COMP9313: Big Data Management



Lecturer: Xin Cao

Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 4.1: Spark I

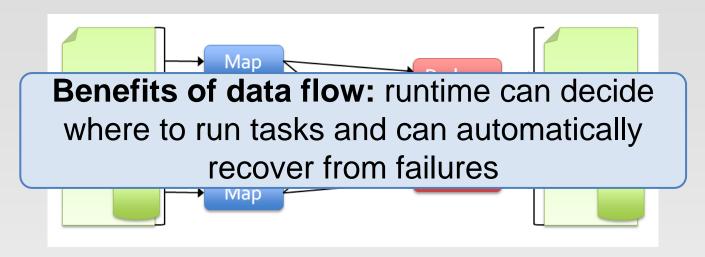


Part 1: Spark Introduction

Limitations of MapReduce

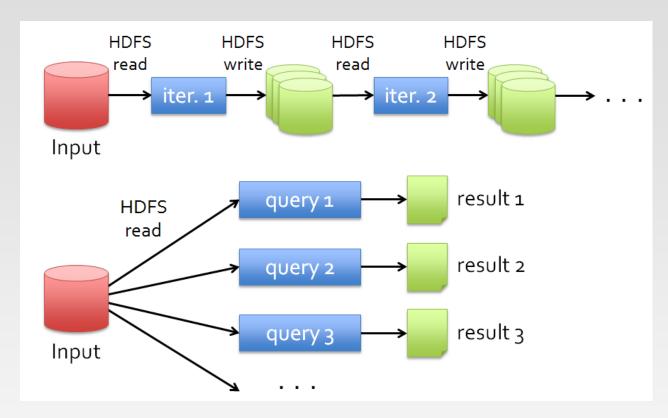
- MapReduce greatly simplified big data analysis on large, unreliable clusters. It is great at one-pass computation.
- But as soon as it got popular, users wanted more:
 - More complex, multi-pass analytics (e.g. ML, graph)
 - More interactive ad-hoc queries
 - More real-time stream processing
- All 3 need faster data sharing across parallel jobs
 - One reaction: specialized models for some of these apps, e.g.,
 - Pregel (graph processing)
 - Storm (stream processing)

Limitations of MapReduce



- As a general programming model:
 - > It is more suitable for one-pass computation on a large dataset
 - Hard to compose and nest multiple operations
 - No means of expressing iterative operations
- As implemented in Hadoop
 - All datasets are read from disk, then stored back on to disk
 - All data is (usually) triple-replicated for reliability
 - Not easy to write MapReduce programs using Java

Data Sharing in MapReduce



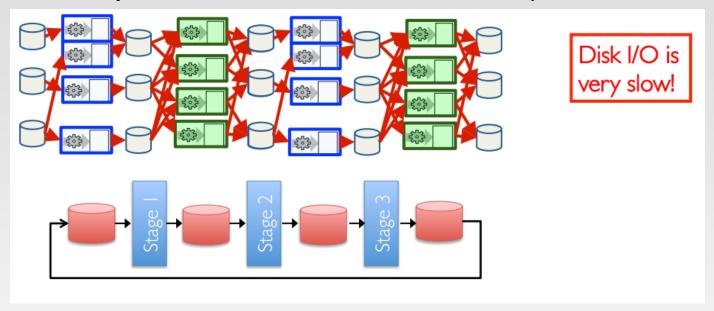
Slow due to replication, serialization, and disk IO

Complex apps, streaming, and interactive queries all need one thing that MapReduce lacks:

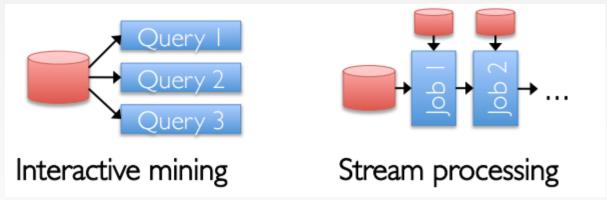
Efficient primitives for data sharing

Data Sharing in MapReduce

Iterative jobs involve a lot of disk I/O for each repetition



Interactive queries and online processing involves lots of disk I/O



Hardware for Big Data



Lots of hard drives



Lots of CPUs

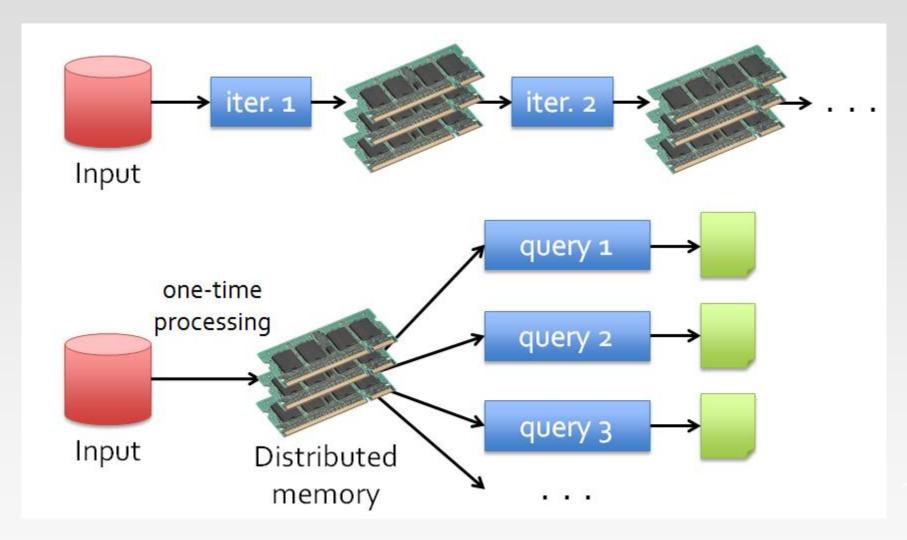


And lots of memory!

Goals of Spark

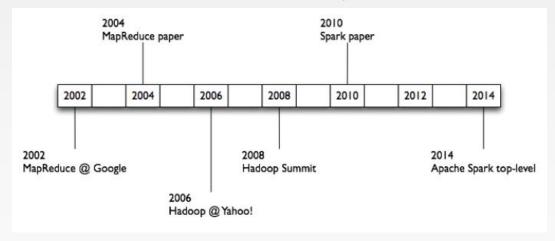
- Keep more data in-memory to improve the performance!
- Extend the MapReduce model to better support two common classes of analytics apps:
 - Iterative algorithms (machine learning, graphs)
 - Interactive data mining
- Enhance programmability:
 - Integrate into Scala programming language
 - Allow interactive use from Scala interpreter

Data Sharing in Spark Using RDD



10-100 × faster than network and disk

- One popular answer to "What's beyond MapReduce?"
- Open-source engine for large-scale distributed data processing
 - Supports generalized dataflows
 - Written in Scala, with bindings in Java, Python, and R
- Brief history:
 - Developed at UC Berkeley AMPLab in 2009
 - Open-sourced in 2010
 - Became top-level Apache project in February 2014
 - Commercial support provided by DataBricks



- Fast and expressive cluster computing system interoperable with Apache Hadoop
- Improves efficiency through:

In-memory computing primitives
 General computation graphs
 Up to 100 × faster
 (10 × on disk)

- Improves usability through:
 - Rich APIs in Scala, Java, Python
 - Interactive shell

→ Often 5 × less code

Spark is not

- a modified version of Hadoop
- dependent on Hadoop because it has its own cluster management
- Spark uses Hadoop for storage purpose only
- Spark's design philosophy centers around four key characteristics:
 - Speed
 - Ease of use
 - Modularity
 - Extensibility

Speed

- Its internal implementation benefits immensely from the performance improvement of CPUs and memory.
 - The framework is optimized to take advantage of memory, multiple cores, and the underlying Unix-based operating system
- Spark builds its query computations as a directed acyclic graph
 - Tasks can execute in parallel across workers on the cluster
- It has a physical execution engine which generates compact code for execution

Ease of Use

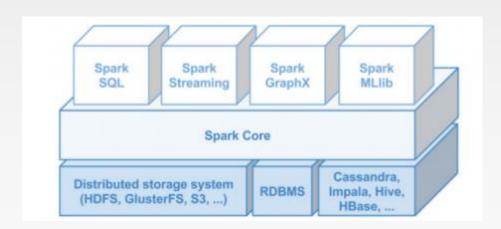
- Spark achieves simplicity by providing a fundamental abstraction of a simple logical data structure called a Resilient Distributed Dataset (RDD)
- Since Spark 2.x, DataFrames and Datasets APIs have been developed upon RDD
- By providing a set of *transformations* and *actions* as operations, Spark offers a simple programming model that you can use to build big data applications in familiar languages.

