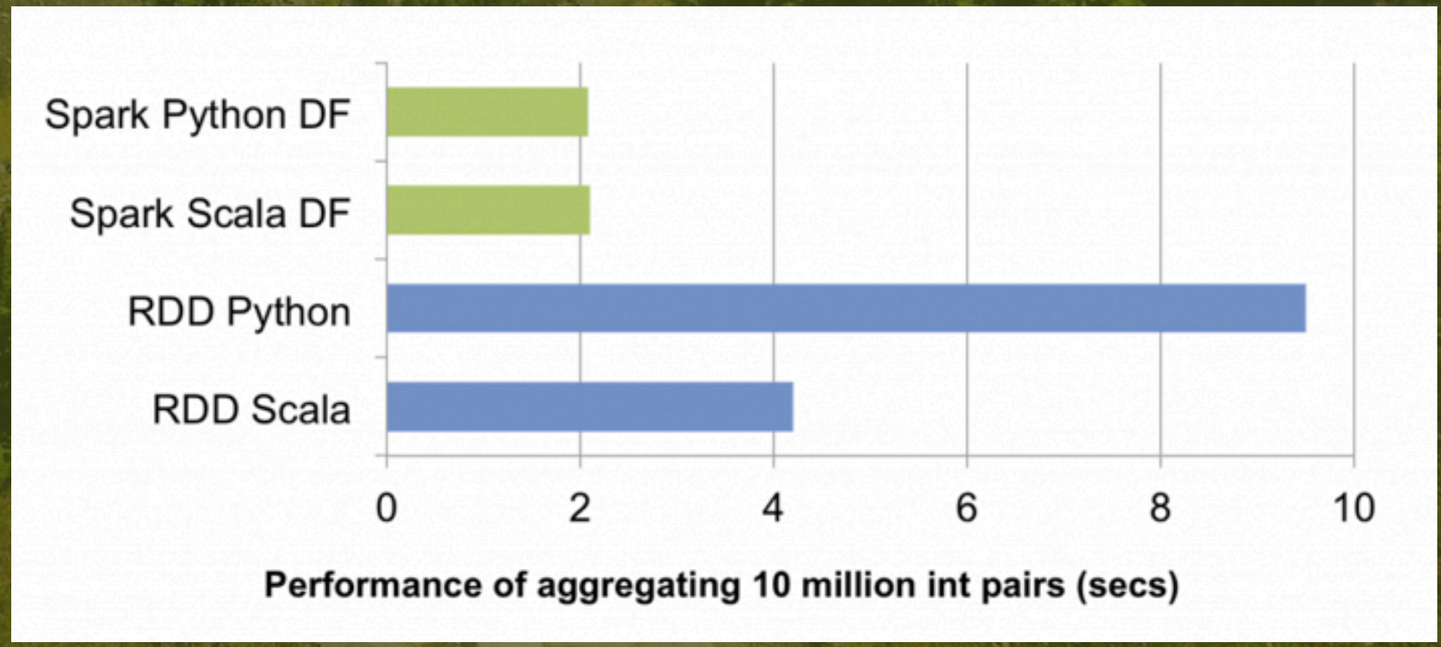

```
val planes_for_flights2 =
  flights.join(planes,
    flights("tailNum") ===
    planes ("tailNum")).limit(100)
```

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

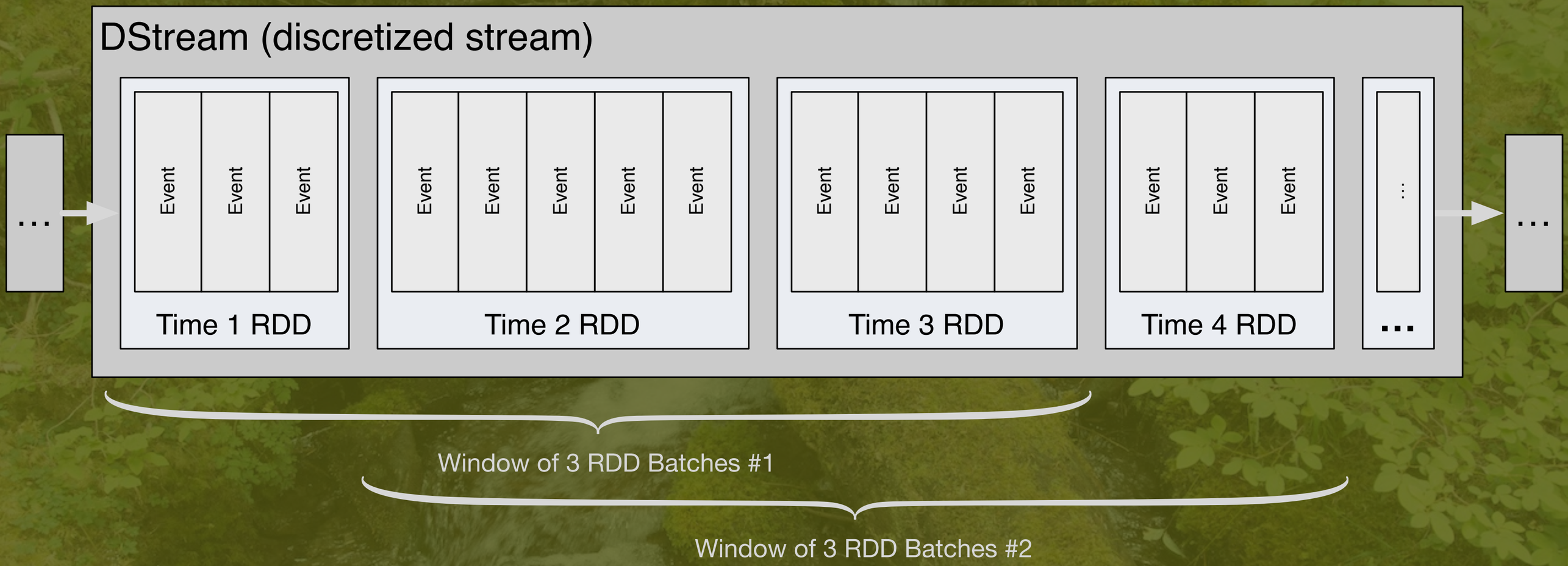
Performance

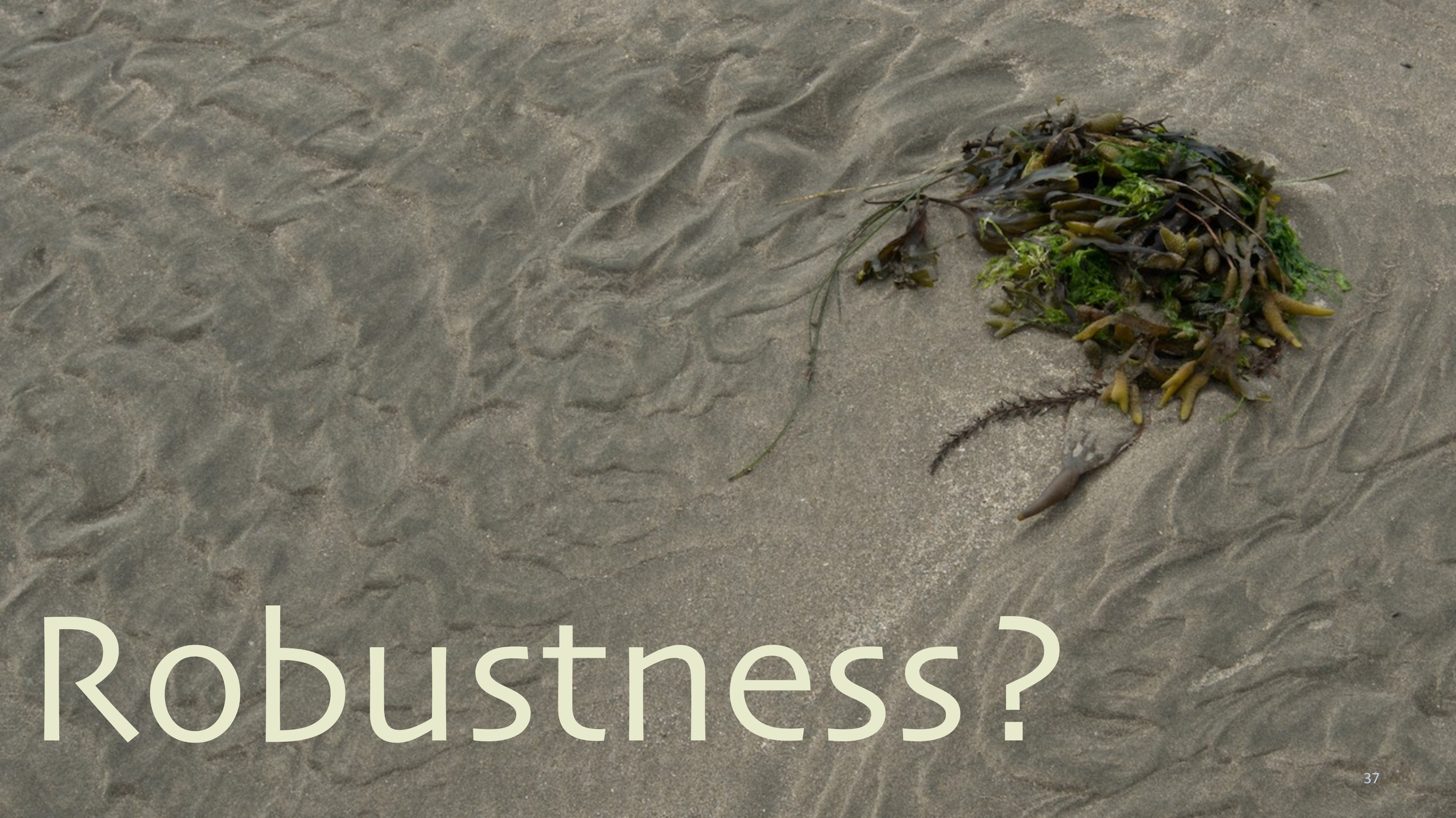
The Dataset API has the same performance for all languages: Scala, Java, Python, R, and SQL!

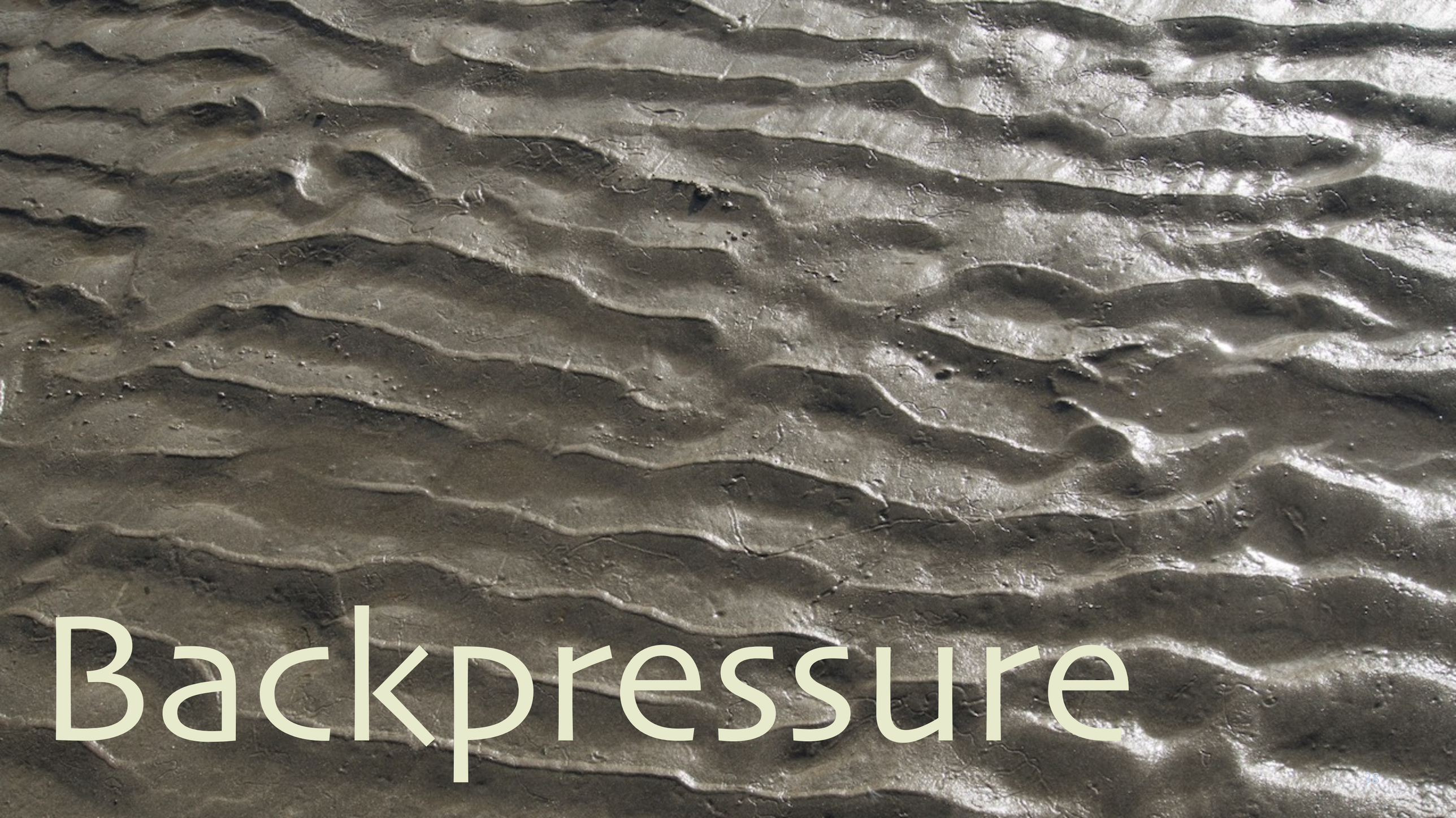


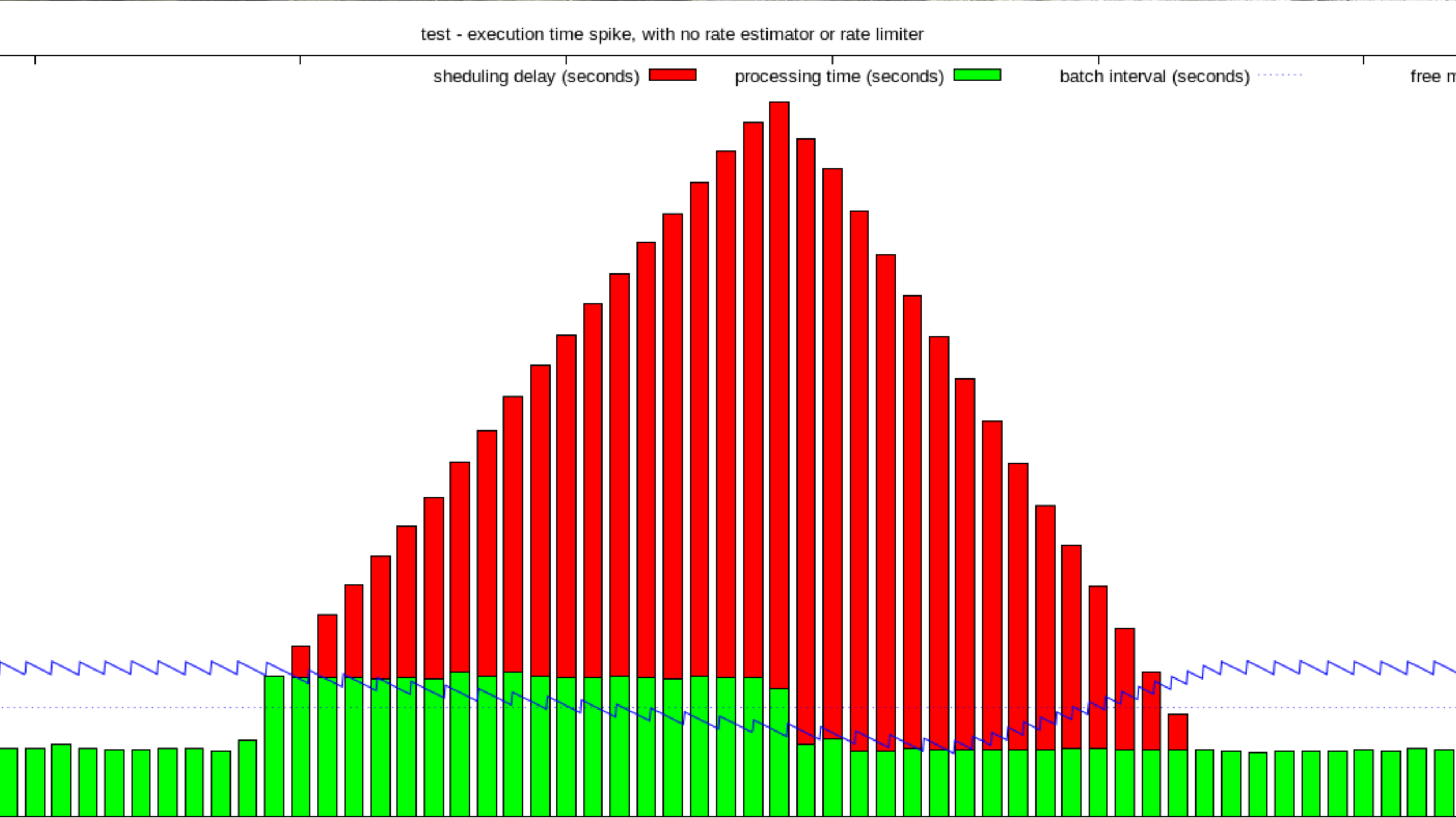
```
def join(right: Dataset[_], joinExprs: Column): DataFrame = {
def groupBy(cols: Column*): RelationalGroupedDataset = {
def orderBy(sortExprs: Column*): Dataset[T] = {
def select(cols: Column*): Dataset[...] = {
def where(condition: Column): Dataset[T] = {
def limit(n: Int): Dataset[T] = {
def intersect(other: 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 = {
```

