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 a novel physical design tool to recommend a multi-level partitioning solution 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 over the network. Thus, there is no overhead to instrument the optimizer code as opposed to some previous works. Note that our predicate-driven method can be applied to any clustering or partitioning scheme in a relational database management system (DBMS) that underlies information systems. We show that the tool's recommendation outperforms a human expert's solution with respect to the total execution time of a given workload. We also demonstrate that the recommendation scales very well with an increasing workload over a growing fact table.

Keywords: Data warehousing, information systems, star schema, fact table, OLAP, analytical workloads, multi-level partitioning

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1. Introduction

Over the past decades much attention has been paid to improve the performance on analytical workloads like OLAP in a data warehousing environment. A relational database management system (DBMS), which underlies information systems, has been exploited to process such analytical queries faster and assist customers to draw a timely business-decision in rapidly-changing enterprise data warehousing. Teradata DBMS has been positioned as leading one in this data warehousing marketplace getting more competitive than ever.

Background: To optimize the performance of analytical processing in the Teradata DBMS, tables and materialized views 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) [1] is an optional horizontal partitioning scheme applied locally on the data belonging to each AMP. In some other DBMSes, this type of 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) [2].

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.

Fig. 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) [3]. (Note that the full table with modified data types was actually used in our experiments.)

```
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 a `LINEORDER` Table with Multi-level Partitioned Primary Index

In the definition of LINEORDER in **Fig. 1**, 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 2×4 = 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.'

Challenge: Consider the below query set Q with 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. Consequently, the DBA is encountered 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 it is based on a general framework allowing general expressions, ranges and case expressions for partition definitions. Note 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.

Fig. 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 detail on each of the three phases, using the running query set *Q* consisting of *q1* and *q2* in the rest of the article.

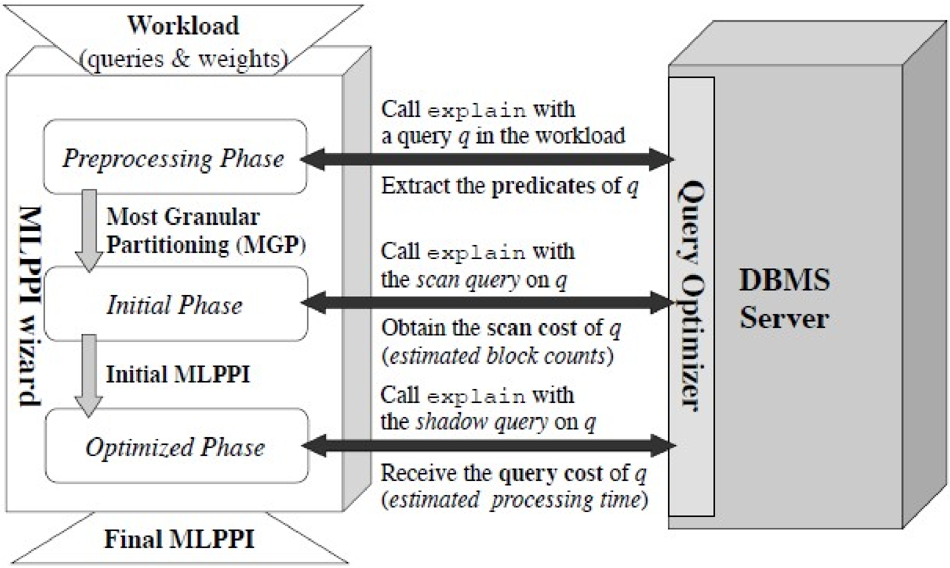


Fig. 2. The MLPPI Wizard Architecture

As illustrated in **Fig. 2**, the wizard resides completely on the client side as opposed to several previous tools [4–6] 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 execution 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.

