



香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen



Ack: Prof. Jignesh Patel @ CMU
Prof. Andy Pavlo @CMU

CSC3170

14: Query Planing & Optimization

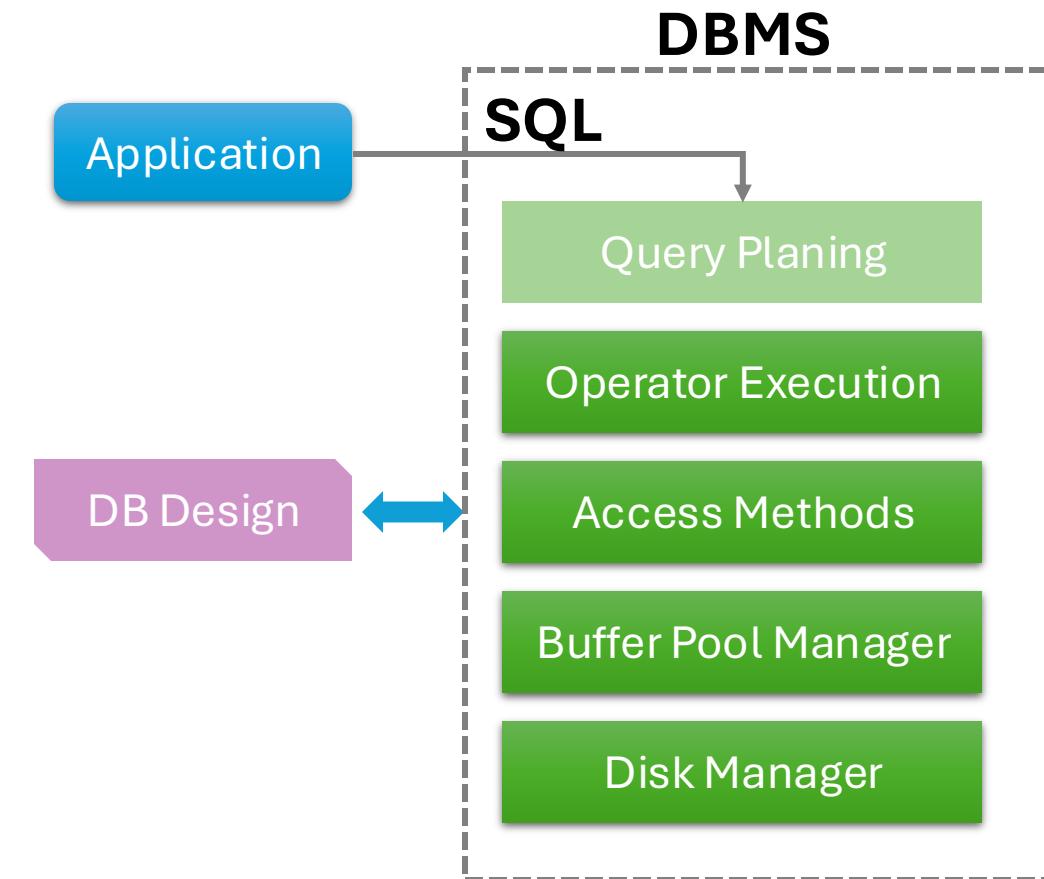
Chenhao Ma

School of Data Science

The Chinese University of Hong Kong, Shenzhen

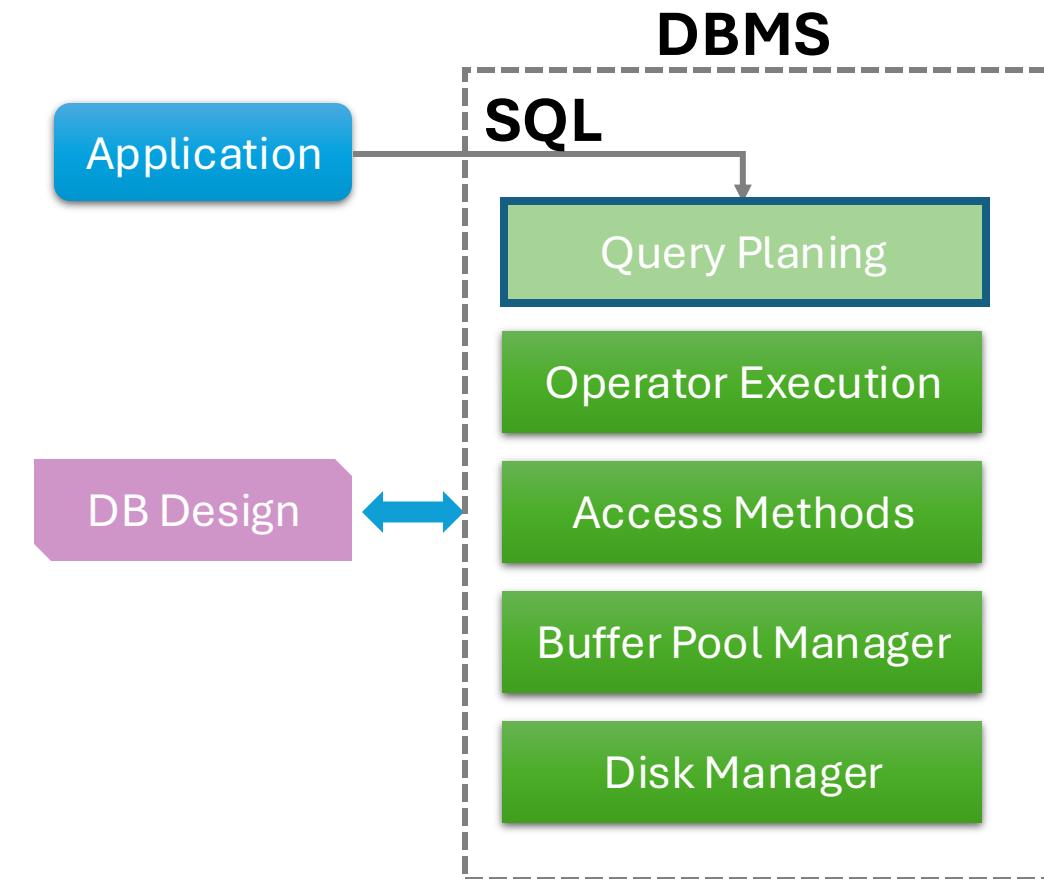
This Lecture

- Query Planing & Optimization



This Lecture

- Query Planing & Optimization




```
SELECT distinct ename  
FROM Emp E, Dept D  
WHERE E.did = D.did AND D.dname = 'Toy'
```

Query

SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'

Query

Catalog

clustered unclustered unclustered
  
EMP (ssn, ename, addr, sal, did)

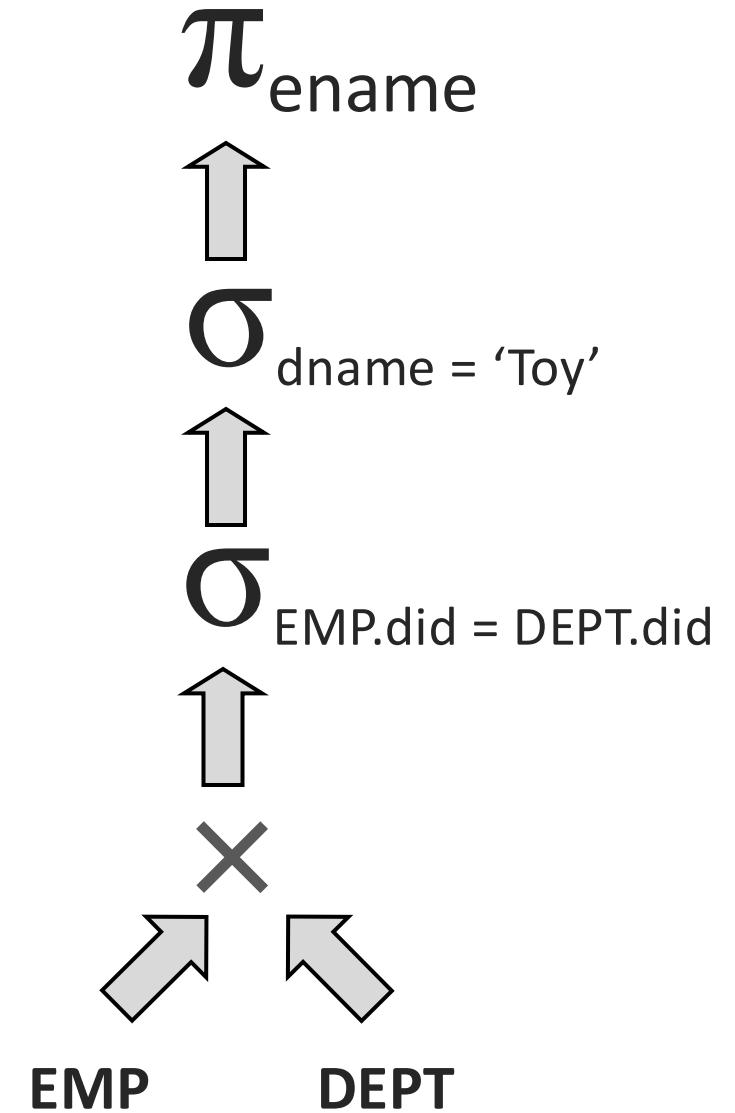
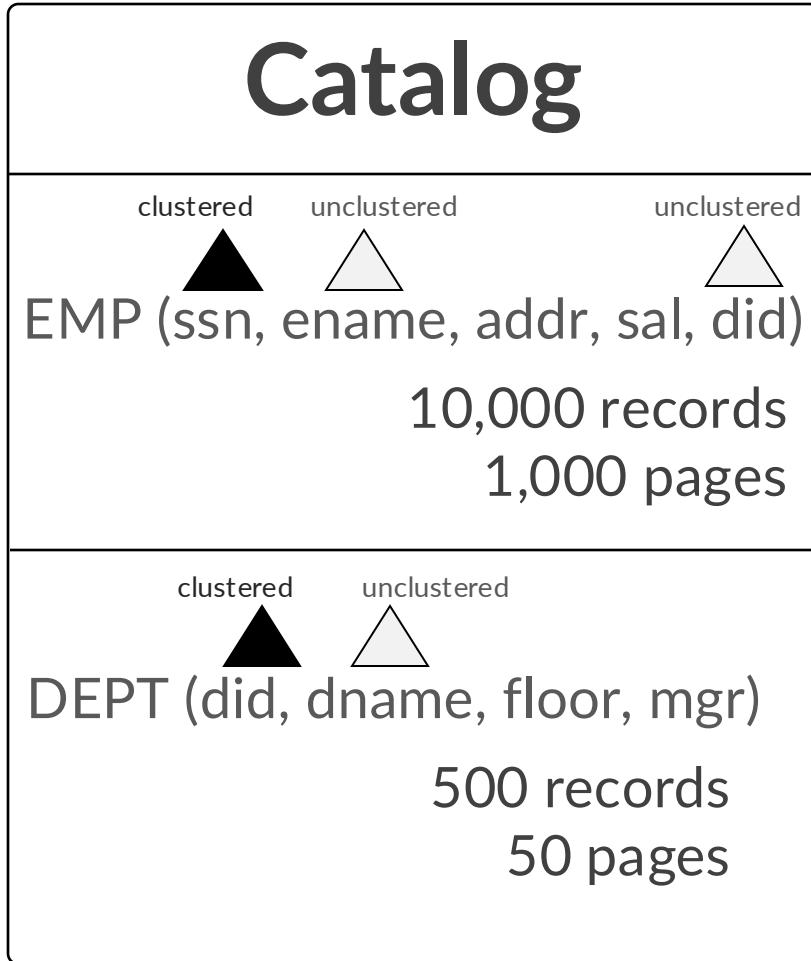
10,000 records
1,000 pages

clustered unclustered
 
DEPT (did, dname, floor, mgr)

500 records
50 pages

SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query



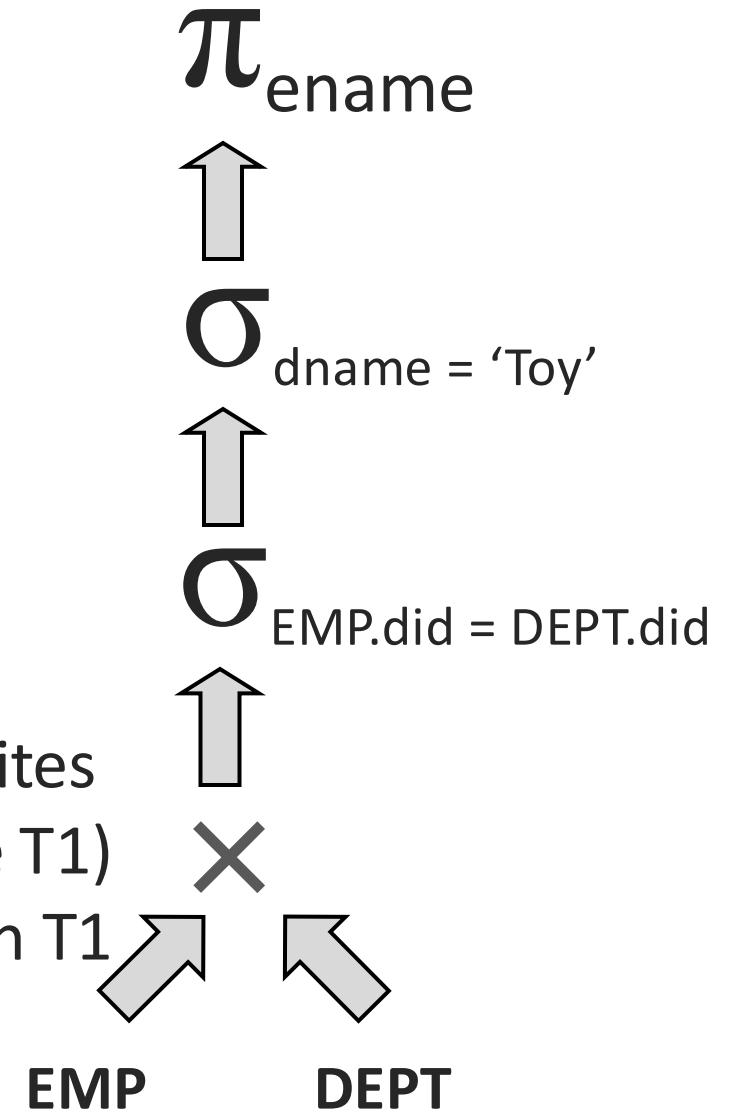
SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query

Catalog			
clustered	unclustered	unclustered	
EMP (ssn, ename, addr, sal, did)			
10,000 records			
1,000 pages			
clustered	unclustered		
DEPT (did, dname, floor, mgr)			
500 records			
50 pages			

50 + 50,000 + 1,000,000 writes
 (write to temp file T1)

5 tuples per page in T1



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

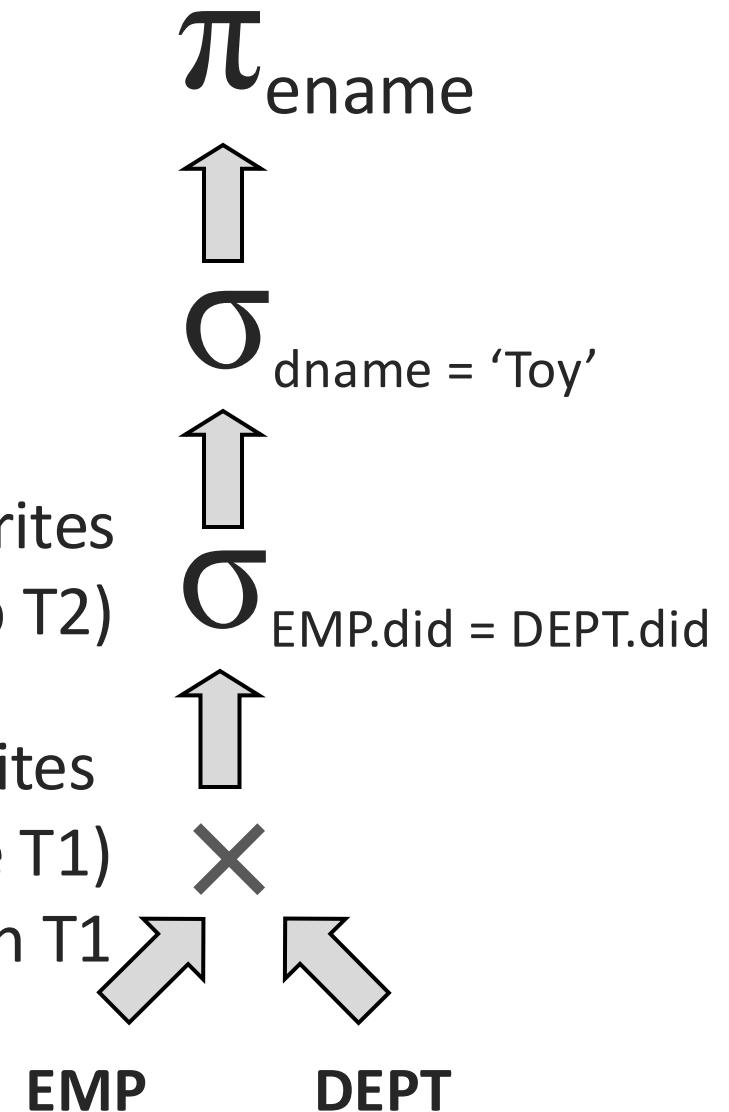
Catalog			
clustered	unclustered	unclustered	
			
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages			
clustered	unclustered		
			
DEPT (did, dname, floor, mgr) 500 records 50 pages			

Query

1,000,000 + 2,000 writes
 (FK join, 10K tuples in temp T2)

50 + 50,000 + 1,000,000 writes
 (write to temp file T1)

5 tuples per page in T1



SELECT distinct ename
 FROM Emp E, Dept D
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Catalog		
clustered	unclustered	unclustered
		
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
		
DEPT (did, dname, floor, mgr) 500 records 50 pages		

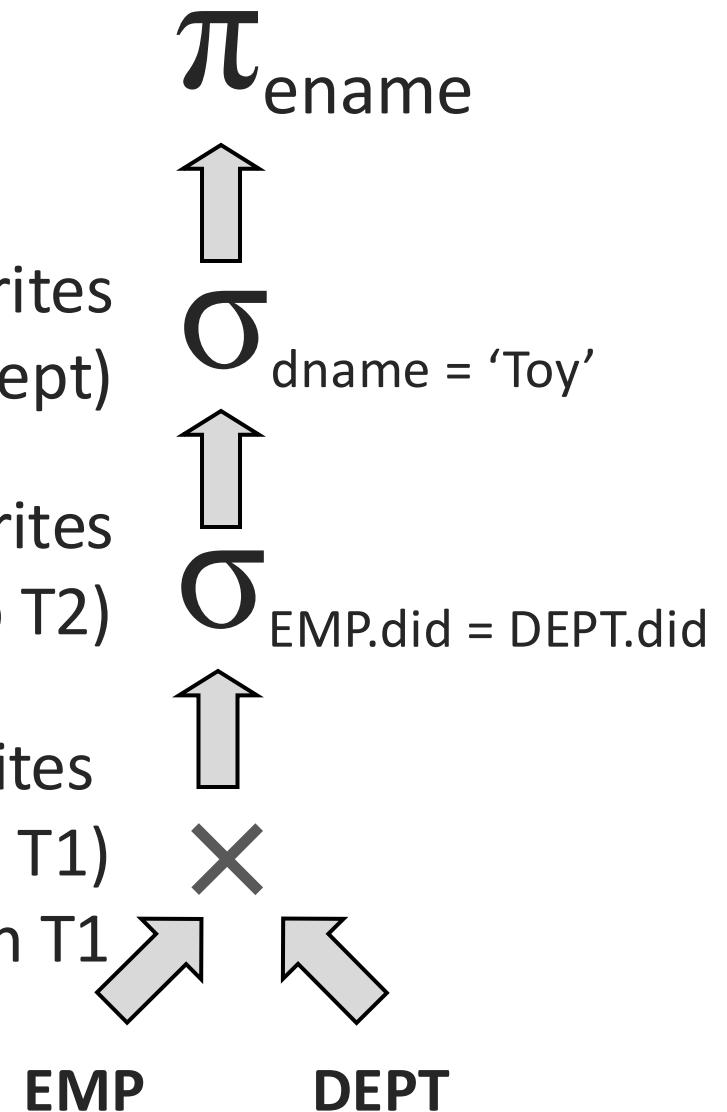
Query

2,000 + 4 writes
 $(10K/500 = 20 \text{ emps per dept})$

1,000,000 + 2,000 writes
 (FK join, 10K tuples in temp T2)

50 + 50,000 + 1,000,000 writes
 (write to temp file T1)

5 tuples per page in T1



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did)		
10,000 records		
1,000 pages		
DEPT (did, dname, floor, mgr)		
clustered	unclustered	
500 records		
50 pages		

4 reads, 1 write

π_{ename}



EMP

DEPT

2,000 + 4 writes
 $(10K/500 = 20 \text{ emps per dept})$

1,000,000 + 2,000 writes
 (FK join, 10K tuples in temp T2)

50 + 50,000 + 1,000,000 writes
 (write to temp file T1)

5 tuples per page in T1

```
SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'
```

Query

Total: 2M I/Os

4 reads, 1 write

π_{ename}

$2,000 + 4 \text{ writes}$
 $(10K/500 = 20 \text{ emps per dept})$



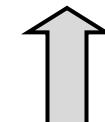
$\sigma_{dname = 'Toy'}$

$1,000,000 + 2,000 \text{ writes}$
 (FK join, 10K tuples in temp T2)



$\sigma_{EMP.did = DEPT.did}$

$50 + 50,000 + 1,000,000 \text{ writes}$
 (write to temp file T1)



5 tuples per page in T1

\times

EMP

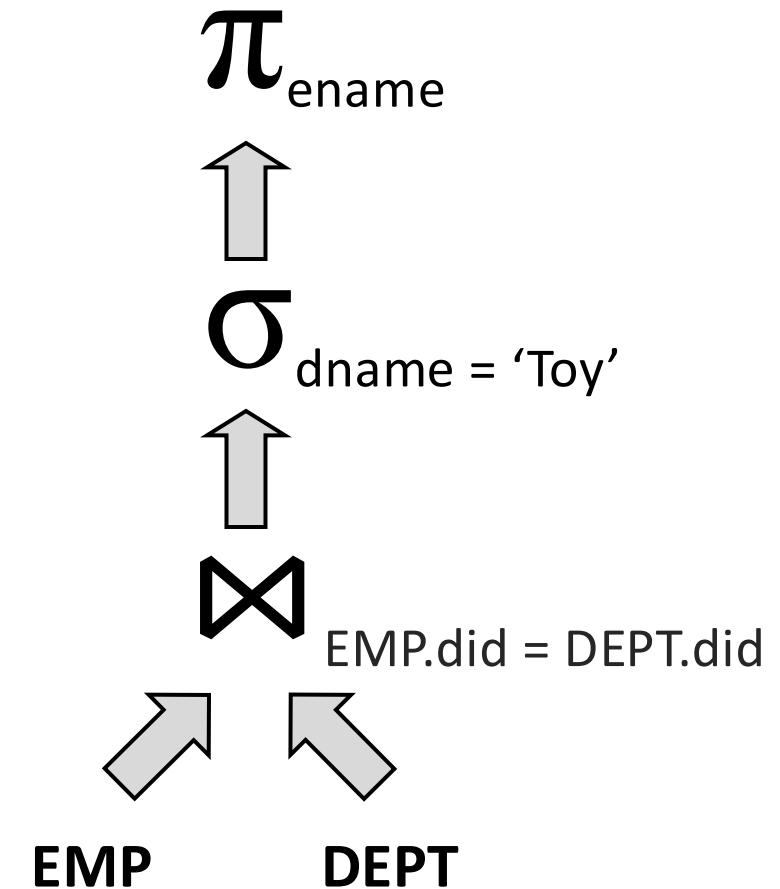
DEPT

Catalog		
clustered	unclustered	unclustered
		
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
		
DEPT (did, dname, floor, mgr) 500 records 50 pages		

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Query

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did)		
10,000 records		
1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr)		
500 records		
50 pages		

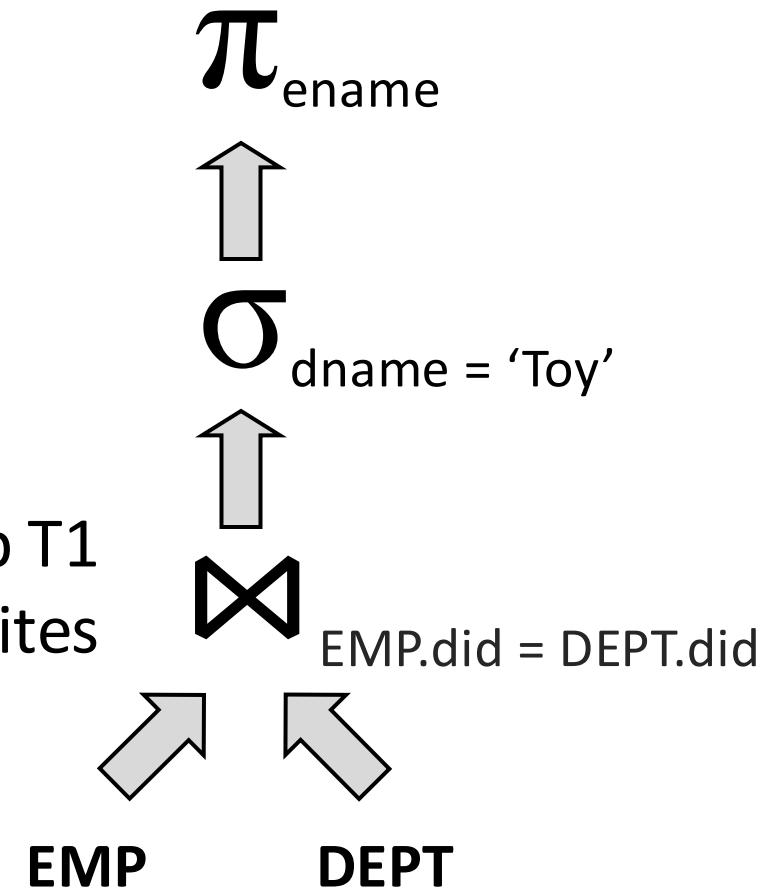


SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

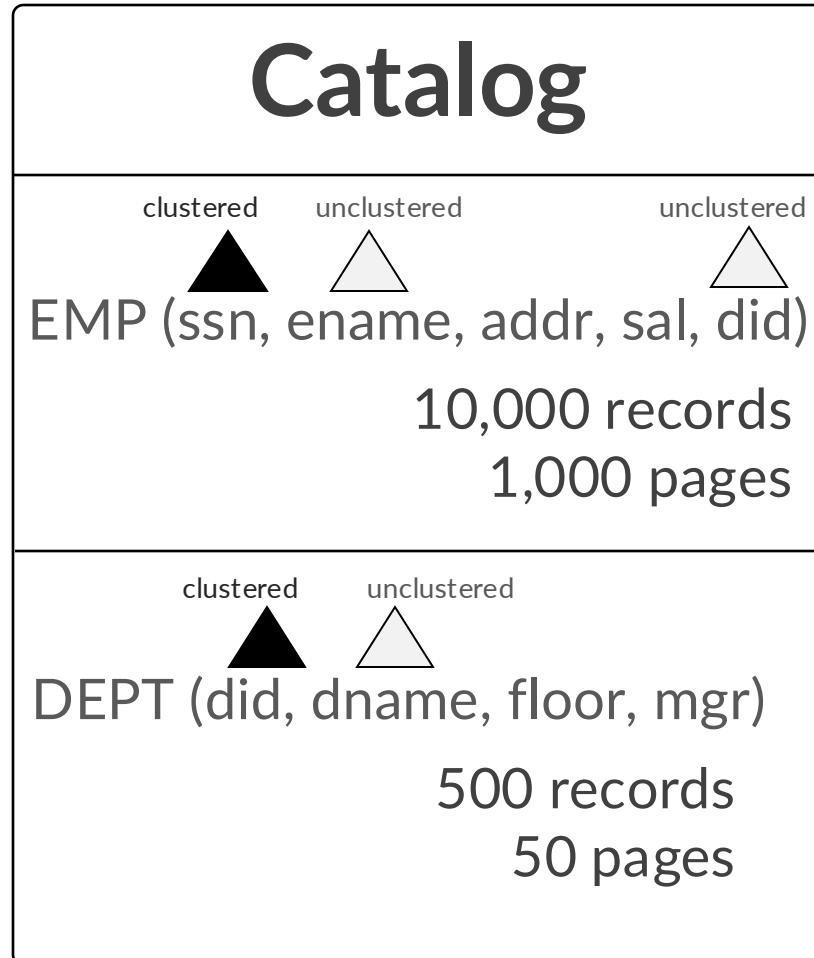
Query

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did)		
10,000 records		
1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr)		
500 records		
50 pages		

Page NL, write to temp T1
 50 + 50,000 + 2000 writes



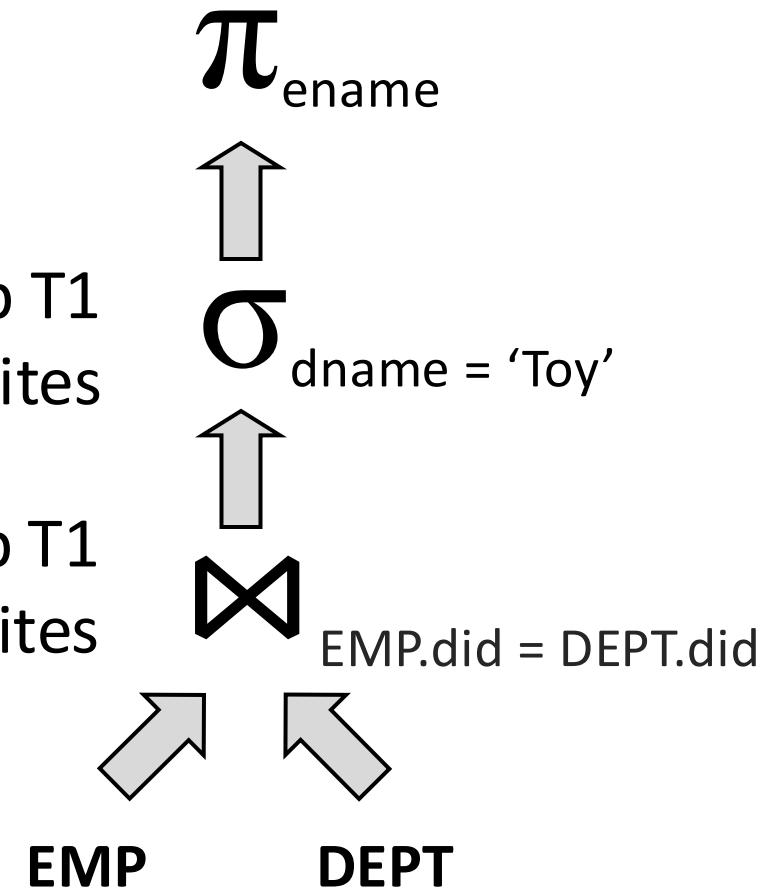
```
SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'
```



Query

Read temp T1
2,000 reads +4 writes

Page NL, write to temp T1
50 + 50,000 + 2000 writes



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

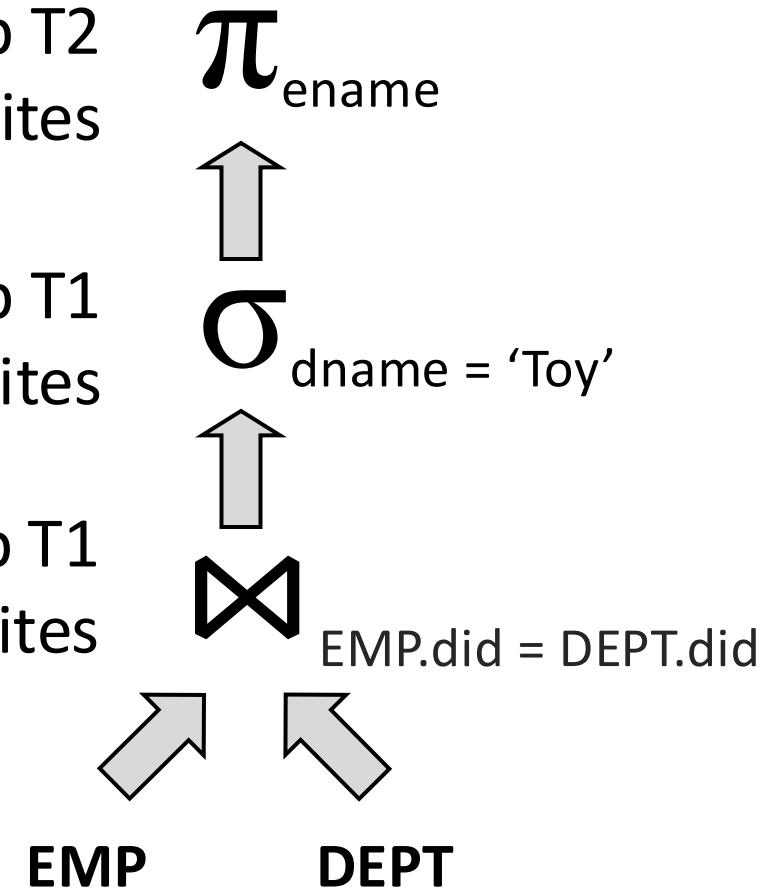
Catalog			
clustered	unclustered	unclustered	
			
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages			
clustered	unclustered		
			
DEPT (did, dname, floor, mgr) 500 records 50 pages			

Query

Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads + 4 writes

Page NL, write to temp T1
 50 + 50,000 + 2000 writes



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query

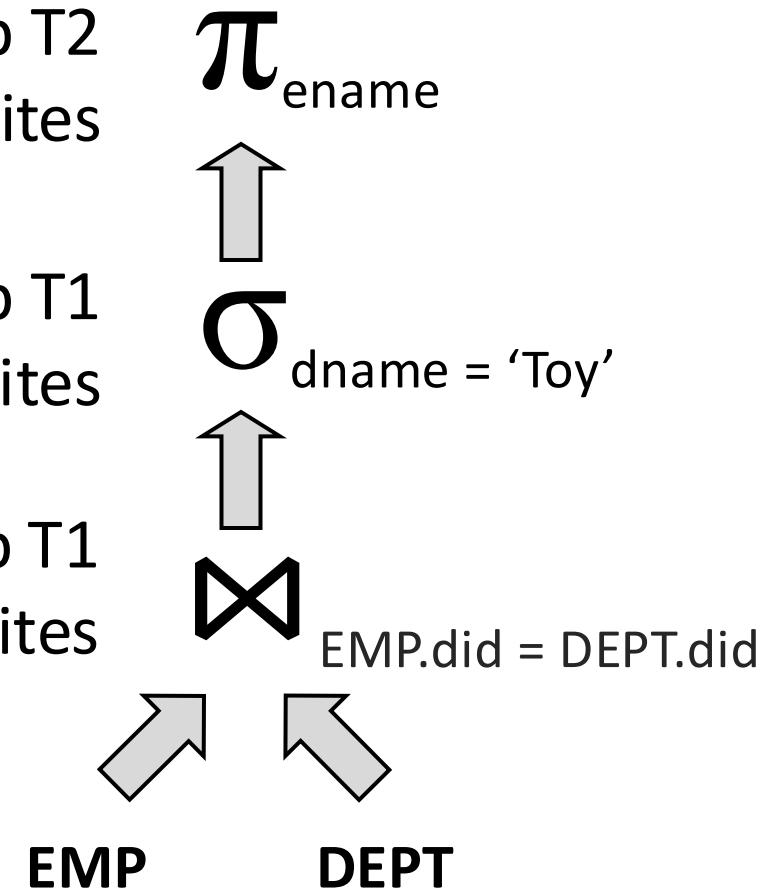
Total: 54K I/Os

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr) 500 records 50 pages		

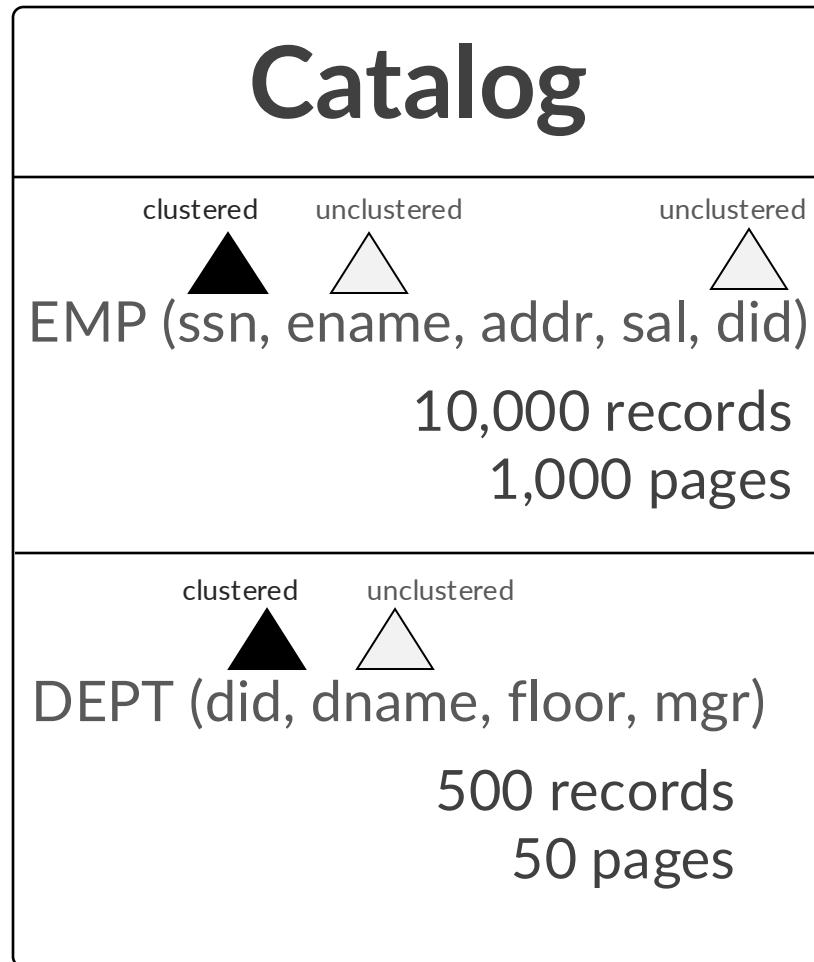
Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads + 4 writes

