Query Optimization in Relational Database Systems

It is safer to accept any chance that offers itself, and extemporize a procedure to fit it, than to get a good plan matured, and wait for a chance of using it.

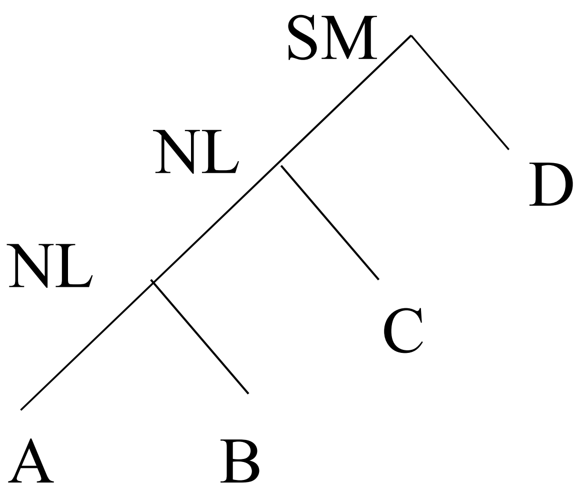
Thomas Hardy (1874)
in *Far from the Madding Crowd*

Query Optimization

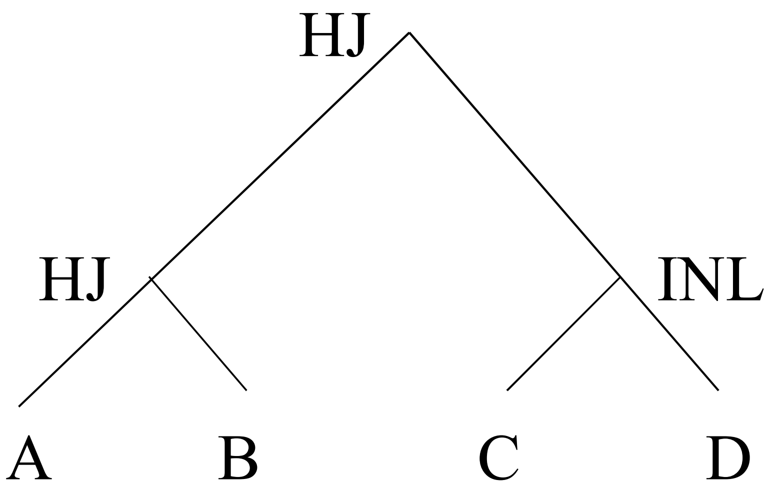
- Since each relational op returns a relation, ops can be *composed*!
- Queries that require multiple ops to be composed may be composed in different ways - thus *optimization* is necessary for good performance, e.g. $A \bowtie B \bowtie C \bowtie D$ can be evaluated as follows:
    - $(((A \bowtie B) \bowtie C) \bowtie D)$
    - $((A \bowtie B) \bowtie (C \bowtie D))$
    - $((B \bowtie A) \bowtie (D \bowtie C))$
    - …

Query Optimization

- Each strategy can be represented as a query evaluation plan (QEP) - Tree of R.A. ops, with choice of algorithms for each op.



$(((A \bowtie B) \bowtie C) \bowtie D)$



$((A \bowtie B) \bowtie (C \bowtie D))$

- Goal of optimization: To find the “best” plan that compute the same answer (to avoid “bad” plans)

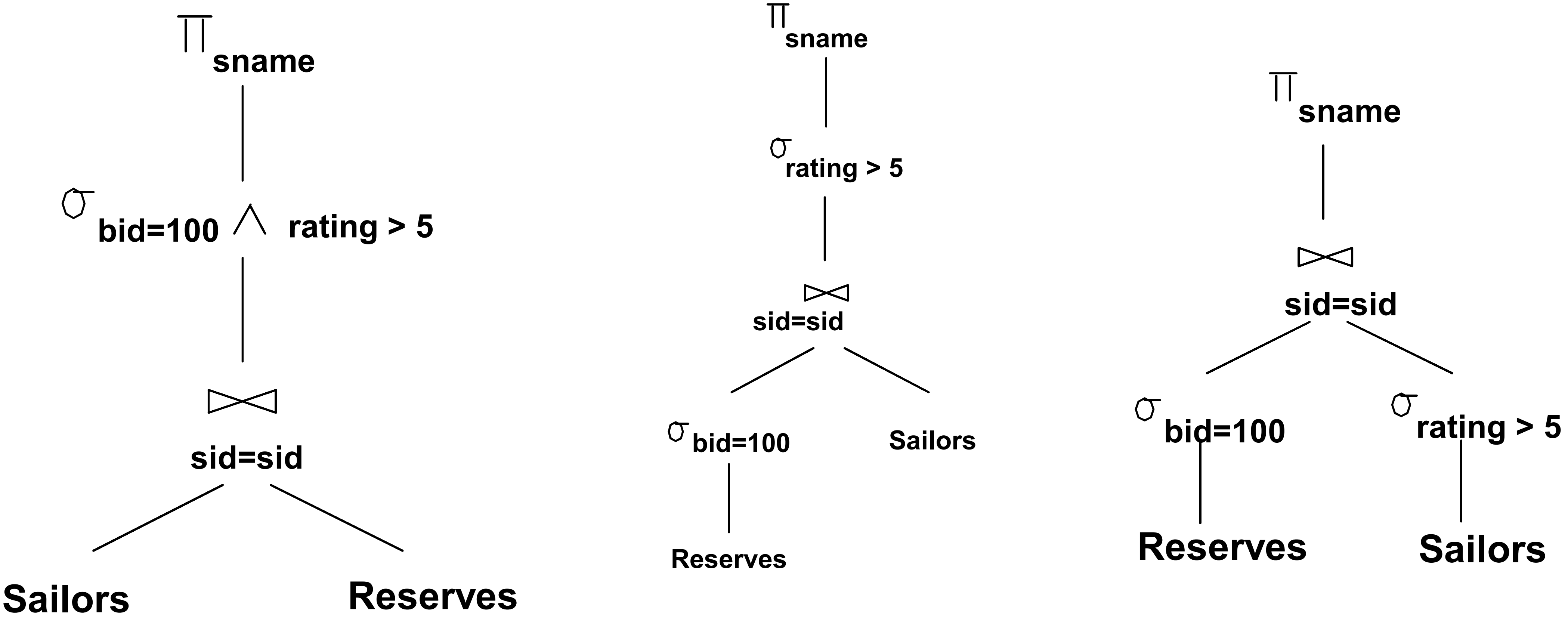
Motivating Examples

Sailors (*sid*: integer, *sname*: string, *rating*: integer, *age*: real)
Reserves (*sid*: integer, *bid*: integer, *day*: dates, *rname*: string)

- Reserves:
  - Each tuple is 40 bytes long, 100 tuples per page, 1000 pages.
- Sailors:
  - Each tuple is 50 bytes long, 80 tuples per page, 500 pages.

```
SELECT  S.sname
FROM  Reserves R, Sailors S
WHERE  R.sid=S.sid AND
   R.bid=100 AND S.rating>5
```

Example



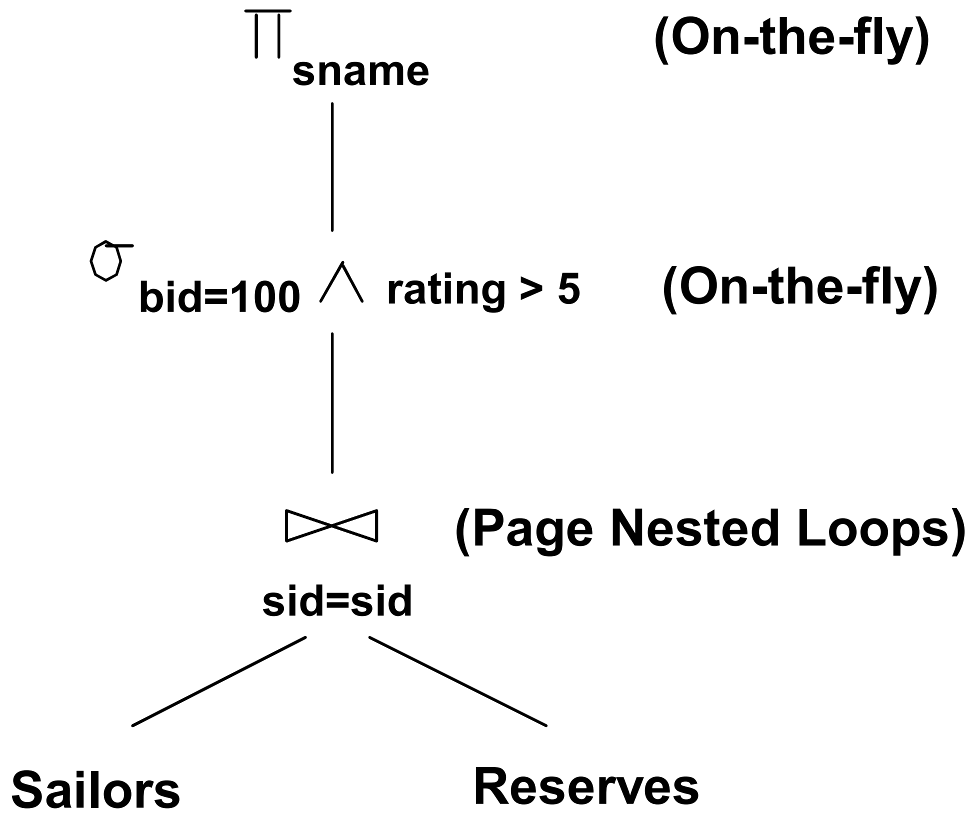
Logical plans

```
SELECT  S.sname
FROM  Reserves R, Sailors S
WHERE  R.sid=S.sid AND
   R.bid=100 AND S.rating>5
```

Example (Cont)

Query Evaluation Plan:

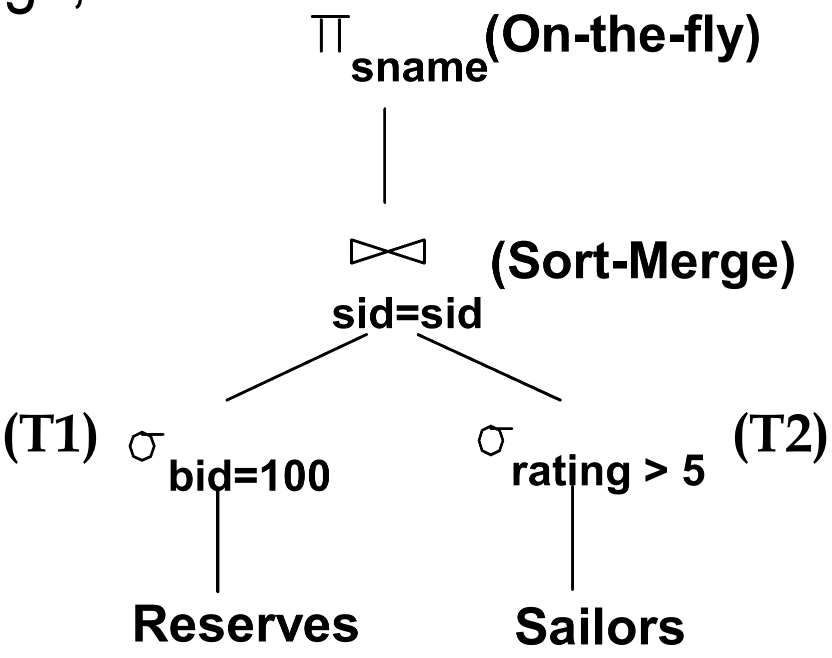
- Cost: 500 + 500 * 1000 IO
- Memory: 3 pages



Physical plan

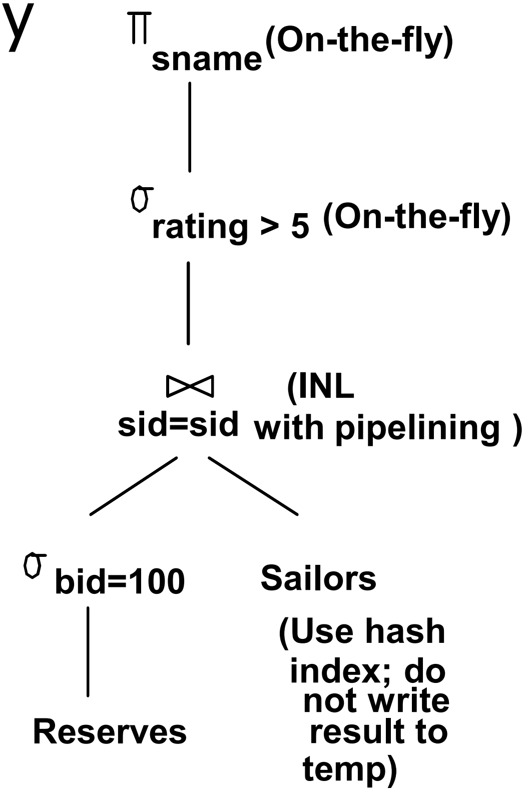
Alternative Plan 1 (No Indexes)

