Spark SQL

BUSINESS INSIDER

The 8 fastest-growing tech skills worth over $110,000

No. 1: Spark, up 120%, worth $113,214

DO you know how to write code in Spark ?

Can you write SQL ?

“SQL is a highly sought-after technical skill due to its ability to work with nearly all databases.”

Ibro Palic, CEO of Resumes Templates

History and Evolution of Big Data Technologies

Procedural
Programing
interface

Declarative
Queries

Automatic
Optimization

So Far…

- We have established that we need platform with Automatic Optimization

What user want ?

1
- ETL from different sources

2
- Advanced Analytics


Solution

Introducing

Spark SQL : Relational Data Processing in Spark

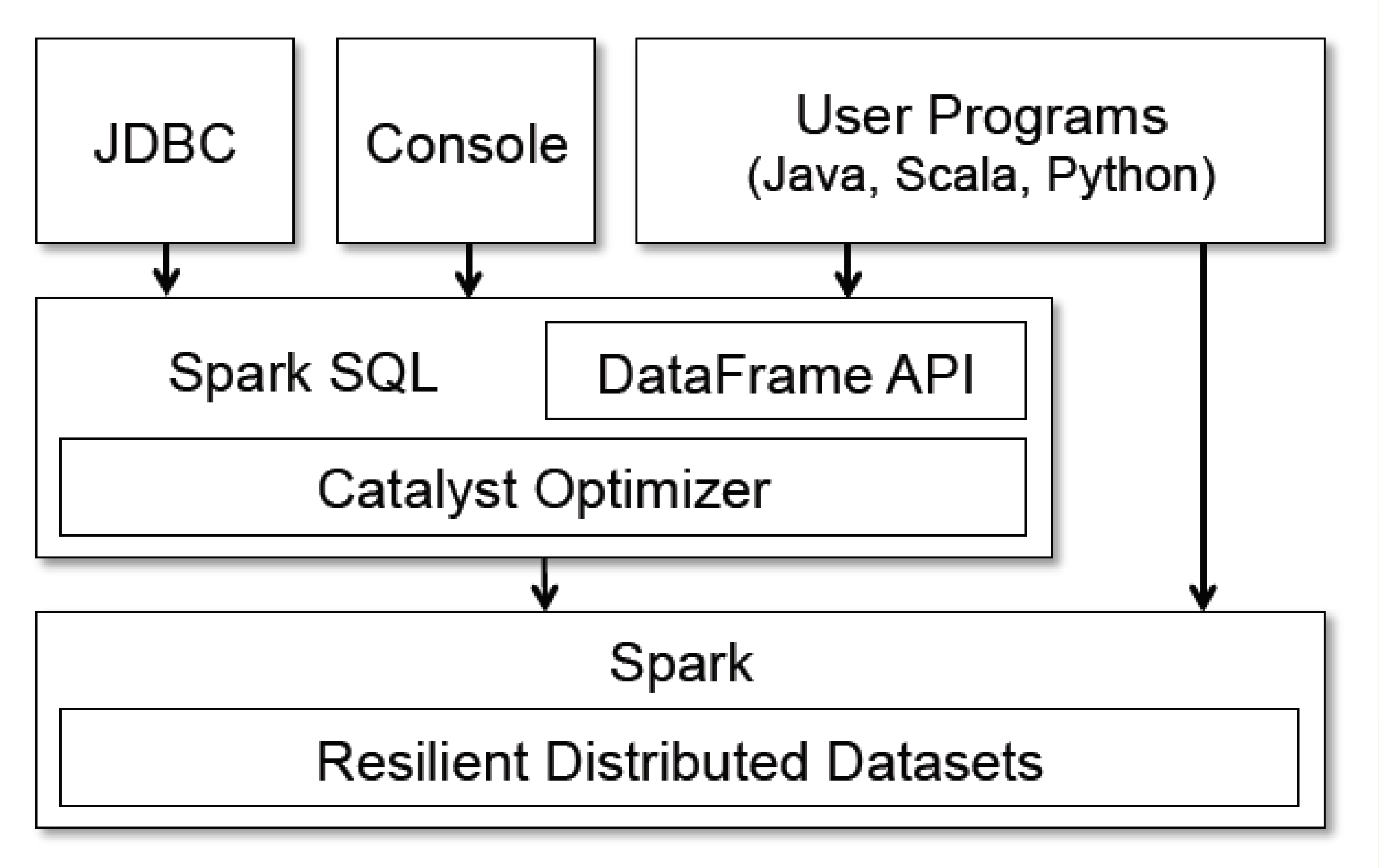
Background

- Apache **Spark** is a **general-purpose cluster computing engine** with APIs in Scala, Java and Python and libraries for streaming, graph processing and machine learning
- **RDDs** are **fault-tolerant**, in that the system can recover lost data using the lineage graph of the RDDs (by rerunning operations such as the filter above to rebuild missing partitions). They can also explicitly be cached in memory or on disk to support iteration
- **Shark**, a modified the Apache **Hive** system to run on Spark and implemented traditional RDBMS optimizations, such as columnar processing, over the Spark engine.

Goals for Spark SQL

- Support **Relational Processing** both within Spark programs and on external data sources
- Provide **High Performance** using established DBMS techniques.
- Easily support **New Data Sources**
- **Enable Extension** with advanced analytics algorithms such as graph processing and machine learning.

Programming Interface



DataFrame API

- DataFrame is a distributed collection of rows with a homogeneous schema

```
ctx = new HiveContext()
users = ctx.table("users")
young = users.where(users("age") < 21)
println(young.count())
```

Keep Track of Hashtags ##

 # A Lazy Computation

Data Model and DataFrame Operations

- Spark SQL uses a nested data model based on Hive
- It supports all major SQL data types, including boolean, integer, double, decimal, string, date, timestamp and also User Defined Data types

Example of DataFrame Operations

```
employees
  .join(dept, employees("deptId") === dept("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept("name"))
  .agg(count("name"))
```

DataFrame Operations Cont.

```
users.where(users("age") < 21)
     .registerTempTable("young")
ctx.sql("SELECT count(*), avg(age) FROM young")
```

