CSE462/562: Database Systems (Spring 23)

Lecture 18: Query Optimization Overview

4/20/2023

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Query processing overview

ODBC/JDBC/ command line frontend

**

SQL Query

```
SELECT S.name,E.grade
FROM student S, enrollment E
WHERE S.sid = E.sid
  AND S.adm_year = 2021
  AND E.cno = 562;
```

*SQL Parser**

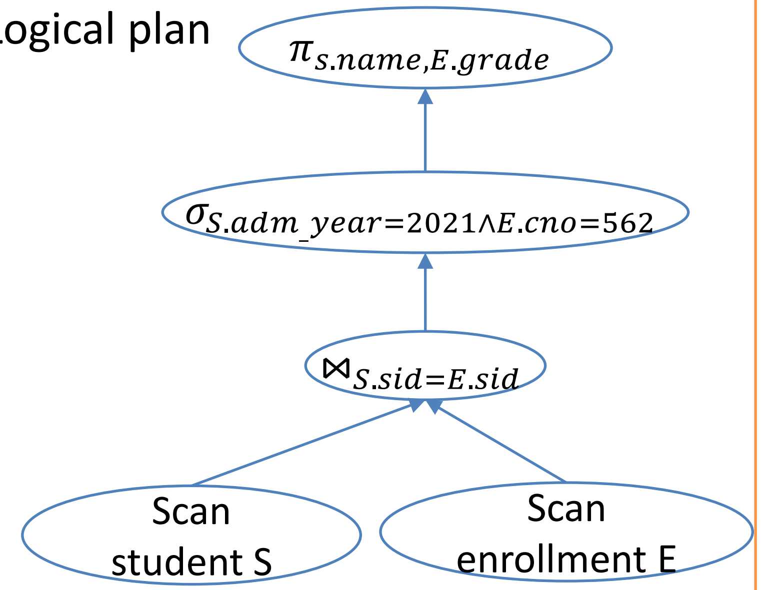
** include multiple intermediate steps (e.g., parsing tree/analysis/rewriting)*

(Extended) Relational Algebra

$$\pi_{S.name,E.grade}\sigma_{S.adm\_year=2021 \land E.cno=562} S \bowtie_{S.sid=E.sid} E$$

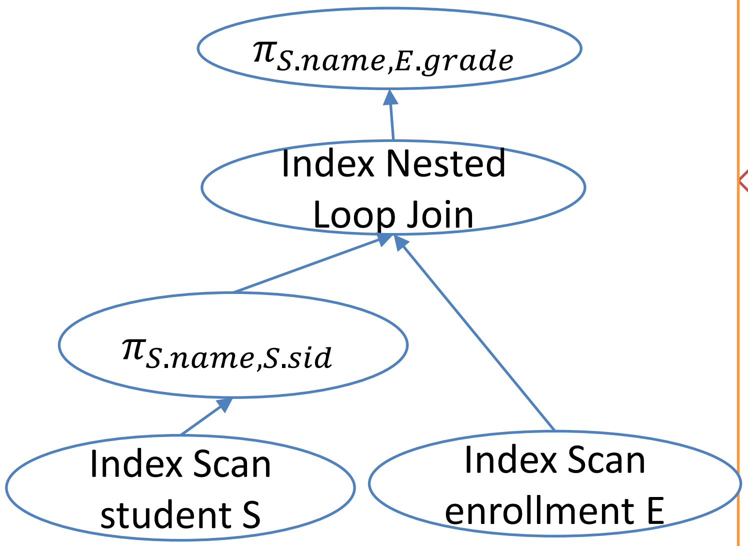
Internally represented as

Logical plan



Query Optimizer

Physical plan



Query Execution

Query result

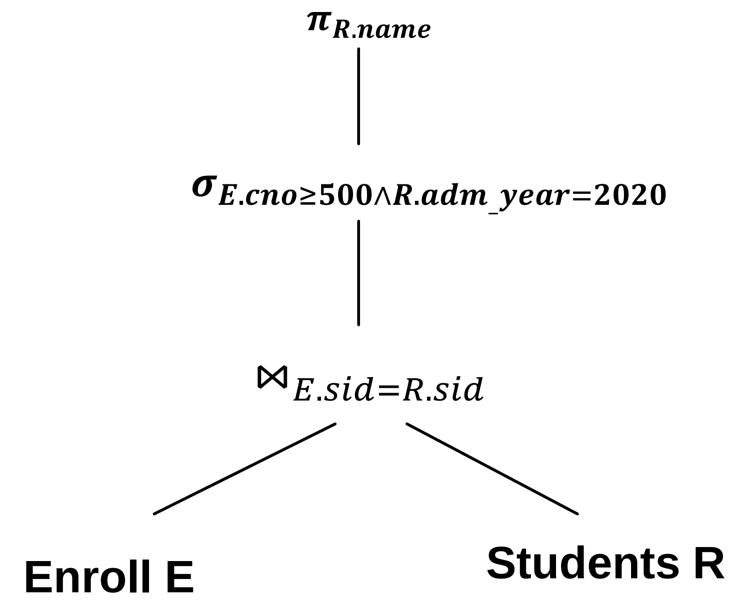
```
S.name | E.grade
Alice  | 4.0
Charlie| 2.3
(2 rows)
```

Query optimization overview

- Query can be converted to relational algebra
- Relational Algebra converted to tree, joins as branches
- Each operator has implementation choices
- Operators can also be applied in different order!

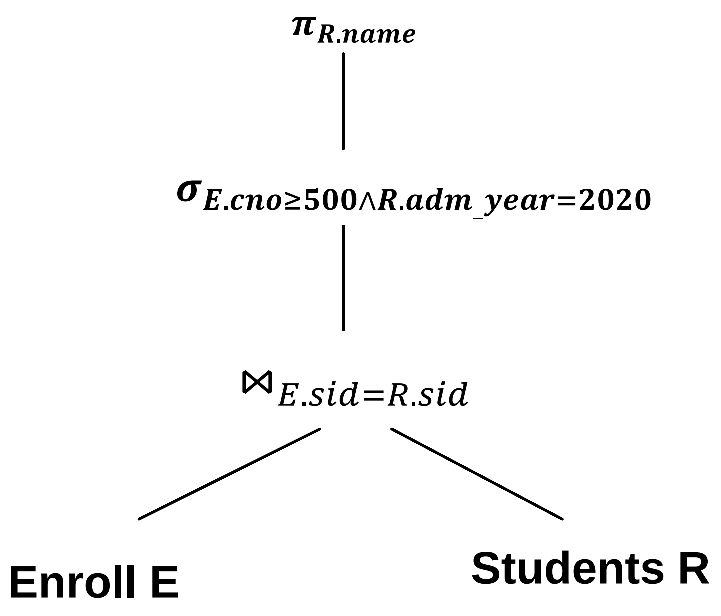
```
SELECT  R.name
FROM  Enroll E, Students R
WHERE  E.sid=R.sid AND
   E.cno>=500 AND R.adm_year = 2020
```

$$\pi_{R.name}\sigma_{E.cno=562\wedge E.grade\geq 3.0}E \bowtie_{E.sid=R.sid} R$$



Query optimization overview

- *<u>Plan</u>: Tree of R.A. ops (and some others) with choice of algorithm for each op.*
  - Each operator typically implemented using a `pull' interface: when an operator is `pulled' for the next output tuples, it `pulls' on its inputs and computes them.
- Two main issues:
  - For a given query, what plans are considered?
    - Algorithm to search plan space for cheapest (estimated) plan.
  - How is the cost of a plan estimated?
- Ideally: Want to find best plan.
- Reality: Avoid worst plans!

