Ingestion, Indexing and Retrieval of High-Velocity Multidimensional Sensor Data on a Single Node

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Abstract—Sources of multidimensional data are becoming more prevalent, partly due to the rise of the Internet of Things (IoT), and with that the need to ingest and analyze data streams at rates higher than before. Some industrial IoT applications require ingesting millions of records per second, while processing queries on recently ingested and historical data. Unfortunately, existing database systems suited to multidimensional data exhibit low per-node ingestion performance, and even if they can scale horizontally in distributed settings, they require large number of nodes to meet such ingest demands. For this reason, in this paper we evaluate a single-node multidimensional data store for high-velocity sensor data. Its design centers around a two-level indexing structure, wherein the global index is an in-memory R*-tree and the local indices are serialized kd-trees. This study is confined to records with numerical indexing fields and range queries, and covers ingest throughput, query response time, and storage footprint.

We show that the adopted design streamlines data ingestion and offers ingress rates two orders of magnitude higher than those of a selection of open-source database systems, namely Percona Server, SQLite, and Druid. Our prototype also reports query response times comparable to or better than those of Percona Server and Druid, and compares favorably in terms of storage footprint. In addition, we evaluate a kd-tree partitioning based scheme for grouping incoming streamed data records. Compared to a random scheme, this scheme produces less overlap between groups of streamed records, but contrary to what we expected, such reduced overlap does not translate into better query performance. By contrast, the local indices prove much more beneficial to query performance. We believe the experience reported in this paper is valuable to practitioners and researchers alike interested in building database systems for high-velocity multidimensional data.

I. INTRODUCTION

Today sensors, systems, and automated processes generate increasing volumes of data. Many of these data sources continuously produce multidimensional records, each with various numerical fields containing measured values and timestamps. Prime examples are mobile devices with positioning modules and various sensors, recording time, location, orientation, and other variables. Other examples are the electric grid, smart buildings, and data centers.

With the proliferation of sensor deployments, multidimensional data streams are expected to grow in number, but also be generated at higher rates. Particularly, some Internet of Things (IoT) applications in industrial settings (e.g., power distribution telemetry [15]) require ingesting unbounded streams each carrying tens of millions of records per second, while running queries on recently ingested and historical data. These demands are beyond the capabilities of most existing database systems and have motivated the development of new ones. New time series databases [34], [14], with time as the only or primary indexing field, have been geared to sustain such high ingestion rates. Also aiming at high-velocity data, new online analytical processing (OLAP) systems have been proposed lately [43], [19], [35], [21]. These OLAP systems are able to index records by multiple fields (multidimensional indexing), offer sub-second responses to analytical queries, and are designed to scale horizontally. Unfortunately, they exhibit low per-node ingestion performance, often far less than 1 million records per second, and hence require large number of nodes to meet the ingest demands mentioned above. A similar observation has been made in [31] about stream processing engines.

For that reason, in this paper we go back to basics and revisit the ingestion, indexing, storage, and retrieval of high-velocity multidimensional sensor data on a single node. We focus on records with numerical indexing fields and range queries, both commonly used in sensor and system monitoring applications. The main question we seek to address is whether it is possible to build a single-node multidimensional data store able to sustain ingestion rates much higher than those of individual nodes of existing database systems, while still offering similar query performance. To answer this question, we adopt a design, presented in [41], which centers around a hierarchical (two-level) indexing structure, reminiscent of EMINC [45], wherein the global index is an in-memory R*-tree [17], [38] and the local indices are serialized k-dimensional trees (kd-trees) [13]. Based on this design, we built a multidimensional data store prototype, called MDDS and described in [17]. It implements a fast data ingestion path that executes almost entirely in memory, leverages task parallelism, and makes data available to queries before being persisted. MDDS is conceived as a...
building block of the nodes in the data ingestion tier of a distributed stream processing system, described in [1].

Our results (§VI) indicate that we can positively answer the question. We observe that MDDS can sustain ingestion rates two orders of magnitude higher than those of the selected competing systems (Percona Server [1], SQLite3 [2], and Druid [43]). MDDS also reports query response times comparable to or better than those of Percona Server (using a single multi-column index) and Druid, even though MDDS’s data retrieval path is not optimized. Moreover, MDDS, using no compression technique, compares favorably in terms of storage footprint against the other systems.

In addition, we evaluate two methods for partitioning ingress streamed data, referred to as data segmentation schemes and presented in §IV. One scheme simply groups incoming records uniformly at random, while the other does so by creating an in-memory kd-tree with the records and partitioning the tree based on the number of nodes in subtrees. MDDS implements both schemes as part of its ingestion path. Compared to the random scheme, the kd-tree partitioning based scheme produces less overlap between groups of streamed data records (i.e., data segments) at the expense of lower ingestion performance. We hypothesize that such reduced overlap among data segments improves query response times by decreasing read amplification. Our results, however, do not support this hypothesis; we observe that the kd-tree partitioning based scheme yields insignificant or no reduction in query response time. By contrast, the use of local indices, implemented as serialized kd-trees, is much more beneficial to query performance.

The contributions of this paper are the following:

1) An experimental study of the design of a single-node multidimensional data store system for high-velocity sensor data. The study covers ingest throughput, query response time, and storage footprint.

2) The characterization of two data segmentation schemes – the random assignment scheme (§IV-A) and the kd-tree partitioning based scheme (§IV-B) – in terms of ingestion and query performance, including the effect query processing has on data ingestion.

3) A comparison of the MDDS prototype against a selection of well-known open-source database systems: Percona Server [1], with several storage engines (XtraDB, MyISAM, and TokuDB), and SQLite3 [2], as representatives of relational database management systems (RDBMSs), and Druid [43], a NoSQL OLAP system.

In our evaluation, we use two publicly available datasets: NYC Taxi Trip dataset [3] and Global Historical Climatology Network - Daily (GHCN-Daily) dataset [29, 30]. We also use two sets of custom SQL range queries, one for each dataset, which are listed in Appendix A.

![Figure 1: Distributed data stream processing system with separate nodes for data ingestion (DI), data storage (DS), and query brokering. A multidimensional data store (MDDS) is a terminal vertex in the stream processing flow graph on a data ingestion node.](image)

**II. TARGET MULTI-NODE SYSTEM**

We consider a multi-node data stream processing system, whose basic architecture is shown in Figure 1. Similar to Druid [43], the system includes separate nodes for data ingestion, data storage, and query brokering. *Data ingestion (DI) nodes* receive data streams and may perform some computation on the data (e.g., filtering and summarization). They offer interim storage for raw or processed streamed data that have recently entered the system. By contrast, *data storage (DS) nodes* are responsible for permanently storing data. DI nodes offload the data to DS nodes once a time interval expires, after a data volume threshold is exceeded, or at times of light system’s loads. DI and DS nodes both serve queries on the data they possess. Moreover, *query broker nodes* receive client queries and re-direct them to the relevant DI and DS nodes; they may also aggregate and filter the query results, if needed. The systems also includes other nodes (not shown) in charge of activities such as global data indexing, replication, and load balancing.

