

Deep Dive Into Catalyst: Apache Spark 2.0's Optimizer

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Spark Summit 2016



Write Programs Using RDD API

```
SELECT count(*)  
FROM (  
    SELECT t1.id  
    FROM t1 JOIN t2  
    WHERE  
        t1.id = t2.id AND  
        t2.id > 50 * 1000) tmp
```

Solution 1

```
t1 join t2
      ↓
val count = t1.cartesian(t2).filter {
    case (id1FromT1, id2FromT2) => id1FromT1 == id2FromT2
}.filter {
    case (id1FromT1, id2FromT2) => id1FromT2 > 50 * 1000
}.map {
    case (id1FromT1, id2FromT2) => id1FromT1
}.count
t1.id = t2.id
t2.id > 50 * 1000
println("Count: " + count)
```

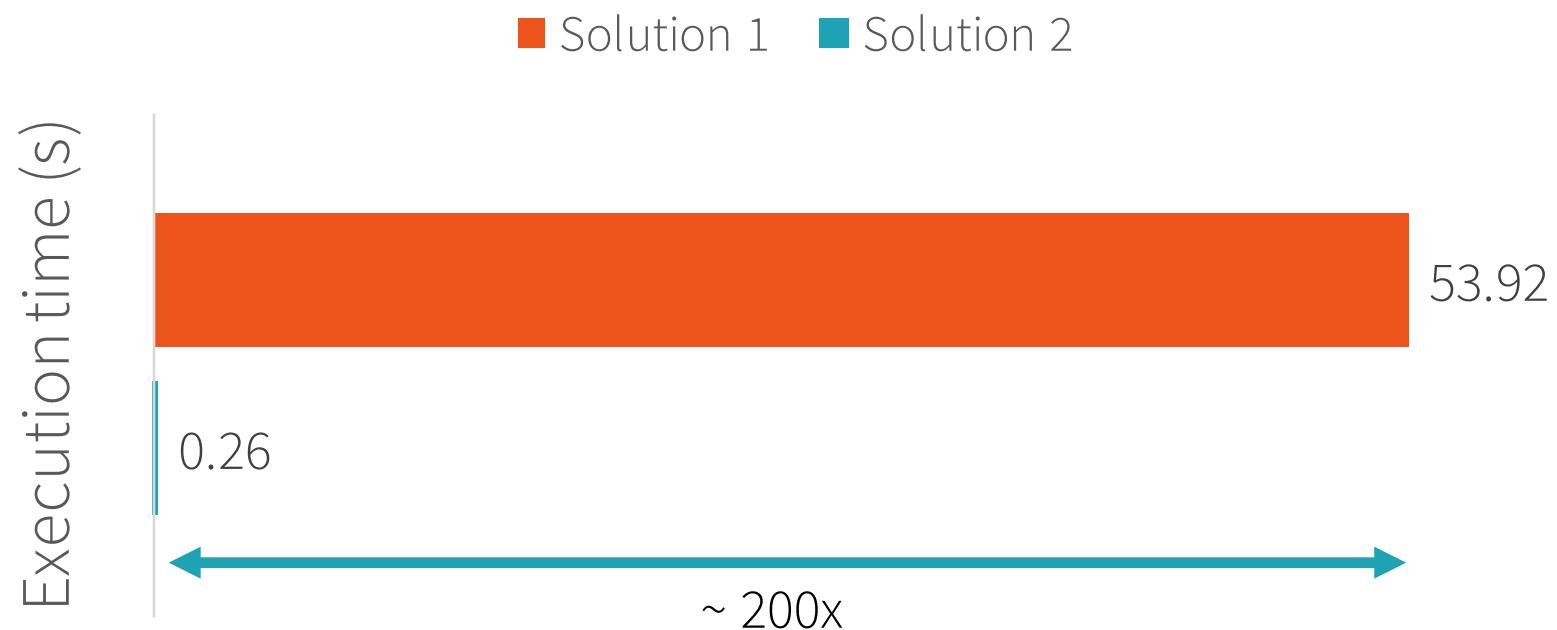
Solution 2

```
val filteredT2 =  
  t2.filter(id1FromT2 => id1FromT2 > 50 * 1000)  
val preparedT1 =  
  t1.map(id1FromT1 => (id1FromT1, id1FromT1))  
val preparedT2 =  
  filteredT2.map(id1FromT2 => (id1FromT2, id1FromT2))  
val count = preparedT1.join(preparedT2).map {  
  case (id1FromT1, _) => id1FromT1  
}.count  
println("Count: " + count)
```

$t2.id > 50 * 1000$

t1 join t2
WHERE t1.id = t2.id

Solution 1 vs. Solution 2



Solution 1

```
t1 join t2
      ↓
val count = t1.cartesian(t2).filter {
    case (id1FromT1, id2FromT2) => id1FromT1 == id2FromT2
}.filter {
    case (id1FromT1, id2FromT2) => id1FromT2 > 50 * 1000
}.map {
    case (id1FromT1, id2FromT2) => id1FromT1
}.count
t1.id = t2.id
t2.id > 50 * 1000
println("Count: " + count)
```

Solution 2

```
          t2.id > 50 * 1000  
  
val filteredT2 =  
  t2.filter(id1FromT2 => id1FromT2 > 50 * 1000)  
val preparedT1 =  
  t1.map(id1FromT1 => (id1FromT1, id1FromT1))  
val preparedT2 =  
  filteredT2.map(id1FromT2 => (id1FromT2, id1FromT2))  
val count = preparedT1.join(preparedT2).map {  
  case (id1FromT1, _) => id1FromT1  
}.count  
println("Count: " + count)      t1 join t2  
                                WHERE t1.id = t2.id
```

Write Programs Using RDD API

- Users' functions are black boxes
 - Opaque computation
 - Opaque data type
- Programs built using RDD API have total control on how to execute every data operation
- Developers have to write efficient programs for different kinds of workloads

Is there an easy way to write efficient programs?

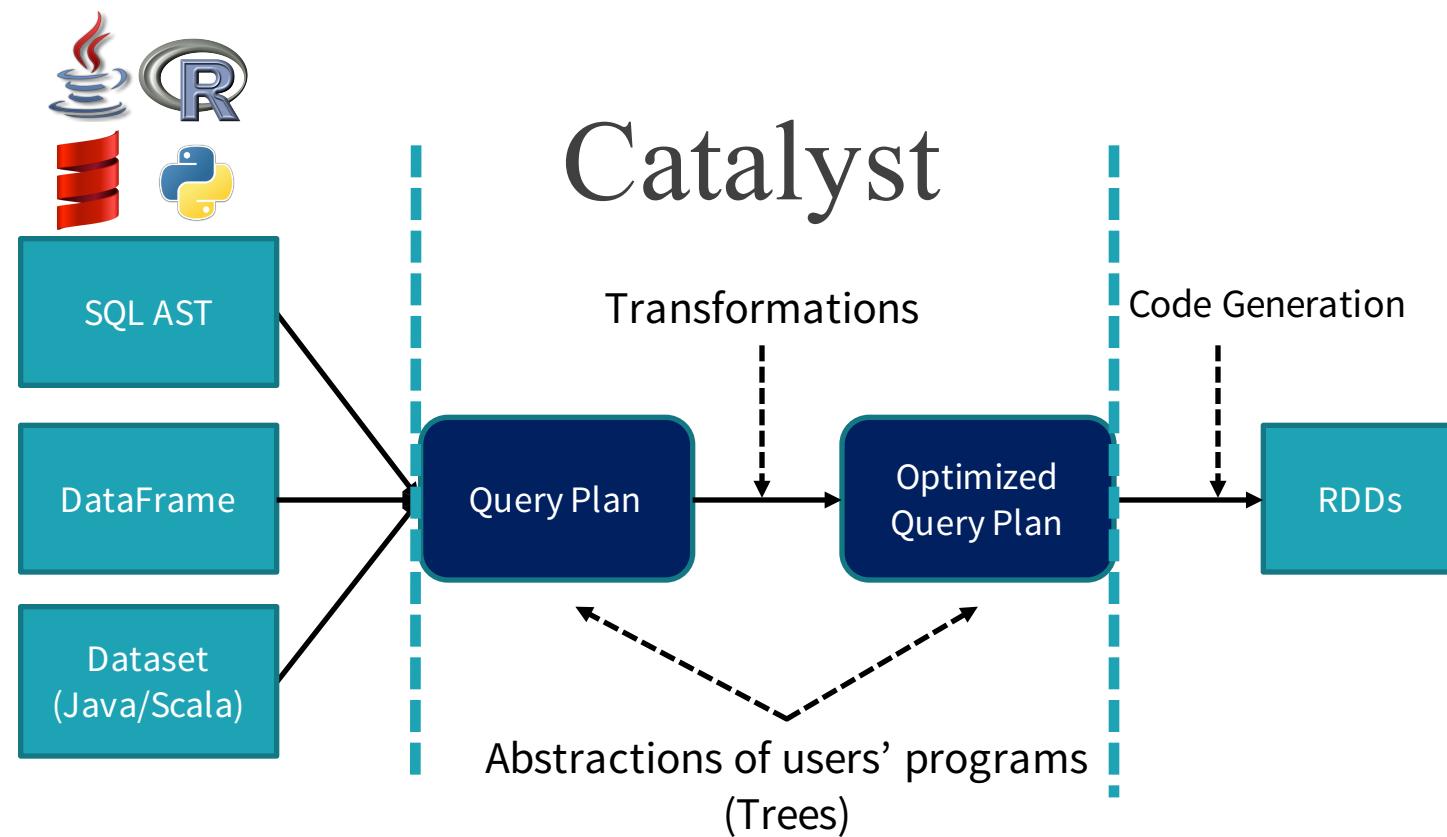
The easiest way to write efficient programs is
to not worry about it and get your programs
automatically optimized

How?