- Main difference: push selections down
- Assume 5 buffers, T1 = 10 pages (100 boats, uniform distribution), T2 = 250 pages (10 ratings, uniform distribution)
- Cost of plan:
  - Scan Reserves (1000) + write temp T1 (10 pages, if we have 100 boats, uniform distribution)
  - Scan Sailors (500) + write temp T2 (250 pages, if we have 10 ratings)
  - Sort T1 (2*2*10), sort T2 (2*4*250), merge (10+250)
  - Total: 4060 page I/Os

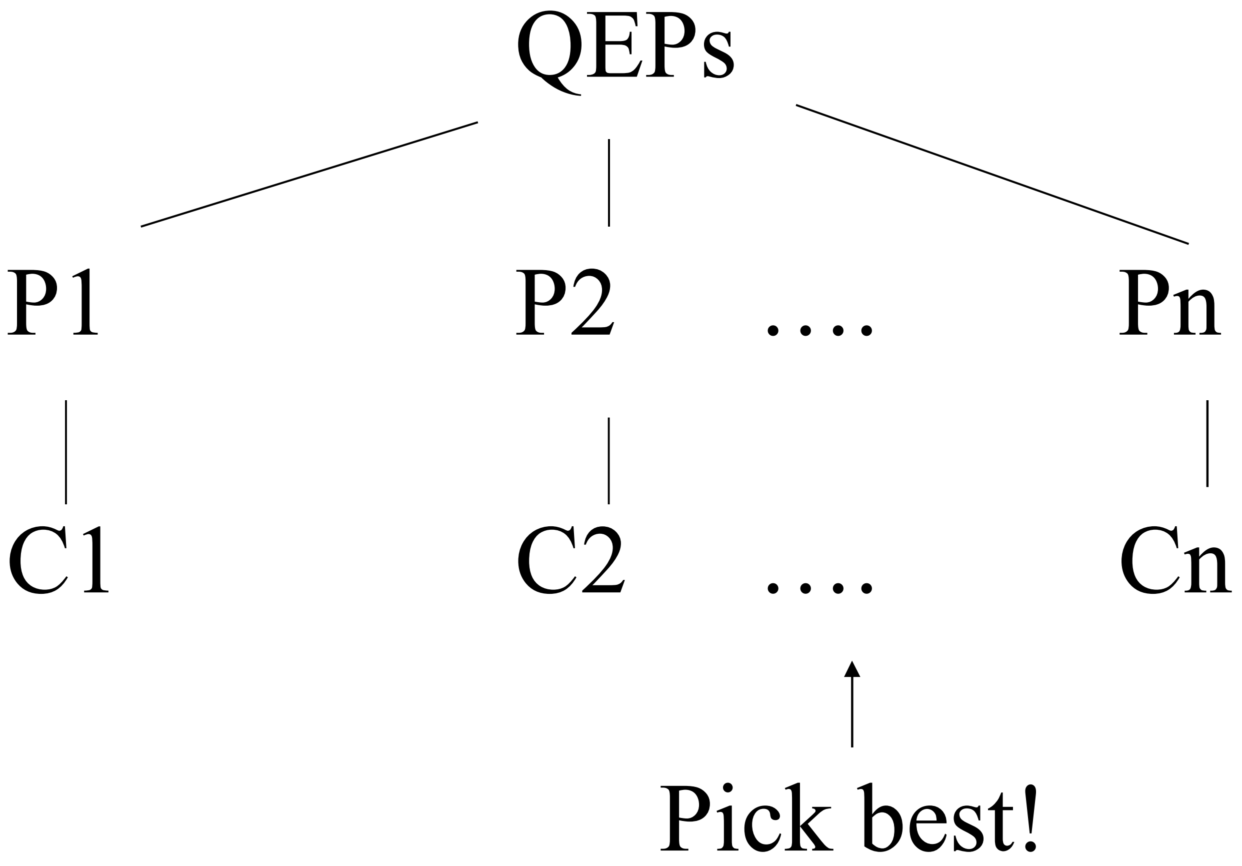

π_{sname} (On-the-fly)
$\bowtie_{sid=sid}$ (Sort-Merge)
(T1) $\sigma_{bid=100}$
$\sigma_{rating > 5}$ (T2)
Reserves
Sailors

Alternative Plan 2 (With Indexes)

- Clustered index on bid of Reserves
  - 100,000/100 = 1000 tuples on 1000/100 = 10 pages
- Hash index on sid (format 2). Join column sid is a key for Sailors
- INL with pipelining (outer is not materialized)
  - Project out unnecessary fields from outer doesn’t help
- At most one matching tuple, unclustered index on sid OK
- Did not push “rating>5” before the join. Why?
- Cost?
  - Selection of Reserves tuples (10 I/Os); for each, must get matching Sailors tuple (1000*2.2); total 2210 I/Os


π_{sname} (On-the-fly)
$\sigma_{rating > 5}$ (On-the-fly)
$\bowtie_{sid=sid}$ (INL with pipelining)
$\sigma_{bid=100}$
Reserves
Sailors
(Use hash index; do not write result to temp)

Query Optimizaton: Find Optimal Plan From A Set of QEPs



QEPs

P1 P2 …. Pn

C1 C2 …. Cn

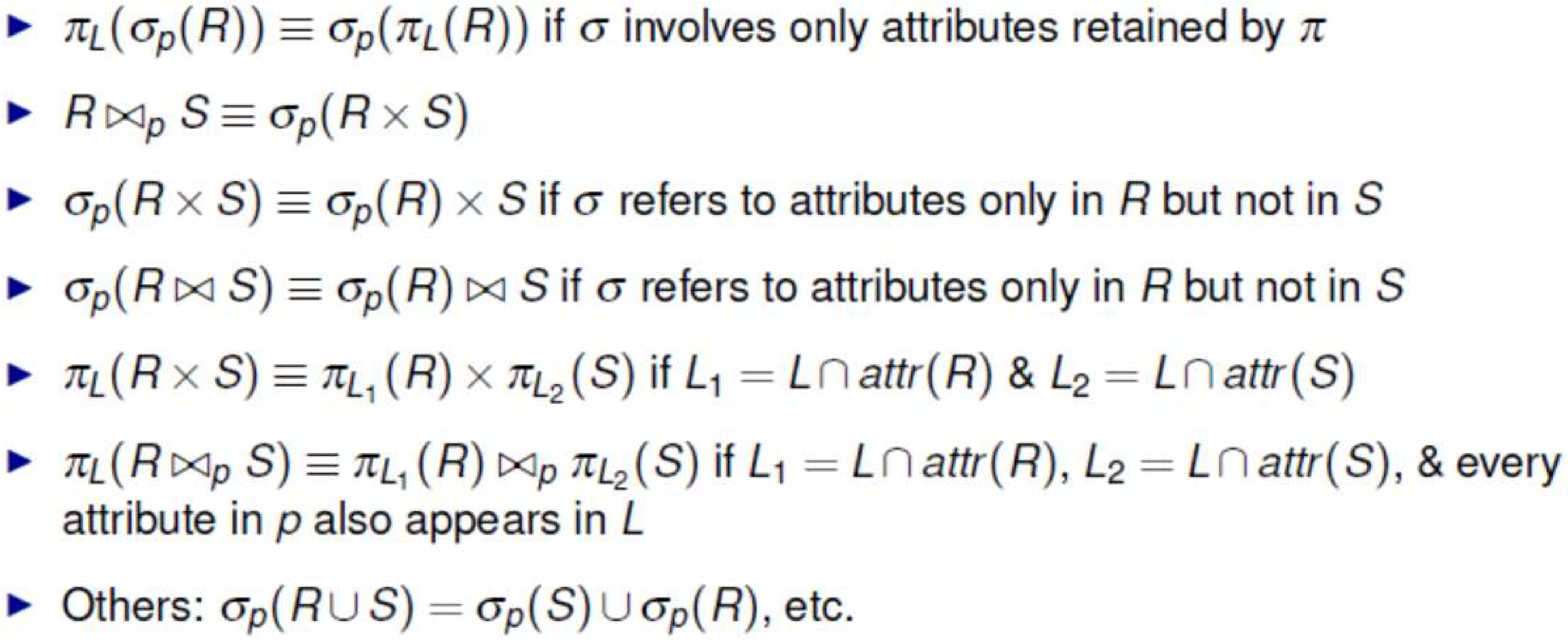
Pick best!

Relational Algebra Equivalences

What about $\sigma_{p1 \vee p2 \ldots \vee pn}(R)$?

- **Cascading of selections**: $\sigma_{p_1 \wedge p_2 \wedge \cdots \wedge p_n}(R) \equiv \sigma_{p_1}(\sigma_{p_2}(\cdots(\sigma_{p_n}(R))\cdots))$
- **Commutativity of selections**: $\sigma_{p_1}(\sigma_{p_2}(R)) \equiv \sigma_{p_2}(\sigma_{p_1}(R))$
- **Cascading of projections**: $\pi_{L_1}(R) \equiv \pi_{L_1}(\pi_{L_2}(\cdots(\pi_{L_n}(R))\cdots))$, where $L_i \subseteq L_{i+1}$ for $i \in [1, n)$
- **Commutativity of cross-products**: $R \times S \equiv S \times R$
- **Associativity of cross-products**: $R \times (S \times T) \equiv (R \times S) \times T$
- **Commutativity of joins**: $R \bowtie S \equiv S \bowtie R$
- **Associativity of joins**: $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$
- **Others**: $R \cup S = S \cup R$, $R \cap S = S \cap R$, $R \cup (S \cup T) = (R \cup S) \cup T$, $R \cap (S \cap T) = (R \cap S) \cap T$, etc.

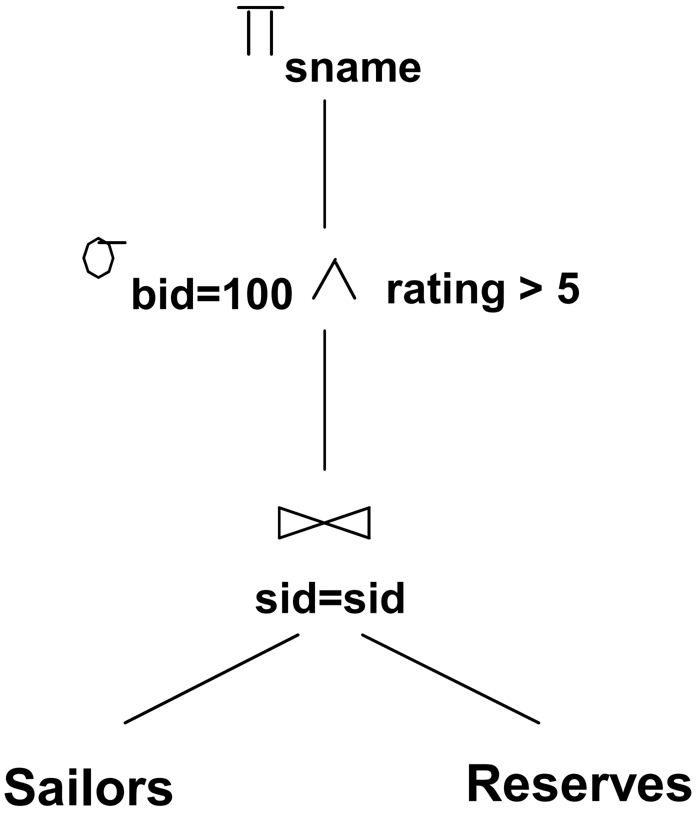
Relational Algebra Equivalences



- $\pi_L(\sigma_p(R)) \equiv \sigma_p(\pi_L(R))$ if σ involves only attributes retained by π
- $R \bowtie_p S \equiv \sigma_p(R \times S)$
- $\sigma_p(R \times S) \equiv \sigma_p(R) \times S$ if σ refers to attributes only in R but not in S
- $\sigma_p(R \bowtie S) \equiv \sigma_p(R) \bowtie S$ if σ refers to attributes only in R but not in S
- $\pi_L(R \times S) \equiv \pi_{L_1}(R) \times \pi_{L_2}(S)$ if $L_1 = L \cap attr(R)$ & $L_2 = L \cap attr(S)$
- $\pi_L(R \bowtie_p S) \equiv \pi_{L_1}(R) \bowtie_p \pi_{L_2}(S)$ if $L_1 = L \cap attr(R)$, $L_2 = L \cap attr(S)$, & every attribute in p also appears in L
- Others: $\sigma_p(R \cup S) = \sigma_p(S) \cup \sigma_p(R)$, etc.

