Columnar Formats for Schemaless LSM-based Document Stores

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ABSTRACT
In the last decade, document store database systems have gained more traction for storing and querying large volumes of semi-structured data. However, the flexibility of the document stores’ data models has limited their ability to store data in a columnar-major layout — making them less performant for analytical workloads than column store relational databases. In this paper, we propose several techniques, based on piggy-backing on Log-Structured Merge (LSM) tree events and tailored to document stores to store document data in a columnar layout. We first extend the Dremel format, a popular on-disk columnar format for semi-structured data, to comply with document stores’ flexible data model. We then introduce two columnar layouts for organizing and storing data in LSM-based storage. We also highlight the potential of using query compilation techniques for document stores, where values’ types known only at runtime. We have implemented and evaluated our techniques to measure their impact on storage, data ingestion, and query performance in Apache AsterixDB. Our experiments show significant performance gains, improving the query execution time by orders of magnitude while minimally impacting ingestion performance.

1 INTRODUCTION
In recent years, columnar storage systems have been widely adopted in data warehouses for analytical workloads, where typical queries access only a few fields of each tuple. By storing columns contiguously as opposed to rows, column store systems only need to read the columns involved in a query and the IO cost becomes significantly smaller compared to reading whole tuples [44, 54]. As a result, open source and commercial relational column-store systems such as MonetDB [11, 56] (and the commercial version Actian Vector [1]), and C-Store [54] (commercialized as Vertica [18]) have gained more popularity as data warehouse solutions.

For semi-structured data, Dremel [44] and its open source implementation Apache Parquet [6] offer a way to store homogenous JSON-like data in a columnar format. Apache Parquet has become the de facto file format for popular big data systems such as Apache Spark and even for “smaller” data processing libraries like Python’s Pandas. However, storing data in a column-oriented fashion for document store systems such as MongoDB [12], Couchbase Server [10] or, Apache AsterixDB [2, 24, 31] is more challenging, as: (1) Declaring a schema before loading or ingesting data is not required in document store systems. Thus, the number of columns and their types are determined upon data arrival. (2) Document store systems do not prohibit a field from having two or more different types, which adds another layer of complexity. Despite the performance gains of columnar formats, many users with big data still choose the flexibility offered by document stores.

Many prominent document stores, such as MongoDB and Couchbase Server, adopt Log-Structured Merge (LSM) trees [48] in their storage engines for their superior write performance. LSM lifecycle events (mainly the flush operations) allow transforming the ingested records upon writing them to disk. This paper proposes several techniques to overcome document challenges to allow storing and querying semi-structured data in a columnar format for LSM-based document stores. We first extend the Dremel format to comply with document stores’ flexible data model, which permits values with heterogeneous types. We then use the same techniques proposed in the tuple compactor framework [23] to exploit the LSM flush operation to infer the schema and write the records (initially in row format) as columns using the extended Dremel format.

We present two new models in our work here for storing columns in an LSM B+-tree index. In the first model, we store columns using a Partitioned Attributes Across (PAX)-like [21] format, where each column occupies a contiguous region (called a minipage) within a B+-tree’s leaf page. We refer to this model as the AsterixDB PAX model or APAX for short. In the second model, we stretch the PAX minipages to become megapages, where a column could occupy multiple pages. We refer to this model as the AsterixDB Mega-Attributes Across (AMAX). Despite their names, these layouts are not system-specific and should only require a few modifications to be adopted by other LSM-based document stores. We evaluate and show the pros and cons of the two approaches in terms of (1) ingestion performance, (2) query performance, and (3) memory and CPU consumption.

The goal of continuously reducing the I/O cost in disk-based databases is objectively justified (and is a focus in this paper). However, with the ever-growing advancements in storage technologies, the role of CPU cost becomes even more apparent. In our evaluation, we observe an interesting phenomenon in certain types of workloads, where we have been able to reduce the size of the data needed to process a query by several factors using the APAX and AMAX formats as compared to the vector-based format (a row-major format) from [23]. However, the associated improvement to query execution time in certain cases was negligible due to increased CPU cost. The dominant factor determining the CPU cost is the query execution model. Modern Database Management Systems (DBMSs) have moved away from using the traditional iterator model [36, 39] to use other execution models (such as the batch model [50] and the materialization model [43]) to minimize the CPU overhead. However, hand-written code outperforms all three models [56]. Thus, code generation and query compilation have become a major contributors to the performance gains of many recent data processing engines [4, 51] and DBMSs [45, 46] alike.

In this work, We shed light on the possibility of using query compilation techniques for document stores, where value types are not known until runtime. We utilize the Oracle Truffle framework.
(called Truffle hereafter) [55] to implement an internal language for processing data stored in a Java-based document store. Even though we only translate part of a query plan, our evaluations show a tremendous improvement over AsterixDB’s existing model.

To show their benefits, we have implemented the proposed techniques to store document data in a columnar format and produce a compiled query plan in Apache AsterixDB. This enabled us to conduct an extensive evaluation of the APAX and AMAX formats and present their tradeoffs for different datasets. We also show the impact of utilizing Truffle to generate and execute queries against different datasets stored as AMAX and APAX, as well as the original schemaless row format of AsterixDB and the recently proposed Vector-based format.

2 BACKGROUND

2.1 Apache AsterixDB

AsterixDB is a parallel semi-structured Big Data Management System (BDMS) that runs on large, shared-nothing, commodity computing clusters. To prepare the reader, here we give a brief overview of AsterixDB’s storage engine [25], its compiler, Algebricks [29], and its query execution engine, Hyracks [28].

2.1.1 Storage Engine: An AsterixDB cluster consists of worker nodes called Node Controllers (NCs) managed by a Cluster Controller (CC) node. Figure 1 shows an AsterixDB cluster with three NCs, each with two data partitions that store data on two separate storage devices. Data partitions within the same NC (e.g., Partition 0 and Partition 1 in NC0) share the same resources (e.g., memory budget) configured for each NC; however, the data stored in each partition is managed independently.

2.1.2 Query Execution Model: To query the data stored in AsterixDB, a user can submit a query written in SQL++ [32, 49] to the CC, which generates an optimized query plan and then compiles it into a Hyracks job. The compiled Hyracks job is then distributed to the query executors in all partitions to run in parallel. Hyracks jobs consist of operators and connectors [28], where data flows between operators over connectors as a batch of tuples. Each batch of tuples received by an operator is processed and passed over to the next operator as a new batch.

2.2 LSM-based Tuple Compaction Framework

The flexibility of document stores is targeted for applications where the schema can change without human intervention. However, document stores’ flexibility is not free, as each record stores its schema instead of storing it in a centralized catalog. In a previous work [23], we presented a Tuple Compactor framework (implemented in Apache AsterixDB) that addresses this issue by exploiting LSMs. Upon completion, the tree manager marks the flushed component as valid by setting a validity bit on the component’s metadata page and freeing the in-memory component to serve subsequent inserts. LSM on-disk components are immutable and, hence, updates and deletes are both handled by inserting new entries. A delete operation adds an “anti-matter” (or tombstone) entry to indicate that a record with a specified key has been deleted. An update simply adds a new record with the same key as the original one. As on-disk components accumulate, the tree manager periodically merges them into larger components in the background according to a configured merge policy [25, 40], which determines when and what to merge. Deleted and old updated records are garbage-collected during the merge operation. In Figure 2b, during the merge of C0 and C1 (from Figure 2a) into a new disk-component (called [C0, C1]), the record with id = 0 and its corresponding anti-matter annihilate each. On completion, the older on-disk components (C0 and C1) are deleted and replaced by the newly created component [C0, C1].
lifecycle events to infer the component’s schema and compact its records using the inferred schema.

![Figure 3: Schema inference workflow](image)

To illustrate, when creating a dataset in AsterixDB, each partition in every NC (Figure 1) starts with an empty dataset. During data ingestion, each partition inserts the received records into the in-memory component as in normal operation. When the memory component is full, the in-memory components’ records are flushed into a new on-disk component, during which time the tuple compactor takes this opportunity to infer the schema and compact the flushed records. Figure 3 depicts the workflow of the tuple compactor along with the inferred schema. In the figure, we see that the tuple compactor has inferred two fields, name and age, with the types string and integer, respectively, from the flushed records. Upon completing the flush operation, the inferred schema is persisted into the component’s metadata page. Subsequent flushes follow the same workflow to build the schema for all of the ingested records. Among the flushed components, the schema of the latest flush is always a super-set of all previous schemas. Thus, we only persist the most recent component’s schema into a merged component’s metadata page during a merge operation.

Also in [23], we introduced the Vector-based format—a non-recursive, compaction-friendly, physical data format for storing semi-structured data. The vector-based format’s main idea is to separate the data values from the records’ metadata, which describes the record’s structure. This separation enables the tuple compactor to efficiently operate on the record’s metadata during the schema inference and record compaction processes. Additionally, being a non-recursive, the vector-based format allows the tuple compactor to iteratively process a record, which is more cache-friendly than AsterixDB’s recursive format [3]. We refer interested readers to [22, 23] for more details about the vector-based format.

