Aalto University
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Apache Spark and Distributed Programming

CS-E4110 Concurrent Programming

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November 30th, 2016

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Apache Spark

- Distributed programming framework for Big Data processing
- Based on functional programming
- Implements distributed Scala collections like interfaces for Scala, Java, Python, and R
- Implemented on top of the Akka actor framework
- Original paper:
  Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauly, Michael J. Franklin, Scott Shenker, Ion Stoica: Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. NSDI 2012: 15-28

Resilient Distributed Datasets

Resilient Distributed Datasets

- Resilient Distributed Datasets (RDDs) are Scala collection-like entities that are distributed over several computers
- The framework stores the RDDs in partitions, where a separate thread can process each partition
- To implement fault tolerance, the RDD partitions record lineage: A recipe to recompute the RDD partition based on the parent RDDs and the operation used to generate the partition
- If a server goes down, the lineage information can be used to recompute its partitions on another server

Spark Tutorials

Spark Tutorials

- Quick start:
  `http://spark.apache.org/docs/latest/quick-start.html`
- Spark Programming Guide:
  `http://spark.apache.org/docs/latest/programming-guide.html`
- Dataframes and Spark SQL:
  `http://spark.apache.org/docs/latest/sql-programming-guide.html`

Spark Quick Start (cnt.)

Spark Tutorials

- After Spark has been installed, the command `spark-shell` can be used to create an interactive Scala shell to run spark code in
- Shell initializes a Spark context in variable `sc`
- For the shell to work, a Spark master has to be running. A local Spark master can be started with the command `start-master.sh` and stopped with `stop-master.sh`
- To create an RDD from a local file, count the number of lines, and show the first line use:

```scala
val textFile = sc.textFile("kalevala.txt")
textFile.count()
textFile.first()
```

Spark Quick Start (cnt.)

Spark Quick Start

- The log is:

```
Spark context available as sc.
SQL context available as sqlContext.
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 1.5.2
      /_/

Using Scala version 2.11.7 (Java HotSpot(TM) 64-Bit Server VM, Java 1.8.0_66)
Type in expressions to have them evaluated.
Type :help for more information.

scala> val textFile = sc.textFile("kalevala.txt")
textFile: org.apache.spark.rdd.RDD[String] = MapPartitionsRDD[1] at textFile at <console>:24

scala> textFile.count()
res0: Long = 14366

scala> textFile.first()
res1: String = Kalevala
```

Spark Quick Start (cnt.)

Spark Quick Start

- To find out how many lines contain the name “Louhi”:

```scala
val textFile = sc.textFile("kalevala.txt")
textFile.filter(line => line.contains("Louhi")).count() // How many lines contain "Louhi"?
```

- The log is:

```
scala> val textFile = sc.textFile("kalevala.txt")
textFile: org.apache.spark.rdd.RDD[String] =
MapPartitionsRDD[1] at textFile at <console>:24

scala> textFile.filter(line => line.contains("Louhi")).count()
// How many lines contain "Louhi"?
res0: Long = 29
```

Creating RDDs

RDDs can be created from:

- From other RDDs using RDD transformations
- Scala collections
- Local files
- Usually with Big Data: Files stored in distributed storage systems: Hadoop Distributed Filesystem (HDFS), Amazon S3, HBase, ...
- When an RDD is created, it is initially split to a number of partitions, which should be large enough (e.g., at least 2-10 x the number of cores) to allow for efficient load balancing between cores
- Each partition should still be large enough to take more than 100 ms to process, so not to waste too much time in starting and finishing the task processing a partition

Example Standalone Spark App

Example Standalone Spark App

```scala
/* SimpleApp.scala */
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark.SparkConf

object SimpleApp {
  def main(args: Array[String]) {
    val logFile = "YOUR_SPARK_HOME/README.md" // Should be some file on your system
    val conf = new SparkConf().setAppName("Simple Application")
    val sc = new SparkContext(conf)
    val logData = sc.textFile(logFile, 2).cache()
    val numAs = logData.filter(line => line.contains("a")).count()
    val numBs = logData.filter(line => line.contains("b")).count()
    println("Lines with a: %s, Lines with b: %s".format(numAs, numBs))
  }
}
```

RDD Transformations

The following RDD transformations are available:

- map(func)
- filter(func)
- flatMap(func)
- mapPartitions(func)
- mapPartitionsWithIndex(func)
- sample(withReplacement, fraction, seed)
- union(otherDataset)
- intersection(otherDataset)
- distinct([numTasks]))

RDD Transformations (cnt.)

The following RDD transformations are available:

- groupByKey([numTasks])
- reduceByKey(func, [numTasks])
- aggregateByKey(zeroValue)(seqOp, combOp, [numTasks])
- sortByKey([ascending], [numTasks])
- join(otherDataset, [numTasks])
- cogroup(otherDataset, [numTasks])
- cartesian(otherDataset)
- pipe(command, [envVars])
- coalesce(numPartitions)

RDD Transformations (cnt.)

