KOREA UNIVERSITY
DATAX LAB

Chapter 16

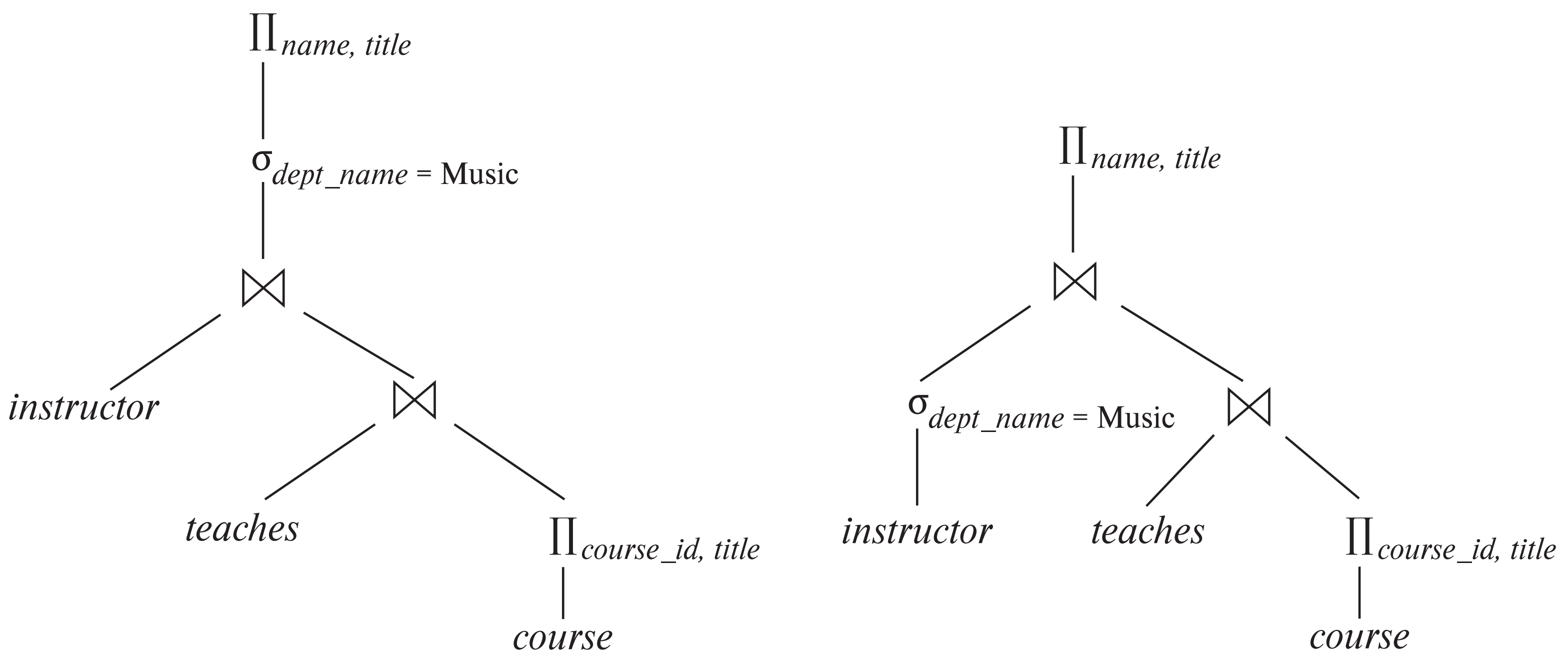
Query Optimization

Outline

- Introduction
- Transformation of Relational Expressions
- Catalog Information for Cost Estimation
- Statistical Information for Cost Estimation
- Cost-based optimization
- Dynamic Programming for Choosing Evaluation Plans
- Additional Optimization Techniques
  - Materialized Views
  - Multiquery Optimization

