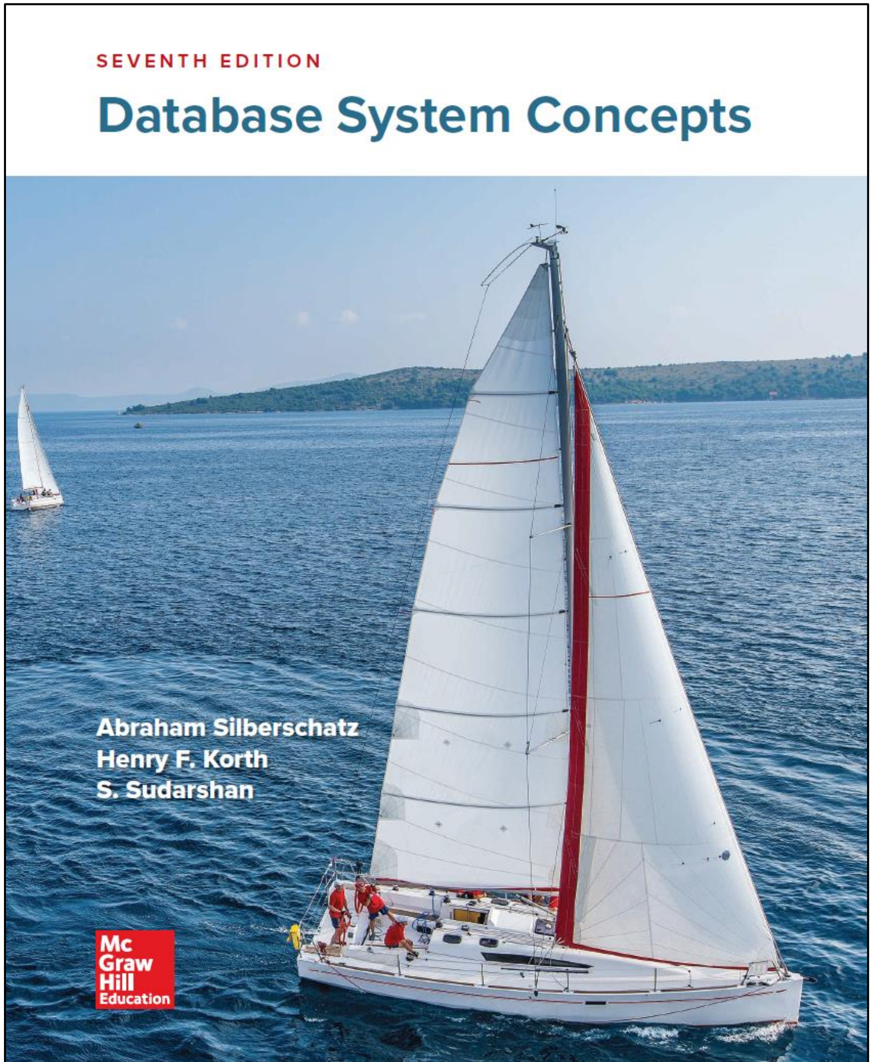
Data Administration in Information Systems

