

# Learning Apache Spark by processing email

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# Talk Overview

This presentation, ETL code for email and all example code available at <https://github.com/medale/spark-mail/> under Creative Commons Attribution-NonCommercial 4.0 International License <http://creativecommons.org/licenses/by-nc/4.0/> (Spark Mail Tutorial Dale et al. 2015)

# Speaker Background

# Hadoop Ecosystem

- ▶ Based on Google GFS (2003)/MapReduce (2004) papers
- ▶ Extremely rich and robust
  - ▶ ~ 2005 Nutch/2006 Yahoo - Doug Cutting/Mike Cafarella
- ▶ HDFS/Hadoop MapReduce
- ▶ DSLs: Pig, Cascading/Scalding, Crunch, Hive (SQL)
- ▶ Graph processing: Giraph
- ▶ Real-time streaming: Storm
- ▶ Machine Learning: Apache Mahout ...

# Hadoop Challenges

- ▶ With rich ecosystem: installation, maintenance, cognitive load for each add-on framework
- ▶ MapReduce is batch only - no interactive shell
- ▶ Must write out to disk between each iteration
- ▶ No memory caching yet (Apache Tez working on complex DAGs of tasks)
- ▶ Hadoop MapReduce programming is very low-level
  - ▶ map phase - (internal shuffle/sort) - reduce phase
  - ▶ Programmer expresses logic in map/reduce

# Why Apache Spark?

- ▶ Different trade-offs
  - ▶ Improved hardware (faster processors, more memory)
- ▶ High-level, scalable processing framework (programmer productivity)
- ▶ Iterative algorithms
- ▶ Interactive data exploration (Spark shell)

# Apache Spark Unified Large Scale Processing System

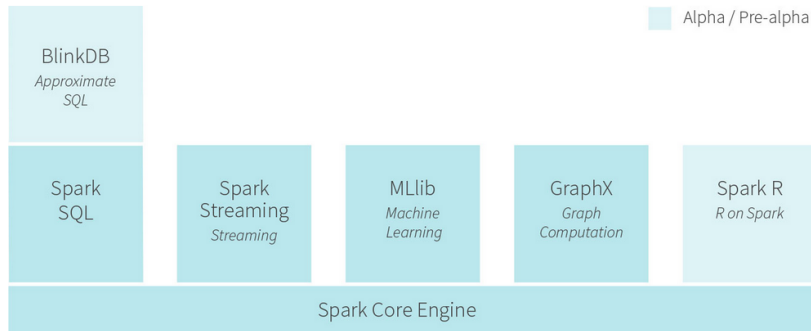


Figure : Databricks Spark Ecosystem (2015)

# Spark Resilient Distributed Dataset (RDD)

- ▶ Treat distributed, immutable data set as a collection
- ▶ Resilient: Use RDD lineage to recompute failed partitions
- ▶ Two forms of RDD operations:
  - ▶ Transformations (applied lazily - optimized evaluation)
  - ▶ Actions (cause transformations to be executed)
- ▶ Scala, Java, Python APIs (Spark R coming)
  - ▶ Rich combinator functions on RDD abstraction



# Exploration: Combinator functions on Scala collections

- ▶ Examples: map, flatMap, filter, reduce, fold, aggregate
- ▶ We will disregard type variance (covariance, contravariance) because RDD is invariant.
- ▶ Background - Combinatory logic, higher-order functions...

