2. SPARK SQL

Apache Spark - December 2021

EDEM
Escuela de Empresarios

1. Introduction to Spark SQL
2. DataFrame & Datasets
3. Spark SQL. Applications
4. Windows Partitioning
5. Catalyst
6. Joins in Spark SQL
7. Cost-Based Optimizer
8. Spark 3 Improvements
9. Caching

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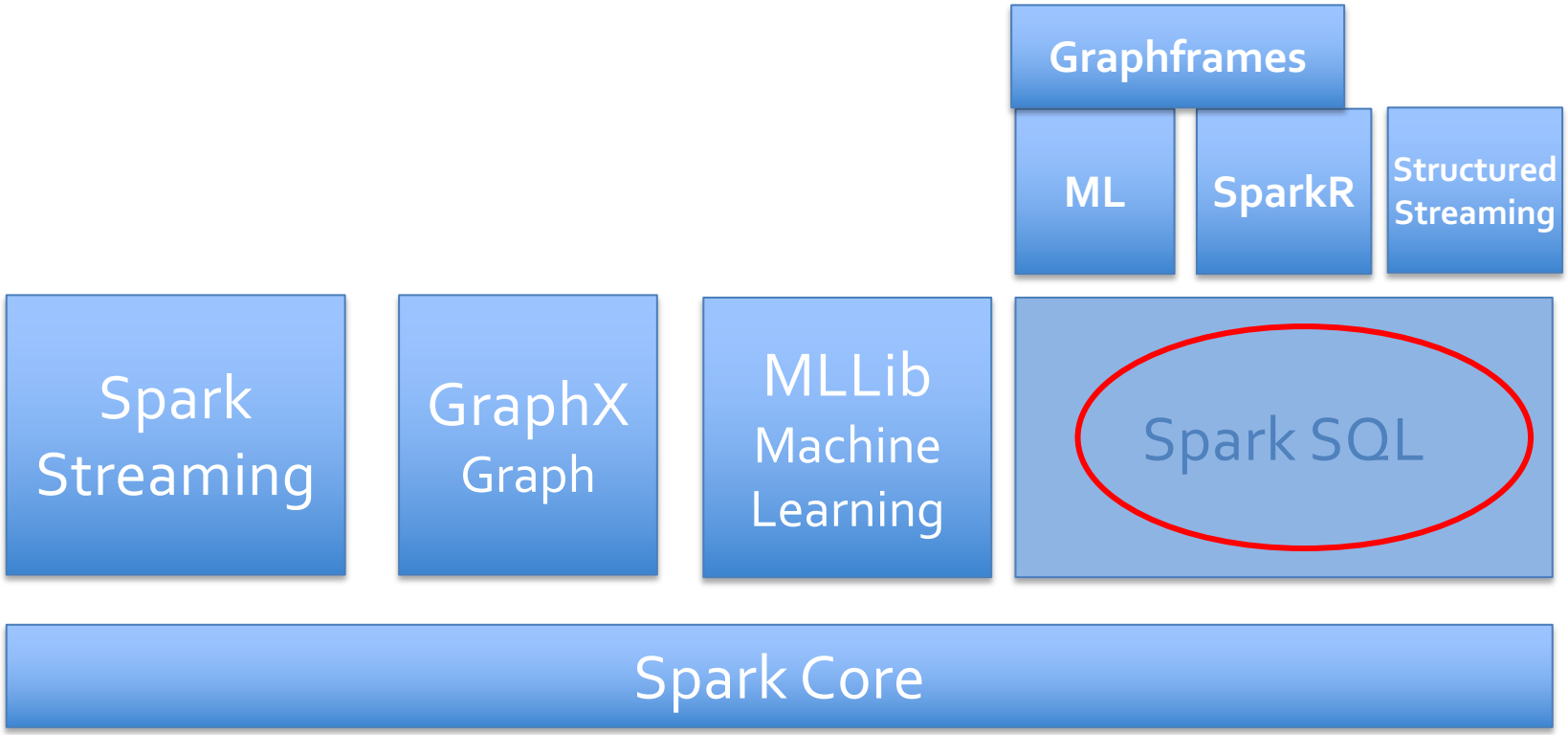
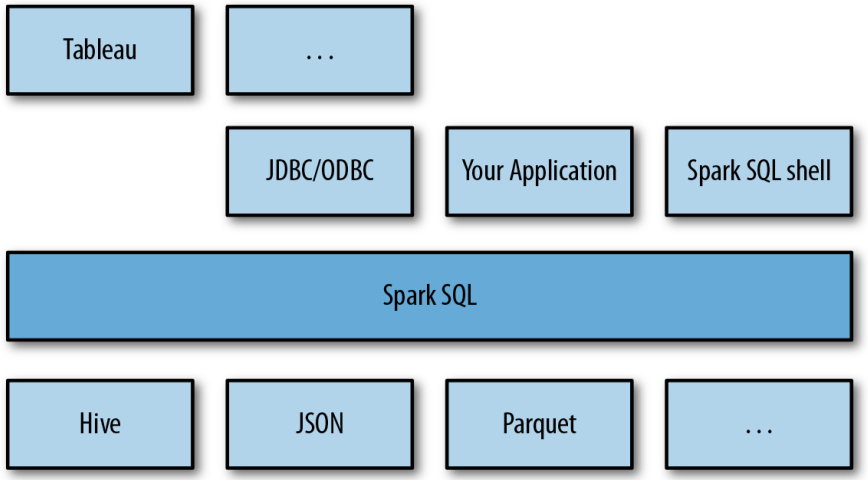
Introduction to Spark SQL

- **Spark SQL** was first released in Spark 1.0 (May, 2014)
- Initial committed by Michael Armbrust & Reynold Xin from **Databricks**



Introduction to Spark SQL

- Interface for working with structured (schema) and semi-structured data
- Spark SQL applies structured views to data stored in different formats
- Three main capabilities:
  - DataFrame abstraction for structured datasets.
    - Similar to tables in Relational database.
  - Read & write in **structured formats** (JSON, Hive, Parquet,…)
  - Query data using SQL inside Spark program & from external tools using JDBC/ODBC



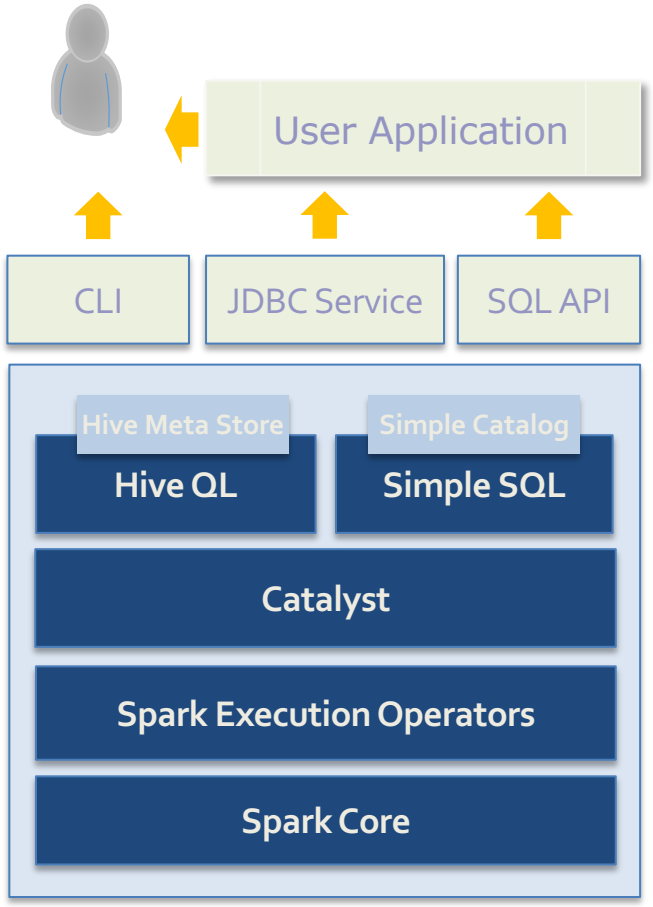
Introduction to Spark SQL

- Mix SQL queries with Spark programs
  - Process structured data (SQL tables, JSON files) as RDDs
- Load and query data from a variety of sources
  - Apache Hive tables
  - Parquet files
  - JSON files
  - Cassandra column families
- Run unmodified Hive queries
  - Reuses the Hive metastore, data, queries, SerDes and UDFs
- Connect through JDBC or ODBC
  - Spark SQL includes a server mode
  - Use BI tools

Component Stack

From a user perspective, Spark SQL:

- Hive-like interface(JDBC Service / CLI)
- SQL API support (LINQ-like)
- Both HiveQL & Simple SQL dialects are Supported
- DDL is 100% compatible with Hive Metastore
- HiveQL aims to 100% compatible with Hive DML
- Simple SQL dialect is now very weak in functionality, but easy to extend



Spark SQL – Hive Integration

- Spark SQL supports reading and writing data store in Hive
- Accessing to Hive UDFs (Hive installation not required)

```
SparkSession.builder().enableHiveSupport().getOrCreate()
```

- It´s necessary to add *spark-hive* dependency

```
libraryDependencies ++= Seq(
        “org.apache.spark” %% “spark-sql” % sparkVersion
        “org.apache.spark” %% “spark-hive” % sparkVersion)
```

- The default Hive Metastore version is 1.2.1.

```
// Create a Hive managed Parquet table, with HQL syntax instead of the Spark SQL native syntax
// `USING hive`
sql("CREATE TABLE hive_records(key int, value string) STORED AS PARQUET")
```

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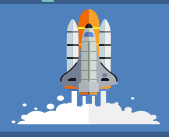
2. DataFrame & Datasets 
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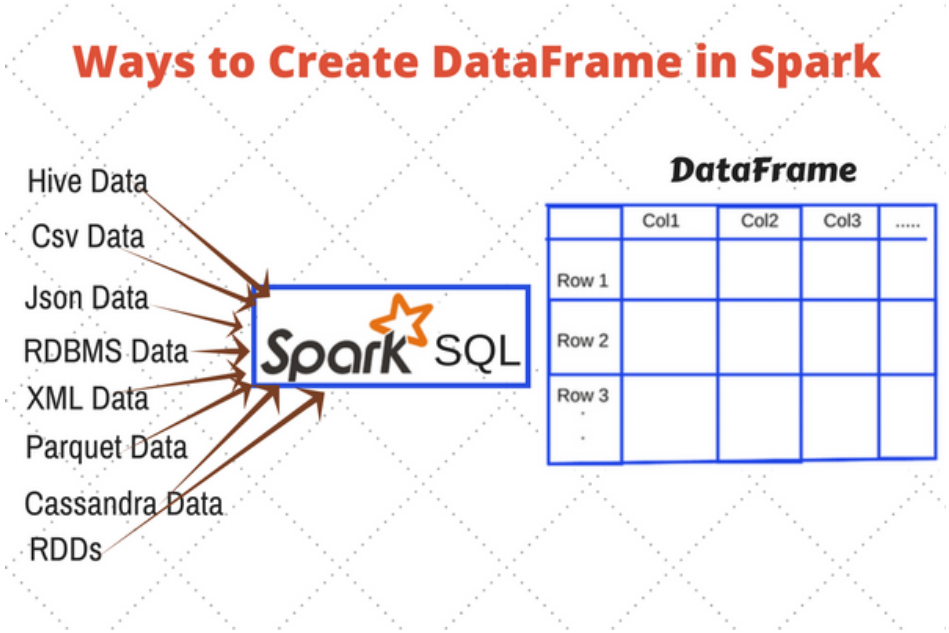
DataFrames & Datasets

- Represent distributed collections (like RDDs)
- **Adding schema** information not found in RDDs
- More **efficient** storage layer (Tungsten)
- Provide **new operations** and can run SQL queries
- Creation from:
  - External data sources
  - Result of queries
  - Regular RDDs
  - …



History of Spark APIs

Distribute collection of JVM objects

Functional Operators (map, filter, etc.)