Query optimization

Query optimization



Chapter 16 Query Optimization

PART SEVEN ■ TRANSACTION MANAGEMENT

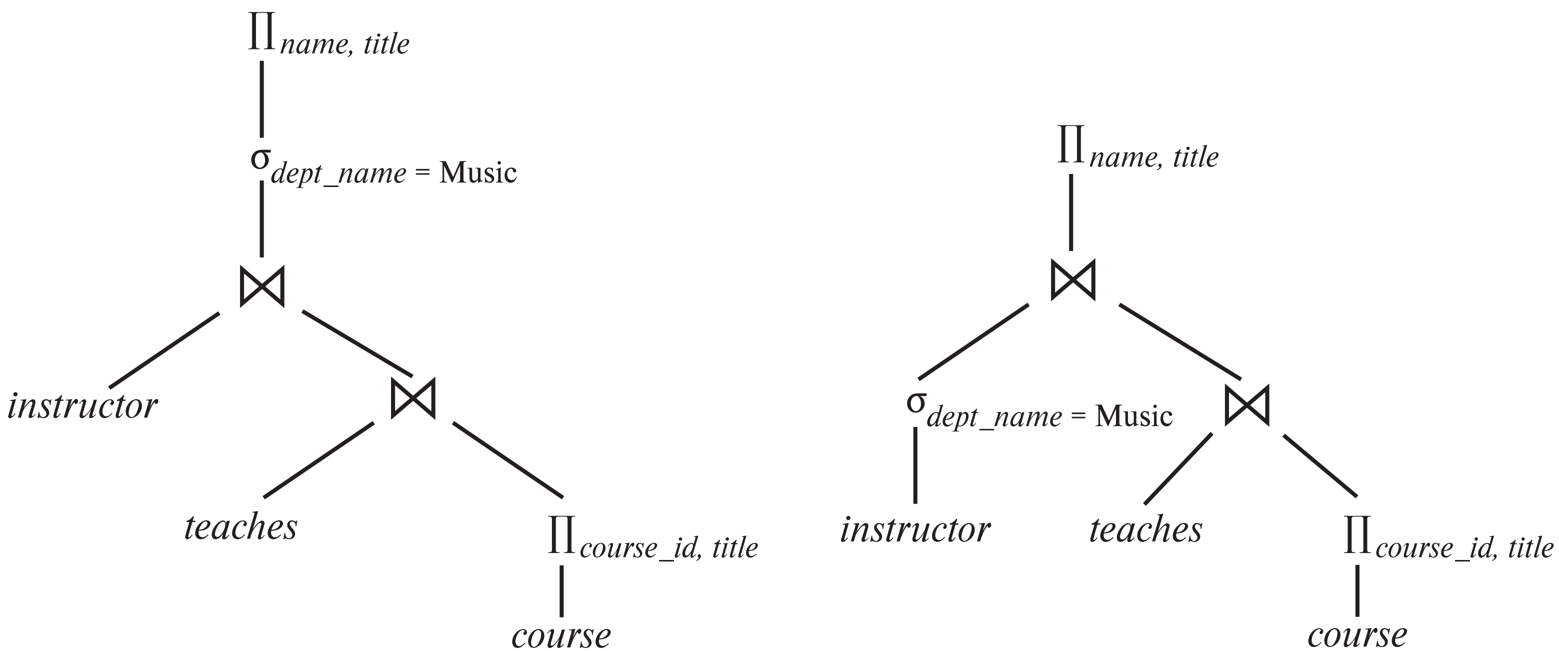
Chapter 17 Transactions

Chapter 18 Concurrency Control

Chapter 19 Recovery System

Introduction

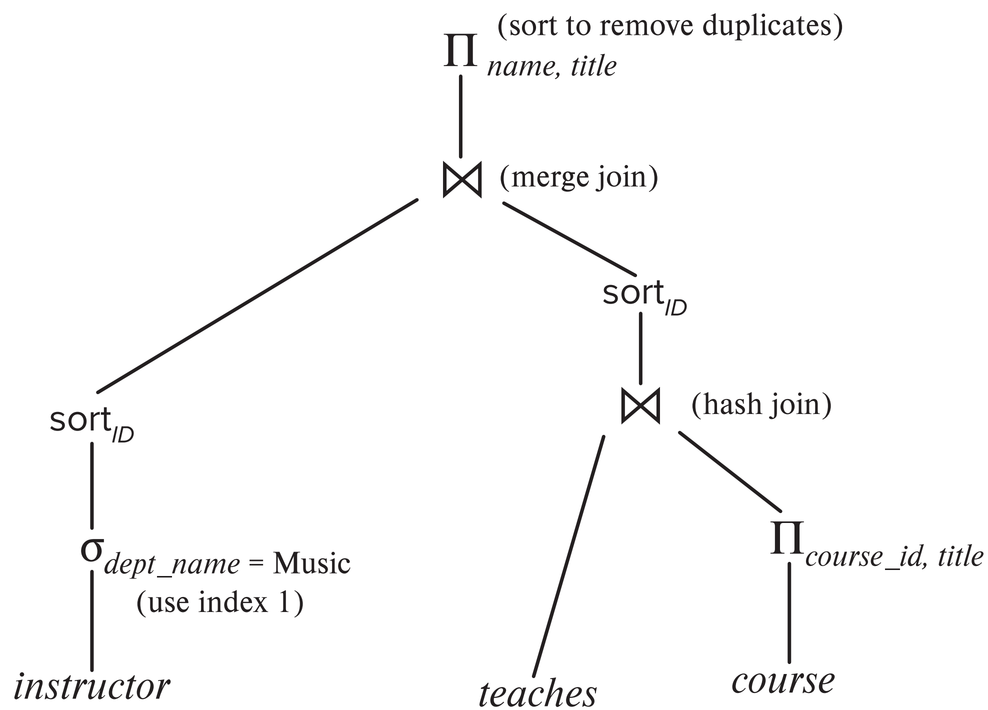
- Alternative ways of evaluating a given query
  - Equivalent expressions
  - Different algorithms for each operation



(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.