#Access DF with DSL or SQL

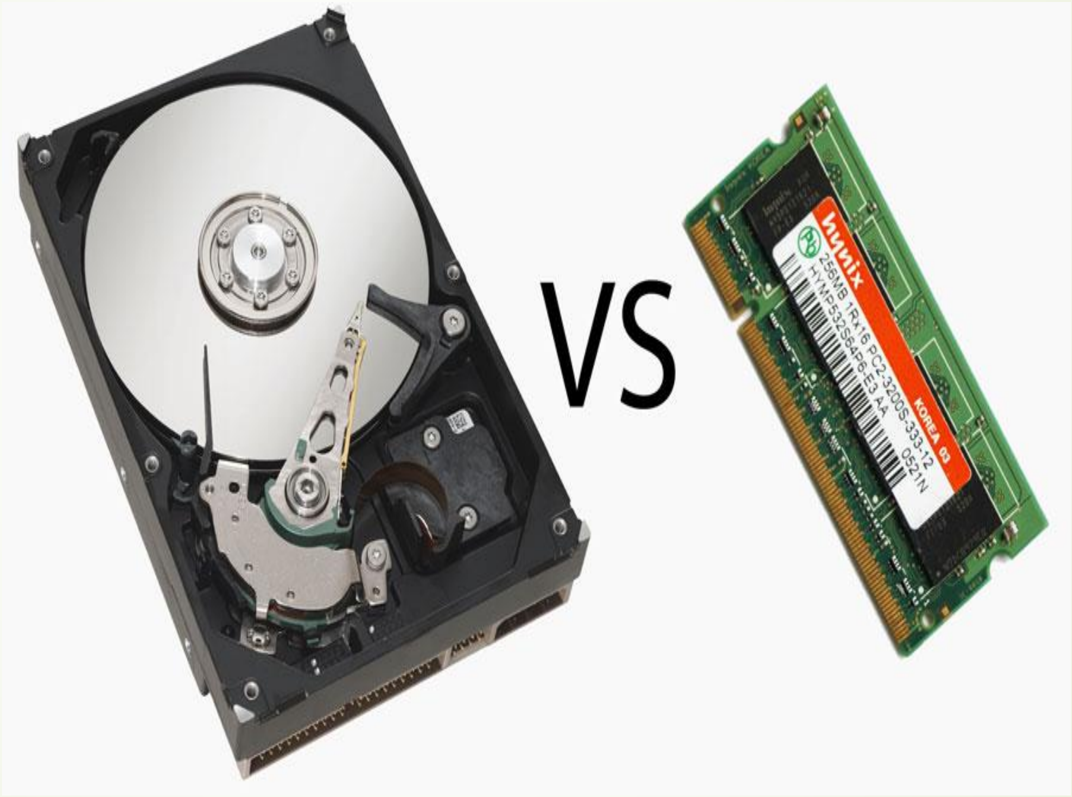
Real World Problems

#Heterogeneous Data Sources

Schema Inference

- Spark SQL can automatically infer the schema of these objects using **reflection**
- **Scala/Java -** extracted from the language's type system
- **Python –** Sampling the Dataset

In – Memory Caching



#Invoked with .cache()

User-Defined Functions

```
val model: LogisticRegressionModel = ...

ctx.udf.register("predict",
  (x: Float, y: Float) => model.predict(Vector(x, y)))

ctx.sql("SELECT predict(age, weight) FROM users")
```

How Spark SQLs User defined functions are different than traditional Database Systems ?

Catalyst Optimizer

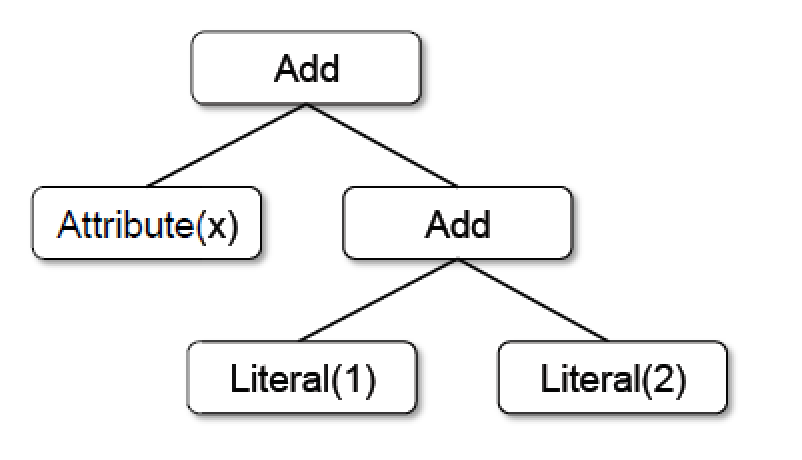
- Catalyst is based on functional programming constructs in Scala

Purposes

- Ability to add new optimization techniques and features to Spark SQL
- Ability to extend the optimizer

Catalyst Optimization

#Trees



#Rules

```
tree.transform {
  case Add(Literal(c1), Literal(c2)) => Literal(c1+c2)
}
```

Catalyst Optimization Cont.

