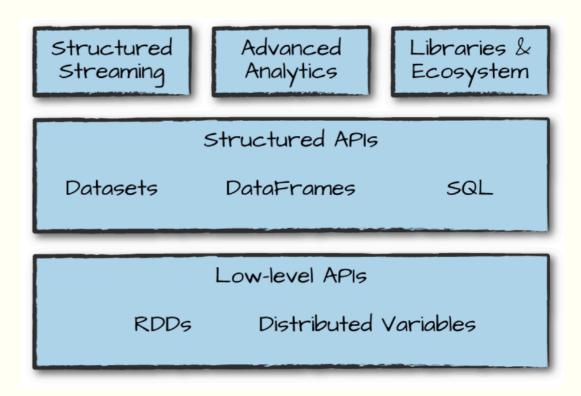
# Apache Spark - PySpark

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#### Spark APIs

- Spark provide three high-level APIs for distributed query and processing:
  - Datasets
  - DataFrames
  - SQL (table)
- In addition, Spark provides low-level APIs in the form of:
  - RDDs
  - Distributed Variables



source: Spark: The Definitive Guide by Bill Chambers, Matei Zaharia

## Spark APIs

|             | Java / Scala | Python / R |
|-------------|--------------|------------|
| Dataset     | Yes          | No         |
| DataFrame   | Yes          | Yes        |
| SQL (table) | Yes          | Yes        |
| RDD         | Yes          | Yes        |

#### Spark Data Sources

- Files:
  - Text, CSV, JSON, HDFS, Parquet, Avro, etc.

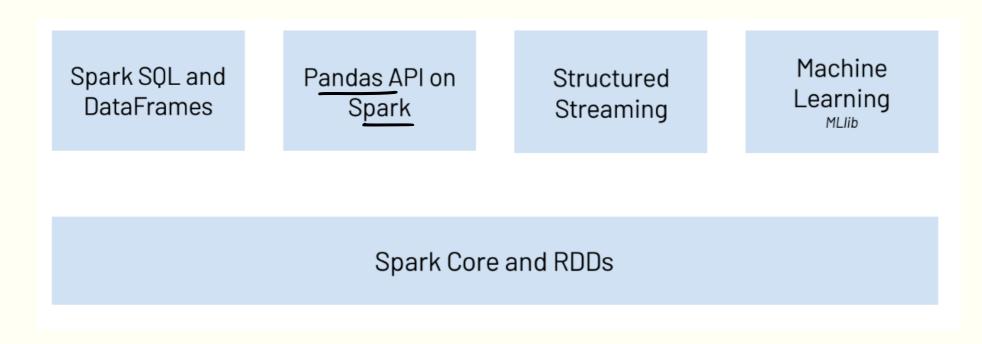
- External Databases:
  - via JDBC:
    - MySQL, Postgres, MongoDB, Cassandra, etc.
  - via connector for specific databases:
    - Cassandra, MongoDB, Neo4J, etc.

#### Spark - Database Connectors

- MongoDB:
  - https://www.mongodb.com/docs/spark-connector/v10.2/getting-started/
- Neo4J:
  - https://neo4j.com/docs/spark/current/quickstart/
- Cassandra:
  - https://github.com/datastax/spark-cassandra-connector/blob/master/doc/ 0\_quick\_start.md
- JDBC to other Databases:
  - https://spark.apache.org/docs/latest/sql-data-sources-jdbc.html#datasource-option

#### pyspark

- Python API for Apache Spark
- Provides support for Spark SQL and DataFrames
- Also supports Structured Streaming, Machine Learning (MLlib),
   Pandas API on Spark, and Spark Core (including RDD)



#### pyspark SparkSession

- Entry point for all APIs
- SparkSession supports different operations, including: creating DataFrames, registering DataFrames as tables, and executing SQL commands on tables
- Create SparkSession using spark builder:
  - from pyspark.sql import SparkSession

```
    spark = SparkSession \
        .builder \
            .master("local") \
             .appName("Word Count") \
             .config("spark.some.config.option", "some-value") \
             .getOrCreate()
```

#### pyspark DataFrame - Reading Data

```
CSV:
    path = "examples/src/main/resources/people.csv"
    • df = spark.read.csv(path)
    • df2 = spark.read.option("delimiter", ";").csv(path)
JDBC Connector:
    ■ df = spark.read \
                .format("jdbc") \
                .option("url", "jdbc:postgresql:dbserver") \
                .option("dbtable", "schema.tablename") \
                .option("user", "username") \
                .option("password", "password") \
                .load()
    df2 = spark.read \
                 .jdbc("jdbc:postgresql:dbserver", "schema.tablename",
                 properties={"user": "username", "password": "password"})
```



#### pyspark DataFrame - Writing Data

```
CSV:
    • df.write.csv("output")
JDBC Connector:
    ■ jdbcDF.write \
             .format("jdbc") \
             .option("url", "jdbc:postgresql:dbserver") \
             .option("dbtable", "schema.tablename") \
             .option("user", "username") \
             .option("password", "password") \
            .save()
jdbcDF2.write \
          .jdbc("jdbc:postgresql:dbserver", "schema.tablename",
          properties={"user": "username", "password": "password"})
```

