BigData Spark – Hands-On

Optimisations

SQL Execution Plan, DAG, SparkUI
Performances

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Objectives of Hands-On

Reminders:
Local Install, spark-shell
Spark File IO
MetaStore tables

1/ Execution Plan, SQL Explain / dataset.explain

2/ Spark UI, DAG, Narrow/Wide Transformations

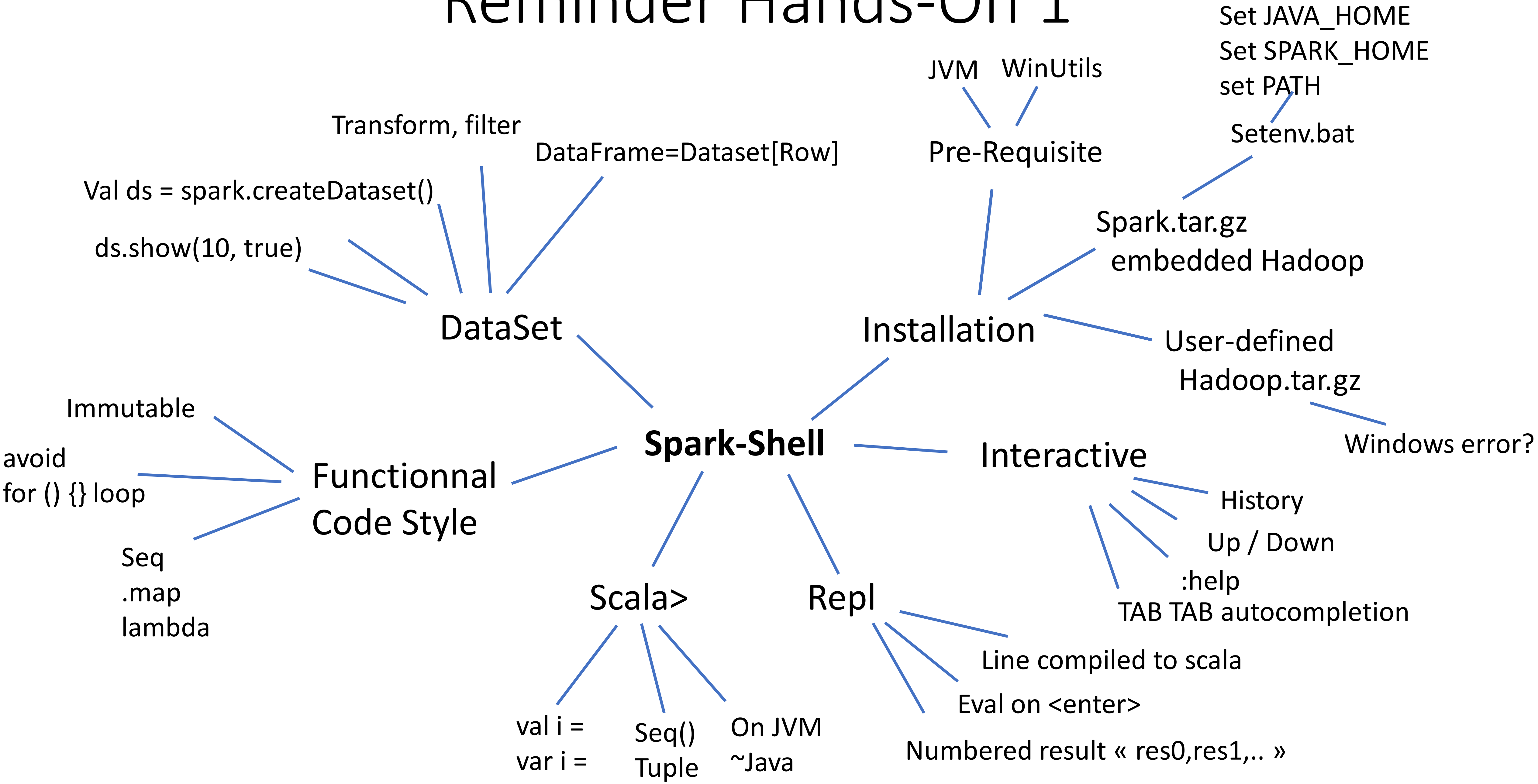
3/ RDD cache / checkpoint

4/ Partition Pruning / Columns Pruning / Predicate-Push-Down

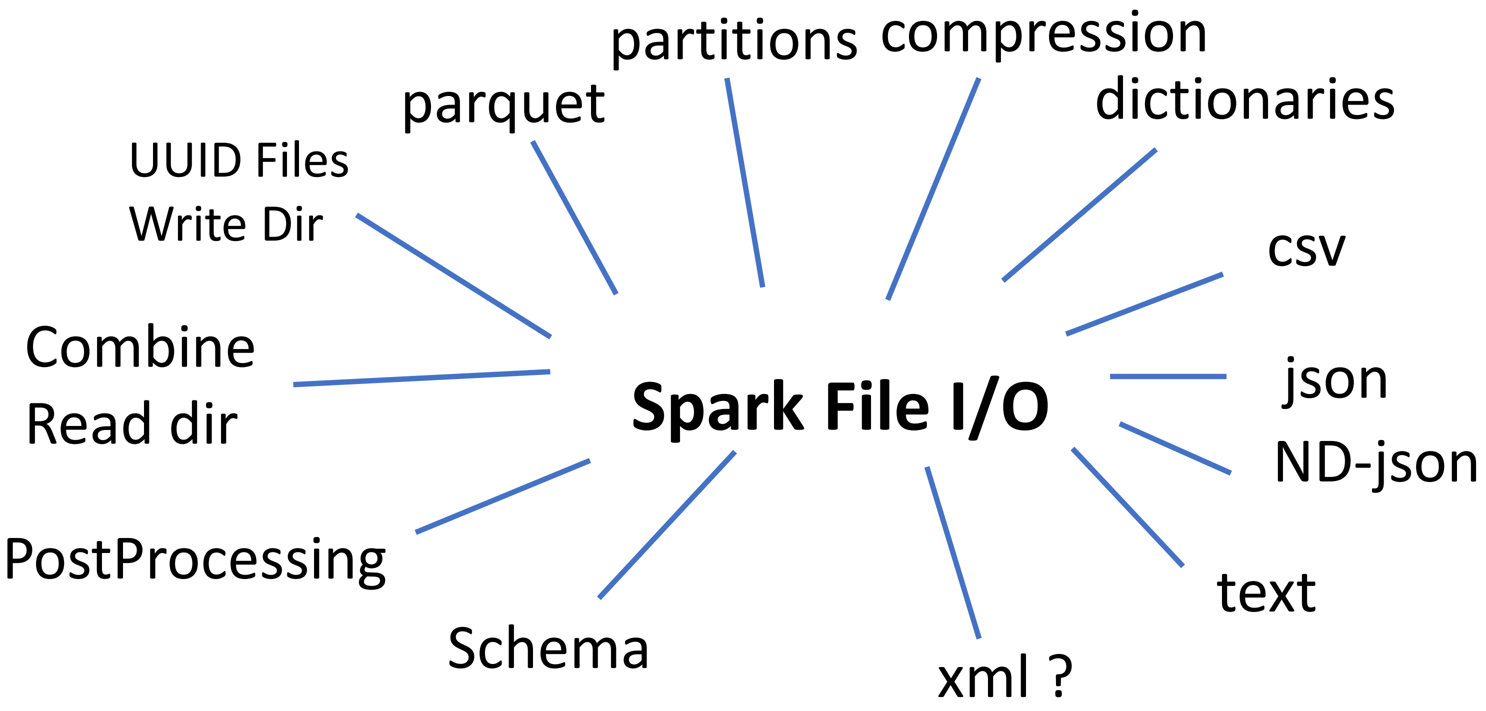
5/ Parquet Optims (Sort, Stats, Dictionary, Bloom, BlockSize)