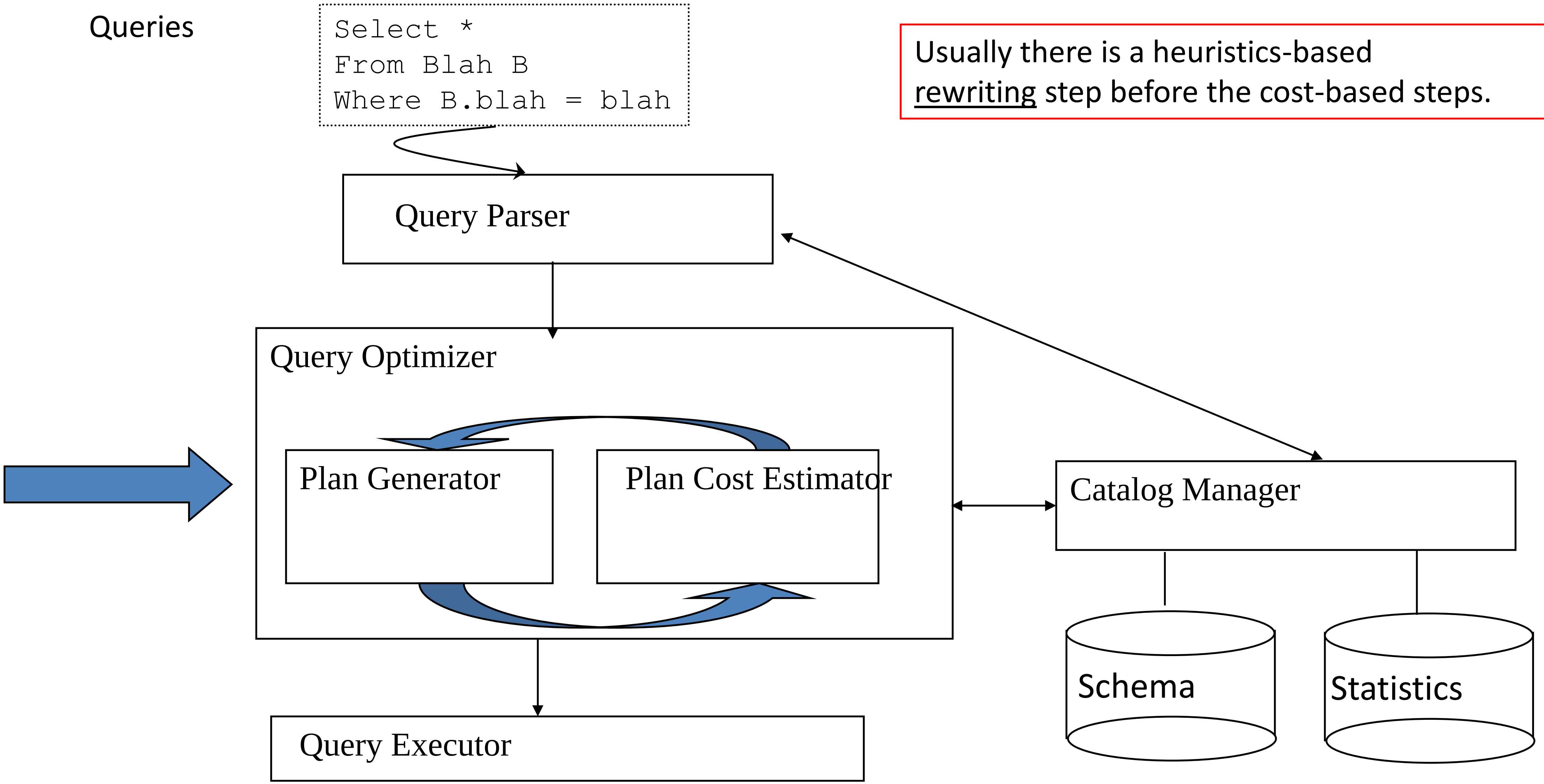


Relational operators have a uniform *iterator* interface:

open( ), get_next( ), close( )

Cost-based query optimizer

Usually there is a heuristics-based rewriting step before the cost-based steps.



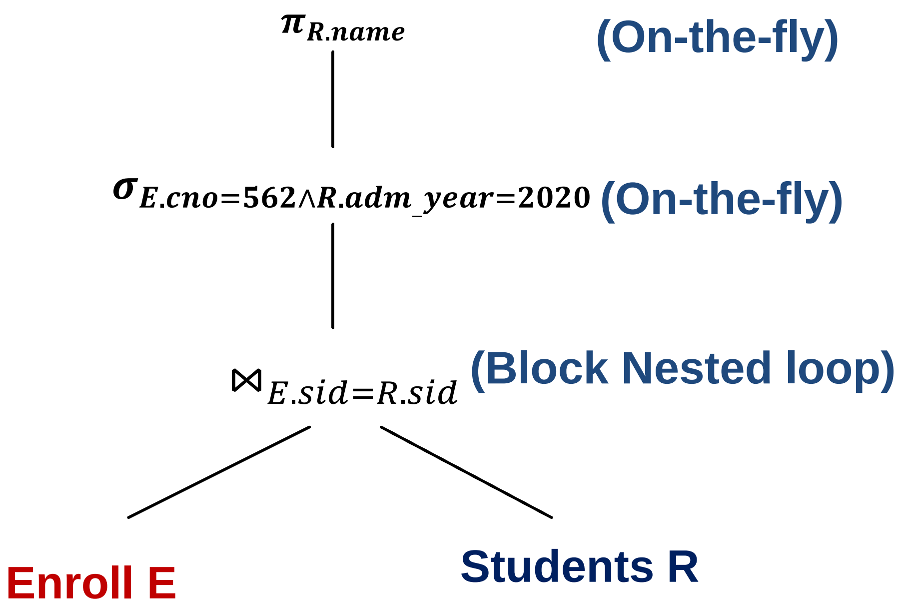
Running example

- Notations: for relation R
  - T_R: number of records, N_R: number of pages in its heap file, B_R: (average) number of tuples per page
  - h_I: height of a B-tree index I over the file
  - M: private workspace size in pages
- Running example
  - Student: R(sid: int, name: varchar(19), login: varchar(19), major: char(2), adm_year: int)
    - 50 bytes/tuple, $B_R = 80$, $T_R = 40{,}000$, $N_R = 500$
    - Assume the student records in the table span 10 years (between 2012 and 2022)
  - Enrollment: E(<u>sid: int, semester: char(4), cno: int</u>, grade: double)
    - 20 bytes/tuple, $B_E = 200$, $T_E = 200{,}000$, $N_E = 1000$
    - Assume 50% of the enrollment records belong to the graduate level (>=500) courses
- Consider a simplified cost model: *cost = #page_transfers* *(i.e., ignoring the random seeks)*
  - Often good enough for approximating the trend of the cost relative to data size
  - *Correct size estimation* is key to a correct comparison of costs
- Assume we have 5 pages in the buffer

Motivating example

```
SELECT  R.name
FROM  Enroll E, Students R
WHERE  E.sid=R.sid AND
   E.cno=562 AND R.adm_year = 2020
```

- By no means the worst plan!
- Misses several opportunities: selections could have been `pushed' earlier, no use is made of any available indexes, etc.
- *Goal of optimization:* To find more efficient plans that compute the same answer.



