Chapter 13: Query Optimization

Database System Concepts, 6th Ed.

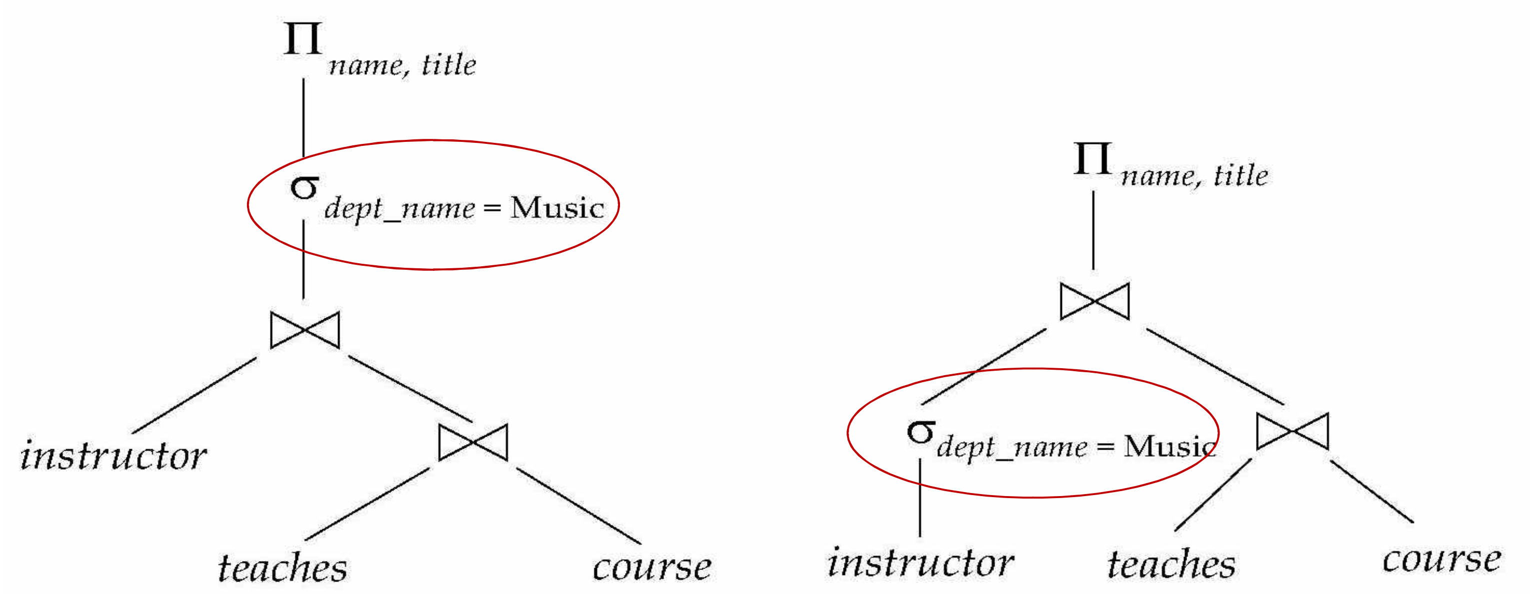
Database System Concepts

Chapter 13: Query Optimization

- 13.1 Overview
- 13.2 Transformation of Relational Expressions
- 13.3 Estimating Statistics of Expression
- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

Overview

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



Initial Expression Tree

Transformed Expression Tree

Fig 13.01

Relations generated by two equivalent expressions have the same set of attributes and contain the same set of tuples, although their attributes may be ordered differently.

Overview (Cont.)

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

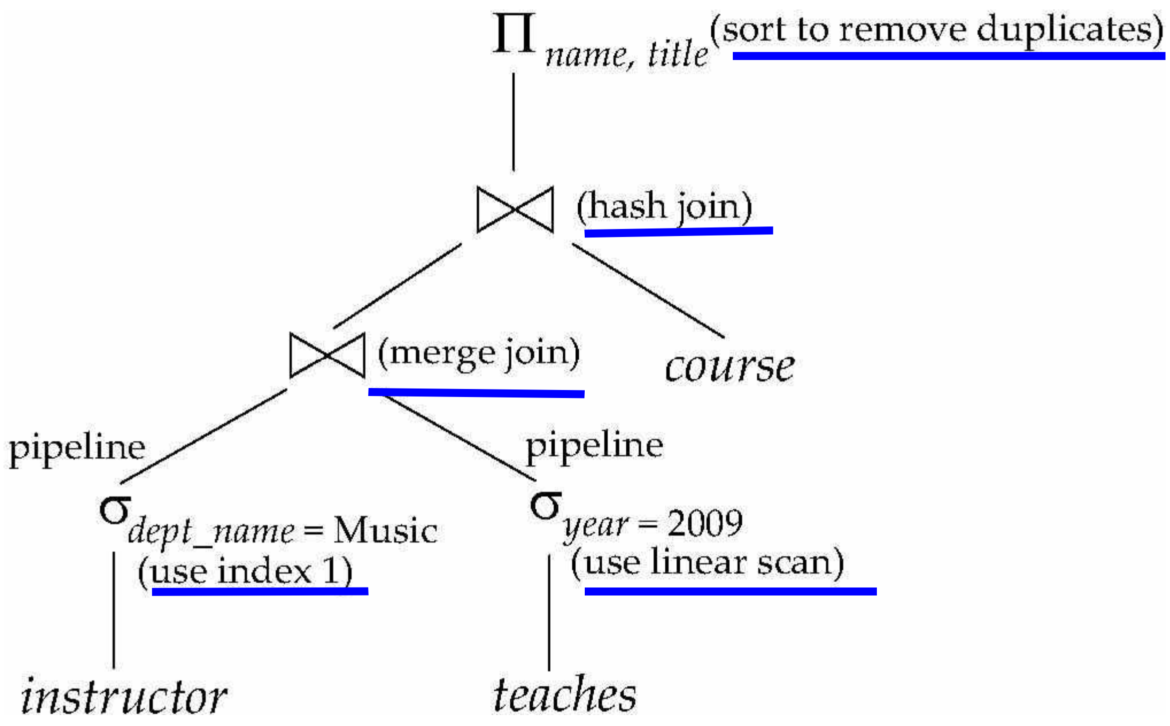


Fig 13.02

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

Overview (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

Chapter 13: Query Optimization

- 13.1 Overview
- 13.2 Transformation of Relational Expressions

  = Generating Equivalent Expressions

- 13.3 Estimating Statistics of Expression
- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

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

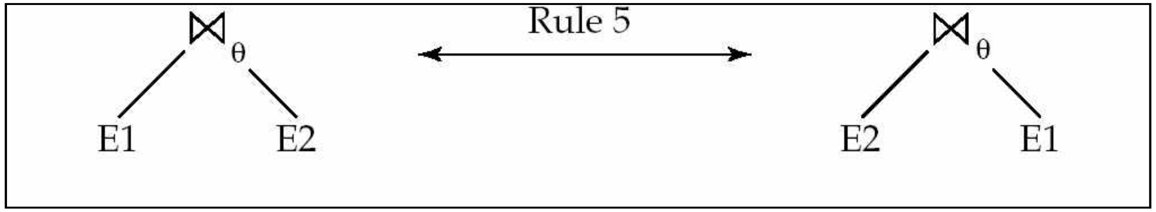
Equivalence Rules

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. $\sigma_\theta(E_1 \times E_2) = E_1 \bowtie_\theta E_2$
   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.