### 3 A FLEXIBLE COLUMNAR FORMAT FOR NESTED SEMI-STRUCTURED DATA

Inferring the schema and compacting schemaless semi-structured records, using the tuple compactor framework [23], reduces their overall storage overhead and consequently improves the query execution time. However, these compacted records are still in a row-major format, which is less than ideal for analytical workloads as compared to columnar formats. One of the main reasons that document stores do not support storing data in a columnar format is the flexibility of their data model. E.g., the Dremel (or Parquet) format still requires a schema that describes all fields to be declared a priori, and all field values must conform to one type. In this section, we give a brief overview of the Dremel format. Then, we present our extensions to Dremel to allow schema changes, such as adding new values and changing their types.

#### 3.1 Dremel Format

The Dremel format allows for storing nested records in a columnar fashion, where atomic values of different records are stored contiguously in chunks. For better illustration, Figure 4 shows an example of four JSON records (Figure 4a) about video gamers stored in Dremel format along with the schema (Figure 4b). The schema’s inner nodes represent the nested values (objects and arrays), whereas the leaf nodes represent the atomic values such as integers and strings. The schema describes the JSON records structure, where the root has three fields id, name, and games with the types integer, object, and array, respectively. The name object consists of first and last name pairs, both of which are of type string. Next is the array of objects games, which stores information about the gamers’ owned games, namely the games’ titles and the different versions of a game the gamers own for different consoles. Every value (nested or atomic) in our example is optional except for the record’s key id. The optionality of all non-key values is synonymous with the schemaless document store model, which is the scope of this paper. We encourage interested readers to refer to [33, 44] for more details on the representation of non-optional values.

The tables underneath the schema’s leaf nodes shown in Figure 4b depict the Dremel’s columnar-striped representation of the records’ atomic values from Figure 4a. Each table consists of three columns: R, D, and Value, where R and D denote the Repetition-Level and Definition-Level of each Value as presented in [44]. The definition levels’ roles determine the NULL occurrence level for a nested value. The repetition levels’ roles determine the start and end of a repeated value (array). The pairs (R, D, y), shown at the top of each table in Figure 4b, indicate the maximum value for the repetition and definition levels for each atomic value.

To explain, the column name.first has a maximum repetition level 0 indicating a non-repeated value (or not an array element), whereas the definition level 2 is the level of the leaf node in the schema’s tree (root (0) → name (1) → first (2)). In the first record 1 in Figure 4a, the definition level for the value name.first is 0, which indicates that only the root was present in the path root → name → first. Thus, the value for the name.first in the first record in our example is NULL. For the second record 2, the definition level for the name.first value is 1, which indicates that the name object is present but not the atomic value first. In record 3, the gamer’s first name is “John”; hence, it has definition level 2. In the last record 4, the name value is missing, indicated by the definition level 0. The key field id is required for all records, and the key’s definition level value is ignored. Thus, the id’s maximum definition level is 0.

For repeated values (array elements) such as the games’ titles column (denoted as games[∗].title) in our example, the repetition levels determine the array starts and ends for each record. Note that for the repeated values games[∗].title, the maximum repetition and definition levels are 1 and 3, respectively. The first record has only one value (0, 3, “NFL”), where the triplet (r, d, v) denotes its repetition level (r), definition level (d), and value (v), respectively. The repetition level 0 indicates that the value “NFL” is the record’s first games[∗].title repeated value, and the definition level 3 indicates that the value is present. The following value (0, 3, “FIFA”) corresponds to the second record, as the repetition level 0 indicates
that the current value is, again, the first games[*].title repeated value. Similarly, the value (0, 3, "NBA") corresponds to the third record; however, the following value (1, 3, "NFL") also corresponds to the same record (i.e., the second element of the array), which is indicated by repetition level 1. Whenever a value’s repetition level is equal to the column’s maximum repetition level, we know that it is the \(i\)th repeated value (or \(i\)th element of the array), where \(i > 0\).

In the last record, the array games itself is missing, and thus its definition level is 0.

In Figure 4b, the array consoles (whose full path is denoted as games[*].consoles[*]) is an ancestor of the outer array games. In other words, the atomic values of consoles belong to two nested arrays games and consoles. Therefore, the maximum repetition level for the column games[*].consoles[*] is 2. Like in the column games[*].title, the value (0, 2, NULL) corresponds to the first record, as indicated by the repetition level 0. However, the first record is missing the field consoles; thus, its definition level 2 indicates that the consoles array is missing, but its parent is present. The following value (0, 4, "PC") is the first games[*].consoles[*]’s value for the second record, as indicated by its repetition level 0. The definition level 4 here means that the value is present and the value is "PC". The next value (2, 4, "PS4") has a repetition level 2, the maximum repetition level for the column games[*].consoles[*], which means it is the second value of the array consoles. Likewise, the following two values (0, 4, "PS4") and (2, 4, "PC") correspond to the third record, and both constitute the first and second elements of the first consoles array. The following value’s (1, 4, "XBOX") repetition level 1 means it still corresponds to the same record; however, the value marks the beginning of the record’s second consoles’ array, which has a single element "XBOX". The last value (0, 0, NULL) indicates that the array games is missing from the last record.

### 3.2 Extended Dremel Format

The Dremel format is designed for storing semi-structured data such as JSON documents in a columnar-oriented fashion. However, the requirement of declaring the schema a priori prohibits flexible document stores from adopting it. Additionally, the Dremel format does not support union types (at the time of writing this paper), where a value (or a column) can be of different types in different records. In this work, we present our extensions to the Dremel format to accommodate document stores with flexible data model.

#### 3.2.1 Array Values

Earlier, we explained the Dremel approach for representing repeated values (arrays) using repetition levels. Here we observe that the repetition levels \((i)\) are redundant among nodes that share the same ancestor array, and \((ii)\) along with the definition levels, they occupy more bits than needed to represent optional repeated values.

In our example, for \((i)\), notice how the repetition levels of the column games[*].name is a subset of the column games[*].consoles[*]’s repetition levels (redundancy), as both share the same array ancestor games[*]. The entire repetition levels of the column games[*].title [0, 0, 0, 1, 0] appear in the same order as the column games[*].consoles[*]’s repetition levels [0, 0, 2, 2, 1, 0]. For \((ii)\), we observe that all values with repetition levels greater than 0 must have definition levels greater or equal to the array’s level. Recall that a value with a repetition level greater than 0 corresponds to the \(i\)th element of an array, where \(i > 0\). When the repetition level is greater than 1, it implies that an array exists and that its length is greater than one. Also recall that when the definition level is smaller than an array’s level in the schema, it means that the array itself is NULL. As a consequence, having a repetition level greater than 0 and a definition level smaller than the array’s level would be contradictory. It would mean the array exists and that its length is greater than one, but that the array itself is NULL (or does not exist). Given that, the number of bits for both the definition and repetition levels is more than what is needed to represent repeated values.

For these reasons, we will adopt a different approach for representing repeated values without repetition levels. Recall \((ii)\), which says that the \(i\)th definition level (where \(i > 0\)) of a repeated value cannot be smaller than the array’s definition level. Thus, we can use such definition level values as delimiters instead of repetition levels. To illustrate, Figure 5 shows the values of both the games[*].title and games[*].consoles[*] columns for the records in Figure 4b using the proposed approach. The repeated values in both columns have the same definition levels as in the original Dremel format.
However, the definition levels also indicate end-of-array by having a delimiter value. In the column games\[\ast\].title, the first three records' repeated values are delimited by the definition level 0, which is the max-delimiter value in the column as shown in Figure 4b. The value that follows a delimiter indicates the start of the next array, and the value itself is the array’s first value — except for the last repeated value in Figure 5, where the definition level 0 that indicates the array games is NULL in the last record. Note that the last value’s definition level of 0 cannot be a delimiter since it is the first value after the preceding delimiter.

In the case of nested arrays, as in the column games\[\ast\].consoles\[\ast\], the max-delimiter is 1, which indicates that the two delimiter values 0 and 1 are for the outer (games) and inner (consoles) arrays, respectively. The first value in the column games\[\ast\].consoles\[\ast\] is NULL with definition level 2, which indicates that the outer array games is present but its sole element is NULL. The following value is a delimiter of the outer array games, indicated by the definition level 0. The next two values are the first and second array elements of the second record’s array consoles, followed by a delimiter with the definition level 0. We omit the definition level 1, the delimiter for the inner array consoles, since the delimiter 0 also encompasses the inner delimiter 1. The next two values are the first and second consoles array elements in the third record. The next delimiter of 1 here indicates the end of the first consoles array ["PS4", "PC"], and the next value marks the start of the second consoles array ["XBOX"] in the same record. The following delimiter 0 indicates the end of the repeated values in the third record. In the last value, the definition level of 0 implies that the games array is NULL in the last record. Like the last value of the column games\[\ast\].title, the definition level 0 here is not a delimiter as it is the first value after the last delimiter.

