High-Dimensional OLAP: A Minimal Cubing Approach*

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Abstract

Data cube has been playing an essential role in fast OLAP (online analytical processing) in many multi-dimensional data warehouses. However, there exist data sets in applications like bioinformatics, statistics, and text processing that are characterized by high dimensionality, *e.g.*, over 100 dimensions, and moderate size, *e.g.*, around 10^6 tuples. No feasible data cube can be constructed with such data sets. In this paper we will address the problem of developing an efficient algorithm to perform OLAP on such data sets.

Experience tells us that although data analysis tasks may involve a high dimensional space, most OLAP operations are performed only on a small number of dimensions *at a time*. Based on this observation, we propose a novel method that computes a thin layer of the data cube together with associated value-list indices. This layer, while being manageable in size, will be capable of supporting flexible and fast OLAP operations in the original high dimensional space. Through experiments we will show that the method has I/O costs that scale nicely with dimensionality. Furthermore, the costs are comparable to that of accessing an existing data cube when full materialization is possible.

1 Introduction

Since the advent of data warehousing and online analytical processing (OLAP) [9], data cube has been playing an essential role in the implementation of fast OLAP operations [10]. Materialization of a data cube is a way to precompute and store multi-dimensional aggregates so that multi-dimensional analysis can be performed on the fly. For this task, there have been many efficient cube computation algorithms proposed, such as ROLAP-based multi-dimensional aggregate computation [1], multiway array aggregation [24], BUC [7], H-cubing [11], and Star-cubing [22]. Since computing the whole data cube not only requires a substantial amount of time but also generates a huge number of cube cells, there have also been many studies on partial materialization of data cubes [12], iceberg cube computation [7, 11, 22], computation of condensed, dwarf, or quotient cubes [19, 18, 13, 14], and computation of approximate cubes [16, 5].

Besides large data warehouse applications, there are other kinds of applications like bioinformatics, survey-based statistical analysis, and text processing that need the OLAP-styled data analysis. However, data in such applications usually are high in dimensionality, *e.g.*, over 100 or even 1000 dimensions but only medium in size, *e.g.*, around 10^6 tuples. This kind of datasets behaves rather differently from the datasets in a traditional data warehouse which may have about 10 dimensions but more than 10^9 tuples. Since a data cube grows exponentially with the number of dimensions, it is too costly in both computation time and storage space to materialize a full high-dimensional data cube. For example, a data cube of 100 dimensions, each with 10 distinct values, may contain as many as 11^{100} aggregate cells. Although the adoption of iceberg cube, condensed cube, or approximate cube delays the explosion, it does not solve the fundamental problem.

In this paper, we propose a new method called *shell-fragment*. It vertically partitions a high dimensional dataset into a set of disjoint low dimensional datasets called *fragments*. For each fragment, we compute its local data cube. Furthermore, we register the set of tuple-ids that contribute to the non-empty cells in the fragment data cube. These tuple-ids are used to bridge the gap between various fragments and re-construct the corresponding cuboids upon request. These shell fragments are pre-computed offline and are used to compute queries in an online fashion. In other words,

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data cubes in the original high dimensional space are dynamically assembled together via the fragments.

We will show that this method achieves high scalability in high dimensional space both in terms of storage space and I/O. When full materialization of the data cube is impossible, our method provides a reasonable solution. In addition, as our experiments show, the I/O costs of our method are competitive with those of the materialized data cube.

The remainder of the paper is organized as follows. In Section 2, we present the motivation of the paper. In Section 3, we introduce the shell fragment data structure and design. In Section 4, we describe how to compute OLAP queries using the fragments. Our performance study on scalability, I/O, and other cost metrics is presented in Section 5. We discuss the related work and the possible extensions in Section 6, and conclude our study in Section 7.

2 Analysis

Numerous studies have been conducted on data cubes to promote fast OLAP. However, most cubing algorithms have been confined to only low or medium dimensional data. We shall show the inherent "*curse of dimensionality*" of data cube in this section and provide motivation for our online computation model.

2.1 Curse of Dimensionality

The computation of data cubes, though valuable for low-dimensional databases, may not be so beneficial for high-dimensional ones. Typically, a high-dimensional data cube requires massive memory and disk space, and the current algorithms are unable to materialize the full cube under such conditions. Let's examine an example.

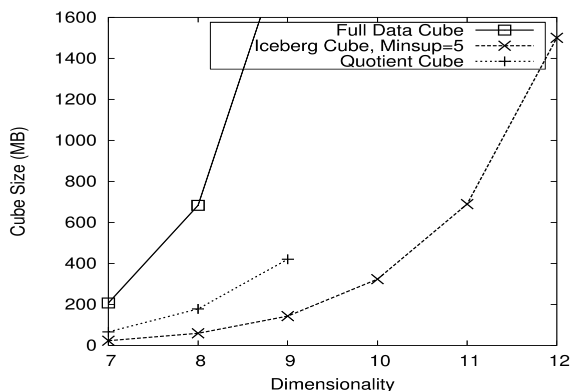

Figure 1: The curse of dimensionality on data cubes

Example 1. We generated a base database of 600,000 tuples. Each dimension had a cardinality of 100 with *zipf* equal to 2. The number of dimensions varies from 7 to 12 on the x-axis in Figure 1. The size of the data cube generated from this base cuboid grows exponentially with the number of dimensions as shown in Figure 1. The size of the full data cube reaches gigabytes when the number of dimensions reaches 9. And it climbs to well above petabytes before it reaches 20 dimensions, not to think about 100 dimensions.

Figure 1 also shows the size of an iceberg cube with minimum support of 5 for our database. It is much smaller than the full data cube because the base cuboid contains not many tuples and most high-dimensional cells fall below the support threshold. This sounds attractive because it may substantially reduce the computation time and disk usage while keeping only the "meaningful" results. However, there are several weaknesses. First, if a high-dimensional cell has the support already passing the iceberg threshold, it cannot be pruned by the iceberg condition and will still generate a huge number of cells. For example, a base-cuboid cell: "$(a_1, a_2, \ldots, a_{60})$:5" (*i.e.*, with count 5) will still generate 2^{60} iceberg cube cells. Second, it is difficult to set up an appropriate iceberg threshold. A too low threshold will still generate a huge cube, but a too high one may invalidate many useful applications. Third, an iceberg cube cannot be incrementally updated. Once an aggregate cell falls below the iceberg threshold and is pruned, incremental update will not be able to recover the original measure.

The situation is not much better for condensed, dwarf, or quotient cubes [19, 18, 13, 14]. The Dwarf cube introduced in [18] compresses the cuboid cells by exploiting sharing of prefixes and suffixes. Its size complexity was shown to be $O(T^{1+1/(\log_d C)})$ [17] where d is the number of dimensions, C is cardinality, and T is the number of tuples. In high dimensional data where d is large, $\log_d C$ could become quite small. In which case, the exponent becomes quite large and the cube size still explodes.

