CS 4440 A

Emerging Database Technologies

Lecture 11

02/17/25

Announcement

Proposal draft feedback will be released this week

- Revised proposal due Mar 5
- Revised proposal instructions will be released later today

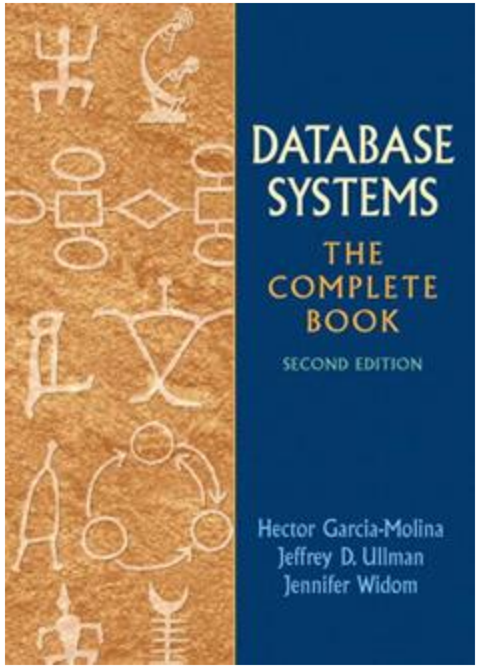
Reading Materials

Query execution (Chapters 15.1 - 15.6)

- Physical operators
- Implementing operators and estimating costs

Query optimization (Chapters 16.1 - 16.5)

- Parsing
- Algebraic laws
- Parse tree -> logical query plan
- Estimating result sizes
- Cost-based optimization



Acknowledgement: The following slides have been adapted from EE477 (Database and Big Data Systems) taught by Steven Whang.

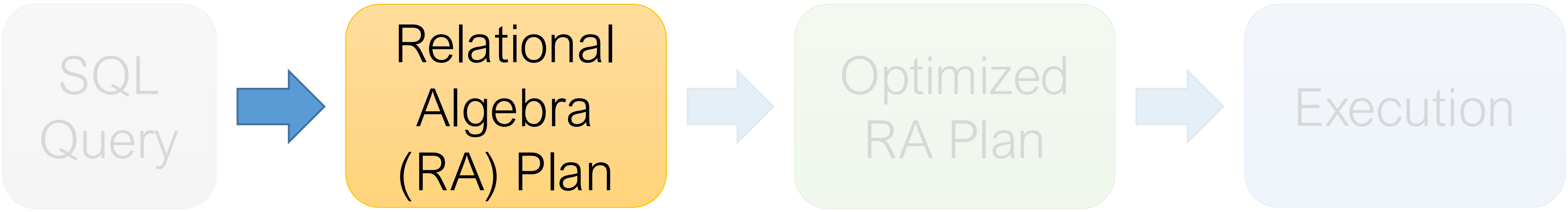
Agenda

1. Logical Optimization
2. Physical Optimization
3. Estimating cost of a physical plan
4. Cost-based Query Optimization

1. Logical Optimization

Recap: RDBMS Architecture

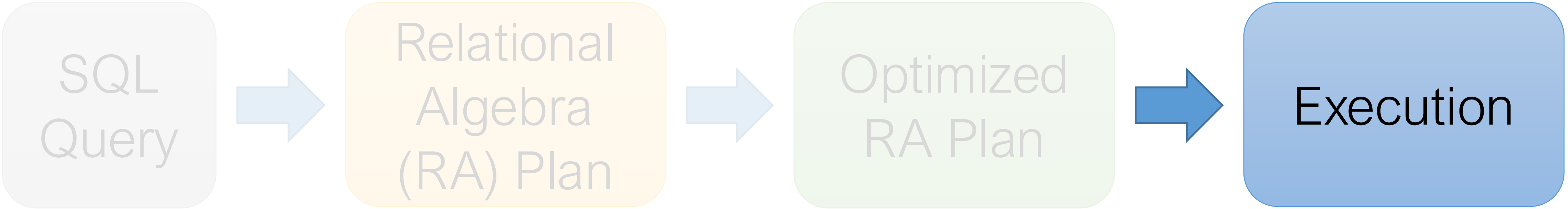
How does a SQL engine work ?



We saw how we can transform declarative SQL queries into precise, compositional RA plans

RDBMS Architecture

How is the RA “plan” executed?



RA Plan Execution

Natural Join / Join:

- Last lecture: how to use **memory & IO cost** considerations to pick the correct algorithm to execute a join with (BNLJ, SMJ, HJ…)!

Selection:

- We saw how to use **indexes to aid selection**
- Can always fall back on scan / binary search as well

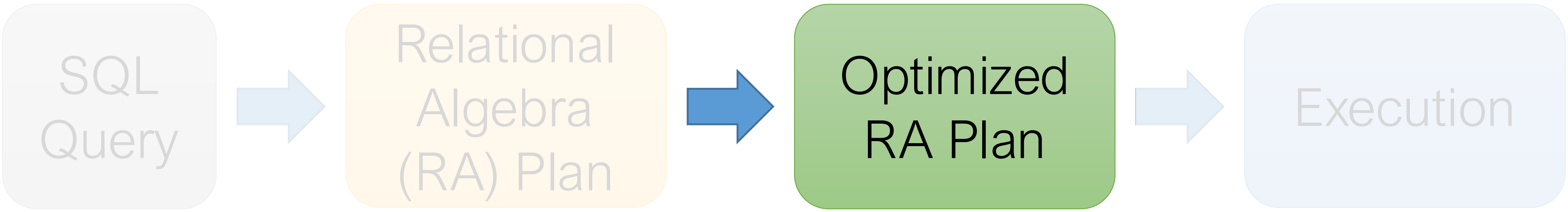
Projection:

- The main operation here is finding *distinct* values of the project tuples; we briefly discussed how to do this with e.g. **hashing** or **sorting**

We already know how to execute all the basic operators!

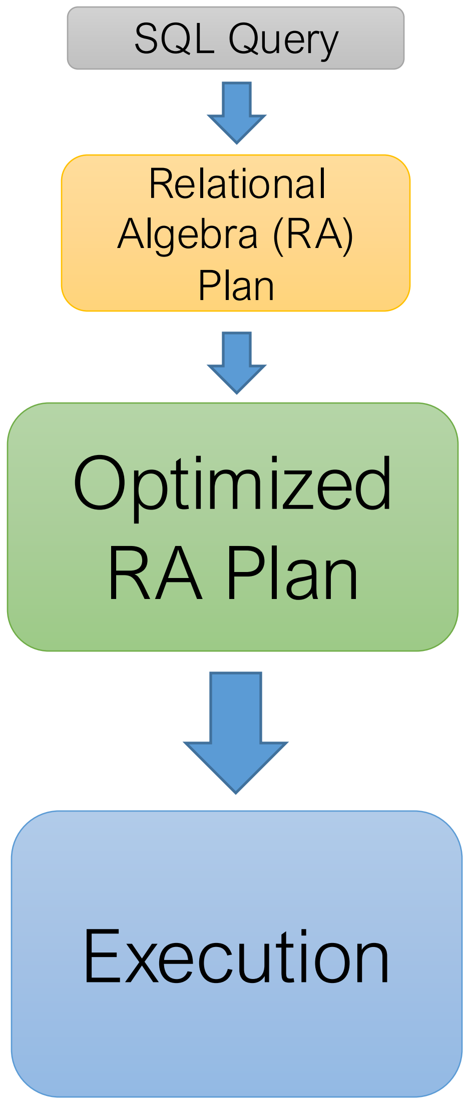
RDBMS Architecture

How does a SQL engine work ?



We'll look at how to then optimize these plans now

Logical vs. Physical Optimization



Logical optimization:

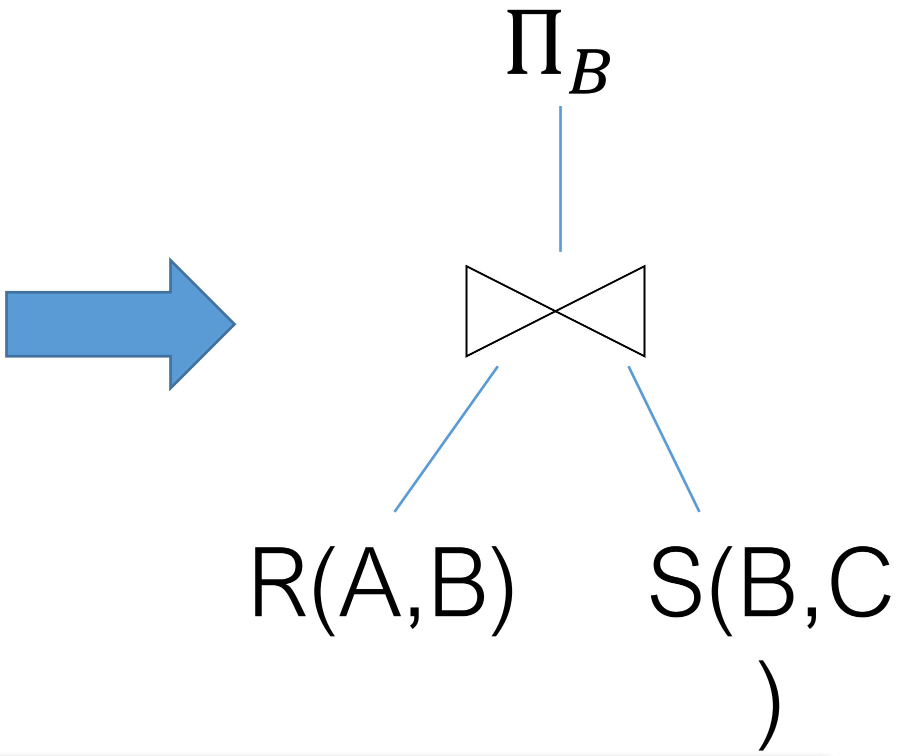
- Find equivalent plans that are more efficient
- *Intuition: Minimize # of tuples at each step by changing the order of RA operators*

Physical optimization:

- Find algorithm with lowest IO cost to execute our plan
- *Intuition: Calculate based on physical parameters (buffer size, etc.) and estimates of data size (histograms)*

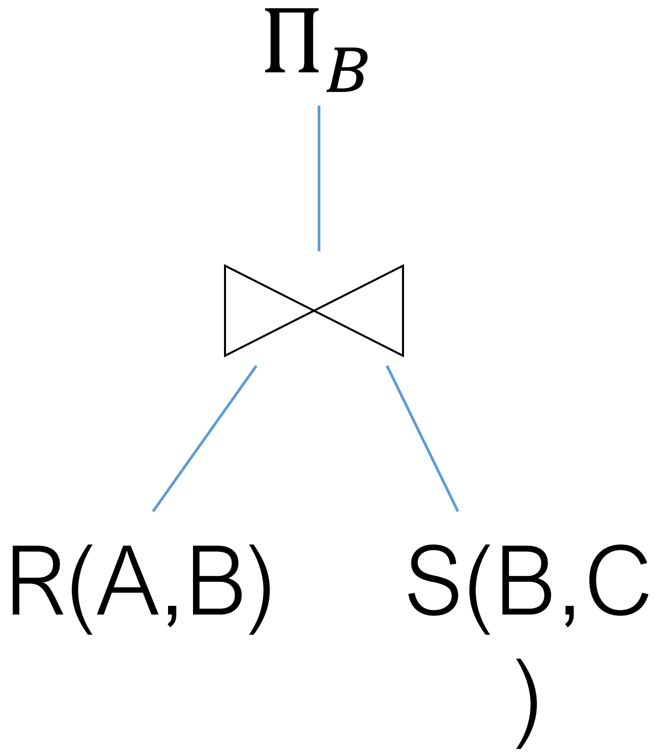
Note: We can visualize the plan as a tree

$$\Pi_B(R(A,B) \bowtie S(B,C))$$



Bottom-up tree traversal = order of operation execution!