6/ perfs: SpillToDisk, JOINs, hint

Reminder Hands-On 1



Reminder Hands-On 2



Reminder Hands-On 3

Spark Catalog - Metastore

- SQL DDL
  - SQL on Files
    - */Files per dir
      1…N new file per insert
    - STORED AS..
      LOCATION
  - CREATE EXTERNAL TABLE
    IF NOT EXISTS
  - SHOW CREATE TABLE
  - SHOW TABLES
- TABLE PARTITIONED
  BY(col type)
  - Insert overwrite
    .. By partition
  - No SQL
    Update/ Delete
  - Read Optim:
    part-pruning
- createTempView
  - SQL on java Dataset
  - List Tables
  - Describe table .OK
    show Create Table KO
- createGlobalTempView
  - temporary
  - Global=Multi Sessions
    (SparkContext)
  - « global_temp »
    hidden Database
- Configure Spark
  ExternalCatalog
  - --conf spark.sql.
    catalogImplementation=..
    - in-memory
    - hive
  - Search +
    Download
    jar
    (postgres,derby..)
- Config
  HADOOP_CONFIG_DIR
  (or HADOOP_HOME)
  /hive-site.xml
- HiveMetaStore
  - Plain old server,
    with relational DB
  - Do not use!
    HiveServer2

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Exercise 1: Query Partitioned Table WHERE partitionColumn=..

a/ remind on previous Hands-On

SHOW CREATE TABLE db1.address => .. Un-partitioned table, PARQUET

SHOW CREATE TABLE db1.address_by_dept => .. Partitioned table, PARQUET

b/ execute queries

```
SELECT * FROM address_by_dept WHERE dept=92
SELECT * FROM address_by_dept WHERE dept in (75,78,91,92)
SELECT * FROM address_by_dept WHERE commune_name = ‘Nanterre’
```

c/ Remind which dir / files should be read by spark… which query is faster

Exercise 2: Execute « EXPLAIN <<SQL>> »

a/ Execute SQL… prefixed by “EXPLAIN” keyword

spark.sql("**EXPLAIN** select count(*) FROM db1.address_by_dept WHERE dept=92")

Hint: display nicely, using .show(false) OR .foreach(println(_))

b/ do you see “PartitionFilters: [..]” ?

c/ read Tree from depth-first :
- start from bottom (leaf) line,
- when understood then read line above (operator)

Exercise 3 : compare « EXPLAIN » queries

a/ Compare both

spark.sql("**EXPLAIN** select count(*) FROM db1.address_by_dept WHERE dept=92")

spark.sql("**EXPLAIN** select count(*) FROM db1.address WHERE dept=92")

b/ what changed ?

… Exercise 3: EXPLAIN [EXTENDED | CODEGEN | COST | FORMATTED]

https://spark.apache.org/docs/latest/sql-ref-syntax-qry-explain.html

EXPLAIN

Description

The `EXPLAIN` statement is used to provide logical/physical plans for an input statement. By default, this clause provides information about a physical plan only.

Syntax

```
EXPLAIN [ EXTENDED | CODEGEN | COST | FORMATTED ] statement
```

Parameters

- **EXTENDED**

  Generates parsed logical plan, analyzed logical plan, optimized logical plan and physical plan. Parsed Logical plan is a unresolved plan that extracted from the query. Analyzed logical plans transforms which translates unresolvedAttribute and unresolvedRelation into fully typed objects. The optimized logical plan transforms through a set of optimization rules, resulting in the physical plan.

- **CODEGEN**

  Generates code for the statement, if any and a physical plan.

