# Chapter 13:  Query Optimization

- Introduction
- Transformation of Relational Expressions
- Catalog Information for Cost Estimation
- Statistical Information for Cost Estimation
- Cost-based optimization
- Dynamic Programming for Choosing Evaluation Plans
- Materialized views

# Query Optimization in a Nutshell

- Cost-based versus rule-based query optimization

- Cost-based: look at all legal/correct execution plans, pick cheapest one
- Problem: how to correctly estimate cost of a plan
- Cost depends in input size, data properties, available space, CPU, disk
- Cost of higher-level operators depends on output of lower levels

- Rule-based: transform into a good plan using rules
- Challenge: there are exceptions to most rules
- Example rules: do selection before join when possible, use an index for a selection if possible, use an index for a join if possible

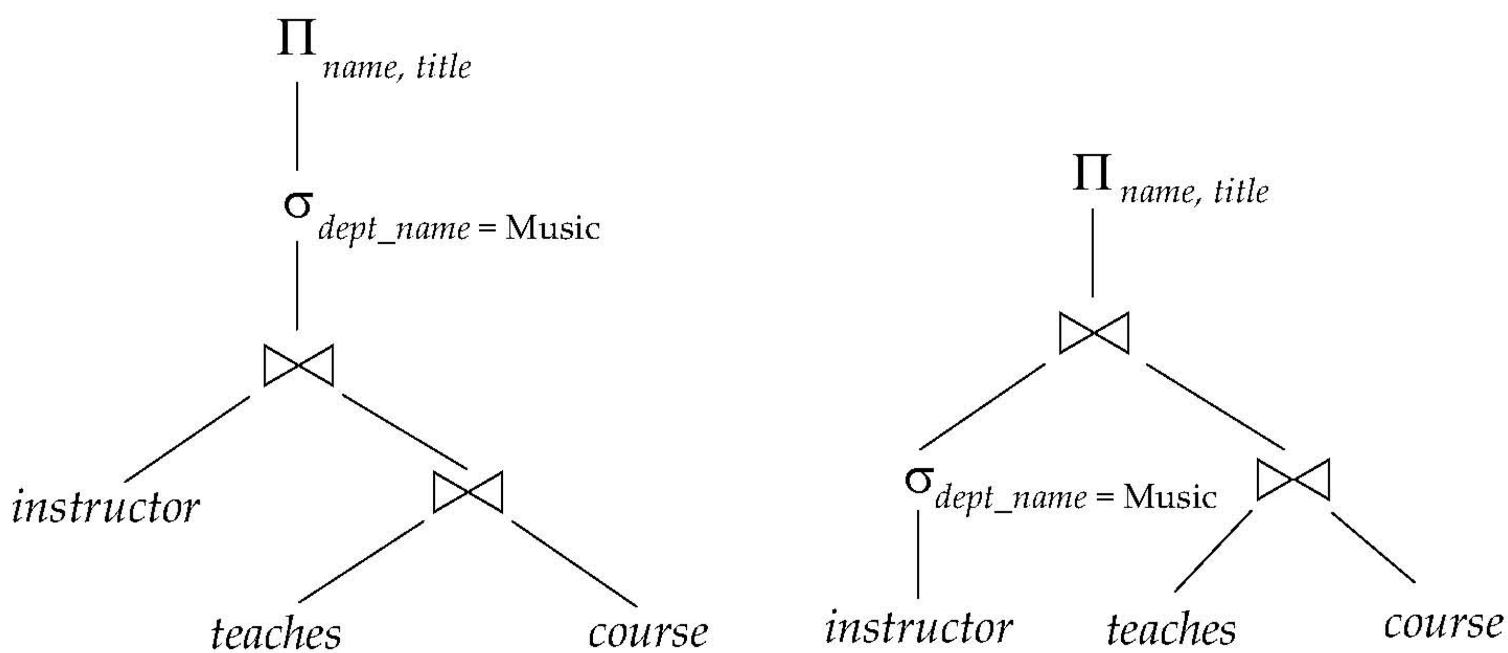
- State of the art: combine rules and cost estimation – use rules to restrict to “reasonable” execution plans, and choose the cheapest of those