DI nodes are tailored to ingesting and storing append-only data at high velocity (a write-heavy workload) while providing good query performance. They should then include data store subsystems featuring indexing structures that are quick to populate and effective for query processing. We focus in this paper on one of such subsystems: a multidimensional data store that, as depicted in Figure 1, is meant to reside in DI nodes as a terminal vertex in the stream processing flow graph. We envision the use of a single-node stream processing engine like StreamBox [31], which has been designed to maximize streaming throughput and minimize latency on modern multicore hardware.

**III. DESIGN APPROACH**

The adopted approach to designing a single-node multidimensional data store treats each incoming data stream as independent, and assumes that data records in a given stream have the same structure. A *multidimensional data record* is assumed to be a tuple \( r \triangleq (f_1, f_2, \ldots, f_{N-1}, f_N) \) with \( N \geq 2 \) fields, where two or more fields are of numerical
The data retrieval path, on the other hand, is implemented by a query processor component, which receives ad-hoc range queries and returns data records within the specified ranges. As shown in Figure 3, upon receiving a query, the query processor first searches the R*-tree index for data segments whose hyperrectangles overlap the query’s range (i.e., segments potentially with records in the range). Then, it reads the selected segments into memory (if not in cache), inspects them, and returns the records in the range.

The adopted approach uses a two-level indexing structure, reminiscent of EMINC [45]. At the first level, the R*-tree indexes data segments based on their bounding hyperrectangles, while at the second level, each data segment includes a kd-tree to index the data records it contains. Also, under this approach, the ingestor can concurrently process multiple data chunks while at the same time the query processor serves concurrent queries, provided thread-safe access to the R*-tree is enforced. Finally, the user is required to provide the structure of the data records – and implicitly the record size (in bytes). The user must also indicate the indexing dimensions and supply the maximum chunk size (as a record count) and the maximum segment size (in bytes). These and other implementation details are discussed in [VI].

IV. DATA SEGMENTATION

As mentioned above, the ingestor component receives records in chunks and performs a data segmentation operation, which divides the records in each chunk into groups to create the data segments. Since data segmentation is key to sustaining high ingestion rates, it is performed only in memory. Besides ingestion speed, it is desirable that data segmentation arrange the data in a way that does not hinder good query performance. Next, we present two data segmentation schemes, and evaluate their merits later in [VI].

A. Uniformly Random Scheme

This scheme iterates over the data records in a chunk and assigns each record to a data segment chosen uniformly at random from a given set. The set initially contains empty data segments, and its cardinality is \[ \left\lceil \frac{c \times r}{S} \right\rceil \] where \( c \) is the record count in the chunk, \( r \) the record size in bytes, and \( S \) the maximum segment size also in bytes. Simplicity and speed are this scheme’s main attributes.

B. Kd-tree Partitioning Based Scheme

This more elaborate scheme tries to create well-populated data segments with small overlap among their bounding hyperrectangles in order to limit read amplification for query processing – a property is often sought in distributed data stores. The scheme uses an in-memory kd-tree as central data structure and includes two main steps – bulkloading and partitioning – that the ingestor performs upon the arrival of each data chunk. These two steps are described below and illustrated in Figure 4.
**Bulkload the records into a kd-tree:** The ingestor first inserts all the records in the chunk into an empty kd-tree. Record bulkloading is performed recursively, where the indexing dimension at each branching level is chosen in a round-robin fashion. In addition to links to the children, each node in the tree includes the number of nodes in its subtree (including itself).

**Partition the kd-tree:** The ingestor traverses the kd-tree in depth-first pre-order and groups the records based on the number of nodes in the subtrees. It visits the subtree with higher node count first, and breaks ties by continuing to the left subtree. The traversal proceeds recursively until the ingestor finds a subtree with a node count less than or equal to a predetermined maximum number of records per segment ($r_{ps}^{max}$). In that case, the ingestor (1) assigns the records in the subtree to a data segment from a given set, (2) detaches the subtree from the kd-tree to avoid traversing it again, and (3) updates the subtree node count of ancestor nodes (still in the tree) as each recursive call returns.

$r_{ps}^{max}$ is calculated as $[S/r] \times \omega$, where $S$ is the maximum segment size, $r$ is the record size (with $r \ll S$), and $\omega$ is the overpacking factor. By allowing the insertion of a greater number of records per segment, $\omega$ helps us compensate for the fact that this segmentation scheme tends to produce partially filled data segments. In our experience, $\omega = 4$ yields good results.

In addition to kd-tree bulkloading and partitioning, the ingestor performs a third step: **segment assembling** (see Figure 4). This step is common to both schemes. It involves creating and populating the segments with the records assigned to them as well as populating their bounding hyperrectangles and serialized kd-trees. Moreover, in both schemes the ingestor determines the dimensional ranges of each segment’s hyperrectangle as it assigns records to the segments.

## V. System Prototype

This section presents our multidimensional data store prototype, called MDDS, which implements the design discussed in III and the segmentation schemes of IV.

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**Figure 4:** Kd-tree partitioning based segmentation.

**Figure 5:** Layout of multidimensional data segment.

### A. Record Descriptor

MDDS requires the user to provide a record descriptor file, in XML format, with the record structure of the ingress data stream. Listing 1 presents the record descriptor for NYC taxi trip data (with time fields in epoch instead of UTC). The file includes the UUID identifying the record’s type and specifies the record’s fields (in order), their types, and given names. It also indicates the subset of numerical fields used as indexing dimensions and the order in which they must be considered.

### B. Multidimensional Data Segment

Figure 5 shows the serialization layout of a data segment. It is the primary agreement on data representation between the data ingestor and the query processor — the former
produces and stores data segments in this format, while the latter inspects them to answer queries.

A data segment includes the following sections. First, the header stores the segment’s unique identifier, its total length in bytes, and the record format’s UUID (the same as in the record descriptor). Second, the indexing dimensions section indicates the record fields used for data indexing, as in the record descriptor. It also contains the minimum and maximum values per dimension that define the bounding hyperrectangle for the records in the segment. Third, the packed kd-tree section contains a kd-tree, in the form of an array of nodes, that indexes the records in the segment. Lastly, the records section stores the sequence of data records as an array of bytes. These sections, except the header, are of variable length, which is stored in their section_length field.

Since most sections are self-explanatory, we only provide further details on the packed kd-tree section. We use the term “packed” to highlight that the kd-tree is serialized and embedded in the data segment. The query processor uses this tree to search for records in the data segment as it often benefits query performance (see §VI-A). The packed kd-tree is stored as an array of PackedKdNodes, each containing the position of the associated record in the segment’s records section, and the positions in the array of its left and right child (with negative values denoting nil child nodes).

