

Spark 2.3 Spark SQL



'Spark SQL is a Spark module for structured data processing '

- Unlike the basic Spark RDD API, the interfaces provided by Spark SQL provide Spark with more information about the structure of both the data and the computation being performed.
- 2. Internally, Spark SQL uses this extra information to perform extra optimizations.
- 3. There are several ways to interact with Spark SQL including SQL and the Dataset API.
- 4. When computing a result the same execution engine is used, independent of which API/language you are using to express the computation.
 - This unification means that developers can easily switch back and forth between different APIs based on which provides the most natural way to express a given transformation.



DataFrame and Datasets

- Originally Spark provided only DataFrames.
- A DataFrame is conceptually a table with <u>typed columns</u>.
- However, it is not typed at compilation.
- Starting with Spark 1.6, Datasets were introduced.
- Represent a table with columns, but, the row is typed at compilation.

trainologic Spark Session

- The entry-point to the Spark SQL.
- It doesn't require a SparkContext (is managed within).
- Supports binding to the current thread (Inherited ThreadLocal) for use with getOrCreate().
- Supports configuration settings (SparkConf, app name and master).

```
SparkSession spark = SparkSession
.builder()
.appName("App Name")
.config("spark.some.config.option", "some-value")
.getOrCreate();
```

trainologic Creating DataFrames

DataFrames are created using spark session

- Dataset<Row> revenueDF = spark.read().json("src/main/resources/sparksql/revenues.csv");
- Dataset<Row> revenueDF = spark.read().parquet("src/main/resources/sparksql/revenues.csv");

Options for constructing the DataFrame

spark.read.option("key","value").option...read.csv(..):

Dataset<Row> revenueDF = spark.read().option("header", true).csv("src/main/resources/sparksql/revenues.csv")

Creating DataFrames

- When reading files using built-in methods
 (spark.read.xxxx(path)) it'll be read as DataFrame (i.e.
 Dataset<Row>)
- 2. Spark will try to resolve the schema out of the file:
 - a. csv looking at sample of the values (you can't guess how 5 will be read...)
 - b. parquet, avro using intenal schema
- 3. Row cause Spark can't guess beforehand what will be the types (kind of Java's Object)

trainologic Schema

- Spark knows in many cases to infer the schema of the data by himself. (By using reflection or sampling)
- Use printSchema() to explore the schema that spark deduce
- Spark also enables to provide the schema yourself
- And to cast types to change existing schema –
 df.withColumn("new_col", df.col("col").cast(IntegerType))

Exploring the DataFrame - Select, Filter

Select

- revenueDF.select("product");
- revenueDF.select(col("product"), col("category"), col("revenue"));

Filtering by columns

- revenueDF.filter("revenue > 3000");
- revenueDF.filter(col("category").equalTo("Tablet"));



Exploring the DataFrame - columns

Drop

revenueDF.drop("category");

withColumn

1. Static value

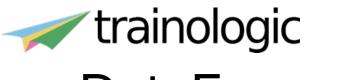
Dataset<Row> wcDF = revenueDF.withColumn("ones", lit(1));

2. Based on other fields:

revenueDF.withColumn("more_money", revenueDF.col("revenue").plus(3000));

3. Casting

revenueDF .withColumn("int_revenue", revenueDF.col("revenue").cast(*IntegerType*));



DataFrames, DataFrames...





DataFrames, DataFrames...

- 1. Load 'airports.csv' file into Dataframe
- 2. Print the schema
- 3. Find all airports that located in 'Greenland'
- 4. Find all airports that located in country started with 'a' AND the airport name is no less than 2 words.
- 5. Add column for the length of the airport name

Exploring the DataFrame - Aggregations

revenueDF.groupBy("category").count();

Or

RelationalGroupedDataset rgs = wColDF.groupBy("category");

rgs.sum("revenue")

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Alias

revenueDF.withColumnRenamed("revenue", "revenue2")



Exploring the DataFrame - Unions, Join

Union

- 1. Add rows to other rows
- 2. Needs the same schema

revenueDF.union(revenueDF)

Join

- 1. You should specify the columns to join on
- 2. You can specify the join type

revenueDF.join(revenueDF, "product");





DataFrames, DataFrames...

