Parallel Processing - Spark

Amir H. Payberah
payberah@kth.se
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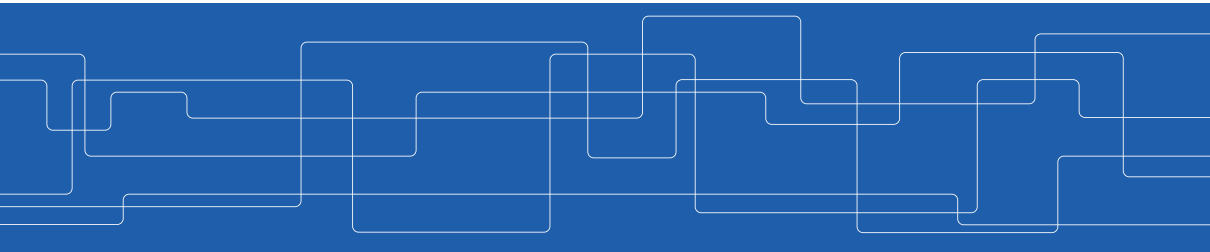


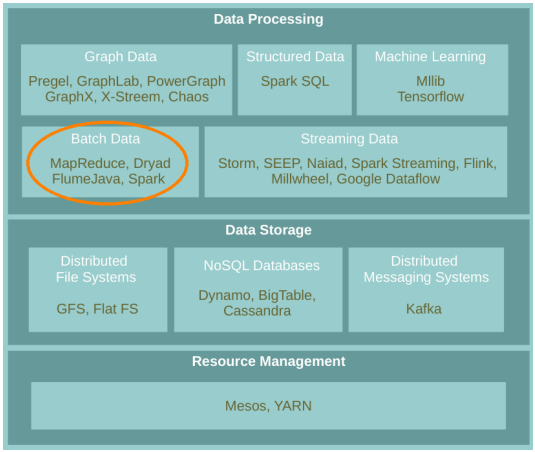
The Course Web Page

https://id2221kth.github.io

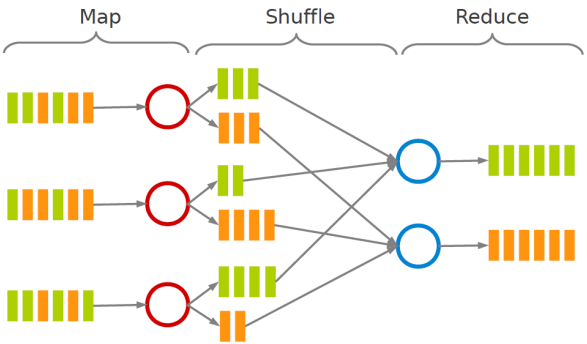
The Questions-Answers Page

https://tinyurl.com/bdenpwc5

Where Are We?

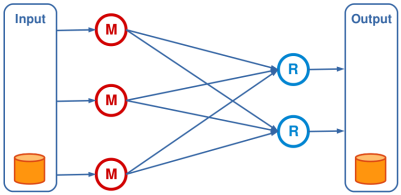

Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

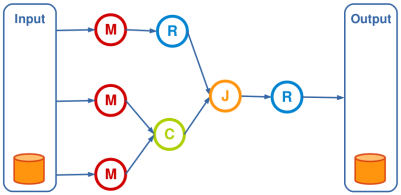
MapReduce Reminder



Motivation (1/2)

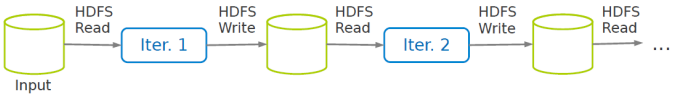
- Acyclic data flow from stable storage to stable storage.