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

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 database instance
  - Note: 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 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.

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

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:

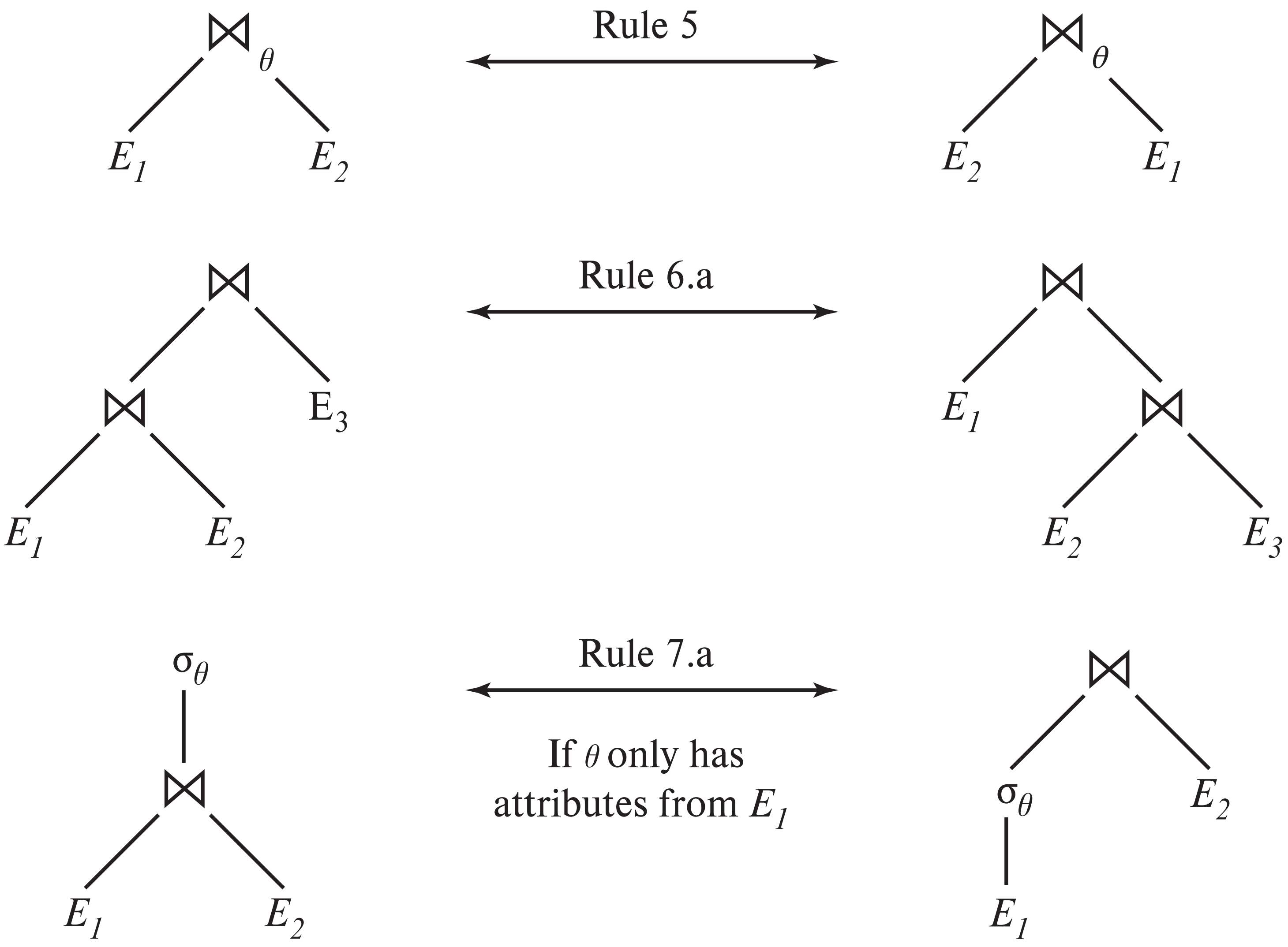
$$(E_1 \bowtie E_2) \bowtie E_3 \equiv E_1 \bowtie (E_2 \bowtie E_3)$$

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

$$(E_1 \bowtie_{\theta_{12}} E_2) \bowtie_{\theta_{13} \wedge \theta_{23}} E_3 \equiv E_1 \bowtie_{\theta_{12} \wedge \theta_{13}} (E_2 \bowtie_{\theta_{23}} E_3)$$

where θ_{ij} involves attributes from E_i and E_j only.

