Query Optimization

Database Systems

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Concepts You Will Learn

- Query optimization, query optimizer
- Logical query plans
- Algebraic laws of equivalence
- Rule-based optimization, Heuristic
- Cost-based optimization
- Join trees
- Dynamic programming
- Physical query plans
- Intermediate results, pipeline, materialization
- Estimating sizes

The Big Picture: Where We Are

Relational Database Systems — **NonRelational** Toolkits

Structured — *SemiStructured* — *Untructured*

Query Language	Relational Databases • SQL
Data/Query Processing	• Relational Algebra • Query Optimization • Query Execution
Data Access	• Indexing
Transaction Management	• Concurrency Control • Logging Recovery
Data Acquisition	Information Extraction
Data Modeling	ER → Relational Model

XML Databases

NoSQL Databases

Map Reduce (Parallel)

Storm (Stream)

Why Do We Learn This?

Overview

Optimization

- At the heart of the database engine
- Step 1: convert the SQL query to some logical plan
- Step 2: find a better logical plan, find an associated physical plan

Converting from SQL to Logical Plans

SELECT a1, …, an

FROM R1, …, Rk

WHERE C

$$\pi_{a_1, \dots, a_n}(\sigma_C (R_1 \times R_2 \times \cdots \times R_k))$$

Optimization: Logical Query Plan

- Now we have one logical plan
- Algebraic laws:
  - foundation for every optimization
- Two approaches to optimizations:
  - Rule-based (heuristics): apply laws that seem to result in cheaper plans
  - Cost-based: estimate size and cost of intermediate results, search systematically for best plan

Motivating Example

Select S.name, C.instructor

From Students S, Enrollment E, Course C

Where S.dept = ‘CS’ and

S.sid=E.sid and E.cid = C.cid

The three components of an optimizer

- We need three things in an optimizer:

- Algebraic laws
- A cost estimator
- An optimization algorithm

Algebraic Laws

Algebraic Laws

- Commutative and Associative Laws
  - $R \cup S = S \cup R,\ R \cup (S \cup T) = (R \cup S) \cup T$
  - $R \cap S = S \cap R,\ R \cap (S \cap T) = (R \cap S) \cap T$
  - $R \bowtie S = S \bowtie R,\ R \bowtie (S \bowtie T) = (R \bowtie S) \bowtie T$
- Distributive Laws
  - $R \bowtie (S \cup T) = (R \bowtie S) \cup (R \bowtie T)$

Q: How to prove these laws?

Algebraic Laws

- Laws involving selection:
  - $\sigma_{C\ AND\ C'}(R) = \sigma_C(\sigma_{C'}(R)) = \sigma_C(R) \cap \sigma_{C'}(R)$
  - $\sigma_{C\ OR\ C'}(R) = \sigma_C(R) \cup \sigma_{C'}(R)$
  - $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
    - When C involves only attributes of R
  - $\sigma_C(R - S) = \sigma_C(R) - S$
  - $\sigma_C(R \cup S) = \sigma_C(R) \cup S$
  - $\sigma_C(R \cap S) = \sigma_C(R) \cap S$

- Q: What do they mean? Make sense?

Algebraic Laws

- Example: $R(A, B, C, D), S(E, F, G)$
  - $\sigma_{F=3}\ (R \ \bowtie_{D=E} S) \ =$?
  - $\sigma_{A=5\ AND\ G=9}\ (R \bowtie_{D=E} S) \ =$?

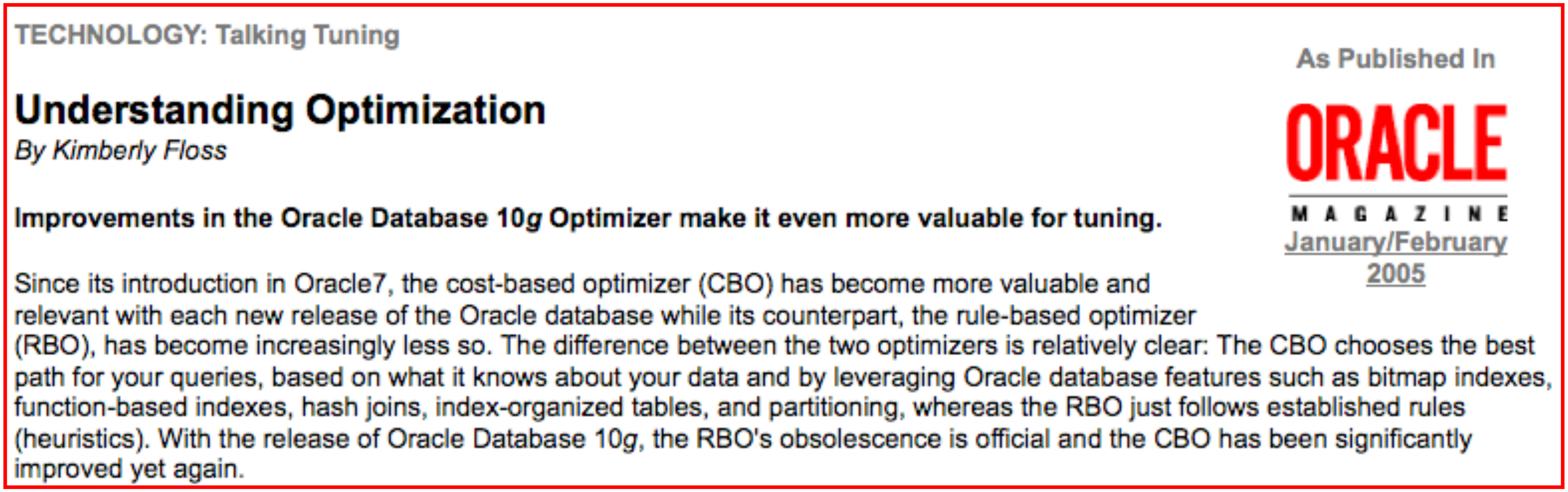
Algebraic Laws

- Laws involving projections
  - $\pi_M(R \bowtie S) = \pi_N(\pi_P(R) \bowtie \pi_Q(S))$
    - Where N, P, Q are appropriate subsets of attributes of M
  - $\pi_M(\pi_N(R)) = \pi_{M \cap N}(R)$

- Example $R(A, B, C, D), S(E, F, G)$
  - $\pi_{A,B,G}(R \bowtie_{D=E} S) = \pi_? (\pi_?(R) \bowtie \pi_?(S))$

Optimizer

Behind the Scene: Oracle RBO and CBO



TECHNOLOGY: Talking Tuning

As Published In

ORACLE MAGAZINE
January/February 2005

Understanding Optimization
By Kimberly Floss

Improvements in the Oracle Database 10*g* Optimizer make it even more valuable for tuning.