Page NL, write to temp T1
 50 + 50,000 + 2000 writes



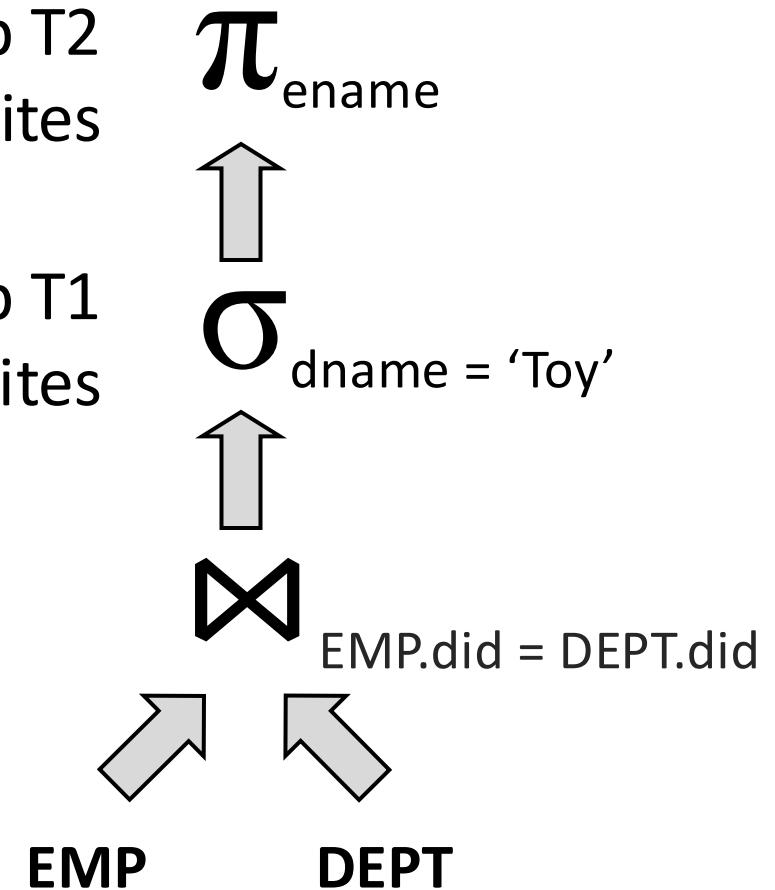
SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'



Query

Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads +4 writes



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Catalog		
clustered	unclustered	unclustered
		
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
		
DEPT (did, dname, floor, mgr) 500 records 50 pages		

Query

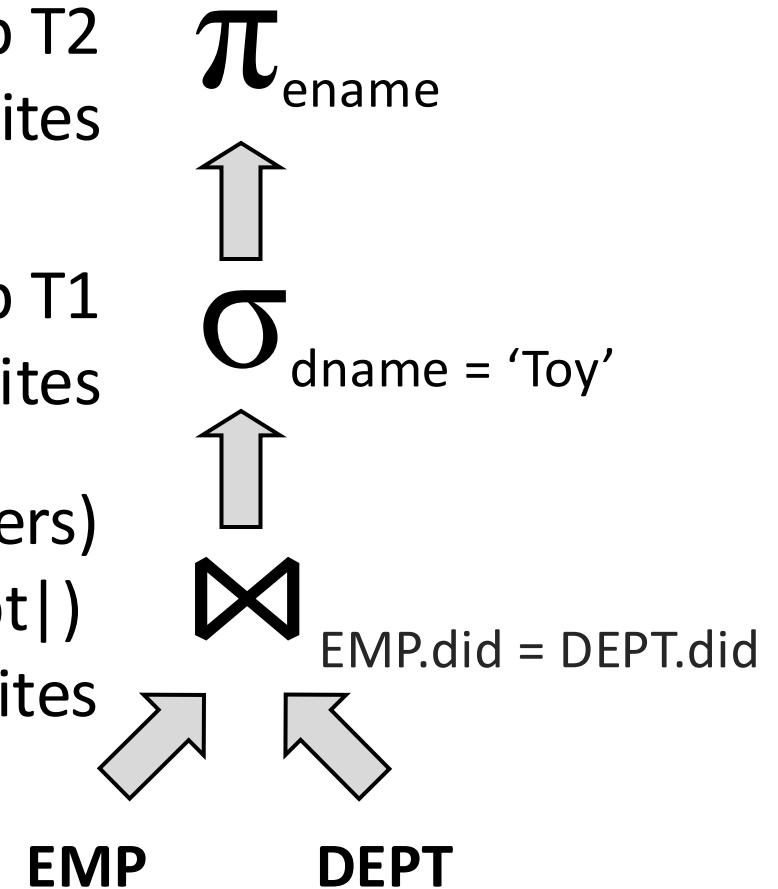
Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads + 4 writes

Sort-merge join (50 buffers)

$$3 * (|Emp| + |Dept|)$$

$$= 3150 + 2000 \text{ writes}$$



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query

Total: 7,159 I/Os

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr) 500 records 50 pages		

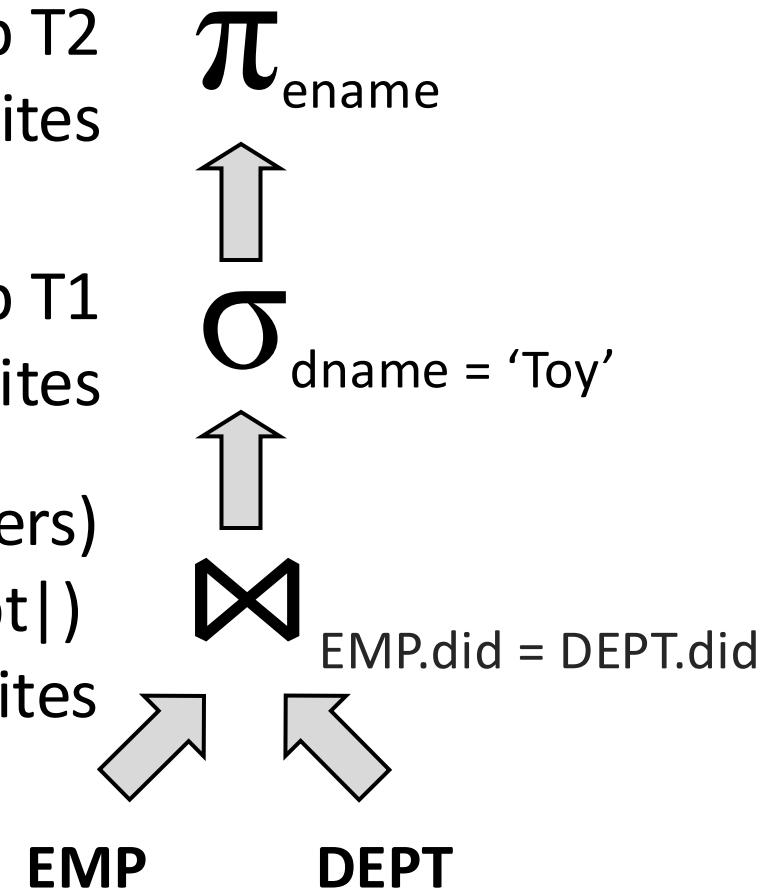
Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads + 4 writes

Sort-merge join (50 buffers)

$$3 * (|Emp| + |Dept|)$$

$$= 3150 + 2000 \text{ writes}$$



```
SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'
```

Query

w/ Materialization

Total: 7,159 I/Os

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr) 500 records 50 pages		

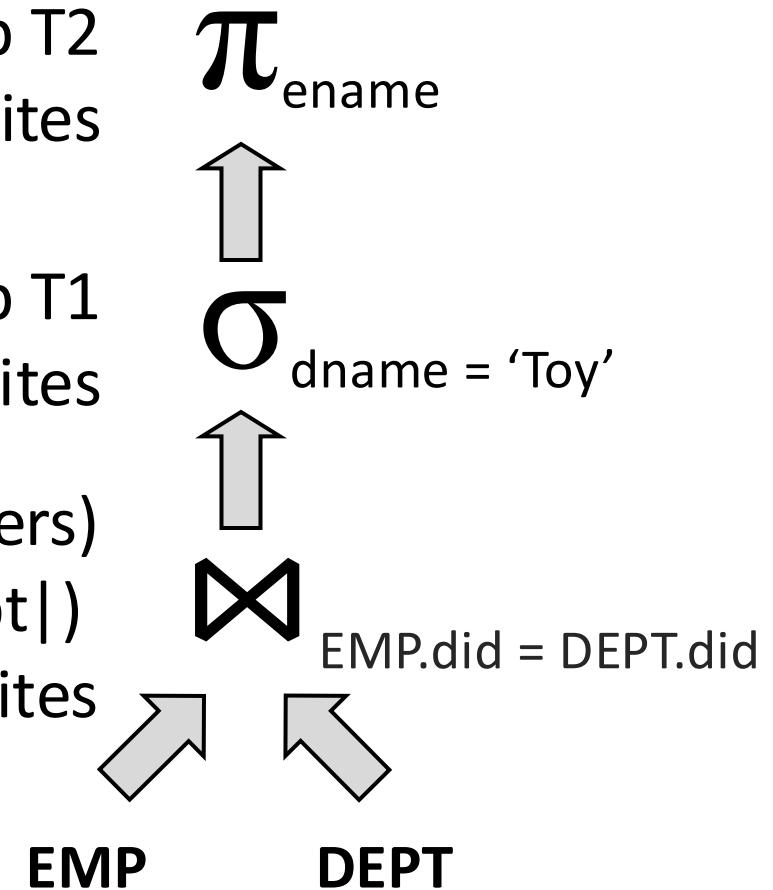
Read temp T2
 4 reads + 1 writes

Read temp T1
 2,000 reads + 4 writes

Sort-merge join (50 buffers)

$$3 * (|\text{Emp}| + |\text{Dept}|)$$

$$= 3150 + 2000 \text{ writes}$$



```
SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'
```

Query

w/ Materialization

Total: 7,159 I/Os

w/ Pipelining

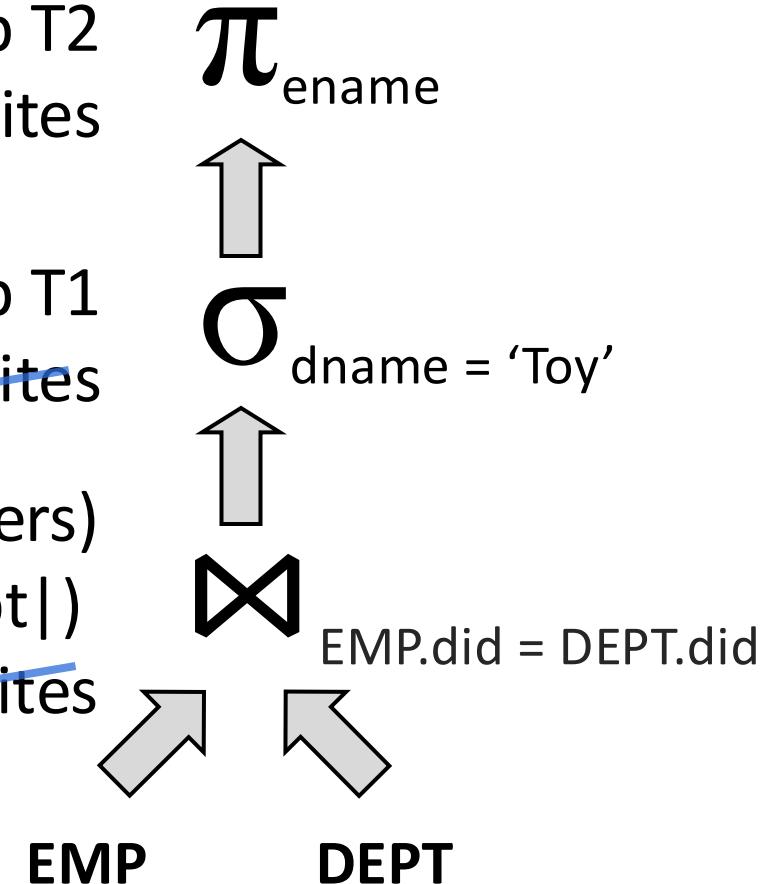
Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did)		
10,000 records		
1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr)		
500 records		
50 pages		

Read temp T2
~~4 reads + 1 writes~~

Read temp T1
~~2,000 reads + 4 writes~~

Sort-merge join (50 buffers)

$$3 * (|\text{Emp}| + |\text{Dept}|) \\ = 3150 + \cancel{2000 \text{ writes}}$$



```
SELECT distinct ename
FROM Emp E, Dept D
WHERE E.did = D.did AND D.dname = 'Toy'
```

Query

w/ Materialization

Total: 7,159 I/Os

w/ Pipelining

Total: 3,151 I/Os

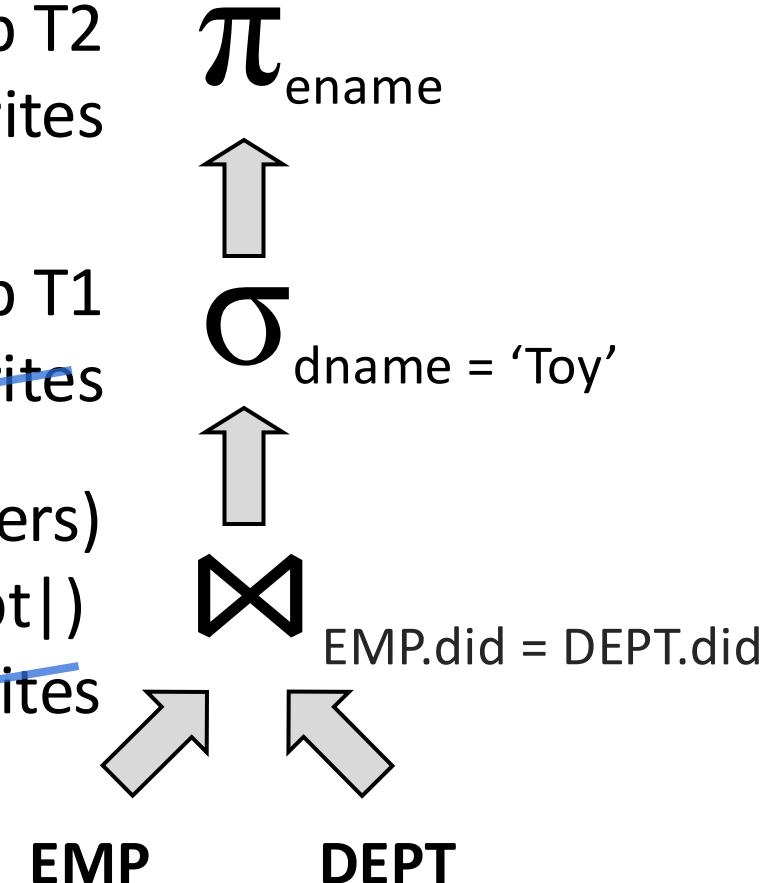
Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did)		
10,000 records		
1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr)		
500 records		
50 pages		

Read temp T2
~~4 reads + 1 writes~~

Read temp T1
~~2,000 reads + 4 writes~~

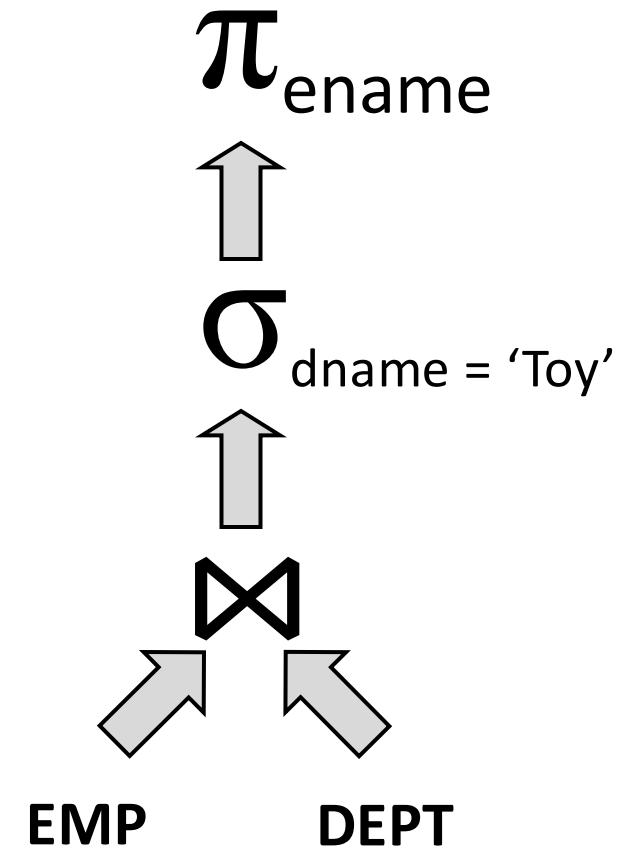
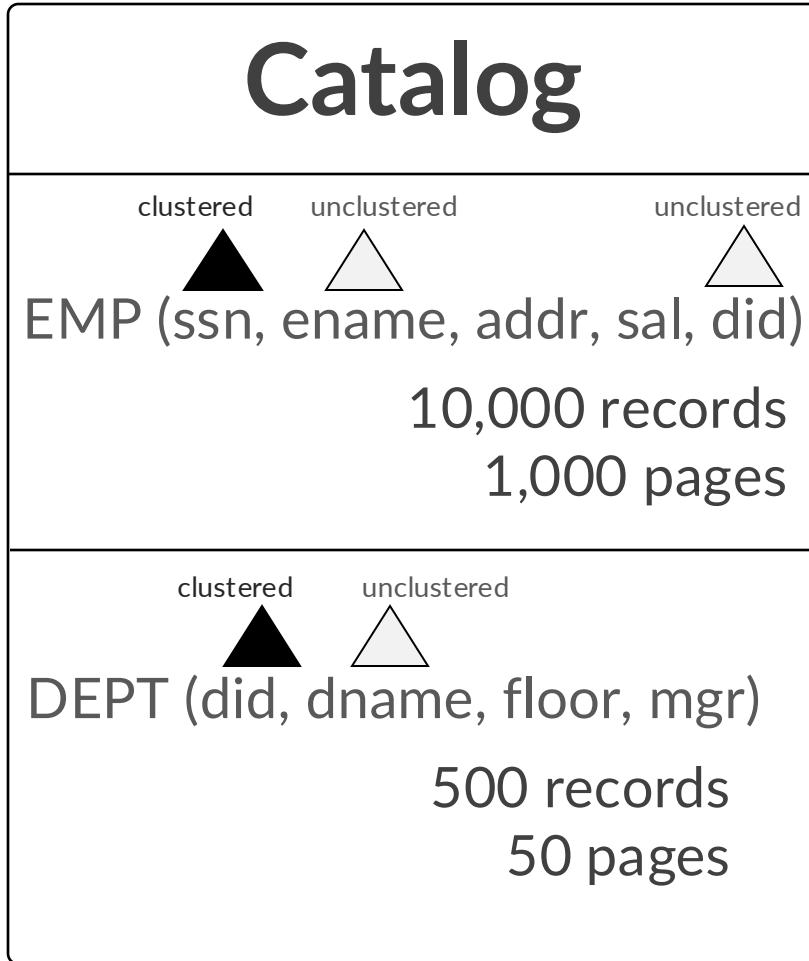
Sort-merge join (50 buffers)

$$3 * (|\text{Emp}| + |\text{Dept}|) \\ = 3150 + \cancel{2000 \text{ writes}}$$

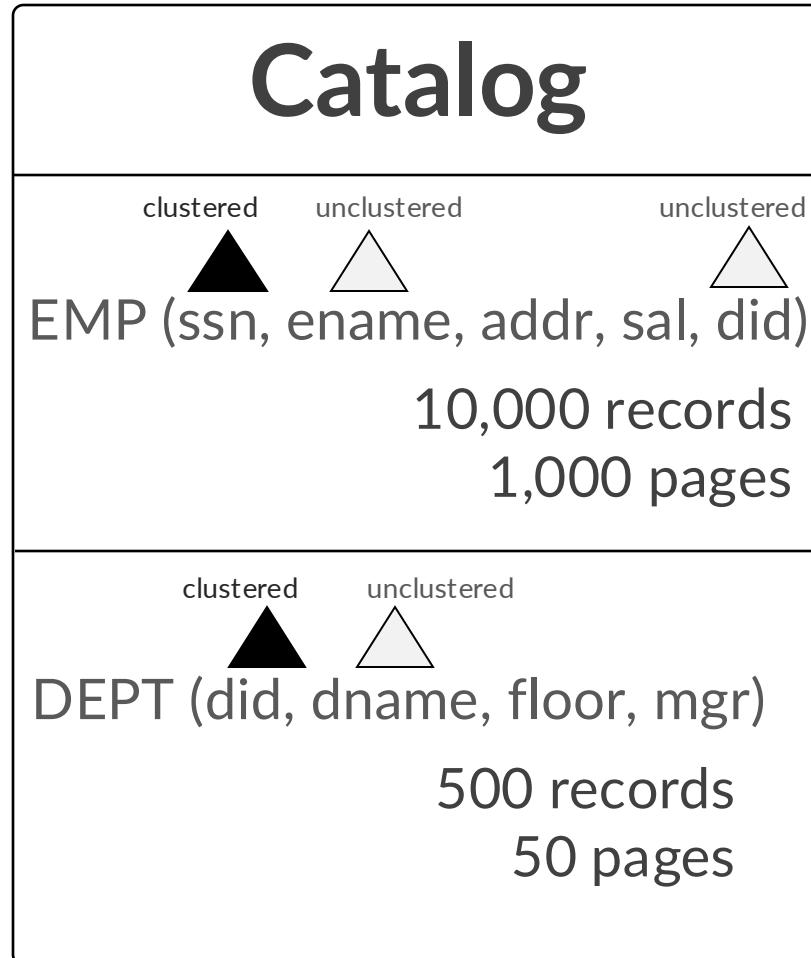


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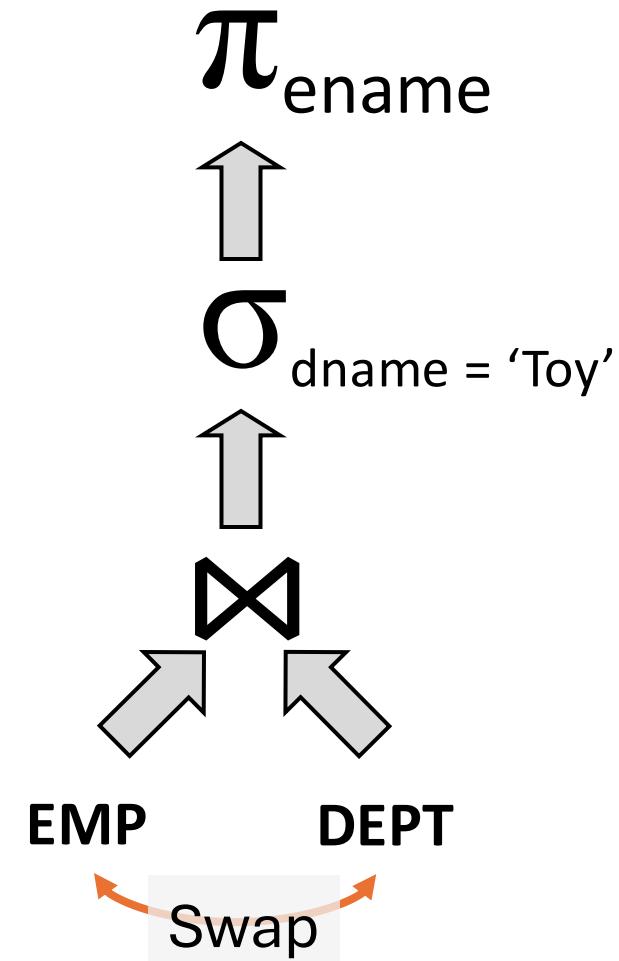
Query



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

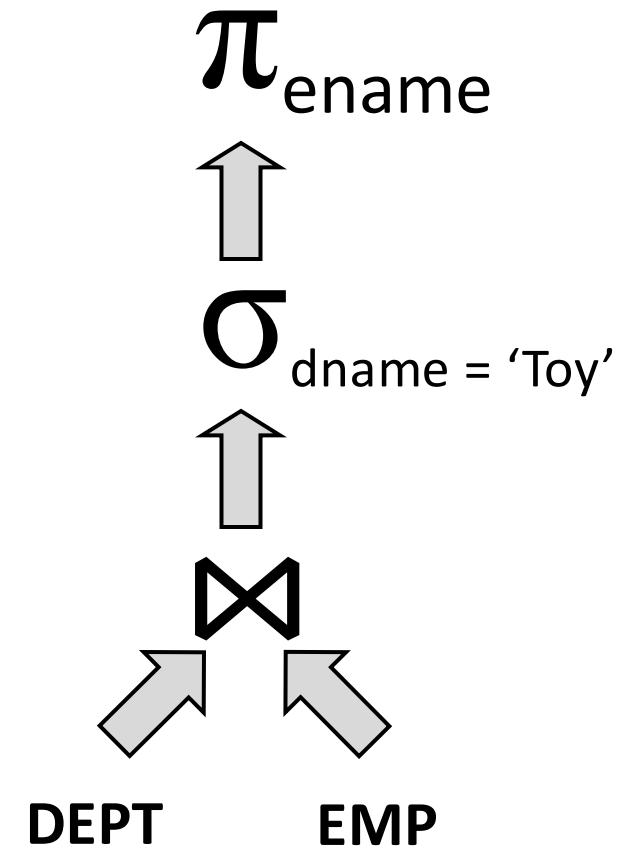
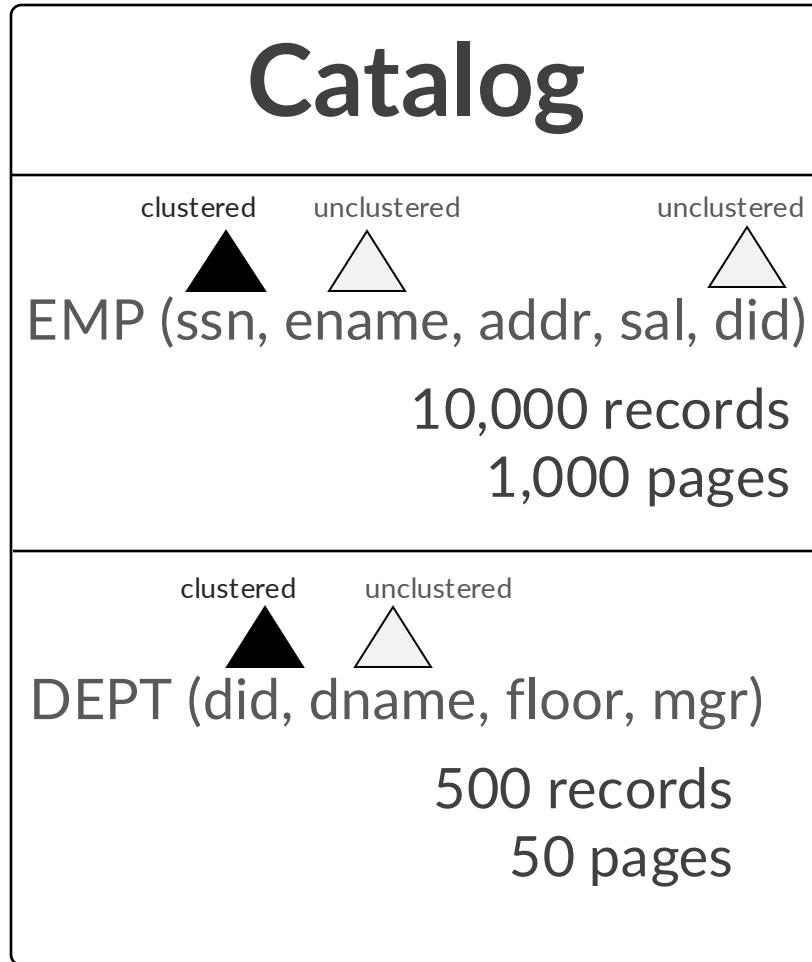


Query

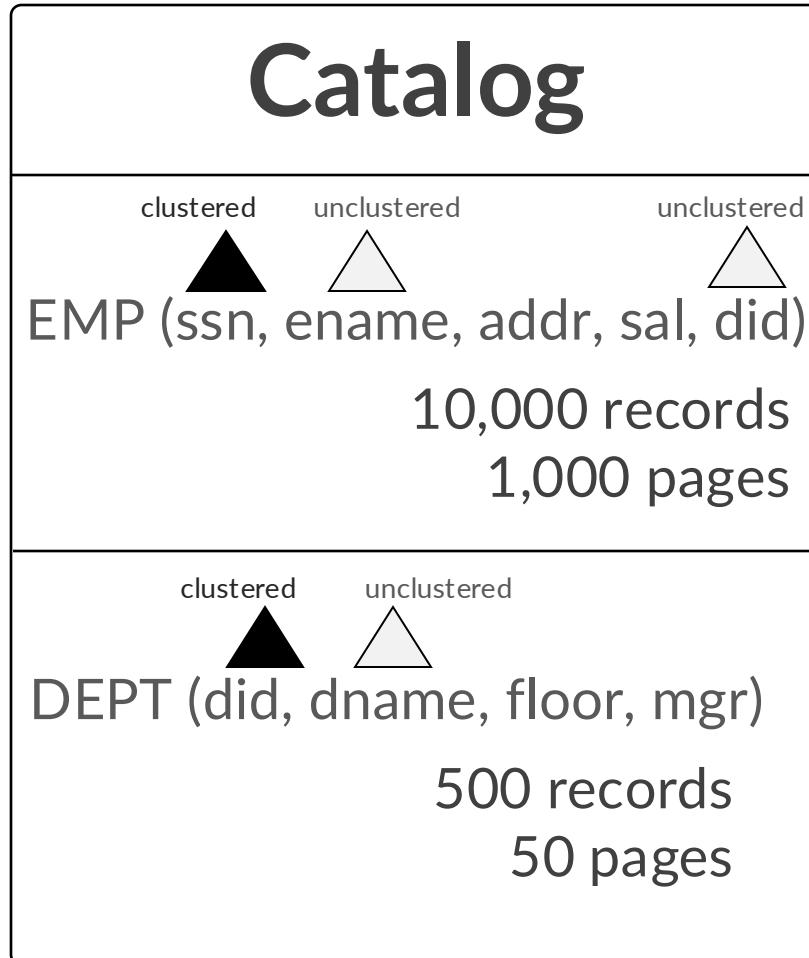


SELECT distinct ename
 FROM Emp E, Dept D
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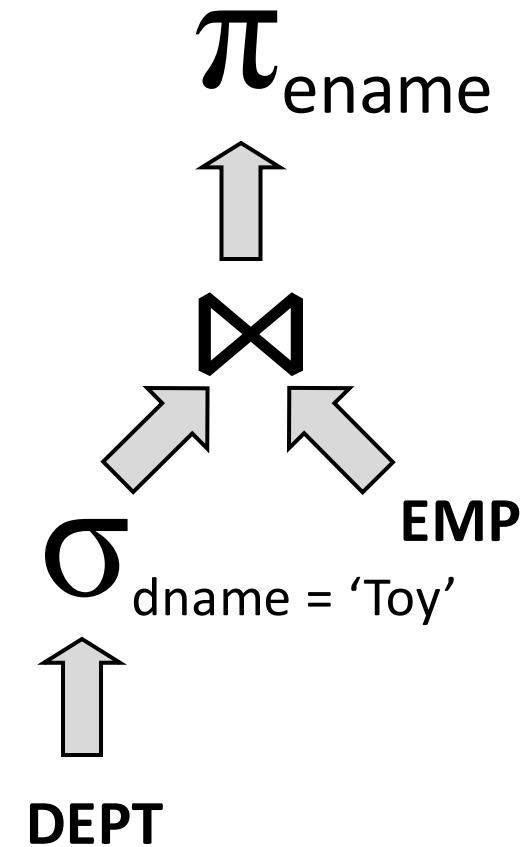
Query



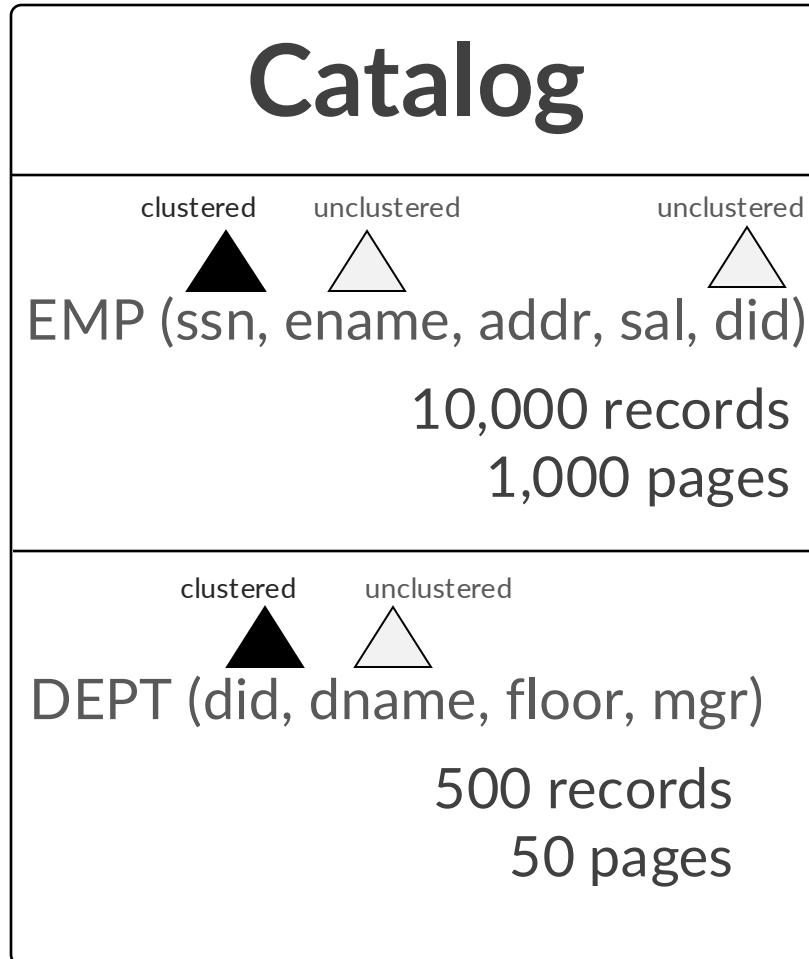
SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'



