CompSci 516

Data Intensive Computing Systems

Lecture 11

Query Optimization

Instructor: Sudeepa Roy

Announcements

- HW2 has been posted on sakai
  - Due on Oct 18, 11 pm
  - Start early!
- Midterm next week
  - Wednesday, Oct 11, in class
  - Closed book, closed electronic devices
  - Everything until and including Lecture 12

Reading Material

- [RG]
  - Query optimization: Chapter 15 (overview only)
- [GUW]
  - Chapter 16.2-16.7
- Original paper by Selinger et al. :
  - P. Selinger, M. Astrahan, D. Chamberlin, R. Lorie, and T. Price. *Access Path Selection in a Relational Database Management System*
  Proceedings of ACM SIGMOD, 1979. Pages 22-34
  - No need to understand the whole paper, but take a look at the example (link on the course webpage)

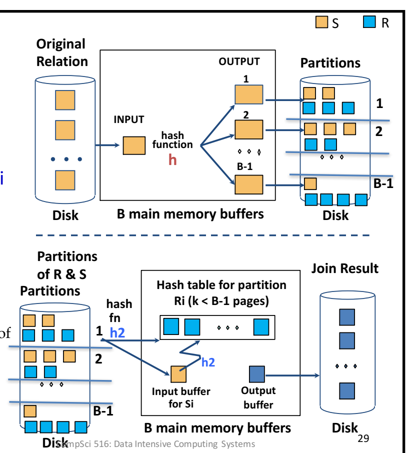
Acknowledgement:
- The following slides have been created adapting the instructor material of the [RG] book provided by the authors Dr. Ramakrishnan and Dr. Gehrke.
- Some of the following slides have been created by adapting slides by Profs. Shivnath Babu and Magda Balazinska

Query Evaluation and Operator Algorithm

Continued from Lecture 10

Hash-Join

- Partition both relations using hash function **h**
- R tuples in partition i will only match S tuples in partition i



- Read in a partition of R, hash it using h2 (≠ h).
- Scan matching partition of S, search for matches.

Cost of Hash-Join

M = 1000 pages in R
p_R = 100 tuples per page

N = 500 pages in S
p_S = 80 tuples per page

- In partitioning phase
  - read+write both relns; 2(M+N)
  - In matching phase, read both relns; M+N I/Os
  - remember – we are not counting final write
- In our running example, this is a total of 4500 I/Os
  - 3 * (1000 + 500)
  - Compare with the previous joins

Sort-Merge Join vs. Hash Join

- Both can have a cost of 3(M+N) I/Os
  - if sort-merge gets enough buffer (see 14.4.2)
- Hash join holds smaller relation in buffer-better if limited buffer
- Hash Join shown to be highly parallelizable
- Sort-Merge less sensitive to data skew
  - also result is sorted

General Join Conditions

- Equalities over several attributes
  - e.g., R.sid=S.sid AND R.rname=S.sname
  - For Index Nested Loop, build index on <sid, sname> (if S is inner); or use existing indexes on sid or sname
  - For Sort-Merge and Hash Join, sort/partition on combination of the two join columns.
- Inequality conditions
  - e.g., R.rname < S.sname
  - For Index NL, need (clustered) B+ tree index.
  - Hash Join, Sort Merge Join not applicable

Review: Join Algorithms

- Nested loop join:
  - for all tuples in R.. for all tuples in S....
  - variations: block-nested, index-nested
- Sort-merge join
  - like external merge sort
- Hash join

- Make sure you understand how the I/O varies
- No one join algorithm is uniformly superior to others
  - depends on relation size, buffer pool size, access methods, skew

Algorithms for Selection

```
SELECT *
FROM   Reserves R
WHERE  R.rname = 'Joe'
```

- No index, unsorted data
  - Scan entire relation
  - May be expensive if not many `Joe's
- No index, sorted data (on 'rname')
  - locate the first tuple, scan all matching tuples
  - first binary search, then scan depends on matches
- B+-tree index, Hash index
  - Discussed earlier
  - Cost of accessing data entries + matching data records
  - Depends on clustered/unclustered
- More complex condition like day<8/9/94 AND bid=5 AND sid=3
  - Either use one index, then filter
  - Or use two indexes, then take intersection, then apply third condition
  - etc.