– We empirically show that a partitioning recommendation of our tool outperforms those of a human expert and no partitioning over increasing workload size and growing fact table.

The article is a substantial extension of a prior work [7]. 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 database system. 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 DBMSes. We conclude this article by summarizing our discussion.

2. The MLPPI wizard

The MLPPI wizard has the three phases for a final partitioning recommendation as shown in **Fig. 2**. 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 six steps, as shown in **Alg. 1**.

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*)

Alg. 1. The Preprocessing Phase

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 in- stance, if a query predicate has the condition of '`LO_DISCOUNT IN (1, 4, 5) AND LO_DISCOUNT IN (2, 3, 4, 5)`', then the predicate can be simplified as '`LO_DISCOUNT IN (4, 5).`' This simplification can be completed 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 finished through an API call to the server. The query predicate is of the form

$$\langle variable\rangle\ \langle op\rangle\ \langle constant\rangle,$$

where ⟨*variable*⟩ is a field from `LINEORDER`, ⟨*op*⟩ is in {= , <, <=, >=, >, `IN`}, and ⟨`constant`⟩ represents a constant value(s). All ⟨*op*⟩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 bidirectional 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*, which is 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 in *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 *p*1 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 per-field distinct range set (*R*) is comprised of the entries below.

R:

`LO_DISCOUNT` = {[1, 1], [4, 5], [7, ∞)}
`LO_QUANTITY` = {(∞, 30], [25, 35]}.

In turn, we build another map, called *M*2, 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*. For instance, *R*[1, 3] indicates range [7, ∞) under `LO_DISCOUNT`. In the running example, M 2 is constructed as follows:

*M*2:

⟨*p*1, {*R*[1, 1], *R*[1, 2]}⟩
⟨*p*2, {*R*[1 ,3]}⟩
⟨*p*3, {*R*[2, 1]}⟩
⟨*p*4, {*R*[2, 2]}⟩.

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.

Alg. 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 adjacent ranges overlap each other or not. If that is the case, we make a split between the ranges. In the example, the split is applied on the overlapping ranges, (∞, 30] and [25, 35] in `LO_QUANTITY`. Subsequently, we then create a common (or intermediate) range ([25, 30]) and insert 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` = {[1, 1], [4, 5], [7, ∞)}
`LO_QUANTITY` = {(∞, 25), [25, 30], [31, 35]}

The update of *R* affects the existing map *M2*. In the running example, *p*3 and *p*4, influenced by the split, are 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` remains unchanged. As a result, in the running example we obtain the updated *M2* in the following.

M2:

⟨*p*1, {*R*[1, 1], *R*[1, 2]}⟩
⟨*p*2, {*R*[1, 3]}⟩
⟨*p*3, {*R*[2, 1], *R*[2, 2]}⟩
⟨*p*4, {*R*[2, 2], R[2, 3]}⟩.

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+1}.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
```