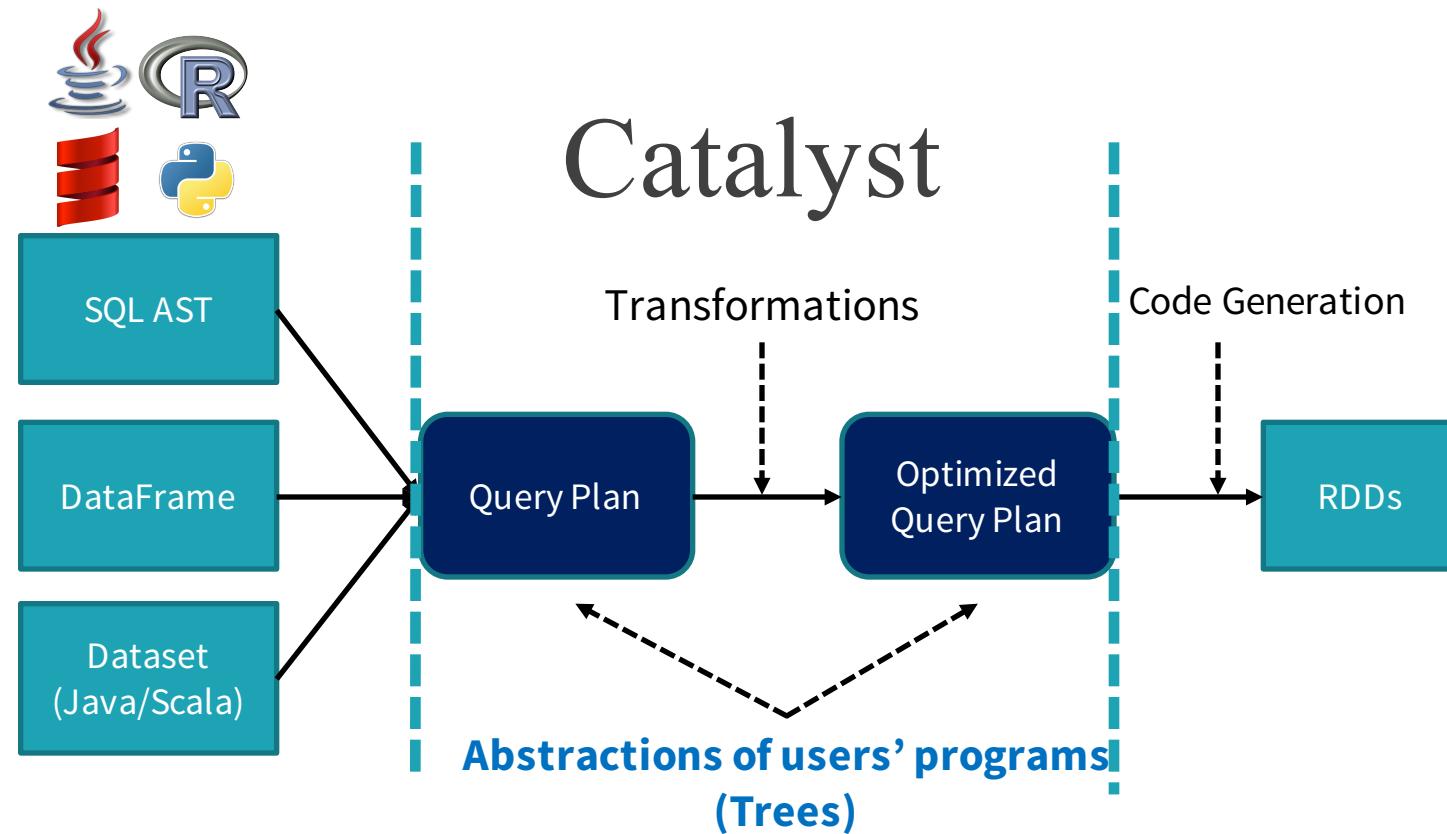
- Write programs using high level programming interfaces
 - Programs are used to describe what data operations are needed without specifying how to execute those operations
 - High level programming interfaces: SQL, DataFrame, and Dataset
- Get an optimizer that **automatically** finds out the most efficient plan to execute data operations specified in the user's program

Catalyst: Apache Spark's Optimizer

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

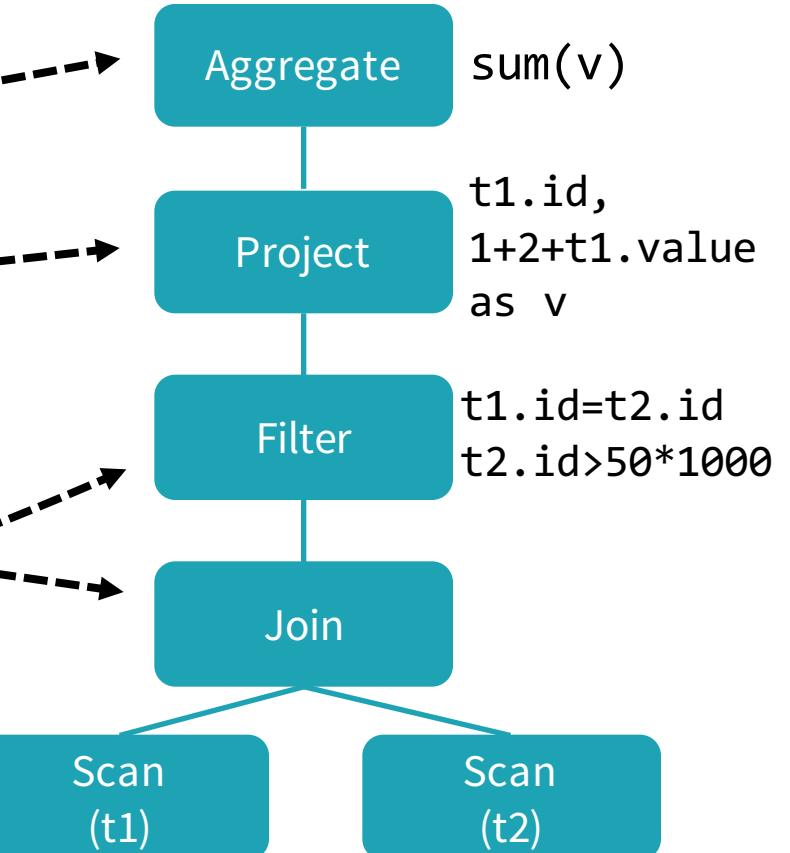
```
SELECT sum(v)
FROM (
  SELECT
    t1.id,
    1 + 2 + t1.value AS v
  FROM t1 JOIN t2
  WHERE
    t1.id = t2.id AND
    t2.id > 50 * 1000) tmp
```

