Lecture 4

Database Management Systems

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CMPUT 391: An Overview of Query Optimization

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Chapter 14 of Textbook

Based on slides by Lewis, Bernstein and Kifer.

Query Evaluation

- ***Problem***: An SQL query is declarative – does not specify a query execution plan.
- A relational algebra expression is procedural – there is an associated query execution plan.
- ***Solution*:** Convert SQL query to an equivalent relational algebra and evaluate it using the associated query execution plan.
  – *But which equivalent expression is best?*

Naïve Conversion

```
SELECT DISTINCT  TargetList
FROM      R1, R2, …, RN
WHERE     Condition
```

is equivalent to

$$\pi_{TargetList}(\sigma_{Condition}(R1 \times R2 \times ... \times RN))$$

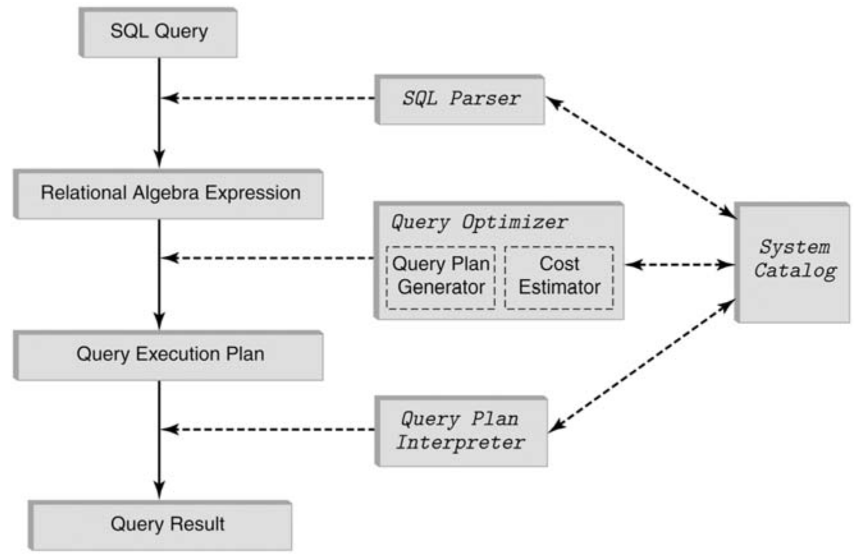
but this may imply a very inefficient query execution plan.

Example: $\pi_{Name}(\sigma_{Id=ProfId\ CrsCode='CS532'}(\text{Professor} \times \text{Teaching}))$

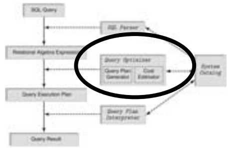
- Result can be < 100 bytes
- But if each relation is 50K then we end up computing an intermediate result Professor × Teaching of size 1G before shrinking it down to just a few bytes.

Problem: Find an *equivalent* relational algebra expression that can be evaluated "*efficiently*".

Query Processing Architecture



Query Optimizer



- Uses heuristic algorithms to evaluate relational algebra expressions. This involves:
  - estimating the cost of a relational algebra expression
  - transforming one relational algebra expression to an equivalent one
  - choosing access paths for evaluating the sub-expressions
- Query optimizers do not "optimize" – just try to find "reasonably good" evaluation strategies

Equivalence Preserving Transformations

- To transform a relational expression into another equivalent expression we need transformation rules that preserve equivalence
- Each transformation rule
  - Is provably correct (ie, does preserve equivalence)
  - Has a heuristic associated with it

Selection and Projection Rules

- Break complex selection into simpler ones:
  - $\sigma_{Cond1 \wedge Cond2}(R) \equiv \sigma_{Cond1}(\sigma_{Cond2}(R))$
- Break projection into stages:
  - $\pi_{attr}(R) \equiv \pi_{attr}(\pi_{attr'}(R))$, if $attr \subseteq attr'$
- Commute projection and selection:
  - $\pi_{attr}(\sigma_{Cond}(R)) \equiv \sigma_{Cond}(\pi_{attr}(R))$, if $attr \supseteq$ all attributes in $Cond$

Commutativity and Associativity of Join

(and Cartesian Product as Special Case)

