LiveGraph: A Transactional Graph Storage System with Purely Sequential Adjacency List Scans

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Abstract

The specific characteristics of graph workloads make it hard to design a one-size-fits-all graph storage system. Systems that support transactional updates use data structures with poor data locality, which limits the efficiency of analytical workloads or even simple edge scans. Other systems run graph analytics workloads efficiently, but cannot properly support transactions.

This paper presents LiveGraph, a graph storage system that outperforms both the best graph transactional systems and the best systems for real-time graph analytics on fresh data. LiveGraph does that by ensuring that adjacency list scans, a key operation in graph workloads, are purely sequential: they never require random accesses even in presence of concurrent transactions. This is achieved by combining a novel graph-aware data structure, the Transactional Edge Log (TEL), together with a concurrency control mechanism that leverages TEL’s data layout. Our evaluation shows that LiveGraph significantly outperforms state-of-the-art (graph) database solutions on both transactional and real-time analytical workloads.

1 Introduction

Graph data is one of the fastest growing areas in data management: applications performing graph processing and graph data management are predicted to double annually through 2022 [1]. Applications using graph data are extremely diverse. There are two broad classes of graph workloads with different requirements: transactional graph data management and graph analytics.

Transactional graph data management workloads continuously update and query single vertices, edges, and adjacency lists.\textsuperscript{1} Facebook, for example, stores posts, friendship relationships, comments, and other critical data in a graph format [15, 19]. Write transactions incrementally update the graph, while read transactions are localized to edges, vertices, or the neighborhood of single vertices. These applications require a graph storage system to have very low latency and high throughput, be it a key-value store, a relational database management system, or a dedicated graph-aware system. The system must also have classic transactional features: concurrency control to deal with concurrent updates and durability persist updates.

Graph analytics tasks run on a consistent read-only graph snapshot and their performance highly depends on efficient scans of the neighborhood of a vertex (i.e., the adjacency list of the vertex). A particular class of analytics, real-time analytics on fresh dynamic graph data, is becoming increasingly important. Consider for example recommendations, where a shopping/social website needs to find products/connections a user might be interested in, are based on the user’s properties and most recent interactions. The freshest interactions imply users’ interests at the moment, and produce the most relevant recommendations. Other applications in this class include knowledge graphs (where personal assistants like Siri answer complex user queries about recent events), finance (where financial institutions establish if groups of people connected through common addresses, telephone numbers, or frequent contacts are issuing fraudulent transactions), or systems security (where monitoring systems detect whether an attacker has performed a sequence of correlated steps to penetrate a system).

It is increasingly attractive to have a graph storage system that simultaneously supports both transactional and (real-time) analytical workloads. Unfortunately, common data structures adopted separately in the two worlds do not fare well when crossing into unfamiliar territories.

Data structures used in state-of-the-art DBMSs and key-value stores do not support well adjacency list scans, a crucial operation in graph analytics and graph database

\textsuperscript{1}We call a workload “transactional” if it consists of simple read/write operations that must be interactive and require very low latency, no matter if they access only one object or multiple-objects atomically.
queries. More specifically, popular structures such as B+ trees and Log-Structured Merge Trees (LSMTs) yield significantly worse performance in graph analytics than graph-aware data structures like Compressed Sparse Rows (CSR). We performed micro-benchmarks and a micro-architectural evaluation comparing alternative data structures for storing graph data, and in particular adjacency lists. The results show that contiguous in-memory storage of adjacency lists not only improves caching efficiency, but also allows better speculation and prefetching, reducing both memory access costs and the number of instructions executed.

At the other end of the spectrum, analytical graph engines often use sequential memory layouts for adjacency lists like CSR. They feature efficient scans but do not support high-throughput, low-latency concurrent transaction processing. In fact, most existing graph engines do not target mutable graphs at all. Adding concurrency control to deal with concurrent updates is not straightforward. The concurrency control algorithm is on the critical path of every operation and thus directly impacts the performance of adjacency list scans. It should not disrupt otherwise sequential scans with random accesses and a complex execution flow. There has been much recent work on in-memory concurrency control and transactional support for relational data [59, 57, 41, 28, 44, 39] but none of this work has specifically targeted the unique requirements of graph workloads.

This paper is a first step towards filling this gap. It proposes LiveGraph, a graph storage system supporting both transactional and (real-time) analytical workloads. A key design goal of LiveGraph is to ensure that adjacency list scans are purely sequential, that is, they never require random access even in presence of concurrent write or read transactions. To this end, we co-design a system’s graph-aware data structure and its concurrency control algorithm. LiveGraph stores adjacency list in a new data structure called the Transactional Edge Log (TEL). The TEL combines multi-versioning with a sequential memory layout. The concurrency control of LiveGraph leverages the cache-aligned timestamps and counters of the TEL to preserve the sequential nature of scans even in presence of concurrent transactions. It is an efficient yet simple algorithm whose regular execution flow enables speculation and prefetching.

Our evaluation compares LiveGraph with several state-of-the-art systems, including specialized graph databases, graph database solutions built on key-value stores or traditional RDBMSs, and graph engines. Results demonstrate that LiveGraph outperforms the current leaders at their specialty, in particular outperforming Facebook’s RocksDB [2] by up to $8.41 \times (2.55 \times$ on average) using Facebook’s social graph benchmark [15]. In addition, LiveGraph dramatically outperforms (up to $36.4 \times$ better than the runner-up) all systems that have implemented the LDBC SNB interactive workload [27], ingesting updates and performing real-time analytics queries concurrently. We further perform microbenchmarking and extensive profiling to understand the performance differences. Finally, LiveGraph allows lower end-to-end processing time by conducting in-situ iterative graph analytics (like PageRank) on its latest snapshot, as the expensive ETL cost can now be completely eliminated.

## 2 Purely Sequential Scans

A key design choice of LiveGraph is ensuring purely sequential adjacency scans: scans should never entail random accesses. Before introducing the details of LiveGraph, we motivate why purely sequential adjacency list scans are important. We use single-threaded micro-benchmarks and micro-architectural analysis to compare different commonly used data structures and quantify the advantage of a sequential memory layout. Then, we discuss how concurrency control algorithms introduce additional complexity in the form of random accesses and branching.

### 2.1 The Benefits of Sequential Edge Storage

Adjacency lists contain the key topological information in a graph. Full or partial scans of these lists are fundamental operations in graph workloads, from simple queries to full-graph analytics. Graph storage must balance fast scans with efficient edge insertions, which are frequent in graph writes [19, 15]. In the following, we compare the scan performance of different data structures used for graph storage.

**Graph data representations** Graph data consists of two types of objects: vertices and edges. Figure 1 illustrates how the same sample graph (Figure 1a) can be stored using different data structures.