Example

$\sigma_p(R \bowtie S) \equiv \sigma_p(R) \bowtie S$ if σ refers to attributes only in R but not in S



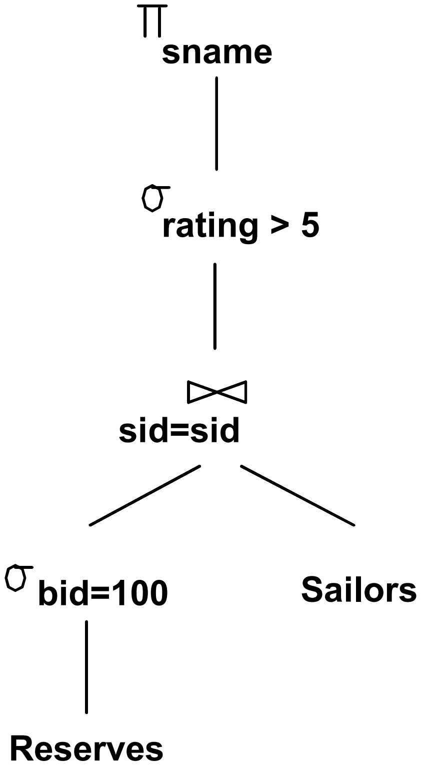
π_{sname}

$\sigma_{\text{bid=100} \wedge \text{rating > 5}}$

$\bowtie_{\text{sid=sid}}$

Sailors

Reserves



π_{sname}

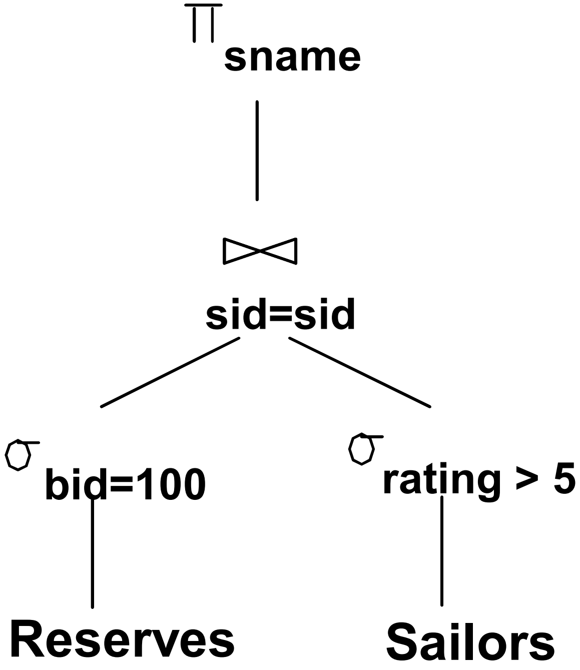
$\sigma_{\text{rating > 5}}$

$\bowtie_{\text{sid=sid}}$

$\sigma_{\text{bid=100}}$

Sailors

Reserves



π_{sname}

$\bowtie_{\text{sid=sid}}$

$\sigma_{\text{bid=100}}$

$\sigma_{\text{rating > 5}}$

Reserves

Sailors

Bags vs. Sets

$R = \{a,a,b,b,b,c\}$

$S = \{b,b,c,c,d\}$

$R \cup S = ?$

- SUM is implemented: $R \cup S = \{a,a,b,b,b,b,b,c,c,c,d\}$
- Some rules cannot be used for bags
  - e.g. $A \cap_s (B \cup_s C) = (A \cap_s B) \cup_s (A \cap_s C)$

Let A, B and C be $\{x\}$

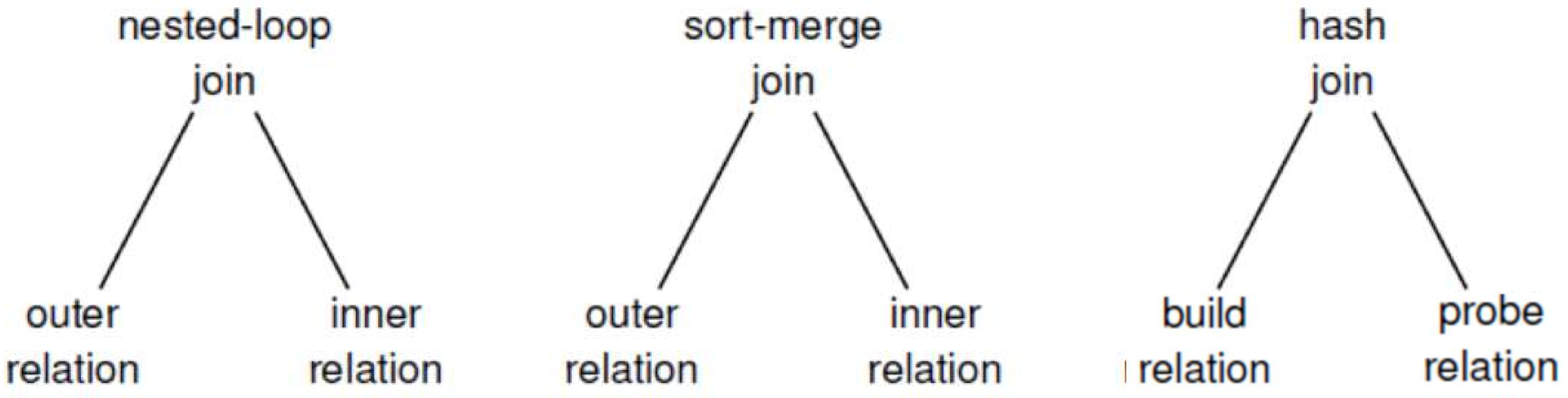
$B \cup_B C = \{x, x\}$ **$A \cap_B (B \cup_B C) = \{x\}$**

$A \cap_B B = \{x\}$ $A \cap_B C = \{x\}$ **$(A \cap_B B) \cup_B (A \cap_B C) = \{x, x\}$**

Query Optimizer

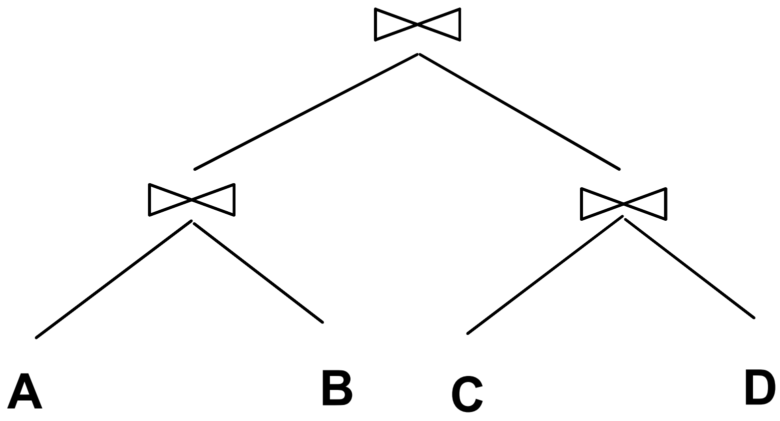
- Find the “best” plan (more often avoid the bad plans)
- Comprises the following
  - Plan space
    - huge number of alternative, semantically equivalent plans
    - computationally expensive to examine all
    - Conventional wisdom: avoid bad plans
      - need to include plans that have low cost
  - Enumeration algorithm (Search space)
    - search strategy (optimization algorithm) that *searches through the plan space*
    - has to be efficient (low optimization overhead)
  - Cost model
    - facilitate comparisons of alternative plans
    - has to be “accurate”

Join Plan Notation

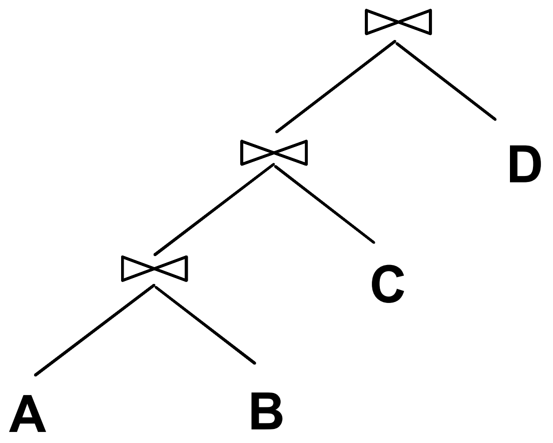


Plan Space

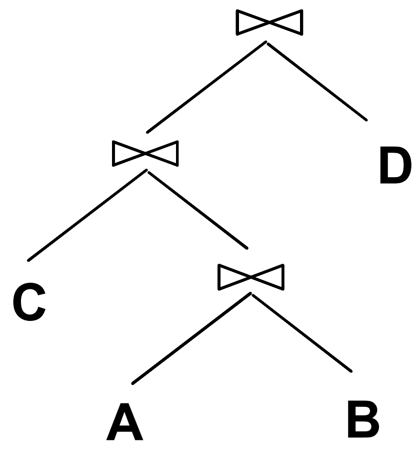
- Left-deep trees: right child has to be a base table
- Right-deep trees: left child has to be a base table
- Deep trees: one of the two children is a base table
- Bushy tree: unrestricted



Bushy tree

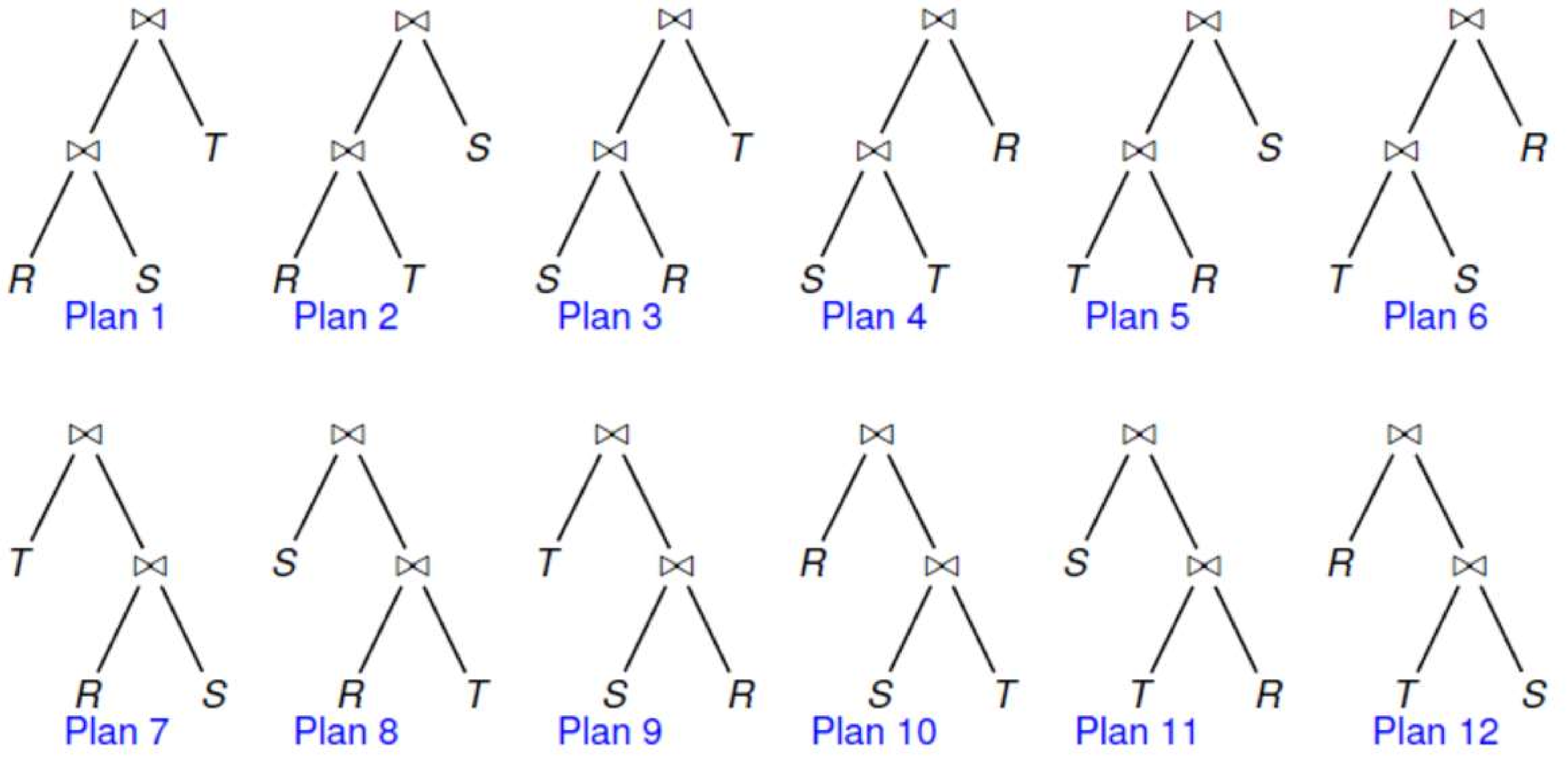


Left-deep tree



Deep tree

Query Plan Space for $R \bowtie S \bowtie T$



This has not accounted for the algorithms!