Pictorial Depiction of Equivalence Rules



Equivalence Rules (Cont.)

7. The selection operation distributes over the theta join operation under the following two conditions:
   (a) When all the attributes in θ_1 involve only the attributes of one of the expressions (E_1) being joined.

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

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

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

Equivalence Rules (Cont.)

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

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

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

   (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_{1*} be attributes of E_1 that are in join condition θ, but are not in $L_1 \cup L_2$

   – Let L_{2*} be attributes of E_2 that are in join condition θ, but are not in $L_1 \cup L_2$

   $$\Pi_{L_1 \cup L_2}(E_1 \bowtie_\theta E_2) \equiv \Pi_{L_1 \cup L_2}(\Pi_{L_1 \cup L_{1*}}(E_1) \bowtie_\theta \Pi_{L_2 \cup L_{2*}}(E_2))$$

Equivalence Rules (Cont.)

9. The set operations union and intersection are commutative

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

(but 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. $\sigma_\theta (E_1 \cap E_2) \equiv \sigma_\theta (E_1) \cap \sigma_\theta(E_2) \equiv \sigma_\theta (E_1) \cap E_2$

c. $\sigma_\theta (E_1 - E_2) \equiv \sigma_\theta (E_1) - \sigma_\theta(E_2) \equiv \sigma_\theta (E_1) - E_2$

12. The projection operation distributes over union

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

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

$$\Pi_{name,\ title}(\sigma_{dept\_name\ =\ \text{'Music'}\ \wedge\ year\ =\ 2017}\ (instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$$

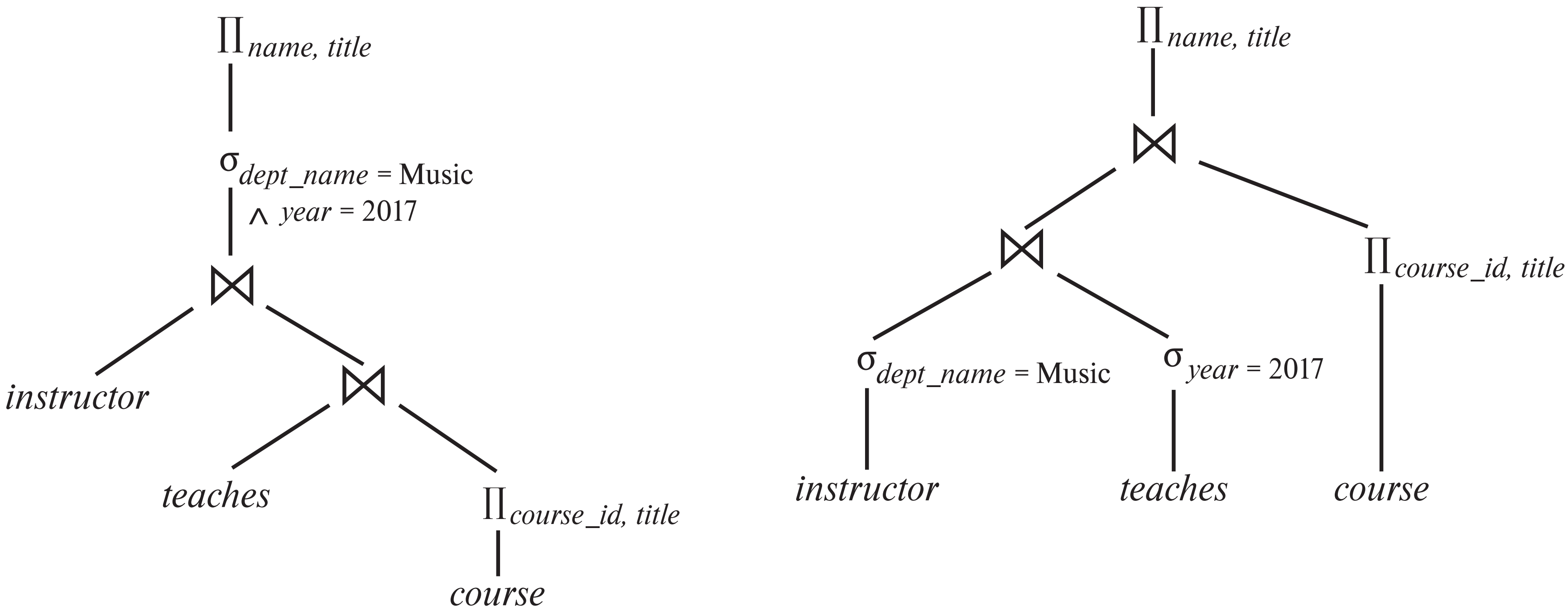
- Transformation using join associatively (Rule 6a):