- Join commutativity: $R \bowtie S \equiv S \bowtie R$
  - used to reduce cost of nested loop evaluation strategies (smaller relation should be in outer loop)
- Join associativity: $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$
  - used to reduce the size of intermediate relations in computation of multi-relational join – first compute the join that yields smaller intermediate result
- N-way join has $T(N) \times N!$ different evaluation plans
  - $T(N)$ is the number of parenthesized expressions
  - $N!$ is the number of permutations
- Query optimizer <u>cannot</u> look at all plans (might take longer to find an optimal plan than to compute query brute-force). Hence it does not necessarily produce optimal plan

Pushing Selections and Projections

- $\sigma_{Cond}(R \times S) \equiv R \bowtie_{Cond} S$
  - *Cond* relates attributes of both R and S
  - Reduces size of intermediate relation since rows can be discarded sooner
- $\sigma_{Cond}(R \times S) \equiv \sigma_{Cond}(R) \times S$
  - *Cond* involves only the attributes of R
  - Reduces size of intermediate relation since rows of R are discarded sooner
- $\pi_{attr}(R \times S) \equiv \pi_{attr}(\pi_{attr'}(R) \times S)$,
  if $attributes(R) \supseteq attr' \supseteq attr$
  - reduces the size of an operand of product

Equivalence Example

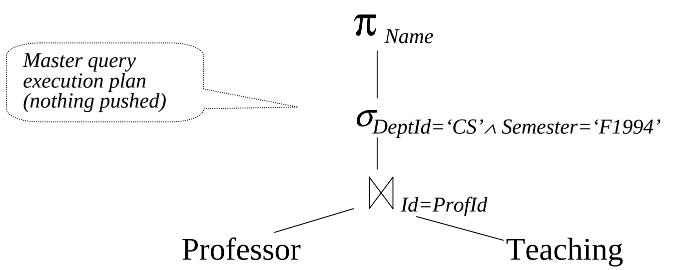
- $\sigma_{C1 \wedge C2 \wedge C3}(R \times S) \equiv \sigma_{C1}(\sigma_{C2}(\sigma_{C3}(R \times S)))$
  $\equiv \sigma_{C1}(\sigma_{C2}(R) \times \sigma_{C3}(S))$
  $\equiv \sigma_{C2}(R) \bowtie_{C1} \sigma_{C3}(S)$

assuming *C2* involves only attributes of R,
C3 involves only attributes of S,
and *C1* relates attributes of R and S

Cost - Example 1

```
SELECT P.Name
FROM   Professor P, Teaching T
WHERE  P.Id = T.ProfId          -- join condition
       AND P. DeptId = 'CS' AND T.Semester = 'F1994'
```

$\pi_{Name}(\sigma_{DeptId='CS' \wedge Semester='F1994'}(\text{Professor} \bowtie_{Id=ProfId} \text{Teaching}))$



Metadata on Tables (in system catalogue)

- Professor (*Id*, *Name*, *DeptId*)
  - *size*: 200 pages, 1000 rows, 50 departments
  - *indexes*: clustered, 2-level B^+tree on *DeptId*, hash on *Id*
- Teaching (*ProfId*, *CrsCode*, *Semester*)
  - *size*: 1000 pages, 10,000 rows, 4 semesters
  - *indexes*: clustered, 2-level B^+tree on Semester;
    hash on *ProfId*
- **Definition**: *Weight of an attribute – average number of rows that have a particular value*
  - *weight* of *Id* = 1 (it is a key)
  - *weight* of *ProfId* = 10 (10,000 classes/1000 professors)

