TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA
Macroarea di Ingegneria
Dipartimento di Ingegneria Civile e Ingegneria Informatica

Apache Spark

Corso di Sistemi e Architetture per Big Data

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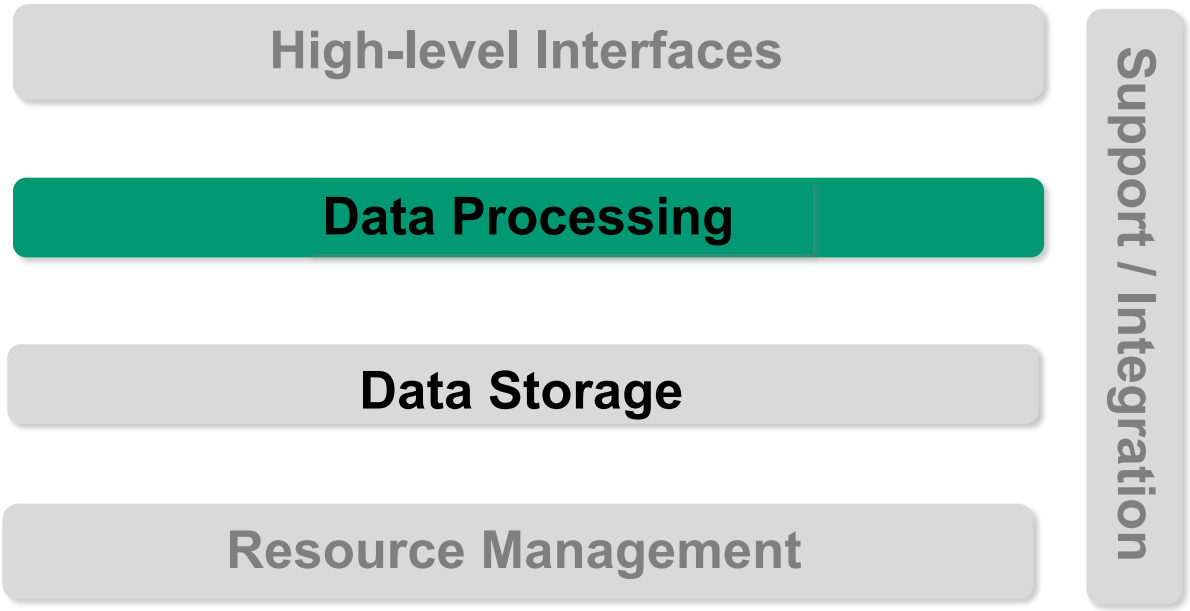
Valeria Cardellini

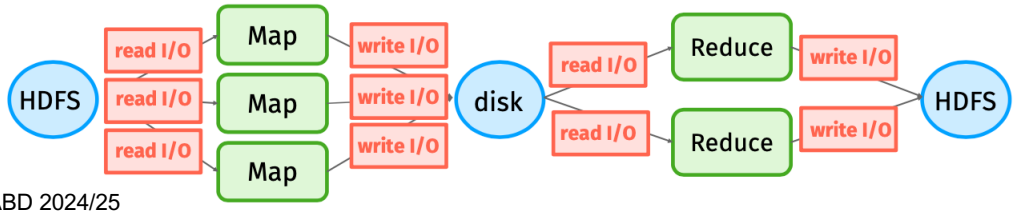
Laurea Magistrale in Ingegneria Informatica

The reference Big Data stack



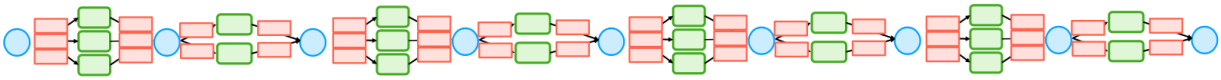
MapReduce (MR): limitations

- Programming model
  - Hard to implement everything as a MR program
  - Multiple MR steps even for simple tasks
    - E.g., sorting words by their frequency requires two MR steps
  - Lack of control, structures and data types
- Efficiency (recall HDFS)
  - High communication cost: compute (map), communicate (shuffle), compute (reduce)
  - Read input and store output from/on disk
  - Limited exploitation of main memory



MapReduce: limitations

- Lack of native support for iteration
  - Each step writes/reads data from disk: I/O overhead
  - But real-world applications (e.g., ML algorithms) require iterating MR steps
    - Partial solution: design algorithms that minimize the number of iterations



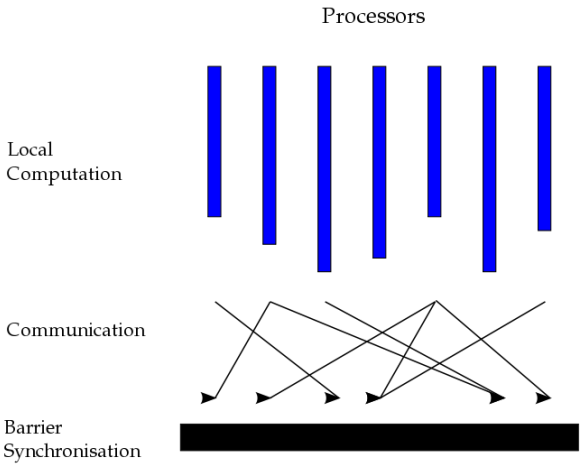
- Not feasible for real-time data stream processing
  - MR job requires to scan entire input before processing it

Alternative programming models

- Based on *directed acyclic graphs* (**DAGs**)
  - Application structured as directed acyclic graph
    - DAG node: operation (or task)
    - DAG edge: dependency (data flow) between operations
  - Spark, Spark Streaming, Flink, Storm, Airflow, TensorFlow, …
- SQL-based
  - Hive, Spark SQL, Trino, Vertica, …
- NoSQL and NewSQL data stores
  - HBase, MongoDB, Cassandra, Spanner, …
- Based on *Bulk Synchronous Parallel*

Alternative programming models: BSP

- Bulk Synchronous Parallel (BSP)
  - Developed by Leslie Valiant during 1980s
  - Considers communication actions *en masse*
  - Suitable for graph analytics at massive scale and massive scientific computations (e.g., matrix, graph and network algorithms)
  - Examples: Google's Pregel, Apache Giraph to perform graph processing on big data

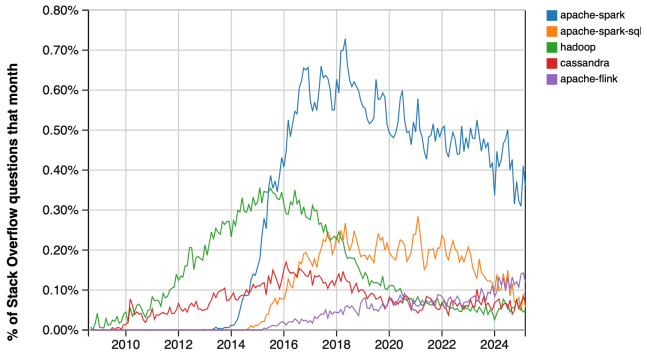


Apache Spark

- Unified engine for large-scale data analytics
  - Leading platform for batch/streaming data, SQL analytics, data science and machine learning on clusters of nodes
  - Multi-language: Scala, Python, Java and R
- In-memory data storage for fast iterative processing
  - At least 10x faster than Hadoop MapReduce
- Suitable for execution of DAGs and powerful optimization
- Compatible with Hadoop's storage APIs
  - Can read/write to any Hadoop-supported system, including HDFS and HBase

Spark milestones

- Spark project started in 2009
- Developed originally at UC Berkeley's AMPLab by Matei Zaharia for his PhD thesis
- Open sourced in 2010, Apache project since 2013
- Zaharia founded Databricks in 2014 https://databricks.com/
- Current release: 3.5.5
- Top open source project for Big Data processing



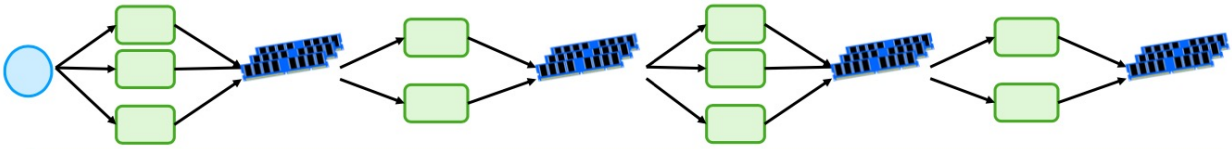
Programming model different from Mapreduce, why?

- MapReduce simplified Big Data analysis
  - But executes jobs in a simple but rigid structure
    - Step to process or transform data (map)
    - Step to synchronize (shuffle)
    - Step to combine results (reduce)

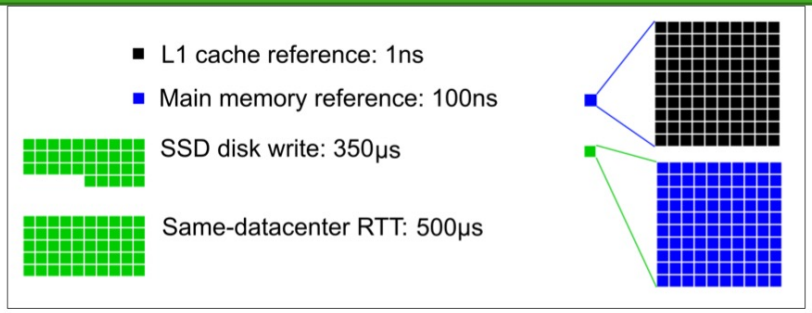
- As soon as MapReduce got popular, users wanted:
  - Iterative computations, e.g., graph and ML algorithms
  - Interactive ad-hoc queries
  - More efficiency
  - Faster **in-memory data sharing** across parallel jobs (required by both iterative and interactive applications)

Spark: In-memory computation

- Key idea: keep and share datasets in main memory
- Distributed in-memory: 10x-100x faster than disk and network



