Spark and Resilient Distributed Datasets

Amir H. Payberah
amir@sics.se

Amirkabir University of Technology
(Tehran Polytechnic)

Motivation

- MapReduce greatly simplified big data analysis on large, unreliable clusters.

- But as soon as it got popular, users wanted more:
  - Iterative jobs, e.g., machine learning algorithms
  - Interactive analytics

Motivation

- Both iterative and interactive queries need one thing that MapReduce lacks:

Motivation

- Both iterative and interactive queries need one thing that MapReduce lacks:

Efficient primitives for data sharing.

Motivation

- Both iterative and interactive queries need one thing that MapReduce lacks:

  Efficient primitives for data sharing.

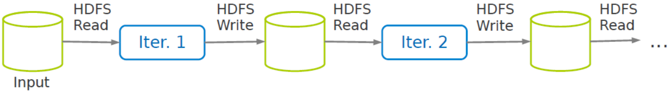
- In MapReduce, the only way to share data across jobs is stable storage, which is slow.

- Replication also makes the system slow, but it is necessary for fault tolerance.

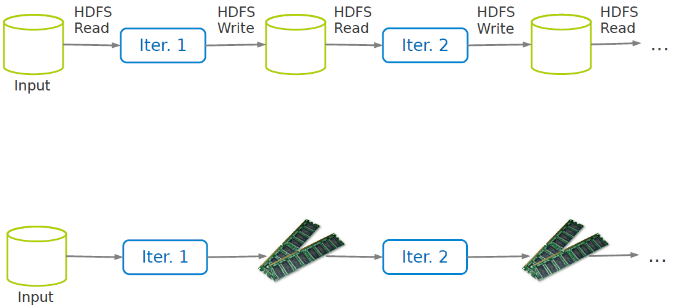
Proposed Solution

In-Memory Data Processing and Sharing.

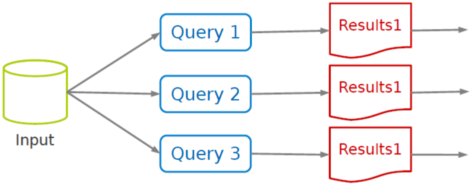
Example


HDFS
Read
Iter. 1
HDFS
Write
HDFS
Read
Iter. 2
HDFS
Write
HDFS
Read
...
Input

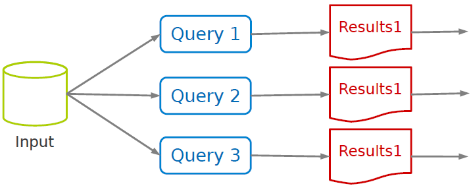
Example

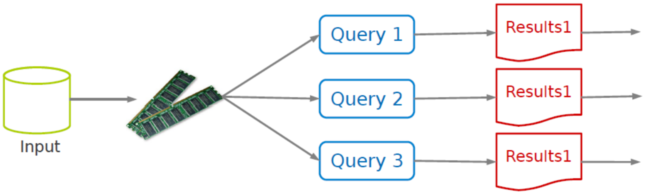

HDFS
Read
Iter. 1
HDFS
Write
HDFS
Read
Iter. 2
HDFS
Write
HDFS
Read
...
Input
Iter. 1
Iter. 2
...
Input

Example



Example


Query 1
Query 2
Query 3
Results1
Results1
Results1
Input


Query 1
Query 2
Query 3
Results1
Results1
Results1
Input

Challenge

How to design a distributed memory abstraction that is both fault tolerant and efficient?

Challenge

How to design a distributed memory abstraction that is both fault tolerant and efficient?

Solution

Resilient Distributed Datasets (RDD)

Resilient Distributed Datasets (RDD) (1/2)

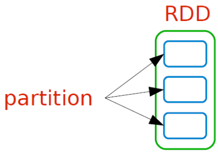
- A distributed memory abstraction.

Resilient Distributed Datasets (RDD) (1/2)

- A distributed memory abstraction.
- Immutable collections of objects spread across a cluster.

Resilient Distributed Datasets (RDD) (2/2)

- 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.

Programming Model

Spark Programming Model (1/2)

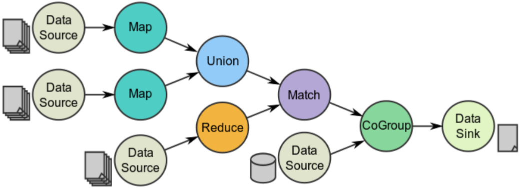
- Spark programming model is based on parallelizable operators.

