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MLPPI Wizard: An Automated Multi-level Partitioning Tool on Analytical Workloads

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Abstract. Typically, it is a daunting task for a database administrator (DBA) to figure out how to partition a huge fact table accessed by query workloads for better performance. To relieve such a burden, we introduce an intelligent partitioning tool to recommend an optimized partitioning on the fact table. This tool uses a greedy algorithm for search space enumeration. This space is driven by predicates of a given query workload. The tool takes advantage of the cost model of a query optimizer to prune the search space. The tool resides completely on a client and interacts with the optimizer via APIs. Thus, there is no overhead to instrument the optimizer code. Furthermore, the predicate-driven method can be applied to any clustering or partitioning scheme. We show that the tool's recommendation outperforms a human expert's solution. We also demonstrate that the recommendation scale very well with increasing workload and growing fact table.

Keywords: Star Schema, Fact Table, Multi-Level Partitioning.

1. Introduction

Over the past decades much attention has been paid to improve the performance on analytical workloads in a data warehousing environment. Typically, a relational database management system (DBMS) has been exploited to process such analytical queries faster and assist its customers to make a timely business-decision in rapidly changing enterprise data warehousing. Teradata DBMS has been a leading database product in this data warehousing marketplace that has been increasingly more competitive than ever.

Background: To optimize the performance of analytical processing, tables and materialized views in the Teradata DBMS are hash-distributed based on a user-specified column or set of columns called *primary index*. Each virtual processor, a unit of parallelism called *AMP* in the Teradata DBMS, receives a subset of the data and stores it in hash order. Users typically choose primary index fields in the DBMS, so that the data is evenly distributed among the AMPs. The primary index fields are also chosen to reflect join fields in workloads to accomplish cheaper local joins that do not require data shuffling.

Partitioned Primary Index (PPI) [19] is an optional horizontal partitioning scheme applied locally on the data belonging to each AMP. In some database products, this type of

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```
CREATE TABLE LINEORDER(
  LO_ORDERKEY INTEGER,
  LO_QUANTITY INTEGER,
  LO_DISCOUNT INTEGER
)
PRIMARY INDEX ( LO_ORDERKEY )
PARTITION BY (
  CASE_N(
    LO_DISCOUNT >= 7,
    NO CASE OR UNKNOWN),
  CASE_N(
    LO_QUANTITY < 25,
    LO_QUANTITY >= 25 AND LO_QUANTITY <= 30,
    LO_QUANTITY > 30 AND LO_QUANTITY <= 35,
    NO CASE OR UNKNOWN)
);
```

Fig. 1. An Example of an MLPPI Table in the Teradata DBMS

partitioning is termed *clustering*, but hereafter we call the term *partitioning* only to avoid confusion. Database administrators (DBAs) usually choose the columns for PPI, based on join fields and single table predicates to optimize the queries included in the workload. The PPI columns are used to physically group data with the same values together in contiguous data blocks. This grouping enables "partition elimination" in scans and joins for performance enhancement. PPI can be specified as single or multiple levels. This type of partitioning scheme is known as Multi-Level PPI (*MLPPI)* [9].

By allowing non-qualified partitions to be eliminated, MLPPI can considerably reduce the amount of data to be scanned to answer a query. But a large number of partitions can create significant overhead, particularly in joins and table maintenance operations such as inserts and deletes, so that the selection of partitions can be usually a balancing act.

Figure 1 exemplifies an MLPPI table with a defined partitioning option. This example is a subset of the `LINEORDER` table from the Star Schema Benchmark (SSB) [14]. (Note that the full table with modified data types was actually used in our experiments.)

In the definition of `LINEORDER` in the figure, the primary index is on `LO_ORDERKEY`. The primary index dictates the AMP on which a row will be located while the partitioning of data will be dictated by the values and ranges associated with `LO_DISCOUNT` and `LO_QUANTITY`. For example, `LO_DISCOUNT` has two ranges: (i) one for values ≥ 7 and (ii) another for all the other values (or `NO CASE OR UNKNOWN`). `LO_QUANTITY` has four ranges. Hence, the relation will have a total of $2 \times 4 = 8$ partitions as follows.

Partition Number	Condition
1	`LO_DISCOUNT >= 7 && LO_QUANTITY < 25`
2	`LO_DISCOUNT >= 7 && 25 <= LO_QUANTITY <= 30`
3	`LO_DISCOUNT >= 7 && 30 < LO_QUANTITY <= 35`
4	`LO_DISCOUNT >= 7 && LO_QUANTITY no case`
5	`LO_DISCOUNT no case && LO_QUANTITY < 25`
6	`LO_DISCOUNT no case && 25 <= LO_QUANTITY < 30`
7	`LO_DISCOUNT no case && 30 < LO_QUANTITY <= 35`
8	`LO_DISCOUNT no case && LO_QUANTITY no case`

Whatever partition is chosen, the selection must be semantically correct; namely, the mapping of rows to partitions must be an injection. In other words, the constraints must form a covering of the entire range, so that a row will belong to exactly one and one partition. The Teradata optimizer then applies partition elimination for queries that specify conditions on LO_DISCOUNT and/or LO_QUANTITY. For example, only partitions 1 and 2 are needed for the query "SELECT * FROM LINEORDER WHERE LO_DISCOUNT >= 7 AND LO_QUANTITY <= 30." Similarly, partitions 1 and 5 are sufficient to answer the query "SELECT * FROM LINEORDER WHERE LO_QUANTITY < 25." The respective sizes of the partitions are a factor of the data distribution. To see MLPPI in greater detail, check our references [9, 19].

Challenge: Consider the below query set Q having two queries $q1$ and $q2$ on the SSB.

$q1$:
```
SELECT SUM(l.LO_EXTENDEDPRICE*l.LO_DISCOUNT)
FROM LINEORDER l, DDATE d
WHERE l.LO_ORDERDATE = d.D_DATEKEY
AND d.D_YEAR = '1993'
AND l.LO_DISCOUNT IN (1, 4, 5)
AND l.LO_QUANTITY <= 30
```

$q2$:
```
SELECT c.C_NATION, SUM(l.LO_REVENUE)
FROM CUSTOMER c, LINEORDER l
WHERE l.LO_CUSTKEY = c.LO_CUSTKEY
AND c.C_REGION='EUROPE'
AND l.LO_DISCOUNT >= 7
AND l.LO_QUANTITY >= 25 AND l.LO_QUANTITY <= 35
GROUP BY c.C_NATION
ORDER BY revenue desc
```

A DBA may focus on the LINEORDER fact table and the predicates involving LINEORDER fields only. He can figure out the following five constraints, identified by the query number and the sequence number of predicates in each query:

$q1.1$: LO_DISCOUNT IN (1,4,5)
$q1.2$: LO_QUANTITY <= 30
$q2.1$: LO_DISCOUNT >= 7
$q2.2$: LO_QUANTITY >= 25
$q2.3$: LO_QUANTITY <= 35.

