

# SparkSQL

Structured big-data processing in Spark

# Structured Data Processing

- Spark RDD is good for general-purpose processing
- For (semi-)structured data, you need to provide your own parser and logic
- Due to the popularity of (semi-) structured data processing, SparkSQL was added to facilitate this task

# Shark (Spark on Hive)

- A small side project that aimed to running RDD jobs on Hive data using HiveQL
- Still limited to the data model of Hive
- Tied to the Hadoop world

# SparkSQL

- Redesigned to consider Spark query processing model
- Supports all the popular relational operators
- Can be intermixed with RDD operations
- Uses the Dataframe API which is an enhancement to the RDD API

Dataframe = RDD + schema

# Dataframes

- SparkSQL's counterpart to relations or tables in RDMBS
- Consists of rows and columns
- A dataframe is **NOT** in 1NF
  - Why?
- Can be created from various data sources
  - CSV file
  - JSON file
  - MySQL database
  - Hive
  - Parquet column-format files

# Dataframe Vs RDD

## Dataframe

- Lazy execution
- Spark is aware of the data model
- Spark is aware of the query logic
- Can optimize the query

## RDD

- Lazy execution
- The data model is hidden from Spark
- The transformations and actions are black boxes
- Cannot optimize the query

# Built-in operations in SprkSQL

- Filter (Selection)
- Select (Projection)
- Join
- GroupBy (Aggregation)
- Load/Store in various formats
- Cache
- Conversion between RDD (back and forth)

# SparkSQL Examples

# Project Setup

```
# In dependencies pom.xml
<!--
https://mvnrepository.com/artifact/org.apache.spark
/spark-sql -->
<dependency>
    <groupId>org.apache.spark</groupId>
    <artifactId>spark-sql_2.12</artifactId>
    <version>3.1.1</version>
</dependency>
```

# Code Setup

```
val conf = new SparkConf()
val sparkSession = SparkSession.builder().config(conf)
    .appName("test")
    .master("local")
    .getOrCreate()
```

```
//val sparkContext = sparkSession.sparkContext
// Read CSV file
val log_file = sparkSession.read
    .option("delimiter", "\t")
    .option("header", "true")
    .option("inferSchema", "true")
    .csv("nasa_19950801.tsv")
```

# Inspect Relations

```
log_file.show()
```

host	logname	time	method	url	response	bytes	referer	useragent
pppa006.compuser...	-	807256800	GET	/images/launch-lo...	200	1713	null	null
vcc7.langara.bc.ca	-	807256804	GET	/shuttle/missions...	200	8677	null	null
pppa006.compuser...	-	807256806	GET	/history/apollo/i...	200	1173	null	null
thing1.cchem.berk...	-	807256870	GET	/shuttle/missions...	200	4705	null	null
202.236.34.35	-	807256881	GET	/whats-new.html	200	18936	null	null
bettong.client.uq...	-	807256884	GET	/history/skylab/s...	200	1687	null	null
202.236.34.35	-	807256884	GET	/images/whatsnew.gif	200	651	null	null
202.236.34.35	-	807256885	GET	/images/KSC-logos...	200	1204	null	null
bettong.client.uq...	-	807256900	GET	/history/skylab/s...	304	0	null	null

```
log_file.printSchema()
```

```
root
|-- host: string (nullable = true)
|-- logname: string (nullable = true)
|-- time: integer (nullable = true)
|-- method: string (nullable = true)
|-- url: string (nullable = true)
|-- response: integer (nullable = true)
|-- bytes: integer (nullable = true)
|-- referer: string (nullable = true)
|-- useragent: string (nullable = true)
```

# Filter Example

```
// Select and count OK lines
val ok_lines = log_file.filter("response=200")
val ok_count = ok_lines.count()
println(s"Number of ok lines is ${ok_count}")
```

