## 732A54/TDDE31 Big Data Analytics

**Exercise Session** 

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# Agenda

- Aims of this exercise session
- Overview of Spark
- RECAP
  - Map-Reduce: Working with key-value pairs
  - Lambda functions
- How to design and write PySpark code
- Lab introduction and exercises
  - Conceptual design
  - ✓ Write PySpark code
- \*How to work on Sigma



## Aims

- An overview introduction of Spark (more details given in tomorrow's lecture)
- Give you an overview introduction of the labs
- Help you understand how to design and write code using Spark in python
- Exercises: start to solve the assignments in the labs (BDA1)



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# Spark – Overview

- A framework for parallel big data processing
- Distributed collection of data can be processed in parallel
- Basic programming interface:
  - Resilient Distributed Dataset (RDD), a fault-tolerant collection of elements that can be operated on in parallel
  - DataFrame, conceptually equivalent to a table in a relational database or a data frame in R/Python
- Higher-level APIs (PySpark, Spark SQL, MLib, etc.)
- For our lab assignments (BDA1, BDA2, BDA3)
  - First, solve them using Map/Reduce model (BDA1, RDD)
  - Second, solve BDA1's questions using Spark SQL (structured data processing, DataFrame)
  - BDA3: iterative processing (...keep intermediate results in memory across iterations, leading to faster convergence.)



## Spark - Data Storage

- How large-scale data is stored and how Spark deals with data?
- One way is to:
  - Organize data in RDDs, divided into partitions,
    - units of parallelism that can be processed independently on different nodes of the cluster

```
data = [1, 2, 3, 4, 5]
distData = sc.parallelize(data)
```

 Parallelizing an existing collection given in your program distFile = sc.textFile("data.txt")

- Referencing a dataset in an external storage system
- ✓ We use this for our labs, data in HDFS



# Spark – Data Operation

- Manipulate and process a distributed collection of data elements
- Transformations:
  - Operations applied to RDDs to create a new RDD by transforming the data in some way (e.g., data pre-processing and cleaning)
    - map(), filter(), reduceByKey()
  - They are executed only when an action is called, triggering the actual computation of the data.
- Actions:
  - Operations trigger the execution of the Spark computation and return results to the program or write data to an external storage system.
    - count(), reduce(), saveAsTextFile()
- Spark triggers transformations until an action is called



## Spark for MapReduce - RDD Operations

|                 | $map(f: I \Rightarrow U)$ :                                  | $RDD[1] \Rightarrow RDD[0]$   |
|-----------------|--|---|
|                 | $filter(f: T \Rightarrow Bool)$ :                            | $RDD[T] \Rightarrow RDD[T]$   |
|                 | $flatMap(f: T \Rightarrow Seq[U])$ :                         | $RDD[T] \Rightarrow RDD[U]$   |
|                 | sample(fraction : Float) :                                   | $RDD[T] \Rightarrow RDD[T]$ (Deterministic sampling)                |
|                 | groupByKey() :   | $RDD[(K, V)] \Rightarrow RDD[(K, Seq[V])]$                          |
|                 | $reduceByKey(f:(V,V) \Rightarrow V)$ :                       | $RDD[(K, V)] \Rightarrow RDD[(K, V)]$                               |
| Transformations | union() :  | $(RDD[T], RDD[T]) \Rightarrow RDD[T]$                               |
|                 | join() :   | $(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (V, W))]$           |
|                 | cogroup() :  | $(RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (Seq[V], Seq[W]))]$ |
|                 | crossProduct() :   | $(RDD[T], RDD[U]) \Rightarrow RDD[(T, U)]$                          |
|                 | $mapValues(f : V \Rightarrow W)$ :                           | $RDD[(K, V)] \Rightarrow RDD[(K, W)]$ (Preserves partitioning)      |
|                 | sort(c: Comparator[K]) :                                     | $RDD[(K, V)] \Rightarrow RDD[(K, V)]$                               |
|                 | <i>partitionBy</i> ( <i>p</i> : Partitioner[K]) :            | $RDD[(K, V)] \Rightarrow RDD[(K, V)]$                               |
|                 | count() : I  | $RDD[T] \Rightarrow Long$   |
|                 | collect() : I  | $RDD[T] \Rightarrow Seq[T]$   |
| Actions         | $reduce(f:(\mathbf{T},\mathbf{T})\Rightarrow\mathbf{T})$ : I | $RDD[T] \Rightarrow T$  |
|                 | lookup(k: K) : I   | $RDD[(K, V)] \Rightarrow Seq[V]$ (On hash/range partitioned RDDs)   |
|                 | save(path:String) : 0  | Outputs RDD to a storage system, <i>e.g.</i> , HDFS                 |

Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

You need more than the above to solve all assignments in the lab.

- ✓ PySpark library: https://spark.apache.org/docs/3.5.1/api/python/reference/index.html
- ✓ Spark 3.5.1 RDD programming guide: https://spark.apache.org/docs/latest/rdd-programming-guide.html



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### RECAP - Map/Reduce: Working with key-value pairs

- Data elements: key-value pairs
- Python's tuple structure fit this key-value pair: (key, value)
  - (1,2), (1,3), (1,4), (1,5), (2,2), (2,3)
- A tuple is a sequence of Python objects
  - ('a', 3) (1, (3, 4)) ((1,1), 2) (1, [1, 2, 3, 4])
- Accessing elements done with [index]

 $\begin{aligned} x &= (3, (`c', [1])), y = ((3, `a'), (`c', [1])) \\ x[0] &= 3, x[1] = x[-1] = (`c', [1]), x[1][1] = [1] \\ y[0] &= (3, `a'), y[0][0] = 3, y[1][1] = [1] \end{aligned}$ 

- Spark operations by a key work on RDDs containing built-in Python tuples
  - 'repartition' operations, 'byKey' operations, 'join' operations



Lambda functions: a way to pass function to a RDD operation, describing the transformation

#### General form

lambda arguments: expression

#### > Examples:

lambda a: 2 \* a \_\_double the argument a lambda a, b: a + b \_\_produce the sum of arguments a and b lambda input\_list : (input\_list[0], input\_list[1]) -get the first elements to generate the (key, value) pair lambda input\_list : max(input\_list) -get the max element in a list



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# Word Count – Conceptual Design

- In terms of map-reduce programming model, how to form key, value pair and what kind of transforms are needed, etc.
- During reduce process, what functions are needed on the values.





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## How to write PySpark code

- Pre-Step. Upload your data to Hadoop Distributed File System (HDFS) (in cluster mode)
- Step 1. To create a SparkContext object which tells Spark how to access a cluster.
- Step 2. To create distributed datasets (RDD)
  - ✓ Use external datasets by local file system or HDFS
- Step 3. RDD operation: transformation, action



- Step 1. To create a SparkContext object
- Step 2. To create distributed datasets (RDD)
  - ✓ Use external datasets by local file system or HDFS
- Step 3. RDD operation: transformation, action







# Lab Introduction

- Working with the historical meteorological data from Swedish Meteorological Hydrological Institute (SMHI)
  - The data includes air temperature and precipitation readings from 812 stations in Sweden.
- Three labs
  - ✓ BDA1 Spark: 5 assignments
    - In general, you need to do filtering, grouping, aggregating ... over the data.
    - Map-reduce programming model, PySpark,
    - working with key-value pairs
  - ✓ BDA2 Spark SQL: Redo the 5 assignments in BDA1 with Spark SQL
  - ✓ BDA3 Machine Learning with Spark
- Example: Find highest temperature for a certain period
  - temperature-readings.csv

Headers for temperature-readings.csv

| Station number | Date | Time | Air temperature (in °C) | Quality <sup>3</sup> |
|----------------|------|------|-------------------------|----------------------|
|                |      |      |                         |                      |
|                |      |      |                         |                      |
|                |      |      |                         |                      |

102170;2013-11-01;06:00:00;6.8;G 102170;2013-11-01;18:00:00;3.8;G 102170;2014-11-02;06:00:00;5.8;G 102170;2014-11-02;18:00:00;-1.1;G 102170;2015-11-03;06:00:00;-0.2;G 102170;2015-11-03;18:00:00;5.6;G 102170;2015-11-04;06:00:00;6.5;G

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#### Find the highest temperature in 2014 and 2015.