At this point the DBA needs to take into account options based only on two fields and the five constraints. There are many other possibilities from a *fine-grained* partition set to a *coarser-grained* definition.

Considering for the time being the column LO_DISCOUNT, one solution is to identify each value for the IN predicate in $q1.1$ and use $q2.1$ as is. This yields the following partitioning expression for LO_DISCOUNT:

```
CASE_N(
  LO_DISCOUNT = 1,
  LO_DISCOUNT = 4,
  LO_DISCOUNT = 5,
  LO_DISCOUNT >= 7,
  NO CASE OR UNKNOWN
).
```

This expression minimizes the size of the partitions by focusing exactly on the values required to satisfy the constraints but creates a large number of small partitions.

Another possibility is to look at the maximum and minimum values in the `IN` set and to build an `AND` clause equivalent to a between clause yielding the following:

```
CASE_N(
 LO_DISCOUNT >= 1 AND LO_DISCOUNT <= 5,
 LO_DISCOUNT >= 7,
 NO CASE OR UNKNOWN
).
```

The above partitioning solution decreases the number of partitions, compared to the previous solution but still focuses sharply on the constraints with still relatively small partitions.

Similar considerations apply to the partitioning associated with `LO_QUANTITY`. The resulting partitioning definition for the table includes both `LO_DISCOUNT` and `LO_QUANTITY`, and thus the number of possible combinations is the product of the potential combinations for each field.

Furthermore, given two queries one partitioning scheme may be favorable for one query but not for the other, or vice versa. As a result, the DBA becomes faced with a daunting combinatorial search problem and no clear basis to decide on which combination is the best. This state of affairs begs for a *tool* for the DBA.

Solution: To ease a burden of partitioning decision, we introduce a novel physical database design tool, called *MLPPI wizard*, designed to recommend an effective partitioning solution for a given workload. This tool uses a greedy algorithm for search space enumeration and is based on a general framework allowing general expressions, ranges and case expressions for partition definitions. We emphasize that the predicate-driven algorithm used by the tool can be applied to *any* clustering or partitioning scheme based on simple fields and expressions or complex SQL predicates in an *arbitrary* DBMS. The wizard also borrows the optimizer's cost model to prune the search space and reach a final solution.

Figure 2 illustrates how our tool recommends the final MLPPI customized for a given workload consisting of a set of queries and corresponding weights. Until yielding a final partitioning recommendation, the wizard passes through a series of phases: *Preprocessing*, *Initial*, and *Optimized* Phases. We elaborate in greater detail on each of the three phases, using the running query set Q consisting of $q1$ and $q2$ in the rest of the article. As illustrated in Figure 2, the wizard resides completely on the client side as opposed to several previous tools [3, 11, 13] that require optimizer code instrumentation. Our tool simply invokes the server's existing APIs used to simplify the queries, capture fact table predicates, and estimate processing costs. To the best of our knowledge, our wizard is the very first physical database design tool to address such a *multi-level partitioning* problem.

Contribution: This article provides the following contributions.

- We propose a physical database design tool, termed MLPPI wizard, to recommend a multi-level partitioning definition for reducing the processing cost of a given query workload on a star schema benchmark.
- This tool is totally outside the database server, thereby incurring no overhead of instrumenting query optimizer's code.

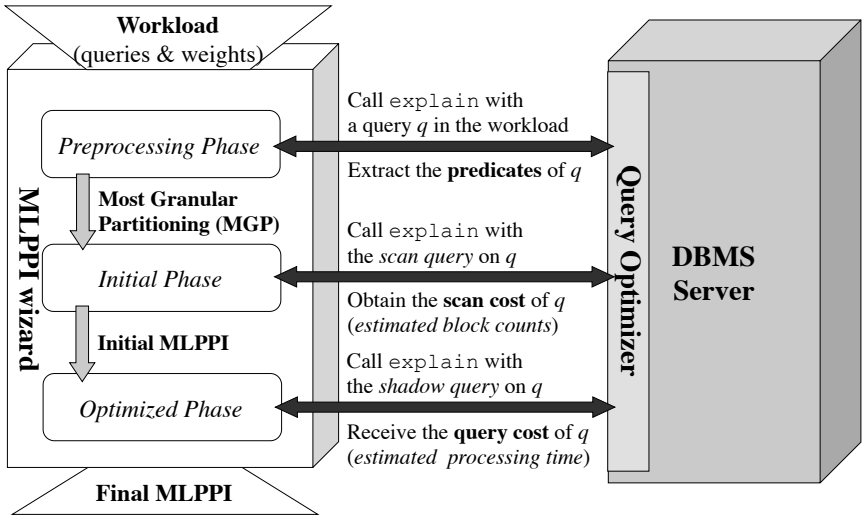


Fig. 2. The MLPPI wizard architecture

– We empirically show that a partitioning recommendation of our tool outperforms that of human expert over increasing workload size and growing fact table.

The article is a substantial extension of prior work [20]. The rest of this article is organized in the following way. In the following section we propose a multi-level partitioning algorithm—consisting of a series of phases—used by our MLPPI wizard, which is applicable to any clustering or partitioning scheme in an arbitrary DBMS. In turn, we conduct a detailed analysis of the complexity of the algorithms. Next, we report the performance evaluation results. We then elaborate on how our wizard is distinguished from several existing tools proposed by other DBMS vendors. Finally, we conclude this article by summarizing our discussion.

2. The MLPPI wizard

As illustrated in Figure 2, the MLPPI wizard has the three phases for a final partitioning recommendation. In this section we delve into each phase. For better exposition we use the running query set Q provided in Section 1.

2.1. The Preprocessing Phase

The first phase is called *Preprocessing* to extract query predicates and check any constraint in partitioning. This phase consists of a total of six steps, as shown in Algorithm 1.

Query Simplification The first step is to simplify the predicates of queries in a given workload. In other words, we remove redundant conditions among the queries. For instance, if a query predicate has the condition of "`LO_DISCOUNT IN (1, 4, 5) AND`

Algorithm 1: The Preprocessing Phase

input : Q (input query set)
output: R (non-overlapping range set), M (query-to-range-set map)
1 Query Simplification (on Q)
2 Range Extraction (from Q)
3 Non-Overlapping Range (R) Construction
4 Field Count Limit Check (on R)
5 Query-to-Range-Set Map (M) Construction
6 Partition Count Limit Check (on R)

`LO_DISCOUNT IN (2, 3, 4, 5)`", then the predicate can be simplified as "`LO_DISCOUNT IN (4, 5)`." This can be done via an API call to the database server. This simplification is not required for the running example.

