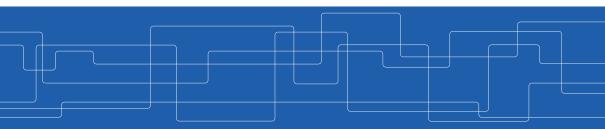


#### Parallel Processing - Spark

Amir H. Payberah payberah@kth.se 2023-09-12





#### The Course Web Page

## https://id2221kth.github.io

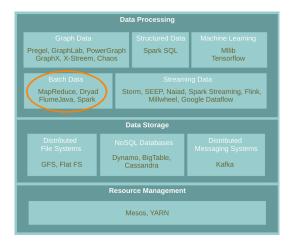


The Questions-Answers Page

## https://tinyurl.com/hk7hzpw5

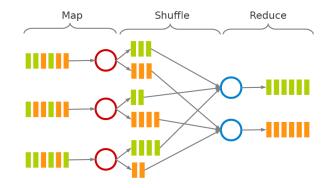


#### Where Are We?





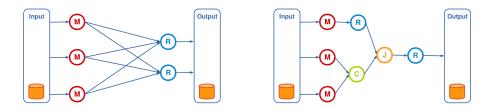
#### MapReduce Reminder





## Motivation (1/2)

• Acyclic data flow from stable storage to stable storage.





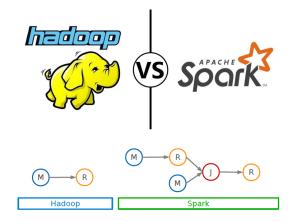
## Motivation (2/2)

► MapReduce is expensive (slow), i.e., always goes to disk and HDFS.





#### So, Let's Use Spark





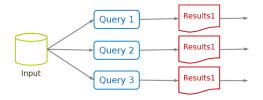
## Spark vs. MapReduce (1/2)

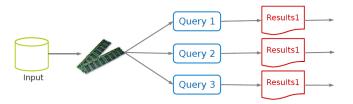






### Spark vs. MapReduce (2/2)





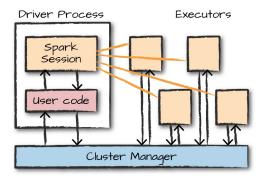


# Spark Application



### Spark Applications Architecture

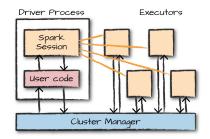
- Spark applications consist of
  - A driver process
  - A set of executor processes



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

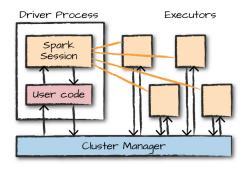


- ► The heart of a Spark application
- Runs the main() function
- Responsible for three things:
  - Maintaining information about the Spark application
  - Responding to a user's program or input
  - Analyzing, distributing, and scheduling work across the executors





- Executing code assigned to it by the driver
- ▶ Reporting the state of the computation on that executor back to the driver





- A driver process that controls a Spark application.
- ► A one-to-one correspondence between a SparkSession and a Spark application.
- Available in console shell as spark.

SparkSession.builder.master(master).appName(appName).getOrCreate()



- ► The entry point for low-level API functionality.
- You access it through the SparkSession.
- Available in console shell as sc.

val conf = new SparkConf().setMaster(master).setAppName(appName)
new SparkContext(conf)



#### SparkSession vs. SparkContext

- Prior to Spark 2.0.0, a the spark driver program uses SparkContext to connect to the cluster.
- In order to use APIs of SQL, Hive and streaming, separate SparkContexts should to be created.
- SparkSession provides access to all the spark functionalities that SparkContext does, e.g., SQL, Hive and streaming.
- SparkSession internally has a SparkContext for actual computation.

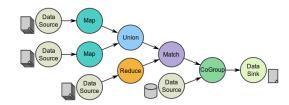


# **Programming Model**



#### Spark Programming Model

- ► Job is described based on directed acyclic graphs (DAG) data flow.
- ► A data flow is composed of any number of data sources, operators, and data sinks by connecting their inputs and outputs.
- Parallelizable operators





## Resilient Distributed Datasets (RDD) (1/3)

- A distributed memory abstraction.
- ► Immutable collections of objects spread across a cluster.
  - Like a LinkedList <MyObjects>





## Resilient Distributed Datasets (RDD) (2/3)

- An RDD is divided into a number of partitions, which are atomic pieces of information.
- ▶ Partitions of an RDD can be stored on different nodes of a cluster.





