Architecture and Implementation of Database Systems (Summer 2018)

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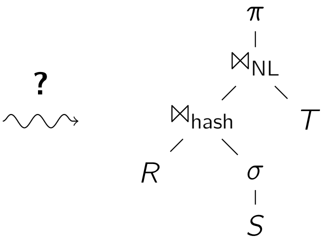
Part VI

Query Optimization

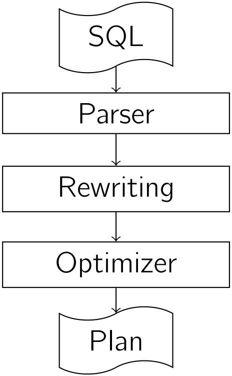
Finding the “Best” Query Plan

```
SELECT  ···
  FROM  ···
 WHERE  ···
```



- We already saw that there may be more than one way to answer a given query.
  - Which one of the join operators should we pick? With which parameters (block size, buffer allocation, . . .)?
- The task of finding the best execution plan is, in fact, the **holy grail** of any database implementation.

Plan Generation Process

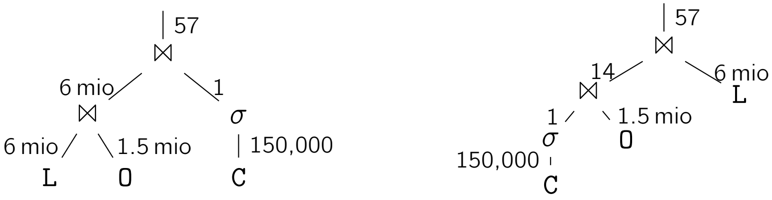


- **Parser:** syntactical/semantical analysis
- **Rewriting:** optimizations **independent** of the current database state (table sizes, availability of indexes, etc.)
- **Optimizer:** optimizations that rely on a **cost model** and information about the current database state
- The resulting **plan** is then evaluated by the system's **execution engine**.

Impact on Performance

Finding the right plan can dramatically impact performance.

```
SELECT L.L_PARTKEY, L.L_QUANTITY, L.L_EXTENDEDPRICE
  FROM LINEITEM L, ORDERS O, CUSTOMER C
 WHERE L.L_ORDERKEY = O.O_ORDERKEY
   AND O.O_CUSTKEY = C.C_CUSTKEY
   AND C.C_NAME = 'IBM Corp.'
```



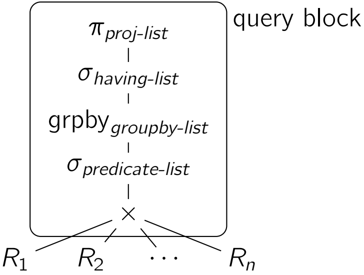
- In terms of execution times, these differences can easily mean "seconds versus days."

The SQL Parser

- Besides some analyses regarding the syntactical and semantical correctness of the input query, the parser creates an **internal representation** of the input query.
- This representation still resembles the original query:
  - Each `SELECT-FROM-WHERE` clause is translated into a **query block**.

`SELECT` *proj-list*
`FROM` R_1 , R_2 , . . . , R_n
`WHERE` *predicate-list*
`GROUP BY` *groupby-list*
`HAVING` *having-list*

$\rightarrow$



  - Each R_i can be a base relation or another query block.

Finding the “Best” Execution Plan

The parser output is fed into a **rewrite engine** which, again, yields a tree of query blocks.

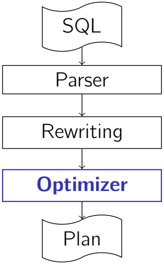
It is then the **optimizer’s** task to come up with the optimal **execution plan** for the given query.

Essentially, the optimizer

1. **enumerates** all possible execution plans,
2. determines the **quality** (cost) of each plan, then
3. **chooses** the best one as the final execution plan.

Before we can do so, we need to answer the question

- What is a “good” execution plan at all?