Alg. 2. Splitting Overlapping Ranges

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*, which is 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. However, 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 ($M1$ to $M2$) 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, we use for cost computation and then update M in accordance with a merge of ranges; 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 **Fig. 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* (i.e., an input range set, or *MGP*) and the prepared *M* (i.e., a 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, the merge may increase I/O cost, in that the full scan on a partition should be carried out 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.

Alg. 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, denoted by s, which can be constructed as follows:

s: `SELECT * FROM` *F* `WHERE` *CP*,

where *F* is a fact table such as `LINE_ORDER`, and *CP* indicates the predicates restored from the ranges mapped to *q* from *M*.

If *q* turns out to be 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*.

To see in **Alg. 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 {(∞, 25), [25, 35]} and {[25, 35]}, respectively. Certainly, 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 in the following.

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

r_m ← Consolidate *rp*
L ← Copy the range set mapped to *q* from *M*;
Delete ranges in *rp* from and insert r_m into *L*.
s ← "`SELECT * FROM LINE_ORDER WHERE`";
foreach *range* $r \in L$ **do**
    Restore a predicate *p* from *r*.
    Add *p* to `WHERE` clause of *s*.
end
Make an API call with s to the server.
Extract the spool size (in bytes) from the result.
blc ← Calculate the block counts from the spool size.
Update *q*'s scan cost to *blc*.
return *blc*;

Alg. 3. Computing scan cost

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 {(∞, 25), [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 (denoted by *blc*) using the spool size. If the merge of a range pair does not influence 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 re-computes 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 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 the 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` = {[1, 1], [4, 5], [7, ∞)}
`LO_QUANTITY` = {(∞, 25), [25, 35]}

M:
⟨*q*1, {*R*[1, 1], *R*[1, 2], *R*[2, 1], *R*[2, 2]}⟩
⟨*q*2, {*R*[1, 3], *R*[2, 2]}⟩

Note that we see that *q*2 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 *q*2. *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*.

Alg. 4 describes the initial phase. 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 (or 4×3=12) by *R* is under the assumed limit (or 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 affects the query optimizer. There also exists an operational threshold that the optimizer can handle the maximum number of the partitions at a time. Thus, further reducing partitions greatly helps the optimizer to manage these partitions.

A similar algorithm, as suggested in the initial phase, is applied. Namely, this phase uses query cost, which is analogous to scan cost; we can obtain the query cost via a feasible MLPPI. The query cost is defined as the estimated processing time of a query on a so-called "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 [8].

input: M (query-to-range-set map) and R (input range set)
output: R with # partitions, fewer than or equal to a specified partition limit

```
W ← Query weights
while ← (# partitions by R > partition limit) do
  foreach range pair, rp ∈ R do
    T_s ← 0;
    foreach q ∈ M do
      w ← Get q's weight from W
      L ← Get the range set mapped to q in M
      if ((rp ∩ L) ≠ ∅) then
          T_s += w·(getSC(q, rp, M)); // Influenced
      else T_s += w·(q's existing scan cost) // See Alg. 3 regarding getSC()
    end
    Associate T_s with rp.
  end
  Find rp(s) with the least Ts.
  If a tie occurs, then choose the rp to make fewer partitions when being consolidated.
  Update M and R by the chosen rp.
end
return R;
```

Alg. 4. The Initial Phase

Alg. 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 (now R'), applying the merge of rp. We then build a shadow query h that is equivalent to the input query q and replaces F in q with H. In turn, we make 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 associated with q. As in the initial phase, the query cost of a query is recomputed only if the merge affects the query.

Alg. 6 proposes the algorithm of the optimized phase. W indicates a set of weights assigned to individual queries in a given workload. Tp keeps track of the existing least query cost sum, and initially is computed on an initial MLPPI. For each range pair, the algorithm computes Tq, the respective weighted sum of query costs of the queries in a given workload. (Tq can be similarly defined as Ts, described in Section 2.2, and thus the definition of Tq is omitted here.) Let the current least Tq be T. If $T <= Tp$ (or the existing least), then for the next iteration Tp 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 this optimization process, until (i) there are no more ranges in R left, or (ii) the number of specified iterations is reached. If $T >= Tp$, 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 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

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

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 ←Merge *rp*;
L ← Copy ranges associated with *q* from *M*;
Remove ranges in *rp* from and add r_m to *L*.
R' ← 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 ← Estimated processing time of *h* extracted from the server response;
Update *q*'s query cost to *ept*.
return *ept*

Alg. 5. Computing query cost

input: *M* (a query-to-range-set map) and *R* (an input range set)
output: an MLPPI solution to produce the minimum total query cost