3.2.2 Schema Changes and Heterogeneous Values: For LSM-based document stores, one could use the approach proposed in [23] (summarized in Section 2.2) to obtain the schema and use it to dissect the values into columns. However, a major challenge for supporting columnar formats in document stores is handling their potentially heterogeneous values. For example, the two records{"id": 1, "age": 25} and{"id": 2, "age": "old"} are valid records and both could be stored in a document store. Similarly, document stores allow storing an array that consists of heterogeneous values, such as the array [0, "1", {"seq": 2}]. Limiting the support for storing data in a columnar format to datasets with homogeneous values is maybe enough for most cases, as evidently shown by the popularity of Parquet. However, including support for datasets with heterogeneous values is a desired feature for certain use cases, especially when the users have no control over how the data is structured, like when ingesting data from web APIs [35, 53]. In this section, we detail our approach for handling schema changes and heterogeneous types.

In our previous work [23], we introduced union types in our inferred schemas to represent values with heterogeneous types. Figure 6 depicts an example of two variant records with their inferred schema. The inferred schema shows that the records have different types for the same value. The first is the field name, which could be a string or an object. Thus, we infer that the name’s type is a union of string and object. The second union type corresponds to the games array’s elements, where each element could be of type string or array of strings. In the schema, we observe that union nodes resemble a special case of object nodes, where the keys of the union nodes’ children are their types. For example, the union node of the field name, in the schema shown in Figure 6, has two children, where the key "string" corresponds to the left child, and the key "object" corresponds to the right child.

Based on this observation, we can columnize the unions’ atomic values by treating them as object atomic values with one modification. Observe that an actual value can only be of a single type in any given record, and, hence, only a single value can be present, whereas the other atomic values associated with the union should be NULLs. To better illustrate, consider an example where the records are inserted one after another, and the schema changes accordingly. Columnizing the records’ values can be performed while inferring the schema in a single pass, as in the compaction process in [23]. After inserting the first record of Figure 6, we infer that field name is of type string, and thus we write the string value “John” with definition level 1 as shown in column 1 in Figure 7. In the following record, the field name is an object consisting of first and last

![Diagram](image-url)
fields. Therefore, we change the field name’s type from string to a union type of string and object as was shown in Figure 6. Since the second record is the first to introduce the field name as an object, we can write NULLs in the newly inferred columns 2 and 3 for all previous records. Then, we write the values "Ann" and "Brown", with definition levels 2 in 2 and 3, respectively. Recall that only a single value can be present in a union type; therefore, we write a NULL in column 1. After injecting the union node in the path root → union → string, we do not change the definition level of column 1 from 1 to 2 for two reasons. First, union nodes are logical guides and do not appear physically in the actual records. Therefore, we can ignore the union node as being part of a path when setting the definition levels even for the two newly inferred columns 2 and 3. The second reason is more technical — changing the definition levels for all previous records is not practical, as we might need to apply the change to millions of records, were it even possible due to the immutable nature of LSM.

When accessing a value of a union type, we need to see which value is present (not NULL) by checking the values of the union type one by one. If none of the values of the union type is present, we can conclude that the requested value is NULL. In the example shown in Figure 6 and Figure 7, accessing name goes as follows. First, we inspect column 1, which corresponds to the string child of the union. If we get a NULL from 1, we need to proceed to the following type: an object with two fields, first 2 and last 3. In this case, we need to inspect one of the values’ definition levels, say column 2. If the definition level is 0, we can conclude that the value name is NULL, as the string and the object values of the union are both NULLs. However, if the definition level is 1, we know that the parent object is present, but the first string value is NULL. Thus, the result of accessing the field name is an object in this case. Inspecting all the values of a union type is not needed when the requested path is a child of a nested type. For instance, when a user requests the value name.last, processing column 3 is sufficient to determine whether the value is present or not. Thus, the results of accessing the value name.last are NULL in the first record and “Brown” in the second record.

The types of repeated values (array elements) can alternate between two or more types, as in the array games in Figure 6. In the first record, the elements’ types of the array games are either a string or an array of strings. Similar to the value name, when accessing the value games, we need to inspect both columns 1 and 5 to determine which element of the two types is present. When accessing the value games, we see that the first value’s definition level in column 1 is 2, which is the maximum definition level of the column for the string value ‘NBA’. In column 2, however, the definition level is 1, which indicates that the inner array of the union type is NULL. Thus, we know that the first element of the array games corresponds to the string alternative of the union type. The following definition level 1 in column 1 indicates that the second element is NULL, whereas it is 3 in column 3, which is the maximum definition level of the column. Hence, the second element of the array is of type array of strings. The two values with definition levels 3 and the following delimiter with definition level 1 correspond to the two elements ["FIFA", "PES"] of the first record. Following the delimiter, the definition level 1 in column 5 indicates that the third element of the outer array is NULL. However, the definition level 2 in column 1 for the value "NFL" indicates that the third value of the outer array is a string. The delimiter 0 in both columns 1 and 5 indicate the game’s end of values for the first record. The final result of accessing the value games in the first record, therefore, is [“NBA”, [“FIFA”, “PES”], “NFL”], which preserves the original value of the record shown in Figure 6. In the second record, we can see that the array consists of two elements, both of type string. Hence, the two NULL values in column 5 indicate that neither of the two elements is of the array of strings alternative of the games’s union type.

3.2.3 LSM Anti-matter: In Section 2.1.1, we briefly explained the process of deleting records in an LSM-based storage engine using anti-matter entries. Anti-matter entries are special records that contain the key of the deleted record. In the example shown in Figure 4b, the id’s maximum definition level is 0, as it is a required value. To represent such anti-matter entries in our proposed columnar format, we set the maximum definition level for the records’ primary key(s) values to 1, i.e., their definition levels’ values could be either 0 or 1. The definition level here does not indicate whether the value is NULL or present; instead, it indicates whether the primary key value corresponds to a record or to anti-matter. When the definition level of a primary key value is 0, it indicates that the primary key value is an anti-matter entry for a previously inserted record with the same key. When the definition level is 1, we know it is a newly inserted record.

3.2.4 Record Assembly: When accessing a nested value such as the nested value name in Figure 4b in our approach, all of its atomic values (i.e., first and last) are stitched together to form an object (e.g., {"first": "John", "last": "Smith"}) using the same record assembly automaton used in [44]. Also, we use the same Dremel algorithm to assemble repeated values (arrays). However, a difference is that we use delimiters to transition the state when constructing the arrays instead of the repetition levels as in Dremel.

4 COLUMNAR FORMATS IN LSM INDEXES

A major feature of representing records’ values as contiguous columns, as in our extended Dremel format, is that it allows us to encode and possibly compress the values of each column according to its type to reduce the overall storage footprint. The immutability of LSM-based storage engines makes them especially good candidates for storing encoded values as in-place updates are not permitted. In this work, we propose two layouts for storing the columns in LSM-based document stores: (i) AsterixDB Partitioned Attributes Across (APAX) and (ii) AsterixDB Mega Attributes Across (AMAX). We have implemented and evaluated both layouts in Apaches AsterixDB, hence the names. In the following sections, we first briefly explain the supported techniques used to encode the column values. Then, we detail the structures of both the APAX and AMAX layouts. Next, we describe the lifecycle of reading and writing the columns, and finally, we cover challenges related to answering queries with secondary indexes.

4.1 Encoding

Apache Parquet offers a rich set of encoding algorithms [13] for different value types, including bit-packing, run-length encoding,
delta encoding, and delta strings. In this work, we use all of Parquet’s encoding algorithms except for dictionary encoding, which requires additional pages to store the dictionary entries. (We leave potential support for dictionary encoding for future work).

4.2 APAX Layout

Ailamaki et al. proposed Partition Attributes Across (PAX) [21], a cache-friendly page layout as compared to the commonly used row-major layout (or N-ary Storage Model, a.k.a., slotted pages). PAX pages store each attribute’s values continuously in minipages. APAX minipages can be reached by relative pointers stored in the pages’ header. Within a PAX page, fixed-length and variable-length values are stored in F-minipages and V-minipages, respectively. Along with the values, F-minipages contain a bit vector to indicate whether a value is present or NULL. The V-minipage stores values similar to the F-minipage; however, instead of the presence bits, the V-minipage uses values’ offsets to determine the lengths of each variable-length value. NULL offsets (e.g., offset zero) indicate NULL values on the V-minipage.