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



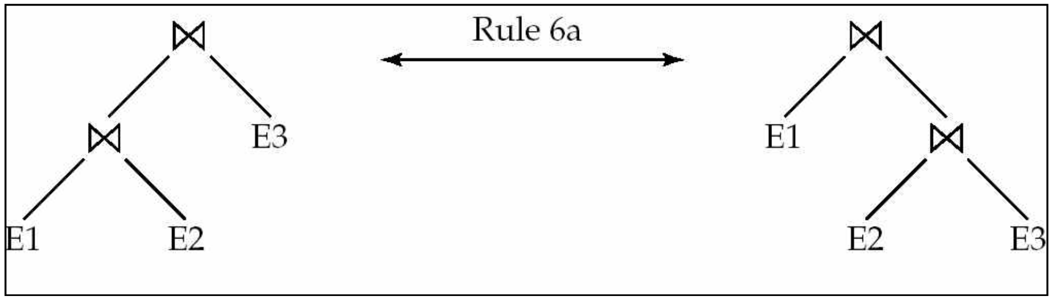
6. (a) Natural join operations are associative:

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

(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 θ_2 involves attributes from only E_2 and E_3.



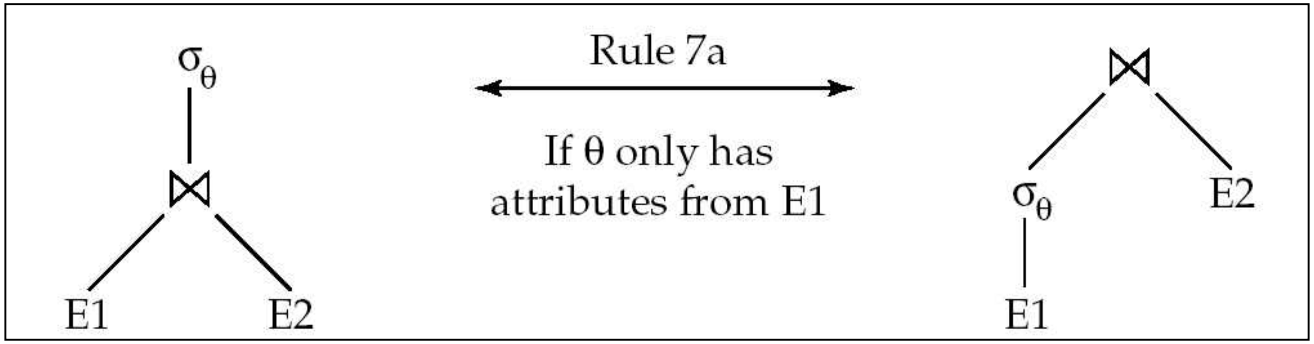
Equivalence Rules (Cont.)

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.

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

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

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



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Equivalence Rule 7-a (1)

- θ_0의 모든 속성들이 조인되는 expression(E_1) 의 한 쪽의 속성들로만 이루어져 있을 때

1) $\sigma_{\theta 0}(E1 \bowtie_{\theta} E2)$

branch-city	branch-name	assets	loan-number	amount
Brighton	Perryridge	7100000	L-15	1500
Brighton	Perryridge	7100000	L-16	1300

$\sigma_{assets > 2000000}$

branch-city	branch-name	assets	loan-number	amount
Bennington	Pownal	300000	L-23	2000
Horseneck	Mianus	400000	L-11	900
Brighton	Perryridge	7100000	L-15	1500
Brighton	Perryridge	7100000	L-16	1300

$\bowtie$

branch

branch-name	branch-city	assets
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

loan

loan-number	branch-name	amount
L-11	Horseneck	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Pownal	2000
L-93	Mianus	500

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Equivalence Rule 7-a (2)

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

Result

branch-city	*branch-name*	*assets*	*loan-number*	*amount*
Brighton	**Perryridge**	**7100000**	**L-15**	**1500**
Brighton	**Perryridge**	**7100000**	**L-16**	**1300**

$\bowtie$

branch-name	*branch-city*	*assets*
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
North Town	Rye	3700000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

loan

loan-number	*branch-name*	*amount*
L-11	Horseneck	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Pownal	2000
L-93	Mianus	500

$\sigma_{\underline{assets} > 2000000}$

branch

branch-name	*branch-city*	*assets*
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

So, $\sigma_{\theta 0}(E1 \bowtie_\theta E2) = (\sigma_{\theta 0}(E1)) \bowtie_\theta E2$

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Equivalence Rule 7-b (1)

- θ_1이 E_1 의 속성들에만 관여되고, θ_2가 E_2의 속성들에만 관여될 때

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

branch-city	branch-name	assets	loan-number	amount
Brighton	Perryridge	7100000	L-15	1500

σ $\underline{assets}$ > 2000000 and $\underline{amount}$ > 1300

branch-city	branch-name	assets	loan-number	amount
Bennington	Pownal	300000	L-23	2000
Horseneck	Mianus	400000	L-11	900
Brighton	Perryridge	7100000	L-15	1500
Brighton	Perryridge	7100000	L-16	1300

$\bowtie$

branch

branch-name	branch-city	assets
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

loan

loan-number	branch-name	amount
L-11	Horseneck	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Pownal	2000
L-93	Mianus	500

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Equivalence Rule 7-b (2)

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

Result

branch-city	*branch-name*	*assets*	*loan-number*	*amount*
Brighton	Perryridge	7100000	L-15	1500

$\bowtie$

branch-name	*branch-city*	*assets*
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
North Town	Rye	3700000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

loan-number Horseneck	*branch-name*	*amount*
L-14	Downtown	1500
L-15	Perryridge	1500
L-23	Pownal	2000

$\sigma_{assets > 2000000}$ $\sigma_{amount > 1500}$

branch

branch-name	*branch-city*	*assets*
Brighton	Perryridge	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

loan

loan-number	*branch-name*	*amount*
L-11	Horseneck	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Pownal	2000
L-93	Mianus	500

So, $\sigma_{\theta 1 \wedge \theta 2}(E1 \bowtie_\theta E2) = (\sigma_{\theta 1}(E1)) \bowtie_\theta (\sigma_{\theta 2}(E2))$

Equivalence Rules (Cont.)