Algorithms for Projection

```
SELECT DISTINCT
       R.sid, R.bid
FROM   Reserves R
```

- Two parts
  - Remove fields: easy
  - Remove duplicates (if distinct is specified): expensive
- Sorting-based
  - Sort, then scan adjacent tuples to remove duplicates
  - Can eliminate unwanted attributes in the first pass of merge sort
- Hash-based
  - Exactly like hash join
  - Partition only one relation in the first pass
  - Remove duplicates in the second pass
- Sort vs Hash
  - Sorting handles skew better, returns results sorted
  - Hash table may not fit in memory – sorting is more standard
- Index-only scan may work too
  - If all required attributes are part of index

Algorithms for Set Operations

- Intersection, cross product are special cases of joins
- Union, Except
  - Sort-based
  - Hash-based
  - Very similar to joins and projection

Algorithms for Aggregate Operations

- SUM, AVG, MIN etc.
  - again similar to previous approaches
- Without grouping:
  - In general, requires scanning the relation.
  - Given index whose search key includes all attributes in the SELECT or WHERE clauses, can do index-only scan
- With grouping:
  - Sort on group-by attributes
  - or, hash on group-by attributes
  - can combine sort/hash and aggregate
  - can do index-only scan here as well

Query Optimization

Query Blocks: Units of Optimization

- Query Block
  - No nesting
  - One SELECT, one FROM
  - At most one WHERE, GROUP BY, HAVING
- SQL query
- => parsed into a collection of query blocks
- => the blocks are optimized one block at a time
- Express single-block it as a relational algebra (RA) expression

```
SELECT S.sname
FROM Sailors S
WHERE S.age IN
  (SELECT MAX (S2.age)
   FROM Sailors S2
   GROUP BY S2.rating)
```

Outer block   Nested block

Cost Estimation

- For each plan considered, must estimate cost:
- Must estimate cost of each operation in plan tree.
  - Depends on input cardinalities
  - We've discussed how to estimate the cost of operations (sequential scan, index scan, joins, etc.)
- Must also estimate size of result for each operation in tree
  - gives input cardinality of next operators
- Also consider
  - whether the output is sorted
  - intermediate results written to disk

Relational Algebra Equivalences

- Allow us to choose different join orders and to `push' selections and projections ahead of joins.
- *Selections*: $\sigma_{c1\wedge\ldots\wedge cn}(R) \equiv \sigma_{c1}(\ldots\sigma_{cn}(R))$ (Cascade)

  $\sigma_{c1}(\sigma_{c2}(R)) \equiv \sigma_{c2}(\sigma_{c1}(R))$ (Commute)
- *Projections*: $\pi_{a1}(R) \equiv \pi_{a1}(\ldots(\pi_{an}(R)))$ (Cascade)
- *Joins*: $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$ (Associative)

  $(R \bowtie S) \equiv (S \bowtie R)$ (Commute)

There are many more intuitive equivalences, see 15.3.4 for details

Notation

- T(R) : Number of tuples in R
- B(R) : Number of blocks (pages) in R
- V(R, A) : Number of distinct values of attribute A in R

Query Optimization Problem

Pick the best plan from the space of physical plans

Cost-based Query Optimization

Pick the plan with least cost

Challenge:

- Do not want to execute more than one plans
- Need to estimate the cost without executing the plan

"heuristic-based" optimizer (e.g. push selections down) have limited power and not used much

Cost-based Query Optimization

Pick the plan with least cost

Tasks:

1. Estimate the cost of individual operators
   done in Lecture 9-11
2. Estimate the size of output of individual operators
   today
3. Combine costs of different operators in a plan
   today
4. Efficiently search the space of plans today

Task 1 and 2 Estimating cost and size of different operators

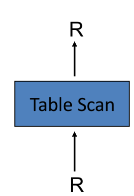
- Size = #tuples, NOT #pages
- Cost = #page I/O
  - but, need to consider whether the intermediate relation fits in memory, is written back to/read from disk (or on-the-fly goes to the next operator), etc.