An important field in the packed kd-tree section is initial_dimension. When the query processor traverses a segment’s packed kd-tree to serve a query, it assumes the indexing dimensions at each branching level follow a round-robin order [40]. This field stores the dimension for the query processor to start round-robin across the dimensions in tree traversals. The random segmentation scheme (IV-A) simply sets the field to zero. But, in the case of the kd-tree partitioning based scheme (IV-B), the value given to initial_dimension is not fixed because the packed kd-tree is built from a subtree of an in-memory kd-tree, and the branching dimension for the subtree’s root may vary.

C. Software Architecture

Next, we discuss implementation details of MDDS’s main components. MDDS has been written in ~8K lines of C++ code and its architecture is illustrated in Figure 6.

Data Ingestor: The data ingestor produces data segments from every chunk of records it receives. To do so, it performs two operations on each chunk: data segmentation and segment assembling. The former divides the records in the chunk into groups, each being the data makeup of a separate segment, and the latter puts together the segments and populates their sections. To ingest data at high velocity, the ingestor executes both operations solely in memory. It keeps the chunk’s data records in their memory location throughout most of the process and copies them at last when assembling the segments. Data segmentation, in particular, mainly relies on pointer manipulations and numerical comparisons.

Since chunks can be processed independently, the ingestor can leverage task (thread) parallelism to increase the ingestion rate.

Indexing and Writing Segments to Storage: Right after being assembled, a data segment is in memory, in the right format to be accessed by the query processor, and ready to be written to storage. At this point, the ingestor creates a reference object for the segment and inserts the reference, along with the segment’s bounding hyperrectangle, into the R*-tree (step 5 in Figure 2). Once its hyperrectangle and reference are in the R*-tree, the segment becomes available to queries through the query processor. Note that, as shown in Figure 6, a mutual exclusion lock controls the access of ingestor threads and query processor threads to the R*-tree, creating a potential contention point.

Next, the ingestor inserts (a pointer to) the reference into a lock-free FIFO queue so that a writer thread can asynchronously pull the reference from the queue and write the segment to storage. After storing a segment, a write thread checks if the segment has been inserted in the data segment cache (by the query processor). If the segment is in cache, the thread does not proceed and lets the query processor be responsible for evicting and unloading the segment. Otherwise, if the segment is not in cache, the thread marks the segment as being-unloaded, deletes it from memory (after ensuring its usage count is zero), and then marks it as being not-in-memory. MDDS offers several configuration parameters for writer threads, such as thread count, activation period (in ms), and maximum number of segments a thread can write every time it wakes up.

A segment’s reference object is an in-memory representative of the segment. It maintains the segment’s state, including its memory residency status, whether it has been written to storage or not, and its current usage count in queries. Segment references allow the query processor to
search for segments, independently of whether the segments are in memory or not.

Data segments are written to storage by the reader/writer component, which provides a simple interface for other components in MDDS to read, write, and delete segments. Its current POSIX implementation stores data segments as separate files in a configurable directory.

**Query Processor:** The query processor answers SQL range queries by performing the operations illustrated in Figure 3. It receives queries through a SQLite3’s virtual table, which is automatically created from the record descriptor (IV-A). When a query arrives, the query processor first creates a cursor object that maintains the query’s state. It initializes the cursor by (1) searching the R*-tree for references to data segments whose bounding hyperrectangles overlap the requested range and (2) inserting the references into a list inside the cursor. Once the cursor is initialized, the query processor uses it to iterate over the identified segments and their records.

As the cursor traverses its list of data segments, it creates a record iterator object per segment. The iterator encapsulates the logic to iterate over the records in the segment and access those enclosed in the query’s range. MDDS offers two types of record iterators: a kd-tree iterator that uses the segment’s packed kd-tree, and a sequential iterator that ignores the packed kd-tree and simply accesses the segment’s records in sequence. Cursor objects can be configured to use either iterator type.

The query processor exploits temporal locality across queries by caching data segments (rather than result sets). It reserves a configurable amount of memory for the cache, and evicts segments when the reserved memory is exhausted. The segment cache uses the Non-blocking Queue-based CLOCK (NbQ-CLOCK) [23], a lock-free variant of the Generalized CLOCK replacement algorithm [39]. We chose it due to its simplicity, good thread scalability, and fast update operation.

Finally, the query processor can serve simultaneous queries. This is enabled by processing queries in separate threads from a pool, and having a cursor per query. The thread pool’s size is configurable.

**Optimizations:** MDDS includes two optimizations for data ingestion. First, the ingestor uses a pre-allocated pool of kd-tree nodes to populate in-memory kd-trees. Once a kd-tree is no longer needed, the ingestor returns the tree’s nodes to the pool. The pool is implemented atop a lock-free multi-producer/multi-consumer queue, and used with both kd-tree partitioning based segmentation (IV-B) and random segmentation (IV-A). With the latter, the ingestor still populates an in-memory kd-tree per segment as an intermediate step to create the segment’s packed kd-tree. The pool is dimensioned at start time according to the maximum chunk size, record size, and maximum number of ingestor threads.

This optimization was adopted after observing it performed better than Linux default memory allocator and scalable memory allocators, such as tcmalloc[1] and jemalloc[2].

Second, to speed up the population of an in-memory kd-tree, the ingestor does not fully sort the records at each branching level. Instead, at each branching level the ingestor – à la quicksort – selects a record as the pivot according to the indexing dimension being considered, and relocates (the pointers to) the records so that records at the left (right) of the pivot record have a dimension value lesser than or equal to (greater than) the pivot’s dimension value. The pivot is determined as the median of \( M = 3 \) records selected uniformly at random from the subset of records considered at current level. \( M \) is configurable, but \( M > 3 \) offered no benefit. For kd-tree partitioning based segmentation, the records are only sorted at the root level because that tends to reduce the overlap between queries.

**Limitations:** MDDS has some limitations, mostly for simplicity of implementation. First, it can only ingest a single data stream. Second, MDDS stores the records as rows in the data segments; the advantages of storing information as columns rather than rows are well documented [13], particularly for aggregation operations. Despite these shortcomings, MDDS allows us to assess the merits of the design approach in III and evaluate the data segmentation schemes in IV.

VI. Evaluation

In this section, we first characterize the two data segmentation schemes of IV and study their influence on MDDS’s ingestion and query performance. We then evaluate MDDS against three well-known open-source database systems: Percona Server [1], SQLite3 [2], and Druid [43].

We use two publicly available datasets. First, the NYC Taxi Trip dataset [3] with \( \sim 169.67M \) records, each having 14 fields, 10 of them numerical and usable by MDDS as indexing dimensions (see Listing [1]). The time fields, originally in UTC format, were converted into epoch. Second, the Global Historical Climatology Network - Daily (GHCN-Daily) dataset v.3.22 [29, 30], from the US NOAA National Climatic Data Center. It contains daily climate observations from over 90K stations worldwide. The GHCN-Daily dataset was converted into CSV flat records sorted by time. Each record has 7 fields, 6 of them numerical and indexable by MDDS (see Listing [2]). We only use the first 100M records from a total over 700M.

