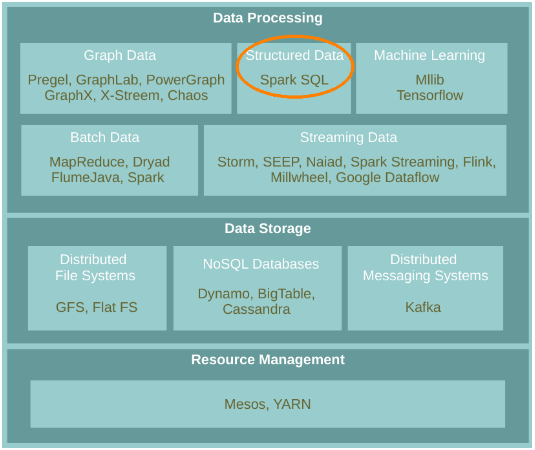
Structured Data Processing - Spark SQL

Amir H. Payberah
payberah@kth.se
24/09/2018

The Course Web Page

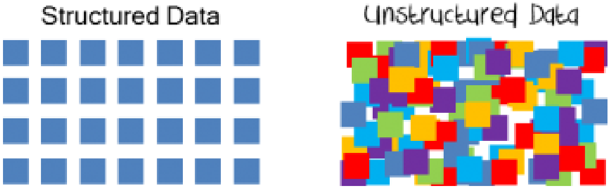
https://id2221kth.github.io

Where Are We?



Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

Motivation

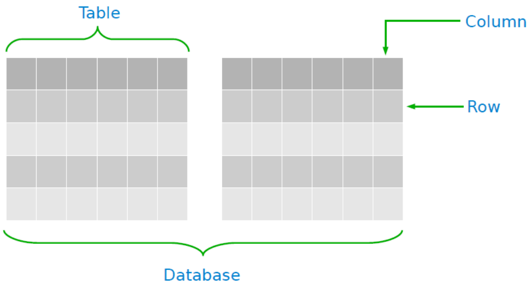


Hive

- A system for managing and querying structured data built on top of MapReduce.
- Converts a query to a series of MapReduce phases.
- Initially developed by Facebook.

Hive Data Model

- Re-used from RDBMS:
  - Database: Set of Tables.
  - Table: Set of Rows that have the same schema (same columns).
  - Row: A single record; a set of columns.
  - Column: provides value and type for a single value.



Hive API (1/2)

- HiveQL: SQL-like query languages

Hive API (1/2)

- HiveQL: SQL-like query languages
- Data Definition Language (DDL) operations
  - Create, Alter, Drop

```
-- DDL: creating a table with three columns
CREATE TABLE customer (id INT, name STRING, address STRING)
ROW FORMAT DELIMITED FIELDS TERMINATED BY '\t';
```

Hive API (2/2)

- Data Manipulation Language (DML) operations
  - Load and Insert (overwrite)
  - Does not support updating and deleting

```
-- DML: loading data from a flat file
LOAD DATA LOCAL INPATH 'data.txt' OVERWRITE INTO TABLE customer;
```

Hive API (2/2)

- Data Manipulation Language (DML) operations
  - Load and Insert (overwrite)
  - Does not support updating and deleting

```
-- DML: loading data from a flat file
LOAD DATA LOCAL INPATH 'data.txt' OVERWRITE INTO TABLE customer;
```

- Query operations
  - Select, Filter, Join, Groupby

```
-- Query: joining two tables
SELECT * FROM customer c JOIN order o ON (c.id = o.cus_id);
```

Executing SQL Questions

- Processes HiveQL statements and generates the execution plan through three-phase processes.

Executing SQL Questions

- Processes HiveQL statements and generates the execution plan through three-phase processes.

    1. Query parsing: transforms a query string to a parse tree representation.

Executing SQL Questions

- Processes HiveQL statements and generates the execution plan through three-phase processes.

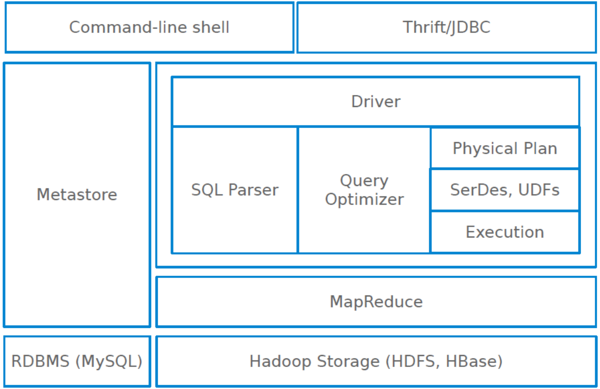
  1. Query parsing: transforms a query string to a parse tree representation.
  2. Logical plan generation: converts the internal query representation to a logical plan, and optimizes it.

Executing SQL Questions

- Processes HiveQL statements and generates the execution plan through three-phase processes.

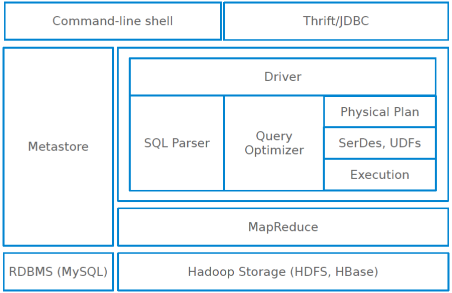
  1. Query parsing: transforms a query string to a parse tree representation.
  2. Logical plan generation: converts the internal query representation to a logical plan, and optimizes it.
  3. Physical plan generation: split the optimized logical plan into multiple map/reduce tasks.

