

Create and run Spark programs faster:

- Write less code
- Read less data
- Let the optimizer do the hard work

DataFrame

noun – [dey-tuh-freym]

- A distributed collection of rows organized into named columns.
- 2. An abstraction for selecting, filtering, aggregating and plotting structured data (*cf. R, Pandas*).
- 3. Archaic: Previously SchemaRDD (cf. Spark < 1.3).



Unified interface to reading/writing data in a variety of formats:

```
df = sqlContext.read \
     .format("json") \
     .option("samplingRatio", "0.1") \
     .load("/home/michael/data.json")
  df.write \
     .format("parquet") \
     .mode("append") \
     .partitionBy("year") \
     .saveAsTable("fasterData")
databricks
```

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read and write functions create new builders for doing I/O

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Builder methods specify:

- **Format**
- Partitioning Handling of existing data

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```

load(...), save(...) or
 saveAsTable(...)
 finish the I/O
 specification

Write Less Code: Data Source API

Spark SQL's Data Source API can read and write DataFrames using a variety of formats.







plain text*

Write Less Code: High-Level Operations

Solve common problems concisely using DataFrame functions:

- Selecting columns and filtering
- Joining different data sources
- Aggregation (count, sum, average, etc)
- Plotting results with Pandas



Write Less Code: Compute an Average

Using RDDs

```
data = sc.textFile(...).split("\t")
data.map(lambda x: (x[0], [int(x[1]), 1])) \
    .reduceByKey(lambda x, y: [x[0] + y[0], x[1] + y[1]]) \
    .map(lambda x: [x[0], x[1][0] / x[1][1]]) \
    .collect()
```

Using SQL

```
SELECT name, avg(age)
FROM people
GROUP BY name
```

Using DataFrames

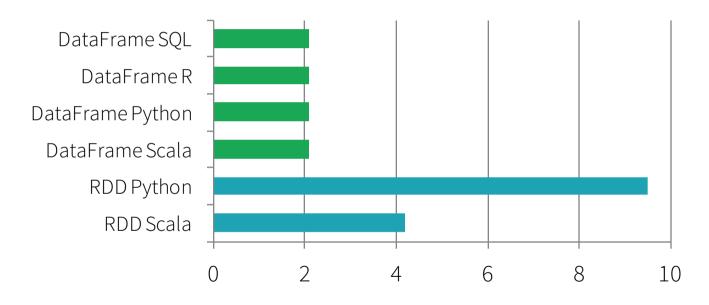
```
sqlCtx.table("people") \
    .groupBy("name") \
    .agg("name", avg("age")) \
    .map(lambda ...) \
    .collect()
```

Full API Docs

- Python
- Scala
- Java
- <u>R</u>



Not Just Less Code, Faster Too!



Time to Aggregate 10 million int pairs (secs)



Seamlessly Integrated

Intermix DataFrame operations with custom Python, Java, R, or Scala code

```
zipToCity = udf(lambda zipCode: <custom logic here>)

def add_demographics(events):
    u = sqlCtx.table("users")
    events \
        .join(u, events.user_id == u.user_id) \
        .withColumn("city", zipToCity(df.zip))
    use
Augment

that could be add_demographics(events):

u = sqlCtx.table("users")

output

user_id) \
user
```

Augments any DataFrame that contains user id

Optimize Full Pipelines

Optimization happens as late as possible, therefore Spark SQL can optimize even across functions.

```
events = add_demographics(sqlCtx.load("/data/events", "json"))
training_data = events \
   .where(events.city == "Amsterdam") \
   .select(events.timestamp) \
   .collect()
```