To evaluate query performance, we created two sets of range queries, one for each dataset. For NYC Taxi data, we use 16 queries that cover 1km×1km areas in New York City and return the average passenger count on the selected taxi trips. Similar queries were used to evaluate Pyro [26], a distributed multidimensional data store. The

1http://goog-perftools.sourceforge.net/doc/tcmalloc.html
2http://jemalloc.net
Our test platform is a Dell PowerEdge R720 server with two 2.50-GHz Intel Xeon CPU E5-2670 v2 processors (20 hardware threads with hyper-threading disabled), 64GB of RAM, and an Intel 750 400GB SSD with ext4 file system. It runs Ubuntu 14.04 LTS x86_64 (Linux kernel 3.13.0-71).

A. Characterizing Segmentation Schemes

We first evaluate MDDS's single-thread ingestion throughput with the random assignment scheme (§IV-A) and kd-tree partitioning scheme (§IV-B). To isolate the effects of text-to-binary conversion and other auxiliary operations, the input file with the test dataset in binary form is loaded entirely into memory before being fed to MDDS. We exclude loading time from our results. We use five indexing fields for NYC Taxi data and six for GHCN-Daily data (see Listings 1 and 2).

Figure 7 reports the mean throughput over 5 runs for different maximum chunk sizes, ranging from 5K to 4M records, and a fixed target segment size of 1MB. MDDS is able to sustain over 900K records/s for NYC Taxi data and over 1.3M records/s for GHCN-Daily data. With both schemes, the throughput reaches the highest values with relatively small chunks (≤50K records), and decreases with the chunk size. Note that the kd-tree partitioning scheme has a more pronounced decrease in throughput as the chunk size increases. This is expected because kd-tree partitioning is more complex than random assignment. Similar results were obtained with 512KB and 4MB target segment sizes.

We also examine the impact of the number of indexing dimensions on MDDS's ingestion throughput for the kd-tree partitioning scheme. (Dimension count has little to no influence for the random segmentation scheme.) Figure 8 reports the average throughput across 5 runs for different dimension counts with both datasets; the maximum chunk size and target segment size are both fixed to 10K records and 10MB, respectively. We observe that increasing the dimension count may cause some degradation in ingestion throughput (up to 20% for NYC Taxi data). But, for small dimension counts (≤9) the effect on ingestion performance is small compared to that of chuck sizes.

Next, we study the influence of both segmentation schemes on MDDS's query performance. We set MDDS with the same maximum chunk size and target segment size as before, and a cache capacity of 1GB. Figure 9 reports the average response times for our test queries on both datasets over 5 runs, after a warm-up phase of 2 runs to avoid performance variability due to cold cache. We observe that compared to the random scheme, the kd-tree partitioning scheme brings no significant reduction to response time and is even worse for some queries (e.g., Q1 and Q6 in Figure 9a, and Q1 and Q8 in Figure 9b). The reason is that the way the kd-tree partitioning scheme organizes the data into segments either increases or just reduces a little the number of segments that need to be inspected to answer the queries.

Figure 7: Ingestion throughput for the random and kd-tree partitioning segmentation schemes.

Listing 2: Record descriptor for GHCN-Daily data.

```xml
<?xml version="1.0"?>
<description typeid="..." <! -- UUID -->
<struct>
  <field name="time" type="epoch_t"/>
  <field name="station" type="char" array_len=12/>
  <field name="latitude" type="float"/>
  <field name="elevation" type="float"/>
  <field name="element_id" type="uint32_t"/>
  <field name="element_value" type="uint32_t"/>
</struct>
</description>
```
queries (i.e., data segment selectivity does not improve).

We should note, however, that the kd-tree partitioning scheme produces the intended result: it tends to create data segments with much less overlap than those created by the random scheme. Table I compares the overlap between segments created by both segmentation schemes for two maximum chunk sizes (10K and 10M records) and four target segment sizes (256KB, 512KB, 1MB, and 4MB). The overpacking factor of kd-tree partitioning is adjusted so that both schemes produce roughly the same number segments with similar average sizes. We observe that, compared to the random scheme, the kd-tree partitioning scheme offers a reduction in segment overlap of 2×-51× in all cases but one (GHCN-Daily, chunk size 10K, segment size 512KB), at the expense of extra computational cost and much more variability in segment sizes (26×-100× increase in standard deviation). Unfortunately, such reduction in segment overlap does not yield commensurate reduction in latency for our test queries.

More important is the strong influence on query performance of the record iterators discussed in Figure 9. Table I also compares MDDS’s query latency with the kd-tree iterator, which leverages the packed kd-tree in each data segment, and the sequential iterator, on data ingested using the random segmentation scheme. It is clear that packed kd-trees along with the kd-tree iterator offer important (17%-58%) reductions in response time across all our test queries.

![Figure 9: Influence of segmentation schemes and record iterators on MDDS’s query performance.](image)

| Dataset          | Scheme          | Chunk Size | Seg. Size | # Segment Overlaps | Mean (StdDev) |
|------------------|-----------------|------------|-----------|--------------------|---------------|
| NYC Taxi         | random kd-tree   | 10K        | 256KB     | 1,945.6 (1,319.9)  | 692.8 (677.5) |
|                  | random kd-tree   | 10K        | 512KB     | 1,987.5 (684.4)    | 613.4 (405.9) |
|                  | random kd-tree   | 1M         | 1MB       | 1,290.6 (1,097.1)  | 24.3 (56.2)   |
|                  | random kd-tree   | 1M         | 4MB       | 405.9 (329.9)      | 27.8 (52.4)   |
|                  | random kd-tree   | 1M         | 256KB     | 816.9 (2,182.9)    | 288.4 (1,099.2)|
|                  | random kd-tree   | 1M         | 512KB     | 416.1 (1,111.5)    | 796.5 (1,061.7)|
|                  | random kd-tree   | 1M         | 1MB       | 3,851.8 (1,587.1)  | 508.2 (480.7) |
| GHHCN-Daily      | random kd-tree   | 10K        | 256KB     | 981.2 (39.4)       | 255.9 (196.9) |
|                  | random kd-tree   | 10K        | 512KB     | 981.2 (39.4)       | 255.9 (196.9) |
|                  | random kd-tree   | 1M         | 1MB       | 981.2 (39.4)       | 255.9 (196.9) |
|                  | random kd-tree   | 1M         | 4MB       | 981.2 (39.4)       | 255.9 (196.9) |

Table I: Number of overlaps among segments for the random and kd-tree partitioning segmentation schemes.