Introduction

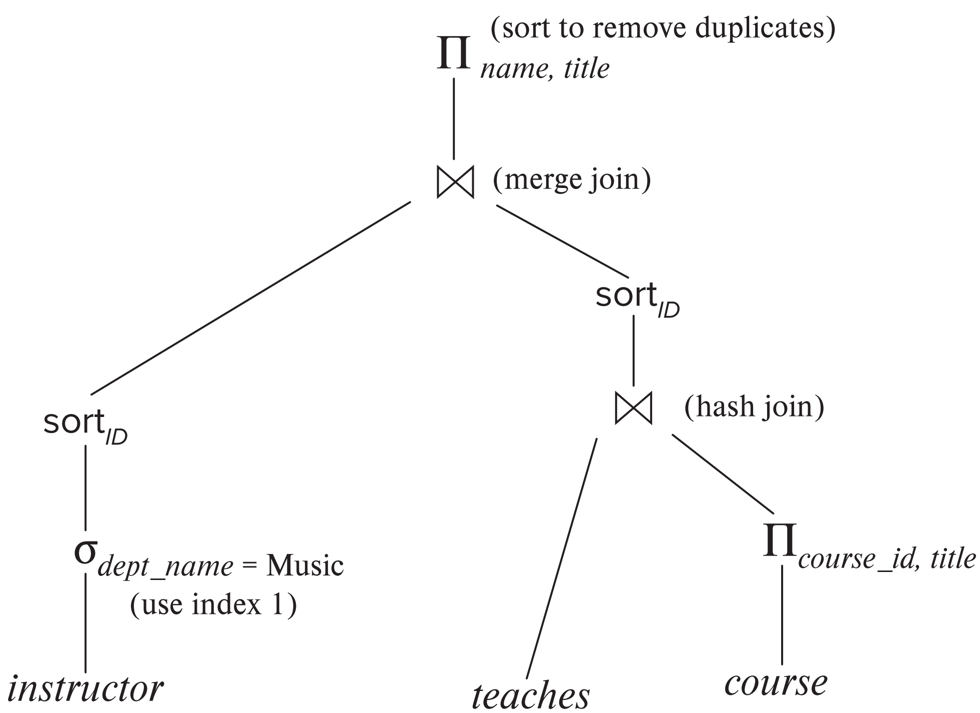
- Alternative ways of evaluating a given query
  - Equivalent expressions
  - Different algorithms for each operation



(a) Initial expression tree (b) Transformed expression tree

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 some commands to display the 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;**
  - PostgreSQL: **explain analyse** <query>**;**

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 that the order of tuples is irrelevant.*
- 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.

$$\Pi_{L_1}(\Pi_{L_2}(\ldots(\Pi_{L_n}(E))\ldots)) \equiv \Pi_{L_1}(E)$$

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.

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

6. (a) Natural join operations are associative:

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

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

$$(E_1 \bowtie_{\theta_1} E_2) \bowtie_{\theta_2 \wedge \theta_3} E_3 \equiv E_1 \bowtie_{\theta_1 \wedge \theta_3} (E_2 \bowtie_{\theta_2} E_3)$$

   where θ_2 involves attributes from only E_2 and E_3.

Equivalence Rules (Cont.)

