Big Data Analytics

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Apache Spark
Outline

1. What is Spark

2. Working with Spark
   2.1 Spark Context
   2.2 Resilient Distributed Datasets

3. MLLib: Machine Learning with Spark
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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

Technical details:

- Written in Scala
- Work seamlessly with Java and Python
- Developed at UC Berkeley
Apache Spark Stack

**Data platform:** Distributed file system / database
- 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
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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 operation on **Resilient Distributed Datasets (RDDs)**: 

- Main data abstraction
- The data used and generated by the application is stored as RDDs
Spark Interactive Shell (Python)

```bash
$ ./bin/pyspark
Welcome to

    _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   _   ____
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

File: mydiary.txt

I had breakfast this morning.
The coffee was really good.
I didn't like the bread though.
But I had cheese.
Oh I love cheese.

RDD: mydata

I had breakfast this morning.
The coffee was really good.
I didn't like the bread though.
But I had cheese.
Oh I love cheese.
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

- **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`: applies a particular function to each RDD element
Actions vs. Transformations

**RDD**
- data
- data
- data
- data

**Action**

**Value**

**BaseRDD**
- data
- data
- data
- data

**Transformation**

**NewRDD**
- data
- data
- data
- data
Actions examples

File: mydiary.txt
I had breakfast this morning. The coffee was really good. I didn't like the bread though. But I had cheese. Oh I love cheese.

RDD: mydata
I had breakfast this morning.
The coffee was really good.
I didn't like the bread though.
But I had cheese.
Oh I love cheese.

>>> mydata = sc.textFile("mydiary.txt")

>>> mydata.count()
5

>>> mydata.first()
"I had breakfast this morning."

>>> mydata.take(2)
[u'I had breakfast this morning.', u'The coffee was really good.']
Transformation examples

RDD: mydata
- I had breakfast this morning.
- The coffee was really good.
- I didn't like the bread though.
- But I had cheese.
- Oh I love cheese.

filter
- I had breakfast this morning.
- I didn't like the bread though.
- But I had cheese.
- Oh I love cheese.

RDD: filtered
- I had breakfast this morning.
- I didn't like the bread though.
- But I had cheese.
- Oh I love cheese.

RDD: filtered
- I had breakfast this morning.
- I didn't like the bread though.
- But I had cheese.
- Oh I love cheese.

map
- I HAD BREAKFAST THIS MORNING.
- I DIDN'T LIKE THE BREAD THOUGH.
- BUT I HAD CHEESE.
- OH I LOVE CHEESE.

map(lambda line: line.upper())

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Apache Spark
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()
- ...

```python
>>> 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 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

\[(d_k, "w_1, \ldots, w_m") \mapsto [(w_i, c_i)]\]

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

Mappers

- (d1, “love ain't no stranger”)
- (d2, “crying in the rain”)
- (d3, “looking for love”)
- (d4, “I'm crying”)
- (d5, “the deeper the love”)
- (d6, “is this love”)
- (d7, “Ain't no love”)

Reducers

- (stranger, 1)
- (love, 1)
- (crying, 1)
- (ain't, 1)
- (love, 2)
- (rain, 1)
- (looking, 1)
- (deeper, 1)
- (this, 1)
- (love, 5)
- (crying, 2)
- (ain't, 2)
- (rain, 1)
- (looking, 1)
- (deeper, 1)
- (this, 1)
Word Count on Spark

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

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ReduceByKey

\[ \text{reduceByKey}(\lambda x, y : x + y) \]

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**: \( \text{reduceByKey}(x,y) = \text{reduceByKey}(y,x) \)
- Must be **associative**: \( \text{reduceByKey}(\text{reduceByKey}(x,y), z) = \text{reduceByKey}(x,\text{reduceByKey}(y,z)) \)

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:

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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:

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

Read the data (LibSVM format):

```python
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))
```