CS 4604: Introduction to Database Management Systems

Query Optimization

Virginia Tech CS 4604 Sprint 2021

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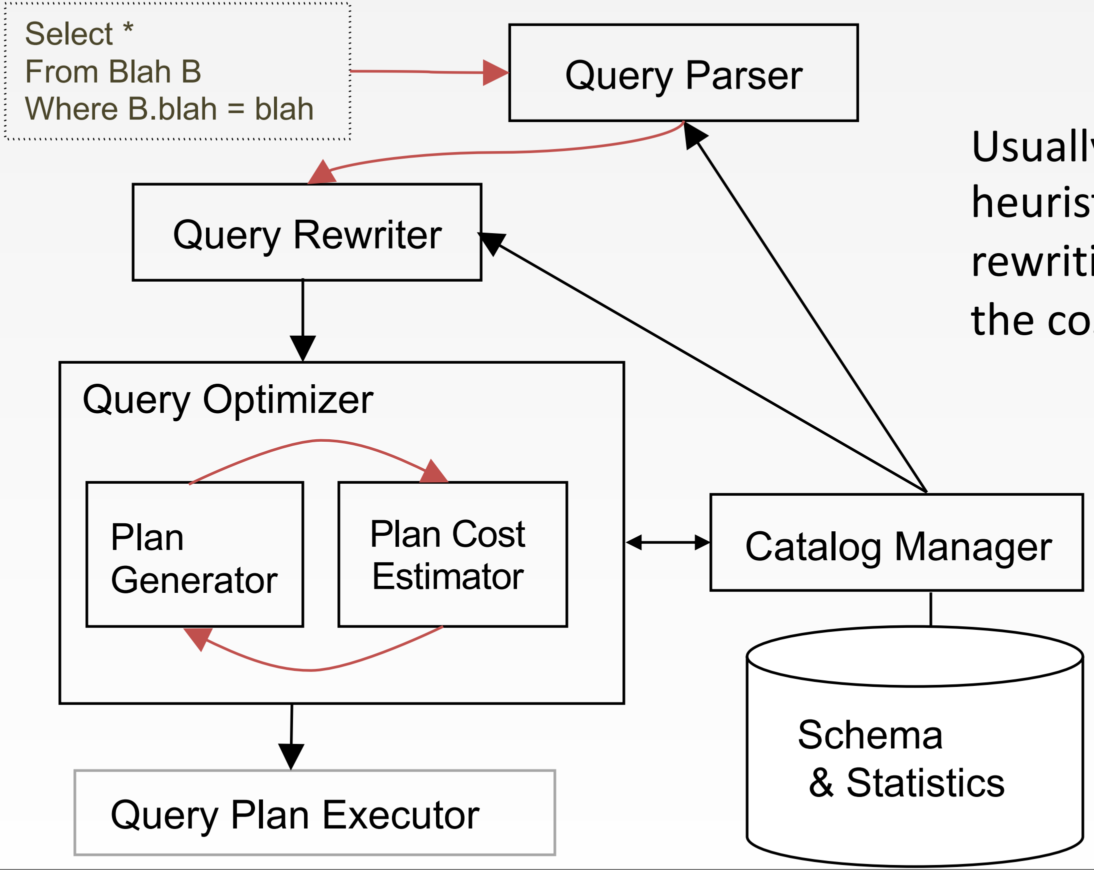
Today’s Topics

- Query Optimization

Query Parsing & Optimization

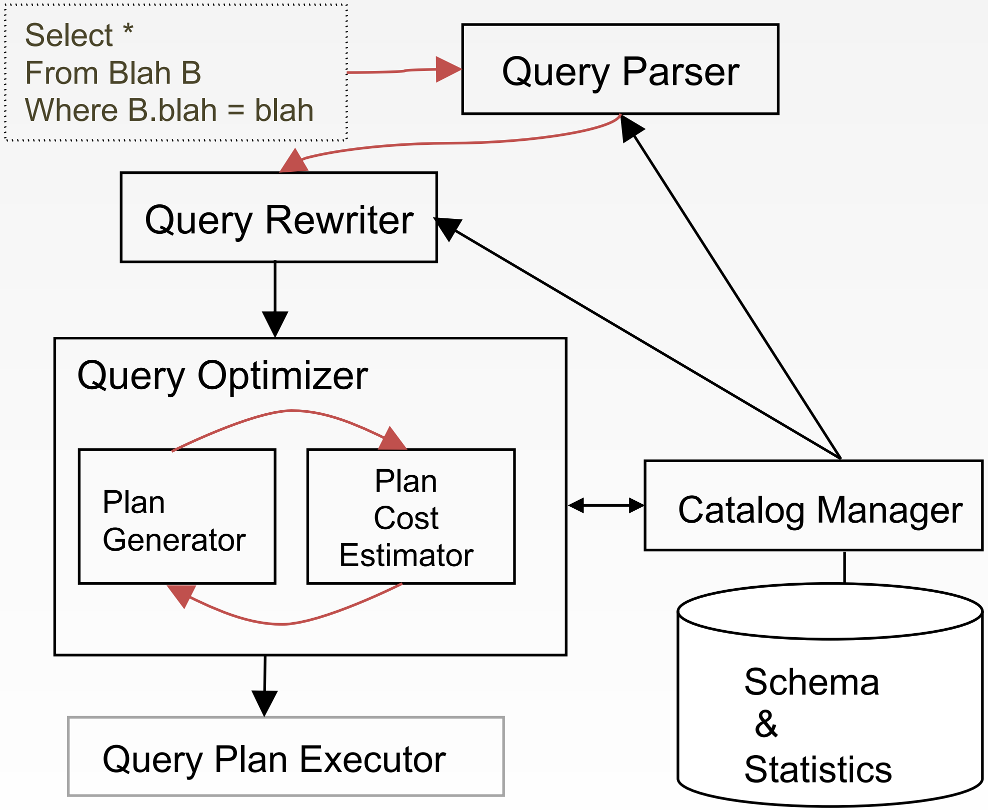


Usually there is a heuristics-based rewriting step before the cost-based steps.

Query Parsing & Optimization

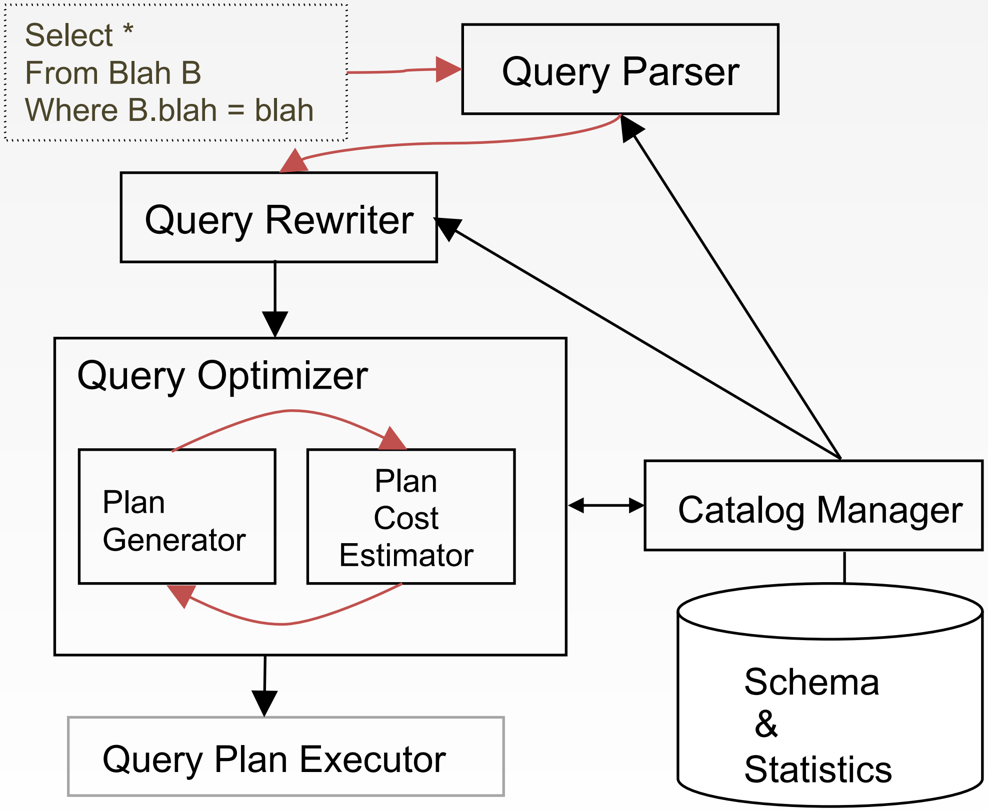
- Query parser
  - Check correctness, authorization
  - Generates a parse tree
  - Straightforward

- Query rewriter
  - Converts queries to canonical form
    - flatten views
    - subqueries into fewer query blocks
  - Weak spot in many open-source DBMSs



Query Parsing & Optimization

- "Cost-based" Query Optimizer
  - Optimizes 1 query block at a time
    - Select, Project, Join
    - GroupBy/Agg
    - Order By (if top-most block)
  - Uses catalog stats to find least-"cost" plan per query block
  - "Soft underbelly" of every DBMS
    - Sometimes not truly "optimal"

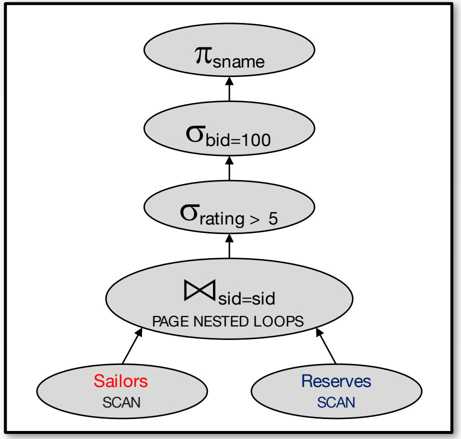


Query Optimization Overview

- Query block can be converted to relational algebra
- Relational algebra converts to tree
- Each operator has implementation choices
- Operators can also be applied in different orders!

```
SELECT S.sname
  FROM Reserves R, Sailors S
 WHERE R.sid=S.sid
   AND R.bid=100
   AND S.rating>5
```

$$\pi_{(sname)}\sigma_{(bid=100 \wedge rating > 5)}(Reserves \bowtie Sailors)$$



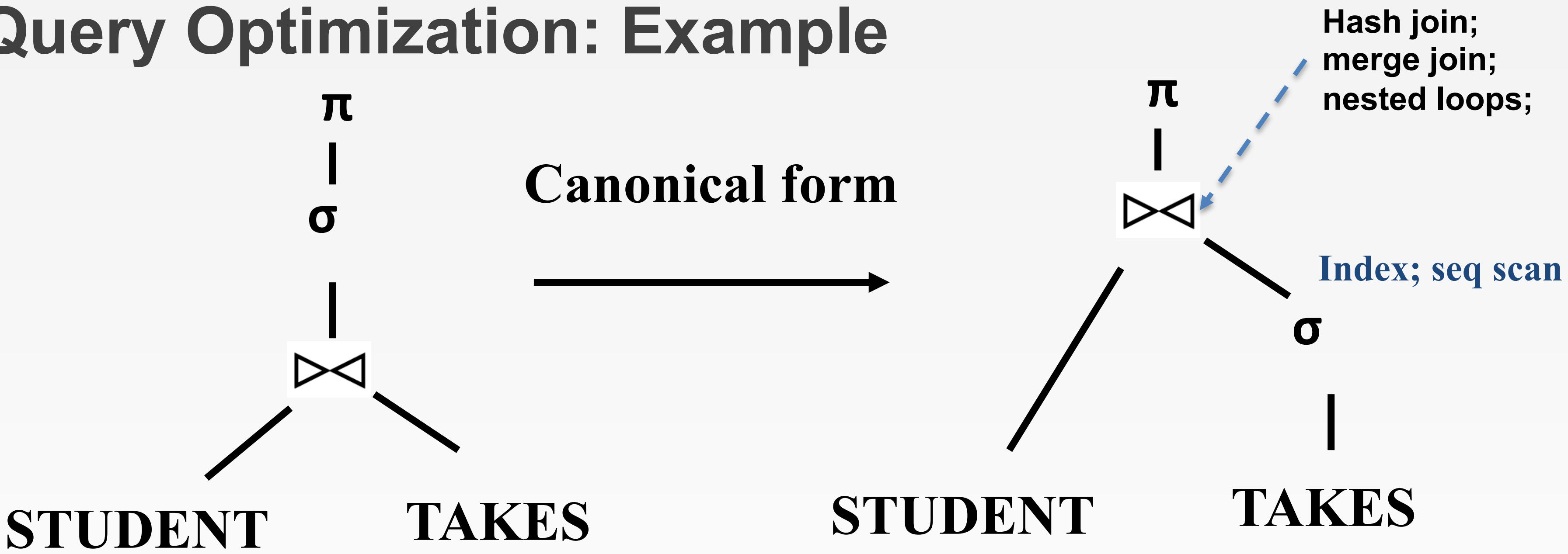
Query Optimization: The Components

- Three beautifully orthogonal concerns:
  - Plan space:
    - for a given query, what plans are considered?
  - Cost estimation:
    - how is the cost of a plan estimated?
  - Search strategy:
    - how do we “search” in the “plan space”?