Cost Metrics

Database systems judge the quality of an execution plan based on a number of **cost factors**, *e.g.*,

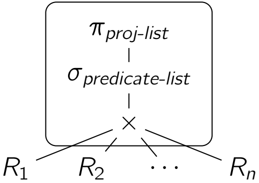
- the number of **disk I/Os** required to evaluate the plan,
- the plan's **CPU cost**,
- the overall **response time** observable by the user as well as the total **execution time**.

A cost-based optimizer tries to **anticipate** these costs and find the cheapest plan before actually running it.

- All of the above factors depend on one critical piece of information: the **size of (intermediate) query results**.
- Database systems, therefore, spend considerable effort into accurate **result size estimates**.

Result Size Estimation

Consider a query block corresponding to a simple SFW query Q.



We can estimate the result size of Q based on

- the size of the input tables, $|R_1|, \ldots, |R_n|$, and
- the **selectivity** $sel(p)$ of the predicate *predicate-list*:

$$|Q| \approx |R_1| \cdot |R_2| \cdots |R_n| \cdot sel(\textit{predicate-list}) \enspace .$$

Table Cardinalities

If not coming from another query block, the size $|R|$ of an input table R is available in the DBMS's **system catalogs**.
E.g., IBM DB2:

```
db2 => SELECT TABNAME, CARD, NPAGES
db2 (cont.) => FROM SYSCAT.TABLES
db2 (cont.) => WHERE TABSCHEMA = 'TPCH';

TABNAME       CARD                 NPAGES
------------- -------------------- --------------------
ORDERS                     1500000                44331
CUSTOMER                    150000                 6747
NATION                          25                    2
REGION                           5                    1
PART                        200000                 7578
SUPPLIER                     10000                  406
PARTSUPP                    800000                31679
LINEITEM                   6001215               207888

  8 record(s) selected.
```

Estimating Selectivities

To estimate the selectivity of a predicate, we look at its structure.

column = *value*

$$sel(\cdot) = \begin{cases} {}^1/_{|I|} & \text{if there is an index } I \text{ on } \textit{column} \\ {}^1/_{10} & \text{otherwise} \end{cases}$$

column$_1$ = *column*$_2$

$$sel(\cdot) = \begin{cases} \frac{1}{\max\{|I_1|,|I_2|\}} & \text{if there are indexes on } \textbf{both} \text{ cols.} \\ \frac{1}{|I_k|} & \text{if there is an index only on col. } k \\ {}^1/_{10} & \text{otherwise} \end{cases}$$

p_1 `AND` p_2

$$sel(\cdot) = sel(p_1) \cdot sel(p_2)$$

p_1 `OR` p_2

$$sel(\cdot) = sel(p_1) + sel(p_2) - sel(p_1) \cdot sel(p_2)$$

Improving Selectivity Estimation

The selectivity rules we saw make a fair amount of assumptions:

- **uniform distribution** of data values within a column,
- **independence** between individual predicates.

Since these assumptions aren't generally met, systems try to improve selectivity estimation by gathering **data statistics**.

- These statistics are collected offline and stored in the system catalog.
  - IBM DB2: `RUNSTATS ON TABLE ...`
- The most popular type of statistics are **histograms**.

Example: Histograms in IBM DB2

```
SELECT SEQNO, COLVALUE, VALCOUNT
  FROM SYSCAT.COLDIST
 WHERE TABNAME = 'LINEITEM'
   AND COLNAME = 'L_EXTENDEDPRICE'
   AND TYPE = 'Q';

SEQNO COLVALUE          VALCOUNT
----- ----------------- --------
    1 +0000000000996.01     3001
    2 +0000000004513.26   315064
    3 +0000000007367.60   633128
    4 +0000000011861.82   948192
    5 +0000000015921.28  1263256
    6 +0000000019922.76  1578320
    7 +0000000024103.20  1896384
    8 +0000000027733.58  2211448
    9 +0000000031961.80  2526512
   10 +0000000035584.72  2841576
   11 +0000000039772.92  3159640
   12 +0000000043395.75  3474704
   13 +0000000047013.98  3789768
              ⋮
```

`SYSCAT.COLDIST` also contains information like

- the *n* most frequent values (and their frequency),
- the number of **distinct** values in each histogram bucket.

