Mainlining Databases: Supporting Fast Transactional Workloads on Universal Columnar Data File Formats

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ABSTRACT
The proliferation of modern data processing tools has given rise to open-source columnar data formats. The advantage of these formats is that they help organizations avoid repeatedly converting data to a new format for each application. These formats, however, are read-only, and organizations must use a heavy-weight transformation process to load data from on-line transactional processing (OLTP) systems. We aim to reduce or even eliminate this process by developing a storage architecture for in-memory database management systems (DBMSs) that is aware of the eventual usage of its data and emits columnar storage blocks in a universal open-source format. We introduce relaxations to common analytical data formats to efficiently update records and rely on a lightweight transformation process to convert blocks to a read-optimized layout when they are cold. We also describe how to access data from third-party analytical tools with minimal serialization overhead. To evaluate our work, we implemented our storage engine based on the Apache Arrow format and integrated it into the DB-X DBMS. Our experiments show that our approach achieves comparable performance on OLTP workloads operating on the relaxed Arrow format. We also implemented an Arrow export layer for our system, and show that it facilitates orders-of-magnitude faster exports to external tools.

1 INTRODUCTION
Data analysis pipelines allow organizations to extrapolate insights from data residing in their OLTP systems. The tools in these pipelines often use open-source binary formats, such as Apache Parquet [9], Apache ORC [8] and Apache Arrow [3]. Such formats allow disparate systems to exchange data through a common interface without converting between proprietary formats. But these formats target write-once, read-many workloads and are not amenable to OLTP systems. This means that a data scientist must transform OLTP data with a heavy-weight process, which is computationally expensive and inhibits analytical operations.

Although a DBMS can perform some analytical duties, modern data science workloads often involve specialized frameworks, such as TensorFlow, PyTorch, and Pandas. Organizations are also heavily invested in personnel, tooling, and infrastructure for the current data science eco-system of Python tools. We contend that the need for DBMS to efficiently export large amounts of data to external tools will persist. To enable analysis of data as soon as it arrives in a database is, and to deliver performance gains across the entire data analysis pipeline, we should look to improve a DBMS’s interoperability with external tools.

If an OLTP DBMS directly stores data in a format used by downstream applications, the export cost is just the cost of network transmission. The challenge in this is that most open-source formats are optimized for read/append operations, not in-place updates. Meanwhile, divergence from the target format in the OLTP DBMS translates into more transformation overhead when exporting data, which can be equally detrimental to performance. A viable design must seek equilibrium in these two conflicting considerations.

To address this challenge, we present a multi-versioned DBMS that operates on a relaxation of an open-source columnar format to support efficient OLTP modifications. The relaxed format can then be transformed into the canonical format as data cools with a light-weight in-memory process. We implemented our storage and concurrency control architecture in DB-X [10] and evaluated its performance. We target Apache Arrow, although our approach is also applicable to other columnar formats. Our results show that we achieve good performance on OLTP workloads operating on the relaxed Arrow format. We also implemented an Arrow export layer for our system, and show that it facilitates orders-of-magnitude faster exports to external tools.

The remainder of this paper is organized as follows: we first discuss in Section 2 the motivation for this work. We then present our storage architecture and concurrency control in Section 3, followed by our transformation algorithm.
in Section 4. In Section 5, we discuss how to export data to external tools. We present our experimental evaluation in Section 6 and discuss related work in Section 7.

2 BACKGROUND

We now discuss challenges in running analysis with external tools with OLTP DBMSs. We begin by describing how data transformation and movement are bottlenecks in data processing. We then present a popular open-source format (Apache Arrow) and discuss its strengths and weaknesses.

2.1 Data Movement and Transformation

A data processing pipeline consists of a front-end OLTP layer and multiple analytical layers. OLTP engines employ the n-ary storage model (i.e., row-store) to support efficient single-tuple operations, while the analytical layers use the decomposition storage model (i.e., column-store) to speed up large scans [22, 29, 38, 43]. Because of conflicting optimization strategies for these two use cases, organizations often implement the pipeline by combining specialized systems.

The most salient issue with this bifurcated approach is data transformation and movement between layers. This problem is made worse with the emergence of machine learning workloads that load the entire data set instead of a small query result set. For example, a data scientist will (1) execute SQL queries to export data from PostgreSQL, (2) load it into a Jupyter notebook on a local machine and prepare it with Pandas, and (3) train models on cleaned data with TensorFlow. Each step in such a pipeline transforms data into a format native to the target framework: a disk-optimized row-store for PostgreSQL, DataFrames for Pandas, and tensors for TensorFlow. The slowest of all transformations is from the DBMS to Pandas because it retrieves data over the DBMS’s network protocol and then rewrites it into the desired columnar format. This process is not optimal for high-bandwidth data movement [46]. Many organizations employ costly extract-transform-load (ETL) pipelines that run only nightly, introducing delays to analytics.

To better understand this issue, we measured the time it takes to extract data from PostgreSQL (v10.6) and load it into a Pandas program. We use the LINEITEM table from TPC-H with scale factor 10 (60M tuples, 8 GB as a CSV file, 11 GB as a PostgresQL table). We compare three approaches for loading the table into the Python program: (1) SQL over a Python ODBC connection, (2) using PostgreSQL’s COPY command to export a CSV file to disk and then loading it into Pandas, and (3) loading data directly from a buffer already in the Python runtime’s memory. The last method represents the theoretical best-case scenario to provide us with an upper bound for data export speed. We pre-load the entire table into PostgreSQL’s buffer pool using the pg_warm extension.

Figure 1: Data Transformation Costs – Time taken to load a TPC-H table into Pandas with different approaches.

Figure 2: SQL Table to Arrow – An example of using Arrow’s API to describe a SQL table’s schema in Python.

To simplify our setup, we run the Python program on the same machine as the DBMS. We use a machine with 128 GB of memory, of which we reserve 15 GB for PostgreSQL’s shared buffers. We provide a full description of our operating environment for this experiment in Section 6.

The results in Figure 1 show that ODBC and CSV are orders of magnitude slower than what is possible. This difference is because of the overhead of transforming to a different format, as well as excessive serialization in the PostgreSQL wire protocol. Query processing itself takes 0.004% of the total export time. The rest of the time is spent in the serialization layer and in transforming the data. Optimizing this export process will significantly speed up analytics pipelines.

