CS x55: Distributed Systems [Spark]

Spark: It's all about transformation and actions

Transformations
- Wrangle with the data
- Consume, and beget, an RDD
- Flock together … to form daisy chains

But it is actions
- That trigger evaluations
  - Providing them potency
    - Revealing their expressive power

Shrideep Pallickara
Computer Science
Colorado State University

Frequently asked questions from the previous class survey

- Why use MapReduce?
- What if the data is too big to fit in memory of a large, distributed cluster?
- Does Spark Streaming relate to streaming movies?

Topics covered in this lecture

- Spark APIs
- Resilient Distributed Datasets
- Common Transformations and Actions

SPARK APIs

Spark APIs

- Spark has two fundamental sets of APIs:
  - The low-level “unstructured” APIs, and
  - The higher-level structured APIs

Structured APIs

- Structured APIs are a tool for manipulating all sorts of data
  - From unstructured log files to semi-structured CSV files and highly structured Parquet files
- Refers to three core types of distributed collection APIs:
  - Datasets
  - DataFrames
  - SQL tables and views
- Majority of the Structured APIs apply to both batch and streaming computation

Spark's Toolset

Structured Streaming	Advanced Analytics	Libraries & Ecosystem

Structured APIs

Datasets DataFrames SQLs

Low Level APIs

RDDs Distributed variables

Spark has two notions of structured collections: DataFrames and Datasets

- DataFrames and Datasets are (distributed) **table-like** collections with well-defined rows and columns

- Each column:
  - Must have the same number of rows as all the other columns (although you can use `null` to specify the absence of a value)
  - Has type information that must be consistent for every row in the collection

DataFrames versus Datasets

- DataFrames are considered “untyped”
- Datasets are considered “typed”

How does Spark view DataFrames and Datasets?

- To Spark, DataFrames and Datasets represent **immutable, lazily evaluated** plans that specify what operations to apply to data residing at a location to generate some output
- When we perform an action on a DataFrame, we instruct Spark to perform the actual transformations and return the result
- These represent **plans** of how to manipulate rows and columns to compute the user's desired result

The DataFrame is the most common Structured API

- Simply represents a **table** of data with rows and columns
- The list that defines the columns and the types within those columns is called the **schema**

The DataFrame concept is not unique to Spark

- R and Python both have similar concepts
  - However, Python/R DataFrames (with some exceptions) exist on one machine rather than multiple machines
  - This limits what you can do with a given DataFrame to the resources that exist on that specific machine

- A Spark DataFrame can span thousands of computers

Core Spark Concepts

Core Spark Concepts

- Drivers
- SparkContext
- Executors

Spark in a nutshell

- Spark allows users to write a program for the **driver** (or master node) on a cluster computing system that can perform *operations* on data in parallel
- Spark represents large datasets as **RDD**s which are stored in the executors (or worker nodes)
- The objects that comprise RDDs are called **partitions** and may be (but do not need to be) computed on different nodes of a distributed system
- The Spark cluster manager handles starting and distributing the Spark executors across a distributed system

Drivers

- Every Spark application consists of a **driver** program
- Driver **launches various parallel operations** on the cluster
- Constituent elements
  - Application's main function
  - Defines distributed datasets on the clusters
  - Applies operations to these datasets

