PLAN SELECTION
based on
QUERY CLUSTERING

Antara Ghosh  Jignashu Parikh  Vibhuti Sengar
Jayant Haritsa

Computer Science & Automation
Indian Institute of Science
Bangalore, INDIA
THANKS TO

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TALK ORGANIZATION

• Overview
• Details
  – Query Feature Vector
  – Query Similarity
  – Query Clustering
• Performance Study
• Applicability of PLASTIC
• Closing Remarks
Query Plan Generation

- Standard technique

  Query (Q) \xrightarrow{\text{Query Optimizer}} \text{Plan } P(Q)

  DB stats \uparrow \quad \text{Cost Model} \quad \downarrow

- Computationally expensive since large number of plan candidates for queries
- Difference between right choice of plan and a sub-optimal choice can be enormous
Reduction of Optimization Overhead

- Plan Cacheing
  - Exact Match: Current commercial optimizers
    - E.g. Oracle’s Stored_Outlines
    - Very limited scope
  - Similarity Match:
    PLASTIC (PLAn Selection Through Incremental Clustering)
    - Based on query clustering
    - Deals with plan templates, not plans (a plan template is the operator tree with variables for the operands – relations/attributes)
    - Facilitates plan sharing

Query Space  Plan Space
Major Benefits of Similarity Approach

- Significant improvements in optimization time due to broad-based plan reuse
- Improvements to the plan associated with the cluster representative (e.g. Plan Hints) automatically percolate to all cluster members
  - Makes it affordable to run optimizers at their highest optimization level since only cluster representatives have to be explicitly optimized
  - Reduces workload on DBAs
- Data updates are automatically reflected in change of plans due to changes in cluster assignments
Motivating Query

Select
    s_acctbal, s_name, n_name, p_partkey,
    p_mfgr, s_address, s_phone, s_comment
From
    part p, supplier s, partsupp ps, nation n, region r
Where
    p_partkey = ps_partkey and
    s_suppkey = ps_suppkey and
    p_size := :1 and p_type like :2 and
    s_nationkey = n_nationkey and
    n_regionkey = r_regionkey and
    r_name := :3 and ps_supplycost := :4
Associated Plan Diagram

Note: 80% of space occupied by 20% of the Plans
Query Clustering (First Cut)

- Cluster Definition: Two queries belong to the same cluster if their plan templates are the same.
- Problem: queries that are very different may have the same plan template.
  - Results in heterogeneous clusters making it difficult to classify new queries.
Different looking Queries - Similar Plan Templates

```
select a.firstname, a.lastname, b.projno, c.resume
from employee as a, emp_act as b, emp_resume as c
where a.empno=b.empno and b.empno=c.empno
and a.empno>'000000' and b.empno<'000400' and c.empno between '000010' and '000390'
```

```
select * 
from employee as a, emp_act as b, emp_photo as c
where a.empno=b.empno and b.empno=c.empno and a.empno>'000000' and b.empno<'000400' and c.empno between '000010' and '000390'
```
Observation

Clustering in Plan Space makes Classification in Query Space difficult …
Query Clustering: PLASTIC Approach

- Cluster Definition: Two queries belong to the same cluster if their Feature Vectors in Query Space are similar
  - Feature vectors have structural + statistical components (explained later)
  - Each cluster is defined by a single representative query
  - Clustering in Query Space may result in multiple clusters mapping to the same plan template
Cluster Diagram for Sample Query
THE PLASTIC SCHEME

Query (Q) → Feature Vector → Sim Check → DecTree → Plan p(qi)

Seed queries → Query Optimizer

q1, p(q1)
q2, p(q2)
...
qk, p(qk)
Proposed Optimizer Architecture
Proposed Optimizer Architecture

- **System Catalogs**
- **Feature Vector Extractor**
- **Query Optimizer**
  - **Query Cluster Database**
    - **Cluster Reorganization**
    - **Similarity Check**
      - **Feature Vector**
      - **No Match**
      - **Match Cluster Id**
- **Plan Template Generator**
- **Plan Template Database**
- **Plan Generator**
- **Plan**

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PLASTIC Presentation (VLDB)
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Query Feature Vector

- **Two components**
  - **Structural Features**
    - Determined from the query and DB schema catalogs
  - **Statistical Features**
    - Derived from DB statistics module

- **Feature selection based on**
  - study of query optimization literature
  - characteristics of plans generated by commercial optimizers
  - not involving computation of any plan specific information
  - not requiring additional inputs beyond those already available to the optimizer
Structural Features (per Table)

• **Degree of the Table (DT)**
  - No. of Join Predicates in which the table is involved

• **Join Predicate Index Counts (JIC)**
  - \[ JIC[k] = \text{Number of join predicates (in which the table participates)} \]
    
    having \( k \) indexed attributes in the join predicate
    
    \( k = 0, 1 \text{ or } 2 \)

