More about Spark

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Key Learning Goals

- What is the purpose of Spark SQL, Spark Streaming, Spark MLlib, and Spark GraphX?
- Why do map and flatMap remove the Partitioner of a pair RDD?
- Why do mapValues and flatMapValues preserve the Partitioner of a pair RDD?
- When can the hash+shuffle join on pair RDDs avoid shuffling?

Introduction

- This module surveys important components and aspects of Spark that have not been covered in detail yet:
  - Spark SQL
  - Spark Streaming
  - Spark MLlib
  - Spark GraphX
  - Partitioning and shuffling in Spark

Let us start with SQL operations in Spark.

SQL Basics

- SQL is based on the relational calculus. A calculus expression describes what we are looking for, not how to compute it.
- The computation steps and their order of execution are expressed in relational algebra. For a given SQL query, the logical query plan corresponds to an expression in relational algebra.
- Relational algebra has only five primitive operators, which can be combined to compose complex queries: selection, projection, Cartesian product (a.k.a. cross product or cross join), set union, and set difference.
  - The renaming operator is needed for formal reasons, but does not manipulate data.
- In addition to the five basic operators, grouping and aggregation operators were introduced as well.
- We already encountered most of these operators before.

Reminder: Selection and Projection

DBMS (SQL): Assume the input relation R has schema (A1, A2, A3); P is a predicate returning true/false; F is a function

Selection:	SELECT * FROM R WHERE F(A1, A2, A3)
Projection (on A1):	SELECT A1 FROM R
Extended projection:	SELECT F(A1, A2, A3) FROM R

Spark:

```
myRDD.filter( P(x) )          // selection
myRDD.map( x => F(x) )        // extended projection

myDS.filter( P(x) )           // selection
myDS.select( “A1” )           // projection
myDS.map( x => F(x) )         // extended projection
```

Reminder: Grouping and Aggregation

DBMS (SQL): Assume the input relation R has schema (Key, Val)

```
SELECT Key, myAGG( Val ) FROM R GROUP BY Key
```

Spark:

```
myPairRDD.aggregateByKey( aggFunction )

myDS.groupBy("Key").agg( aggFunction )
```

Cartesian Product

DBMS (SQL): Cartesian product of relations R and S

```
SELECT * FROM R, S
```

Spark:

```
myRDD.cartesian( otherRDD )

myDF.crossJoin( otherDF )

// The joinWith method of DataSet also supports a version where
join types, including cross, can be selected.
```

Set Difference

- Set functions generally require both inputs to be of the same type.
- rdd1.subtract(rdd2) transformation: returns all elements from rdd1 that are not in rdd2. This is for ordinary RDDs and hence compares the entire element.
- rdd1.subtractByKey(rdd2) transformation: This is for pair RDDs, returning all elements from rdd1 whose keys do not appear as key in rdd2.
- For DataSet, the corresponding transformation is except.
  - Equality checking is performed directly on the encoded representation of the data and thus is not affected by a custom `equals` function defined on the element type.

Union and Intersection in Spark

- rdd1.union(rdd2) transformation: returns all elements that occur in either input, but does not remove duplicates.
  - For DataSet, the corresponding functions are union and unionByName.
- rdd1.intersection(rdd2) transformation: returns all elements that occur in both.
  - For DataSet, the corresponding function is intersect.
- Intersection does not add new functionality—it can be expressed with union and set difference.

Reminder: Joins

- The join can be expressed as a selection applied to the Cartesian product. Then why was it introduced as a separate operator?
  - Joins are very common in practice, and they tend to be expensive. Since most joins in databases are equi-joins, specialized techniques were proposed to reduce their computation cost.
- Refer to the module on joins for Spark join operations.