- **COST**

Exercise 4: dataset.explain()   API

val ds = spark.sql("select count(*) FROM db1.address_by_dept WHERE dept=92")
ds.**explain**

ds.**explain(false)**

ds.**explain(true)**

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Exercise 5 : Open Spark-UI
browse to SQL -> last Query -> Detailed Plan

a/ Open Spark-UI at **http://localhost:4040/**

b/ go in last Tab « SQL / DataFrame »

c/ click on line for SQL Query
read the Execution Plan as Blue rectangles and Arrows(DAG)

d/ search carefully the PartitionFilters: [..]
it appears twice: as mouse-over tooltip, and in Detailed text

Exercise 5 : Spark UI Documentation…

https://spark.apache.org/docs/latest/web-ui.html

3.3.0 Overview Programming Guides API Docs Deploying More Search the docs

Web UI

Apache Spark provides a suite of web user interfaces (UIs) that you can use to monitor the status and resource consumption of your Spark cluster.

Table of Contents

Jobs Tab

The Jobs tab displays a summary page of all jobs in the Spark application and a details page for each job. The summary page shows high-level information, such as the status, duration, and progress of all jobs and the overall event timeline. When you click on a job on the summary page, you see the details page for that job. The details page further shows the event timeline, DAG visualization, and all stages of the job.

Exercise 6 : dataset parralelism (N partitions) => show N tasks in Job->Stage->Tasks

a/ browse from SQL logical plan to execution plan: Jobs->Stages

b/ take SparkUI screenshot showing detailed table results
(time, IO statistics) PER partition.

c/ Check table results has N rows,
where N=ds.toJavaRDD.getNumPartition
Is the dataset well balanced (or skewed) ?

d/ take screenshot of (min-average-max) partition results in DAG

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Reminder: Narrow/Wide Transformations

https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations

Transformations

The following table lists some of the common transformations supported by Spark. Refer to the RDD API doc (Scala, Java, Python, R) and pair RDD functions doc (Scala, Java) for details.

Transformation	Meaning
map(*func*)	Return a new distributed dataset formed by passing each element of the source through a function *func*.
filter(*func*)	Return a new dataset formed by selecting those elements of the source on which *func* returns true.
flatMap(*func*)	Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item).
mapPartitions(*func*)	Similar to map, but runs separately on each partition (block) of the RDD, so *func* must be of type Iterator<T> => Iterator<U> when running on an RDD of type T.
mapPartitionsWithIndex(*func*)	Similar to mapPartitions, but also provides *func* with an integer value representing the index of the partition, so *func* must be of type (Int, Iterator<T>) => Iterator<U> when running on an RDD of type T.
sample(*withReplacement*, *fraction*, *seed*)	Sample a fraction *fraction* of the data, with or without replacement, using a given random number generator seed.
union(*otherDataset*)	Return a new dataset that contains the union of the elements in the source dataset and the argument.
intersection(*otherDataset*)	Return a new RDD that contains the intersection of elements in the source dataset and the argument.
distinct([*numPartitions*]))	Return a new dataset that contains the distinct elements of the source dataset.
groupByKey([*numPartitions*])	When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs. **Note:** If you are grouping in order to perform an aggregation (such as a sum or average) over each key, using `reduceByKey` or `aggregateByKey` will yield much better performance. **Note:** By default, the level of parallelism in the output depends on the number of partitions of the parent RDD. You can pass an optional `numPartitions` argument to set a different number of tasks.
reduceByKey(*func*, [*numPartitions*])	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 *func*, which must be of type (V,V) => V. Like in `groupByKey`, the number of reduce tasks is configurable through an optional second argument.
aggregateByKey(*zeroValue*)(*seqOp*, *combOp*, [*numPartitions*])	When called on a dataset of (K, V) pairs, returns a dataset of (K, U) pairs where the values for each key are aggregated using the given combine functions and a neutral "zero" value. Allows an aggregated value type that is different than the input value type, while avoiding unnecessary allocations. Like in `groupByKey`, the number of reduce tasks is configurable through an optional second argument.
sortByKey([*ascending*], [*numPartitions*])	When called on a dataset of (K, V) pairs where K implements Ordered, returns a dataset of (K, V) pairs sorted by keys in ascending or descending order, as specified in the boolean `ascending` argument.
join(*otherDataset*, [*numPartitions*])	When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key. Outer joins are supported through `leftOuterJoin`, `rightOuterJoin`, and `fullOuterJoin`.
cogroup(*otherDataset*, [*numPartitions*])	When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (Iterable<V>, Iterable<W>)) tuples. This operation is also called `groupWith`.
cartesian(*otherDataset*)	When called on datasets of types T and U, returns a dataset of (T, U) pairs (all pairs of elements).
pipe(*command*, *[envVars]*)	Pipe each partition of the RDD through a shell command, e.g. a Perl or bash script. RDD elements are written to the process's stdin and lines output to its stdout are returned as an RDD of strings.
coalesce(*numPartitions*)	Decrease the number of partitions in the RDD to numPartitions. Useful for running operations more efficiently after filtering down a large dataset.
repartition(*numPartitions*)	Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them. This always shuffles all data over the network.
repartitionAndSortWithinPartitions(*partitioner*)	Repartition the RDD according to the given partitioner and, within each resulting partition, sort records by their keys. This is more efficient than calling `repartition` and then sorting within each partition because it can push the sorting down into the shuffle machinery.

