Polynesia: Enabling Effective Hybrid Transactional/Analytical Databases with Specialized Hardware/Software Co-Design

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ABSTRACT
An exponential growth in data volume, combined with increasing demand for real-time analysis (i.e., using the most recent data), has resulted in the emergence of database systems that concurrently support transactions and data analytics. These hybrid transactional and analytical processing (HTAP) database systems can support real-time data analysis without the high costs of synchronizing across separate single-purpose databases. Unfortunately, for many applications that perform a high rate of data updates, state-of-the-art HTAP systems incur significant drops in transactional (up to 74.6%) and/or analytical (up to 49.8%) throughput compared to performing only transactions or only analytics in isolation, due to (1) data movement between the CPU and memory, (2) data update propagation, and (3) consistency costs.

We propose Polynesia, a hardware–software co-designed system for in-memory HTAP databases. Polynesia (1) divides the HTAP system into transactional and analytical processing islands, (2) implements custom algorithms and hardware to reduce the costs of update propagation and consistency, and (3) exploits processing-in-memory for the analytical islands to alleviate data movement. Our evaluation shows that Polynesia outperforms three state-of-the-art HTAP systems, with average transactional/analytical throughput improvements of 1.70X/3.74X, and reduces energy consumption by 48% over the prior lowest-energy system.

1. INTRODUCTION
Data analytics has become popular due to the exponential growth in data generated annually [3]. Many application domains have a critical need to perform real-time data analysis, and make use of hybrid transactional and analytical processing (HTAP) [1, 26, 66]. An HTAP database management system (DBMS) is a single-DBMS solution that supports both transactional and analytical workloads [1, 11, 45, 51, 59]. An ideal HTAP system should have three properties [51]. First, it should ensure that both transactional and analytical workloads benefit from their own workload-specific optimizations (e.g., algorithms, data structures). Second, it should guarantee data freshness (i.e., access to the most recent version of data) for analytical workloads while ensuring that both transactional and analytical workloads have a consistent view of data across the system. Third, it should ensure that the latency and throughput of the transactional and analytical workloads are the same as if they were run in isolation.

We extensively study state-of-the-art HTAP systems (Section 3) and observe two key problems that prevent them from achieving all three properties of an ideal HTAP system. First, these systems experience a drastic reduction in transactional throughput (up to 74.6%) and analytical throughput (up to 49.8%) compared to when we run each in isolation. This is because the mechanisms used to provide data freshness and consistency induce a significant amount of data movement between the CPU cores and main memory. Second, HTAP systems often fail to provide effective performance isolation. These systems suffer from severe performance interference because of the high resource contention between transactional workloads and analytical workloads. Our goal in this work is to develop an HTAP system that overcomes these problems while achieving all three of the desired HTAP properties, with new architectural techniques.

We propose a novel system for in-memory HTAP databases called Polynesia. The key insight behind Polynesia is to meet all three desired HTAP properties by partitioning the computing resources into two isolated processing islands: transactional islands and analytical islands. Each island consists of (1) a replica of data for a specific workload, (2) an optimized execution engine (i.e., the software that executes queries), and (3) a set of hardware resources (e.g., computation units, memory) that cater to the execution engine and its memory access patterns. We co-design new software and specialized hardware support for the islands. This includes algorithms and accelerators for update propagation (Section 5) and data consistency (Section 6), and a new analytical engine (Section 7) that includes software to handle data placement and runtime task scheduling, along with in-memory hardware for task execution.

In our evaluations (Section 9), we show the benefits of each component of Polynesia, and compare its end-to-end performance and energy usage to three state-of-the-art HTAP systems. Polynesia outperforms all three, with higher transactional (2.20X/1.15X/1.94X; mean of 1.70X) and analytical (3.78X/5.04X/2.76X; mean of 3.74X) throughput. Polynesia consumes less energy than all three as well, 48% lower than the prior lowest-energy system. Overall, we conclude that Polynesia efficiently provides high-throughput real-time analysis, by meeting all three desired HTAP properties.

2. HTAP BACKGROUND
To enable real-time analysis, we need a DBMS that allows us to run analytics on fresh data ingested by transactional engines. Several works from industry (e.g., [23, 27, 44, 45, 46]) and academia (e.g., [8, 10, 11, 29, 38, 41, 48, 51, 54, 64]) attempt to address issues with data freshness by proposing various techniques to support both transactional workloads and analytical workloads in a single database system. This combined approach is known as hybrid transactional and
analytical processing (HTAP). To enable real-time analysis, an HTAP system should exhibit several key properties [51]:

**Workload-Specific Optimizations.** The system should provide each workload with optimizations specific to the workload. Each workload requires different algorithms and data structures, based on the workload’s memory access patterns, to achieve high throughput and performance.

**Data Freshness and Data Consistency.** The system should always provide the analytics workload with the most recent version of data, even when transactions keep updating the data at a high rate. Also, the system needs to guarantee data consistency across the entire system, such that analytic queries observe a consistent view of data, regardless of the freshness of the data.

**Performance Isolation.** The system should ensure that the latency and throughput of either workload is not impacted by running them concurrently within the same system.

Meeting all of these properties at once is very challenging, as these two workloads have different underlying algorithms and access patterns, and optimizing for one property can often require a trade-off in another property.

3. MOTIVATION

There are two major types of HTAP systems: (1) single-instance design systems and (2) multiple-instance design systems. In this section, we study both types, and analyze why neither type can meet all of the desired properties of an HTAP system (as we describe in Section 2).

3.1 Single-Instance Design

One way to design an HTAP system is to maintain a single instance of the data, which both analytics and transactions work on, to ensure that analytical queries access the most recent version of data. Several HTAP proposals from academia and industry are based on this approach [8, 11, 23, 29, 38, 64]. While single-instance design enables high data freshness, we find that it suffers from three major challenges:

(1) **High Cost of Consistency and Synchronization.** To avoid the throughput bottlenecks incurred by locking protocols [21], single-instance-based HTAP systems resort to either snapshotting [8, 38, 54, 65] or multi-version concurrency control (MVCC) [11, 58]. Unfortunately, both solutions have significant drawbacks of their own.

