Query Optimization

Introduction to Databases

CompSci 316 Spring 2017

DUKE COMPUTER SCIENCE

Announcements (Wed., Mar. 29)

- Homework #3
  - 3.3, 3.4, and 3.5 due today

Review QP and QO

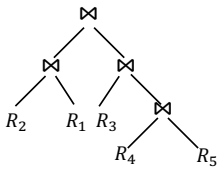
- QO approaches
  - Cost-based QO
  - Heuristic (rule)-based QO
  - Query rewriting, unnesting, and decorrelation
- Equivalence of RA operators
- Estimate cost of individual operators (Lec 16 + 17)
- Estimate output size of individual operators (Lec 18)
  - Uniformity + Independence + Other assumptions
  - Selection
  - Join
- Today:
  - Explore search space for join only plans
  - Combine multiple operators

Search strategy

http://1.bp.blogspot.com/-MoIduSreRKs/TgyAi4ki5QI/AAAAAAAAAKE/mi8ejfZ8S7U/s1600/cornMaze.jpg

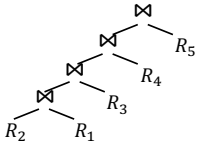
Search space

- Huge!
- "Bushy" plan example:



- Just considering different join orders, there are $\frac{(2n-2)!}{(n-1)!}$ bushy plans for $R_1 \bowtie \cdots \bowtie R_n$
  - 30240 for $n = 6$
    - (FYI: Recurrence relation: f(n)=f(n-1)*(4n-6), where 4n-6 comes from two ways to add the new node to one of n-1 leaves and n-2 internal nodes.)
- And there are more if we consider:
  - Multiway joins
  - Different join methods
  - Placement of selection and projection operators

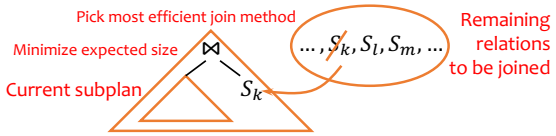
Left-deep plans



- Heuristic: consider only "left-deep" plans, in which only the left child can be a join
  - Tend to be better than plans of other shapes, because many join algorithms scan inner (right) relation multiple times—you will not want it to be a complex subtree
- How many left-deep plans are there for $R_1 \bowtie \cdots \bowtie R_n$?
  - Significantly fewer, but still lots—$n!$ (720 for $n = 6$)

A greedy algorithm

- $S_1, \ldots, S_n$
  - Say selections have been pushed down; i.e., $S_i = \sigma_p(R_i)$
- Start with the pair S_i, S_j with the smallest estimated size for $S_i \bowtie S_j$
- Repeat until no relation is left:
  Pick S_k from the remaining relations such that the join of S_k and the current result yields an intermediate result of the smallest size

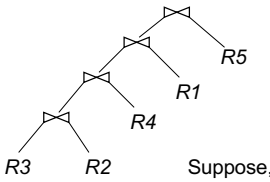


A dynamic programming approach

- Selinger's algorithm
  - IBM System R, frequently adapted and used
- Generate optimal plans bottom-up
  - Pass 1: Find the best single-table plans (for each table)
  - Pass 2: Find the best two-table plans (for each pair of tables) by combining best single-table plans
  - …
  - Pass k: Find the best k-table plans (for each combination of k tables) by combining two smaller best plans found in previous passes
  - …
- Rationale: Any subplan of an optimal plan must also be optimal
  - otherwise, just replace the subplan to get a better overall plan

Principle of Optimality

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

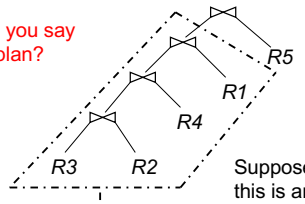


Suppose,
this is an Optimal Plan
for joining R1…R5:

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:

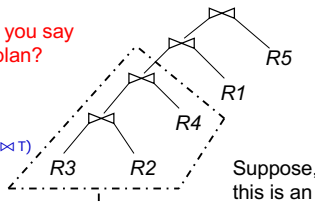
This has to be the optimal plan for joining *R3, R2, R4, R1*

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



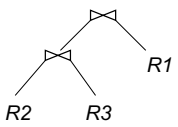
Suppose,
this is an Optimal Plan
for joining R1…R5:

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

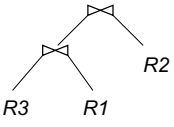
Exploiting Principle of Optimality

Query: *R1* ⋈ *R2* ⋈ … ⋈ *Rn*

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



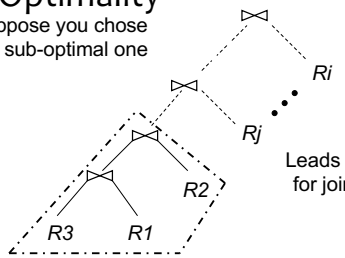
Optimal
for joining *R1, R2, R3*



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

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Selinger Algorithm:

OPT ({ R1, R2, R3 }):

Min
- OPT ({ R1, R2 }) + Join (({R1, R2}), R3)
- OPT ({ R2, R3 }) + Join (({R2, R3}), R1)
- OPT ({ R1, R3 }) + Join (({R3, R1}), R2)}

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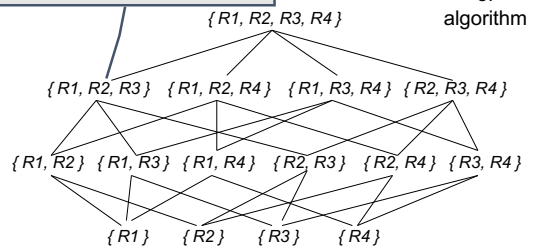
Selinger Algorithm:

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

e.g. All possible permutations of R1, R2, R3 have been considered after OPT({R1, R2, R3}) has been computed

Progress of algorithm



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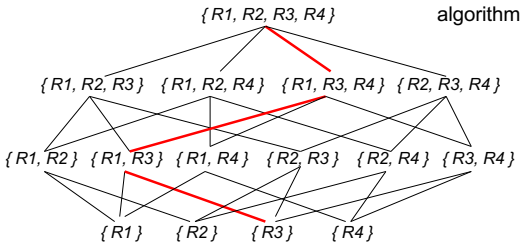
Selinger Algorithm:

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

Progress of algorithm



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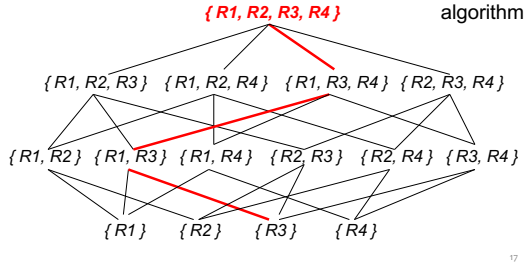
Selinger Algorithm:

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



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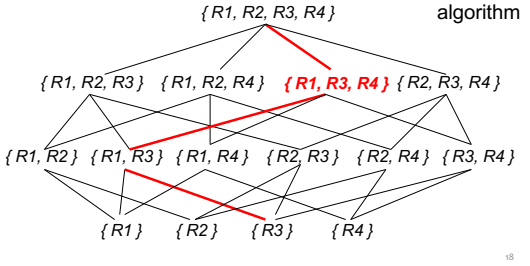
Selinger Algorithm:

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



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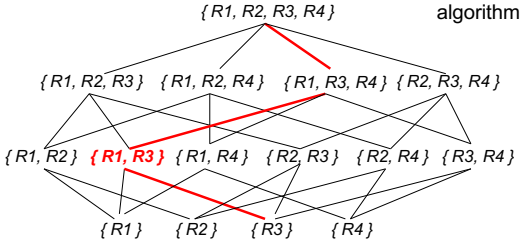
Selinger Algorithm:

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

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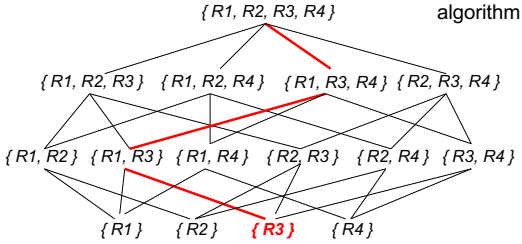
Selinger Algorithm:

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

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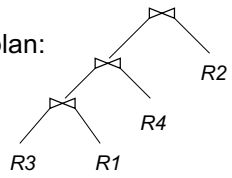
Selinger Algorithm:

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

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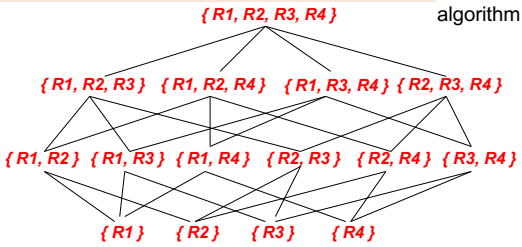
Selinger Algorithm:

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

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Summary: A dynamic programming approach

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- Selinger's algorithm
- Generate optimal plans bottom-up
- Rationale: Any subplan of an optimal plan must also be optimal (otherwise, just replace the subplan to get a better overall plan)

☞Well, not quite...
- for physical plan

The need for "interesting order"

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- Example: $R(A,B) \bowtie S(A,C) \bowtie T(A,D)$
- Best plan for $R \bowtie S$: hash join (beats sort-merge join)
- Best overall plan: sort-merge join R and S, and then sort-merge join with T
  - Subplan of the optimal plan is not optimal!
- Why?
  - The result of the sort-merge join of R and S is sorted on A
  - This is an interesting order that can be exploited by later processing (e.g., join, dup elimination, GROUP BY, ORDER BY, etc.)!

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Dealing with interesting orders

When picking the best plan

- Comparing their costs is not enough
  - Plans are not totally ordered by cost anymore
- Comparing interesting orders is also needed
  - Plans are now partially ordered
  - Plan X is better than plan Y if
    - Cost of X is lower than Y, and
    - Interesting orders produced by X "subsume" those produced by Y
- Need to keep a set of optimal plans for joining every combination of k tables
  - At most one for each interesting order

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Combine cost of different operators in a plan

- Given a Physical Plan
- Size = #tuples, NOT #blocks
- Cost = #page or block 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.

