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of Applied Sciences

CAS Information Engineering

Spark Query Optimization

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Educational Objectives for Today

- Learn about internals of query processing
- Understand concepts of logical and physical query plan
- Understand and apply different query plans for joins
- Get better intuition about query performance

Let Us Analyze a Query

```
SELECT Department, AVG(Age)
FROM Employees
WHERE Location = 'Switzerland'
GROUP BY Department
```

- Which steps are required to execute this query?

```
root
 |-- name: string (nullable = true)
 |-- age: long (nullable = true)
 |-- department: string (nullable = true)
 |-- location: string (nullable = true)
```

```
+----------+-----------------+
|department|         avg(age)|
+----------+-----------------+
|         B|             28.5|
|         C|             65.0|
|         A|32.66666666666664|
+----------+-----------------+
```

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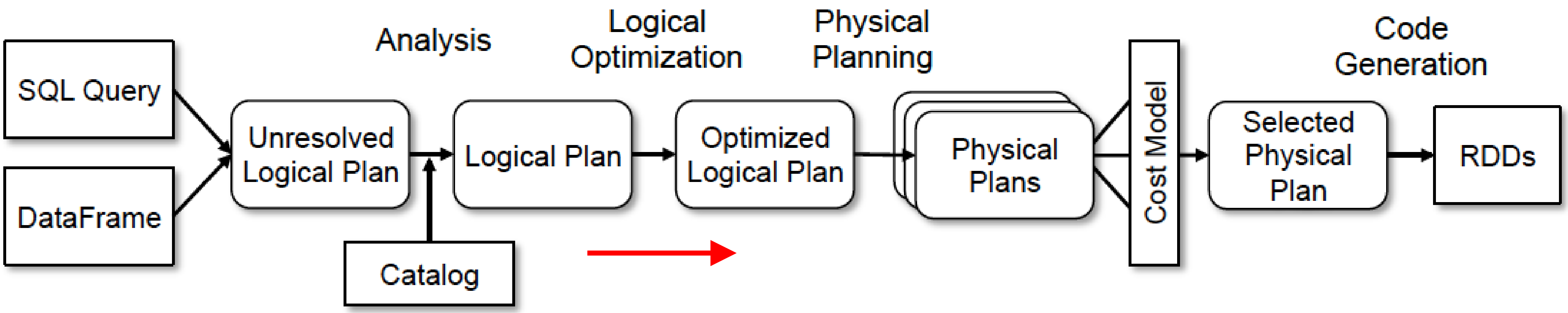
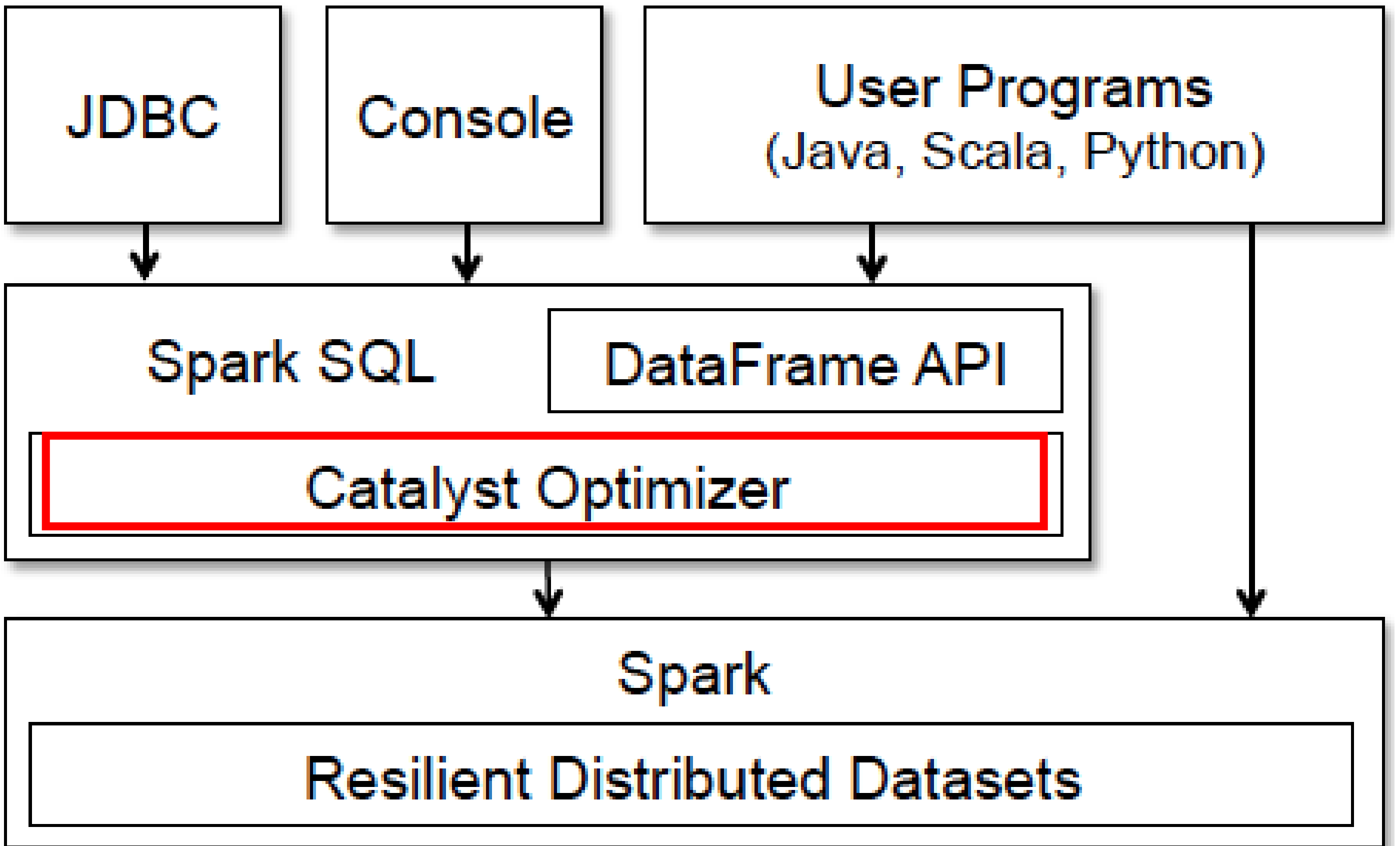
Phases of Query Planning



Interfaces to Spark SQL



Spark DataFrames as SQL
The Tree Abstraction

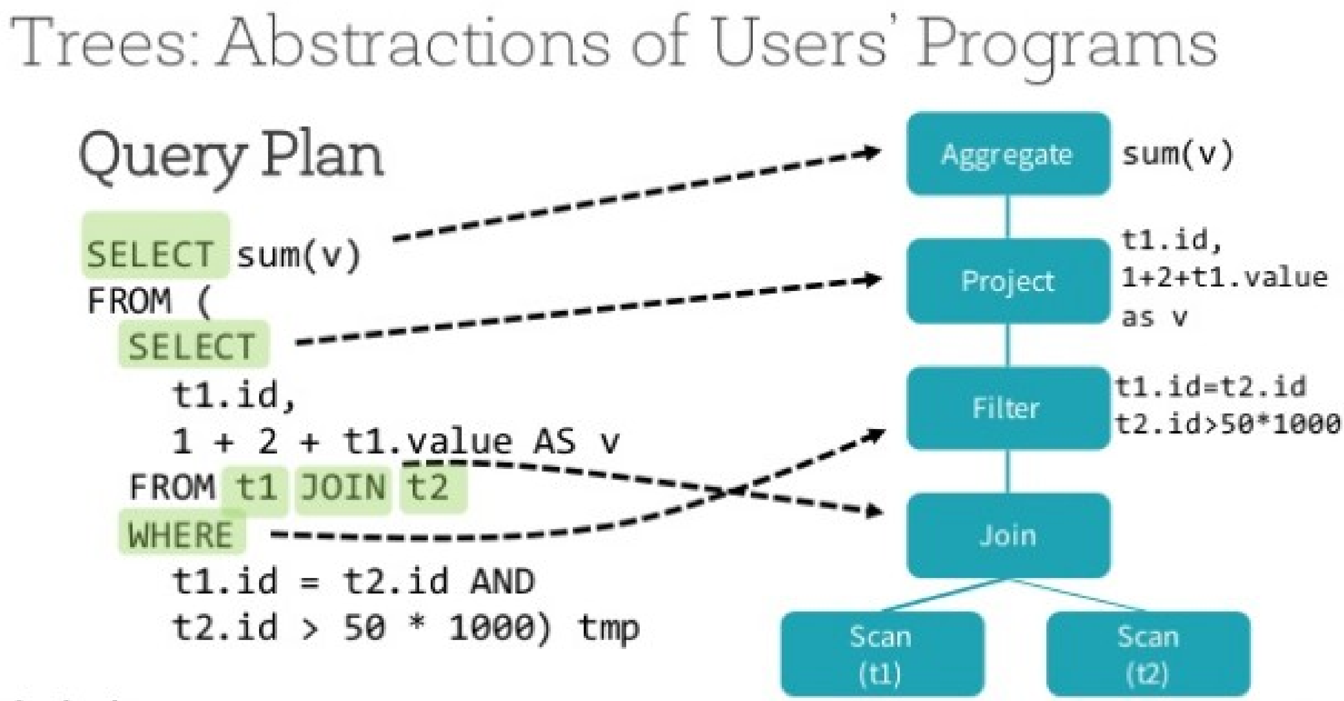
Trees: Abstractions of Users' Programs

Expression

```
SELECT sum(v)
FROM (
  SELECT
    t1.id,
    1 + 2 + t1.value AS v
  FROM t1 JOIN t2
  WHERE
    t1.id = t2.id AND
    t2.id > 50 * 1000) tmp
```

Which steps does this query contain?