**Snapshotting:** Several HTAP systems (e.g., [8, 38, 54]) use a variation of multiversion synchronization, called snapshotting, to provide consistency via snapshot isolation [12, 18]. Snapshot Isolation guarantees that all reads in a transaction see a consistent snapshot of the database state, which is the last committed state before the transaction started. These systems explicitly create snapshots from the most recent version of operational data, and let the analytics run on the snapshot while transactions continue updating the data.

We analyze the effect of state-of-the-art snapshotting [8, 70] on throughput, for an HTAP system with two transactional and two analytical threads (each runs on a separate CPU). Figure 1 (right) shows the transaction throughput with snapshotting, normalized to a zero-cost snapshot mechanism, for three different rates of analytical queries. We make two observations from the figure. First, at 128 analytical queries, snapshotting reduces throughput by 43.4%. Second, the throughput drops as more analytical queries are being performed, with a drop of 74.6% for 512 analytical queries.

**MVCC:** While both MVCC and snapshotting provide snapshot isolation, MVCC avoids making full copies of data for its snapshot. In MVCC, the system keeps several versions of the data in each entry. The versions are chained together with pointers, and contain timestamps. Now, instead of reading a separate snapshot, an analytics query can simply use the timestamp to read the correct version of the data, while a transaction can add another entry to the end of the chain without interrupting. As a result, updates never block reads, which is the main reason that MVCC has been adopted by many transactional DBMSs (e.g., [23, 44, 46]).

However, MVCC is not a good fit for mixed analytical and transactional workloads in HTAP. We study the effect of MVCC on system throughput, using the same hardware configuration that we used for snapshotting. Figure 1 (left) shows the analytical throughput of MVCC, normalized to a zero-cost version of MVCC, for a varying transactional query count. We observe that the analytical throughput significantly decreases (by 42.4%) compared to zero-cost MVCC. We find that long version chains are the root cause of the throughput reduction. Each chain is organized as a linked list, and the chains grow long as many transactional queries take place. Upon accessing a data tuple, the analytics query traverses a lengthy version chain, checking each chain entry’s timestamp to locate the most recent version that is visible to the query. As analytic queries touch a large number of tuples, this generates a very large number of random memory accesses, leading to the significant throughput drop.

(2) **Limited Workload-Specific Optimization.** A single-instance design severely limits workload-specific optimizations, as the instance cannot have different optimizations for each workload. Let us examine the data layout in relational databases as an example. Relational transactional engines use a row-wise or N-ary storage model (NSM) for data layout, as it provides low latency and high throughput for update-intensive queries [37]. Relational analytics engines, on the other hand, employ a column-wise or Decomposition Storage Model (DSM) to store data, as it provides better support for columnar accesses, compression, and vectorized execution.

It is inherently impossible for a single-instance-based system to implement both formats simultaneously, and many such systems simply choose one of the layouts [8, 38, 64]. A few HTAP systems attempt to provide a hybrid data lay-
out (e.g., [11]) or multiple data layouts in a single replica (e.g., [44]). However, these systems need to periodically convert data between different data formats, which leads to significant overhead and compromises data freshness [59].

(3) Limited Performance Isolation. It is critical to ensure that running analytics queries alongside transactions does not violate strict transactional latency and throughput service-level agreements. Unfortunately, running both on the same instance of data, and sharing hardware resources, leads to severe performance interference. We evaluate the effect of performance interference using the same system configuration that we used for snapshotting and MVCC. Each transactional thread executes 2M queries, and each analytical thread runs 1024 analytical queries. We assume that there is no cost for consistency and synchronization. Compared to running transactional queries in isolation, the transactional throughput drops by 31.3% when the queries run alongside analytics. This is because analytics are very data-intensive and generate a large amount of data movement, which leads to significant contention for shared resources (e.g., memory system, off-chip bandwidth). Note that the problem worsens with realistic consistency mechanisms, as they also generate a large amount of data movement.

3.2 Multiple-Instance Design

The other approach to design an HTAP system is to maintain multiple instances of the data using replication techniques, and dedicate and optimize each instance to a specific workload (e.g., [10, 27, 44, 46, 51, 54, 59]). Unfortunately, multiple-instance systems suffer from several challenges:

Data Freshness. One of the major challenges in multiple-instance-based approaches is to keep analytical replicas up-to-date even when the transaction update rate is high, without compromising performance isolation [26, 51]. To maintain data freshness, the system needs to (1) gather updates from transactions and ship them to analytical replicas, and (2) perform the necessary format conversion and apply the updates.

Gathering and Shipping Updates: Given the high update rate of transactions, the frequency of the gathering and shipping process has a direct effect on data freshness. During the update shipping process, the system needs to (1) gather updates from different transactional threads, (2) scan them to identify the target location corresponding to each update, and (3) transfer each update to the corresponding location. We study the effect of update shipping on transactional throughput for a multiple-instance-based HTAP system (see Section 8). Our system has two transactional and two analytical threads (each running on a CPU core). Figure 2 shows the transactional throughput for three configurations: (1) a baseline with zero cost for update shipping and update application, (2) a system that performs only update shipping, and (3) a system that performs both update shipping and update application (labeled as Update-Propagation). We observe from the figure that the transactional throughput of updating shipping reduces by 14.8% compared to zero-cost update shipping and application. Our analysis shows that when the transactional queries are more update-intensive, the overhead becomes significantly higher. For update intensities of 80% and 100%, the throughput drops further (by 19.9% and 21.2%, respectively).

Other Major Challenges. Like with single-instance design, we find that maintaining data consistency for multiple instances without compromising performance isolation is very challenging. Updates from transactions are frequently shipped and applied to analytics replicas while analytical queries run. As a result, multiple-instance-based systems suffer from the same consistency drawbacks that we observe for single-instance-based systems in Section 3.1. Another major challenge we find is the limited performance isolation. While separate instances provide partial performance isolation, this reduction is mostly because the update shipping process generates a large amount of data movement and takes several CPU cycles. Figure 3 shows the breakdown of execution time during update propagation process. We find that update shipping accounts for on average 15.4% of the total execution time.