Exercise 7: combine several **Narrow** transformations filter, sample, select, withColumn …

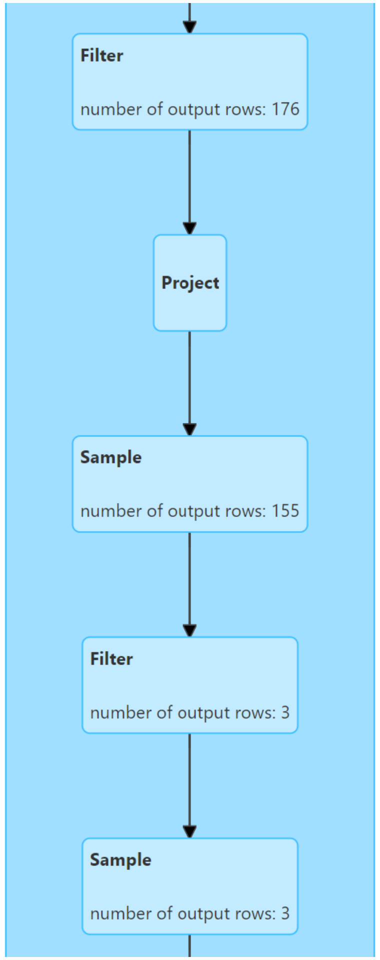
a/ Execute query like

```
val addressDs = …..
 .filter(a).filter(b)   // => check Spark combine as   .filter(a && b) !!
```

b/ ..like

```
addressDs
    .withColumn(..)
    .filter( .. ) .sample(0.9)
    .filter( .. ) .sample (0.9)
    .count
```

b/ Check in Spark UI that there is only 1 « **WholeStageCodegen (1)** » containing several instructions



Exercise 8: WholeStageCodegen java code for(;;) on Dataset<Row>…

a/ Show the corresponding generated Java Code of WholeStageCodegen

use **ds.queryExecution.debug.codegen**

b/ read it …
find « .. extends org.apache.spark.sql.execution.BufferedRowIterator »
https://github.com/apache/spark/blob/master/sql/core/src/main/java/org/apache/spark/sql/execution/BufferedRowIterator.java#L97

c/ find method @Override **protected void processNext() {**
.. It is supposed to map copy all filtered rows x columns to new RDD[Row]

d/ do you find your filter conditions on your columns ?