Desired Properties of Estimating Sizes of Intermediate Relations

Ideally,

- should give accurate estimates (as much as possible)
- should be easy to compute
- should be logically consistent
  - size estimate should be independent of how the relation is computed (e.g. which join algorithm/join order is used)
- But, no "universally agreed upon" ways to meet these goals

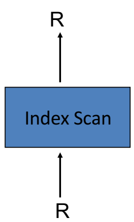
Cost of Table Scan



Cost: B(R)
Size: T(R)

T (R) : Number of tuples in R
B (R) : Number of blocks in R

Cost of Index Scan



Cost: B(R) – if clustered
T(R) – if unclustered

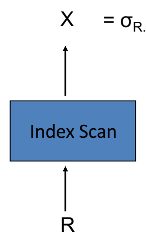
Size: T(R)

T (R) : Number of tuples in R
B (R) : Number of blocks in R

Note:
1. size is independent of the implementation of the scan/index
2. Index scan is bad if unclustered

Cost of Index Scan with Selection

X $= \sigma_{R.A > 50} R$



Cost: B(R) * f – if clustered
T(R) * f – if unclustered

Size: T(R) * f

T (R) : Number of tuples in R
B (R) : Number of blocks in R

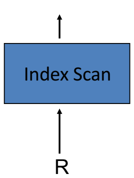
Reduction factor
f = (Max(R.A) - 50) / (Max(R.A) - Min(R.A))
assumes uniform distribution

Cost of Index Scan with Selection (and multiple conditions)

X $= \sigma_{R.A > 50 \text{ and } R.B = c} R$

assume index on (A, B)

What is f1 if the first condition is 100 > R.1 > 50?



Cost: B(R) * f – if clustered
T(R) * f – if unclustered

Size: T(R) * f

Reduction factors
range selection
f1 = (Max(R.A) - 50) / (Max(R.A) - Min(R.A))

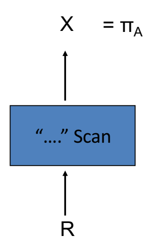
f2 = 1/ V(R, B) value selection

T (R) : Number of tuples in R
B (R) : Number of blocks in R
V(R, A) : Number of distinct values of attribute A in R

f = f1 * f2 (assumes independence and uniform distribution)

Cost of Projection

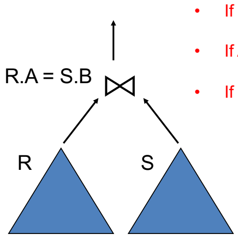
X $= \pi_A R$



Cost: depends on the method of scanning R
B(R) for table scan or clustered index scan

Size: T(R)
But tuples are smaller
If you have more information on the size of the smaller tuples, can estimate #I/O better

Size of Join

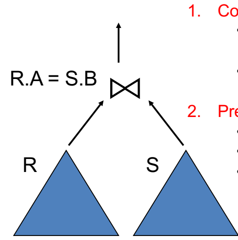


Quite tricky
- If disjoint A and B values
  - then 0
- If A is key of R and B is foreign key of S
  - then T(S)
- If all tuples have the same value of R.A= S.B = x
  - then T(R) * T(S)

T (R) : Number of tuples in R
B (R) : Number of blocks in R
V(R, A) : Number of distinct values of attribute A in R

Size of Join

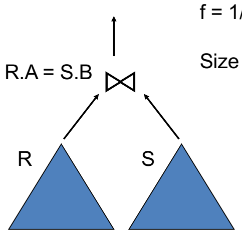
Two standard assumptions



1. Containment of value sets:
   - if V(R, A) <= V(S, B), then all A-values of R are included in B-values of S
   - e.g. satisfied when A is foreign key, B is key
2. Preservation of value sets:
   - $V(R \bowtie S, A) = V(R, A)$
   - $V(R \bowtie S, B) = V(S, B)$
   - No value is lost in join

T (R) : Number of tuples in R
B (R) : Number of blocks in R
V(R, A) : Number of distinct values of attribute A in R

Size of Join



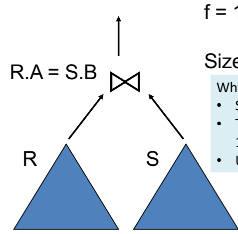
Reduction factor
f = 1/max(V(R, A), V(S, B))

Size = T(R) * T(S) * f

T (R) : Number of tuples in R
B (R) : Number of blocks in R
V(R, A) : Number of distinct values of attribute A in R

Size of Join

Assumes index on both A and B
if one index: 1/V(..., ...)
if no index: say 1/10



Reduction factor
f = 1/max(V(R, A), V(S, B))

Size = T(R) * T(S) * f

Why max?
- Suppose V(R, A) <= V(S, B)
- The probability of a A-value joining with a B-value is 1/V(S.B) = reduction factor
- Under the two assumptions stated earlier + uniformity

T (R) : Number of tuples in R
B (R) : Number of blocks in R
V(R, A) : Number of distinct values of attribute A in R

Task 3: Combine cost of different operators in a plan

With Examples
"Given" the physical plan

- Size = #tuples, NOT #pages
- Cost = #page I/O
  - but, need to consider whether the intermediate relation fits in memory, is written back to disk (or on-the-fly goes to the next operator) etc.