$$\Pi_{name,\ title}(\sigma_{dept\_name=\ \text{'Music'}\ \wedge\ year\ =\ 2017}\ ((instructor \bowtie teaches) \bowtie\ \Pi_{course\_id,\ title}\ (course)))$$

- Now apply the "perform selections early" rule, 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: $\Pi_{name,\ title}(\sigma_{dept\_name\ =\ 'Music'}(instructor) \bowtie teaches \bowtie \Pi_{course\_id,\ title}(course))$

- When we compute

  $\sigma_{dept\_name\ =\ 'Music'}(instructor) \bowtie teaches$

- Push projections using equivalence rules 8a and 8b; eliminate unneeded attributes from intermediate results to get:
  $\Pi_{name,\ title}(\Pi_{name,\ course\_id}(\sigma_{dept\_name\ =\ 'Music'}(instructor) \bowtie teaches) \bowtie \Pi_{course\_id,\ title}(course))$

- 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) $\bowtie$

- 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 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
- Could 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
  - It is not necessary to generate every possible expression
  - Take cost estimates into account; avoid examining many expressions

Cost Estimation

- Cost of different operations described in previous lecture
  - 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

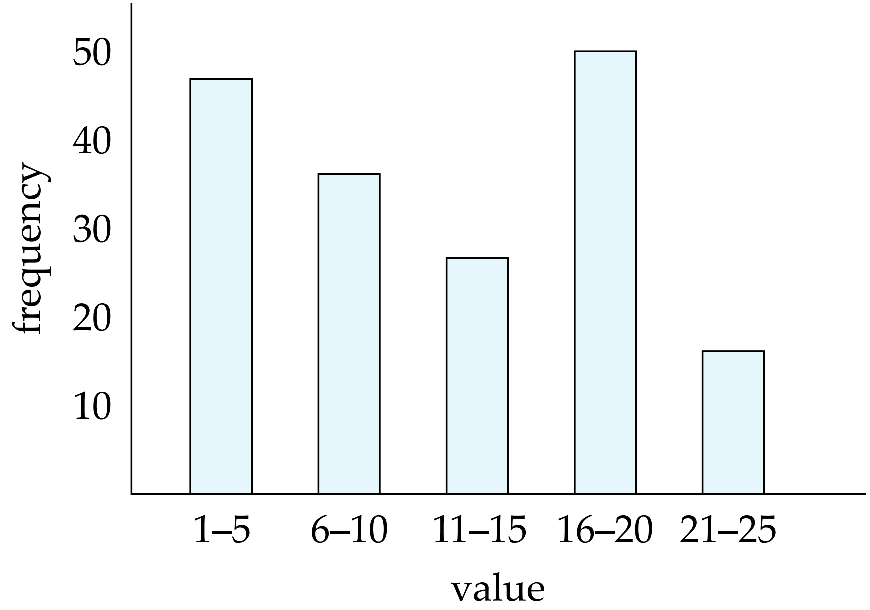
Statistical Information for Cost Estimation

- n_r: number of tuples in a relation *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.
- $V(A, r)$: number of distinct values that appear in *r* for attribute *A;* same as the size of $\prod_A(r)$.
- If tuples of *r* are stored together physically in a file, then:

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

Histograms

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



- **Equi-width** histograms
- **Equi-depth** histograms break up range such that each range has (approximately) the same number of tuples
  - e.g. (4, 8, 14, 19)
- Some 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
  - Some databases have a command to be executed to update statistics
  - Others automatically recompute statistics
    - e.g., when number of tuples in a relation changes by some percentage

Selection Size Estimation

- $\sigma_{A=v}(r)$
  - Number of records that will satisfy the selection: $n_r / V(A,r)$
  - 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 $v < \min(A,r)$
    - $c = n_r$ if $v \geq \max(A,r)$
    - $c = n_r \cdot \dfrac{v - \min(A,r)}{\max(A,r) - \min(A,r)}$
  - If histograms available, can refine above estimate
  - In absence of statistical information, c is assumed to be $n_r / 2$.