For quotient cubes [13, 14], compression can only be effective when the corresponding measures are the same within a local lattice structure, which has limited pruning power as shown in Figure 1.

Lastly, there is a substantial I/O overhead for accessing a full materialized data cube. Cuboids are stored on disk in some fixed order, and that order might be incompatible with a particular query. Processing such queries may need a scan of the entire corresponding cuboid.

One could avoid reading the entire cuboid if there were multi-dimensional indices constructed on all cuboids. But in a high-dimensional database with many cuboids, it might not be practical to build all these indices. Furthermore, reading via an index implies random access for each row in the cuboid, which could turn out to be more expensive than a sequential scan of the raw data.

A partial solution, which has been implemented in some commercial data warehouse systems is to com-

pute a thin *cube shell*. For example, one might compute all cuboids with 3 dimensions or less in a 60-dimensional data cube. There are two disadvantages to this approach. First, it still needs to compute $\binom{60}{3} + \binom{60}{2} + 60 = 36050$ cuboids. Second, it does *not* support OLAP in a large portion of the high-dimensional cube space because (1) it does not support OLAP on 4 or more dimensions (the shell only offers shallow penetration of the entire data cube), and (2) it cannot support drilling along even three dimensions, such as (A_4, A_5, A_6), *on a subset of data* selected based on the constants provided in three *other* dimensions, such as (A_1, A_2, A_3). These types of operations require the computation of the corresponding 6-D cuboid, which the shell does not compute. In contrast, our model supports OLAP operations on the *entire* cube space.

2.2 Computation Model

These observations lead us to consider possibly an online computation model of data cubes. It is quite expensive to online scan a high-dimensional database, extract the relevant dimensions, and then perform on-the-spot aggregation. Instead, a *semi-online computation model with certain pre-processing* seems to be a more viable solution.

Before delving deeper into the *semi-online computation model*, we make the following observation about OLAP in high-dimensional space. Although a data cube may contain many dimensions, most OLAP operations are performed only on a small number of dimensions *at a time*. In other words, an OLAP query is likely to ignore many dimensions (*i.e.*, treating them as *irrelevant*), fix some dimensions (*e.g.*, using query constants as *instantiations*), and leave only a few to be manipulated (for drilling, pivoting, *etc.*). This is because it is not realistic for anyone to comprehend the changes of thousands of cells involving tens of dimensions *simultaneously* in a high-dimensional space at the same time. Instead, it is more natural to first locate some cuboids by certain selections and then drill along one or two dimensions to examine the changes of a few related dimensions. Most analysts only need to examine the space of a small number of dimensions once they select them.

3 Precomputation of Shell Fragments

Stemming from the above motivation, we propose a new approach, called *shell_fragment*, and two new algorithms: one for computing shell fragment cubes, and one for query processing with the fragment cubes. This new approach will be able to handle OLAP in databases of extremely high dimensionality. It explores the inverted index well-studied in information retrieval [4] and value-list index in databases [8]. The general idea is to partition the dimensions into disjoint sets called *fragments*. The base dataset is projected onto each fragment, and data cubes are fully materialized for each fragment. With the precomputed *shell fragment cubes*, one can dynamically assemble and compute cuboid cells of the original dataset online. This is made efficient by set intersection operations on the inverted indices.

3.1 Inverted Index

To illustrate the algorithm, a tiny database, Table 1, is used as a running example. Let the cube measure be `count()`. Other measures will be discussed later.

tid	A	B	C	D	E
1	a1	b1	c1	d1	e1
2	a1	b2	c1	d2	e1
3	a1	b2	c1	d1	e2
4	a2	b1	c1	d1	e2
5	a2	b1	c1	d1	e3

Table 1: The Original Database

The inverted index is constructed as follows. For each attribute value in each dimension, we register a list of tuple IDs (*tids*) associated with it. For example, attribute value a2 appears in tuples 4 and 5. The tid-list for a2 then contains exactly 2 items, namely 4 and 5. The resultant inverted indices for the 5 individual dimensions are shown in Table 2.

Attribute Value	TID List	List Size
a1	1 2 3	3
a2	4 5	2
b1	1 4 5	3
b2	2 3	2
c1	1 2 3 4 5	5
d1	1 3 4 5	4
d2	2	1
e1	1 2	2
e2	3 4	2
e3	5	1

Table 2: Inverted Indices for Individual Dimensions A, B, C, D, and E

Lemma 1 *The inverted index table uses the same amount of storage space as the original database.*

Rationale. Intuitively, we can think of Table 1 as storing the common TIDs for attributes and Table 2 as storing the common attribute values for tuples. Formally, suppose we have a database of $\mathcal{T}$ tuples and $\mathcal{D}$ dimensions. To store it as shown in Table 1 would need $\mathcal{D} \times \mathcal{T}$ integers. Now consider the inverted index. Each tuple ID is associated with $\mathcal{D}$ attributes and thus will appear $\mathcal{D}$ times in the inverted index. Since we

have $\mathcal{T}$ tuple IDs in total, the entire inverted index will still only need $\mathcal{D} \times \mathcal{T}$ integers[1]. ■

3.2 Shell Fragments

The inverted index in Table 2 can be generalized to multiple dimensions where one can store tid-lists for combinations of attribute values across different dimensions. This leads to the computation of *shell fragments* of a data cube as follows.

All the dimensions of a data set are partitioned into independent groups, called *fragments.* For each fragment, we compute the complete *local* data cube while retaining the inverted indices. For example, for a database of 60 dimensions, A_1, A_2, ..., A_{60}, we first partition the 60 dimensions into 20 fragments of size 3: (A_1, A_2, A_3), (A_4, A_5, A_6), ..., (A_{58}, A_{59}, A_{60}). For each fragment, we compute its full data cube while recording the inverted indices. For example, in fragment (A_1, A_2, A_3), we would compute seven cuboids: $A_1, A_2, A_3, A_1A_2, A_2A_3, A_1A_3, A_1A_2A_3$. An inverted index is retained for each cell in the cuboids. The sizing and grouping of the fragments are non-trivial decisions and will be discussed later in Section 4.3.

The benefit of this model can be seen by a simple calculation. For a base cuboid of 60 dimensions, there are only $7 \times 20 = 140$ cuboids to be computed according to the above *shell_fragment* partition. Comparing this to 36050 cuboids for the cube shell of size 3, the saving is enormous.

Let's return to our running example.

