

Database System Internals Query Optimization (part 4)

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

Announcements

- Lab1 is graded and the feedback is pushed
- HW2 due tonight
- Lab2 due on Friday
- Quiz next Wednesday (May 6)

Where We Are

Three components:

- Cost/cardinality estimation
- Search space

 - Restricting the query plans ← ...and this next
- Search algorithm ← then we'll discuss this

These are laws that hold only under constraints

Most common: redundant key foreign-key join

```
Supply(sid, pno, discount)
Part(pno, pname, category, price)
```

select x.sid, x.pno, x.discount from Supply x, Part y where x.pno = y.pno

```
Supply(sid, pno, discount)
Part(pno, pname, category, price)
```

select x.sid, x.pno, x.discount from Supply x, Part y where x.pno = y.pno

hree constraints are needed



select x.sid, x.pno, x.disount from Supply x

```
Supply(sid, pno, discount)
Part(pno, pname, category, price)
```

select x.sid, x.pno, x.discount from Supply x, Part y where x.pno = y.pno



select x.sid, x.pno, x.disount from Supply x

Three constraints are needed

- 1. Part.pno is a key
- 2. Supply.pno is a foreign key
- 3. Supply.pno IS NOT NULL

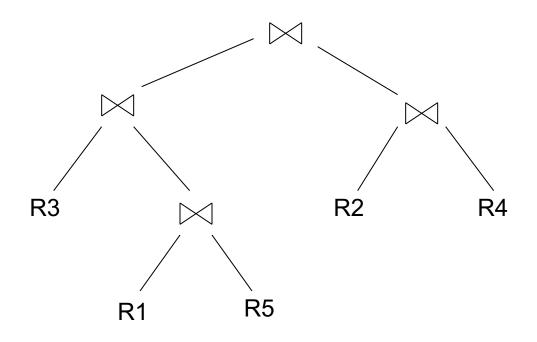
Discussion

- When implemented in the optimizer, algebraic laws are called <u>optimization rules</u>
- More rules → larger search space → better plan
- Less rules → faster optimization → 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

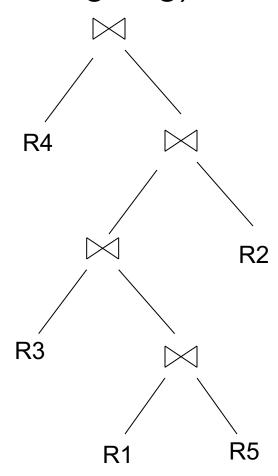
Restricting the Shape of the Query Plans

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

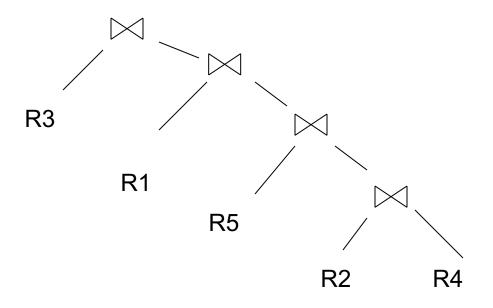
Bushy:



Linear (aka zig-zag):



Right deep:

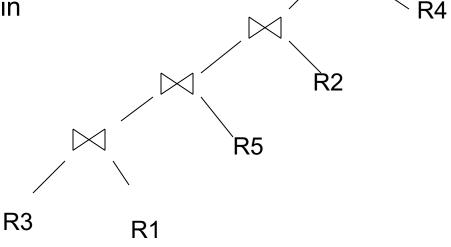


Left deep:

Work well with existing join algos

Nested-loop and hash-join

Facilitate pipelining

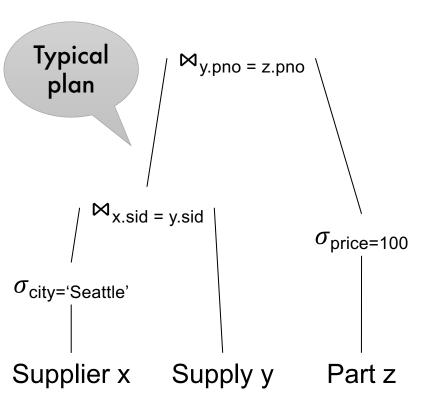


- Cartesian products are usually inefficient
- Most query optimizers avoid them

```
Supplier(sid, name, discount, city)
Supply(sid, pno)
Part(pno, pname, price)
```