.orderBy(desc("count"));

import static org.apache.spark.sql.functions.*;

- 1. Load 'airports.csv' and 'flights.csv' into Dataframe
- 2. Airports:
 - a. How many different countries?
 - b. How many airports per country?
 - c. Printout the top 20 countries who has the bigest airport number?
- 3. And flights:
 - a. How many flights per Country, DayofMonth there is?
 - b. What was the busiest hour per country in 3.1.2008?

trainologic SQL on DataFrame

Register DF as an SQL Table

df.createOrReplaceTempView("table1")

Now we can use sql queries:

spark.sql("select count(*) from table1")

SQL on DataFrame - UDF

- 1. UDF User Defined Function
- There a build in function: https://cwiki.apache.org/confluence/display/Hive/Language Manual+UDF
- 3. The ability to add code to our Spark SQL (and not only...)

SQL on DataFrame - UDF

1. Create the function:

```
UDF1<Integer, Double> square = new UDF1<Integer, Double>() {
    public Double call(Integer integer) throws Exception {
        return Math.sqrt(integer);
    };
```

2. Register:

```
spark.udf().register("sqr", square, DataTypes.DoubleType);
```

3. Use:

```
spark.sql("select category, sqr(revenue) as rev_sum ");
revenueDF.select(callUDF("sqr", col("revenue"))).show();
```





DataFrames, DataFrames... - SQL

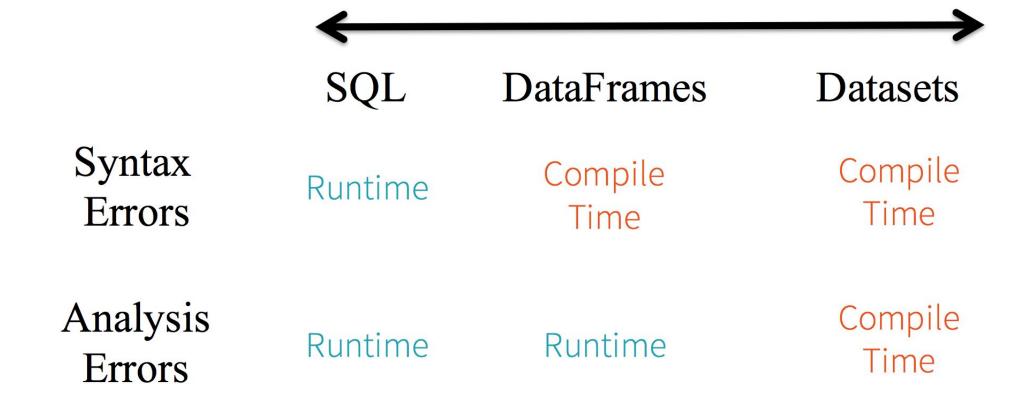
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Datasets are coll!

- Typed checked in completion time.
- You need a VERY good reason to use RDD or DataFrame instead of Dataset
- Datasets can created from classes
- You will need to specify encoder (where is the Scala's case classes when needed:()

trainologic Datasets...



trainologic Datasets...

Dataset<Integer> intDS = spark.createDataset(Arrays.asList(1, 2, 3, 4, 5), Encoders.INT());

Now, this is safe:

intDS.filter((FilterFunction<Integer>) i -> i > 2);

Remember this (on dataframe)?

intDF.filter((FilterFunction<Row>) row -> row.getInt(0) > 3)

trainologic Saving Will Datasets...

Spark provides usuefal method to save your dataset.

- Each dataset has save method: revenueDataset.write().mode("overwrite").csv(path);
- 2. You can choose between few formats: csv, parquet, json, text and more
 - \rightarrow json is actually lined json, i.e. lines that each line is json.
- 3. The default is to write one file per partition, it can be changed: flightsDF.coalesce(3).write().mode("overwrite").json(path);

Saving Will Datasets - Save Modes

Dataset provides 4 saving modes:

- 1. overwrite overwrite file if exists
- 2. append append to file
 - a. Actually it added the new parts into the directory
 - b. Overtime might yield in files explosion
 - c. Harder to maintain reruns and atomic operations
- 3. ignore ignore the operation
- 4. error, errorifexists, default error if the file exists
 - → This is the default mode

Saving Will Datasets - Partitions

- 1. In the default status Spark will create one file per partition
- 2. coalesce reduces the number of partitions flightsDF.coalesce(3)
 - a. Not just for writing good for optimize jobs (on that later)
 - b. No shuffling occurs it just write more than one partition to one file
 - c. coalesce(1) can be good for using the outfile manually (e.g. csv file) but be careful with what you wish for!
- 3. repartition column or just rempartion...

