ADVANCED DATABASE SYSTEMS

Query Optimizer Implementation Part 1

13

Andy Pavlo
CMU 15-721
Spring 2024
Carnegie Mellon University

LAST CLASS

Row-oriented database network protocols via JDBC/ODBC APIs are sufficient for queries that access a small number of tuples.

Large output queries / bulk export operations benefit from Arrow native columnar optimizations via ADBC.

NEXT TWO WEEKS

Optimizer Implementations
Query Rewriting
Plan Enumerations
Cost Models

QUERY OPTIMIZATION

For a given query, find a **correct** physical execution plan for that query with the lowest "cost".

This is the part of a DBMS that is the hardest to implement well (proven to be NP-Complete).

No optimizer truly produces the "optimal" plan
→ Use estimation techniques to guess real plan cost.
→ Use heuristics to limit the search space.

LOGICAL VS. PHYSICAL PLANS

The optimizer generates a mapping of a logical algebra expression to the optimal equivalent physical algebra expression.

Physical operators define a specific execution strategy using an access path.

→ They can depend on the physical format of the data that they process (i.e., sorting, compression).
→ Not always a 1:1 mapping from logical to physical.

COST ESTIMATION

Generate an estimate of the cost of executing a plan for the current state of the database.

→ Interactions with other work in DBMS
→ Size of intermediate results
→ Choices of algorithms, access methods
→ Resource utilization (CPU, I/O, network)
→ Data properties (skew, order, placement)

We will discuss this more next week…

TODAY'S AGENDA

Heuristics

Heuristics + Cost-based Search

Stratified Search

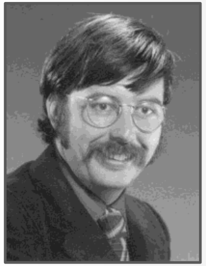
Unified Search

Randomized Search

HEURISTIC-BASED OPTIMIZATION

Define static rules that transform logical operators to a physical plan <u>without</u> a cost model.

→ Perform most restrictive selection early
→ Perform all selections before joins
→ Predicate/Limit/Projection pushdowns
→ Join ordering based on simple rules or cardinality estimates



Stonebraker

Examples: INGRES (until mid-1980s) and Oracle (until mid-1990s), MongoDB, most new DBMSs.

QUERY PROCESSING IN A RELATIONAL DATABASE MANAGEMENT SYSTEM
VLDB 1979

LOGICAL QUERY OPTIMIZATION

Split Conjunctive Predicates

Predicate Pushdown

Replace Cartesian Products with Joins

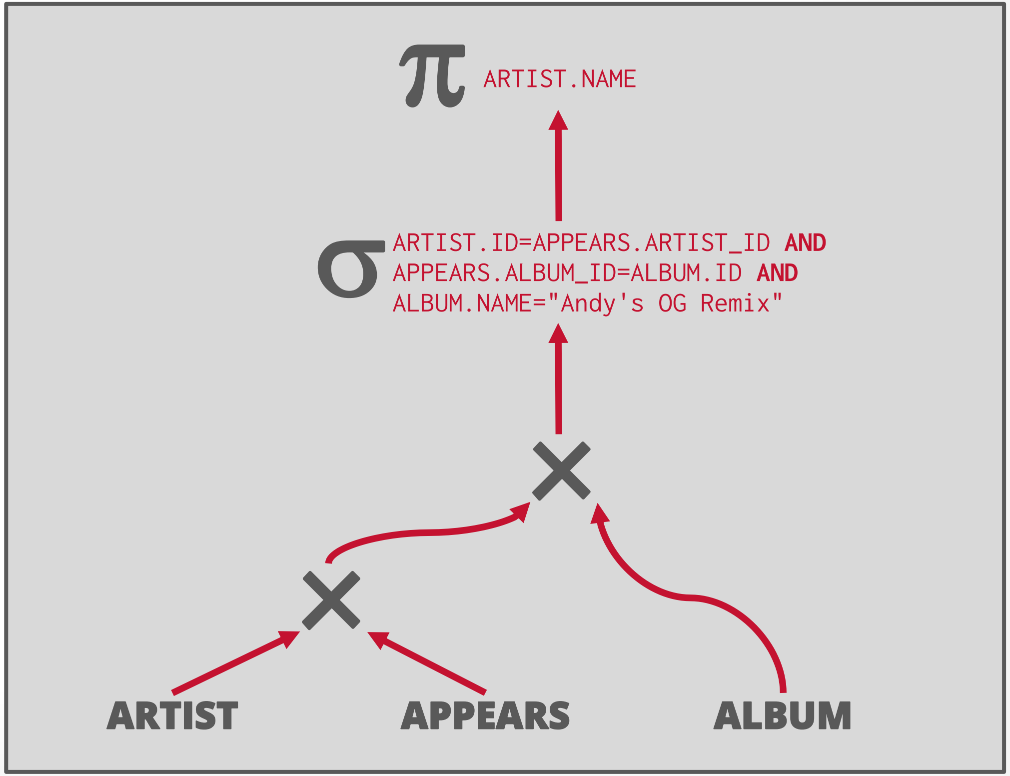
Projection Pushdown

Source: Thomas Neumann

SPLIT CONJUNCTIVE PREDICATES

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

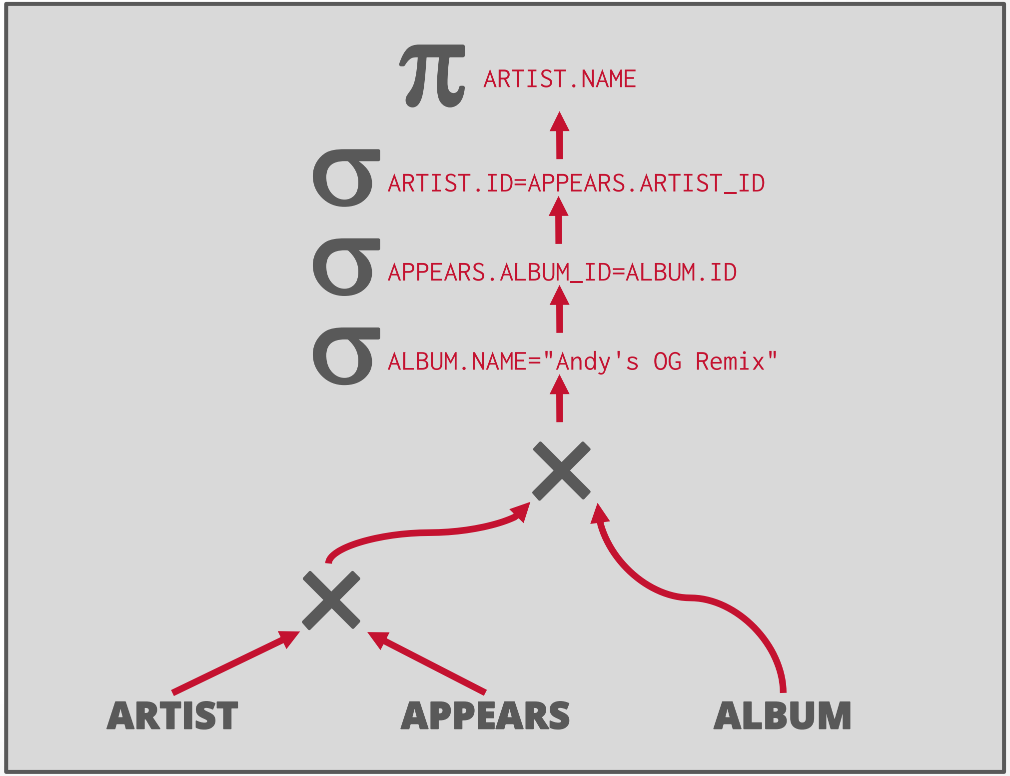
Decompose predicates into their simplest forms to make it easier for the optimizer to move them around.



SPLIT CONJUNCTIVE PREDICATES

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

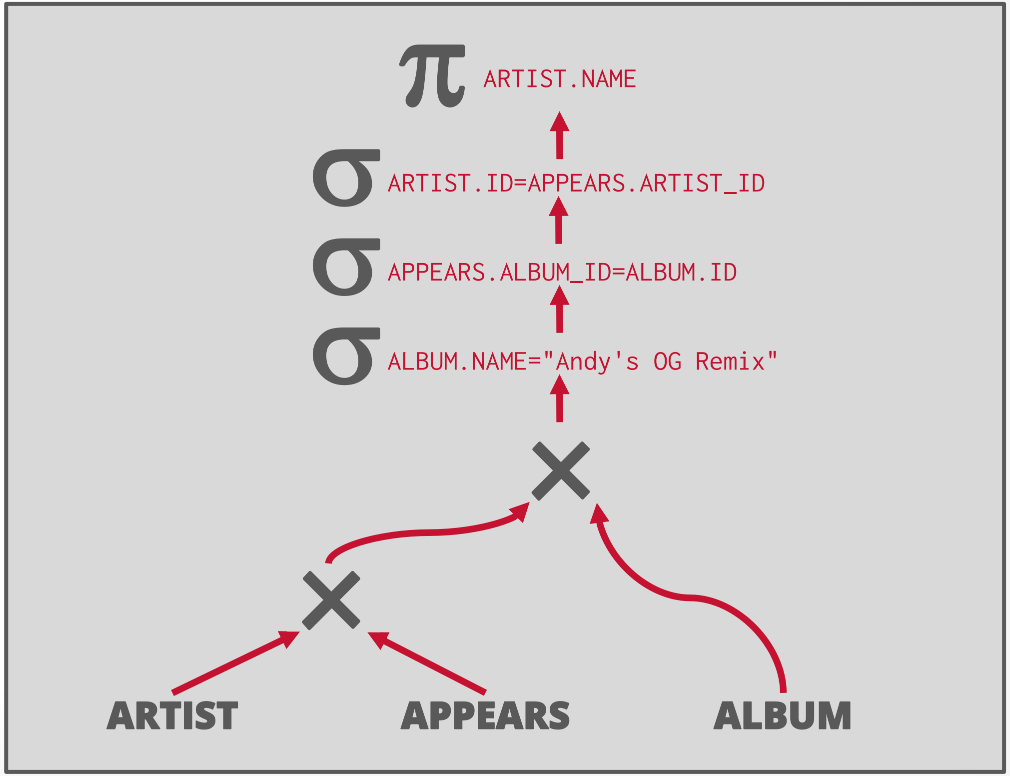
Decompose predicates into their simplest forms to make it easier for the optimizer to move them around.



PREDICATE PUSHDOWN

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

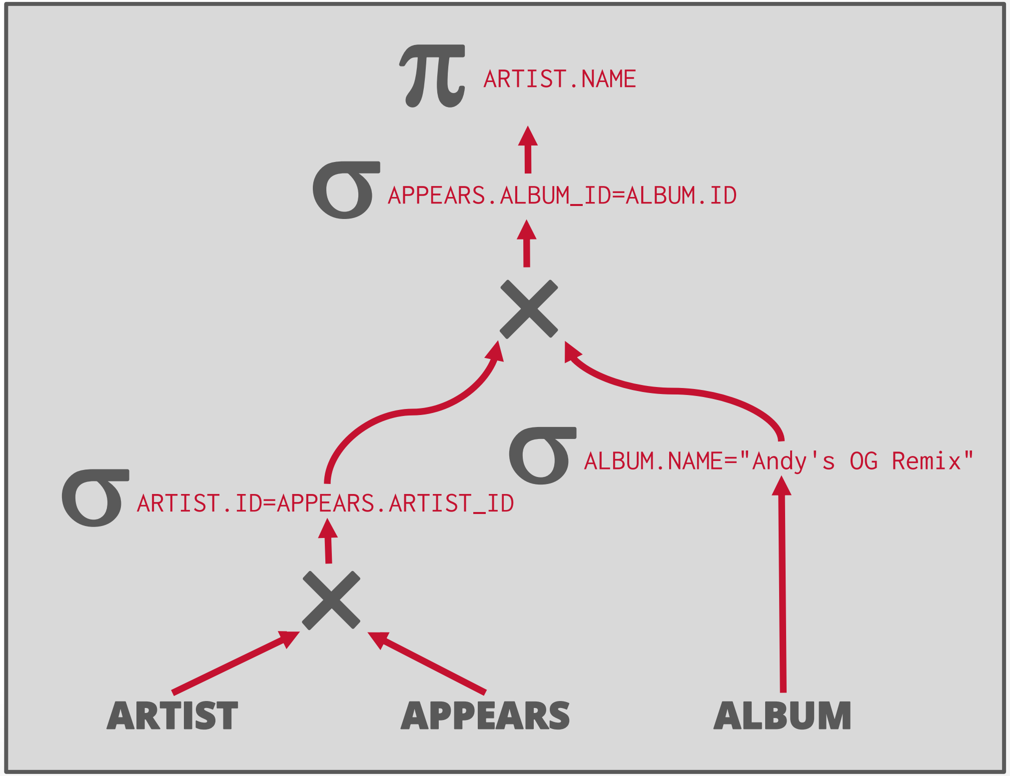
Move the predicate to the lowest point in the plan after Cartesian products.



PREDICATE PUSHDOWN

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

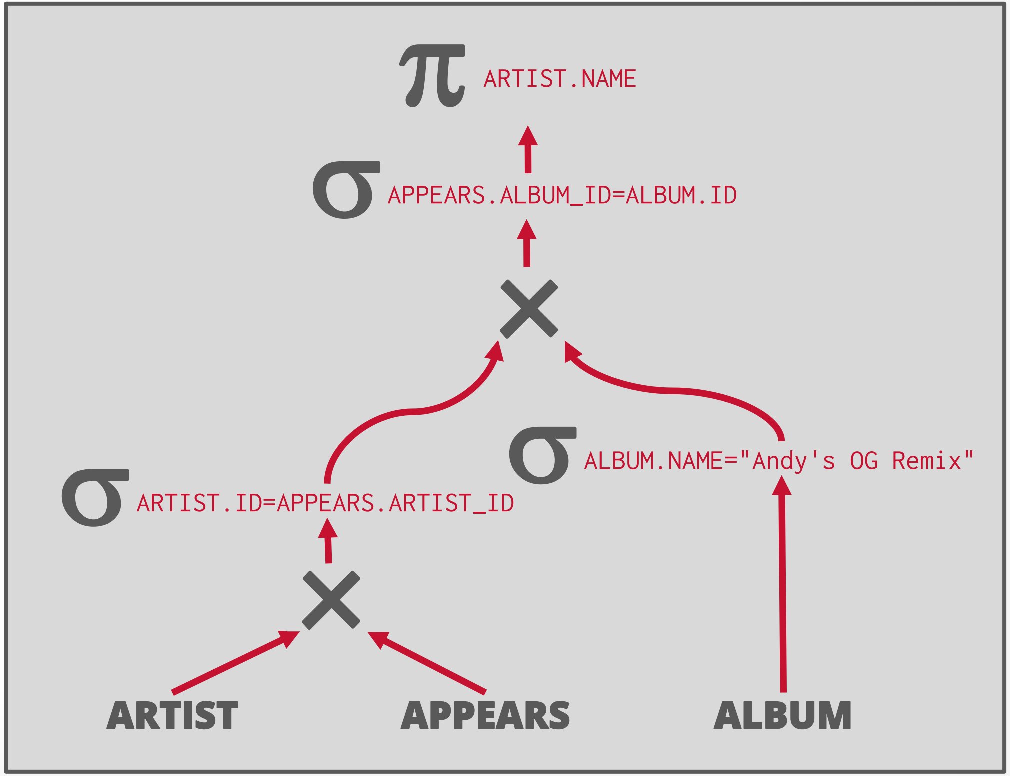
Move the predicate to the lowest point in the plan after Cartesian products.



REPLACE CARTESIAN PRODUCTS

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

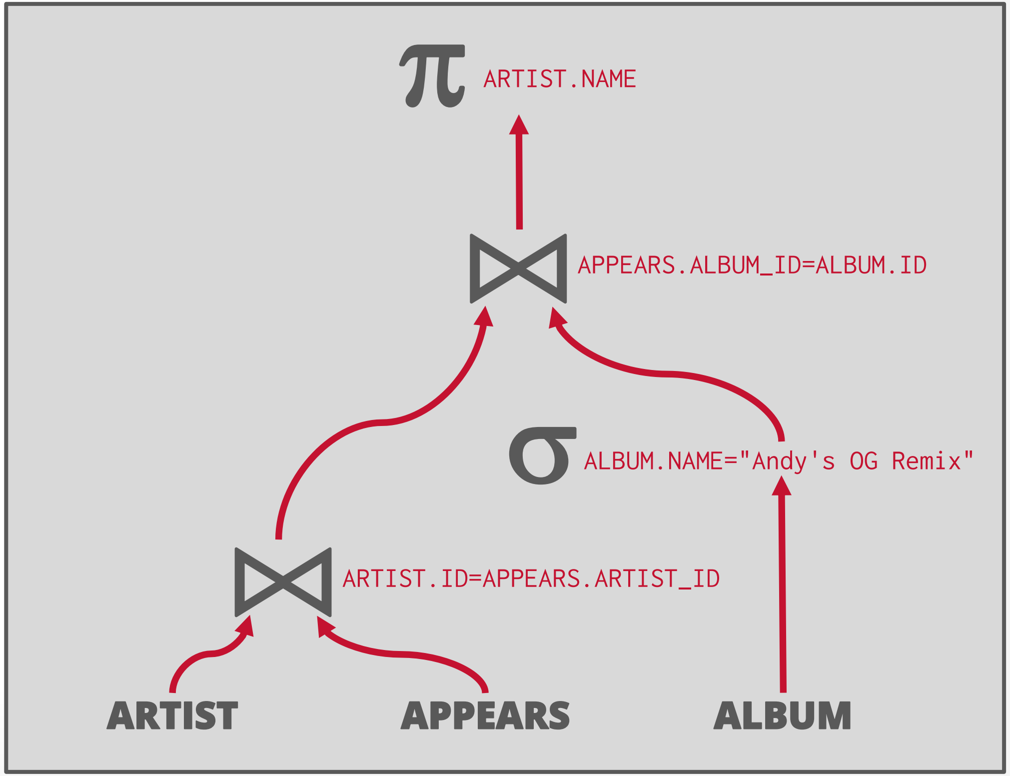
Replace all Cartesian Products with inner joins using the join predicates.



