Parallel Processing - Spark

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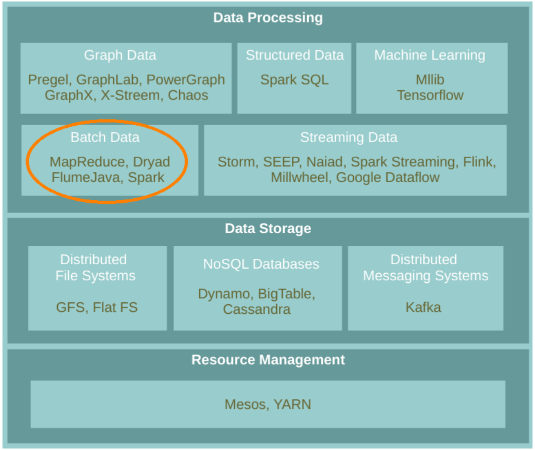
18/09/2018

The Course Web Page

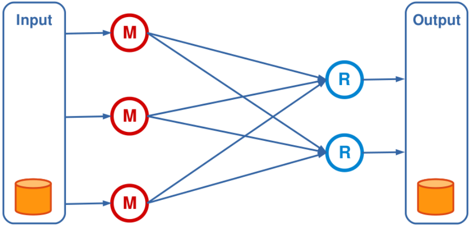
`https://id2221kth.github.io`

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

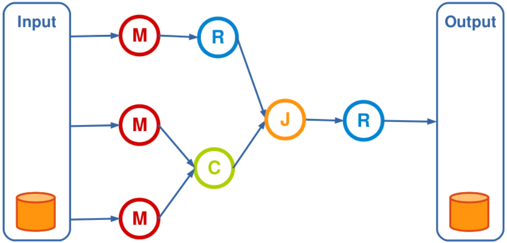
Motivation (1/3)

- Most current cluster programming models are based on acyclic data flow from stable storage to stable storage.
- Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures.
- MapReduce greatly simplified big data analysis on large unreliable clusters.



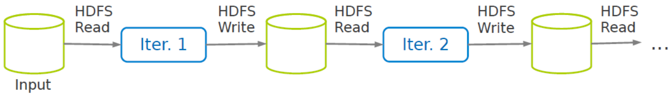
Motivation (2/3)

- MapReduce programming model has not been designed for complex operations, e.g., data mining.



Motivation (3/3)

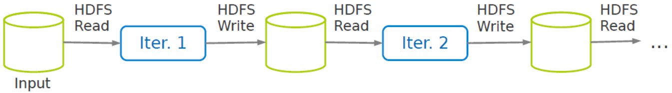
- Very expensive (slow), i.e., always goes to disk and HDFS.



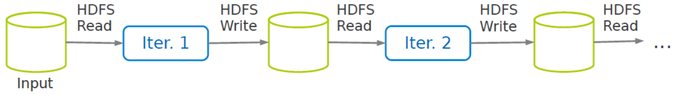
A Proposed Solution - Spark

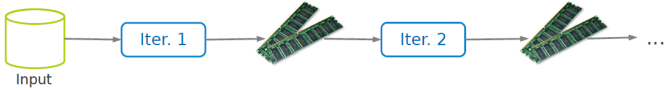
- Extends MapReduce with more operators.
- Support for advanced data flow graphs.
- In-memory and out-of-core processing.

Spark vs. MapReduce (1/2)

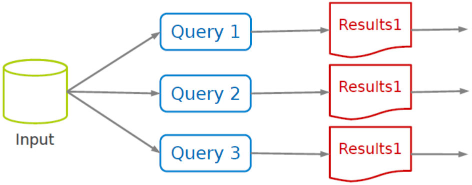


Spark vs. MapReduce (1/2)

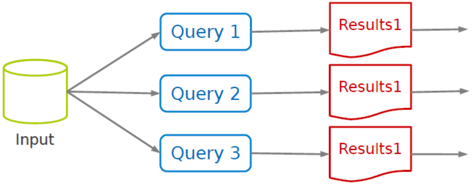


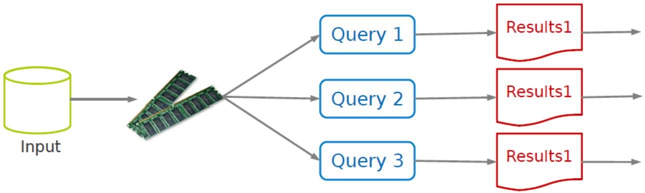


Spark vs. MapReduce (2/2)



