CSE 232A
Graduate Database Systems

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Topic 4: Query Optimization

Chapters 12 and 15 of Cow Book

Slide ACKs: Jignesh Patel, Paris Koutris
Lifecycle of a Query

Database Server

Parser → Optimizer → Query Scheduler → Execute Operators

Query Result

Segments

Syntax Tree and Logical Query Plan → Physical Query Plan
## Recall the Netflix Schema

### Ratings

<table>
<thead>
<tr>
<th>RatingID</th>
<th>Stars</th>
<th>RateDate</th>
<th>UID</th>
<th>MID</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.5</td>
<td>08/27/15</td>
<td>79</td>
<td>20</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

### Users

<table>
<thead>
<tr>
<th>UID</th>
<th>Name</th>
<th>Age</th>
<th>JoinDate</th>
</tr>
</thead>
<tbody>
<tr>
<td>79</td>
<td>Alice</td>
<td>23</td>
<td>01/10/13</td>
</tr>
<tr>
<td>80</td>
<td>Bob</td>
<td>41</td>
<td>05/10/13</td>
</tr>
</tbody>
</table>

### Movies

<table>
<thead>
<tr>
<th>MID</th>
<th>Name</th>
<th>Year</th>
<th>Director</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Inception</td>
<td>2010</td>
<td>Christopher Nolan</td>
</tr>
<tr>
<td>16</td>
<td>Avatar</td>
<td>2009</td>
<td>Jim Cameron</td>
</tr>
</tbody>
</table>
Example SQL Query

```sql
SELECT M.Year, COUNT(*) AS NumBest
FROM Ratings R, Movies M
WHERE R.MID = M.MID
    AND R.Stars = 5
GROUP BY M.Year
ORDER BY NumBest DESC
```

Suppose, we also have a B+Tree Index on Ratings (Stars)
Logical Query Plan

Called “Logical” Operators

From extended RA

Each one has alternate “physical” implementations
Indexed Access
Use Index on Stars

Movies Table

File Scan
Read heapfile

Result Table

External Merge-Sort
In-mem quicksort; B=50

Sort-based
Aggregate

Index-Nested
Loop Join

Physical Query Plan

Called “Physical” Operators
Specifies exact algorithm/code to run for each logical operator, with all parameters (if any)

Aka “Query Evaluation Plan”
This is also a correct PQP for the given LQP!

Q: Which PQP is faster?

This is a key job of the RDBMS Query Optimizer!
So, what is query optimization and how does it work?
Meet Query Optimization

Basic Idea: A given LQP could have several possible PQPs with very different runtime performance.

Goal (Ideal): Get the optimal (fastest) PQP for a given LQP.

Goal (Realistic): Find a PQP that is not a clearly awful PQP.

Jeff Naughton

Query optimization is a metaphor for life itself! It is often hard to even know what an optimal plan would be, but it is feasible to avoid many obviously bad plans!
Query Optimization

❖ Overview of Query Optimizer
❖ Physical Query Plan (PQP)
  Concept: Pipelining
  Mechanism: Iterator Interface
❖ Enumerating Alternative PQPs
  Logical: Algebraic Rewrites
❖ Costing PQPs
❖ Materialized Views
Overview of Query Optimizer

SQL Query

Parser

Logical Query Plan

Plan Enumerator

Plan Cost Estimator

Optimizer

Catalog

Physical Query Plan (Optimized)

To Scheduler/Executor
System Catalog

- Set of pre-defined relations for metadata about DB (schema)
- For each **Relation**:  
  Relation name, File name  
  File structure (heap file vs. clustered B+ tree, etc.)  
  Attribute names and types; Integrity constraints; Indexes
- For each **Index**:  
  Index name, Structure (B+ tree vs. hash, etc.); Index key
- For each **View**:  
  View name, and View definition
Statistics in the System Catalog

❖ RDBMS periodically collects stats about DB (instance)
❖ For each **Table R**: 
  Cardinality, i.e., number of tuples, **NTuples (R)**
  Size, i.e., number of pages, **NPages (R)**, or just **N_R**
❖ For each **Index X**: 
  Cardinality, i.e., number of distinct keys **IKeys (X)**
  Size, i.e., number of pages **IPages (X)** (for a B+ tree, this is the number of leaf pages only)
  Height (for tree indexes) **IHeight (X)**
  Min and max keys in index **ILow (X), IHigh (X)**
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Q: Does the hash-based aggregate have to wait till the entire output of the “upstream” hash join is available?