select *
from Supplier x, Supply y, Part z
where x.sid = y.sid and y.pno = z.pno
 and x.city='Seattle' and z.price=100;

```
Supplier(sid, name, discount, city)
Supply(sid, pno)
Part(pno, pname, price)
```



select *
from Supplier x, Supply y, Part z
where x.sid = y.sid and y.pno = z.pno
 and x.city='Seattle' and z.price=100;

```
Supplier(sid, name, discount, city)
                                                    select *
Supply(<u>sid</u>, <u>pno</u>)
                                                    from Supplier x, Supply y, Part z
Part(pno, pname, price)
                                                    where x.sid = y.sid and y.pno = z.pno
                                                       and x.city='Seattle' and z.price=100;
   Typical
                                              Plan with
                   \bowtie_{y.pno} = z.pno
    plan
                                              Cartesian
                                                                         \bowtie x.sid = y.sid
                                               product
                                                                        and y.pno = z.pno
         \bowtie_{x.sid} = y.sid
                                  \sigma_{\rm price=100}
\sigma_{\text{city='Seattle'}}
                                                    \sigma_{\rm city='Seattle'}
                                                                        \sigma_{
m price=100}
Supplier x
                  Supply y
                                   Part z
                                                                                           Supply z
                                                    Supplier x
                                                                         Part z
                                               Most optimizers will not consider this plan
```

Query Optimization

Three components:

- Cost/cardinality estimation
- Search space
- Search algorithm ← rest of this lecture

Two Types of Optimizers

- Heuristic-based 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 discuss these

Approaches to Search Space Enumeration

Complete plans

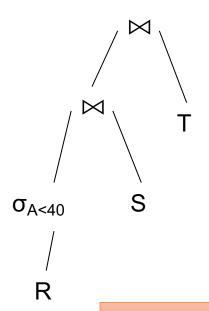
Bottom-up plans

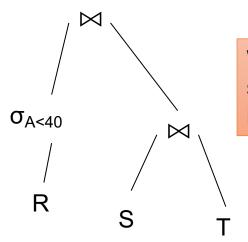
Top-down plans

20

Complete Plans

R(A,B)S(B,C)T(C,D) SELECT *
FROM R, S, T
WHERE R.B=S.B and
S.C=T.C and
R.A<40



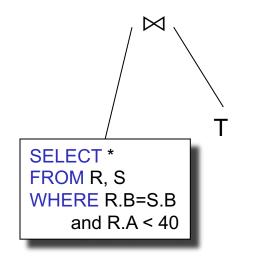


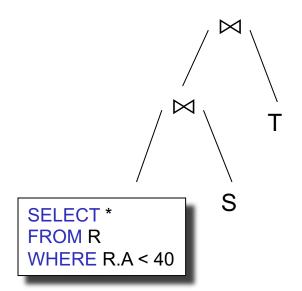
Why is this search space inefficient?

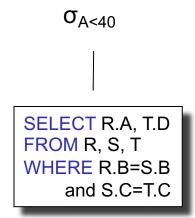
Answer: No way to do early pruning

Top-down Partial Plans

R(A,B)S(B,C)T(C,D) SELECT *
FROM R, S, T
WHERE R.B=S.B and S.C=T.C and R.A<40

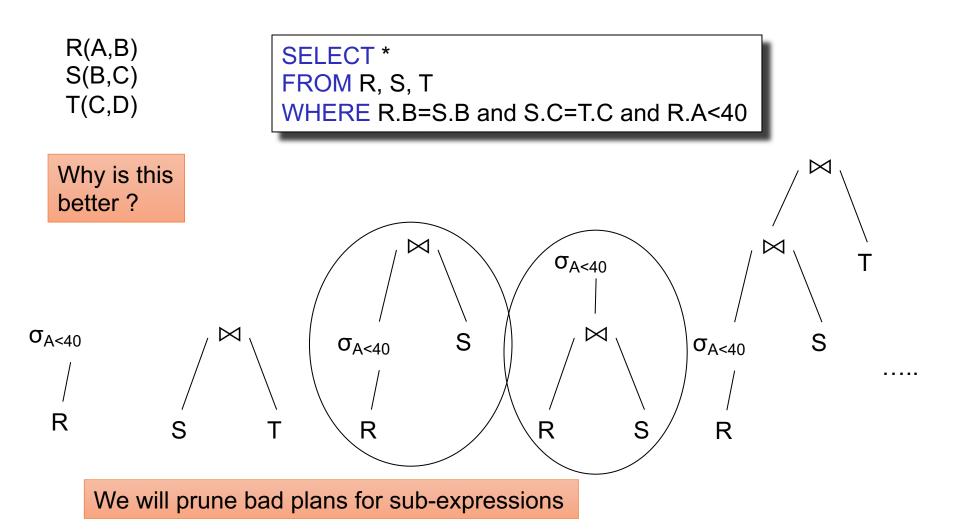






.

