# Automated Selection of Materialized Views and Indexes for SQL Databases

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# **Review : Materialized Views**

• A <u>materialized view</u> is a view whose contents are computed and stored.

Example : Consider the view create view branch\_total\_loan(branch\_name, total\_loan) as select branch\_name, sum(amount) from loan group by branch\_name

- Materializing the above view would be very useful if the total loan amount is required frequently
- Materialized views may also be indexed.
- The join results are computed once (or as often as you refresh your materialized view), rather than each time you select from the materialized view.

# Motivation

- Selecting appropriate set of Indexes and Materialized views influenced by workload of the system.
- A workload consists of a set of SQL data manipulation statements.

• DBA have to administer manually – create indexes, materialized views, indexes on materialized views for performance tuning

Such an approach is

- 1) Time Consuming
- 2) Error Prone
- 3) Might not be able to handle continuosly changing or growing workloads

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# Motivation Example

Consider an Online game which store the records of players in a table LeaderBoard(player\_id,region,score,timestamp)

Mv\_1 : Select max(score) from LeaderBoard;

Mv\_2 : Select region , max(score) from LeaderBoard Group By region;

Mv\_3: Select region, sum(score), max(score) from LeaderBoard Group BY region;

Mv\_4 : Select Top 10 players on the leaderboard

To answer the following queries :

- Current maximum score
   Mv\_1, Mv\_2, Mv\_3
   maximum score of region 'A'
   Mv\_2, Mv\_3
- 3) region with overall best total score Mv 3

# Introduction

- Both indexes and materialized views are fundamentally similar both are redundant structures that speed up query execution.
- Index can logically be considered as single-table, projection only materialized view.

• Though they are similar but a materialized view may be defined over multiple tables, and can have selections and GROUP BY over multiple columns.

• Need for efficient ways for dealing with the large space of potentially interesting materialized views for a given set of SQL queries

# **Key Contributions**

- The paper present an architecture and novel algorithms for addressing automated materialized view selection.
- Takes into account the significant enhancement that can be achieved by interaction between indexes and materialized views
- Introduce a principled way to identify a much smaller set of candidate materialized views .
- Database design tool that can determine an appropriate set of indexes, materialized views for a given database and workload consisting of SQL queries and updates.
- This tool became part of Microsoft SQL Server 2000 and onward releases.

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#### Key Components of this Architecture:

- Syntactic structure selection
- Candidate selection
  - -> Index Selection
  - -> Materialized View Selection
- Configuration enumeration
- Configuration simulation and Cost estimation



#### <u>Step – 1 : Syntactic Structure selection</u>

To identify syntactically relevant indexes, materialized views and indexes on materialized views that can potentially be used to answer the query.

#### For example:

Query **Q**: SELECT Sum(Sales) FROM Sales\_Data WHERE City = 'Delhi'

The syntactically relevant materialized views:

- **v1**: SELECT Sum(Sales) FROM Sales\_Data WHERE City = 'Delhi'
- **v2**: SELECT City, Sum(Sales) FROM Sales\_Data GROUP BY City
- **v3**: SELECT City, Product, Sum(Sales) FROM Sales\_Data GROUP BY City, Product

#### <u>Step – 2 : Candidate Selection</u>

- Eliminate spurious candidates and focus on smaller search space.
- Candidate selection is responsible for Identifying a sets of structure for the given workload which are worthy of further exploration

#### Note:

- This paper focuses only on efficient selection of candidate materialized views.
- The candidate index selection is assumed to be already done.
- The issues related to selection of indexes on materialized views is not discussed in this paper.

#### <u>Step – 3 : Configuration Enumeration</u>

- Search among structures selected in Step-2 , inorder to determine ideal physical design- called <u>configuration</u>.
- Configuration consists of set of traditional indexes , materialized views and indexes on materialized views.
- Search using the naive approach is infeasible
- Thus we adopt the GREEDY algorithm for configuration enumeration.

#### <u>Step – 3 : Configuration Enumeration</u>

#### **The Naive Approach(Index Selection):**

- There are n candidate indexes, and we are asked to find optimal configuration of size at most k structures
- Enumerate all subsets of the candidate structures of size k or less
- Pick the one with lowest total cost.
- This gurantees an optimal solution , but complexity of search is exponentially large.
- For Example : n = 40 , K = 10

#### <u>Step – 3 : Configuration Enumeration(continued)</u>

#### The Greedy(m,k) Algorithm :

- Returns a configuration consisting of a total of k indexes and materialized views
- It first picks an optimal configuration of size up to m ( $\leq$  k) by exhaustively enumerating all configurations of size up to m. (seed)
- Each greedy step considers all possible choices for adding one more index and adds the one resulting in the highest cost reduction
- The alogorithm continues until all k indexes and materialized views have been chosen, or no further reduction in cost is possible by adding a structure.