Since its introduction in Oracle7, the cost-based optimizer (CBO) has become more valuable and relevant with each new release of the Oracle database while its counterpart, the rule-based optimizer (RBO), has become increasingly less so. The difference between the two optimizers is relatively clear: The CBO chooses the best path for your queries, based on what it knows about your data and by leveraging Oracle database features such as bitmap indexes, function-based indexes, hash joins, index-organized tables, and partitioning, whereas the RBO just follows established rules (heuristics). With the release of Oracle Database 10*g*, the RBO's obsolescence is official and the CBO has been significantly improved yet again.

- Oracle 7 (1992) prior (since 1979): RBO.
- Oracle 7-10: RBO + CBO.
- Oracle 10g (2003): CBO.

Behind the Scene: Oracle RBO and CBO

Rule-based optimization sometimes provided better performance than the early versions of Oracle's cost-based optimizer for specific situations. The rule-based optimizer had several weaknesses, including offering only a simplistic set of rules. The Oracle rule-based optimizer had about 20 rules and assigned a weight to each one of them. In a complex database, a query can easily involve several tables, each with several indexes and complex selection conditions and ordering. This complexity means that there were a lot of options, and the simple set of rules used by the rule-based optimizer might not differentiate the choices well enough to make the best choice.

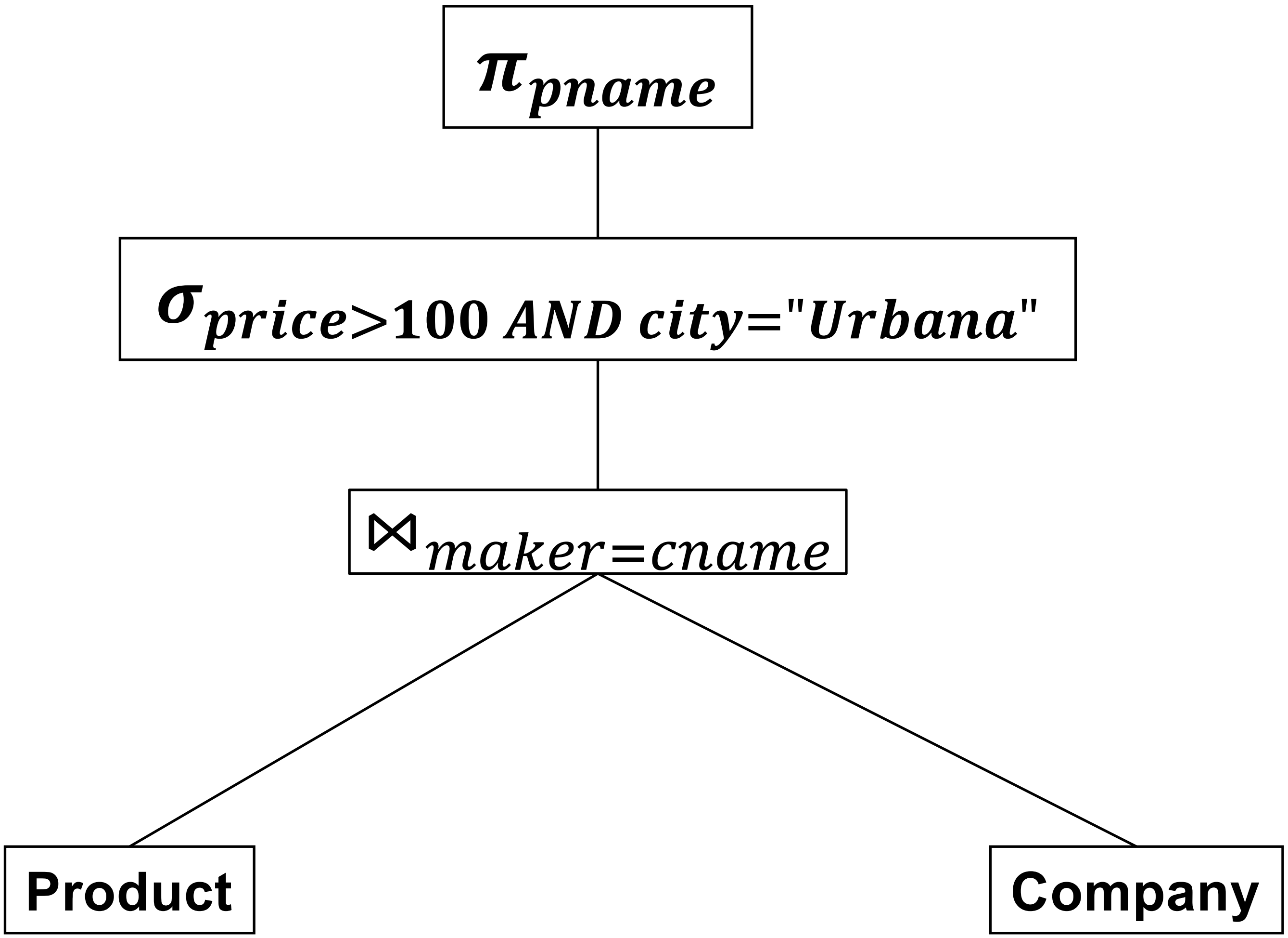
The rule-based optimizer assigned an optimization score to each potential execution path and then took the path with the best optimization score. Another weakness in the rule-based optimizer was resolution of optimization choices made in the event of a "tie" score. When two paths presented the same optimization score, the rule-based optimizer looked to the syntax of the SQL statement to resolve the tie. The winning execution path was based on the order in which the tables occur in the SQL statement.