Number of ok lines is 27972

# SQL Example

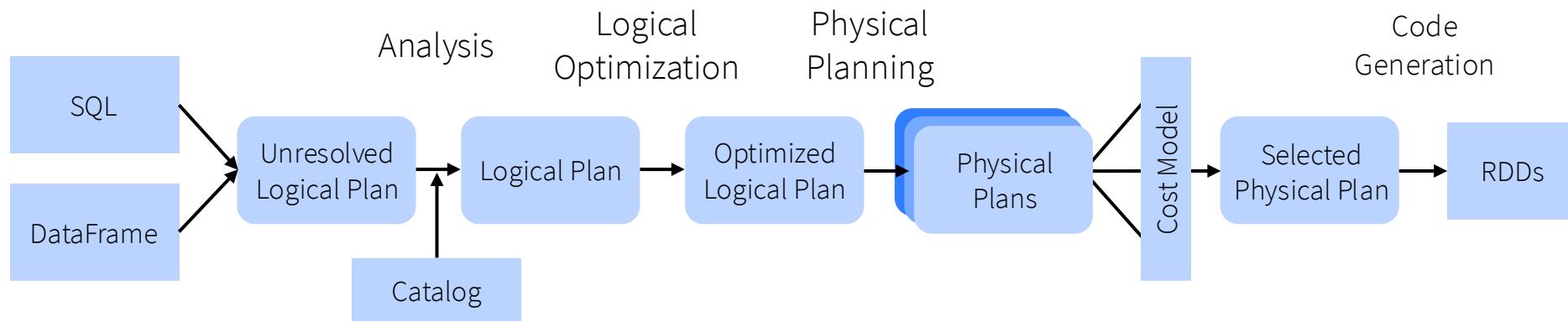
```
log_file.createOrReplaceTempView("log_lines")
log_file.sqlContext.sql("""
    SELECT response, sum(bytes)
    FROM log_lines
    GROUP BY response
""")
.show()
// Cleanup
sparkSession.stop()
```

response	sum(bytes)
404	0
200	481974462
304	0
302	26005

# SparkSQL Features

- Catalyst query optimizer
- Code generation
- Integration with high-level libraries

# SparkSQL Query Plan



DataFrames and SQL share the same optimization/execution pipeline

# Parsing

- Builds an initial unresolved logical plan
- Constructed from either a SQL query or Dataframe code
- Might be logically incorrect, e.g., points to wrong relation names, attribute names, or uses incorrect data types

# Analysis

- Verifies that the plan is logically correct, i.e., can be executed
- Recursively applies several rules to resolve parts of the query
  - Resolve a relation
  - Resolve an attribute type
  - Propagate the name aliases and coerce data types throughout the plan

# Logical Optimizations

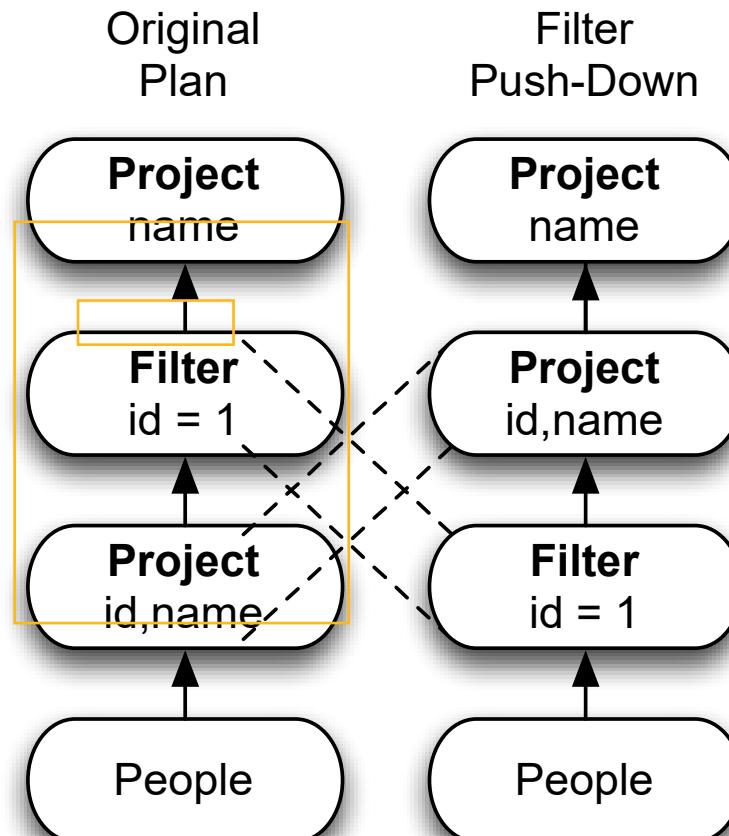
- Rule-based optimization
- Predicate push down for filters
- Projection pruning
- Simplification of wildcard and regular expression matching for strings

# Catalyst Query Optimizer

- Extensible query optimizer
- Can be extended with user-provided rules
- Transforms part of a tree to another tree