Estimating Cost - Example 1

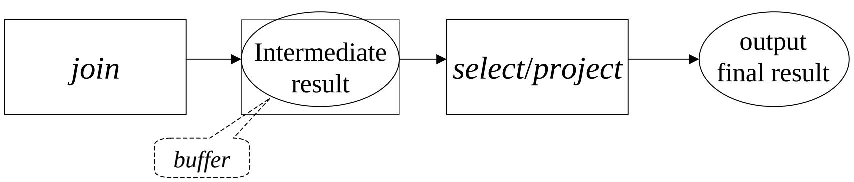
- *Join* - block-nested loops with 52 page buffer (50 pages – input for Professor, 1 page – input for Teaching, 1 – output page
  - Scanning Professor (outer loop): 200 page transfers, (4 iterations, 50 pages each)
  - Finding matching rows in Teaching (inner loop): 1000 page transfers <u>*for each iteration*</u> of outer loop
    - 250 professors in each 50 page chunk * 10 matching Teaching tuples per professor = 2500 tuple fetches = 2500 page transfers for Teaching (Why?)
    - By sorting the record Ids of these tuples we can get away with only 1000 page transfers (Why?)
  - total cost = 200+4*1000 = 4200 page transfers

Estimating Cost - Example 1 (cont'd)

- *Selection* and *projection* – scan rows of intermediate file, discard those that don't satisfy selection, project on those that do, write result when output buffer is full.
- Complete algorithm:
  - do *join*, write result to intermediate file on disk
  - read intermediate file, do *select*/*project*, write final result
  - **Problem**: unnecessary I/O

Pipelining

- **Solution**: use *pipelining:*
  - *join* and *select*/*project* act as coroutines, operate as producer/consumer sharing a buffer in main memory.
    - When join fills buffer; *select*/*project* filters it and outputs result
    - Process is repeated until *select*/*project* has processed last output from join
  - Performing select/project adds no additional cost



Estimating Cost - Example 1 (cont'd)

- Total cost:

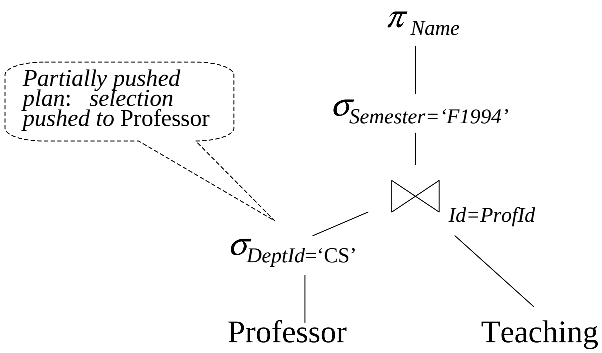
  4200 + (cost of outputting final result)

  - We will *disregard the cost of outputting final result* in comparing with other query evaluation strategies, since this will be same for all

Cost Example 2

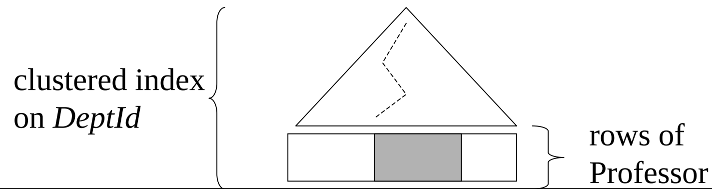
SELECT P.*Name*
FROM Professor P, Teaching T
WHERE P.Id = T.*ProfId* AND
P. *DeptId* = 'CS' AND T.*Semester* = 'F1994'

$\pi_{Name}(\sigma_{Semester=\text{'F1994'}}(\sigma_{DeptId=\text{'CS'}}(\text{Professor}) \bowtie_{Id=ProfId} \text{Teaching}))$



Cost Example 2 -- *selection*

- Compute $\sigma_{DeptId=\text{'CS'}}$ (Professor) (to reduce size of one join table) using clustered, 2-level B+ tree on *DeptId*.
  - 50 departments and 1000 professors; hence *weight* of DeptId is 20 (roughly 20 CS professors). These rows are in ~4 consecutive pages in Professor.
    - Cost = 4 (to get rows) + 2 (to search index) = 6
    - keep resulting 4 pages in memory and pipe to next step

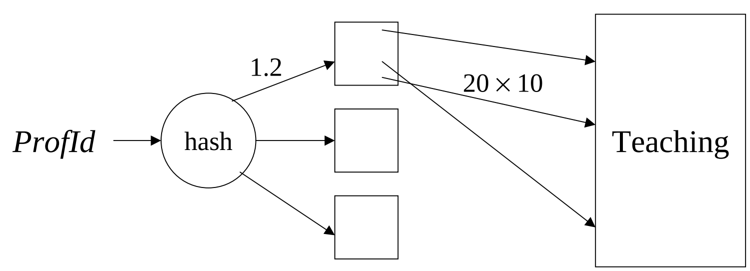


Cost Example 2 -- *join*

- Index-nested loops join using hash index on *ProfId* of Teaching and looping on the selected professors (computed on previous slide)
  - Since selection on *Semester* was not pushed, hash index on *ProfId* of Teaching can be used
  - *Note*: if selection on *Semester* were pushed, the index on *ProfId* would have been lost – an advantage of *not* using a fully pushed query execution plan

