CS 455: Introduction to Distributed Systems [Spark]

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Frequently asked questions from the previous class survey

- Return type for `collect()`? Can we collect somewhere else?
- My team has 3 members: that means each of us can contribute a third less than a 2 member team, correct?
  - No such luck. In fact, the project is expected to be commensurately more complex.

Topics covered in this lecture

- Pair RDDs
- Dependencies and Transformations
- Partitioners

Transformations on Pair RDDs

Transformations on Pair RDDs [1/5]

- Pair RDD = {(1,2), (3,4), (3,6) }
- **`reduceByKey(func)`**
  - Combine values with the same key
  - Invocation: `rdd.reduceByKey((x, y) => x + y)`
  - Result: { (1, 2), (3,10) }

Transformations on Pair RDDs [2/5]

- Pair RDD = {(1,2), (3,4), (3,6) }
- **`groupByKey(func)`**
  - Group values with the same key
  - Invocation: `rdd.groupByKey()`
  - Result: { (1, [2]), (3, [4, 6]) }

Transformations on Pair RDDs [3/5]

- Pair RDD = {(1,2), (3,4), (3,6) }
- **`mapValues(func)`**
  - Apply function to each value of a pair RDD *without* changing the key
  - Invocation: `rdd.mapValues(x => x+1)`
  - Result: { (1, 3), (3, 5), (3, 7) }

Transformations on Pair RDDs [4/5]

- Pair RDD = {(1,2), (3,4), (3,6) }
- **`values()`**
  - Return an RDD of just the values
  - Invocation: `rdd.values()`
  - Result: { 2, 4, 6 }

Transformations on Pair RDDs [5/5]

- Pair RDD = {(1,2), (3,4), (3,6) }
- **`sortByKey()`**
  - Return an RDD sorted by the key
  - Invocation: `rdd.sortByKey()`
  - Result: { (1,2), (3,4), (3,6 }

Transformations on two pair RDDs

Transformations on two Pair RDDs [1/5]

- **`rdd`** = {(1,2), (3,4), (3,6) } **`other`** = {(3,9)}
- **`subtractByKey()`**
  - Remove elements with a key present in the `other` RDD
  - Invocation: `rdd.subtractByKey(other)`
  - Result: { (1,2) }

Transformations on two Pair RDDs [2/5]

- **`rdd`** = {(1,2), (3,4), (3,6) } **`other`** = {(3,9)}
- **`join()`**
  - Perform an **inner join** between two RDDs. Only keys that are present in both pair RDDs are output
  - Invocation: `rdd.join(other)`
  - Result: { (3, (4,9)) , (3, (6,9)) }

Transformations on two Pair RDDs [3/5]

- **rdd** = {(1,2), (3,4), (3,6) } **other** = {(3,9)}
- **`leftOuterJoin()`**
  - Perform a join between two RDDs where the key must be present in the first RDD
  - Value associated with each key is a tuple of the value from the source and an Option for the value from the `other` pair RDD
    - In python if a value is not present, None is used.
  - Invocation: `rdd.leftOuterJoin(other)`
  - Result: { (1, (2,None)) , (3, (4, 9)) , (3, (6, 9)) }

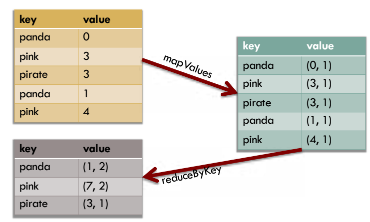
Transformations on two Pair RDDs [4/5]

- **rdd** = {(1,2), (3,4), (3,6) } **other** = {(3,9)}
- **`rightOuterJoin()`**
  - Perform a join between two RDDs where the key must be present in the `other` RDD;
  - Tuple has an option for the source rather than `other` RDD
  - Invocation: `rdd.rightOuterJoin(other)`
  - Result: { (3, (4,9)) , (3, (6,9)) }

Transformations on two Pair RDDs [5/5]

- **rdd** = {(1,2), (3,4), (3,6) } **other** = {(3,9)}
- **`cogroup()`**
  - Group data from both RDDs using the same key
  - Invocation: `rdd.cogroup(other)`
  - Result: { (1, ([2],[])) , (3, ([4, 6], [9])) }

Example of chaining operations: Calculation of per-key average




```
rdd.mapValues(x=> (x, 1)).reduceByKey( (x,y) => (x._1 + y._1, x._2 + y._2))
```