- 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

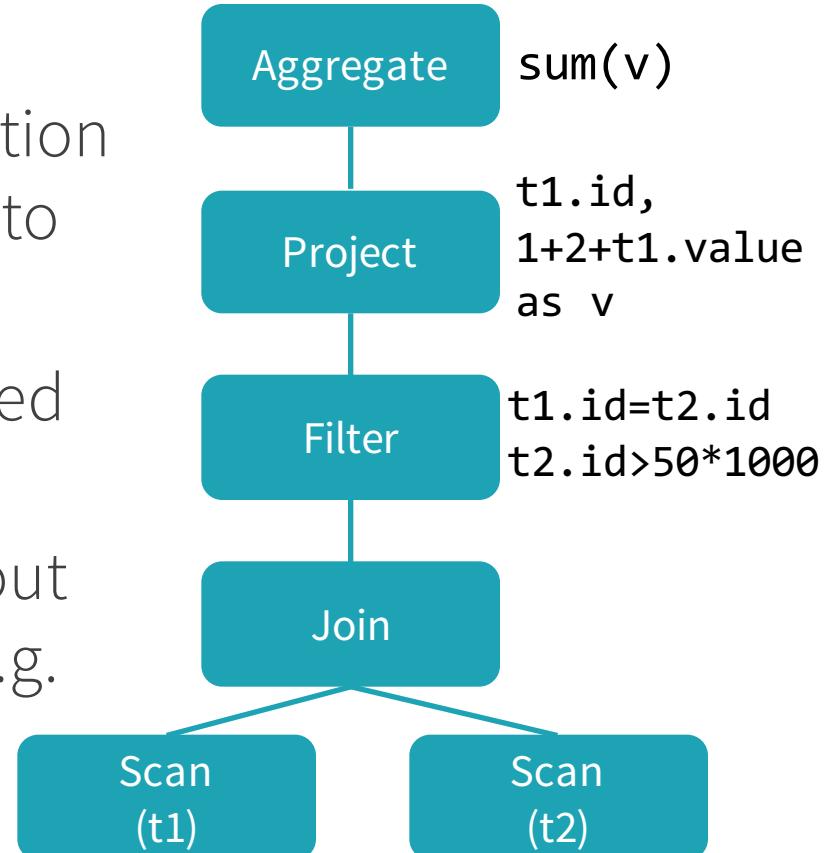
Query Plan

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



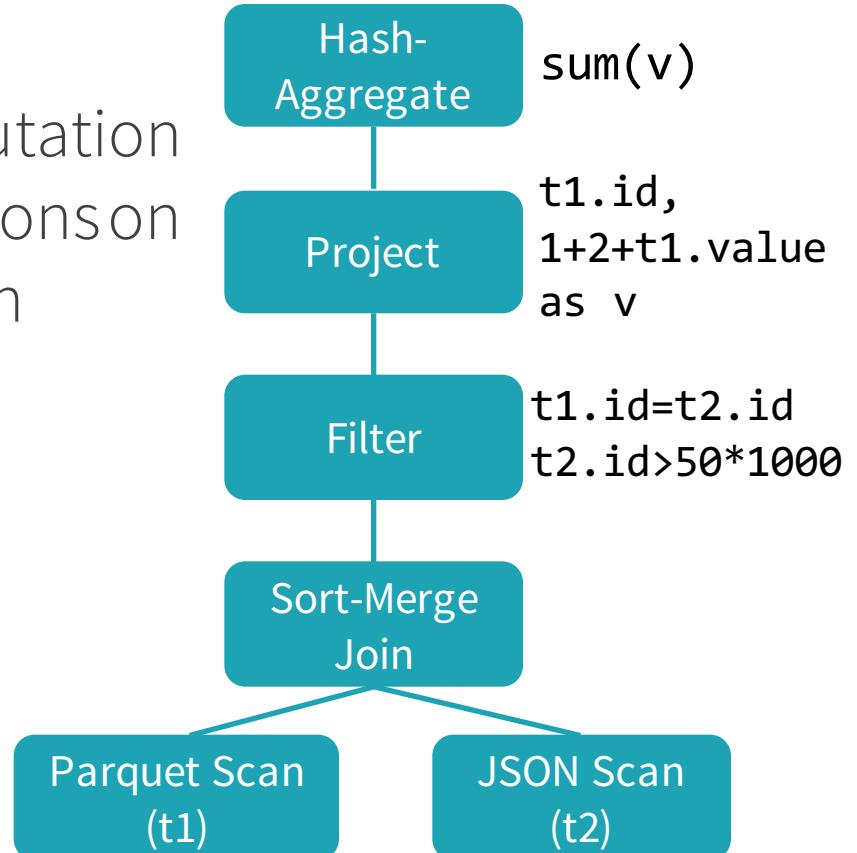
Logical Plan

- 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

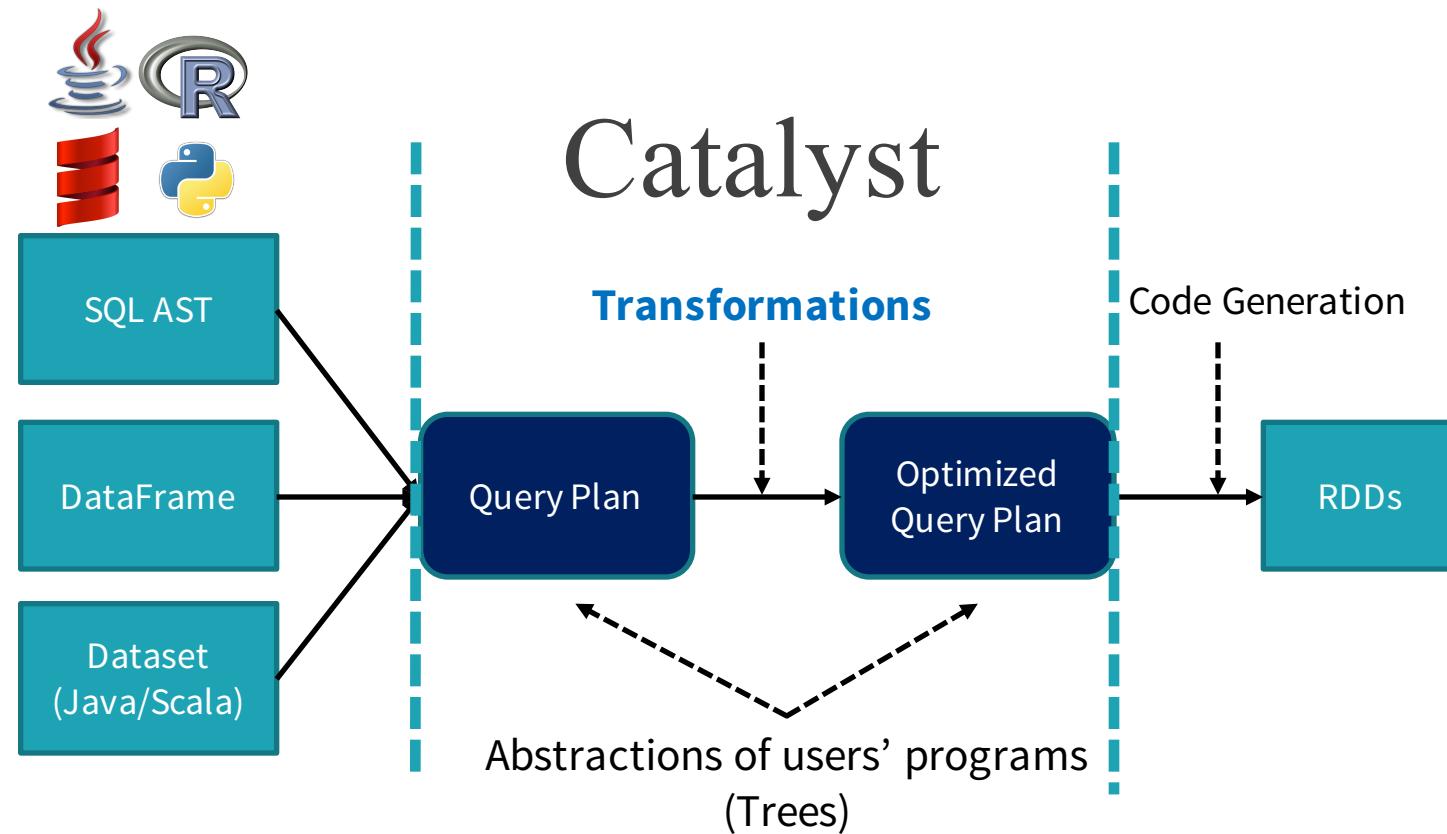


Physical Plan

- 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

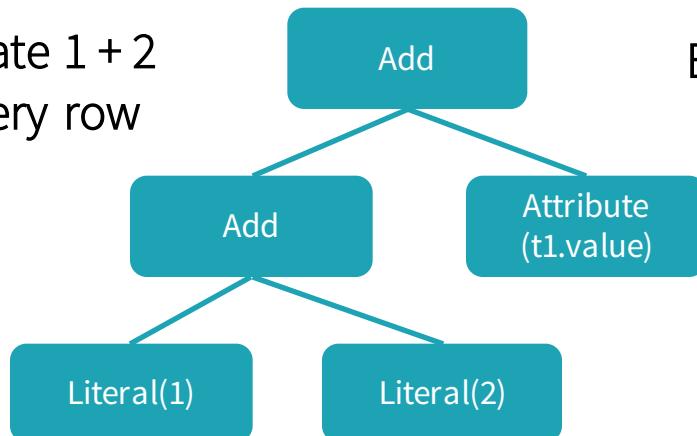
- Transformations without changing the tree type
(Transform and Rule Executor)
 - Expression => Expression
 - Logical Plan => Logical Plan
 - Physical Plan => Physical Plan
- Transforming a tree to another kind of tree
 - Logical Plan => Physical Plan