Histograms may even be manipulated **manually** to tweak the query optimizer.

Join Optimization

- We've now translated the query into a graph of **query blocks**.
  - Query blocks essentially are a **multi-way** Cartesian product with a number of selection predicates on top.
- We can estimate the **cost** of a given **execution plan**.
  - Use result size estimates in combination with the cost for individual join algorithms in the previous chapter.

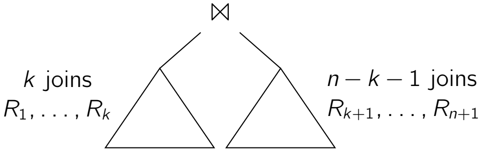
We are now ready to **enumerate** all possible execution plans, *e.g.*, all possible **3-way** join combinations for a query block.

$(R \bowtie S) \bowtie T$ $\quad (S \bowtie R) \bowtie T$ $\quad (R \bowtie T) \bowtie S$ $\quad (S \bowtie T) \bowtie R$ $\quad (T \bowtie R) \bowtie S$ $\quad (T \bowtie S) \bowtie R$

$R \bowtie (S \bowtie T)$ $\quad S \bowtie (R \bowtie T)$ $\quad R \bowtie (T \bowtie S)$ $\quad S \bowtie (T \bowtie R)$ $\quad T \bowtie (R \bowtie S)$ $\quad T \bowtie (S \bowtie R)$

How Many Such Combinations Are There?

- A join over $n+1$ relations $R_1, \ldots, R_{n+1}$ requires n **binary joins**.
- Its **root-level operator** joins sub-plans of k and $n-k-1$ join operators ($0 \leq k \leq n-1$):



- Let C_i be the **number of possibilities** to construct a binary tree of i inner nodes (join operators):

$$C_n = \sum_{k=0}^{n-1} C_k \cdot C_{n-k-1} \quad .$$

Catalan Numbers

This recurrence relation is satisfied by **Catalan numbers**:

$$C_n = \sum_{k=0}^{n-1} C_k \cdot C_{n-k-1} = \frac{(2n)!}{(n+1)!n!} \ ,$$

describing the number of ordered binary trees with $n+1$ leaves.

For **each** of these trees, we can **permute** the input relations $R_1, \dots, R_{n+1}$, leading to

$$\frac{(2n)!}{(n+1)!n!} \cdot (n+1)! = \frac{(2n)!}{n!}$$

possibilities to evaluate an $(n+1)$-way join.

Search Space

The resulting search space is **enormous**:

number of relations n	C_{n-1}	join trees
2	1	2
3	2	12
4	5	120
5	14	1,680
6	42	30,240
7	132	665,280
8	429	17,297,280
10	4,862	17,643,225,600

- And we haven't yet even considered the use of k **different join algorithms** (yielding another factor of $k^{(n-1)}$)!

Dynamic Programming

The traditional approach to master this search space is the use of **dynamic programming**.

Idea:

- Find the cheapest plan for an n-way join in n **passes**.
- In each pass k, find the best plans for all k-relation **sub-queries**.
- **Construct** the plans in pass k from best i-relation and $(k - i)$-relation sub-plans found in **earlier passes** $(1 \leq i < k)$.

Assumption:

- To find the optimal **global plan**, it is sufficient to only consider the optimal plans of its **sub-queries**.

Example: Four-Way Join

Pass 1 (best 1-relation plans)
: Find the best **access path** to each of the R_i individually (considers index scans, full table scans).

Pass 2 (best 2-relation plans)
: For each **pair** of tables R_i and R_j, determine the best order to join R_i and R_j ($R_i \bowtie R_j$ or $R_j \bowtie R_i$?):

$$optPlan(\{R_i, R_j\}) \leftarrow \text{ best of } R_i \bowtie R_j \text{ and } R_j \bowtie R_i \ .$$

$\rightarrow$ 12 plans to consider.

