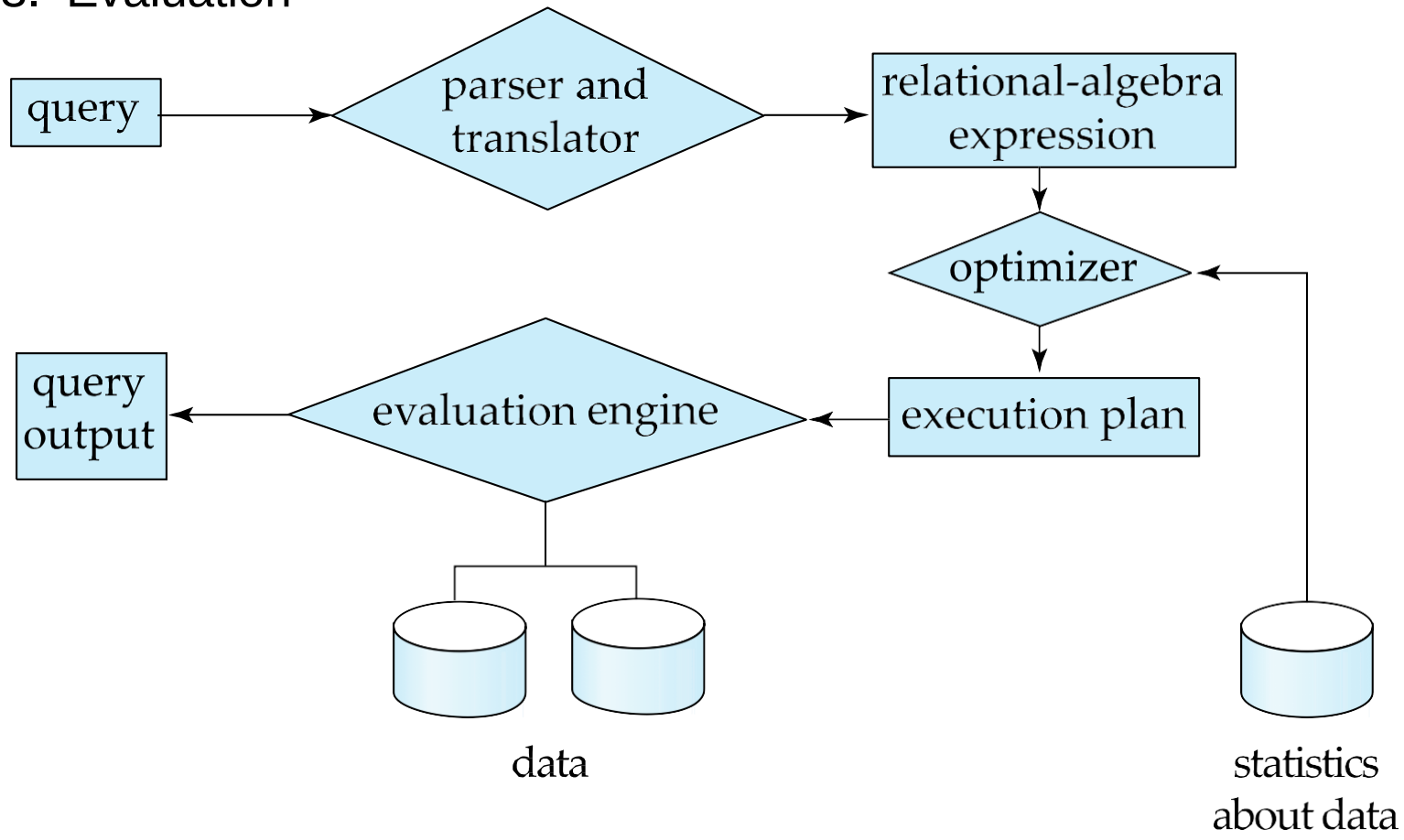
Query Processing & Optimization

Roadmap of This Lecture

- Overview of query processing
- Measures of Query Cost
- Selection Operation
- Sorting
- Join Operation
- Other Operations
- Evaluation of Expressions
- Introduction to query optimization
- Transformation of Relational Expressions
- Cost-based optimization
- Dynamic Programming for Choosing Evaluation Plans

Basic Steps in Query Processing

1. Parsing and translation
2. Optimization
3. Evaluation



Basic Steps in Query Processing (Cont.)

- Parsing and translation
  - translate the query into its internal form. This is then translated into relational algebra.
  - Parser checks syntax, verifies relations
- Evaluation
  - The query-execution engine takes a query-evaluation plan, executes that plan, and returns the answers to the query.

Basic Steps in Query Processing : Optimization

- A relational algebra expression may have many equivalent expressions
  - E.g., $\sigma_{salary<75000}(\Pi_{salary}(instructor))$ is equivalent to $\Pi_{salary}(\sigma_{salary<75000}(instructor))$
- Each relational algebra operation can be evaluated using one of several different algorithms
  - Correspondingly, a relational-algebra expression can be evaluated in many ways.
- Annotated expression specifying detailed evaluation strategy is called an **evaluation-plan**.
  - E.g., can use an index on *salary* to find instructors with salary < 75000,
  - or can perform complete relation scan and discard instructors with salary ≥ 75000

Basic Steps: Optimization (Cont.)

- **Query Optimization**: Amongst all equivalent evaluation plans choose the one with lowest cost.
  - Cost is estimated using statistical information from the database catalog
    - e.g. number of tuples in each relation, size of tuples, etc.
- In this lecture we study
  - How to measure query costs
  - Algorithms for evaluating relational algebra operations
  - How to combine algorithms for individual operations in order to evaluate a complete expression
  - How to optimize queries, that is, how to find an evaluation plan with lowest estimated cost

Measures of Query Cost

- Cost is generally measured as total elapsed time for answering query
  - Many factors contribute to time cost
    - *disk accesses, CPU*, or even network *communication*
- Typically disk access is the predominant cost, and is also relatively easy to estimate. Measured by taking into account:
  - Number of seeks * average-seek-cost
  - Number of blocks read * average-block-read-cost
  - Number of blocks written * average-block-write-cost
    - Cost to write a block is greater than cost to read a block
      - data is read back after being written to ensure that the write was successful

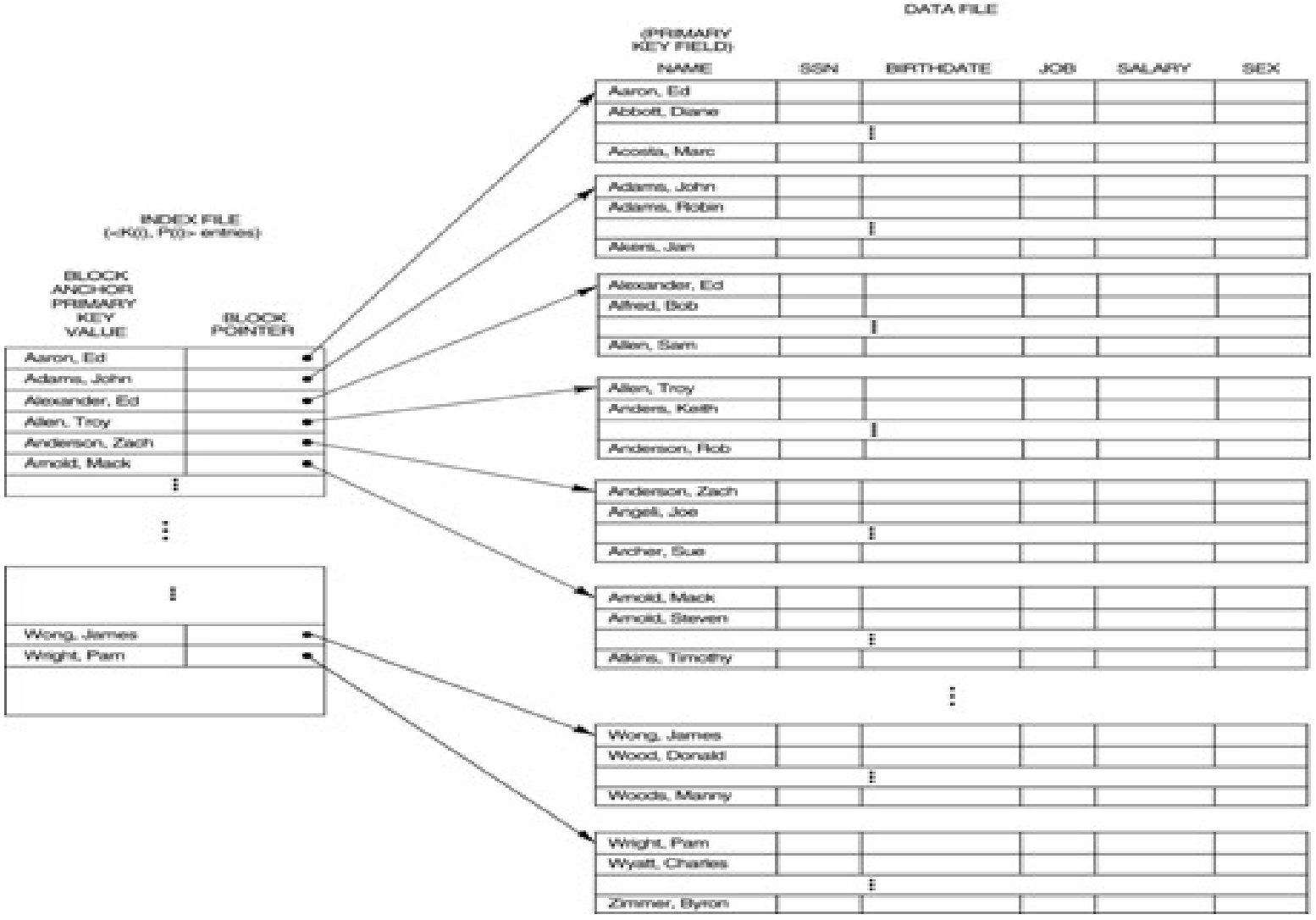
Measures of Query Cost (Cont.)