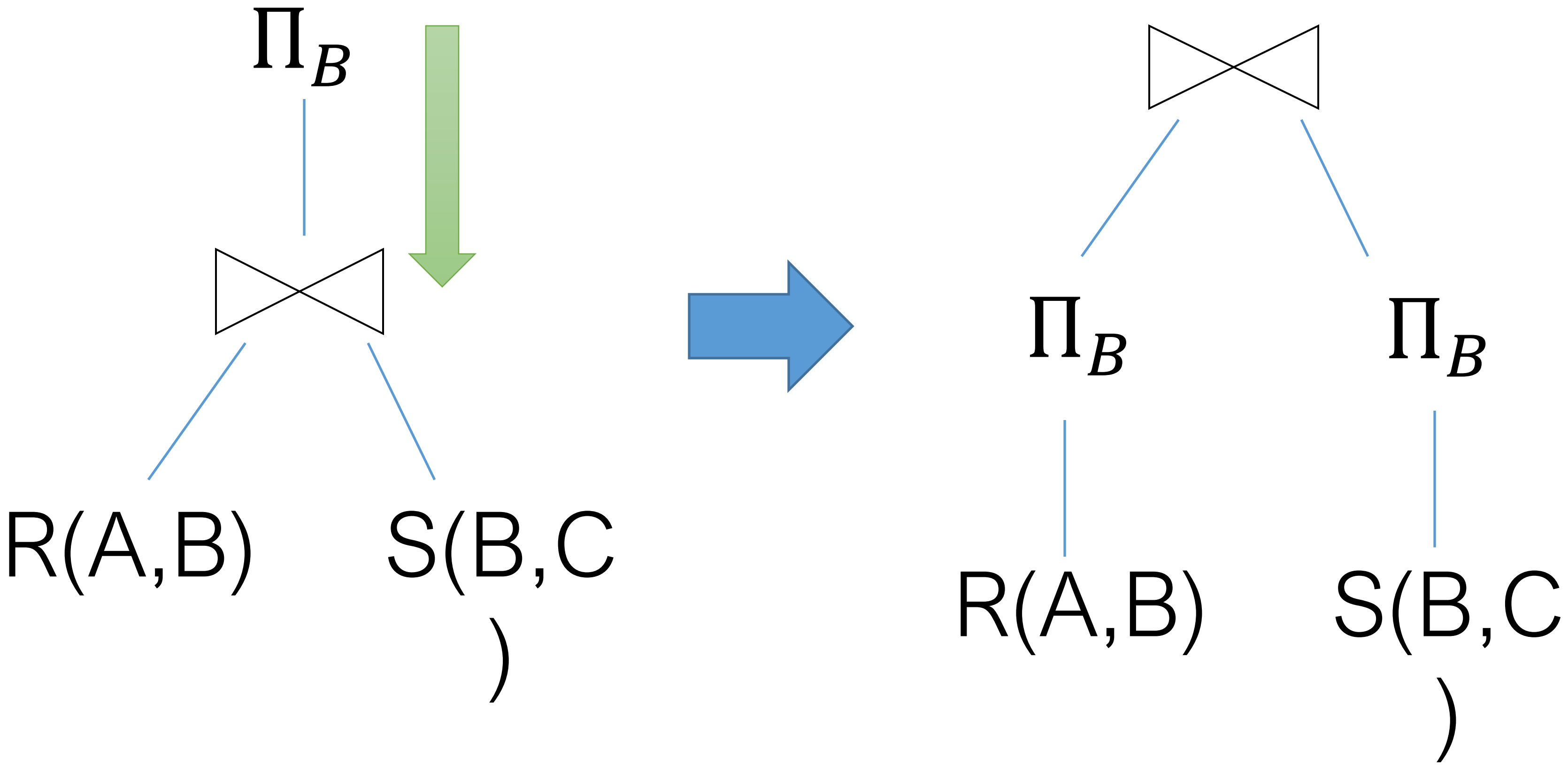
A simple plan



What SQL query does this correspond to?

Are there any logically equivalent RA expressions?

"Pushing down" projection



Why might we prefer this plan?

Logical Optimization

This process is called logical optimization

- Relational algebra is an important abstraction.

Heuristically, we want selections and projections to occur as early as possible in the plan

- Terminology: “push down **selections**” and “pushing down **projections.”**

Intuition: We will have fewer tuples in a plan.

- Could fail if the selection condition is very expensive (say runs some image processing algorithm).

Commutative and associative laws

Example:

$$R \times S = S \times R$$

$$(R \times S) \times T = R \times (S \times T)$$

- Same holds for ⋈, ∪, ∩
- Holds for both set and bag semantics

Laws involving selection

Rule of thumb:

- Since selections tend to reduce the size of relations significantly, it usually helps to push the selections down the tree as far as they will go without changing what the expression does

Example:

$$\sigma_c(R \bowtie S) = \sigma_c(R) \bowtie S$$

R has all attributes mentioned in C

$$\sigma_c(R \bowtie S) = \sigma_c(R) \bowtie \sigma_c(S)$$

R and S both have all attributes mentioned in C

Algebraic Laws for Improving Query Plans

Additional reading: Chapter 16.2

- Laws involving projection
- Laws about joins and product
- Laws involving grouping and aggregations

Note that this is not an exhaustive set of operations

- This covers *local re-writes; global re-writes possible but much harder*

This simple set of tools allows us to greatly improve the execution time of queries by optimizing RA plans!

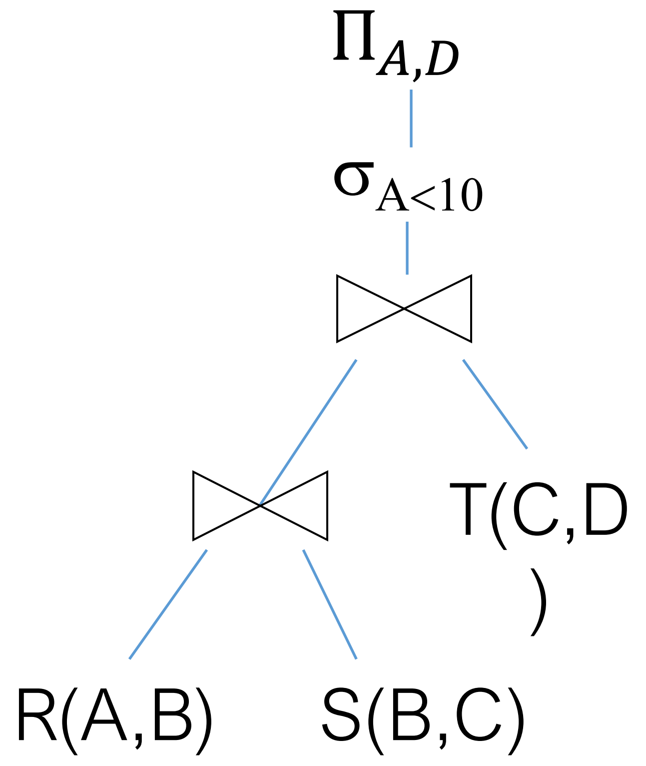
Example: Optimizing the SFW RA Plan

Translating to RA

R(A,B) S(B,C) T(C,D)

```
SELECT R.A,S.D
FROM R,S,T
WHERE R.B = S.B
  AND S.C = T.C
  AND R.A < 10;
```

$$\Pi_{A,D}(\sigma_{A<10}(T \bowtie (R \bowtie S)))$$



Optimizing RA Plan

R(A,B) S(B,C) T(C,D)

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SELECT R.A,S.D
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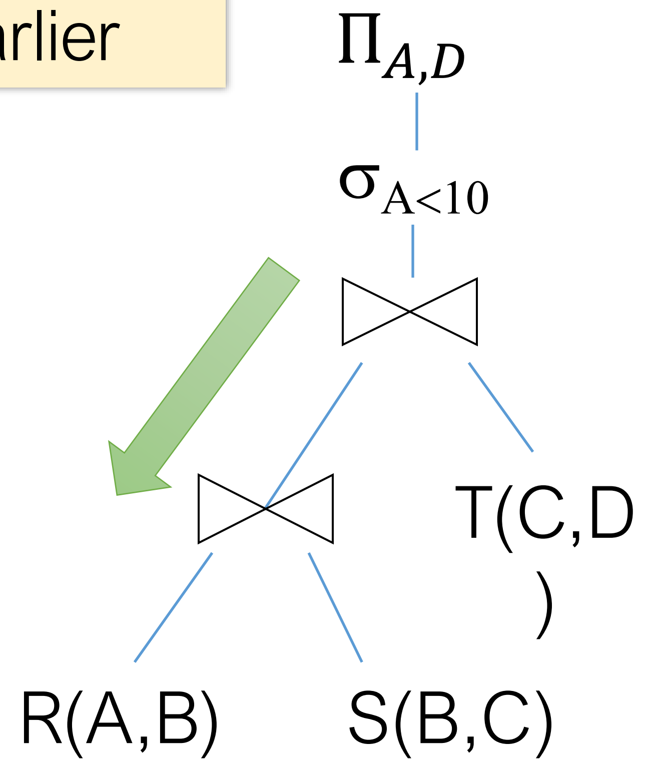
```

$$\Pi_{A,D}(\sigma_{A<10}(T \bowtie (R \bowtie S)))$$

Push down selection on A so it occurs earlier



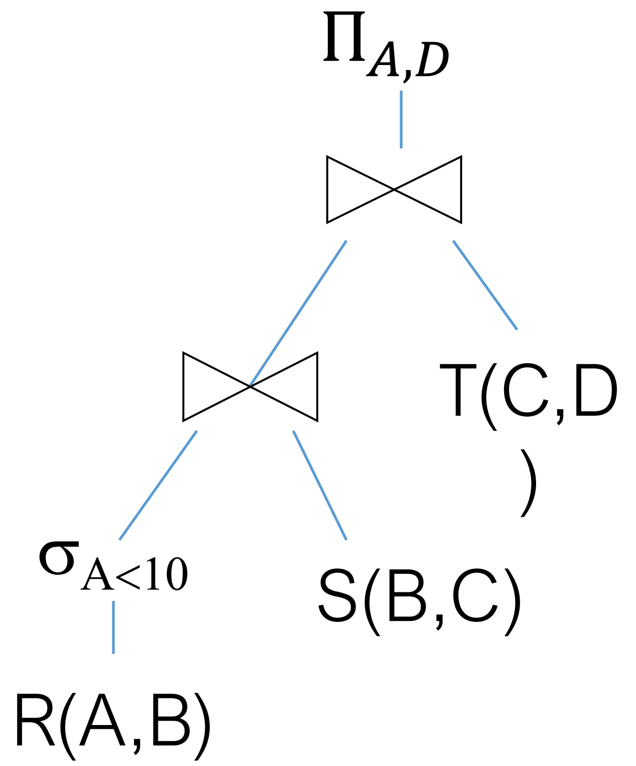
Optimizing RA Plan

R(A,B) S(B,C) T(C,D)

