Automated Multidimensional Data Layouts in Amazon Redshift

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ABSTRACT

Analytic data systems typically use data layouts to improve the performance of scanning and filtering data. Common data layout techniques include single-column sort keys, compound sort keys, and more complex multidimensional data layouts such as the Z-order. An appropriately-selected data layout over a table, in combination with metadata such as zone maps, enables the system to skip irrelevant data blocks when scanning the table, which reduces the amount of data scanned and improves query performance.

In this paper, we introduce Multidimensional Data Layouts (MDDL), a new data layout technique which outperforms existing data layout techniques for query workloads with repetitive scan filters. Unlike existing data layout approaches, which typically sort tables based on *columns*, MDDL sorts tables based on a collection of *predicates*, which enables a much higher degree of specialization to the user's workload. We additionally introduce an algorithm for automatically learning the best MDDL for each table based on telemetry collected from the historical workload. We implemented MDDL within Amazon Redshift. Benchmarks on internal datasets and workloads show that MDDL achieves up to 85% reduction in end-to-end workload runtime compared to using traditional column-based data layout techniques. MDDL is, to the best of our knowledge, the first data layout technique in a commercial product that sorts based on predicates and automatically learns the best predicates.

CCS CONCEPTS

• **Information systems → Data layout**; **Autonomous database administration**; **Online analytical processing engines**.

KEYWORDS

machine learning, data warehouse, analytic database, sort key

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1 INTRODUCTION

Analytic data systems support workloads which typically scan and filter large amounts of data. Therefore, one important method for improving performance is to minimize the amount of data accessed during the scan step. There are generally two approaches to reducing data access for relational database systems. The first is to use columnar storage so that only the relevant columns for each query are accessed. The second is to use an appropriate data layout so that only the relevant rows for each query are accessed.

colA	colB	colC
0	1	black panther
1	2	titanic
2	0	men in black
3	1	black widow
3	2	avatar
5	3	avengers

(a) Single-column sort key over column A.

colA	colB	colC
0	1	black panther
1	2	titanic
2	0	men in black
3	1	black widow
3	2	avatar
5	3	avengers

(b) Highlighted blocks scanned when executing Listing 1.

Figure 1: Example of using a single-column sort key.

Listing 1: Example query

```
SELECT avg(colA) FROM T
WHERE colC ILIKE '%black%'
```

Listing 2: Example query rewritten to use MDDL

```
SELECT avg(colA) FROM T
WHERE mddl_col IN (2, 3)
```

The predominant data layout technique in analytic data systems is to use a sort key (also known as a partitioning key or clustering key) to sort and cluster rows into horizontal partitions, also known as data blocks. Metadata is then constructed and stored for each block, which enables the execution engine to skip irrelevant blocks during query processing. One common form of metadata is to store the minimum and maximum values in each column for the block, often known as a zone map [3, 9] or small materialized aggregate [23]. During query execution, the system uses the zone map for each data block to quickly determine if any row in the block could be relevant to the query, i.e., if any row would satisfy the scan filter. If not, then the entire block is skipped. For instance, assume a scan predicate `colA > 42` and a data block of `colA` with `min = 10` and `max = 20`. Clearly, this block cannot contain any tuple that satisfies the predicate, so it can be safely skipped. Reducing the number of blocks and rows scanned can substantially improve overall query performance.

The choice of sort key—and more generally the data layout technique overall—has a significant impact on the effectiveness of block skipping. Almost all data systems support a single-column sort key, which works well if there is one dominant column that is filtered over in the workload. However, this is not as effective if there are multiple columns that are filtered over. In that case, some systems support compound sort keys (i.e., sort by a series of columns in sequence) or Z-order sorting (i.e., sort by a collection of columns simultaneously, also known as interleaved sort key). However, even these sort orders may fail to specialize to the user's workload.

Fundamentally, a data layout's purpose is to divide the data in such a way that for a given query with a scan filter, the relevant data blocks are physically separated from the irrelevant ones. Sorting by a column or a collection of columns is a coarse-grained way to achieve that. The most direct way is to separate the data based on whether or not they qualify for the expected filters. This is especially effective for workloads with repetitive filter predicates, so that the filters seen in the past are indicative of those that will be seen in the future.

An Illustrative Example. Fig. 1 introduces a running example, which we use throughout the remainder of this paper. Assume a table `T` with three columns, as shown in Fig. 1a. `T` is sorted by column `colA` and is stored in columnar format. Data blocks are denoted by bold black lines (Fig. 1b). Different columns may contain different numbers of rows in a data block depending on the column's data type and encoding. Imagine that scans over `T` almost always contain at least one of these two filter predicates: `colA > colB` and `colC ILIKE '%black%'`. Neither of these filters can take advantage of sort keys or zone maps. For example, if the user issues the query in Listing 1 then even if we sorted the table by `colC`, we would still need to read all blocks from `colC`, because we cannot determine whether a `colC` block contains a value like `'%black%'` based only on per-block min/max statistics. As a result, this query scans many blocks during execution; specifically, in Fig. 1b, we read all predicate column (`colC`) blocks in green and all payload column (`colA`) blocks in orange.

colA	colB	colC	mddl_col
1	2	titanic	0
5	3	avengers	1
3	2	avatar	1
0	1	black panther	2
3	1	black widow	3
2	0	men in black	3

(a) Sorting by MDDL with two predicates (`colA > colB` and `colC ILIKE '%black%'`) results in four distinct regions.

colA	colB	colC	mddl_col
1	2	titanic	0
5	3	avengers	1
3	2	avatar	1
0	1	black panther	2
3	1	black widow	3
2	0	men in black	3

(b) Highlighted blocks are read when executing Listing 1, which is internally rewritten into Listing 2.

Figure 2: For a workload that consists of queries that frequently filter by the same predicates (`colA > colB` and `colC ILIKE '%black%'`), using MDDL results in much fewer rows and blocks scanned compared to column-based sort keys.

To improve scans over this table, we first define a multidimensional sort function which takes a row and returns a number:

```
if (    colC ILIKE '%black%' AND     colA > colB) return 3
if (    colC ILIKE '%black%' AND NOT colA > colB) return 2
if (NOT colC ILIKE '%black%' AND     colA > colB) return 1
if (NOT colC ILIKE '%black%' AND NOT colA > colB) return 0
```

Note that this can be expressed more concisely in SQL as

```
case when colC ILIKE '%black%' then 2 else 0 end +
case when colA > colB then 1 else 0 end
```

Using this function, we can map each row of `T` to a value between 0 and 3. We materialize these values in a new column `mddl_col` and set it as the new sort key (Fig. 2a). Now if the user issues the same query as before (Listing 1), we know based on the sort function definition that any rows satisfying the filter can only have an `mddl_col` value of 2 or 3, so we can rewrite the scan filter to the equivalent `WHERE mddl_col IN (2, 3) AND colC ILIKE '%black%'`. This injected filter allows us to skip blocks over the `mddl_col` column via min/max pruning and therefore reduce the number of rows to scan. In fact, we can do even better: since `mddl_col IN (2, 3)` is semantically equivalent to `colC ILIKE '%black%'`, we can remove the latter predicate altogether. We have essentially rewritten the query in Listing 1 into the equivalent query in Listing 2.

Applying this multidimensional sort function, which we call a multidimensional data layout (MDDL), results in much better performance for this query: firstly, we can now skip blocks based on `mddl_col`. Secondly, we avoid scanning `colC` altogether, which not only reduces I/O but also avoids evaluating an expensive string regex predicate. Thirdly, we read fewer blocks of `colA`, since relevant values are now co-located in the same block. In Fig. 2b, we read all predicate blocks in green and all payload blocks in orange, which is much less than the number of blocks we needed to read for executing the same query under a single-column sort key (Fig. 1b).

We implement MDDL inside Amazon Redshift, AWS's cloud data warehouse product. MDDL is a completely automated feature, which means that Redshift decides when and how to apply MDDL to user tables, as long as users have not already explicitly chosen a sort key. Benchmarks on internal datasets and workloads show that MDDL achieves up to 85% reduction in end-to-end workload runtime and up to 100× faster performance on individual queries, compared to traditional column-based data layouts such as single-column, compound, and interleaved sort keys. MDDL is, to the best of our knowledge, the first data layout technique in a commercial product that sorts based on predicates *and* automatically learns the most effective predicates. MDDL has now been released to customers in Public Preview[1] and will be rolled out in general availability in the coming months.

In the remainder of this paper, we provide background (Section 2), give an overview of MDDL (Section 3), describe how MDDL is physically constructed, maintained, and used on a table (Section 4), describe the algorithm for automatically selecting MDDL (Section 5), present an experimental evaluation (Section 6), discuss design decisions and future directions (Section 7), and conclude (Section 8).

2 BACKGROUND

MDDL is an automated data layout technique implemented in Amazon Redshift. This section provides the background for existing data layout techniques, automation for data layouts, and Redshift itself.

