

Database System Internals Query Optimization (part 1)

Paul G. Allen School of Computer Science and Engineering University of Washington, Seattle

January 31, 2024

CSE 444 – Query Optimization 1

Announcements

Query Optimization

Three components:

- Cost/cardinality estimation
- Search algorithm

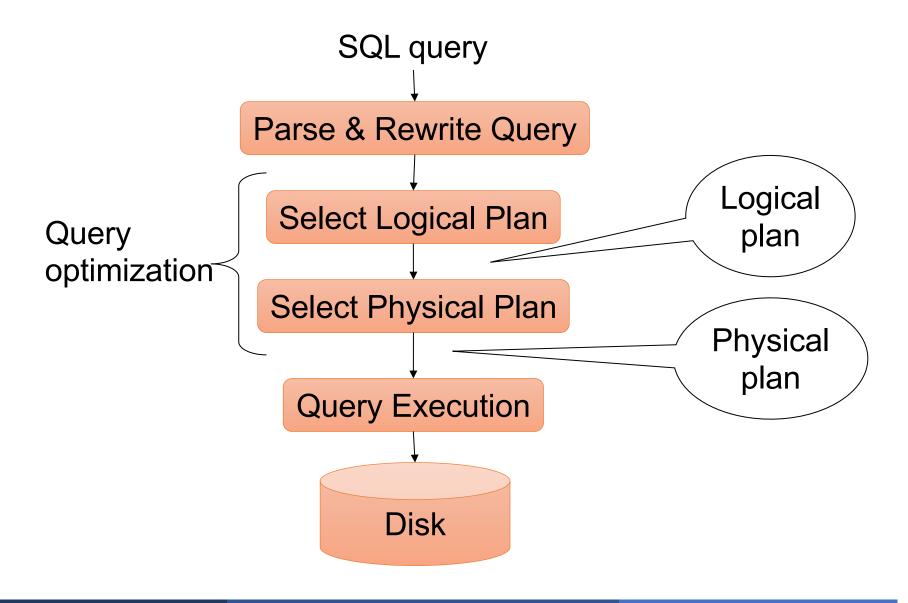
Query Optimization Overview

We know how to compute the cost of a plan

Next: Find a good plan automatically?

This is the role of the query optimizer

Query Optimization Overview



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What We Already Know...

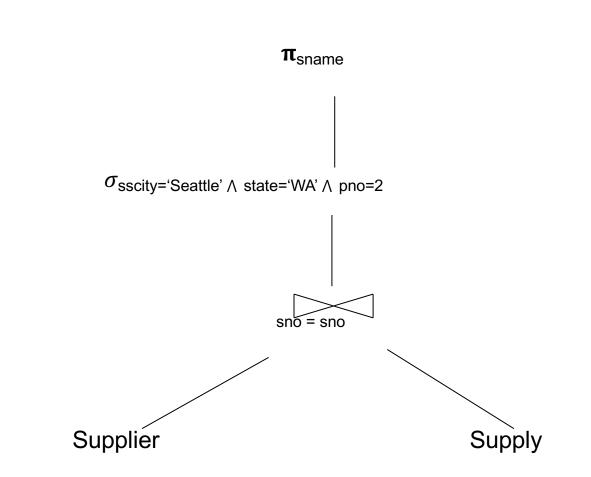
Supplier(sno,sname,scity,sstate)
Part(pno,pname,psize,pcolor)
Supply(sno,pno,price)

For each SQL query....

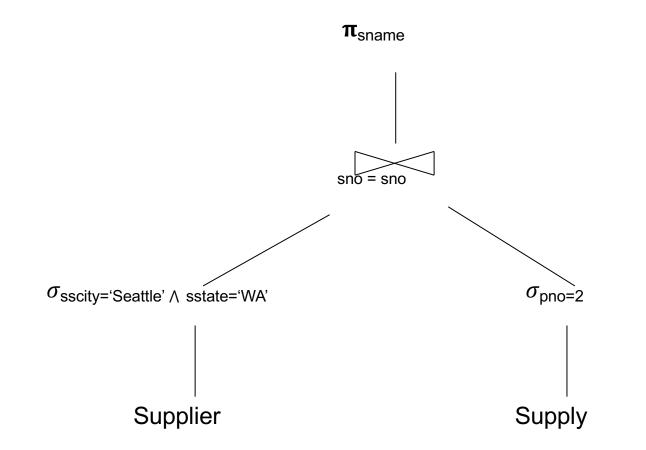
```
SELECT S.sname
FROM Supplier S, Supply U
WHERE S.scity='Seattle' AND S.sstate='WA'
AND S.sno = U.sno
AND U.pno = 2
```

There exist many logical query plans...