# Query Optimization in a Nutshell

- Need to be able to enumerate all legal (or reasonable) plans
- This is done via equivalence rules that tell us when operators can be switched and thus, which other plans can be generated from initial one
- For example, we can push selection from after to before the join, assuming attributes are from only one table
- Pseudocode for combined cost/rule-based optimizer
  - For all legal plans p for the query Q
    - If plan p satisfies a restricted set of rules
      - Estimate cost(p), and our confidence interval for the estimate
  - Choose a plan with minimum or close to minimum cost
- Restricted set of rules to prune search space

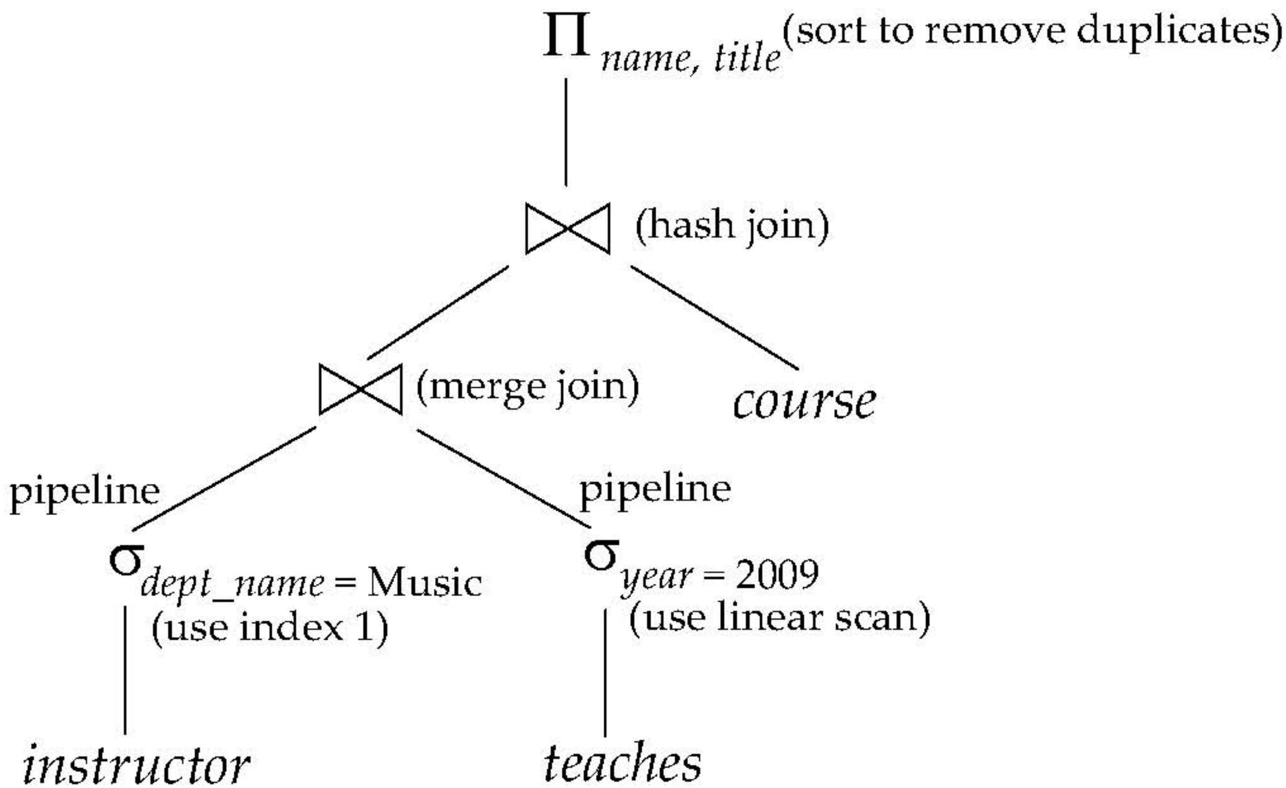
# Introduction

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



# Introduction (Cont.)

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




- Find out how to view query execution plans on your favorite database

# 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

# 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.

$$\sigma_{\theta_1 \wedge \theta_2}(E) = \sigma_{\theta_1}(\sigma_{\theta_2}(E))$$

2. Selection operations are commutative.

$$\sigma_{\theta_1}(\sigma_{\theta_2}(E)) = \sigma_{\theta_2}(\sigma_{\theta_1}(E))$$

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

$$\Pi_{L_1}(\Pi_{L_2}(\ldots(\Pi_{Ln}(E))\ldots)) = \Pi_{L_1}(E)$$

4. Selections can be combined with Cartesian products and theta joins.
   a. $\sigma_{\theta}(E_1 \text{ X } E_2) = E_1 \bowtie_{\theta} E_2$
   b. $\sigma_{\theta 1}(E_1 \bowtie_{\theta 2} E_2) = E_1 \bowtie_{\theta 1 \wedge \theta 2} E_2$