![Figure 8: APAX page layout](image)

Our APAX layout is a modified version of the PAX layout, as shown in Figure 8, where fixed-length and variable-length values are encoded and stored in homogeneous mini-pages (i.e., no F-minipages and V-minipages). Thus, APAX is agnostic of its minipages’ contents, and it is up to the minipages’ readers and decoders to interpret the minipages’ content, where the inferred schema determines the minipages’ appropriate readers and decoders. Figure 8 shows the organization of an APAX page. The reader will read the first four bytes to determine the size of the encoded definition level. Then, it will pass both the encoded definition levels and the encoded values to the appropriate decoders. The resulting decoded definition levels and values are then processed, as explained earlier in Section 3.2. As in PAX, we can reach each minipage via pointers stored in the APAX page header. Since APAX pages reside as leaf pages in a B+-Tree, we store the minimum and the maximum keys (primary keys) within the APAX page header. By doing so, we can access their minimum and maximum keys directly when performing B+-tree operations (e.g., search) without the need to decode the primary keys. The header also stores the number of minipages (or columns) and the number of records stored in the APAX page.

4.3 AMAX Layout

The PAX and APAX layouts each store different columns within a page, and hence in both layouts, we need to read the entire page, regardless of which columns are needed to answer a query. In AMAX, we stretch the minipages of APAX to become megapages that can occupy more than one physical data page. Figure 9 illustrates the structure of the AMAX pages in a B+-tree, where a mega leaf node consists of multiple physical pages. Each mega leaf node starts with Page 0 in the AMAX layout and consists of three segments. The first segment stores the page header, which contains the same information as in the APAX header. Following the page header, it stores fixed-length prefixes of the minimum and maximum values for each megapage (or column). Each minimum and maximum prefix pair occupy 16 bytes (or 8-byte each), and they are used to filter out AMAX pages that do not satisfy a query predicate (e.g., age > 20). In its last segment, Page 0 stores the encoded primary key(s) values.

![Figure 9: AMAX multi-page layout in a B+-tree](image)

Each megapage of the AMAX layout corresponds to a single column (as in APAX minipages). The megapages are ordered by their size from largest to the smallest. In other words, we store the largest megapage’s physical pages contiguously first on disk, followed by the physical pages of the second-largest megapage, and so on. This ordering of megapages allows for better utilization of the empty space of the physical pages. For example, after writing Megapage 1, the physical Page 3 in Figure 9 is mostly empty, and thus, we allow Megapage 2 to share the same physical Page 3 with Megapage 1. After writing Megapage 2, note that Page 4 is not full. A user-provided parameter (called the empty – page – tolerance) allows the AMAX page writer to tolerate a certain percentage of a physical page to be empty if the next column to be written does not fit in the given empty space. Tolerating smaller empty spaces can minimize the number of pages to be read from when retrieving a column’s value. The content of the megapages is similar to APAX minipages, and we use the same readers and decoders for interpreting their content with one difference: The first physical page of each variable-length values’ megapages stores the actual minimum and maximum values, as the prefixes of the minimum and maximum values on Page 0 are not decisive. The actual minimum and maximum values allow us to verify whether the values of a variable-length megapage can be within the range of the predicate.

4.4 Reading

When a user submits a query, the compiler optimizes the query and generates a job that will access the appropriate collections (or datasets in AsterixDB’s terminology) and project the required
attributes from the resulting records. The generated job is then distributed to all partitions in each NC for execution. Before execution, each partition consults the inferred schema to determine the columns needed (i.e., APAX minipages or AMAX megapages) for executing the query. Moreover, in AMAX, we only read the physical pages that correspond to the columns needed by the query. For each requested column, we have an iterator to go over the columns’ values. If a query contains a filtering predicate (e.g., \texttt{WHERE age > 20}), we also use the prefixes of the minimum and maximum values to skip reading the entirety of the requested columns of a leaf page that do not satisfy the query predicate.

When reading from an LSM index, we need to inspect the records stored in all of the components (including the in-memory component) and merge the resulting records to reconcile any deleted or updated records. Thus, deleted and replaced records (by update) are ignored and will not appear in the final result of the query. When reading APAX or AMAX pages, we need to (i) perform the same reconciliation process as in the row-major layout. Also, we need to (ii) process the in-memory component’s records, which are still in a row-major layout. To address those two requirements, we implement an abstracted view of a “tuple”, whether in row-major or column-major format, resulting from reading an LSM component. Additionally, we provide tuple comparators to compare the primary keys of two tuples resulting from two different LSM components. These comparators are agnostic of whether the tuples are from in-memory components (row-major) or on-disk components (column-major).

Reconciling tuples in a row-major layout is performed simply by ignoring the current tuple deleted or replaced record and going to the next one using the tuple’s offset stored on the slotted page. However, in a column-major layout, ignoring a tuple means ignoring its values for all the columns involved in the query by advancing the columns’ iterators by one step. Doing so eagerly is inefficient, as (i) we would need to touch multiple regions of the memory, resulting in many cache misses, and (ii) we would need to decode the values each time we advance a column iterator, which could be a wasted effort as we illustrate next. Let us consider the following query:

\[
\text{SELECT name, salary FROM Employee WHERE age > 30}
\]

Suppose that we have three records with primary keys 1, 2, and 5 stored in an on-disk component in a columnar layout, whether APAX or AMAX. Also, suppose the in-memory component has three records with the same primary keys, i.e., 1, 2, and 5. In this example, the records of the in-memory component will override the records of the on-disk component. If we advance every column’s iterator eagerly (namely the \texttt{name}, \texttt{age}, and \texttt{salary} columns’ iterators) in order to get the next tuple, the decoding of the columns’ values would be a wasted effort. For that reason, we only decode the records’ primary keys during the reconciliation process, and we count the number of ignored records. Once actually accessed, we advance each column’s iterator by the number of ignored records at once, ensuring that the process of advancing the iterator is performed in batches per column. Consequently, none of the columns would be decoded in our example as none were accessed.

### 4.5 Writing

As in [23], we exploit LSM-lifecycle events to infer the schema and split the records in row-major format into columns. During data ingestion, we first insert the records into the in-memory component in our vector-based format. Once it is full, the records of the in-memory component are flushed into a new on-disk component, during which time we infer the schema of the flushed records and split their values into columns – storing the columns as APAX or AMAX pages. Each has different implications in terms of CPU and memory usage. In the following, we show and discuss our approach for writing the columns’ values as APAX and AMAX pages.

#### 4.5.1 Writing APAX Pages

Determining the sizes of our APAX minipages is even more challenging than determining PAX minipages’ sizes, as we incrementally encode each column’s values. To address this issue, we first write the columns’ values into temporary buffers, where each temporary buffer is dedicated to a single column. Once the temporary buffers have a page’s worth of values, we copy and align their contents as APAX minipages and write the resulting APAX page into the disk. We reuse the same temporary buffers to construct the following APAX pages for the remaining records of the flushed in-memory component.

#### 4.5.2 Writing AMAX Pages

As opposed to APAX minipages, AMAX columns can occupy one or more physical pages (megapages), while the smaller columns may share a single physical page. Initially, we do not know which columns might span into multiple physical pages, so we write the values of each column into a growable temporary buffer first. Once a temporary buffer grows beyond a configured threshold, we confiscate (or acquire) a page from the system’s buffer cache, which replaces the temporary buffer for writing the columns’ values. Instead of allocating a memory budget for writing columns, we use the buffer cache as a temporary buffer provider. Allocating a dedicated memory budget for writing columns might be wasteful, especially for cases where writes are not continuous (e.g., loading a dataset once and never updated). As the column size increases, we confiscate more pages from the buffer cache to accommodate the written values of that column, and those physical pages form a megapage. Once done, we write the megapages to disk largest to smallest, during which time we observe the \texttt{empty ~ page ~ tolerance} threshold (Section 4.3).

Page 0 of the AMAX could also, in theory, grow to occupy multiple physical pages. However, we do not permit that, as the number of keys could grow into hundreds of thousands. Consequently, point-lookups would perform poorly, as we need to perform a linear search to find the required key; this could negatively impact both the ingestion rate and answering queries with secondary indexes, as we discuss later in Section 4.6. Therefore, we limit the number of records stored in an AMAX page to 15,000 by default. The limit can be tuned for a given workload. For example, increasing the limit for scan-only workloads, where no secondary indexes are declared, would improve the query execution time while not impacting the ingestion performance.

#### 4.5.3 Impact of LSM Merge Operations

From time to time, an LSM merge operation is scheduled to compact the on-disk components. In both the AMAX and APAX layouts, we need to read the columns’ values from different components and write them again
4.6 Point Lookups and Secondary Indexes

In LSM-based storage engines, one can blindly insert new records into the in-memory component without checking if a record with the same key exists (to ensure the uniqueness of the primary keys), as records with identical keys are reconciled at the query time. However, this mechanism only applies to the primary index and not to its associated secondary indexes. For a secondary index, in addition to adding the new entry, we also need to clean out the old entry (if any). Thus, we need to perform a point lookup to fetch the old value from the primary index to clean the old value by adding appropriate anti-matter entries in each secondary index. Consequently, during data ingestion, point lookups are performed for each newly inserted record to check if a record with an identical key exists. If so, its old values are retrieved to maintain the secondary indexes correctness.