Query Optimization: The Goal

- Optimization goal:
  - Ideally: Find the plan with least actual cost.
  - Reality: Find the plan with least estimated cost.
    - And try to avoid really bad actual plans!

Query Optimization: Example



Canonical Form has the following properties:

1. Push Selections as much as possible.
2. Push Projections as much as possible
3. It is a left-deep join tree (we will see this later)

Relational Algebra Equivalences

- Selections:
  - $\sigma_{c1 \wedge \ldots \wedge cn}(R) \equiv \sigma_{c1}(\ldots(\sigma_{cn}(R))\ldots)$ (cascading)
  - $\sigma_{c1}(\sigma_{c2}(R)) \equiv \sigma_{c2}(\sigma_{c1}(R))$ (commutative)
- Projections:
  - $\pi_{a1}(R) \equiv \pi_{a1}(\ldots(\pi_{a1, \ldots, an-1}(R))\ldots)$ (cascading)

Relational Algebra Equivalences

- Cartesian Product
  - $R \times (S \times T) \equiv (R \times S) \times T$ (associative)
  - $R \times S \equiv S \times R$ (commutative)
- Join
  - $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$ (associative)
  - $R \bowtie S \equiv S \bowtie R$ (commutative)

Are Joins Associative and Commutative?

- After all, just Cartesian Products with Selections
- You can think of them as associative and commutative…
- …But beware of join turning into cross-product!
  - Consider R(a,z), S(a,b), T(b,y)

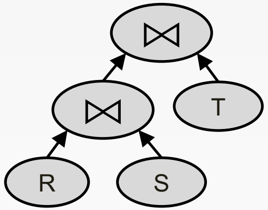
```
SELECT *
  FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b;
```

  - $(S \bowtie_{b=b} T) \bowtie_{a=a} R \not\equiv S \bowtie_{b=b} (T \bowtie_{a=a} R)$ (*not* legal!!)
  - $(S \bowtie_{b=b} T) \bowtie_{a=a} R \not\equiv S \bowtie_{b=b} (T \times R)$ (*not* the same!!)
  - $(S \bowtie_{b=b} T) \bowtie_{a=a} R \equiv S \bowtie_{b=b \wedge a=a} (T \times R)$ (the same!!)

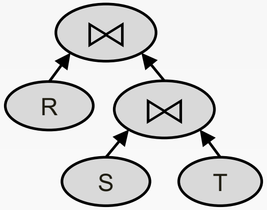
Join Ordering

- Similarly, note that some join orders have cross products, some don't
- Equivalent for the query above:

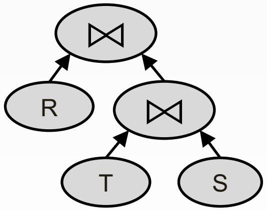
```
SELECT *
  FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b;
```



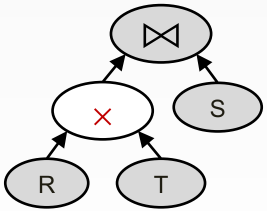
$(R \bowtie_{a=a} S) \bowtie_{b=b} T$



$R \bowtie_{a=a} (S \bowtie_{b=b} T)$



$R \bowtie_{a=a} (T \bowtie_{b=b} S)$



$(R \times T) \bowtie_{a=a \wedge b=b} S$

(Some) Transformation Rules (1)

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. $\sigma_{\theta}(E_1 \text{ X } E_2) = E_1 \bowtie_{\theta} E_2$
   b. $\sigma_{\theta 1}(E_1 \bowtie_{\theta 2} E_2) = E_1 \bowtie_{\theta 1 \wedge \theta 2} E_2$

(Some) Transformation Rules (2)

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.

(Some) Transformation Rules (3)

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.

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

Some Common Heuristics: Selections

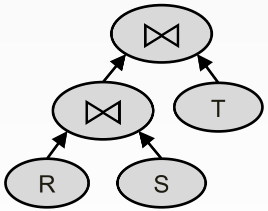
- Selection cascade and pushdown
  - Apply selections as soon as you have the relevant columns
  - Ex:
    - $\pi_{sname} (\sigma_{(bid=100 \wedge rating > 5)} (Reserves \bowtie_{sid=sid} Sailors))$
    - $\pi_{sname} (\sigma_{bid=100} (Reserves) \bowtie_{sid=sid} \sigma_{rating > 5} (Sailors))$

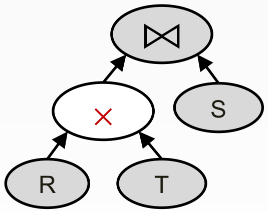
Some Common Heuristics: Projections

- Projection cascade and pushdown
  - Keep only the columns you need to evaluate downstream operators
  - Ex:
    - $\pi_{sname}\sigma_{(bid=100 \wedge rating > 5)}$ (Reserves $\bowtie_{sid=sid}$ Sailors)
    - π_{sname} (π_{sid}($\sigma_{bid=100}$ (Reserves)) $\bowtie_{sid=sid}$ $\pi_{sname,sid}$ ($\sigma_{rating > 5}$ (Sailors)))

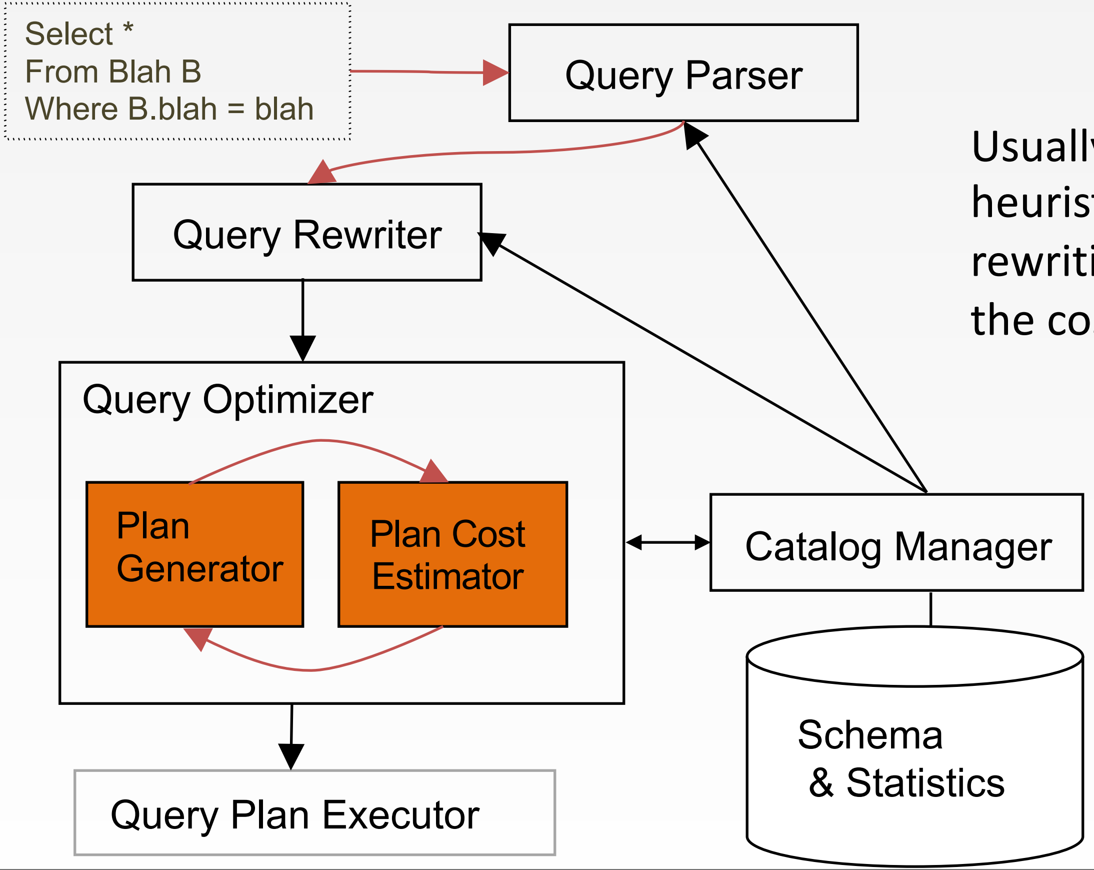
Some Common Heuristics

- Avoid Cartesian products
  - Given a choice, do theta-joins rather than cross-products
  - Consider R(a,b), S(b,c), T(c,d)
  - Favor (R ⋈ S) ⋈ T over (R × T) ⋈ S





Query Parsing & Optimization



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

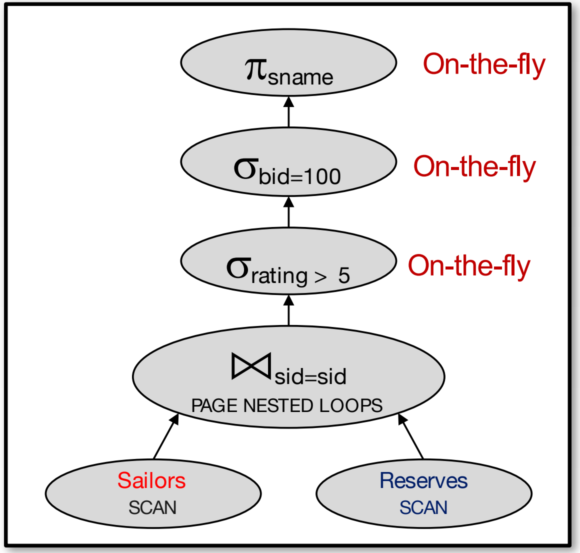
Schema for Examples

```
Sailors  (sid: integer, sname: text, rating: integer, age: real)
Reserves (sid: integer, bid: integer, day: date, rname: text)
```

- Reserves:
  - Each tuple is 40 bytes long, 100 tuples per page, 1000 pages.
  - Assume there are 100 boats
- Sailors:
  - Each tuple is 50 bytes long, 80 tuples per page, 500 pages.
  - Assume there are 10 different ratings
- Assume we have 5 pages to use for joins.

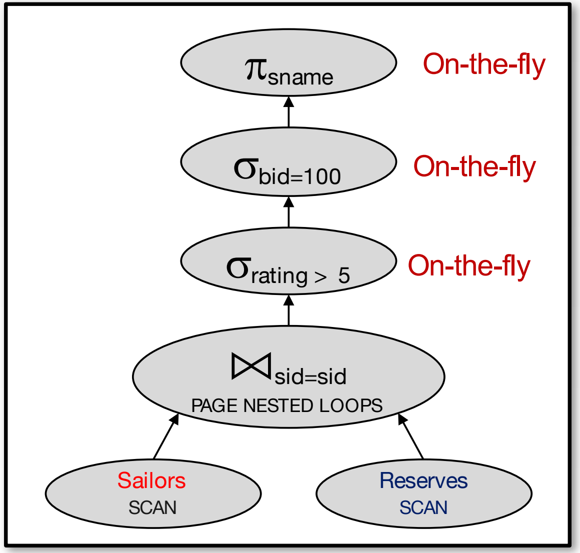
Motivating Example: Plan 1

- Here's a reasonable query plan:



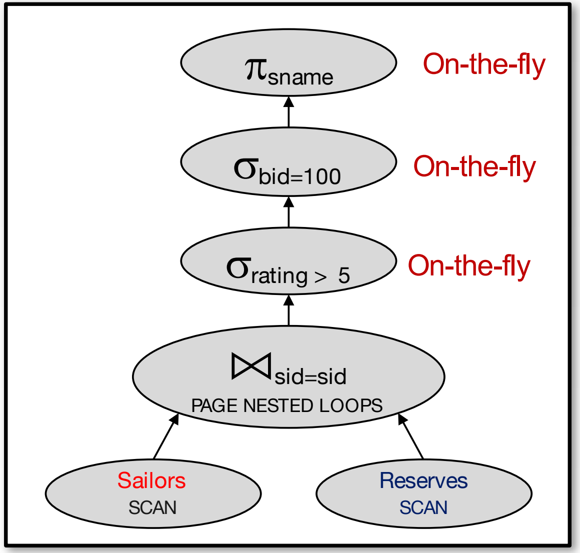

```
SELECT S.sname
  FROM Reserves R, Sailors S
 WHERE R.sid=S.sid
   AND R.bid=100
   AND S.rating>5
```