Example 2. Suppose we are to compute the shell fragments of size 3. We first divide the 5 dimensions into 2 fragments, namely (`A`, `B`, `C`) and (`D`, `E`). For each fragment, we compute the complete data cube by intersecting the tid-lists in Table 2 in a bottom-up depths-first order in the cuboid lattice (as seen in [7]). For example, to compute the cell {`a1 b2 *` }, we intersect the tuple ID lists of `a1` and `b2` to get a new list of {2, 3}. Cuboid `AB` is shown in Table 3.

Cell	Intersection	Tuple ID List	List Size
`a1 b1`	1 2 3 ∩ 1 4 5	1	1
`a1 b2`	1 2 3 ∩ 2 3	2 3	2
`a2 b1`	4 5 ∩ 1 4 5	4 5	2
`a2 b2`	4 5 ∩ 2 3	∅	0

Table 3: Cuboid AB

After computing cuboid `AB`, we can then compute cuboid `ABC` by intersecting all pairwise combinations between Table 3 and the row `c1` in Table 2. Notice that because the entry `a2 b2` is empty, it can be effectively discarded in subsequent computations based on the Apriori property [2]. The same process can be applied to computing fragment (`D`, `E`), which is completely independent from computing (`A`, `B`, `C`). Cuboid `DE` is shown in Table 4. ■

Cell	Intersection	Tuple ID List	List Size
`d1 e1`	1 3 4 5 ∩ 1 2	1	1
`d1 e2`	1 3 4 5 ∩ 3 4	3 4	2
`d1 e3`	1 3 4 5 ∩ 5	5	1
`d2 e1`	2 ∩ 1 2	2	1

Table 4: Cuboid DE

The computed shell fragment cubes with their inverted indices will be used to facilitate online query computation. The question is how much space is needed to store them. In our analysis, we assume an array-like data structure to store the TIDs. If the cardinalities of the dimensions are small, bitmaps can be employed to save space and speed up operations. This and other techniques will be discussed in Section 6.

Lemma 2 *Given a database of $\mathcal{T}$ tuples and $\mathcal{D}$ dimensions, the amount of memory needed to store the shell fragments of size $\mathcal{F}$ is $O(\mathcal{T}(\frac{\mathcal{D}}{\mathcal{F}})(2^{\mathcal{F}} - 1))$.*

Rationale. Consider how many times each tuple ID will be stored in the shell fragments. In the 1-dimensional cuboids of the shell fragments, Lemma 1 tells us each tuple ID will appear $\mathcal{D} = \frac{\mathcal{D}}{\mathcal{F}}\binom{\mathcal{F}}{1}$ times. Now consider the 2-dimensional cuboids. Each tuple ID is associated with $\mathcal{D}$ dimensions and thus will be stored anytime a cuboid is a subset of these $\mathcal{D}$ dimensions. There are exactly $\lceil\frac{\mathcal{D}}{\mathcal{F}}\rceil\binom{\mathcal{F}}{2}$ such 2-dimensional cuboids. Sum over all cuboids (sizes 1 to $\mathcal{F}$), we see that the entire shell fragment will need $O(\mathcal{T}\sum_{i=1}^{\mathcal{F}}\left(\lceil\frac{\mathcal{D}}{\mathcal{F}}\rceil\binom{\mathcal{F}}{i}\right))$ $= O(\mathcal{T}(\frac{\mathcal{D}}{\mathcal{F}})(2^{\mathcal{F}} - 1))$ storage space. ■

Based on Lemma 2, for our 60-dimensional base cuboid of $\mathcal{T}$ tuples, the amount of space needed to store the shell fragment of size 3 is on the order of $\mathcal{T}(\frac{60}{3})(2^3 - 1) = 140\mathcal{T}$. Suppose there are 10^6 tuples in the database and each tuple ID takes 4 bytes. The space needed to store the shell fragments of size 3 is roughly estimated as $140 \times 10^6 \times 4 = 560$ MB.

3.2.1 Computing Other Measures

For the cube with only the *tuple-counting* measure, there is no need to reference the original database for measure computation since the length of the tid-list is equivalent to *tuple-count.* "*But what about other measures, such as* `average()`?" The solution is to keep an *ID_measure* array instead of the original database. For example, to compute `average()`, one just needs to keep an array of three elements: *(tid, count, sum)*. The measures of every aggregate cell can be computed by accessing this *ID_measure* array only. Considering a database with 10^6 tuples, each taking 4 bytes for tid and 8 bytes for two measures, the *ID_measure* array

[1] We assume that a TID and a value take the same unit space (e.g., 4 bytes). Otherwise, the total space usage will differ proportionally to their unit space difference.

is only 12 MB, whereas the corresponding database of 60 dimensions is $(60+3) \times 4 \times 10^6 = 252$ MB. To illustrate the design of the *ID_measure* array, let's look at the following example.

Example 3. Suppose Table 5 shows an example database where each tuple has 2 associated values, `count` and `sum`.

tid	A	B	C	D	E	count	sum
1	a1	b1	c1	d1	e1	5	70
2	a1	b2	c1	d2	e1	3	10
3	a1	b2	c1	d1	e2	8	20
4	a2	b1	c1	d1	e2	5	40
5	a2	b1	c1	d1	e3	2	30

Table 5: A database with two measure values

tid	count	sum
1	5	70
2	3	10
3	8	20
4	5	40
5	2	30

Table 6: ID-measure array of Table 5

To compute a data cube for this database with the measure `avg()` (obtained by `sum()/count()`), we need to have a tid-list for each cell: $\{tid_1, \ldots, tid_n\}$. Because each tid is uniquely associated with a particular set of measure values, all future computations just need to fetch the measure values associated with the tuples in the list. In other words, by keeping an array of the ID-measures in memory for online processing, one can handle any complex measure computation. Table 6 shows what exactly should be kept, which is substantially smaller than the database itself. ∎

Based on the above analysis, for a base cuboid of 60 dimensions with 10^6 tuples, our precomputed *shell fragments* of size 3 will consist of 140 cuboids plus one *ID_measure* array, with the total estimated size of roughly $560 + 12 = 572$ MB in total. In comparison, a shell cube of size 3 will consist of 36050 cuboids, with estimated roughly 144 GB in size. A full 60-dimensional cube will have $2^{60} \approx 10^{18}$ cuboids, with the total cube size beyond the summation of the capacities of all storage devices. In this context, both storage space and computation time of *shell_fragment* are negligible in comparison with those of the complete data cube. Thus our high-dimensional OLAP on the precomputed *shell_fragment* can really be considered as *high-dimensional OLAP with minimal cubing.*

3.2.2 Algorithm for Shell Fragment Computation

Based on the above discussion, the algorithm for shell fragment computation can be summarized as follows.

Algorithm 1 (Frag-Shells) Computation of shell fragments on a given high-dimensional base table (*i.e.*, base cuboid).