Rule-based Optimization

Ruler-ased Optimizations

- Query rewriting based on heuristic/algebraic laws
- Result in better queries most of the time
- Heuristics number 1:
  - Push selections down
- Heuristics number 2:
  - Sometimes push selections up, then down

Predicate Pushdown



Product(pname, maker, price) Company(cname, city)

Cost-based Optimization

Behind the Scene: The Selinger Style!

Patricia Selinger

From Wikipedia, the free encyclopedia

Patricia Selinger is an American computer scientist and IBM Fellow, best known for her work on relational database management systems. She played a fundamental role in the development of System R, a pioneering relational database implementation, and wrote the canonical paper on relational query optimization.[1] The dynamic programming algorithm for determining join order proposed in that paper still forms the basis for most of the query optimizers used in modern relational systems.

She was made an IBM Fellow in 1994, was elected to the National Academy of Engineering in 1999, and won the SIGMOD Edgar F. Codd Innovations Award in 2002. Before her retirement, she was the Vice President of Data Management Architecture and Technology at IBM. She received A.B., S.M., and Ph.D. degrees in applied mathematics from Harvard University.

References [edit]

1. ^ Selinger, P. G.; Astrahan, M. M.; Chamberlin, D. D.; Lorie, R. A.; Price, T. G. (1979), "Access Path Selection in a Relational Database Management System", *Proceedings of the 1979 ACM SIGMOD International Conference on Management of Data*, pp. 23-34, doi:10.1145/582095.582099

ABSTRACT: In a high level query and data manipulation language such as SQL, requests are stated non-procedurally, without reference to access paths. This paper describes how System R chooses access paths for both simple (single relation) and complex queries (such as joins), given a user specification of desired data as a boolean expression of predicates. System R is an experimental database management system developed to carry out research on the relational model of data. System R was designed and built by members of the IBM San Jose Research Laboratory.

Behind the Scene: The Selinger Style!

In my view, the query optimizer was the first attempt at what we call autonomic computing or self-managing, self-timing technology. Query optimizers have been 25 years in development, with enhancements of the cost-based query model and the optimization that goes with it, and a richer and richer variety of execution techniques that the optimizer chooses from. We just have to keep working on this. It's a never-ending quest for an increasingly better model and repertoire of optimization and execution techniques. So the more the model can predict what's really happening in the data and how the data is really organized, the closer and closer we will come [to the ideal system].

In hindsight, I didn't really have enough experience as a system designer and developer to realize that System R was going to be something that people [within IBM] were going to take almost as is, and make a productized copy of it and [sell] it. So designing control blocks, designing interfaces and APIs to programming languages---we just sort of put together something that we thought would work. The error control block, the way that you pass variables and parameters into the system---those were not designed with thought and care and elegance. They were [just]

Cost-based Optimization

- Main idea: apply algebraic laws, until estimated cost is minimal
- Practically: start from partial plans, introduce operators one by one
  - Will see in a few slides
- Problem: there are too many ways to apply the laws, hence too many (partial) plans

Cost-based Optimization

- Approaches:

- Top-down: the partial plan is a top fragment of the logical plan

- Bottom up: the partial plan is a bottom fragment of the logical plan

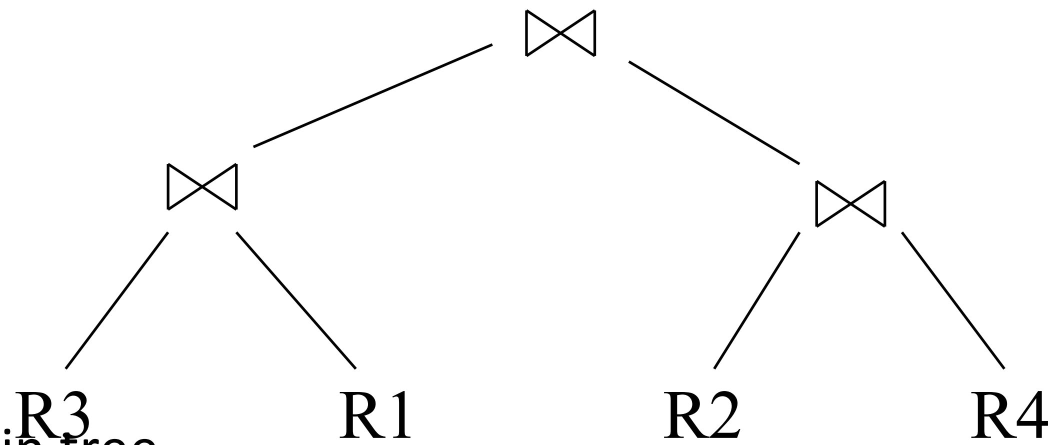
Search Strategies

- Branch-and-bound:
  - Remember the cheapest complete plan P seen so far and its cost C
  - Stop generating partial plans whose cost is > C
  - If a cheaper complete plan is found, replace P, C
- Hill climbing:
  - Remember only the cheapest partial plan seen so far
- Dynamic programming:
  - Remember all cheapest partial plans