**B. System Performance Comparison**

Next, we compare the performance of MDDS and the open-source database systems listed in Table II. First, Percona Server [1] is an enterprise-ready RDBMS and a replacement for MySQL [6] with advertised superior performance. We evaluate its main storage engines: XtraDB (an enhanced version of MySQL’s InnoDB), MyISAM, and TokuDB. TokuDB [4], in particular, uses a write-optimized index called fractal tree [7], which is essentially a B-tree augmented with per node buffers, and a variant of B-tree [20]. Compared to B-trees, fractal trees offer faster data ingestion with matching or improved performance for range queries. Second, SQLite3 [2], a popular embedded relational database, is evaluated because it is the basis of MDDS’s query processor. Third, Druid [43, 5] is a NoSQL, column-oriented, distributed, real-time analytical data store designed for business intelligence (OLAP) queries on event data. It has been adopted by companies such as Alibaba, Cisco, eBay, Netflix, and Yahoo, and production Druid clusters have scaled to over 3 million records per second [9].

Percona Server and SQLite3 store NYC taxi data in a table and use a multi-column index with the indexing fields in the same order as in Listing 1. For Druid, the indexing fields are specified as dimensions (in OLAP parlance), with passenger_count being also a metric so its aggregates can be calculated. Note that pickup_datetime is a dimension and not the timestamp column. The reason is that the timestamp column only accepts current time values (within a specified time window), and stale records are omitted; so, to avoid missing records, the timestamp column
| System / Engine       | Variables                                                                 |
|----------------------|---------------------------------------------------------------------------|
| Percona Server       | autocommit = 0                                                             |
| (for the different   | foreign_key_checks = 0                                                     |
| engines)             | sql_log_bin = 0                                                           |
|                      | performance_schema = 0                                                   |
|                      | innoDB_buffer_pool_size = 32G                                             |
|                      | innodb_flush_method = O_DIRECT                                            |
|                      | innodb_doublewrite = 0                                                   |
|                      | innodb_log_at_trx_commit = 2                                              |
|                      | innodb_log_buffer_size = 8M                                              |
| XtraDB               |                                                                          |
|                      | tokudb_cache_size = 48G                                                  |
|                      | tokudb_dirctio = 1                                                        |
|                      | tokudb_loader_memory_size = 24G                                           |
| MyISAM               |                                                                          |
|                      | synchronous = OFF                                                        |
|                      | journal_mode = OFF                                                       |
|                      | ignore_check_constraints = ON                                             |
| SQLite (set via PRAGMA statements) |                                                                 |
|                      |                                                                          |
| Druid Real-Time Node | maxRowsInMemory = 500,000 (default)                                      |
| Druid & Tranquility Loader Application |                                                                  |
|                      | maxRowsInMemory = 5,000,000                                               |
|                      | Druid worker threads = 10                                                 |
|                      | HTTP (REST) threads = 10                                                  |
|                      | windowPeriod = 1 min                                                     |
|                      | intermediatePersistPeriod = 1 min                                        |
| MDDS                 | seg. scheme = random assignment                                          |
|                      | record iterator = kd-tree iterator                                        |
|                      | target segment size = 1M                                                 |
|                      | overpacking factor = 4                                                   |
|                      | writer thread period = 500 ms                                             |

Table III: System configurations.

is filled out with the current ingestion time. For GHCN-Daily data, Percona Server and SQLite3 use a table with four multi-column indices: three with two indexing fields and one with four. These indices are tailored to our test queries, and unlike Listing 2 they do not include the time field since it appears in no query. In Druid, as before, the indexing fields are dimensions, with element_value being also a metric and the timestamp column storing the current ingestion time.

We run the systems on our test server (single node), where they store data on an SSD. MDDS uses the random segmentation scheme and kd-tree record iterator for better ingestion rates and query response times, as shown in VI-A. Similarly, Percona Server and its engines, SQLite3, and Druid are configured for fast ingestion and good query performance. The systems’ configurations are summarized in Table III variables not shown use default values. Moreover, query results were verified across the systems to ensure correctness.

1) Single-Threaded Ingestion: We evaluate MDDS’s single-threaded ingestion against other systems’ bulk loading. Ingestion rates are measured with different maximum chunk sizes. We load data into Percona Server and SQLite using a shell script that splits the CSV data file into chunks and feeds them in FIFO order from tmpfs (RAM) with the database’s bulk load command. To isolate effects of auxiliary operations, the ingestion throughput calculation only includes the execution times of bulk load commands. In the case of Druid, we load data through its Real-Time Node; it uses a local firehose to ingest records from a CSV file (stream-pull ingestion), and dedicates a single thread to data consumption and aggregation. We only report Druid’s results with maxRowsInMemory = 500,000 (the default value); this parameter indicates the number of rows to aggregate in memory before persisting (similar to MDDS’s maximum chunk size), but we observed no significant variation in ingestion performance when experimenting with it. For MDDS, each dataset is provided in two forms: a CSV file and a binary file. As in VI-A, the input file is loaded entirely into memory before being fed to MDDS. Finally, we ensure across the experiment that each run uses a fresh system; i.e., before loading the data, the database is deleted, if it exists, and a new one is created.

We observe that MDDS outperforms the other systems by at least 2× when reading from a CSV file. Figure 10 reports the systems’ ingestion rates for NYC Taxi data. Results for GHCN-Daily dataset are similar, but more favorable to MDDS; they are omitted for brevity’s sake. Figure 10 also shows that MDDS reaches much higher ingestion throughput when data comes from a binary file rather than a CSV file (e.g., ~4.5× higher for 10K-record chunks). We observe that the text-to-binary conversion (when ingesting CSV files) is the main hotspot, eating a significant number of cycles and masking MDDS’s actual performance. As shown in Figure 7 with data in binary form MDDS reaches above 900K and 1.3M records/s for NYC Taxi and GHCN-Daily datasets, respectively; i.e., 11×-16× better than Druid’s Real-Time Node (the best among the other systems). Note that ingesting binary data is not uncommon, especially when MDDS is a terminal vertex in a stream processing flow graph and upstream vertices have performed the necessary conversions (see Figure 1).

3 We use bulk loading as it offers higher ingestion rates compared to insertion statements.
2) Multi-Threaded Ingestion: Here we compare the ingestion rates MDDS and the other systems can sustain with multiple data feeder threads. All the systems, except Druid, load the data the same way. A data source component reads the whole binary data file into a memory region and divides the region into approximately even slices, one per feeder thread. It then gives the slices to the threads that concurrently push the data in chunks onto the system under test.

The data source component feeds data directly to MDDS, but in the case of Percona Server and SQLite it does so through a wrapper component. The wrapper issues SQL insert statements, with the records received from the data source component, to the database. It opens a separate database connection for each feeder thread and configures the connections for high-ingestion throughput (e.g., no auto-commit). For better performance, the wrapper uses prepared insert statements bound to memory buffers; this way we avoid unnecessary data conversions, but still data records must be copied into the buffers. In addition, a transaction is committed for each data chunk. In this experiment, Percona Server and SQLite are configured as before (see Table III).