Modularity

- Spark operations can be applied across many types of workloads and expressed in any of the supported programming languages: Scala, Java, Python, SQL, and R.
- Spark offers unified libraries with well-documented APIs that include the following modules as core components: Spark SQL, Spark Structured Streaming, Spark MLlib, and GraphX, combining all the workloads running under one engine.
- You can write a single Spark application that can do it all—no need for distinct engines for disparate workloads, no need to learn separate APIs.

Extensibility

- Spark focuses on its fast, parallel computation engine rather than on storage.
 - You can use Spark to read data stored in myriad sources—local file systems, Apache Hadoop, Apache Cassandra, Apache HBase, MongoDB, Apache Hive, RDBMSs, and more—and process it all in memory.
- Spark's DataFrameReaders and DataFrameWriters can also be extended to read data from other sources, such as Apache Kafka, Kinesis, Azure Storage, and Amazon S3



Spark is the basis of a wide set of projects in the Berkeley Data Analytics Stack (BDAS)

Spark SQL (SQL)

Spark
Streaming
(real-time)

GraphX (graph)

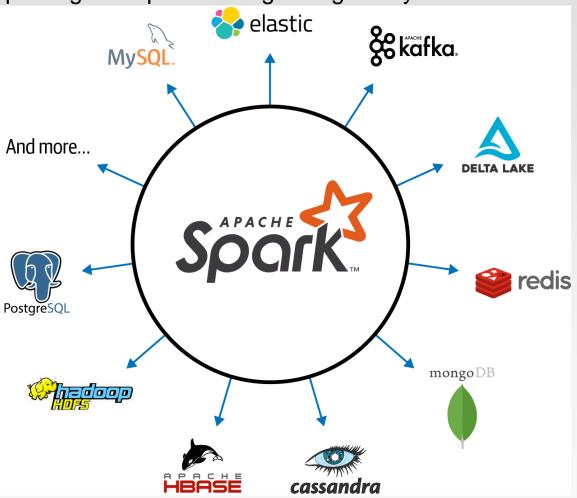
MLlib (machine learning)

Spark Core (Scala, Python, Java, R, SQL)

- Spark SQL (SQL on Spark)
- Spark Streaming (stream processing)
- GraphX (graph processing)
- MLlib (machine learning library)

Spark's Ecosystem of Connectors

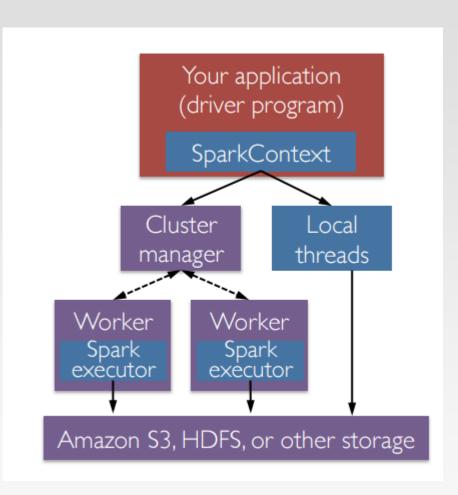
The community of Spark developers maintains a list of third-party Spark packages as part of the growing ecosystem



Spark Ideas

- Expressive computing system, not limited to map-reduce model
- Facilitate system memory
 - avoid saving intermediate results to disk
 - cache data for repetitive queries (e.g. for machine learning)
- Layer an in-memory system on top of Hadoop.
- Achieve fault-tolerance by re-execution instead of replication

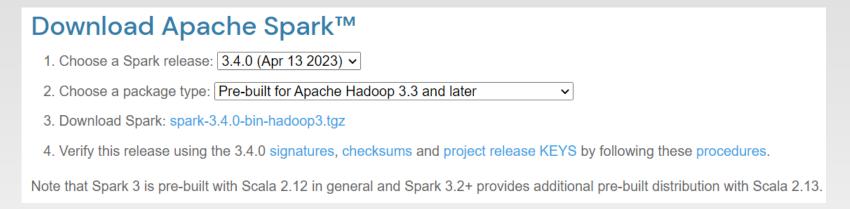
Spark Workflow



- A Spark program first creates a SparkContext object
 - Tells Spark how and where to access a cluster
 - Define RDDs
 - Connect to several types of cluster managers (e.g., YARN, Mesos, or its own manager)
- Cluster manager:
 - Allocate resources across applications
- Spark executor:
 - Run computations
 - Access data storage

Download and Configure Spark

- Current version: 3.4.0. https://spark.apache.org/downloads.html
 - You also need to install Java first