2.2 Column-Stores and Apache Arrow

The inefficiency of loading data through a SQL interface requires us to rethink the data export process and avoid costly data transformations. Lack of interoperability between row-stores and analytical columnar formats is a major source of inefficiency. As discussed previously, OLTP DBMSs are row-stores because conventional wisdom is that column-stores are inferior for OLTP workloads. Recent work, however, has shown that column-stores can also support high-performance transactional processing [45, 48]. We propose implementing a high-performance OLTP DBMS directly on top of a data format used by analytics tools. To do so, we select a representative format (Apache Arrow) and analyze its strengths and weaknesses for OLTP workloads.

Apache Arrow is a cross-language development platform for in-memory data [3]. In the early 2010s, developers from
Apache Drill, Apache Impala, Apache Kudu, Pandas, and others independently explored universal in-memory columnar data formats. These groups joined together in 2015 to develop a shared format based on their overlapping requirements. Arrow was introduced in 2016 and has since become the standard for columnar in-memory analytics, and as a high-performance interface between heterogeneous systems. There is a growing ecosystem of tools built for Arrow, including APIs for several programming languages and computational libraries. For example, Google’s TensorFlow now integrates with Arrow through a Python module [19].

At the core of Arrow is a columnar memory format for flat and hierarchical data. This format enables (1) fast analytical data processing and vectorized execution, and (2) zero-deserialization data interchange. To achieve the former, Arrow organizes data contiguously in 8-byte aligned buffers and uses separate bitmaps for nulls. For the latter, Arrow specifies a standard in-memory representation and provides a C-like data definition language (DDL) for data schema. Arrow uses separate metadata data structures to impose a table-like structure on collections of buffers. An example of this for the TPC-C ITEM table is shown in Figure 2.

Although Arrow’s design targets read-only analytical workloads, its alignment requirement and null bitmaps also benefit write-heavy workloads on fixed-length values. Problems emerge in Arrow’s support for variable-length values (e.g., VARCHARs). Arrow stores them as an array of offsets indexing into a contiguous byte buffer. As shown in Figure 3, the values’ lengths are the difference between their starting offset and the next value. This approach is not ideal for updates because of write amplification. Suppose a program update the value “JOE” to “ANNA” in Figure 3, it must copy the entire Values buffer to a larger one and update the Offsets array. The core of this issue is that a single storage format cannot easily achieve simultaneously (1) data locality and value adjacency, (2) constant-time random access, and (3) mutability [26], which Arrow trades off.

Some researchers have proposed hybrid storage schemes of row-store and column-store to get around this trade-off. Two notable examples are Peloton [25] and H2O [24]. Peloton uses an abstraction layer above the storage engine that transforms cold row-oriented data into a columnar format. In contrast, H2O uses an abstraction layer at the physical operator level and generates code for the optimal format on a per-query basis. Both solutions see an increase in software engineering complexity, and limited speedup in the OLTP scenario (shown in Section 6.1). We therefore argue that while it makes sense to optimize the data layout differently based on access patterns, column-stores are good enough for both OLTP and OLAP use cases.

![Figure 3: Variable Length Values in Arrow](image)

### Figure 3: Variable Length Values in Arrow

Arrow represents variable length values as an offsets array into an array of bytes, which trades off efficient mutability for read performance.

### 3 SYSTEM OVERVIEW

We now present DB-X’s architecture. We first discuss how the DBMS’s transaction engine is minimally intrusive to Arrow’s layout. We then describe how it organizes tables into blocks and its addressing scheme for tuples. Lastly, we describe the garbage collection and recovery components. For simplicity, we assume that data is fixed length; we discuss variable-length data in the next section.

#### 3.1 Transactions on a Column-Store

An essential requirement for our system is that transactional and versioning metadata be separate from the actual data; interleaving them complicates the mechanism for exposing Arrow data to external tools. As shown in Figure 4, our DBMS uses a multi-versed [27] delta-storage that stores the version chains as an extra Arrow column that is invisible to external readers, where the system stores physical pointers to the head of the version chain in the column (null if no version). The version chain is a newest-to-oldest ordering of delta records, which are physical before-images of the modified tuple attributes. This versioning approach enables the system to support Snapshot Isolation guarantees for concurrent transactions. The Data Table API serves as an abstraction layer to transactions, and will materialize the correct version of the tuple into the transaction. This early materialization is required for tuples with active versions, but can be elided for cold blocks, as we will discuss in Section 4. Version deltas are stored within the transaction contexts, external to Arrow storage. The DBMS assigns each transaction an undo buffer as an append-only row-store for deltas. To install an update, the transaction first reserves space for a delta record at the end of its buffer, copies the current image of the modified attributes into the record, appends the record onto the version chain, and finally updates the attribute in-place. The DBMS handles deletes and inserts analogously, but it updates a tuple’s allocation bitmap instead of its contents. This information is later passed to the garbage collector and logging component of our system, as we discuss in Section 3.3 and Section 3.4.
A transaction’s undo buffer needs to grow in size dynamically to support arbitrarily large write sets. The DBMS cannot move delta records, however, as the version chain points physically into the undo buffer. This rules out the use of a naive resizing algorithm that doubles the size of the buffer and copies the content. Instead, the system implements undo buffers as a linked list of fixed-sized segments (currently 4096 bytes) and incrementally adds new segments as needed.

The transaction engine assigns each transaction a timestamp pair (start, commit) that it generates from the same counter. When a transaction starts, commit is the same as start but with its sign bit flipped to denote that the transaction is uncommitted. Each update on the version chain stores the transaction’s commit timestamp. Readers reconstruct their respective versions by copying the latest version, and then traversing the version chain and applying before-images until it sees a timestamp less than its start. Because the system uses unsigned comparison for timestamps, uncommitted versions are never visible. The system disallows write–write conflicts to avoid cascading rollbacks.

When a transaction commits, the DBMS uses a small critical section to obtain a commit timestamp, update delta records’ commit timestamps, and add them to the log manager’s queue. For aborts, the system uses the transaction’s undo records to roll back the in-place updates. It cannot unlink records from the version chain, however, due to potential race conditions. If an active transaction copies a new version before the aborting transaction that modified it performs the rollback, then the reader can traverse the version chain with the undo record already unlinked and convince itself that the aborted version is indeed visible. A simple check that the version pointer does not change while the reader makes a copy is insufficient in this scenario as the DBMS can encounter an “A-B-A” problem between the two checks. To avoid this issue, the DBMS instead restores the correct version before “committing” the undo record by flipping the sign bit on the version’s timestamp. This record is redundant for any readers that obtained the correct copy and fixes the copy of readers with the aborted version.