REPLACE CARTESIAN PRODUCTS

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

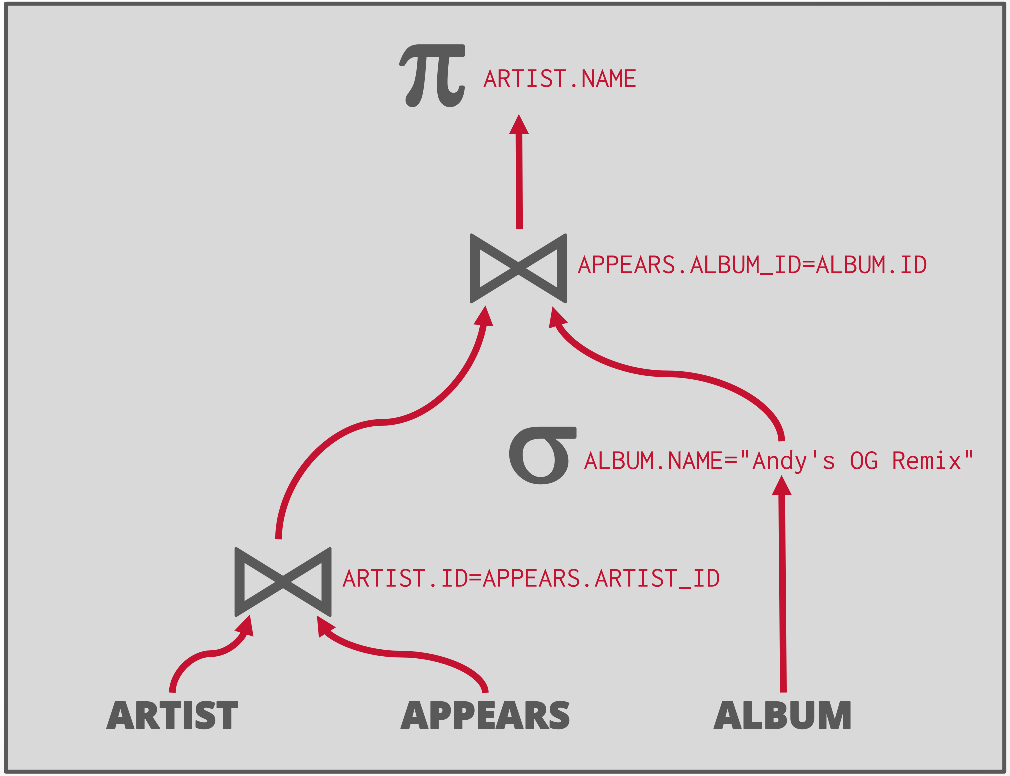
Replace all Cartesian Products with inner joins using the join predicates.



PROJECTION PUSHDOWN

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

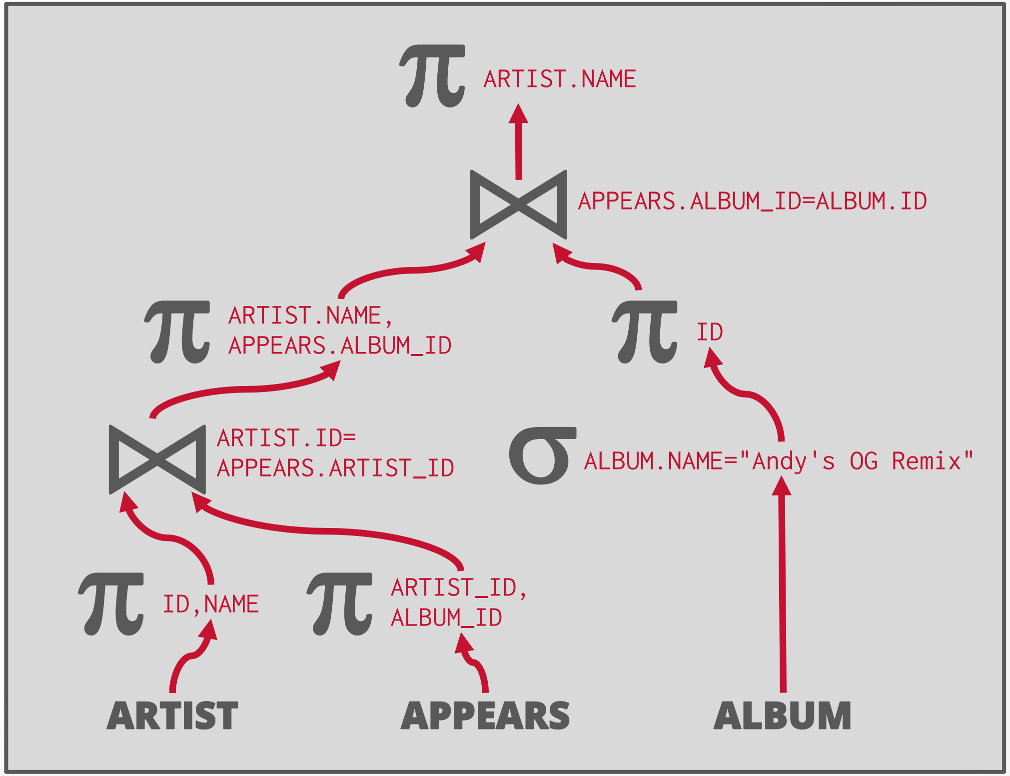
Eliminate redundant attributes before pipeline breakers to reduce materialization cost.



PROJECTION PUSHDOWN

```sql
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
```

Eliminate redundant attributes before pipeline breakers to reduce materialization cost.



INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Decompose into single-value queries

Query #1

```
SELECT ALBUM.ID AS ALBUM_ID INTO TEMP1
  FROM ALBUM
 WHERE ALBUM.NAME="Andy's OG Remix"
```

Query #2

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, TEMP1
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=TEMP1.ALBUM_ID
 ORDER BY APPEARS.ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Decompose into single-value queries

Query #1

```
SELECT ALBUM.ID AS ALBUM_ID INTO TEMP1
  FROM ALBUM
 WHERE ALBUM.NAME="Andy's OG Remix"
```

Query #2

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, TEMP1
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=TEMP1.ALBUM_ID
 ORDER BY APPEARS.ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Decompose into single-value queries

Query #1

```
SELECT ALBUM.ID AS ALBUM_ID INTO TEMP1
  FROM ALBUM
 WHERE ALBUM.NAME="Andy's OG Remix"
```

Query #3

```
SELECT APPEARS.ARTIST_ID INTO TEMP2
  FROM APPEARS, TEMP1
 WHERE APPEARS.ALBUM_ID=TEMP1.ALBUM_ID
 ORDER BY APPEARS.ARTIST_ID
```

Query #4

```
SELECT ARTIST.NAME
  FROM ARTIST, TEMP2
 WHERE ARTIST.ARTIST_ID=TEMP2.ARTIST_ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

ALBUM_ID
9999

Step #1: Decompose into single-value queries

Step #2: Substitute the values from
Query#1 → Query #3 → Query #4

Query #3

```
SELECT APPEARS.ARTIST_ID INTO TEMP2
  FROM APPEARS, TEMP1
 WHERE APPEARS.ALBUM_ID=TEMP1.ALBUM_ID
 ORDER BY APPEARS.ARTIST_ID
```

Query #4

```
SELECT ARTIST.NAME
  FROM ARTIST, TEMP2
 WHERE ARTIST.ARTIST_ID=TEMP2.ARTIST_ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

ALBUM_ID
9999

```
SELECT APPEARS.ARTIST_ID
  FROM APPEARS
 WHERE APPEARS.ALBUM_ID=9999
 ORDER BY APPEARS.ARTIST_ID
```

Step #1: Decompose into single-value queries

Step #2: Substitute the values from Query#1 → Query #3 → Query #4

Query #4

```
SELECT ARTIST.NAME
  FROM ARTIST, TEMP2
 WHERE ARTIST.ARTIST_ID=TEMP2.ARTIST_ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

ALBUM_ID
9999

ARTIST_ID
123
456

Step #1: Decompose into single-value queries

Step #2: Substitute the values from Query#1 → Query #3 → Query #4

Query #4

```
SELECT ARTIST.NAME
  FROM ARTIST, TEMP2
 WHERE ARTIST.ARTIST_ID=TEMP2.ARTIST_ID
```

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

ALBUM_ID
9999

ARTIST_ID
123
456

```
SELECT ARTIST.NAME
  FROM ARTIST
 WHERE ARTIST.ARTIST_ID=123
```

```
SELECT ARTIST.NAME
  FROM ARTIST
 WHERE ARTIST.ARTIST_ID=456
```

Step #1: Decompose into single-value queries

Step #2: Substitute the values from Query#1 → Query #3 → Query #4

INGRES OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

ALBUM_ID
9999

ARTIST_ID
123
456

NAME
O.D.B.

NAME
DJ Premier

Step #1: Decompose into single-value queries

Step #2: Substitute the values from Query#1 → Query #3 → Query #4

HEURISTIC-BASED OPTIMIZATION

Advantages:

→ Easy to implement and debug.
→ Works reasonably well and is fast for simple queries.

Disadvantages:

→ Relies on magic constants that predict the efficacy of a planning decision.
→ Nearly impossible to generate good plans when operators have complex inter-dependencies.

HEURISTIC-BASED OPTIMIZATION

Advantages:

→ Easy to implement and debug.

→ Works reasonably well and is fast

Disadvantages:

→ Relies on magic constants that pre
planning decision.

→ Nearly impossible to generate goo
have complex inter-dependencies

Stonebraker gave the story of the query optimizer as an example. Relational queries were often highly complex. Let's say you wanted your database to give you the name, salary, and job title of everyone in your Chicago office who did the same kind of work as an employee named Alien. (This example happens to come from Oracle's 1981 user guide.) This would require the database to find information in the employee table and the department table, then sort the data. How quickly the database management system did this depended on how cleverly the system was constructed. "If you do it smart, you get the answer a lot quicker than if you do it stupid, Stonebraker said.

He continued. "Oracle had a really stupid optimizer. They did the query in the order that you happened to type in the clauses. Basically, they blindly did it from left to right. The Ingres program looked at everything there and tried to figure out the best way to do it." But Ellison found a way to neutralize this advantage, Stonebraker said. "Oracle was really shrewd. They said they had a syntactic optimizer, whereas the other guys had a semantic optimizer. The truth was, they had no optimizer and the other guys had an optimizer. It was very, very, very creative marketing. . . . They were very good at confusing the market."

"What he's using is semantics himself," Ellison said. Just because Oracle did things differently, "Stonebraker decided we didn't have an optimizer. [He seemed to think] the only kind of optimizer was his optimizer, and our approach to optimization wasn't really optimization at all. That's an interesting notion, but I'm not sure I buy that."

HEURISTICS + COST-BASED SEARCH

First use static rules to perform initial logical→logical optimizations.
Then enumerate plans using physical→logical transformations to find best plan according to a cost model.

Examples: System R, early IBM DB2, most open-source DBMSs.

Selinger

ACCESS PATH SELECTION IN A RELATIONAL DATABASE MANAGEMENT SYSTEM
SIGMOD 1979

PHYSICAL QUERY OPTIMIZATION

Transform a query plan's logical operators into physical operators.

→ Add more execution information
→ Select indexes / access paths
→ Choose operator implementations
→ Choose when to materialize (i.e., temp tables).

This stage must support cost model estimates.

PLAN ENUMERATION

Approach #1: Generative / Bottom-Up

→ Start with nothing and then iteratively assemble and add building blocks to generate a query plan.

→ **Examples:** System R, Starburst

Approach #2: Transformation / Top-Down

→ Start with the outcome that the query wants, and then transform it to equivalent alternative sub-plans to find the optimal plan that gets to that goal.

→ **Examples**: Volcano, Cascades

ON THE CORRECT AND COMPLETE ENUMERATION OF THE CORE SEARCH SPACE
SIGMOD 2013

SYSTEM R OPTIMIZER

Break query up into blocks and generate the logical operators for each block.

For each logical operator, generate a set of physical operators that implement it.
→ All combinations of join algorithms and access paths

Then iteratively construct a "left-deep" join tree that minimizes the estimated amount of work to execute the plan.

SYSTEM R OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Choose the best access paths to each table

ARTIST: Sequential Scan
APPEARS: Sequential Scan
ALBUM: Index Look-up on **NAME**

SYSTEM R OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Choose the best access paths to each table

Step #2: Enumerate all possible join orderings for tables

ARTIST: Sequential Scan
APPEARS: Sequential Scan
ALBUM: Index Look-up on **NAME**

ARTIST ⋈ APPEARS ⋈ ALBUM
APPEARS ⋈ ALBUM ⋈ ARTIST
ALBUM ⋈ APPEARS ⋈ ARTIST
APPEARS ⋈ ARTIST ⋈ ALBUM
ARTIST × ALBUM ⋈ APPEARS
ALBUM × ARTIST ⋈ APPEARS
⋮ ⋮ ⋮

SYSTEM R OPTIMIZER

Retrieve the names of people that appear on Andy's mixtape ordered by their artist id.