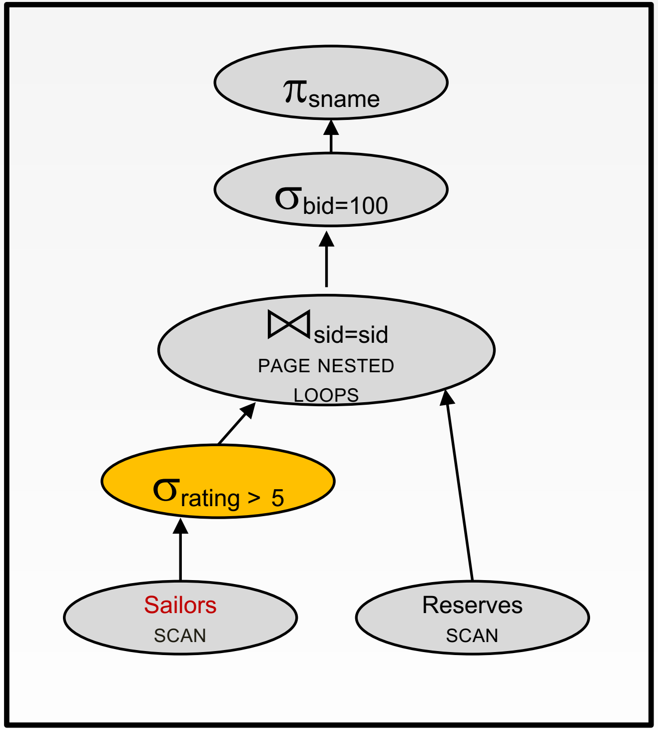
Motivating Example: Plan 1 Cost



- Let's estimate the cost:
- Scan Sailors (500 IOs)
- For each page of Sailors,
  Scan Reserves (1000 IOs)
- Total: 500 + 500*1000
  - 500,500 IOs
- Bad plan!
- Goal of optimization:
  - Find less cost (faster) plan that compute the same answer

Plan 2: Selection Pushdown



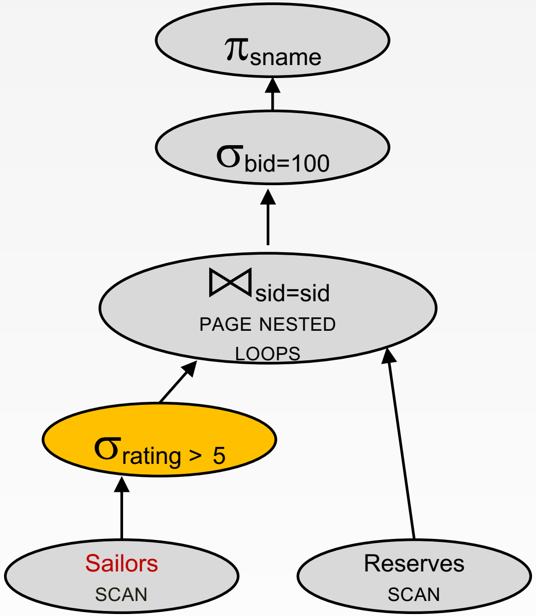


500,500 IOs

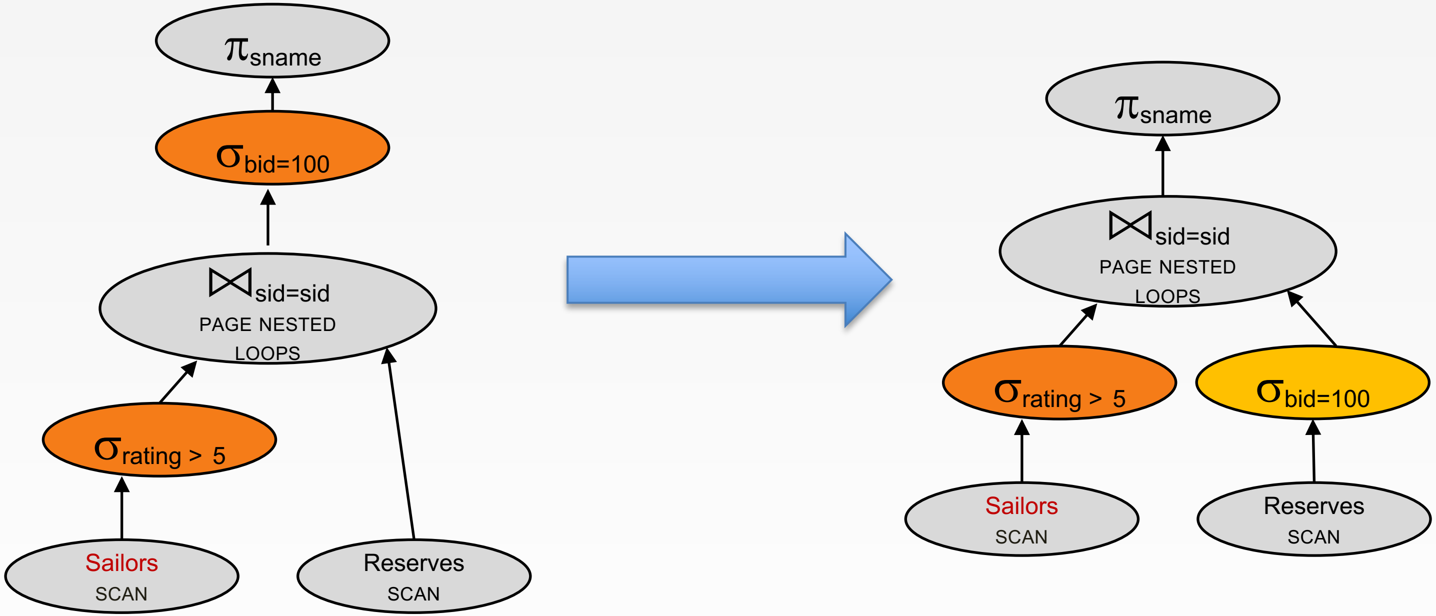
Plan 2 Cost Analysis

- Let's estimate the cost:
- Scan Sailors (500 IOs)
- For each pageful of high-rated Sailors,
  Scan Reserves (1000 IOs)

- Total: 500 + 250*1000 = 250,500 IOs



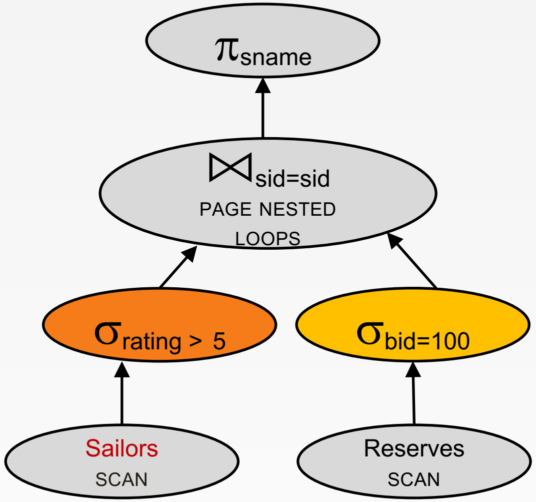
Plan 3: More Selection Pushdown



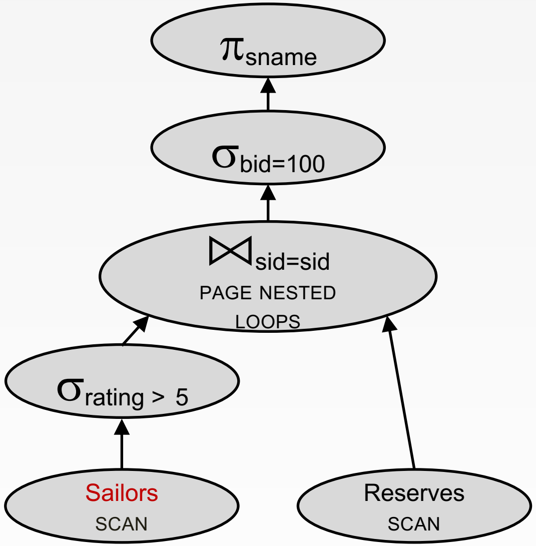
250,500 IOs

Plan 3 Cost Analysis

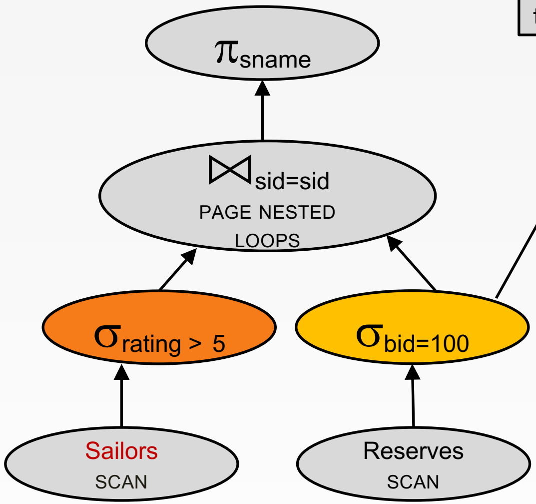
- Let's estimate the cost:
- Scan Sailors (500 IOs)
- For each pageful of high-rated Sailors,
  Scan Reserves (1000 IOs)
- Total: 500 + 250*1000 = 250,500 IOs



More Selection Pushdown Analysis



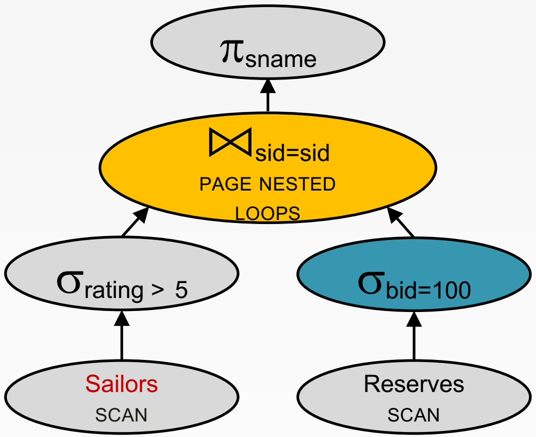
250,500 IOs

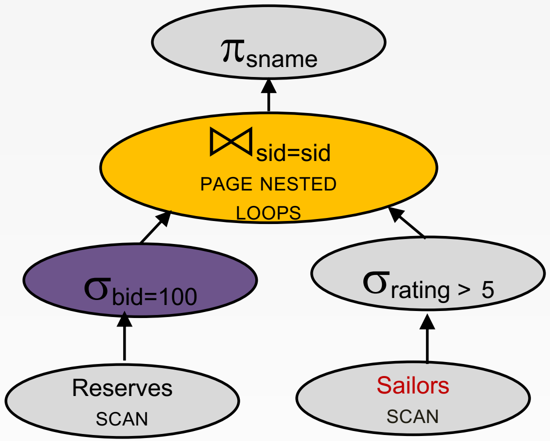


Pushing a selection into the inner loop of a nested loop join doesn't save I/Os! Essentially equivalent to having the selection above.

250,500 IOs

Plan 4: Join Ordering

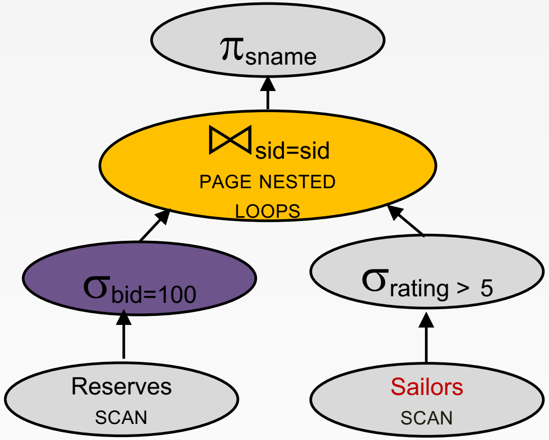




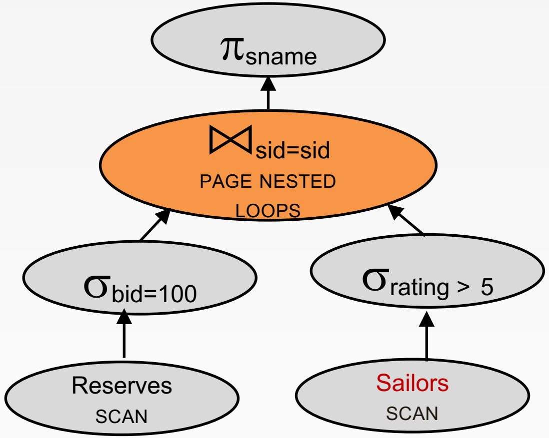
250,500 IOs

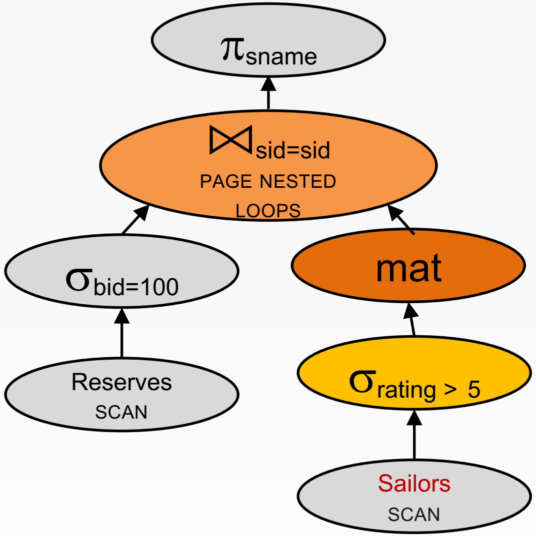
Plan 4 Cost Analysis

- Let's estimate the cost:
- Scan Reserves (1000 IOs)
- For each pageful of Reserves for bid 100,
  Scan Sailors (500 IOs)
- Total: 1000 +10*500 = 6000 IOs