# Combinatory Logic

Moses Schönfinkel and Haskell Curry in the 1920s

*[C]ombinator is a higher-order function that uses only function application and earlier defined combinators to define a result from its arguments (Combinatory Logic Wikipedia 2014)*

- Higher-order function: Function that takes function as argument or returns function

# map

- ▶ applies a given function to every element of a collection
- ▶ returns collection of output of that function (one per original element)
- ▶ input argument - same type as collection type
- ▶ return type - can be any type

## map - Scala

```
def computeLength(w: String): Int = w.length

val words = List("when", "shall", "we", "three",
  "meet", "again")
val lengths = words.map(computeLength)

> lengths    : List[Int] = List(4, 5, 2, 5, 4, 5)
```

## map - Scala syntactic sugar

```
//anonymous function (specifying input arg type)  
val list2 = words.map((w: String) => w.length)
```

```
//let compiler infer arguments type  
val list3 = words.map(w => w.length)
```

```
//use positionally matched argument  
val list4 = words.map(_.length)
```

# map - ScalaDoc

See immutable List ScalaDoc

List[A]

...

```
final def map[B](f: (A) => B): List[B]
```

- ▶ Builds a new collection by applying a function to all elements of this list.
- ▶ B - the element type of the returned collection (can be same as A or different)
- ▶ f - the function to apply to each element.
- ▶ returns - a new list resulting from applying the given function f to each element of this list and collecting the results.

# flatMap

- ▶ ScalaDoc:

```
List[A]
```

```
...
```

```
def flatMap[B](f: (A) =>  
                  GenTraversableOnce[B]): List[B]
```

- ▶ GenTraversableOnce - List, Array, Option...
- ▶ can be empty collection or None
- ▶ flatMap takes each element in the GenTraversableOnce and puts it in order to output List[B]
- ▶ removes inner nesting - flattens
- ▶ output list can be smaller or empty (if intermediates were empty)

## flatMap Example

```
val macbeth = """When shall we three meet again?  
|In thunder, lightning, or in rain?""".stripMargin  
val macLines = macbeth.split("\n")  
// macLines: Array[String] = Array(  
  When shall we three meet again?,  
  In thunder, lightning, or in rain?)  
  
//Non-word character split  
val macWordsNested: Array[Array[String]] =  
  macLines.map{line => line.split("""\W+""")}  
//Array(Array(When, shall, we, three, meet, again),  
  //      Array(In, thunder, lightning, or, in, rain))  
  
val macWords: Array[String] =  
  macLines.flatMap{line => line.split("""\W+""")}  
//Array(When, shall, we, three, meet, again, In,  
  //      thunder, lightning, or, in, rain)
```



# filter

```
List[A]
```

```
...
```

```
def filter(p: (A) => Boolean): List[A]
```

- ▶ selects all elements of this list which satisfy a predicate.
- ▶ returns - a new list consisting of all elements of this list that satisfy the given predicate p. The order of the elements is preserved.

## filter Example

```
val macWordsLower = macWords.map{_.toLowerCase}  
//Array(when, shall, we, three, meet, again, in, thunder,  
//      lightning, or, in, rain)  
  
val stopWords = List("in","it","let","no","or","the")  
val withoutStopWords =  
    macWordsLower.filter(word => !stopWords.contains(word))  
// Array(when, shall, we, three, meet, again, thunder,  
//      lightning, rain)
```

# reduce

```
List[A]
```

```
...
```

```
def reduce[A](op: (A, A) => A): A
```

- ▶ Creates one cumulative value using the specified associative binary operator.
- ▶ op - A binary operator that must be associative.
- ▶ returns - The result of applying op between all the elements if the list is nonempty. Result is same type as list type.
- ▶ UnsupportedOperationException if this list is empty.

## reduce Example

```
//beware of overflow if using default Int!  
val numberOfAttachments: List[Long] =  
    List(0, 3, 4, 1, 5)  
val totalAttachments =  
    numberOfAttachments.reduce((x, y) => x + y)  
//Order unspecified/non-deterministic, but one  
//execution could be:  
//0 + 3 = 3, 3 + 4 = 7,  
//7 + 1 = 8, 8 + 5 = 13  
  
val emptyList: List[Long] = Nil  
//UnsupportedOperationException  
emptyList.reduce((x, y) => x + y)
```

# fold

List[A]