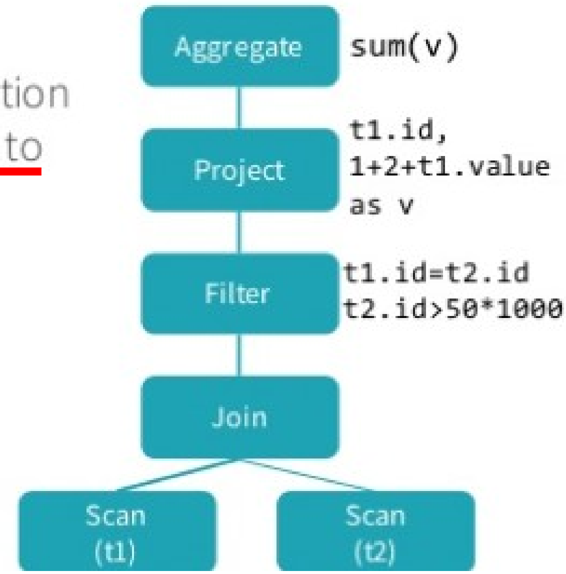
Spark DataFrames as SQL
The Tree Abstraction



Spark DataFrames
Planning Execution

Logical Plan

- A Logical Plan describes computation on datasets **without defining how to conduct the computation**

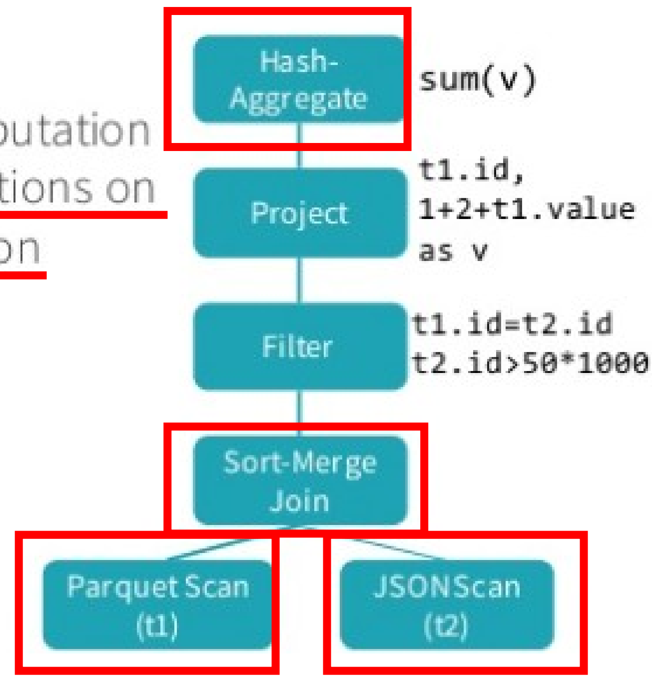


- Output: List of output columns, e.g. `id`, v
- Constraints: `t2.id > 50*1000`

Spark DataFrames
Planning & Optimizing Execution

Physical Plan

- A Physical Plan describes computation on datasets with specific definitions on how to conduct the computation



Parquet: a structured, compressed file format

JSON: an unstructured, clear text file format

Physical Query Optimization of Joins
Excursion: How Do We Execute a Join?

- Given: relations R(A,B) and S(B,C)
- ```
  SELECT *
  FROM R, S
  WHERE R.B = S.B
  ```

R

A	B
A1	0
A2	1
A3	2
A4	1

S

B	C
1	C1
2	C2
1	C3
3	C4
1	C5

$R \bowtie S$

A	B	C
A2	1	C1
A2	1	C3
A2	1	C5
A3	2	C2
A4	1	C1
A4	1	C3
A4	1	C5

Which physical optimizations (algorithms) exist for performing a join?
  ```

Nested-Loop Join #1

Video with more explanations in Moodle!

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- Super-naïve

```
FOR EACH r IN R DO
   FOR EACH s IN S DO
      IF ( r.B=s.B) THEN OUTPUT (r ⋈ s)
```

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Nested-Loop Join #2

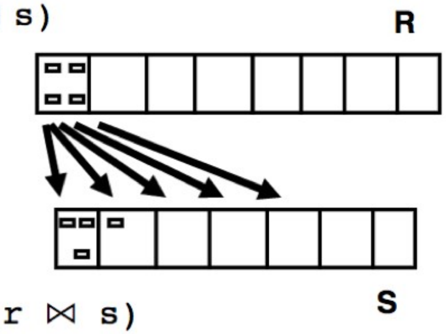
Video with more explanations in Moodle!

- Super-naïve

```
FOR EACH r IN R DO
    FOR EACH s IN S DO
        IF ( r.B=s.B) THEN OUTPUT (r ⋈ s)
```

- Slight improvement

```
FOR EACH block x IN R DO
    FOR EACH block y IN S DO
      FOR EACH r in x DO
          FOR EACH s in y DO
              IF ( r.B=s.B) THEN OUTPUT (r ⋈ s)
```



- Cost estimations:
  - b(R), b(S): number of blocks in R and S, respectively
  - Outer relation: each block is read once
  - Inner relation: read once for each block of our relation
  - Two inner loops are ”free” (only main memory operations)

Sort-Merge Join

Video with
more explanations
in Moodle!

- Approach:
  - Sort both relations on join attributes
  - Merge both sorted relations

Sort-Merge Join Example #1

Video with more explanations in Moodle!

R

A	B
A1	0
A2	1
A3	2
A4	1

S

B	C
1	C1
2	C2
1	C3
3	C4
1	C5

R

A	B
A1	0
A2	1
A4	1
A3	2

S

B	C
1	C1
1	C3
1	C5
2	C2
3	C4

Partial join

$\{\langle A1,0\rangle,\langle A2,1\rangle\} \bowtie S$

A	B	C
A2	1	C1
A2	1	C3
A2	1	C5

Sort-Merge Join Example #2

Video with more explanations in Moodle!

R

A	B
A1	0
A2	1
A4	1
A3	2

S

B	C
1	C1
1	C3
1	C5
2	C2
3	C4

Partial join

$\{<A1,0>,<A2,1>\} \bowtie S$

A	B	C
A2	1	C1
A2	1	C3
A2	1	C5

R

A	B
A1	0
A2	1
A4	1
A3	2

S

B	C
1	C1
1	C3
1	C5
2	C2
3	C4

Partial join

$\{<A1,0>,<A2,1>, <A4,1>\} \bowtie S$

A	B	C
A2	1	C1
A2	1	C3
A2	1	C5
A4	1	C1
A4	1	C3
A4	1	C5

new

Hash Join

Video with more explanations in Moodle!

- Use join attributes as hash keys
- Hash phase:
  - Scan relation S and compute hash table
- Merge phase:
  - Iterate over R tuple-wise
  - Join with S by using hash function
- No sorting is required
- Works best when S is small compared to R (→ many S lookups)

Which Join Algorithm Performs Best?

Which Join Algorithm Performs Best?

- Hash join is typically faster than sort-merge join (as no sorting is required)
- Sort-merge join is typically faster than nested-loop join for larger tables
- But:
  - Sort-merge can can be faster than hash join, if both tables are already sorted
  - If the join condition is an inequality operator (<, >, <>), hash join can’t be used

- Depending on the characteristics of the tables (size, data distribution, indexes, etc.) the optimizer chooses the best join strategy

What is a DataFrame Really?

- DataFrame consists of:
  - Execution plan
  - Result type schema
  - Underlying RDD
- What is an RDD? (*Resilient Distributed Dataset* [M. Zaharia et al., 2012])
  - Lineage – how was the input data calculated
  - Partition information – where is the input data actually distributed
  - Instructions – code to be executed
- What is a DataFrame NOT?
  - Data

Declarative Query APIs

- Vague, general definition of declarative programming:
  Programming where problems are described, or conditions on a solution are described, and the computer finds a solution.
- For querying data, this can mean:
  "Describing the properties of the requested dataset"
  - SQL as a query language:

    ```
    SELECT dept, AVG(age) FROM pdata GROUP BY dept
    ```

  - Equivalent "Builder" Syntax (Python, Scala, Java)

    ```
    pData.groupBy("dept").agg(avg("age"))
    ```

- No assumptions or indications on *how* to fulfil the query.
- Expression order does not necessarily govern execution order.

LowLevel RDD Interface

- High – Level APIs: DataFrame (Declarative)

```
SELECT dept, AVG(age) FROM pdata GROUP BY dept
```

or

```
pData.groupBy("dept").agg(avg("age"))
```

Describes action on column level
Assumes structured, typed data
Executed *somewhere*

- Lower-Level API: **RDD** (Functional)

```
pdata.map(lambda x: (x.dept, [x.age, 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()
```

Describes action on row level
Assumes homogenous data
Executed by 1..n machines

- Generated Intermediate JVM Code: (Imperative)

```
long count = 0;
for (ss_item_sk in store_sales) {
  if (ss_item_sk == 1000) {
    count += 1;
  }
}
```

Describes action on variable level
Assumes typed data
Executed in 1 machine with n CPUs

- Generated byte code (executed on machine)