A word count example

- We are using `flatMap()` to produce a pair RDD of words and the number 1

```
 rdd   = sc.textfile("s3://…")
words = rdd.flatMap(lambda x: x.split(" "))
result = words.map(lambda x: (x,1)).
               reduceByKey(lambda x, y: x+y)
```


Wide and Narrow Transformations

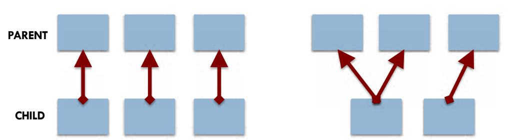
Transformations and Dependencies

- Two categories of **dependencies**
  - Narrow
    - Each partition of the parent RDD is used by **at most one partition of the child** RDD
  - Wide
    - Multiple child RDD partitions may depend on a single parent RDD partition
- The narrow versus wide distinction has significant implications for the way Spark evaluates a transformation and, consequently, for its performance

Narrow Transformations

- Narrow transformations are those in which each partition in the child RDD has simple, finite dependencies on partitions in the parent RDD
- Can be **determined at design time**, irrespective of the values of the records in the parent partitions
- Partitions in narrow transformations can either depend on:
  - One parent (such as in the `map` operator), or
  - A unique subset of the parent partitions that is known at design time (`coalesce`)
- Narrow transformations can be executed on an arbitrary subset of the data without any information about the other partitions.

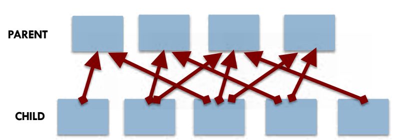
Dependencies between partitions for narrow transformations



Wide Transformations

- Transformations with **wide dependencies** cannot be executed on arbitrary rows
- Require the data to be partitioned in a particular way, e.g., according the **value** of their key
  - In sort, for example, records have to be partitioned so that keys in the same range are on the same partition
- Transformations with wide dependencies include `sort`, `reduceByKey`, `groupByKey`, `join`, and anything that calls the `rePartition` function

Dependencies between partitions for wide transformations



Wide dependencies **cannot be known fully before the data is evaluated**

The dependency graph for any operations that cause a **shuffle** (such as `groupByKey`, `reduceByKey`, `sort`, and `sortByKey`) follows this pattern

TUNING THE LEVEL OF PARALLELISM

Tuning the level of parallelism

- Every RDD has a **fixed number of partitions**
  - Determine the degree of parallelism when executing operations
- During aggregations or grouping operations, you can ask Spark to use a specific number of partitions
  - This will override defaults that Spark uses

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Example: Tuning the level of parallelism

```
data = [("a", 3), ("b", 4), ("a", 1)]

sc.parallelize(data).
       reduceByKey(lambda x, y: x + y) #default

sc.parallelize(data).
       reduceByKey(lambda x, y: x + y, 10) #Custom
```

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What if you want to tune parallelism outside of grouping and aggregation operations?

- There is `repartition()`
  - **Shuffles data across the network** to create a new set of partitions
  - Very **expensive operation!**
- There is the `coalesce()` operation
  - Allows avoiding data movement
    - But only if you are **decreasing** the number of partitions
  - Check `rdd.getNumPartitions()` and make sure you are coalescing to fewer partitions than current

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PAIR RDDS: WHAT TO WATCH FOR

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Despite their utility, key/value operations can lead to a number of performance issues

- Most expensive operations in Spark fit into the key/value pair paradigm
  - Because **most wide transformations** are key/ value transformations,
    - And most require some fine tuning and care to be performant

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In particular, operations on key/ value pairs can cause

1. Out-of-memory errors in the driver
2. Out-of-memory errors on the executor nodes
3. Shuffle failures
4. "Straggler tasks" or partitions, which are especially slow to compute

- The last three performance issues are all most often caused by **shuffles associated with the wide transformations**

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Memory errors in the driver, is usually caused by actions

- Several key/value actions (including `countByKey`, `countByValue`, `lookUp`, and `collectAsMap`) return data to the driver
- In most instances they return unbounded data since the number of keys and the number of values are unknown
- In addition to number of records, the size of each record is an important factor in causing memory errors

Preventing out-of-memory errors with aggregation operations [1/2]

- `combineByKey` and all of the aggregation operators built on top of it (`reduceByKey, foldLeft, foldRight, aggregateByKey`) may lead to memory errors if they cause the accumulator to become too large for one key
- What about `groupByKey`?
  - It is actually implemented using `combineByKey` where the accumulator is an iterator with all the data.