Size Estimation of Complex Selections

- The **selectivity** of a condition θ_i is the probability that a tuple in the relation *r* satisfies θ_i .
  - If s_i is the number of satisfying tuples in *r,* the selectivity of θ_i is: 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:** $\sigma_{\neg\theta 1}(r)$. Estimated number of tuples:

$$n_r * (1 - \frac{s_1}{n_r})$$

Join Operation: Running Example

- Running example: *student* ⋈ *takes*
- Catalog information for join examples:
  - $n_{student}$ = 5000
  - $f_{student}$ = 50, which implies that $b_{student}$ = 5000/50 = 100
  - n_{takes} = 10000
  - f_{takes} = 25, which implies that b_{takes} = 10000/25 = 400
  - $V(ID, takes)$ = 2500, which implies that on average, each student who has taken a course has taken 4 courses
    - Attribute *ID* in *takes* is a foreign key referencing *student*
    - $V(ID, student) = 5000$ (*primary key!*)

Estimation of the Size of Joins

- The Cartesian product r x s contains $n_r . n_s$ tuples
- If $R \cap S = \emptyset$, then $r \bowtie s$ is the same as r x s.
- If $R \cap S$ is a key for R, then a tuple of s will join with at most one tuple from r
  - therefore, the number of tuples in $r \bowtie s$ is no greater than the number of tuples in s.
- If $R \cap S$ 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 in R 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

Estimation of the Size of Joins (Cont.)

- Compute the size estimates for *student* ⋈ *takes* without using information about foreign keys:
  - $n_{student}$ = 5000, n_{takes} = 10000, $V(ID, takes)$ = 2500, and $V(ID, student)$ = 5000
  - The two estimates are:
    - $n_{student} * n_{takes} / V(ID, takes) = 5000 * 10000 / 2500 = 20000$
    - $n_{student} * n_{takes} / V(ID, student) = 5000 * 10000 / 5000 = 10000$
  - We choose the lower estimate, which is the correct one, because not every student takes courses (only half of them do)

Size Estimation for Other Operations

- Projection: estimated size of $\prod_A(r) = V(A,r)$
- 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>.

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., $(A = 1 \vee A = 3 \vee A = 4)$
- If the selection condition θ is of the form $A\ op\ v$
  estimated $V(A,\sigma_\theta(r)) = V(A,r) * s/n_r$
  – where s/n_r is the selectivity of the selection.
- In all the other cases: use approximate estimate of
  $\min\{V(A,r), n_{\sigma_\theta(r)}\}$