Update Application: The update application process can be very challenging, due to the need to transform updates from one workload-specific format to another. For example, in relational analytics, the analytics engine uses several optimizations to speed up long-running scan queries and complex queries with multiple joins. To minimize the amount of data that needs to be accessed, analytics engines employ DSM representation to store data [67], and can compress tuples using an order-preserving dictionary-based compression (e.g., dictionary encoding [15, 50, 61]).
isolation, as transactions and analytics do not compete for the same copy of data, they still share underlying hardware resources such as CPU cores and the memory system. As we discuss in Section 3.1, analytics workloads, as well as data freshness and consistency mechanisms, generate a large amount of data movement and take many cycles. As a result, multiple-instance designs also suffer from limited performance isolation.

We conclude that neither single- nor multiple-instance HTAP systems meet all of our desired HTAP properties. We therefore need a system that can avoid resource contention and alleviate the data movement costs incurred for HTAP.

4. POLYNESIA

We propose Polynesia, which divides the HTAP system into multiple islands. Each island includes (1) a replica of data whose layout is optimized for a specific workload, (2) an optimized execution engine, and (3) a set of hardware resources. Polynesia has two types of islands: (1) a transactional island, and (2) an analytical island. To avoid the data movement and interference challenges that other multiple-instance-based HTAP systems face (see Section 3), we propose to equip each analytical island with (1) in-memory hardware; and (2) co-designed algorithms and hardware for the analytical execution engine, update propagation, and consistency.

Polynesia is a framework that can be applied to many different combinations of transactional and analytical workloads. In this work, we focus on designing an instance of Polynesia that supports relational transactional and analytical workloads. Figure 4 shows the hardware for our chosen implementation, which includes one transactional island and one analytical island, and is equipped with a 3D-stacked memory similar to the Hybrid Memory Cube (HMC) [34], where multiple vertically-stacked DRAM cell layers are connected with a logic layer using through-silicon vias (TSVs). An HMC chip is split up into multiple vaults, where each vault corresponds to a vertical slice of the memory and logic layer. The transactional island uses an execution engine similar to conventional transactional engines [37, 75] to execute a relational transactional workload. The transactional island is equipped with conventional multicore CPUs and multi-level caches, as transactional queries have short execution times, are latency-sensitive, and have cache-friendly access patterns [17]. Inside each vault’s portion of the logic layer in memory, we add hardware for the analytical island, including the update propagation mechanism (consisting of the update shipping and update application units), the consistency mechanism (copy units), and the analytical execution engine (simple programmable in-order PIM cores).

To address potential capacity issues and accommodate larger data, Polynesia can extend across multiple memory stacks. We evaluate Polynesia with multiple stacks in Section 9.5.

5. UPDATE PROPAGATION MECHANISM

We design a new two-part update propagation mechanism to overcome the high costs of analytical replica updates in state-of-the-art HTAP systems. The update shipping unit gathers updates from the transactional island, finds the target location in the analytical island, and frequently pushes these updates to the analytical island. The update application unit receives these updates, converts the updates from the transactional replica data format to the analytical replica data format, and applies the update to the analytical replica.

5.1 Update Shipping

Algorithm. Our update shipping mechanism includes three major stages. For each thread in the transactional engine, Polynesia stores an ordered update log for the queries performed by the thread. Each update log entry contains four fields: (1) a commit ID (a timestamp used to track the total order of all updates across threads), (2) the type of the update (insert, delete, modify), (3) the updated data, and (4) a record key (e.g., pair of row-ID and column-ID) that links this particular update to a column in the analytical replica. The update shipping process is triggered when total number of pending updates reaches the final log capacity, which we set to 1024 entries (see Section 5.2). The first stage is to scan the per-thread update logs, and merge them into a single final log, where all updates are sorted by the commit ID.

The second stage is to find the location of the corresponding column (in the analytical replica) associated with each update log entry. We observe that this stage is one of the major bottlenecks of update shipping, because the fields in each tuple in the transactional island are distributed across different columns in the analytical island. Since the column size is typically very large, finding the location of each update is a very time-consuming process. To overcome this, we maintain a hash index of data on the (column,row) key, and use that to find the corresponding column for each update in the final log. We use the modulo operation as the hash function. We size our hash table based on the column partition size. Similar to conventional analytical DBMSs, we can use soft partitioning [49, 51, 62] to address scalability issues when the column size increases beyond a certain point. Thus, the hash table size does not scale with column size. This stage contains a buffer for each column in the analytical island, and we add each update from the final log to its corresponding column buffer.

The final stage is to ship these buffers to each column in the analytical replica.

Hardware. We find that despite our best efforts to minimize overheads, our algorithm has three major bottlenecks that keep it from meeting data freshness and performance isolation requirements: (1) the scan and merge operation in stage 1, (2) hash index lookups in stage 2, and (3) transferring the column buffer contents to the analytical islands in stage 3. These primitives generate a large amount of data movement and account for 87.2% of our algorithm’s execution time. To avoid these bottlenecks, we design a new hardware accel-
generator, called the update shipping unit, that speeds up the key primitives of the update shipping algorithm. We add this accelerator to each of Polynesia’s in-memory analytical islands.

Figure 5 shows the high-level architecture of our in-memory update shipping unit. The update shipping unit consists of three building blocks: (1) a merge unit, (2) a hash lookup unit, and (3) a copy unit. The merge unit consists of 8 FIFO input queues, where each input queue corresponds to a sorted update log. Each input queue can hold up to 128 updates, which are streamed from DRAM. The merge unit finds the oldest entry among the input queue heads, using a 3-level comparator tree, and adds it to the tail of the final log (a ninth FIFO queue). The final log is then sent to the hash unit to determine the target column for each update.

For our hash unit, we start with a preliminary design that includes a probe unit, a simple finite state machine controller that takes the address (for the key), computes the hash function to find the corresponding bucket in memory, and traverses the linked list of keys in the bucket. We find that having a single probe unit does not achieve our expected performance because (1) we cannot fully exploit the bandwidth of 3D-stacked memory; and (2) each lookup typically includes several pointer chasing operations that often leave the probe unit idle. As a result, we need to perform multiple hash lookups in parallel at each step. However, the challenge is that updates need to be handed to the copy unit in the same commit order they are inserted into the final update log.