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

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

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

   (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 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 $L_1 \cup L_2$.

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

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The Equivalence Rule 8-a

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

- E1 = loan, E2 = branch
- L1 = {loan-number, branch-name}, L2 = {branch-name, assets}
- θ = branch.assets > 75000
- In this condition, join condition involves only attributes in $L_1 \cup L_2$

loan

loan-number	*branch-name*	*amount*
L-11	Round Hill	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Redwood	2000
L-93	Mianus	500

branch

branch-name	*branch-city*	*assets*
Brighton	Brooklyn	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

Equivalence Rule 8-a: left-hand side

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

loan

loan-number	*branch-name*	*amount*
L-11	Round Hill	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Redwood	2000
L-93	Mianus	500

branch

branch-name	*branch-city*	*assets*
Brighton	Brooklyn	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

$$(E_1 \bowtie_\theta E_2)$$

loan-number	branch-name	amount	branch-city	assets
L-11	Round-Hill	900	Horse-neck	8000000
L-14	Downtown	1500	Brook-lyn	9000000
L-17	Downtown	1000	Brook-lyn	9000000

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

loan-number	branch-name	assets
L-11	Round-Hill	8000000
L-14	Downtown	9000000
L-17	Downtown	9000000

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Equivalence Rule 8-a: right-hand side

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

$(\Pi_{L_1}(E_1))$

loan-number	*branch-name*
L-11	Round Hill
L-14	Downtown
L-15	Perryridge
L-16	Perryridge
L-17	Downtown
L-23	Redwood
L-93	Mianus

$(\Pi_{L_2}(E_2))$

branch-name	*assets*
Brighton	7100000
Downtown	9000000
Mianus	400000
North Town	3700000
Perryridge	1700000
Pownal	300000
Redwood	2100000
Round Hill	8000000

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

loan-number	branch-name	assets
L-11	Round-Hill	8000000
L-14	Downtown	9000000
L-17	Downtown	9000000

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Equivalence Rule 8-b:

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

- E1 = loan, E2 = branch
- L1 = {branch-name}, L2 = {branch-name}
- θ = loan.amount > 950 and branch.branch-city = ‘Brooklyn’
- L3 = {amount}, L4 = {branch-city}

loan

loan-number	*branch-name*	*amount*
L-11	Round Hill	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Redwood	2000
L-93	Mianus	500

branch

branch-name	*branch-city*	*assets*
Brighton	Brooklyn	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

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Equivalence Rule 8-b: left-hand side

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

$(E_1 \bowtie_\theta E_2)$

loan-number	branch-name	amount	branch-city	assets
L-14	Downtown	1500	Brook-lyn	9000000
L-17	Downtown	1000	Brook-lyn	9000000

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

branch-name
Downtown

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Equivalence Rule 8-b: right-hand side

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

$(\Pi_{L_1 \cup L_3}(E_1))$

branch-name	*amount*
Round Hill	900
Downtown	1500
Perryridge	1500
Perryridge	1300
Downtown	1000
Redwood	2000
Mianus	500

$(\Pi_{L_2 \cup L_4}(E_2))$

branch-name	*branch-city*
Brighton	Brooklyn
Downtown	Brooklyn
Mianus	Horseneck
North Town	Rye
Perryridge	Horseneck
Pownal	Bennington
Redwood	Palo Alto
Round Hill	Horseneck

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

branch-name	amount	branch-city
Downtown	1500	Brook-lyn
Downtown	1000	Brook-lyn

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

branch-name
Downtown

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

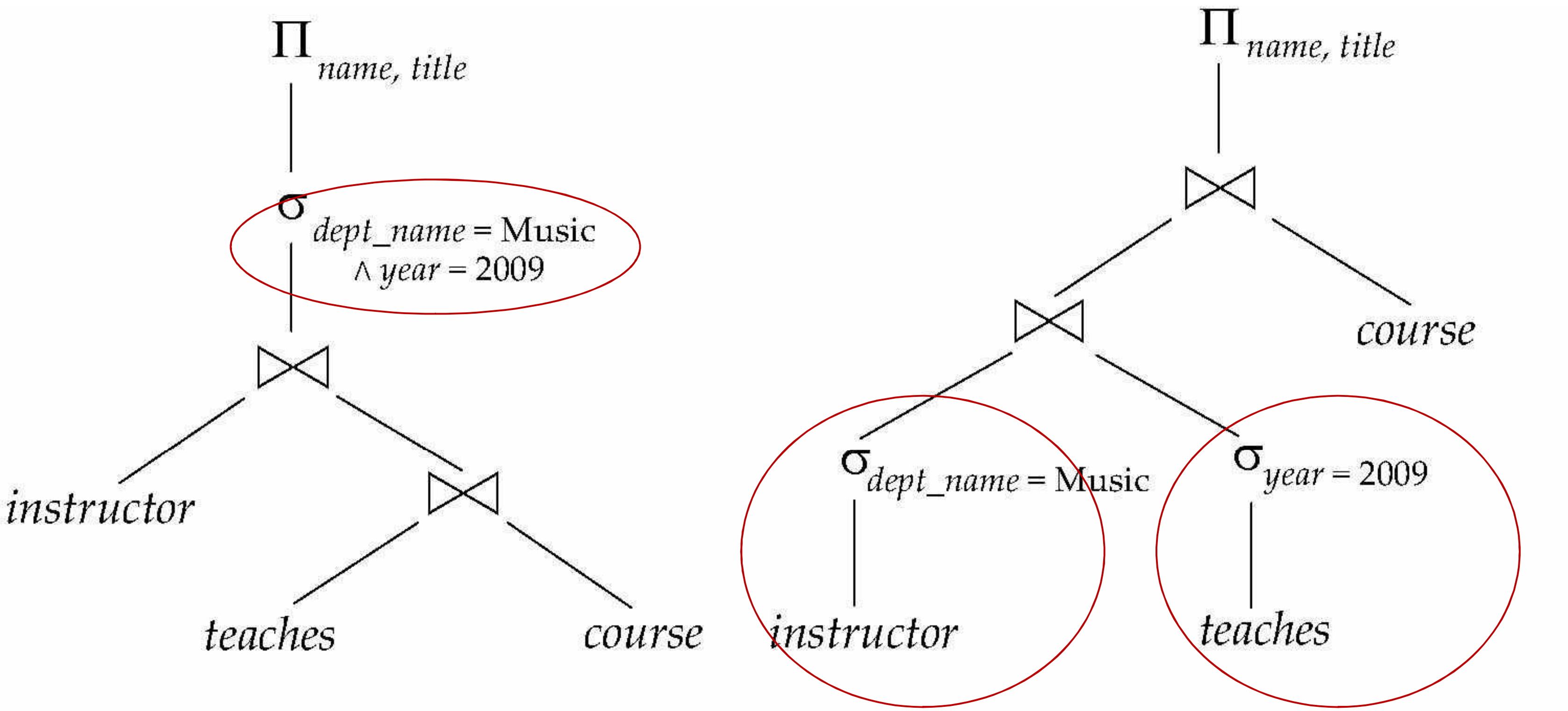
- Query: Find the names of all instructors in the Music department, along with the titles of the courses that they teach
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\text{“Music”}}$ $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$
- Transformation using rule 7a.
  - $\Pi_{name,\ title}((\sigma_{dept\_name=\text{“Music”}}(instructor)) \bowtie$ $(teaches \bowtie \Pi_{course\_id,\ title}\ (course)))$
- Performing the selection as early as possible reduces the size of the relation to be joined.