Acknowledgement: Adapted from slides by Profs. Magda Balazinska and Dan Suciu

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Example Query

Student (sid, name, age, address)
Book(bid, title, author)
Checkout(sid, bid, 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
```

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Assumptions

S(sid,name,age,addr)
B(bid,title,author)
C(sid,bid,date)

- 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 blocks.
- There are 50,000 Book records stored on 5,000 blocks.
- There are 300,000 Checkout records stored on 15,000 blocks.
- There are 500 different authors.
- Student ages range from 7 to 24.

- **T(R) = no. of tuples**
- **B(R) = no. of blocks of R**
- **V(R, A) = no. of distinct values of attributes A of R**

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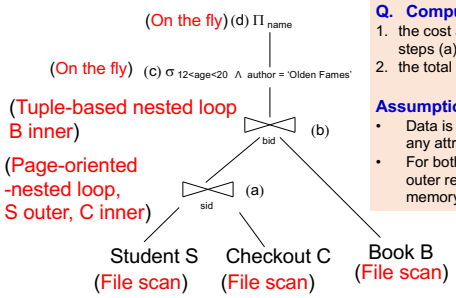
S(sid,name,age,addr)
B(bid,title,author)
C(sid,bid,date)

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

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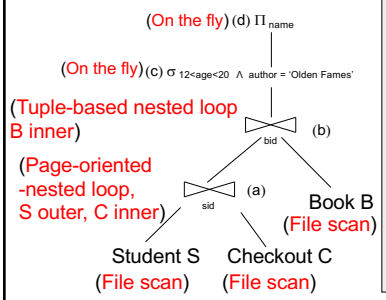
S(sid,name,age,addr)
B(bid,title,author)
C(sid,bid,date)

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

(a)



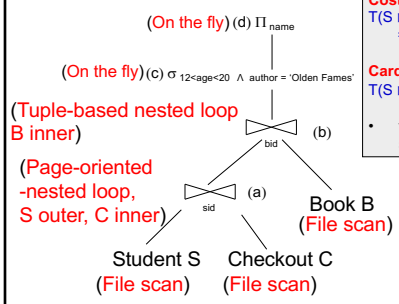
Cost =
B(S) + B(S) * B(C)
= 1000 + 1000 * 15000
= 15,001,000

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

(b)



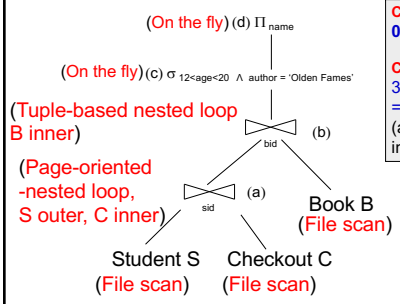
Cost =
T(S ⋈ C) * B(B)
= 300,000 * 5,000 = 15 * 10^8

Cardinality =
T(S ⋈ C) = 300,000

- foreign key join, don't need scanning for outer relation

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

(c, d)

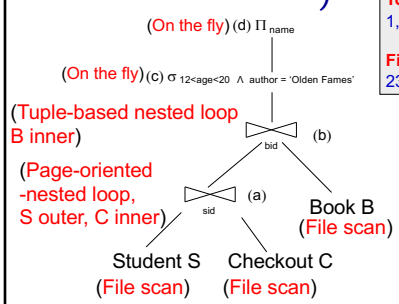


Cost =
0 (on the fly)

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

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

(Total
)

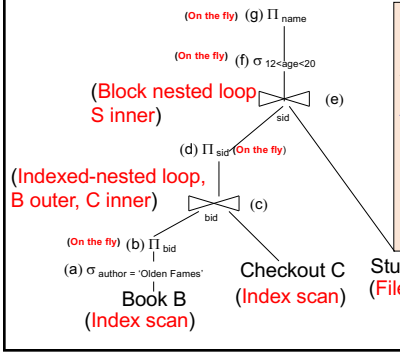


Total cost =
1,515,001,000

Final cardinality =
234 (approx)

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

Physical Query Plan – 2

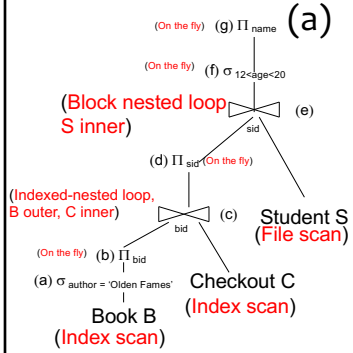


Q. Compute
1. the cost and cardinality in steps (a) to (g)