Transform

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

$1 + 2 + t1.value$

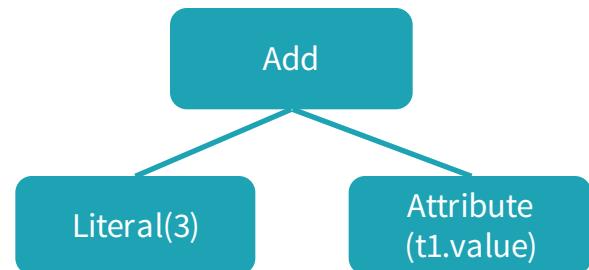
Evaluate $1 + 2$
for every row



Evaluate $1 + 2$ once



$3 + t1.value$



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)
}
```

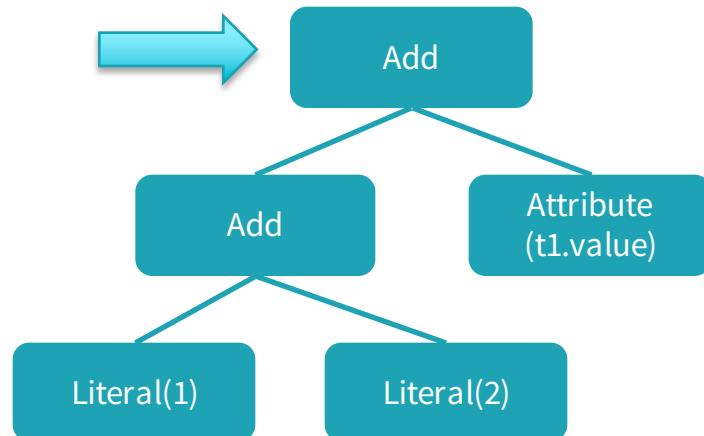


Case statement determine if the partial function is defined for a given input

Transform

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

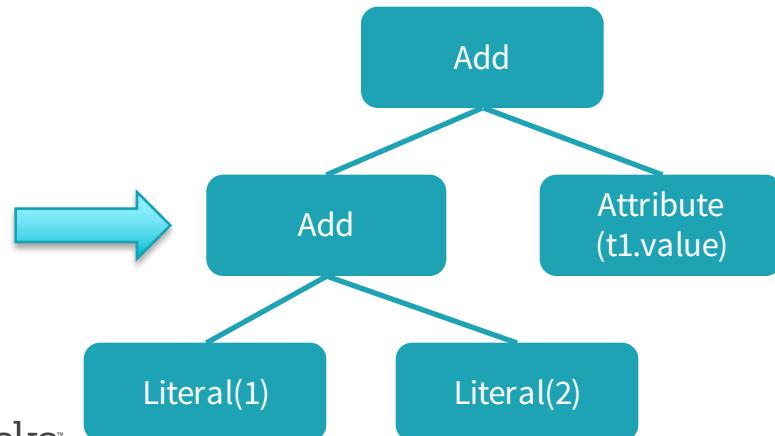
$1 + 2 + t1.value$



Transform

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

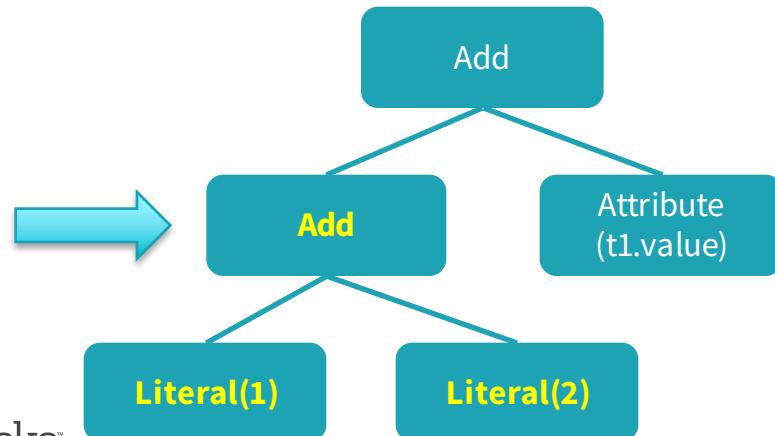
$1 + 2 + t1.value$