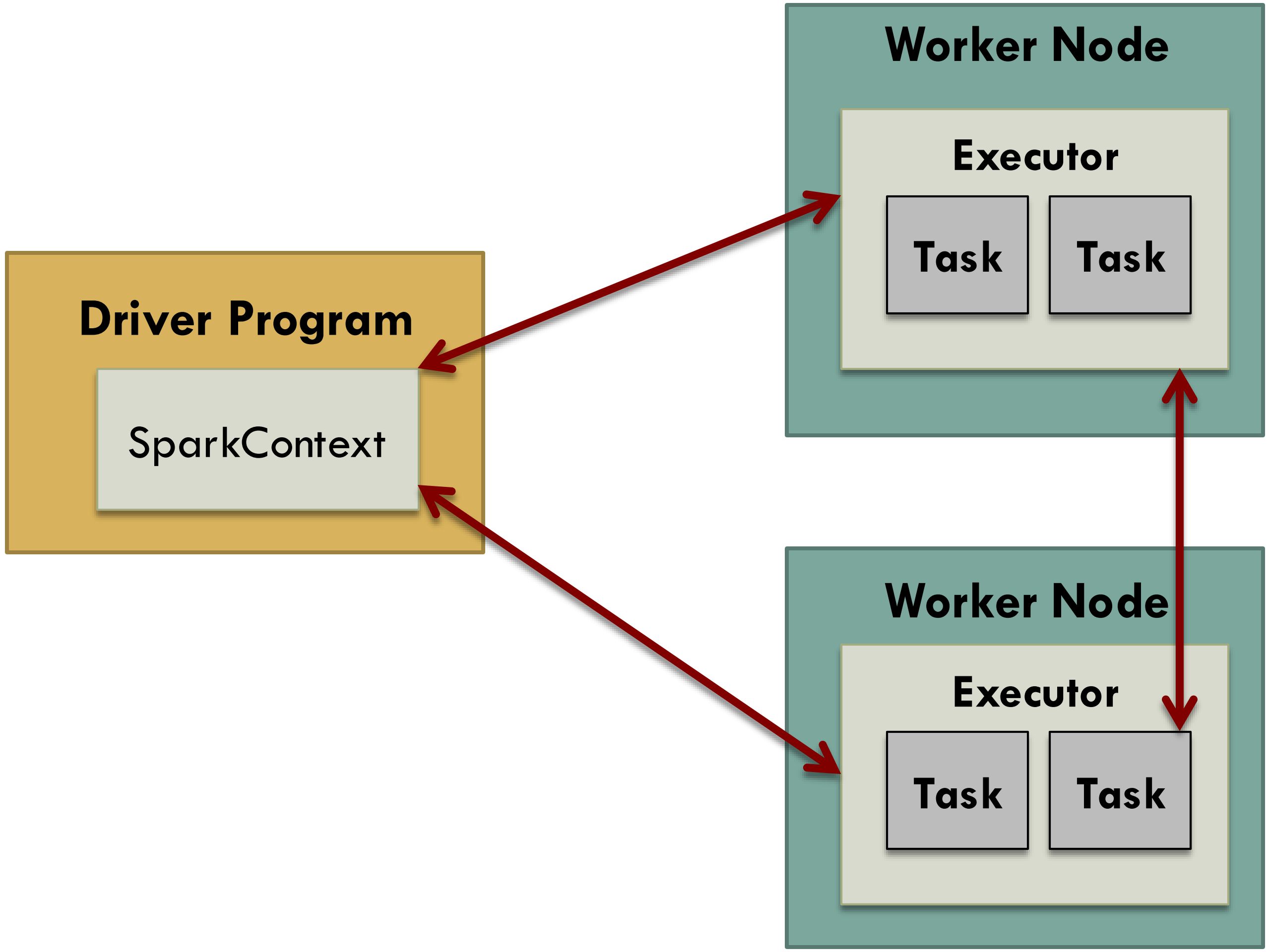
SparkContext

- Driver programs access Spark through a `SparkContext` object
  - Represents a **connection** to a computing cluster
- Within the shell?
  - Created as the variable `sc`
    - You can even print out `sc` to see the the type
- Once you have a `SparkContext`, you can use it to build RDDs
  - And then run operations on the data …

Executors

- Driver programs manage a number of nodes, called **executors**
- Executors are responsible for running operations
- For example:
  - If we were running a `count()` operation on cluster
    - Different machines might count lines in different ranges of the file

Components for distributed execution in Spark



Lambda Expressions: Functions on the Fly

Lambda expressions … functions on the fly

- Sometimes you need a function, but it feels wasteful to give it a name
- You just want to describe *what* to do (right there!) … in the moment
- That's what a lambda expression is
  - A way to write a tiny, disposable function without all the ceremony of a definition
- In everyday terms, a lambda is like giving someone quick instructions
  - "sort by length," "double every number," "keep only the odd ones"
  - Without naming the rulebook

