CS 744: BIG DATA SYSTEMS

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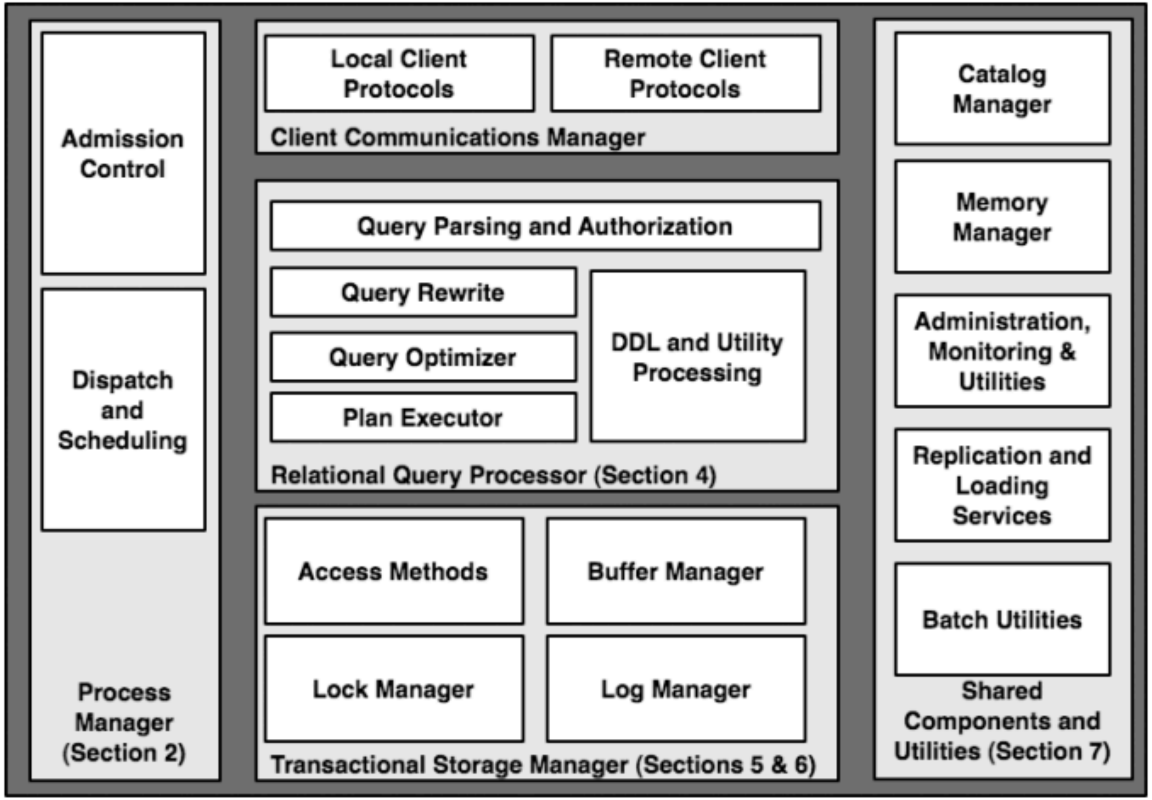
ADMINISTRIVIA

- Assignment 1 grades up, Assignment 2 in progress
- Midterm review session on Nov 2 at 5pm
- Course Project Proposal (5%)

SQL: STRUCTURED QUERY LANGUAGE

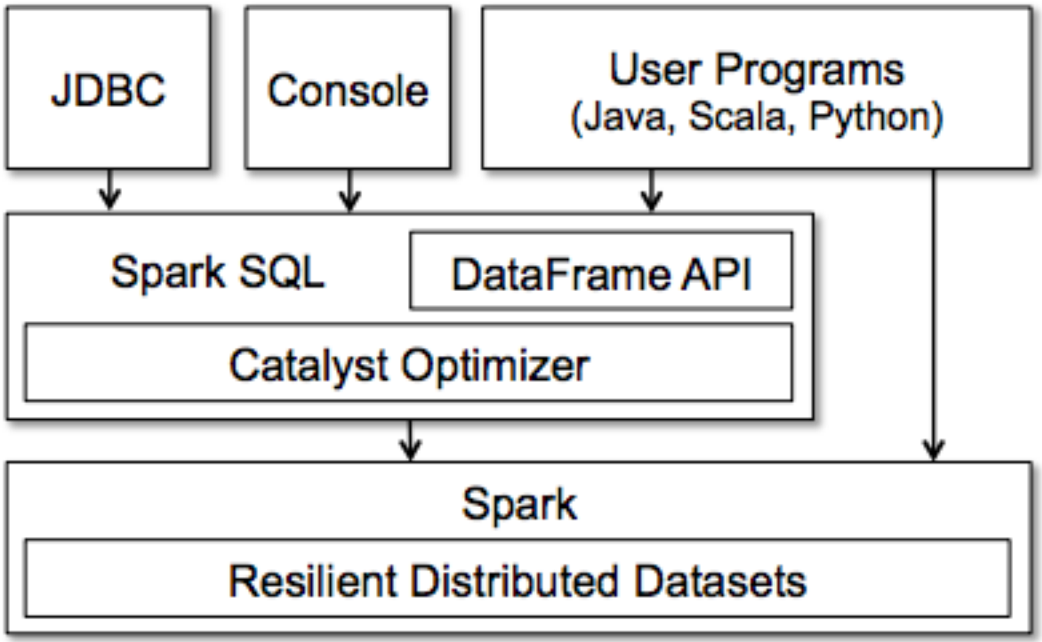
DATABASE SYSTEMS



SQL IN BIG DATA SYSTEMS

- Scale: How do we handle large datasets, clusters ?
- Wide-area: How do we handle queries across datacenters ?
- Hardware: Making efficient use of hardware ?