Zip—A Special Join

- rdd1.zip(rdd2) transformation: for rdd1 of type T and rdd2 of type U, it returns pairs of type (T, U), where the i-th pair consists of the i-th records from rdd1 and from rdd2.
  - Both RDDs have to have the same number of partitions and elements in them.
  - zipPartitions transformation is similar, but more flexible in zipping even partitions with different number of elements.
- When is this useful?
  - Consider computation of PageRank. Conceptually we are dealing with two data sets: the graph and the PageRank values. The former is read repeatedly, while the latter changes in each iteration. Hence we want to store the graph as a pair RDD (nodeID, adjacencyList) and the PageRank values as (nodeID, PRvalue). To compute outgoing contributions for a node N, both N’s adjacency list and current PR value are needed. Using zip to combine the values is much more efficient (and elegant) than using join or trying a workaround with intersection. We just have to make sure that there really is a one-to-one correspondence between records in both data sets.

Spark SQL

- Spark SQL works with DataFrames.
  - Reminder: A DataFrame is like a database table. It consists of rows, each adhering to a fixed schema that defines the name and type of all columns. You can think of a DataFrame as an RDD with additional structure. In recent Spark versions, it is an alias for DataSet[Row].
- DataFrames can be processed using SQL and SQL-inspired functions. Think of Spark SQL as a distributed Spark-powered query processor. It can even be accessed like a DB server using JDBC.
- Operations on DataFrames are translated into optimized low-level RDD operations. Like in a DBMS, the structure enables optimizations not possible for general RDDs.

Implementation Notes

- Spark's default file format for structured data is Parquet.
- DataFrame metadata is managed in a table catalog. Spark applications can then access a DataFrame by name.
  - This information disappears when the Spark context is restarted. To make the catalog persistent, Spark needs to be built with Hive support.

Creating and Storing DataFrames

- DataFrames can be created as follows:
  - Convert an RDD.
  - Run an SQL query.
  - Load external data.
- Spark can easily load and import data from JDBC sources, Hive, and files in JSON, ORC, and Parquet format.
- Parquet organizes the DataFrame column-wise, using compression. By saving the min and max value for each column chunk, some queries can skip chunks.
  - For example, consider a query computing average income for people of age 30 to 40. A chunk with min age 55 and max age 69 is completely irrelevant, but a chunk covering range 37 to 62 would have to be accessed.

Working with DataFrames

- show(n) returns the first n rows as formatted text.
- printSchema returns the schema of the DataFrame.
- columns returns a list of the column names.
- dtypes returns a list of the column names and their types.

SQL-Style Functions

- select: relational projection operator, choosing which columns to keep in the resulting DataFrame.
- drop: relational projection operator, choosing which columns to drop.
- where, filter: relational selection operator, choosing which rows to keep.
- withColumnRenamed: renames a column.
- withColumn: adds a new column.
- orderBy, sort: sort by specified column(s). When sorting on multiple columns, this sorts in “row-major” order, i.e., compares based on one column, then in case of equality compares the next, etc.
- And there is a variety of aggregate, analytic, ranking, and window functions.
- Spark SQL also allows user-defined functions (UDF) in expressions, e.g., to extract information from a string column.

SQL-Style Functions

- groupBy groups by a list of columns, returning a GroupedData object.
  - When calling an aggregate function such as count on a GroupedData object, the result is a DataFrame with an additional column holding the corresponding aggregate values for the groups.
- rollup and cube group by multiple sub-sets of the given list of grouping columns. In fact, cube groups by all 2^d subsets of a set of d columns.
- join performs an equi-join on the specified columns, offering the “outer” option.
  - Join performance may vary significantly, depending on the value of Spark parameter spark.sql.shuffle.partitions, which specifies the DataFrame’s number of partitions after shuffling.

Using Actual SQL Commands

- sql(SQLstring): is a function of SparkSession that executes an SQL query using Spark on a DataFrame, returning a DataFrame.
  - The SQL dialect can be configured with spark.sql.dialect.
- For interactive query mode, Spark also offers an SQL shell.
- Other (non-Spark) applications can also connect using the JDBC or ODBC standard. To those JDBC and ODBC clients, Spark SQL will look just like a (parallel) database server.

