SPARK SQL

SparkSession

In earlier versions of spark, spark context was entry point for Spark. Essentially, SparkContext allows your application to access the cluster through a resource manager. For every other API, we needed to use different contexts. For streaming, we needed StreamingContext, for SQL sqlContext and for hive HiveContext. HiveContext is a super set of SQLContext that you would need if you want to access Hive tables, or to use richer functionalities and the trade-off is that HiveContext requires many dependencies to run.

So in Spark 2.x, we have a new entry point for DataSet and Dataframe API's called as Spark Session.

SparkSession is essentially combination of SQLContext, HiveContext and future StreamingContext. All the API's available on those contexts are available on spark session also. Spark session internally has a spark context for actual computation.

Creating a SparkSession

// The builder automatically reuse an existing SparkContext if one exists and creates a SparkContext if it does not exist.

A SparkSession can be created using a builder pattern.

Configuration options set in the builder are automatically propagated to Spark and Hadoop during I/O.

```
import org.apache.spark.sql.SparkSession
val sparkSession = SparkSession.builder.getOrCreate()
```

//implicits object gives implicit conversions for converting scala objects (incl. RDDs) into a Dataset, DataFrame, Columns

```
import sparkSession.sqlContext.implicits._
```

```
//Check the version of the Spark
spark.version
//Get a spark context out of SparkSession
var sc1=spark.sparkContext
//Get a hiveContext context
val sparkSession =
SparkSession.builder.enableHiveSupport.getOrCreate()
```

Creating a Dataframe

Working with native SQL
Load data from csv, create temp table and write sql queries

Setting log level to Error

```
sparkSession.sparkContext.setLogLevel("ERROR")
```

Loading data from structured files

Working with Dataframes

Spark SQL introduces a tabular functional data abstraction called **DataFrame**. It is designed to ease developing Spark applications for processing large amount of structured tabular data on Spark infrastructure.

A DataFrame is a distributed collection of data, which is organized into named columns. Conceptually, it is equivalent to relational tables with good optimization techniques. DataFrame provides a domain-specific language API for structured data manipulation,
with **structured** and **semi-structured data**.

DataFrame is a collection of rows with a schema that is the result of executing a structured query (once it will have been executed).

DataFrame uses the immutable, in-memory, resilient, distributed and parallel capabilities of RDD, and applies a structure called schema to the data.

a. Inferring the Schema using Reflection

1. Create case class as per the structure of data

2. Iterate on every line of rdd, split on the delimiter and apply the structure calling the case class (SchemaedRDD)

3. Convert the schemaedRDD to DF.

4. Ready to to write DSL

5. register the DF to temp view.

6. Write ISO sql on top of the temp view created.

Case classes are just regular classes that are: Immutable by default. Decomposable through pattern matching. Compared by structural equality instead of by reference.

```
case class Auction(auctionid: String, bid: Float, bidtime: Float, bidder: String, bidderrate: Integer, openbid: Float, price: Float, item: String, daystolive: Integer)
```

// load the data into an RDD

```
val auctionRDD = spark.sparkContext.textFile("file:///home/hduser/sparkdata/auctiondata")
```

// create an RDD of Auction objects

```
val ebay = auctionRDD.map(_.split("~")).map(p => Auction(p(0), p(1).toFloat, p(2).toFloat, p(3), p(4).toInt, p(5).toFloat, p(6).toFloat, p(7), p(8).toInt))
```

// change ebay RDD of Auction objects to a DataFrame

```
val auction = spark.createDataFrame(ebay)
```

DF operations:
// How many auctions were held

```
val count = auction.select("auctionid").distinct.count

System.out.println(count)
```

// Identify maximum bids and amount grouped by items

```
import org.apache.spark.sql.functions.avg

val grpbid =
auction.groupBy("item").agg(max("bid").alias("max_bid"),sum("price").alias("sp")).sort($"sp"
.desc)

auction.printSchema
grpbid.printSchema

grpbid.show(10,false)
auction.show(10,false)
```

//Stores the output in JSON format

```
auction.write.mode("overwrite").json("file:/home/hduser/sparkdata/auctiondata.json");

grpbid.write.mode("overwrite").json("file:/home/hduser/sparkdata/grpbid.json");
```

Creating DataFrame from CSV file

//Reading CSV files in local or distributed filesystem as Spark DataFrames.