Cost Example 2 – *join* (cont'd)

- Each professor matches ~10 Teaching rows. Since 20 CS professors, hence 200 teaching records.
- All index entries for a particular *ProfId* are in same bucket. Assume ~1.2 I/Os to get a bucket.
  - Cost = 1.2 × 20 (to fetch index entries for 20 CS professors) + 200 (to fetch Teaching rows, since hash index is unclustered) = 224



Cost Example 2 – *select*/*project*

- Pipe result of join to *select* (on *Semester*) and *project* (on *Name*) at no I/O cost
- Cost of output same as for Example 1
- Total cost:

  6 (select on Professor) + 224 (join) = 230
- Comparison:

  4200 (example 1) vs. 230 (example 2) !!!

Estimating Output Size

- It is important to estimate the size of the output of a relational expression – size serves as input to the next stage and affects the choice of how the next stage will be evaluated.
- Size estimation uses the following measures on a particular instance of R:
  - *Tuples*(R): number of tuples
  - *Blocks*(R): number of blocks
  - *Values*(R.*A*): number of distinct values of *A*
  - *MaxVal*(R.*A*): maximum value of *A*
  - *MinVal*(R.*A*): minimum value of *A*

Estimating Output Size

- For the query:

```
SELECT TargetList
FROM   R1, R2, …, Rn
WHERE  Condition
```

  - *Reduction factor* is

$$\frac{\textit{Blocks}\text{ (result set)}}{\textit{Blocks}(R_1) \times \ldots \times \textit{Blocks}(R_n)}$$

    - Estimates by how much query result is smaller than input

Estimation of Reduction Factor

- Assume that reduction factors due to target list and query condition are independent
- Thus:

  reduction(Query) =

  reduction(TargetList) × *reduction(Condition)*

Reduction Due to Simple *Condition*

- *reduction* $(R_i.A=val) = \frac{1}{Values(R.A)}$
- *reduction* $(R_i.A=R_j.B) = \frac{1}{max(Values(R_i.A), Values(R_j.B))}$
  - Assume that values are uniformly distributed, $Tuples(R_i) < Tuples(R_j)$, and every row of R_i matches a row of R_j. Then the number of tuples that satisfy *Condition* is:

$$Values(R_i.A) \times (Tuples(R_i.A)/Values(R_i.A)) \times (Tuples(R_j.A)/Values(R_j.A))$$

- *reduction* $(R_i.A > val) = \frac{MaxVal(R_i.A) - val}{Values(R_i.A)}$

Reduction Due to Complex *Condition*

- $reduction(Cond_1 \text{ AND } Cond_2) =$
  $reduction(Cond_1) \times reduction(Cond_2)$
- $reduction(Cond_1 \text{ OR } Cond_2) =$
  $\min(1, reduction(Cond_1) + reduction(Cond_2))$

Reduction Due to *TargetList*

- *reduction(TargetList) =*

$$\frac{number\text{-}of\text{-}attributes\ (TargetList)}{\Sigma_i\ number\text{-}of\text{-}attributes\ (R_i)}$$

Estimating Weight of Attribute

weight(R.*A*) =

$$Tuples(R) \times reduction(R.A=value)$$

Choosing Query Execution Plan

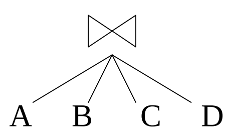
- Step 1: Choose a *logical* plan
- Step 2: Reduce search space
- Step 3: Use a heuristic search to further reduce complexity

Step 1: Choosing a Logical Plan

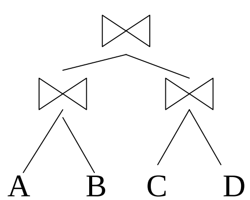
- Involves choosing a query tree, which indicates the order in which algebraic operations are applied
- *Heuristic*: Pushed trees are good, but sometimes “nearly fully pushed” trees are better due to indexing (as we saw in the example)
- **So**: Take the initial “master plan” tree and produce a *fully pushed* tree plus several *nearly fully pushed* trees.