Pass 3 (best 3-relation plans)
: For each **triple** of tables R_i, R_j, and R_k, determine the best three-table join plan, using sub-plans obtained so far:

$$optPlan(\{R_i, R_j, R_k\}) \leftarrow \text{ best of } R_i \bowtie optPlan(\{R_j, R_k\}), \\ optPlan(\{R_j, R_k\}) \bowtie R_i, \quad R_j \bowtie optPlan(\{R_i, R_k\}), \dots \ .$$

$\rightarrow$ 24 plans to consider.

Example (cont.)

Pass 4 (best 4-relation plan)

For each set of **four** tables R_i, R_j, R_k, and R_l, determine the best four-table join plan, using sub-plans obtained so far:

$$\begin{aligned} \mathit{optPlan}(\{R_i, R_j, R_k, R_l\}) \leftarrow \text{ best of } & R_i \bowtie \mathit{optPlan}(\{R_j, R_k, R_l\}), \\ & \mathit{optPlan}(\{R_j, R_k, R_l\}) \bowtie R_i, \quad R_j \bowtie \mathit{optPlan}(\{R_i, R_k, R_l\}), \dots, \\ & \mathit{optPlan}(\{R_i, R_j\}) \bowtie \mathit{optPlan}(\{R_k, R_l\}), \dots \quad . \end{aligned}$$

$\rightarrow$ 14 plans to consider.

- Overall, we looked at only **50** (sub-)plans (instead of the possible 120 four-way join plans; ↗ slide 218).
- All decisions required the evaluation of **simple** sub-plans only (no need to re-evaluate the interior of *optPlan*(·)).

Dynamic Programming Algorithm

Function: `find_join_tree_dp` $(q(R_1, \dots, R_n))$

for $i = 1$ **to** n **do**
    $optPlan(\{R_i\}) \leftarrow$ `access_plans` (R_i) ;
    `prune_plans` $(optPlan(\{R_i\}))$;

for $i = 2$ **to** n **do**
    foreach $S \subseteq \{R_1, \dots, R_n\}$ **such that** $|S| = i$ **do**
        $optPlan(S) \leftarrow \emptyset$;
        foreach $O \subset S$ **do**
            $optPlan(S) \leftarrow optPlan(S) \cup$
                `possible_joins` $(optPlan(O),\ optPlan(S \setminus O))$;
        `prune_plans` $(optPlan(S))$;

return $optPlan(\{R_1, \dots, R_n\})$;

- `possible_joins` (R, S) enumerates the possible joins between R and S (nested loops join, merge join, etc.).
- `prune_plans` (set) discards all but the best plan from *set*.

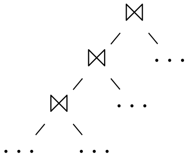
Dynamic Programming—Discussion

- `find_join_tree_dp ()` draws its advantage from **filtering** plan candidates early in the process.
  - In our example on slide 220, pruning in Pass 2 reduced the search space by a factor of 2, and another factor of 6 in Pass 3.
- Some **heuristics** can be used to prune even more plans:
  - Try to avoid **Cartesian products**.
  - Produce **left-deep plans** only (see next slides).
- Such heuristics can be used as a handle to balance plan quality and optimizer runtime.

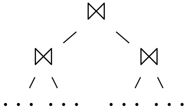
  DB2 UDB: `SET CURRENT QUERY OPTIMIZATION =` *n*

Left/Right-Deep vs. Bushy Join Trees

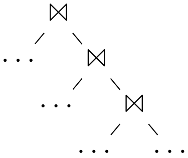
The algorithm on slide 222 explores all possible shapes a join tree could take:



left-deep



bushy
(everything else)