```
SELECT R.A,S.D
FROM R,S,T
WHERE R.B = S.B
  AND S.C = T.C
  AND R.A < 10;
```

$$\Pi_{A,D}(T \bowtie (\sigma_{A<10}(R) \bowtie S))$$

Push down selection on A so it occurs earlier



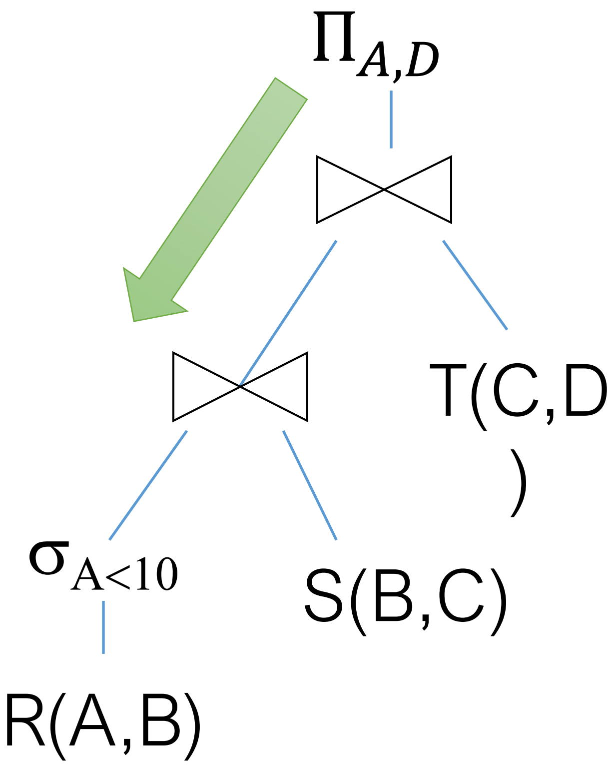
Optimizing RA Plan

R(A,B) S(B,C) T(C,D)

```
SELECT R.A,S.D
FROM R,S,T
WHERE R.B = S.B
  AND S.C = T.C
  AND R.A < 10;
```

$$\Pi_{A,D}(T \bowtie (\sigma_{A<10}(R) \bowtie S))$$

Push down projection so it occurs earlier



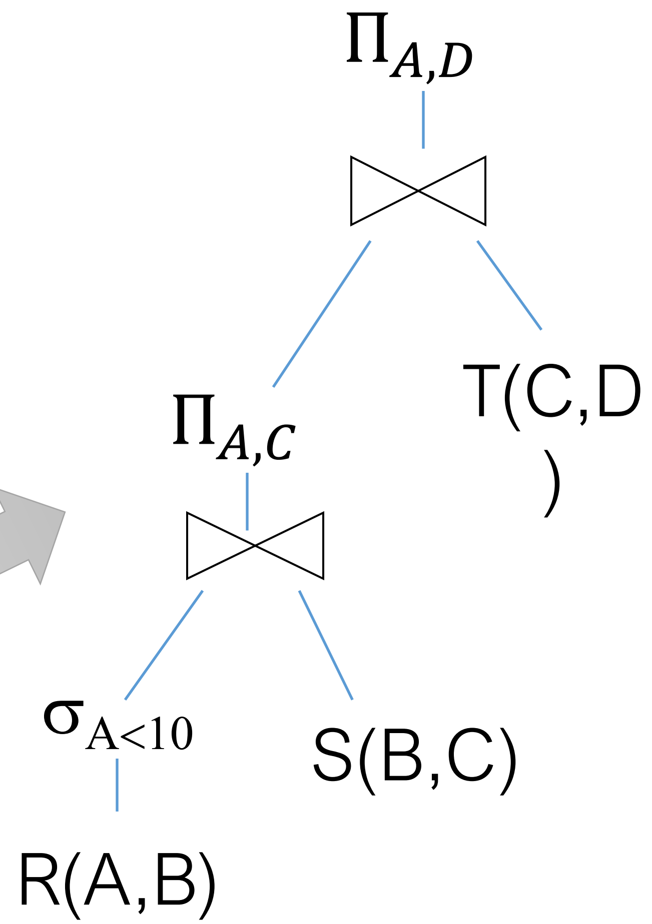
Optimizing RA Plan

R(A,B) S(B,C) T(C,D)

