SPARK SQL: RELATIONAL DATA PROCESSING IN SPARK

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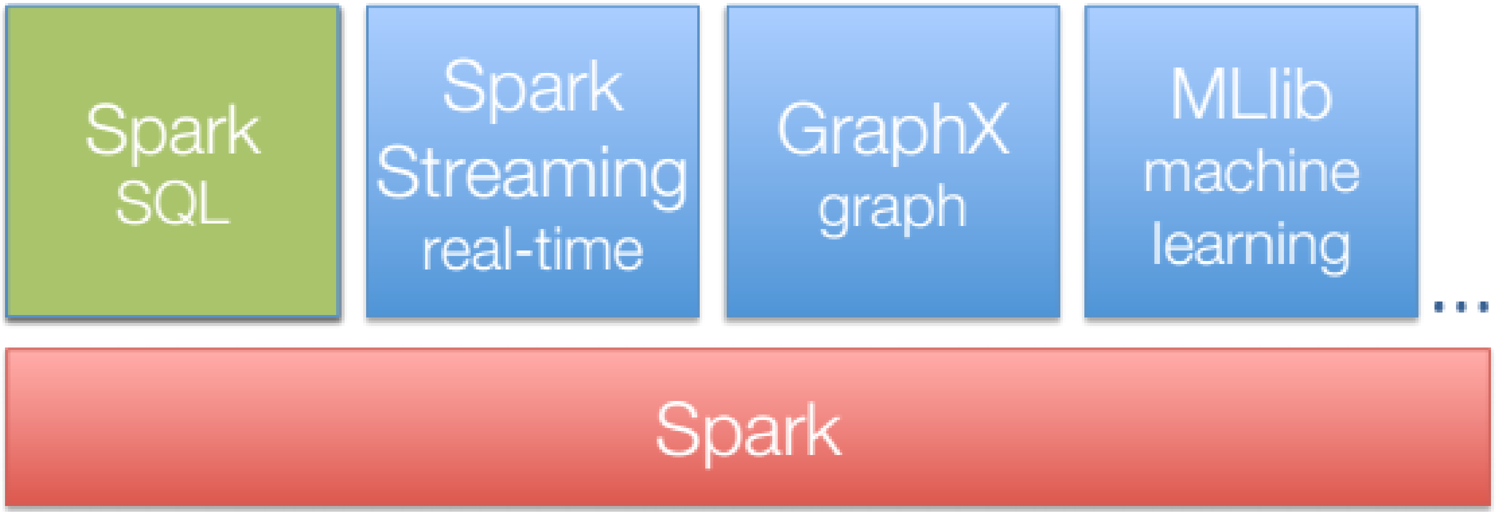
Spark SQL

Background

Apache Spark

- Fast and general cluster computing system
- Improves efficiency through: → Up to 100× faster (2-10× on disk)
  - *In-memory computing primitives*
- Improves usability through: → 2-5× less code
  - *Rich APIs in Scala, Java, Python*
  - *Interactive shell*

A General Stack



Spark SQL

About Spark SQL

- Spark SQL
  - *Part of the core distribution since April 2014.*
  - *Runs SQL / HiveQL queries, optionally* ***alongside*** *or* ***replacing*** *existing* ***Hive deployments****.*

```
SELECT COUNT(*)
FROM hiveTable
WHERE hive_udf(data)
```

Improvement upon Existing Art

Spark

- Engine does not understand the structure of the data in RDDs or the semantics of user functions → limited optimization.

SHARK

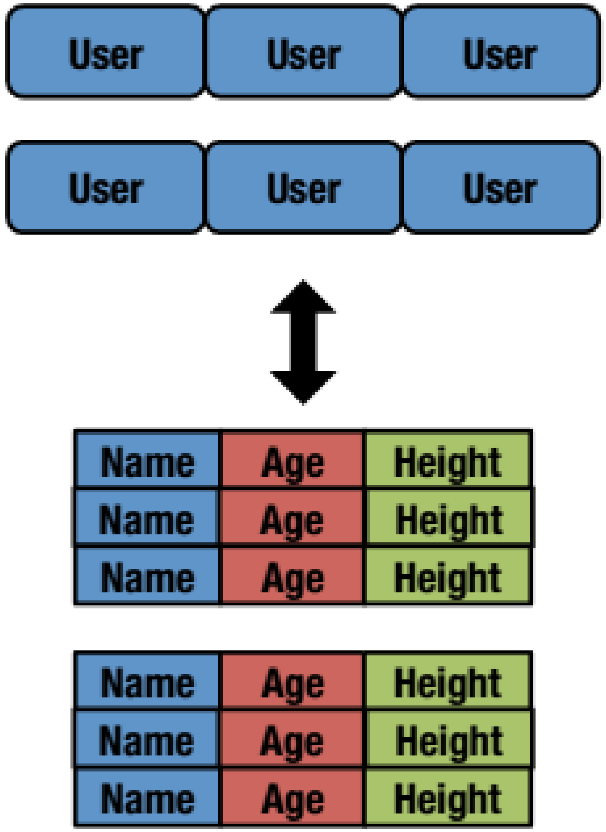
- Can only be used to query external data in Hive catalog → limited data sources
- Can only be invoked via SQL string from Spark→ error prone
- Hive optimizer tailored for MapReduce → difficult

Data Model

- Nested data model
- Supports
    - *Primitive SQL types (boolean, integer, double, decimal, string, data, timestamp)*
    - *Complex types (structs, arrays, maps, and unions)*
    - *User defined types.*

SchemaRDD’s as a Key Concept

- RDD: “Immutable partitioned collection of elements”.
- SchemaRDD: “An RDD of Row objects that has an associated schema”.