Example: 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
  - $\Pi_{name,\ title}(\sigma_{dept\_name = \text{"Music"} \wedge gear\ =\ 2009}$
    $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$
- Transformation using join associatively (Rule 6a):
  - $\Pi_{name,\ title}(\sigma_{dept\_name = \text{"Music"} \wedge gear\ =\ 2009}$
    $((instructor \bowtie teaches) \bowtie \Pi_{course\_id,\ title}\ (course)))$
- 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

Fig 13.04

Example: Transformation with 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

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

  $$(r_1 \bowtie r_2) \bowtie r_3 = r_1 \bowtie (r_2 \bowtie r_3) \quad \text{(Join Associativity)}$$

- 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.

Example: Join Ordering Example

- 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.

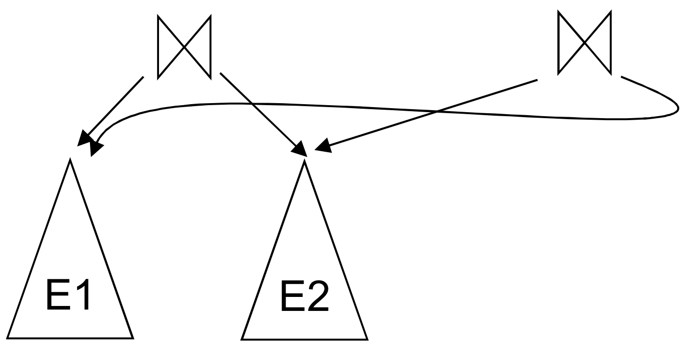
Enumeration of Equivalent Expressions

- 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

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- 13.2 Transformation of Relational Expressions
- 13.3 Estimating Statistics of Expression
  - Statistics for Cost Estimation
- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

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

- $SC(A, r)$: selection cardinality of attribute *A* of relation *r*
  - average number of records that satisfy equality on *A*
- f_i: average fan-out of internal nodes of index *i*, for B+-trees
- HT_i: number of levels in index *i* (i.e., the height of *i* & on attribute *A* of relation *r)*
  - For a B+-tree $HT_i = \lceil \log_{fi}(V(A,r)) \rceil$
  - For a hash index, $HT_i = 1$
- LB_i: number of lowest-level index blocks in *i* (i.e, the # of blocks at the leaf level)

Histograms

- Histogram on attribute *age* of relation *person*

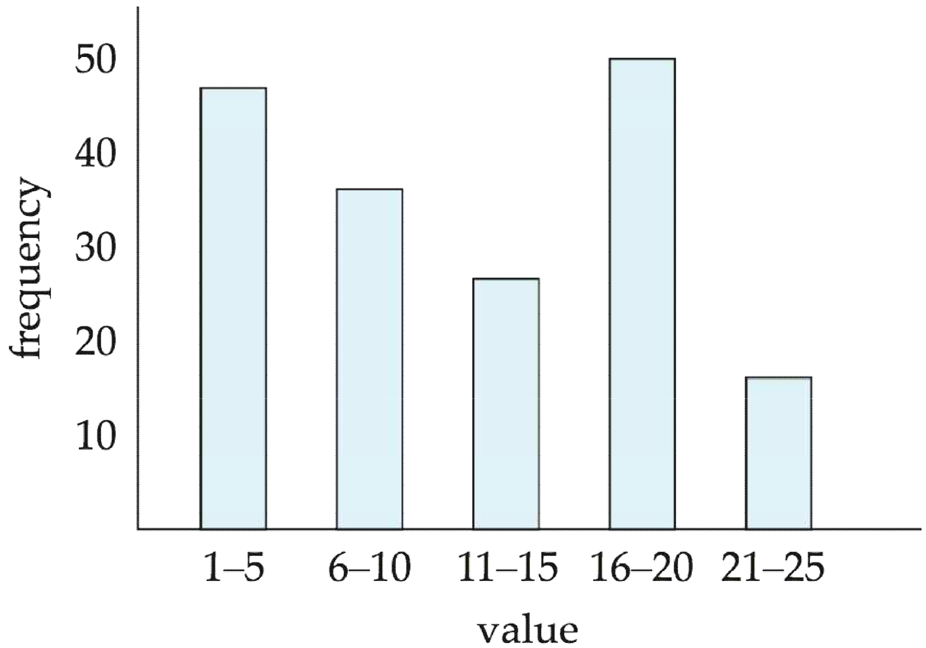


Fig 13.06

- **Equi-width** histograms
- **Equi-depth** histograms

Selection Size Estimation

- **Equality selection** $\sigma_{A=v}(r)$
  - $n_r / V(A,r)$: number of records that will satisfy the selection
  - Equality condition on a key attribute: *size estimate* = 1

- $\sigma_{A \leq V}(r)$ (case of $\sigma_{A \geq V}(r)$ 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 = $$n_r \cdot \frac{v - \min(A,r)}{\max(A,r) - \min(A,r)}$$
  - 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: $\boxed{n_r * \frac{s_1 * s_2 * \ldots * s_n}{n_r^n}}$

- **Disjunction:** $\sigma_{\theta 1 \vee \theta 2 \vee \ldots \vee \theta n}(r)$.

  Estimated number of tuples: $\boxed{n_r * \left(1 - (1 - \frac{s_1}{n_r}) * (1 - \frac{s_2}{n_r}) * \ldots * (1 - \frac{s_n}{n_r})\right)}$

- **Negation:** $\sigma_{\neg\theta}(r)$.