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

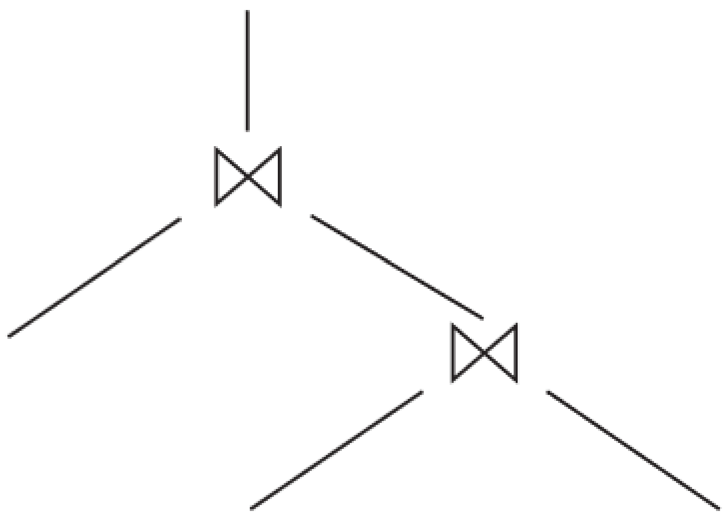
Choice of Evaluation Plans

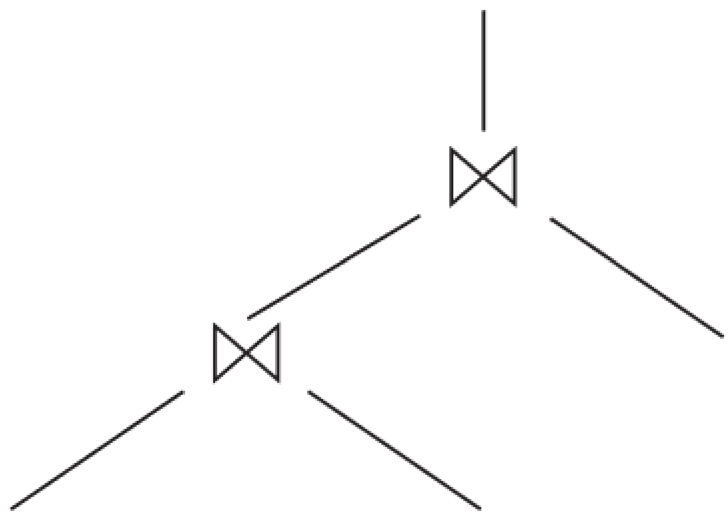
- Must consider the interaction of evaluation techniques when choosing evaluation plans
  - choosing the cheapest algorithm for each operation independently may not yield best overall algorithm. E.g.
    - merge-join may be costlier than hash-join, but may provide a sorted output which reduces the cost 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 $r_1 \bowtie r_2 \bowtie r_3$

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





Cost-Based Optimization (Cont.)

- Now consider finding the best join-order for:

$$(r_1 \bowtie r_2 \bowtie r_3) \bowtie r_4 \bowtie r_5$$

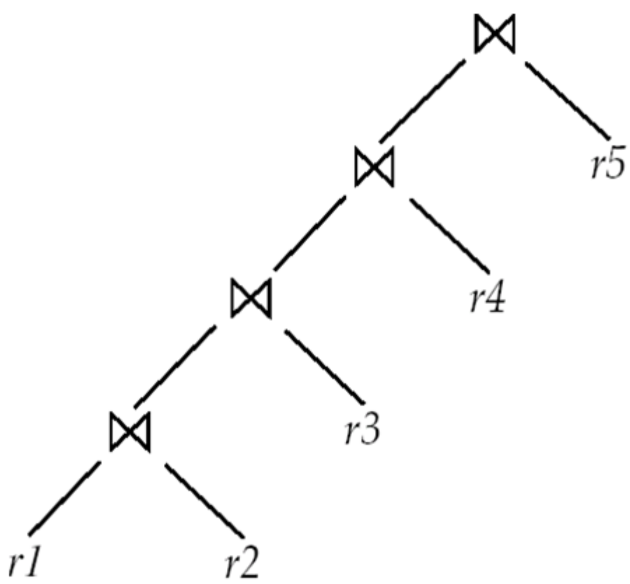
  - There are 12 different join orders for $r_1 \bowtie r_2 \bowtie r_3$ and another 12 orders for (...) $\bowtie r_4 \bowtie r_5$
  - Should we consider 12*12 joins orders?
  - No. Only 12+12. We choose the best order for $r_1 \bowtie r_2 \bowtie r_3$ and the best order for (...) $\bowtie r_4 \bowtie r_5$ independently.
  - When an optimization problem can be solved by optimizing sub-problems independently, we can use **dynamic programming**.

Cost-Based Optimization (Cont.)

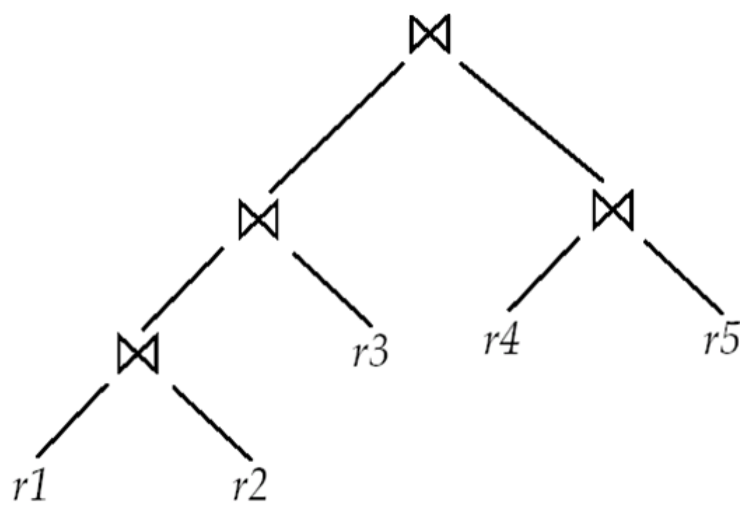
- Consider finding the best join-order for $r_1 \bowtie r_2 \bowtie \ . \ . \ . \bowtie r_n$.
- There are $(2(n-1))!/(n-1)!$ different join orders for above expression. With $n = 7$, the number is 665280, with $n = 10$, the number is greater than 176 billion!
- No need to generate all the join orders. 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.
- Find the best join order for every subset, by finding the best order for each subset of every subset, etc.
  - Do this recursively and reusing previously found solutions for each subset.