Hive Architecure



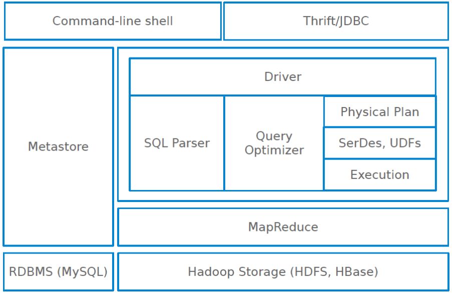
Hive Architecure - Driver

- Manages the life cycle of a HiveQL statement during compilation, optimization and execution.



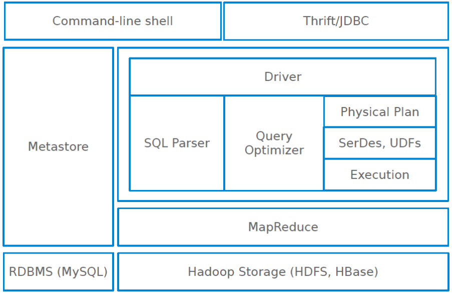
Hive Architecure - Compiler (Parser/Query Optimizer)

- Translates the HiveQL statement into a a logical plan and optimizes it.



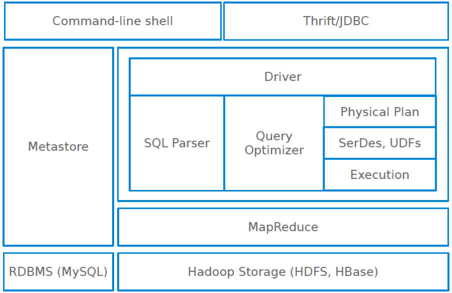
Hive Architecure - Physical Plan

- Transforms the logical plan into a DAG of Map/Reduce jobs.



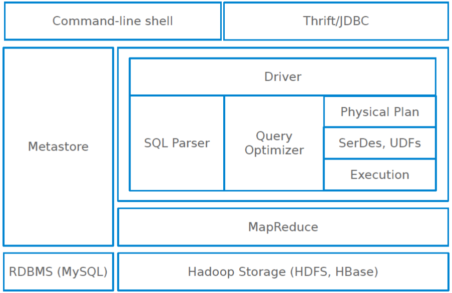
Hive Architecure - Execution Engine

- The driver submits the individual mapreduce jobs from the DAG to the execution engine in a topological order.



Hive Architecure - Metastore

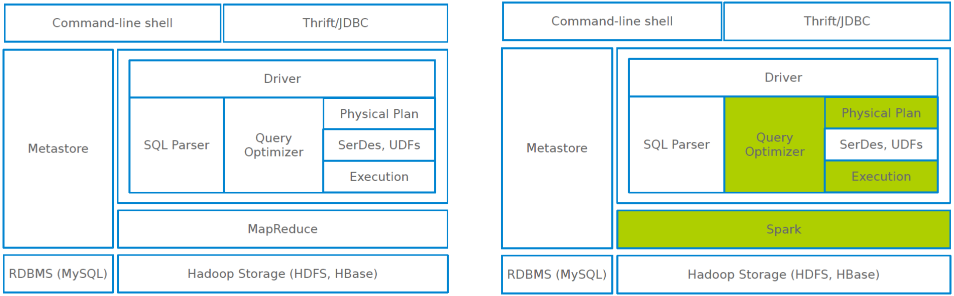
- Stores metadata about the tables.
- Metadata is specified during table creation and reused every time the table is referenced in HiveQL.
- Metadatas are stored on either a traditional relational database, e.g., MySQL, or file system and not HDFS.



Spark SQL

Shark

- Shark modified the Hive backend to run over Spark.



Shark and Hive In-Memory Store

- Caching Hive records as JVM objects is inefficient.
  - 12 to 16 bytes of overhead per object in JVM implementation:
- Shark employs column-oriented storage using arrays of primitive objects.

Row Storage Column Storage

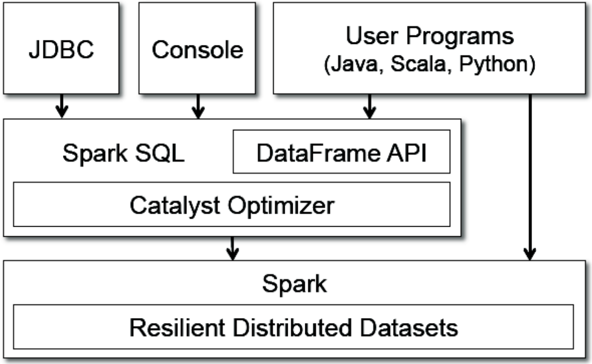
Shark Limitations

- Limited integration with Spark programs.
- Hive optimizer not designed for Spark.

From Shark to Spark SQL

- Borrows from Shark
  - Hive data loading
  - In-memory column store
- Adds by Spark
  - RDD-aware optimizer (catalyst optimizer)
  - Adds schema to RDD (DataFrame)
  - Rich language interfaces

Spark and Spark SQL



Structured Data vs. RDD (1/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`

Structured Data vs. RDD (1/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`
- `RDD[Account]`

Structured Data vs. RDD (1/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`
- `RDD[Account]`
- RDDs don't know anything about the schema of the data it's dealing with.

Structured Data vs. RDD (2/2)

- `case class Account(name: String, balance: Double, risk: Boolean)`
- `RDD[Account]`
- A database/Hive sees it as a columns of named and typed values.

name: String	balance: Double	risk: Boolean
name: String	balance: Double	risk: Boolean
name: String	balance: Double	risk: Boolean
name: String	balance: Double	risk: Boolean

DataFrames and DataSets

- Spark has two notions of structured collections:
  - DataFrames
  - Datasets
- They are distributed table-like collections with well-defined rows and columns.

