Big Data Analytics

7. Resilient Distributed Datasets: Apache Spark

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Outline

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Core Idea

To implement fault-tolerance for primary/original data:

- **replication**:
  - partition large data into parts
  - store each part on several times on different servers
  - if one server crashes, the data is still available on the others

To implement fault-tolerance for secondary/derived data:

- **replication**

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To implement fault-tolerance for secondary/derived data:

- **replication** or
- **resilience**:
  - partition large data into parts
  - for each part, store how it was derived (**lineage**)
    - from which parts of its input data
    - by which operations
  - if a server crashes, recreate its data on the others

How to store data derivation?

journal

- sequence of elementary operations
  - set an element to a value
  - remove a value/index from a list
  - insert a value at an index of a list
  - ...
- generic: supports all types of operations
- but too large
  - often same size as data itself

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coarse-grained transformations

- just store
  - the executable code of the transformations and
  - the input
    - either primary data or a itself an RDD

Resilient Distributed Datasets (RDD)

Represented by 5 components:

1. **partition**: a list of parts
2. **dependencies**: a list of parent RDDs
3. **transformation**: a function to compute the dataset from its parents
4. **partitioner**: how elements are assigned to parts
5. **preferred locations**: which hosts store which parts

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distinction into two types of dependencies:

- **narrow depenencies**:
  each parent part is used to derive at most one part of the dataset
- **wide dependencies**:
  some parent part is used to derive several parts of the dataset

How to cope with expensive operations?

checkpointing:

- traditionally,
  - a long process is broken into several steps A, B, C etc.
  - after each step, the state of the process is saved to disk
  - if the process crashes within step B,
    - it does not have to be run from the very beginning
    - but can be restarted at the beginning of step B reading its state at the end of step A.

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    - it does not have to be run from the very beginning
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- in a distributed scenario,
  - "saving to disk" is not fault-tolerant
  - replicate the data instead (**distributed checkpointing**)

Caching

- RDDs are marketed as technology for in memory cluster computing
- derived RDDs are not saved to disks, but kept in (distributed) memory
- derived RDDs are saved to disks on request (checkpointing)
- allows faster operations

Limitations

- RDDs are read-only
  - as updating would invalidate them as input for possible derived RDDs
- transformations have to be deterministic
  - otherwise lost parts cannot be recreated the very same way
  - for stochastic transformations: store random seed

For more conceptual details see the original paper

- Zaharia, M., Chowdhury, M., Das, T., Dave, A., Ma, J., McCauley, M., Franklin, M.J., Shenker, S. and Stoica, I. 2012. Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing. Proceedings of the 9th USENIX Conference on Networked Systems Design and Implementation (2012).

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Spark Overview

Apache Spark is an open source framework for large scale data processing and analysis

Main Ideas:

- Processing occurs where the data resides
- Avoid moving data over the network
- Works with the data in memory

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Technical details:

- Written in Scala
- Work seamlessly with Java, Python and R
- Developed at UC Berkeley

Apache Spark Stack

Data platform: Distributed file system /data base

- Ex: HDFS, HBase, Cassandra

Execution Environment: single machine or a cluster

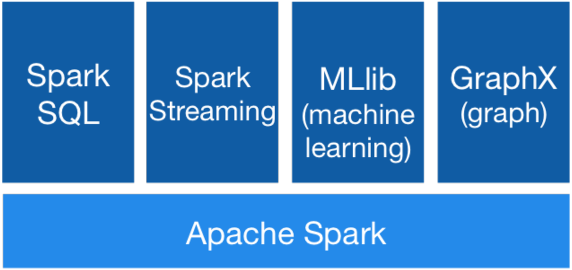
- Standalone, EC2, YARN, Mesos

Spark Core: Spark API

Spark Ecosystem: libraries of common algorithms

- MLLib, GraphX, Streaming

Apache Spark Ecosystem



How to use Spark

Spark can be used through:

- The **Spark Shell**
  - Available in Python and Scala
  - Useful for learning the Framework
- **Spark Applications**
  - Available in Python, Java and Scala
  - For "serious" large scale processing

Outline

Working with Spark

Working with Spark requires accessing a **Spark Context**:

- Main entry point to the Spark API
- Already preconfigured in the Shell

Most of the work in Spark is a set of operations on **Resilient Distributed Datasets (RDDs)**:

- Main data abstraction
- The data used and generated by the application is stored as RDDs