```
SELECT ARTIST.NAME
  FROM ARTIST, APPEARS, ALBUM
 WHERE ARTIST.ID=APPEARS.ARTIST_ID
   AND APPEARS.ALBUM_ID=ALBUM.ID
   AND ALBUM.NAME="Andy's OG Remix"
 ORDER BY ARTIST.ID
```

Step #1: Choose the best access paths to each table

Step #2: Enumerate all possible join orderings for tables

Step #3: Determine the join ordering with the lowest cost

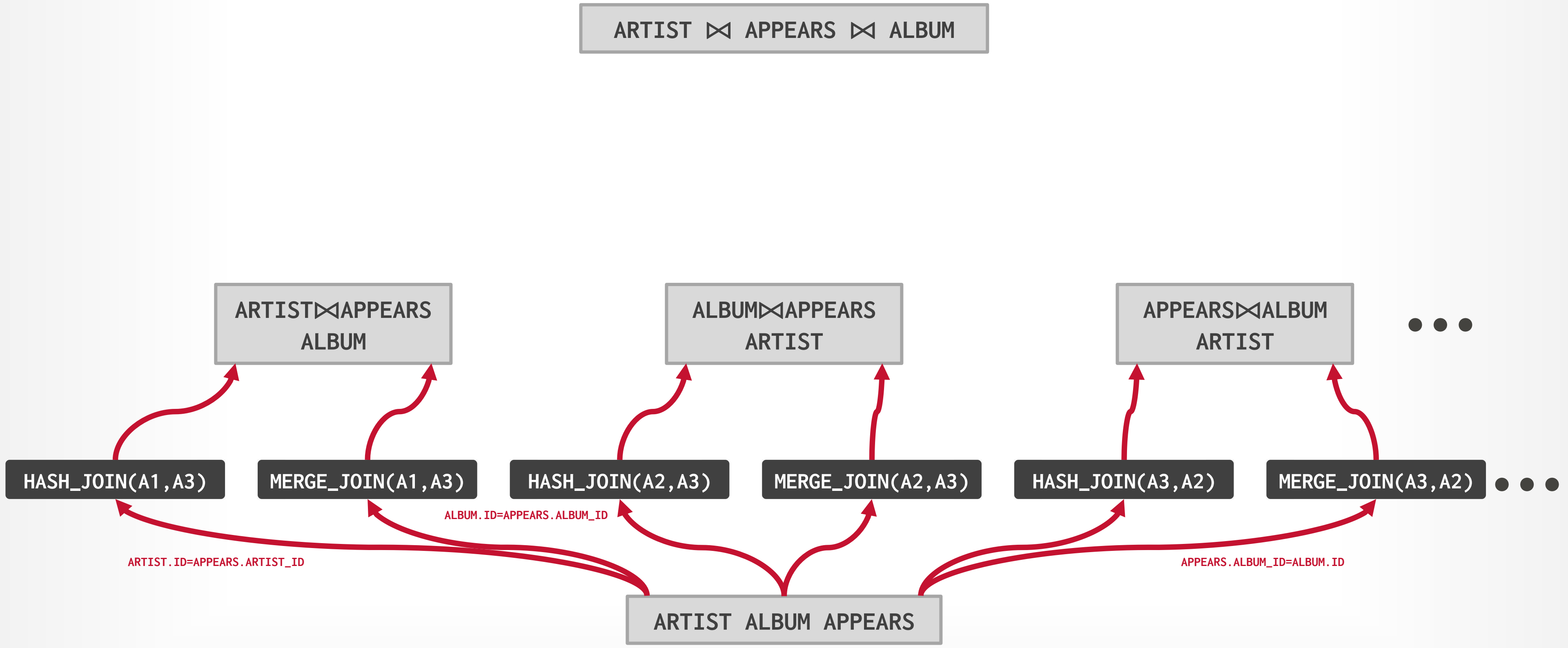
ARTIST: Sequential Scan
APPEARS: Sequential Scan
ALBUM: Index Look-up on **NAME**

ARTIST ⋈ APPEARS ⋈ ALBUM
APPEARS ⋈ ALBUM ⋈ ARTIST
ALBUM ⋈ APPEARS ⋈ ARTIST
APPEARS ⋈ ARTIST ⋈ ALBUM
ARTIST × ALBUM ⋈ APPEARS
ALBUM × ARTIST ⋈ APPEARS
⋮ ⋮ ⋮

Logical Op

Physical Op

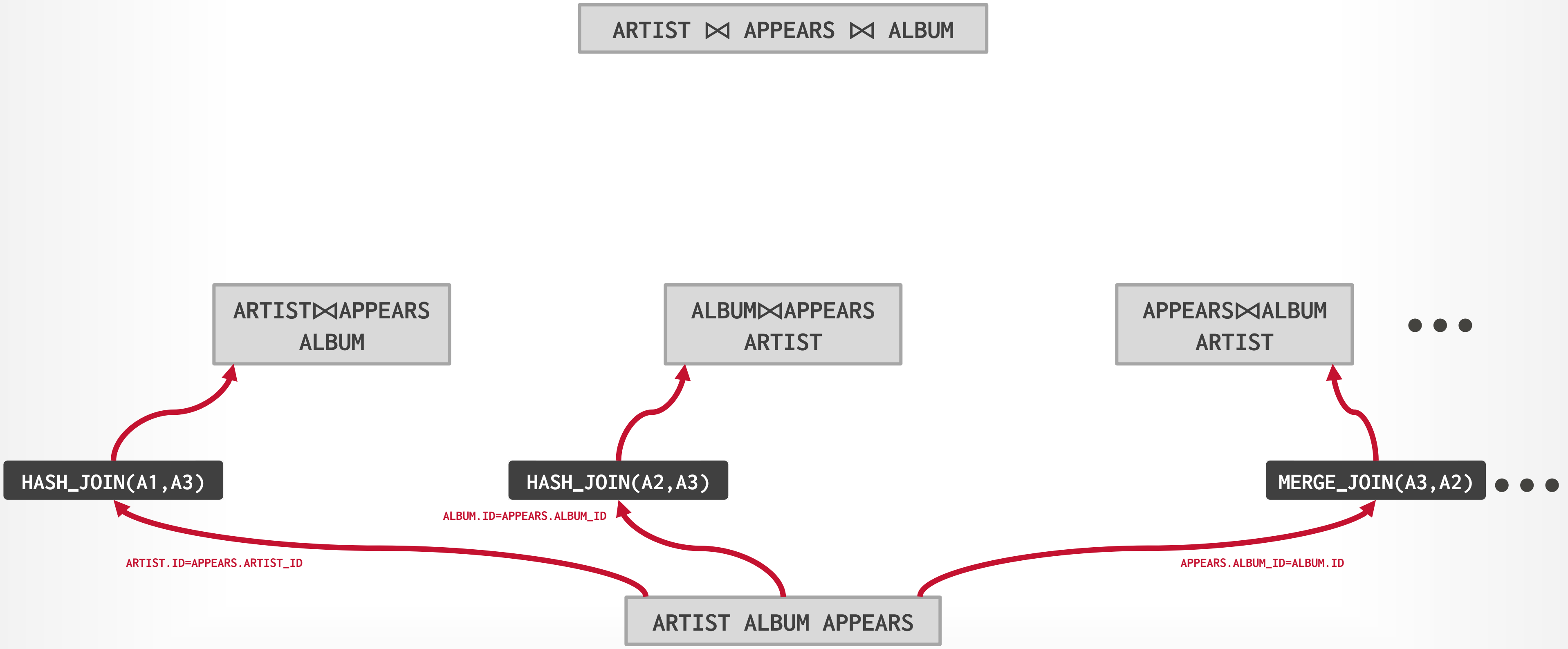
SYSTEM R OPTIMIZER



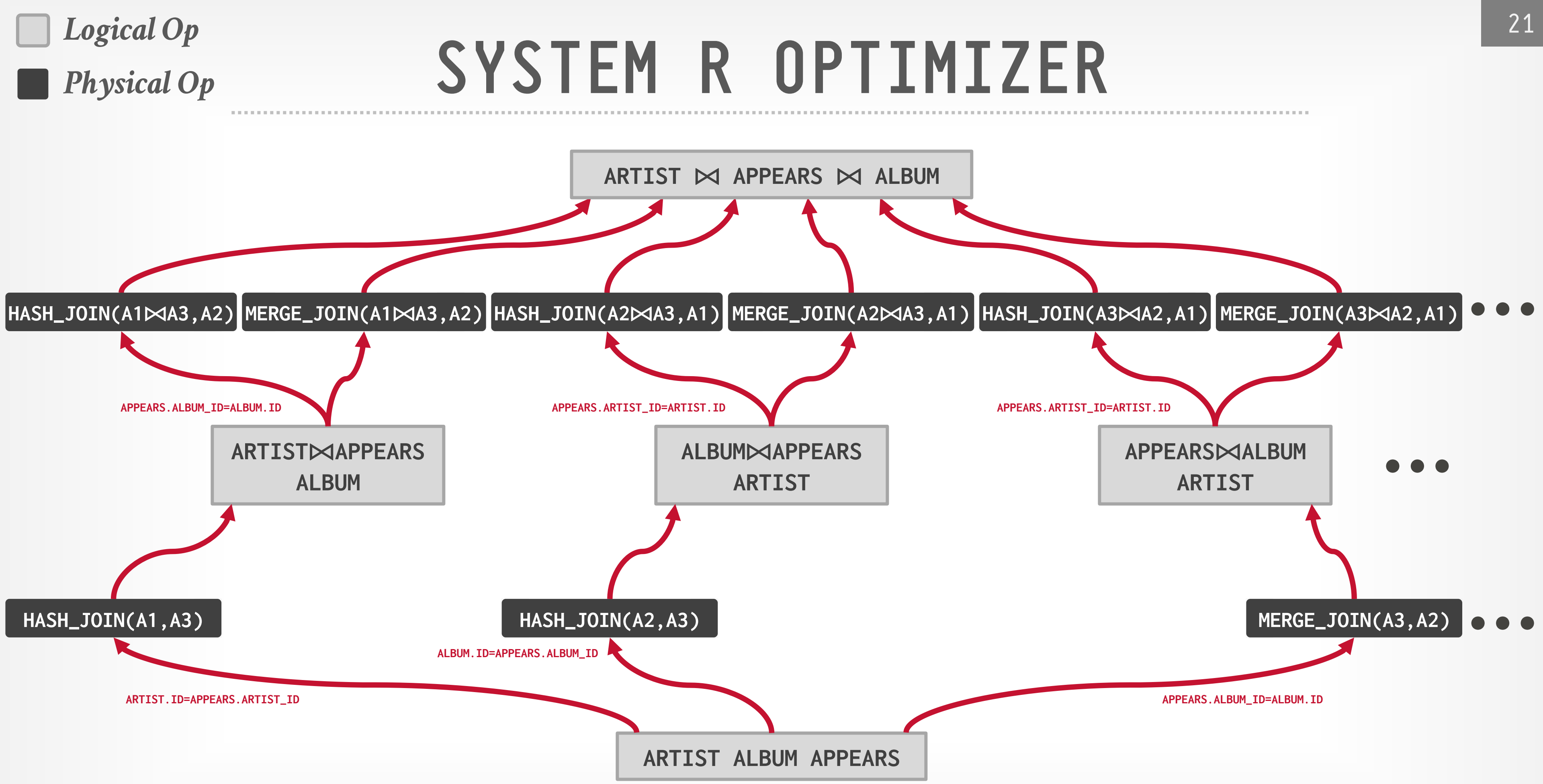
Logical Op

Physical Op

SYSTEM R OPTIMIZER



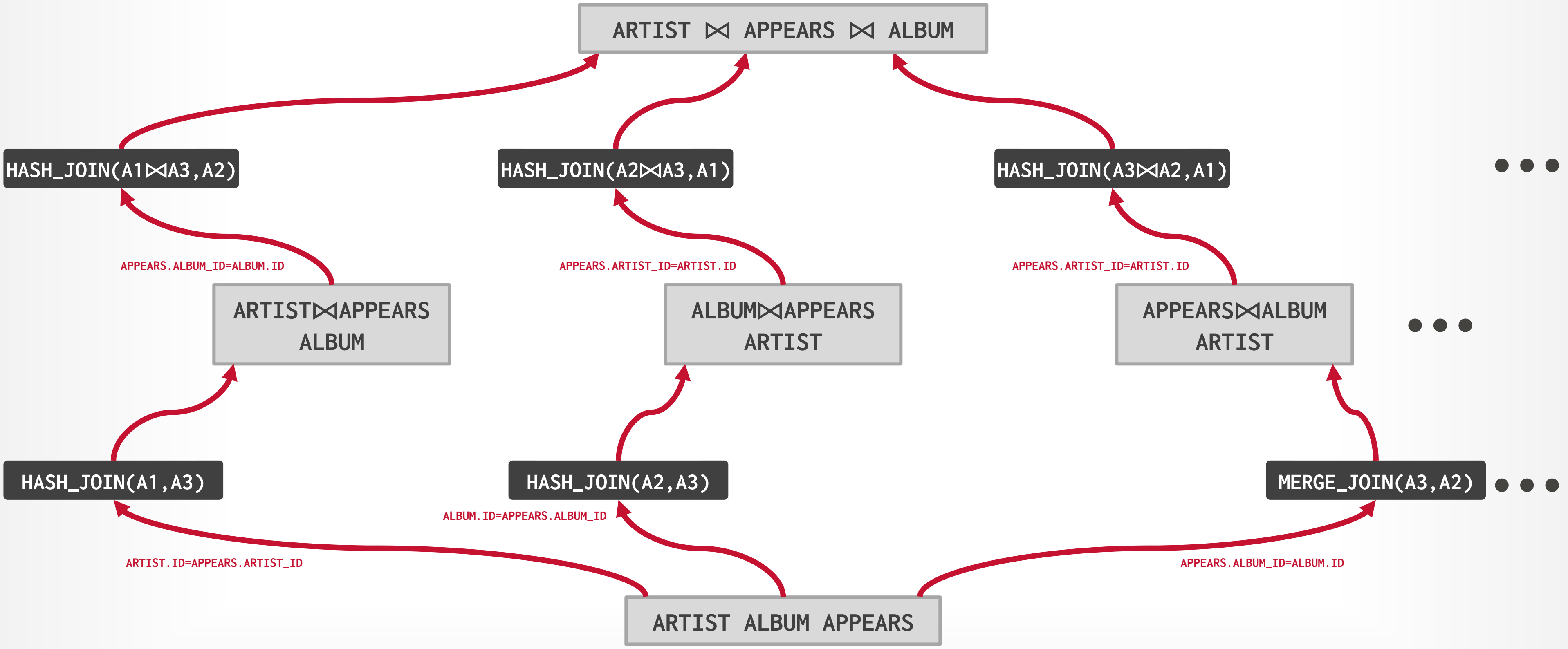
SYSTEM R OPTIMIZER



Logical Op

Physical Op

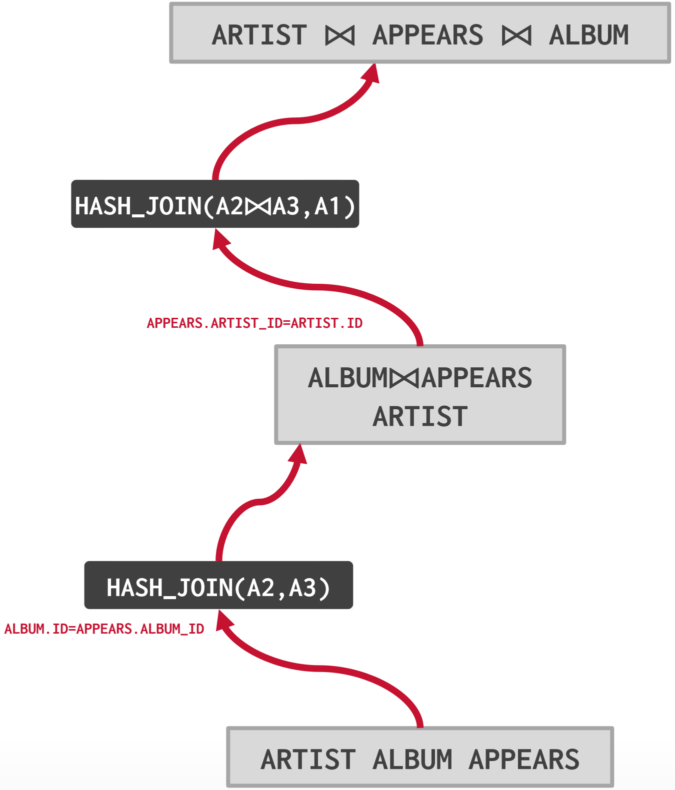
SYSTEM R OPTIMIZER



Logical Op

Physical Op

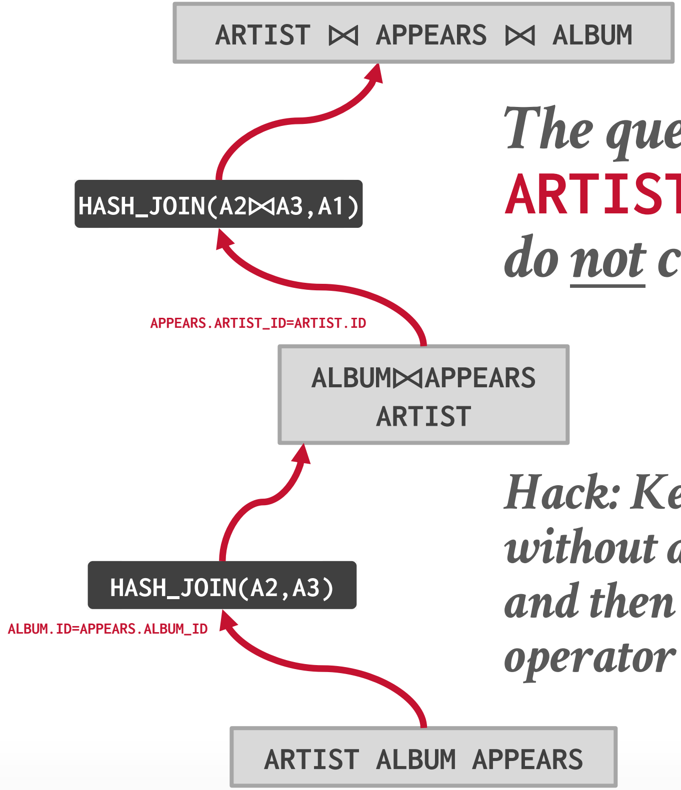
SYSTEM R OPTIMIZER



Logical Op

Physical Op

SYSTEM R OPTIMIZER



The query has **ORDER BY** *on* **ARTIST.ID** *but the logical plans do not contain sorting properties.*

Hack: Keep track of best plans with and without data in proper physical form, and then check whether tacking on a sort operator at the end is better.

SEARCH TERMINATION

Approach #1: Wall-clock Time

→ Stop after the optimizer runs for some length of time.

Approach #2: Cost Threshold

→ Stop when the optimizer finds a plan that has a lower cost than some threshold.

Approach #3: Exhaustion

→ Stop when there are no more enumerations of the target plan. Usually done per sub-plan/group.

Approach #4: Transformation Count

→ Stop after a certain number of transformations have been considered.

HEURISTICS + COST-BASED SEARCH

Advantages:

→ Usually finds a reasonable plan without having to perform an exhaustive search.

Disadvantages:

→ All the same problems as the heuristic-only approach.
→ Left-deep join trees are not always optimal.
→ Must take in consideration the physical properties of data in the cost model (e.g., sort order).

OBSERVATION

Writing query transformation rules in a procedural language is hard and error-prone.

→ No easy way to verify that the rules are correct without running a lot of fuzz tests.

→ Generation of physical operators per logical operator is decoupled from deeper semantics about query.

A better approach is to use a declarative DSL to write the transformation rules and then have the optimizer enforce them during planning.

OPTIMIZER GENERATORS

Framework to allow a DBMS implementer to write the declarative rules for optimizing queries.

→ Separate the search strategy from the data model.

→ Separate the transformation rules and logical operators from physical rules and physical operators.

The implementation of the optimizer's pattern matching method and transformation rules can be independent of its search strategy.

OPTIMIZER GENERATORS

Choice #1: Stratified Search

→ Planning is done in multiple stages (heuristics then cost-based search).

→ Examples: Starburst, CockroachDB

Choice #2: Unified Search

→ Perform query planning all at once.

→ Examples: Cascades, OPT++, SQL Server

STRATIFIED SEARCH

First rewrite the logical query plan using transformation rules.