Cost = 1000 + 1000 * 500 = 501,000 I/Os

Relational algebra equivalence

- Rules that allow the optimizer to transform a logical plan into an equivalent plan with the *same* output over any database instance
- *Selections:*
  - Cascade: $\sigma_{\theta_1 \wedge \theta_2} E \equiv \sigma_{\theta_1} \sigma_{\theta_2} E$
  - Commutative: $\sigma_{\theta_1} \sigma_{\theta_2} E \equiv \sigma_{\theta_2} \sigma_{\theta_1} E$
- *Projections:*
  - Cascade: $\pi_{A_1} \pi_{A_2} \dots \pi_{A_n} E \equiv \pi_{A_1}(E)$ where $A_1 \subseteq A_2 \subseteq \cdots \subseteq A_n$
    - Only need to perform the final projection in a sequence of projections
- *(Inner) Joins or Cartesian product:*
  - Commutative: $E_1 \bowtie_\theta E_2 \equiv E_2 \bowtie_\theta E_1$ (allows switching the inner and outer)
  - Associative
    - Special case natural join: $(E_1 \bowtie E_2) \bowtie E_3 \equiv E_1 \bowtie (E_2 \bowtie E_3)$
    - General theta join: $\left(E_1 \bowtie_{\theta_1} E_2\right) \bowtie_{\theta_2 \wedge \theta_3} E_3 \equiv E_1 \bowtie_{\theta_1 \wedge \theta_3} \left(E_2 \bowtie_{\theta_2} E_3\right)$
  - Implication: inner joins can be done in any order!
    - Join reordering: an important optimization step in DBMS

Assuming θ_2 only involves fields in E_2 and E_3

Relational algebra equivalence

- Rules for more than one operator
  - *Selection can be combined with inner join/cartesian product*

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

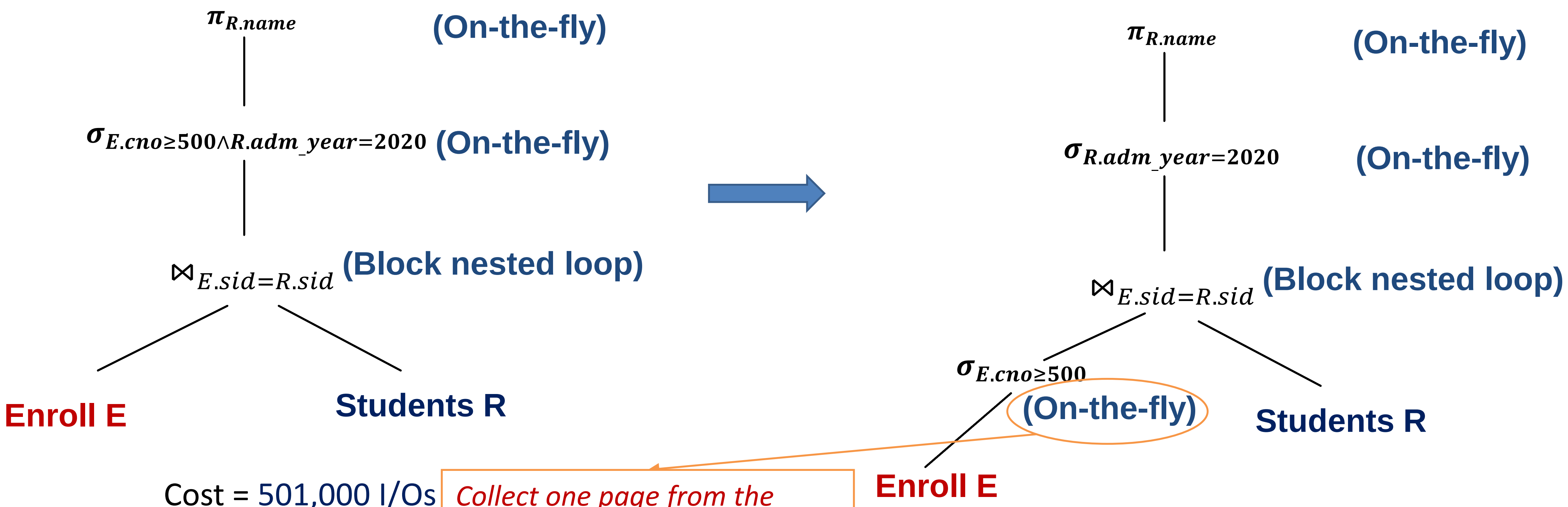
  - Projection push-down: select/join and projection commutes (provided that the predicate only involves the projected fields)
    $\pi_A \sigma_\theta E \equiv \sigma_\theta \pi_A E$ when $Var(\theta) \subseteq A$
    $\pi_{A_1 \cup A_2}(E_1 \bowtie_\theta E_2) \equiv \pi_{A_1} E_1 \bowtie_\theta \pi_{A_2} E_2$ when $Var(\theta) \subseteq A_1 \cup A_2$ and A_1, A_2 only involve fields from E_1, E_2, resp.

  - Selection push-down: join and select commutes (provided that the selection predicate only involves attributes from one side)
    $\sigma_{\theta_1}(E_1 \bowtie_\theta E_2) \equiv \left(\sigma_{\theta_1} E_1\right) \bowtie_\theta E_2$ when $Var(\theta_1) \subseteq A(E_1)$ (set of fields in E_1)
- More rules about other operators, e.g., aggregation, set operations, sort, …

- Note: rules involving outer joins may be different
  - Exercise: Can we always push selection through outer joins? What about projections?

Selection push-down (no index)

- Heuristics 1: perform selections as early as possible
  - Selection is often very cheap or "free" (in I/O only cost model)
  - reduces intermediate size



Cost = 501,000 I/Os

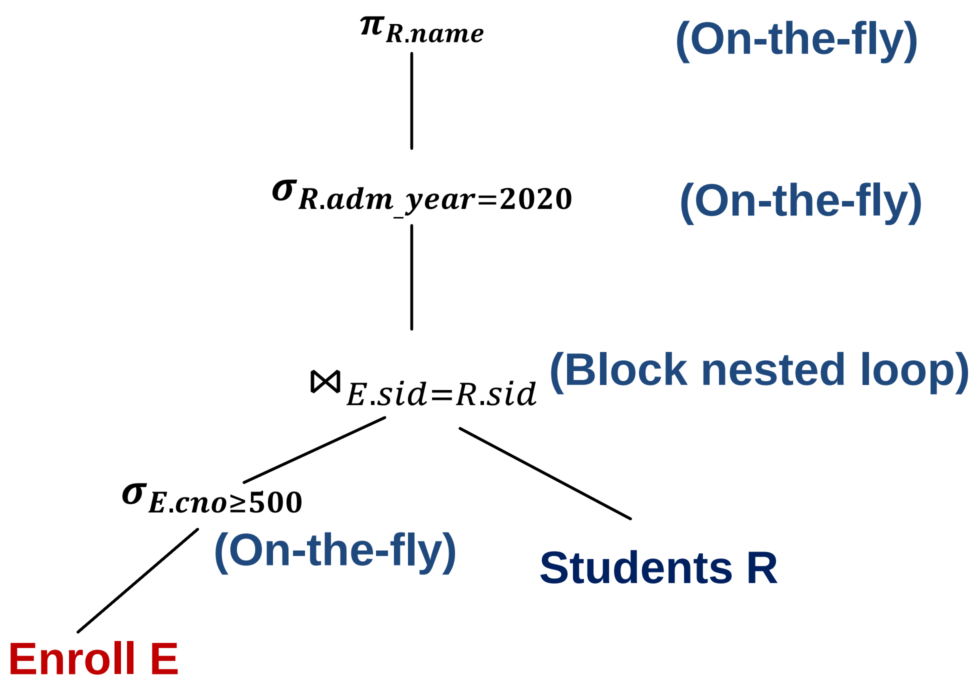
Collect one page from the outer plan, rather than the underlying scan.

