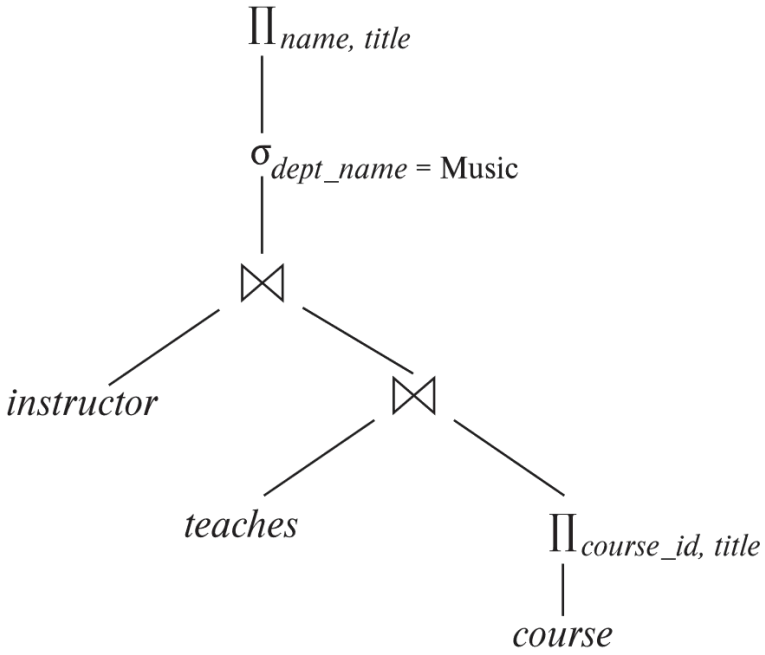
Chapter 16: Query Optimization

Database System Concepts, 7th Ed.

Introduction

List ‘Music’ Dept instructors along with the course titles they are teaching

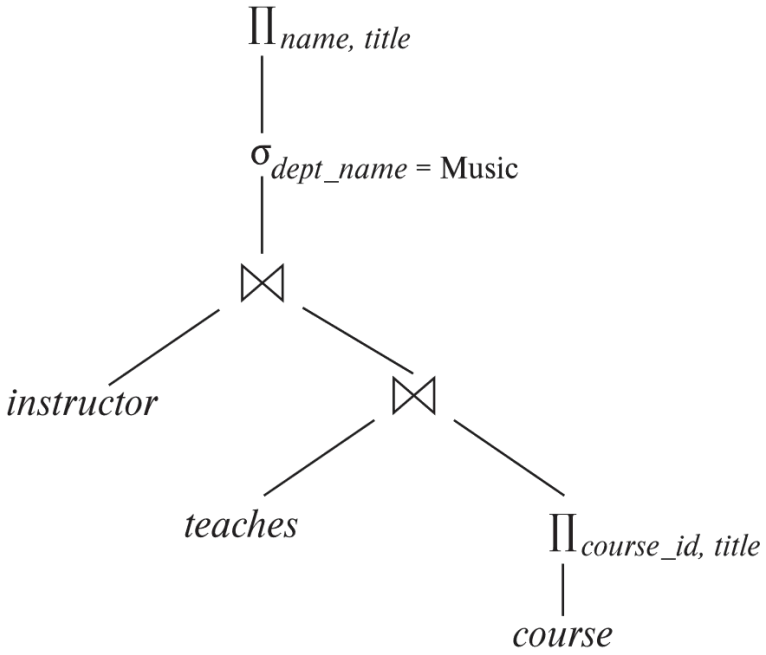


(a) Initial expression tree

Introduction

- Alternative ways of evaluating a given query
  - Equivalent expressions
  - Different algorithms for each operation