Lambda expressions … key ideas

- **Anonymous**
  - Lambdas don't have names; they exist only where they're needed
- **Concise**
- In functional programming, **functions** are first-class participants
  - You can pass them around, store them, and return them
- Contextual
  - Perfect for small jobs: sorting, filtering, mapping, or transforming data in Spark

Lambda in action

```
val nums = List(1, 2, 3, 4)
val squares = nums.map(x => x * x)
println(squares)   // Output: List(1, 4, 9, 16)
```

Here, `x => x * x` is a lambda
See how it describes the transformation without ever naming the function

```
val words = sc.parallelize(List("sun", "moon", "stars", "sky", "light", "air"))
val longWords = words.filter(w => w.length > 3)
println(longWords.collect().mkString(", "))
```

The lambda `w => w.length > 3` is passed to filter,
Spark applies it in parallel to each partition,
The result is a new RDD containing only the elements that meet the condition
    i.e. moon, stars, light

Lot of Spark's API revolves around passing functions to its operators [1/2]

```
def hasPython(line)
   return "Python" in line

pythonLines =
    lines.filter(hasPython)
```

```
pythonLines =
 lines.filter(line => line.contains("Python")
```

Also known as the **lambda or =>** syntax

Lot of Spark’s API revolves around passing functions to its operators [2/2]

```
JavaRDD<String> pythonLines = lines.filter(
   new Function<String, Boolean> () {
     Boolean call(String line) {
        return line.contains(“Python”);
     }
    }
  );
```

```
JavaRDD<String> pythonLines =
    lines.filter(line -> line.contains(“Python”) );
```

Resilient Distributed Dataset [RDD]

Resilient Distributed Dataset (RDD)

- RDD is an **immutable, distributed collection** of objects
- Each RDD is split into *multiple partitions*
  - Maybe computed on different nodes in the cluster
- Can contain any type of Java, Scala, or Python objects
  - Including user-defined classes

Creation of RDDs

1. Loading an external dataset
2. Distributing a collection of objects via the driver program

```
>>> lines = sc.textFile("README.md")
```

Once created, RDDs offer two types of operations

- **Transformations**
  - Construct a new RDD from a previous one
  - E.g.: Filtering data that matches a predicate

- **Actions**
  - Compute a result based on an RDD
  - Return result to the driver program or save it in an external storage system (HDFS)

Some more about RDDs

- Although you can define new RDDs anytime
  - Spark computes them in a **lazy fashion**
  - When?
    - The first time they are used in an *action*

- Loading lazily allows transformations to be performed *before* the action

Lazy loading allows Spark to see the whole chain of transformations

- Allows it to **compute just the data needed** for the result
- Example:

```
lines = sc.textFile("README.md")
pythonLines= lines.filter(lambda line: "Python" in line)
```

- If Spark were to load and store all lines in the file, as soon as we wrote `lines=sc.textFile()`?
  - Would waste a lot of storage space, since we immediately filter out a lot of lines

RDD and actions

- RDDs are **recomputed** (by default) every time you run an action on them

- If you wanted to reuse an RDD?
  - Ask Spark to **persist** it using `RDD.persist()`
  - After computing it the first time, Spark will store RDD contents in memory (*partitioned* across cluster machines)
  - Persisted RDD is used in future actions

RDDs: memory residency and immutability implications

- Spark can keep an RDD loaded in-memory on the executor nodes throughout the life of a Spark application for faster access in **repeated computations**
- RDDs are immutable, so **transforming an RDD returns a new RDD** rather than the existing one
- Cross-cutting implications?
  - Lazy evaluation, in-memory storage, and immutability allows Spark to be easy-to-use, fault-tolerant, scalable, and efficient

Every Spark program and shell works as follows

① **Create** some input RDD from external data

② **Transform** them to define new RDDs using transformations like `filter()`

③ Ask Spark to **`persist()`** any intermediate RDDs that needs to be reused

④ **Launch actions** such as `count()`, etc. to kickoff a parallel computation

- Computing is optimized and executed by Spark

A Closer look at RDD Operations

RDDs support two types of operations

- Transformations
  - Operations that **return a new RDD**. E.g.: `filter()`
- Actions
  - Operations that **return a result** to the driver program or write to storage
  - Kicks of a *computation*. E.g.: `count()`
- Distinguishing aspect?
  - Transformations return RDDs
  - Actions return *some other* data type

