Spark and Resilient Distributed Datasets

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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

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  Efficient primitives for data sharing.

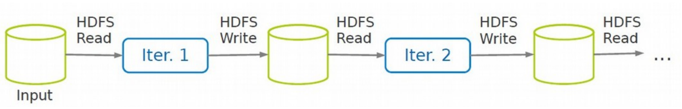
- In MapReduce, the only way to share data across jobs is stable storage, which is slow.

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

Proposed Solution

In-Memory Data Processing and Sharing.

Example


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

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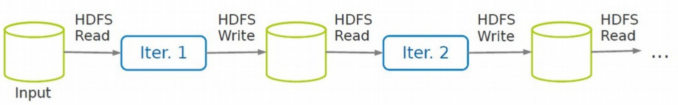
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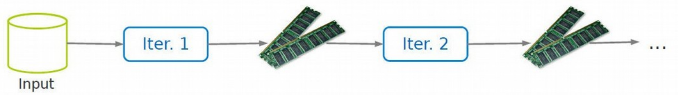
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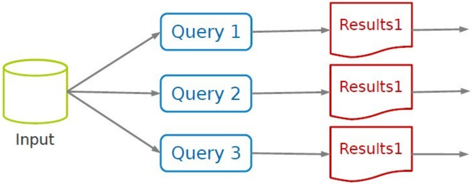

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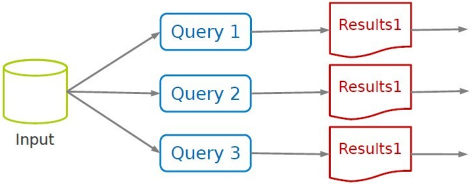
Query 1
Query 2
Query 3
Results1
Results1
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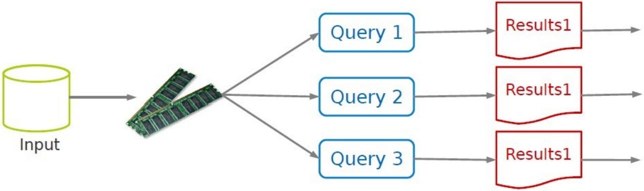
Input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Challenge

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)

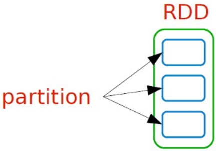
- A distributed memory abstraction.

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

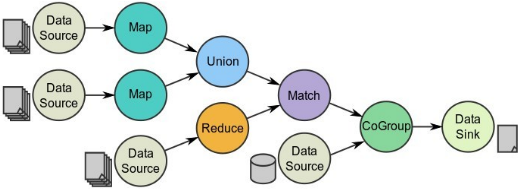
Spark Programming Model (1/2)

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

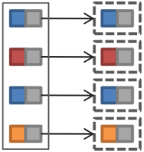
- Transformations: lazy operators that create new RDDs.
- Actions: lunch a computation and return a value to the program or write data to the external storage.

Higher-Order Functions (3/3)

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	RDD[T] ⇒ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	RDD[T] ⇒ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	RDD[T] ⇒ RDD[U]
	$sample(fraction : \mathrm{Float})$	:	RDD[T] ⇒ RDD[T] (Deterministic sampling)
	$groupByKey()$	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V},\mathrm{V}) \Rightarrow \mathrm{V})$	:	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)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
Actions	$count()$	:	RDD[T] ⇒ Long
	$collect()$	:	RDD[T] ⇒ Seq[T]
	$reduce(f : (\mathrm{T},\mathrm{T}) \Rightarrow \mathrm{T})$	:	RDD[T] ⇒ T
	$lookup(k : \mathrm{K})$	:	RDD[(K, V)] ⇒ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

RDD Transformations - Map

- All pairs are independently processed



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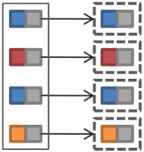


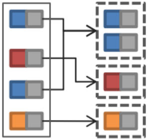
```
// passing each element through a function.
val nums = sc.parallelize(Array(1, 2, 3))
val squares = nums.map(x => x * x) // {1, 4, 9}

// 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.



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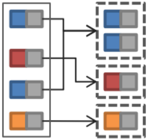


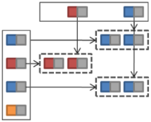
```
val pets = sc.parallelize(Seq(("cat", 1), ("dog", 1), ("cat", 2)))

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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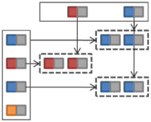


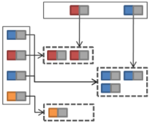
```
val visits = sc.parallelize(Seq(("index.html", "1.2.3.4"),
("about.html", "3.4.5.6"),
("index.html", "1.3.3.1")))

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.



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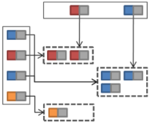

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("index.html", "1.3.3.1")))

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.