Exercise 9: cascade several Wide Transformations: repartition, groupByKey, aggregateByKey, aggregate, join, distinct

a/ Execute query like

```
addressDs
.repartition(3)
.repartition(2, $"commune_insee")
.repartition(4)
.repartition(2, $"commune_nom")
.count
```

b/ Check in Spark UI that there are N stages (=N shuffles)

Exercise 10: Check on 2 consecutive Stages that previous Shuffle Write = next Shuffle Read

Completed Stages (4)

Page: 1

1 Pages. Jump to 1 . Show 100 items in a page. Go

Stage Id	Description		Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
9	show at <console>:23	+details	2022/10/06 17:17:44	41 ms	1/1				
5	show at <console>:23	+details	2022/10/06 17:17:43	0,6 s	2/2			78.8 MiB	36.2 MiB
2	show at <console>:23	+details	2022/10/06 17:17:41	2 s	1/1			39.6 MiB	78.8 MiB
0	show at <console>:23	+details	2022/10/06 17:17:39	2 s	8/8	27.2 MiB			39.6 MiB

Exercise 11: Why do you see Greyed boxes… « Skipped Stages » ?

a/ If you don’t see… check you executed a wide transformation (not narrow)

b/ why all except the last Stage are greyed, and the last is blue?

c/ what is the difference «with green » point like in .cache() ?
(cf next Exercise on dataset.cache() and .checkpoint())

Exercise 12: mix cascade of Narrow and Wide

Example

```
spark.sql("select * from address3")
.repartition(1).sample(0.9)
.repartition(2).sample(0.8).filter("commune_nom like '%a%'")
.repartition(3).sample(0.7).filter("commune_nom like '%t%'").sample(0.6)
.count
```

a/ Explain how many Shuffles you expect

b/ How many instructions you expect in each

WholeStageCodegen (1), WholeStageCodegen (2), WholeStageCodegen (3)

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Exercise 13: Several Actions on same Dataset

a/ Execute several actions on same Dataset
  ds.show
  ds.show

b/ equivalently… several SQL
  select * from address
  select * from address

b/ Check in SparkUI that ds is recomputed each time
   (show screenshots with job ids, stage ids)

c/ Check Spark File IO Statistics, Shuffle, Time elapsed

Exercise 14: Avoiding re-computation dataset .cache()

a/ Same as Exercise 12… but use before

ds.cache() // or equivalent: .persist()

Execute several actions on cached Dataset
  ds.show
  ds.show

b/ Check in SparkUI that ds is NOT recomputed
  … But Full lineage is still displayed several time in greyed / with green point
  give screenshots showing job ids / stage ids

c/ check in SparkUI > Storage > RDD

d/ and after … **ds.unpersist()**

Exercise 15: Execute complex DAG on dataset with lot of duplicates

Example: dataset repeated, with small variations, then union …

```
val ds1 = spark.sql("select * from address3").repartition(2).filter("commune_nom like
'%n%'").repartition(2).sample(0.9);
val ds2 = ds1.union(ds1).limit(1000).repartition(2).sample(0.9);
val ds3 = ds2.union(ds2).limit(1000).repartition(2).sample(0.9).union(ds2);
val ds4 = ds3.union(ds3).limit(1000).repartition(2).sample(0.9).union(ds3);
val ds5 = ds4.union(ds4).limit(1000).repartition(2).sample(0.9).union(ds3);
ds5.count;
```

Open corresponding DAG in Spark UI

Exercise 16: How to simplify DAG display ? … .checkpoint() !

a/ ensure
sc.setCheckpointDir(« c:/data/checkpoint-dir »)

b/ Same as Exercise 15… but use checkpoint:
ds3=..
val ds3 = ds3.checkpoint(); // IMPORTANT TO RE-ASSIGN
ds4=..

c/ Check in SparkUI that ds3 is persisted,
… AND lineage no more displayed

d/ there is NO « unCheckpoint() » as there is for unpersist()

10 mn pause

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Exercise 17: Reminder Partition Pruning

There are 3 « Pruning » Optimizations done by Spark
1/ Column Pruning
2/ Partition Pruning
3/ Predicate-Push-Down

Questions: (interogation on Spark Lesson)

a/ explain in few words what is 1/, 2/, 3/

b/ what are pros/cons of many (small) partitions ?