Transform

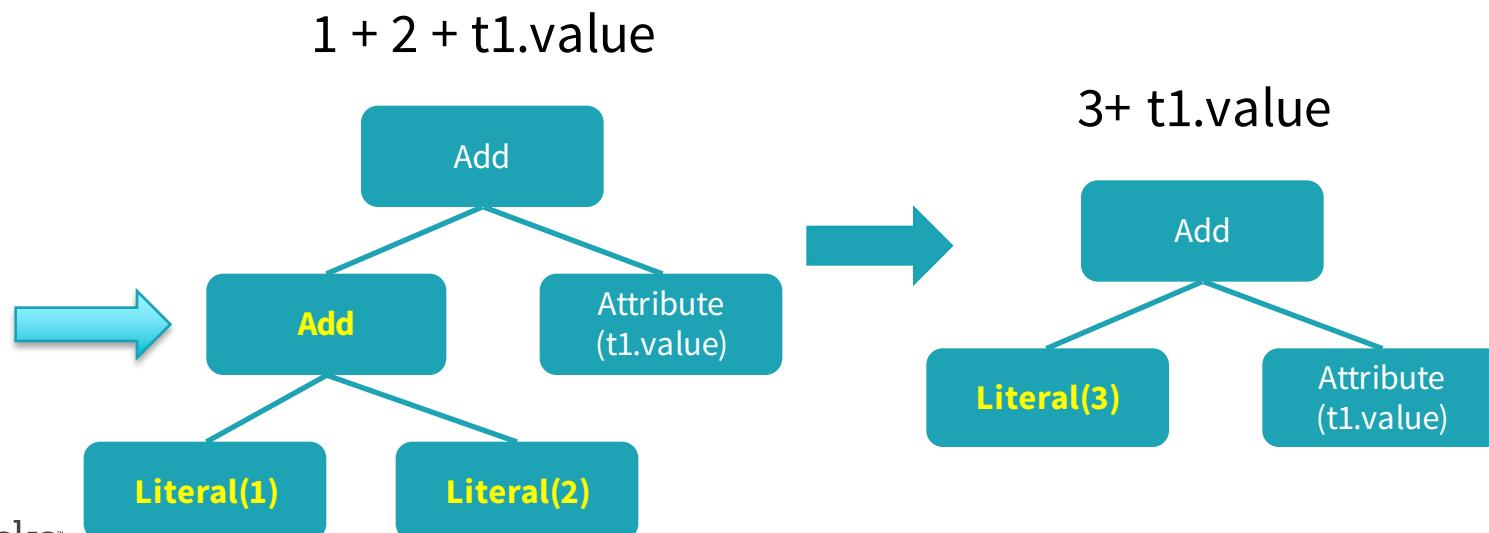
```
val expression: Expression = ...
expression.transform {
  case Add(Literal(x, IntegerType), Literal(y, IntegerType)) =>
    Literal(x + y)
}
```

$1 + 2 + t1.value$



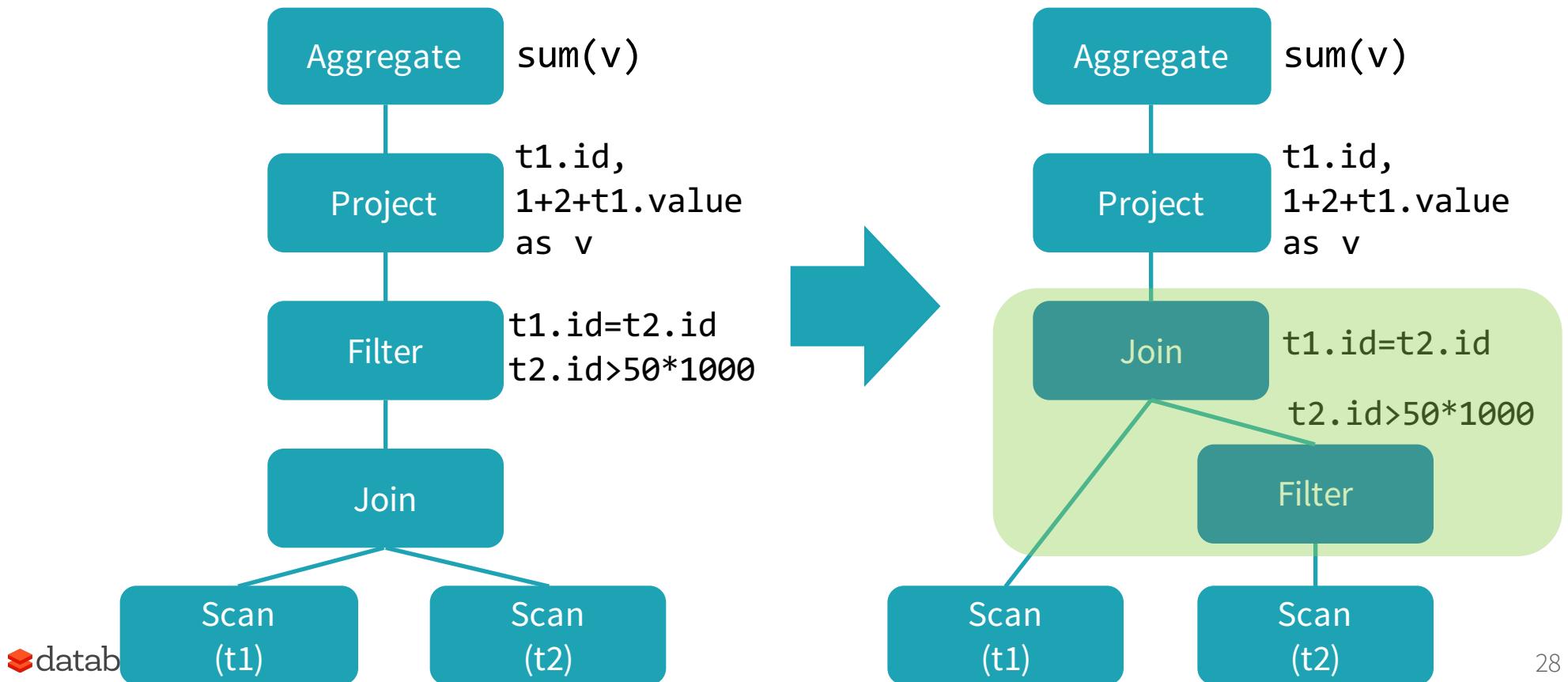
Transform

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



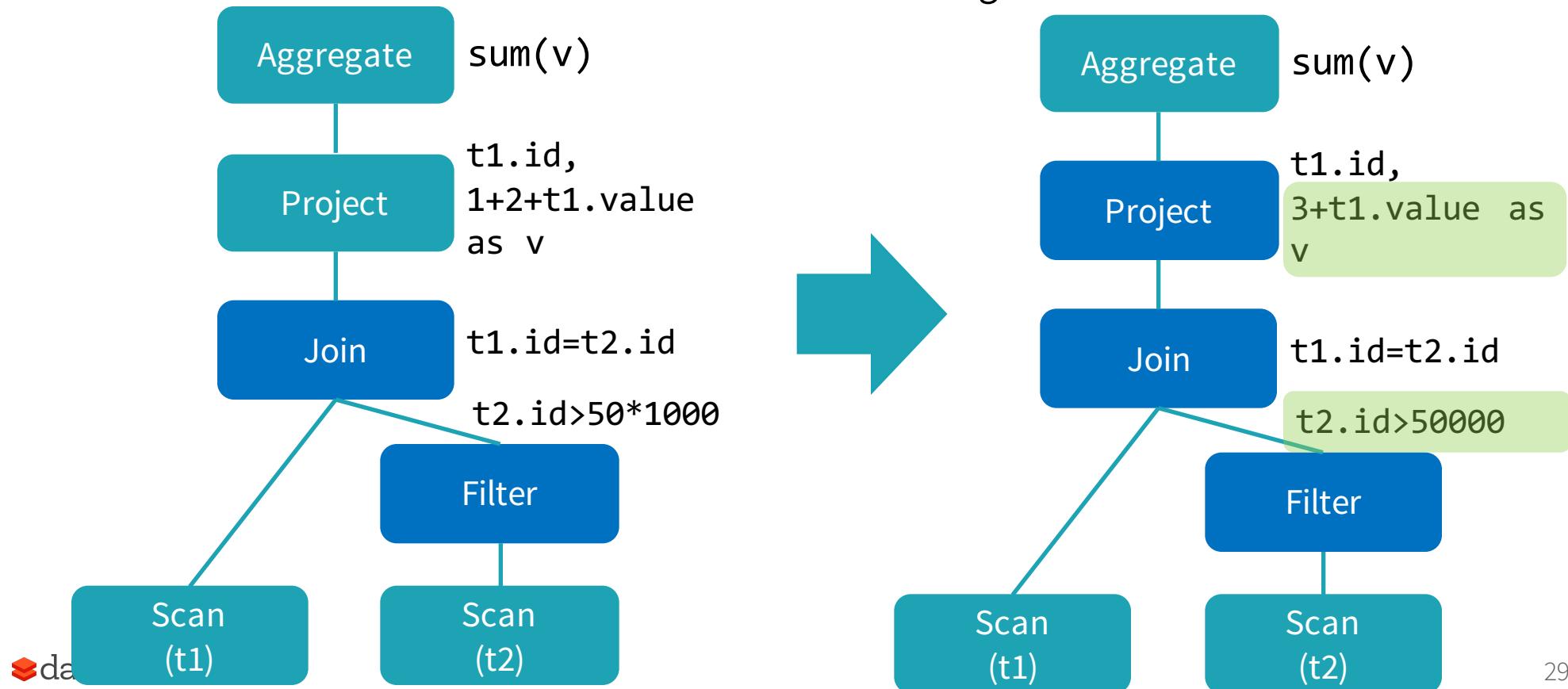
Combining Multiple Rules

Predicate Pushdown

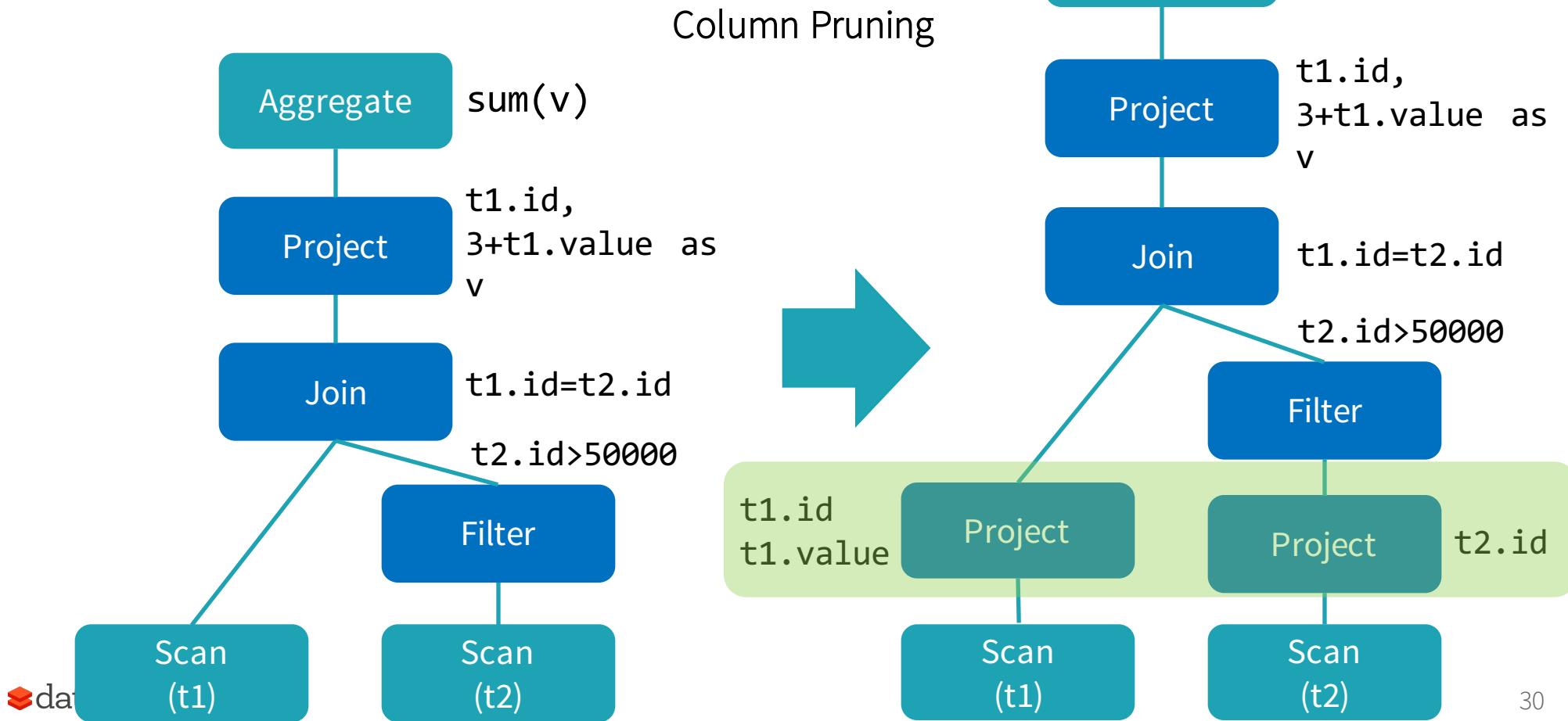


Combining Multiple Rules

Constant Folding

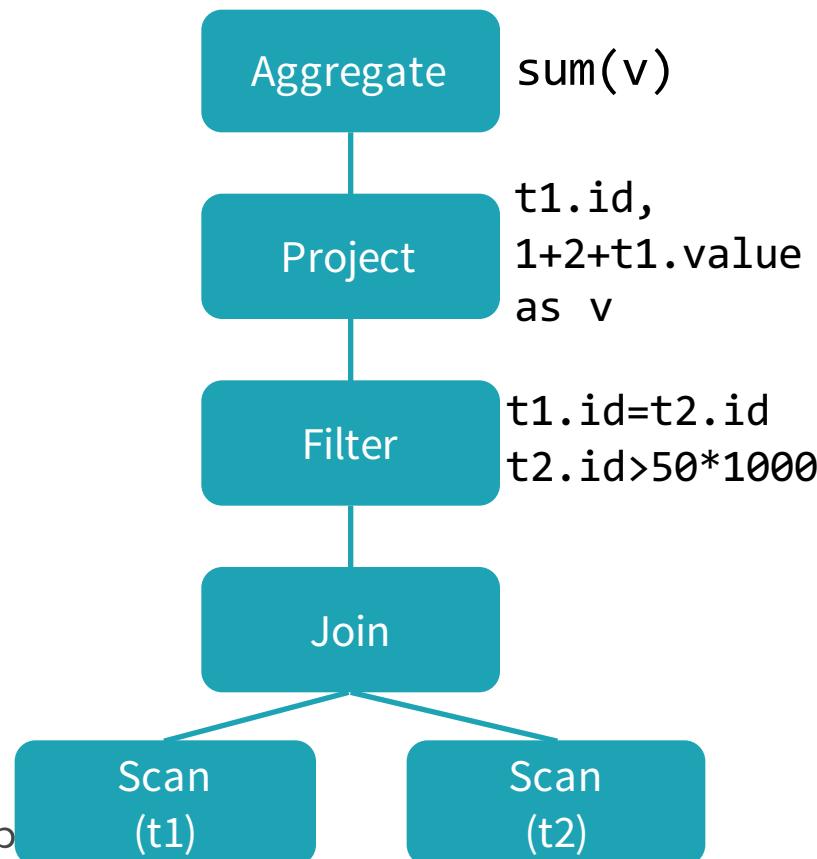


Combining Multiple Rules

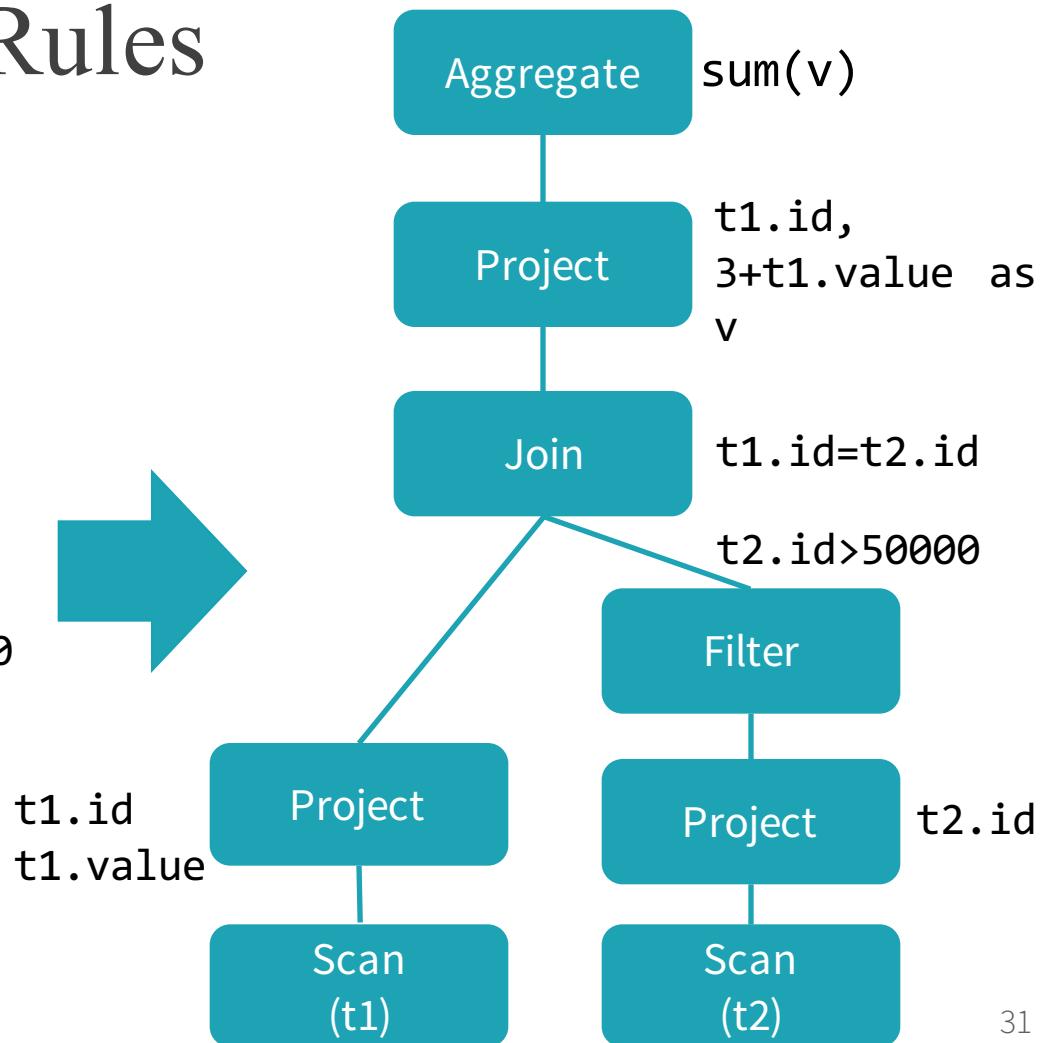


Combining Multiple Rules

