CSE 305 / CSE532

Lecture 20 (Chapter 11)

An Overview of Query Optimization

Lecturer: Sael Lee

Slide adapted from the author’s, Peter Bailis’s and Dr. Ilchul Yoon’s slides.

Query Evaluation

- ***Problem***
  - An SQL query is declarative – does not specify a query execution plan.
  - A relational algebra expression is procedural and there is an associated query execution plan.
- ***Solution***
  - Convert SQL query to an equivalent relational algebra and evaluate it using the associated query execution plan.
  - *But which equivalent expression is best?*

Naive Conversion

SELECT DISTINCT *TargetList*
FROM R1, R2, …, RN
WHERE *Condition*

is equivalent to: $\pi_{TargetList}(\sigma_{Condition}(R_1 \times R_2 \times ... \times R_N))$
but this may imply a very inefficient query execution plan.

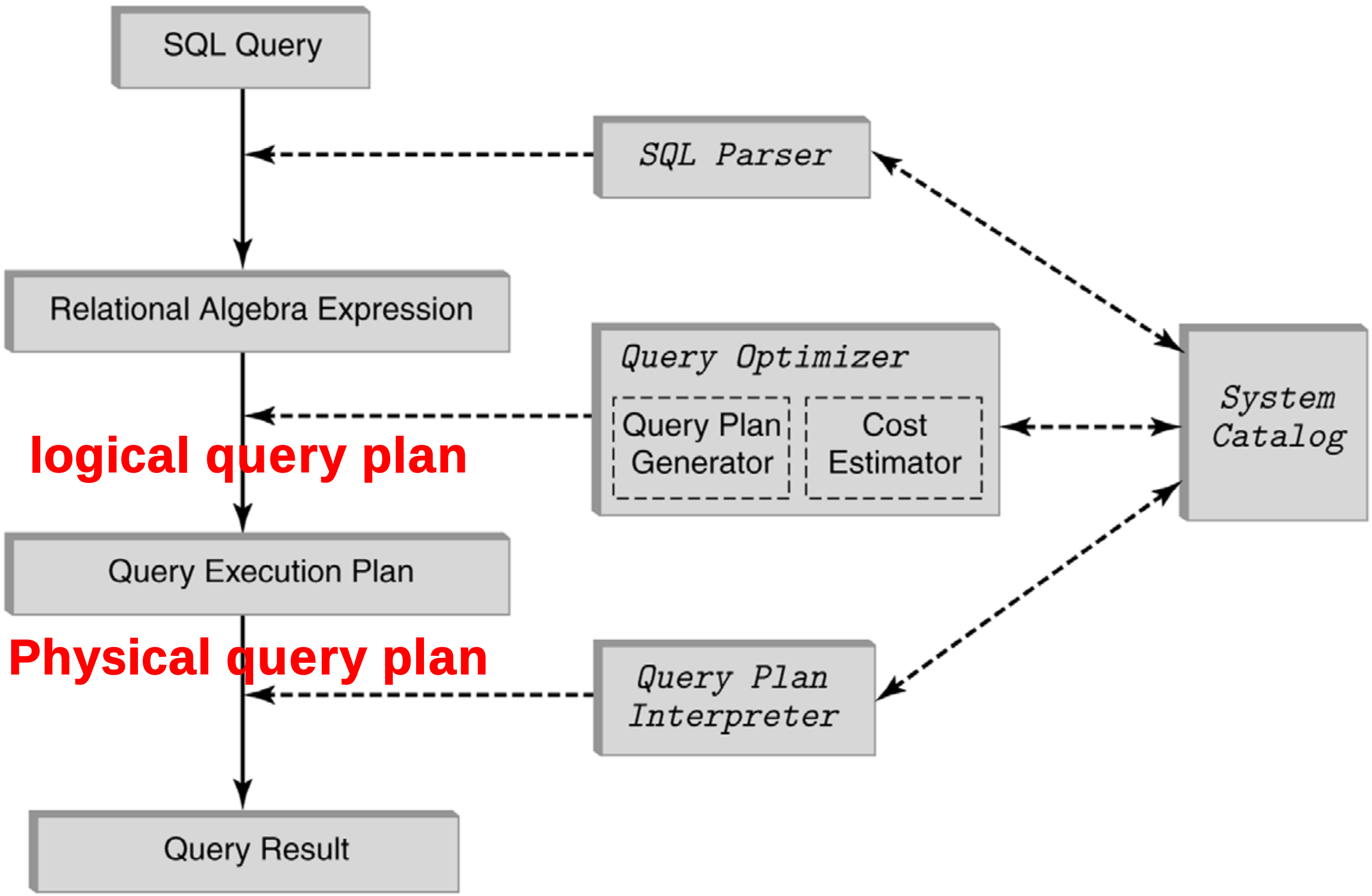
Example: $\pi_{Name}(\sigma_{Id=ProfId \wedge CrsCode='CS532'}(Professor \times Teaching))$

- Result can be < 100 bytes
- But if each relation is 50K then we end up computing an intermediate result Professor × Teaching of size 500M before shrinking it down to just a few bytes.

Problem statement:

Find an *equivalent* relational algebra expression that can be evaluated "*efficiently*".

Query Processing Architecture



Query Optimizer

- Uses heuristic algorithms to evaluate relational algebra expressions. This involves:
  - Estimating the cost of a relational algebra expression
  - Transforming one relational algebra expression to an equivalent one
  - Choosing access paths for evaluating the sub-expressions

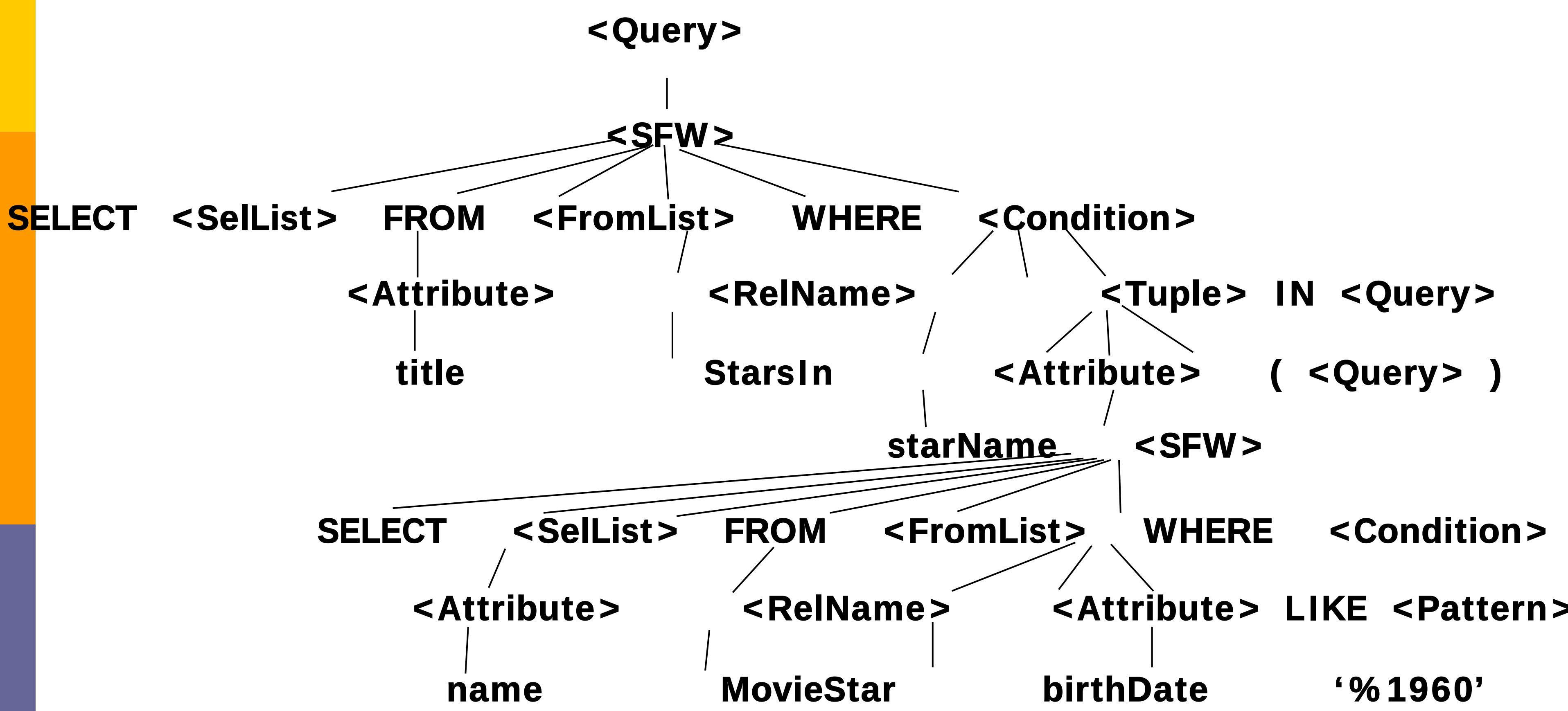
- Query optimizers do not "optimize" – just try to find *"reasonably good"* evaluation strategies