The data source component is configured to feed MDDS with chunks of up to 10K records, which yield the second highest single-thread ingestion rate in Figure 10. For Percona Server and SQLite, the maximum chunk size is set to 1M records. We choose this value because with it Percona Server’s engines and SQLite reach ingestion throughputs close to their best for our datasets, and we observe no significant improvement with larger chunks.

In the case of Druid, we load data with a stand-alone Java application written atop Tranquility [11], a client library for sending real-time event streams directly to Druid (stream-push ingestion) without involving any real-time node. The application runs a configurable number of data loader threads. Instead of binary data, the threads load CSV data as it matches Tranquility’s Tranquilizer API, avoiding unnecessary data conversion. The threads feed data in chunks to prevent out of memory errors and other low memory issues in the application and Druid’s subsystems (e.g., indexing service and historical node). Through experimentation, we observe the loader application performs best with chunks of 1M records and the configuration variables in Table II.

As before, we ensure each run uses a fresh system.

Figure 11 presents our results. We observe that MDDS is able to sustain ~13M records/s of NYC taxi data with 16 feeder threads. Also, it can sustain over 16M records/s of GHCN-Daily data with the same thread count (not shown in the figure). By contrast, Percona Server (with the different engines), SQLite, and Druid (via the Tranquility loader application) exhibit poor thread scaling and sustain much lower ingestion rates; they only report up to 35K, 30K, and 55K records/s, respectively. Note that these systems perform worse in this multi-threaded case than when bulk loading data. To sum up, MDDS can sustain ingestion rates two orders of magnitude higher than the competing systems – at least 230× in the multi-thread scenario and 160× overall.

The previous result is obtained considering binary data. When ingesting CSV data with 16 feeder threads, MDDS only reaches over 2.7M records/s; i.e., 27× overall improvement.

In addition, Figure 11 shows two aspects of MDDS’s ingestion performance: (1) how it varies with the number of feeder threads (thread scaling), and (2) how queries influence it. The top line with downward triangle marker indicates the ingestion throughput with no query processing (inter-query time = ∞). The other lines indicate the ingestion performance while processing queries in sequence with different wait times between queries. The queries are selected uniformly at random from our test set for NYC taxi data. We report mean throughput over 5 runs.

Despite its superior performance, Figure 11 reveals some limitations in our prototype. When no queries are being processed MDDS’s ingestion scales reasonably well up to 16 threads, but not linearly. We have observed that its ingestion throughput starts to plateau after 20 threads on our test platform with hyperthreading enabled (not shown in the figure). In addition, queries can cause noticeable reduction of ingestion performance (e.g., ~20% with 16 feeder threads). These limitations mainly result from contention on the R*-tree’s lock and memory (de)allocation, and addressing them are left as future work.

3) Query Performance: Next we compare the query performance of MDDS and the other systems. The test queries and data schemas are listed in Appendix A. We report the average response time over 5 runs, after a warm-up phase of 2 runs to avoid performance variability due to cold cache.

Figure 12 shows the results for NYC taxi data. SQLite surprisingly beats Percona Server’s engines across all the queries. But it is even more surprising that MDDS performs better than or comparably to Percona Server’s engines for 12 out of 16 queries on NYC taxi data. MDDS only does worse than Percona Server on queries Q3, Q5, Q10 and Q15, and
even outperforms SQLite for Q7 and Q14. This result is unexpected because MDDS’s query processor has not been heavily optimized. We attribute the favorable query performance of SQLite and MDDS, which uses SQLite’s virtual table mechanism, to a nice match between (1) their simple design and implementation, and (2) the simplicity of this test case involving only range queries served using a single (multi-column or multi-dimensional) indexing structure. Our results suggest SQLite is a reasonable choice to be the basis of MDDS’s query processor. Having being optimized over the years for read-heavy workloads, SQLite expectedly reports better query performance than MDDS. A plausible reason is that SQLite’s cache is more effective than MDDS’s – MDDS only caches data segments and not individual records.

We also observe in Figure 12 that Druid is better than MDDS and competitive with SQLite for two-dimensional queries (Q1–Q5), but much worse than MDDS and SQLite for queries Q6–Q16, with 3- to 5-dimensional ranges and one being on 
pickup_datetime. Druid exhibits long response times (>20s) for queries Q6 and Q8–Q16. This result suggests that the number of dimensional ranges may severely impact Druid’s query performance. Another possible explanation for such poor behavior is that 
pickup_datetime values are not stored in the timestamp column, but as a dimension.

As expected, selectivity of matching data segments influences MDDS’s query performance. MDDS tends to perform worse when queries are not selective in terms of segments; e.g., to serve Q3, Q5 and Q10 MDDS inspects all the segments (16,976). By contrast, MDDS answers Q15 much faster, which involves only ~10% of the segments. Selectivity of matching records, on the other hand, appears to be less determinant for MDDS’s query performance; e.g., MDDS takes about the same time and inspects similar number of data segments to serve Q6 and Q10, but with very different matching record counts (Q6: 16,328 segments and ~3.2M records; Q10: 16,976 segments and ~75K records).

Figure 13 reports the results for the set of more realistic queries on GHCN-Daily data. This test case is more favorable to Percona Server and SQLite because they use multiple indices tailored to the queries; by contrast, MDDS uses a single multi-dimensional index. Hence, as expected, these RDBMSs outperforms MDDS across all queries. Note that these queries are not selective in terms of data segments – MDDS inspects 34% of the segments to serve Q2, but 100% (10K segments) or close for Q1, Q3, and Q8, and between 60% and 85% for the rest. As with NYC taxi data, SQLite is the best for most queries, albeit not discernible in Figure 13.

In addition, MDDS outperforms Druid in half of the GHCN-Daily queries (Q3, Q4, Q5, Q7 and Q8). On the queries unfavorable to MDDS (i.e., Q1, Q2, Q6, Q9 and Q10), Druid may benefit from the fact that no query includes a range on the 
time field, not stored in the timestamp column but as a dimension. Moreover, Druid tends to perform worse than MDDS on queries with 3 or more dimensional ranges.

4) Storage Footprint: Table IV reports the space the systems use to store both datasets, including indexing structures. MDDS stores NYC taxi data in 20%-38% less space than the RDBMSs, and only about twice the space Druid occupies
with heavy data compression (dictionary encoding and LZF on data, and run-length encoding on bitmap lookup indices). For GHCN-Daily data, MDDS occupies 26%-42% of the space required by the RDBMSs, but remember they use four multi-column indices that increase their storage needs. Moreover, MDDS occupies 68% of the space needed by Druid to store the GHCN-Daily dataset. Thus, our results indicate that the superior query performance of the competing systems over MDDS comes at the expense of larger storage footprint and much lower ingestion rates, as shown in VI-B1 and VI-B2.

C. Summary of Results

Our comparative system evaluation (VI-B) shows that MDDS can ingest between 13M and 16M records/s with 16 feeder threads. Such ingestion rates are much higher than those of the competing systems – at least 160× higher considering binary data, and about 27× with CSV data.