- **Rule Based Optimization**
- **Cost Based Optimization**

Query Planning in Spark SQL

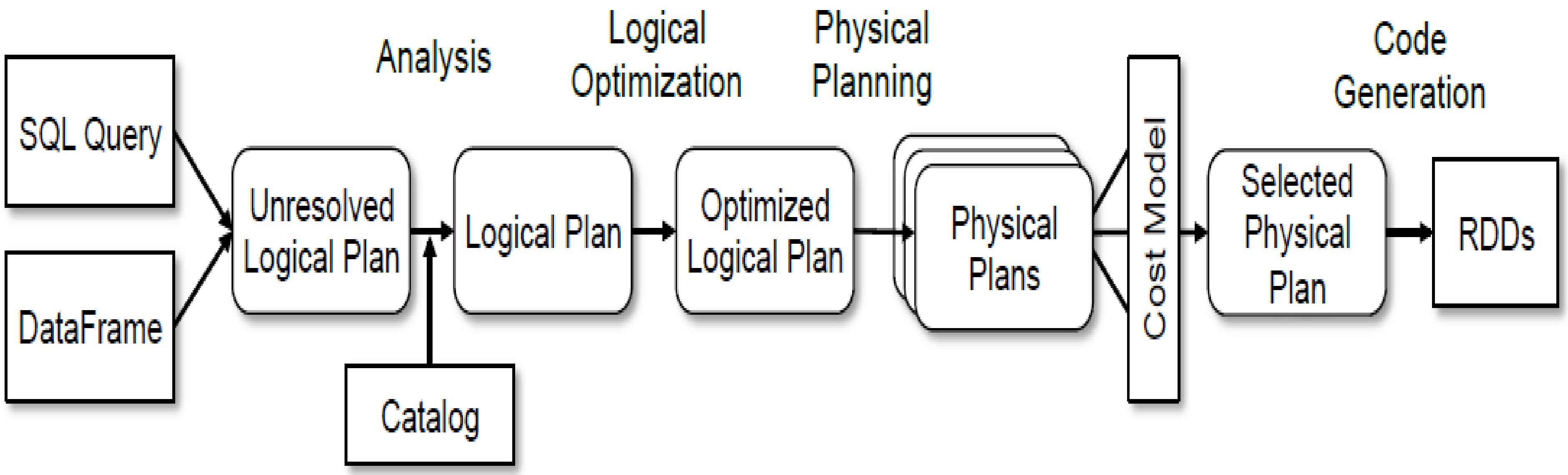
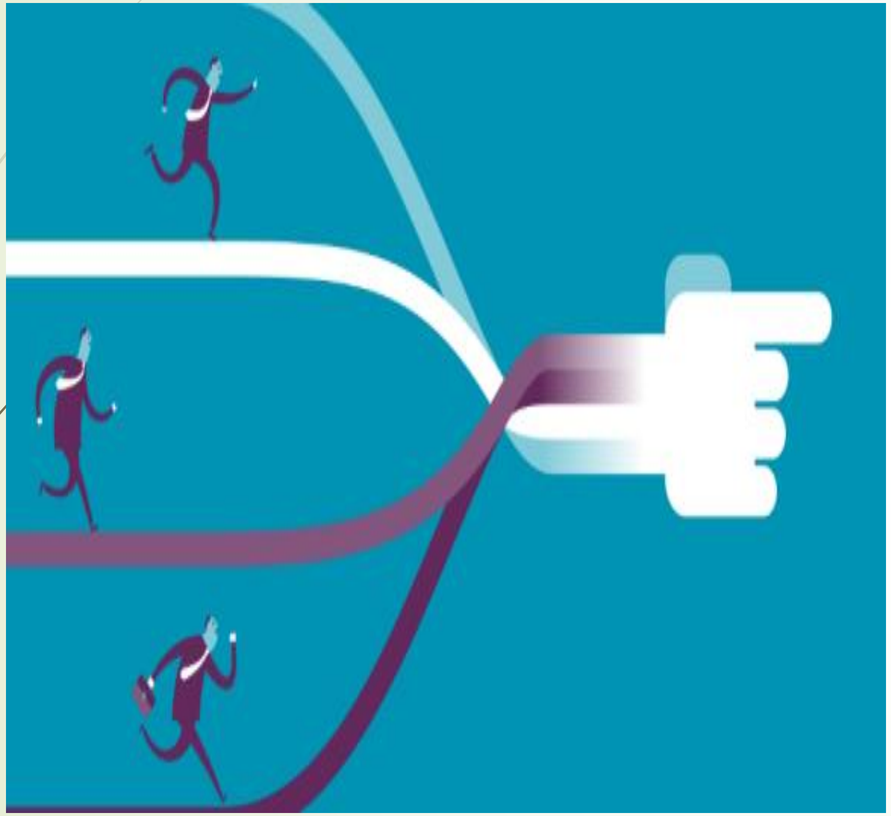


Figure 3: Phases of query planning in Spark SQL. Rounded rectangles represent Catalyst trees.

Extension Points



#Open Source Projects

Extension Points Cont.

- **Data Sources**

  Examples :

  - **CSV**
  - **Avro**
  - **Parquet**
  - **JDBC**

Extension Points Cont.