CSR (Figure 1b) consists of two arrays, the first storing the adjacency lists of all vertices, as sequences of

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| Data Structure | Cost | Seek   | Scan (per edge) |
|---------------|------|--------|-----------------|
| B+ Tree       | $O(\log N)$ | random | sequential w. random |
| LSMT          | $O(\log N)$ | random | sequential w. random |
| Linked List   | $O(1)$ | random | random |
| CSR           | $O(1)$ | random | sequential |
| TEL           | $O(1)$ | random | sequential |

Table 1: Adjacency list scan properties of different data structures. $N$ is the size of the tree.
destination vertex IDs, while the second storing pointers to the first array, indexed by source vertex ID. CSR is very compact, leading to small storage footprint, reduced memory traffic, and high cache efficiency. Also, unlike most other data structures, it enables pure sequential adjacency list scans. These properties make it a top choice for graph engines [45, 31, 63], which target read-only analytical workloads. On the flip side, it is immutable, making it unsuitable for storing dynamic graphs or serving transactional workloads.

Linked list (Figure 1c) is an intuitive choice for storing adjacency lists and is used by Neo4j [3], a popular transactional graph database. The linked list easily supports edge insertions but it suffers from random accesses during scans when traversing through pointers.

Other state-of-the-art graph stores adopt general-purpose data structures such as the B+ tree (Figure 1d) and the LSMT (Log-Structured Merge-Tree, Figure 1e). The adjacency list is represented as a single sorted collection of edges, whose unique key is a \( \langle \text{arc, dest} \rangle \) vertex ID pair.

In this work, we propose a new data structure, the Transactional Edge Log (TEL), which simultaneously allows sequential adjacency list scans and fast edge insertion. Unlike any existing structures used in graph systems, it features purely sequential, yet mutable, edge storage. Figure 1f gives a sneak preview of TEL. For the purpose of this discussion, it suffices to say that edges are stored sequentially in contiguous blocks with empty slots at the tail. Edge insertions and updates are appended at the tail of the block until it fills up, at which point the TEL is upgraded to a larger block. Like CSR, TEL has purely sequential adjacency list scans.

Table 1 summarizes the aforementioned data structures. Each adjacency list scan scan consists of a one-time seek operation, which locates the first edge of the adjacency list, followed by the edge scan, a sequence of edge accesses. Note that the cost of the initial seek often cannot always be amortized, especially considering that most real-world graphs exhibit power-law degree distributions so most vertices have few edges.

**Micro-benchmark results** To see the impact of the data structure choices on actual graph systems, we use a micro-benchmark that performs \( 10^7 \) adjacency list scans, where each start vertex is selected randomly under a power-law distribution. Graphs are generated using the Kronecker generator [40] with sizes ranging from \( 2^{20} \) to \( 2^{26} \) vertices, and an average degree of 4 (similar to those generated by Facebook’s LinkBench [15] benchmark). All graphs fit in the memory of a single socket. For accurate cache monitoring, we perform single-thread experiments, with the workload driver running on a separate socket.

We evaluate LMDB [4] and RocksDB [2], embedded storage systems that adopt B+ trees and LSMTs respectively. To fairly isolate the impact of data structure choices, we disable compression in RocksDB. We also implement an efficient in-memory linked list prototype in C++ rather than running Neo4j on a managed language (Java). We do not evaluate CSR since it is a read-only data structure.

We consider two metrics: seek latency and edge scan latency. Seek latency is the time needed to access the next edge in the adjacency list. Figure 2 shows that using different data structures results in orders of magnitude gaps in these metrics.

The sequential data layout of TEL is clearly superior to other pointer-based data structures. To locate the first edge of the range (seek), B+ trees have a logarithmic number of random accesses. RocksDB’s implementation of LSMTs uses a skip list as memtable, which has a similar behaviour for seeks. However, LSMTs also require scanning SST tables for seeks, since only the first part of the edge key is known (the source vertex ID) while
the second part is unknown (the destination ID). This explains the bad performance of LSMT in Figure 2a. For linked-lists and TELs we consider one data structure instance per adjacency list, as done in Neo4j and LiveGraph, respectively. Therefore, seeks only entail a constant-time index lookup.

Systems using B+ trees and LSMT store edges in a single sorted collection, which corresponds to a single edge table. An adjacency list scan becomes a range query where only the first component of an edge key, the source vertex ID, is given. To iterate over all edges of a vertex (scans), a B+ tree sequentially scans elements of the same node but it needs random accesses whenever an adjacency list spans multiple nodes. LSMTs require scanning SST tables also for scans because, similar to seeks, only the first component of the edge key is known. Skip Lists and Linked List require random accesses for each edge scan. By contrast, scans in TELs are always sequential. Figure 2b shows that TEL has a scan speedup larger than 19× over linked list, 19× over LSMT, and 5× over B+tree.

We performed a more detailed micro-architectural analysis on the $2^{26}$ scale graph to further understand the behavior of different data structures. B+ trees and LSMTs trigger 7.51× and 13.72× more last-level cache misses than TEL. Linked Lists with mostly random memory accesses are the worst, achieve 87.49× LLC-misses than TEL. TEL has a more simple sequential execution flow, which leverages CPU pipelining and prefetching and reduces the likelihood of branch mispredictions. This micro-architectural profiling confirms the huge gap between pointer-based data structures and a sequential data structure like TEL.

In terms of total adjacency list scan latency, TEL yields, on average among different graph scales, a 20× performance improvement over LSMT, 18× over linked list, and 4.5× over B+ tree. For seeks, there is a significant gap between tree-based (logarithmic) and graph-aware (constant) data structures. For scans, TEL performs much better than others as accesses are purely sequential while other data structures involve random accesses and additional branching.

These results show that existing dynamic data structures used by transactional systems leave a lot of performance on the table for graph workloads and it is worth using a graph-aware storage layout like TEL.

### 2.2 Transactions with Sequential Access

The previous experiments show the importance of eliminating random accesses during adjacency list scans through graph-aware data structures. However, they consider a single-threaded setting without concurrency. In transactional workloads, it is necessary to preserve the benefits of sequential scans in presence of concurrent transactions.

Real-time graph analytics feature read-only transactions that need to access a consistent snapshot of the graph. These transactions are potentially long running and access a large fraction of the graph, but they should not hinder the progress of concurrent transactions. Multi-versioning is a common approach to ensuring this property and many efficient concurrency control algorithms have been proposed for relational databases [28, 39, 41, 44, 59]. However, they target data with flat layouts (i.e. indexed records). Representing adjacency list as records is possible but that would make edge updates prohibitively expensive because every time the entire list would have to be overwritten.

Enabling multi-versioned sequential accesses to adjacency lists is to our knowledge an open topic encompassing multiple challenges: (1) different versions of edges belonging to the same adjacency list must be stored in contiguous memory locations; (2) finding the right version of an edge should not require auxiliary data structures that, in turn, require random access to be visited; (3) the concurrency control algorithm should not require random access during scans.

LiveGraph is the first system that guarantees these properties, achieved by co-designing a graph-aware data structure (Section 3) and the concurrency control algorithm (Section 5) to ensure purely sequential scans even in presence of concurrent transactions.

### 3 LiveGraph Data Layout

LiveGraph implements both in-memory and out-of-core graph storage on a single server. It adopts the property graph model [49], where each object (vertex or edge) can have associated properties (e.g., arbitrary key-value pairs).

Edges have a special type of property called label. Edges that are incident to the same vertex are grouped into one adjacency list per label. For simplicity, our discussion considers the case where all edges have the same default label.

