Structuring Apache Spark

SQL, DataFrames, Datasets, and Streaming

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databricks™

Background: What is in an RDD?

- Dependencies
- Partitions (with optional locality info)
- Compute function: Partition => Iterator[T]

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Opaque Data

Struc·ture

[ˈstrək(t)SHər]

verb

1. construct or arrange according to a plan; give a pattern or organization to.

Why structure?

- By definition, structure will *limit* what can be expressed.
- In practice, we can accommodate the vast majority of computations.

Limiting the space of what can be expressed enables optimizations.

Structured APIs In Spark

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

Analysis errors reported before a distributed job starts

Datasets API

Type-safe: operate on domain objects with compiled lambda functions

```
val df = spark.read.json("people.json")

// Convert data to domain objects.
case class Person(name: String, age: Int)
val ds: Dataset[Person] = df.as[Person]
ds.filter(_.age > 30)

// Compute histogram of age by name.
val hist = ds.groupBy(_.name).mapGroups {
  case (name, people: Iter[Person]) =>
    val buckets = new Array[Int](10)
    people.map(_.age).foreach { a =>
      buckets(a / 10) += 1
    }
    (name, buckets)
}
```

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DataFrame = Dataset[Row]

- Spark 2.0 unifies these APIs
- Stringly-typed methods will downcast to generic **`Row`** objects
- Ask Spark SQL to enforce types on generic rows using **`df.as[MyClass]`**

What about python?

Some of the goals of the Dataset API have always been available!

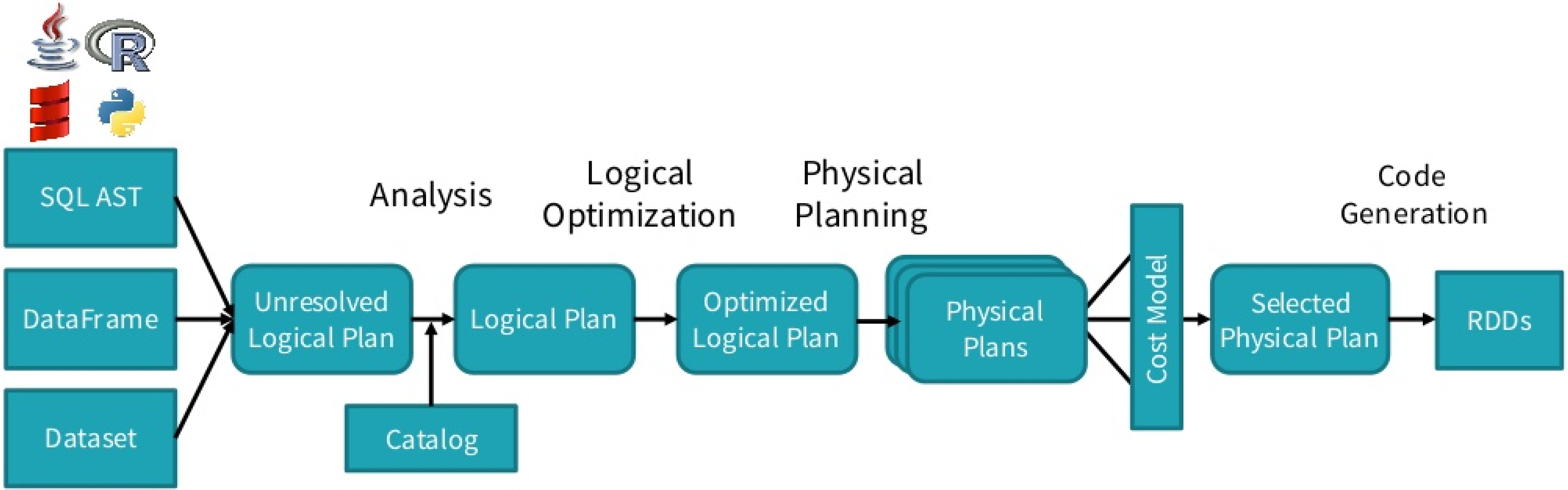
Scala

```
df.map(x => x(0).asInstanceOf[String])
```

python

```
df.map(lambda x: x.name)
```

Shared Optimization & Execution



DataFrames, Datasets and SQL
share the same optimization/execution pipeline

Structuring Computation

```
WITH customer_total_return AS  (SELECT
sr_customer_sk AS ctr_customer_sk,
sr_store_sk AS ctr_store_sk,
sum(sr_return_amt) AS ctr_total_return
FROM store_returns, date_dim  WHERE
sr_returned_date_sk = d_date_sk AND d_year
= 2000  GROUP BY sr_customer_sk,
sr_store_sk) SELECT c_customer_id  FROM
customer_t
```

Columns

New value, computed based on input values.

