Polynesia:
Enabling High-Performance and Energy-Efficient Hybrid Transactional/Analytical Databases with Hardware/Software Co-Design

P&S Processing-in-Memory
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Amirali Boroumand
Geraldo F. Oliveira

Saugata Ghose
Onur Mutlu
## Executive Summary

- **Context:** Many applications need to perform real-time data analysis using an **Hybrid Transactional/Analytical Processing (HTAP) system**
  - An ideal HTAP system should have **three properties:**
    1. **data freshness** and **consistency**,
    2. **workload-specific optimization**, and
    3. **performance isolation**

- **Problem:** Prior works cannot achieve all properties of an ideal HTAP system

- **Key Idea:** Divide the system into transactional and analytical **processing islands**
  - Enables **workload-specific optimizations** and **performance isolation**

- **Key Mechanism:** Polynesia, a novel hardware/software cooperative design for in-memory HTAP databases
  - Implements **custom algorithms and hardware** to reduce the costs of **data freshness** and **consistency**
  - Exploits PIM for analytical processing to alleviate **data movement**

- **Key Results:** Polynesia outperforms three state-of-the-art HTAP systems
  - Average transactional/analytical throughput improvements of **1.7x/3.7x**
  - **48%** reduction on energy consumption
1. Introduction
2. Limitations of HTAP Systems
3. Polynesian: Overview
4. Update Propagation Mechanism
5. Consistency Mechanism
6. Analytical Engine
7. Evaluation
8. Conclusion
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Real-Time Analysis

An explosive interest in many applications domains to perform data analytics on the most recent version of data (real-time analysis)

Use transactions to record each periodic sample of data from all sensors

Run analytics across sensor data to make real-time steering decisions

Self-Driving Cars

For these applications, it is critical to analyze the transactions in real-time as the data’s value diminishes over time
Traditionally, new transactions (updates) are propagated to the analytical database using a periodic and costly process.

To support real-time analysis: a single hybrid DBMS is used to execute both transactional and analytical workloads.
An ideal HTAP system should have three properties:

1. **Workload-Specific Optimizations**
   - Transactional and analytical workloads must benefit from their own specific optimizations.

2. **Data Freshness and Consistency Guarantees**
   - Guarantee access to the most recent version of data for analytics while ensuring that transactional and analytical workloads have a consistent view of data.

3. **Performance Isolation**
   - Latency and throughput of transactional and analytical workloads are the same as if they were run in isolation.

Achieving all three properties at the same time is very challenging.
State-of-the-Art HTAP Systems

We study two major types of HTAP systems:

1. Single-Instance
   - Transactions
   - Analytics
   - Main Replica

2. Multiple-Instance
   - Transactions
   - Analytics
   - Analytics
   - Replica
   - Replica
   - Replica

We observe two key problems:

1. Data freshness and consistency mechanisms are costly and cause a drastic reduction in throughput

2. These systems fail to provide performance isolation because of high main memory contention
State-of-the-Art HTAP Systems

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**Single-Instance**
- Transactions
- Analytics

**Main Replica**

**Multiple-Instance**
- Transactions
- Analytics
- Analytics

We observe two key problems:

1. **Data freshness and consistency mechanisms are costly and cause a drastic reduction in throughput.**

2. **These systems fail to provide performance isolation because of high main memory contention.**
Since both analytics and transactions work on the same data concurrently, we need to ensure that the data is consistent.

There are two major mechanisms to ensure consistency:

1. **Snapshotting**
   - Main Replica
   - Transactional Data
   - Analytical Snapshot

2. **Multi-Version Concurrency Control (MVCC)**
   - Main Replica
   - Column
   - Transaction Updates
   - Time-stamped version chain

** SAFARI **
- Introduction
- Motivation
- Polynesia
- Update Propagation
- Consistency Mechanism
- Analytical Engine
- Evaluation
- Conclusion
Drawbacks of Snapshotting and MVCC

We evaluate the **throughput loss** caused by Snapshotting and MVCC:

Throughput loss comes from **memcpy** operation:
- generates a large amount of data movement

Throughput loss comes from **long version chains**:
- expensive time-stamp comparison and a large number of random memory accesses
State-of-the-Art HTAP Systems

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2. Multiple-Instance
   - Replica
   - Transactions
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We observe two key problems:

1. Data freshness and consistency mechanisms are costly and cause a drastic reduction in throughput.

2. These systems fail to provide performance isolation because of high main memory contention.
One of the major challenges in multiple-instance systems is to keep analytical replicas up-to-date.