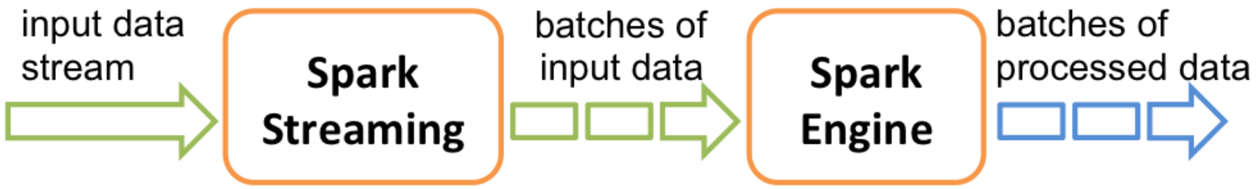
Query Optimization

- Like in a DBMS, Spark's Catalyst optimizer translates a given query into Spark jobs. It goes through several intermediate steps:
  - The query is parsed and relation references are checked to produce the logical plan.
  - This plan is then optimized, mostly by re-arranging (e.g., projection and filter before join) and combining (e.g., apply multiple filters on same relation together) operations. This currently seems to be based on "safe" heuristics, but could be extended to include cost estimation.
  - From this optimized logical plan, a physical plan is generated, which includes operator implementation choices. Here cost models should be used, e.g., to decide between different join implementations.
  - Finally, the physical plan is translated into Spark jobs.
- To see the logical and physical plans, use DataFrame's explain(true) method. Without the "true" argument, only the physical plan is shown. It can also be seen through the Web UI.

We next take a quick look at Spark Streaming.

Spark Streaming

- In an ideal data stream processing scenario, data is continually arriving, while queries are monitoring the stream in order to produce immediate results in real-time, e.g., notifications.
  - An example with mostly simple filter queries are pub/sub systems on the Internet, e.g., to notify users when an article on a topic of interest is published. Other examples include monitoring of traffic, industrial processes, and stock ticker events.
- To support real-time stream processing, a system needs to maintain query state, updating it whenever new records arrive. Spark can maintain state in RDDs much more efficiently than MapReduce with its file-system based storage approach. However, stream processing is still not a perfect fit, because Spark is optimized for batch processing of big data, not small in-place updates to data structures capturing query state.
- Spark Streaming solves this dilemma by turning stream data into a sequence of discrete mini-batches. While not perfect, this can approximate stream processing sufficiently well for many applications.



