

#### MGM COLLEGE OF ENGINEERING AND TECHNOLOGY

# LOTUS SQL

#### Guide:

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# **OBJECTIVE**

- An engine to provide SQL support for dataset abstraction on native backend Lotus
- Convenient SQL processing framework to deal with frontend jobs

#### **INTRODUCTION**

- Rapid development of information technology has brought significant progress to human society
- The amount of data that computer systems need to deal with has increased accordingly
- SQL is a common choice for data analysis
- To evaluate the execution efficiency of SQL queries TPC defines a benchmark TPC-H is widely used for OLAP performance evaluation.
- SparkSQL is designed for processing structured data on Spark.

#### **INTRODUTION (CONT....)**

- Garbage collection and data serialization, are attributable to JVMs
- Lotus is a high performance data-parallel computing engine built with c++
- High performance because of bare-metal runtime environment
- Compact storage strategy, Coarse-grained function call, Memory efficient design
- Uses template usage and automatic type deduction
- Challenges :Semantic gap exists between lotus and SQL and Massive development efforts

#### **BACKGROUND-LOTUS**

- Single machine data parallel computing engine
- Low-overhead storage module & Highly efficient compute modue
- Storage module is designed to have low overhead, combination of buffer caches and compact object models
- Compute model is C++ dataset programming model
- Provides the abstraction of compact collections and efficient operation implementations
- Logically an array of records segmented into multiple partitions

## **BACKGROUND-LOTUS (CONT....)**

- Abstraction is quite similar to spark's RDD for distributed allocation
- Lazy evaluation strategy and supports fault tolerance
- Intermediate result datasets can be cached explicitly
- Employs compact object storage
- Reduce serialization and deserialization overhead
- Supports primary data types
- For string dataset, data are organized into two compact buffers
- Provide a compute engine for LotusSQL

# BACKGROUND-CALCITE

- Open-source software framework
- Provides query processing, optimization and query language support
- Perceives developers of specialized systems encounter related problems such as query optimization or the need to support query language
- Minimize the engineering effort
- Unifying and pluggable framework

# BACKGROUND-CALCITE (CONT....)

- Logical operators is the primary form of operation and it includes filter, project and join
- Physical operator assigns an implementation method
- Operators compose the relational algebra expression tree, which is the representation of an execution plan
- Execution plan consisting mainly of physical operators called physical plan
- Cost-based dynamic programming search to find the best execution plan
- Employs as a frontend to produce a physical execution plan.

#### WORKFLOW

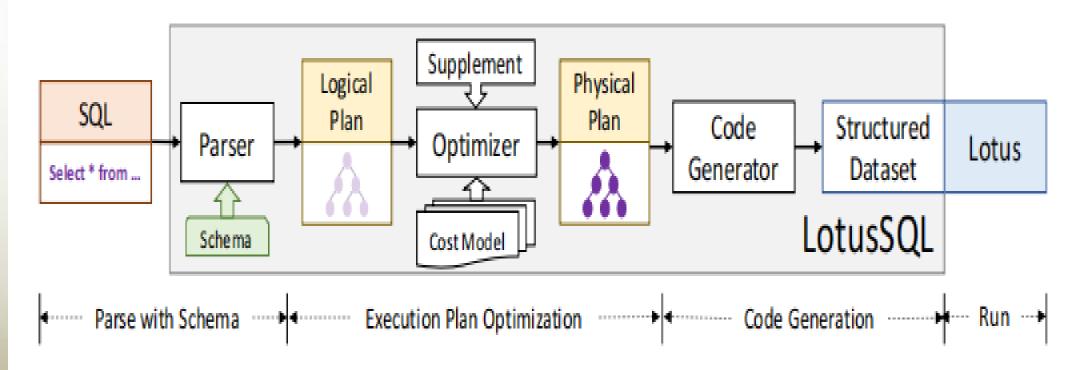


Fig. 1 Workflow overview.

#### PHYSICAL OPERATORS

#### **PHYSICAL OPERATORS-OPERATION FUSION**

- Technique to dataset operation implementation
- Proposed in the main memory database field
- Operation can be fused together to maximize data and code locality
- Leaves tuples in registers and makes the execution cheap

### IMPLEMENTATION AND COST MODEL

Table	1	Operator	list.
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	Table 1	Operator list.
LogicalOp	PhysicalOp	Description
TableScan	L atus Tabla Saan	Read a table (dataset)
	Lotus rabiescan	from the file system.
Filter	LotusFilter	Filter a table by
	LotusFilter	given condition.
Project .	LotusSelect	Select some columns from
	LotusSelect	a table.
	T	Map table rows by given
	LotusMap	expression.
Aggregate .	T -t A	Aggregate all rows by given
	LotusAggregate	function.
	LotusHash	Aggregate rows by given group
	Aggregate	and function via HashMap.
Join .	LotusCartesian	Calculate cartesian product of
	Product	two tables.
	LotusBroadcast	Join two tables via broadcasting
	HashJoin	one to the other and HashMap.
	LotusShuffle	Join two tables via re-partitioning
	HashJoin	tables and using HashMap.
Sort .	LotusSort	Sort all rows by given
	LotusSort	reference key and direction.
	LotusTop K	Find top-k rows by given
	Lotus Top K	reference key and direction.