Spark vs. MapReduce (2/2)

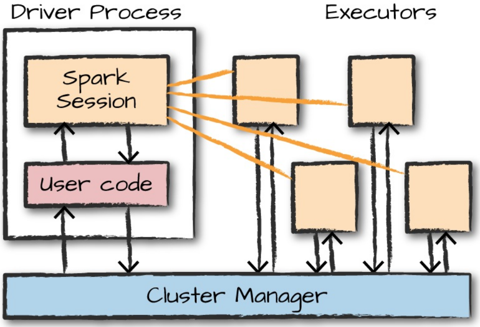




Spark Application

Spark Applications Architecture

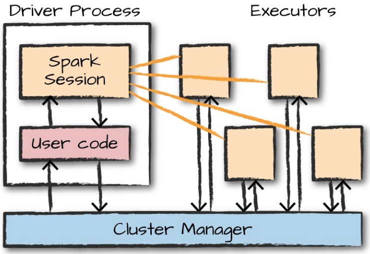
- Spark applications consist of
  - A driver process
  - A set of executor processes



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

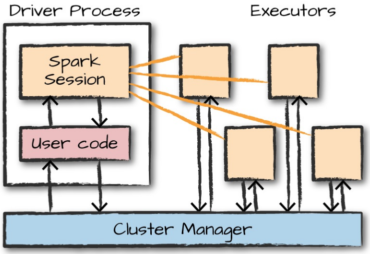
Driver Process

- The heart of a Spark application
- Sits on a node in the cluster
- Runs the `main()` function



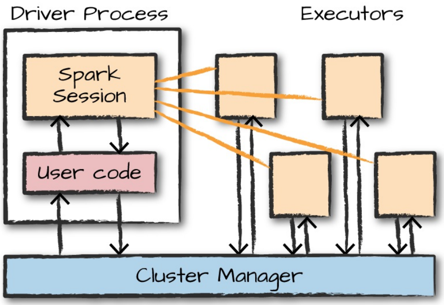
Driver Process

- 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.

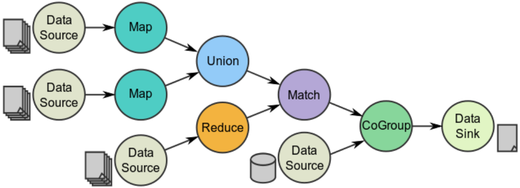
SparkSession vs. SparkContext

- 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

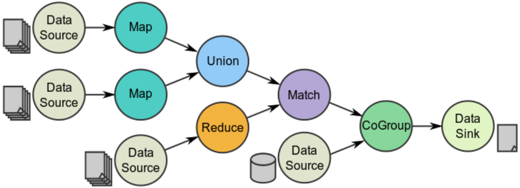
Spark Programming Model

- Job is described based on directed acyclic graphs (DAG) data flow.



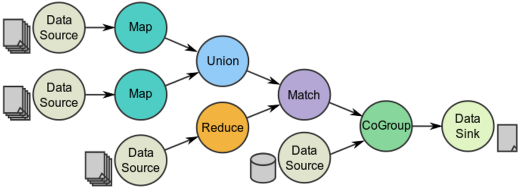
Spark Programming Model

- 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.



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 ver specific reason.

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- But, lack of the optimizations that are available in the Structured APIs.

When To Use RDDs?

- Short answer: you should not manually create RDDs unless you have a ver 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

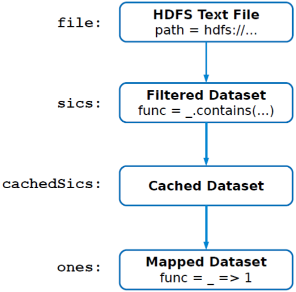
Transformations

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.



