COMPSCI 589
Lecture 14: Data Parallel Programming Abstractions in Spark

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Outline

Apache Spark

- Apache Spark is a parallel and distributed programming framework that adds additional parallel abstractions and allows for distributed in-memory caching as well as distributed on-disk data access. This makes it much faster than MapReduce for ML tasks.

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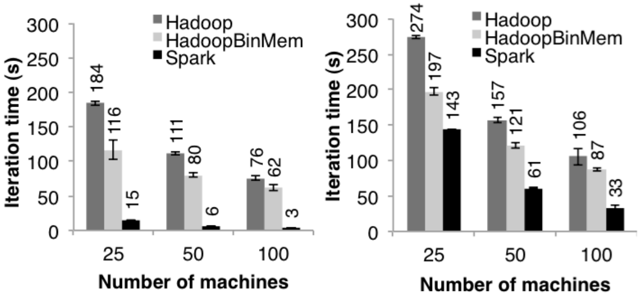

(a) Logistic Regression (b) K-Means

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- RDDs are created by applying a sequence of *transformations* to data. Results are obtained by applying *actions* to RDDs.
- The Spark system keeps track of the transformations used to create each partition of an RDD and can dynamically re-generate lost partitions on other cluster nodes. This makes it very fault-tolerant.

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- Supported methods include $textFile(path)$ to create an RDD from a text file (or a directory of files), and $parallelize(data)$ to partition an existing collection.
- Spark can run over a regular file system or the Hadoop file system (HDFS), which provides on-disk distributed storage.

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- *reduceByKey*(*func*, [*numTasks*]): When called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function f, which must be of type $(V, V) => V$.

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- Why is Spark implemented in this way?

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- *first*(): Return the first element of the dataset.
- *take*(n): Return an array with the first n elements of the dataset.
- *saveAsTextFile*(*path*): Write the elements of the dataset as a text file (or set of text files) in a given directory in the filesystem.

Spark API

The Python Spark RDD API is fully documented here:

http://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD

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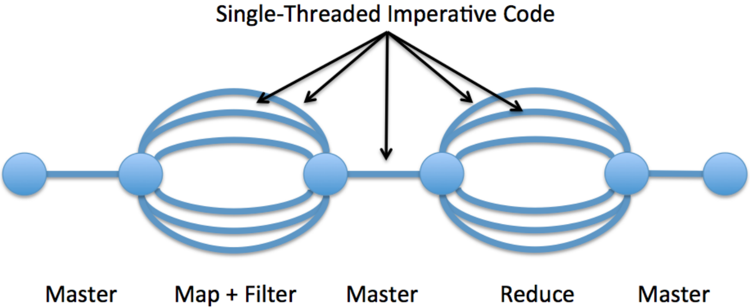

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- A common operation is to map the rows of an RDD to Numpy arrays so that we can apply Numpy operations to them within Spark map and reduce operations.

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- An RDD can be marked for caching by calling $cache()$ on it.

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- To re-write a Python implementation of a method like logistic regression learning or prediction, we need to replace the loops over the data with map and reduce steps.
- Let's look at the fundamental operation of classifying data cases contained in the rows of an RDD using a linear classifier implemented with Spark:

$$w^T x + b = \sum_{i=1}^{D} w_i x_i + b > 0$$