After downloading the package, unpack it and then configure the path variable in file ~/.bashrc

export SPARK_HOME=/home/comp9313/spark export PATH=\$SPARK_HOME/bin:\$PATH

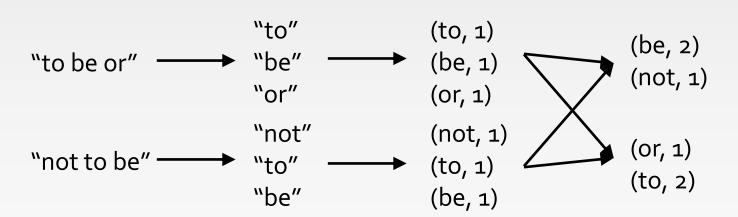
Spark Shell

Spark comes with four widely used interpreters that act like interactive "shells" and enable ad hoc data analysis: pyspark, spark-shell, sparksql, and sparkR

```
comp9313@comp9313-VirtualBox:~$ spark-shell
2021-10-06 21:25:47,310 WARN util.Utils: Your hostname, comp9313-VirtualBox resolves to a loopback address: 127.0.1.1;
using 10.0.2.15 instead (on interface enp0s3)
2021-10-06 21:25:47,311 WARN util.Utils: Set SPARK_LOCAL_IP if you need to bind to another address
WARNING: An illegal reflective access operation has occurred
WARNING: Illegal reflective access by org.apache.spark.unsafe.Platform (file:/home/comp9313/spark/jars/spark-unsafe 2.
12-3.1.2.jar) to constructor java.nio.DirectByteBuffer(long.int)
WARNING: Please consider reporting this to the maintainers of org.apache.spark.unsafe.Platform
WARNING: Use --illegal-access=warn to enable warnings of further illegal reflective access operations
WARNING: All illegal access operations will be denied in a future release
2021-10-06 21:25:47,979 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using bu
iltin-java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
Spark context Web UI available at http://10.0.2.15:4040
Spark context available as 'sc' (master = local[*], app id = local-1633515956456).
Spark session available as 'spark'.
Welcome to
  Using Scala version 2.12.10 (OpenJDK 64-Bit Server VM, Java 11.0.11)
Type in expressions to have them evaluated.
Type :help for more information.
```

Word Count in Spark (Python)

```
textfile = sc.textFile("hdfs://...", 4)
words = textfile.flatMap(lambda line: line.split(" "))
pairs = words.map(lambda word: (word, 1))
count = pairs.reduceByKey(lambda a, b: a + b)
count.collect()
```

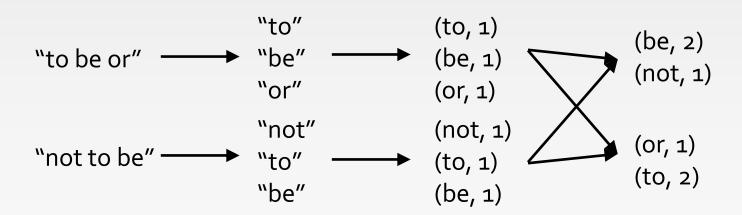


Word Count in Spark (Scala)

```
val file = sc.textFile("hdfs://...")

val counts = file.flatMap(line => line.split(" "))
    .map(word => (word,1))
    .reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```



Part 2: Scala Introduction

Scala (Scalable language)

- Scala is a general-purpose programming language designed to express common programming patterns in a concise, elegant, and type-safe way
- Scala supports both Object Oriented Programming and Functional Programming
- Scala is Practical
 - Can be used as drop-in replacement for Java
 - Mixed Scala/Java projects
 - Use existing Java libraries
 - Use existing Java tools (Ant, Maven, JUnit, etc...)
 - Decent IDE Support (NetBeans, IntelliJ, Eclipse)



Why Scala

- Scala supports object-oriented programming. Conceptually, every value is an object and every operation is a method-call. The language supports advanced component architectures through classes and traits
- Scala is also a functional language. Supports functions, immutable data structures and preference for immutability over mutation
- Seamlessly integrated with Java
- Being used heavily for Big data, e.g., Spark, Kafka, etc.

Scala Basic Syntax

- When considering a Scala program, it can be defined as a collection of objects that communicate via invoking each other's methods.
- Object same as in Java
- Class same as in Java
- Methods same as in Java
- ❖ Fields Each object has its unique set of instant variables, which are called fields. An object's state is created by the values assigned to these fields.
- Traits Like Java Interface. A trait encapsulates method and field definitions, which can then be reused by mixing them into classes.
- Closure A closure is a function, whose return value depends on the value of one or more variables declared outside this function.

closure = function + environment

Object-Oriented Programming in Scala

- Scala is object-oriented, and is based on Java's model
- An object is a singleton object (there is only one of it)
 - Variables and methods in an object are somewhat similar to Java's static variables and methods
 - Reference to an object's variables and methods have the syntax ObjectName. methodOrVariableName
 - The name of an object should be capitalized
- A class may take parameters, and may describe any number of objects
 - The class body is the constructor, but you can have additional constructors
 - With correct use of val and var, Scala provides getters and setters for class parameters

Scala is Statically Typed

- You don't have to specify a type in most cases
- Type Inference