Bottom-up Partial Plans



23

Originally proposed in System R [1979]

Only handles single block queries:

```
\begin{array}{ll} \textbf{SELECT list} \\ \textbf{FROM} & \textbf{R1, ..., Rn} \\ \textbf{WHERE cond_1 AND cond_2 AND ... AND cond_k} \end{array}
```

- Some heuristics for search space enumeration:
 - Selections down
 - Projections up
 - Avoid cartesian products

For each subquery $Q \subseteq \{R1, ..., Rn\}$ compute:

- T(Q) = the estimated size of Q
- Plan(Q) = a best plan for Q
- Cost(Q) = the estimated cost of that plan

SELECT list FROM R1, ..., Rn WHERE $cond_1$ AND $cond_2$ AND . . . AND $cond_k$

- **Step 1**: For each {R_i} do:
 - $T({R_i}) = T(R_i)$
 - Plan({R_i}) = access method for R_i
 - Cost({R_i}) = cost of access method for R_i

- **Step 2**: For each $Q \subseteq \{R_1, ..., R_n\}$ of size k do:
 - T(Q) = use estimator
 - Consider all partitions Q = Q' ∪ Q'' compute cost(Plan(Q') ⋈ Plan(Q''))
 - Cost(Q) = the smallest such cost
 - Plan(Q) = the corresponding plan

Note

- If we restrict to left-linear trees: Q" = single relation
- May want to avoid cartesian products

 $\begin{array}{ll} \textbf{SELECT list} \\ \textbf{FROM} & \textbf{R1, ..., Rn} \\ \textbf{WHERE cond}_1 \ \textbf{AND cond}_2 \ \textbf{AND ... AND cond}_k \end{array}$

Step 3: Return Plan({R₁, ..., R_n})

- R ⋈ S ⋈ T ⋈ U
- Assumptions:

Every join selectivity is 0.001

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000		
S	5000		
Т	3000		
U	1000		
RS			
RT			
RU			
ST			
SU			
TU			
RST			
RSU			
RTU			
STU			
RSTU			

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000		
S	5000		
Т	3000		
U	1000		
RS	10000		
RT	6000		
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Assume B(..) = T(..)/10

	_		_
Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000		
Т	3000		
U	1000		
RS	10000		
RT	6000		
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000		
U	1000		
RS	10000		
RT	6000		
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000		
RT	6000		
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000	R ⋈ S nested loop join	
RT	6000		
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		_

Assume B(..) = T(..)/10

Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000	R ⋈ S nested loop join	
RT	6000	R ⋈ T index join	
RU	2000		
ST	15000		
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Example

Assume B(..) = T(..)/10

Join selectivity is 0.001

Subquery	T	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000	R ⋈ S nested loop join	
RT	6000	R ⋈ T index join	
RU	2000	R ⋈ U index join	
ST	15000	S ⋈ T hash join	
SU	5000		
TU	3000		
RST	30000		
RSU	10000		
RTU	6000		
STU	15000		
RSTU	30000		

Example

Assume B(..) = T(..)/10

Join selectivity is 0.001

Subquery	Т	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000	R ⋈ S nested loop join	
RT	6000	R ⋈ T index join	
RU	2000	R ⋈ U index join	
ST	15000	S ⋈ T hash join	
SU	5000		
TU	3000		
RST	30000	(RT) ⋈ S hash join	
RSU	10000	(SU) ⋈ R merge join	
RTU	6000		
STU	15000		
RSTU	30000		

Example

Assume B(..) = T(..)/10

Join selectivity is 0.001

Subquery	T	Plan	Cost
R	2000	Clustered index scan R.A	200
S	5000	Table scan	500
Т	3000	Table scan	300
U	1000	Unclustered index scan U.F	1000
RS	10000	R ⋈ S nested loop join	
RT	6000	R ⋈ T index join	
RU	2000	R ⋈ U index join	
ST	15000	S ⋈ T hash join	
SU	5000		
TU	3000		
RST	30000	(RT) ⋈ S hash join	
RSU	10000	(SU) ⋈ R merge join	
RTU	6000		
STU	15000		
RSTU	30000	(RT) ⋈ (SU) hash join	

Discussion

■ For the subset {RS}, need to consider both

$$R \bowtie S$$
 and $S \bowtie R$

Because the cost may be different!