Advantages over RDDs

- They express the *how* of a solution better than the *what.*
- They cannot be optimized by Spark.
- They're *slow* on non-JVM languages like Python.
- It's too easy to build an inefficient RDD transformation chain.

```
parsedRDD.reduceByKey(_ + _).                                    <--- INEFFICIENT
          filter { case (project, numRequest) => project == "en" }. <--- ORDERING
          take(100).
          foreach { case (project, requests) => println(s"project: $requests") }
```

Advantages over Relational Query Languages

- Holistic optimization across functions composed in different languages.
- Control structures (e.g. *if*, *for*)
- Logical plan analyzed *eagerly*
  - *Identify code errors associated with data schema issues on the fly.*

DataFrame Operations

- Relational operations (select, where, join, groupBy) via a DSL.
- Operators take *expression* objects.
- Operators build up an abstract syntax tree (AST), which is then optimized by *Catalyst*.

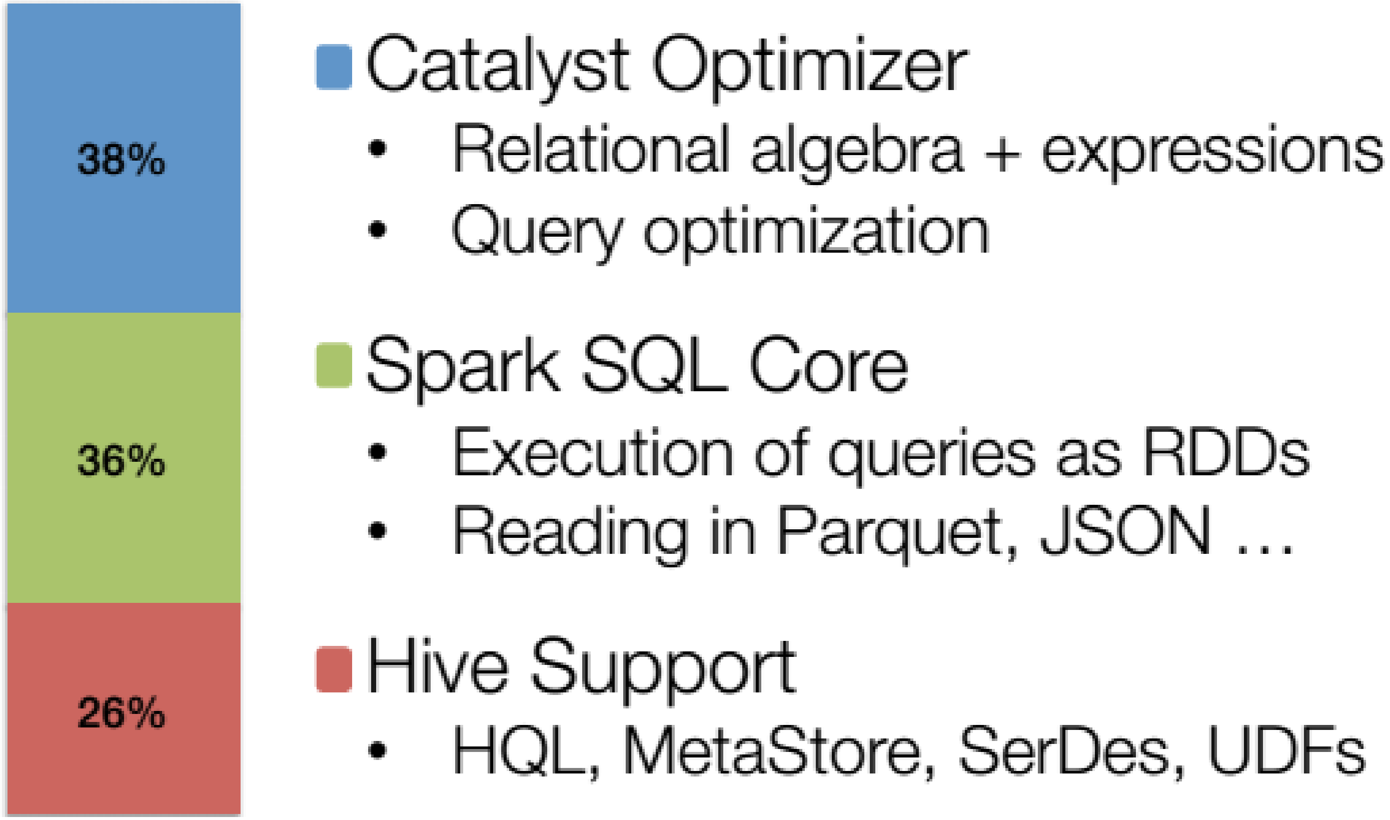
```
employees
  .join(dept, employees("deptId") === dept("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept("name"))
  .agg(count("name"))
```

User-Defined Functions (UDFs)