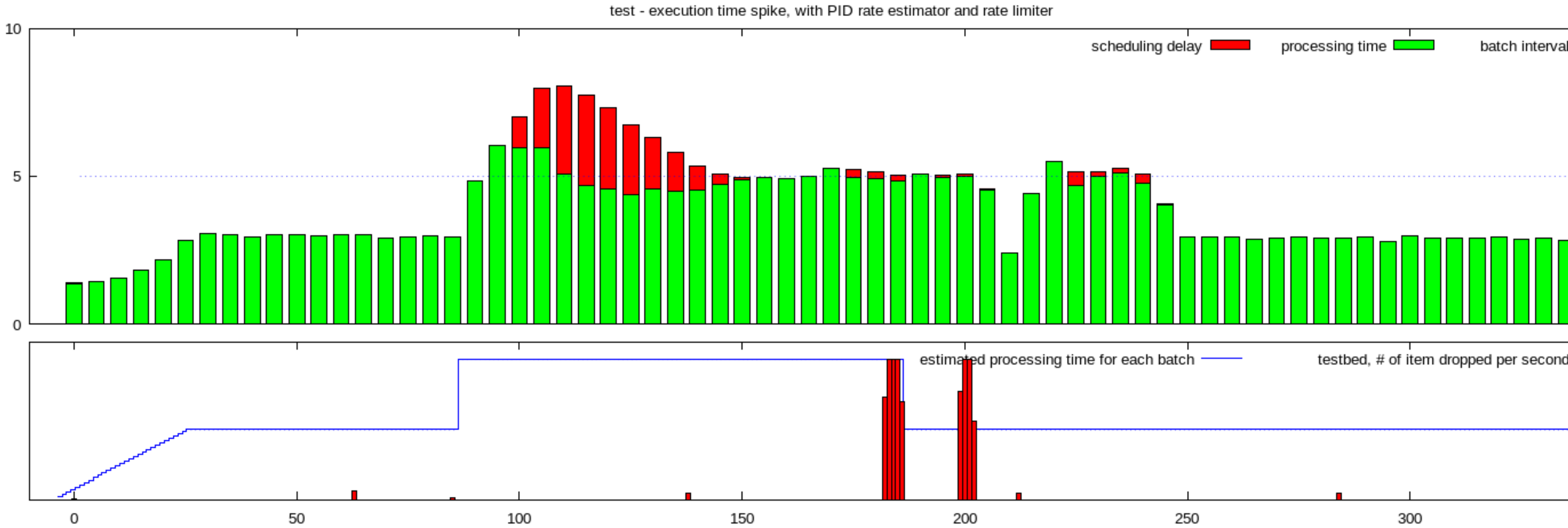
Structured Streaming

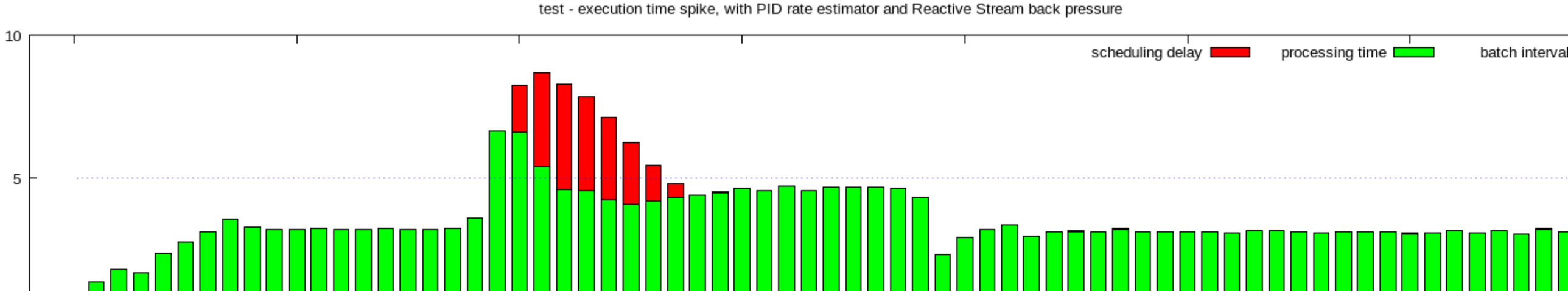

DStream (discretized stream)
Event
Time 1 RDD
Time 2 RDD
Time 3 RDD
Time 4 RDD
Window of 3 RDD Batches #1
Window of 3 RDD Batches #2


Robustness?

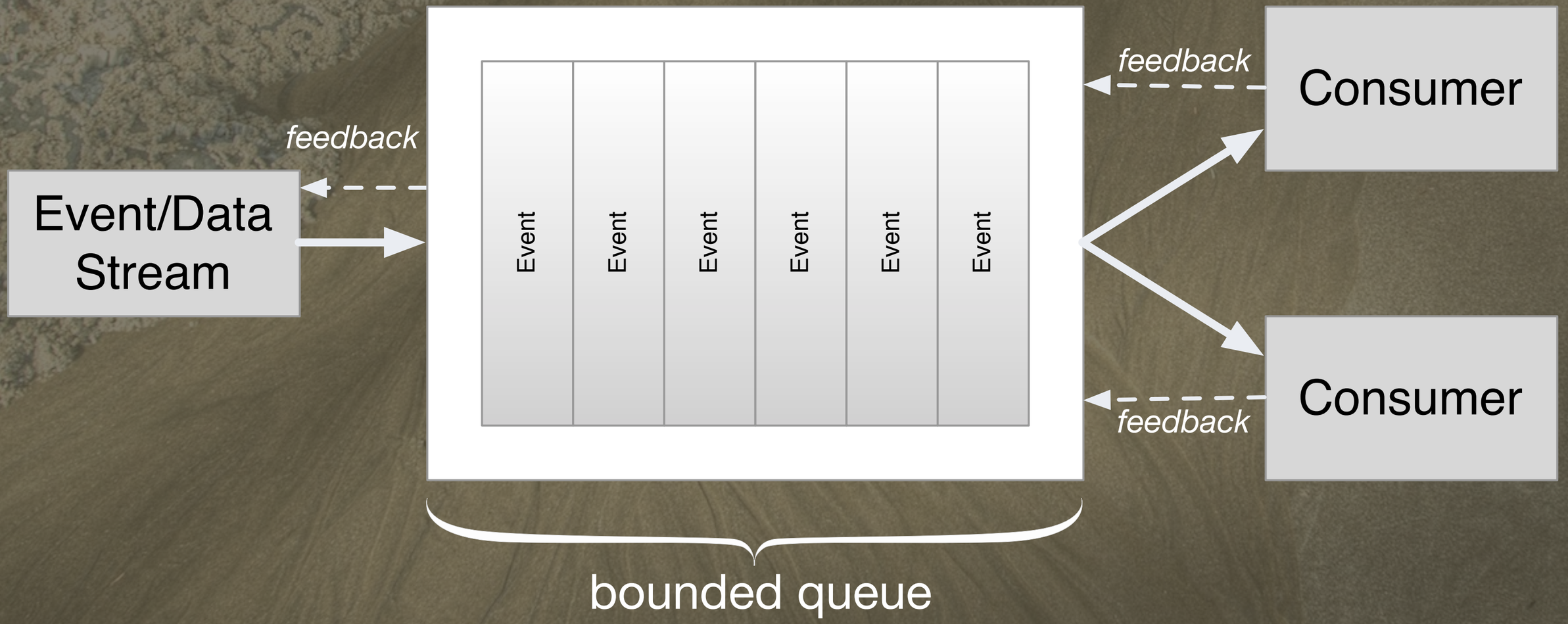

Backpressure


test - execution time spike, with no rate estimator or rate limiter
sheduling delay (seconds)
processing time (seconds)
batch interval (seconds)
free m


test - execution time spike, with PID rate estimator and rate limiter
scheduling delay
processing time
batch interval
10
5
0
estimated processing time for each batch
testbed, # of item dropped per second
0
50
100
150
200
250
300

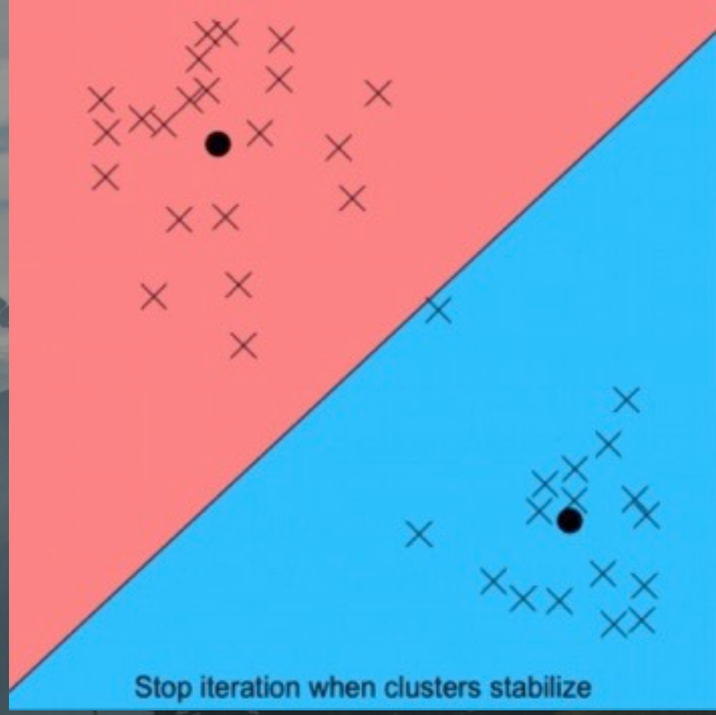

test - execution time spike, with PID rate estimator and Reactive Stream back pressure
scheduling delay
processing time
batch interval
10
5


Reactive
Streams


feedback
Event/Data Stream
Event
Event
Event
Event
Event
Event
feedback
Consumer
feedback
Consumer
bounded queue


ML/MLlib

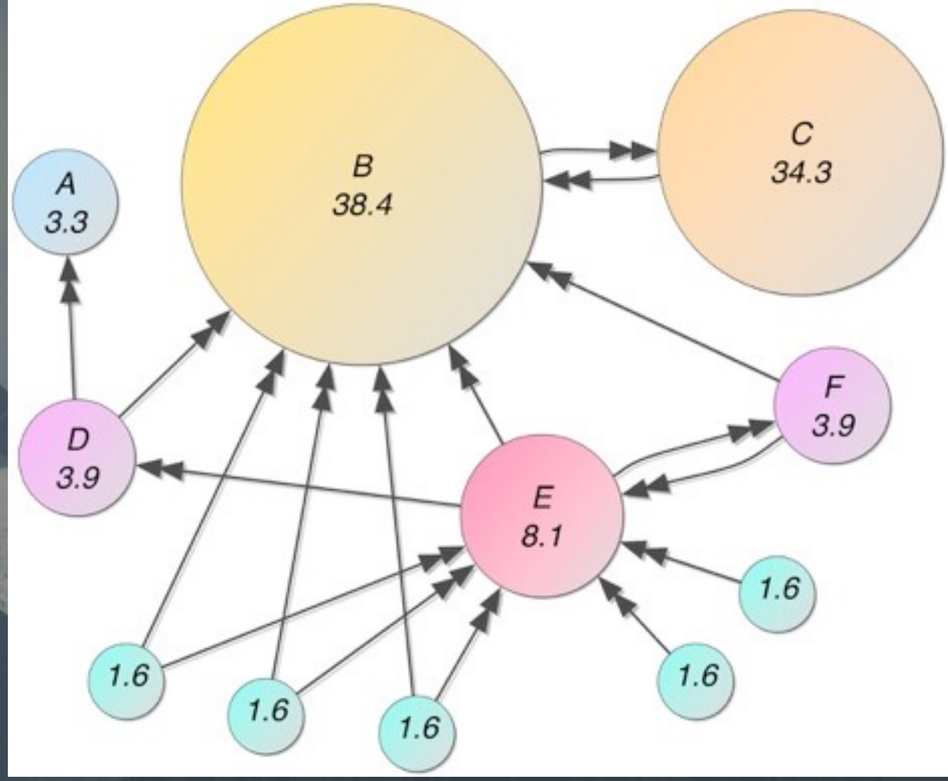
K-Means



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


GraphX

PageRank

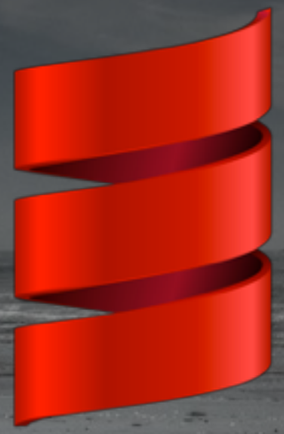


- Graph algorithms require:
  - Incremental traversal.
  - Efficient edge and node reps.


Foundation:
The JVM


20 Years of
DevOps
Lots of Java Devs

Tools and Libraries



Akka
Breeze
Algebird
Spire & Cats
Axle
...

Big Data Ecosystem


But it's
not perfect...


Richer data libs.
in Python & R

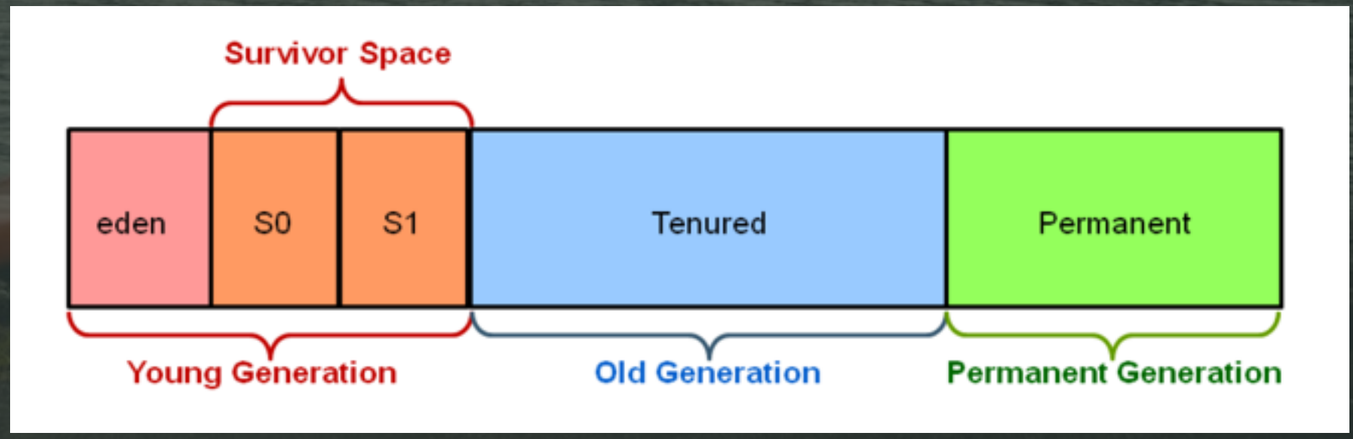
Garbage Collection

GC Challenges

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

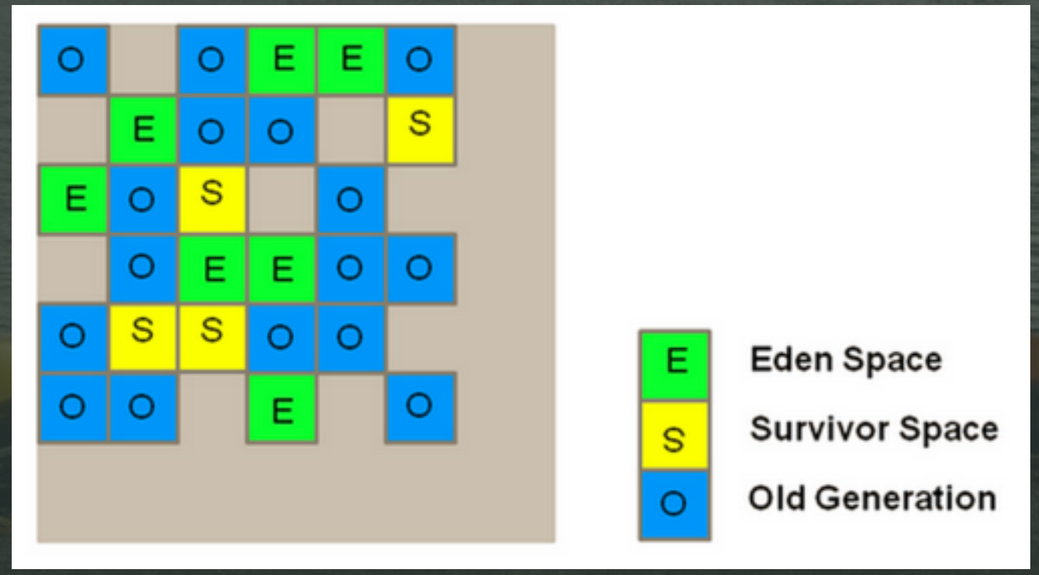
GC Challenges

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



Tuning GC

- Garbage First GC (G1 - JVM 1.6).
  - Balance latency and throughput.
  - More flexible mem. region mgmt.