# Equivalence Rules (Cont.)

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

$$E_1 \bowtie_\theta E_2 = E_2 \bowtie_\theta E_1$$

6. (a) Natural join operations are associative:

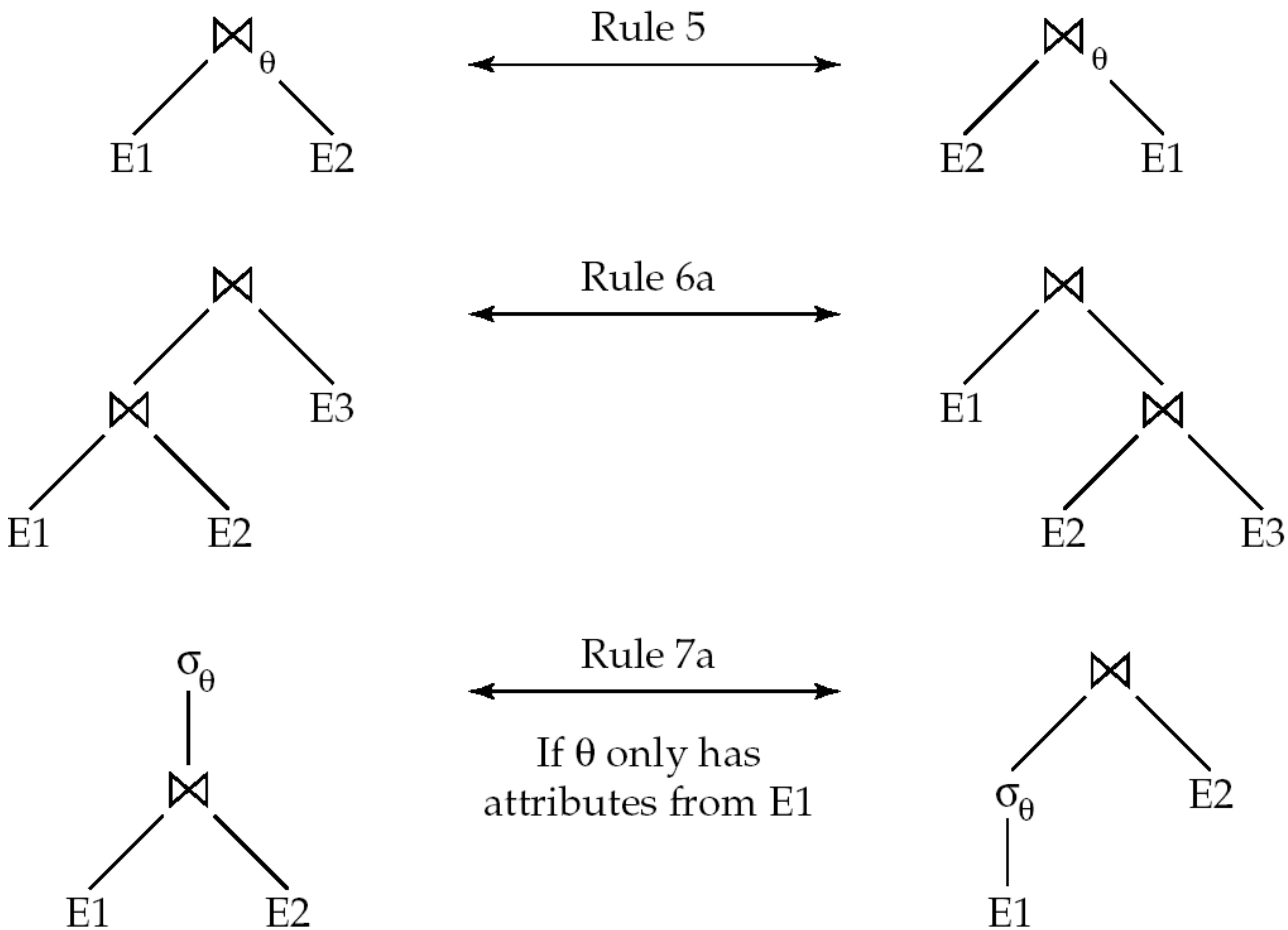
$$(E_1 \bowtie E_2) \bowtie E_3 = E_1 \bowtie (E_2 \bowtie E_3)$$

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

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

where $\theta_2$ 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 $\theta_0$ involve only the attributes of one of the expressions ($E_1$) being joined.