# Catalyst Query Optimizer

- Extensible rule-based optimizer
- Users can define their own rules



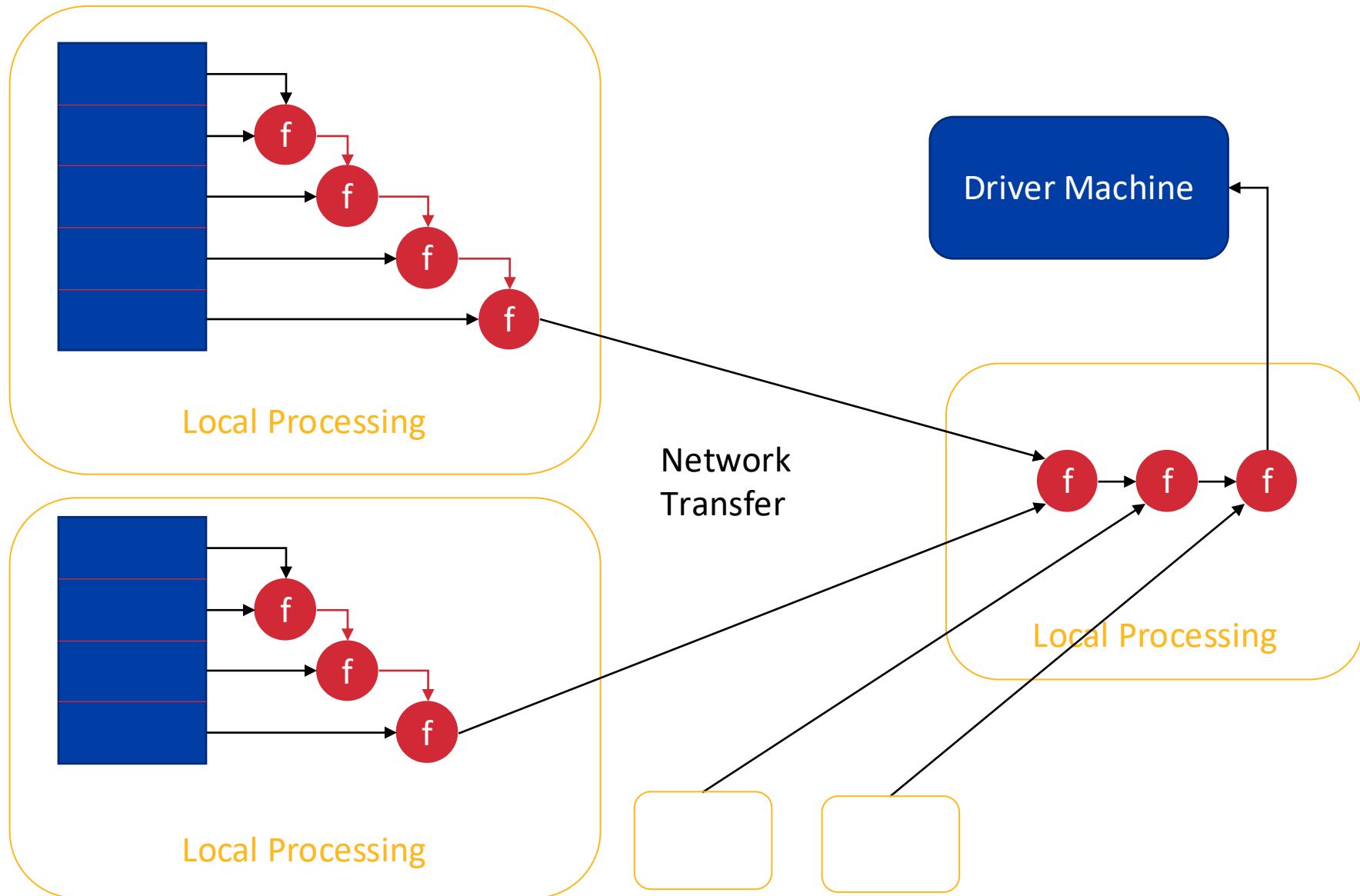
# Physical Optimization

- Generates multiple physical query plans
- Applies a cost model to choose one of them
- Example, use broadcast join when one dataset is known to be very small