Edge storage is particularly critical since (1) usually there are more edges than vertices in a graph and edge operations are more frequent [19], and (2) efficient edge scan is crucial, as discussed earlier. Therefore, LiveGraph stores a graph using a two-dimensional approach. Vertices are stored individually whereas all the edges incident in the same vertex (i.e., in the same adjacency list) are grouped in a single Transactional Edge Log (TEL).

Figure 3 shows the data structures of LiveGraph, which mainly consist of vertex blocks (VB) and TELs. These are stored in a single large memory-mapped file managed by LiveGraph’s memory allocator. The blocks
are accessed via two index arrays, a vertex index and an edge index, storing pointers to appropriate blocks by vertex ID. Though not depicted in Figure 3, there is an additional level of indirection between the edge index and TELs, called label index blocks, used to separate the storage of per-vertex edges with different labels. Since vertex IDs grow contiguously, we use extendable arrays for these indices. We have not found this to be a limiting factor in any of our experiments.

**Vertices** LiveGraph stores each vertex separately into the vertex block. Updates to vertices are relatively infrequent and transactions typically access the latest version. Therefore, for vertices we use a standard copy-on-write approach, where the newest version of the vertex can be found through the vertex index, and each version points to its previous version in the vertex block.

**Adjacency Lists** A TEL is a fixed-size memory block with free space that is resized when filled. This organization combines efficient sequential scans of read-optimized formats for analytics (like CSR) with support for updates of dynamic arrays. Instead of just storing edges constituting the current adjacency list, a TEL represents all edge insertions, deletions, and updates as log entries appended at the tail of the log. Note that while we discuss focuses on using TEL for adjacency list storage, ideas proposed here can be used to implement a general key-value set data structure with sequential snapshot scans and amortized constant-time inserts that do not interfere with each other.

The layout of a TEL block is depicted in Figure 4. Edge log entries are appended backwards, from right to left, and scanned forwards, from left to right. This is because some scan operations benefit from time locality, where more recently added elements are read first. Edge log entries have fixed size with cache-aligned fields. This is required by the transaction processing protocol, as we will see. Each entry has two timestamps, a creation timestamp and an invalidation timestamp, indicating the lifecycle of this entry. Edge properties have variable length and are appended from the beginning of the block forwards. Properties are stored separately from the edge log entries to preserve the data layout alignment of the latter, as required by the transaction processing protocol.

For new vertices, its adjacency list starts small, with 64-byte blocks that accommodate a single edge in our implementation. When a block is full, LiveGraph copies the log to an empty block of twice its current size. Similar to dynamic arrays, appends to the log have a constant amortized cost. The worst-case cost is linear, but copying contiguous blocks of memory is fast and does not result in high tail latency, as our evaluation shows.

This design is particularly suited given that power-law degree distributions are common in real-world graphs. The majority of vertices, being low-degree and less active, will grow slowly in degree, with limited space waste. The high-degree vertices are likely to grow faster and incur higher data copying cost when “upgraded”, but such relocation happens at decreasing frequency with exponentially growing block sizes. The power-law degree distribution also implies that only a small fraction of vertices occupy large log blocks. We describe the details of LiveGraph’s memory management and log relocation in Section 6.

### 4 Single-Threaded Operations

We first describe LiveGraph’s operations in absence of concurrency. LiveGraph uses a multi-versioned data store and each transaction is associated with a read timestamp, which determines the version of the data it operates on. This timestamp is determined by the transaction processing mechanism as described in Section 5.

**Vertex operations** Vertex reads access the vertex index and then the vertex block; writes create a new version of the vertex block in the block storage, including a pointer to the current version, and set the vertex index to point to the new version. In the uncommon case in which a read requires a previous version of the vertex, it follows the per-vertex linked list of vertex block versions in backward timestamp order until it finds a version with timestamp smaller than its read timestamp.

Adding a new vertex first uses an atomic fetch-and-add operation to get the vertex ID, fills in empty pointers in the corresponding locations of vertex and edge indices, and sets the lock status. If the vertex needs to store properties or add edges, it then asks the storage manager to allocate a block according to the size it needs, whose details will be shown in Section 6. Garbage collection for vertex IDs can be achieved by using techniques described later in Section 6, but since vertex deletions are rare, we leave this to future work.

**Sequential adjacency list scans** Scanning adjacency lists efficiently is a key requirement of analytics workloads. LiveGraph achieves purely sequential adjacency list scans by combining a log-structured storage of the adjacency list and double timestamps.
A log structure is a more convenient multi-versioned representation of the adjacency list compared to alternative approaches. For example, a coarse-grained copy-on-write approach to multi-versioning would create a new copy of the entire adjacency list every time an edge is updated. This is the approach used by Grace [48]. However, this makes updates very expensive, especially for high-degree vertices. A more fine-grained approach would be to keep separate copies of each modified edge at different memory locations, with different versions chained through pointers. This would make writes cheaper but it would require random accesses (i.e., pointer-chasing) for scans.

Storing multiple versions of the adjacency list in contiguous memory locations as a log is key to achieving purely sequential adjacency list scans, but it is not sufficient. The same edge, however, can now correspond to multiple entries in the log, as shown in Figure 4. When a thread executing an adjacency list scan reads an edge entry, it cannot tell whether the entry is still valid or if it has been deleted or modified at a later position in the log. The thread could keep a hash map to progressively update the latest version of each edge during the scan. But accessing the map would again require random accesses, which we strive to avoid.

This is why LiveGraph stores a double timestamp for each edge entry. A read operation with a timestamp $T$ considers only edge entries such that $T$ is within the entry’s creation and invalidation timestamps. The creation and invalidation timestamps determine if the entry is valid for the read timestamp of the transaction (see Figure 4). This makes scans of TELs sequential: a transaction can check the validity of an edge entry simply by checking if its read timestamp is within the creation and invalidation timestamps. Scans that access edge properties require two sequential scans, one forwards from “tail” (as shown in Figure 4) to the right end, for edge log entries, and one backwards from the end of the property entries, for properties.

**Edge updates and constant-time insertions** To support fast ingestion of new edges, LiveGraph inserts edges in amortized constant time. Insertions in a regular log-based data structure are simple appends, which can be done in constant time. TELs sometimes require resizing in order to append new entries, but the amortized cost of appends is still constant, like in dynamic arrays (see Section 3). The dual timestamp scheme of LiveGraph, while useful for sequential scans, makes updating the adjacency list more complex. Appending log entries is not always sufficient any longer. If an operation updates or deletes an existing edge, it must also update the invalidation timestamp of the previous entry for that edge, which entails scanning the log. However, if a new edge is inserted, the scan is not necessary and a constant-time append is still sufficient.

LiveGraph includes a Bloom filter in the TEL header to determine whether an edge operation is a simple insert or a more expensive update. Inserting a new edge appends an entry at the end of a TEL and updates the Bloom filter as well as the adjacency list block size. Edge deletions/updates first append a new entry to the TEL and check, using the Bloom filter, if a previous version of the edge is present in the TEL. If so, its invalidation timestamp needs to be updated. The Bloom filter is also handy to support fast “upsert” semantics (such as in the Facebook LinkBench workload [15]), where a lookup is needed to check whether the entity to be inserted already exists. It allows distinguishing which of them are “true insertions” that add new edges, such as “likes” in social networks or new purchases in online stores. Inserts often compose the majority of write operations and LiveGraph processes them in amortized constant time.