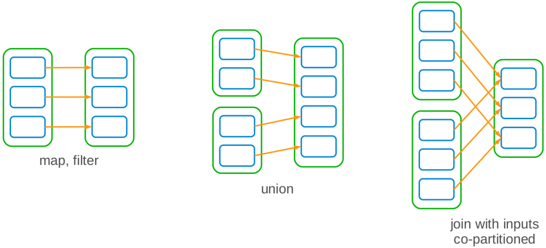

```
val file = sc.textFile("hdfs://...")
val sics = file.filter(_.contains("SICS"))
val cachedSics = sics.cache()
val ones = cachedSics.map(_ => 1)
val count = ones.reduce(_+_)
```

Two Types of Transformations

- Narrow transformations
- Wide transformations

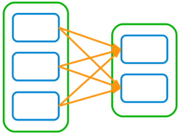
Narrow Transformations

- Consist of narrow dependencies
  - Each input partition will contribute to only one output partition.
- With narrow transformations, Spark perform a pipelining
  - E.g., if we specify multiple narrow transformations on RDDs, they will all be performed in-memory.
  - No network shuffle is required.

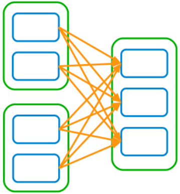


Wide Transformations

- Consist of wide dependencies
  - Each input partition will contribute to many output partition.
- Usually referred to as a shuffle
  - Partitions are exchanged across the cluster.
  - When we perform a shuffle, Spark writes the results to disk.



groupByKey



Join with inputs not co-partitioned

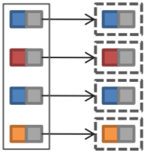
Generic RDD Transformations (1/3)

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

val distinctWords = words.distinct()
// a, this, is, easy,, test, it, take

val even = nums.filter(x => x % 2 == 0)
// 2

def startsWithT(individual:String) = { individual.startsWith("t") }
val tWordList = words.filter(word => startsWithT(word))
// take, 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 words = sc.parallelize("take it easy, this is a test".split(" "))

val squares = nums.map(x => x * x)
// 1, 4, 9

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

val chars = words.flatMap(word => word.toSeq)
// t, a, k, e, i, t, e, a, s, y, ,, t, h, i, s, i, s, a, t, e, s, t
```

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 numRange = sc.parallelize(0 to 6)
val words = sc.parallelize("take it easy, this is a test".split(" "))

val keyword1 = words.map(word => (word.toLowerCase, 1))
// (take,1), (it,1), (easy,,1), (this,1), (is,1), (a,1), (test,1)

val keyword2 = words.keyBy(word => word.toLowerCase.toSeq(0).toString)
// (t,take), (i,it), (e,easy,), (t,this), (i,is), (a,a), (t,test)

val keyword3 = words.zip(numRange)
// (take,0), (it,1), (easy,,2), (this,3), (is,4), (a,5), (test,6)
```

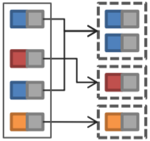
Key-Value RDD Transformations - Basics (2/2)

- `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)
val flatmapV = keyword.flatMapValues(word => word.toUpperCase)
// (t,T), (t,A), (t,K), (t,E), (i,I), (i,T), (e,E), (e,A), (e,S), (e,Y), (e,,), ...
```

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

- Aggregate the values associated with each key.



```
val chars = words.flatMap(word => word.toLowerCase.toSeq)
val kvChars = chars.map(letter => (letter, 1))
// (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))
```

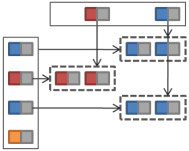
Key-Value RDD Transformations - Aggregation (2/2)

- `groupByKey` or `reduceByKey`?

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 words = sc.parallelize("take it easy, this is a test".split(" "))
val chars = words.flatMap(word => word.toLowerCase.toSeq)
val distinctChars = chars.distinct

val keyedChars = distinctChars.map(c => (c, new Random().nextInt(10)))
// (t,4), (h,6), (,,9), (e,8), (a,3), (i,5), (y,2), (s,7), (k,0)
val kvChars = chars.map(letter => (letter, 1))
// (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.

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- 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,
```

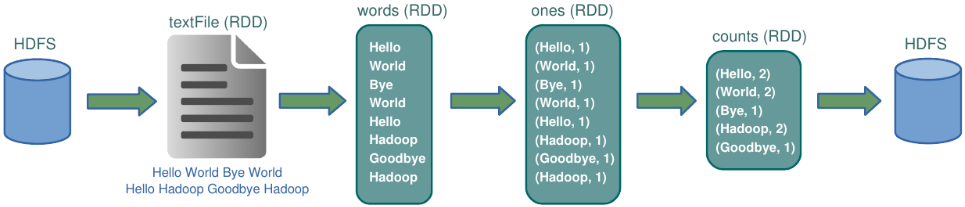
RDD Actions (6/6)