2.1 Data layouts

In modern analytic systems, the physical data layout of a table is typically based on a sort column (e.g., sort all records by their value in the timestamp column, then partition contiguous records into blocks) or more complex multi-column sort orders such as Z-order [8, 31]. However, single-column sort orders are less useful when the workload filters on multiple different columns, and manually tuning multi-column sort orders is laborious and error-prone.

Amazon Redshift and Databricks offer the ability to automatically select the best column-based data layout and evolve the layout over time [5, 14], but neither supports predicate-based layouts. Snowflake and Oracle support clustering or indexing based on predicates [7, 10], but neither supports automatic predicate selection. In contrast, MDDL is an automated predicate-based data layout.

Instance-optimized data layouts [21, 22, 24, 27, 28, 30] are techniques that aim to automatically generate more complex data layouts that are highly specialized to a particular dataset and workload. For example, Flood [24] automatically produces fine-grained grid-based data layouts that are specialized for data stored in memory, and qd-tree [30] automatically produces coarse-grained tree-based data layouts that are specialized for data stored on disk or on remote cloud storage. MDDL takes inspiration from these techniques.

[1] https://aws.amazon.com/blogs/big-data/improve-performance-of-workloads-containing-repetitive-scan-filters-with-multidimensional-data-layout-sort-keys-in-amazon-redshift/

2.2 Amazon Redshift

Amazon Redshift [17] is AWS's cloud data warehouse. Each Redshift cluster uses an MPP execution engine spread across multiple EC2 nodes. Data is persisted on S3 and is cached on the local disk of EC2 nodes for faster access. Redshift uses columnar storage. It stores the data of each column in data blocks (in compressed form), and uses a fixed size of 1MB per data block, therefore data blocks of different columns are not horizontally aligned. This is in contrast to the PAX-style [16] partitions of other analytic systems such as Snowflake and Azure Synapse Analytics [11, 12], in which each column of the partition has the same number of rows.

Redshift maintains min/max values per data block. These are especially helpful for early pruning of blocks whose `[min,max]` range does not overlap with the predicate range of a filter column. When executing scans, Redshift uses this metadata to construct *row ranges* for each column that need to be scanned, based on the column filters. If there are filters over multiple columns, the row ranges are intersected (or unioned in the case of `OR`) to construct an overall set of row ranges. Then, only data blocks across relevant columns that intersect any row range are scanned.

Redshift uses SIMD-vectorized scan execution with late materialization: the query predicates are ordered in decreasing order of estimated selectivity, so that the most selective predicate is evaluated first. Redshift executes each predicate sequentially, maintaining a bitvector that represents the rows that have qualified for all predicates so far. Finally, this bitvector is used to decide which blocks or rows to read from the payload columns, i.e., the columns used for downstream operations.

2.2.1 Automation in Redshift. Redshift automates many decisions that database administrators would traditionally need to make manually. In particular, Redshift Advisor [2] is a component that makes performance-related recommendations about a table's physical design, such as changes in sort key, distribution key [25], and column encoding (compression). These recommendations are continuously re-evaluated in case of workload changes. Unless the user has made explicit choices, Automatic Table Optimization [14] applies these recommended changes in the background on behalf of the users. In terms of sort keys, Advisor currently only recommends single-column sort keys. With the addition of MDDL, we integrate with Advisor so that it not only recommends MDDL, but it also intelligently chooses between the two for each table.

Redshift also offers Automatic Table Sort [4], which uses background tasks to gradually sort a table by its sort key, focusing only on the parts of the table that would improve performance if sorted (e.g., data blocks that are never scanned anyway do not need to be sorted). This capability is scheduled to minimize impact on user's workload and yields if resources become scarce [26]. When Redshift Advisor changes a table's sort key, the table is not immediately re-sorted, but rather relies on Automatic Table Sort to perform the sort incrementally.

3 MDDL OVERVIEW

This section, provides a high-level overview of MDDL, including our design principles, and its strengths and weaknesses. Fig. 3 illustrates the overall life cycle of MDDL:

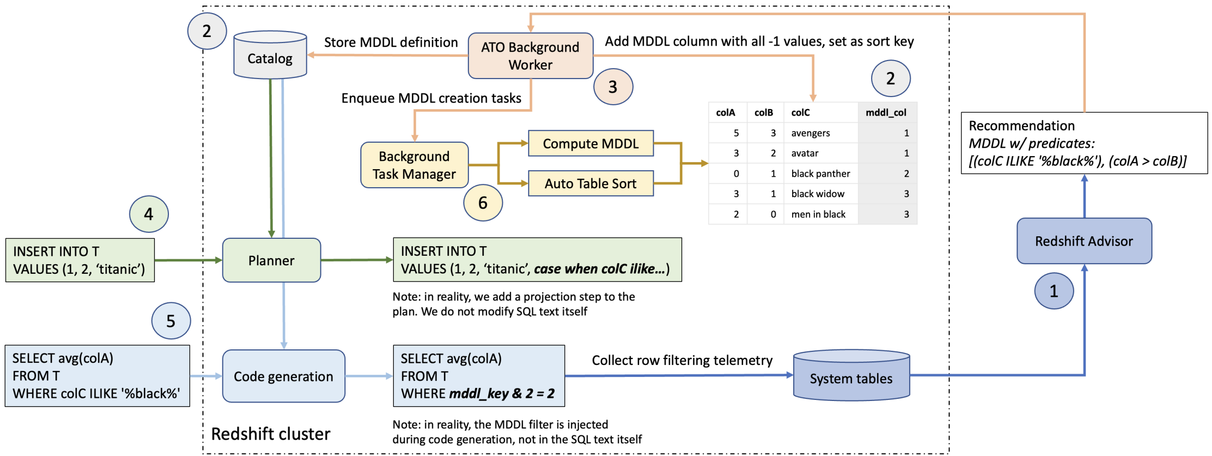


Figure 3: The life cycle of MDDL on a given table.

(1) Redshift Advisor uses historical telemetry to decide which tables should get MDDL, and if so, which predicates to use in MDDL (Section 5).
(2) MDDL is a new physical column in the table, and the predicate definitions are stored in the catalog (Section 4.1).
(3) As part of Automatic Table Optimization (ATO), a background worker receives recommendations from Redshift Advisor and creates the MDDL column in the background. Initially, the column is populated with default values (Section 4.3).
(4) Any inserts and updates into the table will automatically compute the MDDL column values for the new rows (Section 4.4).
(5) Queries with scan filters that match with the MDDL predicates will automatically use the MDDL column to accelerate the scan (Section 4.2).
(6) Background tasks will gradually compute any missing MDDL column values and sort the table by the MDDL column over time (Section 4.3).
(7) (Not shown in Fig. 3) The MDDL column may eventually be dropped from the table, because either the user or Advisor decides to set a different sort key (Section 4.5).

Note that a table does not need to be fully sorted in order to benefit from MDDL (see Section 4.3).

3.1 Design Principles

We followed several design principles while implementing MDDL.

Make data-driven design decisions. Before designing MDDL, we performed fleet-wide analysis to make quantifiable decisions about the most impactful ways to improve performance through data layouts. We found that filter predicates are highly repetitive, and that in over 50% of customer clusters, over 80% of scan filters repeat exactly. As a result, in MDDL we decided to focus on exact match of predicates, unlike existing work on instance-optimized data layouts that typically targets predicate intersection and subsumption (see Section 2.1). Although restricting ourselves to exact match may seem like a missed opportunity, we decided it was appropriate given the statistics we collected; we designed MDDL in such a way that we can extend its capabilities to inexact match in the future, if desired.

Minimize impact on customer workloads. Creation and maintenance of MDDL should impact customer workload performance as little as possible. Therefore, the MDDL design relies as much as possible on background tasks for maintenance operations, which are scheduled when there is least impact to the customer's workload.

Play nice with other components. Redshift is a complex system with many existing components. We designed MDDL to interact nicely with them, and also to build on top of components such as the background task scheduler and Automatic Table Sort where appropriate. See Section 7.2 for a discussion of MDDL's interaction with non-data-layout components.

3.2 Strengths and Limitations

Compared to data layout techniques that rely on column-based sorting, such as single-column sort keys, compound sort keys, and interleaved sort keys, MDDL is able to highly specialize to the user's workload by sorting directly on important frequently-occurring predicates. Many scan filters contain predicates that cannot take advantage of block skipping via zone maps (e.g., the predicates in Fig. 2), but those predicates can be used to skip blocks if used in MDDL. Another subtle but impactful strength is that unlike column-based sorting, which enforces a natural order (e.g., alphanumeric order) over column values, MDDL can use predicates to sort on any arbitrary order. In particular, Redshift does not allow sorting on columns with semistructured data like JSON [13] and spatial data [18] because there is no natural sort order. However, with MDDL we can sort based on predicates over semistructured and geographic data.