W ← Query weights
T_q ← Total query cost sum on an initial MLPPI by *R*;
while ← (Pre-defined iterations || $R \neq \emptyset$) **do**
  foreach *range pair*, $rp \in R$ **do**
    T_q ← 0;
    foreach $q \in M$ **do**
      w ← Get *q*'s weight from W
      L ← Get the range set mapped to *q* in *M*
      if (($rp \cap L) \neq \emptyset$) **then**
        T_q += *w*·(*getQC*(*q*, *rp*, *M*, *R*)); `// Influenced`
      else T_q += *w*·(*q*'s existing query cost) `// See Alg.5 on` *getQC*`()`
    end
    Map T_q to *rp*.
  end
  T ← The least T_q that has been so far seen.
  if $T > T_p$ then break;
  else
    T_p ← *T*;
    Find *rp*(s) with *T*.
    If a tie occurs, then choose the *rp* to make fewer partitions when being consolidated.
    Update M and R by the chosen *rp*.
  end
end
return an MLPPI by *R*;

Alg. 6. The Optimized Phase

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 **Fig. 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 **Fig. 3** can go either way since both levels have the same number of partitions.

In the running example, suppose that in the first round, for instance, a range pair of $R[1, 1]$ and $R[1, 2]$ are chosen for a merge. If so, then the wizard produces a merged range, or [1, 5] under `LO_DISCOUNT`; it 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 **Fig. 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

3. Complexity Analysis

In this section, we analyze the time complexity of the proposed algorithms: preprocessing, initial, and optimized phases. The metric 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

The following Lemma is the analysis on the running time of 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 is $O(N{\cdot}C{\cdot}V)$. □

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

3.2 The Initial and Optimized Phases

The following is the running time complexity on each of 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 $(M\text{-}1) \cdot N$. 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

$$M \cdot N + (M\text{-}1) \cdot N + \cdots + N = \left(\sum_{i=1}^{M} i\right) \cdot N = (M\,(M - 1) / 2) \cdot N$$

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

Our experiments also showed that the above 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. Experiments

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 dur ing 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. We developed our wizard 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 obtained while the recommendations for the workloads were produced. The statistics includes input partitions, range pairs, the number of API calls made, and total iterations observed in each phase.

Approximately 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, there was no need to iterate for further optimization.

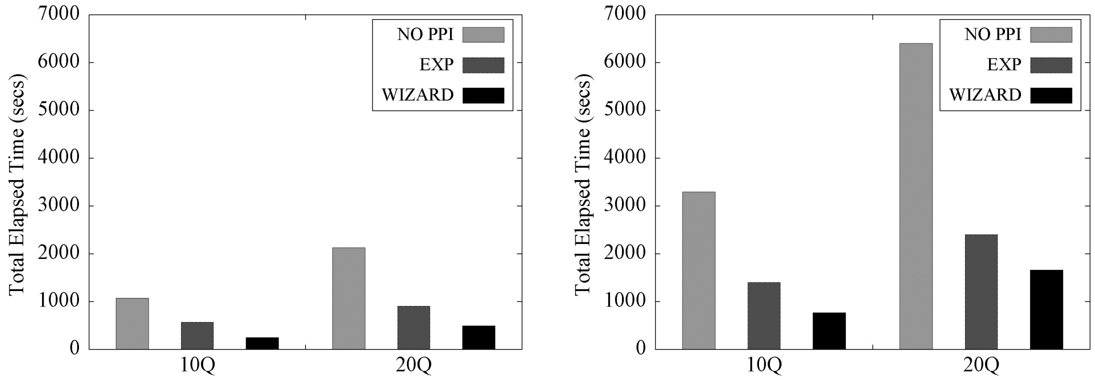
As mentioned in Section 3, for each workload the number of the total calls to the server was extremely small, compared to that of the theoretical worst calls shown in the parentheses (Item #3). The worst call counts were calculated regarding the number of queries and range pairs observed in each phase. 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~#7), while the per-iteration numbers of the average, minimum, and maximum API calls increased more than the scale factor (of 2x) (Items #8~#10). Nevertheless, empirically the number of invoked API calls was much fewer than that of the theoretical bound.