Range Extraction In the subsequent step we gather the simplified predicates and then extract ranges from the collected predicates. This task can also be performed through an API call to the server. The query predicate is of the form

$$\langle \texttt{variable} \rangle \ \langle \texttt{op} \rangle \ \langle \texttt{constant} \rangle,$$

where $\langle \texttt{variable} \rangle$ is a field (column) from `LINEORDER`, $\langle \texttt{op} \rangle$ is in

$$\{=\ , <, <=, >=, >, \texttt{IN}\},$$

and $\langle \texttt{constant} \rangle$ represents a constant value(s). All $\langle \texttt{op} \rangle$s are self-explanatory. In particular, '`IN`' is a list predicate implying '`OR`' operator. In the running example, we can collect a set of predicates P = {$p1$,$p2$,$p3$,$p4$} from Q, where

$p1$: `l.LO_DISCOUNT IN (1, 4, 5)`
$p2$: `l.LO_DISCOUNT >= 7`
$p3$: `l.LO_QUANTITY <= 30`
$p4$: `l.LO_QUANTITY >= 25 AND l.LO_QUANTITY <= 35`.

Next, we construct a bi-directional *map* between a query and associated predicates, so that for each query the corresponding predicate(s) can be found directly in the map, and vice versa. In the example, we get a map, called $M1$, built between Q and P. $M1$ gets filled with the following entries:
$M1$:

$$\langle q1, \{p1, p3\} \rangle$$
$$\langle q2, \{p2, p4\} \rangle.$$

Now we build a set of distinct ranges for each field referenced by the predicates. Specifically, we gather fields referenced by predicates in P, extract ranges from the predicates, and group the ranges of each of the referenced fields. Suppose I to be a list of fact table fields referenced by P. In the workload Q we add to I two fields, `LO_DISCOUNT` and `LO_QUANTITY`, used by P. The whole range of the gathered predicates can be represented by a kind of two-dimensional array, called R.

Each entry under a field in R represents a pair of (start and end) values forming the range. When it comes to range representation for an entry, "[" and "]" are used for closed ranges while "(" and ")" for open ranges. Also, infinity (∞) and -infinity (-∞) can be used for unbounded ranges. In particular, `IN` predicate is represented by multiple ranges. For instance, the above $p1$ can be represented by the following three ranges $[1, 1]$, $[4, 4]$, $[5, 5]$; however, the last two consecutive ranges can be consolidated as $[4, 5]$. In the continuing example the field-wise distinct range set (R) is formed by the entries below.

R:

LO_DISCOUNT	LO_QUANTITY
$[1, 1]$	$(\infty, 30]$
$[4, 5]$	$[25, 35]$
$[7, \infty)$	

In turn, we build another map, called $M2$, between P and R. That is, we associate each predicate in P with a corresponding range in R. Let $R[i, j]$ denote the interval value for the i-th field and j-th range in R. R[1, 3], for instance, indicates range $[7, \infty)$ under `LO_DISCOUNT`. In the running example, $M2$ is constructed as follows:

$M2$:

$\langle p1, \{R[1, 1], R[1, 2]\}\rangle$
$\langle p2, \{R[1, 3]\}\rangle$
$\langle p3, \{R[2, 1]\}\rangle$
$\langle p4, \{R[2, 2]\}\rangle$.

Non-Overlapping Range Construction Since there may be multiple predicates on the same field across queries, extracted ranges for the field may overlap each other. The overlapping ranges must be broken without any common portion, in order that we can consider a pair of consecutive, non-overlapping ranges for a merge in subsequent phases.

Algorithm 2 describes the way of breaking the overlap of ranges. For each field, the algorithm gets associated ranges of each field and sorts them by start value. We then check whether or not adjacent ranges overlap each other. If that is the case, we make a split between the ranges. In the example, the split is applied on the overlapping ranges, $(\infty, 30]$ and $[25, 35]$ in `LO_QUANTITY`. Subsequently, a common (or intermediate) range ($[25, 30]$) is created and inserted into the range set belonging to the `LO_QUANTITY` field, in order to fill the gap. R is shown in the following.

R:

LO_DISCOUNT	LO_QUANTITY
$[1, 1]$	$(\infty, 25)$
$[4, 5]$	$[25, 30]$
$[7, \infty)$	$[31, 35]$

The update of R affects the existing map $M2$. In the running example, $p3$ and $p4$ influenced by the split get mapped to new range sets, $\{R[2, 1], R[2, 2]\}$ and $\{R[2, 2], R[2, 3]\}$, respectively. Of course, the range sets corresponding to $p1$ and $p2$ referencing `LO_DISCOUNT` remain unchanged. As a result, in the running example we obtain the updated $M2$ in the following.

Algorithm 2: Splitting Overlapping Ranges

```
input  : R having overlapping ranges
output: R with consecutive, non-overlapping ranges
foreach field i ∈ R do
    L ← Get the range set of i from R and sort by start value
    j = 0 ;
    while j < |L|-1 do
        r_j, r_{j+1} ← Adjacent ranges in L
        if r_j.end ≥ r_{j+1}.start then
            Make a split by modifying values of r_j and r_{j+1}.
            Insert into L an intermediate range if any.
            Re-sort ranges in L and reset j to 0.
        end
        else j++;
    end
    Update R with the final L.
end
```

$M2$:

$\langle p1, \{R[1, 1], R[1, 2]\}\rangle$
$\langle p2, \{R[1, 3]\}\rangle$
$\langle p3, \{R[2, 1], R[2, 2]\}\rangle$
$\langle p4, \{R[2, 2], R[2, 3]\}\rangle$.

Field Count Limit Check One question that occurs is what if a DBMS has a limit of fields that can be used for a partitioning definition. (In the case of Teradata DBMS, up to 64 fields can be allowed for an MLPPI definition.) If the number of fields present in R exceeds the field count limit, we determine which field(s) should be thrown away to satisfy the limit. (The star schema fact table we use has much fewer fields than the limit, and thus, this step will not be executed.) To choose victim fields, our tool computes the weighted sum of *query cost*, to be discussed in Section 2.3, of queries regarding each field. The sum can be obtained by adding up every query cost on an MLPPI using only the ranges under the field. We incrementally discard a field with the largest sum of query cost until the limit is reached. Correspondingly, we can update the existing $M2$. One might say that such an MLPPI may not be exploited if too many ranges over a partition count limit (65,536 in Teradata DBMS) are found in one field. But we assume that such an extreme case is not expected. Even if such a case happens, the merges of consecutive ranges can make the MLPPI feasible.