```
00000000    push    ebp
00000001    mov     ebp, esp
00000003    movzx   ecx, [ebp+arg_0]
00000007    pop     ebp
00000008    movzx   dx, cl
0000000C    lea     eax, [edx+edx]
0000000F    add     eax, edx
```

Describes actions on byte and processor level

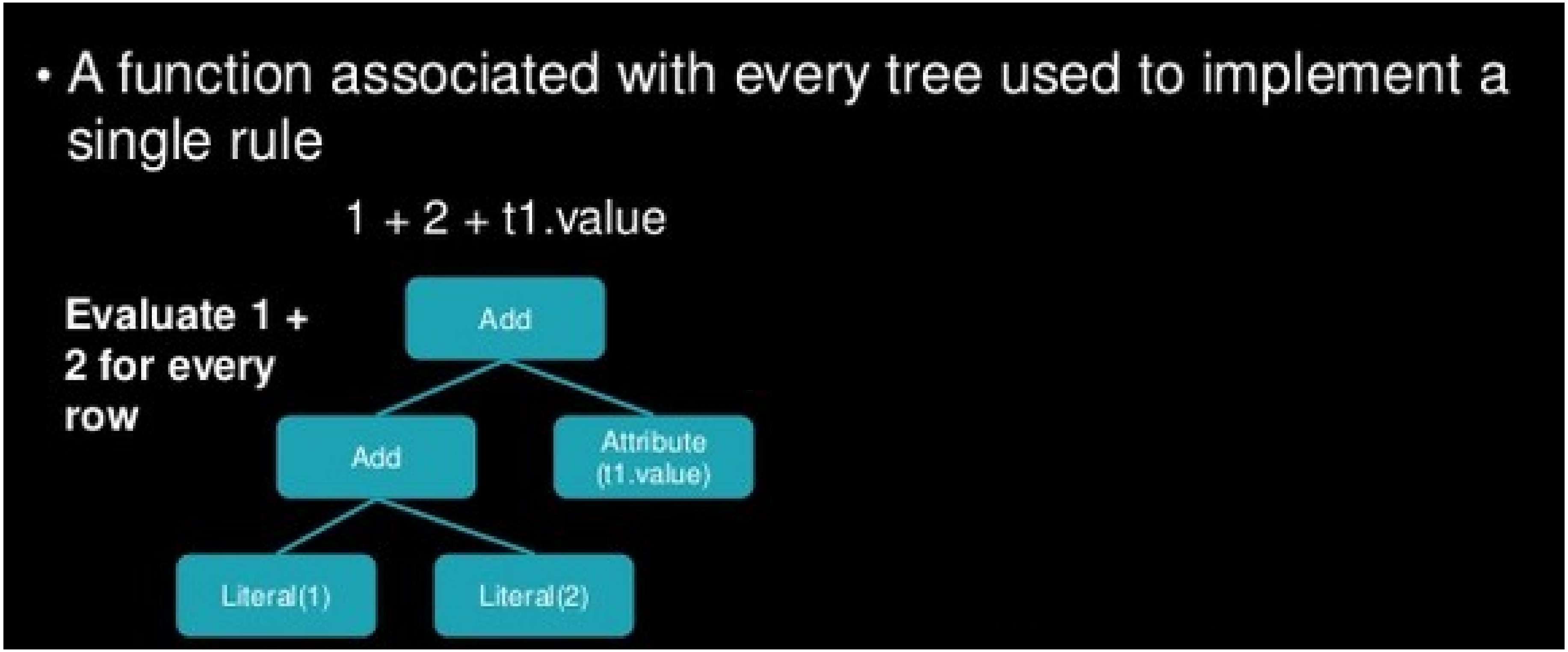
* These code examples are illustrative and almost completely made up,
* don't study them!

Query Optimization: Transformation

- Functions for converting an un-optimized tree to an optimized tree
  - E.g. Transform tree to logical plan and then to physical plan

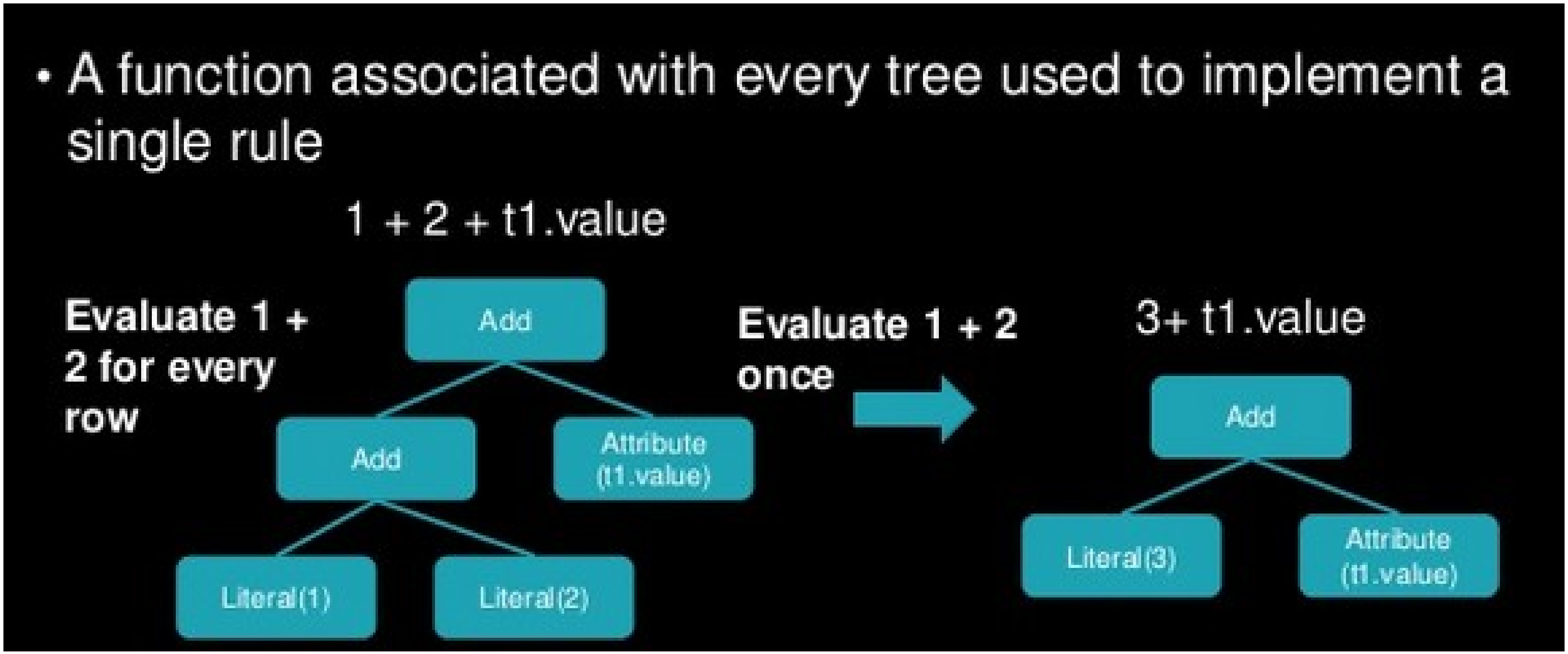
- Assume the function of the previous query:
  - 1 + 2 + t1.value
  - Has to be applied for each row of the table

Transformation Example #1



Need to evaluate this function for every row. Efficient?

Transformation Example #2

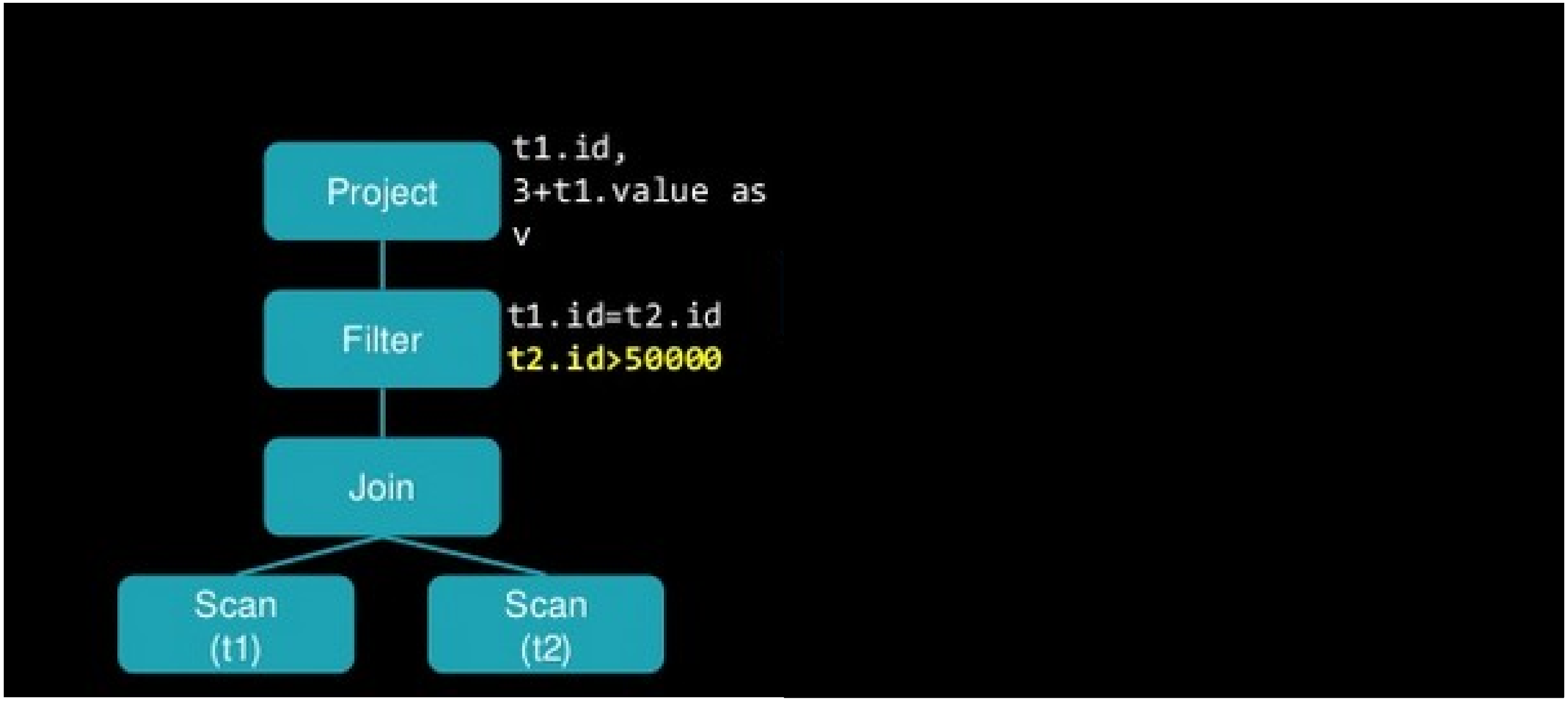


Catalyst Optimizer Strategies