<u>Step – 3 : Configuration Enumeration(continued)</u>

The Greedy(m,k) Algorithm for Index Selection :

- 1. Let S = the best **m** index configuration using the *naïve enumeration algorithm*. If m = k then exit.
- 2. Pick a new index I such that Cost (S U {I}, W) <= Cost(S U{I'}, W) for any choice of I' != I</p>
- 3. If Cost (S U {I}) >= Cost(S) then exit Else S = S U {I}
- 4. If |S| = k then exit
- 5. Goto 2

**Figure** . The Greedy(m, k) enumeration algorithm.

#### <u>Step – 3 : Configuration Enumeration(continued)</u>

The Greedy(m,k) Algorithm :

Note that :

- If the parameter m = 0, then the algorithm takes a pure greedy approach.
- On the other hand, if m = k , the algorithm is identical to the naive enumeration algorithm.
- Therefore, the use of the algorithm is computationally efficient only if m is small relative to k. In such a case, the enumeration exhibits near greedy behavior.

#### <u>Step – 4 : Configuration simulation and Cost estimation</u>

• Responsible for evaluating the cost of configurations.

#### Naive Approach (Index Selection):

- The cost-evaluator asks the optimizer for a cost estimate for each query in the workload.
- For M configurations and Q queries in the workload, such estimation requires asking the optimizer to optimize M\*Q queries.
- Invoking the optimizer many times can be expensive

#### <u>Step – 4 : Configuration simulation and Cost estimation</u>

#### Notion of Atomic Configurations:

• Configuration C is atomic for a workload if for some query in the workload there is a possible execution of the query that uses all indexes in C.

#### To find Cost(Q,C):

- C is a configuration that is not atomic and Q is a Select/Update query in the workload.
- Consider all atomic configurations Ci of Q that are subsets of C.
- Optimizer will choose the atomic configuration from the above set of Ci that has the minimal cost

#### <u>Step – 4 : Configuration simulation and Cost estimation</u>

- <u>Therefore, we can derive</u> Cost (Q, C) = Min {(Cost(Q, Ci)}
- Intuitively in a Select query, it will suffice to take the minimum cost over the largest atomic configurations of Q that are subsets of C.

#### <u>Example :</u>

Consider following Indexes in C :

I1 reduces cost by 50 units , I2 reduces cost by 20 units I3 reduces cost by 30 units , I4 reduces cost by 40 units

```
Possible Ci's = \{11,12\}, \{11,14\}, \{13,14\}
\{11,14,12\}, \{11,13,14\}
```

#### <u>Step – 4 : Configuration simulation and Cost estimation</u>

#### The cost of an Insert/Delete query for a non-atomic configuration C

- Divided in three components:
  - (a) Cost of selection
  - (b) Cost of updating the table and the indexes used for selection
  - (c) Cost for updating indexes that do not affect the selection cost.
- Note : cost for updating each index in (c) is independent of each other and can be assumed to be independent of the plan chosen for (a) and (b).

#### Total cost = T + $\sum (Cost(Q, \{Ij\}) - Cost(Q, \{\}))$

(As in a Select/Update query, we can derive T)

### **Candidate Index Selection**

- 1. For the given workload W that consists of n queries, we generate n workloads  $W_1...W_n$  each consisting of one query each, where  $Wi = \{Q_i\}$
- 2. For each workload  $W_i$ , we use the set of indexable columns  $I_i$  of the query in  $W_i$  as starting candidate indexes.
- 3. Let  $C_i$  be the configuration picked by index selection tool for  $W_i$ , i.e.,  $C_i$  = Enumerate (I<sub>i</sub>,  $W_i$ ).
- The candidate index set for W is the union of all C<sub>i</sub>'s.

#### Figure . Candidate index selection algorithm.

### <u>Goal</u>:

To eliminate materialized views that are syntactically relevant to one or two queries but are never used in answering any query.

#### <u>Naive Approach :</u>

Selecting one candidate materialized view per query that exactly matches each query in the workload.

#### Scenario 1: Storage Constrained Environments

Consider a workload consisting of 1000 queries of the form: SELECT attr\_A, SUM(attr\_B) FROM table\_T WHERE attr\_C BETWEEN <val1> and <val2> GROUP BY attr A

Assume different constants for <val1> and <val2>

<u>Naive Approach</u>: 1000 Materialized Views for each query.