To address these challenges, we design the hash unit shown in Figure 5. Its key idea is to (1) decouple hash computation and bucket address generation from the actual bucket access/traversal, to allow for concurrent operations; and (2) use a small reorder buffer to track in-flight hash lookups, and maintain commit order for completed lookups that are sent to the copy engine. We introduce a front-end engine that fetches the keys from the final update log, computes the hash function, and sends the key address to probe units. The front-end engine allocates an entry (with the bucket address and a ready bit) for each lookup in the reorder buffer. We employ multiple probe units (we find that 4 strikes a balance between parallelism and area overhead), with each taking a bucket address and accessing DRAM to traverse the linked list.

We describe our copy engine in Section 6. Our analysis shows that the total area of our update shipping unit is 0.25 mm².

5.2 Update Application

Similar to other relational analytical DBMSs, our analytical engine uses the DSM data layout and dictionary encoding [15, 22, 23, 43, 50, 61, 67]. With dictionary encoding, each column in a table is transformed into a compressed column using encoded fixed-length integer values, and a dictionary stores a sorted mapping of real values to encoded values. As we discuss in Section 3.2, the layout conversion (our transactional island uses NSM) and column compression make update application process challenging. We design a new update application mechanism for Polynesia that uses hardware–software co-design to address these challenges.

Algorithm. We first discuss an initial algorithm that we develop for update application. We assume each column has \( n \) entries, and that we have \( m \) updates. First, the algorithm decompresses the encoded column by scanning the column and looking up in the dictionary to decode each item. This requires \( n \) random accesses to the dictionary. Second, the algorithm applies updates to the decoded column one by one. Third, it constructs a new dictionary, by sorting the updated column and calculating the number of fixed-length integer bits required to encode the sorted column. Dictionary construction is computationally expensive \( (\Theta((n+m) \log (n+m))) \) because we need to sort the entire column. Finally, the algorithm compresses the new column using our new dictionary. While entry decoding happens in constant time, encoding requires a logarithmic complexity search through the dictionary (since the dictionary is sorted).

This initial algorithm is memory intensive (Steps 1, 2, 4) and computationally expensive (Step 3). Having hardware support is critical to enable low-latency update application and performance isolation. While PIM may be able to help, our initial algorithm is not well-suited for PIM for two reasons, and we optimize the algorithm to address both.

Optimization 1: Two-Stage Dictionary Construction. We eliminate column sorting from Step 3, as it is computationally expensive. Prior work [63, 72] shows that to efficiently sort more than 1024 values in hardware, we should provide a hardware partitioner to split the values into multiple chunks, and then use a sorter unit to sort chunks one at a time. This requires an area of 1.13 mm² [63, 72]. Unfortunately, since tables can have millions of entries [43], we would need multiple sorter units to construct a new dictionary, easily exceeding the total area budget of 4.4 mm² per vault [16, 20, 25].

To eliminate column sorting, we sort only the dictionary, leveraging the fact that (1) the existing dictionary is already sorted, and (2) the new updates are limited to 1024 values. Our optimized algorithm initially builds a sorted dictionary for only the updates, which requires a single hardware sorter (a 1024-value bitonic sorter with an area of only 0.18 mm² [72]). Once the update dictionary is constructed, we now have two sorted dictionaries: the old dictionary and the update dictionary. We merge these into a single dictionary using a linear scan \((O(n+m))\), and then calculate the number of bits required to encode the new dictionary.

Optimization 2: Reducing Random Accesses. To reduce the algorithm’s memory intensity (which is a result of random lookups), we maintain a hash index that links the old encoded value in a column to the new encoded value. This avoids the need to decompress the column and add updates, eliminating data movement and random accesses for Steps 1 and 2, while reducing the number of dictionary lookups required for Step 4. The only remaining random accesses are for Step 4, which decrease from \( O((n+m) \log (n+m)) \) to \( O(n+m) \).

We now describe our optimized algorithm. We first sort the updates to construct the update dictionary. We then merge the old dictionary and the update dictionary to construct the new dictionary and hash index. Finally, we use the index and
the new dictionary to find the new encoded value for each entry in the column.

**Hardware.** We design a hardware implementation of our optimized algorithm, called the *update application unit*, and add it to each in-memory analytical island. The unit consists of three building blocks: a *sort unit*, a *hash lookup unit*, and a *scan/merge unit*. Our sort unit uses a 1024-value bitonic sorter, whose basic building block is a network of comparators. These comparators are used to form *bitonic sequences*, sequences where the first half of the sequence is monotonically increasing and the second half is decreasing. The hash lookup uses a simpler version of the component that we designed for update shipping. The simplified version does not use a reorder buffer, as there is no dependency between hash lookups for update application. We use the same number of hash units (empirically set to 4), each corresponding to one index structure, to parallelize the compression process. For the merge unit, we use a similar design from our update shipping unit. Our analysis shows that the total area of our update application unit is 0.4 mm².

### 6. CONSISTENCY MECHANISM

We design a new consistency mechanism for Polynesia in order to deliver all of the desired properties of an HTAP system (Section 2). Our consistency mechanism must not compromise either the throughput of analytical queries or the rate at which updates are applied. This sets two requirements for our mechanism: (1) analytics must be able to run all of the time without slowdowns, to satisfy the performance isolation property; and (2) the update application process should not be blocked by long-running analytical queries, to satisfy the data freshness property. This means that our mechanism needs a way to allow analytical queries to run concurrently with updates, without incurring the long chain read overheads of similar mechanisms such as MVCC (see Section 3.1).

**Algorithm.** Our mechanism relies on a combination of snapshotting [38] and versioning [13] to provide snapshot isolation [12, 18] for analytics. Our consistency mechanism is based on two key observations: (1) updates are applied at a column granularity, and (2) snapshotting a column is cost-effective using PIM logic. We assume that for each column, there is a chain of snapshots where each chain entry corresponds to a version of this column. Unlike chains in MVCC, each version is associated with a column, not a tuple.