Search Algorithms (and Search Space)

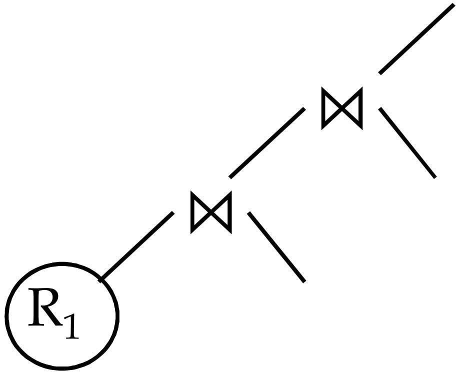
- Exhaustive (*Complete space*)
  - enumerate each possible plan, and pick the best
- Greedy Techniques (Very small – polynomial)
  - smallest relation next
  - smallest result next
  - typically polynomial time complexity
- Randomized/Transformation Techniques (Large space – can be complete if you run the algorithms indefinitely)
- System R approach (Almost complete)
  - Dynamic Programming with Pruning

Multi-Join Queries

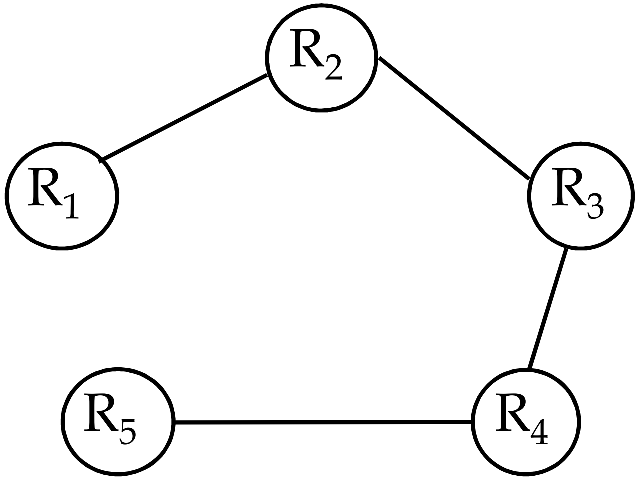
- Focus on multi-join queries first
  - Join is the most expensive operations
  - Selections and projections can be pushed down as early as possible
- Query
  - A query graph whose nodes are relations and edges represent a join condition between the two nodes

Greedy Algorithm (Example)

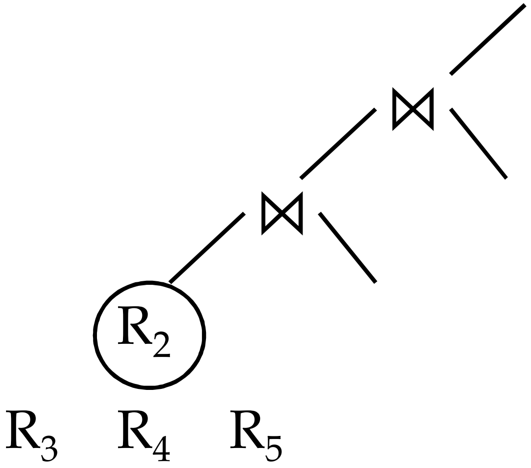
- Heuristic 1: Smallest relation next
  - Suppose R_i < R_k for *i* < *k*



All plans must begin with R_1



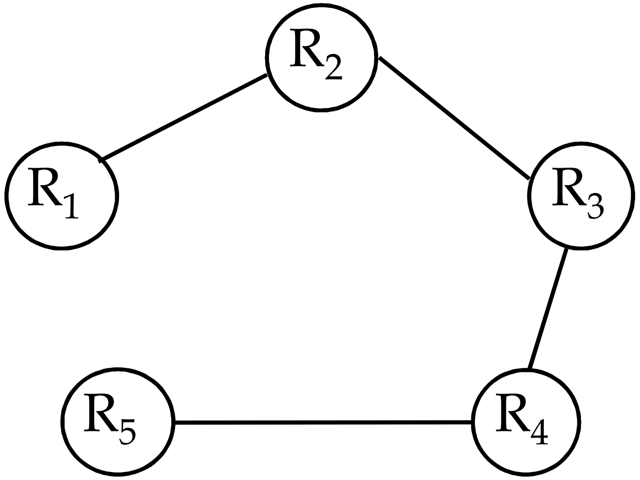
Join Graph



All plans beginning with R_2-R_5 have been pruned!

Greedy Algorithm (Example)

- Smallest relation next
  - What if R1 < R5 < R3 < R2 < R4???



Another heuristic:
Smallest result next?

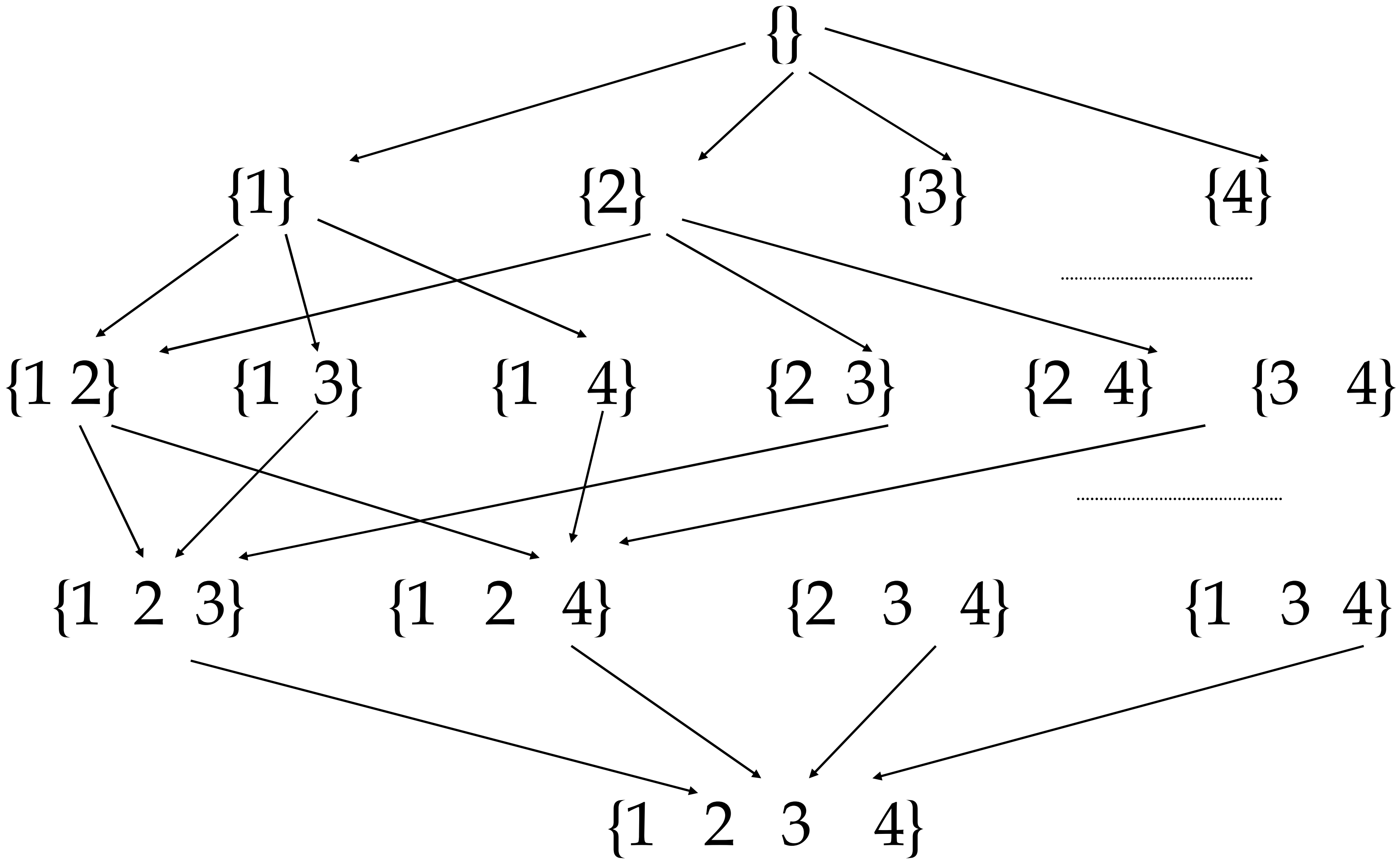
no join condition, cross product

Dynamic Programming (Left-Deep Trees) (System R)

- The algorithm proceeds by considering increasingly larger subsets of the set of all relations
  - Builds a plan bottom-up (beginning from 1 table, then to 2, and so on)
  - Plans for a set of cardinality *i* are constructed as extensions of the best plan for a set of cardinality *i*-1
    - For each set of cardinality *i*, we only keep ONE best plan

Dynamic Programming (Cont)

find best plan for tbl 1, index on diff attribute / table scan



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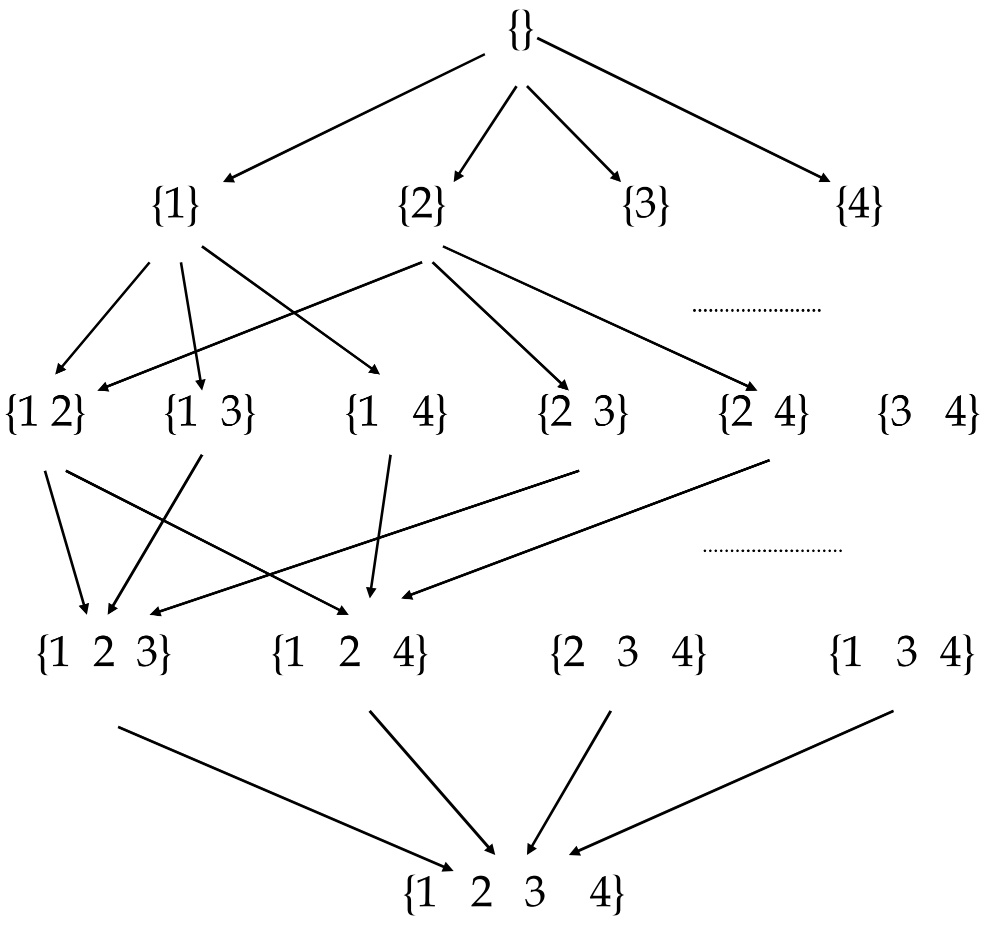
    - Keep only ONE best plan for each set of cardinality *i*
- Search space can be pruned based on the principal of optimality
    - if two plans differ only in a subplan, then the plan with the better subplan is also the better plan