```
SELECT R.A,S.D
FROM R,S,T
WHERE R.B = S.B
  AND S.C = T.C
  AND R.A < 10;
```

$$\Pi_{A,D}\left(T \bowtie \Pi_{A,c}(\sigma_{A<10}(R) \bowtie S)\right)$$

We eliminate B earlier!

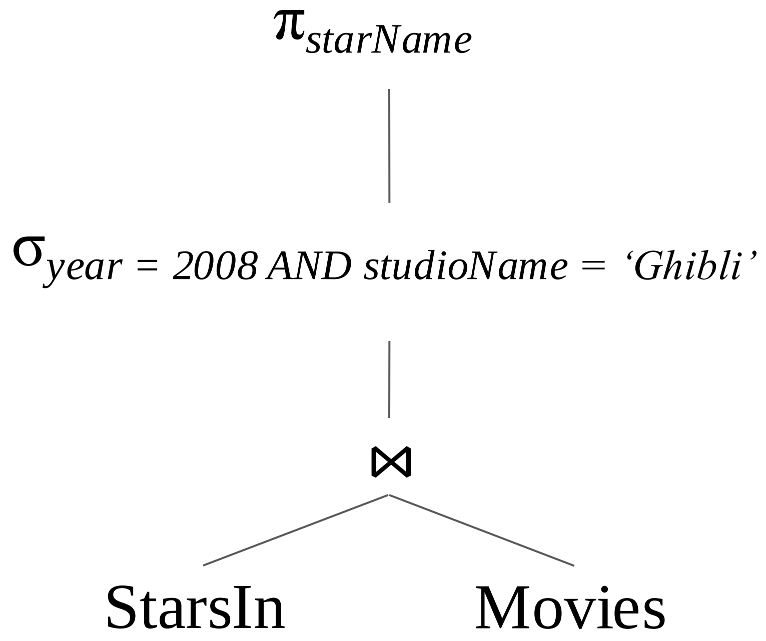


2. Physical Optimization

Select physical query plan

A logical query plan is turned into a physical query plan

- Algorithm for each operator
- Order of execution
- How to access relations

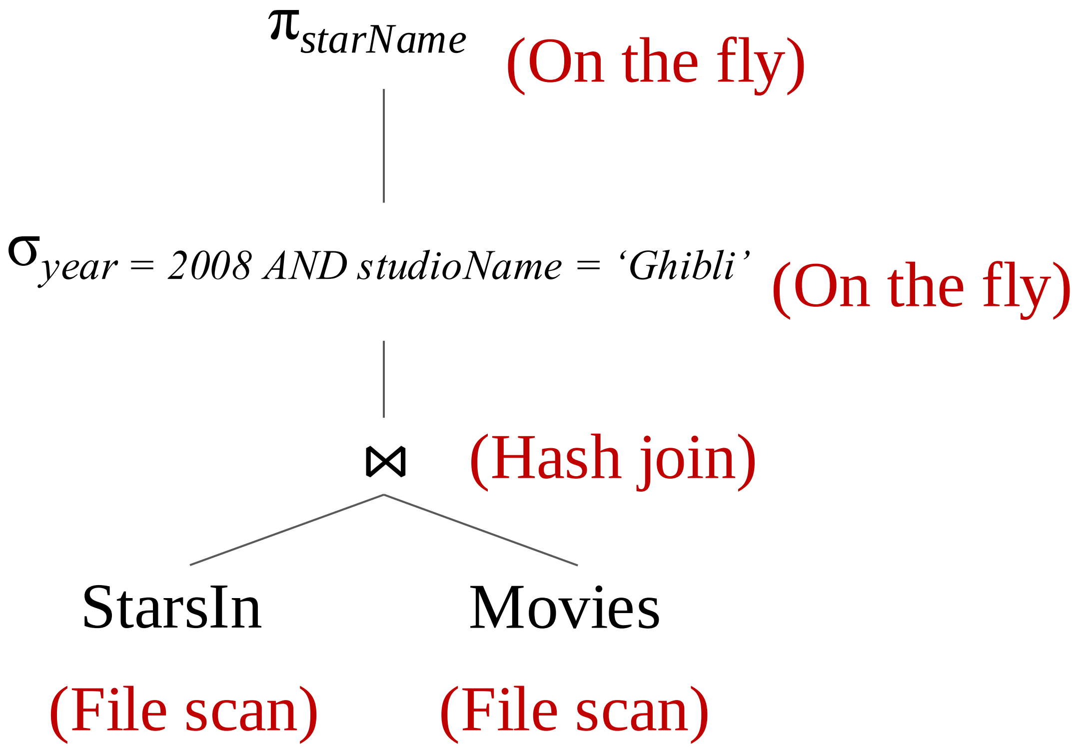


Select physical query plan

A logical query plan is turned into a physical query plan

- Algorithm for each operator
- Order of execution
- How to access relations

Physical query plan 1

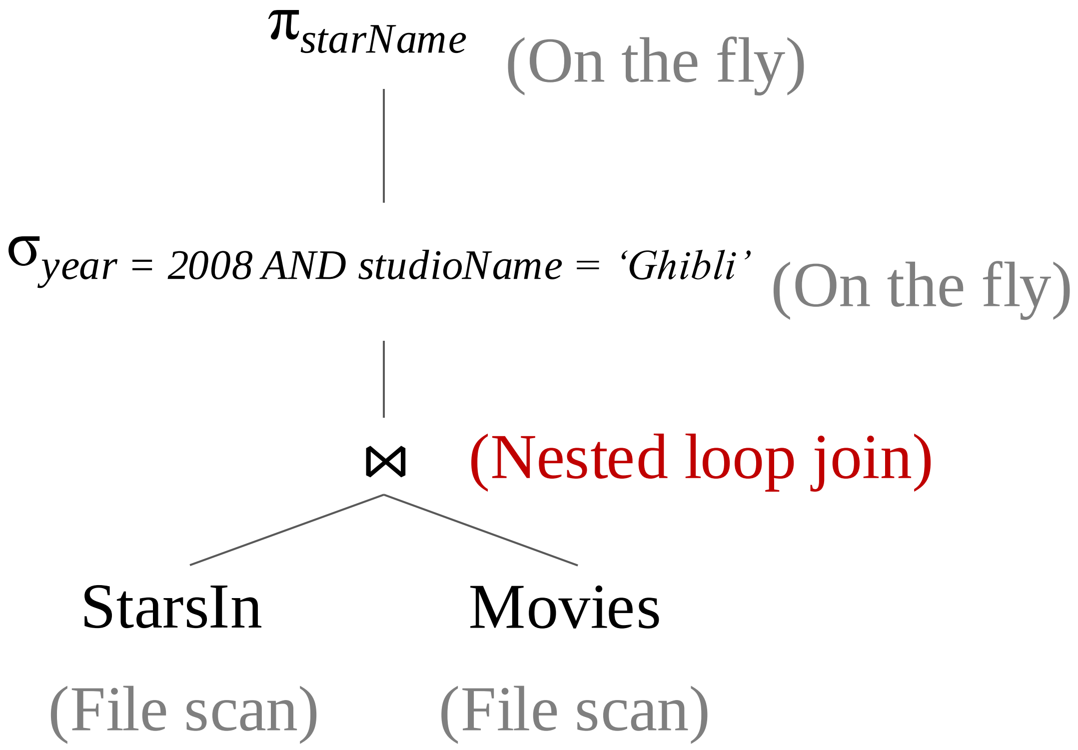


Select physical query plan

A logical query plan is turned into a physical query plan

- Algorithm for each operator
- Order of execution
- How to access relations

Physical query plan 2

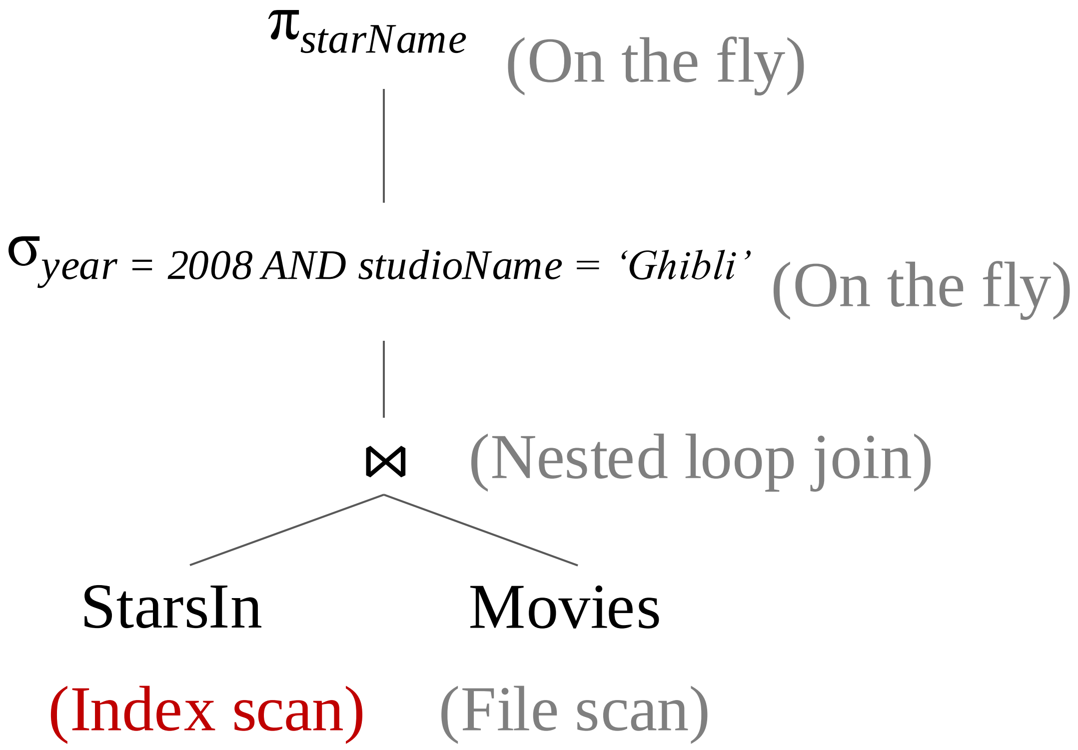


Select physical query plan

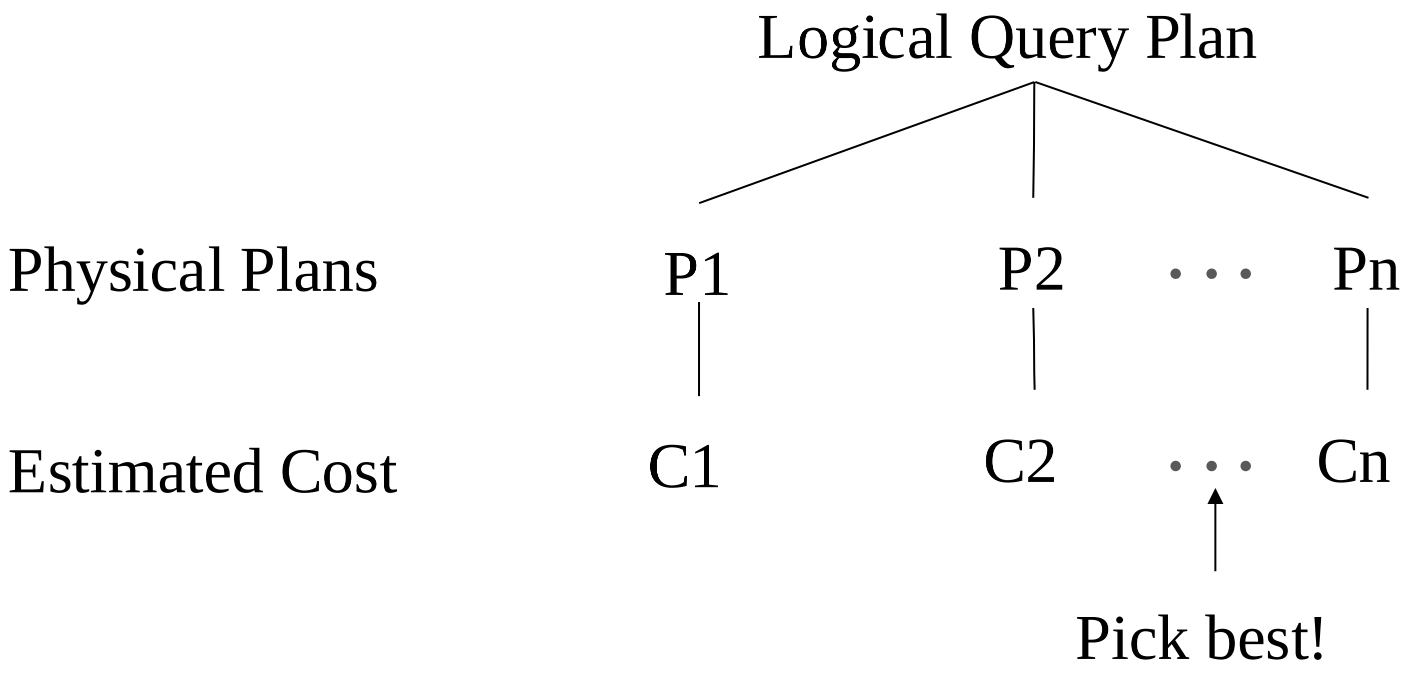
A logical query plan is turned into a physical query plan

- Algorithm for each operator
- Order of execution
- How to access relations

Physical query plan 3



Select physical query plan



In general, there can be many possible physical plans

Query execution

$\pi_{starName}$ (On the fly)

$\sigma_{year\ =\ 2008\ AND\ studioName\ =\ \text{'Ghibli'}}$ (On the fly)

$\bowtie$ (Nested loop join)

StarsIn (File scan)

Movies (File scan)

Machine Code (e.g., C)

The best physical plan is translated to actual machine code

3. Estimating cost of a physical plan

Estimating the cost of a physical query plan

Step 1: Estimate the size of results

- Projection
- Selection
- Joins

Step 2: Estimate the # of disk I/O's

We already know how to do step 2 for joins!

Notation: Size parameters

$B(R)$: # blocks to hold tuples in R

$T(R)$: # tuples in R

$V(R, a)$: # distinct values of attribute a in R

Notation: Size parameters

Example:

R

A	B	C
cat	1	2000
cat	1	2001
dog	1	2002

A: 10 byte string
B: 4 byte integer
C: 8 byte date

$T(R) = 3$
$V(R, A) = 2$
$V(R, B) = 1$
$V(R, C) = 3$

Suppose each block is 100 bytes
Then a block fits 4 tuples
If $T(R) = 1000$
Then $B(R) = 1000 / 4 = 250$

For $\pi_A(R)$, each block fits 10 tuples, so
$B(R) = 1000 / 10 = 100$

Estimating size of selection

A selection generally reduces the number of tuples

Estimated result size
(without any additional information)

$$S = \sigma_{A=c}(R) \quad \Rightarrow \quad T(S) = \frac{T(R)}{V(R,A)}$$

*Assumption: values in A = c are uniformly distributed over possible V(R, A) values

Estimating size of selection

A selection generally reduces the number of tuples

Estimated result size
(without any additional information)

$$S = \sigma_{A<c}(R)$$

$$T(S) = \frac{T(R)}{3}$$

*Assumption: queries involving inequalities tend to retrieve a small fraction of possible tuples

Example: postgres/src/include/utils/selfuncs.h

Estimating size of selection

If selection condition is AND of conditions, multiply all selectivity factors

$$S = \sigma_{A=10 \wedge B<20}(R)$$

$$T(R) = 10{,}000$$
$$V(R, A) = 50$$

Q: What is $T(S)$?

$$T(S) = \frac{T(R)}{50 \times 3} = 67$$

Estimating size of selection

If selection condition is an OR of conditions, can assume independence of conditions

$$S = \sigma_{A=10 \vee B<20}(R)$$

$$T(R) = 10{,}000$$
$$V(R, A) = 50$$

Q: What is $T(S)$?

$$T(S) = \frac{T(R)}{1-(1-1/50)(1-1/3)} = 3466$$

Estimating size of join

We study $R(X,Y) \bowtie S(Y,Z)$

Two simplifying assumptions

- Containment of value sets: if $V(R,Y) \leq V(S,Y)$, then every Y-value of R is a Y-value of S
- Preservation of value sets: $V(R \bowtie S, X) = V(R, X)$

Example when these assumptions are true:
Y is a key in S and the corresponding foreign key in R

Estimating size of join

$R(X, Y) \bowtie S(Y, Z)$

Two simplifying assumptions