- Goal: Minimize end-to-end query response time

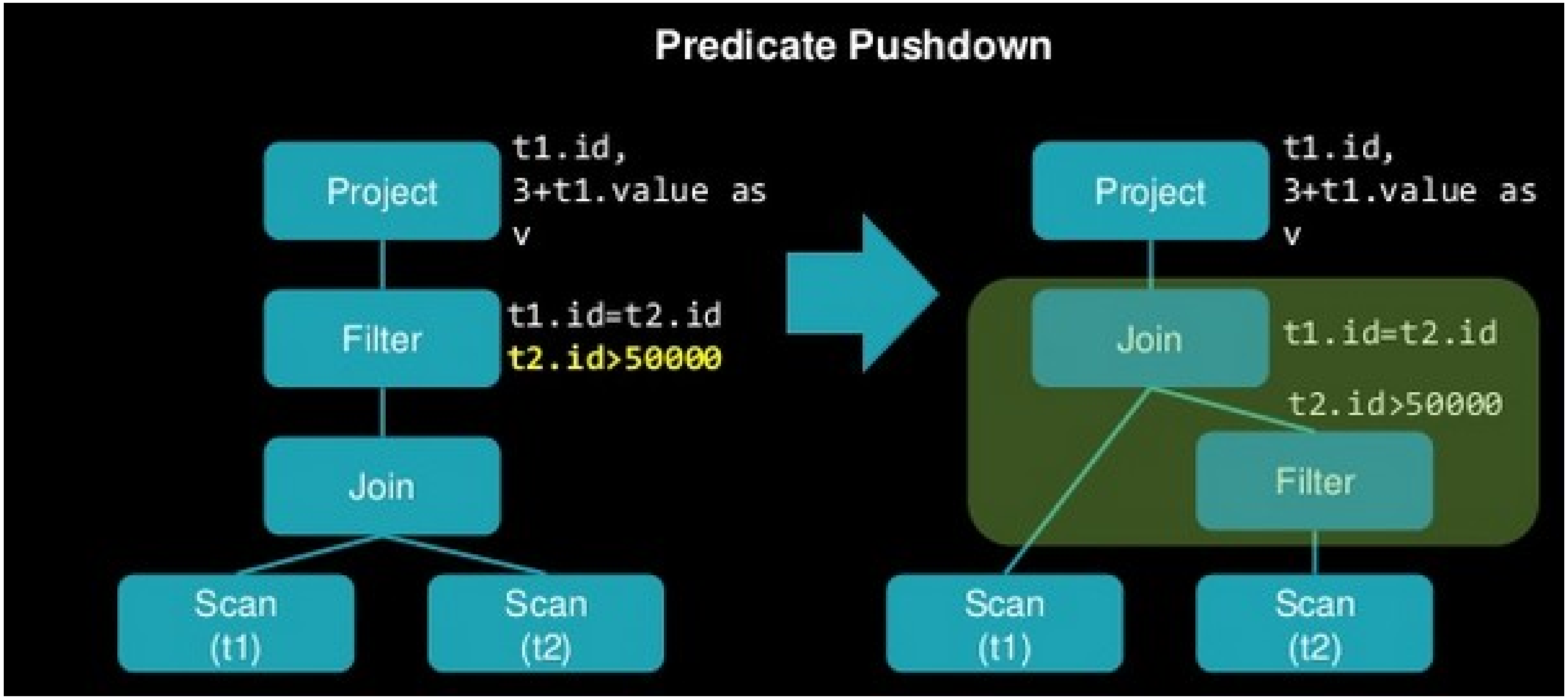
- Two key ideas:
  - Prune unnecessary data as early as possible
    - E.g. filter pushdown, column pruning
  - Minimize per-operator cost
    - E.g. broadcast vs. shuffle, optimal join order

Logical Query Plan

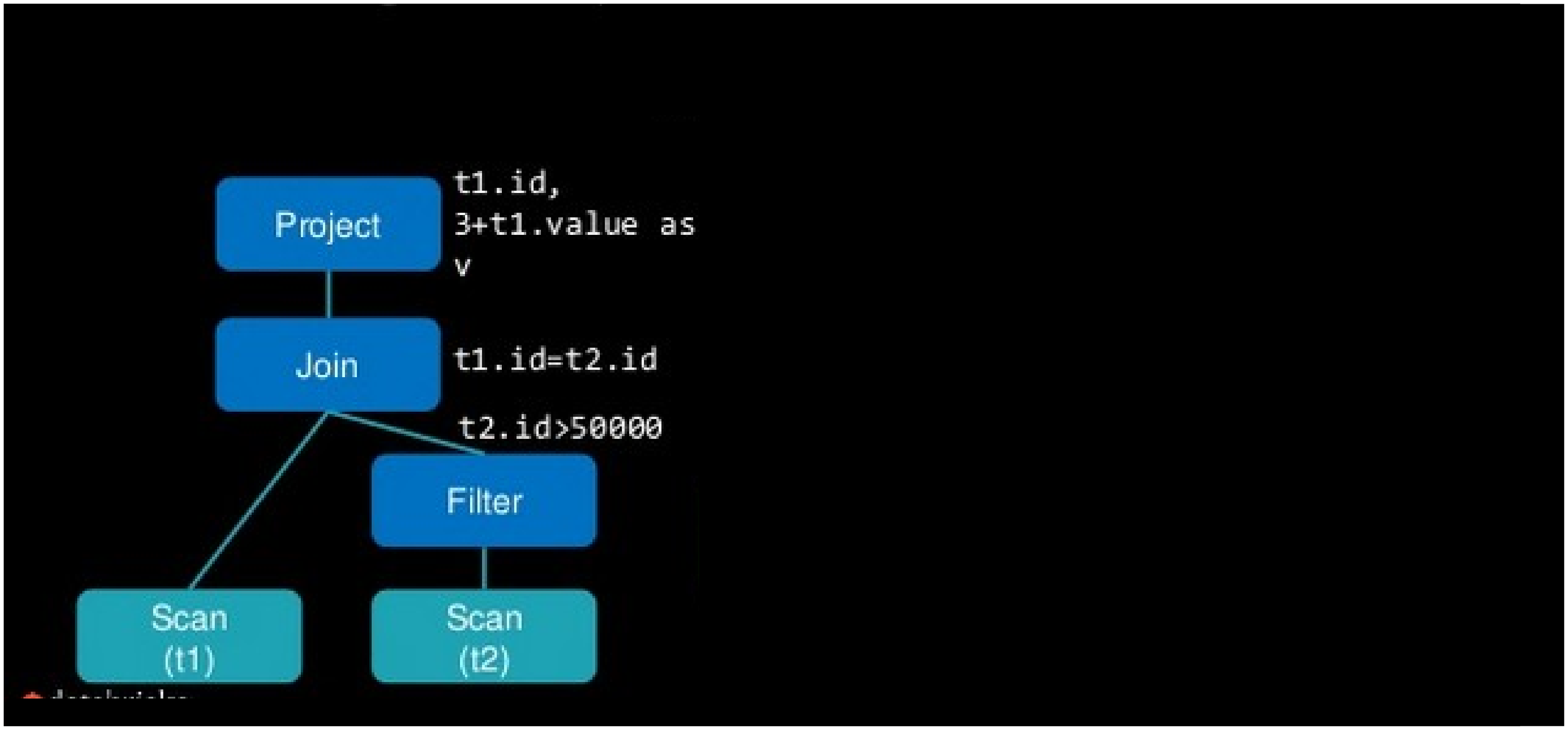


How do we optimize this query plan?

Optimizing Logical Query Plan: Predicate Pushdown

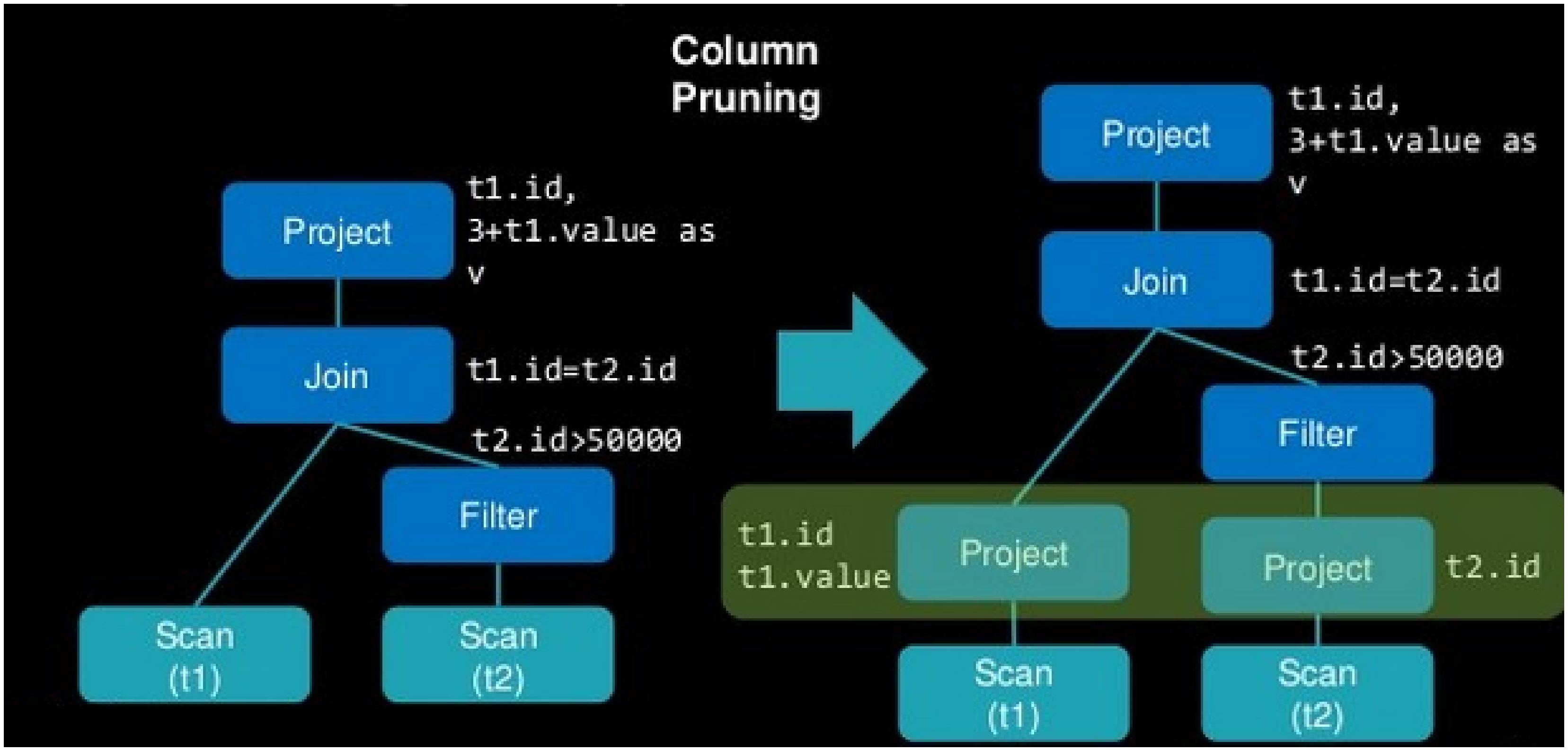


Logical Query Plan

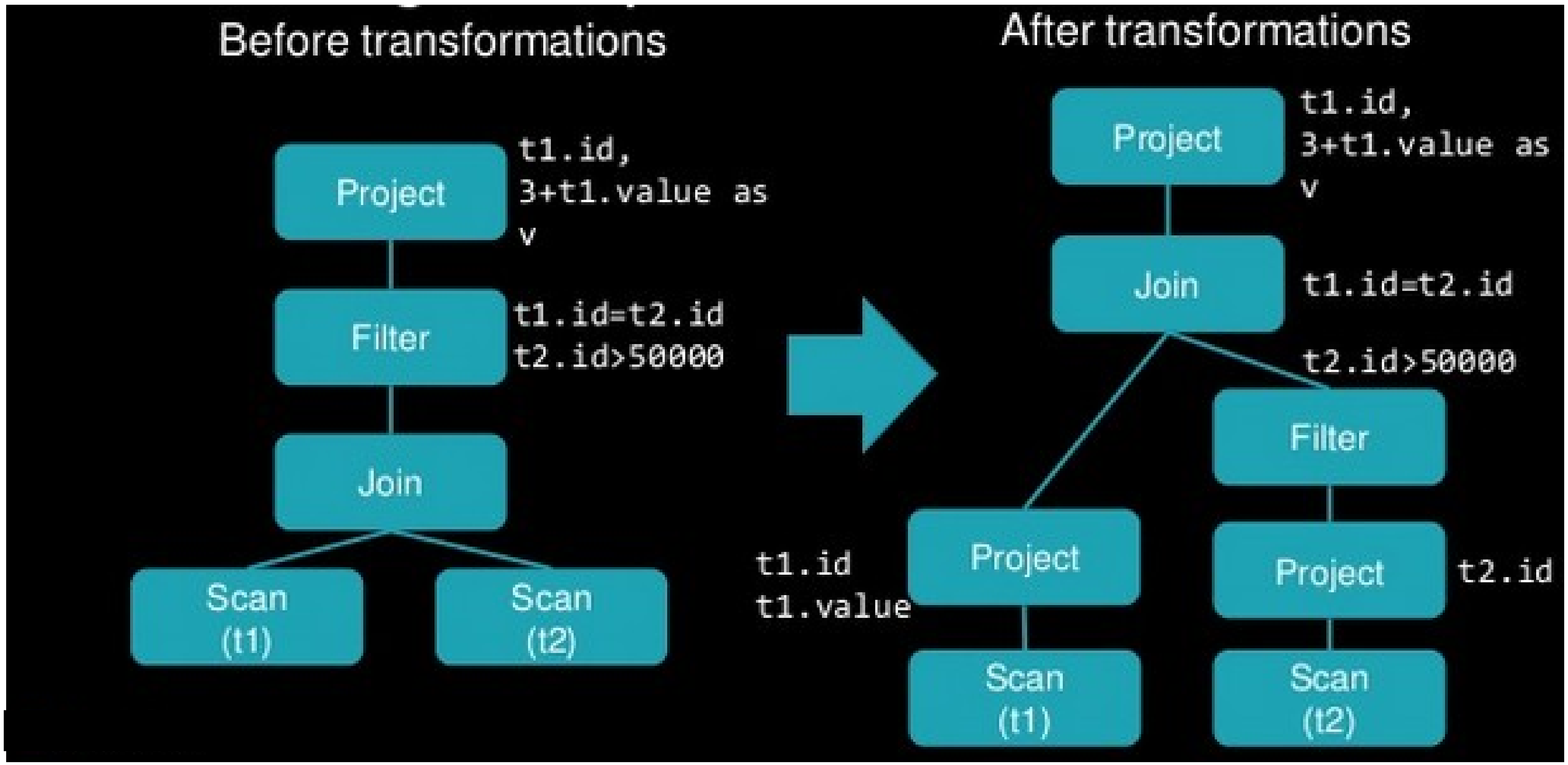


What else can we improve?

Optimizing Logical Query Plan: Column Pruning



Optimized Logical Plan



Takeaway DataFrame API

- A declarative programming API hides complexity
  - How to distribute execution
  - How to treat different data sources
  - How to optimize execution

Spark 3 SQL Improvements

Video with more explanations in Moodle!

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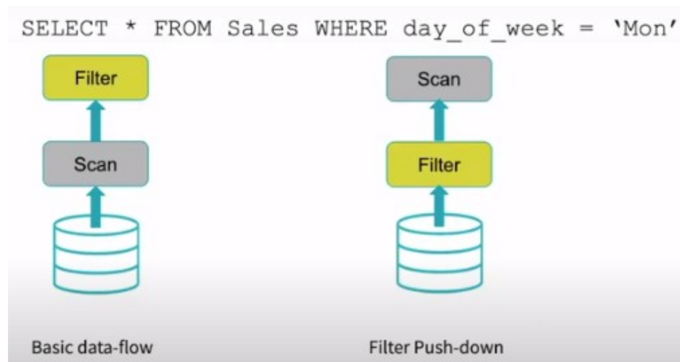