Performing point lookups against datasets stored in APAX or AMAX layouts is more expensive than their row-major counterparts, as we need to decode primary keys and linearly search for the requested value in both the APAX and AMAX layouts. The number of keys on slotted pages is usually smaller than in the APAX and AMAX layouts, and here we can search for a key in a logarithmic time (assuming the records are sorted). Point lookups in the AMAX layout are even more expensive than the APAX layout since the number of keys stored on Page 0 of the AMAX layout is significantly larger. To alleviate the cost of point lookups for APAX and AMAX layouts, we use a "primary key index", a secondary index that stores only primary keys, to first see if that a record with an identical key exists [40, 41]. If the primary key index does not yield any keys, we skip accessing the primary index, as the newly inserted key does not correspond to an older record. Thus, we need to actually access the primary index only to update old records.

When answering queries (e.g., range queries), we first search the appropriate secondary index, which yields the primary keys of records that satisfy the query predicate. Then, we sort the resulting primary keys in ascending order. Finally, we perform a point lookup using the sorted primary keys to retrieve the records that satisfy the query predicate. Luo et al.'s generalized approach [40] exploits the ordered keys to perform these point lookups in batches while preserving the state of the LSM cursor to reduce the cost of subsequent point lookups. This approach allows us to read the columns' values in a single pass by accessing the values of the first record with the smallest key followed by the record with the second smallest key, etc., without the need to start over each time. However, if we were to skip sorting the primary keys resulting from accessing the secondary index, then we would need to decode the columns for each point lookup, making the use of secondary indexes, in most cases, slower than scanning the entire records.

5 CODE GENERATION

When we first evaluated the performance of querying records in the APAX and AMAX layouts in Apache AsterixDB, we saw that, in certain cases, their performance gains were negligible compared to the row-major formats, despite the storage savings of the columnar layouts. Figure 10 shows our early evaluation results, where we ran two queries Q1 and Q2, against records in different formats: (i) AsterixDB’s schemless format (Open), (ii) the Vector-based format (VB), (iii) APAX, and (iv) AMAX. Both Open and VB are row-major formats. Q1 only counts the number of tuples, whereas Q2 is a GROUP BY aggregate query, similar to the query shown in Figure 11. The storage savings in both the APAX and AMAX layouts, as we will see later in Section 6, significantly improved the performance of Q1. However, Q2 (Interpreted) took more time to execute against the AMAX format than the VB format. One reason for these negligible (or even negative) performance gains is the Hyracks batch-at-a-time execution model, in which the tuples are materialized between operators. However, the major reason was the cost of reassembling nested values in APAX and AMAX so that Hyracks operators can process the row-major tuples. Changing Hyracks to operate on columnar values natively would be a laborious task and may not yield better performance. Thus, we opted to use an approach similar to the one proposed in [46], where we generate a code for parts of a query plan. Figure 10 shows the times to execute the same query Q2 using the code generation approach. Even though we only generate a code for parts of the plan, Q2...
Due to the dynamically typed nature of the document data model, the generated code must handle values with heterogeneous types. Thus, we use Truffle, a framework for implementing dynamically typed languages, to produce Truffle Abstract Syntax Trees (AST) for a part of the query plan. Each node of the AST describes a language operation, such as a numerical expression (e.g., arithmetic addition) or a control flow statement (e.g., while loop statement). Also, we specify the expected behavior (or specialization as in Truffle terminology) for each expression given its inputs. For instance, the output for the logical expression 10 > "ten" is NULL, where NULL is the expected output when comparing two values with incompatible types in AsterixDB. After observing a few values by executing the AST in an interpreted mode, Truffle optimizes the AST and generates a bytecode to run it in the Java Virtual Machine (JVM), where the generated bytecode is optimized further to machine code.

Due to the dynamic nature of the data model, Truffle code generation does not actually produce or consume any tuples but are used to translate operators into an AST. In this work, we only generate code for "pipelining" operators. Thus, we do not generate code for the entire query plan, but we stop the code generation process once we see a "pipeline-breaker". In our example, the GROUP operator is a pipeline-breaker, as it requires building a hash-table for the resulting tuples (hash-group-by) or sort by them (sort-group-by) to compute the groups and their aggregate counts.

To illustrate the code generation process, the GROUP operator in Figure 11 calls the produce function of its child PROJECT, and the PROJECT operator calls the UNNEST’s produce function and so on until we call the produce function of the SCAN operator. The consume function is called in the opposite direction (i.e., bottom-up). The generated code, as shown in Figure 11, begins with the function run’s header, which takes two parameters c and r, where c is the tuples’ cursor and r is the field reader. The reader is pre-configured to accept a tuple as an input and produce the value of a requested field. Figure 11 also shows which part of the plan (color-coded) produces which part of the code. First we see the generated code produced from the SCAN operator, which loops through the tuples of the gamers collection (or dataset). Next, the ASSIGN operator contributes the code for using the reader r to get the field games value from the tuple. The UNNEST operator contributes the while loop to produce the items of the array games. Finally, we only write the games’ array items, as they are the only projected values from the PROJECT operator. The resulting values are then pushed to the system’s regular GROUP operator to compute the final result.

6 EXPERIMENTS

In this section, we evaluate an implementation of the proposed techniques in Apache AsterixDB in terms of their (i) on-disk storage size after data ingestion, (ii) data ingestion rate, and (iii) performance when running analytical queries. We evaluate the performance for storing and querying records in different layouts, namely: (i) AsterixDB’s schemless record format (Open), (ii) the Vector-Based (VB) format proposed in [23], (iii) APAX, and (iv) AMAX. Again, Open and VB are both row-major formats, whereas APAX and AMAX are columnar formats.

Experiment Setup We conducted our experiments using a single machine with an 8-core (Intel i9-9900K) processor and 32GB of main memory. The machine is equipped with a 1TB NVMe SSD storage device (Samsung 970 EVO) capable of delivering up to 3400 MB/s for sequential reads and 2500 MB/s for sequential writes. We used AsterixDB v9.6.0 to implement and evaluate our proposed techniques. Unless otherwise noted, we configured AsterixDB with a single NC and eight partitions (Section 2.1.1). The eight partitions share 16GB of total allocated memory, and we allocated 10GB for the system’s buffer cache and 2GB for the in-memory component budget. The remaining 4GB is allocated for use as temporary buffers for query operations such as sorting and grouping as well as transforming records into APAX or AMAX layouts during data ingestion. Additionally, we used 128KB for the on-disk data page size and 64KB for in-memory pages. Throughout our experiments, we used AsterixDB’s page-level compression with the Snappy [16] compression scheme to reduce the overall storage footprint.
6.1 Datasets

In our evaluation, we used five different datasets (real, scaled, and synthetic) that differ in terms of their records’ structures, sizes, and value types. Table 1 lists and summarizes the characteristics of the five datasets. In Table 1, # of Columns refers to the number of inferred columns for records in APAX or AMAX layouts.

| Type | cell | sensors | tweet_1 | wos | tweet_2 |
|------|------|---------|---------|-----|---------|
| Type (GB) | Real | Synthetic | Real | Real | Scaled |
| Size (GB) | 172 | 212 | 210 | 277 | 200 |
| # of Records | 1.43B | 40M | 17M | 48M | 77.2M |
| Avg. Record Size | 141B | 3.8KB | 3.5KB | 6.2KB | 2.7KB |
| # of Columns | 7 | 16 | 933 | 296 | 275 |
| Dominant Type | Mix | Integer | String | String | String |

Table 1: Datasets summary

The cell dataset (provided by a telecom company) contains information about the cellphone activities of anonymized users, such as the call duration and the cell tower used in the call. The cell dataset is the only dataset we used that does not contain nested values (i.e., its data is in first-normal form or 1NF), and its scalar values’ types are a mix of strings, doubles, and integers. The sensors dataset contains primarily numerical values that describe the sensors’ connectivity and battery statuses along with their daily captured readings. In contrast, the wos dataset, as well as tweet_1 and tweet_2, consist mostly of string values. The vos dataset, an acronym for Web of Science[^1] [7], encompasses meta-information about published scientific articles (such as authors, abstracts, and funding) from 1980 to 2014. The original dataset is in XML and we converted it to JSON using an XML-to-JSON converter [19]. After the conversion, the resulting JSON documents contain some fields (resulting from XML elements) with heterogeneous types, specifically a union of an object and an array of objects. Thus, we used the wos dataset to evaluate our extensions to the Dremel format to store heterogeneous values in columnar layouts. Lastly, we obtained the tweet_1 and tweet_2 datasets using the Twitter API [17], where we collected the tweets in tweet_1 from September 2020 to January 2021. The tweet_2 dataset is a sample of tweets (~ 20GB) that we collected back in 2016, which predates Twitter’s announcement of increasing the character limit from 140 to 280. We replicated the tweet_1 dataset to have around 200GB worth of tweets in total. Note that the records of tweet_1 and tweet_2 differ in terms of their sizes and the number of columns that they have, as shown in Table 1.