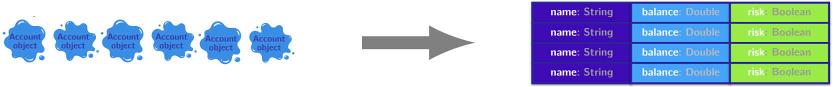
DataFrames and DataSets

- Spark has two notions of structured collections:
  - DataFrames
  - Datasets
- They are distributed table-like collections with well-defined rows and columns.
- They represent immutable lazily evaluated plans.
- When an action is performed on them, Spark performs the actual transformations and return the result.

DataFrame

DataFrame

- Consists of a series of rows and a number of columns.
- Equivalent to a table in a relational database.
- Spark + RDD: functional transformations on partitioned collections of objects.
- SQL + DataFrame: declarative transformations on partitioned collections of tuples.



Schema

- Defines the column names and types of a DataFrame.
- Assume `people.json` file as an input:

```
{"name":"Michael", "age":15, "id":12}
{"name":"Andy", "age":30, "id":15}
{"name":"Justin", "age":19, "id":20}
{"name":"Andy", "age":12, "id":15}
{"name":"Jim", "age":19, "id":20}
{"name":"Andy", "age":12, "id":10}
```

```
val people = spark.read.format("json").load("people.json")
people.schema

// returns:
StructType(StructField(age,LongType,true),
StructField(id,LongType,true),
StructField(name,StringType,true))
```

Column (1/2)

- They are like columns in a table.
- `col` returns a reference to a column.
- `expr` performs transformations on a column.
- `columns` returns all columns on a DataFrame

```
val people = spark.read.format("json").load("people.json")

col("age")

exp("age + 5 < 32")

people.columns
// returns:
Array[String] = Array(age, id, name)
```

Column (2/2)

- Different ways to refer to a column.

```
val people = spark.read.format("json").load("people.json")

people.col("name")

col("name")

column("name")

'name

$"name"

expr("name")
```

Row

- A row is a record of data.
- They are of type `Row`.
- Rows do not have schemas.
  - The order of values should be the same order as the schema of the DataFrame to which they might be appended.
- To accessing data in rows, you need to specify the position that you would like.

```
import org.apache.spark.sql.Row

val myRow = Row("Seif", 65, 0)

myRow(0) // type Any
myRow(0).asInstanceOf[String] // String
myRow.getString(0) // String
myRow.getInt(1) // Int
```

Creating a DataFrame

- Two ways to create a DataFrame:
  1. From an RDD
  2. From raw data sources

Creating a DataFrame - From an RDD (1/2)

- The schema automatically inferred.

Creating a DataFrame - From an RDD (1/2)

- The schema automatically inferred.
- You can use toDF to convert an RDD to DataFrame.

```
val tupleRDD = sc.parallelize(Array(("seif", 65, 0), ("amir", 40, 1)))
val tupleDF = tupleRDD.toDF("name", "age", "id")
```

Creating a DataFrame - From an RDD (1/2)

- The schema automatically inferred.
- You can use toDF to convert an RDD to DataFrame.

```
val tupleRDD = sc.parallelize(Array(("seif", 65, 0), ("amir", 40, 1))
val tupleDF = tupleRDD.toDF("name", "age", "id")
```

- If RDD contains case class instances, Spark infers the attributes from it.

```
case class Person(name: String, age: Int, id: Int)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleDF.toDF
```

Creating a DataFrame - From an RDD (2/2)

- Construct a schema and then apply it to an existing RDD.

Creating a DataFrame - From an RDD (2/2)

- Construct a schema and then apply it to an existing RDD.
  1. Create an RDD of `Row` from the original RDD.

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

// step 1
val myRows = Seq(Row("Seif", 65, 0))
val myRDD = spark.sparkContext.parallelize(myRows)

// step 2
val mySchema = new StructType(Array(new StructField("name", StringType, true),
  new StructField("age", IntegerType, false), new StructField("age", IntegerType, false)))

// step 3
val myDf = spark.createDataFrame(myRDD, mySchema)
```

Creating a DataFrame - From an RDD (2/2)

- Construct a schema and then apply it to an existing RDD.
  1. Create an RDD of `Row` from the original RDD.
  2. Create the schema (`StructType`) matching the structure of `Row` in Step 1.

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

// step 1
val myRows = Seq(Row("Seif", 65, 0))
val myRDD = spark.sparkContext.parallelize(myRows)

// step 2
val mySchema = new StructType(Array(new StructField("name", StringType, true),
  new StructField("age", IntegerType, false), new StructField("age", IntegerType, false)))

// step 3
val myDf = spark.createDataFrame(myRDD, mySchema)
```

Creating a DataFrame - From an RDD (2/2)

- Construct a schema and then apply it to an existing RDD.
  1. Create an RDD of `Row` from the original RDD.
  2. Create the schema (`StructType`) matching the structure of `Row` in Step 1.
  3. Apply the schema to the RDD of `Row` via `createDataFrame` method.

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

// step 1
val myRows = Seq(Row("Seif", 65, 0))
val myRDD = spark.sparkContext.parallelize(myRows)

// step 2
val mySchema = new StructType(Array(new StructField("name", StringType, true),
  new StructField("age", IntegerType, false), new StructField("age", IntegerType, false)))

// step 3
val myDf = spark.createDataFrame(myRDD, mySchema)
```

Creating a DataFrame - From Data Source

- Data sources supported by Spark.
  - CSV, JSON, Parquet, ORC, JDBC/ODBC connections, Plain-text files
  - Cassandra, HBase, MongoDB, AWS Redshift, XML, etc.