A word about files type

- csv as poor performance and usability.
 Good for tests, debug and export data
- Parquet columnar storage format.Performed very well
- If you don't know what to use use Parquet.
 Else → use Parquet;)

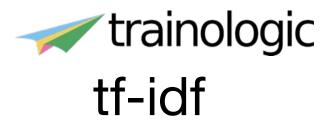


A word about compression

- 1. It is a good idea to compress your data (why?)
- 2. Snappy is widely used







Tf-idf - method in information retrieval to provide score to word - document

tf - term frequency

number of the term occurrences / number of terms in the document

idf - inverse document frequency

log_e(Total number of documents / Number of documents with term t in it)



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TF

- Create function the gets spark session and document and calculates the tf of the document
- 2. Create function that get spark session and list of documents and return on tf dataframe <document, word, tf>

trainologic Web UI

- Spark provides rich web ui
- It can help to monitor and debug problems

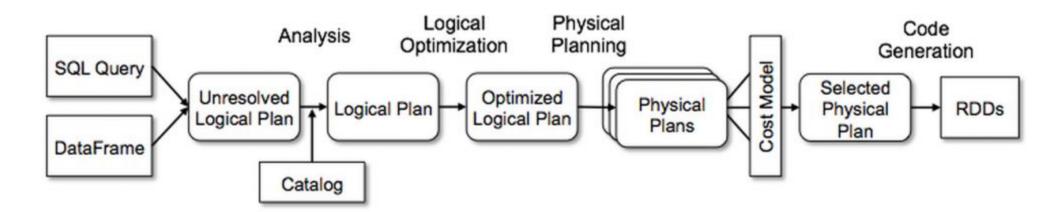


Query planning - Catalyst

- All of the Spark SQL APIs (SQL, Datasets and DataFrames) result in a Catalyst execution.
- Basicly Catalyst build an execution tree
- Trees can be created out of other trees using trasformations

Query planning

- Query execution is composed of 4 stages:
 - Logical plan.
 - Optimized logical plan.
 - Physical plan.
 - Code-gen (Tungesten).



trainologic Logical plan

- Sometimes called Analysis
- In the first stage, the Catalyst creates a logical execution plan.
- A tree composed of query primitives and combinators that
- match the requested query.
- Mapping names to value with unique ids
- Optimzies expressions like col = col
- And much more...

trainologic

Optimized logical plan

- Catalyst runs a set of rules for optimizing the logical plan.
- Cost-based optimization is performed by generating multiple plans using rules, and then computing their costs.
- E.g.:
 - Merge projections.
 - Push down filters.
 - Convert outer-joins to inner-joins.
 - Cast types

trainologic Physical Planning

- Spark SQL takes a logical plan and generates one or more physical plans, using physical operators that match the Spark execution engine
- Than it selects the best plan
- e.g. joins if the dataset is small it'll use broadcast join
- rule-based physical optimizations, such as pipelining projections or filters into one Spark map operation
- it can push operations from the logical plan into data sources that support predicate or projection pushdown



- Spark 2 introduced a new optimization: Whole stage code generation.
- It appears that in many scenarios, the bottleneck is the CPU.
- Wasted on virtual calls and cache-line swapping.
- Simple and query specific code should be favored.