Example Query

Student (<u>sid</u>, name, age, address)
Book(<u>bid</u>, title, author)
Checkout(<u>sid, bid</u>, date)

Query:

```
SELECT S.name
FROM Student S, Book B, Checkout C
WHERE S.sid = C.sid
AND B.bid = C.bid
AND B.author = 'Olden Fames'
AND S.age > 12
AND S.age < 20
```


S(<u>sid</u>,name,age,addr)
B(<u>bid</u>,title,author)
C(<u>sid,bid</u>,date)

Assumptions

- Student: S, Book: B, Checkout: C
- Sid, bid foreign key in C referencing S and B resp.
- There are 10,000 Student records stored on 1,000 pages.
- There are 50,000 Book records stored on 5,000 pages.
- There are 300,000 Checkout records stored on 15,000 pages.
- There are 500 different authors.
- Student ages range from 7 to 24.

Warning: a few dense slides next ☺

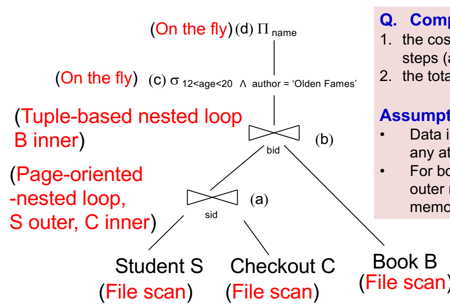
S(<u>sid</u>,name,age,addr)
B(<u>bid</u>,title,author)
C(<u>sid,bid</u>,date)

T(S)=10,000
T(B)=50,000
T(C)=300,000

B(S)=1,000
B(B)=5,000
B(C)=15,000

V(B,author) = 500
7 <= age <= 24

Physical Query Plan – 1



Q. Compute
1. the cost and cardinality in steps (a) to (d)
2. the total cost

Assumptions (given):
- Data is not sorted on any attributes
- For both in (a) and (b), outer relations fit in memory

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author) T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date) T(C)=300,000 B(C)=15,000

(a)

(On the fly) (d) Π_{name}

(On the fly)(c) $\sigma_{12<age<20 \ \wedge \ author = \text{'Olden Fames'}}$

(Tuple-based nested loop B inner) $\bowtie_{bid}$ (b)

(Page-oriented -nested loop, S outer, C inner) $\bowtie_{sid}$ (a)

Book B (File scan)

Student S (File scan) Checkout C (File scan)

Cost =
B(S) + B(S) * B(C)
= 1000 + 1000 * 15000
= 15,001,000

Cardinality =
T(C) = 300,000

- foreign key join, output pipelined to next join
- Can apply the formula as well

T(S) * T(C)/max (V(S, sid), V(C, sid))
= T(C)
since V(S, sid) > = V(C, sid)
and
T(S) = V(S, sid)

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author) T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date) T(C)=300,000 B(C)=15,000

(b)

(On the fly) (d) Π_{name}

(On the fly)(c) $\sigma_{12<age<20 \ \wedge \ author = \text{'Olden Fames'}}$

(Tuple-based nested loop B inner) $\bowtie_{bid}$ (b)

(Page-oriented -nested loop, S outer, C inner) $\bowtie_{sid}$ (a)

Book B (File scan)

Student S (File scan) Checkout C (File scan)

Cost =
T(S ⋈ C) * B(B)
= 300,000 * 5,000 = 15 * 10^8

Cardinality =
T(S ⋈ C) = 300,000

- foreign key join
- don't need scanning for outer relation
  - outer relation fits in memory

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author) T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date) T(C)=300,000 B(C)=15,000

(c, d)

(On the fly) (d) Π_{name}

(On the fly)(c) $\sigma_{12<age<20 \ \wedge \ author = \text{'Olden Fames'}}$

(Tuple-based nested loop B inner) $\bowtie_{bid}$ (b)

(Page-oriented -nested loop, S outer, C inner) $\bowtie_{sid}$ (a)

Book B (File scan)

Student S (File scan) Checkout C (File scan)

Cost =
0 (on the fly)

Cardinality =
300,000 * 1/500 * 7/18
= 234 (approx)
(assuming uniformity and independence)

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author) T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date) T(C)=300,000 B(C)=15,000

(Total)