- Parallelizable operators are higher-order functions that execute user-defined functions in parallel.

Spark Programming Model (2/2)

- A data flow is composed of any number of data sources, operators, and data sinks by connecting their inputs and outputs.

- Job description based on directed acyclic graphs (DAG).



Higher-Order Functions (1/3)

- Higher-order functions: RDDs operators.

- There are two types of RDD operators: transformations and actions.

Higher-Order Functions (2/3)

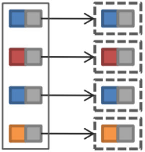
- Transformations: lazy operators that create new RDDs.
- Actions: lunch a computation and return a value to the program or write data to the external storage.

Higher-Order Functions (3/3)

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

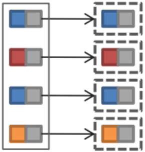
RDD Transformations - Map

- All pairs are independently processed.



RDD Transformations - Map

- All pairs are independently processed.



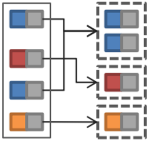
```
// passing each element through a function.
val nums = sc.parallelize(Array(1, 2, 3))
val squares = nums.map(x => x * x) // {1, 4, 9}

// selecting those elements that func returns true.
val even = squares.filter(x => x % 2 == 0) // {4}

// mapping each element to zero or more others.
nums.flatMap(x => Range(0, x, 1)) // {0, 0, 1, 0, 1, 2}
```

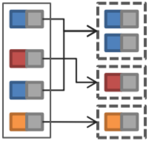
RDD Transformations - Reduce

- Pairs with identical key are grouped.
- Groups are independently processed.



RDD Transformations - Reduce

- Pairs with identical key are grouped.
- Groups are independently processed.



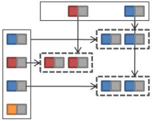
```
val pets = sc.parallelize(Seq(("cat", 1), ("dog", 1), ("cat", 2)))

pets.reduceByKey((x, y) => x + y)
// {(cat, 3), (dog, 1)}

pets.groupByKey()
// {(cat, (1, 2)), (dog, (1))}
```

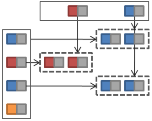
RDD Transformations - Join

- Performs an equi-join on the key.
- Join candidates are independently processed.



RDD Transformations - Join

- Performs an equi-join on the key.
- Join candidates are independently processed.



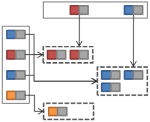
```scala
val visits = sc.parallelize(Seq(("index.html", "1.2.3.4"),
                                ("about.html", "3.4.5.6"),
                                ("index.html", "1.3.3.1")))

val pageNames = sc.parallelize(Seq(("index.html", "Home"),
                                   ("about.html", "About")))

visits.join(pageNames)
  // ("index.html", ("1.2.3.4", "Home"))
  // ("index.html", ("1.3.3.1", "Home"))
  // ("about.html", ("3.4.5.6", "About"))
```

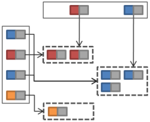
RDD Transformations - CoGroup

- Groups each input on key.
- Groups with identical keys are processed together.



RDD Transformations - CoGroup

- Groups each input on key.
- Groups with identical keys are processed together.



```
val visits = sc.parallelize(Seq(("index.html", "1.2.3.4"),
                                ("about.html", "3.4.5.6"),
                                ("index.html", "1.3.3.1")))

val pageNames = sc.parallelize(Seq(("index.html", "Home"),
                                   ("about.html", "About")))

visits.cogroup(pageNames)
  // ("index.html", (("1.2.3.4", "1.3.3.1"), ("Home")))
  // ("about.html", (("3.4.5.6"), ("About")))
```

RDD Transformations - Union and Sample

- Union: merges two RDDs and returns a single RDD using bag semantics, i.e., duplicates are not removed.

- Sample: similar to mapping, except that the RDD stores a random number generator seed for each partition to deterministically sample parent records.

Basic RDD Actions (1/2)

- Return all the elements of the RDD as an array.

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

Basic RDD Actions (1/2)

- Return all the elements of the RDD as an array.

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

- Return an array with the first n elements of the RDD.

```
nums.take(2) // Array(1, 2)
```

Basic RDD Actions (1/2)

- Return all the elements of the RDD as an array.