→ The engine checks whether the transformation is allowed before it can be applied.

→ Cost is never considered in this step.

Then perform a cost-based search to map the logical plan to a physical plan.

STARBURST OPTIMIZER

Better implementation of the System R optimizer that uses declarative rules.

Stage #1: Query Rewrite

→ Compute a SQL-block-level, relational calculus-like representation of queries.

Stage #2: Plan Optimization

→ Execute a System R-style (**bottoms-up**) dynamic programming phase once query rewrite has completed.

Example: Latest version of IBM DB2

Lohman

GRAMMAR-LIKE FUNCTIONAL RULES FOR REPRESENTING QUERY OPTIMIZATION ALTERNATIVES
SIGMOD 1988

STARBURST

Better implementation of t
that uses declarative rules.

Stage #1: Query Rewrite

→ Compute a SQL-block-level,
representation of queries.

Stage #2: Plan Optimizati

→ Execute a System R-style (**bo**
programming phase once qu

Example: Latest version o

Perspectives

Four DB2 Code Bases?

Many years ago I worked on IBM DB2 and so I occasionally get the question, "how the heck could you folks possibly have four relational database management system code bases?" Some go on to argue that a single code base would have been much more efficient. That's certainly true. And, had we moved to a single code base, that engineering resource efficiency improvement would have led to a very different outcome in the database wars. I'm skeptical on this extension of the argument but the question is an interesting one and I wrote up a more detailed answer than usually possible off the cuff.

————————

IBM Relational Database Code Bases

Few server manufacturers have the inclination and the resources needed to develop a relational database management system and yet IBM has internally developed and continues to support four independent, full-featured relational database products. A production-quality RDBMS with a large customer base is typically well over a million lines of code and represents a multi-year effort of hundreds and, in some cases, thousands of engineers. These are massive undertakings requiring special skills, so the question sometimes comes up, how could IBM possibly end up with four different RDBMS systems that don't share components?

At least while I was at IBM, there was frequent talk of developing a single RDBMS code base for all supported hardware and operating systems. The reasons why this didn't happen are at least partly social and historical, but there are also many strong technical challenges that make it difficult rewind the clock and use a single code base. The diversity of the IBM hardware and operating platforms would have made it difficult, the deep exploitation of unique underlying platform characteristics like the single level store on the AS/400 or the Sysplex Data Sharing on System z would make it truly challenging, the implementation languages used by many of the RDBMS code bases

GRAMMAR-LIKE FUNCTIONAL RULES FOR REPRESENTING
QUERY OPTIMIZATION ALTERNATIVES
SIGMOD 1988

STARBURST

Better implementation of t
that uses declarative rules.

Stage #1: Query Rewrite

→ Compute a SQL-block-level,
representa

Stage #2: Pl

→ Execute a S
programm

Example: I

Perspectives

Four DB2 Code Bases?

