Deep Dive Into Catalyst: Apache Spark's Optimizer

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databricks

Who is Databricks

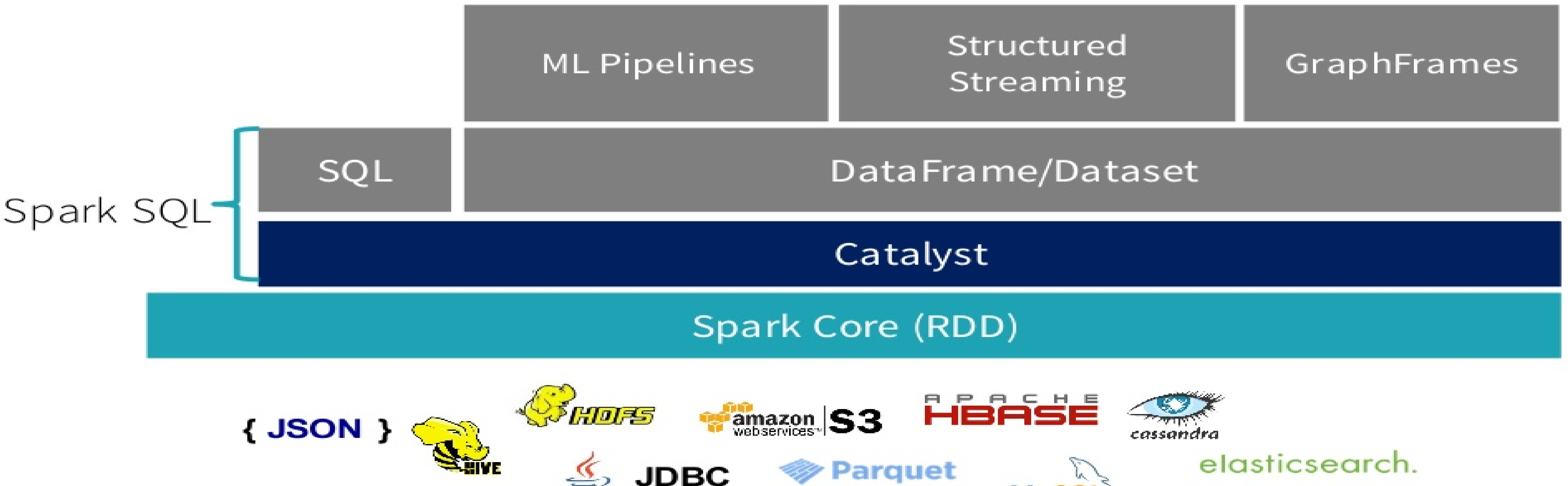
Why Us

- Created Apache Spark to enable big data use cases with a single engine.
- Contributes 75% of Spark's code

Our Product

- Bring Spark to the enterprise: The just-in-time data platform.
- Fully managed platform powered by Apache Spark.
- A unified solution for data science and engineering teams.

Overview



ML Pipelines
Structured Streaming
GraphFrames
SQL
DataFrame/Dataset
Spark SQL
Catalyst
Spark Core (RDD)
{ JSON }
HIVE
HDFS
amazon webservices S3
APACHE HBASE
cassandra
JDBC
Parquet
MySQL
elasticsearch.
and more…

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.

Why structure?

RDD

```
pdata.map { case (dpt, age) => dpt -> (age, 1) }
      .reduceByKey { case ((a1, c1), (a2, c2)) => (a1 + a2, c1 + c2)}
      .map { case (dpt, (age, c)) => dpt -> age/ c }
```

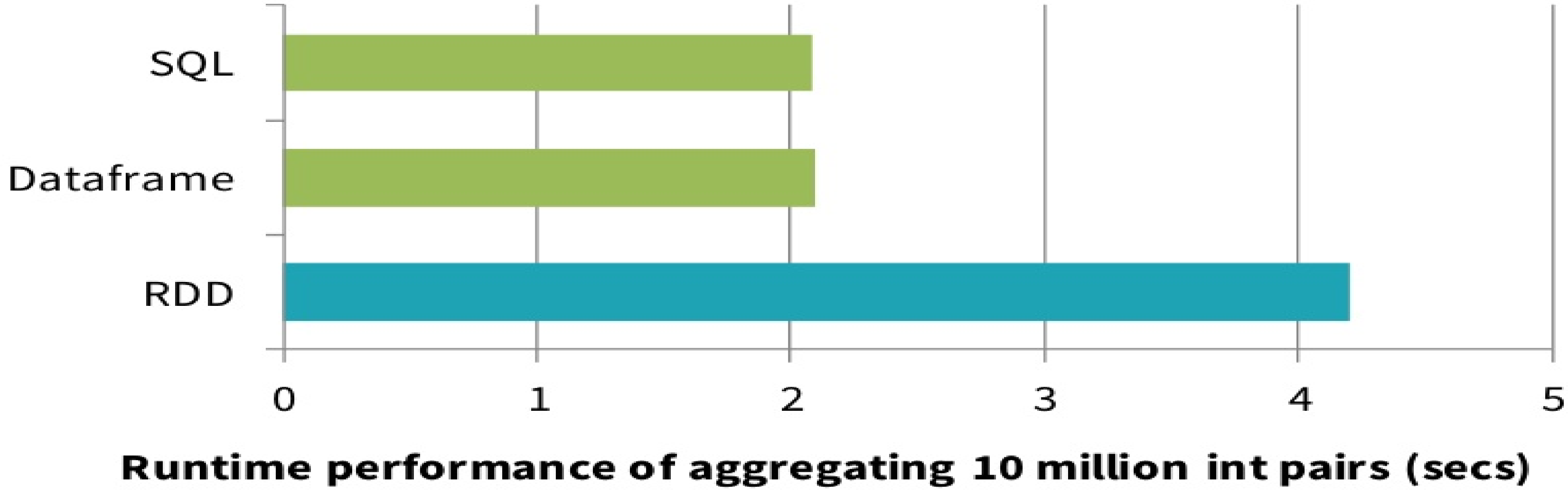
Dataframe

```
data.groupBy("dept").avg("age")
```

SQL

```
select dept, avg(age) from data group by 1
```

Why structure?



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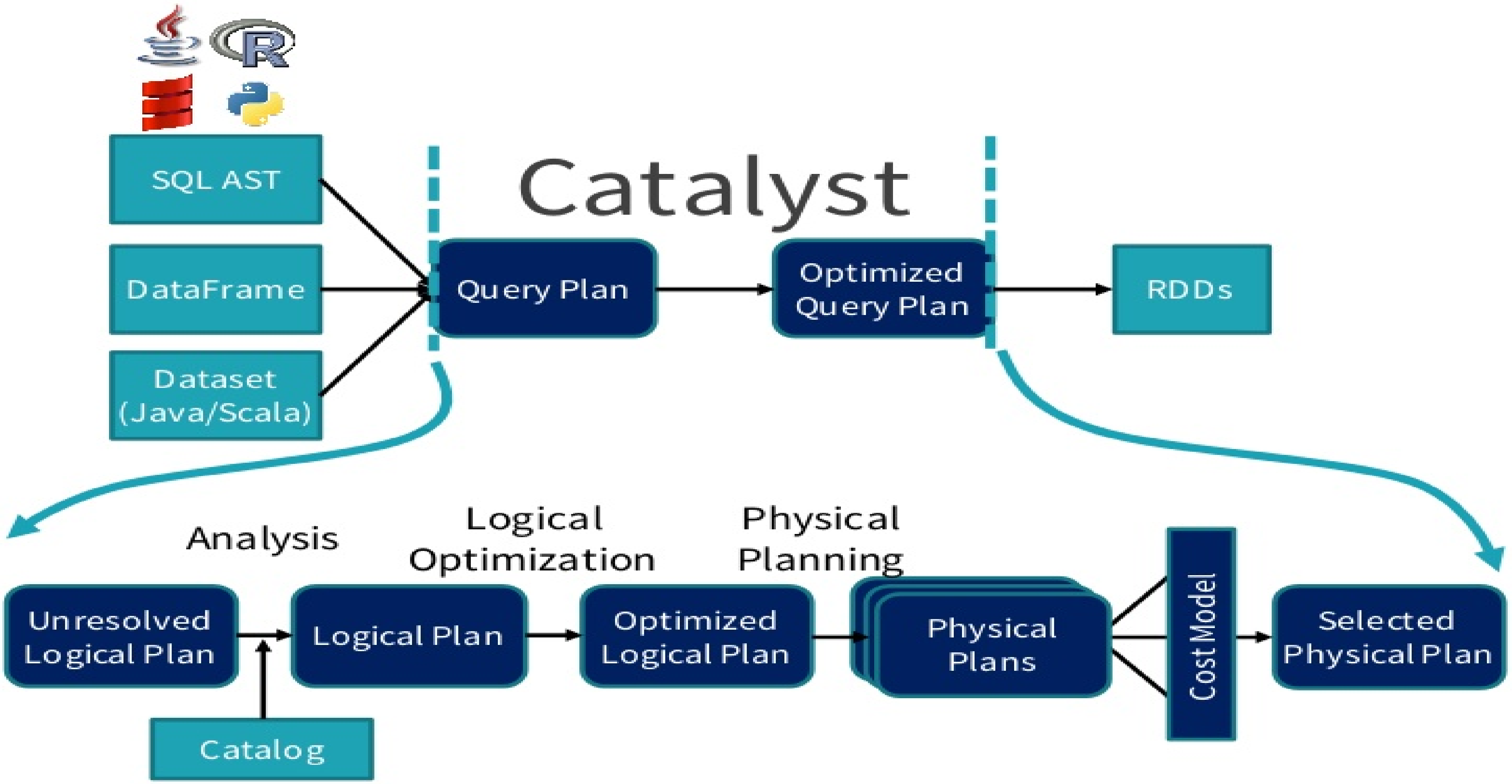
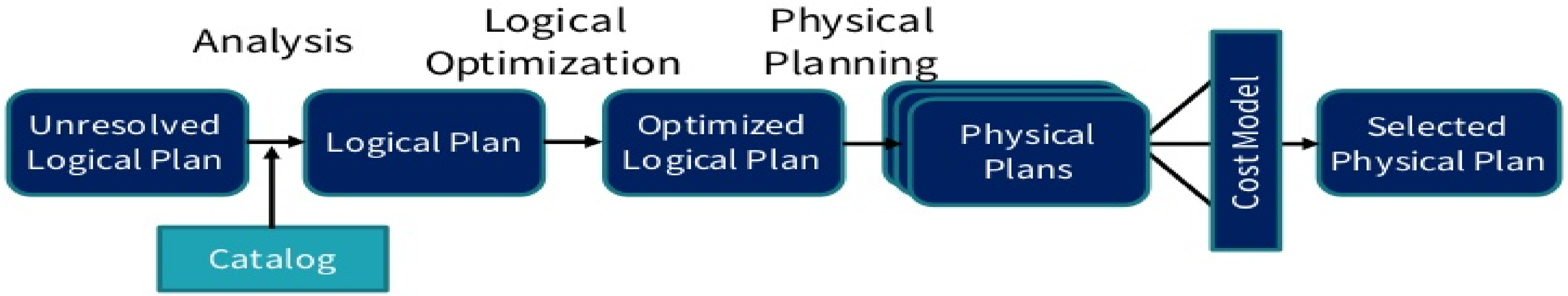
How?