- AQE:
  - consider column statistics, adapt to alternative plans, join-switch
- DPP:
  - avoid scanning unneeded facts partitions in star schema
- JH:
  - override autoselection

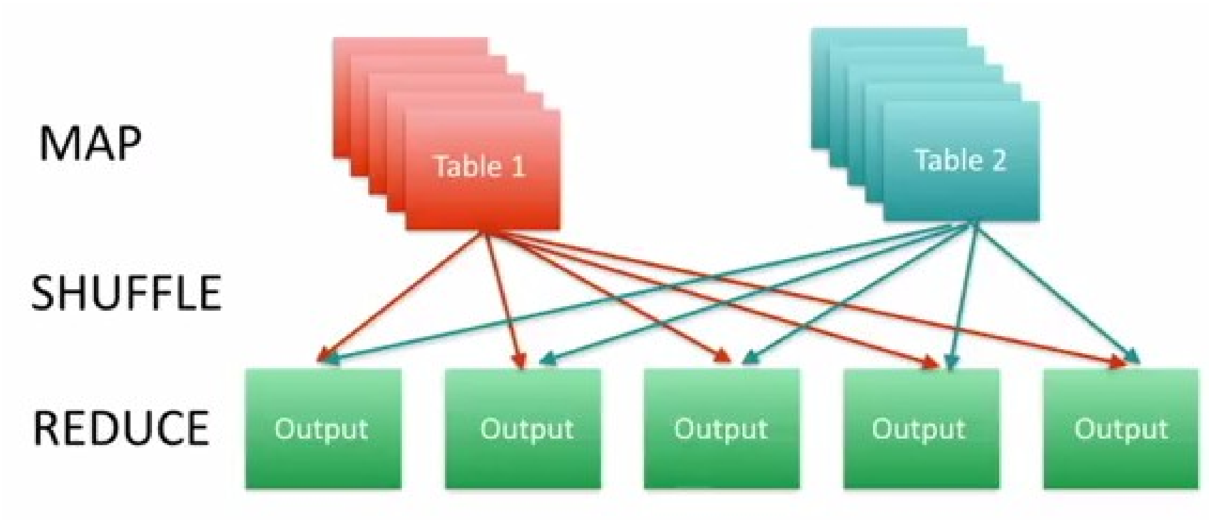
```
-- Spark-SQL
SELECT /*+ SHUFFLE_MERGE(Employee) */ * FROM Employee E
INNER JOIN Department D ON E.DeptID = D.DeptID;
```



Physical Query Optimization: Optimizing Joins for Distributed Data

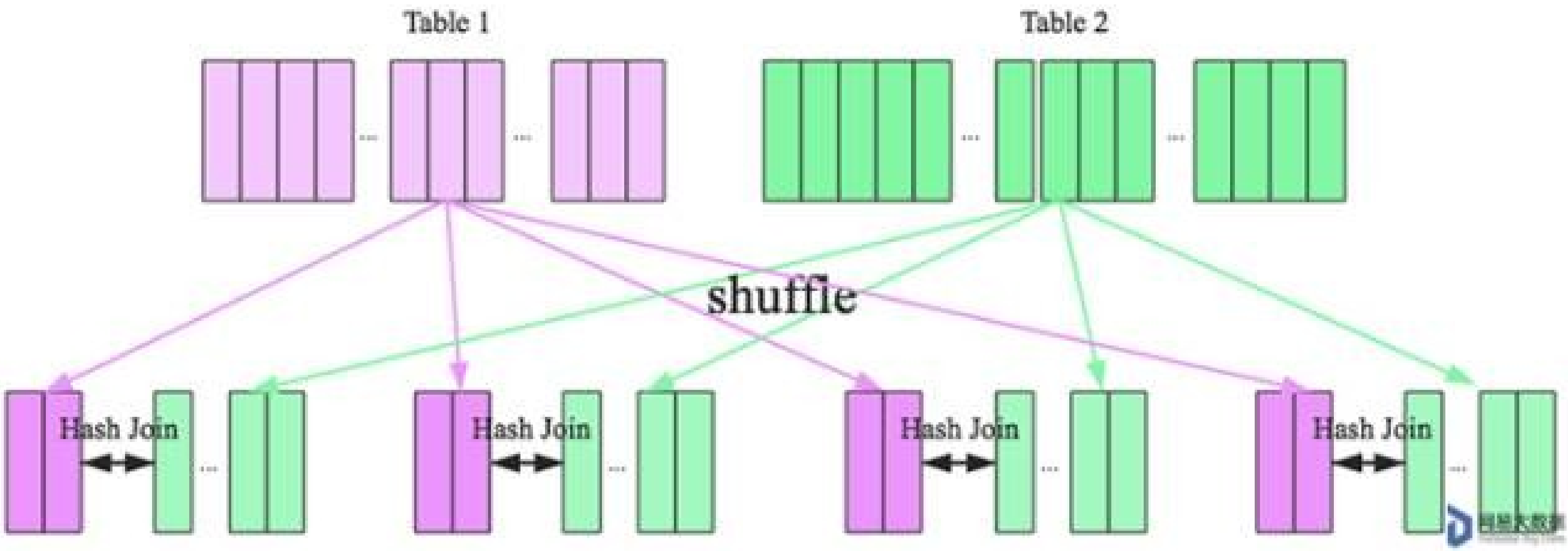
- Shuffle Hash Join
  - (Shuffle Sort Merge)
  - (Shuffle Nested Loop)
- Broadcast Hash Join

Shuffle Hash Join



- Map through two different DataFrames
- Use fields in join condition as the output key
- Shuffle both data sets by the output key
- Reduce phase: join the two data sets
  (note: rows of both tables with the same keys are on the same machine and sorted)

Shuffle Hash Join



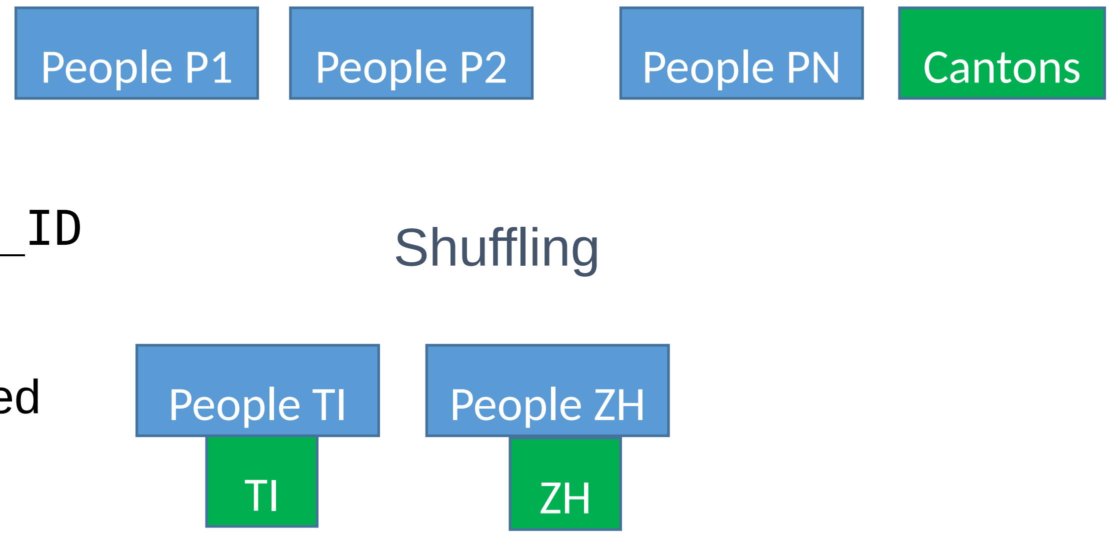
