Spark and Resilient Distributed Datasets

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 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

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

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Efficient primitives for data sharing.

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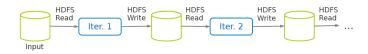
Efficient primitives for data sharing.

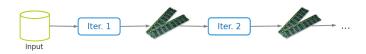
- ► In MapReduce, the only way to share data across jobs is stable storage, which is slow.
- Replication also makes the system slow, but it is necessary for fault tolerance.

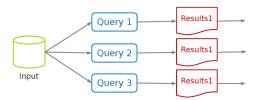
Proposed Solution

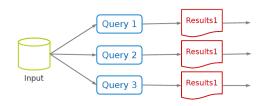
In-Memory Data Processing and Sharing.

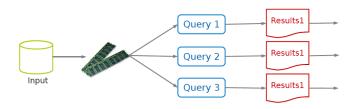












Challenge

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

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Solution

Resilient Distributed Datasets (RDD)

Resilient Distributed Datasets (RDD) (1/2)

► A distributed memory abstraction.

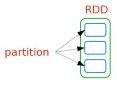
Resilient Distributed Datasets (RDD) (1/2)

► 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.

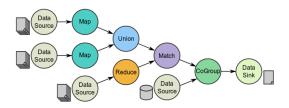
Programming Model

Spark Programming Model (1/2)

- ► Spark programming model is based on parallelizable operators.
- ► Parallelizable operators are higher-order functions that execute userdefined 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)

```
map(f:T\Rightarrow U):
                                                              RDD[T] \Rightarrow RDD[U]
                                  filter(f:T \Rightarrow Bool) : RDD[T] \Rightarrow RDD[T]
                             flatMap(f: T \Rightarrow Seq[U]) : RDD[T] \Rightarrow RDD[U]
                               sample(fraction : Float) : RDD[T] \Rightarrow RDD[T] (Deterministic sampling)
                                         groupByKey() : RDD[(K, V)] \Rightarrow RDD[(K, Seq[V])]
                        reduceBvKev(f:(V,V) \Rightarrow V)
                                                              RDD[(K, V)] \Rightarrow RDD[(K, V)]
Transformations
                                                union()
                                                              (RDD[T], RDD[T]) \Rightarrow RDD[T]
                                                 join()
                                                              (RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (V, W))]
                                                              (RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (Seq[V], Seq[W]))]
                                             cogroup()
                                        crossProduct()
                                                              (RDD[T], RDD[U]) \Rightarrow RDD[(T, U)]
                                                              RDD[(K, V)] \Rightarrow RDD[(K, W)] (Preserves partitioning)
                               mapValues(f: V \Rightarrow W)
                               sort(c: Comparator[K])
                                                              RDD[(K, V)] \Rightarrow RDD[(K, V)]
                                                              RDD[(K, V)] \Rightarrow RDD[(K, V)]
                        partitionBv(p : Partitioner[K])
                                                            RDD[T] \Rightarrow Long
                                              count() :
                                             collect() :
                                                            RDD[T] \Rightarrow Seq[T]
     Actions
                              reduce(f : (T,T) \Rightarrow T) :
                                                            RDD[T] \Rightarrow T
                                       lookup(k:K):
                                                            RDD[(K, V)] \Rightarrow 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.



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```
// 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.



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RDD Transformations - CoGroup

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



RDD Transformations - CoGroup

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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)

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```
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])
```

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```
import org.apache.spark.SparkContext
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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)

```
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)

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

Example (2/2)

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

Example (2/2)

Example - Standalone Application (1/2)

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)

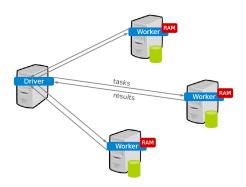
Spark

- ► 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.

```
file: HDFS Text File path = hdfs://...

sics: Filtered Dataset func = _contains(...)

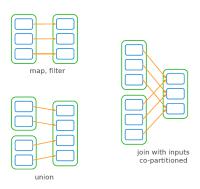
cachedSics: Cached Dataset
ones: Mapped Dataset func = _ => 1
```

```
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.

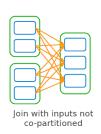
RDD Dependencies: Narrow (2/3)



- ▶ 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)

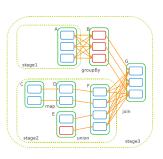




▶ Wide: each partition of a parent RDD is used by multiple partitions of the child RDDs.

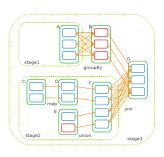
Job Scheduling (1/2)

- 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.

Job Scheduling (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?