Upon a “possibly yes” answer from the Bloom filter, however, finding the edge itself involves a tail-to-head TEL scan, traversing the entire adjacency list in the worst case. In practice though, edge updates and deletions have high time locality: edges appended most recently are most likely to be accessed. They are the closest to the tail of the TEL, making average cost fairly low for edge updates/deletions.

Each Bloom filter is sized 1/16 of the total size of the destination vertex IDs stored in a TEL. We found that
Bloom filters do not pay off for small blocks (i.e., 256 bytes or less).

To ensure consistent versioning, it is necessary to guarantee the invariant that the invalidation timestamp of an entry is always larger than its creation timestamp. Write operations having a timestamp \( T \) must abort if they try to invalidate an entry with creation timestamp larger than \( T \). LiveGraph stores the latest timestamp that has modified a TEL in a commit timestamp variable CT in the TEL header. This way, write operations can simply compare their timestamp against CT instead of paying the cost of scanning the TEL only to later find that they must abort.

**Reading a single edge** Reading a single edge involves checking if the edge is present using the Bloom filter. If it is present, the edge is located with a scan. As with adjacency list scans, the scan skips any version of the entry having a creation or invalidation timestamp inconsistent with the read timestamp.

**Time-based and incremental snapshots** Adjacency list scans benefit significantly from LiveGraph’s sequential adjacency list storage as well as its log-structured organization, which result in a natural temporal ordering of edges. LiveGraph facilitates both contiguous edge access (without pointer chasing) and efficient data truncation to retrieve the TEL “suffix” containing the most recent edges, an important graph transaction operation. Here the processing again relies on TEL scans, checking timestamps to intercept the appropriate edge range. The log structure makes edge entries naturally sorted by creation time, so time-related queries (abundant in graph workloads) can be efficiently processed without sorting. Finally, the existence of timestamps simplifies certain activities, such as group commit and creating persisted snapshots to speedup failure recovery.

## 5 Transaction Processing

A unified graph database needs ACID transactions to enable analytical queries and to support transactional updates. Analytical queries must have access to a consistent read-only snapshot across multiple hops and iterations. Transactions are also useful to ensure atomic concurrent updates to one or more objects, for example for adding bidirectional edges. This section describes how LiveGraph executes transactions consisting of one or more basic read/write operations, which are the operations described in Section 4.

**Data layout and coordination** LiveGraph’s use of a multi-versioned log for adjacency lists is mainly motivated by the need for supporting snapshot isolation efficiently. One key benefit of snapshot isolation is that read and write operations do not need to interfere with each other. In LiveGraph, basic read operations do not acquire locks. Coordination with basic write operations occurs only through cache-aligned 64-bit word variables, which are written and read atomically. Cache alignment is achieved through careful design of the graph blocks and explicit memory management to assign the location of blocks (which will be described in Section 6).

For vertices, coordination occurs through index pointers, where the index has fixed-size entries. For edges, cache-alignment is achieved by separating edge properties and edge log entries in TELs (see Figure 4). Edge properties have variable size, so they are appended from the beginning of the TEL block. Edge log entries have fixed size, so appending them from the end of the TEL ensures that all timestamps are cache aligned. Two additional per-TEL variables are used for coordination: the log commit timestamp LC\( T \) and the log size LS. They are both stored in TEL’s header, which is also fixed-size.

Write-write conflicts are detected using per-vertex locks, implemented with a `futex` array (with a very large size pre-allocated via `mmap`). We also experimented with other choices like concurrent hashtables or spinlock arrays but met scalability problems on certain scenarios.

**Algorithm overview** All transactions obtain a unique read timestamp from a transaction manager when they are started. Basic read operations execute as discussed in Section 4, using the read timestamp to determine which data versions to read. They do not require acquiring locks and adjacency list scans are strictly sequential. The protocol guarantees that the read timestamp of a transaction is always smaller than the write one of any concurrent transaction.

Basic write operations initially store their own updates in a transaction-private working version. The private updates are made visible only after the transaction has committed. Read operations executed by the same write transaction need to see the private updates before commit. In particular, to keep adjacency list scans sequential, LiveGraph stores private working versions as entries in the same TEL used for committed updates. LiveGraph uses timestamps to control the visibility of updates and keep working versions private to its write transaction until commit.

Transactional durability is ensured by using write-ahead-logging. Write transactions are persisted to a sequential commit log on stable storage before they are committed.

A write transaction goes through three phases: **work, persist, and apply**. In the work phase, the transaction starts by computing its unique transaction identifier TID and acquiring vertex locks (to avoid deadlocks, a simple timeout mechanism is used: any transaction waiting for
more than a specified duration has to rollback and restart the operations). It then executes write operations as discussed in Section 4, initializing the timestamps as \(-TID\) to make them private. The work phase finishes when the transaction calls the transaction manager to persist its changes to the write-ahead log, which starts the persist phase. The transaction manager adds the transaction to a sequential write-ahead log (WAL) and uses `fsync` to ensure that the transaction’s entry in the WAL is actually persisted to stable storage. Afterwards, the apply phase starts. The write transaction now receives a write timestamp `TWE` from the transaction manager and updates the commit timestamp of the TEL. Next, it releases all its locks before starting the potentially lengthy process of making its updates visible by converting their timestamps from \(-TID\) to `TWE`. After all updates are made visible, the transaction manager advances the read timestamp so new transactions will be able to observe the new updates.

Figure 5 shows an example of a write operation executed concurrently with reads in two of its phases (the persist phase is done by the logger and omitted due to space limit).

**Detailed description** LiveGraph keeps a pool of transaction-serving threads (henceforth referred to as “workers”) and one transaction manager thread to coordinate and persist transactions. All threads share two global read and write epoch counters called `GRE` and `GWE`, respectively, which are initially set to 0. They also share a reading epoch table to establish a safe timestamp for compaction.

Every time a worker receives a transaction, it initializes two local variables: a transaction-local read epoch counter `TRE`, which the transaction initially sets to `GRE`, and a transaction-local write epoch counter `TWE`, which is determined by the manager at commit time. The worker assigns the transaction a unique transaction identifier `TID`, which is the concatenation of the worker’s unique thread ID and a worker-local logical transaction count.

Basic read operations access a snapshot determined by their `TRE`. When they read a vertex, transactions visit the linked list of vertex versions until they find the right version. In practice, a transaction needs to visit the list only in the rare case in which there are concurrent vertex writes.

When they scan a TEL, read operations only consider edge log entries such that either \((0 <= \text{CreationTS} <= \text{TRE}) \text{ AND } ((\text{TRE} < \text{InvalidationTS}) \text{ OR } (\text{InvalidationTS} < 0))\) or \(\text{CreationTS} == \text{-TID} \text{ AND } \text{InvalidationTS} != \text{-TID}\)\(^2\). The first condition checks that the entry is valid for time `TRE`; the second one guarantees that a write transaction sees its own writes, as it will become clear shortly. The scan starts from the tail of the log, which is indicated in the LS size variable of the TEL header.