Through this design, the transaction engine reasons only about delta records and the version column, and not the underlying physical storage. Maintaining the Arrow abstraction comes at the cost of data locality and forces readers to materialize early, which degrades range-scan performance. Fortunately, for many workloads, only a small fraction of the database is expected to be versioned at any point in time. As a result, the DBMS can ignore checking the version column for every tuple and scan large portions of the database in-place [45]. Blocks are natural units for tracking this information, and the DBMS uses block-level locks to coordinate access to blocks that are not versioned and not frequently updated (i.e., cold). We discuss this further in Section 4.

3.2 Blocks and Physiological Identifiers

Separating tuples and transactional metadata introduces another challenge: the system requires globally unique tuple identifiers to associate the two pieces that are not co-located. Physical identifiers (e.g., pointers) are ideal for performance, but work poorly with column-stores because a tuple does not physically exist at a single location. Logical identifiers, on the other hand, must be translated into a memory location through a lookup (e.g., hash table). This translation step is a severe bottleneck for OLTP workloads because it potentially doubles the number of memory accesses per tuple.

To solve this, our DBMS organizes storage in 1 MB blocks, and uses a physiological scheme to identify tuples. The DBMS arranges data in each block similar to PAX [23], where all attributes of a tuple are within the same block. Every block has a layout object that consists of (1) the number of slots within a block, (2) a list of attributes sizes, and (3) the location offset for each column from the head of the block. Each column and its bitmap are aligned at 8-byte boundaries. The system calculates layout once for a table when the application creates it and uses it to handle every block in the table.

Every tuple in the system is identified by a TupleSlot, which is a combination of (1) physical memory address of the block containing the tuple, and (2) its logical offset in the block. Combining these with the pre-calculated block layout, the DBMS computes the physical pointer to each attribute in constant time. To pack both values into a single 64-bit value, we use the C++11 keyword alignas to instruct the system to align all blocks at 1 MB boundaries within the address space of the process. A pointer to a block will then always
have its lower 20 bits be zero, which the system uses to store the offset. There are enough bits because there can never be more tuples than there are bytes in a block.

3.3 Garbage Collection
In our system, the garbage collector (GC) [40, 41, 51, 54] is responsible for pruning version chains and freeing any associated memory. The DBMS handles the recycling of deleted slots during the transformation to Arrow (Section 4.3). Because the DBMS stores versioning information within a transaction’s buffers, the GC only examines transaction objects.

At the start of each run, the GC first checks the transaction engine’s transactions table for the oldest active transaction’s start timestamp; changes from transactions committed before this timestamp are no longer visible and are safe for removal. The GC inspects all such transactions to compute the set of TupleSlots that have invisible records in their version chains, and then truncates them exactly once. This step avoids the quadratic operation of finding and unlinking each record. Deallocating objects is unsafe at this point, however, as concurrent transactions may be reading the unlinked records. To address this, GC obtains a timestamp from the transaction engine that represents the time of unlink. Any transaction starting after this time cannot possibly access the unlinked record; the records are safe for deallocation when the oldest running transaction in the system has a larger start timestamp than the unlink time. Our approach is similar to an epoch-protection mechanism [30], and is generalizable to ensure thread-safety for other aspects of the DBMS as well.

3.4 Logging and Recovery
Our system achieves durability through write-ahead logging and checkpoints [32, 44]. Logging in the DBMS is analogous to the GC process described above. Each transaction maintains a redo buffer for physical after-images. Each transaction writes changes to its redo buffer in the order that they occur. At commit time, the transaction appends a commit record to its redo buffer and adds itself to the DBMS’s flush queue. The log manager asynchronously serializes the changes from these buffers into an on-disk format before flushing to persistent storage. The system relies on an implicit ordering of the records according to their respective transaction’s commit timestamp instead of log sequence numbers.

Similar to undo buffers, these redo buffers consist of buffer segments drawn from a global object pool. As an optimization, the system flushes out redo records incrementally before the transaction commits. In the case of an abort or crash, the transaction’s commit record is not written, and the recovery process ignores it. In our implementation, we limit the redo buffer to a single buffer segment and observe moderate speedup due to better cache performance from more reuse.

The rest of the system considers a transaction as committed as soon as its commit record is added to the flush queue. All future operations on the transaction’s write-set are speculative until its log records are on disk. The system assigns a callback to each committed transaction for the log manager to notify when the transaction is persistent. The DBMS refrains from sending a transaction’s result to the client until the log manager invokes its callback. With this scheme, a transaction’s modifications that speculatively accessed or updated the write-set of another transaction are not published until the log manager processes their commit record. We implement callbacks by embedding a function pointer in the commit record; when the log manager writes the commit record, it adds that pointer to a list of callbacks to invoke after the next fsync. The DBMS requires read-only transactions also to obtain a commit record to guard against the anomaly shown above. The log manager can skip writing this record to disk after processing the callback.

4 BLOCK TRANSFORMATION
As discussed in Section 2.2, the primary obstacle to running transactions on Arrow is write amplification. Our system uses a relaxed Arrow format to achieve good write performance and then uses a lightweight transformation step to put a block into the full Arrow format once it is cold. In this section, we describe this modified format, introduce a mechanism to detect cold blocks and present our algorithm for transforming them to the full Arrow format.
4.1 Relaxed Columnar Format

Typical OLTP workloads modify only a small portion of a database at any given time, while the other parts of the database are mostly accessed by read-only queries [39]. Therefore, for the hot portion, we can trade off read speed for write performance at only a small impact on overall read performance of the DBMS. To achieve this, we modify the Arrow format for update performance in the hot portion. We detail these changes in this subsection.

There are two sources of write amplification in Arrow: (1) it disallows gaps in a column, and (2) it stores variable-length values consecutively in a single buffer. Our relaxed format adds a validity bitmap in the block header and additional metadata for each variable-length value in the system to overcome them. As shown in Figure 6, within a VarlenEntry field, the system maintains 4 bytes for size and 8 bytes for a pointer to the underlying value. Each VarlenEntry is padded to 16 bytes for alignment reasons, and the additional 4 bytes stores a prefix of the value. If a value is shorter than 12 bytes, the system stores it entirely within the object, writing into the pointer. Transactions only access the VarlenEntry instead of Arrow storage directly. Relaxing adherence to Arrow’s format allows the system to only write updates to VarlenEntry, turning a variable-length update into a constant-time fixed-length one, as shown in Figure 7.