...

```
def fold[A](z: A)(op: (A, A) => A): A
```

- ▶ Very similar to reduce but takes start value z (a neutral value, e.g. 0 for addition, 1 for multiplication, Nil for list concatenation)
- ▶ returns start value z for empty list
- ▶ Note: See also foldLeft/Right (return completely different type)

```
foldLeft[B](z: B)(f: (B, A) => B): B
```

## fold Example

```
val numbers = List(1, 4, 5, 7, 8, 11)
val evenCount = numbers.fold(0) { (count, currVal) =>
    println(s"Count: $count, value: $currVal")
    if (currVal % 2 == 0) {
        count + 1
    } else {
        count
    }
}
```

Count: 0, value: 1

Count: 0, value: 4

Count: 1, value: 5

Count: 1, value: 7

Count: 1, value: 8

Count: 2, value: 11

evenCount: Int = 2

# aggregate

```
List[A]  
...  
def aggregate[B] (z: B) (seqop: (B, A) => B,  
                        combop: (B, B) => B): B
```

- ▶ More general than fold or reduce. Can return different result type.
- ▶ Apply seqop function to each partition of data.
- ▶ Then apply combop function to combine all the results of seqop.
- ▶ On a normal immutable list this is just a foldLeft with seqop (but on a parallelized list both operations are called).

## aggregate Example

```
val wordsAll = List("when", "shall", "we", "three",  
    "meet", "again", "in", "thunder", "lightning",  
    "or", "in", "rain")  
//Map(5 letter words ->3, 9->1, 2->4, 7->1, 4->3)  
val lengthDistro = wordsAll.aggregate(Map[Int, Int]())(  
    seqop = (distMap, currWord) =>  
    {  
        val length = currWord.length()  
        val newCount = distMap.getOrElse(length, 0) + 1  
        val newKv = (length, newCount)  
        distMap + newKv  
    },  
    combop = (distMap1, distMap2) => {  
        distMap1 ++ distMap2.map {  
            case (k, v) =>  
                (k, v + distMap1.getOrElse(k, 0))  
        }  
    })
```



# So what does this have to do with Apache Spark?

- ▶ Resilient Distributed Dataset (RDD)
- ▶ From API docs: "immutable, partitioned collection of elements that can be operated on in parallel"
- ▶ map, flatMap, filter, reduce, fold, aggregate...

## com.uebercomputing.analytics.basic.BasicRddFunctions

```
//compiler can infer bodiesRdd type - reader clarity
val bodiesRdd: RDD[String] =
    analyticInput.mailRecordRdd.map { record =>
        record.getBody
    }
val bodyLinesRdd: RDD[String] =
    bodiesRdd.flatMap { body => body.split("\n") }
val bodyWordsRdd: RDD[String] =
    bodyLinesRdd.flatMap { line => line.split("""\W+""") }
val stopWords = List("in", "it", "let", "no", "or", "the")
val wordsRdd = bodyWordsRdd.filter(!stopWords.contains(_))

//Lazy eval all transforms so far - now action!
println(s"There were ${wordsRdd.count()} words.")
```

# Spark - RDD API

- ▶ RDD API
- ▶ Transforms - map, flatMap, filter, reduce, fold, aggregate...
  - ▶ Lazy evaluation (not evaluated until action! Optimizations)
- ▶ Actions - count, collect, first, take, saveAsTextFile...

# Spark - From RDD to PairRDDFunctions

- ▶ If an RDD contains tuples (K,V) - can apply PairRDDFunctions
- ▶ Uses implicit conversion of RDD to PairRDDFunctions
- ▶ In 1.3 conversion is defined in RDD singleton object
- ▶ In 1.2 and previous versions available by importing `org.apache.spark.SparkContext._`

From 1.3.0 `org.apache.spark.rdd.RDD` (object):

```
implicit def rddToPairRDDFunctions[K, V](rdd: RDD[(K, V)])  
(implicit kt: ClassTag[K], vt: ClassTag[V],  
  ord: Ordering[K] = null): PairRDDFunctions[K, V] = {  
  new PairRDDFunctions(rdd)  
}
```