For basic write operations, a write transaction starts by acquiring a lock on the index entry for the vertex block or the TEL block that is written to. Each block is associated with a log commit timestamp `LCT`, which is a 64-bit cache-aligned word stored in its header. If `LCT` is larger than `TRE`, the transaction aborts to avoid that its updates supersede objects with a larger creation timestamp. Otherwise, the write operation proceeds. New vertex blocks and edge log entries are assigned a creation timestamp `CreationTS` equal to \(-TID\). If the operation appends an edge log entry that updates an edge that has already been inserted in the TEL, the transaction must find that entry and set the invalidation timestamp `InvalidationTS` for that entry to \(-TID\). After a worker has completed a write transaction, it sends the `TID` and the redo log to the transaction manager, and then sleeps. This marks the end of the working phase for that transaction.

The transaction manager uses group commit to optimize throughput. It initiates a new group commit when it receives a sufficiently large batch of redo logs or af-

\(^2\)In our implementation, timestamps are actually stored and compared as unsigned integers, so the comparisons with 0 can be omitted and \(-TID\) is stored as `MAXUINT+1+TID`.
ter a timeout. The group commit procedure increases the $GWE$ counter and executes `fsync` to make sure that the complete batch of redo logs is persisted to disk. When `fsync` completes, the manager wakes up the workers that had sent the committed transactions. The manager sends them a reference to an atomic counter $AC[TWE]$, which is initially set to the number of workers in the commit group. The manager can then proceed to committing the next group.

When they wake up, the workers in the commit group set $TWE = GWE$ and start the apply phase. The workers then modify the header of each TEL block they have modified: they set the commit timestamp to $TWE$, increase the size $LS$ in the header, and finally release the lock on the block. For vertex blocks, they update the version pointers and set the vertex index pointer to the latest version. After doing this, the workers release the lock on the block. At this point, they start modifying all the creation timestamps they had set to $\sim-TID$ and update them to $TWE$. After updating all timestamps, workers notify the transaction manager that it can make their changes visible to new transactions by atomically decreasing the counter $AC[TWE]$. Once the transaction manager notices that the counter for the oldest outstanding group commit epoch, $AC[GWE]$, is set to zero, it sets $GWE=GWE$ to make the changes in this commit visible. This guarantees that the read timestamp of a transaction is always smaller than the write timestamp of any ongoing transaction.

### 6 Storage Management

LiveGraph uses a memory mapped file to store graph data, mainly made by vertex blocks, which store single vertices, and TEL blocks, each storing a TEL (see Figure 3). Manually managing memory allows all operations to access sequential chunks of data, resulting in better cache utilization, branch prediction, and I/O efficiency if data is not in memory. This design allows to store graphs that do not fit in memory and relies on the operating system to decide how data is cached in memory and evicted.

**TEL compaction** The TEL is not just an adjacency list but also, implicitly, a multi-version log record of the adjacency list, with entries sorted by creation timestamps. Invalidated entries are useful for retrieving and analyzing historical snapshots, but their accumulation will eventually bloat the TEL size and impede in-memory processing. Therefore, LiveGraph performs periodic compaction.

LiveGraph provides the capability of a user-specified level of historical data storage, trading off disk space and checkpointing overhead, to allow full or partial historical snapshot analysis. In the prototype evaluated, we performed rather aggressive garbage collection (GC), without saving invalidated copies to disk. LiveGraph periodically (i.e., every 65536 transactions in our default setting) launches a compaction task. Each thread in LiveGraph maintains a *dirty vertex set*, marking vertices whose corresponding blocks have been updated since the last compaction executed within this thread. The thread doing compaction scans through its local dirty set, collecting unused blocks as garbage and removing edge entries invalidated prior to the current time.

The compaction thread processes one TEL at a time, asynchronously and independently, with only minimal interference with regular workloads. It creates a new copy of a TEL, holding the incident vertex lock during the process. This temporarily blocks writes on that specific TEL, but read operations can continue reading the old version, which is kept until it is finally garbage collected. Writes to the new blocks are also committed as with write transactions. Compaction only occurs in memory in a lightweight vertex-wise fashion: unlike LSMT, LiveGraph never needs to compact multiple on-disk files through merging.

**Space overhead for timestamps** Using two timestamps (which are not explicitly used by graph analytics algorithms themselves) dilutes TEL's storage density and lowers its bandwidth/caching efficiency compared to compact data structures such as CSR. This results in a performance gap between running analytics on top of LiveGraph compared to state-of-the-art engines for static graphs such as Ligra [52] or Gemini [63]. However, analytics on top of LiveGraph do not need to perform expensive ETL (Extract-Transform-Load) operations to load the graph into a dedicated tool. Compared to systems that support transactional graph updates and use pointer-based data structures, LiveGraph uses sequential memory regions and thus saves the storage cost of keeping many pointers, in addition to supporting multiversioning. Overall, our evaluation shows that LiveGraph has a similar memory overhead as these systems.

**Memory management** In selecting the adjacency list block size, we have to consider the trade-off between the cost of repeated data relocation and space utilization. In making this decision, we have a rare opportunity that many real-world graphs possess power-law degree distributions [22, 29, 53]. Inspired by the buddy system [37], we consider protocols of fitting each per-vertex edge log into a log block of the closest power-of-2 size.

LiveGraph has TELs starting from a size of 64 bytes (a 36-byte header plus a 28-byte log entry, whose contents were described earlier). This minimal configuration accommodates one edge and occupies one cache line in common processors today. An array of lists $L$ is used for keeping track of the free blocks in the block store, where
\(L[i] \ (i = 0, 1, \ldots, 57)\) contains the positions of blocks with size equal to \(2^i \times 64\) bytes. When a block of certain size is needed, LiveGraph first checks the corresponding free list, allocating new blocks from the tail of the block store only when that list is empty. Vacated blocks or those that do not contain any valid data, meanwhile, are recycled into the proper free lists.

Again considering the power-law degree distribution, we accelerate the allocation process by differentiating the free list management of smaller and larger blocks. We define a tunable threshold \(m\), with each thread maintaining its private free list array \(\{S[0], \ldots, S[m]\}\) and sharing a global free list array \(\{S[m+1], \ldots, S[57]\}\). This significantly reduces the contention over the free lists for allocating highly popular small blocks, while mitigating waste by centralized large block management. Measurements on our 24-core (48 hardware threads) test platform show that block allocation is not a performance bottleneck.

7 Evaluation

7.1 Experimental Setup

Platform We setup experiments on a dual-socket server, whose specification is given in Table 2. The persistence features are enabled for all the systems, except when specified explicitly, the Intel Optane SSD is used for persistence.

| Processor       | 2-socket Intel Xeon Gold 6126 CPU |
|-----------------|-----------------------------------|
| Memory          | 192 GB DDR4 RAM                   |
| Storage         | Intel Optane P4800X 750 GB SSD    |
|                 | Dell Express PM1725a 1.6 TB SSD   |

Table 2: Testbed specification

Workloads For lightweight graph accesses, we use LinkBench [15], a Facebook benchmark based on its social graph interactive workloads. Besides its default configuration (DFLT) with 69% read and 31% write operations, we add a “read-mostly” workload (TAO) with 99.8% of reads, whose parameters are set according to the Facebook TAO paper [19]. All experiments start on a 32M-vertex, 140M-edge base graph generated by the LinkBench driver.