Any readers accessing Arrow storage will be oblivious to the update in VarlenEntry. The system adds a status flag and counter in block headers to coordinate access. For a cold block, the DBMS sets its status flag to frozen, and readers add one to the counter when starting a scan and subtract one when finished. When a transaction updates a cold block, it first sets that block’s status flag to hot, forcing any future readers to materialize instead of reading in-place. It then spins on the counter and waits for lingering readers to leave the block before proceeding with the update. There is no transformation process required for a transaction to modify a cold block because our relaxed format is a super-set of the original Arrow format. Once a block is hot, it remains so until a background process transforms the block back to full Arrow compliance. We will discuss this process next.

4.2 Identifying Cold Blocks

The DBMS maintains access statistics about each block to determine if it is cooling down. Collecting them as transactions operate on the database adds overhead to the critical path [31, 34], which is unacceptable for OLTP workloads. Our system trades the quality of such statistics for better scalability and performance, and then accounts for potential mistakes from this in our transformation algorithm.

A simple heuristic is to mark blocks that have not been modified for some threshold time as cold for each table. Instead of measuring this on the transaction’s critical path, our system takes advantage of the GC’s scan through undo records (Section 3.3). From each undo record, the system obtains the modification type (i.e., delete, insert, update) and the corresponding TupleSlot. Time measurement, however, is difficult because the system cannot measure how much time has elapsed between the modification and invocation of the GC. The DBMS instead approximates this by using the time of each GC invocation as the time for the modifications processed in said GC run. If transactions have a lifetime shorter than the frequency of GC (~10 ms), this approximated time is never earlier than the actual modification and is late by at most one GC period. This “GC epoch” is a good enough substitute for an exact time for short-lived OLTP transactions [49]. Once the system identifies a cold block, it adds the block to a queue for background processing. The user can modify the threshold time value based on how aggressively they want the system to transform blocks. The optimal value is workload-dependent. A threshold that is too low reduces transactional performance because of wasted resources from frequent transformations. But setting it too high reduces the efficiency of readers. We leave the study of more sophisticated policies for future work.

Under this scheme, one thread may identify a block as cold by mistake when another thread is updating it due to delays in access observation. The DBMS reduces the impact of this by ensuring that the transformation algorithm is fast and lightweight. There are two failure cases: (1) a user transaction aborts due to conflicts with the transformation process or (2) the user transaction stalls. There is no way to safely eliminate both cases. Our solution is a two-phase algorithm. The first phase is transactional and operates on a microsecond scale, minimizing the possibility of aborts. The second
phase eventually takes a block-level lock for a short critical section, but yields to user transactions whenever possible.

4.3 Transformation Algorithm

Once the system identifies cooling blocks, it performs a transformation pass to prepare the block for Arrow readers. As mentioned in Section 4.1, the DBMS first needs to compact each block to eliminate any gaps, and then copy variable-length values into a new contiguous buffer. There are three approaches to ensure safety in the face of concurrent user transactions: (1) copying the block, (2) performing operations transactionally, or (3) taking a block-level lock. None of these is ideal. The first approach is expensive, especially when most of the block data is not changed. The second adds additional overhead and results in user transaction aborts. The third stalls user transactions and limits concurrency in the typical case even without transformation. As shown in Figure 8, our system uses a hybrid two-phase approach that combines transactional tuple movement and raw operations under exclusive access. We now discuss this in detail.

Phase #1: Compaction: The access observer identifies a compaction group as a collection of blocks with the same layout to transform. Within a group, the system uses tuples from less-than-full blocks to fill gaps in others and recycle blocks when they become empty. The DBMS uses one transaction per group in this phase to perform all operations.

The DBMS scans the allocation bitmap of every block to identify empty slots that it needs to fill. At the end of this phase, tuples in the compaction group should be "logically contiguous","i.e., a compaction group consisting of $t$ tuples with $b$ blocks with each block having $s$ slots should now have $\left\lceil \frac{t}{s} \right\rceil$ many blocks completely filled, one block filled from beginning to the $(t \mod s)$-th slot, and all remaining blocks empty. To achieve this, the system transactionally shuffles tuples between blocks (delete followed by an insert). This is potentially expensive if the transaction needs to update indexes. The algorithm, therefore, must minimize the number of such delete-insert pairs. We do this in two steps:

1. Select a block set $F$ to be the $\left\lceil \frac{t}{s} \right\rceil$ blocks that are filled in the final state. Also select a block $p$ to be partially filled and hold $t \mod s$ tuples. The rest, $E$, are left empty.
2. Fill all gaps within $F \cup \{p\}$ using tuples from $E \cup \{p\}$, and reorder tuples within $p$ to make them contiguous.

Let $Gap_f$ be the set of unfilled slots in a block $f$, $Gap'_f$ be the set of unfilled slots in the first $t \mod s$ slots in a block $f$, $Filled_f$ be the set of filled slots in $f$, and $Filled'_f$ be the set of filled slots not in the first $t \mod s$ slots in $f$. Then, for any valid selection of $F$, $p$, and $E$,

$$|Gap'_p| + \sum_{f \in F}|Gap_f| = |Filled'_p| + \sum_{e \in E}|Filled_e|$$

because there are only $t$ tuples in total. Therefore, given $F$, $p$, and $E$, an optimal movement is any one-to-one movement between $Filled'_p \cup \bigcup_{e \in E} Filled_e$ and $Gap'_p \cup \bigcup_{f \in F} Gap_f$. The problem is now reduced to finding such $F$, $p$, and $E$.

1. Scan each block’s allocation bitmap for empty slots.
2. Sort the blocks by $\#$ of empty slots in ascending order.
3. Pick out the first $\left\lceil \frac{t}{s} \right\rceil$ blocks to be $F$.
4. Pick an arbitrary block as $p$ and the rest as $E$.