Many years ago I worked on IBM DB2 and so I occasionally get the question, "how the heck could you folks possibly have four relational database management system code bases?" Some go on to argue that a single code base would have been much more efficient. That's certainly true. And, had we moved to a single code base, that engineering resource efficiency improvement would have led to a very different outcome in the database wars. I'm skeptical on this extension of the argument but the question is an interesting one and I wrote up a more detailed answer than usually possible off the cuff.

Bases

to develop a
oped and
products. A
r a million
cases,
l skills, so the
different

RDBMS code
this didn't
ong technical
se. The
t difficult, the
deep exploitation of unique underlying platform characteristics like the single level store on the AS/400 or the Sysplex Data Sharing on System z would make it truly challenging, the implementation languages used by many of the RDBMS code bases

There was a lot to be done and very little time. The pressure was mounting and we were looking at other solutions from a variety of different sources when the IBM Almaden database research team jumped in. They offered to put the entire Almaden database research team on the project, with a goal to both replace the OS/2 DBM optimizer and execution engine with Starburst (Database research project) components and to help solve the scaling and stability problems we were currently experiencing in the field. Taking a research code base is a dangerous step for any development team, but this proposal was different in that the authors would accompany the code base. Pat Selinger of IBM Almaden Research essentially convinced us that we would have a world-class optimizer and execution engine and we would have the full-time commitment from Pat, Bruce Lindsay, Guy Lohman, C. Mohan, Hamid Pirahesh, John McPherson and the rest of the IBM Almaden database research team working shoulder to shoulder with us in making this product successful.

GRAMMAR-LIKE FUNCTIONAL RULES FOR RE
QUERY OPTIMIZATION ALTERNATIVES
SIGMOD 1988

STARBURST OPTIMIZER

Advantages:

→ Works well in practice with fast performance.

Disadvantages:

→ Difficult to assign priorities to transformations

→ Some transformations are difficult to assess without computing multiple cost estimations.

→ Rules maintenance is a huge pain because they are written in IBM's Query Graph Model (QGM) DSL.

UNIFIED SEARCH

Unify the notion of both logical→logical and logical→physical transformations.

- → No need for separate stages because everything is transformations.

This approach generates many transformations, so it makes heavy use of memoization to reduce redundant work.

VOLCANO OPTIMIZER

Graefe

General purpose cost-based query optimizer, based on equivalence rules on algebras.

→ Easily add new operations and equivalence rules.
→ Treats physical properties of data as first-class entities during planning.
→ **Top-down approach** (backward chaining) using branch-and-bound search.

Example: Academic prototypes

THE VOLCANO OPTIMIZER GENERATOR: EXTENSIBILITY AND EFFICIENT SEARCH
ICDE 1993

Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

ARTIST ⋈ APPEARS ⋈ ALBUM
ORDER-BY(ARTIST.ID)

Logical Op

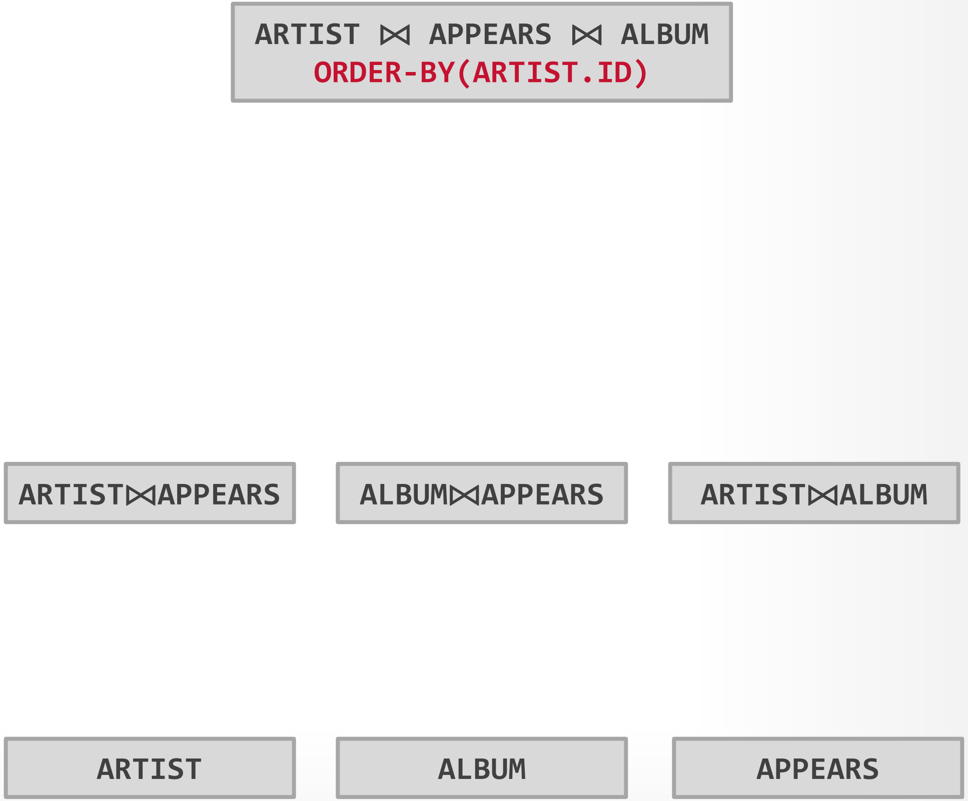
Physical Op

TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)
→ **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

Physical Op

