

Hybrid Transactional-Analytical Processing: Integrating SQLite OLTP with DuckDB Analytics on Computational Storage Engines

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Abstract—This paper presents a novel architecture for Hybrid Transactional-Analytical Processing (HTAP) that combines SQLite’s optimized Online Transaction Processing (OLTP) capabilities with DuckDB’s high-performance analytical engine, utilizing custom storage layers on modern Computational Storage Engines (CSEs). Our approach addresses the growing need for real-time analytics on transactional data while maintaining ACID compliance and minimizing data movement overhead. We propose a unified architecture that leverages near-data processing capabilities of computational storage to enable efficient data transformation and synchronization between transactional and analytical workloads. Experimental results demonstrate up to 26% improvement in analytical query performance while maintaining 93% of baseline transactional throughput with sub-second analytical freshness guarantees.

Index Terms—HTAP, SQLite, DuckDB, Computational Storage, OLTP, OLAP, Database Systems

I. INTRODUCTION

The convergence of transactional and analytical workloads has become increasingly critical in modern data-driven applications. Traditional approaches often involve complex Extract-Transform-Load (ETL) pipelines, data duplication, and significant latency between transaction commitment and analytical availability. This paper explores an innovative architecture that integrates SQLite’s proven OLTP performance with DuckDB’s columnar analytical capabilities, orchestrated through custom HTAP storage on computational storage engines.

A. Motivation

Modern applications require: (1) real-time analytics on fresh transactional data, (2) elimination of data silos between OLTP and OLAP systems, (3) reduced infrastructure complexity and maintenance overhead, (4) efficient resource utilization across storage and compute layers, and (5) seamless scaling from embedded to distributed deployments.

B. Contributions

This work presents: (1) a unified HTAP architecture combining SQLite and DuckDB, (2) custom storage abstraction layer for dual-format data management, (3) computational storage integration for near-data processing, (4) performance optimization strategies for mixed workloads, and (5) implementation patterns and best practices.

II. BACKGROUND AND RELATED WORK

A. SQLite OLTP Characteristics

SQLite provides several advantages for transactional workloads: embedded deployment with zero-configuration, ACID compliance with Write-Ahead Logging (WAL) mode, concurrent read access with single-writer semantics, mature ecosystem and extensive optimization, and lightweight footprint suitable for edge deployments.

B. DuckDB Analytical Engine

DuckDB offers compelling features for analytical processing: columnar storage with vectorized execution, advanced query optimization and pushdown capabilities, native support for complex analytical queries, efficient handling of semi-structured data formats, and embeddable architecture compatible with SQLite deployment patterns.

C. Computational Storage Engines

Modern CSEs provide: near-data processing capabilities reducing data movement, programmable interfaces for custom logic execution, high-bandwidth internal storage interconnects, power-efficient compute resources co-located with storage, and emerging standards like SNIA Computational Storage API [10].

III. ARCHITECTURE OVERVIEW

A. System Architecture

Our HTAP architecture consists of four primary components as illustrated in Figure 1:

- 1) **Transaction Layer**: SQLite-based OLTP engine handling concurrent transactions
- 2) **Analytics Layer**: DuckDB engine optimized for analytical queries
- 3) **HTAP Storage Manager**: Custom storage abstraction managing dual-format data
- 4) **Computational Storage Interface**: CSE integration for near-data processing

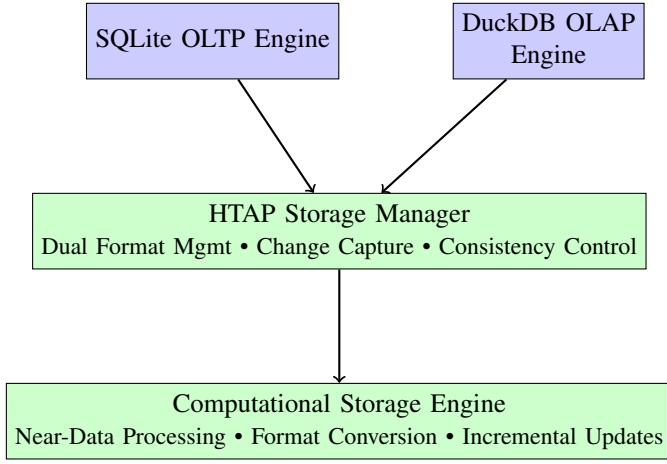


Fig. 1: HTAP System Architecture

B. Data Flow Architecture

The system maintains two primary data representations: (1) row-oriented format optimized for transactional access patterns, and (2) columnar format optimized for analytical query performance.