- For simplicity we just use the **number of block transfers** *from disk* and the **number of seeks** as the cost measures
  - t_T – time to transfer one block
  - t_S – time for one seek
  - Cost for b block transfers plus S seeks
    $b * t_T + S * t_S$
- We ignore CPU costs for simplicity
  - Real systems do take CPU cost into account
- We do not include cost to writing output to disk in our cost formulae

Selection Operation

- **File scan**
- Algorithm **A1** (**linear search**). Scan each file block and test all records to see whether they satisfy the selection condition.
  - Cost estimate = b_r block transfers + 1 seek= $t_s + b_r * t_T$
    - b_r denotes number of blocks containing records from relation *r*
  - Linear search can be applied regardless of
    - selection condition or
    - ordering of records in the file, or
    - availability of indices
- Note: binary search generally does not make sense since data is not stored consecutively
- Algorithm **A2 (binary search)- Applicable if file is ordered** on an attribute and the selection condition is an equality condition on the attribute
- Cost estimate = $\lceil \log_2(b_r) \rceil * (t_{T+} t_s)$

Primary index



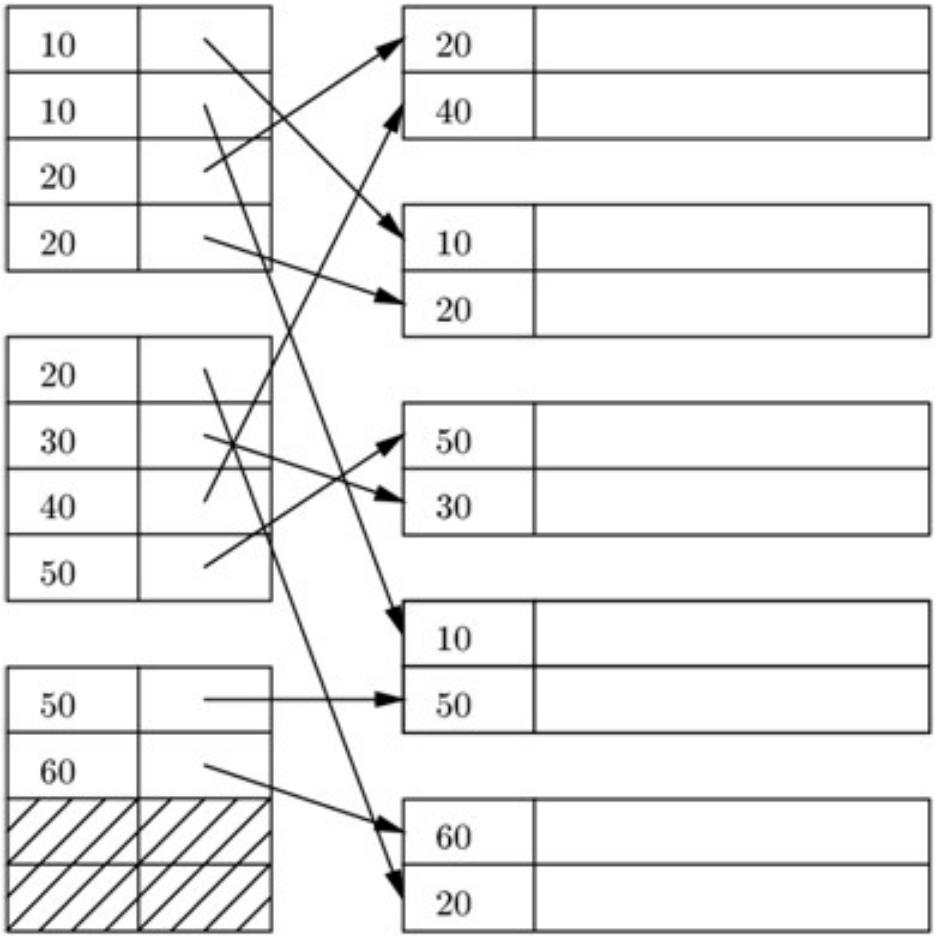
Selections Using Indices

- **Index scan** – search algorithms that use an index
  - selection condition must be on search-key of index.
  - h_i is the height of index tree
- **A3** (**primary index, equality on key**). Retrieve a single record that satisfies the corresponding equality condition
  - $Cost = h_i * (t_T + t_S) + (t_T + t_S) = (h_i + 1) * (t_T + t_S)$

    To identify leaf; To locate the Record
- **A4** (**primary index, equality on nonkey**) Retrieve multiple records.
  - Records will be on consecutive blocks
    - Let b = number of blocks containing matching records
  - $Cost = h_i * (t_T + t_S) + t_S + t_T * b$

    To identify leaf; To locate first Record; To identify all Record sequentially

Secondary Index



Selections Using Indices

- **A5** (**secondary index, equality on nonkey**).
  - Retrieve a single record if the search-key is a candidate key
    - *Cost* = $(h_i + 1) * (t_T + t_S)$
  - Retrieve multiple records if search-key is not a candidate key
    - each of *n* matching records may be on a different block
    - Cost = $h_i * (t_T + t_S) + n * (t_T + t_S)$

      $= (h_i + n) * (t_T + t_S)$
      - Can be very expensive!

Selections Involving Comparisons

- Can implement selections of the form $\sigma_{A \le V}(r)$ or $\sigma_{A \ge V}(r)$ by using
  - a linear file scan,
  - or by using indices in the following ways:
- **A6** (**primary index, comparison**). (Relation is sorted on A)
  - For $\sigma_{A > V}(r)$ *or* $\sigma_{A \ge V}(r)$ use index to find first tuple $\ge v$ and scan ***relation*** sequentially from there

    $Cost = h_i * (t_T + t_S) + t_S + t_T * b$
  - For $\sigma_{A \le V}(r)$ just scan relation sequentially till first tuple > *v;* do not use index