Example: SQL query

```
SELECT title
FROM StarsIn
WHERE starName IN (
        SELECT name
        FROM MovieStar
        WHERE birthdate LIKE '%1960'
);
```

(Find the movies with stars born in 1960)

Example: 1 Parse Tree



Example: 2 Generating Relational Algebra

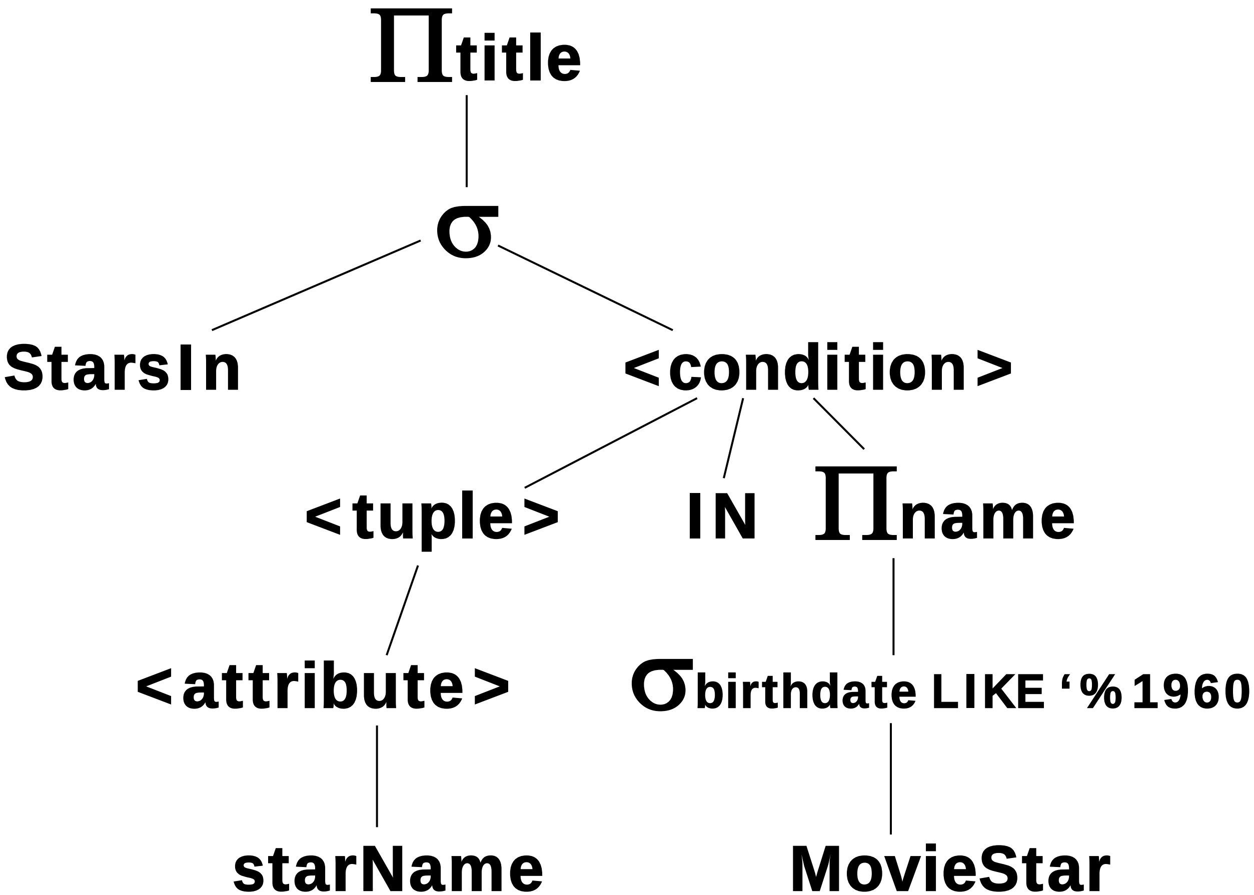


Fig. An expression using a two-argument σ, midway between a parse tree and relational algebra

Example: 3 Logical Query Plan

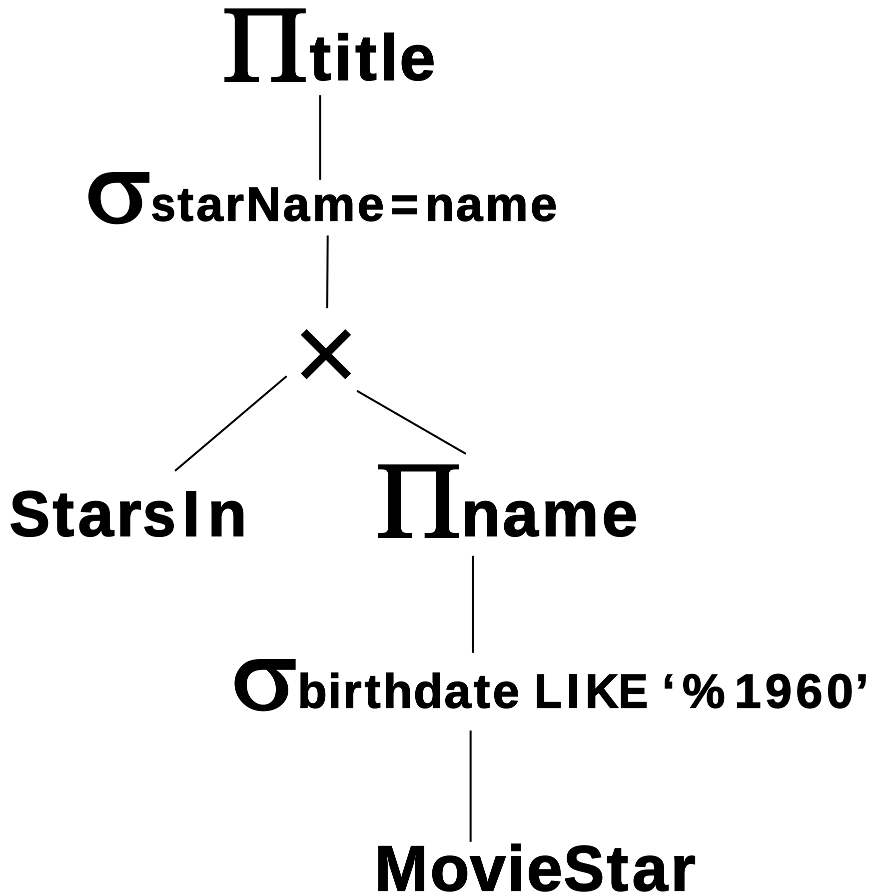
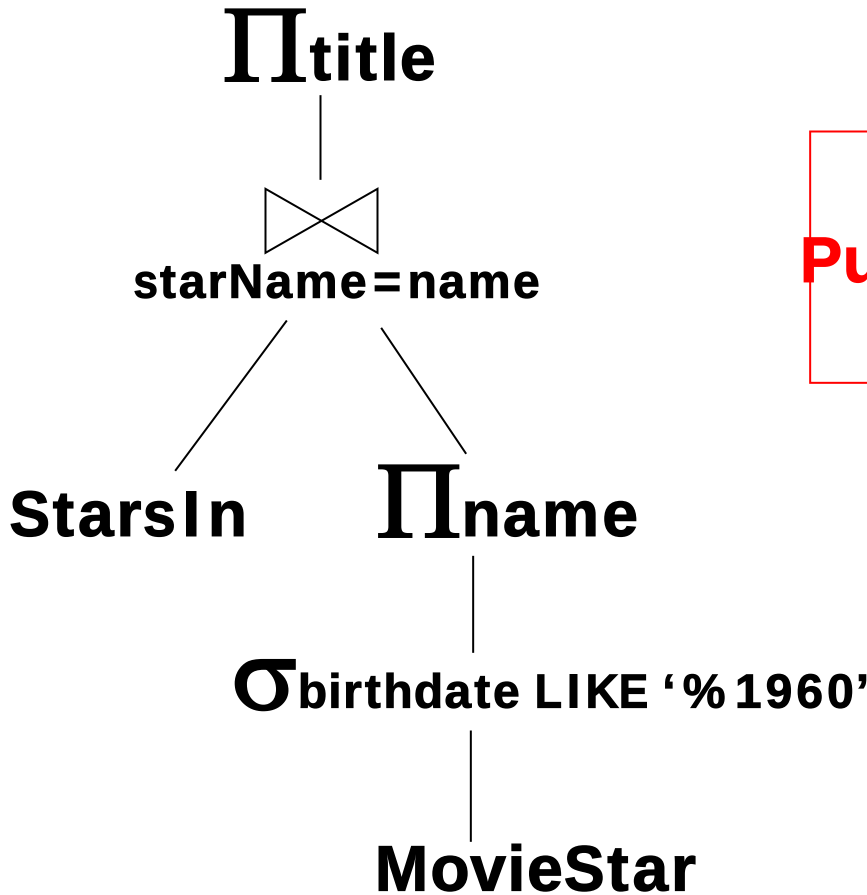