Preventing out-of-memory errors with aggregation operations [2/2]

- Use functions that implement **map-side combinations**
  - Meaning that records with the same key are combined before they are shuffled
  - This can greatly reduce the shuffled read
- The following four functions are implemented to use map-side combinations
  - `reduceByKey`
  - `treeAggregate`
  - `aggregateByKey`
  - `foldByKey`

Two primary techniques to avoid performance problems associated with shuffles

- Shuffle Less
- Shuffle Better

Shuffle Less

- Preserve partitioning across narrow transformations to avoid reshuffling data
- Use the same partitioner on a sequence of wide transformations. This can be particularly useful:
  - To avoid shuffles during joins and …
  - To reduce the number of shuffles required to compute a sequence of wide transformations

Shuffle Better [1/2]

- Sometimes, computation cannot be completed without a shuffle
- However, not all wide transformations and not all shuffles are equally expensive or prone to failure

Shuffle Better [2/2]

- By using wide transformations such as `reduceByKey` and `aggregateByKey` that can preform map-side reductions and that do not require loading all the records for one key into memory?
  - You can prevent memory errors on the executors and
  - Speed up wide transformations, particularly for aggregation operations
- Lastly, shuffling data in which **records are distributed evenly throughout the keys**, and which contain a **high number of distinct keys**?
  - Prevents out-of-memory errors on the executors and "straggler tasks"

Partitioners

Partitioners

- The partitioner defines **how records will be distributed** and thus which records will be completed by each task
- Practically, a partitioner is actually an interface with two methods
  - `numPartitions` that defines the number of partitions in the RDD after partitioning
  - `getPartition` that defines a mapping from a key to the integer index of the partition where records with that key should be sent.

There are two implementations for the partitioner object provided by Spark

- HashPartitioner
  - Determines the index of the child partition based on the hash value of the key
- RangePartitioner
  - Assigns records whose keys are in the same range to a given partition
  - Required for **sorting** since it ensures that by sorting records within a given partition, the entire RDD will be sorted
- It is possible to define a custom partitioner

Partitioners and transformations

- Unless a transformation is known to only change the value part of the key/value pair in Spark
  - The resulting RDD will **not have a known** partitioner
    - Even if the partitioning has not changed

Using narrow transformations that preserve partitioning

- Some narrow transformations, such as `mapValues`, **preserve the partitioning** of an RDD if it exists
- Common transformations like `map` and `flatMap` can change the key
  - So even if your function does not change the key, the resulting RDD will not have a known partitioner.
  - Instead, if you don't want to modify the keys, call the `mapValues` function (defined only on pair RDDs)
    - It keeps the keys, and therefore the partitioner, exactly the same.
    - The `mapPartitions` function will also preserve the partition if the `preservesPartitioning` flag is set to true.

SPARK STREAMING

Spark Streaming

- Act on data **as soon as it arrives**
  - Track statistics of page views in real time, detect anomalies, etc.
- Spark streaming
  - Spark's module for dealing with streaming data
  - Uses an API very similar to what we have seen with batch jobs (centered around RDDs)
- Available in Java and Scala
  - Recent support for Python

Spark Streaming: Core concepts

- Provides an abstraction called **DStreams** (discretized streams)
- A DStream is a **sequence of data** arriving over time
- Internally, a DStream is represented as a **sequence of RDDs** arriving at each time step

DStreams

- DStreams can be created from various input sources
  - Flume, Kafka, or HDFS
- Once built, DStreams offer two types of operations:
  - **Transformations**: Yields a new DStream
  - **Output operations**: Writes data to an external system
- Provides many of the same operations available on RDDs
  - PLUS new operations related to time (e.g. sliding windows)

Example

- Start by creating a `StreamingContext`
  - Main entry point for streaming functionality
  - Specify batch interval, specifying **how often** to process new data
- We will use `socketTextStream()` to create a DStream based on text data received over a port
- Transform DStream with filter to get lines that contain "error"

Example

```
JavaStreamingContext jssc =
      new JavaStreamingContext(conf, Durations.seconds(1));

JavaDStream<String> lines =
      jssc.socketTextStream("localhost", 7777);

JavaDStream<String> errorLines =
      lines.filter(new Function<String, Boolean> () {
          public Boolean call(String line) {
             return line.contains("error");
          }
      };
```

Previous snippet only sets up the computation

- To start receiving the data?
  - Explicitly call `start()` on `StreamContext`
- SparkStreaming will start to schedule Spark jobs on the underlying SparkContext
  - Occurs in a **separate thread**
  - To keep application from terminating?
    - Also call `awaitTermination()`

```
jssc.start();
jssc.awaitTermination()
```


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, 10]