Transformations

- Many transformations are **element-wise**
  - Work on only one element at a time

- Some transformations are not element-wise
  - E.g.: We have a logfile, *log.text*, with several messages, but we only want to select error messages

```
inputRDD = sc.textFile("log.txt")
errorsRDD = inputRDD.filter(lambda x:"error" in x)
```

In our previous example ...

- `filter` **does not mutate** `inputRDD`
  - Returns a pointer to an entirely new RDD
  - `inputRDD` can still be reused later in the program

- We could use `inputRDD` to search for lines with the word “warning”
  - While we are at it, we will use another transformation, `union()`, to print number of lines that contained either

```
errorsRDD = inputRDD.filter(lambda x: “error” in x)
warningsRDD = inputRDD.filter(lambda x: “warning” in x)
badlinesRDD = errorsRDD.union(warningsRDD)
```

In our previous example

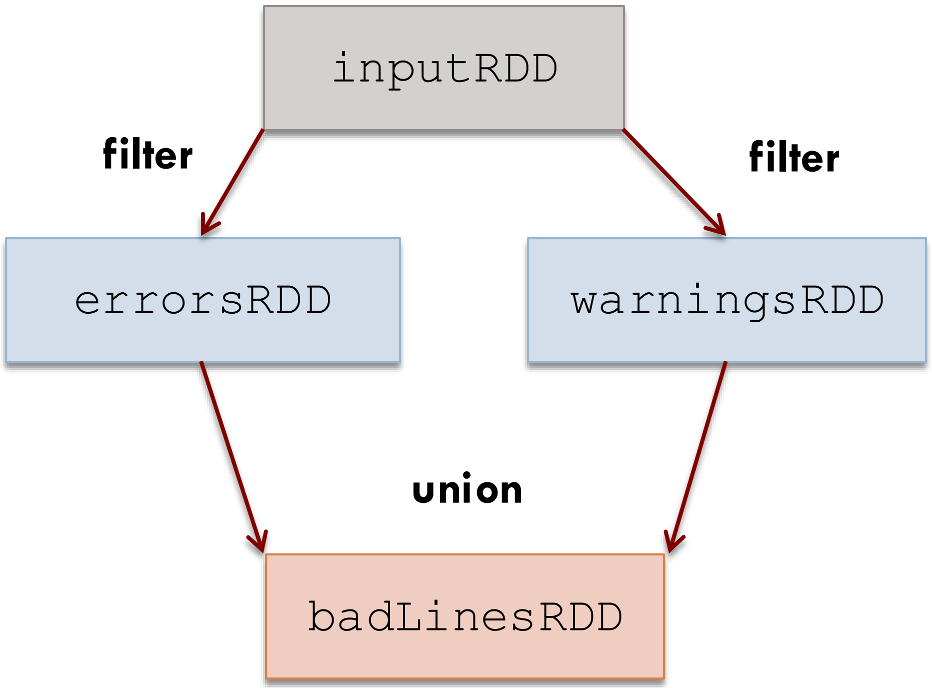
- Note how `union()` is different from `filter()`
  - Operates on 2 RDDs instead of one
- Transformations can actually operate on **any number** of RDDs

RDD Lineage graphs

- As new RDDs are derived from each other using transformations, Spark *tracks dependencies*
  - **Lineage graph**

- Uses lineage graph to
  - Compute each RDD on demand
  - Recover lost data if part of persistent RDD is lost

RDD lineage graph for our example



Actions

- We can create RDDs from each other using transformations
- At some point, we need to actually **do something** with the dataset
  - Actions
- Forces *evaluations of the transformations* required for the RDD they were called on

Let’s try to print information about badlinesRDD

```
print “Input had “ + badLinesRDD.count() + “concerning lines”
print “here are 10 examples:”
for line in badLinesRDD.take(10)
    print  line
```