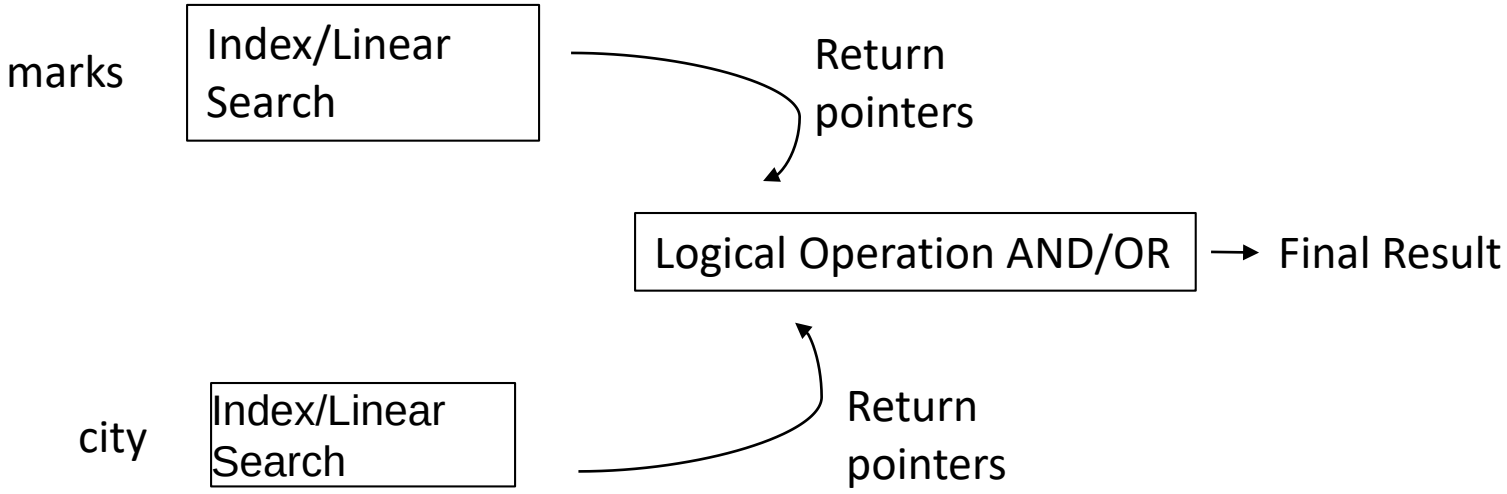
    $Cost = t_S + n * t_T$
- **A7** (**secondary index, comparison**).
  - For $\sigma_{A \ge V}(r)$ use index to find first index entry $\ge v$ and scan ***index*** sequentially from there, to find pointers to records.
    $Cost = h_i * (t_T + t_S) + n* (t_T + t_S)$
  - For $\sigma_{A \le V}(r)$ just scan leaf pages of index finding pointers to records, till first entry > *v*
    - Linear file scan may be cheaper

    $Cost = h_i * (t_T + t_S) + n* (t_T + t_S)$

Implementation of Complex Selections

- **Conjunction:** $\sigma_{\theta 1 \wedge \theta 2 \wedge \ldots \theta n}(r)$
- **A8** (**conjunctive selection using one index**).
  - Select a combination of θ_i and algorithms A1 through A7 that results in the least cost for $\sigma_{\theta i}(r)$.
  - Test other conditions on tuple after fetching it into memory buffer.
- **A9** (**conjunctive selection using composite index**).
  - Use appropriate composite (multiple-key) index if available.
- **A10** (**conjunctive selection by intersection of identifiers**).
  - Requires indices with record pointers.
  - Use corresponding index for each condition, and take intersection of all the obtained sets of record pointers.
  - Then fetch records from file
  - If some conditions do not have appropriate indices, apply test in memory.

select * from student
where marks>50 and city='shirpur';



Algorithms for Complex Selections

- **Disjunction:** $\sigma_{\theta 1 \vee \theta 2 \vee \ldots \theta n}(r)$.
- **A11** (**disjunctive selection by union of identifiers**).
  - Applicable if *all* conditions have available indices.
    - Otherwise use linear scan.
  - Use corresponding index for each condition, and take union of all the obtained sets of record pointers.
  - Then fetch records from file
- **Negation:** $\sigma_{\neg\theta}(r)$
  - Use linear scan on file
  - If very few records satisfy $\neg\theta$, and an index is applicable to θ
    - Find satisfying records using index and fetch from file

Sorting

- We may build an index on the relation, and then use the index to read the relation in sorted order. May lead to one disk block access for each tuple.
- For relations that fit in memory, techniques like quicksort can be used. For relations that don't fit in memory, **external sort-merge** is a good choice.

External Sort-Merge

Let *M* denote memory size (in pages or blocks).

1. **Create sorted runs**. Let *i* be 0 initially.
   Repeatedly do the following till the end of the relation:
   (a) Read *M* blocks of relation into memory
   (b) Sort the in-memory blocks
   (c) Write sorted data to run R_i; increment *i.*
   Let the final value of *i* be *N*
2. *Merge the runs (next slide)…..*

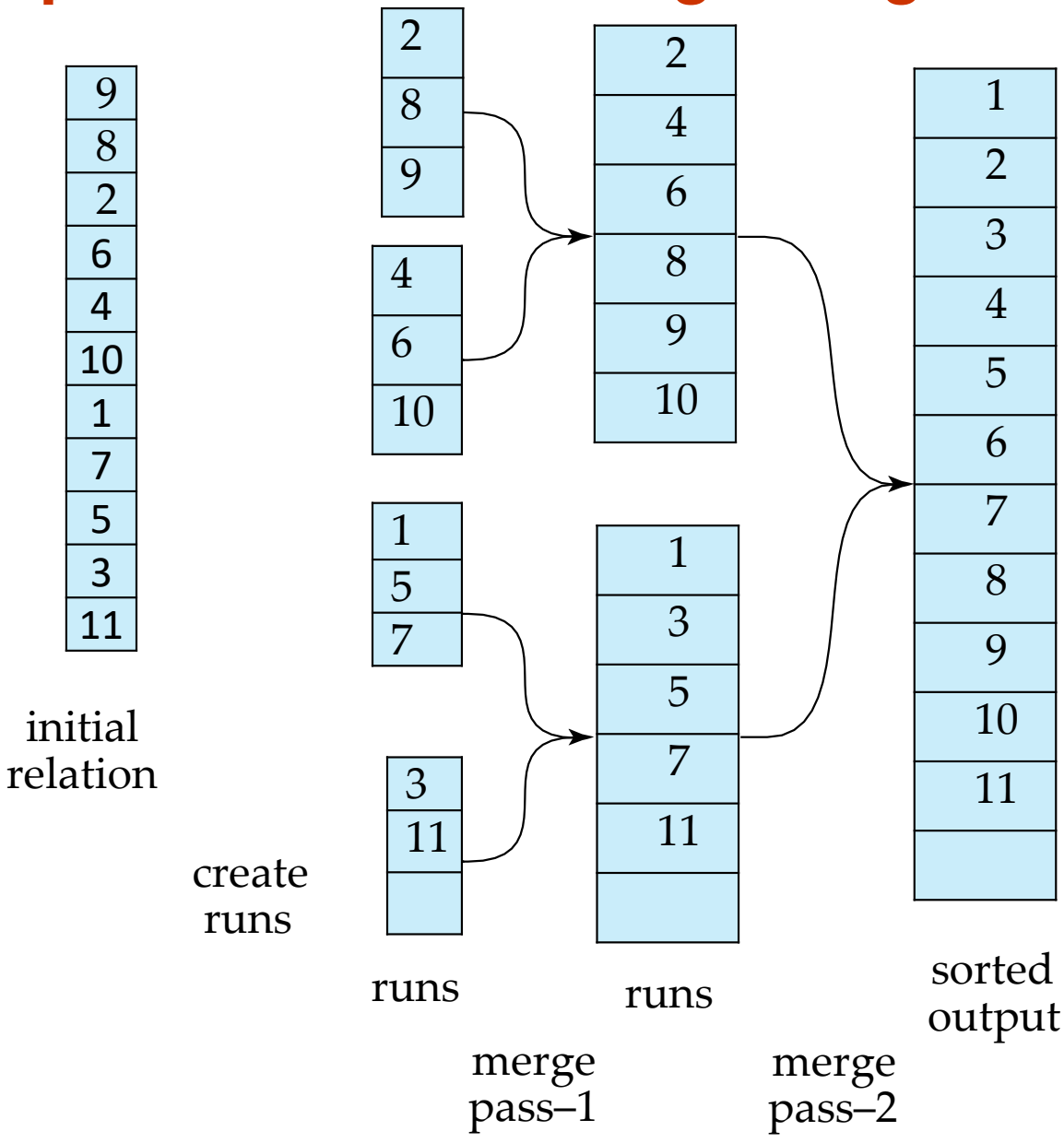
External Sort-Merge (Cont.)