Cost = $1000 + [1000 * 0.5] \times 500 = 251{,}000$ I/Os

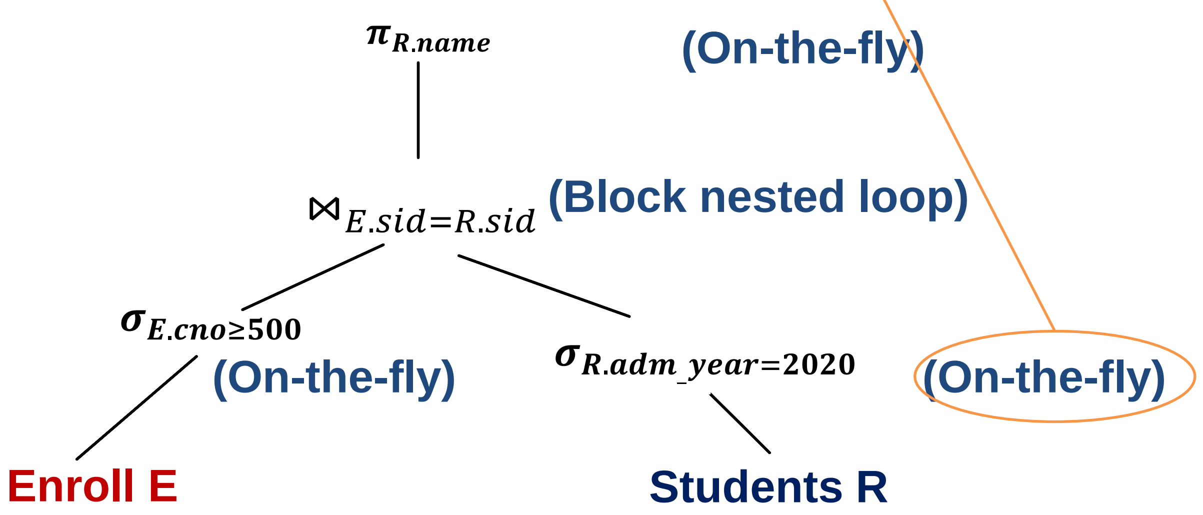
Selection push-down (no index)

- Can also push-down on the other side

No impact on I/O because BNL scans the inner plan once for every outer block.



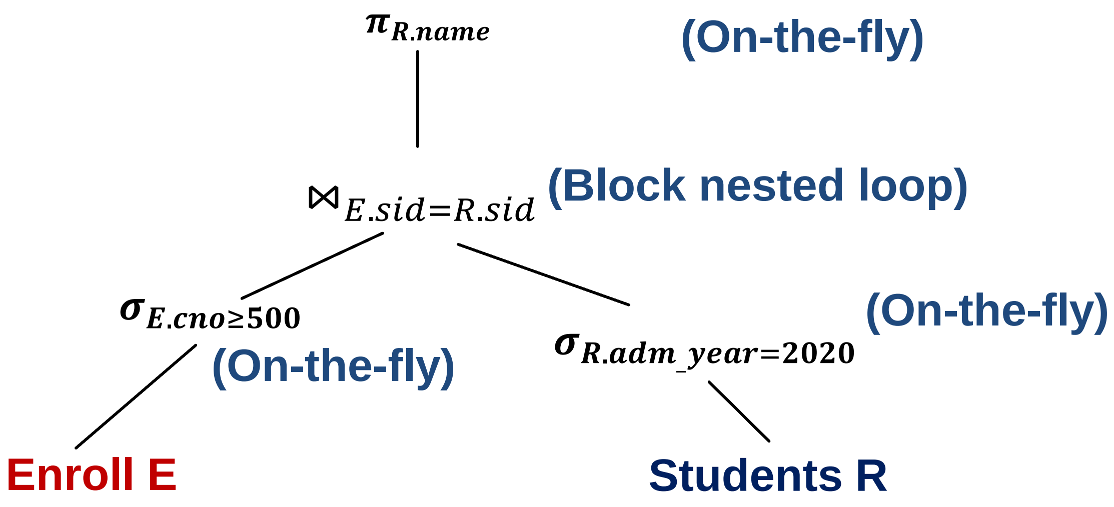
Cost = 251,000 I/Os



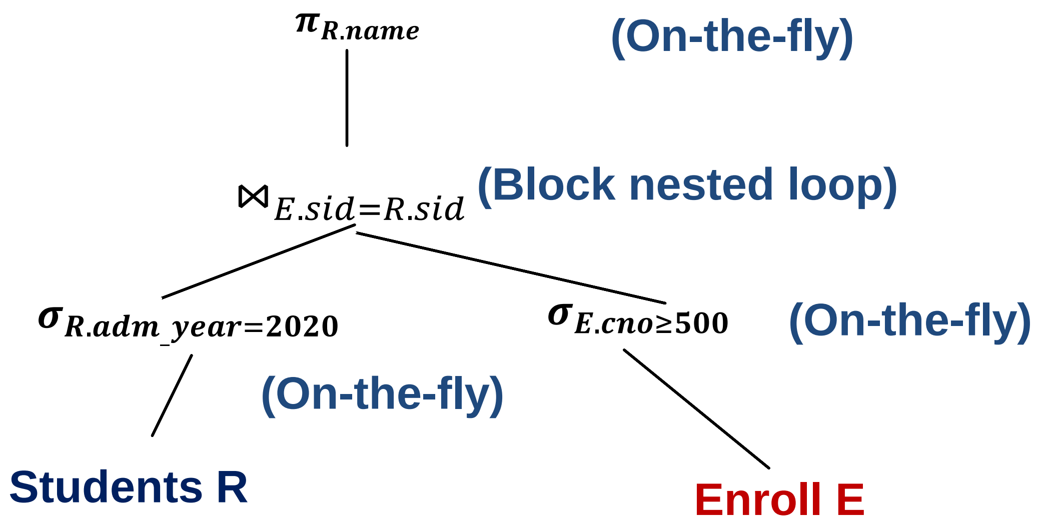
Cost = 251,000 I/Os

Join reordering

- Different join ordering may result in different cost
  - even if we use the same join algorithm
  - *Generally, the outer plan should have a smaller output in BNL*
    - what about hash join/sort merge join?



