# Spark SQL

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# История

2006 MapReduce

2009 Hive

2009 Pig

2010 Spark

2013 Shark[1]

2015 Impala[2]

2015 Spark SQL[3]

[1] Reynold S Xin и др. “Shark: SQL and rich analytics at scale”. В: *Proceedings of the 2013 ACM SIGMOD International Conference on Management of data*. 2013, с. 13—24.

[2] Marcel Kornacker и др. “Impala: A Modern, Open-Source SQL Engine for Hadoop.”. В: *Cidr*. Т. 1. 2015, с. 9.

[3] Michael Armbrust и др. “Spark sql: Relational data processing in spark”. В: *Proceedings of the 2015 ACM SIGMOD international conference on management of data*. 2015, с. 1383—1394.

## Spark
### Limitations

- Low-level procedural code
- No optimizations

# Shark

- First effort to build a relational interface on Spark
- Shark modified the Apache Hive system to run on Spark

# Shark
## Limitations

- Shark could only be used to query external data stored in the Hive catalog
- The only way to call Shark from Spark programs was to put together a SQL string
- Hive optimizer was tailored for MapReduce and difficult to extend

## Наблюдение

*Most data pipelines are combination of relational and procedural algorithms.*

Spark SQL — new module in Apache Spark

- DataFrame API
- Catalyst (optimizer)

### Определение

*DataFrames are collections of structured records that can be manipulated using Spark's procedural API, or using new relational APIs that allow richer optimizations*

They can be created directly from Spark's RDDs, enabling relational processing in existing Spark programs.

# Spark
## RDDs

### Определение

*RDD:*

- *Resilient — отказоустойчивый*
- *Distributed — разбитый на партиции*
- *Dataset*

*read-only, partitioned collection of records*

RDDs can be manipulated through operations like `map`, `filter`, and `reduce`, which take functions and ship them to nodes on the cluster.

# Spark
## Fault-tolerance

- Запомним граф вычислений (linage)
- Тогда если часть данных будет потеряна, то их легко можно восстановить

# Spark
## Lazy evaluation

- Each RDD represents a “logical plan” to compute a dataset
- Spark waits until action to launch a computation
- Allows to do some simple query optimization, such as pipelining operations (narrow dependencies)

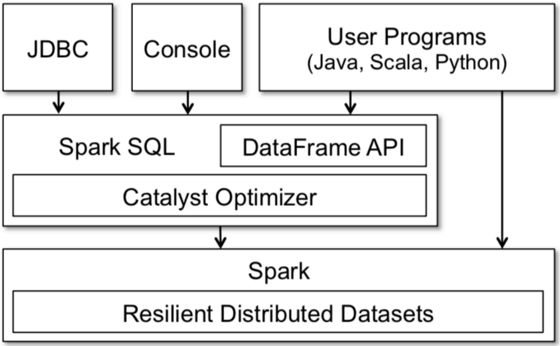
# Spark
## Optimizations

Spark engine does not understand the structure of the data in RDDs (which is arbitrary Java/Python objects) or the semantics of user functions (which contain arbitrary code)

# Цели

1. Support relational processing both within Spark programs (on native RDDs) and on external data sources using a programmer-friendly API.
2. Easily support new data sources, including semi-structured data and external databases amenable to query federation.
3. Enable extension with advanced analytics algorithms such as graph processing and machine learning.

# PROGRAMMING INTERFACE


JDBC
Console
User Programs
(Java, Scala, Python)
Spark SQL
DataFrame API
Catalyst Optimizer
Spark
Resilient Distributed Datasets

- DataFrame — distributed collection of rows with the same *schema*
- DataFrame is equivalent to a table in a relational database
- DataFrames can be manipulated in similar ways to the RDDs
- Schema leads to a more optimized execution

# DataFrame
## Construction

- From external data sources (HDFS, Hive)
- From existing RDDs (schema inference algorithm)

**Замечание**

*DataFrame can be viewd as an RDD of Row objects, allowing user to call procedural Spark APIs such as map*

# DataFrame
## Execution

- Spark DataFrame are *lazy*
- Spark build *logical plan* before execution
- Laziness enables rich optimization
- Logical plan $\rightarrow$ Physical plan

# DSL

Users can perform relational operations on DataFrames using a domain-specific language (DSL) similar to Python Pandas

# Example

## Фильмы с наибольшим средним рейтингом

```
ratings_df \
    .groupby('movie_id') \
    .agg(F.mean('rating').alias('mean_rating'),
         F.count('rating').alias('ratings_count')) \
    .join(movies_df, ratings_df['movie_id'] == movies_df['movieId'],
          how='inner') \
    .sort(F.col('mean_rating').desc()) \
```

# Difference with native Spark API

- All of these operators build up an abstract syntax tree (AST) of the expression, which is then passed to Catalyst for optimization.
- This is unlike the native Spark API that takes functions containing arbitrary Scala/Java/Python code, which are then opaque to the runtime engine.