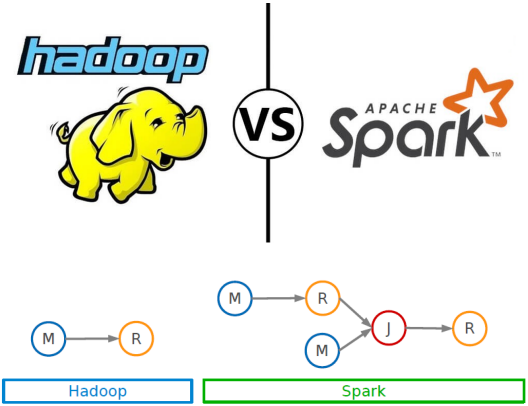


Motivation (2/2)

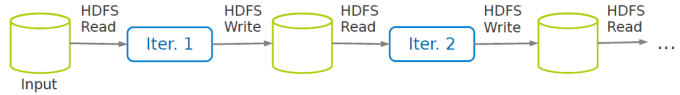
- MapReduce is expensive (slow), i.e., always goes to disk and HDFS.

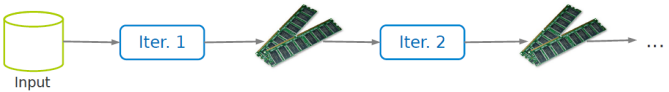


So, Let's Use Spark

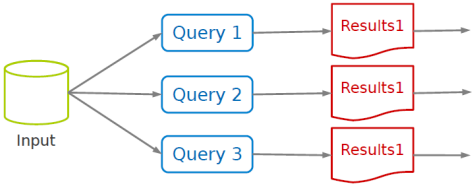


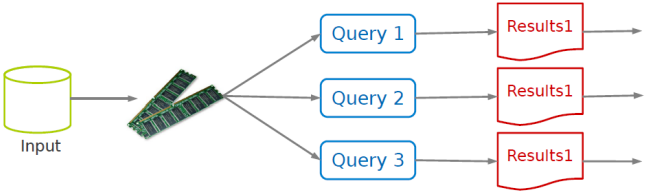
Spark vs. MapReduce (1/2)





Spark vs. MapReduce (2/2)

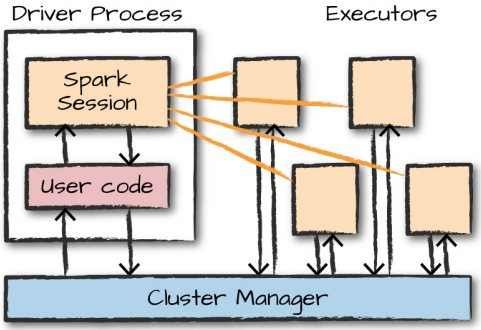




Spark Application

Spark Applications Architecture

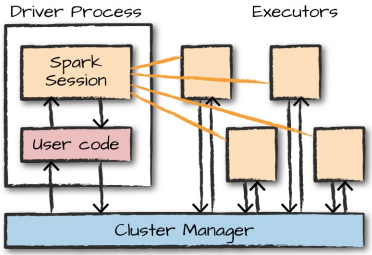
- Spark applications consist of
  - A driver process
  - A set of executor processes



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

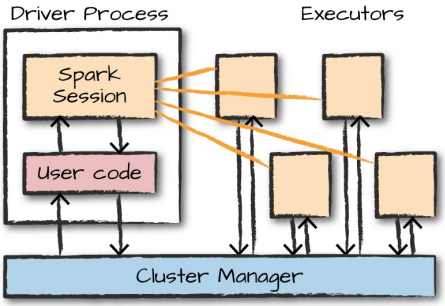
Driver Process

- The heart of a Spark application
- Sits on a node in the cluster
- 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



Executors

- Responsible for two things:
  - Executing code assigned to it by the driver
  - Reporting the state of the computation on that executor back to the driver



SparkSession

- A driver process that controls a Spark application.
- Main entry point to Spark functionality.
- 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()
```

SparkContext

- The entry point for low-level API functionality.
- You access it through the `SparkSession`.
- You can access a `SparkContext` via `spark.sparkContext`.
- Available in console shell as `sc`.

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

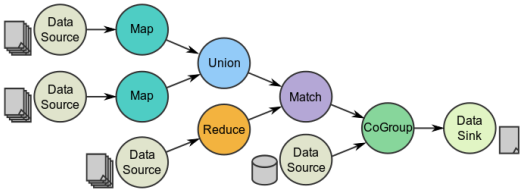
SparkSession vs. SparkContext

- 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.

Types of RDDs

- 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.

When To Use RDDs?

- Short answer: you should not manually create RDDs unless you have a very specific reason.
- They are a much lower-level API that provides a lot of power.
- But, lack of the optimizations that are available in the Structured APIs.
- The most likely reason to use RDDs: custom partitioning of data.
  - Fine-grained control over the physical distribution of data.

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

RDD Operations

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

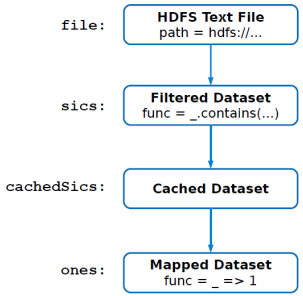
Transformations

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

- 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)

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

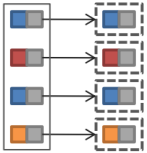
```
val nums = sc.parallelize(Array(1, 2, 3))
val even = nums.filter(x => x % 2 == 0)
// 2
```

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