#### <u>Better Alternative :</u>

SELECT attr\_C,attr\_A, SUM(attr\_B) FROM table\_T GROUP BY attr\_C, attr\_A

#### **Observation**:

Ignoring the commonality across queries in the workload can result in sub-optimal quality. The problem is more severe in case of larger workloads.

### <u>Scenario 2:</u>

Consider a workload consisting of 100 queries: Total Cost of all queries : 10,000 units Let 'T' be a table-subset that occurs in 25 queries: Total Cost these 25 queries : 50 units

Then even if we considered all syntactically relevant materialized views on T, the maximum possible benefit of those materialized views for the workload is 0.5%.

#### <u>Observation</u>:

• There are certain table-subsets such that, even if we were to propose materialized views on those subsets it would only lead to a small reduction in cost for the entire workload.

#### <u>Scenario 3:</u>

Consider a large set of queries in which some tables table\_P, table\_Q, table\_R, table\_S co-occur.

Assume that : table\_P has 5 million tuples & table\_Q has 4 million tuples table\_R has 100 tuples & table\_S has 50 tuples

Hence from above statistics , it is likely that the materialized view on tablesubset {table\_P,table\_Q} is **more useful** than that on {table\_R,table\_S}.

#### <u>Observation</u>:

The benefit of pre-computing the portion of the queries involving {table\_R,table\_S} **is insignificant** compared to the benefit of pre-computing the portion of the query involving {table\_P,table\_Q}.

Based on the previous observations Candidate Materialized View selection can be done in three steps:



#### 1) Finding Interesting Table-Subsets

- The a table-subset T is *interesting* if materializing one or more views on T has the potential to reduce the cost of the workload significantly, i.e., above a given threshold.
- Define a metric that captures the relative importance of a table-subset.
- Two table-subset metric we define here:
  - a) TS-Cost(T)
  - b) TS-Weight(T)

<u>TS-Cost(T)</u> = total cost of all queries in the workload (for the current database) where table-subset T occurs.

 <u>Monotonicity of TS-Cost(T)</u> For table subsets T1, T2: If T1 is subset of T2, then TS-Cost(T1) >= TS-Cost(T2)

 $\sum_{i} Cost(Q_i) * (sum \ of \ sizes \ of \ tables \ in \ T)$ 

(sum of sizes of all tables referenced in  $Q_i$ )

• Also for any threshold C , the following holds good :

<u>TS-Weight(T)</u> =

TS- $Weight(T) \ge C \Rightarrow TS$ - $Cost(T) \ge C$ 

#### <u>TS-Cost(T)</u> v/s <u>TS-Weight(T)</u> :

1) TS-Cost(T) is simple , but not good measure of relative importance of a table-subset. While TS-Weight(T) can discriminate between table-subsets even if ther occur in exactly the same queries in the workload.

2) No efficient algorithm for finding all table subsets whose TS-Weight(T) exceeds a given threshold , while it is possible for TS-Cost(T) as it is monotonic.

- 1. Let  $S_1 = \{T \mid T \text{ is a table-subset of size 1 satisfying } TS-Cost(T) \ge C\}; i = 1$
- 2. While i < MAX-TABLES and  $|S_i| > 0$

3. 
$$i = i + 1; S_i = \{\}$$

4. Let  $G = \{T \mid T \text{ is a table-subset of size } i, and \exists s \in S_{i-1} \text{ such that } s \subset T\}$ 

#### 5. For each $T \in G$ If *TS*-Cost (T) $\geq$ C Then $S_i = S_i \cup \{T\}$

- 6. End For
- 7. End While

8. 
$$S = S_1 \cup S_2 \cup \ldots S_{MAX-TABLES}$$

- 9.  $\mathbf{R} = {\mathbf{T} \mid \mathbf{T} \in \mathbf{S} \text{ and } TS\text{-}Weight(\mathbf{T}) \ge \mathbf{C}}$
- 10. Return R

#### Figure . Algorithm for finding interesting tablesubsets in the workload.

#### 2) Pruning Syntactically Relevant Materialized Views :

• The goal is to prevent syntactically relevant materialized views that are not used in answering any query.

 Intuitively if a materialized view is not part of the best solution for even a single query in the workload, then it is unlikely to be part of the best solution for the entire workload.

- 1.  $M = \{\} /* M \text{ is the set of materialized views that is}$ useful for at least one query in the workload W\*/
- 2. **For** i = 1 to |W|
- 3. Let  $S_i$  = Set of materialized views proposed for query  $Q_i$ .
- 4.  $C = Find-Best-Configuration (Q_i, S_i)$
- 5.  $M = M \cup C;$
- 6. End For
- 7. Return M

# Figure . Cost-based pruning of syntactically relevant materialized views.

#### Step (3) of the Algorithm :

Which syntactically relevant materialized views should be proposed for a query Qi?