No! We can “pipeline” the output of the join – pass on a join output tuple as soon as it is obtained!
Concept: Pipelining

Basic Idea:
Do not force “downstream” physical operators to wait till the entire output is available

Benefits:
Display output to the user incrementally

CPU Parallelism in multi-core systems!

Tuples

File Scan
Hash Join
Hash-based Aggregate
Concept: Pipelining

❖ Crucial for PQPs with workflow of many phy. ops.
❖ Common feature of almost all RDBMSs
❖ Works for many operators: SCAN, HASH JOIN, etc.

Q: Are all physical operators amenable to pipelining?

No! Some may “stall” the pipeline: “Blocking Op”

A blocking op. requires its output to be Materialized as a temporary table

Usually, any phy. op. involving sorting is blocking!
This phy. op. is blocking because we need to sort Movies and sort Ratings (materialize the output) before we can start any aggregate computations!
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Mechanism: Iterator Interface

- Software API to process PQP; makes pipelining easy to impl.
- Enables us to abstract away individual phy. op. impl. details
- Three main functions in usage interface of each phy. op.:
  - **Open()**: Initialize the phy. op. “state”, get arguments
    - Allocate input and output buffers
  - **GetNext()**: Ask the phy. op. impl. to “deliver” next
    - output tuple; pass it on; if blocking, wait
  - **Close()**: Clear phy. op. state, free up space
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SQL Query

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Plan Cost Estimator

Optimizer

Catalog

Physical Query Plan (Optimized)

To Scheduler/Executor
Enumerating Alternative PQPs

- Plan Enumerator explores various PQPs for a given LQP
- **Challenge**: Space of plans is huge! How to make it feasible?
- RDBMS Plan Enumerator has **Rules** to help determine what plans to enumerate, and also consults **Cost models**
- Two main sources of Rules for enumerating plans:
  - **Logical**: Algebraic Rewrites:
    Use relational algebra **equivalence** to rewrite LQP itself!
    Use different phy. op. impl. for a given log. op. in LQP
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Rewrite a given RA query in to another that is equivalent (a logical property) but might be faster (a physical property)

RA operators have some formal properties we can exploit

We will cover only a few rewrite rules:

**Single-operator** Rewrites
- **Unary** operators
- **Binary** operators

**Cross-operator** Rewrites
Unary Operator Rewrites

- Key unary operators in RA: $\sigma \quad \pi$
- Commutativity of $\sigma$

$$\sigma_{p_1}(\sigma_{p_2}(R)) = \sigma_{p_2}(\sigma_{p_1}(R))$$

- Cascading of $\sigma$

$$\sigma_{p_1}(\sigma_{p_2}(\ldots \sigma_{p_n}(R) \ldots )) = \sigma_{p_1 \land p_2 \land \ldots \land p_n}(R)$$

- Cascading of $\pi$

$$A_i \subseteq A_{i+1} \forall i = 1 \ldots (n - 1)$$

$$\pi_{A_1}(\pi_{A_2}(\ldots \pi_{A_n}(R) \ldots )) = \pi_{A_1}(R)$$

Q: Why are cascading rewrites beneficial?
Binary Operator Rewrites

❖ Key binary operator in RA: ▲

❖ Commutativity of ▲  \( R \bowtie S = S \bowtie R \)

❖ Associativity of ▲  \( (R \bowtie S) \bowtie T = R \bowtie (S \bowtie T) \)

**Q:** Why are these properties beneficial?

**Q:** What other binary operators in RA satisfy these?
Cross-Operator Rewrites

❖ Commuting $\sigma$ and $\pi$

\[
\sigma_{p(A)}(\pi_B(R)) = \pi_B(\sigma_{p(A)}(R))
\]

❖ Combining $\sigma$ and $\times$

\[
\sigma_p(R \times S) = R \bowtie_p S
\]