With an unoptimized data retrieval path, MDDS reports query response times comparable to or better than those of Percona Server, when using a single multi-column index, and Druid. But, it is outperformed by SQLite in most queries on NYC Taxi Trip data for which the latter uses a single multi-column index. Not surprisingly, MDDS is outperformed as well by the competing RDBMSs (Percona Server and SQLite) when they use indices tailored for the test queries. Hence, for MDDS to offer competitive query performance its retrieval path should be enhanced and optimized further. These improvements should also reduce the degradation queries currently cause on ingestion performance, especially at peak ingestion rates. Moreover, MDDS, using no compression technique, compares favorably in terms of storage footprint against the other systems.

Our results also indicate that smaller data chunks tend to result in higher ingestion throughput, and the number of dimensions, at least up to nine, does not have a strong influence on the ingest rates.

In addition, our characterization of the segmentation schemes (VI-A) shows that the kd-tree partitioning based scheme (VI-B) brings no clear advantage over the random assignment scheme (VI-A). The random scheme is much simpler, offers ingestions rates that are higher and less susceptible to the number of indexing dimensions, and results in comparable query performance. Note that compared to the random scheme, the kd-tree partitioning based scheme produces less overlap between data segments at the expense of lower ingestion performance. But in our experiments such reduced overlap did not translate into noticeable better query performance, contrary to what we initially hypothesized.

A key observation is that the packed kd-trees in data segments, along with the kd-tree record iterator, offer important reductions in query response times. Hence, the time spent building the packed kd-trees and the storage space they occupy are worth it.

VII. RELATED WORK

Numerous indexing structures for multidimensional data (e.g., R-tree and its variants [23], kd-tree [18], quadtree [24], UB-tree [15], PL-Tree [41], and PH-tree [44]) have been proposed over the years, and some have been integrated into database systems to support application domains like geomatics, data warehousing, and data mining.

Traditional RDBMSs, such as Oracle [25] and MySQL [6], implement R-tree like indices for multidimensional data, typically targeting geospatial applications. Thus, they often support few dimensions and are optimized for query processing and not for fast data ingestion.

Researchers, inspired by NoSQL databases, have also proposed distributed multidimensional data stores offering horizontal scaling, fault tolerance, and high ingestion rates (compared to RDBMSs). These systems partition the data space into smaller subspaces (or shards) that reside in slave nodes. They often use a hierarchical two-level indexing structure, in which a global index, running across the master nodes, coarsely manages the subspaces, and local indices, running on each slave node, manage the data records inside the subspaces. Hence, subspaces along with the local indices resemble our data segments (VI-B). The EMINC indexing structure [45], albeit applied in a distributed setting, is very similar to ours; it uses an R-tree as global index and kd-trees as local indices. The RT-CAN indexing scheme [42] follows the same system architecture, but builds the global index and local indices using content addressable networks [46].

Unlike EMINC and RT-CAN, the UQE-Index framework [27] implements a three-level indexing structure atop HBase key-value store [8]. It is catered to IoT spatio-temporal data, carrying timestamps and locations. The first indexing level handles time intervals using a B+tree, the second level indexes geographical areas with an R-tree, and the third level indexes data records inside each area using either an R-tree or a grid. The first two indexing levels are global and coarse-grained, while the third-level index is fine-grained and runs locally on the slave nodes. Moreover, the framework dedicates a number of nodes to the first two indexing levels handling time intervals and geographical areas.

Other distributed multidimensional data stores, such as MD-HBase [32] and Pyro [26], are also build atop HBase and implement an index layer that casts multidimensional data into a unidimensional index and allows efficient query processing. Pyro is tailored for spatio-temporal data and range queries, whereas MD-HBase can handle higher dimensional data and k nearest neighbors (kNN) queries. By comparison, MDDS can index data using more than three dimensions, but does not offer efficient processing of kNN queries; this is left as future work.

Finally, traditional online analytical processing (OLAP)
systems mainly aim at very quick responses to multidimensional analytical queries (e.g., drill-downs and aggregates) on large data volumes. Now they are also being designed to scale horizontally on commodity hardware and ingest data at high velocity (e.g., [43], [19], [35], [21], [33]). Druid [43], introduced before, focuses on transactional events (logs), in which timestamps is a key dimension and the data tends to be append-heavy. VOLAP [21], proposed recently, is designed to support up-to-date querying of high velocity data. It operates only in-memory, and supports data ingestion but not deletion. Like distributed data stores mentioned above, VOLAP partitions data into shards that it stores in worker nodes. It also adopts a two-level indexing structure, in which the global index is a modified PDC tree [22] and the local indices (for the shards in the worker nodes) are Hilbert PDC trees [37]. Moreover, VOLAP supports dimension hierarchies and offers a synchronization scheme with configurable freshness. Cubrik [33] is a distributed in-memory multidimensional DBMS, developed at Facebook, capable of executing indexed OLAP operations. It partitions the data in ranges by every single dimension and stores the data within containers, called bricks, in an unordered and sparse fashion, providing high ingestion rates and indexed access through any combination of dimensions. The authors report an ingestion rate of $\sim 1M$ rows per second per node on a cluster with only $\sim 20\%$ of CPU utilization. Cubrik’s single-node ingestion performance is superior to that of Druid and VOLAP, but much lower than the ingestion rates reached by MDDS.

VIII. CONCLUSIONS

In this paper, we showed that it is possible to build a single-node multidimensional data store able to ingest high-velocity sensor data while offering reasonably good query performance. The evaluation of our system prototype, MDDS, indicates that the adopted design streamlines data ingestion and offers ingress rates at least $160 \times$ higher than those of Percona Server, SQLite3, and Druid. This result suggests that there is potential for significant reductions in the number of cluster nodes required to ingest high-velocity multidimensional data, leading to more economical deployments. MDDS, with an unoptimized data retrieval path, also offers query response times comparable to or better than those of Percona Server, using a single multi-column index, and Druid on NYC Taxi Trip data. Furthermore, MDDS’s storing footprint, without using any compression technique, compares favorably against that of the other systems.

We also evaluated a kd-tree partitioning based scheme for segmenting incoming streamed data. We verified that, compared to a random assignment scheme, the kd-tree partitioning scheme produces less overlap between data segments at the expense of lower ingestion performance. We, however, could not confirm the hypothesis that such reduced overlap yields better query performance. As a result, the random scheme is our first choice between both methods; it is simpler, offers faster ingestion rates with comparable query performance on our test queries, and its ingestion performance is not influenced by the number of indexing fields (i.e., dimensions). Moreover, we observed that the packed kd-trees in data segments, along with the kd-tree iterator, brings significant improvements on query performance.

All in all, we believe this paper provides useful information to practitioners and researchers tasked with building a database system for high-velocity multidimensional data.