Creating DataFrame from CSV files using spark-csv module

Use spark-csv module to load data from a CSV data source that handles proper parsing and loading.

```
//Get a sql context
var sqlctx =spark.sqlContext
```

b. Create Dataframe programatically or using csv module

```
val uscsvdf =

sqlctx.read.option("header","true").option("inferschema","true").option("delimiter",",").csv(

"file:///home/hduser/sparkdata/usdata.csv")
```

```
uscsvdf.printSchema

uscsvdf.show(10,false)
```

// Creates a temporary view using the DataFrame.

```
uscsvdf.createOrReplaceTempView("custinfo")

spark.catalog.listDatabases.show(10,false);

spark.catalog.listTables.show(10,false);
```

//Creating and registering functions:

```
def addfunc (a:Int,b:Int):Int=
{
return a+b
}

import org.apache.spark.sql.functions.udf
spark.udf.register("addudf",addfunc _)
spark.catalog.listFunctions.filter('name like "%addu%").show(false)
spark.sql("SELECT addudf(20,30) FROM custinfo ").show()
```

// Perform SQL queries directly on the registerd temp view

```
sqlctx.sql("describe custinfo").show(10,false)

sql("select concat(first_name,' ',last_name),company_name,address,city,phone1 from
custinfo where upper(company_name) like 'CH%'").show(10,false)

sql("select count(1),city from custinfo group by city having count(1) >1 order by city").show()

sql("select count(1) as cnt,city from custinfo group by city having count(1)> 5 order by
city").show()
```

```
val agecat = sqlctx.sql("select distinct age,case when age <=10 then 'childrens' when age >10
and age < 20 then 'teen' else 'others' end as agecat  from custinfo order by agecat")
agecat.show()
```

//Stores the output in Parquet and orc format, Parquet files are self-describing so the schema is preserved

```
agecat.write.mode("overwrite").parquet("file:/home/hduser/sparkdata/agecategory.parque
t");
agecat.write.mode("append").orc("file:/home/hduser/sparkdata/agecategory1.orc");
```

// StructType objects define the schema of Spark DataFrames. StructType objects contain a list of StructField objects that define the name, type, and nullable flag for each column in a DataFrame.

```
import org.apache.spark.sql.types.{StructType, StructField, StringType, IntegerType}

val custschema = StructType(Array(StructField("first_name", StringType,
true),StructField("last_name", StringType, true),StructField("company_name", StringType,
true),StructField("address", StringType, true),StructField("city", StringType,
true),StructField("country", StringType, true),StructField("state", StringType,
true),StructField("zip", StringType, true),StructField("age", IntegerType,
true),StructField("phone1", StringType, true),StructField("phone2", StringType,
true),StructField("email", StringType, true),StructField("website", StringType, true)));

val uscsvdf1 =
sqlctx.read.option("delimiter",",").schema(custschema).csv("file:///home/hduser/sparkdata/
usdata.csv")

uscsvdf1.printSchema
```

// Read in the parquet file created above
// Parquet files are self-describing so the schema is preserved
// The result of loading a Parquet file is also a DataFrame

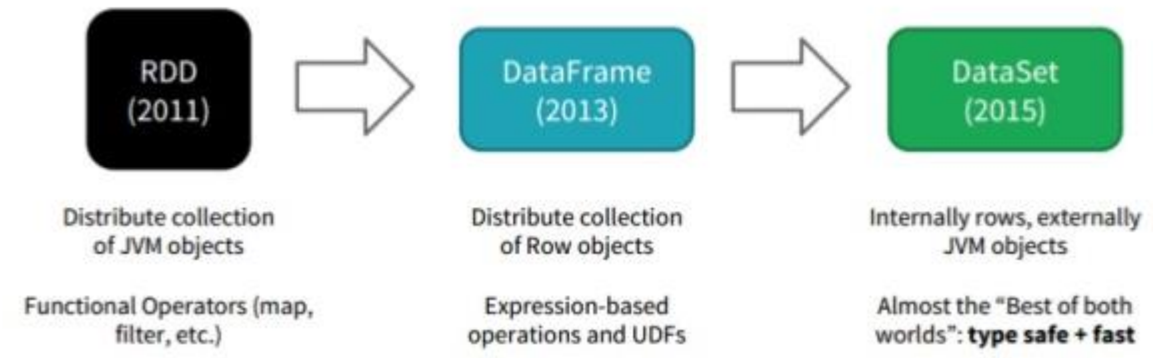
```
val parquetagecatdf =
spark.read.parquet("file:/home/hduser/sparkdata/agecategory.parquet")
```