This choice bounds our algorithm to within $(t \mod s)$ of the optimal number of movements, which we use as an approximate solution. Every gap in $F$ needs to be filled with one movement, and our selection of $F$ results in fewer movements than any other choice. In the worst case, the chosen $p$ is empty in the first $(t \mod s)$ slots, and the optimal one is filled, resulting in at most $(t \mod s)$ movements of difference. The algorithm needs to additionally find the best value of $p$ by trying every block for the optimal solution. In practice, as described in Section 6, we observe only marginal reduction in movements, which does not always justify the extra step.

Phase #2: Gathering: The system now moves variable-length values into contiguous buffers as Arrow requires. To do so safely, we present a novel scheme of multi-stage locking that relies on the GC to guard against races without requiring other operations to obtain the lock.

We extend the block status flag with two additional values: cooling and freezing. The former indicates that the transformation thread intends to lock, while the latter serves as an exclusive lock that blocks user transactions. User transactions are allowed to preempt the cooling status by compare-and-swapping the flag back to hot. When the transformation algorithm has finished compaction, it sets the flag to cooling and scans through the block again to check for any version pointers, which indicate concurrent modification. If there are no versions, and another thread has not changed the block’s cooling status, then the transformation algorithm can change
the block’s status to freezing for the exclusive lock. The cooling flag acts as a sentinel value that detects any concurrent modifications that the single-pass scan missed.

This scheme of access coordination introduces a race, as shown in Figure 9. A thread could have finished checking the status flag and was scheduled out. Meanwhile, the transformation algorithm runs and sets the block to freezing. When the thread wakes up again, it proceeds to update, which is unsafe. The core issue here is that the block status check and the update form a critical section but cannot be atomic without a latch. Adding a latch for every operation is clearly undesirable. To address this, the system relies on its visibility guarantees. Recall from Section 3.3 that GC does not prune any versions that are still visible to running transactions. If the algorithm sets the status flag to cooling after shuffling, but before the compaction transaction commits, the only transactions that could incur the race in Figure 9 must overlap with the compaction transaction. Therefore, as long as such transactions are alive, the garbage collector cannot unlink records of the compaction transaction. The algorithm can commit the compaction transaction and wait for the block to reappear in the processing queue for transformation. The status flag of cooling guards against any transactions modifying the block after the compaction transaction committed. If the transformation algorithm scans the version pointer column and finds no active version, then any transaction that was active at the same time as the compaction transaction must have ended, and it is safe to change the flag into freezing.

After the transformation algorithm obtains exclusive access to the block, it scans each variable-length column and performs gathering in-place. In the same pass, it also computes metadata information, such as null count, for Arrow’s metadata. When the process is complete, the system can safely mark the block as frozen and allow access from in-place readers. Throughout the process, although transactional writes are not allowed, reads can still proceed regardless of the block status. The gathering phase changes only the physical location of values and not the logical content of the table. Because a write to any aligned 8-byte address is atomic on a modern architecture [2], reads can never be unsafe as the DBMS aligns all attributes within a block.

**4.4 Additional Considerations**

Given that we have presented our algorithm for transforming cold blocks into Arrow, we now demonstrate its flexibility by discussing alternative formats for our transformation algorithm with the example of dictionary compression. We also give a more detailed description of memory management in the algorithm and scaling for larger workloads.

**Alternative Formats:** It is possible to change the implementation of the gathering phase to emit a different format, although the algorithm performs best if the target format is close to our transactional representation. To illustrate this, we implement an alternative columnar format with the same kind of dictionary compression [36] found in formats like Parquet [9] and ORC [8]. Instead of building a contiguous variable-length buffer, the system creates a dictionary and an array of dictionary codes. Much of the algorithm remains the same; the only difference is that within the critical section of the gathering phase, the algorithm now scans through the block twice. On the first scan, the algorithm builds a sorted set of values for use as a dictionary. On the second scan, the algorithm replaces pointers within VarLenEntries to point to the corresponding dictionary word and builds the array of dictionary codes. Although the steps for transforming data into this format is mostly the same as Arrow, supporting dictionary compression is an order of magnitude more expensive than a simple variable-length gather. We discuss the effect of this procedure in Section 6.

**Memory Management:** Since the algorithm never blocks readers, the system cannot deallocate memory immediately after the transformation process as its content can be visible to concurrent transactions. In the compaction phase, because writes are transactional, the GC can handle memory management. The only caveat here is that when moving tuples, the system makes a copy of any variable-length value rather than merely copying the pointer. This value copy is necessary because the GC does not reason about the transfer of ownership of variable-length values between two versions and will deallocate them after seeing the deleted tuple. We do not observe this to be a bottleneck. In the gathering phase, we extend our GC to accept arbitrary actions associated with a timestamp in the form of a callback, which it promises to invoke after the oldest alive transaction in the system is started after the given timestamp. As discussed in Section 3.3, this is similar to an epoch protection framework [30]. The system registers an action that reclaims memory for this gathering phase with a timestamp that the compaction thread takes after it completes all of its in-place modifications. This delayed reclamation ensures no transaction reads freed memory.

**Scaling Transformation and GC:** For high-throughput workloads (i.e., millions of transactions per second), a single
GC or transformation thread will not be able to keep up. In this scenario, there is a natural partitioning of these tasks to enable parallelization. For GC, multiple threads can partition work based on transactions: when a transaction finishes, the DBMS assigns its clean-up operations to a random GC thread or according to some other load-balancing scheme. Although the pruning of version chain itself is thread-safe, multiple GC threads pruning the same version chain can do so at a different pace, and deallocate parts of the chain in the other’s path. This concurrency is also wasteful as a version chain only needs to be pruned once every GC invocation. Therefore, in our system, GC threads mark the head of a version chain when pruning as a signal for others to back off. To parallelize transformation, the DBMS can partition threads on a compaction group level. No changes to the transformation process are required, as compaction groups are isolated units of work that never interfere with each other. We use these two techniques in Section 6.1 on high worker thread counts.

5 EXTERNAL ACCESS

Now that we have described how the DBMS converts data blocks into the Arrow format, we discuss how to expose access to external applications. We argue that native Arrow storage can benefit data pipeline builders, regardless of whether they take a "data ships to compute" approach or the opposite. In this section, we present three strategies for enabling applications to access the DBMS’s native Arrow storage to speed up analytical pipelines. We discuss these alternatives in the order of the engineering effort required to change an existing system (from easiest to hardest).