List ‘Music’ Dept instructors along with the course titles they are teaching



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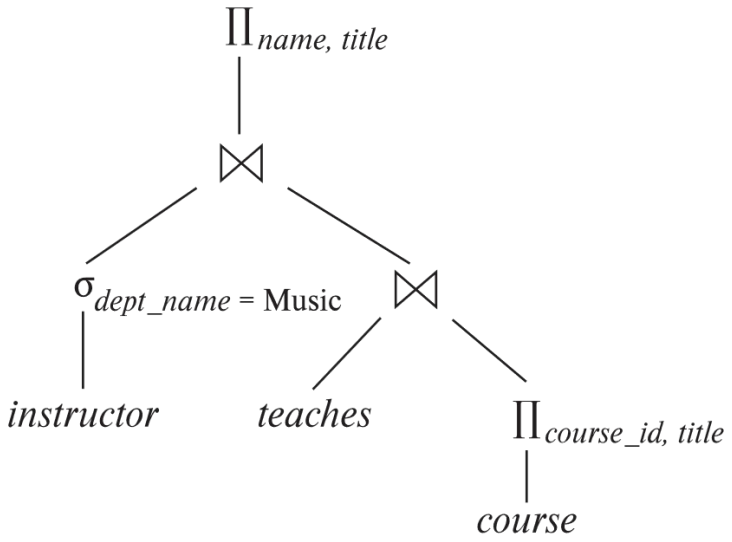
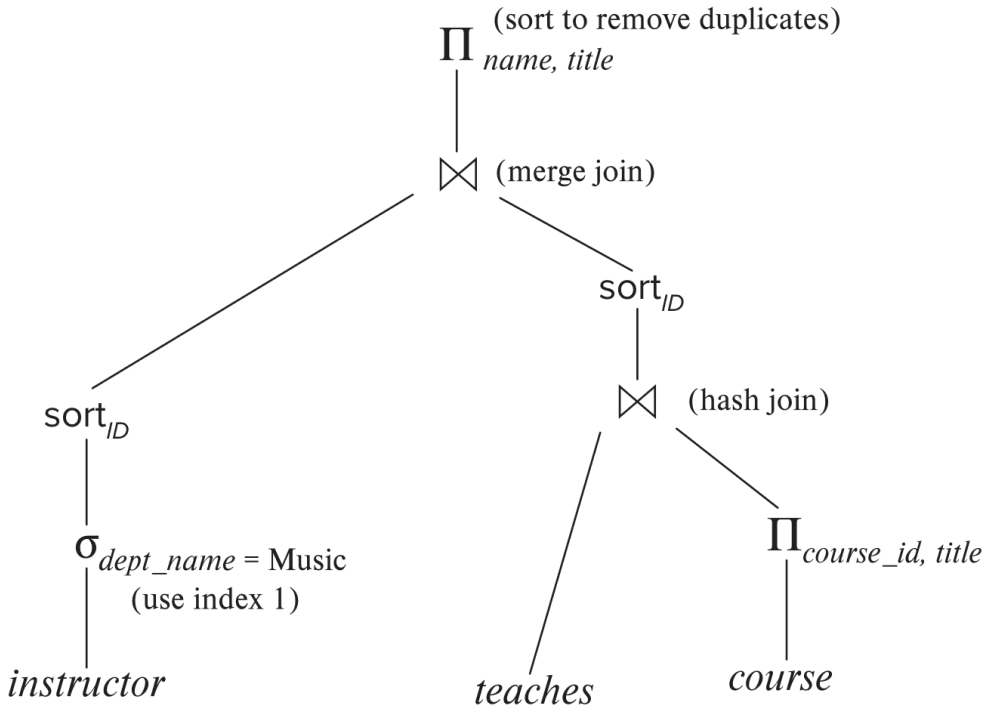


(b) Transformed expression tree

Cost difference between evaluation plans for a query can be enormous

Introduction (Cont.)

- An **evaluation plan** defines exactly what algorithm is used for each operation, and how the execution of the operations is coordinated.



Introduction (Cont.)

- Cost difference between evaluation plans for a query can be enormous
  - E.g., seconds vs. days in some cases
- Steps in **cost-based query optimization**
  1. Generate logically equivalent expressions using **equivalence rules**
  2. Annotate resultant expressions to get alternative query plans
  3. Choose the cheapest plan based on **estimated cost**
- Estimation of plan cost based on:
  - Statistical information about relations. Examples:
    - number of tuples, number of distinct values for an attribute
  - Statistics estimation for intermediate results
    - to compute cost of complex expressions
  - Cost formulae for algorithms, computed using statistics

Viewing Query Evaluation Plans

- Most database support **explain** <query>
  - Displays plan chosen by query optimizer, along with cost estimates
  - Some syntax variations between databases
    - Oracle: **explain plan for** <query> followed by **select** * **from** table (*dbms_xplan.display*)
    - SQL Server: **set showplan_text on**
- Some databases (e.g. PostgreSQL) support **explain analyse** <query>
  - Shows actual runtime statistics found by running the query, in addition to showing the plan

- Find out how to view query execution plans in MySQL????

Generating Equivalent Expressions

Transformation of Relational Expressions

- Two relational algebra expressions are said to be **equivalent** if the two expressions generate the same set of tuples on every *legal* database instance
  - Note: order of tuples is irrelevant
  - we don't care if they generate different results on databases that violate integrity constraints

- In SQL, inputs and outputs are multisets of tuples
  - Two expressions in the multiset version of the relational algebra are said to be equivalent if the two expressions generate the same multiset of tuples on every legal database instance.

- An **equivalence rule** says that expressions of two forms are equivalent
  - Can replace expression of first form by second, or vice versa

Equivalence Rules

1. Conjunctive selection operations can be deconstructed into a sequence of individual selections.

   $$\sigma_{\theta 1 \wedge \theta 2}(E) \equiv \sigma_{\theta 1}(\sigma_{\theta 2}(E))$$

2. Selection operations are commutative.

   $$\sigma_{\theta 1}(\sigma_{\theta 2}(E)) \equiv \sigma_{\theta 2}(\sigma_{\theta 1}(E))$$

3. Only the last in a sequence of projection operations is needed, the others can be omitted.

   $$\Pi_{L1}(\Pi_{L2}(\ldots(\Pi_{Ln}(E))\ldots)) \equiv \Pi_{L1}(E)$$

   where $L_1 \subseteq L_2 \ldots \subseteq L_n$

4. Selections can be combined with Cartesian products and theta joins.

   a. $\sigma_{\theta}(E_1 \times E_2) \equiv E_1 \bowtie_{\theta} E_2$

   b. $\sigma_{\theta 1}(E_1 \bowtie_{\theta 2} E_2) \equiv E_1 \bowtie_{\theta 1 \wedge \theta 2} E_2$

Equivalence Rules (Cont.)