- `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

```
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.

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- 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

```scala
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()
```

Partitioning and Shuffle Operations

Shuffle Operations

- The shuffle is Spark's mechanism for re-distributing data so that it's grouped differently across partitions.
- This typically involves copying data across executors and machines, making the shuffle a complex and costly operation.

Spark Built-in Partitioners

- Hash paritioner
- Range partitioner

Hash Partitioning (1/2)

- Hash partitioning attempts to spread data evenly across partitions based on the key.
- E.g., `groupByKey`
  - First computes the partition `p` of each tuple $(\mathtt{k}, \mathtt{v})$:
    `p = k.hashCode() % numPartitions`
  - Then, all tuples in the same partition `p` are sent to the machine hosting `p`.

Hash Partitioning (2/2)

- Assume a key-value RDD, with keys `k = [8, 96, 240, 400, 401, 800]`, and a desired number of partitions of `p = 4`.
- Assume, that `hashCode()` is the identity, i.e., `n.hashCode() = n`.

Hash Partitioning (2/2)

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- Assume, that `hashCode()` is the identity, i.e., `n.hashCode() = n`.
- The hash partitioning distributes the keys as follows among the partitions (`p = k % 4`):
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  - `partition 1: [401]`
  - `partition 2: []`
  - `partition 3: []`

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  - `partition 0: [8, 96, 240, 400, 800]`
  - `partition 1: [401]`
  - `partition 2: []`
  - `partition 3: []`
- The result is a very unbalanced distribution which hurts performance.

Range Partitioning (1/2)

- Key-value RDDs may contain keys that have an ordering defined, e.g., Int, Char, String, ...

- For such RDDs, range partitioning may be more efficient.

- Using a range partitioner, keys are partitioned according to:
  - An ordering for keys
  - A set of sorted ranges of keys

- Tuples with keys in the same range appear on the same machine.

Range Partitioning (2/2)

- Using range partitioning the distribution can be improved significantly:
  - Assumptions: (a) keys non-negative, and (b) 800 is biggest key in the RDD
  - Set of ranges: `[1, 200]`, `[201, 400]`, `[401, 600]`, `[601, 800]`

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- The range partitioning distributes the keys as follows among the partitions:
  - `partition 0: [8, 96]`
  - `partition 1: [240, 400]`
  - `partition 2: [401]`
  - `partition 3: [800]`
- The resulting partitioning is much more balanced.

Partitioning Data

- How do we set a partitioning for our data?
- There are two ways to create RDDs with specific partitionings:
  1. Call `partitionBy` on an RDD, providing an explicit partitioner.
  2. Using transformations that return RDDs with specific partitioners.

Partitioning Data Using partitionBy

- Invoking partitionBy creates an RDD with a specified partitioner.

```
val words = sc.parallelize("take it easy, this is a test".split(" "), 2)

val keyword = words.map(word => (word, 1))

val tunedPartitioner = new RangePartitioner(3, keyword)

val partitioned = keyword.partitionBy(tunedPartitioner).persist()

partitioned.getNumPartitions
```

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partitioned.getNumPartitions
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- The result of partitionBy should be persisted, otherwise the partitioning is repeatedly applied each time the partitioned RDD is used.

Partitioning Data Using Transformations

- Some operations on RDDs automatically result in an RDD with a known partitioner - for when it makes sense.
- For example
  - When using `sortByKey`, a `RangePartitioner` is used.
  - When using `groupByKey`, a `HashPartitioner` is used.

Partition Operations (1/2)

- mapPartitions is similar to map, but runs separately on each partition of the RDD.
- mapPartitionsWithIndex applies the function on specific partitions.
- The given functions must be of type Iterator<T> => Iterator<U> when running on an RDD of type T.

```
val words = sc.parallelize("take it easy, this is a test".split(" "), 2)

def func(partIndex:Int, withinPartIter: Iterator[String]) = {
  withinPartIter.toList.map(
  value => s"Partition: $partIndex => $value").iterator
}

words.mapPartitionsWithIndex(func).collect()
// Array(Partition: 0 => take, Partition: 0 => it, Partition: 0 => easy,,
// Partition: 1 => this, Partition: 1 => is, Partition: 1 => a, Partition: 1 => test)
```

Partition Operations (2/2)

- foreachPartitions is similar to mapPartition, but does not return a return a value.

