Introduction to Distributed Computing with Spark

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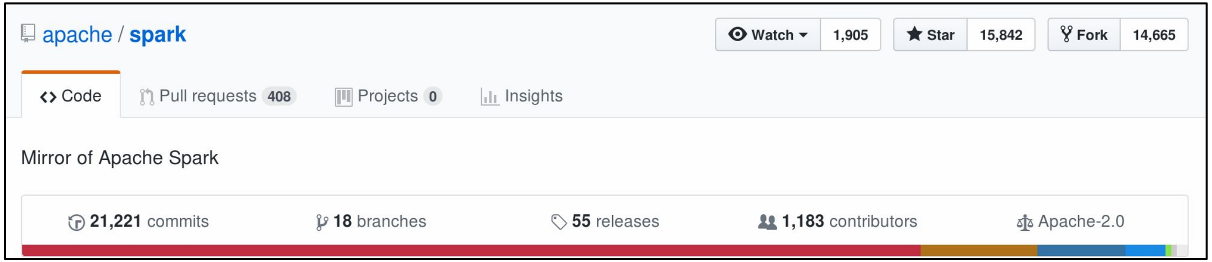
Credit: Tristan Glatard - Big Data Analytics

Scope

- Most active open-source project in Big Data Analytics



- Used in thousands organizations from diverse sectors:
  - Technology, banking, retail, biotech, astronomy
- Deployments with up to 8,000 nodes have been announced

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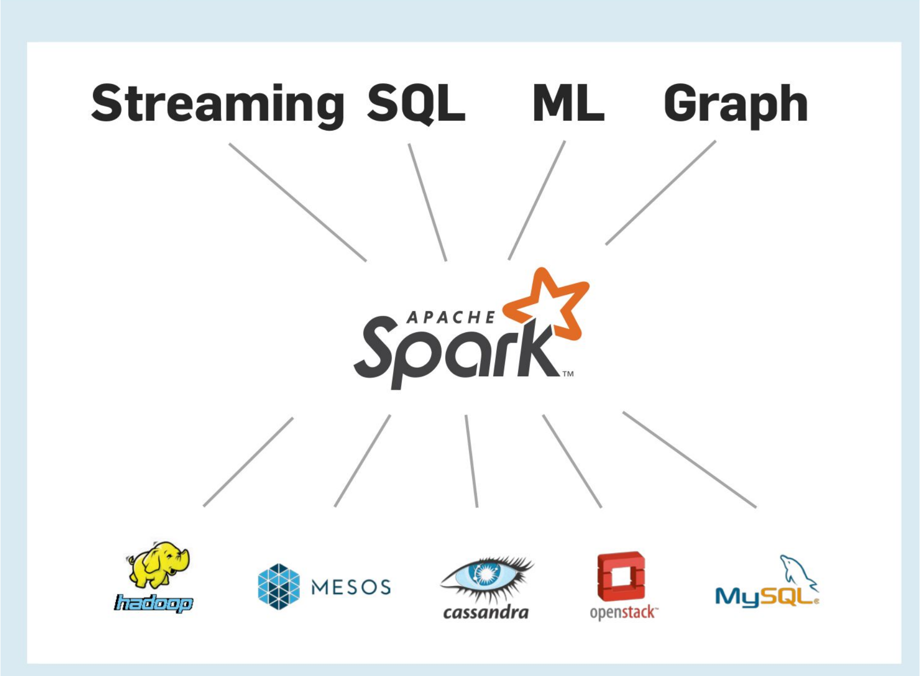
Introduction

- **We need cluster computing to analyse Big Data**
- **There has been an explosion of specialized computing models**
  - MapReduce
  - Google's Dremel (SQL) and Pregel (graphs)
  - Hadoop's Storm, Impala, etc
- **Big Data applications need to combine many types of processing**
  - To handle data variety
  - Users need to stitch systems together

Introduction (2)

- The profusion of systems is detrimental to
  - Usability
  - Performance
- Spark provides a uniform framework for Big Data Analytics

Figure 1. Apache Spark software stack, with specialized processing libraries implemented over the core engine.



Highlights

- **Spark concepts**
  - Built around a *data structure*: Resilient Distributed Datasets (RDDs)
  - Programming model is MapReduce + extensions
- **Added value compared to MapReduce**
  - Easier to program because API is unified
  - Interactive explorations of Big Data are possible (pyspark)
  - More efficient to combine multiple tasks (workflows) due to lazy evaluation.

In-memory processing

- **Spark keeps data in memory**
  - Reduces disk I/O
  - Spills to disk if not enough space

- **MapReduce lacks abstraction to leverage distributed memory**
  - Inefficient for applications that *reuse* intermediate results
  - For instance *iterative* algorithms: kmeans, PageRank

Programming model: RDDs

RDDs are fault-tolerant collections of objects partitioned across a cluster that can be manipulated in parallel.