Dynamic Programming

Join Trees

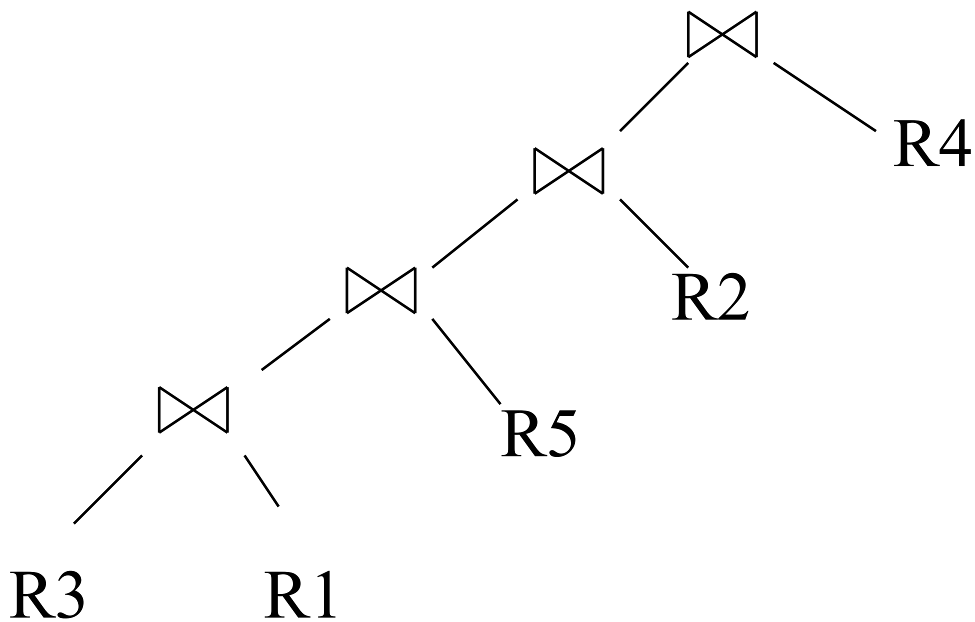
- $R1 \bowtie R2 \bowtie \ldots . \bowtie Rn$
- Join tree:



- A plan = a join tree
- A partial plan = a subtree of a join tree

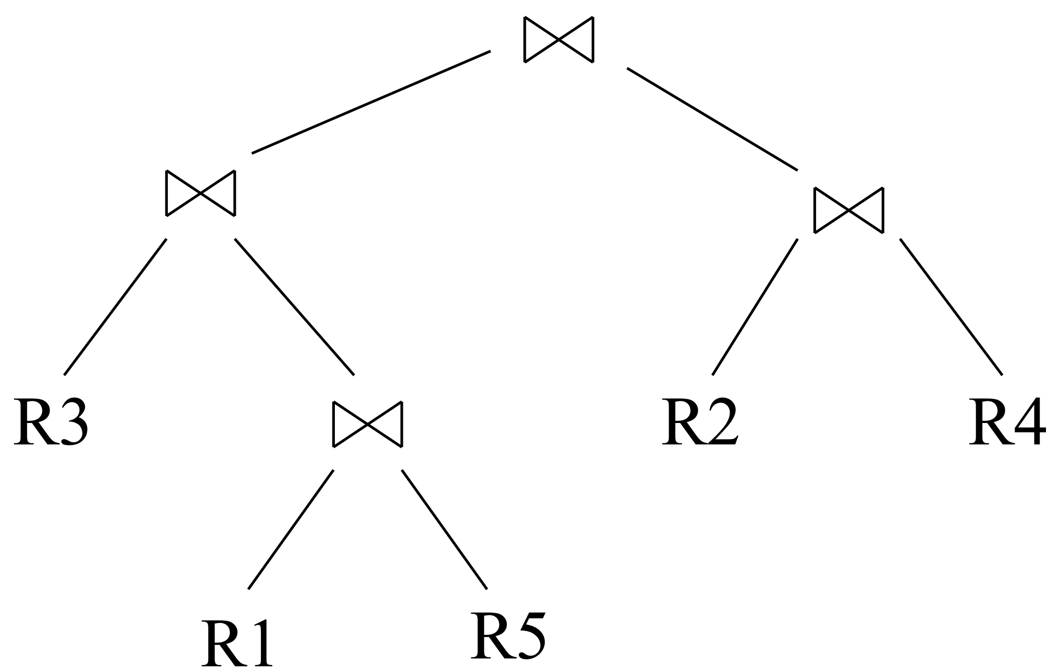
Types of Join Trees

- Left deep:



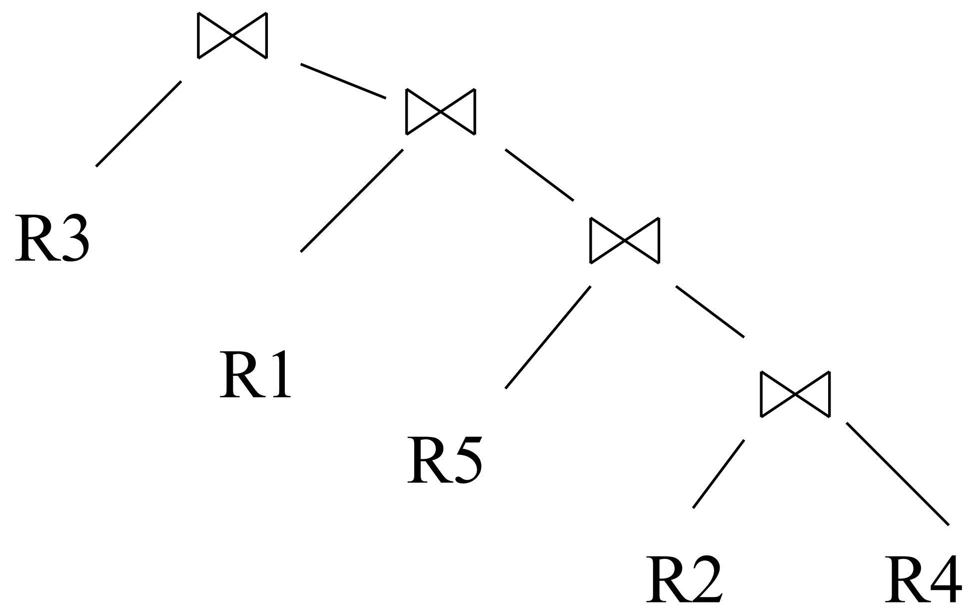
Types of Join Trees

- Bushy:



Types of Join Trees

- Right deep:



Problem

- Given: a query $R1 \bowtie R2 \bowtie \ldots \bowtie Rn$
- Assume we have a function cost() that gives us the cost of every join tree
- Find the best join tree for the query