Source: Andreas Weiler

Shuffle Hash Join Performance

- Works best when
  - Distributed evenly with the key you are joining on
  - Have an adequate number of keys for parallelism
    - E.g. If table A has 1,000,000 rows but only 200 keys, the maximum parallelism is 200

Uneven Sharding & Limited Parallelism

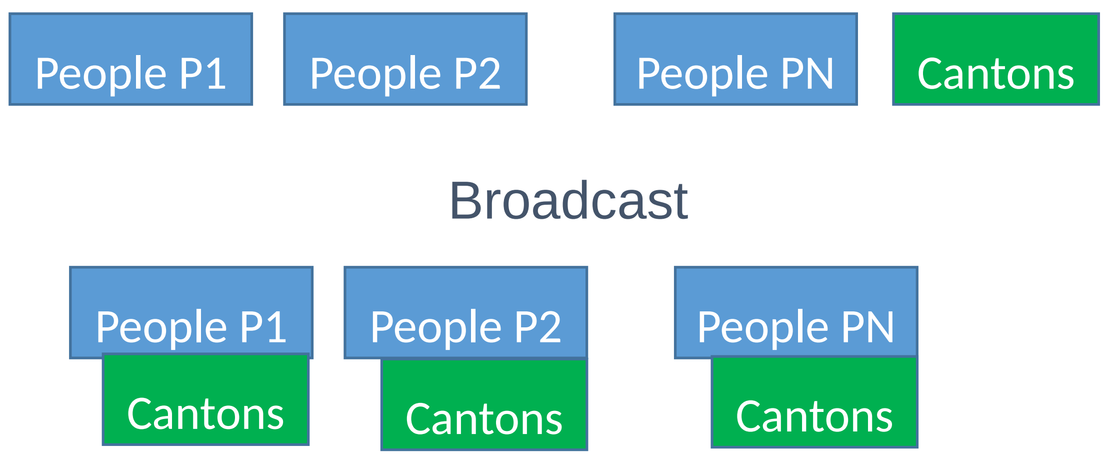
```
SELECT *
FROM PEOPLE_IN_CH p
JOIN CANTONS c
ON p.canton_ID = c.canton_ID
```



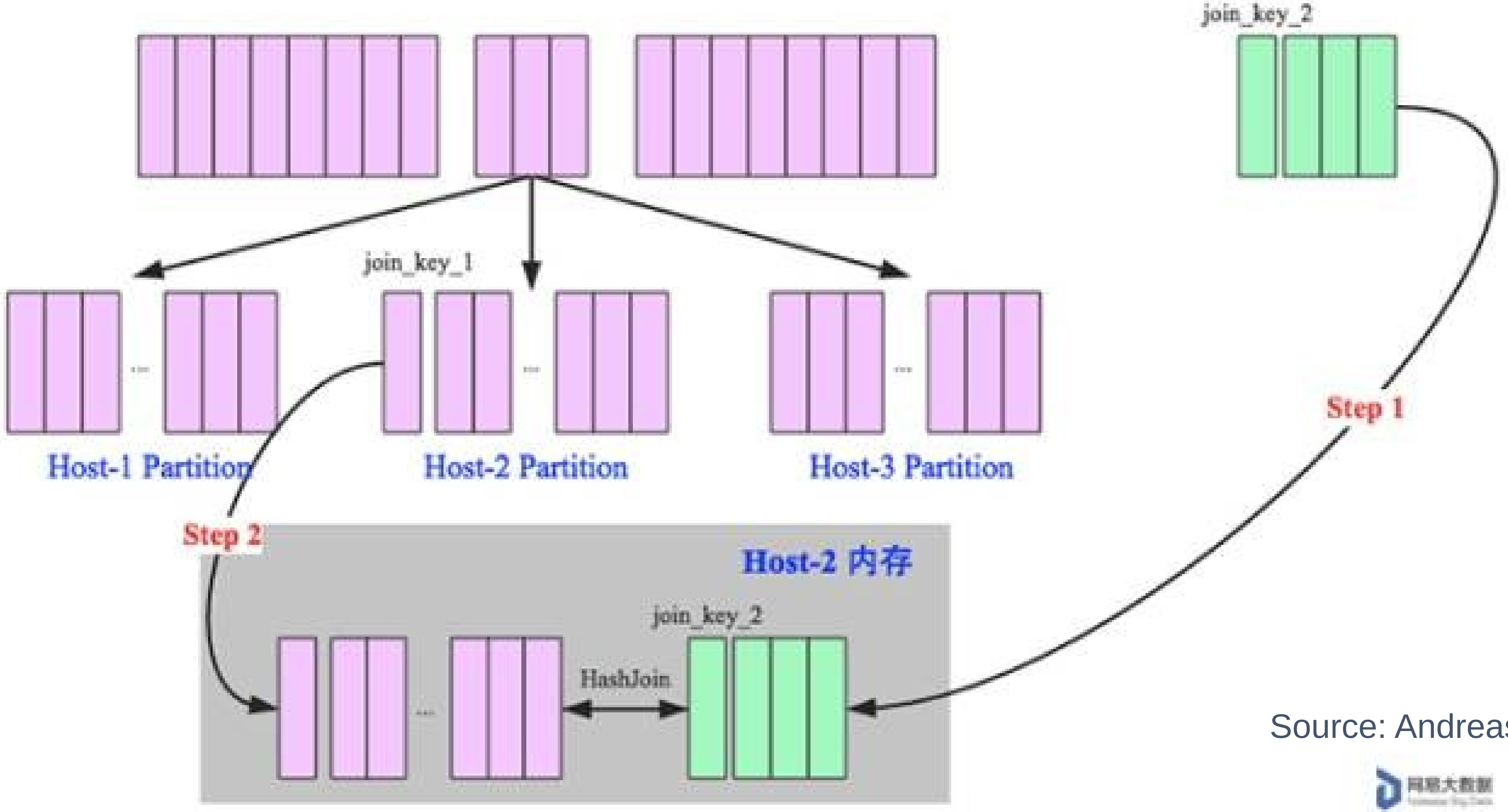
- All the people will only be shuffled into 26 keys for the cantons
- Problem:
  - Uneven sharding
  - Limited parallelism (max. 26)

Broadcast Hash Join

- When one data frame is small enough to fit into main memory:
  - Broad cast “small” DataFrame to all nodes
- Enables partial local join:
  - No shuffling required
  - No additional communication overhead over network



Broadcast Hash Join



Source: Andreas Weiler