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

   (b) When $\theta_1$ involves only the attributes of $E_1$ and $\theta_2$ involves only the attributes of $E_2$.

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

# Equivalence Rules (Cont.)

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

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

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

   (b) 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 $\theta$, but are not in $L_1 \cup L_2$, and
   - let $L_4$ be attributes of $E_2$ that are involved in join condition $\theta$, but are not in $L_1 \cup L_2$.

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

# Equivalence Rules (Cont.)

9. The set operations union and intersection are commutative

$$E_1 \cup E_2 = E_2 \cup E_1$$
$$E_1 \cap E_2 = E_2 \cap E_1$$

- (set difference is not commutative).

10. Set union and intersection are associative.

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

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

$$\sigma_\theta (E_1 - E_2) = \sigma_\theta (E_1) - \sigma_\theta(E_2)$$

and similarly for $\cup$ and $\cap$ in place of $-$

Also: $$\sigma_\theta (E_1 - E_2) = \sigma_\theta(E_1) - E_2$$

and similarly for $\cap$ in place of $-$, but not for $\cup$

12. The projection operation distributes over union

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

# Transformation Example: Pushing Selections

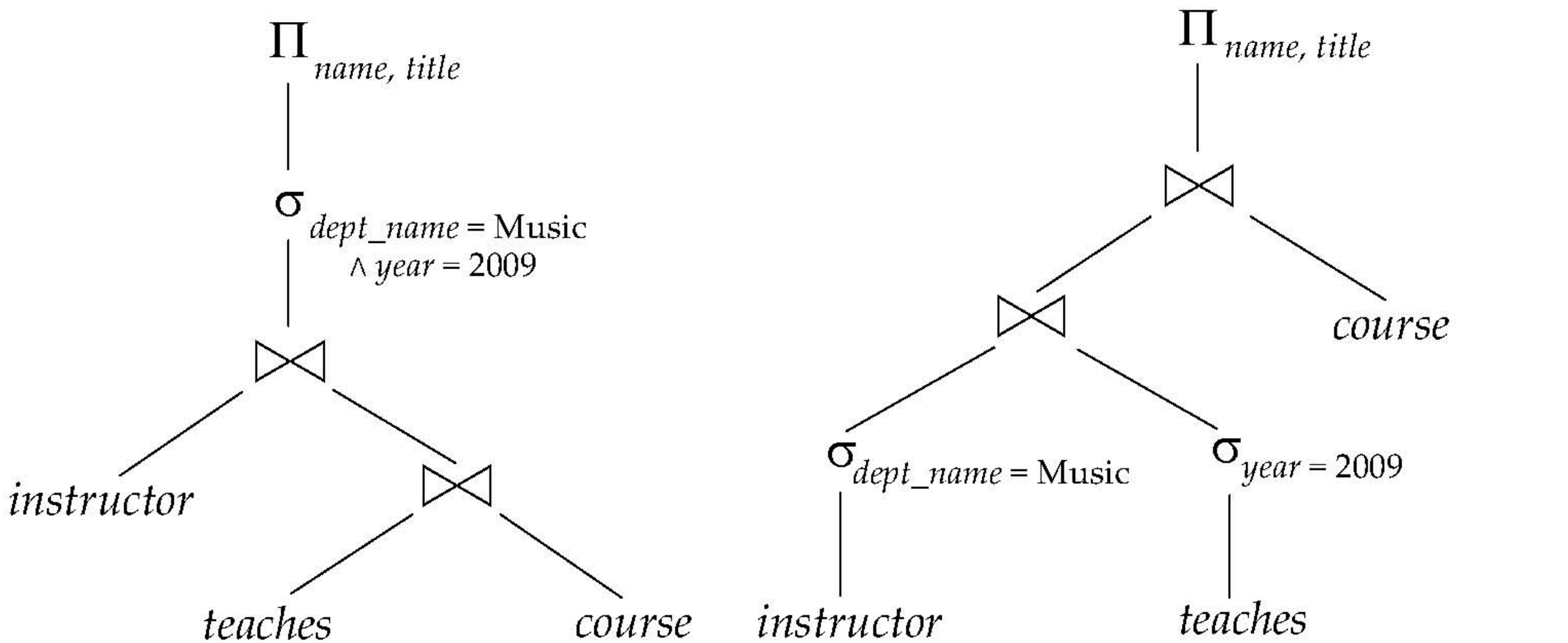
- Query: Find the names of all instructors in the Music department, along with the titles of the courses that they teach
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\ \text{"Music"}}(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course))))$
- Transformation using rule 7a.
  - $\Pi_{name,\ title}((\sigma_{dept\_name=\ \text{"Music"}}(instructor)) \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course)))$
- 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 2009, along with the titles of the courses that they taught
  - $\Pi_{name,\ title}(\sigma_{dept\_name= \text{"Music"} \land year = 2009}$
    $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course))))$
- Transformation using join associatively (Rule 6a):
  - $\Pi_{name,\ title}(\sigma_{dept\_name= \text{"Music"} \land gear = 2009}$
    $((instructor \bowtie teaches) \bowtie \Pi_{course\_id,\ title}(course)))$
- Second form provides an opportunity to apply the "perform selections early" rule, resulting in the subexpression