Fig. Applying the rule for IN conditions

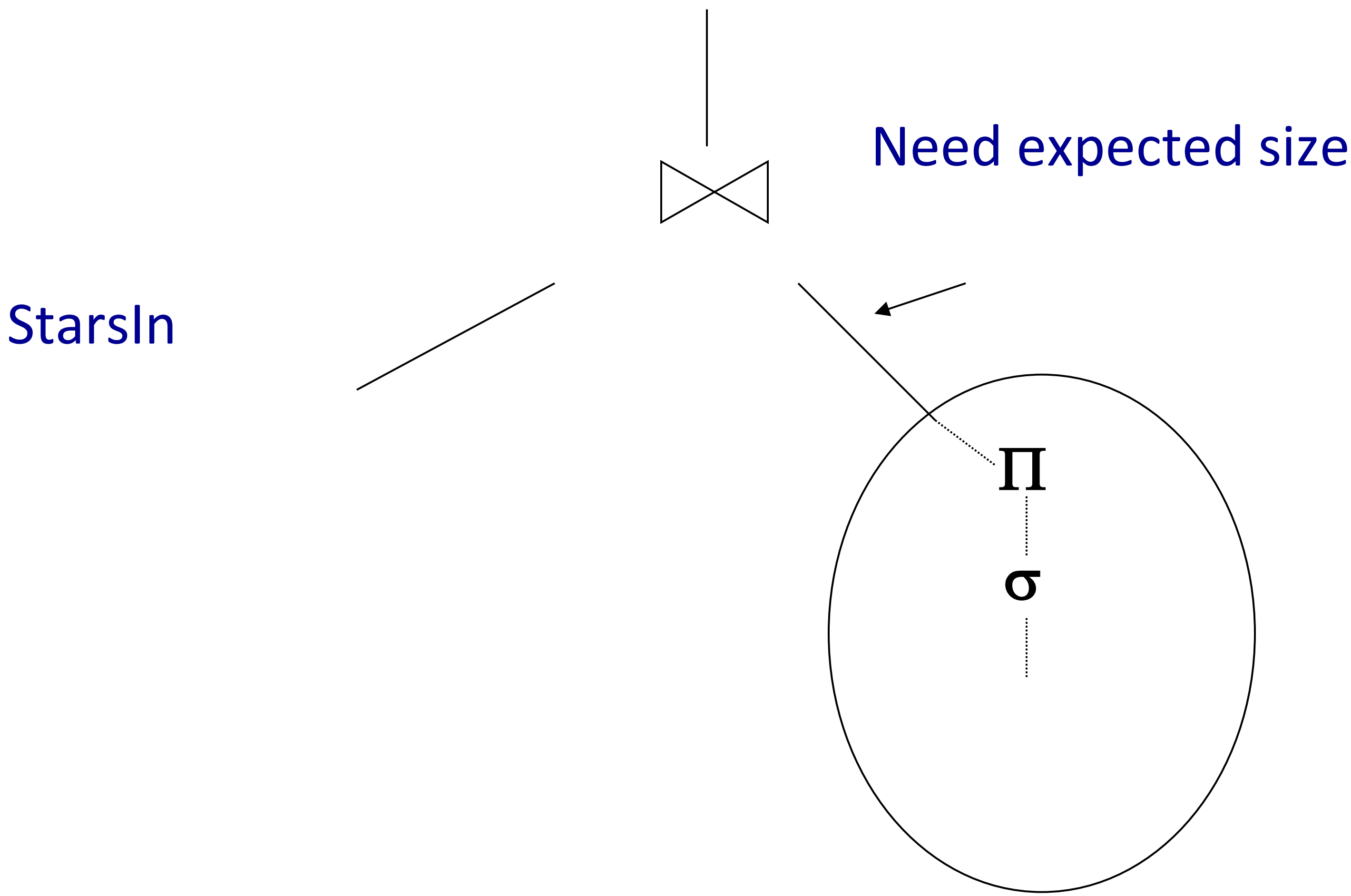
Example: 4 Improve Logical Query Plan



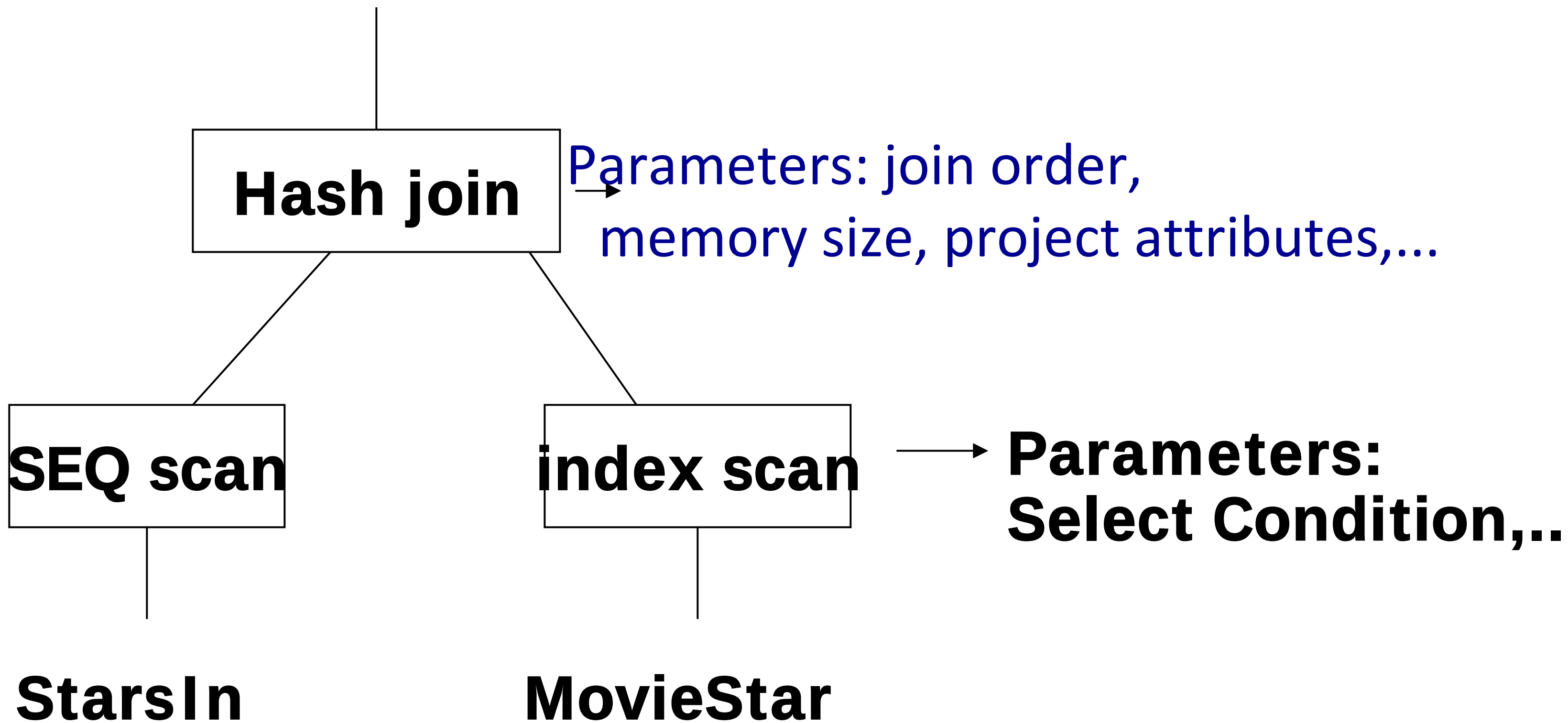
Question: Push project to StarsIn?

Fig. 7.20: An improvement on fig. 7.18.

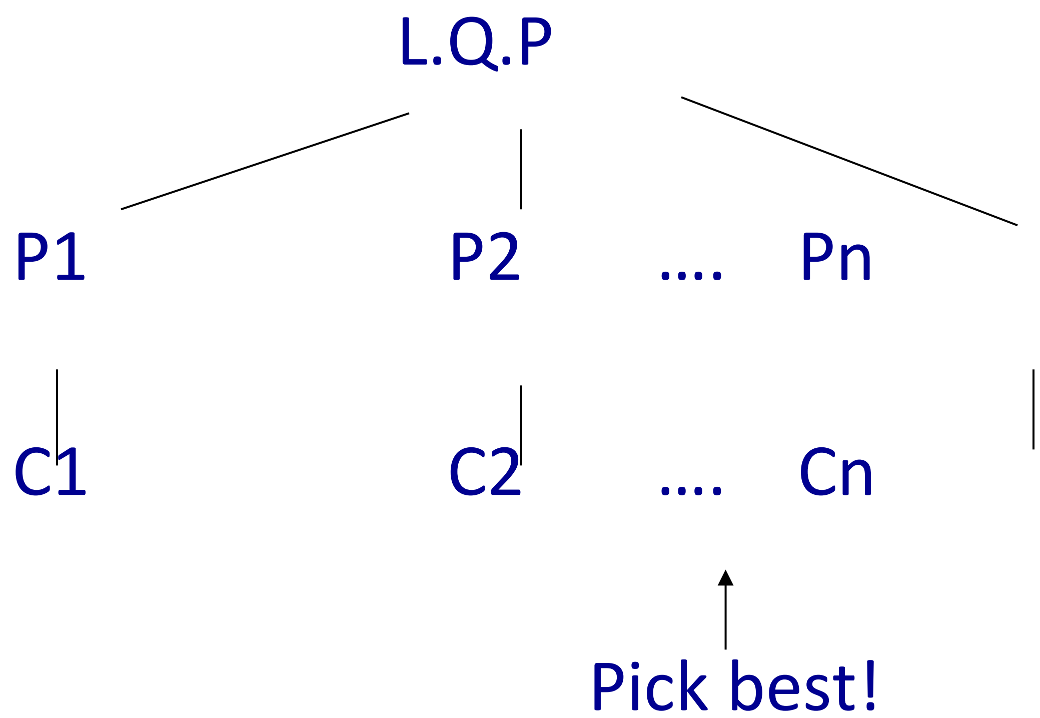
Example: Estimate Result Sizes



Example: One Physical Plan



Example: Estimate costs



Equivalence Preserving Transformations

- To transform a relational expression into another equivalent expression, we need transformation rules that preserve equivalence
- Each transformation rule
  - Is *provably* correct (i.e., does preserve equivalence)
  - Has a heuristic associated with it

Commutativity and Associativity of Join
(and Cartesian Product as Special Case)

- Join commutativity: $R \bowtie S \equiv S \bowtie R$
  - used to reduce cost of nested loop evaluation strategies (smaller relation should be in outer loop)
- Join associativity: $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$
  - used to reduce the size of intermediate relations in computation of multi-relational join – first compute the join that yields smaller intermediate result
- N-way join has $T(N) \times N!$ different evaluation plans
  - $T(N)$ is the number of parenthesized expressions
  - $N!$ is the number of permutations
- Query optimizer cannot look at all plans (might take longer to find an optimal plan than to compute query brute-force). Hence it does not necessarily produce optimal plan

Commutativity and Associativity of Join

Natural joins & cross products & union

$R \bowtie S = S \bowtie R$ **Commutative Law**

$(R \bowtie S) \bowtie T = R \bowtie (S \bowtie T)$ **Associative Law**

R x S = S x R

(R x S) x T = R x (S x T)

R U S = S U R

R U (S U T) = (R U S) U T

Selection and Projection Rules

- Break complex selection into simpler ones:
  - $\sigma_{Cond1 \wedge Cond2}(R) \equiv \sigma_{Cond1}(\sigma_{Cond2}(R))$