To maintain data freshness (via Update Propagation):

1. **Update Gathering and Shipping**: gather updates from transactional threads and ship them to analytical the replica.

2. **Update Application**: perform the necessary format conversation and apply those updates to analytical replicas.
Cost of Update Propagation

We evaluate the **throughput loss** caused by Update Propagation:

Transaction**al throughput reduces by up to 21.2%** during the update gathering & shipping process.

Transaction**al throughput reduces by up to 64.2%** during the update application process.
## Problem and Goal

### Problems:

| 1 | State-of-the-art HTAP systems do not achieve all of the desired HTAP properties |
| 2 | Data freshness and consistency mechanisms are data-intensive and cause a drastic reduction in throughput |
| 3 | These systems fail to provide performance isolation because of high main memory contention |

### Goal:

Take advantage of custom algorithm and processing-in-memory (PIM) to address these challenges
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<th>Section</th>
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<td>Polynesia: Overview</td>
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<td>Consistency Mechanism</td>
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<td>6</td>
<td>Analytical Engine</td>
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**SAFARI**  
Introduction  
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Conclusion
**Key idea**: partition computing resources into two types of isolated and specialized processing islands

Isolating transactional islands from analytical islands allows us to:

1. **Apply workload-specific optimizations to each island**
2. **Avoid high main memory contention**
3. **Design efficient data freshness and consistency mechanisms without incurring high data movement costs**
   - Leverage processing-in-memory (PIM) to reduce data movement
   - PIM mitigates data movement overheads by placing computation units nearby or inside memory
Designed to sustain bursts of updates

Conventional multicore CPUs with multi-level caches

Designed to provide high read throughput

Take advantage of PIM to mitigate data movement bottleneck

Each island includes (1) a replica of data, (2) an optimized execution engine, and (3) a set of hardware resources

Polynesia: High-Level Overview

Polynesia

Update Propagation

Consistency Mechanism

Analytical Engine

Evaluation

Conclusion

SAFARI

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Maintaining Data Freshness

One of the major challenges in multiple-instance systems is to keep analytical replicas up-to-date.

To maintain data freshness (via Update Propagation):

1. **Update Gathering and Shipping**: gather updates from transactional threads and ship them to analytical the replica.

2. **Update Application**: perform the necessary format conversation and apply those updates to analytical replicas.
Update Gathering & Shipping: Algorithm

Update gathering & shipping algorithm has **three major stages**:

1. **Scan and Merge Transactional Updates**
   - **Update Logs**
     - Tnx. 1
     - Tnx. 2
     - ...
     - Tnx. N
     - **Merge + Sort**

2. **Find Target Column at Analytical Replica**
   - **Final Update Log**
   - **Update Table**
   - **Target Column**

3. **Transfer Updates to Analytical Replica**
   - **Copy**
   - **Update_k**
   - **Column_i Buffer**

**2\textsuperscript{nd} and 3\textsuperscript{rd} stages 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 accelerator, called update gathering & shipping unit.

A 3-level comparator tree to merge updates

Decoupled hash computation from the hash bucket traversal to allow for concurrent hash lookups.
Update Propagation: Update Application

**Goal:** perform the necessary format conversation and apply transactional updates to analytical replicas

**Transactional Replica**

<table>
<thead>
<tr>
<th>Row 1</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row 3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Analytical Replica**

<table>
<thead>
<tr>
<th>C1</th>
<th>C2</th>
<th>C3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Update:** Row 2, Column 1 and 3

<table>
<thead>
<tr>
<th>Compressed Column</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dictionary</th>
</tr>
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<tbody>
<tr>
<td>ID</td>
</tr>
<tr>
<td>----</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

1. A simple tuple update in row-wise layout leads to multiple random accesses in column-wise layout

2. Updates change encoded value in the dictionary \(\rightarrow\) (1) Need to reconstruct the dictionary, and (2) recompress the column
We design our update application algorithm to be aware of PIM logic characteristics and constraints.

We maintain a hash index that links the old encoded value in a column to the new encoded value.

Avoids the need to decompress the column and add updates, eliminating data movement and random accesses to 3D DRAM.
We design a **hardware implementation of our algorithm**, and add it to each **in-memory analytical island**.

A **1024-value bitonic sorter**, whose basic building block is a network of comparators.

**Similar design as our update gathering & shipping unit**
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Consistency Mechanism: Algorithm

For each column, there is **a chain of snapshots** where each chain entry corresponds to a **version of the column**.