Broadcast Hash Join vs. Shuffle Hash Join

- Broadcast Hash Join often better than Shuffle Hash Join (no data transfer over network)
- Should in principle be automatic but might require hints:
  - Spark SQL on parquet does this automatically
  - Not if input file is a text file

How Efficient is Parquet for Joins with Respect to CSV ?

Experiment Queries

- Data:
  - Fire1: 122 MB CSV-file, 485,056 rows, 27 columns
  - Fire2: 99 MB CSV-file, 395,658 rows, 27 columns

- Projection:
```
spark.sql("select distinct Postcode_district
    from fire1").show()
```

- Join:
```
spark.sql("select distinct f1.Postcode_district
    from fire1 f1 join fire2 f2
    where f1.Postcode_district =
    f2.Postcode_district").show()
```

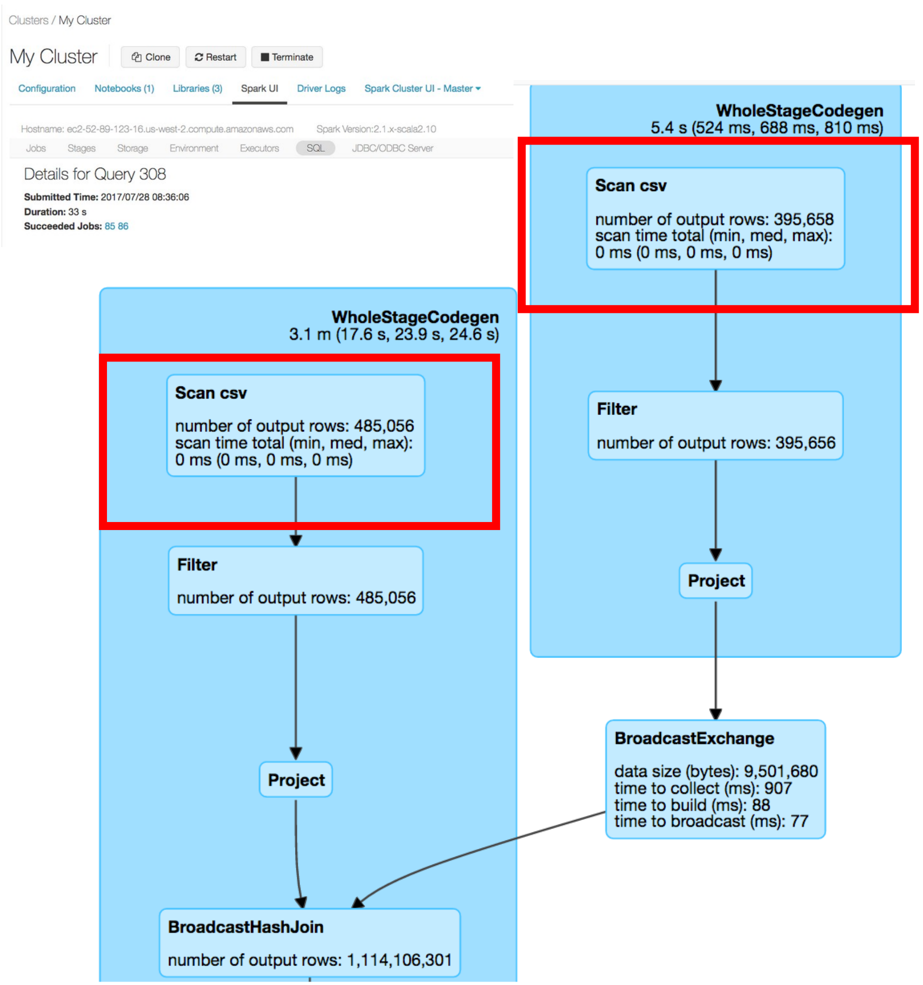
- Self-Join:
```
spark.sql("select distinct f1.Postcode_district
    from fire1 f1 join fire1 f2
    where f1.Postcode_district =
    f2.Postcode_district").show()
```