- Write programs using high level programming interfaces
  - Programs are used to describe what data operations are needed without specifying how to execute those operations
  - High level programming interfaces: SQL, DataFrames, and Dataset

- Get an optimizer that **automatically** finds out the most efficient plan to execute data operations specified in the user's program

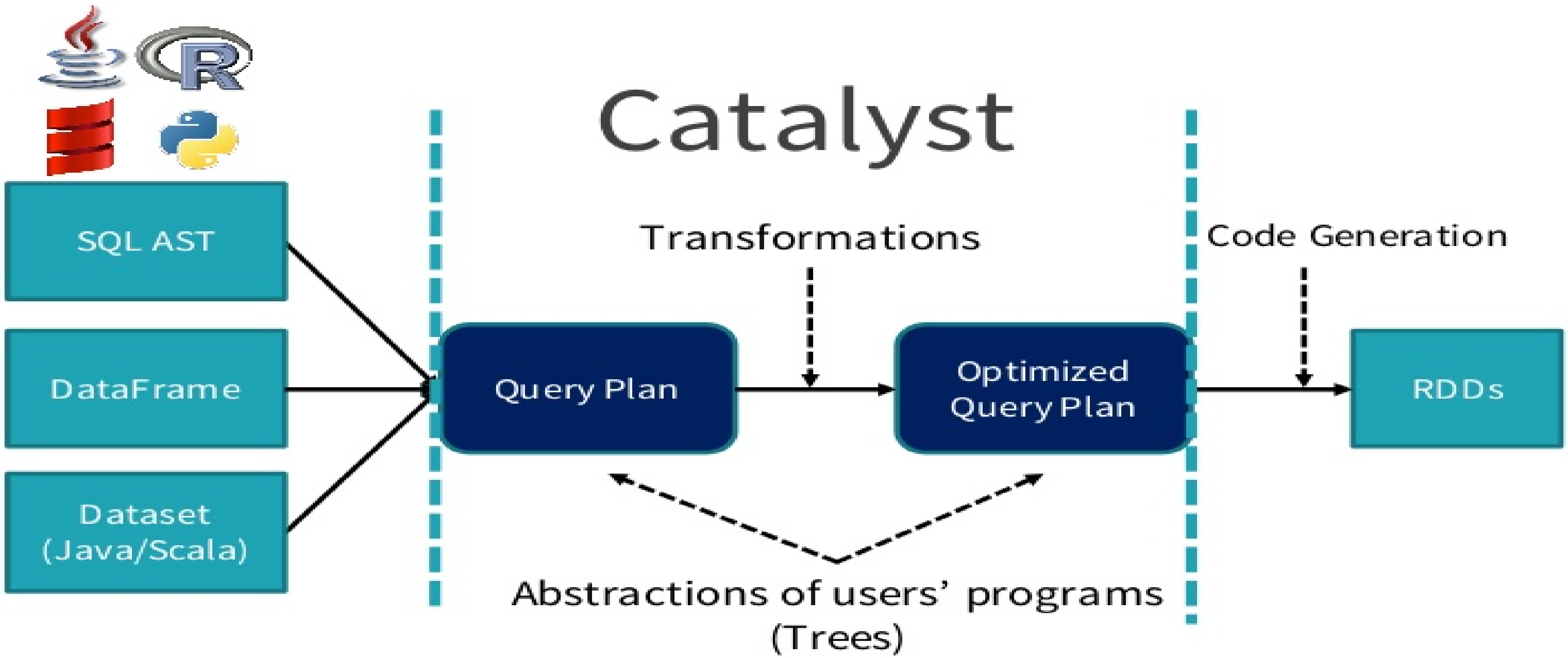
Catalyst:
Apache Spark's Optimizer


Catalyst
SQL AST
DataFrame
Dataset (Java/Scala)
Query Plan
Optimized Query Plan
RDDs
Analysis
Logical Optimization
Physical Planning
Unresolved Logical Plan
Logical Plan
Optimized Logical Plan
Physical Plans
Cost Model
Selected Physical Plan
Catalog

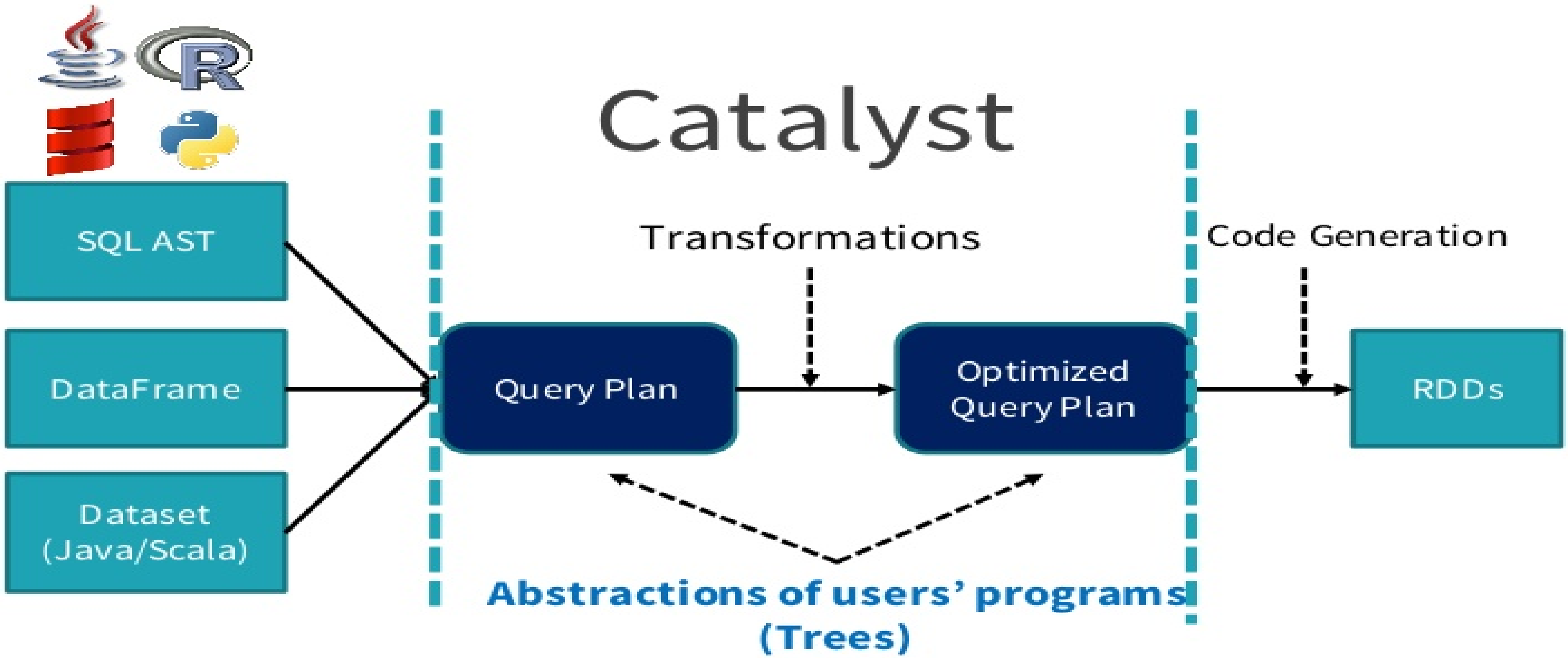


- **Analysis (Rule Executor):** Transforms an Unresolved Logical Plan to a Resolved Logical Plan
  - Unresolved => Resolved: Use Catalog to find where datasets and columns are coming from and types of columns
- **Logical Optimization (Rule Executor)**: Transforms a Resolved Logical Plan to an Optimized Logical Plan
- **Physical Planning (Strategies + Rule Executor)**: Transforms a Optimized Logical Plan to a Physical Plan