- Easy extension of limited operations supported.
- Allows inline registration of UDFs.
- Can be defined on simple data types or entire tables.
- UDFs available to other interfaces after registration

```
val model: LogisticRegressionModel = ...

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

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

Spark SQL Components



Optimizing Queries with Catalyst

What is Query Optimization?

- SQL is a declarative language:
  - *Queries express what data to retrieve.*
  - *Not how to retrieve it.*

- The database must pick the ‘best’ execution strategy through a process known as optimization.

Prior Work: Optimizer Generators

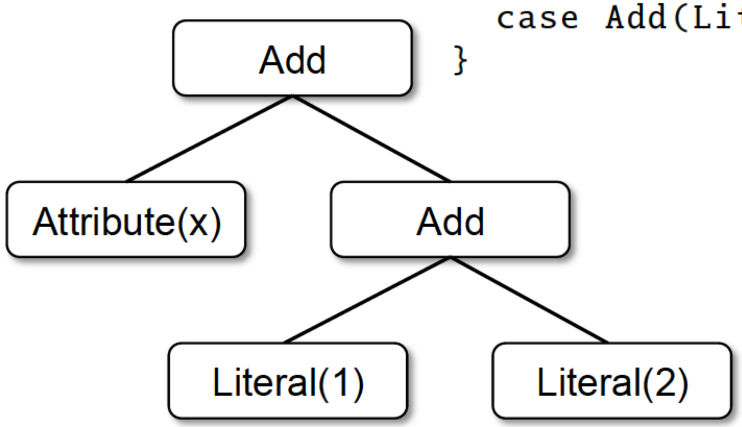
Volcano / Cascades:

- Create a **custom language** for expressing **rules** that rewrite **trees of relational operators**.
- Build a **compiler** that generates **executable** code for these rules.

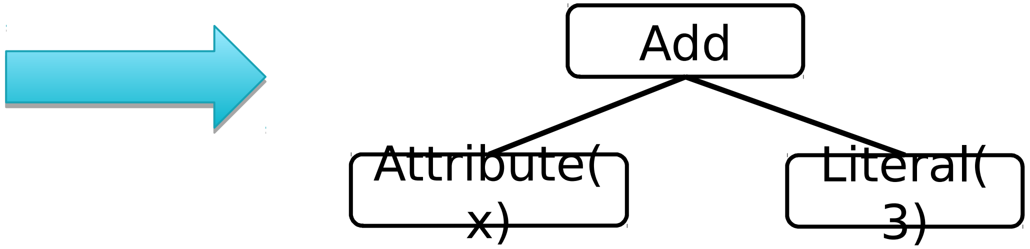
Cons: Developers need to learn this custom language. Language might not be powerful enough.

Catalyst

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



x + (1 + 2)



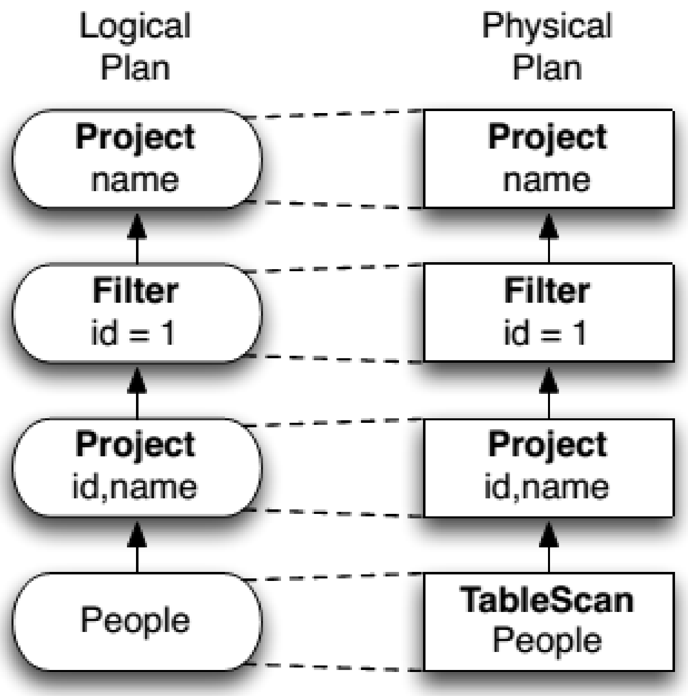
x + 3

Catalyst Rules

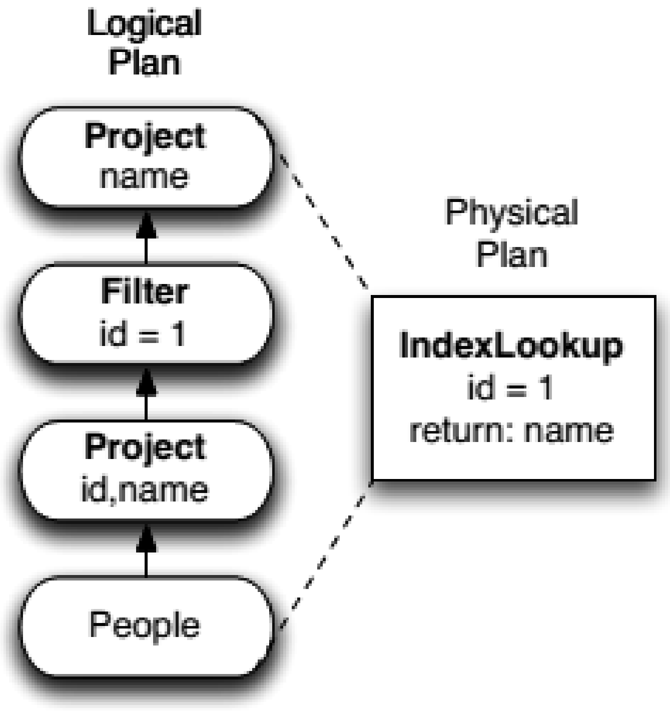
- *Pattern matching* **functions** that transform subtrees into specific structures.
  - *Partial function - skip over subtrees that do not match.*
  - *No need to modify existing rules when adding new types of operators.*
- Multiple patterns in the same *transform* call.
- May take multiple *batches* to reach a *fixed point*.

Naïve Query Planning