Input: A base cuboid B of n dimensions: $(A_1, \ldots, A_n)$.

Output: (1) A set of fragment partitions $\{P_1, \ldots P_k\}$ and their corresponding (local) fragment cubes $\{S_1, \ldots, S_k\}$, where P_i represents some set of dimension(s) and $P_1 \cup \ldots \cup P_k$ are all the n dimensions, and (2) an *ID_measure* array if the measure is not *tuple-count*.

Method:

```
1. partition the set of dimensions (A_1, ..., A_n) into
       a set of k fragments P_1, ..., P_k
2. scan base cuboid B once and do the following {
3.     insert each ⟨tid, measure⟩ into ID_measure array
4.     for each attribute value a_i of each dimension A_i
5.         build an inverted index entry: ⟨a_i, tidlist⟩
6. }
7. for each fragment partition P_i
8.     build a local fragment cube S_i by
       intersecting their corresponding tid-lists
       and computing their measures ∎
```

Note: For Line 1, Section 4.3 will discuss what kind of partitions may achieve good performance. For Line 3, if the measure is *tuple-count*, there is no need to build *ID_measure* array since the length of the tid-list is *tuple-count*; for other measures, such as `avg()`, the needed components should be saved in the array, such as `sum()` and `count()`.

It is possible to use the above algorithm to compute the full data cube: If we let a single fragment include all the dimensions, the computed fragment cube is exactly the full data cube. The order of computation in the cuboid lattice can be bottom-up and depth-first, similar to that of [7]. This ordering also allows for Apriori pruning in the case of iceberg cubes. We name this algorithm *Frag-Cubing.*

4 Online Query Computation

Given the pre-computed shell fragments, one can perform OLAP queries on the original data space. In general, there are two types of queries: (1) *point query* and (2) *subcube query*.

A *point query* seeks a specific cuboid cell in the original data space. All the *relevant* dimensions in the query are instantiated with some particular values. In an n-dimensional data cube $(A_1, A_2, \ldots, A_n)$, a point query is in the form of $\langle a_1, a_2, \ldots, a_n : M \rangle$, where each a_i specifies a value for dimension A_i and M is the inquired measure. For dimensions that are *irrelevant* or aggregated, one can use * as its value. For example, the query $\langle$a2, b1, c1, d1, $*$: count()$\rangle$ for the database in Table 1 is a point query where the

first four dimensions are instantiated to a2, b1, c1, and d1 respectively, the last dimension is irrelevant, and count() is the inquired measure.

A *subcube query* seeks a set of cuboid cells in the original data space. It is one where at least one of the *relevant* dimensions in the query is *inquired.* In an n-dimensional data cube $(A_1, A_2, \ldots, A_n)$, a subcube query is in the form of $\langle a_1, a_2, \ldots, a_n : M\rangle$, where *at least one* a_i is marked ? to denote that dimension A_i is inquired. For example, the query $\langle$a2, ?, c1, $*$, ? : count()$\rangle$ for the database in Table 1 is one where the first and third dimension values are instantiated to a2 and c1 respectively, the fourth is irrelevant, and the second and the fifth are inquired. The subcube query computes all possible value combinations of the inquired dimension(s). It essentially returns a local data cube consisting of the inquired dimensions.

Conceptually, a point query can be seen as a special case of the subcube query where the number of inquired dimensions is 0. On the other extreme, a *full-cube* query is a subcube query where the number of instantiated dimensions is 0.

4.1 Query Processing

The general query for an n-dimensional database is in the form of $\langle a_1, a_2, \ldots, a_n : M\rangle$. Each a_i has 3 possible values: (1) an instantiated value, (2) aggregate $*$, (3) inquire ?. The first step is to gather all the instantiated a_i's if there are any. We examine the shell fragment partitions to check which a_i's are in the same fragments. Once that is done, we retrieve the tid-lists associated with the instantiations at the highest possible aggregate level. For example, suppose a_j and a_k were in the same fragment, we would then retrieve the tid-list from the (a_j, a_k) cuboid cell. The obtained tid-lists are intersected to derive the *instantiated base table.* If the table is empty, query processing stops and returns the empty result.

If there are no inquired dimensions, we simply fetch the corresponding measures from the *ID_measure* array and finish the point query. If there is at least one inquired dimension, we continue as follows. For each inquired dimension, we retrieve all its possible values and their associated tid-lists. If two or more inquired dimensions are in the same fragment, we retrieve all their pre-computed combinations and the tid-lists. Once these tid-lists are retrieved, they are intersected with the instantiated base table to form the local base cuboid of the inquired and instantiated dimensions. Then, any cubing algorithm can be employed to compute the local data cube.

Example 4. Suppose a user wants to compute the subcube query, {a2, b1, ?, *, ?: count()}, for our database in Table 1. The shell fragments are precomputed as described in Section 3.2. We first fetch the tid-list of the instantiated dimensions by looking at cell (a2, b1) of cuboid AB. This returns (a2, b1):{4, 5}. Note that if there were no inquired dimensions in the query, we would finish the query here and report 2 as the final count.

Next, we fetch the tid-lists of the inquired dimensions: C and E. These are {(c1:{1, 2, 3, 4, 5})} and {(e1:{1, 2}), (e2:{3, 4}), (e3:{5})}. Intersect them with the instantiated base and we get {(c1:{4, 5})} and {(e2:{4}), (e3:{5})}. This corresponds to a base cuboid of two tuples: {(c1, e2), (c1, e3)}. Any cubing algorithm can take this as input and compute the 2-D data cube. ∎

4.2 Algorithm for Shell Fragment-Based Query Processing

The above discussion leads to our algorithm for processing both point query and subcube query.

Algorithm 2 (Frag-Query) Processing of point and subcube queries using shell fragments.

Input: (1) A set of precomputed shell fragments for partitions $\{P_1, \ldots, P_k\}$, where P_i represents some set of dimension(s), and $P_1 \cup \ldots \cup P_k$ are all the n dimensions; (2) an *ID_measure* array if the measure is not *tuple-count*; and (3) a query of the form $\langle a_1, a_2, \ldots, a_n : M\rangle$ where each a_i is either instantiated, aggregated, or inquired for dimension A_i. M is the measure of the query.

Output: The computed measure(s) if the query is a point query, *i.e.*, containing only instantiated dimensions. Otherwise, the data cube whose dimensions are the inquired dimensions.