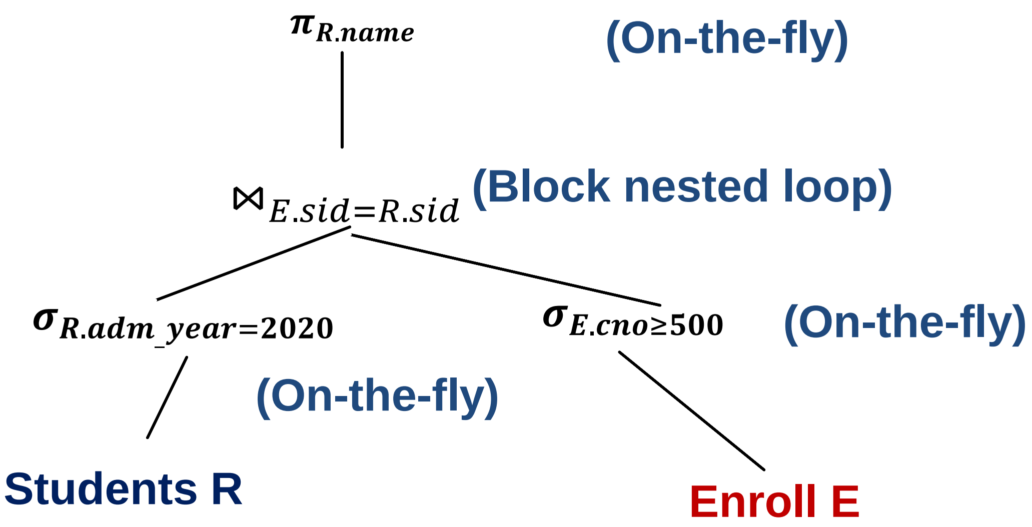
Cost = 251,000 I/Os

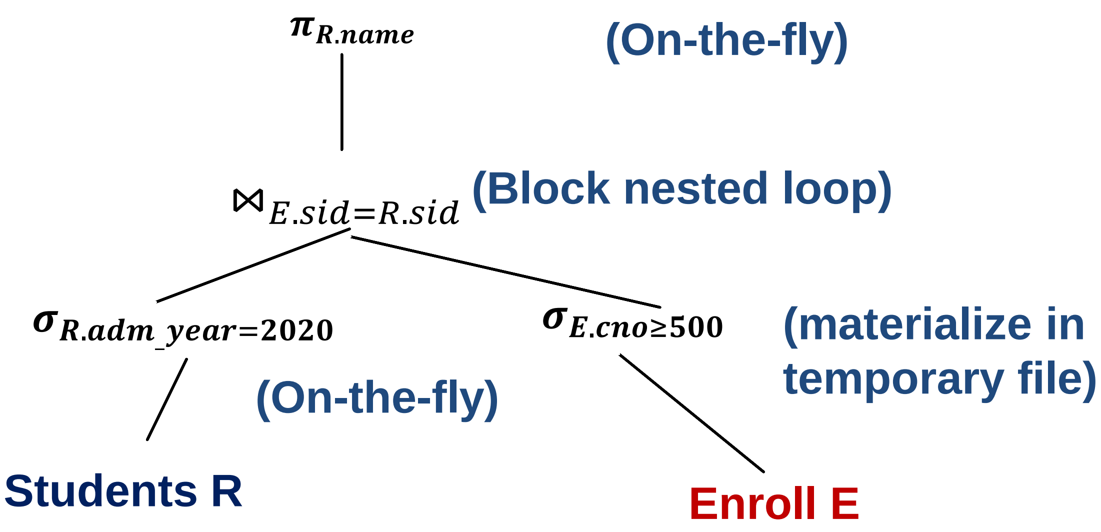


Cost = $500 + [500 \times 0.1] \times 1000 = 50{,}500$ I/Os

Materialization of inner plan

- We can also choose to materialize the inner plan for BNL to save repeated scan on the original relation



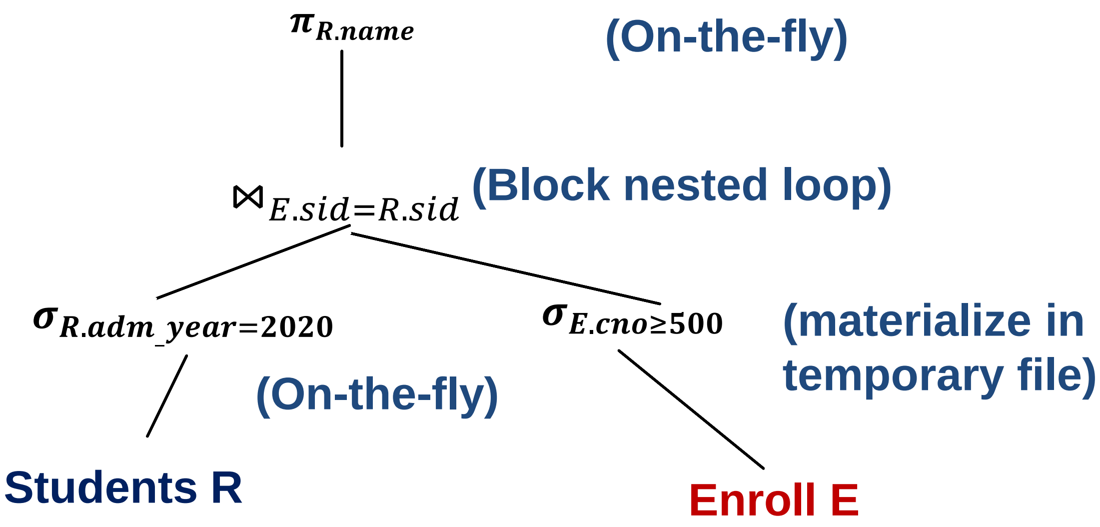


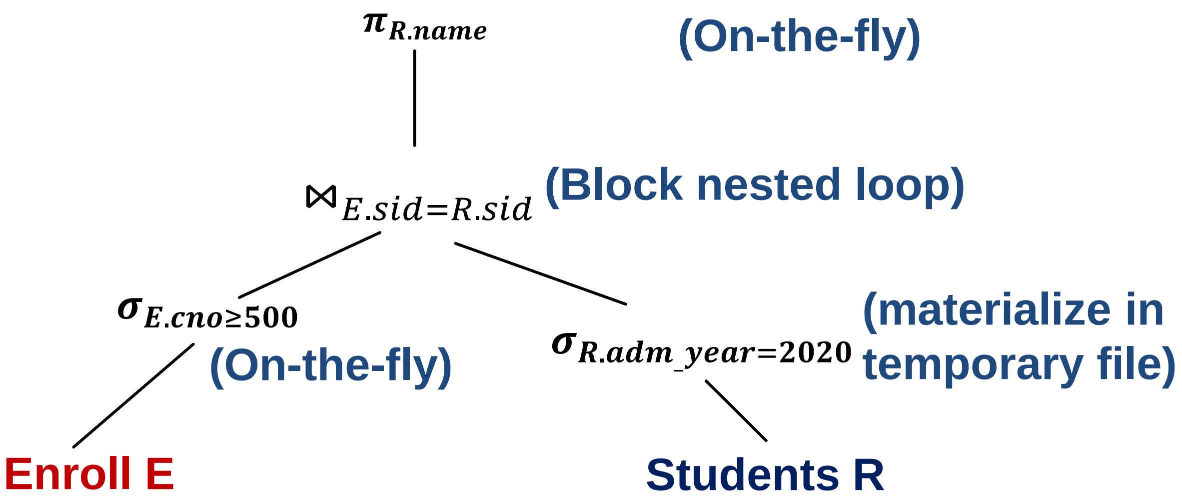
Cost = 50,500 I/Os

Cost = $\underbrace{1000 + [1000 * 0.5]}_{\text{materializing inner plan}} + \underbrace{500}_{\text{BNL outer scan}} + \underbrace{[500 * 0.1] * [1000 * 0.5]}_{\text{BNL inner scan}} = 27{,}000$ I/Os

Materialization of inner plan

- Sometimes with materialization, it might be cheaper to use the larger plan as the outer





Cost = $1000 + [1000 * 0.5] + 500 + [500 * 0.1] * [1000 * 0.5]$
$= 27{,}000$ I/Os

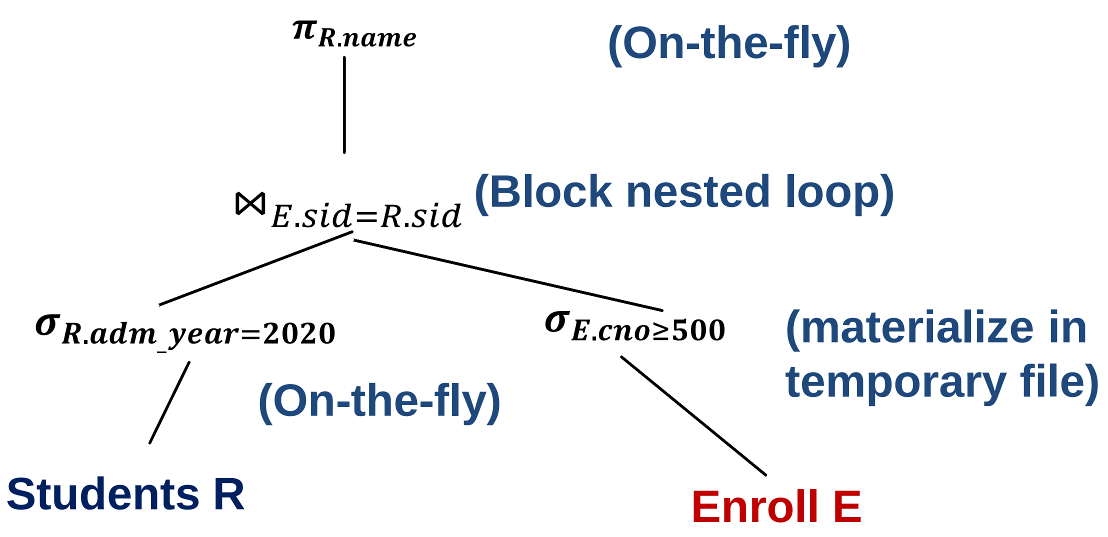
Cost = $500 + [500 * 0.1] + 1000 + [1000 * 0.5] * [500 * 0.1]$
$= 26{,}550$ I/Os