For real-time graph analytics, we use the interactive workload in LDBC Social Network Benchmark (SNB) [27], which simulates the users’ activities in a social network for a period of time. Its schema has 11 entities connected by 20 relations, with attributes of different types and values, providing a rich benchmark dataset. The SNB data generator is designed to produce directed labeled graphs that mimic the characteristics of real-world social graphs. We set 10 as the Scale Factor, with 30M vertices and 177M edges in the generated initial graph. Its requests are classified into three categories: short reads (similar to LinkBench), transactional updates (possibly involving multiple objects), and complex reads (multi-hop traversals and analytical processing including filters, aggregations, and joins). Finally, we run two popular iterative analytical algorithms on top of the generated graph, PageRank and Connected Components (ConnComp). PageRank runs for 20 iterations, while ConnComp runs till convergence.

Choice and rationale of the baselines For LinkBench, we first tested MySQL(v5.7.25) and MyRocks(v5.6.35) using their official adaptor, but found that inter-process communication between the server and client (benchmark driver) amplifies latencies. Thus we compare LiveGraph with three embedded implementations, \(^3\) LMDB(v0.9.22), RocksDB(v5.10.3), and Neo4j(v3.5.4), as representatives for using B+ tree, LSMT, and linked list respectively. This way we focus on comparing the impact of data structure choices. For Neo4j, we use its Core API rather than Cypher, to eliminate potential query language overhead. We build all the implementations with transactions, and the isolation levels are Read Committed for Neo4j, Snapshot Isolation for RocksDB and LiveGraph, and Serializable for LMDB (as it uses a single writer).

For SNB, besides graph databases including Neo4j [3], Stardog(v6.1.3) [5] and TigerGraph (Developer Edition v2.2.4) [25], we also compared with PostgreSQL(v10.7) [6] and Virtuoso(v7)\(^4\) [7], two relational databases. Stardog is based on the RDF model and uses a copy-on-write B+ tree similar to LMDB as the storage backend; TigerGraph is a proprietary graph database that provides the highest performance among graph databases according to a few benchmark reports [8, 50]; PostgreSQL is among one of the most popular relational databases for OLTP; Virtuoso is a multi-modal database that has published its own SNB results (and among existing systems offers state-of-the-art SNB implementation, based on our survey and experiments).

The implementations for these systems are included in the official SNB repository [9], except TigerGraph, whose implementation is from its own repository [10]. TigerGraph currently only implements read-only queries and the driver can only run one type of query each time rather than a mix of concurrent queries spawned.

\(^3\)We record traces collected from MySQL runs and replay them for each system. Thinking times (i.e. the time to generate each request) are also recorded and reproduced.

\(^4\)The feature/analytics branch from https://github.com/v7f asttrack/virtuoso-opensource.git which is about 10× faster than v7.2.5 from master branch.
## 7.2 Transactional Workloads

### In-memory Latency

First we evaluate transaction processing. Given their large differences, we list results in tables.

Tables 3 and 4 give the average latency measured from LMDB, RocksDB, and LiveGraph in memory, with the LinkBench TAO and DFLT workloads respectively, using 24 client threads for request generation and Optane/NAND SSD for transactional durability.

The results demonstrate LiveGraph’s significant performance advantage for both workloads. For the almost read-only TAO, LiveGraph improves the average latency by 2.77× from the runner-up (LMDB), TEL’s major advantage here comes from storing edges by time order, facilitating fast backward partial scans returning latest edges. This type of queries is not only common in social network workloads, but also natural in transactions accessing other graphs (such as traffic maps and financial records). Not only does this accelerate memory accesses, it also improves both spatial and temporal locality, achieving more effective prefetching. In addition, compared to B-trees and LSMTs, TEL has lower complexity for most operations, and avoids pointer chasing through the use of sequential data structures.

For DFLT, which contains 31% writes, LiveGraph remains a consistent winner across all categories. Due to its write-friendly sequential storage, its margin of advantage is even higher, beating the runner-ups in average, p99, and p999 latency by 2.84×, 2.47× and 3.59× respectively. Here LMDB suffers due to B+-tree’s higher insert complexity and its single-threaded writes, while both LiveGraph and RocksDB benefit from their write-friendly log-structured design. However, as DFLT’s majority of transactions are still reads, RocksDB’s overall performance is severely dragged down by its inferior read performance in memory.

LiveGraph has linear complexity (in terms of the size of the adjacency list) when searching for a single edge, as opposed to the logarithmic cost of B+-trees or LSMTs. However, these operations (i.e., read/update/delete a specific edge of a high-degree vertex) are rare in the two LinkBench workloads. In particular, insertions can usually (in more than 99.9% of the cases, as found by our profiling) skip such searches, thanks to early rejection enabled by its embedded Bloom filters. Therefore, these operations do not impact tail latency much. LiveGraph’s use of compaction also does not result in significantly higher tail latency than other systems. This is because its compaction only scans a small subset of blocks: the dirty vertex set maintained by each thread.

### Out-of-core Latency

Tables 5 and 6 list the out-of-core (OOC) results, enabled by limiting memory (using `cgroup` tools) to 4GB, which is about 16% of LiveGraph’s, 9% of LMDB’s and 28% of RocksDB’s memory usage. This cap is the minimal memory for RocksDB (OOC) results, enabled by limiting memory (using `cgroup` tools) to 4GB, which is about 16% of LiveGraph’s, 9% of LMDB’s and 28% of RocksDB’s memory usage. This cap is the minimal memory for RocksDB to run with 128 client threads while delivering its peak throughput.

RocksDB is optimized for OOC writes, by dumping sorted blocks of data sequentially and performing compression for better I/O bandwidth usage. LiveGraph’s design prioritizes reads instead. It performs sequential writes within an adjacency list but it does not ensure sequential storage of multiple dirty adjacency lists. It also issues smaller I/O by doing page write-back, with write size starting at 4KB, as opposed to the several MBs of RocksDB’s LSMT. Fortunately, low-latency SSDs like our Optane device or byte addressable NVM alleviate

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### Table 3: Latency w. LinkBench TAO in memory (ms)

| System   | LiveGraph | RocksDB | LMDB | LiveGraph | RocksDB | LMDB |
|----------|-----------|---------|------|-----------|---------|------|
| Storage  | Optane SSD | NAND SSD | Optane SSD | NAND SSD | Optane SSD | NAND SSD |
| mean     | 0.0639    | 0.0232  | 0.0109 | 0.0041    | 0.0030  | 0.0110 |
| P99      | 0.0705    | 0.0553  | 0.0162 | 0.0066    | 0.0581  | 0.0162 |
| P999     | 0.6763    | 4.8716  | 2.0703 | 0.6510    | 4.8776  | 2.1120 |

### Table 4: Latency w. LinkBench DFLT in memory (ms)

| System   | LiveGraph | RocksDB | LMDB | LiveGraph | RocksDB | LMDB |
|----------|-----------|---------|------|-----------|---------|------|
| Storage  | Optane SSD | NAND SSD | Optane SSD | NAND SSD | Optane SSD | NAND SSD |
| mean     | 0.0450    | 0.1278  | 1.6735 | 0.0915    | 0.1804  | 1.7495 |
| P99      | 0.2598    | 0.6423  | 35.041 | 0.5995    | 0.9518  | 36.783 |
| P999     | 0.9000    | 3.5190  | 74.610 | 1.2558    | 4.0214  | 77.906 |