- **User Defined Types (UDTs)**

```
class PointUDT extends UserDefinedType[Point] {
  def dataType = StructType(Seq(    // Our native structure
    StructField("x", DoubleType),
    StructField("y", DoubleType)
  ))
  def serialize(p: Point) = Row(p.x, p.y)
  def deserialize(r: Row) =
    Point(r.getDouble(0), r.getDouble(1))
}
```

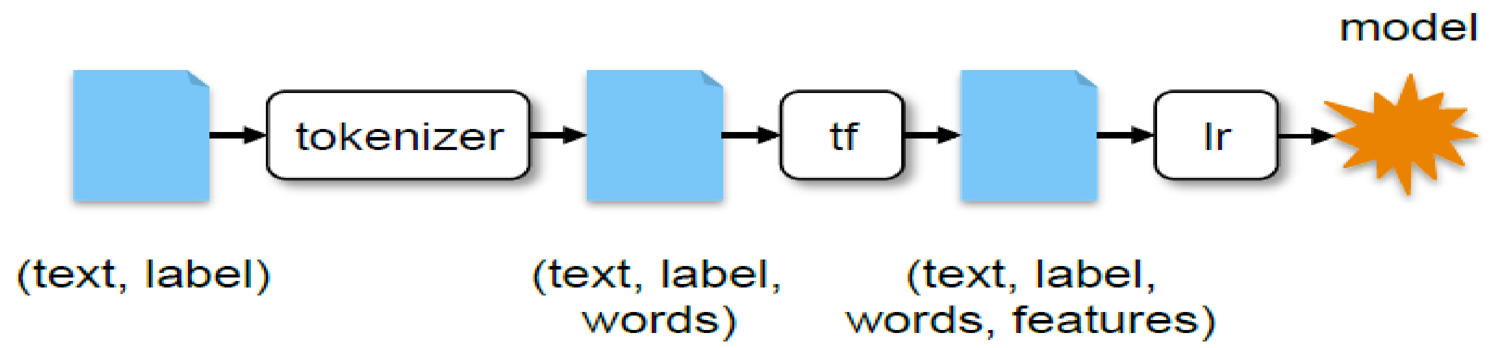
#Useful for Machine Learning

Advanced Analytics Features

- **1.Schema Inference for Semi structured Data**
- **2.Query Federation to External Databases**

Advanced Analytics Features Cont.

3.Integration with Spark’s Machine Learning Library




```
data = <DataFrame of (text, label) records>

tokenizer = Tokenizer()
  .setInputCol("text").setOutputCol("words")
tf = HashingTF()
  .setInputCol("words").setOutputCol("features")
lr = LogisticRegression()
  .setInputCol("features")

pipeline = Pipeline().setStages([tokenizer, tf, lr])
model = pipeline.fit(data)
```

Evaluation

- **SQL Performance**

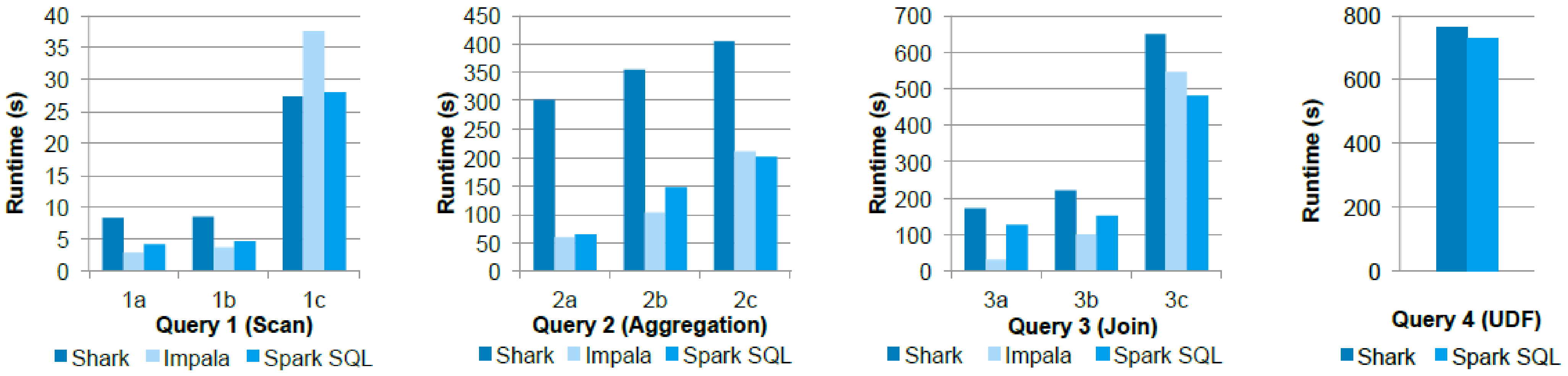


Figure 8: Performance of Shark, Impala and Spark SQL on the big data benchmark queries [31].

