Big Data Analytics

C. Distributed Computing Environments / C.2. Resilient Distributed Datasets: Apache Spark

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Syllabus

Tue.	9.4.	(1)	0. Introduction
			A. Parallel Computing
Tue.	16.4.	(2)	A.1 Threads
Tue.	23.4.	(3)	A.2 Message Passing Interface (MPI)
Tue.	30.4.	(4)	A.3 Graphical Processing Units (GPUs)
			B. Distributed Storage
Tue.	7.5.	(5)	B.1 Distributed File Systems
Tue.	14.5.	(6)	B.2 Partioning of Relational Databases
Tue.	21.5.	(7)	B.3 NoSQL Databases
			C. Distributed Computing Environments
Tue.	28.5.	(8)	C.1 Map-Reduce
Tue.	4.6.	(9)	C.2 Resilient Distributed Datasets (Spark)
Tue.	11.6.	—	— *Pentecoste Break* —
Tue.	18.6.	(10)	C.3 Computational Graphs (TensorFlow)
			D. Distributed Machine Learning Algorithms
Tue.	25.6.	(11)	D.1 Distributed Stochastic Gradient Descent
Tue.	2.7.	(12)	D.2 Distributed Matrix Factorization
Tue.	9.7.	(13)	Questions and Answers

Outline

1. Introduction
2. Apache Spark
3. Working with Spark
4. MLLib: Machine Learning with Spark

Outline

Core Idea

To implement fault-tolerance for primary/original data:

- **replication**:
  - partition large data into parts
  - store each part 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**

Core Idea

To implement fault-tolerance for primary/original 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 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 (immutable)
  - 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).

Outline

Apache Spark Overview

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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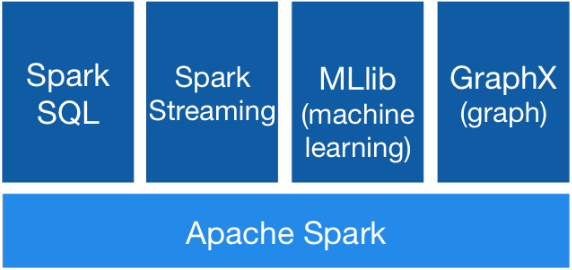
Technical details:

- Written in Scala
- Works 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

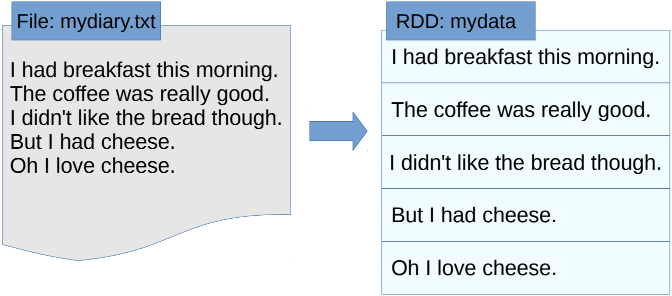
Resilient Distributed Datasets (RDDs)

- 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**
- Examples:
  - Primitive data types: integers, characters, strings, floats, . . .
  - Sequences: lists, arrays, tuples ...
  - Pair RDDs: key-value pairs
  - Serializable Scala/Java objects
- A single RDD may contain elements of different types
- Some specific element types have additional functionality

Example: Text file to RDD

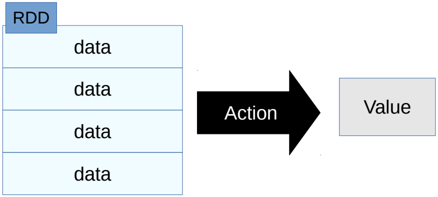


RDD Operations / Actions

There are two types of RDD operations:

1. **Actions**: return a value based on the RDD.

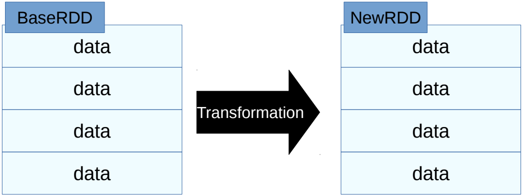
- Examples:
  - `count`: returns the number of elements in the RDD
  - `first()`: returns the first element in the RDD
  - `take(n)`: returns an array with the first *n* elements in the RDD



RDD Operations / Transformations

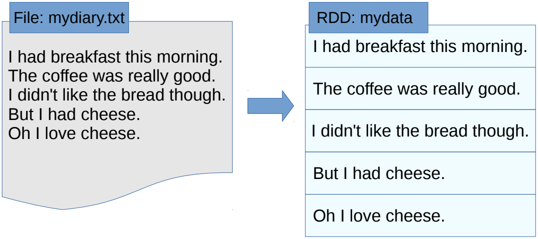
2. **Transformations**: create a new RDD based on the current one.