RDD abstraction

- **An RDD is a read-only, partitioned collection of records.**
  - RDD is fault-tolerant, hence it is read-only.
- **Can be created through operations on:**
  - Data in stable storage (e.g., sc.textFile)
  - Other RDDs: transformations
  - Existing collections (sc.parallelize)

Functional programming API

- Transformations:
    - Return RDDs
    - Are parametrized by user-provided functions

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(
  s => s.startsWith("ERROR"))
println("Total errors: "+errors.count())
```

- Actions return results to application or storage system

RDD transformations and actions

Transformations Return an RDD	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	RDD[T] $\Rightarrow$ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	RDD[T] $\Rightarrow$ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	RDD[T] $\Rightarrow$ RDD[U]
	$sample(fraction : \mathrm{Float})$	RDD[T] $\Rightarrow$ RDD[T] (Deterministic sampling)
	$groupByKey()$	RDD[(K, V)] $\Rightarrow$ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$union()$	(RDD[T], RDD[T]) $\Rightarrow$ RDD[T]
	$join()$	(RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (V, W))]
	$cogroup()$	(RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (Seq[V], Seq[W]))]
	$crossProduct()$	(RDD[T], RDD[U]) $\Rightarrow$ RDD[(T, U)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	RDD[(K, V)] $\Rightarrow$ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
Actions Return something else	$count()$	RDD[T] $\Rightarrow$ Long
	$collect()$	RDD[T] $\Rightarrow$ Seq[T]
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	RDD[T] $\Rightarrow$ T
	$lookup(k : \mathrm{K})$	RDD[(K, V)] $\Rightarrow$ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	Outputs RDD to a storage system, *e.g.*, HDFS

Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

(K, V) is a key-value pair
MapReduce = flatMap + reduceByKey

Credit: Tristan Glatard - Big Data Analytics

Lazy evaluation

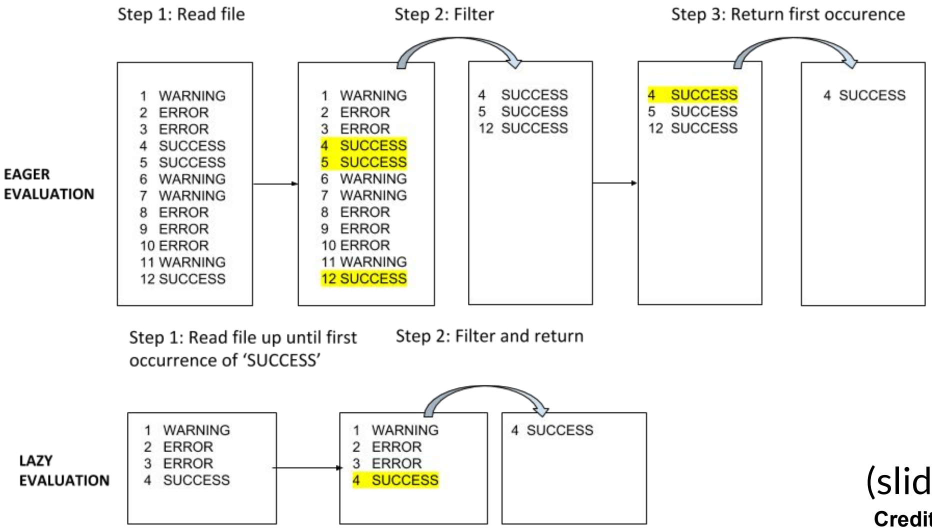
- **Transformations do not compute RDDs immediately**
  - The returned RDD object is a representation of the result
- **Actions trigger computations**
- **This allows optimization in the execution plan**
  - Multiple map operations are fused in one pass
  - While preserving modularity

Lazy evaluation (2)

Computations are costly and memory is limited → Compute only what is necessary

PIPELINE: Read file → Filter lines containing 'SUCCESS' → Return first line containing 'SUCCESS'

Note:
With *eager evaluation*, the entire file must be read and filtered.
Lazy evaluation limits the amount of data that needs to be processed



(slide from V. Hayot-Sasson)

Persistence (or caching)

- By default RDDs are ephemeral
- They might be evicted from memory
- Users can persist RDDs in memory or on disk, by calling .persist()
- persist() accepts priorities for spilling to disk

Example: Log Mining

Reads from HDFS

Nothing has executed so far (lazy)

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
errors.persist()
```

Triggers execution

```
errors.count()
```

```
// Count errors mentioning MySQL:
errors.filter(_.contains("MySQL")).count()
```

Other uses of errors won't reload data from the text file.

```
// Return the time fields of errors mentioning
// HDFS as an array (assuming time is field
// number 3 in a tab-separated format):
errors.filter(_.contains("HDFS"))
      .map(_.split('\t')(3))
      .collect()
```

Lines is never stored in memory!

Lineage graph

An RDD maintains information on how it was derived from other datasets.

From the lineage, the RDD can be completely (re-)computed.