Method:

```
1.  for each P_i {
        // instantiated dimensions
2.      if P_i ∩ {a_1, ..., a_n} includes instantiation(s)
3.          D_i ← P_i ∩ {a_1, ..., a_n} with instantiation(s)
4.          B_{D_i} ← cells in D_i with associated tid-lists
        // inquired dimensions
5.      if P_i ∩ {a_1, ..., a_n} includes inquire(s)
6.          Q_i ← P_i ∩ {a_1, ..., a_n} with inquire(s)
7.          R_{Q_i} ← cells in Q_i with associated tid-lists
    }
8.  if there exists at least one non-null B_{D_i}
9.      B_q ← merge_base(B_{D_1}, ..., B_{D_k})
10. if there exists at least one non-null R_{Q_i}
11.     C_q ← compute_cube(B_q, R_{Q_1}, ..., R_{Q_k})  ∎
```

Note: Function merge_base() is implemented by intersecting the corresponding tid-lists of the B_{D_i}'s. Function compute_cube() takes the merged instantiated base and the inquired dimensions as input, derive the relevant base cuboid, and use the most efficient cubing algorithm to compute the multi-dimensional cube. The *ID_measure* array will be referenced after the cube is derived in this compute_cube() function.

Algorithm 2 covers all the possible OLAP queries. In the case of point query, there exist no inquired dimensions, and Lines 6-7 and 11 are not executed. The subcube query executes all the lines of the algorithm. In the case of full-cube query, there are no instantiated dimensions, Lines 3-4 and 9 will not be executed. Additionally, B_q is instantiated to `all` and the base cuboid derived is essentially the original database.

4.3 Shell Fragment Grouping & Size

The decision of which dimensions to group into the same fragments can be made based on the semantics of the data or expectations of future OLAP queries. The goal is to have many dimensions of a query fall into the same fragments. This makes full use of the pre-computed aggregates and saves both time and I/O.

In our examples, we chose equal-sized grouping of consecutive dimensions in fragment partitioning. However, domain-specific knowledge can be used for better grouping. For example, suppose in a 60-dimensional data set, dimensions $\{A_5, A_9, A_{32}, A_{55}, A_{56}\}$ often appear together in online queries, we can group them into two fragments, such as (A_5, A_9, A_{32}) and (A_{55}, A_{56}), or even one 5-D segment, depending on the historical or expected frequent queries. Furthermore, the groupings need not to be disjoint. We could have two fragments, such as (A_5, A_9, A_{32}) and (A_9, A_{55}, A_{56}). This added redundancy may offer speed-ups in query processing. With the known (or expected) query distribution and/or constraints on dimension set, intelligent grouping can be performed to facilitate the retrieval and manipulation of relevant set of dimensions within a small number of fragments.

The decision of how many dimensions to group into the same fragment can be analyzed more carefully. Suppose each fragment contains an equal number of dimensions and let that number be $\mathcal{F}$. If $\mathcal{F}$ is too small, the space required to store the fragment cubes will be small but the time needed to compute queries online will be long. On the other hand, if $\mathcal{F}$ is big, online queries can be computed quickly but the space needed to store the fragments will be enormous.

The question is whether there exists a $\mathcal{F}$ such that there is a good balance between the amount of space allocated to store the shell fragment cubes and the cost (both time and I/O) of computing queries online.

First, we examine how space grows as a function of $\mathcal{F}$. Lemma 2 describes the exact function. It is exponential with respect to $\mathcal{F}$. However, notice that when $\mathcal{F}$ is small, the growth is actually sub-linear. The original database has size $O(\mathcal{TD})$. When $\mathcal{F} = 2$, the memory usage is $O(3/2\mathcal{TD})$, smaller than the linear growth size of $O(2\mathcal{TD})$. In fact, when $\mathcal{F} \leq 4$, the growth in space is sub-linear.

Second, we examine the implications of $\mathcal{F}$ on query performance. In general, a too small size, such as 1, may lead to fetching and processing of rather long tid-lists. Just having a $\mathcal{F}$ of 2 could greatly reduce this, because many aggregates are pre-computed. Combine this intuition with the previous paragraph, $2 \leq \mathcal{F} \leq 4$ seems like a reasonable range.

5 Performance Study

There are two major costs associated with our proposed method: (1) the cost of storing the shell fragment cubes, and (2) the cost of retrieving tid-lists and computing the queries online. In this section, we perform a thorough analysis of these costs. All algorithms were implemented using C++ and all the experiments were conducted on an Intel Pentium-4 2.6CGHz system with 1GB of PC3200 RAM. The system ran Linux with the 2.6.1 kernel and `gcc` 3.3.2.

As a notational convention, we use $\mathcal{D}$ to denote the number of dimensions, $\mathcal{C}$ the cardinality of each dimension, $\mathcal{T}$ the number of tuples in the database, $\mathcal{F}$ the size of the shell fragment, $\mathcal{I}$ the number of instantiated dimensions, $\mathcal{Q}$ the number of inquired dimensions, and $\mathcal{S}$ the skew or `zipf` of the data. Minimum support level is 1 in all experiments.

5.1 Dimensionality and Storage Size

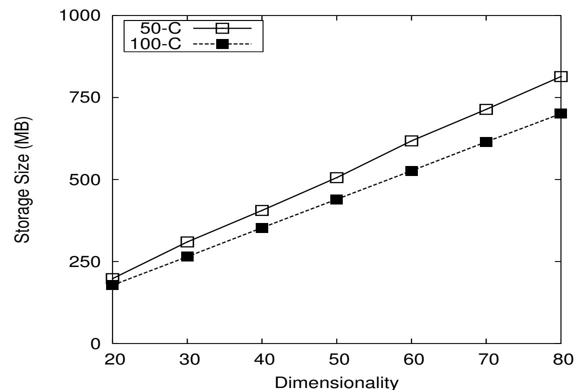

Figure 2: Storage size of shell fragments: (50-C) $\mathcal{T} = 10^6$, $\mathcal{C} = 50$, $\mathcal{S} = 0$, $\mathcal{F} = 3$. (100-C) $\mathcal{T} = 10^6$, $\mathcal{C} = 100$, $\mathcal{S} = 2$, $\mathcal{F} = 2$.

The first cost we are concerned with is the amount of space needed to store the shell-fragment cubes. Specifically, how it scales as dimensionality grows. Figure 2 shows the effect as dimensionality increases from 20 to 80. The number of tuples in both datasets were 10^6. The first dataset, 50-C, has cardinality of 50, skew of 0, and shell-fragment size 3. The second dataset, 100-C, has cardinality of 100, skew of 2, and shell-fragment size 2. The good news is that storage space grows linearly as dimensionality grows. This is expected because additional dimensions only add more fragment cubes, which are independent of the others.