```
val peopleJson = spark.read.format("json").load("people.json")

val peopleCsv = spark.read.format("csv")
  .option("sep", ";")
  .option("inferSchema", "true")
  .option("header", "true")
  .load("people.csv")
```

Data Source (1/2)

- The foundation for reading data in Spark is the `DataFrameReader`.
  - We access this through the `SparkSession` via the `read` attribute: `spark.read`
- The foundation for writing DataFrame in Spark is the `DataFrameWriter`.
  - We access this the `write` attribute of a DataFrame.

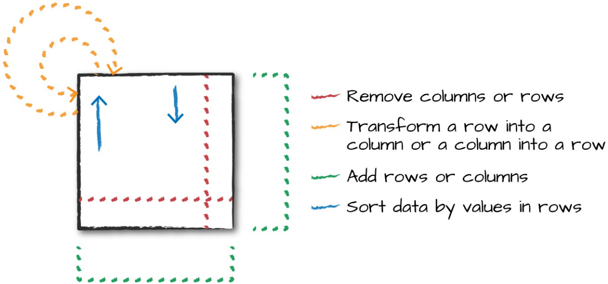
Data Source (2/2)

- After we have a DataFrame reader, we specify several values:
  - The format
  - The schema
  - The read mode
  - A series of option

```
// The core structure for reading data
DataFrameReader.format(...).option(...).schema(...).load()

// The core structure for writing data
DataFrameWriter.format(...).option(...).partitionBy(...).bucketBy(...).sortBy(...).save()

val df = spark.read.format("csv").option("mode", "FAILFAST").option("inferSchema", "true")
  .option("path", "path/to/file(s)").schema(someSchema).load()

df.write.format("csv").option("mode", "OVERWRITE").option("dateFormat", "yyyy-MM-dd")
  .option("path", "path/to/file(s)").save()
```

DataFrame Transformations (1/4)

- Add and remove rows or columns
- Transform a row into a column (or vice versa)
- Change the order of rows based on the values in columns



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

DataFrame Transformations (2/4)

- `select` and `selectExpr` allow to do the DataFrame equivalent of SQL queries on a table of data.

```
// select
people.select("name", "age", "id").show(2)
people.select(col("name"), expr("age + 3")).show()
people.select(expr("name AS username")).show(2)

// selectExpr
people.selectExpr("*", "(age < 20) as teenager").show()
people.selectExpr("avg(age)", "count(distinct(name))", "sum(id)").show()
```

DataFrame Transformations (3/4)

- `filter` and `where` both filter rows.
- `distinct` can be used to extract unique rows.

```
people.filter(col("age") < 20).show()

people.where("age < 20").show()

people.select("name").distinct().count()
```

DataFrame Transformations (4/4)

- `withColumn` adds a new column to a DataFrame.
- `withColumnRenamed` renames a column.
- `drop` removes a column.

```
// withColumn
people.withColumn("teenager", expr("age < 20")).show()

// withColumnRenamed
people.withColumnRenamed("name", "username").columns

// drop
people.drop("name").columns
```

DataFrame Actions

- Like RDDs, DataFrames also have their own set of actions.
- `collect`: returns an array that contains all of rows in this DataFrame.
- `count`: returns the number of rows in this DataFrame.
- `first` and `head`: returns the first row of the DataFrame.
- `show`: displays the top 20 rows of the DataFrame in a tabular form.
- `take`: returns the first n rows of the DataFrame.

Aggregation

Aggregation

- In an aggregation you specify
  - A key or grouping
  - An aggregation function
- The given function must produce one result for each group.

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Summarizing a Complete DataFrame Functions (1/2)

- count returns the total number of values.
- countDistinct returns the number of unique groups.
- first and last return the first and last value of a DataFrame.

```
val people = spark.read.format("json").load("people.json")

people.select(count("age")).show()

people.select(countDistinct("name")).show()

people.select(first("name"), last("age")).show()
```

Summarizing a Complete DataFrame Functions (2/2)

- `min` and `max` extract the minimum and maximum values from a DataFrame.
- `sum` adds all the values in a column.
- `avg` calculates the average.

```
val people = spark.read.format("json").load("people.json")

people.select(min("name"), max("age"), max("id")).show()

people.select(sum("age")).show()

people.select(avg("age")).show()
```

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Group By (1/3)

- Perform aggregations on groups in the data.
- Typically on categorical data.
- We do this grouping in two phases:
  1. Specify the column(s) on which we would like to group.
  2. Specify the aggregation(s).

Group By (2/3)

- Grouping with expressions
  - Rather than passing that function as an expression into a `select` statement, we specify it as within agg.

```
val people = spark.read.format("json").load("people.json")

people.groupBy("name").agg(count("age").alias("ageagg")).show()
```

Group By (3/3)

- Grouping with Maps
  - Specify transformations as a series of Maps
  - The key is the column, and the value is the aggregation function (as a string).

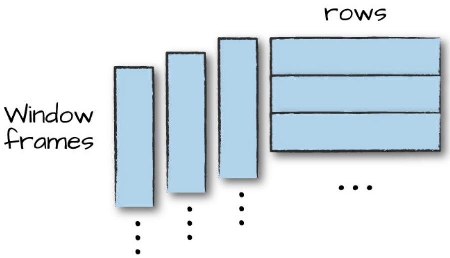
```
val people = spark.read.format("json").load("people.json")

people.groupBy("name").agg("age" -> "count", "age" -> "avg", "id" -> "max").show()
```

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Windowing (1/2)

- Computing some aggregation on a specific window of data.
- The window determines which rows will be passed in to this function.
- You define them by using a reference to the current data.
- A group of rows is called a frame.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Windowing (2/2)

- Unlike grouping, here each row can fall into one or more frames.

```
import org.apache.spark.sql.expressions.Window
import org.apache.spark.sql.functions.col

val people = spark.read.format("json").load("people.json")

val windowSpec = Window.rowsBetween(-1, 1)
val avgAge = avg(col("age")).over(windowSpec)
people.select(col("name"), col("age"), avgAge.alias("avg_age")).show
```

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Cube

- Set our grouping keys on multiple columns.
- Apply aggregate expressions to all possible combinations of the grouping columns.