(On the fly) (d) Π_{name}

(On the fly)(c) $\sigma_{12<age<20 \ \wedge \ author = \text{'Olden Fames'}}$

(Tuple-based nested loop B inner) $\bowtie_{bid}$ (b)

(Page-oriented -nested loop, S outer, C inner) $\bowtie_{sid}$ (a)

Book B (File scan)

Student S (File scan) Checkout C (File scan)

Total cost =
1,515,001,000

Final cardinality =
234 (approx)

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author) T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date) T(C)=300,000 B(C)=15,000 V(B,author) = 500
7 <= age <= 24

Physical Query Plan – 2

(On the fly) (g) Π_{name}

(On the fly) (f) $\sigma_{12<age<20}$

(Block nested loop S inner) $\bowtie_{sid}$ (e)

(d) Π_{sid} (On the fly)

(Indexed-nested loop, B outer, C inner) $\bowtie_{bid}$ (c)

(On the fly) (b) Π_{bid}

(a) $\sigma_{author = \text{'Olden Fames'}}$

Book B (Index scan)

Checkout C (Index scan)

Student S (File scan)

Q. Compute
1. the cost and cardinality in steps (a) to (g)
2. the total cost

Assumptions (given):
- Unclustered B+tree index on B.author
- Clustered B+tree index on C.bid
- All index pages are in memory
- Unlimited memory

S(<u>sid</u>,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(<u>bid</u>,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(<u>sid</u>,<u>bid</u>,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000

(a)

(On the fly) (g) Π_{name}

(On the fly) (f) $\sigma_{12<age<20}$

(Block nested loop S inner) $\bowtie_{sid}$ (e)

(d) Π_{sid} (On the fly)

(Indexed-nested loop, B outer, C inner) $\bowtie_{bid}$ (c)

Student S (File scan)

(On the fly) (b) Π_{bid}

(a) $\sigma_{author = \text{'Olden Fames'}}$

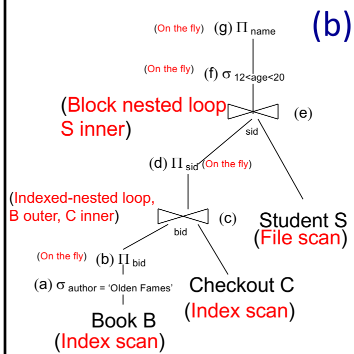
Checkout C (Index scan)

Book B (Index scan)

Cost =
T(B) / V(B, author)
= 50,000/500
= 100 (unclustered)

Cardinality =
100

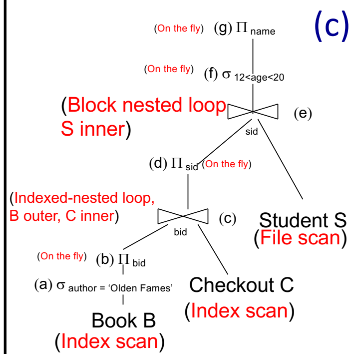
S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



Cost =
0 (on the fly)

Cardinality =
100

S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



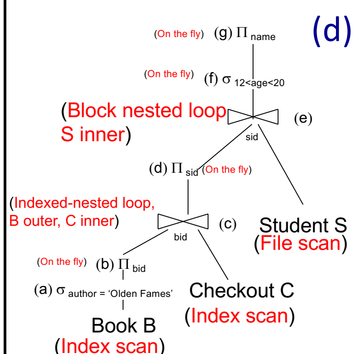
- one index lookup per outer B tuple
- 1 book has T(C)/ T(B) = 6 checkouts (uniformity)
- # C tuples per page = T(C)/B(C) = 20
- 6 tuples fit in at most 2 consecutive pages (clustered) could assume 1 page as well

Cost <=
100 * 2= 200

Cardinality =
100 * 6 = 600

= 100 * T(C)/ MAX(100, V(C, bid)) assuming
V(C, bid) = V(B, bid) = T(B) = 50,000

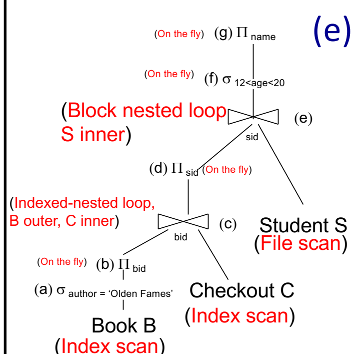
S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



Cost =
0 (on the fly)

