Spark SQL & DataFrames

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Learning Objectives

- Review Spark, RDDs and review SQL
- Introduce spark dataframes and spark SQL
- Be able to use python API and/or SQL method to operate on spark DataFrames
- Understand partitioning and how to query efficiently
- Introduce SQL functions

Review

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Python is an imperative language. What kind of language is SQL? What is the practical difference?

Put the following operations in the order they should appear in a SQL query: (GROUP BY, ORDER BY, SELECT, WHERE)

Put the following operations in the order in which they are EVALUATED in a SQL query: (GROUP BY, ORDER BY, SELECT, WHERE)

What does it mean that Spark is a lazy evaluator?

Why is Spark faster than Hadoop MapReduce?

What piece of code creates an RDD out of another object?

Are RDDs mutable? What are the practical implications of this?

Review: Query Components Structure

This is the order that your queries should take!

SELECT and FROM are the only ones that are required

```
SELECT (DISTINCT, AGG*) <table1.col1, … ,
table1.colm, table2.col1, … ,table2.coln>
FROM <table1>
JOIN <table2>
ON <table1.colj> = <table2.colk>
WHERE <table1.col1 = some_val> AND <table1.col1 =
some_val>
GROUP BY <table1.col>
HAVING <AGG*(table1.col) = some_val>
ORDER BY <table1.col> ASC <table2.col> DESC
```

Review: Query Components vs. **Order of Evaluation**

1. **FROM + JOIN**: first the product of all tables is formed
2. **WHERE**: the where clause filters rows that do not meet the search condition
3. **GROUP BY** + (COUNT, SUM, etc): the rows are grouped using the columns in the group by clause and the aggregation functions are applied on the grouping
4. **HAVING**: like the WHERE clause, but can be applied after aggregation
5. **SELECT**: the targeted list of columns are evaluated and returned
6. **DISTINCT**: duplicate rows are eliminated
7. **ORDER BY**: the resulting rows are sorted

Order of Evaluation - implications

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WHERE clause: eliminate rows you don't want, and if data is smartly partitioned… eliminate entire files! EFFICIENCY!

WHERE and **GROUP BY** are evaluated *before* **SELECT** statement. If you do an aggregation/ name change/other manipulation, you will need to use the original column name here because your new alias won't be recognized.

ORDER BY is evaluated *after* the **SELECT** statement. Use new aliases

WHERE clause and partitions

Remember, your data is being stored in a DISTRIBUTED FILE SYSTEM.

With smartly partitioned data, you can eliminate **entire files** or even directories to search from common queries.

Best practice as an ETL engineer - aim for individual file size of 50-100 MB

Review: JOINS

In practical terms….

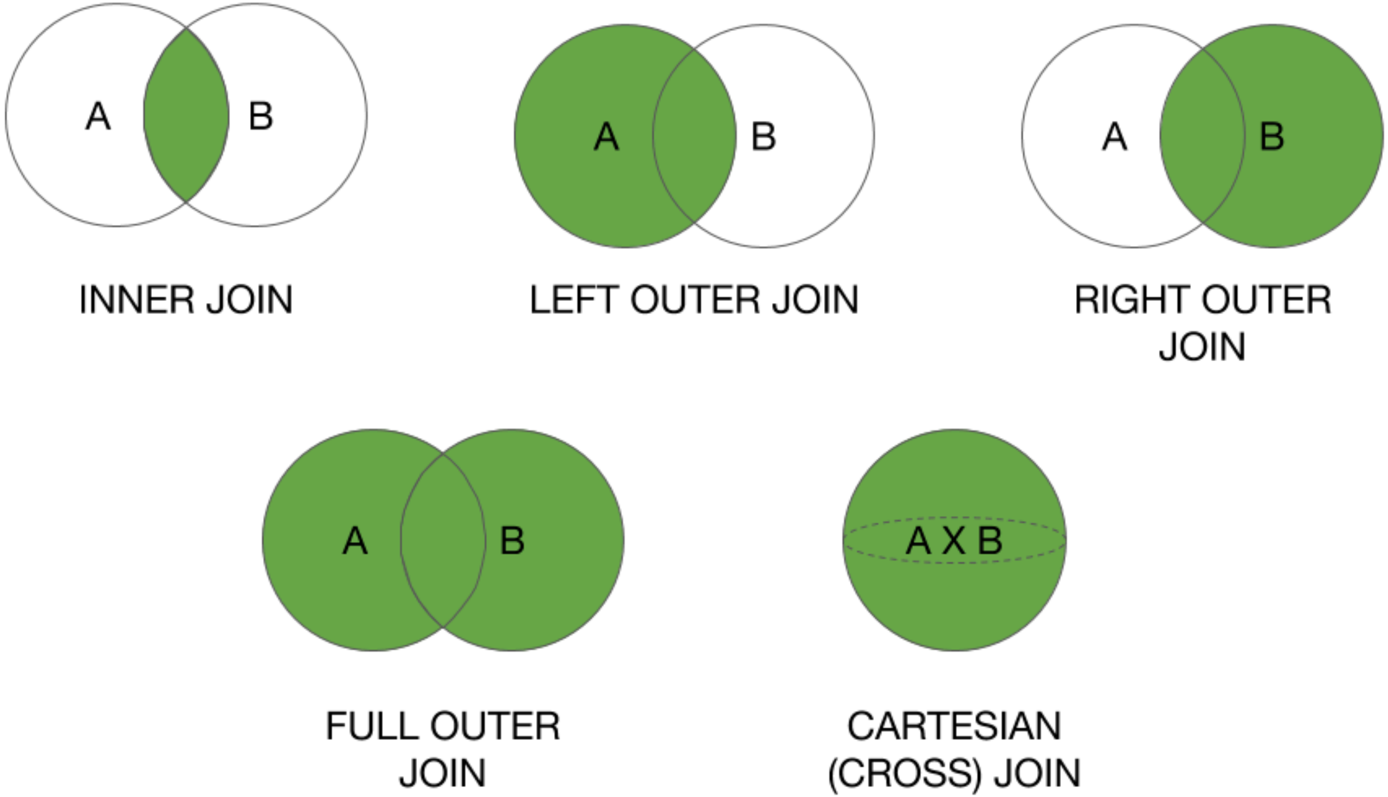
- **(INNER) JOINs:** no null/nan values (only keeps rows that exist in both tables)