# DataFrame construction
## Schema inference

- While building DataFrame from RDD user can manually define schema
- Spark SQL can automatically infer the schema of the dataset using reflection
- In Python, Spark SQL samples the dataset to perform schema inference due to the dynamic type system

# .cache()

- Method `cache` of DataFrame does the same thing as method `persist` of RDD
- Caching is particularly useful for interactive queries and for the iterative algorithms common in machine learning

# UDF
## Example

```
def get_release_year(title):
    result = re.match(r'.*(\(\d+\))', title)
    return int(result.group(1)[1:−1]) if result is not None else None

get_release_year_udf = F.udf(get_release_year, IntegerType())

movies_df \
    .withColumn('year', get_release_year_udf('title')) \
```

# Резюме

- The DataFrame API lets developers seamlessly mix procedural and relational methods.

# CATALYST

Catalyst contains a general library for representing <u>trees</u> and applying <u>rules</u> to manipulate them

# Trees

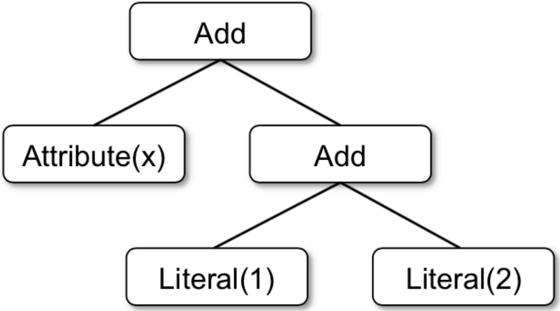



Рис.: Catalyst tree for expression x+(1+2)

# Rules

**Определение**

$Rule : T \mapsto T'$ — *rule maps tree to another tree.*

The most common approach is to use a set of pattern matching functions that find and replace subtrees with a specific structure.

# Rules
## Example

Constant folding

```
tree.transform {
    case Add(Literal(c1), Literal(c2)) => Literal(c1+c2)
    case Add(left, Literal(0)) => left
    case Add(Literal(0), right) => right
}
```

## Rules
### Fixed point

Catalyst groups rules into batches, and executes each batch until it reaches a *fixed point*, that is, until the tree stops changing after applying its rules.

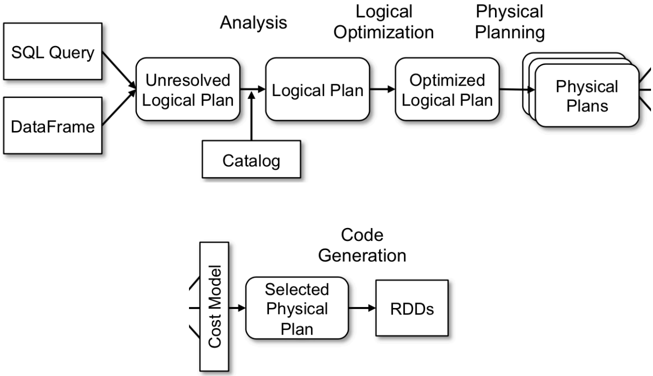



Рис.: Phases of query planning in Spark SQL. Rounded rectangles represent Catalyst trees

# Example
## Query

```
query = """
    SELECT movie_id, COUNT(*), first(title) as title
    FROM ratings INNER JOIN movies ON ratings.movie_id == movies.movieId
    WHERE movies.title LIKE '%(1994)%'
    GROUP BY movie_id
    ORDER BY COUNT(*) DESC
"""

spark.sql(query).explain(True)
```

# Example
## Unresolved Logical Plan

```
== Parsed Logical Plan ==
'Sort ['COUNT(1) DESC NULLS LAST], true
+- 'Aggregate ['movie_id], ['movie_id, unresolvedalias('COUNT(1), None),
    first('title, false) AS title#53]
   +- 'Filter 'movies.title LIKE %(1994)%
      +- 'Join Inner, ('ratings.movie_id = 'movies.movieId)
         :- 'UnresolvedRelation `ratings`
         +- 'UnresolvedRelation `movies`
```