```
def startsWithT(individual:String) = { individual.startsWith("t") }
val tWordList = words.filter(word => startsWithT(word))
// this, test
```

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
```

```
val words = sc.parallelize("take it easy, this is a test".split(" "))
val tWords = words.map(word => (word, word.startsWith("t")))
// (take,true), (it,false), (easy,,false), (this,true), (is,false), (a,false), (test,true)
```

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 `keyBy` to create a key from the current value.
  - 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 keyword2 = words.keyBy(word => word.toSeq(0).toString)
// (t,take), (i,it), (e,easy,), (t,this), (i,is), (a,a), (t,test)
```

```
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.
- `lookup` looks up the values for a particular key with an RDD.
- `mapValues` maps over values.

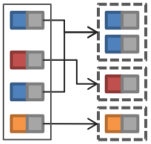
```
val words = sc.parallelize("take it easy, this is a test".split(" "))
val keyword = words.keyBy(word => word.toLowerCase.toSeq(0).toString)
// (t,take), (i,it), (e,easy,), (t,this), (i,is), (a,a), (t,test)

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

```
val tValues = keyword.lookup("t")
// take, this, test
```

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

Key-Value RDD Transformations - Aggregation (1/2)

- Aggregate the values associated with each key.



```
val kvChars = ...
// (t,1), (a,1), (k,1), (e,1), (i,1), (t,1), (e,1), (a,1), (s,1), (y,1), (,,1), ...

val grpChar = kvChars.groupByKey().map(row => (row._1, row._2.reduce(addFunc)))
// (t,5), (h,1), (,,1), (e,3), (a,3), (i,3), (y,1), (s,4), (k,1))
```

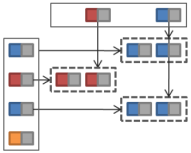
```
def addFunc(left:Int, right:Int) = left + right
val redChar = kvChars.reduceByKey(addFunc)
// (t,5), (h,1), (,,1), (e,3), (a,3), (i,3), (y,1), (s,4), (k,1))
```

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)), (t,(1,4)), (h,(1,6)), (,,(1,9)), (e,(1,8)), ...
```

Actions

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

RDD Actions (1/6)

- `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.
- `countByKey` returns a hashmap of (K, Int) pairs with the count of each key.
  - Only available on key-valye RDDs, i.e., (K, V)

```
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

def wordLengthReducer(leftWord:String, rightWord:String): String = {
  if (leftWord.length > rightWord.length)
    return leftWord
  else
    return rightWord
}

words.reduce(wordLengthReducer)
// easy,
```

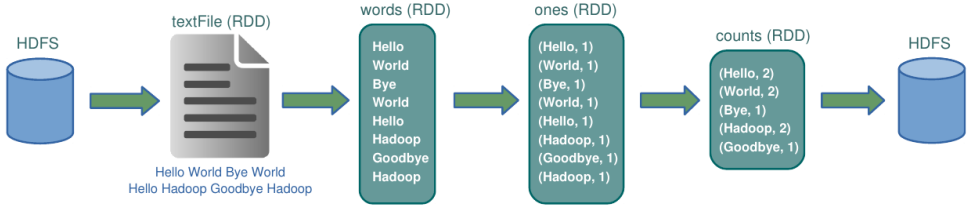
RDD Actions (6/6)

- `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")
```

Example

```scala
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://...")
```



Cache and Checkpoints

Caching

- 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()
```

Checkpointing

- `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.