DSL

```
col("x") === 1
df("x") === 1
expr("x = 1")
sql("SELECT … WHERE x = 1")
```

SQL Parser

Complex Columns With Functions

- 100+ native functions with optimized codegen implementations
  - String manipulation – `concat, format_string, lower, lpad`
  - Data/Time – `current_timestamp, date_format, date_add, …`
  - Math – `sqrt, randn, …`
  - Other – `monotonicallyIncreasingId, sparkPartitionId, …`

python

```python
from pyspark.sql.functions import *
yesterday = date_sub(current_date(), 1)
df2 = df.filter(df.created_at > yesterday)
```

Scala

```scala
import org.apache.spark.sql.functions._
val yesterday = date_sub(current_date(), 1)
val df2 = df.filter(df("created_at") > yesterday)
```

	Functions	Columns
You Type	`(x: Int) => x == 1`	`col("x") === 1`

Spark Sees	`class $anonfun$1{`
	`  def apply(Int): Boolean`
	`}`
		`EqualTo(x, Lit(1))`

Columns: Predicate pushdown

You Write

```
spark.read
  .format("jdbc")
  .option("url", "jdbc:postgresql:dbserver")
  .option("dbtable", "people")
  .load()
  .where($"name" === "michael")
```

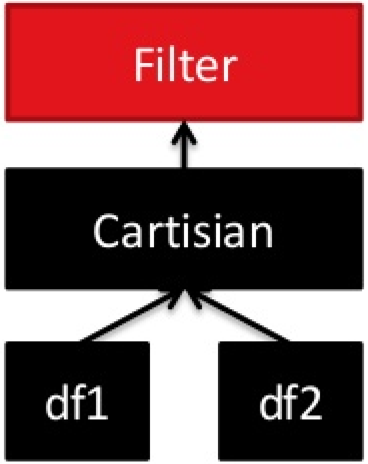
Spark Translates For Postgres

```
SELECT * FROM people WHERE name = 'michael'
```

Columns: Efficient Joins

```python
myUDF = udf(lambda x, y: x == y)
df1.join(df2, myUDF(col("x"), col("y")))
```

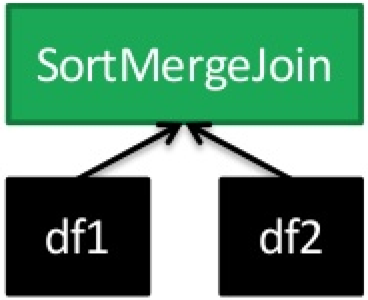
n^2



Equal values sort to the same place

```python
df1.join(df2, col("x") == col("y"))
```