Projection push-down

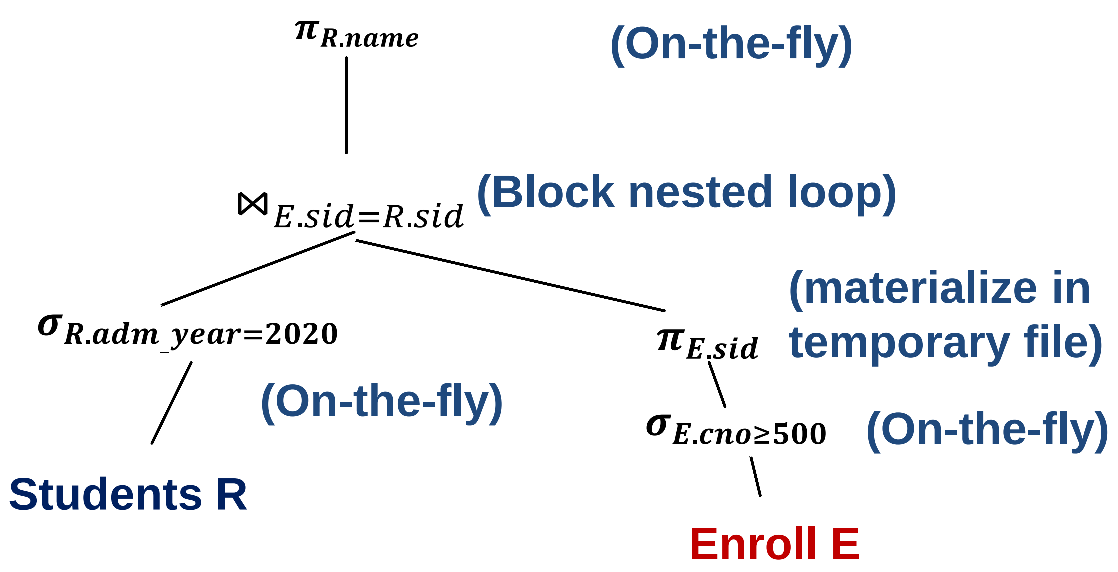
- Heuristics 2: apply projection as early as possible
  - helps if materializing plan output

Enrollment: E(<u>sid: int, semester: char(3), cno: int</u>, grade: double)

20 bytes/tuple => $\pi_{E.sid}$: $\frac{4}{20} = 20\%$ in size after projection



Cost = $1000 + [1000 * 0.5] + 500 + [500 * 0.1] * [1000 * 0.5]$
$= 27{,}000$ I/Os



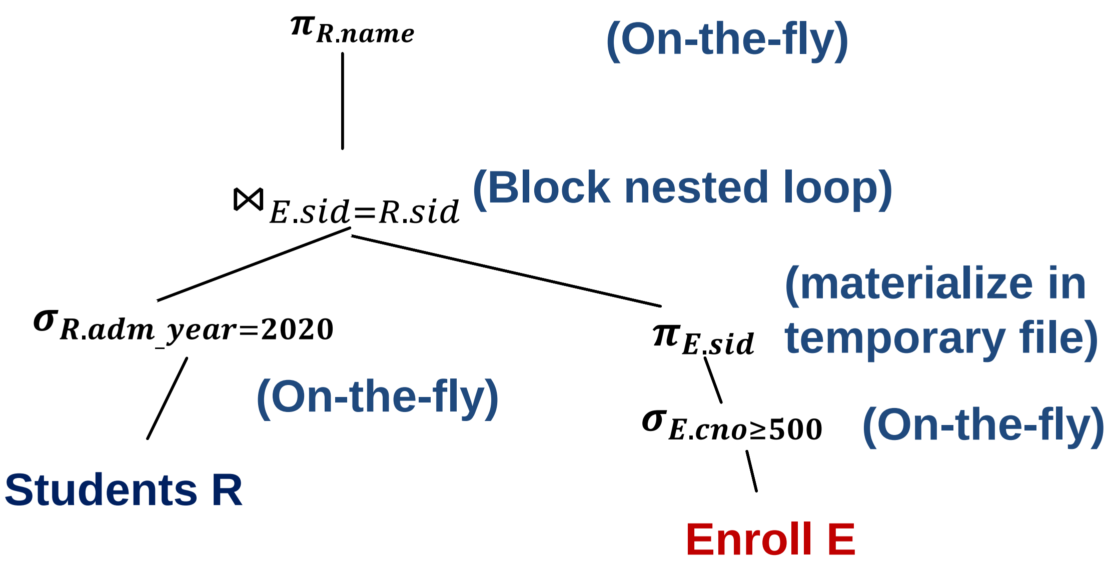
Cost = $1000 + [1000 * 0.5 * 0.2]$
$+ 500 + [500 * 0.1] * [1000 * 0.5 * 0.2]$
$= 6{,}600$ I/Os

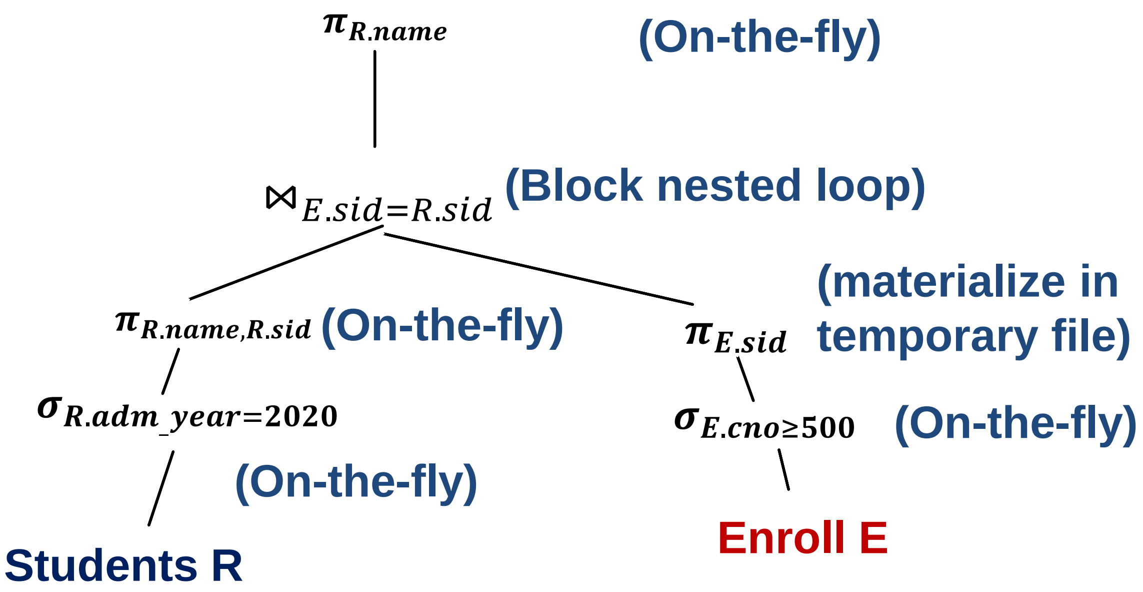
Projection push-down

- More projection push-down on the other side

R(sid: int, name: varchar(19), login: varchar(19), major: char(2), adm_year: int)

50 bytes/tuple => $\pi_{R.name,R.sid}$: $\frac{4+19+1}{50} = 48\%$ -- assuming VARCHAR uses '\0' at the end