- Break projection into stages:
  - $\pi_{attr}(R) \equiv \pi_{attr}(\pi_{attr'}(R))$, if $attr \subseteq attr'$
- Commute projection and selection:
  - $\pi_{attr}(\sigma_{Cond}(R)) \equiv \sigma_{Cond}(\pi_{attr}(R))$,
    if $attr \supseteq$ all attributes in $Cond$

Laws Involving Selects

Splitting Laws:

$\sigma_{p1 \wedge p2}(R) =$ $\sigma_{p1}\ [\sigma_{p2}\ (R)]$

$\sigma_{p1 \vee p2}(R) =$ $[\sigma_{p1}\ (R)] \cup [\sigma_{p2}\ (R)]$

Since **selections** tend to reduce the size of relations markedly, we want to move the selections down the tree as far as they will go

Bags vs. Sets

R = {a,a,b,b,b,c}

S = {b,b,c,c,d}

R U S = ?

- **Option 1** **SUM**

  RUS = {a,a,b,b,b,b,b,c,c,c,d}
- **Option 2** **MAX**

  RUS = {a,a,b,b,b,c,c,d}

SUNY Korea

Laws Involving Project

Let: X = set of attributes

Y = set of attributes

XY = X U Y

$$\pi_{xy}(R) = \cancel{\pi_x[\pi_y(R)]}$$

While selections reduce the size of a relation by a large factor, projection keeps the number of tuples the same and only reduce the length of tuples and sometimes increase the length of tuples

Pushing Selections and Projections

- $\sigma_{Cond}(R \times S) \equiv R \bowtie_{Cond} S$
  - *Cond* relates attributes of both R and S
  - *Reduces* size of intermediate relation since rows can be discarded sooner

- $\sigma_{Cond}(R \times S) \equiv \sigma_{Cond}(R) \times S$
  - *Cond* involves only the attributes of R
  - Reduces size of intermediate relation since rows of R are discarded sooner

- $\pi_{attr}(R \times S) \equiv \pi_{attr}(\pi_{attr'}(R) \times S)$,
  if $attributes(R) \supseteq attr' \supseteq attr \cap attributes(R)$
  - reduces the size of an operand of product

CSE 305 / CSE532

Lecture 21 (Chapter 11)

An Overview of Query Optimization

Lecturer: Sael Lee

Slide adapted from the author's and Dr. Ilchul Yoon's slides.