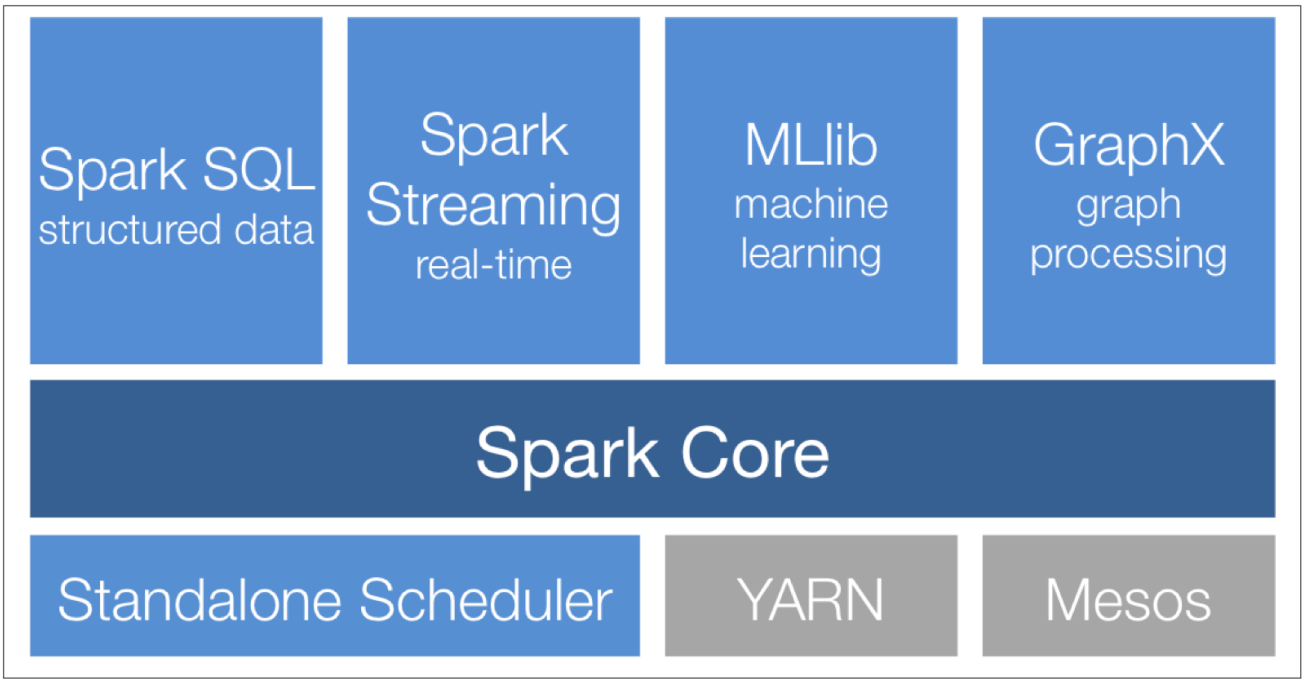
Much faster response time (in practice: 10x-100x)



Spark vs Hadoop MapReduce

- Underlying programming paradigm similar to MapReduce
  - Basically "scatter-gather": scatter data and computation on multiple cluster nodes that run in parallel processing on data portions; gather final results
- Spark offers a more general data model
  - RDDs, DataSets, DataFrames
- Spark offers a more general and developer-friendly programming model
  - Map -> **Transformations** in Spark
  - Reduce -> **Actions** in Spark
- Spark is storage agnostic
  - Not only HDFS, but also Cassandra, S3, Parquet files, …

Spark stack



Spark core

- Provides basic functionalities (including task scheduling, memory management, fault recovery, interacting with storage systems) used by other components
- Provides a data abstraction called **resilient distributed dataset (RDD)**, a collection of items distributed across many compute nodes that can be manipulated in parallel
  - Spark Core provides APIs for building and manipulating these collections
- Written in Scala but APIs for Java, Python and R

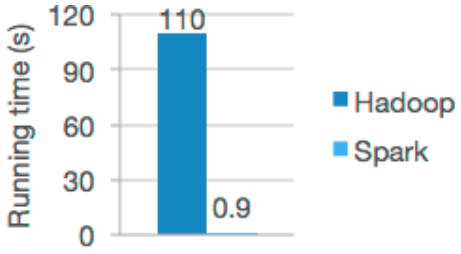
Spark as unified analytics engine

- Rich set of integrated higher-level modules built on top of Spark
  - Can be combined seamlessly within same app
- **Spark SQL**
  - For SQL and structured data processing
  - Supports many data sources (Hive tables, Parquet, JSON, …)
- **Structured Streaming**
  - For incremental computation and stream processing

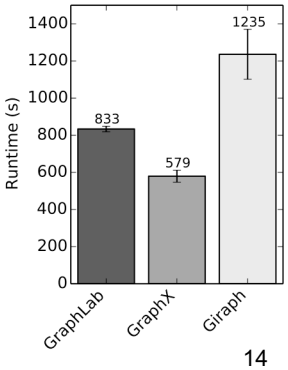
Spark as unified analytics engine

- **MLlib**
  - Scalable ML library
  - Distributed ML algorithms: feature extraction, classification, regression, clustering, recommendation, …
- **GraphX**
  - API for manipulating graphs and performing graph-parallel computations
  - Includes also common graph algorithms (e.g., PageRank)
- **Pandas API on Spark**
  - For pandas workloads

Logistic regression performance



PageRank performance (20 iterations, 3.7B edges)



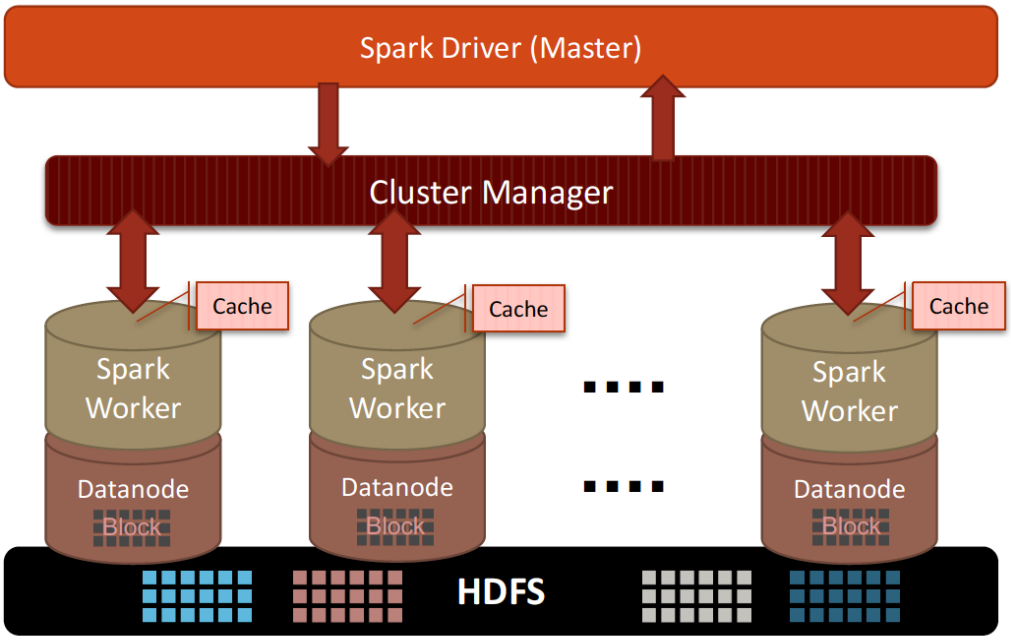
Spark on top of cluster managers

- Spark can exploit many cluster resource managers which allocate cluster resources to run the applications

1. Standalone
   - Simple cluster manager included with Spark that makes it easy to set up a cluster
2. Hadoop YARN
   - Hadoop cluster manager
3. Mesos
   - Cluster manager from AMPLab
4. Kubernetes

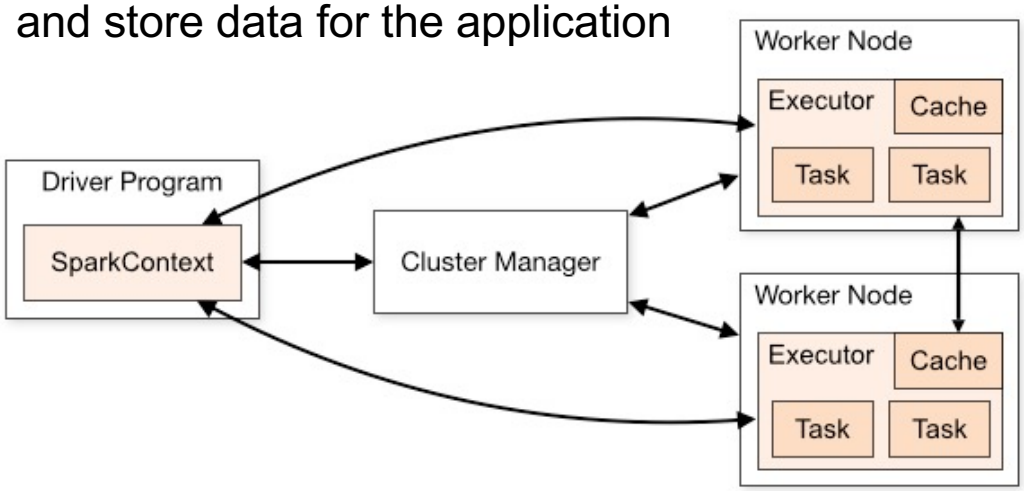
Spark architecture

- Master/worker architecture



Spark architecture

- Main program (called driver program) connects to cluster manager, which allocates resources
- Worker nodes in which executors run
- Executors are processes that run computations and store data for the application

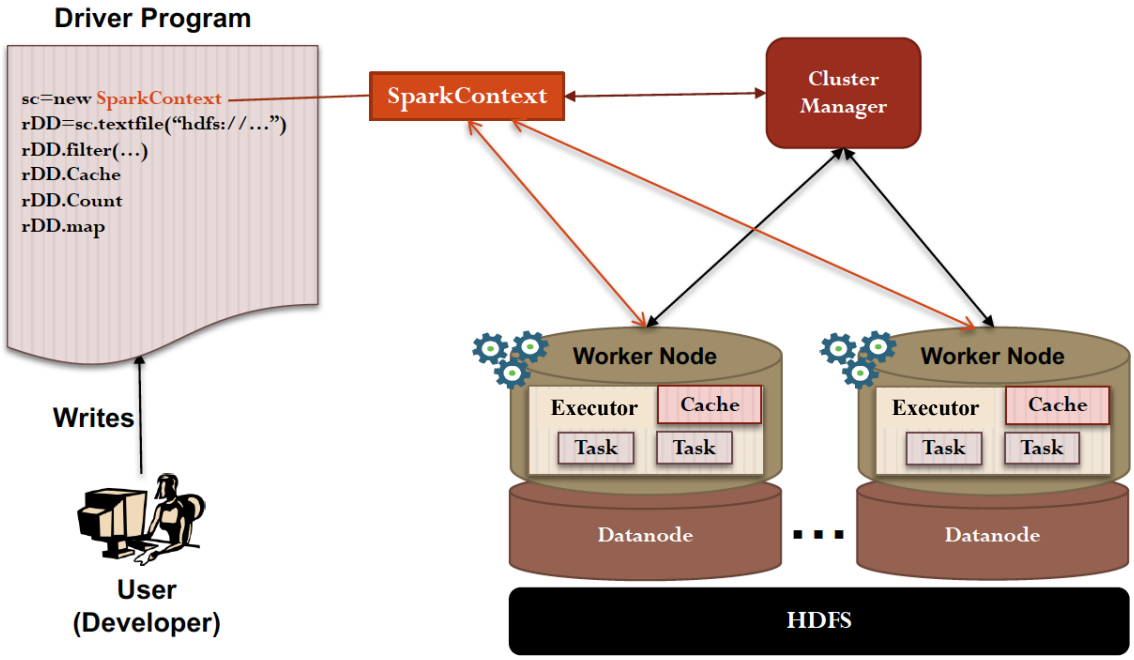


https://spark.apache.org/docs/latest/cluster-overview.html

Spark architecture

- Each application consists of a driver program and executors on the cluster
  - Driver program: process which runs user's `main` function and creates SparkContext object
  - SparkContext: main entry point for Spark functionality, tells Spark how to access a cluster
- Each application gets its own executors, which are processes which stay up for the duration of the application and run tasks in multiple threads
  - Isolation of concurrent applications
- To run on a cluster:
  - SparkContext connects to cluster manager, which allocates cluster resources
  - Once connected, Spark acquires executors on cluster nodes and sends the application code (e.g., jar) to executors
  - Finally, SparkContext sends tasks to executors to run