```
val sum = 1 + 2 + 3
val nums = List(1, 2, 3)
val map = Map("abc" \rightarrow List(1,2,3))
Explicit Types
val sum: Int = 1 + 2 + 3
val nums: List[Int] = List(1, 2, 3)
val map: Map[String, List[Int]] = ...
```

Scala is High level

```
// Java - Check if string has uppercase character
boolean hasUpperCase = false;
for(int i = 0; i < name.length(); i++) {</pre>
    if(Character.isUpperCase(name.charAt(i))) {
        hasUpperCase = true;
         break;
// Scala
val hasUpperCase = name.exists(_.isUpper)
```

Scala is Concise

```
// Java
                                        // Scala
public class Person {
 private String name;
 private int age;
  public Person(String name, Int age) {
   this.name = name;
    this.age = age;
  public String getName() {
                                       // name getter
   return name;
 public int getAge() {
                                       // age getter
   return age;
  public void setName(String name) {      // name setter
   this.name = name;
 public void setAge(int age) {
                               // age setter
   this.age = age;
```

Variables and Values

Variables: values stored can be changed

```
var foo = "foo"
foo = "bar" // okay
```

Values: immutable variable

```
val foo = "foo"
foo = "bar" // nope
```

Scala is Pure Object Oriented

```
// Every value is an object
1.toString
// Every operation is a method call
1 + 2 + 3 \rightarrow (1).+(2).+(3)
// Can omit . and ( )
"abc" charAt 1 \rightarrow "abc".charAt(1)
// Classes (and abstract classes) like Java
abstract class Language(val name:String) {
  override def toString = name
// Example implementations
class Scala extends Language("Scala")
// Anonymous class
val scala = new Language("Scala") { /* empty */ }
```

Scala Traits

```
// Like interfaces in Java
trait JVM {
  // But allow implementation
 override def toString = super.toString+" runs on JVM" }
trait Static {
 override def toString = super.toString+" is Static" }
// Traits are stackable
class Scala extends Language with JVM with Static {
  val name = "Scala"
println(new Scala) → "Scala runs on JVM is Static"
```

Scala is Functional

- First-Class Functions. Functions are treated like objects:
 - passing functions as arguments to other functions
 - returning functions as the values from other functions
 - assigning functions to variables or storing them in data structures

```
// Lightweight anonymous functions
(x:Int) => x + 1

// Calling the anonymous function
val plusOne = (x:Int) => x + 1
plusOne(5) → 6
```

Scala is Functional

Closures: a function whose return value depends on the value of one or more variables declared outside this function.

// plusFoo can reference any values/variables in scope
var foo = 1
val plusFoo = (x:Int) => x + foo

plusFoo(5) → 6

// Changing foo changes the return value of plusFoo
foo = 5
plusFoo(5) → 10

Scala is Functional

- Higher Order Functions
 - A function that does at least one of the following:
 - takes one or more functions as arguments
 - returns a function as its result

```
val plusOne = (x:Int) => x + 1

val nums = List(1,2,3)

// map takes a function: Int => T

nums.map(plusOne) → List(2,3,4)

// Inline Anonymous

nums.map(x => x + 1) → List(2,3,4)

// Short form

nums.map(_ + 1) → List(2,3,4)
```

More Examples on Higher Order Functions

```
val nums = List(1,2,3,4)
// A few more examples for List class
nums.exists(<u>== 2</u>) → true
                    \rightarrow Some(2)
nums.find(\underline{\phantom{a}} == 2)
nums.indexWhere(\_ == 2) \rightarrow 1
// functions as parameters, apply f to the value "1"
def call(f: Int => Int) = f(1)
call(plusOne) \rightarrow 2
call(x \Rightarrow x + 1) \rightarrow 2
              \rightarrow 2
call(_+ 1)
```

More Examples on Higher Order Functions