Exercise 18: Column Pruning

Reminding that Parquet is a « Columnar File Format »

Check by reading only 1 column, that Spark does not read fully Parquet Files
… only Page block of selected column.
This is « Column Pruning »

Example:
spark.sql(« select distinct commune_nom from address »).count

Check in SparkUI the File Bytes read statistics.
Compare with total file size
Check in SparkUI the IO read statistics per partition tasks
Give screenshots of SparkUI

Exercise 19: Predicate-Push-Down

a/ Execute following Queries

select count(*) from db1.address where commune_nom = ‘Nanterre’
select count(*) from db1.address where UPPER(commune_nom) = ‘NANTERRE’
select count(*) from db1.address where commune_nom like ‘%Nanterre%’

b/ Check in SparkUI the execution Plan
Search for « PushedFilters:[..] »

c/ For which query Spark is able to push down « some/all conditions » to parquet library ?

d/ explain how parquet files should be saved for having good read performances

Hint: use sc.setCallSite(« query comment») to find easily your query in Spark UI

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Exercise 20: prepare sorted parquet table for Predicate-Push-Down

We want to have few PARQUET files (1 or several, but not hundred)
Each PARQUET File split in several blocks of 16Mo (default=256Mo)
Each block sorted to have efficient Dictionaries and Min-Max Statistics

```
val allAdressCsvDs = spark.read.options(Map("header" -> "true", "delimiter" -> ";",
"inferSchema" -> "true")).format("csv").load("C:/data/OpenData-gouv.fr/bal/adresses-
france.csv")
.withColumn("dept", regexp_replace(col("commune_insee"), "0*(.*)...", "$1").cast("int"))
.withColumn("code", col("commune_insee").cast("int"))

allAdressCsvDs.repartition(1)
 .sort("dept").sortWithinPartitions("dept", "code", "voie_nom")
 .write.format("parquet").option("parquet.block.size", 16*1024*1024)
 .saveAsTable("db1.address_sorted")

allAdressCsvDs.repartition(10, col("dept"))
 .sortWithinPartitions("dept", "code", "voie_nom")
 .write.format("parquet").option("parquet.block.size", 16*1024*1024)
 .saveAsTable("db1.address_sorted10")
```

Exercise 21: check.. getNumPartitions

Check that

a/ table db1.address_sorted is saved
on 1 parquet file,
and file is split into 55 partitions
giving a total of numPartition=55

b/ table db1.address_sorted10 is saved
on 10 parquet files
and files are split (differently..)
giving a total of numPartition=57

c/ is there a big difference between a/ and b/ ?
Which is « better » ?

Hint: use **dataset.toJavaRDD.getNumPartitions**

Exercise 22: Predicate-Push-Down

Execute several Queries with WHERE clauses « field=value »
and see efficiency of Skipped/Read bytes compared to total file size

select count(*) from db1.address_sorted where …
a/ where commune_nom='Nanterre'
b/ where code=92050
c/ where commune_nom='_UneCommuneQuiNExistePas'
d/ where code=0

Compare Bytes read for queries… Are they same?
Compare Plan « PushedFilters: [..] » / Compare jobs->stage tasks counts

Hint: use « **sc.setCallSite**(« DisplayName »); » to find queries more easily in Spark UI

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Exercise 23: Detect SpillToDisk problems

When Spark has not enough RAM memory, it uses « swapping » to disk.
In Spark, this is called « SpillToDisk ».
This is a dreadfull signal, to ask for more memory (or better algorithm)

a/ execute a task taking to much memory
… example a « .repartition(2).sortWithinPartitions(« commune_insee »)