Example Query: Logical Plan 1



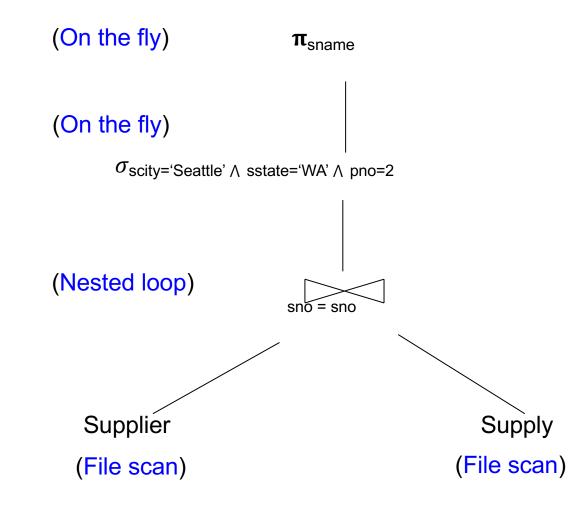
Example Query: Logical Plan 2



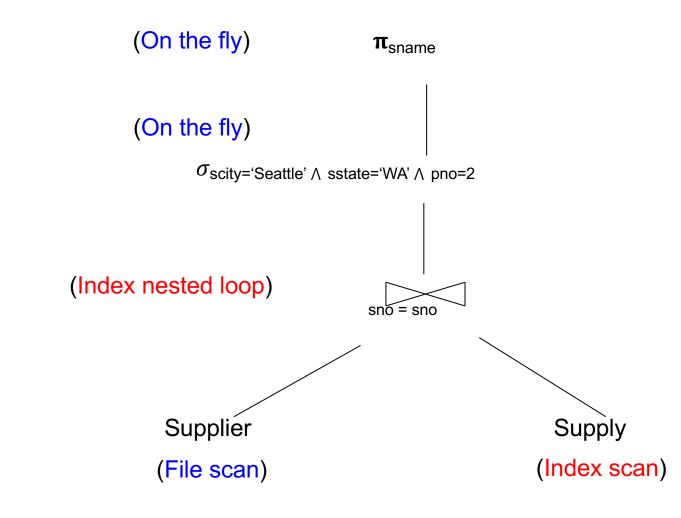
What We Also Know

- For each logical plan...
- There exist many physical plans

Example Query: Physical Plan 1



Example Query: Physical Plan 2



Query Optimizer Overview

- Input: A logical query plan
- Output: A good physical query plan

Query Optimizer Overview

- Input: A logical query plan
- Output: A good physical query plan
- Basic query optimization algorithm
 - Enumerate alternative plans (logical and physical)
 - Compute estimated cost of each plan
 - Compute number of I/Os
 - Optionally take into account other resources
 - Choose plan with lowest cost
 - This is called cost-based optimization

Observations

- No magic "best" plan: depends on the data
- In order to make the right choice
 - Need to have <u>statistics</u> over the data
 - The B's, the T's, the V's
 - Commonly: histograms over base data
 - In SimpleDB as well... lab 5.

Key Decisions for Implementation

Search Space

Optimization rules

Optimization algorithm

Key Decisions for Implementation

Search Space

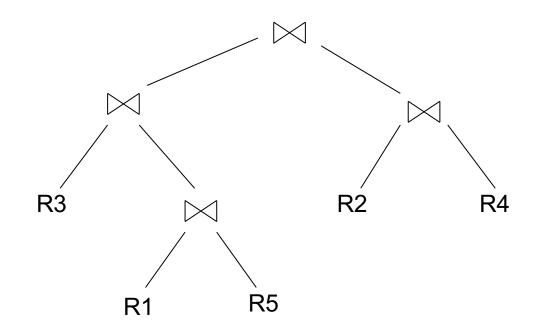
What form of plans do we consider? Optimization rules

Optimization algorithm

Restricting of Query Plans

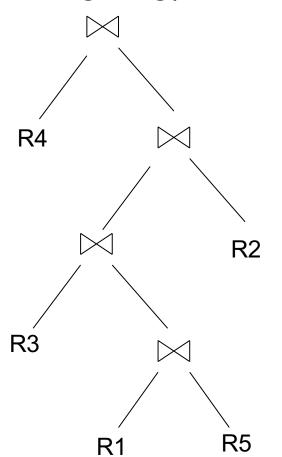
- The number of query plans is huge
- Optimizers often restrict them:
 - Restrict the types of trees
 - Restrict cartesian products