- **LEFT (RIGHT) JOIN:** Keeps all rows from the left (right) table. Expect some null values for rows that don't exist in the right (left) table.*

- **FULL JOIN:** Keeps all the rows! Lots of null values

* in practice, there is no reason to use a right join.

JOINS - specific to SparkSQL



*LEFT SEMI JOINS are also a thing. We won't get into them today

Spark DataFrames

Spark Dataframes: motivation

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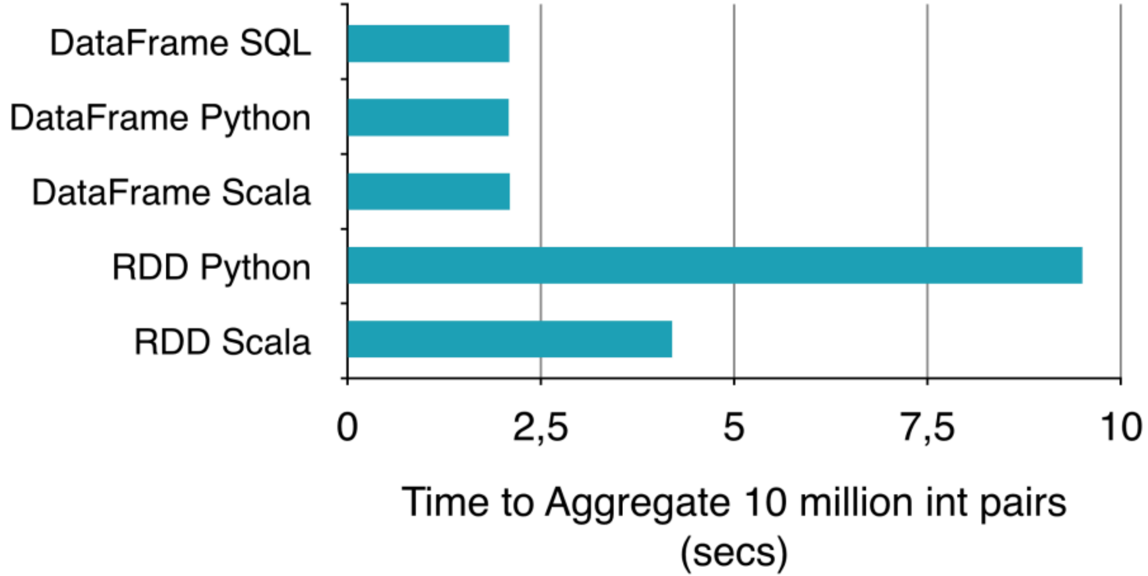
Physical Execution: Unified Across Languages



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Spark DataFrames

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- Primary abstraction in Spark SQL - have a defined schema, unlike RDDs
- Look and behave (mostly) like pandas Dataframes, R dataframes, sql data tables and other tabular data objects
- SQL functionality is great - as of Spark 2.0, Hive, Pig, and SQL functionality are all integrated within the sparkSQL paradigm.
- Can operate on DataFrames with DataFrame methods, SQL functions, or query out of them
- spark.read.csv (or .json or .parquet, etc.) automatically gives you a DataFrame
- immutable, like RDDs

Schemas

You can create a data frame by applying a schema to an RDD, or by inferring one as you read in the file (set the argument inferSchema=True)

What is a schema?

- Schemas are metadata about your data.
- Schemas enable using SQL and DataFrame syntax to query your RDDs, instead of using column positions.
- Schema = Table Names + Column Names + Column Types

What are the benefits of having a schema?