Plan 5: Materializing Inner Loops

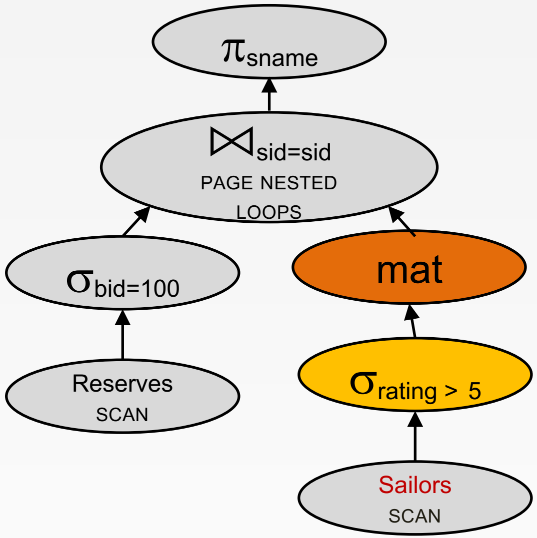




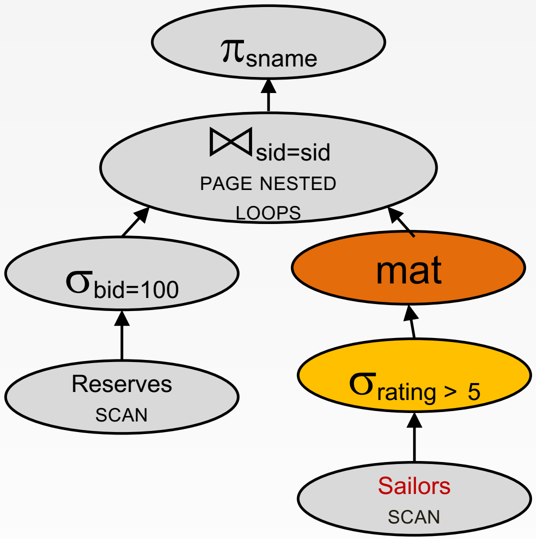
6000 IOs

Plan 5 Cost Analysis

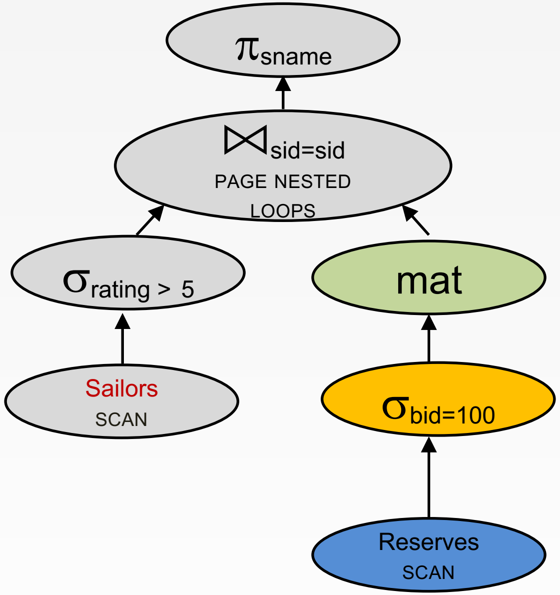
- Let's estimate the cost:
- Scan Reserves (1000 IOs)
- Scan Sailors (500 IOs)
- Materialize Temp table T1 (250 IOs)
- For each pageful of Reserves for bid 100,
  Scan T1 (250 IOs)
- Total: 1000 + 500+ 250 + (10 * 250) = 4250 IOs



Plan 6: Join Ordering Again

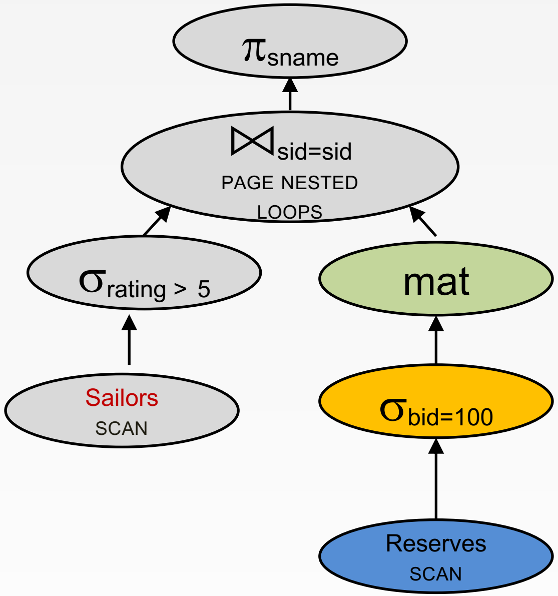


4250 IOs

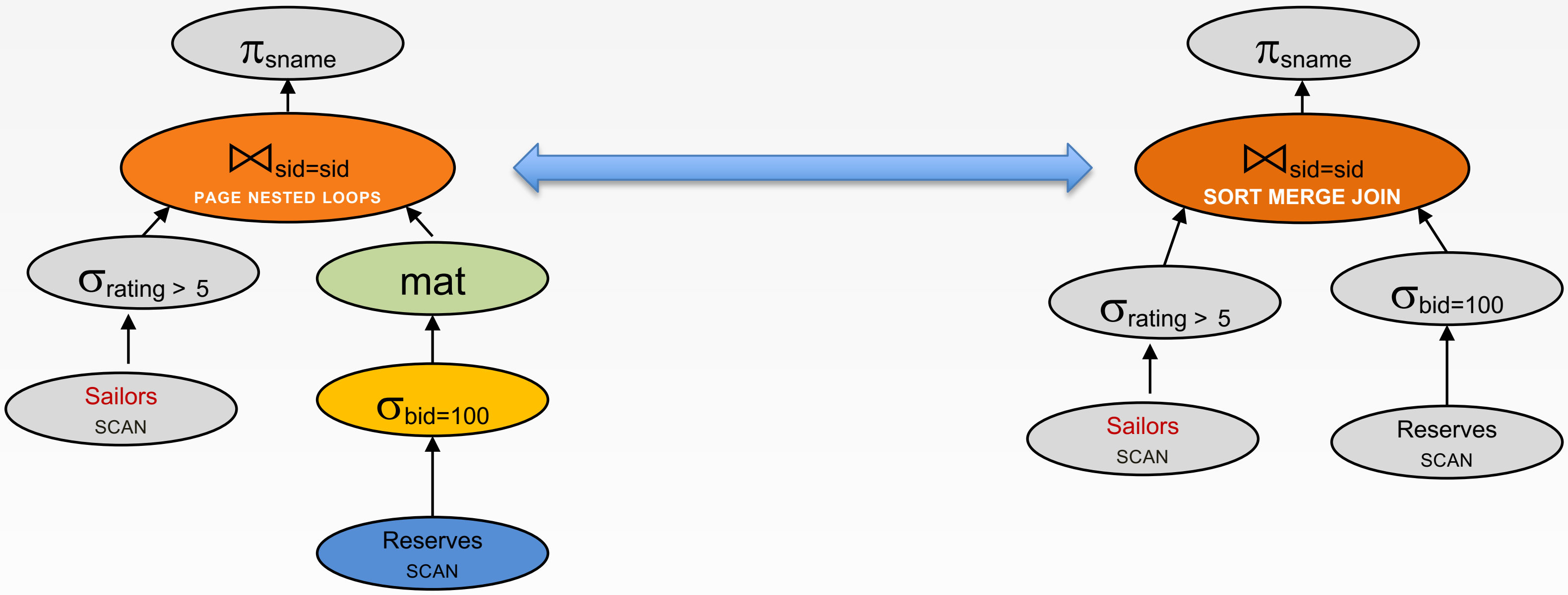


Plan 6 Cost Analysis

- Let's estimate the cost:
- Scan Sailors (500 IOs)
- Scan Reserves (1000 IOs)
- Materialize Temp table T1 (10 IOs)
- For each pageful of high-rated Sailors,
  Scan T1 (10 IOs)
- Total: 500 + 1000 +10 +(250 *10) = 4010 IOs



Plan 7: Join Algorithm



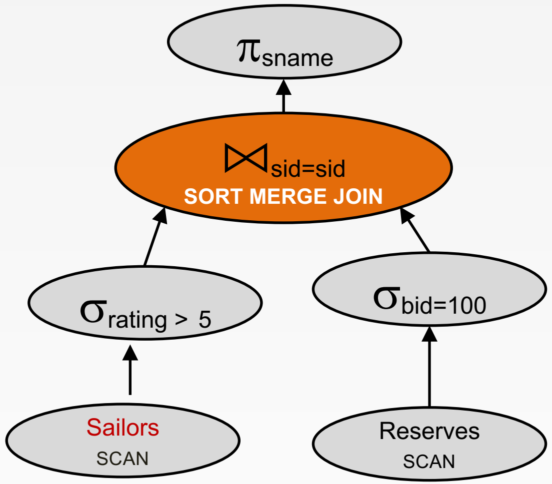
4010 IOs

Plan 7 Cost Analysis

- With 5 buffers, cost of plan:
- Scan Reserves (1000)
- Scan Sailors (500)
- Sort high-rated sailors

  Note: pass 0 doesn't do read I/O, just gets input from select.
- Sort reservations for boat 100

  Note: pass 0 doesn't do read I/O, just gets input from select.
- Merge (10+250) = 260
- Total: sum above



Plan 7 Cost Analysis

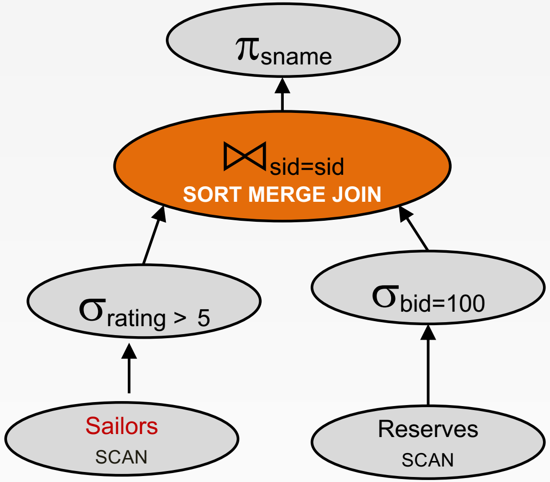
- With 5 buffers, cost of plan:
- Scan Reserves (1000)
- Scan Sailors (500)

- Sort reservations for boat 100
  - 2 passes for reserves
    pass 0 = 10 to write, pass 1 = 2*10 to read/write

- Sort high-rated sailors
  - 4 passes for sailors
    pass 0 = 250 to write, pass 1,2,3 = 2*250 to read/write

- Merge (10+250) = 260

1000 + 500 + sort reserves(10 + 2*10* 1) + sort sailors (250 + 2*250*3) + merge (10+250) = 3540 IOs



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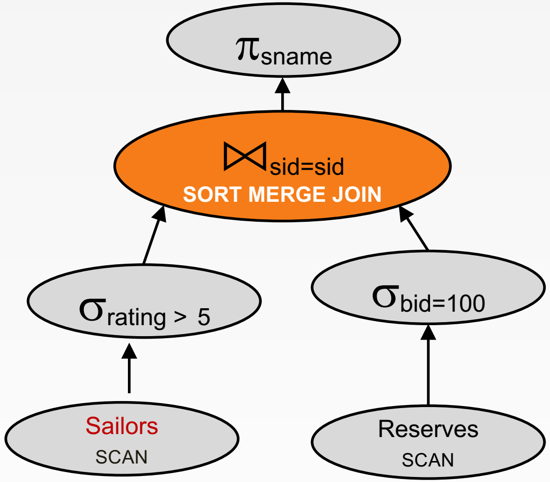
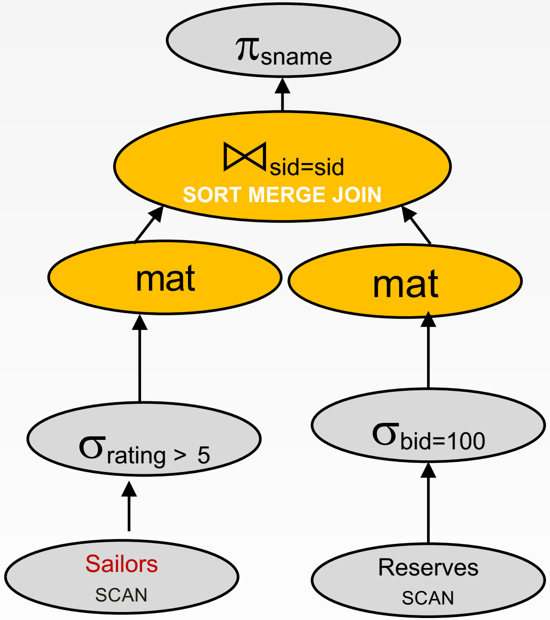
Join Algorithm and Materializing Inner Loops