right-deep

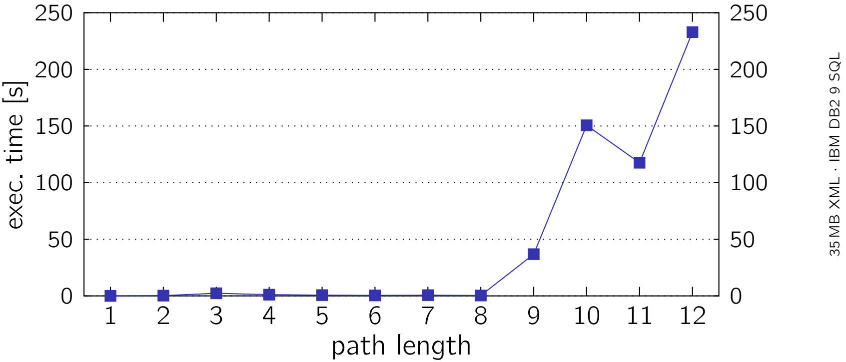
Actual systems often prefer **left-deep** join trees.[15]

- The **inner** relation is always a **base relation**.
- Allows the use of **index nested loops join**.
- Easier to implement in a **pipelined** fashion.

[15] The seminal **System R** prototype, *e.g.*, considered only left-deep plans.

Join Order Makes a Difference

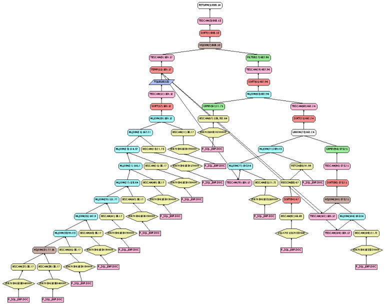
- XPath evaluation over relationally encoded XML data[16]
- *n*-way self-join with a range predicate.



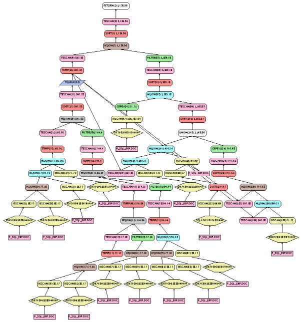
16 ↗ Grust *et al.* Accelerating XPath Evaluation in Any RDBMS. *TODS 2004*. `http://www.pathfinder-xquery.org/`

Join Order Makes a Difference

Contrast the execution plans for a 8- and a 9-step path.



left-deep join tree



bushy join tree

- DB2's optimizer essentially gave up in the face of 9+ joins.

Joining Many Relations

Dynamic programming still has **exponential** resource requirements:

- time complexity: $\mathcal{O}(3^n)$
- space complexity: $\mathcal{O}(2^n)$

This may still be to expensive

- for joins involving many relations ($\sim$ 10–20 and more),
- for simple queries over well-indexed data (where the right plan choice should be easy to make).

The **greedy join enumeration** algorithm jumps into this gap.

Greedy Join Enumeration

Function: `find_join_tree_greedy` $(q(R_1, \dots, R_n))$

worklist $\leftarrow \varnothing$;

for $i = 1$ **to** n **do**

  worklist $\leftarrow$ *worklist* $\cup$ `best_access_plan` (R_i) ;

for $i = n$ **downto** 2 **do**

  // *worklist* $= \{P_1, \dots, P_i\}$

  find $P_j, P_k \in$ *worklist* and $\Join_{\dots}$ such that $cost(P_j \Join_{\dots} P_k)$ is minimal ;

  worklist $\leftarrow$ *worklist* $\setminus \{P_j, P_k\} \cup \{(P_j \Join_{\dots} P_k)\}$;

// *worklist* $= \{P_1\}$

return single plan left in *worklist* ;

- In each iteration, choose the **cheapest** join that can be made over the remaining sub-plans.
- Observe that `find_join_tree_greedy ()` operates similar to finding the optimum binary tree for **Huffman coding**.

Discussion

Greedy join enumeration:

- The greedy algorithm has $\mathcal{O}(n^3)$ time complexity.
  - The loop has $\mathcal{O}(n)$ iterations.
  - Each iteration looks at all remaining pairs of plans in *worklist*. An $\mathcal{O}(n^2)$ task.

Other join enumeration techniques:

- **Randomized algorithms:** randomly rewrite the join tree one rewrite at a time; use **hill-climbing** or **simulated annealing** strategy to find optimal plan.
- **Genetic algorithms:** explore plan space by **combining** plans ("creating offspring") and **altering** some plans randomly ("mutations").