How Catalyst Works: An Overview



How Catalyst Works: An Overview



Trees: Abstractions of Users' Programs

```
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
```

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
```

- An expression represents a new value, computed based on input values
  - e.g. `1 + 2 + t1.value`
- Attribute: A column of a dataset (e.g. **`t1.id`**) or a column generated by a specific data operation (e.g. **`v`**)

Trees: Abstractions of Users’ Programs

Query Plan

```
SELECT sum(v)
FROM (
  SELECT
    t1.id,
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  FROM t1 JOIN t2
  WHERE
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```
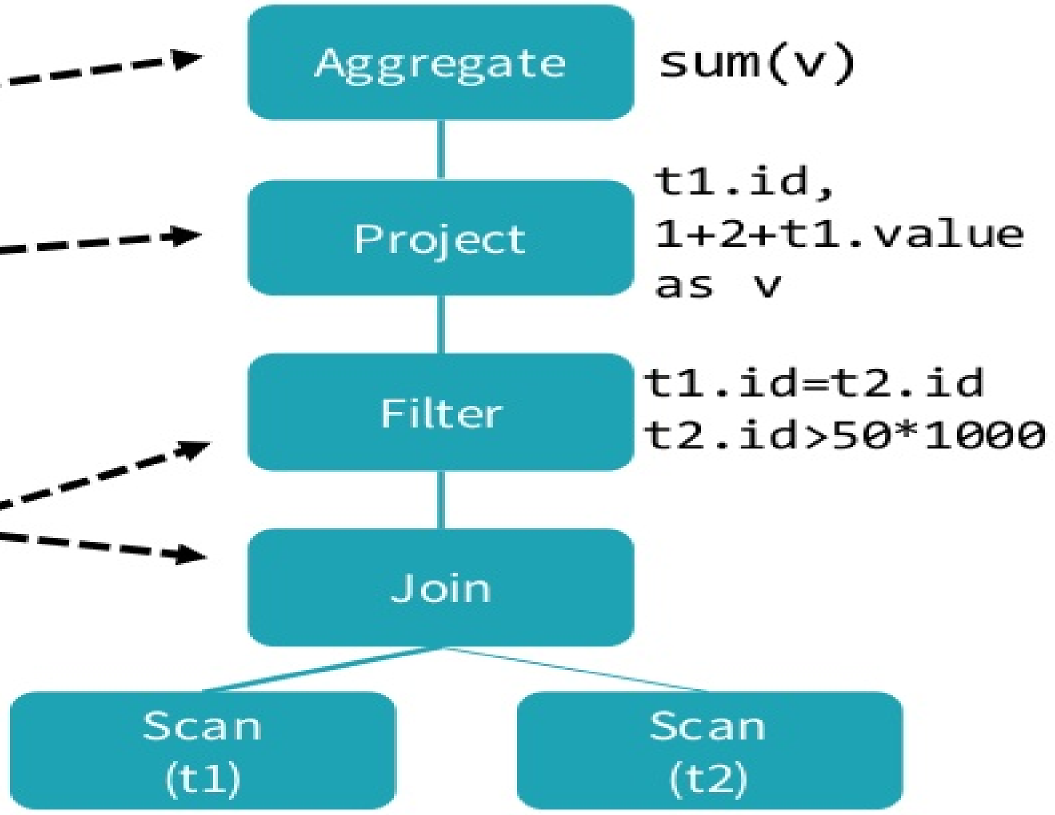
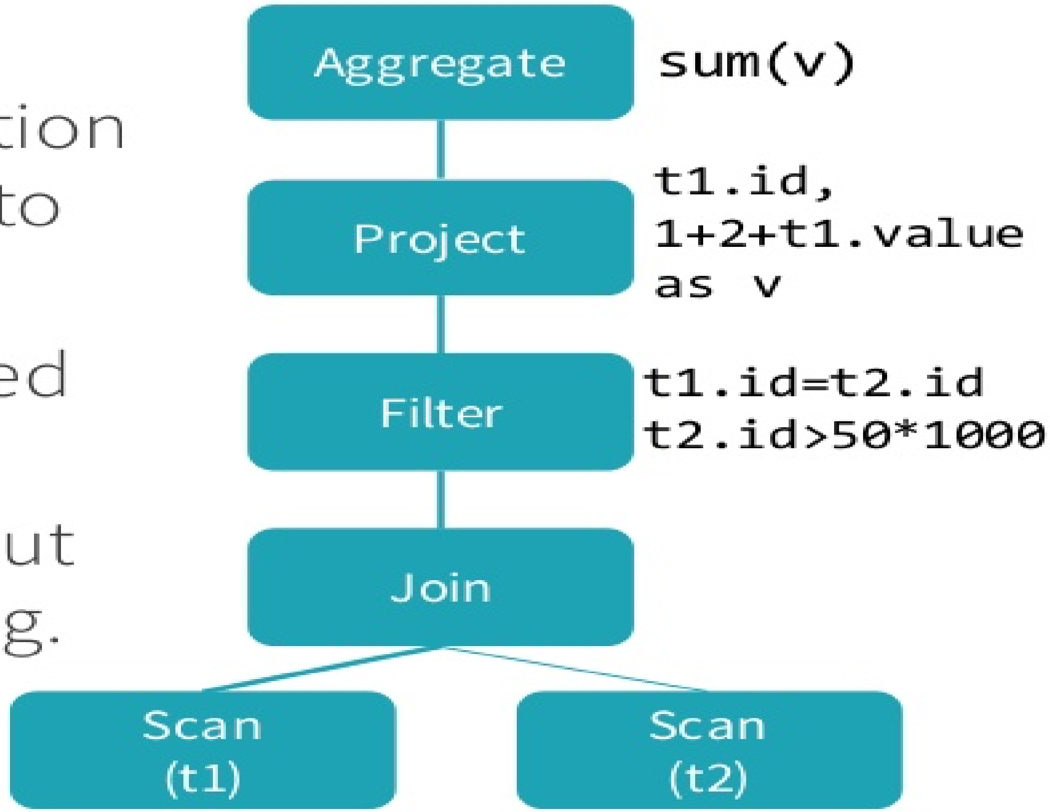



Logical Plan

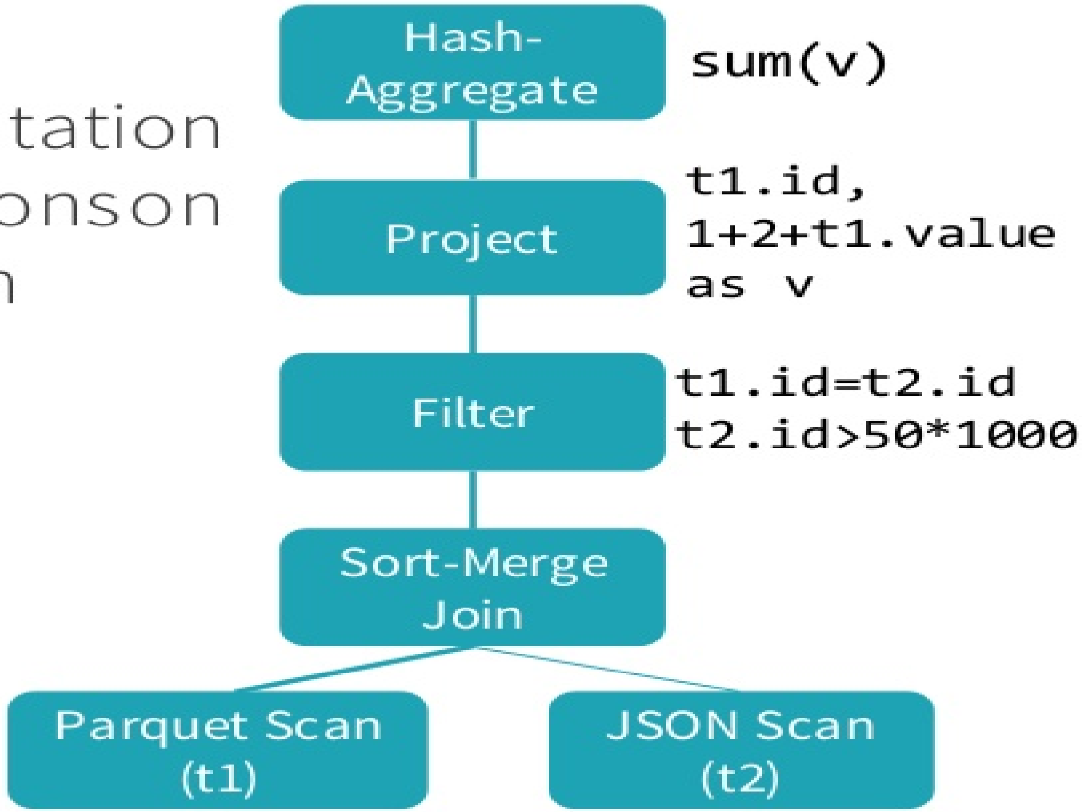
- A Logical Plan describes computation on datasets **without** defining how to conduct the computation
- **output**: a list of attributes generated by this Logical Plan, e.g. [`id, v`]
- **constraints**: a set of invariants about the rows generated by this plan, e.g. `t2.id > 50 * 1000`