```
SELECT name
FROM (
     SELECT id, name
     FROM People) p
WHERE p.id = 1
```



Optimized Execution

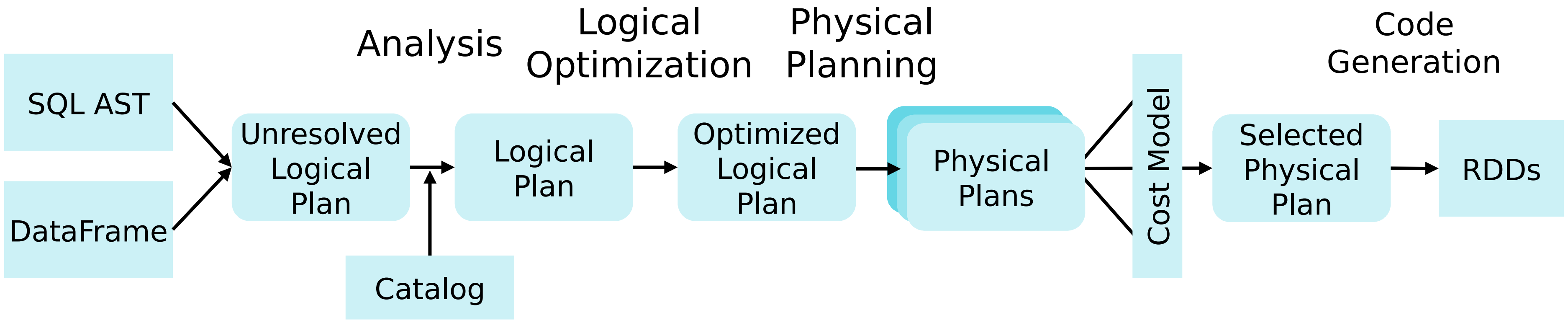


Writing imperative code to optimize all possible Project patterns is hard.

Instead write simple rules:

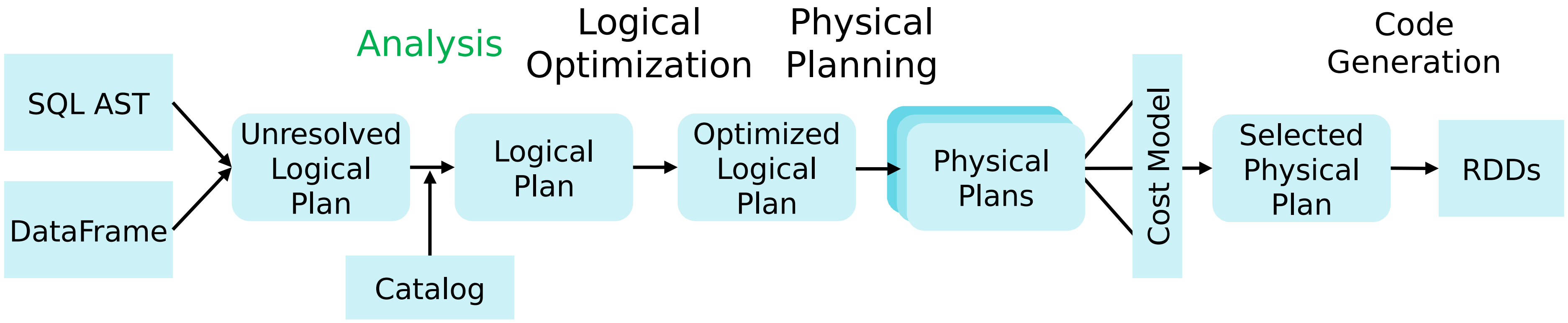
- Each rule makes one change
- Run many rules together to fixed point.

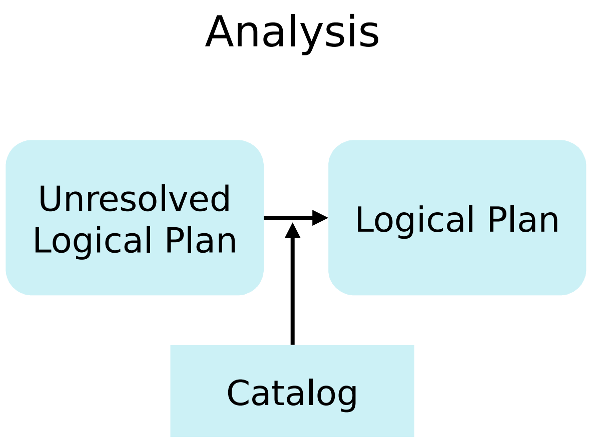
Plan Optimization & Execution



DataFrames and SQL share the same optimization/execution pipeline

Plan Optimization & Execution



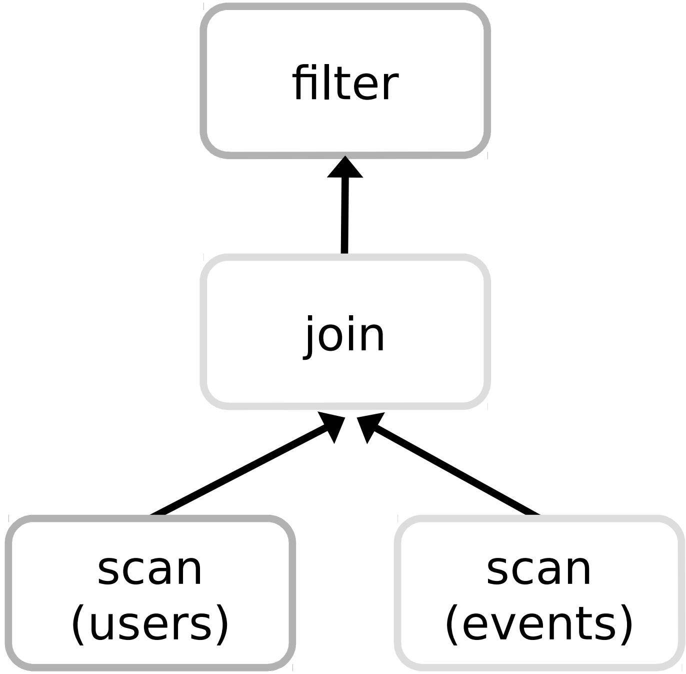


SELECT *col* FROM *sales*

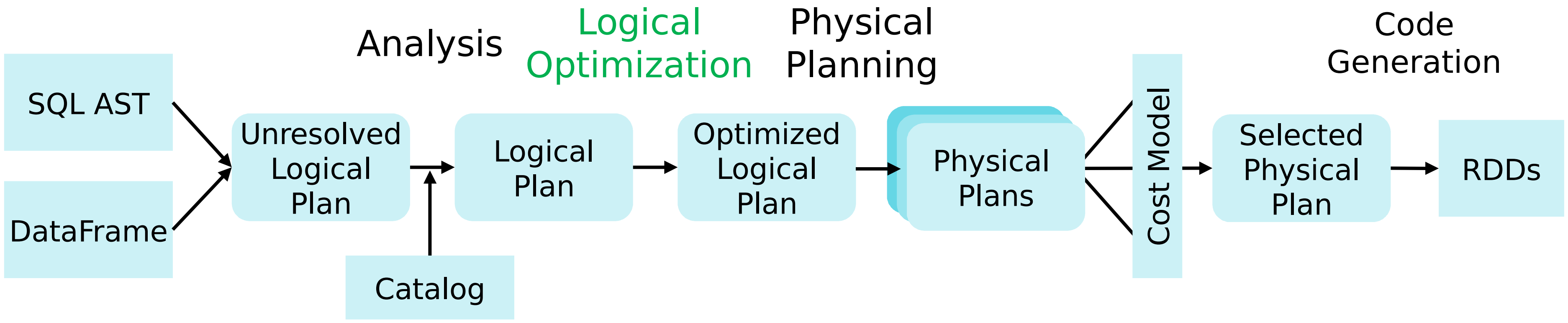
- An attribute is *unresolved* if its type is not known or it's not matched to an input table.
- To resolve attributes:
  - *Look up relations by name from the catalog.*
  - *Map named attributes (col) to the input provided given operator's children.*
  - *UID for references to the same value.*
  - *Propagate and coerce types through expressions (e.g. 1 + col).*