- Schemas enable using column names instead of column positions
- Schemas enable queries using SQL and DataFrame syntax
- Schemas make your data more structured (all columns same data type, etc.)

Creating a Schema from RDD example


```python
from pyspark.sql.types import StructType, StructField, IntegerType, StringType, FloatType

schema = StructType([StructField('id', IntegerType(), True),
                     StructField('date', StringType(), True),
                     StructField('store', IntegerType(),True),
                     StructField('state', StringType(), True),
                     StructField('product', IntegerType(), True),
                     StructField('amount', FloatType(), True)])

# spark is a SparkSession
df = spark.createDataFrame(rdd_sales, schema)

df.show()

df.printSchema()
```

```
+---+----------+-----+-----+-------+------+
| id|      date|store|state|product|amount|
+---+----------+-----+-----+-------+------+
|101|11/13/2014|  100|   WA|    331| 300.0|
|104|11/18/2014|  700|   OR|    329| 450.0|
|102|11/15/2014|  203|   CA|    321| 200.0|
|106|11/19/2014|  202|   CA|    331| 330.0|
|103|11/17/2014|  101|   WA|    373| 750.0|
|105|11/19/2014|  202|   CA|    321| 200.0|
+---+----------+-----+-----+-------+------+
```

```
root
 |-- id: integer (nullable = true)
 |-- date: string (nullable = true)
 |-- store: integer (nullable = true)
 |-- state: string (nullable = true)
 |-- product: integer (nullable = true)
 |-- amount: float (nullable = true)
```

DataFrame methods for EDA

Everything you are used to from RDDs, plus lots more. (not a complete list!)

Actions

- .show(n) or .head(n) to get the first n rows
- .printSchema() gives you the schema of the table (columns and datatypes, like df.info() in pandas)
- .collect() works the same as it does for RDDs, but is ugly. Use show instead!
- Aggregations (.sum(), .count(), .min(), .max(), etc.)

Transformations

- .describe() computes statistics for numeric and string columns
- .sample() and .sampleBy() give you subsets of the data for easier development

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html#pyspark.sql.DataFrame

Spark SQL

Pyspark SQL documentation

Documentation….the spark ml documentation is a little weak (e.g. examples have data frames with two rows and two columns….because that's totally a situation where we should use distributed computing)

This is NOT so for sparkSQL, this documentation is actually very helpful

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html

Spark DataFrames

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Two ways to do the same operation on a DataFrame…

```
# python API way
new_df = df.filter('col1 = some_val').groupBy('col2')\
            .agg({'col3': 'avg', 'col4': 'max'})

# SQL way
df.createOrReplaceTempView('df')
new_df = spark.sql('''
                   SELECT AVG(col3), MAX(col4)
                   FROM df
                   WHERE col1 = some_val
                   GROUP BY col2
                   ''')
```

SQL functions overview

Two ways to use:

- Within SQL query - can use all functions except user-defined functions (udf) without importing
- As operation on dataframe, must import to do this

```
# dataFrame API way
import pyspark.sql.functions as F

new_df = df.select('col1', F.abs('col2').alias('abs_col2'))

# SQL query way
df.createOrReplaceTempView('df')
spark.sql('''
          SELECT
          col1, ABS(col2) AS abs_col2
          FROM df
          ''')
```

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html#module-pyspark.sql.functions

SQL functions overview

- Mathematical (round, floor/ceil, trig functions, exponents, log, factorial, etc.)
- Aggregations (count, average, min, max, first, last, collect_set, collect_list, etc.)
- Datetime manipulations (change timezone, change string/datetime/unix time)
- Hashing functions
- String manipulations (concatenations, slicing)
- Datatype manipulation (array certain columns together, cast to change datatype, etc.)

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html#module-pyspark.sql.functions

SQL functions - user defined functions

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You aren't limited to only the functions available in spark SQL…you can make your own custom function to apply

```
from pyspark.sql.functions import udf
from pyspark.sql.types import *

def foo(args):
  '''
  func foo, returns a string
  '''
  return new_str

udf_foo = udf(lambda x: foo(x, other_args), StringType())
df = df.withCol('new_col', udf_foo(df.old_col))
```

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html#module-pyspark.sql.functions

SQL functions - window functions

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- Especially useful with time series or ordered data
- Rolling mean, exponentially weighted time series models, cumulative sums

```python
from pyspark.sql.window import Window
import pyspark.sql.functions as f
windowSpec = Window.partitionBy().orderBy().rangeBetween() # fill these in

df = df.withCol('new_col', f.max(df.old_col.over(windowSpec))
```

```sql
SELECT
    foo,
    func(old_col) OVER (PARTITION BY partition_col ORDER BY order_col DESC)
```

https://databricks.com/blog/2015/07/15/introducing-window-functions-in-spark-sql.html

Revisit Learning Objectives

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Questions?