Spark architecture



Resilient Distributed Datasets (RDDs)

- RDDs are the key programming abstraction in Spark: a distributed memory abstraction
- Immutable, partitioned and fault-tolerant collection of elements that can be manipulated in parallel
  - Like a LinkedList <MyObjects>
  - Stored in main memory across the cluster nodes
    - Each worker node that is used to run an application contains at least one partition of the RDD(s) that is (are) defined in the application

RDDs: distributed and partitioned

- Stored in main memory of the executors running in the worker nodes (when it is possible) or on node local disk (if not enough main memory)
- Allow executing in parallel the code invoked on them
  - Each executor of a worker node runs the specified code on its partition of the RDD
  - Partition: atomic chunk of data (a logical division of data) and basic unit of parallelism
  - Partitions of an RDD can be stored on different cluster nodes

RDDs: immutable and fault-tolerant

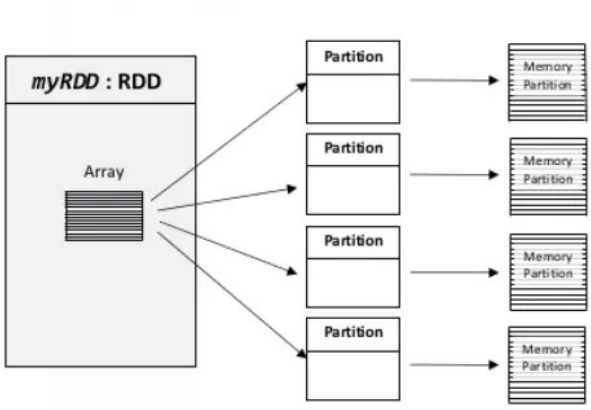
- Immutable once constructed
  - RDD content cannot be modified
  - New RDD is created from existing RDD(s)

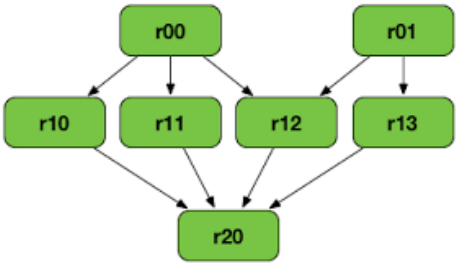
- Automatically rebuilt on failure (without replication)
  - Track lineage information so to efficiently recompute missing or lost data due to (node) failures
  - For each RDD, Spark knows how it has been constructed and can rebuild it if a failure occurs
  - This information is represented by means of RDD lineage DAG which keeps track of one or more operations that lead to the creation of that RDD

RDD: Spark management

- Spark manages the split of RDDs in partitions and allocates RDDs' partitions to cluster nodes

- Spark hides complexity of fault tolerance
  - RDDs are automatically rebuilt in case of failure using the **lineage DAG**, that defines the logical execution plan and represents the dependencies between RDDs (or DataFrames)



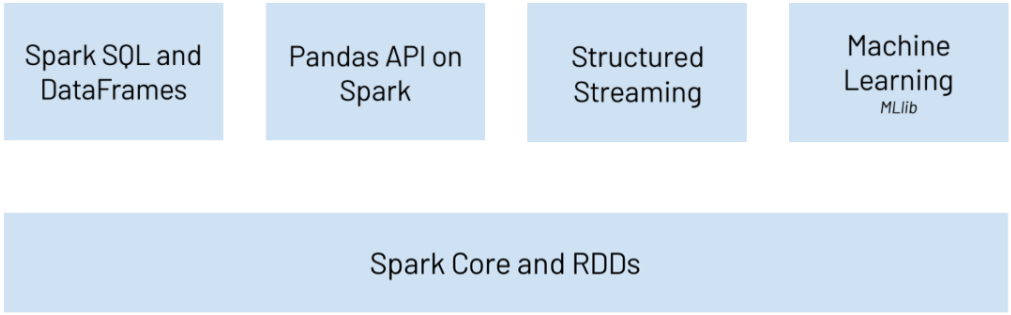


RDD API

- RDD API
  - Clean language-integrated API for Scala, Python, Java, and R
  - Can be used interactively from console (Scala and PySpark)
- RDD suitability
  - Best suited for unstructured data
  - Provides fine-grained control over physical distribution of data
- Also higher-level APIs: DataFrame and DataSet

Python Spark (PySpark)

- PySpark: Python API for Spark supporting the collaboration of Spark and Python
- Provides PySpark shell for interactive analysis
- Supports all of Spark's features such as Spark SQL, DataFrames, Structured Streaming, MLlib and Spark Core



PySpark: SparkContext

- SparkContext: entry point for low-level RDD API, connection to Spark cluster
- To create a SparkContext, you first need to build a SparkConf object that contains information about application

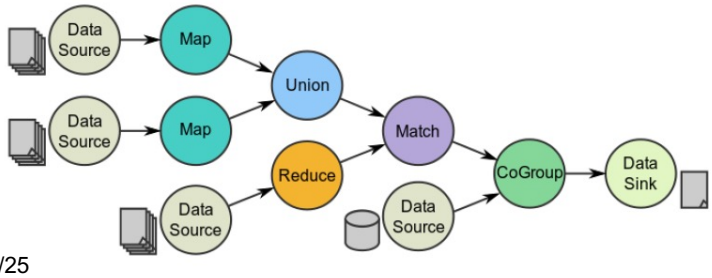
```
conf = SparkConf().setAppName(appName).setMaster(master)
sc = SparkContext(conf=conf)
```

- SparkConf allows to set various Spark parameters, among which
  - `master`: URL of cluster to connect to
  - `appName`: name of job to run
- In the shell, SparkContext is already available as `sc`

See https://spark.apache.org/docs/latest/api/python/

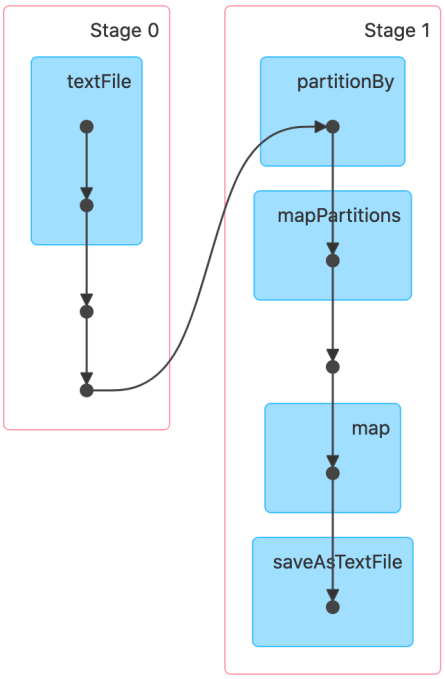
Spark programming model: DAG

- Data flow is composed of any number of data sources, operators, and data sinks by connecting their inputs and outputs
- A Directed Acyclic Graph (DAG) in Spark is a set of nodes and links, where nodes represent the operations on RDDs and directed links represent the data dependencies between operations
  - Acyclic graph: no cycles or loops in the graph
  - Generalization of MapReduce model, which has only two operations (Map and Reduce)



Spark programming model: DAG

- DAG can be visualized using Spark Web UI
  - In figure: WordCount DAG
- DAG is divided into stages
- Stage: set of operations that do not involve a shuffle of data, resulting in a more efficient computation
- As soon as a shuffle of data is needed (i.e., when a *wide transformation* is performed), the DAG will yield a new stage



Operations in RDD API

- Spark programs are written in terms of operations on RDDs
- Programming model based on parallelizable operations
  - Higher-order functions that execute user-defined functions in parallel
- RDDs are created from external data or other RDDs
- RDDs are created and manipulated through operators

See https://spark.apache.org/docs/latest/rdd-programming-guide.html

RDD operations

- RDD operations: *higher-order* functions
- Two types of RDD operations: transformations and actions
- **Transformations**: coarse-grained and lazy operations that define new RDD based on previous one(s)
  - `map`, `filter`, `join`, `union`, `distinct`, …
  - lazy: the new RDD representing the result of a computation is not immediately computed but is materialized on demand when an action is called
- **Actions**: operations that kick off a job to execute on a cluster and return a value to the driver program after running a computation on RDD or write data to external storage
  - `count`, `collect`, `save`, …

Transformations and actions on RDDs

- Common transformations and actions on RDDs
  - Seq[T]: sequence of elements of type T

https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations

https://spark.apache.org/docs/latest/rdd-programming-guide.html#actions

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

How to create RDD

- RDD can be created by:
  - Parallelizing existing data collections of the hosting programming language (e.g., collections and lists of Scala, Java, Python, or R)
    - Number of partitions specified by user
    - RDD API: **`parallelize`**
  - From (large) files stored in HDFS or any other file system
    - One partition per HDFS block
    - RDD API: **`textFile`**
  - Transforming an existing RDD
    - Number of partitions depends on transformation type
    - RDD API: transformation operations (**`map`**, **`filter`**, **`flatMap`**)

How to create RDD

- Turn an existing collection into an RDD

```
lines = sc.parallelize(["pandas", "i like pandas"])
```

  - sc is Spark context variable
  - Important parameter: number of partitions
  - Spark will run one task for each partition of the cluster (typical setting: 2-4 partitions for each CPU in the cluster)
  - Spark tries to set the number of partitions automatically
  - You can also set it manually by passing it as a second parameter to parallelize, e.g., `sc.parallelize(data, 10)`

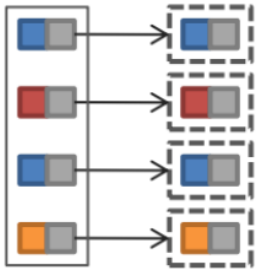
- Load data from storage (local file system, HDFS, or S3)

```
lines = sc.textFile("/path/input.txt")
```

Examples in Python

RDD transformations: map and filter

- **map**: takes as input a function which is applied to each element of the RDD and maps each input element to another element



```
# transform each element through a function
nums = sc.parallelize([1, 2, 3, 4])
squares = nums.map(lambda x: x * x)  # [1,4,9,16]
```

- **filter**: takes as input a function which is applied as filter to each element of the RDD, selecting only those elements on which the function returns true

```
# select those elements that func returns true
even = squares.filter(lambda num: num % 2 == 0)  # [4,16]
```


RDD transformations: flatMap

- **flatMap**: takes as input a function which is applied to each element of the RDD; can map each input item to zero or more output items

```
# map each element to zero or more others
ranges = nums.flatMap(lambda x: range(0, x, 1))
# [0, 0, 1, 0, 1, 2, 0, 1, 2, 3]
```

range function in Python: ordered sequence of integer values in range [start;end) with non-zero step

```
# split input lines into words
lines = sc.parallelize(["hello world", "hi"])
words = lines.flatMap(lambda line: line.split(" "))
# ['hello', 'world', 'hi']
```

RDD transformations: union and mapPartitions

- **union**: returns a new RDD that contains the union of the elements in the source RDD and the argument

```
rdd1 = sc.parallelize([2, 4, 7, 9])
rdd2 = sc.parallelize([1, 4, 5, 8, 9])
rdd3 = rdd1.union(rdd2)
# [2, 4, 7, 9, 1, 4, 5, 8, 9]
```