Query-to-Range-Set Map Construction Using the existing maps $M1$ and $M2$, the tool can create the final bi-directional *query-to-range-set* map, say M, between Q and R. To construct M, we leverage a transitive property from $M1$ to $M2$. Once we compute M, there is no need to keep the intermediate maps ($M1$ and $M2$) for the subsequent phases. In the running example, we can build M in the following.

M:

$$\langle q1, \{R[1, 1], R[1, 2], R[2, 1], R[2, 2]\}\rangle$$
$$\langle q2, \{R[1, 3], R[2, 2], R[2, 3]\}\rangle.$$

In the subsequent phases M gets used for computing costs and updated along with a merge of ranges, and R is refined for an MLPPI recommendation.

Partition Count Limit Check The range set R can be used to define an MLPPI using each field as one level. However, if the current number of partitions by R is greater than the aforementioned partition count limit, then it is not possible to make a feasible MLPPI based on the ranges in R.

The actual partition count limit is ample enough to pass the running example, but to continue our discussion, assume that in our discussion the limit is *15*. From R in the running example, we obtain a total of (number of ranges in `LO_DISCOUNT`) ·(number of ranges in `LO_QUANTITY`) = (3+1) · (3+1) = *16* partitions. Note here that one reserved range covering the rest but the identified is added by default to each field in the calculation, and the default range is equivalent to the "`NO CASE OR UNKNOWN)`" case in Figure 1. Since the total partitions surpass the limit, the tool should go through the initial phase in which we make fewer partitions than the limit. (Otherwise, the wizard can bypass the initial phase and then immediately proceed to the optimized phase.)

The tool is now ready to proceed to the next phases, with R (input range set, or MGP) and the prepared M (query-to-range-set map).

2.2. The Initial Phase

This phase incrementally merges a range pair in R to reduce partitions. The merge continues until the number of ongoing partitions drops below the partition count limit. After finishing the merge, the tool can derive a feasible MLPPI with the remaining partitions.

Overall, I/O cost may be increased by the merge, in that the full scan on a partition is performed to retrieve all the rows potentially matching a given query. In the case of a merged partition, we may read the non-qualifying rows that would not be seen before the merge, thereby paying more I/O to answer the query. To minimize the merge overhead, we pick up the range pair incurring the least I/O increase in a heuristic fashion. To choose a range pair for a merge, we calculate the *scan cost* of a query on the merged range pair.

Algorithm 3 represents how the scan cost can be computed on the range pair that influences a given query. The scan cost represents the I/O cost to answer the query when the range pair is merged. It is defined as the *number of blocks* that are to be read for the given query. To compute the scan cost of a query q, we write a corresponding scan cost query (s), which can be constructed as follows:

$$s\text{: }\texttt{SELECT * FROM } F \texttt{ WHERE } \textit{CP},$$

where F is a fact table, and *CP* indicates a predicate(s) reconstructed from a range(s) mapped to q in M.

If q turns out being affected by the merge of a range pair, then the range set associated with q in M is temporarily updated by removing the parent ranges and adding the merged range. The altered range set is remapped to q in M and then translated to the equivalent predicates. Then *CP* for s can be built based on the predicates. Unless the merge range pair influences q, we can simply derive *CP* from the existing ranges mapped to q.

Algorithm 3: Scan Cost Computation

input : q (query), rp (range pair), M (query-to-range-set map)
output: Scan cost for answering q when considering a merge of rp

```
1  r_m ← Consolidate rp ;
2  L ← Copy the range set mapped to q from M;
3  Delete ranges in rp from and insert r_m into L.
4  s ← "SELECT * FROM FACT_TABLE WHERE " ;
5  foreach range r ∈ L do
6  |   Reconstruct a predicate p from r.
7  |   Add p to WHERE clause of s.
8  end
9  Make an API call with s to the server.
10 Extract the spool size (in bytes) from the result.
11 blc ← Calculate the block counts from the spool size.
12 Update q's scan cost to blc.
13 return blc ;
```

To see in the Algorithm 3 how a scan cost query is built, consider a range pair (rp) of R[2, 2] and R[2, 3] in the running example. rp produces the merged range, $[25, 35]$, under `LO_QUANTITY`. The merge by rp affects both $q1$ and $q2$ in the workload. Thus, the range sets of $q1$ and $q2$ on `LO_QUANTITY` are correspondingly altered to $\{(\infty, 25)$, $[25, 35]\}$ and $\{[25, 35]\}$, respectively. Of course, no change is made to the existing range sets of the queries on `LO_DISCOUNT`. Therefore, the corresponding scan cost queries for $q1$ and $q2$ can be built as shown below:

s1:
```
SELECT * FROM LINEORDER l
  WHERE ((l.LO_DISCOUNT = 1) OR
  (l.LO_DISCOUNT >= 4 AND l.LO_DISCOUNT <= 5))
  AND l.LO_QUANTITY <= 35
```
s2:
```
SELECT * FROM LINEORDER l
  WHERE l.LO_DISCOUNT >= 7
  AND (l.LO_QUANTITY >= 25 AND l.LO_QUANTITY <= 35).
```

Since the altered ranges ($(\infty, 25)$ and $[25, 35]$) of $q1$ are consecutive, we can simply build the merged, single predicate (`l.LO_QUANTITY <= 35`) for *s1*.

In turn, the wizard sends each scan cost query to the server through an API call. The tool extracts from the server's response the *spool size* (in bytes), which is the result size of the sent scan cost query, and then calculates as scan cost the *block counts* (blc) using the spool size. If the merge of a range pair does not impact on any query in the workload, the existing (previously computed) scan cost of queries is reused for the range pair. In other words, the wizard only recomputes the scan cost of a query *only if* the query is affected by the merge of two consecutive ranges. The weighted sum of scan cost of queries, T_s can be computed for each range pair. T_s can be defined as follows:

$$T_s = \sum_{i=1}^{n} (sc_i \cdot w_i),$$

where n is the number of queries in Q, sc_i is the scan cost of a query q_i in Q, and w_i denotes the (non-negative) weight associated with q_i.

Once all range pairs are examined, the tool chooses the range pair with the least T_s for a merge. If several range pairs end up with the same least T_s, then the tool applies the heuristic of favoring the range pair that produces fewer number of partitions when merged, to make it faster to reach the partition count limit.

In the example, suppose that the running range pair rp produces the least T_s, and thus, the tool merges rp. Thus we can update both R and M as follows.