  Estimated number of tuples: $\boxed{n_r - size(\sigma_\theta(r))}$

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 $n_r . n_s$ 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
  - Then, 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 join 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 <u>every tuple *t* in *R*</u> produces tuples in $R \bowtie S$),

  the number of tuples in $R \bowtie S$ is estimated to be: $\boxed{\dfrac{n_r * n_s}{V(A,s)}}$

  If the reverse is true, the estimate obtained will be: $\boxed{\dfrac{n_r * n_s}{V(A,r)}}$

  The lower of these two estimates is probably the more accurate one.
- Can improve on above if histograms are available
- Example: Compute the size estimates for *depositor* $\bowtie$ *customer* 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: 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 $\Pi_A(r)$ = $V(A,r)$
- Aggregation : estimated size of $_A g_F(r)$ = $V(A,r)$
- 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 $\sigma_{\theta 1} \sigma_{\theta 2}(r)$
  - 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 ⟕ 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 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., $(A = 1\ V\ A = 3\ V\ A = 4)$),
- If the selection condition θ 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

Projection: ($\prod$) Estimation of distinct values are straightforward for projections.

- They are the same in $\prod_{A}(r)$ as in r.

Aggregation: 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 $V(G,r)$

Estimation of Distinct Values in Join (1)

보조자료

A의 모든 속성이 r에 있을때의 estimated $V(A, r \bowtie s) = \min(V(A,r), n_{r \bowtie s})$

- Example A = (B)

r

K	B	C
A1	B1	C1
A1	B2	C2
A2	B3	C1
A2	B1	C1
A3	B5	C4

s (case 1)

C	D
C1	D1
C2	D1
C3	D2
C4	D3
C5	D4

s (case 2)

C	D
C1	D1
C5	D2
C12	D3
C5	D4
C6	D5

$r \bowtie s$ (case 1)

K	B	C	D
A1	B1	C1	D1
A2	B3	C1	D1
A2	B1	C1	D1
A1	B2	C2	D1

$\Pi_B(r \bowtie s)$ (case 1)

B
B1
B3
B2

$V(A, r \bowtie s) = V(A,r)$

$r \bowtie s$ (case 2)

K	B	C	D
A1	B1	C1	D1
A2	B3	C1	D1

$\Pi_B(r \bowtie s)$ (case 2)

B
B1
B3

$V(A, r \bowtie s) = n_{r \bowtie s}$

Estimation of Distinct Values in Join (2)

보조자료

A의 속성 A1은 r에, A2는 s에 있을때의 estimated $V(A, r \bowtie s)$ =
$\min(\underline{V(A1,r) * V(A2 - A1,s)}, \underline{V(A1 - A2,r) * V(A2,s)}, \underline{n_{r \bowtie s}})$

❖ Example A = (B, D), 처음 두 개의 경우는 대칭적이므로 처음과 세번째 경우만 고려

r

K	B	C
A1	B1	C1
A1	B2	C2
A2	B2	C1
A2	B1	C1
A3	B2	C4

s (case 1)

C	D
C1	D1
C1	D1
C2	D2
C2	D1

s (case 3)

C	D
C2	D1
C5	D2
C12	D3
C5	D4
C6	D5

$r \bowtie s$ (case 1)

K	B	C	D
A1	B1	C1	D1
…			
A2	B1	C1	D1
A1	B2	C2	D1

$\Pi_A(r \bowtie s)$ (case 1)

B	D
B1	D1
B1	D2
B2	D1
B2	D2

$V(A, r \bowtie s)$ =
$V(A1,r) * V(A2\text{-}A1,s)$
(4 = 2 X 2)
(Join의 결과가 큰 경우)

$r \bowtie s$ (case 3)

K	B	C	D
A1	B2	C2	D1

$\Pi_A(r \bowtie s)$ (case 3)

B	D
B2	D1

$V(A, r \bowtie s) = n_{r \bowtie s}$
(1 = 1)

Chapter 13: Query Optimization

- 13.1 Overview
- 13.2 Transformation of Relational Expressions
- 13.3 Estimating Statistics of Expression
- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

Cost Estimation

- Cost of each operator is computed as described earlier
  - Need statistics data 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 on Multiple Joins

???

- Consider finding the best join-order for $r_1 \bowtie r_2 \ . \ . \ . \bowtie r_n$.
- The number of relations: (n),   The number of joins: (n-1)
- The number of full binary trees with n leaves (with (n-1) internal nodes)

  $1/n \times {}_{2(n-1)}C_{(n-1)} \Rightarrow 1/n \times ((2(n-1))! \ / \ (n-1)! * (n-1)!) \Rightarrow (2(n-1))! \ / \ (n! * (n-1)!)$

- Multiply this by n! (permutations of n leaves)
- Then the number of different join orders: $(2(n – 1))!/(n – 1)!$.
  - 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.

- Full binary tree: every node가 children을 0 or 2만을 가지는 binary tree

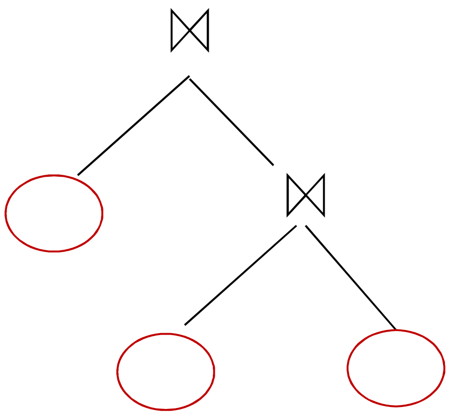
Example: $r_1 \bowtie r_2 \bowtie r_3$

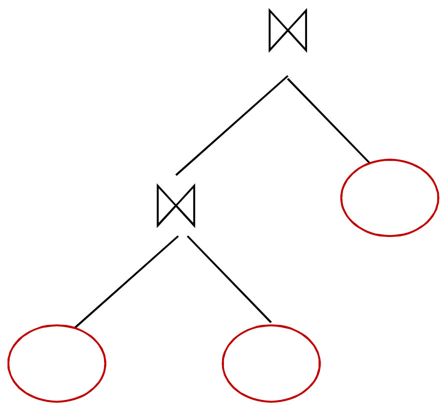
N = 3

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

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

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





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.
    - $nC1 + nC2 + \ldots. nCn = 2^n$
    - Choose the cheapest of the $2^n - 2$ alternatives.
    - Space overhead for storing 2^n *cost* ➔ $O(2^n)$
  - 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 $O(3^n)$
    - $O(3^n)$ by solving the recurrence relation of the next slide