```
val basefunc = (x:Int) \Rightarrow ((y:Int) \Rightarrow x + y)
// interpreted by:
   basefunc(x){
        sumfunc(y){ return x+y;}
        return sumfunc;
   }
val closure1 = basefunc(1) closure1(5) = ?
val closure2 = basefunc(4) closure2(5) = ?
                                                9
```

- basefunc returns a function, and closure1 and closure2 are of function type.
- While closure1 and closure2 refer to the same function basefunc, the associated environments differ, and the results are different

The Usage of "_" in Scala

In anonymous functions, the "_" acts as a placeholder for parameters nums.map(x => x + 1) is equivalent to: nums.map(_ + 1)
List(1,2,3,4,5).foreach(print(_)) is equivalent to:

You can use two or more underscores to refer different parameters.

val sum = List(1,2,3,4,5).reduceLeft(_+_)
is equivalent to:

List(1,2,3,4,5).foreach $(a \Rightarrow print(a))$

val sum = List(1,2,3,4,5).reduceLeft((a, b) \Rightarrow a + b)

The reduceLeft method works by applying the function/operation you give it, and applying it to successive elements in the collection

Part 3: RDD Introduction

RDD: Resilient Distributed Datasets

- Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. Matei Zaharia, et al. NSDI'12
 - RDD is a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a faulttolerant manner.

Resilient

Fault-tolerant, is able to recompute missing or damaged partitions due to node failures.

Distributed

Data residing on multiple nodes in a cluster.

Dataset

- A collection of partitioned elements, e.g. tuples or other objects (that represent records of the data you work with).
- RDD is the primary data abstraction in Apache Spark and the core of Spark. It enables operations on collection of elements in parallel.

RDD: Resilient Distributed Datasets

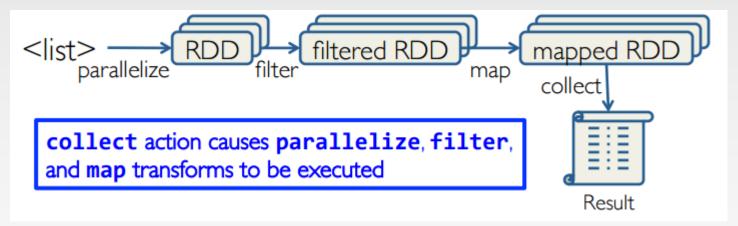
- Resilient Distributed Datasets (RDDs)
 - Distributed collections of objects that can be cached in memory across cluster
 - Manipulated through parallel operators
 - Automatically recomputed on failure based on lineage
- RDDs can express many parallel algorithms, and capture many current programming models
 - Data flow models: MapReduce, SQL, ...
 - > Specialized models for iterative apps: Pregel, ...

RDD Traits

- In-Memory, i.e. data inside RDD is stored in memory as much (size) and long (time) as possible.
- Immutable or Read-Only, i.e. it does not change once created and can only be transformed using transformations to new RDDs.
- Lazy evaluated, i.e. the data inside RDD is not available or transformed until an action is executed that triggers the execution.
- Cacheable, i.e. you can hold all the data in a persistent "storage" like memory (default and the most preferred) or disk (the least preferred due to access speed).
- Parallel, i.e. process data in parallel.
- Typed, i.e. values in a RDD have types, e.g. RDD[Long] or RDD[(Int, String)].
- Partitioned, i.e. the data inside a RDD is partitioned (split into partitions) and then distributed across nodes in a cluster (one partition per JVM that may or may not correspond to a single node).

Working with RDDs

- Create an RDD from a data source
 - by parallelizing existing collections (lists or arrays)
 - by transforming an existing RDDs
 - from files in HDFS or any other storage system
- Apply transformations to an RDD: e.g., map, filter
- Apply actions to an RDD: e.g., collect, count



- Users can control two other aspects:
 - Persistence
 - Partitioning

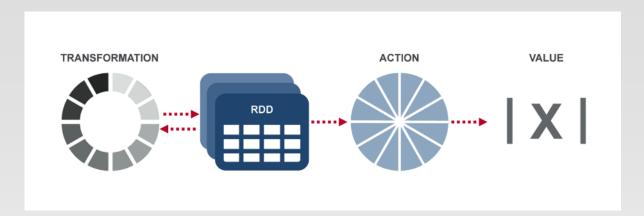
Creating RDDs

- From HDFS, text files, Amazon S3, Apache HBase, SequenceFiles, any other Hadoop InputFormat
- Creating an RDD from a File
 - val inputfile = sc.textFile("...", 4)
 - RDD distributed in 4 partitions
 - Elements are lines of input
 - Lazy evaluation means no execution happens now