Rules: $\sigma + \bowtie$ combined

Let p = predicate with only R attribs

q = predicate with only S attribs

m = predicate with only R,S attribs

$$\sigma_p (R \bowtie S) = [\sigma_p (R)] \bowtie S$$

$$\sigma_q (R \bowtie S) = R \bowtie [\sigma_q (S)]$$

Rules: σ + $\bowtie$ combined

$$\sigma_{p \wedge q} (R \bowtie S) = [\sigma_p (R)] \bowtie [\sigma_q (S)]$$

$$\sigma_{p \wedge q \wedge m} (R \bowtie S) =$$

$$\sigma_m \left[(\sigma_p R) \bowtie (\sigma_q S) \right]$$

$$\sigma_{p \vee q} (R \bowtie S) =$$

$$\left[(\sigma_p R) \bowtie S \right] \cup \left[R \bowtie (\sigma_q S) \right]$$

Rules: π,σ combined

Let x = subset of R attributes

z = attributes in predicate P
(subset of R attributes)

$$\pi_x[\sigma_p(R)] = \{\sigma_p[\pi_x(R)]\}$$

Rules: π,σ combined

Let x = subset of R attributes

z = attributes in predicate P

(subset of R attributes)

$\pi_x[\sigma_p(R)] =$ $\pi_x \{\sigma_p [\pi_{xz} \; \cancel{\pi_x} (R)] \}$

Rules: π, $\bowtie$ combined

Let x = subset of R attributes
y = subset of S attributes
z = intersection of R,S attributes

$$\pi_{xy}(R \bowtie S) =$$

$$\pi_{xy}\{[\pi_{xz}(R)] \bowtie [\pi_{yz}(S)]\}$$

$$\pi_{xy}\{\sigma_p\,(R \bowtie S)\} =$$

$$\pi_{xy}\{\sigma_p\,[\pi_{xz'}(R) \bowtie \pi_{yz'}(S)]\}$$

$$z' = z \cup \{\text{attributes used in } P\}$$

Equivalence Example

- $\sigma_{C1 \wedge C2 \wedge C3}(R \times S)$
  $\equiv \sigma_{C1}(\sigma_{C2}(\sigma_{C3}(R \times S)))$
  $\equiv \sigma_{C1}(\sigma_{C2}(R) \times \sigma_{C3}(S))$
  $\equiv \sigma_{C2}(R) \bowtie_{C1} \sigma_{C3}(S)$

  - assuming that
    C2 involves only attributes of R,
    C3 involves only attributes of S, and
    C1 relates attributes of R and S

Rules σ, U combined:

$\sigma p(R \cup S) = \sigma p(R) \cup \sigma p(S)$

$\sigma p(R - S) = \sigma p(R) - S = \sigma p(R) - \sigma p(S)$

Which are "good" transformations?

- $\sigma_{p1 \wedge p2}(R) \rightarrow \sigma_{p1}[\sigma_{p2}(R)]$
- $\sigma_{p}(R \bowtie S) \rightarrow [\sigma_{p}(R)] \bowtie S$
- $R \bowtie S \rightarrow S \bowtie R$
- $\pi_{x}[\sigma_{p}(R)] \rightarrow \pi_{x}\{\sigma_{p}[\pi_{xz}(R)]\}$

Conventional wisdom:

do **projects** early

Example: R(A,B,C,D,E) x={E}

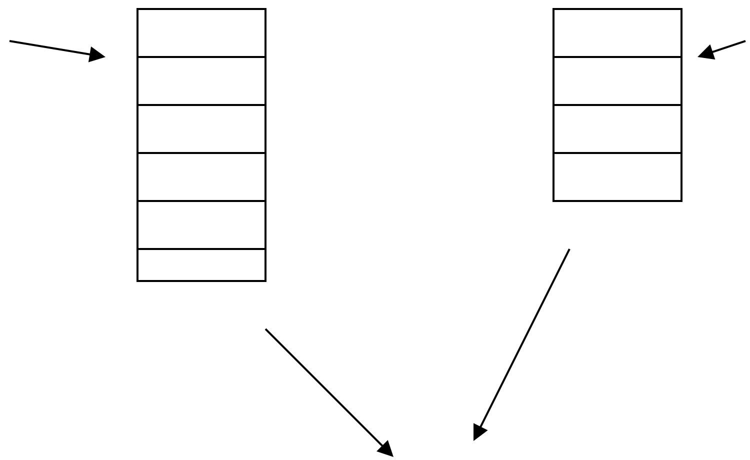
P: (A=3) $\wedge$ (B="cat")

$\pi_x \{\sigma_p (R)\}$ vs. $\pi_E \{\sigma_p \{\pi_{ABE}(R)\}\}$

What if we have A, B indexes?

But

B = “cat”



A=3

Intersect pointers to get

pointers to matching tuples

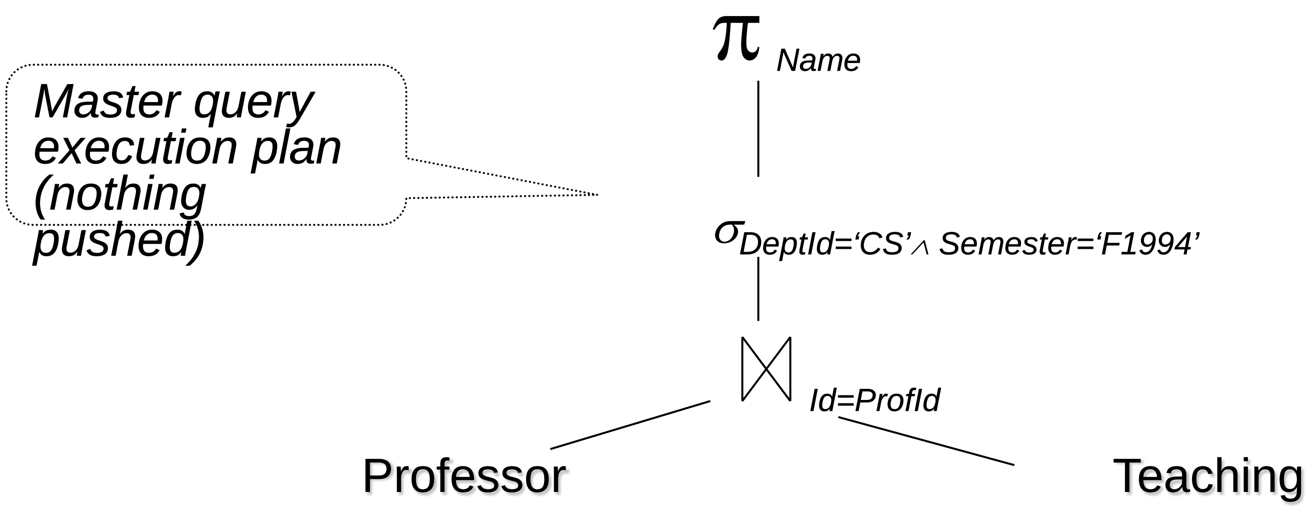
Bottom line:

- No transformation is <u>always</u> good
- Usually good: early selections

Cost - Example 1

SELECT P.*Name*
FROM Professor P, Teaching T
WHERE P.Id = T.*ProfId* -- *join condition*
AND P. *DeptId* = 'CS' AND T.*Semester* = 'F1994'

$$\pi_{Name}(\sigma_{DeptId='CS' \wedge Semester='F1994'}(\text{Professor} \bowtie_{Id=ProfId} \text{Teaching}))$$



Metadata on Tables (in system catalogue)