5. Theta-join operations (and natural joins) are commutative.

$$E_1 \bowtie E_2 \quad \equiv \quad E_2 \bowtie E_1$$

6. (a) Natural join operations are associative:

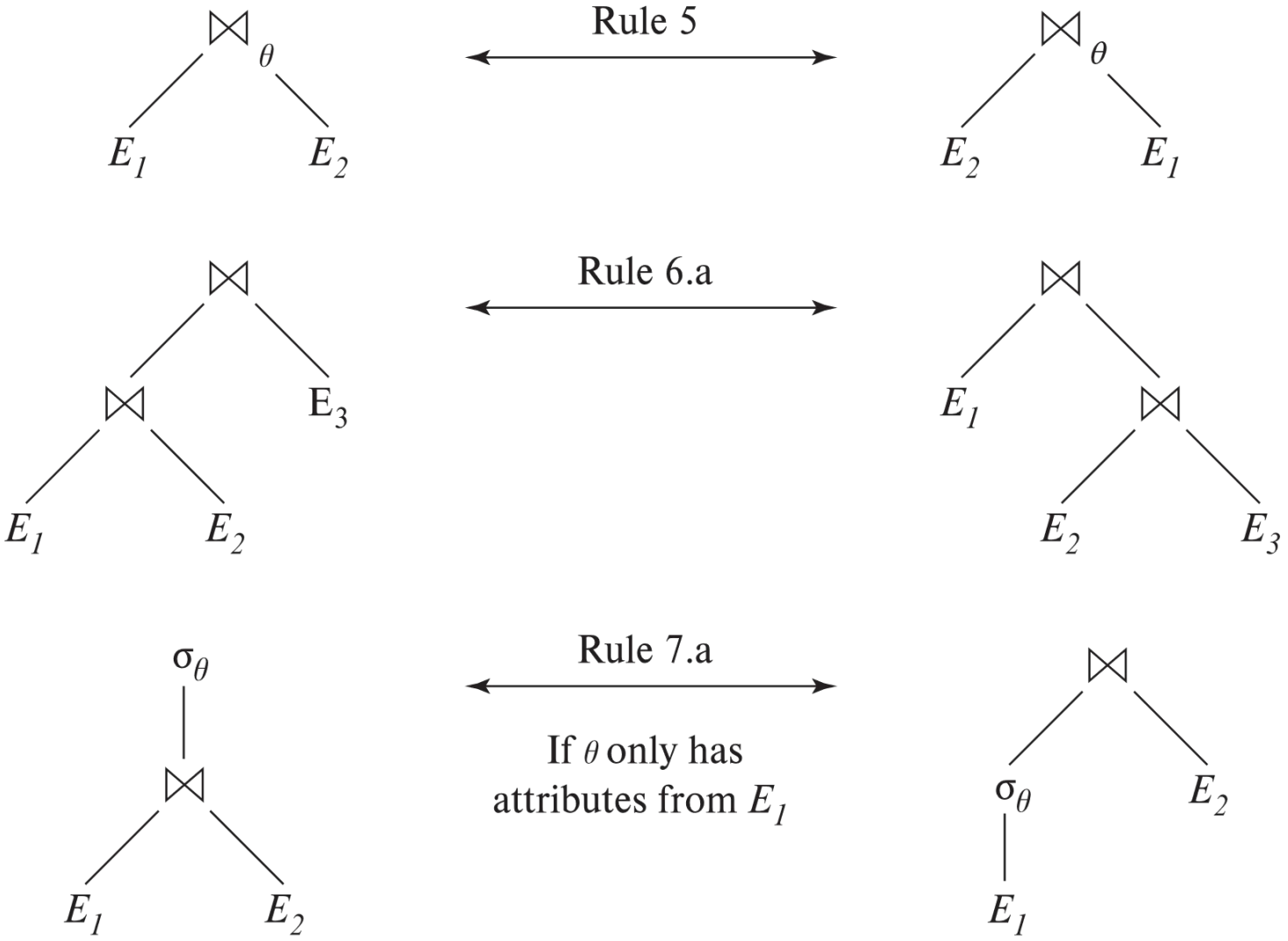
$$(E_1 \bowtie E_2) \bowtie E_3 \quad \equiv \quad E_1 \bowtie (E_2 \bowtie E_3)$$

(b) Theta joins are associative in the following manner:

$$(E_1 \bowtie_{\theta 1} E_2) \bowtie_{\theta 2 \wedge \theta 3} E_3 \quad \equiv \quad E_1 \bowtie_{\theta 1 \wedge \theta 3} (E_2 \bowtie_{\theta 2} E_3)$$

where θ_2 involves attributes from only E_2 and E_3.