Distribute collection of Row objects

Expression-based operations and UDFs

Logical plans and optimizer

Fast/efficient internal representations

Internally rows, externally JVM objects

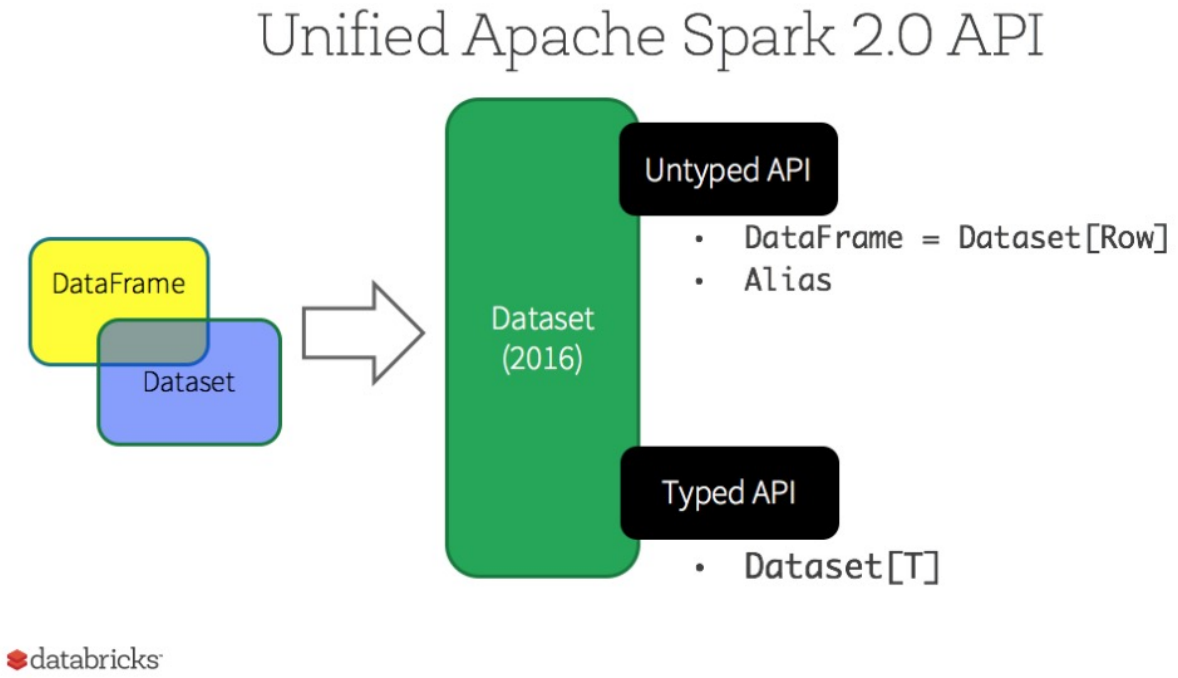
Almost the "Best of both worlds": type safe + fast

But slower than DF
Not as good for interactive analysis, especially Python

databricks

DataFrames & Datasets

- Starting in Spark 2.0, DataFrames and Datasets were unified



DataFrame in PySpark

```
1 fifa_df = spark.read.csv("path-of-file/fifa_players.csv", inferSchema = True, header = True)
2
3 fifa_df.show()
```

```
+-------+-------+-------------+--------------------+-------+-----------------+--------+---------+
|RoundID|MatchID|Team Initials|         Coach Name|Line-up|      Player Name|Position|    Event|
+-------+-------+-------------+--------------------+-------+-----------------+--------+---------+
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|      Alex THEPOT|      GK|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|  Oscar BONFIGLIO|      GK|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S| Marcel LANGILLER|    null|     G40'|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|     Juan CARRENO|    null|     G70'|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|  Ernest LIBERATI|    null|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|     Rafael GARZA|       C|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|  Andre MASCHINOT|    null|G43' G87'|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|    Hilario LOPEZ|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|  Etienne MATTLER|    null|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|   Dionisio MEJIA|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|     Marcel PINEL|    null|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|     Felipe ROSAS|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|  Alex VILLAPLANE|       C|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|     Manuel ROSAS|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|   Lucien LAURENT|    null|     G19'|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|         Jose RUIZ|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|   Marcel CAPELLE|    null|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|  Alfredo SANCHEZ|    null|     null|
|    201|   1096|          FRA|CAUDRON Raoul (FRA)|      S|Augustin CHANTREL|    null|     null|
|    201|   1096|          MEX|   LUQUE Juan (MEX)|      S|   Efrain AMEZCUA|    null|     null|
+-------+-------+-------------+--------------------+-------+-----------------+--------+---------+
only showing top 20 rows
```

DataFrame in PySpark

```
1 fifa_df.printSchema()
```

```
root
 |-- RoundID: integer (nullable = true)
 |-- MatchID: integer (nullable = true)
 |-- Team Initials: string (nullable = true)
 |-- Coach Name: string (nullable = true)
 |-- Line-up: string (nullable = true)
 |-- Player Name: string (nullable = true)
 |-- Position: string (nullable = true)
 |-- Event: string (nullable = true)
```

DataFrames & Datasets

- DataFrames are Datasets of a special **Row object**
- **Row** is a generic untyped JVM object
- Dataset is a collection of strongly-typed JVM
- Python doesn´t support Spark Datasets

```
> case class Person(name: String, age: Int)

  val personDS = Seq(Person("Max", 33), Person("Adam", 32), Person("Muller", 62)).toDS()
  personDS.show()

+------+---+
|  name|age|
+------+---+
|   Max| 33|
|  Adam| 32|
|Muller| 62|
+------+---+
```

DataFrames & Datasets

- DataFrame

```
data.groupBy( “dept”)).avg(“age”)
```

- SQL

```
spark.sql(“select dept, avg(age) from data group by dept”)
```

- RDD

```
data.map {  case (dept, age) => dept -> (age,1) }
        .reduceByKey {  case ( (a1, c1), (a2, c2) ) => (a1 + a2, c1 + c2) }
        .map{ case (dept, (age, c)) => dept -> age/ c }
```

Spark SQL – DataFrames – Datasets

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

Hands-on

- Open "01.Spark_SQL.ipynb" in Google Colab:
  - Execute examples 1 and 2

Dataset Example in Scala

- You can simply call **.toDS()** on a sequence to convert the sequence to a Dataset

```
> val dataset = Seq(1, 2, 3).toDS()
  dataset.show()

+-----+
|value|
+-----+
|    1|
|    2|
|    3|
+-----+
```

Dataset Example in Scala

- *Encoders are also created for case classes -similar to a DTO pattern*

```
> case class Person(name: String, age: Int)

  val personDS = Seq(Person("Max", 33), Person("Adam", 32), Person("Muller", 62)).toDS()
  personDS.show()
```

```
+------+---+
|  name|age|
+------+---+
|   Max| 33|
|  Adam| 32|
|Muller| 62|
+------+---+
```

Dataset Example in Scala

- *Create Dataset from a RDD*
  - *Use rdd.toDS()*

```
> val rdd = sc.parallelize(Seq((1, "Spark"), (2, "Databricks")))
  val integerDS = rdd.toDS()
  integerDS.show()
```

```
+---+----------+
| _1|        _2|
+---+----------+
|  1|     Spark|
|  2|Databricks|
+---+----------+
```

Dataset Example in Scala

- *Create Dataset from a DataFrame*
  - *Use df.as[SomeCaseClass]*

```
> case class Company(name: String, foundingYear: Int, numEmployees: Int)
  val inputSeq = Seq(Company("ABC", 1998, 310), Company("XYZ", 1983, 904), Company("NOP", 2005, 83))
  val df = sc.parallelize(inputSeq).toDF()

  val companyDS = df.as[Company]
  companyDS.show()
```

```
+----+------------+------------+
|name|foundingYear|numEmployees|
+----+------------+------------+
| ABC|        1998|         310|
| XYZ|        1983|         904|
| NOP|        2005|          83|
+----+------------+------------+
```

Hands-on

- Open "01.Spark_SQL.ipynb" in Google Colab:
  - Try the exercises 1, 2, 3 and 4

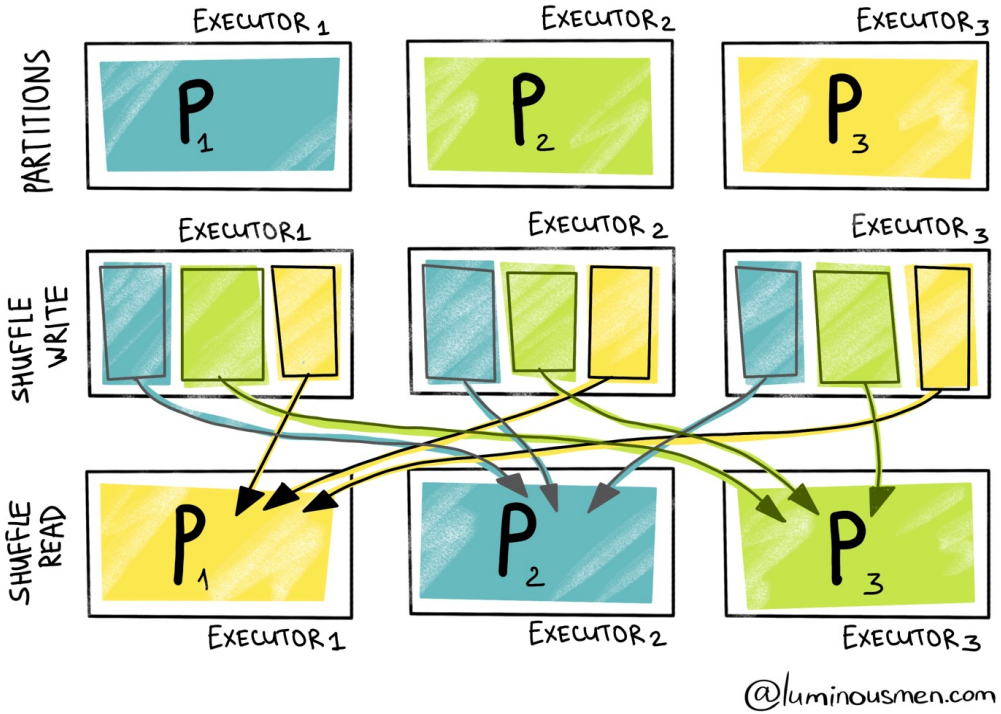
DataFrame – Run SQL directly on files

- Instead of using read API to load a file into DataFrame and query it, you can also query that file directly with SQL

```
df = spark.sql("SELECT * FROM parquet.`./resources/users.parquet`")
```