Improved Wire Protocol: There are still good reasons for applications to interact with the DBMS exclusively through a SQL interface (e.g., developer familiarity, existing ecosystems). As [46] pointed out, adopting columnar batches instead of rows in the wire format can increase performance substantially. Arrow data organized by block is naturally amenable to such wire protocols. However, replacing the wire protocol with Arrow does not achieve the full potential of the speed-up from our storage scheme. This is because the DBMS still serializes data into its wire format, and the client must parse the data. These two steps are not necessary, as the client may want the Arrow format to work with anyway. The DBMS should be able to send stored data directly onto the wire and land them in the client program’s workspace, without writing to or reading from a wire format. For this purpose, Arrow provides a native RPC framework based on gRPC called Flight [4] that avoids serialization when transmitting data, through low-level extensions to gRPC’s internal memory management. Flight enables our DBMS to send a large amount of cold data to the client in a zero-copy fashion. When most data is cold, Flight transmits data significantly faster than real-world DBMS protocols. To handle hot data, the system needs to start a transaction and materialize a snapshot of the block before invoking Flight. Although this is expensive, we observe that Flight still performs no worse than state-of-the-art protocols [46].

Shipping Data with RDMA: To achieve further speed-up, one can consider Remote Direct Memory Access (RDMA) technologies. RDMA bypasses the OS’s network stack and permits high-throughput, low-latency transfer of data. Either the client or the DBMS can RDMA into the other’s memory, and we sketch both scenarios.

The DBMS server can write data to the client's memory through RDMA (i.e., client-side RDMA). Under this scheme, the server retains control over access to its data, and no modification to the concurrency control scheme is required. Aside from increased data export speed, another benefit of using a client-side approach is that the client’s CPU is idle during RDMA operations. Thus, the client can start working on partially available data, effectively pipelining data processing. To achieve this, the DBMS can send messages for partial availability of data periodically to communicate whether it has already written some given chunk of data. This approach reduces the network traffic close to its theoretical lower-bound but still requires additional processing power on the server to handle and service the request.

For workloads that require no computation on the server-side, allowing clients to read the DBMS’s memory (i.e., server-side RDMA) bypasses the DBMS CPU when satisfying bulk export requests. This approach is beneficial to an OLTP DBMS because the system no longer needs to divide its CPU resources between serving transactional workloads and bulk export jobs. Achieving server-side RDMA, however, requires significant changes to the DBMS. Firstly, the DBMS loses control over access to its data as the client bypasses its CPU to get data out, which makes it difficult to lock the Arrow block and guard against updates into them. If the system waits for a separate client completion message, the round-trip time introduces latency to any updating transactions. To avoid this, the DBMS has to implement some form of a lease system to invalidate readers for transactional workloads that have stricter latency requirements. In addition to introducing complexity in the concurrency control protocol of the DBMS, this approach also requires that the client knows beforehand the address of the blocks it needs to access, which requires a separate RPC service or some external directory maintained by the DBMS to convey this information. We envision these challenges to be non-trivial in achieving server-side RDMA.

Shipping Computation to Data: Server- and client-side RDMA allow external tools to access data with extremely low data export overhead. The problem, however, is that
6 EVALUATION

We next present an experimental analysis of our system. We implemented our storage engine in the DB-X DBMS [10]. We performed our evaluation on a machine with a dual-socket 10-core Intel Xeon E5-2630v4 CPU, 128 GB of DRAM, and a 500 GB Samsung 970 EVO Plus SSD. For each experiment, we use numactl to interleave memory allocation on available NUMA regions. All transactions execute as JIT-compiled stored procedures with logging enabled. We run each experiment ten times and report the average.

We first evaluate our OLTP performance and quantify performance interference from the transformation process. We then provide a set of micro-benchmarks to study the performance characteristics of the transformation algorithm. Finally, we compare data export performance in our system against current approaches.

6.1 OLTP Performance

We measure the DBMS’s OLTP performance to demonstrate the viability of our storage architecture and that our transformation process is lightweight. We use TPC-C [50] in this experiment with one warehouse per client. DB-X uses the OpenBw-Tree for all indexes [52]. All transactions are submitted open-loop. We report the DBMS’s throughput and the state of blocks at the end of each run. We use taskset to limit the number of available CPU cores as the sum of worker, logging, and GC threads. To account for the additional resources required by transformation, the system has one logging thread, one transformation thread, and one GC thread for every 8 worker threads. We deploy the DBMS with three transformation configurations: (1) disabled, (2) variable-length gather, and (3) dictionary compression. For trials with DB-X’s block transformation enabled, we use an aggressive threshold time of 10 ms and only target the tables that generate cold data: ORDER, ORDER_LINE, HISTORY, and ITEM. In each run, the compactor attempts to process all blocks from the same table in the same group.

The results in Figure 10a show that the DBMS achieves good scalability and incurs little overhead from the transformation process (at most 10%). The interference is more prominent as the number of workers increases due to more work for the transformation thread. At 20 worker threads, the DBMS’s scaling degrades. This decrease is because our machine only has 20 physical CPU cores, and threads no longer have dedicated cores. The problem of threads swapping is worse with the additional transformation thread. Dictionary compression has a larger performance impact because it is computationally more intensive.

In Figure 10b, we report the percentage of blocks in the cooling and frozen state at the end of each run. We omit results for the ITEM table because it is a read-only table, and its
blocks are always frozen. These results show that the DBMS achieves nearly complete coverage, but starts to lag for a higher number of worker threads in the case of dictionary compression. This is because dictionary compression is an order of magnitude slower than simple gathering, as we will show in Section 6.2. Per our design goal, the transformation process yields resources to user transactions in this situation and does not result in a significant drop in transactional throughput. As discussed in Section 4.4, one can simply parallelize the transformation process by partitioning based on block address when the transformation thread is lagging behind. To achieve full transformation, we ran the benchmark with one additional transformation thread, and observe an additional 15% reduction in transactional throughput.

**Row vs. Column:** To investigate the impact of using a column-store with an OLTP workload, we run a synthetic micro-benchmark that compares our storage architecture against a row-store. We simulate a row-store by declaring a single, large column that stores all of a tuples’ attributes contiguously. Each attribute is an 8-byte fixed-length integer. We fix the number of threads executing queries and scale up the number of attributes per tuple from one to 64. We run a workload comprised of either (1) insert or (2) update queries (10 million each) and report the throughput. We ignore the overhead of maintaining indexes in our measurements as this cost is the same for both storage models.