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

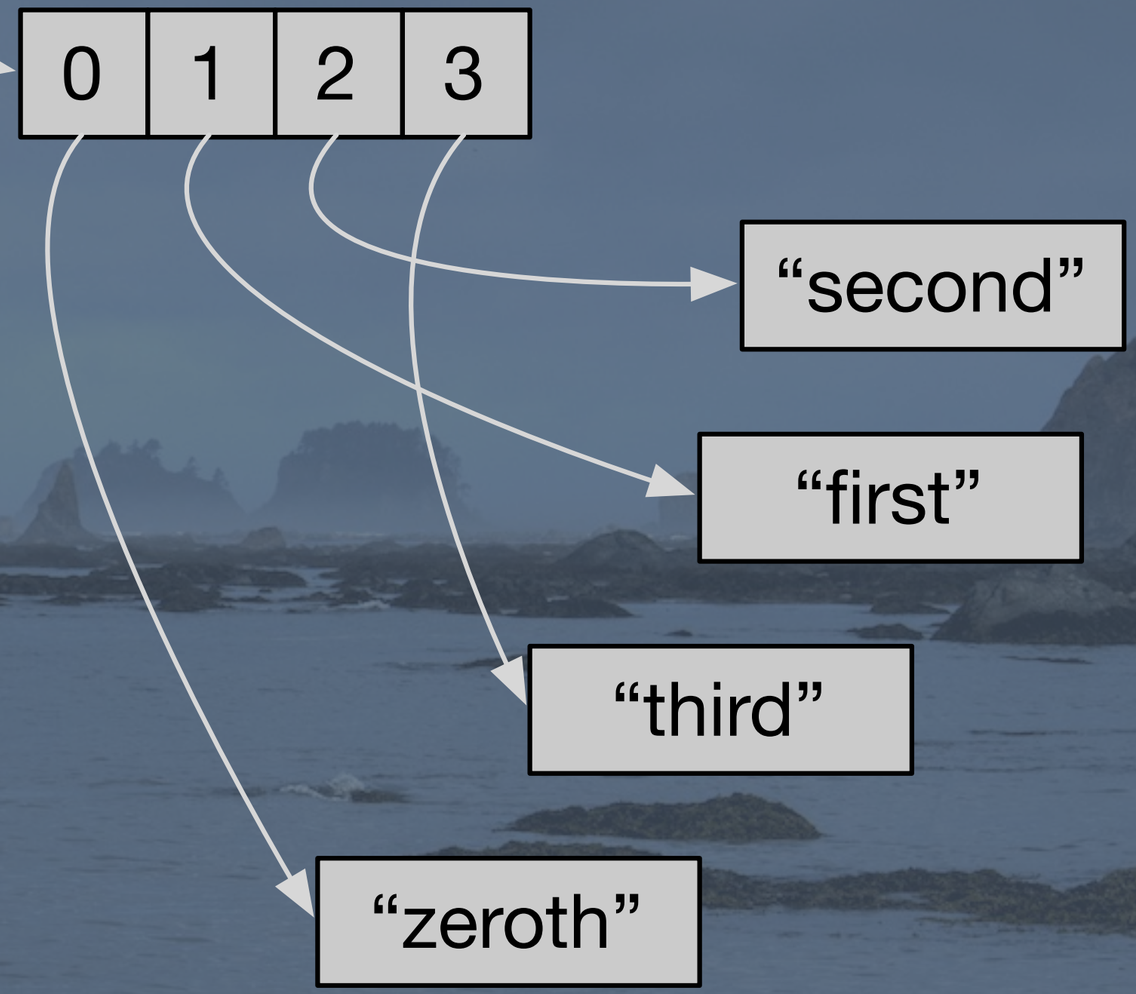
JVM Object Model

Java Objects?

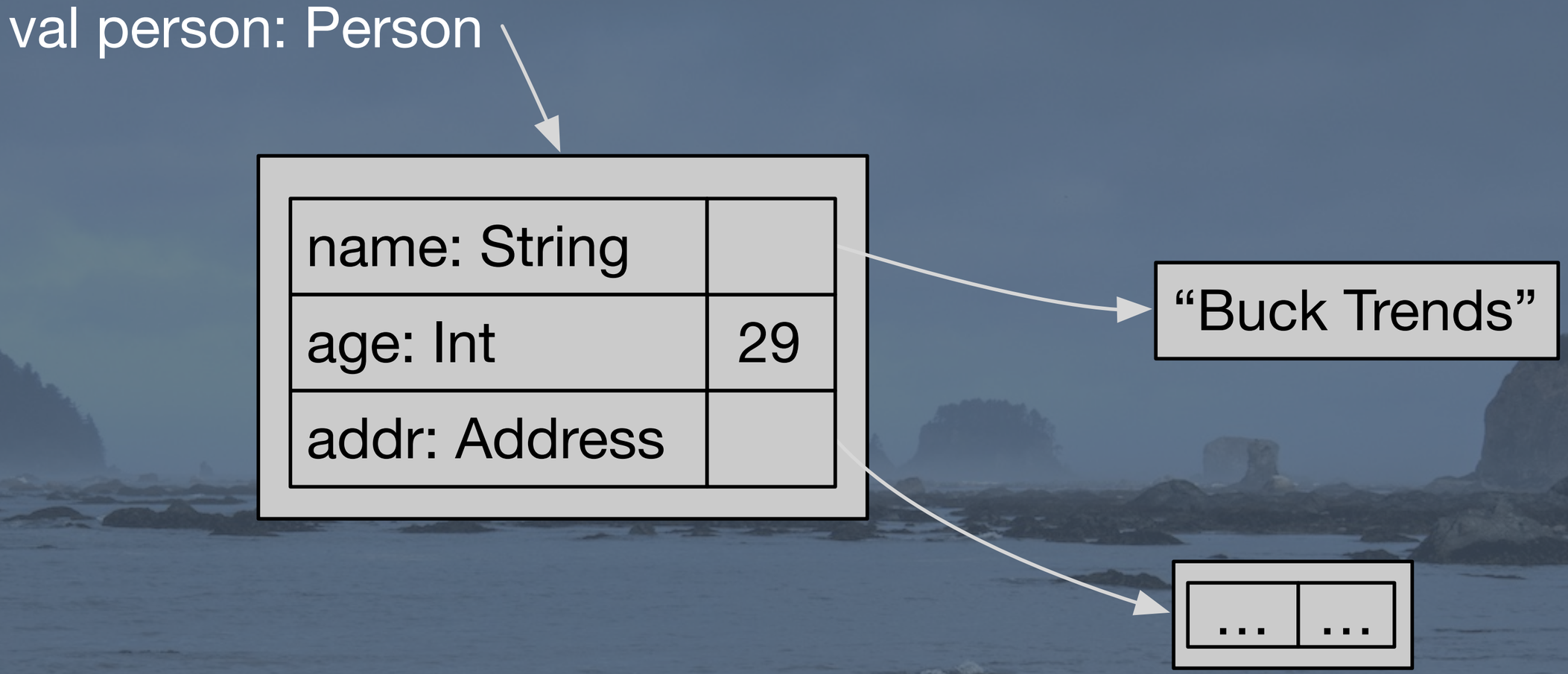
- "abcd": 4 bytes for raw UTF8, right?
- 48 bytes for the Java object:
  - 12 byte header.
  - 8 bytes for hash code.
  - 20 bytes for array overhead.
  - 8 bytes for UTF16 chars.

Arrays

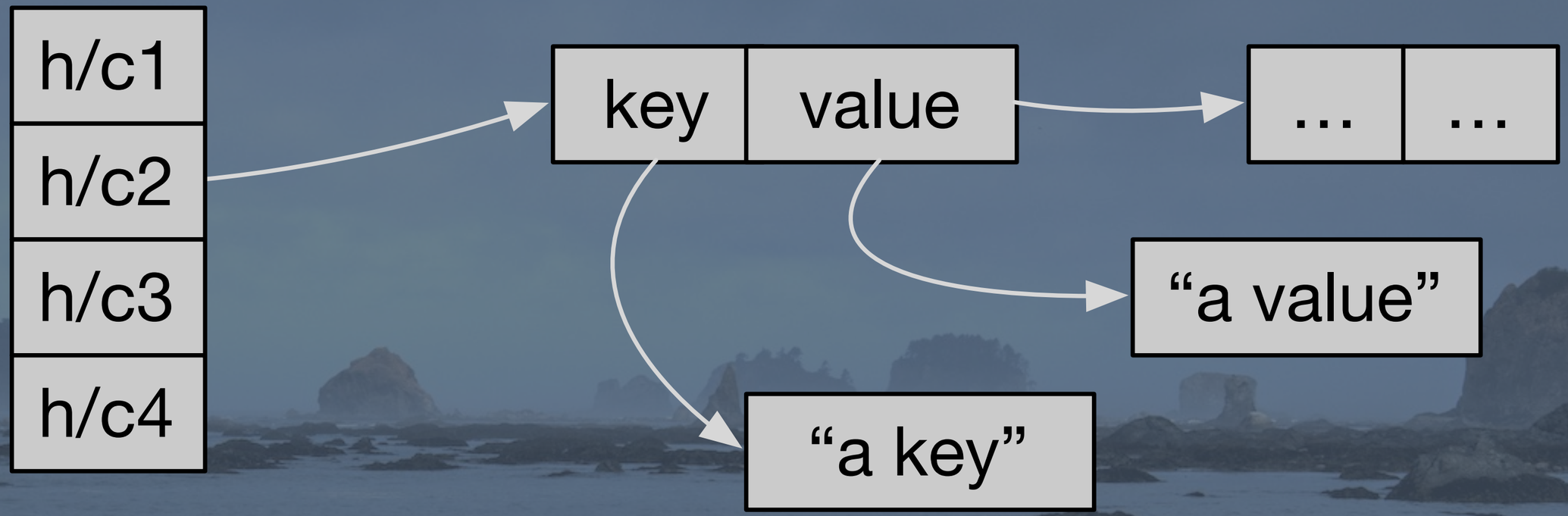
val myArray: Array[String]



Class Instances



Hash Map



Hash Maps

Improving Performance

Why obsess about this?

Spark jobs are CPU bound:

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

What changed?

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

What changed?

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

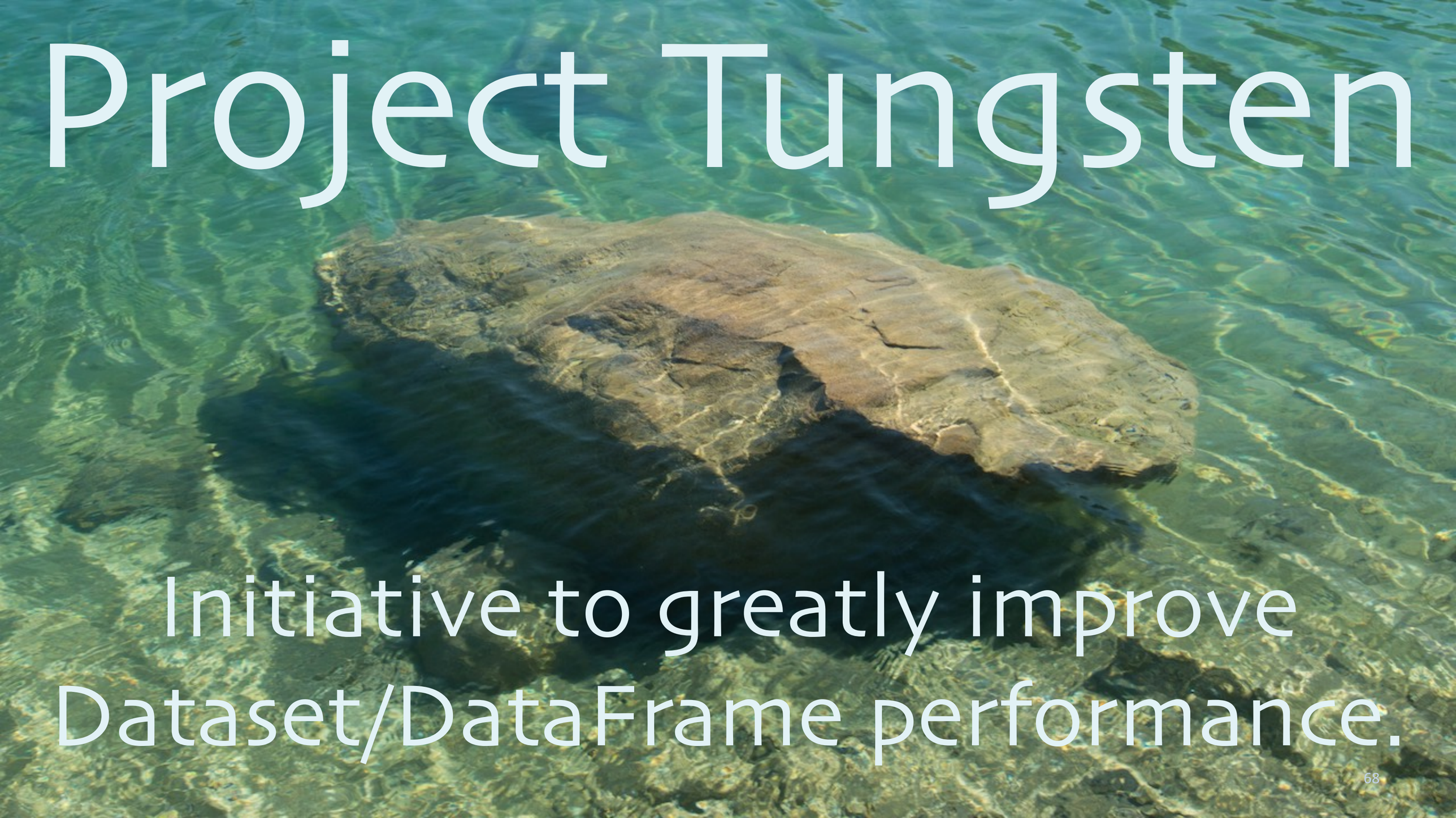
What changed?