❖ “Pushing the select”

\[
\sigma_{p(A)}(R \bowtie S) = \sigma_{p(A)}(R) \bowtie S
\]
\[
\sigma_{p(A)}(R \times S) = \sigma_{p(A)}(R) \times S
\]

❖ Commuting $\pi$ with $\times$ and $\bowtie$

\[
\pi_A(R \times S) = \pi_{A \cap R.*}(R) \times \pi_{A \cap S.*}(S)
\]
\[
\pi_A(R \bowtie_{p(B)} S) = \pi_{A \cap R.*}(R) \bowtie_{p(B)} \pi_{A \cap S.*}(S)
\]
Review Question

Which of the following hold?

\[ \pi_A(R \times S) = \pi_A(R) \times S \quad A \subseteq R \]

\[ \pi_A\left( R \bowtie_{p(B)} S \right) = \pi_A(\pi_{C \cap R}(R) \bowtie_{p(B)} \pi_{C \cap S}(S)) \quad C = A \cup B \]

\[ \sigma_{p_1 \land p_2 \lor p_3}(R) = \sigma_{p_1}(R) \cap \sigma_{p_2}(R) \cup \sigma_{p_3}(R) \quad A \subseteq R \text{ and } B \subseteq S \]

\[ \sigma_{p(A) \land q(B)}(R \bowtie S) = \sigma_{p(A)}(R) \bowtie \sigma_{q(B)}(S) \]
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- Materialized Views

- Given a (rewritten) LQP, pick phy. op. impl. for each log. op.
- Recall various RA op. impl. with their I/O (and CPU costs)

\[
\begin{align*}
\sigma & \quad \text{File scan vs Indexed (B+ Tree vs Hash)} \\
\pi & \quad \text{Hashing-based vs Sorting-based vs Indexed} \\
\bowtie & \quad \text{BNLJ vs INLJ vs SMJ vs HJ} \\
\text{etc.}
\end{align*}
\]

\[
\pi_B(\sigma_{p(A)}(R) \bowtie S)
\]

3 options 3 options 4 options = 36 PQPs!

Q: With algebraic rewrites?!

- Are the indexes clustered or unclustered?
- Are there multiple matching indexes? Use multiple?
- Are index-only access paths possible for some ops?
- Are there “interesting orderings” among the inputs?
- Would sorted outputs benefit downstream ops?
- Estimation of cardinality of intermediate results!
- How best to reorder multi-table joins?

Query optimizers are complex beasts! Still a hard, open research problem!

- Since joins are associative, exponential number of orderings!

\[ R \bowtie S \bowtie T \bowtie U \]

- Left Deep tree
- Right Deep tree
- "Bushy" tree

- Almost all RDBMSs consider only left deep join trees
  Enables easy pipelining! Why?
- “Interesting orderings” idea from System R optimizer paper
- Dynamic program to combine enumeration and costing

“Access Path Selection in a Relational Database Management System” SIGMOD’79
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Overview of Query Optimizer

SQL Query → Parser → Logical Query Plan → Plan Enumerator → Plan Cost Estimator → Optimizer → Physical Query Plan (Optimized) → To Scheduler/Executor
Costing PQPs

❖ For each PQP considered by the Plan Enumerator, the Plan Cost Estimator computes “Cost” of the PQP
   Weighted sum of I/O cost and CPU cost
   (Distributed RDBMSs also include Network cost)
❖ Challenge: Given a PQP, compute overall cost
❖ Issues to consider:
   Pipelining vs. blocking ops; cannot simply add costs!
   Cardinality estimation for intermediate tables!
   Q: What statistics does the catalog have to help?
Costing PQPs

❖ Most RDBMSs use various heuristics to make costing tractable; so, it is approximate!

❖ **Example:** Complex predicates

\[ \sigma_{p_1 \land p_2}(R) \]

Suppose selectivity of \( p_1 \) is 5% and selectivity of \( p_2 \) is 10%

Q. **What is the selectivity of** \( p_1 \land p_2 \)?

Not enough info!

But, most RDBMSs use the **independence** heuristic!