Query



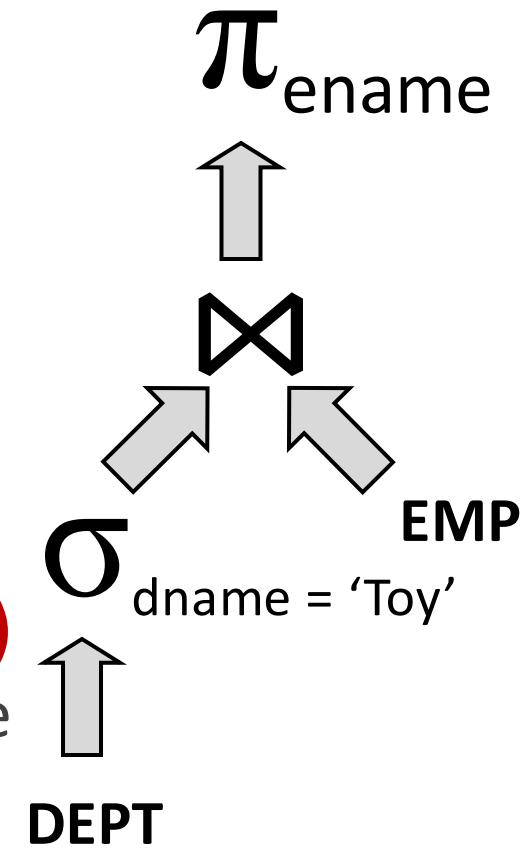
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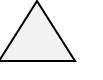
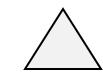
Query

Access: **Index (name)**

3 reads + 1 write



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Catalog		
clustered	unclustered	unclustered
		
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
		
DEPT (did, dname, floor, mgr) 500 records 50 pages		

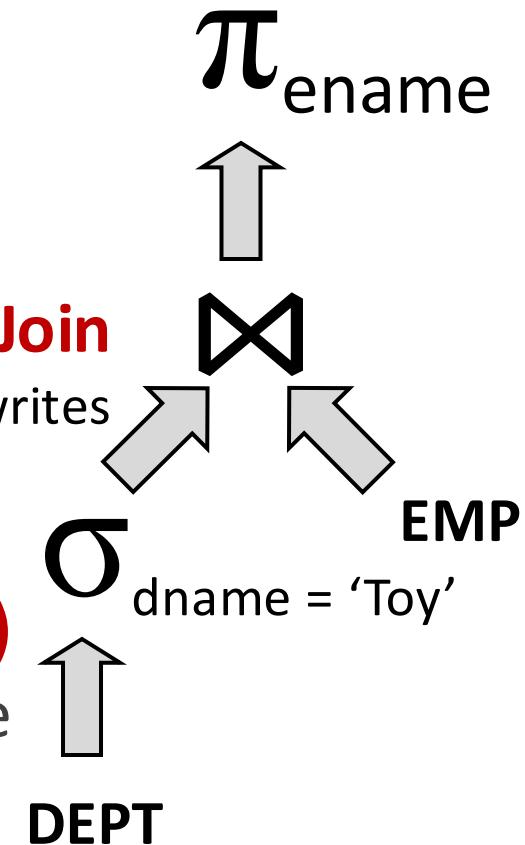
Query

Read temp T1, **NL-IDX Join**

1 + 3 (idx) + 20 (ptr chase) + 4 writes

Access: **Index (name)**

3 reads + 1 write



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
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Query

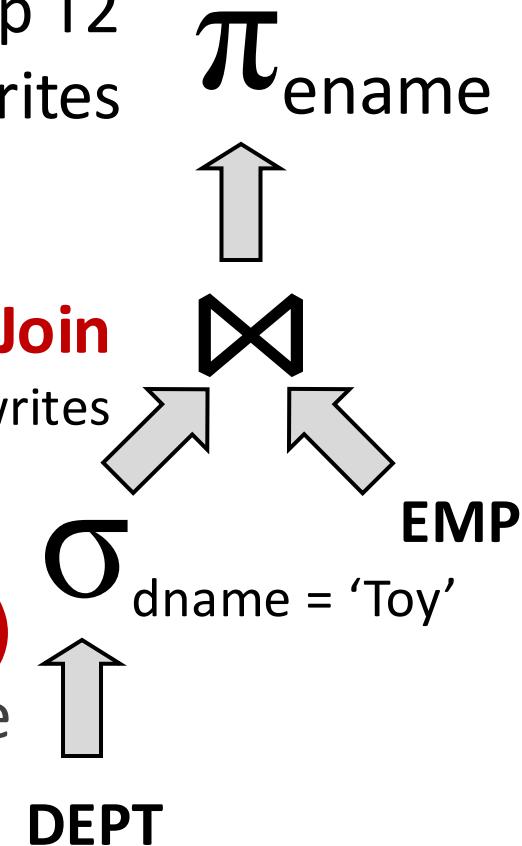
Read temp T2
 4 reads + 1 writes

Read temp T1, **NL-IDX Join**

1 + 3 (idx) + 20 (ptr chase) + 4 writes

Access: **Index (name)**

3 reads + 1 write



SELECT distinct ename
 FROM Emp E, Dept D
 WHERE E.did = D.did AND D.dname = 'Toy'

Query

Total: 37 I/Os

Catalog		
clustered	unclustered	unclustered
EMP (ssn, ename, addr, sal, did) 10,000 records 1,000 pages		
clustered	unclustered	
DEPT (did, dname, floor, mgr) 500 records 50 pages		

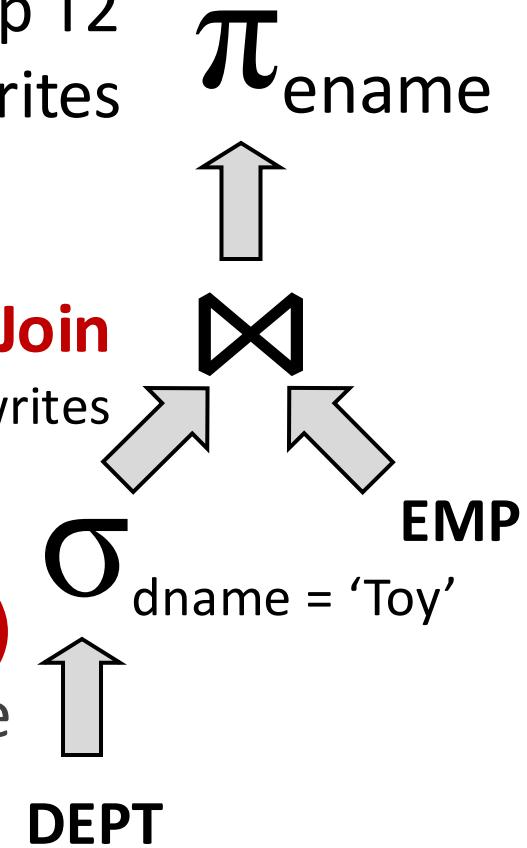
Read temp T2
 4 reads + 1 writes

Read temp T1, **NL-IDX Join**

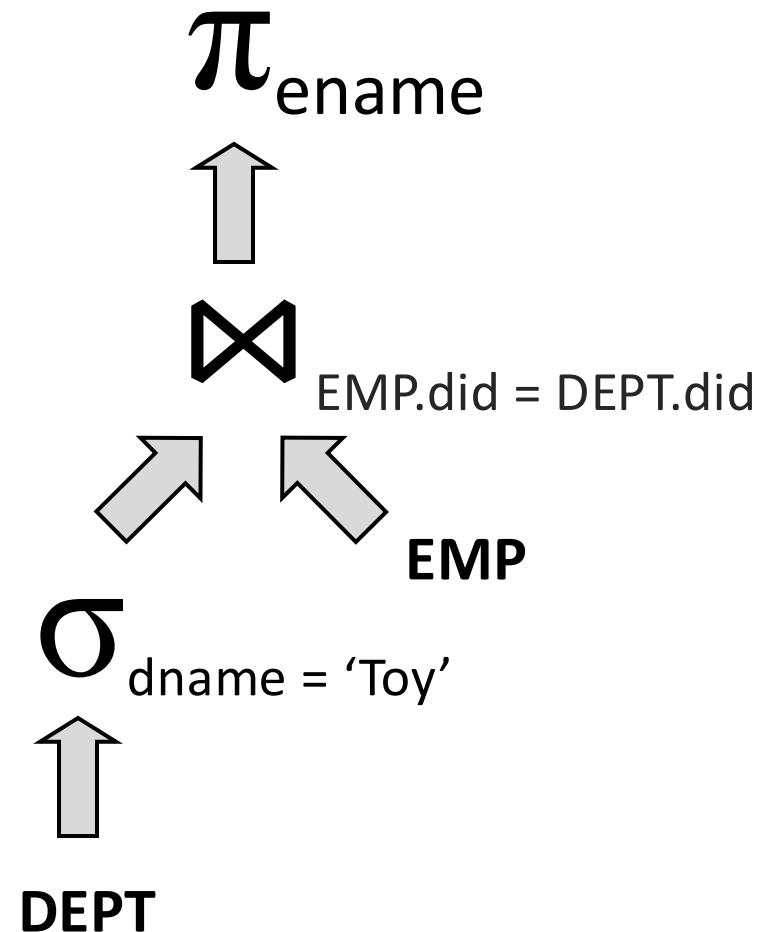
1 + 3 (idx) + 20 (ptr chase) + 4 writes

Access: **Index (name)**

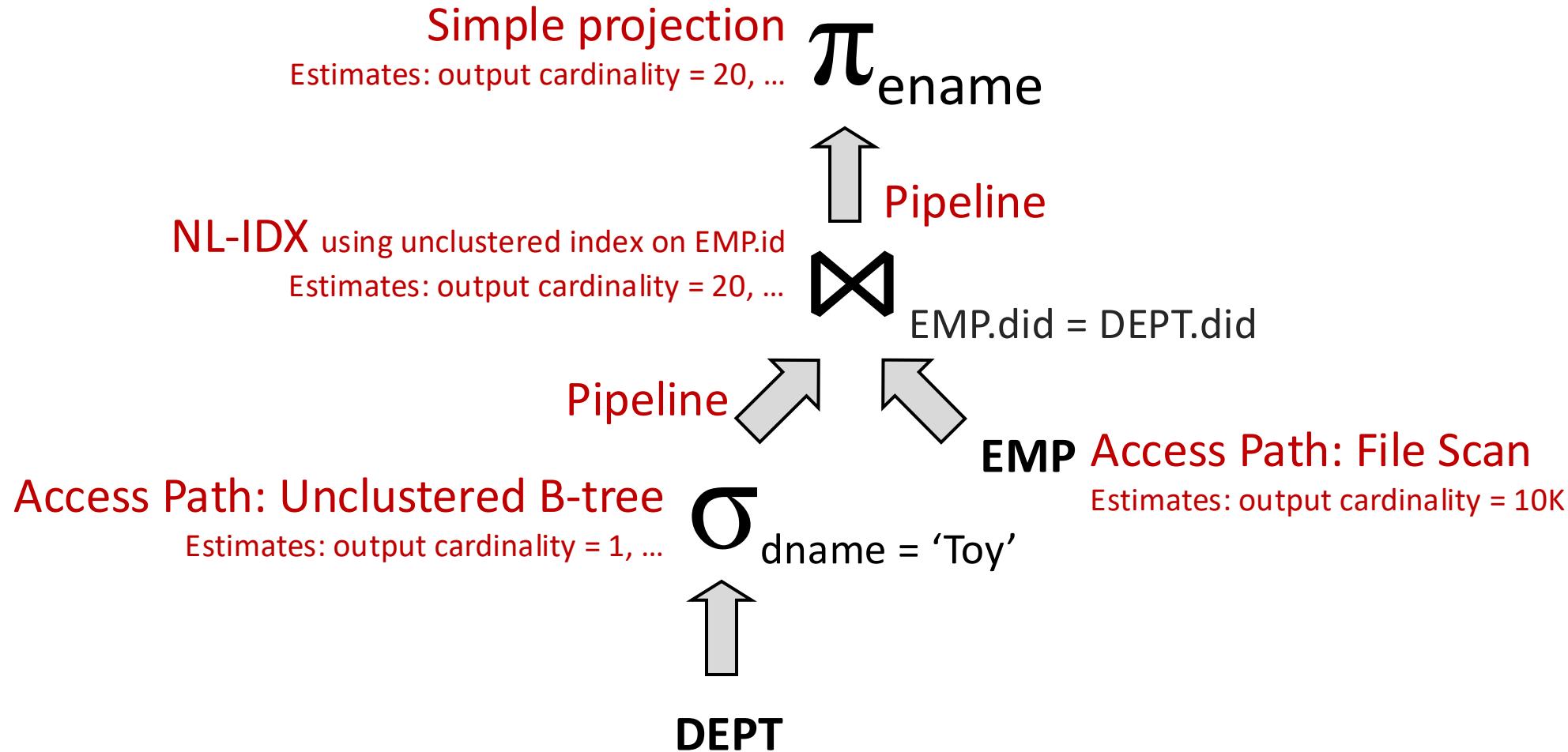
3 reads + 1 write



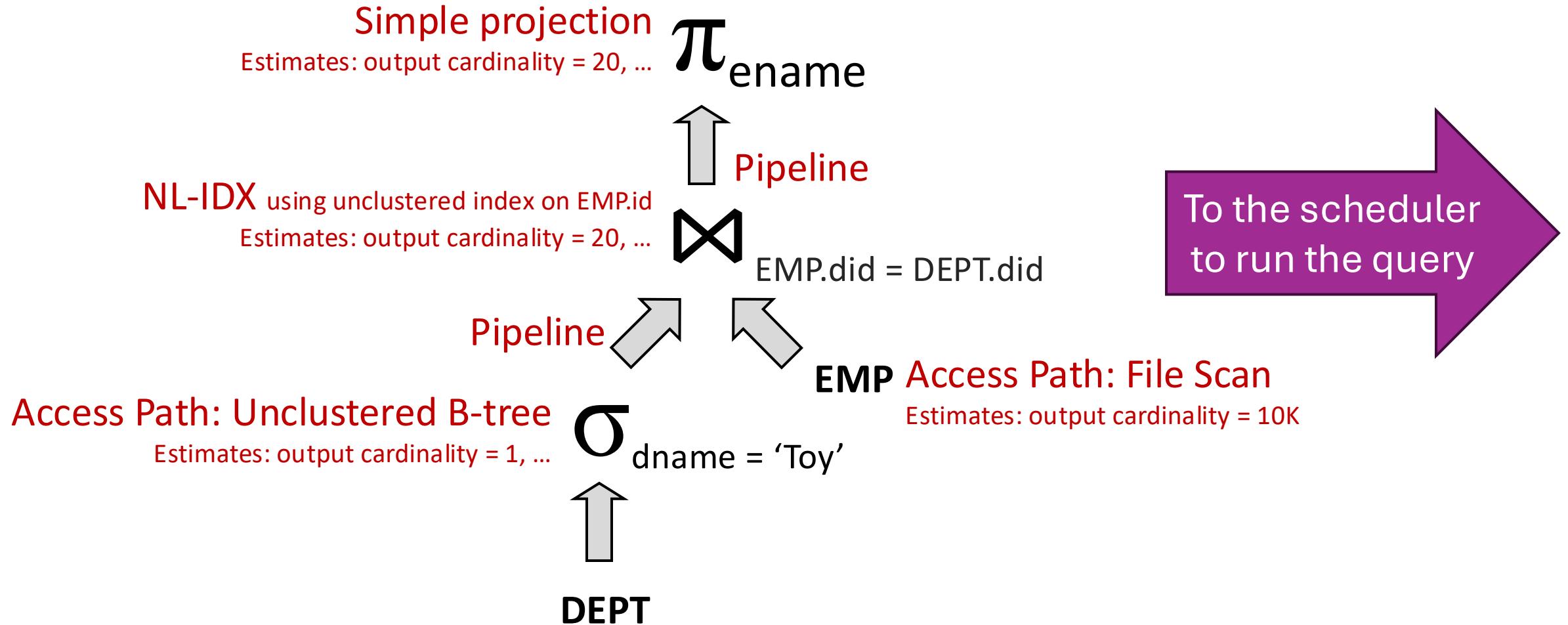
Annotated RA Tree a.k.a. The Physical Plan



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Annotated RA Tree a.k.a. The Physical Plan

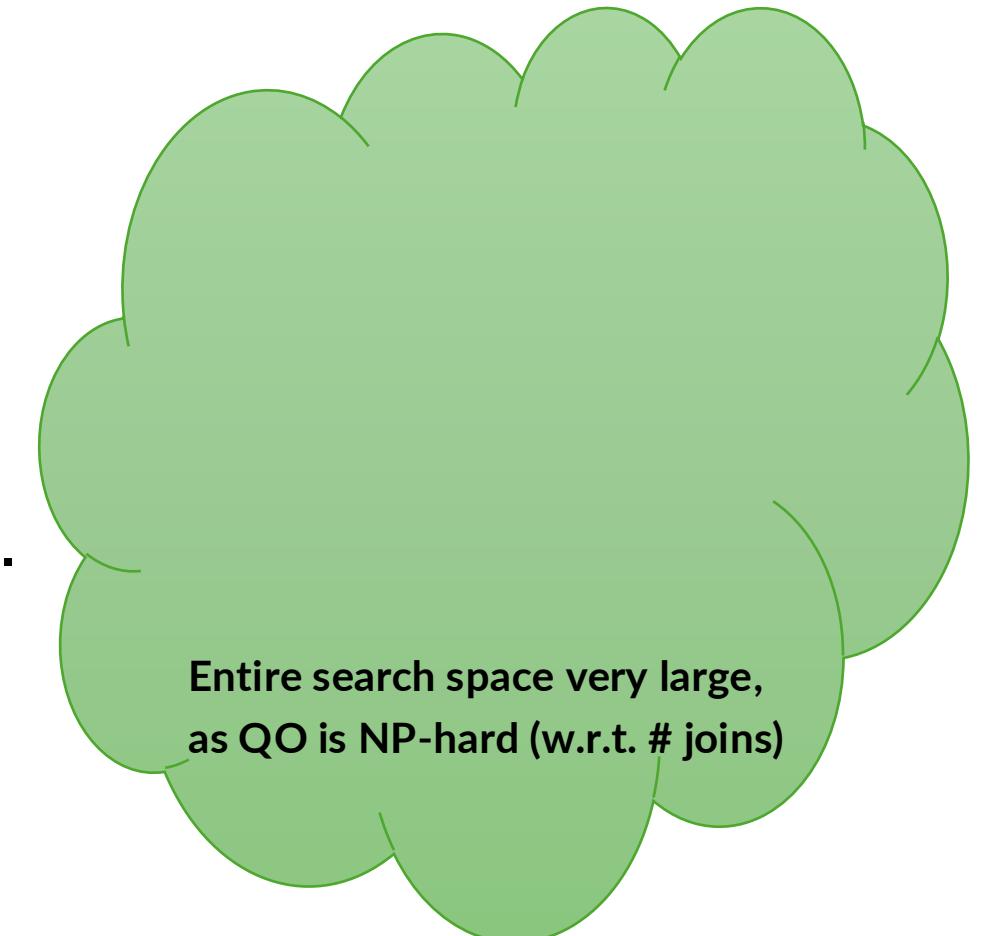


Query Optimization (QO)

1. Identify candidate equivalent trees (logical). It is an NP-hard problem, so the space is large.
2. For each candidate, find the execution plan tree (physical). We need to **estimate** the cost of each plan.
3. Choose the best overall (physical) plan.
 - **Practically: Choose from a subset of all possible plans.**

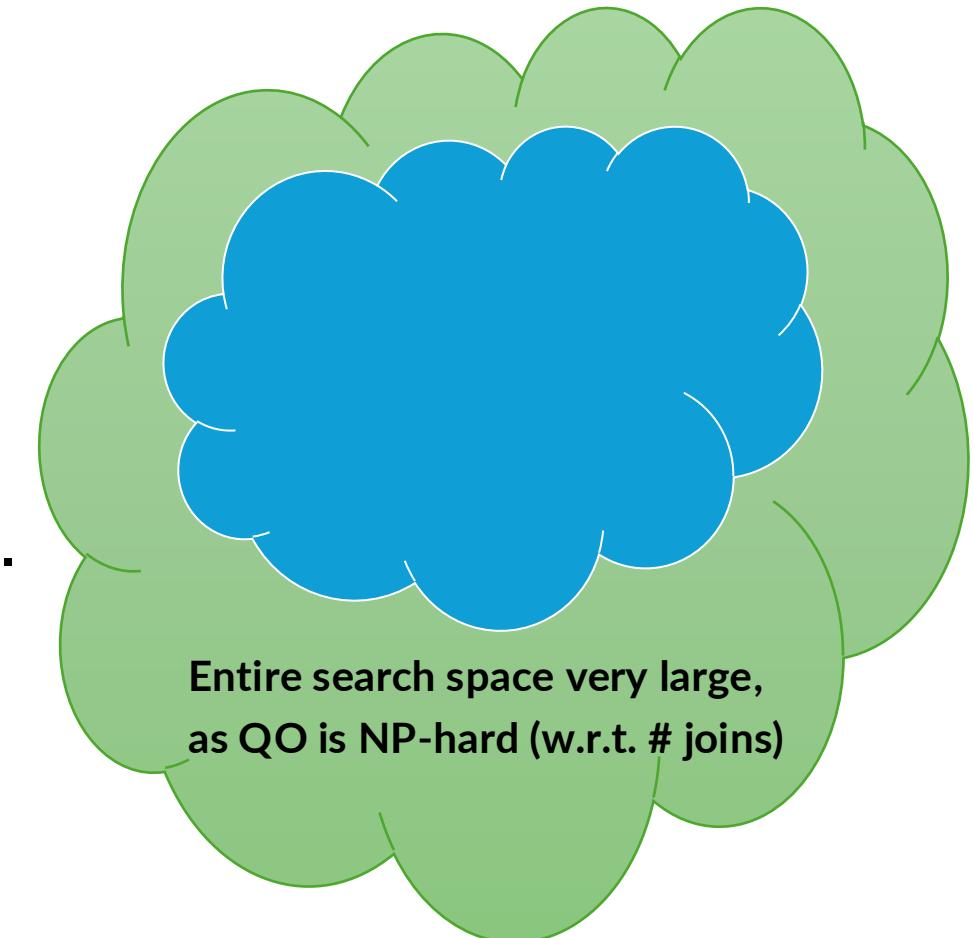
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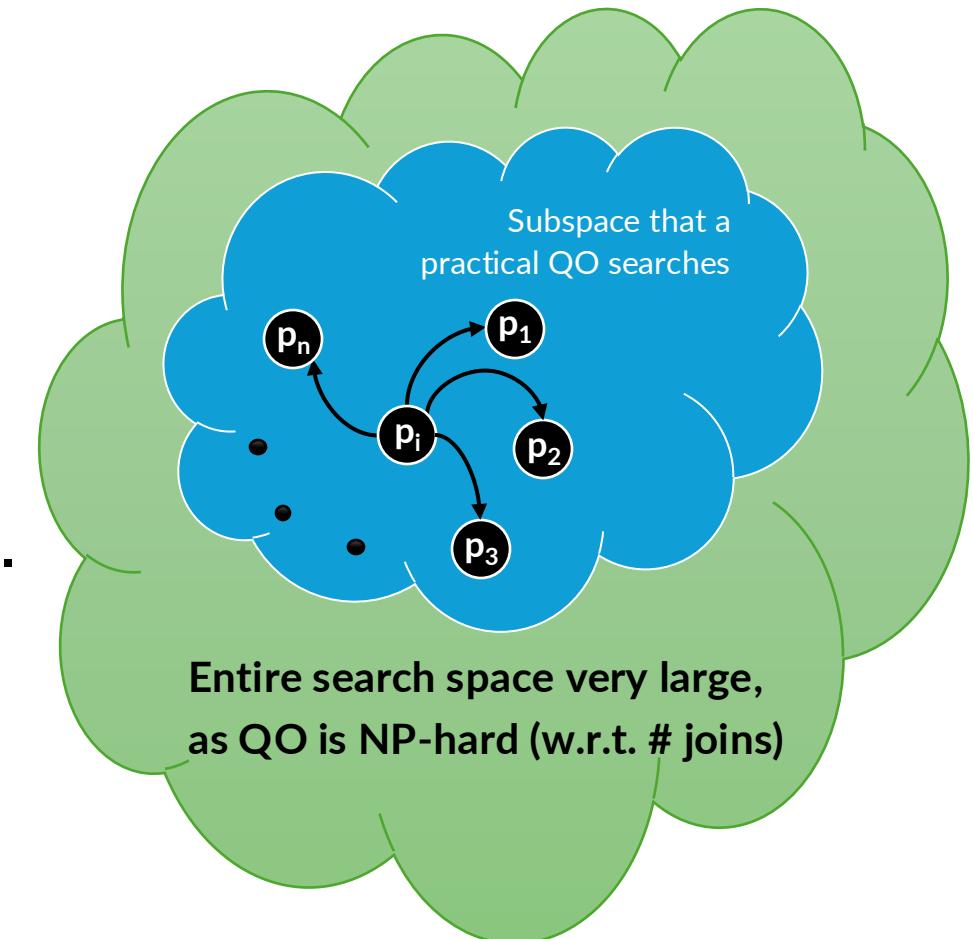
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- **Practically: Choose from a subset of all possible plans.**



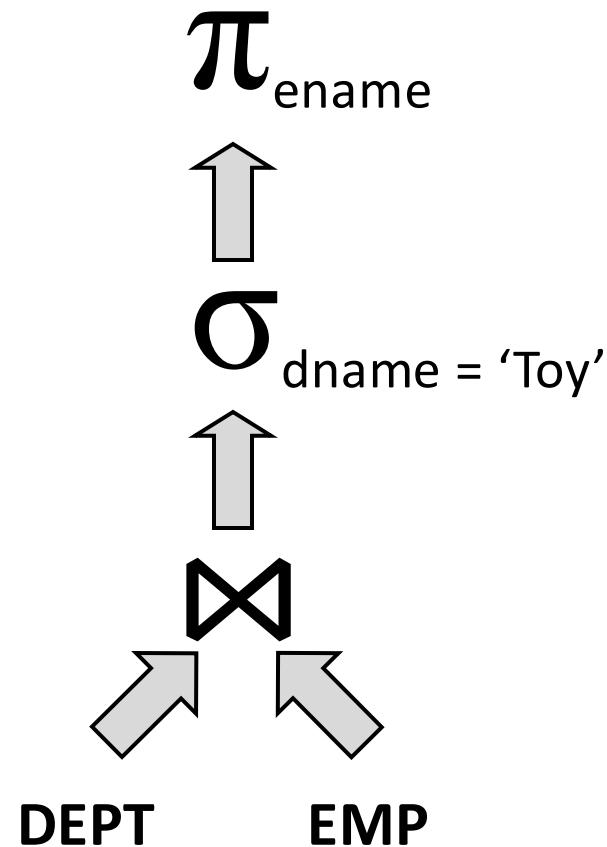
Logical VS. Physical Plans

- 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.

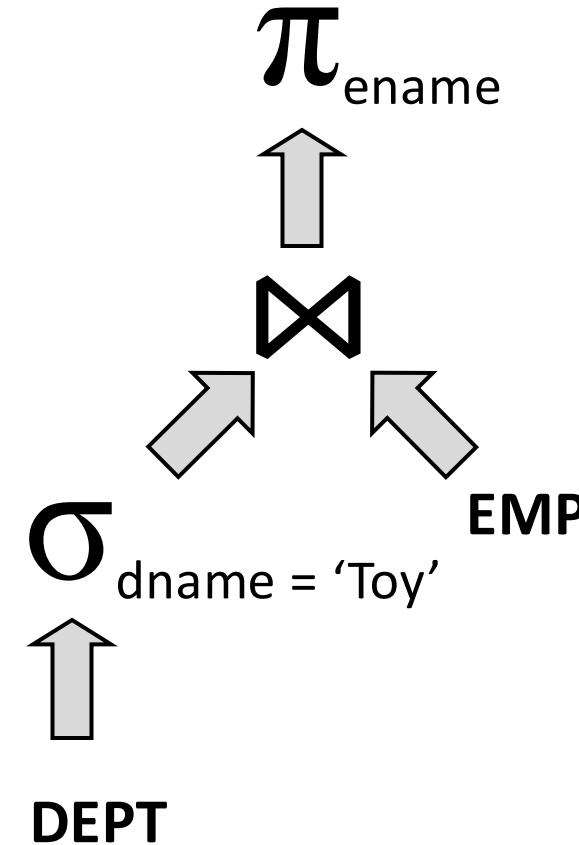
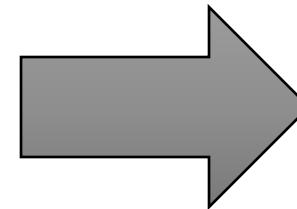
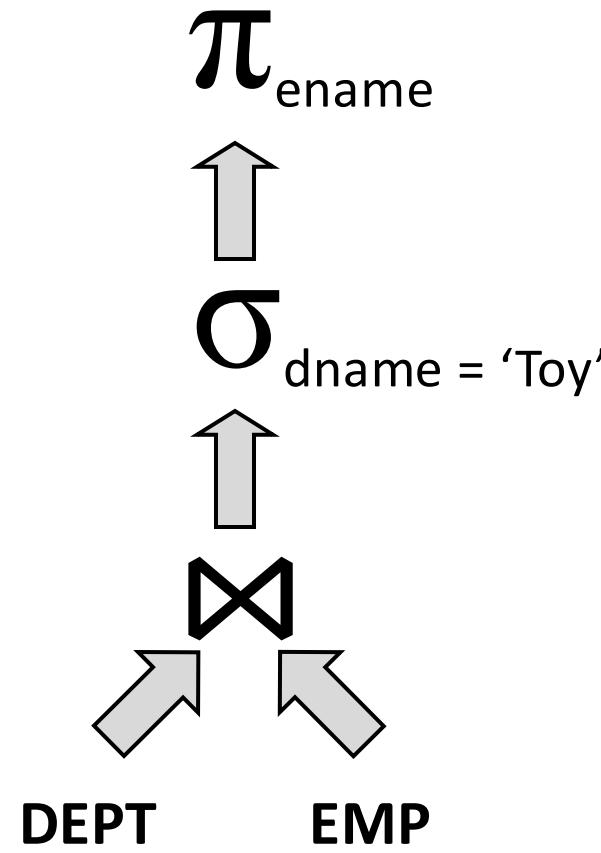
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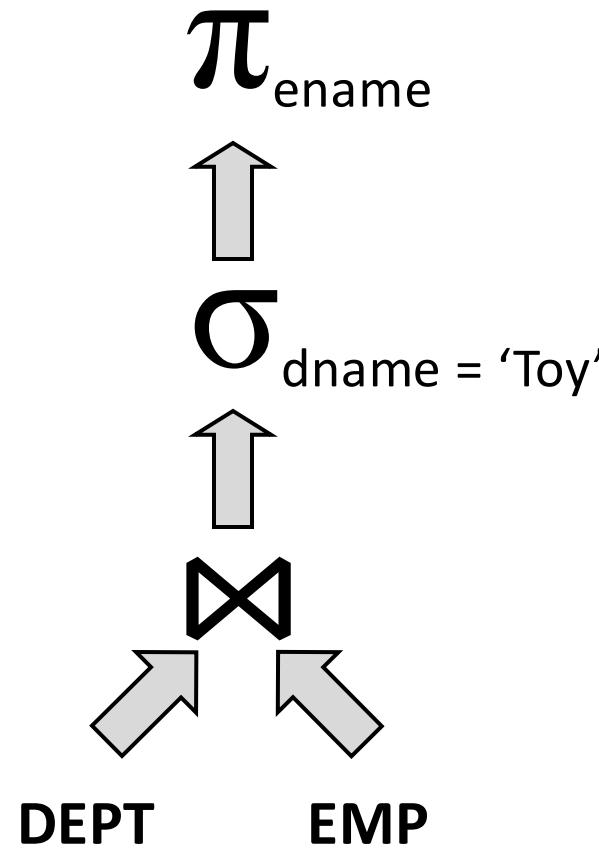
Predicate Pushdown

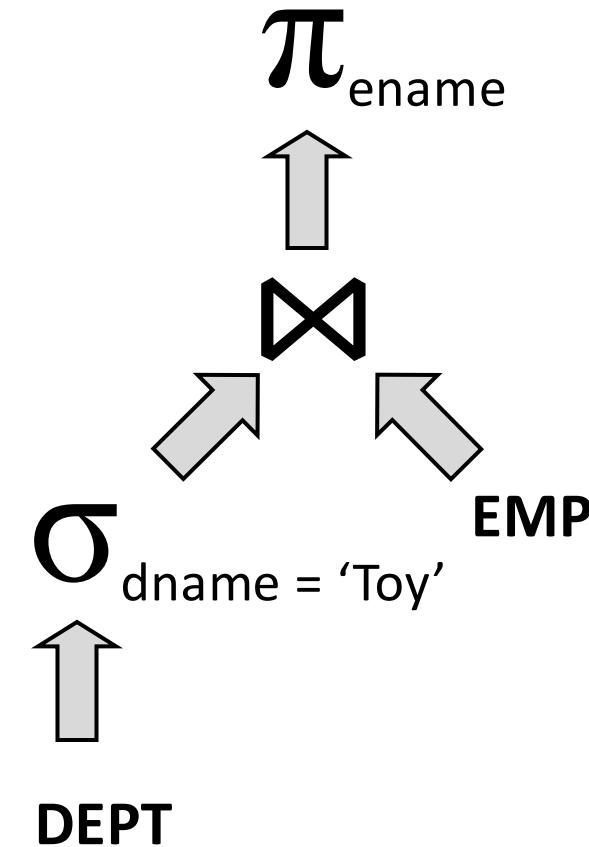


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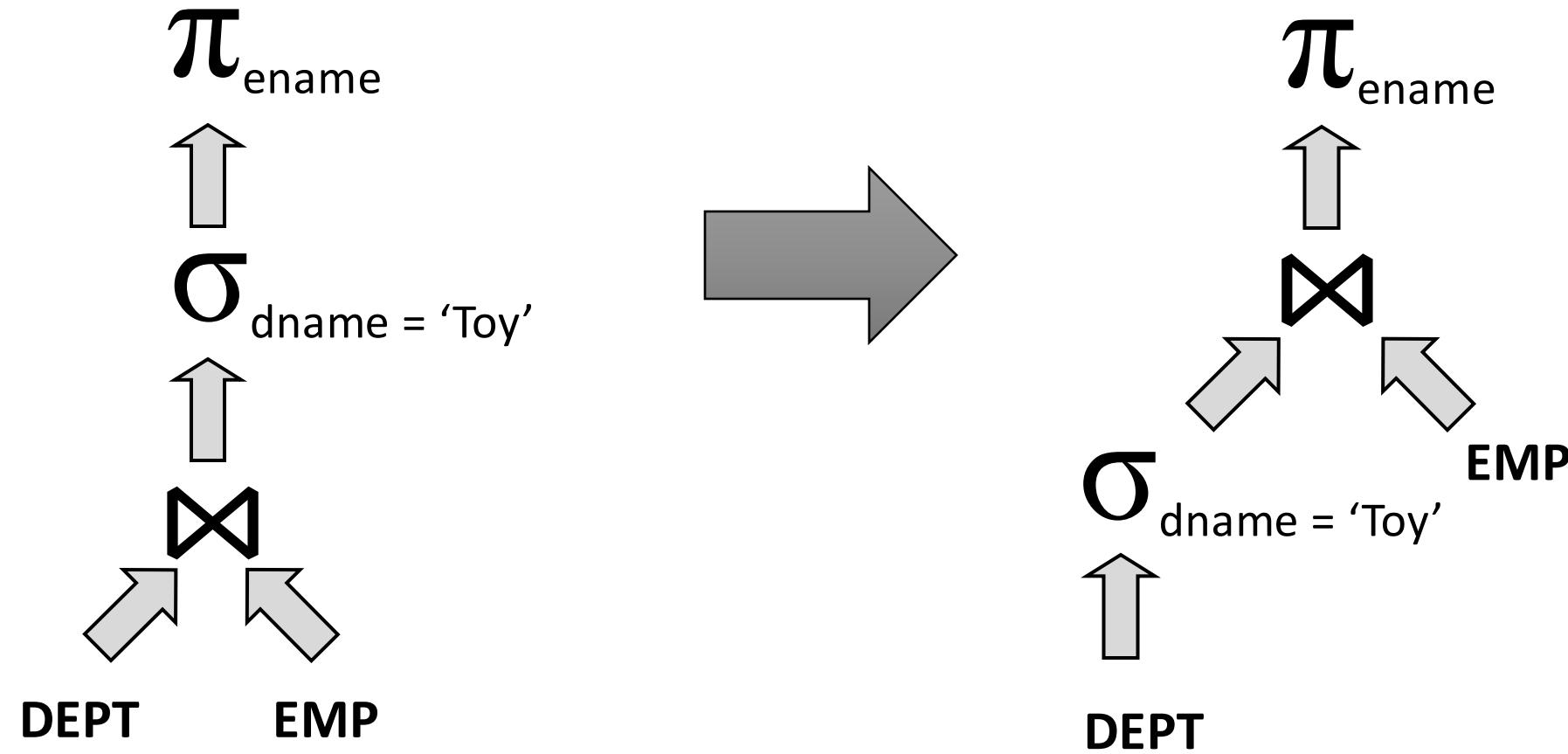