7. The selection operation distributes over the theta join operation under the following two conditions:

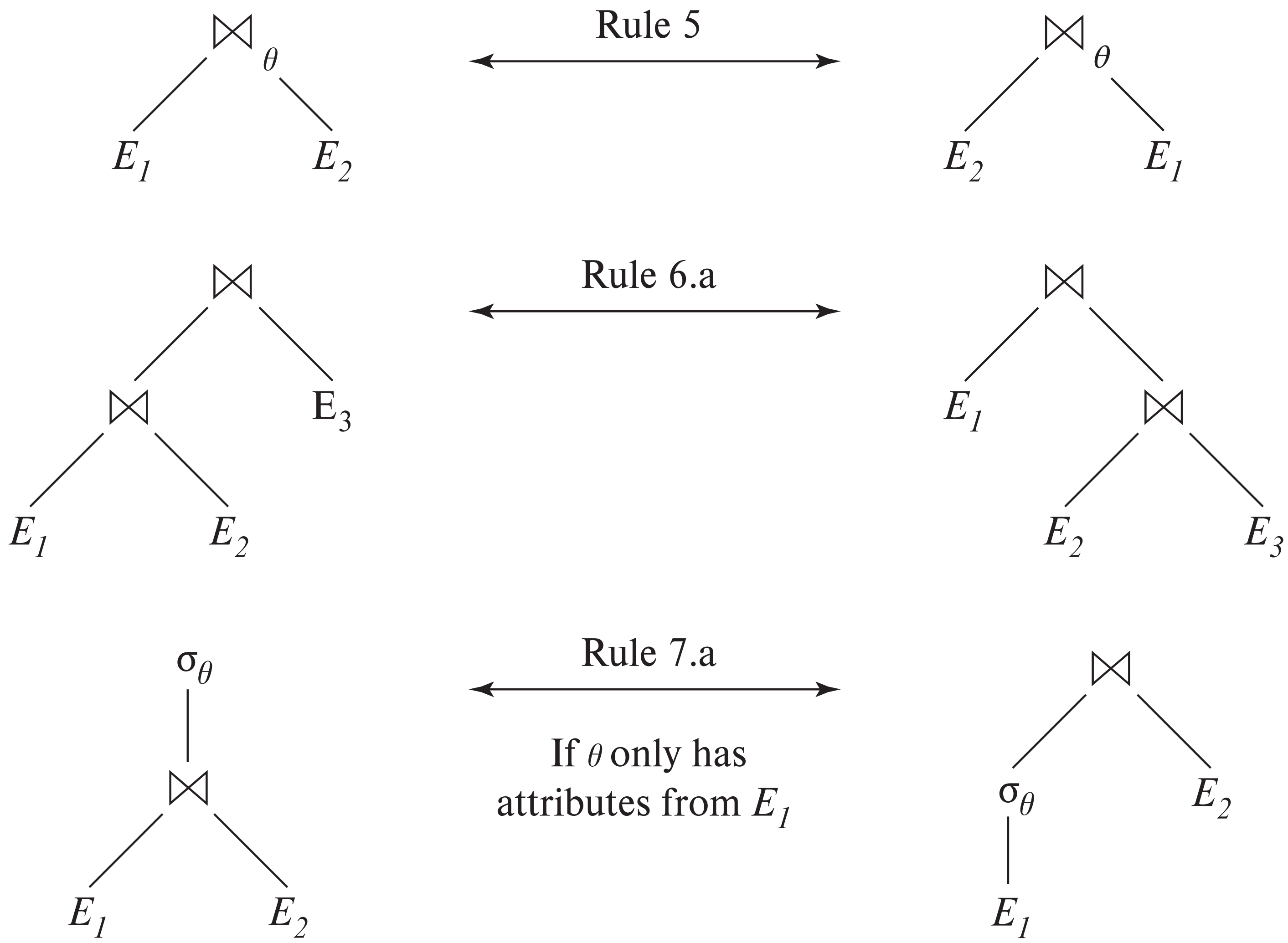
   (a) When all the attributes in θ_0 involve only the attributes of one of the expressions (E_1) being joined.

   $$\sigma_{\theta_0}(E_1 \bowtie_\theta E_2) \equiv (\sigma_{\theta_0}(E_1)) \bowtie_\theta E_2$$

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

   $$\sigma_{\theta_1 \wedge \theta_2}(E_1 \bowtie_\theta E_2) \equiv (\sigma_{\theta_1}(E_1)) \bowtie_\theta (\sigma_{\theta_2}(E_2))$$

Pictorial Depiction of Equivalence Rules



Equivalence Rules (Cont.)

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

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

$$\Pi_{L_1 \cup L_2}(E_1 \bowtie_\theta E_2) \equiv \Pi_{L_1}(E_1) \bowtie_\theta \Pi_{L_2}(E_2)$$

   (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 $L_1 \cup L_2$.
   - Let L_4 be attributes of E_2 that are involved in join condition θ, but are not in $L_1 \cup L_2$.

$$\Pi_{L_1 \cup L_2}(E_1 \bowtie_\theta E_2) \equiv \Pi_{L_1 \cup L_2}(\Pi_{L_1 \cup L_3}(E_1) \bowtie_\theta \Pi_{L_2 \cup L_4}(E_2))$$

e.g. $E_1(ABDE)$, $E_2(BCFG)$

$$\Pi_{A,C}(E_1 \bowtie E_2) \equiv \Pi_{A,C}(\Pi_{A,B}(E_1) \bowtie \Pi_{B,C}(E_2))$$

Similar equivalences hold for outer join 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. $\sigma_\theta (E_1 - E_2) \equiv \sigma_\theta(E_1) - E_2$