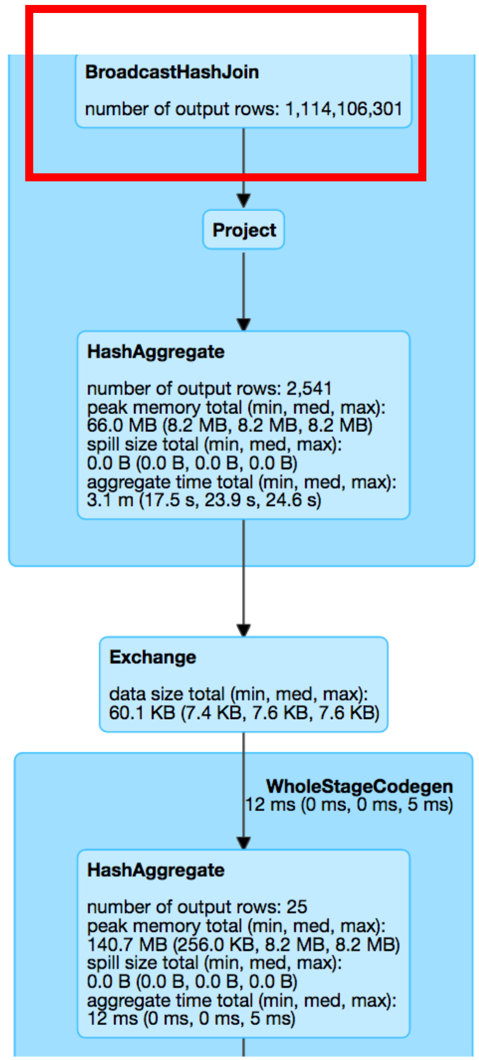
Experiment Results

File Format	Fire 1 Size (MB)	Fire 2 Size (MB)	Join (sec)	Self Join (sec)
CSV	122	99	26	33
Parquet	6	~6	6	2.5

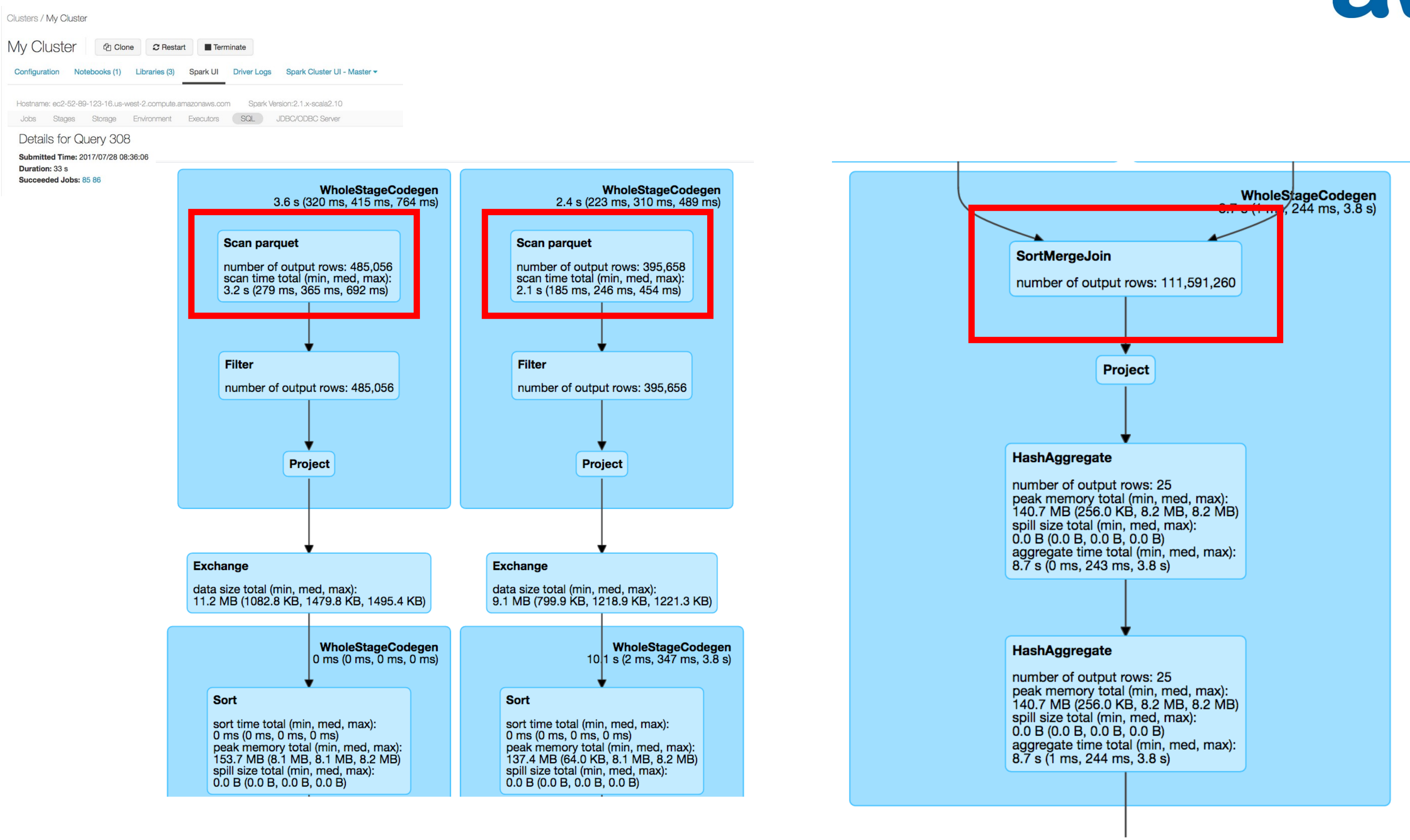
Executed on Databricks Community Edition

Spark UI Inspection – Join: CSV

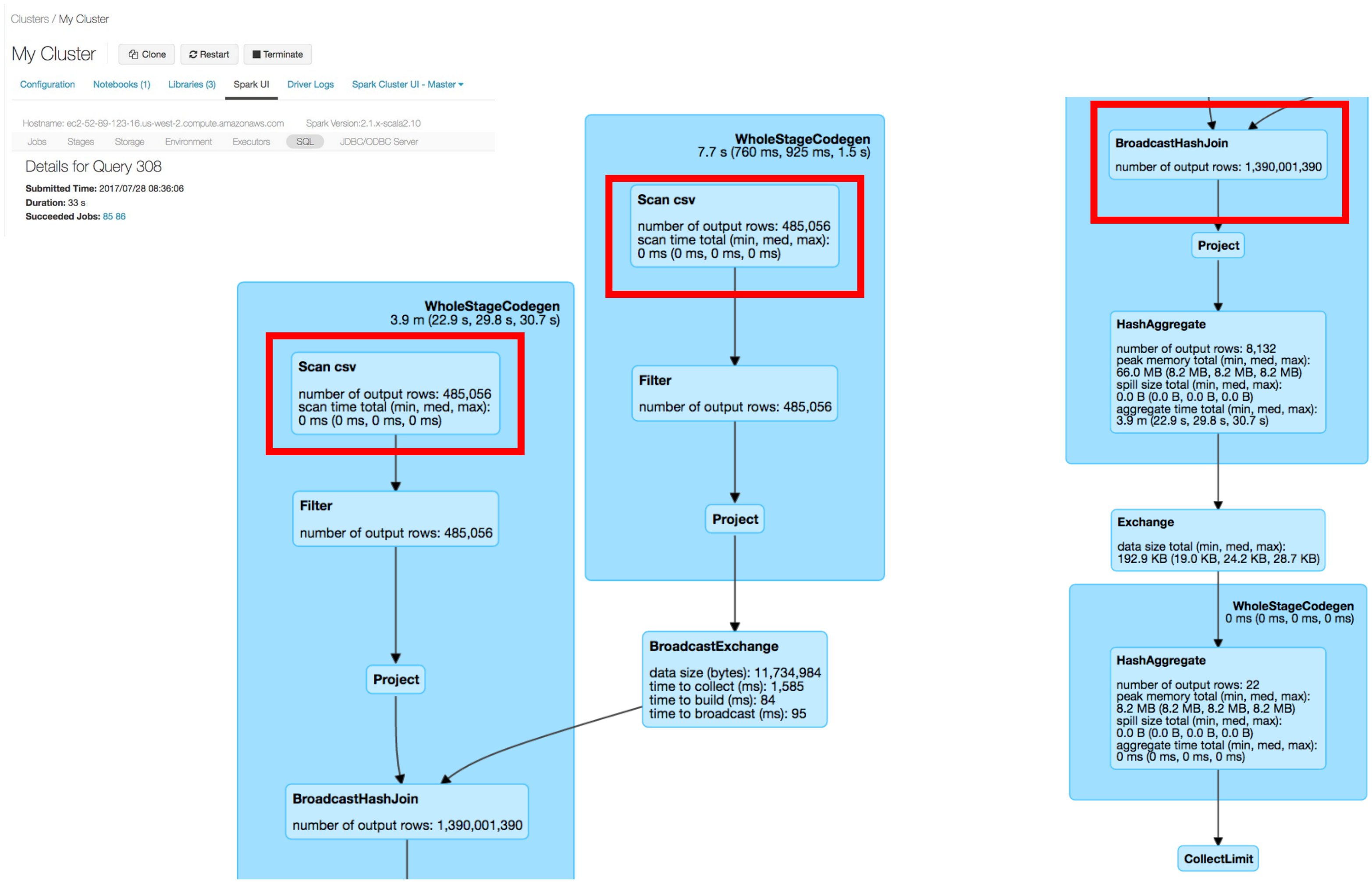




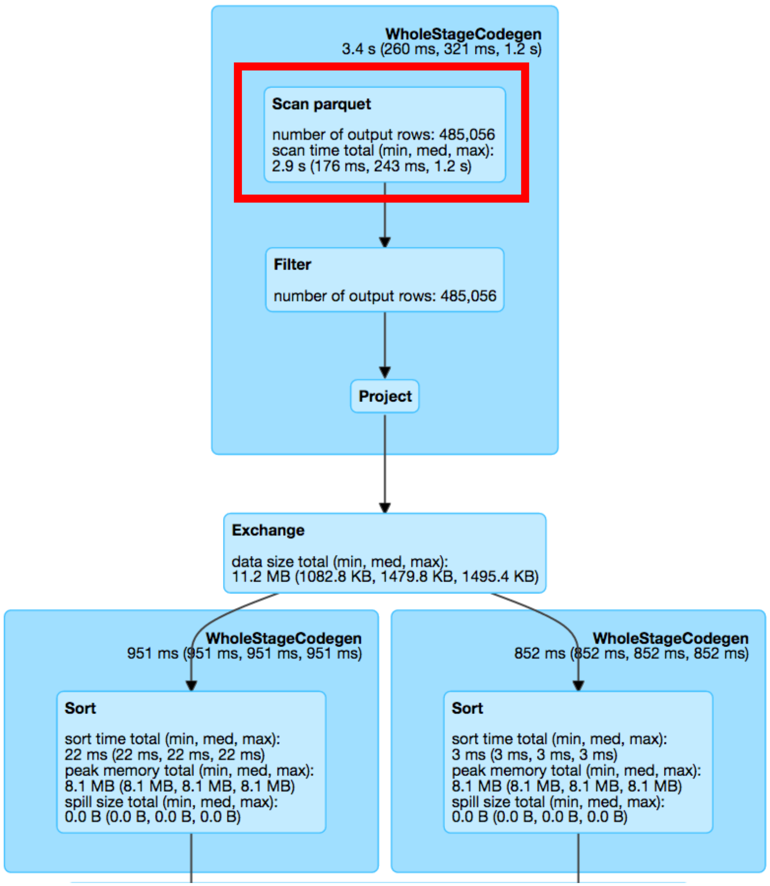
Spark UI Inspection – Join: Parquet



Spark UI Inspection – Self-Join: CSV



Spark UI Inspection – Self-Join Parquet



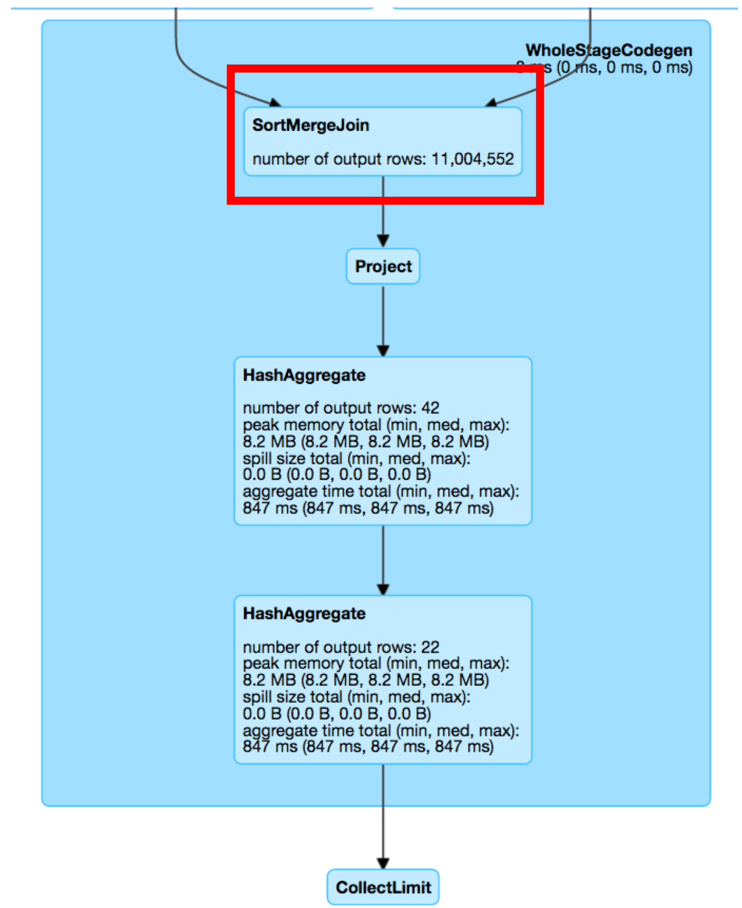


Table is only read once!

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Conclusions

- We learned how a query is analyzed
- Difference between logical and physical query plan
- Performing different types of joins:
  - Nested-loop join
  - Sort-merge join
  - Hash join
- Distributed joins:
  - Shuffle hash join
  - Broadcast hash join
- Join performance on CSV and Parquet file