SPARK SQL: ARCHITECTURE



PROCEDURAL VS. RELATIONAL

```
lines = sc.textFile(“users")
csv = lines.map(x =>
    x.split(‘,’))
young = csv.filter(x =>
    x(1) < 21)
println(young.count())
```

```
ctx = new HiveContext ()
users = ctx.table(“users")
young = users.where(
    users(“age") < 21)
println(young.count())
```

OPERATORS → EXPRESSIONS

Projection (select), Filter, Join, Aggregations take in Expressions

```
employees.join(dept,
  employees (“deptId") === dept ("id ")
)
```

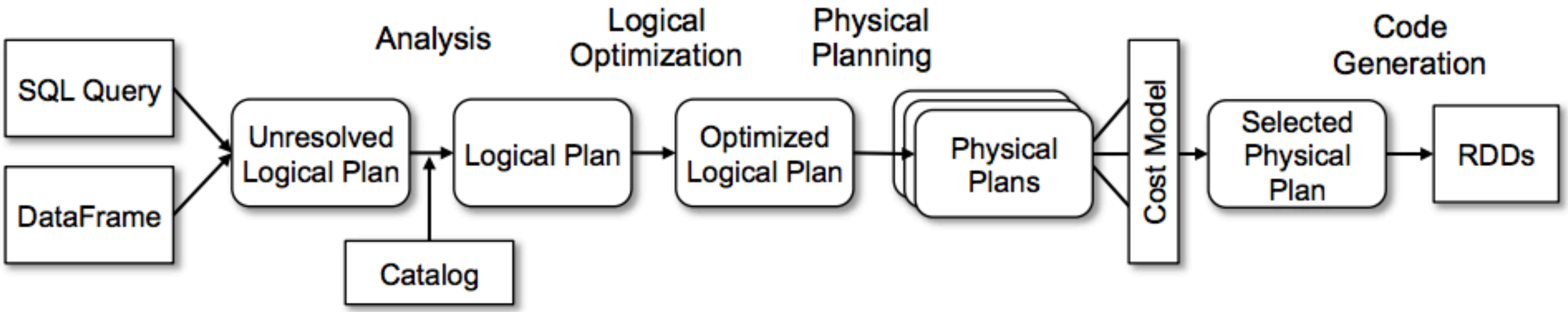
Build up Abstract Syntax Tree (AST)

OTHER FEATURES

1. Debugging: Eager analysis of logical plans
2. Interoperability: Convert RDD to Dataframes
3. Caching: Columnar caching with compression
4. UDFs: Python or Scala functions

CATALYST

Goal: Extensibility to add new optimization rules



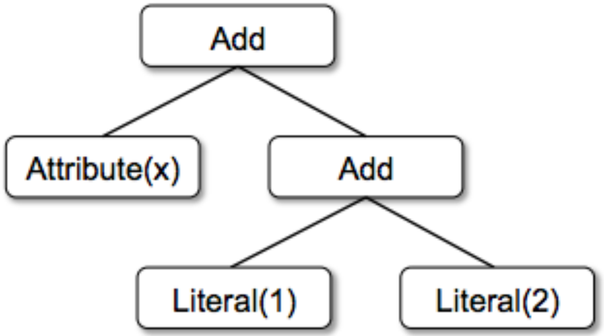
CATALYST DESIGN

Library for representing trees and rules to manipulate them

Pattern match → replace sub-trees

Only applied in sub-trees that match

Run in batches till fixed point




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

LOGICAL, PHYSICAL PLANS

1. Analyzer Lookup relations, map named attributes, propagate types
2. Logical Optimization
   – Constant folding
   – Predicate push-down
   – Project pruning …
3. Physical Planning
   – Select between plans using cost (join algorithm)
   – Pipeline multiple projection, filter into map

CODE GENERATION

CPU bound when data is in-memory

Branches, virtual function calls etc.

```
def compile(node: Node ): AST = node match {
  case Literal(value) => q"$value"
  case Attribute (name) => q"row.get($name)"
  case Add(left, right) =>
     q"${compile(left)} + ${compile(right)}"
}
```

- Literal(1) becomes 1
- Attribute(“x”) becomes row.get(“x”)
- Directly access Java field row.x

EXTENSIONS

Data sources

- Define a `BaseRelation` that contains schema
- `TableScan` returns `RDD[Row]`
- Pruning / Filtering optimizations

User-Defined Types (UDTs)

- Support advanced analytics with e.g. Vector
- Users provide mapping from UDT to Catalyst Row

SCHEMA INFERENCE

Common data formats: JSON, CSV, semi-structured data

JSON schema inference

- Find most specific SparkSQL type that matches instances
  e.g. if tweet.loc.latitude are all 32-bit then it is a INT
- Fall back to STRING if unknown
- Implemented using a reduce over trees of types

SUMMARY, TAKEAWAYS

Relational API

- Enables rich space of optimizations
- Easy to use, integration with Scala, Python

Catalyst Optimizer

- Extensible, rule-based optimizer
- Code generation for high-performance

Evolution of Spark API

QUESTIONS / DISCUSSION ?