Spark Java Application

```
import org.apache.spark.api.java.*;
import org.apache.spark.SparkConf;
import org.apache.spark.api.java.function.Function;

public class HelloWorld {
  public static void main(String[] args) {
    String logFile = "/home/lst/system/spark/README.md";
    SparkConf conf = new SparkConf().setAppName("Simple␣Application");
    JavaSparkContext sc = new JavaSparkContext(conf);
    JavaRDD<String> logData = sc.textFile(logFile).cache();

    long numAs = logData.filter(new Function<String, Boolean>() {
      public Boolean call(String s) { return s.contains("a"); }
    }).count();

    long numBs = logData.filter(new Function<String, Boolean>() {
      public Boolean call(String s) { return s.contains("b"); }
    }).count();

    System.out.println("Lines␣with␣a:␣" + numAs + ",␣lines␣with␣b:␣" + numBs);
  }
}
```

Compile and Run

0. install spark (here in ~/system/spark)

1. compile:

```
javac -cp ~/system/spark/lib/spark-assembly-1.6.1-hadoop2.6.0.jar HelloWorld.java
```

2. create jar archive:

```
jar cf HelloWorld.jar HelloWorld*.class
```

3. run:

```
~/system/spark/bin/spark-submit --master local --class HelloWorld HelloWorld.jar
```

Spark Interactive Shell (Python)

```
$ ./bin/pyspark
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 1.3.1
      /_/

Using Python version 2.7.6 (default, Jun 22 2015 17:58:13)
SparkContext available as sc, SQLContext available as sqlContext.
>>>
   
```

Spark Context

The Spark Context is the main entry point for the Spark functionality.

- It represents the connection to a Spark cluster
- Allows to create RDDs
- Allows to broadcast variables on the cluster
- Allows to create Accumulators

Resilient Distributed Datasets (RDDs)

A Spark application stores data as RDDs

Resilient → if data in memory is lost it can be recreated (fault tolerance)

Distributed → stored *in memory* across different machines

Dataset → data coming from a file or generated by the application

A Spark program is about operations on RDDs

RDDs are **immutable**: operations on RDDs may create new RDDs but never change them

Resilient Distributed Datasets (RDDs)

RDD elements can be stored in different machines (transparent to the developer)

`data` can have various data types

RDD Data types

An element of an RDD can be of any type as long as it is **serializable**

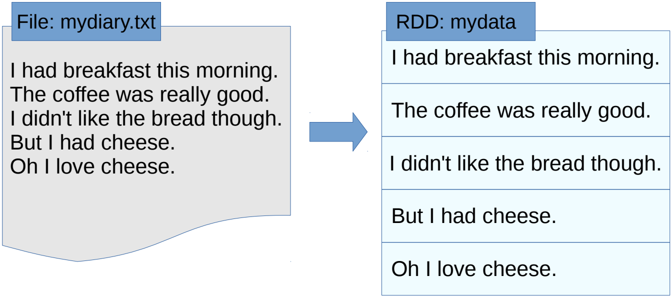
Example:

- Primitive data types: integers, characters, strings, floating point numbers, ...
- Sequences: lists, arrays, tuples ...
- Pair RDDs: key-value pairs
- Serializable Scala/Java objects

A single RDD may have elements of different types

Some specific element types have additional functionality

Example: Text file to RDD



RDD operations

There are two types of RDD operations:

- **Actions**: return a value based on the RDD
- Example:
  - `count`: returns the number of elements in the RDD
  - `first()`: returns the first element in the RDD
  - `take(n)`: returns an array with the first *n* elements in the RDD