Evaluation Cont.

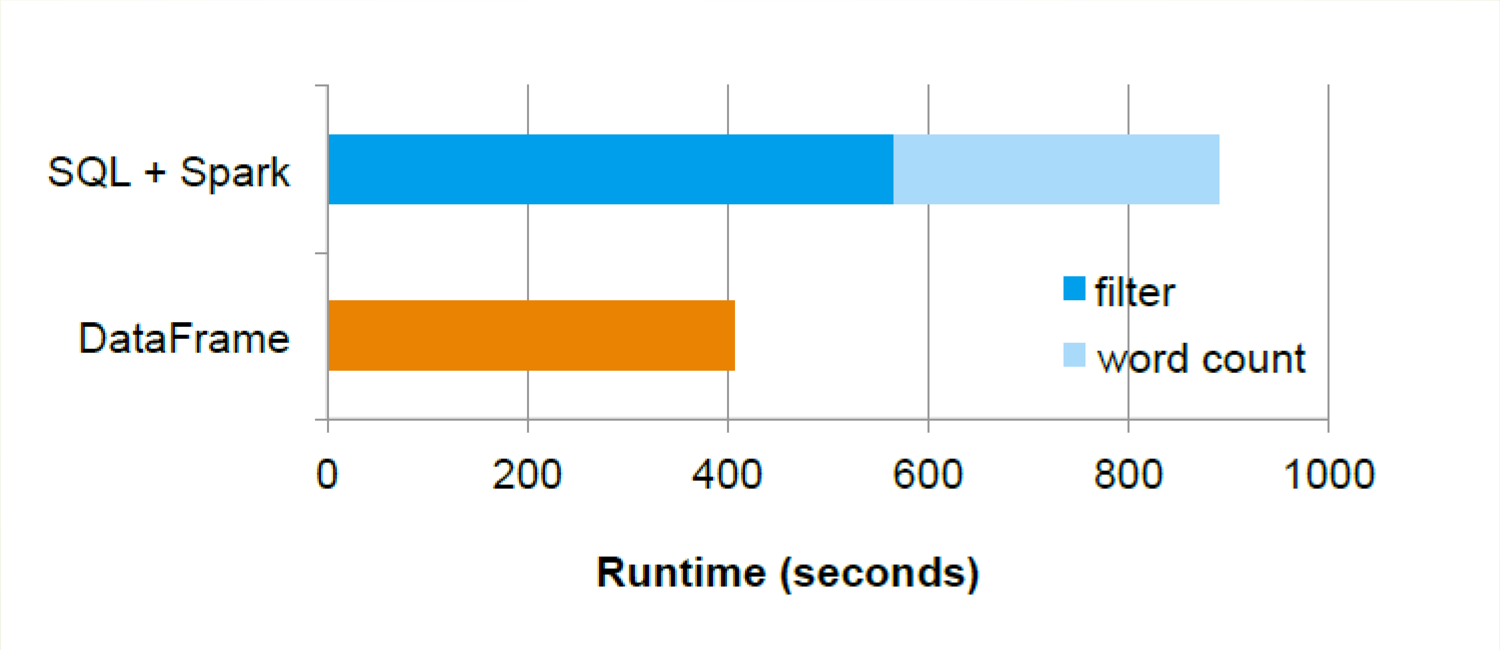
- **DataFrames vs. Native Spark Code**

```
sum_and_count = \
  data.map(lambda x: (x.a, (x.b, 1))) \
      .reduceByKey(lambda x, y: (x[0]+y[0], x[1]+y[1])) \
      .collect()
[(x[0], x[1][0] / x[1][1]) for x in sum_and_count]
```

In contrast, the same program can written as a simple manipulation using the DataFrame API:

```
df.groupBy("a").avg("b")
```

Pipeline Performance



Applications

- Generalized Online Aggregation
- Computational Genomics
- List is infinite only limited by your imagination…

Conclusion

Our Final Hash Tags

#A Platform with

#Automatic optimization

#Complex pipelines that mix relational and complex analytics

#Large-scale data analysis

#Semi-structured data

#Data types for machine learning

#Extensible optimizer called Catalyst

#Easy to add Optimization rules, data sources and data types


Thank
You