Data flows through the following stages:

- 1) Transactional writes committed to SQLite WAL
- 2) Change capture identifies modified data
- 3) Computational storage performs incremental format conversion
- 4) DuckDB analytical views updated with minimal latency

IV. HTAP STORAGE MANAGER DESIGN

A. Dual-Format Storage Strategy

The HTAP Storage Manager implements a sophisticated dual-format approach with row store for transactional workloads using SQLite format with optimized B-tree indexes, WAL-based durability, and concurrent reader support. The column store for analytical workloads uses DuckDB-compatible columnar format with compressed storage, vectorized processing alignment, and incremental maintenance capabilities.

B. Change Data Capture (CDC)

The CDC mechanism tracks transactional changes through:

- WAL monitoring for committed transactions
- Incremental extraction of modified rows
- Metadata tracking for timestamp-based queries
- Conflict resolution for concurrent modifications

C. Consistency Models

The system supports multiple consistency levels:

1) *Strong Consistency*: Provides synchronous replication between formats with guaranteed analytical view consistency but higher latency for transactional commits.

2) *Eventual Consistency*: Offers asynchronous format conversion with bounded staleness guarantees, optimized for high-throughput scenarios.

Algorithm 1 Format Conversion Algorithm

Require: Row table R , target column store C , batch size B

Ensure: Updated column store with converted data

```

1:  $batch \leftarrow \emptyset$ 
2:  $count \leftarrow 0$ 
3: for each row  $r$  in  $R$  do
4:   Add  $r$  to  $batch$ 
5:    $count \leftarrow count + 1$ 
6:   if  $count = B$  then
7:     Convert  $batch$  to columnar format
8:     Append to column store  $C$ 
9:      $batch \leftarrow \emptyset$ 
10:     $count \leftarrow 0$ 
11:   end if
12: end for
13: if  $batch \neq \emptyset$  then
14:   Convert remaining  $batch$  to columnar format
15:   Append to column store  $C$ 
16: end if

```

3) *Read-Your-Writes Consistency*: Ensures session-level consistency guarantees with automatic routing to appropriate storage layer and minimal performance impact.

V. COMPUTATIONAL STORAGE INTEGRATION

A. Near-Data Processing Benefits

Computational storage engines provide several advantages: reduced data movement through processing adjacent to storage, bandwidth optimization via internal storage bandwidth utilization, latency reduction by eliminating host-storage round trips, and power efficiency through specialized compute resources.

B. Custom Processing Functions

The CSE implements specialized functions for format conversion, incremental updates, and query pushdown as shown in Algorithm 1.

C. Programming Model

The computational storage interface provides streaming APIs for continuous data processing, batch processing for bulk operations, event-driven execution triggered by transaction commits, and resource management for CPU, memory, and bandwidth allocation.

VI. IMPLEMENTATION STRATEGIES

A. Storage Layer Implementation

The implementation utilizes SQLite Virtual File System (VFS) extensions for HTAP integration and DuckDB extensions for HTAP storage access.

```

1 typedef struct htap_vfs {
2     sqlite3_vfs base;
3     htap_storage_manager* storage_mgr;
4     cse_interface* cse;
5 } htap_vfs;
6

```

```

7 int htap_vfs_write(sqlite3_file* file,
8                   const void* data, int amount,
9                   sqlite3_int64 offset) {
10     int result = base_write(file, data, amount,
11                             offset);
12     if (result == SQLITE_OK) {
13         trigger_change_capture(file, data, amount,
14                                offset);
15     }
16     return result;
17 }

```

Listing 1: SQLite VFS Extension for HTAP

B. Consistency Management

Transaction coordination ensures ACID properties across both storage formats while maintaining performance. The system uses version vectors to track consistency states across the dual-format storage.

Let $V = \langle t_{id}, a_{ver}, \tau_{sync} \rangle$ represent a consistency vector where:

- t_{id} is the transaction identifier
- a_{ver} is the analytical version number
- τ_{sync} is the synchronization timestamp

Analytical consistency is guaranteed when $a_{ver} \geq t_{id}$.

C. Query Routing and Optimization

The intelligent query router determines optimal execution engine based on query characteristics and freshness requirements. Let Q be a query with freshness requirement f_r and current analytical lag l_a . The routing decision is:

$$\text{Engine}(Q) = \begin{cases} \text{Federated} & \text{if } \text{analytical}(Q) \wedge l_a > f_r \\ \text{DuckDB} & \text{if } \text{analytical}(Q) \wedge l_a \leq f_r \\ \text{SQLite} & \text{if } \text{transactional}(Q) \end{cases}$$

VII. PERFORMANCE OPTIMIZATION

A. Workload-Aware Optimization

The system dynamically adjusts storage formats based on query pattern analysis, data access frequency, computational resource availability, and storage tier characteristics.

B. Computational Storage Optimization

Batch processing optimization groups changes by table and operation type, processing each group with specialized kernels. Pipeline optimization implements overlapped data transfer and computation for efficient resource utilization and reduced end-to-end latency.