- **mapPartitions**: similar to `map`, but runs separately on each partition

```
rdd1 = sc.parallelize([1, 2, 3, 4, 5, 6, 7, 8, 9, 10], 3)
# Define a function to process each partition
def f(iterator): yield sum(iterator)
rdd2 = mapPartitions(f).collect()  # [6, 15, 34]
```


RDD transformations: partitionBy

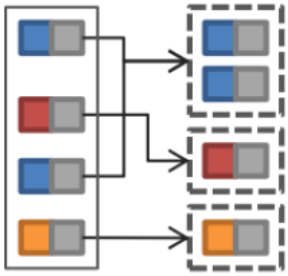
- **partitionBy**: returns a new RDD that contains the RDD partitioned using the specified partitioner and number of partitions

```
rdd = sc.parallelize([("apple", 1), ("banana", 2),
... ("orange", 3), ("apple", 4), ("banana", 1)])
partitioned_rdd = rdd.partitionBy(3)
# Use glom to see data in each partition
partitioned_rdd.glom().collect()
# [[('orange', 3)], [], [('apple', 1), ('banana', 2),
('apple', 4), ('banana', 1)]]
```

- **glom**: returns a new RDD by coalescing all elements within each partition into a list
  - useful for inspecting how data is distributed across partitions or for debugging purposes

RDD transformations: reduceByKey

- **`reduceByKey`**: when called on a RDD of key-value pairs, aggregates values with the same key using the specified function
- Runs parallel reduce operations, one for each key in the RDD



```
x = sc.parallelize([("a", 1), ("b", 1), ("a", 1), ("a", 1),
... ("b", 1), ("b", 1), ("b", 1), ("b", 1)], 3)

# apply reduceByKey operation
y = x.reduceByKey(lambda accum, n: accum + n)
# [('b', 5), ('a', 3)]
```


RDD transformations: reduceByKey

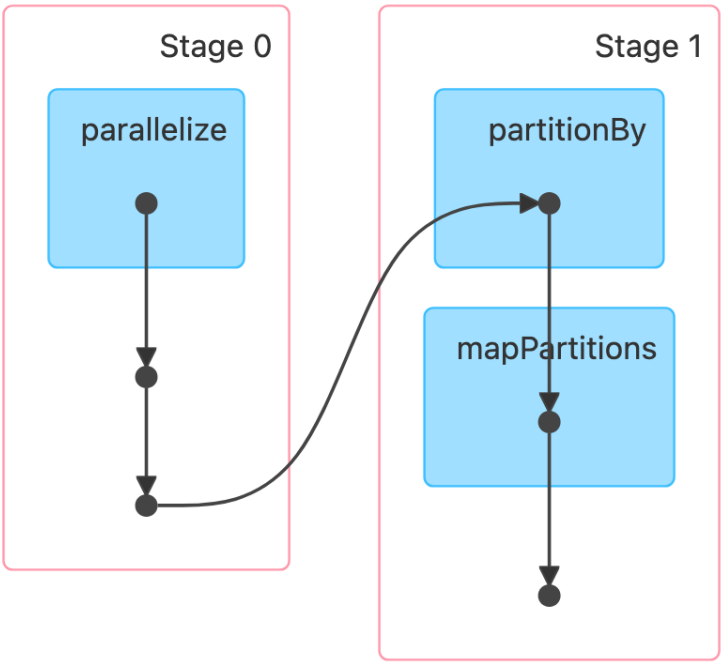
- Let's see the corresponding DAG

2 stages: wide transformation (data shuffling)

See how `reduceByKey` is implemented by Spark

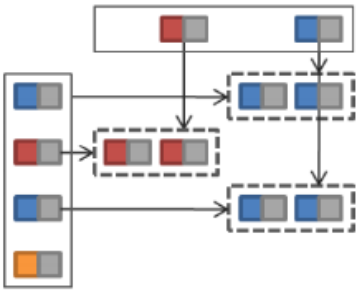
`partitionBy` partitions the data by key

`mapPartitions` performs partition-level aggregation



RDD transformations: join

- **`join`**: performs an inner-join on the keys of two RDDs
- Only keys that are present in both RDDs are output
- Join candidates are independently processed



```
users = sc.parallelize([(0, "Alex"), (1, "Bert"), (2, "Curt"), (3, "Don")])
hobbies = sc.parallelize([(0, "writing"), (0, "gym"), (1, "swimming")])
users.join(hobbies).collect()
# [(0, ('Alex', 'writing')), (0, ('Alex', 'gym')), (1, ('Bert', 'swimming'))]
```


RDD transformations: join

- Let's see the corresponding DAG

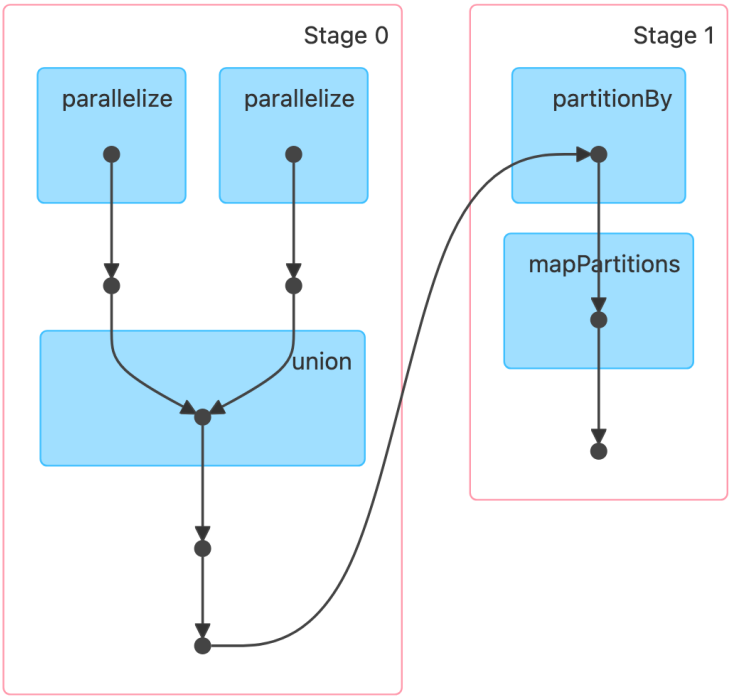
2 stages: wide transformation (data shuffling)

See how `join` is implemented by Spark

After Stage 0, data is shuffled and partitioned

`partitionBy` partitions the data by key

`mapPartitions` performs partition-level aggregation



Other RDD transformations

- **`distinct`**: returns a new RDD that contains the distinct elements of the source RDD
- **`groupByKey`**: when called on a key-value pair RDD, groups the values for each key in the RDD into a single sequence
- **`mapValues`**: passes each value in the key-value pair RDD through a map function without changing the keys
- **`sample`**: samples a fraction of the data, with or without replacement
- **`repartition`**: changes the number of partitions (i.e., the level of parallelism) in the source RDD
- **`coalesce`**: decreases the number of partitions in the source RDD

How to pass functions to transformations

- Lambda expressions, for simple functions that can be written as an expression (see examples)
  - Lambdas do not support multi-statement functions or statements that do not return a value
- Local defs inside the function calling into Spark, for longer code
- Top-level functions in a module

Transformations and actions

- Transformations are **lazy**
  - Are not computed till an action requires a result to be returned to the driver program
  - Spark can build up the logical transformation plan
- This design enables Spark to perform operations more efficiently as they can be grouped together
  - E.g., if there were multiple filter or map operations, Spark can fuse them into one operation
  - E.g., if Sparks knows that data is partitioned, Sparks can avoid moving data over the network for groupBy
- We run an action to trigger the computation
  - Instructs Spark to compute a result from a series of transformations

Some RDD actions

- **`collect`**: returns all the elements of the RDD as a list

```
nums = sc.parallelize([1, 2, 3, 4])
nums.collect()      # [1, 2, 3, 4]
```

- **`take`**: returns an array with the first *n* elements in the RDD

```
nums.take(3) # [1, 2, 3]
```

- **`count`**: returns the number of elements in the RDD

```
nums.count() # 4
```

Some RDD actions

- **`reduce`**: aggregates the elements in the RDD using the specified function

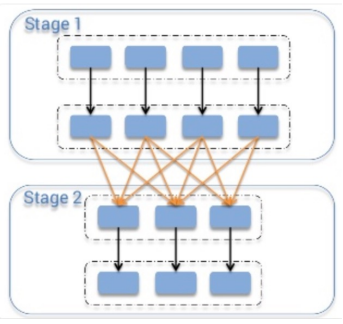
```
sum = nums.reduce(lambda x, y: x + y)
```

- **`saveAsTextFile`**: writes the RDD elements as a text file either to the local file system or HDFS

```
nums.saveAsTextFile("hdfs://file.txt")
```


Shuffle operations

- Shuffle: Spark mechanism for re-distributing data so that it is grouped differently across partitions
  - Involves copying data across executors and machines, making shuffle an expensive operation
- Example: with `reduceByKey` not all values for a single key necessarily reside on the same partition (or even the same machine), but they must be co-located to compute the result by means of an all-to-all operation
- Operations which can cause a shuffle include
  - repartition operations: `repartition` and `coalesce`
  - ByKey operations, e.g., `reduceByKey` and `groupByKey`
  - join operations, e.g., `join` and `cogroup`



Your very first examples in Spark

- After having installed Spark (e.g., Docker official image https://hub.docker.com/_/spark), you can use PySpark in a terminal window to run the examples interactively
  - `sc` is SparkContext variable

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.5.5
      /_/

Using Python version 3.13.3 (main, Apr  8 2025 13:54:08)
Spark context Web UI available at http://09a04056b82e:4040
Spark context available as 'sc' (master = local[*], app id = local-1714590071409
).
SparkSession available as 'spark'.
>>> nums = sc.parallelize([1, 2, 3, 4])
>>> squares = nums.map(lambda x: x * x)
>>> nums.collect()
[1, 2, 3, 4]
>>> squares.collect()
[1, 4, 9, 16]
>>>
```


First examples

- Let's first analyze some simple examples using RDD API
  - Pi estimation
  - WordCount
  - Compute average
- Other examples: see Spark distribution
  - Java
    https://github.com/apache/spark/tree/master/examples/src/main/java/org/apache/spark/examples
  - Python
    https://github.com/apache/spark/tree/master/examples/src/main/python

Pi estimation in Python

```
def inside(p):
  x, y = random.random(), random.random()
  return x*x + y*y < 1

samples = sc.parallelize(range(0, NUM_SAMPLES))
within_circle = samples.filter(inside)
count = within_circle.count()
print("Pi is roughly %f" % (4.0 * count / NUM_SAMPLES))
```


Pi estimation in Python with chaining

- Transformations and actions can be chained together