Selectivity of conjunction = Product of selectivities

Thus, \( \approx 0.05 \times 0.1 = 0.005 \), i.e., 0.5%
Plan Enumerator and Cost Estimator work in lock step:

**Rules** determine what PQPs are enumerated
- Logical: Algebraic rewrites of LQP
- Physical: Op. Impl. and ordering alternatives

**Cost models** and **heuristics** help cost the PQPs

Still an active research area!

- Parametric Q.O., Multi-objective Q.O.,
- Multi-objective parametric Q.O., Multiple Q.O.,
- Online/Adaptive Q.O., Dynamic re-optimization, etc.
### Review Question

<table>
<thead>
<tr>
<th>RatingID</th>
<th>Stars</th>
<th>RateDate</th>
<th>UID</th>
<th>MID</th>
</tr>
</thead>
</table>

Page size 8KB; Buffer memory 4GB; 8B for each field

```sql
SELECT COUNT(DISTINCT UID) FROM Ratings
```

Propose an efficient physical plan and compute its I/O cost.

**Q:** What if there was an unclustered B+ tree index on UID? *(RecordID pointers can be assumed to be 8B too)*
SELECT \( \text{AVG}(\text{Stars}) \) FROM Ratings R, Movies M
WHERE R.MID = M.MID AND
M.Director = "Christopher Nolan" AND
R.UID = 1234;

Propose an efficient physical plan that does not materialize any intermediate data (fully pipelined) and compute its I/O cost.
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Introducing Materialized Views

- **A View** is a “virtual table” created with an SQL query
- **A Materialized View** is a physically instantiated/stored view

<table>
<thead>
<tr>
<th>RatingID</th>
<th>Stars</th>
<th>RateDate</th>
<th>UID</th>
<th>MID</th>
</tr>
</thead>
<tbody>
<tr>
<td>UID</td>
<td>Name</td>
<td>Age</td>
<td>JoinDate</td>
<td>MID</td>
</tr>
</tbody>
</table>

**Example:**

```sql
SELECT AVG(Stars)
FROM Ratings R, Movies M, Users U
WHERE R.MID = M.MID AND R.UID = U.UID
AND M.Director = "Christopher Nolan"
AND U.Age >= 20 AND U.Age < 30;
```

\[
AVG(Stars) \left( \sigma_{\text{Director} = "Christopher Nolan"}(M) \otimes \sigma_{20 \leq \text{Age} < 30}(U) \right)
\]

Requires file scans of R, M, and U and, say, hash joins
Materialized Views Example

Example: | RatingID | Stars | RateDate | UID | MID |
----------|--------|---------|------|-----|
          |        |         |      |     |

| UID | Name | Age | JoinDate | MID | Name | Year | Director |
----------|------|-----|----------|-----|------|-------|----------|

$\gamma_{\text{AVG}(\text{Stars})}(R \bowtie \sigma_{\text{Director} = \text{“Christopher Nolan”}}(M) \bowtie \sigma_{20 \leq \text{Age} < 30}(U))$

CREATE MATERIALIZED VIEW NolanRatings AS
SELECT RatingID, Stars, UID, MID
FROM Ratings R, Movies M
WHERE R.MID = M.MID AND
      M.Director = “Christopher Nolan”;

Creates a subset of R with ratings for only Nolan’s movies

$V \leftarrow \pi_{\text{RatingID, Stars, UID, MID}}(R \bowtie \sigma_{\text{Director} = \text{“Christopher Nolan”}}(M))$
Materialized Views Example

Example:

<table>
<thead>
<tr>
<th>RatingID</th>
<th>Stars</th>
<th>RateDate</th>
<th>UID</th>
<th>MID</th>
</tr>
</thead>
<tbody>
<tr>
<td>UID</td>
<td>Name</td>
<td>Age</td>
<td>JoinDate</td>
<td>MID</td>
</tr>
</tbody>
</table>

\[
\gamma_{AVG(Stars)} (R \bowtie \sigma_{Director=\text{“Christopher Nolan”}} (M) \bowtie \sigma_{20 \leq Age < 30} (U))
\]

Given the materialized view \( V \), RDBMS optimizer can automatically \textit{rewrite} to use \( V \) to avoid scans of \( R \) and \( M \)

\[
V \leftarrow \pi_{RatingID,Stars,UID,MID} (R \bowtie \sigma_{Director=\text{“Christopher Nolan”}} (M))
\]

\[
\gamma_{AVG(Stars)} (V \bowtie \sigma_{20 \leq Age < 30} (U))
\]

Likely much faster since \( V \) is likely much smaller than \( R \), but this depends on data statistics; leave it to optimizer!