One limitation of MDDL is that it only uses predicates over a single table. It does not use join predicates, or join-induced predicates [21]. As a result, it is not as effective on workloads in which scans on large tables can benefit from laying out data based on predicates from smaller tables, such as in TPC-DS. Naturally, MDDL cannot use predicates that are nondeterministic, i.e., whose output might change on each invocation. For example, it skips predicates that use mutable functions such as `RANDOM()`.

4 MDDL LIFE CYCLE

In this section, we provide details about the MDDL life cycle after it has been recommended by Redshift Advisor.

4.1 Storage

A table that uses MDDL as its data layout incurs storage overhead in two places: in an additional column in the table itself and in some further metadata in the catalog.

4.1.1 MDDL Column. Tables that use MDDL have an additional column, which we refer to as the MDDL column. This column is hidden from users: it is not returned for `SELECT *` queries, it cannot be read explicitly with `SELECT mddl_col`, users cannot explicitly insert, delete, or update values in the column, and users cannot alter other column properties such as its encoding style. Instead, Redshift manages setting column entries to the appropriate values (Section 4.4) and usage of the column for accelerating scans (Section 4.2) behind the scenes.

The MDDL column has an integer data type and each column value is interpreted as a bitmap. Each bit position (except for the most significant bit) is potentially associated with a predicate, and the bit's value represents whether that predicate is satisfied on the associated row of the table. The width of the integer data type therefore determines the maximum number of predicates that the MDDL can use (e.g., an MDDL column with 4-byte integer data type supports up to 31 predicates). Some bit positions might not be associated with a predicate, either because we purposefully decided to include fewer predicates in the MDDL than the maximum (see Section 5) or because the bit position was originally associated with a predicate but the predicate was subsequently invalidated (see Section 4.1.2).

The most significant bit of each MDDL column value is set to 0 if and only if the bits in all other positions have been properly set according to their associated predicates (bit positions that are not associated with any predicate do not matter). Therefore, a negative MDDL column value (i.e., an integer with its most significant bit set to 1) is a temporary value which represents that the correct value has not yet been computed. Such *uncomputed values* arise when first creating the MDDL column (see Section 4.3) and in other edge cases (see Section 4.4). MDDL column values may transition from uncomputed to computed (Section 4.3), but once an MDDL column value is computed, it never becomes uncomputed (Section 4.4). We decided to encode computedness in the most significant bit instead of using `NULL` to denote uncomputed values because non-nullable columns have better performance than nullable columns. In fact, values with the most significant bit set represent multiple rows with uncomputed MDDL, as the remaining bits are used as a counter for run length encoding. Thus we can encode sequences of uncomputed MDDL values trivially and also skip them instantly during scans (see Section 4.2).

4.1.2 MDDL in the Catalog. We store the MDDL's definition in the catalog. It consists of (1) the definitions of the predicates that compose the MDDL, in text form, and (2) the bit position that each predicate is associated with. The catalog acts as the single source of truth about the MDDL definition. Over time, some predicates may become invalid. For example, one of the predicates may reference a column that is subsequently dropped from the table, and therefore the predicate becomes semantically meaningless. Redshift detects such cases and

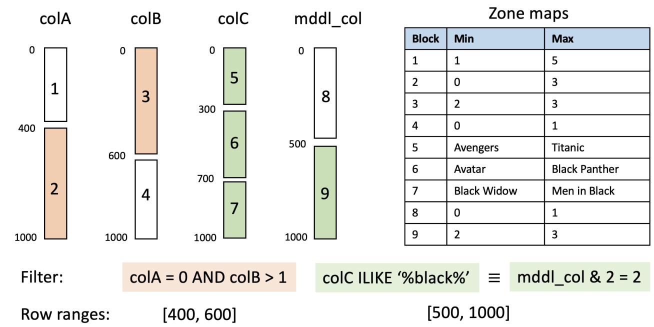


Figure 4: Filters use per-block zone maps to determine the row range(s) that need to be scanned. A scan that filters by `colA = 0 AND colB > 1` would determine row ranges for `colA` and `colB` independently, then intersect them. A scan that filters by `colC ILIKE '%black%'` cannot use zone map information to skip blocks, but the equivalent MDDL filter (`mddl_col & 2 = 2`) can.

automatically invalidates the predicate by deleting its definition from the catalog, so that the associated bit position in the MDDL column is ignored for all future maintenance and scan operations (Sections 4.2 and 4.4). Note that other bits in the MDDL column still remain valid. In other words, an MDDL is created with a set of predicates, and predicates can be removed over time, independently of each other.

On the flip side, we do not allow predicates to be added to the MDDL column after it has been created, since this would require rewriting the entire MDDL column to set the associated bit correctly for each MDDL column value; this would be equivalent to simply creating an entirely new MDDL on the table.

4.2 Usage in Accelerating Scans

At a high level, there are two parts to using MDDL in scans, which we describe in further detail below: (1) Using MDDL to skip blocks, which reduces the number of rows scanned, and (2) skipping redundant user predicates, which reduces the number of columns scanned.

4.2.1 Using MDDL to reduce rows scanned. MDDL operates over a single table. Therefore, we allow a query to pass through the query planner and for filters to be pushed down to scans, before we apply any MDDL logic. If a query scans multiple tables, then MDDL logic is applied to each table scan independently; MDDL usage does not affect the optimal join order or other downstream operators because the output of the scan step is exactly the same regardless of whether MDDL is used. At this point, we have already collected the list of predicates in the filter, and we have an initial ordering of this list by decreasing estimated selectivity, so that the most selective predicate will be evaluated first. Redshift automatically applies MDDL with the following steps:

(1) We read the table's MDDL predicates from the catalog and convert each to an internal AST representation, then perform pairwise comparisons with the predicates in the query filter to find those that exactly match.
(2) If at least one predicate matched, then we construct an MDDL filter, i.e., a predicate over the MDDL column that is semantically

Listing 3: Logic to determine whether to skip a block based on the block's min/max values and the MDDL filter's bitmask.

```
def can_skip_block(bitmask: int, minval: int, maxval: int):
    # Find the first value greater than or equal to minval
    # that satisfies 'value & bitmask = bitmask'. The
    # trick is to find the most significant bit that is 1
    # in bitmask and 0 in minval.
    x: int = bitmask & ~minval
    if (x == 0) return False
    msb: int = get_most_significant_set_bit_position(x)
    trailing_bits_mask: int = (1 << (msb + 1)) - 1
    next_value = ((minval & ~trailing_bits_mask) |
        (bitmask & trailing_bits_mask))
    return next_value > max_val
```

equivalent to the conjunction of all matched user predicates. Conceptually, the MDDL filter checks whether the MDDL column value is one of the valid values (e.g., the filter in Listing 2), but this can result in a long `IN`-list that is expensive to evaluate. Therefore, we write the MDDL filter as a bit comparison that follows the form `mddl_col & bitmask = bitmask`, where `bitmask` is an integer where bits corresponding to matched predicates are 1.

(3) We place the MDDL filter into the filter predicates list, while maintaining the property that predicates are ordered by selectivity.

Fig. 4 continues our running example for a query with slightly different filters. The rectangles depict the various data blocks per column, with the corresponding row ranges denoted at the top and bottom of each block. The zone maps table contains the min/max values per data block. For the orange filter, zone maps can be dirrectly used to determine the row ranges for `colA` and `colB`. Consider the green filter, which is the same as in Listing 1. Without MDDL, we would not be able to use min/max values per block to determine whether a block of `colC` can be skipped. Since MDDL filters always follow the form `mddl_col & bitmask = bitmask`, we can use specialized bit manipulation logic to determine whether any value between the `min` and `max` can satisfy the predicate, without individually checking every qualifying MDDL column value.

Listing 3 contains the pseudocode for the block skipping logic. Unlike literal predicates, simply checking if the `bitmask` overlaps with the `[min, max]` range is not enough. For example, assume the bit representations `min = 01001`, `max = 01100`, and `bitmask = 00100`. Clearly the bitmask value does not fall inside the `[min, max]` range, but there is a value in the range that could satisfy `mddl_col & bitmask = bitmask`, which is `01100`. The pseudocode in Listing 3 finds the smallest value greater than `min` that would satisfy the condition `value & bitmask = bitmask` and checks whether that value is greater than `max`, in which case the block can be skipped.

After skipping blocks, Redshift begins to read the data blocks that qualified. When applying the MDDL filter, we use a specialized vectorized scan operator with SIMD instructions to efficiently evaluate the MDDL filter over the MDDL column. The output is a bitvector that represents rows that have qualified by the MDDL filter, and this is passed to subsequent filter predicates. Note that rows with uncomputed MDDL values (Section 4.1.1) are treated as pass-through, since we cannot filter based on an uncomputed MDDL value.