Dynamic Programming

- Idea: for each subset of $\{R_1, \ldots, R_n\}$, compute the best plan for that subset
- In increasing order of set cardinality:
  - $Step\ 1$: $for\ \{R_1\}, \{R_2\}, \ldots, \{R_n\}$
  - $Step\ 2$: $for\ \{R_1, R_2\}, \{R_1, R_3\}, \ldots, \{R_{n-1}, R_n\}$
  - …
  - $Step\ n$: $for\ \{R_1, \ldots, R_n\}$
  - For each subset of $\{R_1, \ldots, R_n\}$, also called a subquery, compute the following:
    - Size(Q)
    - Best plan for Q: Plan(Q)
    - Cost of that plan: Cost(Q)

Dynamic Programming

- To illustrate, we will make the following simplifications:
- $Cost(P1 \bowtie P2) = Cost(P1) + Cost(P2) + size(intermediate\ result)$
- Intermediate results:
  - If P1 = a join, then the size of the intermediate result is size(P1), otherwise the size is 0
  - Similarly for P2
- Cost of a scan = 0, i.e., $Cost(R)$ = 0.

Dynamic Programming

- Example:
- $Cost(R1 \bowtie R2) = Cost(R1) + Cost(R2) + size(intermediate\ result)$ = 0

- $Cost\big((R1 \bowtie R2) \bowtie R3\big)$
$$= Cost(R1 \bowtie R2) + Cost(R3) + size(R1 \bowtie R2)$$
$$= size(R1 \bowtie R2)$$

Dynamic Programming

- Relations: R, S, T, U
- Number of tuples: 2000, 5000, 3000, 1000
- Size estimation: $T(A \bowtie B) = 0.01 * T(A) * T(B)$

Subquery	Size	Cost	Plan
RS			
RT			
RU			
ST			
SU			
TU			
RST			
RSU			
RTU			
STU			
RSTU			

Subquery	Size	Cost	Plan
RS	100k	0	RS
RT	60k	0	RT
RU	20k	0	RU
ST	150k	0	ST
SU	50k	0	SU
TU	30k	0	TU
RST	3M	60k	(RT)S
RSU	1M	20k	(RU)S
RTU	0.6M	20k	(RU)T
STU	1.5M	30k	(TU)S
RSTU	30M	60k+50k=110k	(RT)(SU)

Dynamic Programming

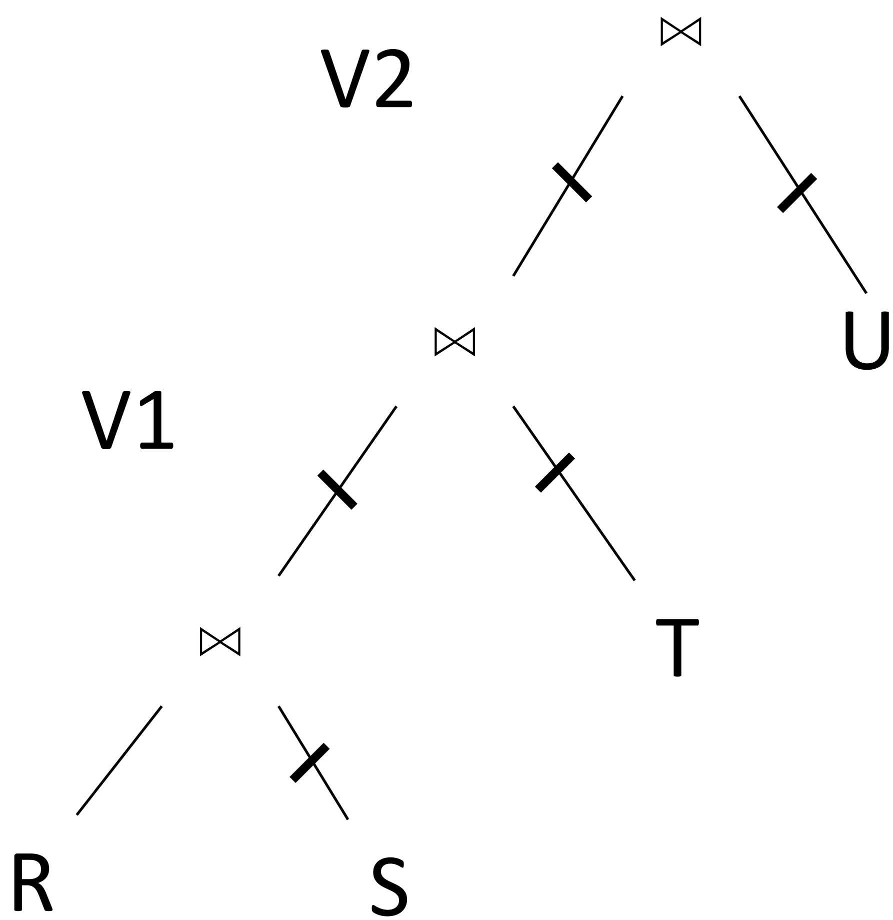
- Summary: computes optimal plans for subqueries:
  - Step 1: {R1}, {R2}, …, {Rn}
  - Step 2: {R1, R2}, {R1, R3}, …, {Rn-1, Rn}
  - …
  - Step n: {R1, …, Rn}
- We used naïve size/cost estimations
- In practice:
  - more realistic size/cost estimations (next time)
  - heuristics for Reducing the Search Space
    - Restrict to left linear trees
    - Restrict to trees “without Cartesian product”:
      - R(A,B), S(B,C), T(C,D)
      - (R join T) join S has a Cartesian product

Completing Physical Query Plan

Completing the Physical Query Plan

- Choose algorithm to implement each operator
  - Need to account for more than cost:
    - How much memory do we have ?
    - Are the input operand(s) sorted ?
- Decide for each intermediate result:
  - To materialize
  - To pipeline