DataFrame Partitioning

- Data Partitioning is **critical** to data processing, especially for large volumen of data
- Spark assigns **one task for each partition**
  - Few partitions, application won't utilize all cores
  - Too many partitions → Overhead



Repartition vs Coalesce

- Repartition can be used to either increase and decrease the number of partitions
  - It's a full shuffle operation
  - Partitions equally distributed

```
val new_df = df.repartition(100)
val new_df = df.repartition(100, $"id")
```

- Coalesce reduces the number of partitions.
  - Avoids shuffle

```
val new_df = df.coalesce(10)
```

Repartition vs Coalesce

Repartitioning	Coalesce
19M repartition/part-00000	
19M repartition/part-00001	
19M repartition/part-00002	33M coalesce/part-00000
19M repartition/part-00003	29M coalesce/part-00001
19M repartition/part-00004	30M coalesce/part-00002
19M repartition/part-00005	31M coalesce/part-00003
19M repartition/part-00006	32M coalesce/part-00004
19M repartition/part-00007	33M coalesce/part-00005
19M repartition/part-00008	
19M repartition/part-00009	

Data Skew

- Repartition data on a more evenly distributed key if you have such.
- Broadcast the smaller DataFrame if possible
- Split data into skewed and non-skewed data and work with them in parallel by redistributing skewed data (differential replication)
- Use an additional random key for better distribution of the data(salting).
- Iterative broadcast join
- More complicated methods that I have never used in my life.

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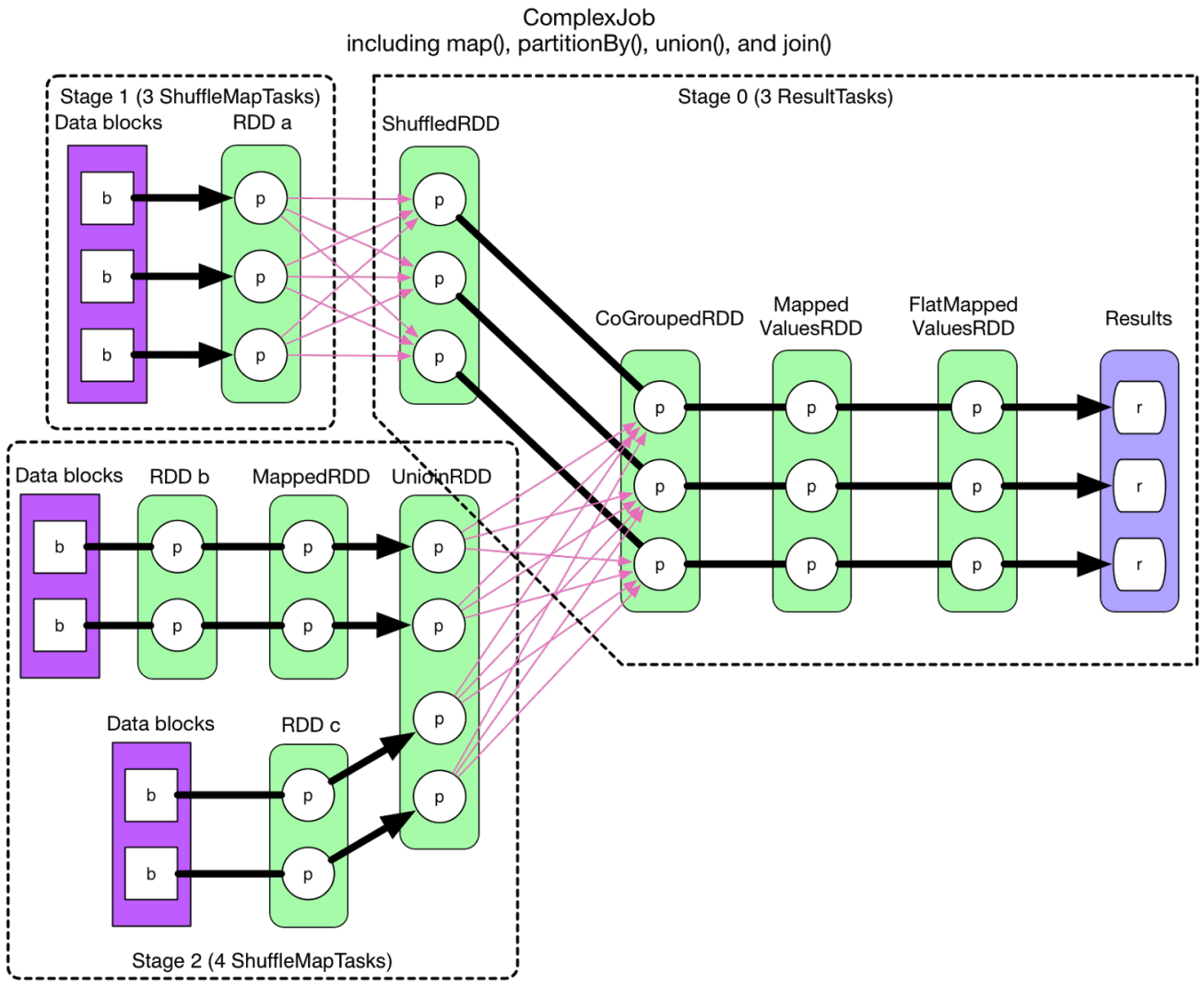
Apache Spark. Concepts

- **Cluster**
  - Group of JVMs (nodes) connected by the network, each of which runs Spark, either in **Driver** or **Worker** roles
- **Driver**
  - This is one of the nodes in the Cluster
  - Don’t run computations
  - It plays the role of a master node
- **Executor**
  - Executors are JVMs that run on a Worker nodes
  - Actually run **Tasks** on data **Partitions**

Apache Spark. Concepts

- **Job**
  - A job is a sequence of **Stages**, triggered by an **Action** such as .count(), read(), write(), …
- **Stage**
  - A stage is a sequence of **Tasks** that cal all be run together, in parallel, without a **shuffle**
- **Task**
  - A **Task** is a single operation applied to a single **partition**
  - Each **Tasks** is executed as a single thread in an **Executor**

Apache Spark. Concepts



Save To Persistent Tables

- When working with a HiveContext, DataFrames can also be saved as persistent tables using the **saveAsTable** command
  - Unlike the **registerTempTable and createOrReplaceTempView** commands, saveAsTable will materialize the contents of the dataframe and create a pointer to the data in the HiveMetastore
  - Persistent tables will still exist even after your Spark program has restarted
  - **By default saveAsTable will create a "managed table"**, meaning that the location of the data will be controlled by the metastore
    - Managed tables will also have their data deleted automatically when a table is dropped

SparkSession

- **SparkSession** was introduce in Spark 2.0
- All contexts unified in only one
- Having access to SparkSession, we automatically have Access to the SparkContext
- SparkSession is now **the new entry point**
- We can start working with DataFrame and Dataset having access to SparkSession

```
val spark = SparkSession
  .builder
  .enableHiveSupport()
  .config("spark.master", "local[*]")
  .appName("Simple Application")
  .getOrCreate()


val persons = spark
  .read
  .json(filePath)
```

SparkSession (PySpark)

```
from pyspark.sql import SparkSession
spark = SparkSession \
    .builder \
    .appName("Python Spark SQL basic example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

Spark Scala Application

```scala
val spark = SparkSession
  .builder
  .enableHiveSupport()
  .config("spark.master", "local[*]")
  .appName("Simple Application")
  .getOrCreate()

val filePath = "person.json"
val persons = spark
  .read
  .json(filePath)

val personsByName = persons
  .groupBy(col("name"))
  .count()

personsByName.show()
```

```
+-------+-----+
|   name|count|
+-------+-----+
|Michael|    2|
|   John|    1|
+-------+-----+
```

DataFrame UDF

- User-defined functions provide you with ways to extend the DataFrame and SQL APIs while keeping the Catalyst optimizer
  - Perfomance issues with Python, since data must still be transferred out of the JVM

```
val squared = (s: Long) => { s * s }

spark.udf.register("square", squared)

spark.sql("select id, square(id) as id_squared from test")
```

- Using UDFs with DataFrames

```
import org.apache.spark.sql.functions.{col, udf}
val squared = udf((s: Long) => s * s)
df.select(squared(col("id")) as "id_squared"))
```

DataFrame UDF – PySpark

- The default return type is *StringType*

```
def squared(s): return s * s
spark.udf.register("squaredWithPython", squared)
```

- You can optionally set the return type of your UDF

```
from pyspark.sql.types import LongType

def squared_typed(s): return s * s

spark.udf.register("squaredWithPython", squared_typed, LongType())
```

DataFrame UDF – PySpark

- Spark SQL (including SQL and the DataFrame and Dataset API) does not guarantee **the order of evaluation of subexpressions**
- There's no guarantee that the null check will happen before invoking the UDF. For example:

```
spark.udf.register("strlen", lambda s: (s), "int")
spark.sql("select s from test1 where s is not null and strlen(s) > 1") # no guarantee
```

- To perform proper null checking, we recommend that you do either of the following:
  - **Make the UDF itself null-aware** and do null checking inside the UDF itself
  - **Use IF or CASE WHEN expressions to do the null check** and invoke the UDF in a conditional branch

```
spark.udf.register("strlen_nullsafe", lambda s:(s) if not s is None else -1, "int")
spark.sql("select s from test1 where s is not null and strlen_nullsafe(s) > 1") // ok
spark.sql("select s from test1 where if(s is not null, strlen(s), null) > 1") // ok
```

Hands-on

- Open “01.Spark_SQL.ipynb” in Google Colab:
  - Try the exercises 5 and 6

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Windows Partitioning

- There are two kinds of functions supported by SparkSQL that could be used to calculated a single return value:
  - UDFs like “substr”, “round”, etc.
  - Aggregated functions like SUM, MAX, etc

- **Window function** calculates a return value for every input row of a table based on a group of rows, called the Frame

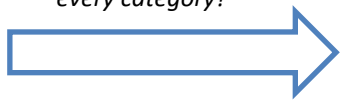
- **Window function** makes them more powerful that other functions and allows users to express various data processing tasks that are hard (if not impossible)

Windows Partitioning

productRevenue

product	category	revenue
Thin	Cell phone	6000
Normal	Tablet	1500
Mini	Tablet	5500
Ultra thin	Cell phone	5000
Very thin	Cell phone	6000
Big	Tablet	2500
Bendable	Cell phone	3000
Foldable	Cell phone	3000
Pro	Tablet	4500
Pro2	Tablet	6500

"What are the best-selling and the second best-selling products in every category?"



