

Apache Spark - The Scala Killer App?

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Slides And Code

- ▶ Slides: <https://github.com/medale/spark-mail/blob/master/presentation/Spark-ScalaKillerApp.pdf>
- ▶ Spark Code Examples:
<https://github.com/medale/spark-mail/>

What's Apache Spark?

- ▶ Next generation large-scale data processing framework written in Scala
- ▶ Replacement for Hadoop MapReduce?
 - ▶ In-memory caching
 - ▶ Advanced directed acyclic graph of computations - optimized
 - ▶ Rich Scala, Java, Python and R APIs - 2-5x less code than Hadoop M/R

Apache Spark Buzz

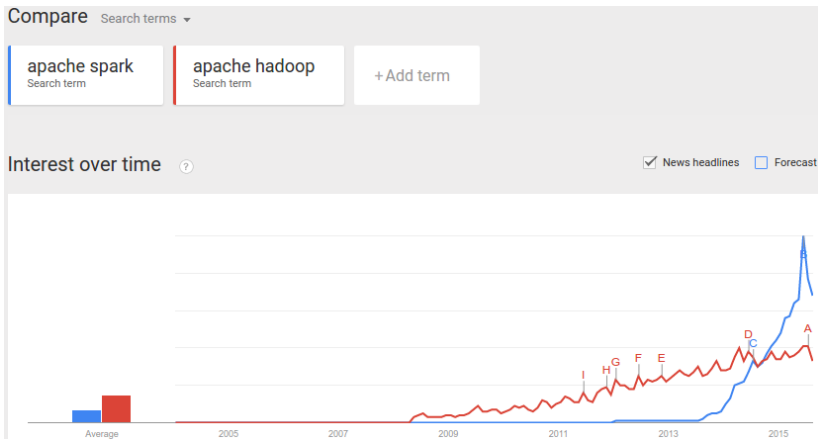


Figure : Google Trends Apache Spark/Apache Hadoop August 2015

Spark Ecosystem

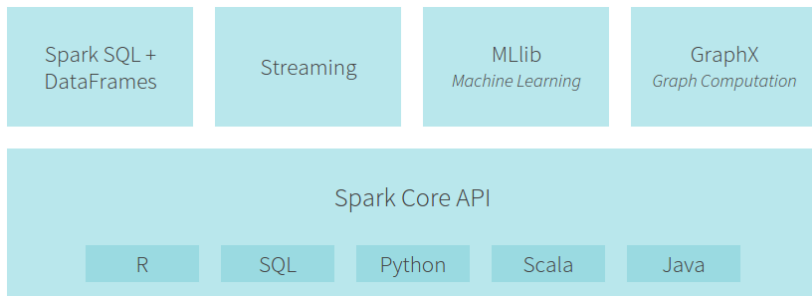
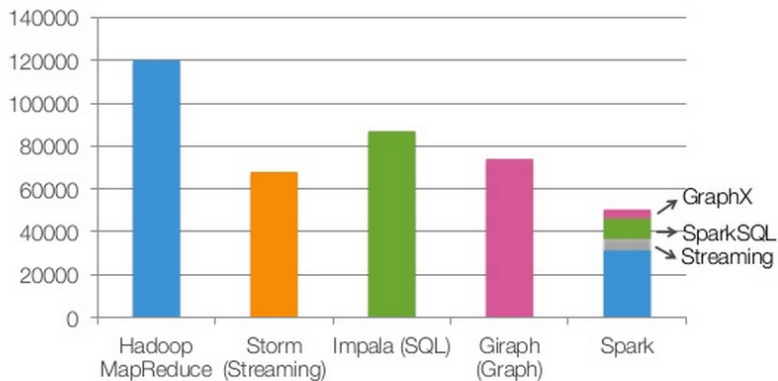


Figure : Databricks Spark 1.4.1 Ecosystem (2015)

Spark Lines of Code



non-test, non-example source lines



Figure : Spark LOC Armbrust (2014)

Spark Academic Papers

- ▶ Spark: Cluster computing with working sets, 2010 (Zaharia et al. 2010)
- ▶ Resilient Distributed Datasets: A fault-tolerant abstraction for in-memory cluster computing, 2012 (Zaharia et al. 2012)
- ▶ GraphX: A Resilient Distributed Graph System on Spark, 2013 (Xin et al. 2013)
- ▶ Spark SQL: Relational data processing in Spark, 2015 (Armbrust et al. 2015)
- ▶ MLlib: Machine Learning in Apache Spark, 2015 (Meng et al. 2015)

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)
- ▶ Rich functions on RDD abstraction (Zaharia et al. 2012)

Combinator functions on Scala collections

- Examples: map, flatMap, filter, reduce, fold, aggregate...

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)
```

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...

```
//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 ...

References I

Armbrust, Michael. 2014. "Intro To Spark and Spark SQL." Berkeley, CA, USA. <http://www.slideshare.net/jeykottalam/spark-sqlamp-camp2014>.

Armbrust, Michael, Reynold S. Xin, Cheng Lian, Yin Huai, Davies Liu, Joseph K. Bradley, Xiangrui Meng, et al. 2015. "Spark SQL - Relational Data Processing in Spark." In *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, 1383–1394. SIGMOD '15. New York, NY, USA: ACM. doi:10.1145/2723372.2742797. <http://doi.acm.org/10.1145/2723372.2742797>.

Ecosystem. 2015. "Databricks Spark Ecosystem." <https://databricks.com/spark/about>.

Meng, Xiangrui, Joseph Bradley, Burak Yavuz, Evan Sparks, Shivaram Venkataraman, Davies Liu, Jeremy Freeman, et al. 2015.

References II

“MLlib - Machine Learning in Apache Spark.” *ArXiv Preprint ArXiv:1505.06807*.

Xin, Reynold S., Joseph E. Gonzalez, Michael J. Franklin, and Ion Stoica. 2013. “GraphX - A Resilient Distributed Graph System on Spark.” In *First International Workshop on Graph Data Management Experiences and Systems*, 2:1–2:6. GRADES '13. New York, NY, USA: ACM. doi:10.1145/2484425.2484427. <http://doi.acm.org/10.1145/2484425.2484427>.

Zaharia, Matei, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, and Ion Stoica. 2012. “Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing.” In *Proceedings of the 9th USENIX Conference on Networked Systems Design and Implementation*, 2–2. NSDI'12. Berkeley, CA, USA: USENIX Association. <http://dl.acm.org/citation.cfm?id=2228298.2228301>.

References III

Zaharia, Matei, Mosharaf Chowdhury, Michael J Franklin, Scott Shenker, and Ion Stoica. 2010. “Spark - Cluster Computing with Working Sets.” In *Proceedings of the 2nd USENIX Conference on Hot Topics in Cloud Computing*, 10:10.