- Examples:
  - `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



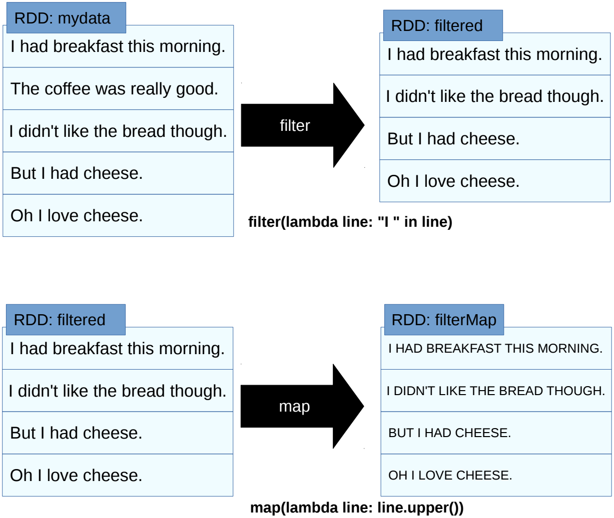
- RDD transformations are **lazy**
  - they are only executed once an action requires a result to be computed

Action 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



Transformation Examples

```
>>> 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 Numbers

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.stddev()
6.0133185513491636
```

Operations on Key-Value Pairs

- Pair RDDs contain pairs (tuples of two elements): (K, V)
  - elements called keys and values
- Keys and values can be of any type
- 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

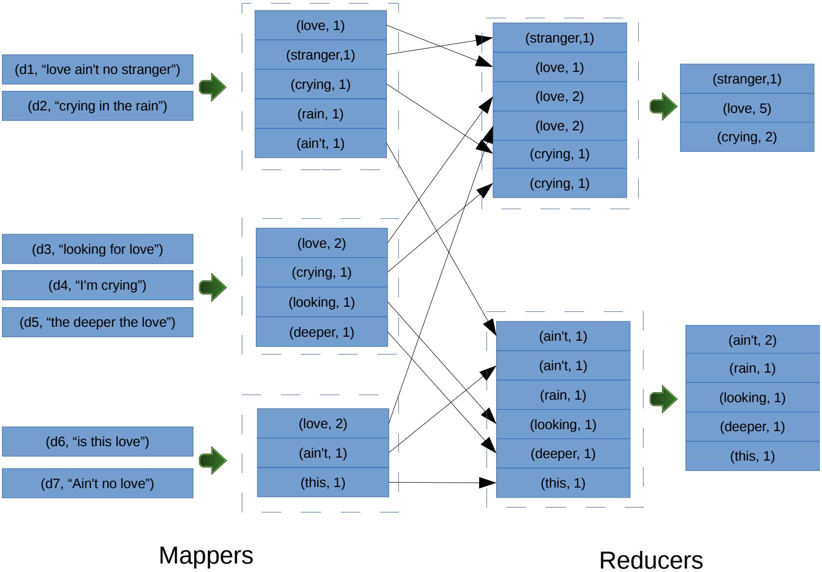
$$(d_n, (w_1, \ldots, w_M)) \mapsto ((w, c_w)_{w \in W : c_w > 0})$$

Reduce:

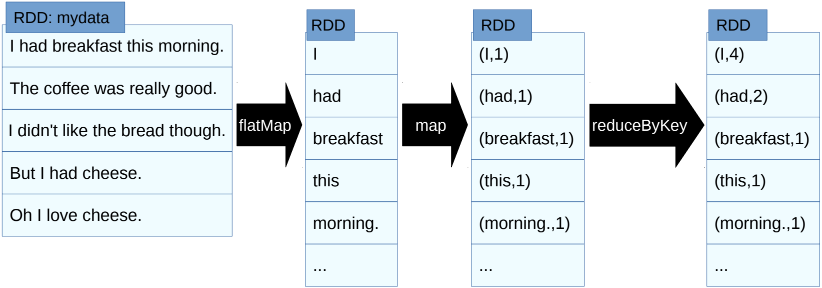
- Input: word-(count list) pairs
- Output: word-count pairs

$$(w, (c_1, \ldots, c_K)) \mapsto (w, \sum_{k=1}^{K} c_k)$$

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 somewhat different from the MapReduce `reduce` function:
  - It combines two values 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))`

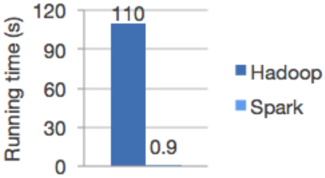
- Spark does not guarantee in which order the `reduceByKey` functions are executed.

Shuffle Operations

- operations are broken automatically into tasks
- each task is executed separately, each on some node
  - e.g., for **ReduceByKey**: one task for each key
- each task needs all its input data locally on the node it is executed on
  - e.g., for **ReduceByKey**: all key/value pairs for a specific key
- if data is not already partitioned by that key,
  it needs to be repartitioned (**shuffled**)
  - expensive operation (network, IO)

MapReduce in Spark and Hadoop

- Spark provides a much more efficient MapReduce implementation than 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

1. Import required packages:

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

2. Read the data (LibSVM format):

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

3. Train the model:

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

4. Evaluate the model:

```
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 = {}'.format(trainErr))
```

Summary

- **Resilient Distributed Datasets** (**RDD**s) make large-scale distributed computations **fault-tolerant**
  - RDDs keep track of **dependencies**:
    - which part of a output data depends on which part of the input data
    - which coarse-grained **transformation** is used
  - if a server storing a part of a dataset fails, this part will be **recomputed**.
- RDDs are **immutable**, transformations have to be deterministic.
  - so that RDDs can be recomputed always exactly the same
- RDDs provide **in memory cluster computing**
  - derived RDDs can be saved to disk on request (**checkpointing**)

Further Readings

- Original Spark paper:
  - Zaharia et al. [2010]
- A broad introduction to Spark:
  - Karau et al. [2015]

References

Holden Karau, Andy Konwinski, Patrick Wendell, and Matei Zaharia. *Learning Spark, Lightning-Fast Big Data Analysis*. O'Reilly Media, 2015.

Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, and Ion Stoica. Spark: Cluster Computing with Working Sets. In *Proceedings of the 2Nd USENIX Conference on Hot Topics in Cloud Computing*, HotCloud'10, pages 10–10, Boston, MA, 2010. USENIX Association.