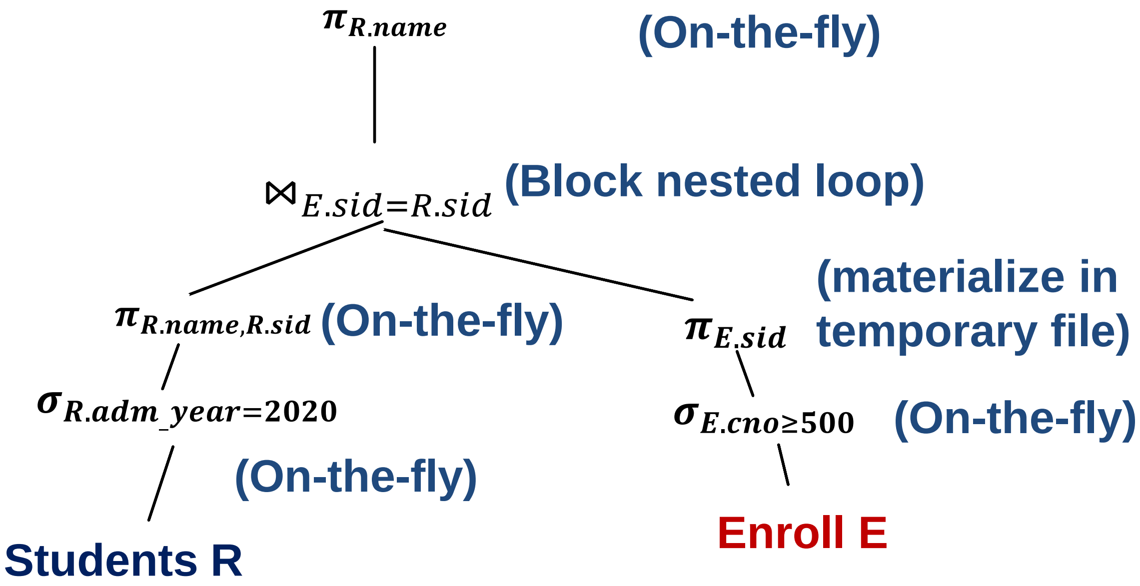


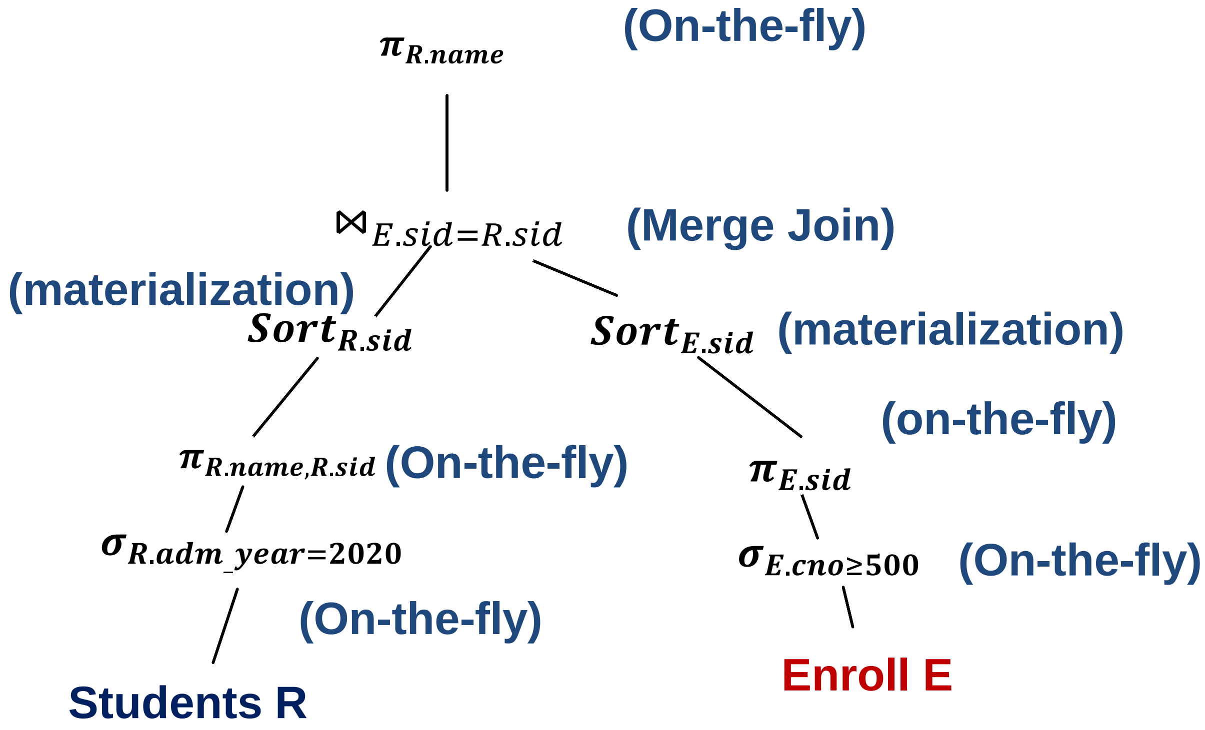
Cost = $1000 + [1000 * 0.5 * 0.2]$
$+500 + [500 * 0.1] * [1000 * 0.5 * 0.2]$
$= 6{,}600$ I/Os

Cost = $1000 + [1000 * 0.5 * 0.2]$
$+500 + [500 * 0.1 * 0.48] * [1000 * 0.5 * 0.2]$
$= 4{,}000$ I/Os

Choice of join algorithms

- If we switch to sort-merge join with 5 buffers





Cost = $1000 + [1000 * 0.5 * 0.2]$

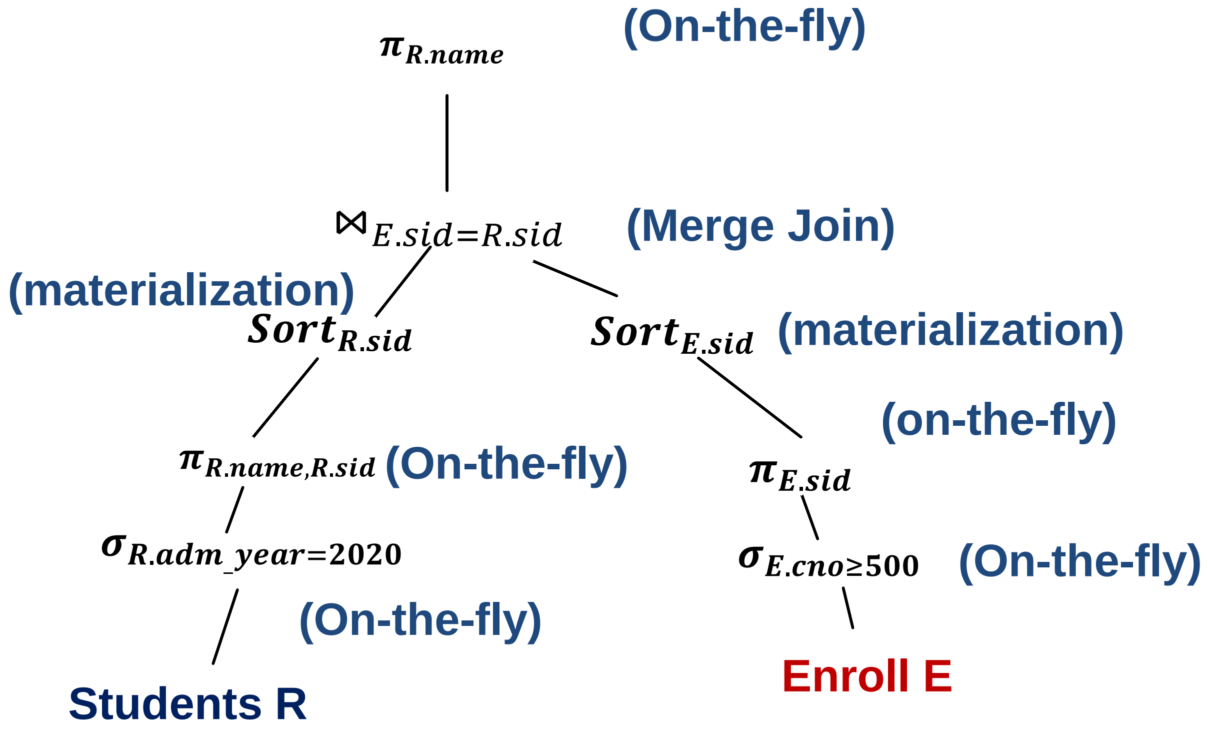
$+500 + [500 * 0.1 * 0.48] * [1000 * 0.5 * 0.2]$

$= 4{,}000$ I/Os

Cost = ?