 It is not sufficient to propose materialized views only on the tablesubset that exactly matches the tables referenced in Qi

 Due to the pruning of table-subsets in previous step the tablesubset that exactly matches the tables referenced in the query may not even be deemed interesting. In such cases, it again becomes important to consider smaller interesting table-subsets that occur in Qi.

### <u>Step (3) of the Algorithm :</u>

For each such interesting table-subset T, we propose :

(1) A "pure-join" materialized view on T containing join and selection conditions in Qi on tables in T.

(2) If Qi has grouping columns, then a materialized view similar to (1) but also containing GROUP BY columns and aggregate expression from Qi on tables in T.

#### Note:

For each materialized view proposed, also propose a set of clustered and non-clustered indexes on the materialized view.

#### Step (4) of the Algorithm :

- Find-Best-Configuration(Q, S) for query Q and a set S of materialized views(with index on them) proposed for Q, returns the best configuration for Q from S.
- The best configuration for a query is that which the optimizer estimates as having the lowest cost for Q.
- Any suitable search method can be used in this function, e.g., the Greedy(m,k) algorithm described earlier.

#### 3) View Merging

#### <u>Example :</u>

Emp(ssn,name,sex,dno) & Works(ssn,pno,hours)

- M\_v1 : Select dno,count(ssn) from Emp,Works Where emp.ssn = Works.ssn And pno = 'p1' Group By dno
- M\_v1 : Select pno,count(ssn) from Emp,Works Where emp.ssn = Works.ssn And dno = 302 Group By pno

Merged View : Select dno , pno , count(ssn) from Emp,Works Where emp.ssn = Works.ssn Group By dno,pno

#### Emp table

Count

2

1

SSN	NAME	SEX	Dno
E101	James	Μ	301
E102	Nick	Μ	301
E103	Ted	Μ	302
E104	Laura	F	302

	Dno	Count
M_v1:	301	1
	302	2

Pno

P1

P2

No	rks	tah	le
		เลม	

SSN	Pno	Hrs
E101	P1	30
E101	P2	40
E102	P2	56
E103	P1	76
E103	P2	78
E104	P1	34

Merged View :	Dno	Pno	Count
	301	P1	1
	301	P2	2
	302	P1	2
	302	P2	1

2	7	
J	/	

#### Important steps in View Merging:



#### Properties of View Merging :

While merging two parent views to generate the merged view , following properties must hold true :

a) All queries that can be answered using either of the parent views should be answerable using the merged view.

b) The cost of answering these queries using the merged view should not be significantly higher than the cost of answering the queries using views in M.

Parent-Closure(v) as the set of views in M from which v is derived. x = Size increase threshold (between 1-2)

- 1. Let  $v_1$  and  $v_2$  be a pair of materialized views that reference the same tables and the same join conditions.
- Let s<sub>11</sub>, ... s<sub>1m</sub> be the selection conditions that occur in v<sub>1</sub> but not in v<sub>2</sub>. Let s<sub>21</sub>, ... s<sub>2n</sub> be the selection conditions that occur in v<sub>2</sub> but not in v<sub>1</sub>.
- Let v<sub>12</sub> be the view obtained by (a) taking the union of the projection columns of v<sub>1</sub> and v<sub>2</sub> (b) taking the union of the GROUP BY columns of v<sub>1</sub> and v<sub>2</sub> (c) pushing the columns s<sub>11</sub>, ... s<sub>1m</sub> and s<sub>21</sub>, ... s<sub>2n</sub> into the GROUP BY clause of v<sub>12</sub> and (d) including selection conditions common to v<sub>1</sub> and v<sub>2</sub>.
- 4. If  $((|v_{12}| > Min Size (Parent-Closure (v_1) \cup Parent-Closure (v_2)) * x)$  Then Return Null.
- 5. **Return** v<sub>12</sub>.

#### Figure MergeViewPair algorithm

- $\mathbf{R} = \mathbf{M}$
- While (|R| > 1)
   Let M' = The set of merged views obtained by calling MergeViewPair on each pair of views in R.

4. If 
$$M' = \{\}$$
 Return (R–M)

5. 
$$R = R \cup M'$$

- 6. For each view  $v \in M'$ , remove both parents of v from R
- 7. End While
- Return (R–M).