RDDs also have a `collect` to retrieve the entire RDD

- Useful if program filters RDD to a very small size and you want to deal locally
  - Your entire dataset must fit in memory on a single machine to use `collect()` on it
    - Should NOT be used on large datasets
- In most cases, RDDs **cannot be** `collect()`ed to the driver
  - Common to write data out to a distributed storage system … HDFS or S3

Lazy Evaluation

- Transformations on RDDs are **lazily evaluated**
  - Spark will not begin to execute until it sees an action

- Uses this to **reduce the number of passes** it has to take over data by grouping operations together

- What does this mean?
  - When you call a transformation on an RDD (for e.g., `map`) the operation is not immediately performed
  - Spark internally records metadata that operation is requested

How you should think of RDDs

- Rather than thinking of it as containing specific data
  - Best to think of it as **containing instructions on how to compute the data** that we build through transformations
- Loading data into a RDD is lazily evaluated just as transformations are

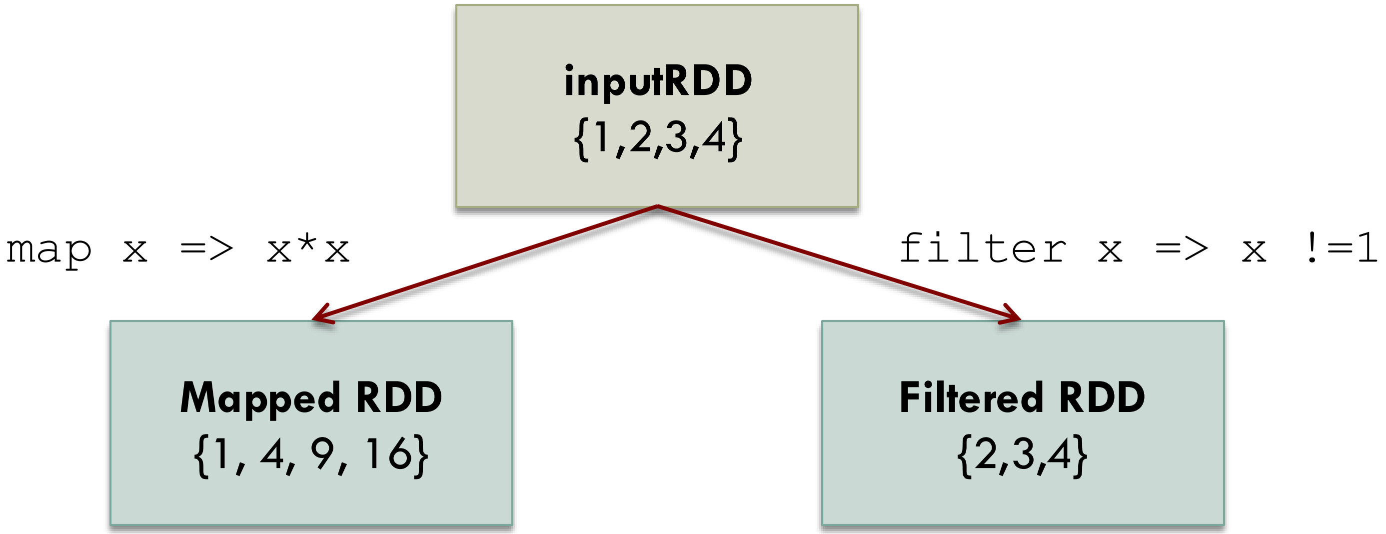
Common transformations and Actions

Element-wise transformations: `filter()`

- Takes in a function and returns an RDD that only has elements that pass the `filter()` function

Element-wise transformations: `map()`

- Takes in a function and applies it to each element in the RDD
- Result of the function is the new value of each element in the resulting RDD



Things that can be done with `map()`

- Fetch website associated with each URL in collection to just squaring numbers
- `map()`'s return type does not have to be the same as its input type
- Multiple output elements for each input element?
  - Use `flatMap()`

```
lines=sc.parallelize(["hello world", "hi"])
words=lines.flatMap(lambda line: line.split(" ") )
words.first()    # returns hello
```