4.2.2 Using MDDL to reduce columns scanned. Since the MDDL filter is semantically equivalent to the matched predicates, if we have already applied the MDDL filter, then we do not even need to apply the matched predicates. Therefore, we can avoid executing the matched predicates altogether, and the predicate columns referenced by those skipped predicates do not need to be read at all. In this sense, MDDL acts as a predicate evaluation cache, so that predicates evaluated in the past do not need to be re-evaluated again, but rather the evaluation result can be read directly from the cache, i.e., the MDDL column.

In cases where the MDDL column is not fully computed, we cannot entirely skip the matched predicates. However, Redshift does not evaluate filters over the entire table at once, but rather in tumbling windows of rows whose size is configured to match cache sizes. Therefore, we perform an adaptive execution, where for windows in which the MDDL column is fully computed, we skip the matched predicates. If the MDDL column is partially computed in the window, we still execute the matched predicates. In this case, using the MDDL filter is still beneficial, since it helps narrow down the bitvector of qualified rows. In cases where the entire window only contains uncomputed MDDL values, then the MDDL filter is truly a no-op and offers no benefit; likewise it does not introduce any overhead, since Redshift skips sequences of rows with uncomputed MDDL instantly by taking advantage of the run length encoding.

4.3 Creation

There are three stages to creating MDDL on a table: (1) creating the MDDL column itself, filled with uncomputed values, and populating the catalog with the predicate definitions, (2) computing the values of the MDDL column, and (3) sorting the table by the MDDL column.

The stages are in increasing order of time consumption. Creating the column itself is highly efficient: we fill the column with repeats of the same uncomputed value (since all uncomputed values are semantically equivalent, we use -1 by default), encoded as a run length, which typically only requires writing a single data block. The second stage of computing the MDDL column values is slightly more costly because we replace all MDDL column blocks with new blocks that contain the computed values. This also requires reading the columns that are referenced in the MDDL predicates. The last stage is the most expensive, since it essentially involves a `VACUUM` operation that requires rewriting all blocks of all columns.

The first stage is performed atomically (i.e., we add the complete column, not a partial column), and the following two stages are performed incrementally (e.g., we compute only a part of the MDDL column at a time). All stages are performed by background tasks in order to minimize interference with the user's workload. Specifically, the background tasks for the first two stages are processed in a FIFO manner by Redshift's background task scheduler along with other background tasks, whereas the background task for stage 3 is scheduled according to the existing logic for Automatic Table Sort, i.e., it is only scheduled when internal telemetry indicates that sorting would improve scan performance.

We separate creation into three distinct stages instead of performing them all at once because it is easier for the background task scheduler to fairly schedule many inexpensive tasks than one expensive task, and longer-duration tasks have a higher probability of preemption due to spikes in the user workload, which results in loss of progress. Also, note that MDDL will already become useful as soon as stage 2 has begun, i.e., as soon as the MDDL column becomes partially computed: even though the table is not sorted by MDDL, we can use MDDL to avoid reading from other predicate columns (see Section 4.2.2).

4.4 Maintenance Under Changing Data

As rows are inserted, updated and deleted from the table, there are two aspects of MDDL that need to be maintained: first, we must maintain the correct values in the MDDL column. Second, we must maintain the overall sorted order of the table by the MDDL column. This subsection only describes maintenance in cases where the data changes but the MDDL definition remains the same. For discussion of when and how we would change the MDDL definition entirely, see Section 4.5.

4.4.1 Maintenance of MDDL Column Values. As long as a row remains unchanged, its MDDL value also remains correct. That is, a given row's MDDL value does not need to change in response to data changes in other rows. Therefore, we only need to maintain correct MDDL values in newly inserted rows[2]. We automatically compute the MDDL value on the write path of inserts and `COPY` commands. This adds minimal overhead to the overall insert, since the computation is performed when the data is already in memory, and is therefore cheap compared to the existing cost of reading data from S3 (in the case of `COPY`), distributing rows to different nodes, and writing to data blocks. In cases where extremely low-latency inserts are required (e.g., Redshift's `APPEND` command [1]), we skip MDDL computation and simply insert an uncomputed MDDL value; a background task will eventually replace it with the correctly-computed value.

4.4.2 Maintenance of Sortedness. Second, we must maintain the overall sortedness of the table according to the MDDL column. In Redshift, inserted rows are appended to the end of the table. If there is a sort key on a table, then all rows inserted by the same command (such as all rows in batch insert with `COPY`) are sorted in memory before they are inserted. Therefore, batch inserts into tables that use MDDL will already be appended to the end of the table in sorted order.

However, even though each batch of inserts is sorted, there is not necessarily a sorted order between batches. To maintain the global sorted order of a table, MDDL relies on the mechanisms that are already in place in Redshift for tables with sort keys. In particular, there are two mechanisms:

(1) The user can manually run `VACUUM SORT`, which fully sorts the table. This can be an expensive operation since it rewrites all data blocks of all columns in the table, and it places the burden on the user to schedule the vacuum.
(2) Redshift offers Automatic Table Sort (ATS), which is a background process that periodically checks historical telemetry to determine whether sorting would improve performance, and only performs sorting if it does. ATS intelligently schedules the sort operations so that they are performed on more impactful tables first. Furthermore, ATS does not sort the entire table, but only the horizontal partitions of the table that would see the most benefit (hot partitions that are often scanned by queries).

4.5 Retirement

Due to either changing data or changing workloads, the MDDL defined on a table may no longer be appropriate: there may be a better alternative MDDL with different predicates, or a traditional single-column sort key may be more performant. To decide when to transition to a different sort key, we use the Advisor algorithm from Section 5. Even after Advisor recommends an MDDL sort key over a table, it continues to run its algorithm over each table, but only computes benefits based on the workload since the last recommendation, not over the entire historical workload. If Advisor determines that the benefit of an alternative sort key becomes higher than the observed benefit of the existing sort key on the table, then it automatically begins the transition. We also maintain a static constant for the minimum amount of time between sort key changes, so that we prevent frequent thrashing between different sort keys.

[2]In Redshift, an update is implemented as a delete followed by an insert.

5 AUTOMATIC MDDL SELECTION

Redshift Advisor automatically decides which tables to create MDDL on and which predicates to use in each MDDL. This section provides background on the existing Advisor service, then describes how MDDL integrates into it.

5.1 Redshift Advisor

Redshift Advisor makes per-table sort key recommendations, which were limited to single-column sort keys before the introduction of MDDL. It relies on historical telemetry collected from the user's workload: for each table scan, Redshift logs the number of rows filtered by each column. At regular time intervals, Advisor reads this telemetry and aggregates the total number of rows filtered by each column across all queries in the entire history of the cluster (or since the last time a recommendation was made), and selects the column with the highest benefit (i.e., the column that filtered the most rows) as its sort key recommendation.

Advisor uses fixed rules to decide whether or not to surface the recommendation to the user or to Automatic Table Optimization background workers. For example, it does not send the recommendation if the user already manually chose a sort key for the table, nor if the telemetry indicates that the existing data layout already achieves a degree of row filtering that is similar to the recommended sort key.

5.2 MDDL in Redshift Advisor

Two adjustments were made to incorporate MDDL into Advisor.

5.2.1 Collecting telemetry. In addition to logging rows filtered by each column during scans, we added instrumentation to log rows filtered by each predicate. For a given scan, the number of rows filtered by a given predicate is composed of both the number of rows in blocks that are skipped using the predicate, as well as the number of rows that are filtered out using the predicate from the scanned row ranges. Both of these metrics are efficient to collect as a side effect of scan execution because the filtering effects of each individual predicate are easily isolated.

For example, consider a query over the table from Fig. 1 that scans the table and applies this filter:

```
colC ILIKE '%black%' AND (colA > colB OR colA = 0)
```

The filter contains two predicates: (1) `colC ILIKE '%black%'` and (2) `(colA > colB OR colA = 0)`. Redshift first performs block skipping on each of the predicates individually, resulting in a set of row ranges for each predicate, then intersects the row ranges to form a global set of row ranges to read (see Fig. 4 for a visualization). Therefore, we can collect the number of rows filtered via block skipping (i.e., the number of rows not in the set of row ranges) for each predicate individually. Then during scan execution, Redshift reads rows from the global set of row ranges, first filtering by the first predicate to produce an intermediate bitvector, and then filtering by the second predicate to produce the final bitvector. By counting the number of set bits in the bitvector after each predicate evaluation, we collect the number of rows filtered for each predicate.

We only collect telemetry for top-level conjuncts in the filter, i.e., the predicates that are combined through conjunction to form the overall scan filter. We do not collect telemetry for disjunctions or sub-components of top-level predicates. In the above example, we would not collect telemetry for `colA > colB` or for `colA = 0` individually.

5.2.2 Selecting MDDL. For a given table, Advisor aggregates the rows filtered by each predicate across all historical queries (or all queries since the last time that a recommendation was made for the cluster) and constructs a candidate MDDL by taking the top k predicates, ranked by number of rows filtered. The benefit of the candidate MDDL is the total number of rows filtered by all of its predicates. Advisor then compares the overall benefit of the candidate MDDL, the candidate single-column sort key and the existing sort key (if any), and recommends the one with the highest benefit, if different from the existing one[3].