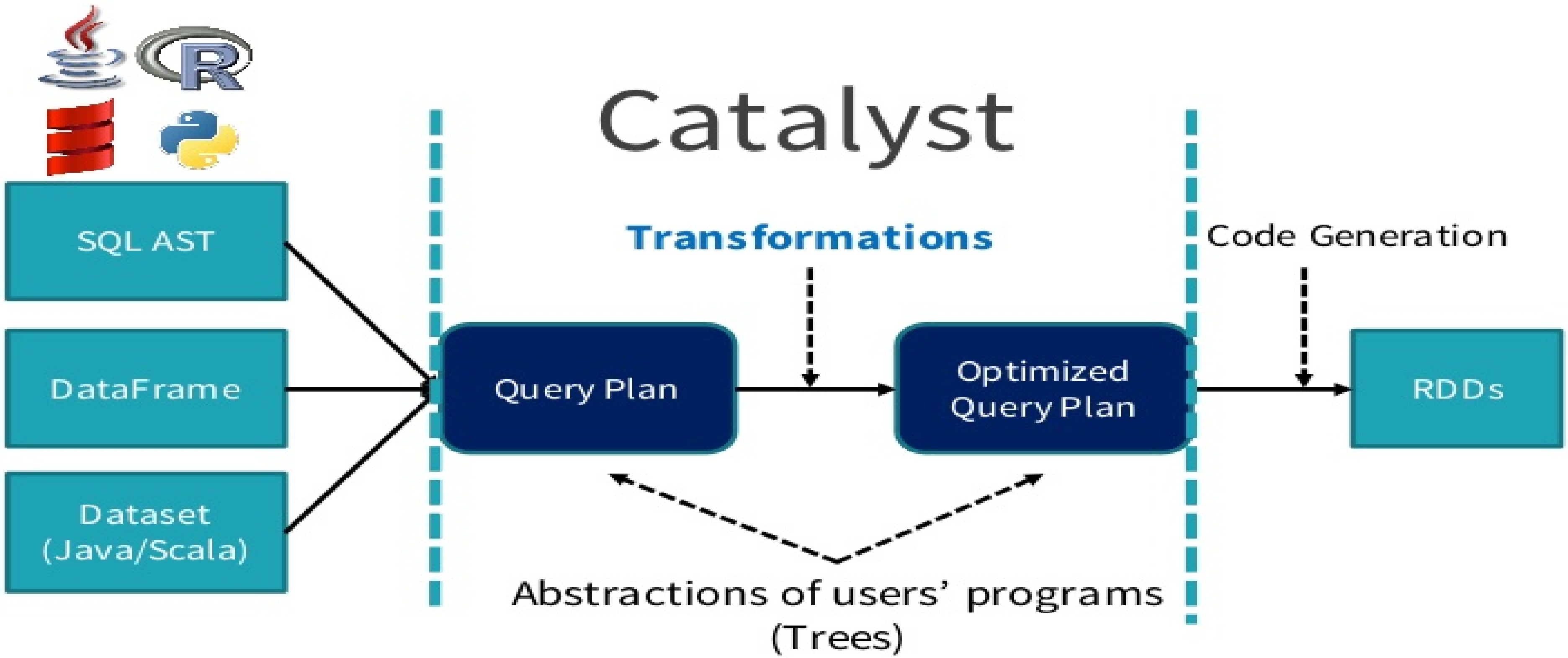
Physical Plan

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

- A Physical Plan is executable



How Catalyst Works: An Overview



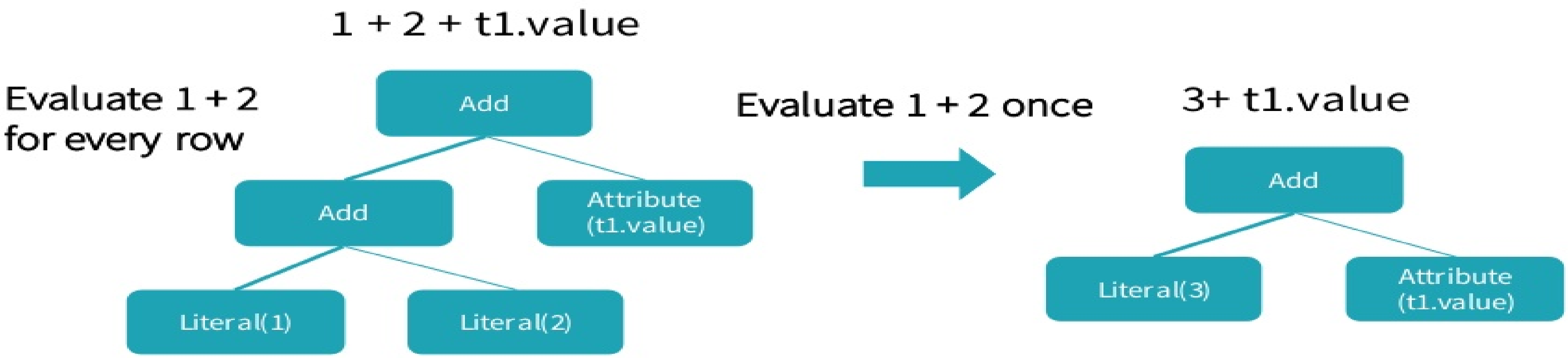
Transformations

- Transformations without changing the tree type (Transform and Rule Executor)
  - Expression => Expression
  - Logical Plan => Logical Plan
  - Physical Plan => Physical Plan

- Transforming a tree to another kind of tree
  - Logical Plan => Physical Plan

Transform

- A function associated with every tree used to implement a single rule



Transform

- A transformation is defined as a Partial Function
- Partial Function: A function that is defined for a subset of its possible arguments

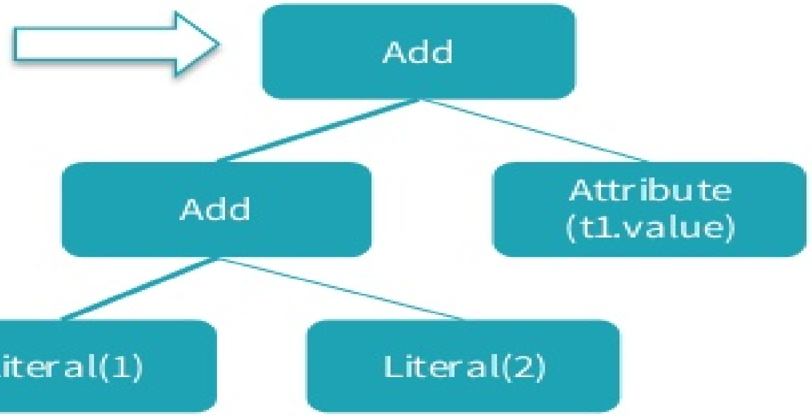
```
val expression: Expression = ...
expression.transform {
  case Add(Literal(x, IntegerType), Literal(y, IntegerType)) =>
    Literal(x + y)
}
```

Case statement determine if the partial function is defined for a given input

Transform

```
val expression: Expression = ...
expression.transform {
  case Add(Literal(x, IntegerType), Literal(y, IntegerType)) =>
    Literal(x + y)
}
```

1 + 2 + t1.value



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Transform

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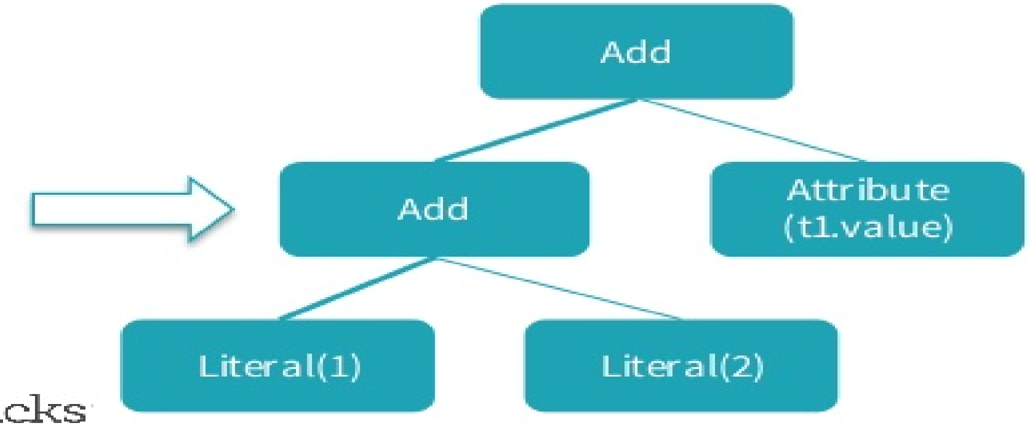