5.2 Shell-Fragment Size and Storage Size

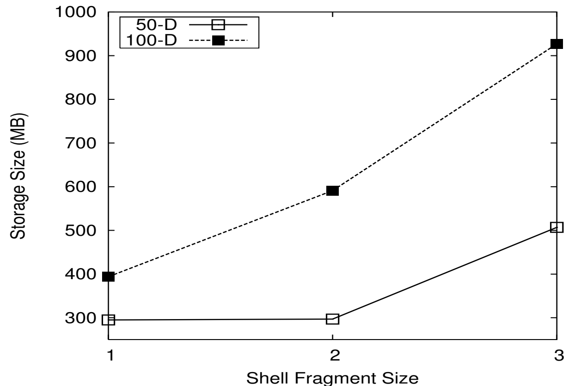

Figure 3: Storage size of shell fragments: (50-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 50$, $\mathcal{C} = 50$, $\mathcal{S} = 0$. (100-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 100$, $\mathcal{C} = 25$, $\mathcal{S} = 2$.

As discussed in Section 4.3, a fragment size between 2 and 4 strikes a good balance between storage space and computation time. In this and the next couple of subsections, we provide some test results to confirm that intuition.

Figure 3 shows the *storage size* of the shell fragment cubes. Figure 4 shows the *time* needed to compute them. Our experiments were conducted on two databases. The first, 50-D, has 10^6 tuples, 50 dimensions, cardinality of 50, and no skew. The second, 100-D, has 10^6 tuples, 100 dimensions, cardinality of 25, and *zipf* of 2. The shell-fragment size varies from 1 to 3.

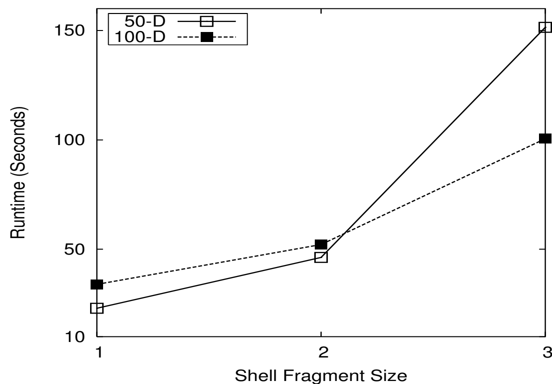

Figure 4: Time needed to compute shell fragments: (50-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 50$, $\mathcal{C} = 50$, $\mathcal{S} = 0$. (100-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 100$, $\mathcal{C} = 25$, $\mathcal{S} = 2$.

The sub-linear growth with respect to $\mathcal{F} \leq 3$ as mentioned in Section 4.3 is confirmed here, both in space and time. This is good news because as we will show in the next few sections, overall performance is improved as $\mathcal{F}$ increases.

5.3 Memory-Based Query Processing

As mentioned previously, the number of tuples in the databases we are dealing with is in the order of 10^6 or less. In statistics studies, it is not unusual to find datasets with thousands of dimensions but less than one thousand tuples. Thus, it is reasonable to suggest that the shell fragment cubes could fit inside main memory. Figure 3 shows with $\mathcal{F}$ equaling 3 or less, the shell fragments for 50 and 100 dimensional databases are under 1GB in size with 10^6 tuples.

In addition, recall our observation that many OLAP operations in high dimensional spaces only revolve around a few dimensions at a time. Most analysis will pin down a small set of dimensions and explore combinations within the set. Through caching of the data warehouse system, only the relevant dimensions and their shell fragments need to reside in main memory.

With the shell fragments in memory, we can perform OLAP on the database with pure in-memory processes. Note that this would be impossible had we chose to materialize the full data cube. Even with a small tuple count, a data cube with 50 or more dimensions requires petabytes and cannot possibly be stored in main memory.

In this section, we examine the implications of $\mathcal{F}$ on the speed of in-memory query processing. In this and the next subsection, we intentionally chose to have small $\mathcal{C}$ values in order to make the subcube queries meaningful. Otherwise in sparse uniform datasets, a random instantiation often leads to an empty result.

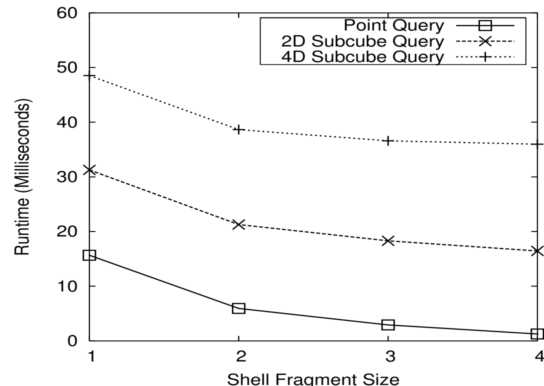

Figure 5: Average computation time per query over 1,000 trials. $\mathcal{T} = 10^6$, $\mathcal{D} = 10$, $\mathcal{C} = 10$, $\mathcal{S} = 0$, $\mathcal{I} = 4$.

Figure 5 shows the time needed to compute point and subcube queries with the shell fragments in memory. The *Frag-Cubing* algorithm is used to compute the online data cubes. The database had 10^6 tuples, 10 dimensions of cardinality 10 each, and 0 *zipf*. Each query had 4 randomly chosen instantiated dimensions, and 0 (or 2 or 4) inquired dimensions. Other dimensions are irrelevant. The times shown are *averages* of

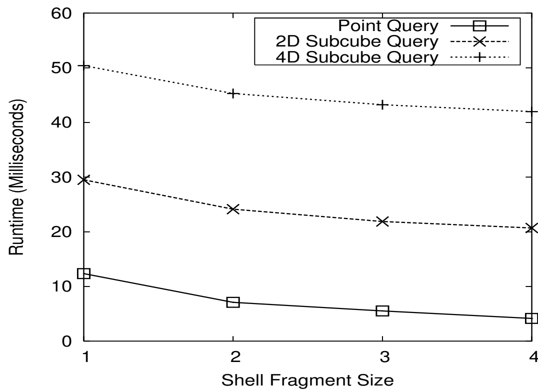

Figure 6: Average computation time per query over 1,000 trials. $\mathcal{T} = 10^6$, $\mathcal{D} = 20$, $\mathcal{C} = 10$, $\mathcal{S} = 1$, $\mathcal{I} = 3$.

1,000 such random queries. The 2D subcube queries returned a table with 84 rows on average, and the 4D subcube queries returned a table with 901 rows on average.

Figure 6 shows a similar experiment on another database. The difference is that this database had 20 dimensions and each query had 3 randomly chosen instantiated dimensions. The 2D subcube queries returned a table with 104 rows on average, and the 4D subcube queries returned a table with 2,593 rows on average.

The results show fast response time, with 50ms or less for various types of queries. They show that having $\mathcal{F} \geq 2$ results in a non-trivial speed-up during query processing over $\mathcal{F} = 1$. If any of the instantiated dimensions are in the same fragment(s), the processing of the tid-lists is much quicker due to their shorter lengths. If the inquired dimensions are in the same fragment(s), the effects are less obvious because the lengths of the tid-lists remain the same. The only difference is that they have been pre-intersected.