Before transformations

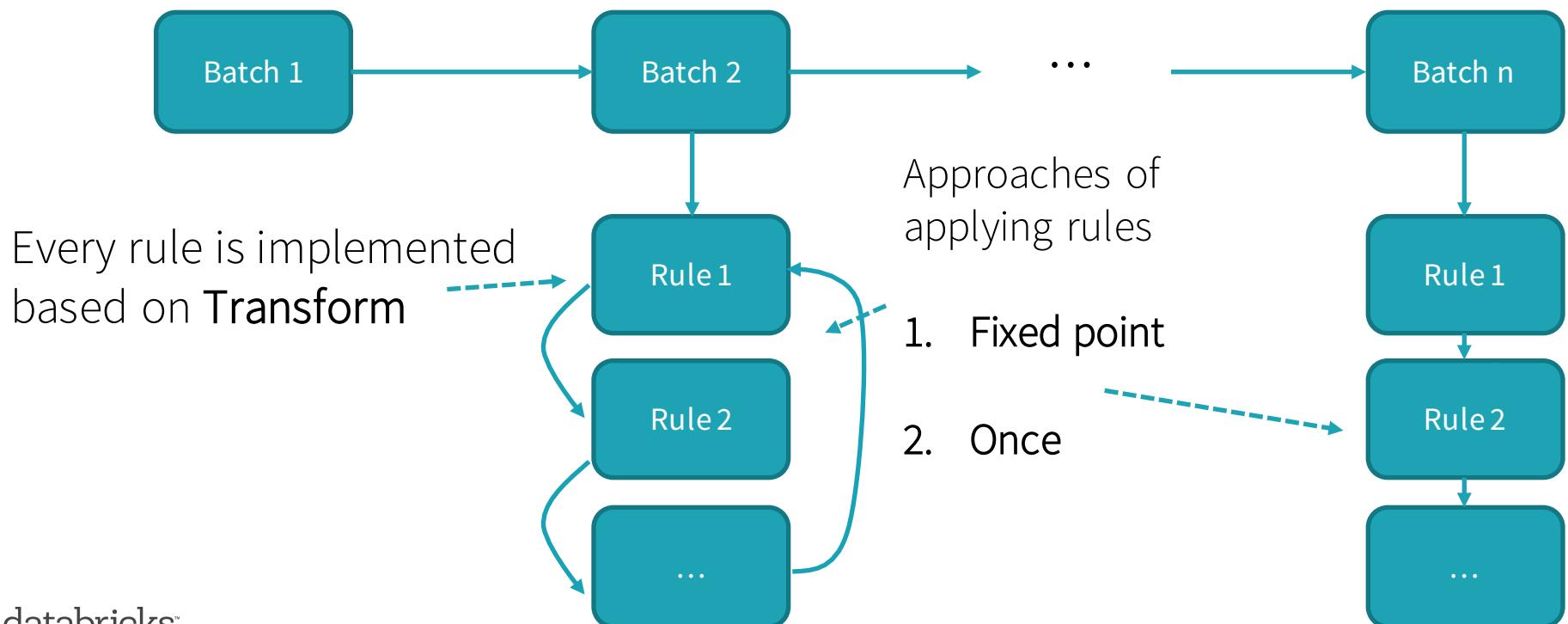


After transformations



Combining Multiple Rules: Rule Executor

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



Transformations

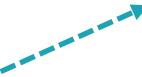
- Transformations without changing the tree type
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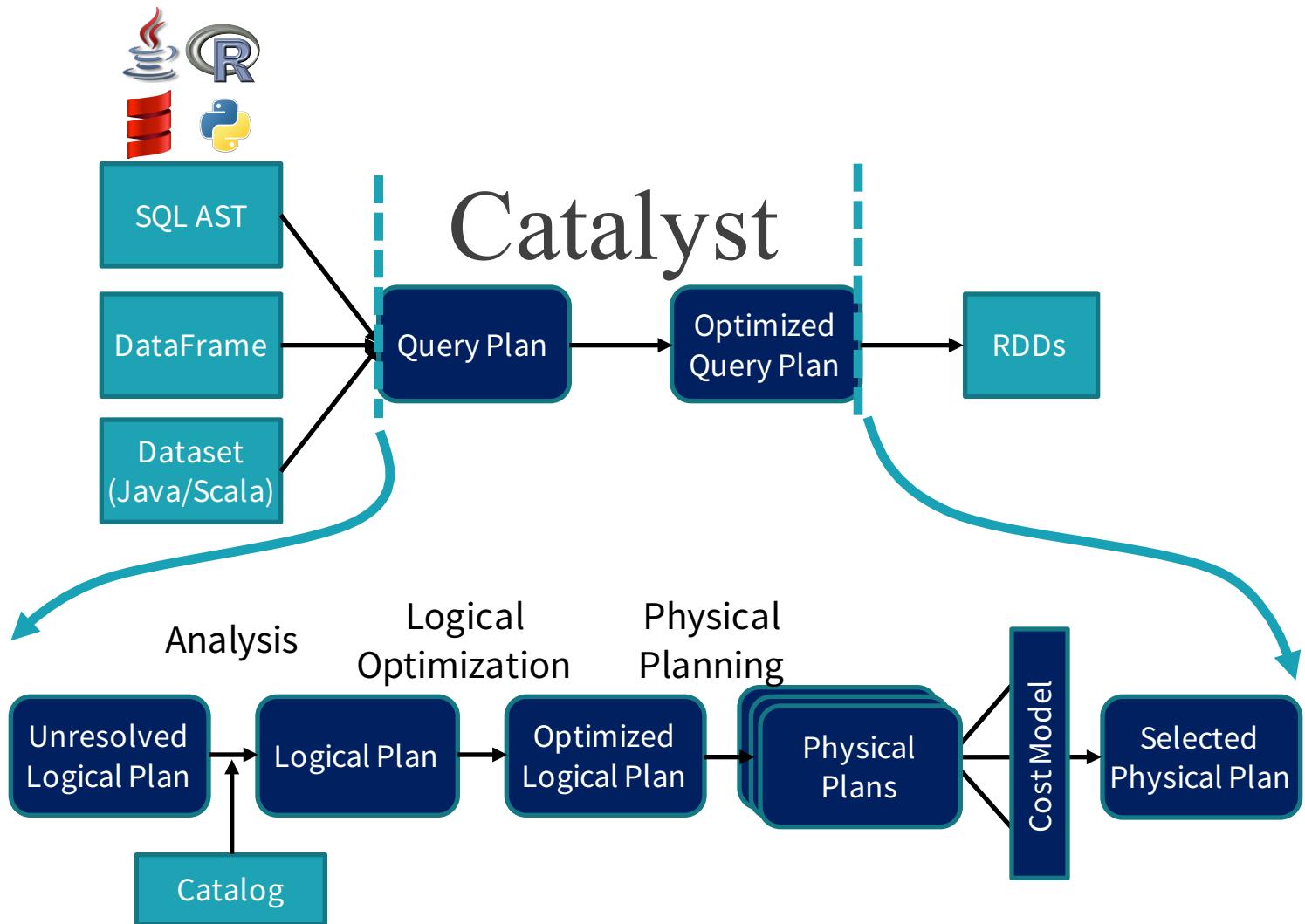
From Logical Plan to Physical Plan

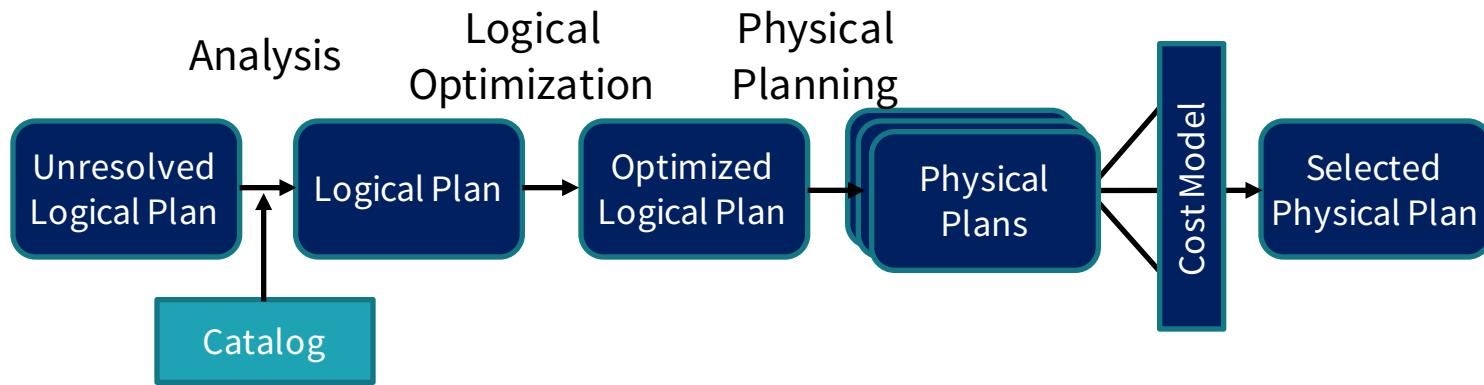
- A Logical Plan is transformed to a Physical Plan by applying a set of **Strategies**
- Every Strategy uses pattern matching to convert a Tree to another kind of Tree