Cardinality =
600

S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000

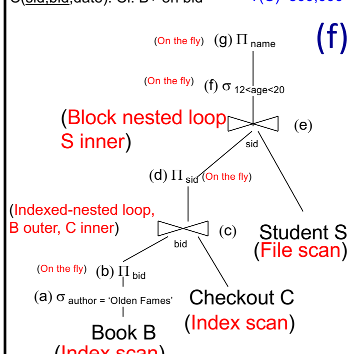


Outer relation is already in (unlimited) memory need to scan S relation

Cost =
B(S) = 1000

Cardinality =
600
(one student per checkout)

S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



Cost =
0 (on the fly)

Cardinality =
600 * 7/18 = 234 (approx)

S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
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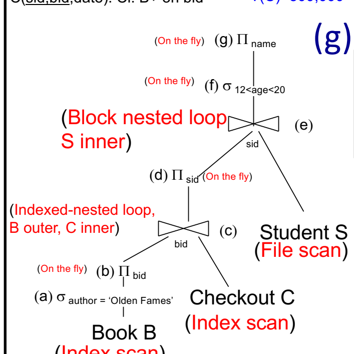
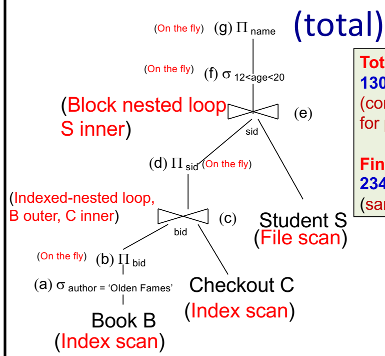


Cost =
0 (on the fly)

Cardinality =
234

S(sid,name,age,addr) T(S)=10,000 B(S)=1,000
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000

V(B,author) = 500
7 <= age <= 24



Total cost =
1300
(compare with 1,515,001,000 for plan 1!)

Final cardinality =
234 (approx)
(same as plan 1!)

Task 4:
Efficiently searching the plan space

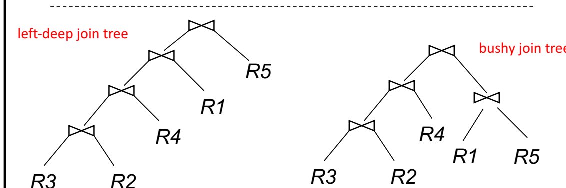
Use dynamic-programming based Selinger's algorithm

Heuristics for pruning plan space

- Apply predicates as early as possible
- Avoid plans with cross products
- Only left-deep join trees

Join Trees

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4 \bowtie R5$



(logical plan space)
- Several possible structure of the trees
- Each tree can have n! permutations of relations on leaves

(physical plan space)
- Different implementation and scanning of intermediate operators for each logical plan

Selinger Algorithm

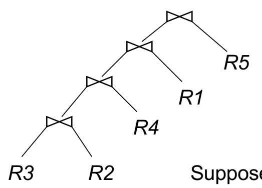
- Dynamic Programming based
- Dynamic Programming:
  - General algorithmic paradigm
  - Exploits "principle of optimality"
    - Useful reading: Chapter 16, Introduction to Algorithms, Cormen, Leiserson, Rivest
- Considers the search space of left-deep join trees
  - reduces search space (only one structure)
  - but still n! permutations
  - interacts well with join algos (esp. NLJ)
  - e.g. might not need to write tuples to disk if enough memory

Principle of Optimality

Optimal for "whole" made up from optimal for "parts"

Principle of Optimality

Query: *R1* ⋈ *R2* ⋈ *R3* ⋈ *R4* ⋈ *R5*

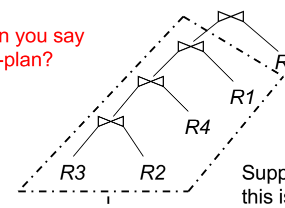


Suppose,
this is an Optimal Plan
for joining R1…R5:

Principle of Optimality

Query: *R1* ⋈ *R2* ⋈ *R3* ⋈ *R4* ⋈ *R5*

Then, what can you say
about this sub-plan?



Suppose,
this is an Optimal Plan
for joining R1…R5:

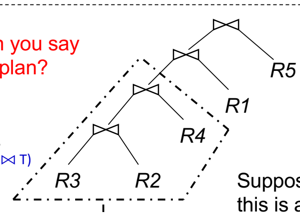
This has to be the
optimal plan for joining *R3, R2, R4, R1*

Principle of Optimality

Query: *R1* ⋈ *R2* ⋈ *R3* ⋈ *R4* ⋈ *R5*

Then, what can you say
about this sub-plan?