\textbf{Q: How did DBA know to materialize a view for Nolan ratings?}
Materialized View Maintenance

Example:

<table>
<thead>
<tr>
<th>RatingID</th>
<th>Stars</th>
<th>RateDate</th>
<th>UID</th>
<th>MID</th>
<th>UID</th>
<th>Name</th>
<th>Age</th>
<th>JoinDate</th>
<th>MID</th>
<th>Name</th>
<th>Year</th>
<th>Director</th>
</tr>
</thead>
</table>

We are given this materialized view $V$ over $R$ and $M$

$$V ← \pi_{RatingID, Stars, UID, MID}(R \bowtie \sigma_{Director=“Christopher Nolan”}(M))$$

**Q:** What if new ratings are inserted to $R$ for Nolan’s movies?

- RDBMS will automatically “trigger” updates to $V$
- Such updates are called **Materialized View Maintenance**
- 2 alternatives: Recompute whole view from scratch vs **Incremental View Maintenance** (IVM)
Recomputing V from scratch may be an overkill. Try to *incrementally* update parts that change.

\[ V = Q(D) \quad V' = Q(D') \]

- D’ can be the outcome of inserts and/or deletes to D
- Q can be a unary query or involve multiple tables
- Computing V’ may require inserts and/or deletes to V; realized as *algebraic rewrite rules* at LQP level
- Whether or not IVM of V is feasible and/or efficient depends on form of Q, nature of updates to D, data statistics, etc.
- We will focus only on inserts to D triggering inserts to V
Incremental View Maintenance (IVM)

Unary IVM for insertions:

\[ R' = R \cup \Delta R \]

Newly inserted tuples

Select:

\[ V \leftarrow \sigma_{\text{SelectCondition}}(R) \]

\[ V' = V \cup \sigma_{\text{SelectCondition}}(\Delta R) \]

Can be just an append (union with “bag” semantics)

Project:

\[ V \leftarrow \pi_{\text{ProjectionList}}(R) \]

\[ V' = V \cup \pi_{\text{ProjectionList}}(\Delta R) \]

Requires full set union with V for deduplication

Select and Project can be composed and reordered as before
Incremental View Maintenance (IVM)

Unary IVM for insertions:

\[ R' = R \cup \Delta R \quad \text{Newly inserted tuples} \]

Group By Agg:

\[ V \leftarrow \gamma_{\text{AggList,Agg}(Y)}(R) \]

Feasibility of IVM Depends on Agg() function!

Rewrite rules exist for SUM, COUNT, and MIN/MAX over bags

AVG not possible in general; needs deeper system changes

\[ V' = \gamma_{\text{AggList},\text{SUM}(Y)}(V \cup \gamma_{\text{AggList},\text{SUM}(Y)} \Delta R) \]

\[ V' = \gamma_{\text{AggList},\text{SUM}(Y)}(V \cup \gamma_{\text{AggList},\text{COUNT}(Y)} \Delta R) \]

\[ V' = \gamma_{\text{AggList},\text{MIN}(Y)}(V \cup \gamma_{\text{AggList},\text{MIN}(Y)} \Delta R) \]
Incremental View Maintenance (IVM)

Join IVM for insertions:

\[ V \leftarrow A \bowtie B \]

Assume no duplicate inserts

\[ A' = A \cup \Delta A \]
\[ B' = B \cup \Delta B \]

\[ V' = V \cup (\Delta A \bowtie B') \cup (A' \bowtie \Delta B) \]

Alternatively, we can just append the output of the following query to \( V \) (union below is just append too):

\[ (\Delta A \bowtie B') \cup (A' \bowtie \Delta B) \setminus (\Delta A \bowtie \Delta B) \]

IVM for complex queries compose such op-level rewrites
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