 $source: Apache \ Spark \ Documentation; \ \underline{https://spark.apache.org/docs/latest/sql-data-sources-jdbc.html}$ 

#### pyspark DataFrame - Column Selection

- . (dot) operator invokes apply() method and returns the selected column:
  - people = spark.createDataFrame([

```
{"deptId": 1, "age": 40, "name": "Hyukjin Kwon", "gender": "M", "salary": 50}, 
{"deptId": 1, "age": 50, "name": "Takuya Ueshin", "gender": "M", "salary": 100}, 
{"deptId": 2, "age": 60, "name": "Xinrong Meng", "gender": "F", "salary": 150}, 
{"deptId": 3, "age": 20, "name": "Haejoon Lee", "gender": "M", "salary": 200}])
```

- age\_col = people.age
- select() returns a new DataFrame with the specified columns or expression:
  - people.select(people.deptId, people.name)
- drop() returns a new DataFrame without the specified columns:
  - df = spark.createDataFrame([(14, "Tom"), (23, "Alice"), (16, "Bob")], ["age", "name"])
  - df.drop('age')
- toDF() returns a new DataFrame with new specified column names:
  - df = spark.createDataFrame([(14, "Tom"), (23, "Alice"), (16, "Bob")], ["age", "name"])
  - df.toDF('f1', 'f2')



#### pyspark DataFrame - Row Selection

- filter() filters rows with the specified condition:
  - df = spark.createDataFrame([(2, "Alice"), (5, "Bob")], schema=["age", "name"])
  - df.filter(df.age > 3)
- distinct() returns a new DataFrame with the distinct rows:
  - df = spark.createDataFrame([(14, "Tom"), (23, "Alice"), (23, "Alice")], ["age", "name"])
  - df.distinct()
- head() returns the first (n) rows as a list of Row:
  - df = spark.createDataFrame([(2, "Alice"), (5, "Bob")], schema=["age", "name"])
  - df.head(2)
- tail() returns the last n) rows as a list of Row:
  - df = spark.createDataFrame([(14, "Tom"), (23, "Alice"), (16, "Bob")], ["age", "name"])
  - df.tail(2)

#### pyspark DataFrame - Join Operations

- join() joins with another DataFrame per the given expression:
  - df = spark.createDataFrame([(2, "Alice"), (5, "Bob")]).toDF("age", "name")
  - df2 = spark.createDataFrame([Row(height=80, name="Tom"), Row(height=85, name="Bob")])
  - df.join(df2, 'name').select(df.name, df2.height)

#### pyspark DataFrame - Miscellaneous Methods

- show() prints the first (n) rows to the console:
  - df = spark.createDataFrame([(2, "Alice"), (5, "Bob")], schema=["age", "name"])
  - df.show(2)
- count() returns the number of rows in the DataFrame:
  - df = spark.createDataFrame([(14, "Tom"), (23, "Alice"), (16, "Bob")], ["age", "name"])
  - df.count()

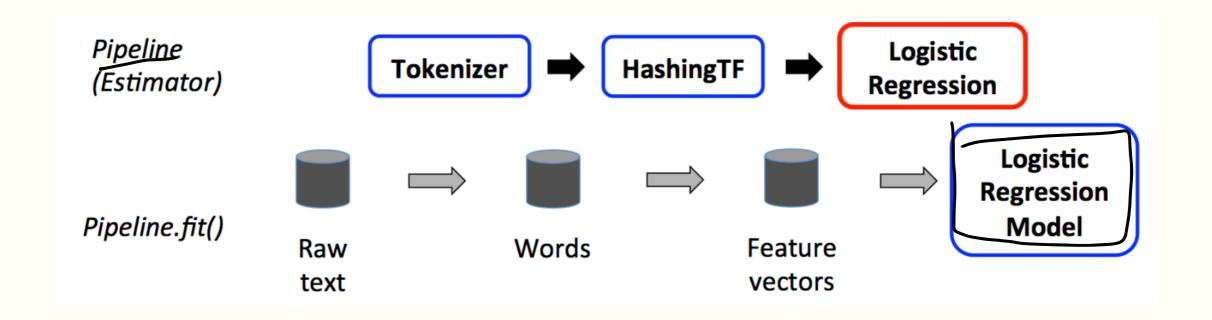


#### Spark MLlib

- Scalable machine learning library for Spark
- Supports common ML algorithms including classification, regression, clustering, and collaborative filtering
- Integrates well with Spark SQL, DataFrames and Structures Streaming APIs
- Supports Scala, Java, Python and R programing languages
- Guide:
  - https://spark.apache.org/docs/latest/ml-guide.html