```
users.join(events, users("id") === events("uid"))
     .filter(events("date") > "2015-01-01")
```

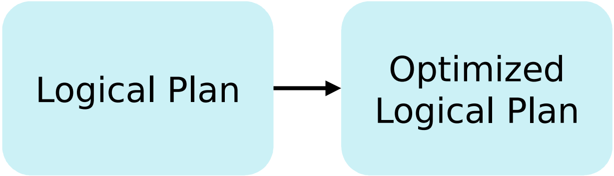
Logical Plan



Plan Optimization & Execution



Logical Optimization

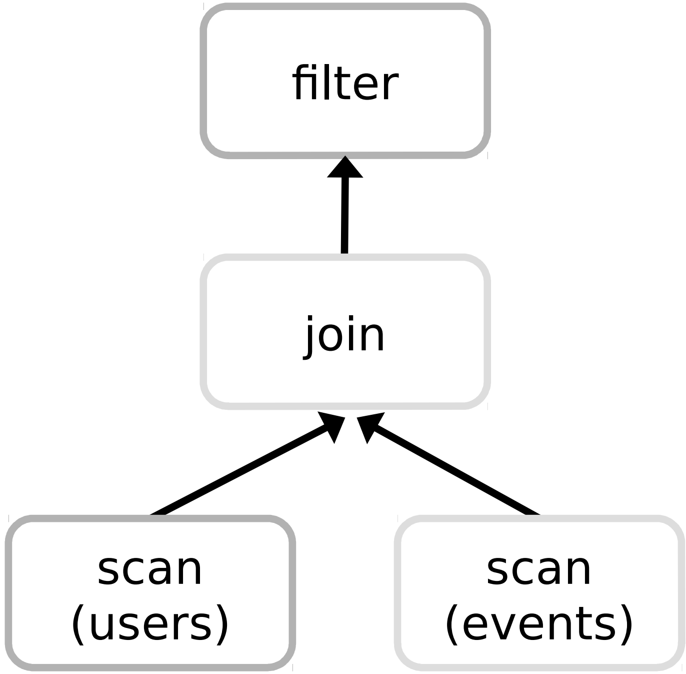


- Applies standard **rule-based optimization** (constant folding, predicate-pushdown, boolean expression simplification, etc)
- 800LOC

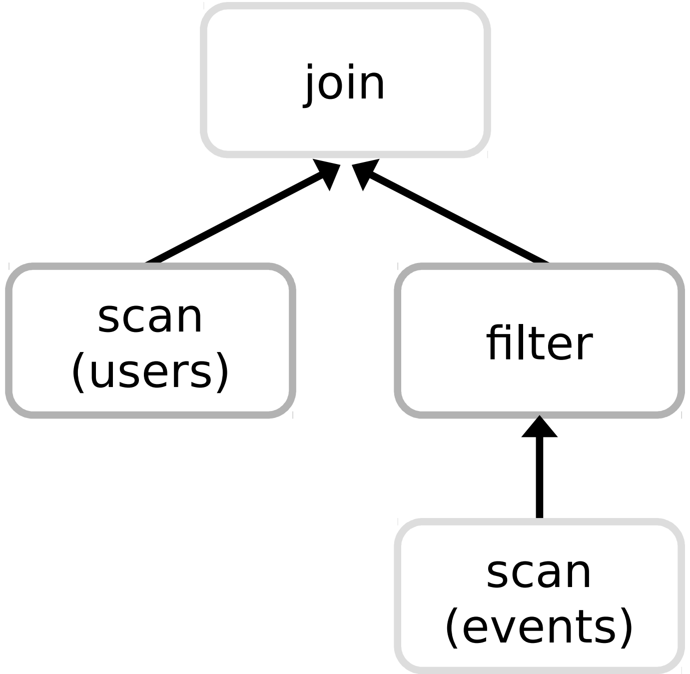
```
object DecimalAggregates extends Rule[LogicalPlan] {
  /** Maximum number of decimal digits in a Long */
  val MAX_LONG_DIGITS = 18

  def apply(plan: LogicalPlan): LogicalPlan = {
    plan transformAllExpressions {
      case Sum(e @ DecimalType.Expression(prec, scale))
              if prec + 10 <= MAX_LONG_DIGITS =>
        MakeDecimal(Sum(LongValue(e)), prec + 10, scale)
    }
}
```