## Resilient Distributed Datasets (RDD) (3/3)

- ▶ RDDs were the primary API in the Spark 1.x series.
- They are not commonly used in the Spark 2.x series.
- ► Virtually all Spark code you run, compiles down to an RDD.



- ► Two types of RDDs:
  - Generic RDD
  - Key-value RDD
- Both represent a collection of objects.
- Key-value RDDs have special operations, such as aggregation, and a concept of custom partitioning by key.



# Creating RDDs



### Creating RDDs - Parallelized Collections

- Use the parallelize method on a SparkContext.
- ► This turns a single node collection into a parallel collection.
- ► You can also explicitly state the number of partitions.
- In the console shell, you can either use sc or spark.sparkContext

```
val numsCollection = Array(1, 2, 3)
val nums = sc.parallelize(numsCollection)
```

```
val wordsCollection = "take it easy, this is a test".split(" ")
val words = spark.sparkContext.parallelize(wordsCollection, 2)
```



#### Creating RDDs - External Datasets

- Create RDD from an external storage.
  - E.g., local file system, HDFS, Cassandra, HBase, Amazon S3, etc.
- ► Text file RDDs can be created using textFile method.

```
val myFile1 = sc.textFile("file.txt")
val myFile2 = sc.textFile("hdfs://namenode:9000/path/file")
```



## **RDD** Operations



- ▶ RDDs support two types of operations:
  - Transformations: allow us to build the logical plan
  - Actions: allow us to trigger the computation



## Transformations

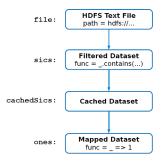


Transformations

- Create a new RDD from an existing one.
- All transformations are lazy.
  - Not compute their results right away.
  - Remember the transformations applied to the base dataset.
  - They are only computed when an action requires a result to be returned to the driver program.



- Lineage: transformations used to build an RDD.
- RDDs are stored as a chain of objects capturing the lineage of each RDD.



```
val file = sc.textFile("hdfs://...")
val sics = file.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_+_)
```



### Generic RDD Transformations (1/3)

- filter returns the RDD records that match some predicate function.
- distinct removes duplicates from the RDD.

```
val nums = sc.parallelize(Array(1, 2, 3))
val even = nums.filter(x => x % 2 == 0)
// 2
```

```
val words = sc.parallelize("this it easy, this is a test".split(" "))
val distinctWords = words.distinct()
// a, this, is, easy,, test, it
```



### Generic RDD Transformations (2/3)

 map and flatMap apply a given function on each RDD record independently.



```
val nums = sc.parallelize(Array(1, 2, 3))
val squares = nums.map(x => x * x)
// 1, 4, 9
```



#### Generic RDD Transformations (3/3)

sortBy sorts an RDD records.

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
```

```
val sortedWords = words.sortBy(word => word.length())
// a, it, is, take, this, test, easy,
```



## Key-Value RDD Transformations - Basics (1/2)

- ► In a (k, v) pairs, k is is the key, and v is the value.
- ► To make a key-value RDD:
  - map over your current RDD to a basic key-value structure.
  - Use the zip to zip together two RDD.

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
val keyword1 = words.map(word => (word, 1))
// (take,1), (it,1), (easy,,1), (this,1), (is,1), (a,1), (test,1)
```

```
val numRange = sc.parallelize(0 to 6)
val keyword3 = words.zip(numRange)
// (take,0), (it,1), (easy,,2), (this,3), (is,4), (a,5), (test,6)
```



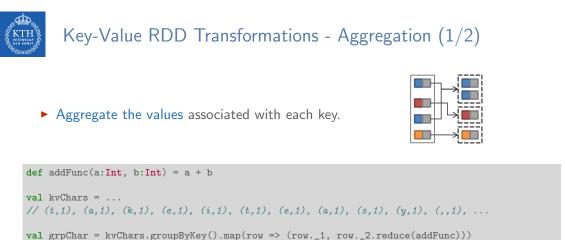
## Key-Value RDD Transformations - Basics (2/2)

- keys and values extract keys and values, respectively.
- mapValues maps over values.