Polynesia does not create a snapshot every time a column is updated. Instead, Polynesia marks the column as **dirty**.

Unlike chains in MVCC, each version is associated **with a column, not a row**.

Polynesia creates a new snapshot only if
(1) any of the columns are dirty, and
(2) no current snapshot exists for the same column.
Our algorithm success at satisfying performance isolation relies on how fast we can do memcpy to minimize snapshotting latency.

Multiple fetch and writeback units to issue multiple memory accesses concurrently.

Look-ups at the tracking buffer limit performance → use a hash index to alleviate performance bottlenecks.

Track outstanding reads, as they may come back from memory out of order. Allows to immediately initiate a write after a read is complete.
Efficient analytical query execution strongly depends on:

1. Data layout and data placement
2. Task scheduling policy
3. How each physical operator is executed

The execution of physical operators of analytical queries significantly benefit from PIM.

Without PIM-aware data placement/task scheduler, PIM logic for operators alone cannot provide throughput.
Analytical Engine: Data Placement

**Problem:** how to partition analytical data across vaults of the 3D-stacked memory

- Creates inter-vault communication overheads
- Limits the area/power/bandwidth available to the analytical engine inside a vault
- Increases the aggregate bandwidth for servicing each query by 4 times, and provides up to 4 times the power/area for PIM logic compared to Local

**Analytical Engine: Data Placement**

- **Local**
  - Vault 1
  - Vault 2
  - Vault 3
  - Vault 4

- **Distributed**
  - Vault 1
  - Vault 2
  - Vault 3
  - Vault 4

- **Hybrid**
  - Vault Group A
  - Vault Group B
  - Vault 1
  - Vault 2
  - Vault 3
  - Vault 4

Limit the area/power/bandwidth available to the analytical engine inside a vault.

Increases the aggregate bandwidth for servicing each query by 4 times, and provides up to 4 times the power/area for PIM logic compared to Local.
Other details in the paper:

**Task scheduling policy**

We design a pull-based task assignment strategy, where PIM threads cooperatively pull tasks from the task queue **at runtime**

**How each physical operator is executed**

We employ the **top-down Volcano (Iterator)** execution model to execute physical operations (e.g., scan, filter, join) while respecting operator’s dependencies
Other details in the paper:

Task scheduling policy

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Amirali Boroumand†
†Google

Saugata Ghose◦
◦Univ. of Illinois Urbana-Champaign

Geraldo F. Oliveira‡
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Methodology

• We adapt previous transactional/analytical engines with our new algorithms
  – **DBx1000** for transactional engine
  – **C-store** for analytical engine

• We use **gem5** to simulate Polynesia
  – Available at: [https://github.com/CMU-SAFARI/Polynesia](https://github.com/CMU-SAFARI/Polynesia)

• We compare **Polynesia** against:
  – Single-Instance-Snapshotting (**SI-SI**)
  – Single-Instance-MVCC (**SI-MVCC**)
  – Multiple-Instance + Polynesia’s new algorithms (**MI+SW**)
  – **MI+SW+HB**: MI+SW with a 256 GB/s main memory device
  – **Ideal-Txn**: the peak transactional throughput if transactional workloads run in isolation
While SI-MVCC is the best baseline for **transactional throughput**, it degrades **analytical throughput** by **63.2%**, due to its **lack of workload-specific optimizations and consistency mechanism**.
Polynesia comes within 8.4% of ideal Txn because it uses custom PIM logic for data freshness/consistency mechanisms, significantly reducing main memory contention and data movement.
MI+SW+HB is the best software-only HTAP for analytical workloads, because it provides workload-specific optimizations, but it still loses 35.3% of the analytical throughput due to high main memory contention.
Polynesia improves over MI+SW+HB by 63.8%, by eliminating data movement, and using custom logic for update propagation and consistency.
Overall, Polynesia achieves all three properties of HTAP system and has a higher transactional/analytical throughput (1.7x/3.74x) over prior HTAP systems.
Polynesia consumes 0.4x/0.38x/0.5x the energy of SI-SS/SI-MVCC/MI+SW since Polynesia eliminates a large fraction (30%) of off-chip DRAM accesses.

Polynesia is an energy-efficient HTAP system, reducing energy consumption by 48%, on average across prior works.
More in the Paper

• Real workload analysis
• Effect of the update propagation technique
• Effect of the consistency mechanism
• Effect of the analytical engine
• Effect of the dataset size
• Area Analysis
More in the Paper

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SAFARI

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Full Draft
Conclusion

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