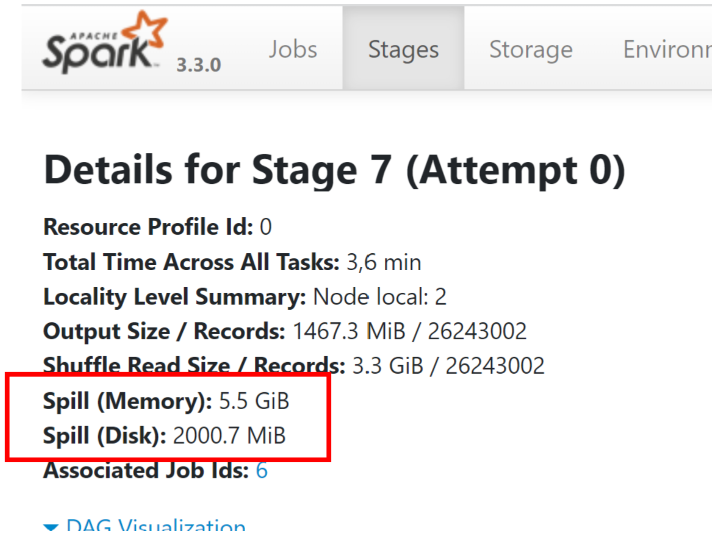
b/ detect the slowness and diagnostic it in SparkUI

c/ retry executing same request with more memory, and compare performances

Exercise 23: SpillToDisk

Example:

```
spark.sql("select * from db1.addr3")
  .repartition(2).sortWithinPartitions("commune_insee")
  .write.saveAsTable("db1.addr_repart2")
```



Find other (more detailed) infos in SparkUI

Exercise 24: Join

a/ Extract and save from table address a new table « city »
Containing « name, code, dept, average_address_longitute, average_address_lattitude »

b/ Join table « address » and « city »,
and compute for each address the offset longitude/latitude to the city average center

c/ study Execution plan
check that Spark is already efficiently « Broadcasting » the small ‘city’ table
=> no need to « SortMerge » the big ‘addr’ table

Exercise 25: HINT to force join strategy

compare with previous Exercise 24/, but with SQL hinting

SELECT /*+ MERGE(a) */ …   FROM addr a …

Cf https://spark.apache.org/docs/latest/sql-ref-syntax-qry-select-hints.html

Examples

```
-- Join Hints for broadcast join
SELECT /*+ BROADCAST(t1) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;
SELECT /*+ BROADCASTJOIN (t1) */ * FROM t1 left JOIN t2 ON t1.key = t2.key;
SELECT /*+ MAPJOIN(t2) */ * FROM t1 right JOIN t2 ON t1.key = t2.key;

-- Join Hints for shuffle sort merge join
SELECT /*+ SHUFFLE_MERGE(t1) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;
SELECT /*+ MERGEJOIN(t2) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;
SELECT /*+ MERGE(t1) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;

-- Join Hints for shuffle hash join
SELECT /*+ SHUFFLE_HASH(t1) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;

-- Join Hints for shuffle-and-replicate nested loop join
SELECT /*+ SHUFFLE_REPLICATE_NL(t1) */ * FROM t1 INNER JOIN t2 ON t1.key = t2.key;
```

Optional Exercise 26: Default Shuffle = 200 ?!

Study number of partitions after a (« merge ») join   (not a « broadcastjoin »)

a/ is it 200 ? Why

b/ How do you change default ?

c/ What should you always do before saving to File(s)?
(to avoid 200 small files)

Exercise 27 : MindMap

Draw a MindMap to summarize
what you did and learn from this Hands-On session

Your MindMap should
start with word « Spark – Optimizations & RDD DAGs» in the middle
Then draw star edges to other word chapters and sub-chapters

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Questions ?

Take-Away

What You learned ?

Next Steps

Unfortunatly,
NO More Lessons
NO More Hands-On

But still, many more Spark concepts to learn :

- Spark Clustering
- Spark on Kubernetes, in Cloud
- Java binding, UDF, map
- Analytical Queries
- Machine Learning
- Spark Streaming
- …