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Transform

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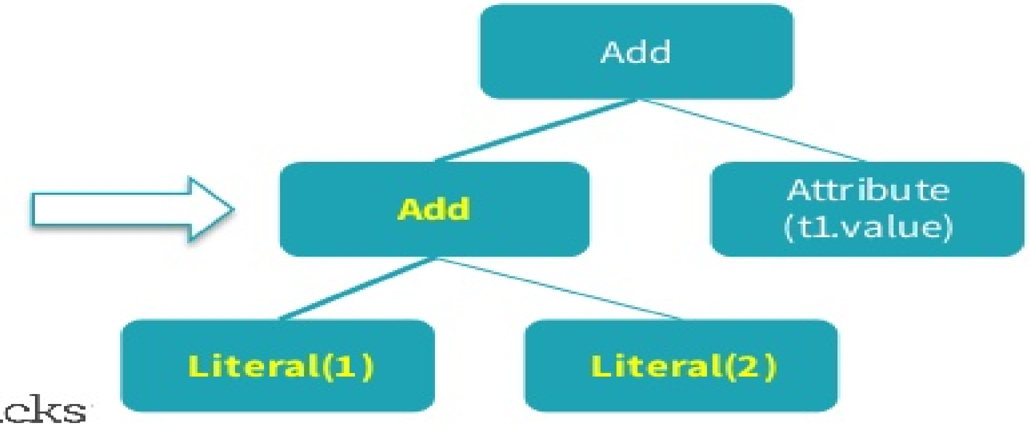

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Transform

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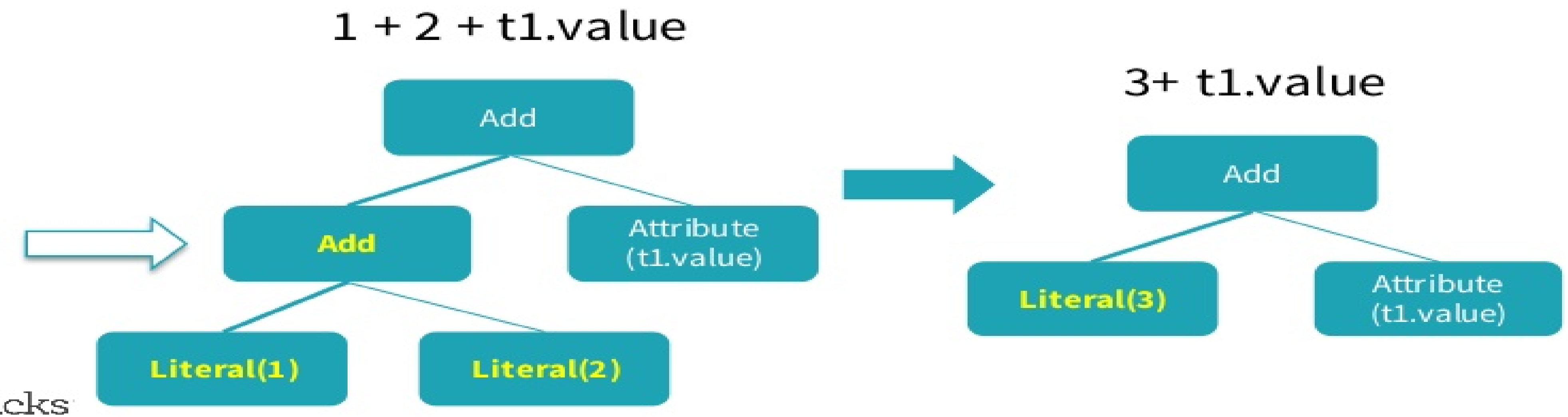
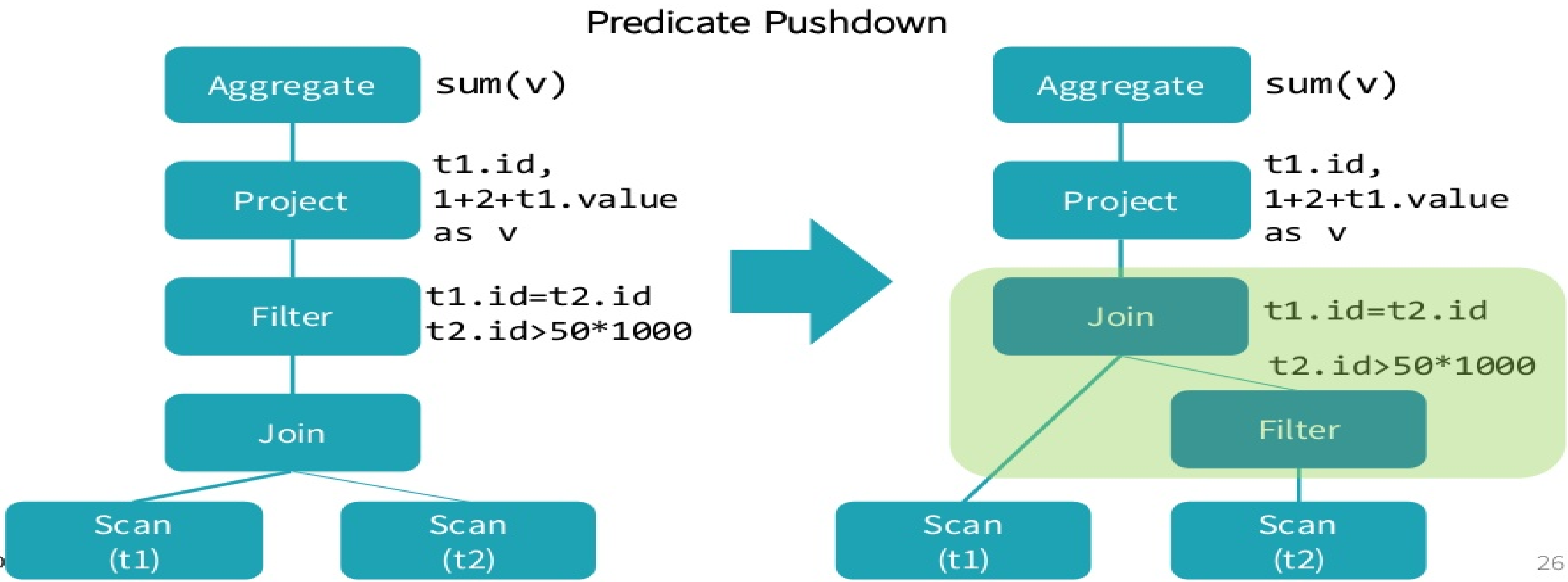


Combining Multiple Rules



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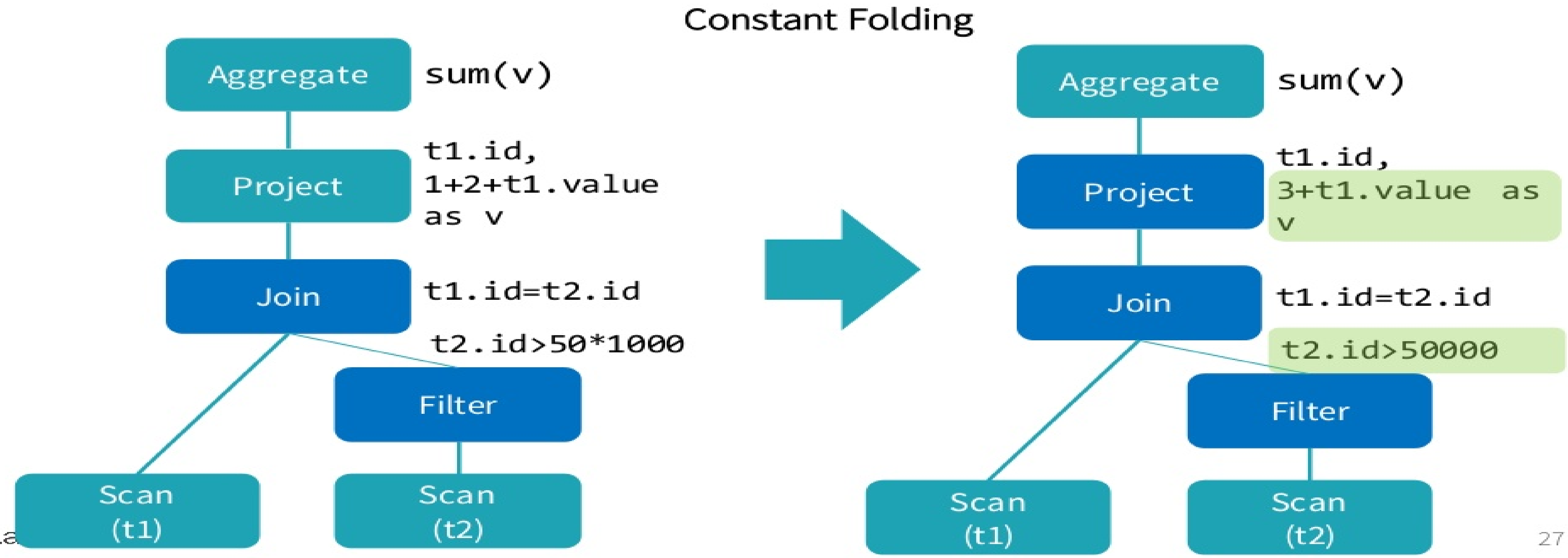