The speed-up of $\mathcal{F} \geq 2$ is slightly less in Figure 6 than in Figure 5, partly because there are more dimensions overall. As a result, it is less likely for the instantiated dimensions to be in the same fragment. In real world datasets where there are semantics attached to the data, the fragments will be presumably constructed so that they might be better matched to the queries.

5.4 Disk-Based Query Processing

I/O with respect to shell-fragment size: In the case that the shell fragments do not fit inside main memory, the individual tid-lists relevant to the query will have to be fetched from disk. In this section, we study the effects of $\mathcal{F}$ on these I/O costs. With a bigger $\mathcal{F}$, more relevant dimensions in a query are likely to be in the same fragment. This results in retrieval of shorter tid-lists from disk because the multi-dimensional aggregates are already computed and stored.

Using the same two databases from the previous subsection, we measured the average number of I/Os needed to process a random query over 1,000 trials[2]. Figure 7 shows I/Os for computing point queries in the 10-D and 20-D databases. Figure 8 shows the same for 4D subcube queries. No caching of tid-lists was used between successive queries (*i.e.*, cold-start in each query testing).

In both graphs, I/O was reduced as $\mathcal{F}$ increased from 1 to 4. This is because when instantiated dimensions were in the same fragments, their aggregated tid-lists were much shorter for retrieval. In Figure 8, the reduction was small relatively to the total I/O because there were 4 inquired dimensions. Since inquired dimensions cover all tuples in the database, shell fragment sizes do not affect the I/O cost much.

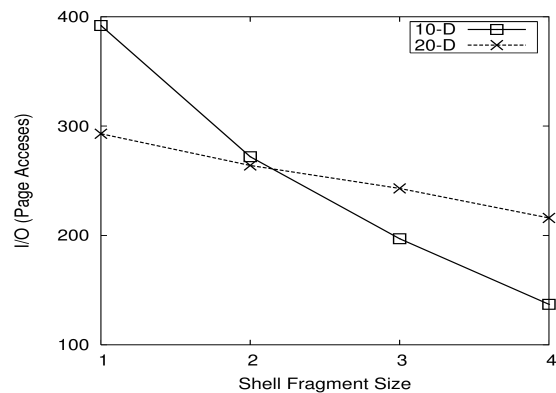

Figure 7: Average I/Os per point query over 1,000 trials. (10-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 10$, $\mathcal{C} = 10$, $\mathcal{S} = 0$, $\mathcal{I} = 4$, $\mathcal{Q} = 0$; (20-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 20$, $\mathcal{C} = 10$, $\mathcal{S} = 1$, $\mathcal{I} = 3$, $\mathcal{Q} = 0$.

I/O cost: shell-fragments vs. full materialized cubes: One may wonder how these I/O numbers compare to the case when full materialization of the data cube is actually possible. In general, a query has $\mathcal{I}$ instantiated dimensions and $\mathcal{Q}$ inquired dimensions. In terms of the fully materialized cube, the query seeks rows in the cuboid of all the relevant dimensions ($\mathcal{I} + \mathcal{Q}$) with certain values according to the instantiations. For example, the query {`?, ?, c1, *, e3, *`} seeks rows in the `ABCE` cuboid with certain values for dimensions `C` and `E`. These rows are used to compute all aggregates within dimensions `A` and `B`.

Because cuboid cells are stored on disk in some fixed order, they might be incompatible with the query. For example, they might happen to be sorted according to the inquired dimensions first. In the worst case, the entire cuboid of the relevant dimensions have to be retrieved. Further, it is necessary to read ($\mathcal{I} + \mathcal{Q} + 1$) integers per row in the cuboid because we have to read

[2]Assuming 4K page sizes and 4 bytes per integer.

Figure 8: Average I/Os per 4D subcube query over 1,000 trials. (10-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 10$, $\mathcal{C} = 10$, $\mathcal{S} = 0$, $\mathcal{I} = 4$, $\mathcal{Q} = 4$; (20-D) $\mathcal{T} = 10^6$, $\mathcal{D} = 20$, $\mathcal{C} = 10$, $\mathcal{S} = 1$, $\mathcal{I} = 3$, $\mathcal{Q} = 4$.

Figure 9: Average I/Os per query over 1,000 trials. $\mathcal{T} = 10^6$, $\mathcal{D} = 10$, $\mathcal{C} = 10$, $\mathcal{S} = 0$, $\mathcal{F} = 1$, $\mathcal{Q} = 7 - \mathcal{I}$.

the dimensional values and measure value. One may argue that the dimensional values can be skipped if there was an index on the cuboid cells. However, retrieval via an index implies random access for each row, which turns out to be much more expensive than just a plain sequential access with the dimensional values.

Figure 9 shows the average number of I/Os needed in a random query of various sizes over 1,000 trials. The number of inquired dimensions was 7 minus the number of instantiated dimensions. No caching was used, and the full data cube on disk was sorted according to the dimensional order: `A`, `B`, `C`, etc. Shell fragment size was set to 1. The relevant dimensions were the first 7 dimensions of the database and their materialized cuboid contained 951,483 rows.

The curves show that the shell-fragment I/O is competitive with the materialized data cube in many cases. Whenever the query had inquired dimensions before the instantiated dimensions in terms of the sort order, the materialized cuboid on disk have to pay the price of scanning useless cells. On average, these costs turn out be just as much as those in our method.

By having a shell-fragment size of 2 or more could lower I/O costs for our method. In addition, in real world applications with caching of recent queries, the I/O costs for both methods would be drastically reduced. Furthermore, had there been fewer relevant dimensions in the queries, the full data cube would have achieved lower I/O numbers due to the smaller cuboid size.

5.5 Experiments with Real-World Data Sets

Besides synthetic data, we also tested our algorithm on two real-world data sets. The first data set was the *Forest CoverType* dataset obtained from the UCI machine learning repository website (www.ics.uci.edu/∼mlearn). This dataset contains 581,012 data points with 54 attributes, including 10 quantitative variables, 4 binary wilderness areas and 40 binary soil type variables. The cardinalities are (1978, 361, 67, 551, 700, 5785, 207, 185, 255, 5827, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 7). We constructed shell-fragments of size 2 using consecutive dimensions as groupings. The construction took 33 seconds and 325MB.

With the shell fragments in memory, running a point query with 1-8 instantiated dimensions took less than 10 milliseconds. This is not surprising because the number of tuples in the database is moderate. More interesting are the subcube queries. Running a 3-D subcube query with 1 instantiated dimension ranged between 67 ms (millisecond) and 1.4 second. Running a 5-D subcube query with 1 instantiated dimension ranged between 85 ms and 3.6 second. The running times were extremely sensitive to the particular dimensions inquired in the query. The high-end numbers reported were queries that included the dimension of cardinality 5827 in the inquired set. When the cardinalities of the inquired dimensions are small, subcube queries are extremely fast.