When computing the cheapest plan for

$$(Q)\bowtie R$$

we may consider new access methods for R, e.g. an index look-up that makes sense only in the context of the join

A bit of math...

• The n'th Catalan number = number of ways to write n pairs of parentheses

$$C_n = \frac{1}{n+1} \binom{2n}{n}$$

n pairs of parentheses go around n+1 items:

A bit of math...

• The n'th Catalan number = number of ways to write n pairs of parentheses

$$C_n = \frac{1}{n+1} \binom{2n}{n}$$

- n pairs of parentheses go around n+1 items:
- 3 items: (AB)C, A(BC) $C_2 = \frac{1}{3} {4 \choose 2} = 2$

A bit of math...

• The n'th Catalan number = number of ways to write n pairs of parentheses

$$C_n = \frac{1}{n+1} \binom{2n}{n}$$

n pairs of parentheses go around n+1 items:

3 items: (AB)C, A(BC)
$$C_2 = \frac{1}{3} {4 \choose 2} = 2$$

■ 4 items: ((AB)C)D, (AB)(CD),
(A(BC))D, A((BC)D),
A(B(CD))
$$C_3 = \frac{1}{4} \binom{6}{3} = 5$$

■ The number of plans with n relations R₁,R₂,...,R_n is

$$P_n = n! C_{n-1} = \frac{n!}{n} {2(n-1) \choose n-1} = \frac{(2(n-1))!}{(n-1)!}$$

Reason: any parenthesis times any permutation

```
■ E.g. n=4: P_4 = 6!/3! = 120

• ((R_1R_2)R_3)R_4, ((R_1R_2)R_4)R_3, ((R_1R_3)R_2)R_4, ((R_1R_3)R_4)R_2...

• (R_1R_2)(R_3R_4), (R_1R_2)(R_4R_3),...

• (R_1(R_2R_3))R_4, (R_1(R_2R_4))R_3,...
```

Given a query with n relations R1, ..., Rn

- How many plans are there?
 - A: (2(n-1))! / (n-1)! = n(n+1)(n+2)...(2n-3)(2n-2)
- How many entries do we have in the dynamic programming table?

For each entry, how many alternative plans do we need to inspect?

Given a query with n relations R1, ..., Rn

- How many plans are there?
 - A: (2(n-1))! / (n-1)! = n(n+1)(n+2)...(2n-3)(2n-2)
- How many entries do we have in the dynamic programming table?
 - A: 2ⁿ 1
- For each entry, how many alternative plans do we need to inspect?
 - A: for each entry with k tables, examine 2^k 2 plans

Reducing the Search Space

Left-linear trees

No cartesian products

Given a query with n relations R1, ..., Rn Assume left-linear plans only

How many plans are there?

• How many entries do we have in the dynamic programming table?

For each entry, how many alternative plans do we need to inspect?

Given a query with n relations R1, ..., Rn Assume left-linear plans only

- How many plans are there?
 - A: n! = 1*2*3*...*n
- How many entries do we have in the dynamic programming table?
 - A: $2^n 1$
- For each entry, how many alternative plans do we need to inspect?
 - A: for each entry with k tables, examine k plan

Reducing the Search Space

Left-linear trees

No cartesian products

Chain join: $R_1(A_0,A_1) \bowtie R_2(A_1,A_2) \bowtie ... \bowtie R_n(A_{n-1},A_n)$ Assume left-linear plans without cartesian product

How many plans are there?

How many entries do we have in the dynamic programming table?

For each entry, how many alternative plans do we need to inspect? Chain join: $R_1(A_0,A_1) \bowtie R_2(A_1,A_2) \bowtie ... \bowtie R_n(A_{n-1},A_n)$ Assume left-linear plans without cartesian product

- How many plans are there?
 - A: 2ⁿ⁻¹
- How many entries do we have in the dynamic programming table?
 - A: n(n-1)/2
- For each entry, how many alternative plans do we need to inspect?
 - A: for each entry with k tables, examine 2 plans