Difference between `map` and `flatMap`

RDD1
{“coffee panda”, “happy panda”, “happiest panda party”}

RDD1.map(tokenize) →

mappedRDD
{[“coffee”, “panda”], [“happy”, “panda”], [“happiest”, “panda”, “party”]}

RDD1.flatMap(tokenize) →

flatMappedRDD
{“coffee”, “panda”, “happy”, “panda”, “happiest”, “panda”, “party”}

Psuedo set operations

- RDDs support many of the operations of mathematical sets such as union, intersection, etc.
  - Even when the RDDs themselves are not properly sets

Some simple set operations

RDD1
{coffee, coffee, panda, tiger, tea}

RDD2
{coffee, tiger, snake}

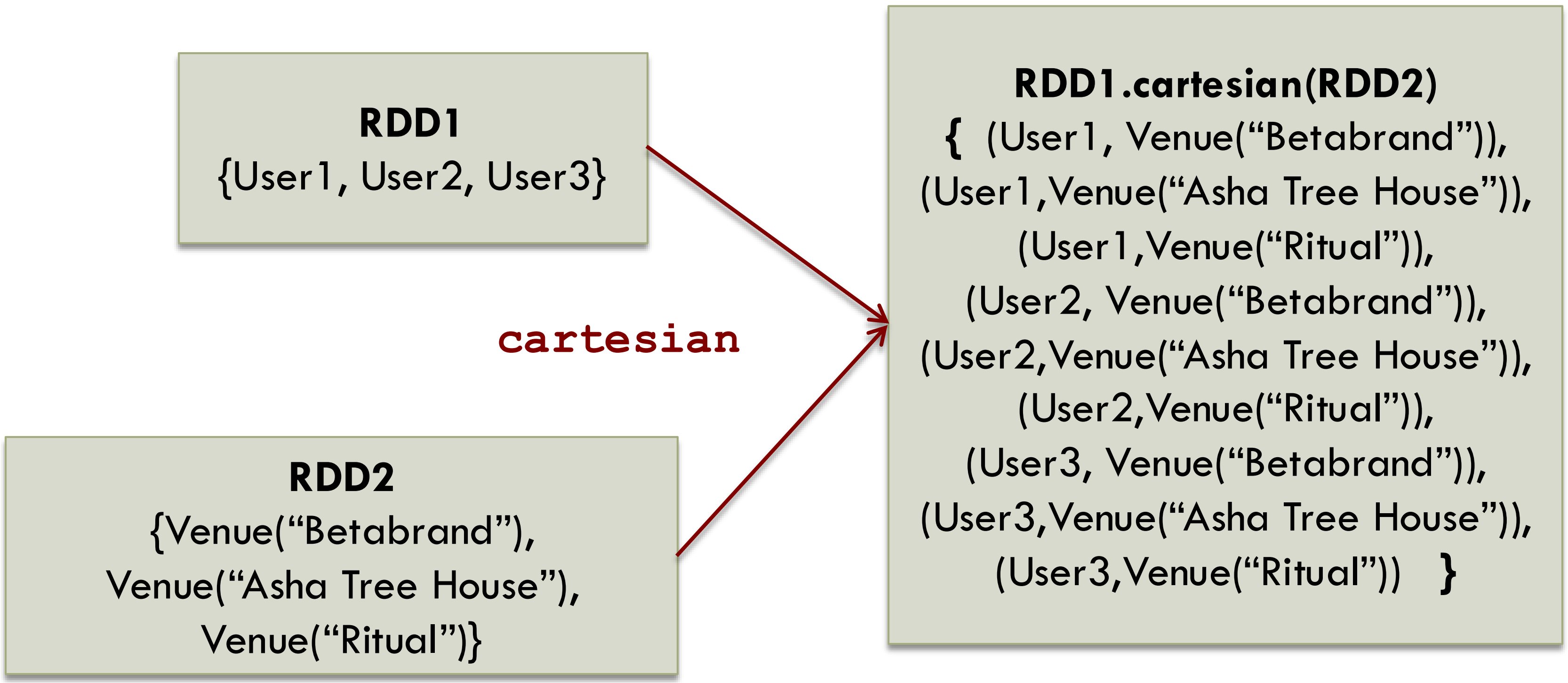
RDD1.distinct()
{coffee, tiger, panda, tea}