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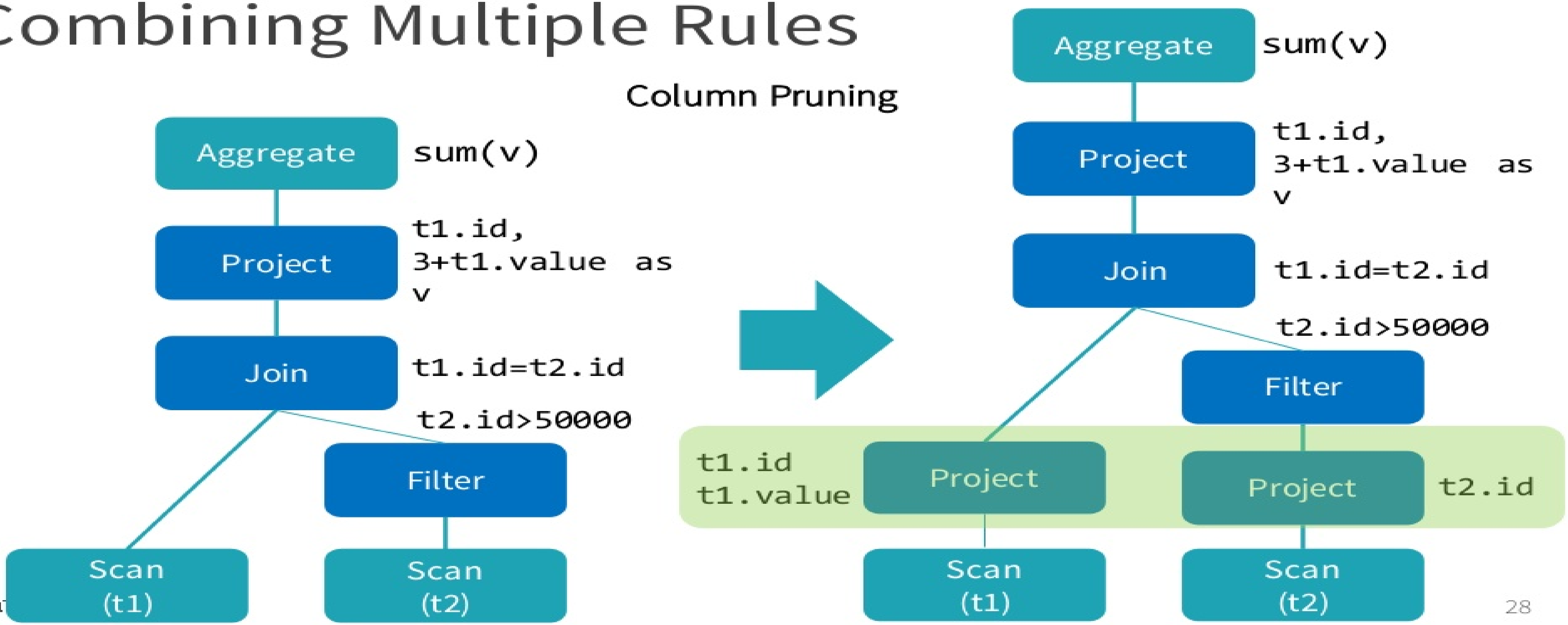

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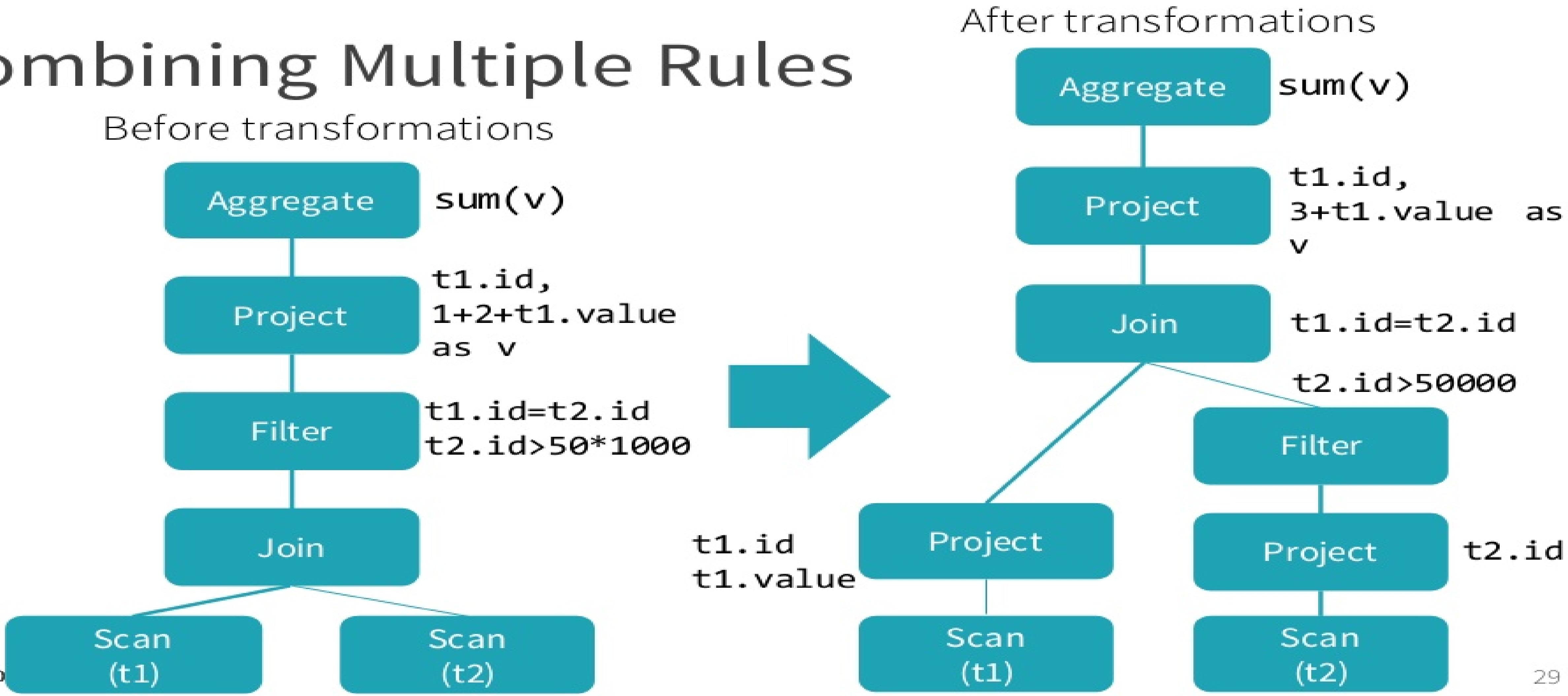
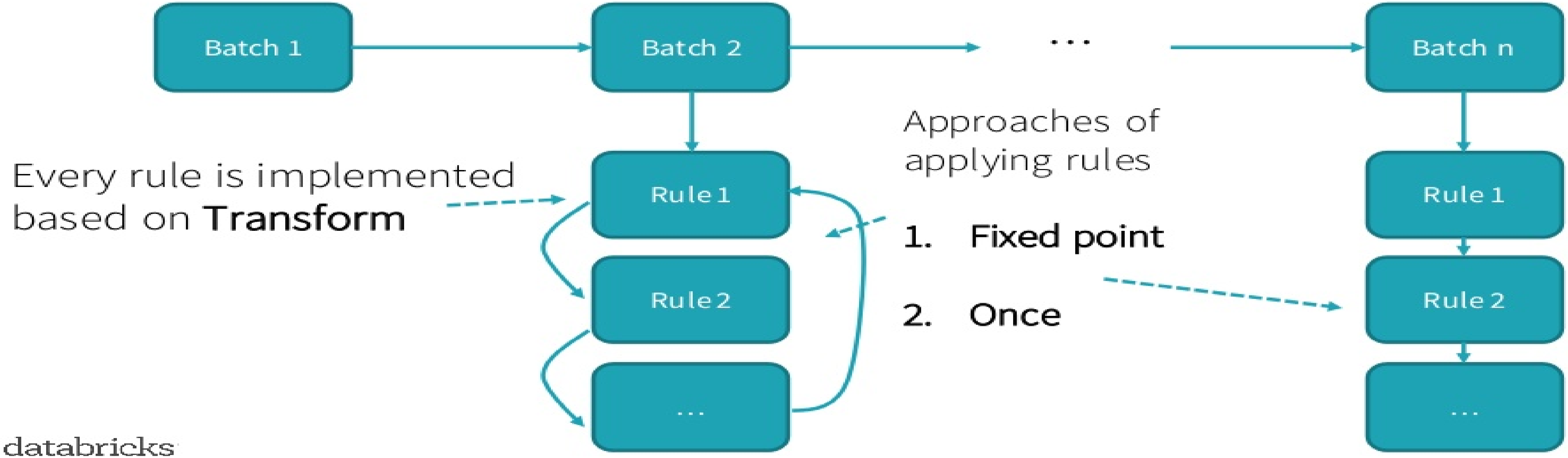


