# Einführung in Datenbanksysteme

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**TUHH**

## Anfrageoptimierung

# Danksagung

- Diese Vorlesung basiert auf dem Kurs

  **Architecture and Implementation of Database Systems**
  **von Jens Teubner, ETH Zürich**

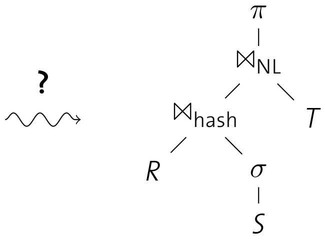
- Ich bedanke mich für die Bereitstellung des Materials

# Part V

# Query Optimization

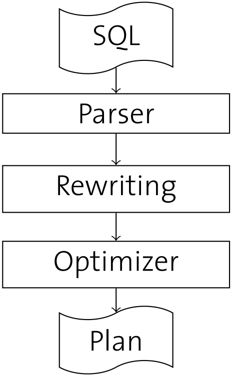
# Finding the “Best” Query Plan

```
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.'
```

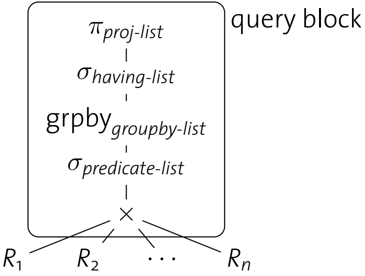

- In terms of execution times, these differences can easily mean “seconds versus days.”

# 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**.

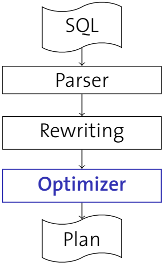
```
SELECT   proj-list
  FROM   R1, R2, ..., Rn
 WHERE   predicate-list
 GROUP   BY groupby-list
HAVING   having-list
```

$\longrightarrow$




  - 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.*,

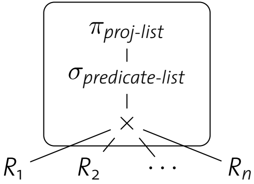
- the number of **disk I/Os** required to evaluate the plan,
- the plan's **CPU cost**,
- the overall **response time** observable by the user as well as the total **execution time**.

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*:

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

# 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*

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

$column_1 = column_2$

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

$p_1$ `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

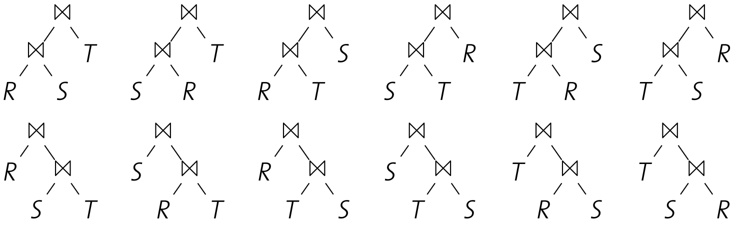
- the *n* most frequent values (and their frequency),
- the number of **distinct** values in each histogram bucket.

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

# Join Optimization

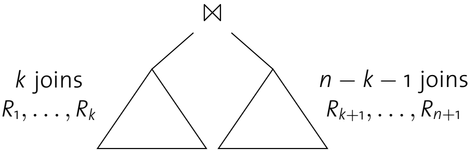
- We've now translated the query into a graph of **query blocks**.
  - Query blocks essentially are a **multi-way** Cartesian product with a number of selection predicates on top.
- We can estimate the **cost** of a given **execution plan**.
  - Use result size estimates in combination with the cost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

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



# 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 $R_1, \ldots, R_{n+1}$, 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 | 5 | 12 |
| 4 | 14 | 120 |
| 5 | 42 | 1,680 |
| 6 | 132 | 30,240 |
| 7 | 429 | 665,280 |
| 8 | 1,430 | 17,297,280 |
| 10 | 16,796 | 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 $R_j \bowtie R_i$?):

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

$\rightarrow$ 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:

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

$\rightarrow$ 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:

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

$\longrightarrow$ 14 plans to consider.