```
val people = spark.read.format("json").load("people.json")
val rolledUpDF = people.cube("name", "id").agg(sum("age")).orderBy("name")
rolledUpDF.show
```

Grouping Types

- Summarizing a complete DataFrame
- Group by
- Windowing
- Cube
- Rollup

Rollup

- Similar to cube, but computes hierarchical subtotals from left to right.

```
val people = spark.read.format("json").load("people.json")
val rolledUpDF = people.rollup("name", "id").agg(sum("age")).orderBy("name")
rolledUpDF.show
```

Joins

Joins

- A join goes throught the following steps:
  - Compares the value of one or more keys of the left and right datasets.
  - Evaluates the result of a join expression.
  - Determines whether Spark should bring together the left set of data with the right set of data.
- Different join types: inner join, outer join, left outer join, right outer join, left semi join, left anti join, cross join

Joins Example

```
val person = Seq(
  (0, "Seif", 0),
  (1, "Amir", 1),
  (2, "Sarunas", 1))
  .toDF("id", "name", "group_id")

val group = Seq(
  (0, "SICS/KTH"),
  (1, "KTH"),
  (2, "SICS"))
  .toDF("id", "department")
```

Joins Example - Inner

```scala
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "inner"

person.join(group, joinExpression, joinType).show()
```

```
+---+-------+--------+---+----------+
| id|   name|group_id| id|department|
+---+-------+--------+---+----------+
|  0|   Seif|       0|  0|  SICS/KTH|
|  1|   Amir|       1|  1|       KTH|
|  2|Sarunas|       1|  1|       KTH|
+---+-------+--------+---+----------+
```

Joins Example - Outer

```
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "outer"

person.join(group, joinExpression, joinType).show()
```

```
+----+-------+--------+---+----------+
|  id|   name|group_id| id|department|
+----+-------+--------+---+----------+
|   1|   Amir|       1|  1|       KTH|
|   2|Sarunas|       1|  1|       KTH|
|null|   null|    null|  2|      SICS|
|   0|   Seif|       0|  0|  SICS/KTH|
+----+-------+--------+---+----------+
```

Joins Example - Right Outer

```scala
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "right_outer"

person.join(group, joinExpression, joinType).show()
```

```
+----+-------+--------+---+----------+
|  id|   name|group_id| id|department|
+----+-------+--------+---+----------+
|   0|   Seif|       0|  0|  SICS/KTH|
|   2|Sarunas|       1|  1|       KTH|
|   1|   Amir|       1|  1|       KTH|
|null|   null|    null|  2|      SICS|
+----+-------+--------+---+----------+
```

Joins Example - Left Semi

```scala
val joinExpression = person.col("group_id") === group.col("id")

var joinType = "left_semi"

person.join(group, joinExpression, joinType).show()
```

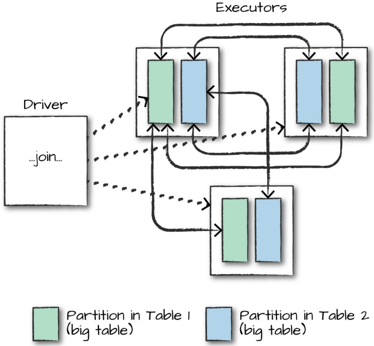
```
+---+-------+--------+
| id|   name|group_id|
+---+-------+--------+
|  0|   Seif|       0|
|  1|   Amir|       1|
|  2|Sarunas|       1|
+---+-------+--------+
```

Joins Communication Strategies

- Two different communication ways during joins:
  - Shuffle join: big table to big table
  - Broadcast join: big table to small table

Shuffle Join

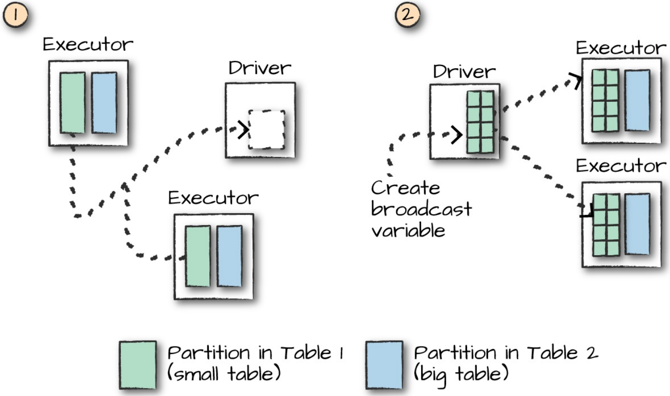
- Every node talks to every other node.
- They share data according to which node has a certain key or set of keys.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Broadcast Join

- When the table is small enough to fit into the memory of a single worker node.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

SQL

SQL

- You can run SQL queries on views/tables via the method `sql` on the `SparkSession` object.

```
spark.sql("SELECT * from people_view").show()
```

```
+---+---+-------+
|age| id|   name|
+---+---+-------+
| 15| 12|Michael|
| 30| 15|   Andy|
| 19| 20| Justin|
| 12| 15|   Andy|
| 19| 20|    Jim|
| 12| 10|   Andy|
+---+---+-------+
```

Temporary View

- `createOrReplaceTempView` creates (or replaces) a lazily evaluated view.
- You can use it like a table in Spark SQL.
- It does not persist to memory unless you cache it.