### Figure . Algorithm for generating a set of merged views from a given set of views M

#### Properties of previous algorithm:

- The number of new merged views can exponential in the size of M in the worst case.
- New merged views can be merged further( implies more than 2 views can also get merged)
- The set of merged views returned by the algorithm does not depend on the exact sequence in which views are merged.

# Alternate approaches for Index & Materialized View Selection

The approach we have used so far considers the *joint enumeration* of the space of candidate indexes and materialized views. The following are alternatives to this :

#### <u>Approach 1 : MVFIRST</u>

To pick *materialized views* first, and then select indexes for the workload given the materialized views picked earlier.

#### Approach 2 : INDFIRST

To pick *indexes* views first, and then select materialized views for the workload given the indexes picked earlier.

# Alternate approaches for Index & Materialized View Selection

Drawback of alternate approaches against Join Enumeration :

1) Some **interactions between candidate indexes and candidate materialized views** that are eliminated in these approaches.

#### For example:

Consider a query Q for which indexes Ind\_1, Ind\_2 and materialized view M\_v are candidates.

Assume that Ind\_1 alone reduces the cost of Q by 25 units

Ind\_2 reduces the cost by 30 units

Ind\_1 and M\_v together reduce the cost by 100 units.

Then, using INDFIRST, Ind\_2 would eliminate Ind\_1 when indexes are picked, and we would not be able to get the optimal recommendation  $_4$  {Ind\_1,M\_v}.

# Alternate approaches for Index & Materialized View Selection

Drawback of alternate approaches against Join Enumeration :

2) A further drawback of MVFIRST is that selecting materialized views first are likely to **preclude selection of potentially useful candidate indexes** for the workload.

3) Another problem relevant to both INDFIRST and MVFIRST is **redundant recommendations** if the feature selected second is better for a query than the feature selected first.

# EXPERIMENTS

 Algorithms presented in this paper are implemented on Microsoft SQL Server 2000 release and tested on TPC-H 1 GB database.

Hypotheses set:

Selecting Candidate materialized views

- Identifying interesting table-subsets substantially reduces materialized views without eliminating useful ones
- View-merging algorithms significantly improves performance especially under storage constraints

## EXPERIMENTS

Architectural issues :

1)Candidate selection module reduces runtime maintaining quality recommendations

2)Configuration enumeration module Greedy(m,k) gives results significantly faster than exhaustive one but still comparable.

3)JOINTSEL better than MVFIRST or INDFIRST

### Identifying interesting table-subsets



### Figure . Reduction in syntactically relevant materialized views proposed compared to Exhaustive

Threshold C = 10%

Significant Pruning of space

View Merging



Add. Merged views:19%

Increase in runtime: 9%

# Figure . Quality vs. storage bound with and without view merging.

• In low storage scenario the version with view merging significantly outperforms the version without view merging.

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### Candidate Selection



# Figure . Scalability of candidate materialized view selection with workload size

No. of mat views grows linearly with workload size - hence scalable

### **Candidate Selection**

Workload	Ratio of running time	% improv. in quality <i>Without</i>	% improv. in quality <i>With</i>
<b>TPC-H</b> queries	64	98.1%	97.6%
$Q_1, Q_2, Q_3$			
<b>TPC-H</b> queries	13	93.6%	93.6%
$Q_4, Q_5$			
TPC-H queries	31	73.4%	73.4%
$Q_6, Q_7, Q_8$			
<b>TPC-H</b> queries	14	66.6%	60.1%
$Q_{9}, Q_{10}, Q_{11}$			

# TableComparison of schemes with and without the<br/>candidate selection module.

candidate selection not only reduces the running time by several orders of magnitude, but the drop in quality resulting from this pruning is very small

### **Configuration Enumeration**

Workload	Ratio of Running Time: Exhaustive to Greedy (m, k)	% improv in quality with Exhaustive	% improv in quality <i>withGreedy</i> (m, k)
TPCH-22	11	83%	81%
TPCH-	9	79%	77%
UPD25			

#### Table . Comparison of Greedy(m,k) and exhaustive enumeration algorithms.<sup>2</sup>

Greedy(m,k) gives a solution comparable in quality to exhaustive enumeration. Yet, in time magnitudes faster

# JoinSel vs MVFirst vs INDFirst

Workload	Drop in quality of MVFIRST compared to JOINTSEL	Drop in quality of INDFIRST compared to JOINTSEL
TPCH-22	8%	0%
TPCH-UPD25	67%	11%

Table . Comparison of alternative schemes without storage bound (i.e., storage = ∞)

• MVFIRST is significantly worse than the quality of JOINTSEL, particularly in the presence of updates in the workload.

• This confirms our intuition that picking materialized views first adversely affects the subsequent selection of indexes

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