Source: spark.apache.org documentation v 2.2.0

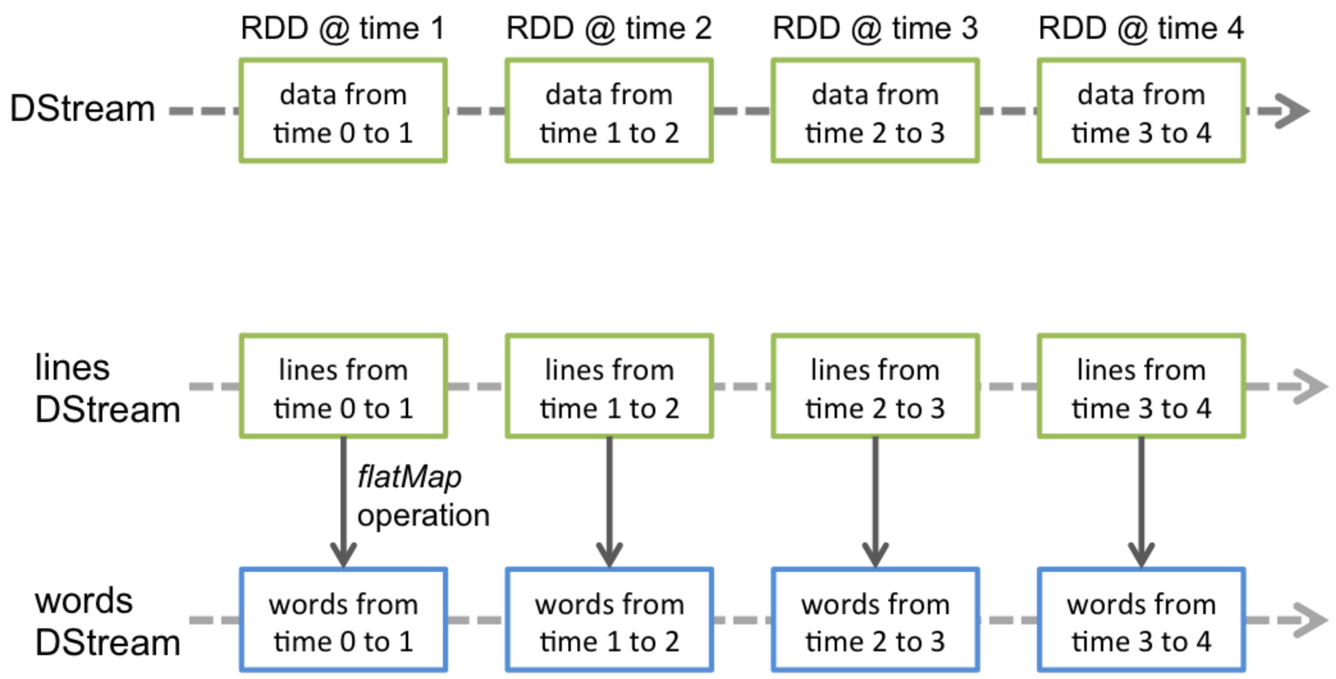
Reading Streaming Data

- Using the appropriate receiver, Spark Streaming can read data from file systems such as HDFS and S3, from TCP/IP sockets, and from distributed systems such as Twitter, Flume, and Kafka.
- Each incoming min-batch is represented by an RDD. Hence the full power of Spark can be applied to combine existing RDDs in memory with the newly arriving mini-batch RDD.
  - When reading from a file system, a mini-batch consists of all the *newly created* files, since the last batch, in the input folder. Data added to existing files will not be included!

Working with Streams

- There are several features in addition to the usual Spark operations.
- The DStream class represents the discretized stream, supporting basic operations such as map, filter, and window.
- For DStreams of key-value pairs, additional functions such as groupByKeyAndWindow and join exist.
  - updateStateByKey updates the state of each key, by applying a supplied function to the old state and newly arriving values for the key.
  - mapWithState generalizes updateStateByKey and can maintain state of some type, while returning data of another. It also apparently can manage larger state (more keys) and is significantly faster than updateStateByKey.
- DStream operations are executed automatically by the streaming context once per new mini-batch.

Mini-Batch Management



Source: spark.apache.org documentation v 2.2.0

Window-Based Processing

- Conceptually, a data stream is infinite. Hence some operations cannot be applied to it, e.g., sorting.
  - W can never output any result, because in the next moment a smaller value might arrive.
- For other operations, state would grow without bounds, e.g., join. By defining windows of bounded length, these problems go away.
- Windows are also useful as a query feature in their own right, e.g., to determine the most active customer in each month or the most active user in the last hour.
- In Spark, windows are defined based on *duration* and *slide*, which have to be multiples of the DStream’s batch interval. (This way each window corresponds to an integer number of mini-batches.)
  - Consider a batch interval of 5 sec, duration of 20 sec and slide of 10 sec. The first window then consists of mini-batches (0, 1, 2, 3), the next of (2, 3, 4, 5), then (4, 5, 6, 7), and so on. Note how the slide parameter results in “jumping” for the first mini-batch in the window.

Performance Considerations

- A smaller batch interval (i.e., mini-batch duration) is better for more timely response to incoming data. However, it has to be large enough, so that all processing of a mini-batch completes within the interval. Note that larger batches tend to reduce per-record processing cost.
  - More formally, a smaller interval is better for low latency, while a larger interval is better for high throughput.
- We can use the Web UI to see if the system can keep up with the arriving mini-batches.
- Since application state depends on a conceptually infinite stream, it is infeasible to recompute it when a **failure** happens.
  - Executor failure: Data replication enables recovery of failed executors on a different machine.
  - Driver failure: Checkpointing of the entire streaming application enables quick recovery by restarting the driver and reading the checkpointed data.