Bushy:

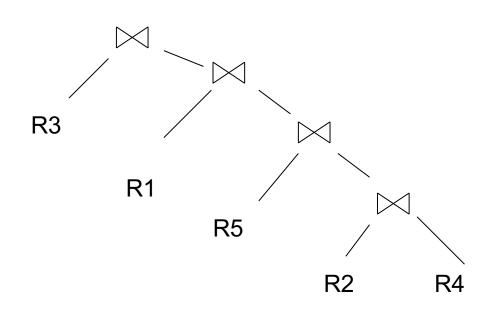


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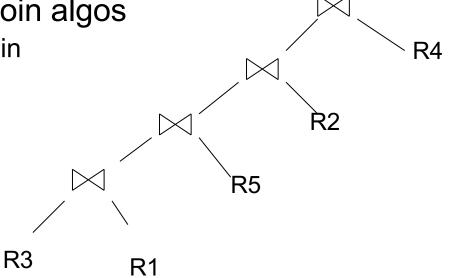
Linear (aka zig-zag):



Right deep:



- Left deep:
 - Work well with existing join algos
 - Nested-loop and hash-join
 - Facilitate pipelining



Key Decisions for Implementation

Search Space

Optimization rules

Which algebraic laws do we apply? **Optimization algorithm**

Discussion

- When implemented in the optimizer, algebraic laws are called <u>optimization rules</u>
- More rules \rightarrow larger search space \rightarrow better plan
- Less rules \rightarrow faster optimization \rightarrow less good plan
- There is no "complete set" of rules for SQL; Commercial optimizers typically use 5-600 rules, constantly adding rules in response to customer's needs

Optimization Rules – RA equivalencies

Selections

- Commutative: $\sigma_{c1}(\sigma_{c2}(R))$ same as $\sigma_{c2}(\sigma_{c1}(R))$
- Cascading: $\sigma_{c1}^{c2}(R)$ same as $\sigma_{c2}(\sigma_{c1}(R))$
- Projections
 - Cascading
- Joins
 - Commutative : $R \bowtie S$ same as $S \bowtie R$
 - Associative: $R \bowtie (S \bowtie T)$ same as $(R \bowtie S) \bowtie T$

Example: Simple Algebraic Laws

Example: R(A, B, C, D), S(E, F, G)

 $\sigma_{F=3}(\mathsf{R}\bowtie_{D=E}\mathsf{S})=$

 $\sigma_{A=5 \text{ AND } G=9} (R \bowtie_{D=E} S) =$

Example: Simple Algebraic Laws

Example: R(A, B, C, D), S(E, F, G)

$\sigma_{\mathsf{F=3}}(\mathsf{R}\bowtie_{\mathsf{D=E}}\mathsf{S}) = \mathsf{R}\bowtie_{\mathsf{D=E}}\sigma_{\mathsf{F=3}}(\mathsf{S})$

$$\sigma_{A=5 \text{ AND } G=9} (\mathsf{R} \bowtie_{\mathsf{D}=\mathsf{E}} \mathsf{S}) =$$

Example: Simple Algebraic Laws

Example: R(A, B, C, D), S(E, F, G)

$\sigma_{\mathsf{F=3}}(\mathsf{R}\bowtie_{\mathsf{D=E}}\mathsf{S}) = \mathsf{R}\bowtie_{\mathsf{D=E}}\sigma_{\mathsf{F=3}}(\mathsf{S})$

 $\sigma_{A=5\,\text{AND}\,G=9}\,(\mathsf{R}\bowtie_{\mathsf{D}=\mathsf{E}}\mathsf{S})=\sigma_{A=5}\,(\mathsf{R})\bowtie_{\mathsf{D}=\mathsf{E}}\sigma_{G=9}(\mathsf{S})$

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 $R \bowtie (S \cup T) = (R \bowtie S) \cup (R \bowtie T)$

$R \cup S = S \cup R, R \cup (S \cup T) = (R \cup S) \cup T$ $R \bowtie S = S \bowtie R, R \bowtie (S \bowtie T) = (R \bowtie S) \bowtie T$