Finding the Best Join Order

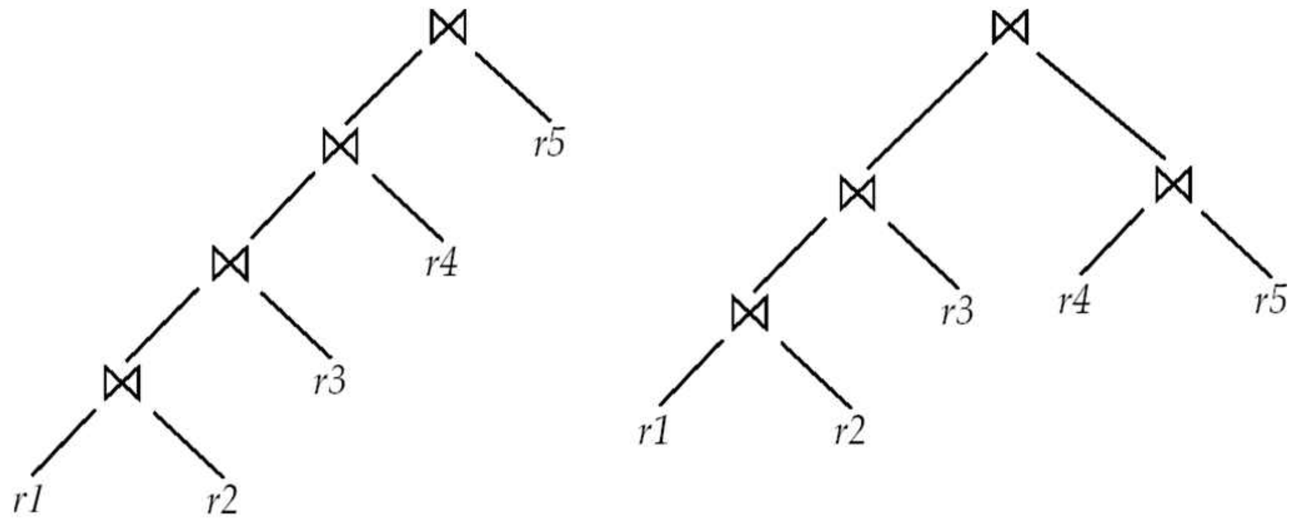
```
procedure findbestplan(S)
    if (bestplan[S].cost ≠ ∞)
            return bestplan[S]
    // else bestplan[S] has not been computed earlier, compute it now
    if (S contains only 1 relation)
            set bestplan[S].plan and bestplan[S].cost based on the best way
            of accessing S  /* 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.
- Left-deep join orders are convenient for pipelined evaluation: the right operand is a stored relation and only one input to each join is pipelined
- Figure (a) would enjoy pipelining while pipelining may not be possible in Figure (b)
- All left-deep join orders is O(n!) while all join orders is $O(3^n)$.

Figure 13.08



(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 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 $O(3^n)$
  - 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

- IBM DB2: Starburst Project (by Loura Haas, et al. 1989)
- SYBASE SQL Server: Volcano project

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.
- Direction in heuristics ➔ reduce the size of intermediate results!

Structure of Query Optimizers

- Finding the best join order is a big mission!
- Many optimizers (including Oracle) 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 the "best" relation to join next
    - Starting from each of n starting points.
    - Pick the best relation among these
- Intricacies of SQL complicate query optimization
  - E.g. nested subqueries

Intricacy: 복잡, 얽히고 설킴

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

Optimizing Nested Subqueries**

- Nested query example:
  select *name*
  from *instructor*
  where exists (**select** *
  from *teaches*
  where *instructor.ID* = *teaches.ID* **and** *teaches.year* = *2007*)
- SQL conceptually treats nested subqueries in the where clause as functions that take parameters and return a single value or set of values
  - Parameters are variables from outer level query that are used in the nested subquery; such variables are called **correlation variables**
- Conceptually, nested subquery is executed once for each tuple in the cross-product generated by the outer level **from** clause
  - Such evaluation is called **correlated evaluation**
  - Note: other conditions in where clause may be used to compute a join (instead of a cross-product) before executing the nested subquery

Optimizing Nested Subqueries (Cont.)

- Correlated evaluation may be quite inefficient since
  - a large number of calls may be made to the nested query
  - there may be unnecessary random I/O as a result
- SQL optimizers attempt to transform nested subqueries to joins where possible, enabling use of efficient join techniques
- E.g.: earlier nested query can be rewritten as
  select *name*
  from *instructor, teaches*
  where *instructor.ID* = *teaches.ID* **and** *teaches.year* = *2007*
  - Note: the two queries generate different numbers of duplicates (why?)
    - teaches can have duplicate IDs
    - Can be modified to handle duplicates correctly as we will see
- In general, it is not possible/straightforward to move the entire nested subquery from clause into the outer level query from clause
  - A temporary relation is created instead, and used in body of outer level query

Optimizing Nested Subqueries (Cont.)

In general, SQL queries of the form below can be rewritten as shown

- Rewrite: **select** …
  from L_1
  where P_1 **and exists** (**select** *
  from L_2
  where P_2)
- To: **create table** t_1 as
  select distinct V
  from L_2
  where P_2^1

  select …
  from L_1, t_1
  where P_1 **and** P_2^2
  - P_2^1 contains predicates in P_2 that do not involve any correlation variables
  - P_2^2 reintroduces predicates involving correlation variables, with relations renamed appropriately
  - V contains all attributes used in predicates with correlation variables

Optimizing Nested Subqueries (Cont.)

- In our example, the original nested query would be transformed to

  create table t_1 **as**
      select distinct *ID*
      from *teaches*
      where *year* = *2007*

  select *name*
  from *instructor*, t_1
  where t_1.*ID* = *instructor.ID*

- The process of replacing a nested query by a query with a join (possibly with a temporary relation) is called **decorrelation.**
- Decorrelation is more complicated when
  - the nested subquery uses aggregation, or
  - when the result of the nested subquery is used to test for equality, or
  - when the condition linking the nested subquery to the other query is **not exists**,
  - and so on.

Chapter 13: Query Optimization

- 13.1 Overview
- 13.2 Transformation of Relational Expressions
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- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

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

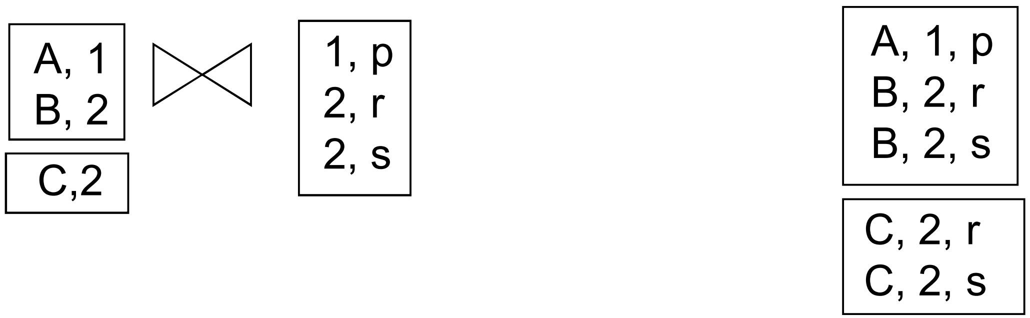
- The task of keeping a materialized view up-to-date with the underlying data is known as **materialized view maintenance**
- Materialized views can be maintained by recomputation on every update
- A better option is to use **incremental view maintenance**
  - **Changes to database relations are used to compute changes to the materialized view, which is then updated**
- 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)
  - Above methods are directly supported by many database systems
    - Avoids manual effort/correctness issues