```
people.createOrReplaceTempView("people_view")

val teenagersDF = spark.sql("SELECT name, age FROM people_view WHERE age BETWEEN 13 AND 19")
```

DataSet

Untyped API with DataFrame

- DataFrames elements are `Row`s, which are generic untyped JVM objects.
- Scala compiler cannot type check Spark SQL schemas in DataFrames.

Untyped API with DataFrame

- DataFrames elements are `Rows`, which are generic untyped JVM objects.
- Scala compiler cannot type check Spark SQL schemas in DataFrames.
- The following code compiles, but you get a runtime exception.
  - `id_num` is not in the DataFrame columns `[name, age, id]`

```
// people columns: ("name", "age", "id")
val people = spark.read.format("json").load("people.json")

people.filter("id_num < 20") // runtime exception
```

Why DataSet?

- Assume the following example

```
case class Person(name: String, age: BigInt, id: BigInt)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleRDD.toDF
```

Why DataSet?

- Assume the following example

```
case class Person(name: String, age: BigInt, id: BigInt)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleRDD.toDF
```

- Now, let's use `collect` to bring back it to the master.

```
val collectedPeople = peopleDF.collect()
// collectedPeople: Array[org.apache.spark.sql.Row]
```

Why DataSet?

- Assume the following example

```scala
case class Person(name: String, age: BigInt, id: BigInt)
val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleRDD.toDF
```

- Now, let's use `collect` to bring back it to the master.

```scala
val collectedPeople = peopleDF.collect()
// collectedPeople: Array[org.apache.spark.sql.Row]
```

- What is in `Row`?

Why DataSet?

- To be able to work with the collected values, we should cast the `Row`s.
  - How many columns?
  - What types?

```scala
// Person(name: Sting, age: BigInt, id: BigInt)

val collectedList = collectedPeople.map {
  row => (row(0).asInstanceOf[String], row(1).asInstanceOf[Int], row(2).asInstanceOf[Int])
}
```

Why DataSet?

- To be able to work with the collected values, we should cast the Rows.
  - How many columns?
  - What types?

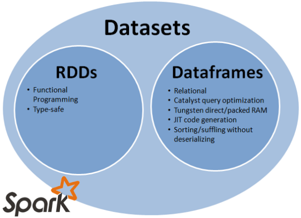
```
// Person(name: Sting, age: BigInt, id: BigInt)

val collectedList = collectedPeople.map {
  row => (row(0).asInstanceOf[String], row(1).asInstanceOf[Int], row(2).asInstanceOf[Int])
}
```

- But, what if we cast the types wrong?
- Wouldn't it be nice if we could have both Spark SQL optimizations and typesafety?

DataSet

- Datasets can be thought of as typed distributed collections of data.
- Dataset API unifies the DataFrame and RDD APIs.
- You can consider a `DataFrame` as an alias for `Dataset[Row]`, where a `Row` is a generic untyped JVM object.

```
type DataFrame = Dataset[Row]
```



[http://why-not-learn-something.blogspot.com/2016/07/apache-spark-rdd-vs-dataframe-vs-dataset.html]

Creating DataSets

- To convert a sequence or an RDD to a Dataset, we can use `toDS()`.
- You can call `as[SomeCaseClass]` to convert the DataFrame to a Dataset.

```scala
case class Person(name: String, age: BigInt, id: BigInt)

val personSeq = Seq(Person("Max", 33, 0), Person("Adam", 32, 1))

val ds1 = personSeq.toDS()

val ds2 = sc.parallelize(personSeq).toDS

val ds3 = spark.read.format("json").load("people.json").as[Person]
```

DataSet Transformations

- Transformations on Datasets are the same as those that we had on DataFrames.
- Datasets allow us to specify more complex and strongly typed transformations.

```scala
case class Person(name: String, age: BigInt, id: BigInt)

val people = spark.read.format("json").load("people.json").as[Person]

people.filter(x => x.age < 40).show()

people.map(x => (x.name, x.age + 5, x.id)).show()
```

DataSet Grouping and Aggregation (1/2)

- Call groupByKey on a Dataset (returns KeyValueGroupedDataset).
    - Aggregation on KeyValueGroupedDataset returns Dataset.
- Call groupBy on a Dataset (returns RelationalGroupedDataset).
    - Aggregation on RelationalGroupedDataset returns DataFrame.

```
case class Person(name: String, age: BigInt, id: BigInt)

val people = spark.read.format("json").load("people.json").as[Person]

people.groupByKey(x => x.name).count().show()

people.groupBy("name").count().show()
```

DataSet Grouping and Aggregation (2/2)

- mapGroups and flatMapGroups are KeyValueGroupedDataset's transformations.
- They apply the given function to each group of data.

```
case class Person(name: String, age: BigInt, id: BigInt)

val people = spark.read.format("json").load("people.json").as[Person]

def grpSum(personName: String, values: Iterator[Person]) = {
  values.filter(_.age > 15).map(x => (personName, x))
}

people.groupByKey(x => x.name).flatMapGroups(grpSum).show()
```

DataSet Joins

- Joins are the same as in DataFrames, using the joinWith method.

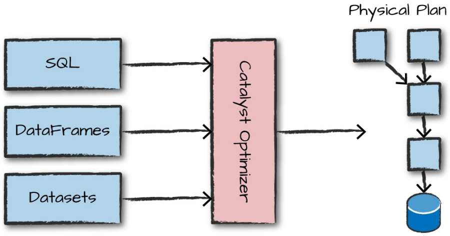
```
case class Person(name: String, gid: Int, pid: Int)
case class Group(gid: Int, name: String)
val personDS = sc.parallelize(Seq(Person("Seif", 0, 0), Person("Amir", 1, 1),
  Person("Sarunas", 1, 2))).toDS()
val groupDS = sc.parallelize(Seq(Group(0, "SICS/KTH"), Group(1, "KTH"),
  Group(2, "SICS"))).toDS()
val joinExpression = personDS.col("gid") === groupDS.col("gid")
val joinDS = personDS.joinWith(groupDS, joinExpression, "inner").show()
```