Developments Since Spark 2.0

- A new structured streaming API supports streaming operations directly on DataFrames, making it more similar to the batch API. Essentially there are ordinary and streaming DataFrames, no special stream objects like DStream.
  - A streaming DataFrame is implemented as an append-only table. A query returns a DataFrame, like for batch processing.
- With this new approach, it is straightforward to join a stream with a (static) table.

We introduced some functionality of Spark MLlib in earlier modules. Here we briefly survey additional functionality.

Spark Machine Learning API

- ML functionality was initially supported by the RDD-based org.apache.spark.mllib package, called MLlib for short. Then org.apache.spark.ml introduced a DataFrame-based version, often called Spark ML. As of Spark 2.0, MLlib is in maintenance mode (no further development) and ML will at some point replace it.
  - To make things more confusing, MLlib is now used to refer to the DataFrame-based spark.ml package as well.
- In short, if you want to use ML features in Spark, work with spark.ml. When we say MLlib, we refer to spark.ml.

Using MLlib

- In principle, it is very easy to build distributed ML pipelines in Spark, once the data is stored in a DataFrame. Functionality for linear algebra, classification, regression, and clustering is readily available and does not require much more than instantiating the right objects for the given data.
- However, to use MLlib *well*, one has to understand (1) the underlying ML techniques and (2) enough about their implementation in Spark to specify parameters controlling tradeoffs affecting model quality and computation time.
  - For part (1), take a data mining or ML course, or read a textbook on the topic.
  - For part (2), it is often difficult to find detailed information. And as implementation changes, information available might be outdated (e.g., applies to spark.mllib, not spark.ml). Consider taking a look at the corresponding source code.

Important Functionality

- ml.clustering offers a variety of clustering techniques, including K-means, Latent Dirchlet Allocation (LDA), and Gaussian Mixture Model (GMM).
- ml.classification offers a variety of models for predicting nominal outcomes (e.g., if a credit card transaction is fraudulent or not) that can be trained on labeled data. This includes RandomForest, gradient-boosted tree, decision tree, logistic regression, artificial neural network (multilayer perceptron), and Naïve Bayes.
- ml.regression offers models for predicting numerical outcomes (e.g., income) from labeled data. This includes RandomForest, gradient-boosted tree, decision tree, and (generalized) linear regression.
- Model evaluation methods can be found in ml.evaluation.
- ml.linalg supports both dense and sparse linear algebra operations, including matrix product and transpose.

Important Functionality

- ml.attribute supports functionality to represent the given data.
- ml.feature offers a variety of pre-processing and data manipulation techniques, commonly used for ML tasks. This includes feature scaling, normalization, PCA, inverse document frequency (IDF), string indexing, and Word2Vec.
- For classification and regression, cross-validation and training/test splitting functionality can be found in ml.tuning.

Random Forest Implementation Notes

- How is training for Random Forest implemented in Spark? One could partition work at the granularity of trees; or one could even parallelize training of a tree itself.
- To support cases with many machines and few trees, Spark implemented the more fine-grained version. This is based on Google research paper [Biswanath Panda and Joshua S. Herbach and Sugato Basu and Roberto J. Bayardo. PLANET: Massively Parallel Learning of Tree Ensembles with MapReduce. Proc. Int. Conf. on Very Large Data Bases (VLDB), 2009].
  - As an artifact of this training approach, there is a maxBins parameter that controls training cost versus the number of split candidates considered for continuous features.
- Apparently the trained model is returned to the driver and stored there in memory. For large data with many trees in the ensemble, this could create a memory bottleneck.
  - A possible workaround would be to implement the ensemble as a set of decision trees, i.e., to explicitly manage the set of trees in user code.