Materialize Intermediate Results Between Operators



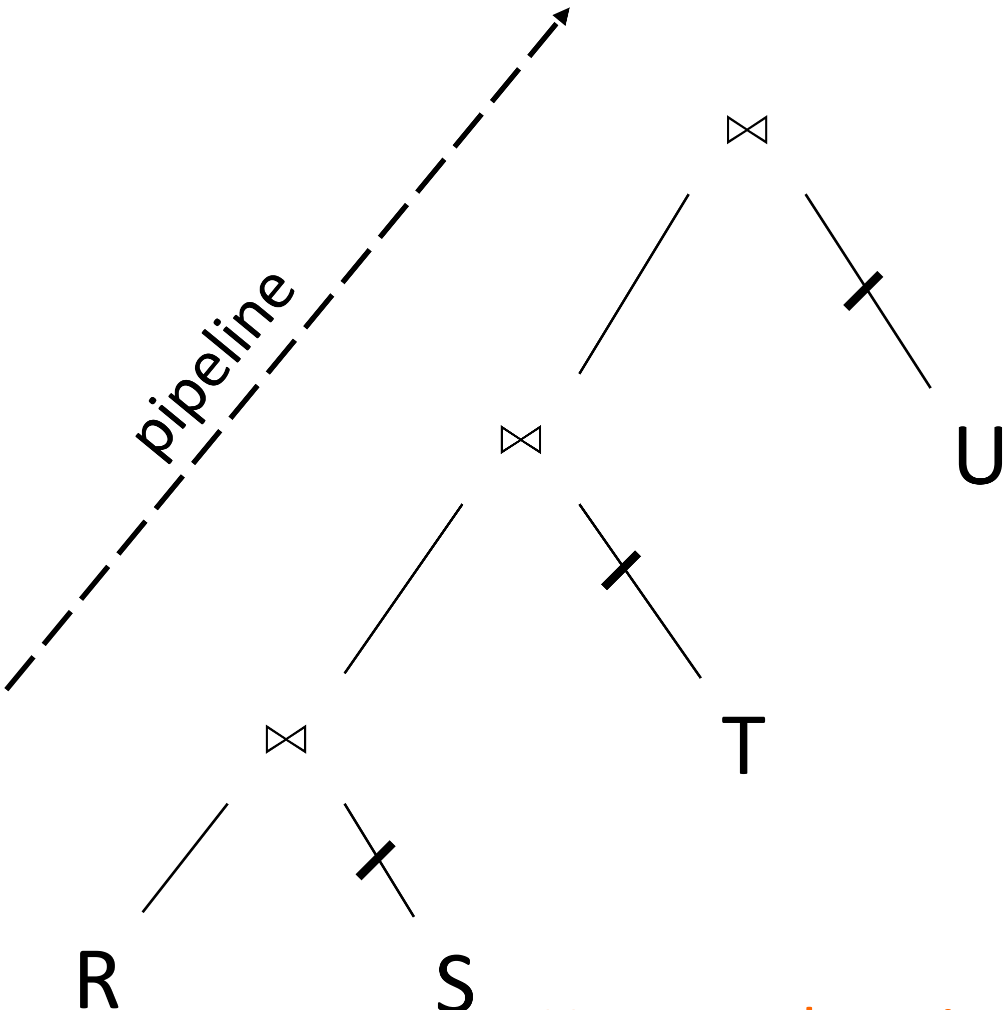

```
HashTable ← S
repeat    read(R, x)
          y ← join(HashTable, x)
          write(V1, y)

HashTable ← T
repeat    read(V1, y)
          z ← join(HashTable, y)
          write(V2, z)

HashTable ← U
repeat    read(V2, z)
          u ← join(HashTable, z)
          write(Answer, u)
```

Materialize Intermediate Results Between Operators

- Given B(R), B(S), B(T), B(U)

- What is the total cost of the plan ?
  - Cost =
- How much main memory do we need ?
  - M =

Pipeline Between Operators




```
HashTable1 ← S
HashTable2 ← T
HashTable3 ← U
repeat    read(R, x)
          y ← join(HashTable1, x)
          z ← join(HashTable2, y)
          u ← join(HashTable3, z)
          write(Answer, u)
```

How much main memory do we need ? M =

Pipeline Between Operators

- Given B(R), B(S), B(T), B(U)

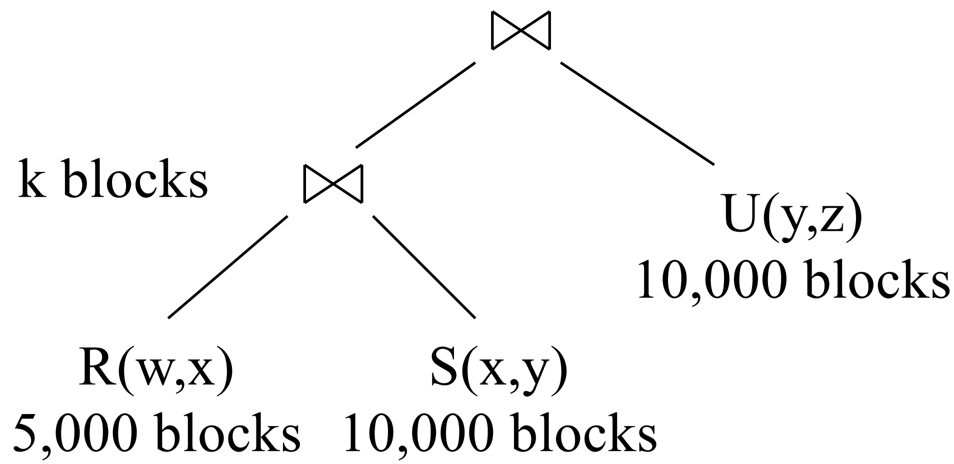
- What is the total cost of the plan ?
  - Cost =
- How much main memory do we need ?
  - M =

Completing the Physical Query Plan

- Choose algorithm to implement each operator
  - Need to account for more than cost:
    - How much memory do we have ?
    - Are the input operand(s) sorted ?
- Decide for each intermediate result:
  - To materialize
  - To pipeline