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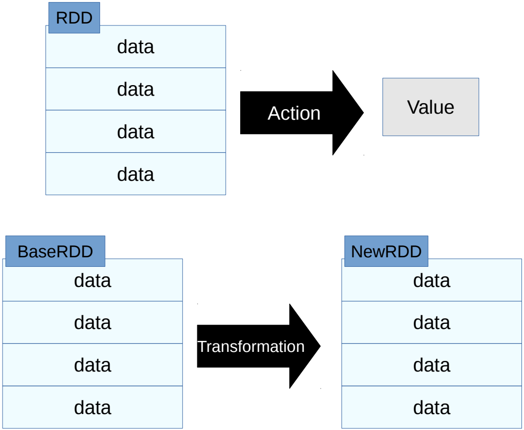
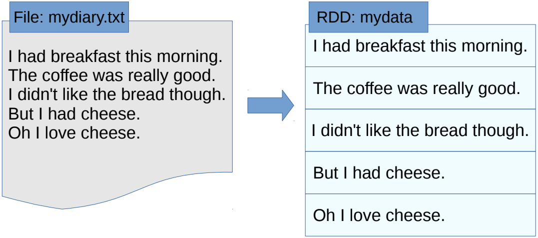
  - `first()`: returns the first element in the RDD
  - `take(n)`: returns an array with the first *n* elements in the RDD
- **Transformations**: creates a new RDD based on the current one
- Example:
  - `filter`: returns the elements of an RDD which match a given criterion
  - `map`: applies a particular function to each RDD element
  - `reduce`: aggregates the elements of a specific RDD

Actions vs. Transformations

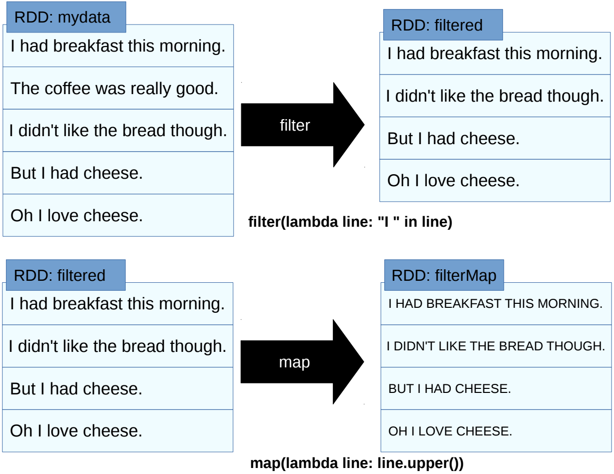


Actions examples




```
>>> mydata = sc.textFile("mydiary.txt")
>>> mydata.count()
5
>>> mydata.first()
u'I had breakfast this morning.'
>>> mydata.take(2)
[u'I had breakfast this morning.', u'The coffee was really good.']
```

Transformation examples



Transformations examples

```python
>>> filtered = mydata.filter(lambda line: "I␣" in line)
>>> filtered.count()
4
>>> filtered.take(4)
[u'I␣had␣breakfast␣this␣morning.',
 u"I␣didn't␣like␣the␣bread␣though.",
 u'But␣I␣had␣cheese.',
 u'Oh␣I␣love␣cheese.']
>>> filterMap = filtered.map(lambda line: line.upper())
>>> filterMap.count()
4
>>> filterMap.take(4)
[u'I␣HAD␣BREAKFAST␣THIS␣MORNING.',
 u"I␣DIDN'T␣LIKE␣THE␣BREAD␣THOUGH.",
 u'BUT␣I␣HAD␣CHEESE.',
 u'OH␣I␣LOVE␣CHEESE.']
```

Operations on specific types

Numeric RDDs have special operations:

- mean()
- min()
- max()
- ...

```
>>> linelens = mydata.map(lambda line: len(line))
>>> linelens.collect()
[29, 27, 31, 17, 17]
>>> linelens.mean()
24.2
>>> linelens.min()
17
>>> linelens.max()
31
>>> linelens.stdev()
6.0133185513491636
```

Operations on Key-Value Pairs

Pair RDDs contain a two element tuple: (K, V)

Keys and values can be of any type

Extremely useful for implementing MapReduce algorithms

Examples of operations:

- `groupByKey`
- `reduceByKey`
- `aggregateByKey`
- `sortByKey`
- ...

Word Count Example

Map:

- Input: document-word list pairs
- Output: word-count pairs

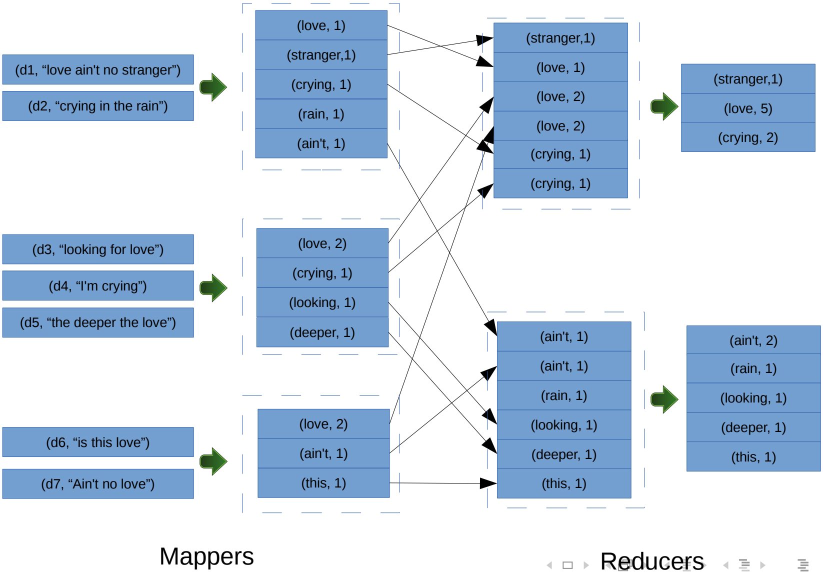
$$(d_k, \text{``}w_1, \ldots, w_m'') \mapsto [(w_i, c_i)]$$

Reduce:

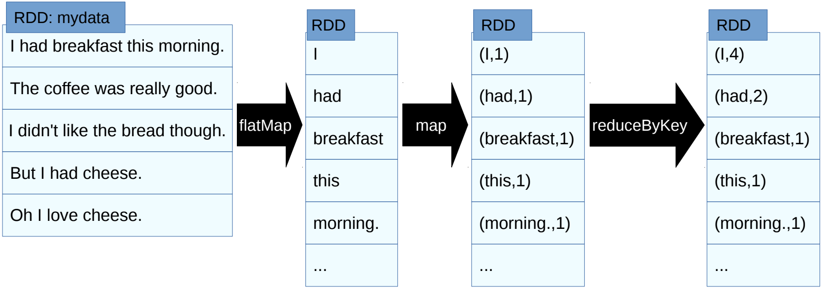
- Input: word-(count list) pairs
- Output: word-count pairs

$$(w_i, [c_i]) \mapsto (w_i, \sum_{c \in [c_i]} c)$$

Word Count Example



Word Count on Spark




```
>>> counts = mydata.flatMap(lambda line: line.split(" ")) \
                   .map(lambda word: (word, 1)) \
                   .reduceByKey(lambda x, y: x + y)
```

ReduceByKey

```
.reduceByKey(lambda x, y: x + y)
```

`ReduceByKey` works a little different from the MapReduce `reduce` function:

- It takes two arguments: combines two values at a time associated with the same key
- Must be **commutative**: `reduceByKey(x,y) = reduceByKey(y,x)`
- Must be **associative**: `reduceByKey(reduceByKey(x,y), z) = reduceByKey(x,reduceByKey(y,z))`

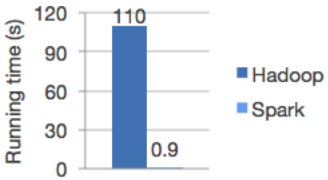
Spark does not guarantee on which order the `reduceByKey` functions are executed!

Considerations

Spark provides a much more efficient MapReduce implementation then Hadoop:

- Higher level API
- In memory storage (less I/O overhead)
- Chaining MapReduce operations is simplified: sequence of MapReduce passes can be done in one job

Spark vs. Hadoop on training a logistic regression model:



Source: Apache Spark. `https://spark.apache.org/`

Outline

Overview

MLLib is a Spark Machine Learning library containing implementations for:

- Computing Basic Statistics from Datasets
- Classification and Regression
- Collaborative Filtering
- Clustering
- Feature Extraction and Dimensionality Reduction
- Frequent Pattern Mining
- Optimization Algorithms

Logistic Regression with MLLib

Import necessary packages:

```
from pyspark.mllib.regression import LabeledPoint
from pyspark.mllib.util import MLUtils
from pyspark.mllib.classification import LogisticRegressionWithSGD
```

Read the data (LibSVM format):

```
dataset = MLUtils.loadLibSVMFile(sc,
                      "data/mllib/sample_libsvm_data.txt")
```

Logistic Regression with MLLib

Train the Model:

```
model = LogisticRegressionWithSGD.train(dataset)
```

Evaluate:

```
labelsAndPreds = dataset
    .map(lambda p: (p.label, model.predict(p.features)))
trainErr = labelsAndPreds
    .filter(lambda (v, p): v != p)
    .count() / float(dataset.count())
print("Training Error = " + str(trainErr))
```