n log n



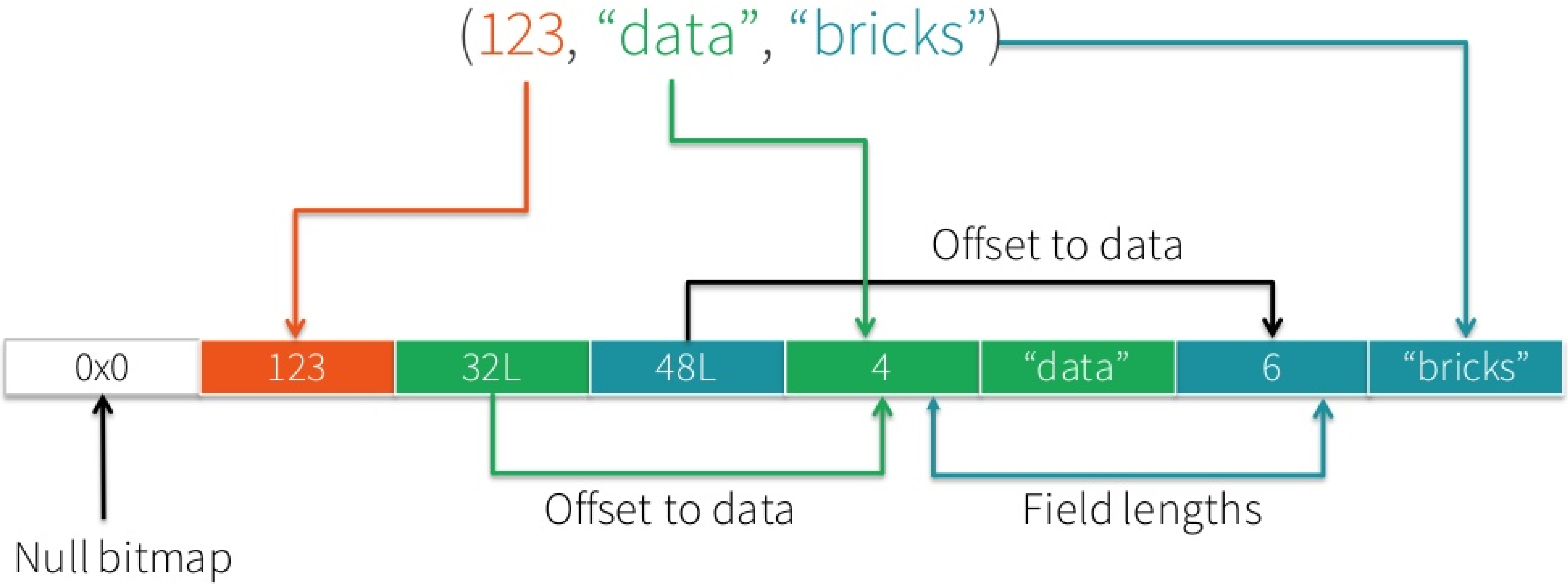
Structuring Data

1010101011101010100010101010111010000101
1101111010101101000101111010100011111001
10101010111010101010101001111010101001010
100010100110001101101011010101010101110
10101000101010101011101000101110111010101
101000101111010100011111001101010101110

Spark's Structured Data Model

- **Primitives**: Byte, Short, Integer, Long, Float, Double, Decimal, String, Binary, Boolean, Timestamp, Date
- **Array[Type]**: variable length collection
- **Struct**: fixed # of nested columns with fixed types
- **Map[Type, Type]**: variable length association

Tungsten's Compact Encoding



Encoders

Encoders translate between domain objects and Spark's internal format

JVM Object

```
MyClass(123, “data”, “bricks”)
```

Internal Representation

0x0	123	32L	48L	4	“data”	6	“bricks”