- Overall, we looked at only **50** (sub-)plans (instead of the possible 120 four-way join plans; $\nearrow$ slide 175).
- All decisions required the evaluation of **simple** sub-plans only (no need to re-evaluate the interior of $\mathit{optPlan}(\cdot)$).

# Dynamic Programming Algorithm

**Function:** `find_join_tree_dp` $(q(R_1, \ldots, R_n))$
**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** $S \subseteq \{R_1, \ldots, R_n\}$ **such that** $|S| = i$ **do**
    $optPlan(S) \leftarrow \varnothing$ ;
    **foreach** $O \subset S$ **do**
      $optPlan(S) \leftarrow optPlan(S) \cup$
        `possible_joins` $(optPlan(O),\ optPlan(S \setminus O))$;
    `prune_plans` $(optPlan(S))$ ;
**return** $optPlan(\{R_1, \ldots, R_n\})$ ;

- `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*.

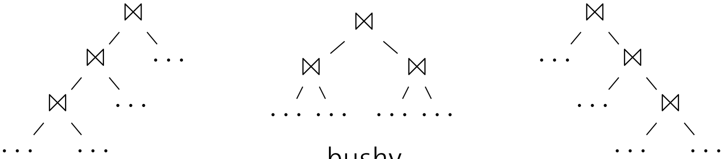
# Dynamic Programming—Discussion

- `find_join_tree_dp ()` draws its advantage from **filtering** plan candidates early in the process.
  - In our example on slide 177, 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 179 explores all possible shapes a join tree could take:



left-deep | bushy (everything else) | right-deep

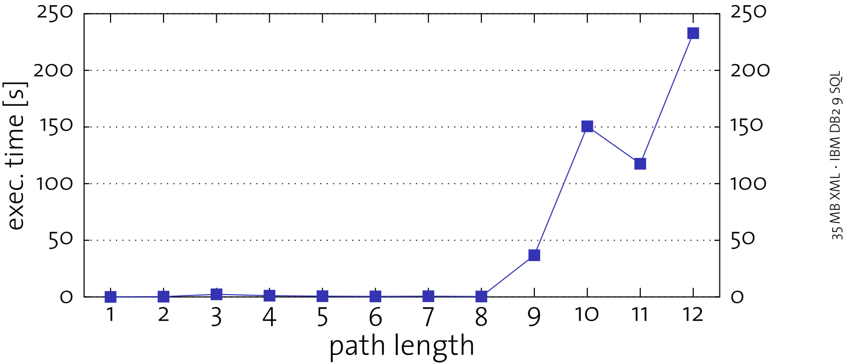
Actual systems often prefer **left-deep** join trees.[11]

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

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

# Join Order Makes a Difference

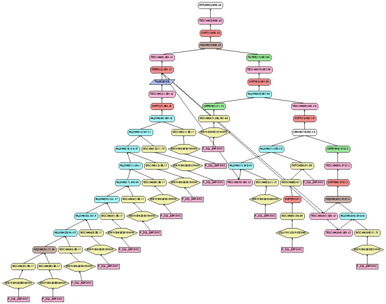
- XPath evaluation over relationally encoded XML data[12]
- *n*-way self-join with a range predicate.



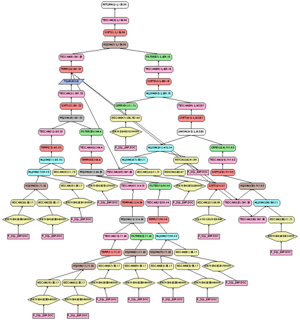

[12] ↗ Grust *et al.* Accelerating XPath Evaluation in Any RDBMS. *TODS 2004*.
`http://www.pathfinder-xquery.org/`

# 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` $(q(R_1, \ldots, R_n))$

$worklist \leftarrow \varnothing$ ;

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

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

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

  // $worklist = \{P_1, \ldots, P_i\}$

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

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

// $worklist = \{P_1\}$

**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.[13]

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 $\approx 2(N_{\texttt{ORDERS}} + N_{\texttt{LINEITEM}})$.

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

[13] 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**.

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

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 ($\rightsquigarrow$ 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...