Show the year and highest temperature in the result

- Conceptual design
  - Understand the question and data
  - ✓ How to form key, value pair and what RDD operations are needed
  - What operations are needed during mapping and reducing?
- Write PySpark code

#### Headers for temperature-readings.csv

| Station number | Date | Time | Air temperature (in °C) | Quality <sup>3</sup> |
|----------------|------|------|-------------------------|----------------------|
|----------------|------|------|-------------------------|----------------------|

102170;2013-11-01;06:00:00;6.8;G 102170;2013-11-01;18:00:00;3.8;G 102170;2014-11-02;06:00:00;5.8;G 102170;2014-11-02;18:00:00;-1.1;G 102170;2015-11-03;06:00:00;-0.2;G 102170;2015-11-03;18:00:00;5.6;G 102170;2015-11-04;06:00:00;6.5;G



.....

### Solution – Conceptual design

- Extract year as key and temperature as value
- Filter data (2014 and 2015)
- Reduce by key and then compare each two values to get the higher temperature.





- Step 1. To create a SparkContext object
- Step 2. To create distributed datasets (RDD) from HDFS.
- Step 3. RDD operation: transformation, action

# Solution

Question : Find the highest temperature in 2014 and 2015.

```
from pyspark import SparkContext
  1
    def max_temperature(a,b):
  2
         if a>=b:
  3
  4
             return a
  5
         else:
             return b
  6
     sc = SparkContext(appName = "exercise test")
  7
    temperature_file = sc.textFile("/user/x_huali/data/temperature-readings.csv")
  8
     lines = temperature_file.map(lambda line: line.split(";"))
  9
    year_temperature = lines.map(lambda x: (x[1][0:4], float(x[3])))
 10
     year_temperature = year_temperature.filter(lambda x: int(x[0])==2014 or int(x[0])==2015)
 11
     #max_temperatures = year_temperature.reduceByKey(lambda a,b: a if a>=b else b)
 12
     #max_temperatures = year_temperature.reduceByKey(max)
 13
    max_temperatures = year_temperature.reduceByKey(max_temperature)
 14
    max_temperatures.saveAsTextFile("max_temperature_2014_2015")
 15
     line 7: create SparkContext object
line 8: get the file on hdfs, default home path '/user/USERNAME/
line 9: transform the data by splitting each line
line 10: transform the data by extracting year and temperature as tuple
line 11: filter data by year
```

- line 14: reducer, to get the max temperature,
  - line 12, line 13, line 14 show the different ways of passing functions to Spark
- line 15: save result in a directory (HDFS)



### For the first assignment in BDA1

- I) What are the highest temperatures measured each year for the period 1950-2014. Provide the listed sorted in the descending order with respect to the maximum temperature
- > Exercise
  - Conceptual design (how to form key, value pairs and what RDD operations are needed)
  - Write PySpark code (Pseudocode)

#### Headers for temperature-readings.csv

| Station number  | Date  | Time | Air temperature (in °C)   | Quality <sup>3</sup> |       |
|---|---|------|---|----------------------|-------|
| 102170;2013-11-01<br>102170;2013-11-01<br>102170;2014-11-02<br>102170;2014-11-02                          | .;06:00:00;6.8;G<br>.;18:00:00;3.8;G<br>2;06:00:00;5.8;G<br>2;18:00:00;-1.1;G |      | How to write P  | ySpark code          | ohiec |
| 102170;2015-11-03;06:00:00;-0.2;G<br>102170;2015-11-03;18:00:00;5.6;G<br>102170;2015-11-04;06:00:00;6.5;G |   |      | Step 2: To create distributed datasets (<br>Step 3: RDD operation |                      |       |