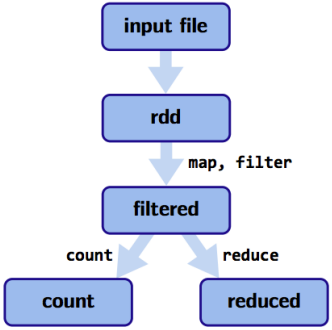
```
val words = sc.parallelize("take it easy, this is a test".split(" "))

sc.setCheckpointDir("/path/checkpointing")
words.checkpoint()
```

Execution Engine

More About Lineage

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

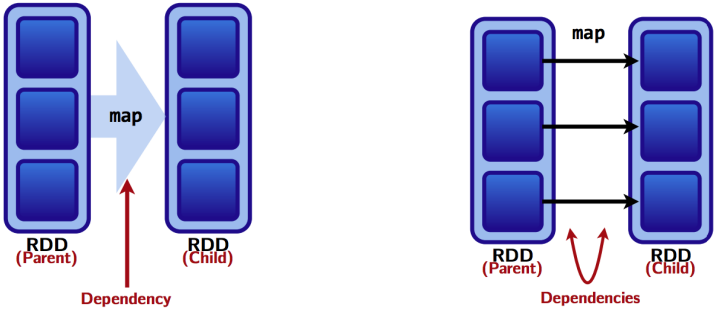
```
val rdd = sc.textFile(...)
val filtered = rdd.map(...).filter(...).persist()
val count = filtered.count()
val reduced = filtered.reduce()
```



[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

Dependencies

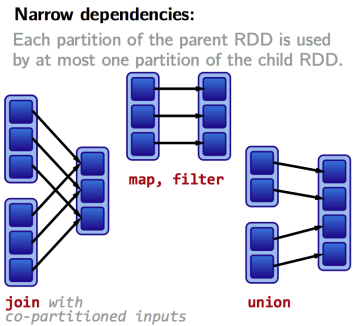
- RDD dependencies encode when data must move across network.



[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

Two Types of Dependencies (1/2)

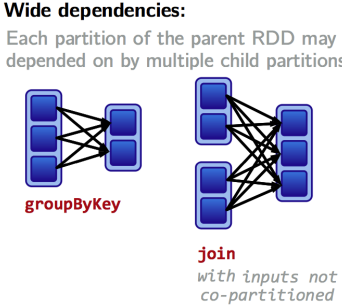
- Narrow transformations (dependencies)
  - Each input partition will contribute to only one output partition.
  - With narrow transformations, Spark can perform a pipelining



[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

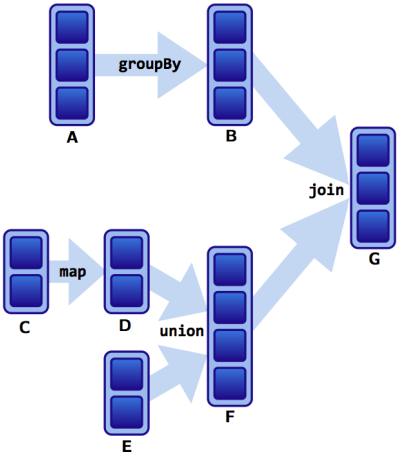
Two Types of Dependencies (2/2)

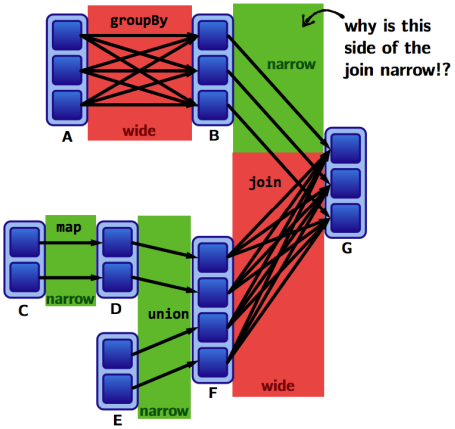
- Wide transformations (dependencies)
  - Each input partition will contribute to many output partition.
  - Usually referred to as a shuffle