Given an MDDL with k predicates, the ones with higher benefit are associated with more significant bit positions in the MDDL column (see Section 4.1.1), so that the sorted table will have fewer contiguous row ranges that satisfy higher-benefit predicates. Any table sorted by MDDL has exactly one contiguous row range that satisfies the highest-benefit predicate but up to two row ranges that satisfy the second-highest-benefit predicate (e.g., Fig. 2a), and up to 2^{n-1} row ranges that satisfy the nth-highest-benefit predicate. Having more row ranges increases the chance that a block with rows not satisfying the predicate (and therefore potentially skippable) also has rows that do satisfy the predicate, which decreases the effectiveness of skipping blocks using the associated predicate.

We select the value of k by using the rule of thumb that if there is an equal number of rows for each distinct MDDL column value, then all rows with the same MDDL value can fit into one 1MB data block. The intuition is that the primary benefit of data layouts comes from block skipping, so once a set of rows have been assigned to a given block, there is minimal further benefit of differentiating the rows within that block. We currently use a conservative estimate for k, based on the assumption that given k predicates, there are 2^k distinct MDDL column values, since each predicate can be either true or false. However, this is likely an overestimate in practice, since it is possible that there are no rows with a given MDDL value, especially since some predicates can be mutually exclusive (e.g., if `colA = 0` and `colA = 1` are both predicates from different queries, then clearly any MDDL value corresponding to both predicates being true in the same query is impossible). Determining a tighter bound for the maximum number of distinct MDDL values would require a robust way to determine predicate intersection and subsumption, and is left as future work.

[3]If the benefit of the best candidate is marginally higher than that of the existing sort key, then Advisor refrains from surfacing the recommendation.

Note that unlike existing work on automated data layout selection which rely on having a sample of the data in order to perform what-if analysis of candidate layouts [21, 22, 24, 30], MDDL only relies on telemetry collected as a side-effect of user query execution. This not only reduces the performance overhead of collecting and storing the data sample, but also avoids privacy and security concerns related to handling customer data.

5.2.3 Discussion. The benefit of an MDDL recommendation is conceptually meant to capture the number of rows we could have filtered on the historical workload using MDDL filters over a hypothetical MDDL column. However, the benefit value we calculate using the procedure described above can be inaccurate in two ways:

(1) By summing the number of rows filtered via block skipping from each individual predicate, we overestimate benefit because different predicates in the same scan filter might skip overlapping row ranges.
(2) Since the bitvector is reduced after each predicate evaluation, we underestimate the number of rows filtered by any predicate that appears second or later in evaluation order.

To mitigate these inaccuracies, we select the k predicates in such a way that out of all observations of the predicates in the historical telemetry, a high percentage are from cases where the predicate was evaluated first. We found that fleet-wide, around half of scans with filters only had one predicate. In cases with multiple predicates, the most selective ones (which filter the most rows and are most likely to be included in MDDL) are placed first in the predicate order anyway.

The first effect can in concept be avoided by logging rows filtered via block skipping not only of individual predicates, but combinations of predicates, but we rejected this technique because it exponentially increases the size of the logged telemetry. Furthermore, both effects can in concept be avoided by using planner selectivity estimates instead of telemetry to compute rows filtered, but we found that inaccuracies in selectivity estimation far outweigh inaccuracies due to the above effects.

6 EVALUATION

This section compares MDDL against existing data layout techniques in Redshift (single-column sort keys, compound sort keys, and interleaved sort keys) across three internal workloads. We also describe the projected impact of MDDL across the entire fleet of Redshift customers, based on historical telemetry. Overall, this evaluation shows that:

(1) MDDL achieves up to 10× better end-to-end workload performance compared to only using the optimal single-column sort keys on each table, and up to 7× better performance compared to using compound and interleaved sort keys.
(2) MDDL is estimated to benefit around 25% of customer tables across the entire Redshift fleet, and to increase workload-wide rows filtered by 2× for the top 5% of clusters.

6.1 Setup

We evaluate on three different internal workloads, described in Table 1. All workloads are derived from actual customer workloads, but have been de-identified and anonymized for internal benchmarking purposes with the consent of the customer.

We compare the following data layout setups:

Table 1: Workload characteristics.

	Workload		
	A	**B**	**C**
Number of tables	2	81	2
Compressed data size (GB)	367	182	337
Number of queries	18	11053	1400
Frac. time spent in scans	0.80	0.13	0.84

(1) **Original data layout**: this is the data layout of the table when it is loaded. For Workload A, the tables already had manually defined sort keys. For Workloads B and C, the table did not have sort keys, so rows were loaded in ingestion order.
(2) **Advisor without MDDL**, also labeled as **SKR (Sort Key Recommendation)**: after running the query workload, we use Redshift Advisor to automatically generate single-column sort key recommendations for relevant tables. Tables that have not been scanned with filters will not get a sort key.
(3) **Advisor with MDDL**, also labeled as **MDDL**: similar to the above, except that in addition to single-column sort key recommendations, we also generate MDDL recommendations.
(4) **Compound sort keys**: Redshift Advisor currently does not have the ability to recommend compound sort keys. For the sake of comparison, we construct a compound sort key for each table using the top three columns, ordered by number of rows filtered by the column in the historical workload. In terms of scan performance, a compound sort key with more columns is never worse than one with fewer columns, as long as they share the same prefix. However, in practice, longer compound sort keys incur higher overhead for maintenance (e.g., it is slower to sort on a compound sort key).
(5) **Interleaved sort keys**: Similar to compound sort keys, Redshift Advisor currently does not have the ability to recommend interleaved sort keys (Z-order). For the sake of comparison, we construct an interleaved sort key for each table using the top two columns, ordered by number of rows filtered by the column in the historical workload. In general, interleaved sort keys are useful when there are multiple predicate columns that are roughly equally important.

For each workload, we use a dedicated Redshift cluster with the same number of nodes and node types as the original customer cluster from which the workload was derived. We load the data using the original data layout and run all queries in the workload sequentially. We then trigger Advisor to automatically generate sort key recommendations based on the historical workload (or we use a separate programmatic process to generate recommendations for the case of compound and interleaved sort keys). We apply these new sort keys to the relevant tables and fully sort them. We then rerun all queries in the workload sequentially to measure the workload performance with the new data layout.

We do not compare against more complex instance-optimized data layout techniques [21, 22, 24, 27, 28, 30] because they are difficult to implement in practice: they assume the existence of robust intersection and subsumption logic over arbitrarily complex predicates (which does not exist in Redshift) and their optimization techniques require access to a data sample, which raises privacy concerns.

6.2 Overall Results

Fig. 5 shows that across the three workloads, MDDL achieves between 1% and 85% reduction in end-to-end workload runtime compared to the alternative data layouts. MDDL not only outperforms single-column sort keys, but also generally outperforms compound sort keys and interleaved sort keys. In fact, in some cases interleaved sort keys are worse than simply using single-column sort keys, especially for workloads in which there is a clear order of importance among the predicate columns. MDDL does not achieve much improvement over single-column sort keys on Workload B, despite achieving larger improvements in rows read and blocks read, because the overall time spent in scans is already low (see Table 1). Furthermore, Workload B is actually best served by compound sort keys—this motivates the benefit of integrating compound sort key into Advisor's search space of recommendations in the future.

In general, the improvement in runtime achieved by MDDL is explained by the fact that MDDL enables Redshift to read fewer rows and fewer blocks during scans. Rows read and blocks read are not perfectly correlated because the number of blocks is different in each column. Also, a row is considered read if we need to access *any* column's value in that row, but the number of column values read in each row (and therefore the number of blocks read) depends on the effectiveness of late materialization, i.e., if leading predicates already filter out a row, then the values for subsequent predicate columns are not read.

Furthermore, the improvement in runtime is sometimes greater than the improvement in rows read or blocks read. At first glance, this behavior may seem illogical, based on the intuition that rows and blocks read are roughly correlated with scan time, and scan time is only a fraction of overall runtime, so relative changes in runtime should be less than relative changes in rows or blocks scanned. However, this behavior is explained by two observations: first, for a query that scans multiple tables, reducing the amount of rows scanned in one table can have a much larger impact than an equivalent reduction in another table, because the cost of filter evaluation and materialization is different on each table. For example, consider a query which scans two tables, where one of the scans takes 80% of runtime and the other scan takes 10% of runtime, but each table has the same number of rows. Reducing rows scanned in the first table by half would reduce overall rows scanned by 25%, but would reduce runtime by 40%. Second, even if improvement in runtime is always less than improvement in rows/blocks read for each individual query, it is not necessarily true when applied to aggregated statistics across a workload of queries: it is possible that queries that read much fewer rows and blocks by using MDDL did not contribute significantly to total runtime in the first place. This can be considered a form of Simpson's Paradox[4].