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

Improving Performance

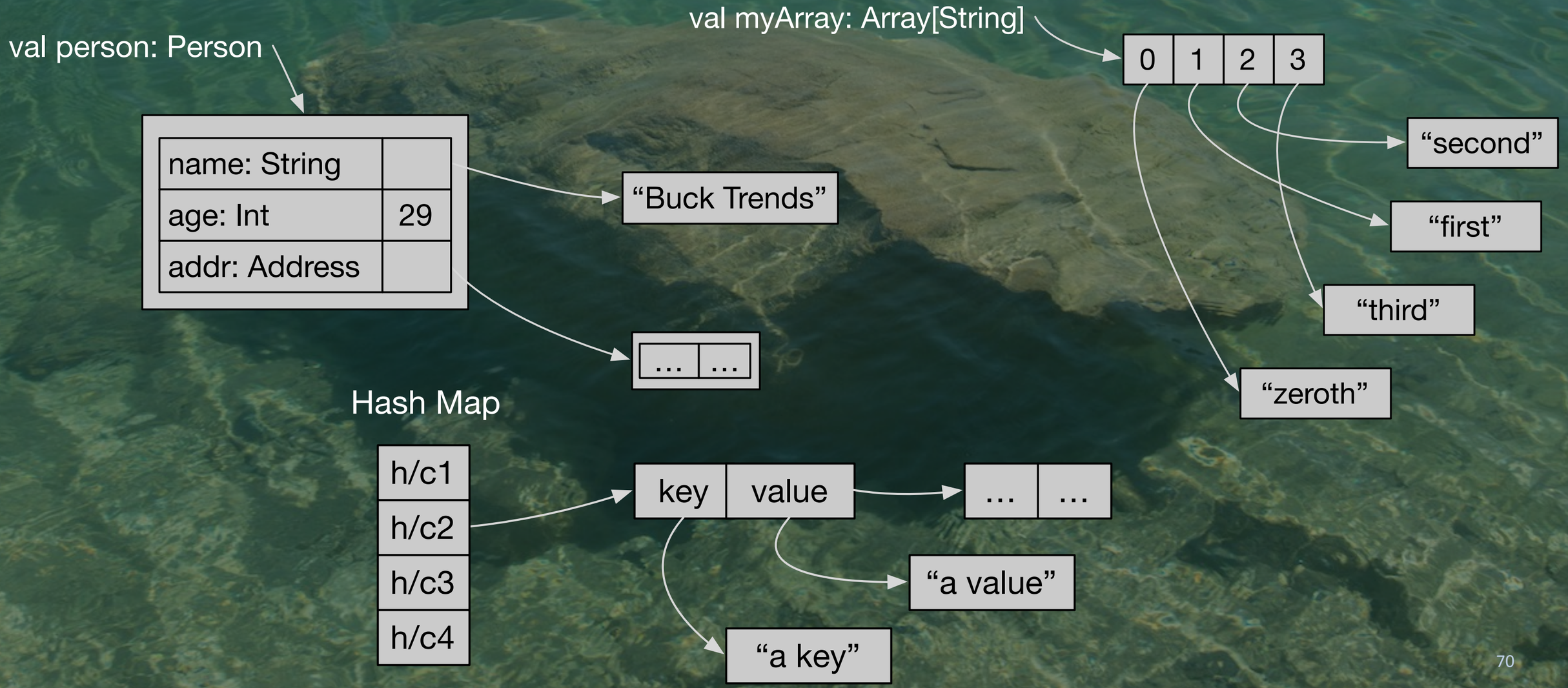
To improve performance, we need to focus on the CPU, the:

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


Project Tungsten
Initiative to greatly improve
Dataset/DataFrame performance.

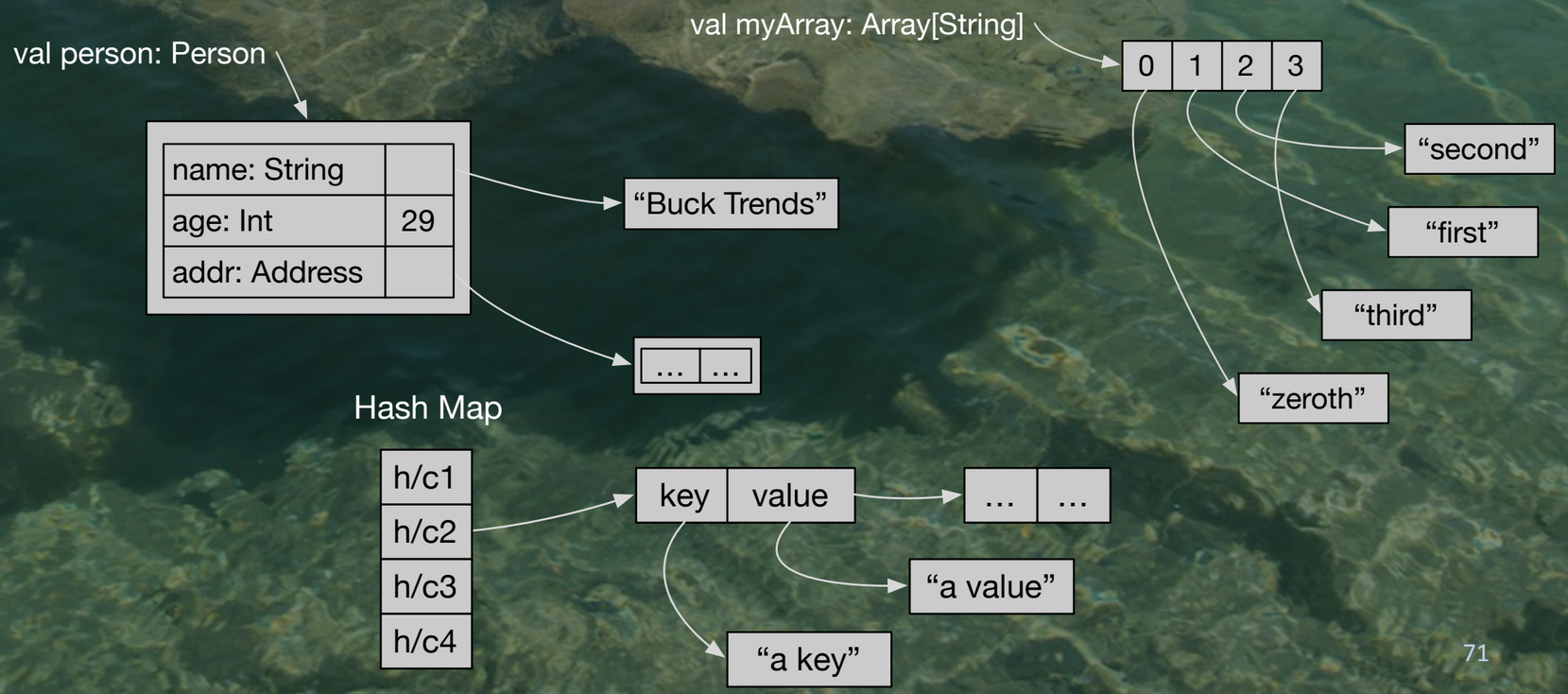
Goals

Reduce References



Reduce References

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



Less Expression Overhead

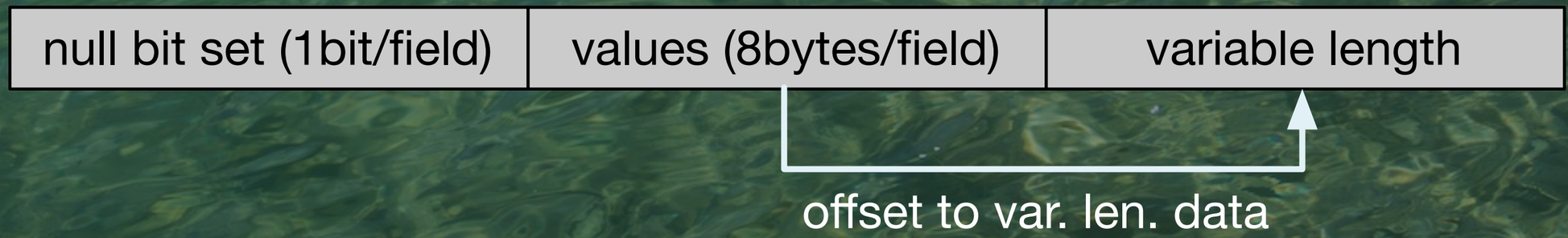
```
sql("SELECT a + b FROM table")
```

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

Implementation

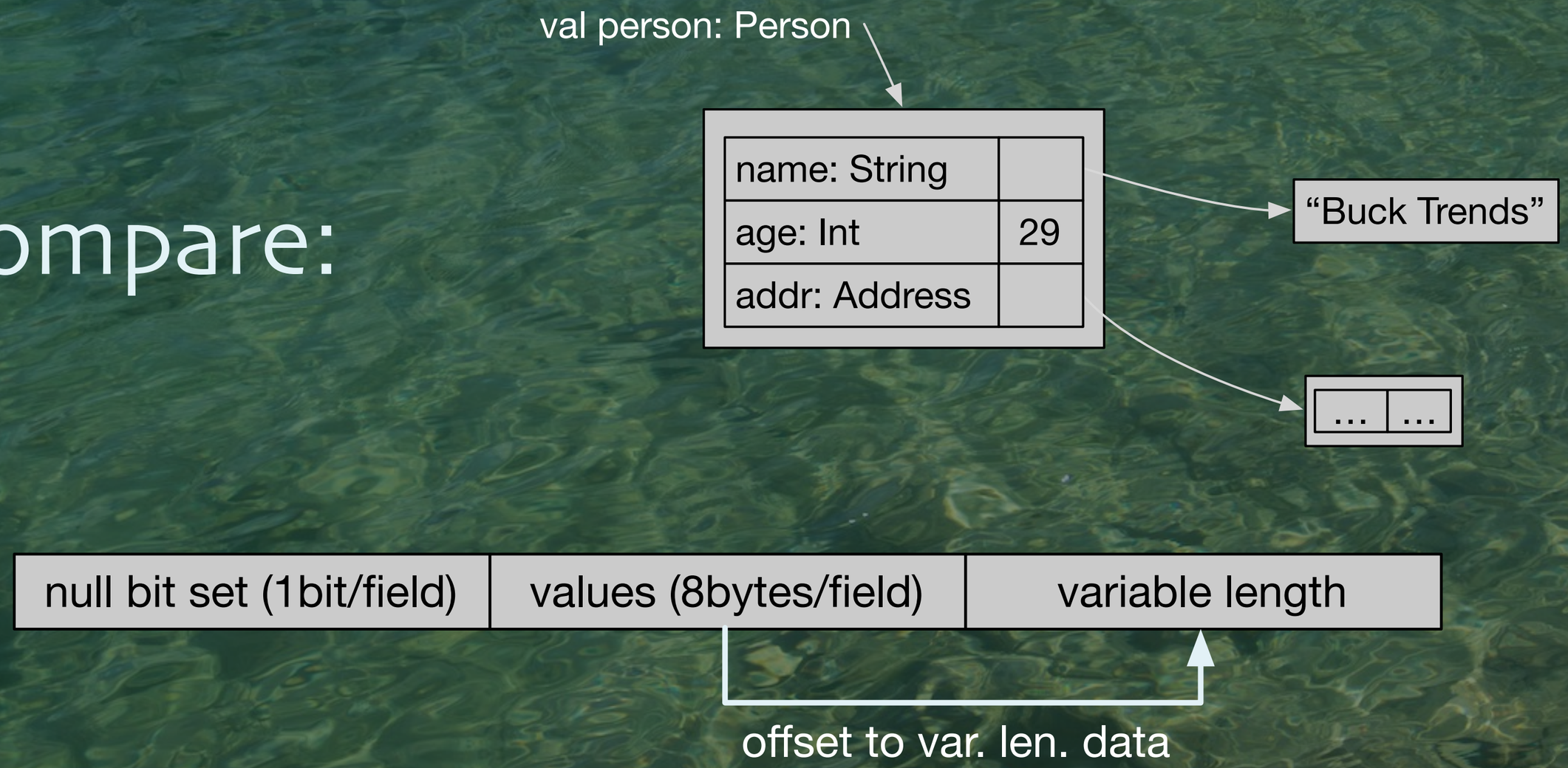
Object Encoding

New CompactRow type:

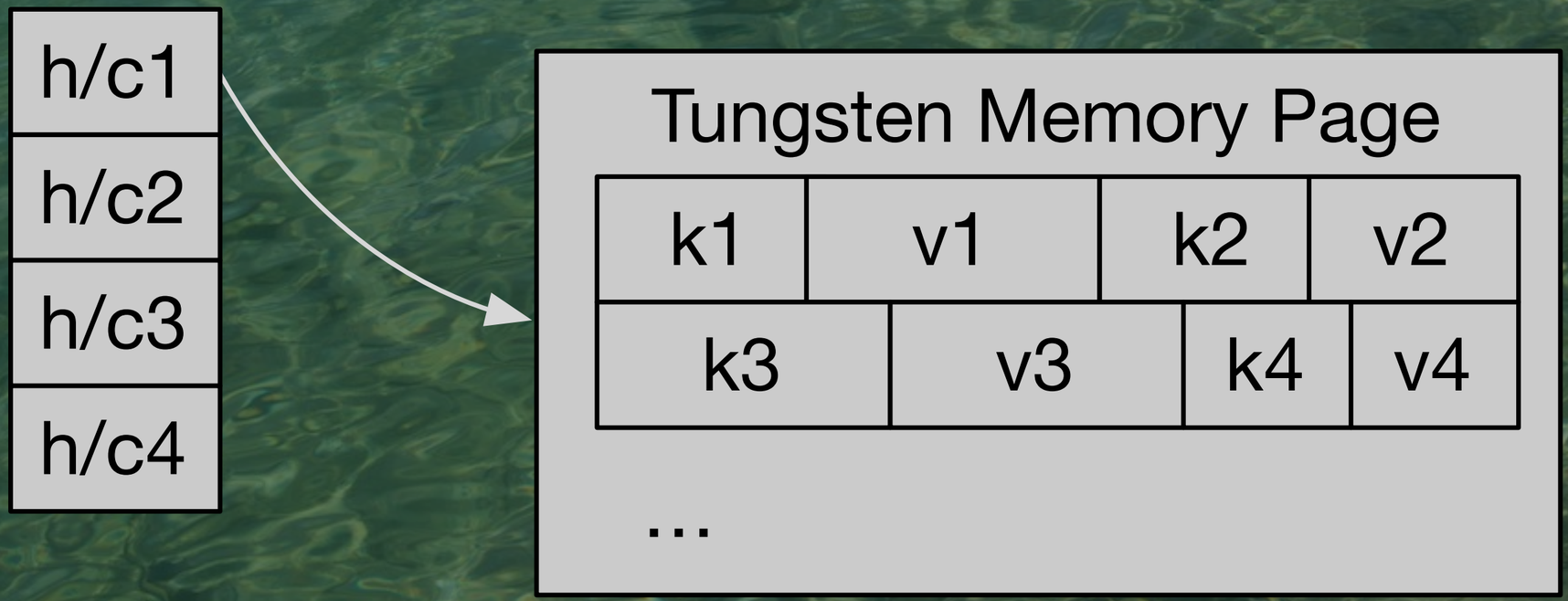


- Compute hashCode and equals on raw bytes.

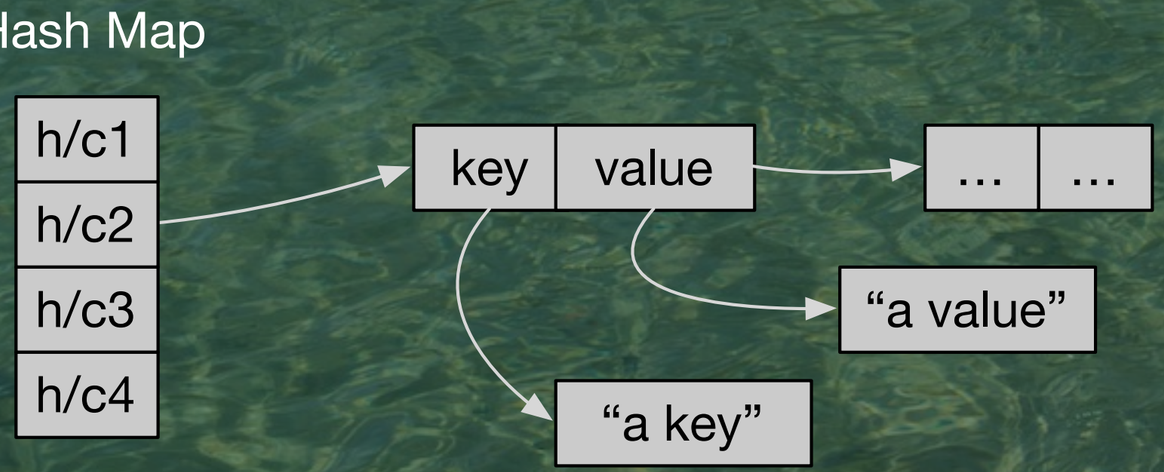
- Compare:

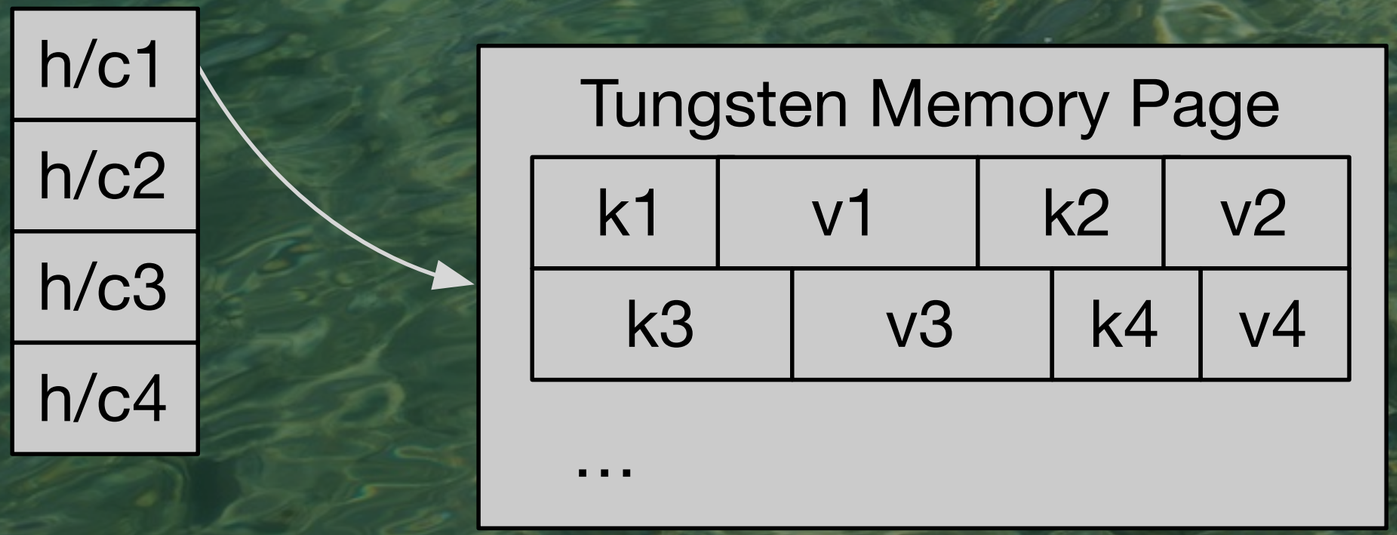

val person: Person
name: String
age: Int
29
addr: Address
“Buck Trends”
…
…
null bit set (1bit/field)
values (8bytes/field)
variable length
offset to var. len. data