4.2 Performance Evaluation

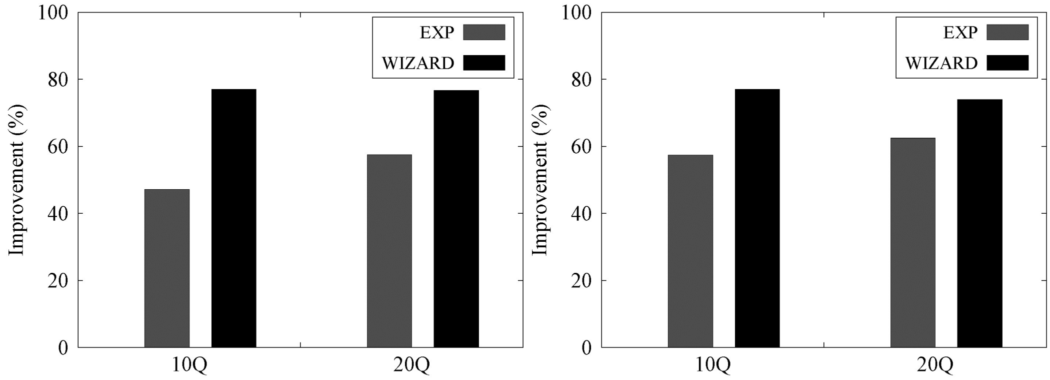
The focus of our experiments is to see the performance (quality) of MLPPI recommendations made by the MLPPI wizard (WIZARD), compared with the performance of NO PPI (no partitioning) and EXP (partitioning by a human expert).

Figs. 4 and 5 exhibit our evaluation results. Fig. 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 experiment results, Fig. 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. The total elapsed time



(a) 1TB (b) 3TB

Fig. 5. Quality comparison

Overall, the WIZARD recommendations were very effective at partitioning the fact table via the predicates in the given workloads. First, regarding the total execution time for the 10Q workload on the 1TB table, our wizard outperformed NO PPI and EXP by about 4x and 2x, respectively, as illustrated in **Fig. 4(a)**. Such a performance gain was retained even when we doubled the workload size to 20Q. As seen in in **Fig. 4(b)**, the proposed tool bettered the total execution time on the 3TB table by almost a factor of four and two, compared with NO PPI and EXP, respectively, regardless of 10Q or 20Q.

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

When we increased the table scale from 1TByte to 3TBbytes, the performance improvement (about 77%) of our wizard for 10Q was almost the same in spite of the increased table scale. In the case of 20Q, the gain was somewhat reduced to 74% for the 3TB table, compared with 77% for the 1TB table, but it was almost negligible. Hence, the WIZARD partitioning recommendation scaled well with the increasing table size.

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

5. Related Work

Physical database design [9–11] 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 [4–6, 12–14], indexes/materialized views [15–21], and integration [22].

Some of the tools in IBM DB2 [5], Oracle [12], and MS SQL Server [4] 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 [5] actually tackles a different problem of automatically recommending the most well suited MDC keys for a given workload. Agrawal's work [4] 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 [5] 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 [4] 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. However, this approach cannot reach an optimized solution in a global perspective. We generate the whole search space upfront and in turn merge 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 [4–6] 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.

In addition, Nehme's work [6], deeply integrated with optimizer, reveals a concern about the quality of the recommendations made by some tools, shallowly integrated with optimizer. However, 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.

Some previous work [6, 14, 20] tackles table partitioning in multi-node systems, but our problem is discussed in the context of a single node system, as in the existing work [23]. Database cracking [24] assumes a single node environment, but it does not address our multi-level partitioning problem.

Lastly, there exists also some other recent work proposing a multi-level algorithm or a recommendation system. Wang et al. [24] aim at improving online service under hybrid deployment, using an effective multi-level scheduling algorithm. Yuan's work [25] proposes a top-k recommendation system for OLAP sessions for better user assistance. Even though these works and our work seems to have something in common in terms of multi-level and recommendation, the existing works are discussed in a different domain from ours giving a main focus on "partitioning" a fact table for better performance of a star schema workload.

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 much 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.

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