Step 2: Reduce Search Space

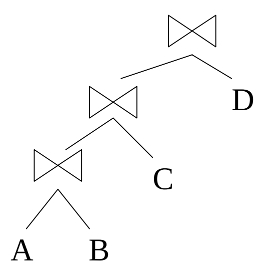
- Deal with *associativity* of binary operators (join, union, …)



Logical query execution plan



Equivalent query tree



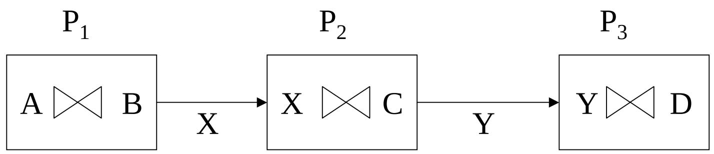
Equivalent *left deep query tree*

Step 2 (cont’d)

- Two issues:
  - Choose a particular *shape* of a tree (like in the previous slide)
    - Equals the number of ways to parenthesize N-way join – grows very rapidly
  - Choose a particular permutation of the leaves
    - E.g., 4! permutations of the leaves A, B, C, D

Step 2: Dealing With Associativity

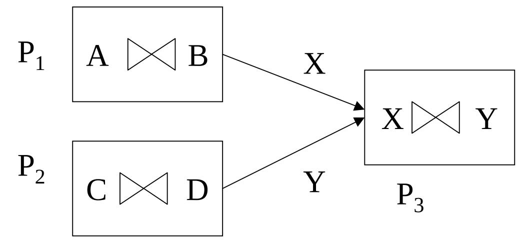
- Too many trees to evaluate: settle on a particular shape: *left-deep tree.*
  - Used because it allows *pipelining*:



  - *Property*: once a row of X has been output by P_1, it need not be output again (but C may have to be processed several times in P_2 for successive portions of X)
  - *Advantage*: none of the intermediate relations (X, Y) have to be completely materialized and saved on disk.
    - Important if one such relation is very large, but the final result is small

Step 2: Dealing with Associativity

- consider the alternative: if we use the association ((A $\bowtie$ B) $\bowtie$ (C $\bowtie$ D))



Each row of X must be processed against all of Y. Hence all of Y (can be very large) must be stored in P_3, or P_2 has to recompute it several times.

Step 3: Heuristic Search

- The choice of left-deep trees still leaves open too many options (N! permutations):
  - (((A $\bowtie$ B) $\bowtie$ C) $\bowtie$ D),
  - (((C $\bowtie$ A) $\bowtie$ D) $\bowtie$ B), …..
- A heuristic (often dynamic programming based) algorithm is used to get a 'good' plan

Step 3: Dynamic Programming Algorithm

- Just an idea – see book for details
- To compute a join of E_1, E_2, …, E_N in a left-deep manner:
  - Start with 1-relation expressions (can involve σ, π)
  - Choose the best and "nearly best" plans for each (a plan is considered nearly best if its output has some "interesting" form, e.g., is sorted)
  - Combine these 1-relation plans into 2-relation expressions. Retain only the best and nearly best 2-relation plans
  - Do same for 3-relation expressions, etc.

Index-Only Queries

- A B^+ tree index with search key attributes $A_1, A_2, \ldots, A_n$ has stored in it the values of these attributes for each row in the table.
  - Queries involving a prefix of the attribute list $A_1, A_2, .., A_n$ can be satisfied using *only the index* – no access to the actual table is required.
- **Example**: Transcript has a clustered B^+ tree index on *StudId*. A frequently asked query is one that requests all grades for a given *CrsCode*.
  - ***Problem***: Already have a clustered index on StudId – cannot create another one (on *CrsCode)*
  - ***Solution***: Create an unclustered index on (*CrsCode, Grade*)
    - Keep in mind, however, the overhead in maintaining extra indices