- BytesToBytesMap:



- Compare


Hash Map
h/c1
h/c2
h/c3
h/c4
key
value
…
…
“a value”
“a key”


h/c1
h/c2
h/c3
h/c4
Tungsten Memory Page
k1
v1
k2
v2
k3
v3
k4
v4
…

Memory Management

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

Less Expression Overhead

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

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

Less Expression Overhead

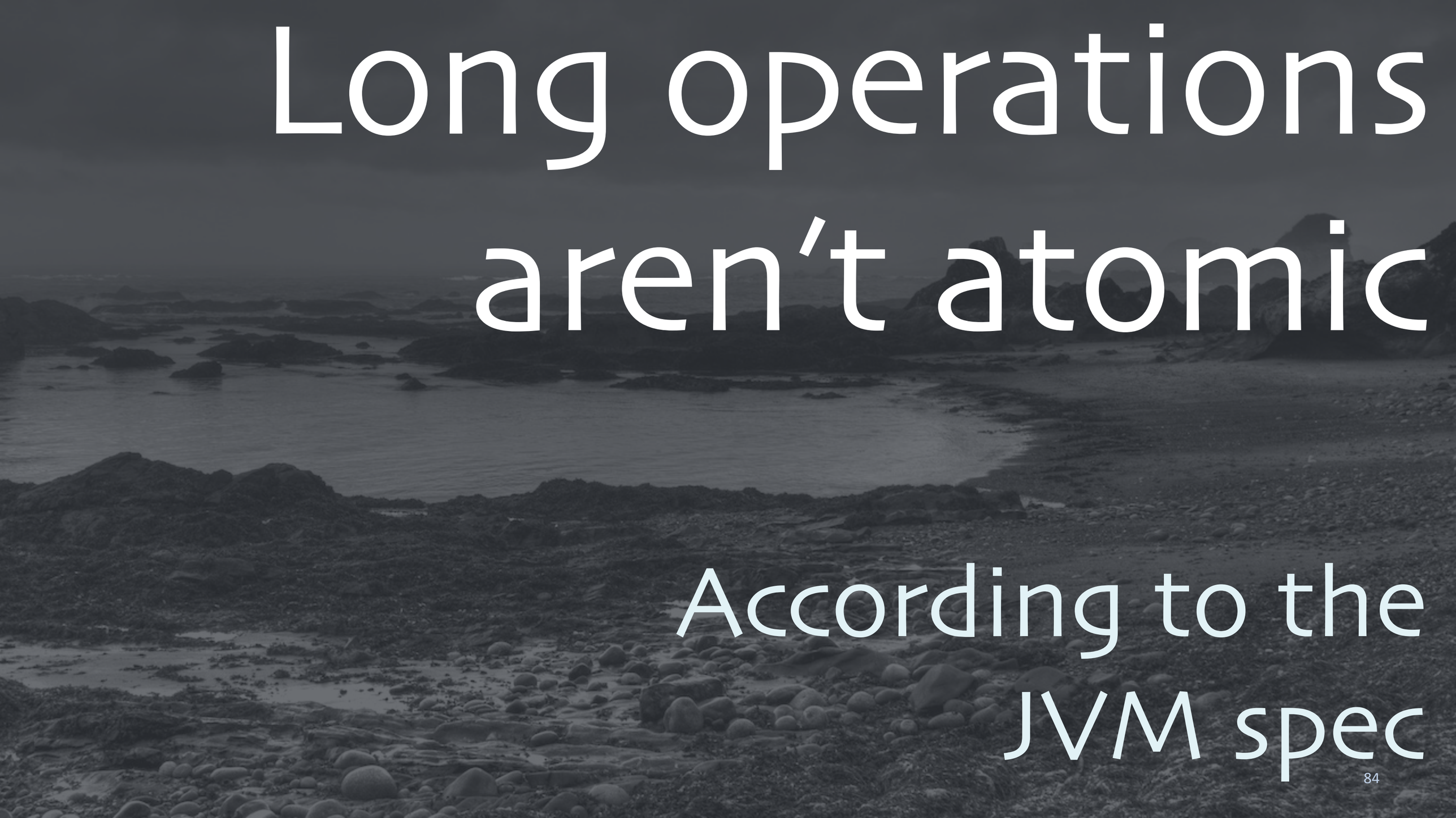
```
sql("SELECT a + b FROM table")
```

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


No Value Types
(Planned for Java 9 or 10)

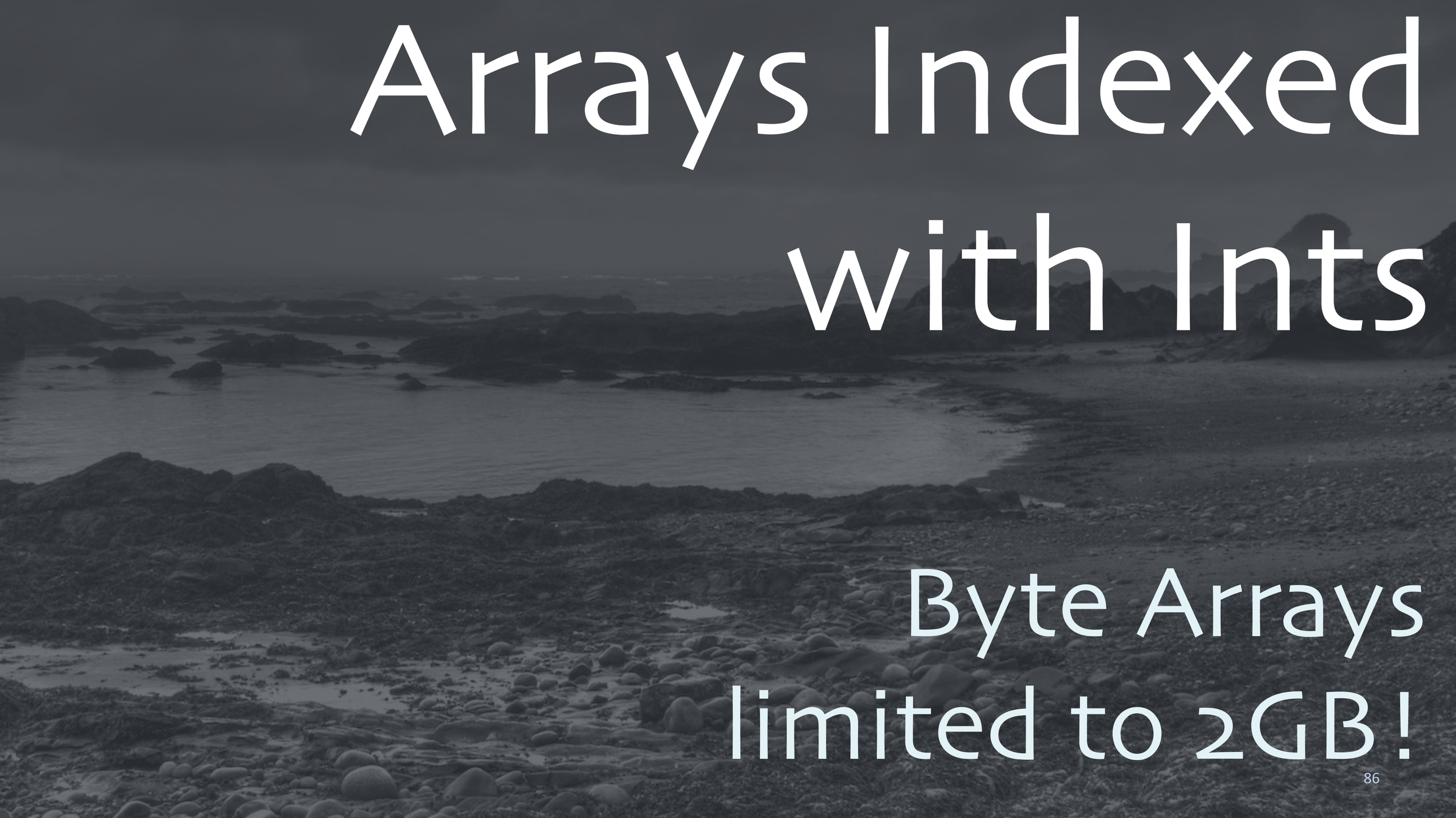
```
case class Timestamp(epochMillis: Long) {

  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.)


Long operations
aren't atomic
According to the
JVM spec

No Unsigned Types

What's factorial(-1)?



Arrays Indexed with Ints

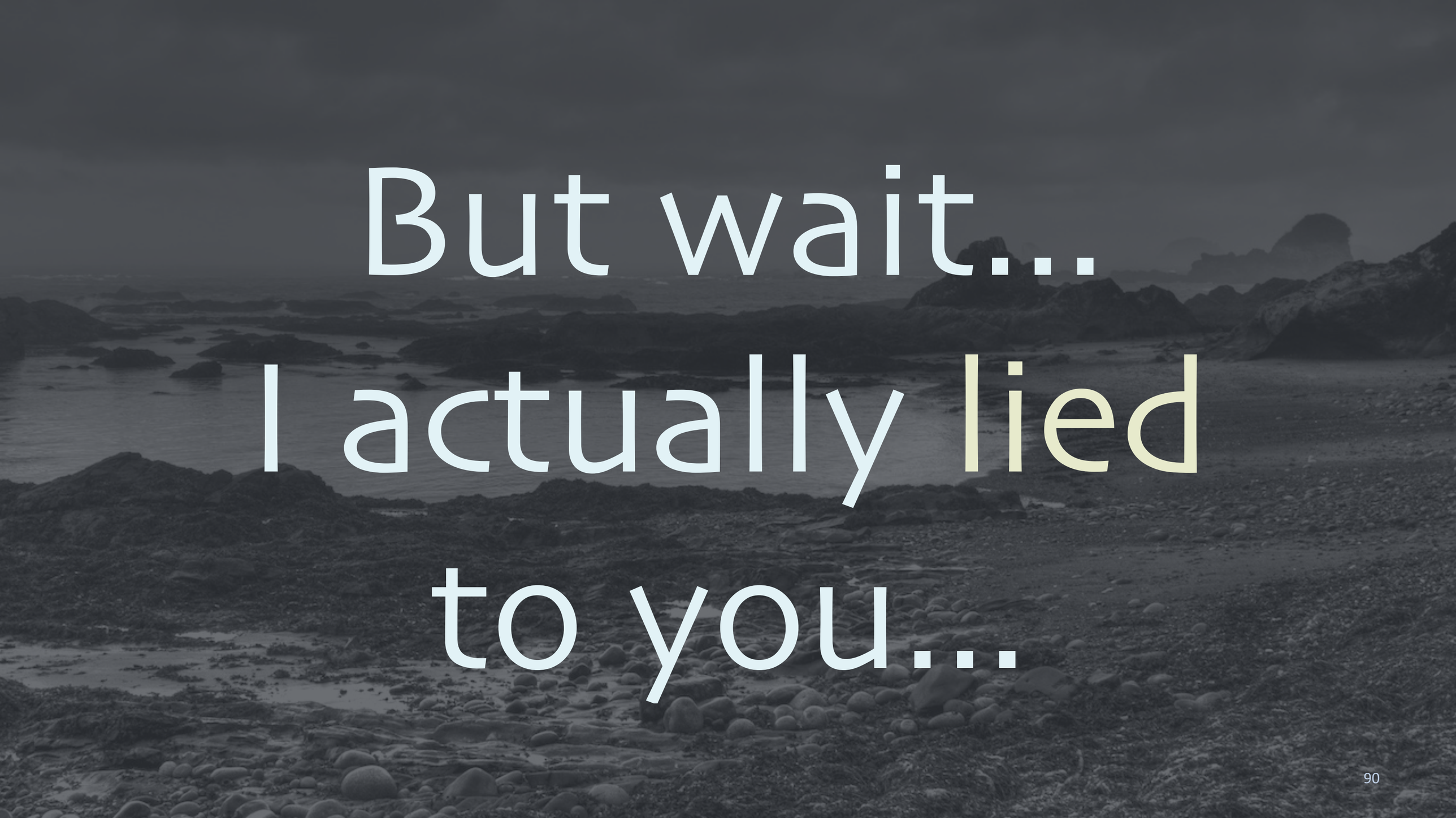
Byte Arrays limited to 2GB!

```
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
```

```
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))
```

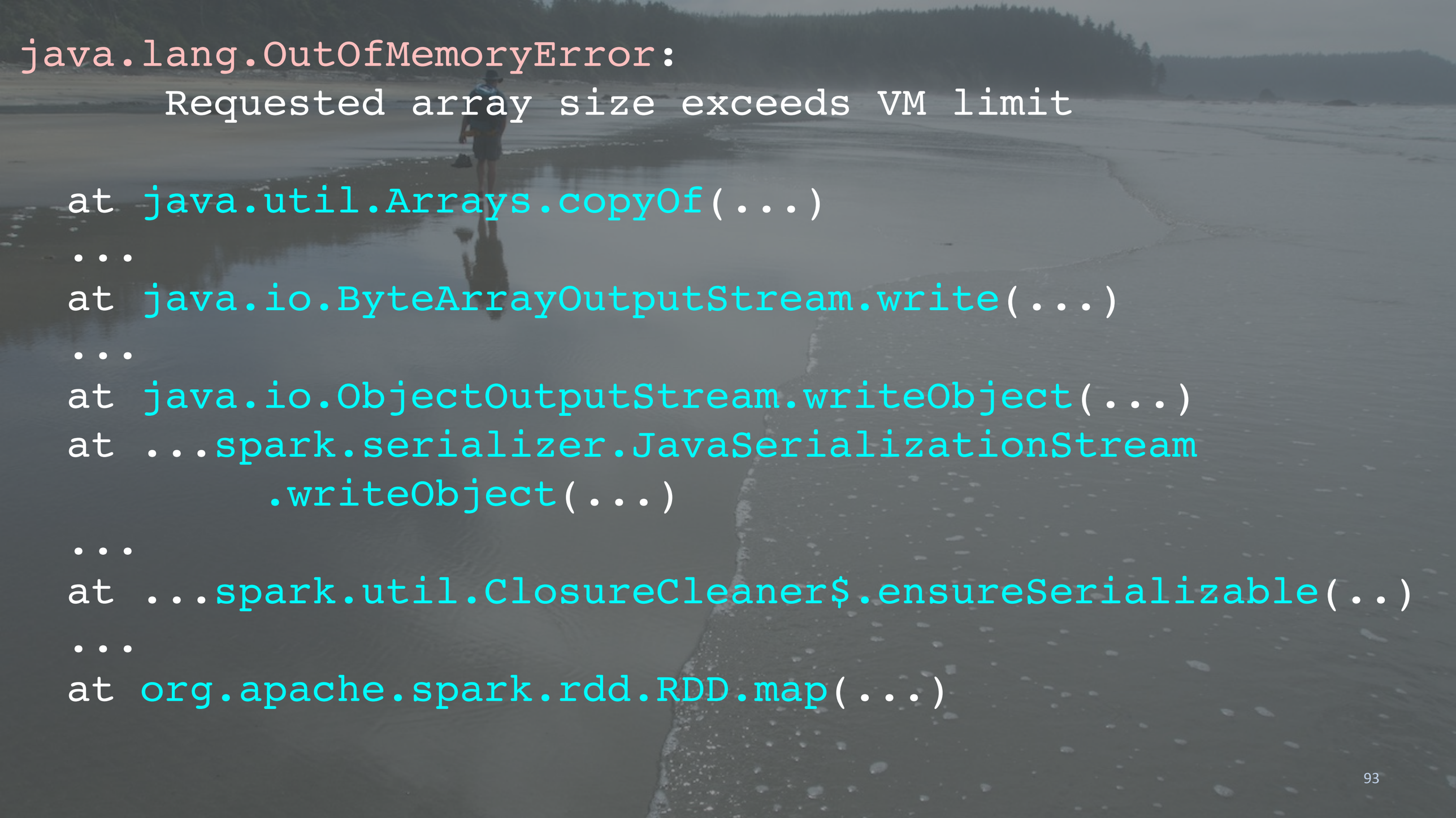
```
scala> SizeEstimator.estimate(b)
res0: Long = 2368