#### IMPLEMENTATION AND COST MODEL

- Cost model evaluates cost of the implementation
- Generally the cost can be calculated in several aspects, such as CPU usage, memory access and I/O bytes.

### IMPLEMENTATION AND COST MODEL

Eg: LotusBroadcastHashJoin

 $\label{eq:cost} Cost_{broadcast} = LeftInputRowCount * \\ LeftInputColumnCount * NumRightPartition$ 

 $Cost_{hashmap} = (LeftInputRowCount * \\ NumRightPartition + RightInputRowCount) * \\ log(LeftDistinctRowCount)$ 

 $Cost_{output} = OutputRowCount * OutputColumnCount$ 

 $Cost = Cost_{broadcast} + Cost_{hashmap} + Cost_{output}$ 

## **QUERY OPTIMIZATION**

#### **DECORRELATION OF SUBQUERIES**

- Subqueries that do not involve external variables are noncorrelated & parsed into independent subtree
- Correlated subquery appears as a *LogicalCorrelate* operator in original logical plan
- Behaves like a special type of join, but the right input subtree refers to variables from left input
- Re-executing the right subtree every time hampers performance in most cases
- Thus decorrelation is necessary
- Calcite adopts several methods for decorrelation, but they are not efficient enough

#### **DECORRELATION OF SUBQUERIES (CONT..)**

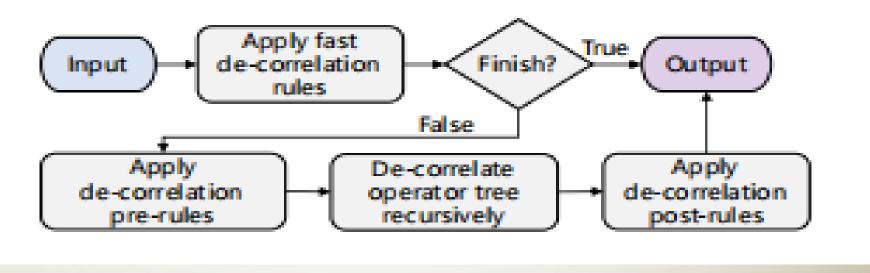


Fig.1 Calcite decorrelation

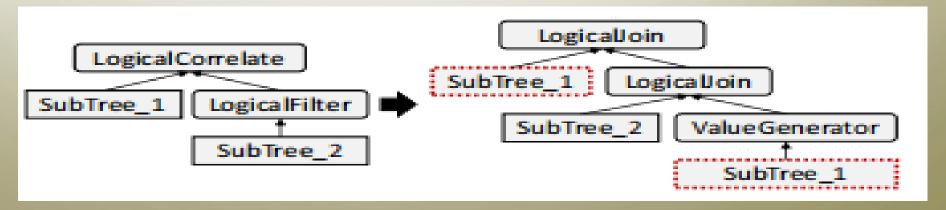


Fig.2 Decorrelation Example

#### ROWCOUNT ESTIMATION

- Calcite users invoke *getRowCount()* to estimate the no: of output rows of an operator
- Estimation is based on Calcite's mechanism that provides metadata
- This estimates RowCount and condition selectivity
- Also tracks inherited properties- unique keys and column origins

#### **ROWCOUNT ESTIMATION**

• Eg: estimation of the output RowCount of the simple query

select \* from Table A, Table B where Table A. x = Table B. y

its estimated number of rows is

RowCount = TableA.RowCount \* TableB.RowCount \* Selectivity(TableA.x = TableB.y)

selectivity is a simple guess that returns a value between 0.5 and 1.0

# **EVALUATION** • Workloads and environment • Query translation analysis Computing time Memory usage

# **ADVANTAGES**

- Big data processing system
- Takes less memory

#### **DISADVANTAGES**

- Complex
- Long queries

#### **CONCLUSION**

- Lotus is a big data processing system developed with native programming language
- To boost lotus we present LotusSQL
- Uses Calcite to compile and optimize queries with the guidance of a physical cost model
- Dependencies are resolved as a whole and compressed during C++ compilation time
- With all the about strategies, LotusSQL outperforms SparkSQL in TPC-H queries by more than twice on average

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