```
SELECT
  product,
  category,
  revenue
FROM (
  SELECT
    product,
    category,
    revenue,
    dense_rank() OVER (PARTITION BY category ORDER BY revenue DESC) as rank
  FROM productRevenue) tmp
WHERE
  rank <= 2
```

product	category	revenue
Pro2	Tablet	6500
Mini	Tablet	5500
Thin	Cell Phone	6000
Very thin	Cell Phone	6000
Ultra thin	Cell Phone	5500

Windows Partitioning

productRevenue

product	category	revenue
Thin	Cell phone	6000
Normal	Tablet	1500
Mini	Tablet	5500
Ultra thin	Cell phone	5000
Very thin	Cell phone	6000
Big	Tablet	2500
Bendable	Cell phone	3000
Foldable	Cell phone	3000
Pro	Tablet	4500
Pro2	Tablet	6500

"What is the difference between the revenue of each product and the revenue of the best selling product in the same category as that product?"

```
import sys
from pyspark.sql.window import Window
import pyspark.sql.functions as func
windowSpec = \
  Window
    .partitionBy(df['category']) \
    .orderBy(df['revenue'].desc()) \
    .rangeBetween(-sys.maxsize, sys.maxsize)
dataFrame = sqlContext.table("productRevenue")
revenue_difference = \
  (func.max(dataFrame['revenue']).over(windowSpec) - dataFrame['revenue'])
dataFrame.select(
  dataFrame['product'],
  dataFrame['category'],
  dataFrame['revenue'],
  revenue_difference.alias("revenue_difference"))
```

product	category	revenue	revenue_difference
Pro2	Tablet	6500	0
Mini	Tablet	5500	1000
Pro	Tablet	4500	2000
Big	Tablet	2500	4000
Normal	Tablet	1500	5000
Thin	Cell Phone	6000	0
Very thin	Cell Phone	6000	0
Ultra thin	Cell Phone	5500	500
Foldable	Cell Phone	3000	3000
Bendable	Cell Phone	3000	3000

Windows Partitioning

	SQL	DataFrame API
Ranking functions	rank	rank
	dense_rank	denseRank
	percent_rank	percentRank
	ntile	ntile
	row_number	rowNumber