2. **Merge the runs (N-way merge)**. We assume (for now) that $N < M$.
    1. Use N blocks of memory to buffer input runs, and 1 block to buffer output. Read the first block of each run into its buffer page
    2. **repeat**
        1. Select the first record (in sort order) among all buffer pages
        2. Write the record to the output buffer. If the output buffer is full write it to disk.
        3. Delete the record from its input buffer page.
           If the buffer page becomes empty **then**
           read the next block (if any) of the run into the buffer.
    3. **until** all input buffer pages are empty:

External Sort-Merge (Cont.)

- If $N \geq M$, several merge *passes* are required.
  - In each pass, contiguous groups of M - 1 runs are merged.
  - A pass reduces the number of runs by a factor of M -1, and creates runs longer by the same factor.
  - Repeated passes are performed till all runs have been merged into one.

Example: External Sorting Using Sort-Merge



External Merge Sort (Cont.)

- Cost analysis:
  - Total number of merge passes required: $\lceil \log_{M-1}(b_r / M) \rceil$

    $\lceil \log_{3-1}(11/3) \rceil = \lceil \log 2(4) \rceil = 2$
    - b_r is the size of all records in blocks=11
    - M-1 input buffer blocks (pages)=2
  - Block transfers for initial run creation as well as in each pass is $2b_r$ *i.e 2*11=22*
  - initial runs is $\lceil b_r / M \rceil = \lceil 11/3 \rceil = \lceil 3.6 \rceil = 4$
  - Total Number of merge passes is $\lceil \log_{M-1}(b_r / M) \rceil = \lceil \log 2(4) \rceil = 2$
    - Thus total number of block transfers for external sorting of the relation:

      $b_r (2 \lceil \log_{M-1}(b_r / M) \rceil + 1)$

      $=11(2*2+1)=55$

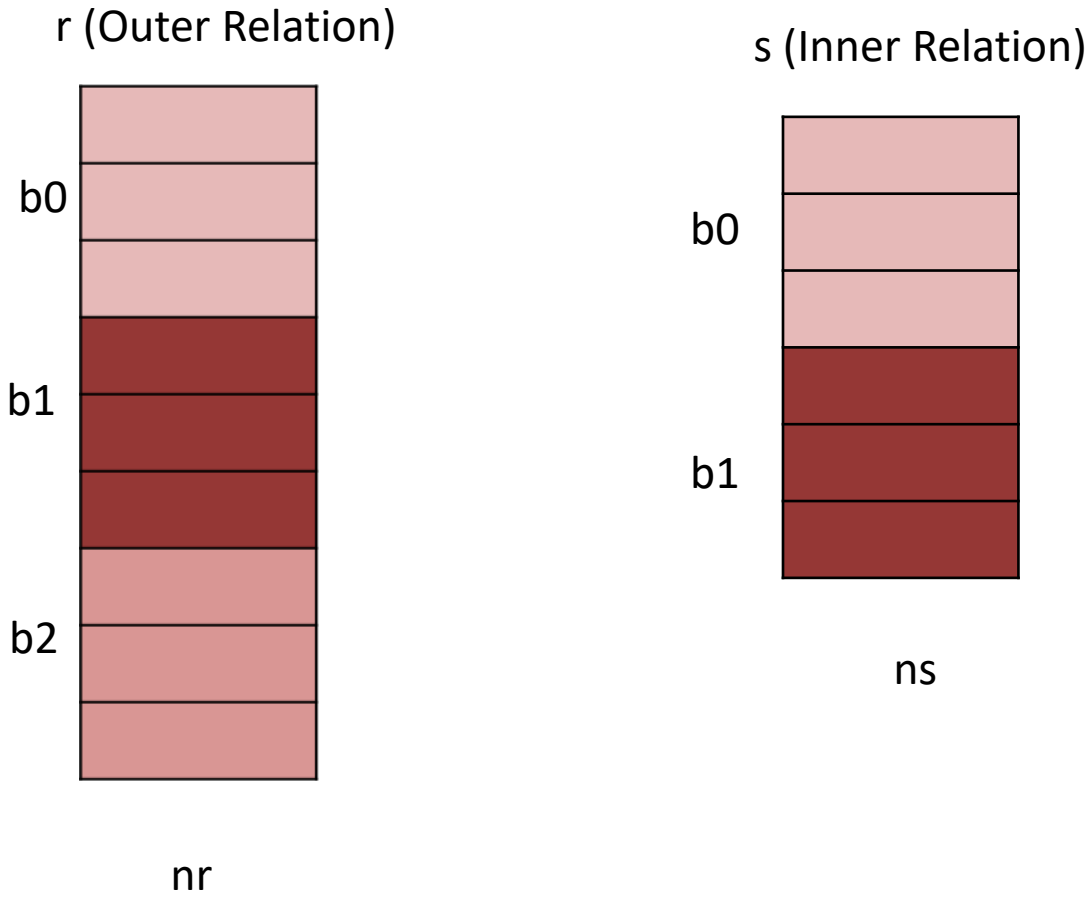
      For given relation=*2*11+11+11+11=55*

External Merge Sort (Cont.)

- Cost of seeks
  - During run generation: one seek to read each run and one seek to write each run
    - $2\lceil b_r / M \rceil$
  - During the merge phase
    - Buffer size: b_b (read/write b_b blocks at a time)
    - Need $2\lceil b_r / b_b \rceil$ seeks for each merge pass
      - except the final one which does not require a write
    - Total number of seeks:
      $2\lceil b_r / M \rceil + \lceil b_r / b_b \rceil (2\lceil \log_{M-1}(b_r / M) \rceil - 1)$

Join Operation

- Several different algorithms to implement joins
  - Nested-loop join
  - Block nested-loop join
  - Indexed nested-loop join
  - Merge-join
  - Hash-join
- Choice based on cost estimate
- Examples use the following information
  - Number of records of *student*: 5,000 *takes*: 10,000
  - Number of blocks of *student*: 100 *takes*: 400


r (Outer Relation)
b0
b1
b2
nr
s (Inner Relation)
b0
b1
ns

Nested-Loop Join

- To compute the theta join $r \bowtie_\theta s$ (equivalent to $\sigma_\theta(r \times s)$)

  for each tuple t_r **in** r **do begin**

  for each tuple t_s **in** s **do begin**

  test pair (t_r, t_s) to see if they satisfy the join condition θ

  if they do, add $t_r \bullet t_s$ to the result.

  end

  end

- r is called the **outer relation** and s the **inner relation** of the join.
- Requires no indices and can be used with any kind of join condition.
- Expensive since it examines every pair of tuples in the two relations.

Nested-Loop Join (Cont.)

- In the worst case, if there is enough memory only to hold one block of each relation, the estimated cost is

  $b_r + n_r * b_s$ block transfers, plus

  $b_r + n_r$ seeks

- If BOTH relation fits entirely in memory,
  Reduces cost to $b_r + b_s$ block transfers and 2 seeks
- Assuming worst case memory availability cost estimate is
  - with *student* as outer relation:
    - 100+5000 ∗ 400 = 2,000,100 block transfers,
    - 100+5000 = 5100 seeks
  - with *takes* as the outer relation
    - 400+10000 ∗ 100 = 1,000,400 block transfers and 10,400 seeks
- If smaller relation (*student*) fits entirely in memory, the cost estimate will be 500 block transfers.
- Block nested-loops algorithm (next slide) is preferable.

Block Nested-Loop Join

- Variant of nested-loop join in which every block of inner relation is paired with every block of outer relation.

for each block B_r **of** r **do begin**
  for each block B_s **of s do begin**
    for each tuple t_r **in** B_r **do begin**
      for each tuple t_s **in** B_s **do begin**
        Check if (t_r, t_s) satisfy the join condition
        if they do, add $t_r \bullet t_s$ to the result.
      end
    end
  end
end

Block Nested-Loop Join (Cont.)