Finally, we note that the improvement in runtime from using any data layout sometimes exceeds the amount of time spent in scans (Table 1). This is explained by the fact that the fraction shown in Table 1 is approximate (due to the fact that different plan steps are fused together in Redshift's generated code, so it is impossible to exactly pinpoint the time spent on each step), but also by the fact that sort orders

[4]https://en.wikipedia.org/wiki/Simpson's_paradox

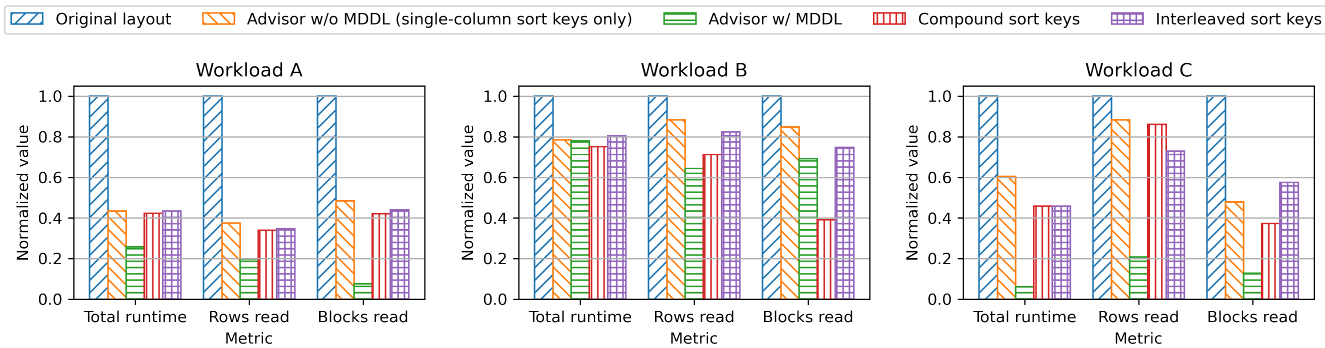


Figure 5: MDDL achieves up to 85% reduction in overall runtime compared to using the optimal single-column sort key on each table. Runtime improves are explained by the corresponding reductions in rows read and blocks read during scans, achieved through MDDL.

can have unintended side effects beyond scan performance. For example, a table that is fully sorted and distributed on the join column is able to perform merge joins instead of hash joins, and a table that is approximately sorted by a column has better cache locality when building a hash table over the column's values for hash joins and group-bys. These extraneous affects are currently not considered by Redshift Advisor, but are an interesting direction for future improvement.

6.3 Deep Dive into Workload A

We perform a deeper dive into the behavior of MDDL on Workload A.

6.3.1 Queries. Table 2 contains the breakdown in performance for each of the 18 queries in Workload A. We see that there is a range of different speedups. We now examine a few specific queries to understand why they benefit from MDDL.

Query 1 is of this form:

```
SELECT season, sum(metric2) AS "__measure__0",
FROM titles
WHERE lower(subregion) like '%united states%'
GROUP BY 1
ORDER BY 1 asc;
```

This query performs an aggregation over the `titles` table, after filtering rows based on the `subregion` column. This was actually the longest-running query in the workload because the filter is expensive to evaluate, since it includes both a function call and a regular expression comparison. A single-column sort key would not help reduce rows read for this query: even if we sorted the table by `subregion`, we would not be able to leverage zone maps to perform block skipping, and Redshift would need to scan all data blocks to evaluate the filter. Compound and interleaved sort keys also do not reduce rows read, for the same reason. However, if the predicate `lower(subregion) like '%united states%'` appears repeatedly in the workload, then Redshift might sort by it as part of MDDL. If that happens, then all rows that satisfy this predicate would be co-located in the same data blocks, and Redshift would automatically leverage MDDL during scans to only scan data blocks that satisfy the predicate. Note that due to a stipulation in Redshift that forces sort key columns to not have any encoding, performance does improve when using the column-based sort keys, despite not having any impact on rows read, but blocks read also increases due to worse compression.

Query 4 is of this form:

```
SELECT * FROM titles
WHERE subregion = 'United States'
AND date >= '2007-01-01' AND date <= '2017-02-28'
AND season_desc IS NULL
LIMIT 1
```

On this query, a single-column sort key over `subregion` was able to reduce runtime by filtering rows and blocks based on the predicate over `subregion`. A compound sort key performs even better because it is able to filter over both the `subregion` and `date` columns, though the improvement is not significant because the filter over the `date` column is not very selective. MDDL performs the best because it uses all of these predicates, and in particular, its improvement over single-column and compound sort keys is not so much due to skipping additional rows (in fact, Table 2 shows that compound sort keys reads only marginally more rows than MDDL, because the predicate over `season_desc` is not very selective anyway), but rather because MDDL is able to avoid reading the blocks of any of the predicate columns, and instead only reads the blocks of the MDDL column.

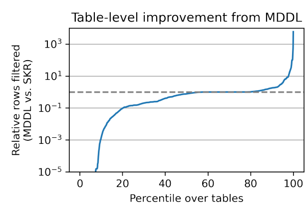
6.3.2 MDDL Creation. As described in Section 4.3, creating MDDL on a table has three distinct stages: creating the MDDL with default values, then computing the MDDL column values and re-sorting the table. Table 3 shows that these three stages vary greatly in terms of time to completion for the largest table of Workload A. Furthermore, the last column of Table 3 shows the total runtime of executing Workload A on the table compared to having no sort key, after each stage. There is no change in runtime after the first stage, because MDDL cannot be used to accelerate scans when column values are not yet computed. After the second stage, we already reduce the workload runtime, because even though we do not reduce rows read, we do reduce blocks read (see Section 4.2.2). This justifies our decision to separate MDDL creation into stages, since we do not need to wait for the table to be fully sorted in order to begin obtaining benefits from MDDL. After the third stage, MDDL is fully created, and this is the same performance illustrated in Fig. 5.

Table 2: Per-query breakdown of runtime, rows read, and blocks read in Workload A for each data layout (SKR = Advisor w/o MDDL, MDDL = Advisor w/ MDDL).

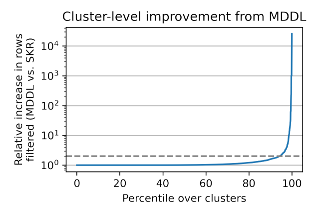
Query	Runtime (relative to original layout)					Rows read (relative to original layout)					Blocks read (relative to original layout)				
	Orig.	SKR	MDDL	Compd.	Interleaved	Orig.	SKR	MDDL	Compd.	Interleaved	Orig.	SKR	MDDL	Compd.	Interleaved
q1	1.0	0.69	0.0729	0.693	0.697	1.0	1.0	0.0704	1.0	1.0	1.0	7.14	0.0239	7.14	7.14
q2	1.0	0.194	0.113	0.189	0.206	1.0	0.105	0.0904	0.0905	0.106	1.0	0.211	0.0678	0.181	0.216
q3	1.0	0.174	0.102	0.162	0.173	1.0	0.105	0.0904	0.0905	0.106	1.0	0.211	0.0678	0.182	0.216
q4	1.0	0.0922	0.00148	0.0802	0.0906	1.0	0.105	0.00288	0.0905	0.106	1.0	0.128	0.00342	0.111	0.138
q5	1.0	0.0726	0.00211	0.0716	0.0831	1.0	0.105	0.00288	0.0905	0.106	1.0	0.0145	0.00596	0.0136	0.0168
q6	1.0	0.864	0.876	1.26	1.27	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.96	9.59	8.59
q7	1.0	0.803	0.577	0.651	0.67	1.0	0.968	0.613	0.666	0.642	1.0	3.74	0.429	2.68	2.49
q8	1.0	0.874	0.907	1.0	1.02	1.0	1.0	1.0	1.0	1.0	1.0	0.857	1.14	2.79	2.38
q9	1.0	0.878	0.875	1.38	1.25	1.0	1.0	1.0	1.0	1.0	1.0	1.04	1.46	7.79	6.58
q10	1.0	0.622	0.392	0.467	0.451	1.0	0.955	0.458	0.533	0.499	1.0	3.06	0.349	1.76	1.56
q11	1.0	0.849	0.88	1.04	1.02	1.0	1.0	1.0	1.0	1.0	1.0	0.96	1.36	3.08	2.98
q12	1.0	0.834	0.854	1.08	1.05	1.0	1.0	1.0	1.0	1.0	1.0	0.958	1.25	4.71	4.21
q13	1.0	0.812	0.543	0.66	0.678	1.0	0.968	0.613	0.666	0.642	1.0	2.56	0.311	1.71	1.54
q14	1.0	0.791	0.614	0.677	0.782	1.0	0.968	0.613	0.666	0.642	1.0	3.45	0.406	2.41	2.24
q15	1.0	0.884	0.912	0.94	0.965	1.0	1.0	1.0	1.0	1.0	1.0	9.47	1.01	12.4	12.2
q16	1.0	0.625	0.602	0.182	0.202	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.94	3.47	3.47
q17	1.0	0.83	0.865	0.993	0.952	1.0	1.0	1.0	1.0	1.0	1.0	0.905	1.26	2.43	2.45
q18	1.0	0.84	0.9	1.12	1.16	1.0	1.0	1.0	1.0	1.0	1.0	1.13	1.57	6.04	5.87
Total	1.0	0.434	0.258	0.423	0.435	1.0	0.375	0.199	0.339	0.347	1.0	0.484	0.0756	0.421	0.44

Table 3: MDDL Creation in Workload A.