# PairRDDFunctions

- ▶ keys, values - return RDD of keys/values
- ▶ mapValues - transform each value with a given function
- ▶ flatMapValues - flatMap each value (0, 1 or more output per value)
- ▶ groupByKey - `RDD[(K, Iterable[V])]`
  - ▶ Note: expensive for aggregation/sum - use `reduce/aggregateByKey`!
- ▶ reduceByKey - return same type as value type
- ▶ foldByKey - zero/neutral starting value
- ▶ aggregateByKey - can return different type
- ▶ lookup - retrieve all values for a given key
- ▶ join (`left/rightOuterJoin`), `cogroup` ...

# From RDD to DoubleRDDFunctions

- ▶ From API docs: "Extra functions available on RDDs of Doubles through an implicit conversion."
- ▶ mean, stddev, stats (count, mean, stddev, min, max)
- ▶ sum
- ▶ histogram ...

# MailRecord

- ▶ We want to analyze email data
- ▶ Started with Enron email dataset from Carnegie Mellon University
  - ▶ Nested directories for each user/folder/subfolder
  - ▶ Emails as text files with headers (To, From, Subject...)
  - ▶ over 500,000 files (= 500,000 splits for FileInputFormat)
- ▶ Don't want our analytic code to worry about parsing

Solution: Create Avro record format, parse once, store (MailRecord)

# Apache Avro

- ▶ JSON - need to encode binary data
- ▶ Hadoop Writable - Java centric
- ▶ Apache Avro
  - ▶ Binary serialization framework created by Doug Cutting in 2009 (Hadoop, Lucene)
  - ▶ Language bindings for: Java, Scala, C, C++, C#, Python, Ruby
  - ▶ Schema in file - can use generic or specific processing

(Apache Avro Cutting 2009)



# Avro Container File

- ▶ Contains many individual Avro records (~ SequenceFile)
- ▶ Schema for each record at the beginning of file
- ▶ Supports compression
- ▶ Files can be split

# Avro Schema for MailRecord

```
record MailRecord {  
  string uuid;  
  string from;  
  union{null, array<string>} to = null;  
  union{null, array<string>} cc = null;  
  union{null, array<string>} bcc = null;  
  long dateUtcEpoch;  
  string subject;  
  union{null, map<string>} mailFields = null;  
  string body;  
  union{null, array<Attachment>} attachments = null;  
}
```

# Avro Schema for Attachment

```
record Attachment {  
  string fileName;  
  int size;  
  string mimeType;  
  bytes data;  
}
```

# com.uebercomputing.mailrecord.MailRecord

- ▶ Avro Maven plugin translates schema into Java source code
- ▶ spark-mail/mailrecord
  - ▶ src/main/avro/
    - ▶ com/uebercomputing/mailrecord/MailRecord.avdl ->
  - ▶ src/main/java
    - ▶ com/uebercomputing/mailrecord/MailRecord.java

# MailRecord.java

```
//Autogenerated by Avro DO NOT EDIT DIRECTLY
package com.uebercomputing.mailrecord;

public class MailRecord extends
    org.apache.avro.specific.SpecificRecordBase...
    public java.lang.String getFrom() {
        return from;
    }
    public java.lang.String getBody() {
        return body;
    }
    public List<Attachment> getAttachments() {
        return attachments;
    }
}
```

# Converting emails to Avro

- ▶ See `spark-mail/README.md`
- ▶ `spark-mail/PstProcessing.md`

for details on how to go from Enron/PST files to Avro.

# Apache Spark execution environments

- ▶ Local, standalone process (can be started command line or Eclipse)
- ▶ Spark Standalone Cluster (master/workers - <http://spark.apache.org/docs/1.3.0/spark-standalone.html>)
- ▶ Mesos resource manager <http://spark.apache.org/docs/1.3.0/running-on-mesos.html>
- ▶ Hadoop YARN resource manager <http://spark.apache.org/docs/1.3.0/running-on-yarn.html>

# Running Spark

- ▶ Command line interactive shell environment (spark-shell)
- ▶ Submit job (spark-submit)

Both methods can be used in all execution environments.