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

- Return an array with the first n elements of the RDD.

```
nums.take(2) // Array(1, 2)
```

- Return the number of elements in the RDD.

```
nums.count() // 3
```

Basic RDD Actions (2/2)

- Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)
or
nums.reduce(_ + _) // 6
```

Basic RDD Actions (2/2)

- Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)
or
nums.reduce(_ + _) // 6
```

- Write the elements of the RDD as a text file.

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

SparkContext

- Main entry point to Spark functionality.
- Available in shell as variable sc.
- In standalone programs, you should make your own.

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

val sc = new SparkContext(master, appName, [sparkHome], [jars])
```

SparkContext

- Main entry point to Spark functionality.
- Available in shell as variable sc.
- In standalone programs, you should make your own.

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

val sc = new SparkContext(master, appName, [sparkHome], [jars])
```

local
local[k]
spark://host:port
mesos://host:port

Creating RDDs

- Turn a collection into an RDD.

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

Creating RDDs

- Turn a collection into an RDD.

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

- Load text file from local FS, HDFS, or S3.

```
val a = sc.textFile("file.txt")
val b = sc.textFile("directory/*.txt")
val c = sc.textFile("hdfs://namenode:9000/path/file")
```

Example (1/2)

- Count the lines containing SICS.

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

Example (1/2)

- Count the lines containing SICS.

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

Transformation

Transformation

Action

Example (2/2)

- Count the lines containing SICS.

```
val file = sc.textFile("hdfs://...")
val count = file.filter(_.contains("SICS")).count()
```

Example (2/2)

- Count the lines containing SICS.

```
val file = sc.textFile("hdfs://...")
val count = file.filter(_.contains("SICS")).count()
```

Transformation

Action

Example - Standalone Application (1/2)

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

object WordCount {
  def main(args: Array[String]) {
    val sc = new SparkContext("local", "SICS", "127.0.0.1",
        List("target/scala-2.10/sics-count_2.10-1.0.jar"))
    val file = sc.textFile("...").cache()
    val count = file.filter(_.contains("SICS")).count()
  }
}
```

Example - Standalone Application (2/2)

- sics.sbt:

```
name := "SICS Count"

version := "1.0"

scalaVersion := "2.10.3"

libraryDependencies += "org.apache.spark" %% "spark-core" % "0.9.0-incubating"

resolvers += "Akka Repository" at "http://repo.akka.io/releases/"
```

Shared Variables (1/2)

- When Spark runs a function in parallel as a set of tasks on different nodes, it ships a copy of each variable used in the function to each task.

- Sometimes, a variable needs to be shared across tasks, or between tasks and the driver program.

Shared Variables (2/2)

- No updates to the variables are propagated back to the driver program.
- General read-write shared variables across tasks is inefficient.
  - For example, to give every node a copy of a large input dataset.
- Two types of shared variables: broadcast variables and accumulators.

Shared Variables: Broadcast Variables

- A read-only variable cached on each machine rather than shipping a copy of it with tasks.

- The broadcast values are not shipped to the nodes more than once.

```
scala> val broadcastVar = sc.broadcast(Array(1, 2, 3))
broadcastVar: spark.Broadcast[Array[Int]] = spark.Broadcast(b5c40191-...)

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

Shared Variables: Accumulators

- They are only added.
- They can be used to implement counters or sums.
- Tasks running on the cluster can then add to it using the $+=$ operator.

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

scala> sc.parallelize(Array(1, 2, 3, 4)).foreach(x => accum += x)
...

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

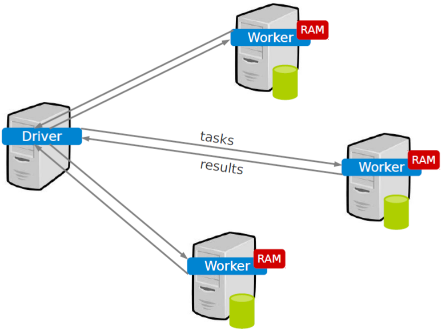
Execution Engine (SPARK)

Spark

- Spark provides a programming interface in Scala.
- Each RDD is represented as an object in Spark.

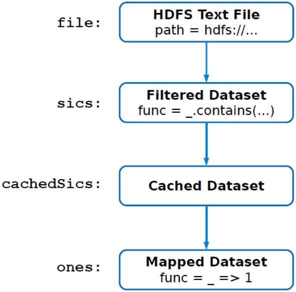
Spark Programming Interface

- A Spark application consists of a driver program that runs the user's main function and executes various parallel operations on a cluster.