Pictorial Depiction of Equivalence Rules



Equivalence Rules (Cont.)

7. The selection operation distributes over the theta join operation under the following two conditions:
   (a) When all the attributes in θ_0 involve only the attributes of one of the expressions (E_1) being joined.

$$\sigma_{\theta 0}(E_1 \bowtie_{\theta} E_2) \equiv (\sigma_{\theta 0}(E_1)) \bowtie_{\theta} E_2$$

   (b) When θ_1 involves only the attributes of E_1 and θ_2 involves only the attributes of E_2.

$$\sigma_{\theta 1 \wedge \theta 2}(E_1 \bowtie_{\theta} E_2) \equiv (\sigma_{\theta 1}(E_1)) \bowtie_{\theta} (\sigma_{\theta 2}(E_2))$$

Equivalence Rules (Cont.)

8. The projection operation distributes over the theta join operation as follows:

   (a) if θ involves only attributes from $L_1 \cup L_2$:

   $$\Pi_{L1 \cup L2}(E_1 \bowtie_\theta E_2) \equiv \Pi_{L1}(E_1) \bowtie_\theta \Pi_{L2}(E_2)$$

   (b) In general, consider a join $E_1 \bowtie_\theta E_2$.

   - Let L_1 and L_2 be sets of attributes from E_1 and E_2, respectively.
   - Let L_3 be attributes of E_1 that are involved in join condition θ, but are not in $L_1 \cup L_2$, and
   - let L_4 be attributes of E_2 that are involved in join condition θ, but are not in $L_1 \cup L_2$.

   $$\Pi_{L1 \cup L2}(E_1 \bowtie_\theta E_2) \equiv \Pi_{L1 \cup L2}(\Pi_{L1 \cup L3}(E_1) \bowtie_\theta \Pi_{L2 \cup L4}(E_2))$$

   Similar equivalences hold for outerjoin operations: ⟕, ⟖, and ⟗

Equivalence Rules (Cont.)

9. The set operations union and intersection are commutative

$$E_1 \cup E_2 \equiv E_2 \cup E_1$$
$$E_1 \cap E_2 \equiv E_2 \cap E_1$$

(set difference is not commutative).

10. Set union and intersection are associative.

$$(E_1 \cup E_2) \cup E_3 \equiv E_1 \cup (E_2 \cup E_3)$$
$$(E_1 \cap E_2) \cap E_3 \equiv E_1 \cap (E_2 \cap E_3)$$

11. The selection operation distributes over $\cup$, $\cap$ and $-$.

a. $\sigma_\theta (E_1 \cup E_2) \equiv \sigma_\theta (E_1) \cup \sigma_\theta(E_2)$
b. $\sigma_\theta (E_1 \cap E_2) \equiv \sigma_\theta (E_1) \cap \sigma_\theta(E_2)$
c. $\sigma_\theta (E_1 - E_2) \equiv \sigma_\theta (E_1) - \sigma_\theta(E_2)$
d. $\sigma_\theta (E_1 \cap E_2) \equiv \sigma_\theta(E_1) \cap E_2$
e. $\sigma_\theta (E_1 - E_2) \equiv \sigma_\theta(E_1) - E_2$

preceding equivalence does not hold for $\cup$

12. The projection operation distributes over union

$$\Pi_L(E_1 \cup E_2) \equiv (\Pi_L(E_1)) \cup (\Pi_L(E_2))$$

Equivalence Rules (Cont.)

13. Selection distributes over aggregation as below
    $\sigma_{\theta}({}_{G}\gamma_{A}(E)) \equiv {}_{G}\gamma_{A}(\sigma_{\theta}(E))$
    provided θ only involves attributes in G
14. a. Full outerjoin is commutative:
    $E_1 \mathbin{⟗} E_2 \equiv E_2 \mathbin{⟗} E_1$
    b. Left and right outerjoin are not commutative, but:
    $E_1 \mathbin{⟕} E_2 \equiv E_2 \mathbin{⟖} E_1$
15. Selection distributes over left and right outerjoins as below, provided θ_1 only involves attributes of E_1
    a. $\sigma_{\theta 1}(E_1 \mathbin{⟕}_{\theta} E_2) \equiv (\sigma_{\theta 1}(E_1)) \mathbin{⟕}_{\theta} E_2$
    b. $\sigma_{\theta 1}(E_1 \mathbin{⟖}_{\theta} E_2) \equiv E_2 \mathbin{⟕}_{\theta} (\sigma_{\theta 1}(E_1))$
16. Outerjoins can be replaced by inner joins under some conditions
    a. $\sigma_{\theta 1}(E_1 \mathbin{⟕}_{\theta} E_2) \equiv \sigma_{\theta 1}(E_1 \bowtie_{\theta} E_2)$
    b. $\sigma_{\theta 1}(E_1 \mathbin{⟖}_{\theta} E_1) \equiv \sigma_{\theta 1}(E_1 \bowtie_{\theta} E_2)$
    provided θ_1 is null rejecting on E_2

Equivalence Rules (Cont.)