Analytic functions	cume_dist	cumeDist
	first_value	firstValue
	last_value	lastValue
	lag	lag
	lead	lead

Hands-on

- Open "02.Spark_SQL_Advanced.ipynb" in Google Colab:
  - Example 1
  - Try exercises 1 and 2

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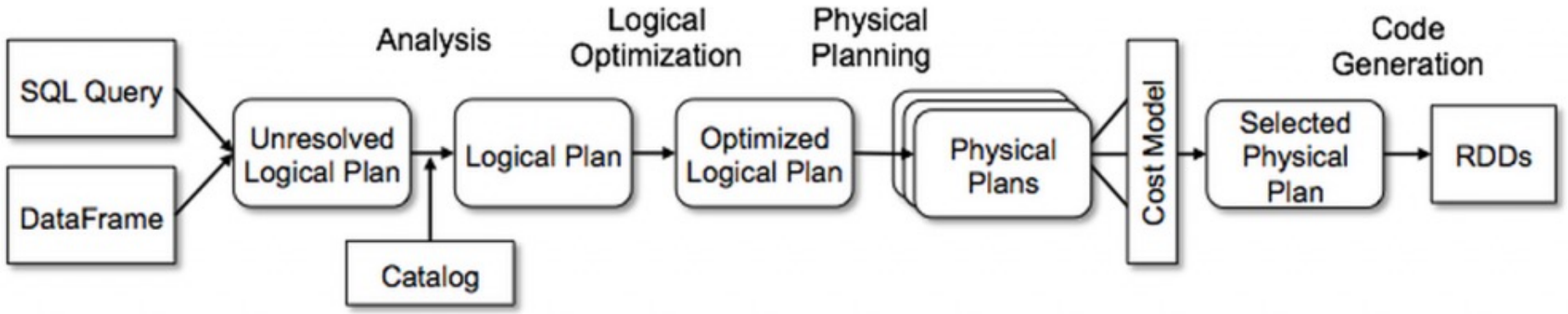
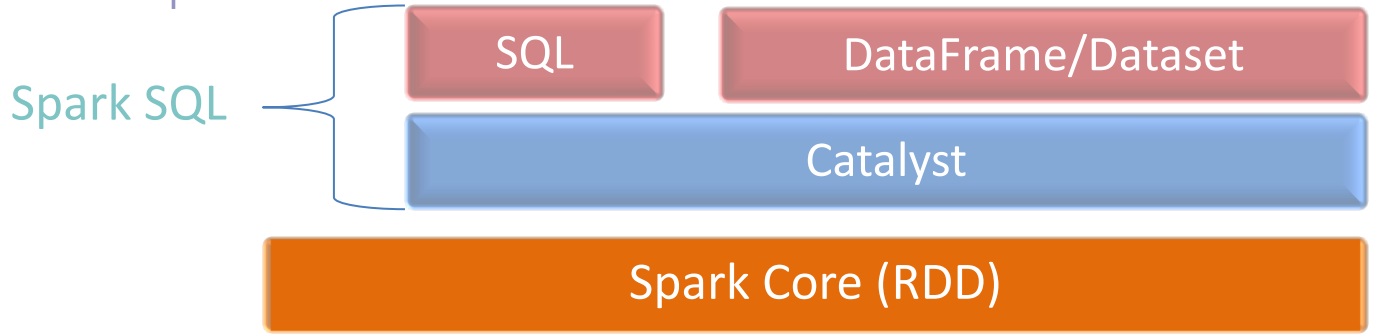
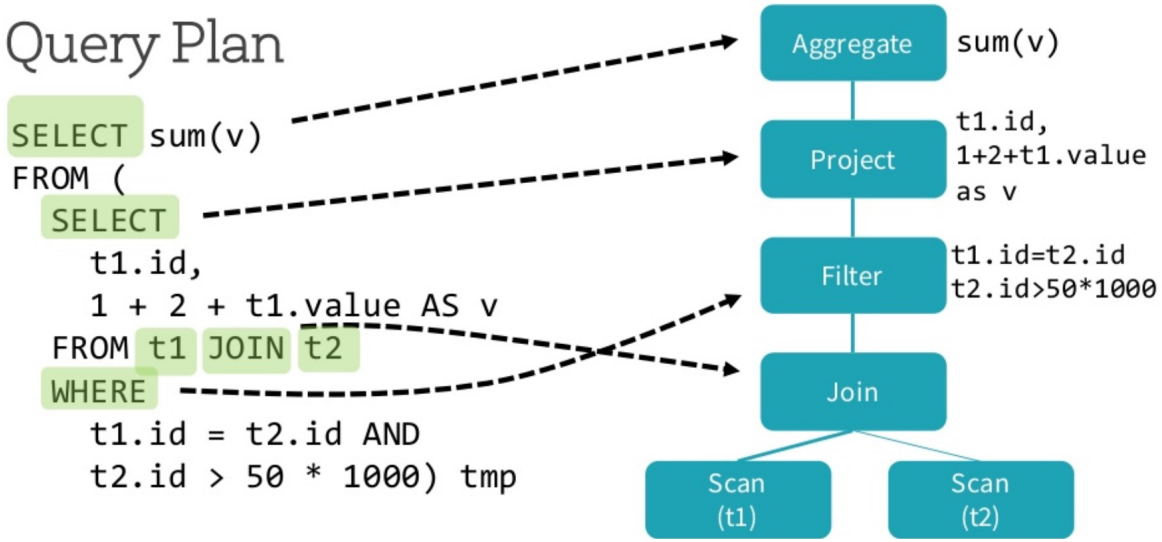
Spark SQL Architecture



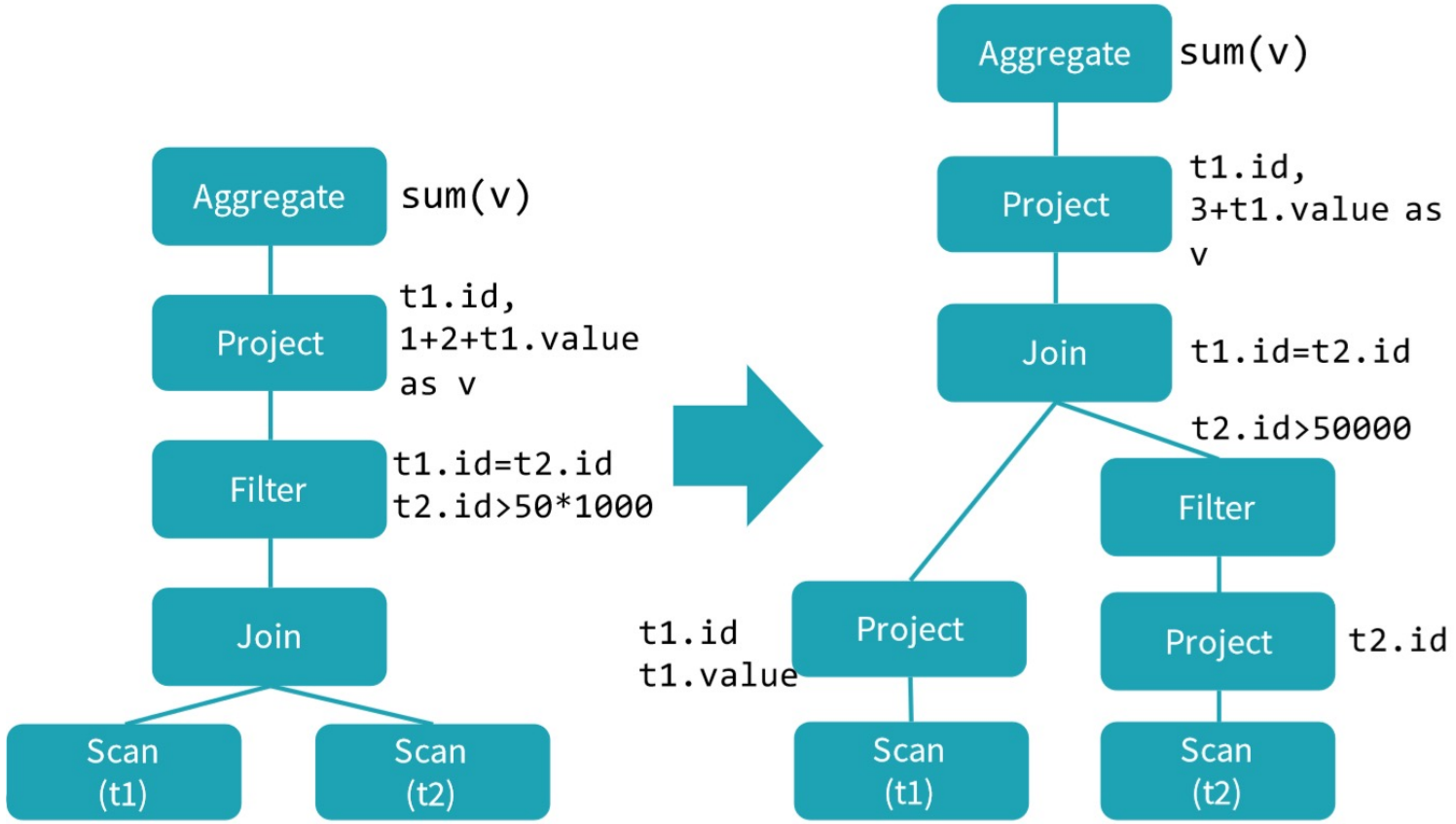
Catalyst

- Catalyst finds out the most efficient plan to execute



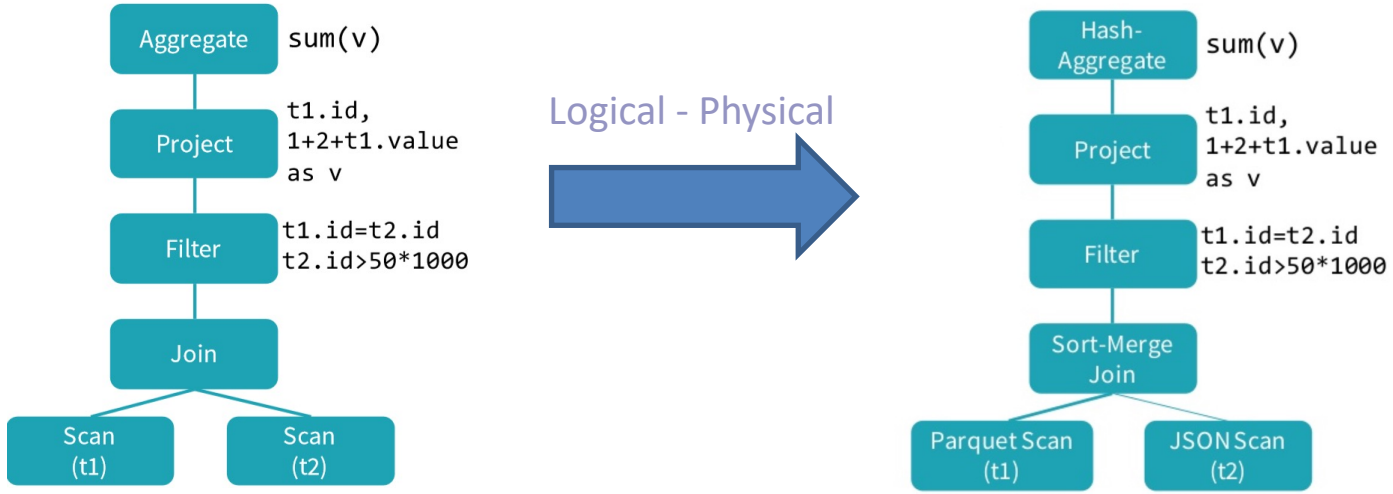


Spark SQL Architecture



Spark SQL Architecture

- A logical plan describes computation on datasets without defining how to conduct the computation
- A physical plan describes computation on datasets with specific definitions on how to conduct the computation



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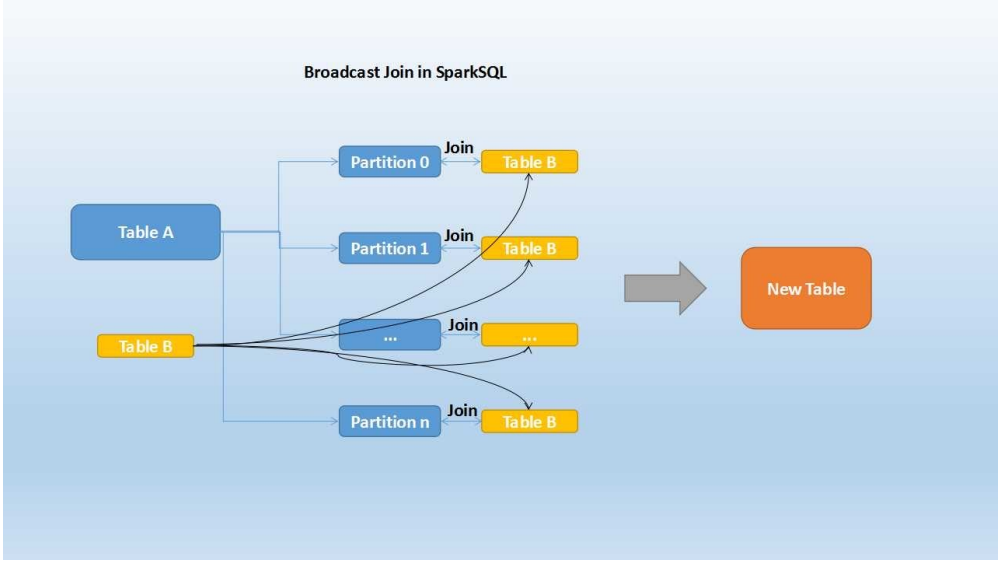
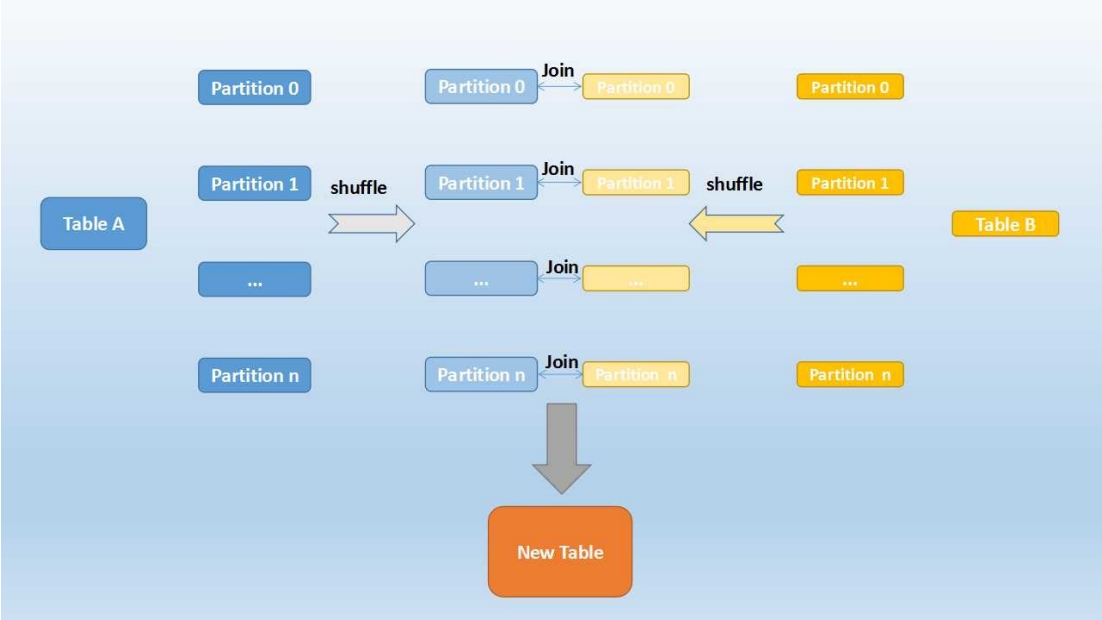
Broadcast Hash Join

- Big/Medium table – Small table
- One table is small enough to be replicated for each executor
- The main idea is to avoid the shuffle
- Small Table needs to be broadcasted less than *spark.sql.autoBroadcastJoinThreshold* (10M) or adding *broadcast* hint



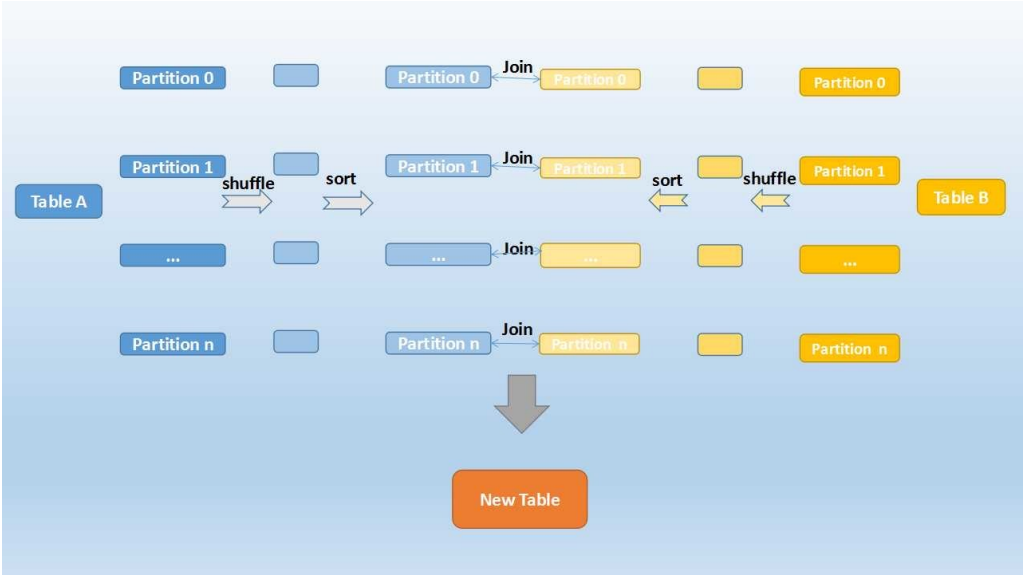
Shuffled Hash Join

- **Shuffled Hash Join** is the default implementation of a join in Spark
- This join needs to fit a hash table in memory
- Memory issues if the smaller table is not small enough



Sort Merge Join

- This is the standard join when both tables are large
- Data is sorted before the join
- Comparing with shuffle hash join, this join could spill to disk
- *spark.sql.join.preferSortMergeJoin property* is true by default



Join – Examples

Table A