```
val words = sc.parallelize("take it easy, this is a test".split(" "), 2)

words.foreachPartition { iter =>
  import java.io._
  import scala.util.Random
  val rndName = new Random().nextInt()
  val pw = new PrintWriter(new File(s"/tmp/file-${rndName}.txt"))
  while (iter.hasNext) {
    pw.write(iter.next())
  }
  pw.close()
}
```

Controlling Partitions (1/2)

- The challenge is that not all values for a single key necessarily reside on the same partition, or even the same worker, but they must be co-located to compute the result.

- For example, the `reduceByKey` generates a tuple of a key and the result of executing a reduce function against all values associated with that key.

Controlling Partitions (2/2)

- With RDDs, you have control over how data is exactly physically distributed across the cluster.
- `coalesce` effectively collapses partitions on the same worker in order to avoid a shuffle.
- `repartition` operation allows you to repartition your data up or down.

```scala
val words = sc.parallelize("take it easy, this is a test".split(" "), 2)

words.coalesce(1).getNumPartitions

words.repartition(10)
```

Distributed Shared Variables

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.

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

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.

- Example: the `counter` is referenced within the `foreach` function, it's no longer the `counter` on the driver node.

```
var counter = 0
val rdd = sc.parallelize(Array(1, 2, 3, 4))

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

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

Shared Variables (2/2)

- General read-write shared variables across tasks is inefficient.
- Two types of shared variables: accumulators and broadcast variables.

Accumulators

- Aggregating values from worker nodes back to the driver program.
  - Example: counting events that occur during job execution.
- Worker code can add to the accumulator with its `+=` method.
- The driver program can access the value by calling the `value` property on the accumulator.

```
val accum = sc.accumulator(0)
val rdd = sc.parallelize(Array(1, 2, 3, 4))

rdd.foreach(x => accum += x)

println("Counter value: " + accum.value)
// Counter value: 10
```

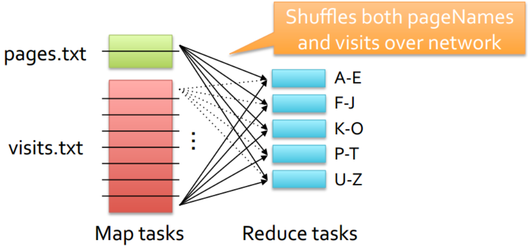
Broadcast Variables (1/4)

- The broadcast values are sent to each node only once, and should be treated as read-only variables.
- The process of using broadcast variables can access its value with the `value` property.

```
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)
```

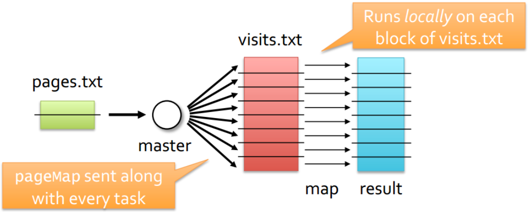
Broadcast Variables (2/4)

```scala
// Load RDD of (URL, name) pairs
val pageNames = sc.textFile("pages.txt").map(...)

// Load RDD of (URL, visit) pairs
val visits = sc.textFile("visits.txt").map(...)

val joined = visits.join(pageNames)
```



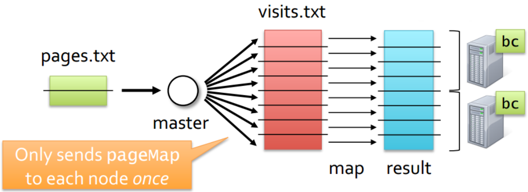
Broadcast Variables (3/4)

```scala
// Load RDD of (URL, name) pairs
val pageNames = sc.textFile("pages.txt").map(...)
val pageMap = pageNames.collect().toMap()

// Load RDD of (URL, visit) pairs
val visits = sc.textFile("visits.txt").map(...)

val joined = visits.map(v => (v._1, (pageMap(v._1), v._2)))
```