Tungesten:

- Memory Management and Binary Processing: leveraging application semantics to manage memory explicitly and eliminate the overhead of JVM object model and garbage collection
- 2. Cache-aware computation: algorithms and data structures to exploit memory hierarchy
- 3. Code generation: using code generation to exploit modern compilers and CPUs

trainologic Query planning

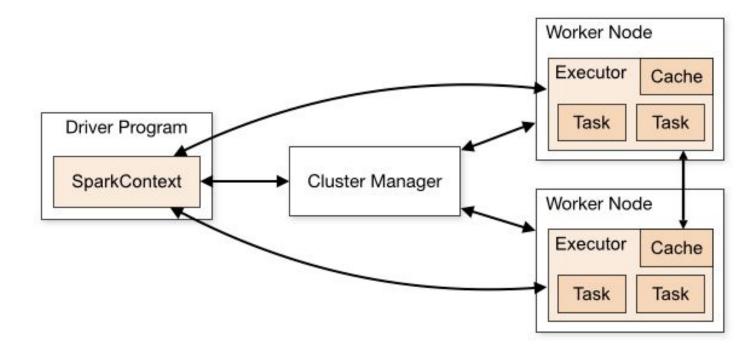
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trainologic Integrating Spark with your App

- How does it work?
- Server vs. client mode

trainologic Integrating Spark with your App

Remember we talked about this





How does it work?

- Cluster manager
 - Responsible for the resource allocation
 - Cluster management
 - Orchestrates work
- Worker nodes:

Driver Program

SparkContext

Cluster Manager

Worker Node

Executor

Cache

Task

Task

Task

Task

Task

Task

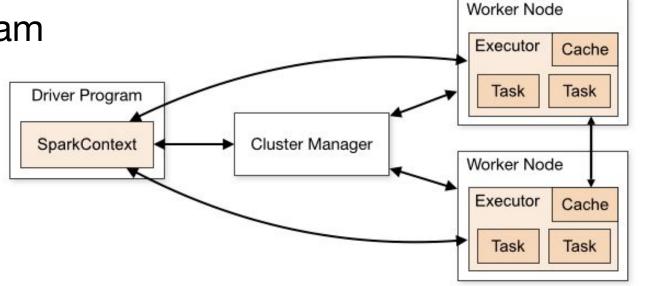
Worker Node

Tracks and spawn application processes



How does it work?

- Driver:
 - Executes the main program
 - Creates the RDDs
 - Collects the results
- Executors:
 - Executes the RDD operations
 - Participate in the shuffle://spark.apache.org/docs/latest/cluster-overview.html



trainologic Spark Cluster Manager

- Stand alone
- Mesos
- Yarn
- Kuberntics
- EMR/Azure

trainologic Spark Client Mode

- The driver is in your app
- Easy to retrieve results
- If the app crashes spark crashes
- --deploy-mode client

trainologic Spark Cluster Mode

- The driver is running on the worker
- The app can recover from crash (using --supervise flag)
- Recommended when the launching app is far from the cluster
- On Yarn get one more container to run on
- Harder to communicate with
- --deploy-mode cluster

trainologic Spark Submit

```
./bin/spark-submit \
--class org.apache.spark.examples.SparkPi \
--master local[8] \
examples/jars/spark-examples_2.11-2.2.0.jar \
100
```

- 1. num-executors the number of excutor
- 2. executor-cores how many cores per executor
- 3. executor-memory how manu memory per executor
- 4. num-executors * executor-cores == worker num
- 5. --driver-memory and --driver-cores driver configuration

Let's assume that we have 3 nodes, 16 cores. 64GB each

Option I

num-executors=3, executor-cores=16, executor-memory=64GB

→ We didn't leave any room for operations system and the node manager...

Let's assume that we have 3 nodes, 16 cores. 64GB each

Option II

num-executors=3, executor-cores=14, executor-memory=64GB

→ As cores using threads, this is too many threads for process

Let's assume that we have 3 nodes, 16 cores. 64GB each

Option III

num-executors=45, executor-cores=1, executor-memory=64GB

→ Too many processes, e.g. broadcast variables will need to create again and again

Let's assume that we have 3 nodes, 16 cores. 64GB each

Option IV

num-executors=9, executor-cores=5, executor-memory=20GB

- 1. 3 executors per node, 5 cores total of 45 workers
- 2. 20GB per executors about 4GB per worker

- 1. Use as least executors as possible
- 2. Use 4-7 cores per executor.
- 3. Secure at least 2GB per worker
- 4. Don't exceed 64GB memory per executor
- 5. Don't forget to leave 1-2 cores for the operation system and for the cluster manager