We used the tweet_2 dataset for evaluating the impact of declaring secondary indexes for an update-intensive workload as we detail later in Section 4.6. Additionally, we evaluated the impact of answering queries using the created secondary indexes. We created two indexes in this experiment. The first index is on the tweet timestamp values, a set of synthetic and monotonically-increasing values that mimics the time when users posted their tweets. We also created a primary key index to reduce the cost of point lookups, as discussed in Section 4.6. We chose tweet_2 for this experiment, instead of tweet_1, since it has a moderate number of columns,

[^1]: We obtained the dataset from Thomson Reuters. Currently, Clarivate Analytics maintains it [8].

![Figure 12](image-url) Figure 12: Storage size and ingestion time — tweet_2 includes secondary indexes

which directly impacts the ingestion performance, as we discuss later in Section 6.3.

6.2 Storage Size

In this experiment, we first evaluated the on-disk storage size after ingesting the five datasets: cell, sensors, tweet_1, wos, and tweet_2. Figure 12a shows the total on-disk storage size after ingesting the five datasets using the four layouts: Open, VB, APAX, and AMAX. For the tweet_2 dataset, the presented total size includes the sizes for storing the two declared secondary indexes (namely the timestamp index and the primary key index).

In the cell dataset, which is the only dataset in 1NF, Figure 12a shows that the records in the two row-major layouts Open and VB took roughly the same space; the VB layout took slightly less space (~ 17% smaller) due to compaction [23]. Similarly, the records in both of the columnar layouts, APAX and AMAX, took about the same space; however, compared to the records in the Open format, the sizes are 45% and 50% smaller, for the APAX and AMAX layouts, respectively. The storage overhead reductions in the APAX and AMAX layouts are due to (i) storing no additional information (e.g., field names) with the values, compared to Open, and (ii) the values being encoded, which is not possible in the row-major layouts.

The impact of encoding in both the APAX and AMAX layouts becomes apparent for storing the sensors dataset, where the values are primarily numeric. Figure 12a shows that the sensors records in the Open and VB layouts took 7.2X and 4.8X more space compared to the records in the APAX layout, respectively, and 8.5X and 5.6X more space compared to the records in the AMAX layout, respectively. This clearly shows that the encoding of numerical values in the same domain is superior to page-level compression alone, making the columnar layout more suitable for numerical data.

In contrast to the sensors dataset, the Twitter dataset tweet_1 contains more textual values than numerical ones and the encoding becomes less effective. Storing this data in a columnar layout did not show a significant improvement, as shown in Figure 12a, compared to the records in a row-major layout. In fact, the records in the APAX layout took 35% more space than the records in the VB layout. The reason behind the high storage overhead in APAX is the excessive number of columns of the tweet_1 dataset, as shown in Table 1, so each minipage stores a small number of values compared to the cell and sensors datasets. Thus, in some instances, the encoding imposes a negative impact, as the encoded values store additional information for decoding, and this information occupies more space than the encoding saves. However, the AMAX layout is not as sensitive to the number of columns, as a column can span...
We next evaluated the ingestion performance for the four different layouts. For the first dataset, which we configured AsterixDB to use a tiering merge policy with a size ratio of 1.2 throughout the experiments. This policy merges a sequence of components when the total size of the younger components is 1.2 times larger than that of the oldest component in the sequence. To measure the ingestion rate accurately, we used the fair merge scheduler as recommended in [42], where the components are merged on a first-come, first-served basis. We set the maximum tolerable number of components to 5, after which a merge operation is triggered. We limited the number of concurrent merges to reduce CPU and memory consumption (Section 4.5.3) while merging the APAX and AMAX components. Additionally, we limited the number of primary keys in AMAX’s Page 0 to 15,000 (default value) for the reasons discussed in Section 4.5.2.

6.3 Ingestion Performance

We next evaluated the ingestion performance for the four different layouts using AsterixDB’s data feeds. We first evaluated the insert-only ingestion performance of the cell, sensors, tweet_1, and wos datasets without updates. In the second experiment, we evaluated the ingestion performance of an update-intensive workload with secondary indexes using the tweet_2 dataset. The latter experiment focuses on measuring the impact of the point lookups needed to maintain the correctness of the declared secondary indexes.

We configured AsterixDB to use a tiering merge policy with a size ratio of 1.2 throughout the experiments. This policy merges a sequence of components when the total size of the younger components is 1.2 times larger than that of the oldest component in the sequence. To measure the ingestion rate accurately, we used the fair merge scheduler as recommended in [42], where the components are merged on a first-come, first-served basis. We set the maximum tolerable number of components to 5, after which a merge operation is triggered. We limited the number of concurrent merges to reduce CPU and memory consumption (Section 4.5.3) while merging the APAX and AMAX components. Additionally, we limited the number of primary keys in AMAX’s Page 0 to 15,000 (default value) for the reasons discussed in Section 4.5.2.

6.3.1 Insert-only: The cell dataset is the smallest in terms of the average record size and the dataset’s overall size, as shown in Table 1. However, it also has the most records. In AsterixDB’s original configuration (i.e., a single NC with eight partitions), the ingestion rate of the cell dataset was the slowest among the datasets — it took more than 8000 seconds to ingest the dataset under the four layouts. The main reason is that the eight partitions share the same resources, including the transaction log buffer where each partition writes entries to commit their transactions. With the cell dataset’s high record cardinality, writing to the transaction log buffer became a bottleneck. To alleviate the contention on the transaction log buffer, we reconfigured AsterixDB to have four NCs 2, each with two partitions. We divided the memory budget equally among the four NCs. Using this configuration, Figure 13a shows the time it took to ingest the cell dataset using the four layouts. We see that the ingestion rate is about the same for the four layouts, as writing to the transaction log buffer is still a major bottleneck. However, the ingestion rate using the new configuration improved significantly — from more than 8000 seconds to the vicinity of 3000 seconds.

In the sensors dataset, in contrast to the cell dataset, the ingestion rate varied among the different layouts as shown in Figure 13a. Ingesting Open records took more time than records in the other layouts due to the record construction cost of the Open layout [23]. The recursive nature of the Open layout requires copying the child’s values to the parent from the leaf to the root of the record, which means multiple memory copy operations for the same value. In contrast, constructing records in the VB layout is more efficient, as the values are written only once [23]. Thus, ingesting records in the VB layout took 50% less time in comparison. Recall that the records of the in-memory components are in the VB format for APAX and AMAX (as discussed in Section 4.5.2), and during the flush operation, the records are transformed into a columnar layout. Thus, the lower construction cost of the VB records contributed to the higher ingestion rate of both the APAX and AMAX layouts. We also observed that the cost of transforming the records into a column-major layout during the flush operation and the impact of decoding and encoding the values during the merge operation were negligible.

For the tweet_1 and wos datasets, the cost of transforming the records into columns became more apparent due to the higher number of columns in those two datasets. Figure 13a shows that the ingestion time for tweet_1 using the APAX layout was the longest. As explained earlier in Section 6.2, a higher number of columns can negatively affect the number of values that we can store in APAX pages, and thus, more pages are required to store the ingested records. Also, recall that the columns’ values are first written into

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Figure 13: Storage size and ingestion time — tweet_2 includes secondary indexes

2 Usually, only a single NC is configured per computing node.
temporary buffers and then copied to form an APAX page (Section 4.5.1). Consequently, we need to iterate over the temporary column buffers (933 in total as shown in Table 1) to construct each APAX page. The cost of constructing a large number of APAX pages took most of the time to ingest the tweet_1 dataset. We did not observe a similar behavior when constructing the AMAX pages; most of the time here was spent performing LSM merges, as we need to fetch all columns for each merge operation. The ingestion performance using the AMAX layout was similar to the row-major layout (Open) and only 25% slower than the VB layout.

The wos dataset is less extreme in terms of the number of columns compared to the tweet_1 dataset; however, its data contains large textual values (e.g., abstracts). As in the sensors dataset, the lower per-record construction cost of the VB layout was the main contributor to the performance gains (shown in Figure 13a) for the APAX and AMAX layouts. Additionally, the records in the Open layout took more space to store, which means that the I/O cost of the LSM flush and merge operations was higher compared to the other layouts. The ingestion performance of the APAX and AMAX layouts was comparable and slightly slower than the VB layout, as the cost of transforming the ingested records into a column-major layout during the flush operation and decoding and encoding the values during the merge operation was higher for the wos dataset compared to the sensors dataset.