Stage	Relative duration	Relative workload runtime after stage
1. Create column	1	1
2. Compute values	67	0.73
3. Sort table	2800	0.26



(a) Around 25% of tables (those above the dashed line) would benefit from MDDL over single-column sort keys.



(b) The top 5% of clusters (those above the dashed line) would increase rows filtered across their workload by 2× by using MDDL.

Figure 6: Table-level and cluster-level analysis performed over the entire Redshift fleet (projection). Redshift Advisor picks the best layout, which avoids regressions due to MDDL.

6.4 Fleet Projections

At Redshift, we collect anonymized telemetry from all customers and clusters across all AWS regions. Using this telemetry, we computed projections for how MDDL would perform across the Redshift fleet. Note that these are only projections, because MDDL has not yet been completely rolled out to all Redshift customers. Even if MDDL were rolled out, any metrics comparing MDDL against alternative data layouts would be estimates, since it would require a hypothetical: each user query is executed on a given layout, and we will never know what the runtime of the equivalent query on an alternative layout would have been.

6.4.1 Table-level projections. First, we determine what fraction of tables would benefit more from MDDL than from single-column sort keys, by simulating the Advisor algorithm over the past day of queries on each cluster (Fig. 6a). We found that on the top 10K tables ranked by number of rows filtered, approximately 25% (those above the dashed line) would filter more rows if they used MDDL instead of the optimal single-column sort key. Of those 25% of tables, the P90 table would filter out 3× more rows by using MDDL. Note that Fig. 6a shows that the other 75% of tables (those below the dashed line) would have worse performance with MDDL—this is only shown for illustrative purposes. In reality, Redshift Advisor would not create MDDL on those tables at all, since it recognizes that performance would be worse than using a single-column sort key.

6.4.2 Cluster-level projections. We considered all clusters which had at least 100 queries with filtered scans in the past day, and estimated the relative additional number of rows filtered if we used MDDL instead of single-column sort keys (Fig. 6b). Overall, the P90 cluster would filter out around 1.5× as many rows across *all scans* on the cluster over the past day, and the P95 cluster would filter out 2× as many rows. When computing these projections, we only use MDDL on tables where it would perform better than the optimal single-column sort key, and on other tables we simply use the optimal single-column sort key. This is why the projected improvement is always at least 1, because adding the capability (but not the requirement) to use MDDL on each table should not degrade performance.

7 DISCUSSION

In this section we discuss our design decisions, MDDL's interactions with other components in Redshift, and directions for future work.

7.1 Design Decisions

In Redshift, we implemented MDDL as a materialized column in the table, and we rely on existing column metadata (i.e., min/max values per block). However, there are several alternative designs.

Using a virtual column. Instead of materializing the column, we could have relied on a virtual column, with physical zone maps over virtual data blocks. The advantage of using a virtual column is that it saves space. However, since Redshift is a cloud-based system, storage space is typically not a bottleneck. The downside of using a virtual column is that values must be recomputed every time they are used, which means that we would not save any row-level predicate evaluation work for rows that are scanned.

Using an index structure. Instead of relying on existing zone maps, we could have introduced a new index structure, e.g., a mapping between predicates to all the blocks containing rows that match the predicate. However, we found zone maps to already provide sufficient block skipping capabilities, and this alternative index structure would have introduced additional maintenance overhead.

7.2 Interactions with Other Components

MDDL complements existing performance-enhancing features in Redshift.

Column-based sort keys. MDDL is not a replacement for single-column sort keys, compound sort keys, and interleaved sort keys, but rather an alternative. Column-based sort keys are useful for tables where scan filters are diverse but filter over only a few dominant columns, whereas MDDL is useful for workloads with a small number of important frequently-repeating scan filters.

Result cache. Redshift has the ability to cache query results, so that if the exact same query is issued again, and no data changes have occurred, then the query can be answered directly from the result cache. MDDL optimizes for scans in queries that do not hit the result cache, so MDDL and the result cache are complementary. In general, we found that although query filters repeat frequently, the queries that contain these repeated filters often do not hit the result cache because there have been data modifications in the intervening time, which invalidate the cached result.

Materialized views. Redshift offers the capability of Automated Materialized Views [6], which automatically creates and refreshes materialized views that are useful for frequently-appearing user query patterns. If a materialized view is created and queries that used to hit a user table are now automatically rewritten to hit the materialized view, then part of the MDDL on the user table might no longer be useful. This can eventually be corrected by the Advisor, which would recommend a new MDDL with different predicates, or a single-column sort key, over the user table. Furthermore, MDDL can be applied on materialized views themselves, like any other sort key.

7.3 Future Directions

There are several directions for future work to improve MDDL.

Inexact match. We can extend MDDL to match based on intersection and subsumption instead of exact match, similar to the approaches proposed in past work on data layouts [21, 22, 24, 30]. However, the matching logic now becomes significantly more difficult. Matching for simple range predicates is simple enough (e.g., clearly the predicate `colA > 10` is subsumed by the predicate `colA > 0`, meaning that any row matching the latter must also match the former, but becomes more involved when predicates contain functions and operators other than the traditional comparison operators. Also, we cannot skip evaluation of user predicates based on inexact match (see Section 4.2.2).

Integration with materialized view selection. Data layouts such as MDDL and materialized views essentially have the same goal, i.e., they identify repeating query patterns in the past workload and speed up similar queries in the future. However, their tradeoffs are different: materialized views speed up the entire query whereas data layouts speed up just the scan, MDDL is always usable whereas materialized views are unusable when stale due to data changes in the base tables, and MDDL maintenance is relatively cheap whereas materialized view refresh cost must be factored into the selection algorithm [29]. It would be interesting to analyze these tradeoffs and combine the selection algorithms for these two.

There has been past work on joint selection of data layouts and materialized views, but they are not directly applicable to our scenario. Microsoft proposed integrated selection of indexes (a clustered primary key index is comparable to a single-column sort key) and materialized views as part of AutoAdmin [15, 19]. However, their framework assumed a constraint on storage space, whereas in the modern cloud environment of Redshift, storage space is typically no longer a bottleneck. Instead, the maintenance overhead of data layouts and materialized views is now the constraint. SageDB [20] likewise proposed joint selection of data layouts and materialized views, but did so without directly comparing the benefits and costs of data layouts and materialized views, instead opting to select the optimal configuration of each component under separate storage budgets.

8 CONCLUSION

In this paper, we introduce a new feature in Amazon Redshift called Multidimensional Data Layouts (MDDL), which is an alternative to traditional data layout techniques such as single-column sort keys, compound sort keys, and interleaved sort keys. MDDL outperforms those traditional data layouts for workloads that exhibit repetitive scan filters. Redshift learns from the user's historical workload to automatically implement, maintain, and use the best MDDL for each table. Benchmarks derived from customer workloads show that MDDL improves end-to-end workload times by up to 10× compared to only using single-column sort keys and by up to 7× compared to using more complex layouts such as compound and interleaved sort keys. Our projections show that around 25% of tables of the Redshift fleet can benefit more from MDDL than from single-column sort keys.

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REFERENCES

[1] [n.d.]. ALTER TABLE APPEND - Amazon Redshift — docs.aws.amazon.com. https://docs.aws.amazon.com/redshift/latest/dg/r_ALTER_TABLE_APPEND.html. [Accessed 25-11-2023].

[2] [n.d.]. Amazon Redshift Advisor recommendations - Amazon Redshift — docs.aws.amazon.com. https://docs.aws.amazon.com/redshift/latest/dg/advisor-recommendations.html. [Accessed 20-11-2023].

[3] [n.d.]. Amazon Redshift Engineering's Advanced Table Design Playbook: Compound and Interleaved Sort Keys | Amazon Web Services — aws.amazon.com. https://aws.amazon.com/blogs/big-data/amazon-redshift-engineerings-advanced-table-design-playbook-compound-and-interleaved-sort-keys/. [Accessed 28-11-2023].

[4] [n.d.]. Amazon Redshift introduces Automatic Table Sort, an automated alternative to Vacuum Sort — aws.amazon.com. https://aws.amazon.com/about-aws/whats-new/2019/11/amazon-redshift-introduces-automatic-table-sort-alternative-vacuum-sort/. [Accessed 20-11-2023].