- Containment of value sets: if $V(R,Y) \le V(S,Y)$, then every Y-value of R is a Y-value of S
- Preservation of value sets: $V(R \bowtie S, X) = V(R, X)$

$$\textbf{Case 1}: V(R,Y) \ge V(S,Y)$$
$$\Rightarrow T(R \bowtie S) = T(R)T(S)/V(R,Y)$$

$$\textbf{Case 2}: V(R,Y) < V(S,Y)$$
$$\Rightarrow T(R \bowtie S) = T(R)T(S)/V(S,Y)$$

For each pair (r, s), we know that the Y-value of S is one of the Y-values of R by containment of value sets, so the probability of r having the same Y-value is 1/V(R,Y)

$$T(R \bowtie S) = T(R)T(S)/\max(V(R,Y), V(S,Y))$$

Joins of many relations

Compute intermediate *T*, *V* results
Example: $R \bowtie S \bowtie T$

$R(A, B)$	$S(B, C)$	$T(C, D)$
$T(R) = 1000$	$T(S) = 2000$	$T(T) = 5000$
$V(R, B) = 20$	$V(S, B) = 50$	$V(T, C) = 500$
	$V(S, C) = 100$	$V(T, D) = 200$

Q: What is $T(R \bowtie S)$ and $V(R \bowtie S, C)$?

Joins of many relations

Compute intermediate T, V results
Example: $R \bowtie S \bowtie T$

$R(A, B)$

$T(R) = 1000$
$V(R, B) = 20$

$S(B, C)$

$T(S) = 2000$
$V(S, B) = 50$
$V(S, C) = 100$

$R \bowtie S\,(A, B, C)$

$T(R \bowtie S) = 40000$
$V(R \bowtie S, C) = 100$

Joins of many relations

Compute intermediate *T*, *V* results
Example: $R \bowtie S \bowtie T$

$R \bowtie S(A, B, C)$	$T(C, D)$	$(R \bowtie S) \bowtie T$
$T(R \bowtie S) = 40000$ $V(R \bowtie S, C) = 100$	$T(T) = 5000$ $V(T, C) = 500$ $V(T, D) = 200$	$T((R \bowtie S) \bowtie T)$ $= 40000 \text{ x } 5000 \,/\, \max\{100, 500\}$ $= 400000$

Joins of many relations

Compute intermediate T, V results
Example: consider $R \bowtie S \bowtie T$

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

$$T(R \bowtie (S \bowtie T)) = 1000 \text{ x } (2000 \text{ x } 5000 \,/\, \max\{100, 500\}) \,/\, \max\{20, 50\}$$
$$= 400000$$

Assuming containment and preservation of value sets, the estimated result size is the same regardless of how we group and order the terms in a natural join of relations.

Natural joins with multiple join attributes

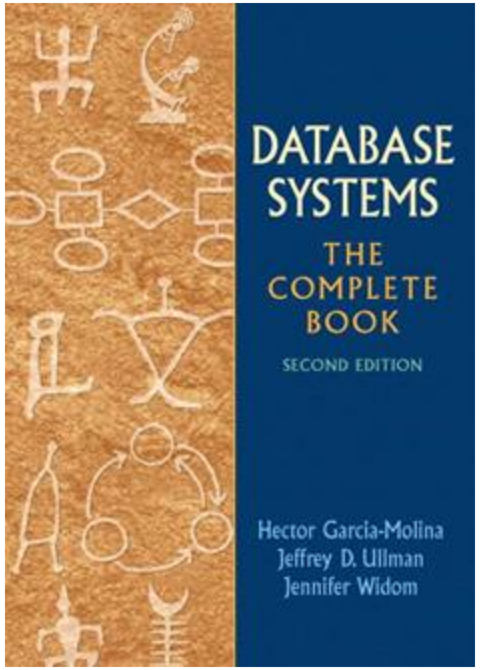
Same as R ⋈ S with single join attribute, but divide by max{V(R, A), V(S, A)} for each joining attribute A

$R(A, B, C)$	$S(B, C, D)$	$R \bowtie S$
$T(R) = 1000$ $V(R, B) = 20$ $V(R, C) = 100$	$T(S) = 2000$ $V(S, B) = 50$ $V(S, C) = 50$	$T(R \bowtie S) = 1000 \text{ x } 2000$ $/ \max\{20, 50\}$ $/ \max\{100, 50\}$ $= 400$

Further reading

- Using similar ideas, can estimate sizes of other operations like union, intersect, difference, duplicate elimination, grouping

- Chapter 16.4.7

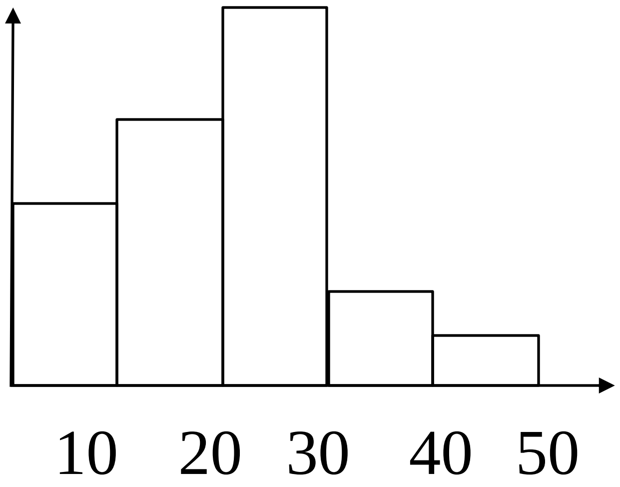


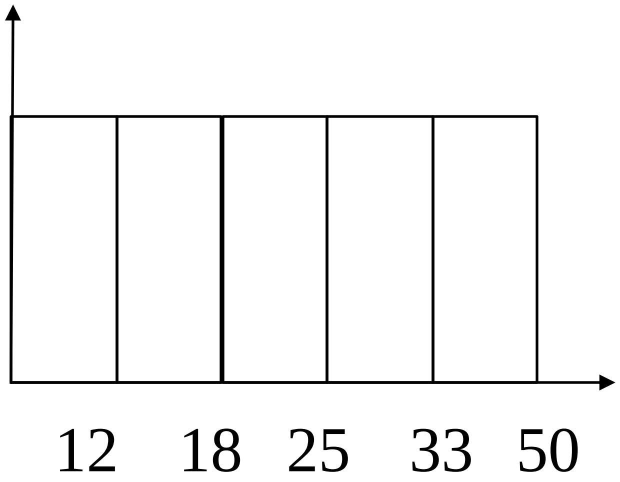
Obtaining estimates for size parameters

Scan entire relation *R* to obtain *T*(*R*), *V*(*R*, *A*), and *B*(*R*)

A DBMS may also compute histograms per attribute for more accurate estimations

- Equal-width and equal-depth histograms





$$\sigma_{A=22}(R) = \ ?$$

Computation of statistics

Computed periodically or by request

Sampling used to compute approximate statistics quickly

Example:

- ANALYZE command in Postgres
- See also: https://www.postgresql.org/docs/current/planner-stats.html

Estimating the cost of a physical query plan

Step 1: Estimate the size of results

- Projection
- Selection
- Joins

Step 2: Estimate the # of disk I/O’s

Ex: Clustered vs. Unclustered Index

Cost to do a range query for M entries over N-page file (P per page):

Suppose we are using a B+ Tree index with:

- Fanout f
- Fill factor 2/3

Clustered:

- To traverse: $\mathrm{Log}_f(1.5N)$
- To scan: 1 random IO + $\left\lceil \frac{M-1}{P} \right\rceil$ sequential IO

Unclustered:

- To traverse: $\mathrm{Log}_f(1.5N)$
- To scan: ~ M random IO

Ex: Nested-loop Join

Suppose (from estimates):

- T(R) = 10,000, T(S) = 5,000

Suppose 10 records fit in one block:

- B(R)=1000, B(S)=500

Compute $R \bowtie S$ on A:

```
for r in R:
  for s in S:
    if r[A] == s[A]:
      yield (r,s)
```

$$B(R) + T(R)*B(S) + OUT$$

For each tuple in R, read all S blocks and join:

Cost($R \bowtie S$): 1000 + 10000 x 500 = 5,001,000 I/O's

Memory usage: 2 blocks

Ex: Block Nested-loop Join

Suppose (from estimates):

- T(R) = 10,000, T(S) = 5,000

Suppose 10 records fit in one block:

- B(R)=1000, B(S)=500

Extra memory M=101:

- read 100 blocks of S at a time

Compute R $\bowtie S \ on \ A$:

```
for each M-1 pages pr of R:
  for page ps of S:
    for each tuple r in pr:
      for each tuple s in ps:
        if r[A] == s[A]:
          yield (r,s)
```

$$\mathrm{B}(R) + \frac{B(R)}{M-1} B(S) + \mathrm{OUT}$$

Total cost of S ⋈ R: 500 + 500/100 x 1000) = 5500 I/O's

Memory Usage: M blocks

4. Cost-based Query Optimization

Query Optimization Overview

Output: A good physical query plan

Basic cost-based query optimization algorithm

- Enumerate candidate query plans (logical and physical)
- Compute estimated cost of each plan (e.g., number of I/Os)
    - Without executing the plan!
- Choose plan with lowest cost

The Three Parts of an Optimizer

Cost estimation

- Estimate size of results
- Also consider whether output is sorted/intermediate results written to disk etc.

Search space

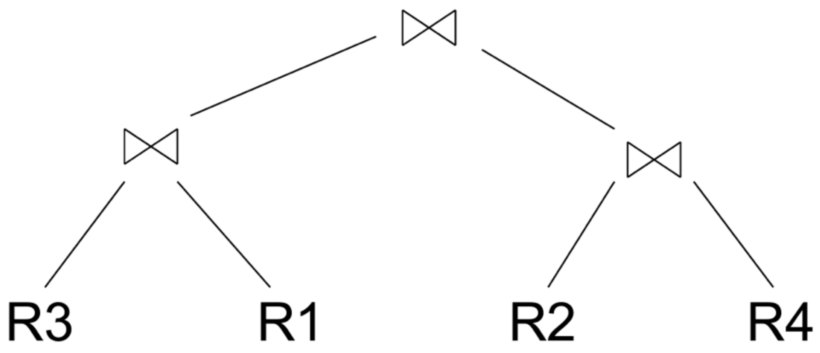
- Algebraic laws, restricted types of join trees

Search algorithm

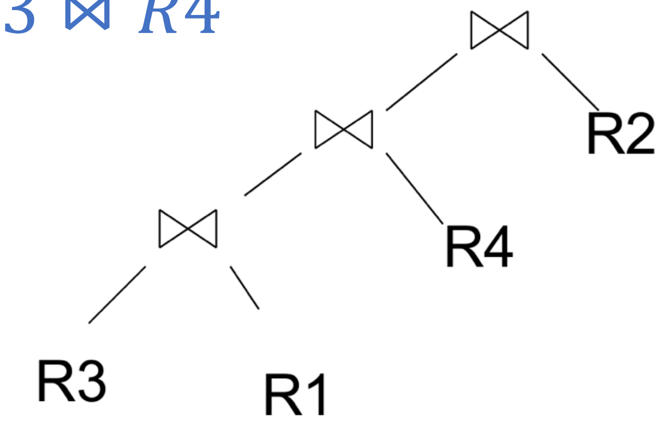
- Example: Selinger algorithm

Search Space

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



Bushy plan



Left-deep plan

Logical plan space:

- Several possible structures of the trees
- Each tree can have n! permutations of relations on leaves

Physical plan space:

- Different implementation (e.g., join algorithm) and scanning of intermediate operators for each logical plan

Heuristic for pruning plan space

Apply predicates as early as possible