### Table 5: Latency w. LinkBench TAO out of core (ms)

| System   | LiveGraph | RocksDB | LMDB | LiveGraph | RocksDB | LMDB |
|----------|-----------|---------|------|-----------|---------|------|
| Storage  | Optane SSD | NAND SSD | Optane SSD | NAND SSD | Optane SSD | NAND SSD |
| mean     | 0.0935    | 0.1342  | 2.8621 | 0.3507    | 0.4399  | 3.8909 |
| P99      | 0.7923    | 0.6364  | 23.569 | 5.0101    | 2.8969  | 43.4528 |
| P999     | 3.0133    | 3.5250  | 42.8470 | 24.2373   | 6.4884  | 73.5255 |

### Table 6: Latency w. LinkBench DFLT out of core (ms)

| System   | LiveGraph | RocksDB | LMDB | LiveGraph | RocksDB | LMDB |
|----------|-----------|---------|------|-----------|---------|------|
| Storage  | Optane SSD | NAND SSD | Optane SSD | NAND SSD | Optane SSD | NAND SSD |
| mean     | 0.0824    | 0.0420  | 0.0364 | 0.0882    | 0.1435  | 0.1556 |
| P99      | 0.2710    | 0.1135  | 0.3701 | 0.9625    | 1.0235  | 1.0269 |
| P999     | 1.1844    | 4.9366  | 3.3600 | 2.5922    | 5.2590  | 4.8174 |
such problems.

Test results confirm the rationale above. With the more read-heavy TAO, LiveGraph wins across the board, cutting average latency by 1.62× from the runner-up LMDB on Optane. On NAND SSD, RocksDB beats LMDB, being more bandwidth-efficient with its compression. Still its average latency is 1.63× higher than LiveGraph.

For DFLT, LiveGraph loses to the predicted winner RocksDB by being 10.99% slower on NAND SSD, but outperforms the latter by by 1.79× on the faster Optane SSD (though losing by up to 24.5% in the tail P99 categories there). Here we performed profiling to understand the closer LiveGraph-vs-RocksDB rivalry. RocksDB triggers 14.51× L3-cache misses than LiveGraph in memory and reads 1.06× data from disk out of core even if RocksDB turns compression on, but LiveGraph write 33% more data to disk due to its less sequential write and lack of compression.

Across the latency tests, by checking the top 2 finishers, it becomes apparent that among existing solutions, the B+-tree-based LMDB and LSMT-based RocksDB offer good performance under mixed and mostly-read workloads, respectively. However, when placed under unfavorable conditions, they switch places, with a 2× to 10× performance gap in between, for each latency category. LiveGraph, in contrast, provides clearly better performance both in memory and out of core with Optane SSD or with the TAO workload, only slightly losing to RocksDB with the OOC+DFLT+NAND combination, making it an appealing choice considering upcoming fast storage hardware.

**Scalability and Throughput** We examine the multi-core scalability of LiveGraph by running LinkBench with an increasing number of clients. Figure 8a gives the result. We can see that LiveGraph’s throughput scales smoothly with more cores being used until 24 clients, when all the physical cores are occupied. For TAO, the scalability curve is very close to the ideal one. For DFLT, the write-ahead-logging bottleneck makes it hard for LiveGraph to achieve perfect scalability. We expect the emergence of NVM devices and related logging protocols [16, 17] would resolve this issue.

We then saturate the systems to measure throughput under the two workloads, removing the think time between requests. Figure 6 and 8 show latency and throughput when increasing the number of clients from 24 (the number of cores in our server) until the peak throughput is reached, which required up to 256 clients.

For TAO (Figure 6), when in-memory on top of Optane (for durability), LMDB saturates at 32 clients (i.e., near to the number of physical cores) with a throughput of 3.24M requests/s, after which the contention on the single mutex intensifies. LiveGraph’s throughput keeps growing to 14.29M requests/s till 128 clients, strained by the context switch overhead afterwards. We get similar results with NAND.

Out of core, running TAO on top of Optane, RocksDB beats LMDB and arrives the peak point at 48 clients with a throughput of 584K requests/s, LiveGraph reaches 670K requests/s at 64 clients. With NAND, LiveGraph still improves the throughput by 1.36× from RocksDB.

For DFLT (Figure 8), RocksDB reaches 228K re-
requests/s in memory and saturates at 48 clients, when compaction starts to pause writes frequently and write/read amplification becomes more significant. By contrast, LiveGraph is able to push beyond 460K at 24 clients, as TEL does not have such limits. NAND SSD results are similar, showing LiveGraph 4.83× and 1.43× faster than the runners-up, respectively. Out of core with Optane, LiveGraph peaks at 300K requests/s with 32 client threads and RocksDB saturates at 212K with 48 clients. With NAND, LiveGraph reaches 95.8% of RocksDB’s peak throughput. When out of core, LiveGraph performs 28.4% less disk I/O than RocksDB (which must merge on-disk SSTs) and 54.0% less than LMDB for the TAO workload, 4.6% more than RocksDB and 73.4% less than LMDB for the DFLT workload.

**Memory consumption** Using our default compaction frequency every 65536 transactions, the DFLT workload, 24 client threads, and 12M transactions totally, LiveGraph consumed 24.9GB in total, against 44.8 GB and 14.4 GB for LMDB and RocksDB, respectively.

For LiveGraph, 706 MB space is recycled but not yet used at the end of the DFLT run. Of the allocated space, the aggregate over-provisioned space is about 4.6GB, leading to 81.2% final occupancy.

Figure 8b gives the TEL block count distribution at different sizes for this workload, which matches the power-law degree distribution among vertices [29], validating TEL’s “buddy-system” design.

Compaction is effective: when it is completely turned off, LiveGraph’s footprint sees a 33.7% increase, requiring 33.3GB space instead. Compaction only scans a small dirty set so its time overhead is fairly small: varying the compaction frequency brings insignificant changes in performance (<5%).

### 7.3 Real-Time Analytics Workloads

| System        | LiveGraph | Virtuoso | PostgreSQL | TigerGraph |
|---------------|-----------|----------|------------|------------|
| Complex-Only  | 9,106     | 292      | 3.79       | 185        |
| Overall       | 9,420     | 259      | 52.4       | –          |

Table 7: Throughput w. SNB in memory (ops/s)

**Real-time analytics** Table 7 gives the throughput measured from LiveGraph, Virtuoso, PostgreSQL and TigerGraph in memory, with only complex reads (referred to as C-O) and all three categories of requests (referred to as “Overall”) respectively, using 48 client threads for request generation and Optane SSD for persistence. The Overall workload uses SNB’s official mix: 7.26% complex queries, 63.82% short queries, and 28.91% updates. RocksDB and LMDB are skipped as (1) these two K-V stores do not have official SNB implementations and (2) our earlier micro-benchmark and LinkBench results of basic graph database operations (upon which more complex queries are built) significantly lags behind LiveGraph. We only report TigerGraph’s Complex-Only result as its implementation for update requests is still absent.⁵

LiveGraph outperforms the runner-up, Virtuoso, by 31.19× and 36.43×, producing gains far larger than those observed in microbenchmarks or LinkBench. Meanwhile, Virtuoso beats TigerGraph by 1.58×, also PostgreSQL by 77.05× and 4.94×. We noticed that TigerGraph suffered from Complex Read 14 due of its under-optimized implementation for this query. Excluding this request, it can reach 717.77 ops/s, which would outperform Virtuoso but still be an order of magnitude slower than LiveGraph.