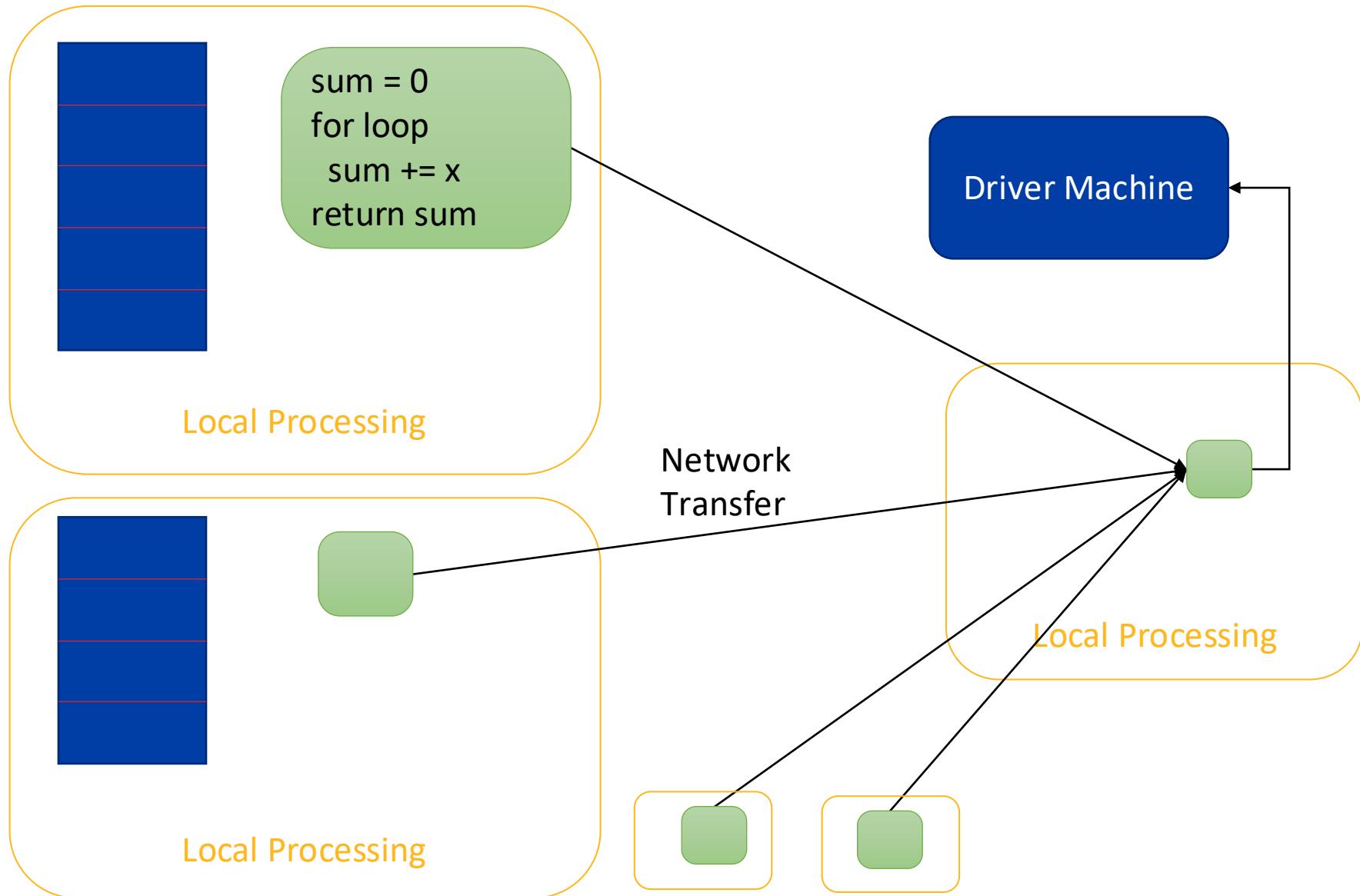
# Code Generation

- Shift from black-box UDF to Expressions
- Example
  - # Filter
  - Dataset<Row> ok\_lines = log\_file.filter("response=200");
  - # Grouped aggregation
  - Dataset<Row> bytesPerCode =  
log\_file.sqlContext().sql("SELECT response, sum(bytes)  
from log\_lines GROUP BY response");
- SparkSQL understands the logic of user queries and rewrites them in a more concise way

# Example: Aggregation (SparkRDD)



# Example: Aggregation (SparkSQL)



# Integration

- SparkSQL is integrated with other high-level interfaces such as MLlib, PySpark, and SparkR
- SparkSQL is also integrated with the RDD interface and they can be mixed in one program

# Further Reading

- Documentation
  - <http://spark.apache.org/docs/latest/sql-programming-guide.html>
- SparkSQL paper
  - M. Armbrust *et al.* “Spark SQL: Relational Data Processing in Spark.” SIGMOD 2015