```
+--------------+-------------+
|            _1|           _2|
+--------------+-------------+
|   [Amir, 1, 1]|      [1, KTH]|
|[Sarunas, 1, 2]|      [1, KTH]|
|   [Seif, 0, 0]|[0, SICS/KTH]|
+--------------+-------------+
```

Structured Data Execution

Structured Data Execution Steps

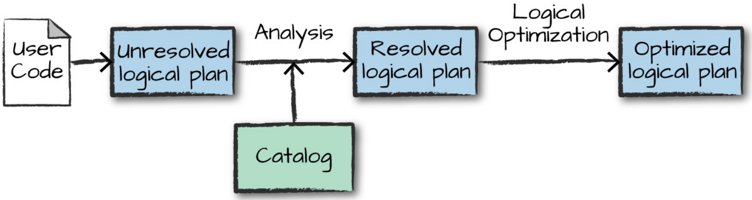
- 1. Write DataFrame/Dataset/SQL Code.
- 2. If valid code, Spark converts this to a logical plan.
- 3. Spark transforms this logical plan to a Physical Plan
  - Checking for optimizations along the way.
- 4. Spark then executes this physical plan (RDD manipulations) on the cluster.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Logical Planning (1/2)

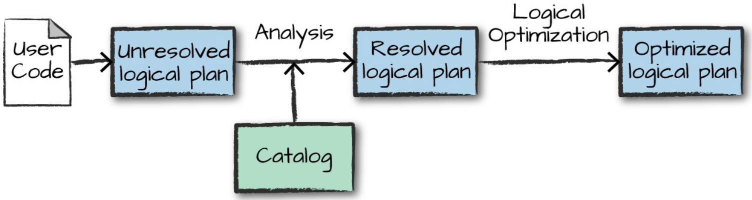
- The logical plan represents a set of abstract transformations.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Logical Planning (1/2)

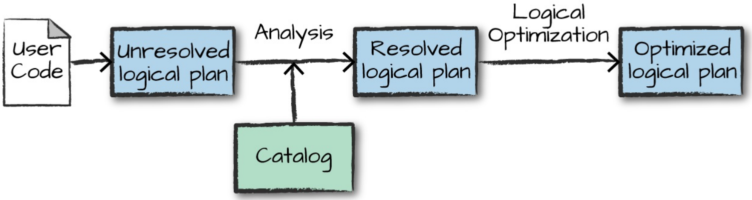
- The logical plan represents a set of abstract transformations.
- This plan is unresolved.
  - The code might be valid, the tables/columns that it refers to might not exist.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Logical Planning (1/2)

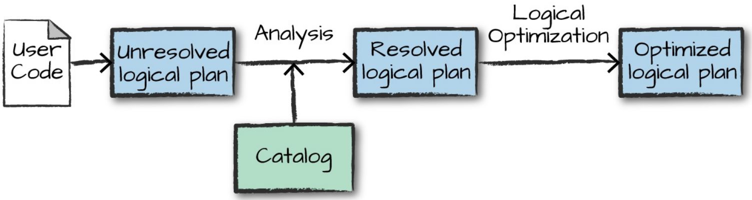
- The logical plan represents a set of abstract transformations.
- This plan is unresolved.
  - The code might be valid, the tables/columns that it refers to might not exist.
- Spark uses the catalog, a repository of all table and DataFrame information, to resolve columns and tables in the analyzer.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Logical Planning (2/2)

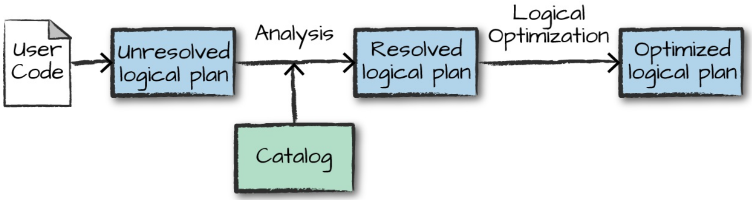
- The analyzer might **reject** the unresolved logical plan.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Logical Planning (2/2)

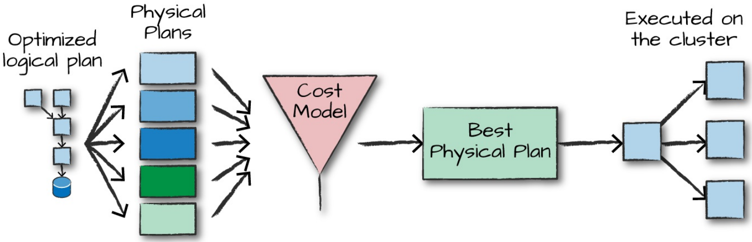
- The analyzer might reject the unresolved logical plan.
- If the analyzer can resolve it, the result is passed through the Catalyst optimizer.
- It converts the user's set of expressions into the most optimized version.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Physical Planning (1/2)

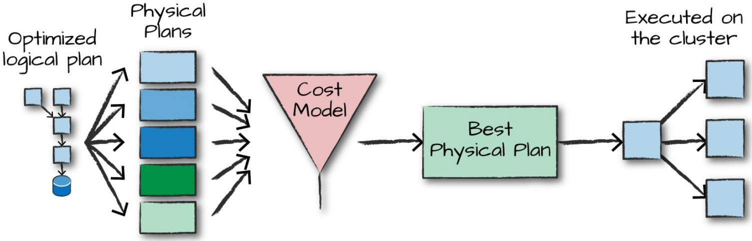
- The physical plan specifies how the logical plan will execute on the cluster.
- Physical planning results in a series of RDDs and transformations.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Physical Planning (2/2)

- Generats different physical execution strategies and compars them through a cost model.
  - E.g., Choosing how to perform a given join by looking at how big the table is or how big its partitions are.



[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Execution

- Upon selecting a physical plan, Spark runs all of this code over RDDs.
- Spark performs further optimizations at runtime.
- Finally the result is returned to the user.

Optimization

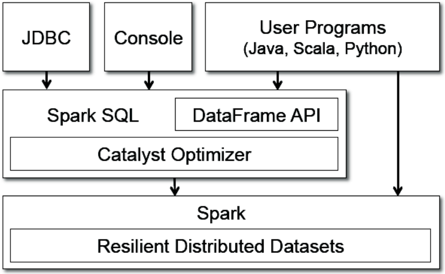
Optimization

- Spark SQL comes with two specialized backend components:
  - Catalyst: a query optimizer
  - Tungsten: off-heap serializer

Catalyst Optimizer

Catalyst Optimizer

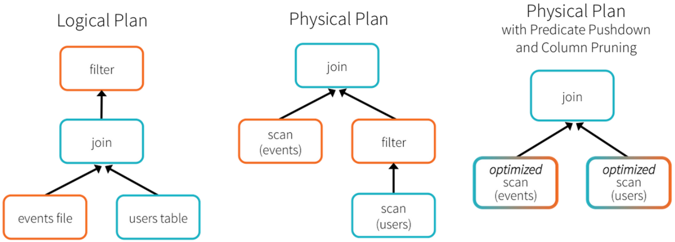
- Catalyst is Spark SQL query optimizer.
- It compiles Spark SQL queries to RDDs and transformations.
- Optimization includes
  - Reordering operations
  - Reduce the amount of data we must read
  - Pruning unneed partitioning



Catalyst Optimizer - Logical Optimization (1/5)

- Applies standard rule-based optimizations to the logical plan.