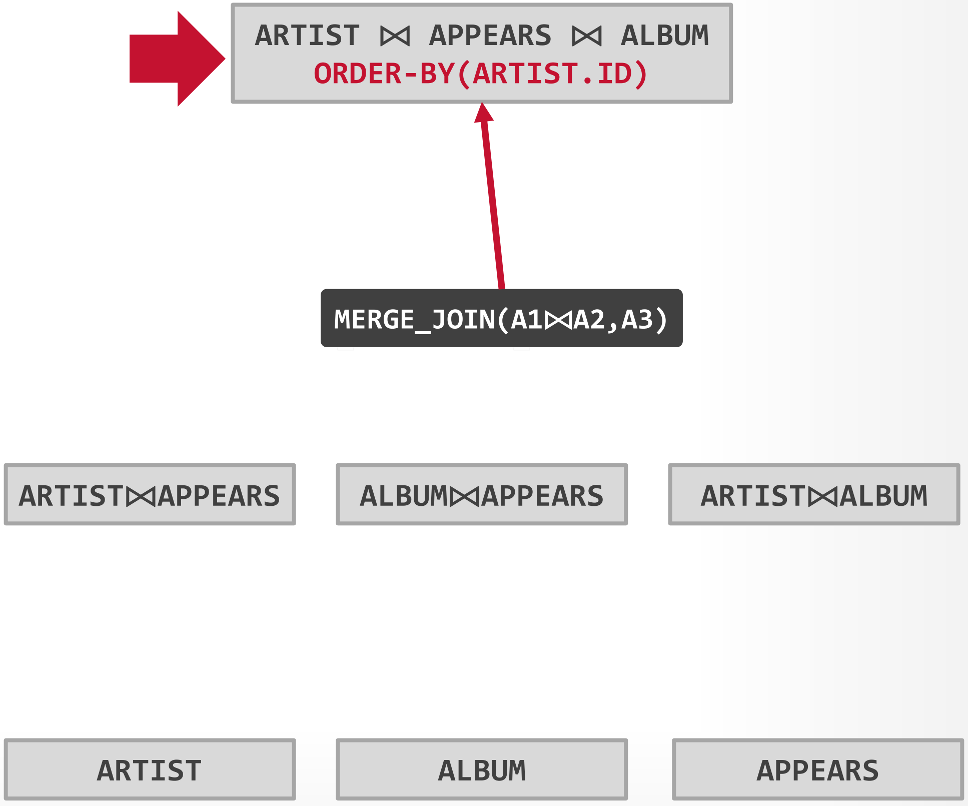
TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

Physical Op

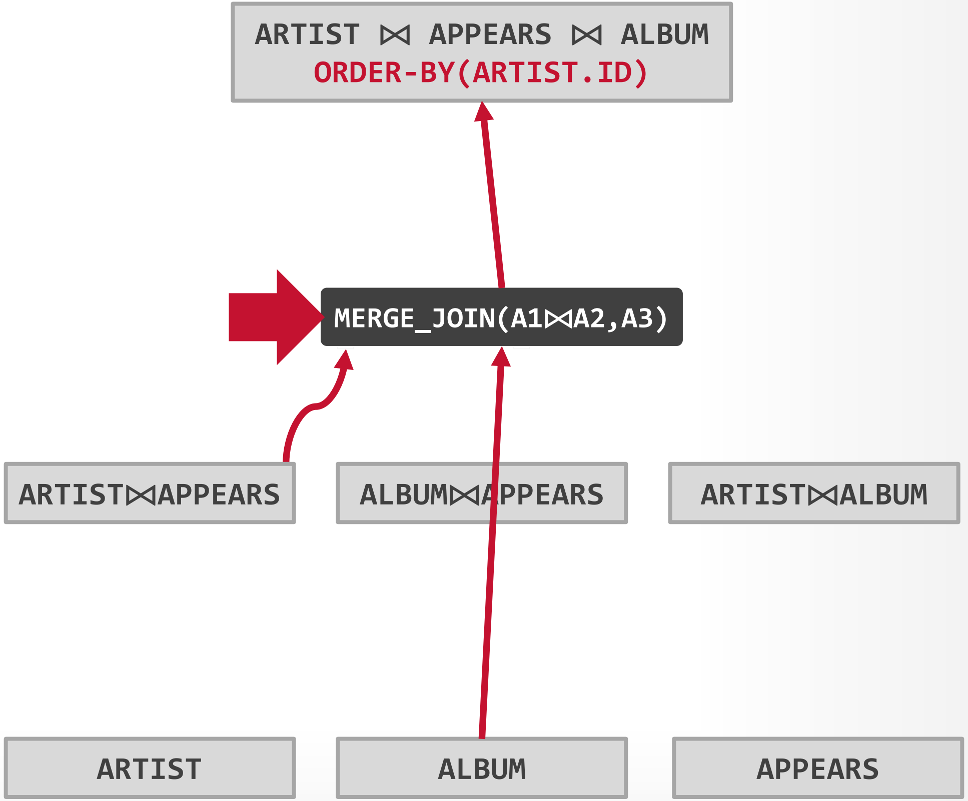
TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

Physical Op

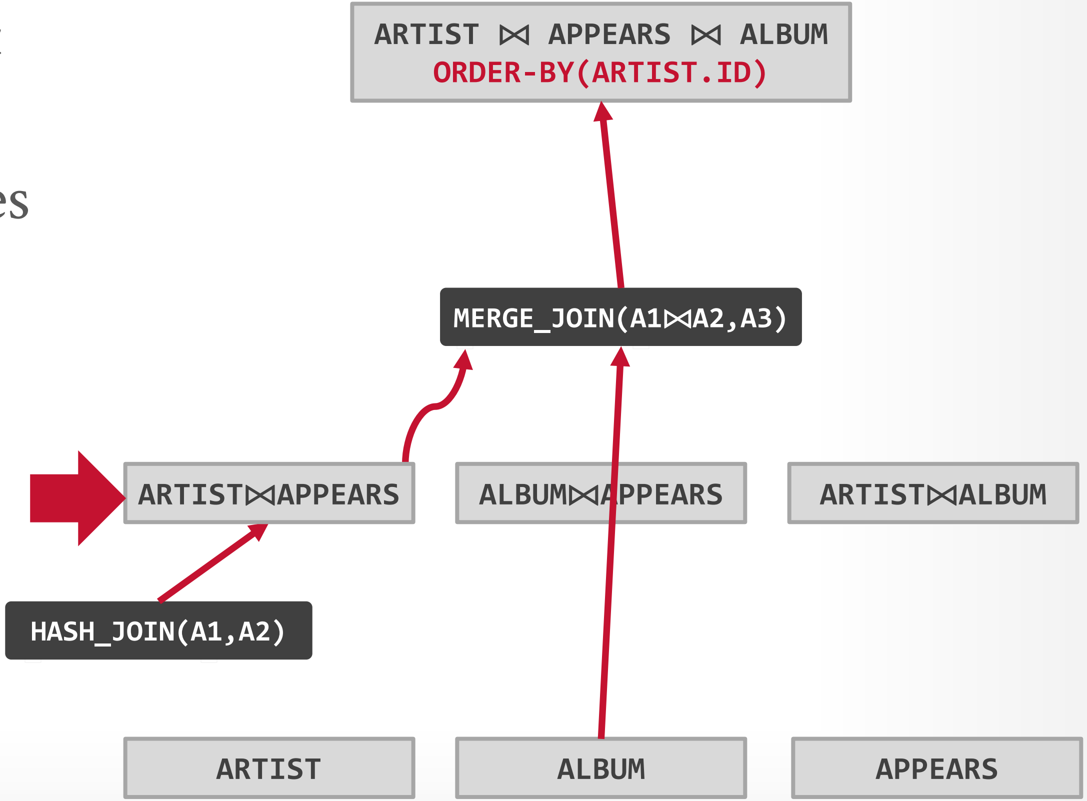
TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:** JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:** JOIN(A,B) to HASH_JOIN(A,B)



Logical Op
Physical Op

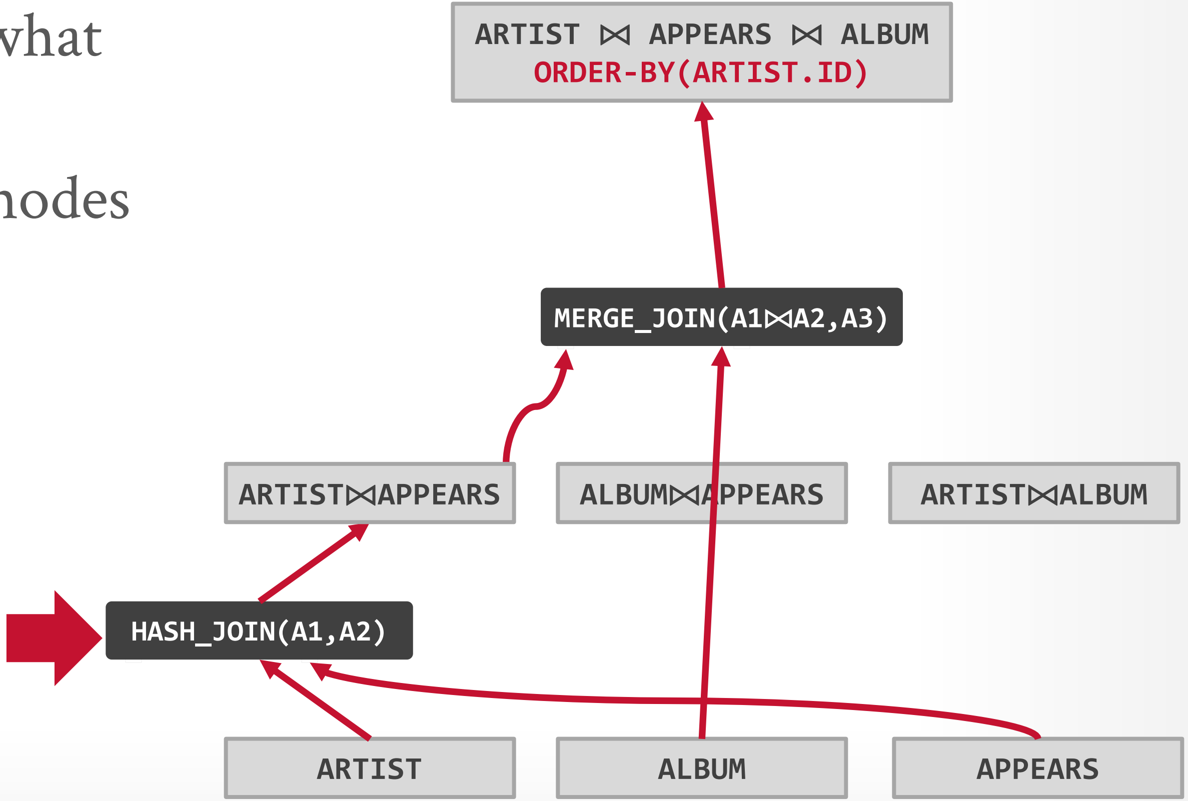
TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

Physical Op

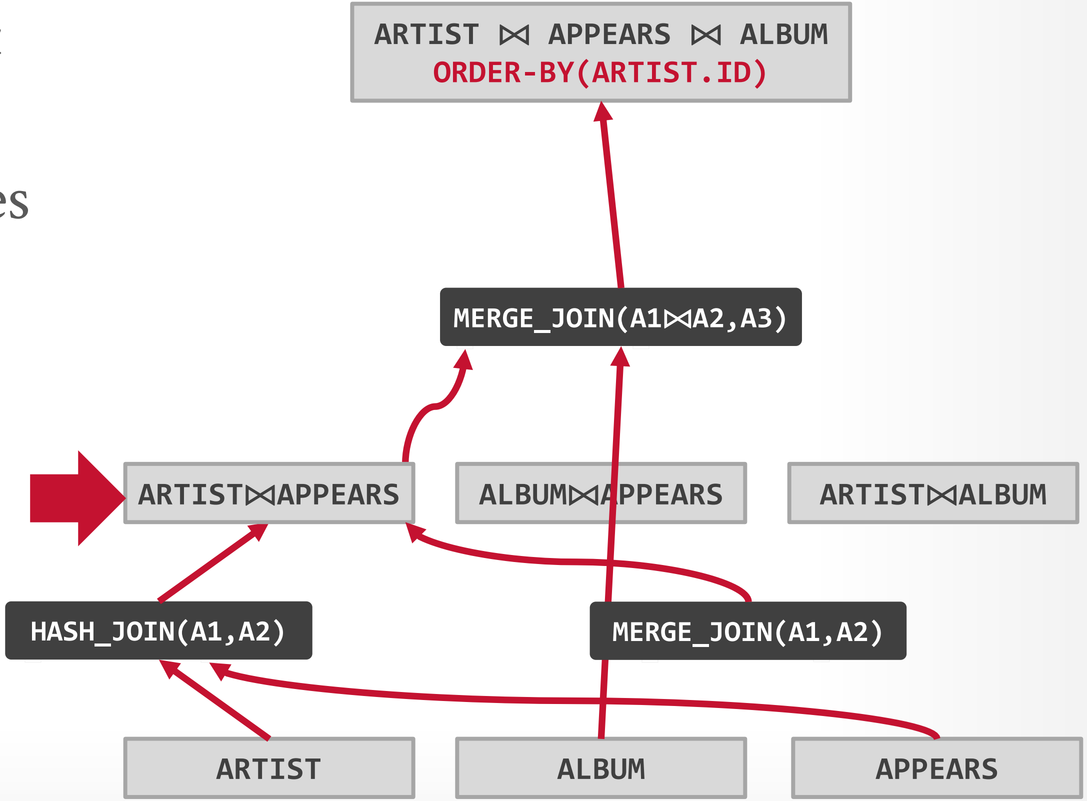
TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

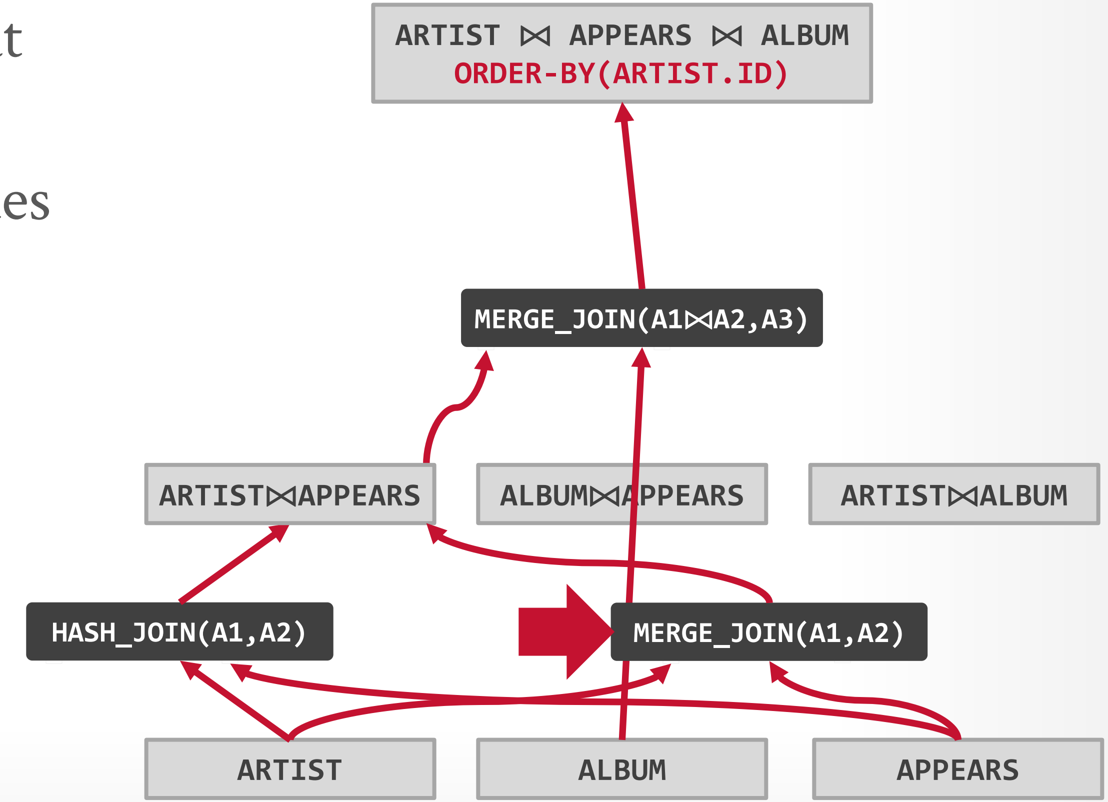
Physical Op

TOP-DOWN OPTIMIZATION

Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

- → **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)
- → **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)



Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

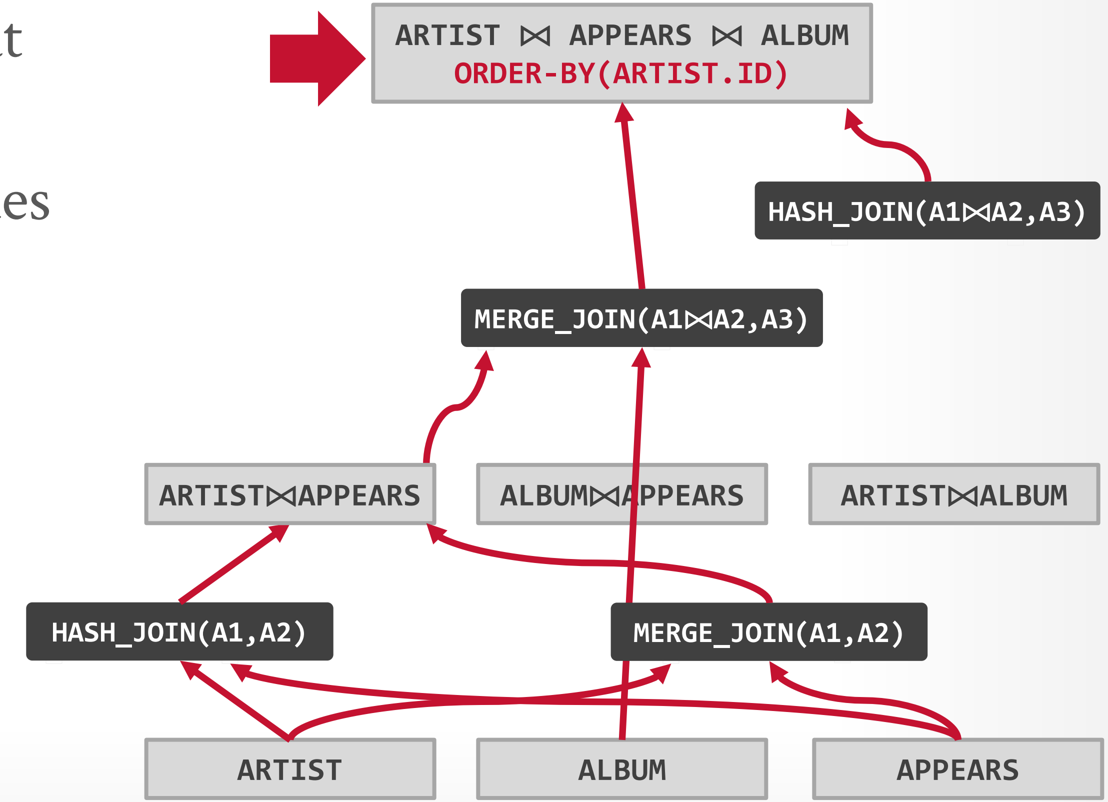
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

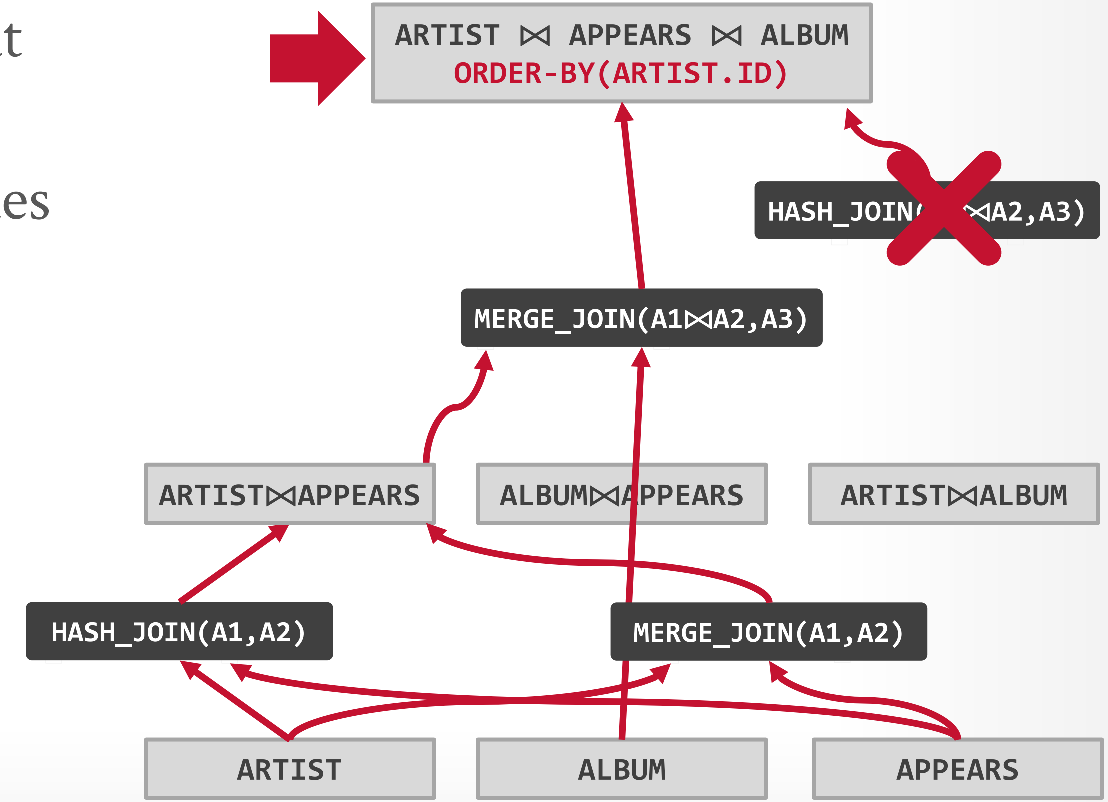
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

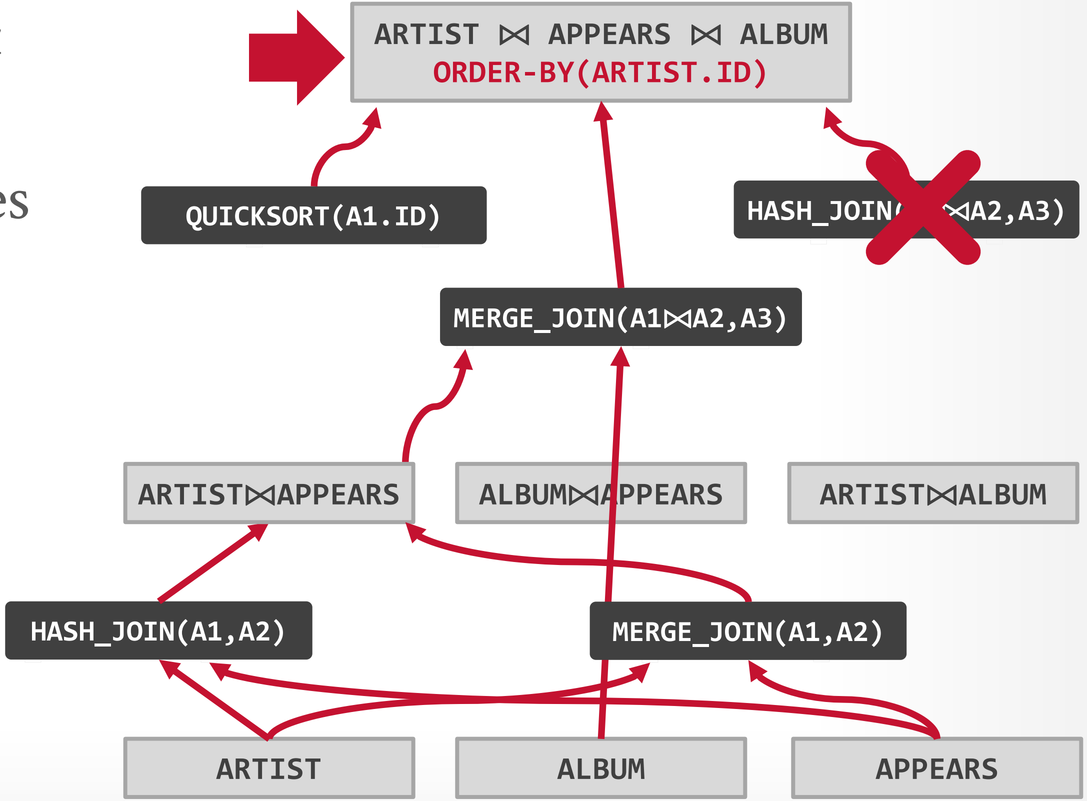
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

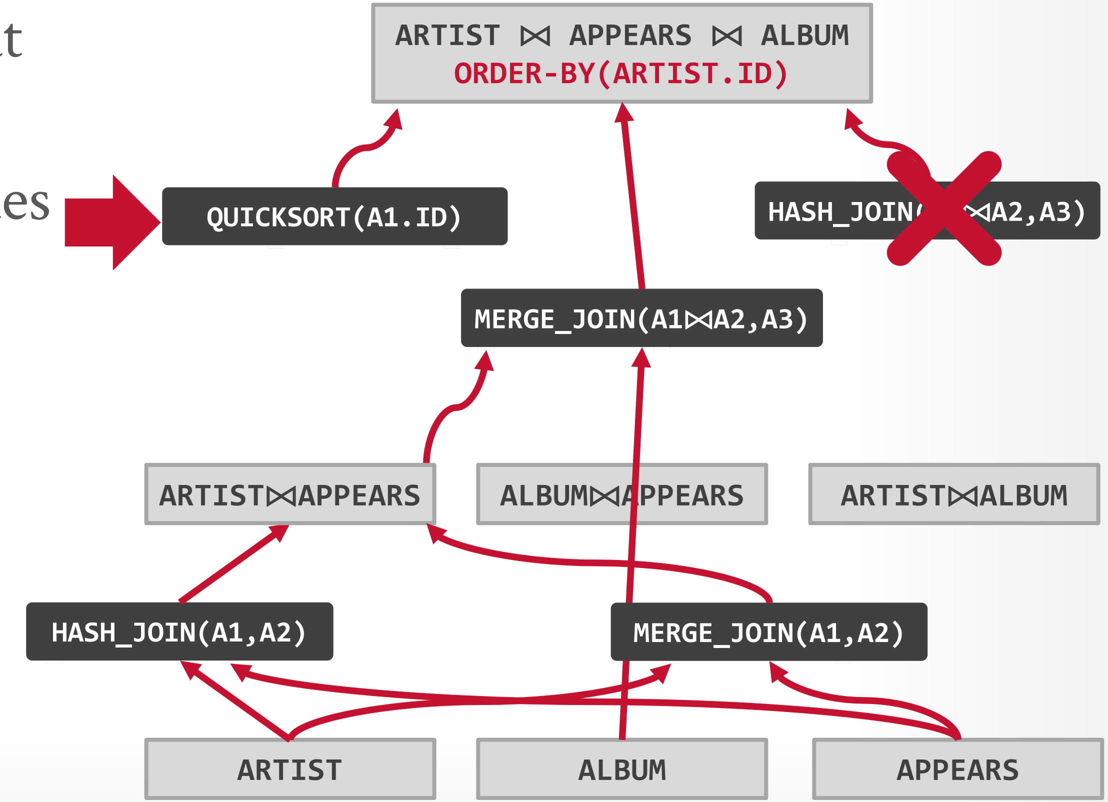
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



Logical Op

Physical Op

TOP-DOWN OPTIMIZATION

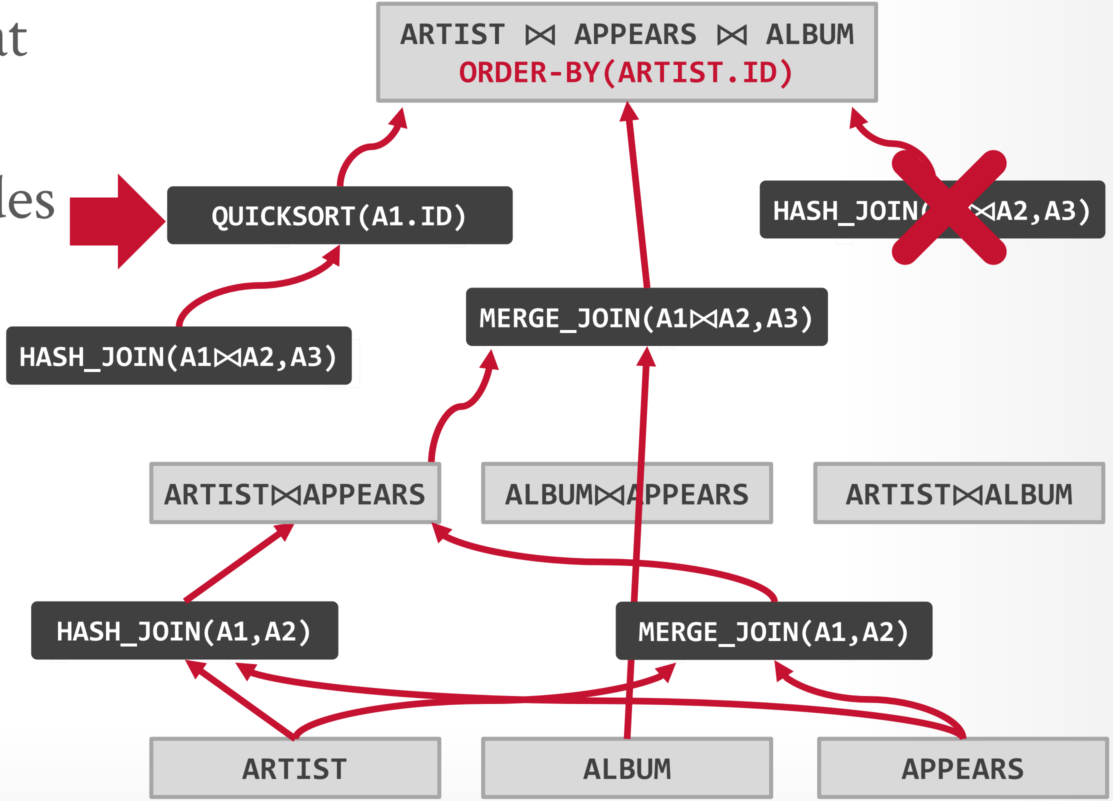
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



Logical Op
Physical Op

TOP-DOWN OPTIMIZATION

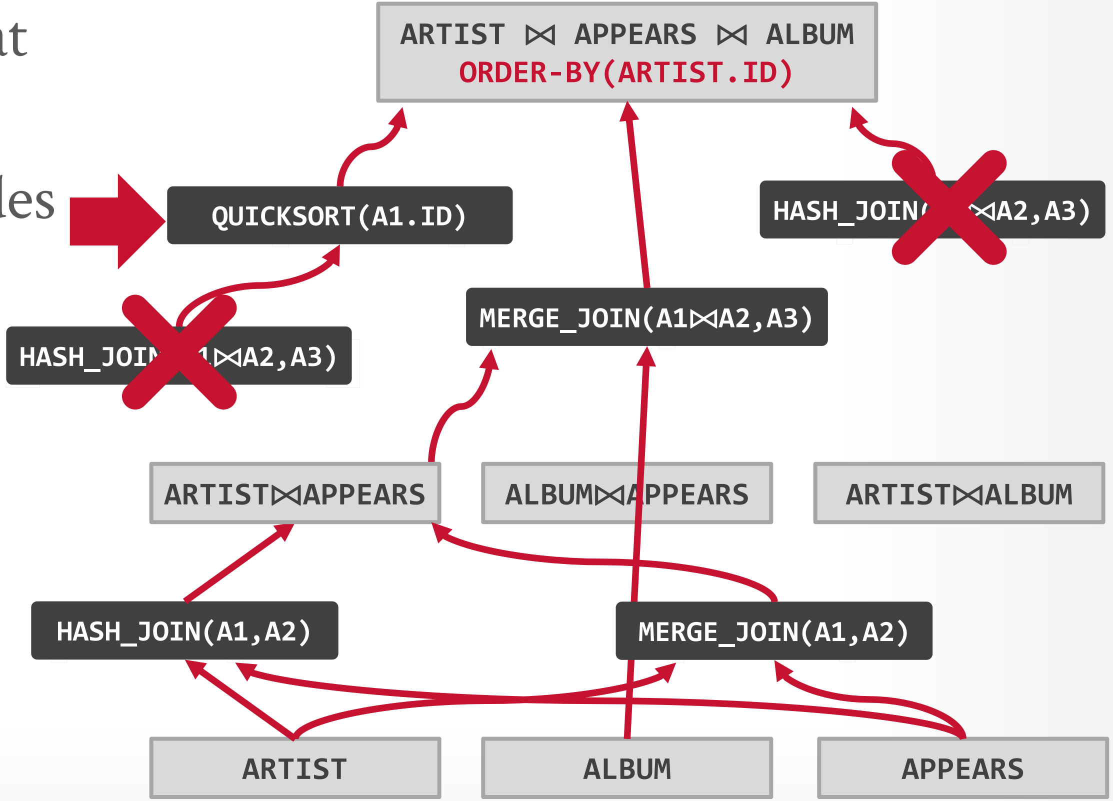
Start with a logical plan of what we want the query to be.

Invoke rules to create new nodes and traverse tree.

→ **Logical→Logical:**
  JOIN(A,B) to JOIN(B,A)

→ **Logical→Physical:**
  JOIN(A,B) to HASH_JOIN(A,B)

Can create "enforcer" rules that require input to have certain properties.



VOLCANO OPTIMIZER

Advantages:

→ Use declarative rules to generate transformations.

→ Better extensibility with an efficient search engine. Reduce redundant estimations using memoization.

Disadvantages:

→ All equivalence classes are completely expanded to generate all possible logical operators before the optimization search.

→ Not easy to modify predicates.

CASCADES OPTIMIZER

Object-oriented implementation of the previous Volcano query optimizer.
→ **Top-down approach** (backward chaining) using branch-and-bound search.

Graefe

Supports expression re-writing through a direct mapping function rather than an exhaustive search.

THE CASCADES FRAMEWORK FOR QUERY OPTIMIZATION
IEEE DATA ENGINEERING BULLETIN 1995

EFFICIENCY IN THE COLUMBIA DATABASE QUERY OPTIMIZER
PORTLAND STATE UNIVERSITY MS THESIS 1998

CASCADES: KEY IDEAS

Optimization tasks as data structures.
→ Patterns to match + Transformation Rule to apply

Rules to place property enforcers.
→ Ensures the optimizer generates correct plans.

Ordering of moves by promise.
→ Dynamic task priorities to find optimal plan more quickly.

Predicates as logical/physical operators.
→ Use same pattern/rule engine for expressions.

EFFICIENCY IN THE COLUMBIA
DATABASE QUERY OPTIMIZER
PORTLAND STATE UNIVERSITY MS THESIS 1998

CASCADES: EXPRESSIONS

An **expression** represents some operation in the query with zero or more input expressions.

→ Optimizer needs to quickly determine whether two expressions are equivalent.