Principle of Optimality



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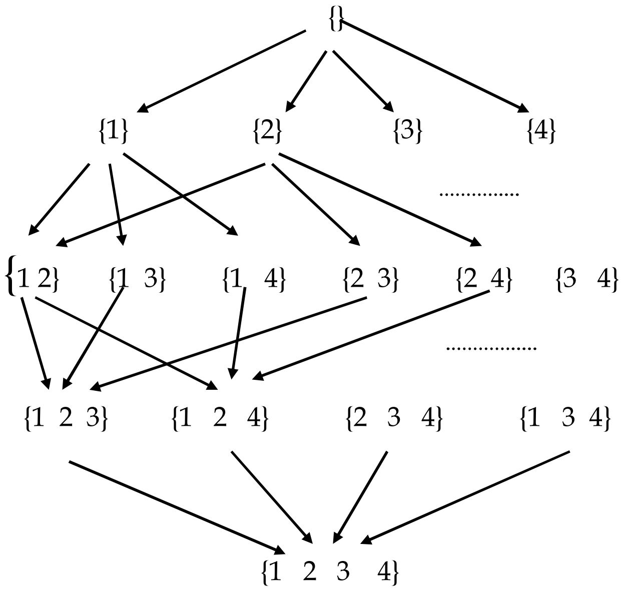
- Search space can be pruned based on the principal of optimality
    - if two plans differ only in a subplan, then the plan with the better subplan is also the better plan
- Computation overhead reduced due to overlapping subproblems
  - Multiple sets of cardinality *i* uses same set at cardinality (*i-1)*

Dynamic Programming (Left-Deep Trees)

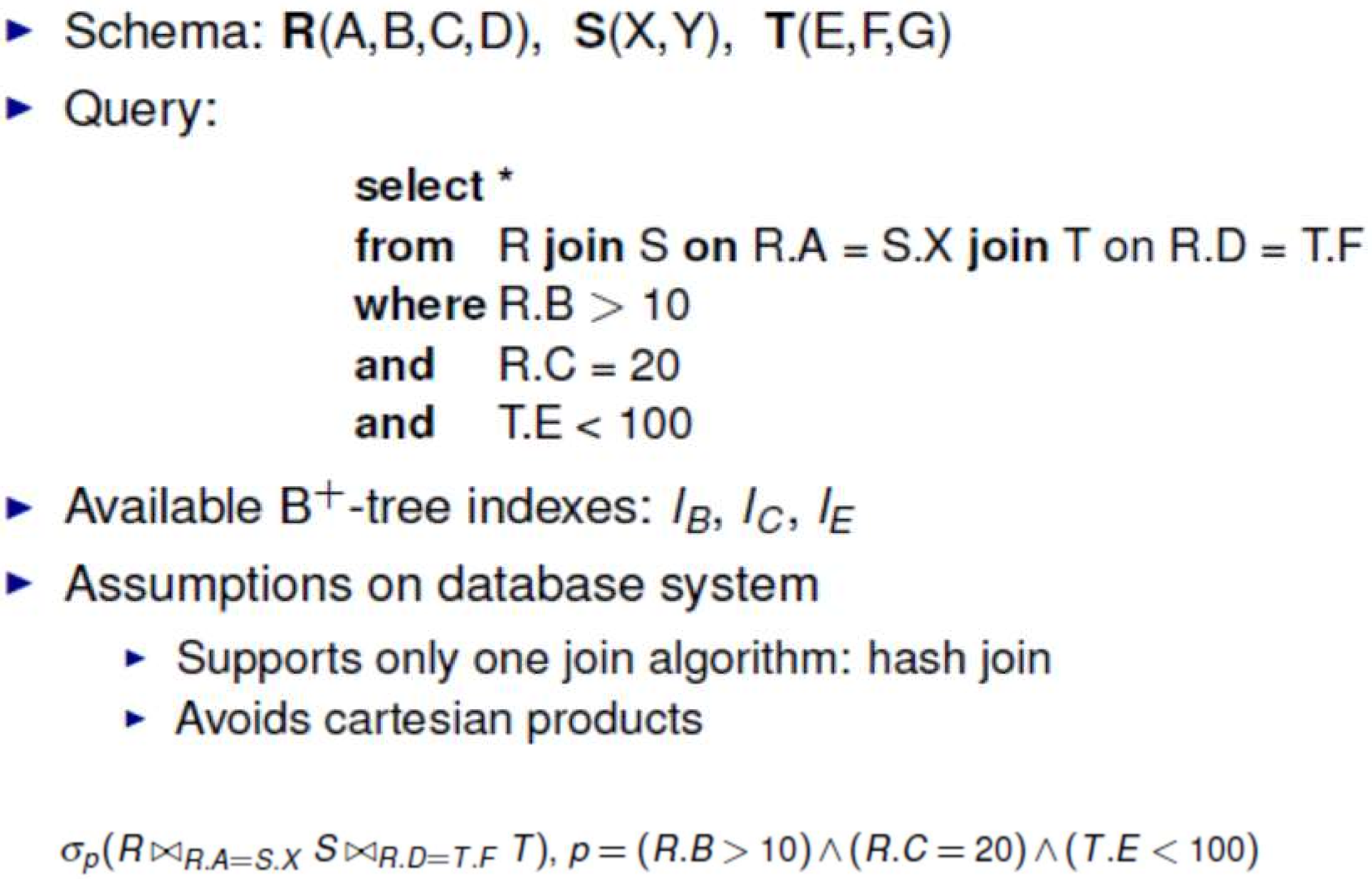
- accessPlan(R) produces the best plan for relation (single table) R
- joinPlan(p1,R) extends the (partial) join plan p1 into another plan p2 in which the result of p1 is joined with R in the best possible way
  - p1 = R1 JOIN R2 JOIN R3
  - p2 = joinPlan(p1, R) = (R1 JOIN R2 JOIN R3) JOIN R4
- Optimal plans for subsets are stored in optplan() array and are reused rather than recomputed

Dynamic Programming (Cont)

```
for i = 1 to N
    optPlan({Ri}) = accessPlan(Ri)
for i = 2 to N {     for all subset of table size i
    forall S subset of {$R_1$, $R_2$, … $R_n$} such that |S|=i {
            bestPlan = dummy plan with infinite cost
            forall Rj, Sj, |Sj| = i-1   such that S = {Rj} U Sj {
                    p = joinPlan(optPlan(Sj), Rj)
                    if cost(p) < cost(bestPlan)
                        bestPlan = p
            }
            optPlan(S) = bestPlan
    }
}
$P_{opt}$ = optPlan{$R_1$, $R_2$, … $R_n$}
```



Dynamic Programming: A Concrete Example



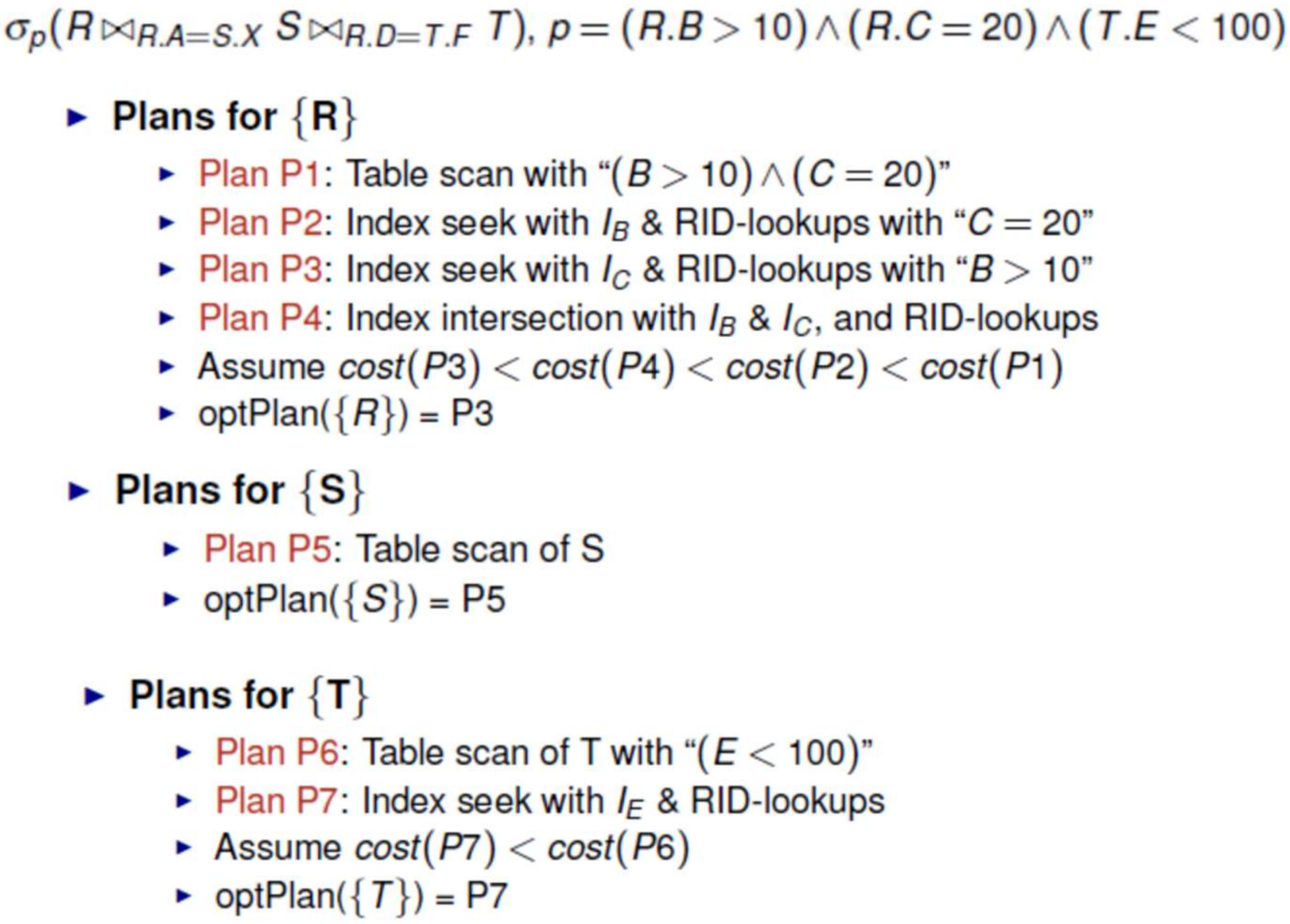
- Schema: **R**(A,B,C,D), **S**(X,Y), **T**(E,F,G)
- Query:

```
select *
from   R join S on R.A = S.X join T on R.D = T.F
where  R.B > 10
and    R.C = 20
and    T.E < 100
```

- Available B$^+$-tree indexes: I_B, I_C, I_E
- Assumptions on database system
  - Supports only one join algorithm: hash join
  - Avoids cartesian products

$$\sigma_p(R \bowtie_{R.A=S.X} S \bowtie_{R.D=T.F} T),\ p = (R.B > 10) \wedge (R.C = 20) \wedge (T.E < 100)$$