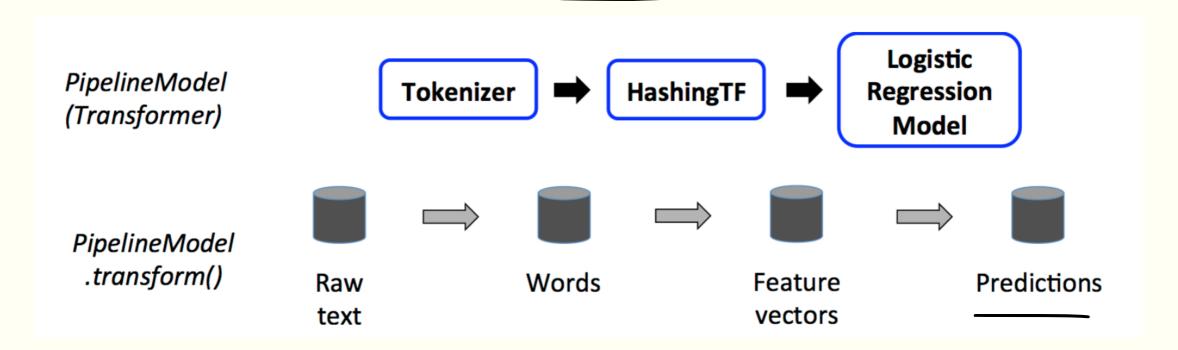
#### Spark MLlib - Pipeline

- Pipeline consists of a sequence of algorithms (Transformers and Estimators)
- Transformer transforms one DataFrame to another
- Estimator can be fit on a DataFrame to produce a Transformer



#### Spark MLlib - Pipeline (cont.)

- Since Pipeline is an Estimator, Pipeline.fit() returns a PipelineModel transformer
- The Transformer can then be applied to test data set (DataFrame) to generate the predictions (DataFrame)





#### GraphFrames <



- Provide DataFrame based Graphs
- Separate package than Apache Spark:
- Provides high-level APIs for Scala, Java and Python
- Download:
  - http://spark-packages.org/package/graphframes/graphframes
- Documentation:
  - https://graphframes.github.io/graphframes/docs/\_site/index.html

#### GraphFrames

- Steps:
  - Create DataFrames for Vertices and Edges
  - Create GraphFrame from the DataFrames

#### Example:

```
from graphframes import * v = spark.createDataFrame([("a", "Alice", 34), ("b", "Bob", 36), ("c", "Charlie", 30),], ["id", "name", "age"])
e = spark.createDataFrame([("a", "b", "friend"), ("b", "c", "follow"), ("c", "b", "follow"),], ["src", "dst", "relationship"])
g = GraphFrame(v, e)
```

### GraphFrames - Algorithms

- Built-In Algorithms:
  - Breadth First Search
  - Shortest Path
  - Page Rank
  - and more ...
- Example:

```
results = g.pageRank(resetProbability=0.01, maxIter=20) results.vertices.select("id", "pagerank").show()
```

#### Spark - Custom Functions

- Custom function support:
  - Spark RDD (Resilient Distributed Dataset) operations
  - Spark UDF (User Defined Functions)

#### pyspark - UDF

- Custom standalone Python functions can be converted to Spark UDFs.
- pyspark supports UDF operation on DataFrames on column-basis
- Supported data types for pyspark UDFs are the types defined in pyspark.sql.types. For example: StringType, IntegerType, FloatType, etc.
- Steps involved:
  - Define standalone Python function
  - Convert the function to a <u>UDF</u> (using <u>@udf</u> annotation or pyspark.sql.functions.udf() constructor)
  - (Optional) register the Python function or <u>UDF</u> as SQL function using pyspark.sql.UDFRegistration.register() method

#### Spark - UDF

```
Example 1:
    from pyspark.sql.types import IntegerType
    from pyspark.sql.functions import udf
    @udf
→ def to_upper(s):
       if s is not None:
         return s.upper()
    df = spark.createDataFrame([(1, "John Doe", 21)], ("id", "name", "age"))
    df.select("name", to_upper("name")).show()
```



#### Spark - UDF

Example 1:

```
from pyspark.sql.types import IntegerType
from pyspark.sql.functions import udf
@udf(returnType=IntegerType())

def add_one(x):
    if x is not None:
        return x + 1

df = spark.createDataFrame([(1, "John Doe", 21)], ("id", "name", "age"))
    df.select("age", add_one("age")).show()
```

source: <a href="https://spark.apache.org/docs/3.1.3/api/python/reference/api/pyspark.sql.functions.udf.html">https://spark.apache.org/docs/3.1.3/api/python/reference/api/pyspark.sql.functions.udf.html</a>

#### Summary

- Spark provides low-level and high-level APIs for distributed data processing:
  - SQL, DataFrames and DataSets
  - RDDs and Distributed Variables
- DataFrame provide rich library of methods:
  - column-based operations, row-based operations and miscellaneous operations
- Spark MLlib module provides machine learning libraries with DataFrames
- GraphFrame (external) package provides Graph support with DataFrames
- Spark RDD and UDF can be used for implementation custom algorithms