## Some Spark command arguments

```
spark-shell --help
```

- ▶ `--master MASTER` - e.g. yarn or local.
- ▶ `--driver-memory MEM` - Memory for driver (e.g. 1000M, 2G) (Default: 512M)
- ▶ `--executor-memory MEM` - Memory per executor (e.g. 1000M, 2G) (Default: 1G).
- ▶ `--jars JARS` - Comma-separated list of local jars for driver and executor classpaths.
- ▶ `--conf PROP=VALUE` Arbitrary Spark configuration property.
- ▶ `--properties-file FILE` Path for extra properties. If not specified, conf/spark-defaults.conf.

# Spark Serialization

- ▶ Default - Java Serialization (`java.io.ObjectOutputStream`).  
Classes must implement `java.io.Serializable` otherwise:

```
java.io.NotSerializableException:
```

```
...
```

```
    at java.io.ObjectOutputStream.writeObject0  
    (ObjectOutputStream.java:1183)
```

- ▶ Better: Kryo "significantly faster and more compact than  
Java serialization (often as much as 10x)"

## com.uebercomputing.mailrecord.MailRecordRegistrar

```
import org.apache.spark.serializer.KryoRegistrar
import com.esotericsoftware.kryo.Kryo
import com.twitter.chill.avro.AvroSerializer

//Uses Twitter's chill-avro library.
class MailRecordRegistrar extends KryoRegistrar {

  def registerClasses(kryo: Kryo): Unit = {
    kryo.register(classOf[MailRecord],
      AvroSerializer.
        SpecificRecordBinarySerializer[MailRecord])
  }
}
```

# Spark Kryo Configurations

- ▶ `spark.serializer` - `org.apache.spark.serializer.KryoSerializer`
- ▶ `spark.kryo.registrator`
- ▶ `spark.kryoserializer.buffer.mb`
- ▶ `spark.kryoserializer.buffer.max.mb`

# Kryo configurations

From command line:

```
--conf spark.serializer=\  
org.apache.spark.serializer.KryoSerializer \  
--conf spark.kryo.registrator=\  
com.uebercomputing.mailrecord.MailRecordRegistrator \  
--conf spark.kryoserializer.buffer.mb=128 \  
--conf spark.kryoserializer.buffer.max.mb=512 \  

```

# Kryo configuration properties file

spark-mail/mailrecord-utils/mailrecord.conf

```
spark.serializer=org...serializer.KryoSerializer  
spark.kryo.registrator=com...MailRecordRegistrator  
spark.kryoserializer.buffer.mb=128  
spark.kryoserializer.buffer.max.mb=512
```

# Starting Spark interactive exploration

From spark-mail directory:

```
spark-shell --master local[4] --driver-memory 4G \  
--executor-memory 4G \  
--jars mailrecord-utils/target/mailrecord-*-shaded.jar \  
--properties-file mailrecord-utils/mailrecord.conf \  
--driver-java-options \  
  "-Dlog4j.configuration=log4j.properties"
```

## Getting an RDD of MailRecords

With spark-mail utilities:

```
import com.uebercomputing.mailrecord._
import com.uebercomputing.mailrecord.Implicits._

val args =
  Array("--avroMailInput",
        "/opt/rpm1/enron/filemail.avro")
val config =
  CommandLineOptionsParser.getConfigOpt(args).get
val recordsRdd =
  MailRecordAnalytic.getMailRecordRdd(sc, config)
```



## Under the Hood - newAPIHadoopRDD in SparkContext

com.uebercomputing.mailrecord.MailRecordAnalytic.scala

```
val sparkHadoopConf = sc.hadoopConfiguration
hadoopConf.addResource(sparkHadoopConf)
hadoopConf.setBoolean(
  FileInputFormat.INPUT_DIR_RECURSIVE, true)
val mailRecordsAvroRdd =
  sc.newAPIHadoopFile(config.avroMailInput,
    classOf[MailRecordInputFormat],
    classOf[AvroKey[MailRecord]],
    classOf[FileSplit], hadoopConf)
```