[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

Example





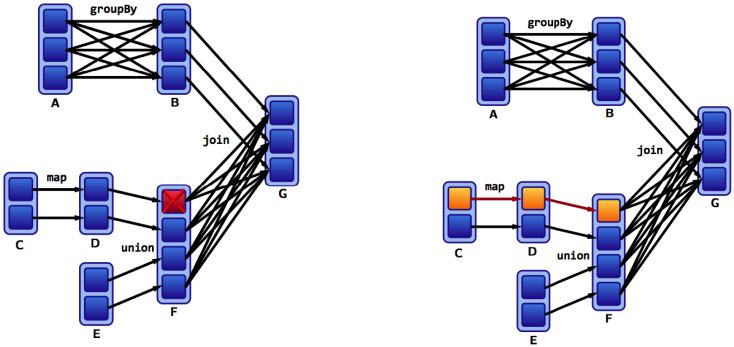
[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

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.

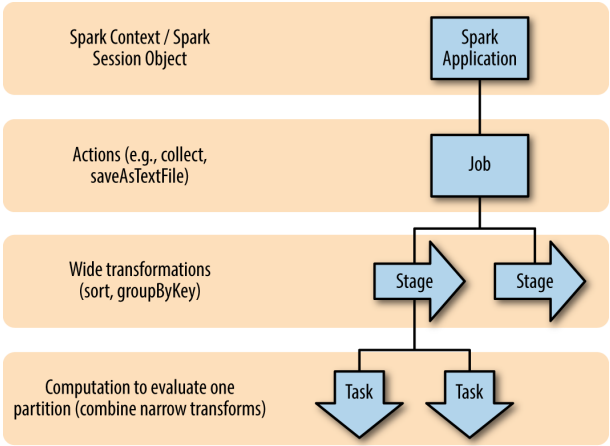
Lineages and Fault Tolerance (2/2)

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



[https://github.com/rohgar/scala-spark-4/wiki/Wide-vs-Narrow-Dependencies]

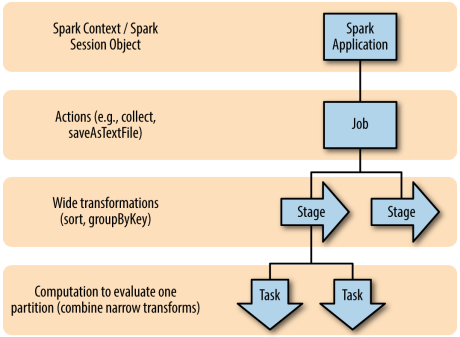
The Anatomy of a Spark Job



[H. Karau et al., High Performance Spark, O'Reilly Media, 2017]

Jobs

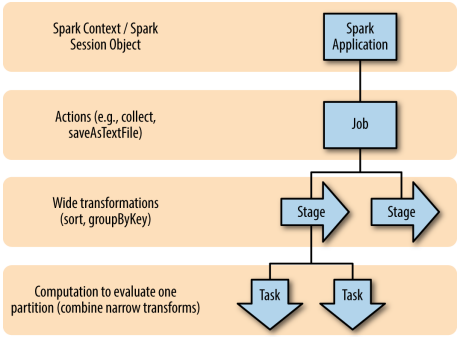
- A Spark job is the highest element of Spark's execution hierarchy.
  - Each Spark job corresponds to one action.
  - Each action is called by the driver program of a Spark application.



[H. Karau et al., High Performance Spark, O'Reilly Media, 2017]

Stages

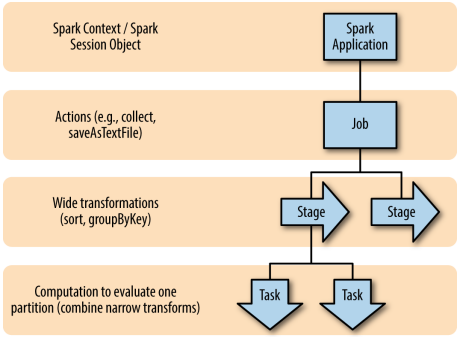
- Each job breaks down into a series of stages.
  - Stages in Spark represent groups of tasks that can be executed together.
  - Wide transformations define the breakdown of jobs into stages.



[H. Karau et al., High Performance Spark, O'Reilly Media, 2017]

Tasks

- 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.



[H. Karau et al., High Performance Spark, O'Reilly Media, 2017]

Summary

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

References

- 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?