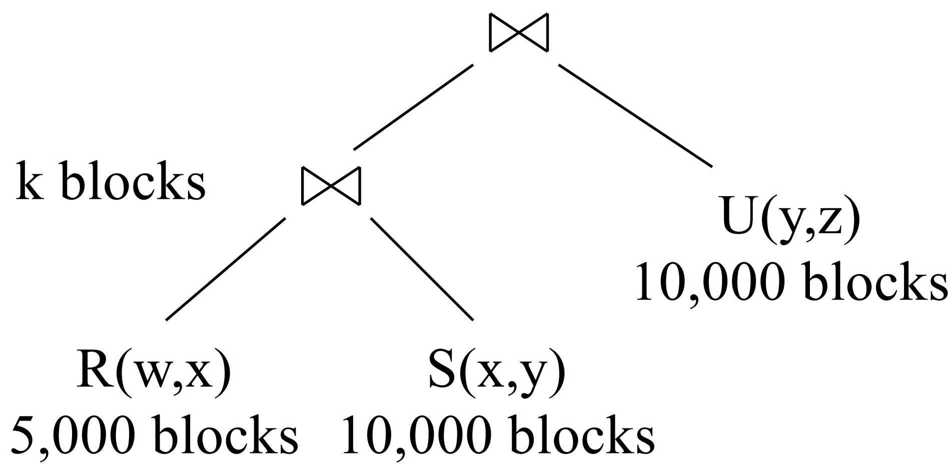
Example

- Logical plan is:



- Main memory M = 101 buffers

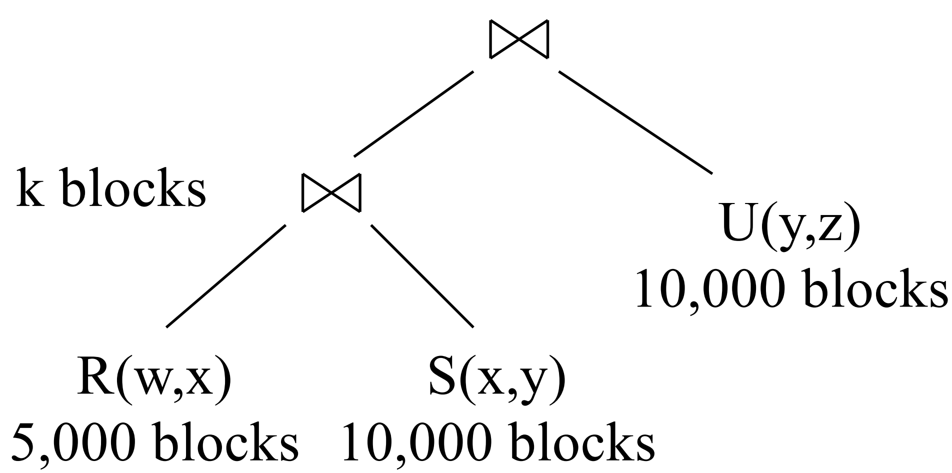
Example



- Naïve evaluation:
- 2 partitioned hash-joins
- Cost 3B(R) + 3B(S) + 4k + 3B(U) = 75000 + 4k

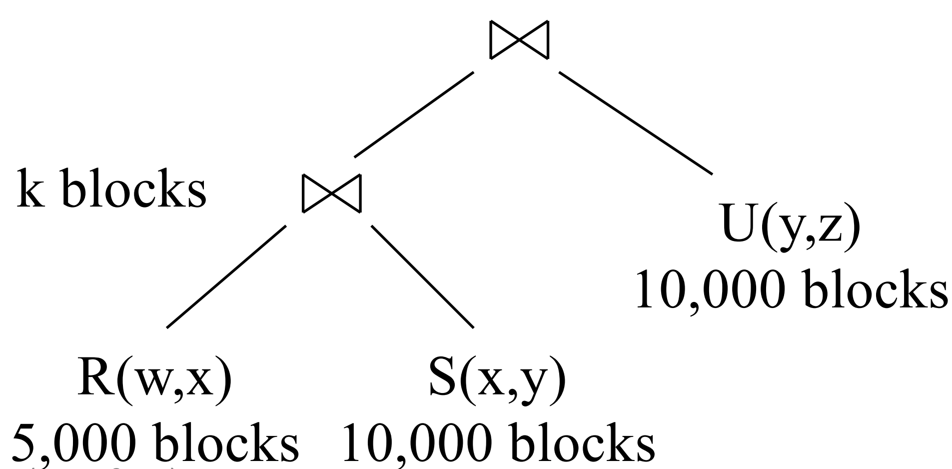
Example

- Smarter:
- Step 1: hash R on x into 100 buckets, each of 50 blocks; to disk
- Step 2: hash S on x into 100 buckets; to disk
- Step 3: read each Ri in memory (50 buffer) join with Si (1 buffer); hash result on y into 50 buckets (50 buffers)   -- here we pipeline
- Cost so far: 3B(R) + 3B(S)



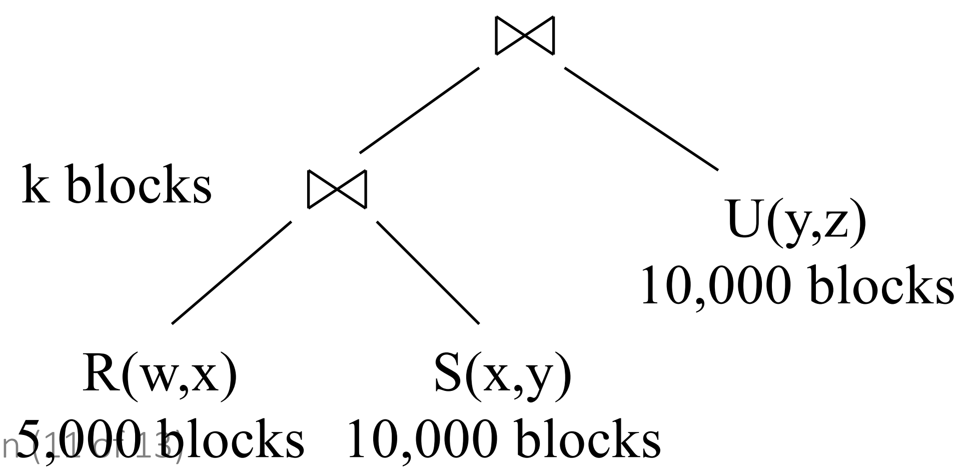
Example

- Continuing:
- How large are the 50 buckets on y ? Answer: k/50.
- If k <= 50 then keep all 50 buckets in Step 3 in memory, then:
- Step 4: read U from disk, hash on y and join with memory
- Total cost: 3B(R) + 3B(S) + B(U) = 55,000