```
+---------+---+
|     name| id|
+---------+---+
|   Pirate|  1|
|   Monkey|  2|
|    Ninja|  3|
|Spaghetti|  4|
+---------+---+
```

Table B

```
+-----------+---+
|       name| id|
+-----------+---+
|   Rutabaga|  1|
|     Pirate|  2|
|      Ninja|  3|
|Darth Vader|  4|
+-----------+---+
```

INNER JOIN

```
inner_join = ta.join(tb, ta.name == tb.name)
inner_join.show()
```

```
+------+---+------+---+
|  name| id|  name| id|
+------+---+------+---+
| Ninja|  3| Ninja|  3|
|Pirate|  1|Pirate|  2|
+------+---+------+---+
```

LEFT JOIN

```
left_join = ta.join(tb, ta.name == tb.name,how='left')
left_join.show()
```

```
+---------+---+------+----+
|     name| id|  name|  id|
+---------+---+------+----+
|Spaghetti|  4|  null|null|
|    Ninja|  3| Ninja|   3|
|   Pirate|  1|Pirate|   2|
|   Monkey|  2|  null|null|
+---------+---+------+----+
```

FULL OUTER JOIN

```
full_outer_join = ta.join(tb, ta.name == tb.name,how='full')
```

```
+---------+----+-----------+----+
|     name|  id|       name|  id|
+---------+----+-----------+----+
|     null|null|   Rutabaga|   1|
|Spaghetti|   4|       null|null|
|    Ninja|   3|      Ninja|   3|
|   Pirate|   1|     Pirate|   2|
|   Monkey|   2|       null|null|
|     null|null|Darth Vader|   4|
+---------+----+-----------+----+
```

RIGHT JOIN

```
right_join = ta.join(tb, ta.name == tb.name,how='right')
```

```
+------+----+-----------+---+
|  name|  id|       name| id|
+------+----+-----------+---+
|  null|null|   Rutabaga|  1|
| Ninja|   3|      Ninja|  3|
|Pirate|   1|     Pirate|  2|
|  null|null|Darth Vader|  4|
+------+----+-----------+---+
```

Hands-on

- Open "02.Spark_SQL_Advanced.ipynb" in Google Colab:
  - Try exercises 3, 4, 5, 6 and 7

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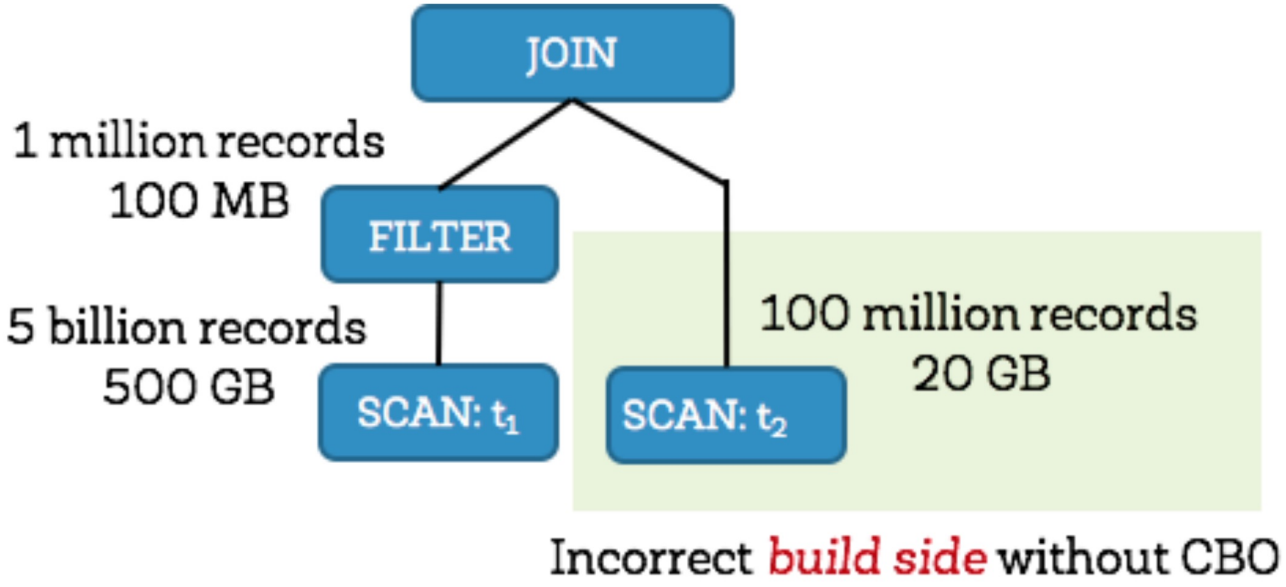
CBO – 2.2.0

- Spark implements this query using a hash join by choosing the smaller join relation as the build side



CBO – 2.2.0

- CBO relies on detailed statistics to optimize a query plan
- To collect these statistics, users can issue these new SQL commands:
  - **ANALYZE TABLE table_name COMPUTE STATISTICS**
  - This SQL statement can collect table level statistics such as number of rows and table size in bytes
  - **ANALYZE TABLE table_name COMPUTE STATISTICS FOR COLUMNS column-name1, column-name2, ….**
- Not necessary to specify every column of a table in the ANALYZE statement—only those that are used in a filter/join condition, or in group by clauses etc

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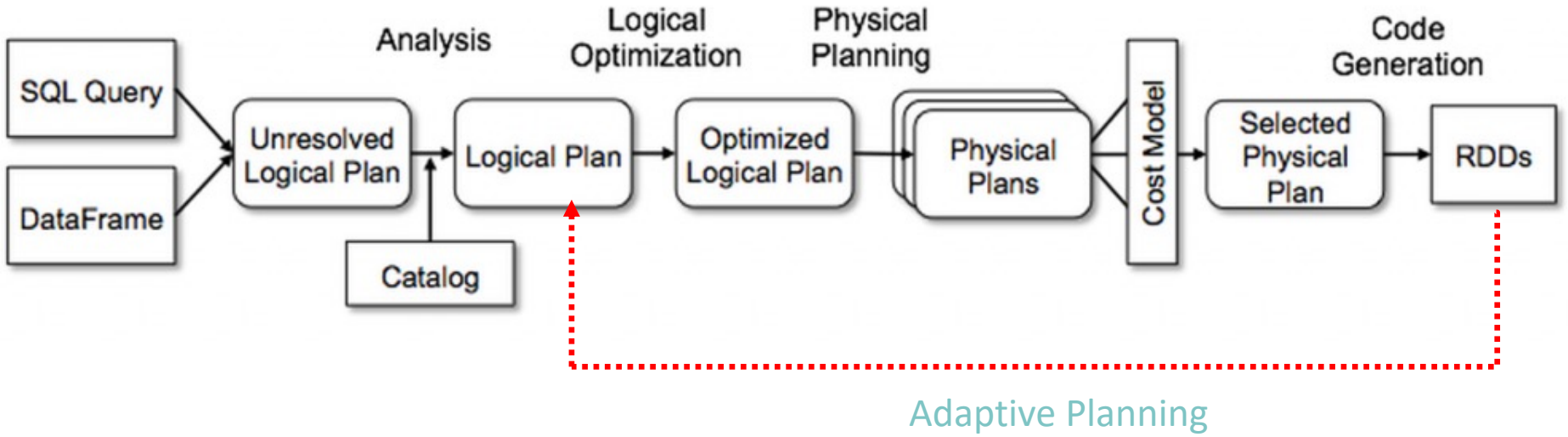
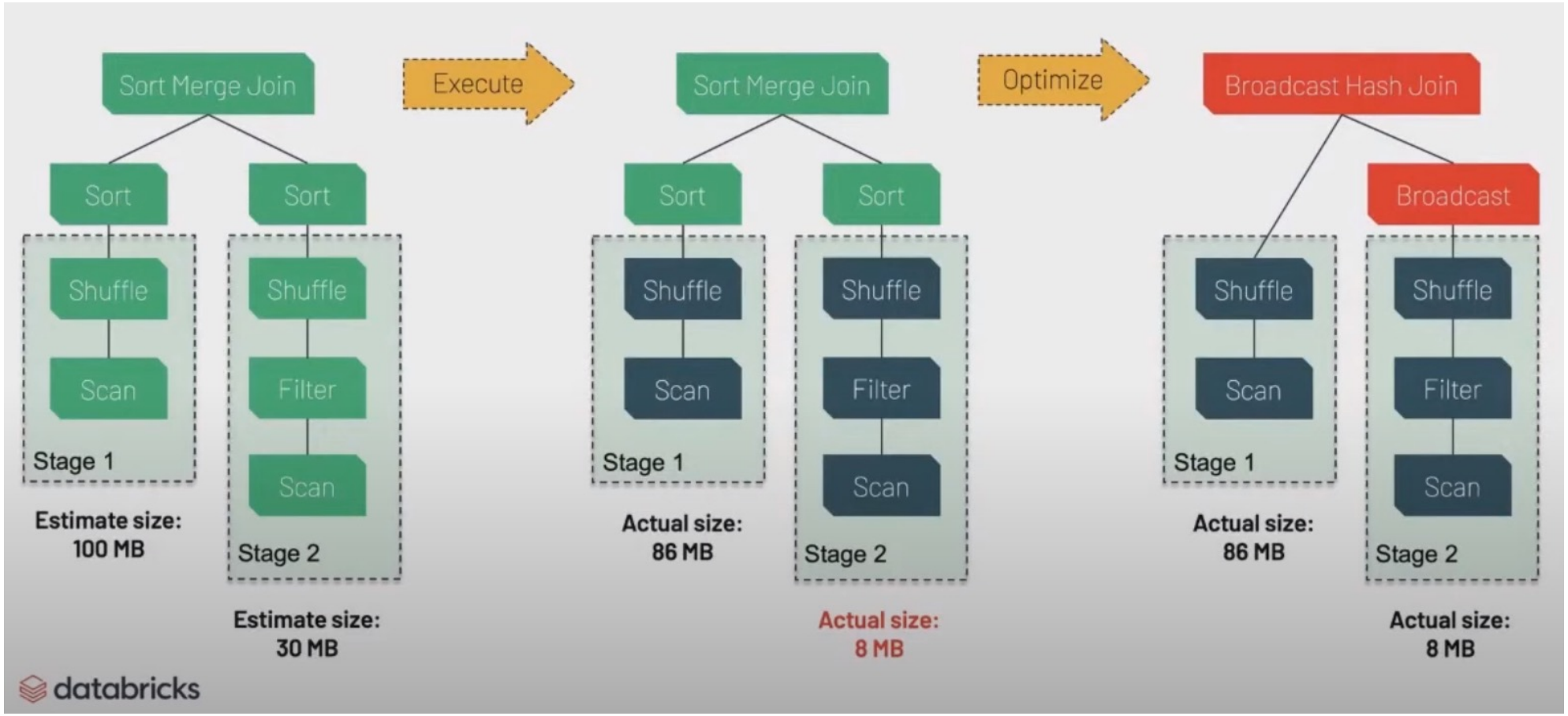
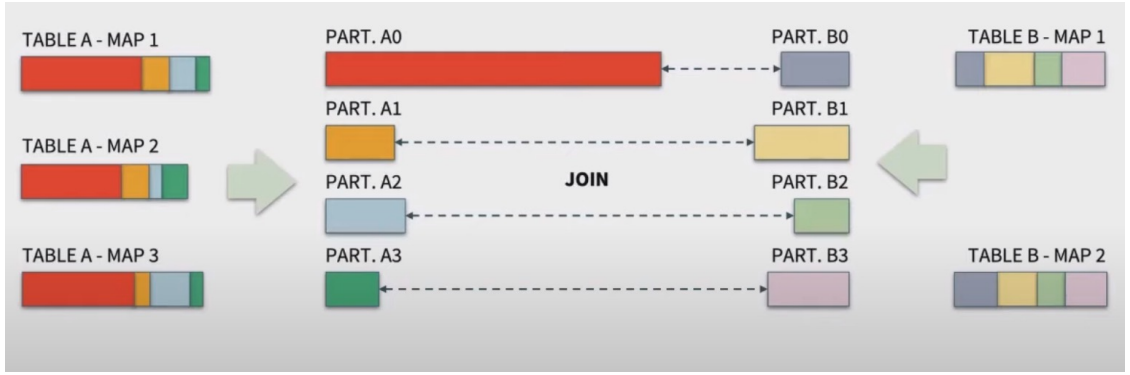
Spark 3.0 – Adaptive Planning

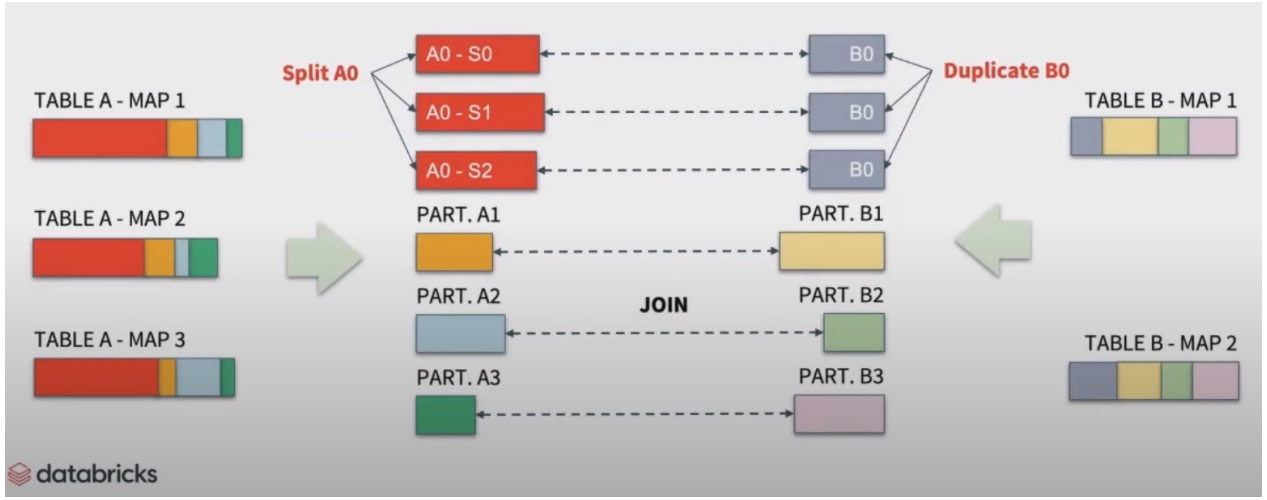


Spark 3.0 – Adaptive Planning



Spark 3.0 – Data Skew Optimization





Spark 3.0 – Data Skew Optimization

Property Name	Default	Meaning	Since Version
`spark.sql.adaptive.skewJoin.enabled`	true	When true and `spark.sql.adaptive.enabled` is true, Spark dynamically handles skew in sort-merge join by splitting (and replicating if needed) skewed partitions.	3.0.0
`spark.sql.adaptive.skewJoin.skewedPartitionFactor`	10	A partition is considered as skewed if its size is larger than this factor multiplying the median partition size and also larger than `spark.sql.adaptive.skewedPartitionThresholdInBytes`.	3.0.0
`spark.sql.adaptive.skewJoin.skewedPartitionThresholdInBytes`	256MB	A partition is considered as skewed if its size in bytes is larger than this threshold and also larger than `spark.sql.adaptive.skewJoin.skewedPartitionFactor` multiplying the median partition size. Ideally this config should be set larger than `spark.sql.adaptive.advisoryPartitionSizeInBytes`.	3.0.0

Spark 3.0 – Data Skew Optimization