The following RDD transformations are available:

- repartition(numPartitions)
- repartitionAndSortWithinPartitions(partitioner)
- ...

RDD Transformations (cnt.)

RDD Transformations:

- RDD transformations build a DAG of dependencies between RDD partitions but do not yet start processing
- The actual data processing is done lazily
- The RDD Actions are needed to start the computation

RDD Actions

Available RDD Actions:

- reduce(func)
- collect()
- count()
- first()
- take(n)
- takeSample(withReplacement, num, [seed])
- takeOrdered(n, [ordering])
- saveAsTextFile(path)
- saveAsSequenceFile(path)

RDD Actions (cnt.)

Available RDD Actions:

- saveAsObjectFile(path)
- countByKey()
- foreach(func)
- . . .

RDD Operations and Actions

RDD Operations and Actions:

- Many well known functional programming costructs such as `map` (or `flatMap`) and `reduce` (`reduceByKey`) are available as operations
- One can implement relational database like functionality easily on top of RDD operations, if needed
- This is how Spark SQL, a Big Data analytics framework, was originally implemented
- Many operations take a user function to be called back as argument
- Freely mixing user code with RDD operations limits the optimization capabilities of Spark RDDs - You get the data processing operations you write

Broadcast Variables

Broadcast Variables

- Broadcast variables are a way to send some read-only data to all Spark workers in a coordinated fashion:

```
scala> val broadcastVar = sc.broadcast(Array(1, 2, 3))
broadcastVar: org.apache.spark.broadcast.Broadcast[Array[Int]] =
Broadcast(0)

scala> broadcastVar.value
res0: Array[Int] = Array(1, 2, 3)
```

Accumulators

- Accumulators allow a way to compute statistics done during operations:

```
scala> val accum = sc.accumulator(0, "My Accumulator")
accum: spark.Accumulator[Int] = 0

scala> sc.parallelize(Array(1, 2, 3, 4)).foreach(x => accum += x)
...
10/09/29 18:41:08 INFO SparkContext: Tasks finished in 0.317106 s

scala> accum.value
res2: Int = 10
```

- Note: If a job is rescheduled during operation execution, the accumulators are increased several times
- Thus the accumulators can also count processing that is “wasted” due to fault tolerance / speculation

Implementing RDD Operations and Actions

Implementing RDD Operations and Actions

- As the RDD operations are run in several computers, there is no shared memory to use to share state between operations
- The functions run in all of the distributed nodes need to copy all of the data they need to all of the Spark workers using so called closures
- To minimize the amount of data that needs to be copied to all nodes, the functions should refer to as little data as possible to keep the closures small
- Note that variables of the closure modified in a Worker node are lost and thus can not be used to communicate back to the driver program
- The only communication is through operations and actions on RDDs

Buggy Code misusing Closures

Buggy Code misusing Closures

- When Spark is run in truly distributed mode, the following code will not work, as changes to `counter` do not propagate back to the driver:

```
// Buggy code!!!

var counter = 0
var rdd = sc.parallelize(data)

// Wrong: Don't do this!!
rdd.foreach(x => counter += x)

println("Counter␣value:␣" + counter)
```

RDD Persistence leveles

RDDs can be configured with different persistence levels for caching RDDs:

- `MEMORY_ONLY`
- `MEMORY_AND_DISK`
- `MEMORY_ONLY_SER`
- `MEMORY_AND_DISK_SER`
- `DISK_ONLY`
- `MEMORY_ONLY_2, MEMORY_AND_DISK_ONLY_2`
- `OFF_HEAP` (experimental)

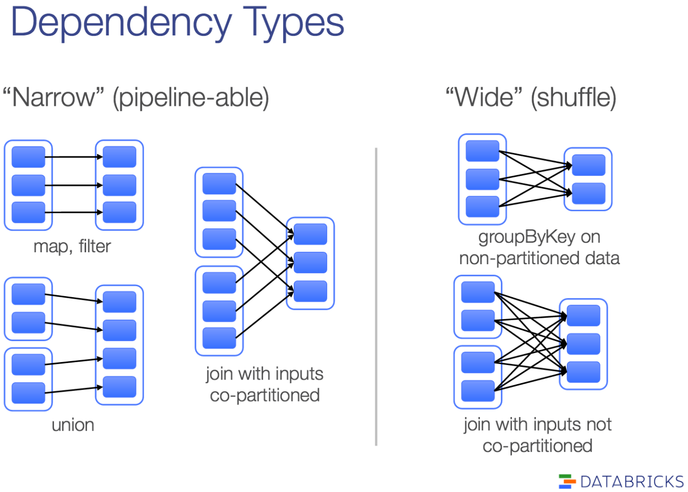
Lineage

Lineage can contain both narrow and wide dependencies:

- Figures in the following from “Databrics Advanced Spark Training by Reynold Xin”: `https://databricks-training.s3.amazonaws.com/slides/advanced-spark-training.pdf`

Lineage (cnt.)