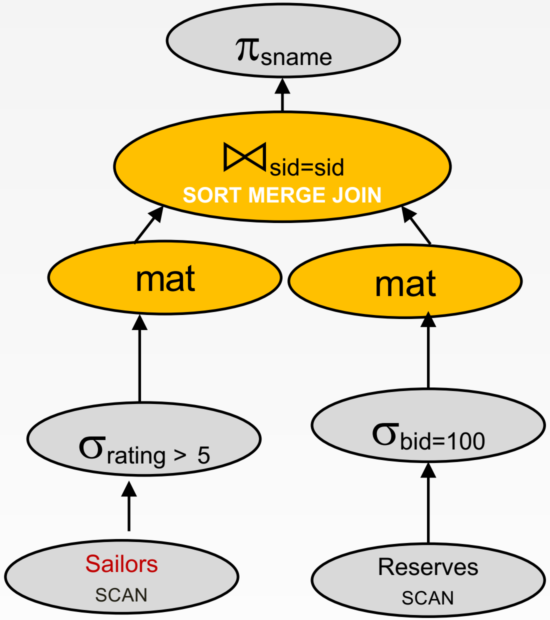


3540 IOs

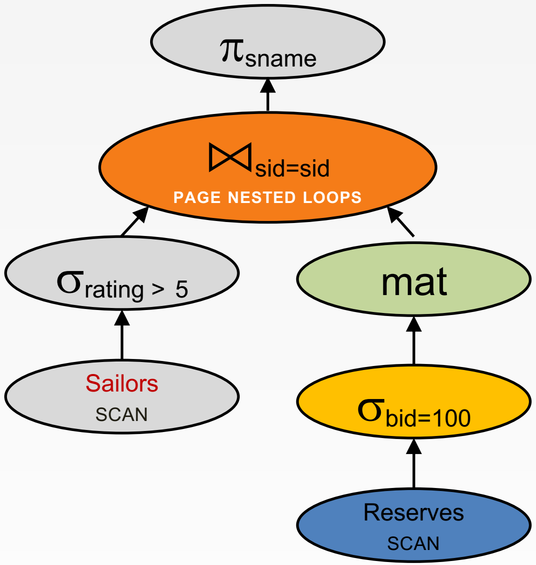


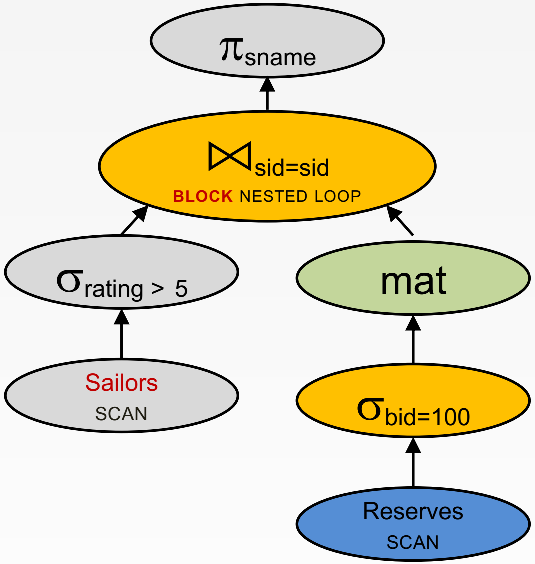
Plan 8 Cost Analysis

- With 5 buffers, cost of plan:
- Scan Sailors (500), write T1 (250)
- Scan Reserves (1000), write T2 (10)
- Sort T1
- Sort T2
- How many passes for each sort?
  - 2 passes for reserves (2*10*2 to read/write)
  - 4 passes for sailors (2*250*4 to read/write)
- Merge (10+250) = 260
- Total:
  1000 + 500 + 10 + 250 + 2*10*2 +
  2*250*4 + merge (10+250) = 4060 IOs



Another Join Algorithm





4010 IOs

Plan 9 Cost Analysis

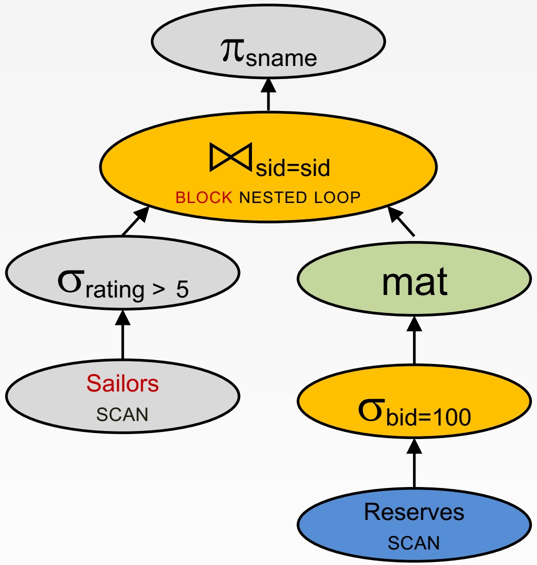
- With 5 buffers, cost of plan:

- Scan Sailors (500)
- Scan Reserves (1000)

- Write Temp T1 (10)
- For each blockful of high-rated sailors
- Loop on T1 (⌈ $[S_h]/(B-2)$ ⌉ * [T])

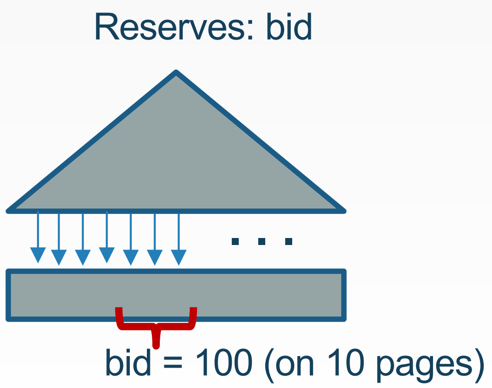
- Total:

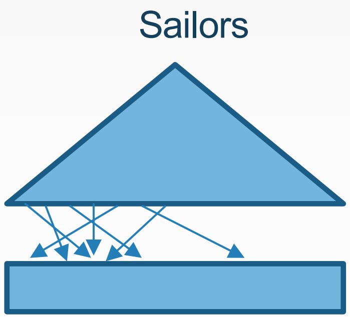
500 + 1000 +10 +(ceil(250/3) *10) = 500 + 1000 +10 +(84 *10) = 2350 IOs

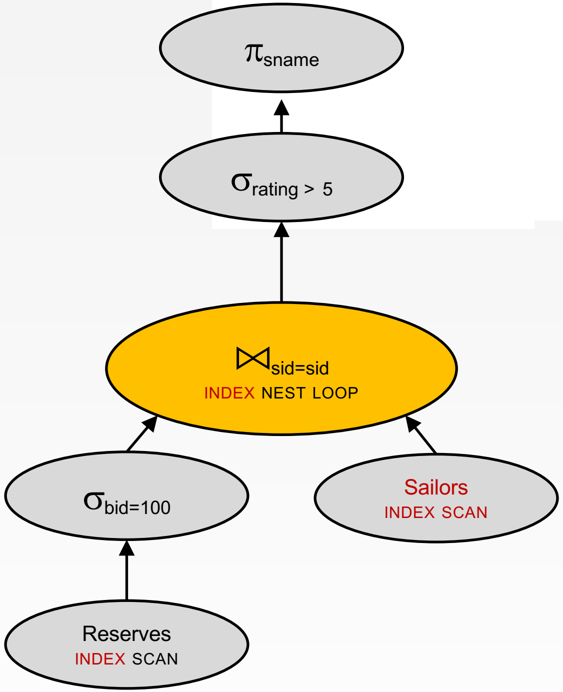


How About Indexes?

- Indexes:
  - Reserves.bid clustered
  - Sailors.sid unclustered
- Assume indexes fit in memory

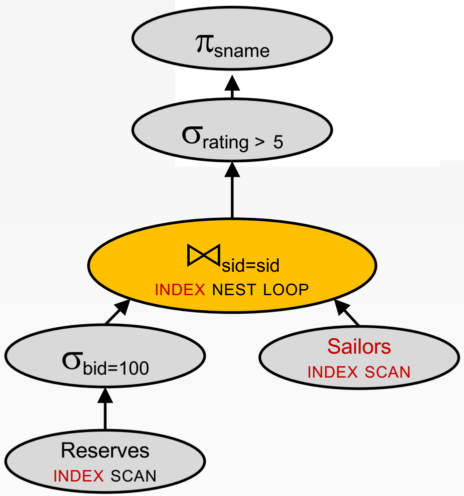






Index Cost Analysis

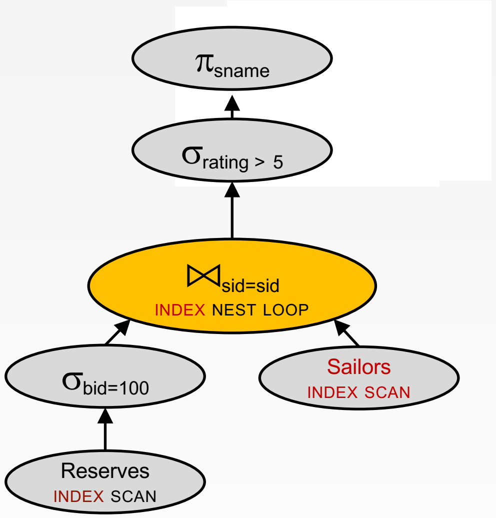
- **No projection pushdown to left** for π_{sname}
  - Projecting out unnecessary fields from **outer of Index NL doesn't make an I/O difference.**
- **No selection pushdown to right** for $\sigma_{rating > 5}$
  - Does not affect Sailors.sid index lookup
- With clustered index on bid of Reserves, we access how many pages of Reserves?:
  - 100,000/100 = 1000 tuples on 1000/100 = 10 pages.
- Join column sid is a **key** for Sailors.
  - At most one matching tuple, unclustered index on sid OK



1010 IOs

Index Cost Analysis Part 2

- With clustered index on bid of Reserves, we access how many pages of Reserves?:
  - 100,000/100 (boats) = 1000 tuples on 1000/100 = 10 pages.
- for each Reserves tuple 1000
  get matching Sailors tuple (1 IO)
  (recall: 100 Reserves per page, 1000 pages)
- 10 + 1000*1 = 1010 IOs
- Cost: Selection of Reserves tuples (10 I/Os); then, for each, must get matching Sailors tuple (1000); total 1010 I/Os.



1010 IOs

Summing up

- There are *lots* of plans
  - Even for a relatively simple query

- Not so clear that's true!
  - Manual query planning can be tedious, technical
  - Machines are better at enumerating options than people
    - Hence AI
  - We will see soon how optimizers make simplifying assumptions

Query Optimization

- Given: A closed set of operators
  - Relational ops (table in, table out)
  - Physical implementations (of those ops and a few more)

- **Plan space**
  - Based on relational equivalences, different implementations
- **Cost Estimation** based on
  - Cost formulas
  - Size estimation, in turn based on
    - Catalog information on base tables
    - Selectivity (Reduction Factor) estimation
- **A search algorithm**
  - To sift through the plan space and find lowest cost option!

A Naïve Query Optimizer

- Given an input query Q:
  1. Enumerate all possible plans for Q
     - Too many plans to consider!
  2. Estimate the cost of each plan
     - Hard to estimate cost accurately given caches etc.
  3. Pick plan with the lowest cost
     - How? Keep all plans in memory?
     - What if there are million alternative ways of executing the Q?