```
def inside(p):
  x, y = random.random(), random.random()
  return x*x + y*y < 1
count = sc.parallelize(range(0, NUM_SAMPLES)) \
      .filter(inside).count()
print("Pi is roughly %f" % (4.0 * count / NUM_SAMPLES))
```

Pi estimation in Scala

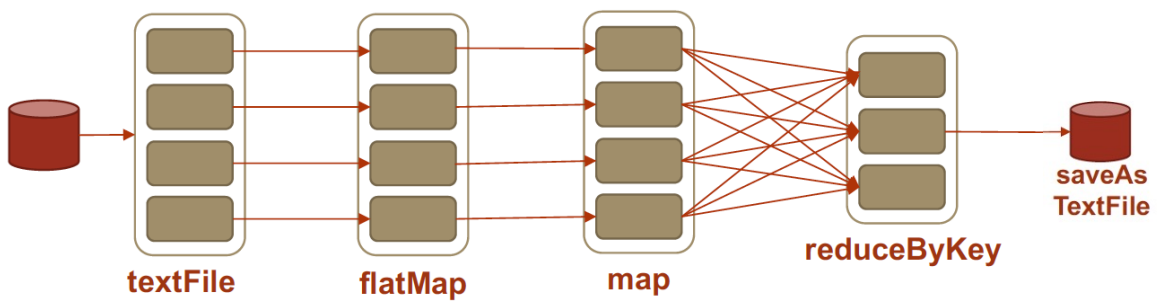
- To run Spark shell in Scala

```
$ spark-shell
```

```
var NUM_SAMPLES = 100000
val count = sc.parallelize(1 to NUM_SAMPLES).filter { _ =>
  val x = math.random
  val y = math.random
  x*x + y*y < 1
}.count()
println(s"Pi is roughly ${4.0 * count / NUM_SAMPLES}")
```


WordCount in Python

```
text_file = sc.textFile("hdfs://inputfile")

counts = text_file.flatMap(lambda line: line.split(" ")) \
        .map(lambda word: (word, 1)) \
        .reduceByKey(lambda a, b: a + b)

counts.saveAsTextFile("hdfs://output")
```



WordCount in Python

- Alternative solution: use `countByValue`
  - Action that returns the count of each unique value in RDD as a dictionary of (value, count) pairs
  - Driver collects the partitions and does the merge

```
text_file = sc.textFile("hdfs://inputfile")
words = text_file.flatMap(lambda line: line.split(" "))
wordCount = words.countByValue()
print(wordCount)
```

- Which solution is better? Depends on dataset size
  - Large dataset: use `map`, `reduceByKey` and `collect` to exploit parallelism of `reduceByKey`
  - Small dataset: using `countByValue` may reduce network traffic (one stage less)

Compute average in Python

- A common pattern in data analysis
- Let's aggregate all the ages for each name, group by name, and then average the ages

```
# Create an RDD of tuples (name, age)
dataRDD = sc.parallelize([("Brooke", 20), ("Denny", 31),
   ("Bob", 40), ("Bob", 35), ("Brooke", 25)])
# Use map and reduceByKey transformations with their lambda
# expressions to aggregate and then compute average
agesRDD = (dataRDD
.map(lambda x: (x[0], (x[1], 1)))
.reduceByKey(lambda x, y: (x[0] + y[0], x[1] + y[1]))
.map(lambda x: (x[0], x[1][0]/x[1][1])))
```

Java: Lambda expressions

- Lambda expressions are short blocks of code which take in parameters and return a value
  - Enable to treat functionality as method argument, or code as data
- Similar to methods (anonymous methods, i.e., methods without names), but do not need a name and can be implemented in the body itself
- Usually passed as parameters to a function
- Arrow operator `->` divides the lambda expression in two parts
  - Left side: parameters required by lambda expression
  - Right side: actions of lambda expression

Pi estimation in Java with chaining

```
List<Integer> l = new ArrayList<>(NUM_SAMPLES);
for (int i = 0; i < NUM_SAMPLES; i++) {
    l.add(i);
}
long count = sc.parallelize(l).filter(i -> {
   double x = Math.random();
   double y = Math.random();
   return x*x + y*y < 1;
}).count();
System.out.println("Pi is roughly " + 4.0 * count / NUM_SAMPLES);
```

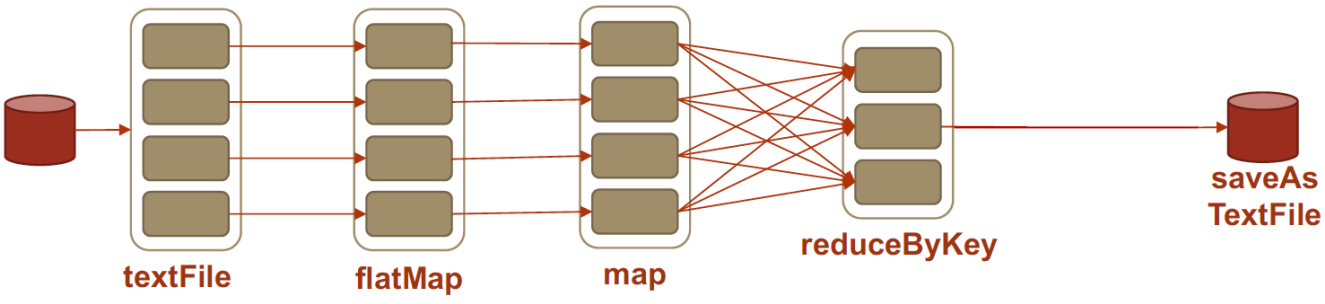
WordCount in Java

- `JavaPairRDD`: RDD containing key/value pairs
- Spark's Java API allows to create tuples using `scala.Tuple2` class

```
JavaRDD<String> lines = sc.textFile("hdfs://inputfile");
JavaRDD<String> words = lines.flatMap(line ->
        Arrays.asList(SPACE.split(line).iterator());
JavaPairRDD<String, Integer> ones = words.mapToPair(w ->
        new Tuple2<>(w, 1));
JavaPairRDD<String, Integer> counts = ones.reduceByKey((x, y) ->
        x+y);
counts.saveAsTextFile("output");
```


WordCount in Java with chaining

```
JavaRDD<String> lines = sc.textFile("hdfs://inputfile");
JavaPairRDD<String, Integer> counts = lines
    .flatMap(s -> Arrays.asList(SPACE.split(line)).iterator())
    .mapToPair(w -> new Tuple2<>(w, 1))
    .reduceByKey((x, y) -> x + y);
counts.saveAsTextFile("output");
```



Initializing Spark: SparkContext

- First step in Spark program using RDD API: create a Spark configuration object (SparkConf) and then a SparkContext object with that configuration
- SparkConf object: configuration for Spark application
  - Used to set various Spark parameters as key-value pairs

```
SparkConf().setMaster("local").setAppName("My app")
```

- SparkContext is the entry point to Spark core functionalities and allows you to interact with Spark cluster, load data, and perform transformations.
- Only one SparkContext may be active per JVM
  - Stop the existing SparkContext before creating a new one using `stop()`

SparkSession

- From Spark 2.0, SparkSession was introduced as single entry point for all functionalities, unifying the different contexts previously used for various APIs
  - Still provides access to SparkContext, which is essential for working directly with RDDs
- From interactive shell: available as variable `spark`
- Within application: use `builder` to create and configure SparkSession

Python

```python
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark SQL basic example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

Java

```java
import org.apache.spark.sql.SparkSession;

SparkSession spark = SparkSession
  .builder()
  .appName("Java Spark SQL basic example")
  .config("spark.some.config.option", "some-value")
  .getOrCreate();
```

Pi estimation in Python: using SparkSession

```python
import sys
from random import random
from operator import add

from pyspark.sql import SparkSession


if __name__ == "__main__":
    """
        Usage: pi [partitions]
    """
    spark = SparkSession\
        .builder\
        .appName("PythonPi")\
        .getOrCreate()

    partitions = int(sys.argv[1]) if len(sys.argv) > 1 else 2
    n = 100000 * partitions

    def f(_: int) -> float:
        x = random() * 2 - 1
        y = random() * 2 - 1
        return 1 if x ** 2 + y ** 2 <= 1 else 0

    count = spark.sparkContext.parallelize(range(1, n + 1), partitions).map(f).reduce(add)
    print("Pi is roughly %f" % (4.0 * count / n))

    spark.stop()
```

Full example using SparkSession and API RDD

Create and configure SparkSession

Slightly different from slide 51: map and reduce instead of filter and count

Access SparkContext from SparkSession and work with RDD

https://github.com/apache/spark/blob/master/examples/src/main/python/pi.py

WordCount in Java: using SparkSession

```java
package org.apache.spark.examples;

import scala.Tuple2;

import org.apache.spark.api.java.JavaPairRDD;
import org.apache.spark.api.java.JavaRDD;
import org.apache.spark.sql.SparkSession;

import java.util.Arrays;
import java.util.List;
import java.util.regex.Pattern;

public final class JavaWordCount {
  private static final Pattern SPACE = Pattern.compile(" ");

  public static void main(String[] args) throws Exception {

    if (args.length < 1) {
      System.err.println("Usage: JavaWordCount <file>");
      System.exit(1);
    }

    SparkSession spark = SparkSession
      .builder()
      .appName("JavaWordCount")
      .getOrCreate();
```

Full example using SparkSession and API RDD

Create and configure SparkSession

WordCount in Java: using SparkSession

Use Dataset Use RDD

```
    JavaRDD<String> lines = spark.read().textFile(args[0]).javaRDD();

    JavaRDD<String> words = lines.flatMap(s -> Arrays.asList(SPACE.split(s)).iterator());

    JavaPairRDD<String, Integer> ones = words.mapToPair(s -> new Tuple2<>(s, 1));

    JavaPairRDD<String, Integer> counts = ones.reduceByKey((i1, i2) -> i1 + i2);

    List<Tuple2<String, Integer>> output = counts.collect();
    for (Tuple2<?,?> tuple : output) {
      System.out.println(tuple._1() + ": " + tuple._2());
    }
    spark.stop();
  }
}
```

https://github.com/apache/spark/blob/master/examples/src/main/java/org/apache/spark/examples/JavaWordCount.java

Launch applications

- Launch Spark application using `bin/spark-submit` script

```
./bin/spark-submit \
  --class <main-class> \
  --master <master-url> \
  --deploy-mode <deploy-mode> \
  --conf <key>=<value> \
  ... # other options
  <application-jar> \
  [application-arguments]
```

See https://spark.apache.org/docs/latest/submitting-applications.html

Launch applications: main options

- `--class`: app entry point (e.g., org.apache.spark.examples.SparkPi)
- `--master`: master URL for cluster (e.g., spark://23.195.26.187:7077) (default: `local`)
- `--deploy-mode`: whether to deploy driver on worker nodes (`cluster`) or locally as external client (default: `client`)
- `--conf`: Spark configuration property in key=value format
- `application-jar`: path to jar including app and all dependencies. Be careful: URL must be globally visible, e.g., `hdfs://` path or a `file://` path that is present on all nodes
- For Python app: pass a .py file in place of `application-jar` and add Python .zip, .egg or .py files to the search path using `--py-files`
- `application-arguments`: arguments passed to the main method of the main class, if any

Launch applications: example

- Launch PageRank in Python passing arguments

```
./bin/spark-submit \
examples/src/main/python/pagerank.py \
data/mllib/pagerank_data.txt 10
```

- Launch Pi estimation in Java configuring Spark and passing argument

```
./bin/spark-submit --class
org.apache.spark.examples.SparkPi \
    --master local \
    --deploy-mode client \
    --num-executors 2 \
    --driver-memory 512m \
    --executor-memory 512m \
    --executor-cores 1 \
    examples/jars/spark-examples*.jar 10
```

Deploy modes and cluster managers

- Spark supports different deploy modes and cluster managers, so it can run in different configurations and environments