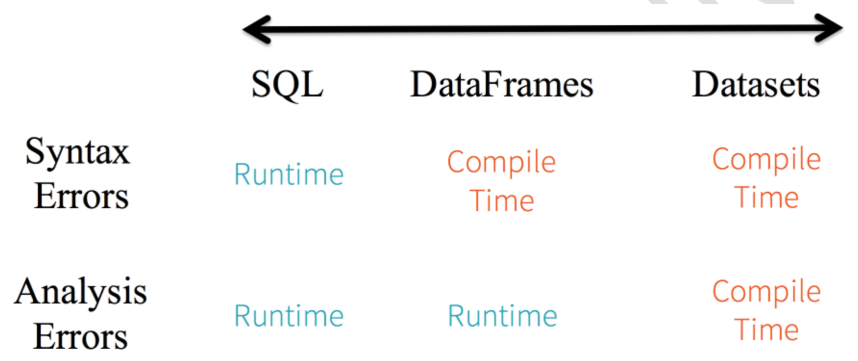
// Parquet files can also be used to create a temporary view and then used in SQL statements

```
parquetagecatdf.createOrReplaceTempView("parquetagecat")

spark.sql("SELECT max(age),min(age),count(distinct agecat) FROM parquetagecat ").show()
```

Dataset Vs Dataframe


RDD (2011)
DataFrame (2013)
DataSet (2015)
Distribute collection of JVM objects
Functional Operators (map, filter, etc.)
Distribute collection of Row objects
Expression-based operations and UDFs
Internally rows, externally JVM objects
Almost the "Best of both worlds": type safe + fast



	SQL	DataFrames	Datasets
Syntax Errors	Runtime	Compile Time	Compile Time
Analysis Errors	Runtime	Runtime	Compile Time

A Dataset is a strongly typed collection of domain-specific objects (like object of type auction declared below) that can be transformed in parallel using functional or relational operations. Each Dataset also has an untyped view called a DataFrame, which is a Dataset of Row.

Dataframe is merged with Dataset API. So we can use any method available for dataframe in datasets.

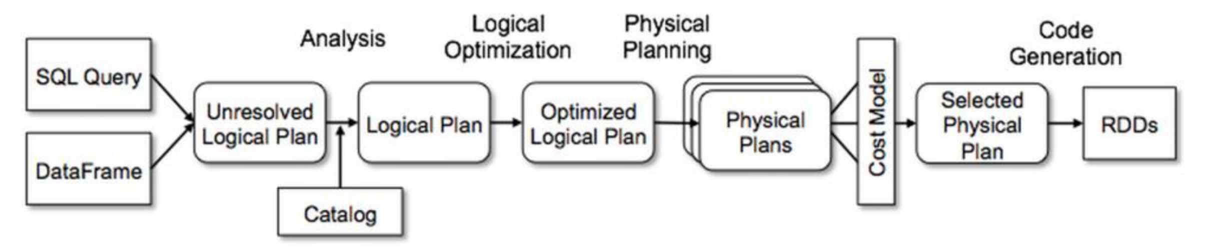
In summation, the choice of when to use RDD or DataFrame and/or Dataset seems obvious. While the former offers you low-level functionality and control, the latter allows custom view and structure, offers high-level and domain specific operations, saves space, and executes at superior speeds.

To simplify Spark for developers, how to optimize and make it performant it was decided to elevate the low-level RDD APIs to a high-level abstraction as DataFrame and Dataset and to build this unified data abstraction across libraries a top Catalyst optimizer and Tungsten.

The goal of Project Tungsten is to improve Spark execution by optimizing Spark jobs for CPU and memory efficiency (as opposed to network and disk I/O which are considered fast enough).