Note that several equivalences that hold for joins do not hold for outerjoins

- $\sigma_{year=2017}(instructor \mathbin{⟗} teaches) \not\equiv \sigma_{year=2017}(instructor \bowtie teaches)$
- Outerjoins are not associative

  $$(r \mathbin{⟗} s) \mathbin{⟗} t \quad \not\equiv \quad r \mathbin{⟗} (s \mathbin{⟗} t)$$

  - e.g. with r(A,B) = {(1,1), s(B,C) = { (1,1)}, t(A,C) = { }

Transformation Example: Pushing Selections

- Query: Find the names of all instructors in the Music department, along with the titles of the courses that they teach
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\text{'Music'}}(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course))))$
- Transformation using rule 7a.
  - $\Pi_{name,\ title}((\sigma_{dept\_name=\text{'Music'}}(instructor)) \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course)))$

- Performing the selection as early as possible reduces the size of the relation to be joined.

Example with Multiple Transformations

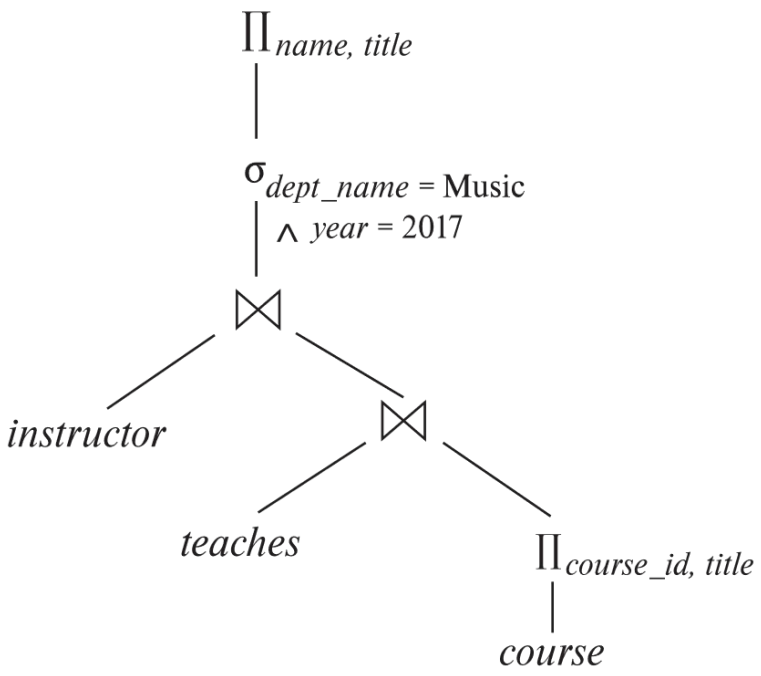
- Query: Find the names of all instructors in the Music department who have taught a course in 2017, along with the titles of the courses that they taught
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\text{"Music"} \wedge year = 2017}$
    $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$

- Transformation using join associatively (Rule 6a):
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\text{“Music”} \wedge year = 2017}$
    $((instructor \bowtie teaches) \bowtie\ \Pi_{course\_id,\ title}\ (course)))$

- Second form provides an opportunity to apply the “perform selections early” rule, resulting in the subexpression

  $\sigma_{dept\_name = \text{“Music”}}\ (instructor) \bowtie \sigma_{\ year = 2017}\ (teaches)$

Multiple Transformations (Cont.)



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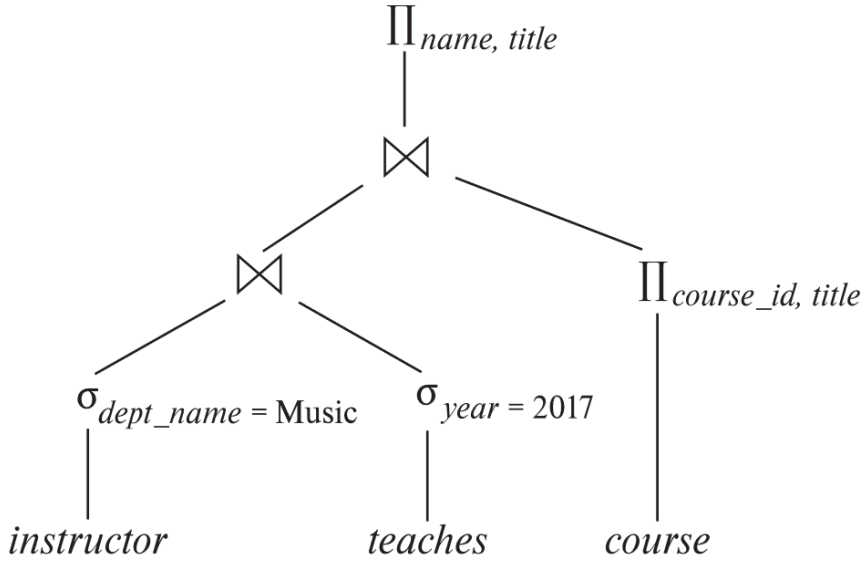