$$\sigma_{dept\_name = \text{"Music"}}(instructor) \bowtie \sigma_{year = 2009}(teaches)$$

# 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.

# Join Ordering Example

- For all relations $r_1$, $r_2$, and $r_3$,

  $$(r_1 \bowtie r_2) \bowtie r_3 = r_1 \bowtie (r_2 \bowtie r_3)$$

  (Join Associativity)

- 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.

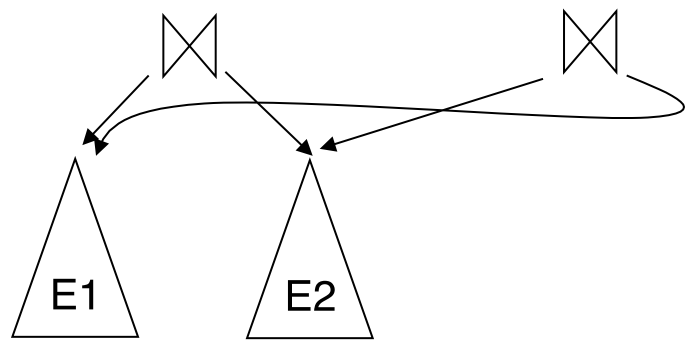
# Enumeration of Equivalent Expressions

- 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
  - Two approaches
    - Optimized plan generation based on transformation rules
    - Special case approach for queries with only selections, projections and joins

# Implementing Transformation Based 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 computed as described in Chapter 12
  - 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 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 $r_1 \bowtie r_2 \bowtie \ldots r_n$.
- 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.

# Dynamic Programming in Optimization

- To find 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

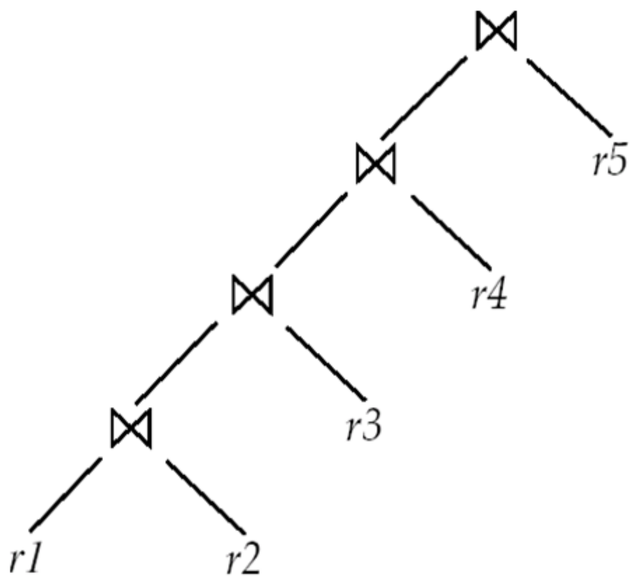
# Join Order Optimization Algorithm

```
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 on S */
    else for each non-empty subset S1 of S such that S1 ≠ S
            P1= findbestplan(S1)
            P2= findbestplan(S - S1)
            A = best algorithm for joining results of P1 and P2
            cost = P1.cost + P2.cost + cost of A
            if cost < bestplan[S].cost
                    bestplan[S].cost = cost
                    bestplan[S].plan = "execute P1.plan; execute P2.plan;
                                            join results of P1 and P2 using A"
    return bestplan[S]
```