Heuristics in Optimization

- Alternatively, use heuristics
  - E.g. in **left-deep join trees,** the right-hand-side input for each join is always a relation, not the result of an intermediate join.
  - Fewer join orders to consider.



(a) Left-deep join tree



(b) Non-left-deep join tree

Heuristics in Optimization (Cont.)

- 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.
- 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.

Heuristics in Optimization (Cont.)

- 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.

Memoization and Plan Cache

- Besides the order of operations, there are multiple algorithms to choose from (e.g. hash join, nested-loop join, merge join)
  - These algorithms are **physically equivalent** (produce the same results)
  - Choice of best plan includes optimizing the query-tree (**equivalence rules**) and choosing the best algorithms (**physical equivalence rules**)
- Concept of **memoization**
  - Store the best plan for a subexpression the first time it is optimized, and reuse it on repeated optimization calls on same subexpression
- Implemented as **plan caching**
  - Reuse previously computed plan if query is resubmitted
  - Even with different constants in query

Materialized Views

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

create view *my_students*(*ID, name*) **as**
select *student.ID, student.name*
from *student*, *takes*
where *student.ID* = *takes.ID*
  and *takes.course_id* = 'CS-347';

- Materializing the above view would be very useful if the list of students is required frequently

Materialized View Maintenance

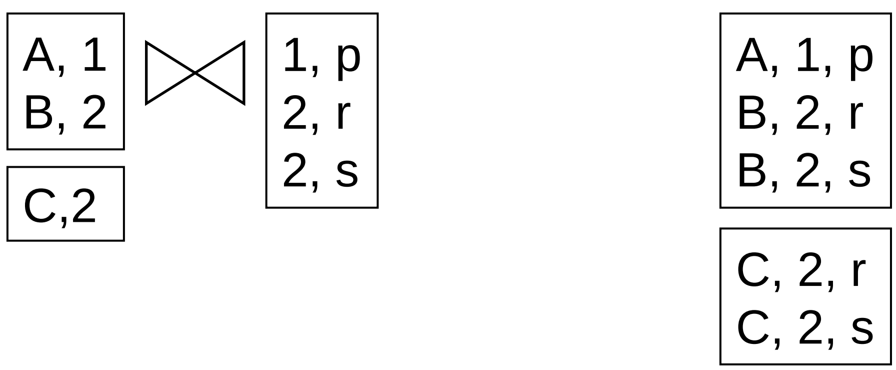
- The task of keeping a materialized view up-to-date with the underlying data is known as **materialized view maintenance**
- Materialized views can be maintained by recomputation on every update
- A better option is to use **incremental view maintenance**
  - **Changes to database relations are used 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)
  - Incremental maintenance 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

- 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: $v^{new} = v^{old} - (d_r \bowtie s)$



Selection Operation

- Selection: Consider a view $v = \sigma_\theta(r)$.
- We modify r by inserting a set of tuples i_r or deleting d_r
- Then:
  - $v^{new} = v^{old} \cup \sigma_\theta(i_r)$
  - $v^{new} = v^{old} - \sigma_\theta(d_r)$

Projection Operation

- 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 (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 $\prod_A(r)$

Other Operations

- 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.

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 options
- Replacing a use of a materialized view:
  - A materialized view $v = r \bowtie s$ is available
  - User submits a query $\sigma_{A=10}(v)$ but the view has no index on A
  - Suppose r has an index on A, and s has an index on the common attribute
  - Then the best plan 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 consider all above options and choose the best overall plan

Materialized View Creation

- **Materialized view creation**: "What is the best set of views to materialize?"
- **Index creation**: "What is the best set of indices to create?"
  - closely related, but simpler
- Materialized view creation and index creation 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 next lectures)
- Commercial database systems provide tools (called "tuning assistants" or "wizards") to help the database administrator choose what indices and materialized views to create.