- Worst case estimate: $b_r + b_r * b_s$ block transfers and $b_r + b_r = 2 * b_r$ seeks
  - Each block in the inner relation *s* is read once for each *block* in the outer relation
- Best case: $b_r + b_s$ block transfers and 2 seeks.
- Improvements to nested loop and block nested loop algorithms:
  - In block nested-loop, use $M - 2$ disk blocks as blocking unit for outer relations, where M = memory size in blocks; use remaining two blocks to buffer inner relation and output
    - Cost = $\lceil b_r / (M-2) \rceil * b_s + b_r$ block transfers + $2 \lceil b_r / (M-2) \rceil$ seeks
  - If equi-join attribute forms a key of inner relation, stop inner loop on first match
  - Scan inner loop forward and backward alternately, to make use of the blocks remaining in buffer (with LRU replacement)
  - Use index on inner relation if available (in text book)

Other Operations

- **Duplicate elimination** can be implemented via hashing or sorting.
  - On sorting duplicates will come adjacent to each other, and all but one set of duplicates can be deleted.
  - *Optimization:* duplicates can be deleted during run generation as well as at intermediate merge steps in external sort-merge.
  - Hashing is similar – duplicates will come into the same bucket.
- **Projection:**
  - perform projection on each tuple
  - followed by duplicate elimination.

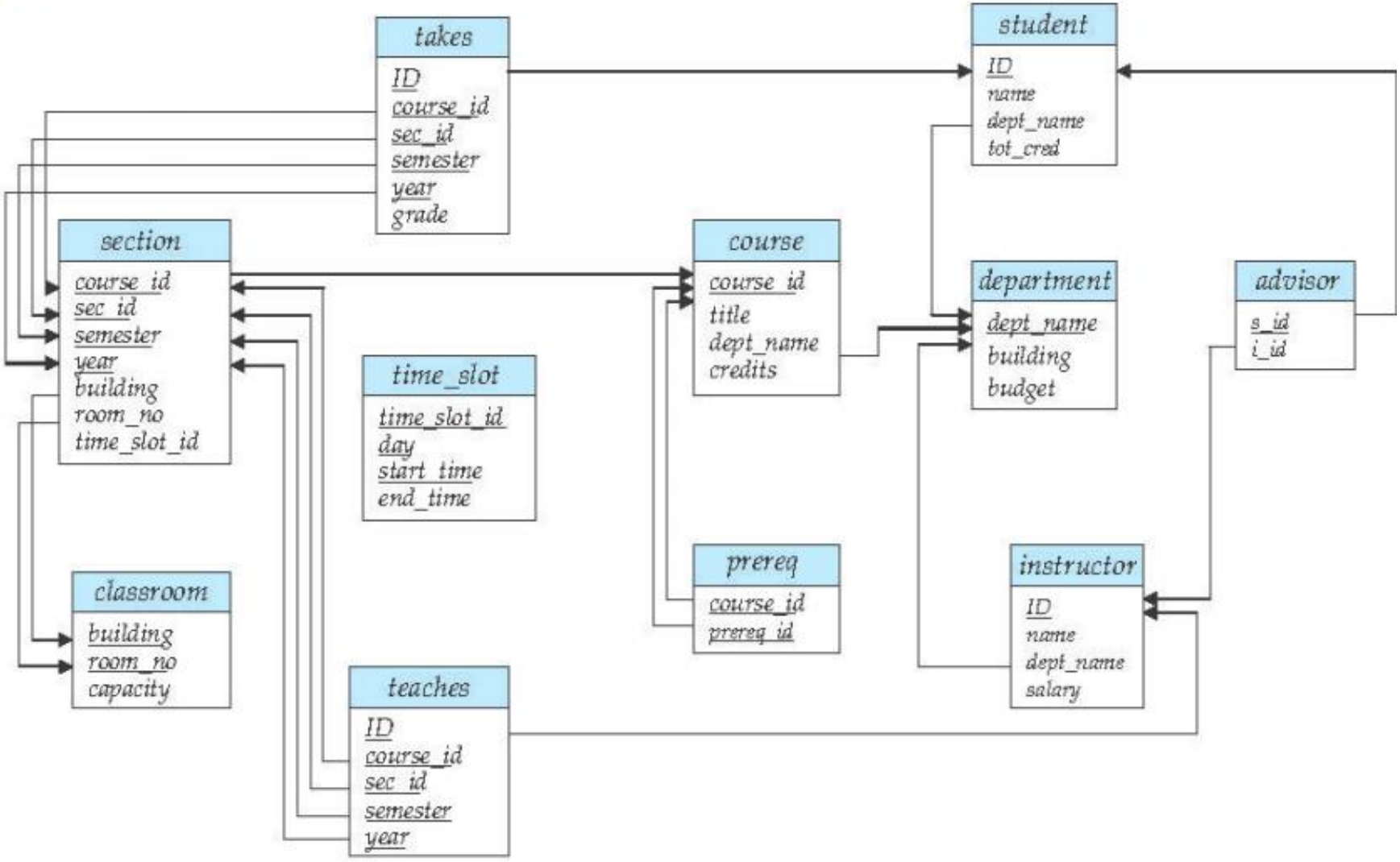
Other Operations : Aggregation

- **Aggregation** can be implemented in a manner similar to duplicate elimination.
  - Sorting or hashing can be used to bring tuples in the same group together, and then the aggregate functions can be applied on each group.
  - *Optimization:* combine tuples in the same group during run generation and intermediate merges, by computing partial aggregate values
    - For count, min, max, sum: keep aggregate values on tuples found so far in the group.
      - When combining partial aggregate for count, add up the aggregates
    - For avg, keep sum and count, and divide sum by count at the end

Evaluation of Expressions

- So far: we have seen algorithms for individual operations
- Alternatives for evaluating an entire expression tree
  - **Materialization**: generate results of an expression whose inputs are relations or are already computed, **materialize** (store) it on disk. Repeat.
  - **Pipelining**: pass on tuples to parent operations even as an operation is being executed
- We study above alternatives in more detail

Schema Diagram for University Database

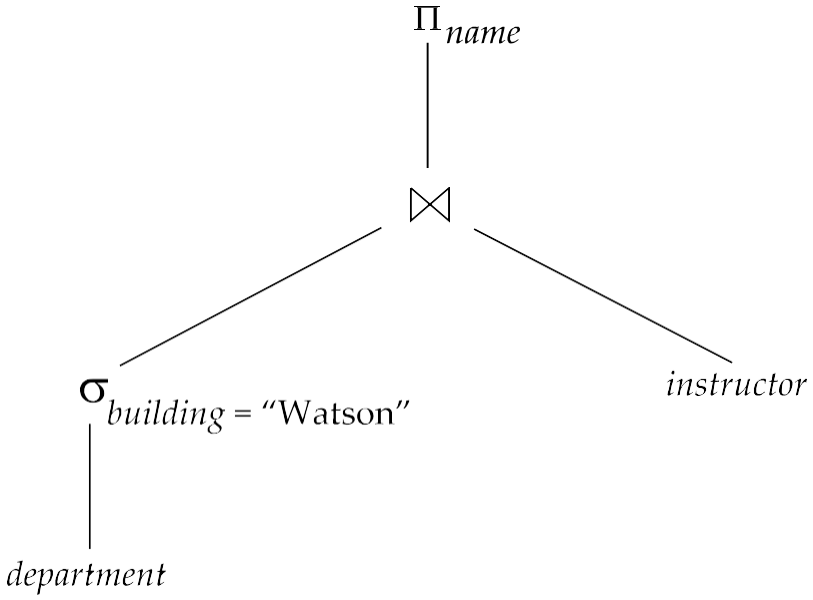


Materialization

- **Materialized evaluation**: evaluate one operation at a time, starting at the lowest-level. Use intermediate results materialized into temporary relations to evaluate next-level operations.
- E.g., in figure below, compute and store

$$\sigma_{building="\text{Watson}"}(department)$$

then compute and store its join with *instructor,* and finally compute the projection on *name.*



Materialization (Cont.)