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(...)
  ...
```

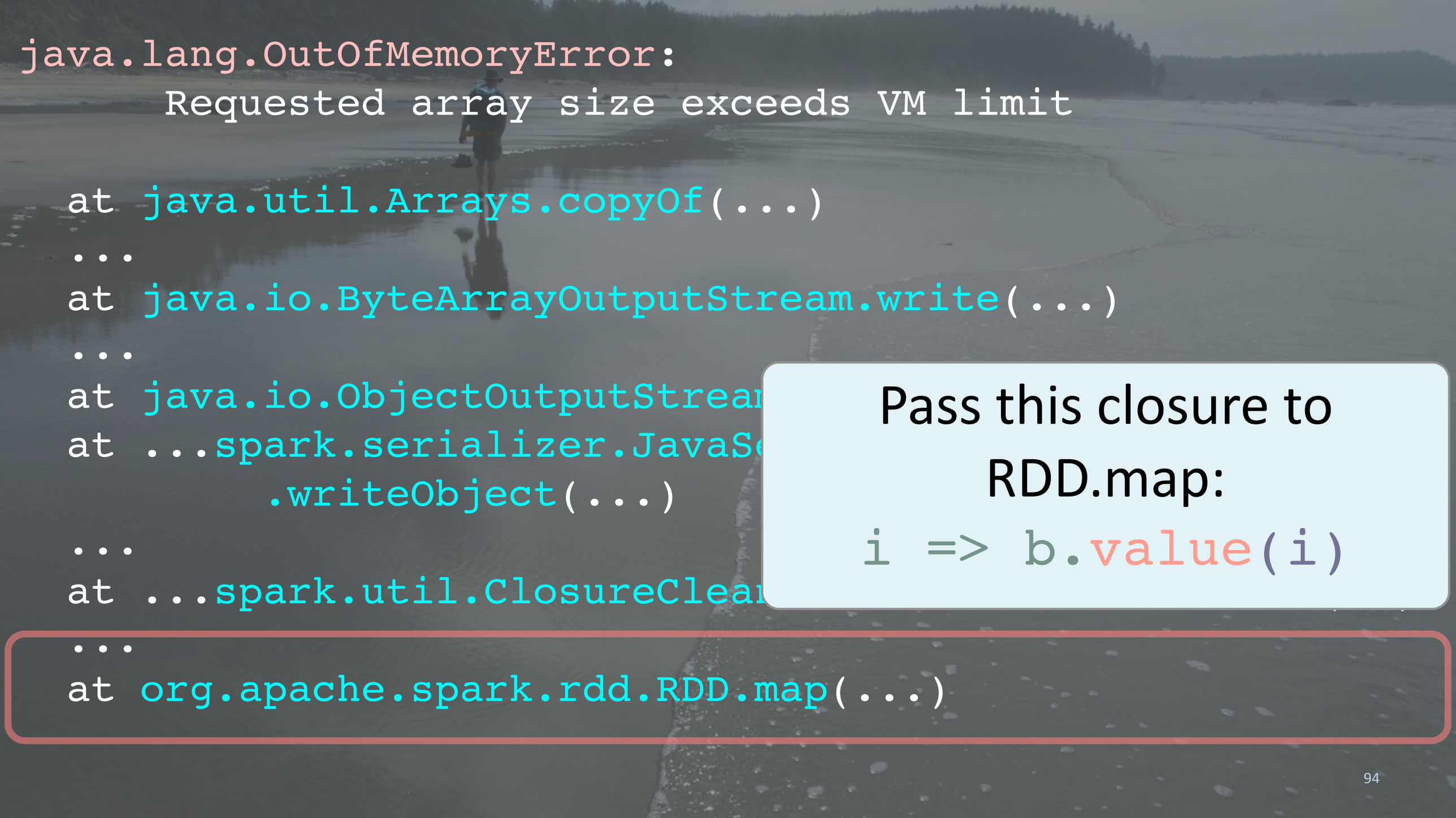
Boom!


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

Spark handles large broadcast variables by breaking them into blocks.

Scala REPL


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(...)


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)

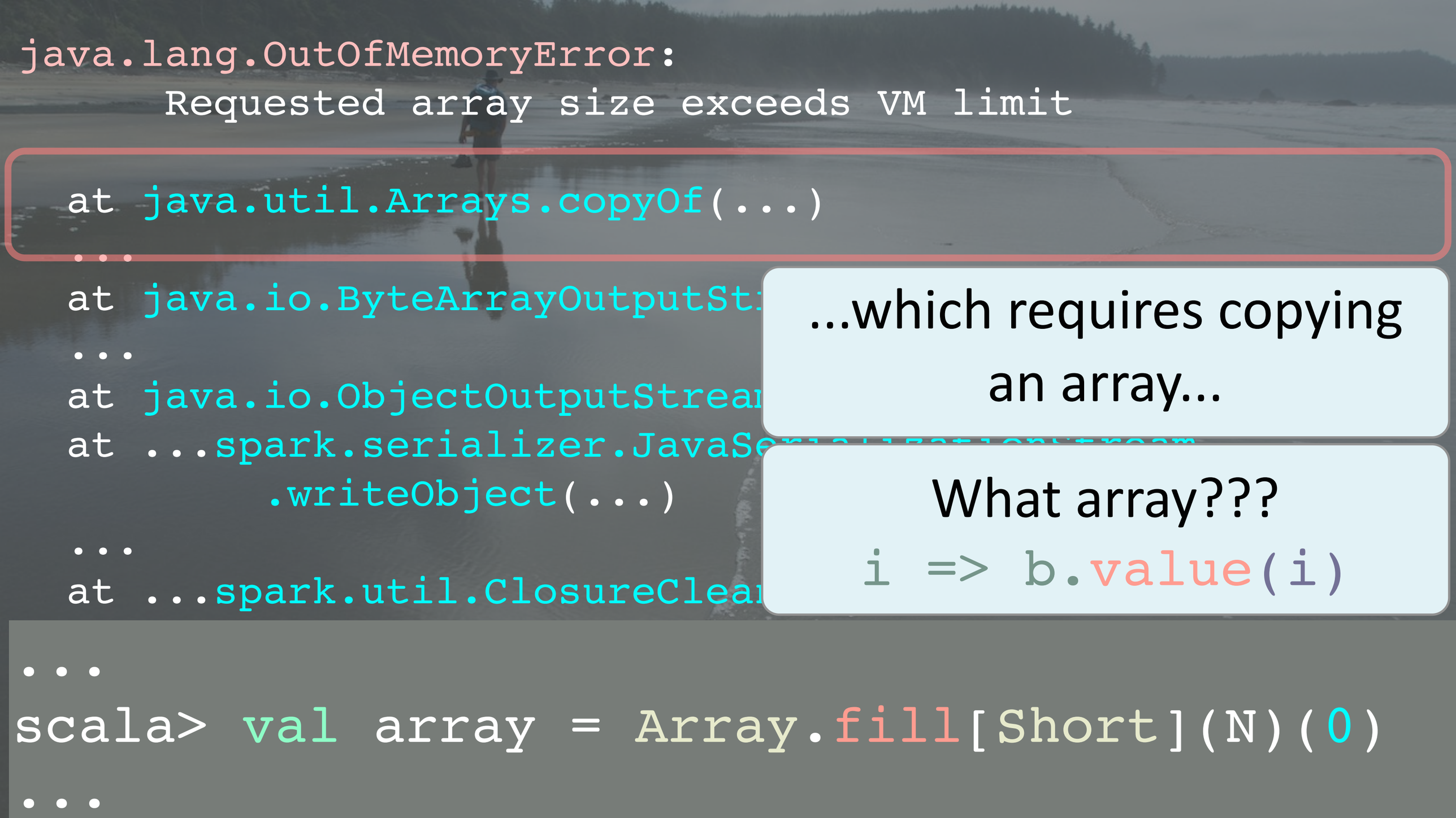
```
java.lang.OutOfMemoryError:
      Requested array size exceeds VM limit

  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)
```

```
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.
```

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


java.lang.OutOfMemoryError:
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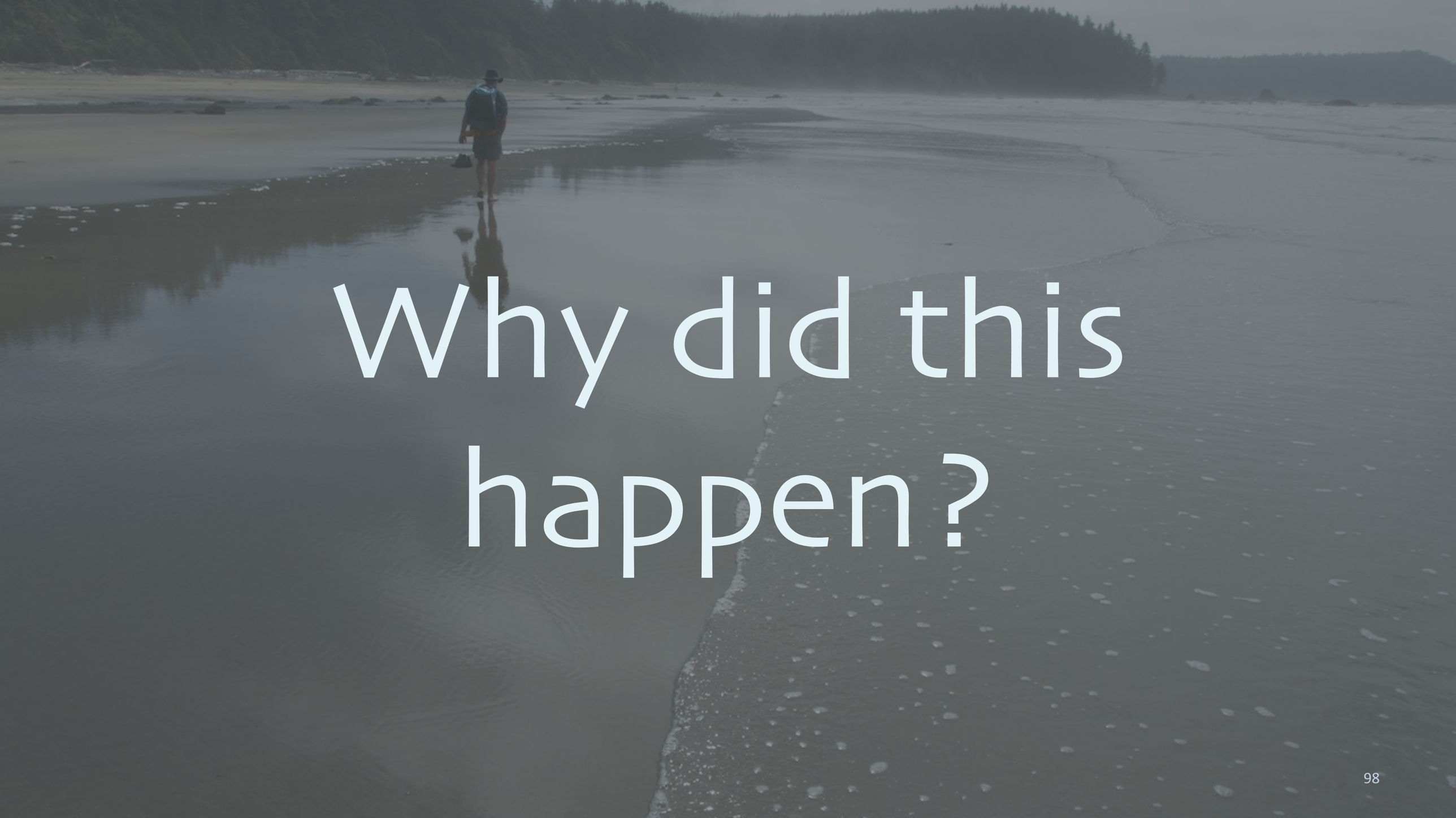
at java.util.Arrays.copyOf(...)
...
at java.io.ByteArrayOutputSt
...
at java.io.ObjectOutputStrea
at ...spark.serializer.JavaSe
.writeObject(...)
...
at ...spark.util.ClosureClea
...
scala> val array = Array.fill[Short](N)(0)
...
...which requires copying an array...
What array???
i => b.value(i)


Why did this
happen?

- 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))
```

```
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))
 }
}
```

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

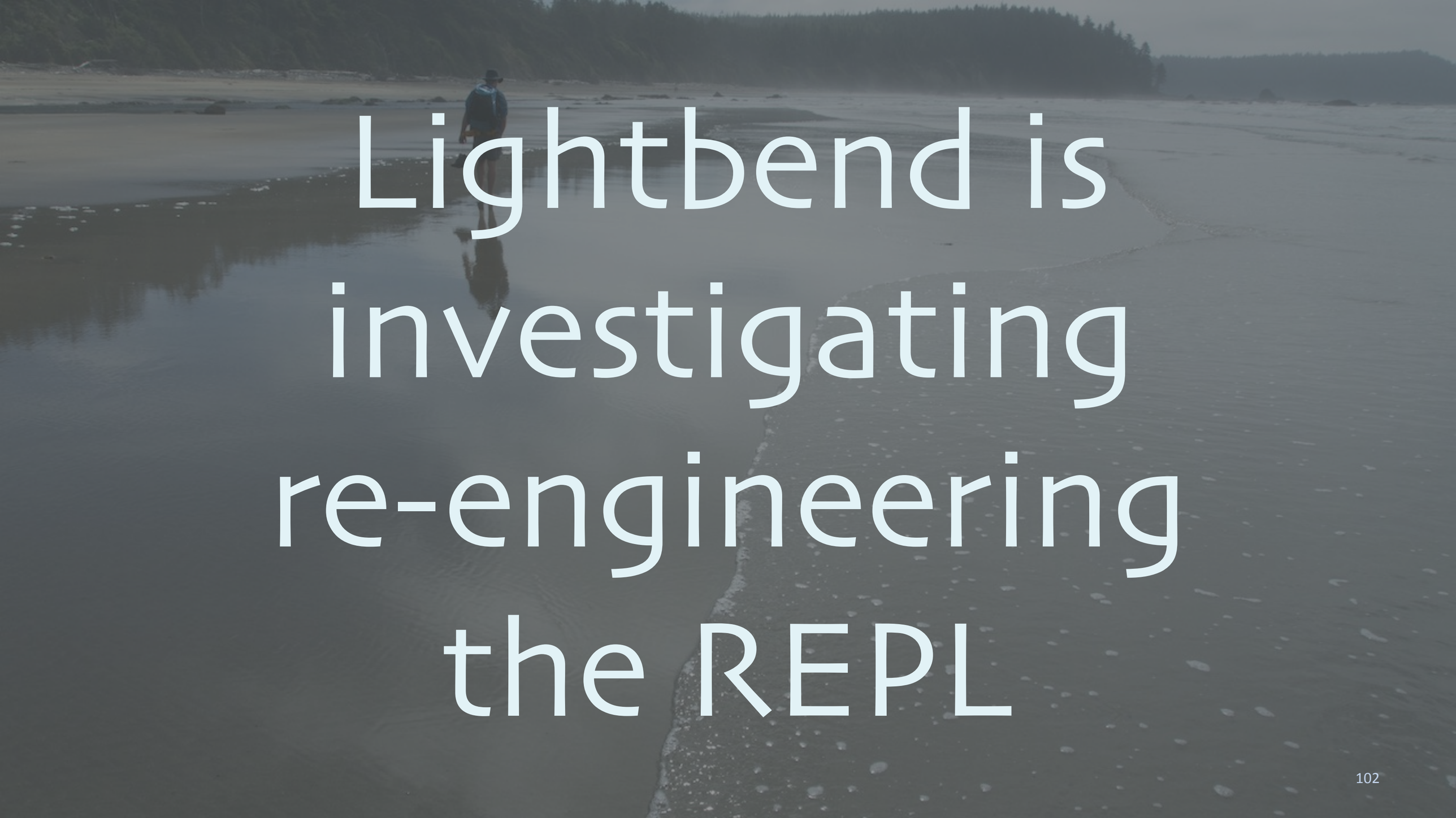
- Scala compiles:

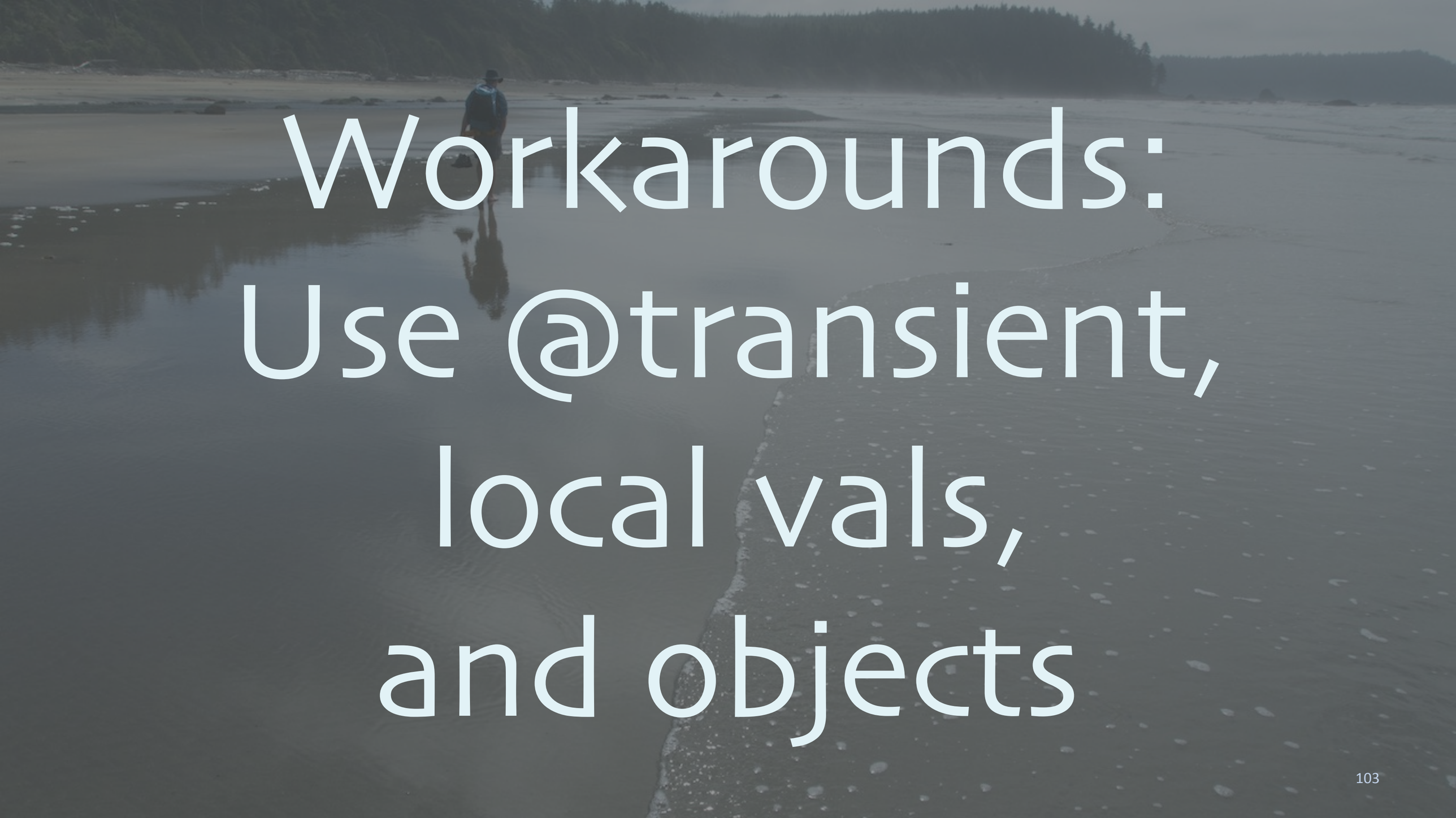
… sucks in all this!

```
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”…


Lightbend is
investigating
re-engineering
the REPL



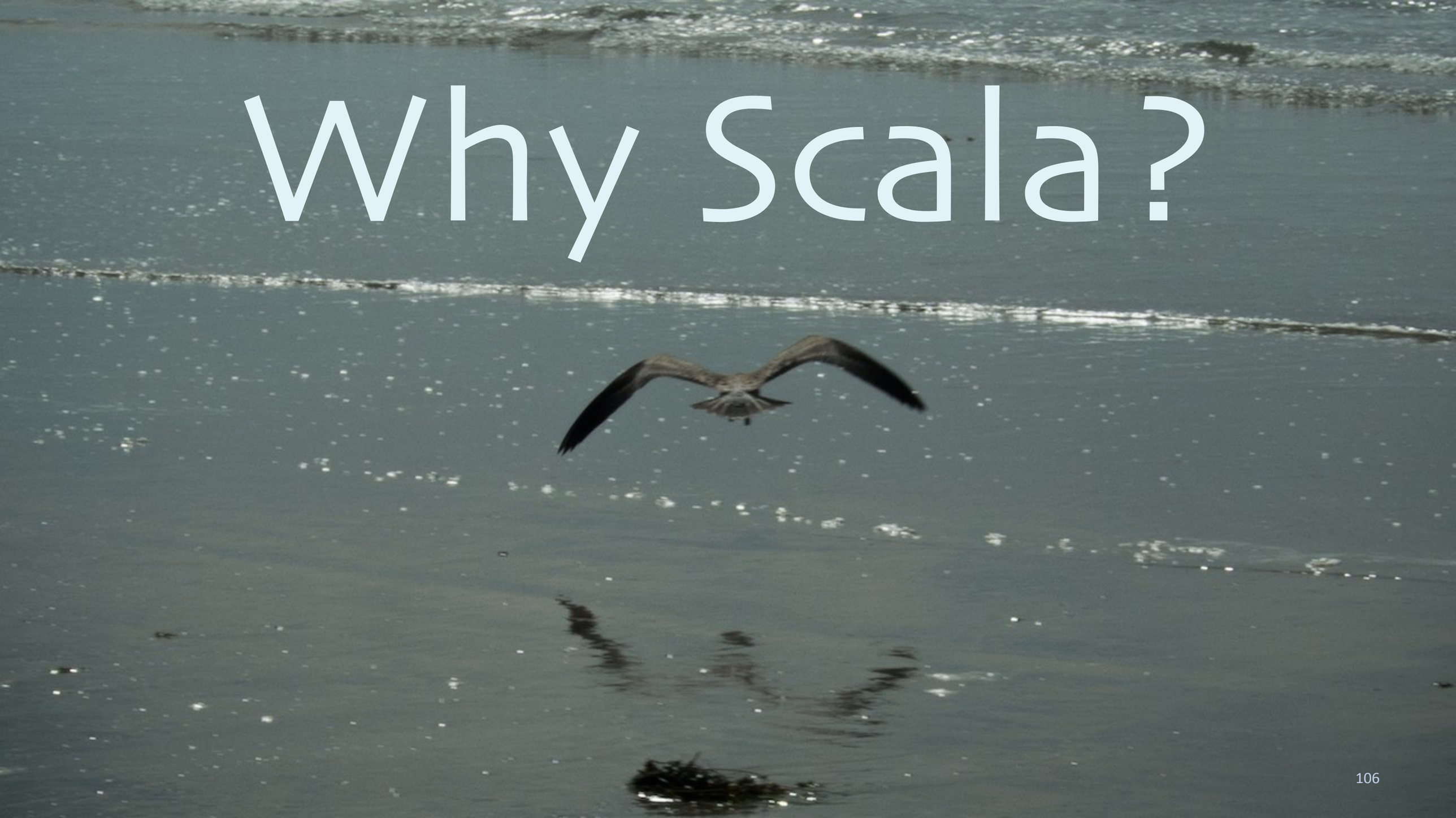
Workarounds: Use @transient, local vals, and objects

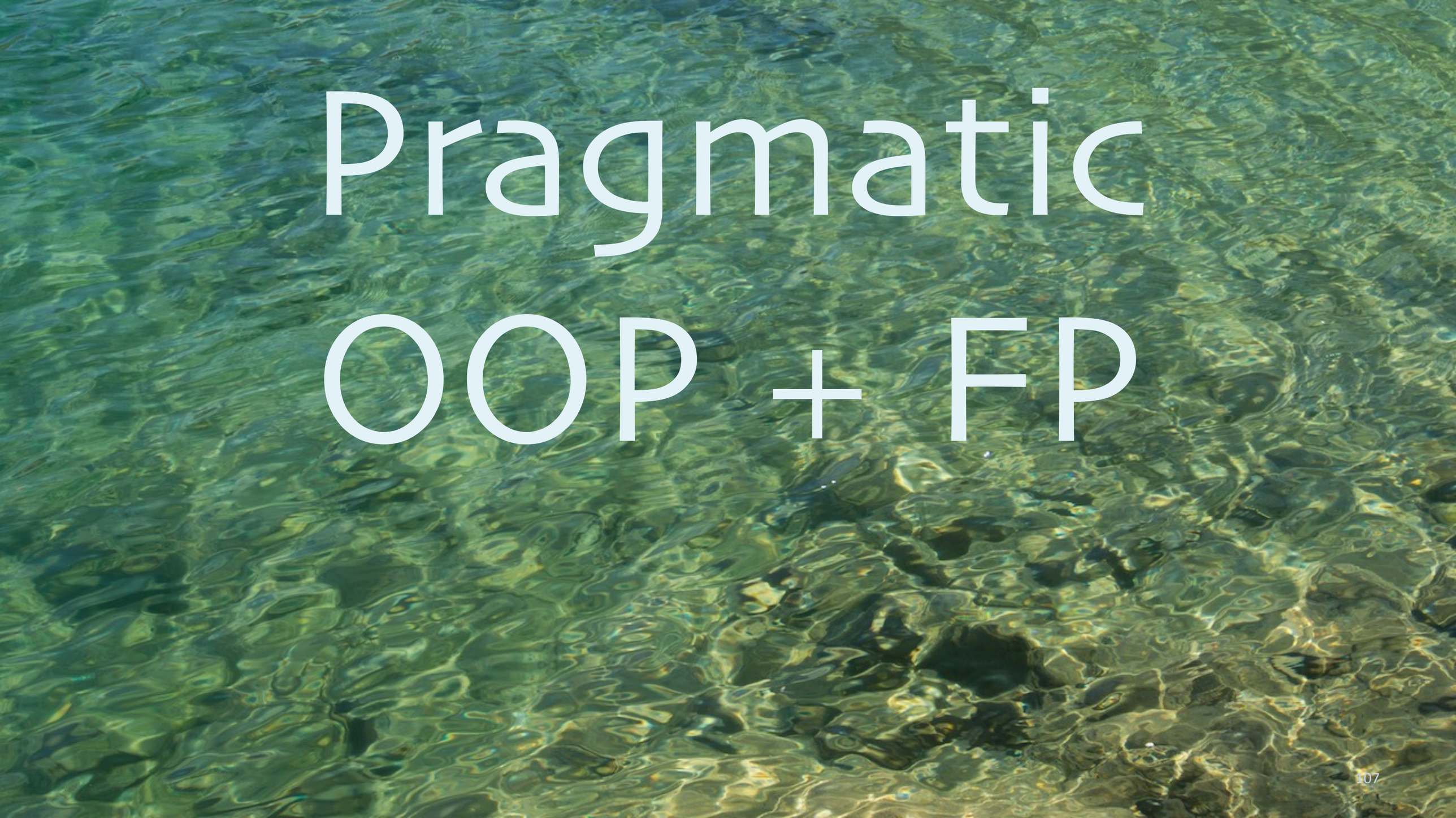
- Transient is often all you need:

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