We found fast edge scans are even more critical with complex analytics workloads. This also explains how PostgreSQL hurts badly as it doesn’t support clustered index [11]. Secondly, MVCC is crucial for fast analytics, when these complex queries are mixed with write transactions. Compared to C-O, Overall has more short queries/updates, therefore LiveGraph and PostgreSQL both produce higher throughput (the reason for LiveGraph’s small C-O vs. Overall difference being that Overall is more write-intensive and throughput is limited by persisting WAL). Virtuoso, on the other hand, performs worse by spending over 60% of its CPU time on locks. Of course, MVCC comes with its space overhead: for this workload LiveGraph consumes about 30GB, PostgreSQL 19GB, and Virtuoso only stores 8.3GB. Compared to PostgreSQL, which also performs MVCC, LiveGraph’s space overhead comes from its longer timestamps, plus its overprovisioning in adjacency lists (key design that helps it achieve outstanding query performance).

One may argue that Virtuoso’s smaller memory footprint helps with out-of-core execution. Table 8 (with 3GB DRAM cap on Optane) shows heavy performance hit for both LiveGraph and Virtuoso when going out-of-core, and the gap between them does shrink. However, LiveGraph is still an order of magnitude better, and for the Overall mix, beats Virtuoso’s in-memory performance by 1.35×.

Again, though results not listed, Neo4j or Stardog lose to all three systems by another 2-3 orders of magnitude. This is in part due to their use of Java, which is not ideal for data-intensive workloads, and in part because of their choice of data structures: Neo4j uses linked list and Stardog builds on copy-on-write B-Trees similar to LMDB. Our examination reveals that multi-hop graph queries dramatically stress Java’s garbage collection.

**Query case study** Due to space limit, we present brief

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⁵Actually like LMDB, TigerGraph allows at most one write transaction. Hence we expect its Overall performance inferior to PostgreSQL and Virtuoso, both allowing multiple concurrent writers.
## 7.4 Iterative Long-Running Analytics

Finally, we evaluate LiveGraph’s capability of performing iterative long-running analytics directly within its primary graph store. Table 10 presents its performance in running two common graph algorithms, PageRank and Connected Components (ConnComp), on a subgraph (with 3.88M edges) of the SNB SF10 dataset, involving all the Person nodes and their relationships.

LiveGraph performs iterative analyses directly on the latest snapshot, finishing both tasks under 300 milliseconds, using 24 threads. For comparison, we give the results of Gemini [63], a state-of-the-art graph engine dedicated to such static graph analytics. Without the compact yet immutable CSR-based graph storage, LiveGraph manages to reach 58.6% and 24.6% of Gemini’s performance, for PageRank and ConnComp respectively. In addition, to enjoy Gemini’s professional processing, one has to export to its data format, then load the graph into its memory. We measured this ETL overhead (converting from TEL to CSR) for the specific graph to be 1520ms, much outweighing the PageRank/ConnComp execution time, not to mention the difference between LiveGraph and Gemini.

### 8 Related Work

#### Transactional Systems

Graph databases can be grouped into two broad categories. Native graph databases [3, 12, 13, 14] are designed from scratch for storing/querying graphs. Non-naive graph databases store graphs using the general-purpose stores, sometimes using a layer on top of existing RDBMS or key-value stores [19, 54, 7, 33, 26].

All these systems support transactional graph workloads and some systems support analytical graph workloads. As discussed in the motivation, these systems which are designed with tree-based [12, 13, 19, 54, 7, 33, 36, 35, 26] or pointer-based [3] data structures require pointer chasing for adjacency list scans, which is a major limitation. Even state-of-the-art systems designed for low latency do not support purely sequential scans [20].

There are some attempts [36, 30, 35, 62] that try to improve the analytical performance of existing transactional systems. These systems generally compare with and offer comparable performance as GraphLab, while reducing loading time. However, GraphLab is not a state-of-the-art baseline, as shown by existing literature [52, 45, 63].

#### Analytics on Dynamic Graphs

Several graph engines support graph analytics over an evolving graph, to study their evolution or to update computation results incrementally. These systems are mainly designed for analytics. Unlike LiveGraph, they either do not provide transactional support, or they do it only in rudimentary form.

Kineograph [23] supports incremental graph analysis, by periodically applying updates and generating snapshots. Chronos [34] and ImmortalGraph [43] are designed to analyze graph evolution, processing a sequence of predefined, read-only graph snapshots. LLAMA [42] applies incoming updates in batches and creates copy-on-write delta snapshots dynamically for temporal graph analysis. Grace [48] supports transactional updates but uses an expensive copy-on-write technique: every time
an adjacency list is modified, the entire list is copied to
the tail of the edge log. This makes scans purely sequen-
tial but it also makes updates very expensive, especially
for high-degree vertices. GraphOne [38] serializes edge
updates simply by appending them onto a single edge
log. It does not provide durability. Updates are trans-
ferred to adjacency lists periodically. Scans to the latest
version of an adjacency list need to scan the entire graph-
wide update log.

These systems focused primarily on graph analysis.
LiveGraph, on the other hand, supports real-time trans-
actional workloads with better performance than existing
graph databases, while supporting whole-graph analyt-
ic on the same primary graph store. Also, incremental
analytics techniques above can readily be incorporated,
leveraging LiveGraph’s multi-versioning mechanism.

Graph engines Graph engines perform analytical pro-
cessing, such as graph processing [31, 32, 63, 52, 45,
55, 60] or graph mining [58, 56, 21]. Their design
assumes an immutable graph topology, hence widely
adopting read-optimized CSR/CSC representations. As
discussed earlier, this delivers superior analytics perform-
ance, but does not tolerate updates/insertions. Hence
existing graph engines have been limited to processing
static, stale snapshots dumped from the data source. In
contrast, LiveGraph supports direct analytics on dynamic
graphs without costly ETL operations.

9 Conclusion and Future Work

Our work shows that it is possible to design graph data
management systems that are fast at both transactional
and analytical workloads. The key is using data struc-
tures that are tailored to the operations of graph work-
loads, as well as associated algorithms for transactional
support. Our evaluation confirms the strength of Live-
Graph as a potential all-around choice across multiple
graph workloads.

LiveGraph’s design is amenable to scaling out, lever-
egaging techniques in distributed graph query process-
ing [51, 61, 26] and distributed transaction manage-
ment [47, 24, 18, 26]. In addition, LiveGraph can be ex-
tended in another direction: the multi-versioning nature
of TELs makes it natural to support temporal graph pro-
cessing [34, 43], with modifications to the compaction
algorithm to efficiently store and index older graph ver-
sions.

6Deletion in algorithms like K-Core or SCC is done by putting
down “tombstones” rather than actually removing vertices/edges.

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