```
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





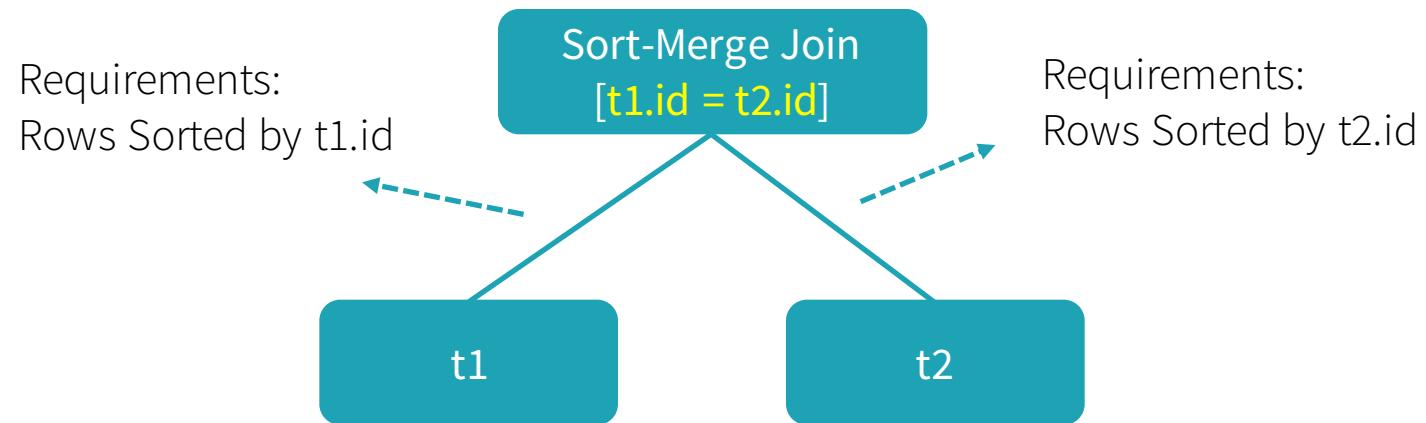


- **Analysis (Rule Executor):** Transforms an Unresolved Logical Plan to a Resolved Logical Plan
 - Unresolved => Resolved: Use Catalog to find where datasets and columns are coming from and types of columns
- **Logical Optimization (Rule Executor):** Transforms a Resolved Logical Plan to an Optimized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