Avoid plans with cartesian products

- $(R(A,B) \bowtie T(C,D)) \bowtie$ S(B,C)

Consider only left-deep join trees

- Studied extensively in traditional query optimization literature
- Works well with existing join algorithms such as nested-loop and hash join
  - e.g., might not need to write tuples to disk if enough memory

Search Algorithm

Selinger Algorithm: dynamic programming based

- Based on System R (aka Selinger) style optimizer [1979]
- Consider different logical and physical plans at the same time
- Limited to joins: join reordering algorithm
- Cost of a plan is I/O + CPU

Exploits ”principle of optimality”

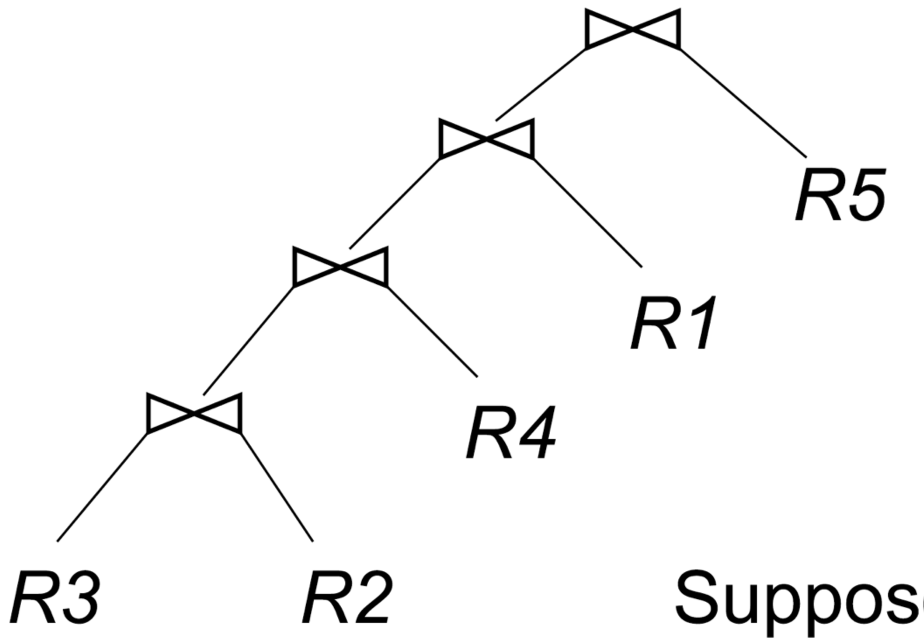
- Optimal for “whole” made up from optimal for ”parts”

Consider the search space of left-deep join trees

- Reduces search space but still n! permutations

Principle of Optimality

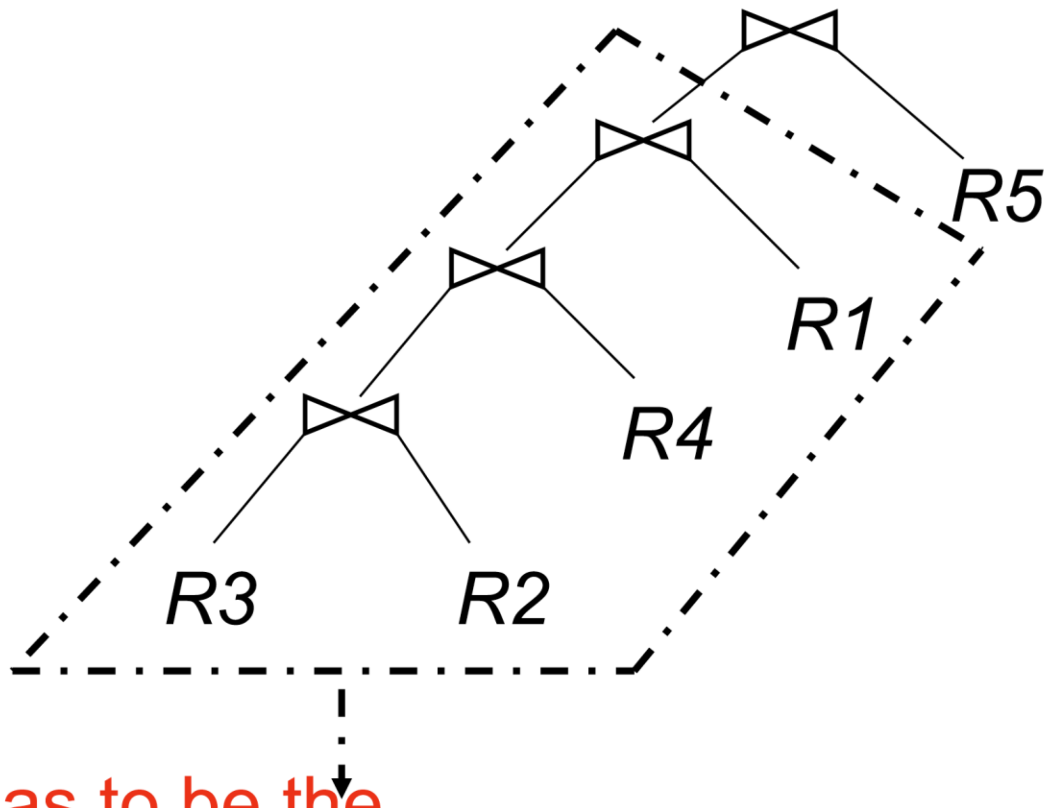
Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4 \bowtie R5$



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

Principle of Optimality

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



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

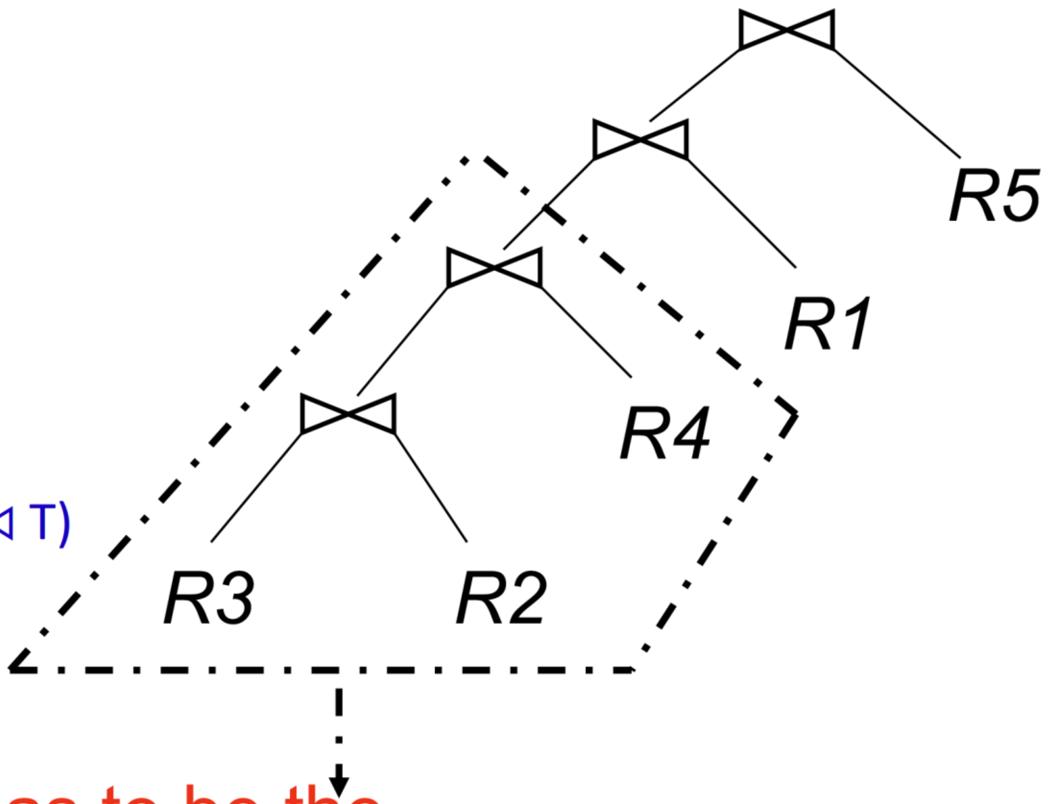
Principle of Optimality

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

We are using the associativity and commutativity of joins

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

$R \bowtie S = S \bowtie R$

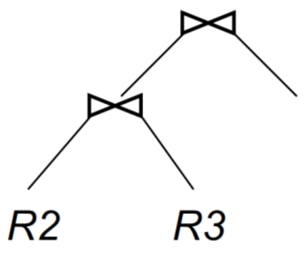


This has to be the optimal plan for joining *R3, R2, R4*

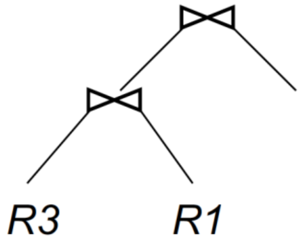
Principle of Optimality

Query: $R1 \bowtie R2 \bowtie \ldots \bowtie Rn$

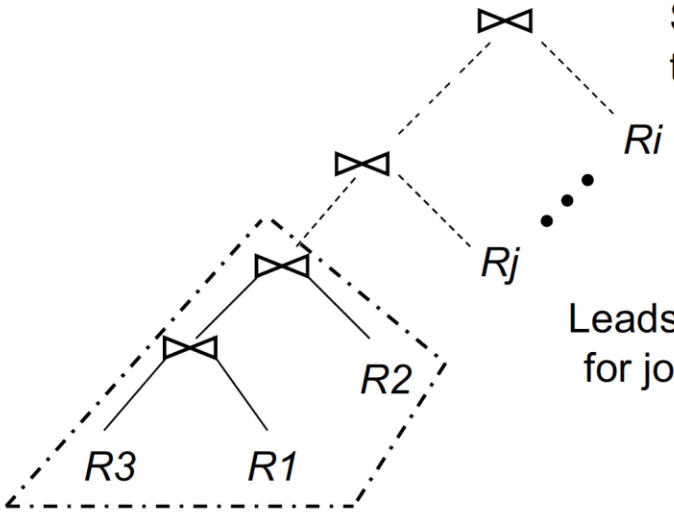
Both are giving the same result
$R2 \bowtie R3 \bowtie R1 = R3 \bowtie R1 \bowtie R2$



Optimal
for joining *R1, R2, R3*



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



Suppose you chose the sub-optimal one