Incremental View Maintenance

- The changes (inserts and deletes) to a relation or expressions are referred to as its **differential**
  - Set of tuples inserted to and deleted from r are denoted $\mathbf{i_r}$ and $\mathbf{d_r}$
- To simplify our description, we only consider inserts and deletes
  - We replace updates to a tuple by deletion of the tuple followed by insertion of the update tuple
- We describe how to compute the change to the result of each relational operation, given changes to its inputs
- We then outline how to handle relational algebra expressions

Join Operation in Materialized View

- Consider the materialized view $v = r \bowtie s$ and an update to r
- Let r^{old} and r^{new} denote the old and new states of relation r
- Consider the case of an insert to r:
  - We can write $r^{new} \bowtie s$ as $(r^{old} \cup i_r) \bowtie s$
  - And rewrite the above to $(r^{old} \bowtie s) \cup (i_r \bowtie s)$
  - But $(r^{old} \bowtie s)$ is simply the old value of the materialized view, so the incremental change to the view is just $i_r \bowtie s$
- Thus, for inserts $v^{new} = v^{old} \cup (i_r \bowtie s)$
- Similarly for deletes $v^{new} = v^{old} - (d_r \bowtie s)$



보조자료

Incremental View Maintenance

- *r = loan, s = branch*

loan-number	*branch-name*	*amount*
L-11	Round Hill	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Redwood	2000
L-93	Mianus	500

branch-name	*branch-city*	*assets*
Brighton	Brooklyn	7100000
Downtown	Brooklyn	9000000
Mianus	Horseneck	400000
North Town	Rye	3700000
Perryridge	Horseneck	1700000
Pownal	Bennington	300000
Redwood	Palo Alto	2100000
Round Hill	Horseneck	8000000

- The materialized view $v = r \bowtie s$

loan-number	branch-name	amount	branch-city	assets
L-11	Round-Hill	900	Horseneck	8000000
L-14	Downtown	1500	Brooklyn	9000000
L-15	Perryridge	1500	Horseneck	1700000
L-16	Perryridge	1300	Horseneck	1700000
L-17	Downtown	1000	Brooklyn	9000000
L-23	Redwood	2000	Palo Alto	2100000
L-93	Mianus	500	Horseneck	400000

보조자료

Incremental Deletion

- *dr = (L-11, Round Hill, 900)*
- *dr* ⋈ *s*

loan-number	branch-name	amount	branch-city	assets
L-11	Round-Hill	900	Horseneck	8000000

- *vnew* = *vold* – (*dr* ⋈ *s*)

loan-number	branch-name	amount	branch-city	assets
L-14	Downtown	1500	Brooklyn	9000000
L-15	Perryridge	1500	Horseneck	1700000
L-16	Perryridge	1300	Horseneck	1700000
L-17	Downtown	1000	Brooklyn	9000000
L-23	Redwood	2000	Palo Alto	2100000
L-93	Mianus	500	Horseneck	400000

보조자료

Incremental Insertion

- *ir = (L-11, Round Hill, 900)*
- *ir* $\bowtie$ *s*

loan-number	branch-name	amount	branch-city	assets
L-11	Round-Hill	900	Horseneck	8000000

- *vnew = vold* $\cup$ (*ir* $\bowtie$ *s*)

loan-number	branch-name	amount	branch-city	assets
L-11	Round-Hill	900	Horseneck	8000000
L-14	Downtown	1500	Brooklyn	9000000
L-15	Perryridge	1500	Horseneck	1700000
L-16	Perryridge	1300	Horseneck	1700000
L-17	Downtown	1000	Brooklyn	9000000
L-23	Redwood	2000	Palo Alto	2100000
L-93	Mianus	500	Horseneck	400000

Selection and Projection Operations in Materialized Views

- Selection: Consider a view $v = \sigma_\theta(r)$.
  - $v^{new} = v^{old} \cup \sigma_\theta(i_r)$
  - $v^{new} = v^{old} - \sigma_\theta(d_r)$
- Projection is a more difficult operation
  - $R = (A,B)$, and r(R) = { (a,2), (a,3)}
  - $\prod_A(r)$ has a single tuple (a).
  - If we delete the tuple (a,2) from r, we should not delete the tuple (a) from $\prod_A(r)$, but if we then delete (a,3) as well, we should delete the tuple
- For each tuple in a projection $\prod_A(r)$, we will keep a count of how many times it was derived
  - On insert of a tuple to r, if the resultant tuple is already in $\prod_A(r)$ we increment its count, else we add a new tuple with count = 1
  - On delete of a tuple from r, we decrement the count of the corresponding tuple in $\prod_A(r)$
    - if the count becomes 0, we delete the tuple from $\prod_A(r)$

Aggregation Operations in Materialized Views

- **count** : $v = {}_A\mathcal{g}_{count(B)}{}^{(r)}$.
  - When a set of tuples i_r is inserted
    - For each tuple r in i_r, if the corresponding group is already present in v, we increment its count, else we add a new tuple with count = 1
  - When a set of tuples d_r is deleted
    - for each tuple t in $i_{r.}$ we look for the group *t.A* in *v*, and subtract 1 from the count for the group.
      - If the count becomes 0, we delete from *v* the tuple for the group *t.A*
- **sum**: $v = {}_A\mathcal{g}_{sum\ (B)}{}^{(r)}$
  - We maintain the sum in a manner similar to count, except we add/subtract the B value instead of adding/subtracting 1 for the count
  - Additionally we maintain the count in order to detect groups with no tuples. Such groups are deleted from v
    - Cannot simply test for sum = 0 (why?)
- To handle the case of **avg**, we maintain the **sum** and **count** aggregate values separately, and divide at the end

Aggregation Operations in Materialized Views (cont.)

- **min**, **max**: $v = {}_{A}g_{min\ (B)}\ (r)$.
  - Handling insertions on r is straightforward.
  - Maintaining the aggregate values **min** and **max** on deletions may be more expensive.
    - We have to look at the other tuples of *r* that are in the same group to find the new minimum

보조자료

Incremental View Maintenance

- **Count**
  - $v = {}_{branch\text{-}name}g_{count(loan\text{-}number)}(loan)$
- **Sum**
  - $v = {}_{branch\text{-}name}g_{sum(amount)}(loan)$
- **Avg**