Mode	Spark driver	Spark executor	Cluster manager
Local	Runs on a single JVM, like a laptop or single node	Runs on the same JVM as the driver	Runs on the same host
Standalone	Can run on any node in the cluster	Each node in the cluster will launch its own executor JVM	Can be allocated arbitrarily to any host in the cluster
YARN (client)	Runs on a client, not part of the cluster	YARN's NodeManager's container	YARN's Resource Manager works with YARN's Application Master to allocate the containers on NodeManagers for executors
YARN (cluster)	Runs with the YARN Application Master	Same as YARN client mode	Same as YARN client mode
Kubernetes	Runs in a Kubernetes pod	Each worker runs within its own pod	Kubernetes Master

Caching and persistence

- By default, RDDs are recomputed each time you run an action on them
  - This can be *expensive* (in time) if you need to use the RDD more than once (e.g., iterative algorithms)
- To avoid recomputing an RDD multiple times, ask Spark to ***persist*** (or ***cache***) data for rapid reuse
  - To persist RDD, use `persist()` or `cache()` methods on it
  - When RDD is persisted, each node stores its partitions in memory and reuses them in future actions on that RDD (or RDDs derived from it): future actions are thus much faster (more than 10x)
- Key tool for iterative algorithms and fast interactive use
- Both `cache` and `persist` can be also applied to DataFrames and Datasets

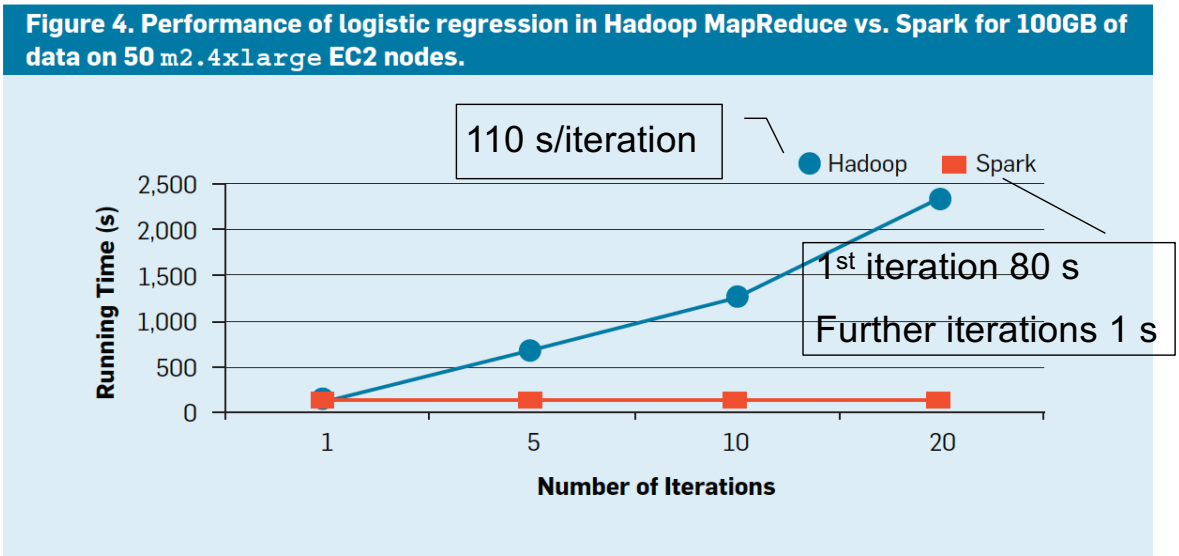
Caching and persistence: storage level

- Using `persist()` you can specify the storage level for persisting an RDD
  - `cache()` is equivalent to `persist()` with default storage level (`MEMORY_ONLY`)
- Main storage levels:
  - `MEMORY_ONLY`: if the RDD does not fit in memory, some partitions will not be cached and will be recomputed on the fly each time they are needed
  - `MEMORY_AND_DISK`
  - `DISK_ONLY`
- Which storage level is best?
  - Try to keep in-memory as much as possible
  - Try not to spill to disk unless the functions that computed your datasets are expensive (e.g., filter a large amount of data)
  - Use replicated storage levels only if you want fast fault recovery

Caching and persistence: performance speedup

- Spark outperforms Hadoop by up to 100x in iterative ML
  - Speedup comes from avoiding I/O and deserialization costs by storing data in memory

Figure 4. Performance of logistic regression in Hadoop MapReduce vs. Spark for 100GB of data on 50 `m2.4xlarge` EC2 nodes.



Source: "Apache Spark: A Unified Engine for Big Data Processing"

Caching and persistence: example

- Let's analyze how persistence is used in iterative algorithms
- Naïve implementation of K-means algorithm
  - At each iteration we need to use the RDD containing the data points to be clustered
  - Let's cache it

```
data = lines.map(parseVector).cache()
```

https://github.com/apache/spark/blob/master/examples/src/main/python/kmeans.py

K-means in Spark

- Name of data file, number of clusters K and convergence threshold are read from command line

```
Usage: kmeans <file> <k> <convergeDist>
$ ./bin/spark-submit --master local \
  $SPARK_HOME/examples/src/main/python/kmeans.py \
  $SPARK_HOME/data/mllib/kmeans_data.txt 2 0.1
```

- Code uses NumPy (package for scientific computing in Python)

K-means in Spark

- Let's first define two utility functions: `parseVector` and `closestPoint`

Convert data into float numbers

```
def parseVector(line):
    return np.array([float(x) for x in line.split(' ')])
```

Return index of the closest centroid for point p. `centers` contains the centroids, where `centers[i]` is the i-th centroid

```
def closestPoint(p, centers):
    bestIndex = 0
    closest = float("+inf")
    for i in range(len(centers)):
        tempDist = np.sum((p - centers[i]) ** 2)
        if tempDist < closest:
            closest = tempDist
            bestIndex = i
    return bestIndex
```


K-means in Spark

- Read data to be clustered from input file, convert data into float numbers and then set `K` and `convergeDist`
- Cache the RDD data to improve performance
- Inizialize randomly the cluster centroids `kPoints`

```
lines = spark.read.text(sys.argv[1]).rdd.map(lambda r: r[0])
data = lines.map(parseVector).cache()
K = int(sys.argv[2])
convergeDist = float(sys.argv[3])

kPoints = data.takeSample(False, K, 1)
tempDist = 1.0
```

takeSample is an action used to retrieve a random sample from the RDD (False means without replacement)

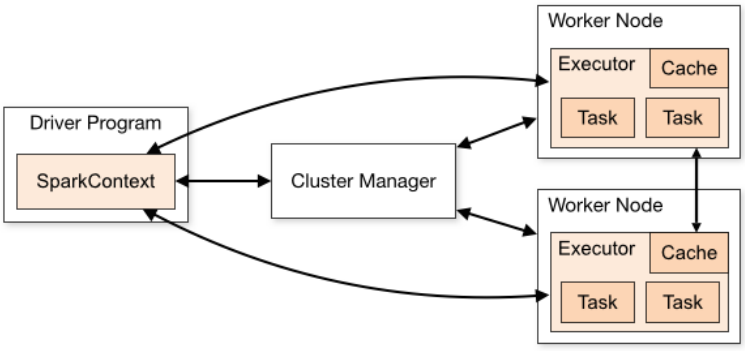
K-means in Spark

- Repeat in a loop until convergence
  - Map each data point to its closest centroid
  - Calculate new cluster centroids (using average pattern)

```
while tempDist > convergeDist:
    closest = data.map(
        lambda p: (closestPoint(p, kPoints), (p, 1)))
    pointStats = closest.reduceByKey(
        lambda p1_c1, p2_c2: (p1_c1[0] + p2_c2[0], p1_c1[1] + p2_c2[1]))
    newPoints = pointStats.map(
        lambda st: (st[0], st[1][0] / st[1][1])).collect()

    tempDist = sum(np.sum((kPoints[iK] - p) ** 2) for (iK, p) in newPoints)

    for (iK, p) in newPoints:
        kPoints[iK] = p

print("Final centers: " + str(kPoints))
```

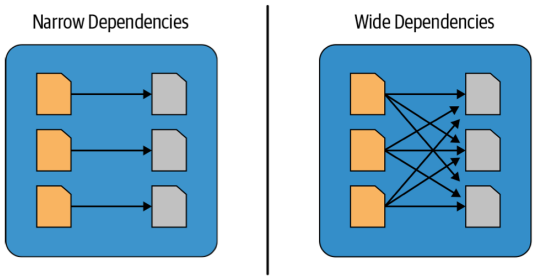

How Spark works on clusters

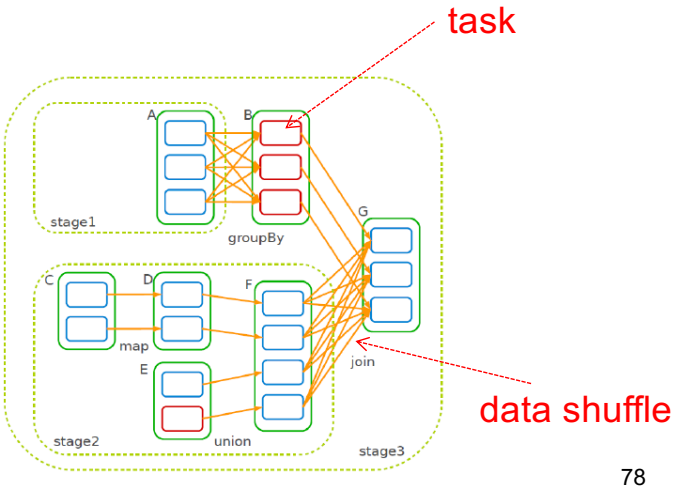
- A Spark application runs as a set of processes (executors) on the cluster, coordinated by the *driver program* of the application
- Executor: process launched on a worker node, that runs tasks and keeps data in memory or disk storage
  - Each application has its own executors



How Spark works at runtime

- Application creates RDDs, transforms them, and runs actions: this results in a DAG of operations
- DAG is transformed into stages
  - Stage: set of tasks without data shuffle in between, contains pipelined transformations with narrow dependencies
  - Task: unit of execution that is sent to one executor and works on a single partition of data
- Actions drive execution





Stage execution

- Spark:
  - Creates a task for each partition in RDD
  - Schedules and assigns tasks to worker nodes
- Task creation and scheduling happens internally (you need to do anything)
- Configuration
  - Number of executors, amount of resources assigned to each executor (cores and memory)
  - By default, each executor runs one task per core

Summary of Spark components

Coarse grain

RDD: parallel dataset with partitions

DAG: logical graph of RDD operations

Stage: set of tasks that run in parallel

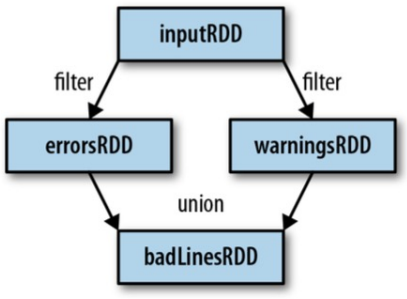
Task: smallest unit of execution

Fine grain

Fault tolerance

- Spark keeps track of transformations used to build RDDs (their lineage DAG)
- Lineage information + RDD immutability = fault tolerance
  - Lineage is used to recover lost data of RDD by replaying transformations on RDDs