Lineage

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

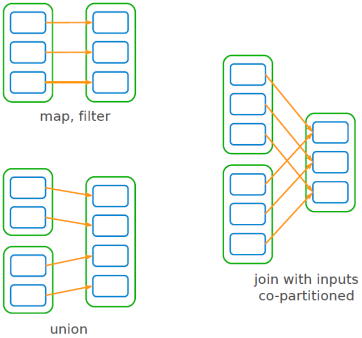



```
val file = sc.textFile("hdfs://...")
val sics = file.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_+_)
```

RDD Dependencies (1/3)

- Two types of dependencies between RDDs: Narrow and Wide.

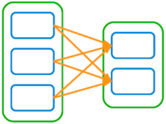
RDD Dependencies: Narrow (2/3)



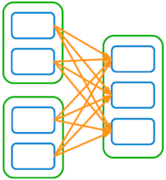
- Narrow: each partition of a parent RDD is used by at most one partition of the child RDD.

- Narrow dependencies allow pipelined execution on one cluster node: a map followed by a filter.

RDD Dependencies: Wide (3/3)



groupByKey



Join with inputs not co-partitioned

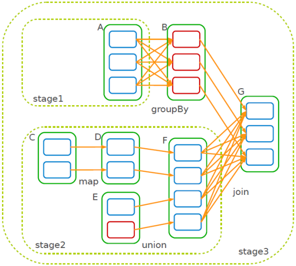
- Wide: each partition of a parent RDD is used by multiple partitions of the child RDDs.

Job Scheduling (1/2)

- When a user runs an action on an RDD: the scheduler builds a DAG of stages from the RDD lineage graph.

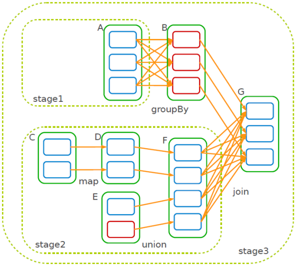
- A stage contains as many pipelined transformations with narrow dependencies.

- The boundary of a stage:
  - Shuffles for wide dependencies.
  - Already computed partitions.



Job Scheduling (2/2)

- The scheduler launches tasks to compute missing partitions from each stage until it computes the target RDD.
- Tasks are assigned to machines based on data locality.
  - If a task needs a partition, which is available in the memory of a node, the task is sent to that node.



RDD Fault Tolerance (1/3)

- RDDs maintain lineage information that can be used to reconstruct lost partitions.
- Logging lineage rather than the actual data.
- No replication.
- Recompute only the lost partitions of an RDD.

RDD Fault Tolerance (2/3)

- The intermediate records of wide dependencies are materialized on the nodes holding the parent partitions: to simplify fault recovery.

- If a task fails, it will be re-ran on another node, as long as its stages parents are available.

- If some stages become unavailable, the tasks are submitted to compute the missing partitions in parallel.

RDD Fault Tolerance (3/3)

- Recovery may be time-consuming for RDDs with long lineage chains and wide dependencies.
- It can be helpful to checkpoint some RDDs to stable storage.
- Decision about which data to checkpoint is left to users.

Memory Management (1/2)

- If there is not enough space in memory for a new computed RDD partition: a partition from the least recently used RDD is evicted.

- Spark provides three options for storage of persistent RDDs:
  1. In memory storage as deserialized Java objects.
  2. In memory storage as serialized Java objects.
  3. On disk storage.

Memory Management (2/2)

- When an RDD is persisted, each node stores any partitions of the RDD that it computes in memory.
- This allows future actions to be much faster.
- Persisting an RDD using `persist()` or `cache()` methods.
- Different storage levels:

  `MEMORY_ONLY`

  `MEMORY_AND_DISK`

  `MEMORY_ONLY_SER`

  `MEMORY_AND_DISK_SER`

  `MEMORY_ONLY_2, MEMORY_AND_DISK_2, etc.`

RDD Applications

- Applications suitable for RDDs
  - Batch applications that apply the same operation to all elements of a dataset.
- Applications not suitable for RDDs
  - Applications that make asynchronous fine-grained updates to shared state, e.g., storage system for a web application.

Summary

- RDD: a distributed memory abstraction that is both fault tolerant and efficient
- Two types of operations: Transformations and Actions.
- RDD fault tolerance: Lineage

Questions?