This is used for **fault-tolerance**.

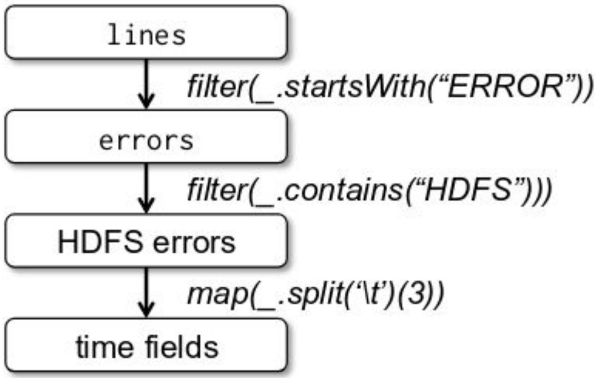


Figure 1: Lineage graph for the third query in our example. Boxes represent RDDs and arrows represent transformations.

Spark programming interface

- **Driver**
  - Runs user program
  - Defines RDDs and invokes actions
  - Tracks the lineage
- **Workers**
  - Long-lived processes
  - Store RDD partitions in RAM across operations

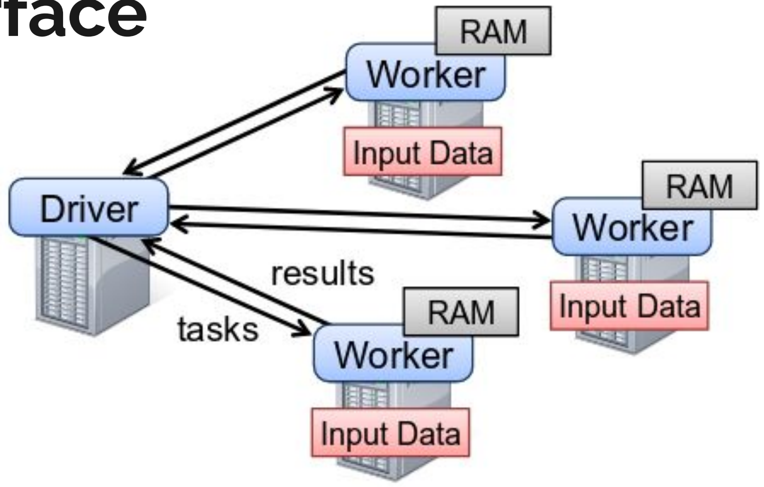


Figure 2: Spark runtime. The user's driver program launches multiple workers, which read data blocks from a distributed file system and can persist computed RDD partitions in memory.

Fault tolerance

- **When a task fail**
  - If parent partitions are available: re-submit to another node
  - Otherwise: resubmit tasks to recompute missing partitions
- **Checkpointing**
  - Lineage-based recovery of RDDs may be time-consuming
  - RDDs can be checkpointed to stable storage, through a flag to .persist()

Spark DataFrames

- A DataFrame is a set of records with a known schema
- A DataFrame is an RDD
- DataFrame operations map to the SQL engine

```
>>> df.printSchema()
root
 |-- Nom_arrond: string (nullable = true)
 |-- Invent: string (nullable = true)
 |-- no_civiq: string (nullable = true)
 |-- Rue: string (nullable = true)
 |-- Rue_De: string (nullable = true)
 |-- Rue_A: string (nullable = true)
 |-- Nom_parc: string (nullable = true)
 |-- Sigle: string (nullable = true)
 |-- Injections: string (nullable = true)
 |-- x: string (nullable = true)
 |-- y: string (nullable = true)
 |-- longitude: string (nullable = true)
 |-- latitude: string (nullable = true)
```

```
>>> df.where(df.Nom_arrond=="Outremont").select(df.Rue)
nt().orderBy(df.Rue).show(100)
+--------------------+-----+
|                 Rue|count|
+--------------------+-----+
|     Ainslie, avenue|    1|
|Antonine-Maillet,...|    1|
|     Beloeil, avenue|   26|
|   Bloomfield, avenue|    6|
|Brunante, avenue ...|    1|
|      Cambrai, place|    1|
```

Recap

General framework (increases usability and performance)

Rich programming model (transformations, actions, libraries)

Data locality (as in MapReduce)

RDDs remain in-memory (reduces disk I/O)

Lazy RDD evaluations (allow for merging transformations)

Fault-tolerance through lineage (better than data replication)

Installing PySpark

- Make sure Java (JDK) is installed.
- Install PySpark:

```
pip install pyspark
```

- For Windows, make sure environment variables are set correctly and winutils.exe is installed. For a step-by-step guide, see here .

PySpark Hello World

```
import pyspark
sc = pyspark.SparkContext('local[*]')

txt = sc.textFile('sample.log')

error_lines = txt.filter(lambda line: 'error' in line)

print(error_lines.count())
```

Credit: https://realpython.com/pyspark-intro/