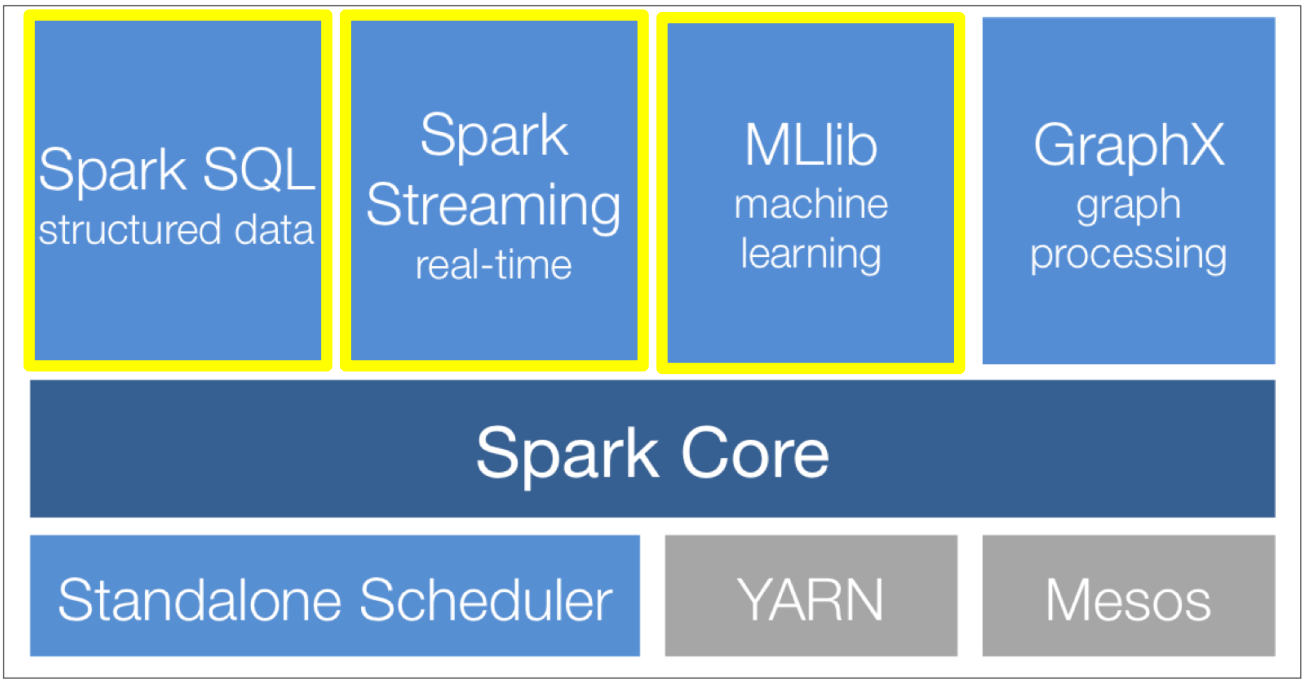
Example: RDD lineage DAG created during log analysis



Application scheduling

- DAG scheduler assigns tasks from Spark app to executors
- When app runs a Spark action (e.g., `collect`), scheduler builds a physical execution plan (DAG of stages) from the logical execution plan (RDD lineage DAG)
- Scheduler determines task scheduling (on which worker node to run each task) on the basis of data locality
  - If a task needs a partition which is available in a node's memory, the task is sent to that node
- Scheduler handles failures to compute missing partitions from each stage

Spark's high-level modules



Spark SQL

- Spark module for structured data processing
- Run SQL queries on top of Spark
- Integrated with Spark ecosystem
  - Seamlessly mix SQL queries with Spark programs, using either SQL or DataFrame API
  - Apply functions to results of SQL queries, e.g.,

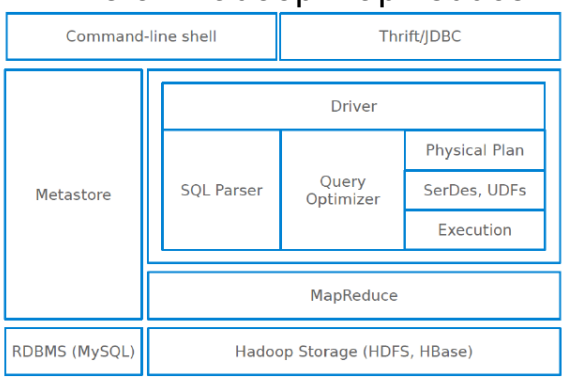
```
results = spark.sql(
  "SELECT * FROM people")
names = results.map(lambda p: p.name)
```

- Compatible with Hive, speedup up to 100x
  - **Hive**: data warehouse built on top of Hadoop that provides data summarization, query, and analysis with SQL-like interface

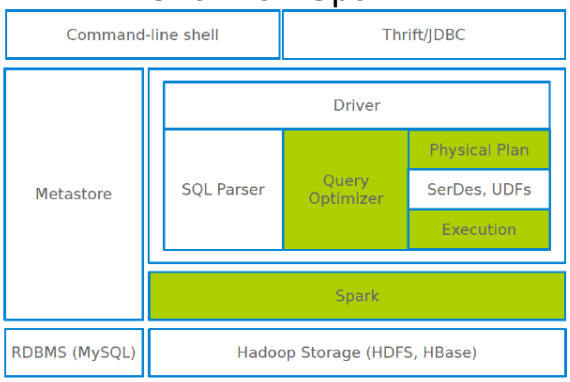
Spark SQL: how it began

- Goal was to extend Hive to run on Spark
  - Shark: modified Hive's backend to run over Spark, employing in-memory columnar storage
  - Shark limits
    - Only Hive data model
    - Query optimizer tied to Hadoop

Hive on Hadoop MapReduce

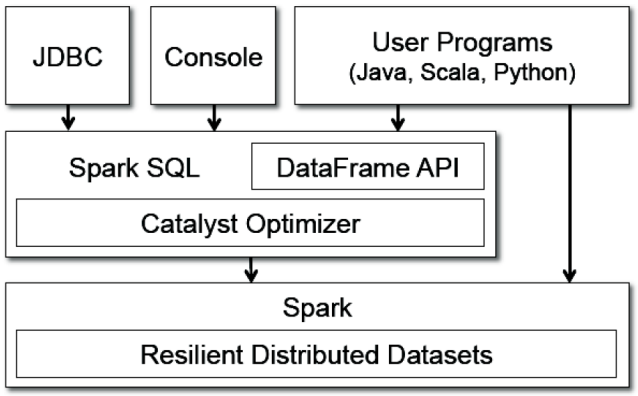


Shark on Spark



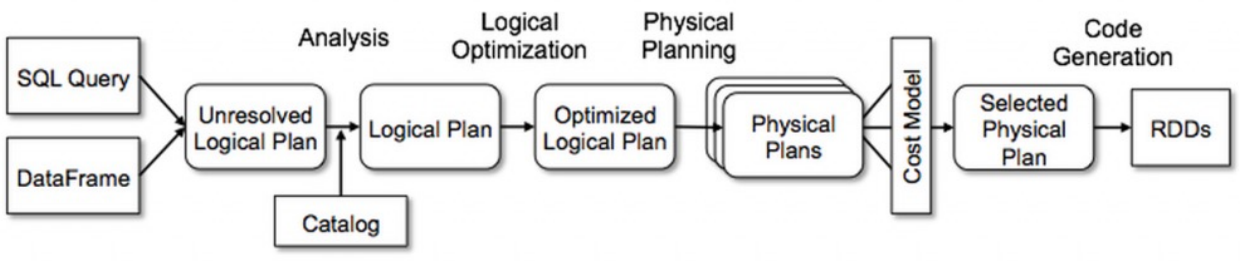
Spark SQL: Features

- Borrows from Shark
  - Hive data loading, in-memory columnar storage
- Adds:
  - RDD-aware query optimizer (Catalyst Optimizer)
  - Schema to RDD (DataFrame and Dataset APIs)
  - Rich language interfaces



Spark SQL: Catalyst optimizer

- Catalyst is based on functional programming constructs in Scala and designed for
  - Easily adding new optimization techniques and features to Spark SQL
  - Enabling developers to extend the optimizer (e.g., adding data source specific rules, support for new data types)
- Phases of query execution: analysis, logical optimization, physical planning, and code generation



DataFrame and Dataset APIs

- Higher-level than RDD
- Best suited for structured and semi-structured data
- SparkSession: entry point
- Exploit Catalyst optimizer
- In common with RDDs:
  - Distributed in-memory collection of data
  - Immutable
  - Manipulated in similar ways to RDDs
  - Evaluated lazily
  - Persisted in memory
  - Spark keeps lineage of transformations

DataFrame and Dataset APIs

- **DataFrame** adds to RDD a schema to describe data
  - Unlike RDD, data is organized into a distributed in-memory table with named columns and schema
  - Spark SQL provides API to run SQL queries on DataFrames with a simple SQL-like syntax

- Table-like format of a DataFrame

```
+------------------+--------+--------------------+--------------------+-----------+------+
|              Name| Surname|             Address|                City|      State|   ZIP|
+------------------+--------+--------------------+--------------------+-----------+------+
|              John|     Doe|   120 jefferson st.|           Riverside|         NJ| 08075|
|              Jack|McGinnis|        220 hobo Av.|               Phila|         PA| 09119|
| "John ""Da Man"""|  Repici|   120 Jefferson St.|           Riverside|         NJ| 08075|
|           Stephen|   Tyler|"7452 Terrace ""A...|            SomeTown|         SD| 91234|
|              null|Blankman|                null|            SomeTown|         SD| 00298|
|"Joan ""the bone""|   Anne"|                 Jet|9th, at Terrace plc|Desert City|    CO|
+------------------+--------+--------------------+--------------------+-----------+------+
```

https://spark.apache.org/docs/latest/sql-programming-guide.html

DataFrame and Dataset APIs

- **Dataset** extends DataFrame providing type-safe, OO programming interface
  - Structured and strongly typed collection of data
  - Dataset: collection of strongly-typed JVM objects in Scala or class in Java

- DataFrame vs Dataset
  - DataFrame: more flexible and efficient in terms of performance
  - Dataset: more type-safe and expressive, but with a limited set of APIs and more memory consumption

- DataFrame and Dataset APIs have with similar interfaces

RDDs vs DataFrames vs Datasets

Feature	Spark RDD	Spark DataFrame	Spark Dataset
Data representation	Immutable distributed collection of data	Structured data organized into named columns	Distributed collection of data with optional schema
Data processing	Fine-grained control	High-level abstraction	Ease of use and performance
Suitability	Developers who require precise control	Data analysts and SQL experts	Data professionals who need a balance of control and convenience
Key distinctions	Offers more control, but more complex	Offers more convenience, but less control	Offers a balance of control and convenience

https://www.databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-and-datasets.html

Dataset API

- Provides the benefits of RDDs (strong typing, ability to use lambda functions) with those of Spark SQL's optimized execution engine
- API available in Scala and Java (not in Python)
- Can be constructed from JVM objects in Scala or class in Java
- Can be manipulated using transformations (`map`, `flatMap`, `filter`, `groupBy`, ...) and actions
- Lazy, i.e. computation is only triggered when an action is invoked
  - Internally, a logical plan describes the computation required to produce data. When an action is invoked, Spark query optimizer optimizes the logical plan and generates a physical plan for efficient execution