### 6.3.2 Update-intensive

We evaluated the ingestion performance for insert-only workloads using different datasets, and we saw that the ingestion rate using columnar layouts, in general, was faster or comparable to the row-major layout Open. We now discuss the performance for an update-intensive workload with secondary indexes using the dataset tweet_2. In this experiment, we randomly updated 50% of the previously ingested records. The updates followed a uniform distribution where all records are updated equally. Prior to starting the data ingestion, we created two indexes: one on the primary keys, which we call a primary key index, to minimize the cost of point lookups of non-existent (new) keys. The second index is on the timestamp values. Figure 13a shows tweet_2 the ingestion time for the four different layouts. The ingestion times for records in the APAX and AMAX were ~24% and ~35% slower than the Open layout, respectively. Updating a record requires accessing the primary index to fetch the old timestamp value to delete it from the timestamp secondary index before inserting the updated value. Recall that the cost of searching for a value in a columnar layout is linear (v.s. logarithmic in a row-major layout), and the values need to be decoded before performing the search. Thus, with 50% of the records being updated, the cost of updating old timestamp values for the columnar layouts became higher than for the row-major layouts. Even though we only need to read the pages corresponding to the timestamp in the AMAX layout (i.e., less I/O cost), its update cost was higher than the APAX layout. This was due to decoding large numbers of timestamp values stored in AMAX megapages (a CPU cost) for each update. We will soon (Section 6.4.5) discuss the benefit of secondary indexes when answering queries; however, the cost of maintaining the correctness of secondary indexes is high for columnar layouts. Thus, one should consider how often the index would be utilized.

### 6.4 Query Performance

Next, we evaluated the performance of executing different analytical queries against the ingested datasets. We first evaluated scan queries (i.e., without secondary indexes) against the cell, sensors, tweet_1, and wos datasets. Table 2 summarizes the queries used for each dataset, and the full queries are listed in A. Q1, which counts the number of records — SELECT COUNT(*) — is executed against all four datasets to measure the I/O cost of scanning records in the different layouts. We executed each query six times, and we report the average execution time for the last five. In this experiment, we report the execution times using our code generation framework (Section 5) for the four layouts (i.e., Open, VB, APAX, and AMAX), as executing queries using the code generation technique was faster compared to AstreixDB’s interpreted execution model. In the next experiment, we evaluated the performance of different queries against the tweet_2 dataset using the created secondary indexes. Throughout our experiments, we evaluated the impact of accessing a different number of columns on the AMAX and APAX layouts for scan and index based queries.

| Query ID | Description                                      |
|----------|--------------------------------------------------|
| Q1       | The number records                               |
| Q2       | The top 10 callers with the longest call durations |
| Q3       | The number of calls with durations ≥ 600 seconds  |
| Q4       | The maximum reading ever recorded                |
| Q5       | The IDs of top 10 sensors with maximum readings  |
| Q6       | Similar to Q3, but for readings in a given day   |
| Q7       | The top 10 users who posted the longest tweets    |
| Q8       | The top 10 users with highest number of tweets that contain a popular hashtag |

Table 2: A summary of the queries used in the evaluation

#### 6.4.1 cell Dataset

Figure 14a shows the execution time for the three queries (summarized in Table 2) executed against the cell dataset using the four different layouts. The execution times for Q1 against different layouts correlated with their storage sizes shown in Figure 12a, except for the AMAX layout, where Q1 took the least time to execute — about 88% faster than the Open and VB layouts. As Q1 only counts the number of records, we only need to count the number of primary keys on Page 0 of the AMAX layout — thereby minimizing the I/O cost. This is also true for Q1 against the other datasets, as discussed in the following sections. In contrast to Q1, Q2 requires grouping, aggregating, and sorting to compute the query’s results, and hence, it takes more time to execute. For the AMAX layout, in addition to the primary keys on Page 0, Q2 accesses two more columns (the caller ID and the call duration columns), which means that more pages were accessed to execute Q2. Despite the additional costs, the execution times for Q2 showed a similar trend as in Q1. Querying the APAX and AMAX formats were 38% and 70% faster than the Open layout, and 40% and 72%
than the VB layout, respectively. The slowdown of querying VB is due to how the fields’ values are linearly accessed, as detailed in [23]. Q3 also shows a similar trend as Q1, where the I/O costs of the two columnar layouts were the smallest.

6.4.2 sensors Dataset: Querying the sensors dataset shows similar trends as in the cell dataset, where the queries’ execution times (Figure 14b) correlated with the formats’ storage sizes (Figure 12a). Executing Q1 against the AMAX layout took 0.65 seconds, and it took 5.1 seconds for APAX. As in the cell dataset, Q1 only read Page 0 of AMAX, and hence, it was the fastest. For Q2 – Q4 (summarized in Table 2), the execution times for the APAX and AMAX records were comparable, as they took 7.7GB and 6.5GB to store the data, respectively, which is less than the 10GB of memory allocated for the system’s buffer cache. Thus, AsterixDB was able to cache the APAX and AMAX records in memory and eliminate the I/O cost. For the two row-major layouts, it was faster to execute the queries against VB than Open, as VB took less space.

6.4.3 tweet_1 Dataset: For tweet_1’s queries (Table 2), we observed an order of magnitude improvement in the query performance using the AMAX layout, vs. the other layouts. VB and APAX used comparable space to store the tweet_1 data; however, reading only the columns involved in the queries for the AMAX layout improved their execution times significantly. For example, Q1 took only 0.6 seconds to execute against the AMAX format compared to 48.4, 26.1, and 38.8 seconds for Open, VB, and APAX, respectively. For Q2, AMAX took 3.1 seconds to execute vs. 48.5, 39.9, and 40.3 seconds for Open, VB, and APAX, respectively. Storing and querying the tweet_1 dataset using APAX showed less improvement than for the sensors dataset. Excluding the AMAX layout, the VB layout, in comparison, was more suitable for storing and querying a text-heavy Twitter dataset, as its records took less space to store and less time to query.

6.4.4 wos Dataset: The wos dataset is the last one used to evaluate scan-based queries. As mentioned earlier in Section 6.1, the wos dataset contains several values with heterogeneous types. We used this dataset to evaluate the impact of querying over heterogeneous types for the columnar layouts. Specifically, Q3 and Q4 (Table 2) access the authors’ affiliated countries, which is stored as either an array, for articles with multiple co-authors, or as an object, for single-authored articles. Figure 14d shows the execution times for Q1 - Q4, where AMAX was the fastest to query. Q1 took only 0.83 seconds to execute, compared to 103.1, 62.5, and 64.4 seconds for Open, VB, and APAX, respectively. For Q2 - Q4, AMAX improved their execution times by at least 64% compared to the other layouts. The queries’ execution times against APAX were slightly shorter than the VB layout. Thus, both the APAX and AMAX layouts can efficiently handle values with heterogeneous types, and the impact of mixed types on query performance was negligible.

6.4.5 tweet_2 Dataset: We used the tweet_2 dataset to evaluate the impact of secondary indexes on query performance for the four different layouts. We used a created timestamp secondary index to run range-queries with different selectivities that count the number of records. For each query selectivity, we executed queries with...
different range predicates to measure their actual I/O cost and report the average execution time. Figure 15 shows the execution times for both low and high selectivity predicates. For queries with low selectivity predicates, their execution times using the four different layouts were comparable, as shown in Figure 15a, and all queries took less than a second to finish. However, the execution times for queries that are 0.1% selective were correlated with storage sizes (Figure 12a). Figure 15b shows the execution times for queries with high selectivity predicates both with and without utilizing the timestamp index. The secondary index accelerated the execution of queries with high selectivity predicates, except for the AMAX layout. We observed that the scan-based query in the AMAX layout (AMAX Scan) was faster to execute than its index-based queries. The previous experiment does not depict a full picture, as counting the number of records only accesses Page 0 of AMAX and skips the rest of the pages. The benefit of using a secondary index for such queries becomes more apparent when a query accesses more columns. Figure 16 shows the impact of running queries that read different number of columns in the APAX and AMAX formats. Each query counts the appearances of different columns’ values (i.e., non-NULL values) and varying the number of columns accessed from 1 to 10. The columns were picked at random and vary in terms of their types and sizes. Figure 16a shows the execution times for scan-based queries that access different number of columns. As expected, accessing more columns in the AMAX format negatively impacts query performance, while the performance was relatively stable in the APAX. For example, reading ten different columns was 9.5X slower than reading a single column for the AMAX layout, whereas the impact was less noticeable in APAX. Despite the slowdown, querying records in the AMAX layout was still faster than APAX. The time variance in accessing different columns shown in both figures is due to the time needed for reading and decoding values with different sizes. For example, change for reading six columns was higher than for seven columns, as the sixth column contained required values, while the seventh column’s values were mostly NULLs. That was for the scan-based queries. Figures 16b – 16d show the execution times of index-based queries with different selectivities (0.001% – 1.0%). The execution times for all queries were comparable for both layouts, despite the number of columns each query reads. Compared to the scan-based queries, the index-based queries took less time to execute and were less sensitive with respect to the number of columns. Thus, as for row-major layout, secondary indexes can accelerate queries against records in a columnar layout and can help to minimize the impact of reading multiple columns for AMAX-like layouts.