```
val users = sqlContext.read.parquet("...")
val events = sqlContext.read.parquet("...")
val joined = events.join(users, ...)
val result = joined.select(...)
```



Catalyst Optimizer - Logical Optimization (2/5)

- Null propagation and constant folding
  - Replace expressions that can be evaluated with some literal value to the value.
  - `1 + null` $\Rightarrow$ `null`
  - `1 + 2` $\Rightarrow$ `3`

Catalyst Optimizer - Logical Optimization (2/5)

- Null propagation and constant folding
  - Replace expressions that can be evaluated with some literal value to the value.
  - `1 + null` $\Rightarrow$ `null`
  - `1 + 2` $\Rightarrow$ `3`
- Boolean simplification
  - Simplifies boolean expressions that can be determined.
  - `false AND x` $\Rightarrow$ `false`
  - `true AND x` $\Rightarrow$ `x`
  - `true OR x` $\Rightarrow$ `true`
  - `false OR x` $\Rightarrow$ `x`

Catalyst Optimizer - Logical Optimization (3/5)

- Simplify filters
  - Removes filters that can be evaluated trivially.
  - `Filter(true, child)` $\Rightarrow$ `child`
  - `Filter(false, child)` $\Rightarrow$ `empty`

Catalyst Optimizer - Logical Optimization (3/5)

- Simplify filters
  - Removes filters that can be evaluated trivially.
  - `Filter(true, child)` $\Rightarrow$ `child`
  - `Filter(false, child)` $\Rightarrow$ `empty`
- Combine filters
  - Merges two filters.
  - `Filter($fc, Filter($nc, child))`
    $\Rightarrow$
    `Filter(AND($fc, $nc), child)`

Catalyst Optimizer - Logical Optimization (4/5)

- Push predicate through project
  - Pushes filter operators through project operator.
  - `Filter(i == 1, Project(i, j, child))`
    $\Rightarrow$
    `Project(i, j, Filter(i == 1, child))`

Catalyst Optimizer - Logical Optimization (4/5)

- Push predicate through project
  - Pushes filter operators through project operator.
  - `Filter(i == 1, Project(i, j, child))`
    $\Rightarrow$
    `Project(i, j, Filter(i == 1, child))`
- Push predicate through join
  - Pushes filter operators through join operator.
  - `Filter("left.i".attr == 1, Join(left, right))`
    $\Rightarrow$
    `Join(Filter(i == 1, left), right)`

Catalyst Optimizer - Logical Optimization (5/5)

- Column pruning
  - Eliminates the reading of unused columns.
  - `Join(left, right, LeftSemi, "left.id".attr == "right.id".attr)`
    $\Rightarrow$
    `Join(left, Project(id, right), LeftSemi)`

Tungsten

Tungsten

- Spark workloads are increasingly bottlenecked by CPU and memory use rather than IO and network communication.

- Tungsten improves the memory and CPU efficiency of Spark backend execution and push performance closer to the limits of modern hardware.

- It provides
  - Highly-specialized data encoders
  - Column-based datastore
  - Off-heap memory management

Tungsten - Data Encoder

- Tungsten can take schema information and tightly pack serialized data into memory.
- More data can fit in memory.
- We have faster serialization and deserialization.

Tungsten - Column-Based

- Most table operations are on specific columns/attributes of a dataset.
- To store data, group them by column, instead of row.
- Faster lookup of data associated with specific column/attribute.

Row Storage   Column Storage

Tungsten - Off-Heap

- Perform manual memory management instead of relying on Java objects.
- Eliminate garbage collection overheads.
- Use `java.unsafe` and off heap memory.

Summary

Summary

- RDD: a distributed memory abstraction
- Two types of operations: transformations and actions
- Lineage graph
- DataFrame: structured processing
- Logical and physical plans
- Catalyst optmizer
- Tungsten project

References

- M. Zaharia et al., "Spark: The Definitive Guide", O'Reilly Media, 2018 - Chapters 4-11.
- M. Armbrust et al., "Spark SQL: Relational data processing in spark", ACM SIGMOD, 2015.

- Some slides were derived from Heather Miller's slides: `http://heather.miller.am/teaching/cs4240/spring2018`

Questions?