# Example
## Logical Plan

```
== Analyzed Logical Plan ==
movie_id: int, count(1): bigint, title: string
Project [movie_id#1, count(1)#56L, title#53]
+- Sort [count(1)#56L DESC NULLS LAST], true
   +- Aggregate [movie_id#1], [movie_id#1, count(1) AS count(1)#56L,
        first(title#19, false) AS title#53]
      +- Filter title#19 LIKE %(1994)%
         +- Join Inner, (movie_id#1 = movieId#18)
            :- SubqueryAlias ‘ratings‘
            :  +- Relation[user_id#0,movie_id#1,rating#2,timestamp#3] csv
            +- SubqueryAlias ‘movies‘
               +- Relation[movieId#18,title#19,genres#20] csv
```

# Example
## Optimized Logical Plan

```
== Optimized Logical Plan ==
Sort [count(1)#56L DESC NULLS LAST], true
+- Aggregate [movie_id#1], [movie_id#1, count(1) AS count(1)#56L, first(
     title#19, false) AS title#53]
   +- Project [movie_id#1, title#19]
      +- Join Inner, (movie_id#1 = movieId#18)
         :- Project [movie_id#1]
         :  +- Filter isnotnull(movie_id#1)
         :     +- Relation[user_id#0,movie_id#1,rating#2,timestamp#3] csv
         +- Project [movieId#18, title#19]
            +- Filter ((isnotnull(title#19) && Contains(title#19, (1994))
                 ) && isnotnull(movieId#18))
               +- Relation[movieId#18,title#19,genres#20] csv
```

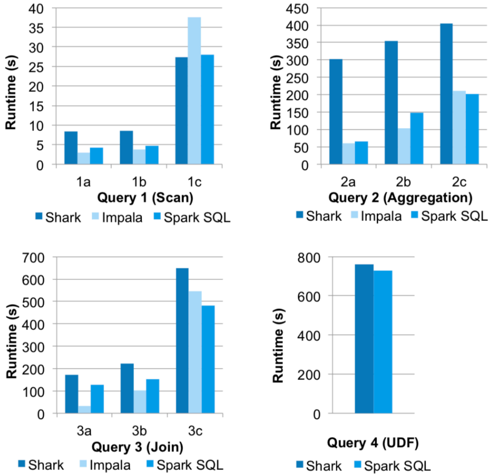
! Filter push down rule !

# EVALUATION

Evaluation of the performance of Spark SQL on two dimensions:

1. SQL query processing performance
2. Spark program performance

# Benchmark[4]




[4] Andrew Pavlo. “A comparison of approaches to large-scale data analysis”. В: *Proceedings of the 2009 ACM SIGMOD international conference on management of data*. 2009, с. 165—178.

# Distributed Aggregation
## Dataset and Task

**Dataset** $1$ billion integer pairs, $(a, b)$ with $100000$ distinct values of $a$

**Task** compute the average of $b$ for each value of $a$

# Distributed Aggregation
## Solutions

### Native Spark

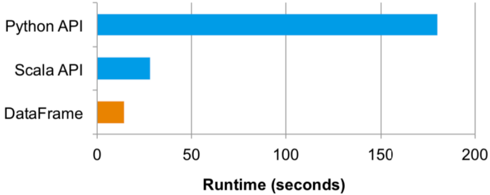
```
sum_and_count = data \
    .map(lambda x: (x.a, (x.b, 1))) \
    .reduceByKey(lambda x, y: (x[0]+y[0], x[1]+y[1])) \
    .collect()

[(x[0], x[1][0] / x[1][1]) for x in sum_and_count]
```

### Spark SQL

```
df.groupBy(”a”).avg(”b”)
```

# Distributed Aggregation
## Performance




In the DataFrame API, only the logical plan is constructed in Python, all physical execution is compiled into native Spark code as JVM bytecode.

Armbrust, Michael и др. "Spark sql: Relational data processing in spark". В: *Proceedings of the 2015 ACM SIGMOD international conference on management of data*. 2015, с. 1383—1394.

Karau, Holden и Rachel Warren. *High performance Spark: best practices for scaling and optimizing Apache Spark*. " O'Reilly Media, Inc.", 2017.

Kornacker, Marcel и др. "Impala: A Modern, Open-Source SQL Engine for Hadoop.". В: *Cidr*. Т. 1. 2015, с. 9.

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Xin, Reynold S и др. "Shark: SQL and rich analytics at scale". В: *Proceedings of the 2013 ACM SIGMOD International Conference on Management of data*. 2013, с. 13—24.