- Materialized evaluation is always applicable
- Cost of writing results to disk and reading them back can be quite high
  - Our cost formulas for operations ignore cost of writing results to disk, so
    - Overall cost =

      Sum of costs of individual operations +
      cost of writing intermediate results to disk
- **Double buffering**: use two output buffers for each operation, when one is full write it to disk while the other is getting filled
  - Allows overlap of disk writes with computation and reduces execution time

Pipelining

- **Pipelined evaluation** : evaluate several operations simultaneously, passing the results of one operation on to the next.
- E.g., in previous expression tree, don't store result of

$$\sigma_{building="\text{Watson}"}(department)$$

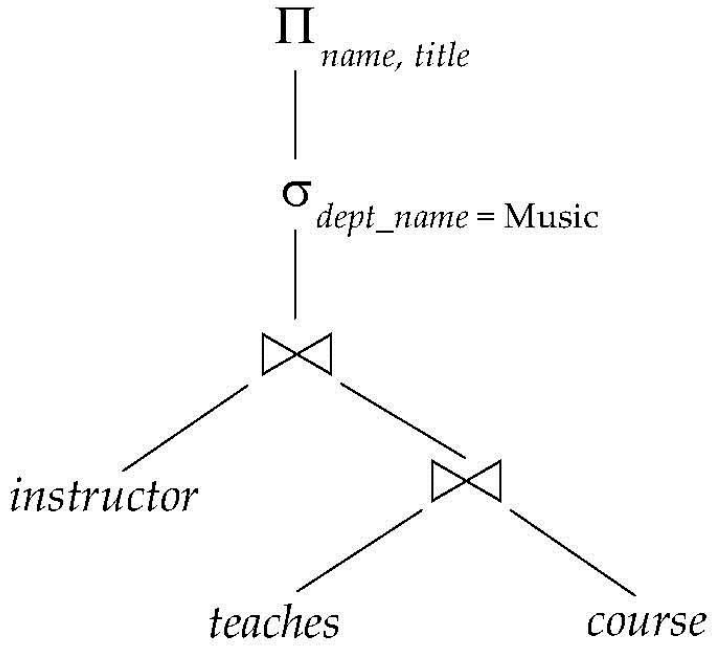
  - instead, pass tuples directly to the join.. Similarly, don't store result of join, pass tuples directly to projection.
- Much cheaper than materialization: no need to store a temporary relation to disk.
- Pipelining may not always be possible – e.g., sort, hash-join.
- For pipelining to be effective, use evaluation algorithms that generate output tuples even as tuples are received for inputs to the operation.
- Pipelines can be executed in two ways: **demand driven** and **producer driven**

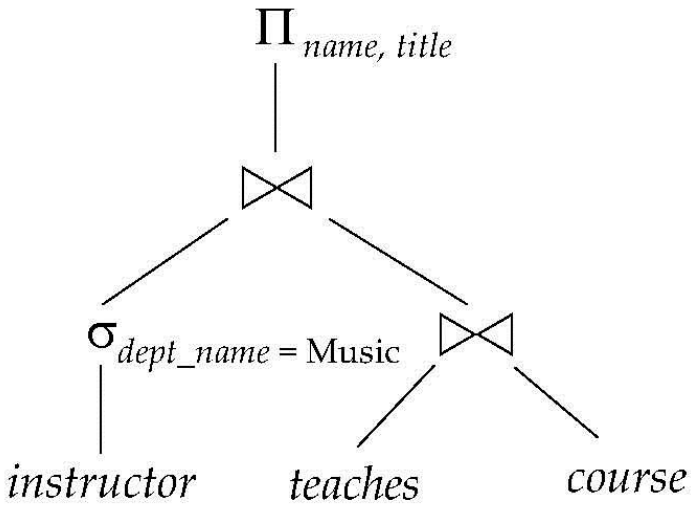
Pipelining (Cont.)

- In **demand driven** or **lazy** evaluation
  - system repeatedly requests next tuple from top level operation
  - Each operation requests next tuple from children operations as required, in order to output its next tuple
  - In between calls, operation has to maintain "**state**" so it knows what to return next
- In **producer-driven** or **eager** pipelining
  - Operators produce tuples eagerly and pass them up to their parents
    - Buffer maintained between operators, child puts tuples in buffer, parent removes tuples from buffer
    - if buffer is full, child waits till there is space in the buffer, and then generates more tuples
  - System schedules operations that have space in output buffer and can process more input tuples
- Alternative name: **pull** and **push** models of pipelining

Query Optimization

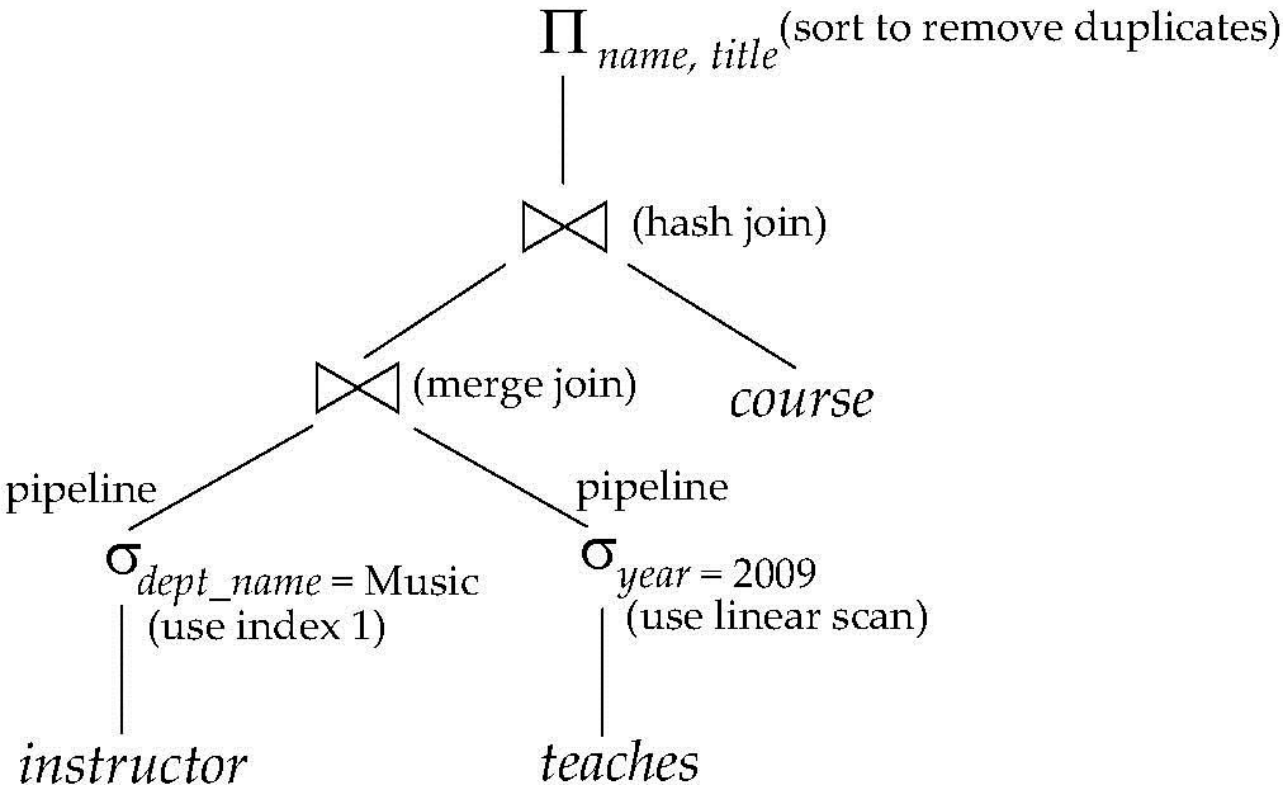
- Alternative ways of evaluating a given query
  - Equivalent expressions
  - Different algorithms for each operation





Query Optimization (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

Query Optimization (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 formula 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
- 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.)