Physical Plan Properties

Consider the query

```
SELECT O.O_ORDERKEY, L.L_EXTENDEDPRICE
  FROM ORDERS O, LINEITEM L
 WHERE O.O_ORDERKEY = L.L_ORDERKEY
```

where table `ORDERS` is indexed with a **clustered index** `OK_IDX` on column `O_ORDERKEY`.

Possible table access plans are:

`ORDERS`
- **full table scan**: estimated I/Os: $N_{\texttt{ORDERS}}$
- **index scan**: estimated I/Os: $N_{\texttt{OK\_IDX}} + N_{\texttt{ORDERS}}$.

`LINEITEM`
- **full table scan**: estimated I/Os: $N_{\texttt{LINEITEM}}$.

Since the **full table scan** is the cheapest access method for both tables, our join algorithms will select them as the best 1-relation plans in Pass 1.[17]

To **join** the two scan outputs, we now have the choices

- **nested loops join**,
- **hash join**, or
- **sort** both inputs, then use **merge join**.

Hash join or sort-merge join are probably the preferable candidates here, incurring a cost of $\approx 2(N_{\texttt{ORDERS}} + N_{\texttt{LINEITEM}})$.

→ **overall cost:** $N_{\texttt{ORDERS}} + N_{\texttt{LINEITEM}} + 2(N_{\texttt{ORDERS}} + N_{\texttt{LINEITEM}})$.

[17] Dynamic programming and the greedy algorithm happen to do the same in this example.

A Better Plan

It is easy to see, however, that there is a better way to evaluate the query:

1. Use an **index scan** to access `ORDERS`. This guarantees that the scan output is already **in `O_ORDERKEY` order**.
2. Then only **sort** `LINEITEM` and
3. join using **merge join**.

→ **overall cost:** $\underbrace{(N_{\texttt{OK\_IDX}} + N_{\texttt{ORDERS}})}_{1.} + \underbrace{3 \cdot N_{\texttt{LINEITEM}}}_{2./3.}$.

Although more expensive as a standalone table access plan, the use of the index pays off in the overall plan.

Interesting Orders

- The advantage of the index-based access to `ORDERS` is that it provides beneficial **physical properties**.
- Optimizers, therefore, keep track of such properties by **annotating** candidate plans.
- System R introduced the concept of **interesting orders**, determined by
  - `ORDER BY` or `GROUP BY` clauses in the input query, or
  - join attributes of subsequent joins ($\leadsto$ merge join).
- In `prune_plans ()`, retain
  - the cheapest "unordered" plan **and**
  - the cheapest plan for each interesting order.

Query Rewriting

Join optimization essentially takes a set of relations and a set of join predicates to find the best join order.

By **rewriting** query graphs beforehand, we can improve the effectiveness of this procedure.

The **query rewriter** applies (heuristic) rules, without looking into the actual database state (no information about cardinalities, indexes, etc.). In particular, it

- **rewrites predicates** and
- **unnests queries**.

Predicate Simplification

Example: rewrite

```
SELECT  *
  FROM  LINEITEM L
 WHERE  L.L_TAX * 100 < 5
```

into

```
SELECT  *
  FROM  LINEITEM L
 WHERE  L.L_TAX < 0.05
```

- Predicate simplification may enable the use of **indexes** and simplify the detection of opportunities for join algorithms.

Additional Join Predicates

Implicit join predicates as in

```
SELECT  *
  FROM  A, B, C
 WHERE  A.a = B.b AND B.b = C.c
```

can be turned into explicit ones:

```
SELECT  *
  FROM  A, B, C
 WHERE  A.a = B.b AND B.b = C.c
   AND  A.a = C.c
```

This enables plans like

$$(\mathtt{A} \bowtie \mathtt{C}) \bowtie \mathtt{B} \quad .$$

($(\mathtt{A} \bowtie \mathtt{C})$ would have been a Cartesian product before.)