```
users.join(events, users("id") === events("uid"))
     .filter(events("date") > "2015-01-01")
```

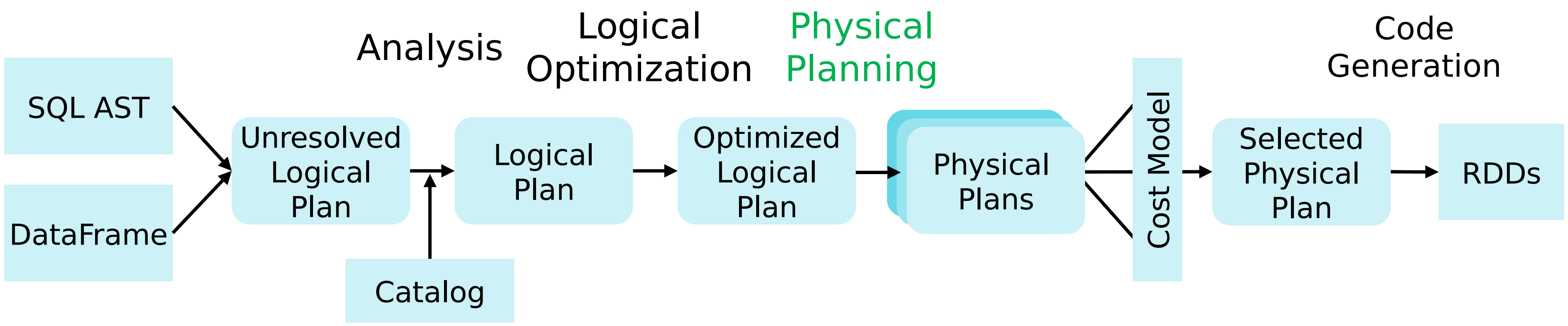
Logical Plan



Optimized plan

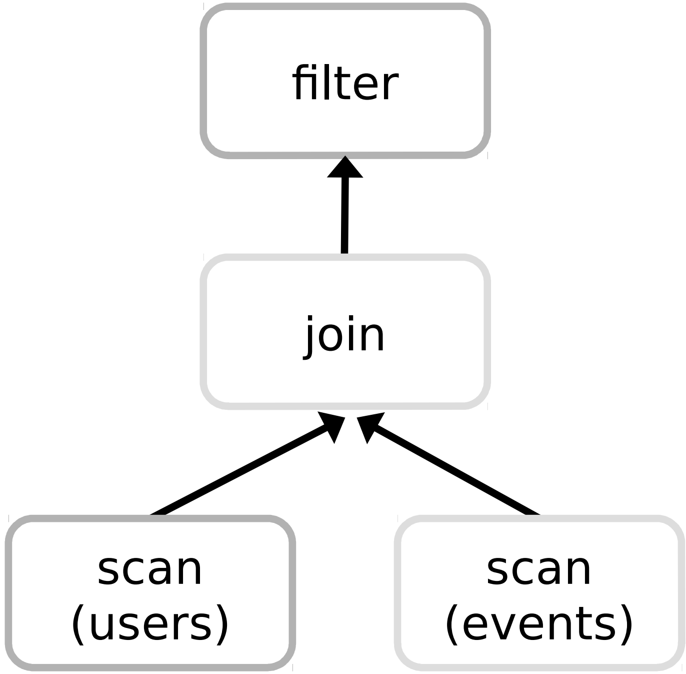


Plan Optimization & Execution

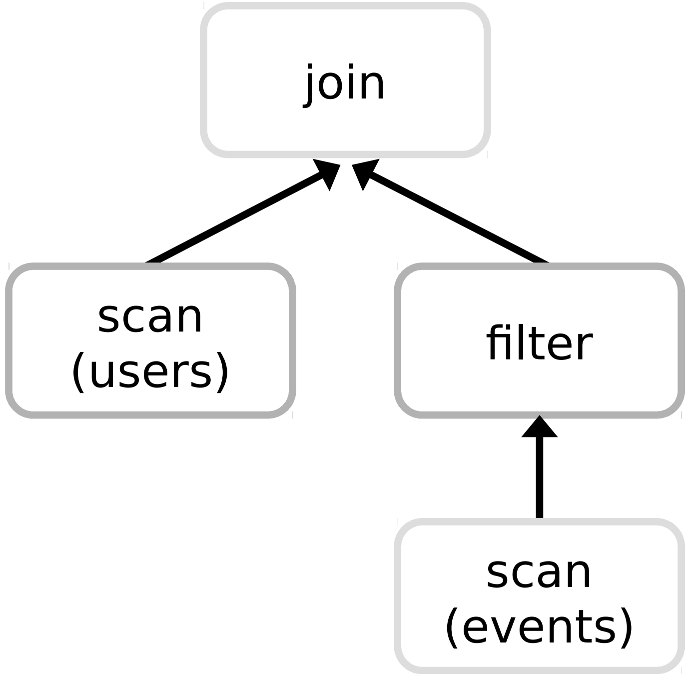