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

    $\sigma_{\theta}({}_{G}\gamma_{A}(E)) \equiv {}_{G}\gamma_{A}(\sigma_{\theta}(E))$

    when θ only involves attributes in G

14. a. Full outer join is commutative:

    $E_1 \text{⟗} E_2 \equiv E_2 \text{⟗} E_1$

    b. Left and right outer join are not commutative, but:

    $E_1 \text{⟕} E_2 \equiv E_2 \text{⟖} E_1$

15. Selection distributes over left and right outer joins as below, provided θ_1 only involves attributes of E_1

    a. $\sigma_{\theta_1}(E_1 \text{⟕}_{\theta} E_2) \equiv (\sigma_{\theta_1}(E_1)) \text{⟕}_{\theta} E_2$

    b. $\sigma_{\theta_1}(E_1 \text{⟖}_{\theta} E_2) \equiv E_2 \text{⟕}_{\theta} (\sigma_{\theta_1}(E_1))$

16. Outer joins can be replaced by inner joins under some conditions

    a. $\sigma_{\theta_1}(E_1 \text{⟕}_{\theta} E_2) \equiv \sigma_{\theta_1}(E_1 \bowtie_{\theta} E_2)$

    b. $\sigma_{\theta_1}(E_2 \text{⟖}_{\theta} E_1) \equiv \sigma_{\theta_1}(E_1 \bowtie_{\theta} E_2)$

    when θ_1 is <u>null rejecting</u> on E_2

    - θ_1 evaluates to false (or unknown) whenever the attributes of E_2 are null
    - (ex) θ_1 is $A < 4$ and A is attributes of E_2. θ_1 would evaluate to unknown if A is null.

Transformation Example: Pushing Selections

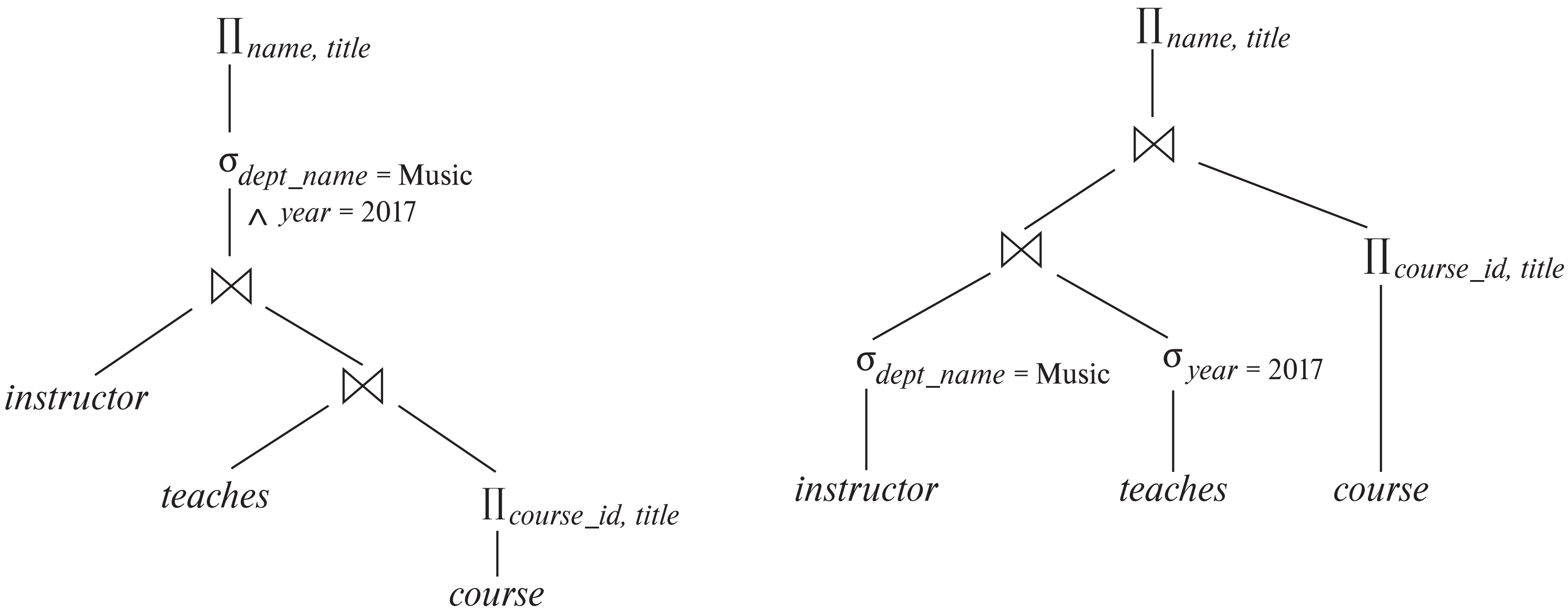
- Query: Find the names of all instructors in the Music department, along with the titles of the courses that they teach
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\ \text{'Music'}}$
    $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$
- Transformation using Rule 7a.
  - $\Pi_{name,\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