```
scala> val inputfile = sc.textFile("pg100.txt")
inputfile: org.apache.spark.rdd.RDD[String] = pg100.txt MapPartitionsRDD[17] at
textFile at <console>:24
```

- Turn a collection into an RDD
 - sc.parallelize([1, 2, 3]), creating from a Python list
 - sc.parallelize(Array("hello", "spark")), creating from a Scala Array
- Creating an RDD from an existing Hadoop InputFormat
 - sc.hadoopFile(keyClass, valClass, inputFmt, conf)

RDD Operations



- Transformation: returns a new RDD.
 - Nothing gets evaluated when you call a Transformation function, it just takes an RDD and return a new RDD.
 - Transformation functions include map, filter, flatMap, groupByKey, reduceByKey, aggregateByKey, join, etc.
- Action: evaluates and returns a new value.
 - When an Action function is called on a RDD object, all the data processing queries are computed at that time and the result value is returned.
 - Action operations include reduce, collect, count, first, take, countByKey, foreach, saveAsTextFile, etc.

Spark Transformations

- Create new datasets from an existing one
- Use lazy evaluation: results not computed right away instead Spark remembers set of transformations applied to base dataset
 - Spark optimizes the required calculations
 - Spark recovers from failures
- Some transformation functions

Transformation	Description
map(func)	return a new distributed dataset formed by passing each element of the source through a function func
filter(func)	return a new dataset formed by selecting those elements of the source on which func returns true
<pre>distinct([numTasks]))</pre>	return a new dataset that contains the distinct elements of the source dataset
<pre>flatMap(func)</pre>	similar to map, but each input item can be mapped to 0 or more output items (so <i>func</i> should return a Seq rather than a single item)

Spark Actions

- Cause Spark to execute recipe to transform source
- Mechanism for getting results out of Spark
- Some action functions

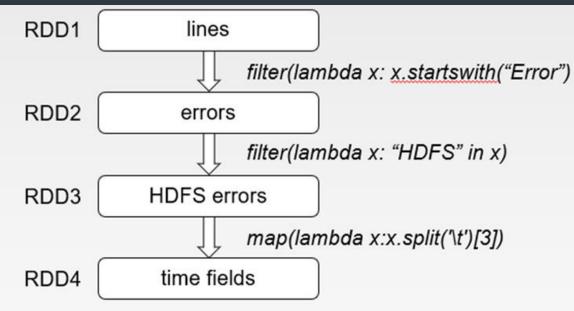
Action	Description
reduce(func)	aggregate dataset's elements using function func. func takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
take(n)	return an array with the first n elements
collect()	return all the elements as an array WARNING: make sure will fit in driver program
<pre>takeOrdered(n, key=func)</pre>	return n elements ordered in ascending order or as specified by the optional key function

Example: words.collect().foreach(println)

Example (Python)

Web service is experiencing errors and an operators want to search terabytes of logs in the Hadoop file system to find the cause.

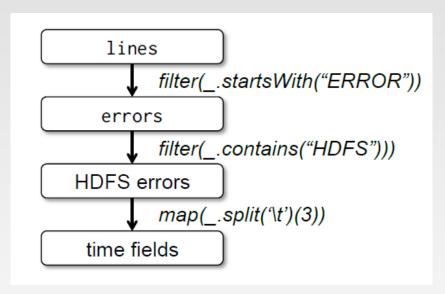
```
lines = sc.textFile("hdfs://...") //base RDD, obtained from a file on HDFS
errors = lines.filter(lambda x: x.startswith("Error")) //get messages that start
errors.persist() //persist the data in memory
errors.count()
errors.filter(lambda x: "HDFS" in x).map(lambda x:x.split('\t')[3]).collect()
```



- Line1: RDD backed by an HDFS file (base RDD lines not loaded in memory)
- Line3: Asks for errors to persist in memory (errors are in RAM)

Example (Scala)

Web service is experiencing errors and an operators want to search terabytes of logs in the Hadoop file system to find the cause.



```
//base RDD

val lines = sc.textFile("hdfs://...")