```
df.hint("skew", ["col1","col2"])
```

```
val joinResults = ds1.hint("skew").as("L").join(ds2.hint("skew").as("R"), $"L.col1" === $"R.col1")
```

```
-- single column, single skew value
SELECT /*+ SKEW('orders', 'o_custId', 0) */ *
  FROM orders, customers
  WHERE o_custId = c_custId

-- single column, multiple skew values
SELECT /*+ SKEW('orders', 'o_custId', (0, 1, 2)) */ *
  FROM orders, customers
  WHERE o_custId = c_custId

-- multiple columns, multiple skew values
SELECT /*+ SKEW('orders', ('o_custId', 'o_storeRegionId'), ((0, 1001), (1, 1002))) */ *
  FROM orders, customers
  WHERE o_custId = c_custId AND o_storeRegionId = c_regionId
```

Spark 3.0 – Dynamic Partition Pruning

- We are going to analyze the following query:

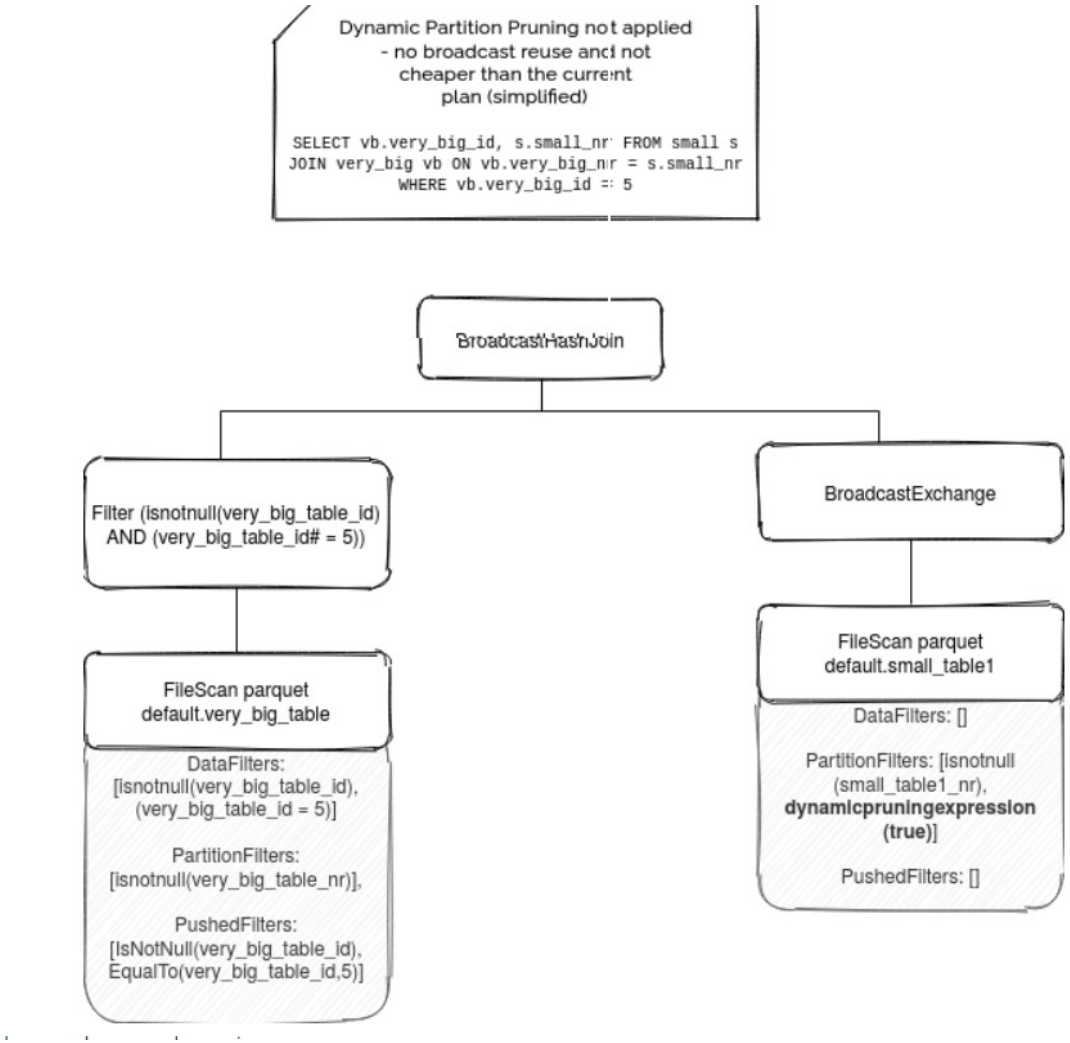
```
SELECT t1.id, t2.part_column FROM table1 t1
JOIN table2 t2 ON t1.part_column = t2.part_column
```