(b) Tree after multiple transformations

Transformation Example: Pushing Projections

- Consider: $\Pi_{name,\ title}(\sigma_{dept\_name=\text{“Music”}}(instructor) \bowtie teaches) \bowtie \Pi_{course\_id,\ title}(course))))$
- When we compute

  $(\sigma_{dept\_name = \text{“Music”}}(instructor \bowtie teaches)$

  we obtain a relation whose schema is:
  (*ID, name, dept_name, salary, course_id, sec_id, semester, year)*

- Push projections using equivalence rules 8a and 8b; eliminate unneeded attributes from intermediate results to get:

$$\Pi_{name,\ title}(\Pi_{name,\ course\_id}(\sigma_{dept\_name=\text{“Music”}}(instructor) \bowtie teaches) \bowtie \Pi_{course\_id,\ title}(course))$$

- Performing the projection as early as possible reduces the size of the relation to be joined.

Join Ordering Example

- For all relations r_1, r_2, and r_3,
  $(r_1 \bowtie r_2) \bowtie r_3 = r_1 \bowtie (r_2 \bowtie r_3)$

- If $r_2 \bowtie r_3$ is quite large and $r_1 \bowtie r_2$ is small, we choose

  $(r_1 \bowtie r_2) \bowtie r_3$

  so that we compute and store a smaller temporary relation.

Join Ordering Example (Cont.)

- Consider the expression

  $\Pi_{name,\ title}((\sigma_{dept\_name=\text{“Music”}}(instructor) \bowtie teaches) \bowtie \Pi_{course\_id,\ title}(course))$

- Could compute $teaches \bowtie \Pi_{course\_id,\ title}(course)$ first, and join result with $\sigma_{dept\_name=\text{“Music”}}(instructor)$
  but the result of the first join is likely to be a large relation.

- Only a small fraction of the university's instructors are likely to be from the Music department
  - it is better to compute

    $\sigma_{dept\_name=\text{“Music”}}(instructor) \bowtie teaches$

    first.

Enumeration of Equivalent Expressions

- Query optimizers use equivalence rules to **systematically** generate expressions equivalent to the given expression
- Can generate all equivalent expressions as follows:
  - Repeat
    - apply all applicable equivalence rules on every subexpression of every equivalent expression found so far
    - add newly generated expressions to the set of equivalent expressions

    Until no new equivalent expressions are generated above
- The above approach is very expensive in space and time
  - Space requirements reduced by sharing common sub-expressions
  - Time requirements are reduced by not generating all expressions (use dynamic programming)
  - Two approaches
    - Optimized plan generation based on transformation rules
    - Special case approach for queries with only selections, projections and joins

Cost-Based Optimization

- Consider finding the best join-order for $r_1 \bowtie r_2 \bowtie \ldots \bowtie r_n$.
- There are $(2(n-1))!/(n-1)!$ different join orders for above expression. With $n = 7$, the number is 665280, with $n = 10$, the number is greater than 176 billion!
- No need to generate all the join orders. Using dynamic programming, the least-cost join order for any subset of $\{r_1, r_2, \ldots r_n\}$ is computed only once and stored for future use.

Heuristic Optimization

- Cost-based optimization is expensive, even with dynamic programming.
- Systems may use *heuristics* to reduce the number of choices that must be made in a cost-based fashion.
- Heuristic optimization transforms the query-tree by using a set of rules that typically (but not in all cases) improve execution performance:
  - Perform selection early (reduces the number of tuples)
  - Perform projection early (reduces the number of attributes)
  - Perform most restrictive selection and join operations (i.e., with smallest result size) before other similar operations.
  - Some systems use only heuristics, others combine heuristics with partial cost-based optimization.

Statistics for Cost Estimation

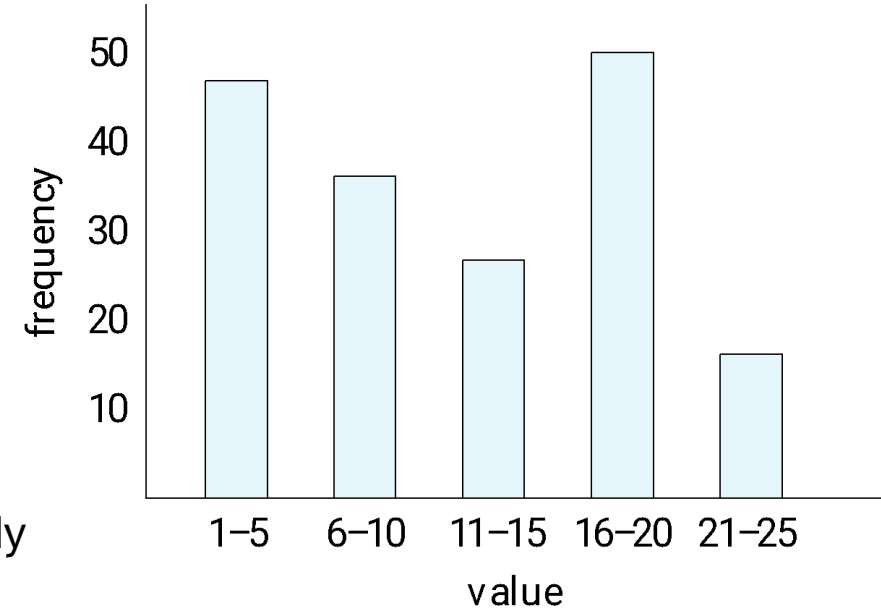
Statistical Information for Cost Estimation