Bridge Objects with Data Sources

Encoders map columns to fields by name

{ JSON } JDBC Parquet

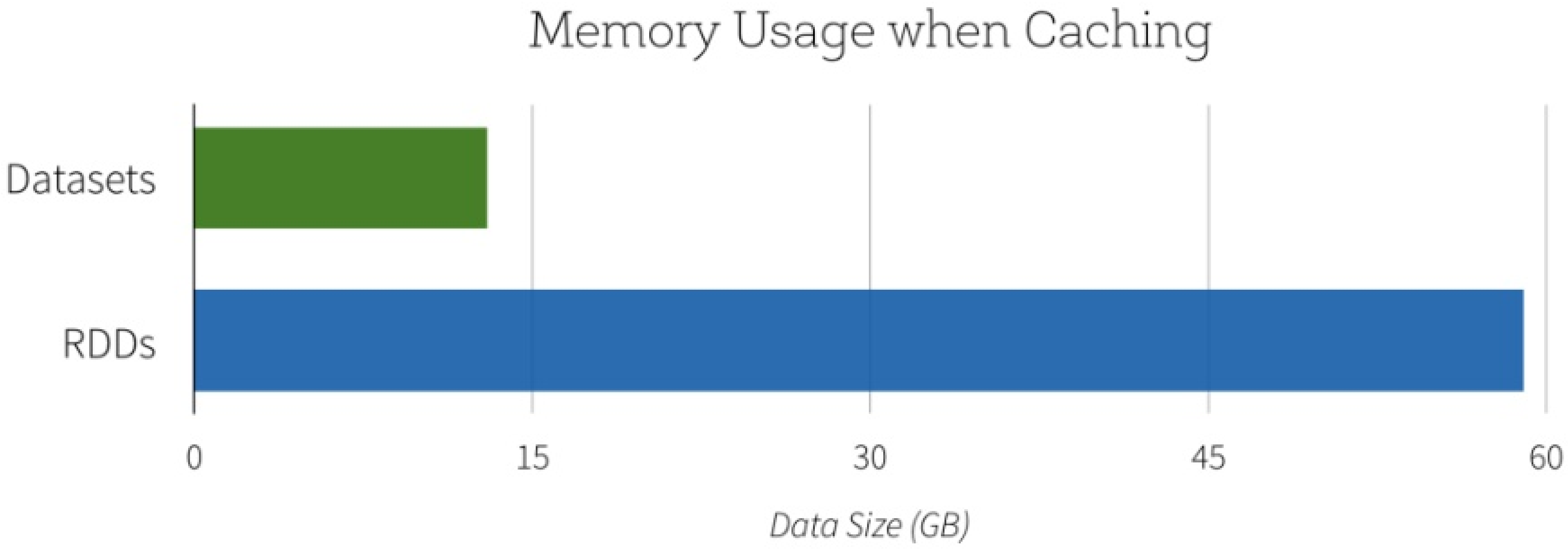
AVRO CSV cassandra

elasticsearch. amazon web services Amazon Redshift memsql

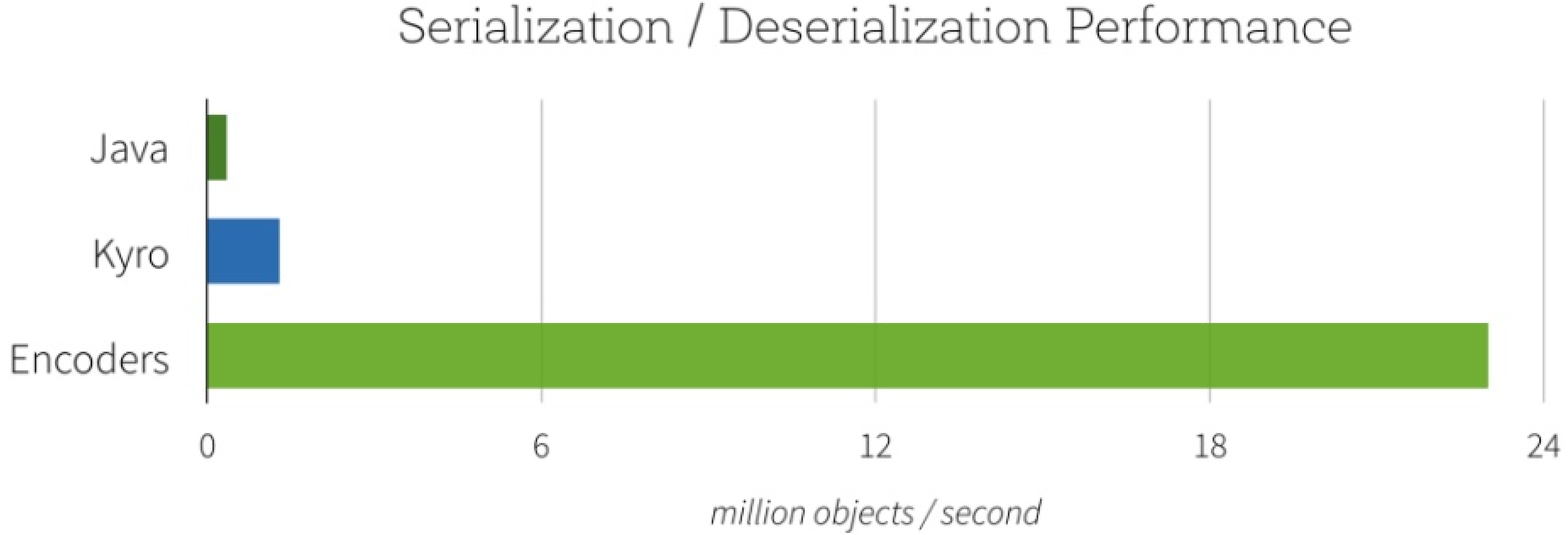
```
{
  "name": "Michael",
  "zip": "94709"
  "languages": ["scala"]
}
```

```
case class Person(
  name: String,
  languages: Seq[String],
  zip: Int)
```

Space Efficiency



Serialization performance



Operate Directly On Serialized Data

DataFrame Code / SQL

```
df.where(df("year") > 2015)
```

Catalyst Expressions

```
GreaterThan(year#234, Literal(2015))
```

Low-level bytecode

```
bool filter(Object baseObject) {
   int offset = baseOffset + bitSetWidthInBytes + 3*8L;
   int value = Platform.getInt(baseObject, offset);
   return value34 > 2015;
}
```

