# Query Processing 5: Query Optimization

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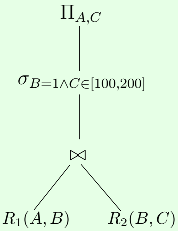
This lecture will provide an overview of **query optimization**, which is a process carried out by a database to select a query execution strategy.

## Example

Relations $R_1(A, B)$ and $R_2(B, C)$.
SQL query:

SELECT $A, C$ FROM $R, S$
WHERE $R_1.B = R_2.B$ AND $S.B = 1$ AND $S.C$ BETWEEN 100 AND 200

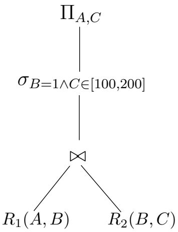
A query plan:



Before running a query plan, the database always estimates its cost.

Assume:

- $B(R_1) = B(R_2) = 10000$ (i.e., each relation has 10000 blocks).
- $R_1 \bowtie R_2$ has $B_1$ blocks.
- $\sigma_{B=1 \wedge C \in [100,200]} R_1 \bowtie R_2$ has $B_2$ blocks.
- $M = 100$ (the memory has 100 blocks).




Strategy 1:

- Compute $R_3 = R_1 \bowtie R_2$ with BNL and **materialize** $R_3$ (i.e., write $R_3$ to the disk) $\Rightarrow 10^4 + 10^6$ I/Os (BNL) $+ B_1$ (mat.).
- Compute $R_4 = \sigma_{B=1 \wedge C \in [100,200](R_3)}$ by reading $R_3$ and materialize $R_4$ $\Rightarrow B_1$ (reading) $+ B_2$ (materialization) I/Os.
- Compute $\Pi_{A,C}(R_4)$ by reading $R_4 \Rightarrow B_2$ I/Os.

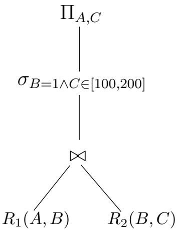
In total: $1010000 + 2(B_1 + B_2)$ I/Os.

Next, we will see several generic methods for improving the strategy.

**Method 1:** Algorithm Selection

Assume:

- $B(R_1) = B(R_2) = 10000$
- $R_1 \bowtie R_2$ has $B_1$ blocks.
- $\sigma_{B=1 \wedge C \in [100,200]} R_1 \bowtie R_2$ has $B_2$ blocks.
- $M = 100$.




Strategy 2:

- Compute $R_3 = R_1 \bowtie R_2$ with **sort join** and materialize $R_3 \Rightarrow$ $5(10^4 + 10^4)$ I/Os (**under no-skew assumption**) + $B_1$ (mat.).
- Compute $R_4 = \sigma_{B=1 \wedge C \in [100,200](R_3)}$ by reading $R_3$ and materialize $R_4$ $\Rightarrow B_1$ (reading) + $B_2$ (materialization) I/Os.
- Compute $\Pi_{A,C}(R_4)$ by reading $R_4 \Rightarrow B_2$ I/Os.

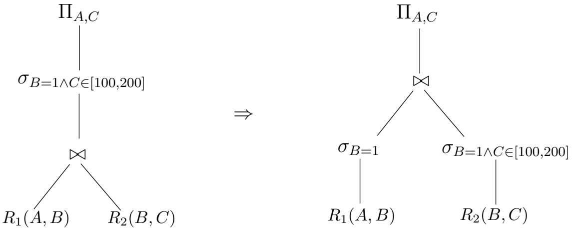
In total: $100000 + 2(B_1 + B_2)$ I/Os.

**Method 2:** Query Rewriting

Observe:

$$\begin{aligned} & \Pi_{A,C}(\sigma_{B=1 \wedge C \in [100,200]}(R_1 \bowtie R_2) \\ = \quad & \Pi_{A,C}(\sigma_{B=1}(R_1) \bowtie \sigma_{B=1 \wedge C \in [100,200]}(R_2)) \end{aligned}$$

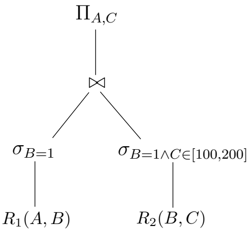
**Query rewriting** converts the original query to an equivalent query using laws of relational algebra.




**Rule of thumb:** In practice, selections are almost always pushed down as much as possible.

Assume:

- $B(R_1) = B(R_2) = 10000$
- $\sigma_{B=1} R_1$ has 1000 blocks
- $\sigma_{B=1 \wedge C \in [100,200]} R_2$ has 800 blocks
- $\sigma_{B=1 \wedge C \in [100,200]} R_1 \bowtie R_2$ has $B_2$ blocks.
- $M = 100$.




Strategy 3:

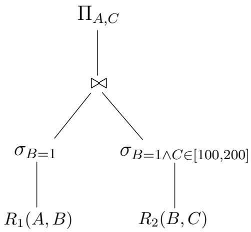
- Compute $R_3 = \sigma_{B=1} R_1$ by reading $R_1$ and materialize $R_3$ $\Rightarrow$ 10000 (reading) + 1000 (mat.) I/Os
- Compute $R_4 = \sigma_{B=1 \wedge C \in [100,200]} R_2$ by reading $R_2$ and materialize $R_4$ $\Rightarrow$ 10000 (reading) + 800 (mat.) I/Os
- Compute $R_5 = R_3 \bowtie R_4$ with sort join and materialize $R_5$ $\Rightarrow$ $5(1000 + 800)$ I/Os (under no-skew assumption) + $B_2$ (mat.).
- Compute $\Pi_{A,C}(R_5)$ by reading $R_5$ $\Rightarrow$ $B_2$ I/Os.