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

Multiple Transformations (Cont.)



(a) Initial expression tree

(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.

Transformation Example: Ordering Joins

- **Join ($\bowtie$) Associativity**: $(r_1 \bowtie r_2) \bowtie r_3 \equiv r_1 \bowtie (r_2 \bowtie r_3)$

- 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.

- Consider the expression

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

  - Could compute $teaches \bowtie \Pi_{course\_id,\ title}(course)$ first, and join the 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

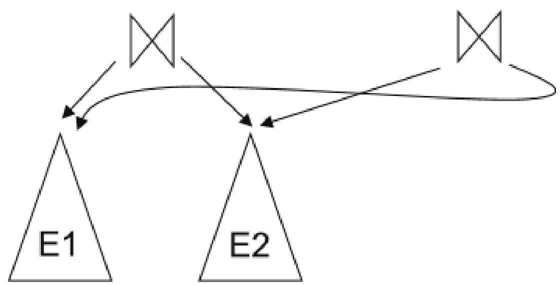
- Query optimizers use equivalence rules to **systematically** generate expressions equivalent to the given expression
- Can generate all equivalent expressions as follows:
  - Repeat
    - apply all applicable equivalence rules on every subexpression of every equivalent expression found so far
    - 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
  - Two approaches avoiding exhaustive search
    1. Space/Time optimization (next slide)
    2. Using heuristics (Slide #31)

Space/Time Optimization

- Space requirements reduced by sharing common sub-expressions:
  - when E1 is generated from E2 by an equivalence rule, usually only the top level of the two are different, subtrees below are the same and can be shared using pointers
    - E.g., when applying join commutativity



  - Same sub-expression may get generated multiple times
    - Detect duplicate sub-expressions and share one copy
- Time requirements are reduced by not generating all expressions
  - Dynamic programming
    - We will study only the special case of dynamic programming for join order optimization

Cost Estimation

- Cost of each operator is computed as described in Chapter 15
  - Need statistics of input relations
    - E.g., number of tuples, sizes of tuples
- Inputs can be results of sub-expressions
  - Need to estimate statistics of expression results
  - To do so, we require additional statistics
    - E.g., number of distinct values for an attribute

- More on cost estimation later

Choice of Evaluation Plans

- Must consider the interaction of evaluation techniques when choosing evaluation plans
  - choosing the cheapest algorithm for each operation independently may not yield the best overall algorithm.
  - E.g.
    - merge-join may be costlier than hash-join but may provide a sorted output which reduces the cost for an outer level aggregation.
    - nested-loop join may provide opportunity for pipelining

- Practical query optimizers incorporate elements of the following two broad approaches:
  1. Search all the plans and choose the best plan in a cost-based fashion.
  2. Uses heuristics to choose a plan.

Cost-Based Optimization

- Consider finding the best join-order for $r_1 \bowtie r_2 \bowtie \ . . . \bowtie r_n$.
- There are $(2(n – 1))!/(n – 1)!$ different join orders for above expression.
  - $n! * C_{n-1} = n! * (2(n – 1))!/(n!(n – 1)!)$
  - C_{n-1} is the (n-1)-th *Catalan* number
    - (ex) number of full binary trees with *n* number of leaf nodes
  - 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 $\{r_1, r_2, . . . r_n\}$ is computed only once and stored for future use.