• **Predicate Counts of a Table (PC)**
  - Count of SARGable and Non-SARGable predicates in which the table is involved

• **Index Flag of a Table (IF)**
  - Set if all the selection attributes and projections on that table can be evaluated through indexes only (i.e., Required information can be obtained solely from the indexes without accessing the actual data tables)
Statistical Features (per Table)

- **Table Size (TS)**
  - Total size (disk occupancy) of the table

- **Effective Table Size (ETS)**
  - Calculated by estimating the impact of pushing down all the projections and selections on the table in the query
Example Feature Vector

Select A.a1,B.b1 from A, B  
Where A.a1 = B.b2 and A.a2 >100 and B.b3 <25

- Combined index on (a1,a2) of Table A
- Index on b2 of Table B
- A2 > 100 has selectivity 0.5
- B3 < 25 has selectivity .005
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Step 1: Structural Comparison

- Equality Checks based on Aggregate Structural Features like
  - Number of tables participating in the query
    - Obvious
  - Degree Sequence (Vector of Table Degrees)
    - Should be same else the plan templates will perforce be different
  - Sum of Index flags
    - Data gathering differs based on flag setting
Step 2: Statistical Similarity (Mapping Tables)

- Query 1 has R1 and R2
- Query 2 has S1 and S2
- Could map R1 to S1 and R2 to S2 or R1 to S2 and R2 to S1

- N! possibilities
  - Reduced by grouping tables with identical structural features and considering only intra-group mappings
Table Distance Function

\[ dist_{ij}(T_i^k, T_j^l) = \frac{w_1(TS_i^k - TS_j^l) + w_2(ETS_i^k - ETS_j^l)}{\max(TS_i^k, TS_j^l)}, \]

- Tables are numbered according to mapping
- \( TS_k^i = \) Table size of \( i^{th} \) Table of Query \( k \)
- \( ETS_k^i = \) Estimated Table size of \( i^{th} \) Table of Query \( k \)
- \( w_1 \) and \( w_2 \) are weights
  - \( w_1, w_2 \in [0,1] \) and \( w_2 = 1-w_1 \)
- Normalization ensures \( dist_{ij} \) is in \((0,1)\)
- After all mappings (within the group) are evaluated the mapping with the \textit{mindist} (minimum aggregate value of \( dist \)) is selected
Query Distance Function

- Let $\text{mindist}_g$ be the distance between the $g^{th}$ group mapping between two queries.

$$\text{TotalDist} = \sum_{g \in G} \text{mindist}_g$$

- Queries are similar only if $\text{TotalDist}$ is less than a predefined $\text{Threshold}$. 

Distance Function Design

- Our investigation of plan choices by optimizers indicates that, given structural compatibility, TS and ETS play a crucial role in determining the plan choices.
- Choices of $w_1$ and $w_2$ determine the relative impacts of TS and ETS.
- Threshold determines the stretch of individual clusters. Lower threshold values result in:
  - smaller percentage of error-causing clusters (i.e. clusters straddling plan boundaries in the plan diagram),
  - larger number of clusters increases the search space for classification.
Similarity Examples

Q1: select * from nation, region
   where
   n_nationkey=r_regionkey
Q2: select n_nationkey
     from nation, region
     where n_nationkey =
     r_regionkey
Q3: select n_comment, r_comment
     from nation, region

- DB2 produces different plans for Q1
  and Q2 although they look similar!!
- Same plan for both these queries Q1
  and Q3 although they seem different!
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Leader Algorithm [Hartigan 1975]

- Algorithm:
  - Match a query with existing cluster leaders and if no match is found, make the query a new leader.
- Leader is an incremental algorithm and we therefore use it for classification also
- Classification becomes slow if large number of clusters
  - Inducing a decision tree on the clusters reduces this problem substantially
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Metrics

- **Prediction Efficiency**
  - Time required for predictions
- **Prediction Accuracy**
  - How often do we guess right?
- **Prediction Risk Factor**
  - Penalty for wrong choices
- **Plan Cache Space Overhead**
  - Storage required by query representatives and their plans
Testbed

- **DBMS:** DB2 Universal Database Version 7
  - Default optimization class of DB2 (level 5)

- **PLATFORM:** P-III / Windows 2000 machine

- **DATABASE:** TPC-H database on scale 1 (1GB)

- **QUERIES:** Simplified (pure SPJ) versions of TPC-H Queries

- **ASSUMPTIONS**
  - Queries are uniformly distributed over the selectivity space (limited to 2D)
  - Static resource configuration
Clustering on Example Query (Q2')

Select

\[ s\_acctbal, s\_name, n\_name, p\_partkey, p\_mfg, s\_add, s\_phone, s\_comment \]

From

\[ part p, supplier s, partsupp ps, nation n, region r \]