## mailrecord-utils - MailRecordInputFormat.scala

```
class MailRecordInputFormat extends
  FileInputFormat[AvroKey[MailRecord], FileSplit]
...
class MailRecordRecordReader(val readerSchema: Schema,
  val fileSplit: FileSplit) extends
  AvroRecordReaderBase
```

# Hadoop InputFormats - Minimize object creation!

- ▶ WARNING: Hadoop InputFormats generally reuse the key/value objects
- ▶ Same with AvroRecordReaderBase in MailRecordInputFormat
- ▶ Generally, not a problem if you just map out the fields you need (getFrom etc.)
- ▶ However, if you want to cache the whole MailRecord you need to copy the original:

```
val mailRecordsRdd = mailRecordsAvroRdd.map {  
  case (mailRecordAvroKey, fileSplit) =>  
    val mailRecord = mailRecordAvroKey.datum()  
    //make a copy - MailRecord gets reused!!!  
    MailRecord.newBuilder(mailRecord).build()  
}
```

# Analytic 1 - Mail Folder Statistics

- ▶ What are the least/most/average number of folders per user?
- ▶ Each MailRecord has user name and folder name

```
lay-k/      <- mailFields(UserName)
  business  <- mailFields(FolderName)
  family
  enron
  inbox
  ...
```

# Hadoop Mail Folder Stats - Mapper

- ▶ read each mail record
- ▶ emits key: userName, value: folderName for each email

# Hadoop Mail Folder Stats - Reducer

- ▶ reduce method
  - ▶ create set from values for a given key (unique folder names per user)
  - ▶ `set.size ==` folder count
  - ▶ keep adding up all `set.size` (`totalNumberOfFolders`)
  - ▶ one up counter for each key (`totalUsers`)
  - ▶ keep track of min/max count
- ▶ cleanup method
  - ▶ compute average for this partition:  
`totalNumberOfFolders/totalUsers`
  - ▶ write out min, max, `totalNumberOfFolders`, `totalUsers`, `avgPerPartition`

# Hadoop Mail Folder Stats - Driver

- ▶ Set Input/OutputFormat
- ▶ Number of reducers

# Hadoop Mail Folder Stats - Results

- ▶ if only one reducer - results are overall lowest/highest/avg
- ▶ if multiple reducers
  - ▶ post-processing overall lowest/highest
  - ▶ add totalNumberOfFolders and totalUsers to compute overall average



# Hadoop Mapper

```
public void map(AvroKey<MailRecord> key,
NullWritable value, Context context) throws ... {
    MailRecord mailRecord = key.datum();
    Map<CharSequence, CharSequence> mailFields =
        mailRecord.getMailFields();
    CharSequence userName =
        mailFields.get(AvroMailMessageProcessor.USER_NAME);
    CharSequence folderName =
        mailFields.get(AvroMailMessageProcessor.FOLDER_NAME);
    userKey.set(userName.toString());
    folderValue.set(folderName.toString());
    context.write(userKey, folderValue);
}
```

# Hadoop Reducer

```
public void reduce(Text userKey,
    Iterable<Text> folderValues,
    Context context) throws ... {
    Set<String> uniqueFolders = new HashSet<String>();
    for (Text folder : folderValues) {
        uniqueFolders.add(folder.toString());
    }
    int count = uniqueFolder.size();
    if (count > maxCount) maxCount = count;
    if (count < minCount) minCount = count;
    totalNumberOfFolder += count
    totalUsers++
}
...
public void cleanup...
//write min, max, totalNumberOfFolders,
//totalUsers, avgPerPartition
```