In total: $30800 + 2B_2$ I/Os.

**Method 3:** Applying Indexes

Assume:

- $B(R_1) = B(R_2) = 10000$
- $\sigma_{B=1} R_1$ has 1000 blocks
- $\sigma_{C \in [100,200]} R_2$ has 3000 blocks
- $R_2$ is **clustered** on $C$.
  There is a **B-tree** on $R_2.C$ with 3 levels.
- $\sigma_{B=1 \wedge C \in [100,200]} R_2$ has 800 blocks
- $\sigma_{B=1 \wedge C \in [100,200]} R_1 \bowtie R_2$ has $B_2$ blocks.
- $M = 100$.



Strategy 4:

- Compute $R_3 = \sigma_{B=1} R_1$ by reading $R_1$ and materialize $R_3$ $\Rightarrow$ 10000 (reading) + 1000 (mat.) I/Os
- Compute $R_4 = \sigma_{B=1 \wedge C \in [100,200]} R_2$ by using the B-tree on $R_2.C$ and materialize $R_4$ $\Rightarrow$ 3 (B-tree) + 3000 (retrieving $\sigma_{C \in [100,200]} R_2$) + 800 (mat.) I/Os
- Compute $R_5 = R_3 \bowtie R_4$ with sort join and materialize $R_5$ $\Rightarrow$ $5(1000 + 800)$ I/Os (under no-skew assumption) + $B_2$ (mat.).
- Compute $\Pi_{A,C}(R_5)$ by reading $R_5$ $\Rightarrow$ $B_2$ I/Os.

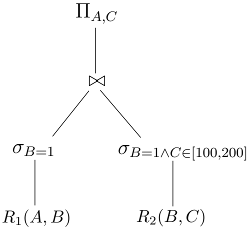
In total: $23803 + 2B_2$ I/Os.

**Method 4:** Pipelining

**Pipelining** processes multiple operations in a query plan **together**.

Assume:

- $B(R_1) = B(R_2) = 10000$
- $\sigma_{B=1} R_1$ has 1000 blocks
- $\sigma_{B=1 \wedge C \in [100,200]} R_2$ has 800 blocks
- $M = 100$.




Strategy 5:

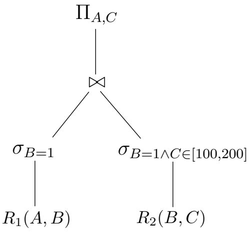
- Compute $R_3 = \sigma_{B=1} R_1$ by reading $R_1$ and materialize $R_3$
  $\Rightarrow$ 10000 (reading) + 1000 (mat.) I/Os
- Compute $R_4 = \sigma_{B=1 \wedge C \in [100,200]} R_2$ by reading $R_2$ and materialize $R_4$
  $\Rightarrow$ 10000 (reading) + 800 (mat.) I/Os
- Compute $R_5 = R_3 \bowtie R_4$ with sort join.
  **For each tuple $t \in R_5$ found in memory, output directly $t.A$.**
  $\Rightarrow 5(1000 + 800)$ I/Os (under no-skew assumption).

In total: 30800 I/Os.

Pipelining may avoid materializing intermediate results altogether, but doing so may **not** necessarily reduce the cost.

Assume:

- $B(R_1) = B(R_2) = 10000$
- $\sigma_{B=1} R_1$ has 1000 blocks. $R_1$ is **clustered** on $B$ and there is a **hash index** on $R_1.B$.
- $\sigma_{B=1 \wedge C \in [100,200]} R_2$ has $T$ tuples occupying 800 blocks
- $M = 100$.



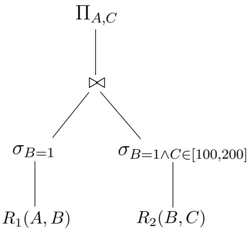

Strategy 6:

- Compute $R_3 = \sigma_{B=1 \wedge C \in [100,200]} R_2$ by reading $R_2 \Rightarrow 10000$ I/Os.
- **As soon as getting a tuple $t \in R_3$ in memory**: probe the hash index on $R_1.B$ to find all tuples $s \in \sigma_{B=1} R_1$; output $(s.A, t.C)$. $\Rightarrow |R_3| \cdot 1000$ I/Os.

In total: $10000 + 10000|R_3|$ I/Os.

Assume:

- $B(R_1) = B(R_2) = 10000$
- $\sigma_{B=1} R_1$ has 1000 blocks. $R_1$ is **clustered** on $B$ and there is a **hash index** on $R_1.B$.
- $\sigma_{B=1 \wedge C \in [100,200]} R_2$ has 800 blocks
- $M = 100$.




Strategy 7:

- Compute $R_3 = \sigma_{B=1 \wedge C \in [100,200]} R_2$ by reading $R_2 \Rightarrow 10000$ I/Os.
- **Every time we have accumulated 99 blocks of new tuples of $R_3$ in memory**, probe the hash index on $R_1.B$ to find $R_4 = \sigma_{B=1} R_1$; output $(s.A, t.C)$ for each $t \in R_3$ in memory and every $s \in R_4$ $\Rightarrow \lceil 800/99 \rceil \cdot 1000 = 9000$ I/Os.

In total: 19000 I/Os.

Query optimization is an art. It is an active research area.

The methods we discussed are representative but far from being comprehensive. The query optimization module of a database system is a highly sophisticated and often kept as a commercial secret.