The results in Figure 11 show that the two approaches do not exhibit a large performance difference. Even for the insert workload, where raw memory copy speed matters more, the gap never exceeds 40%. For the update workload, a column-store outperforms row stores when the number of attributes copied is small due to a smaller memory footprint. As the number of attributes grows, the row-store becomes slightly faster than the column-store, but with a much lower difference due to fixed-cost of maintaining versions. These results indicate that it is unlikely that an optimized row-store will provide a compelling performance improvement in an in-memory setting over a column-store.

### 6.2 Transformation to Arrow

We next evaluate our transformation algorithm and analyze the effectiveness of each sub-component. We use micro-benchmarks to demonstrate the DBMS’s performance when migrating blocks from the relaxed Arrow format to their canonical form. Each trial of this experiment simulates one transformation pass in a system to process data that has become cold since the last invocation.

The database used has a single table of ~16M tuples with two columns: (1) a 8-byte fixed-length column and (2) a variable-length column with values between 12–24 bytes. Under this layout, each block holds ~32K tuples. We also ran these same experiments on a table with more columns or larger varlens, but did not observe a major difference in trends. An initial transaction populates the table, and inserts empty tuples at random to simulate deletion.

**Throughput:** Recall from Section 4.3 that our transformation algorithm is a hybrid two-phase implementation. For this experiment, we assume there is no concurrent transactions and run the two phases consecutively without waiting. We benchmark both versions of our algorithm: (1) gathering variable-length values and copying them into a contiguous buffer (Hybrid-Gather) and (2) using dictionary compression on variable-length values (Hybrid-Compress). We also implemented two baseline approaches for comparison purposes: (1) read a snapshot of the block in a transaction and copy into a Arrow buffer using the Arrow API (Snapshot) and (2) perform the entire transformation in-place in a transaction (In-Place). We use each algorithm to process 500 blocks (1 MB each) and vary the percentage of empty slots in each run.

The results in Figure 12a show that Hybrid-Gather outperforms the alternatives, achieving sub-millisecond performance when blocks are mostly full (i.e., the number of empty slots is less than 5%). Performance drops as emptiness increases since the DBMS needs to move more tuples. Such movement is an order of magnitude more expensive than Snapshot due to the random memory access pattern. As the blocks become more than half empty, the number of tuples that the DBMS moves decreases, and thus the throughput bounces back. In-Place performs poorly because of the version maintenance overhead. Hybrid-Compress is also an order of magnitude slower than Hybrid-Gather and Snapshot because building the dictionary is computationally expensive.

To understand the behavior of these algorithms better, we provide a breakdown of each phase in Figure 12b. We present the graph in log-scale due to the large range of performance changes. When the number of empty slots in a block is low (i.e., <5%), the DBMS completes the compaction phase in microseconds because it is reduced to a bitmap scan. In this best-case scenario, the cost of variable-length gather dominates. The performance of the compaction phase drops as the
Figure 12: Transformation Throughput  – Measurements of the DBMS’s transformation algorithm throughput and movement cost when migrating blocks from the relaxed format to the canonical Arrow format.

Figure 13: Write Amplification – Total write amplification is number of tuple movement times a constant for each table, determined by the layout and number of indexes on that table.

number of empty slots increases and starts to dominate the cost of Hybrid-Gather at 5% empty. Dictionary compression is always the bottleneck in Hybrid-Compress.

We next measure how the column types affect the performance of the four transformation algorithms. We run the same micro-benchmark but make the database’s columns either all fixed-length (Figure 12c) or variable-length (Figure 12d). These results show that the general performance trend does not change based on the data layouts. Snapshot performs better when there are more variable-length values in a block because it does not update nor copy the metadata associated with each value. Given this, we show only 50% variable-length columns results for other experiments.

Write Amplification: The previous throughput results show that Snapshot outperforms our hybrid algorithm when blocks are ∼20% empty. These measurements, however, fail to capture the overhead of updating the index entries for any tuples that change their physical location in memory [53]. The effect of this write amplification depends on the type and number of indexes on the table, but the cost for each tuple movement is constant. Therefore, it suffices to measure the total number of tuple movements that trigger index updates. The Snapshot algorithm always moves every tuple in the compacted blocks. We compare its performance against the approximate and optimal algorithms from Section 4.3.

As shown in Figure 13, our algorithm is several orders of magnitudes more efficient than Snapshot in the best case, and twice as efficient when the blocks are half empty. The gap narrows as the number of empty slots per block increases. There is little difference in the result of the approximate algorithm versus the optimal algorithm, validating our decision to use the approximate algorithm to save one pass through the blocks during transformation.

Sensitivity on Compaction Group Size: For the next experiment, we evaluate the effect of the compaction group size on performance. The DBMS groups blocks together for compaction and then frees any empty blocks. This grouping enables the DBMS to reclaim memory from deleted slots. The size of each compaction group is a tunable parameter in the system. Larger group sizes result in the DBMS freeing more blocks but increases the size of the write-set for compacting transactions, which increases the likelihood that they will abort due to a conflict. We use the same setup from the previous experiment, performing a single transformation pass through 500 blocks while varying group sizes.

Figure 14a shows the number of freed blocks with different compaction group sizes. When blocks are only 1% empty, larger group sizes are required to release any memory. As the vacancy rate of blocks increases, smaller group sizes perform increasingly well, and larger values bring only marginal benefit. We show the cost of larger transactions as the size...
of their write-sets in Figure 14b. These results indicate that larger group sizes increase transactions’ write-set size, but yield a diminishing return on the number of blocks freed. The ideal fixed group size is between 10 and 50, which balances good memory reclamation and relatively small write-sets. To achieve the best possible performance, the DBMS should employ an intelligent policy that dynamically forms groups of different sizes based on the blocks it is compacting. We defer this problem as future work.

6.3 Data Export

For this last experiment, we evaluate the DBMS’s ability to export data to an external tool. We compare four of the data export methods from Section 5: (1) client-side RDMA, (2) the Arrow Flight RPC, (3) vectorized wire protocol from [46], and (4) row-based PostgreSQL wire protocol. We implement (3) and (4) in DB-X according to their specifications. Because RDMA requires specialized hardware, we run these experiments on two different servers with eight-core Intel Xeon D-1548 CPUs, 64 GB of DRAM, and a dual-port Mellanox ConnectX-3 10 GB NIC (PCIe v3.0, eight lanes).