Random Forest Parameters

- Random Forest and Bagged tree ensembles do not require much parameter tuning and tend to produce excellent predictions. We recommend the following default parameter settings.
- Set numTrees high, e.g., to 100. Or start with few trees and then increase the number until model quality reaches a ceiling.
- Do not limit maxDepth, which limits tree height. In practice, splits tend to distribute data unevenly between branches. Hence the number of records in different nodes at the same level can vary by orders of magnitude.
- Set minInstancesPerNode = 50 for binary classification and regression, somewhat larger like 100 for multi-class problems. This ensures each leaf has enough data to capture the fraction of majority class (classification) or average (regression) "reasonably" well and it lets branches with more data grow deeper, stopping when a split produces a branch with too few records. Unfortunately, it might generate overly small trees in the presence of multi-way splits (on categorical attributes).
  - Consider a tree node with 10M records, where the best split is on a categorical attribute resulting in a partitioning of (4M, 3M, 3M-1, 1). Typically, it is beneficial to split such a node, but unless minInstancesPerNode = 1, this split would be prevented because of the branch receiving one record.
  - A better solution would be to offer a parameter that stops splitting not based on *child* branches, but based on the number of records in the *node to be split*.
  - As a workaround, one could convert a categorical attribute with n possible values to n different binary attributes (aka one-hot encoding).

Next we take a quick look at the GraphX library for graph analysis.

GraphX

- The GraphX package supports graph representation as RDDs and a variety of important graph algorithms, including (strongly) connected components, label propagation for community detection, PageRank, shortest path, and triangle count.
- Furthermore, efforts are being undertaken to support the behavior of other popular graph analysis frameworks on top of GraphX. For example, the Pregel object in spark.graphx supports an interface similar to Google's Pregel, with GraphX providing a highly efficient implementation.
- As with MLlib, using existing GraphX algorithms, e.g., PageRank, is easy, but one has to trust that the provided implementation is efficient. Finding implementation details is difficult. For instance, how does the provided PageRank algorithm handle dangling nodes?

Implementing A Graph Algorithm

- When implementing your own graph algorithm in GraphX, intelligent caching is particularly important.
- Many graph algorithms proceed in rounds, reading graph structure such as a node's adjacency list, in each round. It therefore often pays off to have the graph cached, using the cache() or persist() method.
- Other graph information changes in each round, e.g., PageRank values or shortest distance found so far. These changing data sets should *not* be cached.
  - Caching them does not cause memory errors. If too many data sets are to be cached, you leave the decision about which one to evict to the Spark cache manager. Such general-purpose software will probably not make as good a decision for your program as the person who designed it and understands its access pattern.
- Use the checkpoint() command to avoid an overly large RDD DAG for iterative graph computations with many rounds.

Finally, we take a closer look at partitioning of RDDs and DataSets in Spark.

Partitioners in Spark

- In MapReduce, the Partitioner often plays an important role, and it is relatively easy to understand.
- In Spark, the situation is a lot more confusing:
  - Pair RDDs support custom Partitioner objects that behave like MapReduce Partitioners, mapping objects based on the key. The Partitioner object is associated with the pair RDD and can be exploited to eliminate the need for shuffling for equi-joins between pair RDDs that have the same Partitioner.
  - Plain RDDs do not support custom Partitioners. Transformations repartition and coalesce can achieve hash partitioning, but do not assign a known Partitioner to the RDD.
  - DataSet also does not support Partitioners, but we can use the repartition transformation. In general, the idea is to leave partitioning decisions to the optimizer, instead of the user.

Controlling Pair RDD Partitions

- The Partitioner object performs RDD partitioning. The default is HashPartitioner. It assigns an element e to partition hash(e) % numberOfPartitions.
  - hash(e) is the key's hash code for pair RDDs, otherwise the Java hash code of the entire element.
  - The default number of partitions is determined by Spark configuration parameter spark.default.parallelism.
- Alternatively, one can use RangePartitioner. It determines range boundaries by sampling from the RDD. (It should ideally use quantiles.)
- For pair RDDs, one can define a custom Partitioner.