- n_r: number of tuples in a relation *r.*
- b_r: number of blocks containing tuples of *r.*
- l_r: size of a tuple of *r.*
- f_r: blocking factor of *r* — i.e., the number of tuples of *r* that fit into one block.
- *V(A, r):* number of distinct values that appear in *r* for attribute *A;* same as the size of $\prod_A(r)$.
- If tuples of *r* are stored together physically in a file, then:

$$b_r = \left\lceil \frac{n_r}{f_r} \right\rceil$$

Histograms

- Histogram on attribute *age* of relation *person*
- **Equi-width** histograms
- **Equi-depth** histograms break up range such that each range has (approximately) the same number of tuples
- Many databases also store *n* **most-frequent values** and their counts
  - Histogram is built on remaining values only



- Histograms and other statistics usually computed based on a **random sample**
- Statistics may be out of date
  - Some database require an '**analyse**' command to be executed to update statistics
  - Others automatically re-compute statistics
    - e.g., when number of tuples in a relation changes by some percentage

Selection Size Estimation

- $\sigma_{A=v}(r)$
  - n_r / *V(A,r)* : number of records that will satisfy the selection
  - Equality condition on a key attribute: *size estimate* = 1
- $\sigma_{A \le V}(r)$ (case of $\sigma_{A \ge V}(r)$ is symmetric)
  - Let c denote the estimated number of tuples satisfying the condition.
  - If min(A,r) and max(A,r) are available in catalog
    - c = 0 if v < min(A,r)
    - c = $n_r \cdot \dfrac{v - \min(A,r)}{\max(A,r) - \min(A,r)}$
  - If histograms available, can refine above estimate
  - In absence of statistical information *c* is assumed to be n_r / 2.

Size Estimation of Complex Selections

- The **selectivity** of a condition θ_i is the probability that a tuple in the relation *r* satisfies θ_i .
  - If s_i is the number of satisfying tuples in *r,* the selectivity of θ_i is given by s_i / n_r.
- **Conjunction:** $\sigma_{\theta 1 \wedge \theta 2 \wedge \ldots \wedge \theta n}(r)$. *Assuming independence,* estimate of tuples in the result is: $n_r * \frac{s_1 * s_2 * \ldots * s_n}{n_r^n}$
- **Disjunction:** $\sigma_{\theta 1 \vee \theta 2 \vee \ldots \vee \theta n}(r)$. Estimated number of tuples: $n_r * \left(1 - (1 - \frac{s_1}{n_r}) * (1 - \frac{s_2}{n_r}) * \ldots * (1 - \frac{s_n}{n_r})\right)$
- **Negation:** $\sigma_{\neg\theta}(r)$. Estimated number of tuples: $n_r - size(\sigma_\theta(r))$

Join Operation: Running Example

Running example:

$student \bowtie takes$

Catalog information for join examples:

- $n_{student}$ = 5,000.
- $f_{student}$ = 50, which implies that $b_{student}$ =5000/50 = 100.
- n_{takes} = 10000.
- f_{takes} = 25, which implies that b_{takes} = 10000/25 = 400.
- *V(ID, takes)* = 2500, which implies that on average, each student who has taken a course has taken 4 courses.
  - Attribute *ID* in *takes* is a foreign key referencing *student.*
  - *V*(*ID, student*) = 5000 (*primary key!*)

Estimation of the Size of Joins

- The Cartesian product r x s contains $n_r.n_s$ tuples; each tuple occupies $s_r + s_s$ bytes.
- If $R \cap S = \varnothing$, then $r \bowtie s$ is the same as r x s.
- If $R \cap S$ is a key for R, then a tuple of s will join with at most one tuple from r
  - therefore, the number of tuples in $r \bowtie s$ is no greater than the number of tuples in s.
- If $R \cap S$ *in* S is a foreign key in S referencing R, then the number of tuples in $r \bowtie s$ is exactly the same as the number of tuples in s.
    - The case for $R \cap S$ being a foreign key referencing S is symmetric.
- In the example query *student* $\bowtie$ *takes, ID* in *takes* is a foreign key referencing *student*
  - hence, the result has exactly n_{takes} tuples, which is 10000

Estimation of the Size of Joins (Cont.)

- If $R \cap S = \{A\}$ is not a key for R or S.
  If we assume that every tuple t in R produces tuples in $R \bowtie S$, the number of tuples in $R \bowtie S$ is estimated to be:

$$\frac{n_r * n_s}{V(A,s)}$$

  If the reverse is true, the estimate obtained will be:

$$\frac{n_r * n_s}{V(A,r)}$$

  The lower of these two estimates is probably the more accurate one.
- Can improve on above if histograms are available
  - Use formula similar to above, for each cell of histograms on the two relations

Estimation of the Size of Joins (Cont.)