# Spark Mail Folder Stats

- ▶ Create (user,folder) tuple for each email
- ▶ Aggregate by key (PairRDDFunctions)- for each key, create set of folders (distinct)
- ▶ Map values for each key (set) to the set's size:
  - ▶ (String, Int) represents (userName, # of folders for that user)
- ▶ Create an RDD from just the values (folder sizes for all users)
- ▶ Gather statistics on values (DoubleRDDFunction) (count, min, max, mean, stddev)
- ▶ Create a histogram (DoubleRDDFunction)

## Spark - Creating an RDD of 2-Tuples via flatMap

```
val userFolderTuplesRdd: RDD[(String, String)] =  
  analyticInput.mailRecordsRdd.flatMap {  
    mailRecord =>  
      val userNameOpt =  
        mailRecord.getMailFieldOpt(UserName)  
      val folderNameOpt =  
        mailRecord.getMailFieldOpt(FolderName)  
  
      if (userNameOpt.isDefined &&  
          folderNameOpt.isDefined) {  
        Some((userNameOpt.get, folderNameOpt.get))  
      } else {  
        None  
      }  
    }  
  }  
  
userFolderTuplesRdd.cache()
```

## Spark - applying PairRDDFunctions

```
//pre Spark 1.3.0: import org.apache.spark.SparkContext._
import scala.collection.mutable.{ Set => MutableSet }
...
//mutable set - reduce object creation/garbage collection
val uniqueFoldersByUserRdd:
  RDD[(String, MutableSet[String])] =
    userFolderTuplesRdd.aggregateByKey(
      MutableSet[String]())(
      seqOp = (folderSet, folder) => folderSet + folder,
      combOp = (set1, set2) => set1 ++ set2)

val folderPerUserRddExact: RDD[(String, Int)] =
  uniqueFoldersByUserRdd.mapValues { set => set.size }
```

## DoubleRDDFunctions - Stats

```
val folderCounts: RDD[Int] =  
    folderPerUserRddExact.values
```

```
val stats = folderCounts.stats()  
> stats: org.apache.spark.util.StatCounter =  
(count: 150, mean: 22.033333, stdev: 26.773474,  
 max: 193.000000, min: 2.000000)
```

```
//buckets 0-25, 25-50 etc.
```

```
val buckets = Array(0.0,25,50,75,100,125,150,175,200)  
folderCounts.histogram(buckets, evenBuckets=true)  
res13: Array[Long] = Array(116, 16, 11, 3, 2, 1, 0, 1)
```

# Who has 193 folders?

- ▶ RDD - `def max()(implicit ord: Ordering[T]): T`  
`folderPerUserRddExact.max()`  
`Ordering.by(tuple => tuple._2)`  
`> res2: (String, Int) = (kean-s, 193)`

## RDD Lineage - transformations

```
folderCounts.toDebugString
> res18: String =
(22) MappedRDD[27] at values at <console>:35 []
|   MappedValuesRDD[26] at mapValues at <console>:33 []
|   ShuffledRDD[25] at aggregateByKey at <console>:31 []
+--(22) FlatMappedRDD[2] at flatMap at <console>:26 []
|       CachedPartitions: 22; MemorySize: 76.3 MB;
|       TachyonSize: 0.0 B; DiskSize: 0.0 B
|   MappedRDD[1] at map at MailRecordAnalytic.scala:48 []
|   NewHadoopRDD[0] at newAPIHadoopRDD at
|       MailRecordAnalytic.scala:94 []
```



# References I

Cutting, Doug. 2009. "Apache Avro."

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

Dale, Markus, Jeff Schmidt, JT Halbert, and Jason Morris. 2015.  
"Spark Mail Tutorial."

<https://github.com/medale/spark-mail>.

Ecosystem. 2015. "Databricks Spark Ecosystem."

<https://databricks.com/spark/about>.

Wikipedia. 2014. "Combinatory Logic."

[http://en.wikipedia.org/wiki/Combinatory\\_logic](http://en.wikipedia.org/wiki/Combinatory_logic).