R:

LO_DISCOUNT	LO_QUANTITY
$[1, 1]$	$(\infty, 25)$
$[4, 5]$	$[25, 35]$
$[7, \infty)$	

M:

$\langle q1, \{R[1, 1], R[1, 2], R[2, 1], R[2, 2]\}\rangle$
$\langle q2, \{R[1, 3], R[2, 2]\}\rangle$

Note that we see that $q2$ may have the most customized partition based on the updated M. Only the single partition formed by ($R[1, 3] \cap R[2, 2]$) is sufficient to retrieve all the qualifying rows for $q2$; thus, the other partitions can be simply eliminated. In the meantime, to answer $q1$, we need to read the four partitions formed by the top two ranges of each field. As the partitions formed by $((R[1, 1] \cup R[1, 2]) \cap (R[2, 2])$ contain the non-qualifying rows for $q1$, unfortunately, R cannot provide $q1$ with as much benefit as $q2$. R, however, can be a good compromise to satisfy both queries, in that the MLPPI derived by R can potentially minimize the total execution cost of Q.

Algorithm 4 represents the initial phase that has been described so far. Given a query-to-range set map (M) and an input range set (R), the algorithm determines which range pair to yield the least total execution cost (T_s) and updates M and R using the chosen range pair, until the number of the partitions by R falls below a pre-defined partition limit count. Finally, the algorithm produces the final recommendation based on R.

In the running example the total partition counts ($4 \times 3 = 12$) by R is under the assumed limit (15), which meets the partitioning limit. Hence, the wizard can enter the optimized phase with R, without repeating the initial phase.

2.3. The Optimized Phase

After passing the initial phase, we now have an initial MLPPI recommendation based on R, for the LINEORDER fact table. The initial recommendation can be used sufficiently.

But we emphasize that additional merges may make fewer partitions, which actually can enhance the overall workload performance for the following reasons. First, multiple file contexts by many partitions can incur huge overhead that impacts on the query optimizer. There also exists an operational threshold that the optimizer can handle the maximum number of the partitions at a time. Therefore, further reducing partitions greatly helps the optimizer to manage these partitions.

A similar algorithm, as suggested in the initial phase, can be applied. In this phase, we use *query cost*, analogous to scan cost, which can be obtained via a feasible MLPPI. Specifically, the query cost is modeled as the estimated processing time of a query on a *faked* fact table applying the MLPPI definition that reflects the merge of a range pair. This cost estimation technique is similar to the "what-if" approach [4].

Algorithm 4: The Initial Phase

```
input  : M (query-to-range-set map), R (input range set)
output: R with # partitions ≤ partition limit
1  W ← Query weights
2  while (# partitions by R > partition limit) do
3      foreach a range pair (rp) in R do
4          T_s ← 0 ;
5          foreach q in M do
6              w ← Get q's weight from W
7              L ← Get the range set mapped to q in M
8              if ((rp ∩ L) ≠ ∅) then                          // Affected
9                  T_s += w·(getSC(q,rp,M)) ; // See Algo. 3 regarding getSC()
10
11         end
12         Associate T_s with rp.
13     end
14     Find rp(s) with the least T_s.
15     If a tie happens, select the rp to make fewer partitions when consolidated.
16     Update M and R by the chosen rp.
17 end
18 return R;
```

Algorithm 5 illustrates the steps for computing the query cost of a query q. Given a range pair (rp) affecting q when merged, we first create an empty shadow table H with the same definition as F, including all indexes and constraints such as check and referential integrity ones. Next, we propagate all statistics of F to H. This covers field and index statistics. If F has materialized views (MVs), then we create the equivalent MVs on H and subsequently, propagate the statistics of the MVs on F to the new MVs on H. After that, we alter H by an MLPPI with the updated R (R'), applying the merge of rp. The algorithm then builds a *shadow* query h, equivalent to the input query q, which is built by replacing F in q with H. The algorithm in turn makes an API call to the `EXPLAIN` tool with h. Eventually, the algorithm extracts from the result and returns the estimated elapsed time of h as the query cost of q. As done in the initial phase, the query cost of a query is recomputed only if the merge affects the query.

Algorithm 6 proposes the algorithm of the optimized phase. W indicates a set of weights assigned to individual queries in a given workload. T_p keeps track of the existing least query cost sum, and initially is computed on an initial MLPPI. For each range pair, the algorithm computes the respective weighted sum (T_q) of query costs of the queries in a given workload. (T_q can be similarly defined as T_s, described in Section 2.2, and thus the definition of T_q is omitted here.) Let the current least T_q be T. If $T <= T_p$ (existing least), then for the next iteration T_p is updated to T. We perform the merge on the range pair that produces that T and update M and R along with the merge. The algorithm repeats the process until (1) no more ranges in R are left, or (2) predefined iterations are reached. If $T \geq T_p$, then the optimized phase is terminated.

Note that to break a tie between range pairs, we apply the same heuristic to favor one of them that produces fewer partitions. The order of the different partitioning levels

Algorithm 5: Query Cost Computation

input : q (query), rp (range pair), M (query-to-range-set map), R (input range set)
output: Query cost to answer q when considering a merge of rp

Create an empty shadow table H having the same definition as the fact table F, including indexes and all constraints (check and referential integrity constraints).
Propagate all (field and index) statistics of F to H.
if F *has materialized views (MVs)* **then**
    Create the equivalent MVs on H.
    Propagate the statistics of the MVs on F to those of H.
end
$r_m \leftarrow$ Merge rp ;
$L \leftarrow$ Copy ranges associated with q from M;
Remove ranges in rp from and add r_m to L.
$R' \leftarrow$ Update R with L
Alter H using a fictitious MLPPI with R'.
Construct and send to the server an H-based shadow query h equivalent to q.
$ept \leftarrow$ Estimated processing time of h extracted from the server response ;
Update q's query cost to ept.
return ept

may have some impact on the execution time. A range condition on lower levels like the query in Section 1 "`SELECT * FROM LINEORDER WHERE LO_QUANTITY < 25`" requires scanning non-consecutive partitions. This may incur some overhead at run time. To reduce this effect, we sort the partition levels based on the number of partitions in descending order before making the final recommendation. The solution in Figure 1 follows this heuristic making the two-partition case in the first level followed by the four-partition case in the second level. The order in Figure 3 can go either way since both levels have the same number of partitions.

In the running example, suppose that in the first round, ranges $R[1, 1]$ and $R[1, 2]$ are chosen for a merge. Then, the wizard produces a merged range $[1, 5]$ under `LO_DISCOUNT` and proceeds to the next round. If a range pair selected for the subsequent merge fails to improve T_p, then, the tool exits the optimized phase and produces the final MLPPI recommendation for the given workload Q as shown in Figure 3.