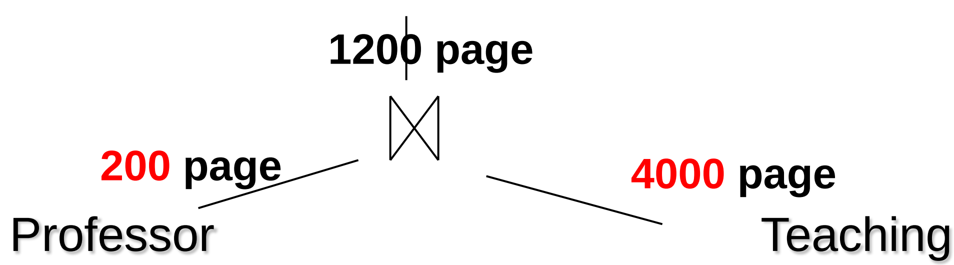
- **Professor** (Id, Name, DeptId)
  - size: 200 pages, 1000 rows, 50 departments (5 tuples/page)
  - indices: clustered 2-level B^+ tree on DeptId,
    hash on Id
- **Teaching** (ProfId, CrsCode, Semester)
  - size: 1000 pages, 10,000 rows, 4 semesters, (10 tuples/page)
  - indices: clustered 2-level B^+ tree on Semester;
    hash on ProfId
- **Definition**: Weight of an attribute – *average number of rows that have a particular value*
  - weight of Id = 1 (it is a key)
  - weight of ProfId = 10 (10,000 classes/1000 professors)

Estimating Cost - Example 1

- *Assumption*
  - 52 page buffer is available for evaluating join
  - Small amount of additional memory is available for aux. info.
- *Join* - index-nested loops with 50 page buffers
  - 50 pages – input for Professor,
  - 5 profs per page and average 10 classes per each prof
  - Cost to scan Professor relation
    - 200 page transfers
  - Cost to find matching tuples in Teaching

Estimating Cost - Example 1 cont.

- Cost to find matching tuples in **Teaching**
  - Max. 2500 tuples (50 pages x 5 faculty/page x avg 10 classes/faculty) in **Teaching** could be matched. (i.e., max. page transfers could be 2500.) for loaded **Professor** pages
  - However, by sorting <u>record ids</u> of the **Teaching** pointed by the 2500 tuples, this can be done in 1000 page transfers = size(**Teaching**)
  - Repeating 4 times (200 pages/50 buffer) makes 4000 page transfers from **Teaching**



Estimating Cost - Example 1 (cont'd)

- 50 pages – input for **Professor**,
- 5 profs per page and average 10 classes per each prof

- Cost to <u>search index</u> of **Teaching** ($_{p.Id=t.ProfId}$)
  - ProfID is hash-indexed.
  - <u>1.2 I/O per index search</u>, assuming good hash function (1.2)
  - If all matching tuples are stored in a single bucket (<u>10 on average</u>), indices for the 10 tuples can be retrieved in one I/O operation.
  - There are 10000 tuples in Teaching. This requires 1000 I/Os makes 1200 page transfers

- So… the total cost is 200 + 4000 + 1200 = 5400 page transfers

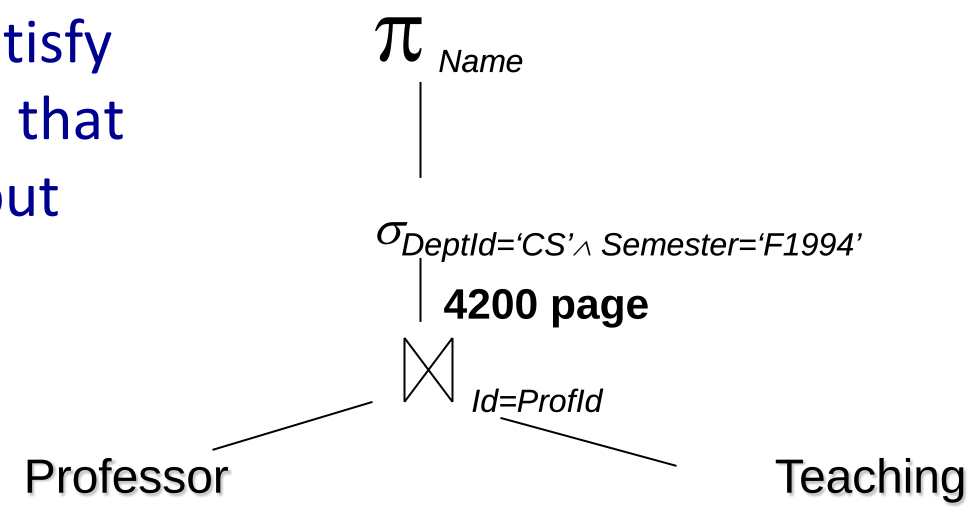
Estimating Cost - Example 1 (cont'd)

- *Join* - block-nested loops with 52 page buffers
  - 50 pages – input for Professor,
  - 1 page – input for Teaching,
  - 1 – output page

  - Scanning Professor (outer loop): 200 page transfers, (4 iterations, 50 transfers each)
  - Finding matching rows in Teaching (inner loop): 1000 page transfers *for each iteration* of outer loop
  - Total cost = 200 + 4*1000 = 4200 page transfers

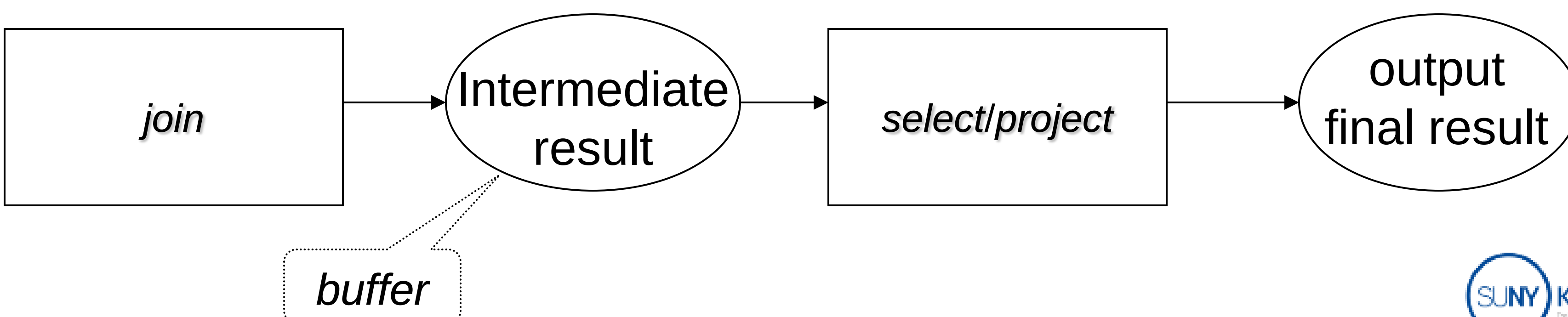
Estimating Cost - Example 1 (cont'd)

- *Selection and projection*
  - scan rows of intermediate file, discard those that don't satisfy selection, project on those that do, write result when output buffer is full.
- Complete algorithm:
  - do ***join***, write result to intermediate file on disk
  - read (big) intermediate file, do *select/project*, write final result
  - <u>**Problem: unnecessary I/O**</u>