```
users.join(events, users("id") === events("uid"))
     .filter(events("date") > "2015-01-01")
```

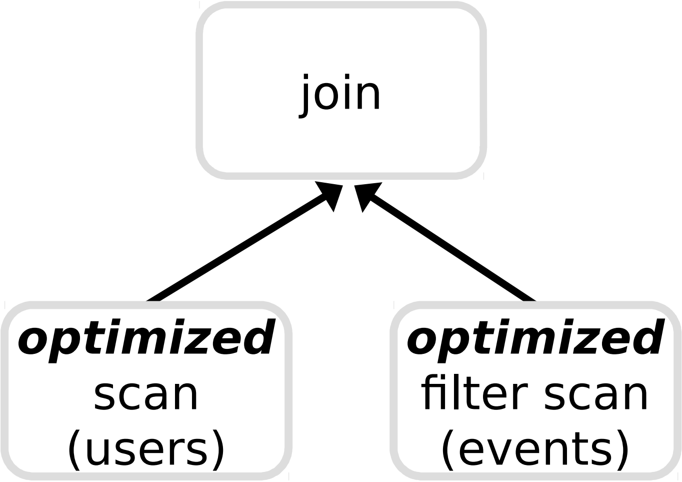
Logical Plan



Optimized plan



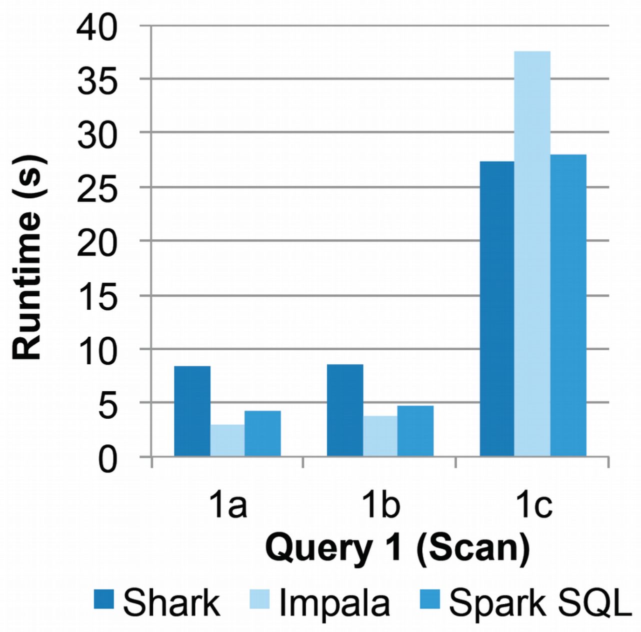
Physical Plan
with Predicate Pushdown and Column Pruning

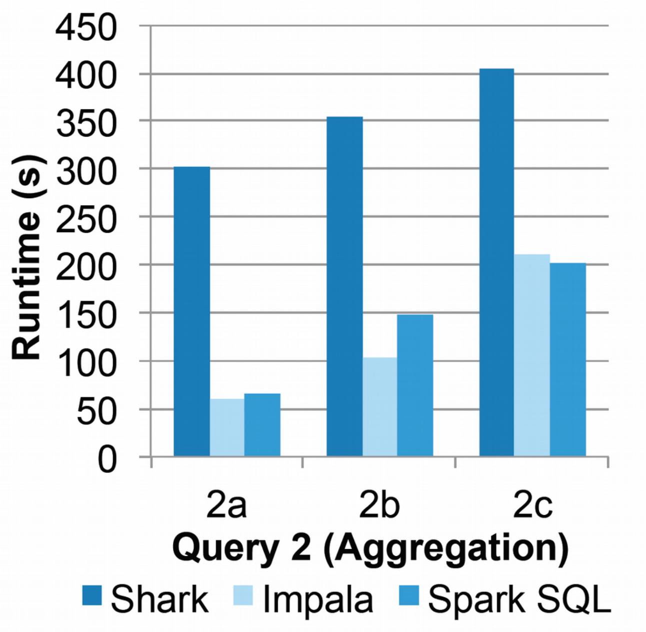


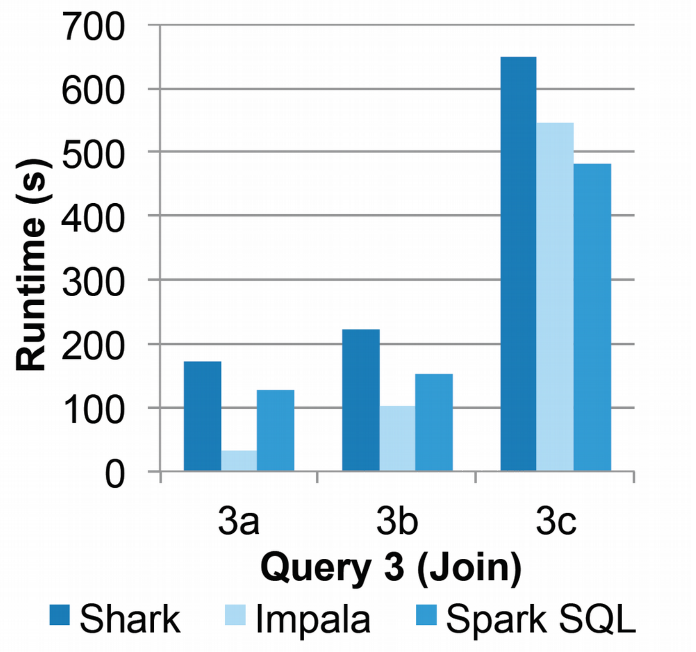
Performance Comparison

- 110GB of data after columnar compression with Parquet
- Cluster of six machines each with 4 cores, 30 GB memory
- 800 GB SSD, running HDFS 2.4, Spark 1.3, Shark 0.9.1 and Impala

- Query 1a, 2a, 3a: The most selective
- Query 1c, 2c, 3c: The least selective and processing more data.







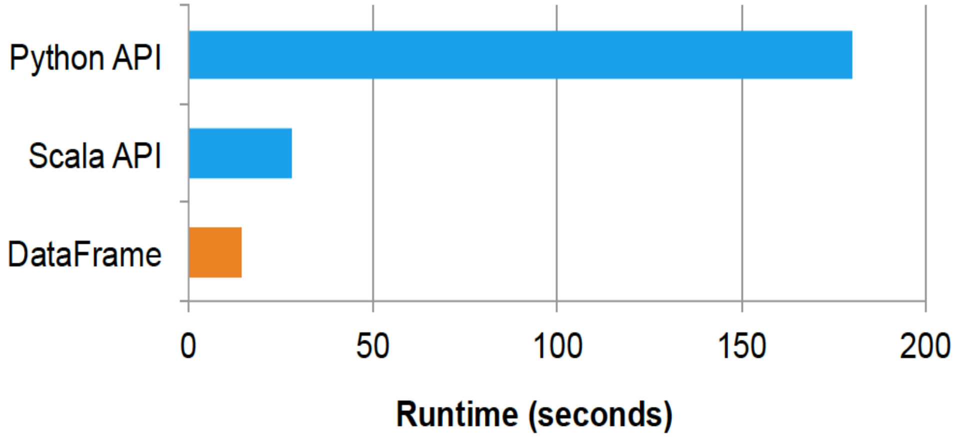
Performance Comparison (cont'd)

The dataset consists of:

- 1 billion integer pairs, *(a, b)* with 100,000 distinct values of *a* on the same five-worker cluster.
- Measure the time taken to compute the average of b for each value of a.