```scala
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.

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

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

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```

- 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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```

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

Creating RDDs

- Turn a collection into an RDD.

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

Creating RDDs

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```
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- 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 UNR.

```
val file = sc.textFile("hdfs://...")
val unr= file.filter(_.contains(”UNR"))
val cachedUNR = unr.cache()
val ones = cachedUNR.map(_ => 1)
val count = ones.reduce(_+_)
```

Example (1/2)

- Count the lines containing UNR.

Transformatio
n

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```

Transformatio
n

Actio
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Example (2/2)

- Count the lines containing UNR.

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val file = sc.textFile("hdfs://...")
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Transformatio
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Actio
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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", ”UNR", "127.0.0.1",
List("/usr/local/spark/examples/jars/spark-examples*.jar"))
      val file = sc.textFile("...").cache()
      val count = file.filter(_.contains(”UNR")).count()
    }
}
```

Example - Standalone Application (2/2)

- unr.sbt:

```
name := ”UNR 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
```

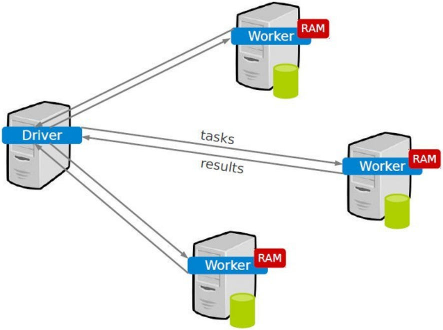
Execution Engine (SPARK)

Spark

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

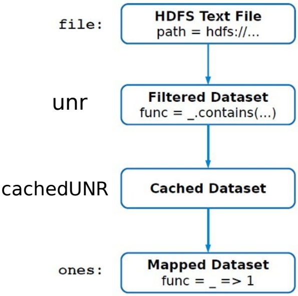
Spark Programming Interface

- 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.

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val count = ones.reduce(_+_)
```
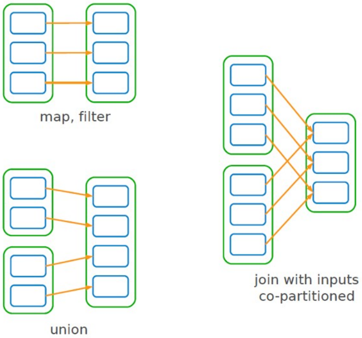

RDD Dependencies (1/3)

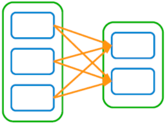
- Two types of dependencies between RDDs: Narrow and Wide.

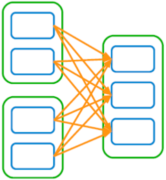
RDD Dependencies: Narrow (2/3)



- 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)

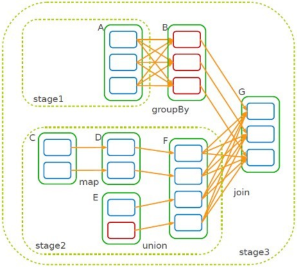




- Wide: each partition of a parent RDD is used by multiple partitions of the child RDDs.

Job Scheduling (1/2)

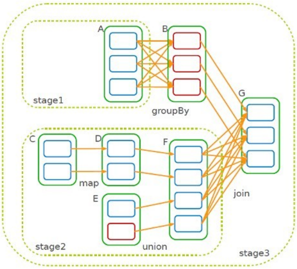
- When a user runs an action on an RDD: the scheduler builds a DAG of stages from the RDD lineage graph.
- A stage contains as many pipelined transformation with narrow dependencies
- The boundary of a stage:
  - Shuffles for wide dependencies.
  - Already computed partitions.



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
?