We adopt a lazy approach (late materialization [4]), where Polynesia does not create a snapshot every time a column is updated. Instead, on a column update, Polynesia marks the column as dirty, indicating that the snapshot chain does not contain the most recent version of the column data. When an analytical query arrives Polynesia checks the column metadata, and creates a new snapshot only if (1) any of the columns are dirty (similar to Hyper [38]), and (2) no current snapshot exists for the same column (we let multiple queries share a single snapshot). During snapshotting, Polynesia updates the head of the snapshot chain with the new value, and marks the column as clean. This provides two benefits. First, the analytical query avoids the chain traversals and timestamp comparisons performed in MVCC, as the query only needs to access the head of the chain at the time of the snapshot. Second, Polynesia uses a simple yet efficient garbage collection: when an analytical query finishes, snapshots no longer in use by any query are deleted (aside from the head of the chain).

To guarantee high data freshness (second requirement), our consistency mechanism always lets transactional updates directly update the main replica using our two-phase update application algorithm (Section 5.2). In Phase 1, the algorithm constructs a new dictionary and a new column. In Phase 2, the algorithm atomically updates the main replica with pointers to the new column and dictionary.

**Hardware.** Our algorithm’s success at satisfying the first requirement for a consistency mechanism (i.e., no slowdown for analytics) relies heavily on its ability to perform fast memory copies to minimize the snapshotting latency. Therefore, we add a custom copy unit to each of Polynesia’s in-memory analytical islands. We have two design goals for the unit. First, the accelerator needs to be able to issue multiple memory accesses concurrently. This is because (1) we are designing the copy engine for an arbitrary-sized memory region (e.g., a column), which is often larger than the memory access granularity per vault (8–16B) in an HMC-like memory; and (2) we want to fully exploit the internal bandwidth of 3D-stacked memory. Second, when a read for a copy completes, the accelerator should immediately initiate the write.

We design our copy unit (Figure 5) to satisfy both design goals. To issue multiple memory accesses concurrently, we leverage the observation that these memory accesses are independent. We use multiple fetch and writeback units, which can read from or write to source/destination regions in parallel. To satisfy the second design goal, we need to track outstanding reads, as they may come back from memory out of order. Similar to prior work on accelerating memcpy [52], we use a tracking buffer in our copy unit. The buffer allocates an entry for each read issued to memory, where an entry contains a memory address and a ready bit. Once a read completes, we find its corresponding entry in the buffer and set its ready bit to trigger the write.

We find that the buffer lookup limits the performance of the copy unit, as each lookup results in a full buffer scan, and multiple fetch units perform lookups concurrently (generating high contention). To alleviate this, we design a hash index based on the memory address to determine the location of a read in the buffer. We make use a similar design as the hash lookup unit in our update shipping unit.

### 7. ANALYTICAL ENGINE

The analytical execution engine performs the analytical queries. When a query arrives, the engine parses the query and generates an algebraic query plan consisting of physical operators (e.g., scan, filter, join). In the query plan, operators are arranged in a tree where data flows from the bottom nodes (leaves) toward the root, and the result of the query is stored in the root. The analytical execution engine employs the top-down Volcano (Iterator) execution model [28, 57] to traverse the tree and execute operators while respecting dependencies between operators. Analytical queries typically exhibit a high degree of both intra- and inter-query parallelism [49, 62, 77]. To exploit this, the engine decomposes a query into multiple tasks, each being a sequence of one or more operators. The engine (task scheduler) then schedules the tasks, often in a way that executes multiple independent tasks in parallel.
Efficient analytical query execution strongly depends on (1) data layout and data placement, (2) the task scheduling policy, and (3) how each physical operator is executed. Like prior works [20, 73], we find that the execution of physical operators of analytical queries significantly benefit from PIM. However, without a HTAP-aware and PIM-aware data placement strategy and task scheduler, PIM logic for operators alone cannot provide significant throughput improvements.

We design a new analytical execution engine based on the characteristics of our in-memory hardware. As we discuss in Section 4, Polynesia uses a 3D-stacked memory that contains multiple vaults. Each vault (1) provides only a fraction (e.g., 8 GB/s) of the total bandwidth available in a 3D-stacked memory, (2) has limited power and area budgets for PIM logic, and (3) can access its own data faster than it can access data stored in other vaults (which take place through a vault-to-vault interconnect). We take these limitations into account as we design our data placement mechanism and task scheduler.

7.1 Data Placement

We evaluate three different data placement strategies for Polynesia. Our analytical engine uses the DSM layout to store data, and makes use of dictionary encoding [15] for column compression. Our three strategies affect which vaults the compressed DSM columns and dictionary are stored in.

**Strategy 1: Store the Entire Column (with Dictionary) in One Vault.** This strategy has two major benefits. First, both the dictionary lookup and column access are to the local vault, which improves analytical query throughput. Second, it simplifies the update application process (Section 5.2), as the lack of remote accesses avoids the need to synchronize updates between multiple update applications units (as each vault has its own unit).

However, this data placement strategy forces us to service tasks that access a particular column using (1) highly-constrained PIM logic (given the budget of a single vault), and (2) only the bandwidth available to one vault. This significantly degrades throughput, as it becomes challenging to benefit from intra-query parallelism with only one highly-constrained set of logic available for a query.

**Strategy 2: Partition Columns Across All Vaults in a Chip.** To address the challenges of Strategy 1, we can partition each column and distribute it across all of the vaults in the 3D-stacked memory chip (i.e., a cube). This approach allows us to (1) exploit the entire internal bandwidth of the 3D-stacked memory, and (2) use all of the available PIM logic to service each query. Note that unlike partitioning the column, partitioning the dictionary across all vaults is challenging because the dictionary is sorted, forcing us to scan the entire column and find the corresponding dictionary entries for each column entry.

However, Strategy 2 suffers from two major drawbacks. First, it makes the update application (Section 5.2) significantly challenging. To perform update application under Strategy 2, we need to (1) perform many remote accesses to gather all of the column partitions, (2) update the column, and then (3) perform many remote accesses to scatter the updated column partitions back across the vaults. Given the high frequency of update application in HTAP workloads, this gather/scatter significantly increases the latency of update application and intra-cube traffic. Second, we need to perform several remote accesses to collect sub-results from each partition and aggregate them, which reduces the throughput.