- Tungsten includes specialized in-memory data structures tuned for the type of operations required by Spark, improved code generation, and a specialized wire protocol.
- As Tungsten does not depend on Java objects, both on-heap and off-heap allocations are supported. Since Tungsten no longer depends on working with Java objects, you can use either on-heap (in the JVM) or off-heap storage.
- Tungsten will not do deserialization when processing data, for example of this is with sorting, a common and expensive operation using tungsten this can be done without having to deserialize the data again.
- By avoiding the memory and GC overhead of regular Java objects, Tungsten is able to process larger data sets than the same hand-written aggregations.

Catalyst Optimizer:



Catalyst supports both rule-based and cost-based optimization.

At its core, Catalyst contains a general library for representing trees and applying rules to manipulate them. On top of this framework, we have built libraries specific to relational query processing (e.g., expressions, logical query plans), and several sets of rules that handle different phases of query execution: analysis, logical optimization, physical planning, and code generation to compile parts of queries to Java bytecode. For the latter, we use another Scala feature, quasiquotes, that makes it easy to generate code at runtime from composable expressions. Finally, Catalyst offers several public extension points, including external data sources and user-defined types.

Pick one—DataFrames and/or Dataset or RDDs APIs—that meets your needs and use-case

// A JSON dataset is pointed to a path. The path can be either a single text file or a directory storing text files

//weakly typed Dataframes

```
hadoop fs -put ~/sparkdata/auctiondata.json

val auctionjson = "/user/hduser/auctiondata.json";
val auctionjsonDF = spark.read.json(auctionjson);
auctionjsonDF.distinct.show
```

//Strongly typed DataSets

```
case class auctionclass
(auctionid:String,bid:Double,bidder:Int,bidderrate:Long,bidtime:Doubl
e,daystolive:Long,item:String,openbid:Double,price:Double)

val auctionjson = "file:/home/hduser/sparkdata/auctiondata.json";

val auctionjsonDS = spark.read.json(auctionjson).as[auctionclass];

case class auctionclass
(auctionid:String,bid:Double,bidder:String,bidderrate:Long,bidtime:Do
uble,daystolive:Long,item:String,openbid:Double,price:Double)

val auctionjsonDS = spark.read.json(auctionjson).as[auctionclass];
```

// The inferred schema can be visualized using the printSchema() method

```
auctionjsonDF.printSchema();
auctionjsonDS.printSchema();
```

// Creates a temporary view using the DataSet

```
auctionjsonDS.createOrReplaceTempView("auctionjsontable");
```

```
val auctionquery = spark.sql("SELECT * FROM auctionjsontable")

auctionquery.show();
```

Hive operations:

```
import spark.implicits._
import spark.sql
```

//Initialize hive context wrapping spark context

~~val hiveContext = new org.apache.spark.sql.hive.HiveContext(sc)~~

//Get a hiveContext context

```
val sparkSession =
SparkSession.builder.enableHiveSupport.getOrCreate()
```

//Create a hive table

```
sql("create database if not exists sparkdb")
sql("use sparkdb")

sql("DROP TABLE IF EXISTS employee ")

sql("CREATE TABLE IF NOT EXISTS employee(id INT, name STRING, age INT) ROW FORMAT
DELIMITED FIELDS TERMINATED BY ',' LINES TERMINATED BY '\n'")

spark.catalog.listDatabases.show(10,false);

spark.catalog.listTables.show(10,false);
```

//Load data

```
sql("LOAD DATA LOCAL INPATH '/home/hduser/sparkdata/employee.txt' INTO TABLE employee")
```

//View data

```
val results = sql("FROM employee SELECT id, name, age")

results.show()
```

<u>Additional Hive Usecases (For self practices):</u>

//Drop table

```
sql("CREATE TABLE IF NOT EXISTS src (key INT, value STRING) ROW FORMAT DELIMITED FIELDS TERMINATED BY ',' LINES TERMINATED BY '\n'")

sql("LOAD DATA LOCAL INPATH '/home/hduser/sparkdata/sampledata' OVERWRITE INTO TABLE src")

sql("SELECT * FROM src").show()

sql("drop table src")
```

//Write the table content into the given hdfs location in orc format

```
results.write.format("orc").save("hdfs:/user/hduser/emp_orc")
```