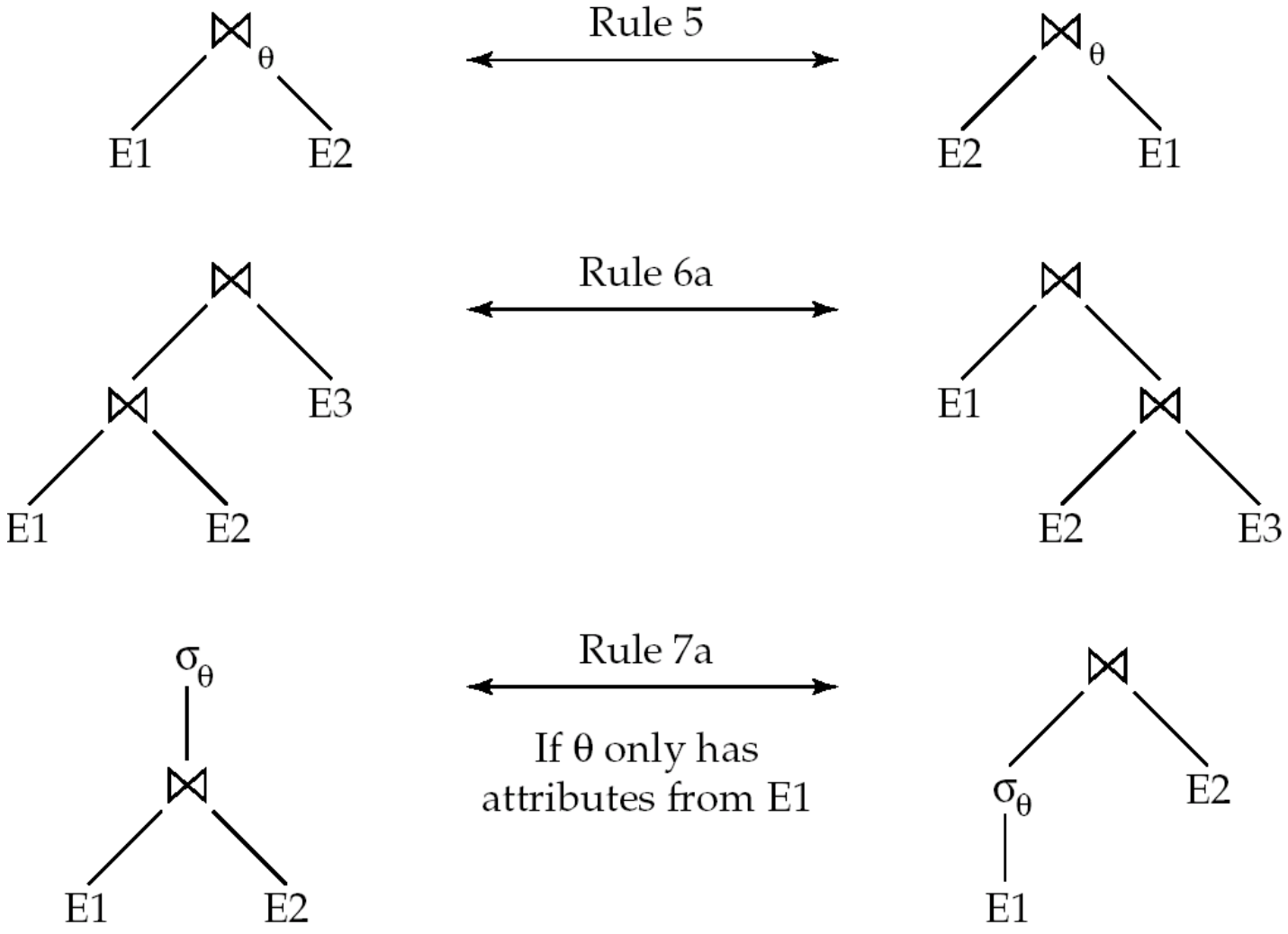
7. The selection operation distributes over the theta join operation under the following two conditions:
   (a) When all the attributes in θ_0 involve only the attributes of one of the expressions (E_1) being joined.

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

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

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

Pictorial Depiction of Equivalence Rules



Equivalence Rules (Cont.)

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

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

$$\Pi_{L_1 \cup L_2}(E_1 \bowtie_\theta E_2) = (\Pi_{L_1}(E1)) \bowtie_\theta (\Pi_{L_2}(E_2))$$

   (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 $L_1 \cup L_2$.

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

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 $-$

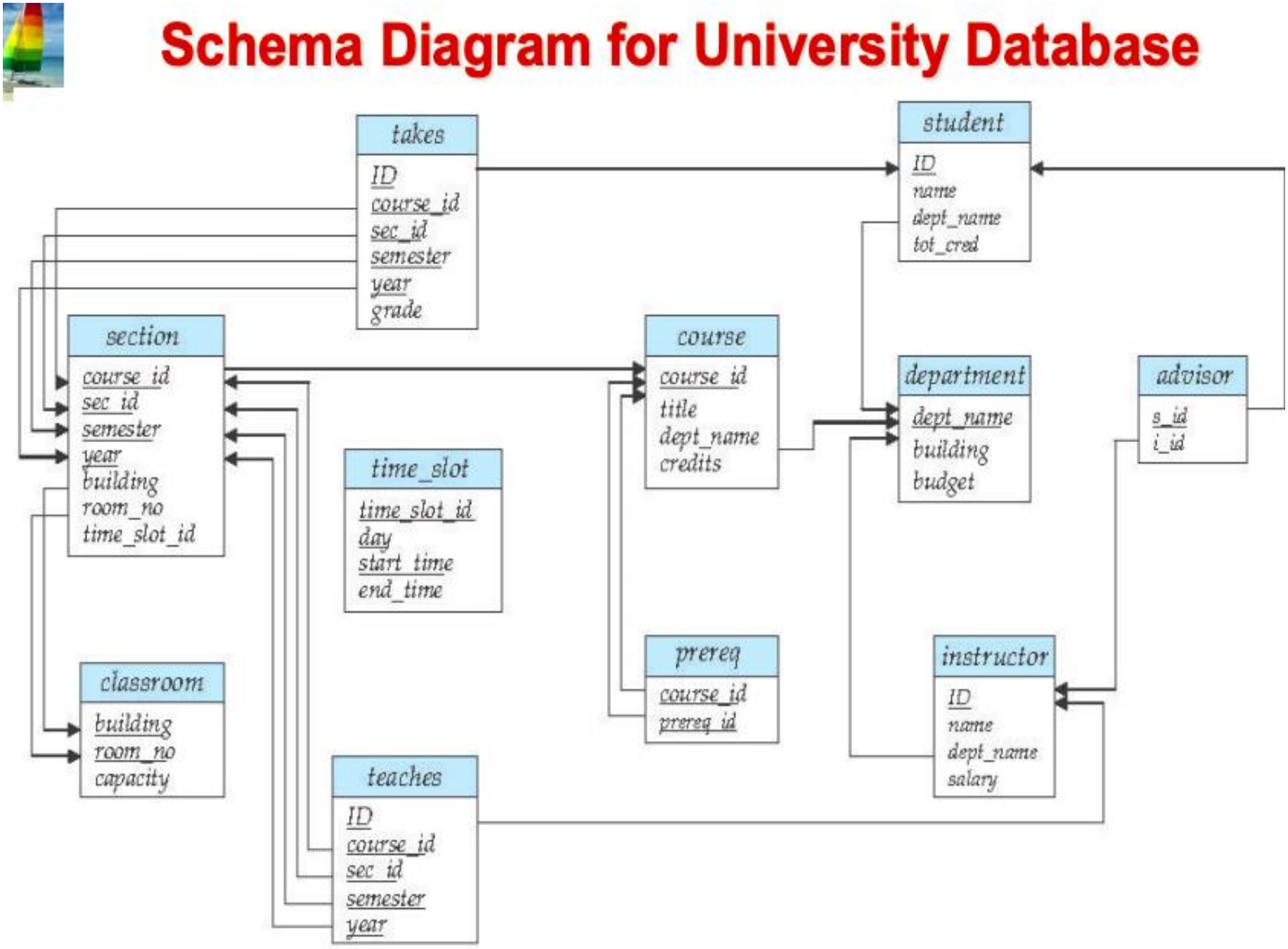
Also:
$$\sigma_\theta (E_1 - E_2) = \sigma_\theta(E_1) - E_2$$