**Strategy 3: Partition Columns Across a Group of Vaults.** To overcome the challenges of Strategies 1 and 2, we propose a hybrid strategy where we create small vault groups, consisting of a fixed number of vaults, and partition a column across the vaults in a vault group. For a group with $v$ vaults, this allows us to increase the aggregate bandwidth for servicing each query by $v$ times, and provides up to $v$ times the power and area for PIM logic. The number of vaults per group is critical for efficiency: too many vaults can complicate the update application process, while not enough vaults can degrade throughput. We empirically find that four vaults per group strikes a good balance.

While the hybrid strategy reduces the cost of update application compared to Strategy 2, it still needs to perform remote accesses within each vault group. To overcome this, we leverage an observation from prior work [43] that the majority of columns have only a limited (up to 32) number of distinct values. This means that the entire dictionary incurs negligible storage overhead (~2 KB). To avoid remote dictionary accesses during update application, Strategy 3 keeps a copy of the dictionary in each vault. Such an approach is significantly costlier under Strategy 2, as for a given column size, the number of dictionary copies scales linearly with the number of columns, which is particularly problematic in a system with multiple memory stacks.

Polynesia makes use of Strategy 3 for data placement.

7.2 Scheduler

Polynesia’s task scheduler plays a key role in (1) exploiting inter- and intra-query parallelism, and (2) efficiently utilizing hardware resources. For each query, the scheduler (1) decides how many tasks to create, (2) finds how to map these tasks to the available resources (PIM threads), and (3) guarantees that dependent tasks are executed in order. We first design a basic scheduler heuristic that generates tasks (statically at compile time) by disassembling the operators of the query plan into operator instances (i.e., an invocation of a physical operator on some subset of the input tuples) based on (1) which vault groups the input tuples reside in; and (2) the number of available PIM threads in each vault group, which determines the number of tasks generated. The scheduler inserts tasks into a global work queue in an order that preserves dependencies between operators, monitors the progress of PIM threads, and assigns each task to a free thread (push-based assignment).

However, we find that this heuristic is not optimized for PIM, and leads to sub-optimal performance due to three reasons. First, the heuristic requires a dedicated runtime component to monitor and assign tasks. The runtime component must be executed on a general-purpose PIM core, either requiring another core (difficult given limited area/power budgets) or preempting a PIM thread on an existing core (which hurts performance). Second, the heuristic’s static mapping is limited to using only the resources available within a single vault group, which can lead to performance issues for queries that operate on very large columns. Third, this heuristic is vulnerable to load imbalance, as some PIM threads might finish their tasks sooner and wait idly for straggling threads.
We add four PIM cores to each vault, where the cores are workloads. To avoid excessive accesses to DRAM and let the greater number of tasks increases opportunities for load balancing. Finally, we optimize the heuristic to allow a PIM thread to steal tasks from a remote vault if its local queue is empty. This enables us to potentially use all available PIM threads to execute tasks, regardless of the data distribution.

### 7.3 Hardware Design

Given area and power constraints, it can be difficult to add enough PIM logic to each vault to saturate the available vault bandwidth [20]. Mondrian [20] attempts to change the access pattern from random to sequential, allowing PIM threads to use stream buffers to increase bandwidth utilization. With our new data placement strategy and scheduler, we instead expose greater intra-query parallelism, and use simple programmable in-order PIM cores to exploit the available vault bandwidth.

We add four PIM cores to each vault, where the cores are similar to those in prior work [20, 24]. We run a PIM thread on each core, and we use these cores to execute the scheduler and other parts of the analytical engine (e.g., query parser).

We find that our optimized heuristic significantly increases data sharing between PIM threads. This is because within each vault group, all 16 PIM threads access the same local task queue, and must synchronize their accesses. The problem worsens when other PIM threads attempt to steal tasks from remote vault groups, especially for highly-skewed workloads. To avoid excessive accesses to DRAM and let PIM threads share data efficiently, we implement a simple fine-grained coherence technique, which uses a local PIM-side directory in the logic layer to implement a low-overhead coherence protocol.

### 8. METHODOLOGY

We use and heavily extend state-of-the-art transactional and analytical engines to implement various single- and multiple-instance HTAP configurations. We use DBx1000 [75, 76] as the starting point for our transactional engine, and we implement an in-house analytical engine similar to C-store [67]. Our analytical engine supports key physical operators for relational analytics (select, filter, aggregate and join), and supports both NSM and DSM layouts, and dictionary encoding [15, 50, 61]. For consistency, we implement both snapshotting (similar to software snapshotting [70], and with snapshots taken only when dirty data exists) and MVCC (adopted from DBx1000 [75]).

Our baseline single-instance HTAP system stores the single data replica in main memory. Each transactional query randomly performs reads or writes on a few randomly-chosen tuples from a randomly-chosen table. Each analytical query uses select and join on randomly-chosen tables and columns. Our baseline multiple-instance HTAP system models a similar system as our single-instance baseline, but provides the transactional and analytical engines with separate replicas (using the NSM layout for transactions, and DSM with dictionary encoding for analytics). Across all baselines, we have 4 transactional and 4 analytical worker threads.

We simulate Polynesia using gem5 [14], integrated with DRAMSim2 [19] to model an HMC-like 3D-stacked DRAM [34]. Table 1 shows our system configuration. For the analytical island, each vault of our 3D-stacked memory contains four PIM cores and three fixed-function accelerators (update shipping unit, update application unit, copy unit). For the PIM core, we model a core similar to the ARM Cortex-A7 [9].

![Table 1: Evaluated system configuration.](image)

**Area and Energy.** Our four PIM cores require 1.8 mm² based on the Cortex-A7 (0.45 mm² each) [9]. We use Calypso Catapult to determine the area of the accelerators for a 22nm process: 0.7 mm² for the update propagation units and 0.2 mm² for the in-memory copy unit for our consistency mechanism. This brings Polynesia’s total to 2.7 mm² per vault. We model system energy similar to prior work [16, 17, 35], which sums the energy consumed by the CPU cores, all caches (modeled using CACTI-P 6.5 [55]), DRAM, and all on-chip and off-chip interconnects.