RDD1.union(RDD2)
{coffee, coffee, coffee, panda, tiger, tiger, tea, snake}

RDD1.intersection(RDD2)
{coffee, tiger}

RDD1.subtract(RDD2)
{panda, tea}

Cartesian product between two RDDs




Common Actions

Actions on Basic RDDs

- `reduce()`
  - Takes a function that operates on two elements in the RDD; returns an element of the same type
    - E.g., of such an operation? + sums the RDD

```
sum = rdd.reduce((x,y) => x + y)
```

- `fold()` takes a function with the same signature as `reduce()`, but also takes a "zero value" for initial call
  - "Zero value" is the **identity element** for initial call
  - E.g., 0 for +, 1 for *, empty list for concatenation

Both `fold()` and `reduce()` require return type of same type as the RDD elements

- The `aggregate()` removes that constraint
  - For e.g., when computing a running average, maintain both the count so far and the number of elements

EXAMPLES: BASIC ACTIONS ON RDDS

Examples: Basic actions on RDDs [1/7]

- Our RDD contains {1, 2, 3, 3}
- **`collect()`**
  - Return all elements from the RDD
  - Invocation: `rdd.collect()`
  - Result: {1, 2, 3, 3}

Examples: Basic actions on RDDs [2/7]

- Our RDD contains {1, 2, 3, 3}
- **`count()`**
  - Number of elements in the RDD
  - Invocation: `rdd.count()`
  - Result: 4

Examples: Basic actions on RDDs [3/7]

- Our RDD contains {1, 2, 3, 3}
- **`countByValue()`**
  - Number of times each element occurs in the RDD
  - Invocation: `rdd.countByValue()`
  - Result: { (1,1), (2,1), (3,2) }

Examples: Basic actions on RDDs [4/7]

- Our RDD contains {1, 2, 3, 3}
- **`take(num)`**
  - Return `num` elements from the RDD
  - Invocation: `rdd.take(2)`
  - Result: { 1, 2}

Examples: Basic actions on RDDs [5/7]

- Our RDD contains {1, 2, 3, 3}
- **`reduce(func)`**
  - Combine the elements of the RDD together in parallel
  - Invocation: `rdd.reduce( (x,y) => x + y )`
  - Result: 9

Examples: Basic actions on RDDs [6/7]

- Our RDD contains {1, 2, 3, 3}
- **`aggregate(zeroValue)(seqOp, combOp)`**
  - Similar to `reduce()` but used to return a different type
  - Invocation:
    - ```
      rdd.aggregate ( (0,0))
                    ((x,y) => (x._1 + y, x._2 + 1),
                     (x,y) => (x._1 + y._1, x._2 + y._2))
      ```
  - Result: (9, 4)
      ```

Examples: Basic actions on RDDs [7/7]

- Our RDD contains {1, 2, 3, 3}
- **`foreach(func)`**
  - Apply the provided function to each element of the RDD
  - Invocation: `rdd.foreach(func)`
  - Result: Nothing

The contents of this slide-set are based on the following references

- *Learning Spark: Lightning-Fast Big Data Analysis. 1st Edition. Holden Karau, Andy Konwinski, Patrick Wendell, and Matei Zaharia. O'Reilly. 2015. ISBN-13: 978-1449358624.* [Chapters 1-4]
- Karau, Holden; Warren, Rachel. High Performance Spark: Best Practices for Scaling and Optimizing Apache Spark. O'Reilly Media. 2017. ISBN-13: 978-1491943205. [Chapter 2]
- Chambers, Bill,Zaharia, Matei. Spark: The Definitive Guide: Big Data Processing Made Simple. O'Reilly Media. ISBN-13: 978-1491912218. 2018. [Chapters 1, 2, and 3].