Dynamic Programming in Optimization

- To find the best join tree for a set of *n* relations:
  - To find best plan for a set S of n relations, consider all possible plans of the form: $S_1 \bowtie (S - S_1)$ where S_1 is any non-empty subset of S.
  - Recursively compute costs for joining subsets of S to find the cost of each plan. Choose the cheapest of the $2^n - 2$ alternatives.
  - Base case for recursion: single relation access plan
    - Apply all selections on R_i using best choice of indices on R_i
  - When plan for any subset is computed, store it and reuse it when it is required again, instead of recomputing it
    - Dynamic programming

Join Order Optimization Algorithm

```
procedure findbestplan(S)
    if (bestplan[S].cost ≠ ∞)
        return bestplan[S]
    // else bestplan[S] has not been computed earlier, compute it now
    if (S contains only 1 relation)
      set bestplan[S].plan and bestplan[S].cost based on the best way
      of accessing S  using selections on S and indices (if any) on S
    else for each non-empty subset S1 of S such that S1 ≠ S
        P1= findbestplan(S1)
        P2= findbestplan(S - S1)
        for each algorithm A for joining results of P1 and P2
           compute plan and cost of using A  (see next page) ..
           if cost < bestplan[S].cost
                bestplan[S].cost = cost
                bestplan[S].plan = plan;
    return bestplan[S]
```

With dynamic programming,
the *time complexity* is $O(3^n)$ and
the *space complexity* is $O(2^n)$.

Join Order Optimization Algorithm (cont.)

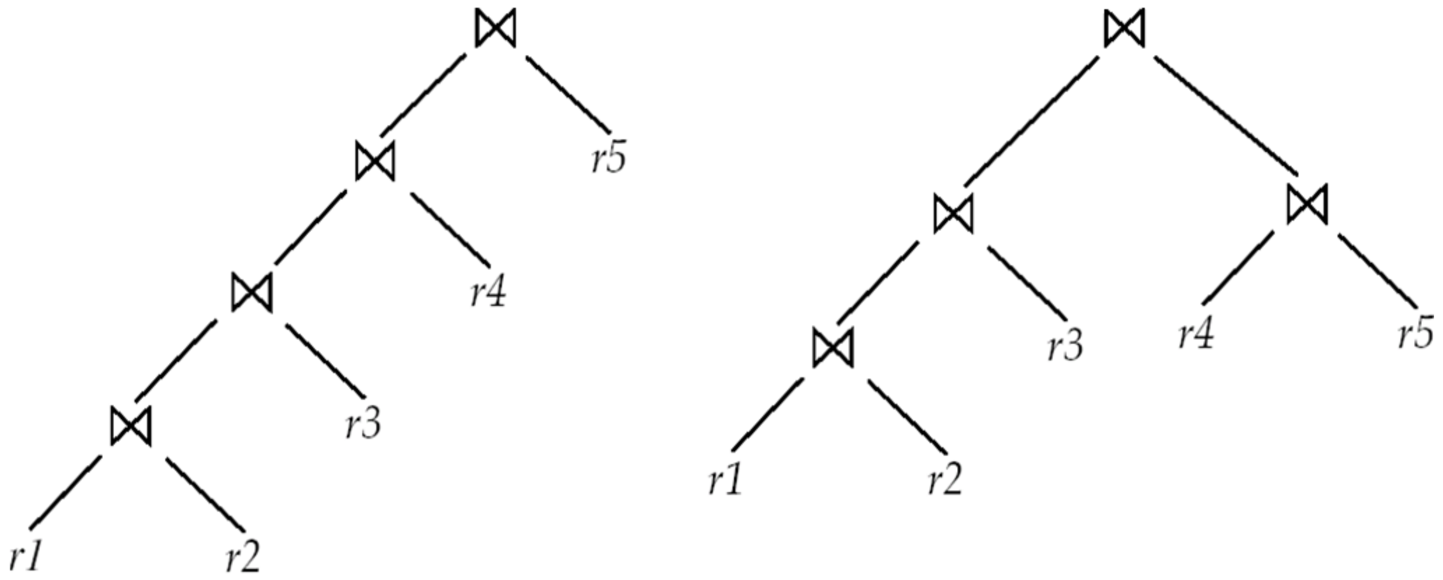
for each algorithm A for joining results of $P1$ and $P2$
// For indexed-nested loops join, the outer could be *P1* or *P2*
// Similarly for hash-join, the build relation could be *P1* or *P2*
// We assume the alternatives are considered as separate algorithms