Combining Multiple Rules: Rule Executor

A Rule Executor transforms a Tree to another same type Tree by applying many rules defined in batches



Transformations

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- Transforming a tree to another kind of tree
  - Logical Plan => Physical Plan

From Logical Plan to Physical Plan

- A Logical Plan is transformed to a Physical Plan by applying a set of Strategies
- Every Strategy uses pattern matching to convert a Tree to another kind of Tree

```
object BasicOperators extends Strategy {
  def apply(plan: LogicalPlan): Seq[SparkPlan] = plan match {
    …
    case logical.Project(projectList, child) =>
      execution.ProjectExec(projectList, planLater(child)) :: Nil
    case logical.Filter(condition, child) =>
      execution.FilterExec(condition, planLater(child)) :: Nil
    …
  }
}
```

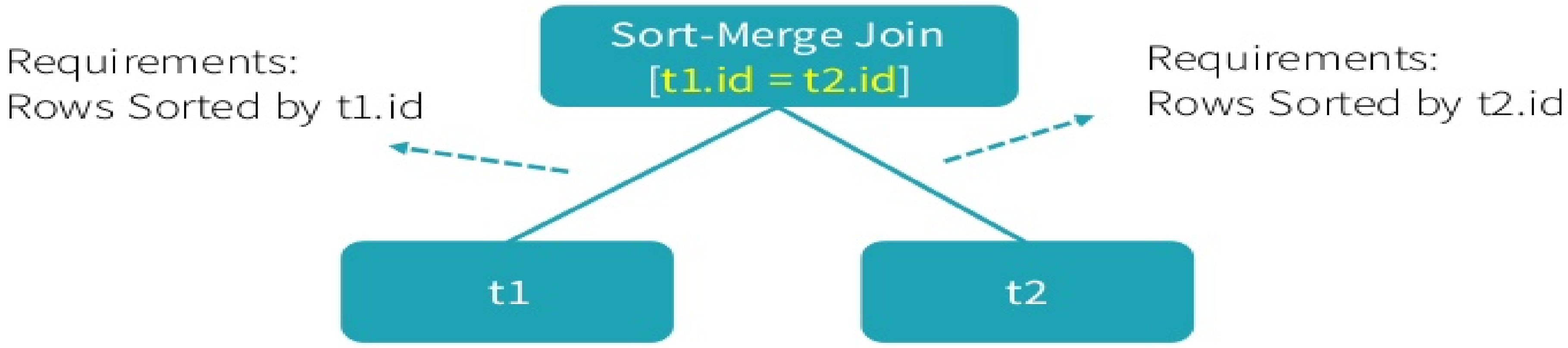
Triggers other Strategies

Spark's Planner

- 1st Phase: Transforms the Logical Plan to the Physical Plan using Strategies

- 2nd Phase: Use a Rule Executor to make the Physical Plan ready for execution
  - Prepare Scalar sub-queries
  - Ensure requirements on input rows
  - Apply physical optimizations

Ensure Requirements on Input Rows



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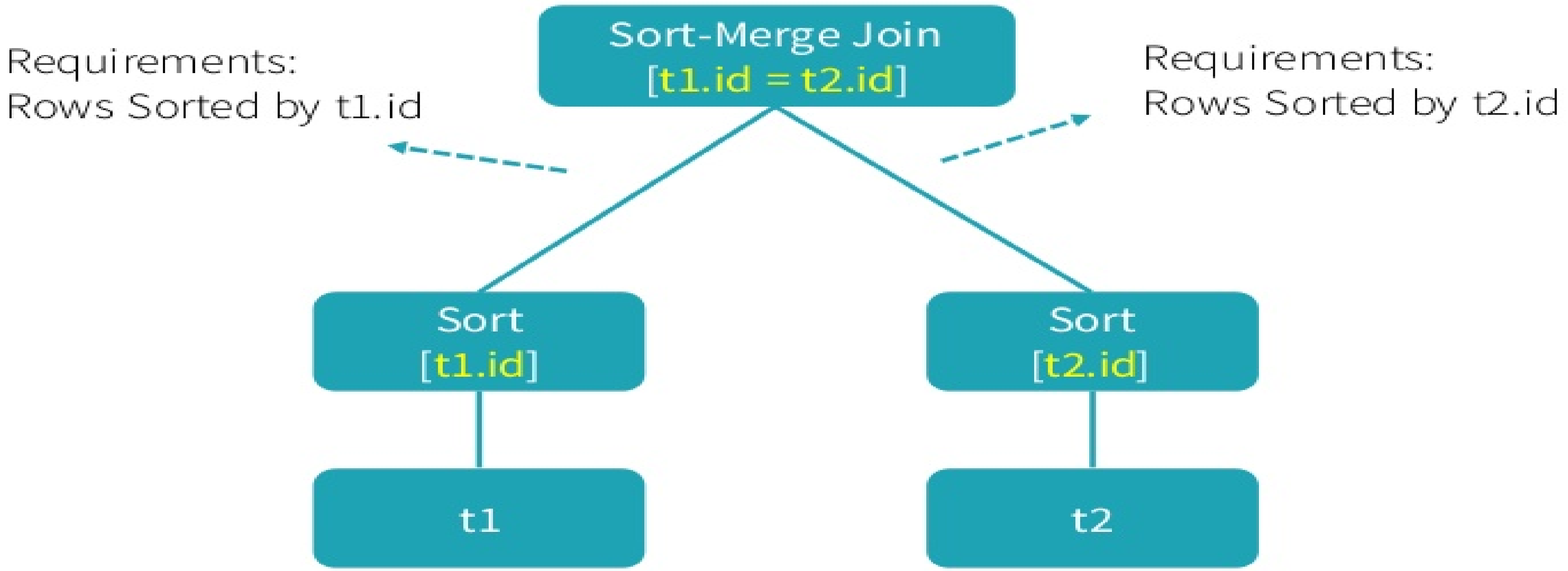