Nested Queries

SQL provides a number of ways to write **nested queries**.

- **Uncorrelated** sub-query:

```
SELECT *
  FROM ORDERS O
 WHERE O_CUSTKEY IN (SELECT C_CUSTKEY
                       FROM CUSTOMER
                      WHERE C_NAME = 'IBM Corp.')
```

- **Correlated** sub-query:

```
SELECT *
  FROM ORDERS O
 WHERE O.O_CUSTKEY IN
           (SELECT C.C_CUSTKEY
              FROM CUSTOMER C
             WHERE C.C_ACCTBAL < O.O_TOTALPRICE)
```

Query Unnesting

- Taking query nesting literally might be **expensive**.
  - An uncorrelated query, *e.g.*, need not be re-evaluated for every tuple in the outer query.
- Oftentimes, sub-queries are only used as a syntactical way to express a **join** (or a semi-join).
- The query rewriter tries to detect such situations and **make the join explicit**.
- This way, the sub-query can become part of the regular **join order optimization**.

↗ Won Kim. On Optimizing an SQL-like Nested Query. *ACM TODS*, vol. 7, no. 3, September 1982.

Summary

Query Parser

Translates input query into (SFW-like) **query blocks**.

Rewriter

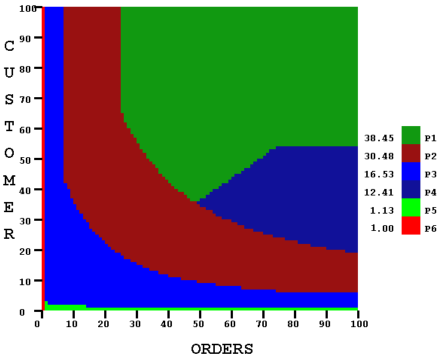
Logical (database state-independent) optimizations; predicate simplification; query unnesting.

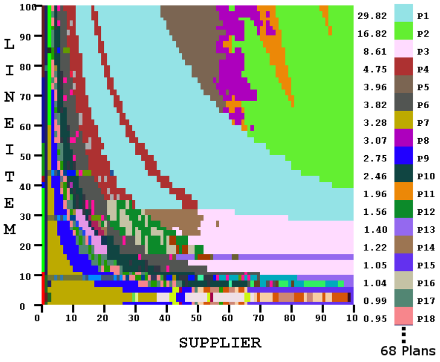
(Join) Optimization

Find "best" query execution plan based on a **cost model** (considering I/O cost, CPU cost, ...); data statistics (histograms); dynamic programming, greedy join enumeration; physical plan properties (interesting orders).

Database optimizers still are true pieces of art...

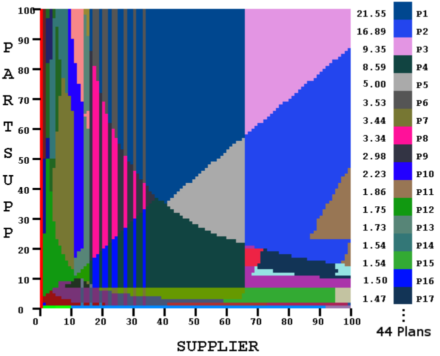
“Picasso” Plan Diagrams

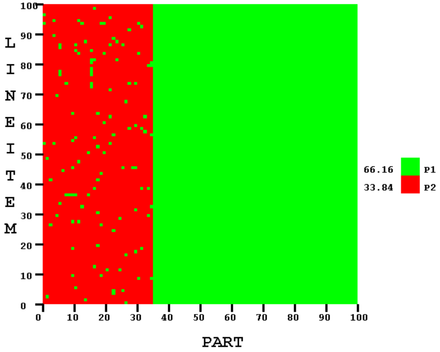




↗ Naveen Reddy and Jayant Haritsa. Analyzing Plan Diagrams of Database Query Optimizers. *VLDB 2005*.

"Picasso" Plan Diagrams





Download Picasso at

http://dsl.serc.iisc.ernet.in/projects/PICASSO/index.html.