Data Shuffling

- Some transformations *preserve partitioning*, e.g., mapValues and flatMapValues.
- Changes to the Partitioner, including changing the number of partitions, requires shuffling.
- map and flatMap remove the RDD's Partitioner, but do not result in shuffling. But any transformation that adds a Partitioner, e.g., reduceByKey, results in shuffling. Transformations causing a shuffle after map and flatMap:
  - Pair RDD transformations that change the RDD's Partitioner: aggregateByKey, foldByKey, reduceByKey, groupByKey, join, leftOuterJoin, rightOuterJoin, fullOuterJoin, subtractByKey
  - RDD transformations: subtract, intersection, groupWith.
  - sortByKey (always causes shuffle)
  - partitionBy and coalesce with shuffle=true setting.

Reminder: Joins

- For pair RDDs, there are join, leftOuterJoin, rightOuterJoin, and fullOuterJoin.
  - These are all equi-joins. When called on an RDD of type (K, V), with an RDD of type (K, W) as input, they return an RDD of type (K, (V, W)), (K, (V, Option(W))), (K, (Option(V), W)), and (K, (Option(V), Option(W))), respectively. Here Option(T) represents any object of type T or None (i.e., NULL). This is needed, because outer joins emit results also for elements from one RDD that have no matches in the other.
- These operations have versions that take a Partitioner object or a number of partitions as parameter.
  - If no Partitioner or number of partitions is specified, Spark takes the Partitioner of the first RDD. This way only the second RDD needs to be shuffled.
  - If the input RDDs have no Partitioners, Spark uses the hash Partitioner with either the default number of partitions set in spark.default.partitions, or, if the default is not defined, the largest number of partitions of the input RDDs.

Changing Partitioning at Runtime

- partitionBy(partitionerObject) transformation for pair RDDs: If and only if the new Partitioner is different from the current one, a new RDD is created and data is shuffled.
- coalesce(numPartitions, shuffle?) transformation: splits or unions existing partitions—depending if numPartitions is greater than the current number of partitions. It tries to balance partitions across machines, but also to keep data transfer between machines low.
  - repartiton is coalesce with shuffle? = true.
- repartitionAndSortWithinPartitions(partitionerObject) transformation for pair RDDs with sortable keys: always shuffles the data and sorts each partition. By folding the sorting into the shuffle process, it is more efficient then applying partitioning and sorting separately.

Mapping at Partition Granularity

- mapPartitions(mapFunction) transformation: mapFunction has signature Iterator[T] => Iterator[U]. Contrast this to map, where mapFunction has signature T => U.
- Why is this useful? Assume, like in Mapper or Reducer class in MapReduce, you want to perform setup and cleanup operations before and after, respectively, processing the elements in the partition. Typical use cases are (1) setting up a connection, e.g., to a database server and (2) creating objects, e.g., parsers that are not serializable, that are too expensive to be created for each element. You can do this by writing a mapFunction like this:
  - Perform setup operations, e.g., instantiate parser.
  - Iterate through the elements in the partition, e.g., apply parser to element.
  - Clean up.
- mapPartitionsWithIndex(idx, mapFunction) transformation: also accepts a partition index idx, which can be used in mapFunction.
- Both operations also have an optional parameter preservePartitioning, by default set to false. Setting false results in removal of the partitioner.

Shuffle Implementation

- Sorting (default) or hashing.
- Parameter spark.shuffle.manager specifies which is used. Sort is the default, because it uses less memory and creates fewer files. However, sorting has higher computational complexity than hashing.
- Several other parameters control options such as consolidation of intermediate files, shuffle memory size, and if spilled data are compressed.

References

- Biswanath Panda and Joshua S. Herbach and Sugato Basu and Roberto J. Bayardo. PLANET: Massively Parallel Learning of Tree Ensembles with MapReduce. Proc. Int. Conf. on Very Large Data Bases (VLDB), 2009
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