```
ALTER TABLE LINEORDER
MODIFY PRIMARY INDEX
PARTITION BY(
  CASE_N(
    LO_DISCOUNT ≥ 1 AND LO_DISCOUNT ≤ 5,
    LO_DISCOUNT ≥ 7,
    NO CASE OR UNKNOWN),
  CASE_N(
    LO_QUANTITY < 25,
    LO_QUANTITY ≥ 25 AND LO_QUANTITY ≤ 35,
    NO CASE OR UNKNOWN)
);
```

Fig. 3. The Final MLPPI Recommendation for the Given Workload Q

Algorithm 6: The Optimized Phase

```
   input  : M (query-to-range-set map), R (input range set)
   output: The MLPPI on which the total query cost is minimal
 1 W ← Query weights
 2 T_p ← Total query cost sum on an initial MLPPI by R
 3 while (Pre-defined iterations or R ≠ ∅) do
 4     foreach range pair rp in R do
 5         T_q ← 0 ;
 6         foreach q in M do
 7             w ← Get q's weight from W
 8             L ← Get the range set mapped to q in M
 9             if ((rp ∩ L) ≠ ∅) then                                  // Affected
10                 T_q += w·(getQC(q,rp,M,R)) ;        // See Algo. 5 regarding
                   getQC()
11             else T_q += w·(q's existing query cost)
12         end
13         Map T_q to rp.
14     end
15     T ← The least T_q that has been so far seen.
16     if T > T_p then break ;
17     else
18         T_p ← T ;                                   // Query Cost Sum Update
19         Find rp(s) with T.
20         If a tie happens, select the rp to make fewer partitions when consolidated.
21         Update M and R by the chosen rp.
22     end
23 end
24 return an MLPPI by R ;
```

3. Complexity Analysis

In this section we analyze the time complexity of the proposed algorithms: preprocessing, initial, and optimized phases. The metric of this complexity analysis on each phase is the logical running time of the wizard, equivalent to the number of API calls made to the database server during that phase.

3.1. The Preprocessing Phase

Lemma 1. *The running time complexity for building a query-to-range map is $O(N{\cdot}C{\cdot}V)$, where N is the number of queries in a workload, C is the total number of fields in the fact table, and V is the max number of values in a field.*

Proof. Consider the worst case such that given a workload of N queries, each query references all the fields of the fact table, and each field is associated with at most V values by the predicates of the queries. Each query may have a single-value range. A range consisting of only one value per field can be mapped to each query. Thus, the running time complexity for the map construction is $O(N{\cdot}C{\cdot}V)$. □

But note that in our experiments the bound of $O(N{\cdot}C{\cdot}V)$ was overly pessimistic.

3.2. The Initial and Optimized Phases

Lemma 2. *The running time complexity for the initial (or optimized) phase is O($M^2 \cdot N$), where M is the number of range pairs, and N is the number of queries in a workload.*

Proof. Suppose that the merge of every range pair influences all the queries. Every iteration, either the scan or query costs need to be recomputed for each query. In the first round we pay the re-computation cost of $M \cdot N$ and merge a victim range pair. In the subsequent round, M-1 range pairs remain, so the cost amounts to (M-1)$\cdot N$. In the worst case we end up consolidating all range pairs, thus having no partition on the target table. The total calls made to the server can be added up to

$$M \cdot N + (M\text{-}1) \cdot N + \cdots + N = (\sum_{i=1}^{M} i) \cdot N = \frac{M(M-1)}{2} \cdot N.$$

Hence, the running time complexity is $O(M^2 \cdot N)$. □

Again, our experiments showed that $O(M^2 \cdot N)$, the running time complexity, was overly pessimistic. Specifically, the number of calls made in our experiments was by far fewer than that bound. That was because it was very rare for a range pair to involve all queries in a given workload (as seen in Table 1).

4. Experiment

In this section we evaluate the performance of our wizard using the proposed algorithms. We first describe our environment settings. We then report the statistics measured during our experiments. Finally, we compare the performance of the recommendation by the MLPPI wizard (WIZARD) with (1) that of no partitioning (NO PPI) and (2) the partitioning of a human expert (EXP) under different setups.

4.1. Environment Settings

Development: We implemented our MLPPI wizard as a prototype on top of the Teradata DBMS server. The wizard was written in Java. We evaluated the performance of the wizard on the Teradata DBMS server machine running Unix.

Workload: When it comes to workload generation, we took advantage of our simple star schema query generator. The generator assumes that (i) available operators, (ii) fields, and (iii) the minimum and maximum values of the fields are already known. For each query, the generator first randomly selects the number of single-table predicates to create. The generator then arbitrarily chooses a field and a specific operator for each predicate. If `IN` operator on a chosen field is picked up, the query generator determines the number of values to add to the `IN` list and then chooses random values within the min-max value range of the field. In this way the generator makes a query involving the generated predicates.

A generated query is based on a template that joins `LINEORDER` and `DDATE` with constraints defined by the predicates. This template is common in customer cases like reports and form templates. Using the query generator we generated two workloads consisting of 10 queries (10Q) and 20 queries (20Q).

For the query workloads we populated the fact table with a scale factor of 1TByte (1TB) and 3TBytes (3TB).

Table 1. The statistics obtained on the used workloads

Item		The Initial Phase		The Optimized Phase	
		10Q	20Q	10Q	20Q
1	# of input partitions	1,008,000	110,739,200	51,840	59,520
2	# of input range pairs	441	4,180	24	48
3	# of total API calls (# of worst calls by Lemma 2)	1,305 (1,944,810)	31,915 (349,448,000)	78 (5,760)	388 (46,080)
4	# of average API calls per range pair	3	8	3	8
5	# of average range pairs compared per iteration	32	76	24	48
6	The maximum # of range pairs compared per an iteration	38	103	24	48
7	The minimum # of range pairs compared per an iteration	25	49	24	48
8	# of average API calls made per iteration	93	580	78	388
9	The maximum # of API calls made per an iteration	123	791	78	388
10	The minimum # of API calls made per an iteration	73	381	78	388

4.2. Statistics Report

Table 1 summarizes the execution statistics of which were obtained while the recommendations for the workloads were produced. The statistics includes input partitions, range pairs, number of API calls made, and total iterations observed in each phase.

About 1 million partitions were initially derived for 10Q, and roughly 110 million partitions for 20Q (Item #1). Although the workload size doubled from 10Q to 20Q, the total number of partitions increased exponentially. Much more predicates with different bindings produced about 110x more ranges in 20Q than those of 10Q. While a huge number of input partitions were made, the number of range pairs collected per field was relatively small (Item #2).

The total number of iterations in the initial phase tended to be proportional to the input partitions generated from the 10Q and 20Q workloads. Note that the optimized phase ran only once for those two workloads. Since the partitions produced by the initial phase were customized enough, no more iterations were necessary for further optimization.