Predicate Pushdown



$$\pi_{ename} (\sigma_{dname = 'Toy'} (DEPT \bowtie EMP))$$


Predicate Pushdown

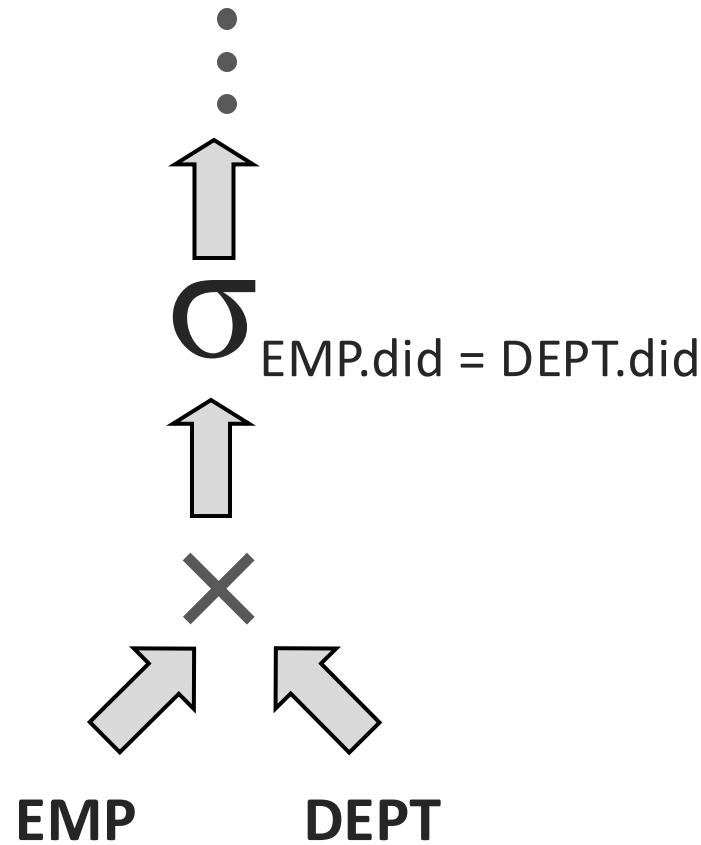


$$\pi_{\text{ename}} (\sigma_{\text{dname} = \text{'Toy'}} (\text{DEPT} \bowtie \text{EMP}))$$

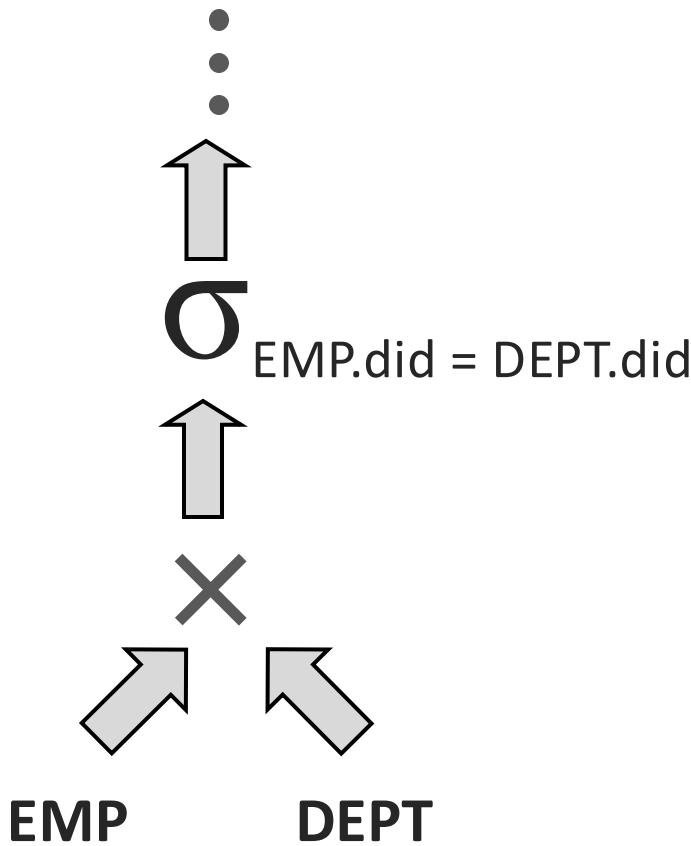
rewrite

$$\pi_{\text{ename}} (\text{EMP} \bowtie \sigma_{\text{dname} = \text{'Toy'}} (\text{DEPT}))$$

Replace Cartesian Product

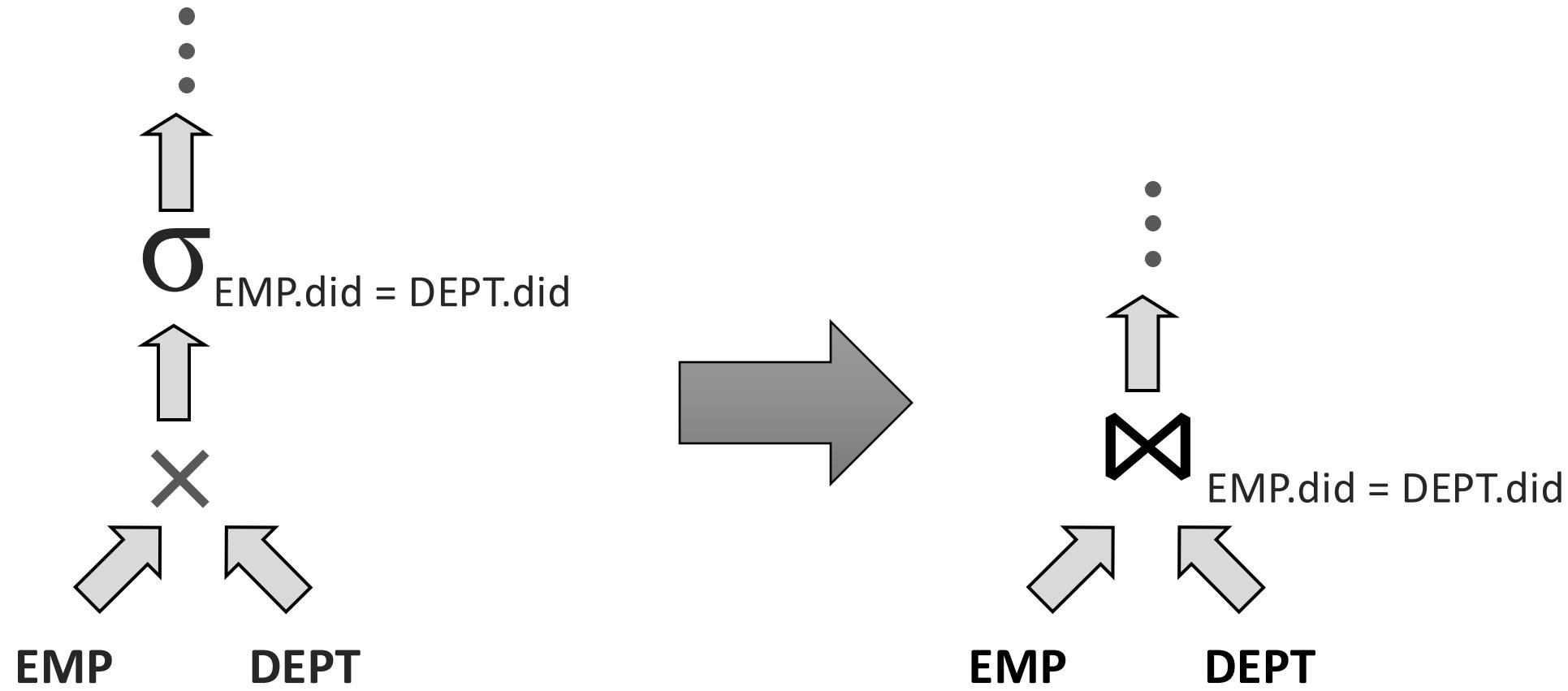


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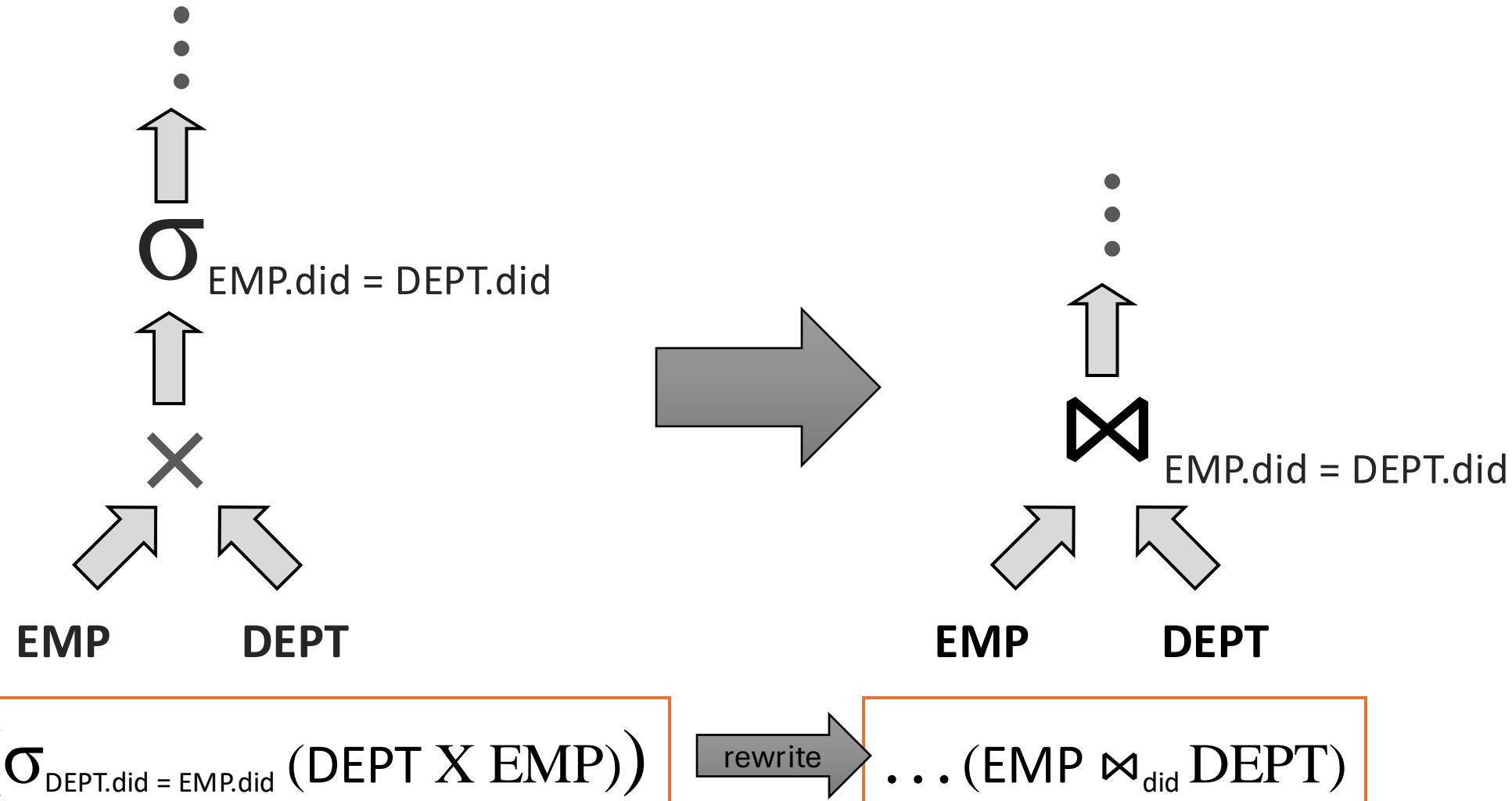
... ($\sigma_{\text{DEPT.did} = \text{EMP.did}} (\text{DEPT} \times \text{EMP})$)

Replace Cartesian Product

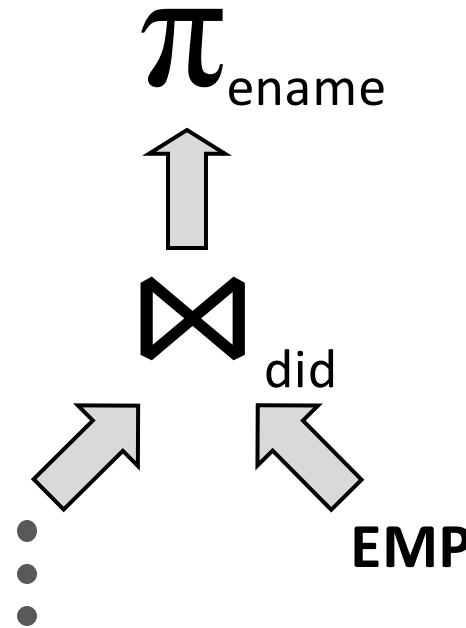


... $(\sigma_{\text{DEPT.did} = \text{EMP.did}} (\text{DEPT} \times \text{EMP}))$

Replace Cartesian Product

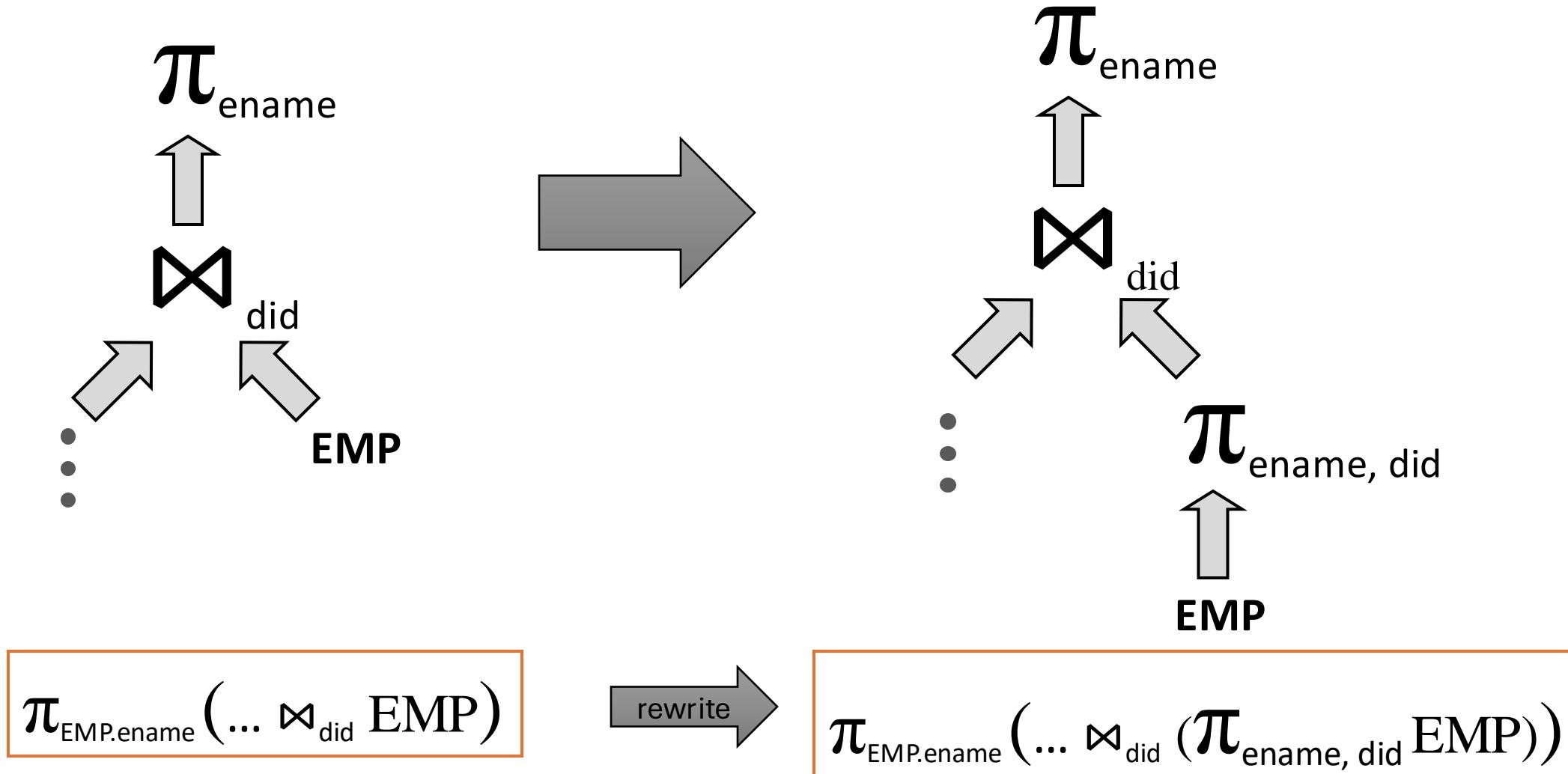


Projection Pushdown



$\boxed{\pi_{EMP.ename} (\dots \bowtie_{did} EMP)}$

Projection Pushdown



Equivalence

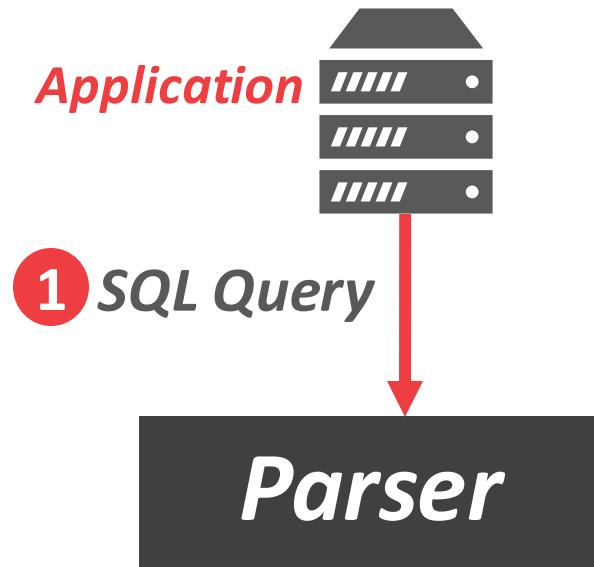
- $\sigma_{P_1}(\sigma_{P_2}(R)) \equiv \sigma_{P_2}(\sigma_{P_1}(R))$ (**σ commutativity**)
- $\sigma_{P_1 \wedge P_2 \dots \wedge P_n}(R) \equiv \sigma_{P_1}(\sigma_{P_2}(\dots \sigma_{P_n}(R)))$ (**cascading σ**)
- $\prod_{a_1}(R) \equiv \prod_{a_1}(\prod_{a_2}(\dots \prod_{a_k}(R)\dots)), a_i \subseteq a_{i+1}$ (**cascading \prod**)
- $R \bowtie S \equiv S \bowtie R$ (**join commutativity**)
- $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$ (**join associativity**)
- $\sigma_P(R \times S) \equiv (R \bowtie_P S)$, if P is a join predicate
- $\sigma_P(R \times S) \equiv \sigma_{P_1}(\sigma_{P_2}(R) \bowtie_{P_4} \sigma_{P_3}(S))$, where $P = p_1 \wedge p_2 \wedge p_3 \wedge p_4$
- $\prod_{A_1, A_2, \dots, A_n}(\sigma_P(R)) \equiv \prod_{A_1, A_2, \dots, A_n}(\sigma_P(\prod_{A_1, \dots, A_n, B_1, \dots, B_M} R))$, where $B_1 \dots B_M$ are columns in P
- ...

Architecture Overview

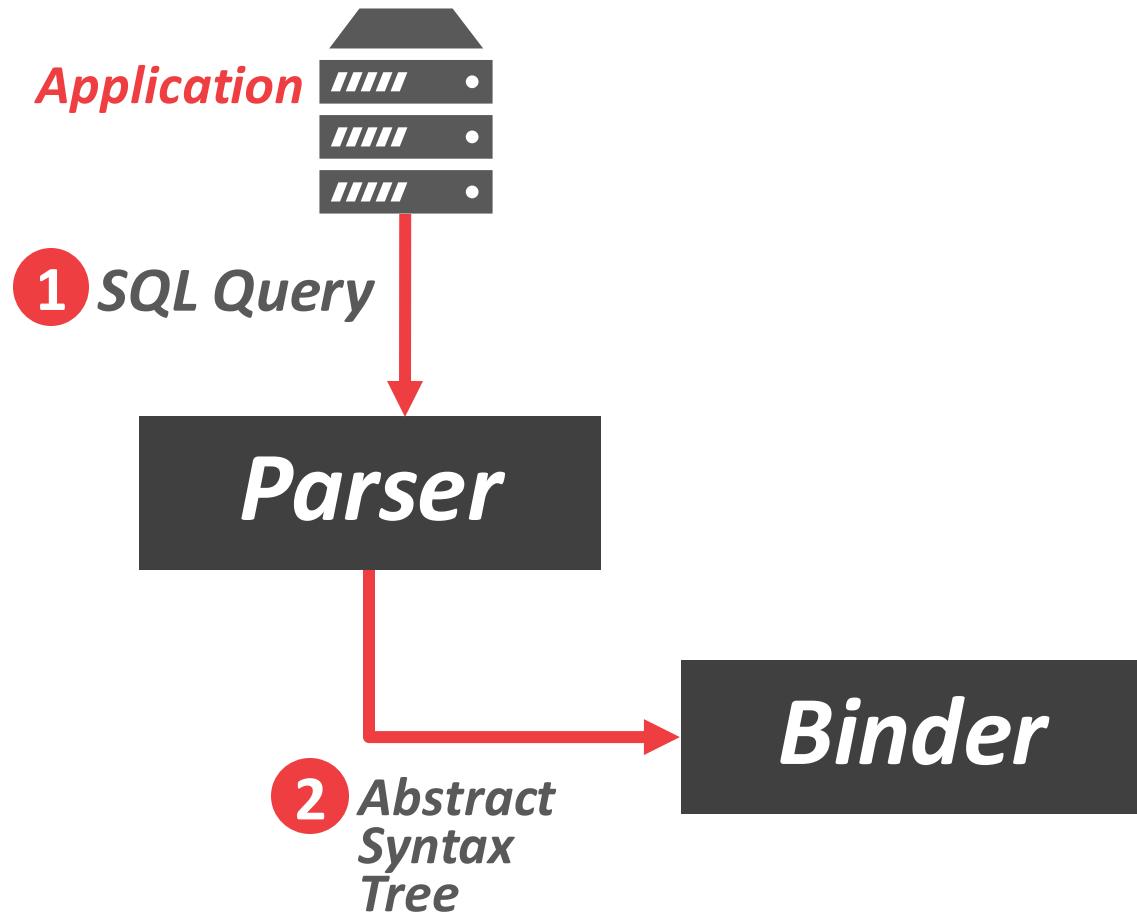
Application



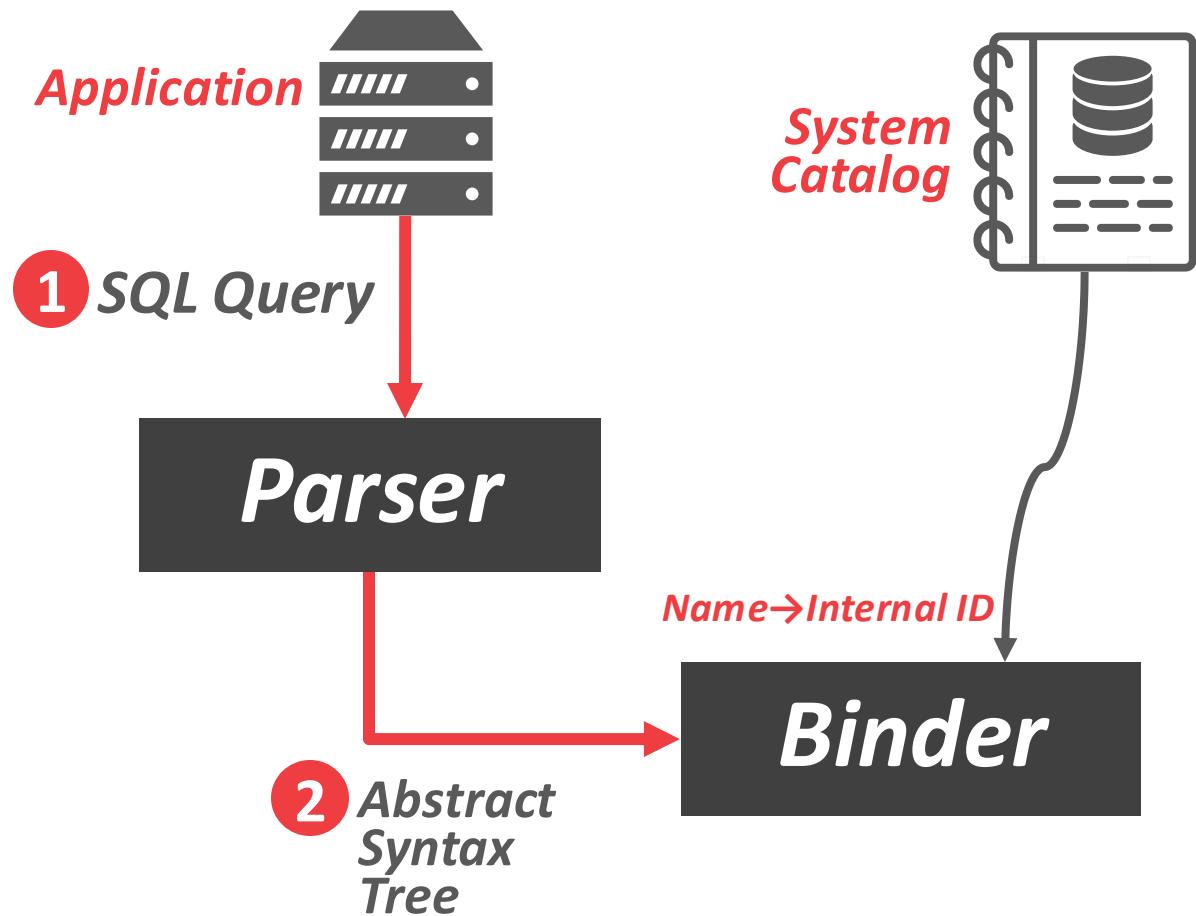
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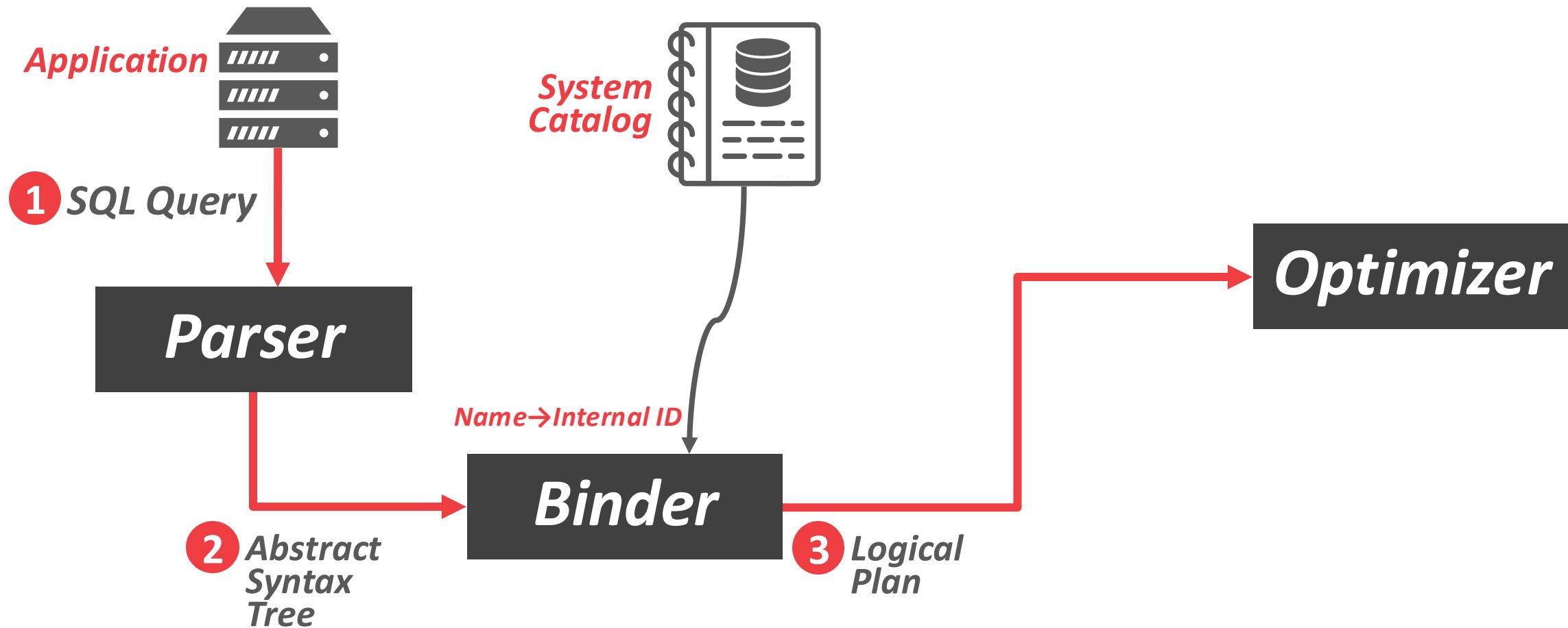
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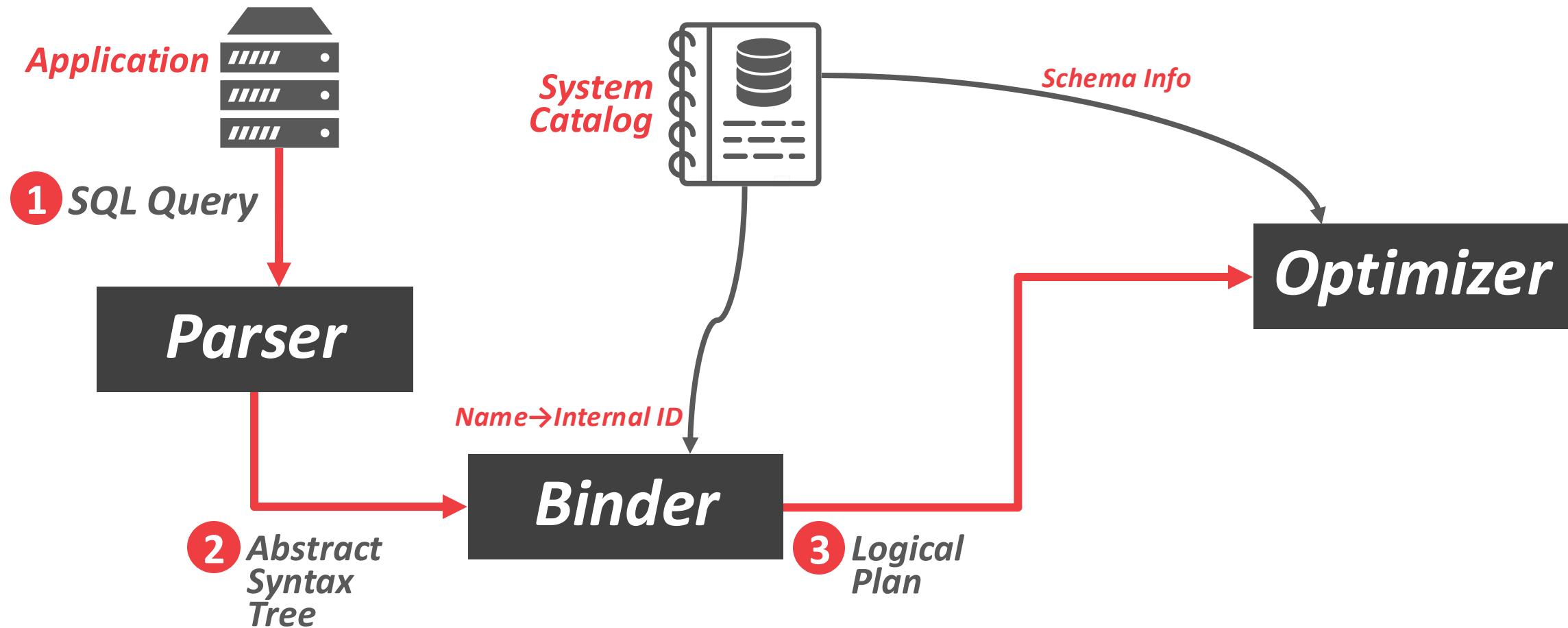
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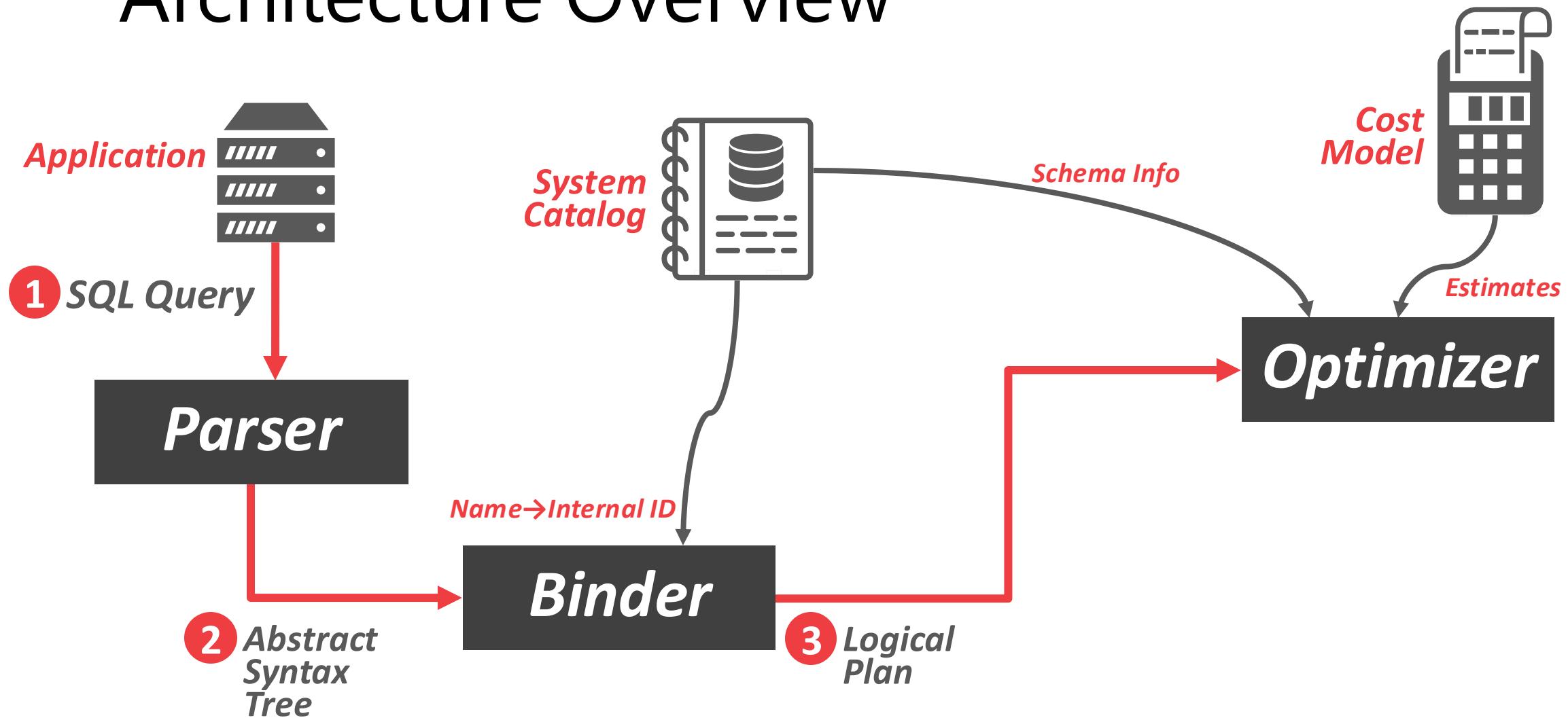
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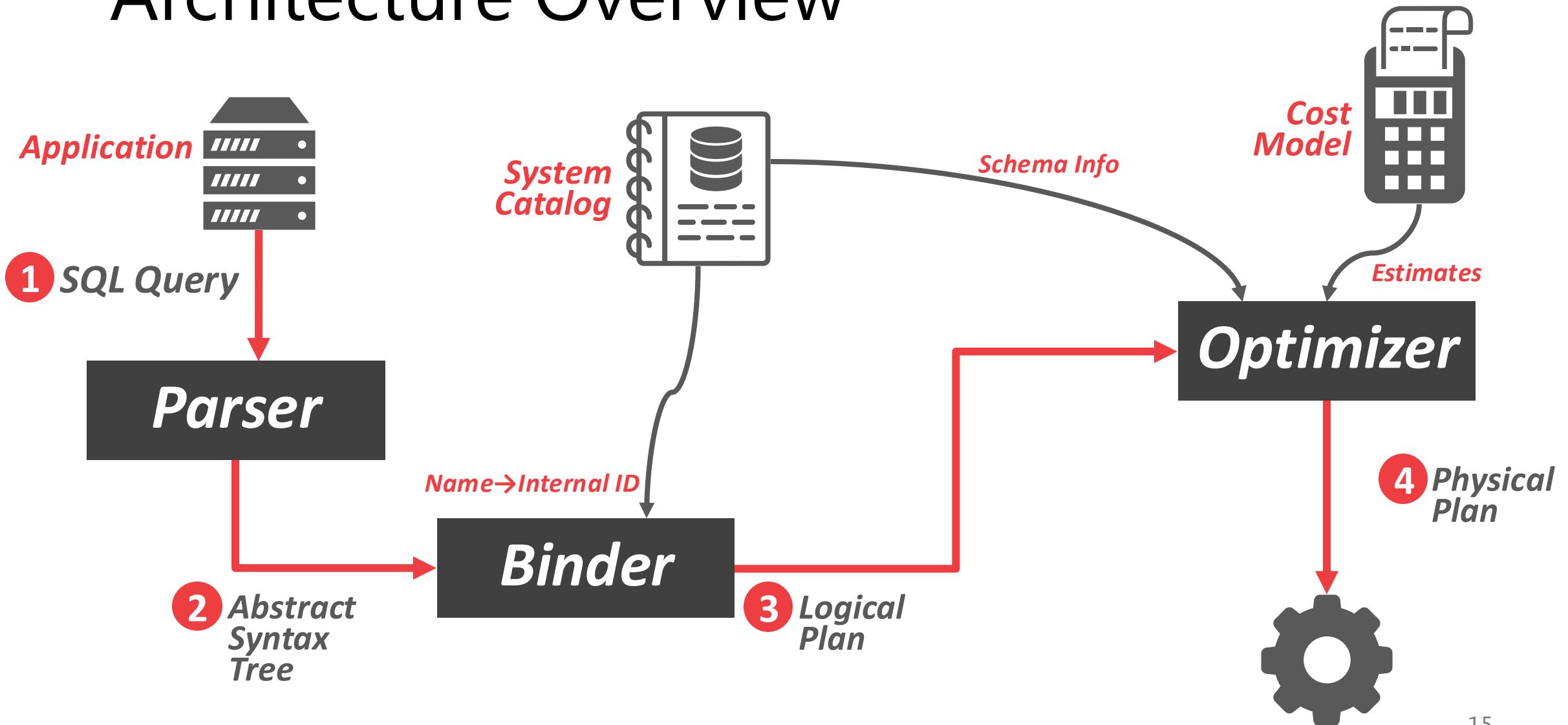
Architecture Overview



Architecture Overview



Architecture Overview



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Cost-based Search

Cost-based Query Optimization

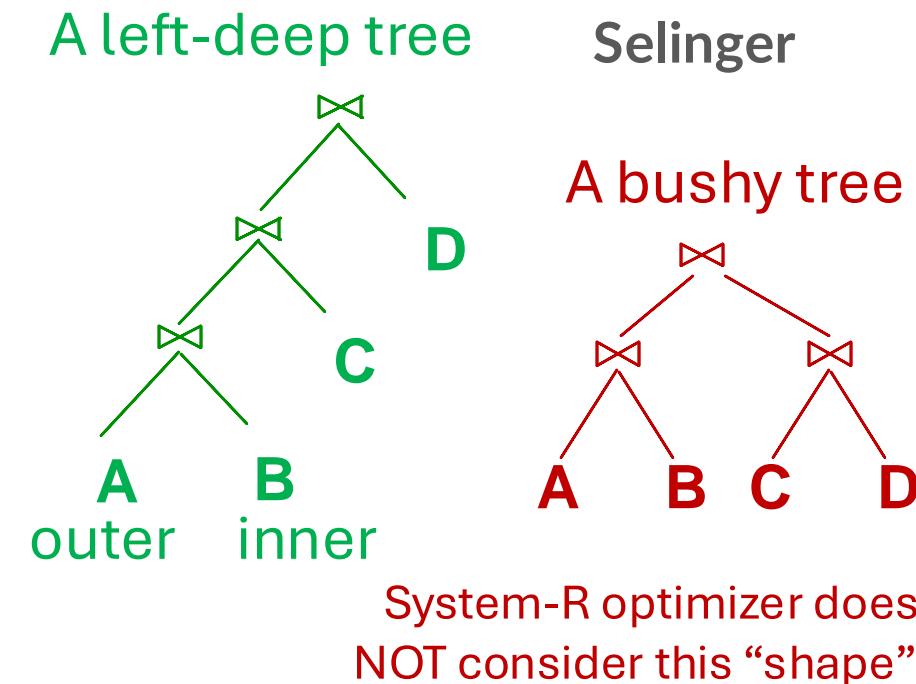
- Let's start with a certain style of QO: cost-based, bottom-up QO (the classic System-R optimizer approach)
- Approach: Enumerate different plans for the query and estimate their costs.
 - Single relation.
 - Multiple relations.
 - Nested sub-queries.
- It chooses the best plan it has seen for the query after exhausting all plans or some timeout.