As part of the future work, we plan to integrate MDDS into a distributed data stream processing system like that depicted in Figure 1. We want to understand the challenges of effectively coupling MDDS with a single-node, high-throughput stream processing engine, like StreamBox [31], and creating a scalable system with these building blocks. We also intend to overcome MDDS’s current limitations, such as thread scalability and ingestion performance degradation caused by queries, as well as those listed in [V-C]. Finally, we plan to support more complex queries and continue investigating swift segmentation schemes for ingress streamed data that can improve query performance.

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A. Schemas and Test Queries

Here we present the schemas and queries, in SQL, used in our comparative evaluation (VI-B). For Druid, the schemas and queries were re-written in the proper JSON format.

1) Schema for NYC Taxi Trip Data:

```sql
CREATE TABLE nyc_taxi_trip (medallion VARCHAR(32), hack_license VARCHAR(32), vendor_id VARCHAR(32), rate_code BIGINT, store_and_fwd_flag VARCHAR(1), pickup_datetime BIGINT UNSIGNED, dropoff_datetime BIGINT UNSIGNED, pickup_longitude FLOAT, pickup_latitude FLOAT, dropoff_longitude FLOAT, dropoff_latitude FLOAT, trip_time_in_secs BIGINT SIGNED, trip_distance FLOAT, passenger_count BIGINT UNSIGNED, store_and_fwd_flag VARCHAR(1), rate_code BIGINT, medallion VARCHAR(32), hack_license VARCHAR(32), vendor_id VARCHAR(32), engine = | InnoDB | MyISAM | TokuDB |);
CREATE INDEX idx1 ON nyc_taxi_trip (pickup_latitude, pickup_longitude, pickup_datetime, passenger_count, trip_time_in_secs);
```

2) Queries for NYC Taxi Trip Data:

Q1. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude > 40.8440829192 AND pickup_longitude > -73.9408829776 AND pickup_longitude = -73.9318979698;

Q4. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude > 40.7319658589 AND pickup_latitude = 40.7403800154 AND pickup_longitude = 40.7318979698 AND pickup_longitude > -73.9318979698;

Q5. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.6394506815 AND pickup_latitude <= 40.648523838 AND pickup_longitude > -73.7786922958 AND pickup_longitude = 40.7318979698;

Q6. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.7766603868 AND pickup_latitude = 40.7856435434 AND pickup_longitude = -73.9849523711 AND pickup_longitude = 40.7318979698;

Q7. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.751741463 AND pickup_latitude = 40.7608757129 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.9849523711;

Q8. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.739082969 AND pickup_latitude = 40.7479914535 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.893454289;

Q9. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.744121105 AND pickup_latitude = 40.7479914535 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.9154593919;

Q10. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.744121105 AND pickup_latitude = 40.7479914535 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.893454289;

Q11. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.744121105 AND pickup_latitude = 40.7479914535 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.893454289;

Q12. SELECT avg(passenger_count) FROM mdds_table WHERE pickup_latitude = 40.744121105 AND pickup_latitude = 40.7479914535 AND pickup_longitude = 40.73920239278 AND pickup_longitude = -73.893454289;
pickup_latitude <= 40.8062907656 AND
pickup_longitude >= -73.9652836263 AND
pickup_longitude <= -73.9562951477 AND
pickup_datetime >= 1358294025 AND
pickup_datetime <= 1369831329 AND
passenger_count <= 1 AND
trip_time_in_secs <= 1800;

Q14. SELECT avg(passenger_count) FROM mdds_table WHERE
pickup_latitude >= 40.7502443406 AND
pickup_latitude <= 40.7592274972 AND
pickup_longitude >= -74.0404189891 AND
pickup_longitude <= -74.0314059325 AND
pickup_datetime >= 1366484530 AND
pickup_datetime <= 1381908856 AND
passenger_count <= 2 AND
trip_time_in_secs <= 1800;

Q15. SELECT avg(passenger_count) FROM mdds_table WHERE
pickup_latitude >= 40.8966859263 AND
pickup_latitude <= 40.9056690829 AND
pickup_longitude >= -73.7811546197 AND
pickup_longitude <= -73.7721573685 AND
pickup_datetime >= 1361340581 AND
pickup_datetime <= 1365432055 AND
passenger_count <= 2 AND
trip_time_in_secs <= 3600;

Q16. SELECT avg(passenger_count) FROM mdds_table WHERE
pickup_latitude >= 40.64089501 AND
pickup_latitude <= 40.6498781666 AND
pickup_longitude >= -73.7831658104 AND
pickup_longitude <= -73.7740165755 AND
pickup_datetime >= 1385293736 AND
pickup_datetime <= 1390390061 AND
passenger_count <= 1 AND
trip_time_in_secs <= 3600;

3) Schema for GHCN-Daily Data:
CREATE TABLE IF ghnc_daily ( 
time BIGINT UNSIGNED, station_id VARCHAR(16),
longitude FLOAT, latitude FLOAT, elevation FLOAT,
element_id INTEGER UNSIGNED, element_value INTEGER)
ENGINE = [ InnoDB | MyISAM | TokuDB ];

CREATE INDEX idx1 ON ghnc_daily(element_id, element_value);
CREATE INDEX idx2 ON ghnc_daily(element_id, elevation);
CREATE INDEX idx3 ON ghnc_daily(element_id, longitude,
latitude, elevation);
CREATE INDEX idx4 ON ghnc_daily(element_id, latitude);

4) Queries for GHCN-Daily Data:
Q1. /* Average elevation where snow has occurred. */
SELECT avg(element_value)/10.0 FROM mdds_table WHERE
longitude > -5.4327 AND longitude < 1.7688 AND
latitude > 50.447 AND latitude < 54.6961 AND
element_id = 1413568071;

Q6. /* Average snow depth for Mount McKinley. */
SELECT avg(element_value) FROM mdds_table WHERE
latitude >= 63.9 AND latitude <= 64.0 AND
longitude >= 126.227 AND longitude <= 129.6442 AND
latitude >= 34.3117 AND latitude <= 38.1043;

Q7. /* Maximum recorded temperature (degrees C) in South Korea. */
SELECT max(element_value)/10.0 FROM mdds_table WHERE
latitude >= 34.4 AND latitude <= 38.4 AND
longitude >= -123.2 AND longitude <= -126.5;

Q8. /* Number of observed temperatures above 54.4 degrees C. */
SELECT count(*) FROM mdds_table WHERE
longitude > -5.4327 AND longitude < 1.7688 AND
latitude > 50.447 AND latitude < 54.6961 AND
element_id = 1413568071;

Q9. /* Number of smoke/haze events below sea-level. */
SELECT count(*) FROM mdds_table WHERE
elevation < 0 AND elevation > -999.9 AND
element_id = 1465135160;

Q10. /* Three highest elevations with dust, volcanic ash or sand blowing. */
SELECT distinct station_id, elevation FROM mdds_table WHERE
element_id = 1465135159 ORDER BY elevation DESC LIMIT 3;