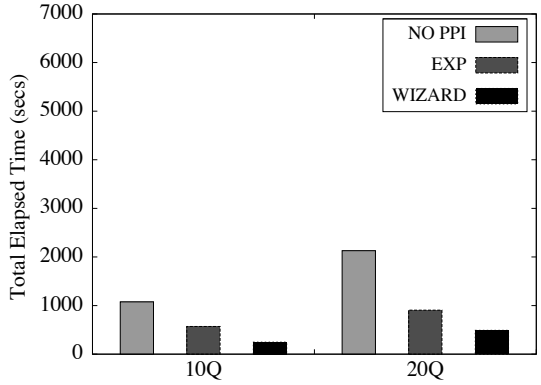
As mentioned in Section 3, for each workload the number of the total calls to the server were extremely small, compared to that of the theoretical worst calls shown in the parentheses (Item #3). The worst call counts were calculated regarding the number of queries and range pairs observed in each phase. Furthermore, the average number of calls per range pair (was limited within 10 across the workloads and phases (Item #4).

Finally, the per-iteration numbers of the average, minimum, and maximum range pairs proportionally increased along with the growing workload size (Items #5$\sim$#7), while the per-iteration numbers of the average, minimum, and maximum API calls increased more than the scale factor (of 2x) (Items #8$\sim$#10). But empirically the number of invoked API calls were much fewer than that of the theoretical bound.

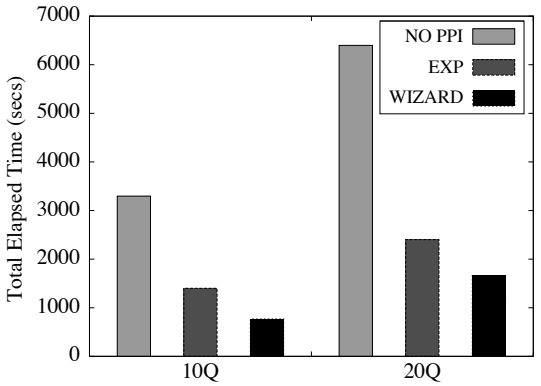
4.3. Performance Evaluation

The main focus of our experiments is to see the performance (quality) of MLPPI recommendations made by the MLPPI wizard (WIZARD), compared with the performance of NO PPI (no partitioning) and EXP (partitioning by a human expert).

Figures 4 and 5 exhibit our evaluation results. Figure 4 shows the times taken to run the 10Q and 20Q workloads over the 1TB and 3TB fact tables that we populated into the database server. Based on the run results, Figure 5 shows how much improvement was gained by the EXP and WIZARD solutions, compared with that of NO PPI.



(a) 1TB



(b) 3TB

Fig. 4. Total Elapsed Time

Overall, the WIZARD recommendations were very effective at partitioning the fact table via the predicates in the given workloads. As shown in Figure 4, the total execution times of the 10Q and 20Q on the WIZARD recommendations was on average about 3.5 and 2 times faster than those of NO PPI and EXP, respectively. The quality of the WIZARD solutions also outperformed that of the EXP solutions; the WIZARD solutions yielded an average of about 77% improvement on the NO PPI solutions.

In addition, the WIZARD recommendations scaled very well with the combination of growing workload/table size, as illustrated in Figure 5. Even though we doubly increased the workload size from 10Q to 20Q, the performance improvement of our solution (WIZARD) retained the same in Figure 5(a). Also, for the 3T table the performance gain of WIZARD was almost unchanged (at around 80%) as shown in Figure 5(b). This result showed that our WIZARD solution was scalable over increasing workload size.

We also increased the table scale from 1TByte to 3TBbytes. For 10Q the performance improvement (about 77%) was almost the same over the increasing scales. For 20Q the gain was reduced from 76% to 74%, but it was almost negligible. Hence, the WIZARD partitioning recommendation scaled well with the increasing table size.

In sum, our experiment results attest the effectiveness of the proposed algorithms for WIZARD and demonstrate the superiority of the recommendations of WIZARD.

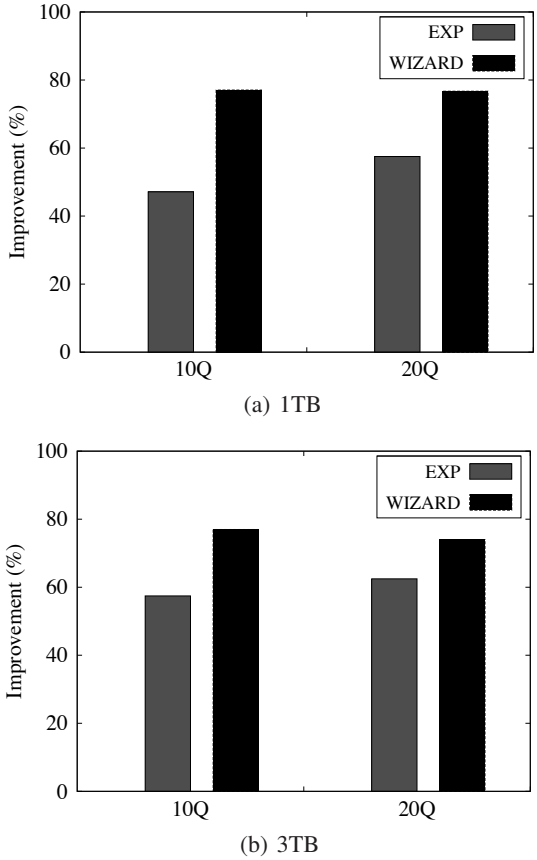


Fig. 5. Recommendation Quality Comparison

5. Related Work

Physical database design [6, 10, 18] has been discussed in academic research and industrial communities in the past decades. The major DBMS vendors have led much of the work. Their specific interests have been around automating the physical design for table partitioning [3, 11, 13, 15–17], indexes/materialized views [1, 2, 5, 8, 12, 22, 24], and integration [23].

Some of the tools in IBM DB2 [11], Oracle [15], and MS SQL Server [3] appear to be similar to our MLPPI wizard. But with respect to problem scope and approach the wizard is *fundamentally different* from the existing tools, except Oracle Partitioning Advisor [15] that provides no published technical details.

First, DB2 MDC Advisor [11] actually tackles a different problem of automatically recommending the most well-suited MDC keys for a given workload. Agrawal's work [3] discusses another problem of merging single-level range partitionings on objects such as tables and indexes. On the other hand, we address the multi-level partitioning problem. Hence, the existing solutions cannot be directly applied to our MLPPI wizard.

Regarding the approach, DB2 MDC Advisor [11] uses the search space driven by fields. In contrast, our search space is driven by *query-predicates*, of which the use is

superior to that of the fields, as utilizing predicates can be more customized and specific to a given workload.

Agrawal's horizontal partitioning scheme [3] also uses the search space driven by simple range predicates, but his technique has a shortcoming. Specifically, his work produces a solution for each individual query and attempt to merge the solutions. But this approach cannot reach an optimized solution in a global perspective. We generate the whole search space upfront and in turn merges partitions, leading to a globally-optimized solution. While his work considers a single column only, our wizard deals with *multiple* fields.