//Transformed RDD

val errors = lines.filter(_.startsWith("Error"))

errors.persist()

errors.count()

errors.filter(_.contains("HDFS"))

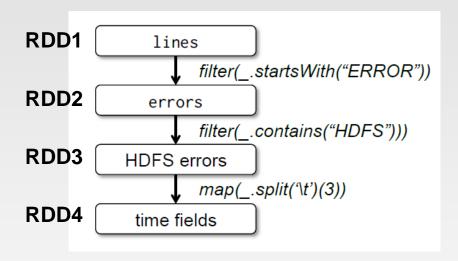
.map(_.split('\t')(3))

.collect()
```

- Line1: RDD backed by an HDFS file (base RDD lines not loaded in memory)
- Line3: Asks for errors to persist in memory (errors are in RAM)

Lineage Graph

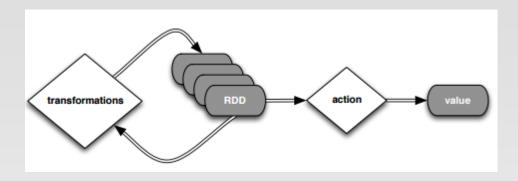
- RDDs keep track of lineage
- RDD has enough information about how it was derived from to compute its partitions from data in stable storage.



Example:

- If a partition of errors is lost, Spark rebuilds it by applying a filter on only the corresponding partition of lines.
- Partitions can be recomputed in parallel on different nodes, without having to roll back the whole program.

Deconstructed



```
//base RDD

lines = sc.textFile("hdfs://...")

//Transformed RDD

errors = lines.filter(lambda x: x.startswith("Error"))

errors.persist()

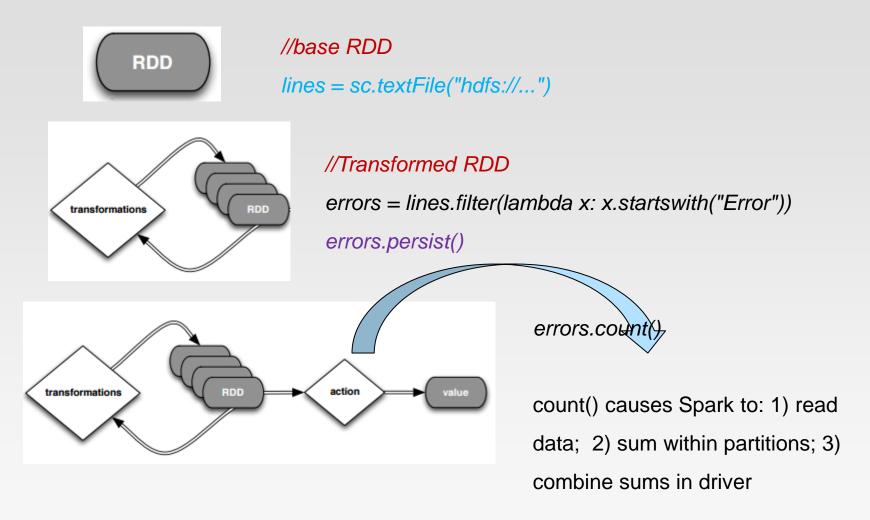
errors.count()

errors.filter(lambda x: "HDFS" in x).

map(lambda x: x.split('\t')[3]).

collect()
```

Deconstructed



Put transform and action together:

errors.filter(lambda x: "HDFS" in x).map(lambda x: x.split('\t')[3]).collect()

RDD Persistence: Cache/Persist

- One of the most important capabilities in Spark is persisting (or caching) a dataset in memory across operations.
- When you persist an RDD, each node stores any partitions of it. You can reuse it in other actions on that dataset
- Each persisted RDD can be stored using a different storage level, e.g.
 - MEMORY_ONLY:
 - Store RDD as deserialized Java objects in the JVM.
 - If the RDD does not fit in memory, some partitions will not be cached and will be recomputed when they're needed.
 - This is the default level.
 - MEMORY_AND_DISK:
 - If the RDD does not fit in memory, store the partitions that don't fit on disk, and read them from there when they're needed.
- cache() = persist(StorageLevel.MEMORY_ONLY)

Why Persisting RDD?

```
lines = sc.textFile("hdfs://...")
errors = lines.filter(lambda x: x.startswith("Error"))
errors.persist()
errors.count()
```

- If you do errors.count() again, the file will be loaded again and computed again.
- Persist will tell Spark to cache the data in memory, to reduce the data loading cost for further actions on the same data
- erros.persist() will do nothing. It is a lazy operation. But now the RDD says "read this file and then cache the contents". The action will trigger computation and data caching.

References

- http://spark.apache.org/docs/latest/index.html
- http://www.scala-lang.org/documentation/
- http://www.scala-lang.org/docu/files/ScalaByExample.pdf
- A Brief Intro to Scala, by Tim Underwood.
- Learning Spark. 1st and 2nd Edition

End of Chapter 4.1