7 RELATED WORK

Columnar layouts with dynamic schema: Storing schemaless semi-structured data in a columnar layout has gained more traction lately, and several approaches have been proposed to address the issues imposed by schema changes. Delta Lake [27], a storage layer for cloud object stores, addresses the challenges of updating and deleting records stored in Parquet files. Delta Lake recently added support for schema evolution; however, it still lacks support for storing heterogeneous values, as per Parquet’s limitation. Alsubaaee et al. proposed a patented technique [26] that exploits Parquet’s file organization to store datasets with heterogeneous values. The main idea of their approach is congregating records with the same value types within a group. In this work, we proposed an extension to Dremel to natively support union types, storing values with different types as different columns. Additionally, our extension to Dremel is independent of how the columns are organized — making it a suitable format for different detailed storage organizations such as APAX, AMAX, or even Parquet’s row groups. In [34], the authors have proposed Json Tiles, a columnar format for semi-structured records integrated into Umbra [47], a disk-based column-store RDBMS. The proposed approach infers the structure of the ingested records and materializes the common parts of the records’ values, including heterogeneous values, as JSON Tiles. In our proposed work, we transform entire (nested and variant) records into columns. Additionally, we have targeted LSM-based systems, where in-place updates are not permitted, whereas JSON Tiles are designed for systems where updates are performed in-place.

For LSM-based document stores, Rockset [15] supports storing values of semi-structured records in a columnar format, with the values of a column being stored in RocksDB [14] (RocksDB’s storage engine) using a shared key prefix. To illustrate, let us consider an example of two records with the ids 1 and 2, where both records have additional fields age and name. The keys age.1 and age.2 for the records with ids 1 and 2, respectively, share the same prefix name, which corresponds to the field age. Similarly, name.1 and name.2 share the same prefix name. When stored in RocksDB, the keys age.1 and age.2 and their values will be stored contiguously first, followed by the name’s values, as the RocksDB’s ordering of keys dictates. Hence, when accessing either value, Rockset will only read the required values from disk, which minimizes the I/O cost. This approach does not support encoding the column’s values (e.g., via run-length encoding), however, which means more I/O.

LSM-based column stores: Most column-store databases employ a similar mechanism to LSM-based storage engines, where newly inserted records are batched in memory and then flushed to disk, during which time the flushed records are encoded and compressed. For example, Vertica [54] and Microsoft SQL Server’s column store [37, 38] employ an LSM-like mechanism, while column-store systems such as Apache Kudu [5] and ClickHouse [9] are LSM-based. Update and delete operations may slightly differ from system to system, but they mostly share the objective of minimizing the cost of modifying columns’ values in place. Deleted records are, therefore, usually marked and garbage-collected at a later stage, and updates are handled as a delete followed by an insert. This work is no exception, as we share similar challenges and objectives. Again, however, our focus is on nested and schemaless data.

Code generation and query compilation: Data processing engines like Spark and DBMSs like Vector and Umbre have moved from using the iterator model or the vectorized model for their query execution engines. Instead, they use code generation techniques to improve performance. Most such systems utilize strongly-typed languages for code generation, which is sufficient for schemaful systems. However, for schemaless systems like MongoDB and Apache AsterixDB, utilizing a strongly-typed language would require adding additional checks to ensure the types of each processed
value, which means more branches in the generated code. The Truffle framework addresses this issue for dynamically-typed languages such as Python and JavaScript. Earlier, Truffle was used to execute stored procedures and user-defined functions in the Oracle database and MySQL [30]. Recent work [52] has proposed using the Truffle framework for code generation and query compilation to run Language-integrated Query (LINQ) over a dynamically-typed collection in JavaScript or R and showed that the performance of their approach was comparable to handwritten code. In this work, we have also used the Truffle framework, where we generate code for parts of a query plan in Apache AsterixDB, after which the generated code is distributed and executed in parallel.

8 CONCLUSION AND FUTURE WORK

In this paper, we presented several techniques to store and query data in a columnar format for schemaless, LSM-based document stores. We first proposed several extensions to the Dremel format to make storing arrays’ values more concise and to accommodate heterogeneous data values. Next, we introduced APAX and AMAX, two columnar layouts for organizing and storing records in LSM-based document stores. Furthermore, we highlighted the challenges involved reading and writing records in the APAX and AMAX layouts and proposed solutions to overcome those challenges. Experiments showed that the AMAX layout significantly reduced the overall storage overhead compared to the row-major formats. The impact of transforming records into columns during data ingestion varied according to the structure of the ingested records, and it was seen that the AMAX layout’s ingestion rate was relatively stable compared to APAX and faster as compared to AsterixDB’s current schemaless format.

Additionally, we presented an approach for code generation and query compilation for schemaless document stores using the Truffle framework’s JIT compilation capability to process values with heterogeneous types. Although we only generate code for a part of the query, our experiments showed a significant improvement over the current Hyracks execution model, even for row-major formats. In our evaluation, queries against the AMAX were the fastest to execute compared to other layouts, and for certain queries, the AMAX layout improved the query performance by orders of magnitude.

To the best of our knowledge, most column store databases, except Vector [1], do not support secondary indexes, as scan-based queries are often considered good enough for data warehouse workloads. In this work, we evaluated the impact of secondary indexes on data ingestion and query performance for columnar formats and showed that the ingestion rate might be negligibly impacted; however, the impact of reading multiple columns in AMAX was reduced when answering queries with secondary indexes.

In future work, we plan to extend the AMAX layout to support dictionary encoding, where we will dedicate different pages to store the values’ dictionaries. Moreover, we plan to explore ways to merge dictionary pages efficiently during the LSM merge operation. Finally, we plan to expand our code generation framework to the entire quer library to include pipeline-breakers such as group-by, order-by, and join operators.

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A. QUERIES
In this section, we show the queries we ran in our experiments against the cell, tweets_1, sensors, and wos datasets.

A.1 cell Queries

Q1:
SELECT VALUE COUNT(*)
FROM Tweets

Q2:
SELECT caller, MAX(c.duration) as m
FROM Cell c
GROUP BY c.caller AS caller
ORDER BY m DESC
LIMIT 10

Q3:
SELECT VALUE COUNT(*)
FROM Cell c
WHERE c.duration >= 600

A.2 tweets_1 Queries

Q1:
SELECT VALUE COUNT(*)
FROM Tweets

Q2:
SELECT value.uname, a
FROM Tweets t
GROUP BY t.users.name AS value
WITH a AS MAX(length(t.text))
ORDER BY a DESC
LIMIT 10

Q3
SELECT value.uname, COUNT(*) as c
FROM Tweets t
WHERE
  SOME ht IN t.entities.hashtags
  SATISFIES LOWERCASE(ht.text) = "jobs"
GROUP BY t.users.name AS value
ORDER BY c DESC
LIMIT 10

A.3 Sensors Dataset’s Queries

Q1:
SELECT VALUE COUNT(*)
FROM Sensors s, s.readings r

Q2:
SELECT MAX(r.temp), MIN(r.temp)
FROM Sensors s, s.readings r

Q3:
SELECT sid, max_temp
FROM Sensors s, s.readings r
GROUP BY s.sensor_id as sid
WITH max_temp as MAX(r.temp)
ORDER BY max_temp DESC
LIMIT 10

Q4:
SELECT sid, max_temp
FROM Sensors s, s.readings r
WHERE s.report_time > 1556496000000
AND s.report_time < 1556496000000 + 24 * 60 * 60 * 1000
GROUP BY s.sensor_id as sid
WITH max_temp as MAX(r.temp)
ORDER BY max_temp DESC
LIMIT 10

A.4 wos Queries

Q1:
SELECT VALUE COUNT(*)
FROM Publications as t

Q2:
SELECT v, COUNT(*) as cnt
FROM Publications as t,
  t.static_data.fullrecord_metadata.category_info.subjects.subject
AS subject
WHERE subject.ascatype = "extended"
GROUP BY subject.value as v
ORDER BY cnt DESC
LIMIT 10

Q3:
SELECT country, COUNT(*) as cnt
FROM (SELECT value.countries
      FROM Publications as t
      LET address = t.static_data.fullrecord_metadata.addresses.address_name,
        countries = ARRAY_DISTINCT(address[∗].address_spec.country)
      WHERE IS_ARRAY(address)
      AND ARRAY_COUNT(countries) = 1
      AND ARRAY_CONTAINS(countries, "USA")

      )
Q4:
SELECT pair, COUNT(*) as cnt
FROM (SELECT value ARRAY_PAIRS(countries)
FROM Publications as t

LET address = t.static_data
.fullrecord_metadata
.addresses.address_name,
countries = ARRAY_DISTINCT(
  address[∗].address_spec.country
)
WHERE IS_ARRAY(address)
AND ARRAY_COUNT(countries) > 1
) as country_pairs
UNNEST country_pairs as pair
GROUP BY pair
ORDER BY cnt DESC
LIMIT 10