Implementations of previous tools [3, 11, 13] required instrumentation for optimizer code. These instrumentations are needed to facilitate the required information for the physical design tools API calls. The instrumentation code need to be enhanced and tested for new database releases that add complexity and additional cost for software upgrades. But our algorithm is based existing APIs supported by an optimizer (like Teradata), which requires no code change in the optimizer.

Also, Nehme's work [13], deeply-integrated with optimizer, reveals a concern about the quality of the recommendations made by some tools, shallowly integrated with optimizer. But we observed in our experiments that the quality of the wizard's solutions was much superior to that of the base solutions. In addition, some might argue that in our loosely-coupled approach the cost to invoke the optimizer might be significant. But the measured call counts were much fewer than the theoretical bound, since most calls were made only when queries were affected by a merge.

Lastly, there has been some previous work [13, 17, 21] regarding table partitioning in multi-node systems, but our problem is discussed in the context of a single node system, as in the existing work [3]. Database cracking [7] assumes a single node environment, but it does not address our multi-level partitioning problem.

6. Conclusion

Given workloads, it is difficult for DBAs to select appropriate fields in partitioning the fact table due to large search space. DBAs cannot easily determine how granular partitions should be made for the workloads.

To address this concern, we presented the MLPPI wizard to recommend a fact-table partitioning for a given star schema workload. Since query-predicates are exploited to capture necessary ranges for fields and define partitions, the MLPPI recommendation can be very optimized, customized to the workload.

We proposed the wizard's algorithms consisting of the three phases. The wizard incrementally reduced its search space by merging the range pair with the least scan or query cost, and eventually reached an MLPPI recommendation. We also analyzed the running complexity for the initial and optimized phases. Despite the theoretically high bound, the wizard in practice invoked much fewer calls in these phases.

Using synthetic workloads, we evaluated the performance of the recommendation produced by the wizard. We demonstrated that the produced MLPPI solutions by the wizard reduced the total elapsed time by more than a factor of two, compared with those of no partitioning approach and partitioning done by a human expert.

References

1. Agrawal, S., Chaudhuri, S., Kollar, L., Marathe, A., Narasayya, V., Syamala, M.: Database Tuning Advisor for Microsoft SQL Server 2005: Demo. In: SIGMOD. pp. 930–932 (2005)
2. Agrawal, S., Chaudhuri, S., Narasayya, V.R.: Automated Selection of Materialized Views and Indexes in SQL Databases. In: VLDB. pp. 496–505 (2000)
3. Agrawal, S., Narasayya, V., Yang, B.: Integrating Vertical and Horizontal Partitioning into Automated Physical Database Design. In: SIGMOD. pp. 359–370 (2004)
4. Chaudhuri, S., Narasayya, V.: AutoAdmin 'What-If' Index Analysis Utility. SIGMOD Record 27(2), 367–378 (1998)
5. Dash, D., Polyzotis, N., Ailamaki, A.: Cophy: A scalable, portable, and interactive index advisor for large workloads. PVLDB 4(6), 362–372 (2011)
6. Finkelstein, S., Schkolnick, M., Tiberio, P.: Physical Database Design for Relational Databases. ACM Trans. on Databas. Syst. 13(1), 91–128 (1988)
7. Idreos, S., Kersten, M.L., Manegold, S.: Database Cracking. In: CIDR. pp. 68–78 (2007)
8. Kimura, H., Narasayya, V., Syamala, M.: Compression Aware Physical Database Design. PVLDB 4(10), 657–668 (2011)
9. Klindt, J.: Single-level and Multilevel Partitioned Primary Indexes, [Online]. Available: http://www.teradata.com/white-papers/Single-level-and-Multilevel-Partitioned-Primary-Indexes-eb1889/ (current July 2015)
10. Labio, W., Quass, D., Adelberg, B.: Physical Database Design for Data Warehouses. In: ICDE. pp. 277–288 (1997)
11. Lightstone, S.S., Bhattacharjee, B.: Automated Design of Multi-dimensional Clustering Tables for Relational Databases. In: VLDB. pp. 1170–1181 (2004)
12. Microsoft SQL Server 2000: Index Tuning Wizard SQL Server 2000, [Online]. Available: http://technet.microsoft.com/en-us/library/cc966541.aspx (current March 2012)
13. Nehme, R., Bruno, N.: Automated Partitioning Design in Parallel Database Systems. In: SIGMOD. pp. 1137–1148 (2011)
14. O'Neil, P., O'Neil, B., Chen, X.: The Star Schema Benchmark (SSB), [Online]. Available: http://www.cs.umb.edu/ poneil/StarSchemaB.PDF (current February 2017)
15. Oracle: Partitioning Advisor, [Online]. Available: http://www.oracle.com/technetwork/database/options/partitioning/twp-partitioning-11gr2-2009-09-130569.pdf (current February 2017)
16. Oracle: SQL Access Advisor, [Online]. Available: http://docs.oracle.com/cd/B19306_01/server.102/b14211/advisor.htm (current March 2012)
17. Rao, J., Zhang, C., Megiddo, N., Lohman, G.: Automating Physical Database Design in A Parallel Database. In: SIGMOD. pp. 558–569 (2002)
18. Rozen, S., Shasha, D.: A Framework for Automating Physical Database Design. In: VLDB. pp. 401–411 (1991)
19. Sinclair, P.: Using PPIs to Improve Performance (2008), [Online]. Available: http://www.teradata.com/tdmo/v08n03/pdf/AR5731.pdf (current August 2015)
20. Suh, Y.K., Ghazal, A., Crolotte, A., Kostamaa, P.: A New Tool for Multi-level Partitioning in Teradata. In: CIKM. pp. 2214–2218 (2012)
21. Tatarowicz, A.L., Curino, C., Jones, E.P.C., Madden, S.: Lookup Tables: Fine-grained Partitioning for Distributed Databases. In: ICDE (2012)
22. Valentin, G., Zuliani, M., Zilio, D.C., Lohman, G., Skelley, A.: DB2 Advisor: An Optimizer Smart Enough to Recommend Its Own Indexes. In: ICDE. pp. 101–110 (2000)
23. Zilio, D.C., Rao, J., Lightstone, S., Lohman, G., Storm, A., Garcia-Arellano, C., Fadden, S.: DB2 Design Advisor: Integrated Automatic Physical Database. In: VLDB. pp. 1087–1097 (2004)
24. Zilio, D.C., Zuzarte, C., Lohman, G.M., Pirahesh, H., Gryz, J., Alton, E., Liang, D., Valentin, G.: Recommending Materialized Views and Indexes with the IBM DB2 Design Advisor. In: Proc. of the Int'l Conf. on Autonomic Computing. pp. 180–188 (2004)