2. the total cost

Assumptions:
- Unclustered B+tree index on B.author
- Clustered B+tree index on C.bid
- All index blocks are in memory
- Unlimited memory

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

(a)

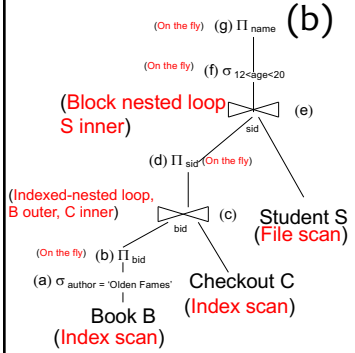


Cost =
T(B) / V(B, author)
= 50,000/500
= 100 (unclustered)

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

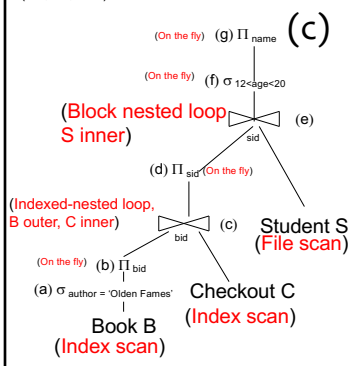
(b)



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



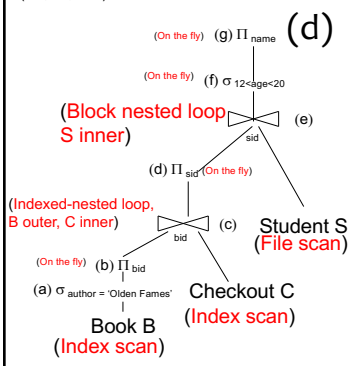
- one index lookup per outer B tuple
- 1 book has T(C)/ T(B) = 6 checkouts (uniformity)
- # C tuples per page = T(C)/B(C) = 20
- 6 tuples fit in at most 2 consecutive blocks (clustered) could assume 1 page as well

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

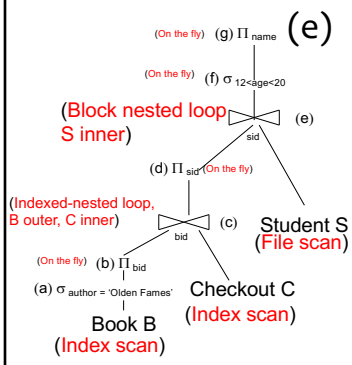
S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



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

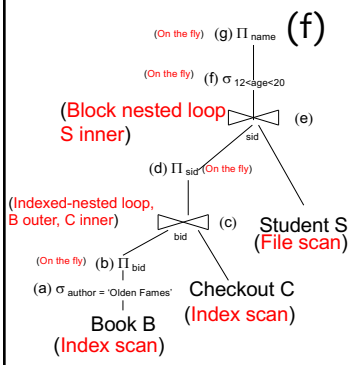


Outer relation is already in (unlimited) memory
need to scan S relation

Cost =
B(S) = 1000

Cardinality =
600

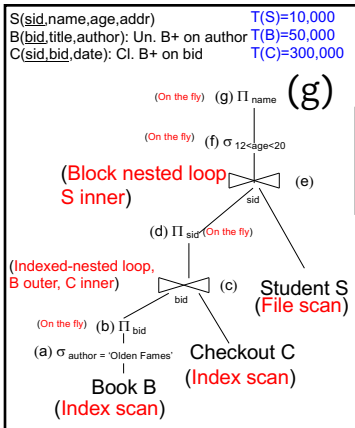
S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



Cost =
0 (on the fly)

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

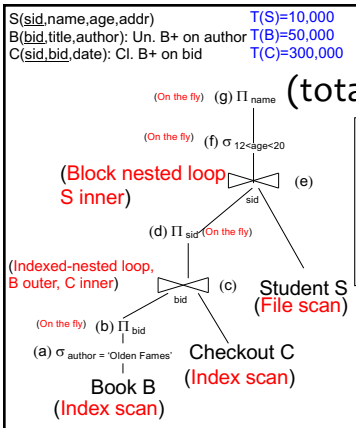
S(sid,name,age,addr) T(S)=10,000 B(S)=1,000 V(B,author) = 500
B(bid,title,author): Un. B+ on author T(B)=50,000 B(B)=5,000 7 <= age <= 24
C(sid,bid,date): Cl. B+ on bid T(C)=300,000 B(C)=15,000



Cost =
0 (on the fly)

Cardinality =
234

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



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

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

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Summary

- Relational algebra equivalence
- SQL rewrite tricks
- Heuristics-based optimization
- Cost-based optimization
  - Need statistics to estimate sizes of intermediate results
  - Greedy approach
  - Dynamic programming approach
- Combination of cost and size estimation along a plan