```
SELECT * FROM A
  JOIN B ON A.id = B.id
  JOIN C ON C.id = A.id;
```

Logical Expression: $(A \bowtie B) \bowtie C$

Physical Expression: $(A_{Seq} \bowtie_{HJ} B_{Seq}) \bowtie_{NL} C_{Idx}$

CASCADES: GROUPS

A **group** is a set of logically equivalent logical and physical expressions that produce the same output.

→ All logical forms of an expression.

→ All physical expressions that can be derived from selecting the allowable physical operators for the corresponding logical forms.

Group

Output: [ABC] Properties: *None*	Logical Exps	Physical Exps
	1. (A⋈B)⋈C	1. $(A_{Seq} \bowtie_{NL} B_{Seq}) \bowtie_{NL} C_{Seq}$
	2. (B⋈C)⋈A	2. $(B_{Seq} \bowtie_{NL} C_{Seq}) \bowtie_{NL} A_{Seq}$
	3. (A⋈C)⋈B	3. $(A_{Seq} \bowtie_{NL} C_{Seq}) \bowtie_{NL} B_{Seq}$
	4. A⋈(B⋈C)	4. $A_{Seq} \bowtie_{NL} (C_{Seq} \bowtie_{NL} B_{Seq})$
	⋮	⋮

CASCADES: GROUPS

A **group** is a set of logically equivalent logical and physical expressions that produce the same output.

→ All logical forms of an expression.

→ All physical expressions that can be derived from selecting the allowable physical operators for the corresponding logical forms.

Group

Output: [ABC] Properties: *None*	Logical Exps	Physical Exps
	1. $(A \bowtie B) \bowtie C$	1. $(A_{Seq} \bowtie_{NL} B_{Seq}) \bowtie_{NL} C_{Seq}$
	2. $(B \bowtie C) \bowtie A$	2. $(B_{Seq} \bowtie_{NL} C_{Seq}) \bowtie_{NL} A_{Seq}$
	3. $(A \bowtie C) \bowtie B$	3. $(A_{Seq} \bowtie_{NL} C_{Seq}) \bowtie_{NL} B_{Seq}$
	4. $A \bowtie (B \bowtie C)$	4. $A_{Seq} \bowtie_{NL} (C_{Seq} \bowtie_{NL} B_{Seq})$
	⋮	⋮

Equivalent Expressions

CASCADES: MULTI-EXPRESSION

Instead of explicitly instantiating all possible expressions in a group, the optimizer implicitly represents redundant expressions in a group as a **multi-expression**.

→ This reduces the number of transformations, storage overhead, and repeated cost estimations.

Output: [ABC] Properties: *None*	Logical Multi-Exps	Physical Multi-Exps
	1. [AB]⋈[C]	1. $[AB]\bowtie_{SM}[C]$
	2. [BC]⋈[A]	2. $[AB]\bowtie_{HJ}[C]$
	3. [AC]⋈[B]	3. $[AB]\bowtie_{NL}[C]$
	4. [A]⋈[BC]	4. $[BC]\bowtie_{SM}[A]$
	⋮	⋮

CASCADES: RULES

A **rule** is a transformation of an expression to a logically equivalent expression.

→ **Transformation Rule:** Logical to Logical

→ **Implementation Rule:** Logical to Physical

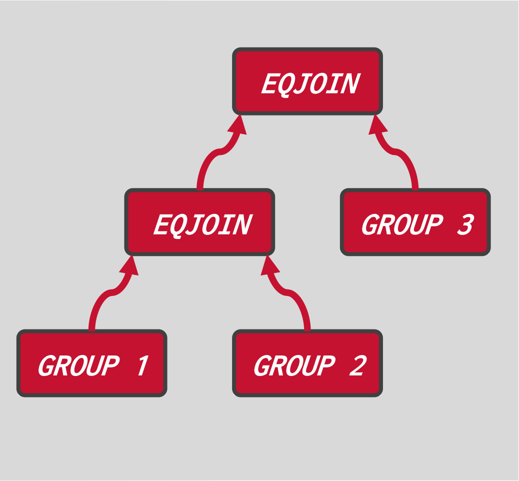
Each rule is represented as a pair of attributes:

→ **Pattern**: Defines the structure of the logical expression that can be applied to the rule.

→ **Substitute**: Defines the structure of the result after applying the rule.

CASCADES: RULES

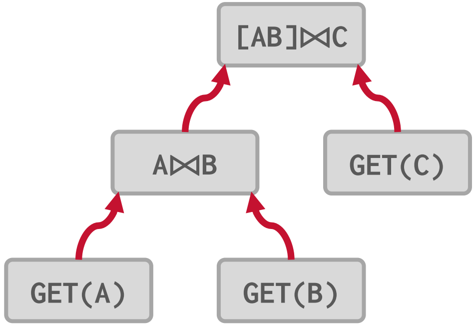
Pattern



Group

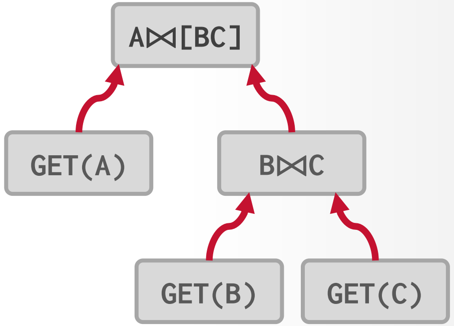
Logical Expr

Physical Expr

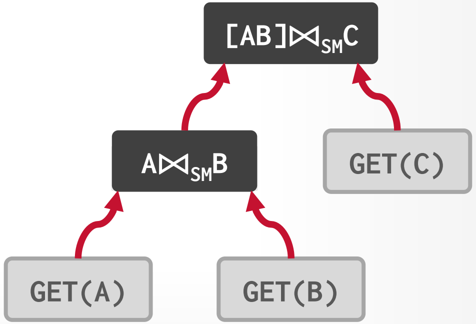


Matching Plan

Transformation Rule
Rotate Left-to-Right



Implementation Rule
EQJOIN→SORTMERGE



CASCADES: MEMO TABLE

Stores all previously explored alternatives in a compact graph structure / hash table.

Equivalent operator trees and their corresponding plans are stored together in groups.

Provides an overview of the optimizer's search progress that is used in multiple ways:
→ Transformation Result Memorization
→ Duplicate Group Detection
→ Property + Cost Management.

PRINCIPLE OF OPTIMALITY

Every sub-plan of an optimal plan is itself optimal.

This allows the optimizer to restrict the search space to a smaller set of expressions.

→ The optimizer never has to consider a plan containing sub-plan **P1** that has a greater cost than equivalent plan **P2** with the same physical properties.

EXPLOITING UPPER AND LOWER BOUNDS IN TOP-DOWN QUERY OPTIMIZATION
IDEAS 2001

CASCADES: MEMO TABLE

	Best Expr	Cost
[ABC]		
[AB]		
[A]		
[B]		
[C]		

Output: [ABC] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [AB]⋈[C]	

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]		
[B]		
[C]		

Output:
[ABC]

Properties:
None

Logical M-Exps
1. [AB]⋈[C]

Physical M-Exps

Output:
[AB]

Properties:
None

Logical M-Exps
1. [A]⋈[B]

Physical M-Exps

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]		
[B]		
[C]		

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [AB]⋈[C]	

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [A]⋈[B]	

Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	1. SeqScan(A) 2. IdxScan(A)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]		
[C]		

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [AB]⋈[C]	

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [A]⋈[B]	

Cost: 10

Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	1. SeqScan(A) 2. IdxScan(A)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]		
[C]		

Output: [ABC] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [AB]⋈[C]	

Output: [AB] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [A]⋈[B]	

Cost: 10

Output: [A] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(A)	1. SeqScan(A)
		2. IdxScan(A)

Output: [B] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(B)	1. SeqScan(B)
		2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	Cost
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		

Output: [ABC] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [AB]⋈[C]	

Output: [AB] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [A]⋈[B]	

Cost: 10

Output: [A] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(A)	1. SeqScan(A)
		2. IdxScan(A)

Cost: 20

Output: [B] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(B)	1. SeqScan(B)
		2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	Cost
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		

Output: [ABC] Properties: None	Logical M-Exps	Physical M-Exps
	1. [AB]⋈[C]	

Output: [AB] Properties: None	Logical M-Exps	Physical M-Exps
	1. [A]⋈[B] 2. [B]⋈[A]	

Cost: 10

Output: [A] Properties: None	Logical M-Exps	Physical M-Exps
	1. GET(A)	1. SeqScan(A) 2. IdxScan(A)

Cost: 20

Output: [B] Properties: None	Logical M-Exps	Physical M-Exps
	1. GET(B)	1. SeqScan(B) 2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		

Output: [ABC] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [AB]⋈[C]	

Output: [AB] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. [A]⋈[B]	
	2. ~~[B]⋈[A]~~	

Cost: 10

Output: [A] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(A)	1. SeqScan(A)
		2. IdxScan(A)

Cost: 20

Output: [B] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(B)	1. SeqScan(B)
		2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]		
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [AB]$\bowtie$[C]	

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [A]$\bowtie$[B] 2. [B]$\bowtie$[A]	1. [A]$\bowtie_{NL}$[B] 2. [A]$\bowtie_{HJ}$[B] 3. [B]$\bowtie_{NL}$[A] 4. [B]$\bowtie_{HJ}$[A]

Cost: 10

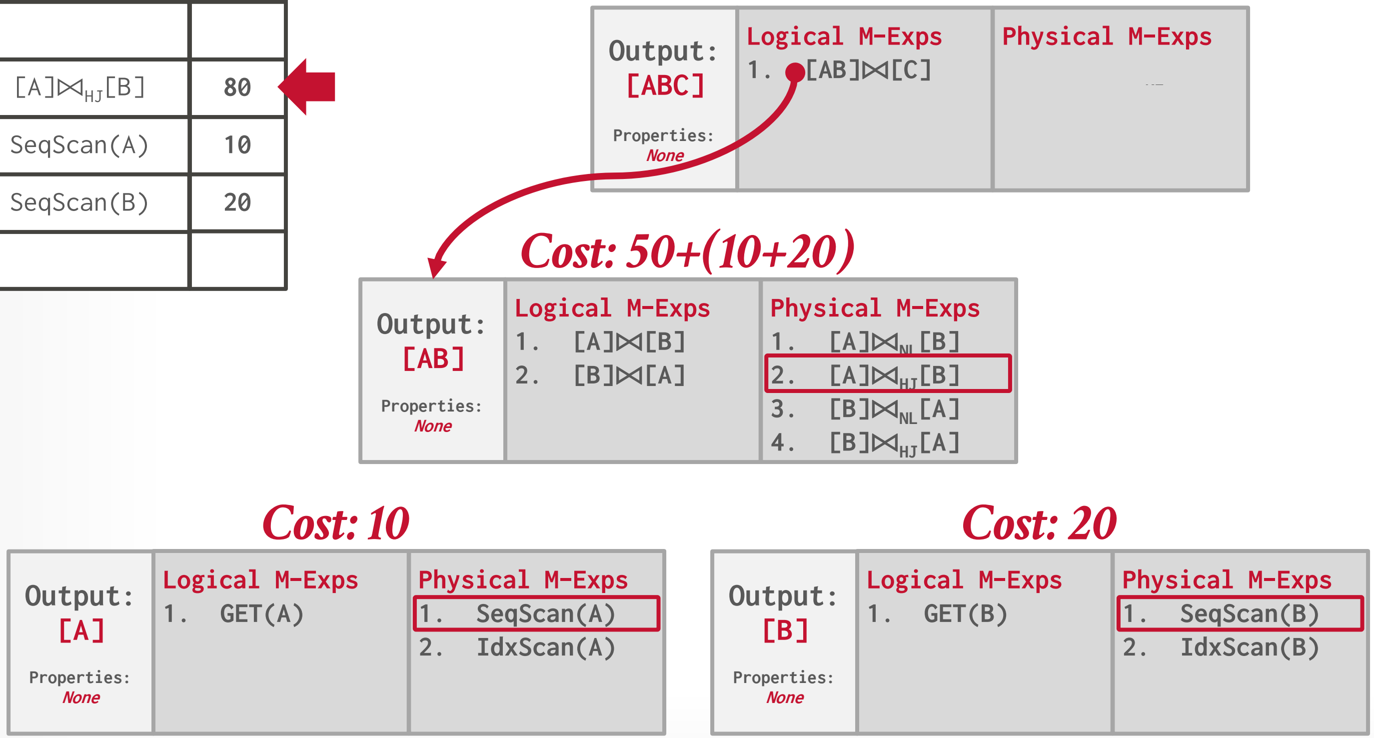
Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	$\boxed{\text{1. SeqScan(A)}}$ 2. IdxScan(A)

Cost: 20

Output: [B]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(B)	$\boxed{\text{1. SeqScan(B)}}$ 2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	Cost
[ABC]		
[AB]	$[A]\bowtie_{HJ}[B]$	80
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		



CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]	[A]$\bowtie_{HJ}$[B]	80
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]		

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [AB]⋈[C]	