```
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]
```

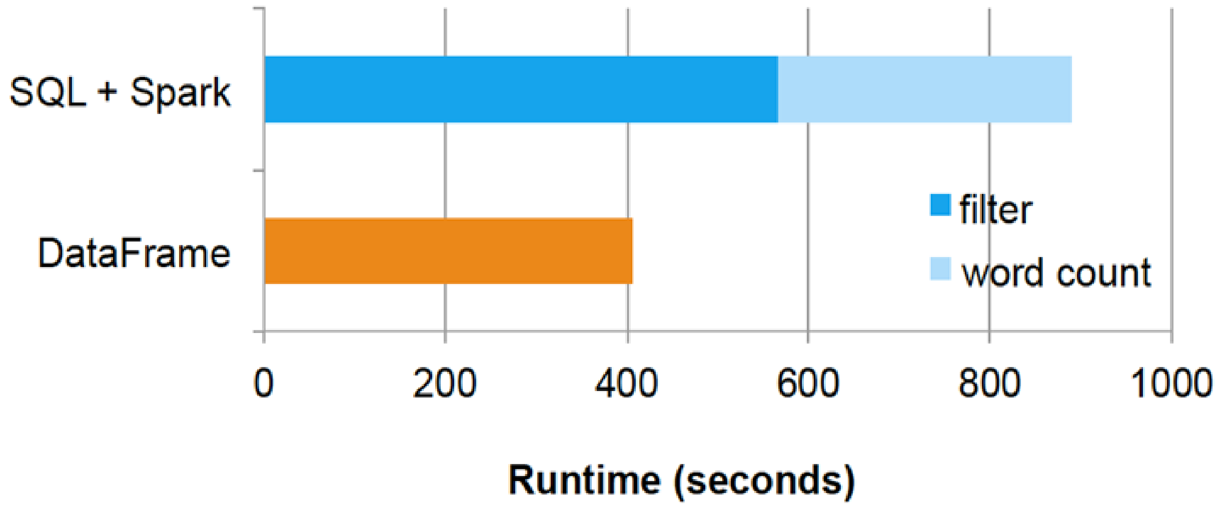
```
df.groupBy("a").avg("b")
```



Performance Comparison (cont’d)

Synthetic dataset of 10 billion messages in HDFS
Each message contained 10 words

- The first stage of the pipeline uses a relational filter to select 90% of the messages.
- The second stage computes the word count.



Summary

■Challenges

- Perform ETL to and from various (semi- or unstructured) data sources.
- Perform advanced analytics (e.g. machine learning, graph processing) that are hard to express in relational systems.

■Solutions

- A *DataFrame* API that can perform relational operations on both external data sources and Spark's built-in RDDs.
- A highly extensible optimizer, *Catalyst*, that uses features of Scala to add composable rule, control code gen., and define extensions.

Future Work: Project Tungsten

- Improving the efficiency of *memory and CPU* for Spark applications, to push performance closer to the limits of modern hardware.

Project Tungsten: Bringing Apache Spark Closer to Bare Metal

■ Overcome JVM limitations:

- **Memory Management and Binary Processing**: leveraging application semantics to manage memory explicitly and eliminate the overhead of JVM object model and garbage collection.
- **Cache-aware computation**: algorithms and data structures to exploit memory hierarchy.
- **Code generation**: using code generation to exploit modern compilers and CPUs.

Apache Spark is already pretty fast, but can we make it 10x faster?

- Rethink about Spark’s physical execution layer.
- Majority of the CPU cycles are spent in useless work.
  - *Making virtual function calls.*
  - *Reading or writing intermediate data to CPU cache or memory.*
- Collapses the entire query into a single function.
  - *Eliminating virtual function calls.*
  - *Leveraging CPU registers for intermediate data .*
  - *“whole-stage code generation”*

“whole-stage code generation”

- In the past
  - *Spark only applied code generation to **expression evaluation** and was limited to a **small number of operators** (e.g. Project, Filter).*

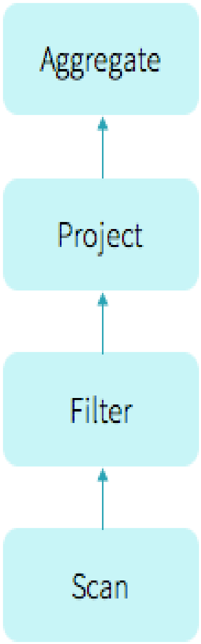
x + (1 + 2)

- Today
  - *Generate code for the entire query plan.*

The Past: Volcano Iterator Model

Spark leveraged a popular classic query evaluation strategy based on an iterator model (commonly referred to as the Volcano model).

```
select count(*) from store_sales
where ss_item_sk = 1000
```




```
class Filter(child: Operator, predicate: (Row => Boolean))
  extends Operator {
  def next(): Row = {
    var current = child.next()
    while (current == null || predicate(current)) {
      current = child.next()
    }
    return current
  }
}
```

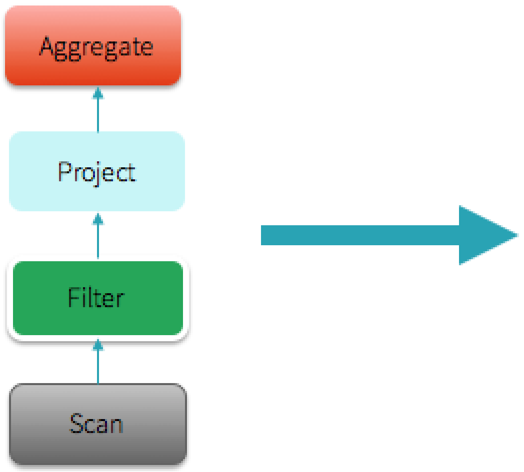
Hand-written code is faster than the Volcano model

- No virtual function dispatches.
- Intermediate data in memory vs CPU registers.
- Loop unrolling and SIMD.

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

Whole-stage code generation

- The engine can achieve the performance of hand-written code, yet provide the functionality of a general purpose engine.
- Rather than relying on operators for processing data at runtime:
    - *Collapse each fragment of the query into a single function and execute that generated code instead.*




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

Thanks for your attention

Questions?