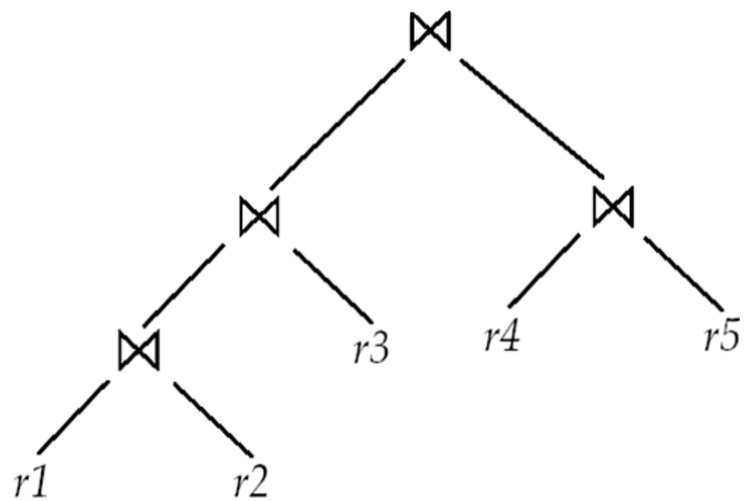
* Some modifications to allow indexed nested loops joins on relations that have selections (see book)

# 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

- With dynamic programming time complexity of optimization with bushy trees is $O(3^n)$.
  - With $n$ = 10, this number is 59000 instead of 176 billion!
- Space complexity is $O(2^n)$
- To find best left-deep join tree for a set of $n$ 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 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)

# Interesting Sort Orders

- Consider the expression $(r_1 \bowtie r_2) \bowtie r_3$ (with A as common attribute)
- An **interesting sort order** is a particular sort order of tuples that could be useful for a later operation
  - Using merge-join to compute $r_1 \bowtie r_2$ may be costlier than hash join but generates result sorted on A
  - Which in turn may make merge-join with $r_3$ cheaper, which may reduce cost of join with $r_3$ and minimizing overall cost
  - Sort order may also be useful for order by and for grouping
- Not sufficient to find the best join order for each subset of the set of $n$ given relations
  - must find the best join order for each subset, **for each interesting sort order**
  - Simple extension of earlier dynamic programming algorithms
  - Usually, number of interesting orders is quite small and doesn't affect time/space complexity significantly

# Cost Based Optimization with Equivalence Rules

- **Physical equivalence rules** allow logical query plan to be converted to physical query plan specifying what algorithms are used for each operation.
- Efficient optimizer based on equivalent rules depends on
  - A space efficient representation of expressions which avoids making multiple copies of subexpressions
  - Efficient techniques for detecting duplicate derivations of expressions
  - A form of dynamic programming based on **memoization**, which stores the best plan for a subexpression the first time it is optimized, and reuses in on repeated optimization calls on same subexpression
  - Cost-based pruning techniques that avoid generating all plans
- Pioneered by the Volcano project and implemented in the SQL Server optimizer

# 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.

- So this is a hybrid of cost- and rule-based optimization

# Structure of Query Optimizers

- 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.
- Heuristic optimization used in some versions of Oracle:
  - Repeatedly pick "best" relation to join next
    - Starting from each of n starting points.  Pick best among these
- Intricacies of SQL complicate query optimization
  - E.g. nested subqueries

# Structure of Query Optimizers (Cont.)

- Some query optimizers integrate heuristic selection and the generation of alternative access plans.
  - Frequently used approach
    - heuristic rewriting of nested block structure and aggregation
    - followed by cost-based join-order optimization for each block
  - Some optimizers (e.g. SQL Server) apply transformations to entire query and do not depend on block structure
  - **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
- Even with the use of heuristics, cost-based query optimization imposes a substantial overhead.
  - But is worth it for expensive queries
  - Optimizers often use simple heuristics for very cheap queries, and perform exhaustive enumeration for more expensive queries