if algorithm *A* is indexed nested loops
Let P_i and P_o denote inner and outer inputs
if P_i has a single relation r_i and r_i has an index on the join attribute
plan = "execute P_o.*plan*; join results of P_o and r_i using *A*",
with any selection conditions on P_i performed as part of the join condition
cost = P_o.*cost* + cost of *A*
else *cost* = ∞; /* cannot use indexed nested loops join */
else
plan = "execute *P1.plan*; execute *P2.plan*;
join results of *P1* and *P2* using *A*;"
cost = *P1.cost* + *P2.cost* + cost of *A*

(see previous page)

Left Deep Join Trees

- In **left-deep join trees,** the right-hand-side input for each join is a relation, not the result of an intermediate join.



(a) Left-deep join tree

(b) Non-left-deep join tree

Cost of Optimization

- (Instead of bush trees) To find the best left-deep join tree for *n* relations:
  - Consider *n* alternatives with one relation as right-hand side input and the other relations as left-hand side input.
  - Modify optimization algorithm:
    - Replace " **for each** non-empty subset $S1$ of S such that $S1 \neq S$ "
    - By: " **for each** relation r in S"
      let S1 = S – r .
- If only left-deep trees are considered, time complexity of finding the best join order is $O(n\, 2^n)$
  - Space complexity remains at $O(2^n)$
- Cost-based optimization is expensive, but worthwhile for queries on large datasets (typical queries have small n, generally < 10)

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.

Structure of Query Optimizers

- Most systems adopt hybrid approach:
  Heuristics + Cost-based optimization
- Many optimizers considers only left-deep join orders.
  - Plus heuristics to push selections and projections down the query tree
  - Reduces optimization complexity and generates plans amenable to pipelined evaluation.
- Optimization cost budget to stop optimization early (if cost of plan is less than cost of optimization)
- Plan caching to reuse previously computed plan if query is resubmitted
  - Even with different constants in query
- Optimizers often use simple heuristics for very cheap queries, and perform exhaustive enumeration for more expensive queries
- Intricacies of SQL complicate query optimization
  - E.g., nested subqueries

Statistics for Cost Estimation

Statistical Information for Cost Estimation

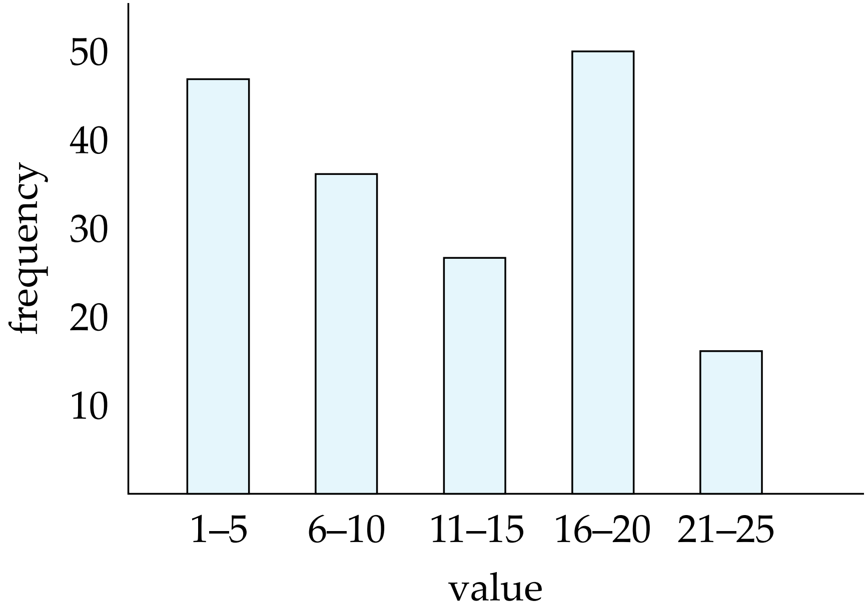
- n_r: number of tuples in a relation *r.*
- l_r: size of a tuple of *r.*
- b_r: number of blocks containing tuples of *r.*
- f_r: blocking factor of *r* — i.e., the number of tuples of *r* that fit into one block.
  - If tuples of *r* are stored together physically in a file, then:

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

- *V(A, r):* number of distinct values that appear in *r* for attribute *A;* same as the size of $\prod_A(r)$.