Dataset API

- How to create a Dataset?
  - From file using `read` function
  - From existing RDD by converting it
  - Through transformations applied on existing Datasets

- When creating a Dataset you have to know the schema (i.e., data types)
  - With JSON and CSV files it is possible to infer the schema

DataFrame API

- DataFrame: a *Dataset* organized into named columns
- Conceptually equivalent to a table in a relational database, with richer optimizations
- API available in Scala, Java, Python, and R
  - Can be used in PySpark shell
  - In Scala and Java, a DataFrame is a Dataset of Rows
- Can be manipulated in similar ways to RDDs
- Can be constructed from:
  - Structured data files (JSON, CSV, Parquet, Avro, ORC, protobuf)
  - Existing RDDs, either inferring the schema using reflection or programmatically specifying the schema
  - Tables in Hive

DataFrame API: constructing data frames

- Create DataFrame from RDD, list or pandas DataFrame

```
>>> data_df = spark.createDataFrame([("Brooke", 20), ("Denny", 31), ("Jules", 30),
... ("TD", 35), ("Brooke", 25)], ["name", "age"])
>>> data_df.show()
+------+---+
|  name|age|
+------+---+
|Brooke| 20|
| Denny| 31|
| Jules| 30|
|    TD| 35|
|Brooke| 25|
+------+---+
```

DataFrame API: constructing data frames

- Spark supports many file formats, including text, CSV, JSON, Parquet, ORC, and Avro
- Create DataFrame from file
  - To load a file into a DataFrame, use generic `read.load` function and its options (default file format is Parquet)
  - Can also specify manually file format along with extra options (see example below)
  - For some format, specific read methods, e.g., `read.csv`, `read.json`, `read.parquet`
  - Spark can infer schema for CSV and JSON
  - Example: load CSV file using `read.load` (default separator is ",")

```
df = spark.read.load(
   "/opt/spark/examples/src/main/resources/people.csv",
   format="csv", sep=";", inferSchema="true", header="true")
```

https://github.com/apache/spark/blob/master/examples/src/main/python/sql/datasource.py

DataFrame API: load CSV file

- Example: load CSV file using `read.csv`

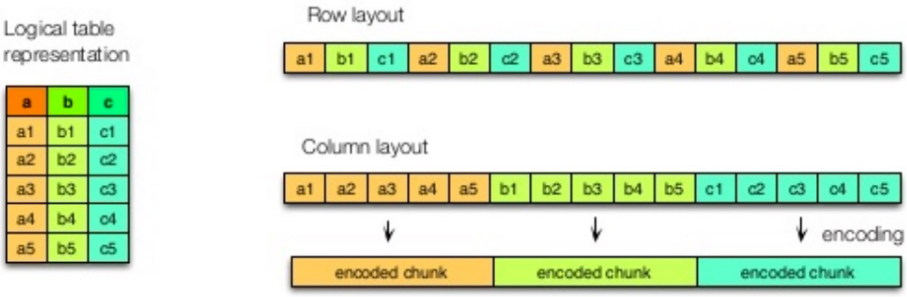
```
>>> df = spark.read.csv("/data/address.csv", header=True)
>>> df.show()
+------------------+--------+--------------------+------------------+----------+------+
|              Name| Surname|             Address|              City|     State|   ZIP|
+------------------+--------+--------------------+------------------+----------+------+
|              John|     Doe|   120 jefferson st.|         Riverside|        NJ| 08075|
|              Jack|McGinnis|        220 hobo Av.|             Phila|        PA| 09119|
| "John ""Da Man"""|  Repici|   120 Jefferson St.|         Riverside|        NJ| 08075|
|           Stephen|   Tyler|"7452 Terrace ""A...|          SomeTown|        SD| 91234|
|              NULL|Blankman|                NULL|          SomeTown|        SD| 00298|
|"Joan ""the bone""|   Anne"|                 Jet|9th, at Terrace plc|Desert City|    CO|
+------------------+--------+--------------------+------------------+----------+------+
```

- Spark can infer schema of each column from CSV file

```
>>> df.printSchema()
root
 |-- Name: string (nullable = true)
 |-- Surname: string (nullable = true)
 |-- Address: string (nullable = true)
 |-- City: string (nullable = true)
 |-- State: string (nullable = true)
 |-- ZIP: string (nullable = true)
```

Parquet file format

- Columnar data file format designed for efficient data storage and retrieval https://parquet.apache.org
- Spark provides support for reading and writing Parquet files
  - Also supported by other data processing frameworks, regardless of data model or programming language choice
- Interoperable with other data storage formats
  - Avro, Thrift, Protocol Buffers, ...



Parquet file format

- Provides efficient data compression and encoding schemes
  - Several compression codecs (e.g., gzip, snappy) with different compression ratio and processing cost
- Example: Parquet vs. CSV

Dataset	Size on Amazon S3	Query Run time	Data Scanned	Cost
Data stored as CSV files	1 TB	236 seconds	1.15 TB	$5.75
Data stored in Apache Parquet format*	**130 GB**	**6.78 seconds**	**2.51 GB**	**$0.01**
Savings / Speedup	**87% less with Parquet**	**34x faster**	**99% less data scanned**	**99.7% savings**

- Schema of original data is automatically preserved
- Supports schema evolution, allowing schema changes
- Supports predicate pushdown
  - Optimization technique whereby data filtering operations are performed into scan operator responsible for reading in the data

DataFrame API: using Parquet

```
peopleDF = spark.read.json("examples/src/main/resources/people.json")

# DataFrames can be saved as Parquet files, maintaining the schema information.
peopleDF.write.parquet("people.parquet")

# Read in the Parquet file created above.
# Parquet files are self-describing so the schema is preserved.
# The result of loading a parquet file is also a DataFrame.
parquetFile = spark.read.parquet("people.parquet")

# Parquet files can also be used to create a temporary view and then used in SQL statements.
parquetFile.createOrReplaceTempView("parquetFile")
teenagers = spark.sql("SELECT name FROM parquetFile WHERE age >= 13 AND age <= 19")
teenagers.show()
# +------+
# |  name|
# +------+
# |Justin|
# +------+
```

Spark SQL can automatically infer the schema of a JSON file using `SparkSession.read.json()`

https://spark.apache.org/docs/latest/sql-data-sources-parquet.html

From DataFrame to RDD and viceversa

- To convert DataFrame to RDD when greater control is needed, call `.rdd` method on DataFrame object
- Reverse conversion can be done by calling `spark.createDataFrame()` on an existing RDD

DataFrame API: benefits

- Let's consider expressivity and simplicity
- Example: aggregate all the ages for each name, group by name, and then average the ages
  - With RDDs (see slide 55), we instruct Spark *how to* aggregate keys and compute averages using lambda functions: hard to read and cryptic
  - With DataFrames, we instruct Spark *what to do*

```
from pyspark.sql.functions import avg
# Create a DataFrame
data_df = spark.createDataFrame([("Brooke", 20), ("Denny",
31), ("Jules", 30), ("TD", 35), ("Brooke", 25)], ["name",
"age"])
# Group the same names together, aggregate their ages,
# and compute an average
avg_df = data_df.groupBy("name").agg(avg("age"))
# Show the results of the final execution
avg_df.show()
```


Spark Streaming and Structured Streaming

- Spark Streaming (legacy): streaming engine
  - Data streams are ingested and analyzed in micro-batches
  - Uses a high-level abstraction called Dstream (discretized stream)
    - A continuous stream of data, represented as a sequence of RDDs
  - Internally, it works as:

- Structured Spark Streaming
  - Spark's stream processing engine built on Spark SQL engine

See hands-on lesson

Spark MLlib

- Spark Mllib: Spark library for machine learning
  - Includes 2 packages:
    - `spark.ml`: MLlib DataFrame-based API to support a variety of data types
    - `spark.mllib`: MLlib RDD-based API (maintenance mode)
- Provides common ML algorithms
  - Classification (e.g., logistic regression), regression, clustering (e.g., K-means), recommendation (e.g., collaborative filtering), decision trees, random forests, and more
- Provides also utilities
  - For ML: feature transformations, model evaluation and hyper-parameter tuning
  - For distributed linear algebra (e.g., PCA) and statistics (e.g., summary statistics, hypothesis testing)

Spark MLlib: logistic regression example

- Logistic regression: popular method to predict a categorical response
  - Binomial and multinomial
- Dataset of labels and features
- Load training data and fit model using binomial logistic regression

ML package

```
from pyspark.ml.classification import LogisticRegression

# Load training data
training = spark.read.format("libsvm").load("data/mllib/sample_libsvm_data.txt")

lr = LogisticRegression(maxIter=10, regParam=0.3, elasticNetParam=0.8)

# Fit the model
lrModel = lr.fit(training)

# Print the coefficients and intercept for logistic regression
print("Coefficients: " + str(lrModel.coefficients))
print("Intercept: " + str(lrModel.intercept))
```

LIBSVM format

Create a LogisticRegression instance

Learn a LogisticRegression model, which uses the parameters stored in `lr`

Spark MLlib: K-means

- MLlib implementation of K-means includes a parallelized variant of K-means++ called Kmeans||
  - K-means++ goal: find K initial cluster centroids by spreading them out so as to improve solution quality and convergence
    - 1st cluster centroid is chosen uniformly from data points
    - Each subsequent centroid is chosen from the *remaining* data points with probability proportional to its squared distance from the point's closest existing cluster centroid
  - Since K-means++ is sequential (it needs K passes over the data), Spark uses its parallel variant Kmeans||
- K-means input is feature vector
- K-means output is predicted cluster centers

https://en.wikipedia.org/wiki/K-means%2B%2B

Bahmani et al, Scalable k-means++, Proc. VLDB Endow., 2012.
theory.stanford.edu/~sergei/papers/vldb12-kmpar.pdf

Spark ML: k-means example

```
from pyspark.ml.clustering import KMeans
from pyspark.ml.evaluation import ClusteringEvaluator

# Loads data.
dataset = spark.read.format("libsvm").load("data/mllib/sample_kmeans_data.txt")

# Trains a k-means model.
kmeans = KMeans().setK(2).setSeed(1)
model = kmeans.fit(dataset)

# Make predictions
predictions = model.transform(dataset)

# Evaluate clustering by computing Silhouette score
evaluator = ClusteringEvaluator()

silhouette = evaluator.evaluate(predictions)
print("Silhouette with squared euclidean distance = " + str(silhouette))

# Shows the result.
centers = model.clusterCenters()
print("Cluster Centers: ")
for center in centers:
    print(center)
```

Silhouette is used to evaluate separation distance between resulting clusters

Silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters and provides a way to assess the number of clusters visually

Combining processing tasks with Spark

- It is easy to seamlessly combine different Spark libraries in the same application
- Example in Scala combining SQL, ML and streaming libraries in Spark
  - Read historical Twitter data using Spark SQL
  - Train a K-means clustering model using MLlib
  - Apply the model to a new stream of tweets in order to predict language from location

Combining processing tasks with Spark

```
// Load historical data as an RDD using Spark SQL
val trainingData = sql(
"SELECT location, language FROM old_tweets")

// Train a K-means model using MLlib
val model = new KMeans()
.setFeaturesCol("location")
.setPredictionCol("language")
.fit(trainingData)

// Apply the model to new tweets in a stream
TwitterUtils.createStream(...)
.map(tweet => model.predict(tweet.location))
```

References

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