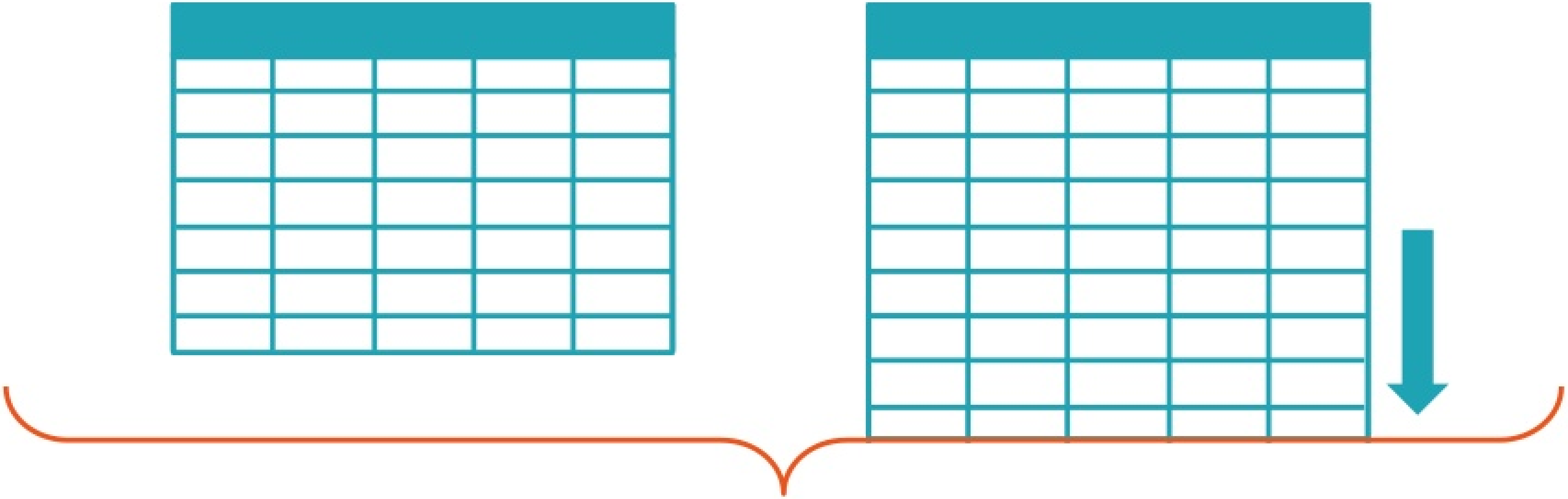
JVM *intrinsic* JIT-ed to pointer arithmetic

Structured Streaming

The simplest way to perform streaming analytics is not having to ***reason*** about streaming.

Apache Spark 1.3
Static DataFrames

Apache Spark 2.0
Continuous DataFrames



Single API !

Structured Streaming

- **High-level streaming API built on Apache Spark SQL engine**
  - Runs the same queries on DataFrames
  - Event time, windowing, sessions, sources & sinks

- **Unifies streaming, interactive and batch queries**
  - Aggregate data in a stream, then serve using JDBC
  - Change queries at runtime
  - Build and apply ML models

Example: Batch Aggregation

```
logs  = spark.read.format("json").open("s3://logs")

logs.groupBy(logs.user_id).agg(sum(logs.time))
    .write.format("jdbc")
    .save("jdbc:mysql//...")
```

Example: Continuous Aggregation

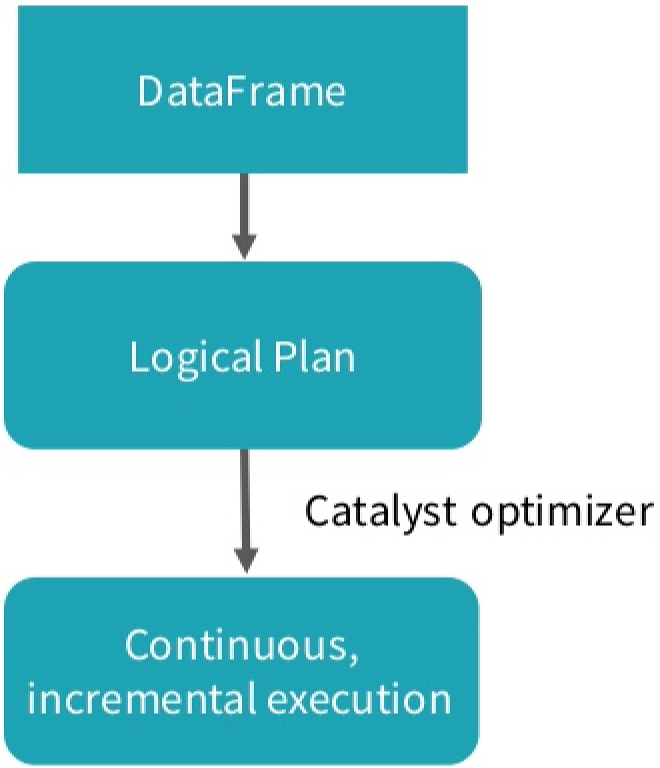
```
logs  = spark.read.format("json").stream("s3://logs")

logs.groupBy(logs.user_id).agg(sum(logs.time))
    .write.format("jdbc")
    .stream("jdbc:mysql//...")
```