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### Solution – Conceptual design

- Extract year and temperature
- Filter data (2014 and 2015) 1950-2014
- Reduce by key to get maximum
- Sort





## Solution

- Pre steps: Distribute your data
- Step 1. To create a SparkContext object
- Step 2. To create distributed datasets (RDD) from HDFS.
- Step 3. RDD operating: transformation, action

```
from pyspark import SparkContext
   def max_temperature(a,b):
2
       if a>=b:
3
           return a
4
       else:
5
6
           return b
   sc = SparkContext(appName = "exercise test")
7
   temperature_file = sc.textFile("/user/x_huali/data/temperature-readings.csv")
8
   lines = temperature file.map(lambda line: line.split(";"))
9
   year_temperature = lines.map(lambda x: (x[1][0:4], float(x[3])))
10
   year_temperature = year_temperature.filter(lambda x: int(x[0])>=1950 and int(x[0])<=2014)</pre>
11
   #max_temperatures = year_temperature.reduceByKey(lambda a,b: a if a>=b else b)
12
   #max_temperatures = year_temperature.reduceByKey(max)
13
   max_temperatures = year_temperature.reduceByKey(max_temperature)
14
   max_temperaturesSorted = max_temperatures.sortBy(ascending = False, keyfunc=lambda k: k[1])
15
   max_temperaturesSorted.saveAsTextFile("max_temperature")
16
   line 7: create SparkContext object
   line 8: get the file on hdfs, default home path '/user/USERNAME/
   line 9: transform the data by splitting each line
   line 10: transform the data by extracting year and temperature as tuple
   line 11: filter data by a time period
   line 14: reducer, to get the max temperature,
        line 12, line 13, line 14 show the different ways of passing functions to Spark
   line 15: sort result by temperature
```

line 16: save result in a directory (HDFS)







#### Connection

- Option 1: ssh –X username@sigma.nsc.liu.se
  - 1.1: Connect the University environment first. You can use thinlinc to connect 'thinlinc.edu.liu.se', then use 'ssh -X' to connect sigma.
  - 1.2: With your own laptop, you need a X forwarding configuration.
    - An X server software installed on your computer.
      - If you run Linux, this is already taken care of.
      - If you run MacOS, you might need to install and start <u>X11.app</u> (XQuartz: https://www.xquartz.org) which is included in MacOS but not always installed.
      - If you run Windows, you need to find a third-party X server software (e.g <u>Xming</u> https://sourceforge.net/projects/xming/), as this is not normally included in Windows.





#### Connection

- Option 2: Thinlinc connection to Sigma directly (sigma.nsc.liu.se)
  - If you are at a computer in an SU room at the university, to use thinlinc, you need to run following two commands first in a terminal:
    - module load course/732A54 or module load course/TDDE31
    - tlclient
  - If you use your own computers, you just need to download thinlinc and then connect Sigma
  - Notice: During the lab sessions, for each group, please just use at most one thinlinc connection.





- Submit, monitor, cancel jobs at Sigma sbatch, squeue, scancel commands
- Demo on sigma

/software/sse2/tetralith\_el9/manual/spark/course-examples/BDA\_demo/

- The script for running pyspark code
  - Client (local) or Cluster (yarn) mode
    - Input and output paths/files need to be changed accordingly
    - ! Client mode is just for testing with smaller size data
  - History server, log details for debugging

```
run_yarn.q,
run_yarn_with_historyserver.q
run_local.q,
run_local_with_historyserver.q,
```



## How to work on Sigma (run demo code)

- Step 1: Login Sigma
- Step 2: Copy the code to your home folder on Sigma





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source /software/sse2/generic/manual/ssetools/v1.9.5/bin/hpc\_usereservation RESERVATIONNAME



- Step 3: Submit a job on Sigma
- Step 4: Check the result/output/history server log









- You will need to make changes on this file, when run your own code.
- run\_yarn\_with\_historyserver.q or one of the other run\_\*.q scripts







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