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
val keyword = words.keyBy(word => word.toLowerCase.toSeq(0).toString)
// (t,take), (i,it), (e,easy,), (t,this), (i,is), (a,a), (t,test)
```

```
val k = keyword.keys
val v = keyword.values
```

```
val mapV = keyword.mapValues(word => word.toUpperCase)
// (t,TAKE), (i,IT), (e,EASY,), (t,THIS), (i,IS), (a,A), (t,TEST)
```



//(t,5), (h,1), (.,1), (e,3), (a,3), (i,3), (y,1), (s,4), (k,1))

val redChar = kvChars.reduceByKey(addFunc)
// (t,5), (h,1), (,,1), (e,3), (a,3), (i,3), (y,1), (s,4), (k,1))



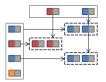
### Key-Value RDD Transformations - Aggregation (2/2)

- groupByKey or reduceByKey?
- In groupByKey, each executor must hold all values for a given key in memory before applying the function to them.
  - This is problematic in massive skewed key.
- In reduceByKey, the reduce happens within each partition, and does not need to put everything in memory.



### Key-Value RDD Transformations - Join

- join performs an inner-join on the key.
- fullOtherJoin, leftOuterJoin, rightOuterJoin, and cartesian.



```
val keyedChars = ...
// (t,4), (h,6), (,,9), (e,8), (a,3), (i,5), (y,2), (s,7), (k,0)
val kvChars = ...
// (t,1), (a,1), (k,1), (e,1), (i,1), (t,1), (e,1), (a,1), (s,1), (y,1), (,,1), ...
val joinedChars = kvChars.join(keyedChars)
// (t,(1,4)), (t,(1,4)), (t,(1,4)), (t,(1,4)), (h,(1,6)), (,,(1,9)), (e,(1,8)), ...
```



# Actions



- ► Transformations allow us to build up our logical transformation plan.
- We run an action to trigger the computation.
  - Instructs Spark to compute a result from a series of transformations.
- There are three kinds of actions:
  - Actions to view data in the console
  - · Actions to collect data to native objects in the respective language
  - Actions to write to output data sources



- collect returns all the elements of the RDD as an array at the driver.
- first returns the first value in the RDD.

```
val nums = sc.parallelize(Array(1, 2, 3))
nums.collect()
// Array(1, 2, 3)
nums.first()
// 1
```



## RDD Actions (2/6)

- take returns an array with the first n elements of the RDD.
- Variations on this function: takeOrdered and takeSample.

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
words.take(5)
// Array(take, it, easy,, this, is)
words.takeOrdered(5)
// Array(a, easy,, is, it, take)
val withReplacement = true
val numberToTake = 6
val randomSeed = 100L
words.takeSample(withReplacement, numberToTake, randomSeed)
// Array(take, it, test, this, test, take)
```



## RDD Actions (3/6)

- count returns the number of elements in the dataset.
- countByValue counts the number of values in a given RDD.

```
val words = sc.parallelize("take it easy, this is a test, take it easy".split(" "))
words.count()
// 10
words.countByValue()
// Map(this -> 1, is -> 1, it -> 2, a -> 1, easy, -> 1, test, -> 1, take -> 2, easy -> 1)
```



## RDD Actions (4/6)

#### max and min return the maximum and minimum values, respectively.

```
val nums = sc.parallelize(1 to 20)
val maxValue = nums.max()
// 20
val minValue = nums.min()
// 1
```



### RDD Actions (5/6)

- reduce aggregates the elements of the dataset using a given function.
- The given function should be commutative and associative so that it can be computed correctly in parallel.

```
sc.parallelize(1 to 20).reduce(_ + _)
// 210
```



## RDD Actions (6/6)

- saveAsTextFile writes the elements of an RDD as a text file.
  - Local filesystem, HDFS or any other Hadoop-supported file system.
- saveAsObjectFile explicitly writes key-value pairs.

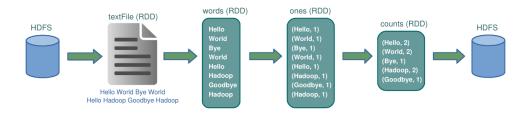
val words = sc.parallelize("take it easy, this is a test".split(" "))

words.saveAsTextFile("file:/tmp/words")



#### Spark Word-Count

```
val textFile = sc.textFile("hdfs://...")
val words = textFile.flatMap(line => line.split(" "))
val ones = words.map(word => (word, 1))
val counts = ones.reduceByKey(_ + _)
counts.saveAsTextFile("hdfs://...")
```