Enumeration of Single-relation Plans



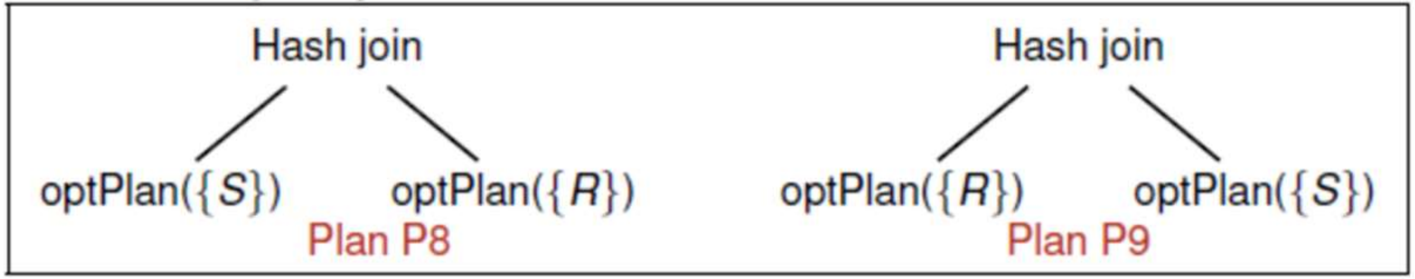
$\sigma_p(R \bowtie_{R.A=S.X} S \bowtie_{R.D=T.F} T)$, $p = (R.B > 10) \wedge (R.C = 20) \wedge (T.E < 100)$

- **Plans for {R}**
  - Plan P1: Table scan with "$(B > 10) \wedge (C = 20)$"
  - Plan P2: Index seek with I_B & RID-lookups with "$C = 20$"
  - Plan P3: Index seek with I_C & RID-lookups with "$B > 10$"
  - Plan P4: Index intersection with I_B & I_C, and RID-lookups
  - Assume $cost(P3) < cost(P4) < cost(P2) < cost(P1)$
  - optPlan($\{R\}$) = P3
- **Plans for {S}**
  - Plan P5: Table scan of S
  - optPlan($\{S\}$) = P5
- **Plans for {T}**
  - Plan P6: Table scan of T with "$(E < 100)$"
  - Plan P7: Index seek with I_E & RID-lookups
  - Assume $cost(P7) < cost(P6)$
  - optPlan($\{T\}$) = P7

Enumeration of Two-Relation Plans

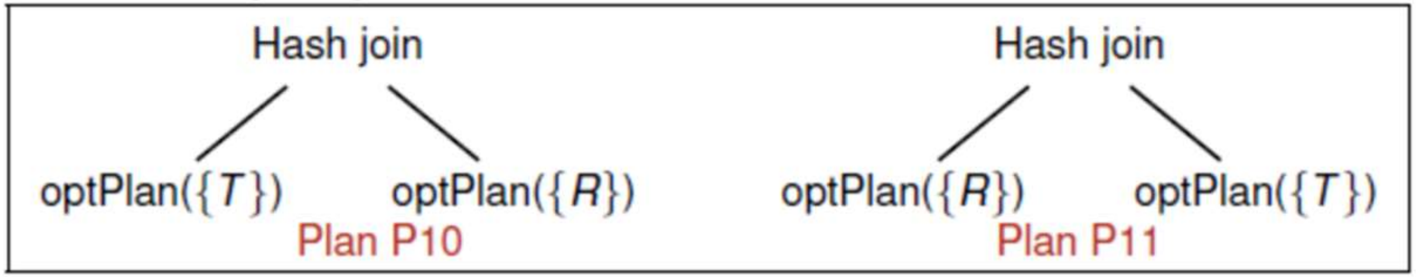
$\sigma_p(R \bowtie_{R.A=S.X} S \bowtie_{R.D=T.F} T)$, $p = (R.B > 10) \wedge (R.C = 20) \wedge (T.E < 100)$

- **Plans for $\{$R, S$\}$**



  - Assume $cost(P8) < cost(P9)$
  - optPlan($\{R, S\}$) = P8

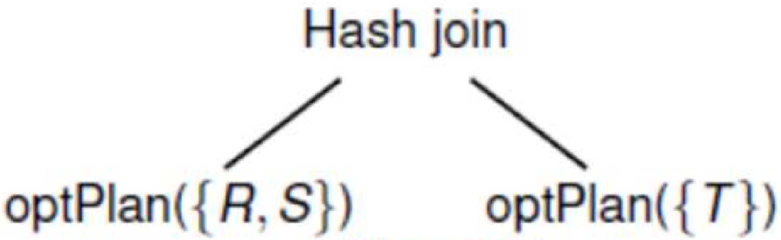
- **Plans for $\{$R, T$\}$**



  - Assume $cost(P11) < cost(P10)$
  - optPlan($\{R, T\}$) = P11

Enumeration of Three-Relation Plans

$$\sigma_p(R \bowtie_{R.A=S.X} S \bowtie_{R.D=T.F} T),\ p = (R.B > 10) \wedge (R.C = 20) \wedge (T.E < 100)$$

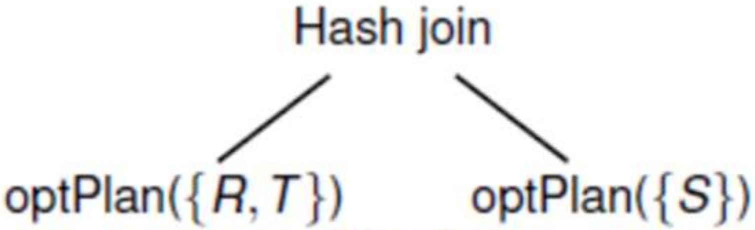


Hash join

optPlan($\{R, S\}$)

optPlan($\{T\}$)

Plan P12



Hash join

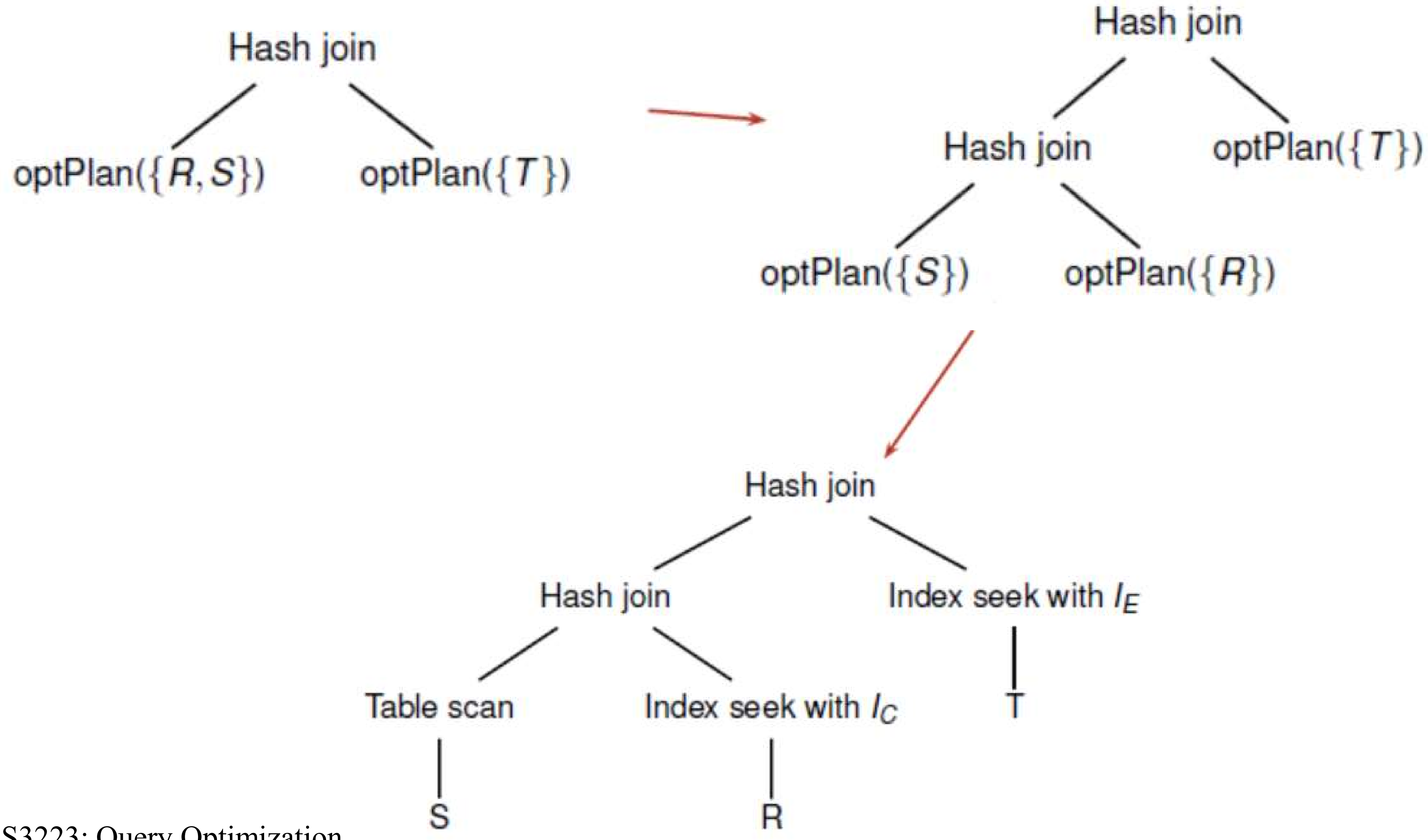
optPlan($\{R, T\}$)

optPlan($\{S\}$)

Plan P13

- Assume $cost(P12) < cost(P13)$
- optPlan($\{R, S, T\}$) = P12

Optimal Plan



Hash join

optPlan({R, S})

optPlan({T})

Hash join

Hash join

optPlan({T})

optPlan({S})

optPlan({R})

Hash join

Hash join

Index seek with I_E

Table scan

Index seek with I_C

T

S

R

Dynamic Programming (Cont)

- Time & Space complexity
  - For k relations, for left-deep trees, $2^k - 1$ entries!
  - For bushy trees, $O(3^k)$
- Is DP (as presented) optimal?

Dynamic Programming (Cont)

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  - For bushy trees, $O(3^k)$
- Is DP optimal?
- DP may maintain multiple plans per subset of relations
  - Interesting orders

Dynamic Programming (Cont)

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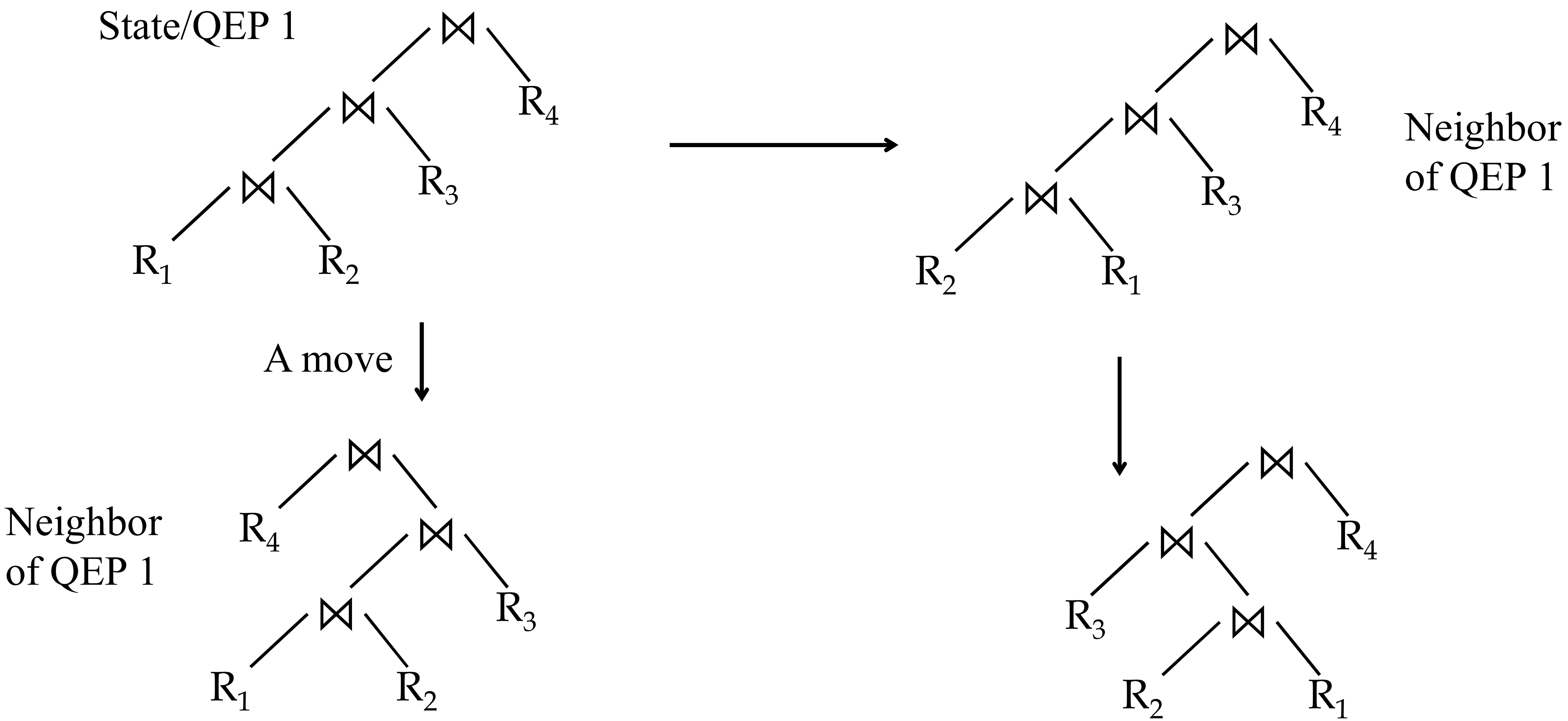
  - For k relations, for left-deep trees, $2^k – 1$ entries!
  - For bushy trees, $O(3^k)$
- Is DP optimal?
- DP may maintain multiple plans per subset of relations
  - Interesting orders
- Is DP with interesting orders optimal?