- Compute the size estimates for *student* ⋈ *takes* without using information about foreign keys:
  - $n_{student}$ = 5,000.
  - n_{takes} = 10000.
  - *V(ID, takes)* = 2500, and
    V(ID, student) = 5000
  - The two estimates are 5000 * 10000/2500 = 20,000 and 5000 * 10000/5000 = 10000
  - We choose the lower estimate, which in this case, is the same as our earlier computation using foreign keys.

Size Estimation for Other Operations

- Projection: estimated size of $\prod_A(r)$ = $V(A,r)$
- Aggregation : estimated size of ${}_G\gamma_A(r)$ = $V(G,r)$
- Set operations
  - For unions/intersections of selections on the same relation: rewrite and use size estimate for selections
    - E.g., $\sigma_{\theta 1}(r) \cup \sigma_{\theta 2}(r)$ can be rewritten as $\sigma_{\theta 1 \text{ or } \theta 2}(r)$
  - For operations on different relations:
    - estimated size of $r \cup s$ = size of r + size of s.
    - estimated size of $r \cap s$ = minimum size of r and size of s.
    - estimated size of $r - s$ = r.
    - All the three estimates may be quite inaccurate, but provide upper bounds on the sizes.
- Outer join:
  - Estimated size of $r \mathbin{⟖} s$ = *size of* $r \bowtie s$ + *size of* r
    - Case of right outer join is symmetric
  - Estimated size of $r \mathbin{⟗} s$ = *size of* $r \bowtie s$ + size of r + size of s

Query Optimization and Materialized Views

- Rewriting queries to use materialized views:
  - A materialized view $v = r \bowtie s$ is available
  - A user submits a query $r \bowtie s \bowtie t$
  - We can rewrite the query as $v \bowtie t$
    - Whether to do so depends on cost estimates for the two alternative
- Replacing a use of a materialized view by the view definition:
  - A materialized view $v = r \bowtie s$ is available, but without any index on it
  - User submits a query $\sigma_{A=10}(v)$.
  - Suppose also that *s* has an index on the common attribute B, and r has an index on attribute A.
  - The best plan for this query may be to replace *v* by $r \bowtie s$, which can lead to the query plan $\sigma_{A=10}(r) \bowtie s$
- Query optimizer considers these alternatives and choose the best overall plan.

Materialized View Selection

- **Materialized view selection**: "What is the best set of views to materialize?"
- **Index selection**: "what is the best set of indices to create"
  - closely related, to materialized view selection
    - but simpler
- Materialized view selection and index selection based on typical system **workload** (queries and updates)
  - Typical goal: minimize time to execute workload, subject to constraints on space and time taken for some critical queries/updates
  - One of the steps in database tuning
- Commercial database systems provide tools (called "tuning assistants" or "wizards") to help the database administrator choose what indices and materialized views to create

Multiquery Optimization

- Example

  Q1: **select** * **from** (r **natural join** t) **natural join** s

  Q2: **select** * **from** (r **natural join** u) **natural join** s

  - Both queries share common subexpression (r natural join s)
  - May be useful to compute (r natural join s) once and use it in both queries
    - But this may be more expensive in some situations
      - e.g. (r natural join s) may be expensive, plans as shown in queries may be cheaper
- **Multiquery optimization**: find best overall plan for a set of queries, expoiting sharing of common subexpressions between queries where it is useful

Multiquery Optimization (Cont.)

- Simple heuristic used in some database systems:
  - optimize each query separately
  - detect and exploiting common subexpressions in the individual optimal query plans
    - May not always give best plan, but is cheap to implement
  - **Shared scans**: widely used special case of multiquery optimization
- Set of materialized views may share common subexpressions
  - As a result, view maintenance plans may share subexpressions
  - Multiquery optimization can be useful in such situations

Parametric Query Optimization

- Example
  select *
  from r **natural join** s
  where r.a < $1
  - value of parameter $1 not known at compile time
    - known only at run time
  - different plans may be optimal for different values of $1
- Solution 1: optimize at run time, each time query is submitted
    - can be expensive
- Solution 2: **Parametric Query Optimization**:
  - optimizer generates a set of plans, optimal for different values of $1
    - Set of optimal plans usually small for 1 to 3 parameters
    - Key issue: how to do find set of optimal plans efficiently
  - best one from this set is chosen at run time when $1 is known
- Solution 3: **Query Plan Caching**
  - If optimizer decides that same plan is likely to be optimal for all parameter values, it caches plan and reuses it, else reoptimize each time
  - Implemented in many database systems

Adaptive Query Processing

- Some systems support adaptive operators that change execution algorithm on the fly
  - E.g., (indexed) nested loops join or hash join chosen at run time, depending on size of outer input
- Other systems allow monitoring of behavior of plan at run time and adapt plan
  - E.g., if statistics such as number of rows is found to be very different in reality from what optimizer estimated
  - Can stop execution, compute fresh plan, and restart
    - But must avoid too many such restarts

End of Chapter