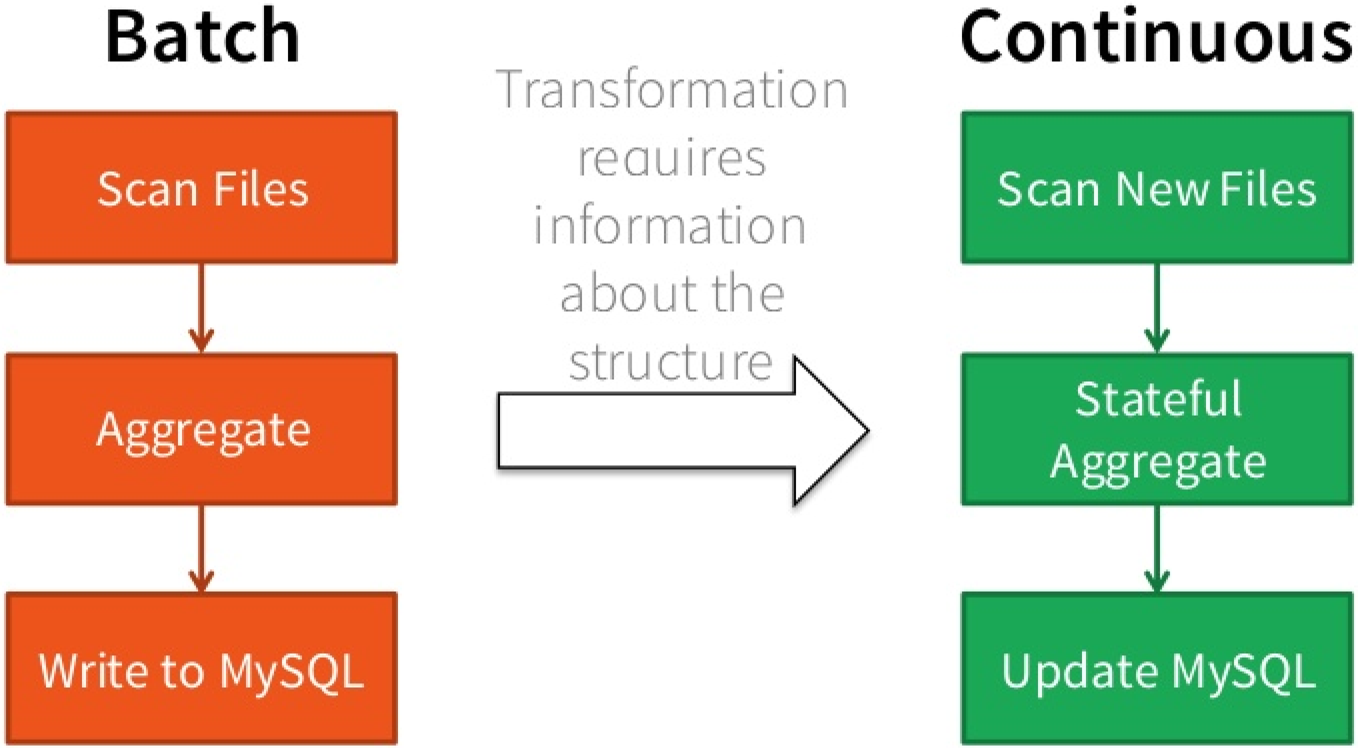
Execution

Logically:
DataFrame operations on static data
(i.e. as easy to understand as batch)

Physically:
Spark automatically runs the query in streaming fashion
(i.e. incrementally and continuously)



Incrementalized By Spark



What's Coming?

- Apache Spark 2.0
  - Unification of the DataFrame/Dataset & *Context APIs
  - Basic streaming API
  - Event-time aggregations
- Apache Spark 2.1+
  - Other streaming sources / sinks
  - Machine learning
  - Watermarks
- Structure in other libraries: MLlib, GraphFrames

Questions?

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