### 9. EVALUATION

#### 9.1 End-to-End System Analysis

Figure 6 (left) shows the transactional throughput for six DBMSs: (1) Single-Instance-Snapshot (SI-SS); (2) Single-Instance-MVCC (SI-MVCC); (3) MI+SW, an improved version of Multiple-Instance that includes all of our software optimizations for Polynesia (except those specifically targeted for PIM); (4) MI+SW+HR, a hypothetical version of MI+SW with 8x bandwidth (256 GB/s), equal to the internal bandwidth of HBM; (5) PIM-Only, a hypothetical version of MI+SW which uses general-purpose PIM cores to run both transactional and analytical workloads; and (6) Polynesia, our full hardware–software proposal. We normalize throughput to an ideal transaction-only DBMS (Ideal-Txn) for each transaction count. Of the single-instance DBMSs, SI-MVCC performs best, coming within 20.0% of the throughput of Ideal-Txn on average. Its use of MVCC over snapshotting overcomes the high performance penalties incurred by SI-SS. For the two software-only multiple instance DBMSs (MI+SW and MI+SW+HR), despite our enhancements, both
fall significantly short of SI-MVCC due to their lack of performance isolation and, in the case of MI+SW, the overhead of update propagation. MI+SW+HB, even with its higher available bandwidth, cannot data movement or contention on shared resources. As a result, its transactional throughput is still 41.2% lower than Ideal-Txn. PIM-only significantly hurts transactional throughput (by 67.6% vs. Ideal-Txn), and even performs 7.6% worse than SI-SS. Polynesia improves the average throughput by 51.0% over MI+SW+HB, and by 14.6% over SI-MVCC, because it (1) uses custom PIM logic for analytics along with its update propagation and consistency mechanisms to significantly reduce contention, and (2) reduces off-chip bandwidth contention by reducing data movement. As a result, Polynesia comes within 8.4% of Ideal-Txn.

Figure 6: Normalized transactional (left) and analytical (right) throughput for end-to-end HTAP systems.

Figure 6 (right) shows the analytical throughput across the same DBMSs. We normalize throughput at each transaction count to a baseline where analytics are running alone on our multicore system. We see that while SI-MVCC is the best software-only DBMS for transactional throughput, it degrades analytical throughput by 63.2% compared to the analytics baseline, due to its lack of workload-specific optimizations and poor consistency mechanism (MVCC). Neither of these problems can be addressed by providing higher bandwidth. MI+SW+HB is the best software-only HTAP DBMS for analytics, because it provides workload-specific optimizations, but it still loses 35.3% of the analytical throughput of the baseline. MI+SW+HB improves throughput by 41.2% over MI+SW but still suffers from resource contention due to update propagation and the consistency mechanism. PIM-Only performs similar to MI+SW+HB but reduces throughput by 11.4% compared to that, as it suffers from resource contention caused by co-running transactional queries. Polynesia improves over the baseline by 63.8%, by eliminating data movement, having low-latency accesses, and using custom logic for update propagation and consistency.

Overall, averaged across all transaction counts in Figure 6, Polynesia has a higher transactional throughput (2.20X over SI-SS, 1.15X over SI-MVCC, and 1.94X over MI+SW; mean of 1.70X), and a higher analytical throughput (3.78X over SI-SS, 5.04X over SI-MVCC, and 2.76X over MI+SW; mean of 3.74X).

Real Workload Analysis. To model more complex queries, we evaluate Polynesia using a mixed workload from TPC-C [68] (for our transactional workload) and TPC-H [69] (for our analytical workload). TPC-C’s schema includes nine relations (tables) that simulate an order processing application. We simulate two transaction types defined in TPC-C, Payment and New order, which together account for 88% of the TPC-C workload [75]. We vary the number of warehouses from 1 to 4, and we assume that our transactional workload includes an equal number of transactions from both Payment and New order. TPC-H’s schema consists of eight separate tables, and we use TPC-H Query 6, a long and complex work-load that performs selection over the Lineitem table, whose cardinality (i.e., number of rows) is 6 million.

We evaluate the transactional and analytical throughput for Polynesia and for three baselines: (1) SI-SS, (2) SI-MVCC, (3) MI+SW (results not shown). We find that, averaged across all warehouse counts, Polynesia has a higher transactional throughput (2.31X over SI-SS, 1.19X over SI-MVCC, and 1.78X over MI+SW; mean of 1.76X), and a higher analytical throughput (3.41X over SI-SS, 4.85X over SI-MVCC, and 2.2X over MI+SW; mean of 3.48X) over all three baselines.

We conclude that Polynesia’s ability to meet all three HTAP properties enables better transactional and analytical performance over all three of our state-of-the-art systems. In Sections 9.2, 9.3, and 9.4, we study how each component of Polynesia contributes to performance.

9.2 Update Propagation

Figure 7 shows the transactional throughput for Polynesia’s update propagation mechanism and Multiple-Instance, normalized to a multiple-instance baseline with zero cost for update propagation (Ideal). We assume each analytical worker thread executes 128 queries, and vary both the number of transactional queries per worker thread and the transactional query read-to-write ratio. To isolate the impact of different update propagation mechanisms, we use a zero-cost consistency mechanism, and ensure that the level of interference remains the same for all mechanisms.

Figure 7: Effect of update propagation mechanisms on transactional throughput.

We find that Multiple-Instance degrades transactional throughput on average by 49.5% compared to Ideal, as it severely suffers from resource contention and data movement cost. 27.7% of the throughput degradation comes from the update shipping latencies associated with data movement and with merging updates from multiple transactional threads together. The remaining degradation is due to the update application process, where the major bottlenecks are column compression/decompression and dictionary reconstruction. Our update propagation mechanism, on the other hand, improves throughput by 1.8X compared to Multiple-Instance, and comes within 9.2% of Ideal. The improvement comes from (1) significantly reducing data movement by offloading update propagation process to PIM, (2) freeing up CPUs from performing update propagation by using a specialized hardware accelerator, and (3) tuning both hardware and software. In all, our mechanism reduces the latency of update propagation by 1.9X compared to Multiple-Instance (not shown). We conclude that our update propagation mechanism provides data freshness (i.e., low update latency) while maintaining high transactional throughput (i.e., performance isolation).