[5] [n.d.]. Announcing Delta Lake 3.0 with New Universal Format and Liquid Clustering — databricks.com. https://www.databricks.com/blog/announcing-delta-lake-30-new-universal-format-and-liquid-clustering. [Accessed 28-11-2023].

[6] [n.d.]. Automated materialized views - Amazon Redshift — docs.aws.amazon.com. https://docs.aws.amazon.com/redshift/latest/dg/materialized-view-auto-mv.html. [Accessed 28-11-2023].

[7] [n.d.]. Clustering Keys & Clustered Tables | Snowflake Documentation — docs.snowflake.com. https://docs.snowflake.com/en/user-guide/tables-clustering-keys. [Accessed 28-11-2023].

[8] [n.d.]. Data skipping with Z-order indexes for Delta Lake — docs.databricks.com. https://docs.databricks.com/en/delta/data-skipping.html. [Accessed 28-11-2023].

[9] [n.d.]. Data Warehousing Guide — docs.oracle.com. https://docs.oracle.com/en/database/oracle/oracle-database/19/dwhsg/using-zone-maps.html. [Accessed 28-11-2023].

[10] [n.d.]. Indexing Expressions — docs.oracle.com. https://docs.oracle.com/cd/E16338_01/appdev.112/e14919/exprn_indexexpressions.htm. [Accessed 28-11-2023].

[11] [n.d.]. Micro-partitions & Data Clustering | Snowflake Documentation — docs.snowflake.com. https://docs.snowflake.com/en/user-guide/tables-clustering-micropartitions. [Accessed 28-11-2023].

[12] [n.d.]. Partitioning tables in dedicated SQL pool - Azure Synapse Analytics — learn.microsoft.com. https://learn.microsoft.com/en-us/azure/synapse-analytics/sql-data-warehouse/sql-data-warehouse-tables-partition. [Accessed 28-11-2023].

[13] [n.d.]. SUPER type - Amazon Redshift — docs.aws.amazon.com. https://docs.aws.amazon.com/redshift/latest/dg/r_SUPER_type.html. [Accessed 21-11-2023].

[14] [n.d.]. Working with automatic table optimization - Amazon Redshift — docs.aws.amazon.com. https://docs.aws.amazon.com/redshift/latest/dg/t_Creating_tables.html. [Accessed 20-11-2023].

[15] Sanjay Agrawal, Surajit Chaudhuri, and Vivek R. Narasayya. 2000. Automated Selection of Materialized Views and Indexes in SQL Databases. In *Proceedings of the 26th International Conference on Very Large Data Bases (VLDB '00)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 496–505.

[16] Anastassia Ailamaki, David J. DeWitt, and Mark D. Hill. 2002. Data Page Layouts for Relational Databases on Deep Memory Hierarchies. *The VLDB Journal* 11, 3 (nov 2002), 198–215. https://doi.org/10.1007/s00778-002-0074-9

[17] Nikos Armenatzoglou, Sanuj Basu, Naga Bhanoori, Mengchu Cai, Naresh Chainani, Kiran Chinta, Venkatraman Govindaraju, Todd J. Green, Monish Gupta, Sebastian Hillig, Eric Hotinger, Yan Leshinksy, Jintian Liang, Michael McCreedy, Fabian Nagel, Ippokratis Pandis, Panos Parchas, Rahul Pathak, Orestis Polychroniou, Foyzur Rahman, Gaurav Saxena, Gokul Soundararajan, Sriram Subramanian, and Doug Terry. 2022. Amazon Redshift Re-Invented. In *Proceedings of the 2022 International Conference on Management of Data* (Philadelphia, PA, USA) *(SIGMOD '22)*. Association for Computing Machinery, New York, NY, USA, 2205–2217. https://doi.org/10.1145/3514221.3526045

[18] Nemanja Borić, Hinnerk Gildhoff, Menelaos Karavelas, Ippokratis Pandis, and Ioanna Tsalouchidou. 2020. Unified Spatial Analytics from Heterogeneous Sources with Amazon Redshift. In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data* (Portland, OR, USA) *(SIGMOD '20)*. Association for Computing Machinery, New York, NY, USA, 2781–2784. https://doi.org/10.1145/3318464.3384704

[19] Nicolas Bruno and Surajit Chaudhuri. 2005. Automatic Physical Database Tuning: A Relaxation-Based Approach. In *Proceedings of the 2005 ACM SIGMOD International Conference on Management of Data* (Baltimore, Maryland) *(SIGMOD '05)*. Association for Computing Machinery, New York, NY, USA, 227–238. https://doi.org/10.1145/1066157.1066184

[20] Jialin Ding, Ryan Marcus, Andreas Kipf, Vikram Nathan, Aniruddha Nrusimha, Kapil Vaidya, Alexander van Renen, and Tim Kraska. 2022. SageDB: An Instance-Optimized Data Analytics System. *Proc. VLDB Endow.* 15, 13 (2022), 4062–4078. https://www.vldb.org/pvldb/vol15/p4062-ding.pdf

[21] Jialin Ding, Umar Farooq Minhas, Badrish Chandramouli, Chi Wang, Yinan Li, Ying Li, Donald Kossmann, Johannes Gehrke, and Tim Kraska. 2021. *Instance-Optimized Data Layouts for Cloud Analytics Workloads*. Association for Computing Machinery, New York, NY, USA, 418–431. https://doi.org/10.1145/3448016.3457270

[22] Jialin Ding, Vikram Nathan, Mohammad Alizadeh, and Tim Kraska. 2020. Tsunami: A Learned Multi-Dimensional Index for Correlated Data and Skewed Workloads. *Proc. VLDB Endow.* 14, 2 (Oct. 2020), 74–86. https://doi.org/10.14778/3425879.3425880

[23] Guido Moerkotte. 1998. Small Materialized Aggregates: A Light Weight Index Structure for Data Warehousing. In *Proceedings of the 24rd International Conference on Very Large Data Bases (VLDB '98)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 476–487.

[24] Vikram Nathan, Jialin Ding, Mohammad Alizadeh, and Tim Kraska. 2020. Learning Multi-dimensional Indexes. In *Proceedings of the 2020 International Conference on Management of Data* (Portland, OR, USA) *(SIGMOD '20)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3318464.3380579

[25] Panos Parchas, Yonatan Naamad, Peter Van Bouwel, Christos Faloutsos, and Michalis Petropoulos. 2020. Fast and Effective Distribution-Key Recommendation for Amazon Redshift. *Proc. VLDB Endow.* 13, 12 (jul 2020), 2411–2423. https://doi.org/10.14778/3407790.3407834

[26] Gaurav Saxena, Mohammad Rahman, Naresh Chainani, Chunbin Lin, George Caragea, Fahim Chowdhury, Ryan Marcus, Tim Kraska, Ippokratis Pandis, and Balakrishnan (Murali) Narayanaswamy. 2023. Auto-WLM: Machine Learning Enhanced Workload Management in Amazon Redshift. In *Companion of the 2023 International Conference on Management of Data* (Seattle, WA, USA) *(SIGMOD '23)*. Association for Computing Machinery, New York, NY, USA, 225–237. https://doi.org/10.1145/3555041.3589677

[27] Sivaprasad Sudhir, Michael Cafarella, and Samuel Madden. 2021. Replicated Layout for In-Memory Database Systems. *Proc. VLDB Endow.* 15, 4 (dec 2021), 984–997. https://doi.org/10.14778/3503585.3503606

[28] Sivaprasad Sudhir, Wenbo Tao, Nikolay Laptev, Cyrille Habis, Michael Cafarella, and Samuel Madden. 2023. Pando: Enhanced Data Skipping with Logical Data Partitioning. *Proc. VLDB Endow.* 16, 9 (may 2023), 2316–2329. https://doi.org/10.14778/3598581.3598601

[29] Christoforos Svingos, Andre Hernich, Hinnerk Gildhoff, Yannis Papakonstantinou, and Yannis Ioannidis. 2023. Foreign Keys Open the Door for Faster Incremental View Maintenance. *Proc. ACM Manag. Data* 1, 1, Article 40 (may 2023), 25 pages. https://doi.org/10.1145/3588720

[30] Zongheng Yang, Badrish Chandramouli, Chi Wang, Johannes Gehrke, Yinan Li, Umar F. Minhas, Per-Åke Larson, Donald Kossmann, and Rajeev Acharya. 2020. Qd-tree: Learning Data Layouts for Big Data Analytics. In *Proceedings of the 2020 International Conference on Management of Data*.

[31] Zack Slayton. 2017. Z-Order Indexing for Multifaceted Queries in Amazon DynamoDB. https://aws.amazon.com/blogs/database/z-order-indexing-for-multifaceted-queries-in-amazon-dynamodb-part-1/.