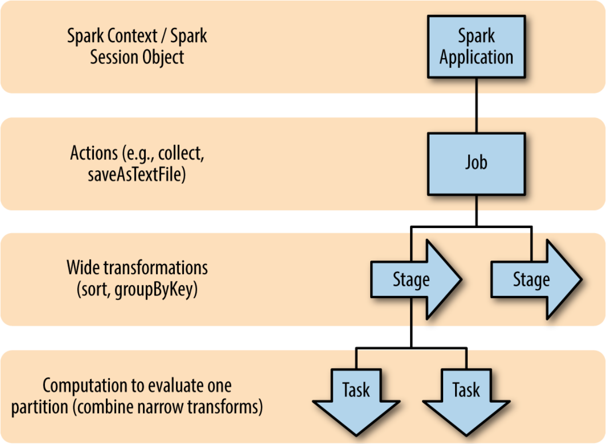
Broadcast Variables (4/4)

```
// Load RDD of (URL, name) pairs
val pageNames = sc.textFile("pages.txt").map(...)
val pageMap = pageNames.collect().toMap()
val bc = sc.broadcast(pageMap)

// Load RDD of (URL, visit) pairs
val visits = sc.textFile("visits.txt").map(...)

val joined = visits.map(v => (v._1, (bc.value(v._1), v._2)))
```



Execution Engine

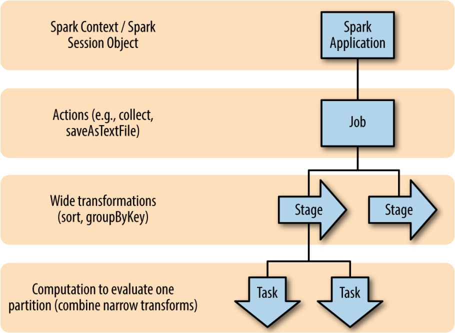
The Anatomy of a Spark Job



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

Jobs

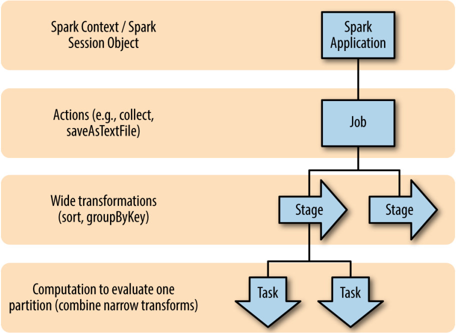
- A Spark job is the highest element of Spark's execution hierarchy.
  - Each Spark job corresponds to one action.
  - Each action is called by the driver program of a Spark application.



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

Stages

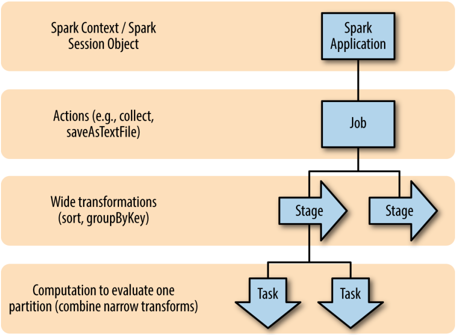
- Each job breaks down into a series of stages.
  - Stages in Spark represent groups of tasks that can be executed together.
  - Wide transformations define the breakdown of jobs into stages.



[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.



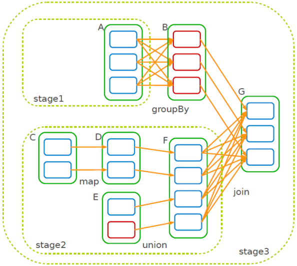
[H. Karau et al., High Performance Spark, O'Reilly Media, 2017]

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.

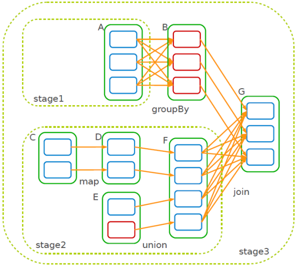
- The boundary of a stage:
  - Shuffles for wide dependencies.
  - Already computed partitions.



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 (1/2)

- 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 (2/2)

- 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.

Memory Management

- 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.

Summary

Summary

- RDD: a distributed memory abstraction
- Two types of operations: transformations and actions
- Lineage graph
- Wide vs. narrow dependencies
- Caching
- Paritioning and shuffle
- Shared variables

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.
- Some slides were derived from Heather Miller’s slides: `http://heather.miller.am/teaching/cs4240/spring2018`

Questions?