The System R Optimizer

- Plan Space
  - Many plans have the same high cost subtree that can be pruned
  - Heuristics(aka tricks that usually work):
    - Consider only left-deep plans
    - Avoid Cartesian products
    - Don’t optimize the entire query at once
- Cost estimation
  - Inexact is fine as long as we can compare plans
    - Better estimators have been developed
- Search Algorithm
  - Dynamic Programming

Query Optimization

1. **Plan Space**
2. Cost Estimation
3. Search Algorithm

Query Blocks: Units of Optimization

- Break query into query blocks
- Optimize one block at a time
- Uncorrelated nested blocks computed once
- Correlated nested blocks are like function calls
  - But sometimes can be "decorrelated"
  - Recall relational algebra lecture

```
SELECT S.sname
  FROM Sailors S
 WHERE S.age IN
```

Outer block

```
  (SELECT MAX (S2.age)
     FROM  Sailors S2
GROUP BY  S2.rating)
```

Nested block

Query Blocks: Units of Optimization

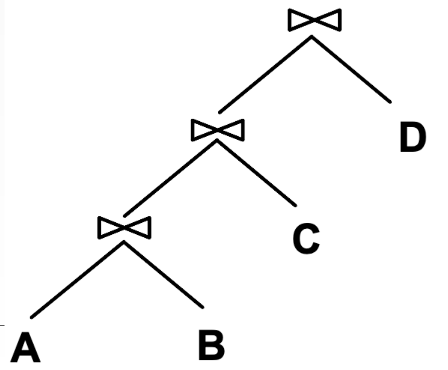
- For each block, the plans considered are:
  - All relevant access methods, for each relation in FROM clause
  - All left-deep join trees
    - right branch always a base table
    - consider all join orders and join methods

```
SELECT S.sname
  FROM Sailors S
 WHERE S.age IN
```

Outer block

```
  (SELECT MAX (S2.age)
       FROM  Sailors S2
GROUP BY  S2.rating)
```

Nested block



Schema for Examples

```
Sailors (sid: integer, sname: text, rating: integer,
         age: float)
Reserves (sid: integer, bid: integer, day: date,
         rname: text)
```

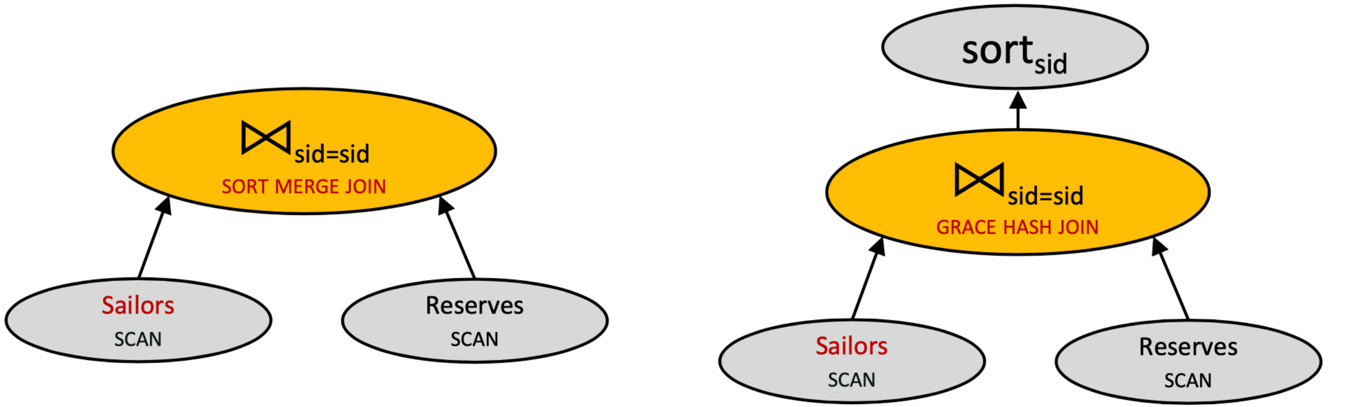
- Reserves:
  - Each tuple is 40 bytes long,
  - 100 tuples per page, 1000 pages.
  - 100 distinct bids.
- Sailors:
  - Each tuple is 50 bytes long,
  - 80 tuples per page, 500 pages.
  - 10 ratings, 40,000 sids.

“Physical” Properties

- Two common “physical” properties of an output:
  - Sort order
  - Hash Grouping
- Certain operators produce these properties in output
  - E.g., Index scan (result is sorted)
  - E.g., Sort (result is sorted)
  - E.g., Hash (result is grouped)
- Certain operators require these properties at input
  - E.g., MergeJoin requires sorted input
- Certain operators preserve these properties from inputs
  - E.g., MergeJoin preserves sort order of inputs
  - E.g., Index nested loop join (INLJ) preserves sort order of outer (left) input

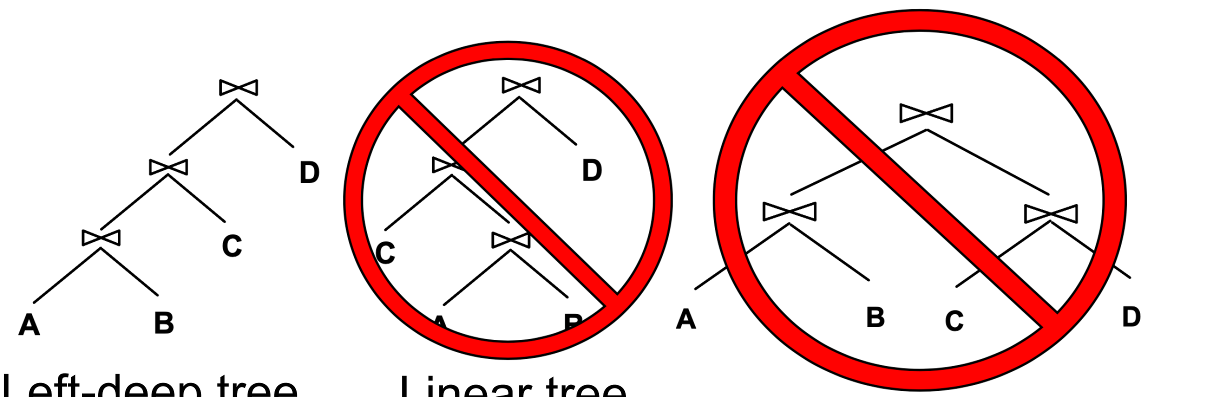
Physically Equivalent Plans

- Same content and same physical properties



Queries Over Multiple Relations

- A System R heuristic: only left-deep join trees considered
  - Restricts the search space
  - Left-deep trees allow us to generate all fully pipelined plans
    - i.e., intermediate results not written to temporary files
    - Not all left-deep trees are fully pipelined (e.g., SM join).



Left-deep tree Linear tree Bushy tree

Plan Space Review

- For a SQL query, full plan space:
  - All equivalent relational algebra expressions
    - Based on the equivalence rules we learned
  - All mixes of physical implementations of those algebra expressions
- We might prune this space:
  - Selection/Projection pushdown
  - Left-deep trees only
  - Avoid Cartesian products
- Along the way we may care about physical properties like sorting
  - Because downstream ops may depend on them
  - And enforcing them later may be expensive

Query Optimization

1. Plan Space

2. **Cost Estimation**

3. Search Algorithm

Cost Estimation

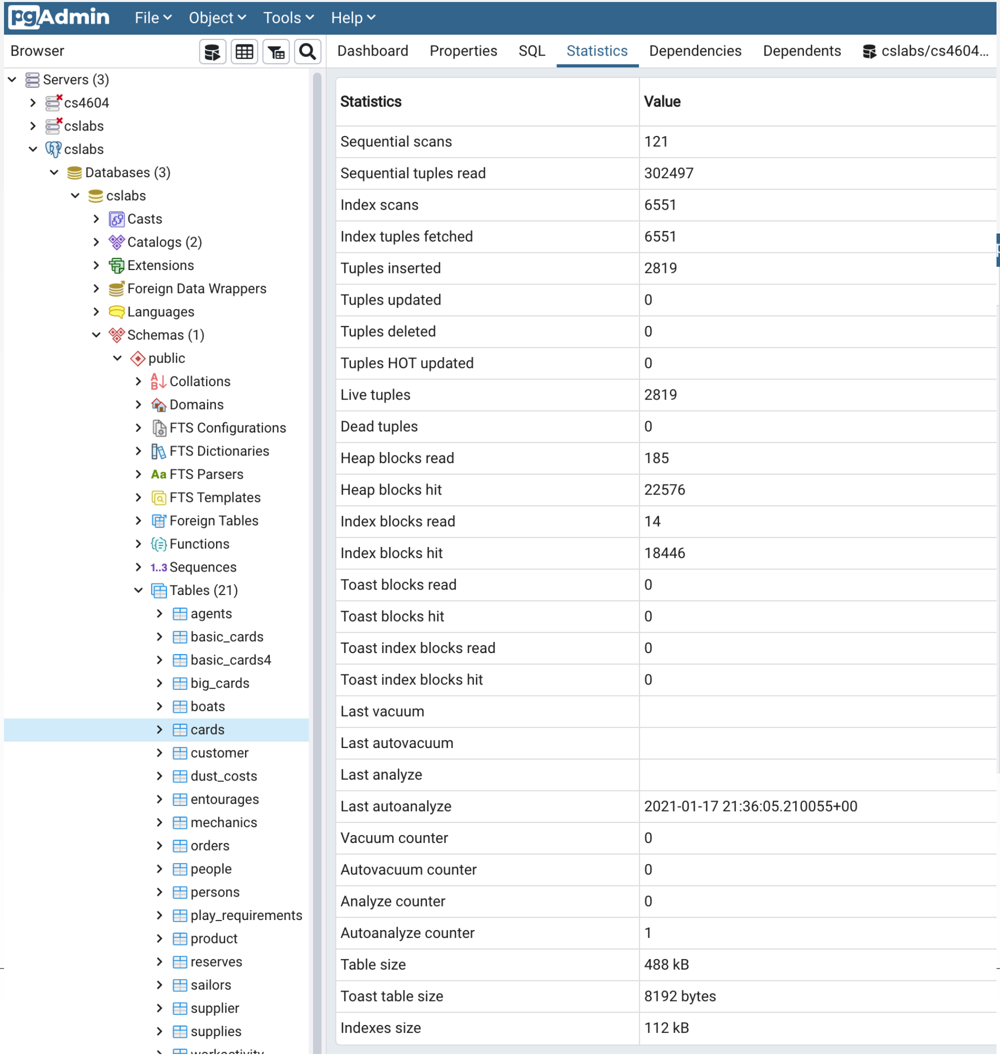
- For each plan considered, must estimate total cost:
  - Must estimate ***cost*** of each operation in plan tree
    - Depends on input cardinalities.
    - sequential scan, index scan, joins, etc.
- Must estimate ***size of result*** for each operation in tree!
  - Because it determines downstream input cardinalities!
  - Use information about the input relations.
  - For selections and joins, assume independence of predicates.
- In System R, cost is boiled down to a single number consisting of #I/O + ***CPU-factor*** * #tuples
  - Second term estimate the cost of tuple processing

Statistics and Catalogs

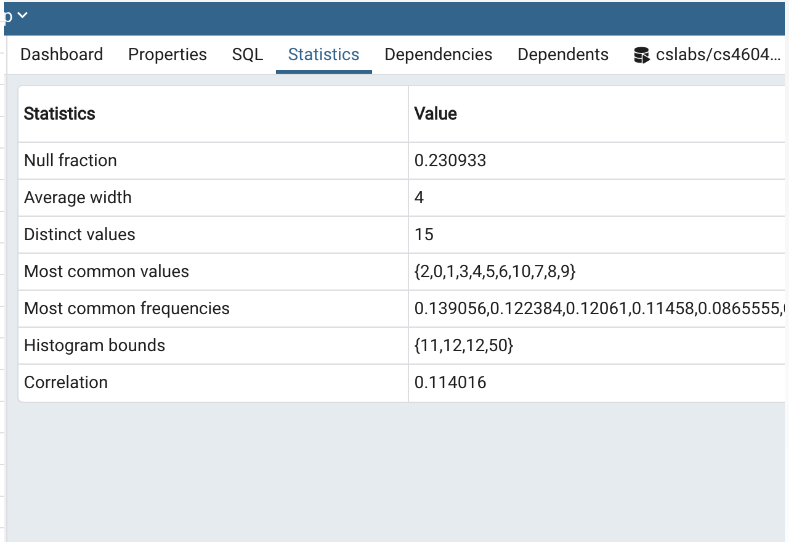
- Need info on relations and indexes involved.
- **Catalogs** typically contain at least:

Statistic	Meaning
NTuples	# of tuples in a table (cardinality)
NPages	# of disk pages in a table
Low/High	min/max value in a column
Nkeys	# of distinct values in a column
IHeight	the height of an index
INPages	# of disk pages in an index

- Catalogs updated periodically.
  - Too expensive to do continuously
  - Lots of approximation anyway, so a little slop here is ok.
- Modern systems do more
  - Especially keep more detailed statistical information on data values. e.g., histograms