//Read the table from the given hdfs location in orc format and create a dataset out of it.

```
case class empclass (id :Int,name :String,age:Int);

val empdata_orc =
spark.read.format("orc").load("hdfs:/user/hduser/emp_orc").as[empclass];

empdata_orc.createOrReplaceTempView("orcdata")

sql("SELECT * from orcdata").collect.foreach(println)
```

Hive Partitioning:

```
sql("""create table txnrecords(txnno INT, txndate STRING, custno INT, amount DOUBLE,
category STRING, product STRING, city STRING, state STRING, spendby STRING) row format
delimited fields terminated by ','
lines terminated by '\n'
stored as textfile""")
```

```
sql("LOAD DATA LOCAL INPATH '/home/hduser/hive/data/txns' OVERWRITE INTO TABLE
txnrecords")
```

```
sql("select * from txnrecords order by 1 limit 10").show
```

```
sql ("""create external table exttxnrecsByCat(txnno INT, txndate STRING, custno INT, amount
DOUBLE, product STRING, city STRING, state STRING, spendby STRING)
partitioned by (category STRING) row format delimited
fields terminated by ','
stored as textfile
location '/user/hive/warehouse/exttxnrecsbycat'""")
```

```
sql("""Insert into table exttxnrecsbycat partition (category='Games')
select txnno,txndate,custno,amount,product,city,state,spendby
from txnrecords
where category='Games'""")
```

```
sql("select count(1) from exttxnrecsbycat").show
```

<u>Adding UDFS in hive</u>

```
spark-shell --jars /home/hduser/hive/replaceword.jar
sql("use sparkdb")
sql("create function repwords as 'inceptez.training.replacewords.replaceword'")
sql("select repwords(product,'Archery','Arc') from txnrecords where product='Archery' limit
10")
```

Supported Hive Features

Spark SQL supports the vast majority of Hive features, such as:

- Hive query statements, including:
    - SELECT
    - GROUP BY
    - ORDER BY
    - CLUSTER BY
    - SORT BY
- All Hive operators, including:
    - Relational operators (=, ⇔, ==, <>, <, >, >=, <=, etc)
    - Arithmetic operators (+, -, *, /, %, etc)
    - Logical operators (AND, &&, OR, ||, etc)
    - Complex type constructors
    - Mathematical functions (sign, ln, cos, etc)
    - String functions (instr, length, printf, etc)
- User defined functions (UDF)
- User defined aggregation functions (UDAF)
- User defined serialization formats (SerDes)
- Window functions
- Joins
- Unions
- Sub-queries
    - SELECT col FROM (SELECT a + b AS col from t1) t2
- Sampling
- Explain
- Partitioned tables including dynamic partition insertion
- View
- All Hive DDL Functions, including:
    - CREATE TABLE
    - CREATE TABLE AS SELECT
    - ALTER TABLE
- Most Hive Data types, including:
    - TINYINT
    - SMALLINT
    - INT
    - BIGINT
    - BOOLEAN
    - FLOAT
    - DOUBLE
    - STRING
    - BINARY
    - TIMESTAMP
    - DATE
    - ARRAY<>
    - MAP<>
    - STRUCT<>

Unsupported Hive Functionality

Below is a list of Hive features that we don’t support yet. Most of these features are rarely used in Hive deployments.

Major Hive Features

- Tables with buckets: bucket is the hash partitioning within a Hive table partition. Spark SQL doesn’t support buckets yet.

Hive Input/Output Formats

- File format for CLI: For results showing back to the CLI, Spark SQL only supports TextOutputFormat.
- Hadoop archive

Hive Optimizations

A handful of Hive optimizations are not yet included in Spark. Some of these (such as indexes) are less important due to Spark SQL’s in-memory computational model. Others are slotted for future releases of Spark SQL.

- Block level bitmap indexes and virtual columns (used to build indexes)
- Automatically determine the number of reducers for joins and groupbys: Currently in Spark SQL, you need to control the degree of parallelism post-shuffle using “SET spark.sql.shuffle.partitions=[num_tasks];”.
- Meta-data only query: For queries that can be answered by using only meta data, Spark SQL still launches tasks to compute the result.
- STREAMTABLE hint in join: Spark SQL does not follow the STREAMTABLE hint.
- Merge multiple small files for query results: if the result output contains multiple small files, Hive can optionally merge the small files into fewer large files to avoid overflowing the HDFS metadata. Spark SQL does not support that.