We use the TPC-C ORDER_LINE table with 6000 blocks (∼7 GB total size, including variable-length values) on the server. On the client-side, we run a Python application, and report the time taken between sending a request for data and the beginning of execution of analysis. For each export method, we write a corresponding client-side protocol in C++, and use Arrow’s cross-language API [21] to expose it to the Python program in a zero-copy fashion. The client runs a TensorFlow program that passes all data through a single linear unit, as the performance of this component is irrelevant to our system. We vary the percentage of blocks frozen in the DBMS to study the effect of concurrent transactions on export speed. Recall that if a block is not frozen, the DBMS must materialize it transactionally before sending.

The results in Figure 15 shows that DB-X exports data orders-of-magnitude faster than the base-line implementations. When all blocks are frozen, RDMA saturates the available network bandwidth, and Arrow Flight can utilize up to 80% of the available network bandwidth. When the system has to materialize every block, the performance of Arrow Flight drops to be equivalent to the vectorized wire protocol. RDMA performs slightly worse than Arrow Flight with a large number of hot blocks, because Flight has the materialized block in its CPU cache, whereas the NIC bypasses this cache when sending data. Both the PostgreSQL wire protocol and the vectorized protocol do not benefit much from eliding transactions on cold, read-only data. Hence, this experiment indicates that the main bottleneck of the data export process in a DBMS is this serialization/deserialization step. Using Arrow as a drop-in replacement wire protocol in the current architecture does not achieve its full potential. Instead, storing data in a common format reduces this cost and boosts data export performance.

7 RELATED WORK

We presented our system for high transaction throughput on a storage format optimized for analytics, and now discuss three key facets of related work. In particular, we provide an overview of other universal storage formats, OLTP systems on column-stores, and optimizations for DBMS data export.

Universal Storage Formats: The idea of building a data processing system on top of universal storage formats has been explored in other implementations. Systems such as
Apache Hive [5], Apache Impala [6], Dremio [12], and OmniSci [17] support data ingestion from universal storage formats to lower the data transformation cost. These are analytical systems that ingest data already generated in the format from an OLTP system, whereas our DBMS natively generates data in the storage format as a data source for these systems. Among the storage formats other than Arrow, Apache ORC [8] is the most similar to our DBMS in its support for ACID transactions. ORC is a self-describing type-aware columnar file format designed for Hadoop. It divides data into stripes that are similar to our concept of blocks. Related to ORC is Databricks’ Delta Lake engine [11] that acts as a ACID transactional engine on top of cloud storage. These solutions are different from our system because they are intended for incremental maintenance of read-only data sets and not high-throughput OLTP. Transactions in these systems are infrequent, not performance critical, and have large write-sets. Apache Kudu [7] is an analytical system that is similar in architecture to our system, and integrates natively with the Hadoop ecosystem. However, transactional semantics in Kudu is restricted to single-table updates or multi-table scans and does not support general-purpose SQL transactions [20].

OLTP on Column-Stores: Since Ailamaki et al. first introduced the PAX model [23], the community has implemented several systems that supports transactional workloads on column-stores. PAX stores data in columnar format, but keeps all attributes of a single tuple within a disk page to reduce I/O cost for single tuple accesses. HYRISE [35] improved upon this scheme by vertically partitioning each table based on access patterns. SAP HANA [48] implemented migration from row-store to column-store in addition to partitioning. MemSQL’s SingleStore [14] improved their transactional performance on columnar data by adding hash indexes, sub-segment access, and fine-grain locking. Writes are absorbed by an in-memory skip list, while deletes are marked directly in the columnar data. Background optimization routines are responsible for eventually flushing and compacting the results of these operations. Peloton [25] introduced the logical tile abstraction to enable migration without a need for disparate execution engines. Our system is most similar to HyPer [34, 37, 39, 45] and L-Store [47]. HyPer runs exclusively on columnar format and guarantees ACID properties through a multi-versioned delta-based concurrency control mechanism similar to our system; it also implements a compression for cold data chunks by instrumenting the OS for access observation. Our system is different from HyPer in that it is built around the open-source Arrow format and provides native access to it. HyPer’s hot-cold transformation also assumes heavy-weight compression operations, whereas our transformation process is designed to be fast and computationally inexpensive, allowing more fluid changes in a block’s state. L-Store also leverages the hot-cold separation of tuple access to allow updates to be written to tail-pages instead of more expensive cold storage. In contrast to our system, L-Store achieves this through tracing data lineage and an append-only storage within the table itself.

Optimized DBMS Networking: There has been considerable work on using RDMA to speed up DBMS workloads. IBM’s DB2 pureScale [13] and Oracle Real Application Cluster (RAC) [18] use RDMA to exchange database pages and achieve shared-storage between nodes. Microsoft Analytic’s Platform Systems [15] and Microsoft SQL Server with SMB Direct [16] utilize RDMA to bring data from a separate storage layer to the execution layer. Binnig et al. [28] and Dragojević et al. [33] proposed using RDMA for distributed transaction processing [28]. Li et al. [42] proposed a method for using RDMA to speed up analytics with remote memory. All of these work attempts to improve the performance of distributed DBMS through using RDMA within the cluster. Our paper looks to improve efficiency across the data processing pipeline through better interoperability with external tools.

Raasveldt and Mühleisen demonstrated that transferring large amounts of data from the DBMS to a client is expensive over existing wire row-oriented protocols (e.g., JDBC/ODBC) [46]. They then explored how to improve server-side result set serialization to increase transmission performance. A similar technique was proposed in the olap4j extension for JDBC in the early 2000s [1]. These works, however, optimize the DBMS’s network layer, whereas this paper tackles the challenge more broadly through changes in both the network layer and the underlying DBMS storage.

8 CONCLUSION

We presented DB-X’s Arrow-native storage architecture for in-memory OLTP workloads. The system implements a multi-versionsed, delta-store transactional engine capable of directly emitting Arrow data to external analytical tools. To ensure OLTP performance, the system allows transactions to work with a relaxed Arrow format and employs a lightweight in-memory transformation process to convert cold data into full Arrow in milliseconds. This allows the DBMS to support bulk data export to external analytical tools at zero serialization overhead. We evaluated our implementation, and show good OLTP performance while achieving orders-of-magnitudes faster data export compared to current approaches.

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