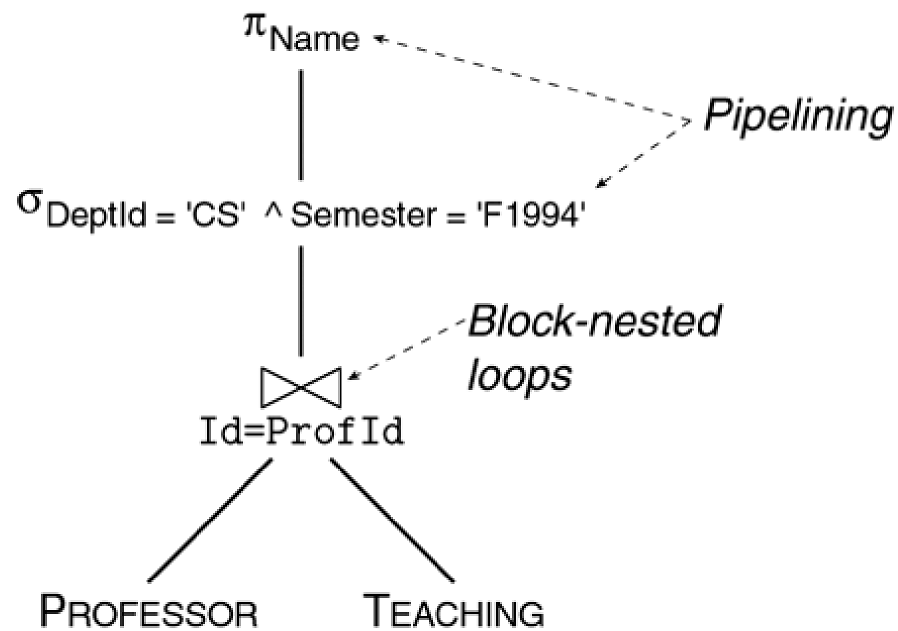
Pipelining

- **Solution**: use *pipelining:*
  - ***join* and *select/project* act as co-routines**, operate as producer/consumer sharing a buffer in main memory.
  - Output of one relational operator is "piped" to the input of the next operator without saving the intermediate result on disk.
    - When *join* fills buffer; *select/project* filters it and outputs result
    - Process is repeated until *select/project* has processed last output from join
  - Performing select/project adds no additional cost



Estimating Cost - Example 1 (cont'd)

- I/O operations required for storing data will be reduced



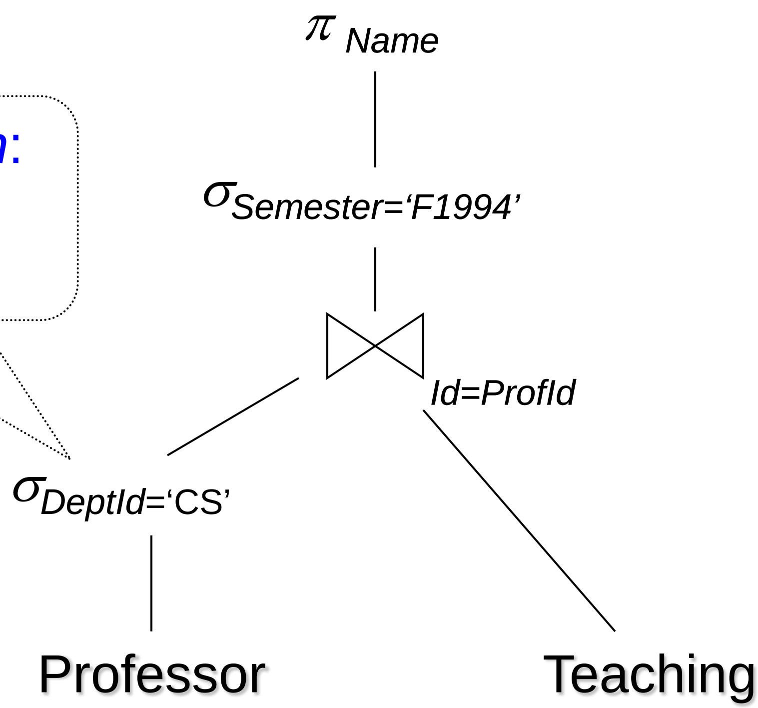
- Total cost:
  - 4200 + (cost of outputting final result)
  - We will *disregard the cost of outputting final result* in comparing with other query evaluation strategies, since this will be same for all

Cost Example 2

SELECT P.*Name*
FROM Professor P, Teaching T
WHERE P.Id = T.*ProfId* AND
P. *DeptId* = 'CS' AND T.*Semester* = 'F1994'

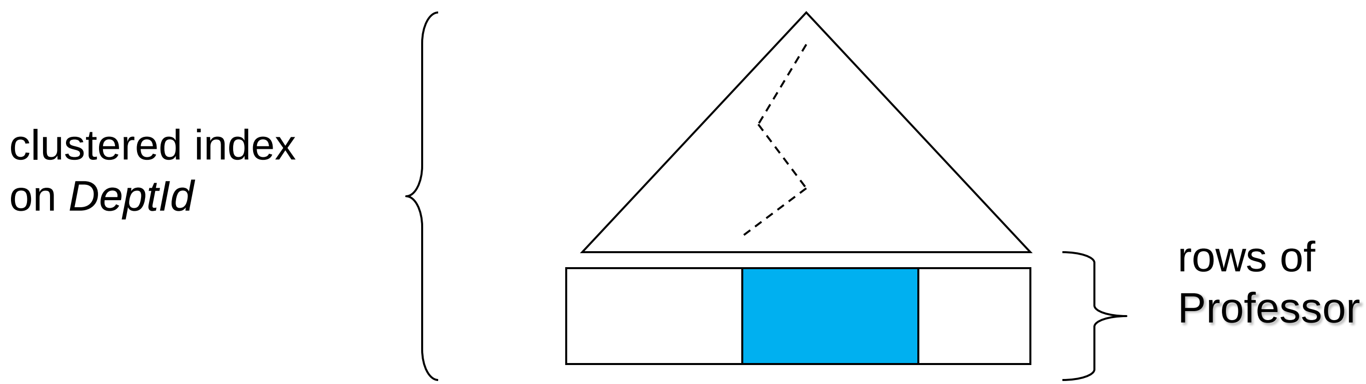
$$\pi_{Name}(\sigma_{Semester='F1994'}(\sigma_{DeptId='CS'}(\text{Professor}) \bowtie_{Id=ProfId} \text{Teaching}))$$

Partially pushed plan: *selection pushed to* Professor



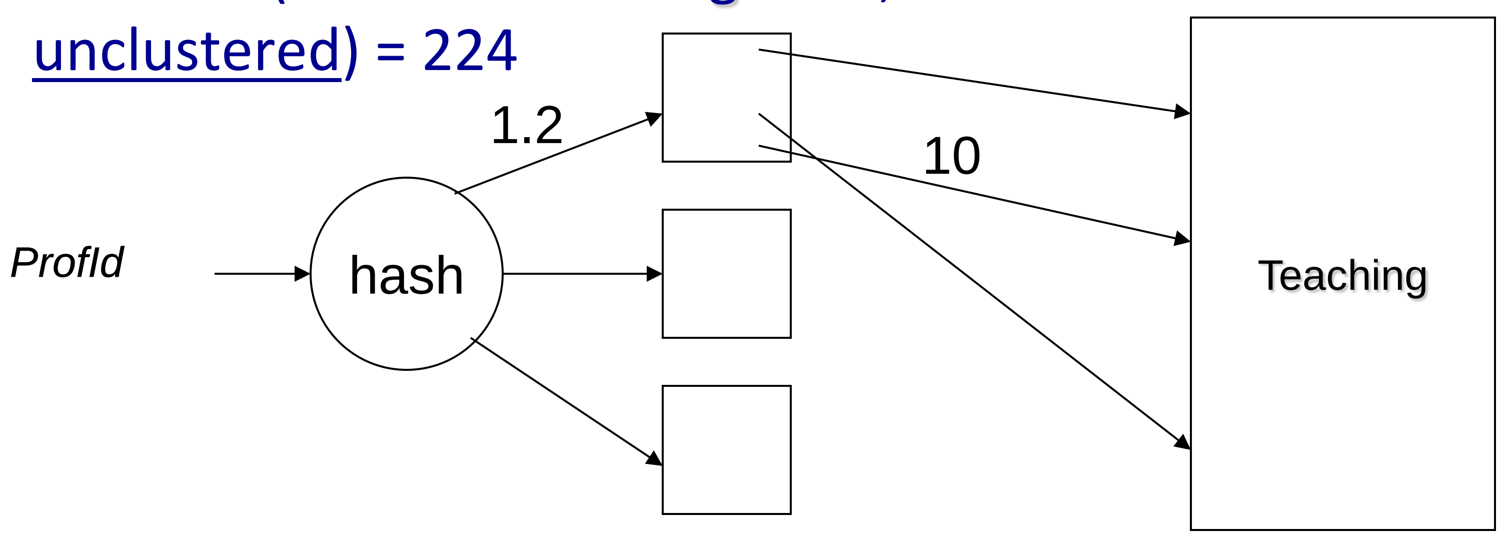
Cost Example 2 -- *selection*

- Compute $\sigma_{DeptId='CS'}$ (Professor) to reduce size of one join table) using clustered, 2-level B^+ tree on *DeptId*.
  - 50 departments and 1000 professors; hence *weight* of DeptId is 20 (roughly 20 CS professors).
  - These rows are in ~ 4 consecutive pages in Professor.
    - Cost = 4 (to get rows) + 2 (to search index) = 6
    - keep resulting 4 pages in memory and pipe to next step