Single-relation Query Planing

- Pick the best access method.
 - Sequential Scan
 - Binary Search (clustered indexes)
 - Index Scan
- Predicate evaluation ordering.
- Simple heuristics are often good enough for this.

System R Optimizer

- Break the query 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

```
SELECT ARTIST.NAME
      FROM ARTIST, APPEARS, ALBUM
     WHERE ARTIST.ID=APPEARS.ARTIST_ID
       AND APPEARS.ALBUM_ID=ALBUM.ID
       AND ALBUM.GENRE="Blues"
  ORDER BY ARTIST.ID
```

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

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ARTIST: Sequential Scan
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ALBUM: Index Look-up on GENRE

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ARTIST	⊗	APPEARS	⊗	ALBUM
APPEARS	⊗	ALBUM	⊗	ARTIST
ALBUM	⊗	APPEARS	⊗	ARTIST
APPEARS	⊗	ARTIST	⊗	ALBUM
ARTIST	×	ALBUM	⊗	APPEARS
ALBUM	×	ARTIST	⊗	APPEARS
:		:		:

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

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APPEARS: Sequential Scan

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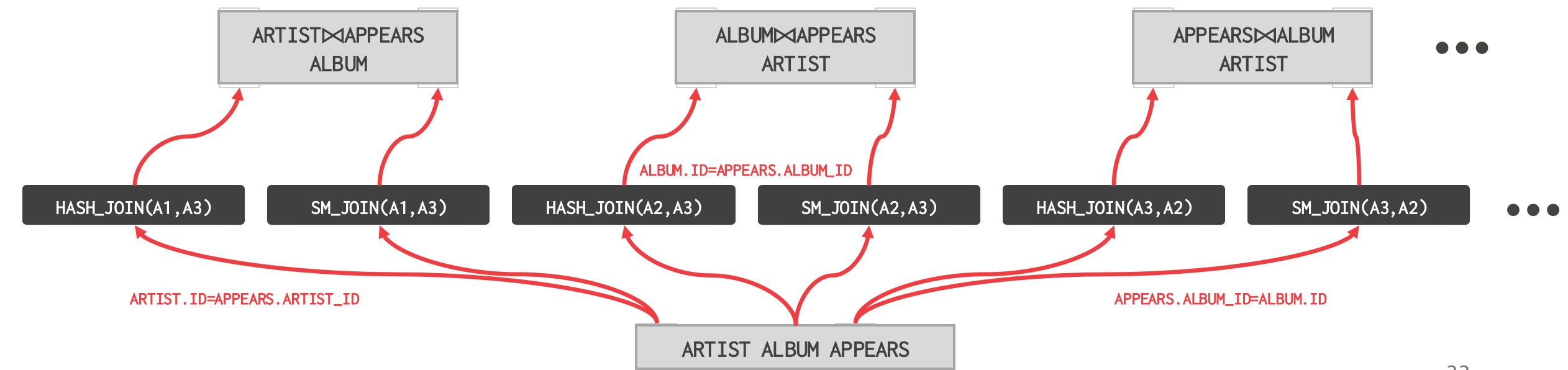
ARTIST	⊗	APPEARS	⊗	ALBUM
APPEARS	⊗	ALBUM	⊗	ARTIST
ALBUM	⊗	APPEARS	⊗	ARTIST
APPEARS	⊗	ARTIST	⊗	ALBUM
ARTIST	×	ALBUM	⊗	APPEARS
ALBUM	×	ARTIST	⊗	APPEARS
:		:		:

System R Optimizer

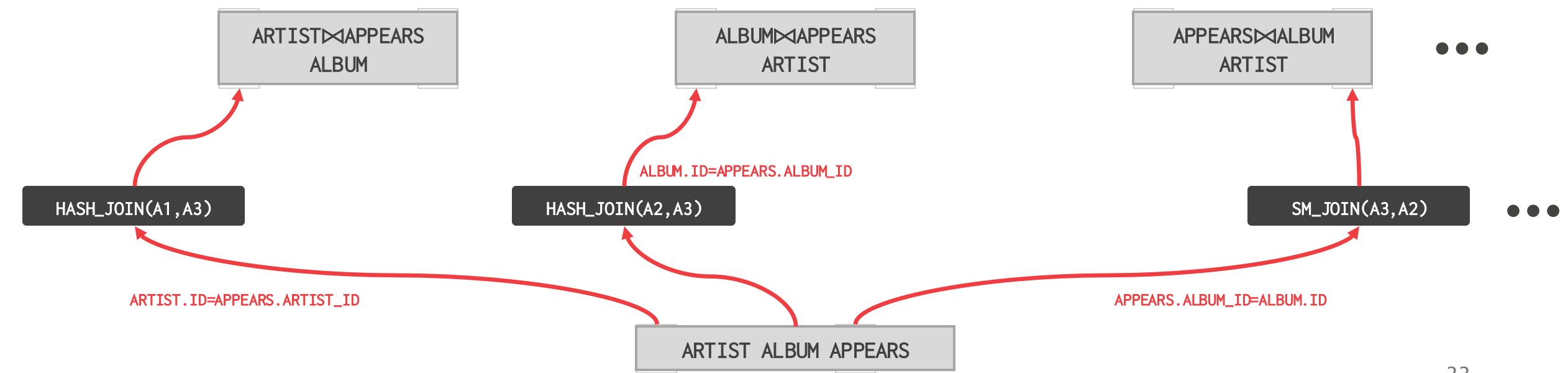
ARTIST ⚡ APPEARS ⚡ ALBUM

ARTIST ALBUM APPEARS

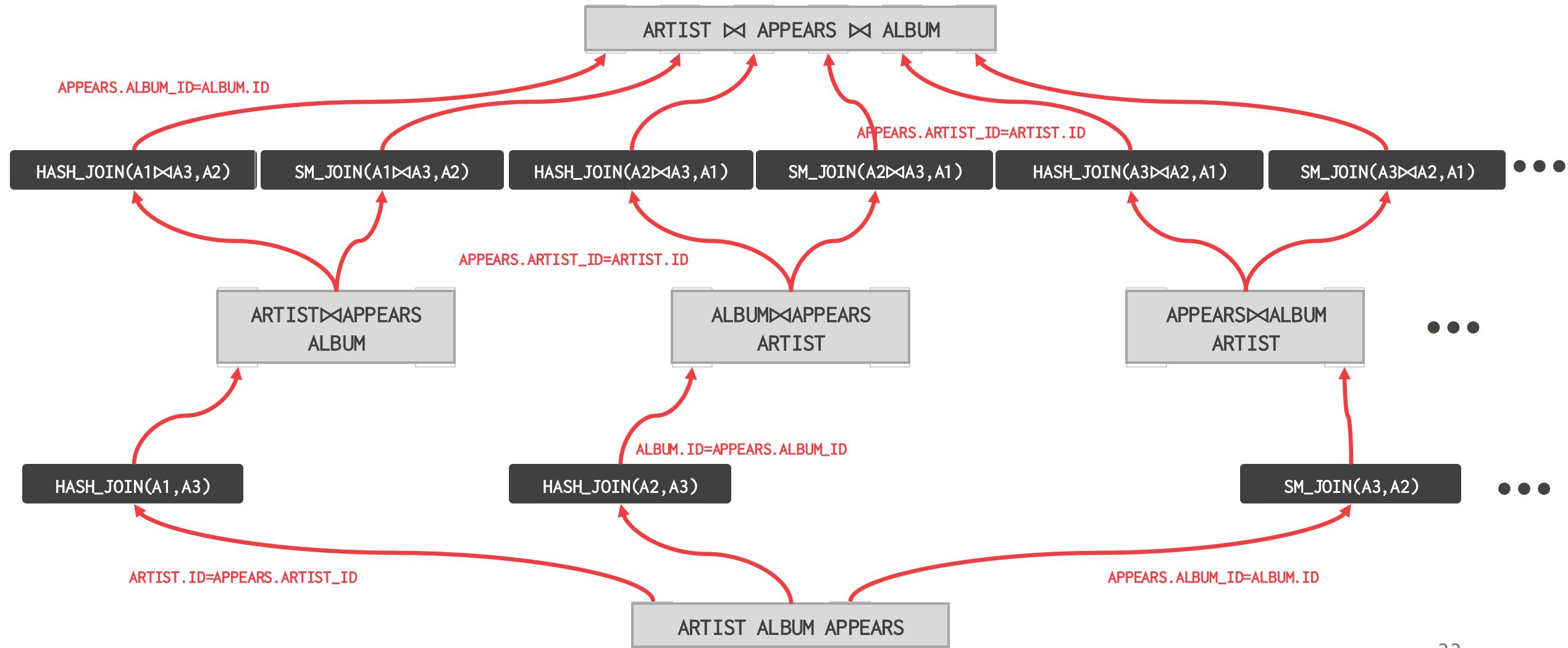
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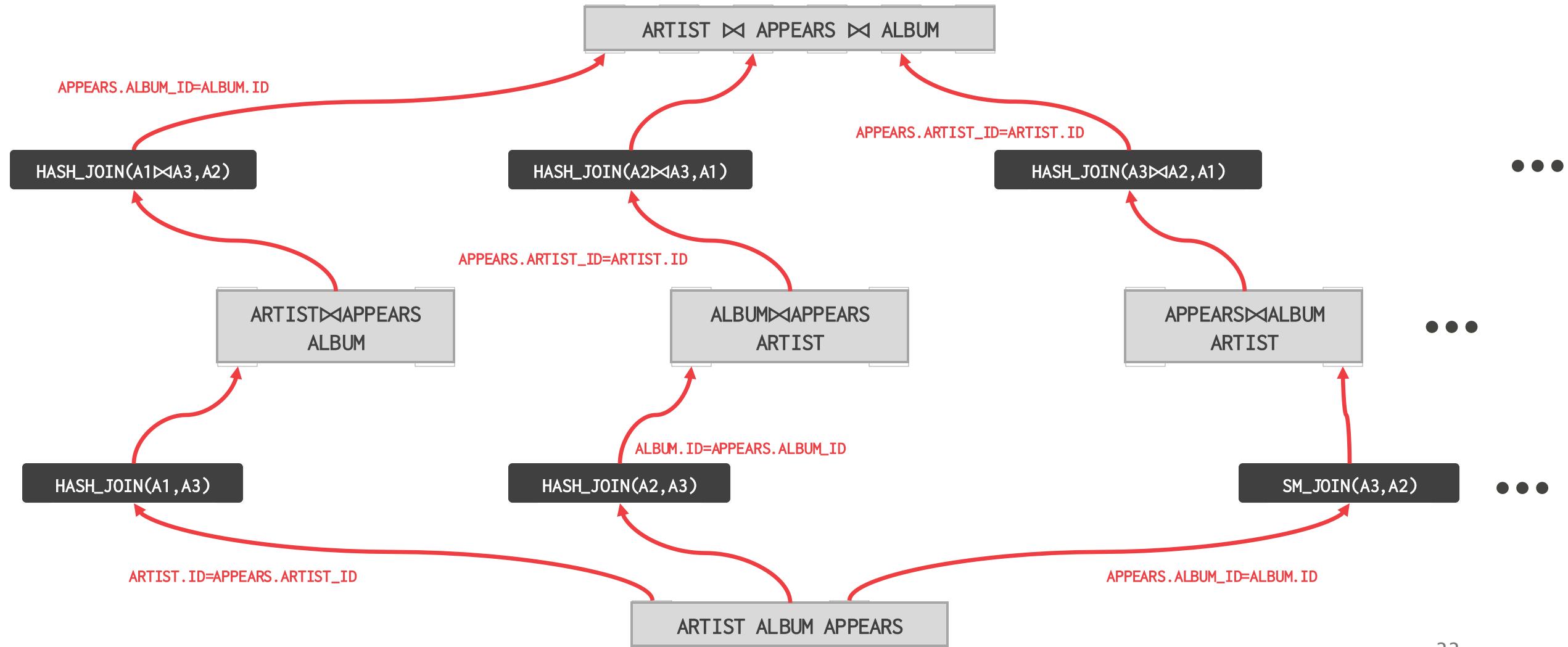
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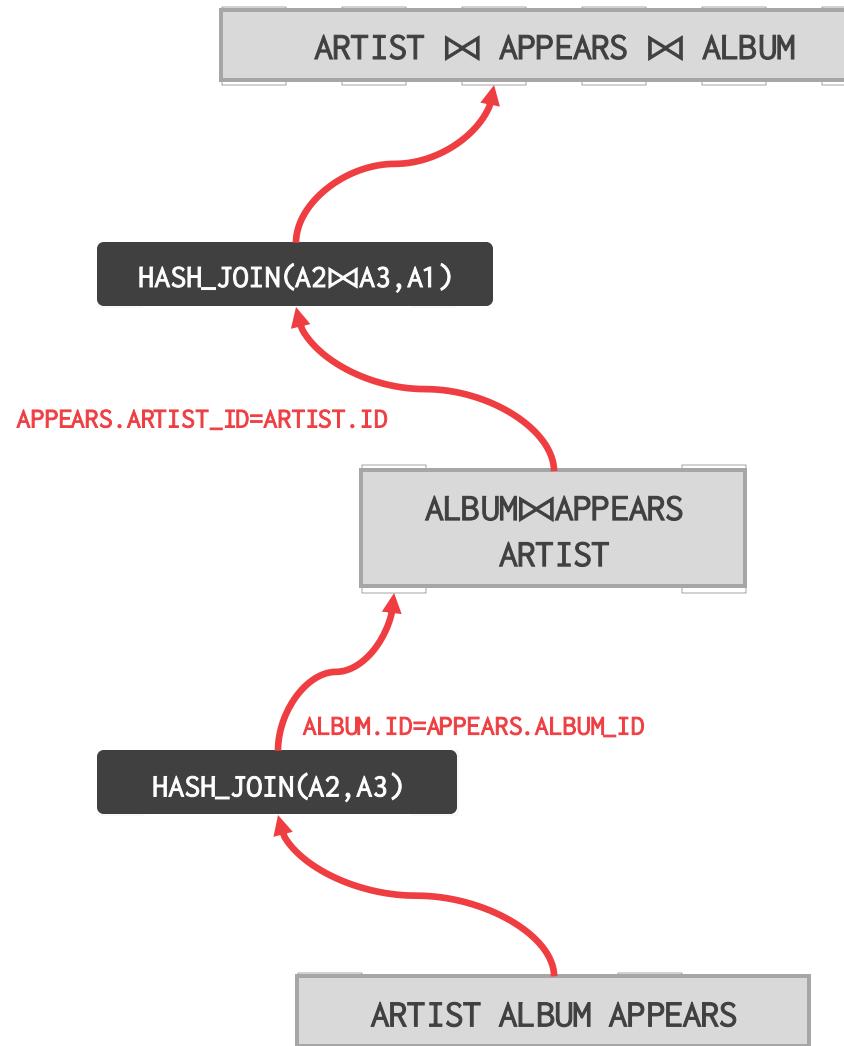
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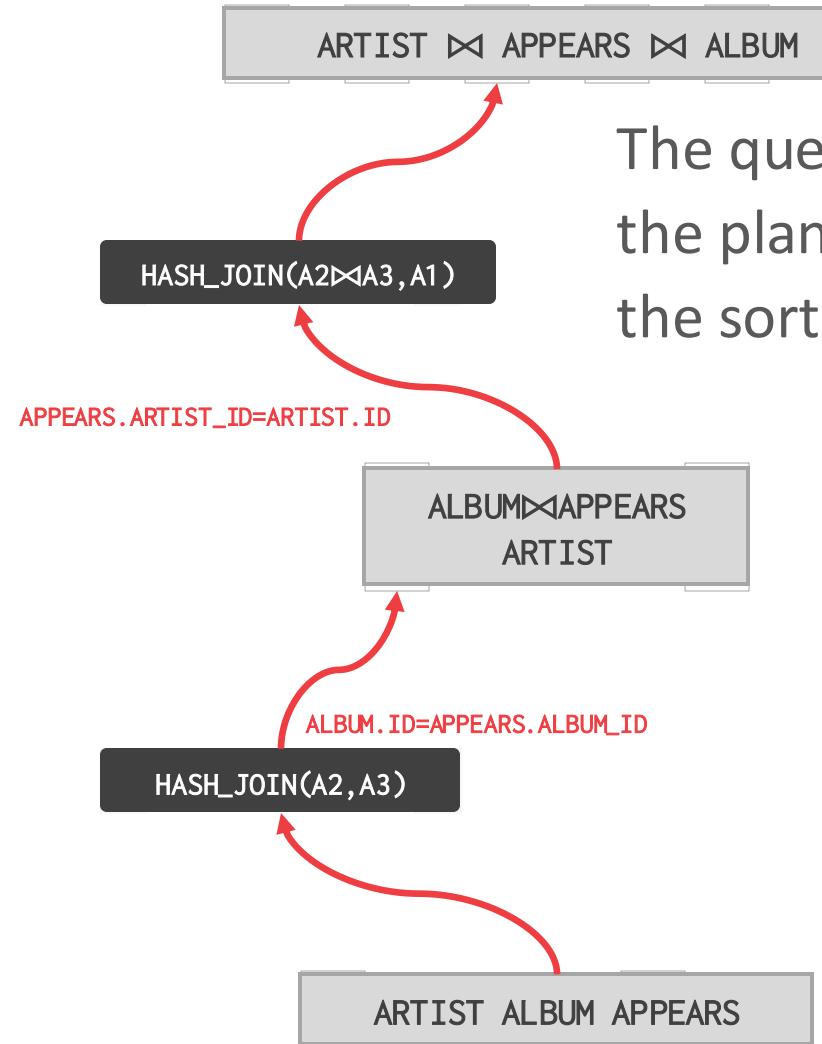
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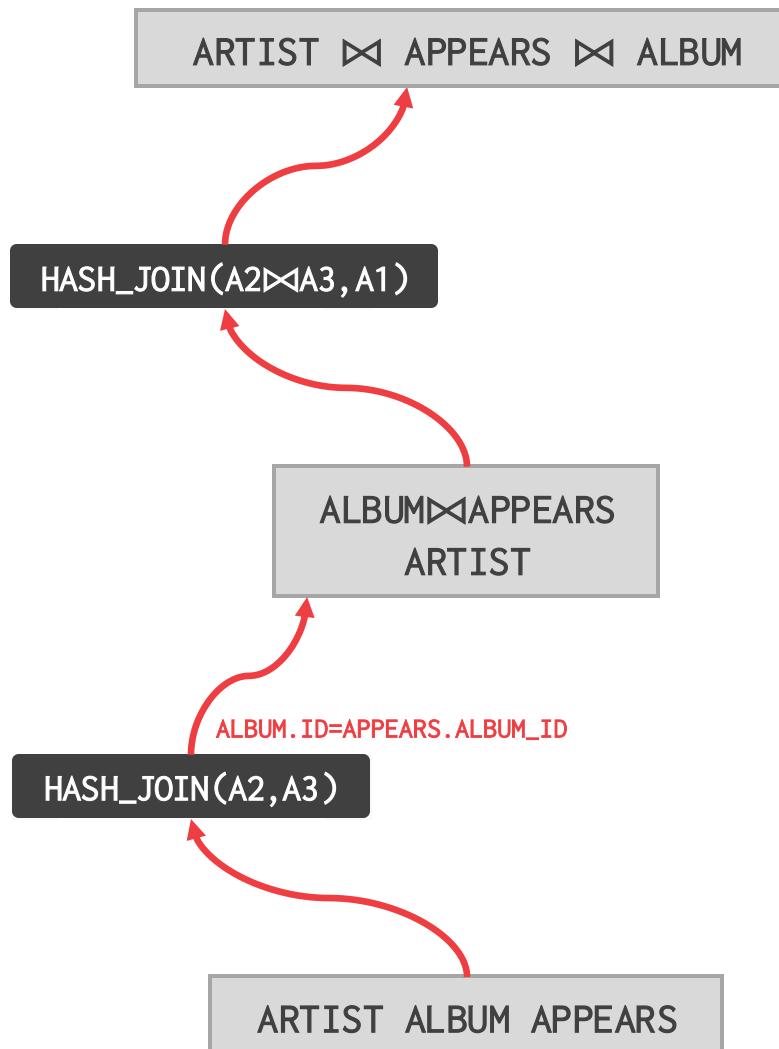
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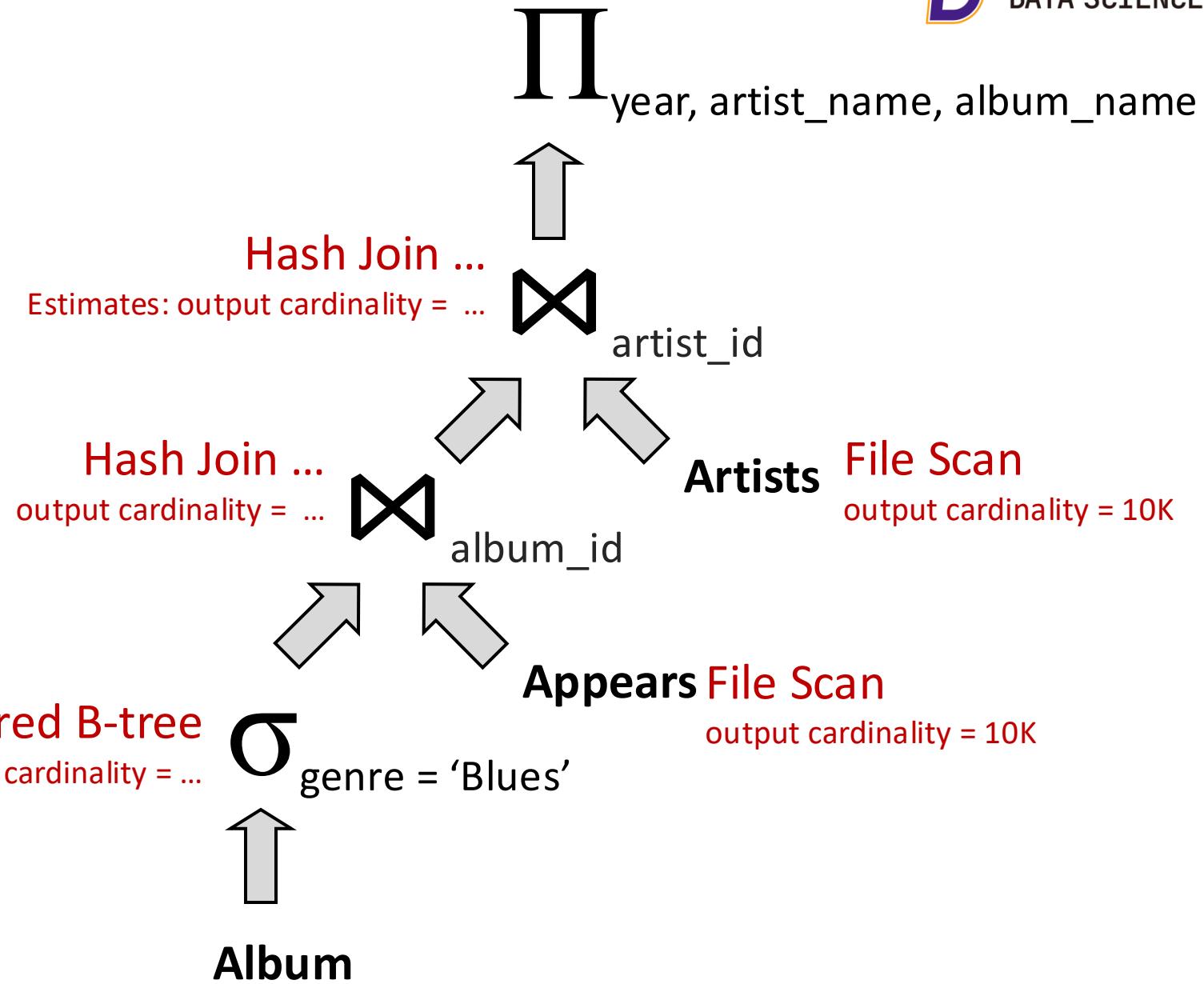
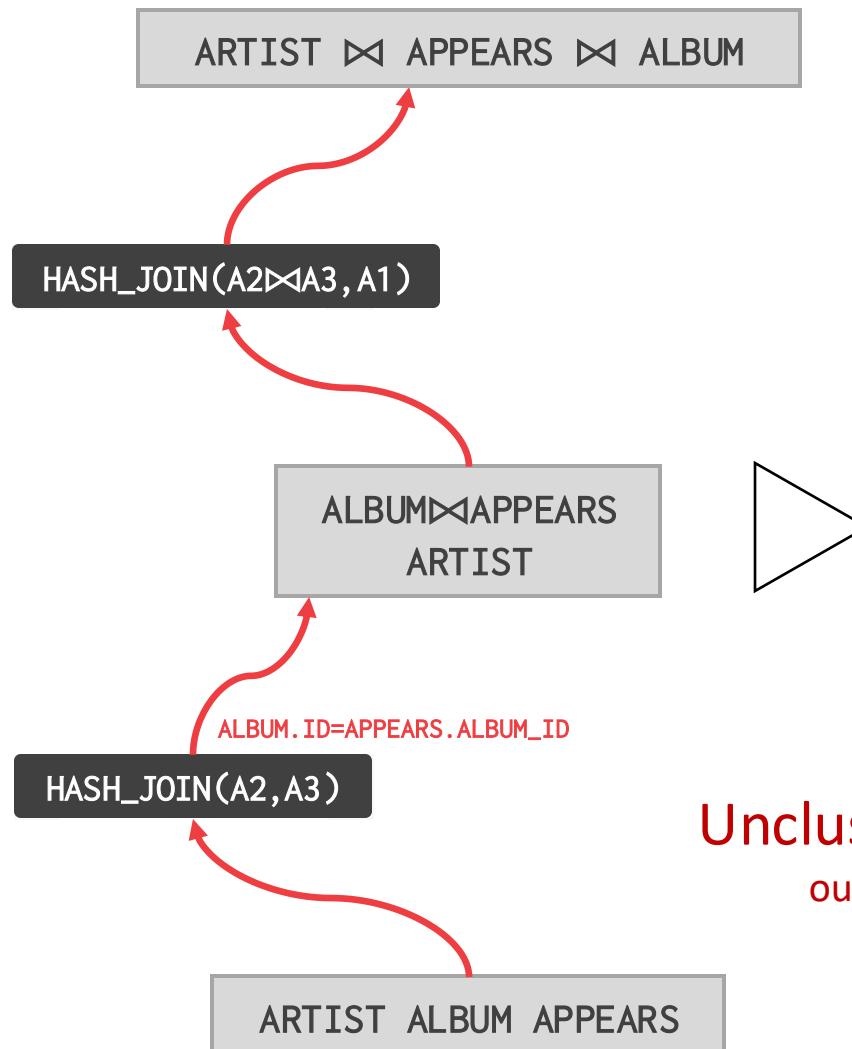


System R Optimizer



The query has **ORDER BY** on **ARTIST.ID** but the plans do not carry an explicit notion of the sorting properties.





Multi-Relation Query Planning

- **Choice #1: Bottom-up Optimization**
 - Start with nothing and then build up the plan to get to the outcome that you want.
- **Choice #2: Top-down Optimization**
 - Start with the outcome that you want, and then work down the tree to find the optimal plan that gets you to that goal.

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We just saw an example of this, the System R approach

Bottom-up Optimization

- Use static rules to perform initial optimization.
Then use dynamic programming to determine
the best join order for tables using a divide-and-conquer search
method
- **Examples:** IBM System R, DB2, MySQL, Postgres, most open-source DBMSs.

Top-down Optimization

- Start with a logical plan of what we want the query to be.
Perform a branch-and-bound search to traverse the plan tree by converting logical operators into physical operators.
- Keep track of global best plan during search.
- Treat physical properties of data as first-class entities during planning.
- **Example:** MSSQL, Greenplum, CockroachDB

Top-down Optimization

Top-down Optimization

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

Top-down Optimization

Invoke rules to create new nodes
and traverse the tree.