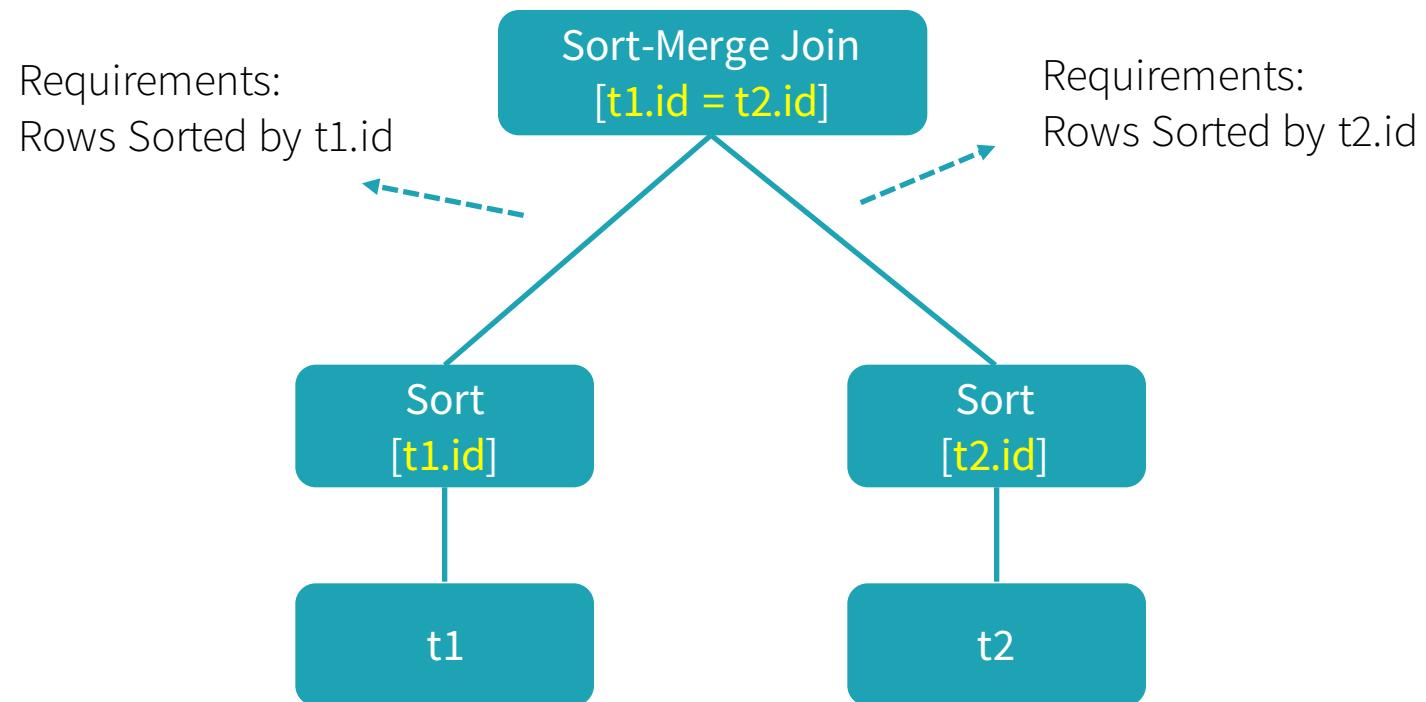
Spark's Planner

- 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

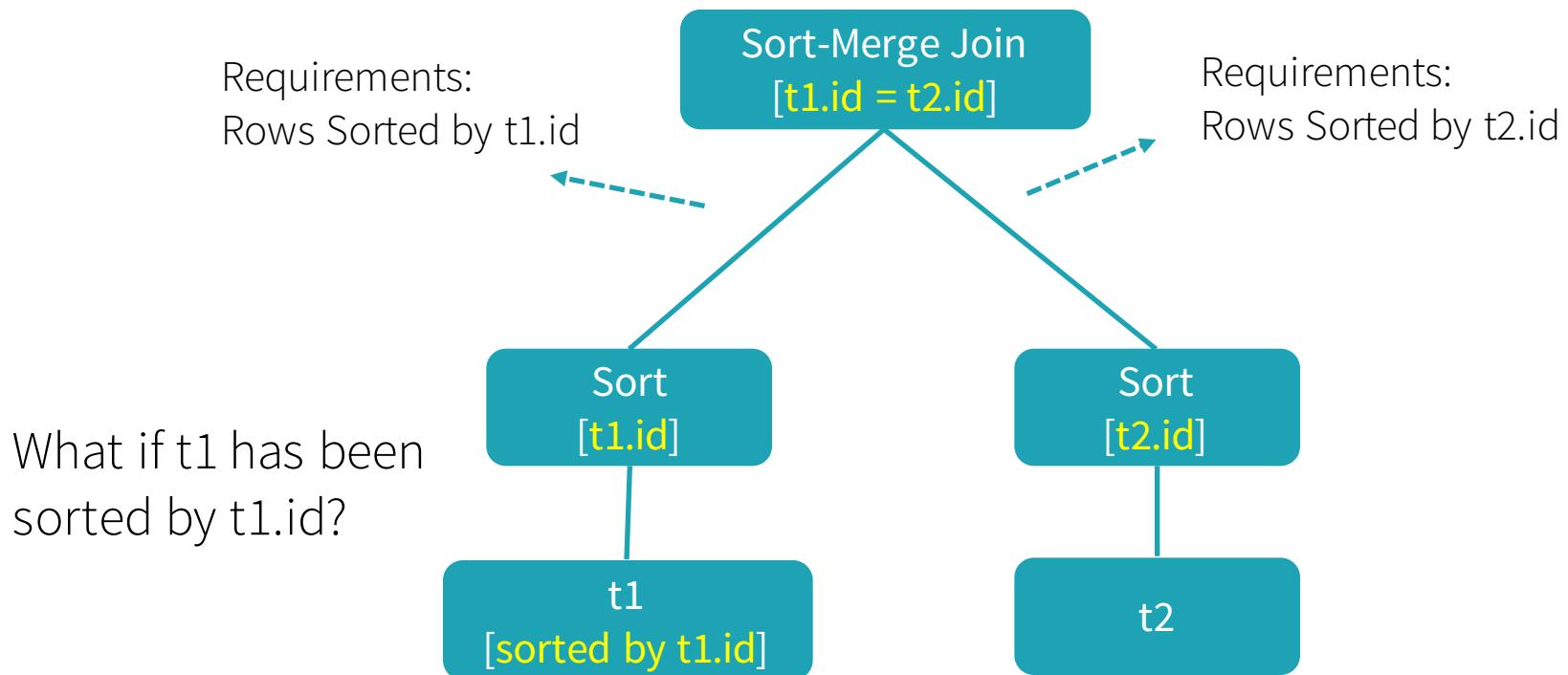
Ensure Requirements on Input Rows



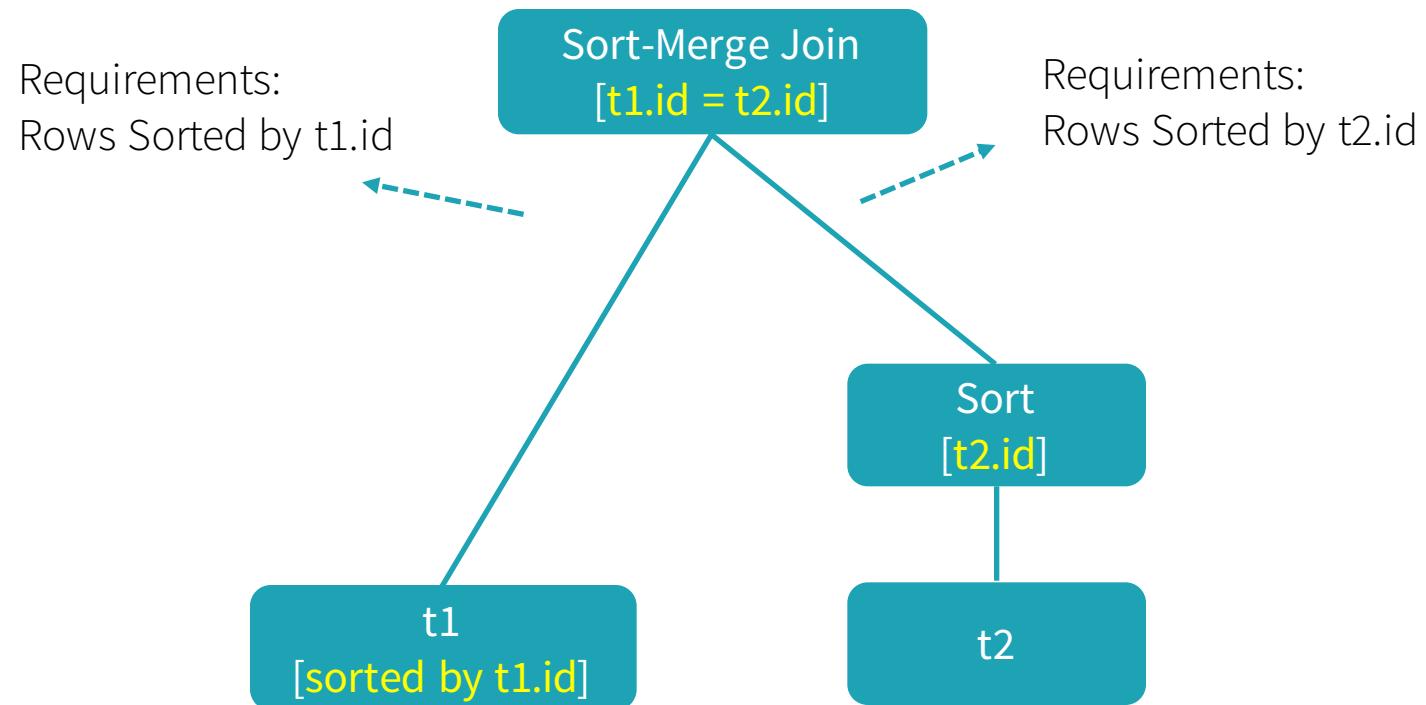
Ensure Requirements on Input Rows



Ensure Requirements on Input Rows

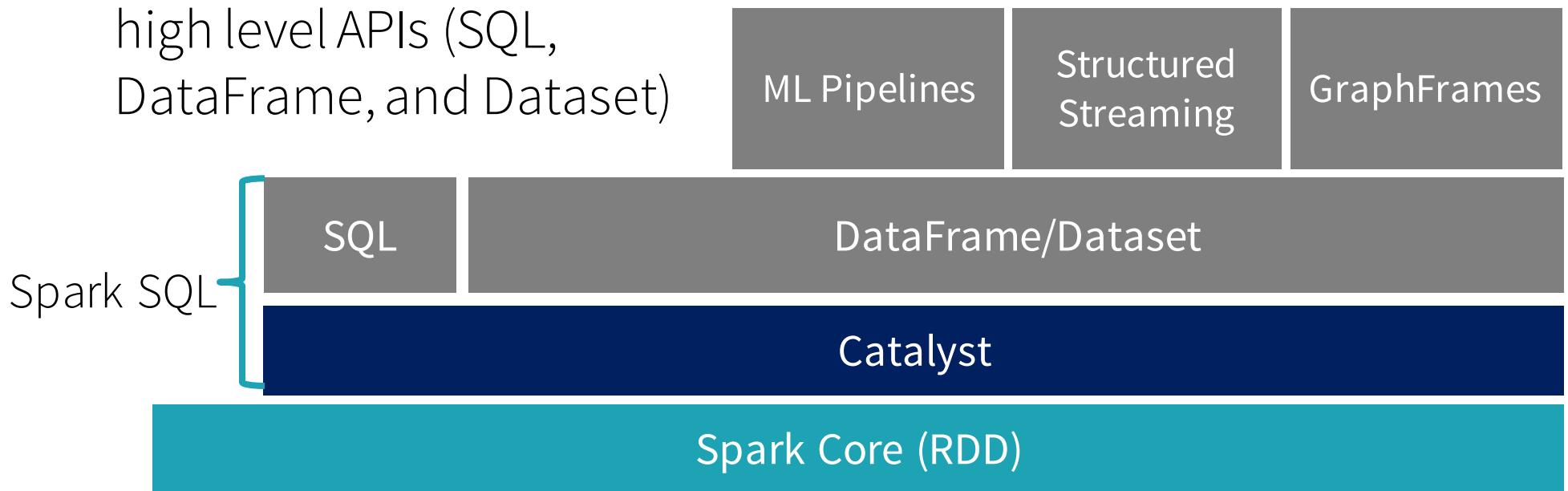


Ensure Requirements on Input Rows



Catalyst in Apache Spark

With Spark 2.0, we expect most users to migrate to high level APIs (SQL, DataFrame, and Dataset)



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

SPARK-12032

[SPARK-12032] [SQL] Re-order inner joins to do join with conditions f...

[Browse files](#)

...irst

Currently, the order of joins is exactly the same as SQL query, some conditions may not pushed down to the correct join, then those join will become cross product and is extremely slow.

This patch try to re-order the inner joins (which are common in SQL query), pick the joins that have self-contain conditions first, delay those that does not have conditions.

After this patch, the TPCDS query [Q64/65](#) can run hundreds times faster.

cc marmbrus nongli

Author: Davies Liu <davies@databricks.com>

Closes [#10073](#) from davies/reorder_joins.

 master (#1)  2.0.0-preview

 davies committed with davies on Dec 7, 2015

 Showing 3 changed files with 185 additions and 6 deletions.

Certain workloads can
run hundreds times
faster

~ 200 lines of changes
(95 lines are for tests)

[Unified](#) [Split](#)

SPARK-8992

[SPARK-8992][SQL] Add pivot to dataframe api

This adds a pivot method to the dataframe api.

Following the lead of cube and rollup this adds a Pivot operator that is translated into an Aggregate by the analyzer.

Currently the syntax is like:

```
~~courseSales.pivot(Seq($"year"), $"course", Seq("dotNET", "Java"), sum($"earnings"))~~
```

~~Would we be interested in the following syntax also/alternatively? and~~

```
courseSales.groupBy($"year").pivot($"course", "dotNET", "Java").agg(sum($"earnings"))
//or
courseSales.groupBy($"year").pivot($"course").agg(sum($"earnings"))
```

Later we can add it to `SQLParser`, but as Hive doesn't support it we cant add it there, right?

~~Also what would be the suggested Java friendly method signature for this?~~

Author: Andrew Ray <ray.andrew@gmail.com>

Closes #7841 from aray/sql-pivot.

⌚ master (#3) ⏲ 2.0.0-preview

 aray committed with yhuai on Nov 11, 2015

~ 250 lines of changes
1 parent: 1a21be1 commit: b8fff6d89e16b43718dd40bfc2d4b9c759710a195

Showing 6 changed files with 255 additions and 10 deletions.

(99 lines are for tests)

Unified Split



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- Try latest version of Apache Spark and preview of Spark 2.0

<http://databricks.com/try>



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SIGN UP

Thank you.

Officehour: 2:45pm – 3:30pm @ Expo Hall