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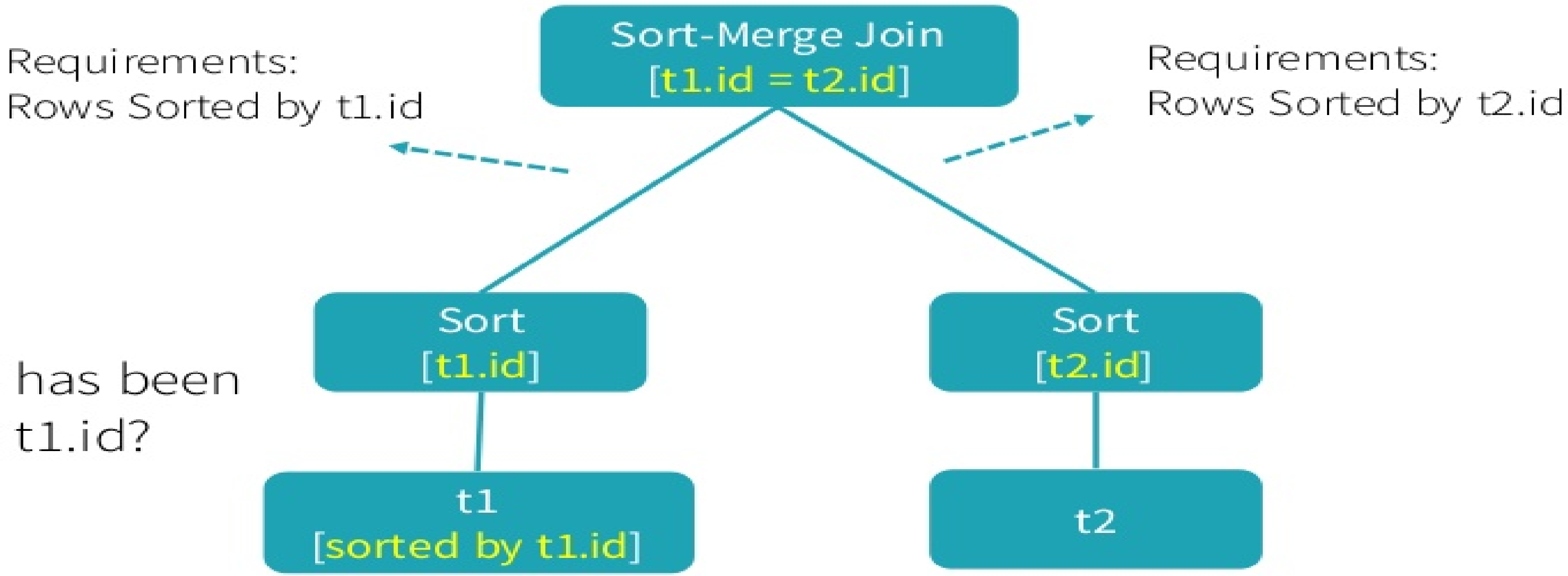
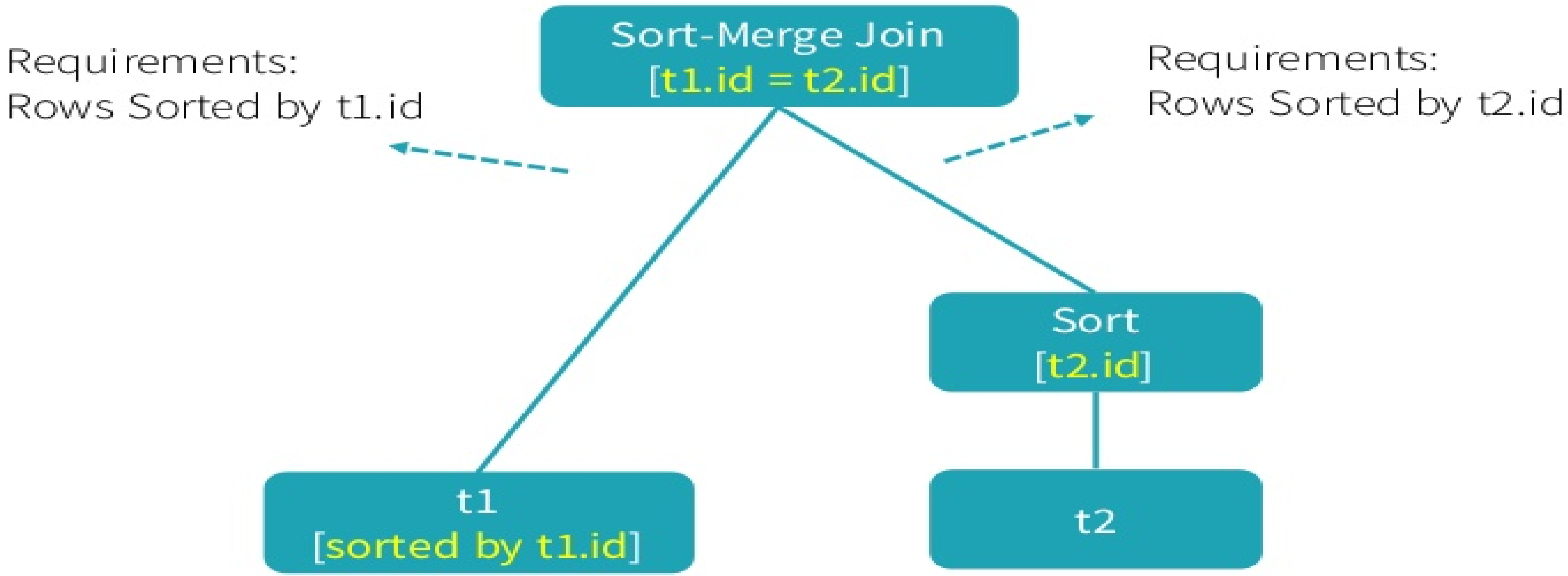


What if t1 has been sorted by t1.id?

Ensure Requirements on Input Rows



Roll your own Planning Rule

Roll your own Planner Rule

```scala
import org.apache.spark.sql.functions._

val tableA = spark.range(100000000).as('a)
val tableB = spark.range(100000000).as('b)

val result = tableA
    .join(tableB, $"a.id" === $"b.id")
    .groupBy()
    .count()
result.count()
```

This takes ~22 Seconds on Databricks Community edition

Roll your own Planner Rule

Can we do better?

Roll your own Planner Rule - Analysis

```
== Physical Plan ==
*HashAggregate(keys=[], functions=[count(1)], output=[count#43L])
+- Exchange SinglePartition
   +- *HashAggregate(keys=[], functions=[partial_count(1)], output=[count#48L])
      +- *Project
         +- *SortMergeJoin [id#21L], [id#25L], Inner
            :- *Sort [id#21L ASC], false, 0
            :  +- Exchange hashpartitioning(id#21L, 200)
            :     +- *Range (0, 100000000, step=1, splits=Some(8))
            +- *Sort [id#25L ASC], false, 0
               +- Exchange hashpartitioning(id#25L, 200)
                  +- *Range (0, 100000000, step=1, splits=Some(8))
```

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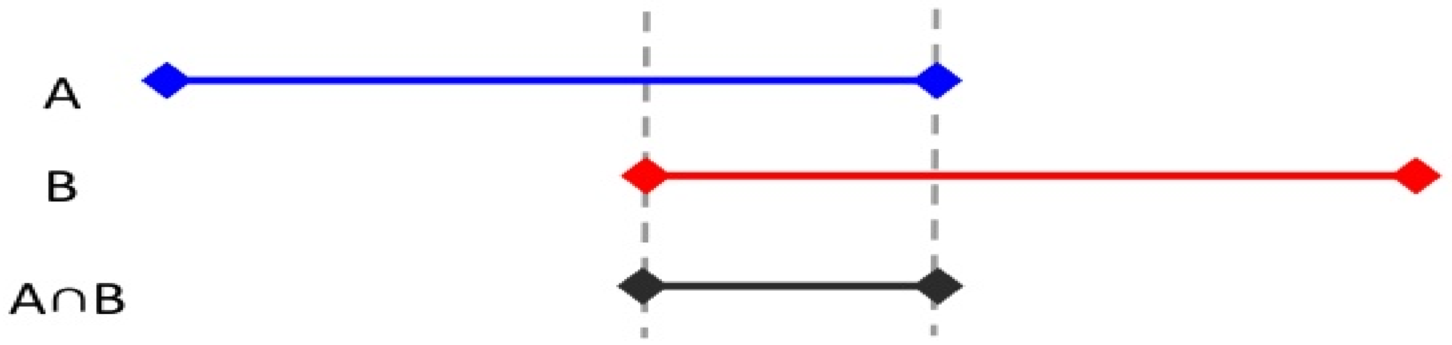
Roll your own Planner Rule

Exploit the structure of the problem

We are joining two intervals; the result will be the intersection of these intervals



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Roll your own Planner Rule - Matching

```
case object IntervalJoin extends Strategy with Serializable {
  def apply(plan: LogicalPlan): Seq[SparkPlan] = plan match {
    case Join(
           Range(start1, end1, 1, part1, Seq(o1)),
           Range(start2, end2, 1, part2, Seq(o2)),
           Inner,
           Some(EqualTo(e1, e2)))
               if ((o1 semanticEquals e1) && (o2 semanticEquals e2)) ||
                  ((o1 semanticEquals e2) && (o2 semanticEquals e1)) =>
           // Rule...
    case _ => Nil
  }
}
```

Roll your own Planner Rule - Body

```
if astart1 <= end2) && (end1 >= end2)) {
  val start = math.max(start1, start2)
  val end = math.min(end1, end2)
  val part = math.max(part1.getOrElse(200), part2.getOrElse(200))
  val result = RangeExec(Range(start, end, 1, part, o1 :: Nil))
  val twoColumns = ProjectExec(
    Alias(o1, o1.name)(exprId = o1.exprId) :: Nil,
    result)
  twoColumns :: Nil
} else {
  Nil
}
```

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Roll your own Planner Rule

Hook it up with Spark

```
spark.experimental.extraStrategies = IntervalJoin :: Nil
```

Use it

```
result.count()
```

This now takes 0.46 seconds to complete

Roll your own Planner Rule

```
== Physical Plan ==
*HashAggregate(keys=[], functions=[count(1)],
output=[count#43L])
+- Exchange SinglePartition
   +- *HashAggregate(keys=[], functions=[partial_count(1)],
output=[count#48L])
      +- *Project
         +- *Project [id#21L AS id#21L]
            +- *Range (0, 100000000, step=1, splits=Some(8))
```

Community Contributed Transformations

SPARK-3462 push down filters and projections into Unions #2345

Closed **koeninger** wants to merge 3 commits into `apache:master` from `mediacrossinginc:SPARK-3462`

Conversation 15 Commits 3 Files changed 2 +110 −0

Showing 2 changed files with **110 additions** and **0 deletions**. Unified Split

110 line patch took this user's query from "never finishing" to 200s.

Overall 200+ people have contributed to the analyzer/optimizer/planner in the last 2 years.

Where to Start

- Source Code:
  - Trees: TreeNode, Expression, Logical Plan, and Physical Plan
  - Transformations: Analyzer, Optimizer, and Planner
- Check out previous pull requests
- Start to write code using Catalyst
- Open a pull request!

Try Apache Spark with Databricks

- Try latest version of Apache Spark
  http://databricks.com/try

Questions?

I will be available in the Databricks booth (D1) afterwards

@Westerflyer

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