Cost Example 2 – *join* (cont'd)

- Each professor matches ~ roughly 10 Teaching rows. Since 20 CS professors, hence 200 teaching records.
- All index entries for a particular *ProfId* are in same bucket. Assume ~1.2 I/Os to get a bucket.
  - Index fetch cost: 1.2×20 (to fetch index entries for 20 CS professors)
- Total Cost
  - 24 + 200 (to fetch Teaching rows, since hash index is unclustered) = 224



Cost Example 2 – *select/project*

- Pipe result of join to *select* (on *Semester*) and *project* (on *Name*) at no I/O cost
- Cost of output same as for Example 1
- Total cost:

    6 (select on Professor) + 224 (join) = 230

- Comparison:

    4200 (example 1) vs. 230 (example 2) !!!

Choosing Query Execution Plan

- Step 1: Choose a *logical* plan
- Step 2: Reduce search space
- Step 3: Use a heuristic search to further reduce complexity

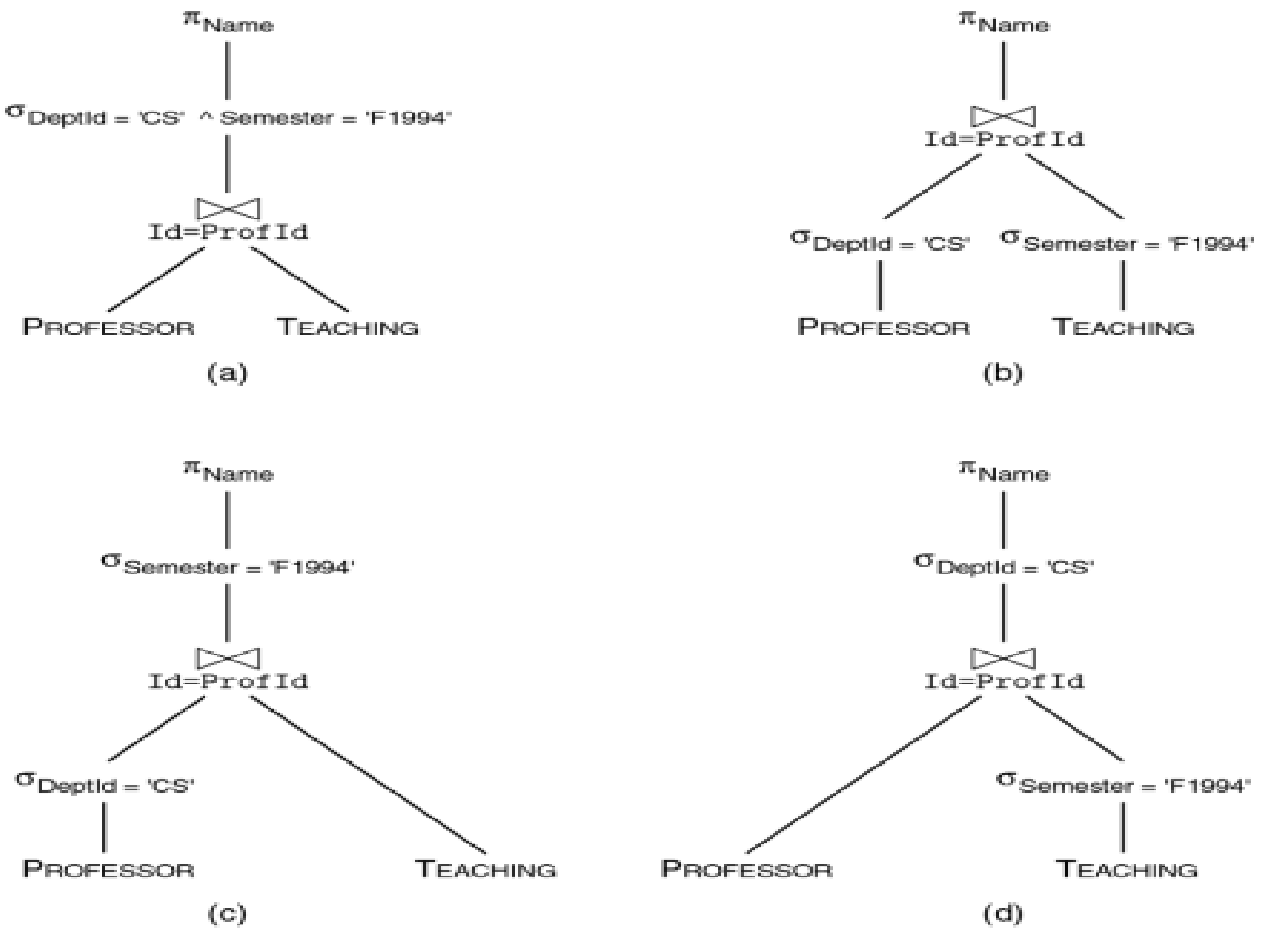
Step 1: Choosing a Logical Plan

- Involves choosing a query tree, which indicates the order in which algebraic operations are applied

- *Heuristic*:
  - Pushed trees are good, but sometimes "nearly fully pushed" trees are better due to indexing
  - Avoid exponential complexity problem by grouping consecutive binary operators of the same kind into one node

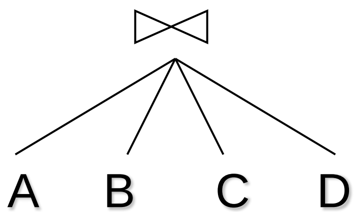
- **So**: Take the initial "master plan" tree and produce a *fully pushed* tree plus several *nearly fully pushed* trees.

Step 1: Choosing a Logical Plan (cont'd)

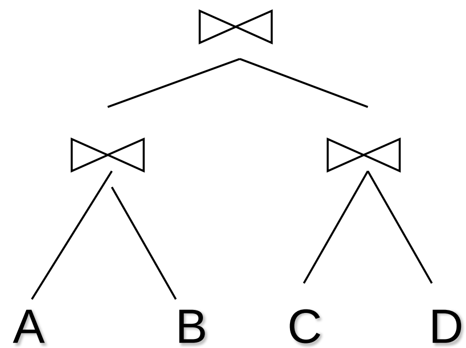


Step 2: Reduce Search Space

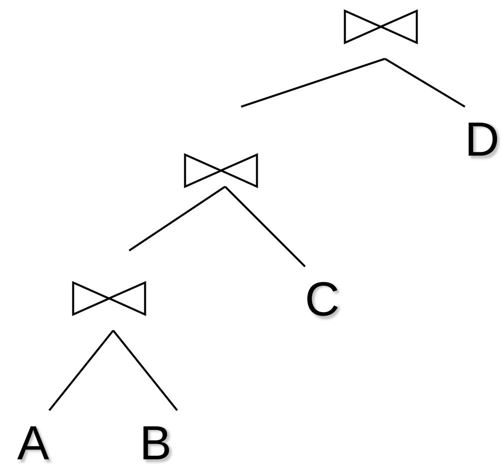
- Deal with *associativity* of binary operators (join, union, …)



Logical query execution plan



Equivalent query tree



Equivalent *left deep query tree*