Where

\[ p\_partkey = ps\_partkey \text{ and } s\_suppkey = ps\_suppkey \text{ and } p\_size := :1 \text{ and } p\_type \text{ like } :2 \text{ and } s\_nationkey = n\_nationkey \text{ and } n\_regionkey = r\_regionkey \text{ and } r\_name := :3 \text{ and } ps\_supplycost := :4 \]

65 Clusters Generated with Threshold value of 0.01
\[ W_1 = 0.7 \text{ and } W_2 = 0.3 \]
P-DB2 Performance on Example Query

<table>
<thead>
<tr>
<th>Metric</th>
<th>DB2</th>
<th>P-DB2 Leader</th>
<th>P-DB2 Decision Tree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>100%</td>
<td>90.76%</td>
<td>88.8%</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.1s</td>
<td>0.004s</td>
<td>0.00025s</td>
</tr>
<tr>
<td>Space</td>
<td>-</td>
<td>1.97KB</td>
<td>3.96KB</td>
</tr>
</tbody>
</table>

Risk Factor

<table>
<thead>
<tr>
<th>Error Case</th>
<th>DB2 Cost timeron</th>
<th>P-DB2 Cost timeron</th>
<th>Risk Factor (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>261209</td>
<td>266260</td>
<td>1.9</td>
</tr>
<tr>
<td>2</td>
<td>241054</td>
<td>246000</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>173913</td>
<td>188684</td>
<td>1.1</td>
</tr>
<tr>
<td>4</td>
<td>158577</td>
<td>158681</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>161814</td>
<td>159078</td>
<td>-0.02</td>
</tr>
</tbody>
</table>
Summary of Results

- For SPJ queries and static resource availability, PLASTIC provides x10 improvement in query optimization time with 90% accuracy in correct plan prediction.
- Mistakes are not expensive since they occur on plan boundaries ( < 10% error penalty )
- Space overhead is miniscule
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Inter-query Plan Sharing

• PLASTIC works across queries with
  – Different Selection Predicates
  – Different Projection Attributes
  – Different Join Attributes
  – Different Tables

• PLASTIC broadens the scope of plan sharing beyond mere syntactic matching
Example (Different Join Attributes)

Select l_extendedprice, l_discount
From customer, orders, lineitem, supplier, nation, region
Where
    c_custkey = o_orderkey
and L_COMMITDATE = O_ORDERDATE
and l_suppkey = s_suppkey
and c_nationkey = s_nationkey
and s_nationkey = n_nationkey
and n_regionkey = r_regionkey
and r_name = 'AFRICA'
and o_orderdate >= date ('1997-01-01')
and year(o_orderdate) < (year ('1997-01-01')+1);
Example (Different Join Attributes)

Select l_extendedprice, l_discount
From customer, orders, lineitem, supplier, nation, region
Where

  c_custkey = o_orderkey
and L_COMMITDATE = O_ORDERDATE
and l_suppkey = s_suppkey
and c_nationkey = s_nationkey
and s_nationkey = n_nationkey
and n_regionkey = r_regionkey
and r_name = 'AFRICA'
and o_orderdate >= date ('1997-01-01')
and year(o_orderdate) < (year ('1997-01-01')+1);
Example (Different Join Attributes)

Select `l_extendedprice`, `l_discount`  
From `customer`, `orders`, `lineitem`, `supplier`, `nation`, `region`  
Where  
  `c_custkey` = `o_orderkey`  
  and `L_SHIPDATE` = `O_ORDERDATE`  
  and `l_suppkey` = `s_suppkey`  
  and `c_nationkey` = `s_nationkey`  
  and `s_nationkey` = `n_nationkey`  
  and `n_regionkey` = `r_regionkey`  
  and `r_name` = 'AFRICA'  
  and `o_orderdate` >= date('1997-01-01')  
  and `year(o_orderdate)` < (`year('1997-01-01')`+1);

• No change in plan generated by DB2
• PLASTIC correctly identifies this since the Join Index Counts in both queries remain same
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Future Work

- Need to extend PLASTIC to
  - handle correlated nested queries, as well as GROUP BY and HAVING clauses
  - handle changes in the system resource availability between training and operational stages

- Variable-sized clusters
  - Error varies with table selectivities
  - Cluster sizes should thus be made sensitive to selectivities

- Automated parameter settings \((w_1, w_2 \text{ and } T)\)
Comparison with Related Work

- **Unlike MQO**
  - No attempt to *optimize* Queries
  - Instead, we aim to *reuse* previous optimization results
  - PLASTIC’s plan selection is not specific to a temporal window of queries

- **Unlike PQO**
  - We do not try to characterize the plan space for a given query
  - Our approach extends to *sharing* of plans across similar queries
Take Away

- PLASTIC significantly increases the scope of “plan recycling”, thereby substantially improving the utility of plan caching.

- A query optimizer’s best friend.