Statistics	Value
Sequential scans	121
Sequential tuples read	302497
Index scans	6551
Index tuples fetched	6551
Tuples inserted	2819
Tuples updated	0
Tuples deleted	0
Tuples HOT updated	0
Live tuples	2819
Dead tuples	0
Heap blocks read	185
Heap blocks hit	22576
Index blocks read	14
Index blocks hit	18446
Toast blocks read	0
Toast blocks hit	0
Toast index blocks read	0
Toast index blocks hit	0
Last vacuum	
Last autovacuum	
Last analyze	
Last autoanalyze	2021-01-17 21:36:05.210055+00
Vacuum counter	0
Autovacuum counter	0
Analyze counter	0
Autoanalyze counter	1
Table size	488 kB
Toast table size	8192 bytes
Indexes size	112 kB



Statistics	Value
Null fraction	0.230933
Average width	4
Distinct values	15
Most common values	{2,0,1,3,4,5,6,10,7,8,9}
Most common frequencies	0.139056,0.122384,0.12061,0.11458,0.0865555,
Histogram bounds	{11,12,12,50}
Correlation	0.114016

Size Estimation and Selectivity

- Max output cardinality = product of input the cardinalities of the relations in **FROM**
- **Selectivity (sel)** associated with each **term** in **WHERE**
  - Reflects the impact of the term in reducing result size.
  - Selectivity = |output| / |input|
  - Selectivity: “Reduction Factor” (RF)
  - Always between 0 and 1

```
SELECT  attribute list
  FROM  relation list
 WHERE  term1 AND ... AND termk
```

Result Size Estimation

- Result cardinality = Max # tuples * **product** of all selectivities.
- Term col=value (given Nkeys(col) unique values of col)
  - sel = 1/NKeys(col)
- Term col1=col2 (handy for joins too...)
  - sel = 1/MAX(NKeys(col1), NKeys(col2))
- Term col>value
  - sel = (High(col)-value)/(High(col)-Low(col))
- Term in
  - sel = 1/NKeys(col) * # items in the list

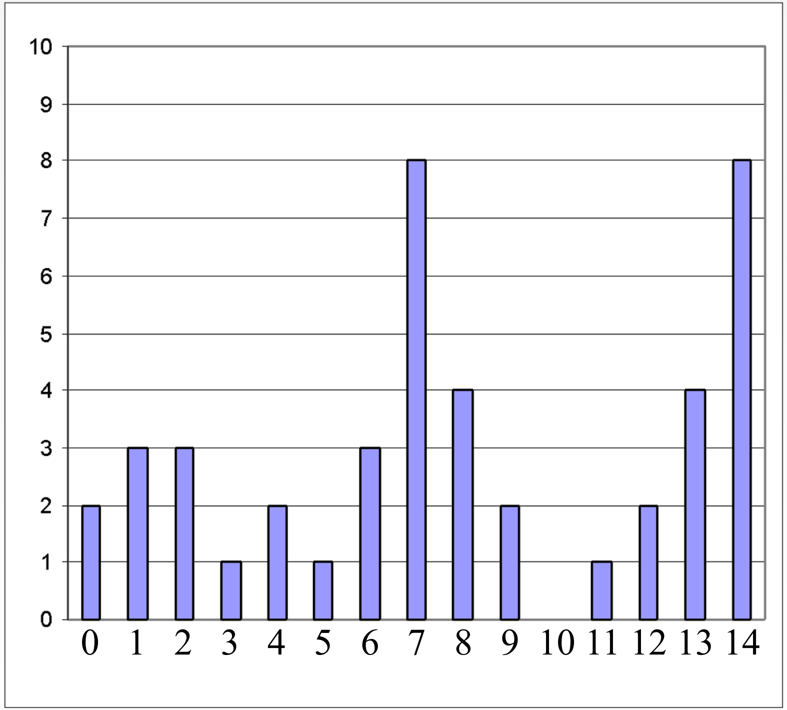
postgres/src/include/utils/selfuncs.h

https://github.com/postgres/postgres

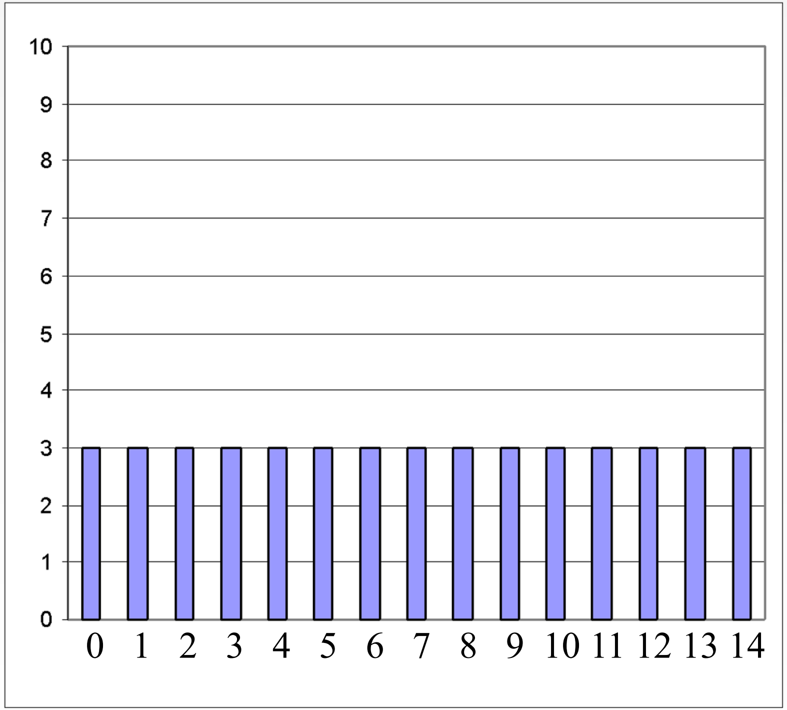
```
/*
 * Note: the default selectivity estimates are not chosen entirely at random.
 * We want them to be small enough to ensure that indexscans will be used if
 * available, for typical table densities of ~100 tuples/page.  Thus, for
 * example, 0.01 is not quite small enough, since that makes it appear that
 * nearly all pages will be hit anyway.  Also, since we sometimes estimate
 * eqsel as 1/num_distinct, we probably want DEFAULT_NUM_DISTINCT to equal
 * 1/DEFAULT_EQ_SEL.
 */

/* default selectivity estimate for equalities such as "A = b" */
#define DEFAULT_EQ_SEL  0.005

/* default selectivity estimate for inequalities such as "A < b" */
#define DEFAULT_INEQ_SEL  0.3333333333333333

/* default selectivity estimate for range inequalities "A > b AND A < c" */
#define DEFAULT_RANGE_INEQ_SEL  0.005

/* default selectivity estimate for multirange inequalities "A > b AND A < c" */
#define DEFAULT_MULTIRANGE_INEQ_SEL 0.005

/* default selectivity estimate for pattern-match operators such as LIKE */
#define DEFAULT_MATCH_SEL   0.005

/* default selectivity estimate for other matching operators */
#define DEFAULT_MATCHING_SEL    0.010

/* default number of distinct values in a table */
#define DEFAULT_NUM_DISTINCT  200

/* default selectivity estimate for boolean and null test nodes */
#define DEFAULT_UNK_SEL         0.005
#define DEFAULT_NOT_UNK_SEL     (1.0 - DEFAULT_UNK_SEL)
```

Reduction Factors & Histograms

Distribution D

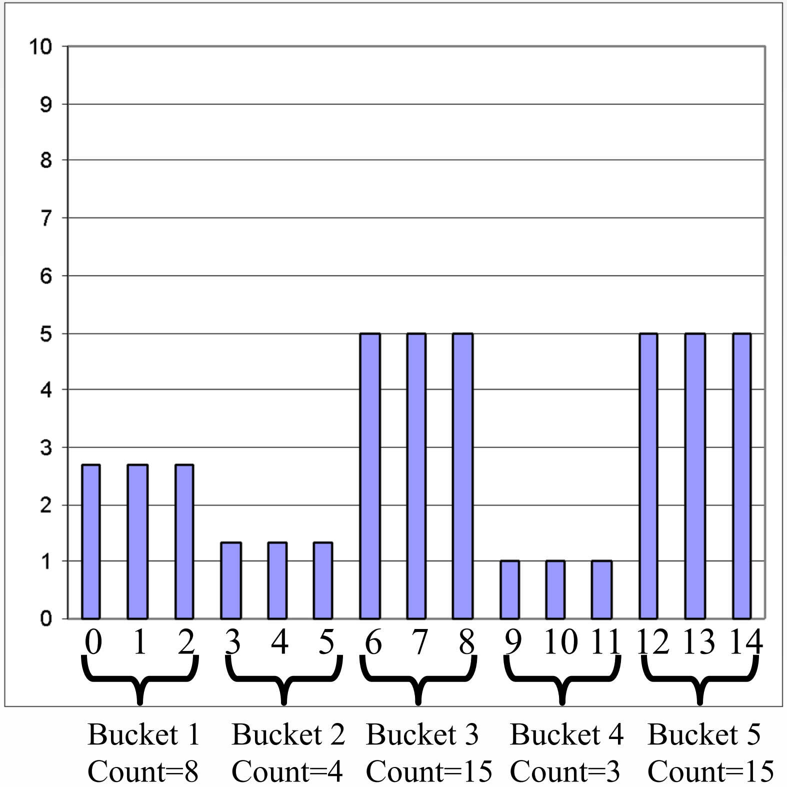


Uniform distribution approximating D

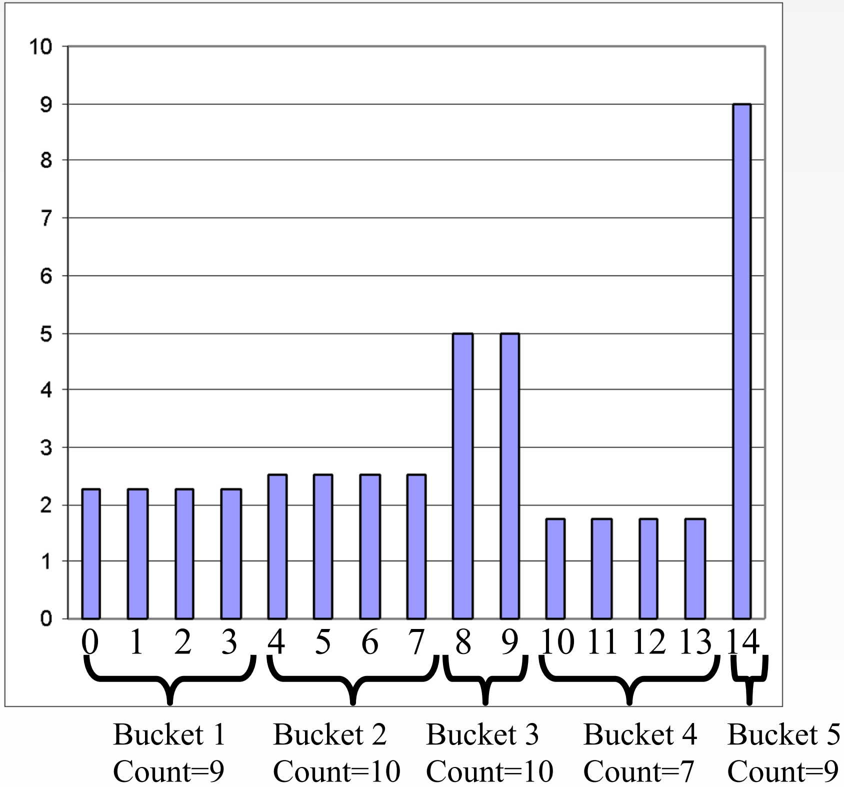


Reduction Factors & Histograms

Equiwidth histogram



Equidepth histogram ~ quantiles



Selectivity Example: Join Selectivity

$$R \bowtie_p \sigma_q(S)$$

algebraic equivalence: $R \bowtie_p S \equiv \sigma_p(R \times S)$

Join selectivity is selectivity s_p → Total rows: $s_p \times |R| \times |S|$

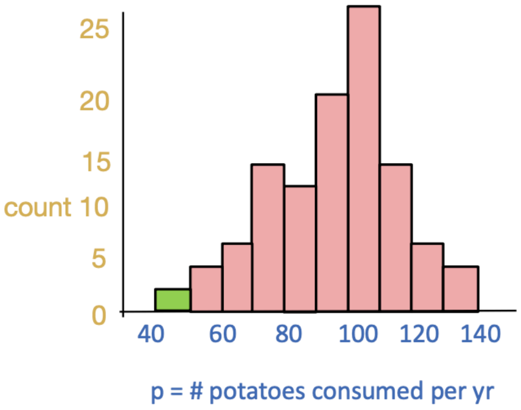
$$R \bowtie_p \sigma_q(S) \equiv \sigma_p(R \times \sigma_q(S)) \equiv \sigma_{p \wedge q}(R \times S))$$

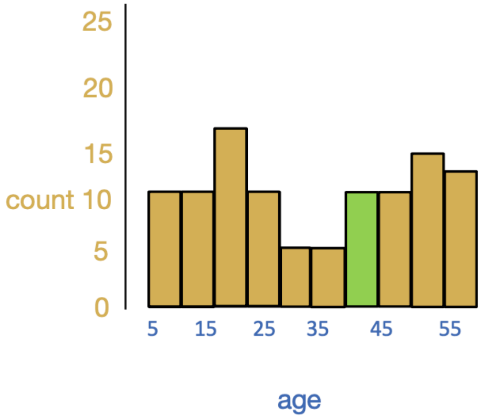
Join selectivity is selectivity $s_p s_q$ → Total rows: $s_p s_q \times |R| \times |S|$

Selectivity Example: Column Equality

T.p = T.age ??