Commutativity, Associativity, Distributivity

Laws Involving Selection

$$\sigma_{C \text{ AND } C'}(R) = \sigma_{C}(\sigma_{C'}(R)) = \sigma_{C}(R) \cap \sigma_{C'}(R)$$

$$\sigma_{C \text{ OR } C'}(R) = \sigma_{C}(R) \cup \sigma_{C'}(R)$$

$$\sigma_{C}(R \bowtie S) = \sigma_{C}(R) \bowtie S$$

$$\sigma_{C}(R - S) = \sigma_{C}(R) - S$$

$$\sigma_{C}(R \cup S) = \sigma_{C}(R) \cup \sigma_{C}(S)$$

$$\sigma_{C}(R \bowtie S) = \sigma_{C}(R) \bowtie S$$

Assuming C on
attributes of R

Laws Involving Projections

$$\begin{split} \Pi_{M}(\mathsf{R}\bowtie\mathsf{S}) &= \Pi_{M}(\Pi_{\mathsf{P}}(\mathsf{R})\bowtie\Pi_{\mathsf{Q}}(\mathsf{S})) \\ \Pi_{M}(\Pi_{\mathsf{N}}(\mathsf{R})) &= \Pi_{\mathsf{M}}(\mathsf{R}) \\ /^{*} \text{ note that } \mathsf{M} \subseteq \mathsf{N} */ \end{split}$$

• Example R(A,B,C,D), S(E, F, G) $\Pi_{A,B,G}(R \bowtie_{D=E} S) = \Pi_{?}(\Pi_{?}(R) \bowtie_{D=E} \Pi_{?}(S))$

Laws Involving Projections

$$\begin{split} \Pi_{M}(\mathsf{R} \bowtie \mathsf{S}) &= \Pi_{M}(\Pi_{\mathsf{P}}(\mathsf{R}) \bowtie \Pi_{\mathsf{Q}}(\mathsf{S})) \\ \Pi_{M}(\Pi_{\mathsf{N}}(\mathsf{R})) &= \Pi_{\mathsf{M}}(\mathsf{R}) \\ /^{*} \text{ note that } \mathsf{M} \subseteq \mathsf{N} */ \end{split}$$

■ Example R(A,B,C,D), S(E, F, G) $\Pi_{A,B,G}(R \bowtie_{D=E} S) = \Pi_{A,B,G}(\Pi_{A,B,D}(R) \bowtie_{D=E} \Pi_{E,G}(S))$

Laws for grouping and aggregation

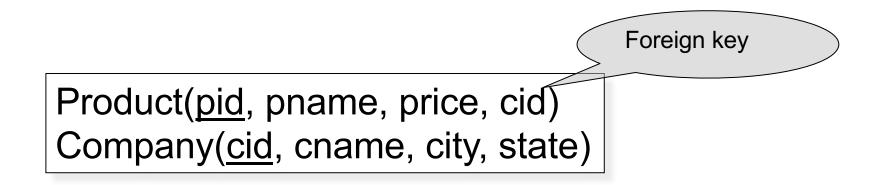
$$\gamma_{A, \operatorname{agg}(D)}(\mathsf{R}(A,B) \bowtie_{B=C} \mathsf{S}(C,D)) = \gamma_{A, \operatorname{agg}(D)}(\mathsf{R}(A,B) \bowtie_{B=C} (\gamma_{C, \operatorname{agg}(D)} \mathsf{S}(C,D)))$$

Laws for grouping and aggregation

$$\begin{split} &\delta(\gamma_{A, \text{ agg}(B)}(\mathsf{R})) = \gamma_{A, \text{ agg}(B)}(\mathsf{R}) \\ &\gamma_{A, \text{ agg}(B)}(\delta(\mathsf{R})) = \gamma_{A, \text{ agg}(B)}(\mathsf{R}) \\ & \text{ if agg is ``duplicate insensitive ''} \end{split}$$

Which of the following are "duplicate insensitive"? sum, count, avg, min, max

Laws Involving Constraints



$\Pi_{pid, price}$ (Product $\bowtie_{cid=cid}$ Company) = $\Pi_{pid, price}$ (Product)

Search Space Challenges

Search space is huge!

- Many possible equivalent trees
- Many implementations for each operator
- Many access paths for each relation
 - File scan or index + matching selection condition

Cannot consider ALL plans

• Heuristics: only partial plans with "low" cost

Key Decisions

Logical plan

- What logical plans do we consider (left-deep, bushy?) Search Space
- Which algebraic laws do we apply, and in which context(s)? Optimization rules
- In what order do we explore the search space? Optimization algorithm

Even More Key Decisions!

Physical plan

- What physical operators to use?
- What access paths to use (file scan or index)?
- Pipeline or materialize intermediate results?
- These decisions also affect the search space

Two Types of Optimizers

- Rule-based (heuristic) optimizers:
 - Apply greedily rules that always improve plan
 - Typically: push selections down
 - Very limited: no longer used today
- Cost-based optimizers:
 - Use a cost model to estimate the cost of each plan
 - Select the "cheapest" plan
 - We focus on cost-based optimizers