Cost: 50+(10+20)

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. [A]⋈[B] 2. [B]⋈[A]	1. [A]$\bowtie_{NL}$[B] $\boxed{\text{2. [A]}\bowtie_{HJ}\text{[B]}}$ 3. [B]$\bowtie_{NL}$[A] 4. [B]$\bowtie_{HJ}$[A]

Output: [C]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(C)	

Cost: 10

Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	$\boxed{\text{1. SeqScan(A)}}$ 2. IdxScan(A)

Cost: 20

Output: [B]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(B)	$\boxed{\text{1. SeqScan(B)}}$ 2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]		
[AB]	$[A]\bowtie_{HJ}[B]$	80
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]	IdxScan(C)	5

Output: [ABC] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. $[AB]\bowtie[C]$	

Cost: 50+(10+20)

Output: [AB] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. $[A]\bowtie[B]$	1. $[A]\bowtie_{NL}[B]$
	2. $[B]\bowtie[A]$	2. $[A]\bowtie_{HJ}[B]$
		3. $[B]\bowtie_{NL}[A]$
		4. $[B]\bowtie_{HJ}[A]$

Cost: 5

Output: [C] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(C)	1. SeqScan(C)
		2. IdxScan(C)

Cost: 10

Output: [A] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(A)	1. SeqScan(A)
		2. IdxScan(A)

Cost: 20

Output: [B] Properties: *None*	Logical M-Exps	Physical M-Exps
	1. GET(B)	1. SeqScan(B)
		2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	Cost
[ABC]		
[AB]	$[A]\bowtie_{HJ}[B]$	80
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]	IdxScan(C)	5

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. $[AB]\bowtie[C]$ 2. $[BC]\bowtie[A]$ 3. $[AC]\bowtie[B]$ 4. $[B]\bowtie[AC]$	1. $[AB]\bowtie_{NL}C$ 2. $[BC]\bowtie_{NL}A$ 3. $[AC]\bowtie_{NL}B$ ⋮

Cost: 50+(10+20)

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. $[A]\bowtie[B]$ 2. $[B]\bowtie[A]$	1. $[A]\bowtie_{NL}[B]$ 2. $\boxed{[A]\bowtie_{HJ}[B]}$ 3. $[B]\bowtie_{NL}[A]$ 4. $[B]\bowtie_{HJ}[A]$

Cost: 5

Output: [C]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(C)	1. SeqScan(C) 2. IdxScan(C)

Cost: 10

Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	1. SeqScan(A) 2. IdxScan(A)

Cost: 20

Output: [B]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(B)	1. SeqScan(B) 2. IdxScan(B)

CASCADES: MEMO TABLE

	Best Expr	*Cost*
[ABC]	$([A]\bowtie_{HJ}[B])\bowtie_{HJ}[C]$	125
[AB]	$[A]\bowtie_{HJ}[B]$	80
[A]	SeqScan(A)	10
[B]	SeqScan(B)	20
[C]	IdxScan(C)	5

Cost: 40+(80+5)

Output: [ABC]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. $[AB]\bowtie[C]$	1. $[AB]\bowtie_{NL}C$
	2. $[BC]\bowtie[A]$	2. $[BC]\bowtie_{NL}A$
	3. $[AC]\bowtie[B]$	3. $[AC]\bowtie_{NL}B$
	4. $[B]\bowtie[AC]$	⋮

Cost: 50+(10+20)

Output: [AB]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. $[A]\bowtie[B]$	1. $[A]\bowtie_{NL}[B]$
	2. $[B]\bowtie[A]$	2. $[A]\bowtie_{HJ}[B]$
		3. $[B]\bowtie_{NL}[A]$
		4. $[B]\bowtie_{HJ}[A]$

Cost: 5

Output: [C]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(C)	1. SeqScan(C)
		2. IdxScan(C)

Cost: 10

Output: [A]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(A)	1. SeqScan(A)
		2. IdxScan(A)

Cost: 20

Output: [B]	Logical M-Exps	Physical M-Exps
Properties: *None*	1. GET(B)	1. SeqScan(B)
		2. IdxScan(B)

CASCADES IMPLEMENTATIONS

Standalone:

→ Wisconsin OPT++ (1990s)
→ Portland State Columbia (1990s)
→ Greenplum Orca (2010s)
→ Apache Calcite (2010s)

Integrated:

→ Microsoft SQL Server (1990s)
→ Tandem NonStop SQL (1990s)
→ CockroachDB (2010s)

RANDOMIZED ALGORITHMS

Perform a random walk over a solution space of all possible (valid) plans for a query.

Continue searching until a cost threshold is reached or the optimizer runs for a length of time.

Examples: Postgres' genetic algorithm.

SIMULATED ANNEALING

Start with a query plan that is generated using the heuristic-only approach.

Compute random permutations of operators (e.g., swap the join order of two tables):

→ Always accept a change that reduces cost.
→ Only accept a change that increases cost with some probability.
→ Reject any change that violates correctness (e.g., sort ordering).

QUERY OPTIMIZATION BY SIMULATED ANNEALING
SIGMOD 1987

POSTGRES GENETIC OPTIMIZER

More complicated queries use a **genetic algorithm** that selects join orderings (GEQO).

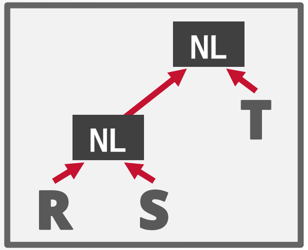
At the beginning of each round, generate different variants of the query plan.

Select the plans that have the lowest cost and permute them with other plans. Repeat.
→ The mutator function only generates valid plans.

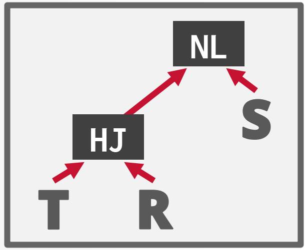
Source: Postgres Documentation

POSTGRES GENETIC OPTIMIZER

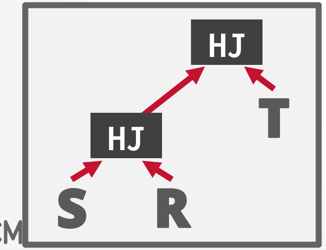
1st Generation



Cost: 300

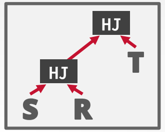


Cost: 200



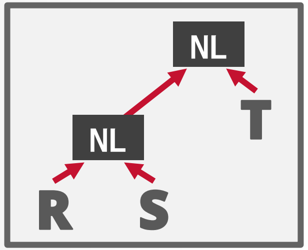
Cost: 100

POSTGRES GENETIC OPTIMIZER

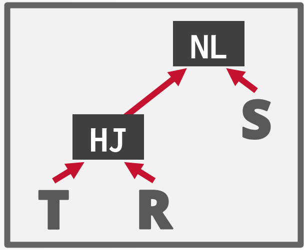


Best:100

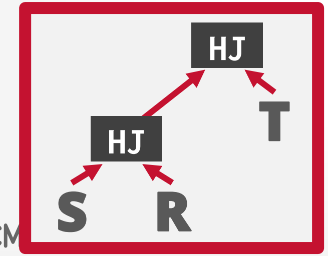
1st Generation



Cost: 300

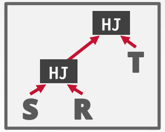


Cost: 200



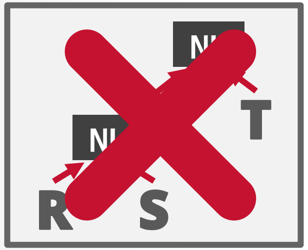
Cost: 100

POSTGRES GENETIC OPTIMIZER

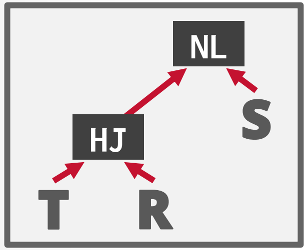


Best:100

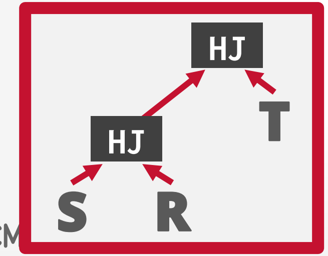
1st Generation



Cost:
300

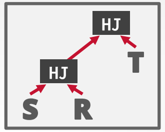


Cost:
200



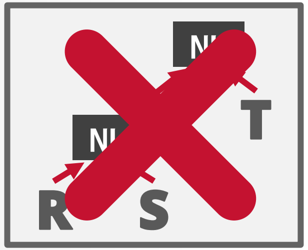
Cost:
100

POSTGRES GENETIC OPTIMIZER

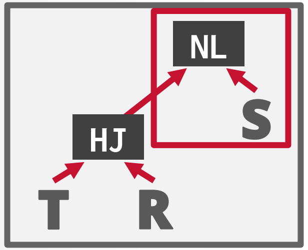


Best:100

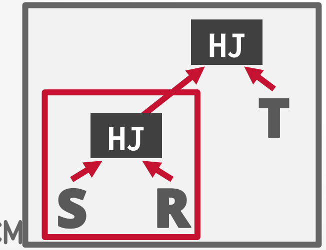
1st Generation



Cost: 300

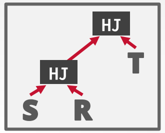


Cost: 200



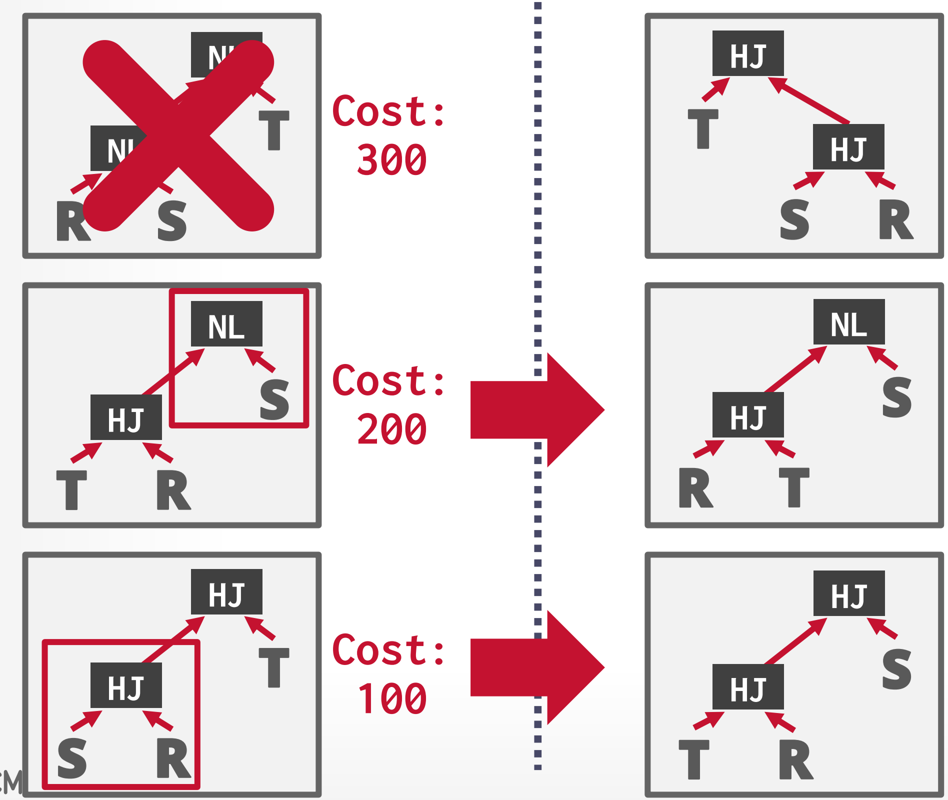
Cost: 100

POSTGRES GENETIC OPTIMIZER

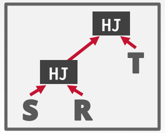


Best:100

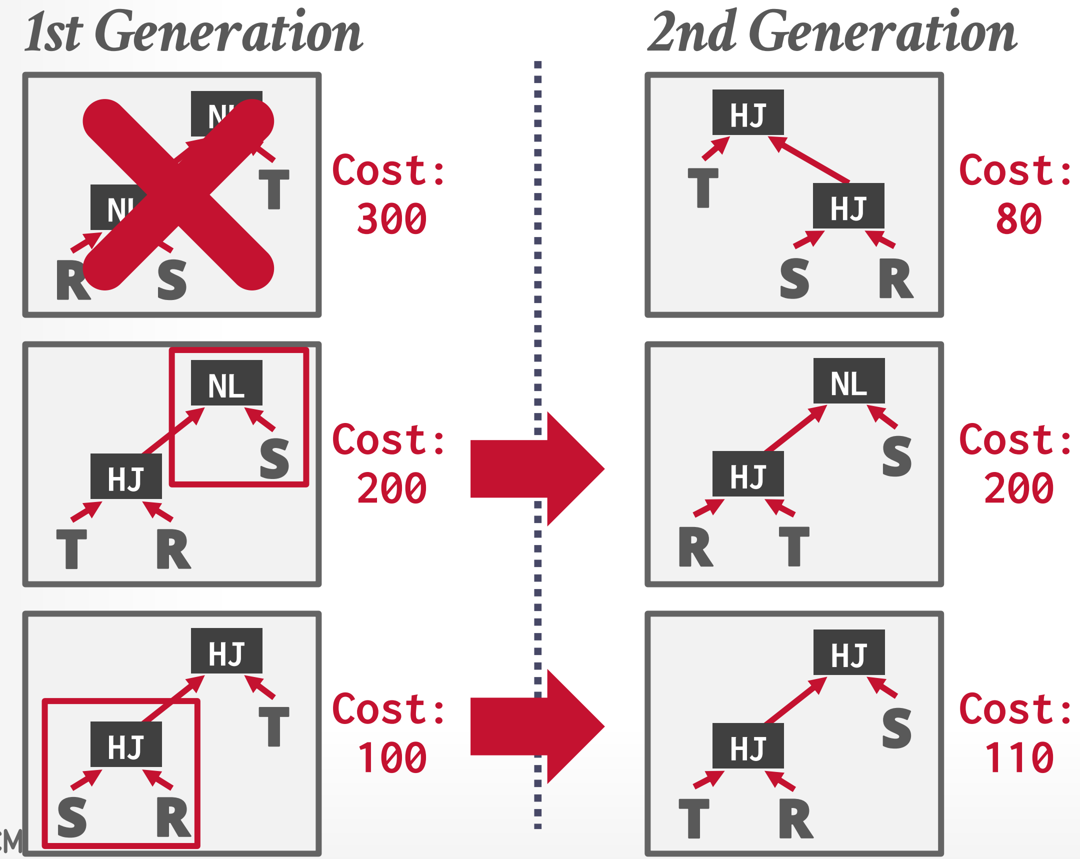
1st Generation *2nd Generation*



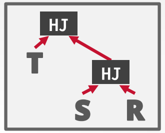
POSTGRES GENETIC OPTIMIZER



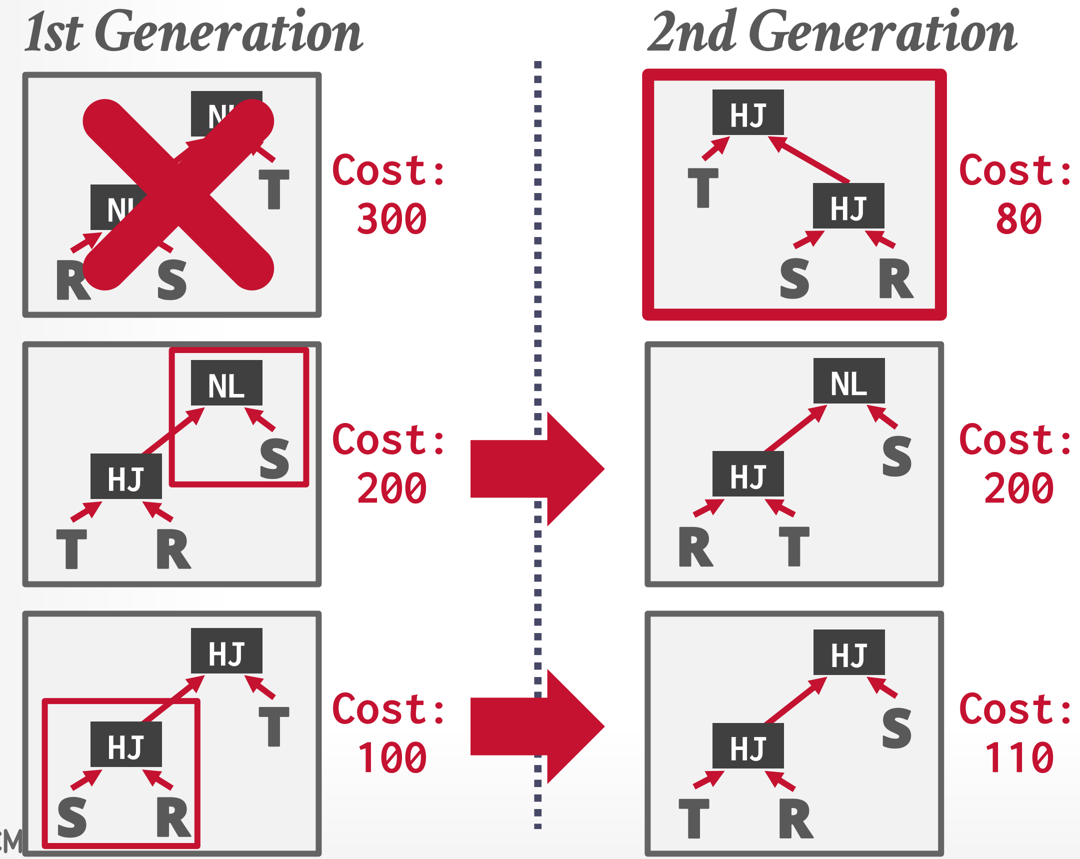
Best:100



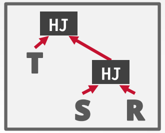
POSTGRES GENETIC OPTIMIZER



Best:80

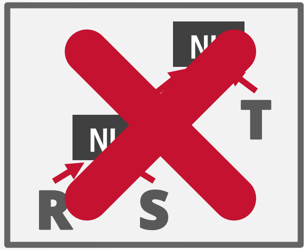


POSTGRES GENETIC OPTIMIZER

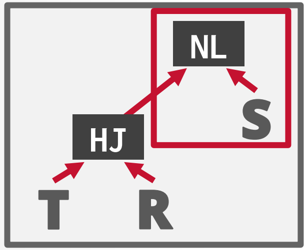


Best:80

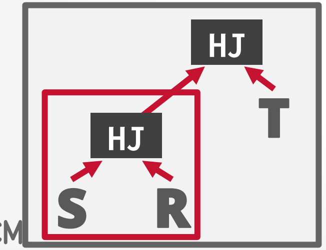
1st Generation



Cost: 300

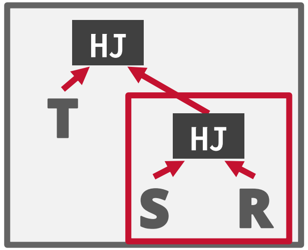


Cost: 200

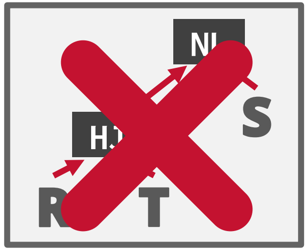


Cost: 100

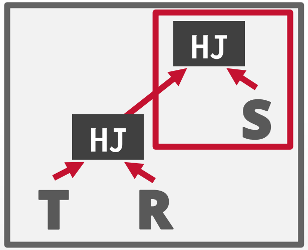
2nd Generation



Cost: 80

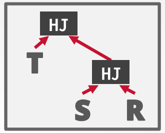


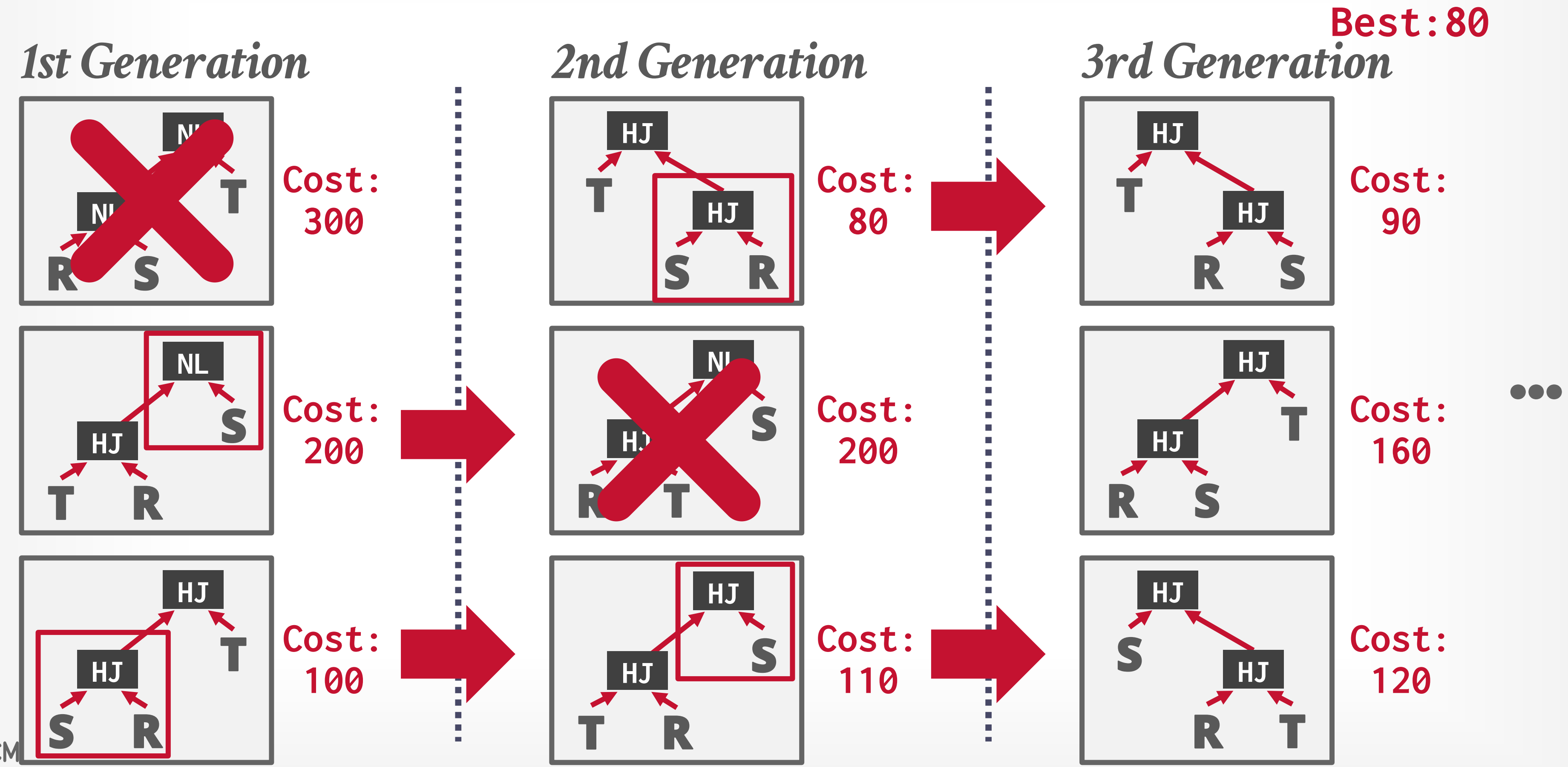
Cost: 200



Cost: 110

POSTGRES GENETIC OPTIMIZER





RANDOMIZED ALGORITHMS

Advantages:

→ Jumping around the search space randomly allows the optimizer to get out of local minimums.
→ Low memory overhead (if no history is kept).

Disadvantages:

→ Difficult to determine why the DBMS may have chosen a plan.
→ Must do extra work to ensure that query plans are deterministic.
→ Still must implement correctness rules.

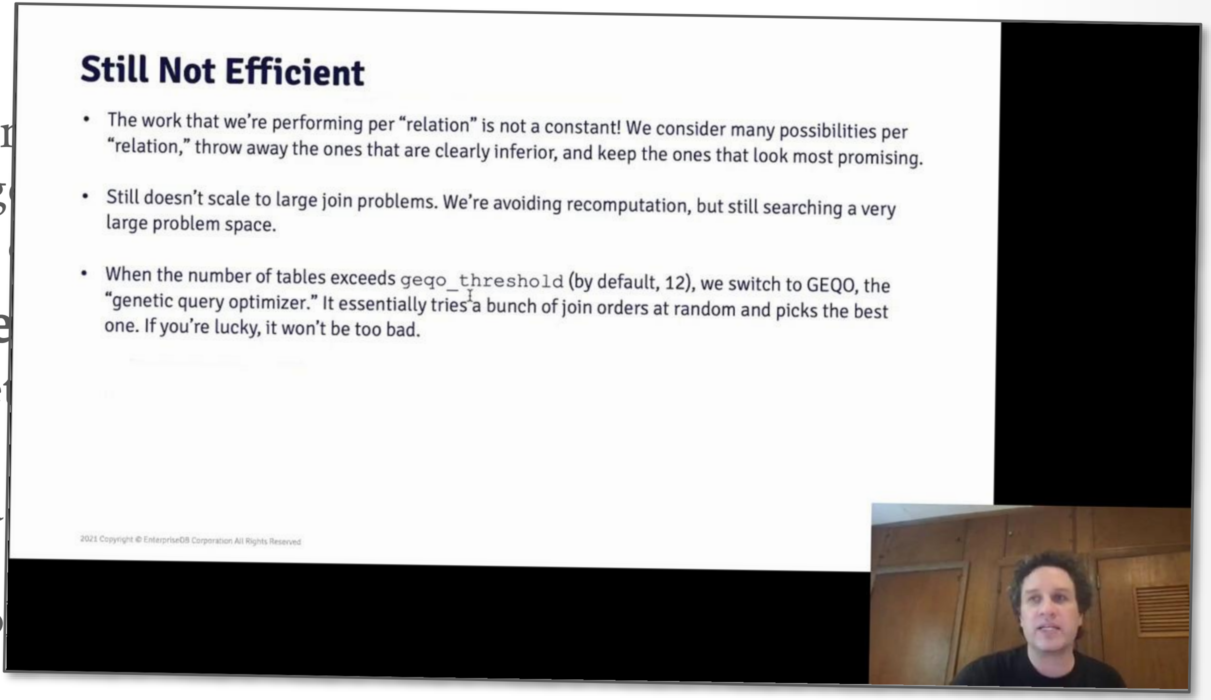
RANDOMIZED ALGORITHMS

Advantages:

→ Jumping arour
optimizer to g
→ Low memory

Disadvantage

→ Difficult to de
plan.
→ Must do extra
deterministic.
→ Still must imp



PARTING THOUGHTS

Query optimization is hard.

This difficulty is why NoSQL systems didn't implement optimizers (at first).

Playlist of CMU-DB Query Optimizer talks:

→ https://cmudb.io/youtube-optimizers

PARTING THOUGHTS

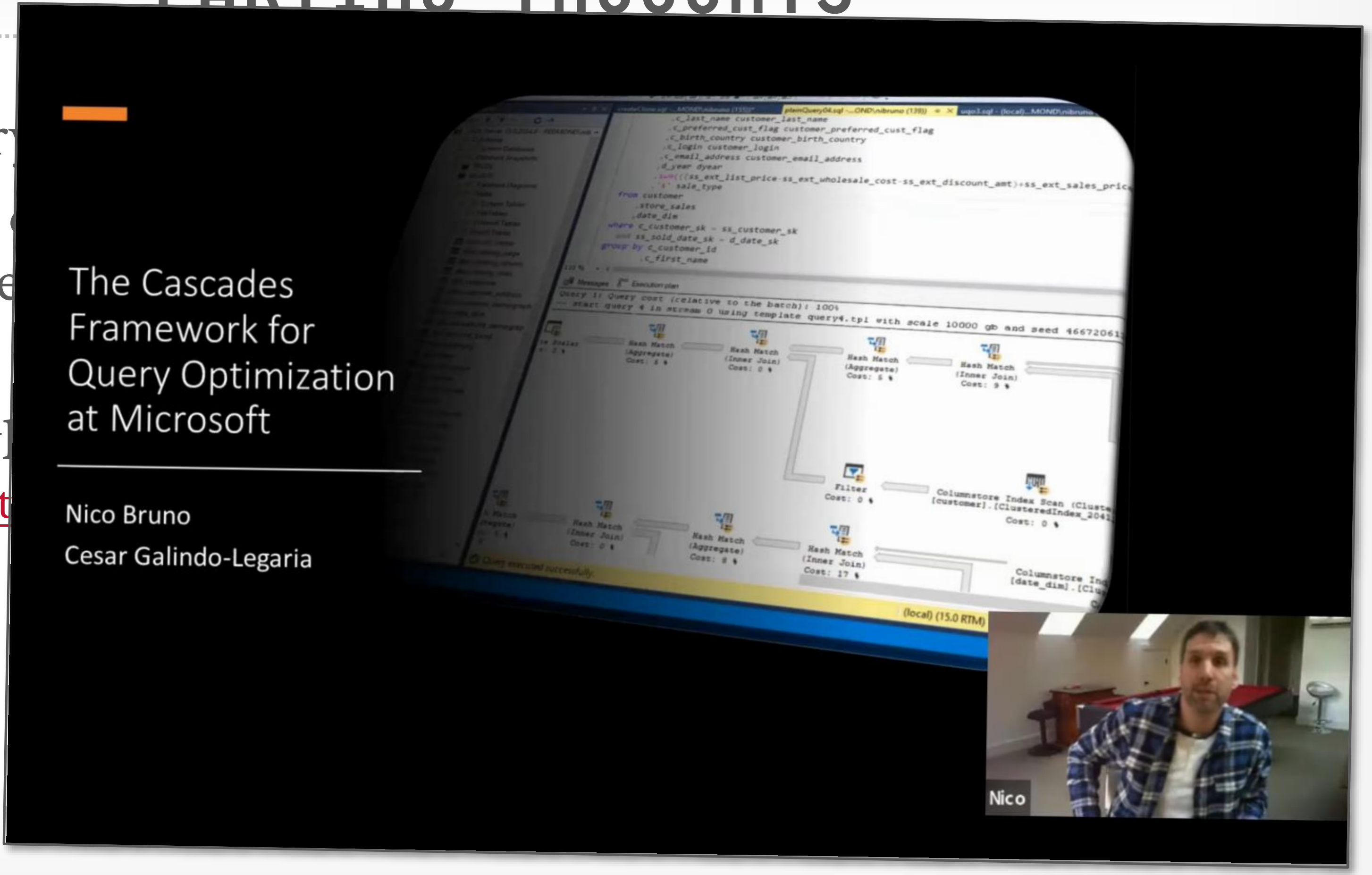
Quer

This

imple

Playl

→ htt



NEXT CLASS

German-style Unnesting Sub-Queries
German-style Dynamic Programming