→ **Logical** → **Logical**:

JOIN(A,B) to JOIN(B,A)

→ **Logical** → **Physical**:

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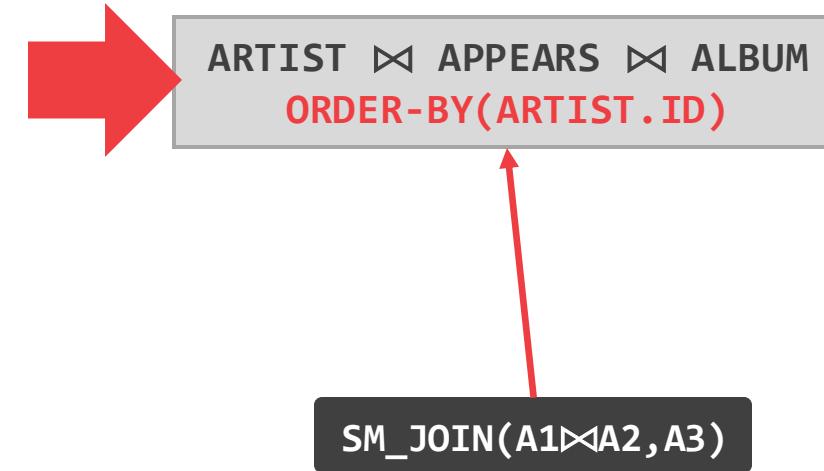
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ARTIST

ALBUM

APPEARS

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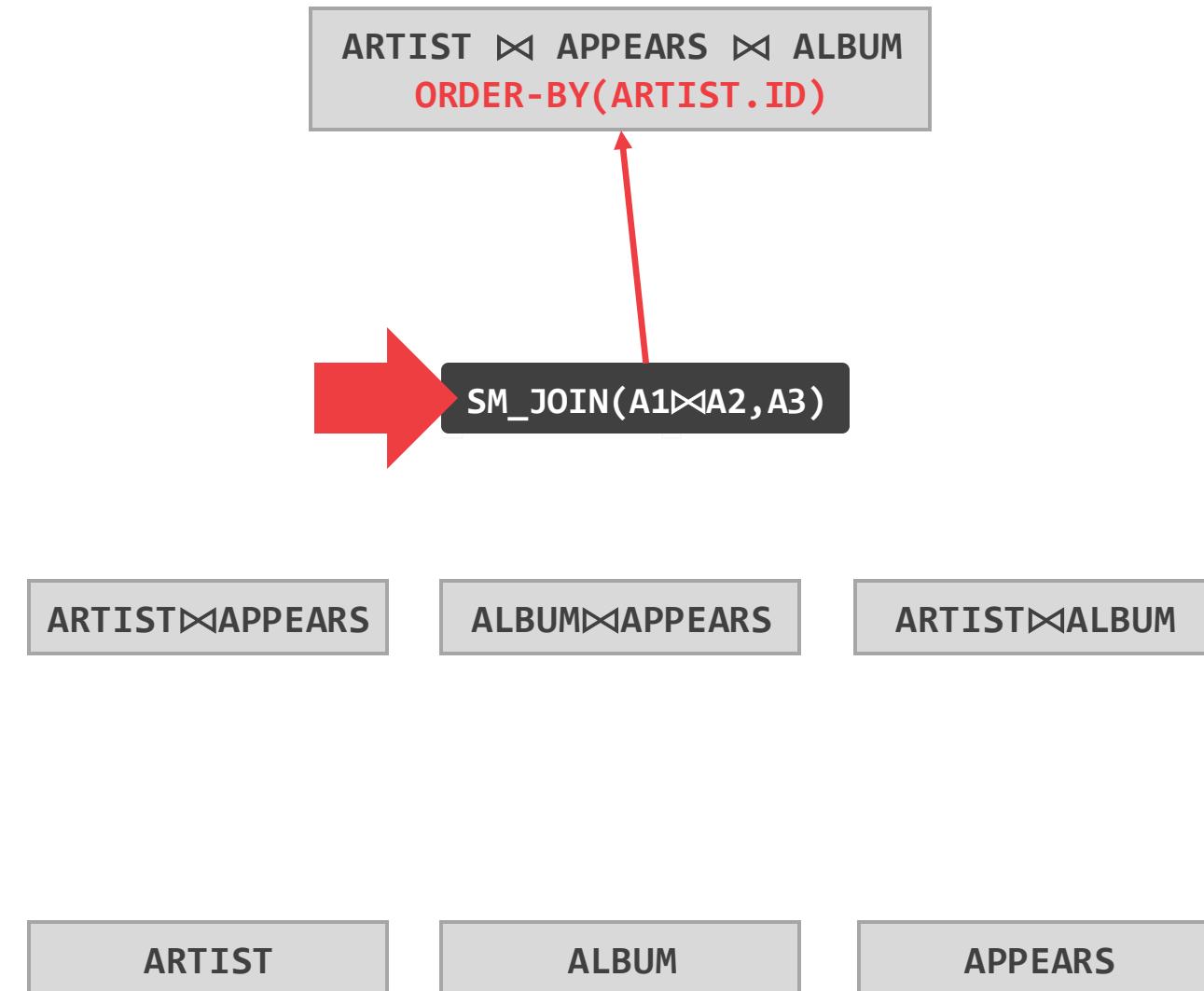
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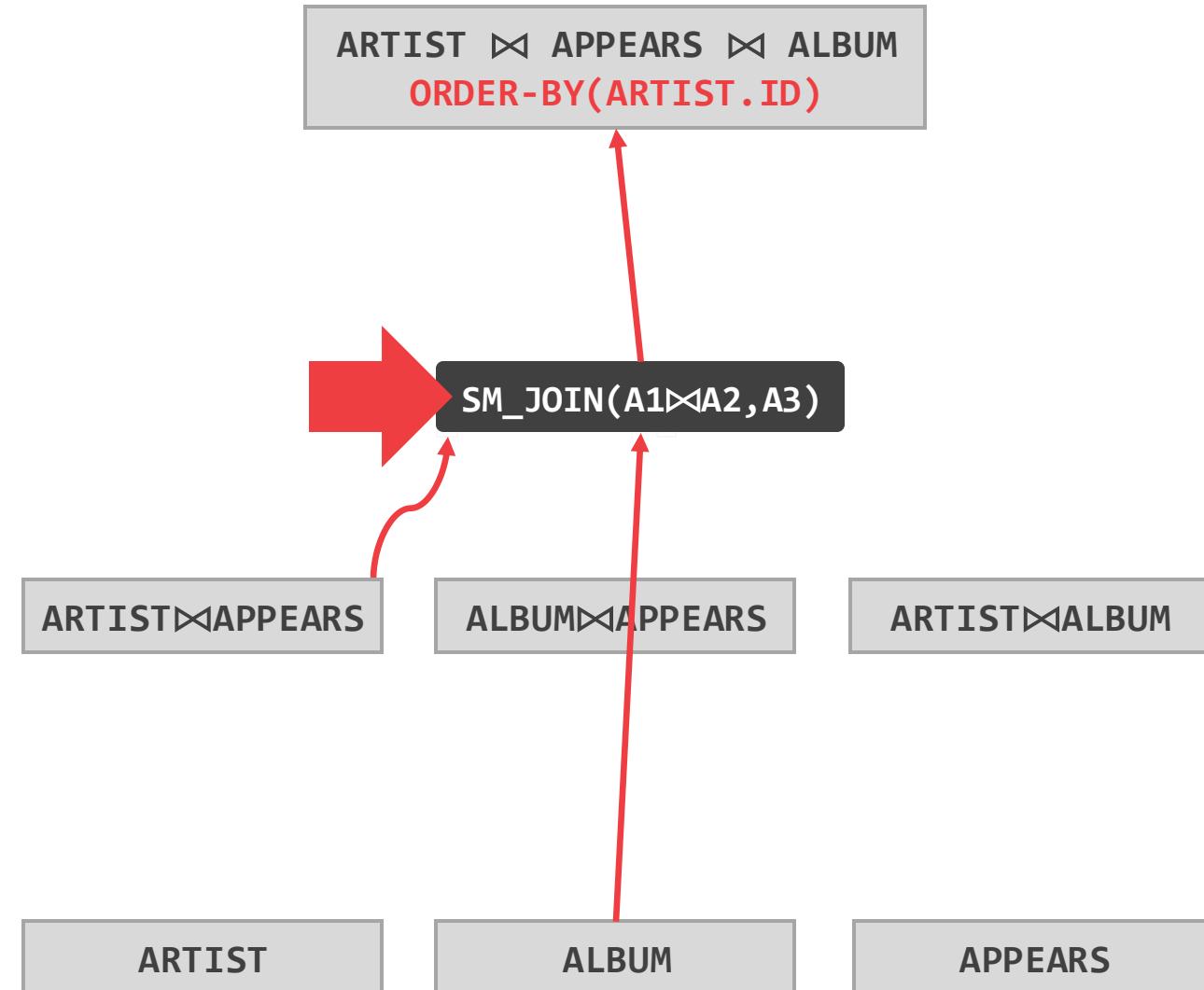
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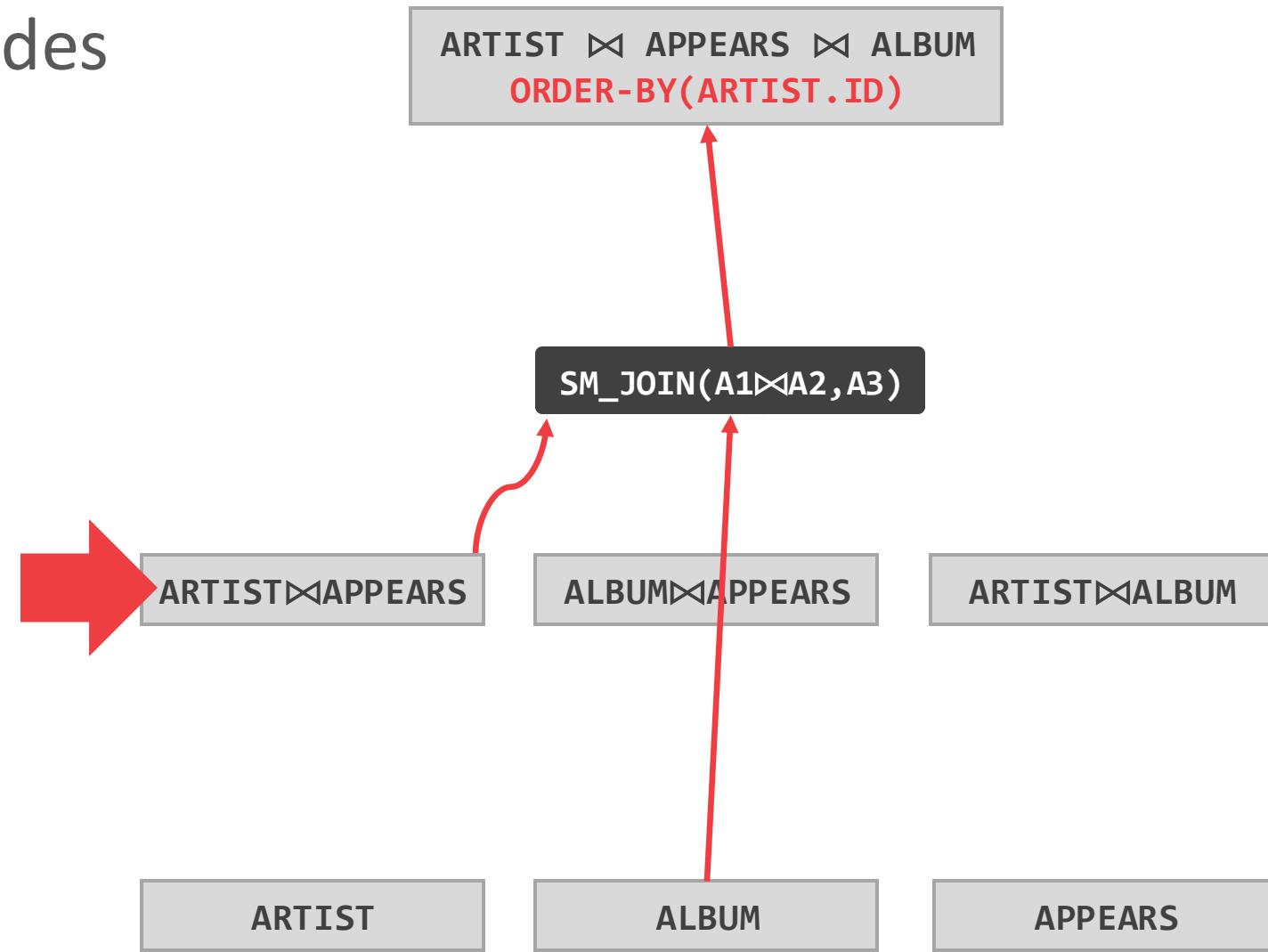
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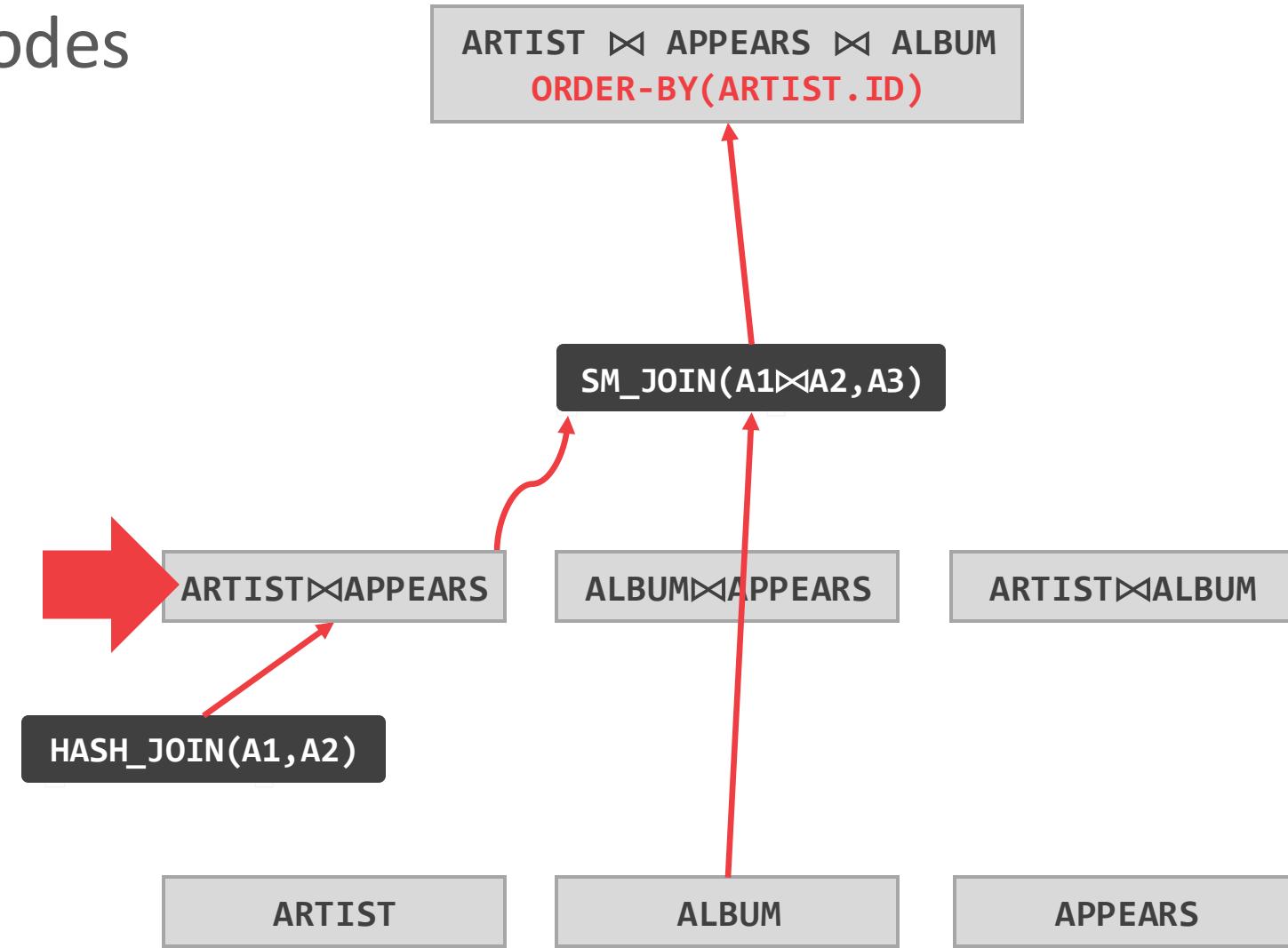
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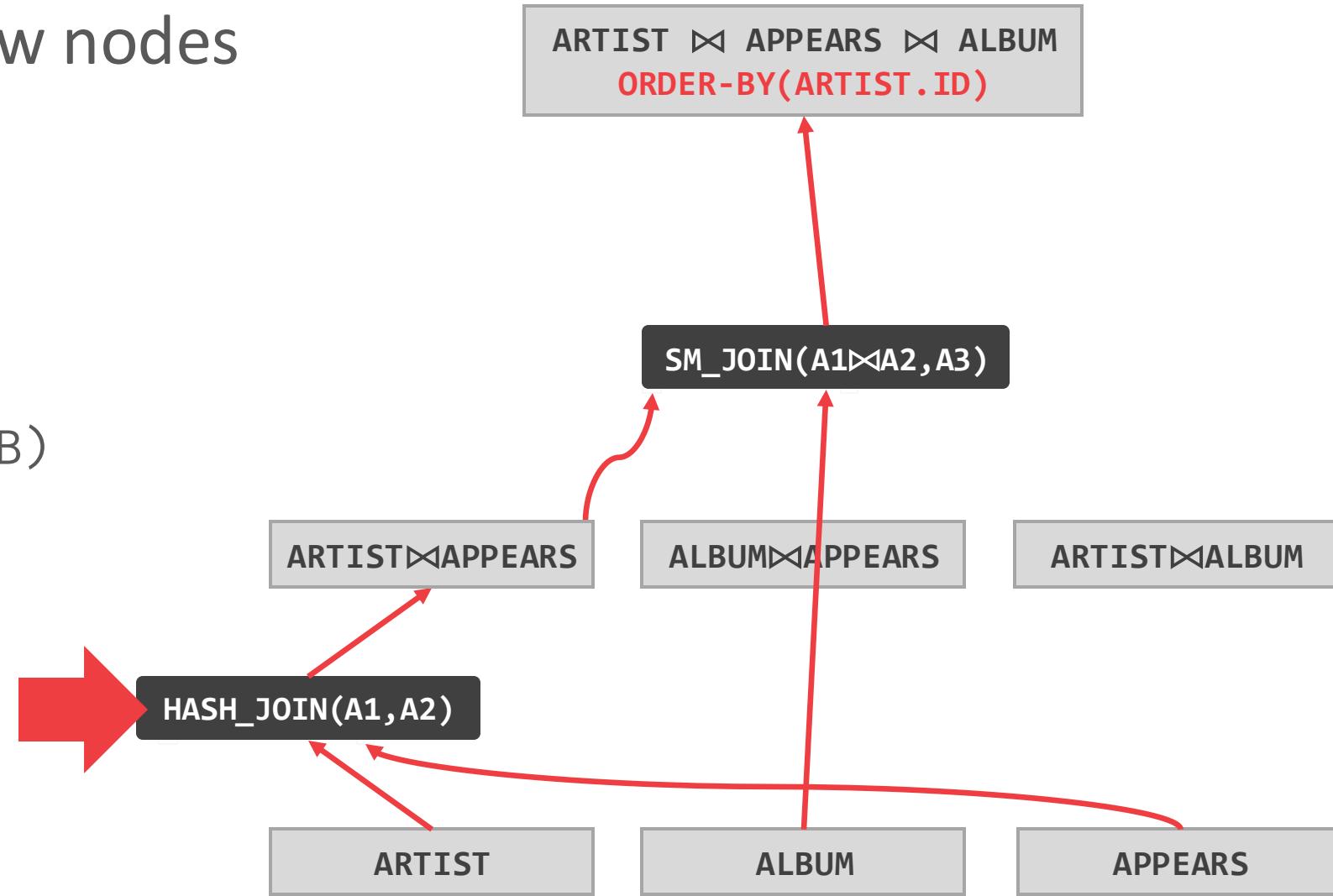
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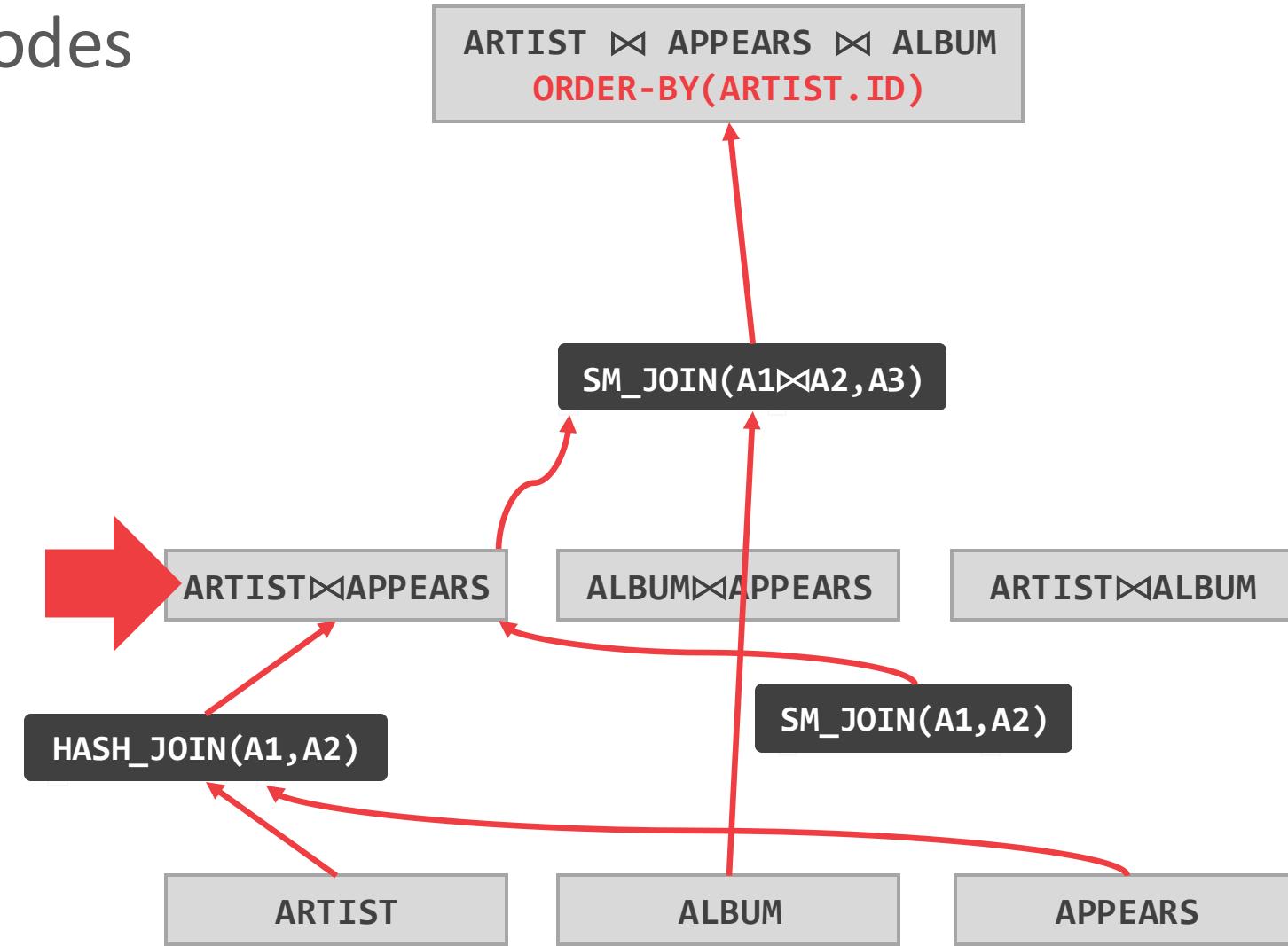
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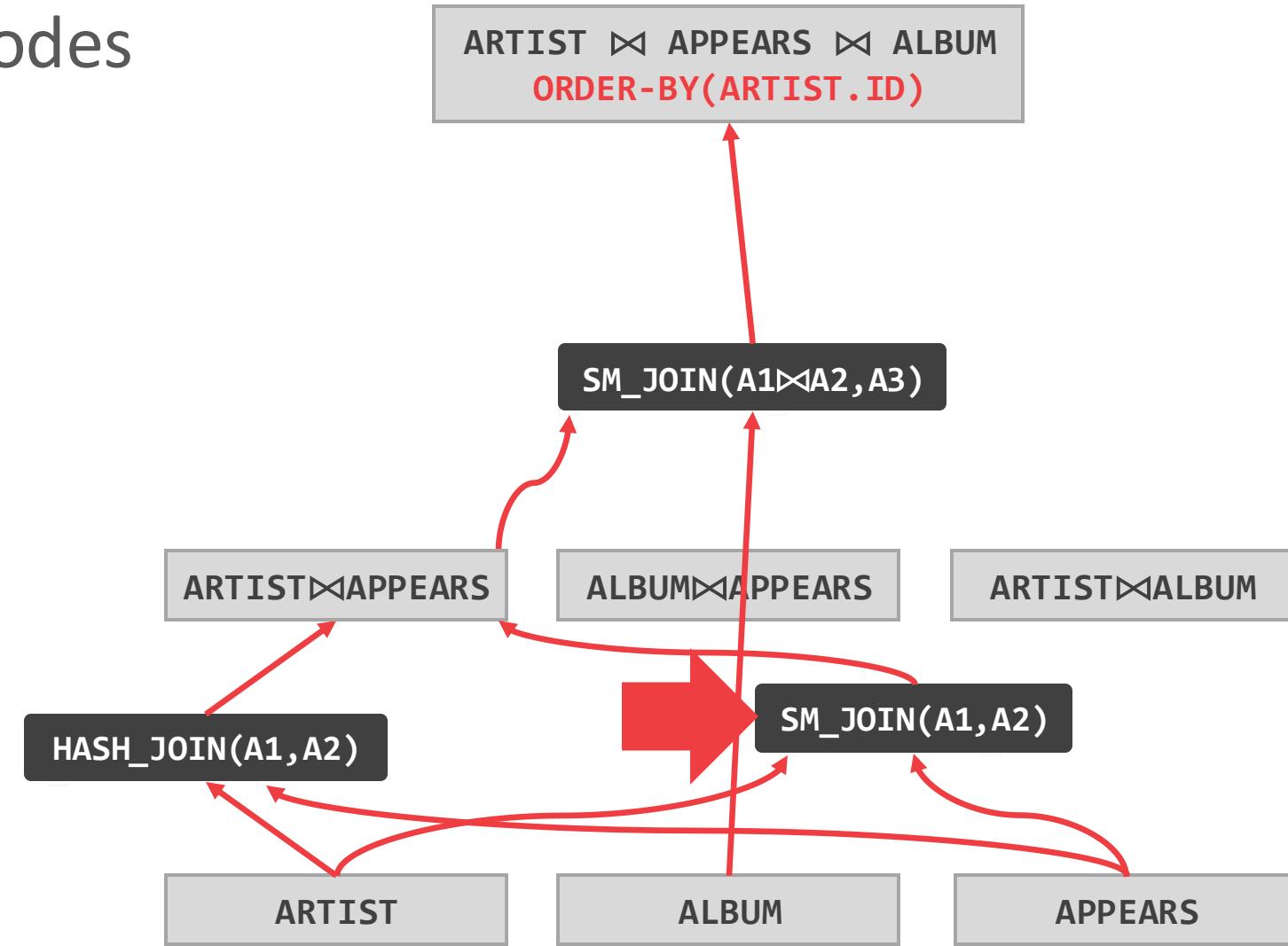
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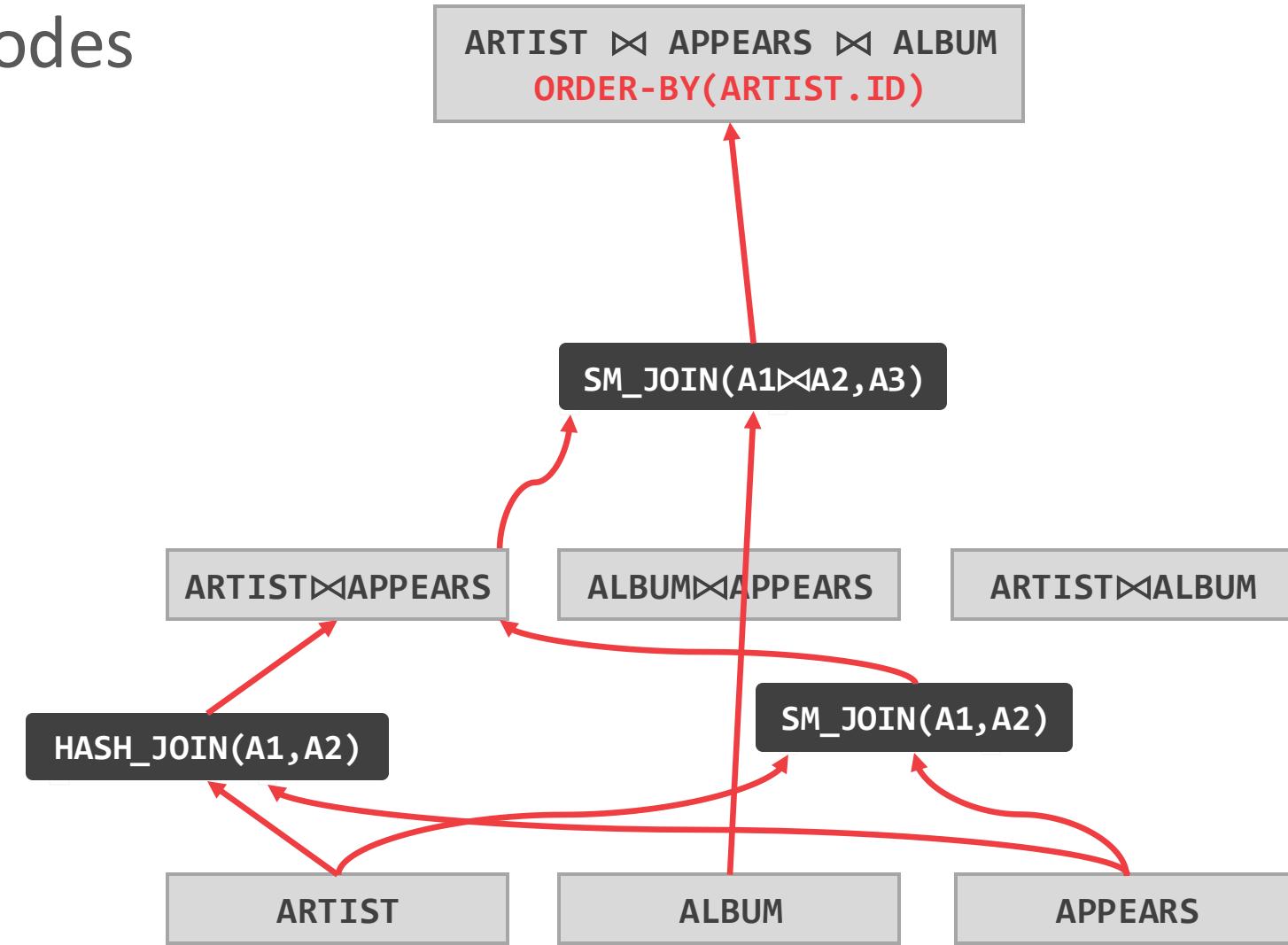
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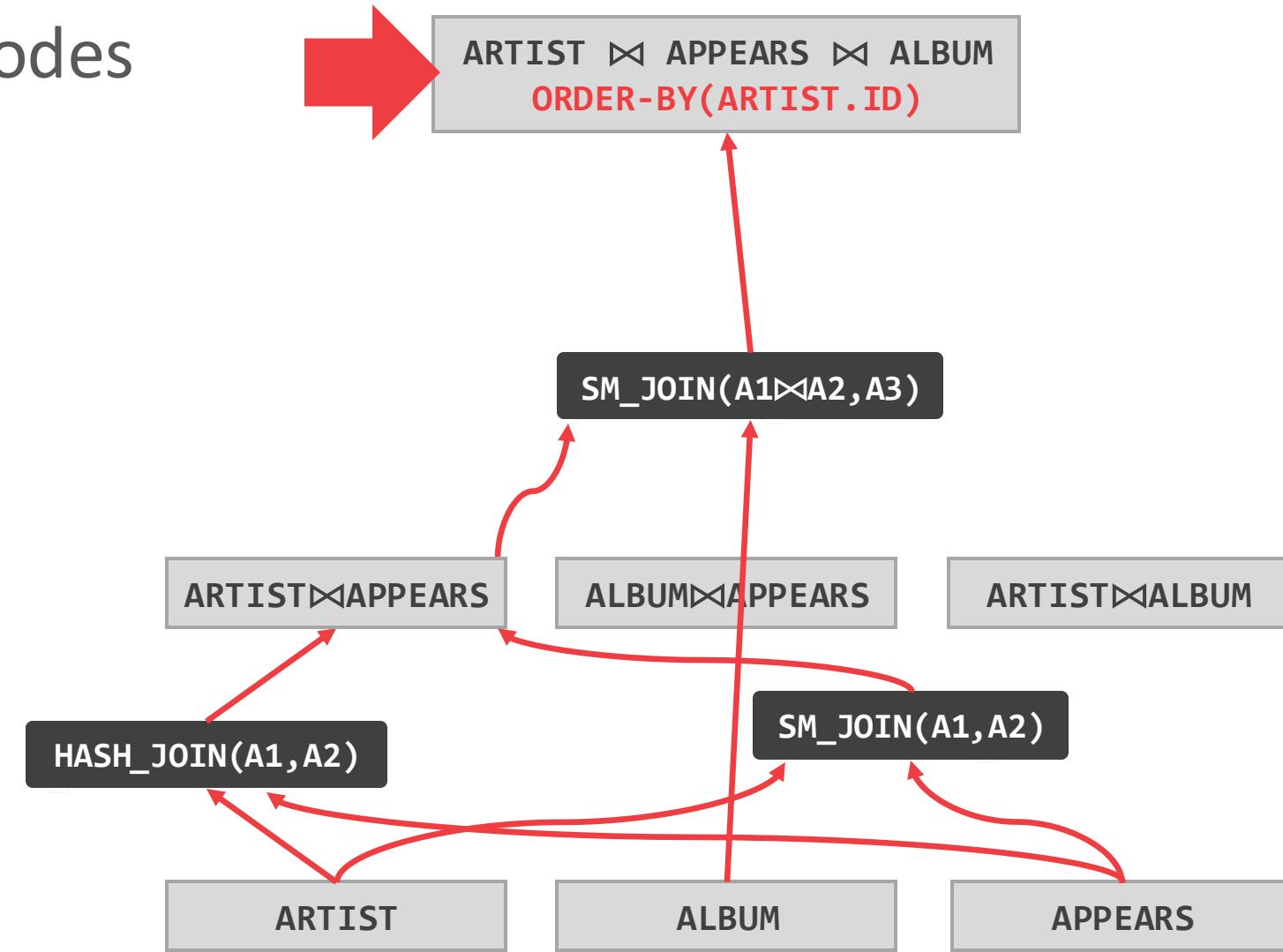
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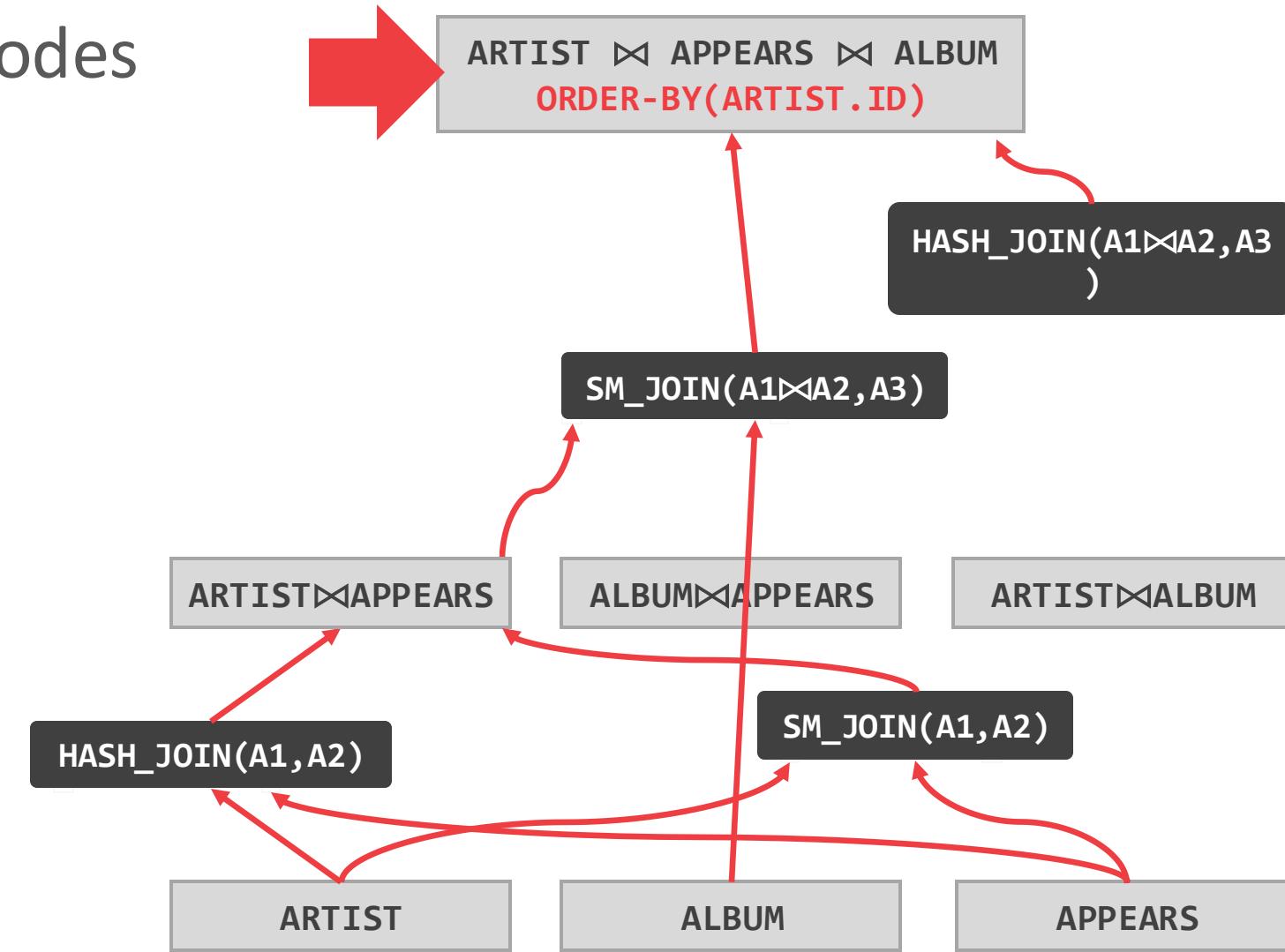
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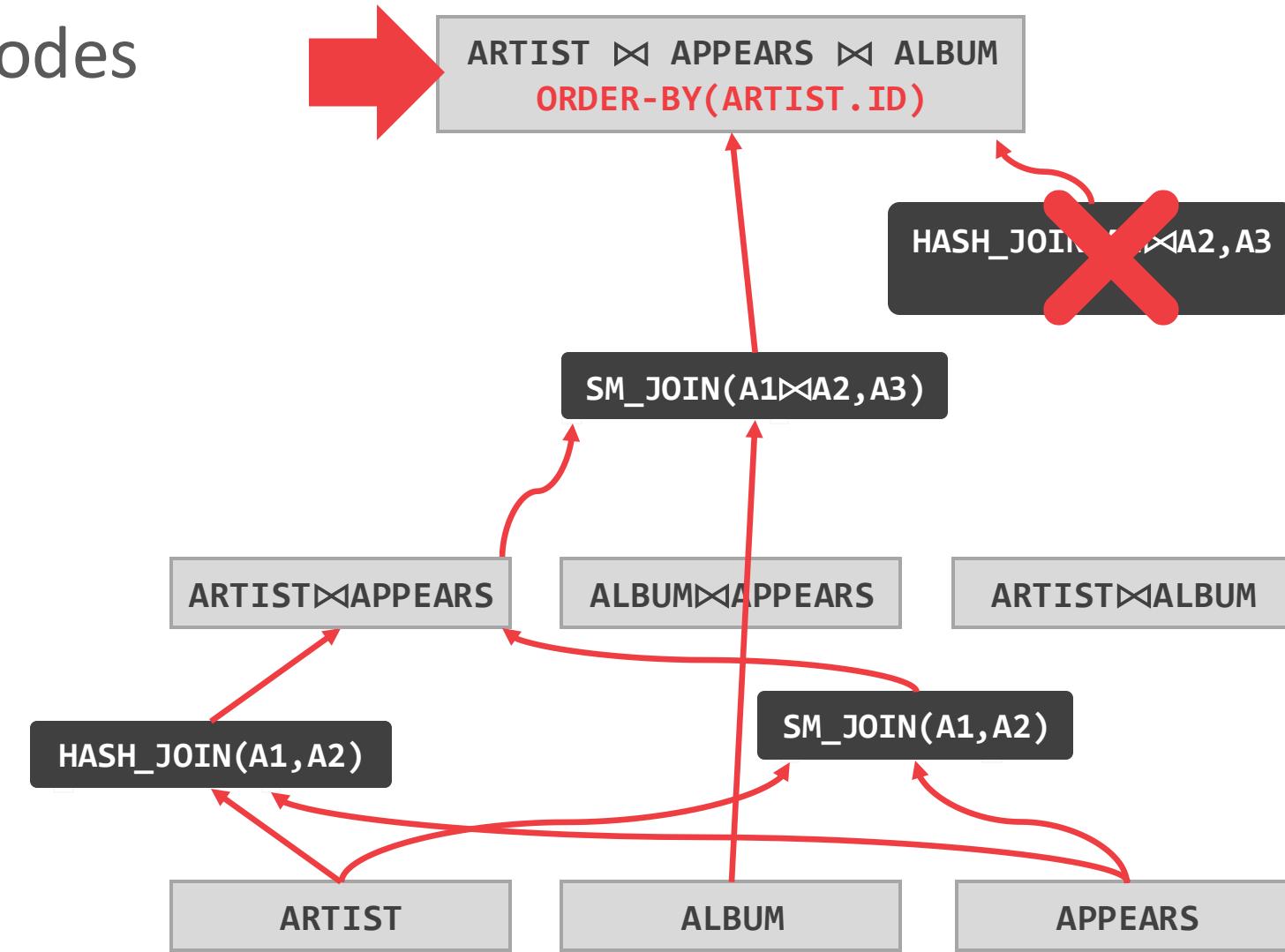
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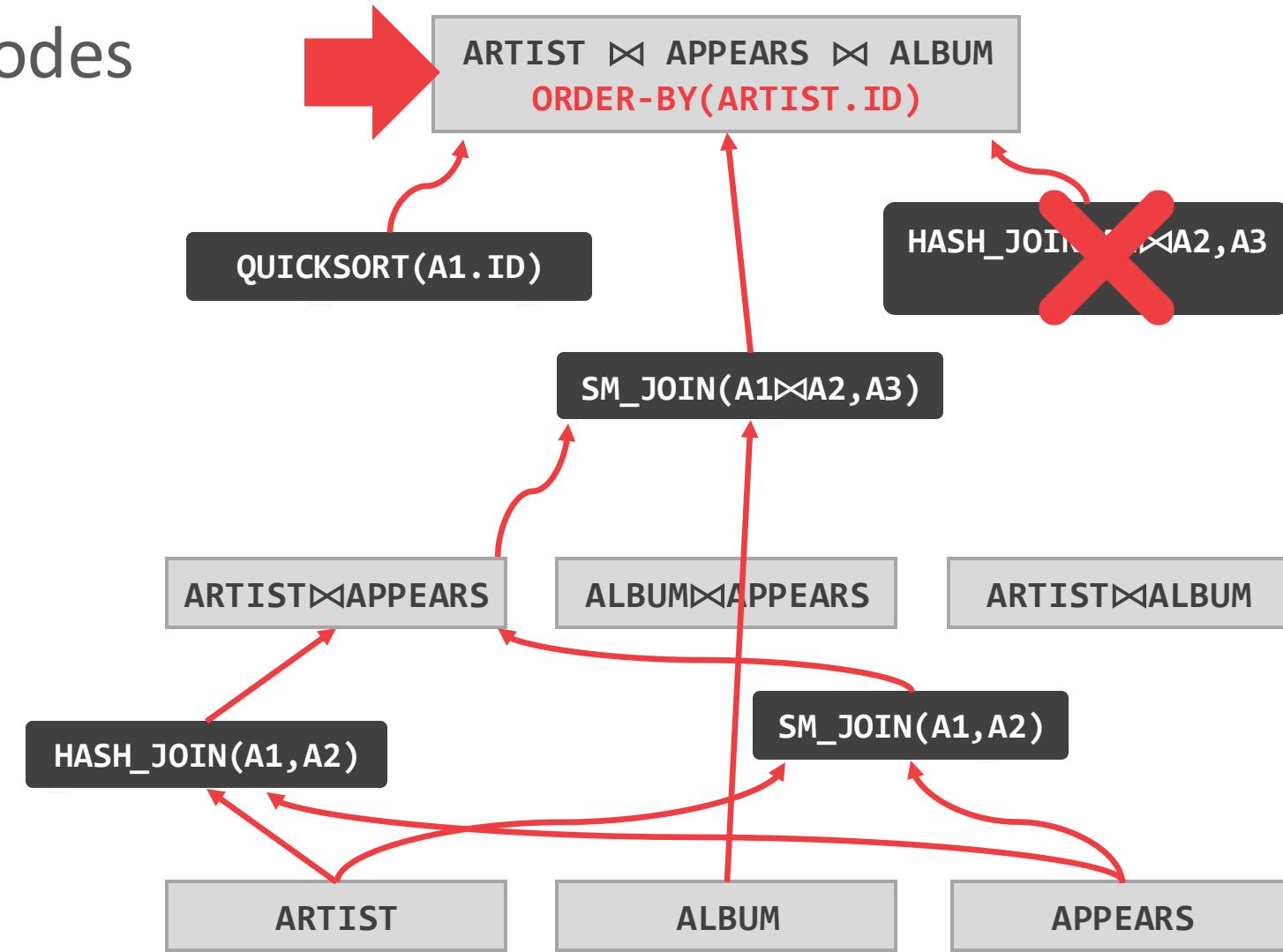
→ **Logical** → **Logical**:

$\text{JOIN}(A, B)$ to $\text{JOIN}(B, A)$

→ **Logical** → **Physical**:

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Can create “enforcer” rules
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Top-down Optimization

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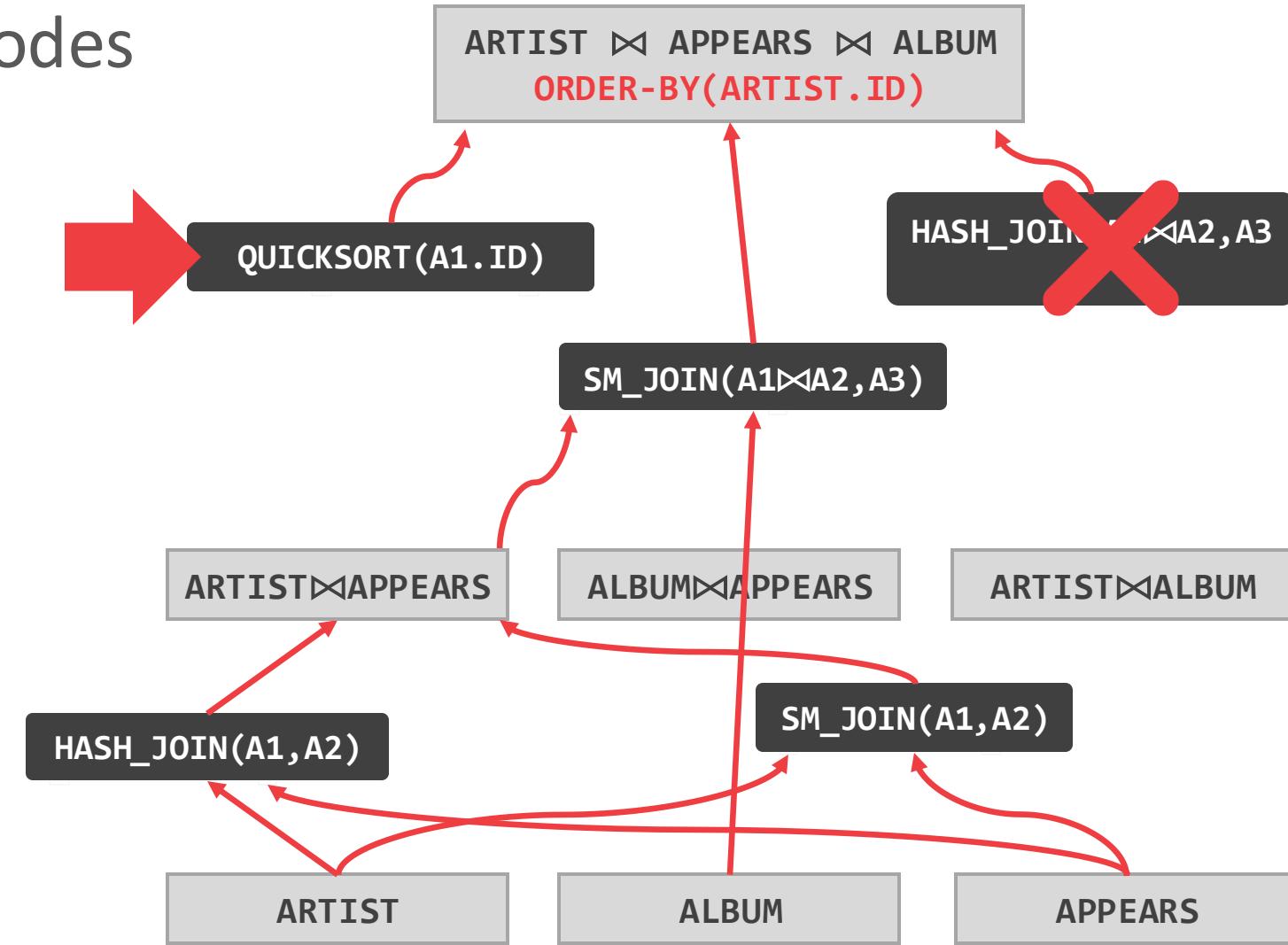
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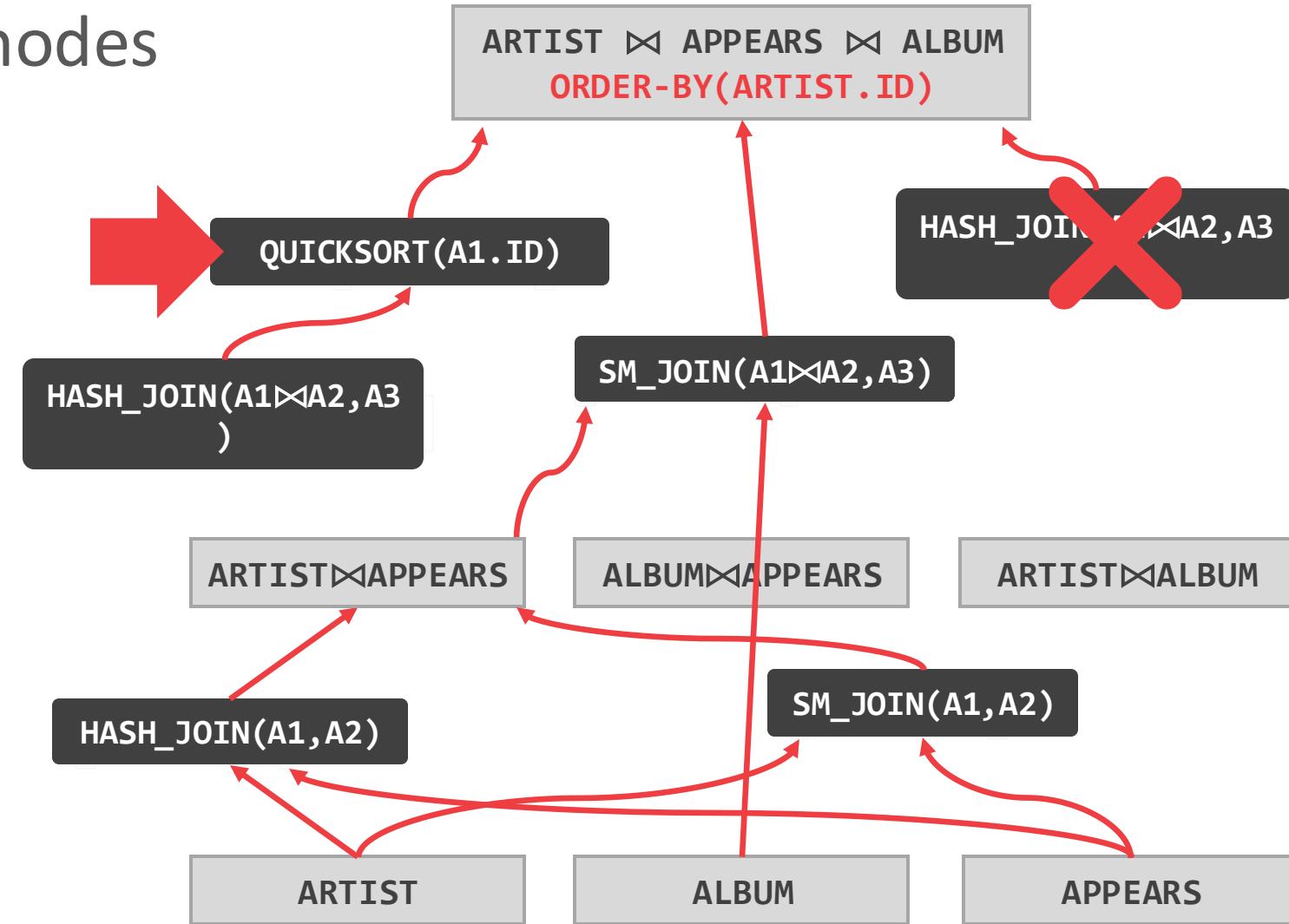
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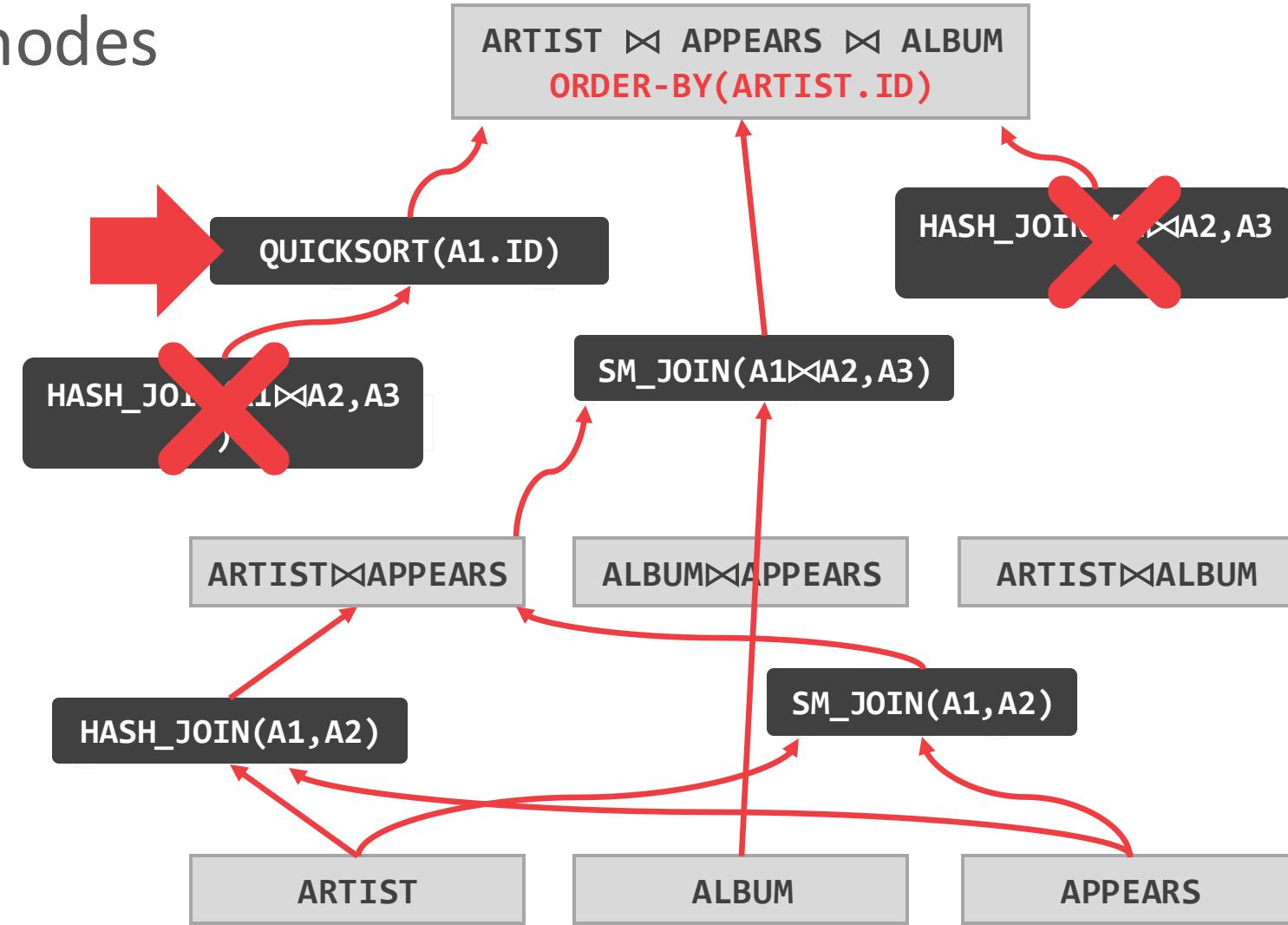
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Life so far ... single block QO

- Often, we get nested queries.
 - We could optimize each block using the methods we have discussed.
 - However, this may be inefficient since we optimize each block separately without a global approach.
- What if we could flatten a nested query into a single block and optimize it?
 - Then, apply single-block query optimization methods.
 - Even if one can't flatten to a single block, flattening to fewer blocks is still beneficial.

Nested Queries

Nested Queries

- The DBMS treats nested sub-queries in the where clause as functions that take parameters and return a single value or set of values.
- Two Approaches:
 - Rewrite to de-correlate and/or flatten them.
 - Decompose nested query and store results in a temporary table.

Nested Sub-queries: Rewrite

```
SELECT name FROM sailors AS S
WHERE EXISTS (
    SELECT * FROM reserves AS R
    WHERE S.sid = R.sid
    AND R.day = '2022-10-25'
)
```

Nested Sub-queries: Rewrite

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SELECT name FROM sailors AS S
WHERE EXISTS (
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)
```



```
SELECT name
FROM sailors AS S, reserves AS R
WHERE S.sid = R.sid
AND R.day = '2022-10-25'
```

Decomposing Queries

- For harder queries, the optimizer breaks up queries into blocks and then concentrates on one block at a time.
- Sub-queries are written to temporary tables that are discarded after the query finishes.

Decomposing Queries

```
SELECT S.sid, MIN(R.day)
      FROM sailors S, reserves R, boats B
     WHERE S.sid = R.sid
       AND R.bid = B.bid
       AND B.color = 'red'
       AND S.rating = (SELECT MAX(S2.rating)
                        FROM sailors S2)
 GROUP BY S.sid
 HAVING COUNT(*) > 1
```

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Nested Block

Decomposing Queries

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SELECT MAX(rating) FROM sailors
```

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   AND S.rating = ### ←
```

```
GROUP BY S.sid
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```

Decomposing Queries

Inner Block

```
SELECT MAX(rating) FROM sailors
```

```
SELECT S.sid, MIN(R.day)
  FROM sailors S, reserves R, boats B
 WHERE S.sid = R.sid
   AND R.bid = B.bid
   AND B.color = 'red'
   AND S.rating = ###←
```

```
GROUP BY S.sid
HAVING COUNT(*) > 1
```

Outer Block

Expression Rewriting

Expression Rewriting

- An optimizer transforms a query's expressions (e.g., WHERE/ON clause predicates) into the minimal set of expressions.
- Implemented using if/then/else clauses or a pattern-matching rule engine.
 - Search for expressions that match a pattern.
 - When a match is found, rewrite the expression.
 - Halt if there are no more rules that match.

Expression Rewriting

- Impossible / Unnecessary Predicates

```
SELECT * FROM A WHERE 1 = 0;
```

Expression Rewriting

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Expression Rewriting

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```
SELECT * FROM A WHERE false;
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- Merging Predicates

```
SELECT * FROM A
WHERE val BETWEEN 1 AND 100
    OR val BETWEEN 50 AND 150;
```

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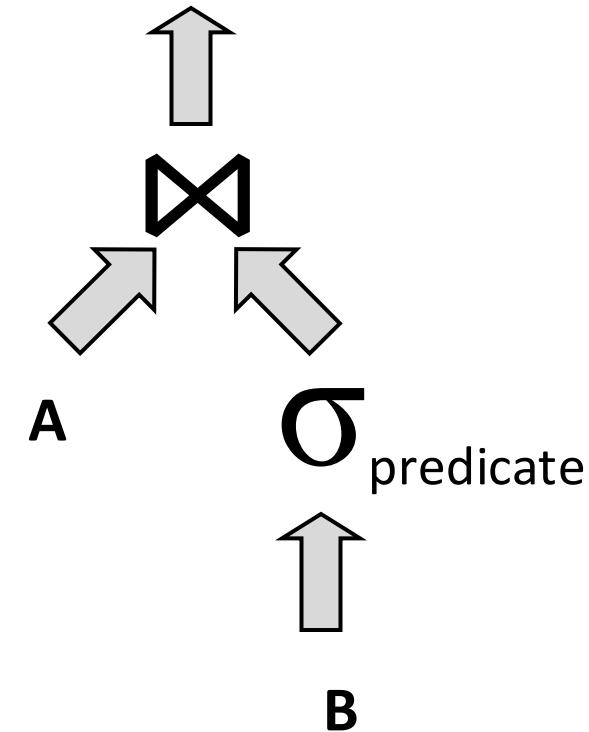
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Cost Estimation

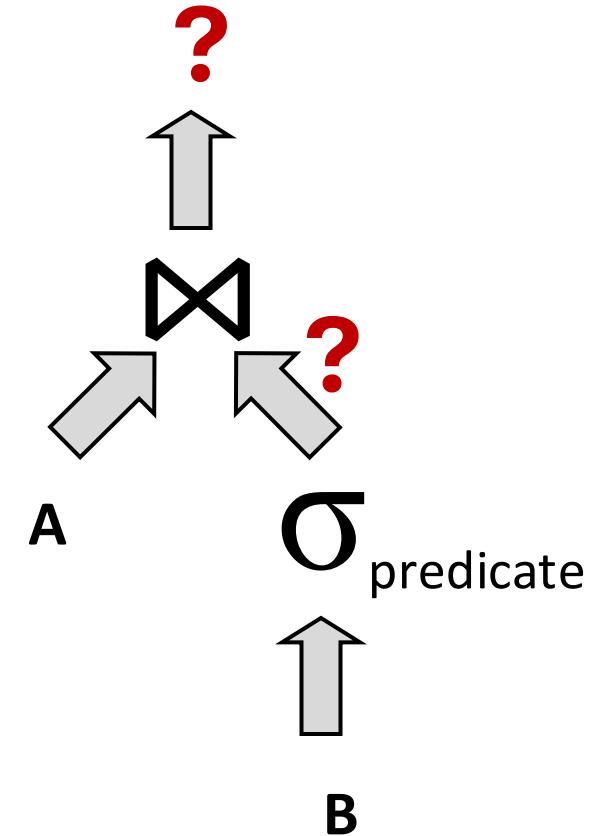
How do we calculate the cost of the plans?

- We have formulas for the operator algorithms (e.g. the cost formulae for hash join, sort merge join, ...), but we also need to estimate the size of the output that an operator produces.



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Cost Estimation

- The DBMS uses a cost model to predict the behavior of a query plan given a database state.
 - This is an internal cost that allows the DBMS to compare one plan with another.
- It is too expensive to run every possible plan to determine this information, so the DBMS need a way to derive this information.

Cost Model Components

- **Choice #1: Physical Costs**
 - Predict CPU cycles, I/O, cache misses, RAM consumption, network messages...
 - Depends heavily on hardware.
- **Choice #2: Logical Costs**
 - Estimate output size per operator.
 - Independent of the operator algorithm.
 - Need estimations for operator result sizes.

Postgres Cost Model

- Uses a combination of CPU and I/O costs that are weighted by “magic” constant factors.
- Default settings are obviously for a disk-resident database without a lot of memory:
 - Processing a tuple in memory is **400x** faster than reading a tuple from disk.
 - Sequential I/O is **4x** faster than random I/O.

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19.7.2. Planner Cost Constants

The *cost* variables described in this section are measured on an arbitrary scale. Only their relative values matter, hence scaling them all up or down by the same factor will result in no change in the planner's choices. By default, these cost variables are based on the cost of sequential page fetches; that is, `seq_page_cost` is conventionally set to 1.0 and the other cost variables are set with reference to that. But you can use a different scale if you prefer, such as actual execution times in milliseconds on a particular machine.

Note: Unfortunately, there is no well-defined method for determining ideal values for the cost variables. They are best treated as averages over the entire mix of queries that a particular installation will receive. This means that changing them on the basis of just a few experiments is very risky.

`seq_page_cost` (floating point)

Sets the planner's estimate of the cost of a disk page fetch that is part of a series of sequential fetches. The default is 1.0. This value can be overridden for tables and indexes in a particular tablespace by setting the tablespace parameter of the same name (see [ALTER TABLESPACE](#)).

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Statistics

- The DBMS stores internal statistics about tables, attributes, and indexes in its internal catalog.
- Different systems update them at different times.
- Manual invocations:
 - Postgres/SQLite: **ANALYZE**
 - Oracle/MySQL: **ANALYZE TABLE**
 - SQL Server: **UPDATE STATISTICS**
 - DB2: **RUNSTATS**