Lineage can contain both narrow and wide dependencies:



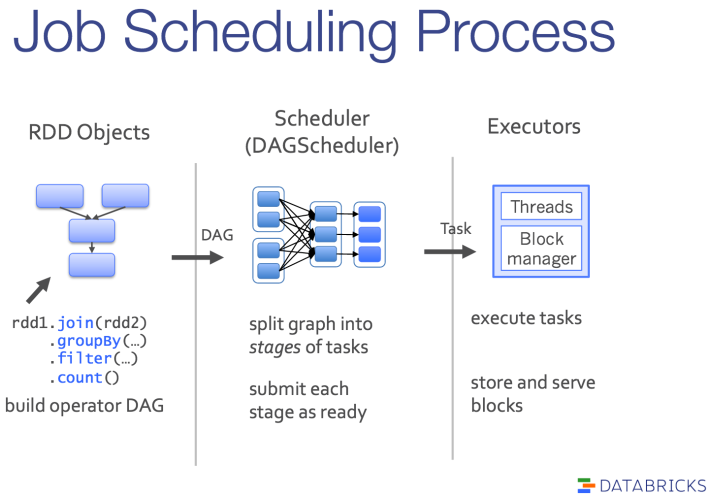
Narrow and Wide Dependencies

Narrow and Wide Dependencies

- In narrow dependencies, the data partition from an input RDD can be scheduled on the same physical machine as the out RDD. This is called “pipelining”
- Thus computing RDD operations with only narrow dependencies can scheduled to be done without network traffic
- Wide dependencies require all RDD partitions at the previous level of the lineage to be inputs to computing an RDD partition
- This requires sending most of the input RDD data over the network
- This operation is called the “shuffle” in Spark (and MapReduce) terminology
- Shuffles are unavoidable for applications needing e.g., global sorting of the output data

DAG Scheduling

DAG scheduler is used to schedule RDD operations:



Pipelining into Stages

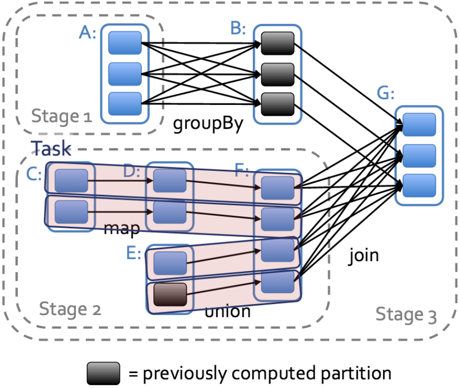
Scheduler pipelines work into stages separated by wide dependencies:

Scheduler Optimizations

Pipelines operations within a stage

Picks join algorithms based on partitioning (minimize shuffles)

Reuses previously cached data



Spark Motivation

Spark Motivation

- The MapReduce framework is one of the most robust Big Data processing frameworks
- MapReduce has several problems that Spark is able to address:
  - Reading and storing data from main memory instead of hard disks - Main memory is much faster than the hard drives
  - Running iterative algorithms much faster - Especially important for many machine learning algorithms

Spark Benchmarking

Spark Benchmarking

- The original papers claim Spark to be upto 100x faster when data fits into RAM vs MapReduce, or upto 10x faster when data is on disks
- Large speedups can be observed in the RAM vs HD case
- However, independent benchmarks show when both use HDs, Spark is upto 2.5-5x faster for CPU bound workloads, however MapReduce can still sort faster: Juwei Shi, Yunjie Qiu, Umar Farooq Minhas, Limei Jiao, Chen Wang, Berthold Reinwald, Fatma Özcan: Clash of the Titans: MapReduce vs. Spark for Large Scale Data Analytics. PVLDB 8(13): 2110-2121 (2015)
  `http://www.vldb.org/pvldb/vol8/p2110-shi.pdf`
  `http://www.slideshare.net/ssuser6bb12d/a-comparative-performance-evaluation-of-apache-flink`

Spark Extensions

Spark Extensions

- MLlib - Distributed Machine learning Library
- Spark SQL - Distributed Analytics SQL Database - Can be tightly integrated with Apache Hive Data Warehouse, uses HQL (Hive SQL variant)
- Spark Streaming - A Streaming Data Processing Framework
- GraphX - A Graph processing system

Data Frames

- The Spark project has introduced a new data storage and processing framework - Data Frames - to eventually replace RDDs for many applications
- Problem with RDDs: As RDDs are operated by arbitrary user functions in Scala/Java/Python, optimizing them is very hard
- DataFrames allow only a limited number of DataFrame native operations, and allows the Spark SQL optimizer to rewrite user DataFrame code to equivalent but faster codes
- Instead of executing what the user wrote (as with RDDs), execute an optimized sequence of operations
- Allows DataFrame operations to be also implemented in C/C++ (LLVM) level