```
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)
}}
```

Why Scala?

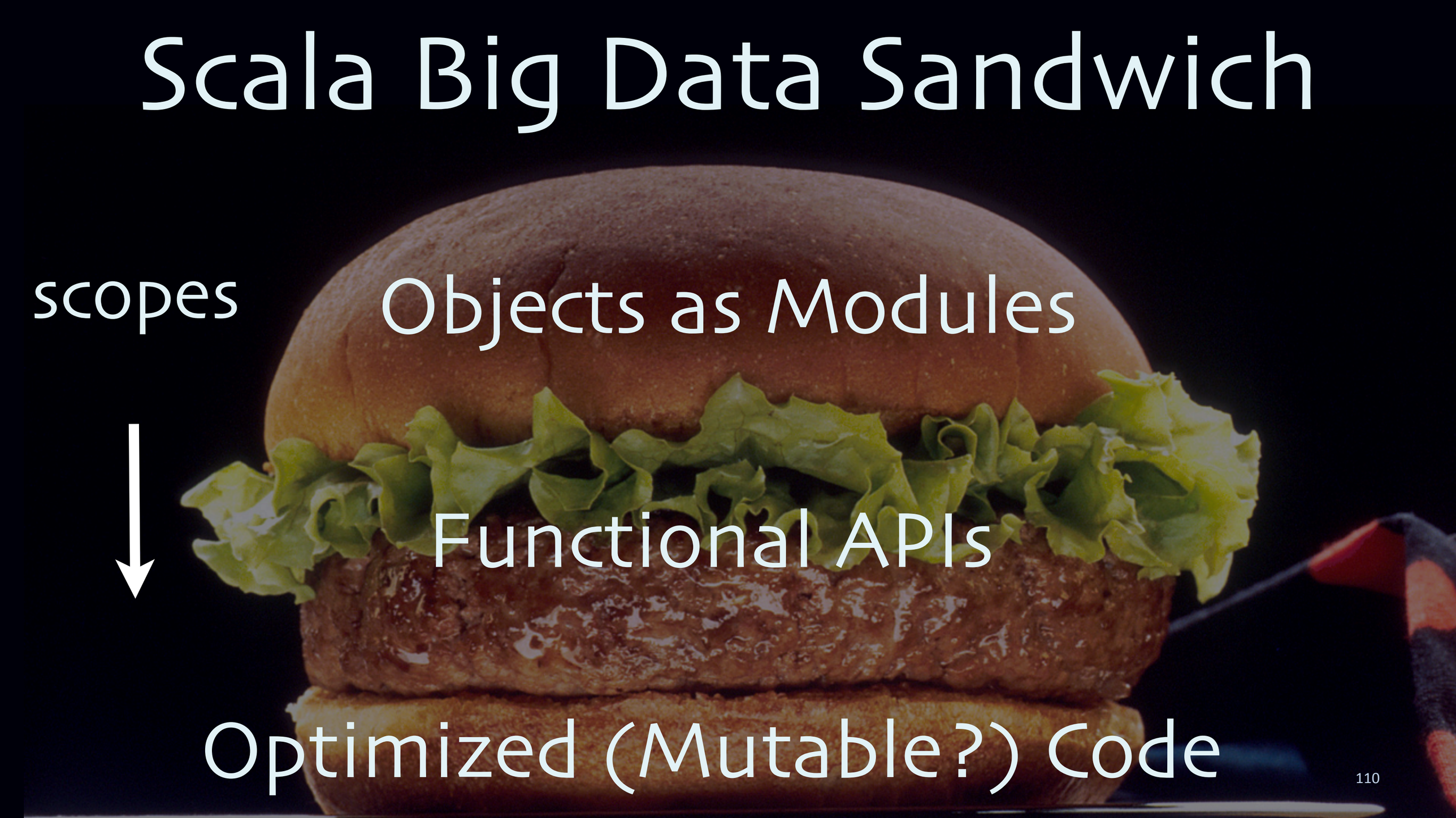



Pragmatic
OOP + FP

- Abstractions vs. implementations:
  - Pure functional abstractions?
  - Mutable implementations, when necessary.
  - Performance is critical.

Scala Big Data Sandwich

Scala Big Data Sandwich



scopes

Objects as Modules

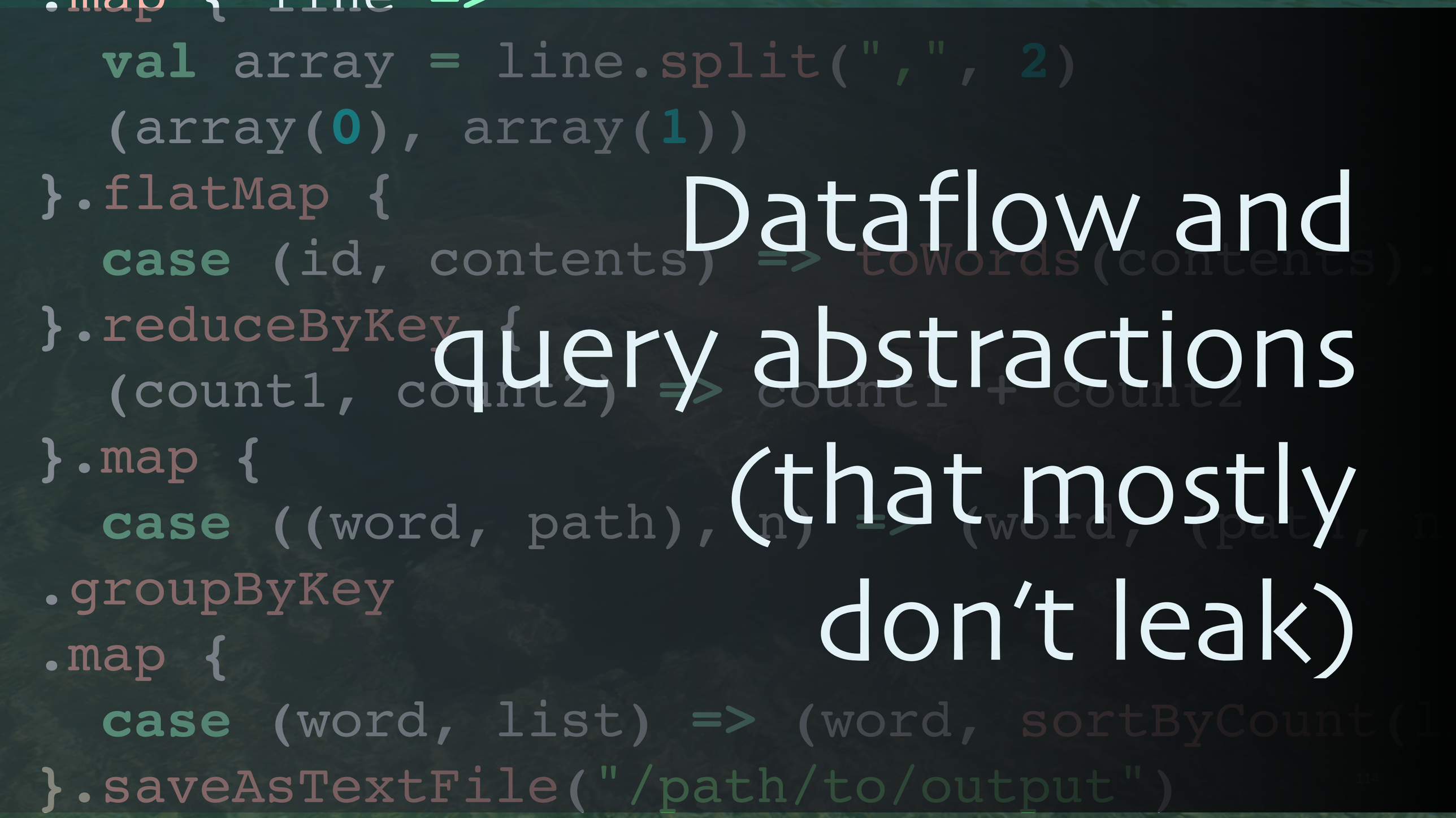
Functional APIs

Optimized (Mutable?) Code

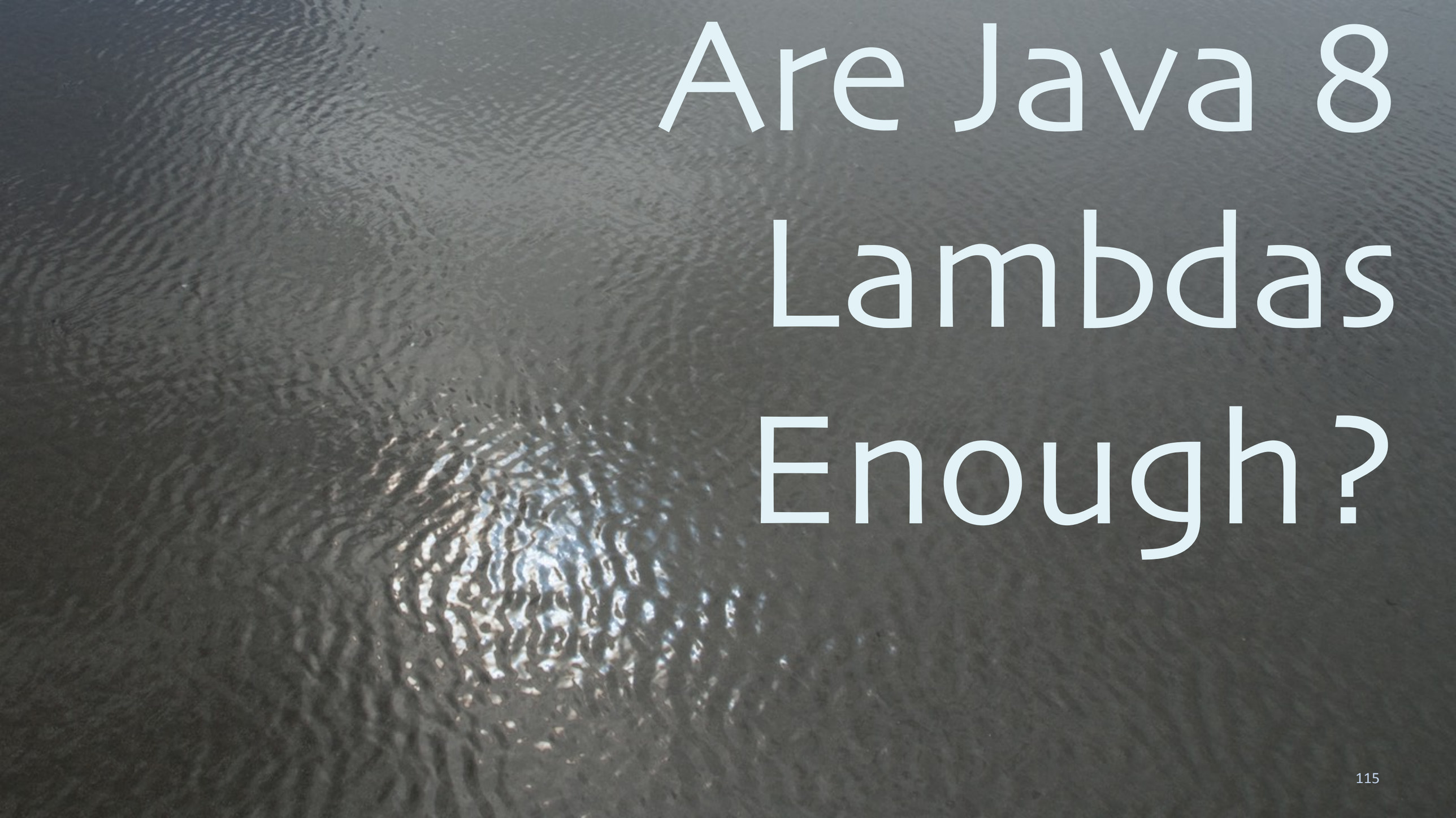

REPL
& Notebooks

Collections API


Inspired Spark's
API



Dataflow and query abstractions (that mostly don't leak)

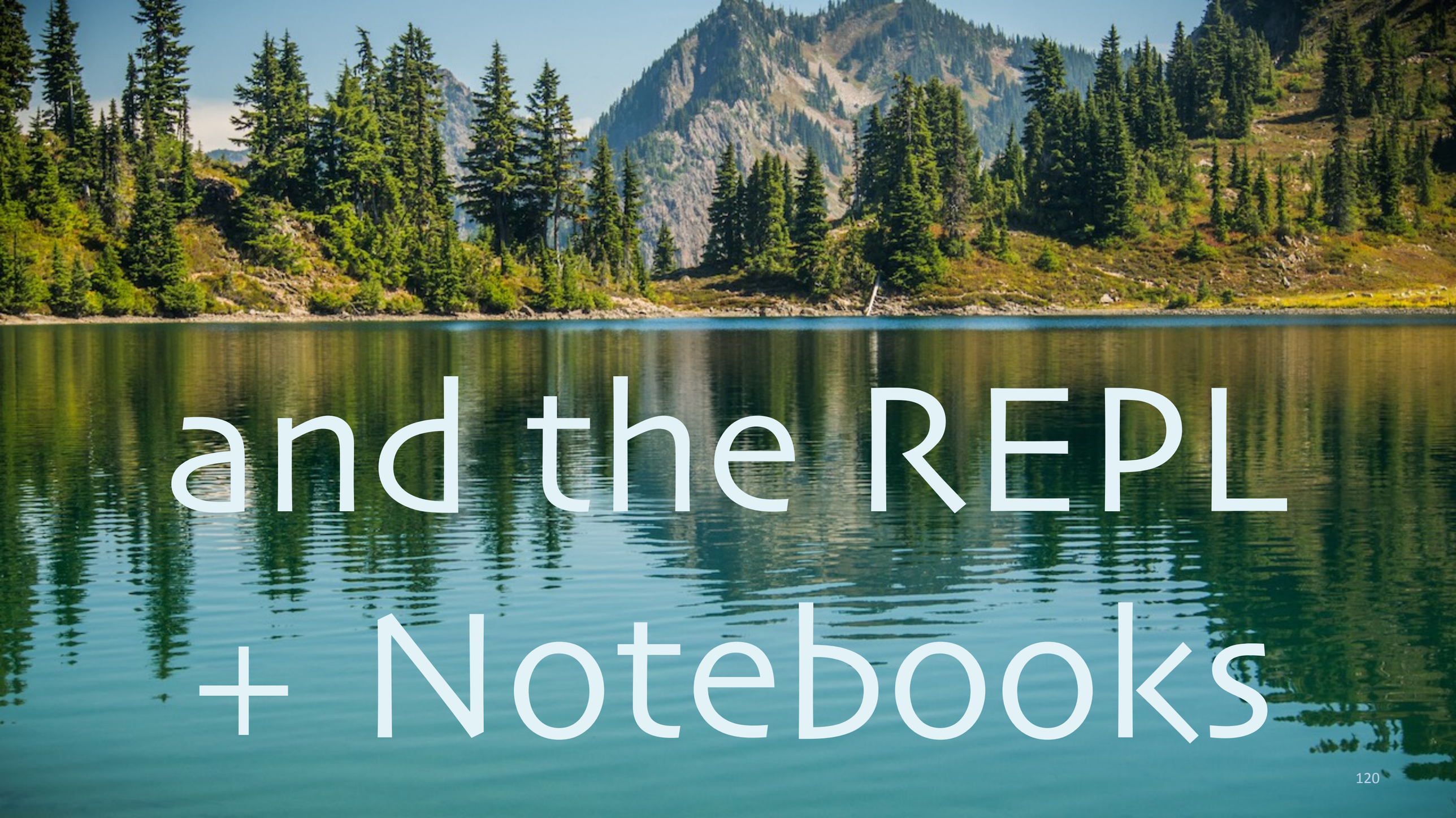

Are Java 8
Lambdas
Enough?

Tuples

Pattern Matching

Type Inference


DSLs


and the REPL
+ Notebooks

Conclusions

Spark Is Driving Scala Adoption

Spark has some technical debt.

Scala collections need a refresh.

spark-summit.org/eu-2015/events/spark-the-ultimate-scala-collections/

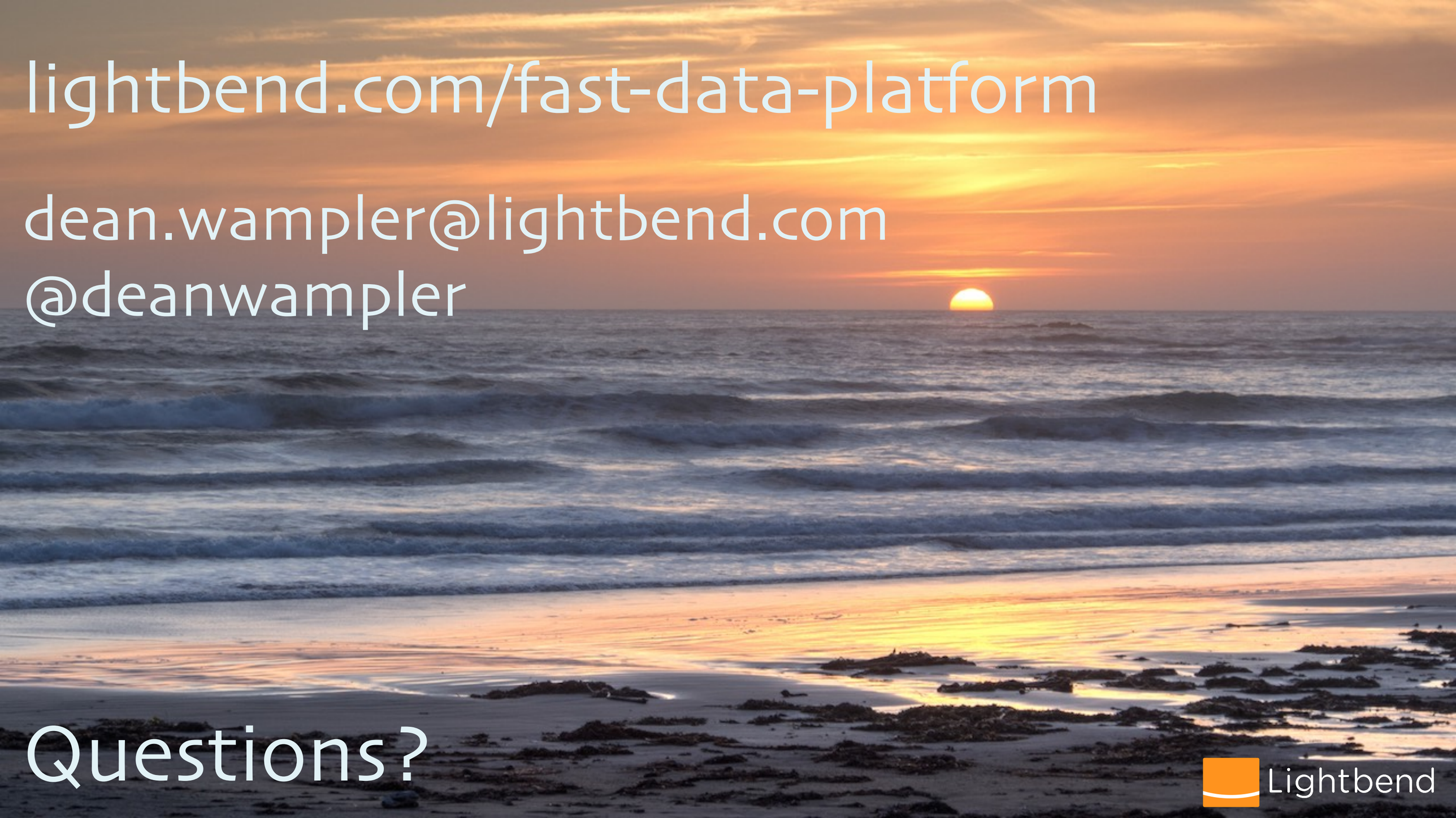
```
[22:11:28] deanwampler@deantypesafe:~/Documents/training/sparkworkshop/spark-workshop-exercises
✔ grep 'def.*ByKey' ~/projects/spark/spark-git/core/src/main/scala/org/apache/spark/rdd/PairRDD
def combineByKey[C](createCombiner: V => C,
def combineByKey[C](createCombiner: V => C,
def aggregateByKey[U: ClassTag](zeroValue: U, partitioner: Partitioner)(seqOp: (U, V) => U,
def aggregateByKey[U: ClassTag](zeroValue: U, numPartitions: Int)(seqOp: (U, V) => U,
def aggregateByKey[U: ClassTag](zeroValue: U)(seqOp: (U, V) => U,
def foldByKey(
def foldByKey(zeroValue: V, numPartitions: Int)(func: (V, V) => V): RDD[(K, V)] = self.withScop
def foldByKey(zeroValue: V)(func: (V, V) => V): RDD[(K, V)] = self.withScope {
def sampleByKey(withReplacement: Boolean,
def sampleByKeyExact(
def reduceByKey(partitioner: Partitioner, func: (V, V) => V): RDD[(K, V)] = self.withScope {
def reduceByKey(func: (V, V) => V, numPartitions: Int): RDD[(K, V)] = self.withScope {
def reduceByKey(func: (V, V) => V): RDD[(K, V)] = self.withScope {
def reduceByKeyLocally(func: (V, V) => V): Map[K, V] = self.withScope {
def reduceByKeyToDriver(func: (V, V) => V): Map[K, V] = self.withScope {
def countByKey(): Map[K, Long] = self.withScope {
def countByKeyApprox(timeout: Long, confidence: Double = 0.95)
def countApproxDistinctByKey(
def countApproxDistinctByKey(
def countApproxDistinctByKey(
def countApproxDistinctByKey(relativeSD: Double = 0.05): RDD[(K, Long)] = self.withScope {
def groupByKey(partitioner: Partitioner): RDD[(K, Iterable[V])] = self.withScope {
def groupByKey(numPartitions: Int): RDD[(K, Iterable[V])] = self.withScope {
def combineByKey[C](createCombiner: V => C, mergeValue: (C, V) => C, mergeCombiners: (C, C) =>
def groupByKey(): RDD[(K, Iterable[V])] = self.withScope {
def subtractByKey[W: ClassTag](other: RDD[(K, W)]): RDD[(K, V)] = self.withScope {
def subtractByKey[W: ClassTag](
def subtractByKey[W: ClassTag](other: RDD[(K, W)], p: Partitioner): RDD[(K, V)] = self.withScop
[22:12:21] deanwampler@deantypesafe:~/Documents/training/SparkWorkshop/spark-workshop-exercises
```

Scala should adopt some Tungsten optimizations…

… & could the JVM adopt Tungsten's object encoding?

The JVM needs long indexing, value types & unsigned types


polyglotprogramming.com/talks
Lightbend


lightbend.com/fast-data-platform
dean.wampler@lightbend.com
@deanwampler
Questions?
Lightbend