We are using the
associativity and
commutativity of joins
(R ⋈ S) ⋈ T = R ⋈ (S ⋈ T)
R ⋈ S = S ⋈ R



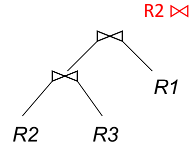
Suppose,
this is an Optimal Plan
for joining R1…R5:

This has to be the
optimal plan for joining *R3, R2, R4*

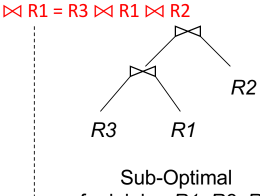
Exploiting Principle of Optimality

Query: *R1* ⋈ *R2* ⋈ … ⋈ *Rn*

Both are giving the same result
R2 ⋈ R3 ⋈ R1 = R3 ⋈ R1 ⋈ R2



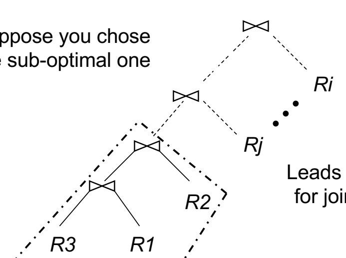
Optimal
for joining *R1, R2, R3*



Sub-Optimal
for joining *R1, R2, R3*

Exploiting Principle of Optimality

Suppose you chose
the sub-optimal one



Leads to sub-Optimal
for joining R1,…,Rn

A sub-optimal sub-plan cannot lead to an
optimal plan

Notation

OPT ({ *R1, R2, R3* }):

Cost of optimal plan to join *R1,R2,R3*

T ({ *R1, R2, R3* }):

Number of tuples in *R1* ⋈ *R2* ⋈ *R3*

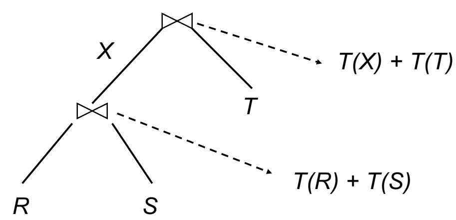
Simple Cost Model

Cost (R ⋈ S) = T(R) + T(S)

All other operators have 0 cost

Note: The simple cost model used for illustration only, it is not used in practice

Cost Model Example



Total Cost: *T(R) + T(S) + T(T) + T(X)*

Selinger Algorithm:

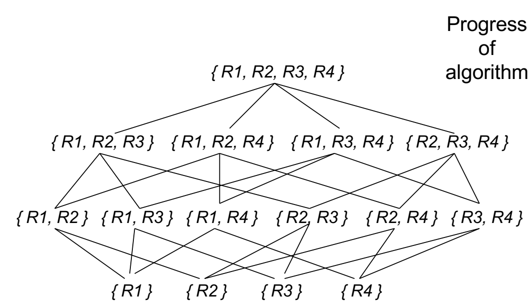
OPT ({ R1, R2, R3 }):

$$\text{Min} \begin{cases} \text{OPT (\{ R1, R2 \}) + T (\{ R1, R2 \}) + T(R3)} \\ \text{OPT (\{ R2, R3 \}) + T (\{ R2, R3 \}) + T(R1)} \\ \text{OPT (\{ R1, R3 \}) + T (\{ R1, R3 \}) + T(R2)} \end{cases}$$

Note: Valid only for the simple cost model

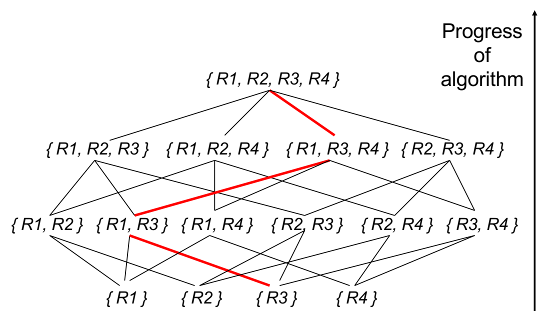
Selinger Algorithm:

Query: *R1 ⋈ R2 ⋈ R3 ⋈ R4*



Selinger Algorithm:

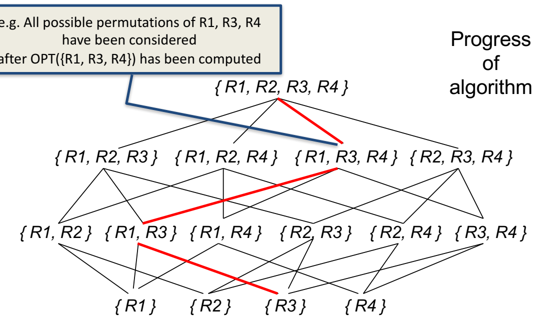
Query: *R1 ⋈ R2 ⋈ R3 ⋈ R4*



Selinger Algorithm:

Query: *R1 ⋈ R2 ⋈ R3 ⋈ R4*

e.g. All possible permutations of R1, R3, R4 have been considered after OPT({R1, R3, R4}) has been computed



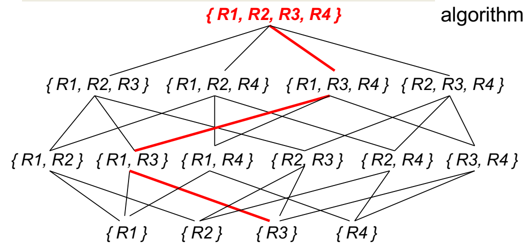
Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

Q. How to optimally compute join of {R1, R2, R3, R4}?

Ans: First optimally join {R1, R3, R4} then join with R2 as inner.

Progress of algorithm



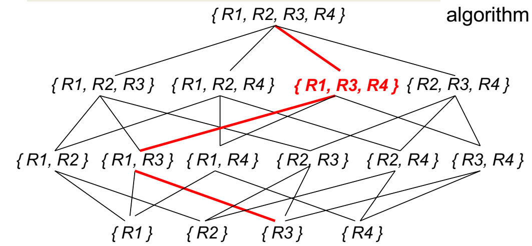
Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

Q. How to optimally compute join of {R1, R3, R4}?

Ans: First optimally join {R1, R3}, then join with R4 as inner.

Progress of algorithm



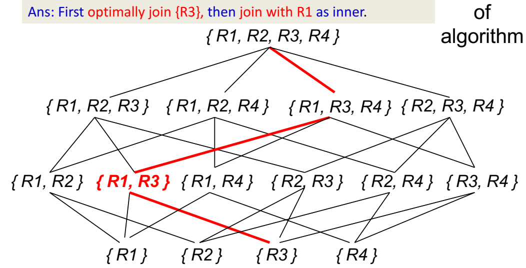
Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

Q. How to optimally compute join of {R1, R3}?

Ans: First optimally join {R3}, then join with R1 as inner.

Progress of algorithm



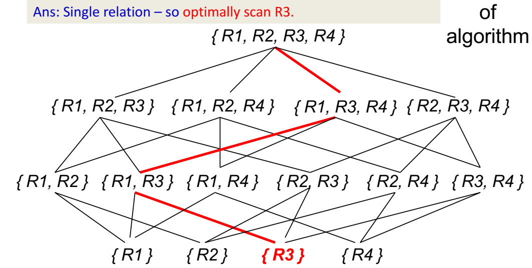
Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

Q. How to optimally compute join of {R3}?

Ans: Single relation – so optimally scan R3.

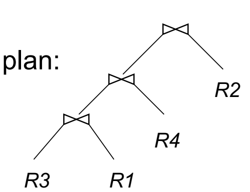
Progress of algorithm



Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

Final optimal plan:



NOTE : There is a one-one correspondence between the permutation (R3, R1, R4, R2) and the above left deep plan

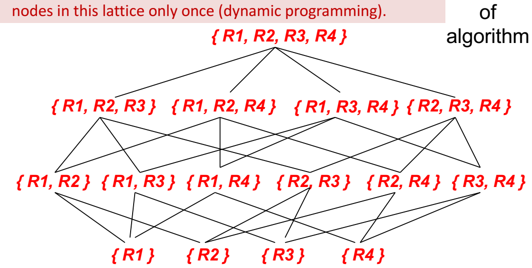
Selinger Algorithm:

Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$

NOTE: (*VERY IMPORTANT*)

- This is *NOT* done by top-down recursive calls.
- This is done BOTTOM-UP computing the optimal cost of *all* nodes in this lattice only once (dynamic programming).

Progress of algorithm



More on Query Optimizations

- See the survey (on course website):

"An Overview of Query Optimization in Relational Systems" by Surajit Chaudhuri

- Covers other aspects like
  - Pushing group by before joins
  - Merging views and nested queries
  - "Semi-join"-like techniques for multi-block queries
    - covered later in distributed databases
  - Statistics and optimizations
  - Starbust and Volcano/Cascade architecture, etc