#### What Is The Problem?

# https://tinyurl.com/yc5jkrx5





# Cache and Checkpoints



- When you cache an RDD, each node stores any partitions of it that it computes in memory.
- An RDD that is not cached is re-evaluated each time an action is invoked on that RDD.
- ► A node reuses the cached RDD in other actions on that dataset.
- There are two functions for caching an RDD:
  - cache caches the RDD into memory
  - persist(level) can cache in memory, on disk, or off-heap memory

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
words.cache()
```



- checkpoint saves an RDD to disk.
- Checkpointed data is not removed after SparkContext is destroyed.
- When we reference a checkpointed RDD, it will derive from the checkpoint instead of the source data.

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
sc.setCheckpointDir("/path/checkpointing")
words.checkpoint()
```



# **Execution Engine**



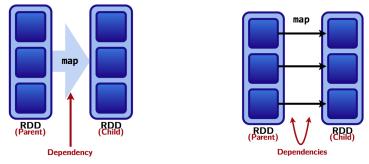
#### More About Lineage

► A DAG representing the computations done on the RDD is called lineage graph.





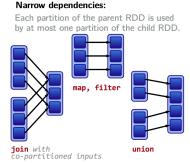
► RDD dependencies encode when data must move across network.





### Two Types of Dependencies (1/2)

- Narrow transformations (dependencies)
  - Each input partition will contribute to only one output partition.
  - With narrow transformations, Spark can perform a pipelining





### Two Types of Dependencies (2/2)

- Wide transformations (dependencies)
  - Each input partition will contribute to many output partition.
  - Usually referred to as a shuffle

#### Wide dependencies:

Each partition of the parent RDD may be depended on by multiple child partitions.

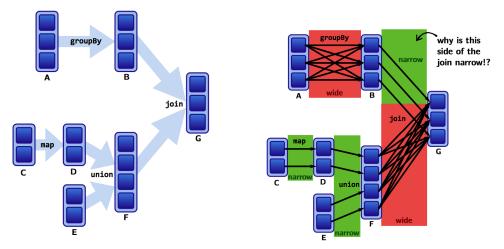




**join** with inputs not co-partitioned



#### Example





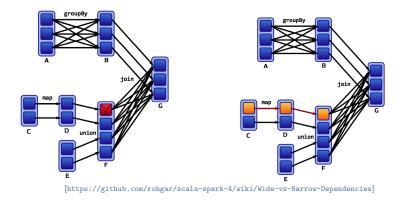
### Lineages and Fault Tolerance (1/2)

- ► No replication.
- Lineages are the key to fault tolerance in Spark.
- Recompute only the lost partitions of an RDD.



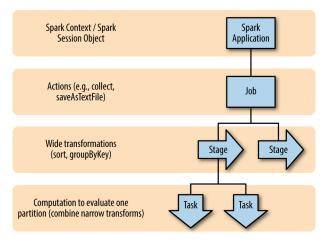
### Lineages and Fault Tolerance (2/2)

- Assume one of the partitions fails.
- ▶ We only have to recompute the data shown below to get back on track.



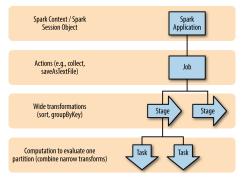


### The Anatomy of a Spark Job



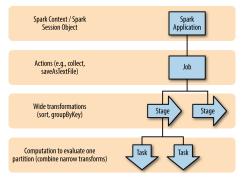


- ► A Spark job is the highest element of Spark's execution hierarchy.
  - Each Spark job corresponds to one action.
  - Each action is called by the driver program of a Spark application.



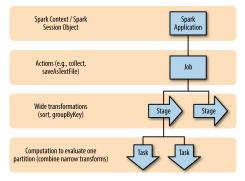


- Each job breaks down into a series of stages.
  - Stages in Spark represent groups of tasks that can be executed together.
  - Wide transformations define the breakdown of jobs into stages.





- ► A stage consists of tasks, which are the smallest execution unit.
  - Each task represents one local computation.
  - All of the tasks in one stage execute the same code on a different piece of the data.





# Summary





- ▶ RDD: a distributed memory abstraction
- ▶ Two types of operations: transformations and actions
- Lineage graph
- ► Caching
- ► Jobs, stages, and tasks
- ► Wide vs. narrow dependencies



- M. Zaharia et al., "Spark: The Definitive Guide", O'Reilly Media, 2018 Chapters 2, 12, 13, and 14
- M. Zaharia et al., "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing", USENIX NSDI, 2012.



# Questions?