CS 455: Introduction to Distributed Systems [Spark]

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Frequently asked questions from the previous class survey

- 48-bit bookending in Bzip2: does the number have to be "special"?
- Spark seems to have "too many" features/extension libraries??
  - Good or bad
- Code inspection?

Topics covered in this lecture

- Resilient Distributed Datasets
- Common Transformations and Actions

Resilient Distributed Dataset [RDD]

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)
```

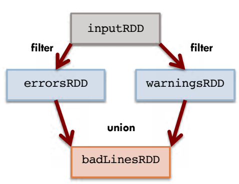
In our previous example

- 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

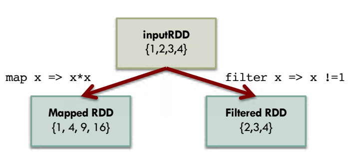
Common transformations and Actions

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

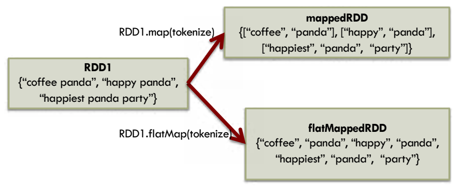


Things that can be done with `map()`

- 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
```

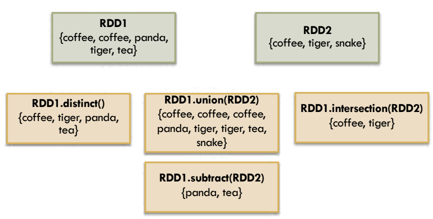
Difference between `map` and `flatMap`



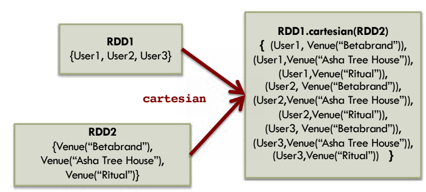
Psuedo set operations

- 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



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

Persistence (Caching)

Why persistence?

- Spark RDDs are lazily evaluated, and we may sometimes wish to use the same RDD multiple times
  - Naively, Spark will **recompute RDD and all of its dependencies** each time we call an action on the RDD
    - Super expensive for iterative algorithms
- To avoid recomputing RDD multiple times?
  - Ask Spark to **persist** the data
  - The nodes that compute the RDD, store the partitions
  - E.g.: `result.persist(StorageLevel.DISK_ONLY)`

Coping with failures

- If a node that has data persisted on it fails?
  - Spark recomputes lost partitions of data when needed
- Also, replicate data on multiple nodes
  - To handle node failures without slowdowns
      ```

Persistence Levels for Spark

Level	Space Used	CPU time	In Memory	On disk	Comments
MEMORY_ONLY	High	Low	Y	N	
MEMORY_ONLY_SER	Low	High	Y	N	
MEMORY_AND_DISK	High	Medium	Some	Some	Spills to disk if there is too much data to fit in memory
MEMORY_AND_DISK_SER	Low	High	Some	Some	Spills to disk if there is too much data to fit in memory. Stores serialized representation in memory
DISK_ONLY	Low	High	N	Y	

What if you attempt to cache too much data that does not fit in memory?

- Spark will **evict old partitions** using a Least Recently Used Cache policy
  - For memory only storage partitions, it will be recomputed the next time they are accessed
  - For memory_and_disk ones? Write them out to disk
- RDDs also come with a method, `unpersist()`
  - Manually remove data elements from the cache

Working with Key/Value Pairs

RDDs of key/value pairs

- Key/value RDDs are commonly used to perform aggregations
  - Might have to do ETL (Extract, Transform, and Load) to get data into key/value formats
- Advanced feature to control layout of pair RDDs across nodes
  - **Partitioning**

RDDs containing key/value pairs

- Are called **pair RDDs**
- Useful *building block* in many programs
  - Expose operations that allow actions on each key in parallel or regroup data across network
  - `reduceByKey()` to aggregate data separately for each key
  - `join()` to merge two RDDs together by grouping elements of the same key

Pair RDDs

Pair RDDs

- RDDs that contain **key/value pairs**
- Expose partitions that allow you to act on each key in parallel or regroup data across the network

Creating Pair RDDs

- `pairs=lines.map(lambda x:  (x.split(" ") )[0], x))`
  - Creates a pairRDD using the first word as the key
- Java does not have a built-in tuple type
  - `scala.Tuple2` class
    - `new Tuple2(elem1, elem2)`

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]