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

Notation and Setup

$\mathrm{OPT}(\{\mathrm{R1}, \mathrm{R2}, \mathrm{R3}\})$:

Cost of optimal plan to join R1, R2, R3

$\mathrm{T}(\{\mathrm{R1}, \mathrm{R2}, \mathrm{R3}\})$:

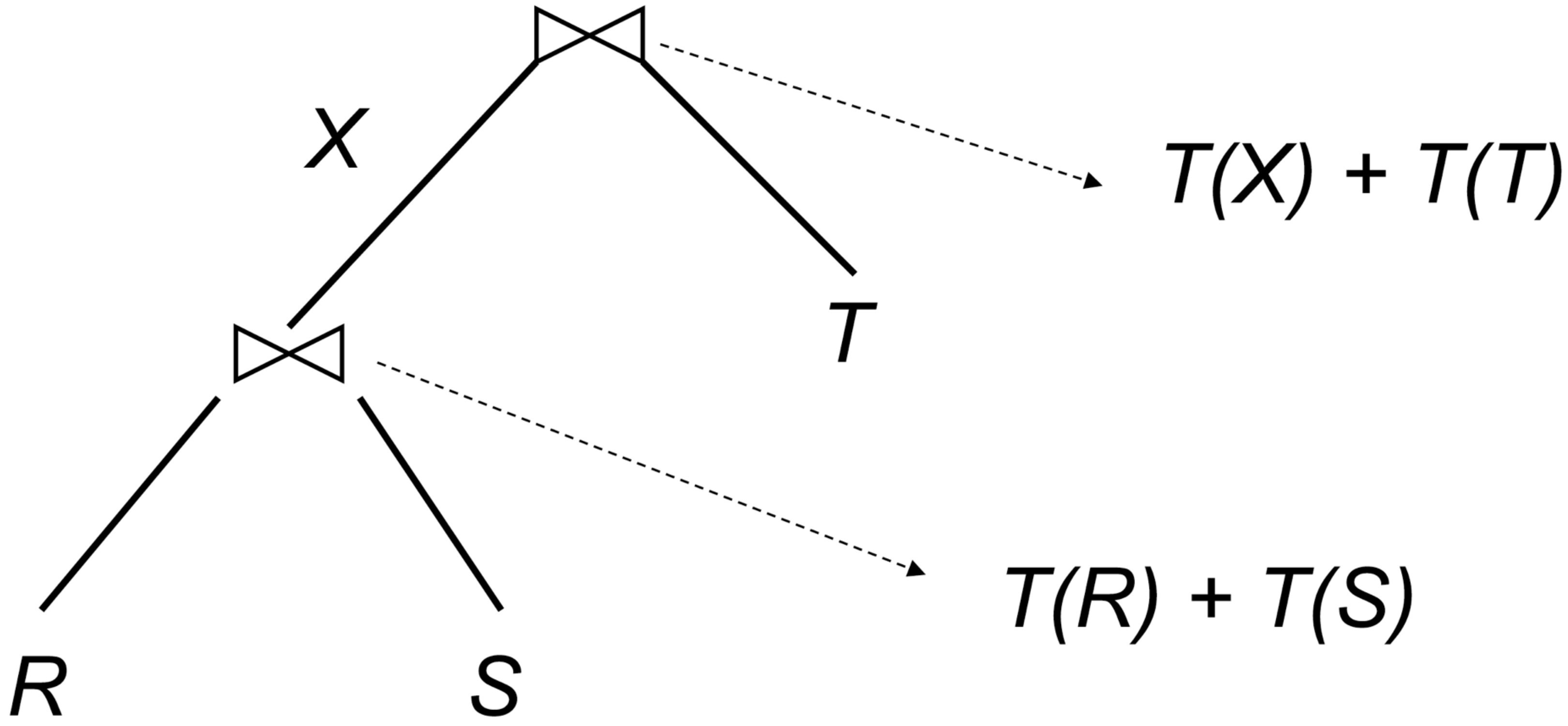
Number of tuples in $R1 \bowtie R2 \bowtie R3$

Simple Cost Model: $\mathrm{Cost}(R \bowtie S) = T(R) + T(S)$

All other operations have 0 cost

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

Cost Model Example



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

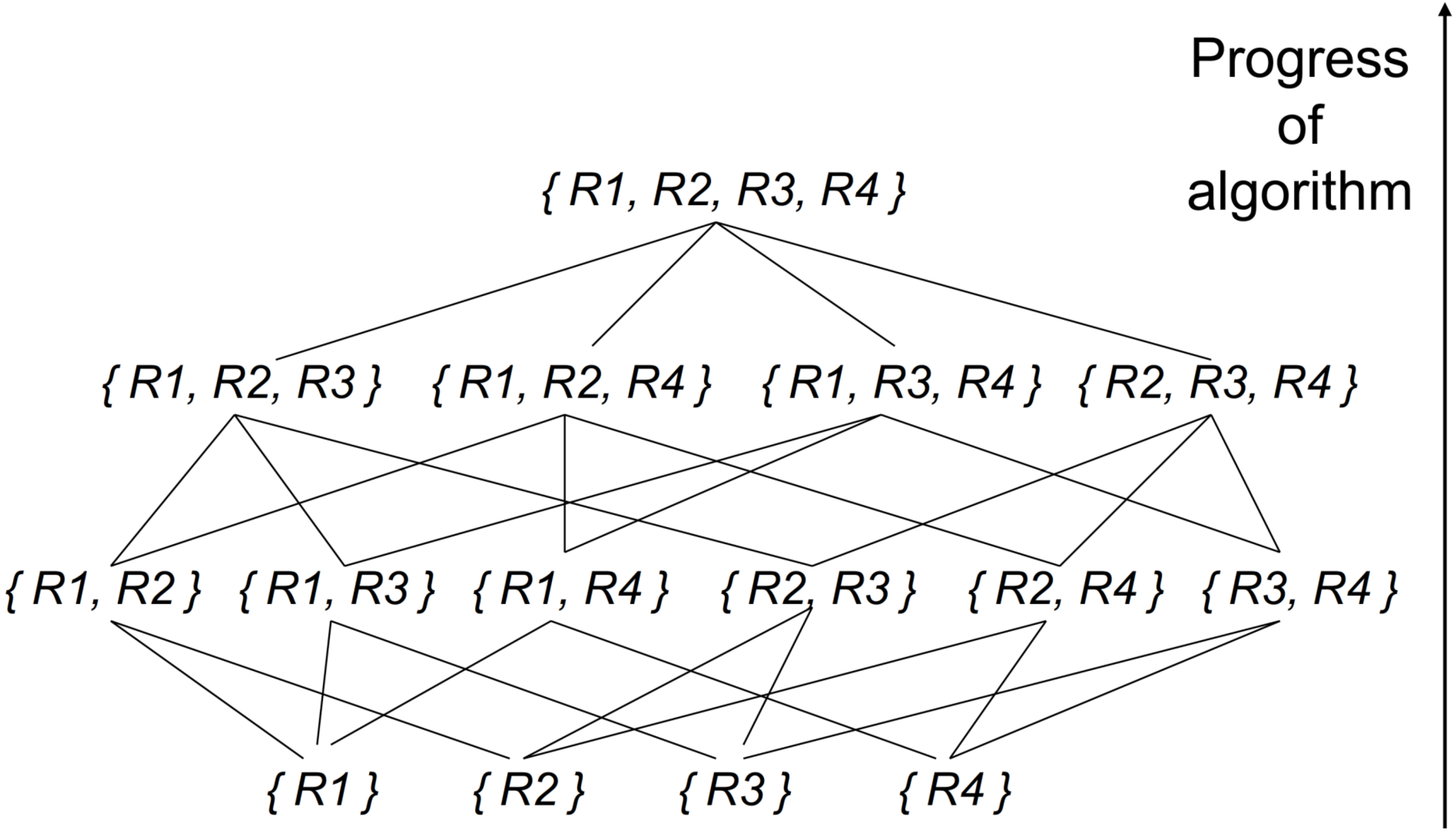
Selinger Algorithm

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

* Valid only for the simple cost model

Selinger Algorithm

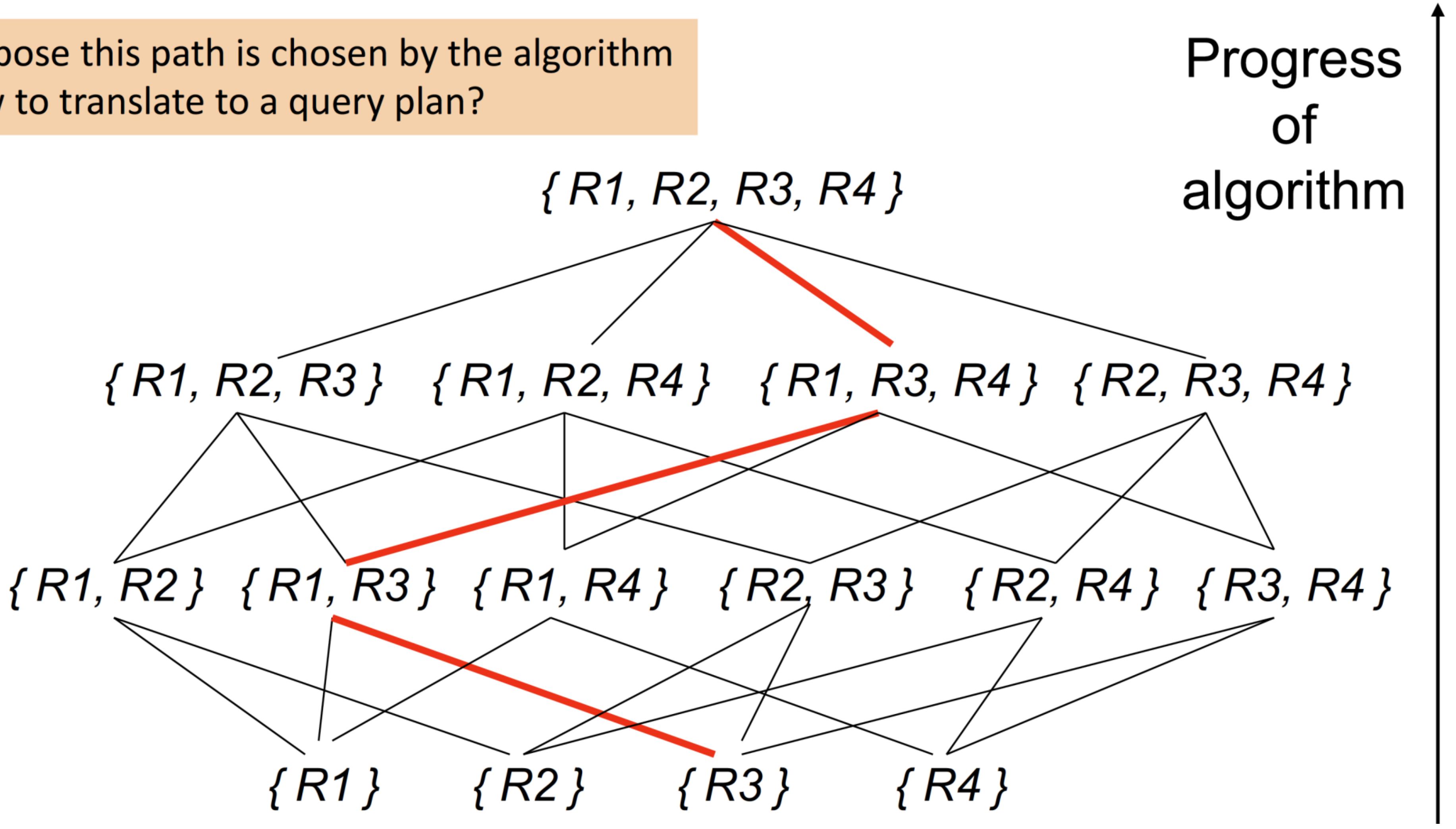
Query: $R1 \bowtie R2 \bowtie R3 \bowtie R4$



Selinger Algorithm

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

Suppose this path is chosen by the algorithm
How to translate to a query plan?

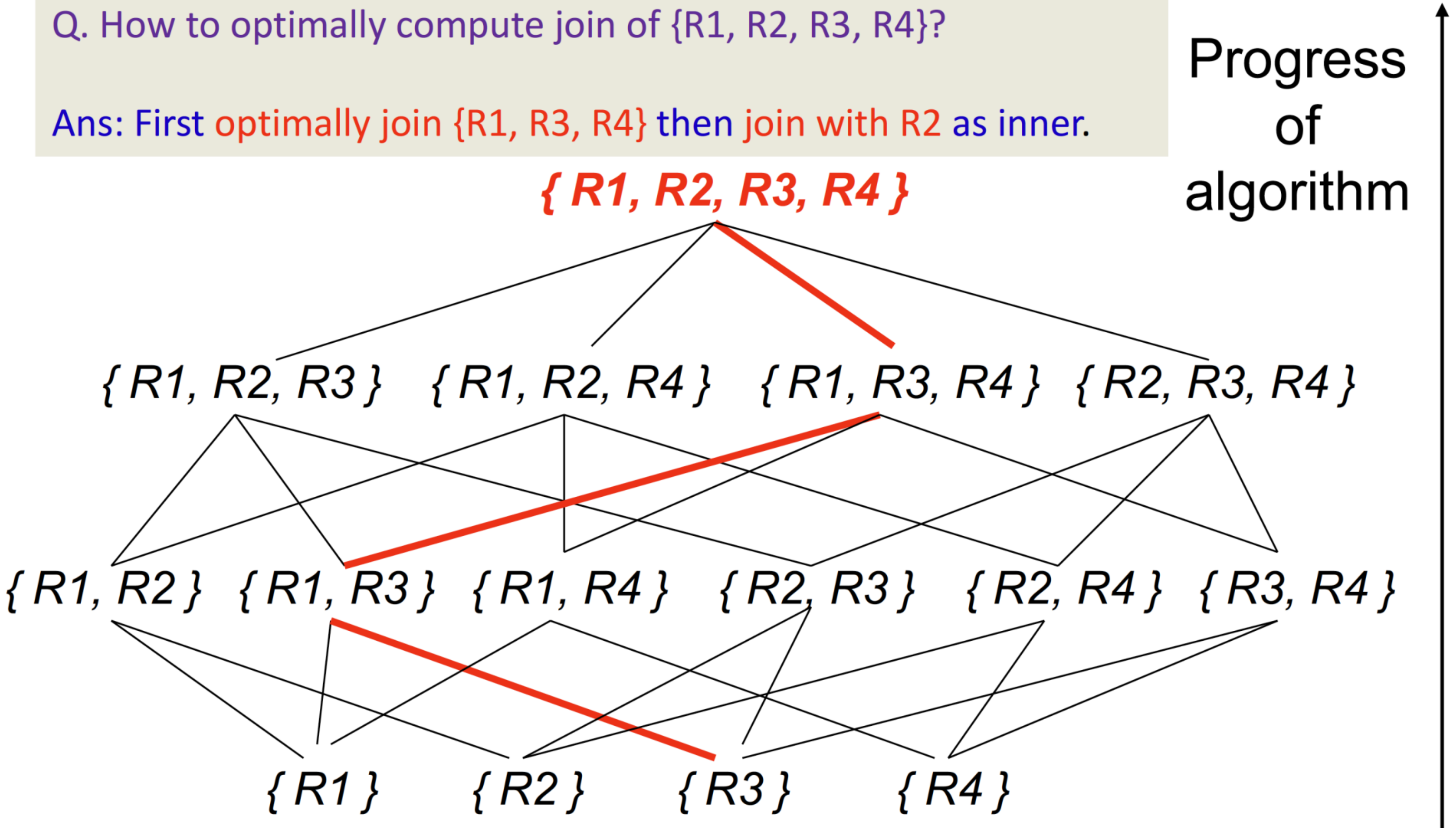


Selinger Algorithm

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.

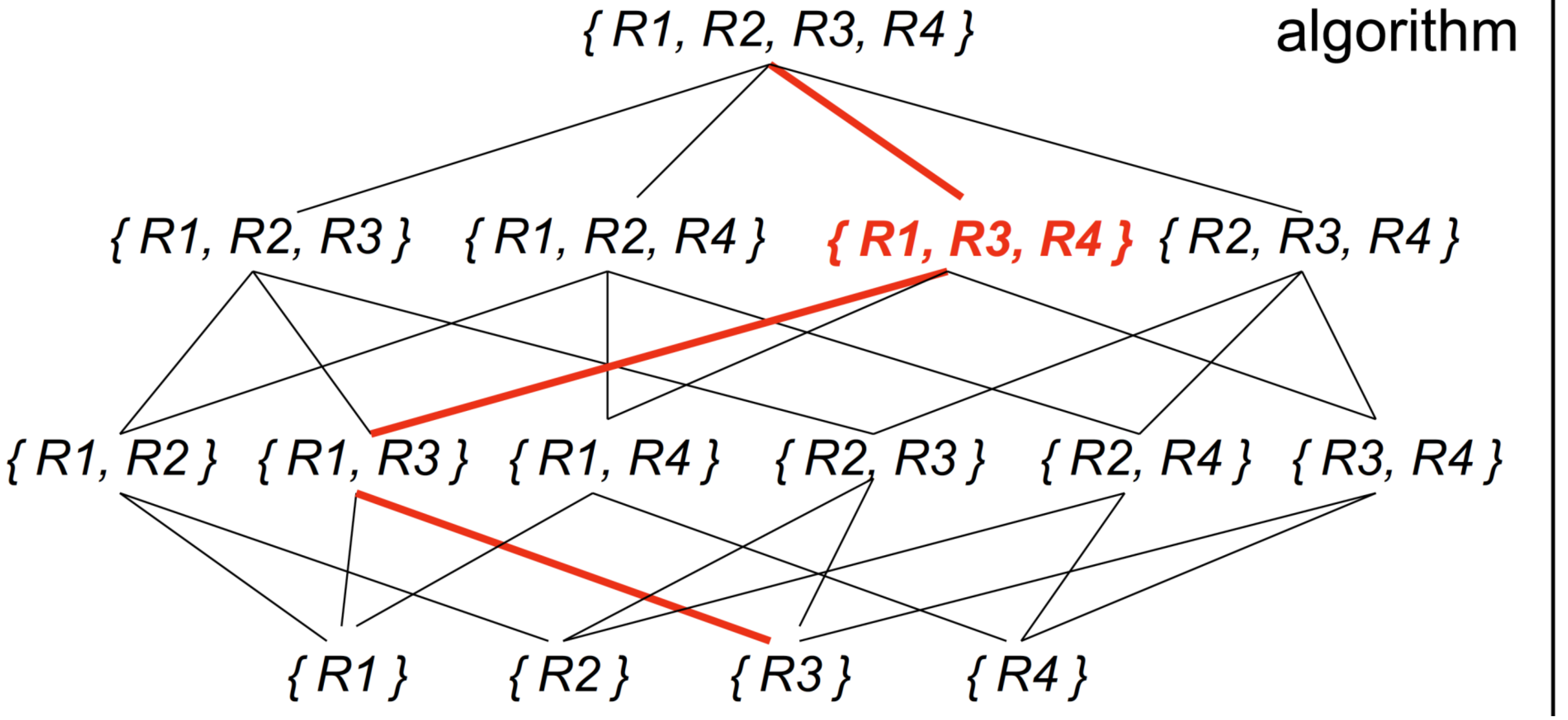


Selinger Algorithm

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.

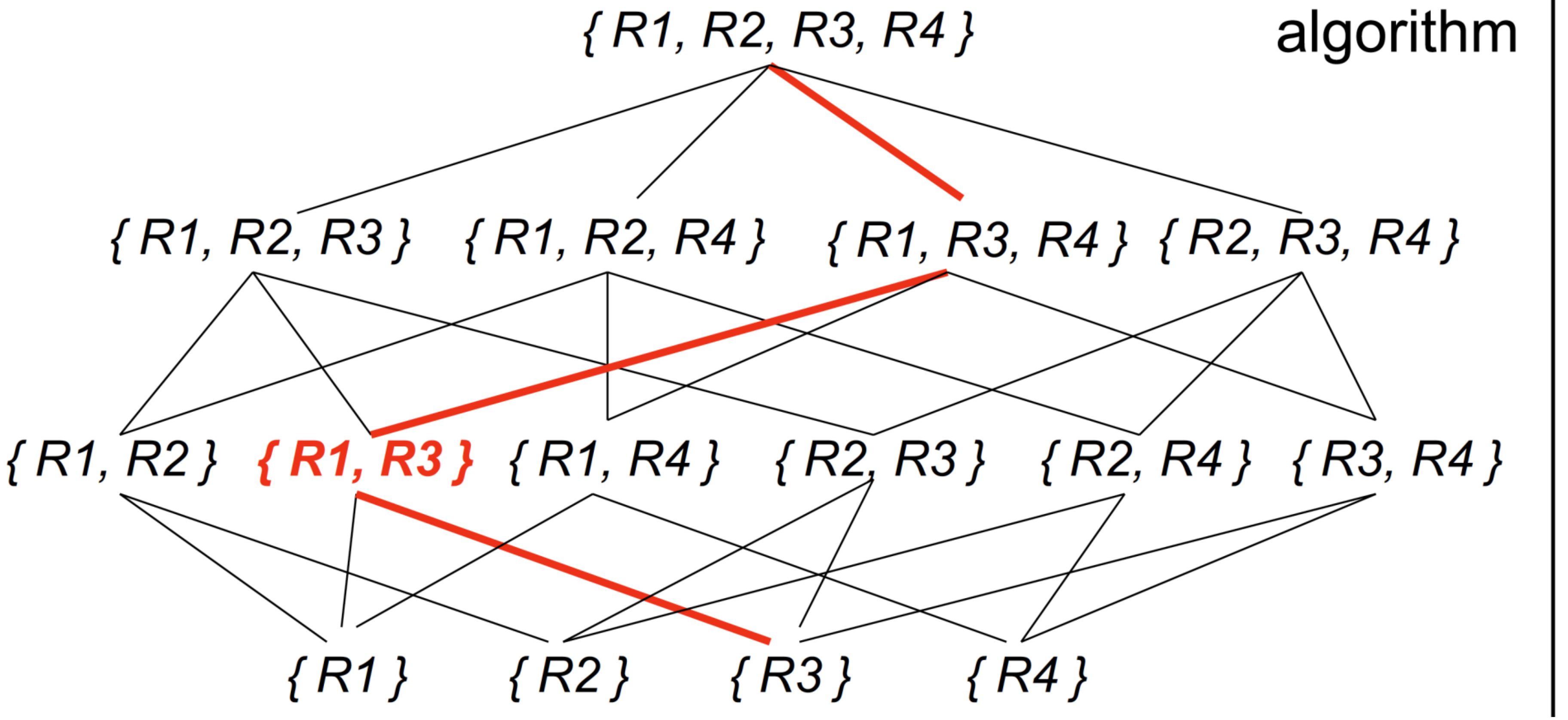


Selinger Algorithm

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.

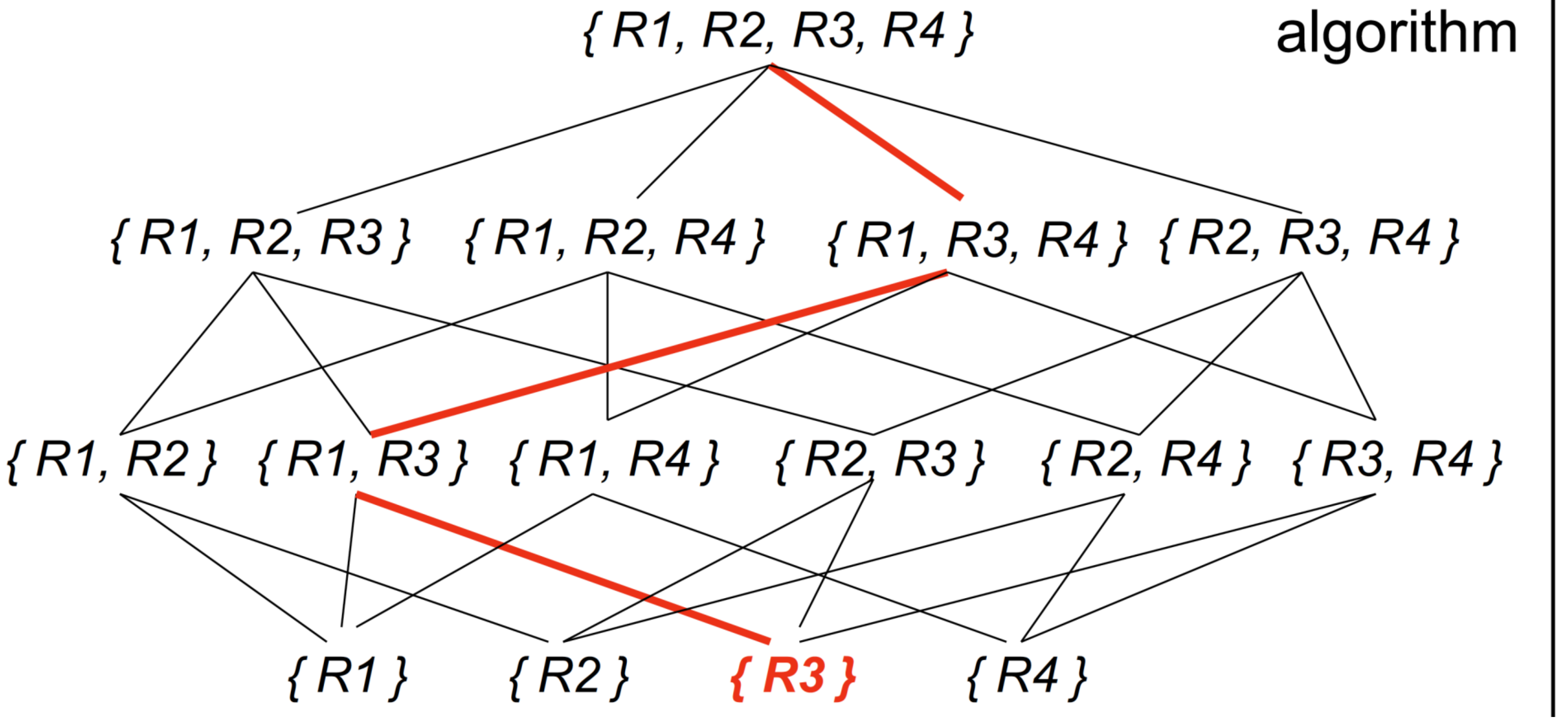


Selinger Algorithm

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

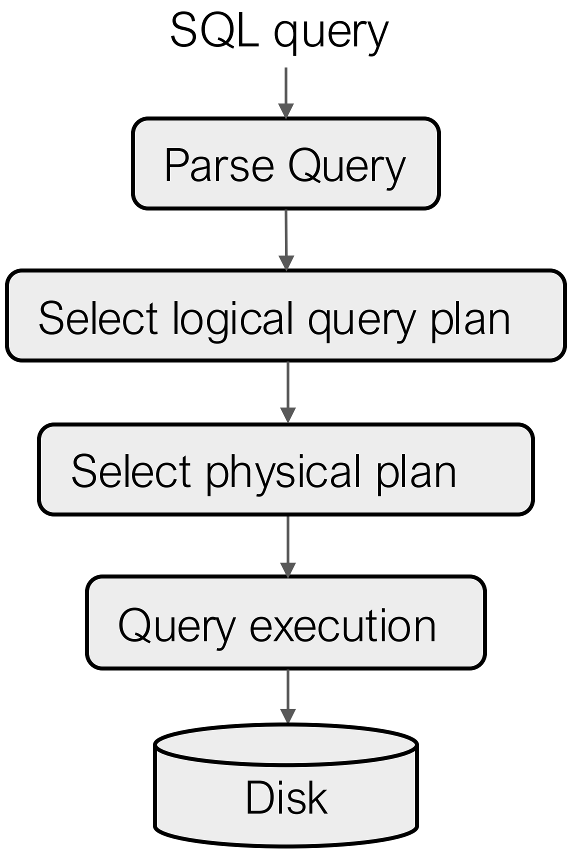
Q. How to optimally compute join of {R3}?

Ans: Single relation – so optimally scan R3.



Putting it all together: RDBMS Architecture

How does a SQL engine work ?



Translate to RA expression and find logically equivalent but more efficient plans

Cost-based query optimization: estimate cost and select physical plan with the smallest cost

Query execution (e.g., run join algorithms against tuples on disk)