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

12. The projection operation distributes over union

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

Schema Diagram for University Database



Transformation Example: Pushing Selections

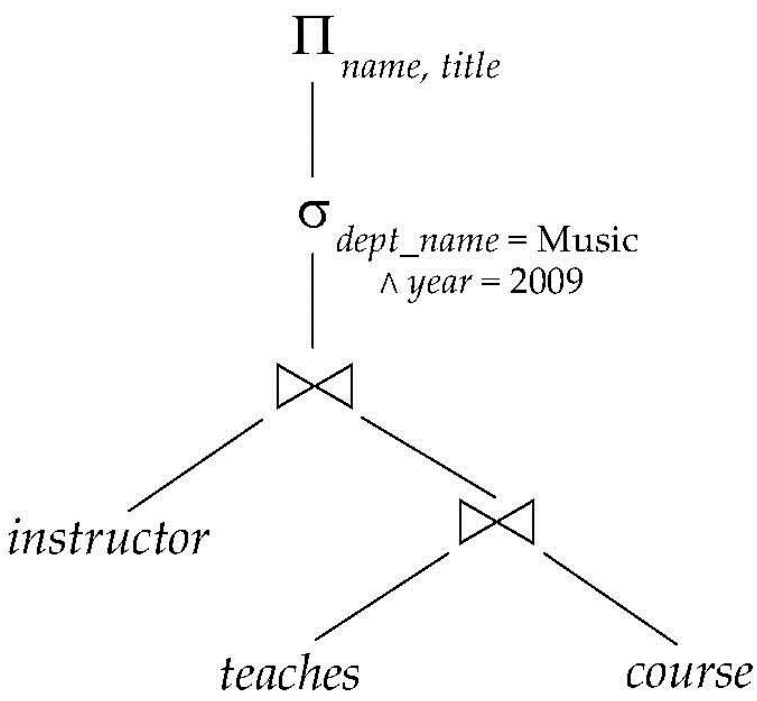
- Query: Find the names of all instructors in the Music department, along with the titles of the courses that they teach
  - $\Pi_{name,\ title}(\sigma_{dept\_name=\ \text{“Music”}}(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}(course))))$
- Transformation using rule 7a.
  - $\Pi_{name,\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

Example with Multiple Transformations

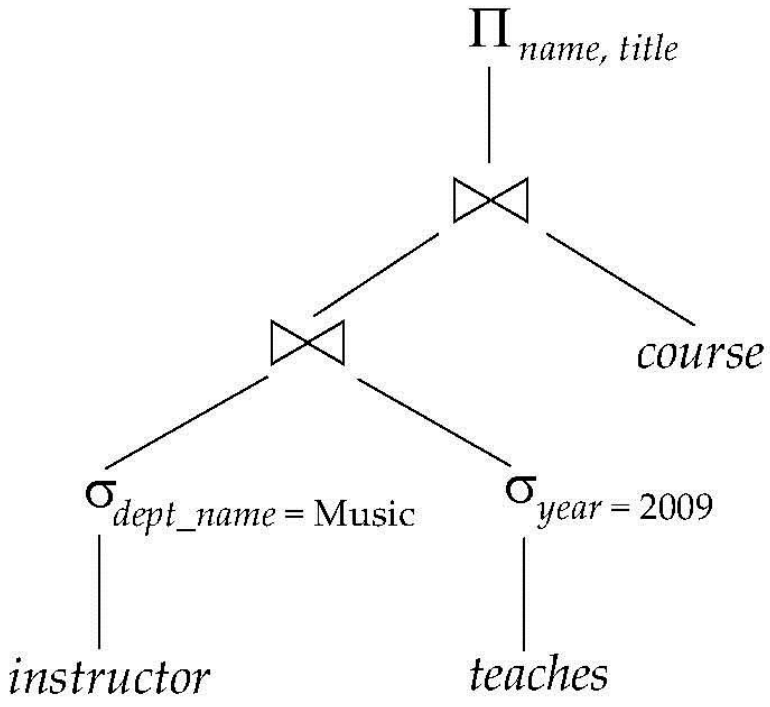
- Query: Find the names of all instructors in the Music department who have taught a course in 2009, along with the titles of the courses that they taught
  - $\Pi_{name,\ title}(\sigma_{dept\_name = \text{“Music”} \wedge year = 2009}$
    $(instructor \bowtie (teaches \bowtie \Pi_{course\_id,\ title}\ (course))))$
- Transformation using join associativity (Rule 6a):
  - $\Pi_{name,\ title}(\sigma_{dept\_name = \text{“Music”} \wedge year = 2009}$
    $((instructor \bowtie teaches) \bowtie \Pi_{course\_id,\ title}\ (course)))$
- 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 $\Pi_{name,\ course\_id}$ 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.

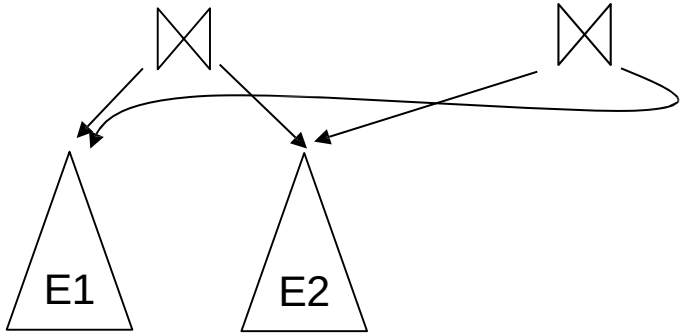
Enumeration of Equivalent Expressions

- 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 last 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
- More on cost estimation in text book

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.
    - nested-loop join may provide opportunity for pipelining
    - merge-join may be costlier than hash-join, but may provide a sorted output which reduces the cost for an outer level aggregation.
- 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

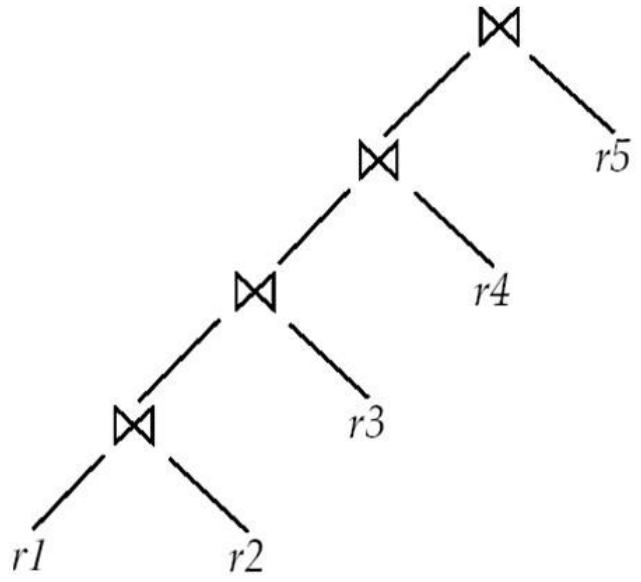
- To find best join tree for a set of *n* relations:
  - To find best plan for a set *S* of *n* relations, consider all possible plans of the form: $S_1 \bowtie (S - S_1)$ where S_1 is any non-empty subset of *S*.
  - Recursively compute costs for joining subsets of *S* to find the cost of each plan. 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

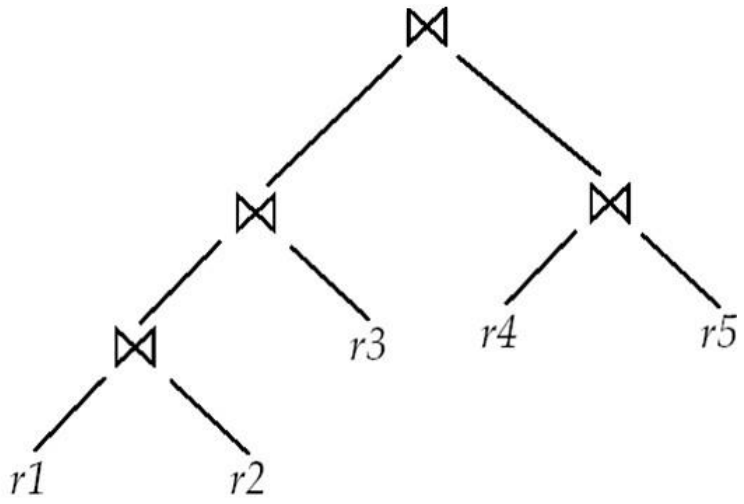
```
procedure findbestplan(S)
    if (bestplan[S].cost ≠ ∞)
            return bestplan[S]
    // else bestplan[S] has not been computed earlier, compute it now
    if (S contains only 1 relation)
            set bestplan[S].plan and bestplan[S].cost based on the best way
            of accessing S  /* 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]
```

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)

Summary of Cost Based Optimization

- **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

Heuristic Optimization

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

Structure of Query Optimizers

- 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:
  - Starting from each of n starting points → pick best among these
  - Repeatedly pick "best" relation to join next
- 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

End