Idea: scan over all values of p and age, and check when they are equal





Selectivity Example: Column Equality

T.p = T.age ??

Idea: scan over all values of p and age, and check when they are equal

T.p = T.age

= (T.p = 40 ∧ T.age = 40) ∨ (T.p = 41 ∧ T.age = 41) ∨ (T.p = 42 ∧ T.age = 42) …

= (T.p = 40 ∧ T.age = 40) + (T.p = 41 ∧ T.age = 41) + (T.p = 42 ∧ T.age = 42) …

= (T.p = 40 * T.age = 40) + (T.p = 41 * T.age = 41) + (T.p = 42 * T.age = 42) …

Independence assumption

(T.p = 40)

$$= \frac{\text{height}(\text{bin}_p(40))}{\text{width}(\text{bin}_p(40)) * n}$$

(T.age = 40)

$$= \frac{\text{height}(\text{bin}_{age}(40))}{\text{width}(\text{bin}_{age}(40)) * n}$$

Uniform assumption

Just add up all the values…

Compute Selectivities

- Know how to compute selectivities for basic predicates
  - The System R version
  - The histogram version
- Assumption 1: uniform distribution within histogram bins
  - Within a bin, fraction of range = fraction of count
- Assumption 2: independent predicates
  - Selectivity of AND = **product** of selectivities of predicates
  - Selectivity of OR = **sum** of selectivities of predicates - **product** of selectivities of predicates
  - Selectivity of NOT = 1 – selectivity of predicates
- Joins are not a special case
  - Simply compute the selectivity of all predicates
  - And multiply by the product of the table sizes

Summary: Selectivity Estimation

- We need a way to estimate the size of the intermediate tables

  Recall cost of each operator =
  I/Os (to bring in input) + *CPU-factor* * # tuples processed

- Output size = input size * operator selectivity

System R

- col=value
  - 1/uniq-keys(col)
- col1=col2
  - 1/MAX(uniq-keys(col1), uniq-keys(col2))
- col>value

$$\frac{\text{High(col) - value}}{\text{High(col) – Low(col) + 1}}$$

Histogram

- col=value

$$\frac{\text{bar height containing value}}{\text{\# values contained in bar}}$$

- col1=col2
  - Breakdown into
    (col1 = v1 ∧ col2 = v1) ∨
    (col1 = v2 ∧ col2 = v2) ∨ …
- col>value

$$\frac{\text{sum of bar heights >value}}{\text{total number of rows}}$$

Summary: Selectivity Estimation

- In both cases, for more complex predicates:
  - p1∧p2
    - selectivity(p1) * selectivity(p2)
  - p1∨p2
    - selectivity(p1) + selectivity(p2) – (selectivity(p1) * selectivity(p2))
    - Last term is 0 if p1 and p2 are **non-overlapping** (e.g., age>60 OR age<21)
  - Not p1 = 1 – selectivity(p1)

Query Optimization

1. Plan Space

2. Cost Estimation

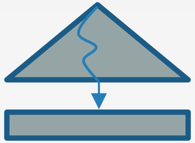
3. **Search Algorithm**

Enumeration of Alternative Plans

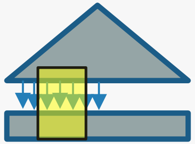
- There are two main cases:
  - **Single-table plans (base case)**
  - **Multiple-table plans (induction)**
- Single-table queries include selects, projects, and GroupBy/aggregation:
  - Consider each available access path (file scan / index)
    - Choose the one with the **least estimated cost**
  - Selection/Projection done **on the fly**
  - Result pipelined into grouping/aggregation

Cost Estimates for Single-Relation Plans

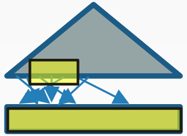
- Index I on primary key matches selection:
  - Cost is (Height(I) + 1) + 1 for a B+ tree.



- Clustered index I matching selection:
  - (NPages(I)+**NPages**(R)) * selectivity.



- Non-clustered index I matching selection:
  - (NPages(I)+**NTuples**(R)) * selectivity.



- Sequential scan of file:
  - NPages(R).

- Recall: Must also charge for **duplicate elimination** if required

Example

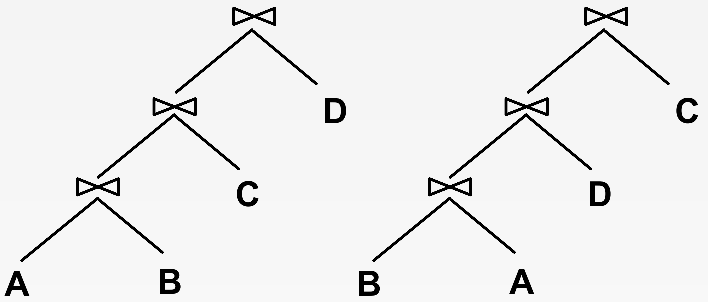
```
SELECT S.sid
  FROM Sailors S
 WHERE S.rating=8
```

- If we have an index on rating:
  - **Cardinality** = (1/NKeys(I)) * NTuples(R) = (1/10) * 40000 tuples
  - **Clustered index:** (1/NKeys(I)) * (NPages(I)+NPages(R))
    = (1/10) * (50+500) = **55 pages are retrieved**. (This is the cost.)
  - **Unclustered index**: (1/NKeys(I)) * (NPages(I)+NTuples(R))
    = (1/10) * (50+40000) = **4005 pages are retrieved**.

- If we have an index on sid:
  - Would have to retrieve all tuples/pages. With a clustered index, the cost is 50+500, with unclustered index, 50+40000.

- Doing a file scan:
  - We retrieve all file pages (500).

Enumeration of Left-Deep Plans



- Left-deep plans differ in
  - the order of relations
  - the access method for each leaf operator
  - the join method for each join operator
- Enumerated using N passes (if N relations joined):
  - **Pass 1:** Find best 1-relation plan for each relation
  - **Pass i:** Find best way to join result of an (i -1)-relation plan (as outer) to the i' th relation. (i between 2 and N.)
- For each subset of relations, retain only:
  - **Cheapest** plan overall, plus
  - **Cheapest** plan for each *interesting order* of the tuples.

The Principle of Optimality

- Bellman ’57 (slightly adapted to our setting)
- The best overall plan is composed of best decisions on the subplans
  - Optimal result has optimal substructure
- For example, the best left-deep plan to join tables A, B, C is either:
  - (The best plan for joining A, B) ⋈ C
  - (The best plan for joining A, C) ⋈ B
  - (The best plan for joining B, C) ⋈ A
- This is great!
  - When optimizing a subplan (e.g. A ⋈ B), we don’t have to think about how it will be used later (e.g. when dealing with C)!
  - When optimizing a higher-level plan (e.g. A ⋈ B ⋈ C) we can reuse the best results of subroutines (e.g. A ⋈ B)!

Dynamic Programming Algorithm for System R

- Principle of optimality allows us to build best subplans “bottom up”
  - Pass 1: Find best plans of height 1 (base table accesses), and record them in a table
  - Pass 2: Find best plans of height 2 (joins of base tables) by combining plans of height 1, record them in a table
  - …
  - Pass i: Find best plans of height i by combining plans of height i - 1 with plans of height 1, record them in a table
  - …
  - Pass *n:* Find best plan overall by combining plans of height *n-1* with plans of height 1.

The Basic Dynamic Programming Table

Table keyed on 1st column

Subset of tables in FROM clause	Best plan	Cost
{R, S}	hashjoin(R,S)	1000
{R, T}	mergejoin(R,T)	700

A Note on “Interesting Orders”

- Physical property: Order.
  When should we care? When is it “interesting”?

- An intermediate result has an “interesting order” if it is sorted by anything we can **use later** in the query (“downstream” the arrows (operator)):
  - ORDER BY attributes
  - GROUP BY attributes
  - Join attributes of yet-to-be-added joins
    - subsequent merge join might be good

The Dynamic Programming Table

Table keyed on concatenation of 1st two columns

Subset of tables in FROM clause	Interesting-order columns	Best plan	Cost
{R, S}	<none>	hashjoin(R,S)	1000
{R, S}	<R.a, S.b>	sortmerge(R,S)	1500

←Higher cost, but may lead to global optimal plan!

Enumeration of Plans (Contd.)

- First figure out the scans and joins (select-project-join) using dynamic programming
  - **Avoid Cartesian Products** in dynamic programming as follows:
    When matching an i -1 way subplan with another table, only consider it if
    - There is a join condition between them, **or**
    - All predicates in WHERE have been "used up" in the i -1 way subplan.

- Then handle ORDER BY, GROUP BY, aggregates etc. as a post-processing step
  - Via "interestingly ordered" plan if chosen (free!)
  - Or via an additional sort/hash operator

- Despite pruning, this System R dynamic programming algorithm is **exponential** in #tables.

Example

```
SELECT S.sid, COUNT(*) AS number
FROM Sailors S, Reserves R, Boats B
WHERE S.sid = R.sid
AND R.bid = B.bid
AND B.color = “red”
GROUP BY S.sid
```

<u>Sailors:</u>
Hash, B+ tree indexes on *sid*
<u>Reserves:</u>
Clustered B+ tree on *bid*
B+ on *sid*
<u>Boats</u>
B+ on *color*

Pass 1: Best plan(s) for each relation

- Sailors, Reserves: File Scan
- Also B+ tree on Reserves.bid as interesting order
- Also B+ tree on Sailors.sid as interesting order
- Boats: B+ tree on color

Best plans after pass 1

Subset of tables in FROM clause	Interesting-order columns	Best plan	Cost
{Sailors}	--	filescan	
{Reserves}	--	Filescan	
{Boats}	--	B-tree on color	
{Reserves}	(bid)	B-tree on bid	
{Sailors}	(sid)	B-tree on sid	

Pass 2

```
// for each left-deep logical plan
for each plan P in pass 1
  for each FROM table T not in P
      // for each physical plan
      for each access method M on T
         for each join method
            generate P ⋈ M(T)
```

- File Scan Reserves (outer) with Boats (inner)
- File Scan Reserves (outer) with Sailors (inner)
- Reserves Btree on bid (outer) with Boats (inner)
- Reserves Btree on bid (outer) with Sailors (inner)
- File Scan Sailors (outer) with Boats (inner)
- File Scan Sailors (outer) with Reserves (inner)
- Boats Btree on color with Sailors (inner)
- Boats Btree on color with Reserves (inner)

- Retain cheapest plan for each (pair of relations, order)

Best plans after pass 2

Subset of tables in FROM clause	Interesting-order columns	Best plan	Cost
{Sailors}	--	filescan	
{Reserves}	--	Filescan	
{Boats}	--	B-tree on color	
{Reserves}	(bid)	B-tree on bid	
{Sailors}	(sid)	B-tree on sid	
{Boats, Reserves}	(B.bid) (R.bid)	SortMerge(B-tree on Boats.color, filescan Reserves)	
Etc...			

Pass 3 and beyond

- Using Pass 2 plans as outer relations, generate plans for the next join in the same way as Pass 2
  - E.g. {SortMerge(B-tree on Boats.color, filescan Reserves)} (outer) | with Sailors (B-tree sid) (inner)
- Then, add cost for groupby/aggregate:
  - This is the cost to sort the result by sid, *unless it has already been sorted by a previous operator.*
- Then, choose the cheapest plan

Now you understand the optimizer!

- Benefit #1: You could build one.
- Benefit #2: You can influence one
  - People who write non-trivial SQL often get frustrated with the optimizer
    - It picked a crummy plan!
    - It didn't use the index I built!
    - Etc.
  - Understanding the optimizer can lead you to:
    - Design your DB & Indexes better
    - Avoid "weak spots" in your optimizer's implementation
    - Coax your optimizer to do what you want

Summary

- Optimization is the reason for the lasting power of the relational system
- But it is primitive in some SQL databases, and in the Big Data stack
- Many new areas:
  - Smarter statistics (fancy histograms, “sketches”)
  - Auto-tuning statistics
  - Adaptive runtime re-optimization
  - Multi-query optimization
  - Parallel scheduling issues

Reading and Next Class

- Query Optimization: Ch 15
- Next: Security & SQL injection: Ch 21