Randomized Techniques

- Employ randomized/transformation techniques for query optimization
- State space -- space of plans, State -- plan
- Each state has a cost associated with it
  - determined by some cost model
- A move is a perturbation applied to a state to get to another state
  - a move set is the set of moves available to go from one state to another
  - any one move is chosen from this move set randomly
  - each move set has a probability associated to indicate the probability of selecting the move
- Two states are *neighboring states* if one move suffices to go from one state to the other

Randomized Algorithm (Example)



State/QEP 1

A move

Neighbor of QEP 1

Neighbor of QEP 1

More on Randomized Techniques

- A local minimum in the state space is a state such that its cost is lower than that of all neighboring states
- A global minimum is a state which has the lowest cost among all local minima
  - at most one global minimum
- A move that takes one state to another state with a lower cost is called a downward move; otherwise it is an upward move
  - in a local/global minimum, all moves are upward moves

Local Optimization

Repeat until
a near-optimal
minimum
Is reached

```
S = initialize()  // initial plan
minS = S // cost of plan S – currently the best
repeat {
    repeat {
        newS = move(S)  // move to a new plan
        if (cost(newS) < cost(S))
            S = newS
    } until (“local minimum reached”)
    if (cost(S) < cost(minS))
        minS = S
    newStart(S);  // iterate with a different initial plan
} until (“stopping condition satisfied”)
return (minS);
```

By doing so
repeatedly,
a local minimum
can
be reached

A move is accepted if it is a
downward move, i.e., has
a lower cost

Issues on Local Optimization

- How is the start state obtained?
  - The state in which we start a run
  - The start state of the first run is the initial state
  - All start states should be different
  - Should be obtained quickly
    - Random
    - greedy heuristics
    - making a number of moves from the local minimum, except that this time each move is accepted irrespective of whether it increases or decreases the cost
- How is the local minimum detected?
- How is the stopping criterion detected?

Run: sequence of moves to a local minimum from the start state

Issues on Local Optimization (Cont)

- How is the local minimum detected?
  - Not practical to examine all neighbors to verify that one has reached a local minimum
  - Based on random sampling
    - examine a sufficiently large number of neighbors
      - if any one is lower, we move to that state, and repeat the process
      - if no tested neighbor is of lower cost, the current state can be considered a local minimum
    - the number of neighbors to examine can be specified as a parameter, and is called the sequence length
      - Can also be time-based

Issues in Local Optimization (Cont)

- How is the stopping criterion detected?
  - Determines the number of times that the outer loop is executed
  - Can be fixed and is given by sizeFactor*N, where sizeFactor is a parameter, N is the number of relations
    - Why N? Can it be a constant?

What about the MOVEs? Transformation Rules

- Restricted to left-deep trees
  - all possible permutations of the N relations
  - let S be the current state, S = (… i … j … k …)
  - swap
    - select two relations, say i and j at random. Swapped i and j to get the new state newS = (… j … i … k …)
  - 3Cycle
    - select three relations, say i and j and k at random. The move consists of cycling i, j and k: i is moved to the position of j, j is moved to the position of k and k is moved to the position of i. The resultant new state newS = (… k … i … j …)
- Other methods (e.g., join methods)? Bushy trees?

Comparison between Exhaustive, Greedy and Randomized Algorithms

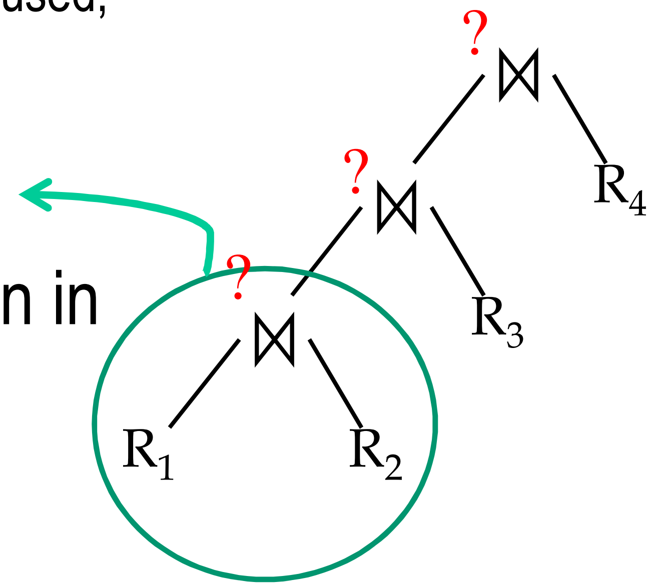
- Search space
- Plan quality
- Optimization overhead

Cost Models

- Typically, a combination of CPU and I/O costs
- Objective is to be able to rank plans
  - exact value is not necessary
- Relies on
  - statistics on relations and indexes
  - formulas to estimate CPU and I/O cost
  - formulas to estimate selectivities of operators and intermediate results

Cost Estimation

- For each plan considered, must estimate cost:
  - Must estimate cost of each operation in plan tree
    - Depends on input cardinalities
    - Depends on buffer size, availability of indexes, algorithms used, etc.
      - We've already discussed how to estimate the cost of operations (sequential scan, index scan, joins, etc.)
  - Must estimate size of result for each operation in tree!
    - Use information about the input relations
    - Typical assumptions like *uniform distribution* of data and *independence* of predicates can simplify size estimation but is error prone



Statistics and Catalogs

- Need information about the relations and indexes involved Catalogs typically contain at least:
  - # tuples of R (||R||), #bytes in each R tuple (S(R))
  - # blocks/pages to hold all R tuples (|R|)
  - # distinct values in R for attribute A (V(R,A))
  - NPages for each index
  - Index height, low/high key values (Low/High) for each tree index
- Catalogs updated periodically
  - Updating whenever data changes is too expensive; lots of approximation anyway, so slight inconsistency ok

Estimation Assumptions

- Uniformity assumption
  - Uniform distribution of attribute values
- Independence assumption
  - Independent distribution of values in different attributes
- Inclusion assumption
  - For $R \bowtie_{R.A=S.B} S$, if $V(R, A) \leq V(R, B)$, then $\pi_A(R) \subseteq \pi_B(S)$
  - $V(R, A)$ is the number of distinct values of R.A

Example

R

A	B	C	D
cat	1	10	a
cat	1	20	b
dog	1	30	a
dog	1	40	c
bat	1	50	d

A: 20 byte string

B: 4 byte integer

C: 8 byte string

D: 5 byte string

||R|| = 5 S(R) = 37

V(R,A) = 3 V(R,C) = 5

V(R,B) = 1 V(R,D) = 4

Size estimate for W $= \sigma_{Z=val}$ *(R)*

R

A	B	C	D
cat	1	10	a
cat	1	20	b
dog	1	30	a
dog	1	40	c
bat	1	50	d

V(R,A)=3

V(R,B)=1

V(R,C)=5

V(R,D)=4

$$\|W\| = \frac{\|R\|}{V(R,Z)}$$

S(W) = S(R)

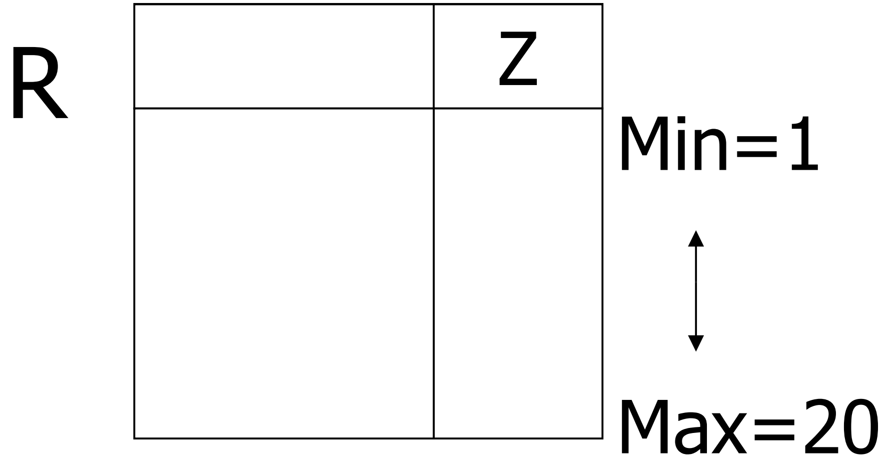
Assumption:

Values in select expression Z = val are *uniformly distributed* over possible V(R,Z) values

Alternative assumption: use DOM(R,Z)

What about W = $\sigma_{z \geq \text{val}}$ ***(R)?***

Solution: Estimate values in range



$V(R,Z)=10$

$W = \sigma_{Z \geq 15}(R)$

$$\text{f (fraction of range)} = \frac{20\text{-}15\text{+}1}{20\text{-}1\text{+}1} = \frac{6}{20} \qquad ||W|| = f \times ||R||$$

Alternative: (Max(Z)-value)/(Max(Z)-Min(Z))

$W = R1 \bowtie R2$

R1

A	B	C

R2

A	D

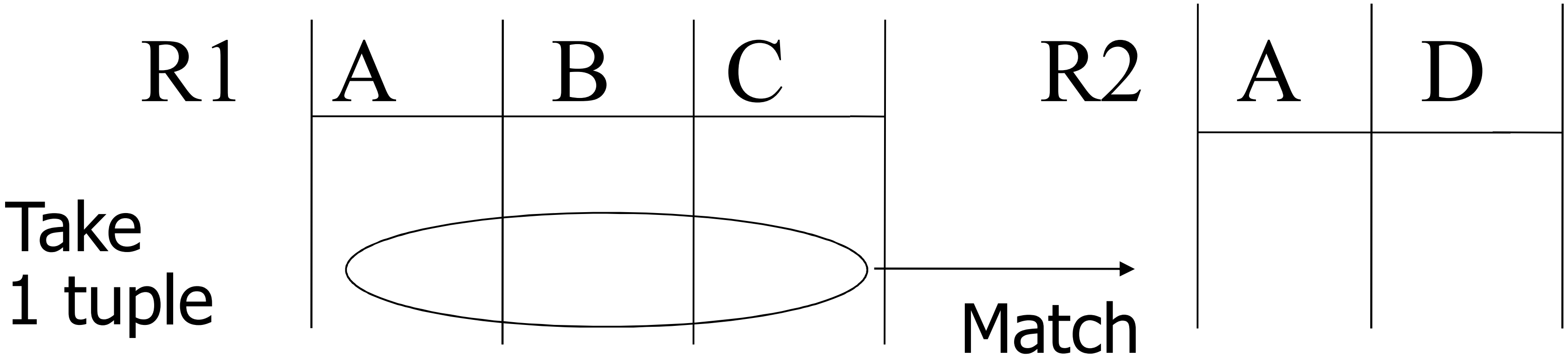
<u>Assumption:</u>

V(R1,A) $\leq$ V(R2,A) $\Rightarrow$ Every A value in R1 is in R2

V(R2,A) $\leq$ V(R1,A) $\Rightarrow$ Every A value in R2 is in R1

“containment of value sets”

Computing T(W) when V(R1,A) ≤ V(R2,A)



1 tuple of R1 matches with $\frac{||R2||}{V(R2,A)}$ tuples of R2

so $||W|| = ||R1|| \times \frac{||R2||}{V(R2,A)}$

If V(R2,A) ≤ V(R1,A) $\quad ||W|| = \frac{||R2|| \times ||R1||}{V(R1,A)}$

For complex expressions, need intermediate T,S,V results

E.g. $W = [\underbrace{\sigma_{A=a}(R1)}_{\text{Treat as relation U}}] \bowtie R2$

$\|U\| = \|R1\|/V(R1,A) \qquad S(U) = S(R1)$

Also need V (U, *) !!