```
SELECT t1.id, t2.part_column FROM table1 t1
JOIN table2 t2 ON t1.part_column = t2.part_column
WHERE t2.id < 5
```

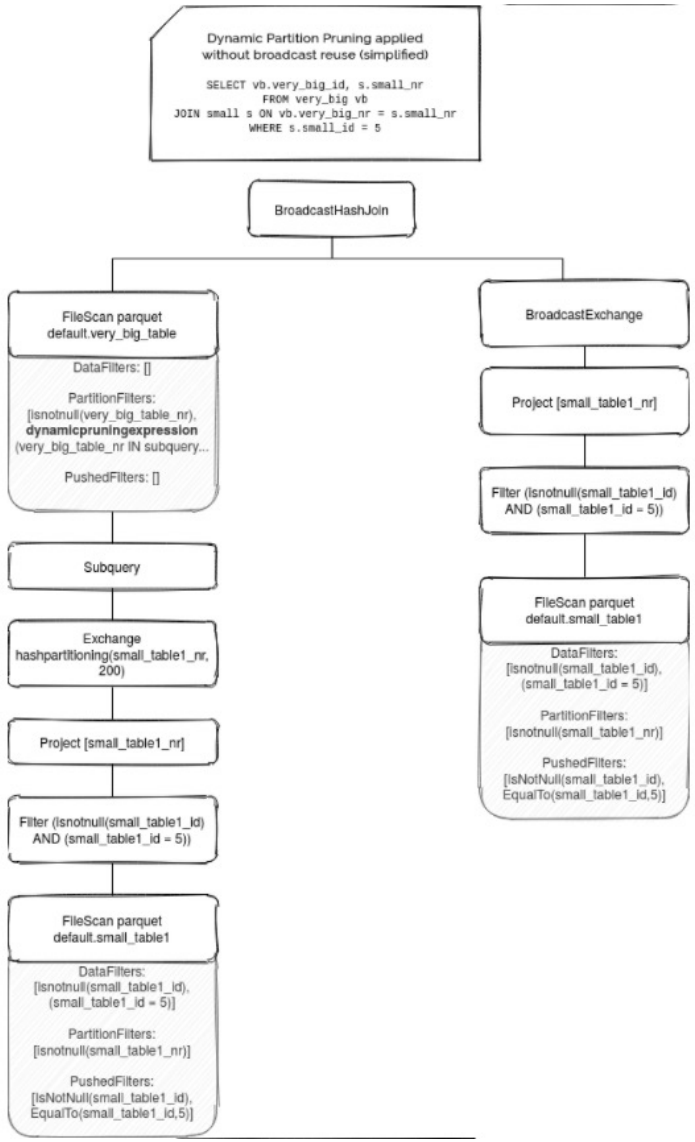
```
SELECT t1.id, t1.part_column FROM table1 t1
WHERE t1.part_column IN (
SELECT t2.part_column FROM table2 t2
WHERE t2.id < 5
)
```

spark.sql.optimizer.dynamicPartitionPruning
spark.sql.optimizer.dynamicPartitionPruning.reuseBroadcastOnly
spark.sql.optimizer.dynamicPartitionPruning.useStats
spark.sql.optimizer.dynamicPartitionPruning.fallbackFilterRatio

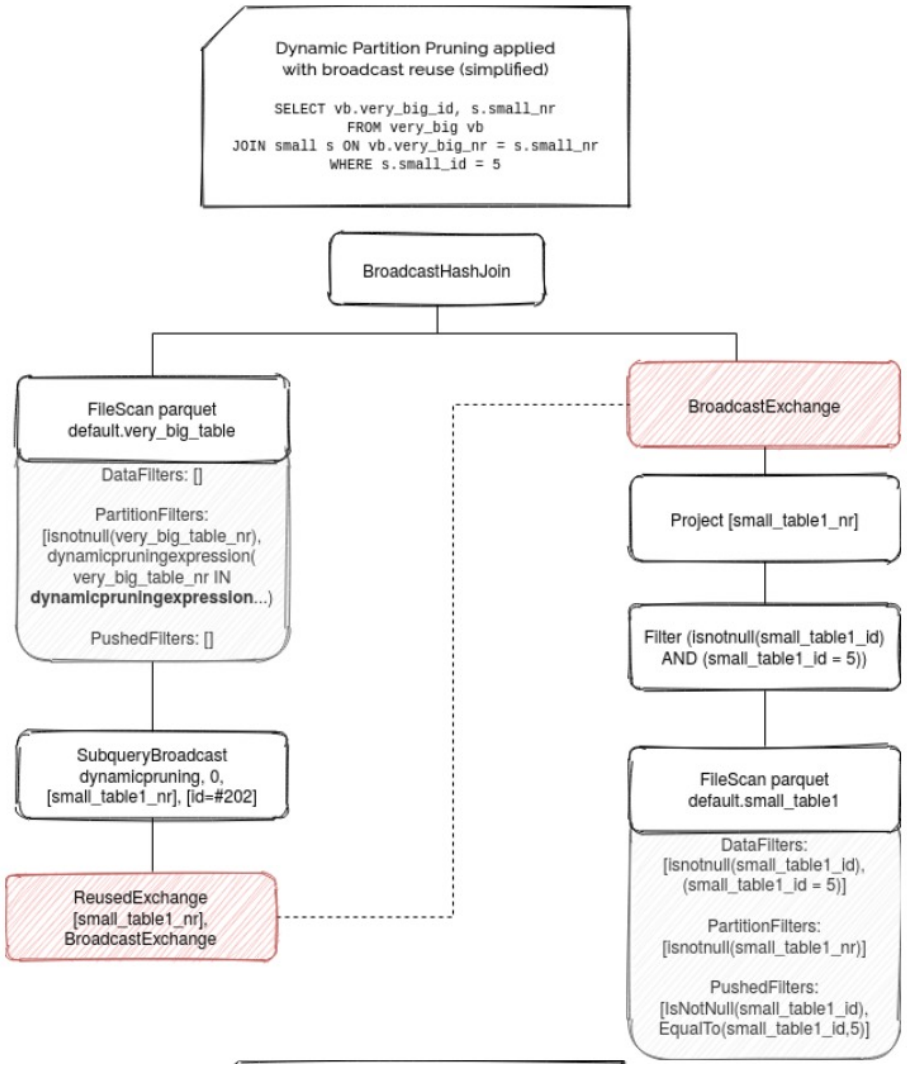
Spark 3.0 – Dynamic Partition Pruning



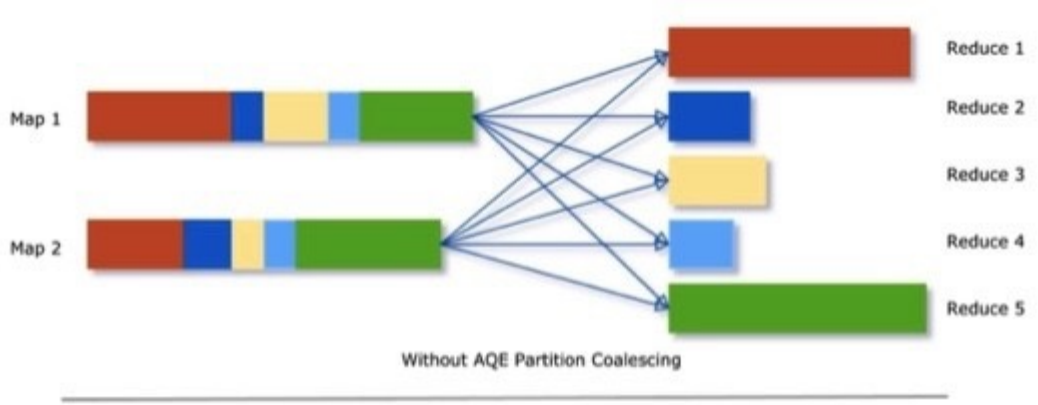
Spark 3.0 – Dynamic Partition Pruning

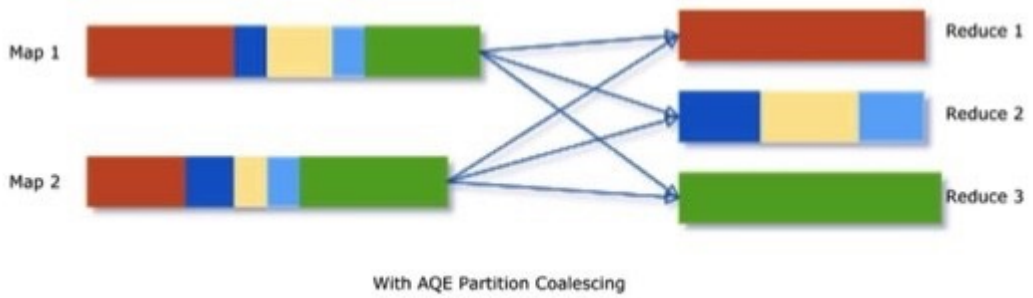


Spark 3.0 – Dynamic Partition Pruning



Spark 3.0 – Coalesce the number of shuffle partitions





Spark 3.0 – Coalesce the number of shuffle partitions

Property Name	Default	Meaning	Since Version
`spark.sql.adaptive.coalescePartitions.enabled`	true	When true and `spark.sql.adaptive.enabled` is true, Spark will coalesce contiguous shuffle partitions according to the target size (specified by `spark.sql.adaptive.advisoryPartitionSizeInBytes`), to avoid too many small tasks.	3.0.0
`spark.sql.adaptive.coalescePartitions.minPartitionNum`	Default Parallelism	The minimum number of shuffle partitions after coalescing. If not set, the default value is the default parallelism of the Spark cluster. This configuration only has an effect when `spark.sql.adaptive.enabled` and `spark.sql.adaptive.coalescePartitions.enabled` are both enabled.	3.0.0
`spark.sql.adaptive.coalescePartitions.initialPartitionNum`	200	The initial number of shuffle partitions before coalescing. By default it equals to `spark.sql.shuffle.partitions`. This configuration only has an effect when `spark.sql.adaptive.enabled` and `spark.sql.adaptive.coalescePartitions.enabled` are both enabled.	3.0.0
`spark.sql.adaptive.advisoryPartitionSizeInBytes`	64 MB	The advisory size in bytes of the shuffle partition during adaptive optimization (when `spark.sql.adaptive.enabled` is true). It takes effect when Spark coalesces small shuffle partitions or splits skewed shuffle partition.	3.0.0

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DataFrames – Caching

- Cache()
  - Cache in **Memory only**
- Persist()
  - Used to store it to **user-defined storage level**
- UnPersist()
  - Drop Spark DataFrame from Cache

Level	Space used	CPU time	In memory	On disk	Comments
MEMORY_ONLY	High	Low	Y	N	
MEMORY_ONLY_SER	Low	High	Y	N	
MEMORY_AND_DISK	High	Medium	Some	Some	Spills to disk if there is too much data to fit in memory.
MEMORY_AND_DISK_SER	Low	High	Some	Some	Spills to disk if there is too much data to fit in memory. Stores serialized representation in memory.
DISK_ONLY	Low	High	N	Y	

Spark SQL – Caching

- Caching in Spark SQL works different:
  - You can also cache using HiveSQL statements

```
CACHE TABLE tableName;
UNCACHE TABLE tableName;
```

- When caching a table Spark SQL represents the data in an in-memory columnar format (Parquet-like)

- The cached table will remain in memory only for the life of our driver program