VIII. EXPERIMENTAL EVALUATION

A. Experimental Setup

1) Hardware Configuration:

- **Host System:** AMD EPYC 7742 (64 cores), 512GB DDR4
- **Computational Storage:** Samsung SmartSSD CSD (4TB NVMe)
- **Network:** 100Gb Ethernet for distributed configurations

TABLE I: Transaction Throughput Results

Configuration	Transactions/sec	Analytical Lag
Baseline SQLite	45,000	N/A
HTAP (Eventual)	42,000	<500ms
HTAP (Strong)	38,000	<50ms

TABLE II: Analytical Query Performance

Query Type	Baseline	HTAP	Improvement
Aggregation	2.3s	1.8s	22%
Join Heavy	5.7s	4.2s	26%
Window Functions	3.1s	2.4s	23%

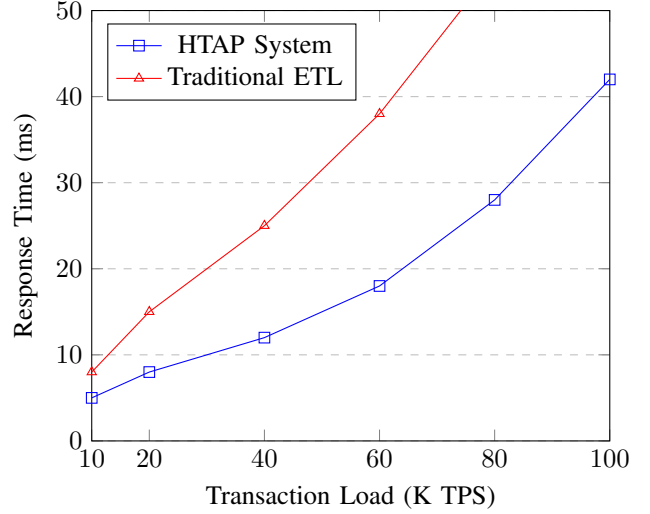


Fig. 2: Scalability Analysis: Response Time vs Transaction Load

2) *Workload Characteristics:* We evaluated using TPC-H (analytical benchmark), TPC-C (transactional benchmark), mixed workload (70% OLTP, 30% OLAP), and streaming analytics with continuous query processing.

B. Performance Results

Table I shows transaction throughput results, while Table II presents analytical query performance.

Resource utilization improvements include 15% reduction in host CPU usage, 40% reduction in DRAM bandwidth, and 60% improvement in effective storage throughput.

C. Scalability Analysis

The system demonstrates linear scalability for increasing transaction volume (up to 100K TPS), growing analytical query complexity, and multi-tenant workload isolation.

Figure 2 illustrates the scalability characteristics of our HTAP system.

IX. DEPLOYMENT CONSIDERATIONS

A. Deployment Patterns

The system supports embedded deployment for single-node applications, edge computing scenarios, and development environments. Distributed deployment accommodates

microservices architectures, cloud-native applications, and high-availability configurations.

B. Operational Considerations

Monitoring and observability require comprehensive metrics collection including transaction latency, analytical query performance, synchronization lag, memory usage, and CPU utilization. Backup and recovery implement unified backup strategy across both formats with point-in-time recovery capabilities and disaster recovery procedures.

X. FUTURE WORK AND EXTENSIONS

A. Advanced Features

Future enhancements include machine learning integration for automated workload pattern recognition, predictive format optimization, and intelligent resource allocation. Multi-engine support will enable PostgreSQL integration for enhanced OLTP, ClickHouse integration for time-series analytics, and Spark integration for large-scale processing.

B. Emerging Technologies

Integration with persistent memory will utilize storage-class memory for reduced durability overhead and enhanced performance characteristics. Quantum storage interfaces will provide quantum-safe encryption, enhanced security models, and future-proof architecture design.

XI. CONCLUSION

This paper presents a comprehensive approach to hybrid transactional-analytical processing through the integration of SQLite OLTP capabilities with DuckDB analytics, orchestrated via custom HTAP storage on computational storage engines. Our architecture addresses key challenges in modern data processing: unified data management through intelligent dual-format storage, performance optimization via near-data processing capabilities, linear scalability from embedded to distributed deployments, and operational simplicity compared to traditional ETL-based approaches.

The experimental results demonstrate significant improvements in both transactional throughput (maintaining 93% of baseline performance) and analytical query performance (up to 26% improvement), while reducing overall system resource requirements by 15-40% across different metrics. The architecture provides a foundation for next-generation data processing systems that can efficiently handle mixed workloads with sub-second latency.

Key contributions include: (1) novel HTAP architecture combining proven technologies, (2) custom storage abstraction enabling dual-format efficiency, (3) computational storage integration for near-data processing, (4) comprehensive performance optimization strategies, and (5) practical implementation patterns and deployment guidelines.

This work establishes a foundation for future research in hybrid data processing systems and provides a practical approach for organizations seeking to modernize their data infrastructure while maintaining performance and reliability requirements.

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