The second data set was obtained from the *Longitudinal Study of the Vocational Rehabilitation Services Program* (www.ed.gov/policy/speced/leg/rehab/eval-studies.html). It has 8818 transactions with 24 dimensions. The cardinalities are (83, 9, 2, 7, 4, 3165, 470, 131, 1511, 409, 144, 53, 21, 14, 12, 13, 27, 21, 18, 140, 130, 50, 23, 505). We constructed shell-fragments of size 3 using consecutive dimensions as the fragment groupings. The construction took 0.9 seconds and 60MB.

With the shell fragments in memory, running a point query on the dataset with 1-8 instantiated dimensions either in different fragments or the same took basically no time. Running a 3-D subcube query with no instantiations ranged between 50 ms and 1.6 sec-

ond. A 3-D subcube query with 1 instantiated dimension took on average only 90 ms to compute. A 5-D subcube query with 0 instantiated dimensions ranged between 227ms and 2.6 second. We also tried a similar data set from the same collection with 6600 tuples and 96 dimensions and obtained very similar results.

6 Discussion

In this section, we discuss related work and further implementation considerations.

6.1 Related Work

There are several threads of work related to our model. First, partial materialization of data cubes has been studied previously, such as [12]. Viewing the data cube as a lattice of cuboids, some cuboids can be computed from others. Thus to save storage space, only the cuboids which are deemed most beneficial are materialized and the rest are computed online when needed. In this spirit, our approach may seem similar to theirs; however, the two models of computation are very different. In our approach, low dimensional cuboids facilitate the online construction of high dimensional cuboids via tid-lists. In [12], it is in the opposite direction: high dimensional cuboids facilitate the online construction of low dimensional cuboids by further aggregation.

Our work utilizes the construct of an *inverted index* as termed in information retrieval and *value-list index* as termed in databases. A large body of work has been devoted to this area. Inverted index has been widely used in information retrieval and Web-based information systems [4, 20]. Similar structures have been proposed and used in bitmap index of data cubes [9] and vertical format association mining [23]. Bitmaps and other compression techniques have been studied to optimize space and time usage [3, 8, 21]. In [15], projection indices and summary tables are used in OLAP query evaluations. However, all of these works have only focused on single dimensional indexing with or without aggregation. Our model studies the construction of multi-dimensional data structures (*i.e.*, 2-D, 3-D fragments) and the corresponding measure aggregation. Such structures and pre-computations not only reduce I/O costs but also speed up online computation over the single dimensional counterparts.

In [6], the authors investigated the usage of low dimensional data structures for indexing a high dimensional space. Their method, *tree-striping*, also partitions a high dimensional space into a set of disjoint low dimensional spaces. However, their data structures and algorithms were only designed to index data points, lacking the aggregations and other elements needed for data cubing.

One interesting observation made in [6] is that in trying to optimize the tradeoffs between pre-calculated result access and online computation, partitioning the original space into sets of 2 or 3 dimensions was often better than partitioning into single dimensions. Our studies from the point of view of data cubing derives a similar conclusion as they did for indexing: shell-fragment sizes between 2 and 4 achieve a good balance between storage size and online computation time.

6.2 Further Implementation Considerations

6.2.1 Incremental Update

The shell fragments and *ID_measure* array are quite adaptable to incremental updates. When a new tuple is inserted, a new $\langle tid : measure \rangle$ pair is added into the *ID_measure* array. Moreover, this new tuple is vertically partitioned according to the existing fragments and added to the corresponding inverted indices in the fragment cubes. Incremental deletion is performed similarly with the reverse process. These operations do not require the re-computation of existing data and are thus truly incremental. Furthermore, query performance with incrementally changed data is exactly the same as that of fragments re-computed from scratch.

Another interesting observation is that one can incrementally add new dimensions to the existing data. This is difficult for normal data cubes. The new dimensions ($D_i, \ldots, D_j$) together with the new data form new inverted lists, still in the form of $\langle dimension_value : tidlist \rangle$. These new dimensions can either form new fragments or be merged with the existing ones. Similarly, existing dimensions can be deleted by removing them from their respective fragments.

6.2.2 Bitmap Indexing

Throughout the paper, we have discussed I/O and computation costs with the assumption that the tid-lists are stored on disk as an array of integers. However, in data sets where cardinalities of the dimensions are small, bitmap indexing [3, 8, 15, 21] can improve space usage and speed. For example, if a column only has 2 possible values: male or female, the savings in storage space is high. Furthermore, the intersection operation can be performed much faster using the `bit-AND` operation than the standard merge-intersect operation.

6.2.3 Inverted Index Compression

Another compression method of the tid-lists come from information retrieval [4, 20]. The main observation is that the numbers in the tid-list are stored in ascending order. Thus, it would be possible to store a list of *d-gaps* instead of the actual numbers. In general, for a list of numbers $\langle d_1, d_2, \ldots, d_k \rangle$, the d-gap list would be $\langle d_1, d_2 - d_1, \ldots, d_k - d_{k-1} \rangle$. For example, suppose we have the list $\langle 7, 10, 19, 22, 45 \rangle$. The

d-gaps list would be $\langle 7, 3, 9, 3, 23 \rangle$. The insight is that the largest number in the d-gap list is bounded by the difference between d_1 and d_k. Thus, it maybe possible to store them using less than the standard 32 bits of an integer. If many of the gap integers are small, the compression could be substantial. The details of compression have been exploited in information retrieval. Some of the popular techniques are unary, binary, δ, γ, and Bernoulli [20].

7 Conclusions

We have proposed a novel approach for OLAP in high-dimensional datasets with a moderate number of tuples. It partitions the high dimensional space into a set of disjoint low dimensional spaces (*i.e.*, shell fragments). Using inverted indices and pre-aggregated results, OLAP queries are computed online by dynamically constructing cuboids from the fragment data cubes. With this design, for high-dimensional OLAPing, the total space that needs to store such *shell-fragments* is negligible in comparison with a high-dimensional cube, so is the online computation overhead. In our experiments, we showed that the storage cost grows linearly with the number dimensions. Moreover, the query I/O costs for large data sets are reasonable and are comparable with reading answers from a materialized data cube, when such a cube is available. And we also showed evidence of how different shell fragment sizes can affect query processing.

We have been performing further refinements of the proposed approach and exploring many potential applications. Traditional data warehouses have difficulties at supporting fast OLAP in high dimensional data sets, including spatial, temporal, multimedia, and text data. A systematic study of the applications of this new approach to such data could be a promising direction for future research.

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