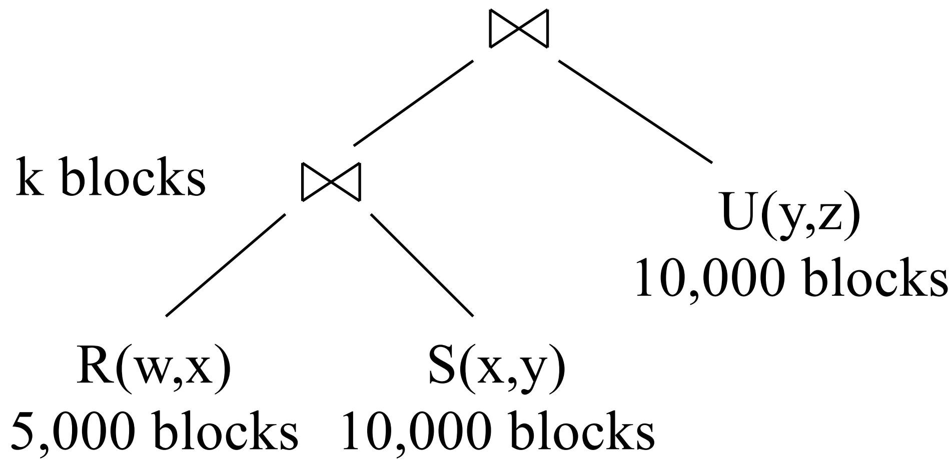


Example

- Continuing:
- If 50 < k <= 5000 then send the 50 buckets in Step 3 to disk
  - Each bucket has size k/50 <= 100
- Step 4: partition U into 50 buckets
- Step 5: read each partition and join in memory
- Total cost: 3B(R) + 3B(S) + 2k + 3B(U) = 75,000 + 2k



Example



- Continuing:
- If k > 5000 then materialize instead of pipeline
- 2 partitioned hash-joins
- Cost 3B(R) + 3B(S) + 4k + 3B(U) = 75000 + 4k

Example

- Summary:
- If $k <= 50$, cost = 55,000
- If $50 < k <= 5000$, cost = 75,000 + 2k
- If $k > 5000$, cost = 75,000 + 4k

Estimating Sizes

Estimating Sizes

- Need size in order to estimate cost
- Example:
  - Cost of partitioned hash-join $E1 \bowtie E2$ is $3B(E1) + 3B(E2)$
  - $B(E1) = T(E1)/\ block\ size$
  - $B(E2) = T(E2)/\ block\ size$
  - So, we need to estimate $T(E1), T(E2)$

Estimating Sizes

- Estimating the size of a projection
- Easy: $T(\pi_L(R)) \; = \; T(R)$
- A projection doesn't eliminate duplicates

Estimating Sizes

- Estimating the size of a selection
- $S = \sigma_{A=c}(R)$
  - T(S) can be anything from 0 to $T(R)$ – $V(R, A) + 1$
  - Mean value: $T(S) = T(R)/V(R, A)$
- $S = \sigma_{A<c}(R)$
  - T(S) can be anything from 0 to $T(R)$
  - Heuristics: $T(S) = T(R)/3$

Estimating Sizes

- Estimating the size of a natural join, $R \bowtie_A S$
- When the set of A values are disjoint, then
- $\quad T(R \bowtie_A S) = 0$
- When A is a key in S and a foreign key in R, then $T(R \bowtie_A S) = T(R)$
- When A has a unique value, the same in R and S, then $T(R \bowtie_A S) = \min\big(T(R), T(S)\big)$.

Estimating Sizes

- Assumptions:
- Containment of values: if $V(R, A) \ <= \ V(S, A)$, then the set of R.A values is included in the set of S.A values
  - Indeed holds when A is a foreign key in R, and a key in S

- Preservation of values: for any other attribute B,
- $V(R \bowtie_A S, B) = V(R, B)$ or $V(S, B)$.

Estimating Sizes

- Assume $V(R, A) \ <= \ V(S, A)$

- Then each tuple t in R joins some tuple(s) in S
  - How many?
  - On average $S/V(S, A)$
  - It will contribute $S/V(S, A)$ tuples in $R \bowtie_A S$

  - Hence $T(R \bowtie_A S) = T(R)T(S)/V(S, A)$

  - In general:
  - $T(R \bowtie_A S) = T(R)T(S)/\max(V(R, A), V(S, A))$

Estimating Sizes

- Example:
- $T(R) = 10000,\ T(S) = 20000$
- $V(R, A) = 100,\ V(S, A) = 200$
- How large is $R \bowtie_A S$?

- Answer:
- $T(R \bowtie_A S) = 10000 * 20000/200 = 1M$

Estimating Sizes

- Joins on more than one attribute:
- $T(R \bowtie_{A,B} S) = \frac{T(R)T(S)}{\max(V(R,A), V(S,A)) \cdot \max(V(R,B), V(S,B))}$

More statistics helps: E.g., Histograms

- Statistics on data maintained by the RDBMS
- Makes size estimation much more accurate (hence, cost estimations are more accurate)

- Ranks(rankName, salary)
- Estimate the size of $Employee \bowtie_{Salary} Ranks$

Employee	0..20k	20k..40k	40k..60k	60k..80k	80k..100k	> 100k
	200	800	5000	12000	6500	500

Ranks	0..20k	20k..40k	40k..60k	60k..80k	80k..100k	> 100k
	8	20	40	80	100	2