Example

R1

A	B	C	D
cat	1	10	10
cat	1	20	20
dog	1	30	10
dog	1	40	30
bat	1	50	10

V(R1,A)=3

V(R1,B)=1

V(R1,C)=5

V(R1,D)=3

$U = \sigma_{A=a} (R1)$

V(U,A) = ? V(U, B) = ? V(U,C) = ?

V(D,U) … somewhere in between V(U,B) and V(U,C)

For Joins $U = R1(A,B) \bowtie R2(A,C)$

$V(U,A) = \min \{ V(R1, A), V(R2, A) \}$

$V(U,B) = V(R1, B)$

$V(U,C) = V(R2, C)$

(Assumption: Preservation of value sets)

Example

$$Z = R1(A,B) \bowtie R2(B,C) \bowtie R3(C,D)$$

$\boxed{\text{R1}}$ $\|R1\| = 1000$ $V(R1,A)=50$ $V(R1,B)=100$

$\boxed{\text{R2}}$ $\|R2\| = 2000$ $V(R2,B)=200$ $V(R2,C)=300$

$\boxed{\text{R3}}$ $\|R3\| = 3000$ $V(R3,C)=90$ $V(R3,D)=500$

$Z = R1(A,B) \bowtie R2(B,C) \bowtie R3(C,D)$

$\|R1\| = 1000 \quad V(R1,A)=50 \quad V(R1,B)=100$

$\|R2\| = 2000 \quad V(R2,B)=200 \quad V(R2,C)=300$

$\|R3\| = 3000 \quad V(R3,C)=90 \quad V(R3,D)=500$

Partial Result: U = R1 ⋈ R2

$$\|U\| = \frac{1000 \times 2000}{200}$$

$V(U,A) = 50$

$V(U,B) = 100$

$V(U,C) = 300$

Z = U ⋈ R3

$$\|Z\| = \frac{1000 \times 2000 \times 3000}{200 \times 300}$$

$V(Z,A) = 50$

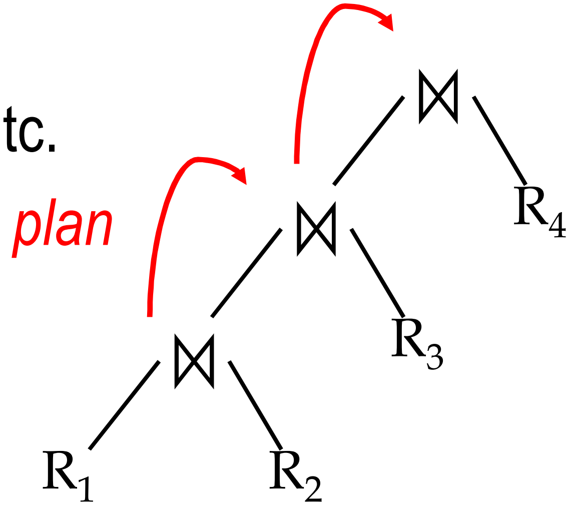
$V(Z,B) = 100$

$V(Z,C) = 90$

$V(Z,D) = 500$

Errors in Estimating Size of Plan

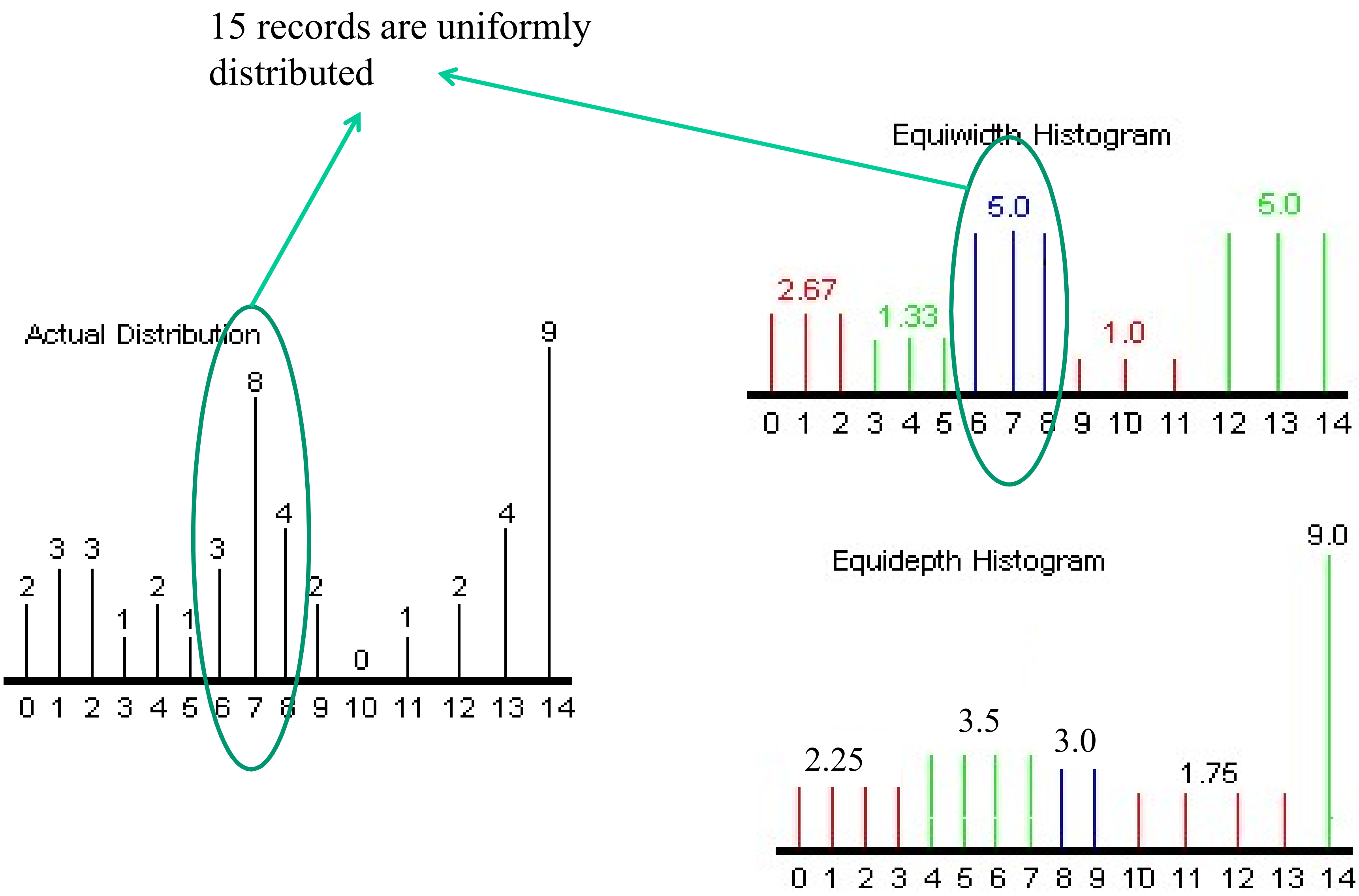
- Errors
  - source include uniformity assumption, and inability to capture correlation, accuracy of cost model, statistics, etc.
  - *propagated to other operators at the higher level of the plan tree*
- Dealing with errors
  - Maintain more detailed statistics (at finer granularity)
  - During runtime, may need to sample the actual intermediate results
    - *dynamic* query optimization



Statistical Summaries of Data

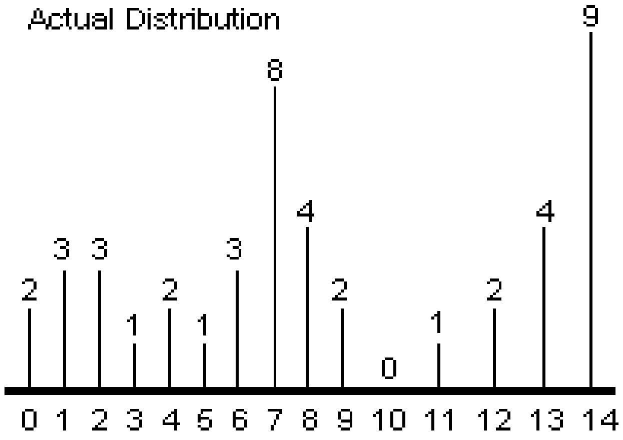
- More detailed information are sometimes stored e.g., histograms of the values in some attributes
  - a histogram divides the values on a column into k buckets
    - k is predetermined or computed based on space allocation
  - several choices for “bucketization” of values
    - If a table has n records, an equi-depth histogram divides the set of values on a column into k ranges such that each range has *approximately* the same number of records, i.e., n/k
    - Equi-width histogram – each bucket has (almost) equal number of values
    - Witihin each bucket, records are uniformly distributed across the range of the bucket
    - Frequently occurring values may be placed in singleton buckets

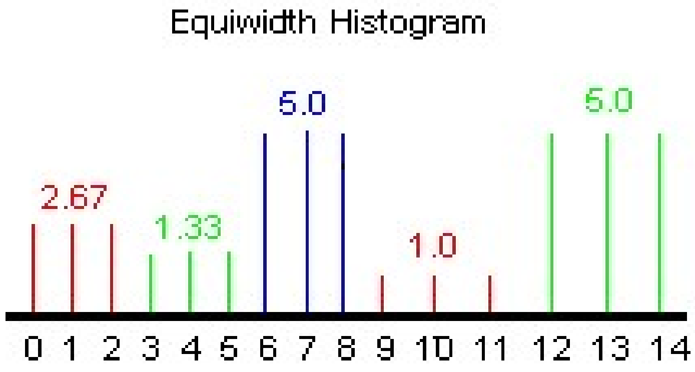
Histograms

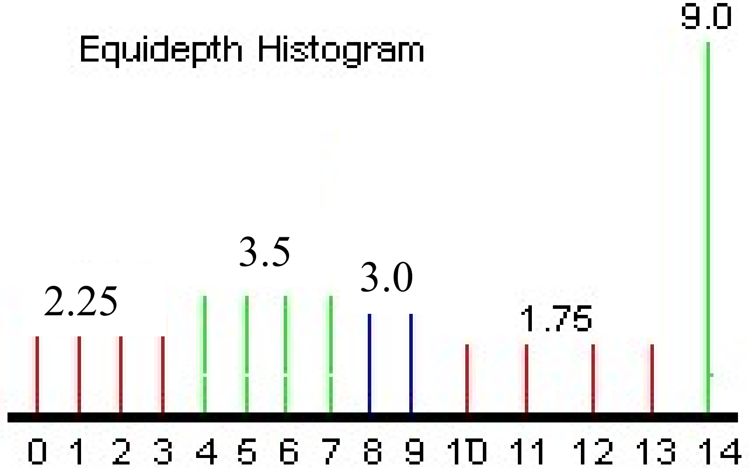


15 records are uniformly distributed

Estimations with Histograms


Actual Distribution


Equiwidth Histogram


Equidepth Histogram

Query Q: $\sigma_{A=6}$ (R)

Actual value, ||Q|| = 3
Without histogram, ||Q|| = 45/15 = 3
Equiwidth histogram, ||Q|| = 15/3 = 5
Equidepth histogram, ||Q|| = 14/4 = 3.5

Query Q: $\sigma_{A=10}$ (R)

Actual value, ||Q|| = 0
Without histogram, ||Q|| = 45/15 = 3
Equiwidth histogram, ||Q|| = 1
Equidepth histogram, ||Q|| = 1.75

Summary

- Query optimization is NP-hard
- Instead of finding the best, the objective is largely to avoid the bad plans
- Many different optimization strategies have been proposed
  - greedy heuristics are fast but may generate plans that are far from optimal
  - dynamic programming is effective at the expense of high optimization overhead