  - $v = {}_{branch\text{-}name}g_{avg(amount)}(loan)$

loan-number	*branch-name*	*amount*
L-11	Round Hill	900
L-14	Downtown	1500
L-15	Perryridge	1500
L-16	Perryridge	1300
L-17	Downtown	1000
L-23	Redwood	2000
L-93	Mianus	500

보조자료

Incremental View Maintenance

- **Materialized View (Count)**

branch-name	count
Round Hill	1
Downtown	2
Perryridge	2
Red Wood	1
Mianus	1

Materialized View (Sum)

branch-name	sum
Round Hill	900
Downtown	2500
Perryridge	2800
Red Wood	2000
Mianus	500

- **Materialized View (Avg)**

branch-name	avg
Round Hill	900
Downtown	1250
Perryridge	1400
Red Wood	2000
Mianus	500

보조자료

Insertion to Base Relation

- Base relation loan에 tuple (L-30, Round Hill, 1300) 이 삽입된 경우
  - Count: Materialized View Count 에 Round Hill 이 있는가? ➔ Yes
    - Update the tuple (Round Hill, 1) ➔ (Round Hill, 2)
  - Sum: Materialized View Sum 에 RoundHill 이 있는가? ➔ Yes
    - Update the tuple (RoundHill, 900) ➔ (RoundHill, 2200) // 900+1300
  - Avg: Materialized View Sum 에 RoundHill 이 있는가? ➔ Yes
    - Update the tuple (RoundHill, 900) ➔ (RoundHill, 1100) // (900 + 1300) / 2

- Base relation loan에 tuple (L-70, Seoul, 1000) 이 삽입된 경우
  - Count: Materialized View Count 에 Seoul 이 있는가? ➔ No
    - Insert a new tuple (Seoul, 1) to Count
  - Sum: Materialized View Sum 에 Seoul 이 있는가? ➔ No
    - Insert a new tuple (Seoul, 1000) to Sum
  - Avg: Materialized View Sum 에 Seoul 이 있는가? ➔ No
    - Insert a new tuple (Seoul, 1000) to Sum

보조자료

Delete from Base Relation

- Base relation loan에 tuple (L-11, Round Hill, 900)이 삭제된 경우
  - Count: Attribute 'count' value를 1감소. 0인가?
    - If so, Tuple (Round Hill, 1)을 Count에서 삭제
  - Sum: 구릅별 count 에서 1감소. 0인가?
    - If so, Tuple (Round Hill, 900)을 Sum에서 삭제
  - Avg: 구릅별 count 에서 1감소. 0인가?
    - If so, Tuple (Round Hill, 900)을 Avg에서 삭제

- Base relation loan에 tuple (L-15, Downtown, 1500) 삭제된 경우
  - Count: Attribute 'count' value를 1감소. 0인가?
    - If not, update (Downtown, 2) ➔ (Downtown, 1)
  - Sum: . Group별 count에서 1감소. 0인가?
    - If not, update Tuple (Downtown, 2500) ➔ (Downtown, 1000) // 2500 - 1500
  - Avg: Group별 count에서 1감소. 0인가?
    - If not, update Tuple (Downtown, 2500) ➔ (Downtown, 1000) // (2500 – 1500)/ (2 -1)

Other Operations in Materialized View

- **Set intersection**: $v = r \cap s$
  - when a tuple is inserted in *r* we check if it is present in *s*, and if so we add it to *v*.
  - If the tuple is deleted from r, we delete it from the intersection if it is present.
  - Updates to *s* are symmetric
  - The other set operations, *union* and *set difference* are handled in a similar fashion.
- **Outer joins** are handled in much the same way as joins but with some extra work
  - we leave details to you.

Handling Expressions in Materialized View

- To handle an entire expression, we derive expressions for computing the incremental change to the result of each sub-expressions, starting from the smallest sub-expressions.

- E.g. consider $E_1 \bowtie E_2$ where each of E_1 and E_2 may be a complex expression
  - Suppose the set of tuples to be inserted into E_1 is given by D_1
    - Computed earlier, since smaller sub-expressions are handled first
  - Then the set of tuples to be inserted into $E_1 \bowtie E_2$ is given by $D_1 \bowtie E_2$
    - This is just the usual way of maintaining joins

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 should be extended to consider all above 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
    - more on tuning in later chapters
- Commercial database systems provide tools (called “tuning assistants” or “wizards”) to help the database administrator choose what indices and materialized views to create

Chapter 13: Query Optimization

- 13.1 Overview
- 13.2 Transformation of Relational Expressions
- 13.3 Estimating Statistics of Expression
- 13.4 Choice of Evaluation Plans
- 13.5 Materialized views**
- 13.6 Advanced Topics in Query Optimization**

Top-K Queries

- **Top-K queries**

  select *
  from r, s
  where r.B = s.B
  order by r.A **ascending**
  limit 10

  - Alternative 1: Indexed nested loops join with r as outer
  - Alternative 2: estimate highest r.A value in result and add selection (**and** r.A <= H) to where clause
    - If < 10 results, retry with larger H

Optimization of Updates

- **Halloween problem**

  update R **set** A = 5 * A
  where A > 10

  - If index on A is used to find tuples satisfying A > 10, and tuples updated immediately, same tuple may be found (and updated) multiple times
  - Solution 1: *Always defer updates*
    - collect the updates (old and new values of tuples) and update relation and indices in second pass
    - Drawback: extra overhead even if e.g. update is only on R.B, not on attributes in selection condition
  - Solution 2: *Defer only if required*
    - Perform immediate update if update does not affect attributes in where clause, and deferred updates otherwise.

Join Minimization

- **Join minimization**

  select r.A, r.B
  from r, s
  where r.B = s.B

- Check if join with s is redundant, drop it
  - E.g. join condition is on foreign key from r to s, no selection on s
  - Other sufficient conditions possible

    select r.A, s1.B
    from r, s **as** s1, s **as** s2
    where r.B=s1.B **and** r.B = s2.B **and** s1.A < 20 **and** s2.A < 10

    - join with s2 is redundant and can be dropped (along with selection on s2)
  - Lots of research in this area since 70s/80s!

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

End of Chapter