Choice of join algorithms

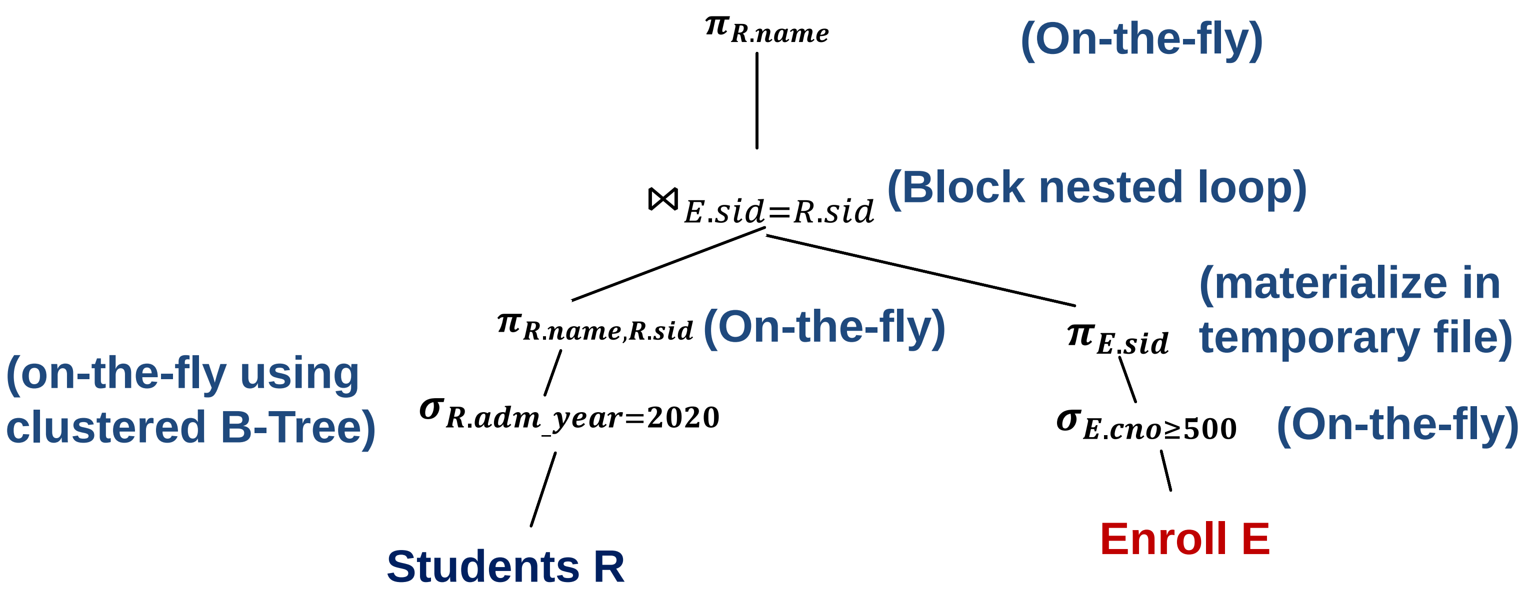
- Sort outer:
  - Size after pass 0: $\lceil 500 * 0.1 * 0.48 \rceil = 24$
    - 4 pages/run, 6 runs
      (need one input buffer for table scan)
  - # merge passes = $\lceil \log_4 6 \rceil = 2$
  - Total I/O: $500 + 24 + 2 \times 2 \times 24 = 620$
- Sort inner: # I/O = 1700
- Merge
  - assuming d = 5 and always fit in one page
  - 24 + 100 = 124
- Total cost = 620 + 1700 + 124 = 2,444 I/Os
  - vs BNL: 4,000 I/Os



Cost = ?

Using indexes

- If we have a clustered B-Tree index over $R(adm\_yaer)$, h = 3

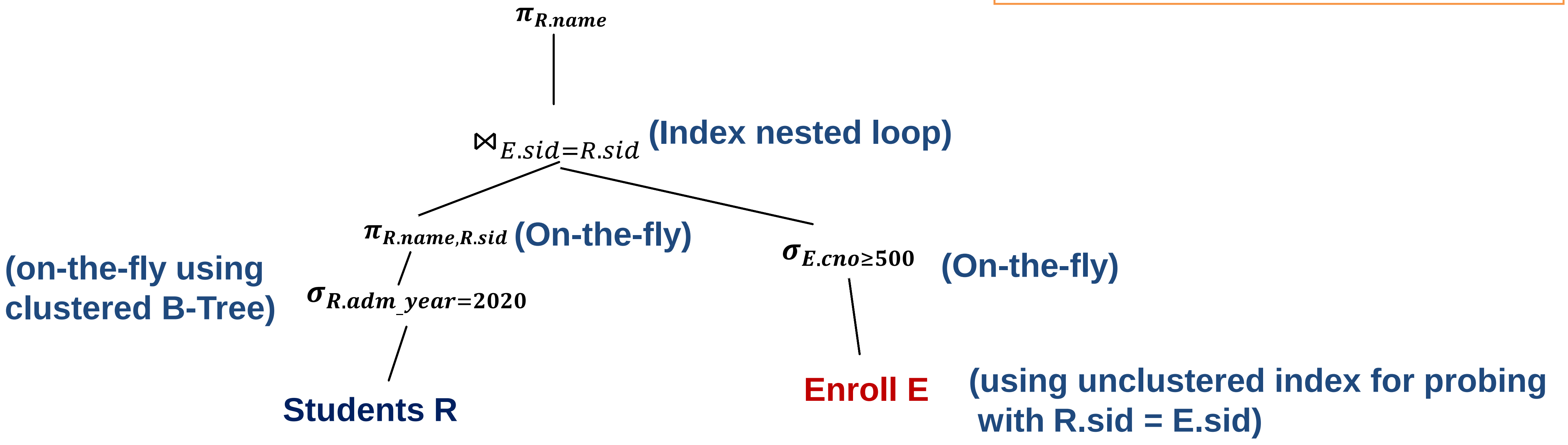


Cost = $1000 + [1000 * 0.5 * 0.2]$
$+3 + [500 * 0.1 * 0.48]$
$+[500 * 0.1 * 0.48] * [1000 * 0.5 \; * 0.2]$
$=$ 3,527 I/Os

Using indexes

- If we have an unclustered B-Tree index over $E(sid)$, h = 3
  - *Generally, index nested loop is a bad choice unless both of the following is true*
    - *outer plan output size is small*
    - *join is very selective*

assuming each student has 5 enrollment record on average



Cost = $3 + [500 * 0.1 * 0.48] + [40000 * 0.1] * (3 + 5)$
$= 32{,}027$ I/Os (vs 3,527 I/Os with BNL!)

What's needed for query optimization?

- A closed set of operators
    - Relational ops (table in, table out)
    - Encapsulation based on iterators
- Plan space, based on
    - Based on relational equivalences
- Cost Estimation, based on
    - Cost formulas
    - Size estimation, based on
        - Catalog information on base tables
        - Selectivity (Reduction Factor) estimation
- A search algorithm
    - To sift through the plan space based on cost!

Summary

- Today's lecture
  - Query optimization overview
  - Relational algebra equivalence
  - Query optimization is needed to ensure not-too-bad performance if not the best
    - Need to understand the impact of cost model/physical data layout/indexing for a given query
- Next lecture(s)
  - Plan size and cost estimation
  - How to search in the optimization space
    - System R style query optimizer