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
  - E.g. (4, 8, 14, 19)
- Many databases also store *n* **most-frequent values** and their counts
  - Histogram is built on remaining values only

Histograms (cont.)

- Histograms and other statistics usually computed based on a **random sample**
- Statistics may be out of date
  - Many systems automatically recompute statistics
    - e.g., when number of tuples in a relation changes by some percentage
  - Some database require the **analyze** command to be executed to update statistics (e.g. PostgreSQL and Oracle)

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 $v < min(A, r)$
    - $c = n_r . \dfrac{v - \min(A,r)}{\max(A,r) - \min(A,r)}$
  - If histograms available, the above estimate can be refined
  - 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 $r \times s$ contains $n_r \times n_s$ tuples; each tuple occupies $s_r + s_s$ bytes.
- If $R \cap S = \emptyset$, then $r \bowtie s$ is the same as $r \times s$.
- 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* ⋈ *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.

- The above can be further improved if histograms are available

Estimation of the Size of Joins (Cont.)

- Compute the size estimates for *depositor* $\bowtie$ *customer* without using information about foreign keys:
  - *V(ID, takes)* = 2500, and
    V(ID, student) = 5000
  - The two estimates are 5000*10000/2500 = 20000 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.
      - <u>All the three estimates may be quite inaccurate but provide approximate bounds on the sizes</u>.
- Outer join:
  - Estimated size of r ⟕ s = size of r ⋈ s + size of r
    - Case of right outer join is symmetric
  - Estimated size of r ⟗ s = size of r ⋈ s + size of r + size of s

Estimation of Number of Distinct Values from Selection/Projection Results

Selections: $\sigma_\theta(r)$

- If θ forces A to take a specified value: $V(A,\sigma_\theta(r)) = 1$ (e.g., $A = 3$)
- If θ forces A to take on one of a specified set of values:
  $V(A,\sigma_\theta(r))$ = number of specified values.
  - (e.g., ($A = 1 \vee A = 3 \vee A = 4$)),
- If the selection condition θ is of the form ***A op r*** : $V(A, \sigma_\theta(r)) = V(A, r) * s$
  - where s is the selectivity of the selection.
- In all the other cases: use approximate estimate of min($V(A, r)$, $n_{\sigma\theta(r)}$)
  - More accurate estimate can be got using probability theory, but this one works fine generally

Projections: $\prod_A(r)$

- Estimation of distinct values are straightforward for projections.
  - $V(A, \prod_A(r)) = V(A, r)$
- The same holds for grouping attributes of aggregation.

Additional Optimization Techniques

Materialized Views

- A **materialized view** is a view whose contents are computed and stored.
- Consider the view

  create view *department_total_salary*(*dept_name, total_salary*) **as**
  select *dept_name*, **sum**(*salary*)
  from *instructor*
  group by *dept_name*

- Materializing the above view would be very useful if the total salary by department is required frequently
  - Saves the effort of finding multiple tuples and adding up their amounts

Materialized View Maintenance

- The task of keeping a materialized view up-to-date with the underlying data is known as **materialized view maintenance**
- Materialized views can be maintained by recomputation on every update
- View maintenance can be done by
  - Manually defining triggers on insert, delete, and update of each relation in the view definition
  - Manually written code to update the view whenever database relations are updated
  - Periodic recomputation (e.g. nightly)
  - Incremental maintenance supported by many database systems

- **Incremental view maintenance**
  - **Changes to database relations are used to compute changes to the materialized view, which is then updated**

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, exploiting sharing of common subexpressions between queries where it is useful

Multiquery Optimization (Cont.)

- **Common subexpression elimination**
  - (A simple heuristic when a batch of queries are submitted together)
  1. optimize each query separately
  2. detect and exploit common subexpressions in the individual optimal query plans
     - May not always give best plan, but is cheap to implement
- **Shared scans**: a 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

End of Chapter 16