Selection Cardinality

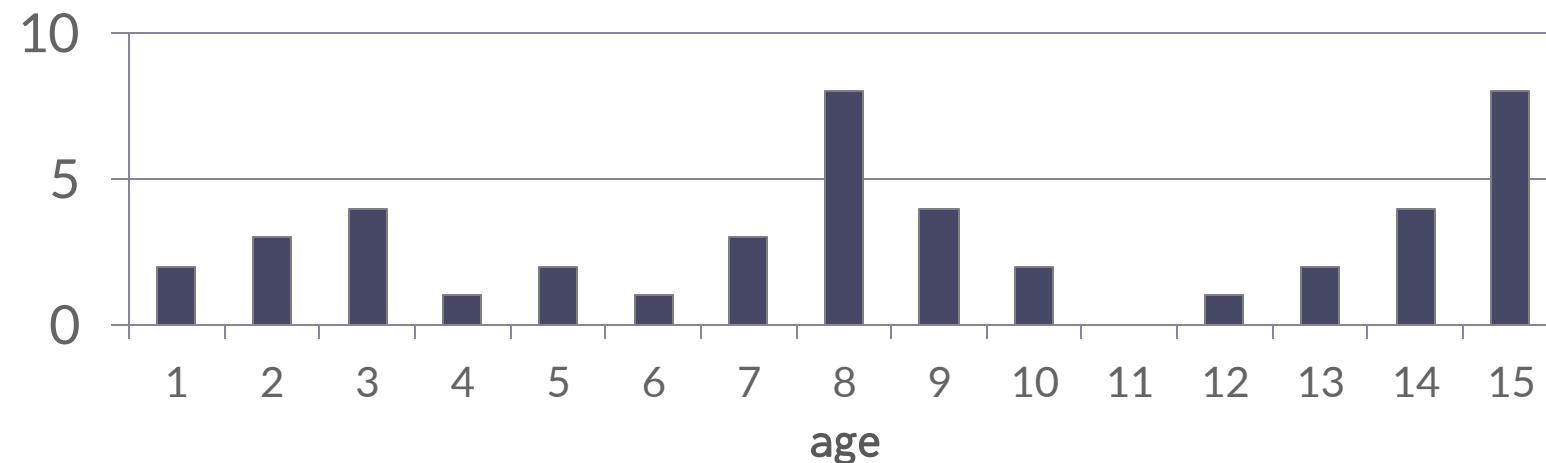
- The selectivity (*sel*) of a predicate P is the fraction of tuples that qualify.
- **Equality Predicate:** $A=\text{constant}$
 - $\text{sel}(A=\text{constant}) = \#\text{occurrences} / |R|$

```
SELECT * FROM people
WHERE age = 9
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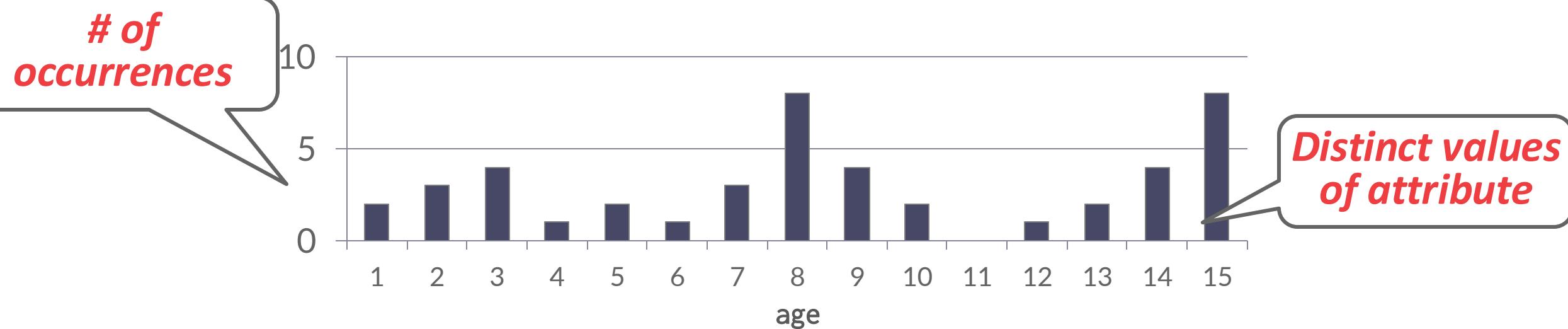
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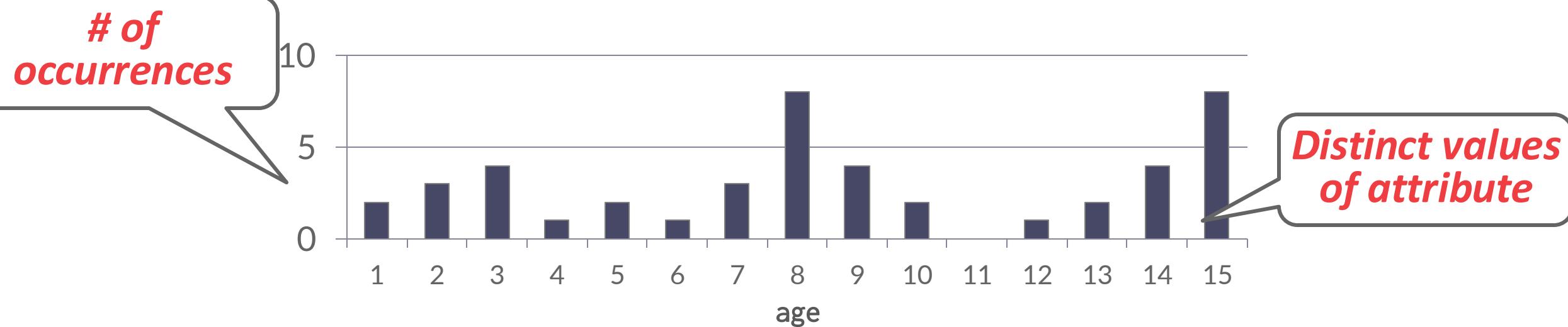
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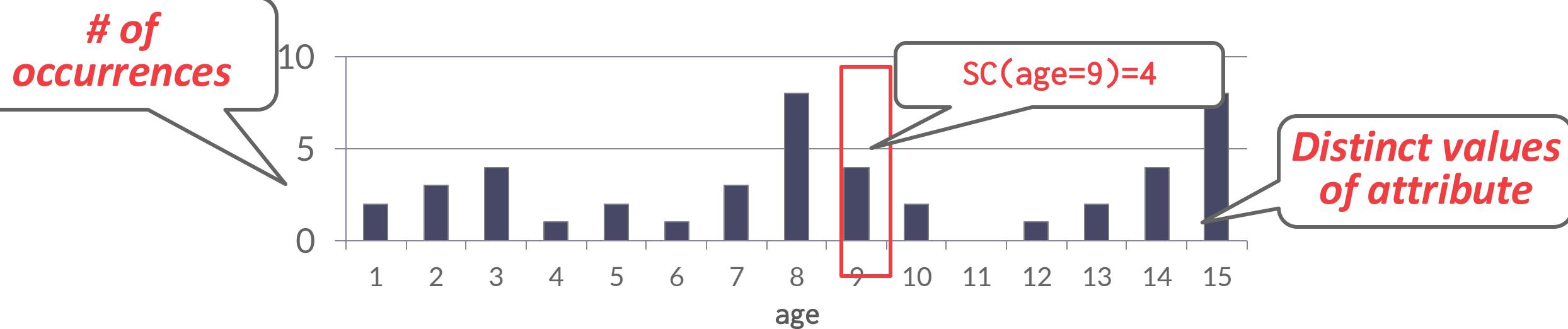
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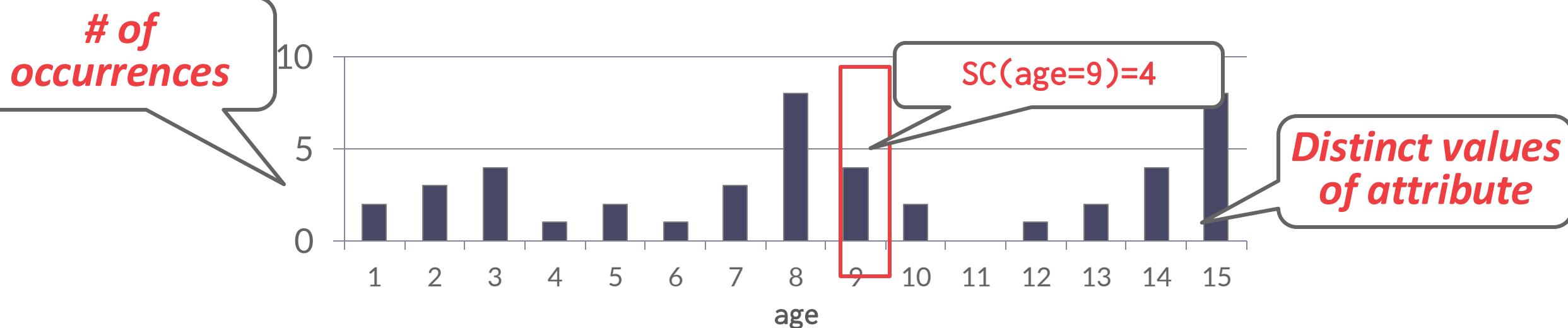
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 - Example: $\text{sel}(\text{age}=9) = 4/45$

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```



Selection Cardinality

- **Assumption #1: Uniform Data**
 - The distribution of values (except for the heavy hitters) is the same.
- **Assumption #2: Independent Predicates**
 - The predicates on attributes are independent
- **Assumption #3: Inclusion Principle**
 - The domain of join keys overlap such that each key in the inner relation will also exist in the outer table.

Correlated Attributes

- Consider a database of automobiles:
 - # of Makes = 10, # of Models = 100
- And the following query:
 - (make="Honda" AND model="Accord")

Source: [Guy Lohman](#)

Correlated Attributes

- Consider a database of automobiles:
 - # of Makes = 10, # of Models = 100
- And the following query:
 - `(make="Honda" AND model="Accord")`
- With the independence and uniformity assumptions, the selectivity is:
 - $1/10 \times 1/100 = 0.001$
- But since only Honda makes Accords the real selectivity is $1/100 = 0.01$

Source: [Guy Lohman](#)

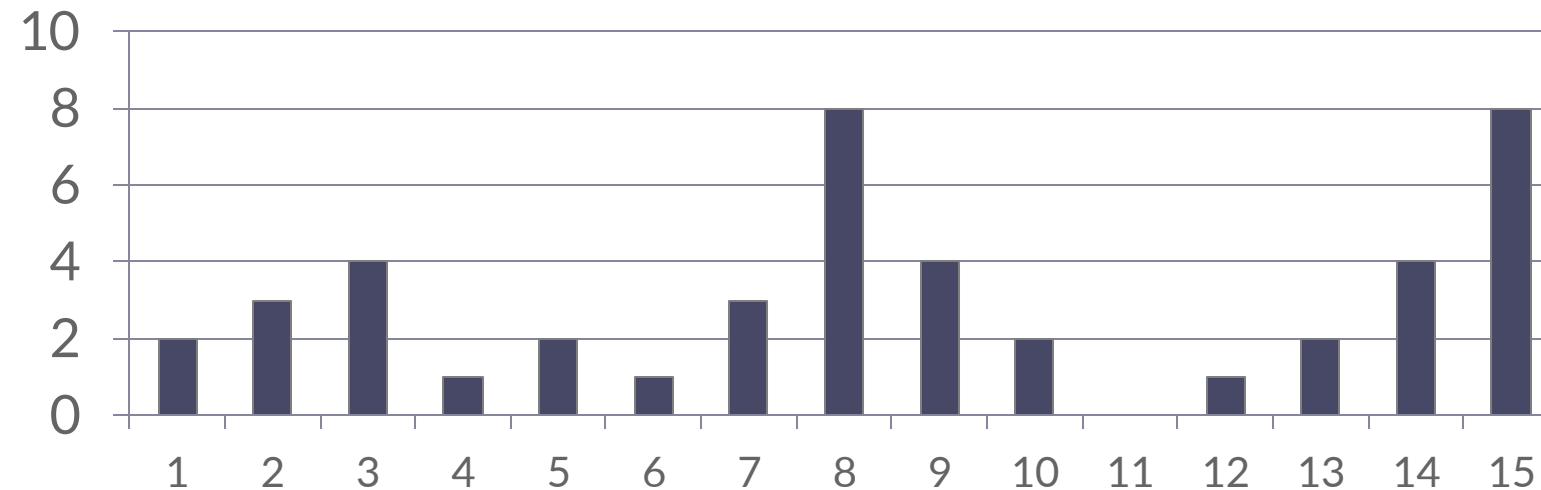
Statistics

- **Choice #1: Histograms**
 - Maintain an occurrence count per value (or range of values) in a column.
- **Choice #2: Sketches**
 - Probabilistic data structure that gives an approximate count for a given value.
- **Choice #3: Sampling**
 - DBMS maintains a small subset of each table that it then uses to evaluate expressions to compute selectivity.

Histograms

- Our formulas are nice, but we assume that data values are uniformly distributed.

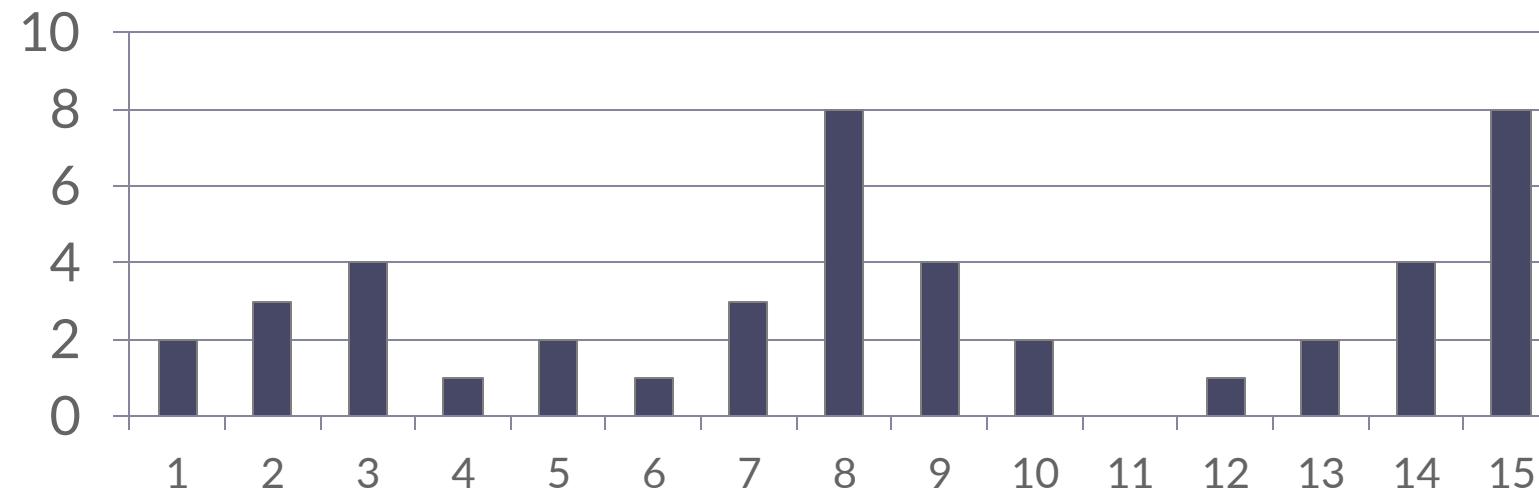
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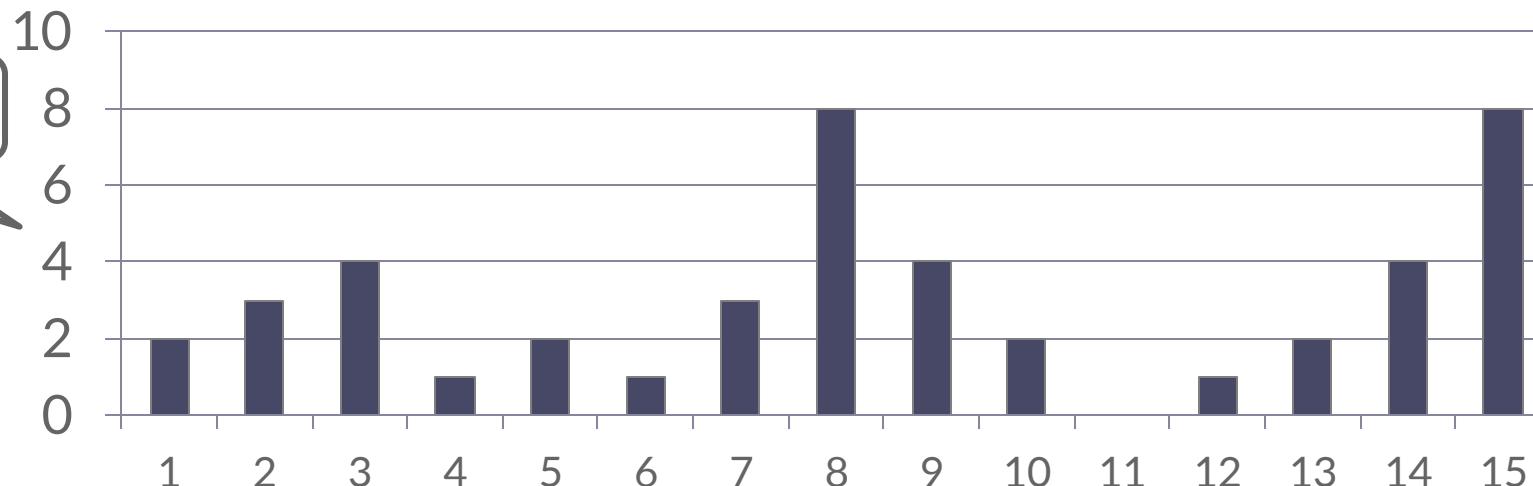
15 Keys × 32-bits = 60 bytes

Histograms

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Histogram

of occurrences



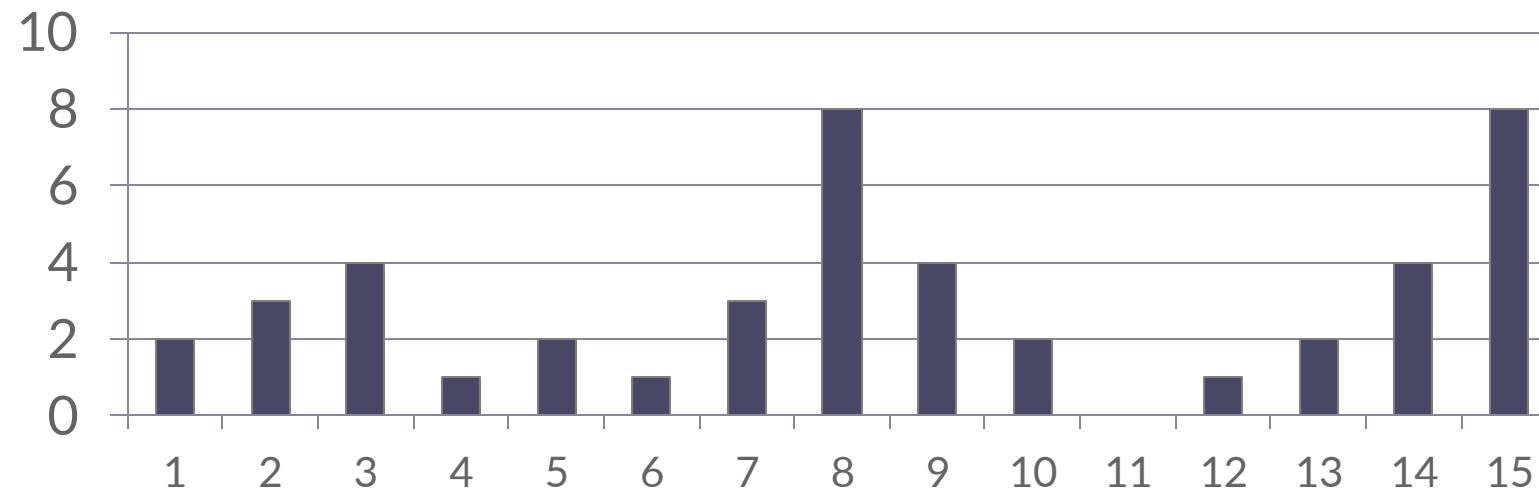
$15 \text{ Keys} \times 32\text{-bits} = 60 \text{ bytes}$

Distinct values of attribute

Equi-width Histogram

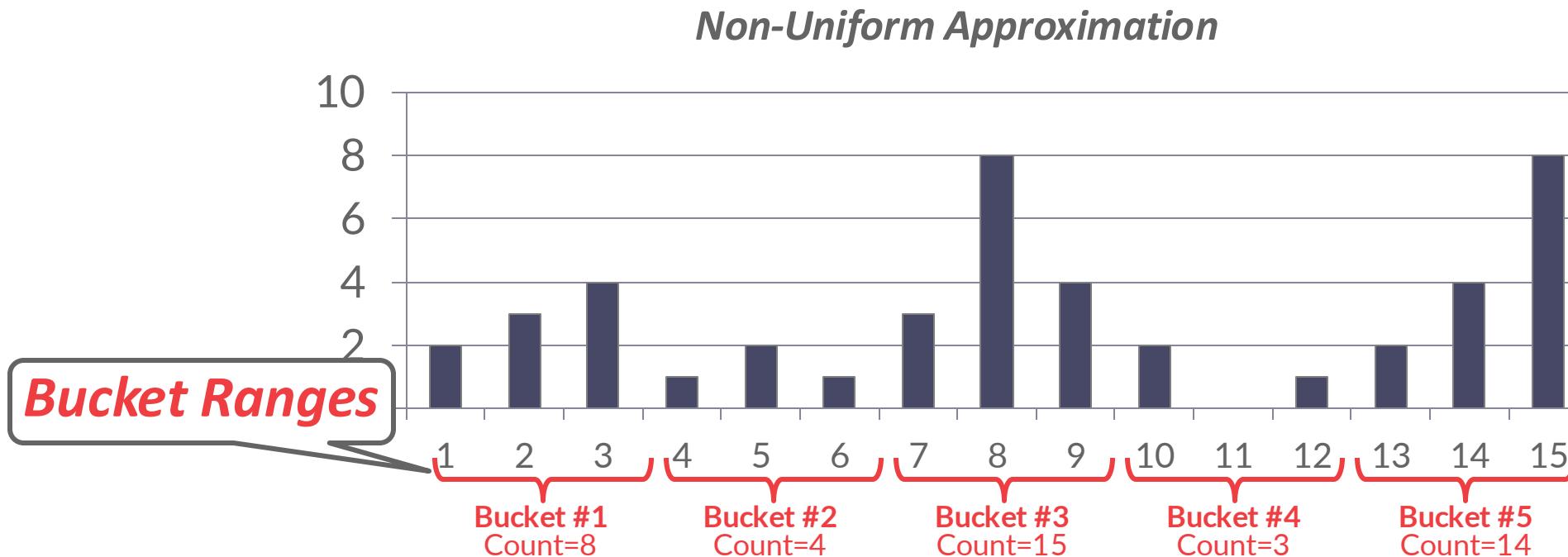
- Maintain counts for a group of values instead of each unique key. All buckets have the same width (i.e., same # of value).

Non-Uniform Approximation



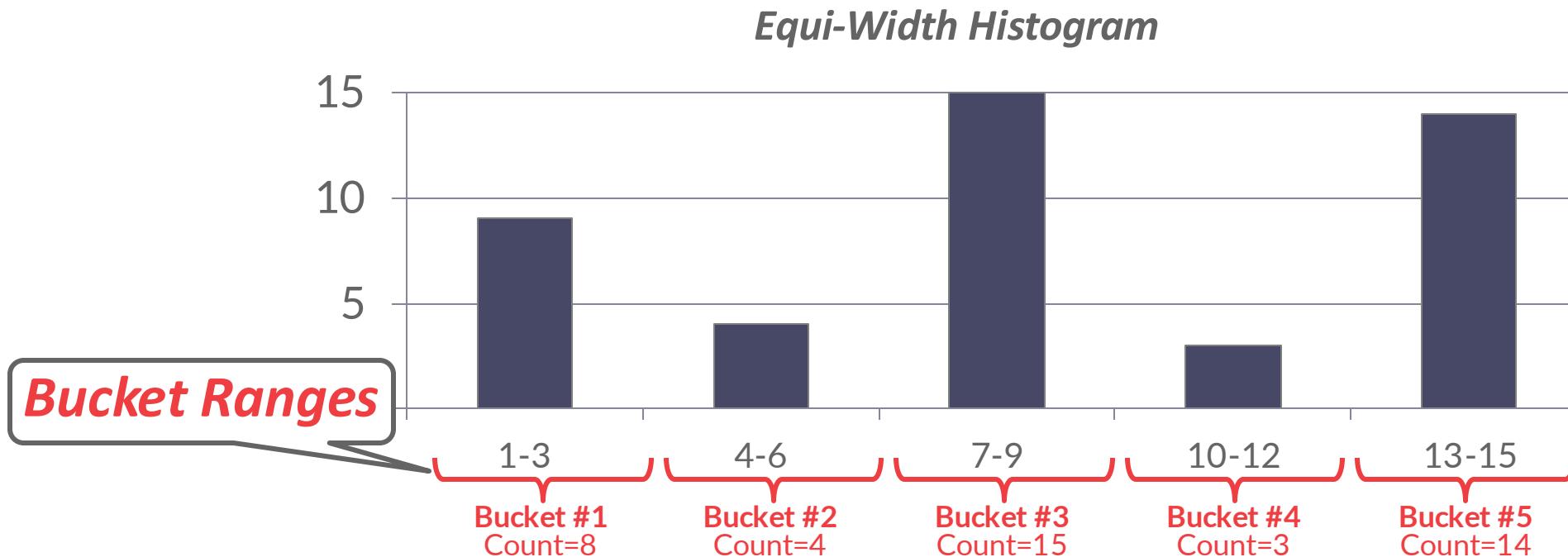
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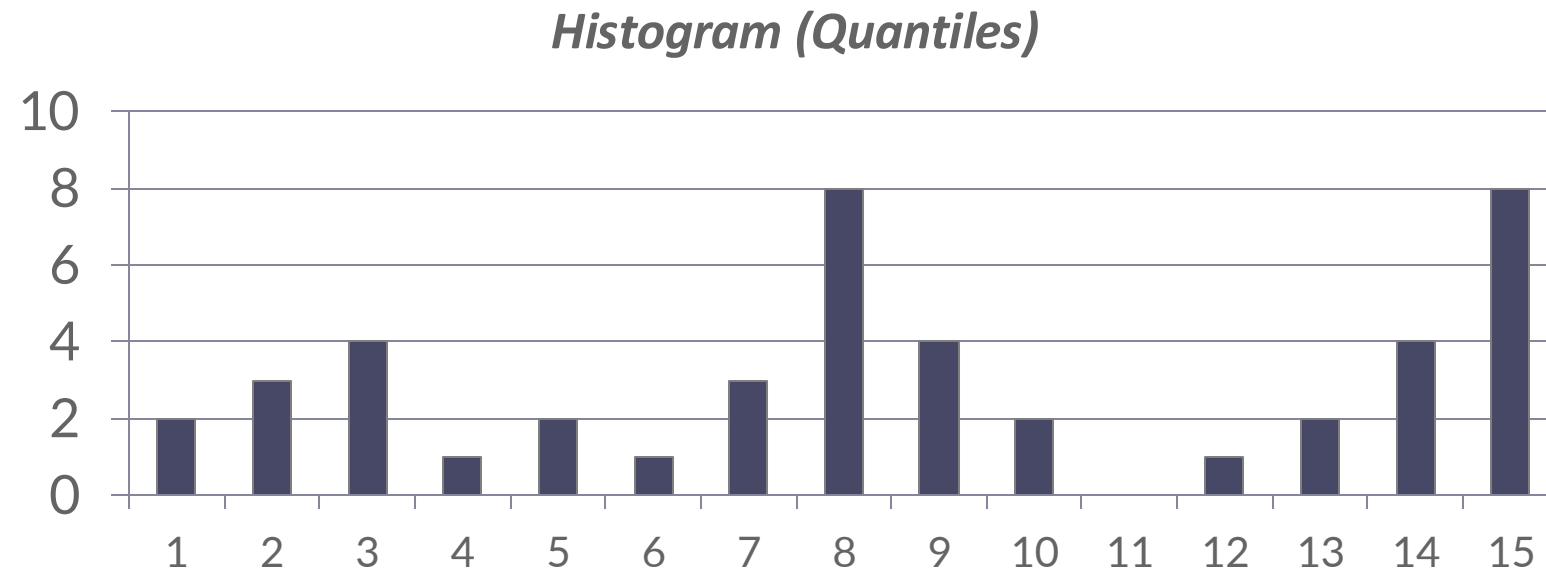
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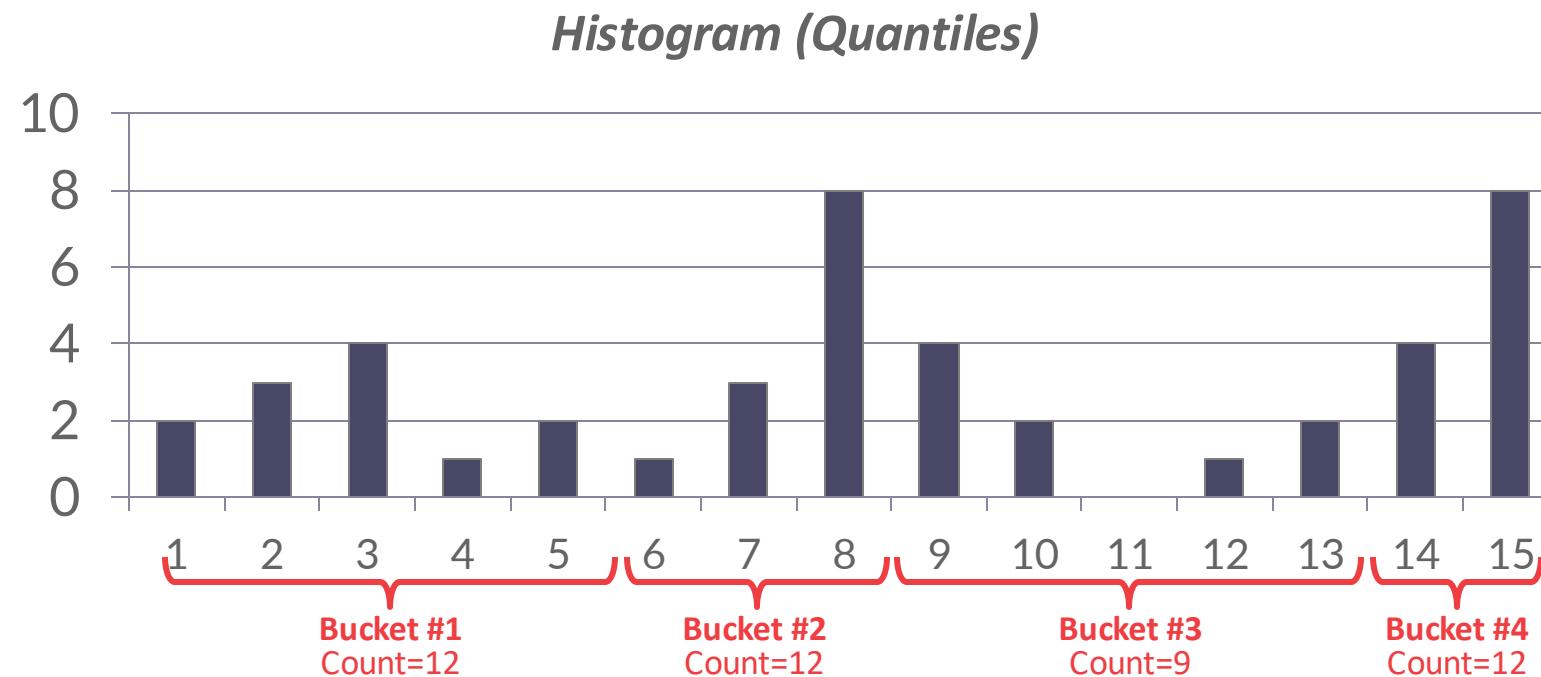
Equi-depth Histogram

- Vary the width of buckets so that the total number of occurrences for each bucket is roughly the same.



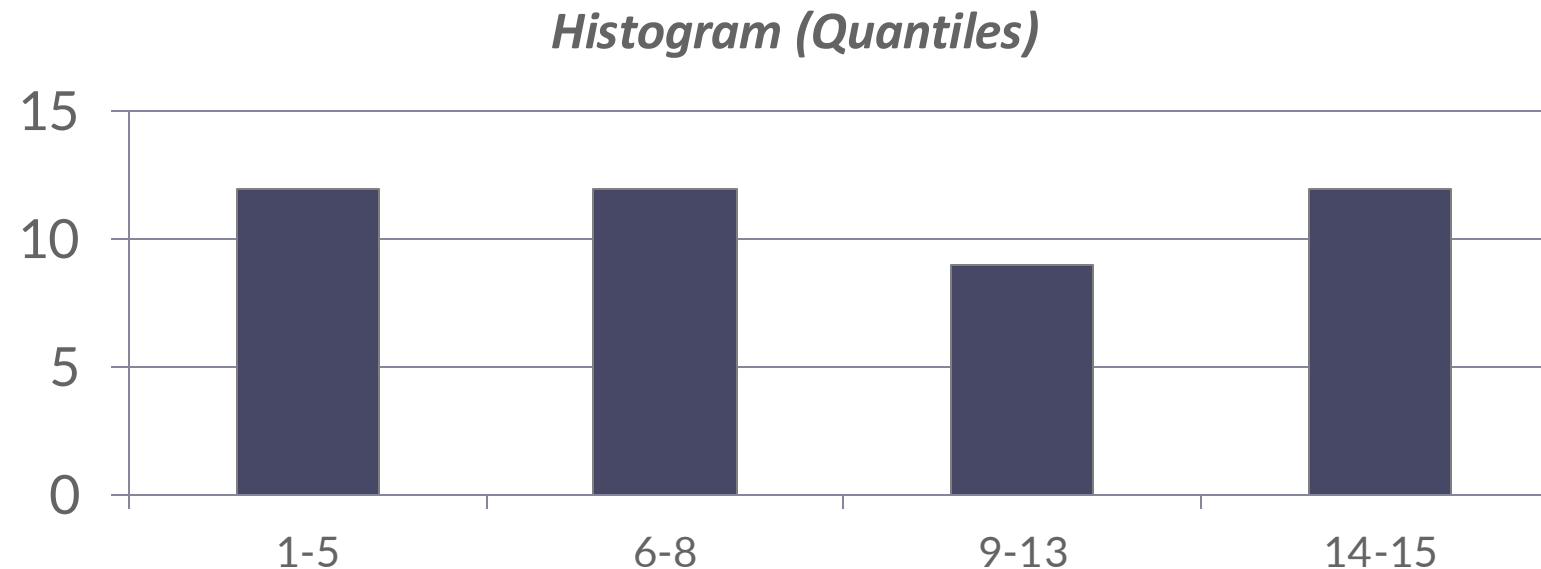
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Equi-depth Histogram

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Sketches

- Probabilistic data structures that generate approximate statistics about a data set.
- Cost-model can replace histograms with sketches to improve its selectivity estimate accuracy.
- Most common examples:
 - [Count-Min Sketch](#) (1988): Approximate frequency count of elements in a set.
 - [HyperLogLog](#) (2007): Approximate the number of distinct elements in a set.

Sampling

- Modern DBMSs also collect samples from tables to estimate selectivities.
- Update samples when the underlying tables changes significantly.

```
SELECT AVG(age)
  FROM people
 WHERE age > 50
```

id	name	age	status
1001	Obama	61	Rested
1002	Kanye	45	Weird
1003	Tupac	25	Dead
1004	Bieber	28	Crunk
1005	Andy	41	Illin
1006	TigerKing	59	Jailed

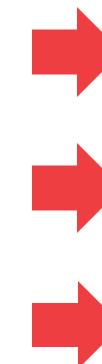
• *1 billion tuples*

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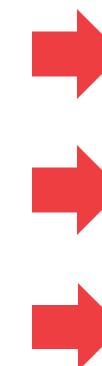
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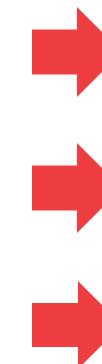
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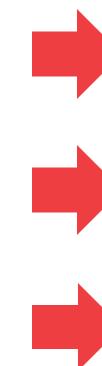
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$\text{sel}(\text{age}>50) = 1/3$

Table Sample

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Conclusion

- Query optimization is critical for a database system.
- SQL -> logical plan -> physical plan.
- Flatten queries before going to the optimization part.
Expression handling is also important.
- QO enumeration can be bottom-up or top-down.
- Need to cost each plan, so need cost-estimation methods.

Essential Query Optimization papers

An Overview of Query Optimization in Relational Systems

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1. OBJECTIVE

There has been extensive work in query optimization since the early '70s. It is hard to enumerate and list all of this large body of work in a single place. Therefore, I have decided to focus primarily on the optimization of SQL queries in relational database systems and present my biased and incomplete view of this field. The goal of this article is not to be comprehensive, but rather to explain the foundations and present samplings of significant work in this area. I would like to apologize to the many contributors in this area whose work I have failed to explicitly acknowledge due to oversight or lack of space. I take the liberty of trading technical precision for ease of presentation.

2. INTRODUCTION

Relational query languages provide a high-level "declarative" interface to access data stored in relational databases. Over time, SQL [41] has emerged as the standard for relational query languages. Two key components of the query evaluation component of a SQL database system are the *query optimizer* and the *query execution engine*.

The query execution engine implements a set of *physical operators*. An operator takes as input one or more data streams and produces an output data stream. Examples of physical operators are (external) sort, sequential scan, index scan, nested-loop join, and sort-merge join. I refer to such operators as *physical operators* since they are not necessarily tied one-to-one with relational operators. The simplest way to think of physical operators is as pieces of code that are built-in blocks to make possible the execution of SQL queries. An abstract representation of such an execution is a *physical operator tree*, as illustrated in Figure 1. The edges in an operator tree represent the data flow among the physical operators. We use the terms *physical operator tree* and *execution plan* (or, simply *plan*) interchangeably. The execution engine responds to the execution of the plan just as you respond to an answer to the query. Therefore, the capabilities of the query optimization engines determine the structure of the operator trees that are feasible. We refer the reader to [20] for an overview of query evaluation techniques.

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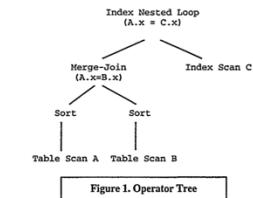


Figure 1. Operator Tree

The query optimizer is responsible for generating the input for the execution engine. It takes a parsed representation of a SQL query as input and is responsible for generating an *efficient* execution plan for the given SQL query from the space of possible execution plans. The task of an optimizer is nontrivial since for a given SQL query, there can be a large number of possible operator trees:

- The algebraic representation of the given query can be transformed into many other logically equivalent algebraic representations; e.g., $\text{Join}(\text{Join}(A, B), C) = \text{Join}(\text{Join}(B, C), A)$
- For a given algebraic representation, there may be many operator trees that implement the algebraic expression, e.g., typically there are several join algorithms supported in a database system.

For each operator, there are the various choices for the execution of these plans may be widely different. Therefore, a judicious choice of an execution by the optimizer is of critical importance. Thus, query optimization can be viewed as a difficult search problem. In order to solve this problem, we need to provide:

- A space of plans (*search space*).
- A cost estimation technique so that a cost may be assigned to each plan in the search space. Intuitively, this is an estimation of the resources needed for the execution of the plan.
- An enumeration algorithm that can search through the execution space.

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The Volcano Optimizer Generator: Extensibility and Efficient Search

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Abstract
Emerging database application domains demand not only new functionality but also high performance. To satisfy these two requirements, the Volcano project provides efficient, extensible tools for query and request processing, particularly for object-oriented and scientific database systems. One of these tools is a new optimizer generator. Data model, logical algebra, physical algebra, and optimization rules are all defined in a separate language that is then used to generate source code. Compared with our earlier EXODUS optimizer generator prototype, the search engine is more extensible and powerful; it provides effective support for non-trivial cost models and for physical properties such as sort order. The search engine is also more efficient, due to the use of heuristics and data model semantics to guide the search and to prune futile parts of the search space. Finally, it had to support flexible cost models that permit generating dynamic plans for incompletely specified queries.

In this paper, we describe the Volcano Optimizer Generator, which will soon fulfill all the requirements above. Section 2 introduces the main concepts of the Volcano optimizer generator and motivates factors for tailoring a new optimizer. Section 3 discusses the optimizer search strategy in detail. Functionality, extensibility, and search efficiency of the EXODUS and Volcano optimizer generators are compared in Section 4. In Section 5, we describe and compare other research into extensible query optimization. We offer our conclusions from this research in Section 6.

1. Introduction

While extensibility is an important goal and requirement for many current database research projects and system prototypes, performance must not be sacrificed for two reasons. First, data volumes stored in database systems continue to grow, in many application domains far beyond the capabilities of most existing database systems. Second, in order to overcome acceptance problems in enterprise environments, database management systems must achieve at least some performance as the file systems currently in use. Additional software layers for database management must be counterbalanced by database performance advantages normally not used in these application areas. Optimization and parallelization are prime candidates to provide these performance advantages, and tools and techniques for optimizing parallelized execution are crucial for the wider use of extensible database technology.

For a number of research projects, namely the Volcano extensible parallel query processor [4], the REVELATION OODBMS project [11] and optimization and parallelization in scientific databases [20] as well as to assist research efforts by other researchers, we have built a new extensible query optimization system. Our earlier experience with the EXODUS optimizer generator was not conclusive; while it had proven the feasibility and validity of the optimizer generator paradigm, it was difficult to construct efficient, production-quality optimizers. Therefore, we designed a new optimizer generator, requiring several important improvements over the EXODUS prototype.

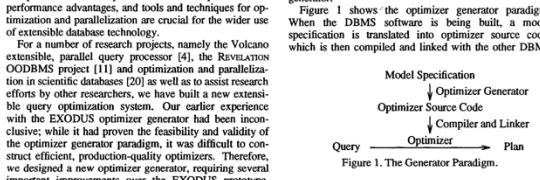


Figure 1. The Generator Paradigm.

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Access Path Selection in a Relational Database Management System

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ABSTRACT
In a high level query and data manipulation language such as SQL requests are stated non-procedurally. A short reference to access paths. This paper describes how System R chose access paths for both simple and complex queries. The paper illustrates the use of Boolean expressions (such as joins), given a user specification of desired data as a Boolean expression of predicates. A brief description of System R is given. System R is an experimental database management system developed to carry out research on the relational model. System R was designed and built by members of the IBM San Jose Research Laboratory.

This paper will address the issues of access path selection for queries. Retrieval for data manipulation (UPDATE, DELETE) is treated similarly. Section 2 will discuss the choice of access paths optimized in the processing of SQL statements. Section 3 will describe the storage component access paths available on single physically stored table. Section 4 describes the optimizer cost formulas are introduced for single table access. Section 5 discusses the joining of two or more tables, and their corresponding costs. Nested queries (queries in predicates) are covered in section 6.

2. Processing of an SQL statement

System R is an experimental database management system based on the relational model of data which has been under development at the IBM San Jose Research Laboratory since 1979. The system is designed and used as a research vehicle in relational database, and is not generally available outside the IBM Research Division.

This paper deals mainly with relational data model terminology as described in Codd < \rightarrow > and Date < \rightarrow >. The user interface in System R is a query language SQL. Statements in SQL can be issued both from an on-line user-oriented terminal interface or from programming languages such as PL/I and COBOL.

In System R a user need not know how the tuples are physically stored and what access methods are used, which columns have indexes. SQL statements do not require the user to specify anything about the physical organization of data or data retrieval. Nor does a user specify in what order joins are to be performed. The System R optimizer chooses both join order and an access path.

The four phases of statement processing are parsing, optimization, code generation, and execution. The parser is the first step of the parser, where it is checked for correct syntax. A query block is represented by a SQL statement. The query block contains, respectively, the list of items to be retrieved, the table(s) referenced, and the conditions that must be true for the predicates specified by the user. A single SQL statement may have many query blocks which may have one operand which is itself a query.

If the parser returns without any errors detected, the OPTIMIZER component is called. The OPTIMIZER accumulates the names

Of Nests and Trees: A Unified Approach to Processing Queries That Contain Nested Subqueries, Aggregates, and Quantifiers

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SQL [CHAM76, DATE85] and **DAPLEX** [SHIP81], [SMITS83] have many features (e.g. nested subquery blocks, aggregation over multiple rows, grouping, and quantifiers) that cannot be mapped to the restricted-project-join subset of the relational algebra. Such languages pose an important challenge for query optimization. The semantics of queries that use these features are often described procedurally, and existing query optimizers are severely limited in their tactics for processing such queries.

Consider, for example, the following relations:

EMP (Emp#, Name, Dept#, Sal)
DEPT (Dept#, Name, Loc, Mgr)

and the following SQL query, which contains a nested subquery block:

Query 1

```

SELECT E.Name
FROM EMP E
WHERE E.Dept# IN
      (SELECT D.Dept#
       FROM DEPT D
       WHERE D.Dept# = D.Mgr)
  
```

This semantics of SQL prescribes that the tuple of the EMP relation be substituted in turn into the inner subquery block, for each tuple E of EMP, the inner block is evaluated to yield a list of Dept# values; if E. Dept# is in this list, then E.Name is inserted into the result. The system R optimizer follows this prescription quite literally, optimizing only the execution of the inner block (after the substitution, the inner block contains two selected tuples). The outer query considers strategies for efficiently evaluating them [SEL79].

In [KIM92], Kim showed that some nested SQL queries could be transformed into equivalent "canonical" queries that did not contain nesting; for example, query 1 could be transformed into query 2 (the queries are not quite equivalent, but more on this issue later):

Query 2

```

SELECT E.Name
FROM EMP E, DEPT D
WHERE E.Dept# = D.Dept#
      AND D.Dept# = D.Mgr
      AND E.Dept# = D.Mgr
  
```

Proceedings of the 13th VLDB Conference, Brighton 1987

Surajit Chaudhuri: An Overview of Query Optimization in Relational Systems. PODS 1998: 34-43

Goetz Graefe, William J. McKenna: The Volcano Optimizer Generator: Extensibility and Efficient Search. ICDE 1993: 209-218

Patricia G. Selinger, Morton M. Astrahan, Donald D. Chamberlin, Raymond A. Lorie, Thomas G. Price: Access Path Selection in a Relational Database Management System. SIGMOD Conference 1979: 23-34

Umeshwar Dayal: Of Nests and Trees: A Unified Approach to Processing Queries That Contain Nested Subqueries, Aggregates, and Quantifiers. VLDB 1987: 197-208

Suggestions if you are going to build a QO

- **Rule 1: Read lots of papers, especially from the 80s & 90s.**
 - Expect new combinations, only partially new core inventions.
- **Rule 2: Early on, test various workloads on the QO.**
 - QOs harden over time as they “see” new workloads. Let them see more ASAP.
- **Rule 3: Throw away the initial one (or two) and start anew.**
 - The hard part is going to be nitty-gritty details like data structures and pointers to shared objects; e.g., the list of predicates and the query graph structure, ... You will NOT get this right in the first pass. Don’t try to patch; be prepared to rewrite.

Next Lecture

- DB Design
 - ER-diagrams, FDs