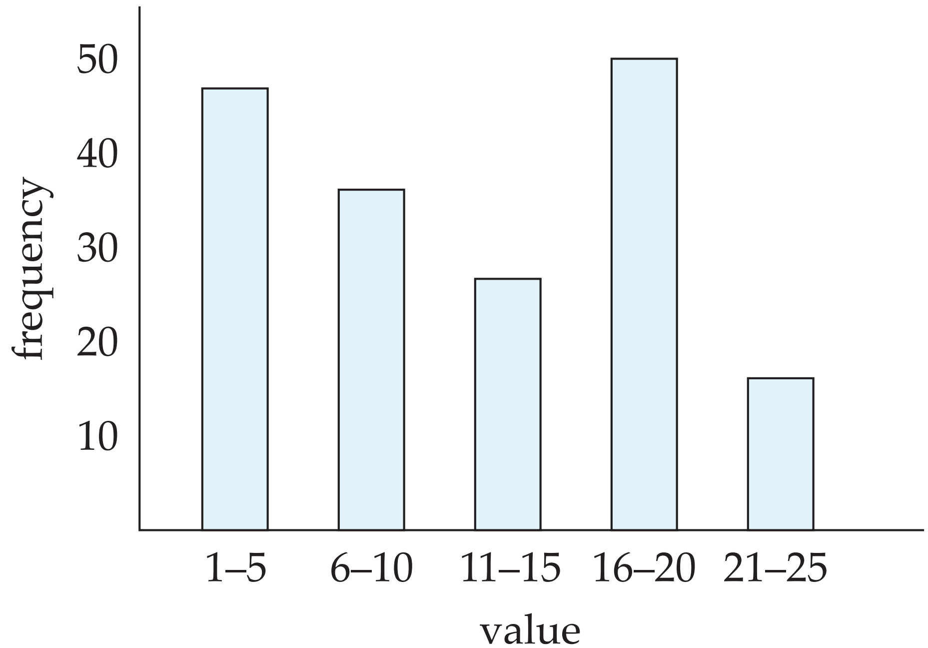
# Statistical Information for Cost Estimation

- $n_r$: 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

# 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 $\theta_i$ is the probability that a tuple in the relation *r* satisfies $\theta_i$ .
  - If $s_i$ is the number of satisfying tuples in *r*, the selectivity of $\theta_i$ is given by $s_i / n_r$.
- **Conjunction:** $\sigma_{\theta 1 \wedge \theta 2 \wedge \ldots \wedge \theta n}(r)$. *Assuming indepdence,* 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* ⋈ *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 $n_r.n_s$ 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* $\bowtie$ *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 *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 = 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 ${}_A\mathcal{g}_F(r)$ = $V(A,r)$
- 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 $\sigma_{\theta 1 \vee \theta 2}(r)$
  - 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 upper bounds on the sizes</u>.

# Size Estimation (Cont.)

- Outer join:
  - Estimated size of $r ⟕ s$ = *size of* $r \bowtie s$ + *size of* $r$
    - Case of right outer join is symmetric
  - Estimated size of $r ⟗ s$ = *size of* $r \bowtie s$ + size of $r$ + size of $s$

# Estimation of Number of Distinct Values

Selections: $\sigma_\theta\,(r)$

- If $\theta$ forces $A$ to take a specified value: $V(A,\sigma_\theta\,(r)) = 1$.
  - e.g., $A = 3$
- If $\theta$ forces A to take on one of a specified set of values: $V(A,\sigma_\theta\,(r))$ = number of specified values.
  - (e.g., ($A = 1\ \ V\ A = 3\ \ V\ A = 4$ )),
- If the selection condition $\theta$ is of the form $A$ *op* $r$
  estimated $V(A,\sigma_\theta\,(r)) = V(A.r) * s$
  - 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

# Estimation of Distinct Values (Cont.)

Joins: $r \bowtie s$

- If all attributes in $A$ are from $r$
  estimated $V(A, r \bowtie s) = \min(V(A,r), n_{r \bowtie s})$
- If $A$ contains attributes $A1$ from $r$ and $A2$ from $s$, then estimated $V(A, r \bowtie s)$ =

$$\min(V(A1,r) * V(A2 - A1,s),\ V(A1 - A2,r) * V(A2,s),\ n_{r \bowtie s})$$

  - More accurate estimate can be got using probability theory, but this one works fine generally

# Estimation of Distinct Values (Cont.)

- Estimation of distinct values are straightforward for projections.
  - They are the same in $\prod_{A}(r)$ as in $r$.
- The same holds for grouping attributes of aggregation.
- For aggregated values
  - For min($A$) and max($A$), the number of distinct values can be estimated as min(V($A,r$), $V$($G,r$)) where G denotes grouping attributes
  - For other aggregates, assume all values are distinct, and use $V$($G,r$)

# Happy Thanksgiving!