9.3 Consistency Mechanism

Figure 8 (left) shows the analytical throughput of Polynesia’s consistency mechanism and of Single-Instance-MVCC (MVCC), normalized to a single-instance baseline with zero
cost for MVCC (Zero-Cost-MVCC) for each query count. We assume each analytical worker thread executes 128 queries, and we vary the transactional query count per worker thread. For a fair comparison, we implement our consistency mechanism in a single-instance system. MVCC degrades analytical throughput, on average, by 37.0% compared to Ideal-MVCC, as it forces each analytical query to traverse a lengthy version chain and perform expensive timestamp comparisons to locate the most recent version. Our consistency mechanism, on the other hand, improves analytical throughput by 1.4X compared to MVCC, and comes within 11.7% of Ideal-MVCC, because it does not force analytical queries to scan lengthy version chains when accessing each tuple.

**Figure 9:** Effect of data placement/scheduling on throughput (left) and update application latency (right).

Figure 9 (left) shows the analytical throughput, normalized to the CPU-only baseline for each analytic workload count, where one core services all queries to the same column. We find that Local reduces throughput by 23.9% on average over CPU-only, because in Local, each analytical query can only use (1) the PIM cores in the local vault, which cannot issue many memory requests concurrently, and (2) a single vault’s bandwidth. In contrast, CPU-only leverages the out-of-order cores to issue many memory requests in parallel. Remote improves throughput by 4.1X/3.1X over Local/CPU-only. This is because under Remote, each column is partitioned across all of the vaults, allowing us to service each query using (1) all of the PIM cores, and (2) the entire internal bandwidth of the memory. However, Remote increases the update application latency, on average, by 45.8% (Figure 9 (right)), and thus, degrades data freshness. This is because of the high update application costs that we discuss in Section 7.1, which does not occur.

We find that Hybrid addresses the shortcomings of Local, improving throughput by 57.2% over CPU-only, while having a similar update application latency (0.7ms). This is because the local dictionary copies eliminate most of the remote accesses. However, the throughput under Hybrid is 49.8% lower than Remote, because each query is serviced only using resources (bandwidth and computation) available in the local vault group. Hybrid-sched overcomes this thanks to task stealing, making idle resources in remote vaults available for analytical queries, and comes within 3.2% of Remote, while maintaining the same update application latency as Hybrid. Note that Remote’s slightly higher throughput than Hybrid-sched is because in Hybrid-sched, every memory access for a task stolen from another vault group is remote.

**9.5 Multiple Memory Stacks**

Figure 10 (left) shows how Polynesia performs as the dataset size grows. To accommodate the larger data, we increase the number of HMC stacks, doubling the data set size as we double the stack count. In these studies, we use a workload with 32M transactional and 60K analytical queries, and analyze analytical throughput normalized to Multiple-Instance (MI) as a case study. We assume stacks are connected together using a processor-centric topology [17]. To provide a fair comparison, we double the number of cores available to the analytical threads in the MI baseline as we double the number of stacks, to compensate for the doubling of hardware resources available to Polynesia (since there are twice as many vaults). We find that Polynesia significantly outperforms MI (up to 3.0X) and scales well as we increase the stack count. This is because, as we increase stack count, columns can be distributed more evenly across vault groups, which reduces the probability of multiple queries colliding in the same vault group. On the other hand, with increasing dataset size, the overheads of consistency mechanism, update propagation, and analytical query execution are all higher for MI, which hurts its scalability. The transactional throughput (not shown) decreases by 54.4% at four stacks for MI, compared to one stack, but decreases by only 8.8% for Polynesia.

**9.6 Energy Analysis**

Figure 10 (right) shows the total system energy across different HTAP DBMSs. We find that MI+Sw performs better
than SI-MVCC and SI-SS in terms of energy consumption, but still uses a large amount of energy due to a large number of accesses to off-chip memory, large caches, and using power-hungry CPU cores. These challenges cannot be solved by providing high bandwidth to CPU cores. Polynesia eliminates a significant amount of off-chip accesses, and uses custom logic and simple in-order PIM cores, reducing its energy consumption by 48% over MI+SW.

10. RELATED WORK

To our knowledge, this is the first work that (1) comprehensively examines HTAP systems and their major challenges, (2) proposes a hardware–software co-designed HTAP system, and (3) describes an HTAP system that meets all desired HTAP properties. We briefly discuss related works.

HTAP Systems. Several works from industry (e.g., [23, 27, 44, 45, 46]) and academia (e.g., [8, 10, 11, 29, 38, 41, 54, 64]) propose various techniques to support HTAP. Many of them use a single-instance design [8, 11, 23, 29, 38, 64], while others are multiple-instance [2, 27, 51]. All of these proposals suffer from the drawbacks we highlight in Section 3, and none can fully meet the desired HTAP properties.

Analytics Acceleration. Other prior works focus solely on analytical workloads [20, 42, 53, 71, 72, 73]. Some of these works propose to use specialized on-chip accelerators [42, 71, 72] while others propose to use PIM to speed up analytical operators [20, 53, 73]. However, none of these works study the effect of data placement or task scheduling for the analytical workload in the context of PIM or HTAP systems.

PIM. Several other recent works (e.g., [5, 6, 7, 16, 24, 25, 30, 31, 32, 33, 39, 56, 60, 74, 78, 79]) add compute units to the logic layer of 3D-stacked memory [34, 36, 40, 47]. None of these works are designed specifically for HTAP systems, and are largely orthogonal.

11. CONCLUSION

We propose Polynesia, a novel HTAP system that makes use of workload-optimized transactional and analytical islands to enable real-time analytics without sacrificing throughput. Our analytical islands alleviate the data movement and workload interference costs incurred in state-of-the-art HTAP systems, while still ensuring that data replicas for analytics workloads are kept up-to-date with the most recent version of the transactional data replicas. Polynesia outperforms three state-of-the-art HTAP systems (with a 1.70X/3.74X higher transactional/analytical throughput on average), while consuming less energy (48% lower than the best).

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